Drools Planner User Guide

Version 5.6.0.Final

by *The JBoss Drools team* [http://www.jboss.org/drools/team.html]

Drools Planner

Chapter 1. Planner introduction

1.1. What is Drools Planner?

***Drools Planner* [http://www.jboss.org/drools/drools-planner] is a lightweight, embeddable planning engine that optimizes planning problems.** It solves use cases, such as:

- **Employee shift rostering**: timetabling nurses, repairmen, ...
- **Agenda scheduling**: scheduling meetings, appointments, maintenance jobs, advertisements, ...
- **Educational timetabling**: scheduling lessons, courses, exams, conference presentations, ...
- **Vehicle routing**: planning vehicles (trucks, trains, boats, airplanes, ...) with freight and/or people
- **Bin packing**: filling containers, trucks, ships and storage warehouses, but also cloud computers nodes, ...
- **Job shop scheduling**: planning car assembly lines, machine queue planning, workforce task planning, ...
- **Cutting stock**: minimizing waste while cutting paper, steel, carpet, ...
- **Sport scheduling**: planning football leagues, baseball leagues, ...
- **Financial optimization**: investment portfolio optimization, risk spreading, ...

Every organization faces planning problems: provide products and services with a limited set of *constrained* resources (employees, assets, time and money).

Drools Planner helps normal Java^{TM} programmers solve planning problems efficiently. Under the hood, it combines optimization heuristics and metaheuristics with very efficient score calculation.

Drools Planner, like the rest of Drools, is business-friendly *open source* software under *the Apache Software License 2.0* [http://www.apache.org/licenses/LICENSE-2.0] (*layman's explanation* [http://www.apache.org/foundation/licence-FAQ.html#WhatDoesItMEAN]). It is 100% pure Java^{TM} and runs on any JVM.

1.2. What is a planning problem?

1.2.1. A planning problem is NP-complete

All the use cases above are *probably* NP-complete [http://en.wikipedia.org/wiki/NP-complete]. In layman's terms, this means:

- It's easy to verify a given solution to a problem in reasonable time.

- There is no silver bullet to find the optimal solution of a problem in reasonable time (*).

Note

(*) At least, none of the smartest computer scientists in the world have found such a silver bullet yet. But if they find one for 1 NP-complete problem, it will work for every NP-complete problem.

In fact, there's a $ 1,000,000 reward for anyone that proves if *such a silver bullet actually exists or not* [http://en.wikipedia.org/wiki/P_%3D_NP_problem].

The implication of this is pretty dire: solving your problem is probably harder than you anticipated, because the 2 common techniques won't suffice:

- A brute force algorithm (even a smarter variant) will take too long.
- A quick algorithm, for example in bin packing, *putting in the largest items first*, will return a solution that is usually far from optimal.

By using advanced optimization algorithms, **Planner does find a good solution in reasonable time for such planning problems.**

1.2.2. A planning problem has (hard and soft) constraints

Usually, a planning problem has at least 2 levels of constraints:

- A *(negative) hard constraint* must not be broken. For example: *1 teacher can not teach 2 different lessons at the same time*.
- A *(negative) soft constraint* should not be broken if it can be avoided. For example: *Teacher A does not like to teach on Friday afternoon*.

Some problems have positive constraints too:

- A *positive soft constraint (or reward)* should be fulfilled if possible. For example: *Teacher B likes to teach on Monday morning*.

Some toy problems (such as N Queens) only have hard constraints. Some problems have 3 or more levels of constraints, for example hard, medium and soft constraints.

These constraints define the *score calculation* (AKA *fitness function*) of a planning problem. Each solution of a planning problem can be graded with a score. **With Planner, score constraints are written in an Object Orientated language, such as Java code or Drools rules**. Such code is easy, flexible and scalable.

1.2.3. A planning problem has a huge search space

A planning problem has a number of *solutions*. There are several categories of solutions:

- A *possible solution* is any solution, whether or not it breaks any number of constraints. Planning problems tend to have an incredibly large number of possible solutions. Many of those solutions are worthless.
- A *feasible solution* is a solution that does not break any (negative) hard constraints. The number of feasible solutions tends to be relative to the number of possible solutions. Sometimes there are no feasible solutions. Every feasible solution is a possible solution.
- An *optimal solution* is a solution with the highest score. Planning problems tend to have 1 or a few optimal solutions. There is always at least 1 optimal solution, even in the case that there are no feasible solutions and the optimal solution isn't feasible.
- The *best solution found* is the solution with the highest score found by an implementation in a given amount of time. The best solution found is likely to be feasible and, given enough time, it's an optimal solution.

Counterintuitively, the number of possible solutions is huge (if calculated correctly), even with a small dataset. As you can see in the examples, most instances have a lot more possible solutions than the minimal number of atoms in the known universe (10^80). Because there is no silver bullet to find the optimal solution, any implementation is forced to evaluate at least a subset of all those possible solutions.

Drools Planner supports several optimization algorithms to efficiently wade through that incredibly large number of possible solutions. Depending on the use case, some optimization algorithms perform better than others, but it's impossible to tell in advance. **With Planner, it is easy to switch the optimization algorithm**, by changing the solver configuration in a few lines of XML or code.

1.3. Status of Drools Planner

Drools Planner is production ready. The API is almost stable but backward incompatible changes can occur. With the recipe called `UpgradeFromPreviousVersionRecipe.txt` [https://github.com/droolsjbpm/drools-planner/blob/master/drools-planner-distribution/src/main/assembly/filtered-resources/UpgradeFromPreviousVersionRecipe.txt] you can easily upgrade to a newer version and quickly deal with any backwards incompatible changes. That recipe file is included in every release.

1.4. Download and run the examples

1.4.1. Get the release zip and run the examples

To try it now:

- Download a release zip of Drools Planner from *the Drools download site* [http://www.jboss.org/drools/downloads.html].
- Unzip it.

- Open the directory `examples` and run the script.

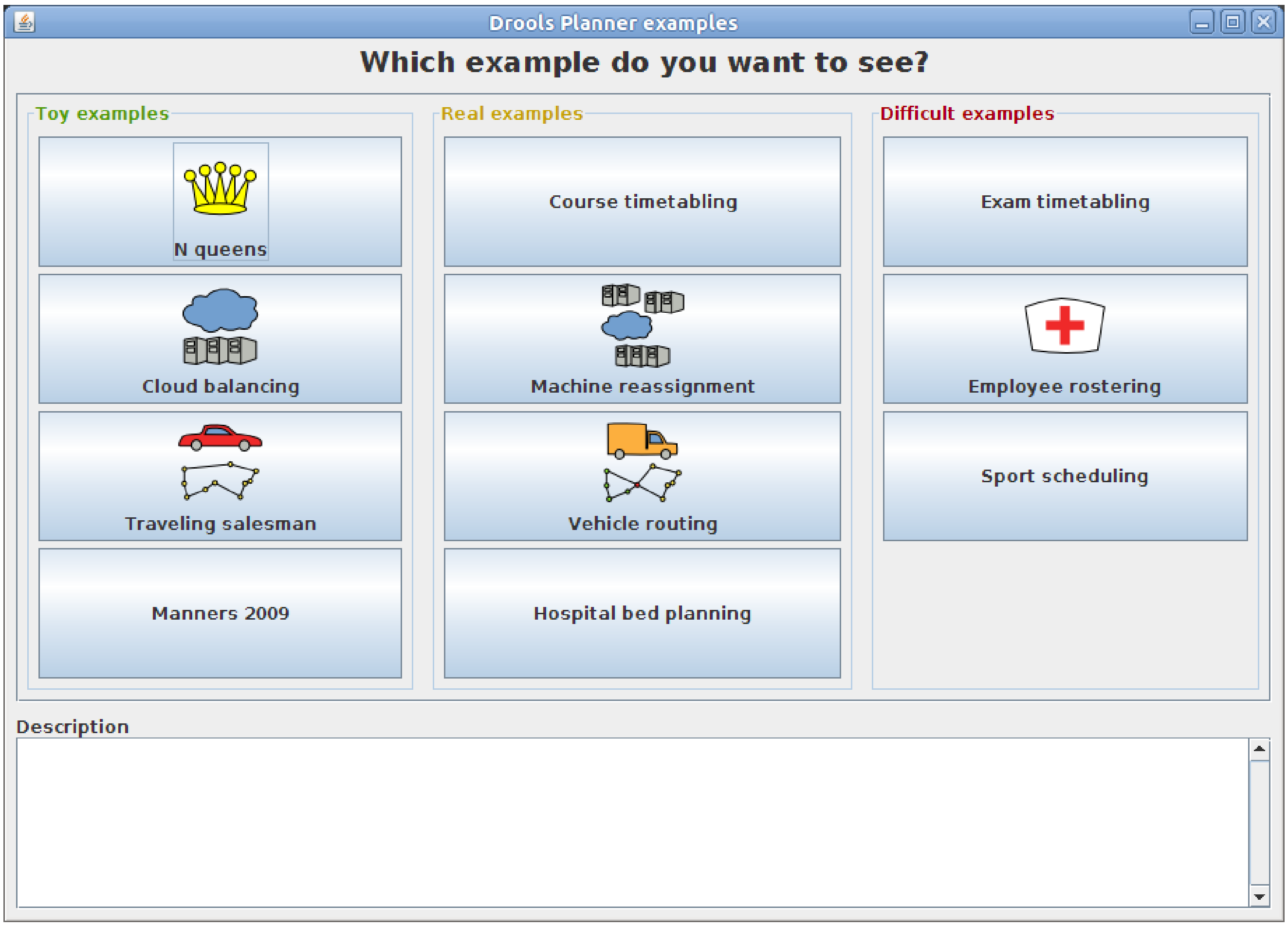
  Linux or Mac:

```
$ cd examples
$ ./runExamples.sh
```

  Windows:

```
$ cd examples
$ runExamples.bat
```

The Examples GUI application will open. Just pick an example:



Note

Planner itself has no GUI dependencies. It runs just as well on a server or a mobile JVM as it does on the desktop.

1.4.2. Run the examples in an IDE (IntelliJ, Eclipse, NetBeans)

To run the examples in your favorite IDE, first configure your IDE:

- In IntelliJ and NetBeans, just open the file `examples/sources/pom.xml` as a new project, the maven integration will take care of the rest.
- In Eclipse, open a new project for the directory `examples/sources`.
  - Add all the jars to the classpath from the directory `binaries` and the directory `examples/binaries`, except for the file `examples/binaries/drools-planner-examples-*.jar`.
  - Add the Java source directory `src/main/java` and the Java resources directory `src/main/resources`.

Next, create a run configuration:

- Main class: `org.drools.planner.examples.app.DroolsPlannerExamplesApp`
- VM parameters (optional): `-Xmx512M -server`
- Working directory: `examples` (this is the directory that contains the directory `data`)

1.4.3. Use Drools Planner with maven, gradle, ivy, buildr or ANT

The Drools Planner jars are available in *the central maven repository* [http://search.maven.org/#search|ga|1|org.drools.planner] (and also in *the JBoss maven repository* [https://repository.jboss.org/nexus/index.html#nexus-search;gav~org.drools.planner~~~~]).

If you use maven, just add a dependency to `drools-planner-core` in your project's `pom.xml`:

```
    <dependency>
      <groupId>org.drools.planner</groupId>
      <artifactId>drools-planner-core</artifactId>
      <version>...</version>
    </dependency>
```

This is similar for gradle, ivy and buildr. To identify the latest version, check *the central maven repository* [http://search.maven.org/#search|ga|1|org.drools.planner].

If you're still using ant (without ivy), copy all the jars from the download zip's `binaries` directory and manually verify that your classpath doesn't contain duplicate jars.

Note

The download zip's `binaries` directory contains far more jars then `drools-planner-core` actually uses. It also contains the jars used by other modules, such as `drools-planner-benchmark`.

Check the maven repository `pom.xml` files to determine the minimal dependency set for a specific version of a specific module.

1.4.4. Build Drools Planner from source

You can also easily build Drools Planner from source yourself.

Set up Git [http://help.github.com/set-up-git-redirect] and clone `drools-planner` from GitHub (or alternatively, download *the zipball* [https://github.com/droolsjbpm/drools-planner/zipball/master]):

```
$ git clone git@github.com:droolsjbpm/drools-planner.git drools-planner
...
```

Then do a *Maven 3* [http://maven.apache.org/] build:

```
$ cd drools-planner
$ mvn -DskipTests clean install
...
```

After that, you can run any example directly from the command line, just run this command and pick an example:

```
$ cd drools-planner-examples
$ mvn exec:exec
...
```

1.5. Questions, issues and blog

Your questions and comments are welcome on *the user mailing list* [http://www.jboss.org/drools/lists.html]. Start the subject of your mail with `[planner]`. You can read/write to the user mailing list without littering your mailbox through *this web forum* [http://drools.46999.n3.nabble.com/Drools-User-forum-f47000.html] or *this newsgroup* [nntp://news.gmane.org/gmane.comp.java.drools.user].

Feel free to report an issue (such as a bug, improvement or a new feature request) for the Drools Planner code or for this manual to *the drools issue tracker* [https://jira.jboss.org/jira/browse/JBRULES]. Select the component `drools-planner`.

Pull requests (and patches) are very welcome and get priority treatment! Include the pull request link to a JIRA issue and optionally send a mail to the dev mailing list to get the issue fixed fast. By open sourcing your improvements, you 'll benefit from our peer review and from our improvements made upon your improvements.

Check *our blog* [http://blog.athico.com/search/label/planner], Google+(*Drools Planner* [https://plus.google.com/112724449845406009021], *Geoffrey De Smet* [https://plus.google.com/112811208792575157490]) and twitter (*Geoffrey De Smet* [http://twitter.com/geoffreydesmet]) for news and articles. If Drools Planner helps you solve your problem, don't forget to blog or tweet about it!

Chapter 2. Quick start

2.1. Cloud balancing tutorial

2.1.1. Problem statement

Suppose your company owns a number of cloud computers and needs to run a number of processes on those computers. Assign each process to a computer under the following 4 constraints.

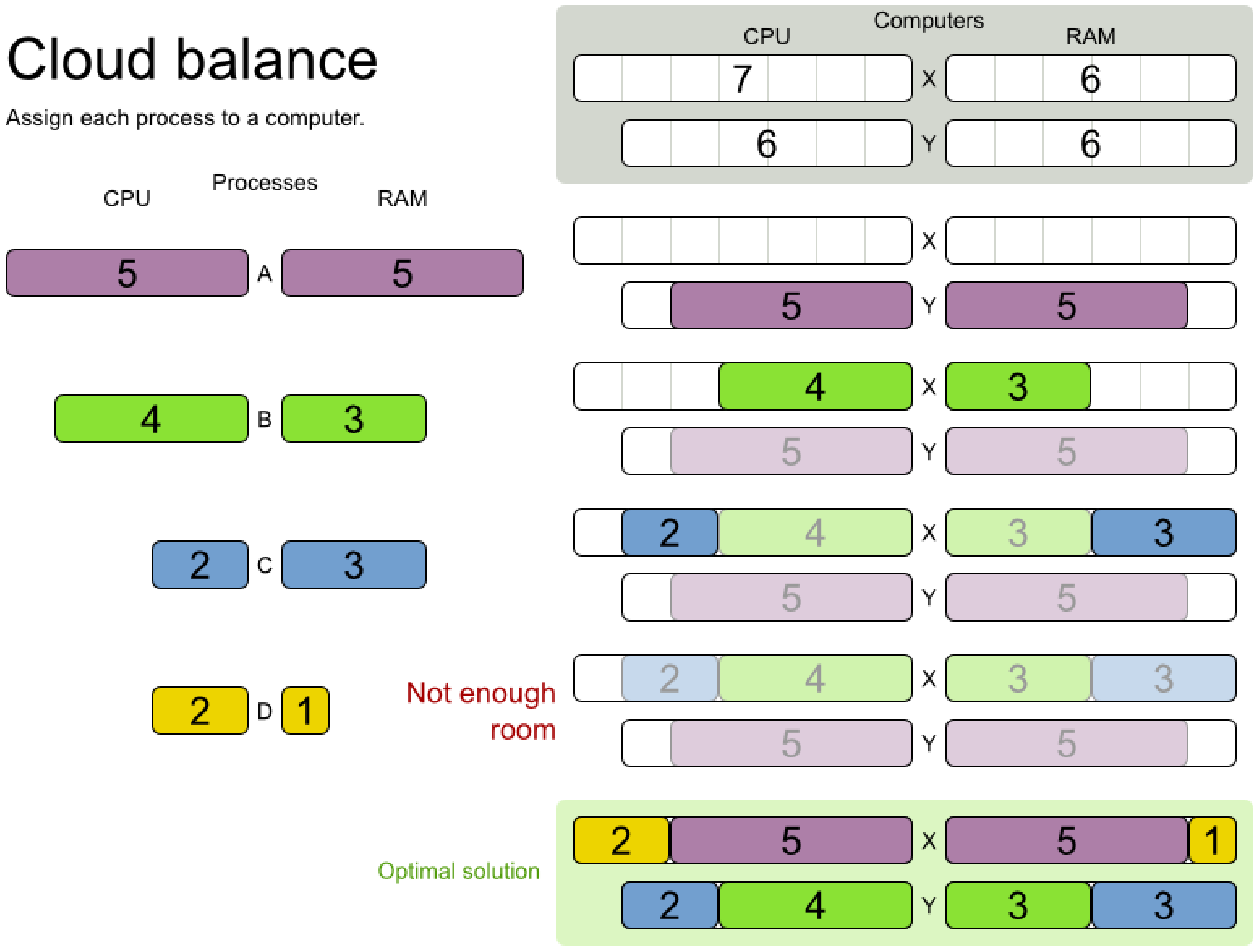
Hard constraints which must be fulfilled:

- Every computer must be able to handle the minimum hardware requirements of the sum of its processes:
  - The CPU power of a computer must be at least the sum of the CPU power required by the processes assigned to that computer.
  - The RAM memory of a computer must be at least the sum of the RAM memory required by the processes assigned to that computer.
  - The network bandwidth of a computer must be at least the sum of the network bandwidth required by the processes assigned to that computer.

Soft constraints which should be optimized:

- Each computer that has one or more processes assigned, incurs a maintenance cost (which is fixed per computer).
  - Minimize the total maintenance cost.

How would you do that? This problem is a form of *bin packing*. Here's a simplified example where we assign 4 processes to 2 computers with 2 constraints (CPU and RAM) with a simple algorithm:



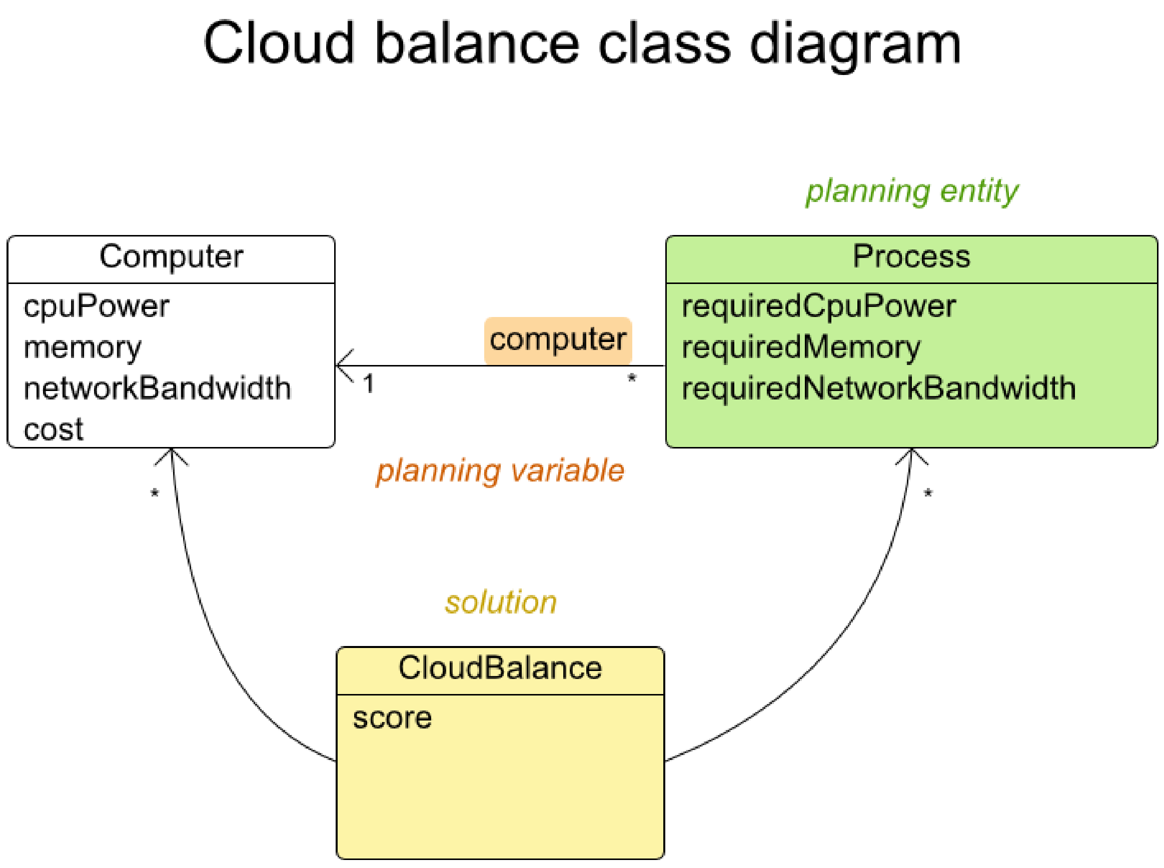
The simple algorithm used here is the *First Fit Decreasing* algorithm, which assigns the bigger processes first and assigns the smaller processes to the remaining space. As you can see, it's not optimal, because it does not leave enough room to assign the yellow process D.

Drools Planner does find the more optimal solution fast, by using additional, smarter algorithms. And it scales too: both in data (more processes, more computers) and constraints (more hardware requirements, other constraints). So let's take a look how we can use Planner for this.

2.1.2. Domain model diagram

Let's start by taking a look at the domain model. It's pretty simple:

- `Computer`: represents a computer with certain hardware (CPU power, RAM memory, network bandwidth) and maintenance cost.
- `Process`: represents a process with a demand. Needs to be assigned to a `Computer` by Drools Planner.
- `CloudBalance`: represents a problem. Contains every `Computer` and `Process` for a certain data set.



In the UML class diagram above, the Planner concepts are already annotated:

- Planning entity: the class (or classes) that changes during planning. In this example that's the class `Process`.
- Planning variable: the property (or properties) of a planning entity class that changes during planning. In this examples, that's the property `computer` on the class `Process`.
- Solution: the class that represents a data set and contains all planning entities. In this example that's the class `CloudBalance`.

2.1.3. Main method

Try it yourself. *Download and configure the examples in your favorite IDE.* Run `org.drools.planner.examples.cloudbalancing.app.CloudBalancingHelloWorld`. By default, it is configured to run for 120 seconds. It will execute this code:

Example 2.1. CloudBalancingHelloWorld.java

```
public class CloudBalancingHelloWorld {
    public static void main(String[] args) {
        // Build the Solver
        SolverFactory solverFactory = new XmlSolverFactory(
                           "/org/drools/planner/examples/cloudbalancing/solver/
cloudBalancingSolverConfig.xml");
        Solver solver = solverFactory.buildSolver();

        // Load a problem with 400 computers and 1200 processes
        CloudBalance unsolvedCloudBalance = new CloudBalancingGenerator().createCloudBalance(40

        // Solve the problem
        solver.setPlanningProblem(unsolvedCloudBalance);
        solver.solve();
      CloudBalance solvedCloudBalance = (CloudBalance) solver.getBestSolution();

        // Display the result
         System.out.println("\nSolved cloudBalance with 400 computers and 1200
 processes:\n"
                + toDisplayString(solvedCloudBalance));
    }

    ...

}
```

The code above does this:

- Build the `Solver` based on a solver configuration (in this case an XML file).

```
        SolverFactory solverFactory = new XmlSolverFactory(
                         "/org/drools/planner/examples/cloudbalancing/solver/
cloudBalancingSolverConfig.xml");
        Solver solver = solverFactory.buildSolver();
```

- Load the problem. `CloudBalancingGenerator` generates a random problem: you'll replace this with a class that loads a real problem, for example from a database.

```
        CloudBalance unsolvedCloudBalance = new CloudBalancingGenerator().createCloudBalance(
```

- Solve the problem.

```
        solver.setPlanningProblem(unsolvedCloudBalance);
        solver.solve();
        CloudBalance solvedCloudBalance = (CloudBalance) solver.getBestSolution();
```

- Display the result.

```
        System.out.println("\nSolved cloudBalance with 400 computers and 1200
processes:\n"
                + toDisplayString(solvedCloudBalance));
```

The only non-obvious part is building the `Solver`. Let's examine that.

2.1.4. Solver configuration

Take a look at the solver configuration:

Example 2.2. cloudBalancingSolverConfig.xml

```
<?xml version="1.0" encoding="UTF-8"?>
<solver>
  <!--<environmentMode>DEBUG</environmentMode>-->

  <!-- Domain model configuration -->
<solutionClass>org.drools.planner.examples.cloudbalancing.domain.CloudBalance</
solutionClass>
<planningEntityClass>org.drools.planner.examples.cloudbalancing.domain.CloudProcess</
planningEntityClass>

  <!-- Score configuration -->
  <scoreDirectorFactory>
    <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>

solver.score.CloudBalancingSimpleScoreCalculator</
simpleScoreCalculatorClass>
              <!--<scoreDrl>/org/drools/planner/examples/cloudbalancing/solver/
cloudBalancingScoreRules.drl</scoreDrl>-->
  </scoreDirectorFactory>

  <!-- Optimization algorithms configuration -->
  <termination>
    <maximumSecondsSpend>120</maximumSecondsSpend>
  </termination>
  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT_DECREASING</constructionHeuristicType>

<constructionHeuristicPickEarlyType>FIRST_LAST_STEP_SCORE_EQUAL_OR_IMPROVING</
constructionHeuristicPickEarlyType>
  </constructionHeuristic>
  <localSearch>
    <acceptor>
      <planningEntityTabuSize>7</planningEntityTabuSize>
    </acceptor>
    <forager>
      <minimalAcceptedSelection>1000</minimalAcceptedSelection>
    </forager>
  </localSearch>
</solver>
```

This solver configuration consists out of 3 parts:

- **Domain model configuration**: What can Planner change? We need to make Planner aware of our domain classes:

```
<solutionClass>org.drools.planner.examples.cloudbalancing.domain.CloudBalance</
  solutionClass>
<planningEntityClass>org.drools.planner.examples.cloudbalancing.domain.CloudProcess</
  planningEntityClass>
```

- **Score configuration**: How should Planner optimize the planning variables? Since we have hard and soft constraints, we use a `HardAndSoftScore`. But we also need to tell Planner how to calculate such the score, depending on our business requirements. Further down, we 'll look into 2 alternatives to calculate the score: using a simple Java implementation or using Drools DRL.

```
    <scoreDirectorFactory>
      <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>

olver.score.CloudBalancingSimpleScoreCalculator</
  simpleScoreCalculatorClass>
              <!--<scoreDrl>/org/drools/planner/examples/cloudbalancing/solver/
  cloudBalancingScoreRules.drl</scoreDrl>-->
    </scoreDirectorFactory>
```

- **Optimization algorithms configuration**: How should Planner optimize it? Don't worry about this for now: this is a good default configuration that works on most planning problems. It will already surpass human planners and most in-house implementations. Using the Planner benchmark toolkit, you can tweak it to get even better results.

```
    <termination>
      <maximumSecondsSpend>120</maximumSecondsSpend>
    </termination>
    <constructionHeuristic>
```

```
                                 <constructionHeuristicType>FIRST_FIT_DECREASING</
    constructionHeuristicType>

<constructionHeuristicPickEarlyType>FIRST_LAST_STEP_SCORE_EQUAL_OR_IMPROVING</
    constructionHeuristicPickEarlyType>
      </constructionHeuristic>
      <localSearch>
        <acceptor>
          <planningEntityTabuSize>7</planningEntityTabuSize>
        </acceptor>
        <forager>
          <minimalAcceptedSelection>1000</minimalAcceptedSelection>
        </forager>
      </localSearch>
```

Let's examine the domain model classes and the score configuration.

2.1.5. Domain model implementation

2.1.5.1. The class `Computer`

The class `Computer` is a POJO (Plain Old Java Object), nothing special. Usually, you'll have more of these kind of classes.

Example 2.3. CloudComputer.java

```
public class CloudComputer ... {

    private int cpuPower;
    private int memory;
    private int networkBandwidth;
    private int cost;

    ... // getters
}
```

2.1.5.2. The class `Process`

The class `Process` is a little bit special. We need to tell Planner that it can change the field `computer`, so we annotate the class with `@PlanningEntity` and the getter `getComputer` with `@PlanningVariable`:

Example 2.4. CloudProcess.java

```
@PlanningEntity(...)
public class CloudProcess ... {
    private int requiredCpuPower;
    private int requiredMemory;
    private int requiredNetworkBandwidth;

    private CloudComputer computer;

    ... // getters

    @PlanningVariable(...)
    @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "computerList"
    public CloudComputer getComputer() {
        return computer;
    }

    public void setComputer(CloudComputer computer) {
        computer = computer;
    }

    // ************************************************************************
    // Complex methods
    // ************************************************************************

    public CloudProcess clone() {
        CloudProcess clone = new CloudProcess();
        clone.id = id;
        clone.requiredCpuPower = requiredCpuPower;
        clone.requiredMemory = requiredMemory;
        clone.requiredNetworkBandwidth = requiredNetworkBandwidth;
        clone.computer = computer;
        return clone;
    }

    ...

}
```

The values that Planner can choose from for the field `computer`, are retrieved from a method on the `Solution` implementation: `CloudBalance.getComputerList()` which returns a list of all computers in the current data set. We tell Planner about this by using the annotation `@ValueRange`.

The method `clone()` is used by the class `CloudBalance`.

2.1.5.3. The class `CloudBalance`

The class `CloudBalance` implements the `Solution` interface. It holds a list of all computers and processes. We need to tell Planner how to retrieve the collection of process which it can change, so we need to annotate the getter `getProcessList` with `@PlanningEntityCollectionProperty`.

The `CloudBalance` class also has a property `score` which is the `Score` of that `Solution` instance in it's current state:

Example 2.5. CloudBalance.java

```java
public class CloudBalance ... implements Solution<HardAndSoftScore> {

    private List<CloudComputer> computerList;

    private List<CloudProcess> processList;

    private HardAndSoftScore score;

    public List<CloudComputer> getComputerList() {
        return computerList;
    }

    @PlanningEntityCollectionProperty
    public List<CloudProcess> getProcessList() {
        return processList;
    }

    ...

    public HardAndSoftScore getScore() {
        return score;
    }

    public void setScore(HardAndSoftScore score) {
        this.score = score;
    }

    // ************************************************************************
    // Complex methods
    // ************************************************************************

    public Collection<? extends Object> getProblemFacts() {
        List<Object> facts = new ArrayList<Object>();
        facts.addAll(computerList);
        // Do not add the planning entity's (processList) because that will
 be done automatically
        return facts;
    }

    /**
     * Clone will only deep copy the {@link #processList}.
     */
    public CloudBalance cloneSolution() {
        CloudBalance clone = new CloudBalance();
        clone.id = id;
        clone.computerList = computerList;
        List<CloudProcess> clonedProcessList = new ArrayList<CloudProcess>(
                processList.size());
        for (CloudProcess process : processList) {
            CloudProcess clonedProcess = process.clone();
            clonedProcessList.add(clonedProcess);
        }
        clone.processList = clonedProcessList;
        clone.score = score;
        return clone;
    }

    ...

}
```

The method `getProblemFacts()` is only needed for score calculation with Drools. It's not needed for the other score calculation types.

The method `clone()` is required. Planner uses it to make a clone of the best `Solution` in encounters during search.

2.1.6. Score configuration

Planner will search for the `Solution` with the highest `Score`. We're using a `HardAndSoftScore`, which means Planner will look for the solution with no hard constraints broken (fulfill hardware requirements) and as little as possible soft constraints broken (minimize maintenance cost).

There are several ways to implement the score function:

- Simple Java
- Incremental Java
- Drools

Let's take a look look at 2 different implementations:

2.1.6.1. Simple Java score configuration

One way to define a score function is to implement the interface `SimpleScoreCalculator` in plain Java.

```
  <scoreDirectorFactory>
    <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>
```

```
solver.score.CloudBalancingSimpleScoreCalculator</
    simpleScoreCalculatorClass>
      </scoreDirectorFactory>
```

Just implement the method `calculateScore(Solution)` to return a `DefaultHardAndSoftScore` instance.

Example 2.6. CloudBalancingSimpleScoreCalculator.java

```
public class CloudBalancingSimpleScoreCalculator implements SimpleScoreCalculator<CloudBalance>

    /**
     * A very simple implementation. The double loop can easily be removed by using Maps as sho
     * {@link CloudBalancingMapBasedSimpleScoreCalculator#calculateScore(CloudBalance)}.
     */
    public HardAndSoftScore calculateScore(CloudBalance cloudBalance) {
        int hardScore = 0;
        int softScore = 0;
        for (CloudComputer computer : cloudBalance.getComputerList()) {
            int cpuPowerUsage = 0;
            int memoryUsage = 0;
            int networkBandwidthUsage = 0;
            boolean used = false;

            // Calculate usage
            for (CloudProcess process : cloudBalance.getProcessList()) {
                if (computer.equals(process.getComputer())) {
                    cpuPowerUsage += process.getRequiredCpuPower();
                    memoryUsage += process.getRequiredMemory();
                networkBandwidthUsage += process.getRequiredNetworkBandwidth();
                    used = true;
                }
            }

            // Hard constraints
            int cpuPowerAvailable = computer.getCpuPower() - cpuPowerUsage;
            if (cpuPowerAvailable < 0) {
                hardScore += cpuPowerAvailable;
            }
            int memoryAvailable = computer.getMemory() - memoryUsage;
            if (memoryAvailable < 0) {
                hardScore += memoryAvailable;
            }
            int networkBandwidthAvailable = computer.getNetworkBandwidth() - networkBandwidthUs
            if (networkBandwidthAvailable < 0) {
                hardScore += networkBandwidthAvailable;
            }

            // Soft constraints
            if (used) {
                softScore -= computer.getCost();
            }
        }
        return DefaultHardAndSoftScore.valueOf(hardScore, softScore);
    }

}
```

Even if we optimize the code above to use `Maps` to iterate through the `processList` only once, **it is still slow** because it doesn't do incremental score calculation. To fix that, either use an incremental Java score function or a Drools score function. Let's take a look at the latter.

2.1.6.2. Drools score configuration

To use the Drools rule engine as a score function, simply add a `scoreDrl` resource in the classpath:

```
  <scoreDirectorFactory>
    <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>
                  <scoreDrl>/org/drools/planner/examples/cloudbalancing/solver/
cloudBalancingScoreRules.drl</scoreDrl>
  </scoreDirectorFactory>
```

First, we want to make sure that all computers have enough CPU, RAM and network bandwidth to support all their processes, so we make these hard constraints:

Example 2.7. cloudBalancingScoreRules.drl - hard constraints

```
...

import org.drools.planner.examples.cloudbalancing.domain.CloudBalance;
import org.drools.planner.examples.cloudbalancing.domain.CloudComputer;
import org.drools.planner.examples.cloudbalancing.domain.CloudProcess;

global HardAndSoftScoreHolder scoreHolder;

// ############################################################################
// Hard constraints
// ############################################################################

rule "requiredCpuPowerTotal"
```

```
    when
        $computer : CloudComputer($cpuPower : cpuPower)
        $requiredCpuPowerTotal : Number(intValue > $cpuPower) from accumulate(
            CloudProcess(
                computer == $computer,
                $requiredCpuPower : requiredCpuPower),
            sum($requiredCpuPower)
        )
    then
            insertLogical(new  IntConstraintOccurrence("requiredCpuPowerTotal",
 ConstraintType.NEGATIVE_HARD,
                $requiredCpuPowerTotal.intValue() - $cpuPower,
                $computer));
end

rule "requiredMemoryTotal"
    ...
end

rule "requiredNetworkBandwidthTotal"
    ...
end

// ############################################################################
// Calculate hard score
// ############################################################################

// Accumulate hard constraints
rule "hardConstraintsBroken"
        salience -1 // Do the other rules first (optional, for performance)
    when
        $hardTotal : Number() from accumulate(
         IntConstraintOccurrence(constraintType == ConstraintType.NEGATIVE_HARD,
 $weight : weight),
            sum($weight)
        )
    then
        scoreHolder.setHardConstraintsBroken($hardTotal.intValue());
end
```

Next, if those constraints are met, we want to minimize the maintenance cost, so we add that as a soft constraint:

Example 2.8. cloudBalancingScoreRules.drl - soft constraints

```
// ############################################################################
// Soft constraints
// ############################################################################

rule "computerCost"
    when
        $computer : CloudComputer($cost : cost)
        exists CloudProcess(computer == $computer)
    then
                    insertLogical(new  IntConstraintOccurrence("computerCost",
 ConstraintType.NEGATIVE_SOFT,
                $cost,
                $computer));
end

// ############################################################################
// Calculate soft score
// ############################################################################

// Accumulate soft constraints
rule "softConstraintsBroken"
        salience -1 // Do the other rules first (optional, for performance)
    when
        $softTotal : Number() from accumulate(
         IntConstraintOccurrence(constraintType == ConstraintType.NEGATIVE_SOFT,
 $weight : weight),
            sum($weight)
        )
    then
        scoreHolder.setSoftConstraintsBroken($softTotal.intValue());
end
```

If you use the Drools rule engine for score calculation, you can integrate with other Drools technologies, such as decision tables (XSL or web based), the Guvnor rule repository, ...

2.1.7. Beyond this tutorial

Now that this simple example works, try going further. Enrich the domain model and add extra constraints such as these:

- Each `Process` belongs to a `Service`. A computer can crash, so processes running the same service should be assigned to different computers.
- Each `Computer` is located in a `Building`. A building can burn down, so processes of the same services should be assigned to computers in different buildings.

Chapter 3. Use cases and examples

3.1. Introduction

Drools Planner has several examples. In this manual we explain Drools Planner mainly using the n queens example. So it's advisable to read at least the section about that example. For advanced users, the following examples are recommended: curriculum course and nurse rostering.

You can find the source code of all these examples in the distribution zip under `examples/sources` and also in git under `drools-planner/drools-planner-examples`.

3.2. Toy examples

3.2.1. N queens

3.2.1.1. Problem statement

The *n queens puzzle* is a puzzle with the following constraints:

- Use a chessboard of *n* columns and *n* rows.
- Place *n* queens on the chessboard.
- No 2 queens can attack each other. Note that a queen can attack any other queen on the same horizontal, vertical or diagonal line.

The most common n queens puzzle is the 8 queens puzzle, with *n = 8*. We'll explain Drools Planner using the 4 queens puzzle as the primary example.

A proposed solution could be:

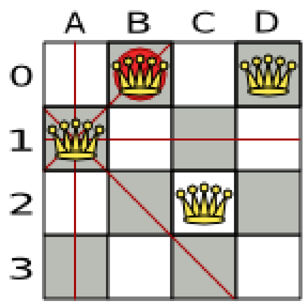


Figure 3.1. A wrong solution for the 4 queens puzzle

The above solution is wrong because queens `A1` and `B0` can attack each other (so can queens `B0` and `D0`). Removing queen `B0` would respect the "no 2 queens can attack each other" constraint, but would break the "place n queens" constraint.

3.2.1.2. Solution(s)

Below is a correct solution:

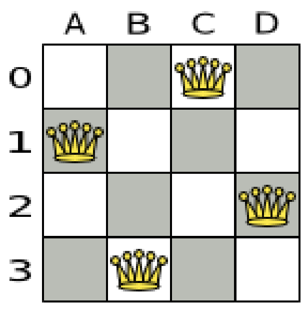


Figure 3.2. A correct solution for the 4 queens puzzle

All the constraints have been met, so the solution is correct. Note that most n queens puzzles have multiple correct solutions. We'll focus on finding a single correct solution for a given n, not on finding the number of possible correct solutions for a given n.

3.2.1.3. Screenshot

Here is a screenshot of the example:

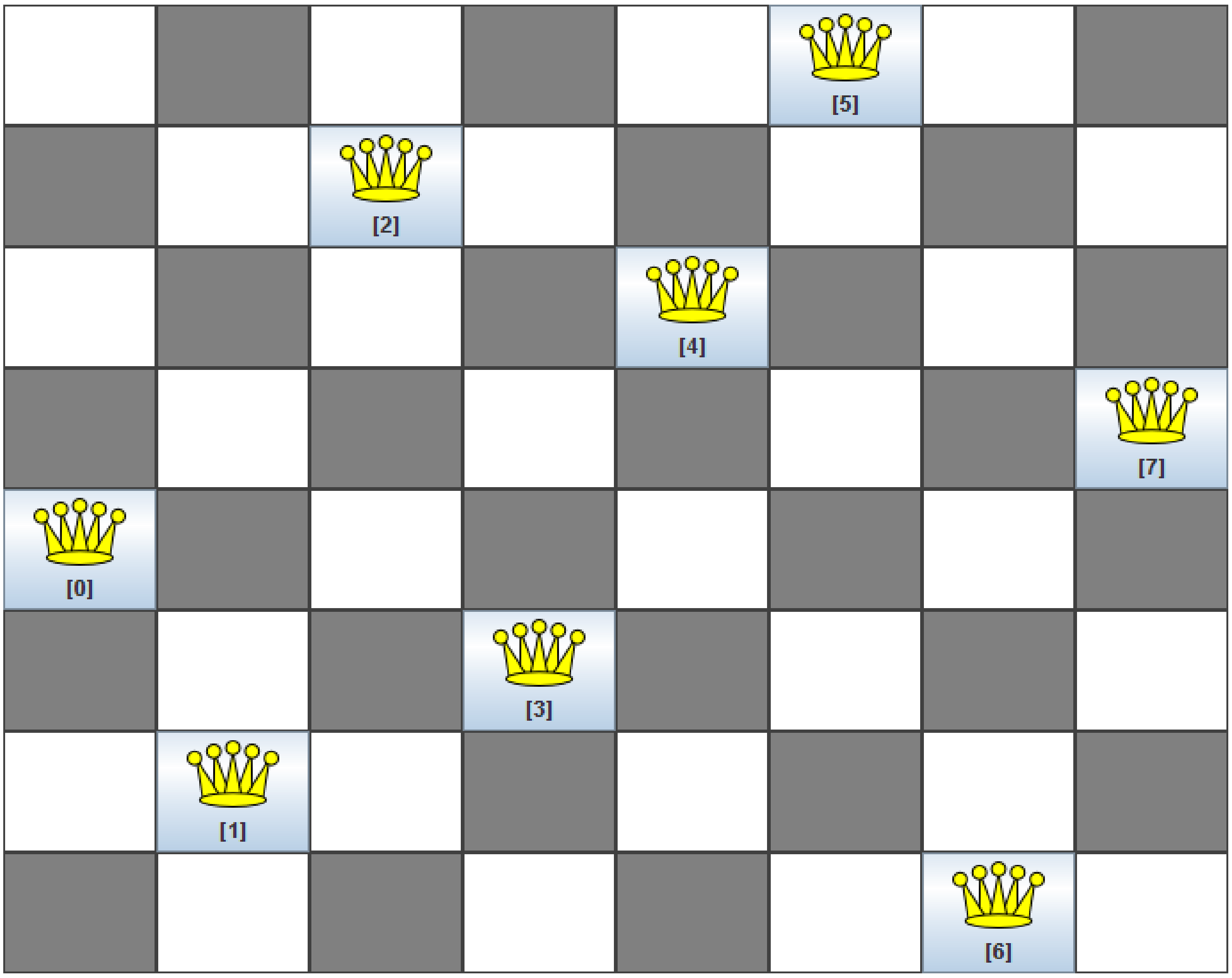


Figure 3.3. Screenshot of the n queens example

3.2.1.4. Problem size

These numbers might give you some insight in the size of this problem.

Table 3.1. NQueens problem size

# queens (n)	# possible solutions (each queen its own column)	# feasible solutions (= optimal in this use case)	# optimal solutions	# optimal *out of* # possible
4	256	2	2	1 *out of* 128
8	16777216	64	64	1 *out of* 262144
16	18446744073709551616	14772512	14772512	1 *out of* 1248720872503

# queens (n)	# possible solutions (each queen its own column)	# feasible solutions (= optimal in this use case)	# optimal solutions	# optimal *out of* # possible
32	1.46150163733090291820368483e+48	?	?	?
64	3.94020061963944792122790401e+115	?	?	?
n	n ^ n	?	# feasible solutions	?

The Drools Planner implementation of the N queens example has not been optimized because it functions as a beginner example. Nevertheless, it can easily handle 64 queens.

3.2.1.5. Domain model

Use a good domain model: it will be easier to understand and solve your planning problem with Drools Planner. This is the domain model for the n queens example:

```
public class Column {

    private int index;

    // ... getters and setters
}
```

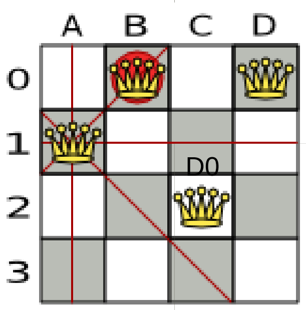
```
public class Row {

    private int index;

    // ... getters and setters
}
```

```
public class Queen {

    private Column column;
    private Row row;

    public int getAscendingDiagonalIndex() {...}
    public int getDescendingDiagonalIndex() {...}

    // ... getters and setters
}
```

```
public class NQueens implements Solution<SimpleScore> {

    private int n;
    private List<Column> columnList;
    private List<Row> rowList;

    private List<Queen> queenList;

    private SimpleScore score;

    // ... getters and setters
}
```

A `Queen` instance has a `Column` (for example: 0 is column A, 1 is column B, ...) and a `Row` (its row, for example: 0 is row 0, 1 is row 1, ...). Based on the column and the row, the ascending diagonal line as well as the descending diagonal line can be calculated. The column and row indexes start from the upper left corner of the chessboard.

Table 3.2. A solution for the 4 queens puzzle shown in the domain model

A solution	Queen	columnIndex	rowIndex	ascendingDia (columnIndex + rowIndex)	descendingDi (columnIndex - rowIndex)
		0	1	**1 (**)**	-1
		1	**0 (*)**	**1 (**)**	1
		2	2	4	0
		3	**0 (*)**	3	3

When 2 queens share the same column, row or diagonal line, such as (*) and (**), they can attack each other.

A single `NQueens` instance contains a list of all `Queen` instances. It is the `Solution` implementation which will be supplied to, solved by and retrieved from the Solver. Notice that in the 4 queens example, NQueens's `getN()` method will always return 4.

3.2.2. Cloud balancing

This example is explained in *a tutorial*.

3.2.3. Traveling salesman (TSP - Traveling salesman problem)

3.2.3.1. Problem statement

Given a list of cities, find the shortest tour for a salesman that visits each city exactly once. *See the wikipedia definition of the traveling Salesman Problem.* [http://en.wikipedia.org/wiki/Travelling_salesman_problem]

It is *one of the most intensively studied problems* [http://www.tsp.gatech.edu/] in computational mathematics. Yet, in the real world, it's often only part of a planning problem, along with other constraints, such as employee shift time constraints.

3.2.4. Manners 2009

3.2.4.1. Problem statement

In Manners 2009, miss Manners is throwing a party again.

- This time she invited 144 guests and prepared 12 round tables with 12 seats each.
- Every guest should sit next to someone (left and right) of the opposite gender.
- And that neighbour should have at least one hobby in common with the guest.
- Also, this time there should be 2 politicians, 2 doctors, 2 socialites, 2 sports stars, 2 teachers and 2 programmers at each table.
- And the 2 politicians, 2 doctors, 2 sports stars and 2 programmers shouldn't be the same kind.

Drools Expert also has the normal miss Manners examples (which is much smaller) and employs a brute force heuristic to solve it. Drools Planner's implementation employs far more scalable heuristics while still using Drools Expert to calculate the score..

3.3. Real examples

3.3.1. Course timetabling (ITC 2007 track 3 - Curriculum course scheduling)

3.3.1.1. Problem statement

Schedule each lecture into a timeslot and into a room.

The problem is defined by *the International Timetabling Competition 2007 track 3* [http://www.cs.qub.ac.uk/itc2007/curriculmcourse/course_curriculm_index.htm].

3.3.2. Machine reassignment (Google ROADEF 2012)

3.3.2.1. Problem statement

Assign each process to a machine. All processes already have an original (unoptimized) assignment. Each process requires an amount of each resource (such as CPU, RAM, ...). This is more complex version of the Cloud balancing example.

The problem is defined by *the Google ROADEF/EURO Challenge 2012* [http://challenge.roadef.org/2012/en/].

Hard constraints:

- Maximum capacity: The maximum capacity for each resource for each machine must not be exceeded.
- Conflict: Processes of the same service must run on distinct machines.
- Spread: Processes of the same service must be spread across locations.
- Dependency: The processes of a service depending on another service must run in the neighborhood of a process of the other service.
- Transient usage: Some resources are transient and count towards the maximum capacity of both the original machine as the newly assigned machine.

Soft constraints:

- Load: The safety capacity for each resource for each machine should not be exceeded.
- Balance: Leave room for future assignments by balancing the available resources on each machine.
- Process move cost: A process has a move cost.
- Service move cost: A service has a move cost.
- Machine move cost: Moving a process from machine A to machine B has another A-B specific move cost.

3.3.2.2. Problem size

```
model_a1_1: 2 resources, 1 neighborhoods, 4 locations, 4 machines, 79 services,
 100 processes and 1 balancePenalties with flooredPossibleSolutionSize (10^60).
model_a1_2: 4 resources, 2 neighborhoods, 4 locations, 100 machines, 980
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^2000).
```

```
model_a1_3:  3  resources,  5  neighborhoods,  25  locations,  100  machines,  216
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^2000).
model_a1_4:  3  resources,  50  neighborhoods,  50  locations,  50  machines,  142
 services, 1000 processes and 1 balancePenalties with flooredPossibleSolutionSize
 (10^1698).
model_a1_5:  4  resources,  2  neighborhoods,  4  locations,  12  machines,  981
 services, 1000 processes and 1 balancePenalties with flooredPossibleSolutionSize
 (10^1079).
model_a2_1:  3  resources,  1  neighborhoods,  1  locations,  100  machines,  1000
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^2000).
model_a2_2:  12  resources,  5  neighborhoods,  25  locations,  100  machines,  170
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^2000).
model_a2_3:  12  resources,  5  neighborhoods,  25  locations,  100  machines,  129
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^2000).
model_a2_4:  12  resources,  5  neighborhoods,  25  locations,  50  machines,  180
 services, 1000 processes and 1 balancePenalties with flooredPossibleSolutionSize
 (10^1698).
model_a2_5:  12  resources,  5  neighborhoods,  25  locations,  50  machines,  153
 services, 1000 processes and 0 balancePenalties with flooredPossibleSolutionSize
 (10^1698).
```

3.3.3. Vehicle routing

3.3.3.1. Problem statement

Using a fleet of vehicles, pick up the objects of each customer and bring them to the depot. Each vehicle can service multiple customers, but it has a limited capacity.

The capacitated vehicle routing problem (CRVP) is defined by *the VRP web* [http://neo.lcc.uma.es/radi-aeb/WebVRP/].

3.3.4. Hospital bed planning (PAS - Patient admission scheduling)

3.3.4.1. Problem statement

Assign each patient (that will come to the hospital) into a bed for each night that the patient will stay in the hospital. Each bed belongs to a room and each room belongs to a department. The arrival and departure dates of the patients is fixed: only a bed needs to be assigned for each night.

There are a couple of hard constraints:

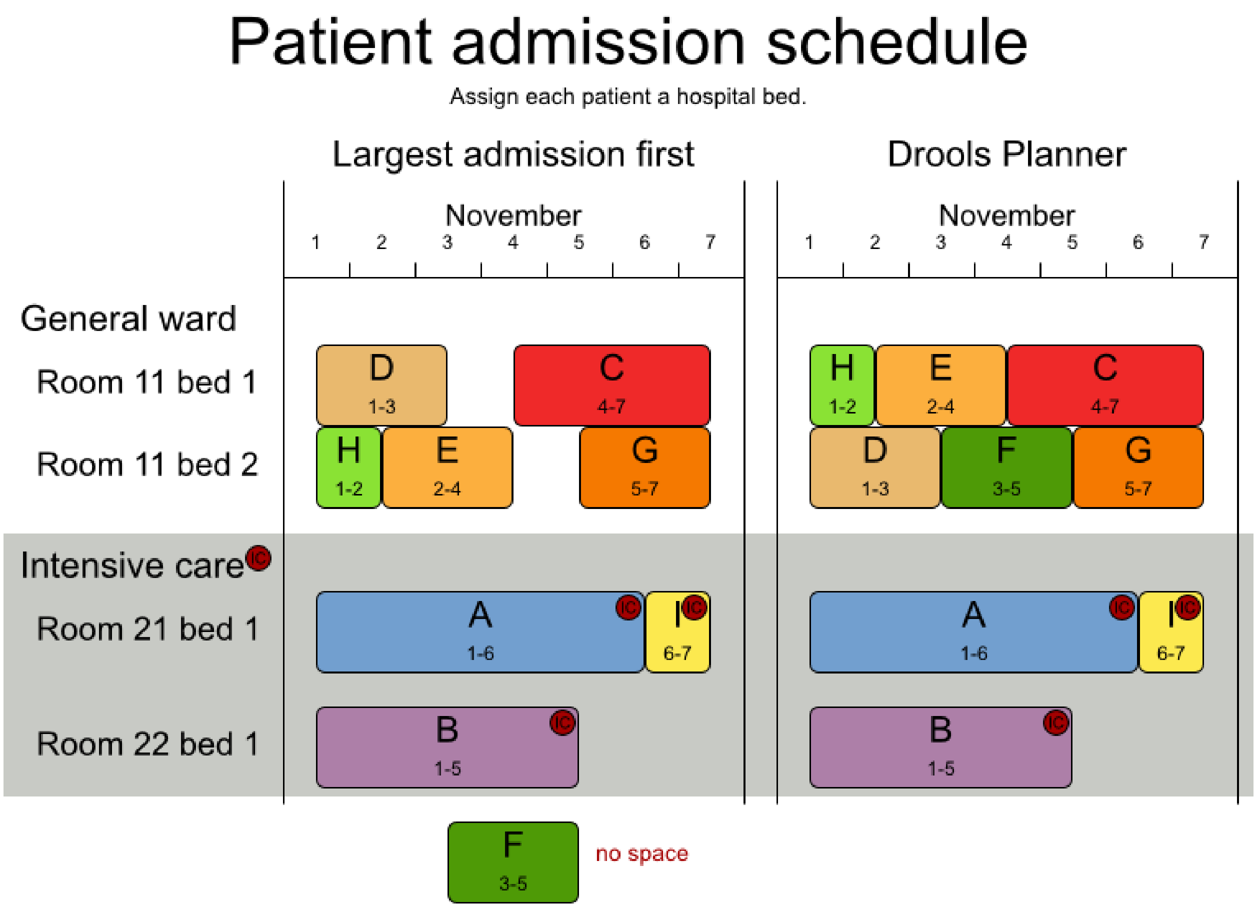
- 2 patients shouldn't be assigned to the same bed in the same night.

- A room can have a gender limitation: only females, only males, the same gender in the same night or no gender limitation at all.
- A department can have a minimum or maximum age.
- A patient can require a room with specific equipment(s).

And of course, there are also some soft constraints:

- A patient can prefer a maximum room size, for example if he/she want a single room.
- A patient is best assigned to a department that specializes in his/her problem.
- A patient is best assigned to a room that specializes in his/her problem.
- A patient can prefer a room with specific equipment(s).

The problem is defined on *this webpage* [http://allserv.kahosl.be/~peter/pas/] and the test data comes from real world hospitals.



3.4. Difficult examples

3.4.1. Exam timetabling (ITC 2007 track 1 - Examination)

3.4.1.1. Problem statement

Schedule each exam into a period and into a room. Multiple exams can share the same room during the same period.

There are a number of hard constraints that cannot be broken:

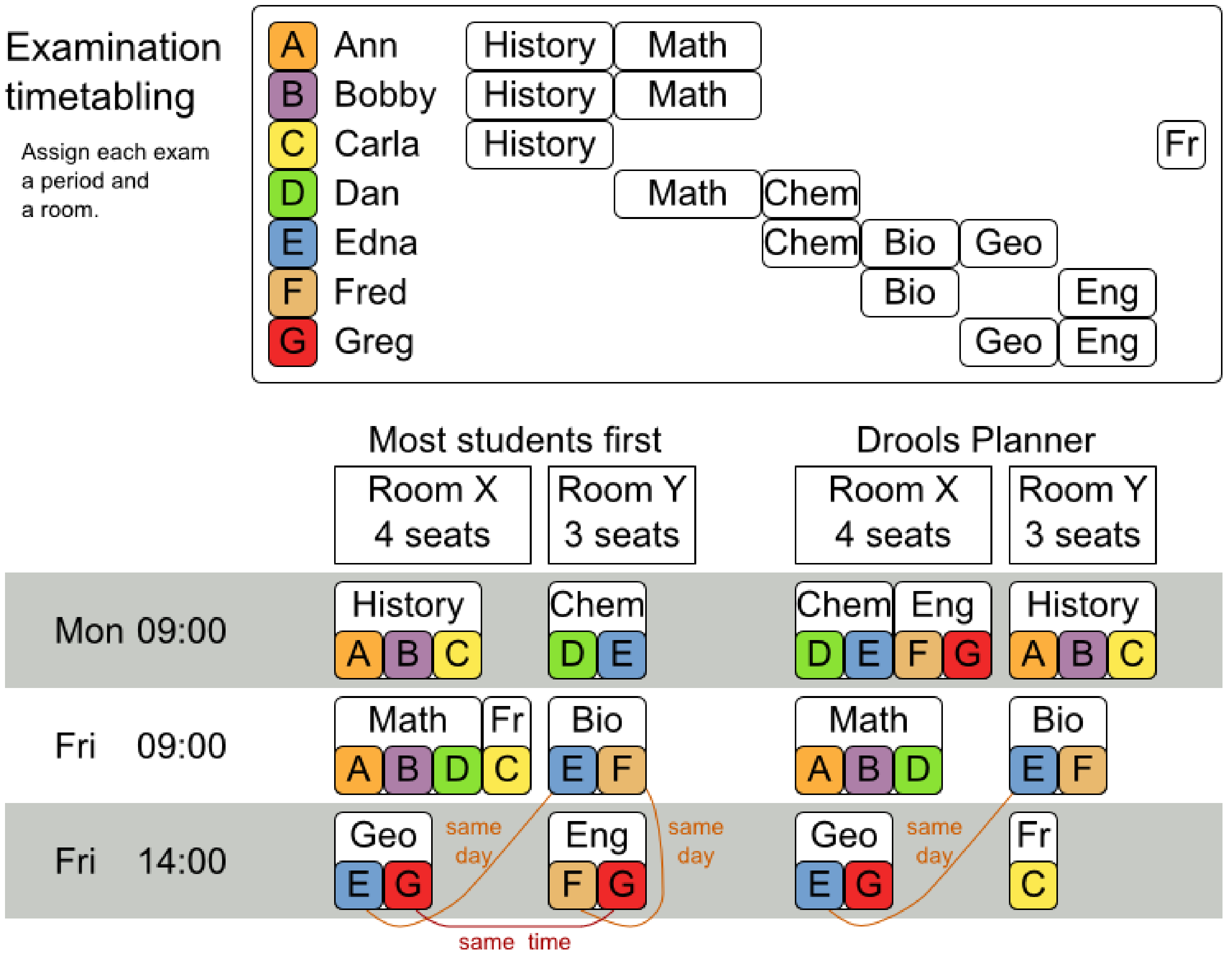
- Exam conflict: 2 exams that share students should not occur in the same period.
- Room capacity: A room's seating capacity should suffice at all times.
- Period duration: A period's duration should suffice for all of its exams.
- Period related hard constraints should be fulfilled:
  - Coincidence: 2 exams should use the same period (but possibly another room).
  - Exclusion: 2 exams should not use the same period.
  - After: 1 exam should occur in a period after another exam's period.
- Room related hard constraints should be fulfilled:
  - Exclusive: 1 exam should not have to share its room with any other exam.

There are also a number of soft constraints that should be minimized (each of which has parametrized penalty's):

- 2 exams in a row.
- 2 exams in a day.
- Period spread: 2 exams that share students should be a number of periods apart.
- Mixed durations: 2 exams that share a room should not have different durations.
- Front load: Large exams should be scheduled earlier in the schedule.
- Period penalty: Some periods have a penalty when used.
- Room penalty: Some rooms have a penalty when used.

It uses large test data sets of real-life universities.

The problem is defined by *the International Timetabling Competition 2007 track 1* [http://www.cs.qub.ac.uk/itc2007/examtrack/exam_track_index.htm].



3.4.1.2. Problem size

These numbers might give you some insight on the size of this problem.

Table 3.3. Examination problem size

Set	# students	# exams/ topics	# periods	# rooms	# possible solutions	# feasible solutions	# optimal solutions
exam_comp_set1	7883	607	54	7	10^1564	?	1?
exam_comp_set2	12484	870	40	49	10^2864	?	1?
exam_comp_set3	16365	934	36	48	10^3023	?	1?
exam_comp_set4	4421	273	21	1	10^360	?	1?
exam_comp_set5	8719	1018	42	3	10^2138	?	1?
exam_comp_set6	7909	242	16	8	10^509	?	1?

Set	# students	# exams/ topics	# periods	# rooms	# possible solutions	# feasible solutions	# optimal solutions
exam_comp_set7	13795	1096	80	28	10^3671	?	1?
exam_comp_set8	7718	598	80	8	10^1678	?	1?
?	s	t	p	r	(p * r) ^ e	?	1?

Geoffrey De Smet (the Drools Planner lead) finished 4th in the International Timetabling Competition 2007's examination track with a very early version of Drools Planner. Many improvements have been made since then.

3.4.1.3. Domain model

Below you can see the main examination domain classes:

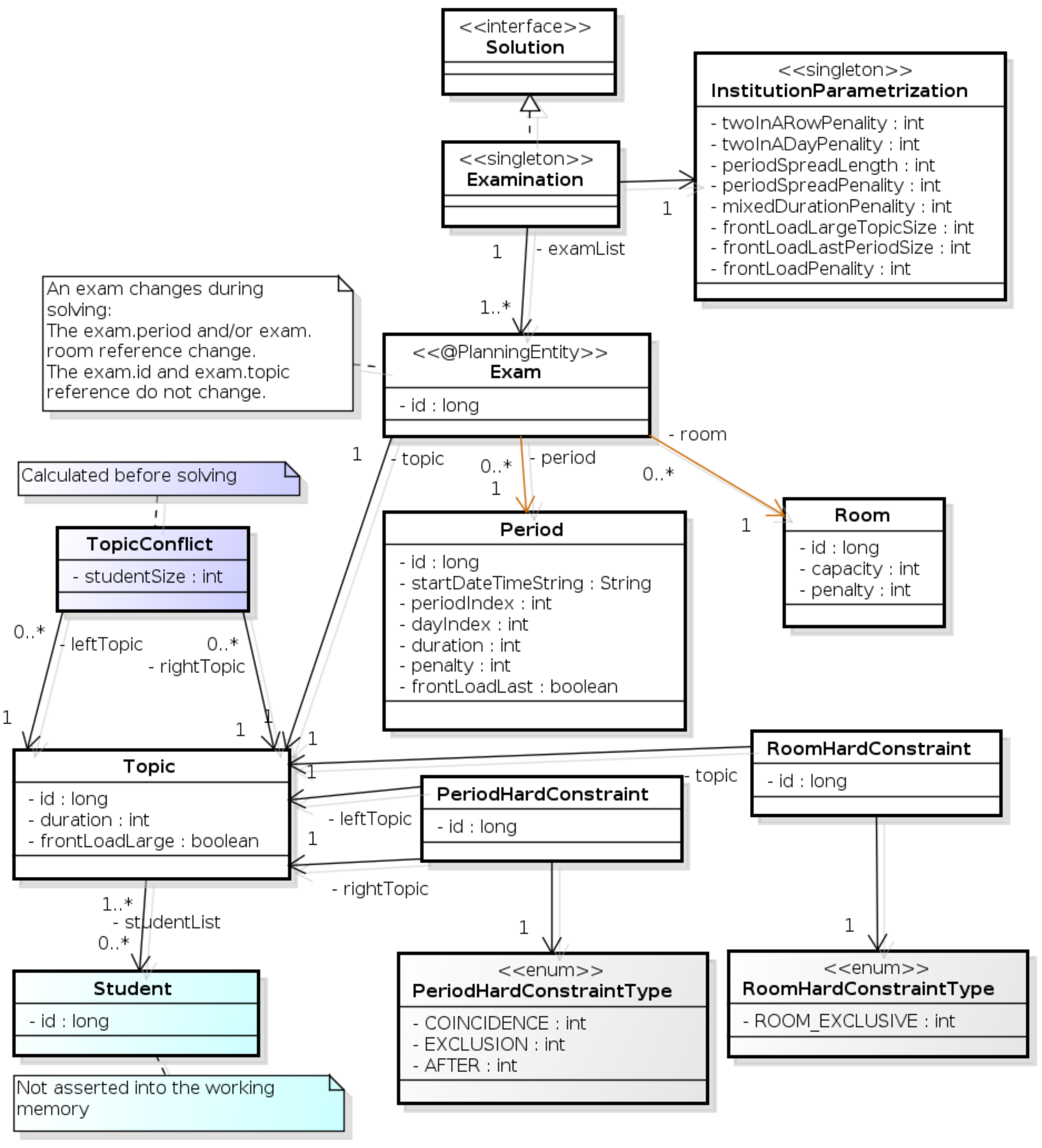


Figure 3.4. Examination domain class diagram

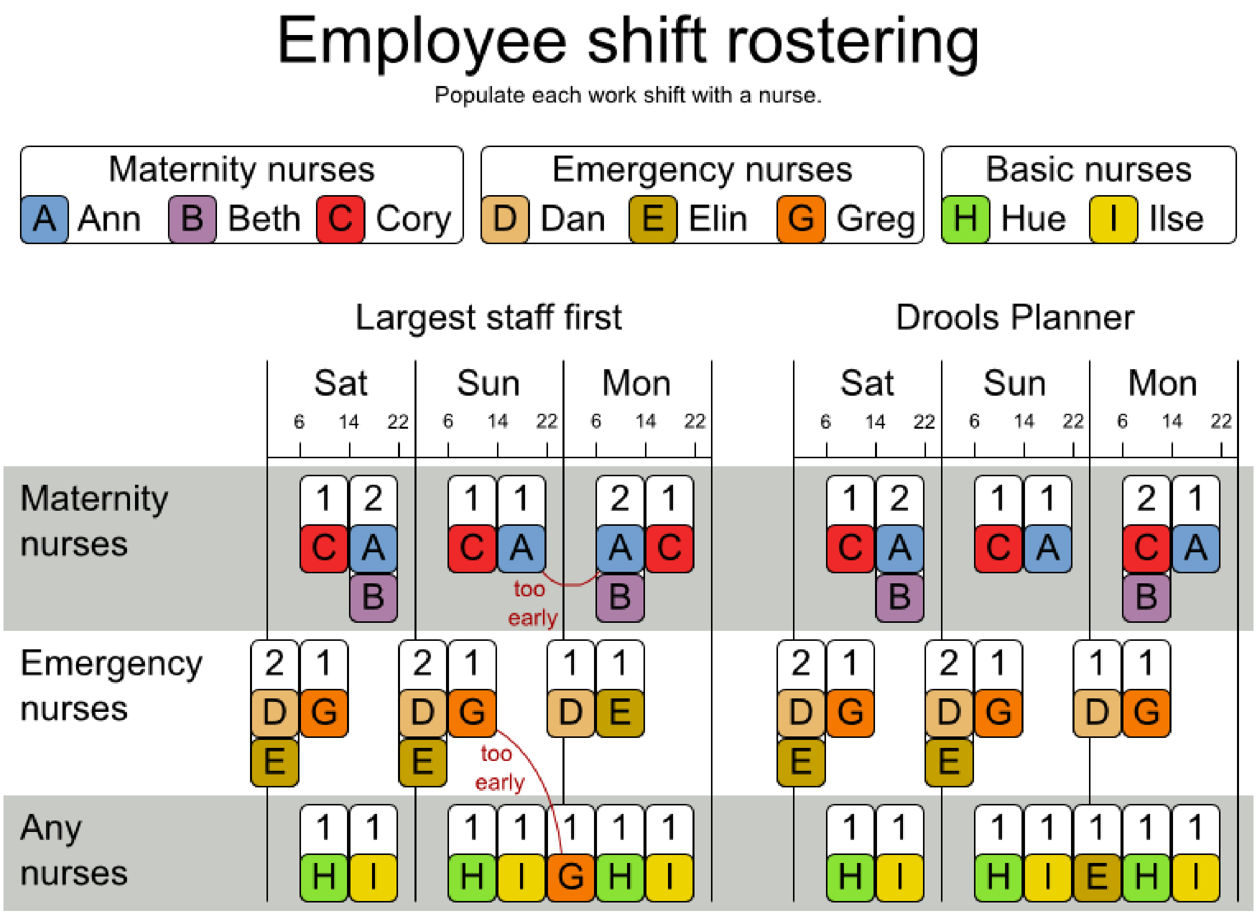
Notice that we've split up the exam concept into an `Exam` class and a `Topic` class. The `Exam` instances change during solving (this is the planning entity class), when they get another period or room property. The `Topic`, `Period` and `Room` instances never change during solving (these are problem facts, just like some other classes).

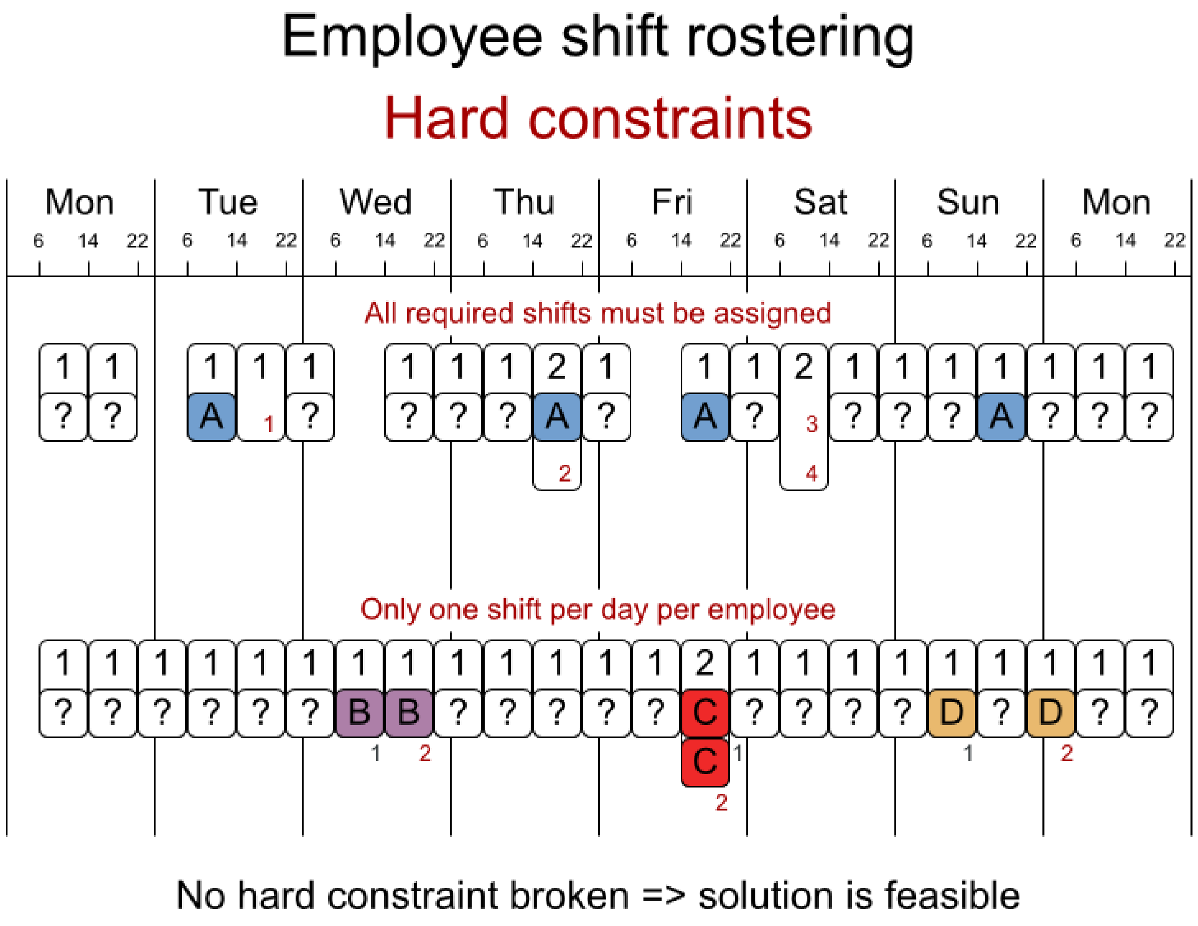
3.4.2. Employee rostering (INRC 2010 - Nurse rostering)

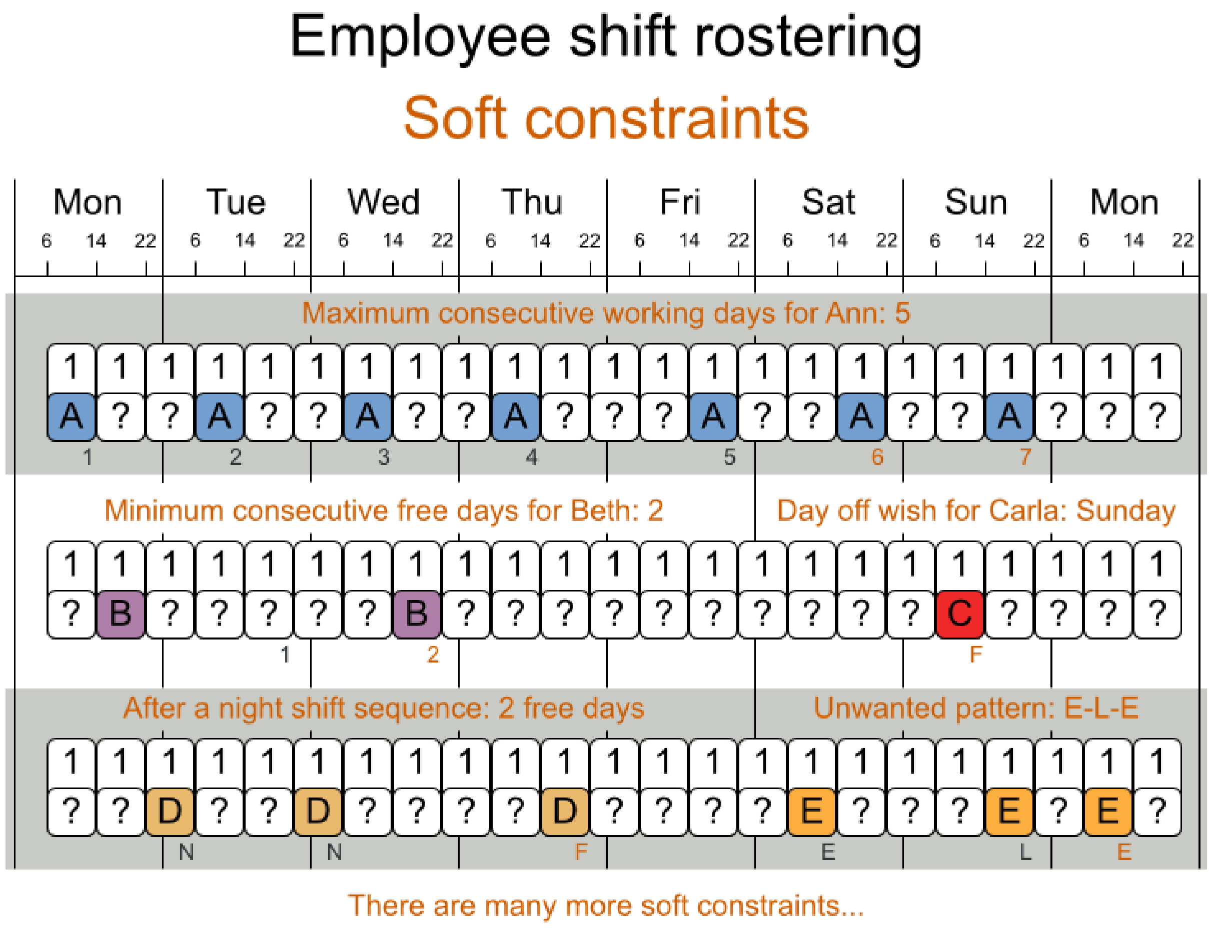
3.4.2.1. Problem statement

For each shift, assign a nurse to work that shift.

The problem is defined by *the International Nurse Rostering Competition 2010* [http://www.kuleuven-kortrijk.be/nrpcompetition].




Employee shift rostering
Hard constraints
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
6
14
22
All required shifts must be assigned
Only one shift per day per employee
No hard constraint broken => solution is feasible


Employee shift rostering
Soft constraints
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
Maximum consecutive working days for Ann: 5
Minimum consecutive free days for Beth: 2
Day off wish for Carla: Sunday
After a night shift sequence: 2 free days
Unwanted pattern: E-L-E
There are many more soft constraints...

3.4.3. Sport scheduling (TTP - Traveling tournament problem)

3.4.3.1. Problem statement

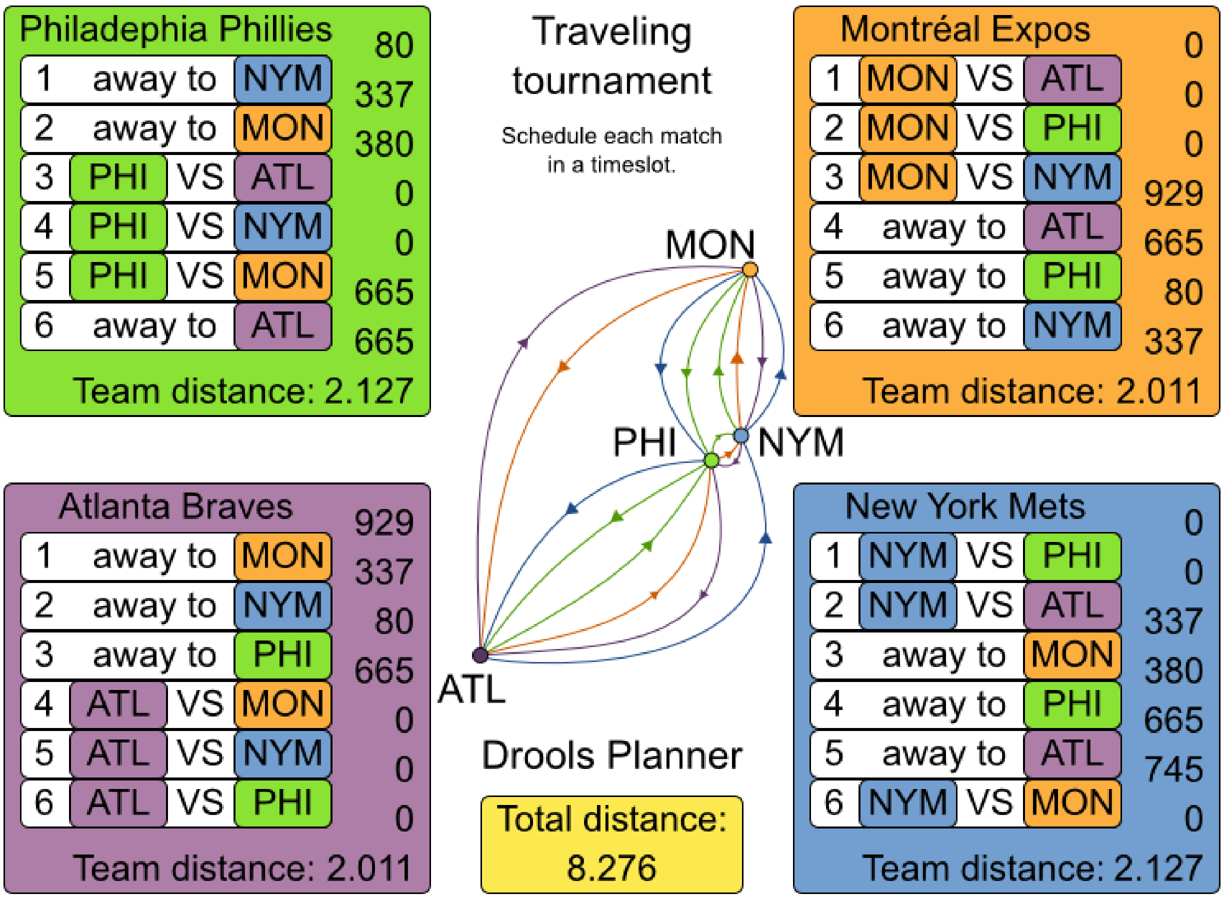
Schedule matches between *n* teams with the following hard constraints:

- Each team plays twice against every other team: once home and once away.
- Each team has exactly 1 match on each timeslot.
- No team must have more than 3 consecutive home or 3 consecutive away matches.
- No repeaters: no 2 consecutive matches of the same 2 opposing teams.

and the following soft constraint:

- Minimize the total distance traveled by all teams.

The problem is defined on *Michael Trick's website (which contains several world records too)* [http://mat.gsia.cmu.edu/TOURN/].



Philadephia Phillies

1	away to	NYM		80
2	away to	MON		337
3	PHI	VS	ATL	380
4	PHI	VS	NYM	0
5	PHI	VS	MON	0
6	away to	ATL		665
				665

Team distance: 2.127

Montréal Expos

1	MON	VS	ATL	0
2	MON	VS	PHI	0
3	MON	VS	NYM	0
4	away to	ATL		929
5	away to	PHI		665
6	away to	NYM		80
				337

Team distance: 2.011

Atlanta Braves

1	away to	MON		929
2	away to	NYM		337
3	away to	PHI		80
4	ATL	VS	MON	665
5	ATL	VS	NYM	0
6	ATL	VS	PHI	0
				0

Team distance: 2.011

New York Mets

1	NYM	VS	PHI	0
2	NYM	VS	ATL	0
3	away to	MON		337
4	away to	PHI		380
5	away to	ATL		665
6	NYM	VS	MON	745
				0

Team distance: 2.127

3.4.3.2. Simple and smart implementation

There are 2 implementations (simple and smart) to demonstrate the importance of some performance tips. The `DroolsPlannerExamplesApp` always runs the smart implementation, but with these commands you can compare the 2 implementations yourself:

```
$                        mvn                        exec:exec                        -
Dexec.mainClass="org.drools.planner.examples.travelingtournament.app.simple.SimpleTravelingTour
...
$                        mvn                        exec:exec                        -
Dexec.mainClass="org.drools.planner.examples.travelingtournament.app.smart.SmartTravelingTourna
...
```

The smart implementation performs and scales exponentially better than the simple implementation.

3.4.3.3. Problem size

These numbers might give you some insight on the size of this problem.

Table 3.4. Traveling tournament problem size

# teams	# days	# matches	# possible solutions (simple)	# possible solutions (smart)	# feasible solutions	# optimal solutions
4	6	12	2176782336	<= 518400	?	1?
6	10	30	1000000000000000000000000000000	<= 47784725839872000000	?	1?
8	14	56	1.52464943788290465606136043e+64	<= 5.77608277425558771434498864e+43	?	1?
10	18	90	9.43029892325559280477052413e+112	<= 1.07573451027871200629339068e+79	?	1?
12	22	132	1.58414112478195320415135060e+177	<= 2.01650616733413376416949843e+126	?	1?
14	26	182	3.35080635695103223315189511e+257	<= 1.73513467024013808570420241e+186	?	1?
16	30	240	3.22924601799855400751522483e+354	<= 2.45064610271441678267620602e+259	?	1?
n	2 * (n - 1)	n * (n - 1)	(2 * (n - 1)) ^ (n * (n - 1))	<= (((2 * (n - 1))!) ^ (n / 2))	?	1?

Chapter 4. Planner configuration

4.1. Overview

Solving a planning problem with Drools Planner consists out of 5 steps:

1. **Model your planning problem** as a class that implements the interface `Solution`, for example the class `NQueens`.
2. **Configure a `Solver`**, for example a first fit and tabu search solver for any `NQueens` instance.
3. **Load a problem data set** from your data layer, for example a 4 Queens instance. Set it as the planning problem on the `Solver` with `Solver.setPlanningProblem(...)`.
4. **Solve it** with `Solver.solve()`.
5. **Get the best solution found** by the `Solver` with `Solver.getBestSolution()`.

4.2. Solver configuration

4.2.1. Solver configuration by XML file

You can build a `Solver` instance with the `XmlSolverFactory`. Configure it with a solver configuration XML file:

```
        XmlSolverFactory solverFactory = new XmlSolverFactory();
          solverFactory.configure("/org/drools/planner/examples/nqueens/solver/
nqueensSolverConfig.xml");
        Solver solver = solverFactory.buildSolver();
```

A solver configuration file looks something like this:

```
<?xml version="1.0" encoding="UTF-8"?>
<solver>
  <!-- Define the model -->
            <solutionClass>org.drools.planner.examples.nqueens.domain.NQueens</
solutionClass>
        <planningEntityClass>org.drools.planner.examples.nqueens.domain.Queen</
planningEntityClass>

  <!-- Define the score function -->
  <scoreDirectorFactory>
    <scoreDefinitionType>SIMPLE</scoreDefinitionType>
```

```
                         <scoreDrl>/org/drools/planner/examples/nqueens/solver/
nQueensScoreRules.drl</scoreDrl>
  </scoreDirectorFactory>

  <!-- Configure the optimization algorithm(s) -->
  <termination>
    ...
  </termination>
  <constructionHeuristic>
    ...
  </constructionHeuristic>
  <localSearch>
    ...
  </localSearch>
</solver>
```

Notice the 3 parts in it:

- Define the model
- Define the score function
- Configure the optimization algorithm(s)

We'll explain these various parts of a configuration later in this manual.

Drools Planner makes it relatively easy to switch optimization algorithm(s) just by changing the configuration. There's even a `Benchmark` utility which allows you to play out different configurations against each other and report the most appropriate configuration for your problem. You could for example play out tabu search versus simulated annealing, on 4 queens and 64 queens.

4.2.2. Solver configuration by Java API

As an alternative to the XML file, a solver configuration can also be configured with the `SolverConfig` API:

```
        SolverConfig solverConfig = new SolverConfig();

        solverConfig.setSolutionClass(NQueens.class);
        Set<Class<?>> planningEntityClassSet = new HashSet<Class<?>>();
        planningEntityClassSet.add(Queen.class);
        solverConfig.setPlanningEntityClassSet(planningEntityClassSet);

        ScoreDirectorFactoryConfig scoreDirectorFactoryConfig = solverConfig.getScoreDirectorFa
        scoreDirectorFactoryConfig.setScoreDefinitionType(ScoreDirectorFactoryConfig.ScoreDefin
        scoreDirectorFactoryConfig.setScoreDrlList(
                    Arrays.asList("/org/drools/planner/examples/nqueens/solver/
nQueensScoreRules.drl"));

      TerminationConfig terminationConfig = solverConfig.getTerminationConfig();
        // ...
        List<SolverPhaseConfig> solverPhaseConfigList = new ArrayList<SolverPhaseConfig>();
        ConstructionHeuristicSolverPhaseConfig constructionHeuristicSolverPhaseConfig
                = new ConstructionHeuristicSolverPhaseConfig();
        // ...
        solverPhaseConfigList.add(constructionHeuristicSolverPhaseConfig);
        LocalSearchSolverPhaseConfig localSearchSolverPhaseConfig = new LocalSearchSolverPhaseC
        // ...
        solverPhaseConfigList.add(localSearchSolverPhaseConfig);
        solverConfig.setSolverPhaseConfigList(solverPhaseConfigList);
        Solver solver = solverConfig.buildSolver();
```

It is highly recommended to configure by XML file instead of this API. To dynamically configure a value at runtime, use the XML file as a template and extract the `SolverConfig` class with `getSolverConfig()` to configure the dynamic value at runtime:

```
        XmlSolverFactory solverFactory = new XmlSolverFactory();
          solverFactory.configure("/org/drools/planner/examples/nqueens/solver/
nqueensSolverConfig.xml");

        SolverConfig solverConfig = solverFactory.getSolverConfig();
        solverConfig.getTerminationConfig().setMaximumMinutesSpend(userInput);
        Solver solver = solverConfig.buildSolver();
```

4.3. Model your planning problem

4.3.1. Is this class a problem fact or planning entity?

Look at a dataset of your planning problem. You 'll recognize domain classes in there, each of which is one of these:

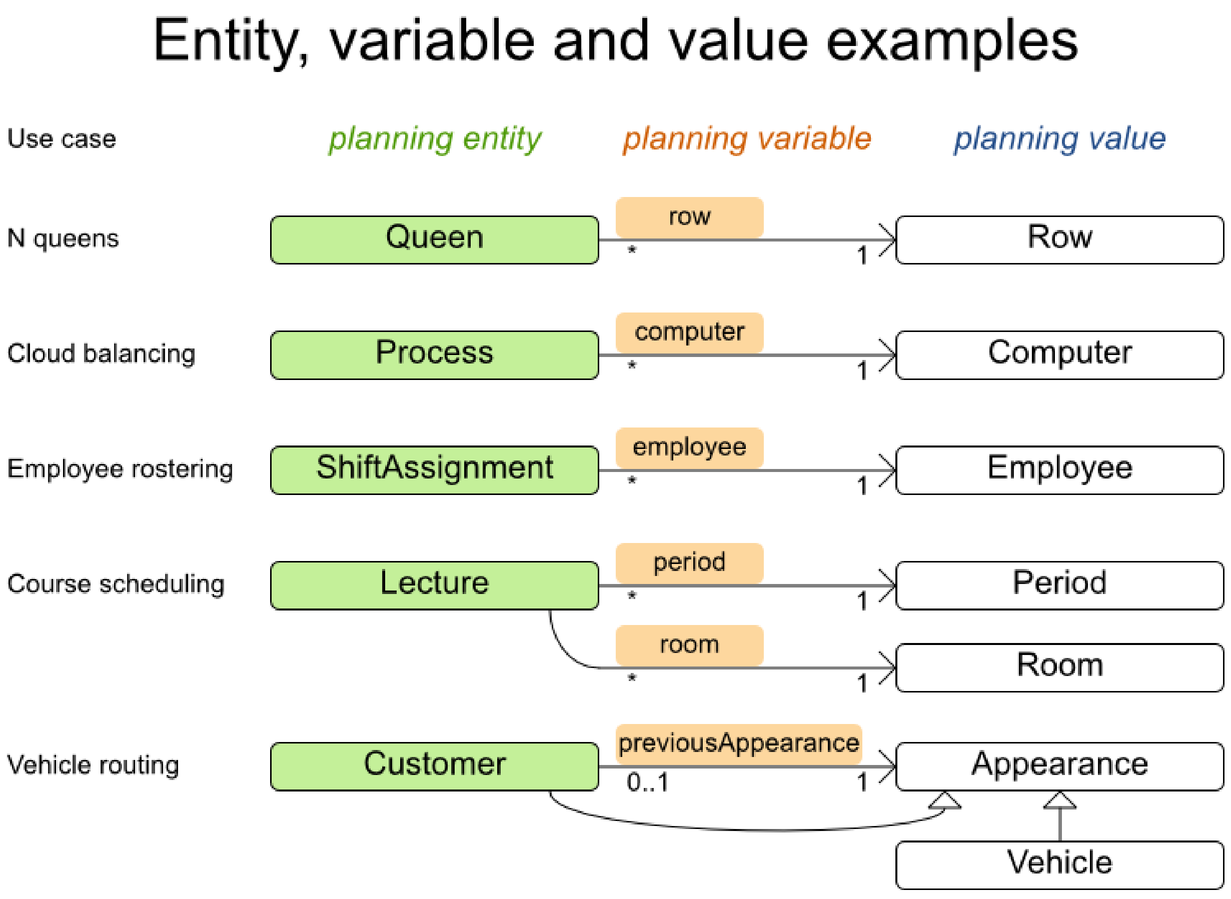
- A unrelated class: not used by any of the score constraints. From a planning standpoint, this data is obsolete.
- A **problem fact** class: used by the score constraints, but does NOT change during planning (as long as the problem stays the same). For example: `Bed`, `Room`, `Shift`, `Employee`, `Topic`, `Period`, ...
- A **planning entity** class: used by the score constraints and changes during planning. For example: `BedDesignation`, `ShiftAssignment`, `Exam`, ...

Ask yourself: *What class changes during planning? Which class has variables that I want the `Solver` to change for me?* That class is a planning entity. Most use cases have only 1 planning entity class.

Note

In *real-time planning*, problem facts can change during planning, because the problem itself changes. However, that doesn't make them planning entities.

A good model can greatly improve the success of your planning implementation. For inspiration, take a look at how the examples modeled their domain:



When in doubt, it's usually the many side of a many to one relationship that is the planning entity. For example in employee rostering, the planning entity class is `ShiftAssignment`, not `Employee`. Vehicle routing is special, because it uses a *chained planning variable*.

In Drools Planner all problems facts and planning entities are plain old JavaBeans (POJO's). You can load them from a database (JDBC/JPA/JDO), an XML file, a data repository, a noSQL cloud, ...: Drools Planner doesn't care.

4.3.2. Problem fact

A problem fact is any JavaBean (POJO) with getters that does not change during planning. Implementing the interface `Serializable` is recommended (but not required). For example in n queens, the columns and rows are problem facts:

```
public class Column implements Serializable {

    private int index;

    // ... getters
}
```

```
public class Row implements Serializable {

    private int index;

    // ... getters
}
```

A problem fact can reference other problem facts of course:

```
public class Course implements Serializable {

    private String code;

    private Teacher teacher; // Other problem fact
    private int lectureSize;
    private int minWorkingDaySize;

    private List<Curriculum> curriculumList; // Other problem facts
    private int studentSize;

    // ... getters
}
```

A problem fact class does *not* require any Planner specific code. For example, you can reuse your domain classes, which might have JPA annotations.

Note

Generally, better designed domain classes lead to simpler and more efficient score constraints. Therefore, when dealing with a messy legacy system, it can sometimes be worth it to convert the messy domain set into a planner specific POJO set first. For example: if your domain model has 2 `Teacher` instances for the same teacher that teaches at 2 different departments, it's hard to write a correct score constraint that constrains a teacher's spare time.

Alternatively, you can sometimes also introduce *a cached problem fact* to enrich the domain model for planning only.

4.3.3. Planning entity and planning variables

4.3.3.1. Planning entity

A planning entity is a JavaBean (POJO) that changes during solving, for example a `Queen` that changes to another row. A planning problem has multiple planning entities, for example for a single n queens problem, each `Queen` is a planning entity. But there's usually only 1 planning entity class, for example the `Queen` class.

A planning entity class needs to be annotated with the `@PlanningEntity` annotation.

Each planning entity class has 1 or more *planning variables*. It usually also has 1 or more *defining* properties. For example in n queens, a `Queen` is defined by its `Column` and has a planning variable `Row`. This means that a Queen's column never changes during solving, while its row does change.

```
@PlanningEntity
public class Queen {

    private Column column;

    // Planning variables: changes during planning, between score calculations.
    private Row row;

    // ... getters and setters
}
```

A planning entity class can have multiple planning variables. For example, a `Lecture` is defined by its `Course` and its index in that course (because 1 course has multiple lectures). Each `Lecture` needs to be scheduled into a `Period` and a `Room` so it has 2 planning variables (period and room). For example: the course Mathematics has 8 lectures per week, of which the first lecture is Monday morning at 08:00 in room 212.

```
@PlanningEntity
public class Lecture {

    private Course course;
    private int lectureIndexInCourse;

    // Planning variables: changes during planning, between score calculations.
    private Period period;
    private Room room;

    // ...
}
```

The solver configuration also needs to be made aware of each planning entity class:

```
<solver>
  ...
       <planningEntityClass>org.drools.planner.examples.nqueens.domain.Queen</
planningEntityClass>
  ...
</solver>
```

Some uses cases have multiple planning entity classes. For example: route freight and trains into railway network arcs, where each freight can use multiple trains over its journey and each train can carry multiple freights per arc. Having multiple planning entity classes directly raises the implementation complexity of your use case.

Note

Do not create unnecessary planning entity classes. This leads to difficult `Move` implementations and slower score calculation.

For example, do not create a planning entity class to hold the total free time of a teacher, which needs to be kept up to date as the `Lecture` planning entities change. Instead, calculate the free time in the score constraints and put the result per teacher into a logically inserted score object.

If historic data needs to be considered too, then create problem fact to hold the historic data up to, but *not including*, the planning window (so it doesn't change when a planning entity changes) and let the score constraints take it into account.

4.3.3.2. Planning entity difficulty

Some optimization algorithms work more efficiently if they have an estimation of which planning entities are more difficult to plan. For example: in bin packing bigger items are harder to fit, in course scheduling lectures with more students are more difficult to schedule and in n queens the middle queens are more difficult to fit on the board.

Therefore, you can set a `difficultyComparatorClass` to the `@PlanningEntity` annotation:

```
@PlanningEntity(difficultyComparatorClass = CloudProcessDifficultyComparator.class)
public class CloudProcess {
    // ...
}
```

```
public class CloudProcessDifficultyComparator implements Comparator<CloudProcess> {

    public int compare(CloudProcess a, CloudProcess b) {
        return new CompareToBuilder()
              .append(a.getRequiredMultiplicand(), b.getRequiredMultiplicand())
                .append(a.getId(), b.getId())
                .toComparison();
    }

}
```

Note

If you have multiple planning entity classes, the `difficultyComparatorClass` needs to implement a `Comparator` of a common superclass (for example `Comparator<Object>`) and be able to handle comparing instances of those different classes.

Alternatively, you can also set a `difficultyWeightFactoryClass` to the `@PlanningEntity` annotation, so you have access to the rest of the problem facts from the solution too:

```
@PlanningEntity(difficultyWeightFactoryClass = QueenDifficultyWeightFactory.class)
public class Queen {
    // ...
}
```

```
public interface PlanningEntityDifficultyWeightFactory {
    Comparable createDifficultyWeight(Solution solution, Object planningEntity);

}
```

```
public class QueenDifficultyWeightFactory implements PlanningEntityDifficultyWeightFactory {

    public Comparable createDifficultyWeight(Solution solution, Object planningEntity) {
        NQueens nQueens = (NQueens) solution;
        Queen queen = (Queen) planningEntity;
        int distanceFromMiddle = calculateDistanceFromMiddle(nQueens.getN(), queen.getColumnInd
        return new QueenDifficultyWeight(queen, distanceFromMiddle);
    }

    // ...

    public static class QueenDifficultyWeight implements Comparable<QueenDifficultyWeight> {

        private final Queen queen;
        private final int distanceFromMiddle;

        public QueenDifficultyWeight(Queen queen, int distanceFromMiddle) {
            this.queen = queen;
            this.distanceFromMiddle = distanceFromMiddle;
        }

        public int compareTo(QueenDifficultyWeight other) {
            return new CompareToBuilder()
                    // The more difficult queens have a lower distance to the middle
                          .append(other.distanceFromMiddle, distanceFromMiddle) //
 Decreasing
                    .append(queen.getColumnIndex(), other.queen.getColumnIndex())
                      .toComparison();
        }

    }

}
```

None of the current planning variable state may be used to compare planning entities. They are likely to be `null` anyway. For example, a `Queen`'s `row` variable may not be used.

4.3.3.3. Planning variable

A planning variable is a property (including getter and setter) on a planning entity. It points to a planning value, which changes during planning. For example, a `Queen`'s `row` property is a planning variable. Note that even though a `Queen`'s `row` property changes to another `Row` during planning, no `Row` instance itself is changed.

A planning variable getter needs to be annotated with the `@PlanningVariable` annotation. Furthermore, it needs a `@ValueRange` annotation too.

```
@PlanningEntity
public class Queen {

    private Row row;

    // ...

    @PlanningVariable
    @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = rowList")
    public Row getRow() {
        return row;
    }

    public void setRow(Row row) {
        this.row = row;
    }

}
```

4.3.3.4. Nullable planning variable

Warning

Nullable planning variables are not supported for construction heuristics in 5.5.x or lower.

By default, an initialized planning variable cannot be `null`, so an initialized solution will never use `null` for any of its planning variables. In over-constrained use case, this can be contra productive. For example: in task assignment with too many tasks for the workforce, we would rather leave low priority tasks unassigned instead of assigning them to an overloaded worker.

To allow an initialized planning variable to be `null`, set `nullable` to `true`:

```
    @PlanningVariable(nullable = true)
    @ValueRange(...)
    public Worker getWorker() {
        return worker;
    }
```

Important

Planner will automatically add the value `null` to the value range. There is no need to add `null` in a collection used by a `ValueRange`.

Repeated planning (especially *real-time planning*) does not mix well with a nullable planning variable: every time the Solver starts or a problem fact change is made, the construction heuristics will try to initialize all the null variables again, which can be a huge waste of time. One way to deal with this, is to change when a planning entity is initialized.

4.3.3.5. When is a planning entity initialized?

A planning entity is considered initialized if all of its planning variables are initialized.

By default, a planning variable is considered initialized if its value is not `null`, but for nullable planning variables you can overwrite this with an `uninitializedEntityFilter`:

```
    @PlanningVariable(nullable = true, uninitializedEntityFilter = UninitializedTaskFilter.clas
    @ValueRange(...)
    public Worker getWorker() {
        return worker;
    }
```

4.3.4. Planning value and planning value ranges

4.3.4.1. Planning value

A planning value is a possible value for a planning variable. Usually, a planning value is a problem fact, but it can also be any object, for example a double. It can even be another planning entity or even a interface implemented by a planning entity and a problem fact.

A planning value range is the set of possible planning values for a planning variable. This set can be a discrete (for example row `1`, `2`, `3` or `4`) or continuous (for example any `double` between `0.0` and `1.0`). Continuous planning variables are currently undersupported and require the use of custom moves.

There are several ways to define the value range of a planning variable with the `@ValueRange` annotation.

4.3.4.2. Planning value range

4.3.4.2.1. `ValueRange` from `Solution` property

All instances of the same planning entity class share the same set of possible planning values for that planning variable. This is the most common way to configure a value range.

The `Solution` implementation has property which returns a `Collection`. Any value from that `Collection` is a possible planning value for this planning variable.

```
    @PlanningVariable
    @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "rowList")
    public Row getRow() {
        return row;
    }
```

```
public class NQueens implements Solution<SimpleScore> {

    // ...

    public List<Row> getRowList() {
        return rowList;
    }

}
```

That `Collection` must not contain the value `null`, even for a *nullable planning variable*.

4.3.4.2.2. `ValueRange` from planning entity

Important

ValueRange from planning entity is currently not yet supported by the new MoveSelectors.

Each planning entity has its own set of possible planning values for a planning variable. For example, if a teacher can **never** teach in a room that does not belong to his department, lectures of that teacher can limit their room value range to the rooms of his department.

```
    @PlanningVariable
    @ValueRange(type = ValueRangeType.FROM_PLANNING_ENTITY_PROPERTY, planningEntityProperty = "
    public Room getRoom() {
        return room;
    }

    public List<Room> getPossibleRoomList() {
        return getCourse().getTeacher().getPossibleRoomList();
    }
```

Never use this to enforce a soft constraint (or even a hard constraint when the problem might not have a feasible solution). For example: *Unless there is no other way*, a teacher can not teach in a room that does not belong to his department. In this case, the teacher should *not* be limited in his room value range (because sometimes there is no other way).

Note

By limiting the value range specifically of 1 planning entity, you are effectively making a *build-in hard constraint*. This can be a very good thing, as the number of possible solutions is severely lowered. But this can also be a bad thing because it takes away the freedom of the optimization algorithms to temporarily break such a hard constraint.

A planning entity should *not* use other planning entities to determinate its value range. That would only try to make it solve the planning problem itself and interfere with the optimization algorithms.

4.3.4.2.3. `ValueRange` undefined

Leaves the value range undefined. Some optimization algorithms do not support this value range.

```
    @PlanningVariable
    @ValueRange(type = ValueRangeType.UNDEFINED)
    public Row getRow() {
        return row;
    }
```

4.3.4.2.4. Combining ValueRanges

Value ranges can be combined, for example:

```
    @PlanningVariable(...)
    @ValueRanges({
            @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "compa
            @ValueRange(type = ValueRangeType.FROM_PLANNING_ENTITY_PROPERTY, planningEntityProp
    public Car getCar() {
        return car;
    }
```

4.3.4.2.5. A `ValueRange` which includes other planning entities

In some cases (such as in chaining), the planning value itself is sometimes another planning entity. In such cases, it's often required that a planning entity is only eligible as a planning value if it's initialized:

```
    @PlanningVariable
    @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "copList", exc
    public Cop getPartner() {
        return partner;
    }
```

TODO: this is likely to change in the future (*jira* [https://issues.jboss.org/browse/JBRULES-3408]), as it should support specific planning variable initialization too.

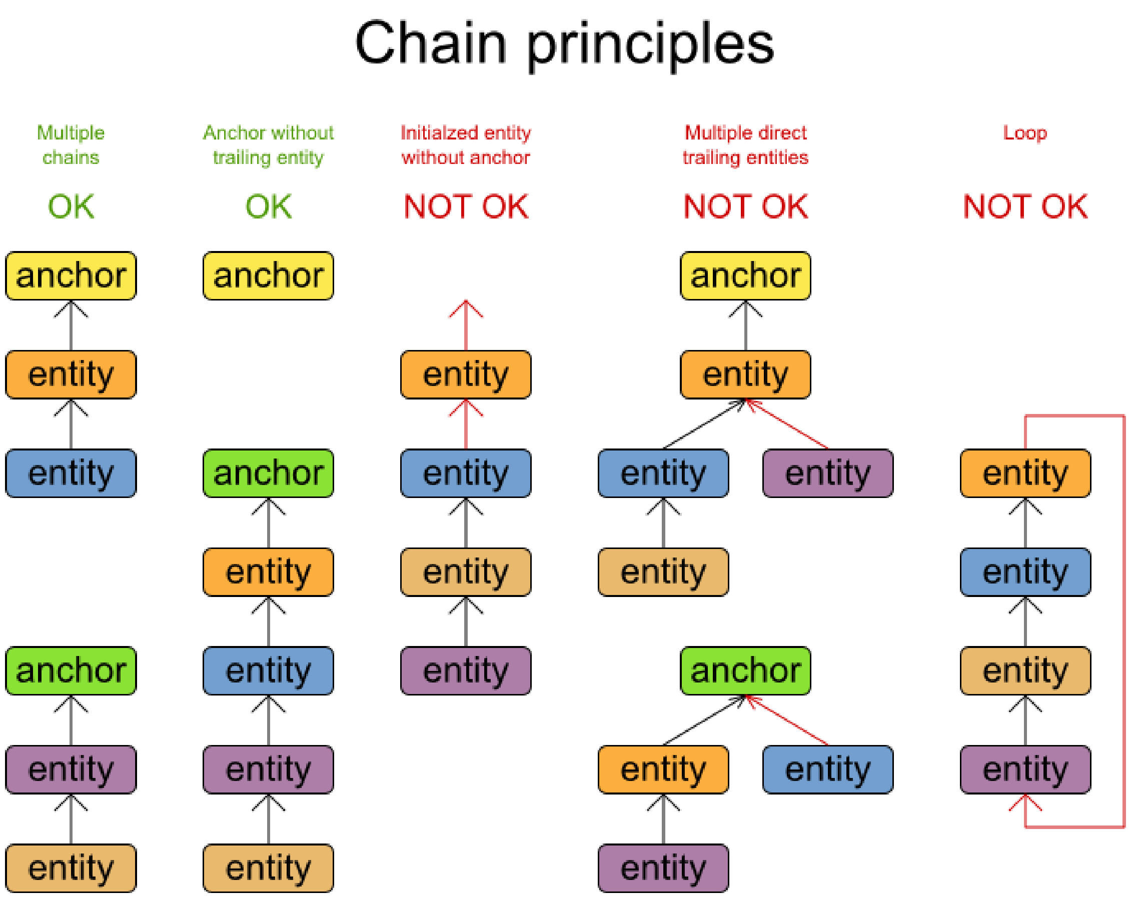
4.3.4.3. Chained planning variable

Some use cases, such as TSP and Vehicle Routing, require *chaining*. This means the planning entities point to each other and form a chain.

A planning variable that is chained either:

- Directly points to a planning fact, which is called an *anchor*.
- Points to another planning entity with the same planning variable, which recursively points to an anchor.

Here are some example of valid and invalid chains:


Chain principles
Multiple chains
OK
Anchor without trailing entity
OK
Initialzed entity without anchor
NOT OK
Multiple direct trailing entities
NOT OK
Loop
NOT OK
anchor
entity

Every initialized planning entity is part of an open-ended chain that begins from an anchor. A valid model means that:

- A chain is never a loop. The tail is always open.
- Every chain always has exactly 1 anchor. The anchor is a problem fact, never a planning entity.
- A chain is never a tree, it is always a line. Every anchor or planning entity has at most 1 trailing planning entity.
- Every initialized planning entity is part of a chain.
- An anchor with no planning entities pointing to it, is also considered a chain.

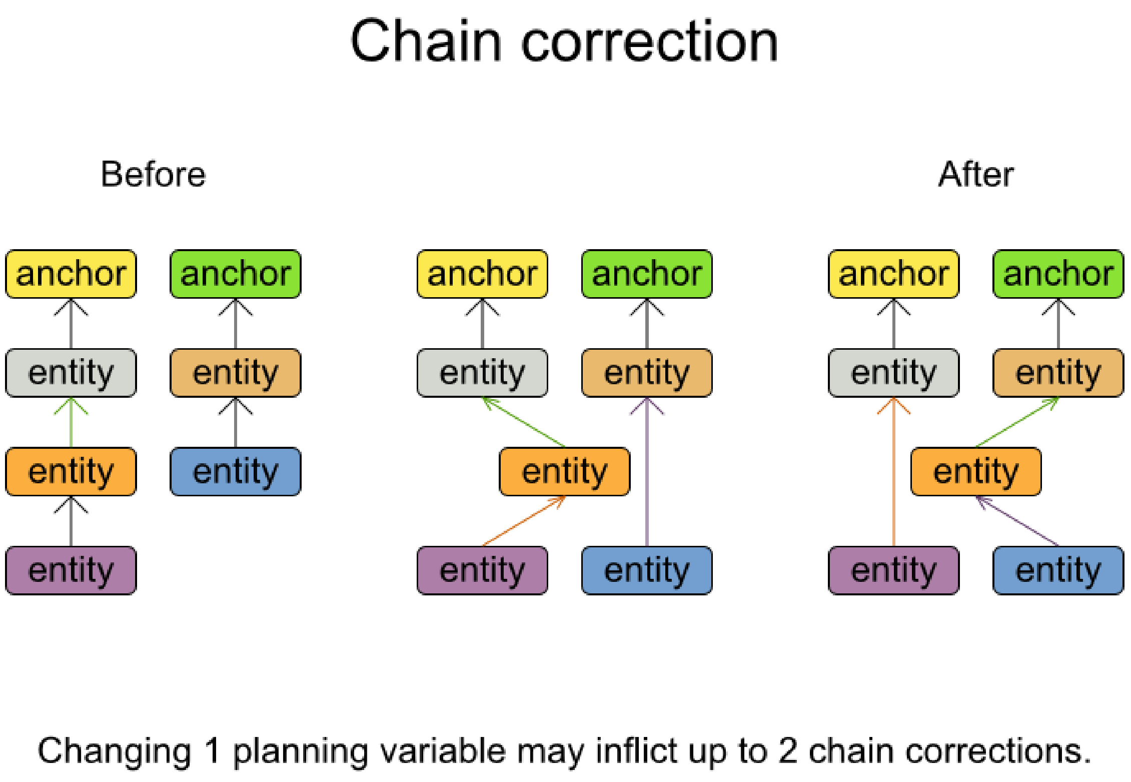
Warning

A planning problem instance given to the `Solver` must be valid.

Note

If your constraints dictate a closed chain, model it as an open-ended chain (which is easier to persist in a database) and implement a score constraint for the last entity back to the anchor.

The optimization algorithms and build-in `MoveFactory`'s do chain correction to guarantee that the model stays valid:



Warning

A custom `Move` implementation must leave the model in a valid state.

For example, in TSP the anchor is a `Domicile` (in vehicle routing it is the vehicle):

```
public class Domicile ... implements Appearance {
    ...

    public City getCity() {...}

}
```

The anchor (which is a problem fact) and the planning entity implement a common interface, for example TSP's `Appearance`:

```
public interface Appearance {

    City getCity();

}
```

That interface is the return type of the planning variable. Furthermore, the planning variable is chained. For example TSP's `Visit` (in vehicle routing it is the customer):

```
@PlanningEntity
public class Visit ... implements Appearance {

    ...

    public City getCity() {...}

    @PlanningVariable(chained = true)
    @ValueRanges({
            @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "domic
            @ValueRange(type = ValueRangeType.FROM_SOLUTION_PROPERTY, solutionProperty = "visit
                    excludeUninitializedPlanningEntity = true)})
    public Appearance getPreviousAppearance() {
        return previousAppearance;
    }

    public void setPreviousAppearance(Appearance previousAppearance) {
        this.previousAppearance = previousAppearance;
    }

}
```

Notice how 2 value ranges need to be combined:

- The value range which holds the anchors, for example `domicileList`.

- The value range which holds the initialized planning entities, for example `visitList`. This always requires an enabled `excludeUninitializedPlanningEntity`, because an initialized entity should never point to an uninitialized entity: that would break the principle that every chain must have an anchor.

4.3.4.4. Planning value strength

Some optimization algorithms work more efficiently if they have an estimation of which planning values are stronger, which means they are more likely to satisfy a planning entity. For example: in bin packing bigger containers are more likely to fit an item and in course scheduling bigger rooms are less likely to break the student capacity constraint.

Therefore, you can set a `strengthComparatorClass` to the `@PlanningVariable` annotation:

```
    @PlanningVariable(strengthComparatorClass = CloudComputerStrengthComparator.class)
    // ...
    public CloudComputer getComputer() {
        // ...
    }
```

```
public class CloudComputerStrengthComparator implements Comparator<CloudComputer> {

    public int compare(CloudComputer a, CloudComputer b) {
        return new CompareToBuilder()
                .append(a.getMultiplicand(), b.getMultiplicand())
                    .append(b.getCost(), a.getCost()) // Descending (but this
 is debatable)
                .append(a.getId(), b.getId())
                .toComparison();
    }

}
```

Note

If you have multiple planning value classes in the *same* value range, the `strengthComparatorClass` needs to implement a `Comparator` of a common superclass (for example `Comparator<Object>`) and be able to handle comparing instances of those different classes.

Alternatively, you can also set a `strengthWeightFactoryClass` to the `@PlanningVariable` annotation, so you have access to the rest of the problem facts from the solution too:

```
    @PlanningVariable(strengthWeightFactoryClass = RowStrengthWeightFactory.class)
    // ...
    public Row getRow() {
        // ...
    }
```

```
public interface PlanningValueStrengthWeightFactory {

    Comparable createStrengthWeight(Solution solution, Object planningValue);

}
```

```
public class RowStrengthWeightFactory implements PlanningValueStrengthWeightFactory {

    public Comparable createStrengthWeight(Solution solution, Object planningValue) {
        NQueens nQueens = (NQueens) solution;
        Row row = (Row) planningValue;
        int distanceFromMiddle = calculateDistanceFromMiddle(nQueens.getN(), row.getIndex());
        return new RowStrengthWeight(row, distanceFromMiddle);
    }

    // ...

    public static class RowStrengthWeight implements Comparable<RowStrengthWeight> {

        private final Row row;
        private final int distanceFromMiddle;

        public RowStrengthWeight(Row row, int distanceFromMiddle) {
            this.row = row;
            this.distanceFromMiddle = distanceFromMiddle;
        }

        public int compareTo(RowStrengthWeight other) {
            return new CompareToBuilder()
                    // The stronger rows have a lower distance to the middle
                      .append(other.distanceFromMiddle, distanceFromMiddle) //
 Decreasing (but this is debatable)
                    .append(row.getIndex(), other.row.getIndex())
                    .toComparison();
        }

    }
}
```

None of the current planning variable state in any of the planning entities may be used to compare planning values. They are likely to be `null` anyway. For example, none of the `row` variables of any `Queen` may be used to determine the strength of a `Row`.

4.3.5. Planning problem and planning solution

4.3.5.1. Planning problem instance

A dataset for a planning problem needs to be wrapped in a class for the `Solver` to solve. You must implement this class. For example in n queens, this in the `NQueens` class which contains a `Column` list, a `Row` list and a `Queen` list.

A planning problem is actually a unsolved planning solution or - stated differently - an uninitialized `Solution`. Therefor, that wrapping class must implement the `Solution` interface. For example in n queens, that `NQueens` class implements `Solution`, yet every `Queen` in a fresh `NQueens` class is not yet assigned to a `Row` (their `row` property is `null`). So it's not a feasible solution. It's not even a possible solution. It's an uninitialized solution.

4.3.5.2. The `Solution` interface

You need to present the problem as a `Solution` instance to the `Solver`. So you need to have a class that implements the `Solution` interface:

```
public interface Solution<S extends Score> {

    S getScore();
    void setScore(S score);

    Collection<? extends Object> getProblemFacts();

    Solution<S> cloneSolution();

}
```

For example, an `NQueens` instance holds a list of all columns, all rows and all `Queen` instances:

```
public class NQueens implements Solution<SimpleScore> {

    private int n;

    // Problem facts
    private List<Column> columnList;
    private List<Row> rowList;
    // Planning entities
    private List<Queen> queenList;

    // ...
}
```

4.3.5.3. The getScore and setScore methods

A `Solution` requires a score property. The score property is `null` if the `Solution` is uninitialized or if the score has not yet been (re)calculated. The `score` property is usually typed to the specific `Score` implementation you use. For example, `NQueens` uses a `SimpleScore`:

```
public class NQueens implements Solution<SimpleScore> {

    private SimpleScore score;

    public SimpleScore getScore() {
        return score;
    }

    public void setScore(SimpleScore score) {
        this.score = score;
    }

    // ...
}
```

Most use cases use a `HardAndSoftScore` instead:

```
public class CurriculumCourseSchedule implements Solution<HardAndSoftScore> {

    private HardAndSoftScore score;

    public HardAndSoftScore getScore() {
        return score;
    }

    public void setScore(HardAndSoftScore score) {
        this.score = score;
    }

    // ...
}
```

See the Score calculation section for more information on the `Score` implementations.

4.3.5.4. The getProblemFacts method

The method is only used if Drools is used for score calculation. Other score directors do not use it.

All objects returned by the `getProblemFacts()` method will be asserted into the Drools working memory, so the score rules can access them. For example, `NQueens` just returns all `Column` and `Row` instances.

```
    public Collection<? extends Object> getProblemFacts() {
        List<Object> facts = new ArrayList<Object>();
        facts.addAll(columnList);
        facts.addAll(rowList);
         // Do not add the planning entity's (queenList) because that will be
 done automatically
        return facts;
    }
```

All planning entities are automatically inserted into the Drools working memory. Do not add them in the method `getProblemFacts()`.

The method `getProblemFacts()` is not called much: at most only once per solver phase per solver thread.

4.3.5.5. Cached problem fact

A cached problem fact is a problem fact that doesn't exist in the real domain model, but is calculated before the `Solver` really starts solving. The method `getProblemFacts()` has the chance to enrich the domain model with such cached problem facts, which can lead to simpler and faster score constraints.

For example in examination, a cached problem fact `TopicConflict` is created for every 2 `Topic`'s which share at least 1 `Student`.

```
    public Collection<? extends Object> getProblemFacts() {
        List<Object> facts = new ArrayList<Object>();
        // ...
        facts.addAll(calculateTopicConflictList());
        // ...
        return facts;
    }

    private List<TopicConflict> calculateTopicConflictList() {
        List<TopicConflict> topicConflictList = new ArrayList<TopicConflict>();
        for (Topic leftTopic : topicList) {
            for (Topic rightTopic : topicList) {
                if (leftTopic.getId() < rightTopic.getId()) {
                    int studentSize = 0;
                    for (Student student : leftTopic.getStudentList()) {
                        if (rightTopic.getStudentList().contains(student)) {
                            studentSize++;
                        }
                    }
                    if (studentSize > 0) {
                        topicConflictList.add(new TopicConflict(leftTopic, rightTopic, studentS
                    }
                }
            }
        }
        return topicConflictList;
    }
```

Any score constraint that needs to check if no 2 exams have a topic which share a student are being scheduled close together (depending on the constraint: at the same time, in a row or in the same day), can simply use the `TopicConflict` instance as a problem fact, instead of having to combine every 2 `Student` instances.

4.3.5.6. The cloneSolution method

Most optimization algorithms use the `cloneSolution()` method to clone the solution each time they encounter a new best solution (so they can recall it later) or to work with multiple solutions in parallel.

The `NQueens` implementation only deep clones all `Queen` instances. When the original solution is changed during planning, by changing a `Queen`, the clone stays the same.

```
    /**
     * Clone will only deep copy the {@link #queenList}.
     */
    public NQueens cloneSolution() {
        NQueens clone = new NQueens();
        clone.id = id;
        clone.n = n;
        clone.columnList = columnList;
        clone.rowList = rowList;
        List<Queen> clonedQueenList = new ArrayList<Queen>(queenList.size());
        for (Queen queen : queenList) {
            clonedQueenList.add(queen.clone());
        }
        clone.queenList = clonedQueenList;
        clone.score = score;
        return clone;
    }
```

The `cloneSolution()` method should only deep clone the planning entities. Notice that the problem facts, such as `Column` and `Row` are normally *not* cloned: even their `List` instances are *not* cloned.

Note

If you were to clone the problem facts too, then you'd have to make sure that the new planning entity clones also refer to the new problem facts clones used by the solution. For example, if you 'd clone all `Row` instances, then each `Queen` clone and the `NQueens` clone itself should refer to the same set of new `Row` clones.

4.3.5.7. Build an uninitialized solution

Build a `Solution` instance to represent your planning problem, so you can set it on the `Solver` as the planning problem to solve. For example in n queens, an `NQueens` instance is created with the required `Column` and `Row` instances and every `Queen` set to a different `column` and every `row` set to `null`.

```
    private NQueens createNQueens(int n) {
        NQueens nQueens = new NQueens();
        nQueens.setId(0L);
        nQueens.setN(n);
        List<Column> columnList = new ArrayList<Column>(n);
        for (int i = 0; i < n; i++) {
            Column column = new Column();
            column.setId((long) i);
            column.setIndex(i);
            columnList.add(column);
        }
        nQueens.setColumnList(columnList);
        List<Row> rowList = new ArrayList<Row>(n);
        for (int i = 0; i < n; i++) {
            Row row = new Row();
            row.setId((long) i);
            row.setIndex(i);
            rowList.add(row);
        }
        nQueens.setRowList(rowList);
        List<Queen> queenList = new ArrayList<Queen>(n);
        long id = 0;
        for (Column column : columnList) {
            Queen queen = new Queen();
            queen.setId(id);
            id++;
            queen.setColumn(column);
           // Notice that we leave the PlanningVariable properties (row) on null
            queenList.add(queen);
        }
        nQueens.setQueenList(queenList);
        return nQueens;
    }
```

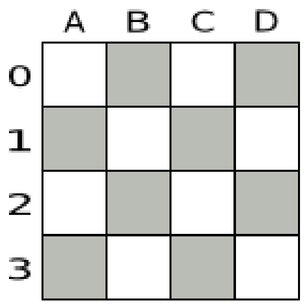


Figure 4.1. Uninitialized solution for the 4 queens puzzle

Usually, most of this data comes from your data layer, and your `Solution` implementation just aggregates that data and creates the uninitialized planning entity instances to plan:

```
        private void createLectureList(CurriculumCourseSchedule schedule) {
            List<Course> courseList = schedule.getCourseList();
          List<Lecture> lectureList = new ArrayList<Lecture>(courseList.size());
            for (Course course : courseList) {
                for (int i = 0; i < course.getLectureSize(); i++) {
                    Lecture lecture = new Lecture();
                    lecture.setCourse(course);
                    lecture.setLectureIndexInCourse(i);
                       // Notice that we leave the PlanningVariable properties
 (period and room) on null
                    lectureList.add(lecture);
                }
            }
            schedule.setLectureList(lectureList);
        }
```

4.4. Use the `Solver`

4.4.1. The Solver interface

A `Solver` implementation will solve your planning problem.

```
public interface Solver {

    void setPlanningProblem(Solution planningProblem);

    void solve();

    Solution getBestSolution();

    // ...

}
```

A `Solver` can only solve 1 planning problem instance at a time. A `Solver` should only be accessed from a single thread, except for the methods that are specifically javadocced as being thread-safe. It's build with a `SolverFactory`, do not implement or build it yourself.

4.4.2. Solving a problem

Solving a problem is quite easy once you have:

- A `Solver` build from a solver configuration
- A `Solution` that represents the planning problem instance

Just set the planning problem, solve it and extract the best solution:

```
    solver.setPlanningProblem(planningProblem);
    solver.solve();
    Solution bestSolution = solver.getBestSolution();
```

For example in n queens, the method `getBestSolution()` will return an `NQueens` instance with every `Queen` assigned to a `Row`.

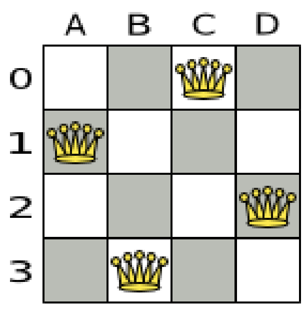


Figure 4.2. Best solution for the 4 queens puzzle in 8 ms (also an optimal solution)

The `solve()` method can take a long time (depending on the problem size and the solver configuration). The `Solver` will remember (actually clone) the best solution it encounters during its solving. Depending on a number factors (including problem size, how much time the `Solver` has, the solver configuration, ...), that best solution will be a feasible or even an optimal solution.

Note

The `Solution` instance given to the method `setPlanningProblem()` will be changed by the `Solver`, but it do not mistake it for the best solution.

The `Solution` instance returned by the method `getBestSolution()` will most likely be a clone of the instance given to the method `setPlanningProblem()`, which means it's a different instance.

Note

The `Solution` instance given to the method `setPlanningProblem()` does not need to be uninitialized. It can be partially or fully initialized, which is likely to be the case in *repeated planning*.

4.4.3. Environment mode: Are there bugs in my code?

The environment mode allows you to detect common bugs in your implementation. It does not affect the logging level.

You can set the environment mode in the solver configuration XML file:

```
<solver>
  <environmentMode>DEBUG</environmentMode>
  ...
</solver>
```

A solver has a single `Random` instance. Some solver configurations use the `Random` instance a lot more than others. For example simulated annealing depends highly on random numbers, while tabu search only depends on it to deal with score ties. The environment mode influences the seed of that `Random` instance.

There are 4 environment modes:

4.4.3.1. TRACE

The trace mode is reproducible (see the reproducible mode) and also turns on all assertions (such as assert that the incremental score calculation is uncorrupted) to fail-fast on rule engine bugs.

The trace mode is very slow (because it doesn't rely on delta based score calculation).

4.4.3.2. DEBUG

The debug mode is reproducible (see the reproducible mode) and also turns on most assertions (such as assert that an undo Move's score is the same as before the Move) to fail-fast on a bug in your Move implementation, your score rule, ...

The debug mode is slow.

It's recommended to write a test case which does a short run of your planning problem with debug mode on.

4.4.3.3. REPRODUCIBLE (default)

The reproducible mode is the default mode because it is recommended during development. In this mode, 2 runs in the same Planner version will execute the same code in the same order. **Those 2 runs will have the same result**, except if they rely on time based termination and they have a sufficiently large difference in allocated CPU time. This allows you to consistently reproduce bugs. It also allows you to benchmark certain refactorings (such as a score constraint optimization) fairly across runs.

The reproducible mode is not much slower than the production mode. If your production environment requires reproducibility, use it in production too.

In practice, this mode uses the default random seed, and it also disables certain concurrency optimizations (such as work stealing).

4.4.3.4. PRODUCTION

The production mode is the fastest and the most robust, but not reproducible. It is recommended for a production environment.

The random seed is different on every run, which makes it more robust against an unlucky random seed. An unlucky random seed gives a bad result on a certain data set with a certain solver configuration. Note that in most use cases the impact of the random seed is relatively low on the result (even with simulated annealing). An occasional bad result is far more likely to be caused by another issue (such as a score trap).

4.4.4. Logging level: What is the `Solver` doing?

The best way to illuminate the black box that is a `Solver`, is to play with the logging level:

- **ERROR**: Log errors, except those that are thrown to the calling code as a `RuntimeException`.

  Note

  If an error happens, Planner normally fails fast: it throws a subclass of `RuntimeException` with a detailed message to the calling code. It does not log it as an error itself to avoid duplicate log messages. Unless the calling code explicitly catches and eats that `RuntimeException`, a `Thread`'s default `ExceptionHandler` will log it as an error anyway. Meanwhile, the code is disrupted from doing further harm or obfuscating the error.

- **WARN**: Log suspicious circumstances.
- **INFO**: Log every phase and the solver itself. See *scope overview*.
- **DEBUG**: Log every step of every phase. See *scope overview*.
- **TRACE**: Log every move of every step of every phase. See *scope overview*.

Note

Turning on `TRACE` logging, will slow down performance considerably: it's often 4 times slower. However, it's invaluable during development to discover a bottleneck.

For example, set it to `DEBUG` logging, to see when the phases end and how fast steps are taken:

```
INFO  Solving started: time spend (0), score (null), new best score (null), random seed (0).
DEBUG     Step index (0), time spend (1), score (0), initialized planning entity (col2@row0).
DEBUG     Step index (1), time spend (3), score (0), initialized planning entity (col1@row2).
DEBUG     Step index (2), time spend (4), score (0), initialized planning entity (col3@row3).
DEBUG     Step index (3), time spend (5), score (-1), initialized planning entity (col0@row1).
INFO  Phase constructionHeuristic finished: step total (4), time spend (6), best score (-1).
DEBUG     Step index (0), time spend (10), score (-1),     best score (-1), accepted/selected move count (12/12) for picked step (col1@row2 => row3).
DEBUG     Step index (1), time spend (12), score (0), new best score (0), accepted/selected move count (12/12) for picked step (col3@row3 => row2).
INFO  Phase localSearch ended: step total (2), time spend (13), best score (0).
INFO  Solving ended: time spend (13), best score (0), average calculate count per second (4846).
```

All time spends are in milliseconds.

Everything is logged to *SLF4J* [http://www.slf4j.org/], which is a simple logging facade which delegates every log message to Logback, Apache Commons Logging, Log4j or java.util.logging. Add a dependency to the logging adaptor for your logging framework of choice.

If you're not using any logging framework yet, use Logback by adding this Maven dependency (there is no need to add an extra bridge dependency):

```
    <dependency>
      <groupId>ch.qos.logback</groupId>
      <artifactId>logback-classic</artifactId>
      <version>1.x</version>
    </dependency>
```

Configure the logging level on the package `org.drools.planner` in your `logback.xml` file:

```
<configuration>

  <logger name="org.drools.planner" level="debug"/>

  ...

<configuration>
```

If instead, you're still using Log4J (and you don't want to switch to its faster spiritual successor, Logback), add the bridge dependency:

```
    <dependency>
      <groupId>org.slf4j</groupId>
      <artifactId>slf4j-log4j12</artifactId>
      <version>1.x</version>
    </dependency>
```

And configure the logging level on the package `org.drools.planner` in your `log4j.xml` file:

```
<log4j:configuration xmlns:log4j="http://jakarta.apache.org/log4j/">

  <category name="org.drools.planner">
    <priority value="debug" />
  </category>

  ...

</log4j:configuration>
```

Chapter 5. Score calculation

5.1. Score terminology

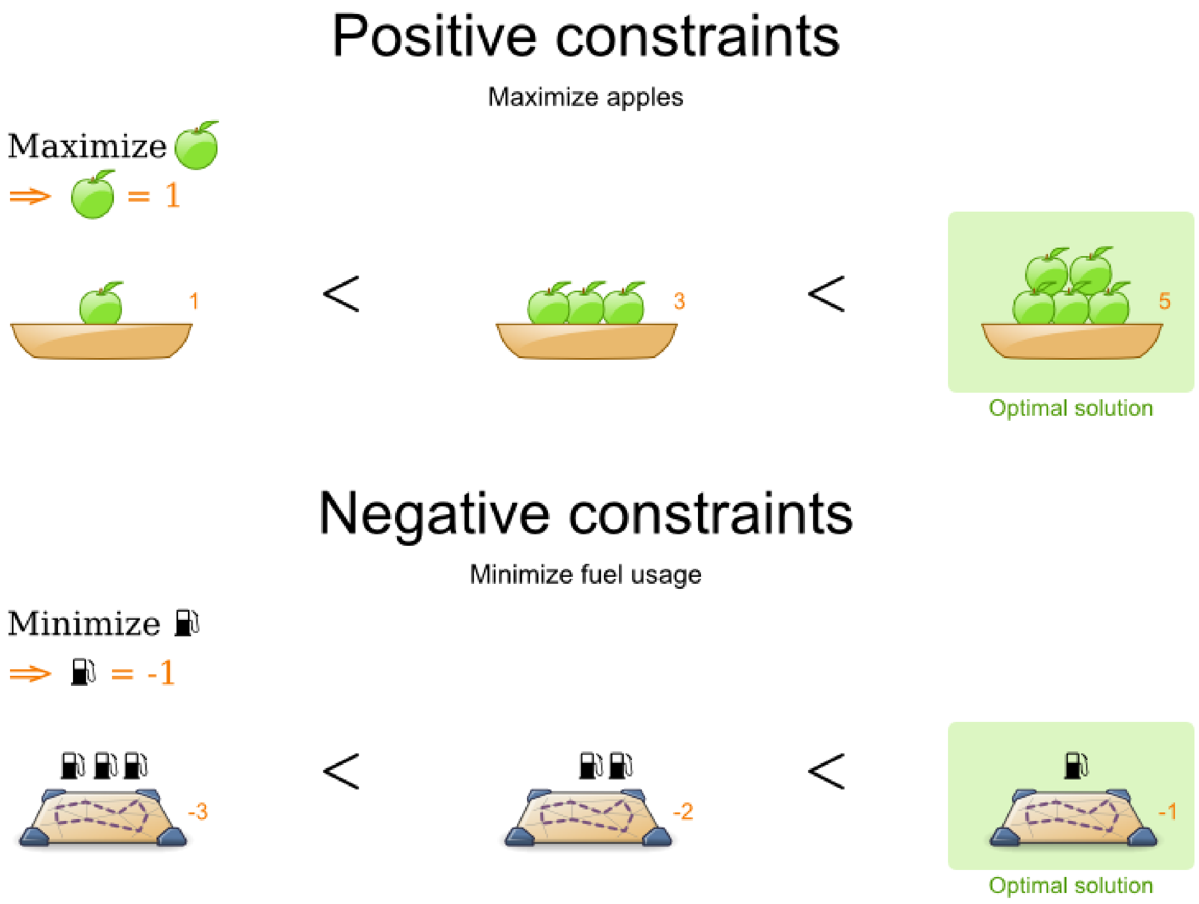
5.1.1. What is a score?

Every initialized `Solution` has a score. That score is an objective way to compare 2 solutions: the solution with the higher score is better. The `Solver` aims to find the `Solution` with the highest `Score` of all possible solutions. The *best solution* is the `Solution` with the highest `Score` that `Solver` has encountered during solving, which might be the *optimal solution*.

Planner cannot automatically know which `Solution` is best for your business, so you need to tell it how to calculate the score of a given `Solution` according to your business needs. There are multiple score techniques that you can use and combine.

5.1.2. Positive and negative constraints

All score techniques are based on constraints. Such a constraint can be a simple pattern (such as *Maximize the apple harvest in the solution*) or a more complex pattern. a positive constraint is a constraint you're trying to maximize. A negative constraint is a constraint you're trying to minimize.



Notice in the image above, that the optimal solution always has the highest score, regardless if the constraints are positive or negative.

Most planning problems have only negative constraints and therefore have a negative score. In that case, the score is usually the sum of the weight of the negative constraints being broken, with a perfect score of 0. This explains why the score of a solution of 4 queens is the negative (and not the positive!) of the number of queen couples which can attack each other.

Negative and positive constraints can be combined, even in the same score level.

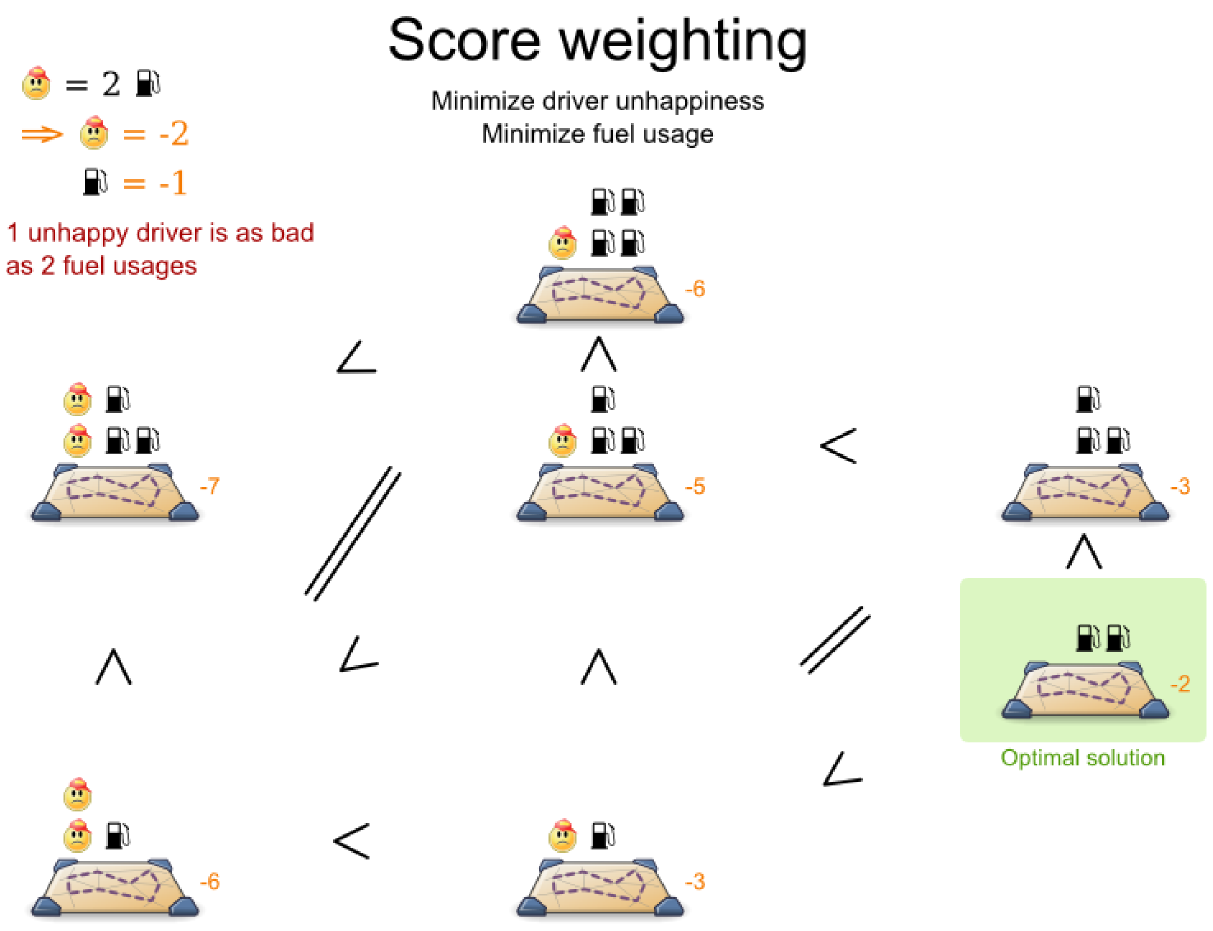
Note

Don't presume your business knows all its score constraints in advance. Expect score constraints to be added or changed after the first releases.

When a constraint activates (because the negative constraint is broken or the positive constraint is fulfilled) on a certain planning entity set, it is called a *constraint occurrence*.

5.1.3. Score constraint weighting

Not all score constraints are equally important. If breaking one constraint is equally bad as breaking another constraint x times, then those 2 constraints have a different weight (but they are in the same score level). For example in vehicle routing, you can make 2 "unhappy driver" constraint occurrences count as much as 1 "fuel tank usage" constraint occurrence:



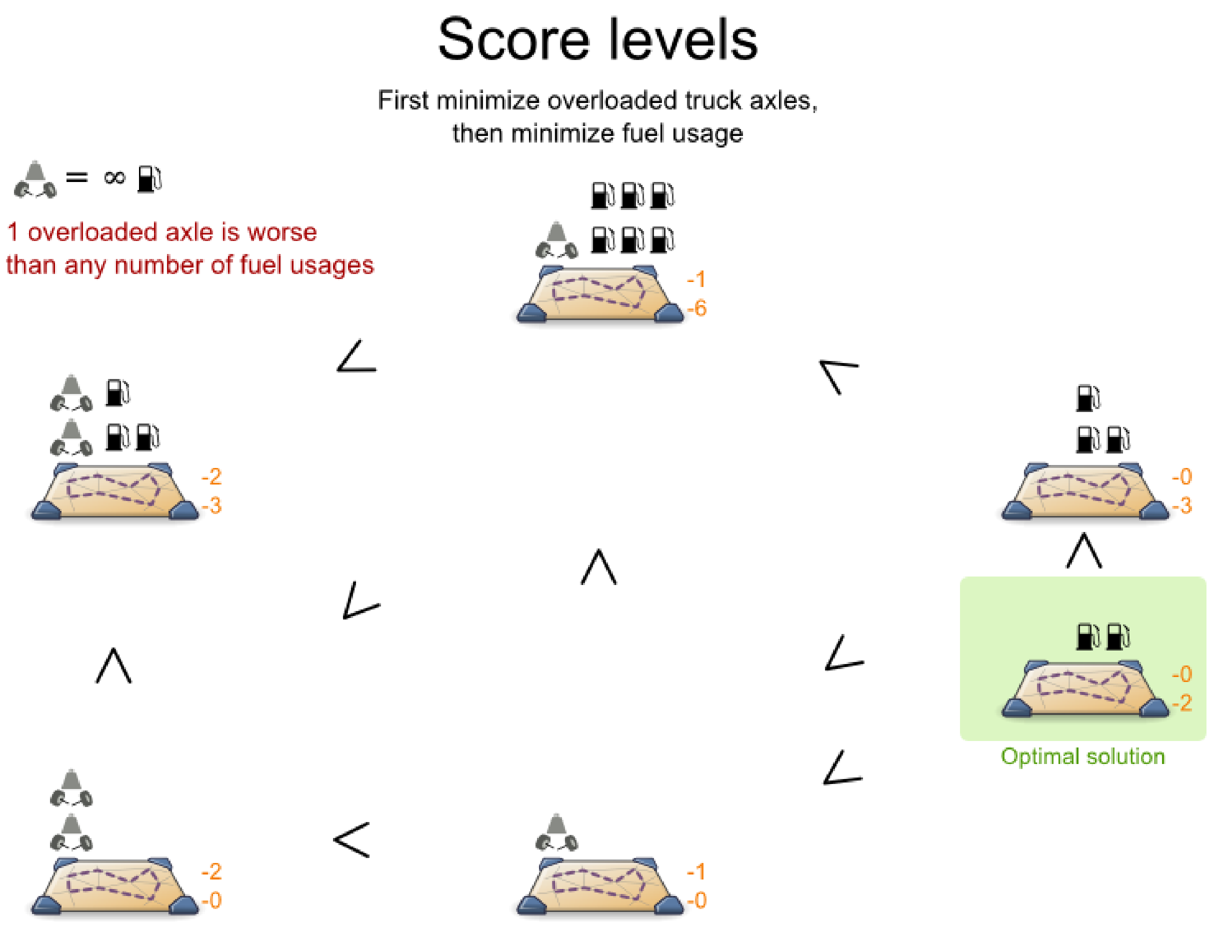
Score weighting is often used in use cases where you can put a price tag on everything. In that case, the positive constraints maximize revenue and the negative constraints minimize expenses: together they maximize profit. Alternatively, score weighting is also often used to create social fairness. For example: nurses that request a free day on New Year's eve pay a higher weight than on a normal day.

The weight of a constraint occurrence can be dynamically based on the planning entities involved. For example in cloud balance: the weight of the soft constraint occurrence for an active `Computer` is the `cost` of that `Computer`.

5.1.4. Score level

Sometimes a score constraint outranks another score constraint, no matter how many times the other is broken. In that case, those score constraints are in different levels. For example: a nurse cannot do 2 shifts at the same time (due to the constraints of physical reality), this outranks nurse happiness constraints.

Most use cases have only 2 score levels: hard and soft. When comparing 2 scores, they are compared lexicographically: the first score level gets compared first. If those differ, the others score levels are ignored. For example: a score that breaks 0 hard constraints and 1000000 soft constraints is better than a score that breaks 1 hard constraint and 0 soft constraints.



Score levels
First minimize overloaded truck axles, then minimize fuel usage
= ∞
1 overloaded axle is worse than any number of fuel usages
-1
-6
-2
-3
-0
-3
-0
-2
Optimal solution
-2
-0
-1
-0

Score levels often employ score weighting per level. In such case, the hard constraint level usually makes the solution feasible and the soft constraint level maximizes profit by weighting the constraints on price.

Note

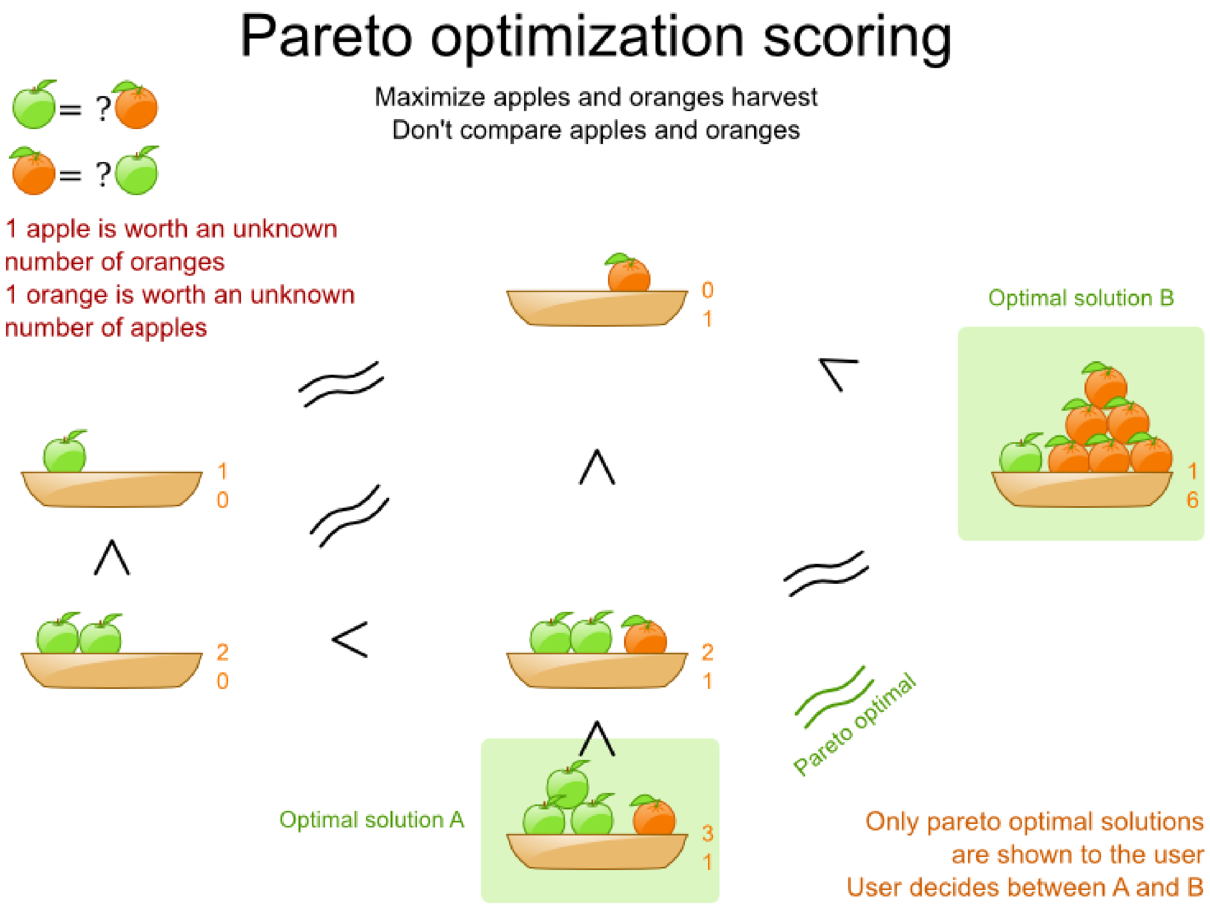
Your business will probably tell you that your hard constraints all have the same weight, because they cannot be broken (so their weight does not matter). This is not true and it could create a *score trap*. For example in cloud balance: if a `Computer` has 7 CPU too little for its `Processes`, then it must be weighted 7 times as much as if it had only 1 CPU too little. This way, there is an incentive to move a `Process` with 6 CPU or less away from that Computer.

3 or more score levels is supported. For example: a company might decide that profit outranks employee satisfaction (or visa versa), while both are outranked by the constraints of physical reality.

5.1.5. Pareto scoring (AKA multi-objective optimization scoring)

Far less common is the use case of pareto optimization, which is also known under the more confusing term multi-objective optimization. In pareto scoring, score constraints are in the same score level, yet they are not weighted against each other. When 2 scores are compared, each of the score constraints are compared individually and the score with the most dominating score constraints wins. Pareto scoring can even be combined with score levels and score constraint weighting.

Consider this example with positive constraints, where we want to get the most apples and oranges. Since it's impossible to compare apples and oranges, we can't weight them against each other. Yet, despite that we can't compare them, we can state that 2 apples are better then 1 apple. Similarly, we can state that 2 apples and 1 orange are better than just 1 orange. So despite our inability to compare some Scores conclusively (at which point we declare them equal), we can find a set of optimal scores. Those are called pareto optimal.


Pareto optimization scoring
Maximize apples and oranges harvest
Don't compare apples and oranges
= ?
= ?
1 apple is worth an unknown number of oranges
1 orange is worth an unknown number of apples
0 1
1 0
2 0
2 1
3 1
1 6
Optimal solution B
Optimal solution A
Pareto optimal
Only pareto optimal solutions are shown to the user
User decides between A and B

Scores are considered equal far more often. It's left up to a human to choose the better out of a set of best solutions (with equal scores) found by Planner. In the example above, the user must choose between solution A (3 apples and 1 orange) and solution B (1 apples and 6 oranges). It's guaranteed that Planner has not found another solution which has more apples or more oranges or even a better combination of both (such as 2 apples and 3 oranges).

To implement pareto scoring in Planner, *implement a custom `ScoreDefinition` and `Score`*. Future versions will provide out-of-the-box support.

Note

A pareto `Score`'s method `compareTo` is not transitive because it does a pareto comparison. For example: 2 apples is greater than 1 apple. 1 apples is equal to 1 orange. Yet, 2 apples are not greater than 1 orange (but actually equal). Pareto comparison violates the contract of the interface `java.lang.Comparable`'s method `compareTo`, but Planner's systems are *pareto comparison safe*, unless explicitly stated otherwise in this documentation.

5.1.6. The `Score` interface

A score is represented by the `Score` interface, which naturally extends `Comparable`:

```
public interface Score<...> extends Comparable<...> {
    ...
}
```

The `Score` implementation to use depends on your use case. Your score might not efficiently fit in a single `double` value. Planner has several build-in Score implementations, but you can implement a custom Score too. Most use cases will just use the build-in `HardAndSoftScore`.

The `Score` implementation (for example `DefaultHardAndSoftScore`) must be the same throughout a `Solver` runtime. The `Score` implementation is configured in the solver configuration as a ScoreDefinition:

```
  <scoreDirectorFactory>
    <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>
    ...
  </scoreDirectorFactory>
```

Based on your score constraints and score level requirements, you'll choose a certain `ScoreDefinition`:

5.2. Choose a Score definition

5.2.1. SimpleScore

The `SimpleScoreDefinition` defines the `Score` as a `SimpleScore` which has a single `int` value, for example `-123`. It has a single score level.

```
  <scoreDirectorFactory>
    <scoreDefinitionType>SIMPLE</scoreDefinitionType>
    ...
  </scoreDirectorFactory>
```

Variants:

- `SimpleDoubleScore`: Uses a `double` value instead of an `int` value. Configure it with `scoreDefinitionType` `SIMPLE_DOUBLE`.

5.2.2. HardAndSoftScore (recommended)

The `HardAndSoftScoreDefinition` defines the `Score` as a `HardAndSoftScore` which has a hard `int` value and a soft `int` value, for example `-123hard/-456soft`. It has 2 score levels (hard and soft).

```
<scoreDirectorFactory>
  <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>
  ...
</scoreDirectorFactory>
```

Variants:

- `HardAndSoftLongScore`: Uses `long` values instead of `int` values. Configure it with `scoreDefinitionType` `HARD_AND_SOFT_LONG`.

5.2.3. Implementing a custom Score

The `ScoreDefinition` interface defines the score representation.

To implement a custom Score, you'll also need to implement a custom `ScoreDefinition`. Extend `AbstractScoreDefinition` (preferable by copy pasting `HardAndSoftScoreDefinition` or `SimpleScoreDefinition`) and start from there.

Then hook you custom `ScoreDefinition` in your `SolverConfig.xml`:

```
<scoreDirectorFactory>

efinitionClass>org.drools.planner.examples.my.score.definition.MyScoreDefinition</
scoreDefinitionClass>
  ...
</scoreDirectorFactory>
```

5.3. Calculate the `Score`

5.3.1. Score calculation types

There are several ways to calculate the `Score` of a `Solution`:

- **Simple Java score calculation**: implement a single Java method
- **Incremental Java score calculation**: implement multiple Java methods
- **Drools score calculation**: implement score rules

Every score calculation type can use any Score definition. For example, simple score calculation can output a `HardAndSoftScore`.

All score calculation types are Object Orientated and can reuse existing Java code.

5.3.2. Simple Java score calculation

A simple way to implement your score calculation in Java.

- Advantages:
  - Plain old Java: no learning curve
  - Opportunity to delegate score calculation to an existing code base or legacy system
- Disadvantages:
  - Slower and less scalable
    - Because there is no *incremental score calculation*

Just implement one method of the interface `SimpleScoreCalculator`:

```
public interface SimpleScoreCalculator<Sol extends Solution> {

    Score calculateScore(Sol solution);

}
```

For example in n queens:

```
public class NQueensSimpleScoreCalculator implements SimpleScoreCalculator<NQueens> {

    public SimpleScore calculateScore(NQueens nQueens) {
        int n = nQueens.getN();
        List<Queen> queenList = nQueens.getQueenList();

        int score = 0;
        for (int i = 0; i < n; i++) {
            for (int j = i + 1; j < n; j++) {
                Queen leftQueen = queenList.get(i);
                Queen rightQueen = queenList.get(j);
               if (leftQueen.getRow() != null && rightQueen.getRow() != null) {
                    if (leftQueen.getRowIndex() == rightQueen.getRowIndex()) {
                        score--;
                    }
                    if (leftQueen.getAscendingDiagonalIndex() == rightQueen.getAscendingDiagona
                        score--;
                    }
                    if (leftQueen.getDescendingDiagonalIndex() == rightQueen.getDescendingDiago
                        score--;
                    }
                }
            }
        }
        return DefaultSimpleScore.valueOf(score);
    }

}
```

Configure it in your solver configuration:

```
  <scoreDirectorFactory>
    <scoreDefinitionType>...</scoreDefinitionType>

ner.examples.nqueens.solver.score.NQueensSimpleScoreCalculator</
simpleScoreCalculatorClass>
  </scoreDirectorFactory>
```

Alternatively, build a `SimpleScoreCalculator` instance at runtime and set it with the programmatic API:

```
    solverFactory.getSolverConfig().getScoreDirectorFactoryConfig.setSimpleScoreCalculator(simp
```

5.3.3. Incremental Java score calculation

A way to implement your score calculation incrementally in Java.

- Advantages:
  - Very fast and scalable
    - Currently the fastest if implemented correctly
- Disadvantages:
  - Hard to write
    - A scalable implementation heavily uses maps, indexes, ... (things the Drools rule engine can do for you)
    - You have to learn, design, write and improve all these performance optimizations yourself
  - Hard to read

- Regular score constraint changes can lead to a high maintenance cost

Implement all the methods of the interface `IncrementalScoreCalculator` and extend the class `AbstractIncrementalScoreCalculator`:

```
public interface IncrementalScoreCalculator<Sol extends Solution> {

    void resetWorkingSolution(Sol workingSolution);

    void beforeEntityAdded(Object entity);

    void afterEntityAdded(Object entity);

    void beforeAllVariablesChanged(Object entity);

    void afterAllVariablesChanged(Object entity);

    void beforeVariableChanged(Object entity, String variableName);

    void afterVariableChanged(Object entity, String variableName);

    void beforeEntityRemoved(Object entity);

    void afterEntityRemoved(Object entity);

    Score calculateScore();

}
```

For example in n queens:

```
public class NQueensAdvancedIncrementalScoreCalculator extends AbstractIncrementalScoreCalculat

    private Map<Integer, List<Queen>> rowIndexMap;
    private Map<Integer, List<Queen>> ascendingDiagonalIndexMap;
    private Map<Integer, List<Queen>> descendingDiagonalIndexMap;

    private int score;

    public void resetWorkingSolution(NQueens nQueens) {
        int n = nQueens.getN();
        rowIndexMap = new HashMap<Integer, List<Queen>>(n);
        ascendingDiagonalIndexMap = new HashMap<Integer, List<Queen>>(n * 2);
        descendingDiagonalIndexMap = new HashMap<Integer, List<Queen>>(n * 2);
        for (int i = 0; i < n; i++) {
            rowIndexMap.put(i, new ArrayList<Queen>(n));
```

```
                ascendingDiagonalIndexMap.put(i, new ArrayList<Queen>(n));
                descendingDiagonalIndexMap.put(i, new ArrayList<Queen>(n));
                if (i != 0) {
                  ascendingDiagonalIndexMap.put(n - 1 + i, new ArrayList<Queen>(n));
                    descendingDiagonalIndexMap.put((-i), new ArrayList<Queen>(n));
                }
            }
            score = 0;
            for (Queen queen : nQueens.getQueenList()) {
                insert(queen);
            }
        }

        public void beforeEntityAdded(Object entity) {
            // Do nothing
        }

        public void afterEntityAdded(Object entity) {
            insert((Queen) entity);
        }

        public void beforeAllVariablesChanged(Object entity) {
            retract((Queen) entity);
        }

        public void afterAllVariablesChanged(Object entity) {
            insert((Queen) entity);
        }

        public void beforeVariableChanged(Object entity, String variableName) {
            retract((Queen) entity);
        }

        public void afterVariableChanged(Object entity, String variableName) {
            insert((Queen) entity);
        }

        public void beforeEntityRemoved(Object entity) {
            retract((Queen) entity);
        }

        public void afterEntityRemoved(Object entity) {
            // Do nothing
        }

        private void insert(Queen queen) {
            Row row = queen.getRow();
            if (row != null) {
                int rowIndex = queen.getRowIndex();
                List<Queen> rowIndexList = rowIndexMap.get(rowIndex);
                score -= rowIndexList.size();
                rowIndexList.add(queen);
                List<Queen> ascendingDiagonalIndexList = ascendingDiagonalIndexMap.get(queen.getAsc
                score -= ascendingDiagonalIndexList.size();
                ascendingDiagonalIndexList.add(queen);
                List<Queen> descendingDiagonalIndexList = descendingDiagonalIndexMap.get(queen.getD
                score -= descendingDiagonalIndexList.size();
                descendingDiagonalIndexList.add(queen);
            }
        }

        private void retract(Queen queen) {
            Row row = queen.getRow();
            if (row != null) {
                List<Queen> rowIndexList = rowIndexMap.get(queen.getRowIndex());
                rowIndexList.remove(queen);
                score += rowIndexList.size();
                List<Queen> ascendingDiagonalIndexList = ascendingDiagonalIndexMap.get(queen.getAsc
                ascendingDiagonalIndexList.remove(queen);
                score += ascendingDiagonalIndexList.size();
                List<Queen> descendingDiagonalIndexList = descendingDiagonalIndexMap.get(queen.getD
                descendingDiagonalIndexList.remove(queen);
                score += descendingDiagonalIndexList.size();
            }
        }

        public SimpleScore calculateScore() {
            return DefaultSimpleScore.valueOf(score);
        }

    }
```

Configure it in your solver configuration:

```
  <scoreDirectorFactory>
    <scoreDefinitionType>...</scoreDefinitionType>

re.NQueensAdvancedIncrementalScoreCalculator</
incrementalScoreCalculatorClass>
  </scoreDirectorFactory>
```

Optionally, to get better output when the `IncrementalScoreCalculator` is corrupted in `environmentMode` `DEBUG` or `TRACE`, you can overwrite the method `buildScoreCorruptionAnalysis` from `AbstractIncrementalScoreCalculator`.

5.3.4. Drools score calculation

5.3.4.1. Overview

Implement your score calculation using the Drools rule engine. Every score constraint is written as one or more score rules.

- Advantages:
  - Incremental score calculation for free
    - Because most DRL syntax uses forward chaining, it does incremental calculation without any extra code
  - Score constraints are isolated as separate rules
    - Easy to add or edit existing score rules
  - Flexibility to augment your score constraints by
    - Defining them in decision tables
      - Excel (XLS) spreadsheet
      - Guvnor WebUI
    - Translate them into natural language with DSL
    - Store and release in the Guvnor repository
  - Performance optimizations in future versions for free
    - In every release, the Drools rule engine tends to become faster.
- Disadvantages:
  - DRL learning curve
  - Usage of DRL
    - Polyglot fear can prohibit the use of a new language such as DRL in some organizations

5.3.4.2. Drools score rules configuration

There are several ways to define where your score rules live.

5.3.4.2.1. A scoreDrl resource on the classpath

This is the easy way: the score rule live in a DRL file which is a resource on the classpath. Just add your score rules `*.drl` file in the solver configuration:

```
  <scoreDirectorFactory>
    <scoreDefinitionType>...</scoreDefinitionType>
                         <scoreDrl>/org/drools/planner/examples/nqueens/solver/
nQueensScoreRules.drl</scoreDrl>
  </scoreDirectorFactory>
```

You can add multiple `<scoreDrl>` entries if needed, but normally you'll define all your score rules in 1 file.

5.3.4.2.2. A RuleBase (possibly defined by Guvnor)

If you prefer to build the `RuleBase` yourself or if you're combining Planner with Guvnor, you can set the `RuleBase` on the `SolverFactory` before building the `Solver`:

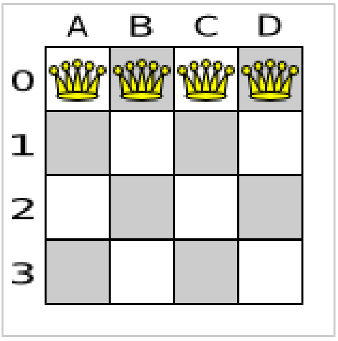
```
    solverFactory.getSolverConfig().getScoreDirectorFactoryConfig.setRuleBase(ruleBase);
```

5.3.4.3. Implementing a score rule

Here's an example of a score constraint implemented as a score rule in a DRL file:

```
rule "multipleQueensHorizontal"
    when
        $q1 : Queen($id : id, $y : y);
        $q2 : Queen(id > $id, y == $y);
    then
                                                              insertLogical(new
 UnweightedConstraintOccurrence("multipleQueensHorizontal", $q1, $q2));
end
```

This score rule will fire once for every 2 queens with the same `y`. The `(id > $id)` condition is needed to assure that for 2 queens A and B, it can only fire for (A, B) and not for (B, A), (A, A) or (B, B). Let's take a closer look at this score rule on this solution of 4 queens:



In this solution the multipleQueensHorizontal score rule will fire for 6 queen couples: (A, B), (A, C), (A, D), (B, C), (B, D) and (C, D). Because none of the queens are on the same vertical or diagonal line, this solution will have a score of `-6`. An optimal solution of 4 queens has a score of `0`.

> **Note**
>
> Notice that every score rule will relate to at least 1 planning entity class (directly or indirectly though a logically inserted fact).
>
> This is normal: it would be a waste of time to write a score rule that only relates to problem facts, as the consequence will never change during planning, no matter what the possible solution.

5.3.4.4. Aggregating the score rules into the `Score`

A `ScoreHolder` instance is asserted into the `WorkingMemory` as a global called `scoreHolder`. Your score rules need to (directly or indirectly) update that instance. Usually you'll make a single rule as an aggregation of the other rules to update the score:

```
global SimpleScoreHolder scoreHolder;

rule "multipleQueensHorizontal"
    when
        $q1 : Queen($id : id, $y : y);
        $q2 : Queen(id > $id, y == $y);
    then
                                                              insertLogical(new
 UnweightedConstraintOccurrence("multipleQueensHorizontal", $q1, $q2));
end

// multipleQueensVertical is obsolete because it is always 0

rule "multipleQueensAscendingDiagonal"
    when
        $q1 : Queen($id : id, $ascendingD : ascendingD);
        $q2 : Queen(id > $id, ascendingD == $ascendingD);
    then
                                                              insertLogical(new
 UnweightedConstraintOccurrence("multipleQueensAscendingDiagonal", $q1, $q2));
end

rule "multipleQueensDescendingDiagonal"
    when
        $q1 : Queen($id : id, $descendingD : descendingD);
        $q2 : Queen(id > $id, descendingD == $descendingD);
    then
```

```
                                                              insertLogical(new
 UnweightedConstraintOccurrence("multipleQueensDescendingDiagonal", $q1, $q2));
end

rule "hardConstraintsBroken"
    when
        $occurrenceCount : Number() from accumulate(
            $unweightedConstraintOccurrence : UnweightedConstraintOccurrence(),
            count($unweightedConstraintOccurrence)
        );
    then
        scoreHolder.setScore(- $occurrenceCount.intValue());
end
```

Most use cases will also weigh their constraints differently, by multiplying the count of each score rule with its weight.

Here's an example from CurriculumCourse, where assigning a `Lecture` to a `Room` which is missing 2 seats is weighted equally bad as having 1 isolated `Lecture` in a `Curriculum`:

```
// RoomCapacity: For each lecture, the number of students that attend the course
 must be less or equal
// than the number of seats of all the rooms that host its lectures.
// Each student above the capacity counts as 1 point of penalty.
rule "roomCapacity"
    when
        ...
    then
                    insertLogical(new  IntConstraintOccurrence("roomCapacity",
 ConstraintType.NEGATIVE_SOFT,
                ($studentSize - $capacity),
                ...));
end

// CurriculumCompactness: Lectures belonging to a curriculum should be adjacent
// to each other (i.e., in consecutive periods).
// For a given curriculum we account for a violation every time there is one
 lecture not adjacent
// to any other lecture within the same day.
// Each isolated lecture in a curriculum counts as 2 points of penalty.
rule "curriculumCompactness"
    when
        ...
    then
            insertLogical(new  IntConstraintOccurrence("curriculumCompactness",
 ConstraintType.NEGATIVE_SOFT,
                2,
                ...));
```

```
end


// Accumulate soft constraints
rule "softConstraintsBroken"
        salience -1 // Do the other rules first (optional, for performance)
    when
        $softTotal : Number() from accumulate(
         IntConstraintOccurrence(constraintType == ConstraintType.NEGATIVE_SOFT,
 $weight : weight),
            sum($weight)
        )
    then
        scoreHolder.setSoftConstraintsBroken($softTotal.intValue());
end
```

5.3.5. Detecting invalid scores

Put the `environmentMode` in `TRACE` (or `DEBUG`) to detect corruption in the *incremental score calculation*. On the difference between `TRACE` and `DEBUG`, *see the section about `environmentMode`*. However, that will not detect if your score calculator implements your score constraints as your business actually desires.

A piece of incremental score calculator code can be difficult to write and to review. You can assert its correctness by using a different implementation (for example a `SimpleScoreCalculator`) to do the assertions trigged by the `environmentMode`. Just configure it as `assertionScoreDirectorFactory`:

```
  <environmentMode>DEBUG</environmentMode>
  ...
  <scoreDirectorFactory>
    <scoreDefinitionType>...</scoreDefinitionType>
                         <scoreDrl>/org/drools/planner/examples/nqueens/solver/
nQueensScoreRules.drl</scoreDrl>
    <assertionScoreDirectorFactory>
      <scoreDefinitionType>...</scoreDefinitionType>

ner.examples.nqueens.solver.score.NQueensSimpleScoreCalculator</
simpleScoreCalculatorClass>
    </assertionScoreDirectorFactory>
  </scoreDirectorFactory>
```

5.4. Score calculation performance tricks

5.4.1. Overview

The `Solver` will normally spend most of its execution time running the score calculation (which is called in its deepest loops). Faster score calculation will return the same solution in less time with the same algorithm, which normally means a better solution in equal time.

5.4.2. Average calculation count per second

After solving a problem, the `Solver` will log the *average calculation count per second*. This is a good measurement of Score calculation performance, despite that it is affected by non score calculation execution time. It depends on the problem scale of the problem dataset. Normally, even for high scale problems, it is higher than `1000`, except when you're using `SimpleScoreCalculator`.

Important

When improving your score calculation, focus on maximizing the average calculation count per second, instead of maximizing the best score. A big improvement in score calculation can sometimes yield little or no best score improvement, for example when the algorithm is stuck in a local or global optima. If you're watching the calculation count instead, score calculation improvements are far more visible.

Furthermore, watching the calculation count, allows you to remove or add score constraints, and still compare it with the original calculation count. Comparing the best score with the original would be wrong, because it's comparing apples and oranges.

5.4.3. Incremental score calculation (with delta's)

When a `Solution` changes, incremental score calculation (AKA delta based score calculation), will calculate the delta with the previous state to find the new `Score`, instead of recalculating the entire score on every solution evaluation.

For example, if a single queen A moves from row `1` to `2`, it won't bother to check if queen B and C can attack each other, since neither of them changed.

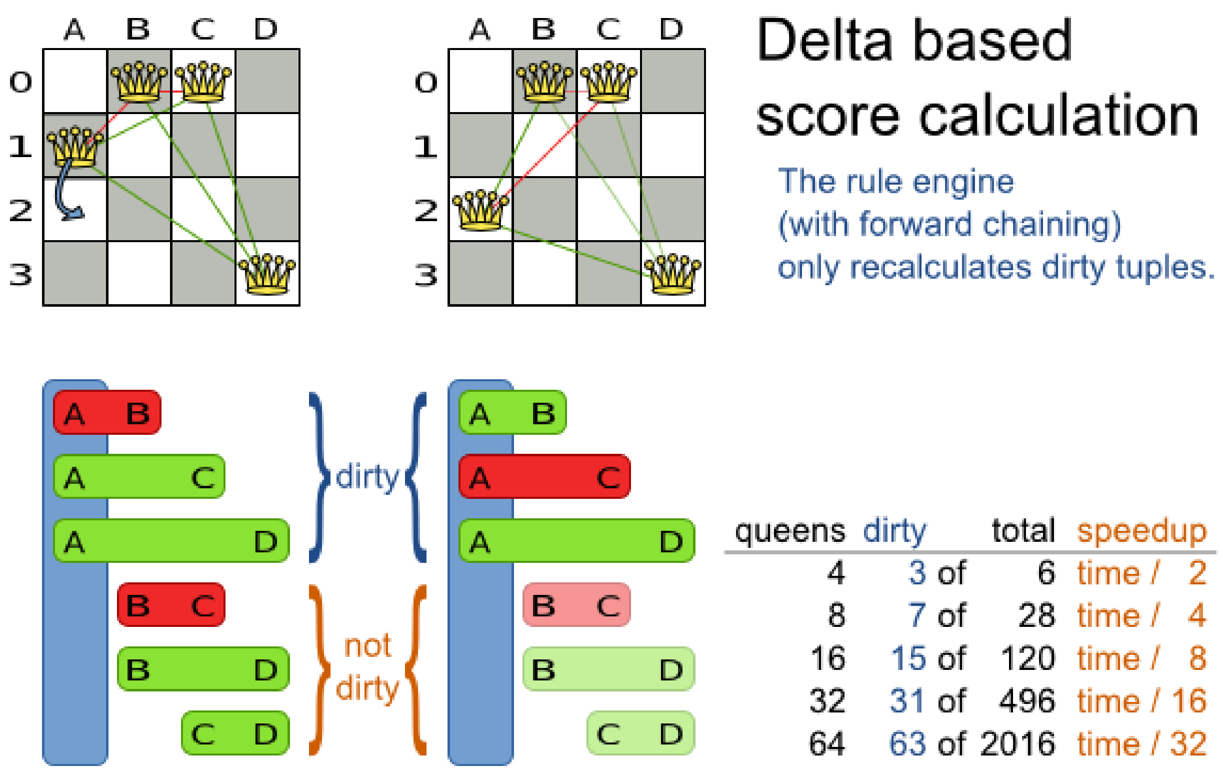


Figure 5.1. Incremental score calculation for the 4 queens puzzle

This is a huge performance and scalability gain. **Drools score calculation gives you this huge scalability gain without forcing you to write a complicated incremental score calculation algorithm.** Just let the Drools rule engine do the hard work.

Notice that the speedup is relative to the size of your planning problem (your *n*), making incremental score calculation far more scalable.

5.4.4. Caching

Do not call remote services in your score calculation (except if you're bridging `SimpleScoreCalculator` to a legacy system). The network latency will kill your score calculation performance. Cache the results of those remote services if possible.

If some parts of a constraint can be calculated once, when the `Solver` starts, and never change during solving, then turn them into *cached problem facts*.

5.4.5. Unused constraint

If you know a certain constraint can never be broken, don't bother writing a score constraint for it. For example in n queens, the score calculation doesn't check if multiple queens occupy the same column, because a `Queen`'s `column` never changes and every `Solution` starts with each `Queen` on a different `column`.

> **Note**
>
> Don't go overboard with this. If some datasets don't use a specific constraint but others do, just return out of the constraint as soon as you can. There is no need to dynamically change your score calculation based on the dataset.

5.4.6. Build-in hard constraint

Instead of implementing a hard constraint, you can sometimes make it build-in too. For example: If `Course` A should never be assigned to `Room` X, but it uses ValueRange from Solution, the `Solver` will often try to assign it to `Room` X too (only to find out that it breaks a hard constraint). Use *filtered selection* to define that Course A should only be assigned a `Room` other than X.

This tends to give a good performance gain, not just because the score calculation is faster, but mainly because most optimization algorithms will spend less time evaluating unfeasible solutions.

> **Note**
>
> Don't go overboard with this. Many optimization algorithms rely on the freedom to break hard constraints when changing planning entities, to get out of local optima. There is a real risk of trading short term benefits for long term harm.

5.4.7. Other performance tricks

- Verify that your score calculation happens in the correct `Number` type. If you're making the sum of `int` values, don't let Drools sum it in a `double` which takes longer.
- For optimal performance, always use server mode (`java -server`). We have seen performance increases of 50% by turning on server mode.
- For optimal performance, use at least java 1.6. We have seen performance increases of 30% by switching from java 1.5 to 1.6.
- Always remember that premature optimization is the root of all evil. Make sure your design is flexible enough to allow configuration based tweaking.

5.4.8. Score trap

Be watchful for score traps. A score trap is a state in which several moves need to be done to resolve or lower the weight of a single constraint occurrence. Some examples of score traps:

- If you need 2 doctors at each table, but you're only moving 1 doctor at a time, then the solver has no incentive to move a doctor to a table with no doctors. Punish a table with no doctors more then a table with only 1 doctor in your score function.

- If you only add the table as a cause of the ConstraintOccurrence and forget the jobType (which is doctor or politician), then the solver has no incentive to move a doctor to table which is short of a doctor and a politician.

5.4.9. stepLimit benchmark

Not all score constraints have the same performance cost. Sometimes 1 score constraint can kill the score calculation performance outright. Use the benchmarker to do a 1 minute run and check what happens to the average calculation count per second if you comment out all but 1 of the score constraints.

5.5. Reusing the score calculation outside the Solver

Other parts of your application, for example your webUI, might need to calculate the score too. Do that by reusing the `ScoreDirectorFactory` of the `Solver` to build a separate `ScoreDirector` for that webUI:

```
ScoreDirectorFactory scoreDirectorFactory = solver.getScoreDirectorFactory();
ScoreDirector guiScoreDirector = scoreDirectorFactory.buildScoreDirector();
```

Then use it when you need to calculate the `Score` of a `Solution`:

```
guiScoreDirector.setWorkingSolution(solution);
Score score = guiScoreDirector.calculateScore();
```

Currently it's not officially supported to get the specific constraint occurrences, to explain in the GUI what entities are causing which part of the `Score`. But if you're using the `DroolsScoreDirector`, it's possible to extract it. See the examples.

Chapter 6. Optimization algorithms

6.1. The size of real world problems

The number of possible solutions for a planning problem can be mind blowing. For example:

- 4 queens has `256` possible solutions (`4 ^ 4`) and 2 optimal solutions.
- 5 queens has `3125` possible solutions (`5 ^ 5`) and 1 optimal solution.
- 8 queens has `16777216` possible solutions (`8 ^ 8`) and 92 optimal solutions.
- 64 queens has more than `10^115` possible solutions (`64 ^ 64`).
- Most real-life planning problems have an incredible number of possible solutions and only 1 or a few optimal solutions.

For comparison: the minimal number of atoms in the known universe (10^80). As a planning problem gets bigger, the search space tends to blow up really fast. Adding only 1 extra planning entity or planning value can heavily multiply the running time of some algorithms.

An algorithm that checks every possible solution (even with pruning) can easily run for billions of years on a single real-life planning problem. What we really want is to **find the best solution in the limited time at our disposal**. Planning competitions (such as the International Timetabling Competition) show that local search variations (tabu search, simulated annealing, ...) usually perform best for real-world problems given real-world time limitations.

6.2. The secret sauce of Drools Planner

Drools Planner is the first framework to combine optimization algorithms (metaheuristics, ...) with score calculation by a rule engine such as Drools Expert. This combination turns out to be a very efficient, because:

- A rule engine such as Drools Expert is **great for calculating the score** of a solution of a planning problem. It makes it easy and scalable to add additional soft or hard constraints such as "a teacher shouldn't teach more then 7 hours a day". It does delta based score calculation without any extra code. However it tends to be not suitable to actually find new solutions.
- An optimization algorithm is **great at finding new improving solutions** for a planning problem, without necessarily brute-forcing every possibility. However it needs to know the score of a solution and offers no support in calculating that score efficiently.

6.3. Optimization algorithms overview

Table 6.1. Optimization algorithms overview

Algorithm	Scalable?	Optimal solution?	Needs little configuration?	Highly configurable?	Requires initialized solution?
Exact algorithms					
Brute force	0/5	5/5 - Guaranteed	5/5	0/5	No
Branch and bound	0/5	5/5 - Guaranteed	4/5	1/5	No
Construction heuristics					
First Fit	5/5	1/5 - Stops after initialization	5/5	1/5	No
First Fit Decreasing	5/5	2/5 - Stops after initialization	4/5	2/5	No
Best Fit	5/5	2/5 - Stops after initialization	4/5	2/5	No
Best Fit Decreasing	5/5	2/5 - Stops after initialization	4/5	2/5	No
Cheapest Insertion	3/5	2/5 - Stops after initialization	5/5	2/5	No
Metaheuristics					
Local search					
Hill-climbing	4/5	2/5 - Gets stuck in local optima	3/5	3/5	Yes
Tabu search	4/5	4/5	3/5	5/5	Yes
Simulated annealing	4/5	4/5	2/5	5/5	Yes

Algorithm	Scalable?	Optimal solution?	Needs little configuration?	Highly configurable?	Requires initialized solution?
Late acceptance	4/5	4/5	2/5	5/5	Yes
Evolutionary algorithms					
Evolutionary strategies	4/5	?/5	?/5	?/5	Yes
Genetic algorithms	4/5	?/5	?/5	?/5	Yes

If you want to learn more about metaheuristics, read the free book *Essentials of Metaheuristics* [http://www.cs.gmu.edu/~sean/book/metaheuristics/] or *Clever Algorithms* [http://www.cleveralgorithms.com/].

6.4. Which optimization algorithms should I use?

The *best* optimization algorithms configuration for your use case depends heavily on your use case. Nevertheless, this vanilla recipe will get you into the game with a pretty good configuration, probably much better than what you're used to.

Start with a quick configuration that involves little or no configuration and optimization code:

1. First Fit

Next, implement planning entity difficulty comparison and turn it into:

1. First Fit Decreasing

Next, implement moves and add tabu search behind it:

1. First Fit Decreasing
2. Tabu search (use planning entity tabu)

At this point *the free lunch is over*. The return on invested time lowers. The result is probably already more than good enough.

But you can do even better, at a lower return on invested time. Use the Benchmarker and try a couple of simulated annealing configurations:

1. First Fit Decreasing
2. Simulated annealing (try several starting temperatures)

And combine them with tabu search:

1. First Fit Decreasing

2. Simulated annealing (relatively long time)

3. Tabu search (relatively short time)

If you have time, continue experimenting even further. Blog about your experiments!

6.5. `SolverPhase`

A `Solver` can use multiple optimization algorithms in sequence. **Each optimization algorithm is represented by a `SolverPhase`.** There is never more than 1 `SolverPhase` solving at the same time.

> **Note**
>
> Some `SolverPhase` implementations can combine techniques from multiple optimization algorithms, but they are still just 1 `SolverPhase`. For example: a local search `SolverPhase` can do simulated annealing with planning entity tabu.

Here's a configuration that runs 3 phases in sequence:

```
<solver>
  ...
  <constructionHeuristic>
    ... <!-- First phase: First Fit decreasing -->
  </constructionHeuristic>
  <localSearch>
    ... <!-- Second phase: Simulated annealing -->
  </localSearch>
  <localSearch>
    ... <!-- Third phase: Tabu search -->
  </localSearch>
</solver>
```

The solver phases are run in the order defined by solver configuration. When the first phase terminates, the second phase starts, and so on. When the last phase terminates, the `Solver` terminates.

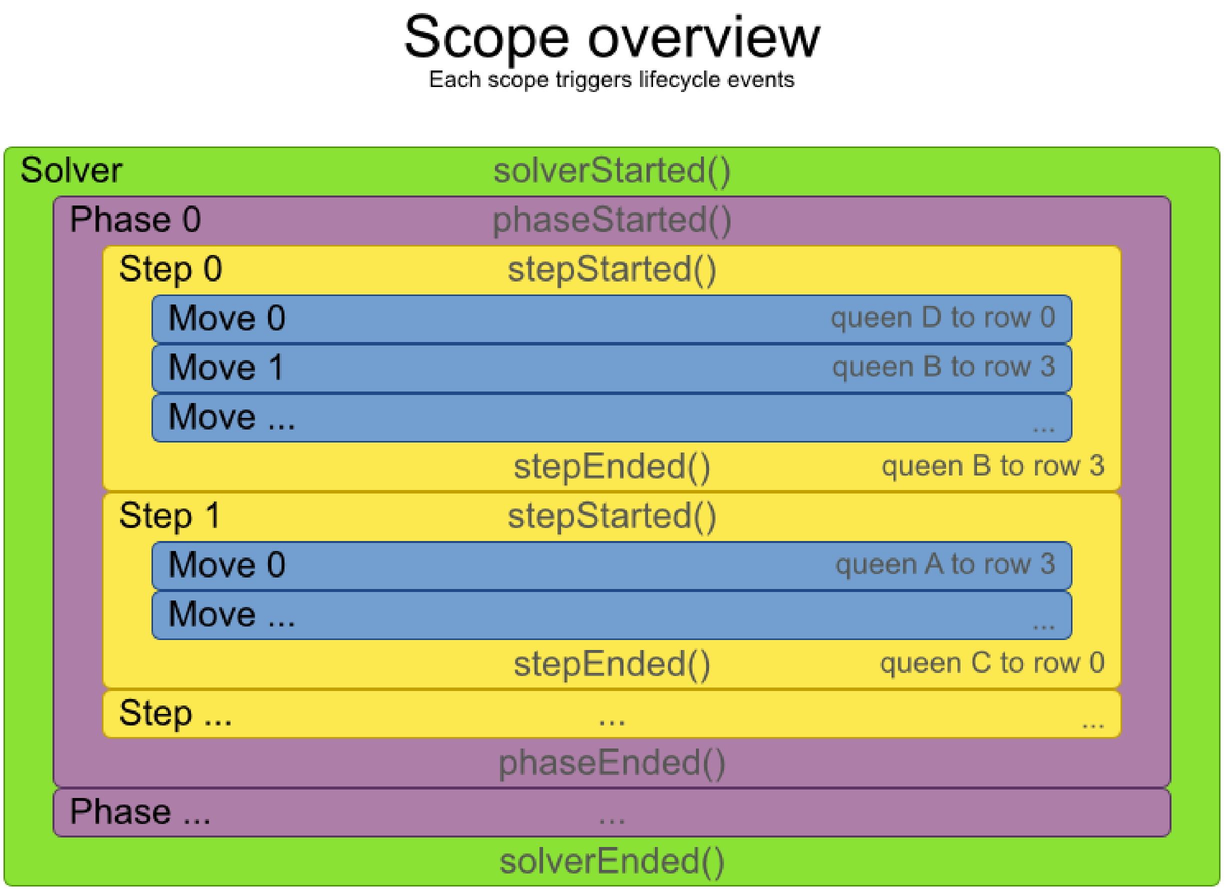
Some phases (especially construction heuristics) will terminate automatically. Other phases (especially metaheuristics) will only terminate if the phase is configured to terminate:

```
<solver>
  ...
  <termination><!-- Solver termination -->
    <maximumSecondsSpend>90</maximumSecondsSpend>
  </termination>
  <localSearch>
    <termination><!-- Phase termination -->
       <maximumSecondsSpend>60</maximumSecondsSpend><!-- Give the next phase a
 chance to run too, before the Solver terminates -->
    </termination>
    ...
  </localSearch>
  <localSearch>
    ...
  </localSearch>
</solver>
```

If the `Solver` terminates (before the last phase terminates itself), the current phase is terminated and all subsequent phases won't run.

6.6. Scope overview

A solver wll iteratively run phases. Each phase will usually iteratively run steps. Each step, in turn, usually iteratively runs moves. These form 4 nested scopes: solver, phase, step and move.



Configure *logging* to display the log messages of each scope.

6.7. Termination

Not all phases terminate automatically and sometimes you don't want to wait that long anyway. A `Solver` can be terminated synchronously by up-front configuration or asynchronously from another thread.

Especially metaheuristics phases will need to be told when to stop solving. This can be because of a number of reasons: the time is up, the perfect score has been reached, ... The only thing you can't depend on, is on finding the optimal solution (unless you know the optimal score), because a metaheuristics algorithm generally doesn't know it when it finds the optimal solution. For real-life problems this doesn't turn out to be much of a problem, because finding the optimal solution could take billions of years, so you 'll want to terminate sooner anyway. The only thing that matters is finding the best solution in the available time.

For synchronous termination, configure a `Termination` on a `Solver` or a `SolverPhase` when it needs to stop. You can implement your own `Termination`, but the build-in implementations should suffice for most needs. Every `Termination` can calculate a *time gradient* (needed for some optimization algorithms), which is a ratio between the time already spend solving and the estimated entire solving time of the `Solver` or `SolverPhase`.

6.7.1. TimeMillisSpendTermination

Terminates when an amount of time has been reached:

```
<termination>
    <maximumTimeMillisSpend>500</maximumTimeMillisSpend>
</termination>
```

```
<termination>
    <maximumSecondsSpend>10</maximumSecondsSpend>
</termination>
```

```
<termination>
    <maximumMinutesSpend>5</maximumMinutesSpend>
</termination>
```

```
<termination>
    <maximumHoursSpend>1</maximumHoursSpend>
</termination>
```

Note

If you use this `Termination`, you will most likely sacrifice perfect reproducibility (even with `environmentMode REPRODUCIBLE`) because of an available CPU time difference:

- The available CPU time influences the number of steps that can be taken, which might be a few more or less.
- The `Termination` might produce slightly different time gradient values, which will send time gradient based algorithms (such as simulated annealing) on a radically different path.

6.7.2. ScoreAttainedTermination

Terminates when a certain score has been reached. You can use this `Termination` if you know the perfect score, for example for 4 queens:

```
    <termination>
        <scoreAttained>0</scoreAttained>
    </termination>
```

For a planning problem with hard and soft constraints, it could look like this:

```
    <termination>
        <scoreAttained>0hard/-5000soft</scoreAttained>
    </termination>
```

You can use this `Termination` to terminate once it reaches a feasible solution.

6.7.3. StepCountTermination

Terminates when an amount of steps has been reached:

```
    <termination>
        <maximumStepCount>100</maximumStepCount>
    </termination>
```

This `Termination` can only be used for a `SolverPhase`, not for the `Solver` itself.

6.7.4. UnimprovedStepCountTermination

Terminates when the best score hasn't improved in a number of steps:

```
    <termination>
        <maximumUnimprovedStepCount>100</maximumUnimprovedStepCount>
    </termination>
```

If the score hasn't improved recently, it's probably not going to improve soon anyway and it's not worth the effort to continue. We have observed that once a new best solution is found (even after a long time of no improvement on the best solution), the next few steps tend to improve the best solution too.

This `Termination` can only be used for a `SolverPhase`, not for the `Solver` itself.

6.7.5. Combining multiple Terminations

Terminations can be combined, for example: terminate after 100 steps or if a score of 0 has been reached:

```
    <termination>
        <terminationCompositionStyle>OR</terminationCompositionStyle>
        <maximumStepCount>100</maximumStepCount>
        <scoreAttained>0</scoreAttained>
    </termination>
```

Alternatively you can use AND, for example: terminate after reaching a feasible score of at least -100 and no improvements in 5 steps:

```
    <termination>
        <terminationCompositionStyle>AND</terminationCompositionStyle>
        <maximumUnimprovedStepCount>5</maximumUnimprovedStepCount>
        <scoreAttained>-100</scoreAttained>
    </termination>
```

This example ensures it doesn't just terminate after finding a feasible solution, but also completes any obvious improvements on that solution before terminating.

6.7.6. Asynchronous termination from another thread

Sometimes you'll want to terminate a Solver early from another thread, for example because a user action or a server restart. This cannot be configured by a `Termination` as it's impossible to predict when and if it will occur. Therefore the `Solver` interface has these 2 thread-safe methods:

```
public interface Solver {

    // ...

    boolean terminateEarly();
    boolean isTerminateEarly();

}
```

If you call the `terminateEarly()` method from another thread, the `Solver` will terminate at its earliest convenience and the `solve()` method will return in the original `Solver` thread.

6.8. SolverEventListener

Each time a new best solution is found, the `Solver` fires a `BestSolutionChangedEvent`.

To listen to such events, add a `SolverEventListener` to the `Solver`:

```
public interface Solver {

    // ...

    void addEventListener(SolverEventListener eventListener);
    void removeEventListener(SolverEventListener eventListener);

}
```

6.9. Custom SolverPhase

Between phases or before the first phase, you might want to execute a custom action on the `Solution` to get a better score. Yet you'll still want to reuse the score calculation. For example, to implement a custom construction heuristic without implementing an entire `SolverPhase`.

Note

Most of the time, a custom construction heuristic is not worth the hassle. The supported constructions heuristics are configurable (so you can tweak them with the `Benchmarker`), `Termination` aware and support partially initialized solutions too.

Implement the `CustomSolverPhaseCommand` interface:

```
public interface CustomSolverPhaseCommand {
    void changeWorkingSolution(ScoreDirector scoreDirector);

}
```

For example:

```
public class ExaminationSolutionInitializer implements CustomSolverPhaseCommand {

    public void changeWorkingSolution(ScoreDirector scoreDirector) {
        Examination examination = (Examination) scoreDirector.getWorkingSolution();
        for (Exam exam : examination.getExamList()) {
            Score unscheduledScore = scoreDirector.calculateScore();
            ...
            for (Period period : examination.getPeriodList()) {
                scoreDirector.beforeVariableChanged(exam, "period");
                exam.setPeriod(period)
                scoreDirector.afterVariableChanged(exam, "period");
                Score score = scoreDirector.calculateScore();
                ...
            }
            ...
        }
    }

}
```

Warning

Any change on the planning entities in a `CustomSolverPhaseCommand` must be notified to the `ScoreDirector`.

Warning

Do not change any of the planning facts in a `CustomSolverPhaseCommand`. That will corrupt the `Solver` because any previous score or solution was for a different problem. If you want to do that, see *repeated planning* and real-time planning instead.

And configure it like this:

```
<solver>
```

```
    ...
    <customSolverPhase>

ializer.ExaminationSolutionInitializer</
customSolverPhaseCommandClass>
    </customSolverPhase>
    ... <!-- Other phases -->
</solver>
```

It's possible to configure multiple `customSolverPhaseCommandClass` instances, which will be run in sequence.

Important

If the changes of a `CustomSolverPhaseCommand` don't result in a better score, the best solution won't be changed (so effectively nothing will have changed for the next `SolverPhase` or `CustomSolverPhaseCommand`). To force such changes anyway, use `forceUpdateBestSolution`:

```
    <customSolverPhase>
                <customSolverPhaseCommandClass>...MyUnitializer</
customSolverPhaseCommandClass>
      <forceUpdateBestSolution>true</forceUpdateBestSolution>
    </customSolverPhase>
```

Note

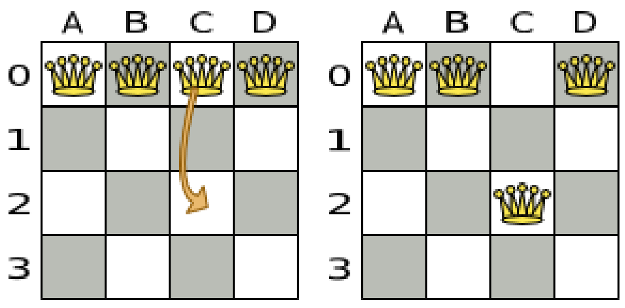
If the `Solver` or `SolverPhase` wants to terminate while a `CustomSolverPhaseCommand` is still running, it will wait to terminate until the `CustomSolverPhaseCommand` is done, however long that takes.

Chapter 7. `Move` and neighborhood selection

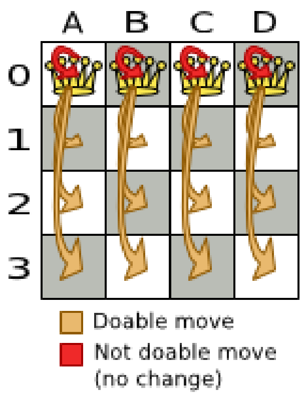
7.1. `Move` and neighborhood introduction

7.1.1. What is a `Move`?

A `Move` is a change (or set of changes) from a solution A to a solution B. For example, the move below changes queen `C` from row `0` to row `2`:

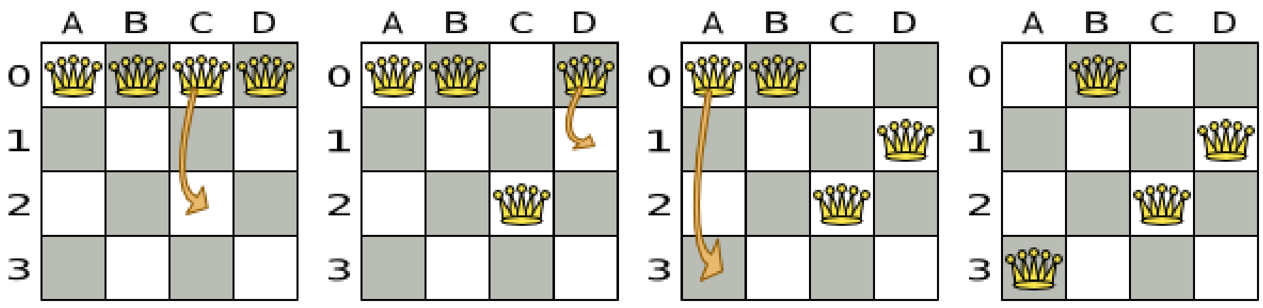


The new solution is called a *neighbor* of the original solution, because it can be reached in a single `Move`. Although a single move can change multiple queens, the neighbors of a solution should always be a very small subset of all possible solutions. For example, on that original solution, these are all possible `changeMove`'s:



If we ignore the 4 `changeMove`'s that have not impact and are therefore not doable, we can see that number of moves is `n * (n - 1) = 12`. This is far less than the number of possible solutions, which is `n ^ n = 256`. As the problem scales out, the number of possible moves increases far less than the number of possible solutions.

Yet, in 4 `changeMove`'s or less we can reach any solution. For example we can reach a very different solution in 3 `changeMove`'s:



Note

There are many other types of moves besides `changeMove`'s. Many move types are included out-of-the-box, but you can also implement custom moves.

A `Move` can affect multiple entities or even create/delete entities. But it must not change the problem facts.

All optimization algorithms use `Move`'s to transition from one solution to a neighbor solution. Therefor, all the optimization algorithms are confronted with `Move` selection: the craft of creating and iterating moves efficiently and the art of finding the most promising subset of random moves to evaluate first.

7.1.2. What is a `MoveSelector`?

A `MoveSelector`'s main function is to create `Iterator<Move>` when needed. An optimization algorithm will iterate through a subset of those moves.

Here's an example how to configure a `changeMoveSelector` for the optimization algorithm Local Search:

```
<localSearch>
  <changeMoveSelector/>
  ...
</localSearch>
```

Out of the box, this works and all properties of the `changeMoveSelector` are defaulted sensibly (unless that fails fast due to ambiguity). On the other hand, the configuration can be customized significantly for specific use cases. For example: you want want to configure a filter to discard pointless moves.

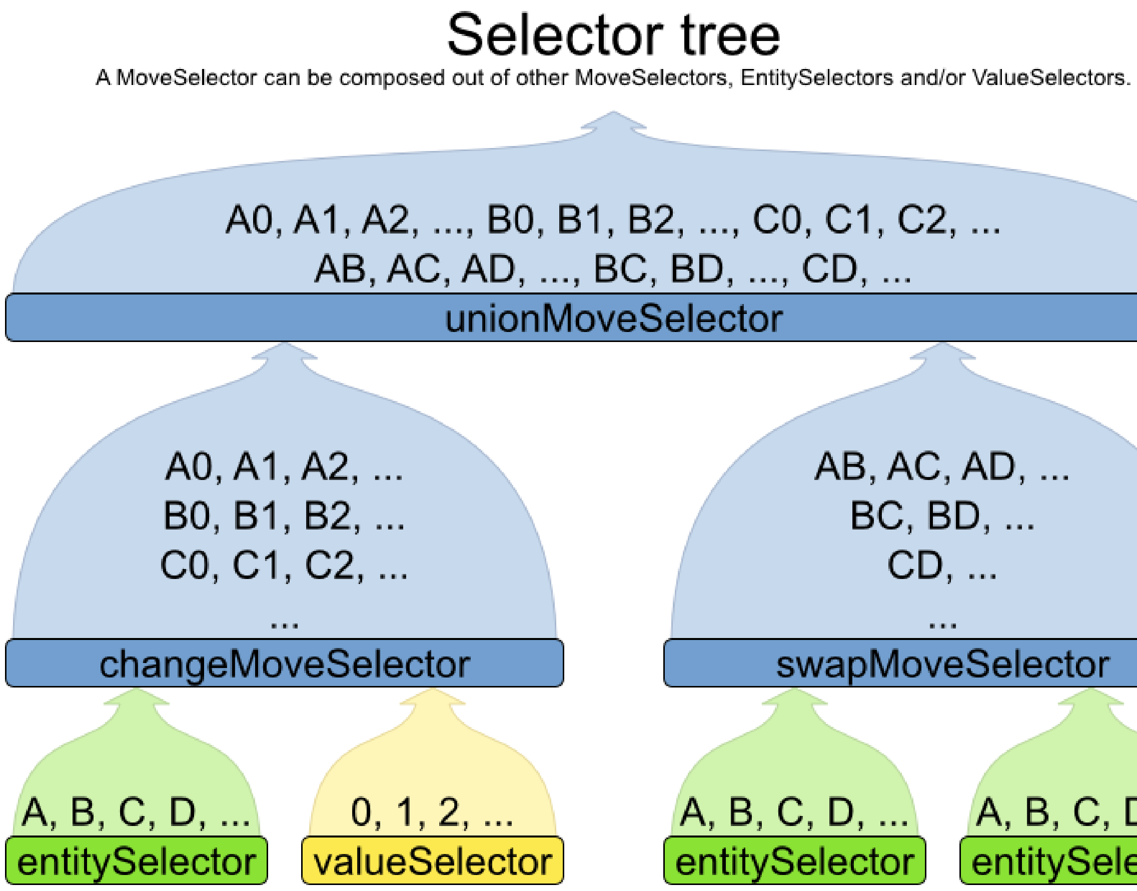
7.1.3. Subselecting of entities, values and other moves

To create a `Move`, we need to select 1 or more planning entities and/or planning values to move. Just like `MoveSelectors`, `EntitySelectors` and `ValueSelectors` need to support a similar feature set (such as scalable just-in-time selection). Therefor, they implement a common interface `Selector` and they are configured similarly.

A MoveSelector is often composed out of `EntitySelectors`, `ValueSelectors` or even other `MoveSelectors`, which can be configured individually if desired:

```
    <unionMoveSelector>
      <changeMoveSelector>
        <entitySelector>
          ...
        </entitySelector>
        <valueSelector>
          ...
        </valueSelector>
        ...
      </changeMoveSelector>
      ...
    </unionMoveSelector>
```

Together, this structure forms a `Selector` tree:



The root of this tree is a `MoveSelector` which is injected into the optimization algorithm implementation to be (partially) iterated in every step.

7.2. General `Selector` features

7.2.1. `cacheType`: Create moves in advance or Just In Time

A `Selector`'s `cacheType` determines when a selection (such as a `Move`, an entity, a value, ...) is created and how long it lives.

Almost every `Selector` supports setting a `cacheType`:

```
<changeMoveSelector>
  <cacheType>PHASE</cacheType>
  ...
</changeMoveSelector>
```

The following `cacheType`s are supported:

- `JUST_IN_TIME` (default): Not cached. Construct each selection (`Move`, ...) just before it's used. This scales up well in memory footprint.
- `STEP`: Cached. Create each selection (`Move`, ...) at the beginning of a step and cache them in a list for the remainder of the step. This scales up badly in memory footprint.
- `PHASE`: Cached. Create each selection (`Move`, ...) at the beginning of a `SolverPhase` and cache them in a list for the remainder of the `SolverPhase`. Some selections cannot be phase cached because the list changes every step. This scales up badly in memory footprint, but has a slight performance gain.
- `SOLVER`: Cached. Create each selection (`Move`, ...) at the beginning of a `Solver` and cache them in a list for the remainder of the `Solver`. Some selections cannot be solver cached because the list changes every step. This scales up badly in memory footprint, but has a slight performance gain.

A `cacheType` can be set on composite selectors too:

```
    <unionMoveSelector>
      <cacheType>PHASE</cacheType>
      <changeMoveSelector/>
      <swapMoveSelector/>
      ...
    </unionMoveSelector>
```

Nested selectors of a cached selector cannot be configured to be cached themselves, unless it's a higher `cacheType`. For example: a `STEP` cached `unionMoveSelector` can hold a `PHASE` cached `changeMoveSelector`, but not a `STEP` cached `changeMoveSelector`.

7.2.2. SelectionOrder: original, random or shuffled selection

A `Selector`'s `selectionOrder` determines the order in which the selections (such as `Moves`, entities, values, ...) are iterated. An optimization algorithm will usually only iterate through a subset of its `MoveSelector`'s selections, starting from the start, so the `selectionOrder` is critical to decide which `Moves` are evaluated.

Almost every `Selector` supports setting a `selectionOrder`:

```
    <changeMoveSelector>
      ...
      <selectionOrder>ORIGINAL</selectionOrder>
      ...
    </changeMoveSelector>
```

The following `selectionOrders` are supported:

- ORIGINAL: Select the selections (Moves, ...) in default order. Each selection will be selected only once.
  - For example: A0, A1, A2, A3, ..., B0, B1, B2, B3, ...
- RANDOM (default): Select the selections (Moves, ...) in non-shuffled random order. A selection might be selected multiple times. This scales up well in performance.
  - For example: C2, A3, C2, B1, A0, C0, ...
- SHUFFLED: Select the selections (Moves, ...) in shuffled random order. Each selection will be selected only once. Requires cacheType >= STEP. This scales up badly in performance because a random number is generated for each element, even if it's not selected (which is the grand majority when scaling up).
  - For example: C2, A3, B1, A0, C0, ...

A selectionOrder can be set on composite selectors too.

Note

When a Selector is cached, all of its nested Selectors will naturally default to selectionOrder ORIGINAL. Avoid overwriting the selectionOrder of those nested Selectors.

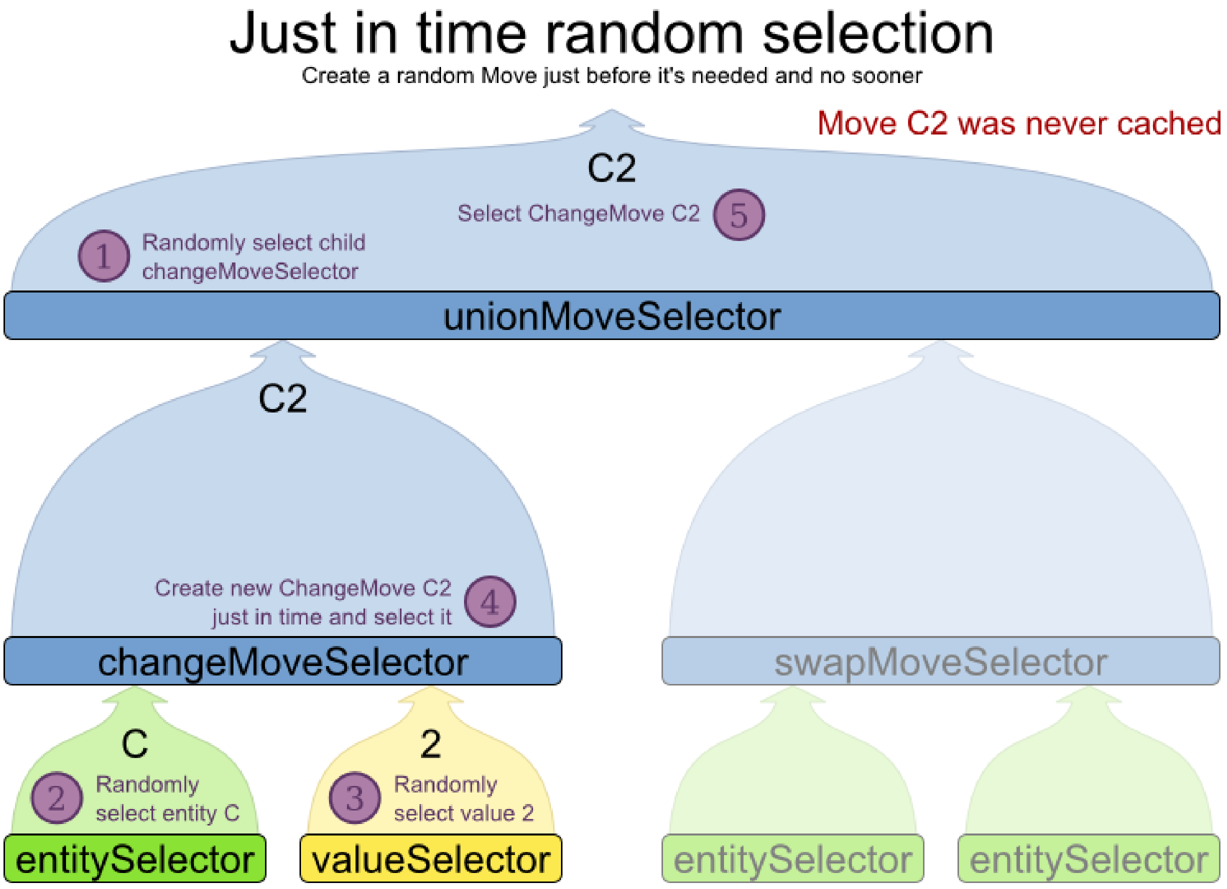
7.2.3. Recommended combinations of cacheType and selectionOrder

7.2.3.1. Just in time random selection (default)

This combination is great for big use cases (10 000 entities or more), as it scales up well in memory footprint and performance. Other combinations are often not even viable on such sizes. It works for smaller use cases too, so it's a good way to start out. It's the default, so this explicit configuration of cacheType and selectionOrder is actually obsolete:

```
    <unionMoveSelector>
      <cacheType>JUST_IN_TIME</cacheType>
      <selectionOrder>RANDOM</selectionOrder>

      <changeMoveSelector/>
      <swapMoveSelector/>
    </unionMoveSelector>
```

Here's how it works. When Iterator<Move>.next() is called, a child MoveSelector is randomly selected (1), which creates a random Move is created (2, 3, 4) and is then returned (5):



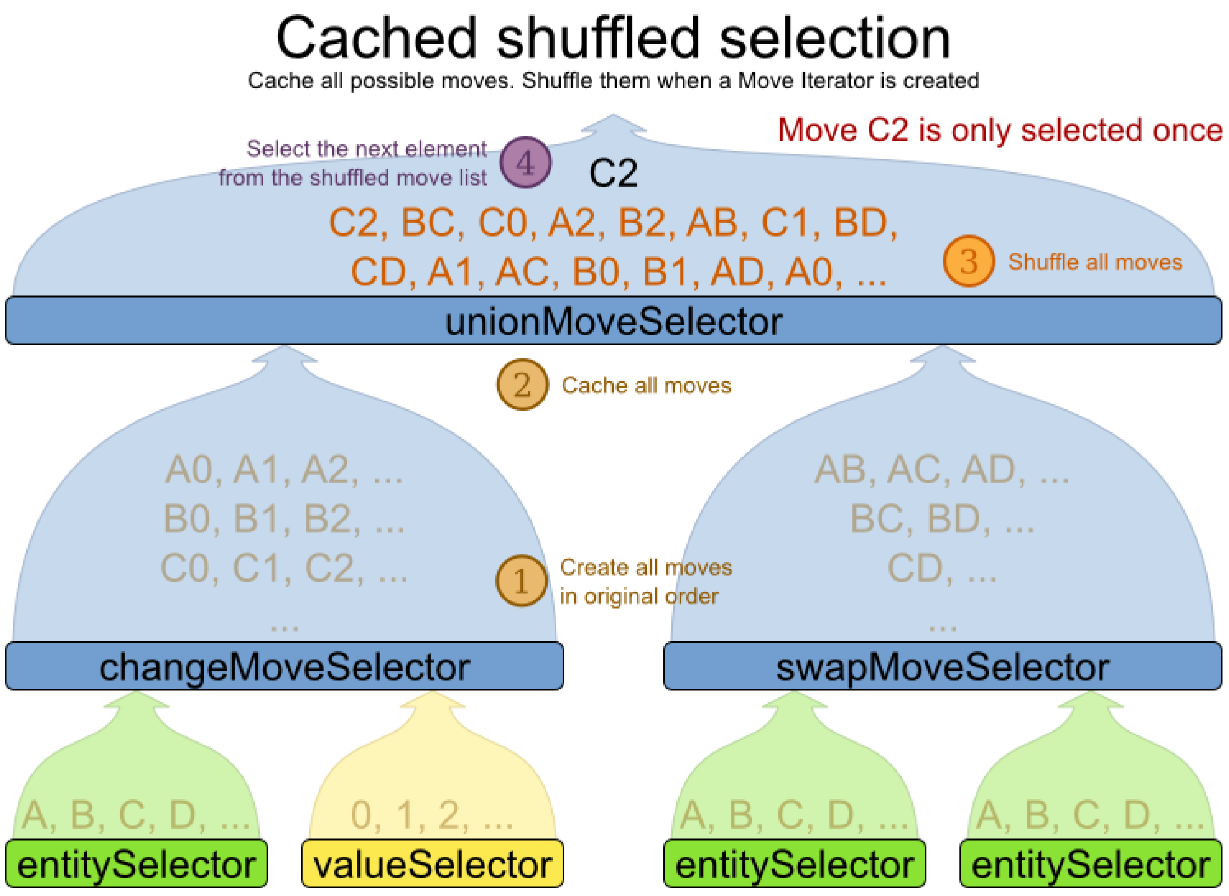
Notice that **it never creates a list of `Moves`** and it generates random numbers only for `Moves` that are actually selected.

7.2.3.2. Cached shuffled selection

This combination often wins for small and medium use cases (5000 entities or less). Beyond that size, it scales up badly in memory footprint and performance.

```
    <unionMoveSelector>
      <cacheType>PHASE</cacheType>
      <selectionOrder>SHUFFLED</selectionOrder>

      <changeMoveSelector/>
      <swapMoveSelector/>
    </unionMoveSelector>
```

Here's how it works. At the start of the phase (or step depending on the `cacheType`), all moves are created (1) and cached (2). When `MoveSelector.iterator()` is called, the moves are shuffled (3). When `Iterator<Move>.next()` is called, the next element in the shuffled list is returned (4):



Notice that **each `Move` will only be selected once**, even though they are selected in random order.

Use cacheType PHASE if none of the (possibly nested) Selectors require `STEP`. Otherwise, do something like this:

```
    <unionMoveSelector>
      <cacheType>STEP</cacheType>
      <selectionOrder>SHUFFLED</selectionOrder>

      <changeMoveSelector>
        <cacheType>PHASE</cacheType>
      </changeMoveSelector>
      <swapMoveSelector/>
        <cacheType>PHASE</cacheType>
      </swapMoveSelector>
      <pillarSwapMoveSelector/><!-- Does not support cacheType PHASE -->
    </unionMoveSelector>
```

7.2.3.3. Cached random selection

This combination is often a worthy competitor for medium use cases, especially with fast stepping optimization algorithms (such as simulated annealing). Unlike cached shuffled selection, it doesn't waste time shuffling the move list at the beginning of every step.

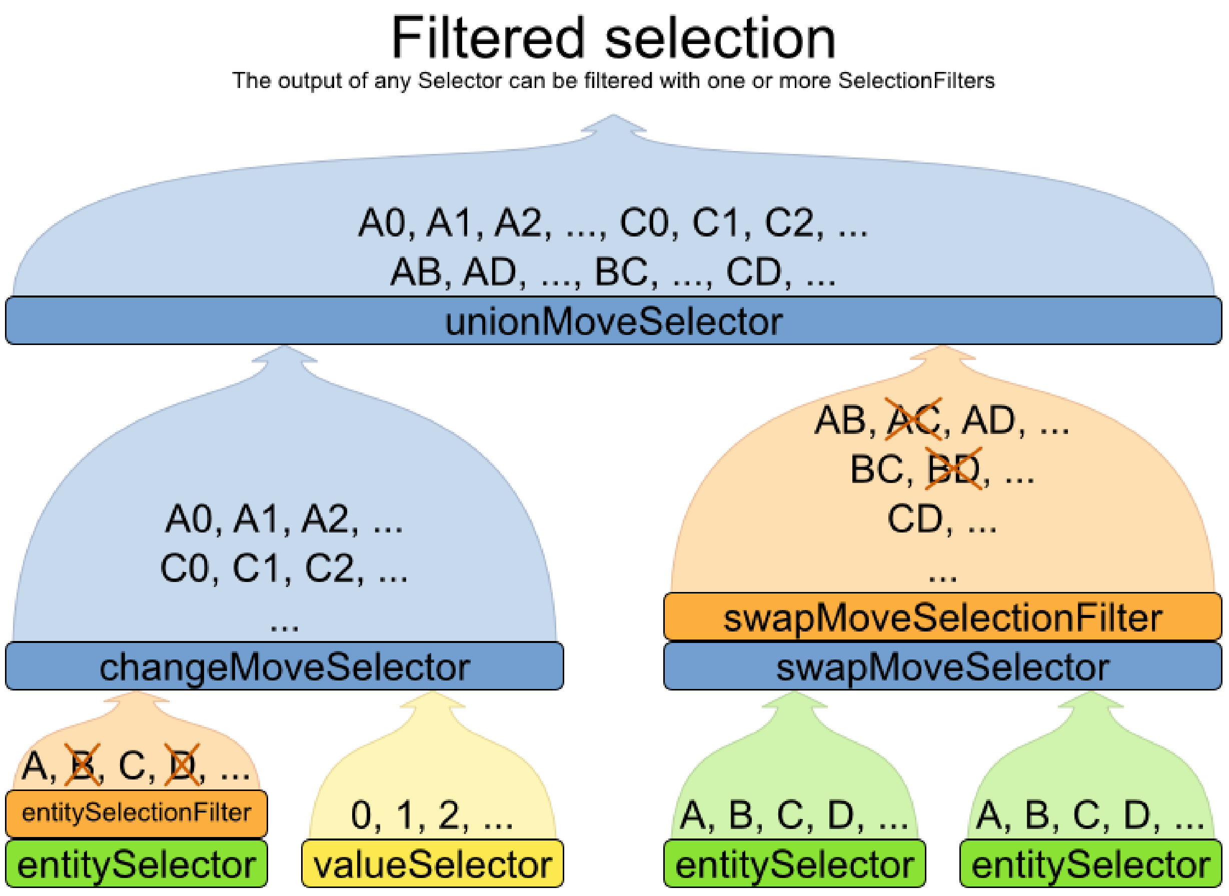
```
    <unionMoveSelector>
      <cacheType>PHASE</cacheType>
      <selectionOrder>RANDOM</selectionOrder>

      <changeMoveSelector/>
      <swapMoveSelector/>
    </unionMoveSelector>
```

7.2.4. Filtered selection

There are certain moves that you don't want to select, because:

- The move is pointless and would only waste CPU time. For example, swapping 2 lectures of the same course will result in the same score and the same schedule because all lectures of 1 course are interchangeable (same teacher, same students, same topic).
- Doing the move would break *a build-in hard constraint*, so the solution would be infeasible but the score function doesn't check build-in hard constraints (for performance gain). For example, don't change a gym lecture to a room which is not a gym room.
  - Note that any build-in hard constraint must usually be filtered on every move type. For example, don't swap the room of a gym lecture with another lecture if the other lecture's original room isn't a gym room.

Filtered selection can happen on any Selector in the selector tree, including any `MoveSelector`, `EntitySelector` or `ValueSelector`:



Filtering us the interface `SelectionFilter`:

```
public interface SelectionFilter<T> {

    boolean accept(ScoreDirector scoreDirector, T selection);

}
```

Implement the method `accept` to return `false` on a discarded `selection`. Unaccepted moves will not be selected and will therefore never have their method `doMove` called.

```
public class DifferentCourseSwapMoveFilter implements SelectionFilter<SwapMove> {

    public boolean accept(ScoreDirector scoreDirector, SwapMove move) {
        Lecture leftLecture = (Lecture) move.getLeftEntity();
        Lecture rightLecture = (Lecture) move.getRightEntity();
        return !leftLecture.getCourse().equals(rightLecture.getCourse());
    }
}
```

Apply the filter on the lowest level possible. In most cases, you 'll need to know both the entity and the value involved and you'll have to apply a `moveFilterClass` on the `moveSelector`:

```
    <swapMoveSelector>

mples.curriculumcourse.solver.move.DifferentCourseSwapMoveFilter</
moveFilterClass>
    </swapMoveSelector>
```

But if possible apply it on a lower levels, such as an `entityFilterClass` on the `entitySelector` or a `valueFilterClass` on the `valueSelector`:

```
    <changeMoveSelector>
      <entitySelector>
        <entityFilterClass>...EntityFilter</entityFilterClass>
      </entitySelector>
    </changeMoveSelector>
```

Filtered selection works with any kind of `cacheType` and `selectionOrder`. You can configure multiple `*FilterClass` elements on a single selector.

7.2.5. Sorted selection

TODO Not yet implemented.

7.2.6. Probability selection

TODO

7.3. Generic MoveSelectors

7.3.1. `changeMoveSelector`

For 1 planning variable, the `ChangeMove` selects 1 planning entity and 1 planning value and assigns the entity's variable to that value.

Simplest configuration:

```
    <changeMoveSelector/>
```

Advanced configuration:

```
<changeMoveSelector>
  ... <!-- Normal moveSelector properties -->
  <entitySelector>
    ...
  </entitySelector>
  <valueSelector>
    ...
  </valueSelector>
</changeMoveSelector>
```

A `ChangeMove` is the finest grained move.

Important

Almost every `moveSelector` configuration injected into a metaheuristic algorithm should include a changeMoveSelector or a custom implementation. This guarantees that every possible `Solution` can be reached through applying a number of moves in sequence (not taking *score traps* into account). Of course, normally it is unioned with other, more course grained moves.

7.3.2. swapMoveSelector

The `SwapMove` selects 2 different planning entities and swaps the planning values of all their planning variables.

Simplest configuration:

```
<swapMoveSelector/>
```

Advanced configuration:

```
<swapMoveSelector>
  ... <!-- Normal moveSelector properties -->
  <entitySelector>
    ...
  </entitySelector>
  <secondaryEntitySelector>
    ...
  </secondaryEntitySelector>
</swapMoveSelector>
```

The `secondaryEntitySelector` is rarely needed: if it is not specified, entities from the same `entitySelector` are swapped.

Although a `SwapMove` on a single variable is essentially just 2 `ChangeMoves`, it's often the winning step where the first of the 2 `ChangeMoves` would not be the winning step because it leave the solution in a state with broken hard constraints. For example: swapping the room of 2 lectures doesn't bring the solution in a intermediate state where both lectures are in the same room which breaks a hard constraint.

7.3.3. pillarSwapMoveSelector

A *pillar* is a set of planning entities which have the same planning value(s) for each of their planning variables. The `pillarSwapMove` selects 2 different entity pillars and swaps the values of all their variables for all their entities.

Simplest configuration:

```
    <pillarSwapMoveSelector/>
```

Advanced configuration:

```
    <pillarSwapMoveSelector>
      ... <!-- Normal moveSelector properties -->
      <pillarSelector>
        <entitySelector>
          ...
        </entitySelector>
      </pillarSelector>
      <secondaryPillarSelector>
        <entitySelector>
          ...
        </entitySelector>
      </secondaryPillarSelector>
    </pillarSwapMoveSelector>
```

The `secondaryPillarSelector` is rarely needed: if it is not specified, entities from the same `pillarSelector` are swapped.

7.3.4. subChainChangeMoveSelector

TODO

7.3.5. subChainSwapMoveSelector

TODO

7.4. Combining multiple `MoveSelector`s

7.4.1. unionMoveSelector

A `unionMoveSelector` selects a `Move` by selecting 1 of its child `MoveSelectors` to supply the next `Move`.

Simplest configuration:

```
    <unionMoveSelector>
      <...MoveSelector/>
      <...MoveSelector/>
      <...MoveSelector/>
      ...
    </unionMoveSelector>
```

Advanced configuration:

```
    <unionMoveSelector>
      ... <!-- Normal moveSelector properties -->
           <selectorProbabilityWeightFactoryClass>...ProbabilityWeightFactory</
selectorProbabilityWeightFactoryClass>
      <changeMoveSelector>
        <fixedProbabilityWeight>...</fixedProbabilityWeight>
        ...
      </changeMoveSelector>
      <swapMoveSelector>
        <fixedProbabilityWeight>...</fixedProbabilityWeight>
        ...
      </swapMoveSelector>
      <...MoveSelector>
        <fixedProbabilityWeight>...</fixedProbabilityWeight>
        ...
      </...MoveSelector>
      ...
    </unionMoveSelector>
```

In `selectionOrder RANDOM`, the `selectorProbabilityWeightFactory` determines how often a child MoveSelector is selected to supply the next Move. By default, each child `MoveSelector` has the same chance of being selected. Change the fixedProbabilityWeight of such a child to select it more often. For example, the `unionMoveSelector` can return a `SwapMove` twice as often as a `ChangeMove`:

```
    <unionMoveSelector>
```

```
      <changeMoveSelector>
        <fixedProbabilityWeight>1.0</fixedProbabilityWeight>
        ...
      </changeMoveSelector>
      <swapMoveSelector>
        <fixedProbabilityWeight>2.0</fixedProbabilityWeight>
        ...
      </swapMoveSelector>
    </unionMoveSelector>
```

The number of possible `ChangeMoves` is very different from the number of possible `SwapMoves` and it's problem dependent. To give each individual `Move` the same selection chance (as opposed to each `MoveSelector`), use the `FairSelectorProbabilityWeightFactory`:

```
    <unionMoveSelector>

SelectorProbabilityWeightFactory</
selectorProbabilityWeightFactoryClass>
      <changeMoveSelector/>
      <swapMoveSelector/>
    </unionMoveSelector>
```

7.4.2. cartesianProductMoveSelector

A `cartesianProductMoveSelector` selects a new `CompositeMove`. It builds that `CompositeMove` by selecting 1 `Move` per child `MoveSelector` and adding it to the `CompositiveMove`.

Simplest configuration:

```
    <cartesianProductMoveSelector>
      <...MoveSelector/>
      <...MoveSelector/>
      <...MoveSelector/>
      ...
    </cartesianProductMoveSelector>
```

Advanced configuration:

```
    <cartesianProductMoveSelector>
      ... <!-- Normal moveSelector properties -->
      <changeMoveSelector>
        ...
      </changeMoveSelector>
      <swapMoveSelector>
```

```
          ...
        </swapMoveSelector>
        <...MoveSelector>
          ...
        </...MoveSelector>
        ...
      </cartesianProductMoveSelector>
```

7.5. EntitySelector

7.5.1. TODO

TODO

7.6. ValueSelector

7.6.1. TODO

TODO

7.7. Custom moves

7.7.1. Which move types might be missing in my implementation?

To determine which move types might be missing in your implementation, run a benchmarker *for a short amount of time* and *configure it to write the best solutions to disk*. Take a look at such a best solution: it will likely be a local optima. Try to figure out if there's a move that could get out of that local optima faster.

If you find one, implement that course-grained move, mix it with the existing moves and benchmark it against the previous configurations to see if you want to keep it.

7.7.2. Custom moves introduction

Instead of reusing the generic `Move`s (such as `ChangeMove`) you can also implement your own `Move`s. Generic and custom `MoveSelector`s can be combined as wanted.

A custom `Move` can be tailored to work to the advantage of your constraints. For example, in examination scheduling, changing the period of an exam A also changes te period of all the exams that need to coincide with exam A.

A custom `Move` is also slightly faster than a generic `Move`. However, it's far more work to implement and much harder to avoid bugs. After implementing a custom `Move`, make sure to turn on `environmentMode` `TRACE` to check for score corruptions.

7.7.3. The interface `Move`

Your custom moves must implement the `Move` interface:

```
public interface Move {

    boolean isMoveDoable(ScoreDirector scoreDirector);

    Move createUndoMove(ScoreDirector scoreDirector);
    void doMove(ScoreDirector scoreDirector);

    Collection<? extends Object> getPlanningEntities();
    Collection<? extends Object> getPlanningValues();

}
```

Let's take a look at the `Move` implementation for 4 queens which moves a queen to a different row:

```
public class RowChangeMove implements Move {

    private Queen queen;
    private Row toRow;

    public RowChangeMove(Queen queen, Row toRow) {
        this.queen = queen;
        this.toRow = toRow;
    }

    // ... see below

}
```

An instance of `RowChangeMove` moves a queen from its current row to a different row.

Planner calls the `doMove(ScoreDirector)` method to do a move. The `Move` implementation must notify the `ScoreDirector` of any changes it make to the planning entities's variables:

```
    public void doMove(ScoreDirector scoreDirector) {
          scoreDirector.beforeVariableChanged(queen, "row"); // before changes
 are made to the queen.row
        queen.setRow(toRow);
         scoreDirector.afterVariableChanged(queen, "row"); // after changes are
 made to the queen.row
    }
```

You need to call the methods `scoreDirector.beforeVariableChanged(Object, String)` and `scoreDirector.afterVariableChanged(Object, String)` directly before and after modifying the entity. Alternatively, you can also call the methods `scoreDirector.beforeAllVariablesChanged(Object)` and `scoreDirector.afterAllVariablesChanged(Object)`.

Note

You can alter multiple entities in a single move and effectively create a big move (also known as a coarse-grained move).

Warning

A `Move` can only change/add/remove planning entities, it must not change any of the problem facts.

Planner automatically filters out *non doable moves* by calling the `isDoable(ScoreDirector)` method on a move. A *non doable move* is:

- A move that changes nothing on the current solution. For example, moving queen B0 to row 0 is not doable, because it is already there.
- A move that is impossible to do on the current solution. For example, moving queen B0 to row 10 is not doable because it would move it outside the board limits.

In the n queens example, a move which moves the queen from its current row to the same row isn't doable:

```
    public boolean isMoveDoable(ScoreDirector scoreDirector) {
        return !ObjectUtils.equals(queen.getRow(), toRow);
    }
```

Because we won't generate a move which can move a queen outside the board limits, we don't need to check it. A move that is currently not doable could become doable on the working `Solution` of a later step.

Each move has an *undo move*: a move (normally of the same type) which does the exact opposite. In the example above the undo move of *C0 to C2* would be the move *C2 to C0*. An undo move is created from a `Move`, before the `Move` has been done on the current solution.

```
    public Move createUndoMove(ScoreDirector scoreDirector) {
        return new RowChangeMove(queen, queen.getRow());
    }
```

Notice that if C0 would have already been moved to C2, the undo move would create the move *C2 to C2*, instead of the move *C2 to C0*.

A solver phase might do and undo the same `Move` more than once. In fact, many solver phases will iteratively do an undo a number of moves to evaluate them, before selecting one of those and doing that move again (without undoing it this time).

A `Move` must implement the `getPlanningEntities()` and `getPlanningValues()` methods. They are used by entity tabu and value tabu respectively. When they are called, the `Move` has already been done.

```
    public List<? extends Object> getPlanningEntities() {
        return Collections.singletonList(queen);
    }

    public Collection<? extends Object> getPlanningValues() {
        return Collections.singletonList(toRow);
    }
```

If your `Move` changes multiple planning entities, return all of them in `getPlanningEntities()` and return all their values (to which they are changing) in `getPlanningValues()`.

```
    public Collection<? extends Object> getPlanningEntities() {
        return Arrays.asList(leftCloudProcess, rightCloudProcess);
    }

    public Collection<? extends Object> getPlanningValues() {
        return Arrays.asList(leftCloudProcess.getComputer(), rightCloudProcess.getComputer());
    }
```

A `Move` must implement the `equals()` and `hashCode()` methods. 2 moves which make the same change on a solution, should be equal.

```
    public boolean equals(Object o) {
        if (this == o) {
            return true;
        } else if (o instanceof RowChangeMove) {
            RowChangeMove other = (RowChangeMove) o;
            return new EqualsBuilder()
                    .append(queen, other.queen)
                    .append(toRow, other.toRow)
                    .isEquals();
        } else {
            return false;
        }
    }

    public int hashCode() {
        return new HashCodeBuilder()
                .append(queen)
                .append(toRow)
                .toHashCode();
    }
```

Notice that it checks if the other move is an instance of the same move type. This `instanceof` check is important because a move will be compared to a move with another move type if you're using more then 1 move type.

It's also recommended to implement the `toString()` method as it allows you to read Planner's logging more easily:

```
    public String toString() {
        return queen + " => " + toRow;
    }
```

Now that we can implement a single custom `Move`, let's take a look at generating such custom moves.

7.7.4. `MoveListFactory`: the easy way to generate custom moves

The easiest way to generate custom moves is by implementing the interface `MoveListFactory`:

```
public interface MoveListFactory {

    List<Move> createMoveList(Solution solution);

}
```

For example:

```
public class RowChangeMoveFactory implements MoveListFactory {

    public List<Move> createMoveList(Solution solution) {
        NQueens nQueens = (NQueens) solution;
        List<Move> moveList = new ArrayList<Move>();
        for (Queen queen : nQueens.getQueenList()) {
            for (Row toRow : nQueens.getRowList()) {
                moveList.add(new RowChangeMove(queen, toRow));
            }
        }
        return moveList;
    }

}
```

Simple configuration (which can be nested in a `unionMoveSelector` just like any other `MoveSelector`):

```
    <moveListFactory>

ols.planner.examples.nqueens.solver.move.factory.RowChangeMoveFactory</
moveListFactoryClass>
    </moveListFactory>
```

Advanced configuration:

```
    <moveListFactory>
      ... <!-- Normal moveSelector properties -->

ols.planner.examples.nqueens.solver.move.factory.RowChangeMoveFactory</
moveListFactoryClass>
    </moveListFactory>
```

Because the `MoveListFactory` generates all moves at once in a List<Move>, it does not support `cacheType JUST_IN_TIME`. Therefore, `moveListFactory` uses `cacheType STEP` by default and it scales badly in memory footprint.

7.7.5. `MoveIteratorFactory`: generate custom moves just in time

Use this advanced form to generate custom moves by implementing the interface `MoveIteratorFactory`:

```
public interface MoveIteratorFactory {

    long getSize(ScoreDirector scoreDirector);

    Iterator<Move> createOriginalMoveIterator(ScoreDirector scoreDirector);

    Iterator<Move> createRandomMoveIterator(ScoreDirector scoreDirector, Random workingRandom);
}
```

The method `getSize()` must give an estimation of the size. It doesn't need to be correct. The method `createOriginalMoveIterator` is called if the `selectionOrder` is `ORIGINAL` or if it is cached. The method `createRandomMoveIterator` is called for `selectionOrder` `RANDOM` combined with cacheType `JUST_IN_TIME`.

Important

Don't create a collection (list, array, map, set) of `Moves` when creating the `Iterator<Move>`: the whole purpose of `MoveIteratorFactory` over `MoveListFactory` is giving you the ability to create a `Move` just in time in the `Iterator`'s method `next()`.

Simple configuration (which can be nested in a `unionMoveSelector` just like any other `MoveSelector`):

```
    <moveIteratorFactory>
      <moveIteratorFactoryClass>...</moveIteratorFactoryClass>
    </moveIteratorFactory>
```

Advanced configuration:

```
    <moveIteratorFactory>
      ... <!-- Normal moveSelector properties -->
      <moveIteratorFactoryClass>...</moveIteratorFactoryClass>
    </moveIteratorFactory>
```

7.7.6. Move generation through DRL

Not yet supported.

Chapter 8. Construction heuristics

8.1. Overview

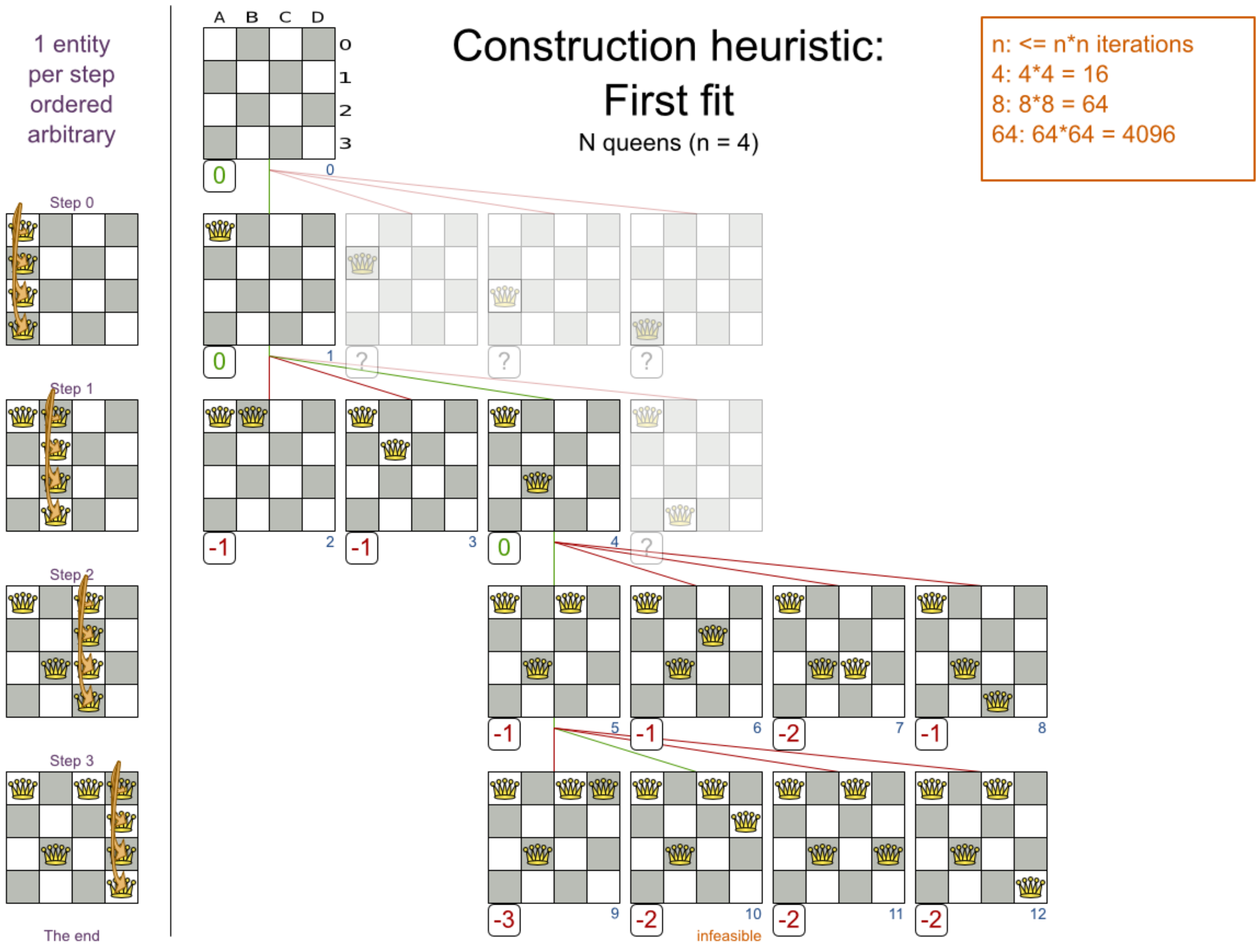
A construction heuristic builds a pretty good initial solution in a finite length of time. Its solution isn't always feasible, but it finds it fast and metaheuristics can finish the job.

Construction heuristics terminate automatically, so there's usually no need to configure a `Termination` on the construction heuristic phase specifically.

8.2. First Fit

8.2.1. Algorithm description

The *First Fit* algorithm cycles through all the planning entities (in default order), initializing 1 planning entity at a time. It assigns the planning entity to the best available planning value, taking the already initialized planning entities into account. It terminates when all planning entities have been initialized. It never changes a planning entity after it has been assigned.



Notice that it starts with putting `Queen` A into row 0 (and never moving it later), which makes it impossible to reach the optimal solution. Suffixing this construction heuristic with metaheurstics can remedy that.

8.2.2. Configuration

Configure this `SolverPhase`:

```
  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT</constructionHeuristicType>
    <!-- Speedup that can be applied to most, but not all use cases: -->
                                                                        <!--

constructionHeuristicPickEarlyType> -->
  </constructionHeuristic>
```

Note

The `constructionHeuristicPickEarlyType` of `FIRST_LAST_STEP_SCORE_EQUAL_OR_IMPROVING` is a big speedup, which should be applied when initializing a planning entity which can only make the score lower or equal. So if:

- There are no positive constraints.
- There is no negative constraint that can stop being broken by adding a planning entity (except if another negative constraint gets broken which outweighs the first negative constraint).

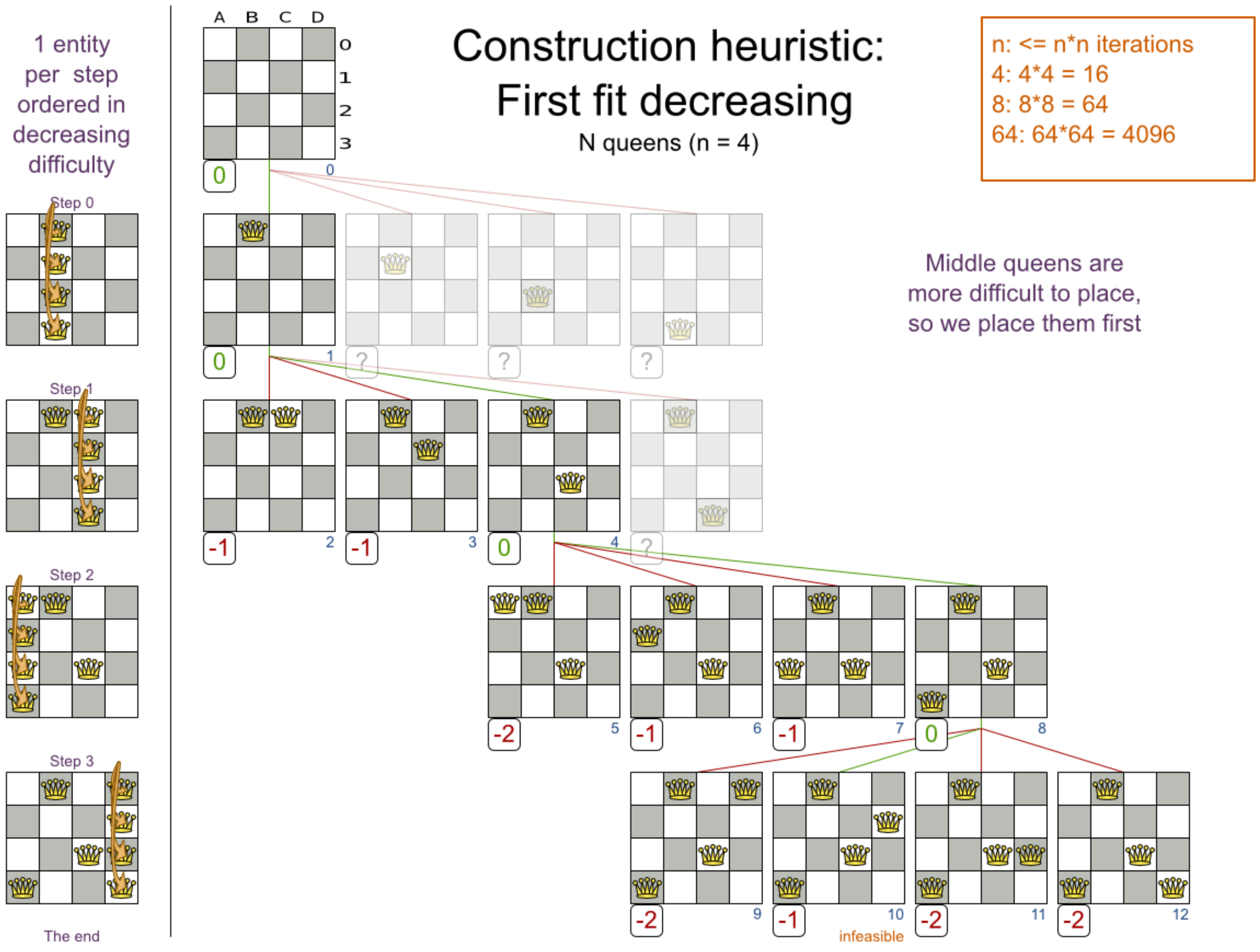
If that is not the case, then it can still be good to apply it in some cases, but not in most cases. Use the `Benchmarker` to decide.

8.3. First Fit Decreasing

8.3.1. Algorithm description

Like `First Fit`, but assigns the more difficult planning entities first, because they are less likely to fit in the leftovers. So it sorts the planning entities on decreasing difficulty.

Requires the model to support *planning entity difficulty comparison*.


1 entity per step ordered in decreasing difficulty
Step 0
Step 1
Step 2
Step 3
The end
Construction heuristic: First fit decreasing
N queens (n = 4)
n: <= n*n iterations
4: 4*4 = 16
8: 8*8 = 64
64: 64*64 = 4096
Middle queens are more difficult to place, so we place them first
infeasible

> **Note**
>
> One would expect that this algorithm always performs better than `First Fit`. That's not always the case, but usually is.

8.3.2. Configuration

Configure this `SolverPhase`:

```
  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT_DECREASING</constructionHeuristicType>
    <!-- Speedup that can be applied to most, but not all use cases: -->
                                                                     <!--

constructionHeuristicPickEarlyType> -->
  </constructionHeuristic>
```

8.4. Best Fit

8.4.1. Algorithm description

Like `First Fit`, but uses the weaker planning values first, because the strong planning values are more likely to be able to accommodate later planning entities. So it sorts the planning values on increasing strength.

Requires the model to support *planning value strength comparison*.

> **Note**
>
> One would expect that this algorithm always performs better than `First Fit`. That's not always the case.

8.4.2. Configuration

Configure this `SolverPhase`:

```
  <constructionHeuristic>
    <constructionHeuristicType>BEST_FIT</constructionHeuristicType>
    <!-- Speedup that can be applied to most, but not all use cases: -->
                                                                        <!--
constructionHeuristicPickEarlyType> -->
  </constructionHeuristic>
```

8.5. Best Fit Decreasing

8.5.1. Algorithm description

Combines `First Fit Decreasing` and `Best Fit`. So it sorts the planning entities on decreasing difficulty and the planning values on increasing strength.

Requires the model to support *planning entity difficulty comparison* and *planning value strength comparison*.

> **Note**
>
> One would expect that this algorithm always performs better than `First Fit`, `First Fit Decreasing` and `Best Fit`. That's not always the case.

8.5.2. Configuration

Configure this `SolverPhase`:

```
  <constructionHeuristic>
    <constructionHeuristicType>BEST_FIT_DECREASING</constructionHeuristicType>
    <!-- Speedup that can be applied to most, but not all use cases: -->
                                                                         <!--

constructionHeuristicPickEarlyType> -->
  </constructionHeuristic>
```

8.6. Cheapest insertion

8.6.1. Algorithm description

TODO

8.6.2. Configuration

TODO Not implemented yet.

Chapter 9. Local search

9.1. Overview

Local search starts from an initial solution and evolves that single solution into a mostly better and better solution. It uses a single search path of solutions, not a search tree. At each solution in this path it evaluates a number of moves on the solution and applies the most suitable move to take the step to the next solution. It does that for a high number of iterations until it's terminated (usually because its time has run out).

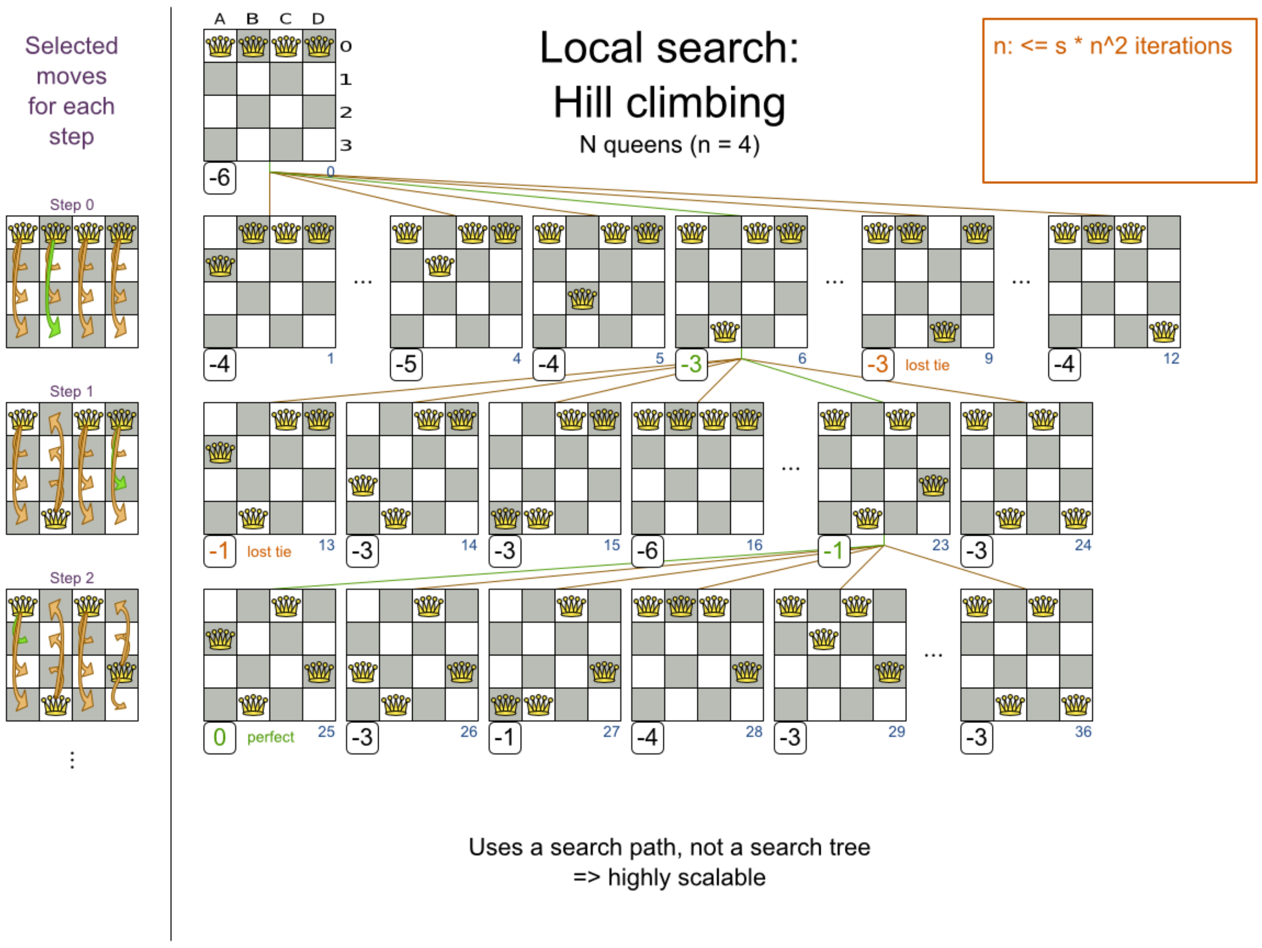
Local search acts a lot like a human planner: it uses a single search path and moves facts around to find a good feasible solution. Therefore it's pretty natural to implement.

Local search often needs to start from an initialized solution, therefore it's recommended to configure a construction heuristic solver phase before it.

9.2. Hill climbing (simple local search)

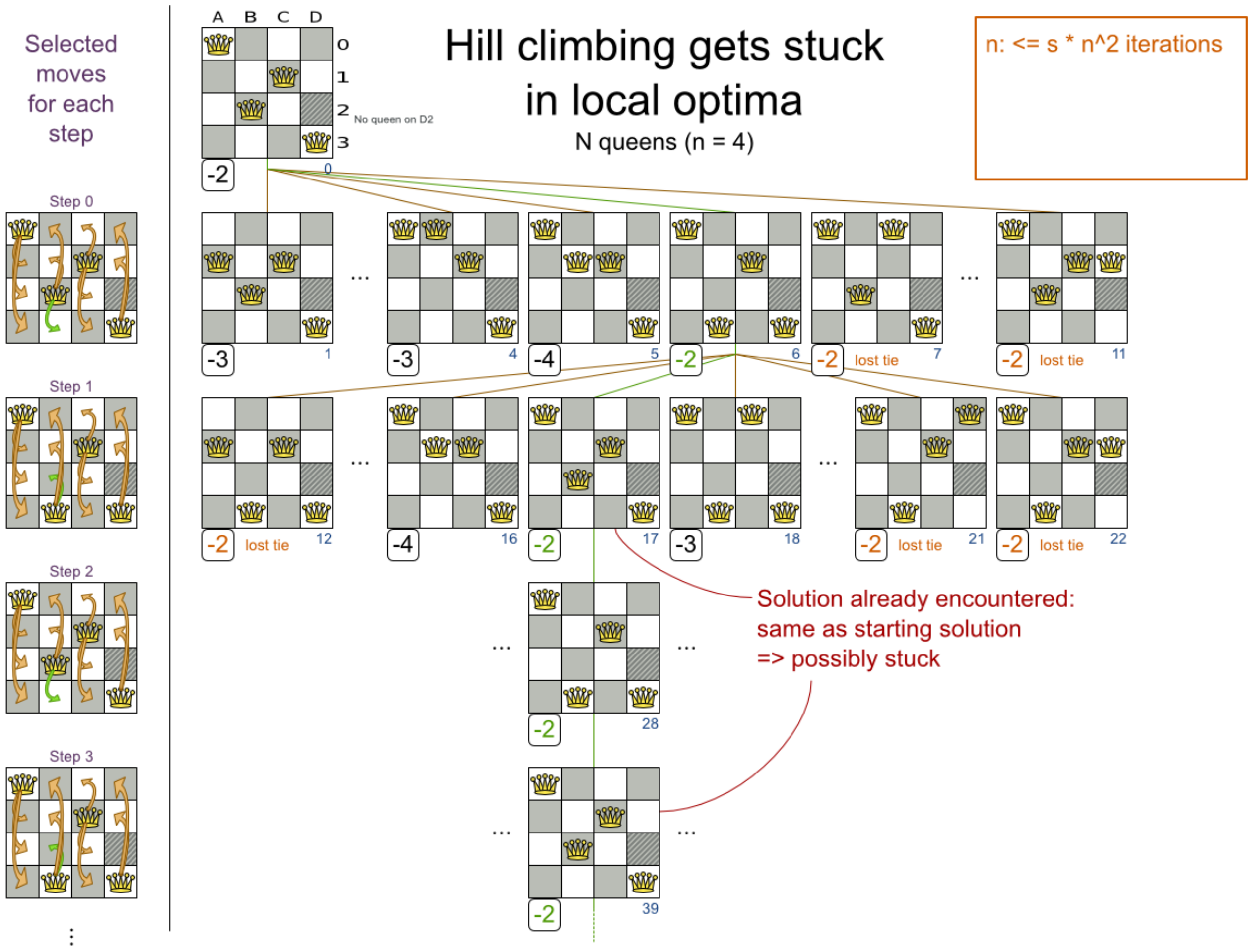
9.2.1. Algorithm description

Hill climbing tries all selected moves and then takes the best move, which is the move which leads to the solution with the highest score. That best move is called the step move. From that new solution, it again tries all selected moves and takes the best move and continues like that iteratively. If multiple selected moves tie for the best move, one of them is randomly chosen as the best move.



Notice that one a queen has moved, it can be moved again later. This is a good thing, because in an NP-complete problem it's impossible to predict what will be the optimal final value for a planning variable.

Hill climbing can easily get stuck in a local optima:

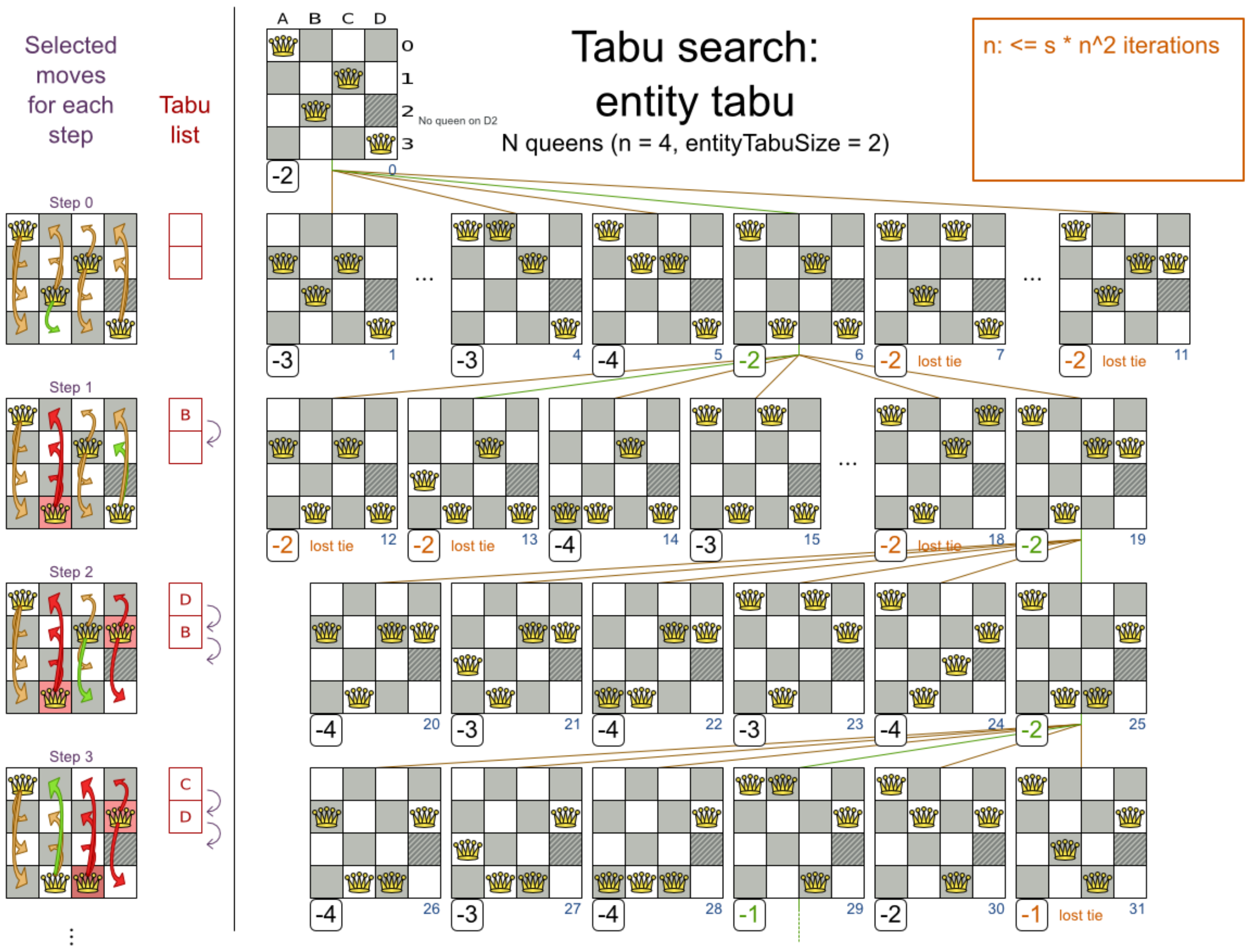


Improvements upon hill climbing (such as tabu search and simulated annealing) address the problem of being stuck in local optima.

9.3. Tabu search

9.3.1. Algorithm description

Tabu search works like hill climbing, but it maintains a tabu list to avoid getting stuck in local optima. The tabu list holds recently used objects that are *taboo* to use for now. Moves that involve an object in the tabu list, are not accepted. The tabu list objects can be anything related to the move, such as the planning entity, planning value, move, solution, ... Here's an example with entity tabu for 4 queens, so the queens are put in the tabu list:



See Tabu Search acceptor below.

9.4. Simulated annealing

9.4.1. Algorithm description

See Simulated Annealing acceptor below.

9.5. Late acceptance

9.5.1. Algorithm description

See Late Acceptance acceptor below.

9.6. About neighborhoods, moves and steps

9.6.1. Move generation tips

At each solution, local search will try all possible moves and pick the best move to change to the next solution. It's up to you to generate those moves. Let's take a look at all the possible moves on the starting solution of 4 queens:

It's highly recommended that you verify all solutions are connected by your move set. This means that by combining a finite number of moves you can reach any solution from any solution. Otherwise you're already excluding solutions at the start. Especially if you're using only big moves, you should check it. Just because big moves outperform small moves in a short test run, it doesn't mean that they will outperform them in a long test run.

You can mix different move types. Usually you're better off preferring small (fine-grained) moves over big (course-grained) moves because the score delta calculation will pay off more. However, as the traveling tournament example proves, if you can remove a hard constraint by using a certain set of big moves, you can win performance and scalability. Try it yourself: run both the simple (small moves) and the smart (big moves) version of the traveling tournament example. The smart version evaluates a lot less unfeasible solutions, which enables it to outperform and outscale the simple version.

9.6.2. A step

A step is the winning move. The local search solver tries every move on the current solution and picks the best accepted move as the step:

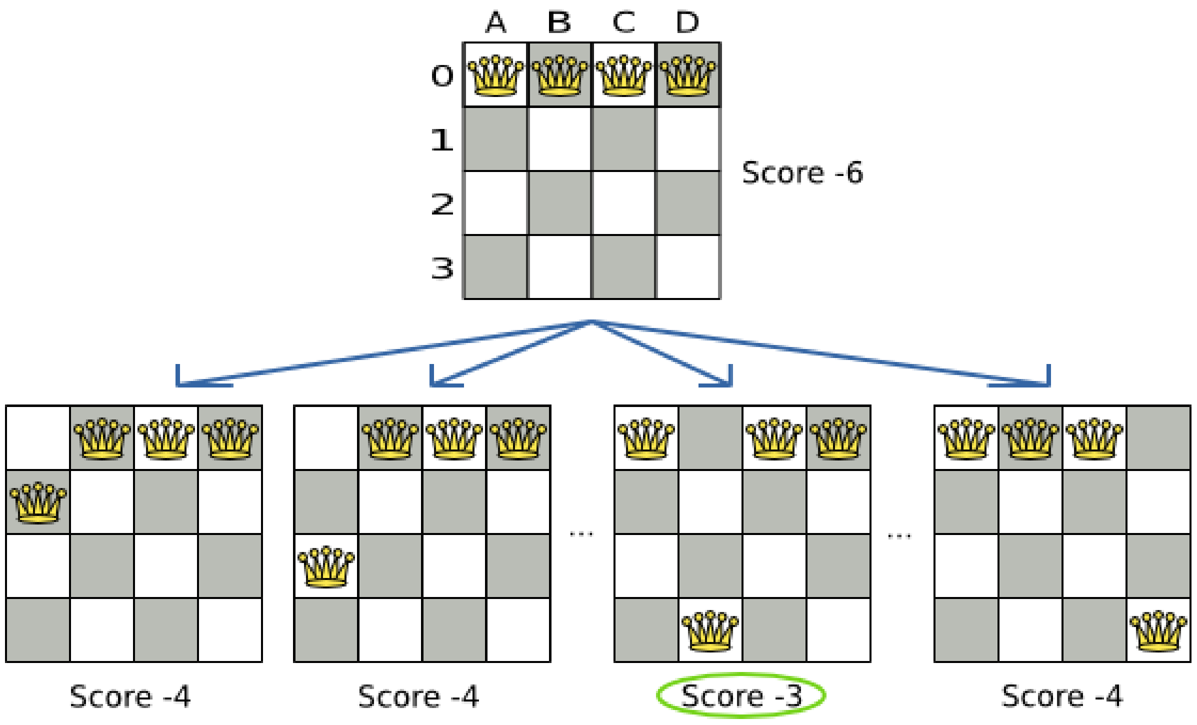


Figure 9.1. Decide the next step at step 0 (4 queens example)

Because the move *B0 to B3* has the highest score (`-3`), it is picked as the next step. Notice that *C0 to C3* (not shown) could also have been picked because it also has the score `-3`. If multiple moves have the same highest score, one is picked randomly, in this case *B0 to B3*.

The step is made and from that new solution, the local search solver tries all the possible moves again, to decide the next step after that. It continually does this in a loop, and we get something like this:

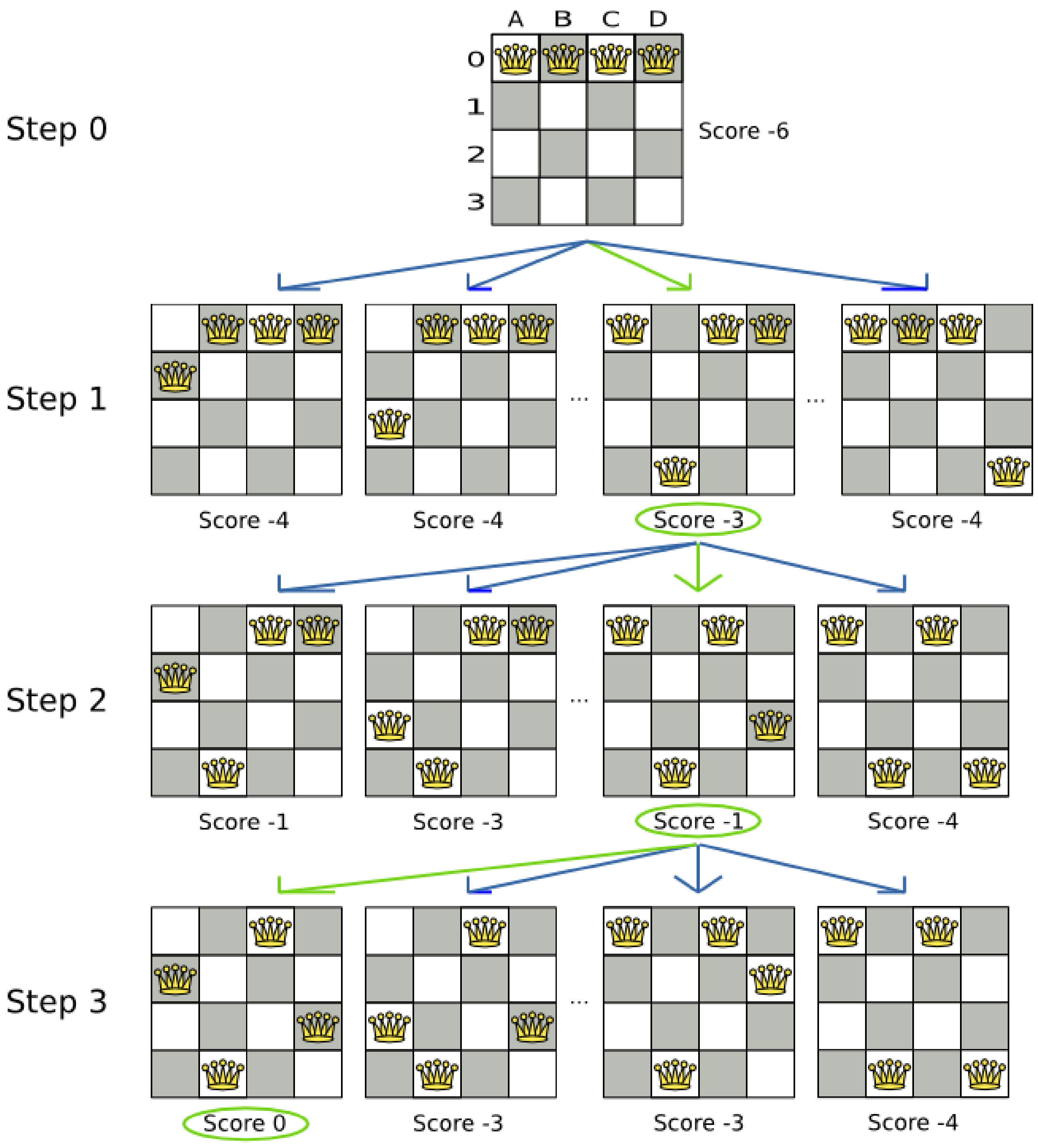


Figure 9.2. All steps (4 queens example)

Notice that the local search solver doesn't use a search tree, but a search path. The search path is highlighted by the green arrows. At each step it tries all possible moves, but unless it's the step, it doesn't investigate that solution further. This is one of the reasons why local search is very scalable.

As you can see, the local search solver solves the 4 queens problem by starting with the starting solution and make the following steps sequentially:

1. *B0 to B3*
2. *D0 to B2*
3. *A0 to B1*

If we turn on `DEBUG` logging for the category `org.drools.planner`, then those steps are shown into the log:

```
INFO  Solving started: time spend (0), score (-6), new best score (-6), random
 seed (0).
DEBUG      Step index (0), time spend (20), score (-3), new best score (-3),
 accepted/selected move count (12/12) for picked step (col1@row0 => row3).
DEBUG      Step index (1), time spend (31), score (-1), new best score (-1),
 accepted/selected move count (12/12) for picked step (col0@row0 => row1).
DEBUG      Step index (2), time spend (40), score (0), new best score (0),
 accepted/selected move count (12/12) for picked step (col3@row0 => row2).
INFO  Phase localSearch ended: step total (3), time spend (41), best score (0).
INFO  Solving ended: time spend (41), best score (0), average calculate count
 per second (1780).
```

Notice that the logging uses the `toString()` method of our `Move` implementation: `col1@row0 => row3`.

The local search solver solves the 4 queens problem in 3 steps, by evaluating only 37 possible solutions (3 steps with 12 moves each + 1 starting solution), which is only fraction of all 256 possible solutions. It solves 16 queens in 31 steps, by evaluating only 7441 out of 18446744073709551616 possible solutions. Note: with construction heuristics it's even a lot more efficient.

9.6.3. Getting stuck in local optima

A *hill climber* always takes improving moves. This may seem like a good thing, but it's not. It suffers from a number of problems:

- It can get stuck in a local optimum. For example if it reaches a solution X with a score -1 and there is no improving move, it is forced to take a next step that leads to a solution Y with score -2, after that however, it's very real that it will pick the step back to solution X with score -1. It will then start looping between solution X and Y.
- It can start walking in its own footsteps, picking the same next step at every step.

Of course Drools Planner implements better local searches, such as *tabu search* and *simulated annealing* which can avoid these problems. We recommend to never use a hill climber, unless you're absolutely sure there are no local optima in your planning problem.

9.7. Deciding the next step

The local search solver decides the next step with the aid of 3 configurable components:

- A `MoveSelector` which selects the possible moves of the current solution. See the chapter about Move and neighborhood selection.
- An *acceptor* which filters out unacceptable moves. It can also weigh a move it accepts.
- A *forager* which gathers all accepted moves and picks the next step from them.

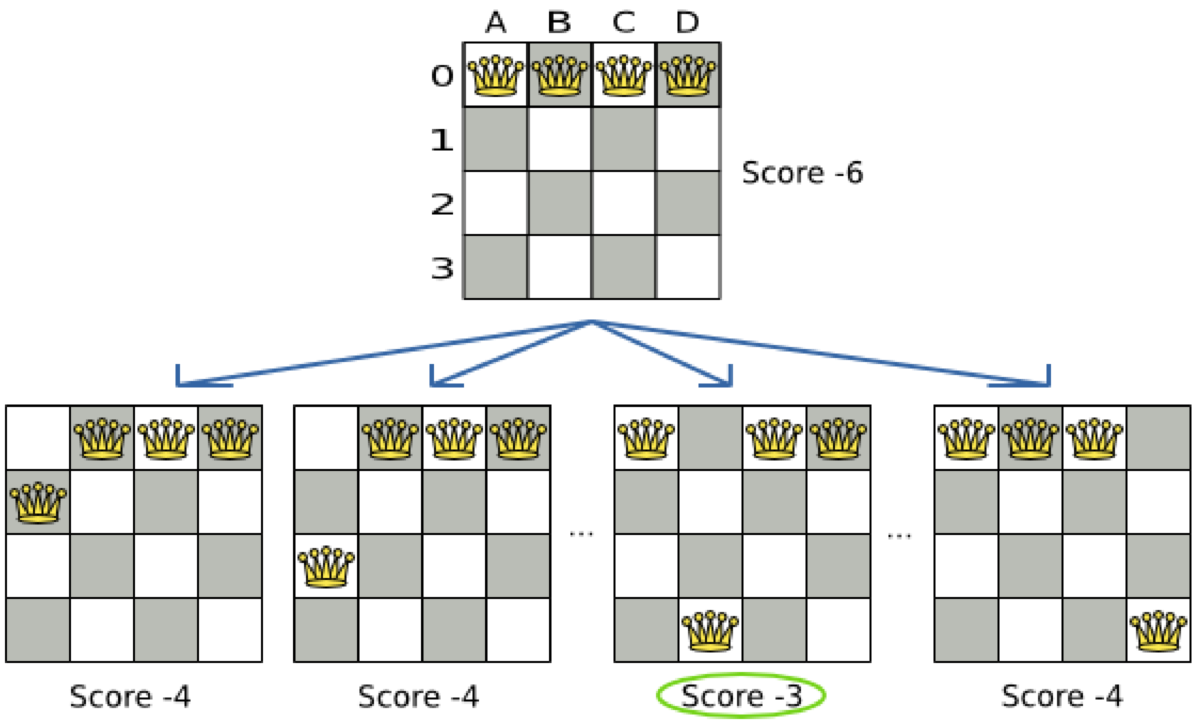


Figure 9.3. Decide the next step at step 0 (4 queens example)

In the above example the selector generated the moves shown with the blue lines, the acceptor accepted all of them and the forager picked the move *B0 to B3*.

If we turn on `TRACE` logging for the category `org.drools.planner`, then the decision making is shown in the log:

```
INFO  Solver started: time spend (0), score (-6), new best score (-6), random
 seed (0).
TRACE         Ignoring not doable move (col0@row0 => row0).
TRACE          Move index (1), score (-4), accepted (true) for move (col0@row0
 => row1).
TRACE          Move index (2), score (-4), accepted (true) for move (col0@row0
 => row2).
```

```
TRACE          Move index (3), score (-4), accepted (true) for move (col0@row0
 => row3).
...
TRACE          Move index (6), score (-3), accepted (true) for move (col1@row0
 => row3).
...
TRACE          Move index (9), score (-3), accepted (true) for move (col2@row0
 => row3).
...
TRACE          Move index (12), score (-4), accepted (true) for move (col3@row0
 => row3).
DEBUG      Step index (0), time spend (6), score (-3), new best score (-3),
 accepted/selected move count (12/12) for picked step (col1@row0 => row3).
...
```

Because the last solution can degrade (especially in tabu search and simulated annealing), the `Solver` remembers the best solution it has encountered through the entire search path. Each time the current solution is better than the last best solution, the current solution is cloned and referenced as the new best solution.

9.7.1. Acceptor

An acceptor is used (together with a forager) to active tabu search, simulated annealing, great deluge, ... For each move it checks whether it is accepted or not.

You can implement your own `Acceptor`, although the build-in acceptors should suffice for most needs. You can also combine multiple acceptors.

9.7.1.1. Tabu search acceptor

When tabu search takes steps it creates tabu's. It does not accept a move as the next step if that move breaks tabu. Drools Planner implements several tabu types:

- *Solution tabu* makes recently visited solutions tabu. It does not accept a move that leads to one of those solutions. If you can spare the memory, don't be cheap on the tabu size.

```
    <acceptor>
        <solutionTabuSize>1000</solutionTabuSize>
    </acceptor>
```

- *Move tabu* makes recent steps tabu. It does not accept a move equal to one of those steps.

```
    <acceptor>
        <moveTabuSize>7</moveTabuSize>
    </acceptor>
```

* *Undo move tabu* makes the undo move of recent steps tabu.

```
    <acceptor>
        <undoMoveTabuSize>7</undoMoveTabuSize>
    </acceptor>
```

* *Planning entity tabu* makes the planning entities of recent steps tabu. For example, for N queens it makes the recently moved queens tabu.

```
    <acceptor>
        <planningEntityTabuSize>7</planningEntityTabuSize>
    </acceptor>
```

* *Planning value tabu* makes the planning values of recent steps tabu. For example, for N queens it makes the recently moved to rows tabu.

```
    <acceptor>
        <planningValueTabuSize>7</planningValueTabuSize>
    </acceptor>
```

You can even combine tabu types:

```
    <acceptor>
        <solutionTabuSize>1000</solutionTabuSize>
        <moveTabuSize>7</moveTabuSize>
    </acceptor>
```

If you pick a too small tabu size, your solver can still get stuck in a local optimum. On the other hand, with the exception of solution tabu, if you pick a too large tabu size, your solver can get stuck by bouncing of the walls. Use the benchmarker to fine tweak your configuration. Experiments teach us that it is generally best to use a prime number for the move tabu, undo move tabu, entity tabu or value tabu size.

A tabu search acceptor should be combined with a high subset selection, such as `1000`.

9.7.1.2. Simulated annealing acceptor

Simulated annealing does not always pick the move with the highest score, neither does it evaluate many moves per step. At least at first. Instead, it gives non improving moves also a chance to be picked, depending on its score and the time gradient of the `Termination`. In the end, it gradually turns into a hill climber, only accepting improving moves.

In many use cases, simulated annealing surpasses tabu search. By changing a few lines of configuration, you can easily switch from tabu search to simulated annealing and back.

Start with a `simulatedAnnealingStartingTemperature` set to the maximum score delta a single move can cause. Use the `Benchmarker` to tweak the value.

```
    <acceptor>
      <simulatedAnnealingStartingTemperature>2hard/100soft</simulatedAnnealingStartingTemperature>
    </acceptor>
    <forager>
        <minimalAcceptedSelection>4</minimalAcceptedSelection>
    </forager>
```

A simulated annealing acceptor should be combined with a low subset selection. The classic algorithm uses a `minimalAcceptedSelection` of `1`, but usually `4` performs better.

You can even combine it with a tabu acceptor at the same time. Use a lower tabu size than in a pure tabu search configuration.

```
    <acceptor>
      <simulatedAnnealingStartingTemperature>10.0</simulatedAnnealingStartingTemperature>
      <planningEntityTabuSize>5</planningEntityTabuSize>
    </acceptor>
    <forager>
        <minimalAcceptedSelection>4</minimalAcceptedSelection>
    </forager>
```

This differs from phasing, another powerful technique, where first simulated annealing is used, followed by tabu search.

9.7.1.3. Late acceptance acceptor

Late acceptance accepts any move that has a score which is higher than the best score of a number of steps ago. That number of steps is the `lateAcceptanceSize`.

```
    <acceptor>
      <lateAcceptanceSize>500</lateAcceptanceSize>
    </acceptor>
    <forager>
        <minimalAcceptedSelection>1000</minimalAcceptedSelection>
    </forager>
```

9.7.2. Forager

A forager gathers all accepted moves and picks the move which is the next step. Normally it picks the accepted move with the highest score. If several accepted moves have the highest score, one is picked randomly.

You can implement your own `Forager`, although the build-in forager should suffice for most needs.

9.7.2.1. Subset selection

When there are many possible moves, it becomes inefficient to evaluate all of them at every step. To evaluate only a random subset of all the moves, use:

- An `minimalAcceptedSelection` integer, which specifies how many accepted moves should have be evaluated during each step. By default it is positive infinity, so all accepted moves are evaluated at every step.

```
    <forager>
      <minimalAcceptedSelection>1000</minimalAcceptedSelection>
    </forager>
```

Unlike the n queens problem, real world problems require the use of subset selection. Start from an `minimalAcceptedSelection` that takes a step in less then 2 seconds. Turn on INFO logging to see the step times. Use the `Benchmarker` to tweak the value.

Important

With a low `minimalAcceptedSelection` it is recommended to avoid using `selectionOrder` SHUFFLED because the shuffling generates a random number for every element in the selector, taking up a lot of time, but only a few are actually selected.

9.7.2.2. Pick early type

A forager can pick a move early during a step, ignoring subsequent selected moves. There are 3 pick early types:

- `NEVER`: A move is never picked early: all accepted moves are evaluated that the selection allows. This is the default.

```
      <forager>
```

```
        <pickEarlyType>NEVER</pickEarlyType>
    </forager>
```

- `FIRST_BEST_SCORE_IMPROVING`: Pick the first accepted move that improves the best score. If none improve the best score, it behaves exactly like the pickEarlyType NEVER.

```
    <forager>
        <pickEarlyType>FIRST_BEST_SCORE_IMPROVING</pickEarlyType>
    </forager>
```

- `FIRST_LAST_STEP_SCORE_IMPROVING`: Pick the first accepted move that improves the last step score. If none improve the last step score, it behaves exactly like the pickEarlyType NEVER.

```
    <forager>
        <pickEarlyType>FIRST_LAST_STEP_SCORE_IMPROVING</pickEarlyType>
    </forager>
```

9.8. Using a custom Termination, MoveSelector, EntitySelector, ValueSelector or Acceptor

You can plug in a custom `Termination`, `MoveSelector`, `EntitySelector`, `ValueSelector` or `Acceptor` by extending the abstract class and also the related `*Config` class.

For example, to use a custom `MoveSelector`, extend the `AbstractMoveSelector` class, extend the `MoveSelectorConfig` class and configure it in the solver configuration.

Note

It's not possible to directly inject a `Termination`, ... instance, instead of also extend a `Config` class because:

- A `SolverFactory` can build multiple `Solver` instances, which each require a distinct `Termination`, ... instance.
- A solver configuration needs to be serializable to and from XML. This makes benchmarking with `PlannerBenchmark` particularly easy because you can configure different `Solver` variants in XML.
- A `Config` class is often easier and clearer to configure. For example: `TerminationConfig` translates `maximumMinutesSpend` and `maximumSecondsSpend` into `maximumTimeMillisSpend`.

If you build a better implementation that's not domain specific, consider contributing it back as a pull request on github and we'll optimize it and take it along in future refactors.

Chapter 10. Evolutionary algorithms

10.1. Overview

Evolutionary algorithms work on a population of solutions and evolve that population.

10.2. Evolutionary Strategies

This algorithm has not been implemented yet.

10.3. Genetic algorithms

This algorithm has not been implemented yet.

Chapter 11. Exact methods

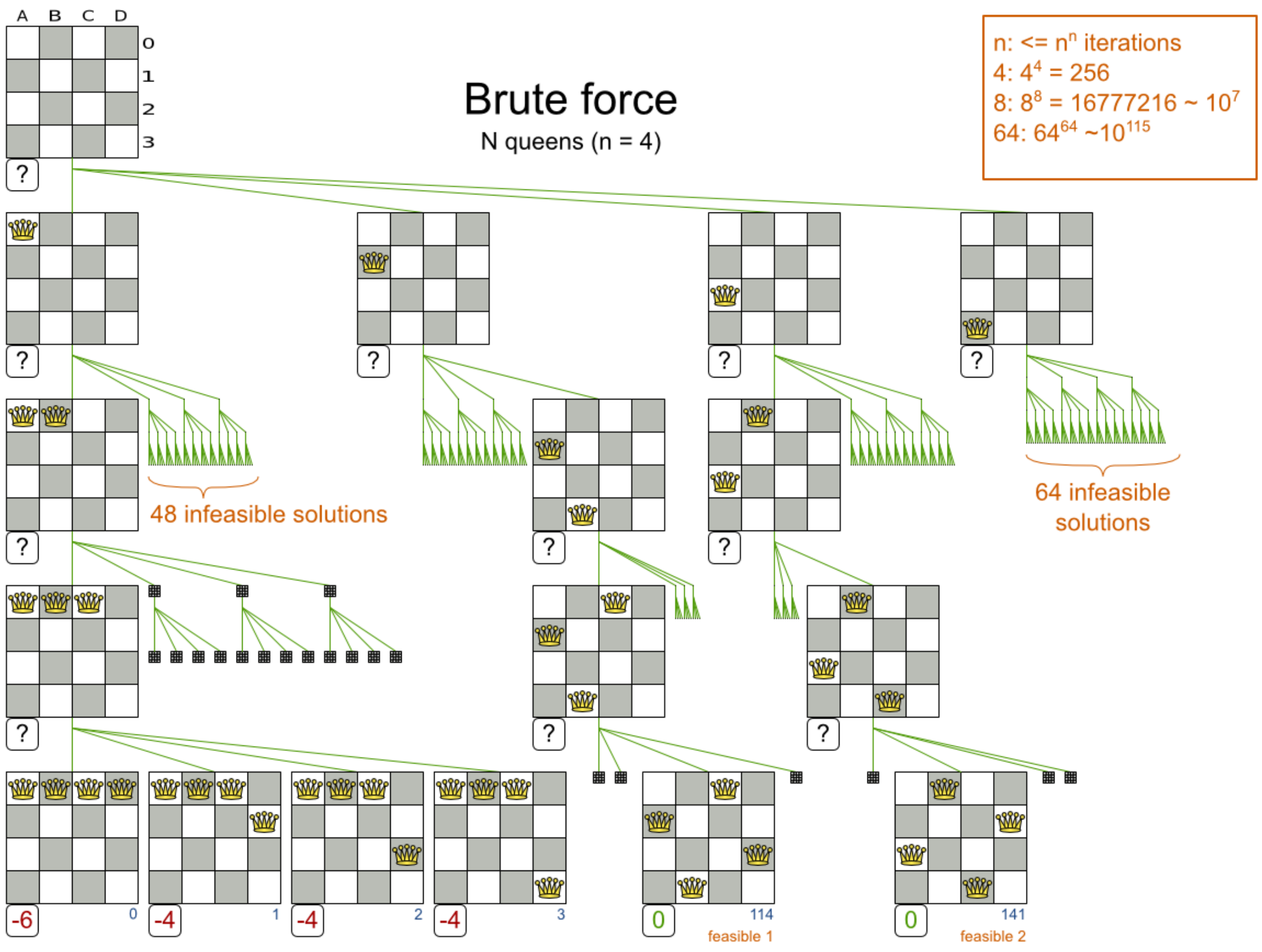
11.1. Overview

Exact methods will always find the global optimum and recognize it too. That being said, they don't scale (not even beyond toy problems) and are therefore mostly useless.

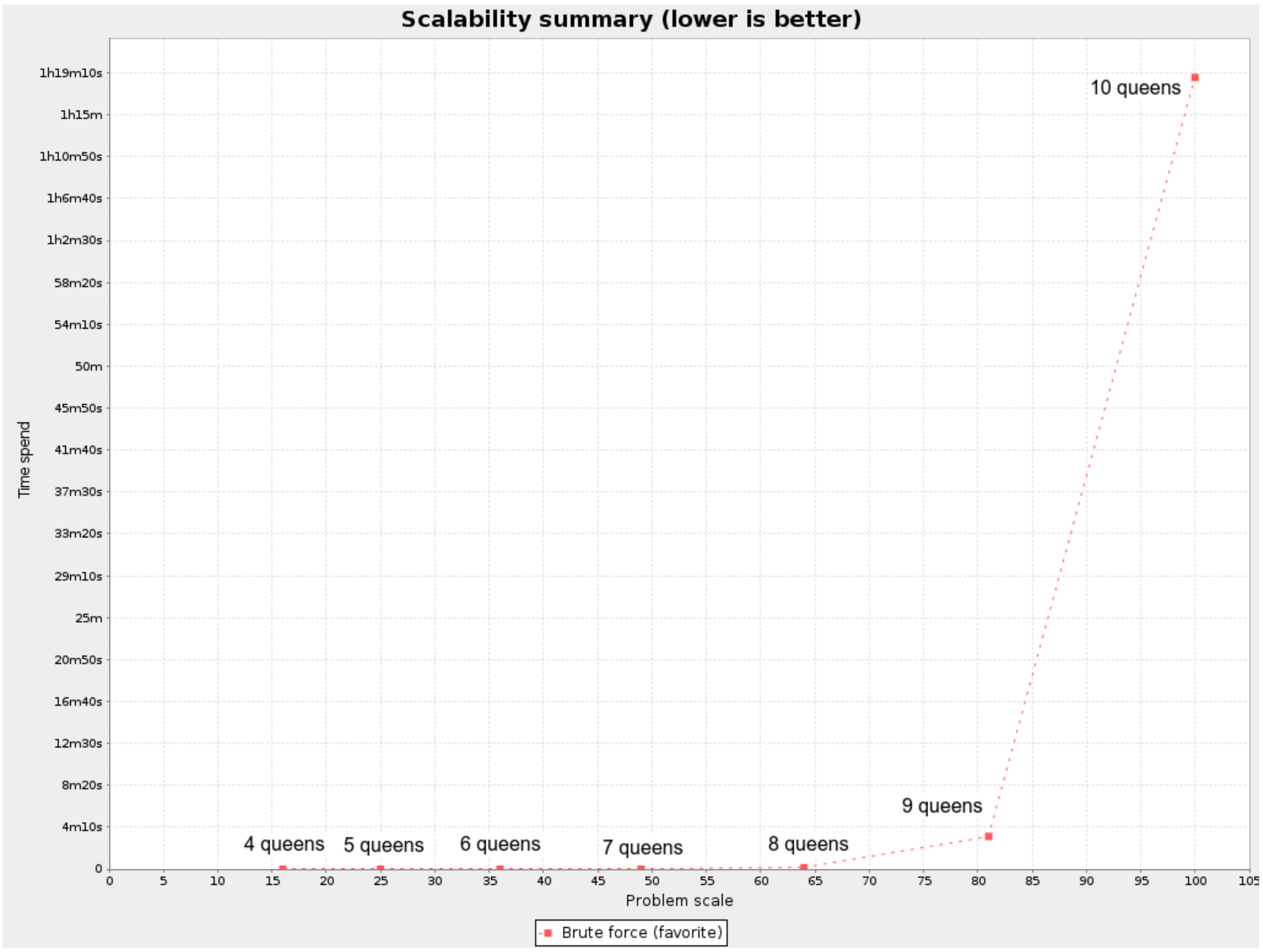
11.2. Brute Force

11.2.1. Algorithm description

The Brute Force algorithm creates and evaluates every possible solution.



Notice that it creates a search tree that explodes as the problem size increases. **Brute Force is mostly unusable for a real-world problem due to time limitations**, as proven by this scalability graph from the benchmarker:



11.2.2. Configuration

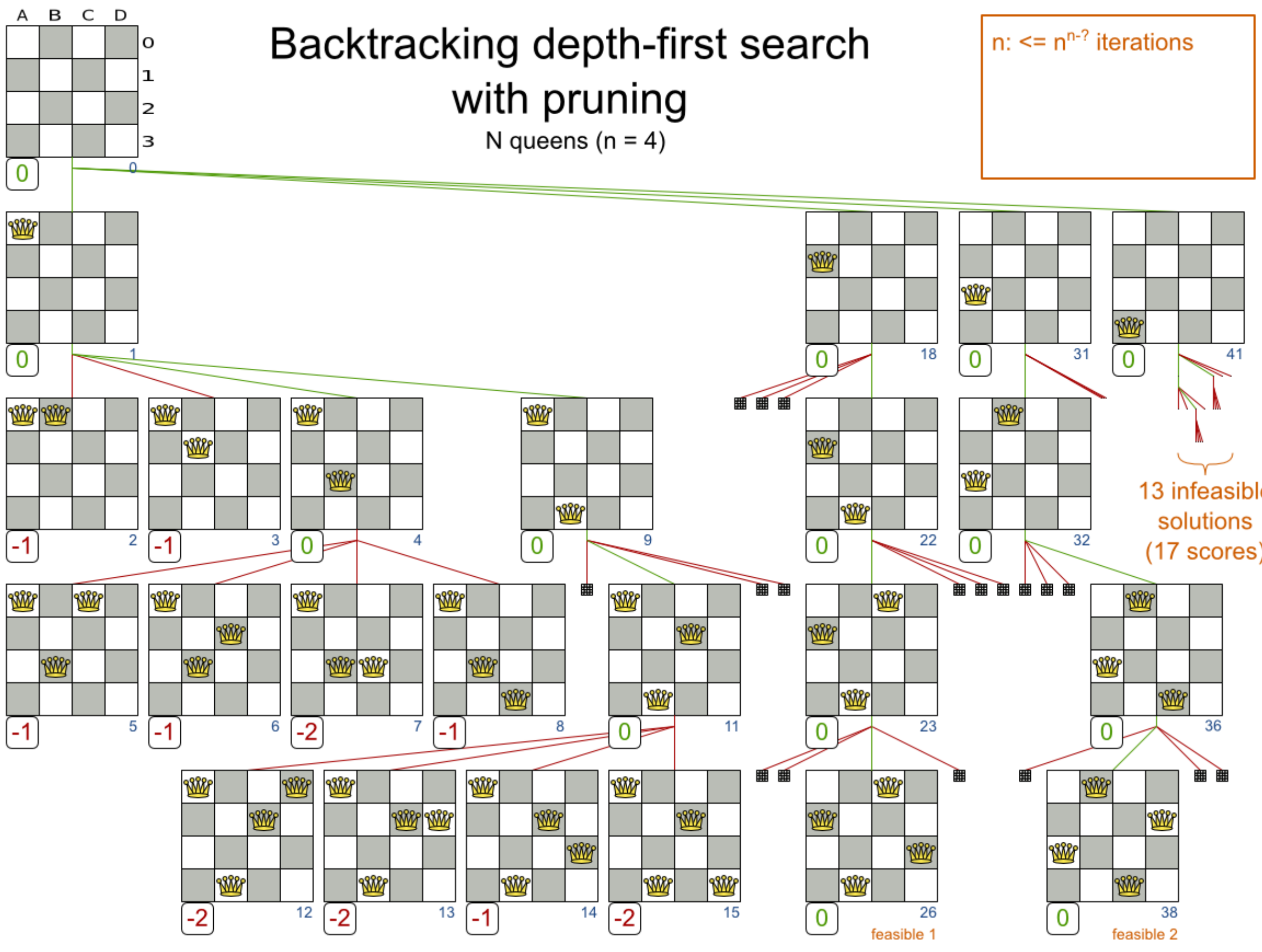
Using the brute force algorithm is easy:

```
<solver>
  ...
  <bruteForce>
  </bruteForce>
</solver>
```

11.3. Depth-first search

11.3.1. Algorithm description

Depth-First Search is an improvement over Brute Force, as it regularly prunes away an entire subset of solutions which cannot have a better solution than the best solution already found at that point. for example: at index 15, it can prune away all unvisited solutions with queen A on row 0, because none will be better than the solution of index 14 with a score of `-1`.



Backtracking depth-first search with pruning
N queens (n = 4)
n: <= n^{n-?} iterations
A B C D
0 1 2 3
13 infeasible solutions (17 scores)
feasible 1
feasible 2

Notice that it (much like Brute Force) creates a search tree that explodes as the problem size increases. **Depth-First Search is mostly unusable for a real-world NP-complete problem due to time limitations.**

Technically, this Backtracking Depth-First Search with pruning is a form of *Branch And Bound*, although Branch and Bound is often more flexible in its pruning.

11.3.2. Configuration

Depth-first search is not yet implemented. Patches welcome.

Chapter 12. Benchmarking and tweaking

12.1. Finding the best `Solver` configuration

Drools Planner supports several optimization algorithms, but you're probably wondering which is the best one? Although some optimization algorithms generally perform better than others, it really depends on your problem domain. Most solver phases have parameters which can be tweaked. Those parameters can influence the results a lot, even though most solver phases work pretty well out-of-the-box.

Luckily, Drools Planner includes a benchmarker, which allows you to play out different solver phases with different settings against each other, so you can pick the best configuration for your planning problem.

12.2. Doing a benchmark

12.2.1. Adding the extra dependency

The benchmarker is in a separate artifact called `drools-planner-benchmark`.

If you use maven, add a dependency in your `pom.xml` file:

```
    <dependency>
      <groupId>org.drools.planner</groupId>
      <artifactId>drools-planner-benchmark</artifactId>
      <version>...</version>
    </dependency>
```

This is similar for gradle, ivy and buildr. The version must be exactly the same as the `drools-planner-core` version used.

If you use ANT, you've probably already copied the required jars from the download zip's `binaries` directory.

12.2.2. Building and running a `PlannerBenchmark`

You can build a `PlannerBenchmark` instance with the `XmlPlannerBenchmarkFactory`. Configure it with a benchmark configuration xml file:

```
    XmlPlannerBenchmarkFactory plannerBenchmarkFactory = new XmlPlannerBenchmarkFactory();
       plannerBenchmarkFactory.configure("/org/drools/planner/examples/nqueens/
benchmark/nqueensBenchmarkConfig.xml");
```

```
    PlannerBenchmark plannerBenchmark = benchmarkFactory.buildPlannerBenchmark();
    plannerBenchmark.benchmark();
```

A basic benchmark configuration file looks something like this:

```
<?xml version="1.0" encoding="UTF-8"?>
<plannerBenchmark>
  <benchmarkDirectory>local/data/nqueens</benchmarkDirectory>
  <!--<parallelBenchmarkCount>AUTO</parallelBenchmarkCount>-->
  <warmUpSecondsSpend>30</warmUpSecondsSpend>

  <inheritedSolverBenchmark>
    <problemBenchmarks>

      <xstreamAnnotatedClass>org.drools.planner.examples.nqueens.domain.NQueens</
xstreamAnnotatedClass>
               <inputSolutionFile>data/nqueens/unsolved/unsolvedNQueens32.xml</
inputSolutionFile>
               <inputSolutionFile>data/nqueens/unsolved/unsolvedNQueens64.xml</
inputSolutionFile>
      <problemStatisticType>BEST_SOLUTION_CHANGED</problemStatisticType>
    </problemBenchmarks>
    <solver>
            <solutionClass>org.drools.planner.examples.nqueens.domain.NQueens</
solutionClass>
        <planningEntityClass>org.drools.planner.examples.nqueens.domain.Queen</
planningEntityClass>
      <scoreDirectorFactory>
        <scoreDefinitionType>SIMPLE</scoreDefinitionType>
                         <scoreDrl>/org/drools/planner/examples/nqueens/solver/
nQueensScoreRules.drl</scoreDrl>
      </scoreDirectorFactory>
      <termination>
        <maximumSecondsSpend>20</maximumSecondsSpend>
      </termination>
      <constructionHeuristic>
                              <constructionHeuristicType>FIRST_FIT_DECREASING</
constructionHeuristicType>

<constructionHeuristicPickEarlyType>FIRST_LAST_STEP_SCORE_EQUAL_OR_IMPROVING</
constructionHeuristicPickEarlyType>
      </constructionHeuristic>
    </solver>
  </inheritedSolverBenchmark>

  <solverBenchmark>
    <name>Entity tabu</name>
    <solver>
      <localSearch>
        <changeMoveSelector>
          <selectionOrder>ORIGINAL</selectionOrder>
        </changeMoveSelector>
        <acceptor>
          <planningEntityTabuSize>5</planningEntityTabuSize>
        </acceptor>
        <forager>
          <pickEarlyType>NEVER</pickEarlyType>
        </forager>
      </localSearch>
    </solver>
  </solverBenchmark>
  <solverBenchmark>
    <name>Value tabu</name>
    <solver>
      <localSearch>
        <changeMoveSelector>
          <selectionOrder>ORIGINAL</selectionOrder>
        </changeMoveSelector>
        <acceptor>
          <planningValueTabuSize>5</planningValueTabuSize>
        </acceptor>
        <forager>
          <pickEarlyType>NEVER</pickEarlyType>
        </forager>
      </localSearch>
    </solver>
  </solverBenchmark>
  <solverBenchmark>
    <name>Move tabu</name>
    <solver>
      <localSearch>
        <changeMoveSelector>
          <selectionOrder>ORIGINAL</selectionOrder>
        </changeMoveSelector>
        <acceptor>
          <moveTabuSize>5</moveTabuSize>
        </acceptor>
        <forager>
          <pickEarlyType>NEVER</pickEarlyType>
        </forager>
      </localSearch>
    </solver>
  </solverBenchmark>
</plannerBenchmark>
```

This `PlannerBenchmark` will try 3 configurations (1 move tabu, 1 entity tabu and 1 value tabu) on 2 data sets (32 and 64 queens), so it will run 6 solvers.

Every `solverBenchmark` element contains a solver configuration (for example with a local search solver phase) and one or more `inputSolutionFile` elements. It will run the solver configuration on each of those unsolved solution files. The element `name` is optional, because it is generated if absent. The inputSolutionFile is read by a *ProblemIO*.

To lower verbosity, the common part of multiple `solverBenchmark` entities can be extracted to the `inheritedSolverBenchmark` element. Yet, every element can still be overwritten per `solverBenchmark` element. Note that inherited solver phases such as `<constructionHeuristic>` or `<localSearch>` are not overwritten but instead are added to the tail of the solver phases list.

You need to specify a `benchmarkDirectory` (relative to the working directory). A benchmark report will be written in that directory.

Note

It's recommended that the `benchmarkDirectory` is a directory ignored for source control and not cleaned by your build system. This way the generated files are not bloating your source control and they aren't lost when doing a build. Usually that directory is called `local`.

12.2.3. ProblemIO: input and output of Solution files

12.2.3.1. `ProblemIO` interface

The benchmarker needs to be able to read the input files to contain a `Solution` write the best `Solution` of each benchmark to an output file. For that it uses a class that implements the `ProblemIO` interface:

```
public interface ProblemIO {

    String getFileExtension();

    Solution read(File inputSolutionFile);

    void write(Solution solution, File outputSolutionFile);

}
```

Warning

Your input files need to have been written with the same `ProblemIO` class as they are being read by the benchmarker.

12.2.3.2. `XStreamProblemIO`: the default `ProblemIO`

By default, a benchmarker uses a `XStreamProblemIO` instance to read and write solutions.

You need to tell the benchmarker about your `Solution` class which is annotated with XStream annotations:

```
    <problemBenchmarks>

      <xstreamAnnotatedClass>org.drools.planner.examples.nqueens.domain.NQueens</
xstreamAnnotatedClass>
                <inputSolutionFile>data/nqueens/unsolved/unsolvedNQueens32.xml</
inputSolutionFile>
      ...
    </problemBenchmarks>
```

Your input files need to have been written with a `XStreamProblemIO` instance, not just any `XStream` instance, because the `XStreamProblemIO` uses a customized `XStream` instance.

Warning

XStream and XML in general is a very verbose format. Reading or writing large datasets in this format can cause an `OutOfMemoryError` and performance degradation.

12.2.3.3. Custom `ProblemIO`

Alternatively, you can implement your own `ProblemIO` implementation and configure it with the `problemIOClass` element:

```
    <problemBenchmarks>

es.machinereassignment.persistence.MachineReassignmentProblemIO</
problemIOClass>
              <inputSolutionFile>data/machinereassignment/input/model_a1_1.txt</
inputSolutionFile>
      ...
    </problemBenchmarks>
```

Warning

A `ProblemIO` implementation must be thread-safe.

12.2.4. Writing the output solution of the benchmark runs

The best solution of each benchmark run can be written to the in the `benchmarkDirectory`. By default, this is disabled, because the files are rarely used and considered bloat. Also, on large datasets, writing the best solution of each single benchmark can take quite some time and memory (causing an `OutOfMemoryError`), especially in a verbose format like XStream.

You can enable to write the output solution in the `benchmarkDirectory` with `writeOutputSolutionEnabled`:

```
    <problemBenchmarks>
      ...
      <writeOutputSolutionEnabled>true</writeOutputSolutionEnabled>
      ...
    </problemBenchmarks>
```

12.2.5. Warming up the HotSpot compiler

Without a warm up, the results of the first (or first few) benchmarks are not reliable, because they will have lost CPU time on HotSpot JIT compilation (and possibly DRL compilation too).

The avoid that distortion, the benchmarker can run some of the benchmarks for a specified amount of time, before running the real benchmarks. Generally, a warm up of 30 seconds suffices:

```
<plannerBenchmark>
  ...
  <warmUpSecondsSpend>30</warmUpSecondsSpend>
  ...
</plannerBenchmark>
```

12.3. Benchmark report

12.3.1. HTML report

After the running a benchmark, a HTML report will be written in the `benchmarkDirectory` with the filename `index.html`. Open it in your browser. It has a nice overview of your benchmark including:

- Summary statistics: graphs and tables
- Problem statistics per `inputSolutionFile`
- Each solver configuration (ranked): easy to copy and paste.
- Benchmark information

The HTML report will use your default locale to format numbers. If you need to share the benchmark report with people from another country, you might want to overwrite the `benchmarkReportLocale`:

```
<plannerBenchmark>
  ...
  <benchmarkReportLocale>en_US</benchmarkReportLocale>
  ...
</plannerBenchmark>
```

12.3.2. Summary statistics

12.3.2.1. Best score summary

Shows the best score per `inputSolutionFile` and solver configuration.

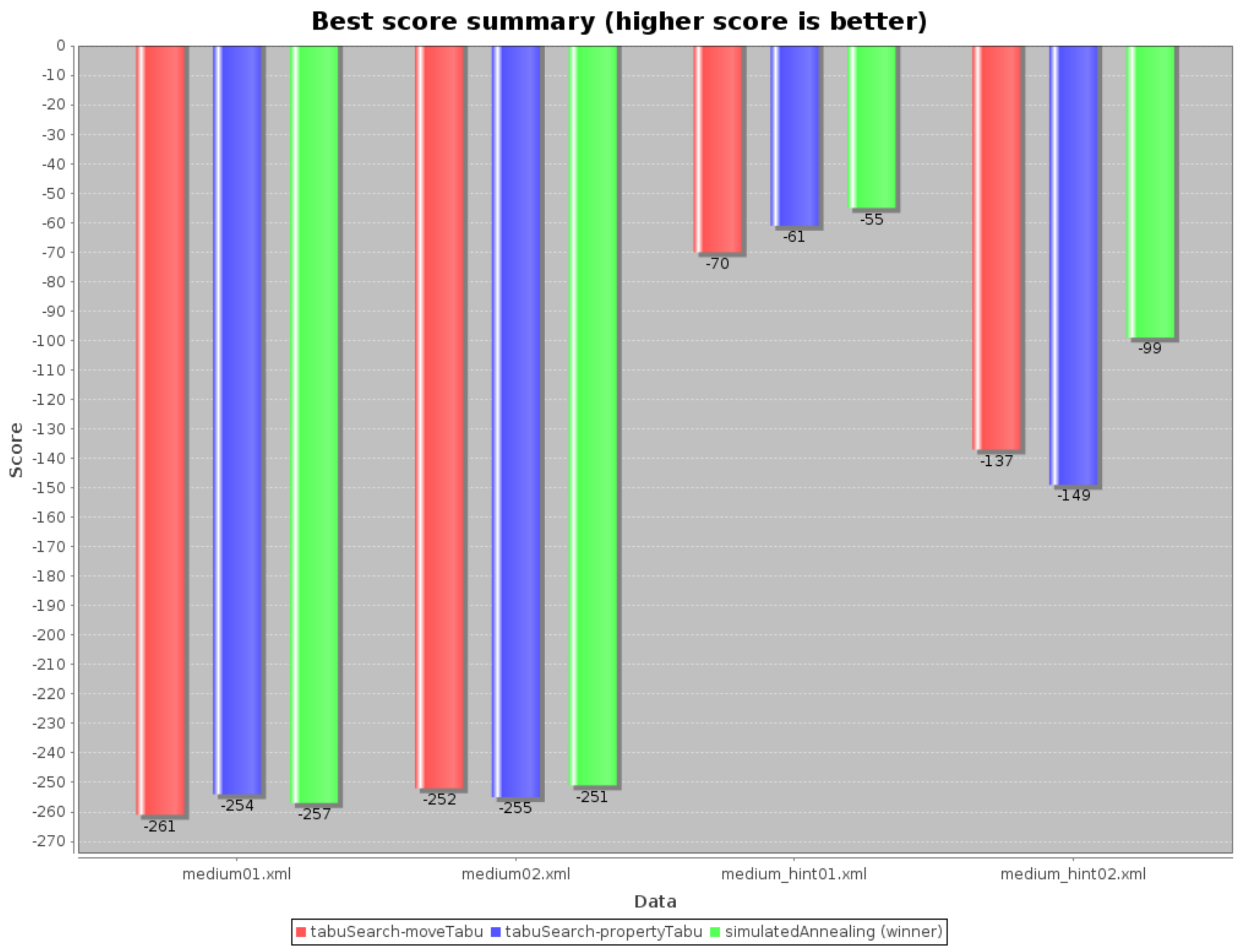


Figure 12.1. Best score summary statistic

12.3.3. Statistic per data set (graph and CSV)

12.3.3.1. Enabling a problem statistic

The benchmarker supports outputting problem statistics as graphs and CSV (comma separated values) files to the `benchmarkDirectory`.

To configure graph and CSV output of a statistic, just add a `problemStatisticType` line:

```
<plannerBenchmark>
  <benchmarkDirectory>local/data/nqueens/solved</benchmarkDirectory>
  <inheritedSolverBenchmark>
    <problemBenchmarks>
      ...
      <problemStatisticType>BEST_SOLUTION_CHANGED</problemStatisticType>
      <problemStatisticType>CALCULATE_COUNT_PER_SECOND</problemStatisticType>
    </problemBenchmarks>
    ...
  </inheritedSolverBenchmark>
  ...
</plannerBenchmark>
```

Multiple `problemStatisticType` elements are allowed. Some statistic types might influence performance and benchmark results noticeably. The following types are supported:

12.3.3.2. Best score over time statistic (graph and CSV)

To see how the best score evolves over time, add `BEST_SOLUTION_CHANGED` as a `problemStatisticType`.

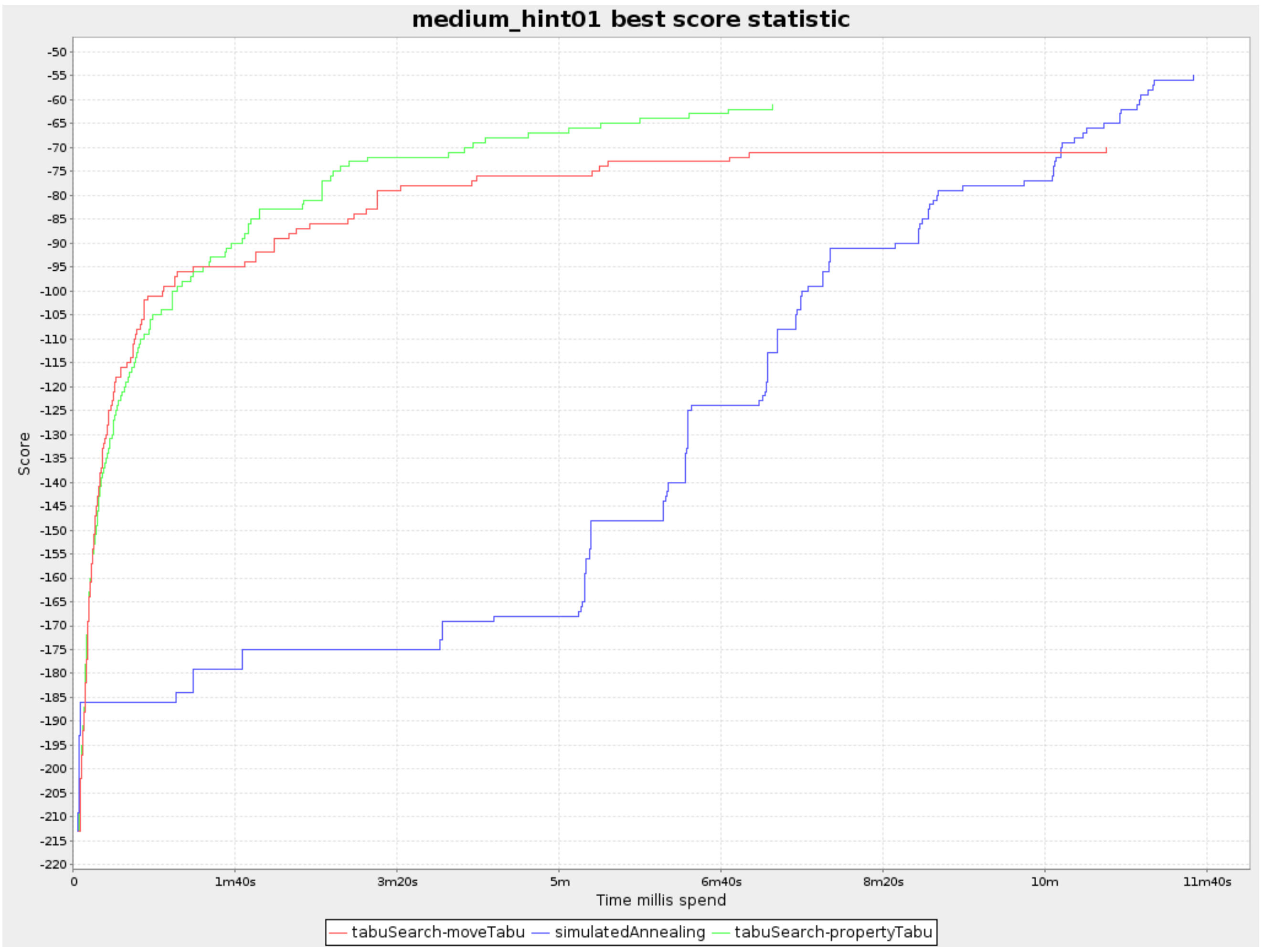


Figure 12.2. Best score over time statistic

The best score over time statistic is very useful to detect abnormalities, such as score traps.

Note

Don't be fooled by the simulated annealing line in this graph. If you give simulated annealing only 5 minutes, it might still be better than 5 minutes of tabu search. That's because this simulated annealing implementation automatically determines its velocity based on the amount of time that can be spend. On the other hand, for the tabu search, what you see is what you'd get.

12.3.3.3. Calculate count per second statistic (graph and CSV)

To see how fast the scores are calculated, add `CALCULATE_COUNT_PER_SECOND` as a `problemStatisticType`.

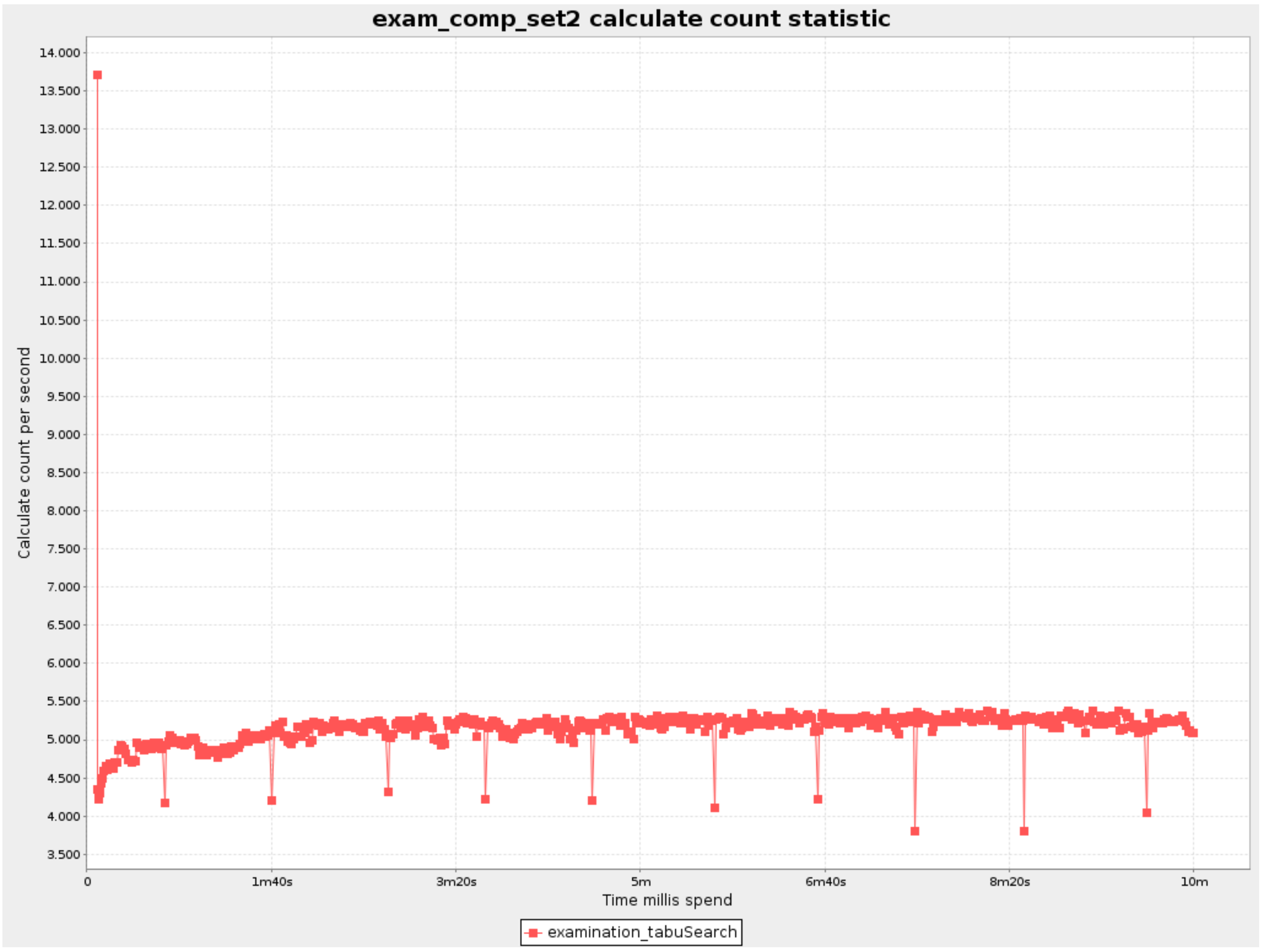


Figure 12.3. Calculate count per second statistic

Note

The initial high calculate count is typical during solution initialization. In this example, it's far easier to calculate the score of a solution if only a handful exams have been added, in contrast to all of them. After those few seconds of initialization, the calculate count is relatively stable, apart from an occasional stop-the-world garbage collector disruption.

12.3.3.4. Memory use statistic (graph and CSV)

To see how much memory is used, add `MEMORY_USE` as a `problemStatisticType`.

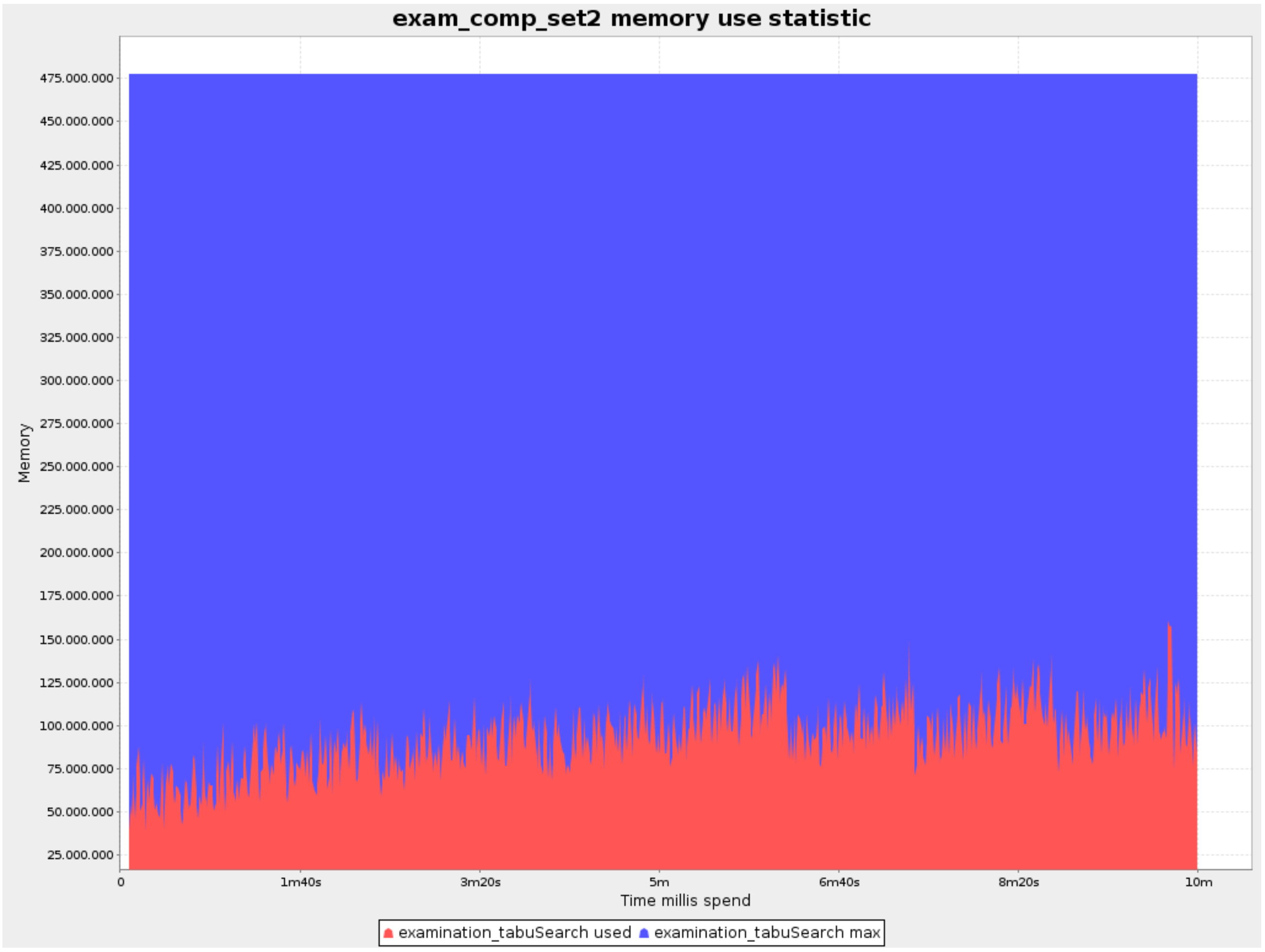


Figure 12.4. Memory use statistic

12.3.4. Ranking the `Solver`s

The benchmark report automatically ranks the solvers. The `Solver` with rank `0` is called the favorite `Solver`: it performs best overall, but it might not be the best on every problem. It's recommended to use that favorite `Solver` in production.

However, there are different ways of ranking the solvers. You can configure how:

```
<plannerBenchmark>
  ...
  <solverBenchmarkRankingType>TOTAL_SCORE</solverBenchmarkRankingType>
  ...
</plannerBenchmark>
```

The following `solverBenchmarkRankingTypes` are supported:

- `TOTAL_SCORE` (default): Maximize the overall score, so minimize the overall cost if all solutions would be executed.
- `WORST_SCORE`: Minimize the worst case scenario.
- `TOTAL_RANKING`: Maximize the overall ranking. Use this if your datasets differ greatly in size or difficulty, producing a difference in `Score` magnitude.

You can also use a custom ranking, by implementing a `Comparator`:

```
solverBenchmarkRankingComparatorClass>...TotalScoreSolverBenchmarkRankingComparator</
  solverBenchmarkRankingComparatorClass>
```

Or a weight factory:

```
hmarkRankingWeightFactoryClass>...TotalRankSolverBenchmarkRankingWeightFactory</
  solverBenchmarkRankingWeightFactoryClass>
```

12.4. Advanced benchmarking

12.4.1. Benchmarking performance tricks

12.4.1.1. Parallel benchmarking on multiple threads

If you have multiple processors available on your computer, you can run multiple benchmarks in parallel on multiple threads to get your benchmarks results faster:

```
<plannerBenchmark>
  ...
  <parallelBenchmarkCount>AUTO</parallelBenchmarkCount>
  ...
```

```
</plannerBenchmark>
```

Warning

Running too many benchmarks in parallel will affect the results of benchmarks negatively. Leave some processors unused for garbage collection and other processes.

We tweak `parallelBenchmarkCount` `AUTO` to maximize the reliability and efficiency of the benchmark results.

The following `parallelBenchmarkCounts` are supported:

- `1` (default): Run all benchmarks sequentially.
- `AUTO`: Let Planner decide how many benchmarks to run in parallel. This formula is based on experience. It's recommended to prefer this over the other parallel enabling options.
- Static number: The number of benchmarks to run in parallel.

```
<parallelBenchmarkCount>2</parallelBenchmarkCount>
```

- JavaScript formula: Formula for the number of benchmarks to run in parallel. It can use the variable `availableProcessorCount`. For example:

```
<parallelBenchmarkCount>(availableProcessorCount / 2) + 1</parallelBenchmarkCount>
```

Note

The `parallelBenchmarkCount` is always limited to the number of available processors. If it's higher, it will be automatically decreased.

Note

In the future, we will also support multi-JVM benchmarking. This feature is independent of *multi-threaded solving* [https://issues.jboss.org/browse/JBRULES-681] or multi-JVM solving.

12.4.2. Template based benchmarking and matrix benchmarking

Matrix benchmarking is benchmarking a combination of value sets. For example: benchmark 4 `planningEntityTabuSize` values (`5`, `7`, `11` and `13`) combined with 3 `minimalAcceptedSelection` values (`500`, `1000` and `2000`), resulting in 12 solver configurations.

To reduce the verbosity of such a benchmark configuration, you can use a *Freemarker* [http://freemarker.sourceforge.net/] template for the benchmark configuration instead:

```
<plannerBenchmark>
  ...

  <inheritedSolverBenchmark>
    ...
  </inheritedSolverBenchmark>

<#list [5, 7, 11, 13] as planningEntityTabuSize>
<#list [500, 1000, 2000] as minimalAcceptedSelection>
  <solverBenchmark>

<name>entityTabu${planningEntityTabuSize}acceptedSelection${minimalAcceptedSelection}</
name>
    <solver>
      <localSearch>
        <unionMoveSelector>
          <changeMoveSelector/>
          <swapMoveSelector/>
        </unionMoveSelector>
        <acceptor>
                            <planningEntityTabuSize>${planningEntityTabuSize}</
planningEntityTabuSize>
        </acceptor>
        <forager>
                        <minimalAcceptedSelection>${minimalAcceptedSelection}</
minimalAcceptedSelection>
        </forager>
      </localSearch>
    </solver>
  </solverBenchmark>
</#list>
</#list>
</plannerBenchmark>
```

And configure it with the method `configureFromTemplate`:

```
    XmlPlannerBenchmarkFactory plannerBenchmarkFactory = new XmlPlannerBenchmarkFactory();
   plannerBenchmarkFactory.configureFromTemplate("/org/drools/planner/examples/
cloudbalancing/benchmark/cloudBalancingBenchmarkConfigTemplate.xml.ftl");
   PlannerBenchmark plannerBenchmark = benchmarkFactory.buildPlannerBenchmark();
```

Chapter 13. Repeated planning

13.1. Introduction to repeated planning

The world constantly changes. The planning facts used to create a solution, might change before or during the execution of that solution. There are 3 types of situations:

- *Unforeseen fact changes*: For example: an employee assigned to a shift calls in sick, an airplane scheduled to take off has a technical delay, one of the machines or vehicles break down, ... Use **backup planning**.
- *Unknown long term future facts*: For example: The hospital admissions for the next 2 weeks are reliable, but those for week 3 and 4 are less reliable and for week 5 and beyond are not worth planning yet. Use **continuous planning**.
- *Constantly changing planning facts*: Use **real-time planning**.

Waiting to start planning - to lower the risk of planning facts changing - usually isn't a good way to deal with that. More CPU time means a better planning solution. An incomplete plan is better than no plan.

Luckily, the Drools Planner algorithms support planning a solution that's already (partially) planned, known as repeated planning.

13.2. Backup planning

Backup planning is the technique of adding extra score constraints to create space in the planning for when things go wrong. That creates a backup plan in the plan. For example: try to assign an employee as the spare employee (1 for every 10 shifts at the same time), keep 1 hospital bed open in each department, ...

Then, when things go wrong (one of the employees calls in sick), change the planning facts on the original solution (delete the sick employee leave his/her shifts unassigned) and just restart the planning, starting from that solution, which has a different score now. The construction heuristics will fill in the newly created gaps (probably with the spare employee) and the metaheuristics will even improve it further.

13.3. Continuous planning (windowed planning)

Continuous planning is the technique of planning one or more upcoming planning windows at the same time and repeating that process monthly, weekly, daily or hourly. Because time is infinite, there are infinite future windows, so planning all future windows is impossible. Instead, plan only a fixed number of upcoming planning windows.

Past planning windows are immutable. The first upcoming planning window is considered stable (unlikely to change), while later upcoming planning windows are considered draft (likely to change during the next planning effort). Distant future planning windows are not planned at all.

Past planning windows have only *immovable* planning entities: the planning entities can no longer be changed (they are unable to move), but some of them are still needed in the score calculation, as they might affect some of the score constraints that apply on the upcoming planning entities. For example: when an employee should not work more than 5 days in a row, he shouldn't work today and tomorrow if he worked the past 4 days already.

Sometimes some planning entities are semi-immovable: they can be changed, but occur a certain score penalty if they differ from their original place. For example: avoid rescheduling hospital beds less than 2 days before the patient arrives (unless it's really worth it), avoid changing the airplane gate during the 2 hours before boarding (unless there is no alternative), ...

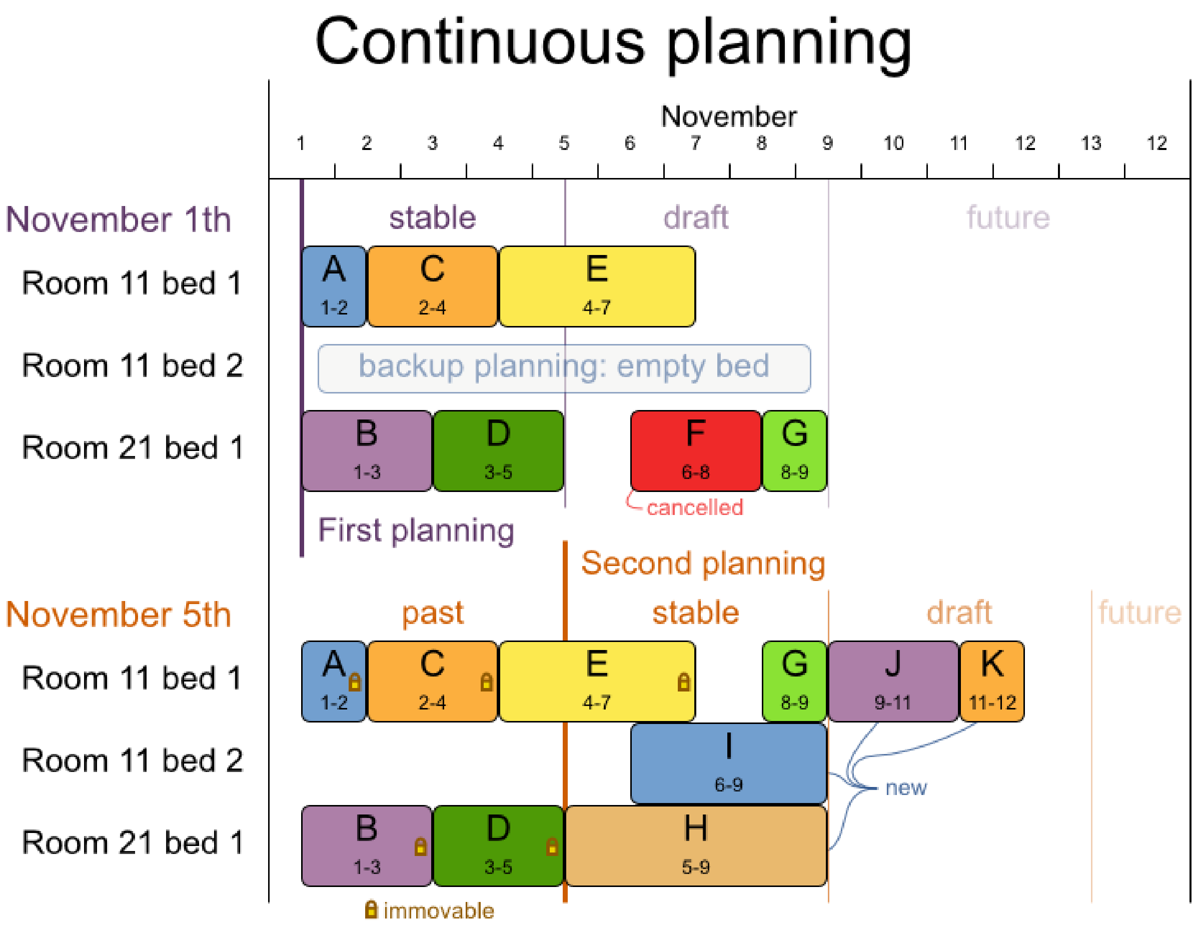


Figure 13.1. Continuous planning diagram

Notice the difference between the original planning of November 1th and the new planning of November 5th: some planning facts (F, H, I, J, K) changed, which results in unrelated planning entities (G) changing too.

13.3.1. Immovable planning entities

To make some planning entities immovable, simply add an entity `SelectionFilter` that returns `true` if an entity is movable and `false` if it is immovable.

```
public class MovableShiftAssignmentSelectionFilter implements SelectionFilter<ShiftAssignment>

    public boolean accept(ScoreDirector scoreDirector, ShiftAssignment shiftAssignment) {
        ShiftDate shiftDate = shiftAssignment.getShift().getShiftDate();
        NurseRoster nurseRoster = (NurseRoster) scoreDirector.getWorkingSolution();
        return nurseRoster.getNurseRosterInfo().isInPlanningWindow(shiftDate);
    }

}
```

And configure it like this:

```
@PlanningEntity(movableEntitySelectionFilter = MovableShiftAssignmentSelectionFilter.class)
public class ShiftAssignment {
    ...
}
```

Warning

Custom `MoveListFactory` and `MoveIteratorFactory` implementations must make sure that they don't move immovable entities.

13.4. Real-time planning (event based planning)

To do real-time planning, first combine backup planning and continuous planning with short planning windows to lower the burden of real-time planning.

While the `Solver` is solving, an outside event might want to change one of the problem facts, for example an airplane is delayed and needs the runway at a later time. Do not change the problem fact instances used by the `Solver` while it is solving, as that will corrupt it. Instead, add a `ProblemFactChange` to the `Solver` which it will execute in the solver thread as soon as possible.

```
public interface Solver {

    ...

    boolean addProblemFactChange(ProblemFactChange problemFactChange);
    boolean isEveryProblemFactChangeProcessed();

    ...

}
```

```
public interface ProblemFactChange {

    void doChange(ScoreDirector scoreDirector);

}
```

Here's an example:

```
    public void deleteComputer(final CloudComputer computer) {
        solver.addProblemFactChange(new ProblemFactChange() {
            public void doChange(ScoreDirector scoreDirector) {
                CloudBalance cloudBalance = (CloudBalance) scoreDirector.getWorkingSolution();
                  // First remove the planning fact from all planning entities
 that use it
                for (CloudProcess process : cloudBalance.getProcessList()) {
                    if (ObjectUtils.equals(process.getComputer(), computer)) {
                      scoreDirector.beforeVariableChanged(process, "computer");
                        process.setComputer(null);
                       scoreDirector.afterVariableChanged(process, "computer");
                    }
                }
                // Next remove it the planning fact itself
                for (Iterator<CloudComputer> it = cloudBalance.getComputerList().iterator(); it
                    CloudComputer workingComputer = it.next();
                    if (ObjectUtils.equals(workingComputer, computer)) {
                       scoreDirector.beforeProblemFactRemoved(workingComputer);
                        it.remove(); // remove from list
                       scoreDirector.beforeProblemFactRemoved(workingComputer);
                        break;
                    }
                }
            }
        });
    }
```

Warning

Any change on the problem facts or planning entities in a `ProblemFactChange` must be done on the instances of the `Solution` of `scoreDirector.getWorkingSolution()`. Note that these are not the same entity instances as in the bestSolution (or therefore your user interface): they are clones.

Warning

Any change on the problem facts or planning entities in a `ProblemFactChange` must be told to the `ScoreDirector`.

Note

Many types of changes can leave a planning entity uninitialized, resulting in a partially initialized solution. That's fine, as long as the first solver phase can handle it. All construction heuristics solver phases can handle that, so it's recommended to configure such a `SolverPhase` as the first phase.

In essence, the `Solver` will stop, run the `ProblemFactChange` and restart. Each `SolverPhase` will run again. Each configured `Termination` (except `terminateEarly`) will reset. This means the construciton heuristic will run again, but because little or no planning variables will be uninitialized (unless you have a *nullable planning variable*), this won't take long.

Normally, you won't configure any `Termination`, just call `Solver.terminateEarly()` when the results are needed. Alternatively, you can subscribe to the `BestSolutionChangedEvent`. A `BestSolutionChangedEvent` doesn't guarantee that every `ProblemFactChange` has been processed already, so check `Solver.isEveryProblemFactChangeProcessed()` and ignore any `BestSolutionChangedEvent` fired while that method returns `false`.