

deductive db & logic programming

#Datalog #DeductiveDatabases #LogicProgramming #Java #Servlet #Maven #Python #JupyterNotebooks #Combinatorics #PrescriptiveAnalytics

The case

Knowledge - We want to build an assistant for solving the popular Mastermind game [\[1\]](#) implemented as an ["expert system"](#) [☑](#) in which we won't have a cryptic algorithm but we will just lay down a set of simple and easy-to-read rules of the game. These will be the knowledge base that an inference engine will use to guess the secret.

Usability - we want to have a sleek user interface that we will be using for instructing the engine with the rules of the game; talking with the engine (ie, receive guesses and submit feedbacks); calibrating the model, its performance and its strategy; debugging and testing.

Jupyter Notebook seems to be an obvious choice. Unfortunately, we could not find a reliable python implementation that lets us write such engine.

Interoperability - we take an open source logic programming engine in Java, we embed it inside a servlet so as to be talking with as a web application, and we develop a python REST client, obtaining a system that is interactive, technologically heterogeneous and based on deductive rules.

Strategy - once we have the game solver, we design a prescriptive analytics process in which we evaluate the performance of a few different game approaches and we identify the strategy that, on average, cracks the secret faster.

We present the project in accordance with the CRISP-DM framework.

The 'business' issue

background

We want a digital assistant that help us solve the Mastermind board game. On the board, once the 'codemaker' sets a secret combination of colored pegs, we, the 'codebreakers', start an iteration of guesses by proposing our combination of pegs and receiving a feedback that confirms, with respect to the secret combination, how many pegs are in the right position and how many are there but in the wrong position. We make new new, more informed guesses by considering the knowledge we acquire on the go. That is what the digital assistant will do for us.

objectives and success criteria

We want to build a model that follows a strategy that minimize the number of guesses needed to crack the secret.

data mining goals

from a technical standpoint, we want to have measurable evidence that the strategy we eventually choose is statistically better than other strategies.

project plan

We will have to setup a user-friendly environment to develop, test, tune and use the model.

We will use Jupyter Notebook to build, test and use with python.

We will choose an engine that will either be a python library or an easy-to-use RESTful API.

The chosen technology

- The solution of many [combinatorial games](#) ^[1] are often implemented through a recursion algorithm in a program that follows the imperative paradigm (Java, Python).
- recursions might sometimes have high memory requirements and are not trivial to code, to read and to maintain. Moreover, in this case, we should be coding *two nested recursions* ^[2]
- The declarative paradigm of logic programming offers the opportunity, *only for a limited types of problems*, to completely specify the behaviour of a problem solver through the definition of a few, clear rules. The actual steps, triggered by a simple query, are executed by the logic Engine behind the scenes.



A notable advantage of the logic programming paradigm is that it is *explainable* / *white-box*, thus falling into the 'XAI' domain. ^[3]

- The two most popular languages and engines seem to be Prolog and Datalog.
- We wanted to test an implementation in Datalog, a pure declarative paradigm. ^[4]
- After searching for a python implementation of [Datalog](#) ^[5], we found [pyDatalog](#) ^[6] which unfortunately does not seem to support, at the time of evaluation, writing rules in pure Datalog language.
- We then opted for a java, robust, pure Datalog implementation: the HarvardPL AbcDatalog.
- Given that we want to stick to a Jupyter Notebook user interface, we will create a stack with:
 - the original datalog implementation
 - a small ad hoc wrapper that implement a stateful Datalog-as-a-service engine with an http REST interface.
 - a python notebook user interface.

The data


The size of the combination and the number of available colors are both fixed upfront. In our case, we go for games with four pegs that may assume six colors.

The secret and the guesses must both have all four pegs with any of the six available colors.

The data in this project is generated and not acquired, so there is no data preparation phase.

We will base our tests on a couple of secrets that will verify that the game feedbacks are properly taken into account while formulating the next guesses.

Modeling

This is a combinatorial optimization problem and we are going to use the [Branch-and-Bound](#)  method.

The application of a fixed set of **logic** rules to the guess-and-feedback history will rule out more and more combinations. After that, we will pick one of the survived combinations. We want to better understand if there is a good way and a bad way to choose a survived combination for our next guess.

The implementation of the business rules in Datalog

The code below covers the key facts and rules of the business logic.

The full set is available at <https://github.com/a-moscatelli/home/tree/main/am-wiki-assets/logicprogramming/datalog-kb> 

glossary:

- ho = 4 holes: h0 to h3
- co = 6 guess colors: c0 to c5
- black, white, not-given: original feedback set, non-positional.

In our implementation, changing the number of colors will require the change of one line of code.

The number of holes is structural and hard-coded. Changing that requires a more extensive adaptation of the code.

```

1 | % mmind-datalog---entities.ps BEGIN
2 |
3 | %holes:
4 | isa(h0,ho). isa(h1,ho). isa(h2,ho). isa(h3,ho).
5 | %peg colors:
6 | isa(c0,co). isa(c1,co). isa(c2,co). isa(c3,co). isa(c4,co). isa(c5,co).
7 | %feedback peg colors:
8 | isa(b,fb). isa(w,fb). isa(o,fb).
9 |
10 | % sequencing
11 | follows(h1,h0,ho). follows(h2,h1,ho). follows(h3,h2,ho).
12 |
13 | % mmind-datalog---entities.ps END
```

Above,

- h1 follows h1 in the sequence of holes, etc.
- c0 is a color, h1 is a hole, etc.

a data model based on facts like `isa(c0,co)` rather than facts defined as `isacolor(c0)`, provides the opportunity to implement universal definition of `permutation()`, `product()`, `combination()` and `follows()` rules that can be applied to any class.

```

1  % mmind-datalog---itertools.ps BEGIN
2
3  % OC = class
4
5  itertools_product4(X0,X1,X2,X3,OC) :- isa(X0,OC), isa(X1,OC), isa(X2,OC), isa(X3,OC).    % sz = 1296 = NOC**NOH
6
7  % the rules based on follows are only valid when at least one follows() is defined ie when at least two items exist.
8  isNotTheOnly(X1,OC) :- isa(X1,OC), isa(X2,OC), X1 != X2.
9  isTheOnly(X0,OC) :- not isNotTheOnly(X0,OC), isa(X0,OC).
10 isNotTheFirst(X2,OC) :- follows(X2,X1,OC).
11 isNotTheLast(X1,OC) :- follows(X2,X1,OC).
12 isTheFirst(X1,OC) :- follows(X2,X1,OC), not isNotTheFirst(X1,OC).
13 isTheFirst(X1,OC) :- isTheOnly(X1,OC).
14 isTheLast(X2,OC) :- follows(X2,X1,OC), not isNotTheLast(X2,OC).
15 isTheLast(X1,OC) :- isTheOnly(X1,OC).
16
17 % mmind-datalog---itertools.ps END

```

The above are general Combinatorics rules. The rules to generate Combinations are given as flat definitions based on ordered items, hence the dependency on the follows() rule, while the Permutations are defined through a tree-like divide-and-conquer rule-set.

```

1  % mmind-datalog---bizlogic.ps BEGIN
2
3  itertools_permutations_fb(GID, H0P,H0, H1P,H1, H2P,H2, H3P,H3) :-
4      isa_validfb2vert(GID, H0P,H0),
5      isa_validfb2vert(GID, H1P,H1),
6      isa_validfb2vert(GID, H2P,H2),
7      isa_validfb2vert(GID, H3P,H3),
8      H0P != H1P, H0P != H2P, H0P != H3P,
9      H1P != H2P, H1P != H3P,
10     H2P != H3P.
11
12 % projection
13 isa_feedbackpermut(GID,H0,H1,H2,H3) :- itertools_permutations_fb(GID, H0P,H0, H1P,H1, H2P,H2, H3P,H3).
14
15 % head(3):
16 % isa_feedbackpermut(g0, p3, x, p1, w, p0, b, p2, w)
17 % isa_feedbackpermut(g0, p1, w, p3, x, p2, w, p0, b)
18 % isa_feedbackpermut(g0, p3, x, p0, b, p1, w, p2, w)
19
20 isa_solution_exante(CH0,CH1,CH2,CH3) :- itertools_product4(CH0,CH1,CH2,CH3,co).
21

```

```

22 isa_validguess_evenafter_gid(GID,CH0,CH1,CH2,CH3) :-
23     isa_validatedGuess(GID,GC0,GC1,GC2,GC3),
24     isa_feedbackpermut(GID, H0, H1, H2, H3),
25     isa_solution_exante(CH0,CH1,CH2,CH3),
26     isa_121match(GC0,H0,CH0),
27     isa_121match(GC1,H1,CH1),
28     isa_121match(GC2,H2,CH2),
29     isa_121match(GC3,H3,CH3),
30     isa_12anymatch(GC0,H0,CH0,CH1,CH2,CH3),
31     isa_12anymatch(GC1,H1,CH0,CH1,CH2,CH3),
32     isa_12anymatch(GC2,H2,CH0,CH1,CH2,CH3),
33     isa_12anymatch(GC3,H3,CH0,CH1,CH2,CH3).
34
35 isa_121match(GCX,HX,CHX) :- isa(GCX,co), isa(HX,fb), isa(CHX,co), GCX = CHX, HX=b.
36 % ... etc
37
38 isa_12anymatch(GCX,HX,CH0,CH1,CH2,CH3) :- HX=w, GCX = CH0, isa_solution_exante(CH0,CH1,CH2,CH3), isa(GCX,co).
39 % ... etc
40 isa_12anymatch(GCX,HX,CH0,CH1,CH2,CH3) :- HX=b, isa_solution_exante(CH0,CH1,CH2,CH3), isa(GCX,co).
41 isa_12anymatch(GCX,HX,CH0,CH1,CH2,CH3) :- HX=o, isa_solution_exante(CH0,CH1,CH2,CH3), isa(GCX,co).
42
43 isa(GG,CL) :- isa_validatedGuess(GG,_,_,_,_), CL=gg.
44 % when a user submits : api_isa_guess(g0,c0,c0,c0,c1). then you must accept that g0 is a gg.
45
46
47 % gid = guess label (example: g3)
48
49 % recursive:
50 isa_validguess_evenafter_gg_upto_gid(GID,CH0,CH1,CH2,CH3) :- isa_validguess_evenafter_gid(GID,CH0,CH1,CH2,CH3), isa_validatedGuessWithFback(GID), isTheFirst(G
51 isa_validguess_evenafter_gg_upto_gid(GID,CH0,CH1,CH2,CH3) :- isa_validguess_evenafter_gid(GID,CH0,CH1,CH2,CH3),
52     follows(GID,LOWERGID,gg),
53     isa_validguess_evenafter_gg_upto_gid(LOWERGID,CH0,CH1,CH2,CH3).
54
55
56 % mmind-datalog---bizlogic.ps END

1 % mmind-datalog---queries.ps BEGIN
2
3 % reading API:
4
5 api_isa_validguess_evenafter_all_gg(CH0,CH1,CH2,CH3) :-
6     isa_validguess_evenafter_gg_upto_gid(GID,CH0,CH1,CH2,CH3),
7     isa_validatedGuessWithFback(GID),
8     isTheLast(GID,gg).

```

```

9 |
10 | % mmind-datalog---queries.ps END

```

The user "that seeks assistance" is expected to submit this query:

```

1 | api_isa_validguess_evenafter_all_gg(CH0,CH1,CH2,CH3)?

```

The user, after each attempt, will add further information to the KB in this format (below is an example of guess and feedback #g2):

```

1 | % guess #1 with id = g0:
2 | api_isa_guess(g0,c0,c0,c0,c1).
3 | isa_fback(g0,b,w,o,o).
4 |
5 | % guess #2 with id = g1:
6 | api_isa_guess(g1,c0,c5,c5,c5).
7 | isa_fback(g1,b,w,w,o).
8 | follows(g1,g0,gg).

```

the datalog rules above may be merged with this script:

```

1 | set TARGET=mm-dtlg.ps
2 | copy /Y /B mm-dtlg---*.ps %TARGET%
3 | rem TARGET is the initial KB text that is submitted to the engine.

```

The datalog engine tolerates duplicated terms and duplicated rules and is not sensitive to their order.
Polymorphism applies to facts and rules.

The web service based on the HarvardPL AbcDatalog engine

The HarvardPL AbcDatalog is a standalone desktop application. We will wrap it in a servlet that we will deploy onto a servlet container to obtain a web application.

The RESTful API of the engine

```
curl -X POST -d '{"kb":"after(a,b). before(X,Y):-after(Y,X)."}' http://localhost:8080/AbcDatalogREST
```

to append facts and rules to the engine's KB, initially empty.

```
curl -X DELETE http://localhost:8080/AbcDatalogREST
```

to delete the engine's KB.

```
curl -X GET http://localhost:8080/AbcDatalogREST
```

to get info about the KB (size and timestamps)

```
curl -X GET http://localhost:8080/AbcDatalogREST?rule=before%28X%2CY%29
```

to submit a query "before(X,Y)?"

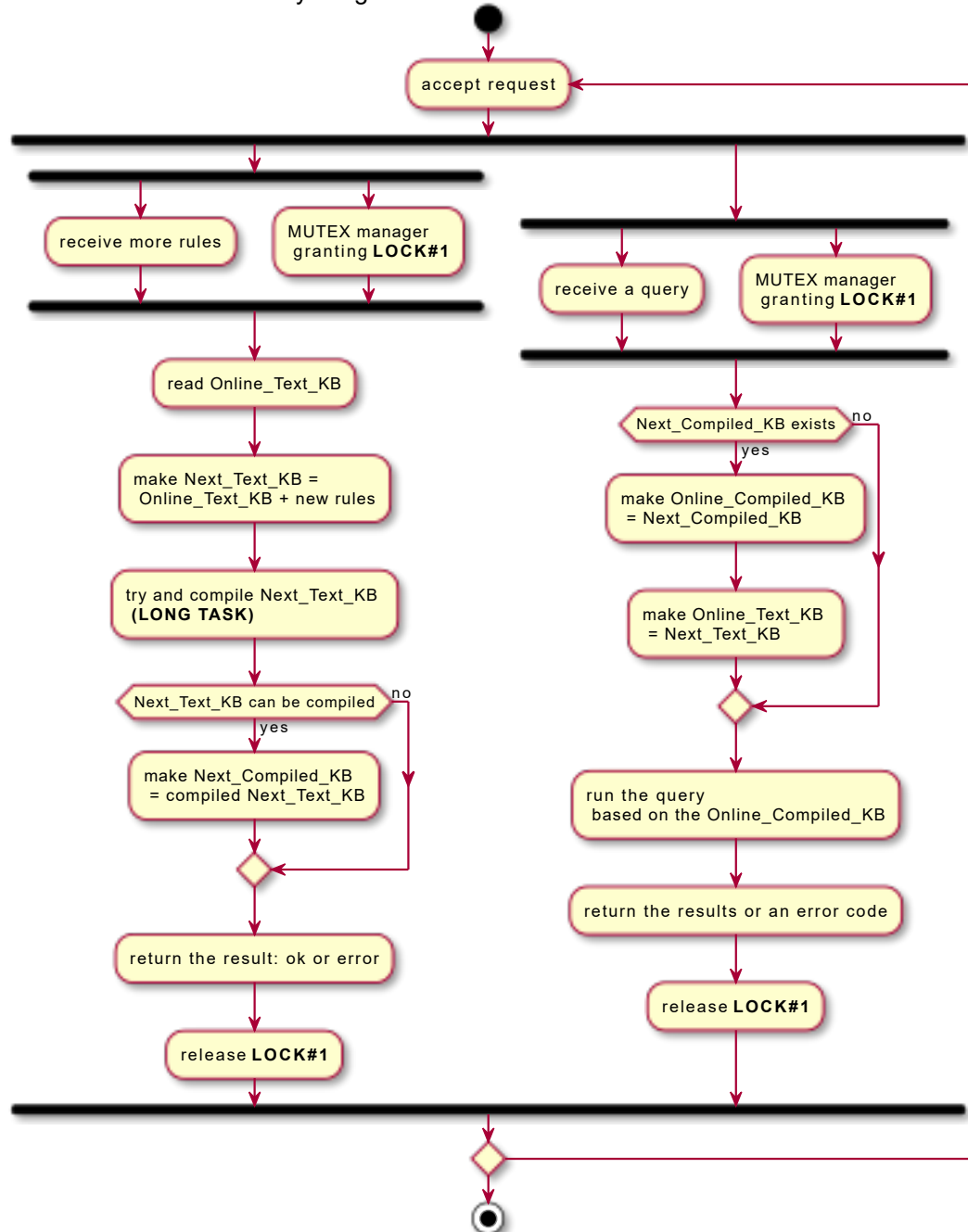
expected answer: "before(b,a)"



The concurrency management logic in our servlet

We want to prepare the service for a multi-user usage.

The update of the Knowledge Base and the queries are a shared memory area that must be protected from inconsistencies. Who submit queries should receive a result that is either coming from the old full Knowledge Base or the new full Knowledge Base and not from anything in between.

UML activity diagram of the REST API multi-user service



- the engine java desktop application was taken from
<https://github.com/HarvardPL/AbcDatalog> 
<https://harvardpl.github.io/AbcDatalog/> 
- the ad hoc engine servlet wrapper

<https://github.com/a-moscatelli/home/blob/main/am-wiki-assets/logicprogramming/datalog-as-a-service/webapp1/src/main/java/HelloWorld.java> 

the servlet wrapper mimics the AbcDatalog class:

<https://github.com/HarvardPL/AbcDatalog/blob/master/src/main/java/edu/harvard/seas/pl/abcdatalog/engine/EngineExample.java> 

- the maven project
<https://github.com/a-moscatelli/home/blob/main/am-wiki-assets/logicprogramming/datalog-as-a-service/webapp1/pom.xml> 

the container is deployed in jetty or in winstone (a compact servlet container shipped with Jenkins):

```

1  rem Windows batch file
2  set APPDIR=webapp1
3  cd %APPDIR%
4  call mvn package
5  goto start_winstone
6  :start_winstone
7  java -jar .\ext-libs\winstone-0.9.10.jar --commonLibFolder=ext-libs --httpPort 8080 --warfile .\%APPDIR%\target\my-web-app-1.0.0.war
8  goto end
9  :start_jetty
10 java -jar .\ext-libs\jetty-runner-9.4.0.M1.jar --port 8080 .\%APPDIR%\target\my-web-app-1.0.0.war --jar .\ext-libs\AbcDatalog-0.6.0.jar
11 goto end
12 :end

```

The python user interface

The python notebooks import the definition of the RESTful servlet http client:

```

1  class ExpertSystem():
2      ...
3      def submitkb(self, datalog_text):
4          # POST
5          ...
6      def resetkb(self):
7          # DELETE
8          ...
9      def getkbstat(self):

```

```
10 | # GET /
11 | ...
12 | def submitquery(self, query):
13 | # GET /?rule=X
14 | ...
```

full code here:

https://github.com/a-moscatelli/home/blob/main/am-wiki-assets/logicprogramming/python_restful_client/mmind.py 

Evaluation

We have two layers.

In the **first layer**, we have an digital assistant that performs the branch-and-bound and, after each feedback, will propose a narrower *search space*. We, the assisted user, will pick **one** of the allowed solutions as a next guess to submit to the codemaker.

In the **second layer**, for each of the game strategies we were able to think of, we run a stochastic simulation in which the whole game is automated: the first guess is random (but conforms to the chosen strategy) and picking one of the subsequent guesses from the allowed solutions is also made by following the chosen strategy.

The prescriptive analytics model: simulate with different strategies

The goal of the game solver is to narrow down the acceptable options given the black/white feedbacks collected after each guess.

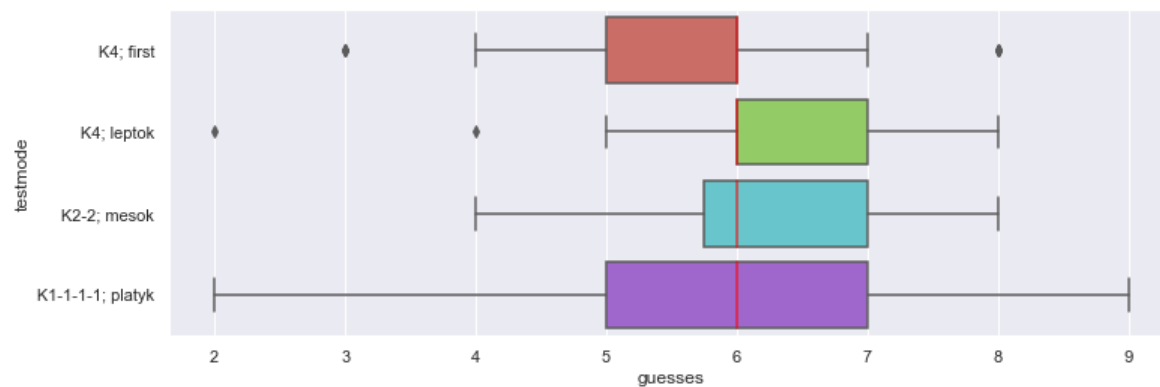
Every guess will be a pick from the acceptable options and will have a pattern that we call here platykurtic, mesokurtic and leptokurtic by taking the liberty of borrowing the names used to describe the tailedness of continuous distributions:

- ▶ we call a guess like red-red-red-red or red-red-red-blue **leptokurtic** - a combo with a very dominant mode: **monochromatic** or almost monochromatic
- ▶ we call a guess like red-blue-green-magenta **platykurtic** - no mode, highest variance: like a **rainbow**
- ▶ we call a guess like red-red-blue-blue **mesokurtic** - somewhere in between

Given that our KPI is "average number of guesses needed to solve a game" and our goal is to keep the KPI as low as possible,

we want to check if the solver performs better by choosing a leptokurtic, mesokurtic or platykurtic option at each round.

We also consider a 'just-pick-the-first-option' strategy for **benchmarking**. We may consider this strategy equivalent to a random picking.



the boxplots above are based on data available at this link:

https://github.com/a-moscatelli/home/blob/main/am-wiki-assets/logicprogramming/second-game-crackingloop/run2/mmind_games_log.tsv

The sample size is $1/18^{\text{th}}$ of the population size = 4^6 .

The logic rules implemented in our engine are pretty good but not the best possible rule set.

The **conclusion** we can draw from the statistics above, based on the implemented rules, are quite clear:



the PICK-THE-FIRST-OPTION strategy seems to be the best performing strategy.

This strategy is likely close to a PICK-AN-OPTION-AT-RANDOM.

The t-test

Given that we have observed a sample (1/18) of the population of all the games, we want to know if we can confidently proclaim a clear winner among the four strategies we have defined, so we t-test whether the means of two independent samples of number_of_guesses are significantly different:

normality-test

dataset	sample size	variance	shapiro test
first	72	1.56	~not gaussian (p-value=0.000)
mesok	72	0.92	~not gaussian (p-value=0.000)
platyk	72	2.21	~not gaussian (p-value=0.003)
leptok	72	1.02	~not gaussian (p-value=0.000)

t-test

ttest_ind	p-value	conclusion
mesok-platyk	0.6	~same
leptok-mesok	0.4	~same
leptok-platyk	0.24	~same
first-mesok	0.02	~different
first-platyk	0.17	~same
first-leptok	0.003	~different

(NB p-value is underestimated if variances are different)

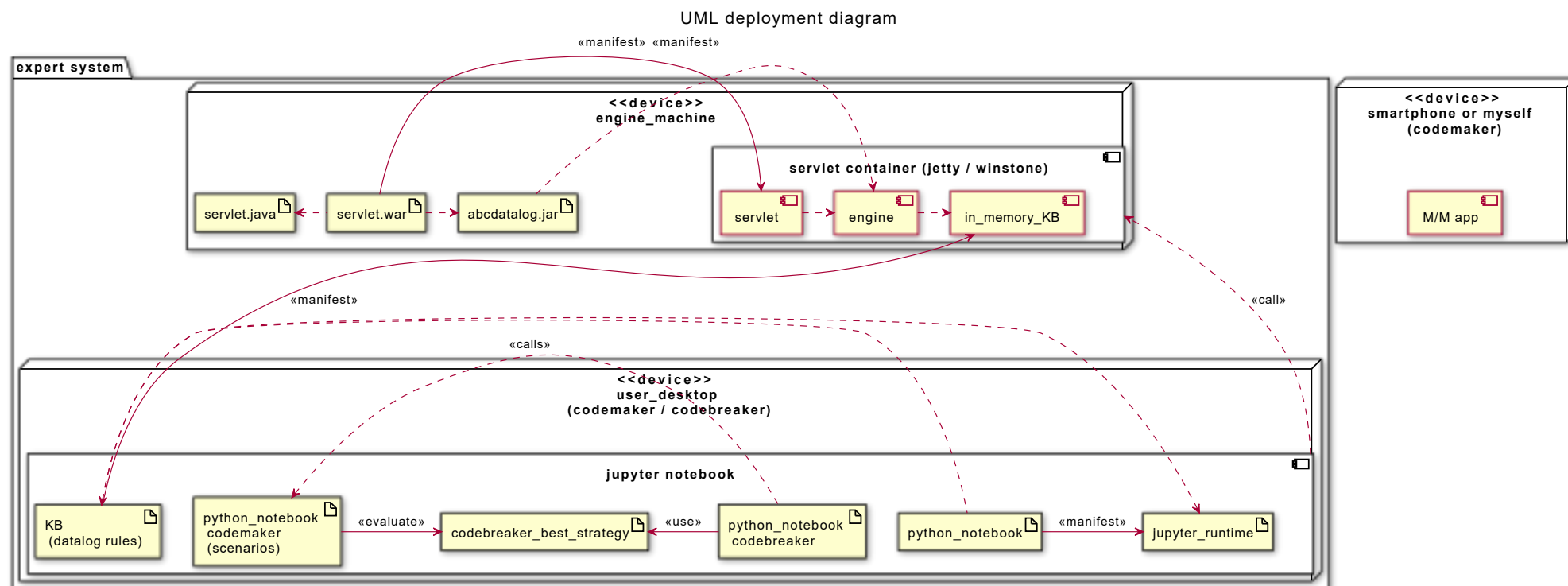
summary:

- first is significantly different from mesokurtic and leptokurtic.
- the other distributions are similar.

NB t-tests assumptions on same variance and gaussian distribution are not met for all samples

Deployment

In the final deployment, we, the 'codemakers', will open a Jupyter Notebook and we think of a secret, then we start the program that will propose a series of guesses to which we reply with our back-and-white feedbacks until the program manages to crack the secret.



The end-user process

The three actors are:

- the Expert system (Datalog Engine embedded inside a Java Web application + Python Client)
- the User
- a M/M game App (a codemaker)

use case 1: the user is an assisted codebreaker

1. A knowledge base KB with facts and rules is loaded into the engine and the user starts the M/M App game which creates a **secret** that will be found with the support of the digital assistant.
2. The user specifies, in a M/M App, an initial **guess** (a set of *ordered*, colored pegs).
3. The M/M App returns a **feedback** (a set of *unordered*, black, white and null pegs).
4. The user updates the KB of the Assistant with the last guess submitted to the App and the last feedback received from the App.
5. The Assistant suggests a new informed guess after considering the previous information added to the KB and by following the 'best strategy'.
6. The user specifies, in the App, the suggested guess.

7. Steps 3. to 6. are repeated until the App confirms that the last guess matches the secret in step 3.

use case 2: the user is a codemaker

1. A knowledge base KB with facts and rules is loaded into the engine
2. The user sets a **secret** that will be found by the digital assistant.
3. The digital assistant makes an initial **guess** (a set of *ordered*, colored pegs)
4. The user submits a **feedback** (a set of *unordered*, black, white and null pegs). That will update the KB of the assistant.
5. The digital assistant makes another **guess** after considering the previous information added to the KB and by following the 'best strategy'.
6. Steps 4. to 5. are repeated until the assistant returns the only combination left.

A demo run

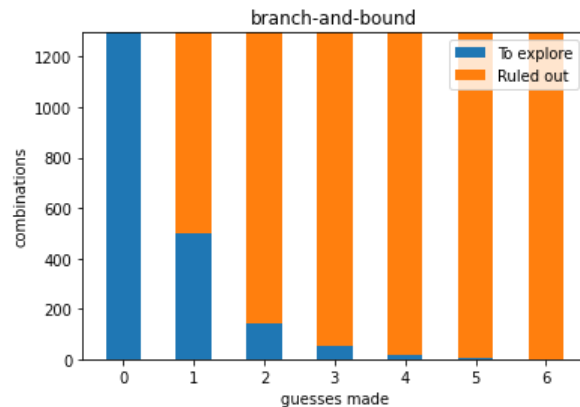
The python notebook with a complete game is here:

https://ampub.s3.eu-central-1.amazonaws.com/am-wiki-js/logicpro/using_my_rest_abcdatalog_as_an_assistant.html 

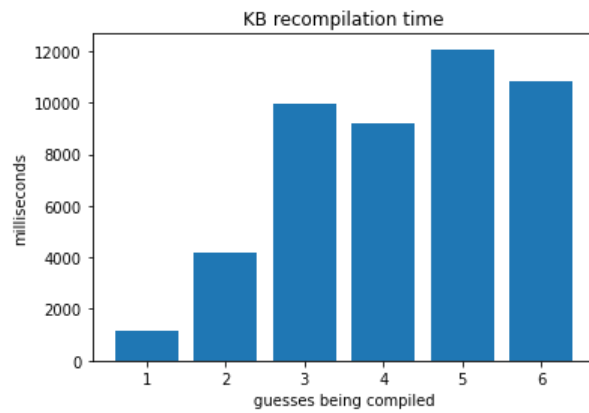


picture taken from the App used for the simulation - <https://www.microsoft.com/en-us/p/mastermind-classic/9wzdncrdpbbx> 

evolution of the *search space* of the possible options:








evolution of the recompilation time of the knowledge base:



NB - the **QUERY response** time of the engine is almost flat and less than 5 ms.

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[backlog](#) 

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1. [https://en.wikipedia.org/wiki/Mastermind_\(board_game\)](https://en.wikipedia.org/wiki/Mastermind_(board_game))  
 2. one level of recursion to make hypotheses on the holes the a-positional feedback colors refer to, and one level to make hypotheses on the holes the white pegs should have been instead 
 3. https://en.wikipedia.org/wiki/Backward_chaining  
 4. https://en.wikipedia.org/wiki/Explainable_artificial_intelligence 