# Training Logical Mouses

A logical approach to agent design

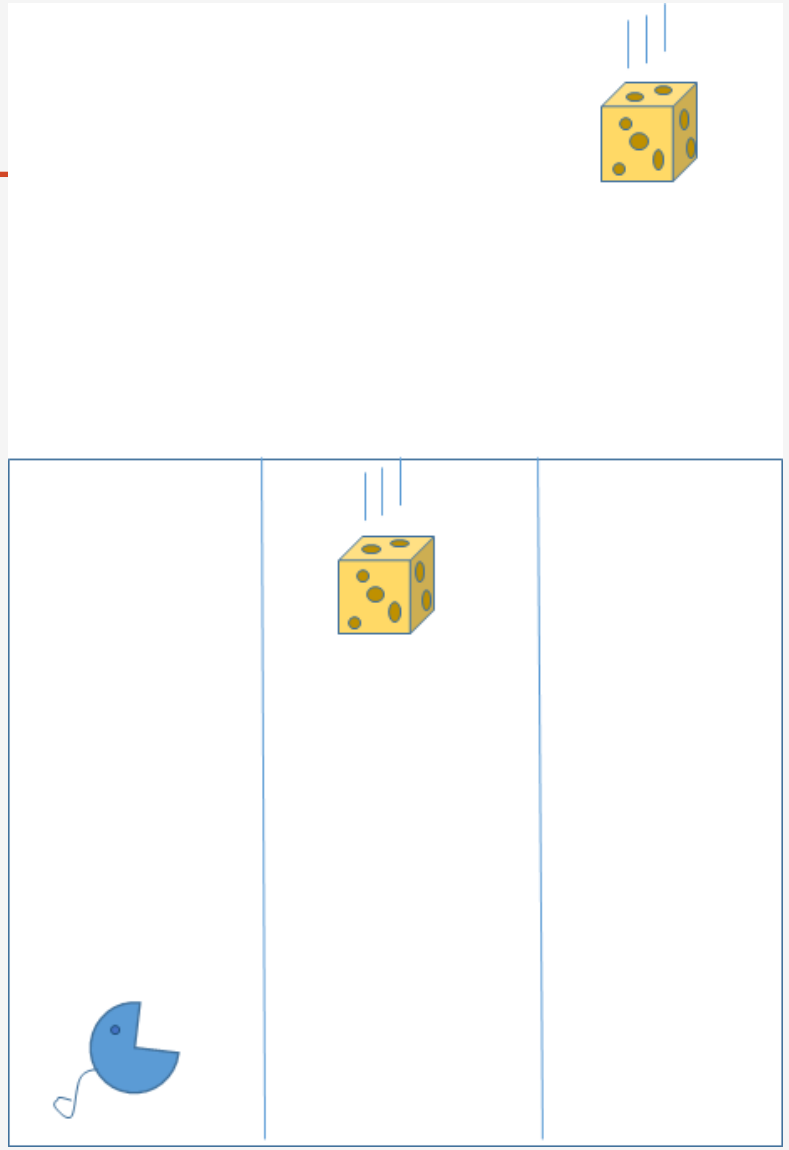
R. Basili (Univ. Roma, Tor Vergata), a.a. 2020-21

# Overview

- Progettiamo un agente logico in Prolog
- Progettiamo la sua base di conoscenza, con l'intento di ottimizzarne la capacità di raggiungere l'obbiettivo
- Osserviamo il comportamento autonomo dell'agente
- Ci porremo il problema: *può la conoscenza dell'agente essere appresa e non codificata manualmente*?
- Vedremo come collezionare esempi (positivi) del comportamento dell'agente (i.e. scelte della azione)
- Introdurremo un'ambiente per acquisire modelli di classificazione mediante Machine Learning: Weka
- Applicando Weka al caso del nostro agente, acquisiremo un modello decisionale (regole) attraverso l'apprendimento di una funzione di classificazione mediante Decision trees.
- Vedremo le analogie tra la base di conoscenza (Prolog) progettata top-down e il modello di azioni (albero delle decisioni) indotto dai dati dal DTL.

# Mouse And Cheese

Nel mondo proposto, è necessario animare un piccolo topolino a raccogliere i pezzi di formaggio in caduta dall'alto in un ambienet 3x3 (vedi figura a lato).



Si progetti in Prolog il mondo del topolino (ambiente, sensori e mondi possibili) in modo da poter programmare le azioni del topolino che massimizzano l'utilità del goal:

*mangiare il numero massimo di pezzetti di formaggio.*

Definire la strategia di scelta delle azioni separatamente dalla applicazione delle azioni, in modo da favorire lo sviluppo di stategie diverse.

Si usi il predicato random/1 per generare a caso le posiizoni del topolino e del formaggio di volta in volta.

# Describing the state

The world corresponds to a 3x3 Map, where coordinates X (row) and Y (column) define an individual position.

There are two main objects in a map:

**Cheese Position**: predicate *cheese(X,Y)*

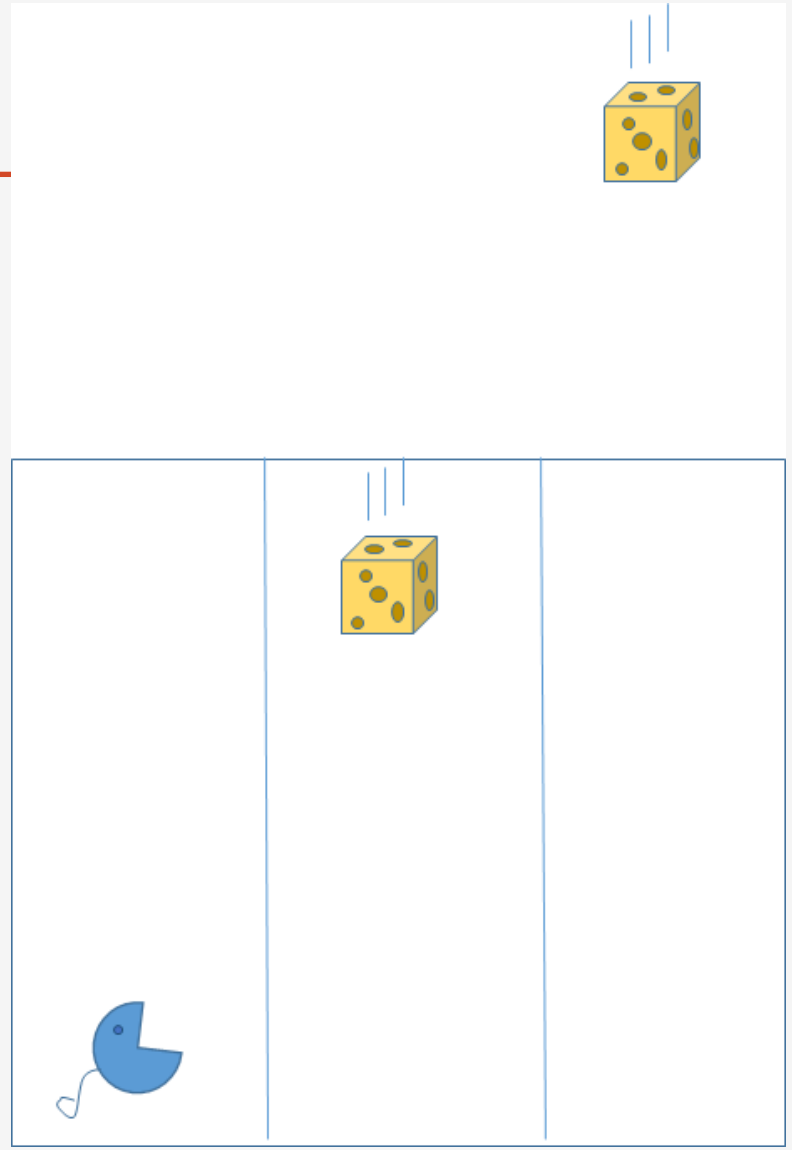
**Mouse Position**: predicate *mouse(X,Y)*

The State is thus defined as a pair (Prolog list)

*[cheese(XC,YC), mouse(XM, YM)]*

At every time stamp, the State list (i.e. the pair) represents the current state of the environment.

"*There is only one cheese at a time*" is implied by the fact that there is only ONE cheese(X,Y) predicate in the State declaration.



# Goal & Utility

**Goal**: The mouse stops when **there is no further cheese** that is falling down

As *[cheese(XC,YC), mouse(XM, YM)]*

describes the State of the World, any value YC outside the *[1,3]* range is a valid indicator of the fact that there is no bit of cheese falling.

Default: When *YC == 0*, assume the Goal has been satisfied and the mouse stop acting.

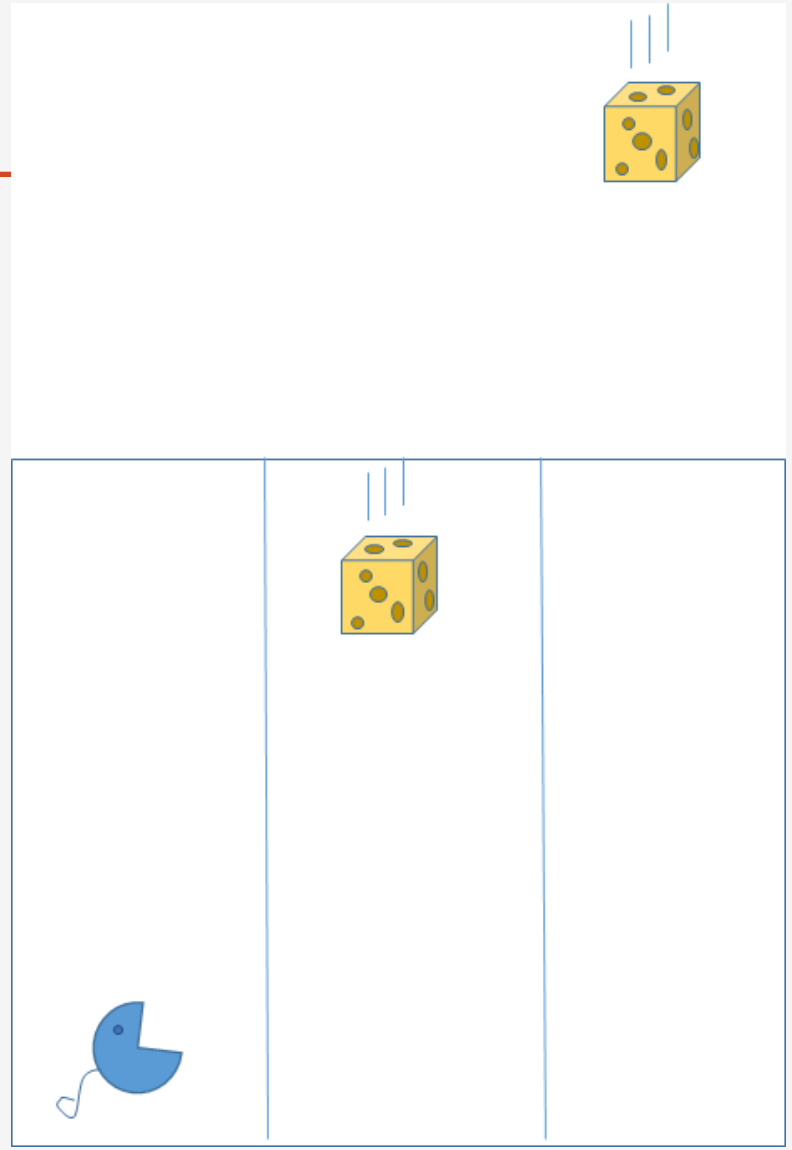
Moreover, as **the mouse does not jump**, at each time stamp ***XM == 1***.

Eating is possible when the mouse is under the falling column of the cheese, and at the time the cheese touches the ground he is able to reach the same cell.

The **EATing** action is possible thus ONLY WHEN for some *YC=YM<>0*,

***XC == XM == 1.***

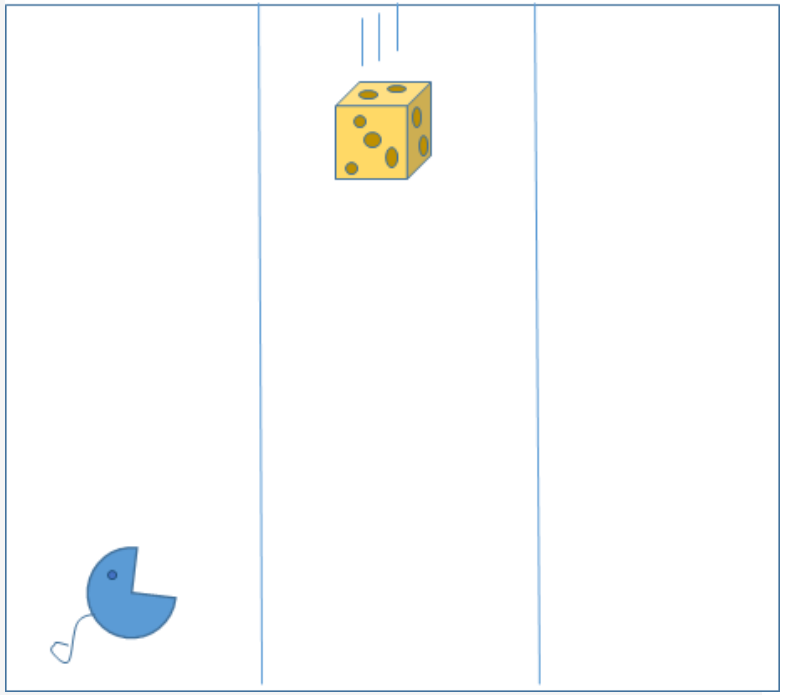
**Utility**: **The mouse has to maximize the bit of cheese he is able to eat when they are on the ground** (i.e. *XC=1*).



# The Mouse as an agent: requirements

**The following notions have to be specified**:

- **Initialization** of the world (Use random/1)
- Synchronization of the world changes (i.e. the stepwise falling process of the cheese) with the mouse observations and actions
- The actions is selected by the mouse at each step in the attempt to maximize the utility
- ***Goal-satisfaction check*** at each step

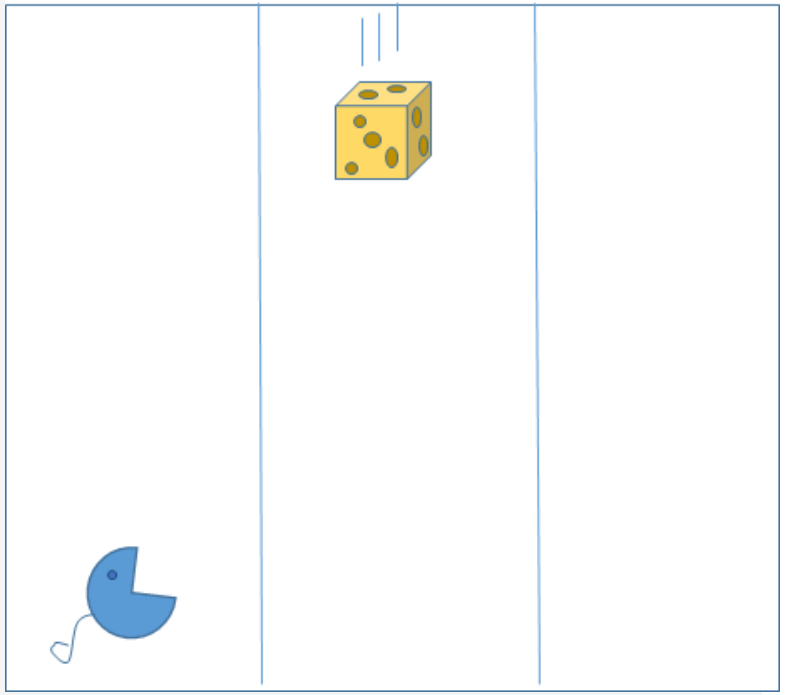


# The Mouse as an agent: requirements

**Main problem instance cycle**:

- Syncronize each requirements above in a step-by-step process. In Prolog:

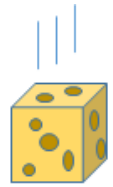
```
run_problem_instance :-
    init_the_world( YC, YM),
    solve([cheese(3,YC), mouse(1,YM)], 0, Feed),
    write("\n Task carried out: !!"),nl, write("The mouse has eaten "),
     write(Feed), write(" cheese bits!!\n"), nl.
```



where:

```
init_the_world(CheeseNextColumn, MouseNextColumn)  :-
    random_pos_the_cheese(CheeseNextColumn),
    random_pose_the_mouse(MouseNextColumn).
```

# Solving the task



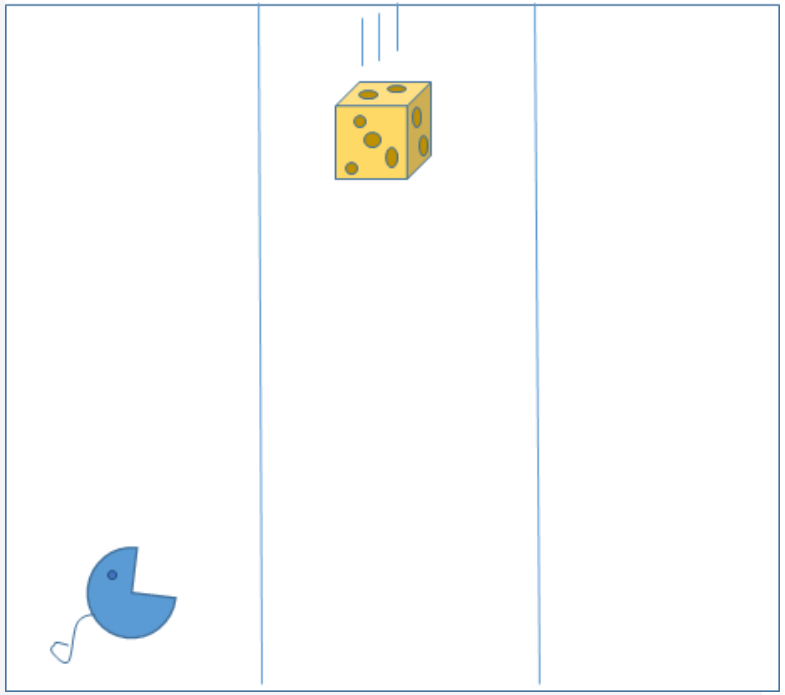
**Two major actions**:

- Check if the goal has been reached (no more cheese)
- OBSERVE/DECIDE/ACT cycle

**Main** solve **cycle**:

- In Prolog:

```
solve([cheese(XC,YC), mouse(_,_)], CurrFeed, CurrFeed) :-
        check_goal_satisfaction(cheese(XC,YC)),
        !.
solve([cheese(XC,YC), mouse(XM, YM)], CurrFeed, AllFeeds) :-
        decide_rule( [cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule),
        apply_action(Rule, [cheese(XC,YC), mouse(XM, YM)], CurrFeed, NewState, NewFeed),
        env_step(NewState, NextState),
        !,
        solve( NextState, NewFeed, AllFeeds).
```



where:

```
env_step([cheese(1, _), mouse(XM, YM)], [cheese(3, NewYC), mouse(XM, YM)]) :-
                                        /* generate a new starting position at column NewYC */
        random_pos_the_cheese(NewYC),
env_step([cheese(XC, YC), mouse(XM, YM)], [cheese(NewXC, YC), mouse(XM, YM)]) :- /* falling down ...*/
        XC > 1, NewXC is XC-1.
```

# Decision Rules for acting

```
decide_rule( [cheese(1, Y), mouse(1,Y)], _, eat) :-
        !.
decide_rule( [cheese(_anyXC, Y), mouse(_anyXM, Y)], _, stand) :-
        \+(_anyXC == _anyXM),
        !.
decide_rule( [cheese(_, NewYC), mouse(_, YM)], _, moveright) :-
        NewYC > YM,
        !.
decide_rule( [cheese(_, NewYC), mouse(_, YM)], _, moveleft) :-
        NewYC < YM,
        !.
decide_rule( _anyState, _anyFeed, _, stand).
```

# Run the program

The program is accessible in file: Mouse.pl

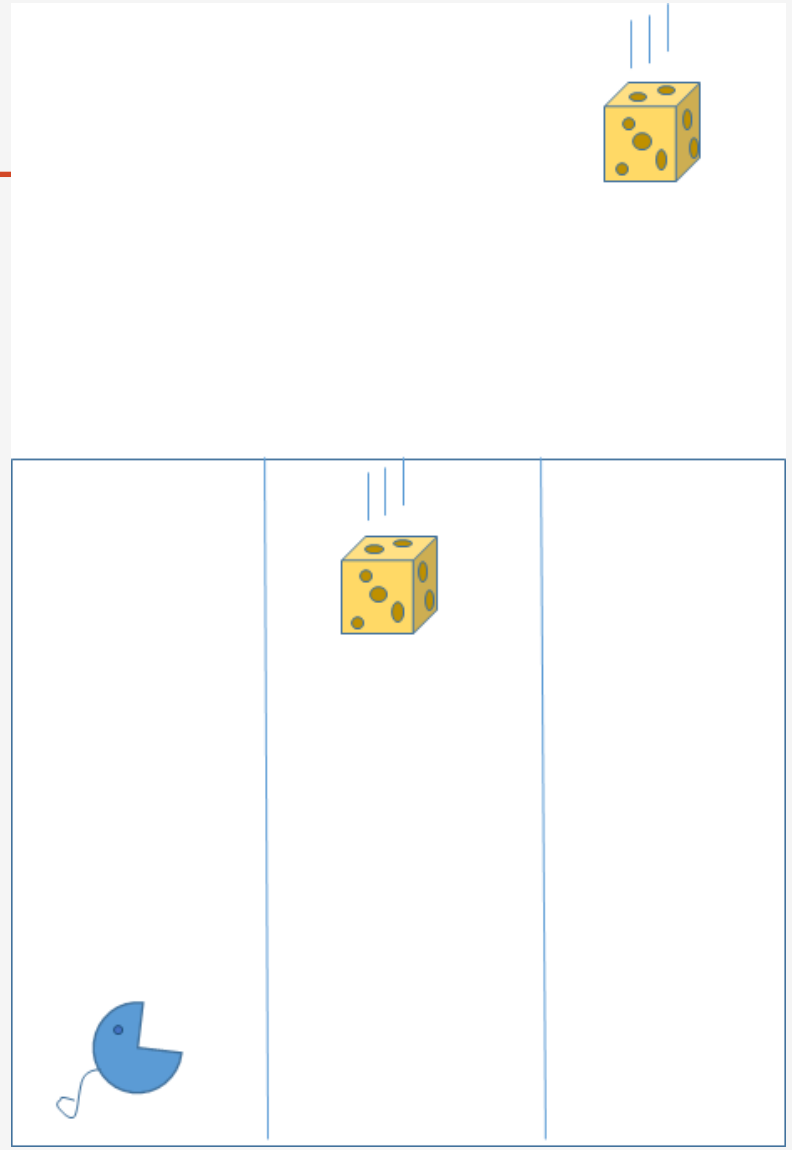
Use the predicate

*?- run_problem_instance.*

to run the agent.

The program includes:

- Messages to inspect the Mouse behaviour
- The (hand coded) decision rules that are optimal
- Logging of examples  (see Machine Learning approach next slides)



# Training (Logical) Mouses

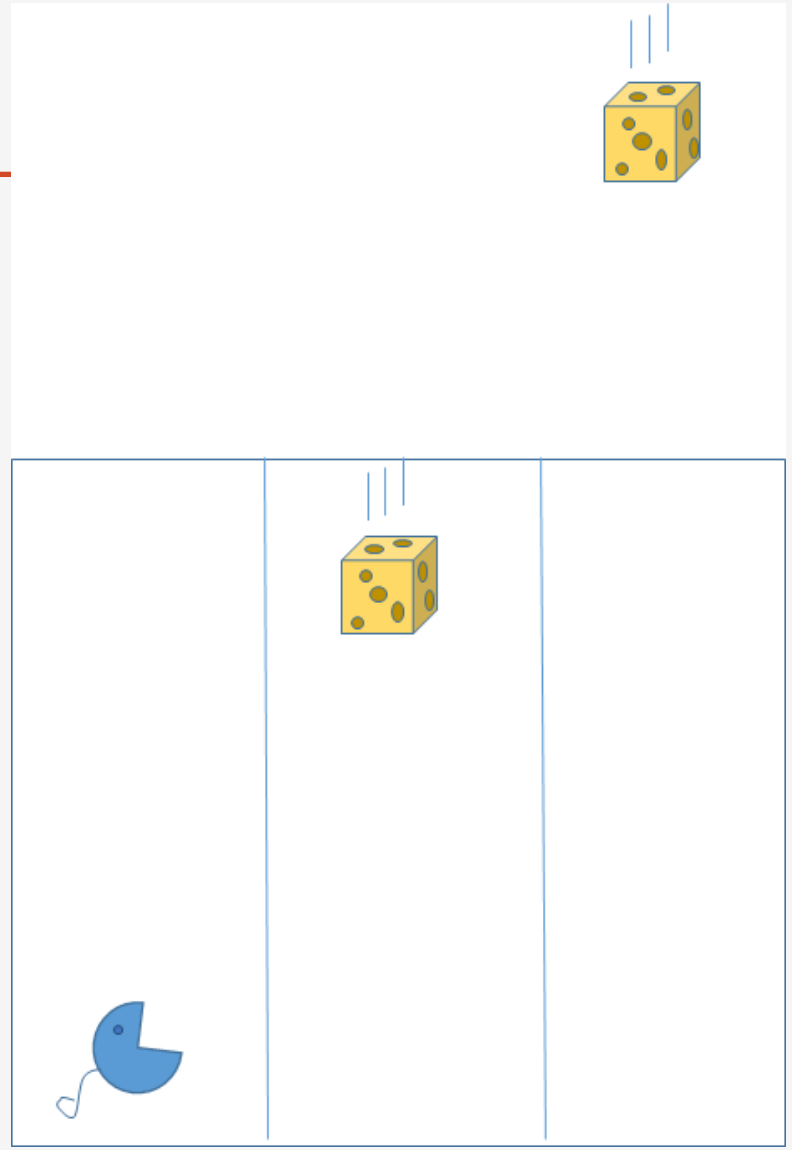
Adopting Machine Learning to design logical decisions

R. Basili (Univ. Roma Tor Vergata), a.a. 2019-20

# How can we train the Mouse to the proper decisions?

Let's for a while imagine that we got no decision rule, and that the system is blind, i.e. forced to decide randomly. e.g.

```
/* RANDOM, i.e. Non intelligent CHOICE */
decide_rule( _anyState, _AnyFeed, Action) :-
        N is random(4)+1,
        select_ith(N, [eat,left,moveleft,moveright], Action).
```



Can we do better by Machine Learning the rules?

Where to start?

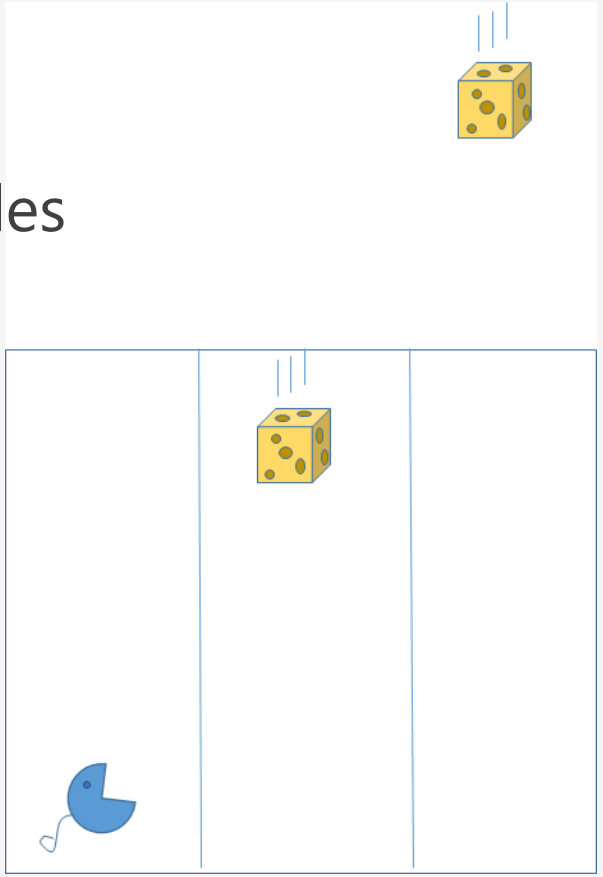
IDEA: Let's start running the *Mouse.pl* program and collect its behavior (i.e. actions taken when the mouse observe States) and try to learn the Prolog code for decision rules.

What we need: collecting examples and a learning algorithm

# Training the Mouse: collecting examples

Few lines of Prolog code (see file *Mouse_to_Learn.pl*) allow us to store the examples of State-Action choices.

After having decided to act the Prolog agent can store the choice (through dynamic predicates) by memorizing as examples every chosen State-Action pair.



```
storerules([cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule) :-
    example(N, _, _, _),  /* <== a dynamic predicate */
    NewN is N+1,
   asserta(example(NewN, [cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule)),
    !.
storerules([cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule) :-
    asserta(example(1, [cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule)),
    !.
```

# Training the Mouse: collecting examples

Can we make the *example/4* predicate facts available in a machine learning platform, such as Weka?

We need to store every example in terms of **features** (i.e. the observable properties of each recorded step) and associate to them **the chosen action** (as the target classification choice).

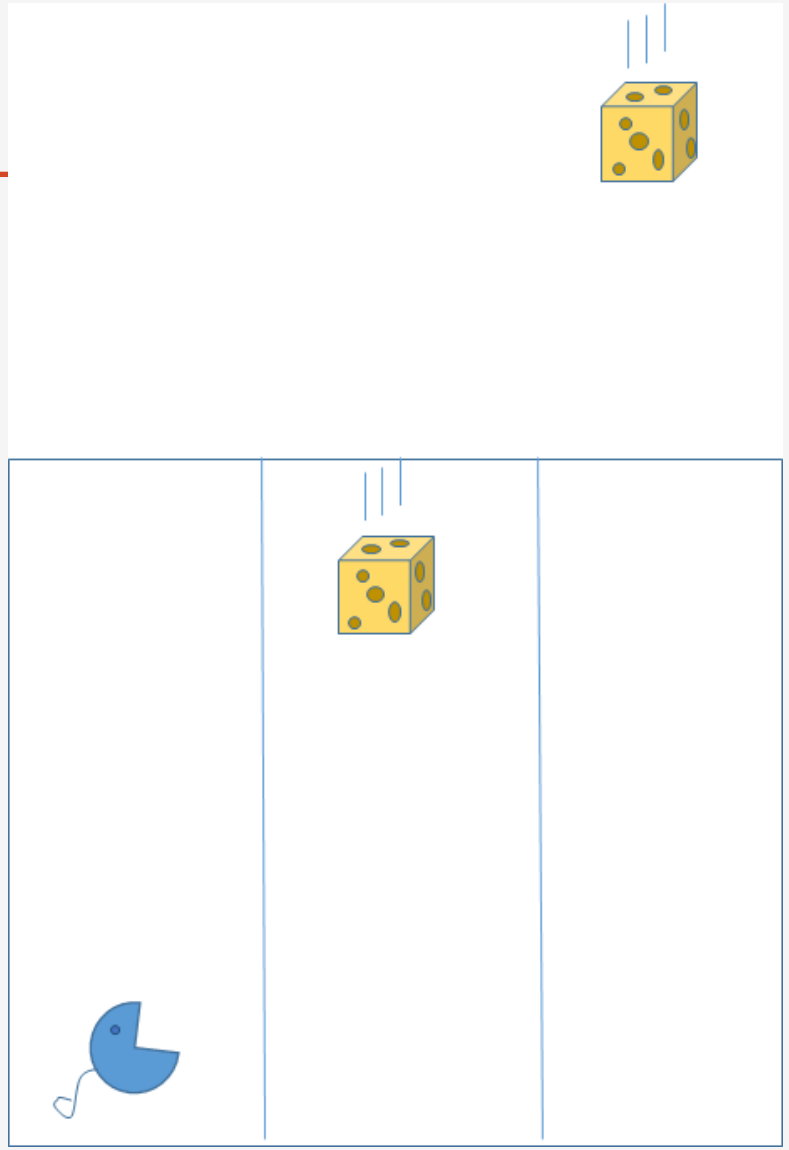
**Features** are states of the world, i.e. positions of cheese bits and mouses.

The **action** is the target decision

The learning is devoted to induce a classification function from states to actions.

In order to write on file all the meaningful attributes of the examples:

```
?- tell('Esempi2.data'),
   example(_, [cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule),
   write(XC),write(','),write(YC), write(','),write(XM),write(','),write(YM),write(','),
   write(CurrFeed), write(','),write(Rule),nl,
   fail.
?- told.
```



# Training the Mouse: collecting examples

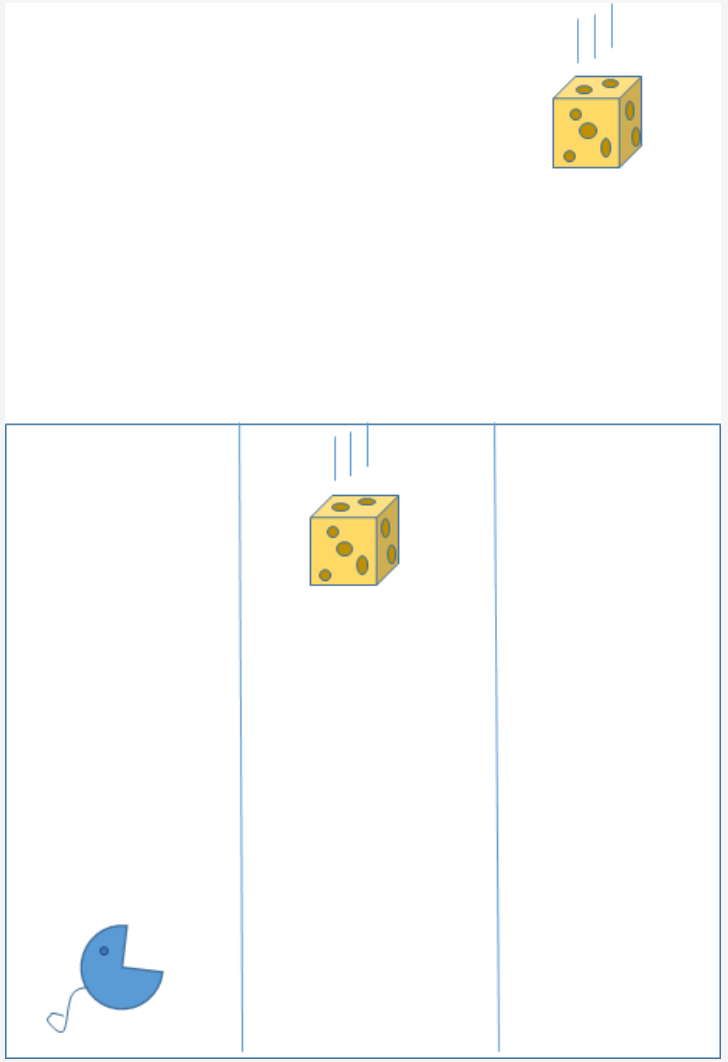
```
?- tell('Esempi2.data'),
   example(_, [cheese(XC,YC), mouse(XM, YM)], CurrFeed, Rule),
   write(XC),write(','),write(YC), write(','),write(XM),write(','),write(YM),write(','),
   write(CurrFeed), write(','),write(Rule),nl,
   fail.
?- told.
```

This is the outcome in an ARFF file (Mouse2.arff) … from the header:

```
@RELATION Mouse

@ATTRIBUTE cheesePosX           INTEGER
@ATTRIBUTE cheesePosY           INTEGER
@ATTRIBUTE mousePosX            INTEGER
@ATTRIBUTE mousePosY            INTEGER
@ATTRIBUTE eatenBits            INTEGER
@ATTRIBUTE class       {eat,moveleft,moveright,stand}

@DATA
1,2,1,2,13,eat
…
1,2,1,2,3,eat
2,2,1,2,3,stand
3,2,1,1,3,moveright
2,1,1,2,2,moveleft
…
```



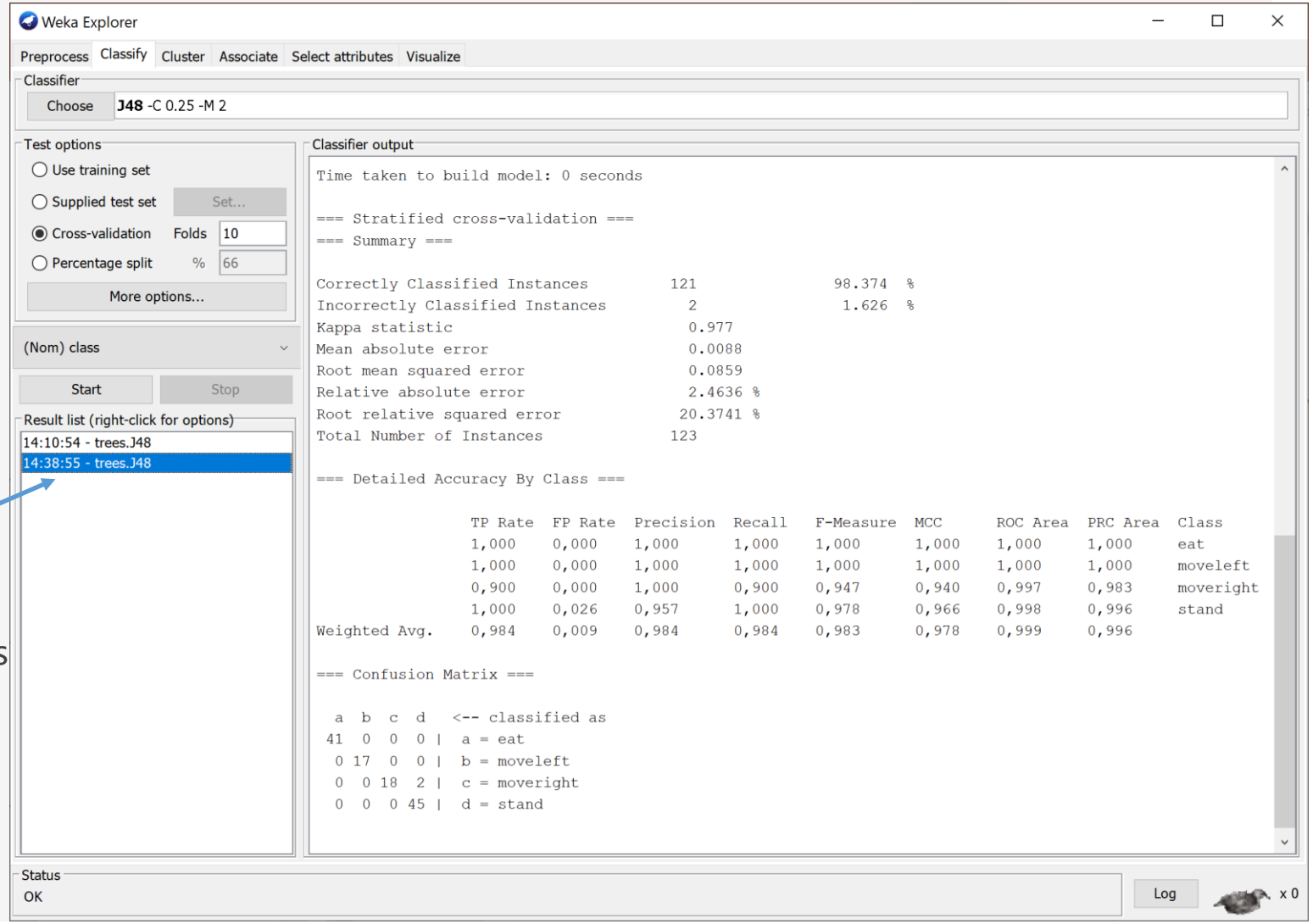
# Learning a decision tree

With Weka we can apply the J48 algorithm to induce the corresponding decision tree

The outcome is a model whose performance is 98.37% as shown on the left

In the 2 errors the system predicted action *stand* in the case it needed to *moveright* (i.e. a possibel error in the training data)

In Weka, the model, i.e. the decision tree in this case, can be inspected by clicking (with the right side) on the Result list elements



# The acquired decision tree

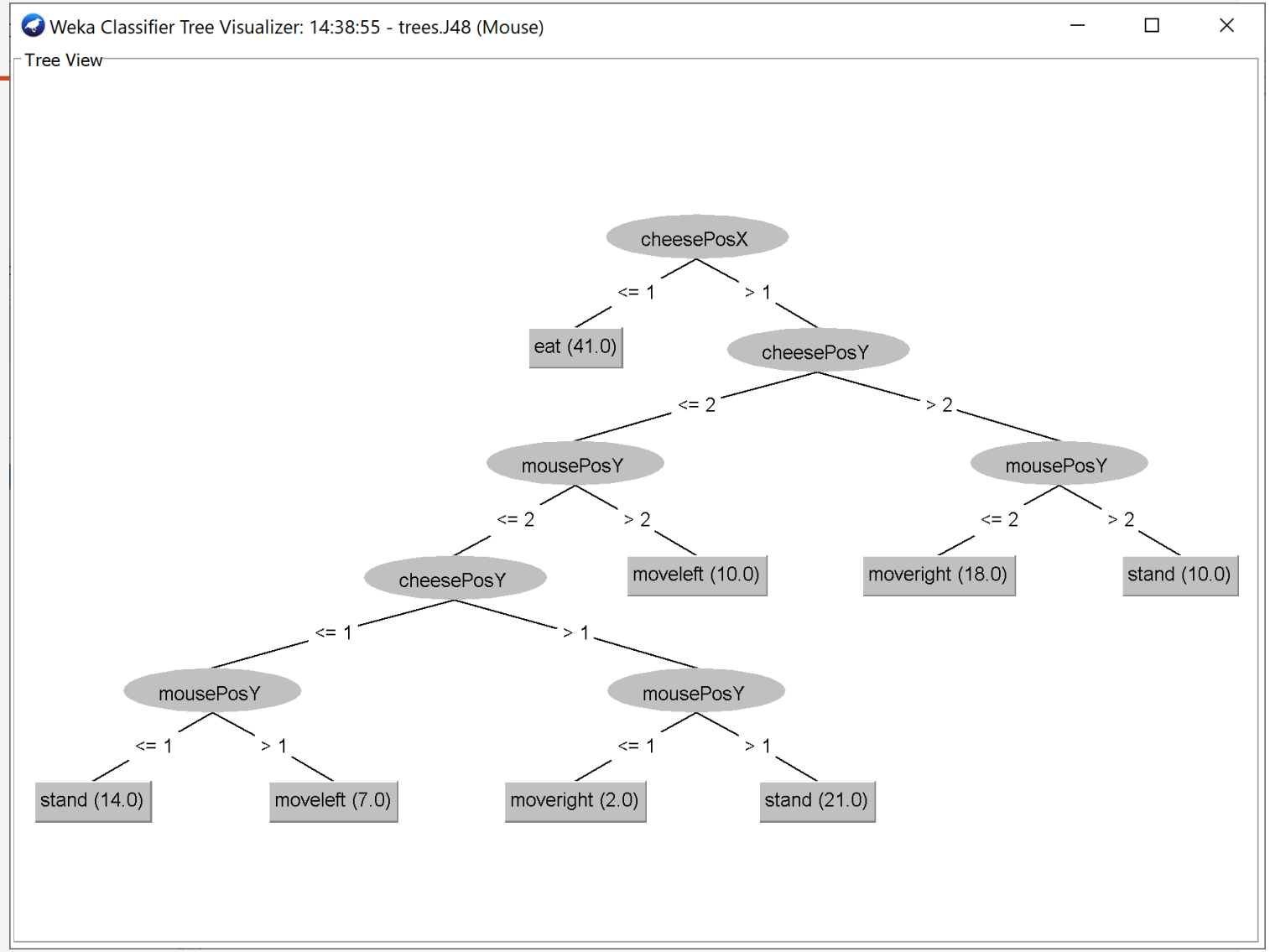
**The decision tree** acquired in the right hand side of the slide **is very close to the Prolog code for the *decide_rule/4* predicate**.
Surprised?

The variables used to decide the action class by the tree are:

| | |
|---|---|
| @ATTRIBUTE cheesePosX | INTEGER |
| @ATTRIBUTE cheesePosY | INTEGER |
| @ATTRIBUTE mousePosX | INTEGER |
| @ATTRIBUTE mousePosY | INTEGER |

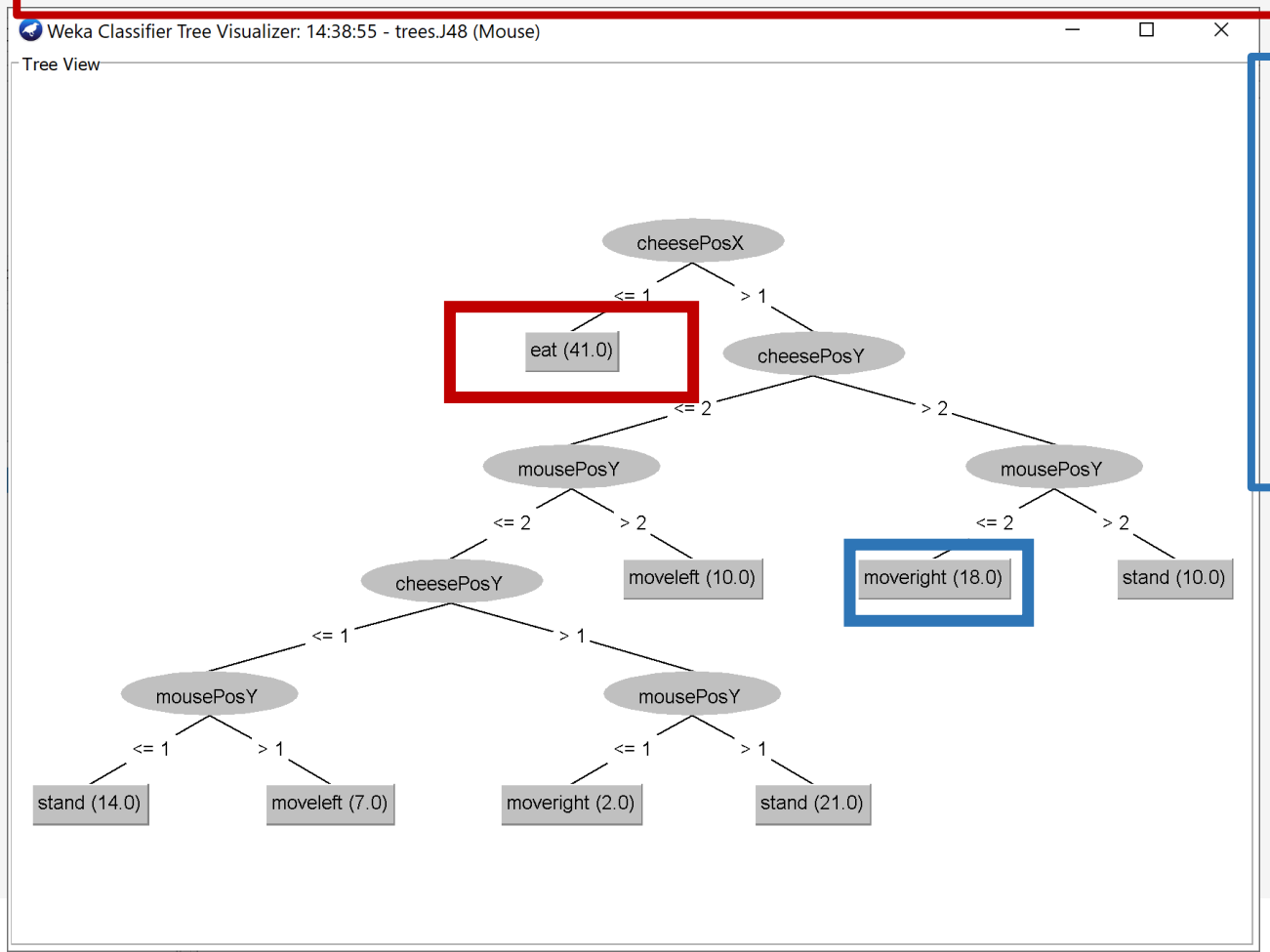
These do not include the ***eatenBits* attribute that is in fact irrelevant to the decision**: this has been rediscovered by the DT learning algorithm

As in the Prolog code, only the relative positions of the cheese and the mouse (i.e. mousePosX, mousePosY, cheesePosX, cheesePosY) are influencial to the decisions.



# Examples of Prolog rules induced by the DT algorithm

```
weka_decide_rule([cheese(CheesePosX, _), mouse(_, _)], _, eat) :-
        CheesePosX =< 1,
        !.
```




```
weka_decide_rule([cheese(CheesePosX, CheesePosY),
                  mouse(_, MousePosY)], _, moveright) :-
        CheesePosX > 1,
        CheesePosY > 2,
        MousePosY =< 2,
        !.
```

# The acquired decision tree

Obviousy the learning machine has been exposed to the perfect behaviour of the hand-coded Prolog program and it has been easy to rebuild such a simple model.

In case *no such knowledge is available* the question is: can we train the system? Where are the examples? We could use the estimated quality of individual moves (i.e. an empirical measure of their advantage), and then train the system to select the optimal move (e.g. a regression task)? Randomly selected actions could be used to gather training data.

Modify the provided Prolog code to formulate a quality estimate function and to train the random agent mouse from scratch.