

# AN INTRODUCTION TO ANSWER SET PROGRAMMING

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(Based on slides by Torsten Schaub)

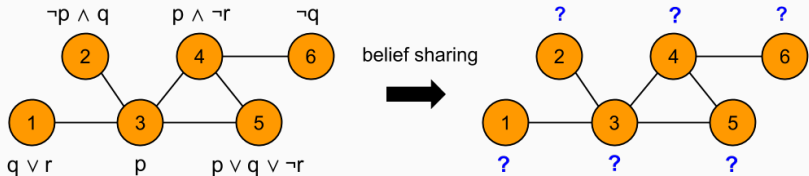
0. My Research
1. Declarative Problem Solving
2. ASP Syntax and Semantics
3. Modeling Problems in ASP

## MY RESEARCH

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# MULTI-AGENT BELIEF CHANGE

- We have a network of agents
- Each agent has some initial beliefs about the state of the world
- Agents communicate and share information
- **Goal:** Determine what each agent believes after learning as much as possible from other agents
- My research deals with ways to do this

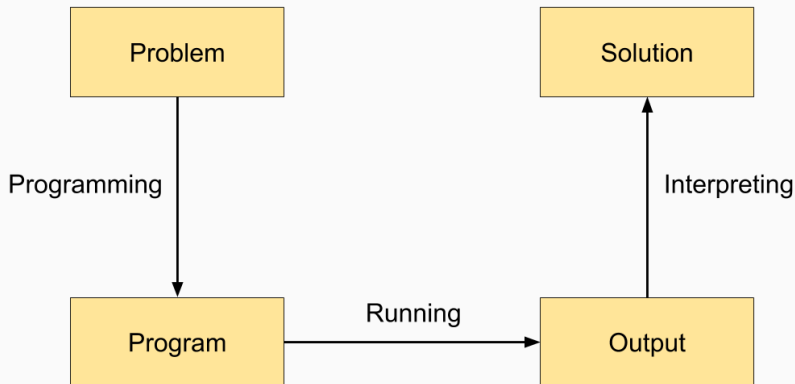


# DECLARATIVE PROBLEM SOLVING

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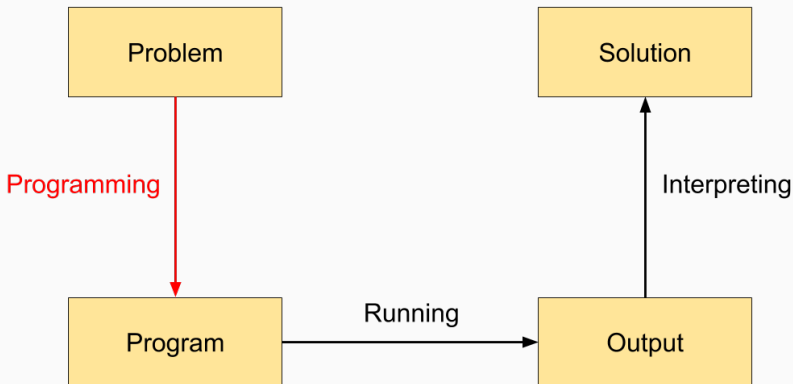
# TRADITIONAL IMPERATIVE PROGRAMMING

- Convert a problem specification into imperative code that solves instances of the problem
- Deal with algorithms and data structures
- The focus is on **how to solve the problem**



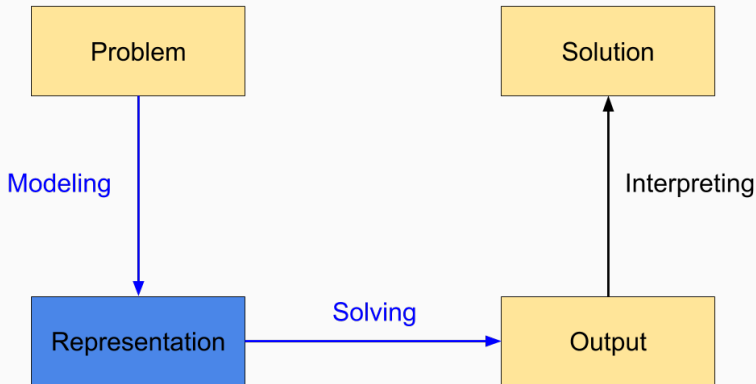
# TRADITIONAL IMPERATIVE PROGRAMMING

- Convert a problem specification into imperative code that solves instances of the problem
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## DECLARATIVE PROBLEM SOLVING

- Directly encode the problem specification using a *modeling language*
- *How do we solve the problem?* vs *What is the problem?*
- Focus on **how to describe the problem**





- Write your problem in a formal representation (i.e. using logic)
- The representation defines an *implicit* search space, and gives a description of a solution
- An off-the-shelf *solver* takes the representation and finds its logical models
  - The problem representation should be such that these models represent solutions

# WHAT IS ANSWER SET PROGRAMMING?

- ASP is a declarative problem-solving paradigm that combines an *expressive modeling language* with a *high-performance solver*
- It is geared towards solving NP-hard combinatorial search problems
- Originally developed for AI applications dealing with Knowledge Representation and Reasoning (KRR)
  - Led to a rich modeling language, compared to SAT
- Useful for solving combinatorial problems in  $P$ ,  $NP$ , and  $NP^{NP}$ , in areas like
  - Bioinformatics
  - Robotics
  - Music Composition
  - Decision Support Systems used by NASA
  - Product Configuration

- The best ASP tools are developed by the University of Potsdam, Germany
- Download their ASP solver `clingo` from <http://potassco.sourceforge.net/index.html>

- Theorem-Proving-Based Approach (Prolog)
  - Solution given by the derivation of a query
- Model-Generation-Based Approach (ASP)
  - Solution given by a *model* of the representation

### Is Prolog Declarative?

- Not really... shuffling rules in a program can break it
- Prolog program:

```
edge(1,2).
```

```
edge(2,3).
```

```
reachable(X,Y) :- edge(X,Y).
```

```
reachable(X,Y) :- edge(X,Z), reachable(Z,Y).
```

- A query:

```
?- reachable(1,3).
```

```
true.
```

## COMPARISON TO PROLOG (CONTD.)

- If we shuffle the program as follows:

```
edge(1,2).
```

```
edge(2,3).
```

```
reachable(X,Y) :- reachable(Z,Y), edge(X,Z).
```

```
reachable(X,Y) :- edge(X,Y).
```

- Then we get:

```
?- reachable(1,3).
```

```
Fatal Error: local stack overflow.
```

- This is *not* a bug in Prolog; it is intrinsic in the fixed execution of its inference algorithm
- Prolog provides constructs to alter program execution
  - The *cut* operator allows you to prune the search space, at the risk of losing solutions

## COMPARISON TO PROLOG (CONTD.)

- Prolog is a *programming language*; it allows the user to exercise control
  - For a programming language, control is good
- ASP provides a *representation language*
  - Completely decouples *problem specification* from *problem solving*

Prolog	ASP
Query Derivation	Model Generation
Top-down	Bottom-up
Fixed execution order	No fixed execution order
Programming Language	Modeling Language

## ASP SYNTAX AND SEMANTICS

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- A *logic program* over a set of atoms  $\mathcal{A}$  is a set of rules of the form:

$$a_0 \leftarrow a_1, \dots, a_m, \sim a_{m+1}, \dots, \sim a_n$$

where each  $a_i \in \mathcal{A}$ .

- Rules are a way of expressing constraints on a *set of atoms*
- “ $\sim$ ” represents *default negation*
  - An atom is assumed to be false until it is *proven* to be true
- Let  $X$  be the set of atoms representing a solution
- This rule says: “If  $a_1, \dots, a_m$  are all in  $X$ , and *none* of  $a_{m+1}, \dots, a_n$  are in  $X$ , then  $a_0$  should be in  $X$ ”

$$\varphi = q \wedge (q \wedge \neg r \rightarrow p)$$

- $\varphi$  has three classical models:  $\{p, q\}$ ,  $\{q, r\}$ , and  $\{p, q, r\}$ 
  - $\{p, q\}$  represents the model where:

$$p \mapsto 1, q \mapsto 1, r \mapsto 0$$

- The logic program representation of  $\varphi$  is  $P_\varphi$ :

$$q \leftarrow$$

$$p \leftarrow q, \sim r$$

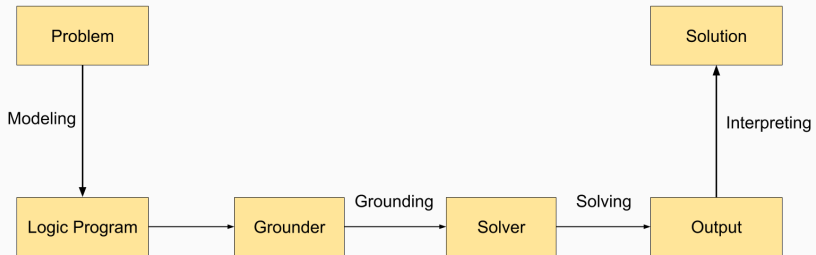
- This logic program has one *stable model* (a.k.a *answer set*):  $\{p, q\}$
- A set  $X$  of atoms is a *stable model* of a logic program  $P$  if  $X$  is a (classical) model of  $P$  and all atoms in  $X$  are **justified** by some rule in  $P$

## MODELING PROBLEMS IN ASP

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- Model your problem as a logic program
- The ASP solver only deals with *propositional* logic programs
- But it's more convenient (and much more flexible) to write first-order programs with variables
- Thus, the ASP solving process consists of two steps:
  1. A **grounder** converts a first-order program into a propositional program, by systematically replacing variables with concrete values from some domain
  2. A **solver** takes the *ground program* and assigns truth values to atoms to obtain the stable models of the program

# ASP SOLVING STEPS



- Facts
  - `a.`
  - `person(bill).`
  - `person(alice;bob;james).`
    - Is shorthand for `person(alice). person(bob). person(james).`
  - `num(1..10).`
    - Is shorthand for `num(1). num(2). num(3). num(4). etc.`
- Rules
  - `a :- b.`
  - `reachable(X,Z) :- edge(X,Y), reachable(Y,Z).`

## GROUNDING EXAMPLE

- If we have a logic program

```
r(a,b).
```

```
r(b,c).
```

```
t(X,Y) :- r(X,Y).
```

- Then the full *ground instantiation* is:

```
r(a,b).
```

```
r(b,c).
```

```
t(a,a) :- r(a,a).
```

```
t(b,a) :- r(b,a).
```

```
t(c,a) :- r(c,a).
```

```
...
```

- Which is trivially reduced to:

```
r(a,b).
```

```
r(b,c).
```

```
t(a,b) :- r(a,b).
```

```
t(b,c) :- r(b,c).
```

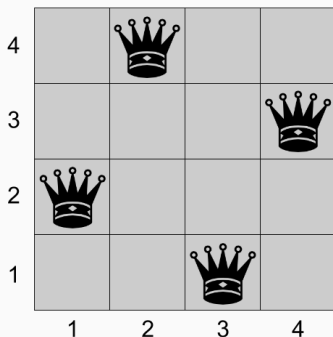
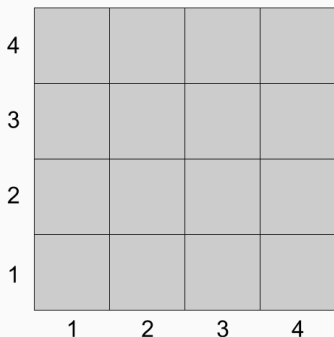
- General methodology: *generate and test* (or “guess and check”)
  1. **Generate** candidate solutions through non-deterministic constructs (like choice rules)
  2. **Test** them to eliminate invalid candidate solutions



- Choice Rules
  - `1 { has_property(X,C) : property(C) } 1 :- item(X).`
- Integrity Constraints
  - `:- in_clique(2), in_clique(3), not edge(2,3).`
  - “It *cannot* be the case that nodes 2 and 3 are in a clique, *and* there is no edge between 2 and 3.”
- Aggregates
  - `within_budget :- 10 #sum { Amount : paid(Amount) } 100.`
- Optimization Statements
  - `#maximize { 1,X:in_clique(X),node(X) }.`

# N-QUEENS PROBLEM

- **Goal:** Place  $n$  queens on an  $n \times n$  chess board such that no queens attack each other



- Define the board:

```
row(1..n).
```

```
col(1..n).
```

```
$ clingo queens.lp --const n=4
```

```
Answer: 1
```

```
row(1) row(2) row(3) row(4) \
```

```
col(1) col(2) col(3) col(4)
```

```
SATISFIABLE
```

- **Generate:** Place any number of queens on the board:

```
{ queen(I,J) : row(I), col(J) }.
```

```
$ clingo queens.lp --const n=4 3
```

```
Answer: 1
```

```
row(1) row(2) row(3) row(4) \
```

```
col(1) col(2) col(3) col(4)
```

```
Answer: 2
```

```
row(1) row(2) row(3) row(4) \
```

```
col(1) col(2) col(3) col(4) queen(2,1)
```

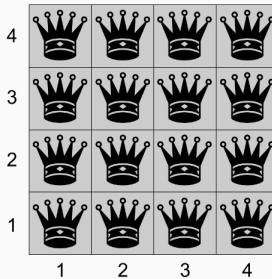
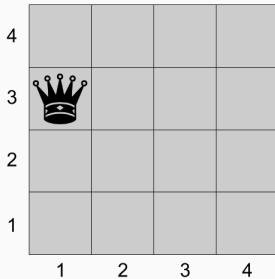
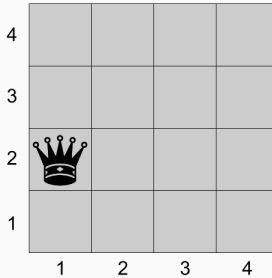
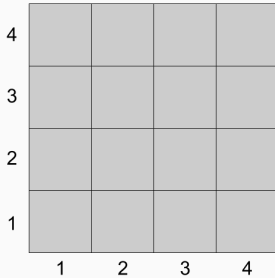
```
Answer: 3
```

```
row(1) row(2) row(3) row(4) \
```

```
col(1) col(2) col(3) col(4) queen(3,1)
```

```
SATISFIABLE
```

# N-QUEENS - PLACING QUEENS



- We need to say that there should only be  $n$  queens
- Expressed by an integrity constraint using *double negation*
  - “It should *not* be the case that there are *not*  $n$  queens.”

```
:- not n { queen(I,J) } n.
```

```
$ clingo queens.lp --const n=4
```

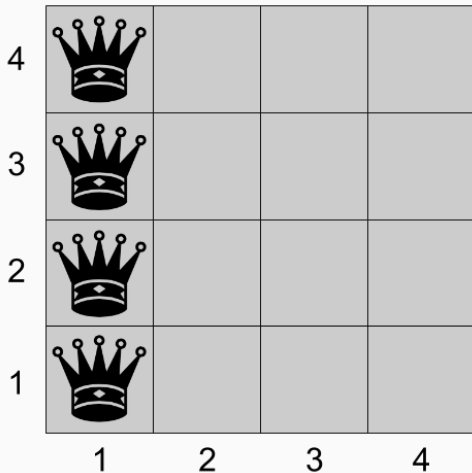
```
Solving...
```

```
Answer: 1
```

```
queen(1,1) queen(2,1) queen(3,1) queen(4,1)
```

## N-QUEENS - RESTRICTING THE NUMBER OF QUEENS

- The last solution looks like this:



- Prevent attacks by adding *integrity constraints*
- Forbid horizontal attacks (two queens in the same row):  
:- queen(I,J1), queen(I,J2), J1 != J2.
- Forbid vertical attacks (two queens in the same column):  
:- queen(I1,J), queen(I2,J), I1 != I2.
- And forbid diagonal attacks:

:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ), I+J == II+JJ.

:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ), I-J == II-JJ.



```
queens.lp
```

```
row(1..n).
```

```
col(1..n).
```

```
% Generate
```

```
n { queen(I,J) : row(I), col(J) } n.
```

```
% Test
```

```
:- queen(I,J1), queen(I,J2), J1 != J2.
```

```
:- queen(I1,J), queen(I2,J), I1 != I2.
```

```
:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ), I+J == II+JJ.
```

```
:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ), I-J == II-JJ.
```

```
#show queen/2.
```

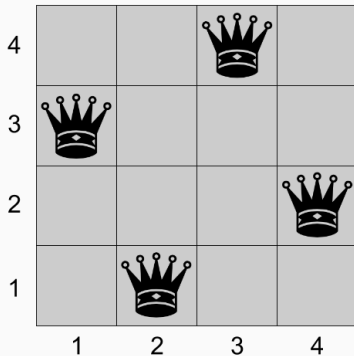
# N-QUEENS - SOLUTION

```
$ clingo queens.lp --const n=4
```

```
Solving...
```

```
Answer: 1
```

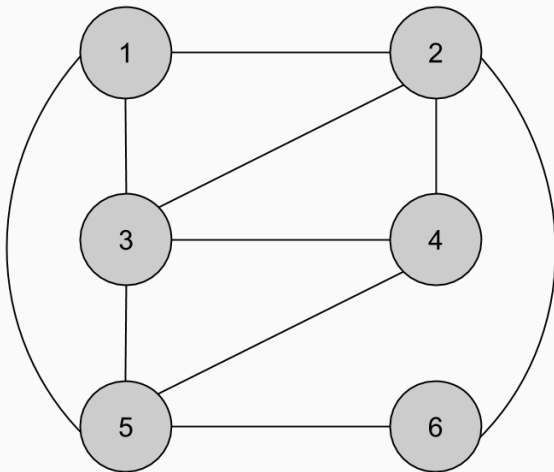
```
queen(3,1) queen(1,2) queen(4,3) queen(2,4)
```



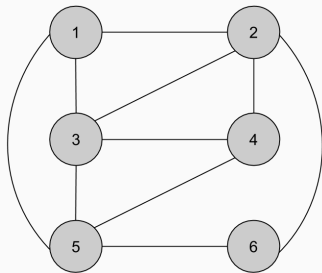
- ASP is very tolerant to elaboration in the problem specification
- Start with a large search space, and keep adding constraints to whittle down results
- Helps you to understand your problem, and is useful for prototyping

## GRAPH 3-COLOURING PROBLEM

- **Problem instance:** A graph  $G = \langle V, E \rangle$ .
- **Goal:** Assign one colour to each node, such that no two nodes connected by an edge have the same colour.



## GRAPH 3-COLOURING - INSTANCE



- Represent the graph using node/1 and edge/2 predicates:

```
node(1..6).
```

```
edge(1,2). edge(1,3). edge(1,5).
```

```
edge(2,3). edge(2,4). edge(2,6).
```

```
edge(3,4). edge(3,5). edge(4,5). edge(5,6).
```

```
col(red;green;blue).
```

- Choice Rules
  - `1 { has_property(X,C) : property(C) } 1 :- item(X).`
- Integrity Constraints
  - `:- in_clique(2), in_clique(3), not edge(2,3).`
  - “It *cannot* be the case that nodes 2 and 3 are in a clique, *and* there is no edge between 2 and 3.”
- Aggregates
  - `within_budget :- 10 #sum { Amount : paid(Amount) } 100.`
- Optimization Statements
  - `#maximize { 1,X:in_clique(X),node(X) }.`

- **Generate:** Assign one colour to each node using a *choice rule*

```
1 { node_col(X,C) : col(C) } 1 :- node(X).
```

- **Test:** Eliminate candidate solutions where two nodes connected by an edge get the same colour, using an *integrity constraint*

```
:- edge(X,Y), node_col(X,C), node_col(Y,C).
```

```
col.lp
```

```
node(1..6).
```

```
edge(1,2). edge(1,3). edge(1,5).
```

```
edge(2,3). edge(2,4). edge(2,6).
```

```
edge(3,4). edge(3,5).
```

```
edge(4,5).
```

```
edge(5,6).
```

```
col(red;green;blue).
```

```
1 { node_col(X,C) : col(C) } 1 :- node(X).
```

```
:- edge(X,Y), node_col(X,C), node_col(Y,C).
```

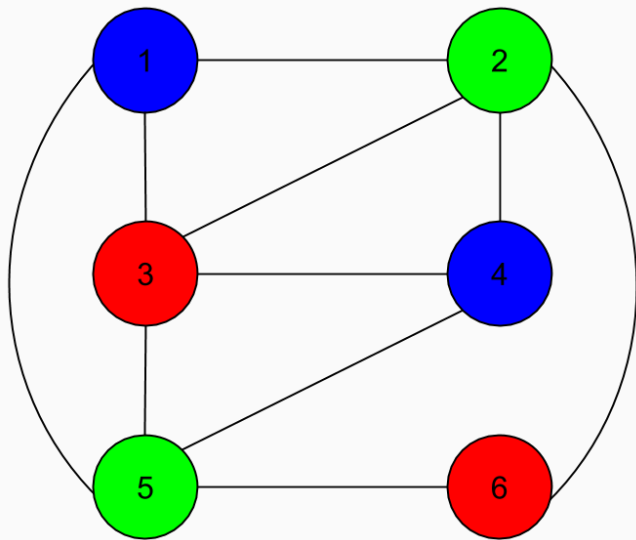
```
#show node_col/2.
```



```
$ clingo col.lp
Answer: 1
node_col(2,green) node_col(1,blue) node_col(3,red) \
node_col(5,green) node_col(4,blue) node_col(6,red)
SATISFIABLE

Models      : 1+
Calls       : 1
Time        : 0.003s (Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s)
CPU Time    : 0.000s
```

## GRAPH 3-COLOURING - INTERPRETING



- We also can enumerate all possible solutions:

```
$ clingo col_encoding.lp col_instance.lp 0
```

```
Answer: 1
```

```
node_col(2,green) node_col(1,blue) node_col(3,red) \  
node_col(5,green) node_col(4,blue) node_col(6,red)
```

```
Answer: 2
```

```
node_col(2,green) node_col(1,blue) node_col(3,red) \  
node_col(5,green) node_col(4,blue) node_col(6,blue)
```

```
Answer: 3
```

```
node_col(1,red) node_col(2,green) node_col(3,blue) \  
node_col(5,green) node_col(4,red) node_col(6,red)
```

```
Answer: 4
```

```
node_col(1,red) node_col(2,green) node_col(3,blue) \  
node_col(5,green) node_col(4,red) node_col(6,blue)
```

```
Answer: 5
```

```
node_col(1,red) node_col(2,blue) node_col(3,green) \  
node_col(5,blue) node_col(4,red) node_col(6,red)
```

# XKCD KNAPSACK PROBLEM STATEMENT

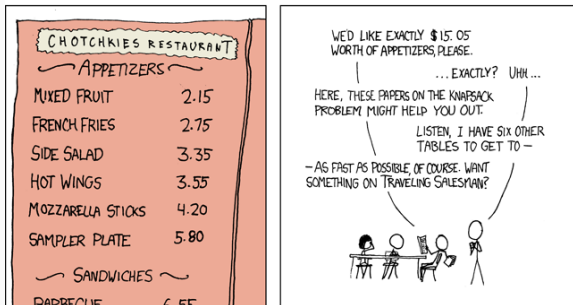
## MY HOBBY: EMBEDDING NP-COMPLETE PROBLEMS IN RESTAURANT ORDERS

CHOTCHKIES RESTAURANT	
APPETIZERS	
MIXED FRUIT	2.15
FRENCH FRIES	2.75
SIDE SALAD	3.35
HOT WINGS	3.55
MOZZARELLA STICKS	4.20
SAMPLER PLATE	5.80
SANDWICHES	
BARBECUE	6.55



# XKCD KNAPSACK PROBLEM PART 1

## MY HOBBY: EMBEDDING NP-COMPLETE PROBLEMS IN RESTAURANT ORDERS



- Order some amount (possibly 0) of each food
- Such that the sum of the costs of the foods times the number ordered is *exactly* some desired amount

- We can encode the foods and costs as follows:

```
food(fruit;fries;salad;wings;mozz_sticks;sampler).
```

```
cost(fruit,215).
```

```
cost(fries,275).
```

```
cost(salad,335).
```

```
cost(wings,355).
```

```
cost(mozz_sticks,420).
```

```
cost(sampler,580).
```

## XKCD KNAPSACK PROBLEM PART 3

```
#const total = 1505.  
#const max_order = 10.  
  
food(fruit;fries;salad;wings;mozz_sticks;sampler).  
  
cost(fruit,215). cost(fries,275). cost(salad,335).  
cost(wings,355). cost(mozz_sticks,420). cost(sampler,580).  
  
% Have to set an upper bound on the orders for a specific food  
num(0..max_order).  
  
% Order some amount (possibly 0) of each type of food  
1 { order(Food, Number) : num(Number) } 1 :- food(Food).  
  
% We want the prices to sum to the desired total  
#sum{(Cost*N),F : order(F,N) : cost(F,Cost), num(N)} == total.
```

- `clingo --const total=1505 xkcd.lp`  
`order(fruit,7) order(fries,0) order(salad,0)`  
`order(wings,0) order(mozz_sticks,0) order(sampler,0)`
- `clingo --const total=19000 xkcd.lp 0`



## Is ASP Declarative?

- In many ways, yes:
  - You provide a specification of the problem, and a problem instance, and you get a result
  - The order of rules doesn't matter
  - You don't have to think about *how* your problem is solved (algorithm, data structures), just *what* your problem is
- However...
  - Different problem encodings can yield different solving times
  - Efficiency still depends on *how* you specify your problem

- Performance generally depends on the size of the ground instantiation
  - This is what the solver has to look at
- *Intelligent grounding* techniques attempt to automatically reduce the size of the ground program by eliminating unnecessary rules
- But still, you can never recover from a bad encoding

## PERFORMANCE OF N-QUEENS

- The previous encoding of n-Queens becomes slow at  $n \approx 15$
- The encoding below is much better (gets to  $n \approx 250$  in the same amount of time):

```
1 { queen(I,1..n) } 1 :- I = 1..n.  
1 { queen(1..n,J) } 1 :- J = 1..n.  
:- 2 { queen(D-J,J) }, D = 2..2*n.  
:- 2 { queen(D+J,J) }, D = 1-n..n-1.
```

- A version of this encoding was used to go to  $n = 5000$ 
  - Solving took about 1 hour