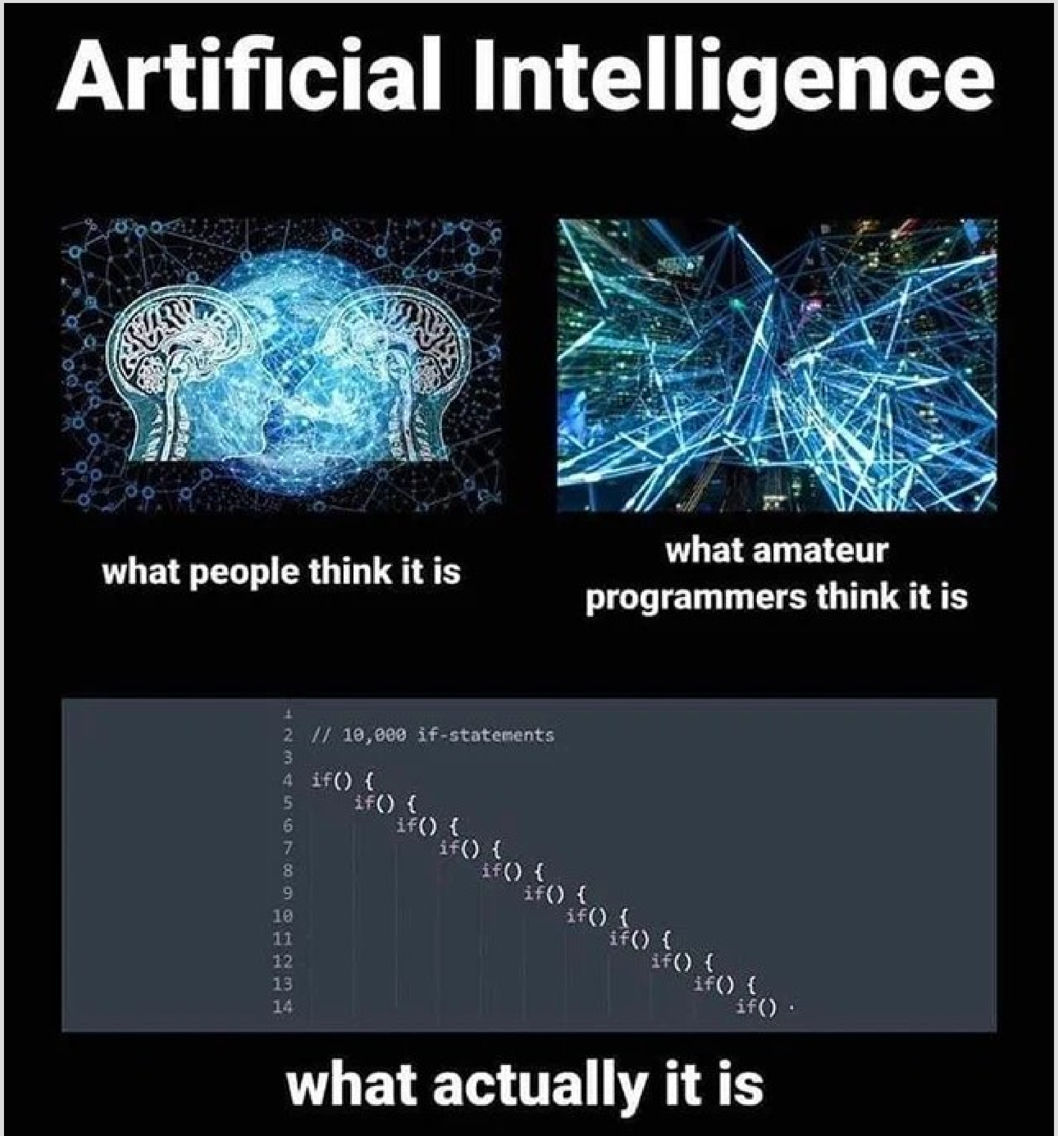
Planning (Ch. 10)



GraphPlan: states

Let's consider this problem:

Initial: $Clean \wedge Garbage \wedge Quiet$

Goal: $Food \wedge \neg Garbage \wedge Present$

Action: ($MakeFood$,
Precondition: $Clean$,
Effects: $Food$)

Action: ($Takeout$,
Precondition: $Garbage$,
Effects: $\neg Garbage \wedge \neg Clean$)

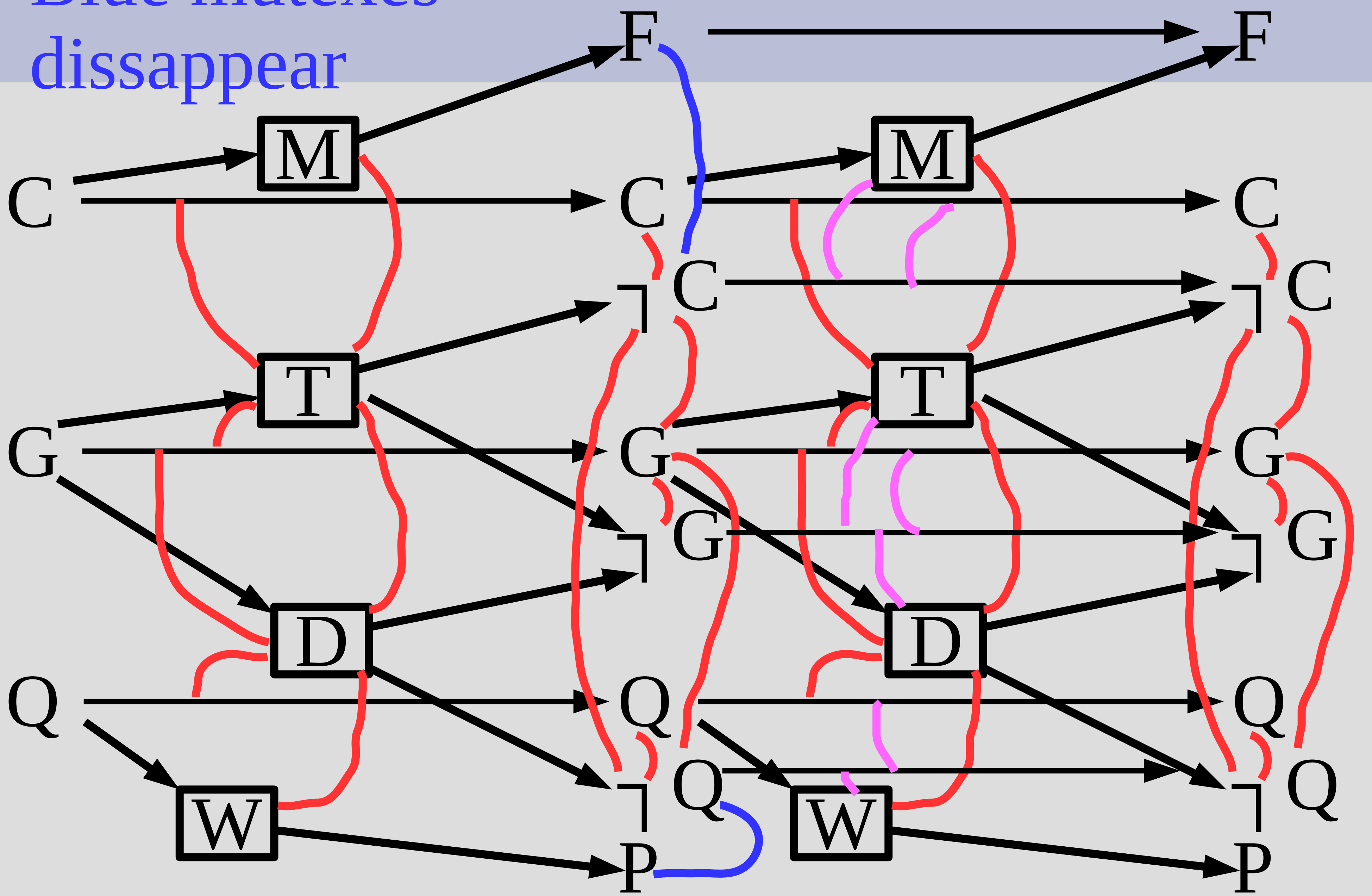
Action: ($Wrap$,
Precondition: $Quiet$,
Effects: $Present$)

Action: ($Dolly$,
Precondition: $Garbage$,
Effects: $\neg Garbage \wedge \neg Quiet$)

Mutexes

Blue mutexes dissappear

Pink = new mutex



GraphPlan as heuristic

GraphPlan is optimistic, so if any pair of goal states are in mutex, the goal is impossible

3 basic ways to use GraphPlan as heuristic:

(1) Maximum level of all goals
(2) Sum of level of all goals (not admissible)
(3) Level where no pair of goals is in mutex

(1) and (2) do not require any mutexes, but are less accurate (quick 'n' dirty)

GraphPlan as heuristic

For heuristics (1) and (2), we relax as such:

1. Multiple actions per step, so can only take fewer steps to reach same result
2. Never remove any states, so the number of possible states only increases

This is a valid simplification of the problem, but it is often too simplistic directly

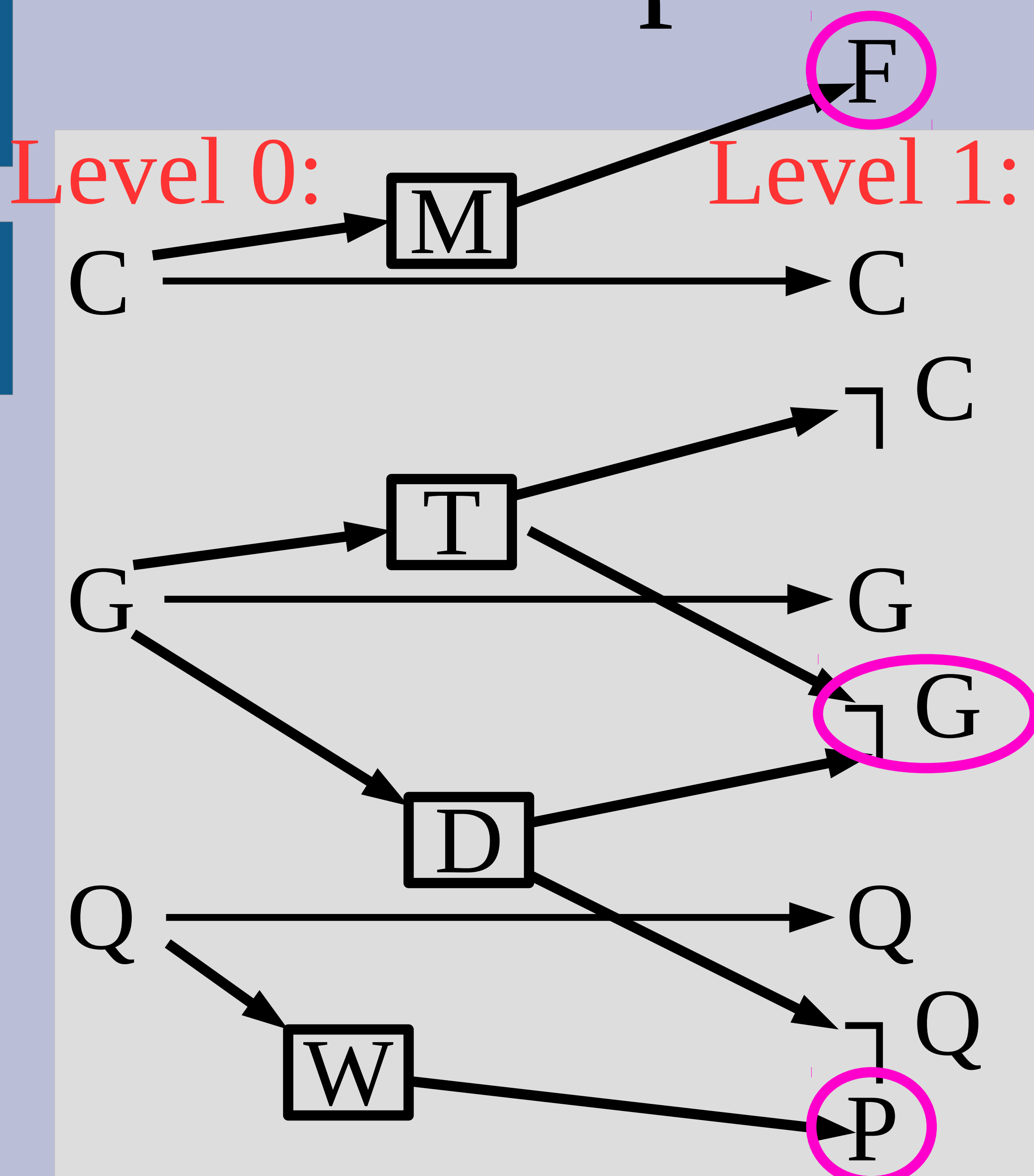
GraphPlan as heuristic

Heuristic (1) directly uses this relaxation and finds the first time when all 3 goals appear at a state level

(2) tries to sum the levels of each individual first appearance, which is not admissible (but works well if they are independent parts)

Our problem: goal={Food, ¬ Garbage, Present}
First appearance: F=1, ¬ G=1, P=1

GraphPlan: states



Heuristic (1):
Max(1,1,1) = 1

Heuristic (2):
1+1+1=3

GraphPlan as heuristic

Often the problem is too trivial with just those two simplifications

So we add in mutexes to keep track of invalid pairs of states/actions

This is still a simplification, as only impossible state/action pairs in the original problem are in mutex in the relaxation

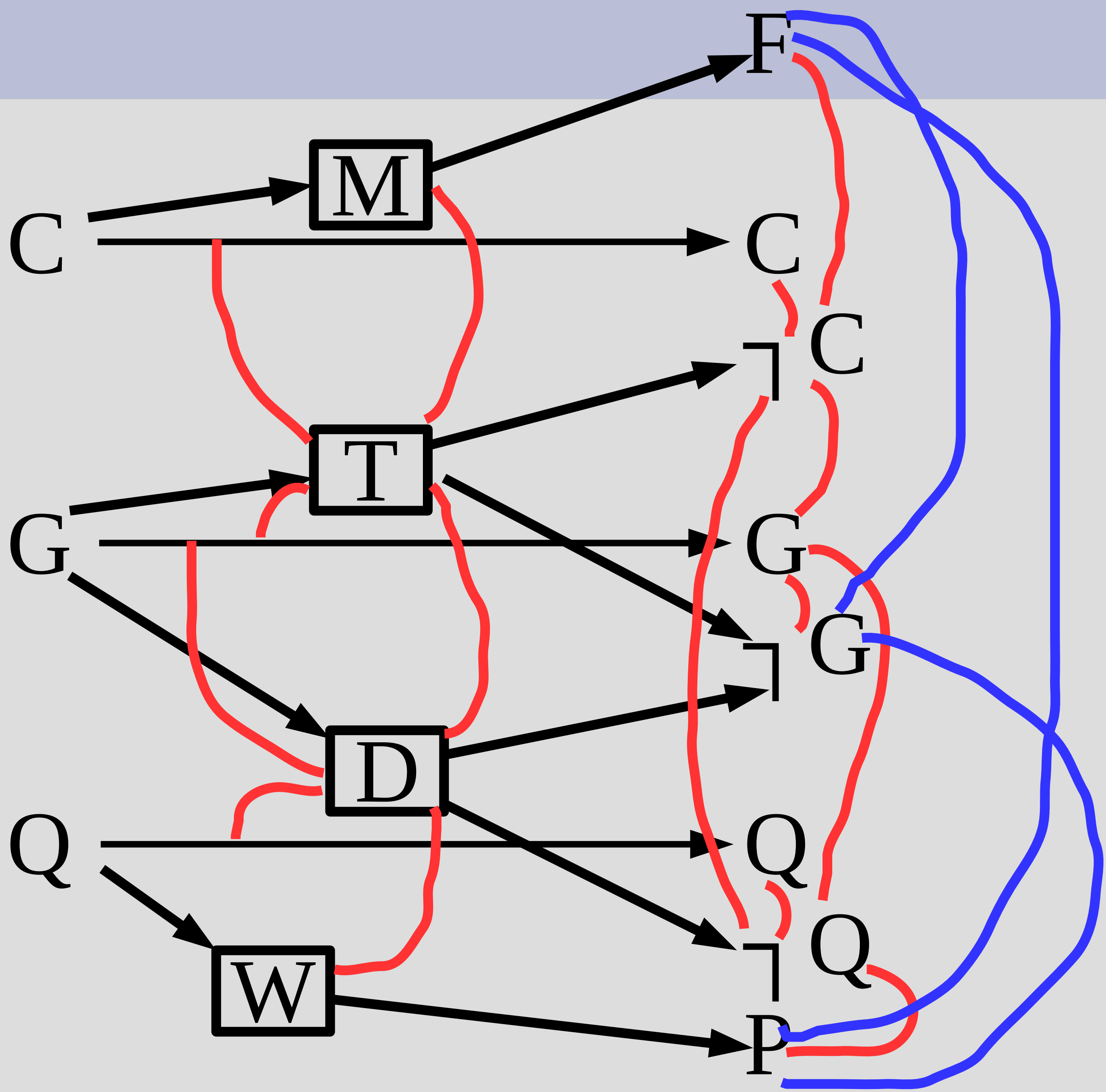
GraphPlan as heuristic

Heuristic (3) looks to find the first time none of the goal pairs are in mutex

For our problem, the goal states are:
(Food, ¬ Garbage, Present)

So all pairs that need to have no mutex:
(F, ¬ G), (F, P), (¬ G, P)

Mutexes



None of the pairs are in mutex at level 1

This is our heuristic estimate

Finding a solution

GraphPlan can also be used to find a solution:
(1) Converting to a Constraint Sat. Problem
(2) Backwards search

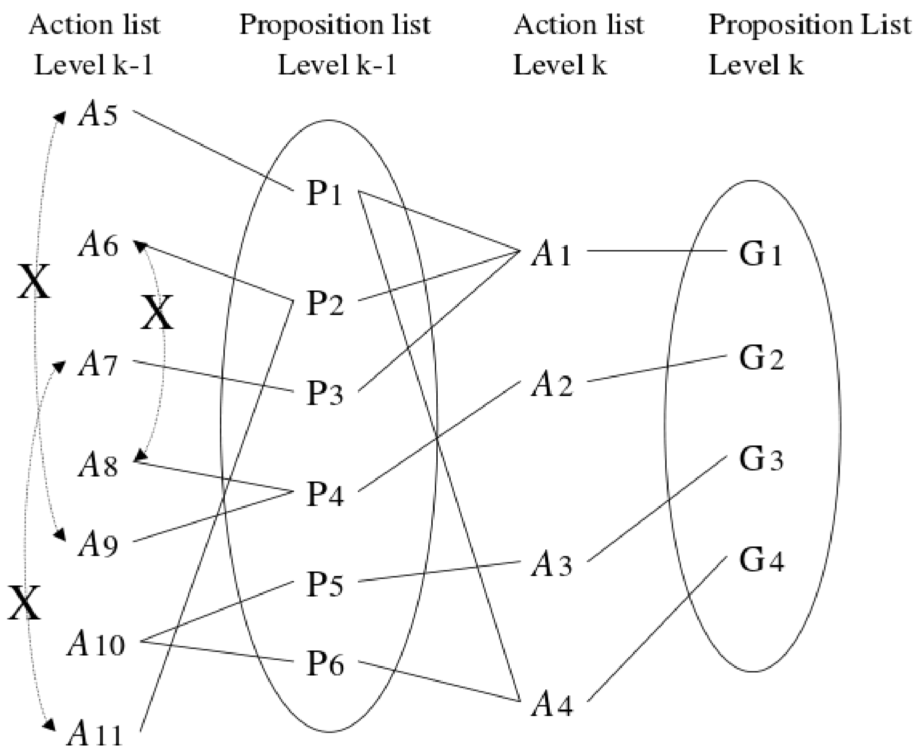
Both of these ways can be run once GraphPlan has all goal pairs not in mutex (or converges)

Additionally, you might need to extend it out a few more levels further to find a solution (as GraphPlan underestimates)

GraphPlan as CSP

Variables = states, Domains = actions out of

Constraints = mutexes & preconditions



(a) Planning Graph

Variables: $G_1, \cdots, G_4, P_1 \cdots P_6$

Domains: $G_1 : \{A_1\}, G_2 : \{A_2\} G_3 : \{A_3\} G_4 : \{A_4\}$
$P_1 : \{A_5\} P_2 : \{A_6, A_{11}\} P_3 : \{A_7\} P_4 : \{A_8, A_9\}$
$P_5 : \{A_{10}\} P_6 : \{A_{10}\}$

Constraints (normal): $P_1 = A_5 \Rightarrow P_4 \neq A_9$
$P_2 = A_6 \Rightarrow P_4 \neq A_8$
$P_2 = A_{11} \Rightarrow P_3 \neq A_7$

Constraints (Activity): $G_1 = A_1 \Rightarrow Active\{P_1, P_2, P_3\}$
$G_2 = A_2 \Rightarrow Active\{P_4\}$
$G_3 = A_3 \Rightarrow Active\{P_5\}$
$G_4 = A_4 \Rightarrow Active\{P_1, P_6\}$

Init State: $Active\{G_1, G_2, G_3, G_4\}$

(b) DCSP

from Do & Kambhampati

Finding a solution

For backward search, attempt to find arrows back to the initial state(without conflict/mutex)

Start by finding actions that satisfy all goal conditions, then recursively try to satisfy all of the selected actions' preconditions

If this fails to find a solution, mark this level and all the goals not satisfied as: (level, goals)
(level, goals) stops changing, no solution

Graph Plan

Remember this...

Initial: $\neg Money \wedge \neg Smart \wedge \neg Debt$

Goal: $\neg Money \wedge Smart \wedge \neg Debt$

Action($School$,
Precondition: ,
Effect: $Debt \wedge Smart$)

Action(Job,
Precondition: ,
Effect: $Money \wedge \neg Smart$)

Action(Pay,
Precondition: $Money$,
Effect: $\neg Money \wedge \neg Debt$)

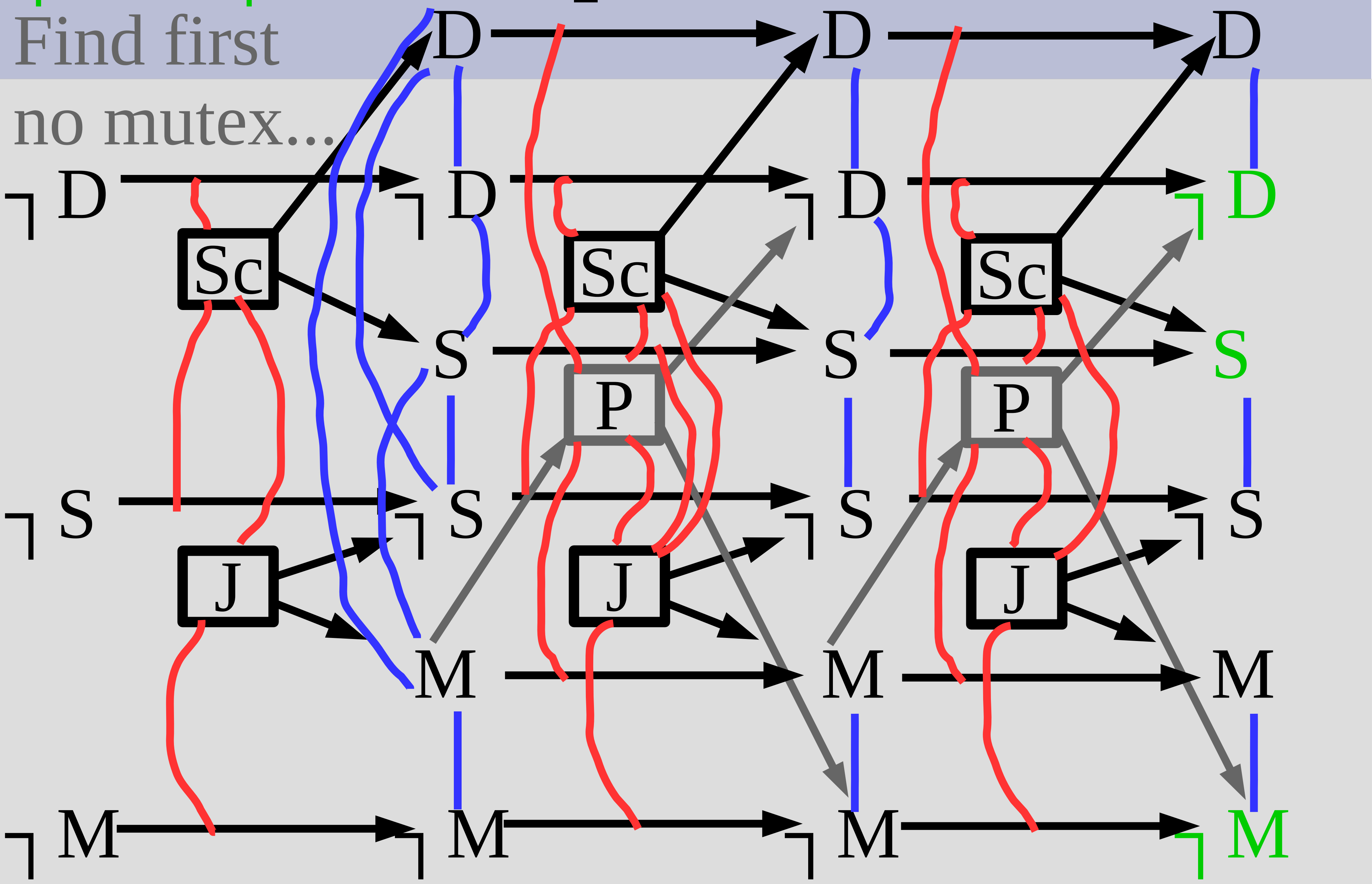
Graph Plan

Ask:

¬ D^S^¬ M

Find first

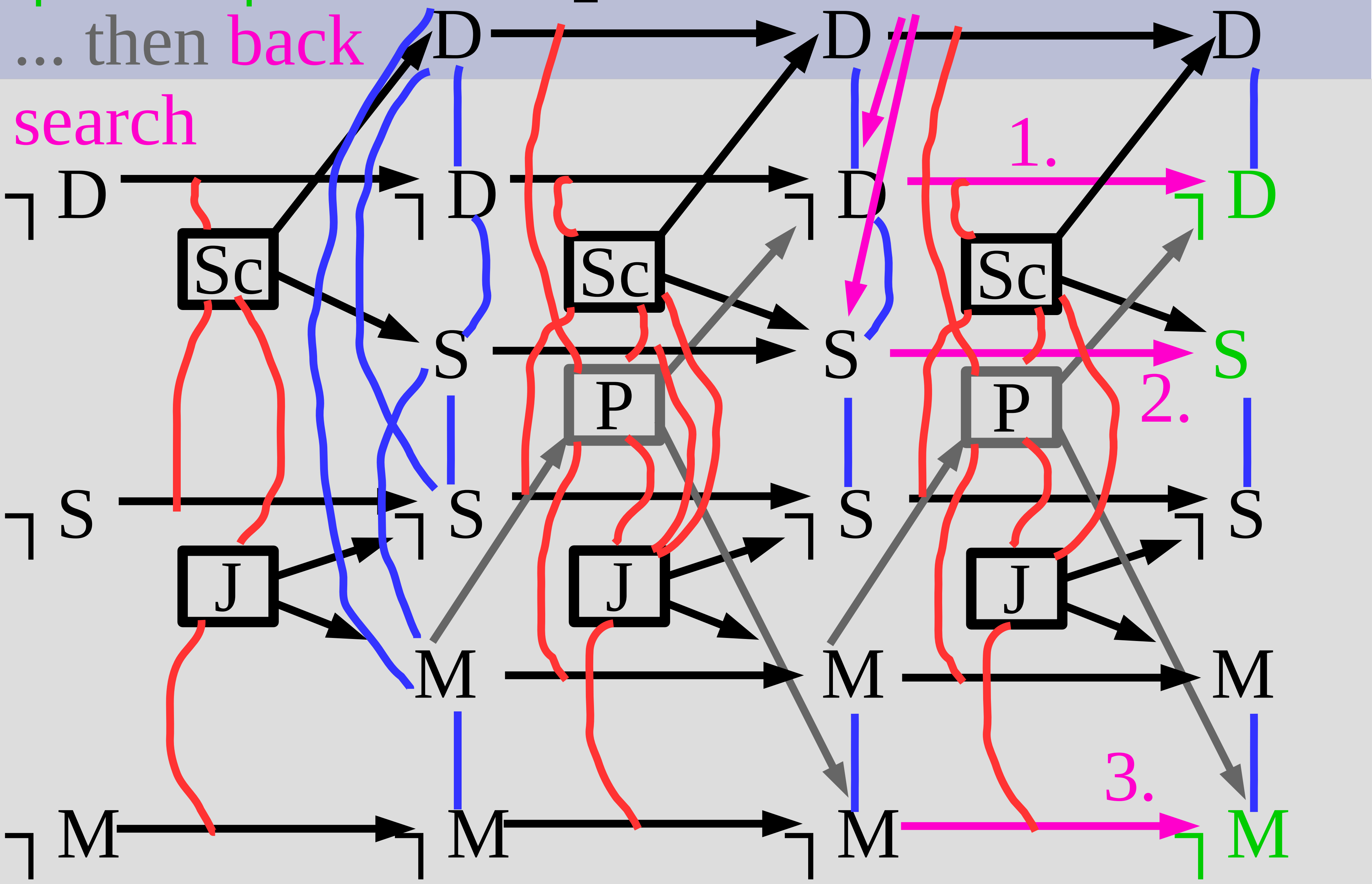
no mutex...



Graph Plan

Ask:
¬D^S^¬M
... then back search

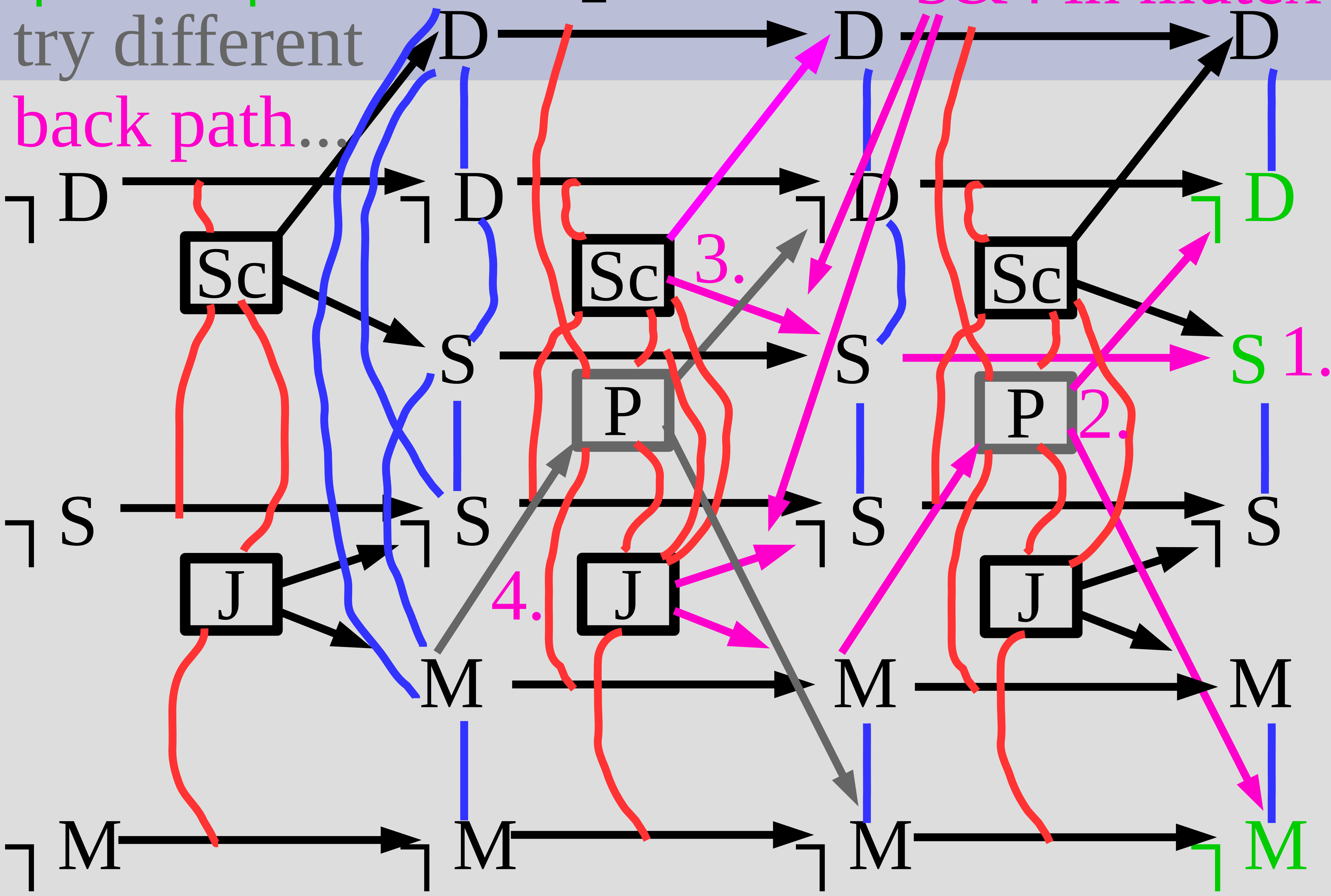
Error! States of 1&4 in mutex



Graph Plan

Ask:
¬ D^S^¬ M
try different
back path...

Error, actions
3&4 in mutex

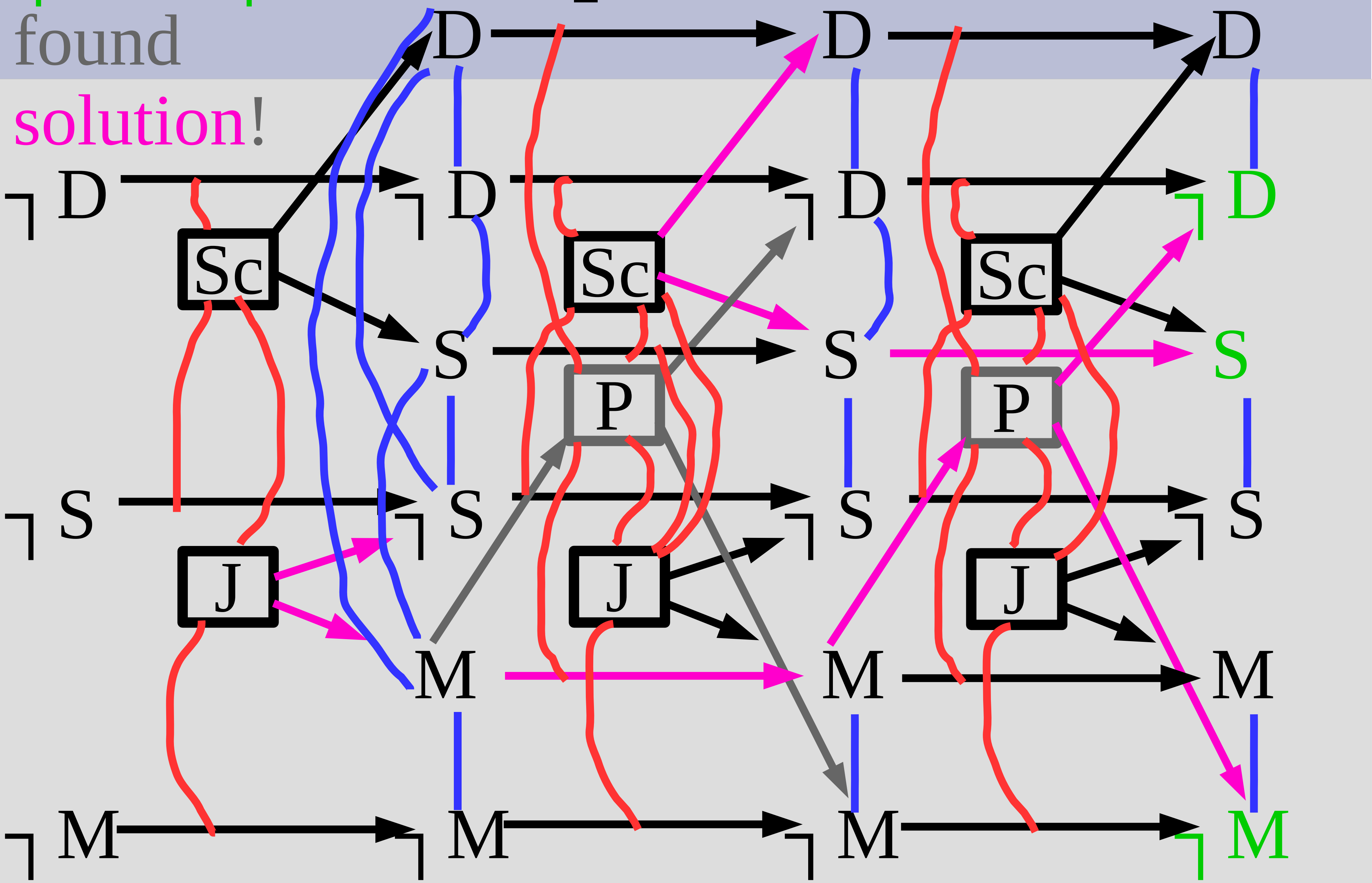


Ask:

¬D^S^¬M found

solution!

Graph Plan



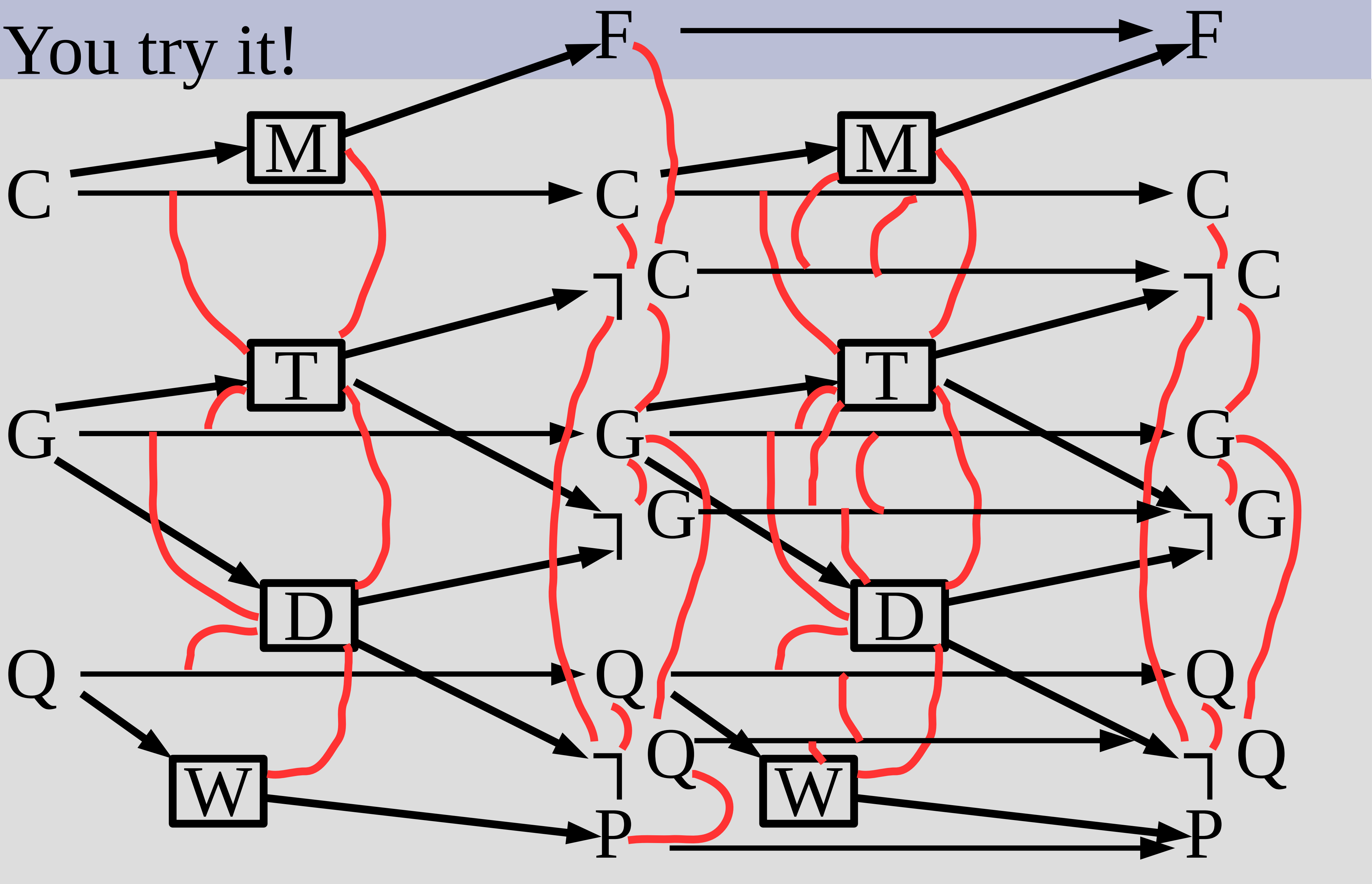
Finding a solution

Formally, the algorithm is:

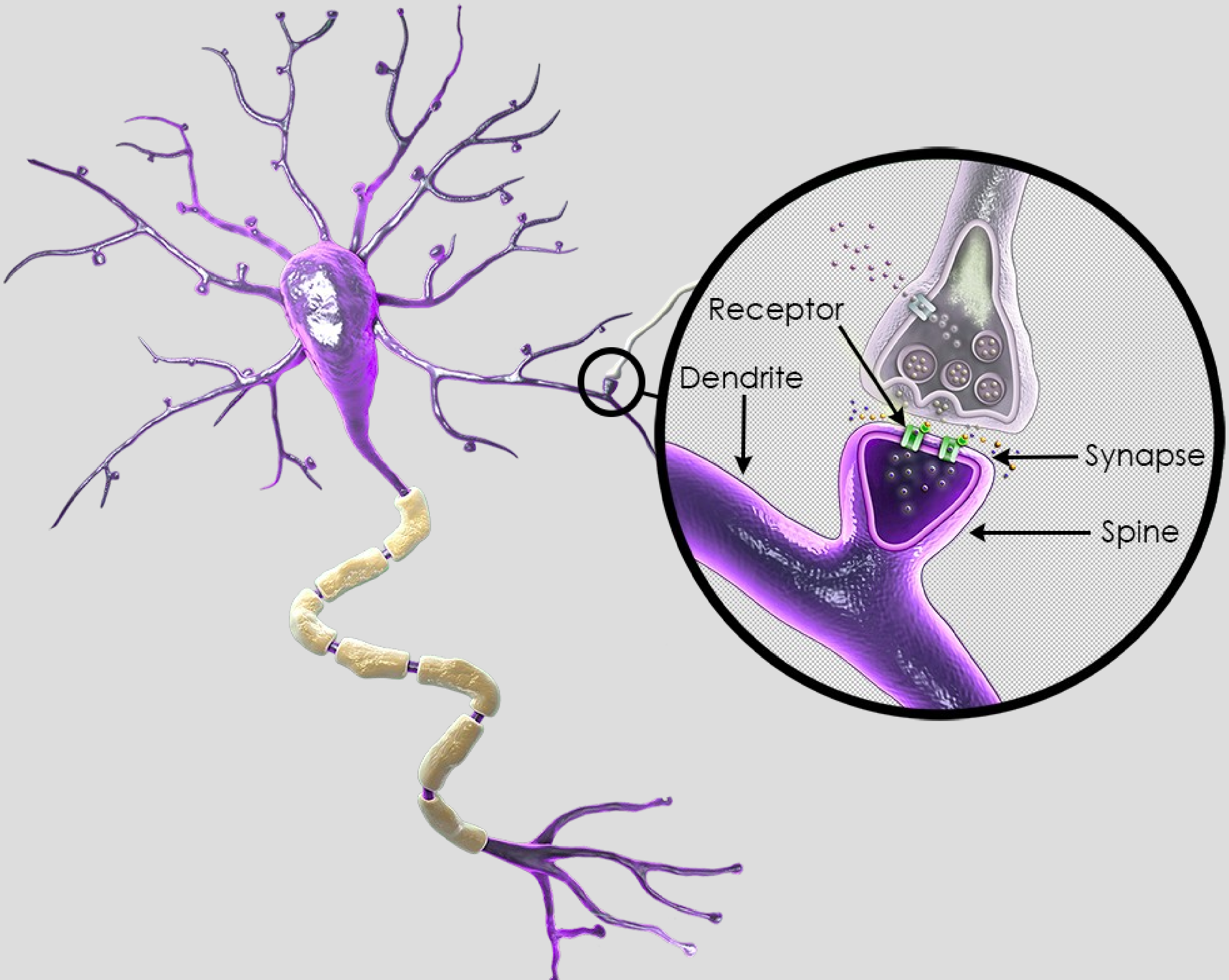
```
graph = initial
noGoods = empty table (hash)
for level = 0 to infinity
    if all goal pairs not in mutex
        solution = recursive search with noGoods
        if success, return paths
    if graph & noGoods converged, return fail
    graaph = expand graph
```

$$\text{Initial: } Clean \wedge Garbage \wedge Quiet$$
$$\text{Goal: } Food \wedge \neg Garbage \wedge Present$$

You try it!



Neural networks (Ch. 12)



Biology: brains

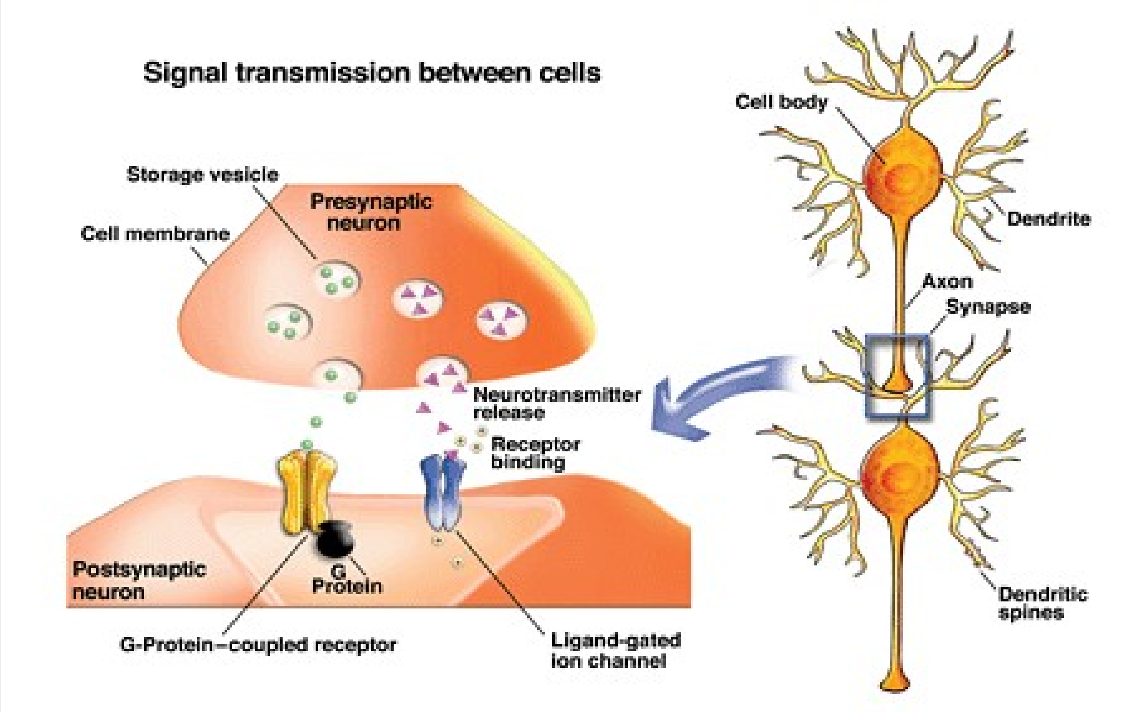
Computer science is fundamentally a creative process: building new & interesting algorithms

As with other creative processes, this involves mixing ideas together from various places

Neural networks get their inspiration from how brains work at a fundamental level (simplification... of course)

Biology: brains

(Disclaimer: I am **not** a neuroscience-person)
Brains receive small chemical signals at the "input" side, if there are enough inputs to "activate" it signals an "output"



Biology: brains

An analogy is sleeping: when you are asleep, minor sounds will not wake you up

However, specific sounds in combination with their volume will wake you up

Biology: brains

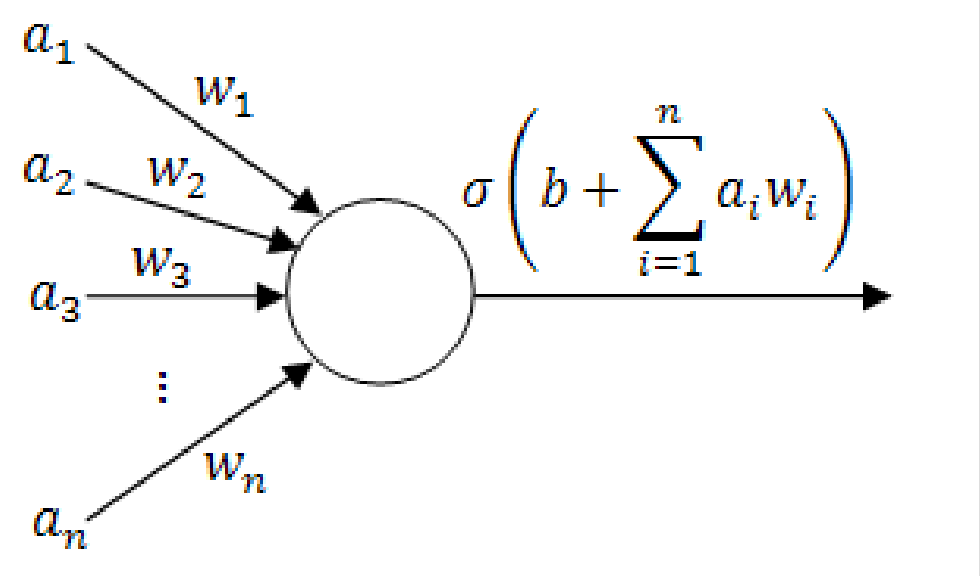
Other sounds might help you go to sleep (my majestic voice?)

Many babies tend to sleep better with “white noise” and some people like the TV/radio on

Neural network: basics

Neural networks are connected nodes, which can be arranged into layers (more on this later)

First is an example of a perceptron, the most simple NN; a single node on a single layer



Neural network: basics

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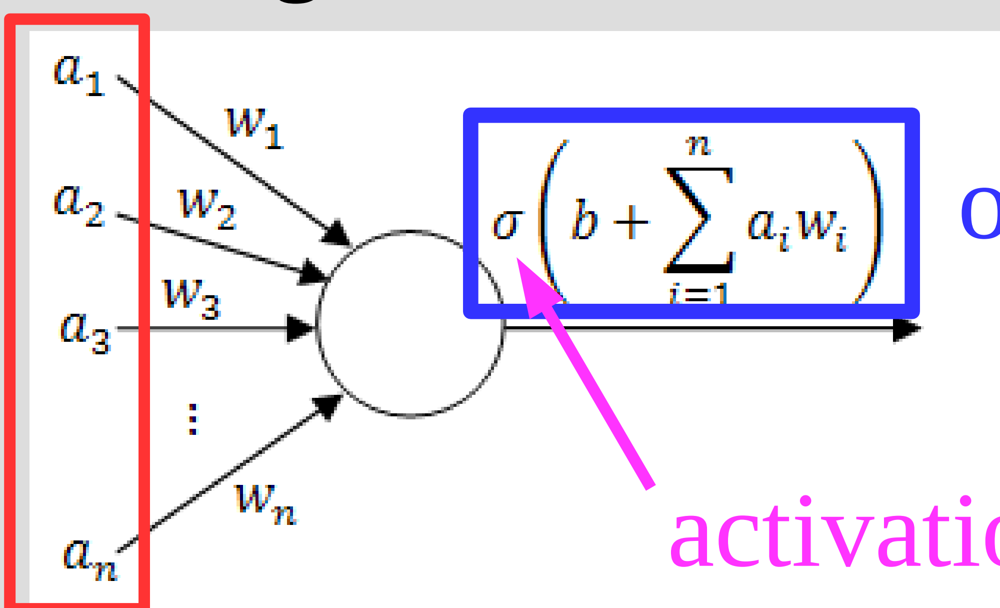
inputs



output

activation function

Mammals

Let's do an example with mammals...

First the definition of a mammal (wikipedia):

Mammals [posses]:
(1) a neocortex (a region of the brain),
(2) hair,
(3) three middle ear bones,
(4) and mammary glands

Mammals

Common mammal misconceptions:
(1) Warm-blooded
(2) Does not lay eggs

Let's talk dolphins for one second.
http://mentalfloss.com/article/19116/if-dolphins-are-mammals-and-all-mammals-have-hair-why-arent-dolphins-hairy

Dolphins have hair (technically) for the first week after birth, then lose it for the rest of life ... I will count this as “not covered in hair”

Perceptrons

Consider this example: we want to classify whether or not an animal is mammal via a perceptron (weighted evaluation)

We will evaluate on:

1. Warm blooded? (WB) Weight = 2
2. Lays eggs? (LE) Weight = -2
3. Covered hair? (CH) Weight = 3

$$\mathrm{If}(2 \cdot WB + -2 \cdot LE + 3 \cdot CH > 1) \Rightarrow Mammal$$

Perceptrons

Consider the following animals:

Humans {WB=y, LE=n, CH=y}, mam=y

$2(1) + -2(-1) + 3(1) = 7 > 1$ ... Correct!

Bat {WB=sorta, LE=n, CH=y}, mam=y

$2(0.5) + -2(-1) + 3(1) = 6 > 1$ ... Correct!

What about these?

Platypus {WB=y, LE=y, CH=y}, mam=y

Dolphin {WB=y, LE=n, CH=n}, mam=y

Fish {WB=n, LE=y, CH=n}, mam=n

Birds {WB=y, LE=y, CH=n}, mam=n

Perceptrons

But wait... what is the general form of:

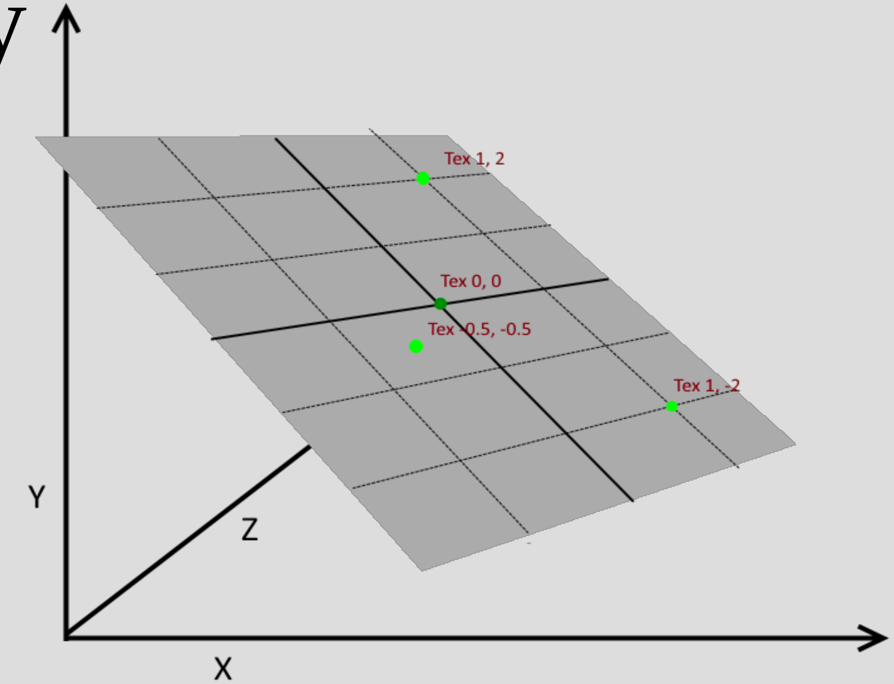
$$w_1 x + w_2 \cdot y + w_3 \cdot z > c$$

Perceptrons

But wait... what is the general form of:

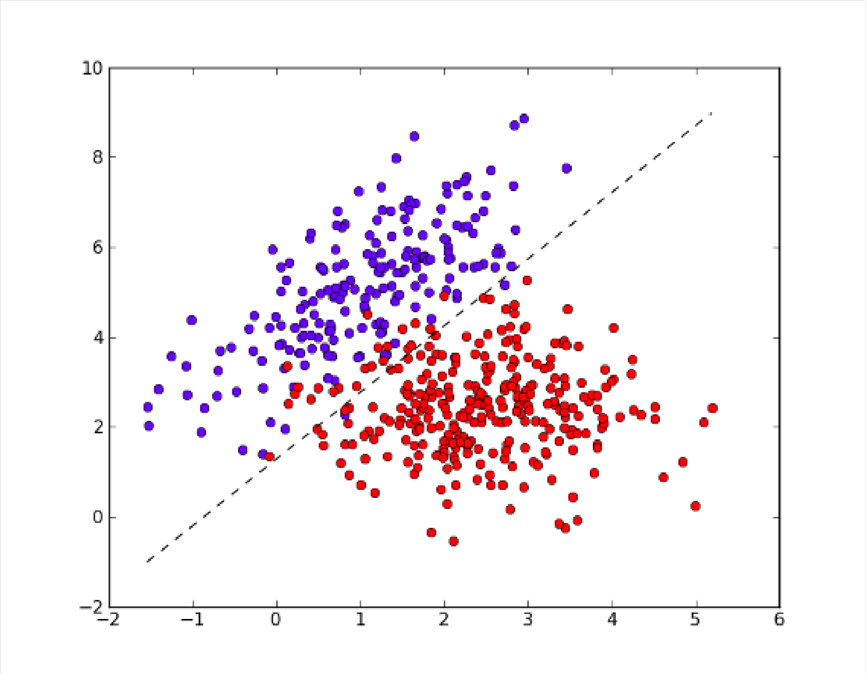
$$w_1 x + w_2 \cdot y + w_3 \cdot z > c$$

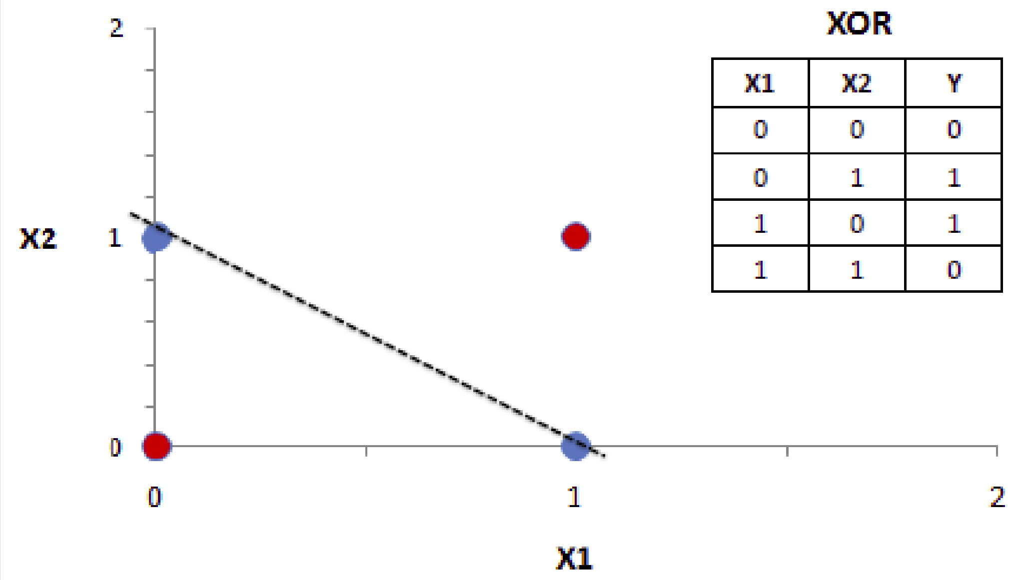
This is simply one side of a plane in 3D, so this is trying to classify all possible points using a single plane...



Perceptrons

If we had only 2 inputs, it would be everything above a line in 2D, but consider XOR on right





X1	X2	Y
0	0	0
0	1	1
1	0	1
1	1	0

There is no way a line can possibly classify this (limitation of perceptron)

Neural network: feed-forward

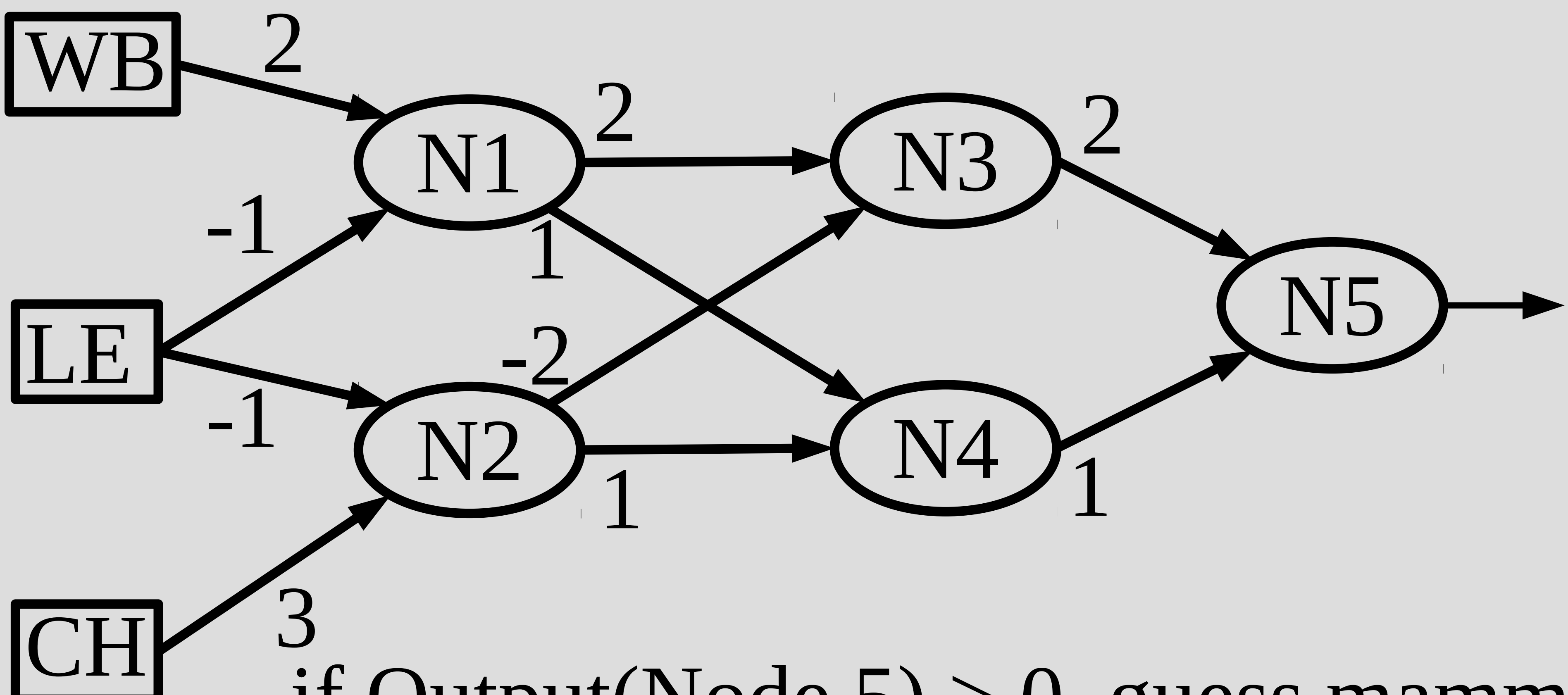
Today we will look at <u>feed-forward</u> NN, where information flows in a single direction

<u>Recurrent</u> networks can have outputs of one node loop back to inputs as previous

This can cause the NN to not converge on an answer (ask it the same question and it will respond differently) and also has to maintain some “initial state” (all around messy)

Neural network: feed-forward

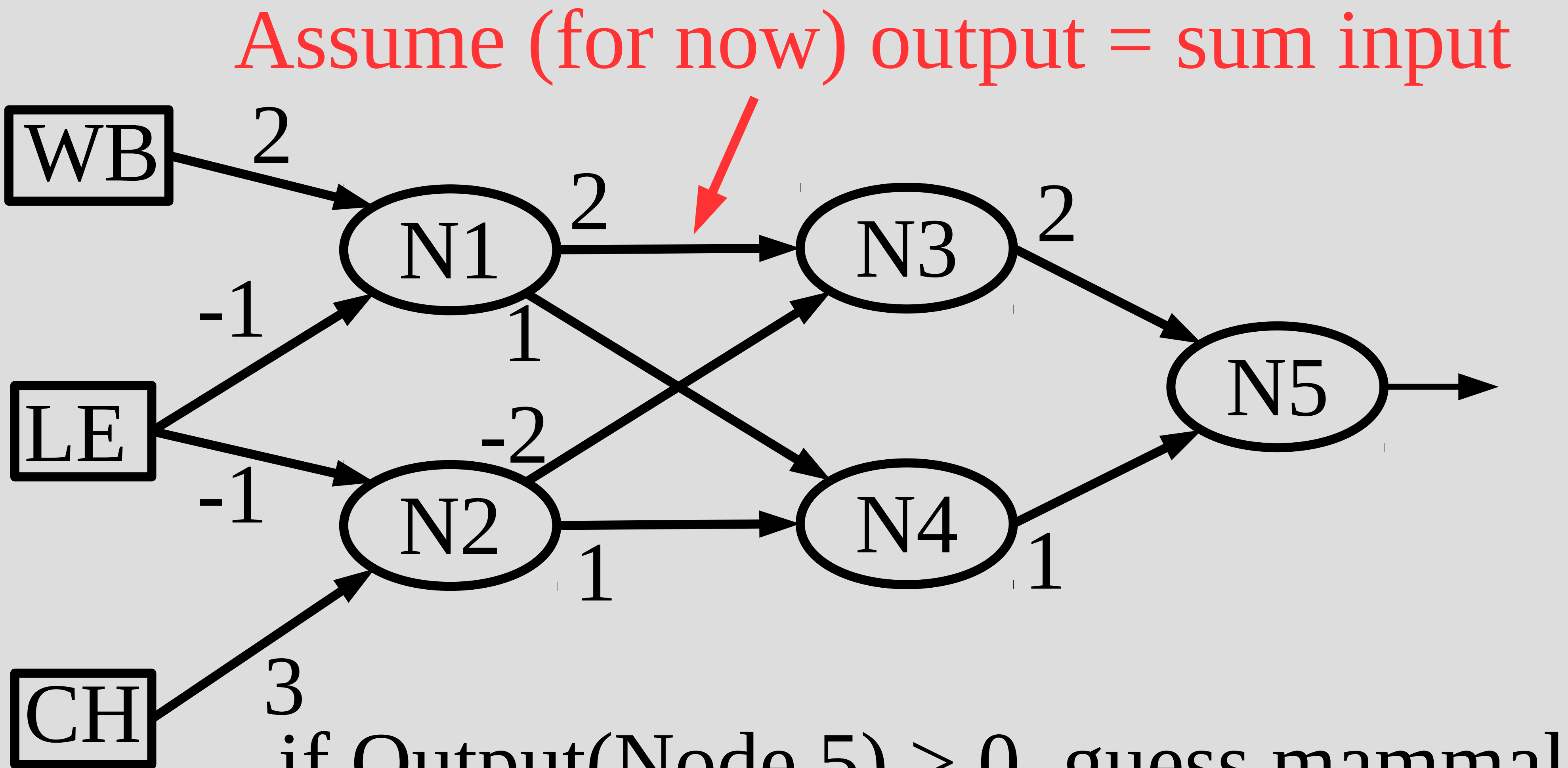
Let's expand our mammal classification to 5 nodes in 3 layers (weights on edges):



if Output(Node 5) > 0, guess mammal

Neural network: feed-forward

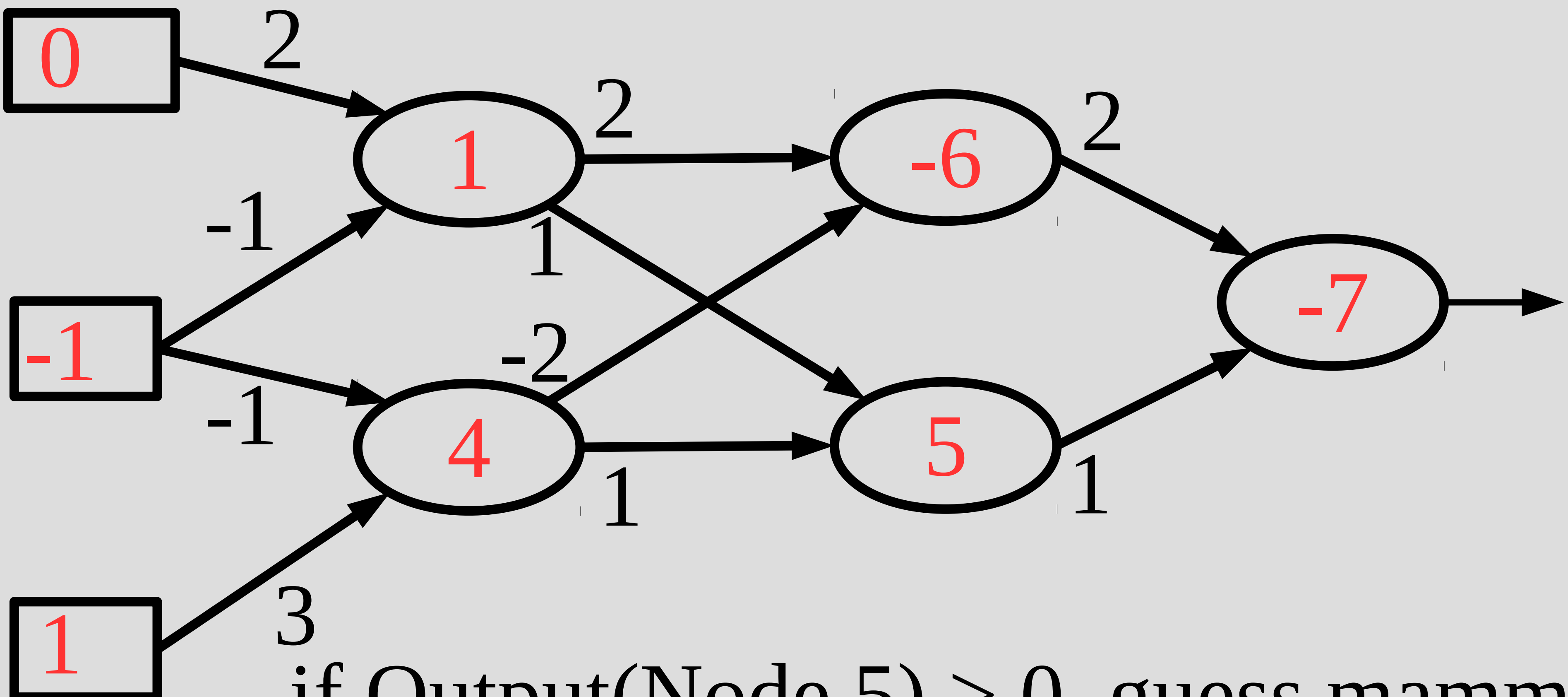
You try Bat on this:{WB=0, LE=-1, CH=1}



if Output(Node 5) > 0, guess mammal

Neural network: feed-forward

Output is -7, so bats are not mammal... Oops...



if Output(Node 5) > 0, guess mammal

Neural network: feed-forward

In fact, this is no better than our 1 node NN

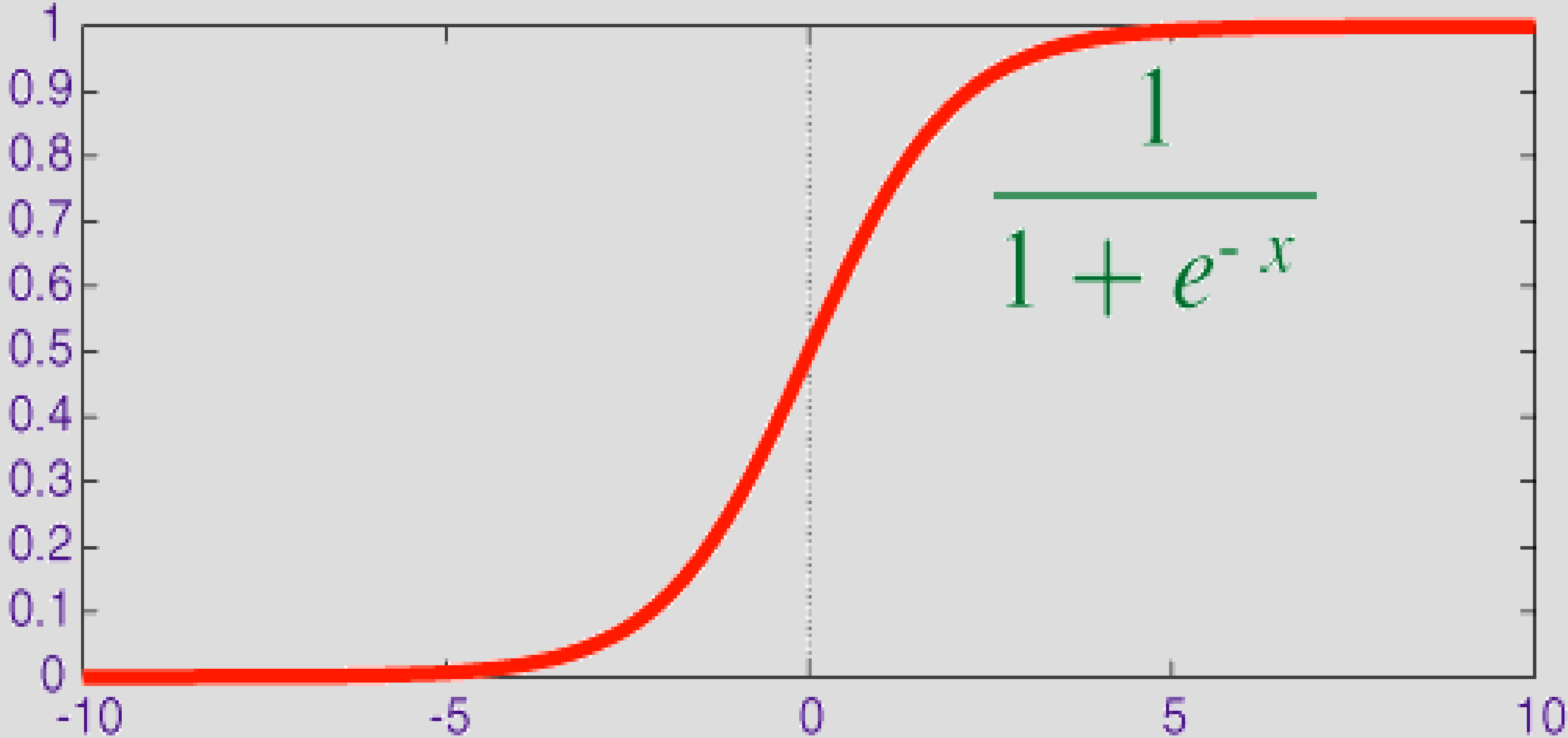
This is because we simply output a linear combination of weights into a linear function (i.e. if f(x) and g(x) are linear... then g(x)+f(x) is also linear)

Ideally, we want a activation function that has a limited range so large signals do not always dominate

Neural network: feed-forward

One commonly used function is the sigmoid:

$$S(x) = \frac{1}{1+e^{-x}}$$



Back-propagation

The neural network is as good as it's structure and weights on edges

Structure we will ignore (more complex), but there is an automated way to learn weights

Whenever a NN incorrectly answer a problem, the weights play a “blame game”...

- Weights that have a big impact to the wrong answer are reduced

Back-propagation

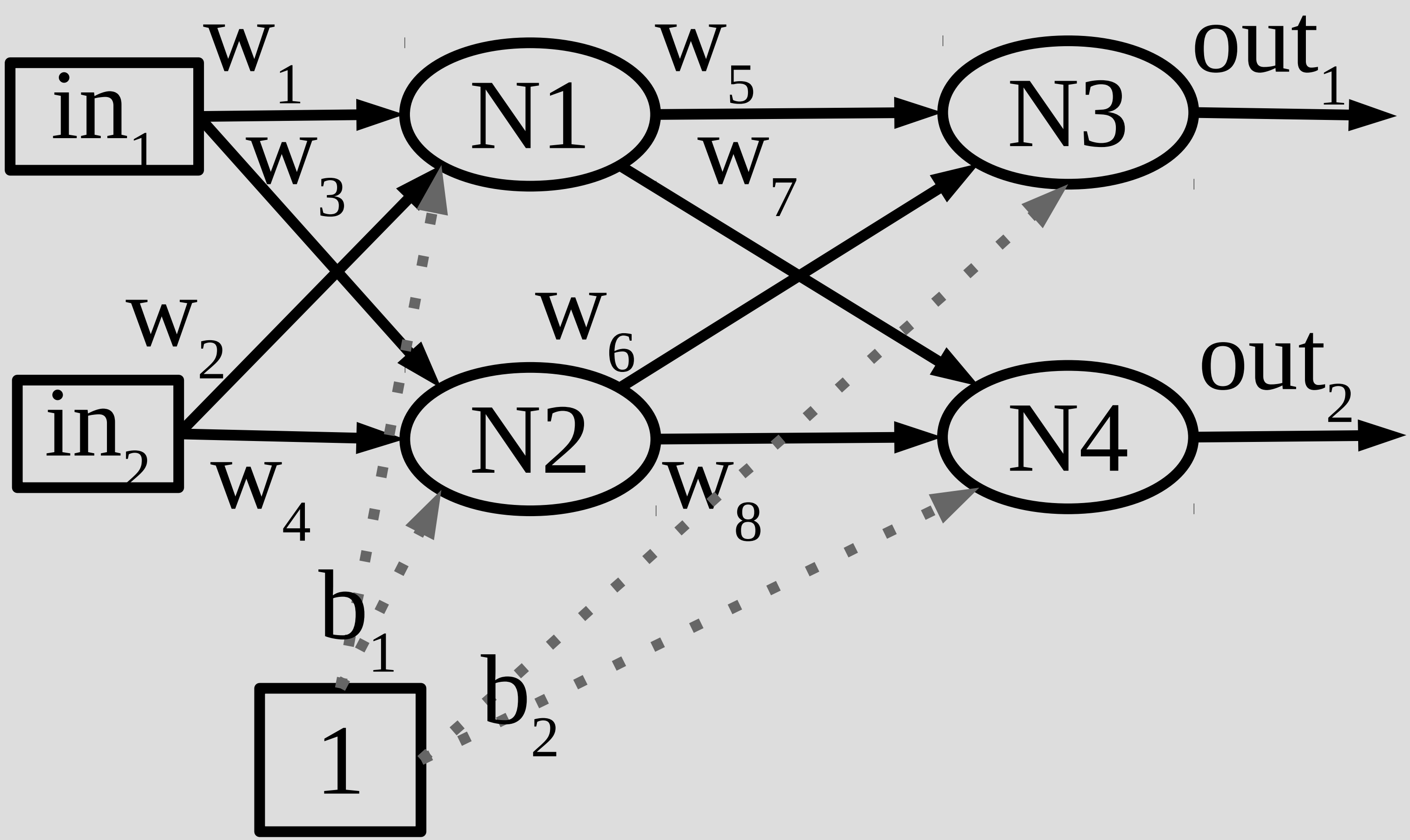
To do this blaming, we have to find how much each weight influenced the final answer

Steps:

1. Find total error
2. Find derivative of error w.r.t. weights
3. Penalize each weight by an amount proportional to this derivative

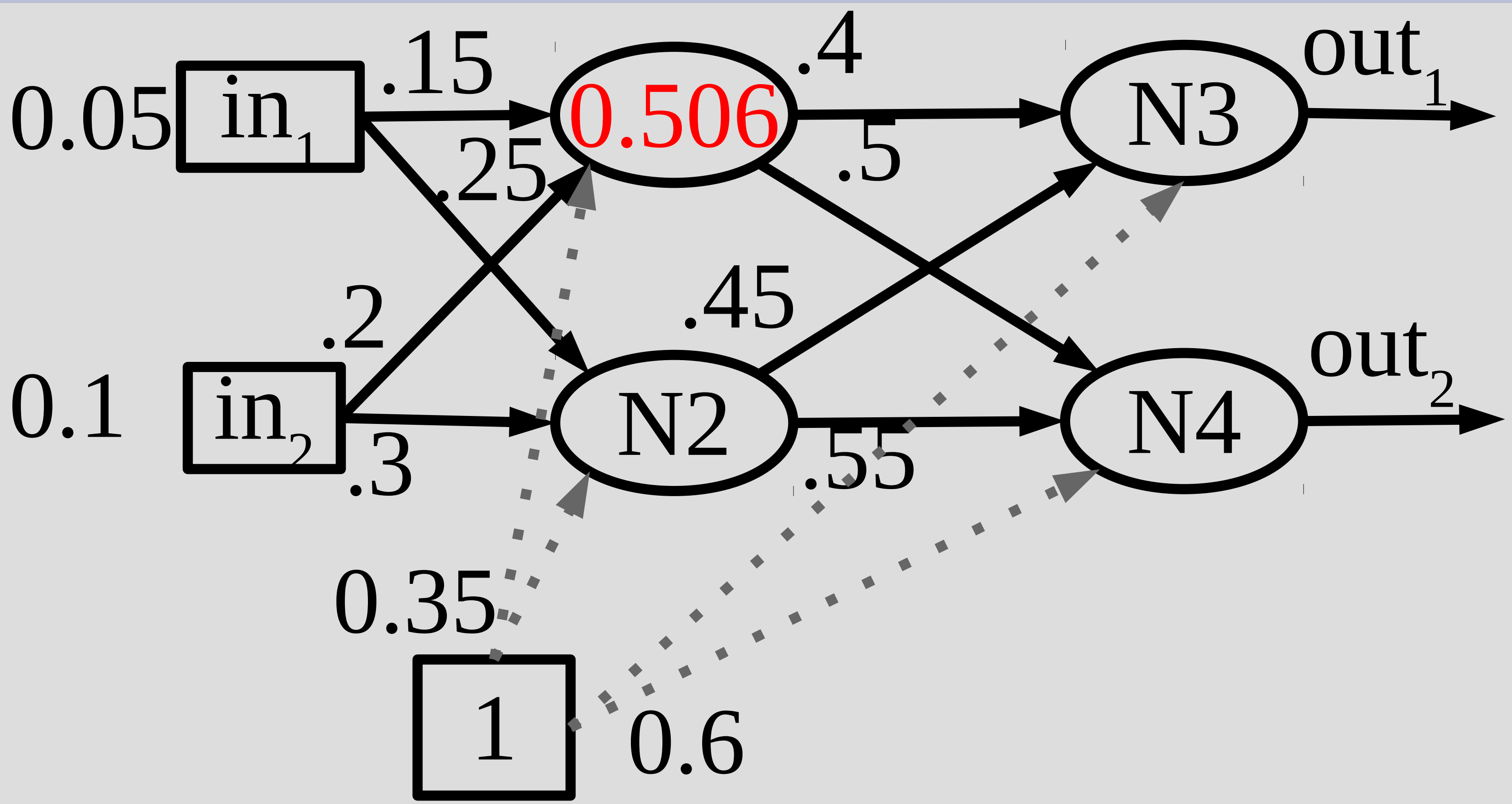
Back-propagation

Consider this example: 4 nodes, 2 layers



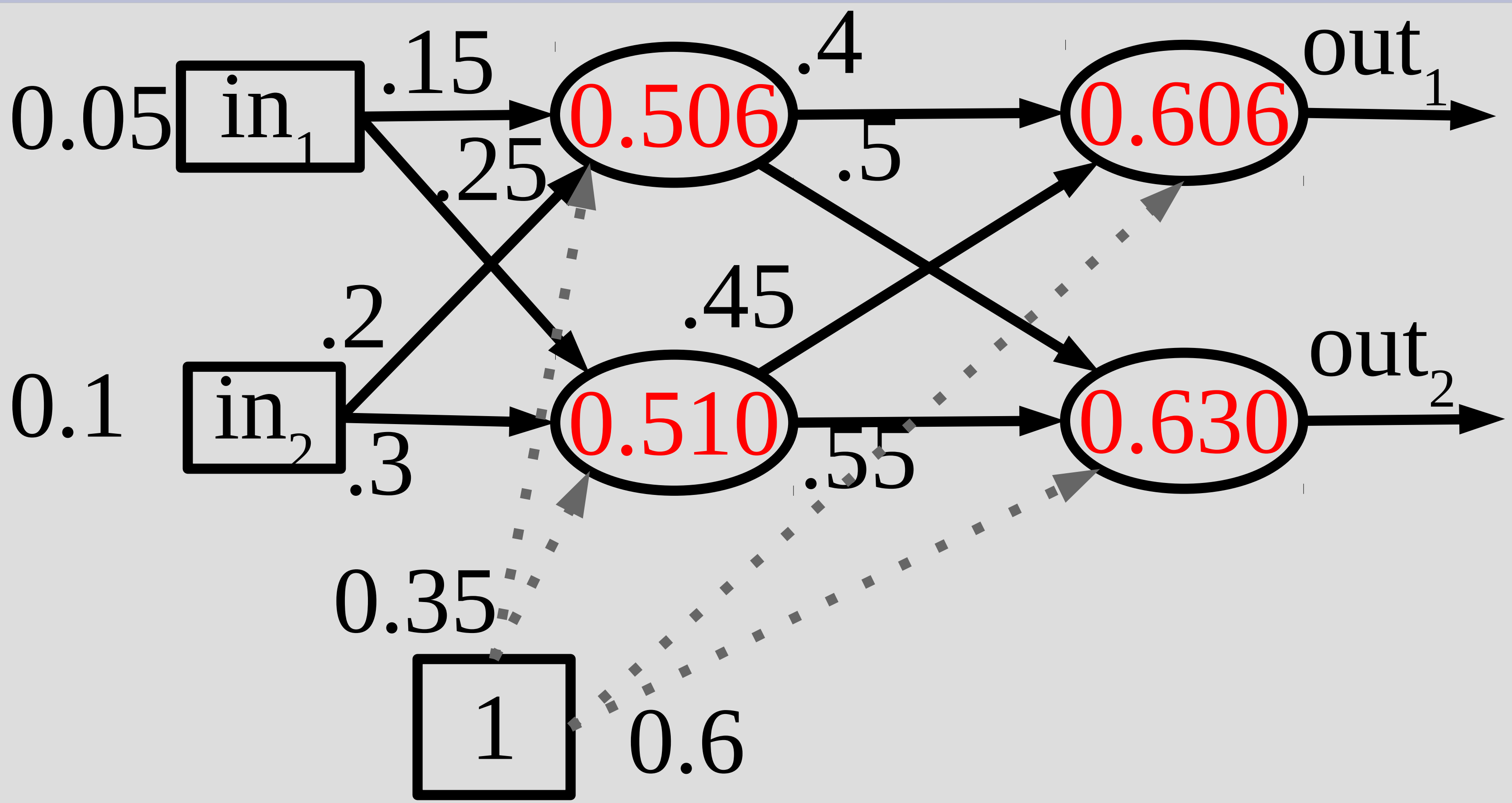
This node as a constant bias of 1

Back-propagation



Node 1: 0.15*0.05 + 0.2*0.1 = 0.35 as input thus it outputs (all edges) S(0.35)=0.59327

Back-propagation



Eventually we get: $out_1 = 0.606$, $out_2 = 0.630$

Suppose wanted: $out_1 = 0.01$, $out_2 = 0.99$

Back-propagation

We will define the error as: $\frac{\sum_i (correct_i - output_i)^2}{2}$
(you will see why shortly)

Suppose we want to find how much w_5 is to blame for our incorrectness

We then need to find: $\frac{\partial Error}{\partial w_5}$
Apply the chain rule:

$$\frac{\partial Error}{\partial out_1} \cdot \frac{\partial S(In(N_3))}{\partial In(N_3)} \cdot \frac{\partial In(N_3)}{\partial w_5}$$

Back-propagation

$$Error = \frac{\sum_i (correct_i - output_i)^2}{2}$$

$$\frac{\partial Error}{\partial out_1} = -(correct_1 - out_1)$$
$$= -(0.01 - 0.606) = 0.596$$

As $S'(x) = S(x) \cdot (1 - S(x))$

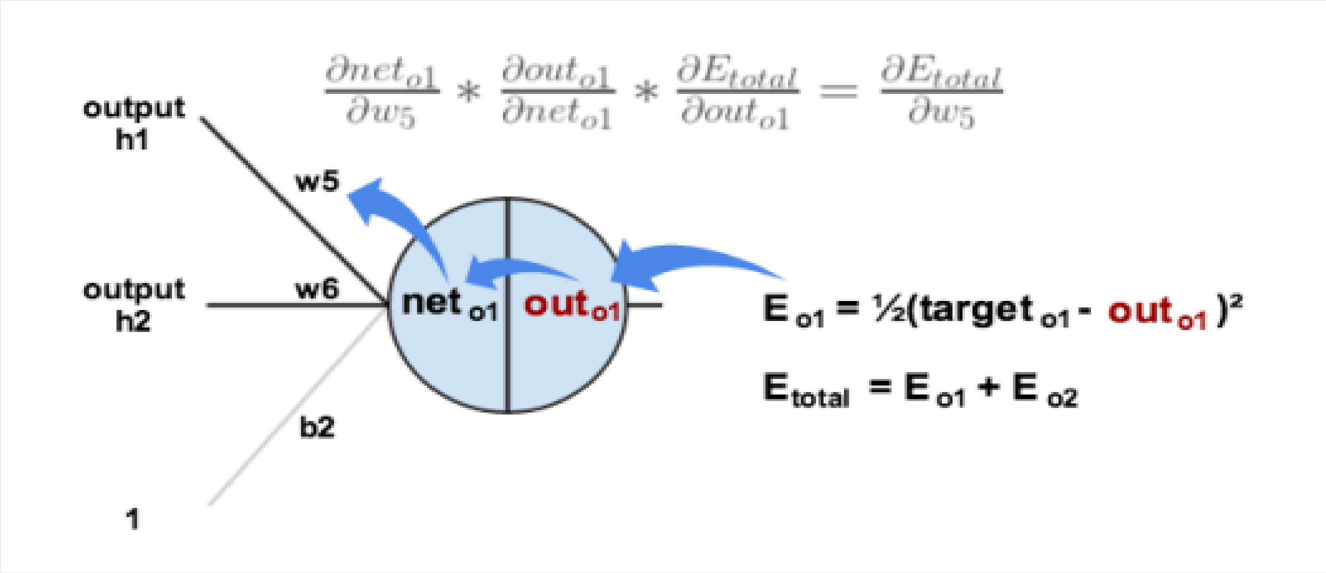
$$\frac{\partial S(In(N_3))}{\partial In(N_3)} = S(In(N_3)) \cdot (1 - S(In(N_3)))$$
$$= 0.606 \cdot (1 - 0.606) = 0.214$$

$$\frac{\partial In(N_3)}{\partial w_5} = \frac{\partial w_5 \cdot Out(N_1) + w_6 \cdot Out(N_2) + b_2 \cdot 1}{\partial w_5}$$
$$= Out(N_1) = 0.506$$

Thus, $\frac{\partial Error}{\partial w_5} = 0.596 \cdot 0.214 \cdot 0.506 = 0.0645$

Back-propagation

In a picture we did this:



Now that we know w5 is 0.08217 part responsible, we update the weight by:

$w_5 \leftarrow w_5 - \alpha * 0.0645 = 0.374$ (from 0.4)

α is learning rate, set to 0.5

Back-propagation

Updating this w_5 to w_8 gives:

$w_5 = 0.3589$

$w_6 = 0.4067$

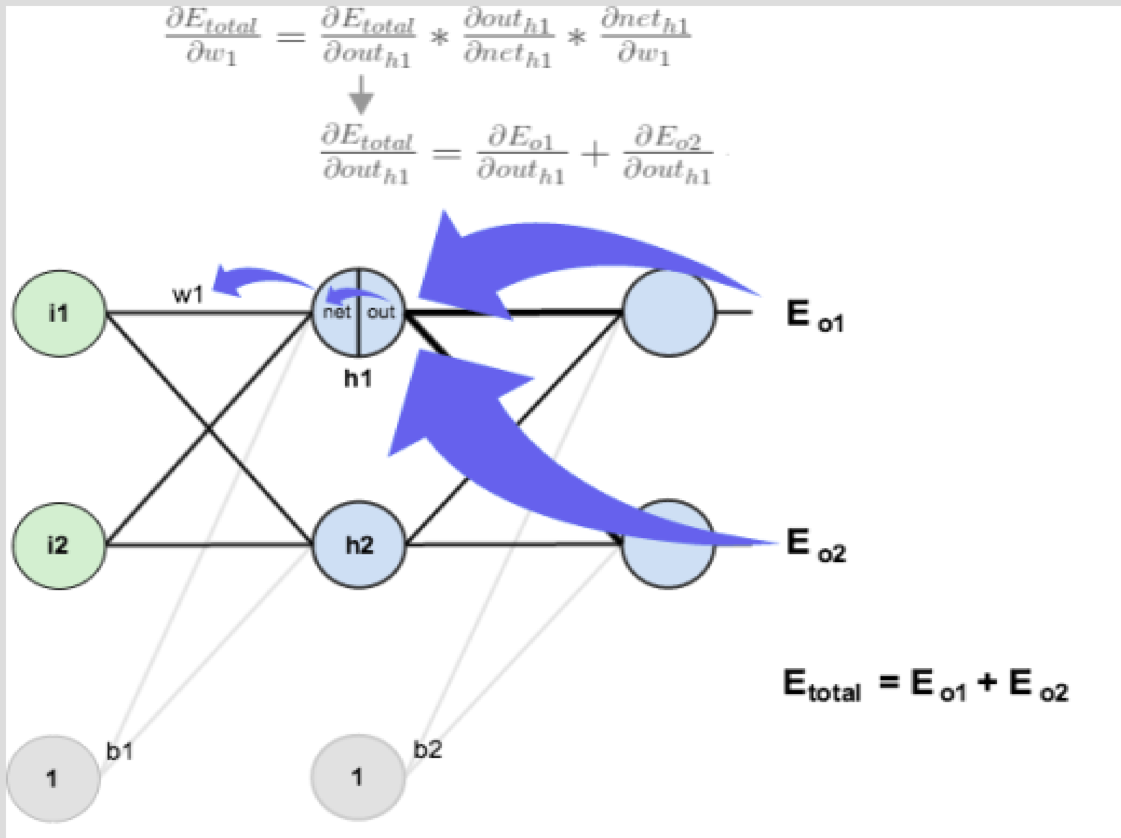
$w_7 = 0.5113$

$w_8 = 0.5614$

For other weights, you need to consider all possible ways in which they contribute

Back-propagation

For w_1 it would look like:



(book describes how to dynamic program this)

Back-propagation

Specifically for w_1 you would get:

$$\frac{\partial Error}{\partial S(In(N_1))} = \frac{\partial Error_1}{\partial S(In(N_1))} + \frac{\partial Error_2}{\partial S(In(N_1))}$$

$$\frac{\partial S(In(N_1))}{\partial In(N_1)} = S(In(N_1)) \cdot (1 - S(In(N_1))$$
$$= 0.506 \cdot (1 - 0.506) = 0.250$$

$$\frac{\partial In(N_3)}{\partial w_5} = \frac{\partial w_1 \cdot In_1 + w_2 \cdot In_2 + b_1 \cdot 1}{\partial w_5}$$
$$= In_1 = 0.05$$

Next we have to break down the top equation...

Back-propagation

$$\frac{\partial Error}{\partial S(In(N_1))} = \frac{\partial Error_1}{\partial S(In(N_1))} + \frac{\partial Error_2}{\partial S(In(N_1))}$$

$$\frac{\partial Error_1}{\partial S(In(N_1))} = \frac{\partial Error_1}{\partial S(In(N_3))} \cdot \frac{\partial S(In(N_3))}{\partial In(N_3)} \cdot \frac{\partial In(N_3)}{\partial S(In(N_1))}$$

From before... $\frac{\partial Error_1}{\partial S(In(N_3))} \cdot \frac{\partial S(In(N_3))}{\partial In(N_3)}$
$= 0.596 \cdot 0.214 = 0.128$

$$\frac{\partial In(N_3)}{\partial S(In(N_1))} = \frac{\partial w_5 \cdot S(In(N_1)) + w_6 \cdot S(In(N_2)) + b_1 \cdot 1}{\partial S(In(N_1))}$$
$$= w_5 = 0.4$$

Thus, $\frac{\partial Error_1}{\partial S(In(N_1))} = 0.128 \cdot 0.4 = 0.0510$

Back-propagation

Similarly for Error_2 we get:

$$\frac{\partial Error}{\partial S(In(N_1))} = \frac{\partial Error_1}{\partial S(In(N_1))} + \frac{\partial Error_2}{\partial S(In(N_1))}$$
$$= 0.0510 + -0.0190 = 0.0320$$

Thus, $\frac{\partial Error}{\partial w_1} = 0.0320 \cdot 0.250 \cdot 0.05 = 0.000400$

Update $w_1 \leftarrow w_1 - \alpha \frac{\partial Error}{\partial w_1} = 0.15 - 0.5 \cdot 0.0004 = 0.1498$

You might notice this is small...
This is an issue with neural networks, deeper the network the less earlier nodes update