


March 2016



Mainstream Media



tagesthemen 



1997





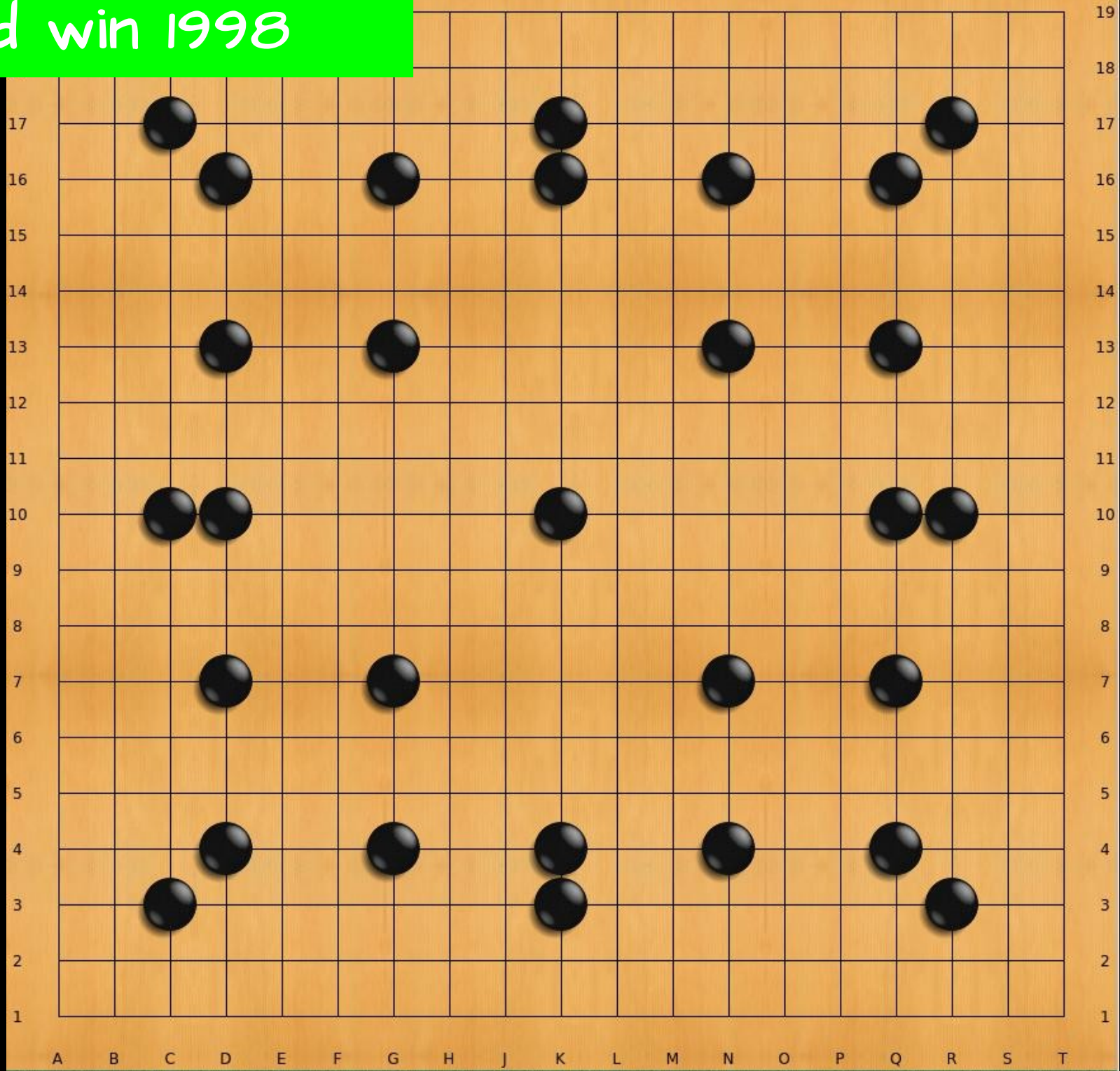
2000 “應氏杯” 世界電腦圍棋錦標賽
2000 ING CUP WORLD COMPUTER GOE CHAMPIONSHIP

主辦：應昌期圍棋教育基金會
承辦：貴陽市棋類協會
貴陽應氏圍棋活動中心

(1985-2000)



5d win 1998



October 2015



January 2016

This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

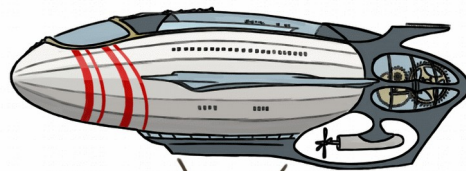
Silver, D. et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), p.484-489.

What did AlphaGo do to beat the strongest human Go player?

Tobias Pfeiffer

@PragTob

pragtob.info



bitcrowd

Go



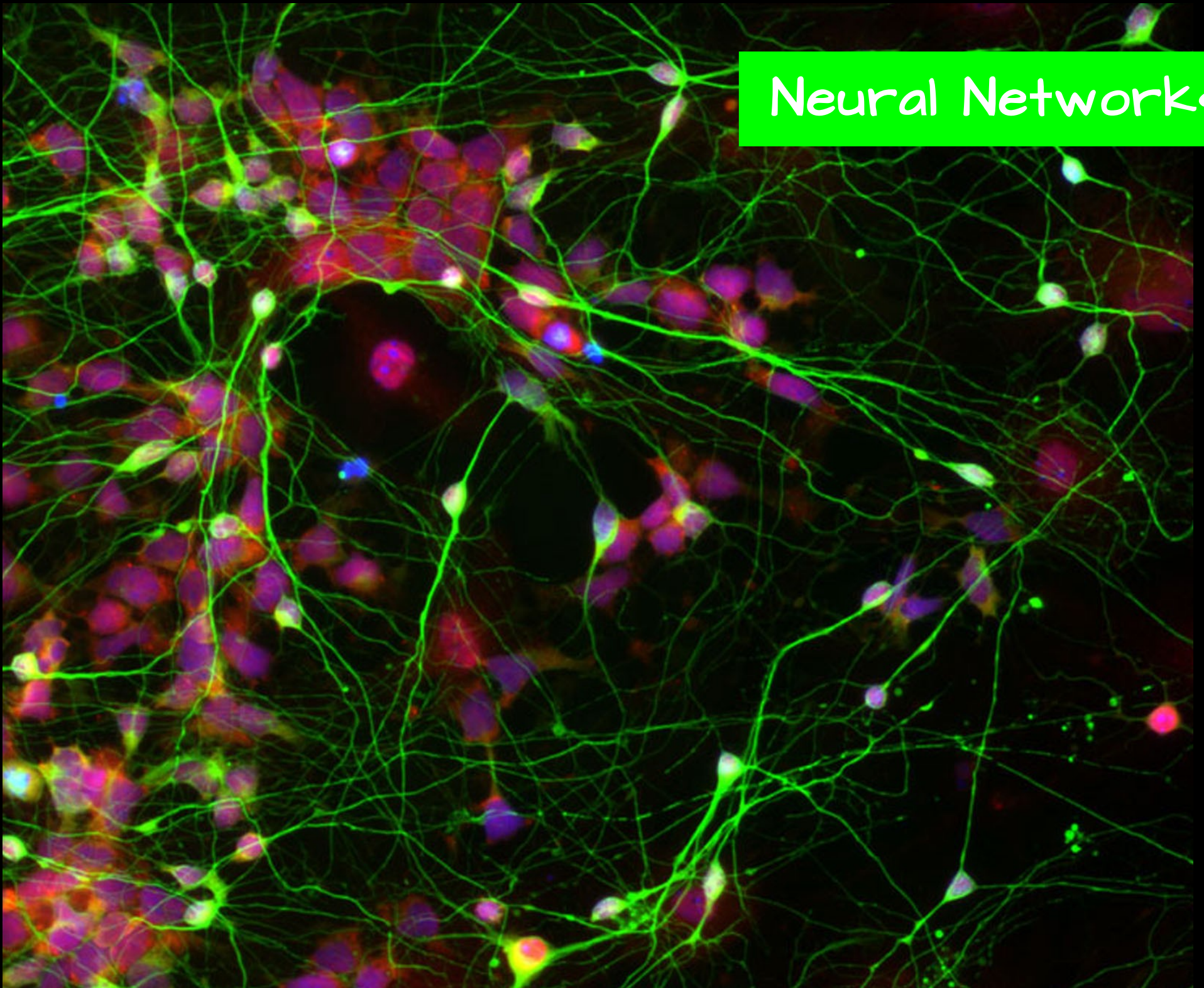


Computational Challenge

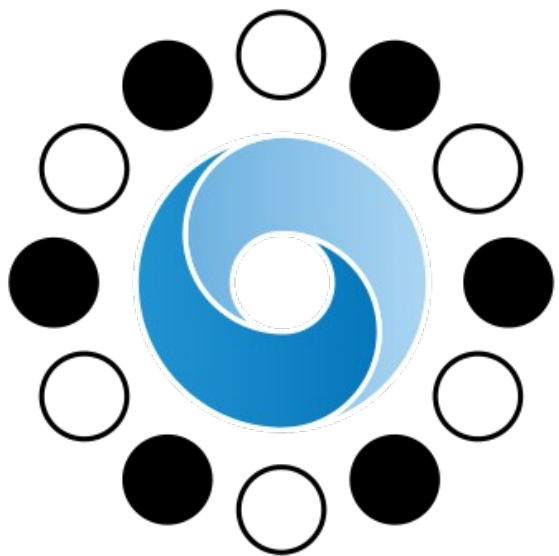
Monte Carlo Method



Neural Networks



Revolution with Neural Networks



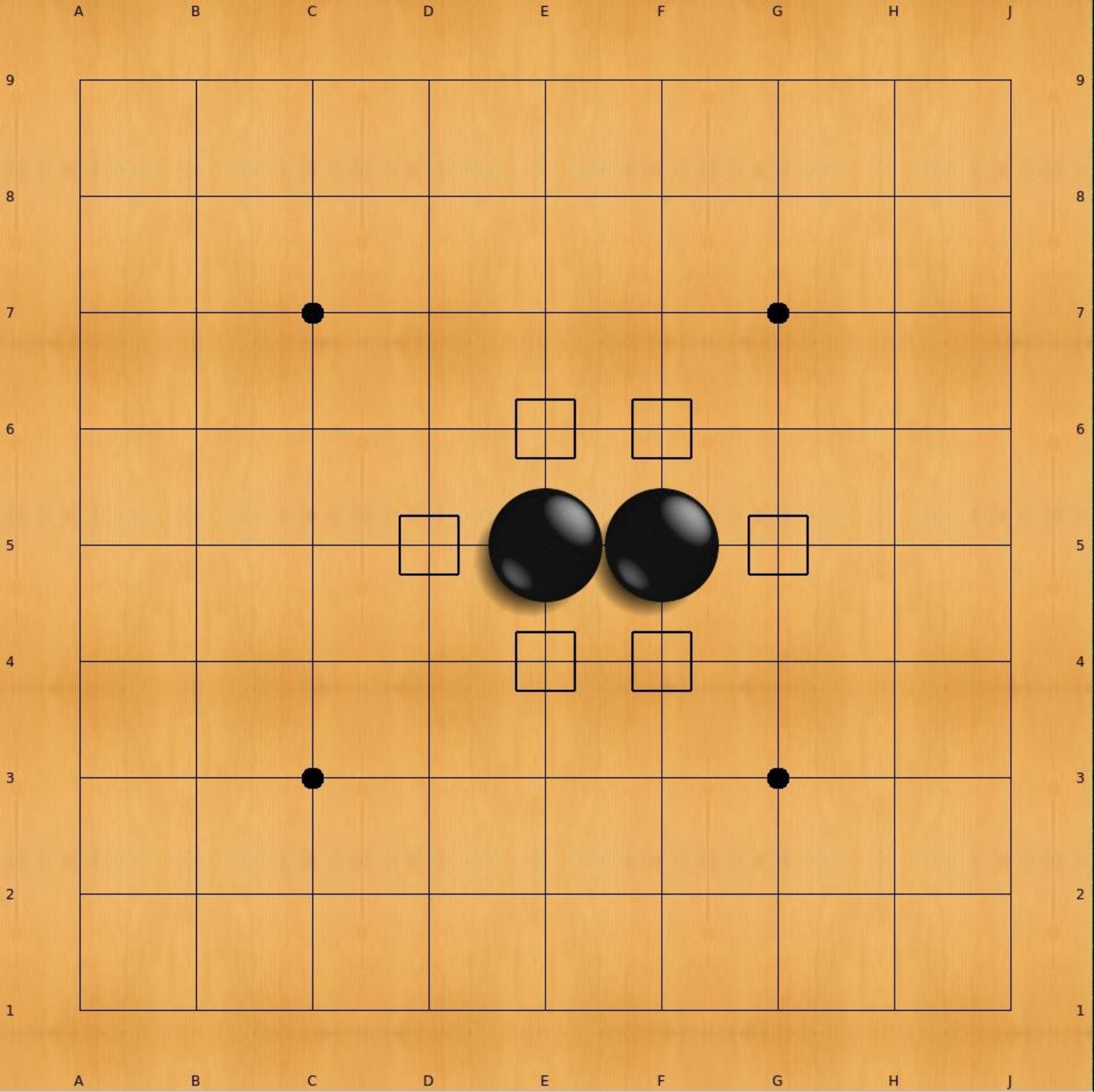
AlphaGo

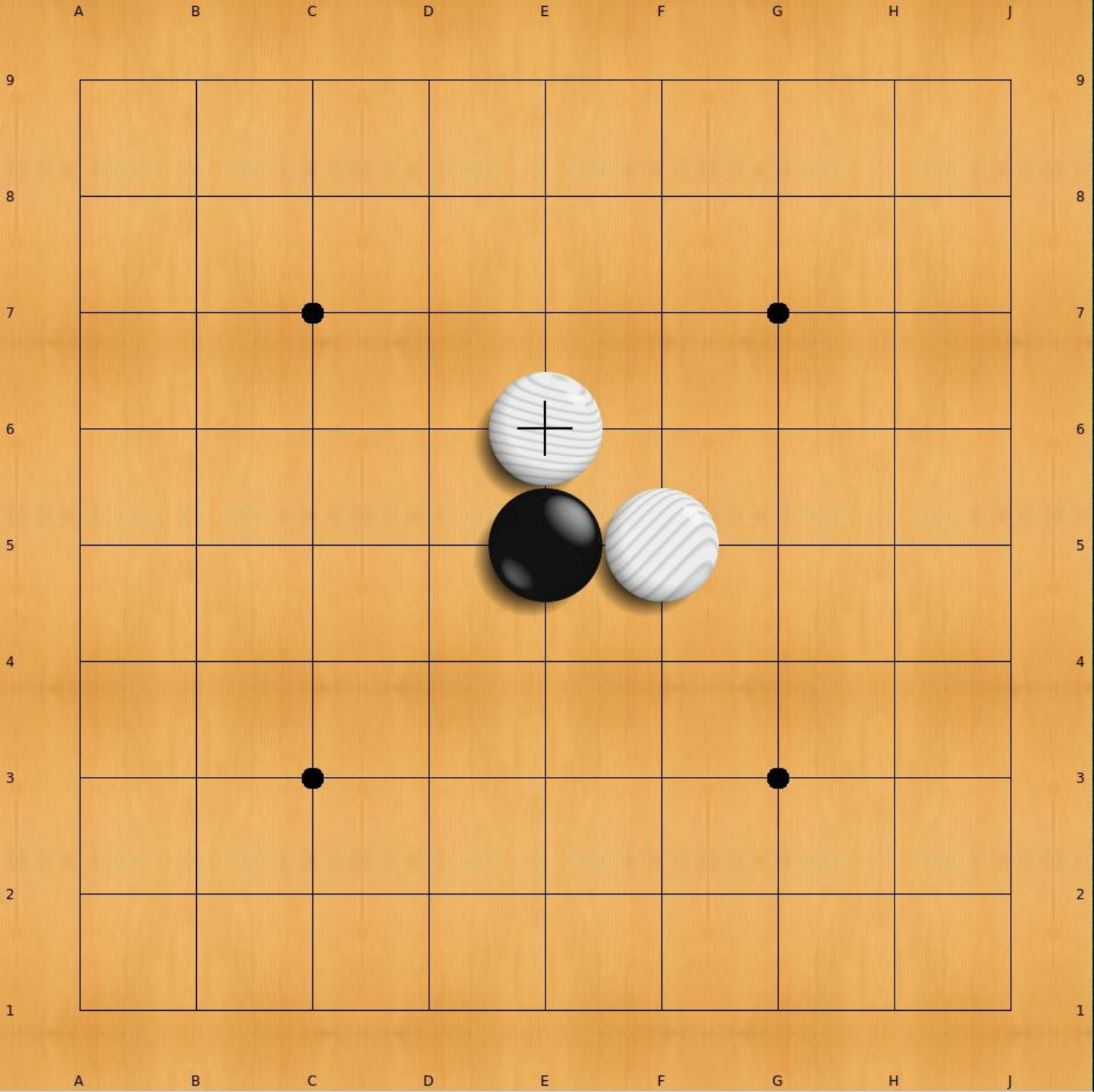
What did we learn?

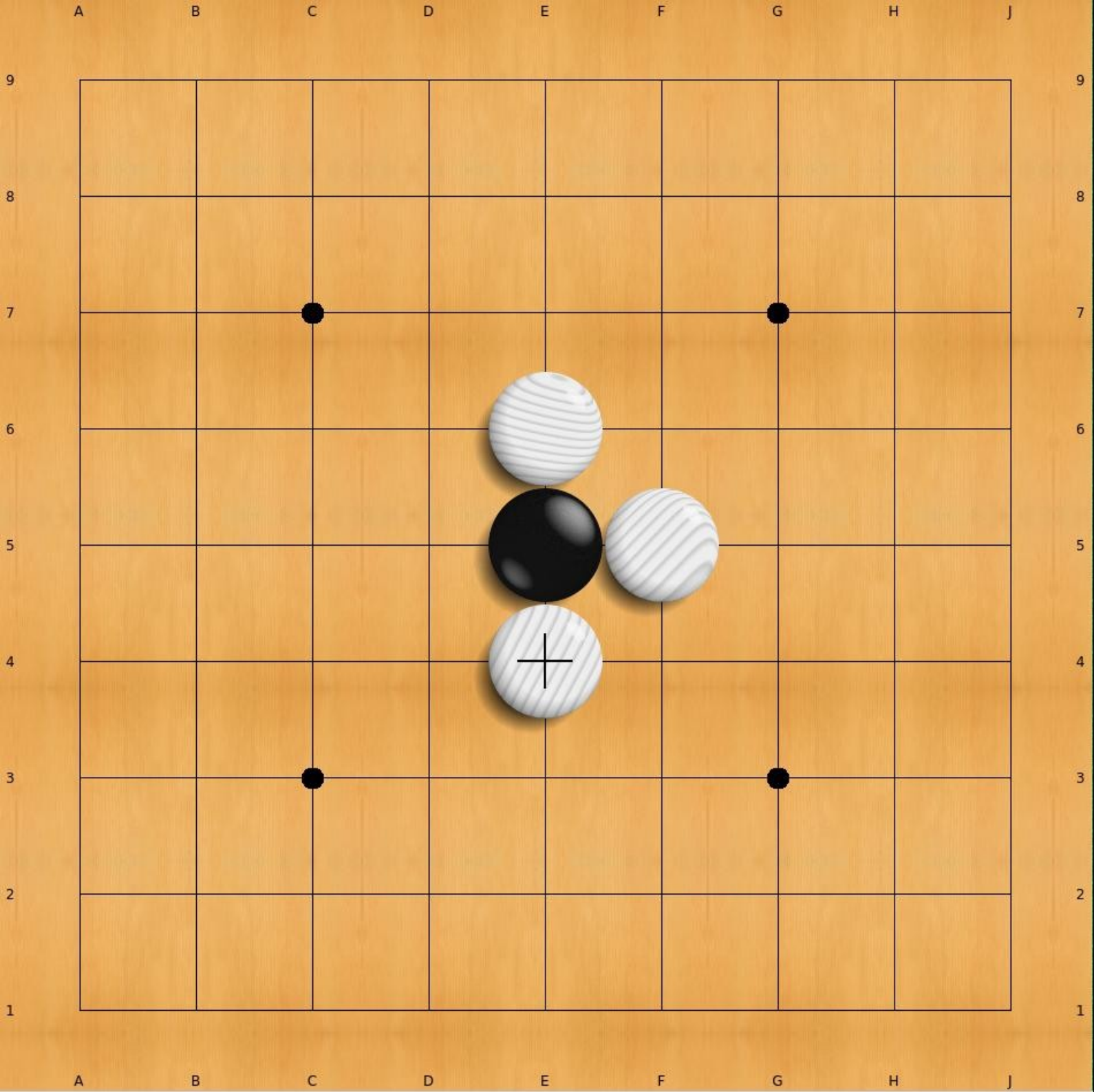


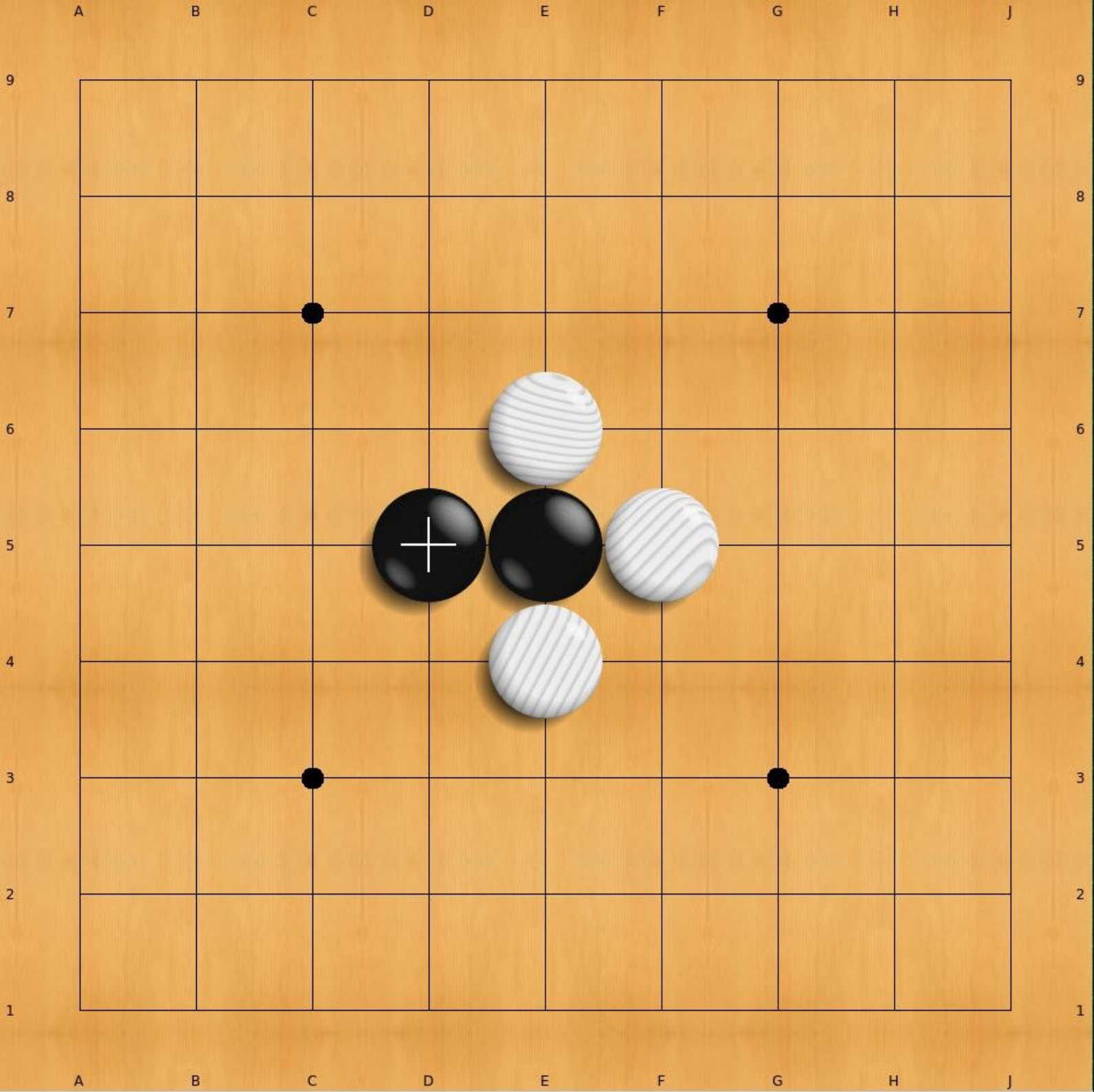
Go

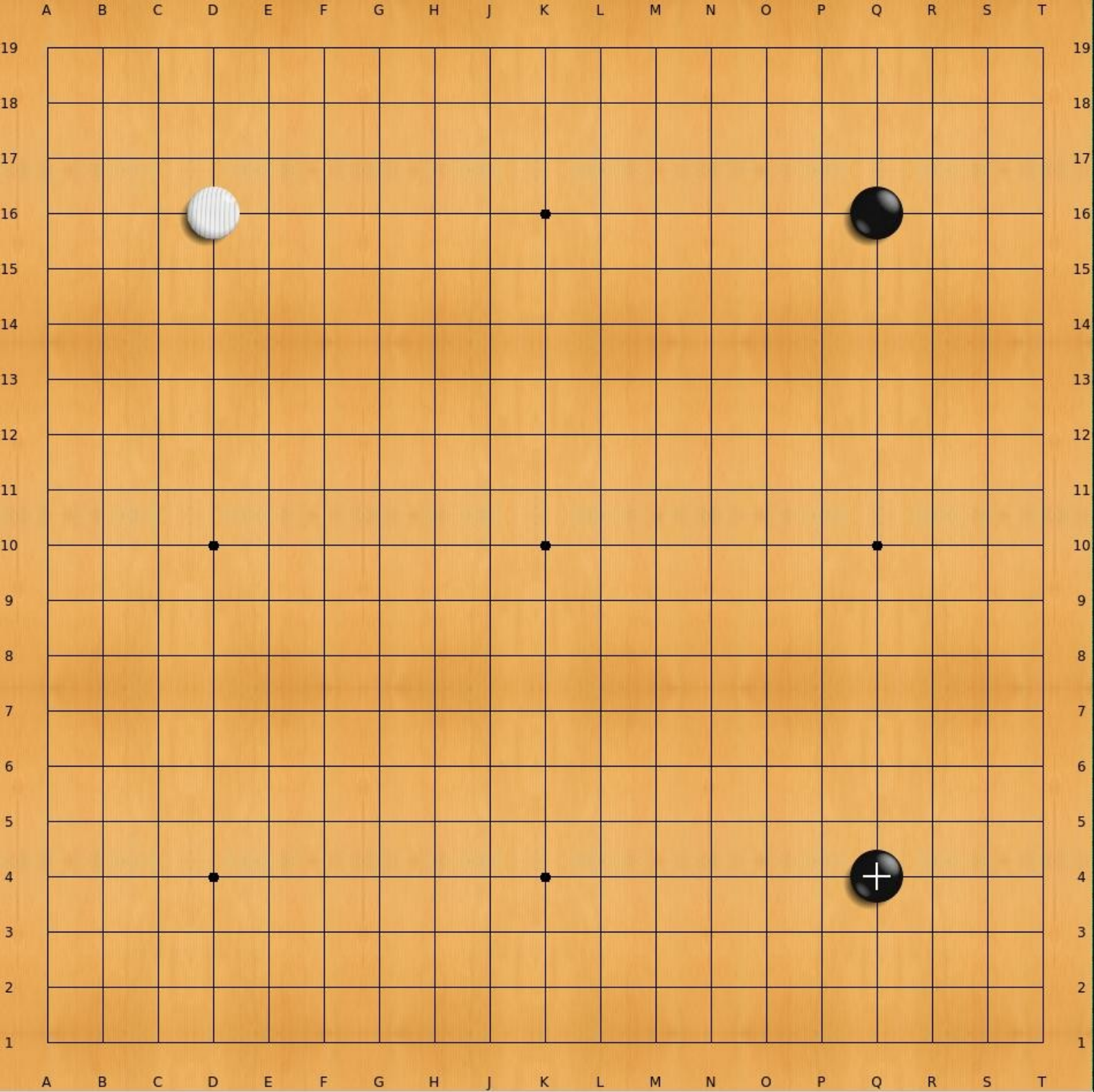


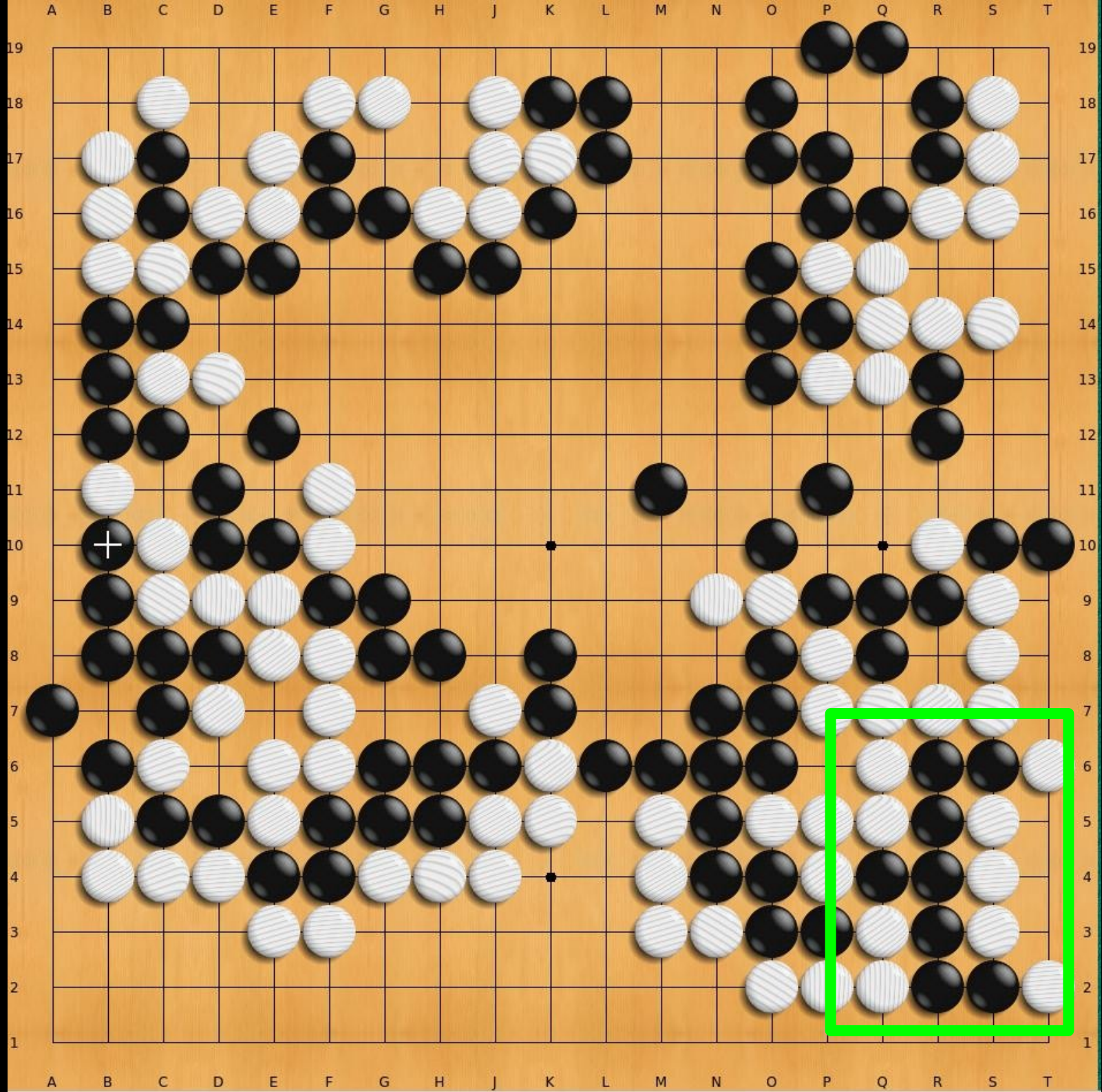


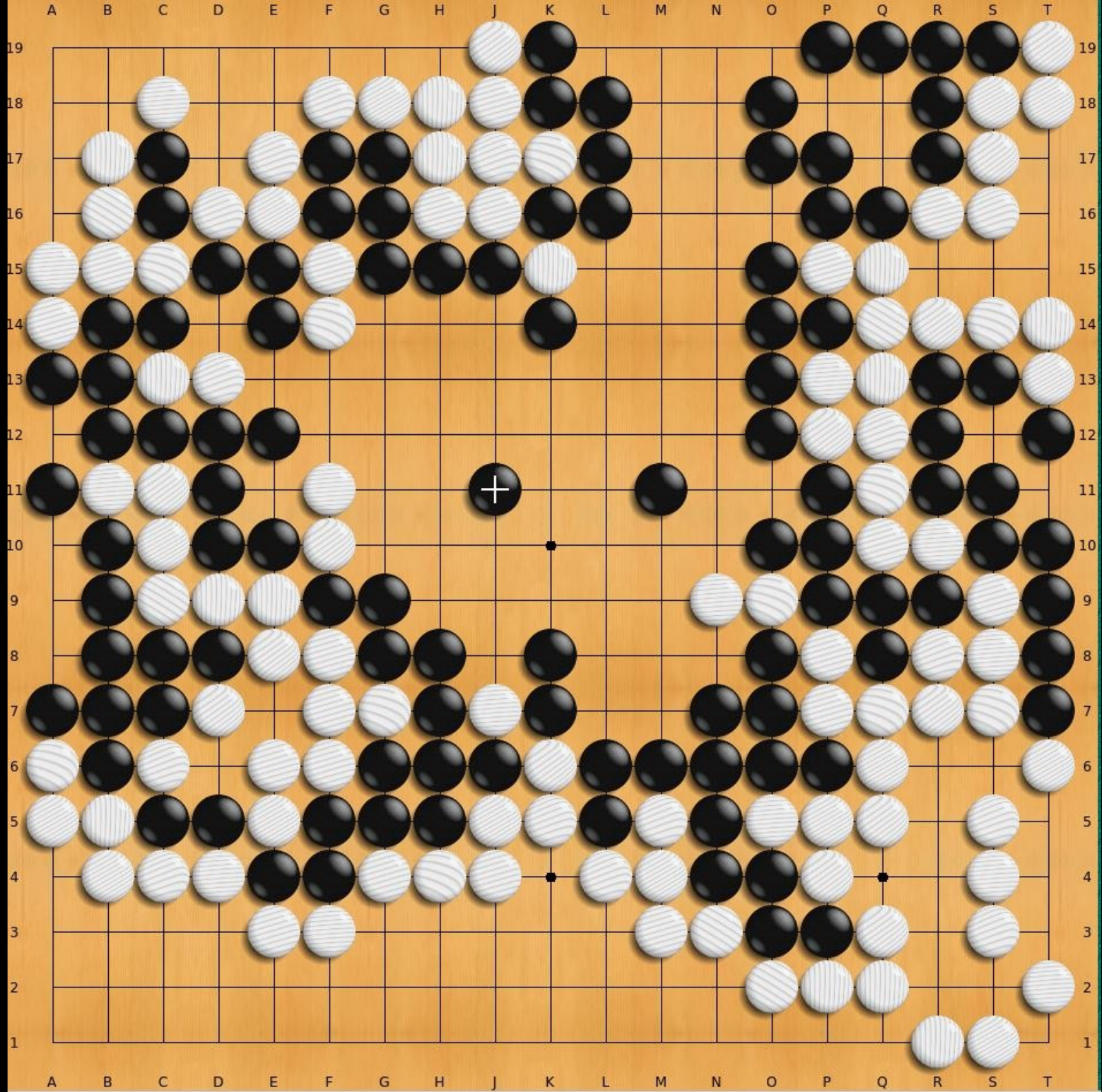


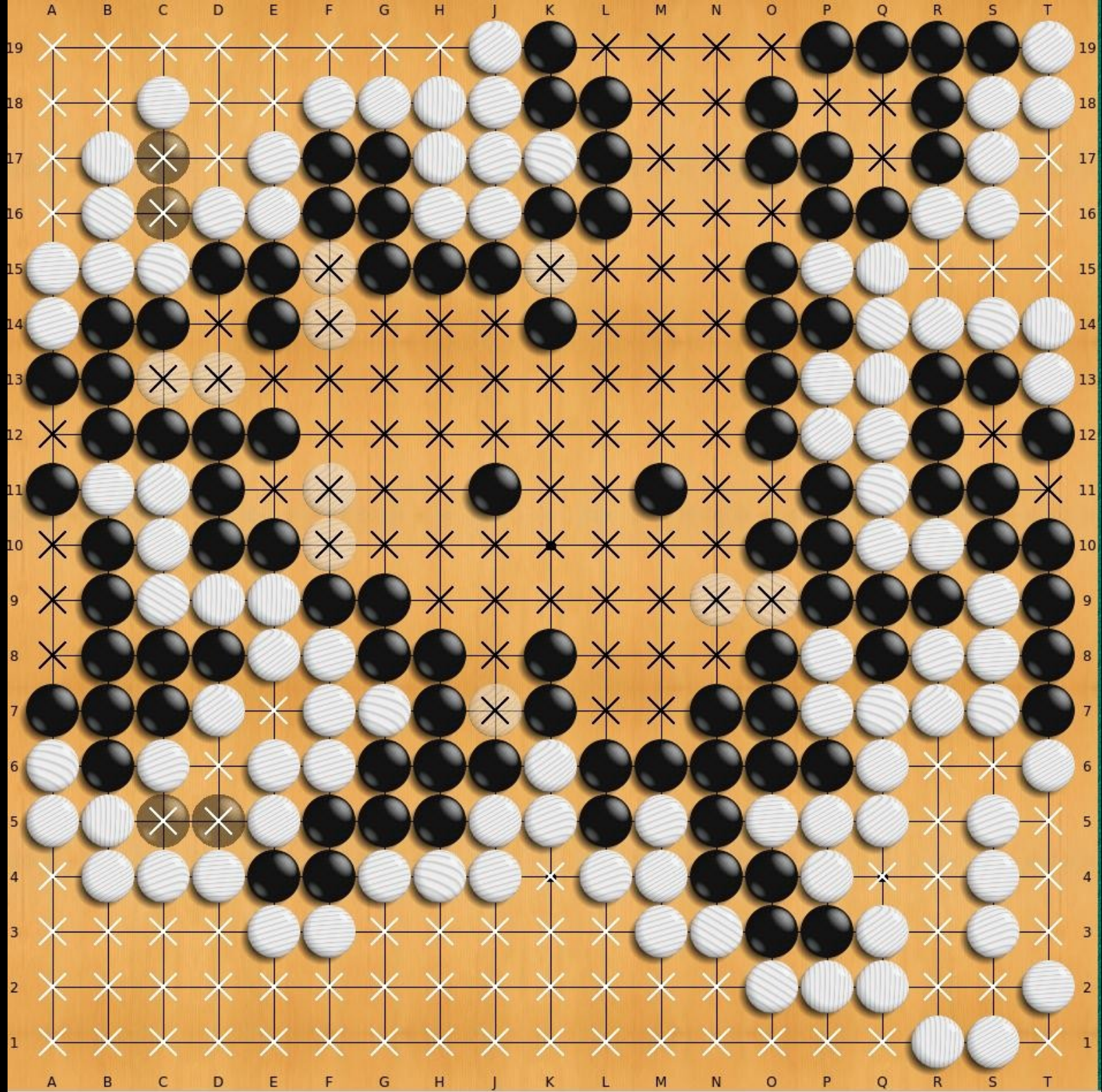















Computational Challenge

Go vs. Chess

Complex vs. Complicated

*„While the Baroque rules of **chess could only have been created by humans**, the rules of **go** are so elegant, organic, and rigorously logical that **if intelligent life forms exist** elsewhere in the universe, they almost **certainly play go.**“*

Edward Lasker (chess grandmaster)

Larger board

19x19 vs. 8x8

Almost every move is legal

Average branching factor:

250 vs 35

State Space Complexity:

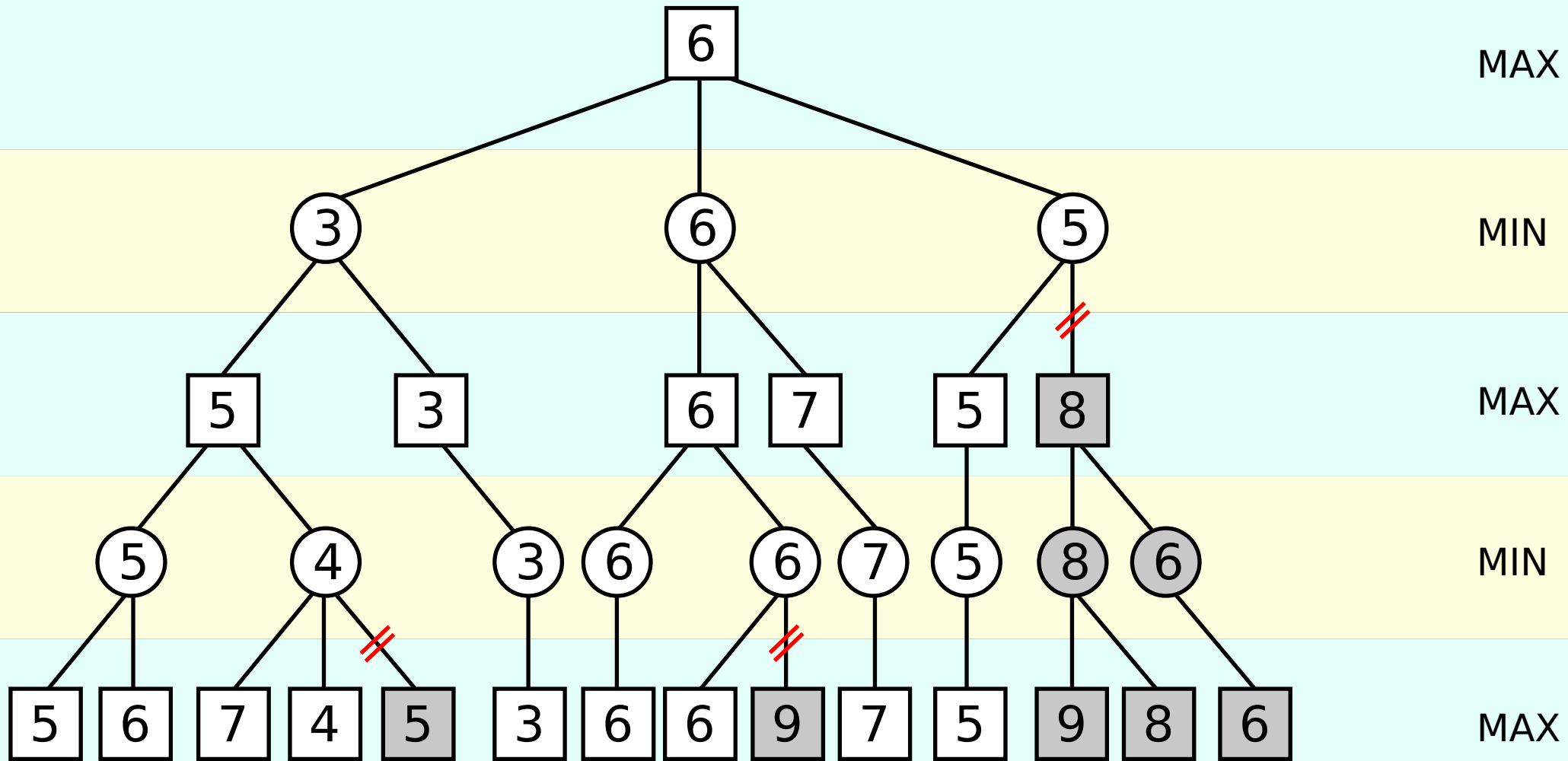
$$10^{171} \text{ vs } 10^{47}$$

10^{80}

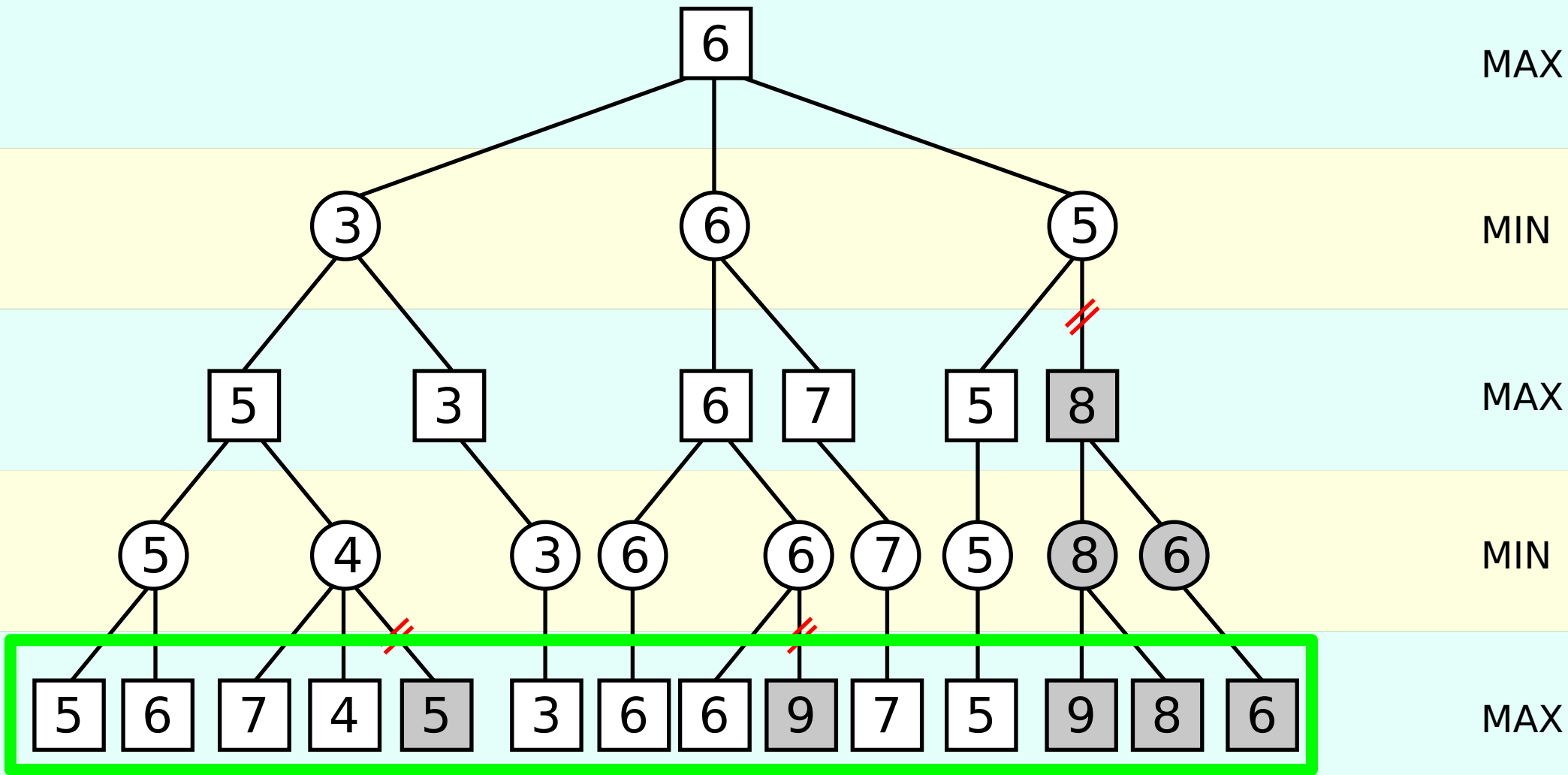


Global impact of moves

Traditional Search



Evaluation Function



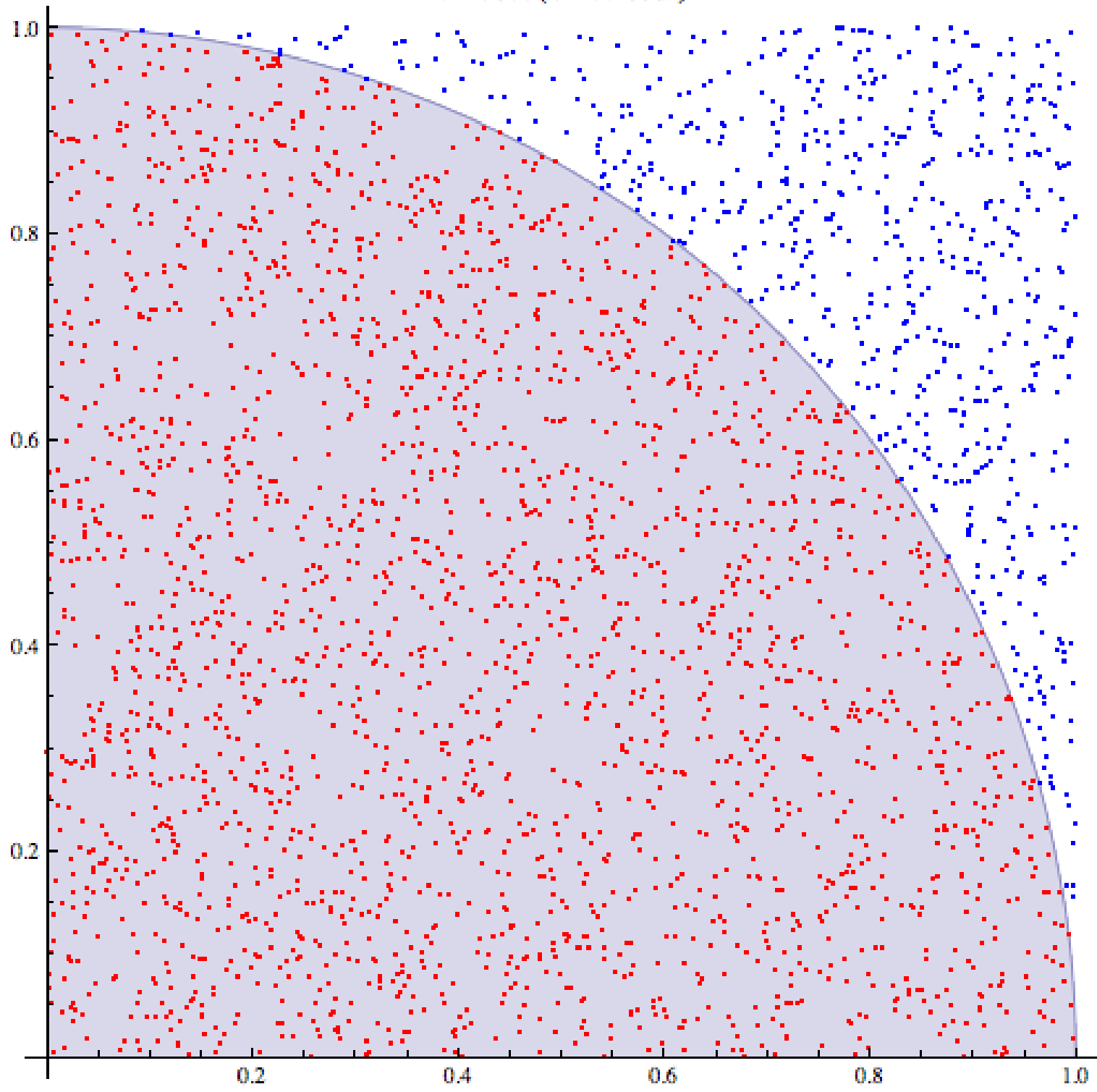
Monte Carlo Method



What is π ?

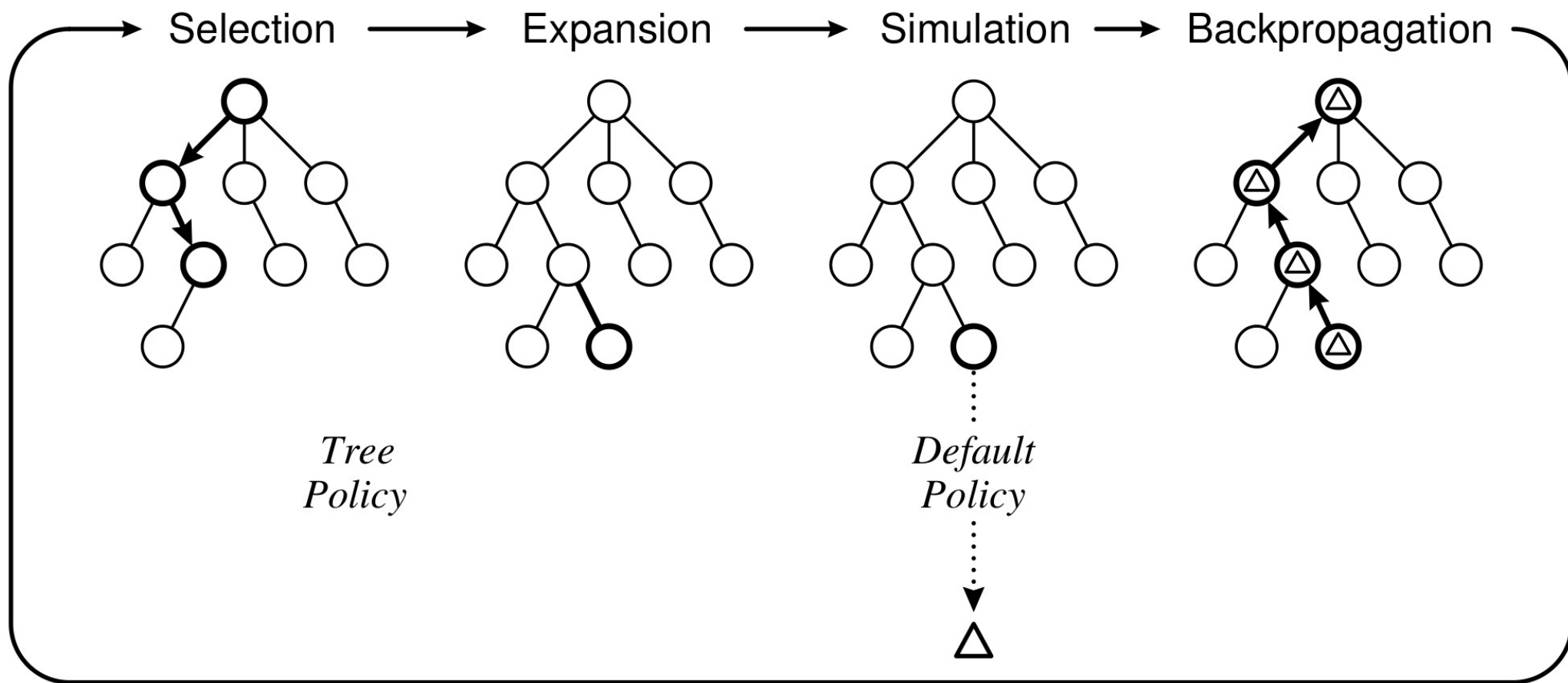
How do you determine π ?

$n = 3000$ ($\pi \approx 3.16667$)

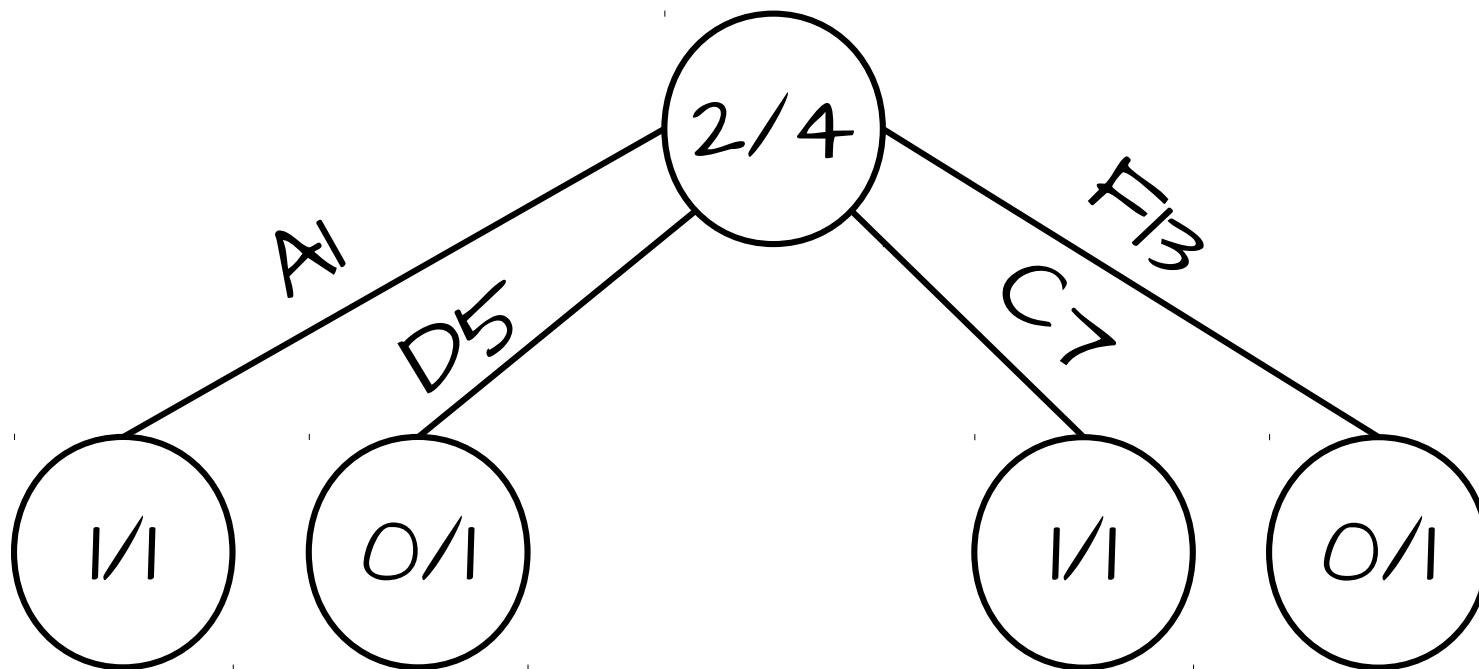


2006

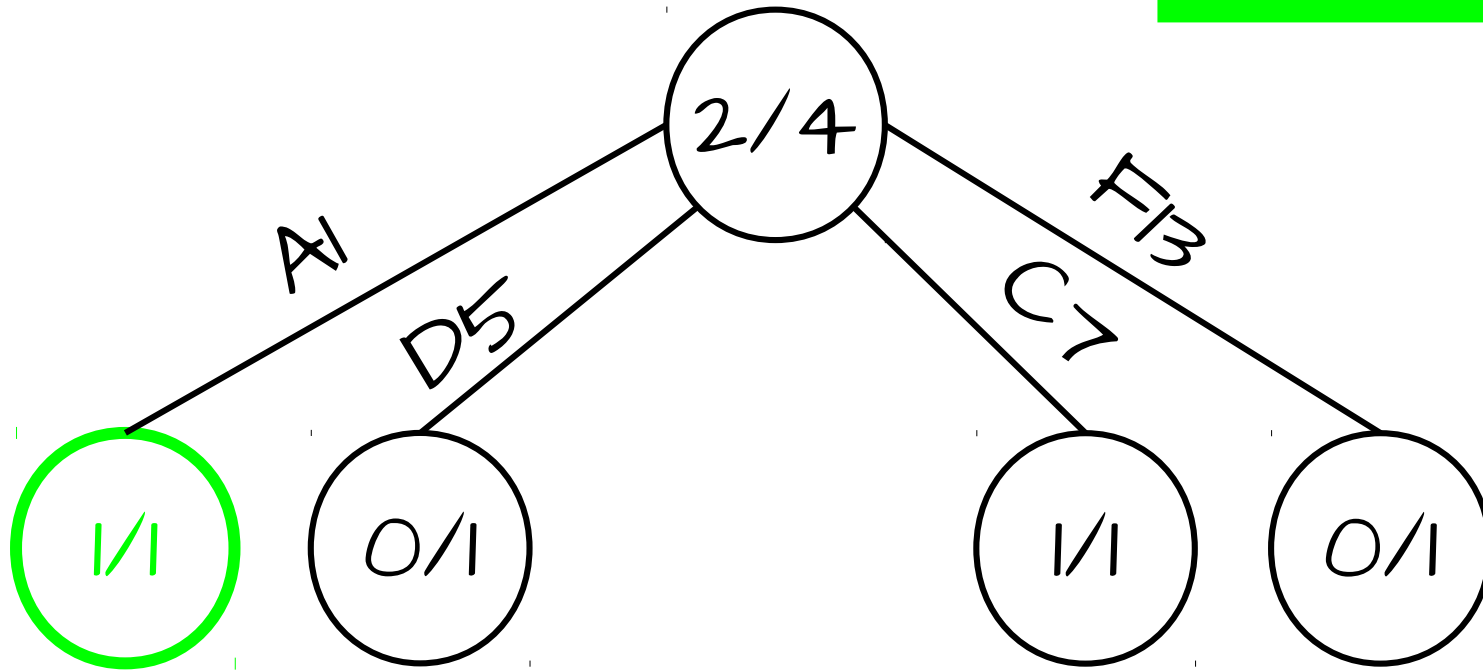




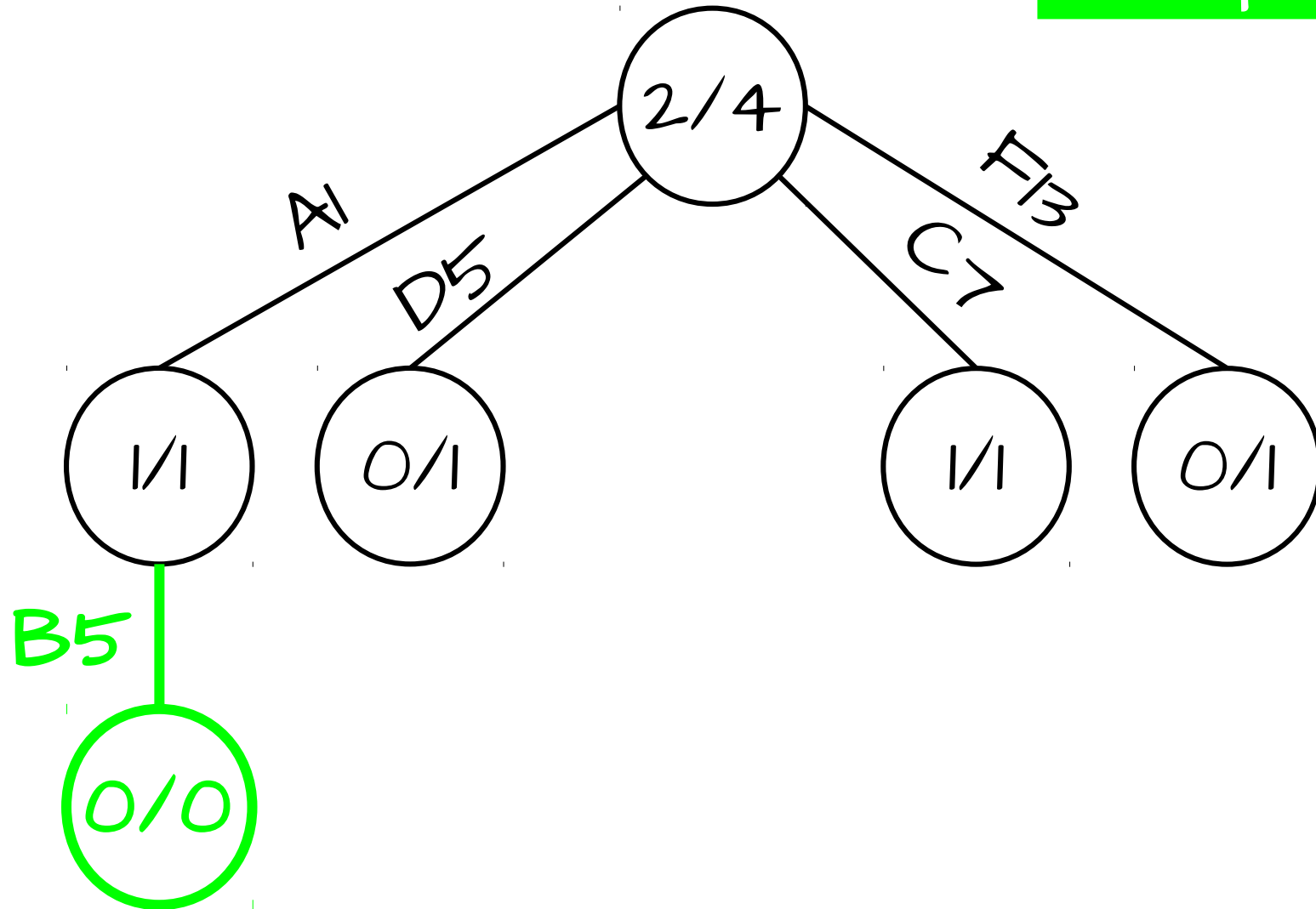
Browne, Cb, and Edward Powley. 2012. A survey of monte carlo tree search methods. *Intelligence and AI* 4, no. 1: 1-49



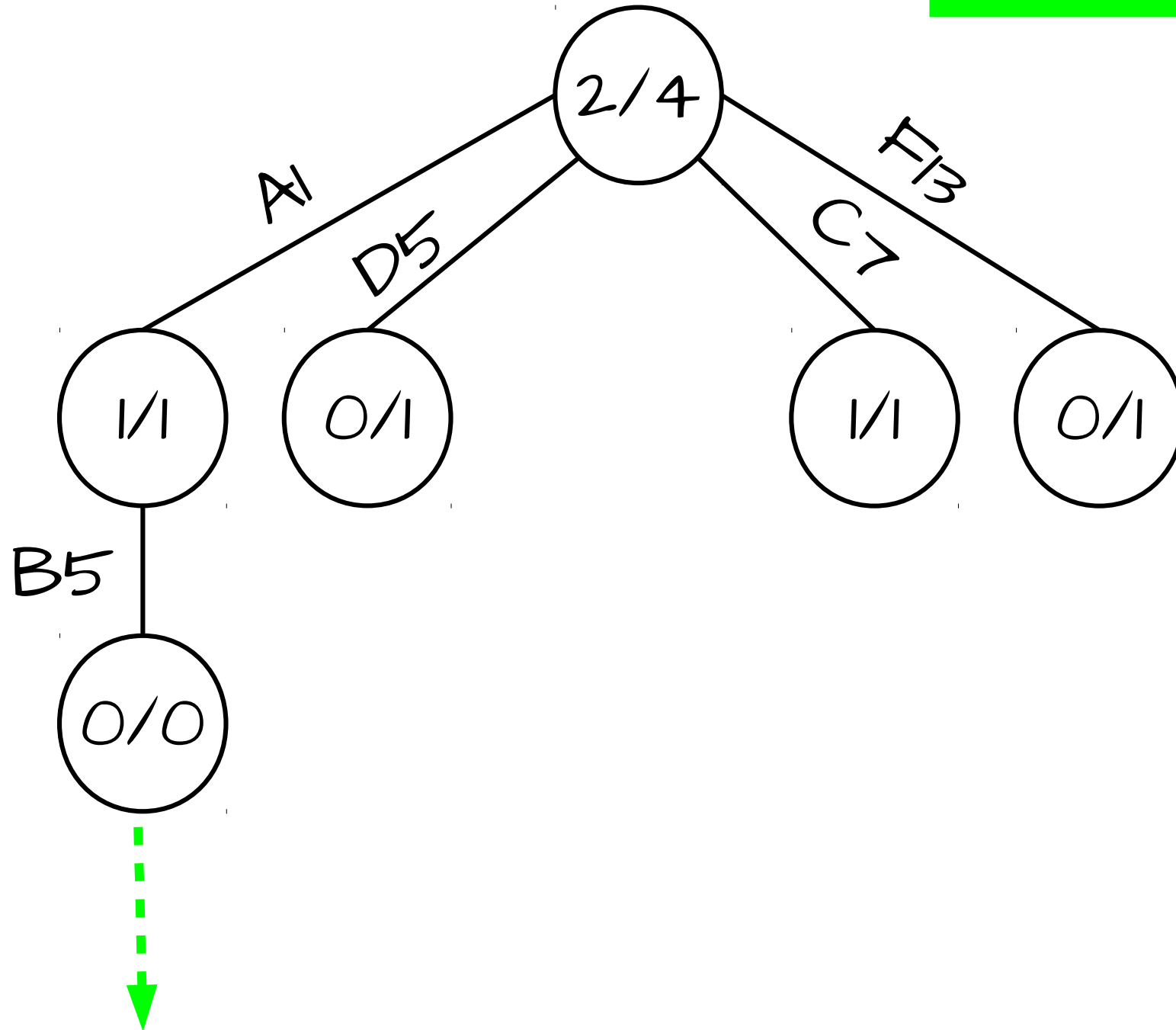
Selection



Expansion



Simulation



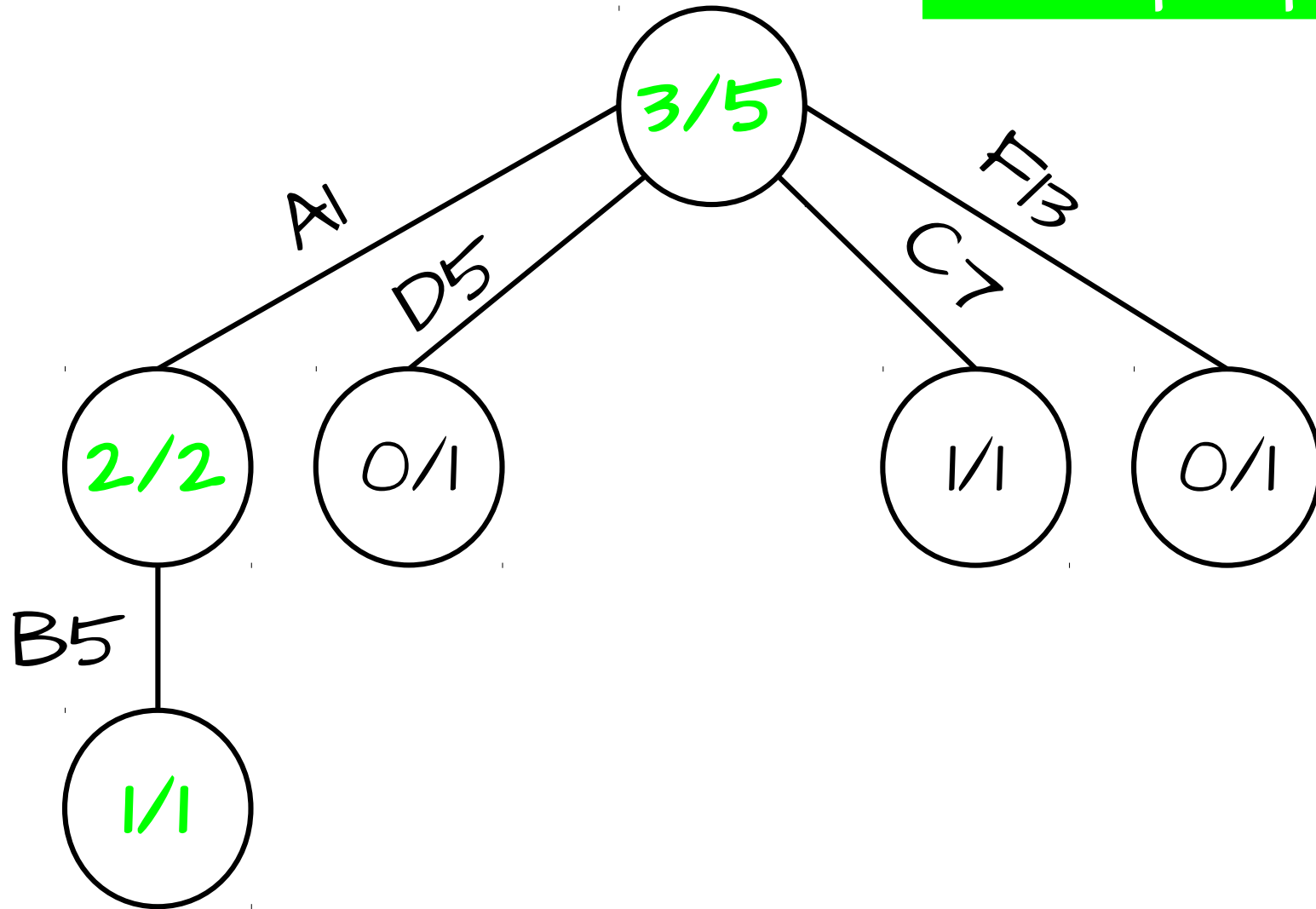
Random



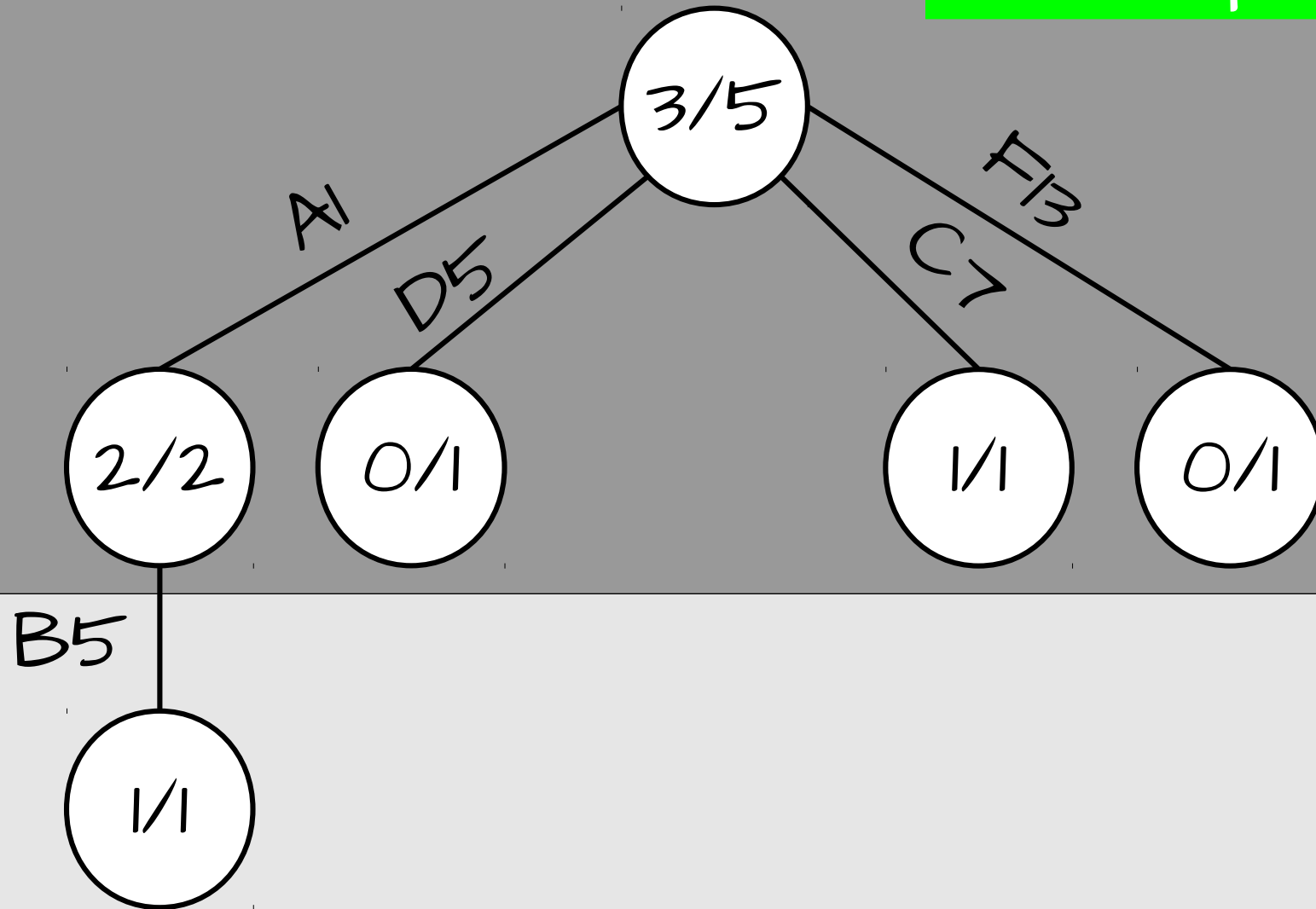
Not Human like?



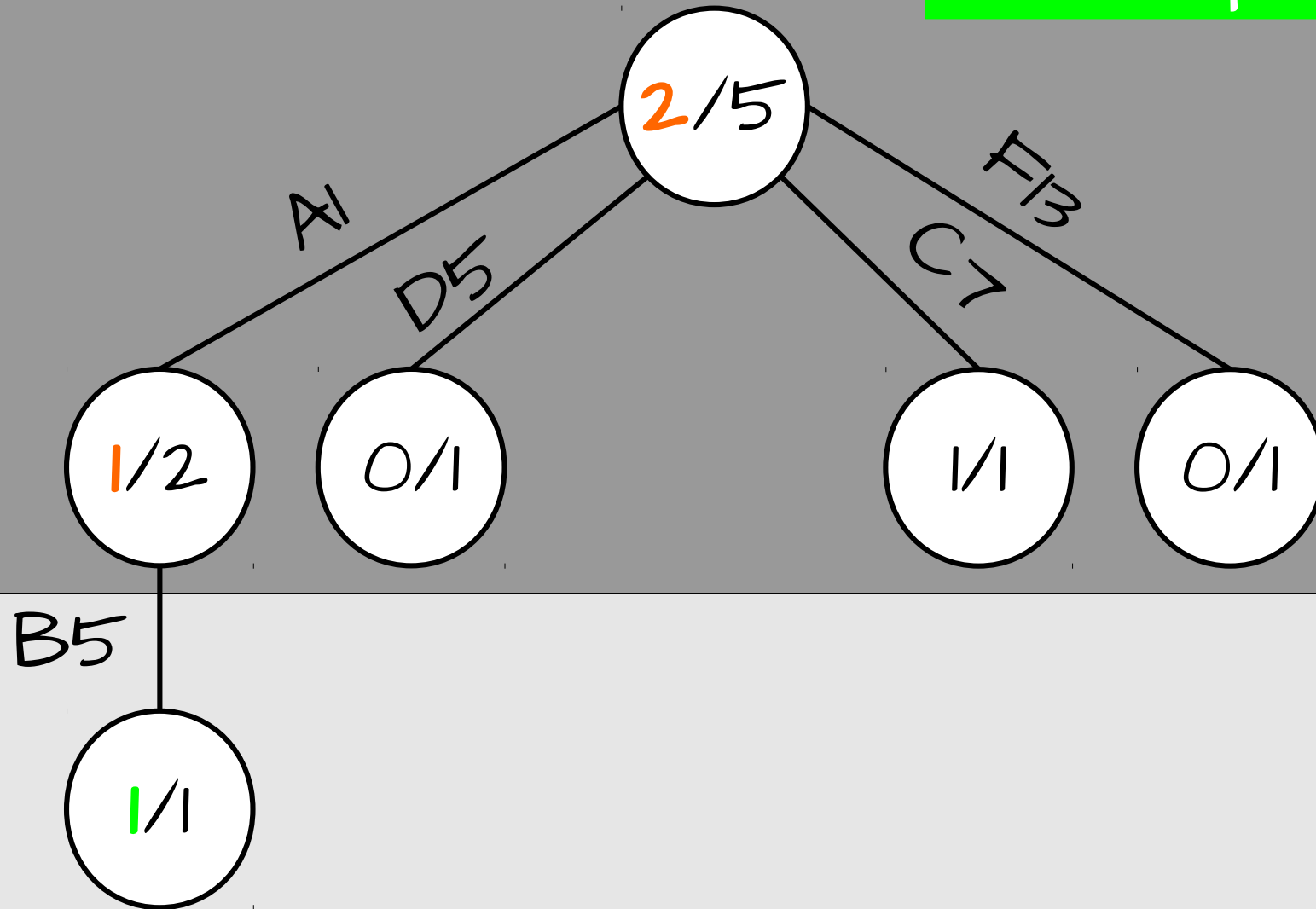
Backpropagation



Perspective



Perspective





Multi Armed Bandit



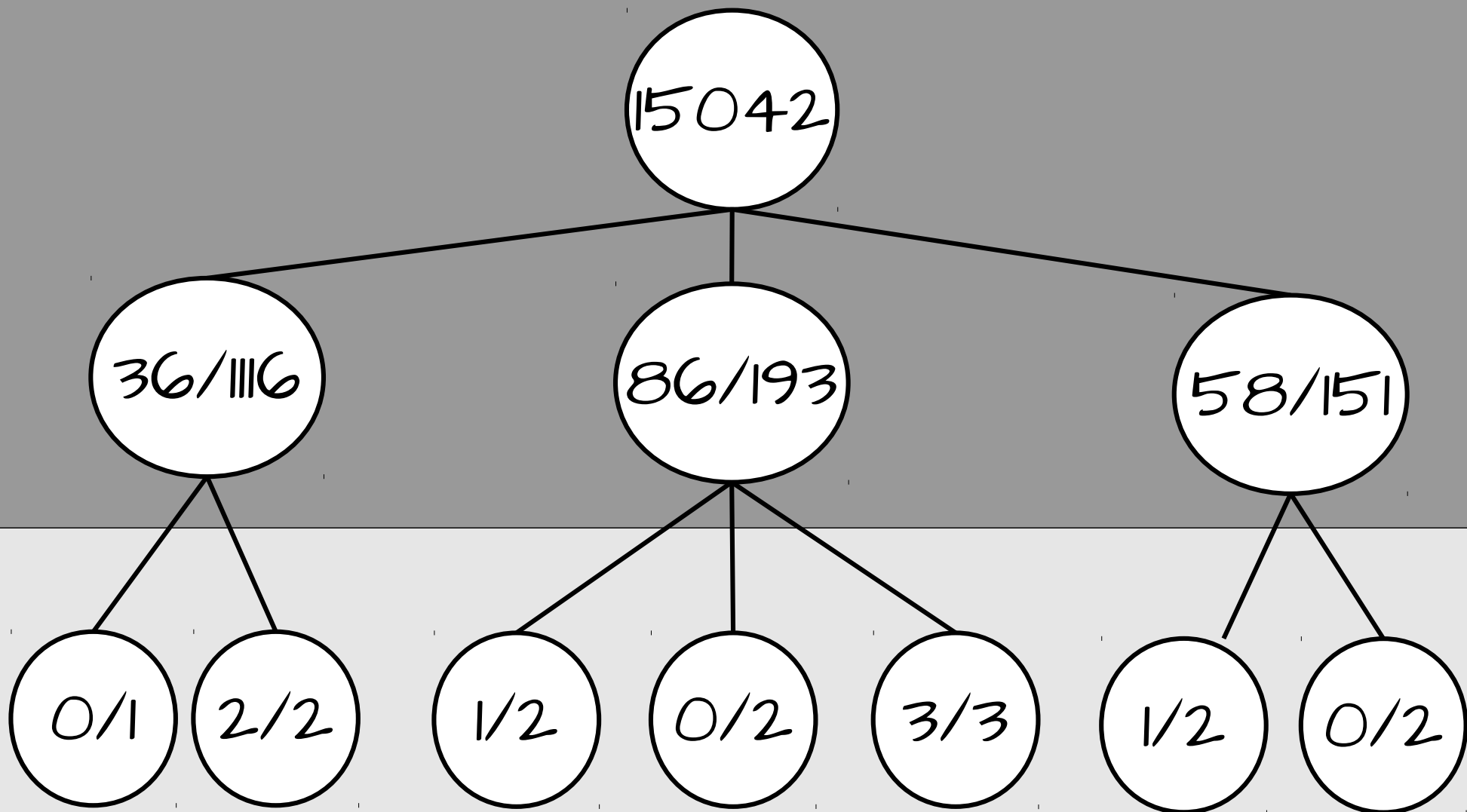


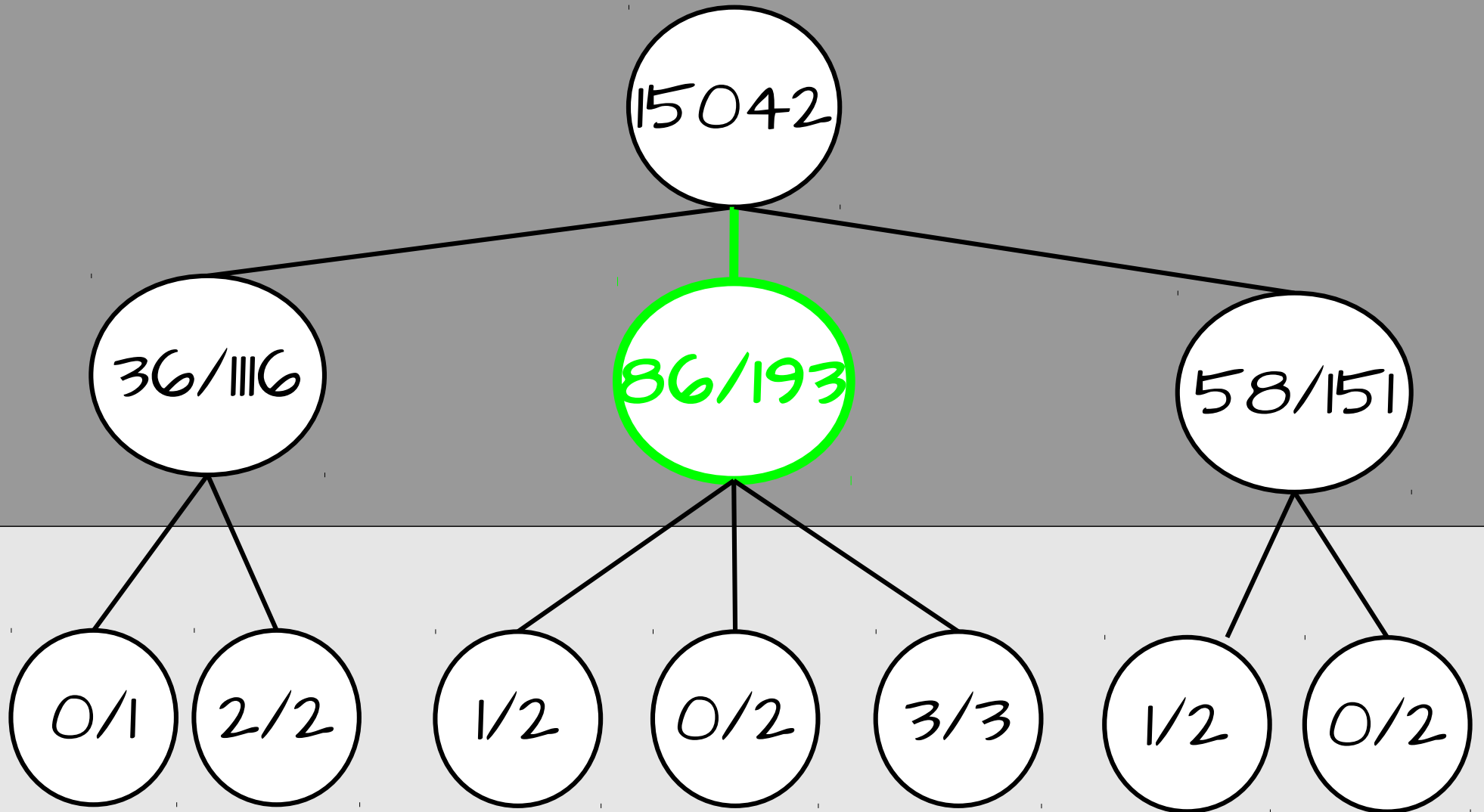
Multi Armed Bandit

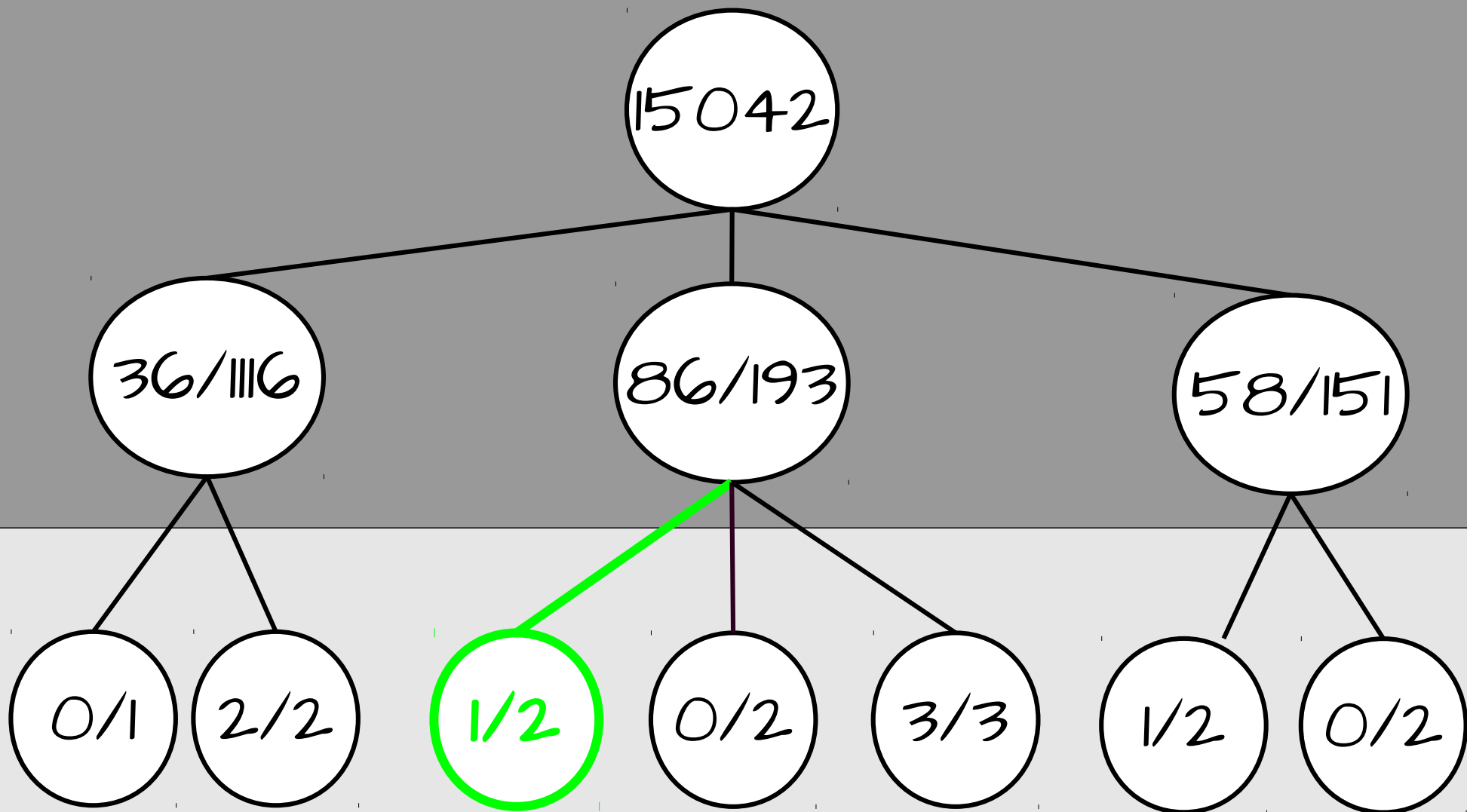


Exploitation vs Exploration

$$\frac{wins}{visits} + explorationFactor \sqrt{\frac{\ln(totalVisits)}{visits}}$$







Generate a valid random move

Who has won?

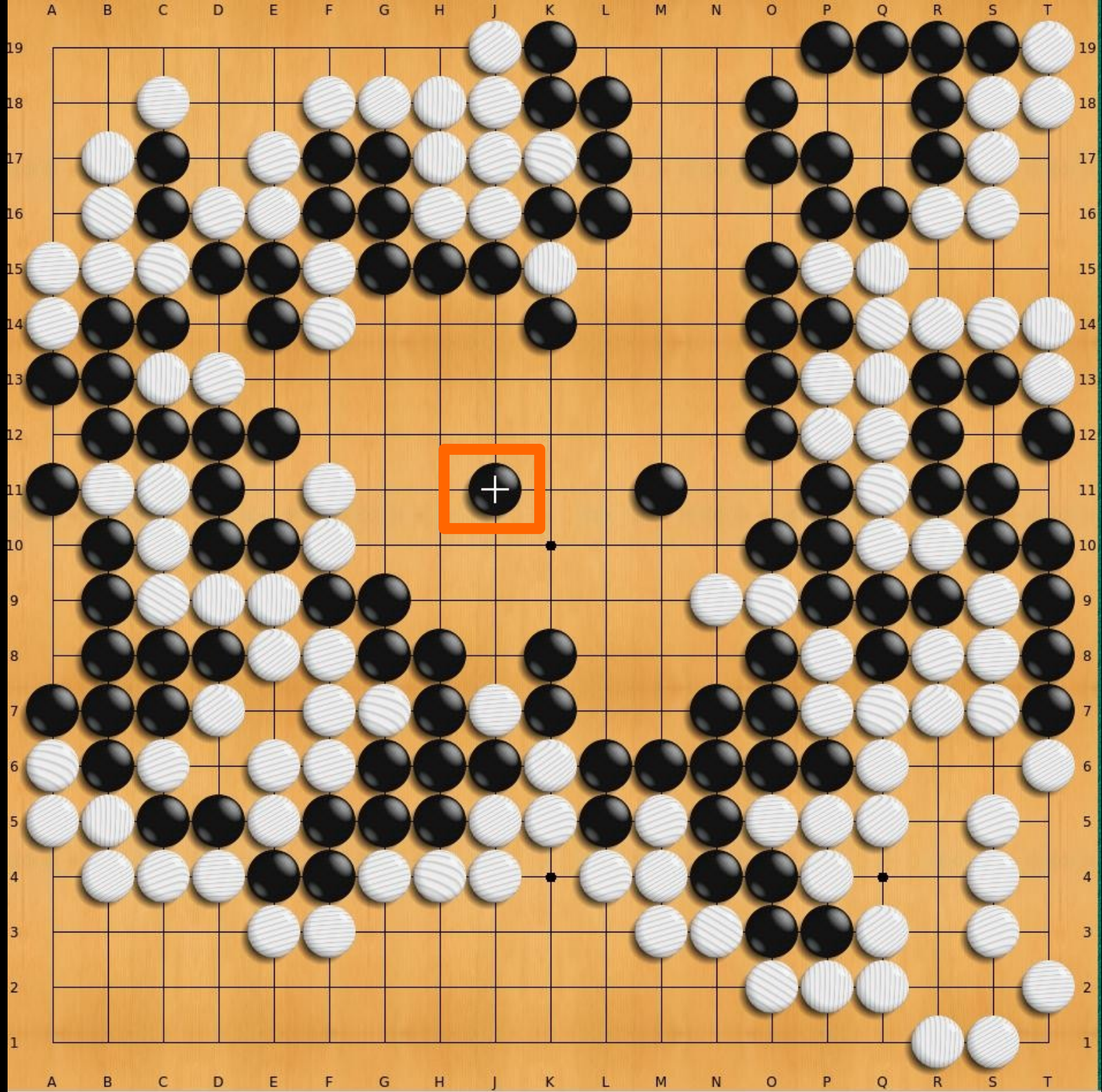


General Game Playing

Anytime

Lazy

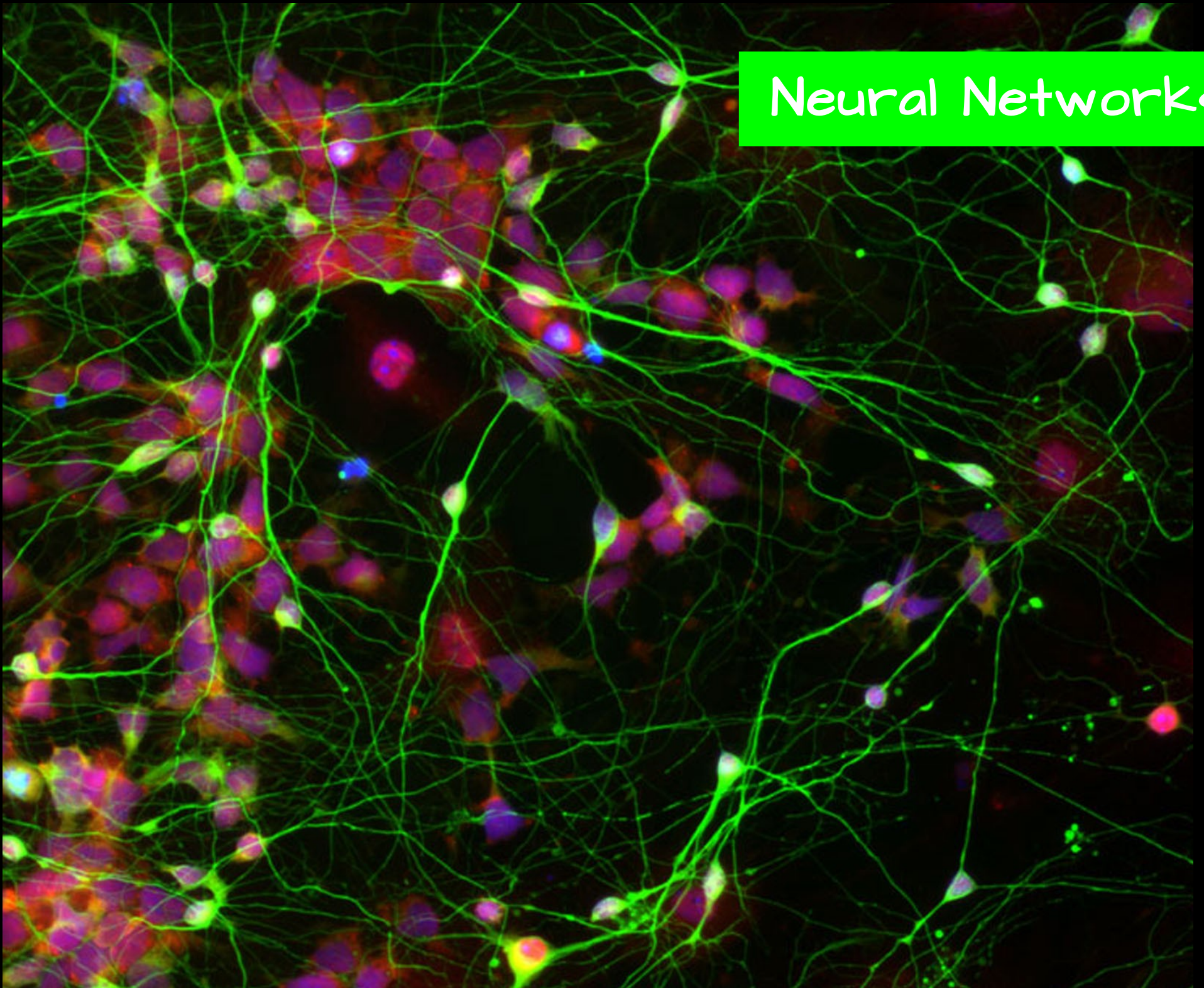




Expert Knowledge



Neural Networks



MOVE EVALUATION IN GO USING DEEP CONVOLUTIONAL NEURAL NETWORKS

Chris J. Maddison

University of Toronto

cmaddis@cs.toronto.edu

2014

Aja Huang¹, Ilya Sutskever², David Silver¹

Google DeepMind¹, Google Brain²

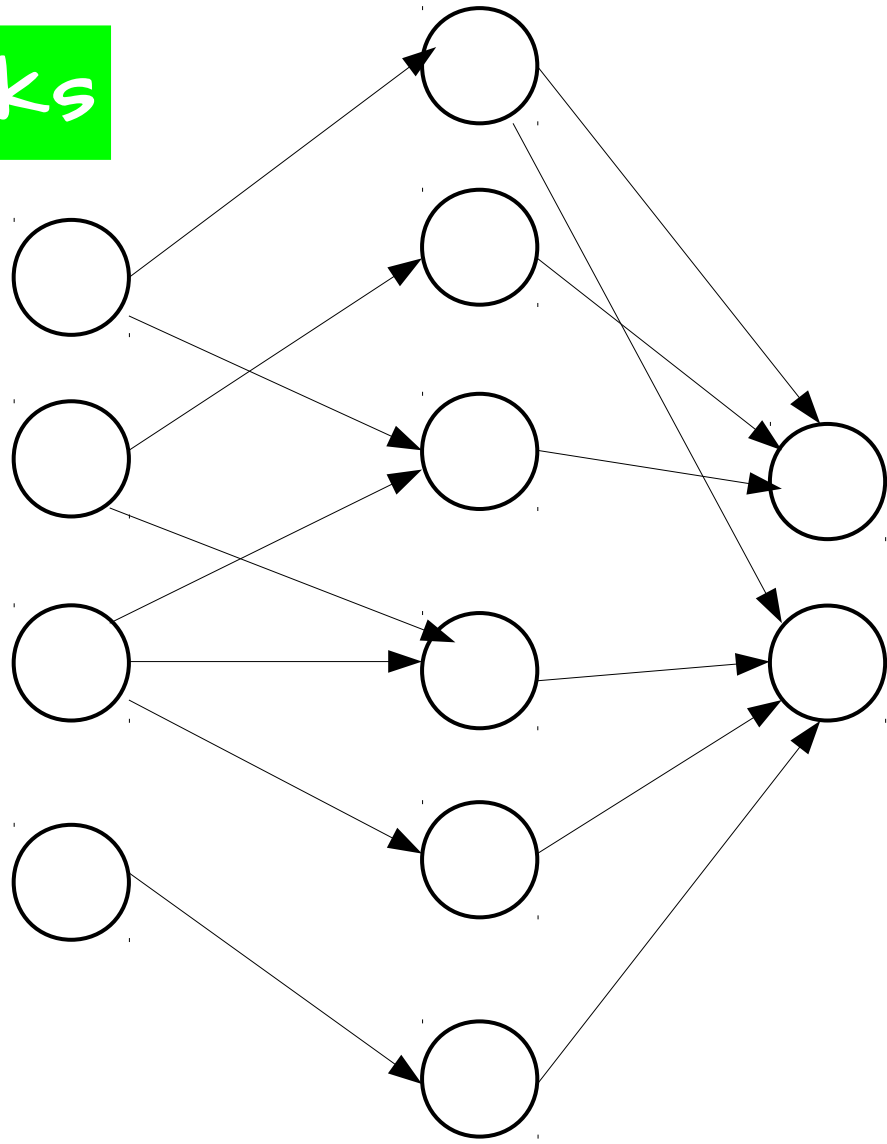
{ajahuang, ilyasu, davidsilver}@google.com

ABSTRACT

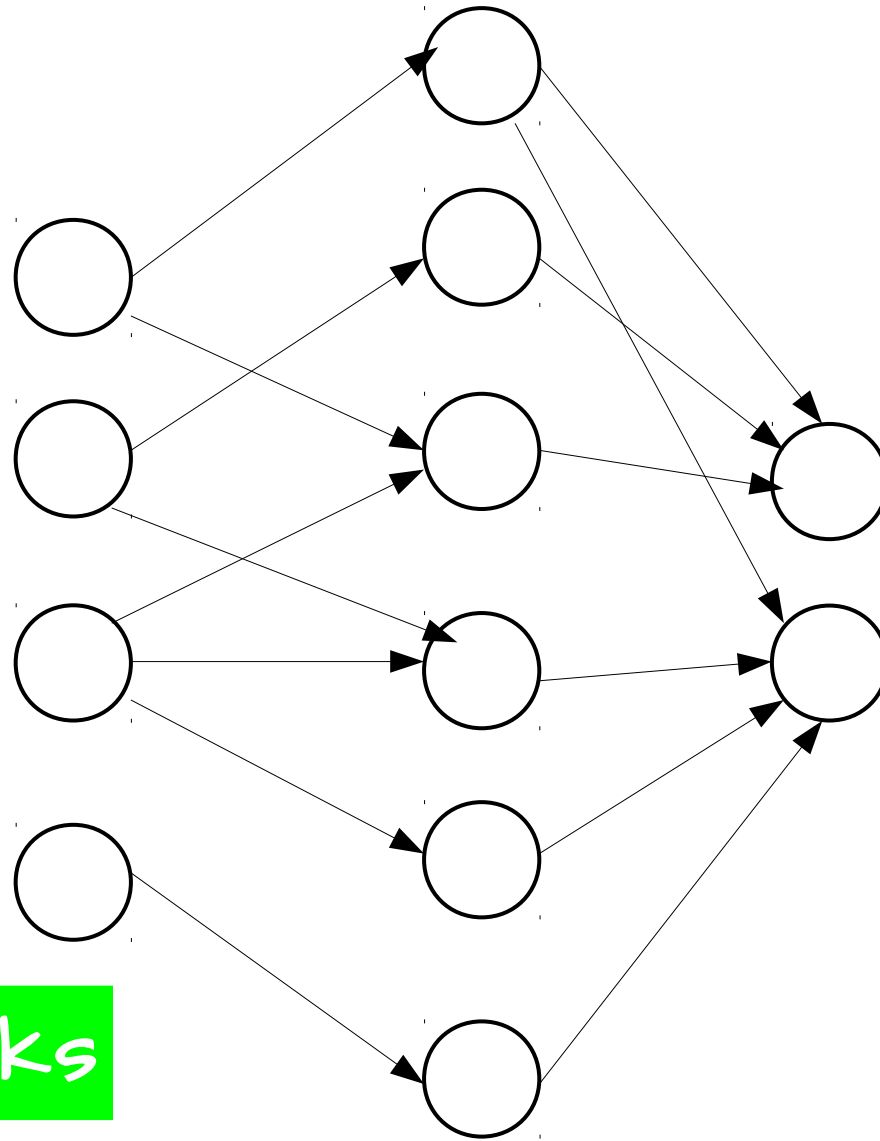
The game of Go is more challenging than other board games, due to the difficulty of constructing a position or move evaluation function. In this paper we investigate whether deep convolutional networks can be used to directly represent and learn this knowledge. We train a large 12-layer convolutional neural network by supervised learning from a database of human professional games. The network correctly predicts the expert move in 55% of positions, equalling the accuracy of a 6 dan human player. When the trained convolutional network was used di-

What does this even mean?

Neural Networks

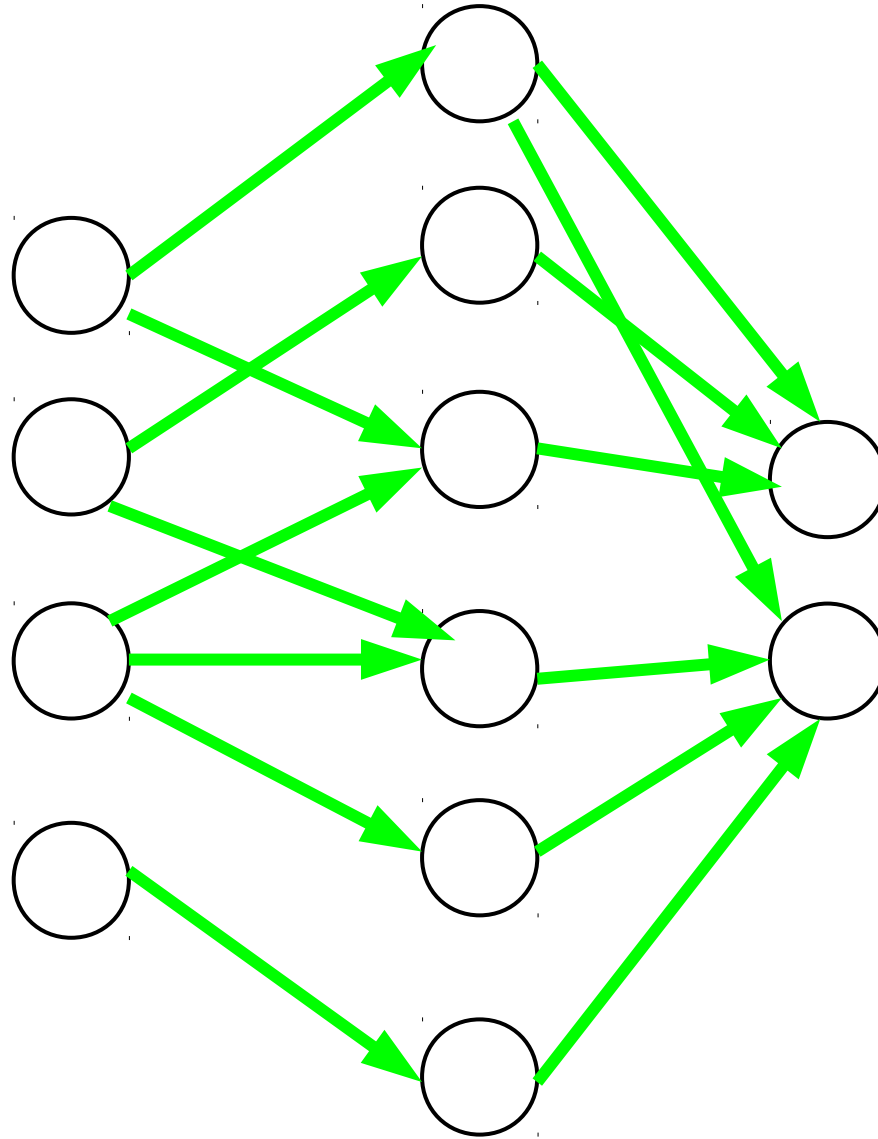


Input "Hidden" Layer Output

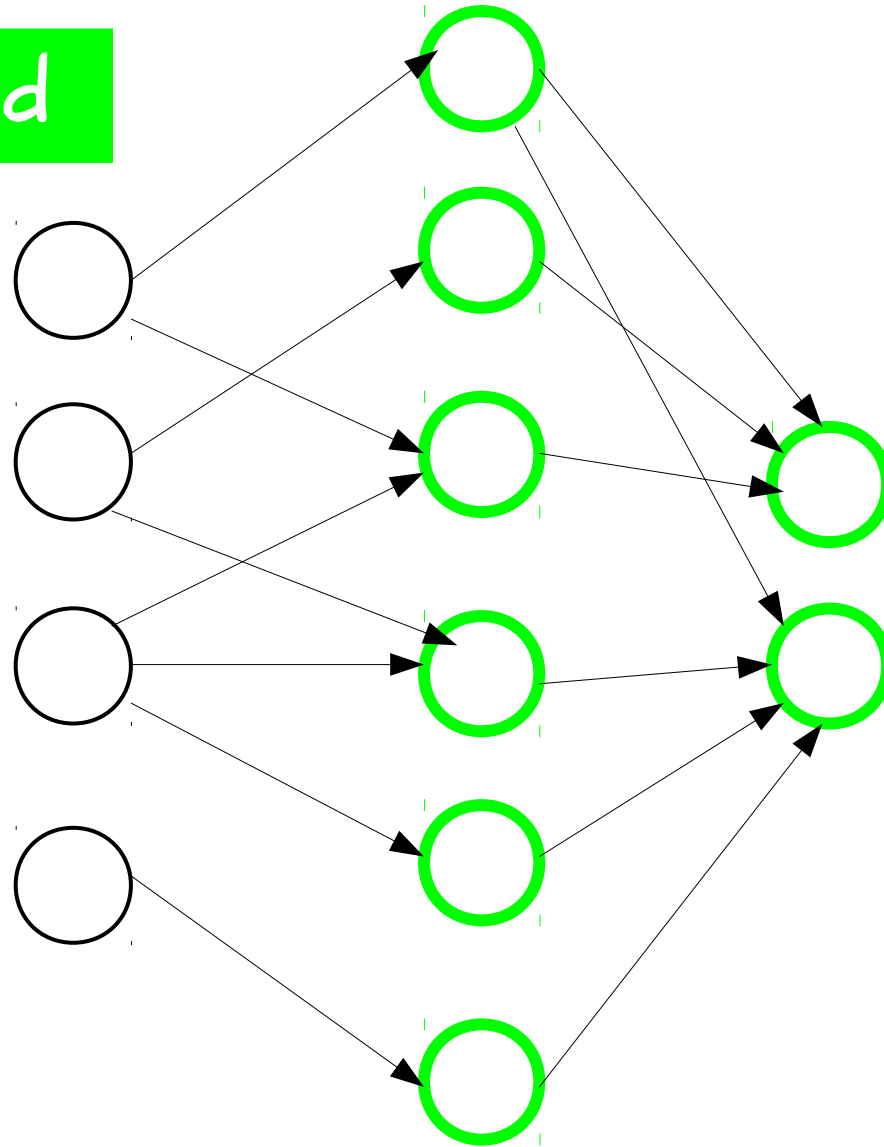


Neural Networks

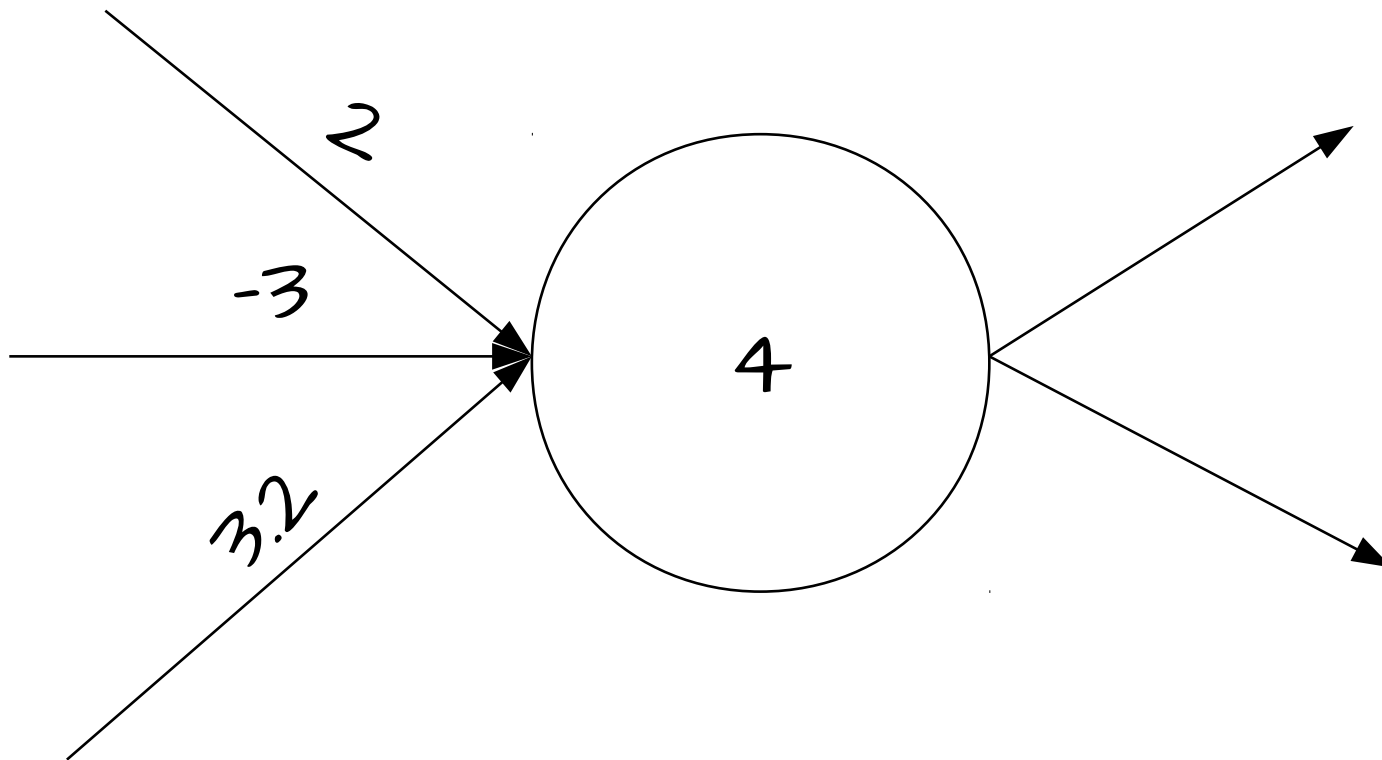
Weights



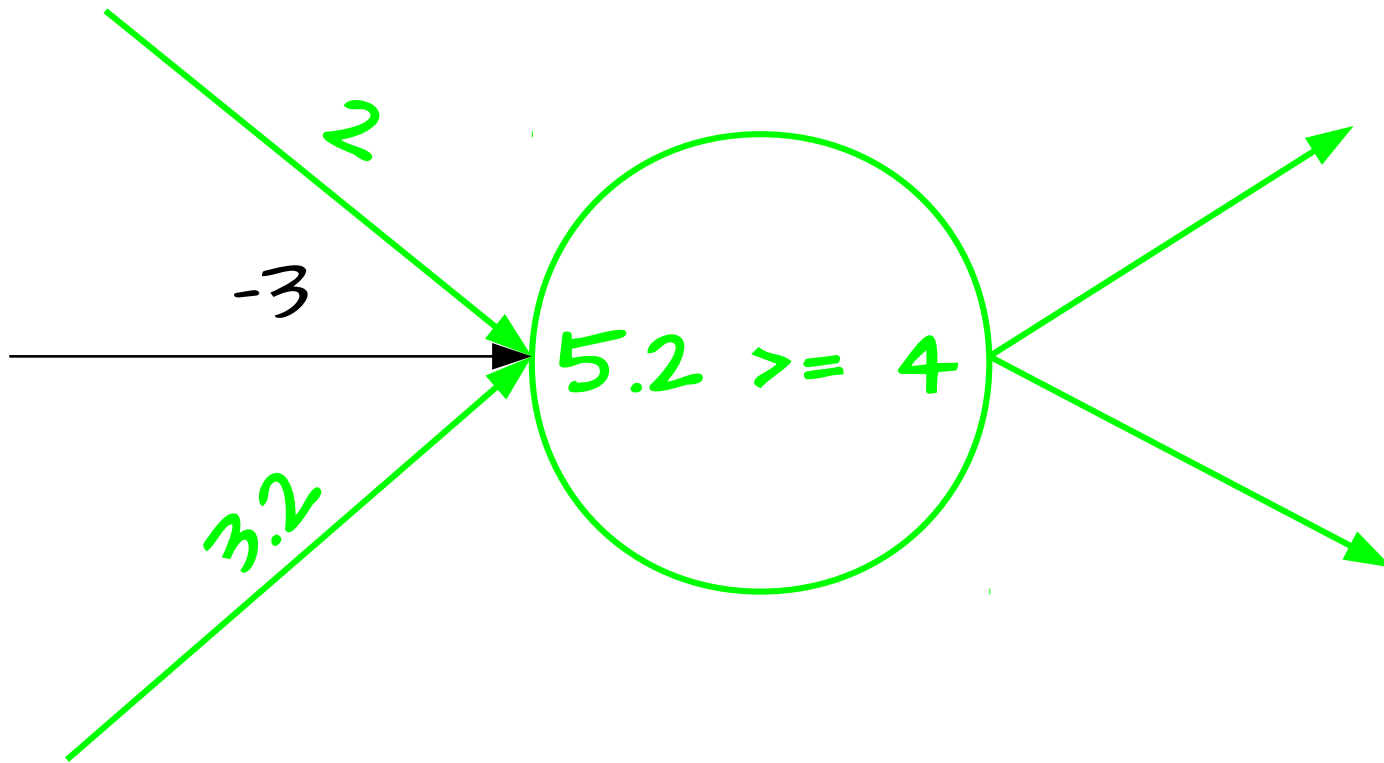
Bias/Threshold



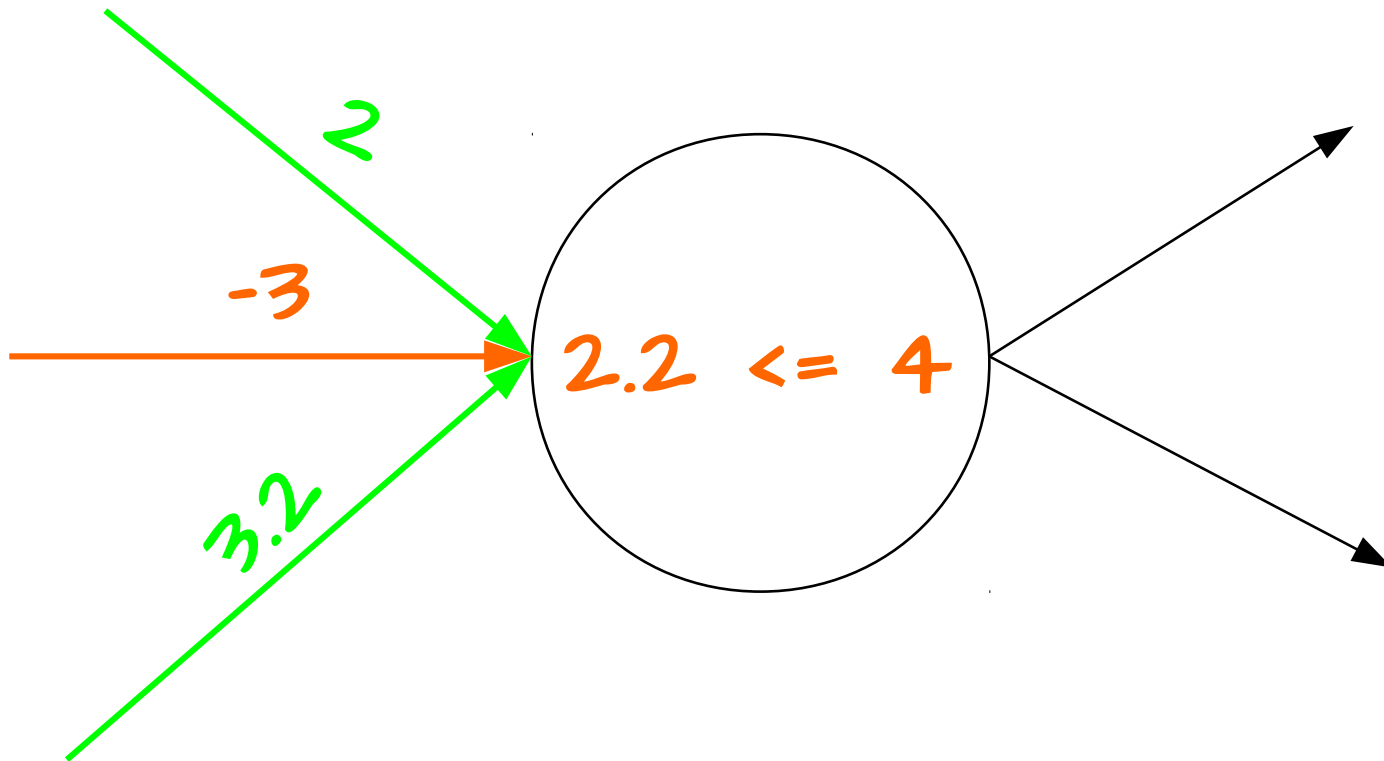
Activation



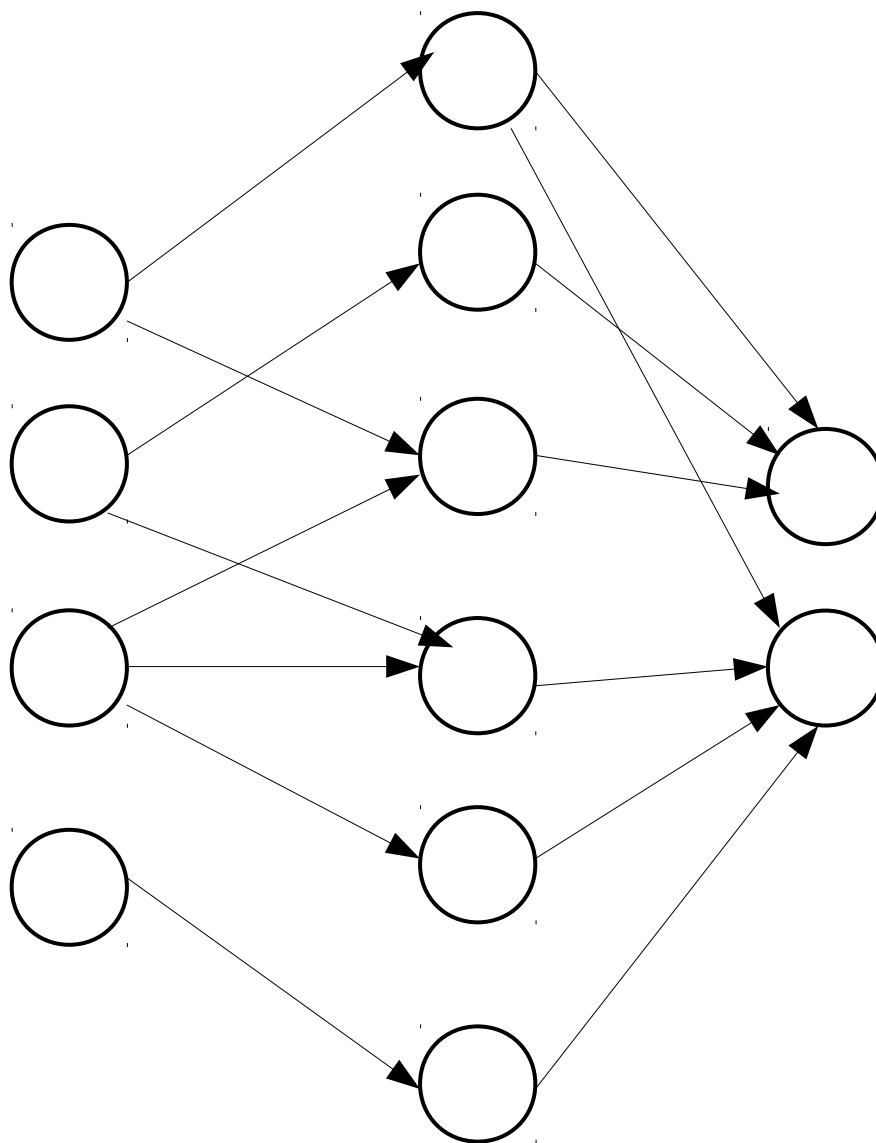
Activation



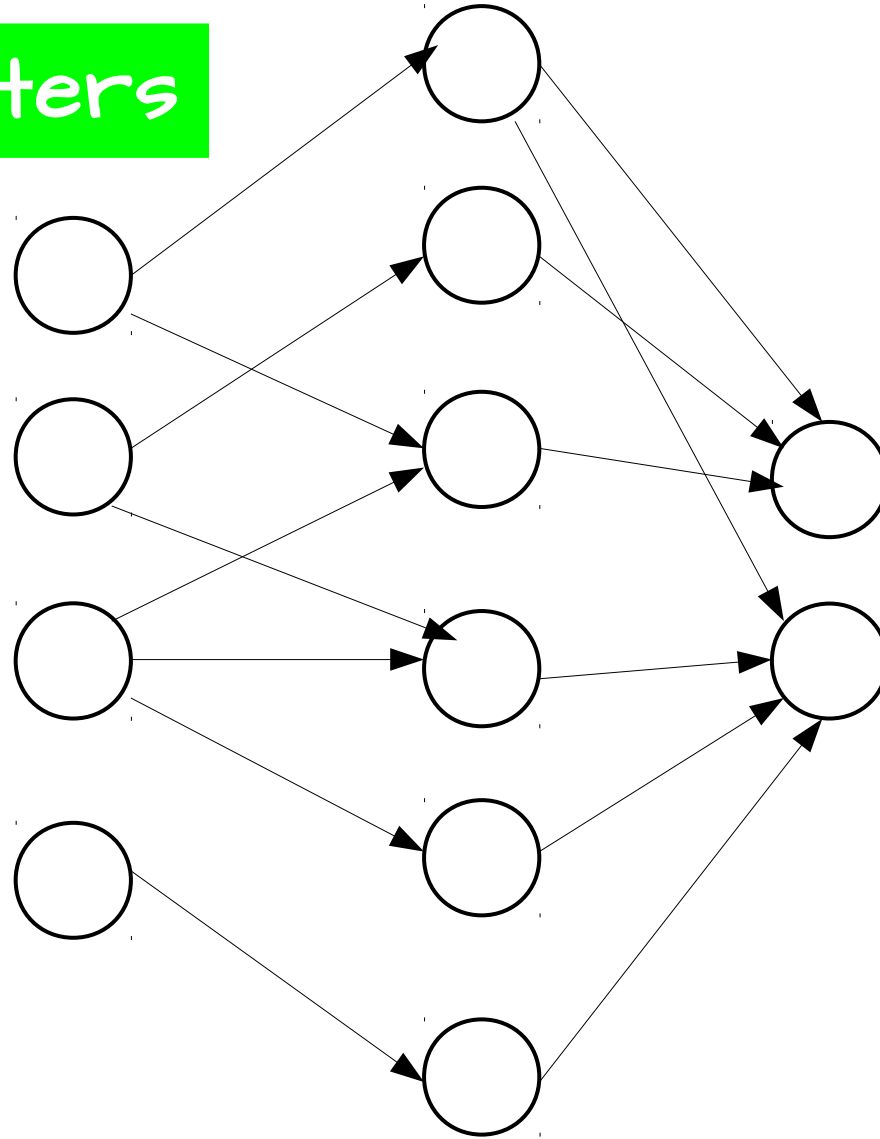
Activation



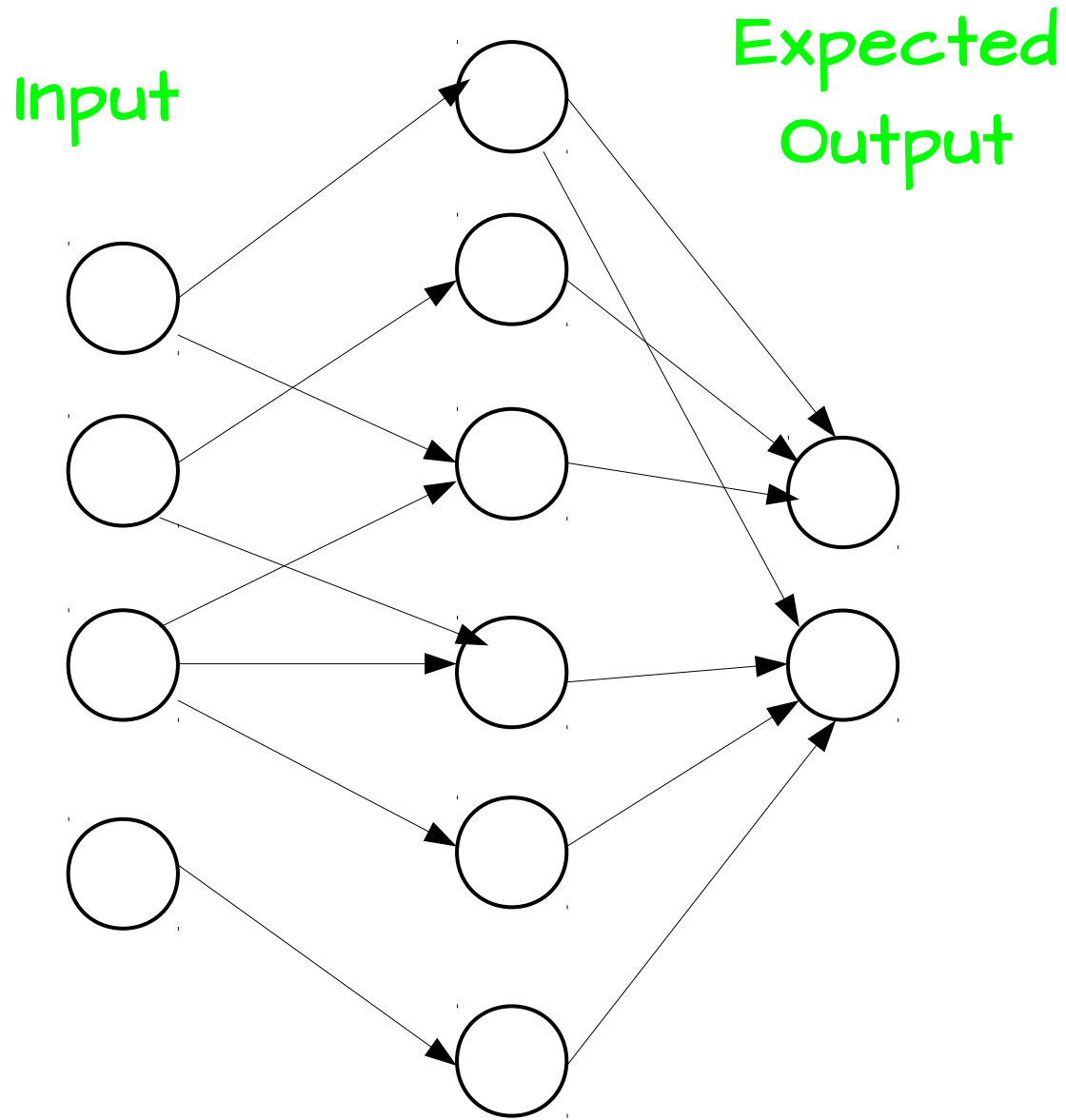
Training



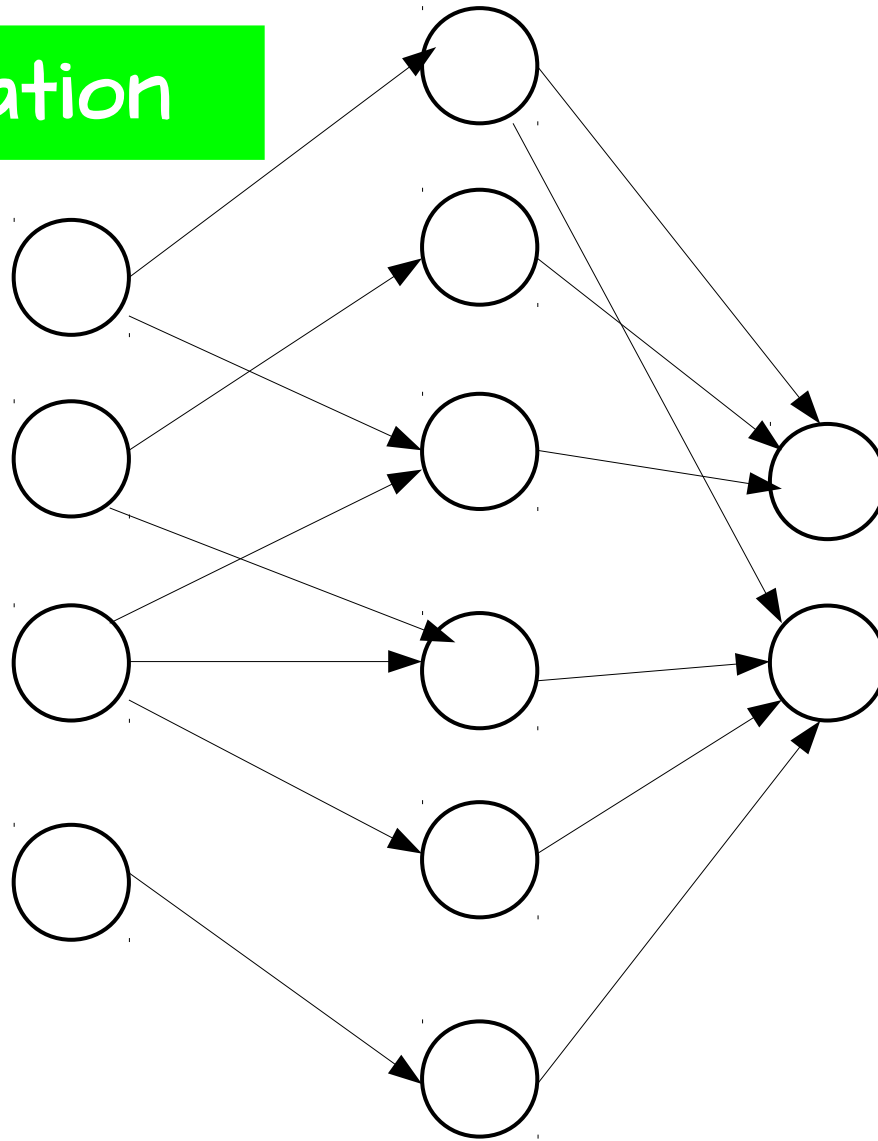
Adjust parameters



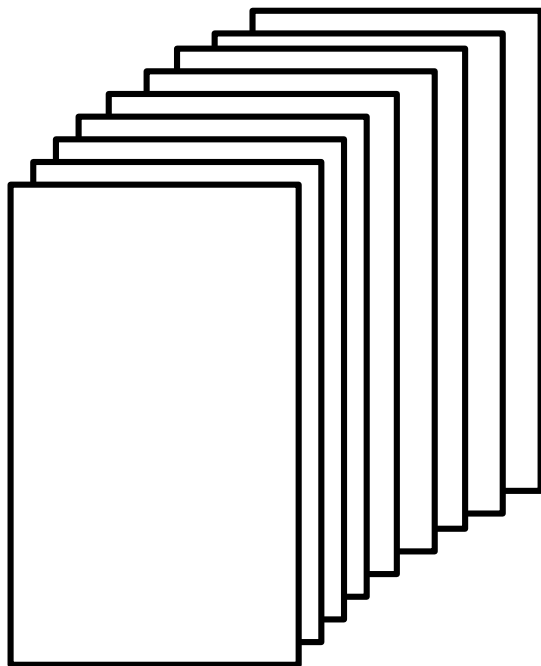
Supervised Learning



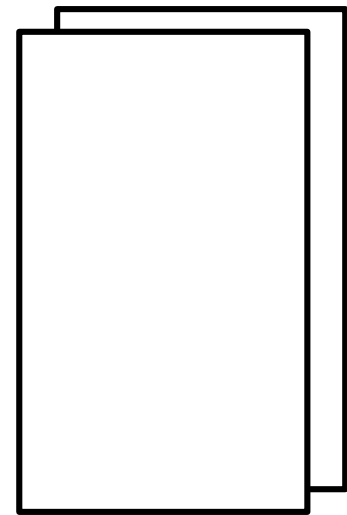
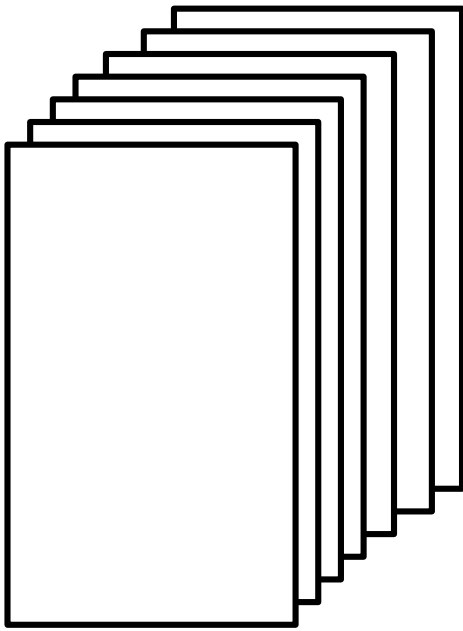
Backpropagation



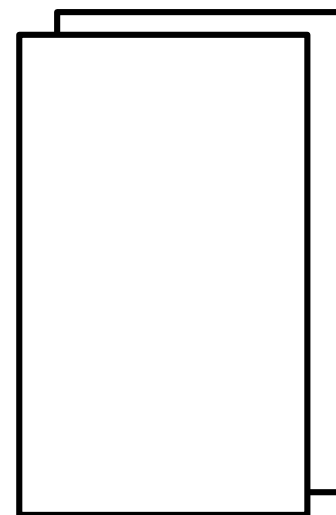
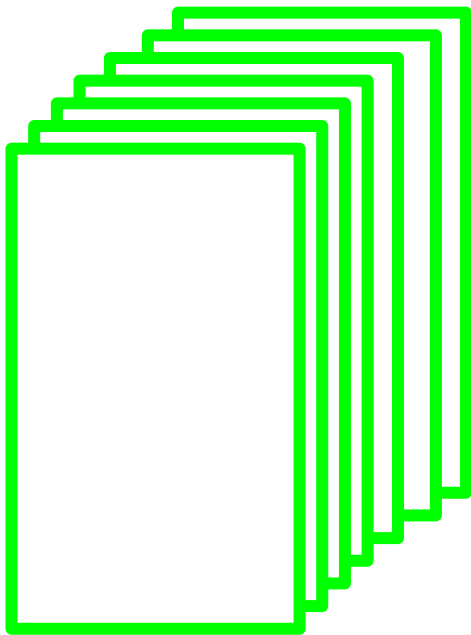
Data set



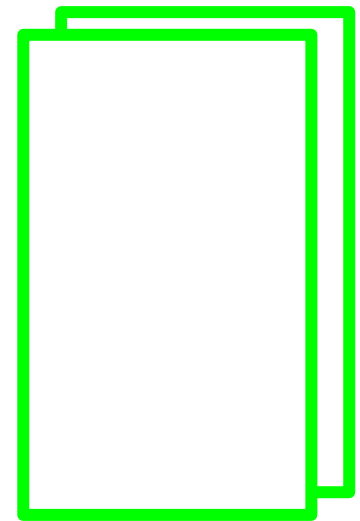
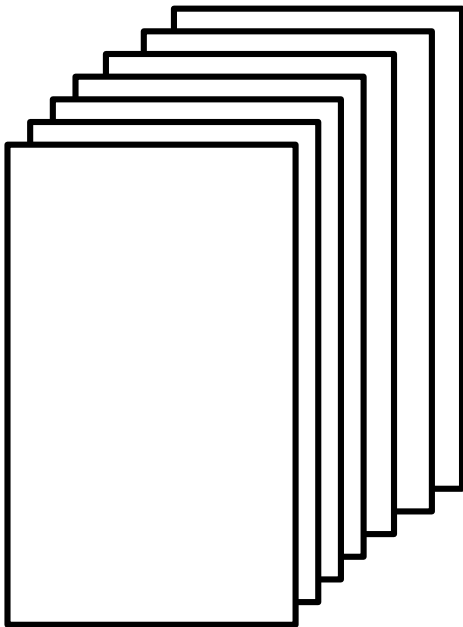
Training data + test data



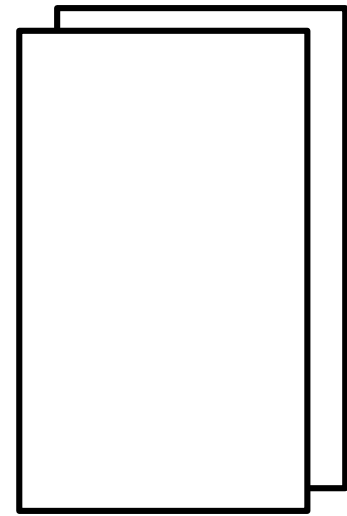
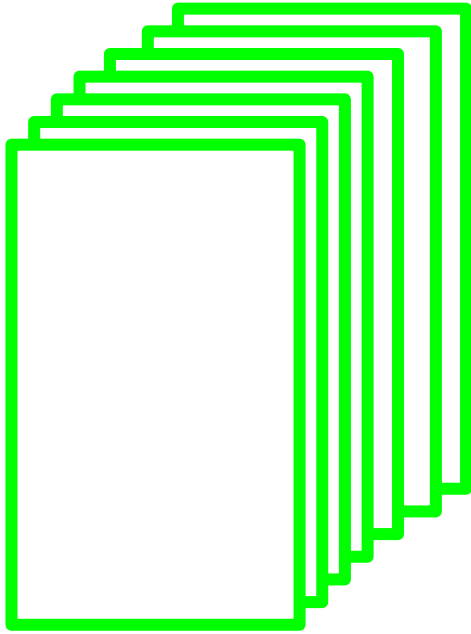
Training



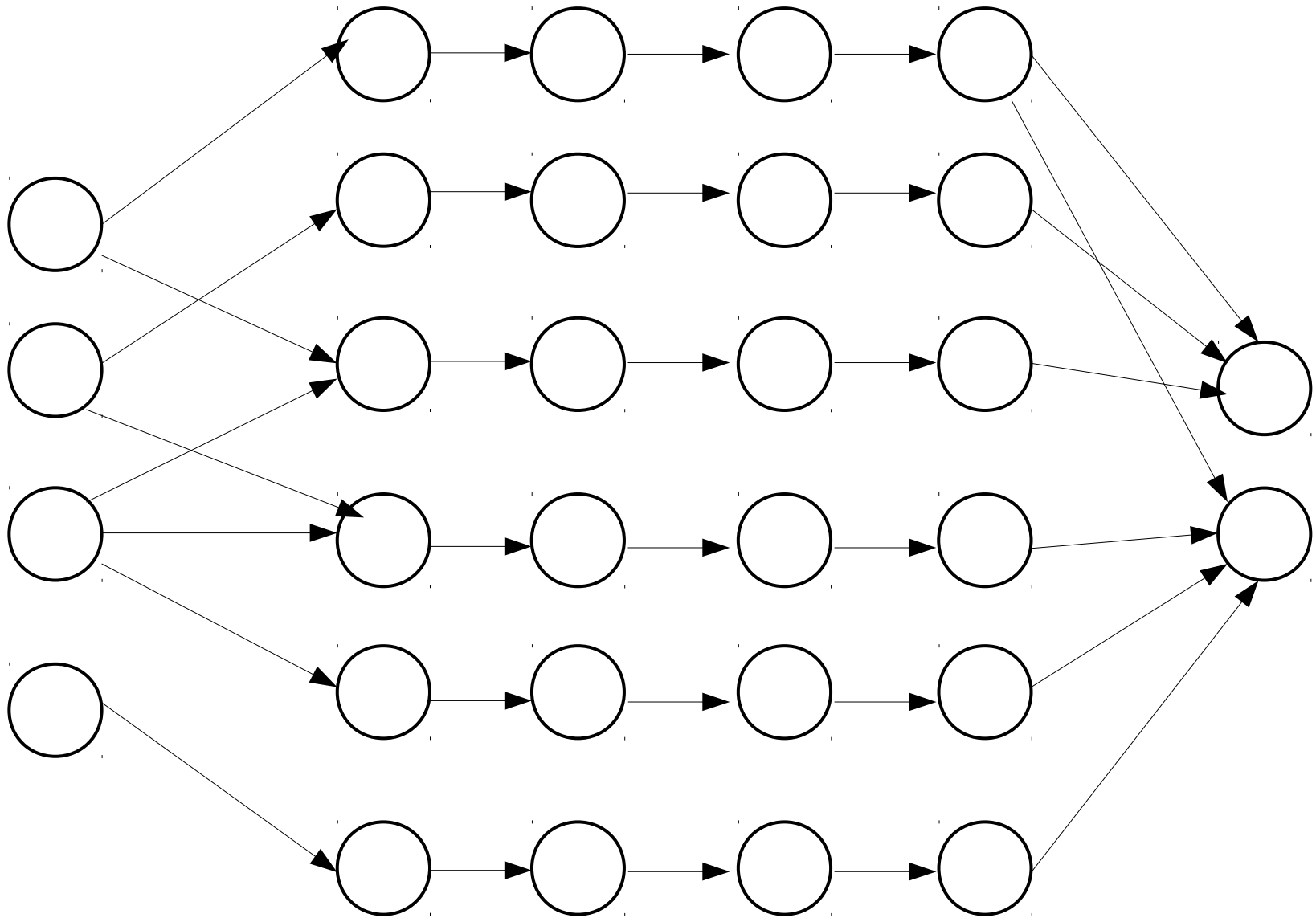
Verify



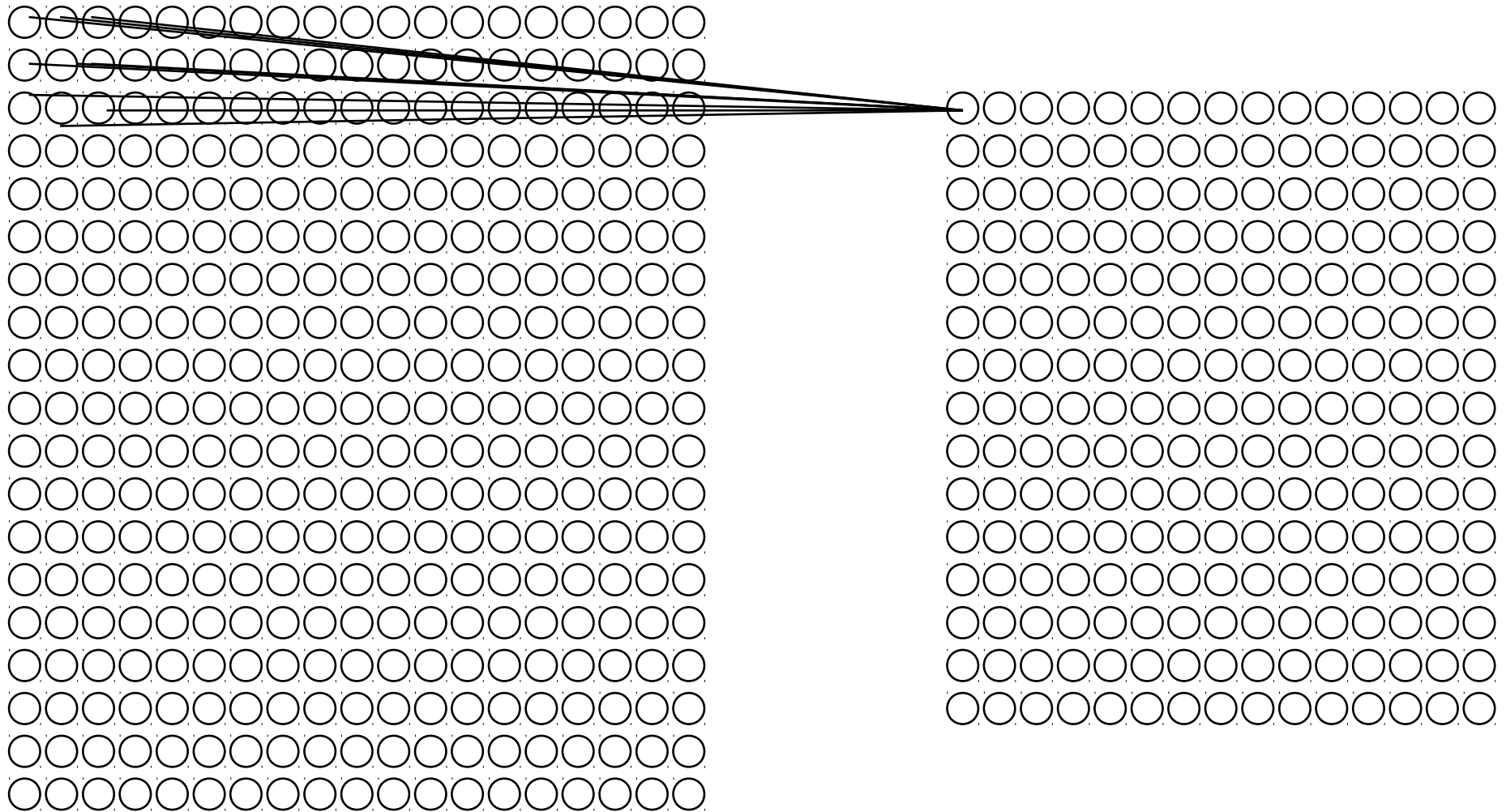
Overfitting



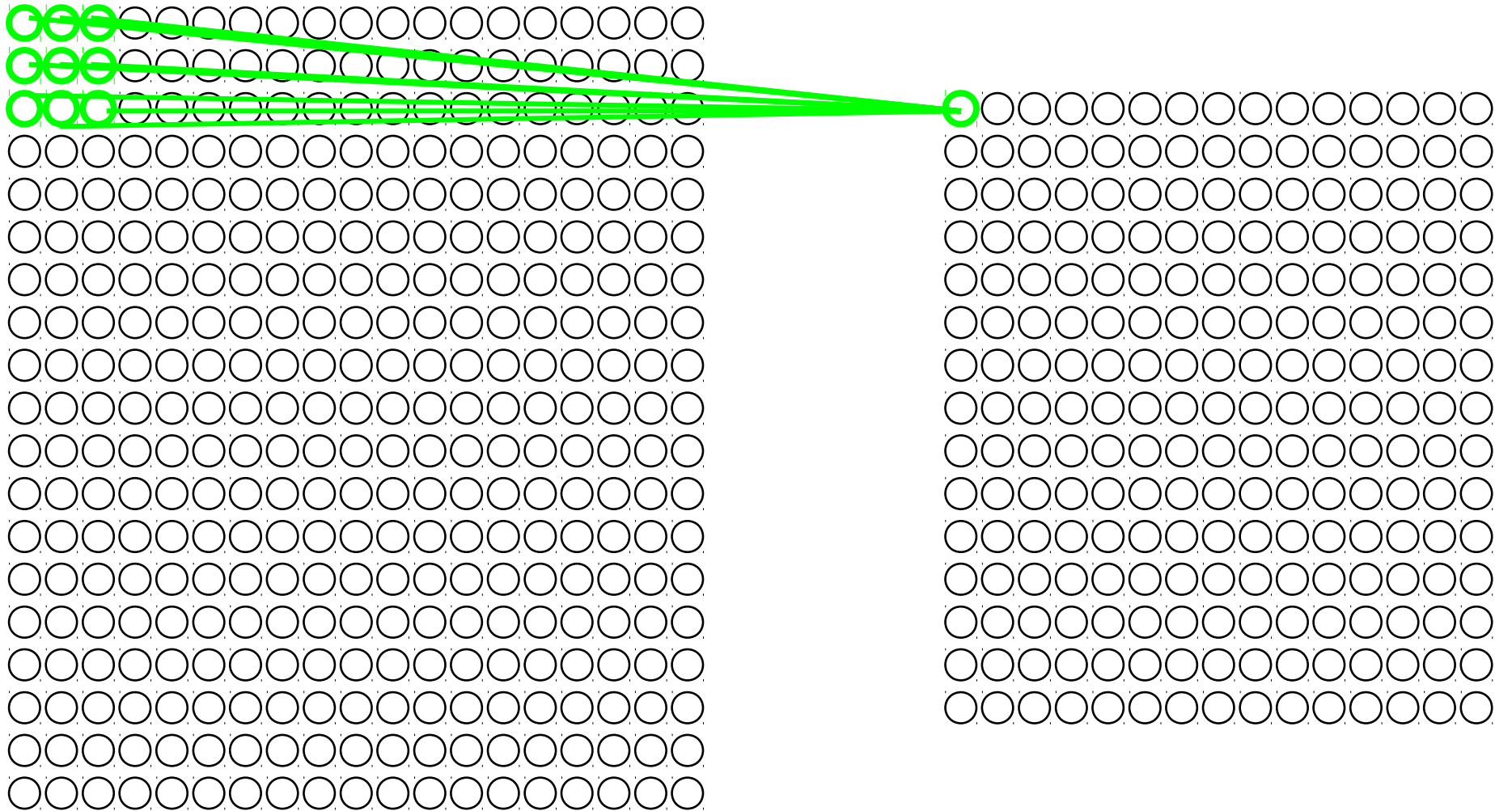
Deep Neural Networks



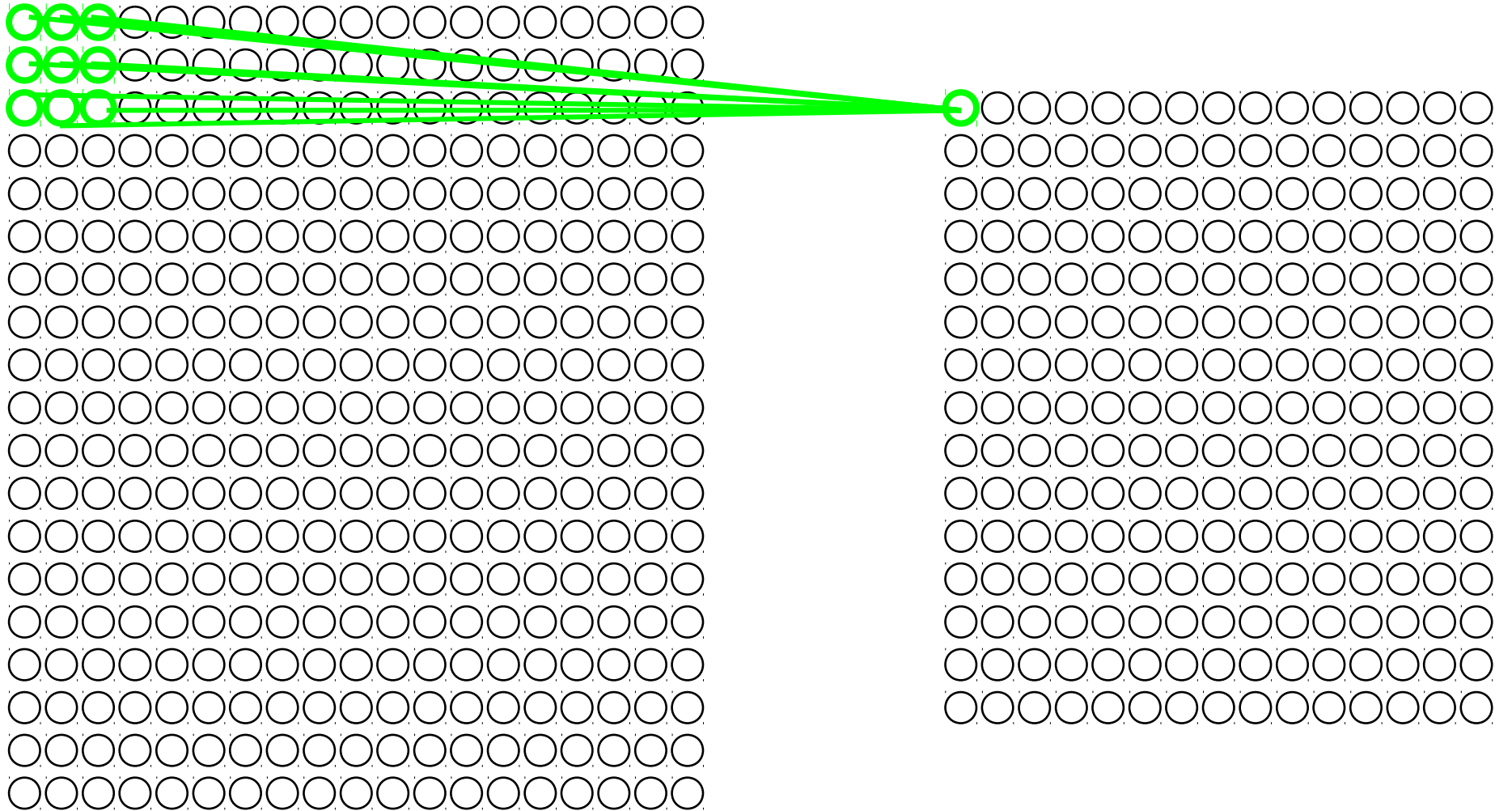
Convolutional Neural Networks



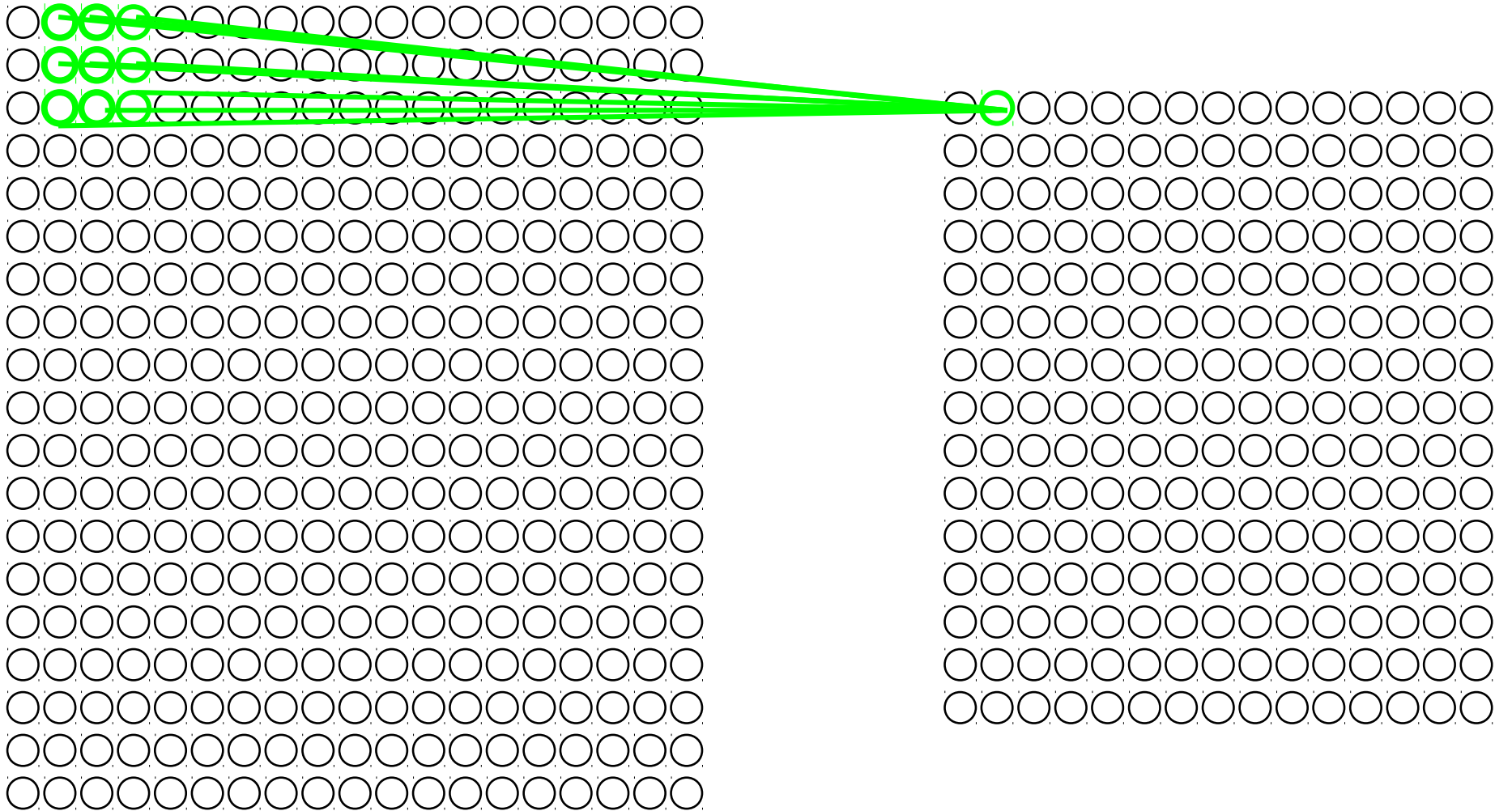
Local Receptive Field



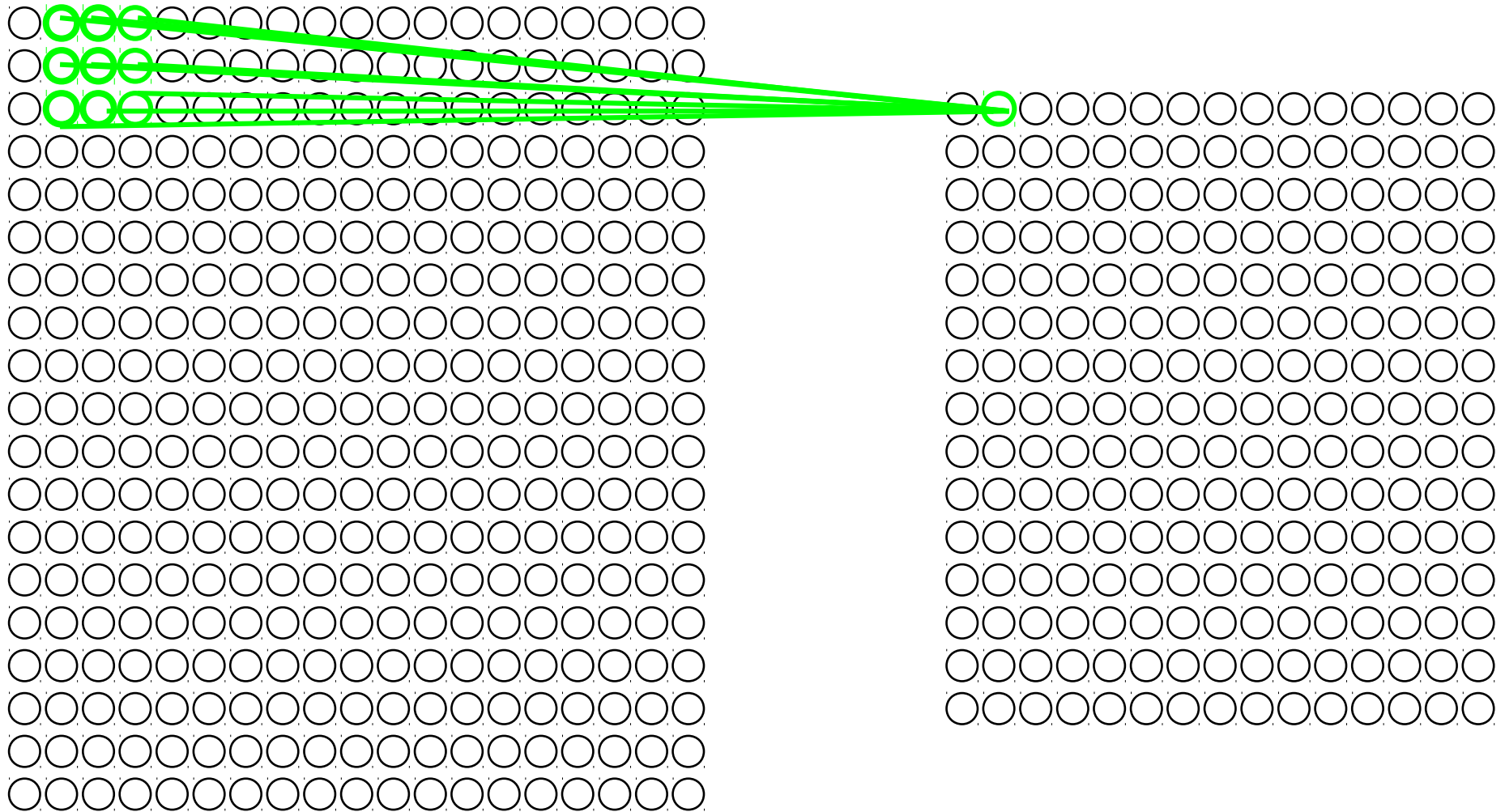
Feature Map



Stride



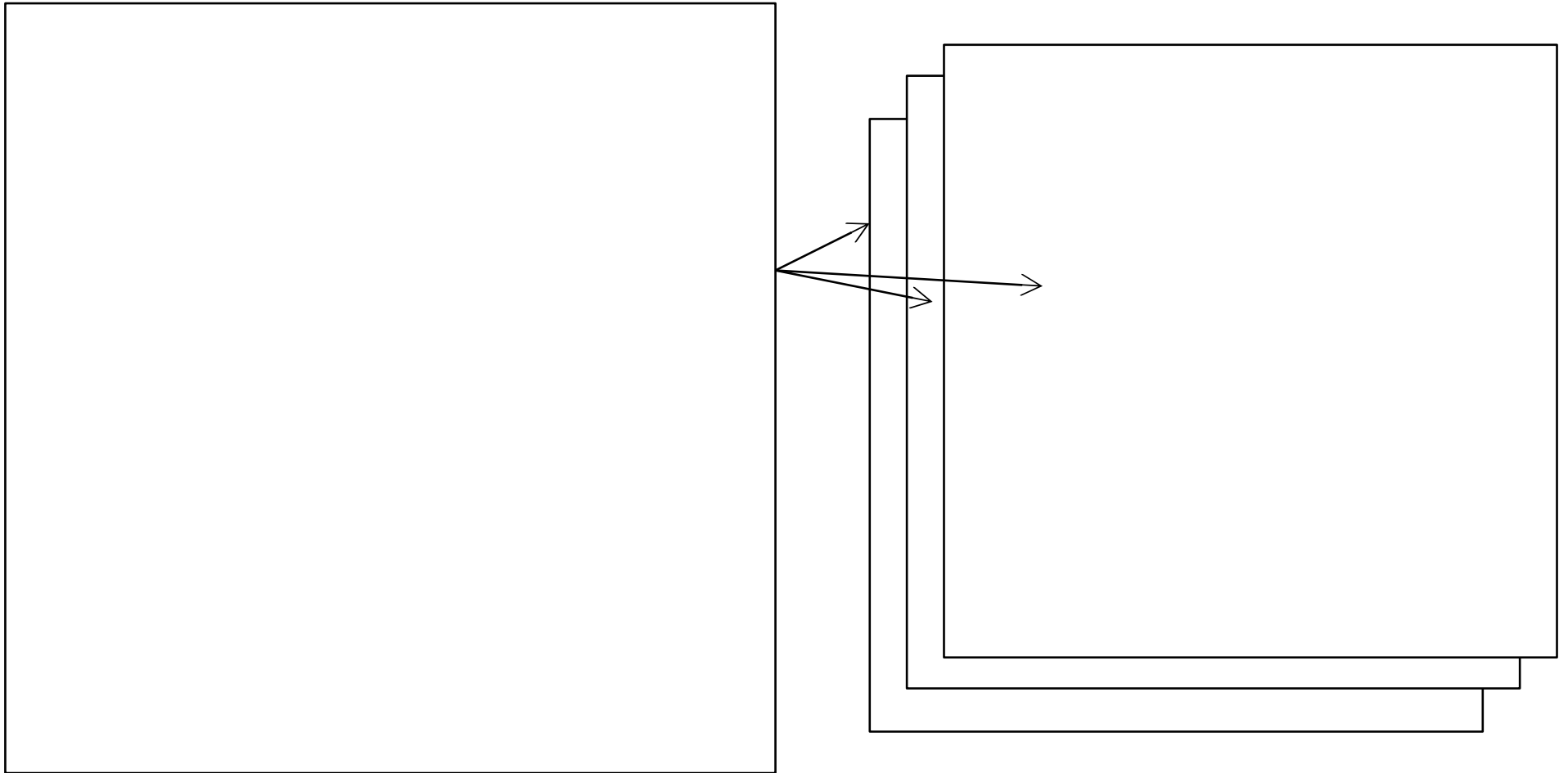
Shared weights and biases



Multiple Feature maps/filters

19 x 19

3 x 17 x 17

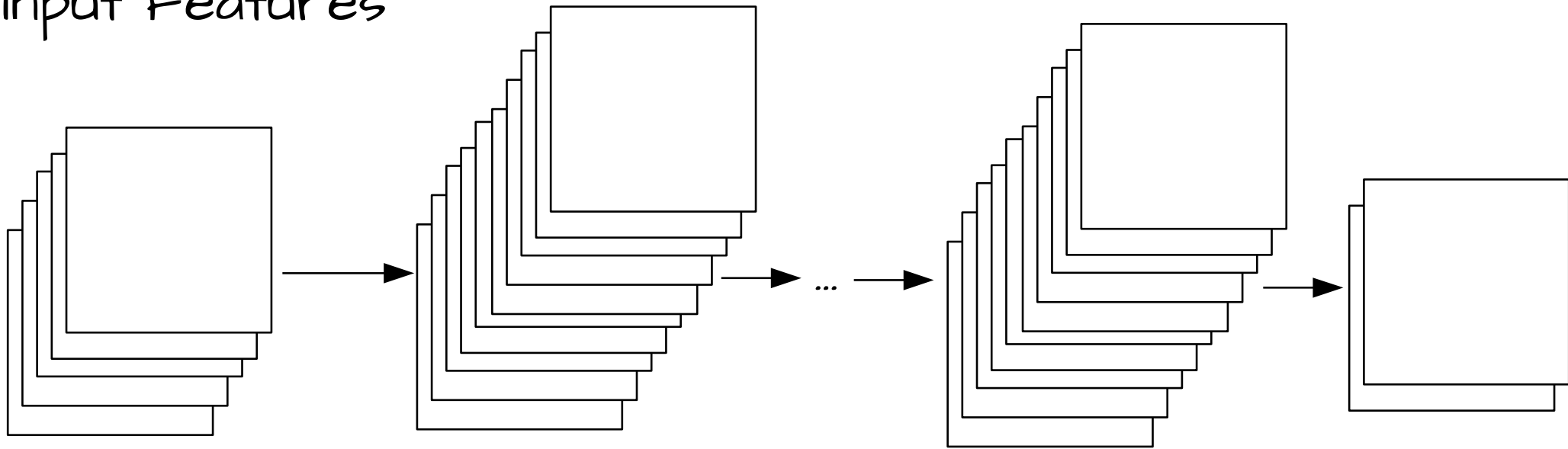


Architecture

12 layers with 64 - 192
filters

Output

Input Features

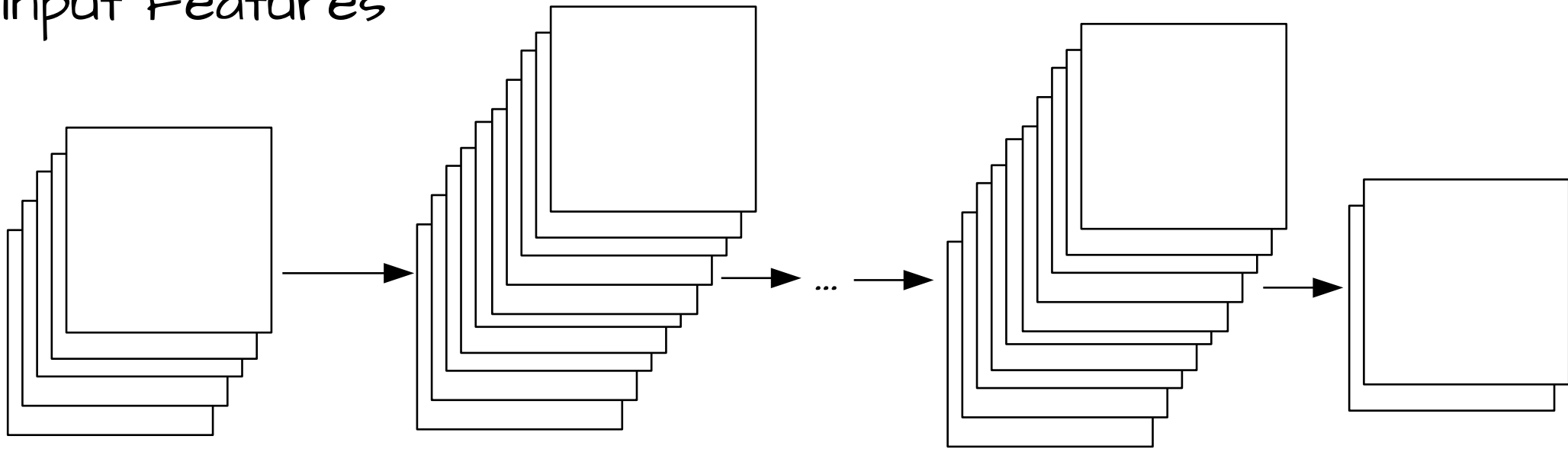


Architecture

12 layers with 64 - 192
filters

Output

Input Features

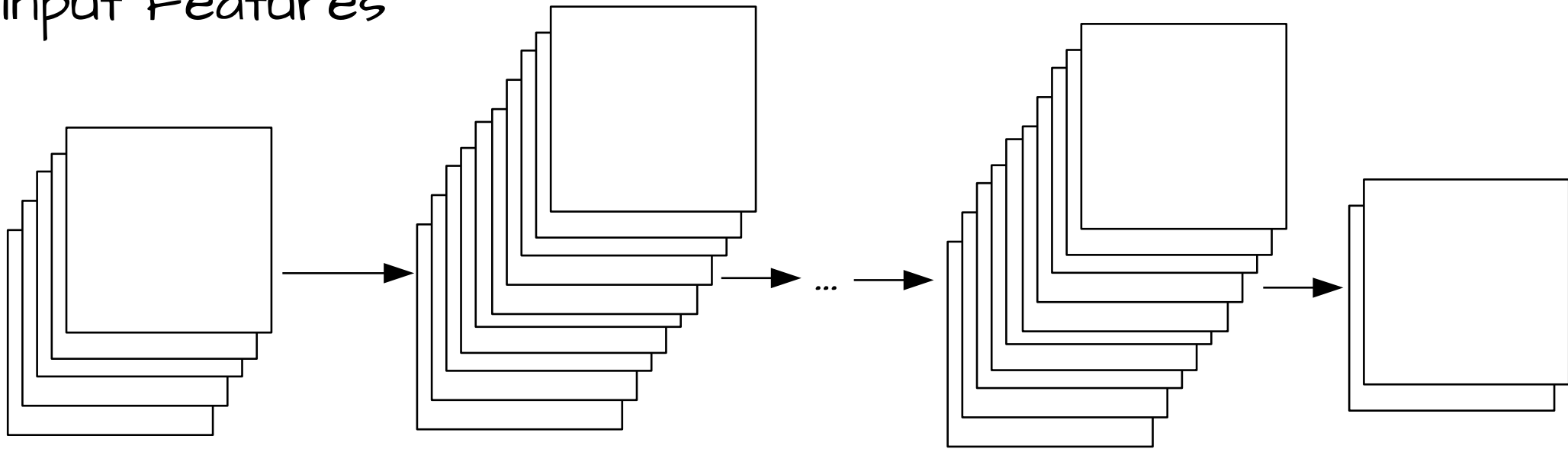


Architecture

12 layers with 64 - 192
filters

Output

Input Features



2.3 million parameters
630 million connections

Input Features

- Stone Colour x 3
- Liberties x 4
- Liberties after move played x 6
- Legal Move x 1
- Turns since x 5
- Capture Size x 7
- Ladder Move x 1
- KGS Rank x 9

Training on game data predicting
the next move

55% Accuracy

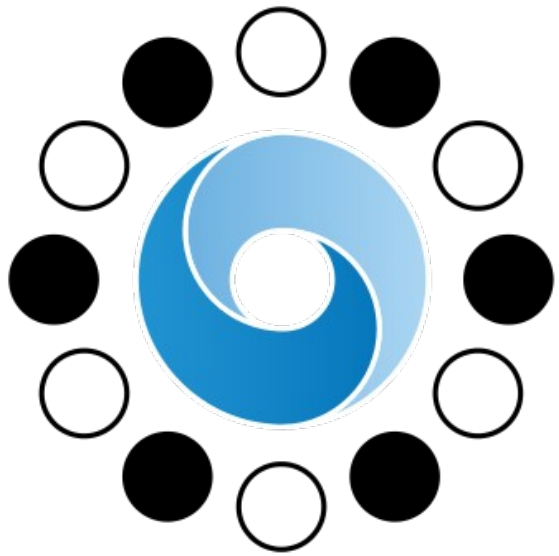
Mostly beats GnuGo

Combined with MCTS in the
Selection

Asynchronous GPU Power



Revolution



AlphaGo

Networks in Training

Rollout policy

SL policy network

RL policy network

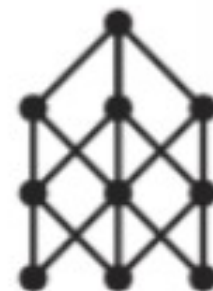
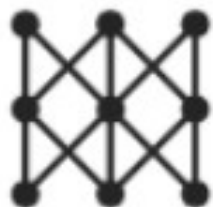
Value network

P_{π}

P_{σ}

P_{ρ}

V_{θ}



Human expert positions

Self-play Positions

Silver, D. et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), p.484-489.

Networks in Training

Rollout policy

SL policy network

RL policy network

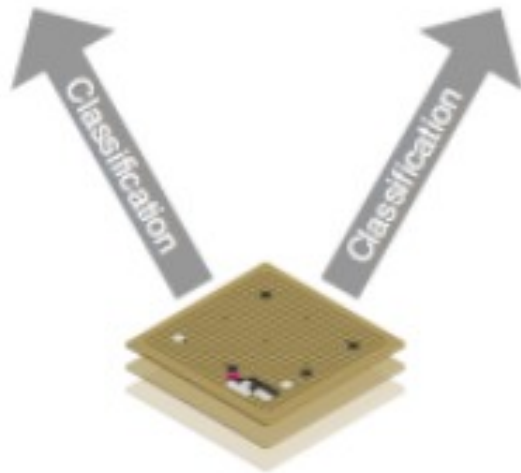
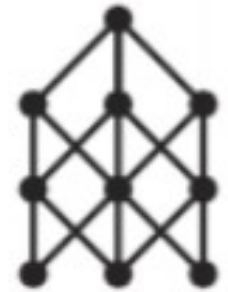
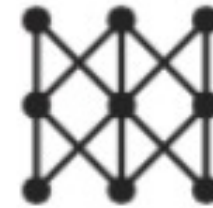
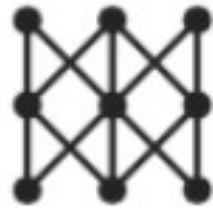
Value network

P_{π}

P_{σ}

P_{ρ}

V_{θ}

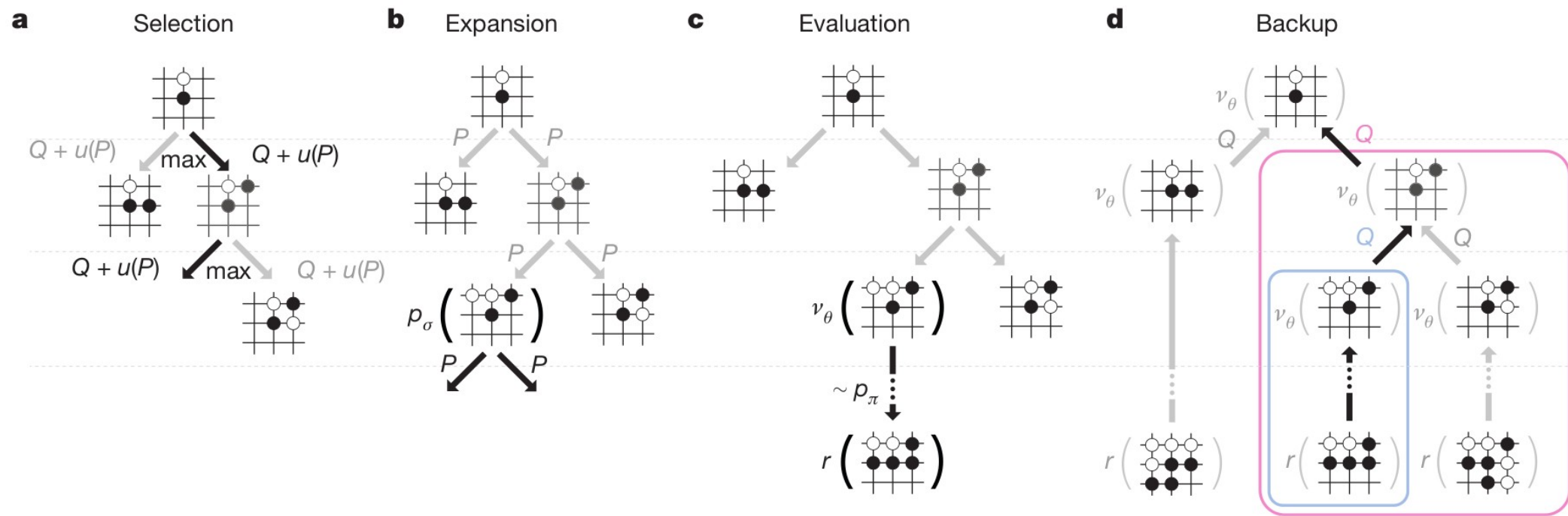


Human expert positions

Self-play Positions

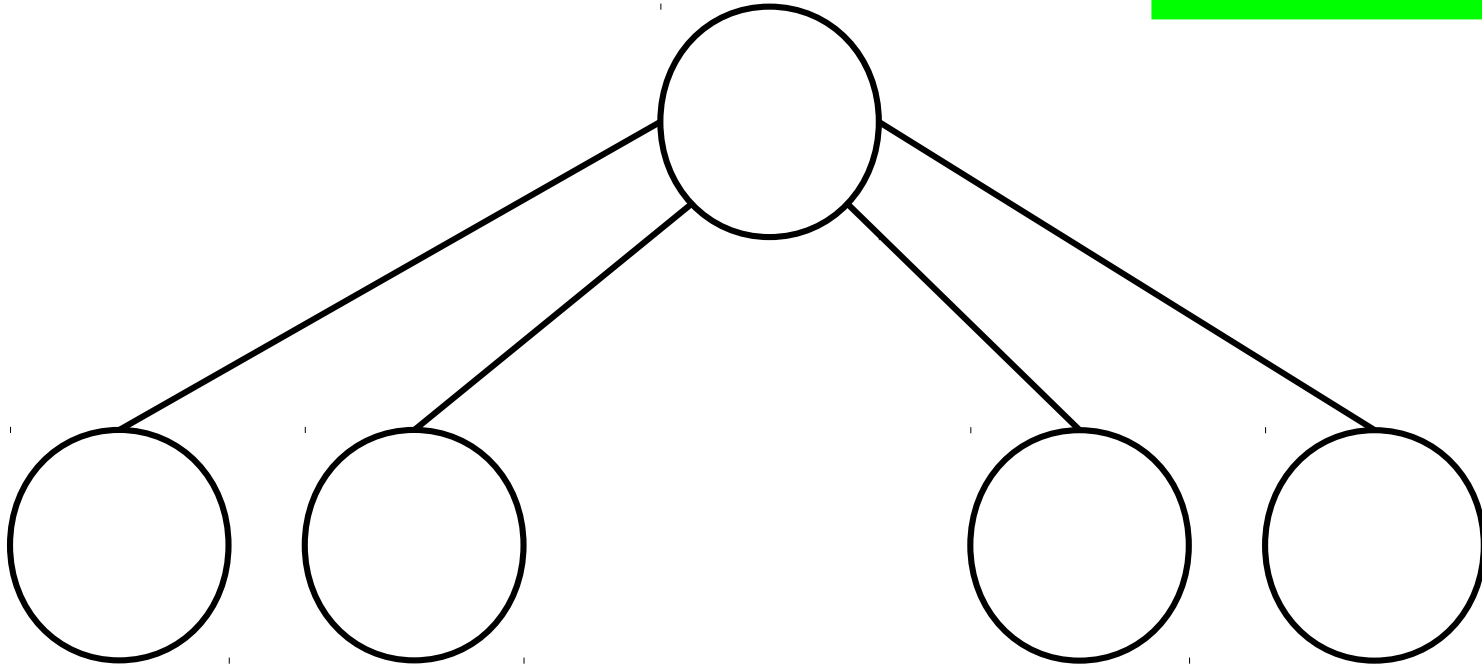
Silver, D. et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), p.484-489.

AlphaGo Search

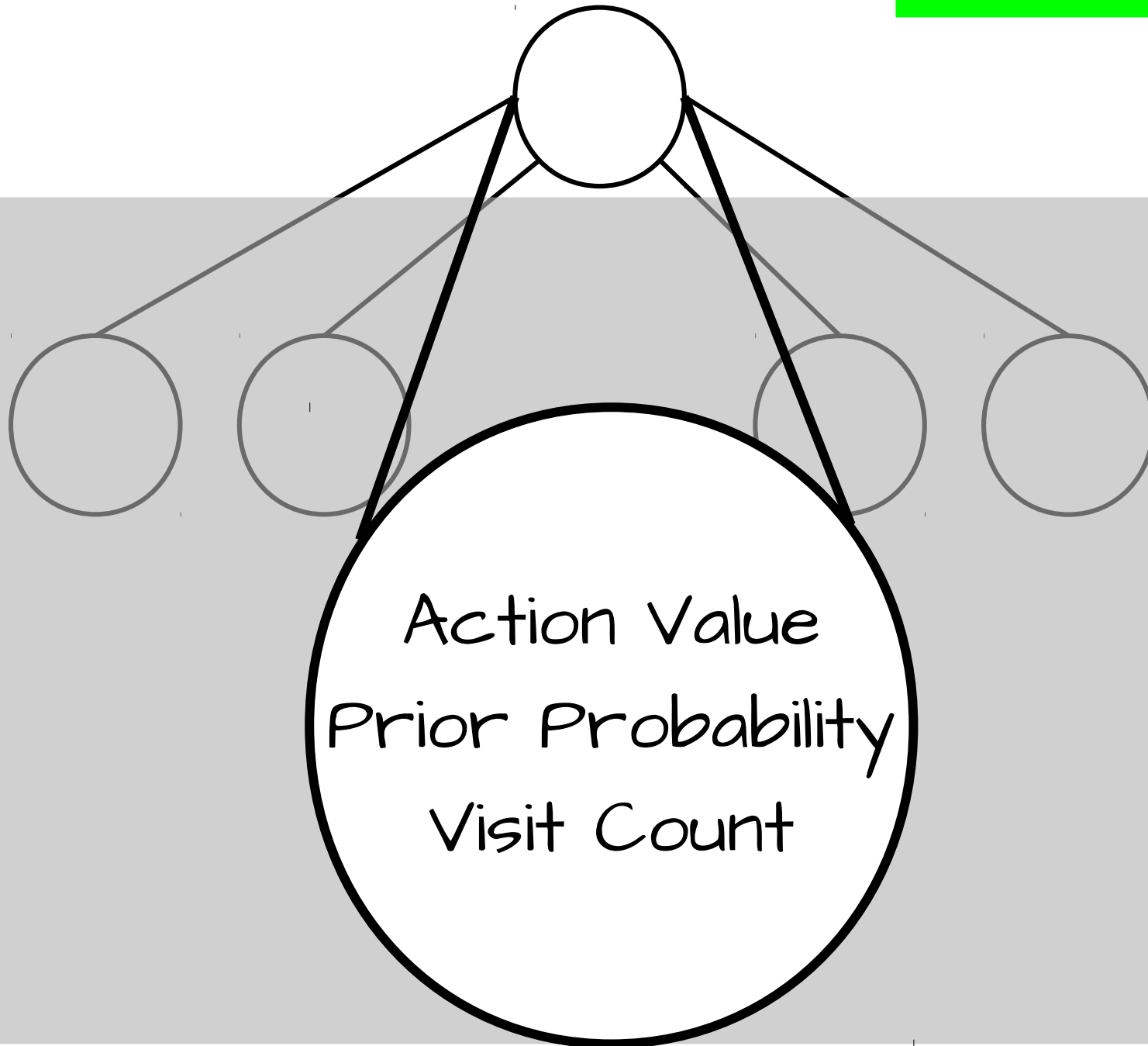


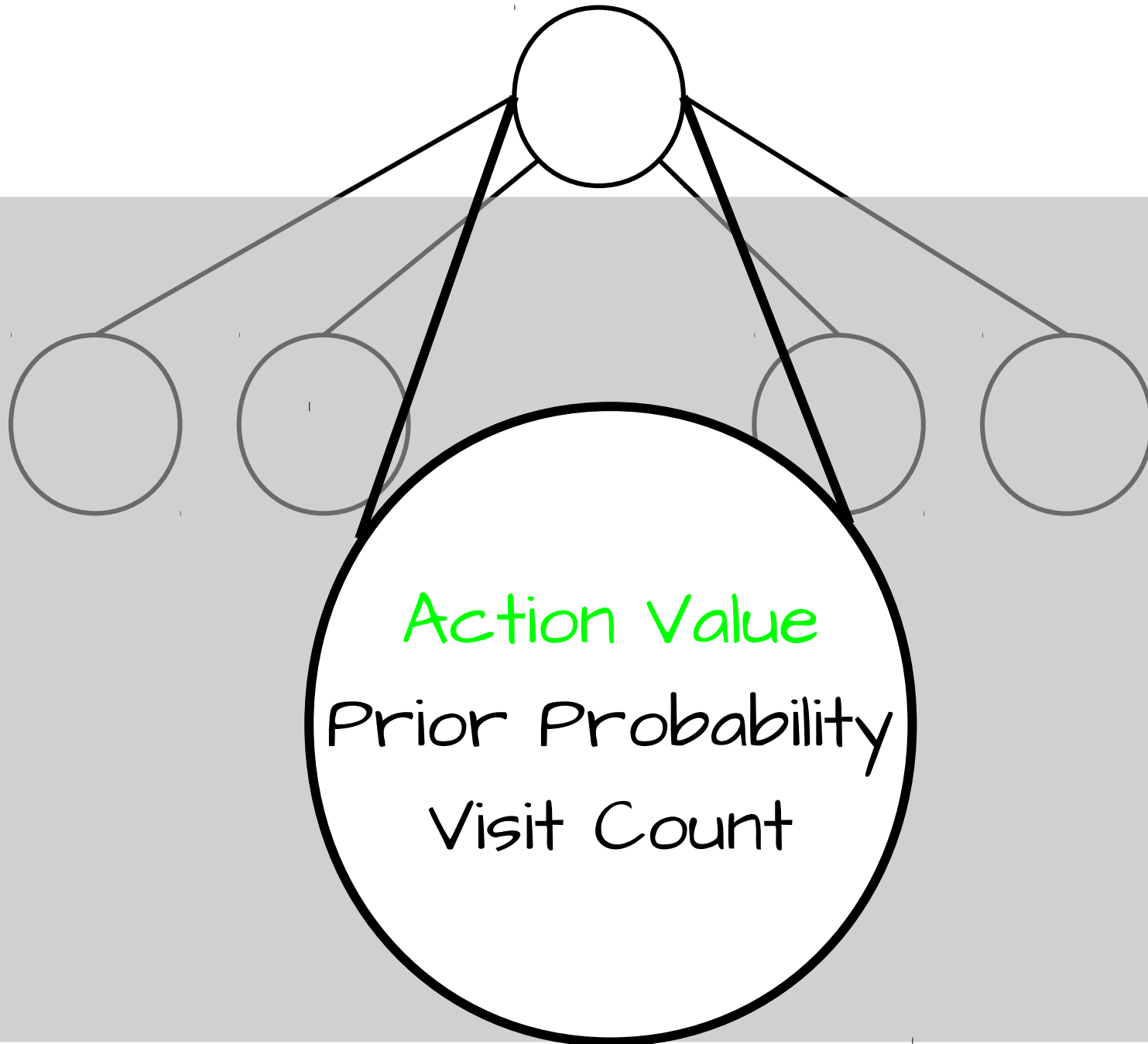
Silver, D. et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), p.484-489.

Selection

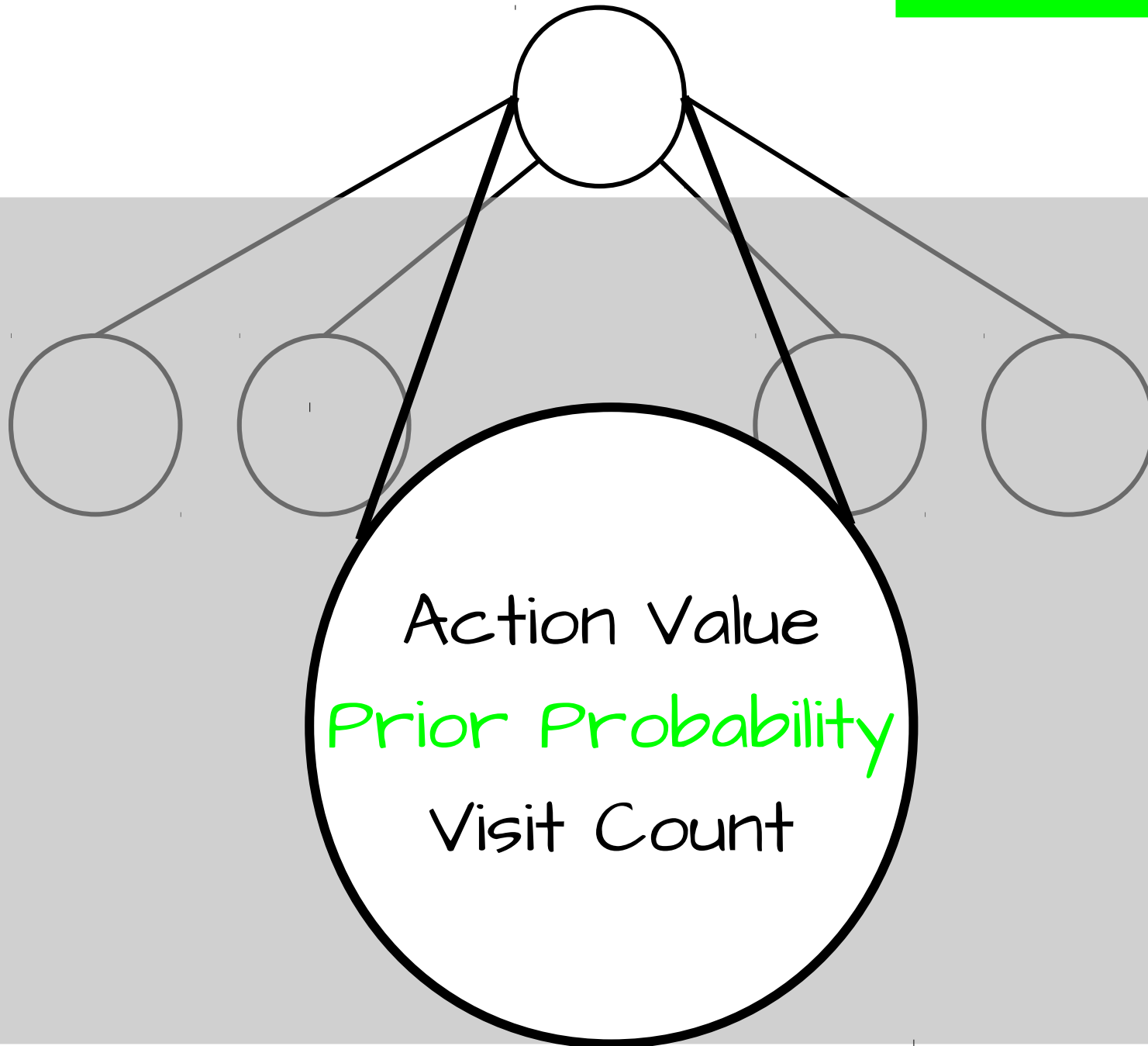


Selection

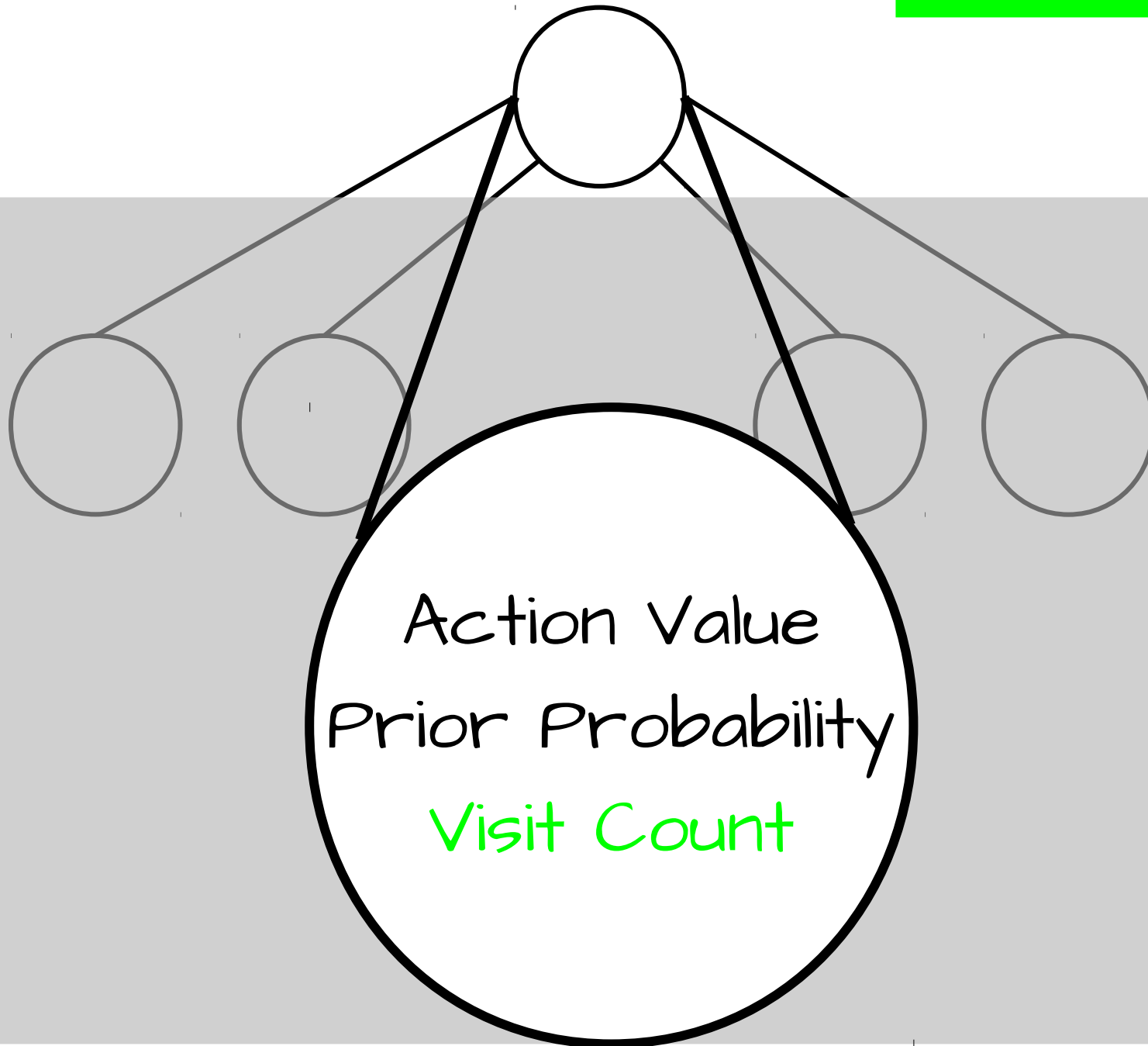




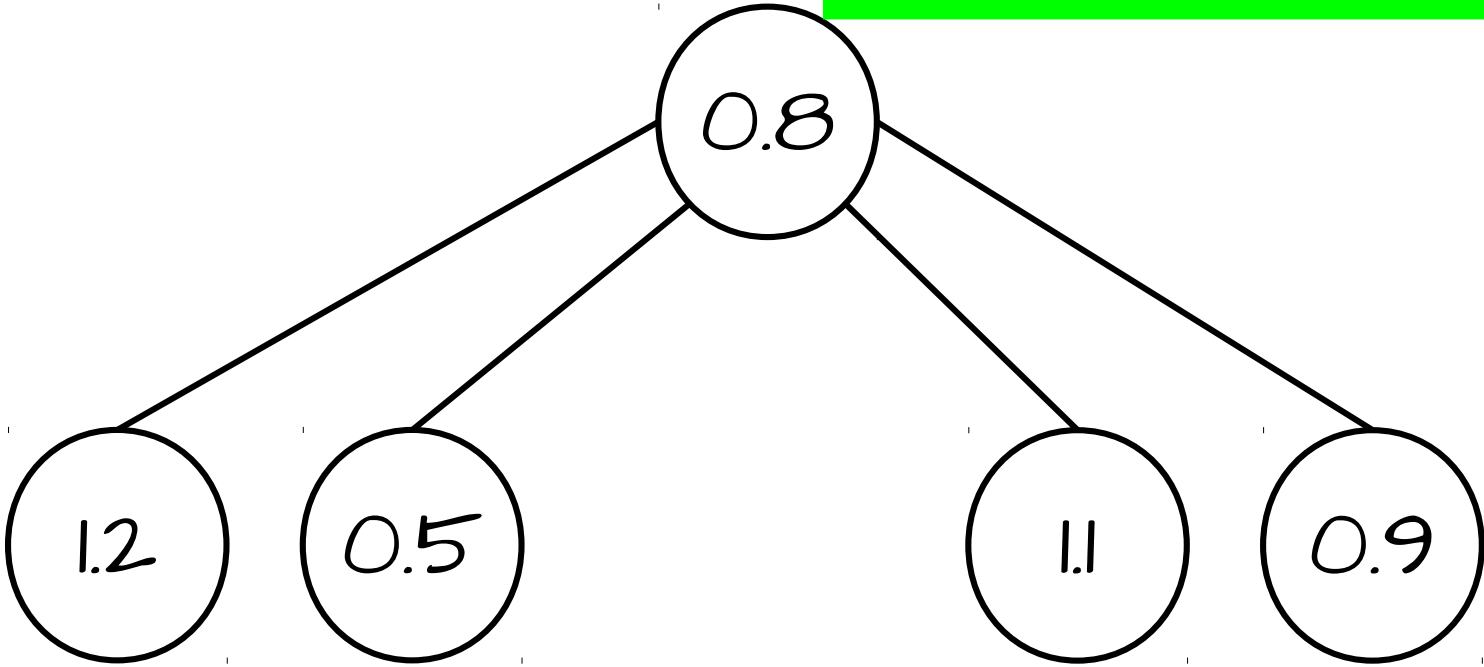
Selection



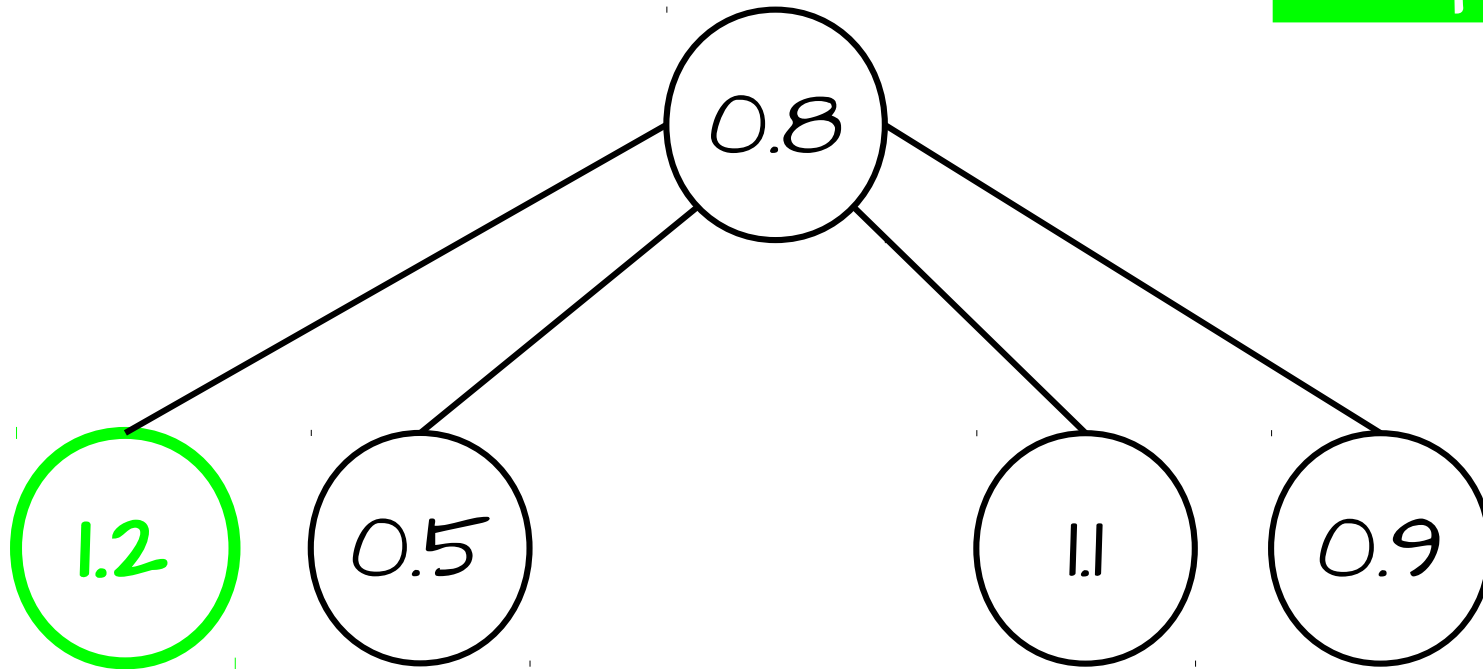
Selection



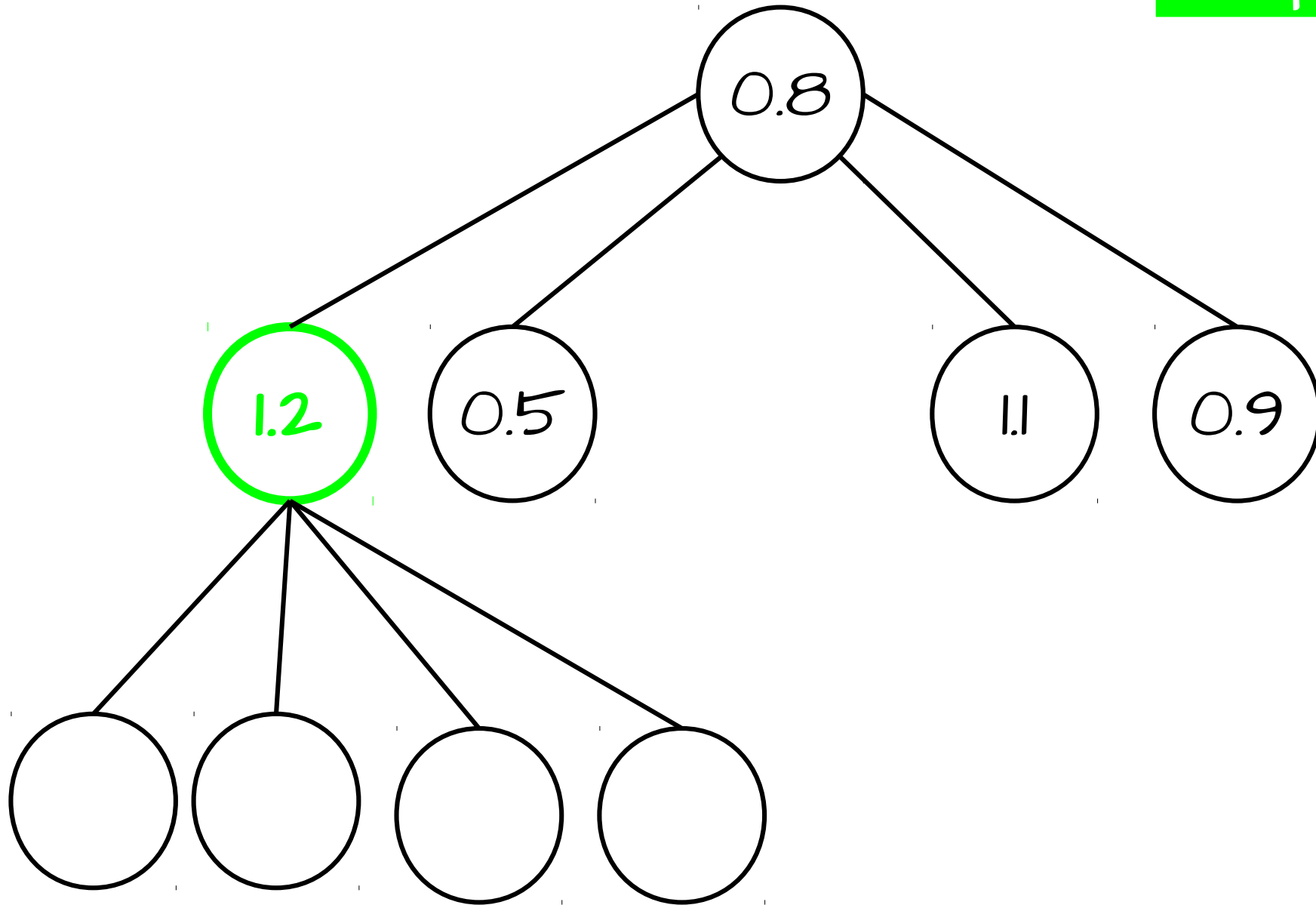
Action Value + Bonues



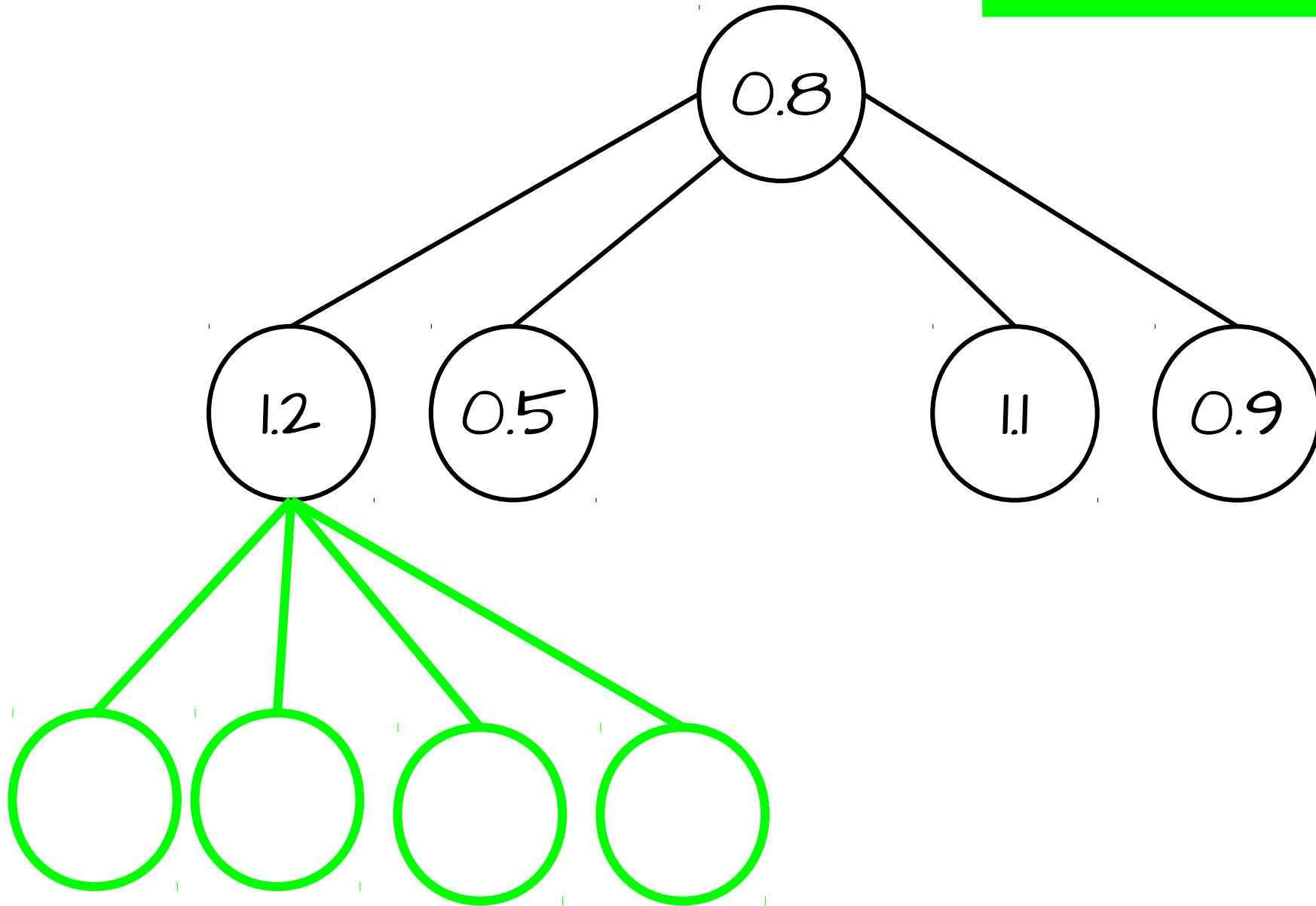
Expansion



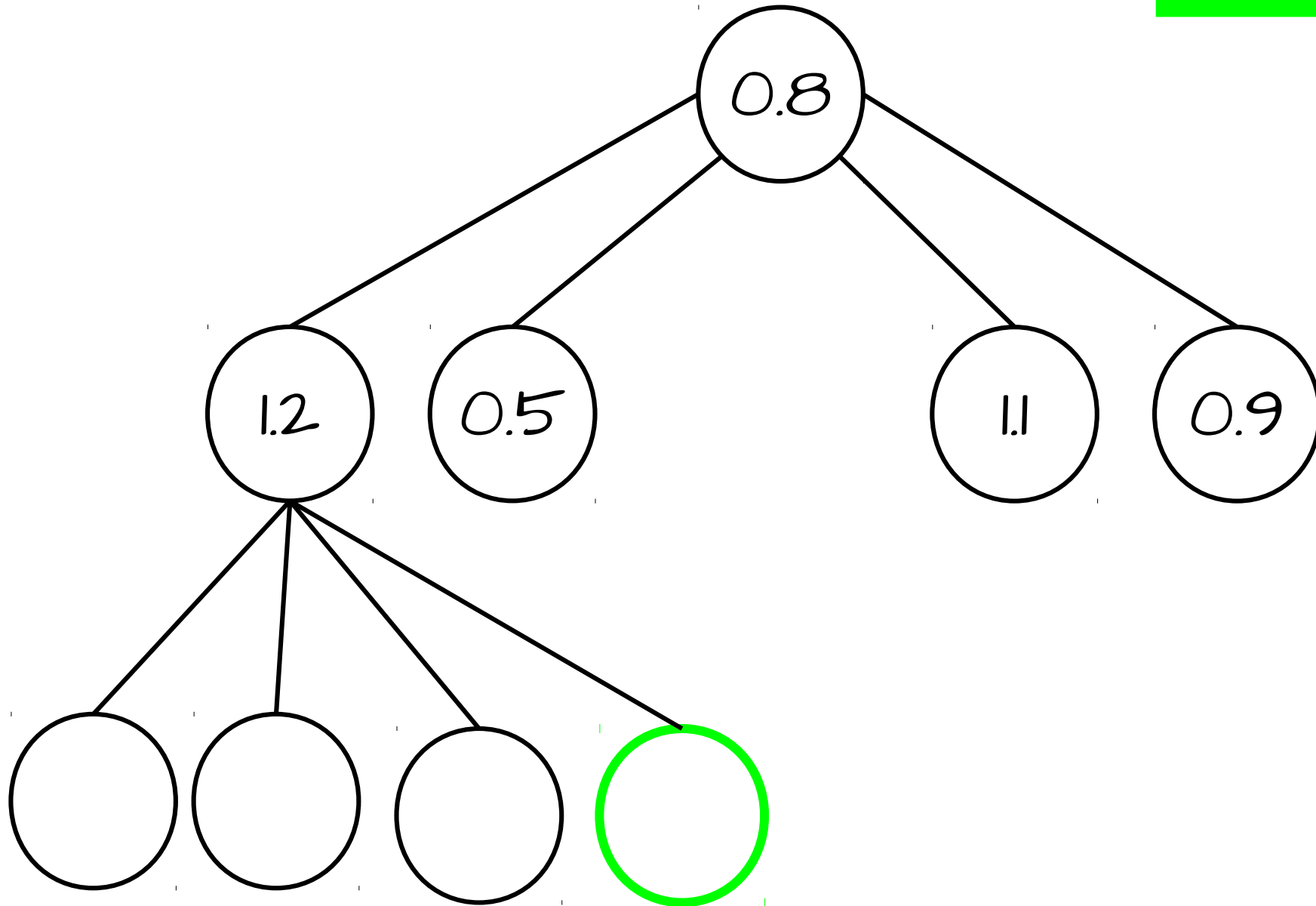
Expansion



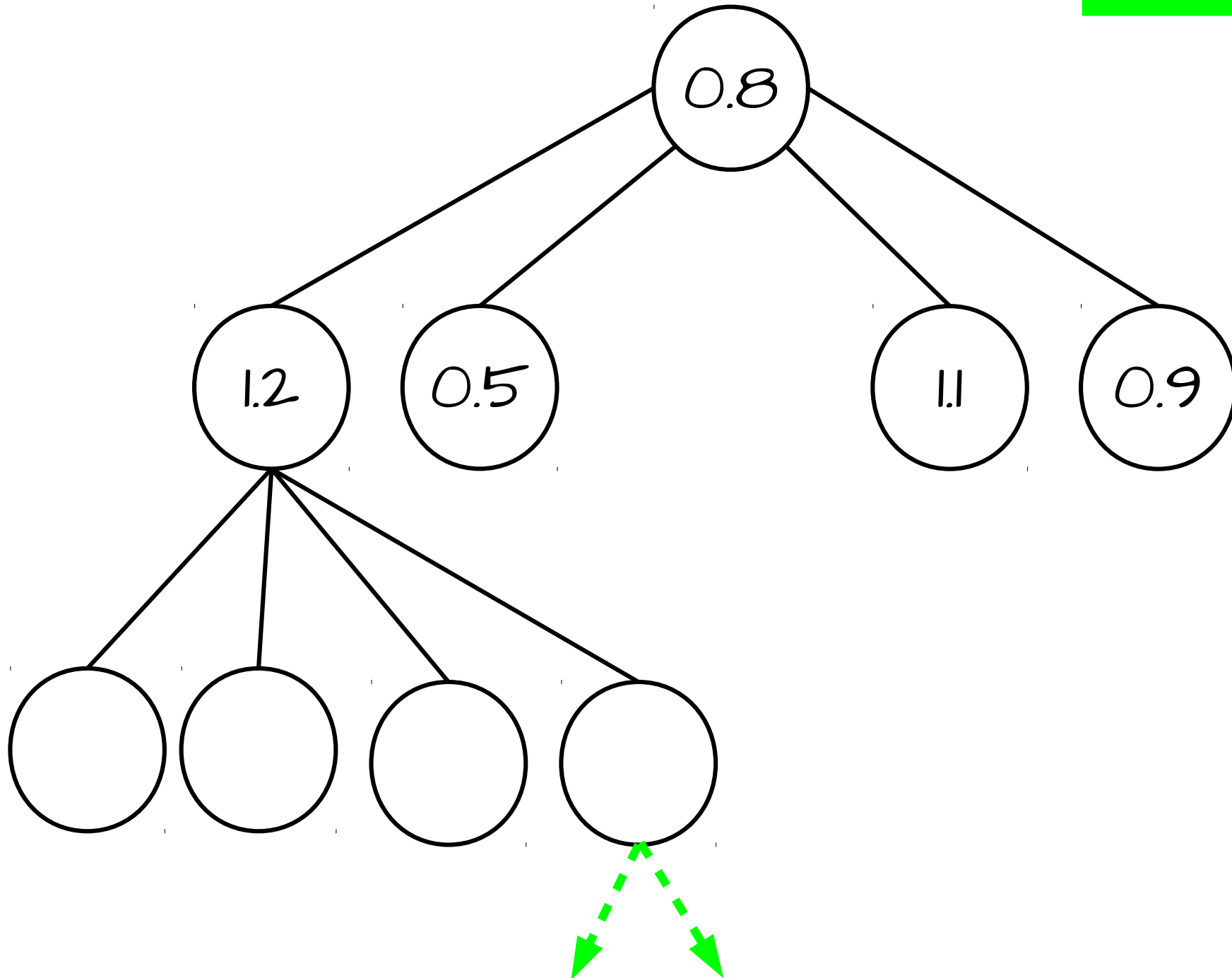
Prior Probability



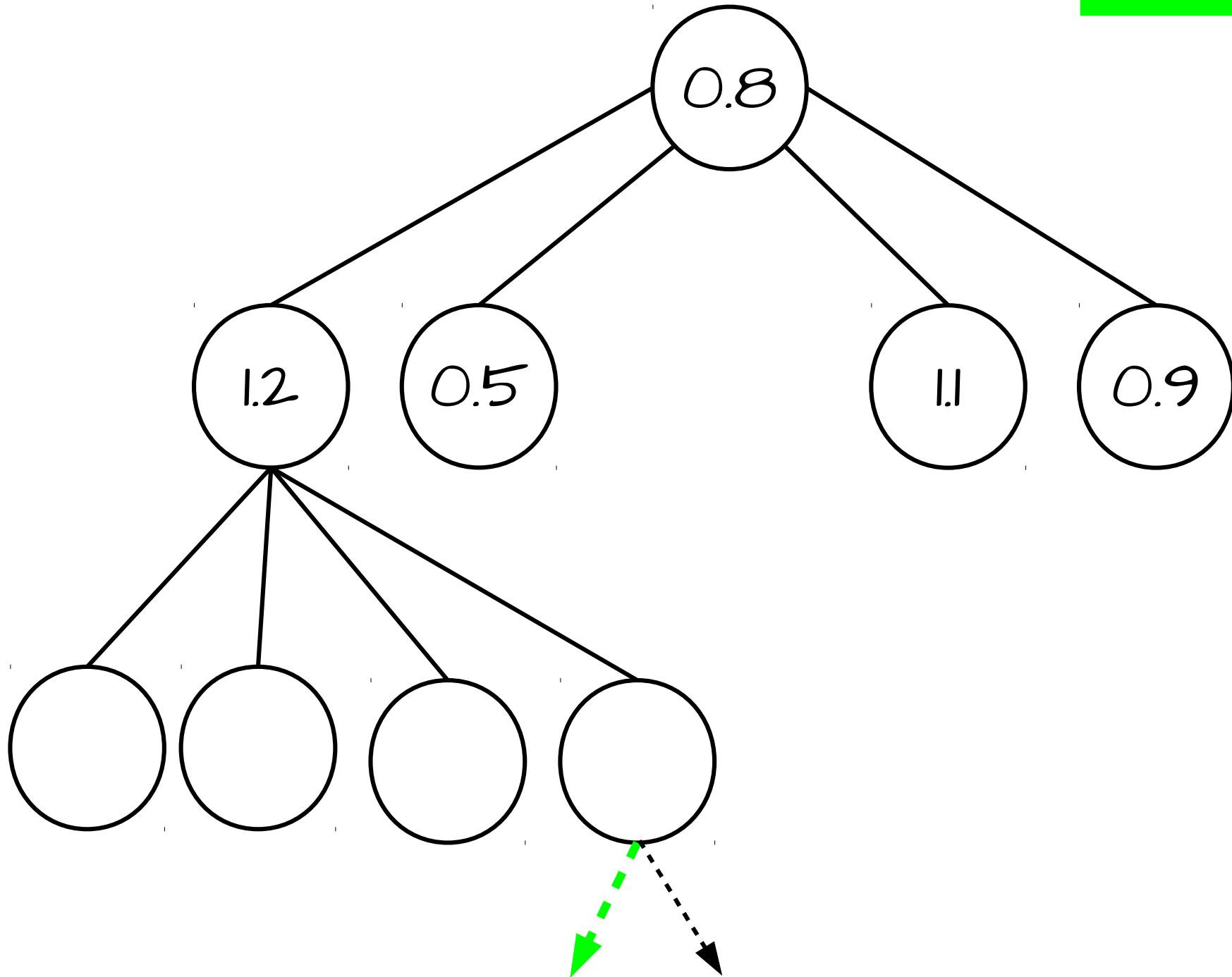
Evaluation



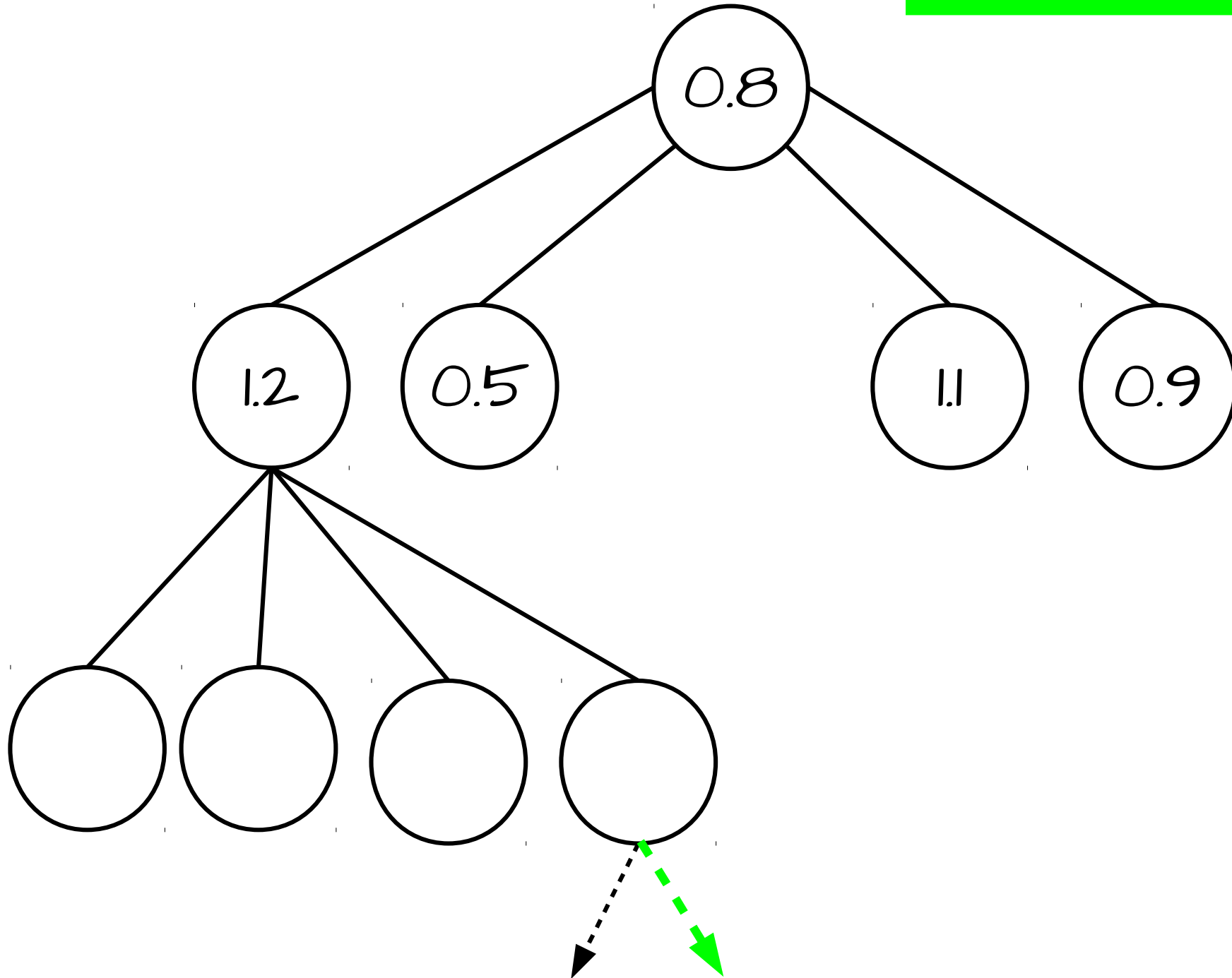
Evaluation



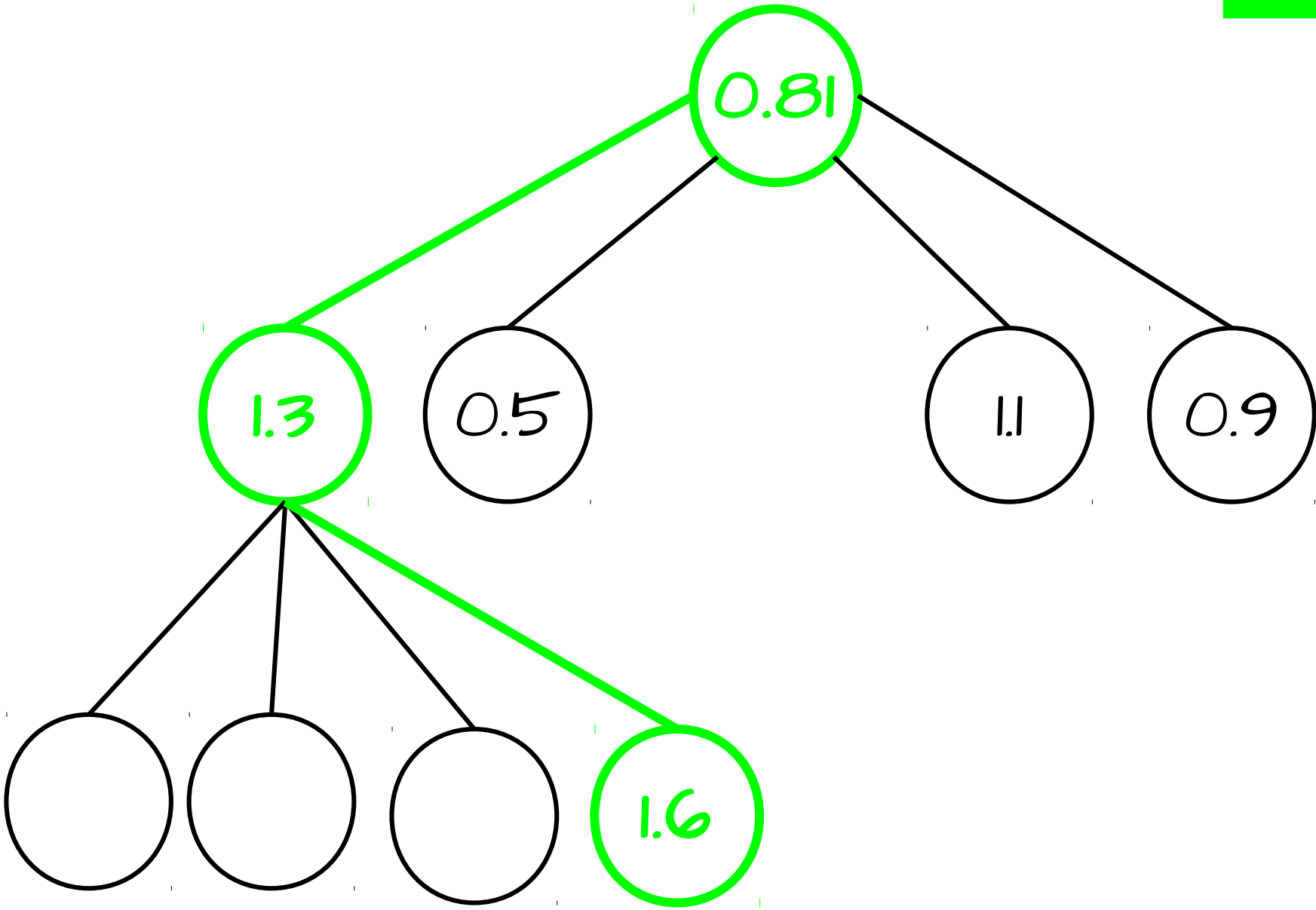
Rollout



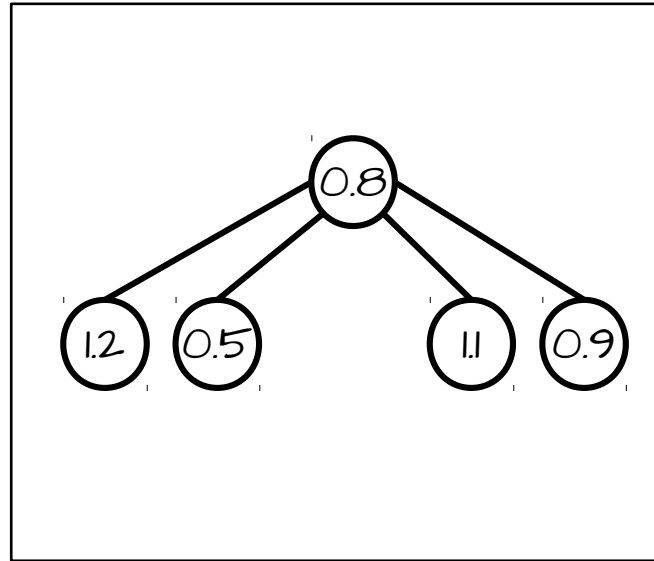
Value Network



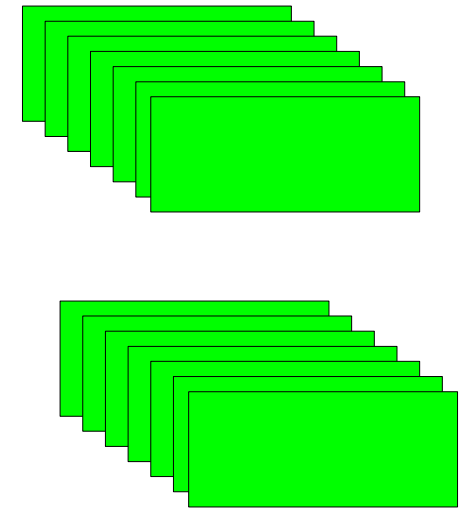
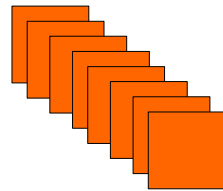
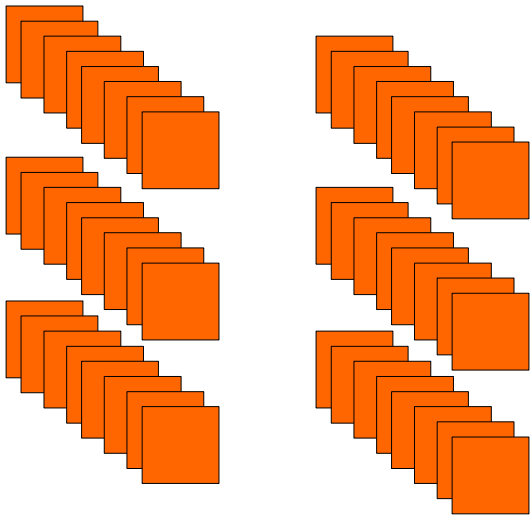
Backup



1202 CPUs



176 GPUS



Tensor



3 Strengths of AlphaGo

Human Instinct

Reading Capability

Positional Judgement

Policy Network

Search

Value Network

Most Important Strength

Human Instinct

Policy Network

Reading Capability

Search

Positional Judgement Value Network

More Natural



Lee Sedol match



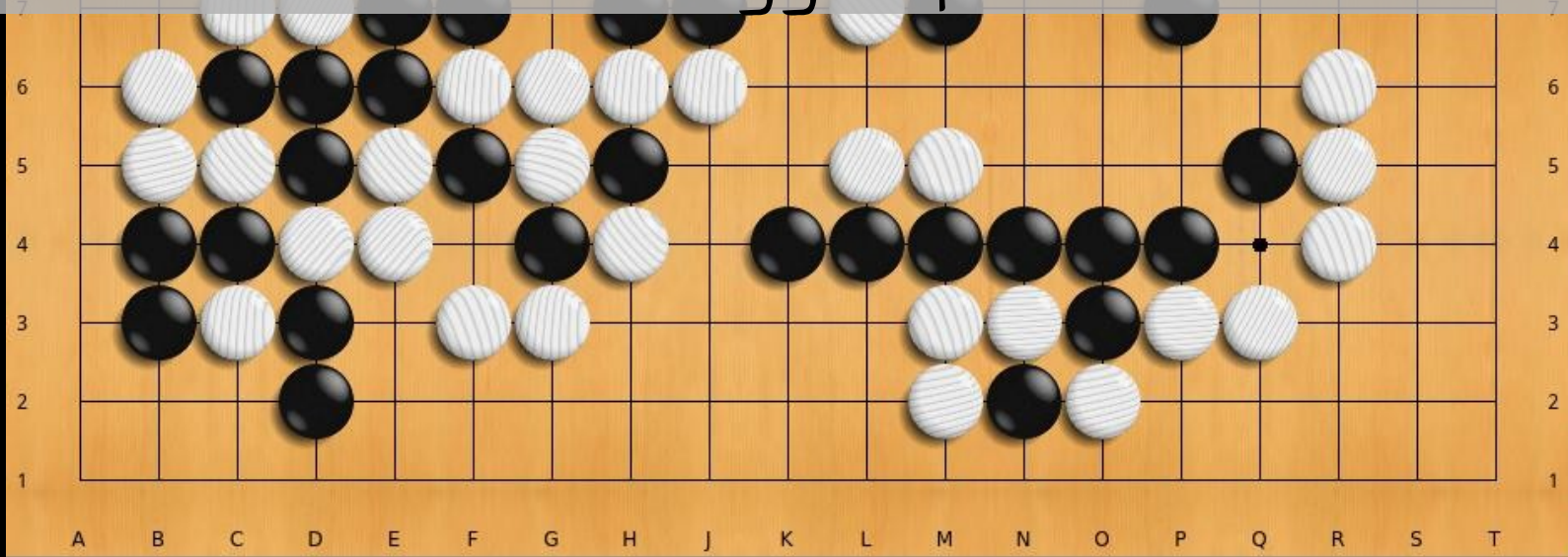
Style





So when AlphaGo plays a **slack looking move**,
we may regard it as a mistake,
but perhaps it should more accurately be viewed
as a **declaration of victory**?

An Younggil 8p



Game 2



Game 4



Game 4



Game 4



What can we learn?



Making X faster

vs

Doing less of X

Benchmark everything

Solving problems the **human** way

vs

Solving problems the **computer**
way

Don't **blindly dismiss** approaches
as infeasible

One Approach

vs

Combination of Approaches

Joy of Creation

white's turn to move!

Make a move in the form XY, e.g. A19, D7 as the labels indicate!

```
> F8
  A B C D E F G H J
9 . . . . . 9
8 . X . . . 0 X . . 8
7 . 0 0 . . . 0 . . 7
6 . . . . 0 . . . . 6
5 . 0 0 X . . . 0 . 5
4 . X X . . . . . 4
3 . . X . . X . . . 3
2 . . . . . X . . . 2
1 . . . . . 1
```

```
white played at F8
black's turn to move!
Rubykon is thinking...
D2 => 0.4881516587677725
C8 => 0.4827586206896552
F4 => 0.4827586206896552
F5 => 0.47761194029850745
G4 => 0.47474747474747475
E8 => 0.4744897959183674
G6 => 0.47150259067357514
D6 => 0.46875
D4 => 0.4627659574468085
F7 => 0.46236559139784944
```

```
  A B C D E F G H J
9 . . . . . 9
8 . X . . . 0 X . . 8
7 . 0 0 . . . 0 . . 7
6 . . . . 0 . . . . 6
5 . 0 0 X . . . 0 . 5
4 . X X . . . . . 4
3 . . X . . X . . . 3
2 . . . X . . . X . 2
1 . . . . . 1
```

black played at D2
white's turn to move!
Make a move in the form XY, e.g. A19, D7 as the labels indicate!

```
> F5
  A B C D E F G H J
9 . . . . . 9
8 . X . . . 0 X . . 8
7 . 0 0 . . . 0 . . 7
6 . . . . 0 . . . . 6
5 . 0 0 X . 0 . 0 . 5
4 . X X . . . . . 4
3 . . X . . X . . . 3
2 . . . X . . . X . 2
1 . . . . . 1
```

```
white played at F5
black's turn to move!
Rubykon is thinking...
```

```
3 $LOAD_PATH.unshift($lib) unless $LOAD_PATH.include?(lib)
4 require 'rubykon/version'
5
6 Gem::Specification.new do |spec|
7   spec.name           = "rubykon"
8   spec.version        = "Rubykon::VERSION"
9   spec.authors        = ["Tobias Pfeiffer"]
10  spec.email           = ["pragjob@gmail.com"]
11
12  spec.summary         = %q{An AI to play Go using Monte Carlo Tree Search.}
13  spec.description     = %q{An AI to play Go using Monte Carlo Tree Search. Currently includes the acts
14  spec.homepage        = "https://github.com/PragTob/rubykon"
15  spec.license         = "MIT"
16
17  spec.files           = `git ls-files -z`.split("\x0").reject { |f| f.match(%r{^(test|spec|features)/}) }
18  spec.bindir          = "exe"
19  spec.executables     = spec.files.grep(%r{^exe/}) { |f| File.basename(f) }
20  spec.require_paths  = ["lib"]
21 end
22
```

- 1 Gemfile
- 2 profiling
- 3 README
- 4 README.md
- 5 pkg/

PragTob/Rubykon

Don't ignore rules
10ex

Minimalistic Go MCTS Engine

117 commits

2 branches

0 releases

5 contributors



Branch: master

michi / +

Fork this project and create a new file



pasky Merge pull request #5 from traveller42/master

Latest commit 2f22d84 18 days

.gitignore

Keep only repository specific entries in repository .gitignore

a month

README.md

Update links to michi-c and michi-c2

a month

michi.py

Test for Pass in the GTP code was too strict

18 days

pasky/michi

Michi --- Minimalistic Go MCTS Engine

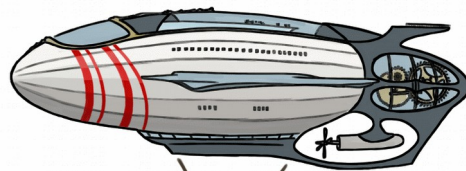
Michi aims to be a minimalistic but full-fledged Computer Go program based on state-of-art methods (Monte Carlo Tree Search) and written in Python. Our goal is to make it easier for new people to enter the domain of Computer Go, peek under the hood of a "real" playing engine and be able to learn by

What did AlphaGo do to beat the
strongest human Go player?

Tobias Pfeiffer

@PragTob

pragtob.info



bitcrowd

Sources

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- Silver, D. et al., 2016. Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), p.484-489.
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- <https://www.youtube.com/watch?v=LX8Knl0g0LE&index=9&list=WL>

Photo Credit

- <http://www.computer-go.info/events/ing/2000/images/bigcup.jpg>
- <https://en.wikipedia.org/wiki/File:Kasparov-29.jpg>
- <http://www.geforce.com/hardware/desktop-gpus/geforce-gtx-titan-black/product-images>
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