Course Review and AlphaGo

CS 287

Today's Lecture

- Overview of the models/tasks covered course
- AlphaGo

Contents

Foundational Challenge: Turing Test

Q: Please write me a sonnet on the subject of the Forth Bridge.

A : Count me out on this one. I never could write poetry.

Q: Add 34957 to 70764.

A: (Pause about 30 seconds and then give as answer) 105621.

Q: Do you play chess?

A: Yes.

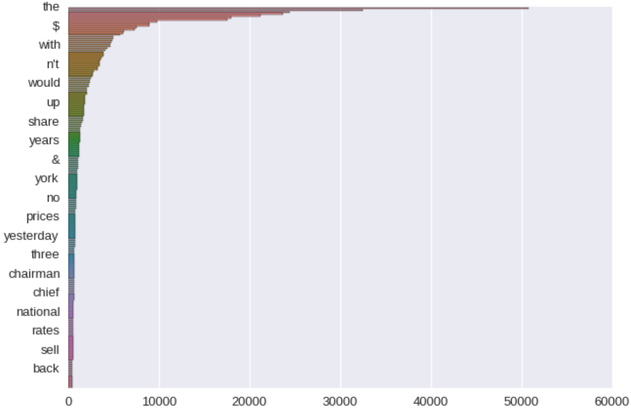
Q: I have K at my K1, and no other pieces. You have only K at K6 and R at R1. It is your move. What do you play?

A: (After a pause of 15 seconds) R-R8 mate. - Turing (1950)

(1) Lexicons and Lexical Semantics

Zipf' Law (1935,1949):

The frequency of any word is inversely proportional to its rank in the frequency table.



(2) Structure and Probabilistic Modeling

The Shannon Game (Shannon and Weaver, 1949):

Given the last n words, can we predict the next one?

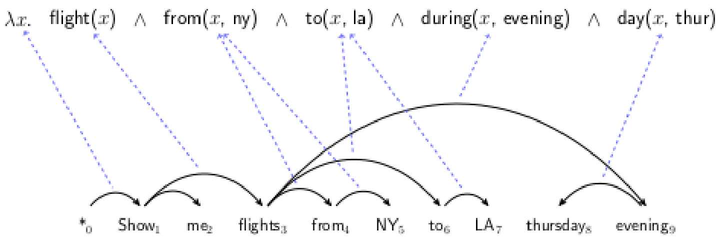
`The pin-tailed snipe (Gallinago stenura) is a small stocky wader. It breeds in northern Russia and migrates to spend the __`

- Probabilistic models have become very effective at this task.
- Crucial for speech recognition (Jelinek), OCR, automatic translations, etc.

(3) Compositionality of Syntax and Semantics

Probabilistic models give no insight into some of the basic problems of syntactic structure - Chomsky (1956)

`Show me flights from NY to LA Thursday evening.`



(4) Document Structure and Discourse

Language is not merely a bag-of-words but a tool with particular properties - Harris (1954)

(5) Knowledge and Reasoning Beyond the Text

> *It is based on the belief that in modeling language understanding, we must deal in an integrated way with all of the aspects of language syntax, semantics, and inference.* - Winograd (1972)

`The city councilmen refused the demonstrators a permit because they [feared/advocated] violence.`

- Recently (2011) posed as a challenge for testing commonsense reasoning.

Contents

Machine Learning Approaches to NLP

Many problem-specific modeling questions,

- $\mathbf{x}$; input representation
- $\mathbf{y}$; output representation
- Model architecture
- Objective

This Course: Focus on supervised data-driven, end-to-end approaches

Input Representations

1. Sparse Features
2. Dense Features (Embeddings)
3. Convolutional NN
4. Recurrent NN

Deep Learning for NLP

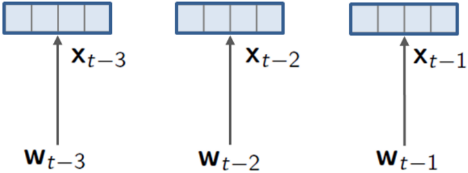
> *Deep Learning waves have lapped at the shores of computational linguistics for several years now, but 2015 seems like the year when the full force of the tsunami hit major NLP conferences.*

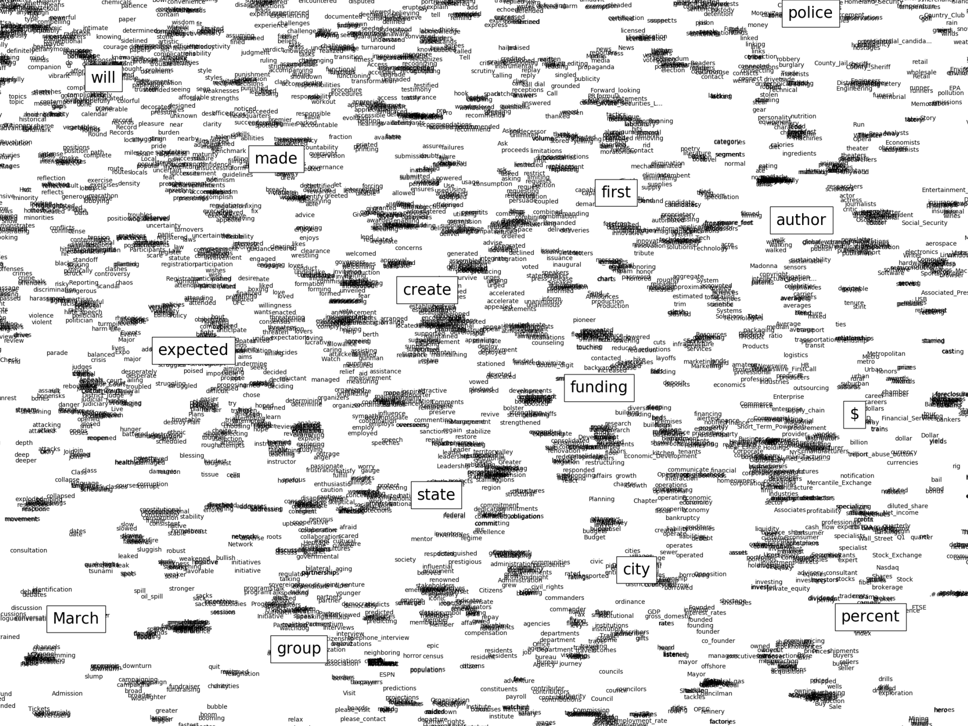
- Chris Manning (Computational Linguistics and Deep Learning)

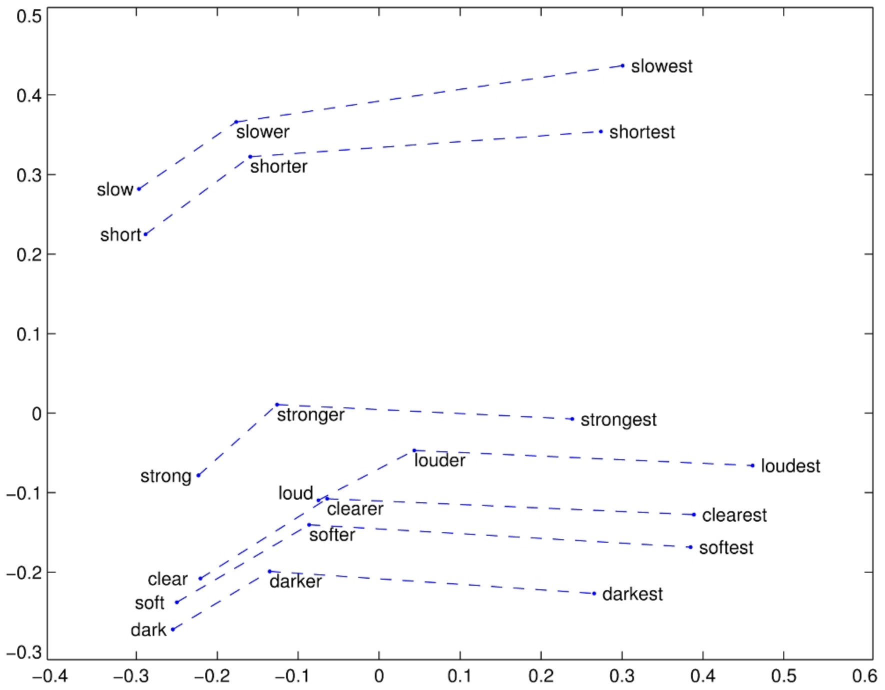
Neural Network Toolbox

Embeddings	sparse features	$\Rightarrow$	dense features
Convolutions	feature n-grams	$\Rightarrow$	dense features
RNNs	feature sequences	$\Rightarrow$	dense features

Embeddings sparse features $\Rightarrow$ dense features



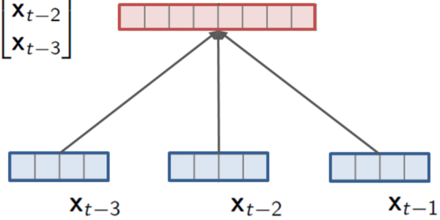

police
will
made
first
author
create
expected
funding
$
state
city
March
group
percent

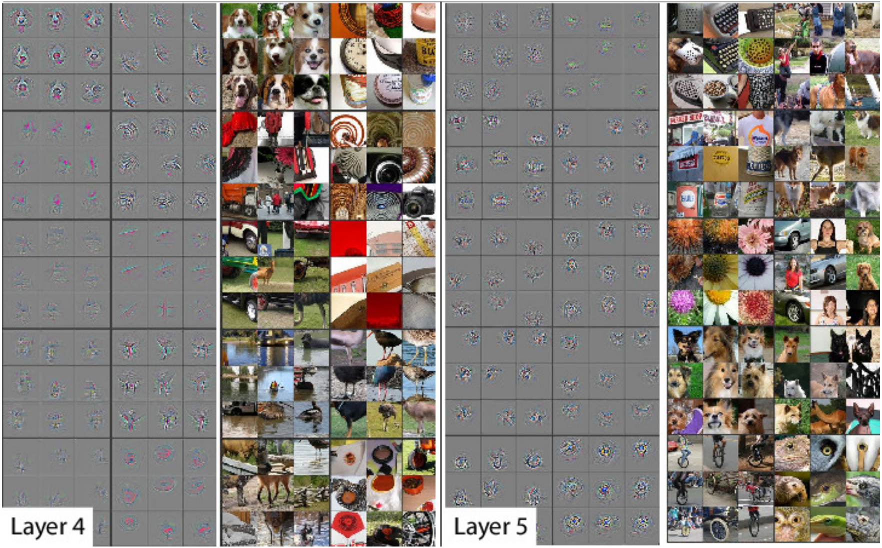


0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.3
−0.2
−0.1
0
0.1
0.2
0.3
0.4
0.5
0.6
slowest
slower
shortest
shorter
slow
short
stronger
strongest
strong
louder
loudest
loud
clearer
clearest
softer
softest
clear
darker
darkest
soft
dark

Convolutions feature n-grams $\Rightarrow$ dense features

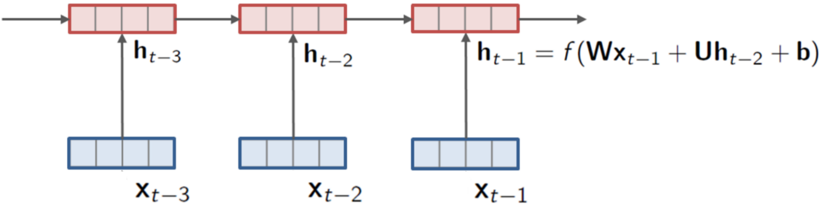
$$\mathbf{h}_{t-1} = \mathbf{W} \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{x}_{t-2} \\ \mathbf{x}_{t-3} \end{bmatrix}$$





(Zeiler and Fergus, 2014)

RNNs/LSTMs feature sequences $\Rightarrow$ dense features



A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

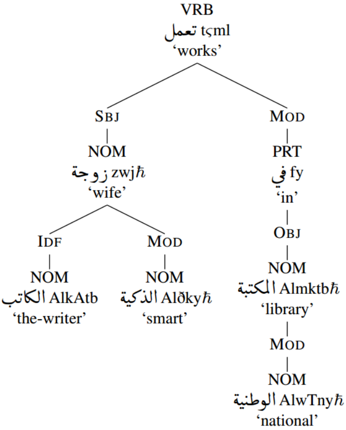
(Xu et al, 2015)

The Fantasy

> *I get pitched regularly by startups doing generic machine learning which is, in all honesty, a pretty ridiculous idea. Machine learning is not undifferentiated heavy lifting, its not commoditizable like EC2, and closer to design than coding.*

- Joseph Reisinger (Computational Linguistics and Deep Learning)

تعمل زوجة الكاتب الذكية في المكتبة الوطنية



(Marton et al., 2010)

Pipeline Steps

- Morphological Seg
- Morphological Tagging
- Part-of-Speech
- Entity Recognition
- Syntactic Parsing
- Role Labeling
- Discourse Analysis

What model should I use?

Questions to ask:

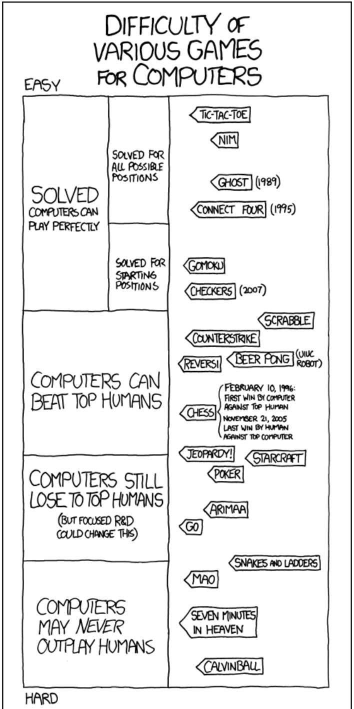
- Do I have significant amounts of supervised data?
- Do I have prior knowledge of my problem/domain?
- What is the underlying metric of interest?
- Do I need interpretability of the model?
- Is the structure of the text important?
- Is training efficiency/prediction efficiency important?

Example: Simple Question Answering

```
10 Mary moved to the hallway.
11 Daniel travelled to the office.
12 Where is Daniel?     office  11
```

- Input is the sentences and the question
- Output is a set of possible answers.
- How might you go about selecting an answer?

Contents


DIFFICULTY OF VARIOUS GAMES FOR COMPUTERS
EASY
SOLVED
COMPUTERS CAN PLAY PERFECTLY
SOLVED FOR ALL POSSIBLE POSITIONS
TIC-TAC-TOE
NIM
GHOST (1989)
CONNECT FOUR (1995)
SOLVED FOR STARTING POSITIONS
GOMOKU
CHECKERS (2007)
COMPUTERS CAN BEAT TOP HUMANS
SCRABBLE
COUNTERSTRIKE
REVERSI
BEER PONG (UIUC ROBOT)
CHESS
FEBRUARY 10, 1996: FIRST WIN BY COMPUTER AGAINST TOP HUMAN
NOVEMBER 21, 2005 LAST WIN BY HUMAN AGAINST TOP COMPUTER
JEOPARDY!
STARCRAFT
POKER
COMPUTERS STILL LOSE TO TOP HUMANS
(BUT FOCUSED R&D COULD CHANGE THIS)
ARIMAA
GO
COMPUTERS MAY NEVER OUTPLAY HUMANS
SNAKES AND LADDERS
MAO
SEVEN MINUTES IN HEAVEN
CALVINBALL
HARD

https://www.youtube.com/watch?v=Jq5SObMdV3o

ASIA PACIFIC

Google's Computer Program Beats Lee Se-dol in Go Tournament

By **CHOE SANG-HUN** MARCH 15, 2016

Lee Se-dol with his daughter Lee Hye-lim on his way to the last Go match with Google's AlphaGo artificial intelligence program in Seoul, South Korea. Kim Hong-Ji/Reuters

AlphaGo Overview

1. Learn a model to predict one-step move from experts
2. Refine by self-play reinforcement learning
3. Use as part of game-tree search.

Policy Setup

Given current board state s, distribution over actions a.

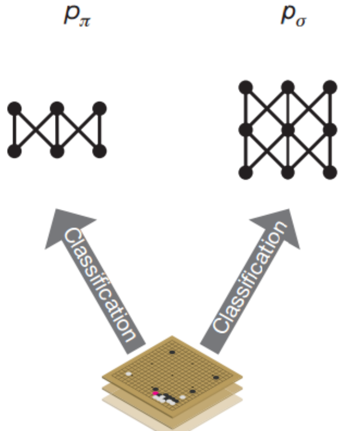
- Learn a policy, $p(a|s)$
- Estimate distribution with softmax.
- Gives a one-step Go player.

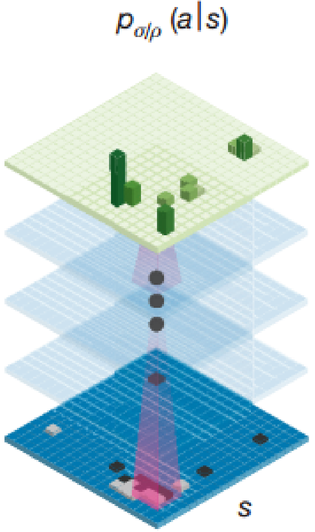
(1) Policy Network

Learned from 29.4 million positions from 160,000 expert games

Two models:

- $p_\pi(a|s)$; multiclass logistic regression (pattern+sparse features)
- $p_\sigma(a|s)$; deep convolutional network




$p_{\sigma|\rho}(a|s)$
s

Deep Convolutional Network

The first hidden layer zero pads the input into a 23x23 image, then convolves k filters of kernel size 5x5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21x21 image, then convolves k filters of kernel size 33 with stride 1, again followed by a rectifier nonlinearity.

Deep Convolutional Network

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The step size α was initialized to 0.003 and was halved every 80 million training steps, without momentum terms, and a mini-batch size of $m = 16$. Updates were applied asynchronously on 50 GPUs using DistBelief 61; gradients older than 100 steps were discarded. Training took around 3 weeks for 340 million training steps.

(2) Reinforcement Learning

- Refine one-step player by playing against itself.
- Popular technique for stochastic games (TD-Gammon)
- Reinforcement learning objects to account for single-step bias

Self-Play with Policy Gradient

Start with p_σ and play against itself to learn:

- $p_\rho(a|s)$; deep convolution network (policy gradient)

Process: Training epoch $J+1$

1. Sample opponent from previous version of model $j < J$
2. Play game between players p_{ρ^J} and p_{ρ^j}
3. Update weights using policy gradient on RL objective

$$\Delta\rho \propto \frac{\partial \log p_\rho(a_t|s_t)}{\partial \rho} z_t$$

where $z_t \in \{-1, 1\}$ represents the final outcome of the game.

Value Network

- Policy network trains only move at state.
- Useful also to know the value of a state.

$$v(s) = E_{p_\rho}[z_t|s]$$

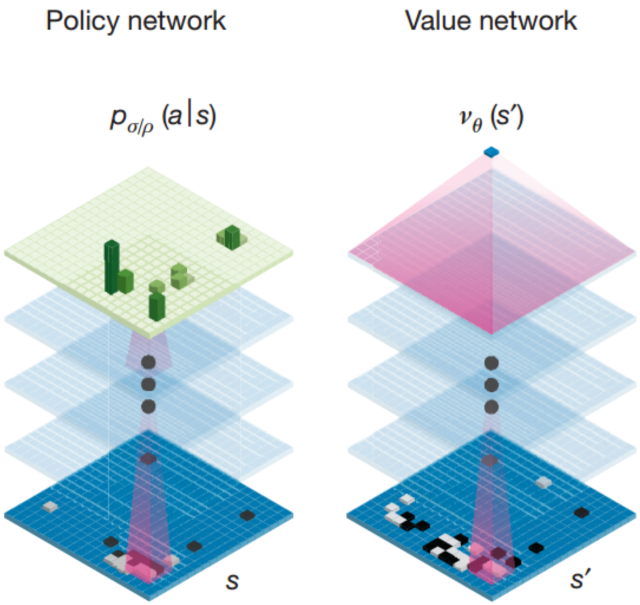
Generally done using game-specific heuristics.

Value Network

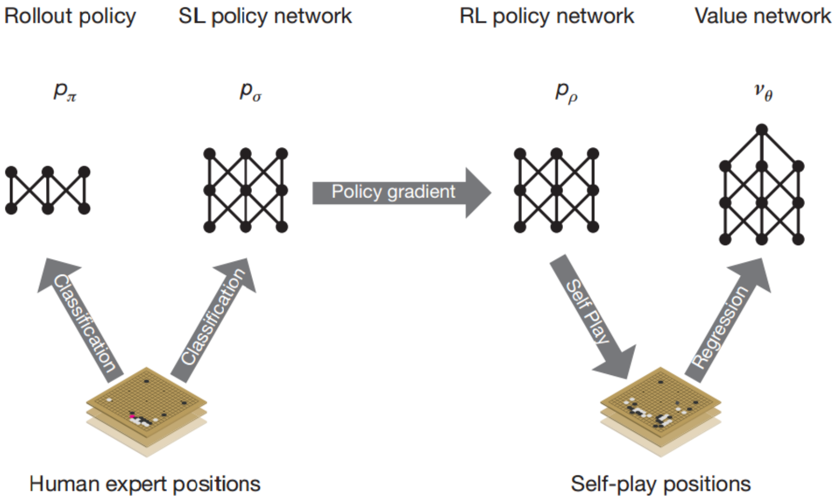
Apply similar architecture for computing state value,

- v_θ; deep CNN regression
- Trained on self-play data set.
- Minimize MSE with final self-play result.

When trained on the KGS data set in this way, the value network memorized the game outcomes rather than generalizing to new positions, achieving a minimum MSE of 0.37 on the test set, compared to 0.19 on the training set. To mitigate this problem, we generated a new self-play data set consisting of 30 million distinct positions, each sampled from a separate game. Each game was played between the RL policy network and itself until the game terminated.



Policy network
Value network
$p_{\sigma/\rho}(a|s)$
$v_\theta(s')$
s
s'


Rollout policy
SL policy network
RL policy network
Value network
p_π
p_σ
p_ρ
v_θ
Policy gradient
Classification
Classification
Self Play
Regression
Human expert positions
Self-play positions

(3) Game Search

Utilize the learned models with an advanced game-search algorithm

- Similar to standard game tree algorithms (CS182)
- Monte Carlo Tree Search (MCTS)
  - Select
  - Expand
  - Eval
  - Update/Backup
- Progressively expands the search space based on models

Select and Expansion

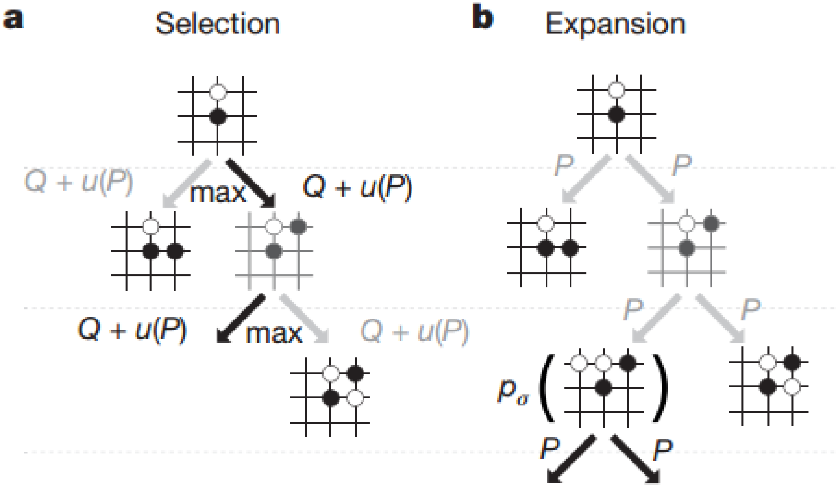
- $Q(s, a)$; current expected value of taking action a at s
- $u(s, a)$; prior for taking a at s defined by p_σ

Selection step at state s,

$$\arg\max_a Q(s, a) + u(s, a)$$

Based on selection, either move to seen node or **expand**.

Game Search



a
Selection
Q + u(P)
max
Q + u(P)
Q + u(P)
max
Q + u(P)
b
Expansion
P
P
P
P
p_σ
P
P

State Evaluation

Reached "leaf" state s_L, want to **evaluate**

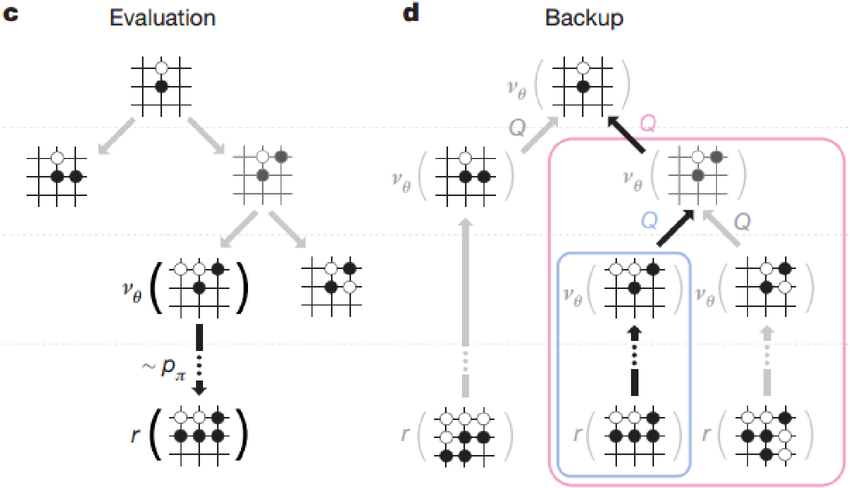
- Compute value as $V(s_L)$,

  $$V(s_L) = (1-\lambda)v_\theta(s_l) + \lambda(R(s_L))$$

  where R is a rollout. Monte carlo simulation using p_π

- Convex combination of value network and simulation under simple model

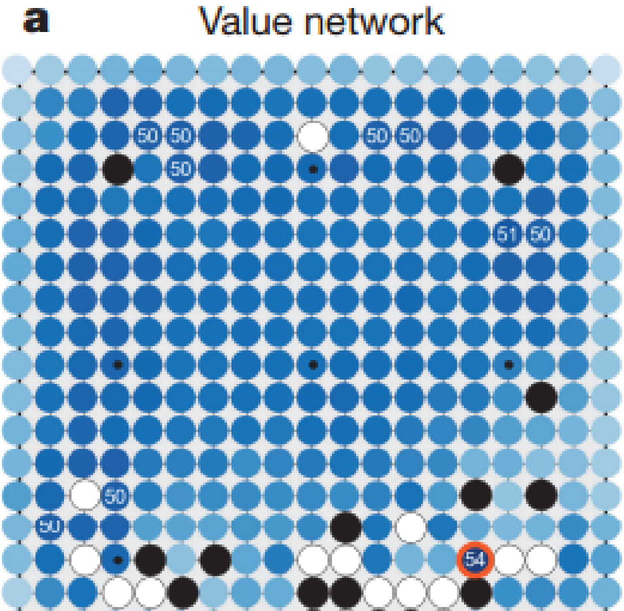
Why not p_σ? Where did p_ρ go?


c
Evaluation
d
Backup
v_θ
$\sim p_\pi$
r
Q

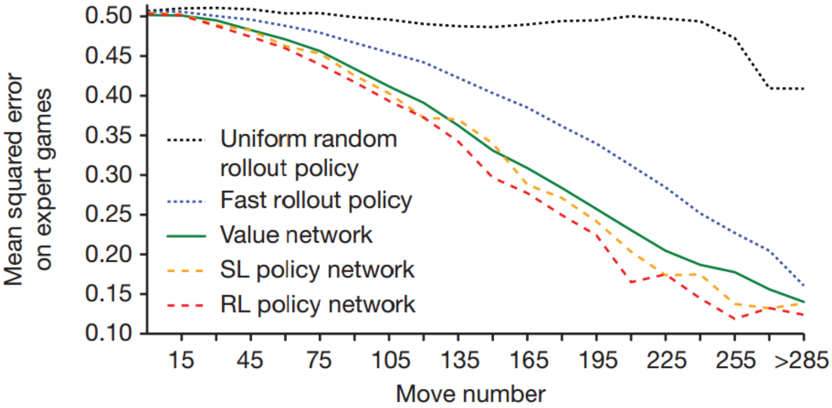
Move Selection

- After leaf evaluation all previous Q values are **updated** based on $V(s_L)$
- Process is run many times.
- Actual play is based on most commonly taken action.

Results

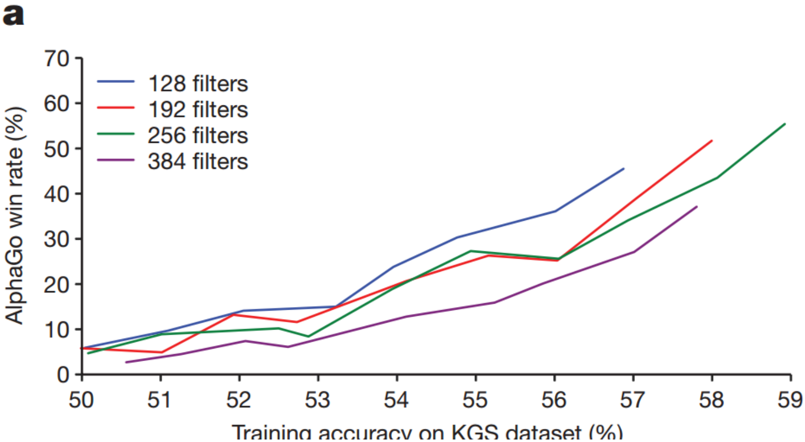


Results

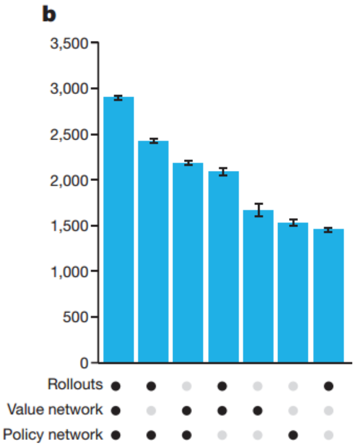


Mean squared error on expert games
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
Uniform random rollout policy
Fast rollout policy
Value network
SL policy network
RL policy network
15
45
75
105
135
165
195
225
255
>285
Move number

Results


a
128 filters
192 filters
256 filters
384 filters
AlphaGo win rate (%)
70
60
50
40
30
20
10
0
50
51
52
53
54
55
56
57
58
59
Training accuracy on KGS dataset (%)

Results


b
3,500
3,000
2,500
2,000
1,500
1,000
500
0
Rollouts
Value network
Policy network