Lecture 18
GANs and AlphaGo

CMSC 35246: Deep Learning

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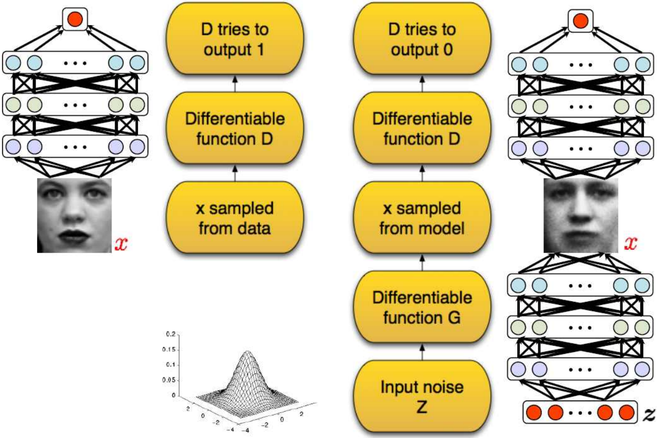
May 31, 2017

Recap: Generative Adversarial Networks



Slide adapted from Ian Goodfellow

Recap: Generative Adversarial Networks

- Minimax value function

Generator: generate samples that D would classify as real

$$\min_G \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

Discriminator: Pushes up

Discriminator: Classify data as being real

Discriminator: Classify generator samples as being fake

Generator: Pushes down

- Optimal strategy for Discriminator is:

$$D(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{model}}(x)}$$

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- This is good since we can use the machinery for neural networks

Divergences and Distances between distributions

1. KL

$$KL(P||Q) = \mathbb{E}_P \log \frac{P}{Q}$$

2. JS

$$JS(P||Q) = \frac{1}{2} KL(P||\frac{P+Q}{2}) + \frac{1}{2} KL(Q||\frac{P+Q}{2})$$

3. Wasserstein

$$W(P||Q) = \inf_{\gamma \in \Pi(P,Q)} \mathbb{E}_{(x,y)\sim\gamma}[||x-y||]$$

- $\Pi(P,Q)$ denotes the set of all joint distributions $\gamma(x,y)$ whose marginals are P and Q, respectively
- $\gamma(x,y)$ indicates a plan to transport "mass" from x to y, when deforming P into Q.
  The Wasserstein (or Earth-Mover) distance is then the "cost" of the **optimal** transport plan

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- Generator:

$$\mathbb{E}_{\mathbf{x}\sim P_g}[\log(1 - D(\mathbf{x}))] \text{ Method 1}$$

$$\mathbb{E}_{\mathbf{x}\sim P_g}[-D(\mathbf{x}))] \text{ Method 2}$$

Problems

- In practice $\mathbb{E}_{\mathbf{x}\sim P_g}[\log(1 - D(\mathbf{x}))]$ does not give sufficient gradient to work with, so we use $\mathbb{E}_{\mathbf{x}\sim P_g}[-D(\mathbf{x}))]$ instead

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- Plugging into the generator loss:

$$\mathbb{E}_{P_r}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{x}\sim P_g}[\log(1 - D(\mathbf{x}))]$$

makes the loss $2JS(P_r||P_g) - 2\log 2$

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- $KL(P_r||P_g)$ imposes high cost to not covering parts of the data, and a low cost on fake looking samples

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$$W(P_r, P_g) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{\mathbf{x}\sim P_r}[f(\mathbf{x})] - \mathbb{E}_{\mathbf{x}\sim P_g}[f(\mathbf{x})]$$

$$W(P_r, P_g) = \frac{1}{K} \sup_{\|f\|_L \leq K} \mathbb{E}_{\mathbf{x}\sim P_r}[f(\mathbf{x})] - \mathbb{E}_{\mathbf{x}\sim P_g}[f(\mathbf{x})]$$

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- Optimize over a parameterized family w of functions that are all K-Lipschitz

Vanilla GAN

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Wasserstein GAN

Algorithm 1 WGAN, our proposed algorithm. All experiments in the paper used the default values $\alpha = 0.00005$, $c = 0.01$, $m = 64$, $n_{\text{critic}} = 5$.

Require: : α, the learning rate. c, the clipping parameter. m, the batch size. n_{critic}, the number of iterations of the critic per generator iteration.
Require: : w_0, initial critic parameters. θ_0, initial generator's parameters.

while θ has not converged **do**
  for $t = 0, ..., n_{\text{critic}}$ **do**
    Sample $\{x^{(i)}\}_{i=1}^m \sim \mathbb{P}_r$ a batch from the real data.
    Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
    $g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^m f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right]$
    $w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$
    $w \leftarrow \text{clip}(w, -c, c)$
  end for
  Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.
  $g_\theta \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))$
  $\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta)$
end while

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  - The log in the loss for D and G is removed
  - Clip the parameters of D in an interval centered at 0
  - Don't use momentum based optimization

AlphaGo

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- Predictions are inherently ambiguous, need to find statistical structure
- Board games are a classic AI domain which relied heavily on sophisticated search techniques with a little bit of machine learning
- Full observations, deterministic environment - why would we need uncertainty?

Overview

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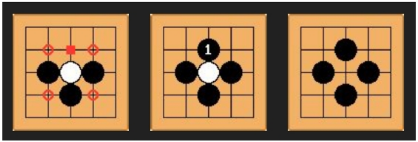
- 1997: DeepBlue defeats Garry Kasparov

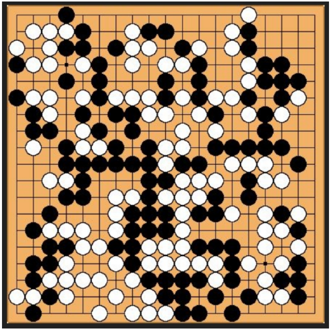
Go

- Played on a 19×19 board
- Two players, black and white, each place one stone per turn
- Capture opponent's stones by surrounding them



Go

- Goal is to surround as much territory as possible



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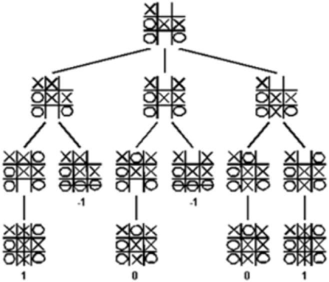
- Unlike in chess, endgames are too complicated to solve exactly
- Heavily dependent on pattern recognition

Game Trees



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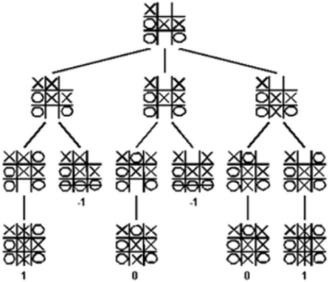

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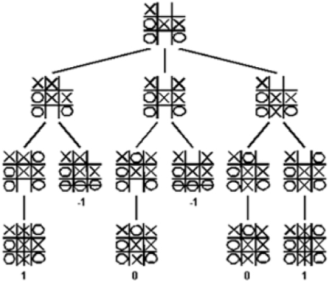

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- Leaf nodes are ones where we can compute the value since a win/draw condition was met

Figure: Russel and Norvig

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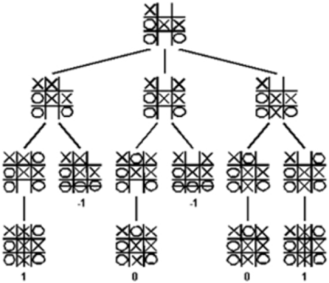

- To label the internal nodes, take the max over the children is its player 1's turn, min over the children if its player 2's turn

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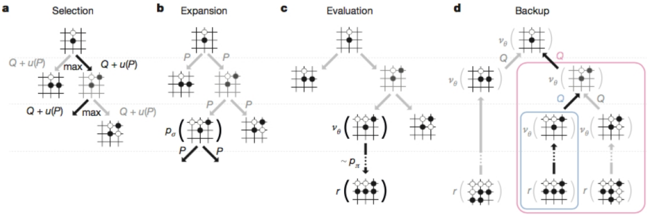
- Having a good evaluation function is the key to good performance
- Traditionally this was the main application of Machine Learning to game playing (in DeepBlue it was a learned linear function of hand desgined features)

Monte Carlo Tree Search



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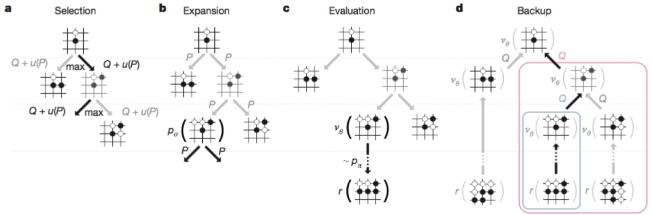

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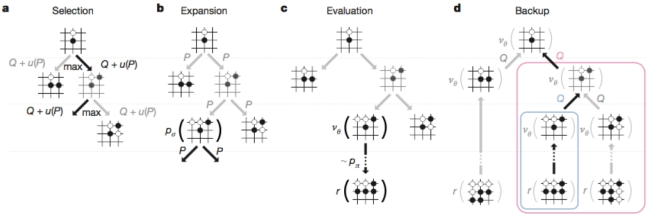

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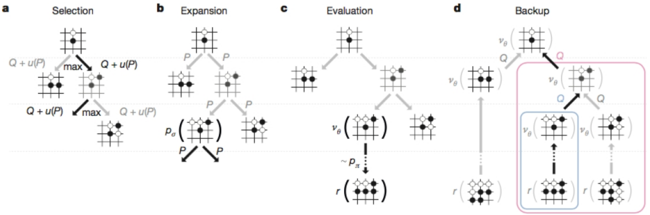

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- Keep track of wins and losses for each node in the tree
- How to select which parts of the tree to evaluate?

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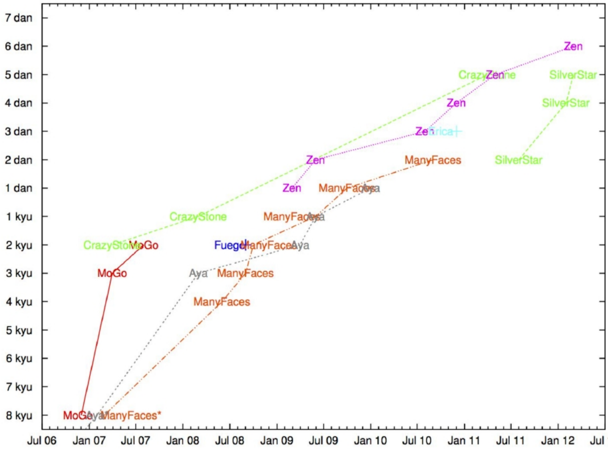
- μ_i is the fraction of wins for action i, N_i number of times we've tried action i, N is the total number of times we have visited this node

Monte Carlo Tree Search

Improvement of computer Go since MCTS (plot is within the amateur range



AlphaGo: Predicting Expert Moves

- Can a computer play Go without any computer search?

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- Architecture: 11 layer generic conv net
- In real game play: Pick position with highest probability
- Just a network that predicted expert moves could beat most of the previous Go programs that used search 97 % of the times

RL 101

- The basic Reinforcement Learning model consists of:
  - A set of environment and agent states S

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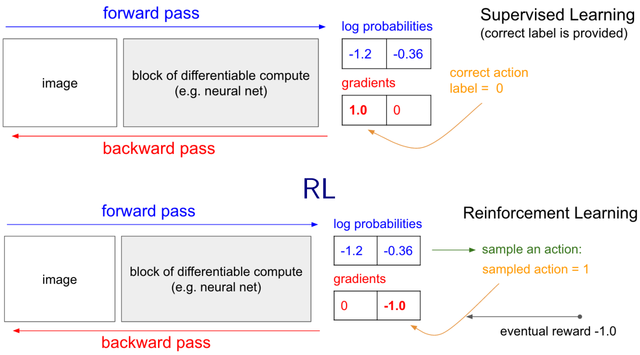
  - Rules that determine the immediate scalar reward of a transition
  - Rules that determine what the agent observes

RL 101


forward pass
log probabilities
Supervised Learning
(correct label is provided)
image
block of differentiable compute
(e.g. neural net)
-1.2
-0.36
gradients
correct action
label = 0
1.0
0
backward pass
RL
forward pass
log probabilities
Reinforcement Learning
-1.2
-0.36
sample an action:
sampled action = 1
image
block of differentiable compute
(e.g. neural net)
gradients
0
-1.0
eventual reward -1.0
backward pass

Self-Play and REINFORCE

- If θ denotes the parameters of the policy network, a_t is the action at time t and s_t is the state of the board, and z the rollout of the rest of the game using the current policy

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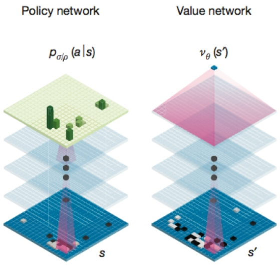
- Gradient of expected reward:

$$\begin{aligned}
\frac{\partial R}{\partial \boldsymbol{\theta}} &= \frac{\partial R}{\partial \boldsymbol{\theta}} \mathbb{E}_{a_t \sim p_{\boldsymbol{\theta}}(a_t \mid s_t)}[\mathbb{E}[r(z) \mid s_t, a_t]] \\
&= \frac{\partial}{\partial \boldsymbol{\theta}} \sum_{a_t} \sum_{z} p_\theta(a_t \mid s_t) p(z|s_t, a_t) R(z) \\
&= \sum_{a_t} \sum_{z} p(z) R(z) \frac{\partial}{\partial \boldsymbol{\theta}} p_\theta(a_t \mid s_t) \\
&= \sum_{a_t} \sum_{z} p(z \mid s_t, a_t) R(z) p_\theta(a_t \mid s_t) \frac{\partial}{\partial \boldsymbol{\theta}} \log p_\theta(a_t \mid s_t) \\
&= \mathbb{E}_{p_{\boldsymbol{\theta}}(a_t \mid s_t)} \left[\mathbb{E}_{p(z \mid s_t, a_t)} \left[R(z) \frac{\partial}{\partial \boldsymbol{\theta}} \log p_\theta(a_t \mid s_t) \right] \right]
\end{aligned}$$

Self-Play and REINFORCE

- In English: Sample action from the policy, then sample the rollout for the rest of the game. If you win, update the parameters to make the action more likely. If you lose, update them to make them less likely

Policy and Value Network



Silver et al., 2016

- We have seen the policy and expert move networks, but AlphaGo has another network called the value network

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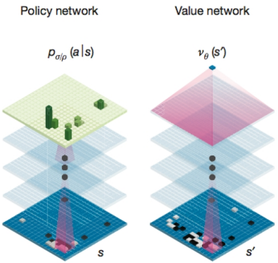

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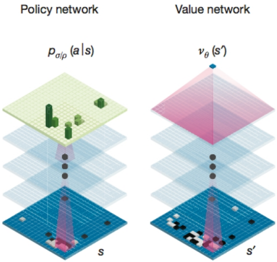

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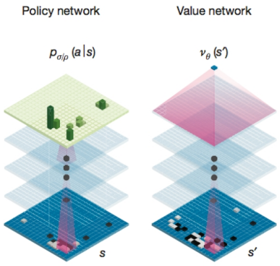

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- This network tries to predict, for a given position, which player has the advantage
- This is again, a conv net with a generic architecture trained with least squares regression
- Data comes from board positions and outcomes from self-play

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- Policy network used to simulate rollouts
- Value networks to evaluate leaf positions

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- Its one loss occurred when Lee Sedol played a key move unlike anything in the training data
- Last week AlphaGo defeated Ke Jie, arguably the best human Go player 3-0, and retired from competitive Go

End