CSC413/2516 Lecture 10: Generative Models & Reinforcement Learning

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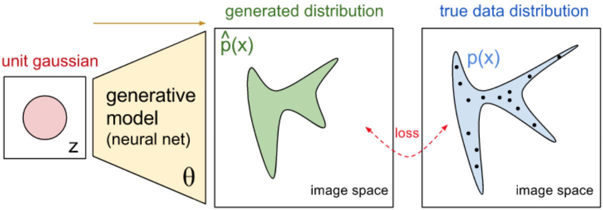
Overview

- In generative modeling, we'd like to train a network that models a distribution, such as a distribution over images.
- We have seen a few approaches to generative modeling:
  - Autoregressive models (Lectures 3, 7, and 8)
  - Generative adversarial networks (last lecture)
  - Reversible architectures (this lecture)
  - Variational autoencoders (this lecture)

  All four approaches have different pros and cons.

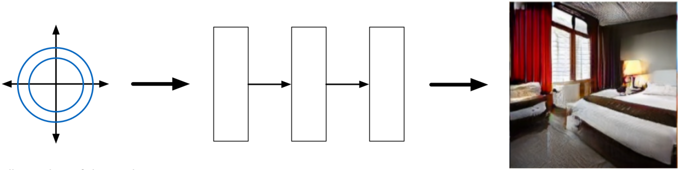
Generator Networks

- Start by sampling the code vector $\mathbf{z}$ from a fixed, simple distribution (e.g. spherical Gaussian)
- The generator network computes a differentiable function G mapping $\mathbf{z}$ to an $\mathbf{x}$ in data space



https://blog.openai.com/generative-models/

Generator Networks



Each dimension of the code vector is sampled independently from a simple distribution, e.g. Gaussian or uniform.

This is fed to a (deterministic) generator network.

The network outputs an image.

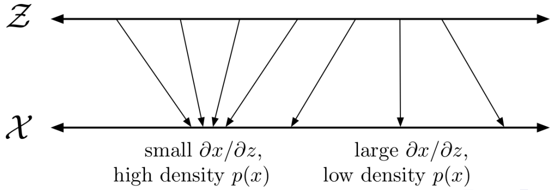
- We have seen how to learn generator networks by training a discriminator in GANs.
- Problem:
  - Learning can be very unstable. Need to tune many hyperparameters.
  - No direct evaluation metric to assess the trained generator networks.
- Idea: learn the generator directly via change of variables. (Calculus!)

Change of Variables Formula

- Let f denote a differentiable, bijective mapping from space $\mathcal{Z}$ to space $\mathcal{X}$. (I.e., it must be 1-to-1 and cover all of $\mathcal{X}$.)
- Since f defines a one-to-one correspondence between values $\mathbf{z} \in \mathcal{Z}$ and $\mathbf{x} \in \mathcal{X}$, we can think of it as a change-of-variables transformation.
- Change-of-Variables Formula from probability theory: if $\mathbf{x} = f(\mathbf{z})$, then

$$p_X(\mathbf{x}) = p_Z(z) \left| \det \left(\frac{\partial \mathbf{x}}{\partial \mathbf{z}} \right) \right|^{-1}$$

- Intuition for the Jacobian term:



Change of Variables Formula

- Suppose we have a generator network which computes the function f. It's tempting to apply the change-of-variables formula in order to compute the density $p_X(\mathbf{x})$.
- I.e., compute $\mathbf{z} = f^{-1}(\mathbf{x})$

$$p_X(\mathbf{x}) = p_Z(z) \left| \det \left(\frac{\partial \mathbf{x}}{\partial z} \right) \right|^{-1}$$

- Problems?

Change of Variables Formula

- Suppose we have a generator network which computes the function f. It's tempting to apply the change-of-variables formula in order to compute the density $p_X(\mathbf{x})$.
- I.e., compute $\mathbf{z} = f^{-1}(\mathbf{x})$

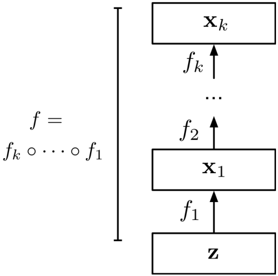
$$p_X(\mathbf{x}) = p_Z(z) \left| \det \left(\frac{\partial \mathbf{x}}{\partial z} \right) \right|^{-1}$$

- Problems?
  - It needs to be differentiable, so that the Jaobian $\partial \mathbf{x} / \partial z$ is defined.
  - The mapping f needs to be invertible, with an easy-to-compute inverse.
  - We need to be able to compute the (log) determinant.
- Differentiability is easy (just use a differentiable activation function), but the other requirements are trickier.

Reversible Blocks

- Now let's define a reversible block which is invertible and has a tractable determinant.

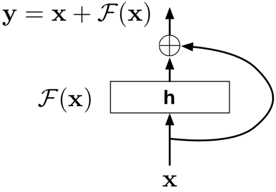
- Such blocks can be composed.
  - Inversion: $f^{-1} = f_1^{-1} \circ \cdots \circ f_k^{-1}$
  - Determinants: $\left|\frac{\partial \mathbf{x}_k}{\partial \mathbf{z}}\right| = \left|\frac{\partial \mathbf{x}_k}{\partial \mathbf{x}_{k-1}}\right| \cdots \left|\frac{\partial \mathbf{x}_2}{\partial \mathbf{x}_1}\right| \left|\frac{\partial \mathbf{x}_1}{\partial \mathbf{z}}\right|$



Reversible Blocks

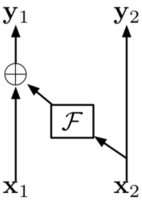
- Recall the residual blocks:

$$\mathbf{y} = \mathbf{x} + \mathcal{F}(\mathbf{x})$$



- Reversible blocks are a variant of residual blocks. Divide the units into two groups, $\mathbf{x}_1$ and $\mathbf{x}_2$.

$$\mathbf{y}_1 = \mathbf{x}_1 + \mathcal{F}(\mathbf{x}_2)$$
$$\mathbf{y}_2 = \mathbf{x}_2$$



- Inverting a reversible block:

$$\mathbf{x}_2 = \mathbf{y}_2$$
$$\mathbf{x}_1 = \mathbf{y}_1 - \mathcal{F}(\mathbf{x}_2)$$

Reversible Blocks

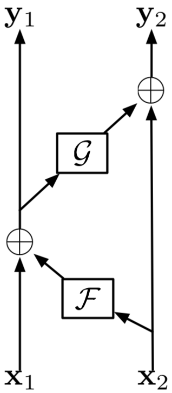
Composition of two reversible blocks, but with $\mathbf{x}_1$ and $\mathbf{x}_2$ swapped:

- Forward:

$$\mathbf{y}_1 = \mathbf{x}_1 + \mathcal{F}(\mathbf{x}_2)$$
$$\mathbf{y}_2 = \mathbf{x}_2 + \mathcal{G}(\mathbf{y}_1)$$

- Backward:

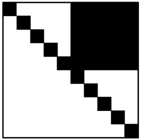
$$\mathbf{x}_2 = \mathbf{y}_2 - \mathcal{G}(\mathbf{y}_1)$$
$$\mathbf{x}_1 = \mathbf{y}_1 - \mathcal{F}(\mathbf{x}_2)$$



Volume Preservation

- It remains to compute the log determinant of the Jacobian.
- The Jacobian of the reversible block:

$$\begin{aligned} \mathbf{y}_1 &= \mathbf{x}_1 + \mathcal{F}(\mathbf{x}_2) \\ \mathbf{y}_2 &= \mathbf{x}_2 \end{aligned} \qquad \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \begin{pmatrix} \mathbf{I} & \frac{\partial \mathcal{F}}{\partial \mathbf{x}_2} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$



- This is an upper triangular matrix. The determinant of an upper triangular matrix is the product of the diagonal entries, or in this case, 1.
- Since the determinant is 1, the mapping is said to be volume preserving.

Nonlinear Independent Components Estimation

- We've just defined the reversible block.
  - Easy to invert by subtracting rather than adding the residual function.
  - The determinant of the Jacobian is 1.
- Nonlinear Independent Components Estimation (NICE) trains a generator network which is a composition of lots of reversible blocks.
- We can compute the likelihood function using the change-of-variables formula:

$$p_X(\mathbf{x}) = p_Z(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{x}}{\partial \mathbf{z}} \right) \right|^{-1} = p_Z(\mathbf{z})$$

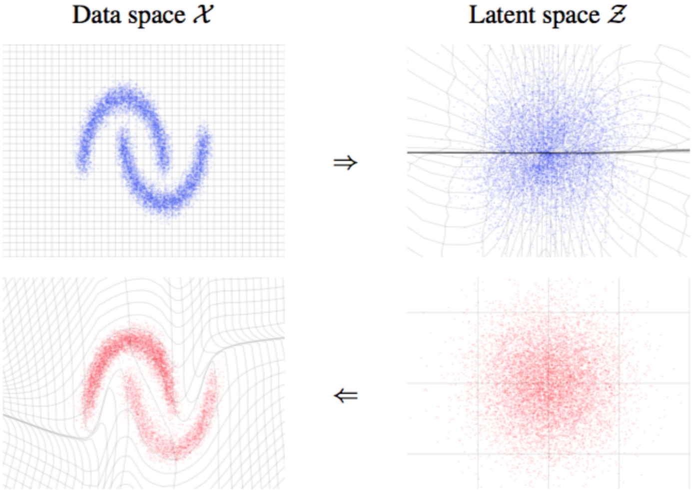
- We can train this model using maximum likelihood. I.e., given a dataset $\{\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(N)}\}$, we maximize the likelihood

$$\prod_{i=1}^{N} p_X(\mathbf{x}^{(i)}) = \prod_{i=1}^{N} p_Z(f^{-1}(\mathbf{x}^{(i)}))$$

Nonlinear Independent Components Estimation

- Likelihood:
$$p_X(\mathbf{x}) = p_Z(\mathbf{z}) = p_Z(f^{-1}(\mathbf{x}))$$
- Remember, p_Z is a simple, fixed distribution (e.g. independent Gaussians)
- Intuition: train the network such that f^{-1} maps each data point to a high-density region of the code vector space $\mathcal{Z}$.
  - Without constraints on f, it could map everything to $\mathbf{0}$, and this likelihood objective would make no sense.
  - But it can't do this because it's volume preserving.

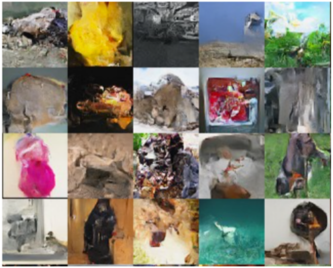
Nonlinear Independent Components Estimation



Dinh et al., 2016. Density estimation using RealNVP.

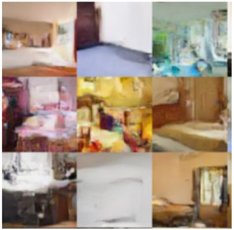
Nonlinear Independent Components Estimation

Samples produced by RealNVP, a model based on NICE.



ImageNet

celebrities



bedrooms

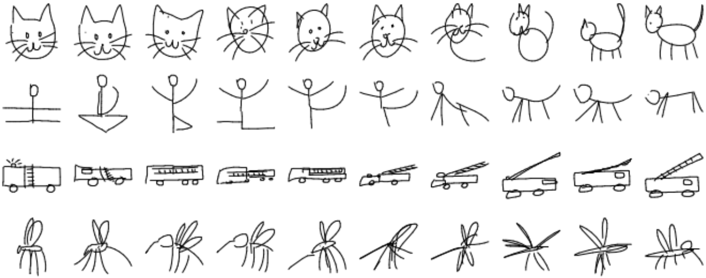
Dinh et al., 2016. Density estimation using RealNVP.

RevNets (optional)

- A side benefit of reversible blocks: you don't need to store the activations in memory to do backprop, since you can reverse the computation.
  - I.e., compute the activations as you need them, moving backwards through the computation graph.
- Notice that reversible blocks look a lot like residual blocks.
- We recently designed a reversible residual network (RevNet) architecture which is like a ResNet, but with reversible blocks instead of residual blocks.
  - Matches state-of-the-art performance on ImageNet, but without the memory cost of activations!
  - Gomez et al., NIPS 2017. "The revesible residual network: backrpop without storing activations".

Latent Space Interpolations

- You can often get interesting results by interpolating between two vectors in the latent space:



Ha and Eck, "A neural representation of sketch drawings"

Latent Space Interpolations

- Latent space interpolation of music:
  `https://magenta.tensorflow.org/music-vae`

Trade-offs of Generative Approaches

- So far, we have seen four different approaches:
  - Autoregressive models (Lectures 3, 7, and 8)
  - Generative adversarial networks (last lecture)
  - Reversible architectures (this lecture)
  - Variational autoencoders (optional)
- They all have their own pro and con. We often pick a method based on our application needs.
- Some considerations for computer vision applications:
  - Do we need to evaluate log likelihood of new data?
  - Do we prefer good samples over evaluation metric?
  - How imporant is representation learning, i.e. meaningful code vectors?
  - How much computational resource can we spent?

Trade-offs of Generative Approaches

- In summary:

	Log-likelihood	Sample	Representation	Computation
Autoregressive	**Tractable**	**Good**	Poor	O(#pixels)
GANs	Intractable	**Good**	**Good**	O(#layers)
Reversible	**Tractable**	Poor	Poor	O(#layers)
VAEs (optional)	**Tractable***	Poor	**Good**	O(#layers)

- There is no silver bullet in generative modeling.

After the break

After the break: **Reinforcement Learning: Policy Gradient**

Overview

- Most of this course was about supervised learning, plus a little unsupervised learning.
- Reinforcement learning:
  - Middle ground between supervised and unsupervised learning
  - An agent acts in an environment and receives a reward signal.
- Today: policy gradient (directly do SGD over a stochastic policy using trial-and-error)
- Next lecture: combine policies and Q-learning

Reinforcement learning

- An **agent** interacts with an **environment** (e.g. game of Breakout)
- In each time step t,
  - the agent receives **observations** (e.g. pixels) which give it information about the **state** $\mathbf{s}_t$ (e.g. positions of the ball and paddle)
  - the agent picks an **action** $\mathbf{a}_t$ (e.g. keystrokes) which affects the state
- The agent periodically receives a **reward** $r(\mathbf{s}_t, \mathbf{a}_t)$, which depends on the state and action (e.g. points)
- The agent wants to learn a **policy** $\pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t)$
  - Distribution over actions depending on the current state and parameters $\boldsymbol{\theta}$

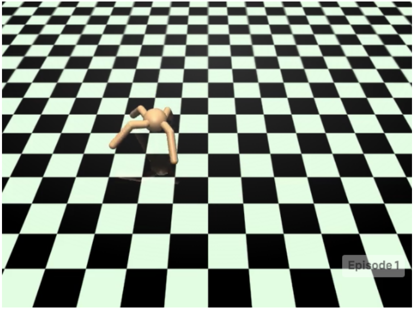
Markov Decision Processes

- The environment is represented as a Markov decision process $\mathcal{M}$.
- Markov assumption: all relevant information is encapsulated in the current state; i.e. the policy, reward, and transitions are all independent of past states given the current state
- Components of an MDP:
  - initial state distribution $p(\mathbf{s}_0)$
  - policy $\pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t)$
  - transition distribution $p(\mathbf{s}_{t+1} \mid \mathbf{s}_t, \mathbf{a}_t)$
  - reward function $r(\mathbf{s}_t, \mathbf{a}_t)$
- Assume a fully observable environment, i.e. $\mathbf{s}_t$ can be observed directly
- Rollout, or trajectory $\tau = (\mathbf{s}_0, \mathbf{a}_0, \mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)$
- Probability of a rollout

$$p(\tau) = p(\mathbf{s}_0)\, \pi_{\boldsymbol{\theta}}(\mathbf{a}_0 \mid \mathbf{s}_0)\, p(\mathbf{s}_1 \mid \mathbf{s}_0, \mathbf{a}_0) \cdots p(\mathbf{s}_T \mid \mathbf{s}_{T-1}, \mathbf{a}_{T-1})\, \pi_{\boldsymbol{\theta}}(\mathbf{a}_T \mid \mathbf{s}_T)$$

Markov Decision Processes

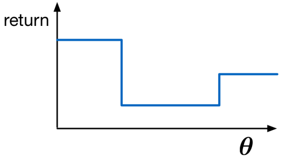
Continuous control in simulation, e.g. teaching an ant to walk



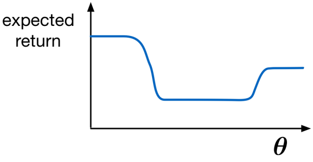
- State: positions, angles, and velocities of the joints
- Actions: apply forces to the joints
- Reward: distance from starting point
- Policy: output of an ordinary MLP, using the state as input
- More environments: `https://gym.openai.com/envs/#mujoco`

Markov Decision Processes

- Return for a rollout: $r(\tau) = \sum_{t=0}^{T} r(\mathbf{s}_t, \mathbf{a}_t)$
  - Note: we're considering a finite horizon T, or number of time steps; we'll consider the infinite horizon case later.
- Goal: maximize the expected return, $R = \mathbb{E}_{p(\tau)}[r(\tau)]$
- The expectation is over both the environment's dynamics and the policy, but we only have control over the policy.
- The stochastic policy is important, since it makes R a continuous function of the policy parameters.
  - Reward functions are often discontinuous, as are the dynamics (e.g. collisions)



deterministic policies



stochastic policies

REINFORCE

- REINFORCE is an elegant algorithm for maximizing the expected return $R = \mathbb{E}_{p(\tau)}[r(\tau)]$.
- Intuition: trial and error
  - Sample a rollout τ. If you get a high reward, try to make it more likely. If you get a low reward, try to make it less likely.
- Interestingly, this can be seen as stochastic gradient ascent on R.

REINFORCE

- Recall the derivative formula for log:

$$\frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau) = \frac{\frac{\partial}{\partial \boldsymbol{\theta}} p(\tau)}{p(\tau)} \qquad \Longrightarrow \qquad \frac{\partial}{\partial \boldsymbol{\theta}} p(\tau) = p(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau)$$

- Gradient of the expected return:

$$\begin{aligned}
\frac{\partial}{\partial \boldsymbol{\theta}} \mathbb{E}_{p(\tau)}\left[r(\tau)\right] &= \frac{\partial}{\partial \boldsymbol{\theta}} \sum_{\tau} r(\tau) p(\tau) \\
&= \sum_{\tau} r(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} p(\tau) \\
&= \sum_{\tau} r(\tau) p(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau) \\
&= \mathbb{E}_{p(\tau)}\left[r(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau) \right]
\end{aligned}$$

- Compute stochastic estimates of this expectation by sampling rollouts.

REINFORCE

- For reference:

$$\frac{\partial}{\partial \boldsymbol{\theta}} \mathbb{E}_{p(\tau)}\left[r(\tau)\right] = \mathbb{E}_{p(\tau)}\left[r(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau)\right]$$

- If you get a large reward, make the rollout more likely. If you get a small reward, make it less likely.
- Unpacking the REINFORCE gradient:

$$\begin{aligned}
\frac{\partial}{\partial \boldsymbol{\theta}} \log p(\tau) &= \frac{\partial}{\partial \boldsymbol{\theta}} \log \left[p(\mathbf{s}_0) \prod_{t=0}^{T} \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t) \prod_{t=1}^{T} p(\mathbf{s}_t \mid \mathbf{s}_{t-1}, \mathbf{a}_{t-1})\right] \\
&= \frac{\partial}{\partial \boldsymbol{\theta}} \log \prod_{t=0}^{T} \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t) \\
&= \sum_{t=0}^{T} \frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t)
\end{aligned}$$

- Hence, it tries to make *all* the actions more likely or less likely, depending on the reward. I.e., it doesn't do credit assignment.
  - This is a topic for next lecture.

REINFORCE

Repeat forever:

Sample a rollout $\tau = (\mathbf{s}_0, \mathbf{a}_0, \mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)$
$r(\tau) \leftarrow \sum_{k=0}^{T} r(\mathbf{s}_k, \mathbf{a}_k)$
For $t = 0, \ldots, T$:

$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha r(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \,|\, \mathbf{s}_t)$

- Observation: actions should only be reinforced based on future rewards, since they can't possibly influence past rewards.
- You can show that this still gives unbiased gradient estimates.

Repeat forever:

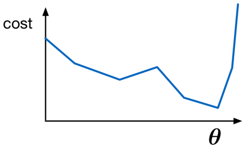
Sample a rollout $\tau = (\mathbf{s}_0, \mathbf{a}_0, \mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)$
For $t = 0, \ldots, T$:

$r_t(\tau) \leftarrow \sum_{k=t}^{T} r(\mathbf{s}_k, \mathbf{a}_k)$
$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha r_t(\tau) \frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \,|\, \mathbf{s}_t)$

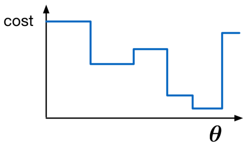
Optimizing Discontinuous Objectives

- A classification task under RL formulation
  - one time step
  - state $\mathbf{x}$: an image
  - action $\mathbf{a}$: a digit class
  - reward $r(\mathbf{x}, \mathbf{a})$: 1 if correct, 0 if wrong
  - policy $\pi(\mathbf{a} \mid \mathbf{x})$: a distribution over categories
    - Compute using an MLP with softmax outputs – this is a policy network

Optimizing Discontinuous Objectives



Non-differentiable: OK



Discontinuous: not OK

- Original solution: use a surrogate loss function, e.g. logistic-cross-entropy
- RL formulation: in each episode, the agent is shown an image, guesses a digit class, and receives a reward of 1 if it's right or 0 if it's wrong
- We'd never actually do it this way, but it will give us an interesting comparison with backprop

Optimizing Discontinuous Objectives

- Let z_k denote the logits, y_k denote the softmax output, t the integer target, and t_k the target one-hot representation.
- To apply REINFORCE, we sample $\mathbf{a} \sim \pi_{\boldsymbol{\theta}}(\cdot \,|\, \mathbf{x})$ and apply:

$$\begin{aligned}
\boldsymbol{\theta} &\leftarrow \boldsymbol{\theta} + \alpha r(\mathbf{a}, \mathbf{t}) \frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a} \,|\, \mathbf{x}) \\
&= \boldsymbol{\theta} + \alpha r(\mathbf{a}, \mathbf{t}) \frac{\partial}{\partial \boldsymbol{\theta}} \log y_a \\
&= \boldsymbol{\theta} + \alpha r(\mathbf{a}, \mathbf{t}) \sum_k (a_k - y_k) \frac{\partial}{\partial \boldsymbol{\theta}} z_k
\end{aligned}$$

- Compare with the logistic regression SGD update:

$$\begin{aligned}
\boldsymbol{\theta} &\leftarrow \boldsymbol{\theta} + \alpha \frac{\partial}{\partial \boldsymbol{\theta}} \log y_t \\
&\leftarrow \boldsymbol{\theta} + \alpha \sum_k (t_k - y_k) \frac{\partial}{\partial \boldsymbol{\theta}} z_k
\end{aligned}$$

Reward Baselines

- For reference:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha r(\mathbf{a}, \mathbf{t}) \frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a} \,|\, \mathbf{x})$$

- Clearly, we can add a constant offset to the reward, and we get an equivalent optimization problem.
- Behavior if $r = 0$ for wrong answers and $r = 1$ for correct answers
  - wrong: do nothing
  - correct: make the action more likely
- If $r = 10$ for wrong answers and $r = 11$ for correct answers
  - wrong: make the action more likely
  - correct: make the action more likely (slightly stronger)
- If $r = -10$ for wrong answers and $r = -9$ for correct answers
  - wrong: make the action less likely
  - correct: make the action less likely (slightly weaker)

Reward Baselines

- Problem: the REINFORCE update depends on arbitrary constant factors added to the reward.
- Observation: we can subtract a baseline b from the reward without biasing the gradient.

$$
\begin{aligned}
\mathbb{E}_{p(\tau)}\left[(r(\tau)-b)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] &= \mathbb{E}_{p(\tau)}\left[r(\tau)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] - b\mathbb{E}_{p(\tau)}\left[\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] \\
&= \mathbb{E}_{p(\tau)}\left[r(\tau)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] - b\sum_{\tau} p(\tau)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau) \\
&= \mathbb{E}_{p(\tau)}\left[r(\tau)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] - b\sum_{\tau} \frac{\partial}{\partial \boldsymbol{\theta}} p(\tau) \\
&= \mathbb{E}_{p(\tau)}\left[r(\tau)\frac{\partial}{\partial \boldsymbol{\theta}}\log p(\tau)\right] - 0
\end{aligned}
$$

- We'd like to pick a baseline such that good rewards are positive and bad ones are negative.
- $\mathbb{E}[r(\tau)]$ is a good choice of baseline, but we can't always compute it easily. There's lots of research on trying to approximate it.

More Tricks

- We left out some more tricks that can make policy gradients work a lot better.
  - Natural policy gradient corrects for the geometry of the space of policies, preventing the policy from changing too quickly.
  - Rather than use the actual return, evaluate actions based on estimates of future returns. This is a class of methods known as actor-critic, which we'll touch upon next lecture.
- Trust region policy optimization (TRPO) and proximal policy optimization (PPO) are modern policy gradient algorithms which are very effective for continuous control problems.

Evolution Strategies

- REINFORCE can handle discontinuous dynamics and reward functions, but it requires a differentiable network since it computes $\frac{\partial}{\partial \boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_t \mid \mathbf{s}_t)$
- Evolution strategies (ES) take the policy gradient idea a step further, and avoid backprop entirely.
- ES can use deterministic policies. It randomizes over the choice of policy rather than over the choice of actions.
    - I.e., sample a random policy from a distribution $p_{\boldsymbol{\eta}}(\boldsymbol{\theta})$ parameterized by $\boldsymbol{\eta}$ and apply the policy gradient trick

$$\frac{\partial}{\partial \boldsymbol{\eta}} \mathbb{E}_{\boldsymbol{\theta} \sim p_{\eta}} [r(\tau(\boldsymbol{\theta}))] = \mathbb{E}_{\boldsymbol{\theta} \sim p_{\eta}} \left[r(\tau(\boldsymbol{\theta})) \frac{\partial}{\partial \boldsymbol{\eta}} \log p_{\boldsymbol{\eta}}(\boldsymbol{\theta}) \right]$$

- The neural net architecture itself can be discontinuous.

Evolution Strategies

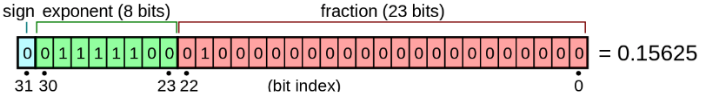
Algorithm 1 Evolution Strategies

1: **Input:** Learning rate α, noise standard deviation σ, initial policy parameters θ_0
2: **for** $t = 0, 1, 2, \ldots$ **do**
3: Sample $\epsilon_1, \ldots \epsilon_n \sim \mathcal{N}(0, I)$
4: Compute returns $F_i = F(\theta_t + \sigma\epsilon_i)$ for $i = 1, \ldots, n$
5: Set $\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n\sigma} \sum_{i=1}^{n} F_i \epsilon_i$
6: **end for**

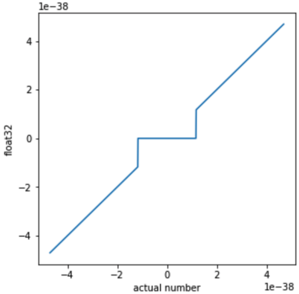
https://arxiv.org/pdf/1703.03864.pdf

Evolution Strategies

- The IEEE floating point standard is nonlinear, since small enough numbers get truncated to zero.



- This acts as a discontinuous activation function, which ES is able to handle.
- ES was able to train a good MNIST classifier using a "linear" activation function.
- `https://blog.openai.com/nonlinear-computation-in-linear-`



Discussion

- What's so great about backprop and gradient descent?
  - Backprop does credit assignment – it tells you exactly which activations and parameters should be adjusted upwards or downwards to decrease the loss on some training example.
  - REINFORCE doesn't do credit assignment. If a rollout happens to be good, all the actions get reinforced, even if some of them were bad.
  - Reinforcing all the actions as a group leads to random walk behavior.

Discussion

- Why policy gradient?
  - Can handle discontinuous cost functions
  - Don't need an explicit model of the environment, i.e. rewards and dynamics are treated as black boxes
    - Policy gradient is an example of model-free reinforcement learning, since the agent doesn't try to fit a model of the environment
    - Almost everyone thinks model-based approaches are needed for AI, but nobody has a clue how to get it to work