# The Nuts and Bolts of Deep RL Research

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# Outline

# Approaching New Problems

# New Algorithm? Use Small Test Problems

- Run experiments quickly
- Do hyperparameter search
- Interpret and visualize learning process: state visitation, value function, etc.
- Counterpoint: don't overfit algorithm to contrived problem
- Useful to have medium-sized problems that you're intimately familiar with (Hopper, Atari Pong)

# New Task? Make It Easier Until Signs of Life

- Provide good input features
- Shape reward function

# POMDP Design

- Visualize random policy: does it sometimes exhibit desired behavior?
- Human control
  - Atari: can you see game features in downsampled image?
- Plot time series for observations and rewards. Are they on a reasonable scale?
  - `hopper.py` in gym:
    `reward = 1.0 - 1e-3 * np.square(a).sum() + delta_x / delta_t`
- Histogram observations and rewards

# Run Your Baselines

- Don't expect them to work with default parameters
- Recommended:
  - Cross-entropy method[1]
  - Well-tuned policy gradient method[2]
  - Well-tuned Q-learning + SARSA method

[1] István Szita and András Lörincz (2006). "Learning Tetris using the noisy cross-entropy method". In: *Neural computation*.

[2] https://github.com/openai/rllab

# Run with More Samples Than Expected

- Early in tuning process, may need huge number of samples
  - Don't be deterred by published work
- Examples:
  - TRPO on Atari: 100K timesteps per batch for KL$= 0.01$
  - DQN on Atari: update freq=10K, replay buffer size=1M

# Ongoing Development and Tuning

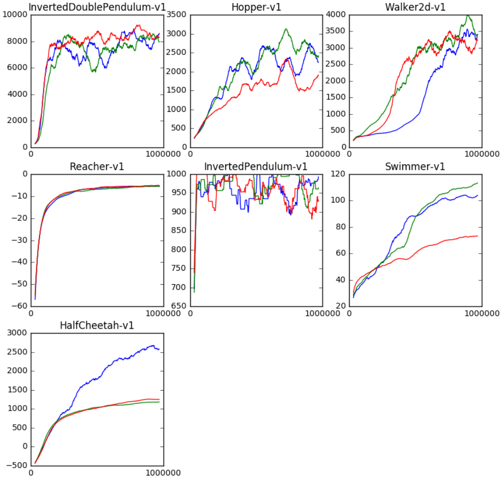
# It Works! But Don't Be Satisfied

- Explore sensitivity to each parameter
  - If too sensitive, it doesn't really work, you just got lucky
- Look for health indicators
  - VF fit quality
  - Policy entropy
  - Update size in output space and parameter space
  - Standard diagnostics for deep networks

# Continually Benchmark Your Code

- If reusing code, regressions occur
- Run a battery of benchmarks occasionally

# Always Use Multiple Random Seeds



# Always Be Ablating

- Different tricks may substitute
  - Especially whitening
- "Regularize" to favor simplicity in algorithm design space
  - As usual, simplicity $\rightarrow$ generalization

# Automate Your Experiments

- Don't spend all day watching your code print out numbers
- Consider using a cloud computing platform (Microsoft Azure, Amazon EC2, Google Compute Engine)

# General Tuning Strategies for RL

# Whitening / Standardizing Data

- If observations have unknown range, standardize
  - Compute running estimate of mean and standard deviation
  - $x' = \text{clip}((x - \mu)/\sigma, -10, 10)$
- Rescale the rewards, but don't shift mean, as that affects agent's will to live
- Standardize prediction targets (e.g., value functions) the same way

# Generally Important Parameters

- Discount
  - $\text{Return}_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots$
  - Effective time horizon: $1 + \gamma + \gamma^2 + \cdots = 1/(1-\gamma)$
    - I.e., $\gamma = 0.99 \Rightarrow$ ignore rewards delayed by more than 100 timesteps
  - Low $\gamma$ works well for well-shaped reward
  - In TD($\lambda$) methods, can get away with high $\gamma$ when $\lambda < 1$
- Action frequency
  - Solvable with human control (if possible)
  - View random exploration

# General RL Diagnostics

- Look at min/max/stdev of episode returns, along with mean
- Look at episode lengths: sometimes provides additional information
  - Solving problem faster, losing game slower

# Policy Gradient Strategies

# Entropy as Diagnostic

- Premature drop in policy entropy $\Rightarrow$ no learning
- Alleviate by using entropy bonus or KL penalty

# KL as Diagnostic

- Compute $\mathrm{KL}\left[\pi_{\mathrm{old}}(\cdot \mid s), \pi(\cdot \mid s)\right]$
- KL spike $\Rightarrow$ drastic loss of performance
- No learning progress might mean steps are too large
    - batchsize=100K converges to different result than batchsize=20K.

# Baseline Explained Variance

- explained variance $= \frac{1 - \mathrm{Var}[\text{empirical return} - \text{predicted value}]}{Var[\text{empirical return}]}$

# Policy Initialization

- More important than in supervised learning: determines initial state visitation
- Zero or tiny final layer, to maximize entropy

# Q-Learning Strategies

- Optimize memory usage carefully: you'll need it for replay buffer
- Learning rate schedules
- Exploration schedules
- Be patient. DQN converges slowly
  - On Atari, often 10-40M frames to get policy much better than random

Thanks to Szymon Sidor for suggestions

# Miscellaneous Advice

- Read older textbooks and theses, not just conference papers
- Don't get stuck on problems—can't solve everything at once
  - Exploration problems like cart-pole swing-up
  - DQN on Atari vs CartPole

# Thanks!