# Closing the Sim-To-Real Gap with Evolutionary Meta-Learning

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# Locomotion

Locomotion is one of the most fundamental skills of all land animals:

Cheetahs

Elephants

Humans

# Robot Locomotion

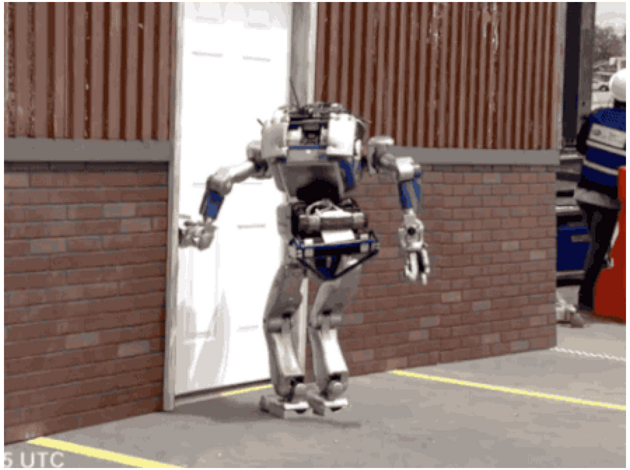
So far, Robot Locomotion research has displayed an impressive set of results to reproduce this natural skill.


Boston Dynamics Spot


MIT Cheetah

# Slight Changes in Dynamics

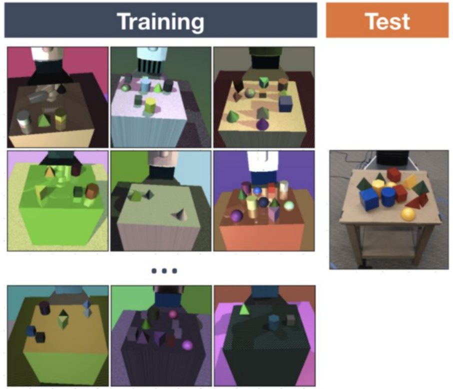
But unfortunately, robots can be fragile to slight changes in dynamics.




DARPA Robotics Challenge, 2015

Asimo Robot, 2006

# Prior Works: Robustness to Real World Changes

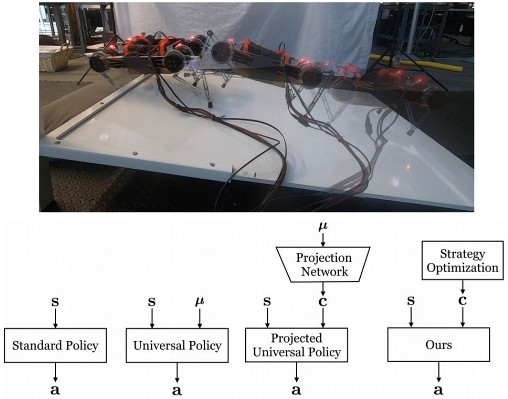



Domain Randomization
(Tobin et al, 2017)

- Only trains in sim
- Assumes all tasks use same optimal policy.


Model Based Adaptation
(Nagabandi et al, 2019)

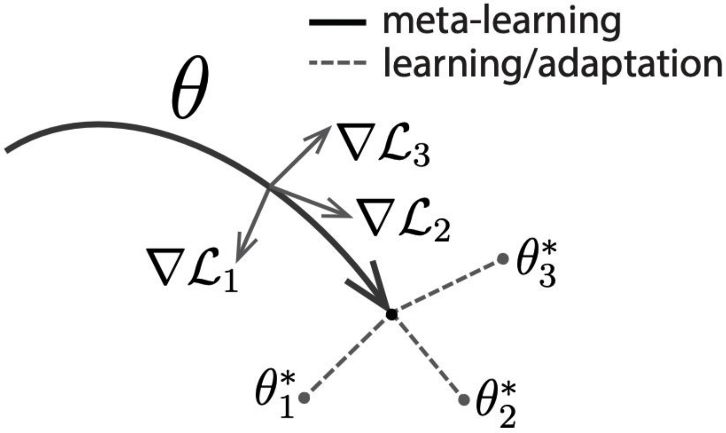
- Compounding error with dynamics models
- Acquiring an accurate model can be difficult.




Meta Strategy Optimization
(Yu et al, 2020)

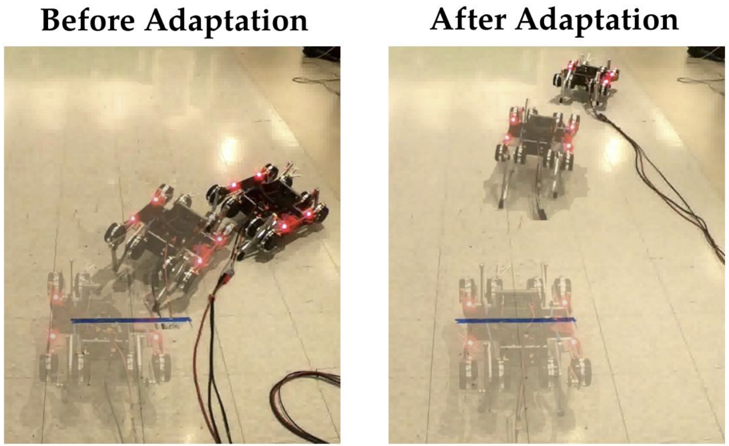
- Latent context vectors appended to the state
- Context may not contain necessary information

# But what about MAML?



# Our Strategy: MAML + Adaptation w/ Real world Data

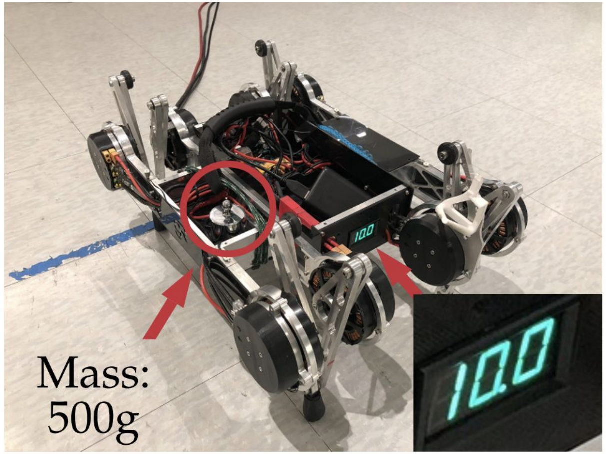
- **Train most skills in sim: "meta-policy"**
- **Fine-Tune + Adapt w/ a little real world data: "adapted-policy"**
- **Model-Free:** Only needs feed-forward policy mapping **state -> action**.



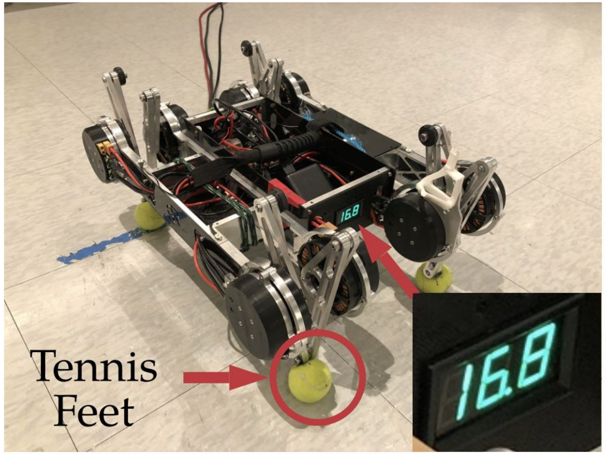

Minitaur Robot adapts to mass imbalances and voltage changes.

# Task Setup

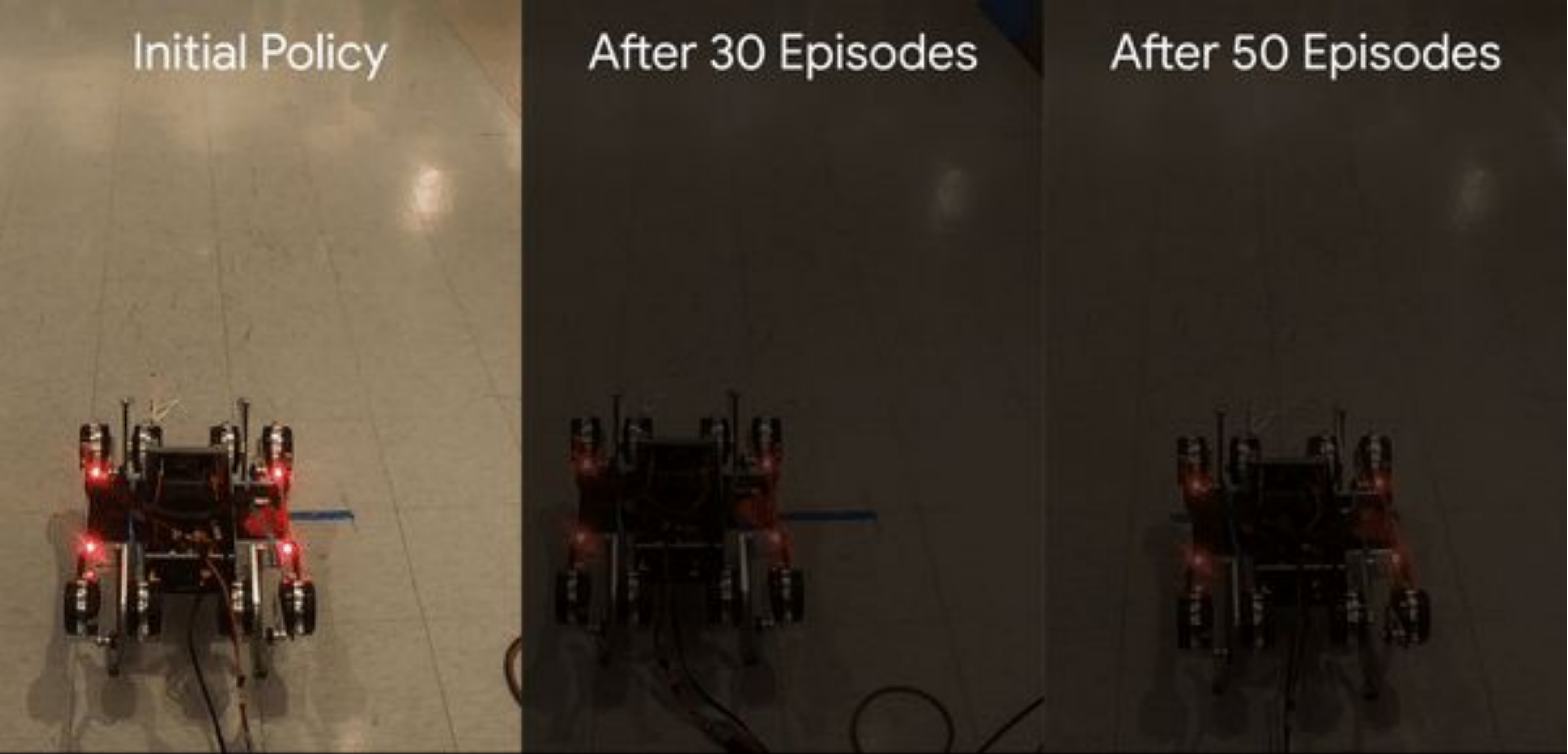
**Mass-Voltage Task**



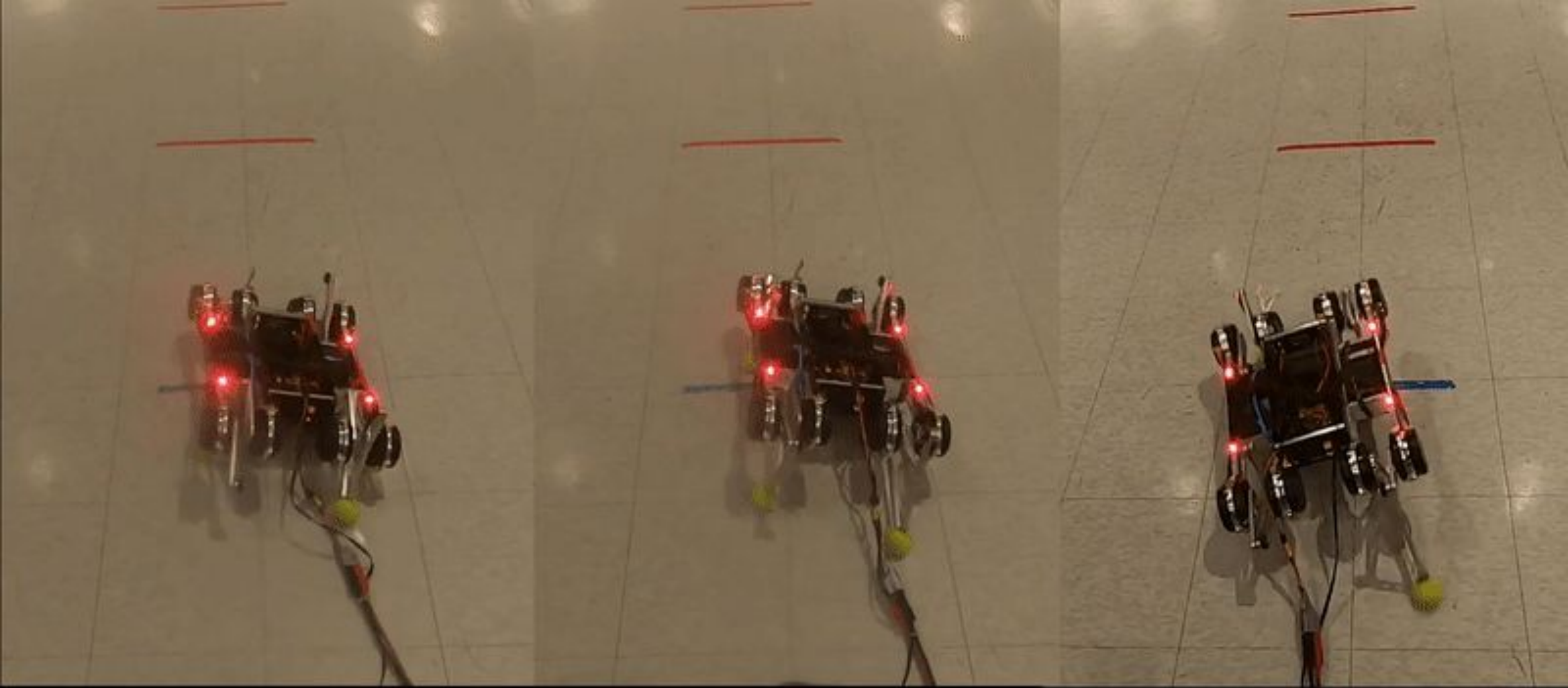

**Friction Task**




- Mass Voltage: 500g mass on side, voltage reduced to disrupt leg synchronization
- Friction: Tennis Balls on feet, to reduce gait via slipping.




The initial policy shifts to the right.


Domain Randomization

PG-MAML

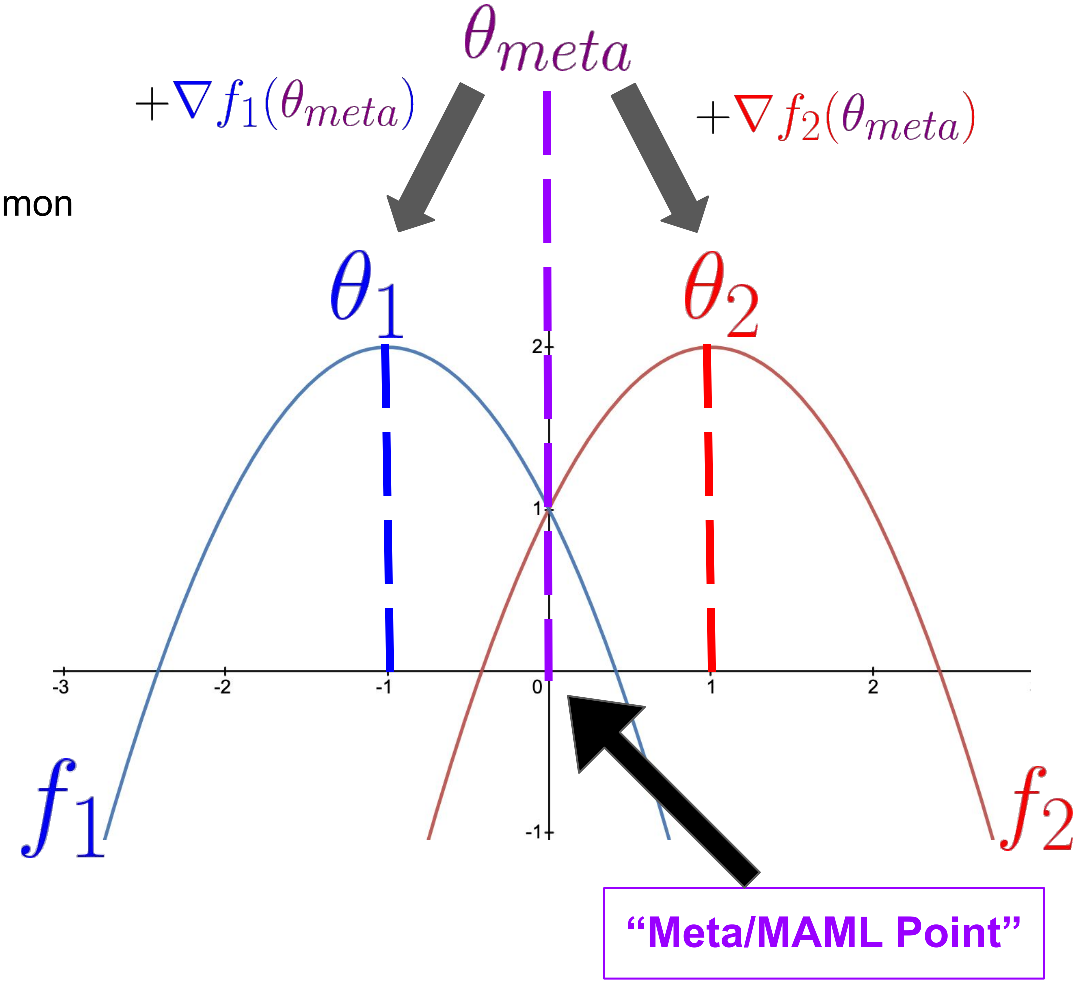
Our Method

# How did we get here?
# (Questions?)

# Intuition of MAML

**Problem:** Objectives/tasks don't have common optima.

**Solution:** Find a Meta-Point!



# Reaching the Meta-Point

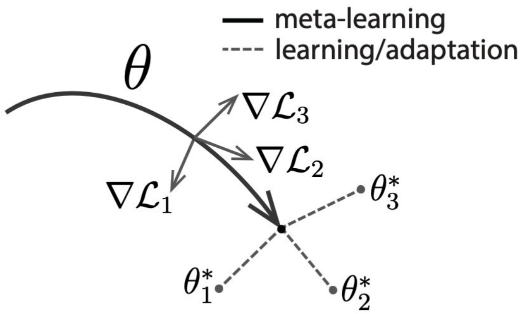
**Define Adaptation Operator/Inner Loop:** $U(\theta, f) = \theta + \nabla f(\theta)$

**Optimize:**

✗ $f_1(\theta) + f_2(\theta)$

✓ $f_1(U(\theta, f_1)) + f_2(U(\theta, f_2))$

# Formalism of Meta-Learning




- Adaptation uses little data

$$\max_{\theta} J(\theta) := \mathbb{E}_{T\sim\mathcal{P}(\mathcal{T})}\left[\mathbb{E}_{\tau'\sim\mathcal{P}_T(\tau'|\theta')}\left[R_T(\tau')\right]\right]$$

bilevel optimization formulation

$$\theta' = U(\theta, T) = \theta + \alpha\nabla_\theta\mathbb{E}_{\tau\sim\mathcal{P}_T(\tau|\theta)}\left[R(\tau)\right]$$

one-shot gradient-based adaptation operator

$\mathcal{P}_T(\cdot|\eta)$ - **distribution over trajectories given a task and conditioned on a policy**

# Gradient-Based Meta Learning is Complicated!

$$\nabla_\theta J(\theta) = \mathbb{E}_{T\sim\mathcal{P}(\mathcal{T})}[\mathbb{E}_{r'\sim\mathcal{P}_T(\tau'|\theta')}[\nabla_{\theta'} \log \mathcal{P}_T(\tau'|\theta')R(\tau')\nabla_\theta U(\theta, T)]]$$

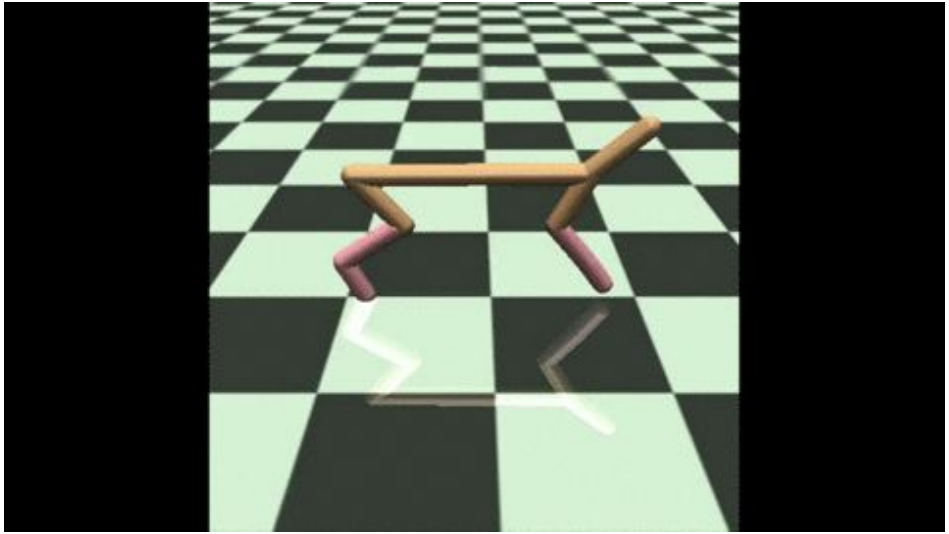
$$\nabla_\theta U = \mathbf{I} + \alpha \int \mathcal{P}_T(\tau|\theta)\nabla^2_\theta \log \pi_\theta(\tau)R(\tau)d\tau + \alpha \int \mathcal{P}_T(\tau|\theta)\nabla_\theta \log \pi_\theta(\tau)\nabla_\theta \log \pi_\theta(\tau)^T R(\tau)d\tau$$

- **Policy Gradient (PG)-MAML**
- **Challenge:** Estimation of the gradient is very complicated.
- **Limitations: Doesn’t allow non-differentiable operators U**

# Previous Results in MAML

Restricted to **reward function** changes, not **dynamics changes.**

Example: Forwards + Backwards HalfCheetah



https://github.com/tristandeleu/pytorch-maml-rl

# Importance of Dynamics Adaptation

- In real world, we care more about **dynamics changes** for robust walking.


# Minitaur RL Framework

Minitaur MDP: (Observation, Action, Reward)

- **Observation:** Roll + Pitch Angle, 8 Motor Angles, and sin/cos phase variable
- **Action:** Swing and Extension of each leg
- **Reward:** Velocity minus energy (torque * angular velocity), encourages straight walking

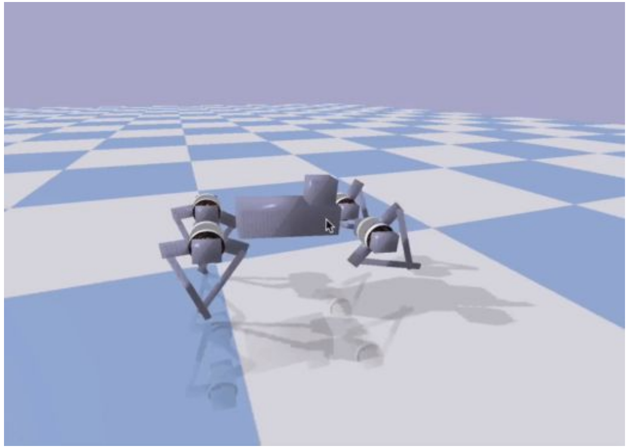
$$r(t) = \min(v, v_{\max})dt - 0.005 \sum_{i=1}^{8} \tau_i \omega_i dt$$

# MAML Simulation Experiment Setup

We train the meta policy in simulation using Pybullet.

Each task samples a different combination of physics parameters:

- Body and Leg Mass
- Battery Voltage, Foot Friction
- Motor Damping, Motor Strength, Control Latency



# PG-MAML for Legged Robots - Challenges

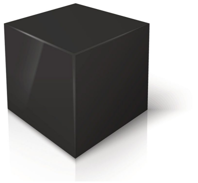
- PG-MAML is **stochastic: Jerky random actions can be bad** for real robots.

$$a \sim \pi_\theta(s) = \mathcal{N}(\mu, \sigma)$$

- Real world is never deterministic. If $f(\theta)$ is objective, we always observe (non-Markovian) noise:

$$\widetilde{f}(\theta, \varepsilon) = f(\theta) + \varepsilon$$

# Alternative: Evolutionary/Blackbox Methods

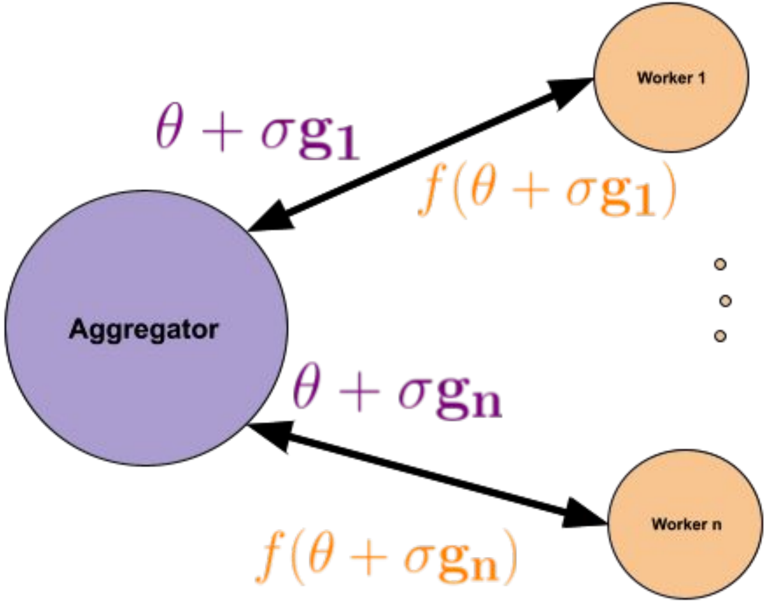


## Evolutionary Strategies (ES):

1. Treat total reward as **blackbox function**
2. Estimate gradients via local perturbations

$$\nabla_\theta \tilde{f}_\sigma(\theta) = \frac{1}{\sigma}\mathbb{E}_{\mathbf{g}\sim\mathcal{N}(0,\mathbf{I}_d)}[f(\theta + \sigma\mathbf{g})\mathbf{g}]$$

**Gradient of the Gaussian Smoothing of the function**

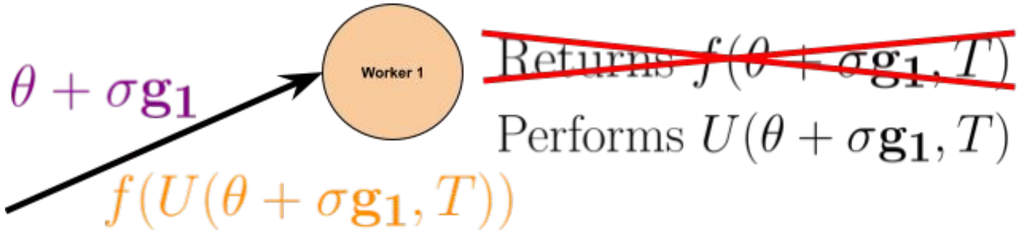



**ESGrad** $(f, \theta, n, \sigma)$
- **inputs:** function $f$, policy $\theta$, number of perturbations $n$, precision $\sigma$
- Sample $n$ i.i.d $N(0, I)$ vectors $g_1, \ldots, g_n$;
- **return** $\frac{1}{n\sigma}\sum_{i=1}^{n} f(\theta + \sigma g_i)g_i$;

# Evolutionary Meta Learning (ES-MAML)

**ES-MAML**: Estimate the meta gradient using ES. (Song et al, 2019)

**for** $t = 0, 1, \ldots$ **do**
  Sample $n$ tasks $T_1, \ldots, T_n$ and iid vectors $\mathbf{g}_1, \ldots, \mathbf{g}_n \sim \mathcal{N}(0, \mathbf{I})$;
  **foreach** $(T_i, \mathbf{g}_i)$ **do**
    $v_i \leftarrow f^{T_i}(U(\theta_t + \sigma \mathbf{g}_i, T_i))$
  **end**
  $\theta_{t+1} \leftarrow \theta_t + \frac{\beta}{\sigma n} \sum_{i=1}^{n} v_i \mathbf{g}_i$
**end**




- Can use non-differentiable adaptation operator *U*.
- Example: **Hill-climbing**, which enforces **monotonic improvement** (in Deterministic Environments).

# PG-MAML vs ES-MAML Conceptually

**PG-MAML's Catch 22:**

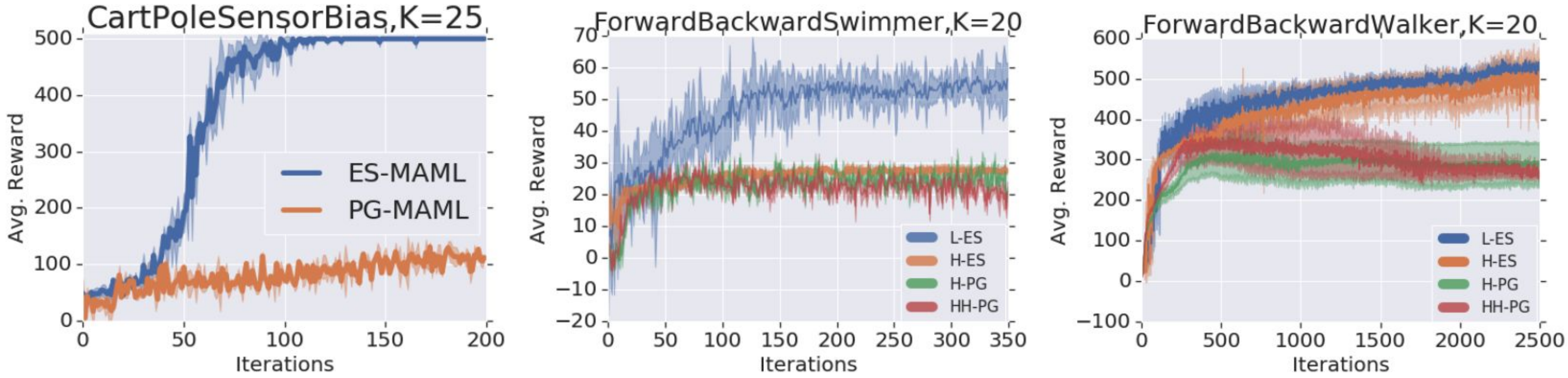
- Needs stochastic policies
  - Makes **random actions**
  - Noise problem becomes even worse.
- Action-based exploration
  - Relies on **random actions**
- Inner + Outer loop both **gradient-based**
- Adaptation improvement **not guaranteed.**

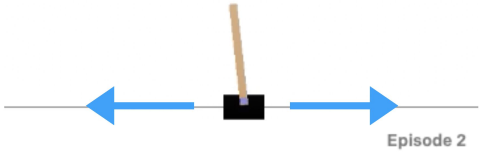
**ES-MAML:**

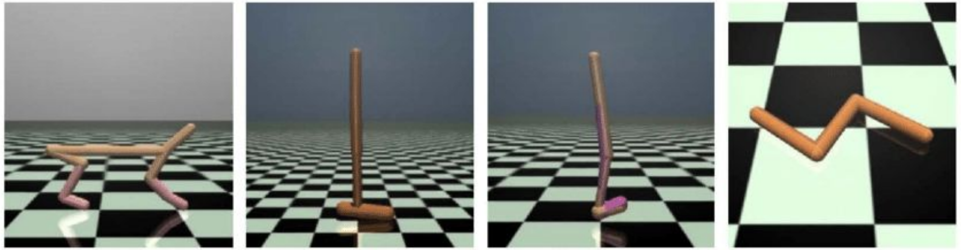
- Allows ***deterministic* policies**
  - Doesn't exacerbate noise problem.
- Parameter Space Exploration
  - Also **doesn't add randomness to policy.**
- Inner + Outer loop both **Zeroth-order optimization.**
- Hill-Climb Operator **enforces improvement.**

# ES-MAML: Continuous Control Benefits

Figure 4: Stability comparisons of ES and PG on the Biased-Sensor CartPole and Swimmer, Walker2d environments. (L), (H), and (HH) denote linear, one- and two-hidden layer policies.

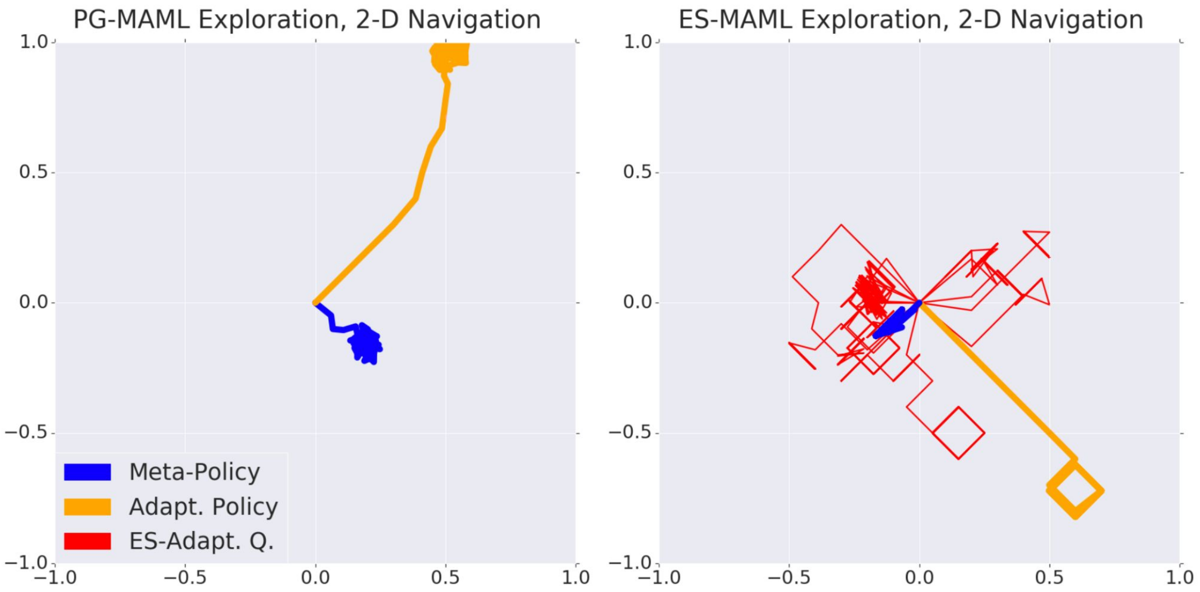


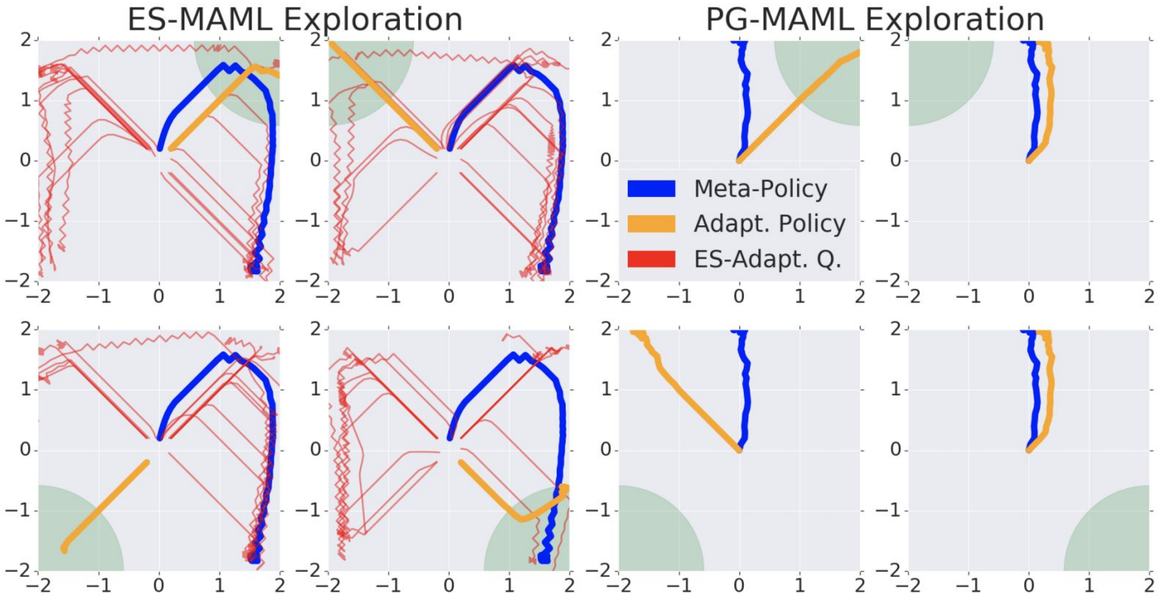
# ES-MAML vs PG-MAML: Exploration Fundamentals

- PG-MAML makes small moves, triangulates goal location
- ES-MAML moves different directions, figures out goal from total reward



# ES-MAML: Exploration Benefits - 4 Corners

- 4-Corner Task: Only give reward signal near the corner
- ES-MAML explores in **parameter space + wins!**

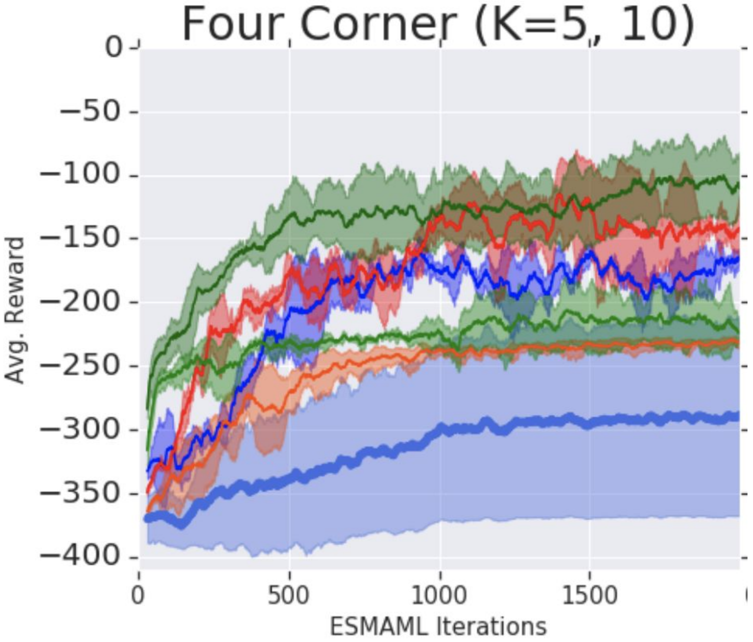


# ES-MAML: Different Adaptation Operators

- **Hill-Climbing (HC)** is strongest adaptation operator across **Monte-Carlo Gradient Estimation (MC)** and **DPP-Gradient Estimation (DPP)**

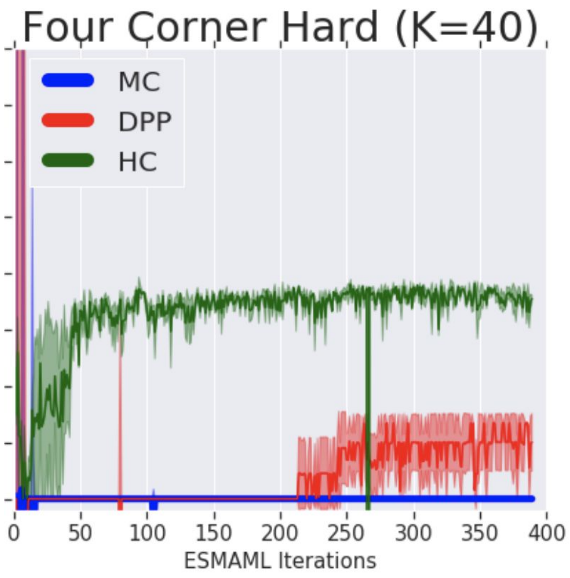
(K) Number of trials allowed in adaptation

K = 10: **Darker Colors**
K = 5: **Lighter Colors**

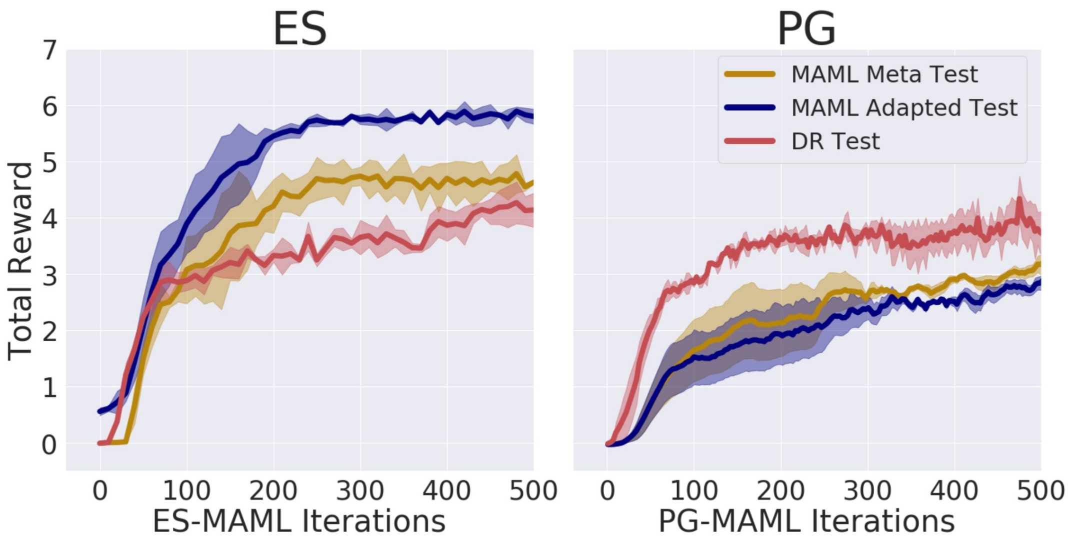


# ES-MAML: Hill-Climbing

- **Hard mode:** What if I penalized wrong goals with -100000000?
- **Hill-Climbing (HC)** still works!



# Minitaur Sim Results: ES-MAML vs PG-MAML

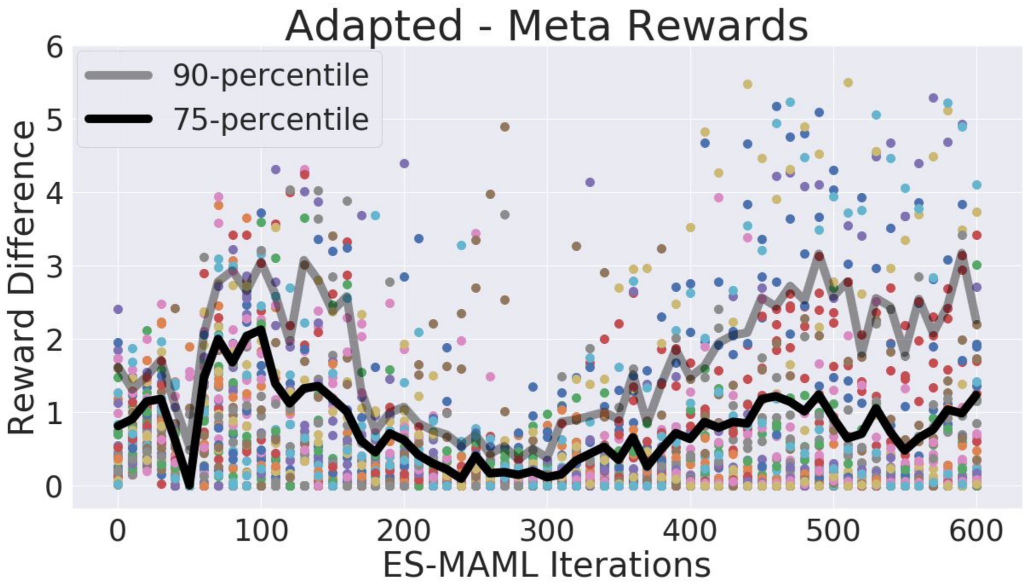



- **ES-MAML** > **PG-MAML and Domain Randomization (DR)**
- Hill-Climbing **enforces Adapted > Meta**, while PG-MAML **has no guarantees.**

# Minitaur Sim: Distribution Across Tasks

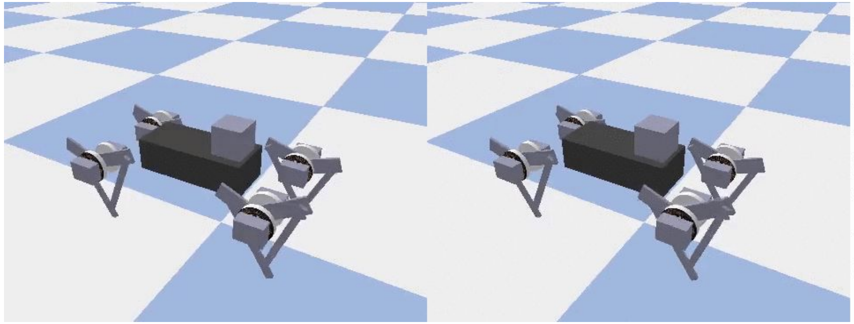
**Is adaptation even needed for this benchmark?**

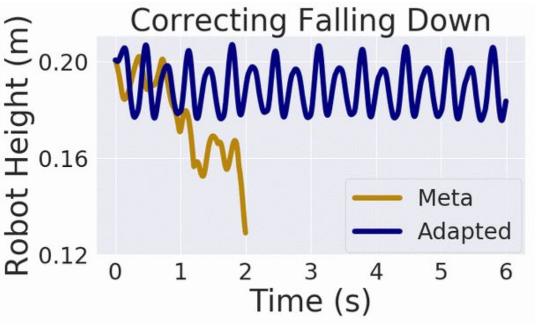
**Yes!** Multiple tasks need improvement by adaptation



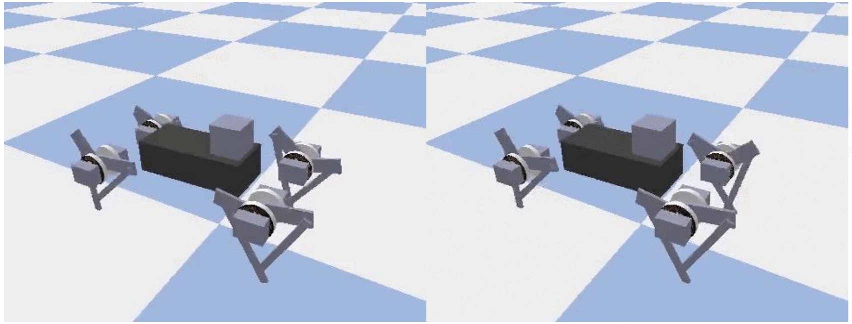
# Simulation Results: Qualitative Changes

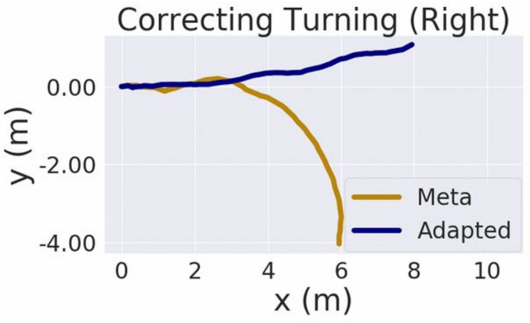
**Correction from falling:**






**Correcting walking direction:**



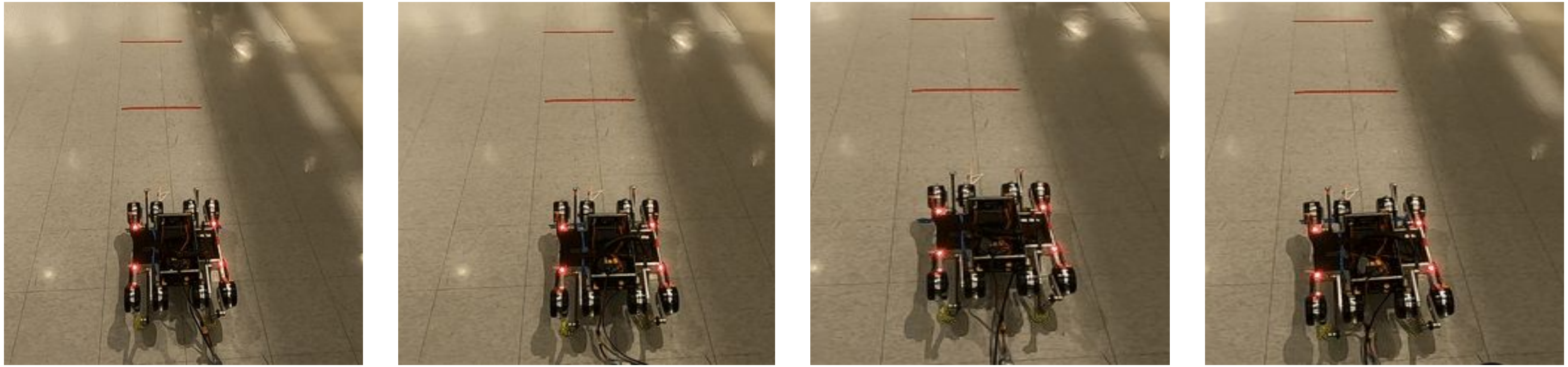


# What about the noisy real world?
# (Questions?)

# Adaptation in the noisy real world

When there is noise:

$$\widetilde{f}(\theta, \varepsilon) = f(\theta) + \varepsilon$$



How do we modify hill-climbing?

# Sequential Hill-Climbing

**Sequential (Original)**:

- Monotonic increase only in the deterministic case.
- Susceptible to noise in the real world.

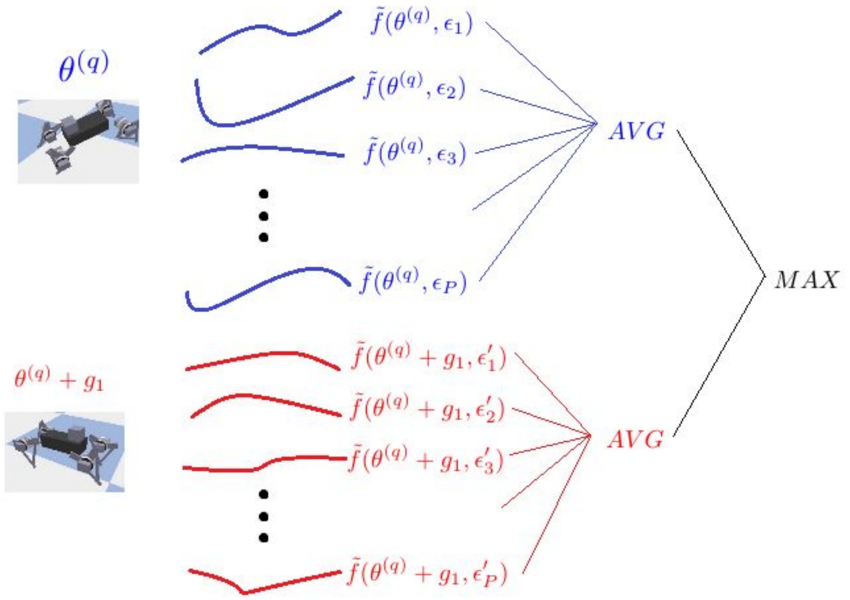
$$\theta^{(q+1)} = \underset{\theta \in \{\theta^{(q)}, \theta^{(q)} + \alpha \mathbf{g}\}}{\operatorname{argmax}} f(\theta)$$

$$\theta_{meta} \rightarrow \theta^{(1)} \rightarrow \ldots \rightarrow \theta^{(Q)}$$

# Average Hill-Climbing

**Average** evaluation over *P* trials - Assumption of **expected objective**

- **Fails** when noise is:
  - **Not IID**. Ex: Robot motor overheats over time.
  - **Not zero mean**. Ex: Robot falls randomly
- **Low sample efficiency** - Multiple rollouts committed to single parameter
  - Need to know noise magnitude in advance




$$\theta^{(q+1)} = \underset{\theta \in \{\theta^{(q)}, \theta^{(q)} + \alpha \mathbf{g}\}}{\operatorname{argmax}} \frac{1}{P} \sum_{i=1}^{P} \tilde{f}(\theta, \varepsilon_i)$$

# Understanding the Problem

- Allowed fixed number of noisy objective evaluations **T**
  - Total Hill-Climb Trajectory T = Q*P
    - Q = “length”: # proposed parameter changes
    - P = “parallel”: # parallel evaluations
- We don’t know exactly what is **signal** or **noise**:

$$\widetilde{f}(\theta, \varepsilon) = f(\theta) + \varepsilon$$

# Adversarial Noise

Big Question: **How should we model noise?**

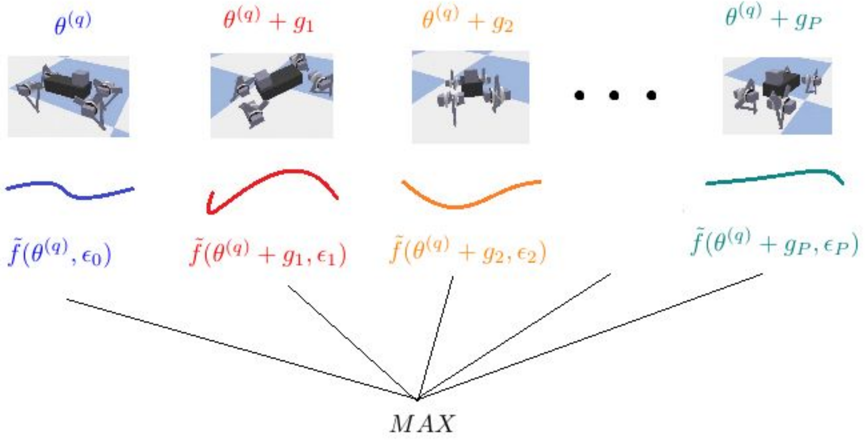
- Roughly speaking, **we shouldn't.**
  - Ends up being unrealistic + complicated
  - We don't know what is noise or signal anyways.
- We should just assume it's near **adversarial**.

$$\widetilde{f}(\theta, \varepsilon) = f(\theta) + \mathcal{E}$$

# Batch Hill-Climbing

**Batch** evaluation over *P* perturbed trials
- Take the best trial, **even if noisy**:

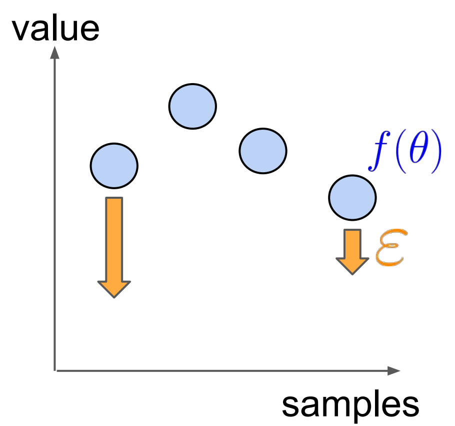
- **Sample efficient** - P diverse parameter samples.
- Works even in the case of adversarial noise - does not require strict noise assumptions!




$$\theta^{(q+1)} = \underset{\theta \in \{\theta^{(q)}, \theta^{(q)} + \alpha \mathbf{g}_1, \ldots, \theta^{(q)} + \alpha \mathbf{g}_P\}}{\operatorname{argmax}} \tilde{f}(\theta, \varepsilon)$$

# Intuitive Explanation

1. Suppose I sample ***P* objectives**
2. Nature **negatively corrupts** a fraction of these samples




Behavior of Operations:

- **Summation:** Even **one** sample can affect the outcome.
  - Easily affected by **magnitude of noise**
- **Argmax:** Affected only if argmax got chosen.
  - **Independent** of noise magnitude of neighbors.
  - Picking **second place** isn't bad either!

# Regret Minimization

- How do you show a method can **"make progress"?**
- Answer: **Regret Minimization.**

$$\frac{\sum_{t=0}^{T-1}\left(f(\theta^{opt}) - f(\theta_t)\right)}{T}$$

**Regardless of noise, our method should still converge to optimum.**

# The Mathematics of Batch Hill-Climbing

**Batch Hill-Climbing:**

- producing strong convergence (see: right) with high probability even if substantial number of measurements is **arbitrarily corrupted**

standard averaging-operator
is not resistant to
arbitrary noise

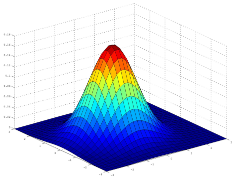
$f : \mathbb{R}^d \rightarrow \mathbb{R}$ *is a* $(\mu, \rho)$*-strong concave function*

**diameter of f-domain**

$$\frac{\sum_{t=0}^{T-1}(f(\theta^{\mathrm{opt}}) - f(\theta_t))}{T} \leq \frac{1}{\sqrt{T}}\left(\frac{D^2}{2} + \left(L + \frac{4L^2}{\sqrt{T}}\right)^2 + 8DL^2\right) + D\phi$$

**number of iterations of the algorithm**

**upper-bound on the norm on the L2-norm of f-gradient**



**any constant satisfying:**

$$\phi > \frac{4(\rho-\mu)\sqrt{T}d\sigma}{7} + \frac{16\Lambda\sqrt{T}}{7\sigma\sqrt{d}}$$

**upper bound on the measurement error of small-error measurements**

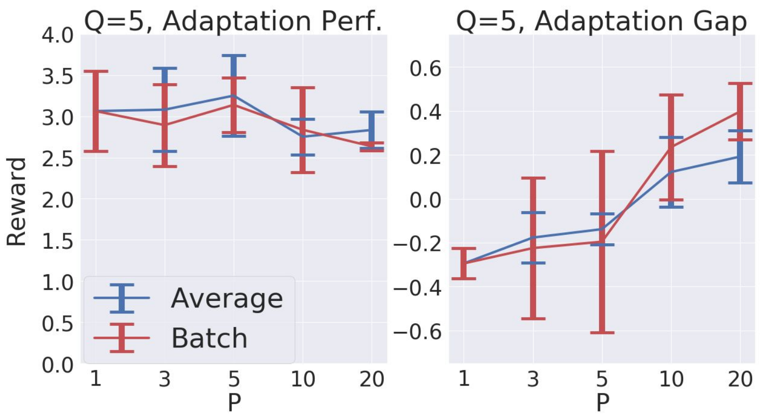
**any constant satisfying:**

$$\sigma \leq 4\sqrt{\frac{\Lambda}{7\sqrt{d}}}$$

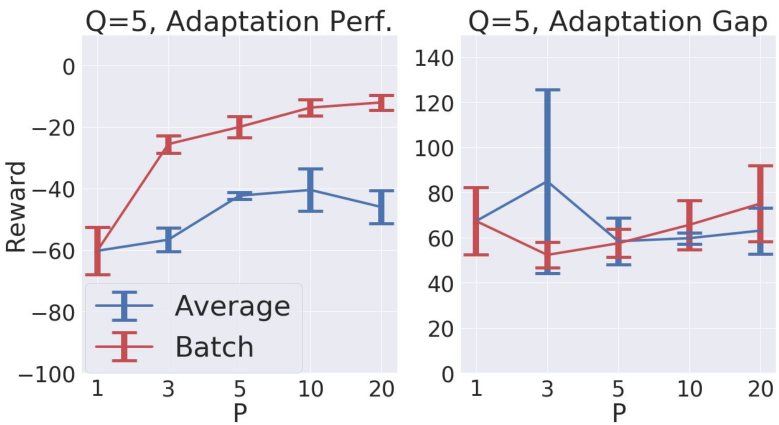
$$or\ |f(\theta^{\mathrm{opt}}) - f(\theta_i)| \leq D\phi\ for\ some\ \theta_i$$

# Simulation Results: Average vs Batch

- Given same number of parameter changes (Q) and parallel (P) rollouts:
  - **(Left):** On **Noisy Minitaur,** Batch produces higher adaptation gap.
  - **(Right):** On **Noisy Nav-2D** (toy env. from (Finn et al, 2017)), Batch Produces higher raw adaptation performance.



Noisy Minitaur Environment

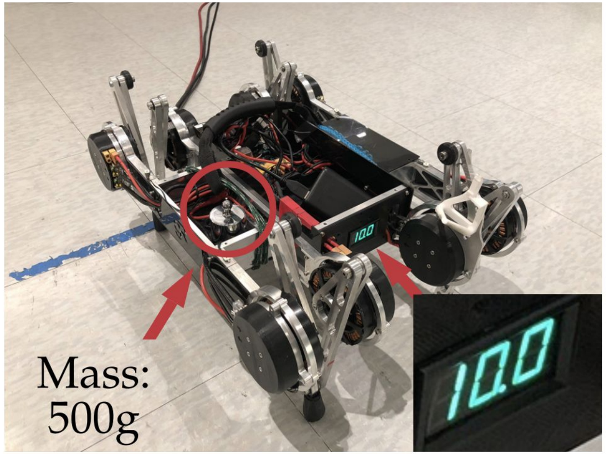


Noisy Nav-2D Environment

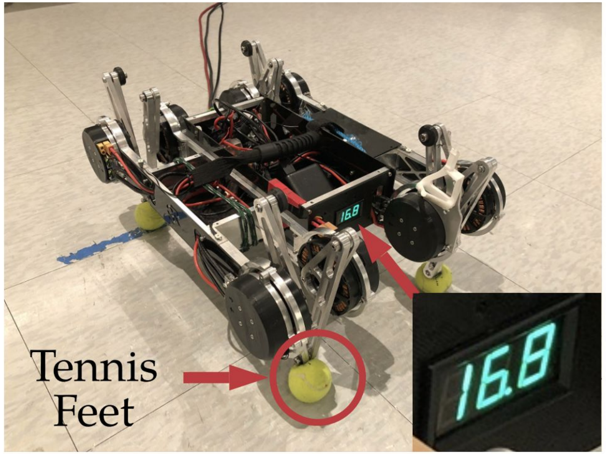
# Real-Robot Experimental Ablations (Questions?)

# Task Setup (Reminder)

**Mass-Voltage Task**

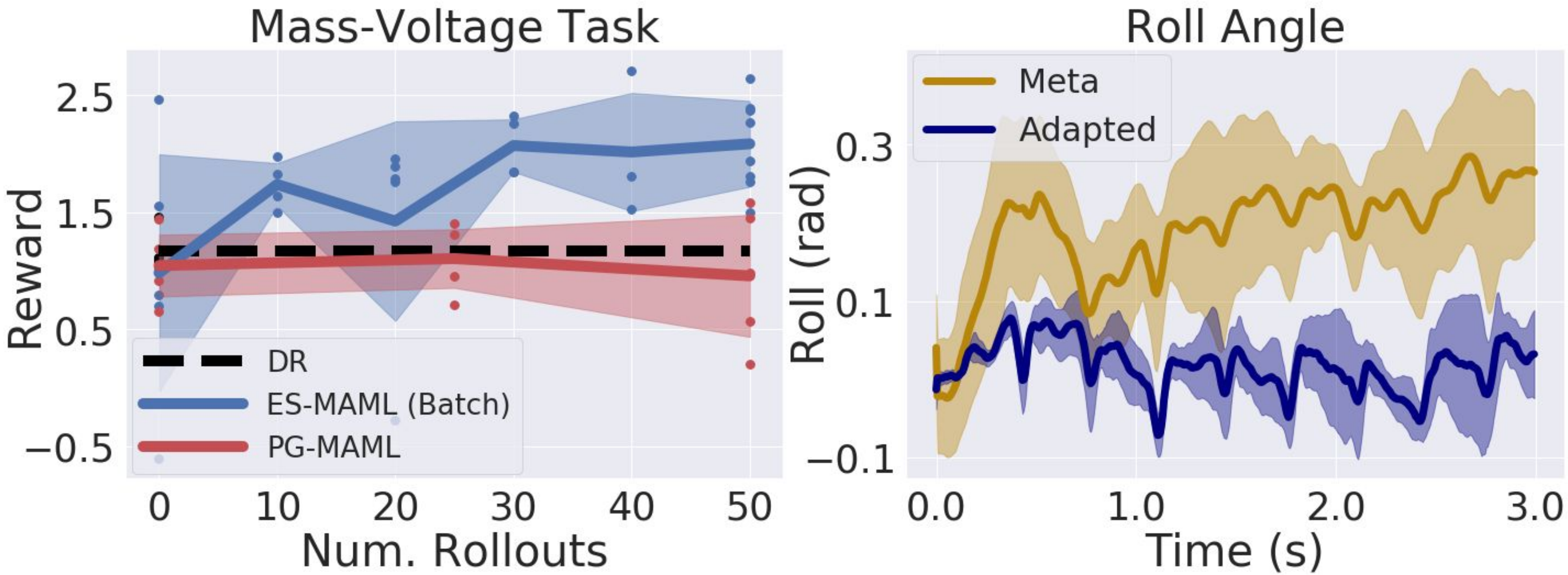



**Friction Task**



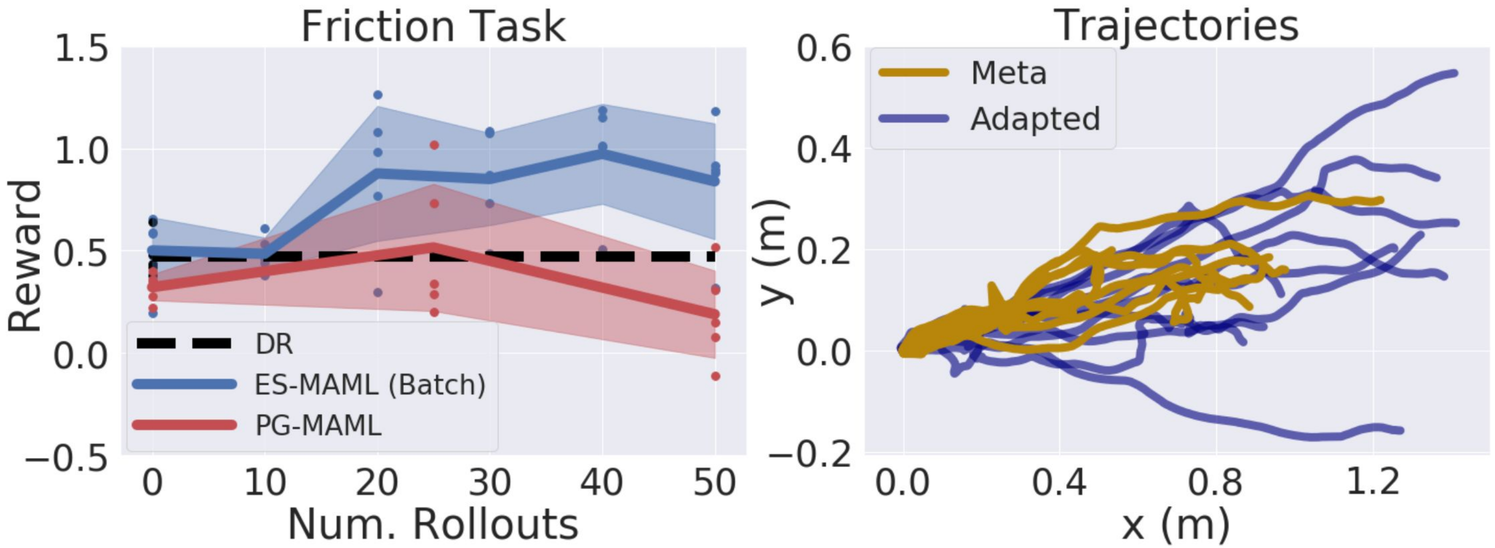

- Mass Voltage: 500g mass on side, voltage reduced to disrupt leg synchronization
- Friction: Tennis Balls on feet, to reduce gait via slipping.

# Mass-Voltage Task




- ES-MAML outperforms PG-MAML and Domain Randomization (DR)
- ES-MAML stabilizes the roll angle to 0 after adaptation.

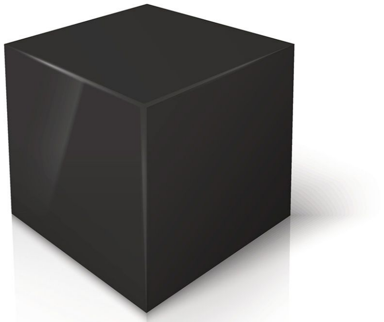
# Friction Task




- ES-MAML outperforms PG-MAML and Domain Randomization (DR)
- ES-MAML produces longer trajectories.

# Conclusion

- We demo'ed one of the **first successful applications of MAML on a challenging real robot task**.
- ES-MAML + Batch Hill-Climbing (our method) enables fast adaptation on robots.
    - Noise-resilient + Theoretically sound (Regret Minimization)
    - Benefits of Zero-Order/Blackbox methods for robotics:
        - Deterministic, stable policies
        - Exploration via parameter space



# Future Work

- Continuous Adaptation:
  - Adapt robot to constantly changing environments?
- Improving Sample Efficiency:
  - Model-based techniques = less real-world data needed?
  - Better model-free adaptation operators?
- Other applications of blackbox outer + inner loops
  - NAS, Genetic Programming, Hyperparameter Optimization, etc.

# More Details

Please see our following links for more information:

- arXiv (Robot Application Paper at IROS 2020): https://arxiv.org/abs/2003.01239
- arXiv (ES-MAML Paper at ICLR 2020): https://arxiv.org/abs/1910.01215
- ES-MAML Code: https://github.com/google-research/google-research/tree/master/es_maml
- Google AI Blog: https://ai.googleblog.com/2020/04/exploring-evolutionary-meta-learning-in.html
- Experiment Video: https://youtu.be/_QPMCDdFC3E
- Talk Video: https://youtu.be/-_GP5ghLy-w
- Code: https://github.com/google-research/google-research/tree/master/es_maml

# Thank you!