Research Project Proposal:

Transfer of generative models in reinforcement learning

Pierluca D’Oro
pierluca.doro@mail.polimi.it
CSE track

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HONOURS PROGRAMME HP-SR in Information Technology

Outline

- Motivation
- State of the art
  - Generative models
  - Model-based RL
- Research idea and plan

- **Motivation**
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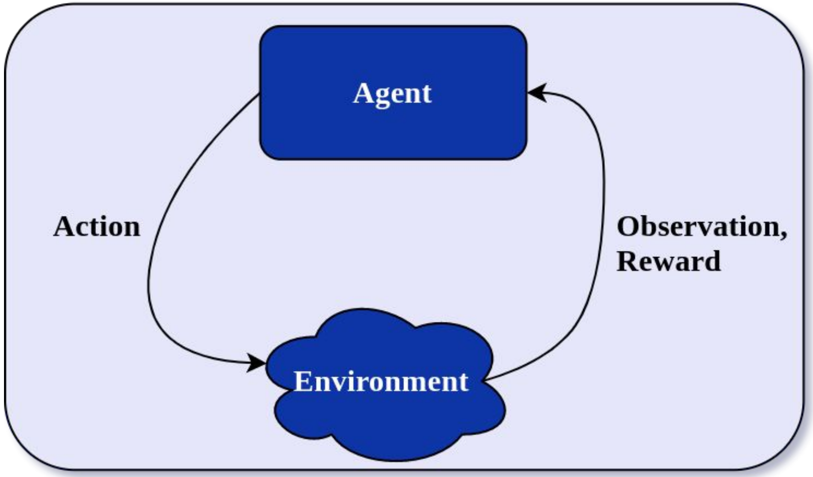
8 - 15 March 2016
AlphaGo
Lee Sedol
Google DeepMind
Challenge Match
8 - 15 March 2016

Reinforcement Learning

An **agent** acts to maximize a **reward** collected in an **environment**.

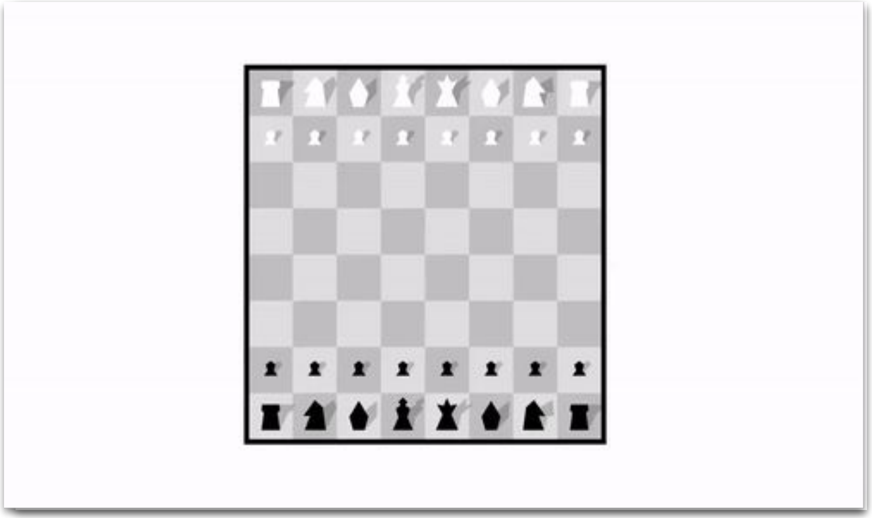


The RL problem is modeled as a Markov Decision Process:

- States
- Actions
- Initial state distribution
- Reward function
- Discount factor
- *Transition distribution* (i.e., environmental dynamics)

We want the agent to learn the **optimal policy**, possibly estimating the **value** of a state.

Superhuman Machines?



David et al. **Mastering the game of Go without human knowledge**

Mnih et al. **Playing atari with deep reinforcement learning**

Data collection is hard

For many tasks, collecting experience can be:

- Slow
- Expensive
- Dangerous

In the real world, you cannot speedup time, you have to pay to execute actions or set up a system, and you can break things.

Examples: autonomous driving, robotics, healthcare applications.

Goal of the project

Address data shortage through:

- Sample efficiency
- Transfer from related settings

We plan to leverage:

- Experience generated by **multiple policies**
- Experience generated in **multiple environments**

We want to use it to train a policy for acting in previously unseen scenarios.

Model-based RL

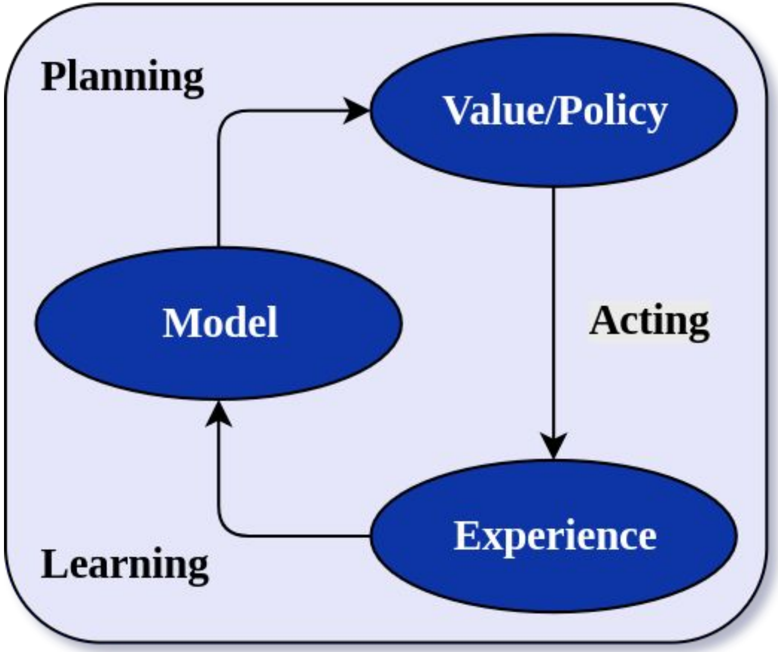
RL approaches can be divided into:

- **Model-free**
- **Model-based**

In model-based RL, the agent uses an approximation of the dynamics of the environment, usually called *model*.

Pros and cons of *model-based RL*:

✓ Sample efficiency
✓ Easier transfer
✗ Bias introduced by the model class



How can we approximate the probability distribution of future states?

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Generative Models

They model the distribution that underlies the generation of some data, performing **density estimation**.

Two families of generative models:

- **Explicit** density estimators
  - Modeling the probability density function $p(\mathbf{x})$ of the generating distribution
  - Use simplifying assumptions to maximize data likelihood
  - Examples: autoregressive models, VAE, flow methods
- **Implicit** density estimators
  - Able to draw samples from the approximated distribution
  - Examples: generative adversarial networks

Variational Autoencoders

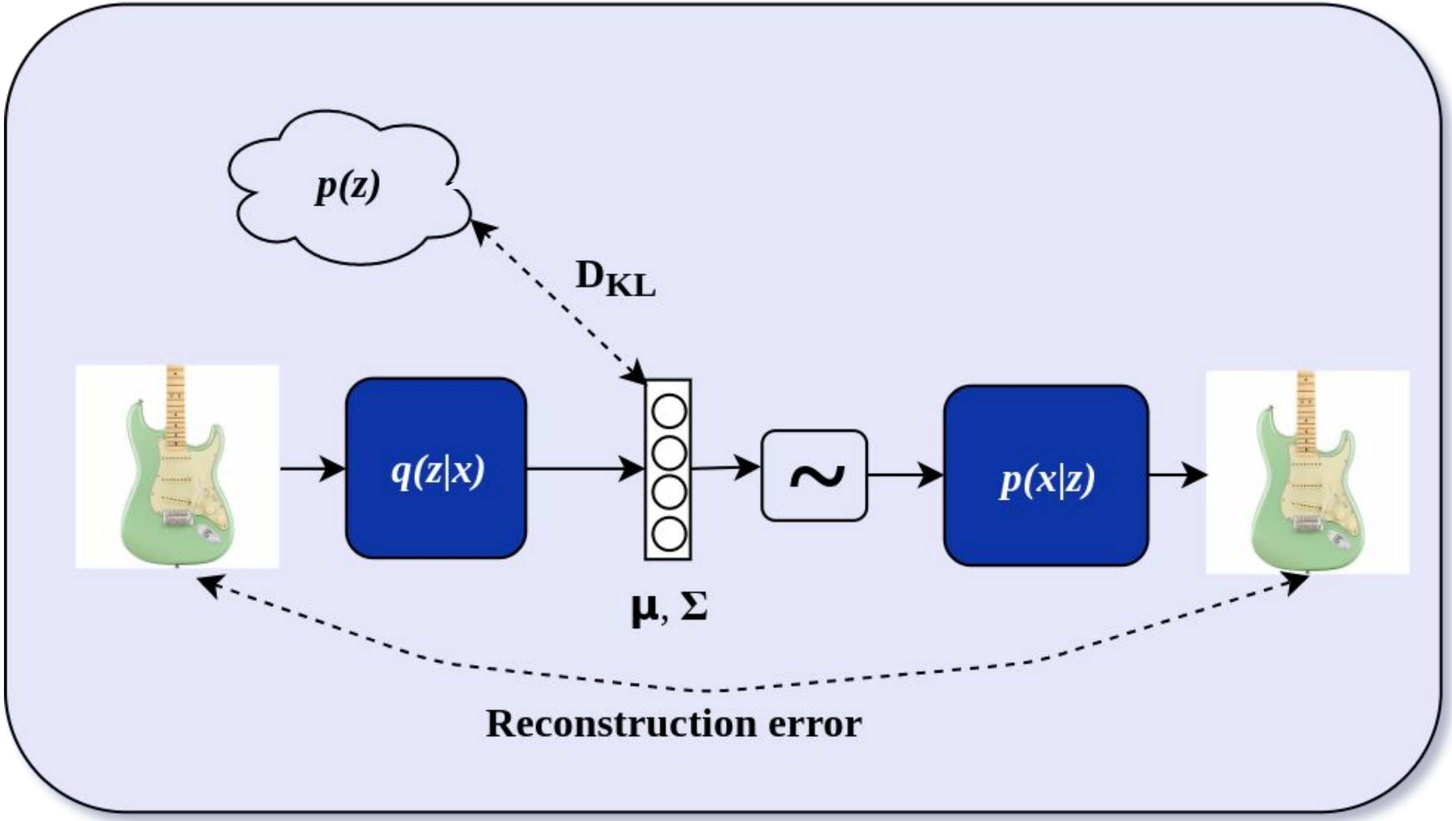
Hourglass-shaped model by *Kingma and Welling (2013)*:

- An **encoder** $q(z|x)$ maps the input data into latent variables
- A **decoder** $p(x|z)$ converts latent variables into data
- Training for reconstruction of encoded data
- $q(z|x)$ constrained to be as close as possible to a prior distribution $p(z)$
- Samples generated by sampling from the prior $p(z)$ and feeding to $p(x|z)$

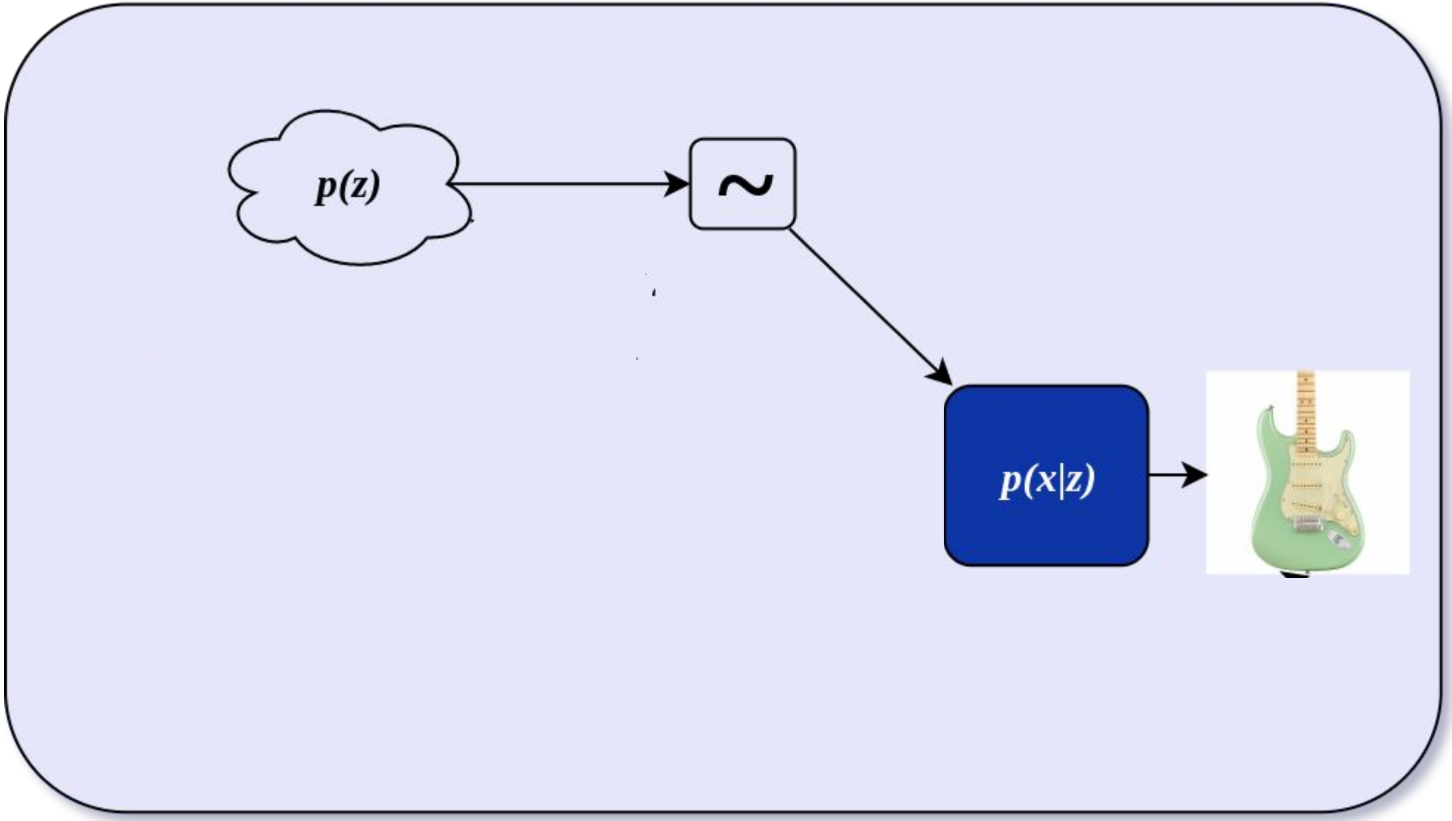
A lower bound is maximized in place of the intractable likelihood:

$$\mathbb{E}_{z\sim q(z|x)}[\log(p(x|z))] - D_{KL}(q(z|x)||p(z)) \leq \log(p(\mathbf{x}))$$

Variational Autoencoders



Variational Autoencoders



Generative Adversarial Networks

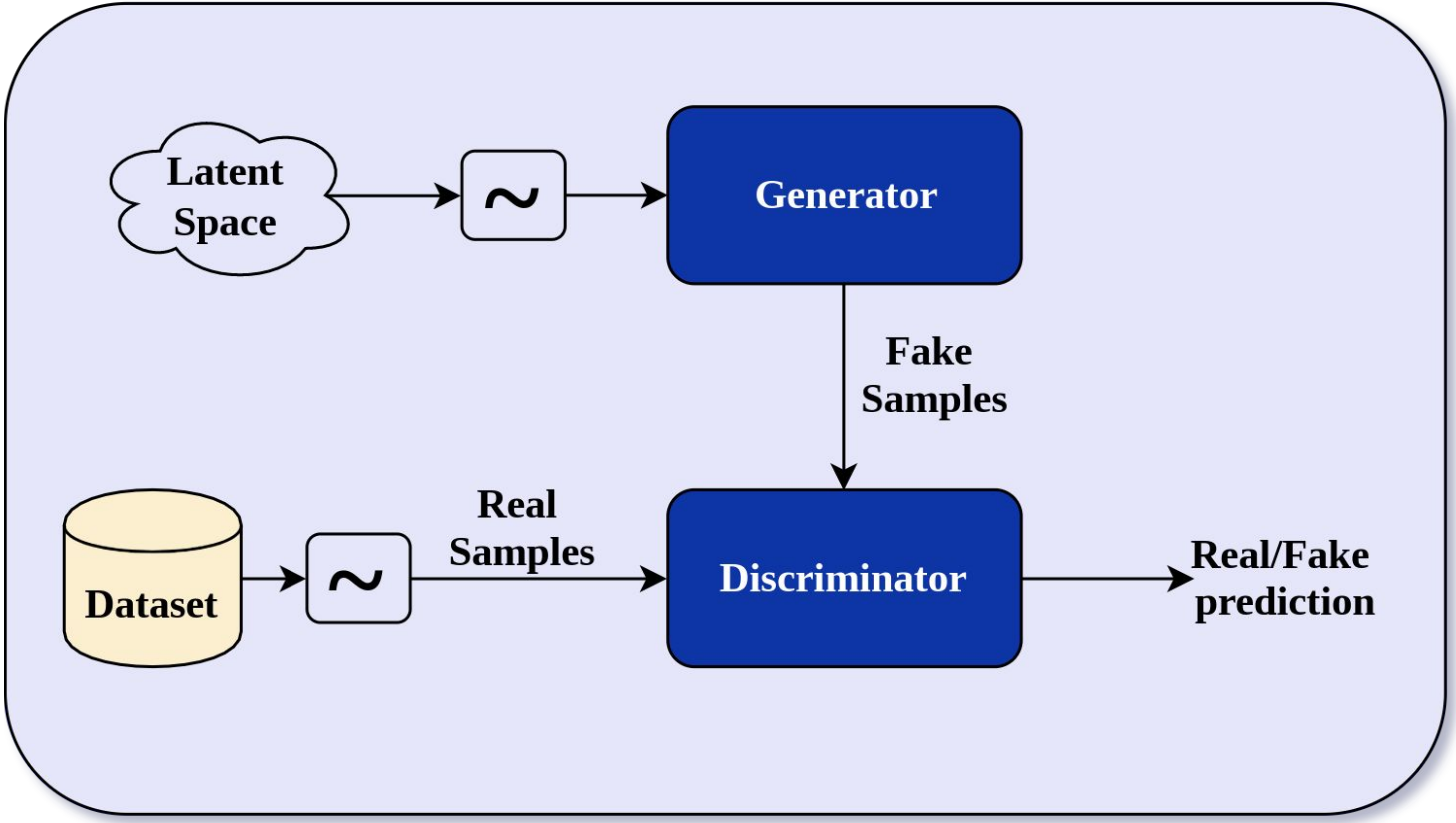
Generation is framed as a game:

- A **generator** produces fake samples mimicking a dataset
- A **discriminator** has to distinguish between real and fake samples
- Joint training
- Real and fake samples provided alternately to the discriminator

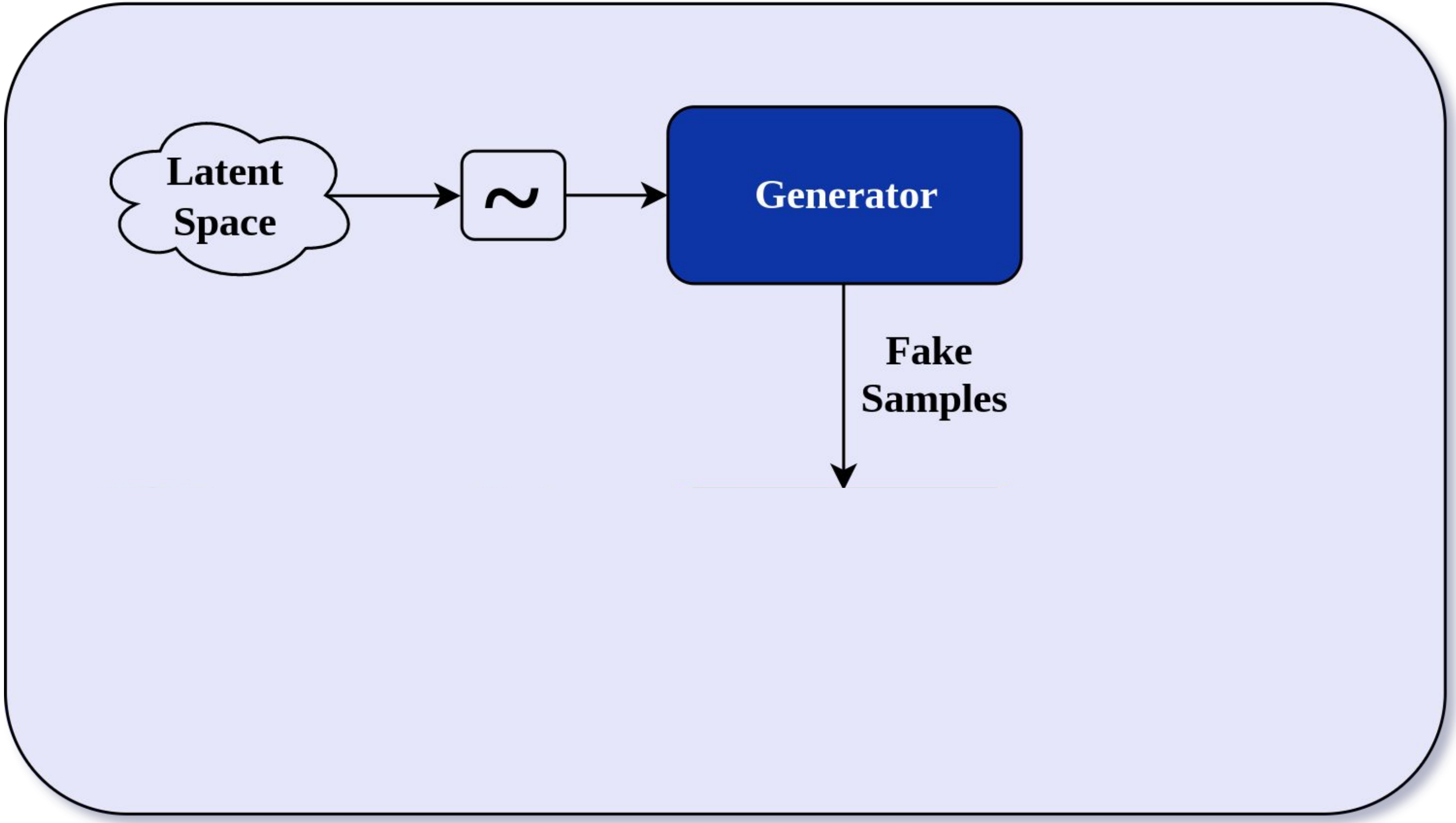
Original formulation from *Goodfellow et al (2014)*:

$$\min_G \max_D \mathbb{E}_{x \sim P_{\text{data}}}[\log(D(x))] + \mathbb{E}_{z \sim P(z)}[\log(1 - D(G(z)))]$$

Generative Adversarial Networks



Generative Adversarial Networks



How well do they generate?

Wang et al. **Video-to-Video Synthesis**

Karras et al. **Progressive Growing of GANs for Improved Quality, Stability, and Variation**

Brock et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis**

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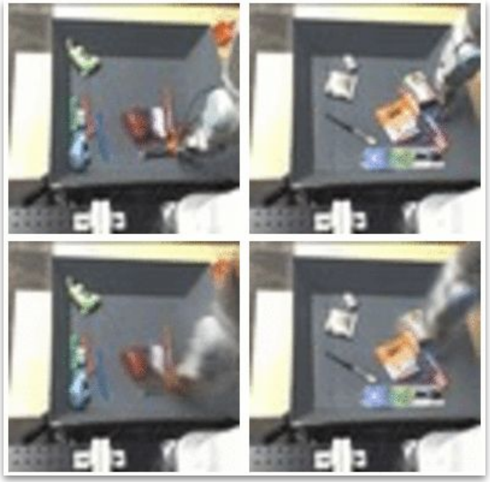
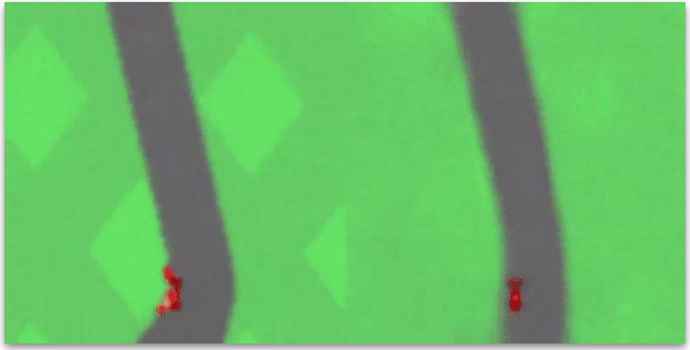
Modeling single-step transitions

Most of the approaches have modeled the **single-step** transition distribution.
Example applications: planning, learning in an "imagined" world, transfer.

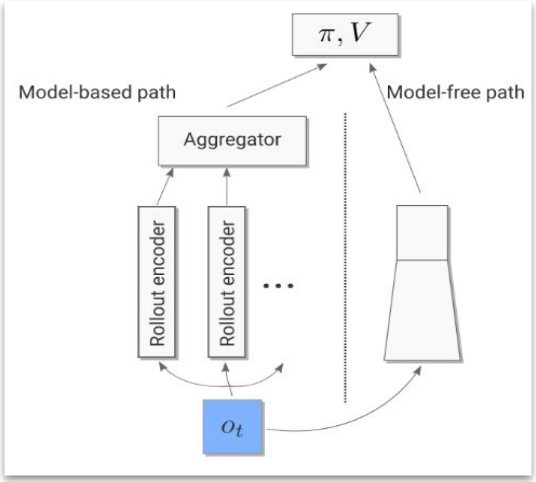
Finn and Levine. **Deep visual foresight for planning robot motion**



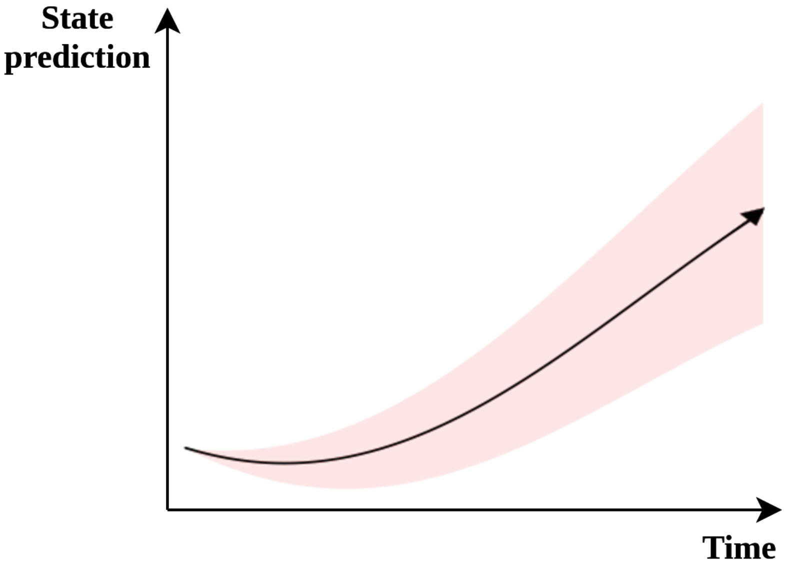
Ha and Schmidhuber. **Recurrent World Models Facilitate Policy Evolution**



Racanière et al. **Imagination-augmented agents for deep reinforcement learning**



Drawback of single-step modeling



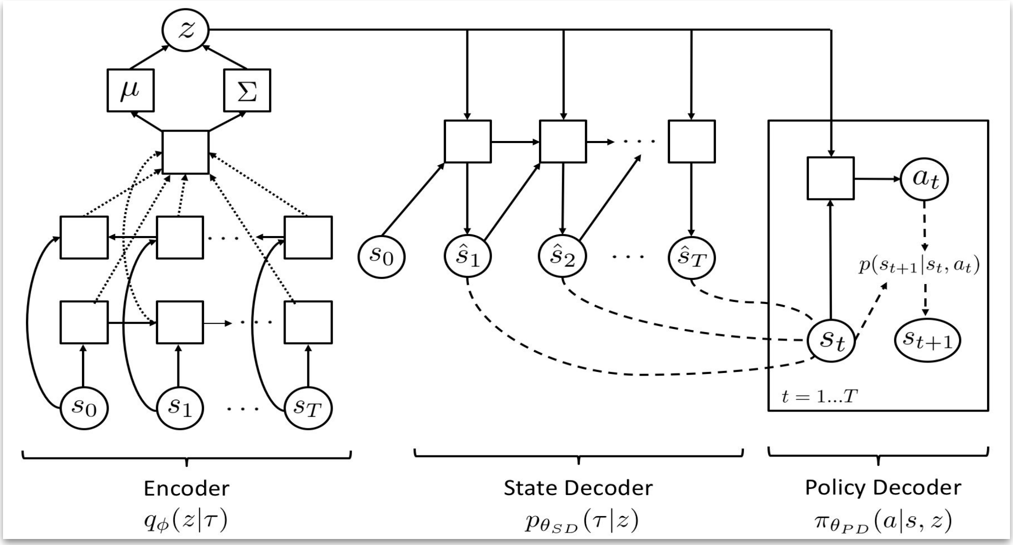
Unrolling single-step future estimates for several timesteps compounds errors.

The reason? *Uncertainty*:

- Error in model estimate
- Environment stochasticity

Modeling trajectories

Co-Reyes et al. **Self-consistent trajectory autoencoder**



Mishra et al. **Prediction and Control with Temporal Segment models**

Main drawback: longer trajectories = fewer samples to train our model on!

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Data is precious

What if the experience is generated by **multiple agents** acting in a single environment?

What if the experience is generated acting in **multiple related environments**?

If we want to learn a model to be used by a target policy in a target environment:

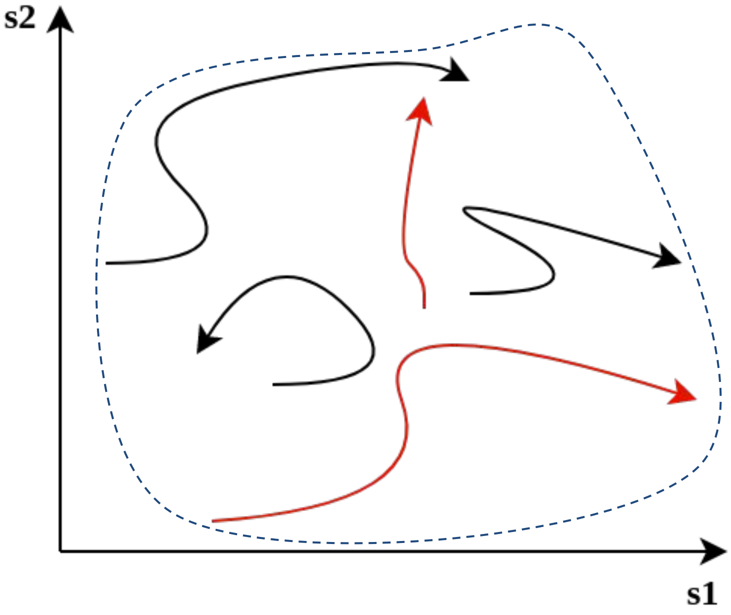
- We should not waste data we have at our disposal
- We should consider differences among agent policies and environments

Why it is relevant

Autonomous Driving

Functional Electrical Stimulation

A baseline: the monolithic approach



Consider multiple policies in a fixed environment. We want to learn the **approximate dynamics** of the environment to be used just by the policy that generated the red trajectories.

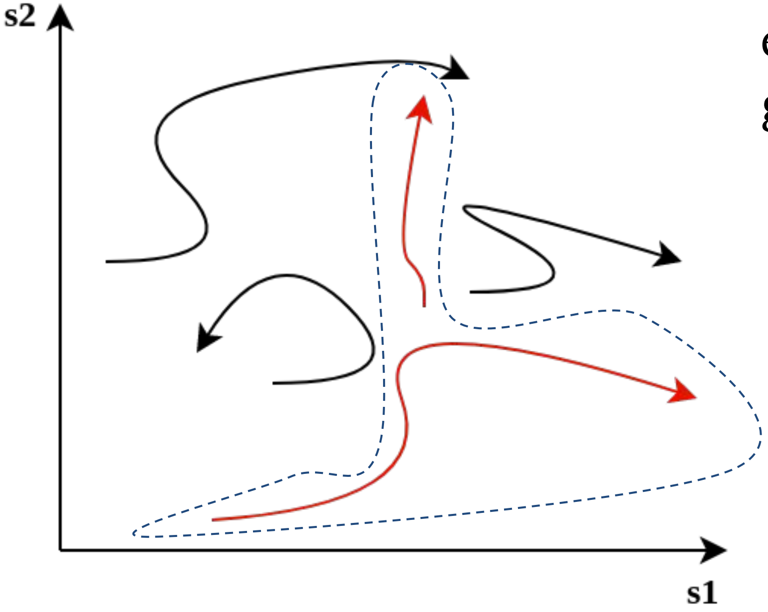
Using all trajectories:

- ✓ No waste of data
- ✗ Difficult fit (model has limited capacity)

Only using trajectories generated by target policy:

- ✓ Easier fit
- ✗ Waste of data

A baseline: the monolithic approach



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Idea: adaptable generative models

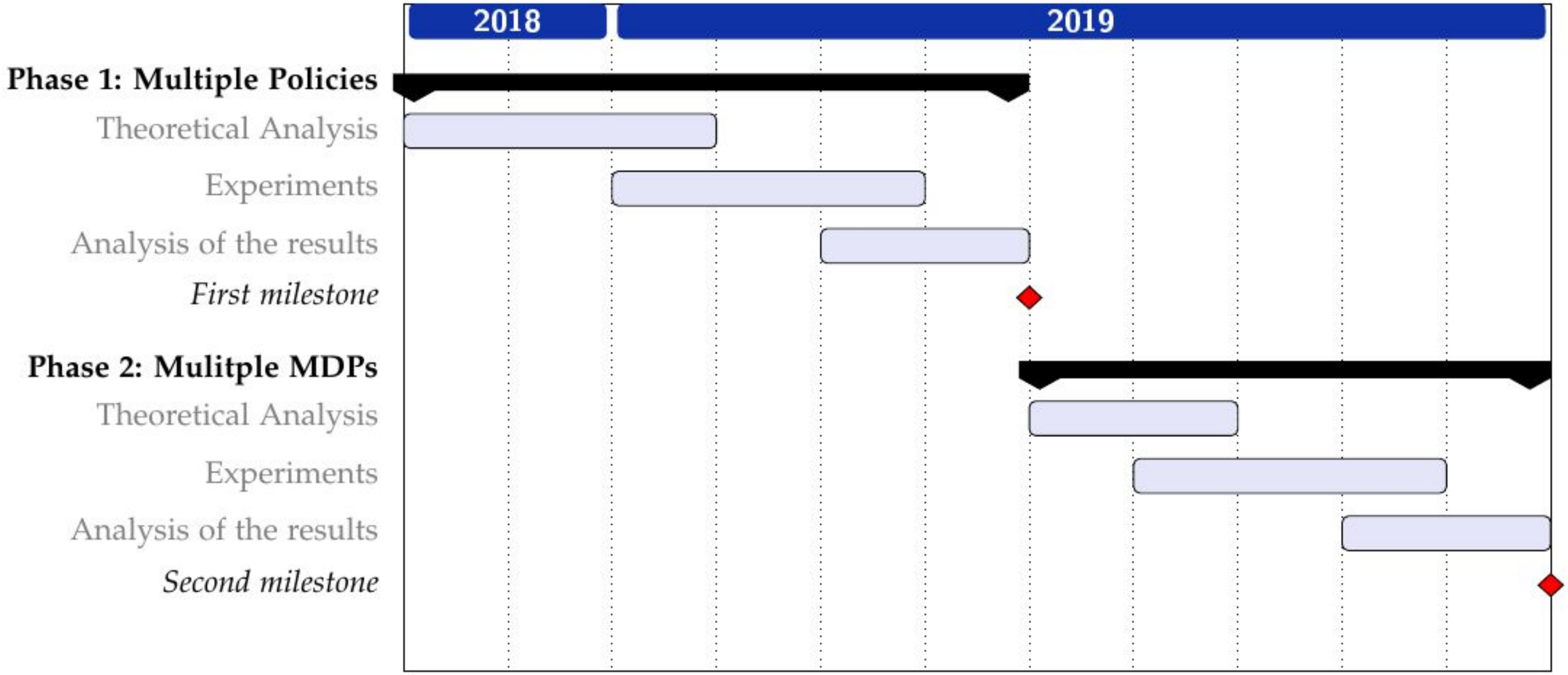
Generative models of the dynamics could be adaptable and learn in a clever way from trajectories experienced

- by multiple policies in a single environment,
- in multiple, related, environments.

Desiderata:

- Proper weighting of transitions while learning environmental dynamics
- Faster training or zero-shot transfer for target policies and environments
- Nice theoretical properties (e.g., good efficiency bounds)

Research Plan



Thank you for your attention!