

State of art of generative models in robotics applications

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Master thesis in engineering in computer science

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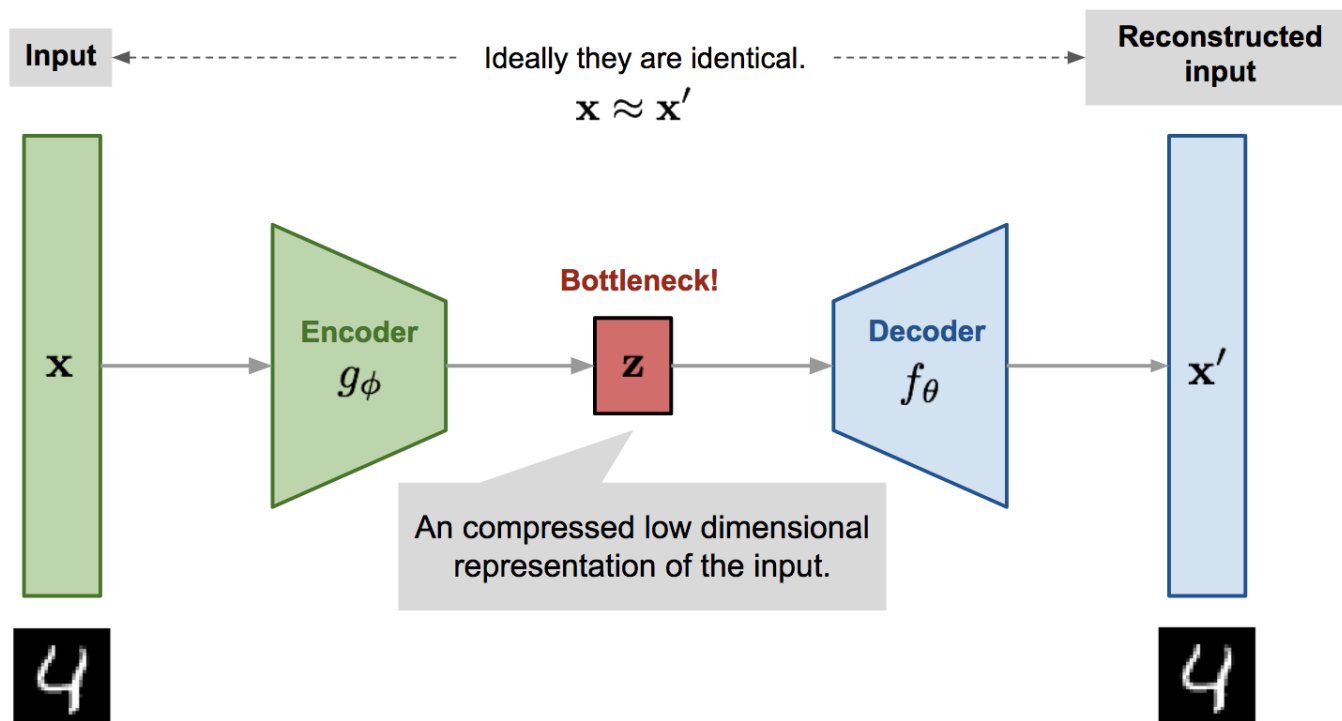
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Variational Autoencoders VAEs



Variational Autoencoder VAE

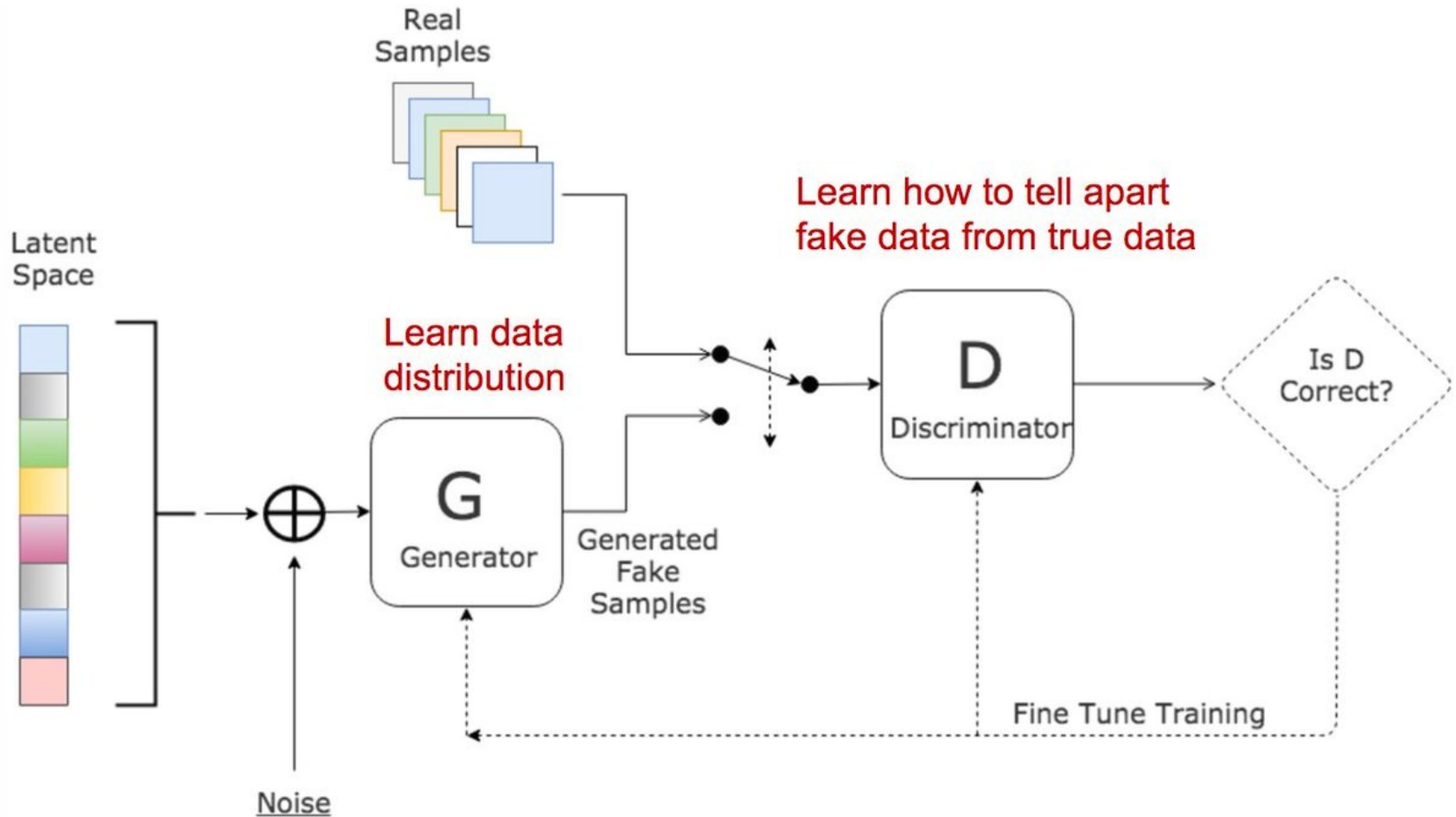
Encoder:

- Find latent space.
- Low dimensional representation of the original data.

Decoder:

- Given the latent or the data representation returned from the encoder, generates new data.
- Reconstruct the original data.

Generative Adversarial networks



Generative Adversarial Networks GANs

- Distinguish between authentic and fake data.
- Discriminator loss function:

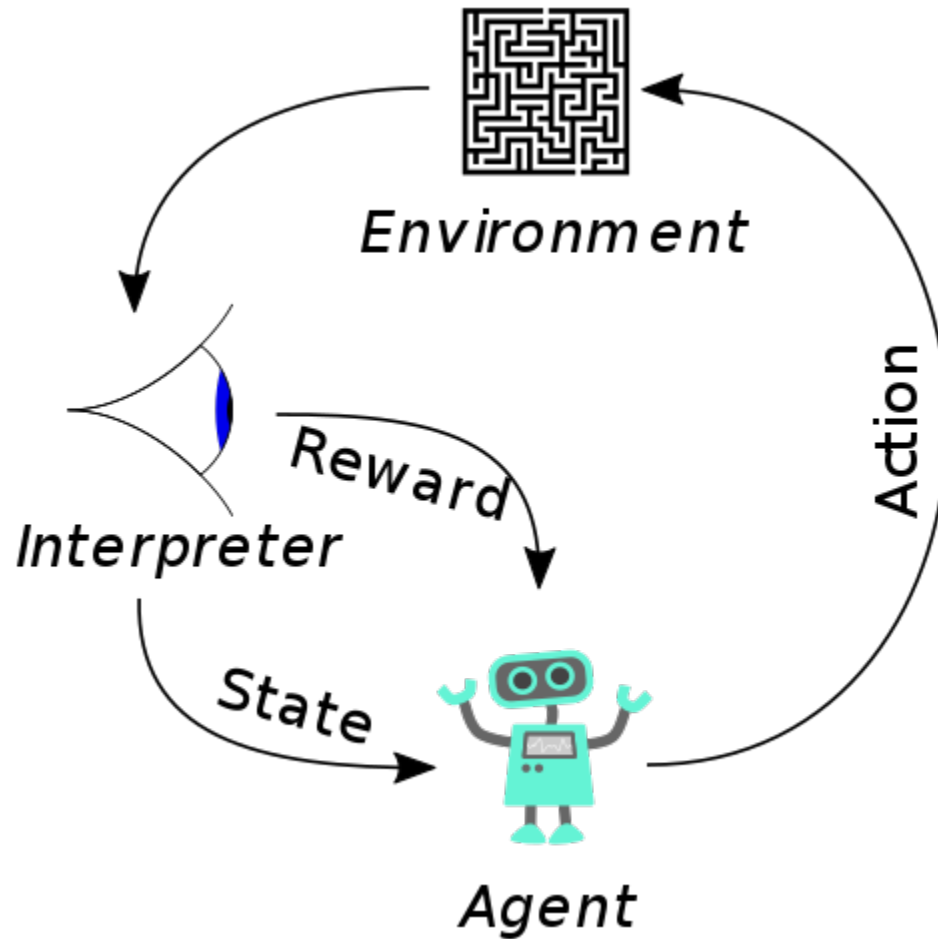
$$E_x[\log(D(x))] + E_z[\log(1 - D(G(z)))]$$

- Generate new data.
- Generator loss function:

$$E_z[\log(1 - D(G(z)))]$$

- Find saddle point

Reinforcement Learning



Reinforcement Learning RL

Basically is modeled as a Markov decision process:

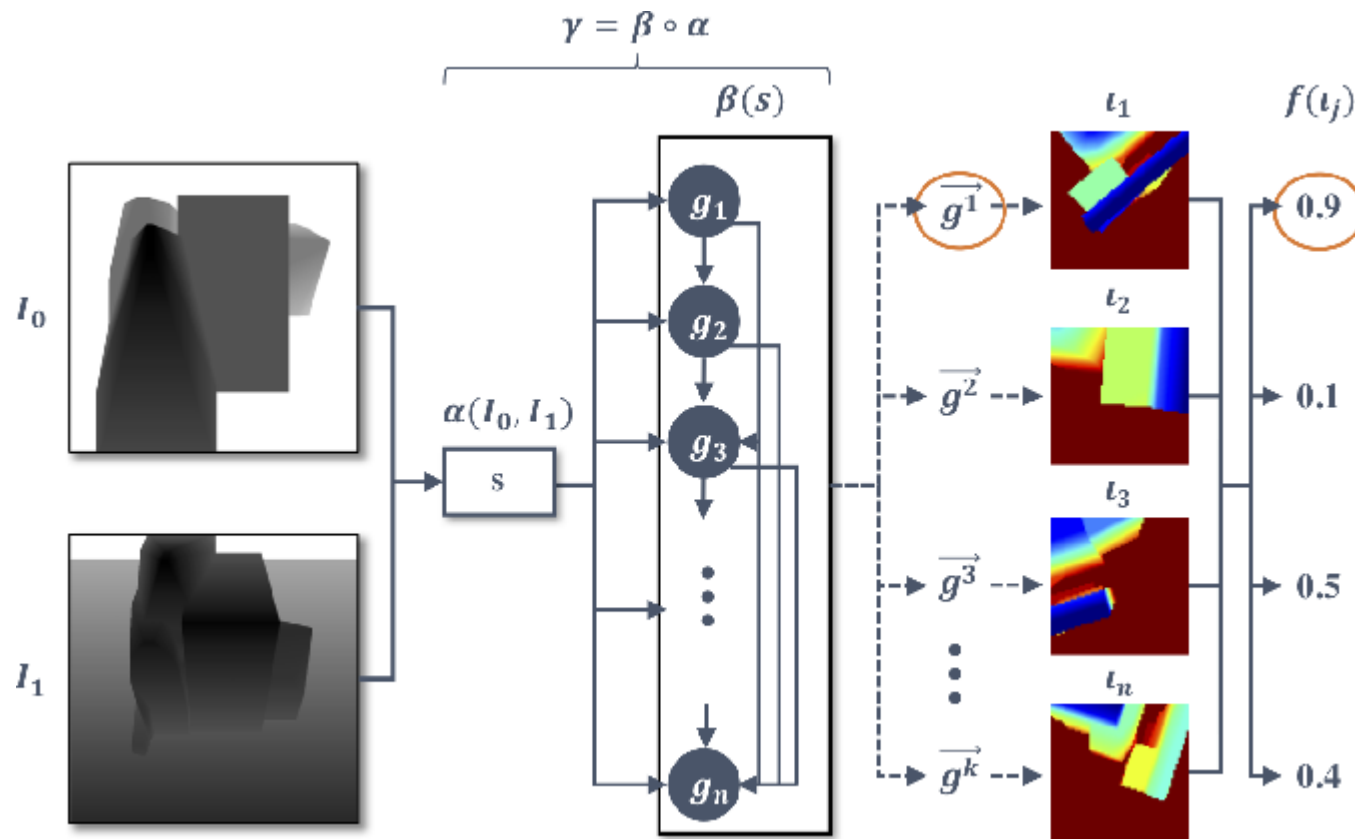
$$(S, A, P, R, \gamma)$$

- S is a set of environment a agent states.
- A is a set of actions the agent can perform.
- P is the transition probability between the states.
- R is the immediate reward after transition from s to s' with action a .
- γ is a discount factor, to discount the future reward.

Domain randomization and generative models for robotic grasping

- Perform the grasp planning for randomized objects domain.
- Objects generation was achieved by placing random meshes sequentially so that each mesh intersects with at least one of the preceding meshes.
- The first part is the grasp planning module that outputs is a probability distribution over possible grasps.
- The second part is grasp evaluation model that outputs a value corresponding to the likelihood of success of that grasp.

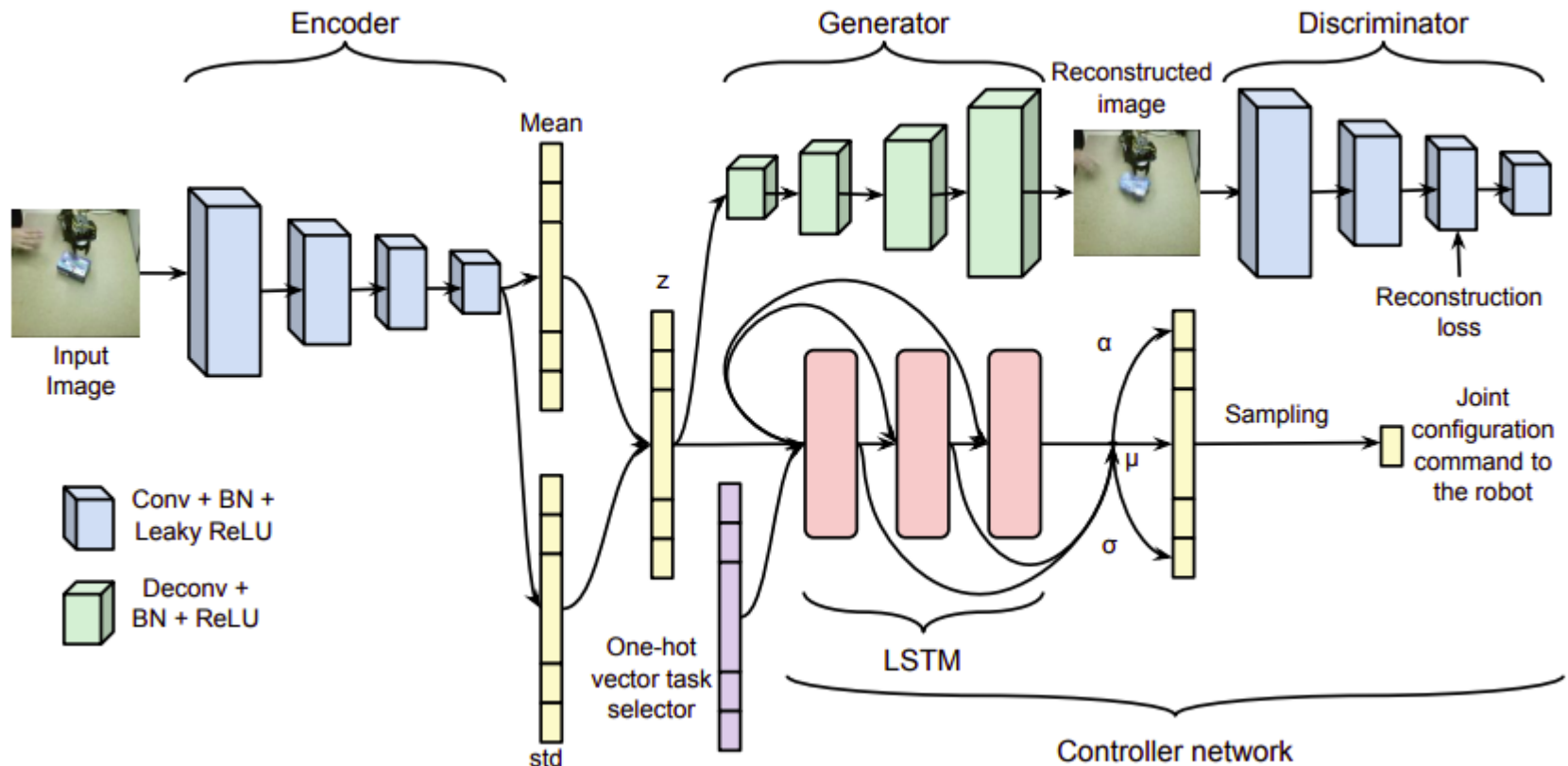
Domain randomization and generative models for robotic grasping



Vision-Based Multi-Task Manipulation for Inexpensive Robots Using End-To-End Learning from Demonstration

- The encoder finds the distribution of the data and then sample a latent representation.
- The decoder is a GAN.
- The policy controller that interact with the environment is an LSTM.
 - The output of the LSTM is a GMM.
- The approach does not require a reward signal as RL.

Vision-Based Multi-Task Manipulation for Inexpensive Robots Using End-To-End Learning from Demonstration



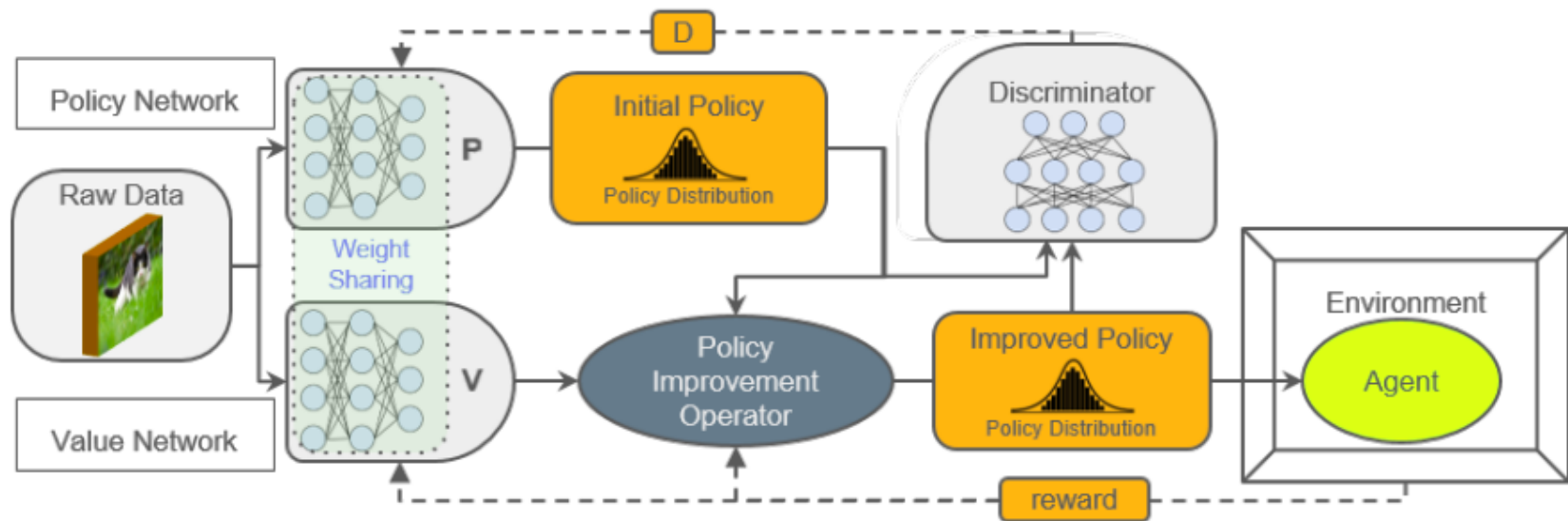
Generative Adversarial Imitation Learning (GAIL)

- GAIL is a combination between GAN and RL.
- The generator is the policy to be learned, and follows TRPO algorithm.
- discriminator distinguishes between the expert trajectories and those generated by the generator.
- Again there is no need to design a reward function.

Self-Improving Generative Adversarial Reinforcement Learning

- A network to generate initial policies.
- A value function network to approximate how good is the current state.
- Policy improvement black box (TRPO).
- The improved policy interact with the environment.
- A discriminator represents a classifier and assigns a low loss to the improved policies and a high loss to the initial ones.

Self-Improving Generative Adversarial Reinforcement Learning



Discussion

➤ **Cons**

- Generative models are hard to train.
- Generally requires a large amount of data.
- VAEs explore places that does not always make sense.

➤ **Pros**

- Once the saddle point is found, GAN achieve a very good results.
- VAEs are the best option to move to latent space.

Conclusion

- Work in latent space using VAEs.
- The introduction of GANs in RL transformed the actor-critic approach of reinforcement learning to generative adversarial network.
- Avoiding reward function, led to achieve multi-task frameworks for robotics.
- Private robots able to learn and perform multi-tasks.

