1704.03012 - Stochastic Neural Networks for Hierarchical Reinforcement Learning

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- Other reference: https://github.com/DanielTakeshi/Paper_Notes/blob/master/reinforcement_learning/Stochastic_Neural_Networks_for_Hierarc
- Further reading: 1710.09767 - Meta Learning Shared Hierarchies

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1. Introduction

- Challenges: sparse rewards and long horizons, this is same with Feudal Network
- Our work:
  - Learns a span of skills in a pre-training environment
    - The environment is employed with only proxy reward signal
    - The design only requires very minimal domain knowledge about downstream tasks
  - Proxy reward:
    - A form of intrinsic motivation
    - Encourage the agent to explore its own capabilities + Do not need any goal information or sensor readings specific to each downstream task
  - The set of skills can be used later for other tasks
  - Use Stochastic NN to learn the span of skills
    - Can easily represent multi-modal policies
    - Achieve weight sharing among different modes

2. Related Work

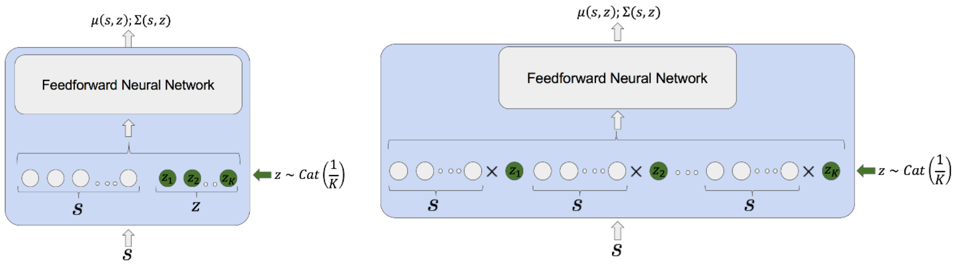
- Hierarchy over actions: **FeUdal Net is recent work**
  - Composing low-level actions into high-level primitives
  - Search space can be reduced exponentially
  - Require domain-specific knowledge and careful hand-engineering
- Use intrinsic rewards to guide exploration:
  - Do not require domain-specific knowledge
  - Hard to generalize $\rightarrow$ high overall complexity

3. Problem Statement

- Assumptions:
  - For each MDP $m \in M$, the state space S^m can be factored into S_{agent} and S^m_{rest}, which are weakly interact with each other
  - S_{agent} is same for all MDPs
  - All MDPs shapre same action space
- Goal: given a collection of tasks satisfying the assumptions, minimize the total sample complexity required to solve these tasks
- We takes advantage of a pre-training task that can be constructed with minimal domain knowledge, and can be applied to the more challenging scenario

4. Method

- Construct pretraining environment:
  - Let the agent freely interact with the environment in a minimal setup
  - Skills learned depend on the reward given to the agent $\rightarrow$ we use a generic proxy reward as the only reward signal to guide skill learning
    - The design of the proxy reward should encourage the existence of locally optimal solutions
    - It encodes the prior knowledge about what high level behaviors might be useful in the downstream tasks, rewarding all of them roughly equally
  - Every time we train a usual uni-modal gaussian policy in this environment, it should converge towards a potentially different skill
- Learn skills via sthchastic NN $\rightarrow$ represent multi-model policies



(a) Concatenation (b) Bilinear integration

Figure 1: Different architectures for the integration of the latent variables in a FNN

- Information-theoretic regularization $\rightarrow$ prevent multi-model policies from collapsing into a single mode
- Learn high-level polocies : instead of learning from scratch the low-level controls, we leverage the provided skills by freezing them and training a high-level policy (Manager Neural Network) that operates by selecting a skill and committing to it for a fixed amount of time steps

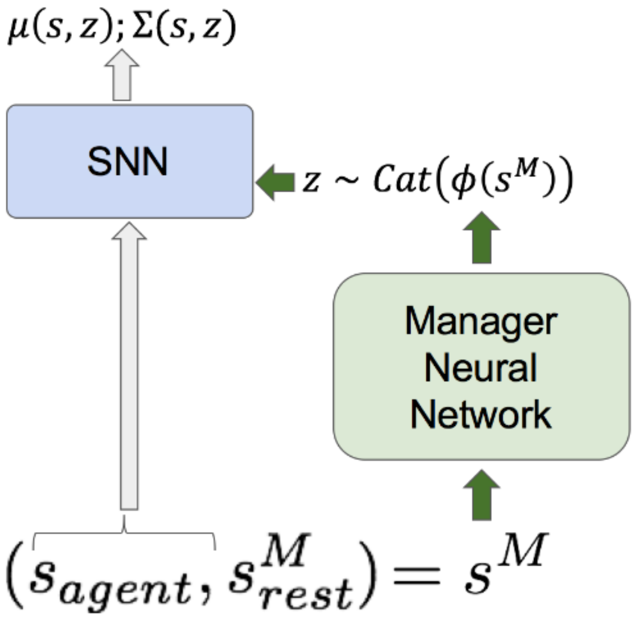


Figure 2: Hierarchical SNN architecture to solve downstream tasks

- Policy optimization: TRPO

5. Experiment

- Locomotion + Maze and Locomotion + Food Collection (Gather)

6. My thoughts

- More abstract than FeUdal Network, and I wonder whether this work can be better
- Maybe I can find more interesting later :D