

Research Presentation

Active Learning with V-Learning

Thorben Werner

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Information Systems and Machine Learning Lab (ISMLL)
Institute for Computer Science
University of Hildesheim

$\mathcal{L} \in \mathbb{R}^{\lambda \times m}$ Labeled Set

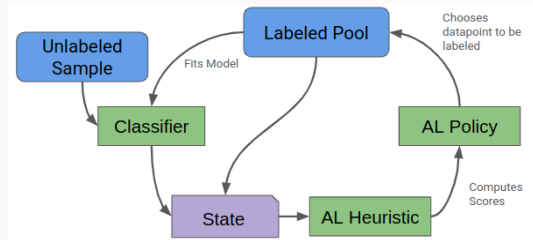
$\mathcal{U} \in \mathbb{R}^{\mu \times m}$ Unlabeled Set

$\phi_{\theta} := \mathbb{R}^m \rightarrow \mathbb{R}^c$ Classifier

$\mathcal{K} \in \mathbb{R}^{k \times m}$ Unlabeled Sample

$\psi := \mathbb{R}^{k \times m} \rightarrow \mathbb{R}^k$ Active Learning Heuristic

$\pi_{\psi} := \operatorname{argmax} \psi(\mathcal{S})$ Active Learning Policy

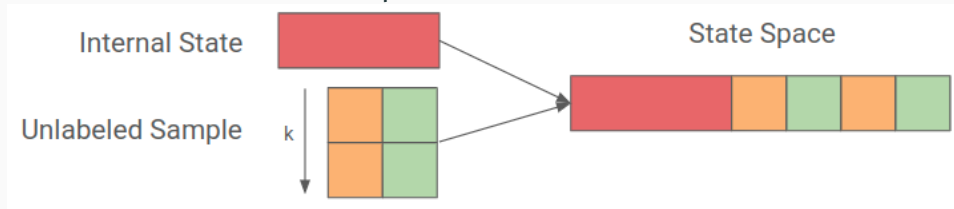


Active Learning Cycle

State Space:

1. Internal state of the environment: content of labeled pool \mathcal{L} , state of the classifier θ , remaining budget, current F1-Score, etc. $\rightarrow \mathbb{R}^a$
2. Information about the unlabeled sample \mathcal{K} : Output of the classifier $\phi_\theta(k_t)$, the datapoints themselves, other metrics, etc. $\rightarrow \mathbb{R}^{k \times b}$

Results in a flattened state space of $\mathcal{S} \in \mathbb{R}^{a+k \times b}$



$\mathcal{A} \in [0, \dots, k]$ Action Space

$\mathcal{R} := \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ Reward Function

$\tau := \{\mathcal{S}, \mathcal{A}, \mathcal{S}, \mathcal{R}, \mathbb{R}\}$ Transition

Problems:

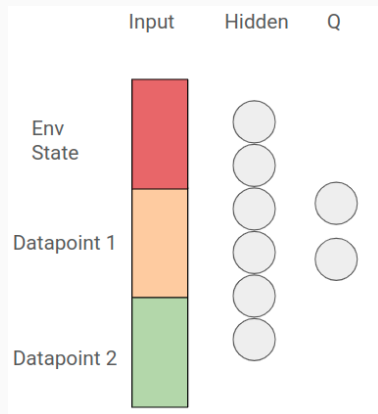
- Fixed Sample size
- Expensive Transitions
- Same actions in different places

Sample Size $k = 2$

The same datapoint can appear in multiple places in the input

Both output nodes essentially learn the same function since the datapoints are sampled randomly and independently.

A permutation invariant network can fix the problem and create a ranking of actions

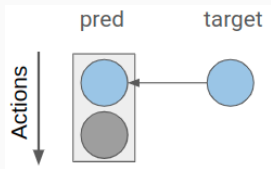


Q-Learning Target: What is the expected discounted improvement in F1-Score under the current policy when we choose a given datapoint?

The Bellman target does not rank actions, but tries to estimate their independent, global value under the current policy

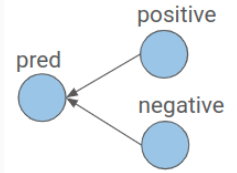
Reinforcement Learning

$$\mathcal{L}_Q := \hat{\pi}(s_t, a_t) - r_t + \gamma \max_a (\pi(s_{t+1}))$$



Ranking (Triplet Loss)

$$\mathcal{L}_{triplet} := \max(0, m + d(z_a, z_p) - d(z_a, z_n))$$



TODO

Adaptations

- We use the batch dimension for representing the sample size k
- No action space needed

$\mathcal{S} \in \mathbb{R}^\sigma$ State Space

$\mathcal{R} := \mathcal{S} \rightarrow \mathbb{R}$ Reward Function

$V_\theta := \mathcal{S} \rightarrow \mathbb{R}$ Agent Network

Example:

State is generated : $s \in \mathbb{R}^{b \times \sigma}$

Agents makes prediction : $v = V_{\theta}(s)$

Policy selects a point : $a = \underset{b}{\operatorname{argmax}} v_b$

Action is applied : $s' = \operatorname{env}(a)$

Reward is observed : $r = \mathcal{R}(s')$

Transition is stored : $\tau = \{s_a, r, \bar{s}', \text{done}\}$

$$\textbf{with} : \bar{s}' = \frac{1}{b} \sum_{i=0}^b s'_i$$

Q-Learning:

$$O(\tau) = \mathcal{S} \times \mathcal{A} \times \mathcal{S} \times \mathcal{R} \times \mathbb{R}$$

$$O(\tau) = k^2 \times \sigma^2 + 3$$

V-Learning:

$$O(\tau) = \mathcal{S} \times \mathcal{A} \times \mathcal{S} \times \mathcal{R} \times \mathbb{R}$$

$$O(\tau) = 2 \times \sigma^2 + 3$$

