Research Presentation

Active Learning with V-Learning

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Pool-Based Active Learning

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

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

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

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

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

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

Active Learning with Q-Learning

Problems:

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

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

$\mathcal{A} \in [0, \ldots, k]^{b}$ Action Space

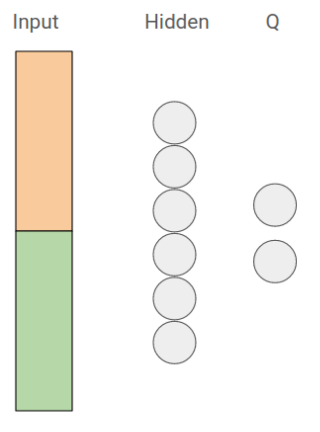
$\mathcal{R} := \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}^{b}$ Reward Function

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

Sample size $k = 2$

The same datapoint can appear in multiple places in the input

Both output nodes essentially learn the same function



Active Learning with V-Learning

Adaptations

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

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

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

Storing Transitions in Memory

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:

$$O(\tau) = \mathcal{S} \times \mathcal{A} \times \mathcal{S} \times \mathcal{R} \times \mathbb{R}$$
$$O(\tau) = 2 \times \sigma^2 + 3$$

Pool-Based Active Learning

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