Meta-Learning for Batch Mode Active Learning

2018.11.5

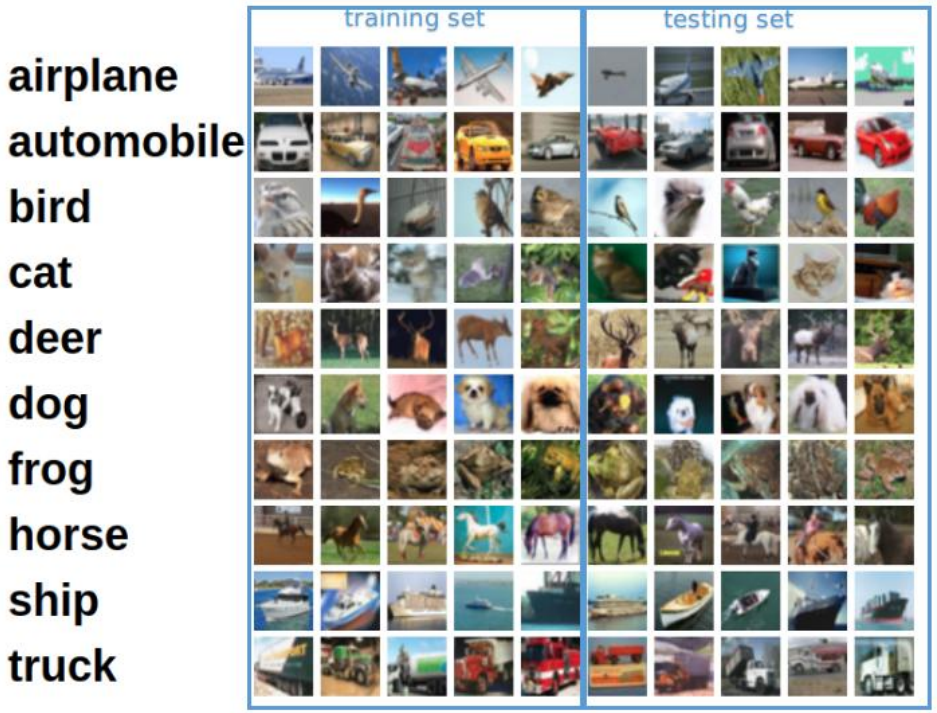
Outline

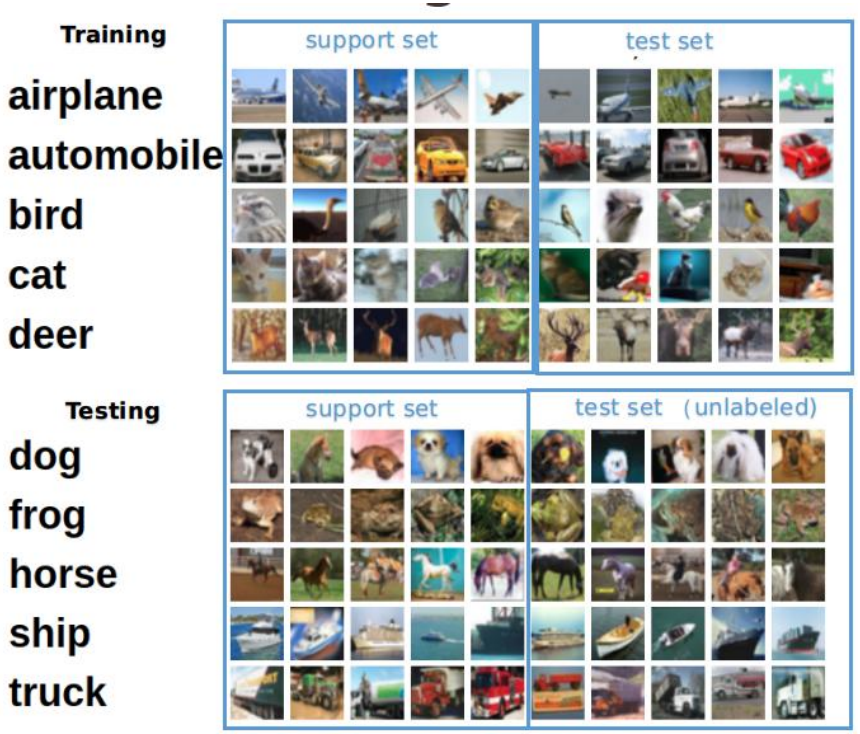
Meta-Learning for Batch Mode Active Learning

Prototypical Networks for Few-shot Learning

Few-shot Learning

- Supervised Classification vs Few-shot Classification





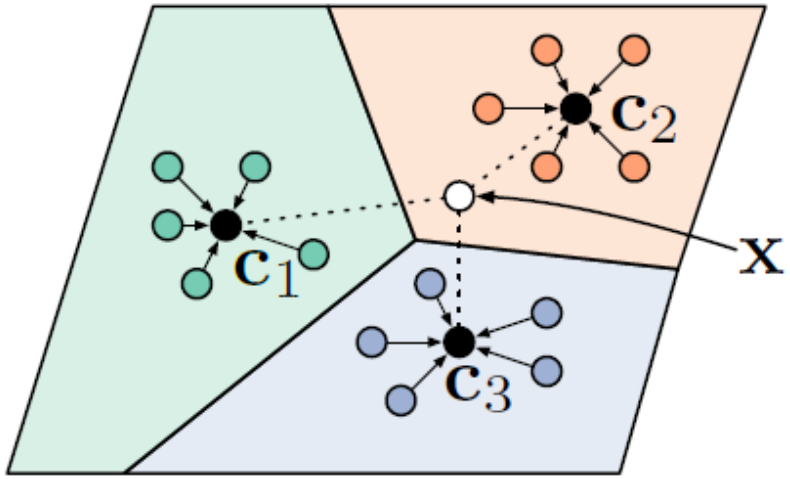
- Episode

  Each episode is designed to mimic the few-shot task by subsampling classes as well as data points.

Motivation

- Idea

  There exists an embedding in which points cluster around a single prototype representation for each class.



(a) Few-shot

- Embedding Function

$$f_{\phi} : \mathbb{R}^{D} \rightarrow \mathbb{R}^{M}$$

Model

- Compute prototype of support points

$$\mathbf{c}_k = \frac{1}{|S_k|} \sum_{(\mathbf{x}_i, y_i) \in S_k} f_{\boldsymbol{\phi}}(\mathbf{x}_i)$$

- Produce a distribution over classes for each query point

A distance function

$$p_{\boldsymbol{\phi}}(y = k \mid \mathbf{x}) = \frac{\exp(-d(f_{\boldsymbol{\phi}}(\mathbf{x}), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_{\boldsymbol{\phi}}(\mathbf{x}), \mathbf{c}_{k'}))}$$

Minimizing $J(\phi) = -\log p_{\boldsymbol{\phi}}(y = k \mid \mathbf{x})$ → Update parameters ϕ

Prototypical Networks

Input: Training set $\mathcal{D} = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, where each $y_i \in \{1, \ldots, K\}$. $\mathcal{D}_k$ denotes the subset of $\mathcal{D}$ containing all elements $(\mathbf{x}_i, y_i)$ such that $y_i = k$.

Output: The loss J for a randomly generated training episode.

$V \leftarrow \textsc{RandomSample}(\{1, \ldots, K\}, N_C)$ ▷ Select class indices for episode

for k in $\{1, \ldots, N_C\}$ **do**

$S_k \leftarrow \textsc{RandomSample}(\mathcal{D}_{V_k}, N_S)$ ▷ Select support examples

$Q_k \leftarrow \textsc{RandomSample}(\mathcal{D}_{V_k} \setminus S_k, N_Q)$ ▷ Select query examples

$$\mathbf{c}_k \leftarrow \frac{1}{N_C} \sum_{(\mathbf{x}_i, y_i) \in S_k} f_{\boldsymbol{\phi}}(\mathbf{x}_i)$$ ▷ Compute prototype from support examples

end for

$J \leftarrow 0$ ▷ Initialize loss

for k in $\{1, \ldots, N_C\}$ **do**

for $(\mathbf{x}, y)$ in Q_k **do**

$$J \leftarrow J + \frac{1}{N_C N_Q} \left[d(f_{\boldsymbol{\phi}}(\mathbf{x}), \mathbf{c}_k)) + \log \sum_{k'} \exp(-d(f_{\boldsymbol{\phi}}(\mathbf{x}), \mathbf{c}_{k'})) \right]$$ ▷ Update loss

end for

end for

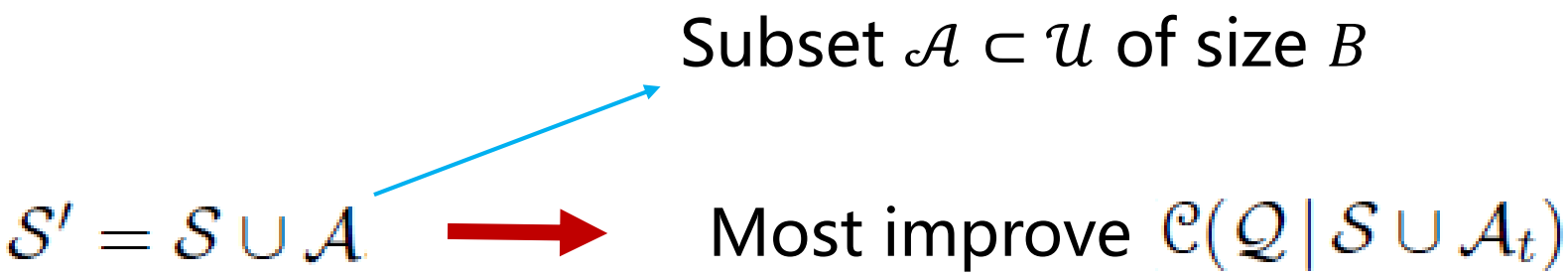
Meta-Learning for Batch Mode Active Learning

- Batch Model Active Learning
  - It should be designed to directly optimize its effectiveness at finding sets of items to label that improve the model’s ultimate performance
  - it should have linear complexity in selecting each additional item
  - it should work well in the presence of distractors

Motivation

- Active Learning is most effective and valuable in situations where the initial amount of labeled data is small.

- Modify the episode structure to accommodate a batch mode active learning.



Method

- The probability of a B-size subset $\mathcal{A} = \{\tilde{x}_1, \ldots, \tilde{x}_B\}$

  Chain rule: $p(\mathcal{A}) = p(\tilde{x}_1, \ldots, \tilde{x}_B) = \prod_{i=1}^{B} p(\tilde{x}_i \,|\, \tilde{x}_1, \ldots \tilde{x}_{i-1})$

  $$p(\tilde{x} \,|\, \mathcal{A}) = p(\tilde{x} \,|\, \tilde{x}_1, \ldots, \tilde{x}_j)$$

- Statistics relating to each unlabeled item $\tilde{x}_i \in \mathcal{U}$

  Prototypes $\{c_k\}_{k=1}^{K}$ → $\Pi\left(\{c_k\}_{k=1}^{K}, \tilde{x}_i\right)$

Method

- Quality Distribution

A MLP with parameters q

$$p_{quality}(\tilde{x}_i) \propto \exp(q_i), \text{ where } q_i = f_{\mathbf{q}}\left(\Pi\left(\{c_k\}_{k=1}^{K}, \tilde{x}_i\right)\right)$$

- Diversity Distribution

$$\phi_i = f_{\phi}\left(\Pi\left(\{c_k\}_{k=1}^{K}, \tilde{x}_i\right)\right)$$

$$p_{diversity}(\tilde{x}_i \mid \mathcal{A}) \propto \exp(v(\phi_i)/\tau), \text{ where } v(\phi_i) = \min_{\tilde{x}_j \in \mathcal{A}} \{\sin \theta_{ij}\}$$

$$p(\tilde{x} \mid \mathcal{A}) \propto p_{quality}(\tilde{x}) \cdot p_{diversity}(\tilde{x} \mid \mathcal{A}) \cdot \mathbb{1}_{\tilde{x} \notin \mathcal{A}}$$

→ Update the parameters $\theta' = \{\phi, \mathbf{q}, \tau\}$

Method

- Training

For any given episode, $p_{\theta'}(\tilde{x}|\mathcal{A})$ can be repeatedly sampled to create a subset $\mathcal{A} \subseteq \mathcal{U}$ of size B so that the prototypes computed on the new support set $S' = S \cup \mathcal{A}$ have high classification performance on the query set Q

$$\beta_{-t} = \frac{1}{T-1} \sum_{t' \neq t}^{T} \mathcal{C}_\theta(\mathcal{Q} \,|\, \mathcal{S} \cup \mathcal{A}_{t'})$$

$$\nabla_{\theta'} \mathbb{E}_{p_{\theta'}(\mathcal{A})}[\mathcal{C}(\mathcal{Q} \,|\, \mathcal{S} \cup \mathcal{A})] \approx \frac{1}{T} \sum_{t=1}^{T} [(\mathcal{C}(\mathcal{Q} \,|\, \mathcal{S} \cup \mathcal{A}_t) - \beta_{-t}) \nabla_{\theta'} \log p_{\theta'}(\mathcal{A}_t)]$$

$$\mathcal{C}(\mathcal{Q} \cup \mathcal{U} \,|\, \mathcal{S} \cup \mathcal{A})$$

where $\mathcal{A}_t \sim p_{\theta'}(\mathcal{A})$

Experiment

- CIFAR100 and *mini*Imagenet
  - 100 classes, 600 images per class
  - 64 classes for training, 16 classes for validation, 20 class for testing
- Comparison with
  - Max-Entropy
  - Min-Max Sim
  - Random

Experiment

- Result

Method	$B = 5$ $M = 100$	$B = 10$ $M = 100$	$B = 20$ $M = 200$	$B = 5$ w/ D $M = 200$	$B = 10$ w/ D $M = 200$	$B = 20$ w/ D $M = 400$
Max-Entropy	+1.5%	+7.3%	+13.8%	-1.4%	+0.7%	+5.3%
Min-Max Sim	+2.2%	+5.3%	+10.0%	+0.9%	+2.1%	+4.5%
Random	+3.3%	+10.0%	+17.2%	-1.1%	+2.6%	+8.6%
Meta-Learner	**+7.3%**	**+11.6%**	**+17.4%**	**+3.2%**	**+6.2%**	**+10.80%**

Method	$B = 5$ $M = 100$	$B = 10$ $M = 100$	$B = 20$ $M = 200$	$B = 5$ w/ D $M = 200$	$B = 10$ w/ D $M = 200$	$B = 20$ w/ D $M = 400$
Max-Entropy	-0.5%	+5.0%	+11.3%	-3.3%	-1.3%	+2.8%
Min-Max Sim	+0.3%	+3.6%	+7.7%	-0.8%	-0.1%	+2.0%
Random	+1.6%	+8.6%	+17.8%	-2.9%	+2.1%	+7.5%
Meta-Learner	**+6.6%**	**+11.1%**	**+18.1%**	**+1.3%**	**+6.1%**	**+11.20%**

Thanks