Bias-Aware Heapified Policy for Active Learning

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Abstract

The data efficiency of learning-based algorithms is more and more important since high-quality and clean data is expensive as well as hard to collect. In order to achieve high model performance with the least number of samples, active learning is a technique that queries the most important subset of data from the original dataset. In active learning domain, one of the mainstream research is the heuristic uncertainty-based method which is useful for the learning-based system. Recently, a few works propose to apply policy reinforcement learning (PRL) for querying important data. It seems more general than heuristic uncertainty-based method owing that PRL method depends on data feature which is reliable than human prior. However, there are two problems - sample inefficiency of policy learning and overconfidence, when applying PRL on active learning. To be more precise, sample inefficiency of policy learning occurs when sampling within a large action space, in the meanwhile, class imbalance can lead to the overconfidence. In this paper, we propose a bias-aware policy network called heapified active learning (HAL) which prevents overconfidence, and improves sample efficiency of policy learning by heapified structure without ignoring global information (overview of the whole unlabeled set). In our experiment, HAL outperforms other baseline methods on MNIST dataset and duplicated MNIST. Last but not least, we investigate the generalization of the HAL policy learned on MNIST dataset by directly applying it on MNIST-M. We show that the agent can generalize and outperform directly-learned policy under constrained labeled sets.

1 Introduction

Nowadays, deep learning has been widely used in several fields, like medical field or automatic driving. However, to reach the whole potential of deep learning, we still struggle to prepare tons of annotated data for training. The progress of collecting such amount of data is obviously a tedious and laborious work. Thus, it is a critical bottleneck to obtain adequate data for training an accurate model. To solve the problem, simply collecting more data may be the most intuitive idea, yet it is highly time-consuming and expensive in certain domains such as cancer detection, Natural Language Processing tasks, etc. Thus, active learning comes in handy to minimize the cost by querying important data in order to improve accuracy by labeling as few data as possible.

As to the methodology of active learning, there have been quite a few heuristic methods querying data according to uncertainty [Shannon 2001; Zhou and Sun 2014; Tang et al. 2017], diversity [Sener and Savarese 2018; Wang et al. 2017], etc. Additionally, some work carries out active learning by virtue of multi-heuristic methods such as RALF [Ebert, Fritz, and Schiele 2012] which tries to manage different methods with hybrid strategies according to the time, considering that exploration/exploitation criteria should be balanced in different moment.

Nevertheless, imbalanced data is the one that possesses stronger relation to the strategy rather than time, which brings about overconfidence, quite problematic as querying data. To cope with it, many works [Sener and Savarese 2018; Wang et al. 2019; Geirhos et al. 2019; Bachem, Lucic, and Krause 2017; Lakshminarayanan, Pritzel, and Blundell 2017; Pop and Fulop 2018] intend to eliminate the overconfidence effect. One of the approaches is to query by commit-
Our method across datasets. This demonstrates the great generalization of features which mimics properties in static surveillance videos. Moreover, our model outperforms other baseline methods in short, our HAL enables the agent to make use of features to other target domains and remain high performance. In this paper, we propose a bias-aware heapified active learning method for pooling labeled and unlabeled data and DFAL (Ducoffe and Precioso 2018) using adversarial image to build up an image decision boundary, finding its nearby unlabeled sample as uncertain data. However, those meta-heuristic strategies cannot be general enough. Our method uses data-driven policy to learn switching strategy for disagreement samples instead, which can be more general in other cases.

Learning to Active Learning. Instead of designing the algorithm for selecting unlabeled data heuristically, some adopt stream-based learning (Fang, Li, and Cohn 2017) by considering it as a decision process with Reinforcement Learning
Figure 2: Pipeline overview. First we extract features of every data in $D_u$ by $F(x; D_l, \phi)$ and randomly pair all the data together for comparison. ($E_L, E_u$ is labeled/unlabeled set embedding feature $\in \mathbb{R}^{f_n}$) In every single comparison with heapified policy, $\pi_\theta$, the agent will choose a preferable data. After a series of comparison, the data which is estimated as the most valuable will be annotated and added to the training set $D_l$. By training the prediction model $f_\phi$ with the new labeled set $D_l$ and evaluating by validation set, $D_{val}$, we can obtain the performance growth of $f_\phi$ which can be used as the reward for the agent $\pi_\theta$.

Through training on Deep Q Network (DQN), it can learn the selecting policy and choose informative data that enable the model to be more robust to certain types of errors. As the number of selected data reaches the budget, the Markov Decision Process (MDP) terminates. The state for the agent is composed of the content, marginals and the confidence of prediction. By doing so, the agent can give consideration to both the uncertainty of every word class prediction and the architecture of every sentence which can avoid the bias in the prediction model. At last, taking the performance growth as reward can enable the model to predict the reward of every selection precisely as to make great progress on the performance of the prediction model.

### 3 Method

In the following, first, we overview our active learning pipeline in Sec. 3.1. Second, we describe the design of the observation features for policy learning and introduce each of them individually in Sec. 3.2. Third, in Sec. 3.3, we propose a new structure of policy which is "heapified" as querying data, and each policy is learned with offline policy gradient. Before that, we define some common notations below.

**Notation:** We have three sets, labeled set, validation set, and unlabeled set, which are denoted as $\{D_l, D_{val}\}$ and $\{D_u\}$, respectively, where $x_i \in \mathbb{R}^{C \times H \times W}$ is image, we assume there are $L$ classes and denote $y_i \in \{1, 2, ..., L\}$ as labels. Besides, we have two models; one is a classification model $f_\phi$ with parameter $\phi$, and the other is an agent $\pi_\theta$ with parameter $\theta$. In the classification model, we extract embedding feature which is denoted as $f_E^E(.) \in \mathbb{R}^{f_n}$.

#### 3.1 Overview

As illustrated in Fig. 2 in our active learning procedure we have a prediction model $f_\phi$ supervised by $D_l$. Next, our agent $\pi_\theta$ will repeatedly pick two random samples from $D_u$ and compare which unlabeled data has more impact on classification model $f_\phi$ until the whole $D_u$ has already been compared. After iterating the comparisons, a final image will be determined and annotated by annotators, and then we add it to $D_l$ for the training of the prediction model $f_\phi$. Finally, the reward can be calculated by evaluating the marginal performance of the task with the evaluation set $D_{val}$, offering the agent $\pi_\theta$ to learn. Through the steps mentioned above, the agent $\pi_\theta$ is able to learn a querying policy from the data.

#### 3.2 Observation Feature Designing

As the objective of active learning, we aim to find out the hard samples and the disagreement samples. The disagree-
ment samples include unseen samples and the in-class potential uncertain samples. The unseen samples are the data far from labeled set distribution. The in-class potential uncertain samples are predicted incorrectly but possess high confidence from the classification model. Therefore, feature design can be divided into three parts, bias-aware feature, uncertainty to deal with hard samples, and the disagreement sample learning, respectively.

Bias-aware: maximum component suppression During query procedure, imbalanced data usually results in overconfidence of certain labels, which introduces bias on them. Thus, we design bias-aware feature, enabling the agent to observe the distribution of each class for the query policy.

As shown in Fig. 3 overconfidence usually occurs as the real data distribution is non-continuous. Additionally, the blue region in Fig. 3 is where some samples are predicted incorrectly but possess high confidence from the classification model, we called that in-class potential uncertainty sample. Therefore, in this case, selecting samples with high uncertainty is not an optimal policy. In contrast, if the data distribution is continuous, selecting samples located at the boundary area benefits the training of the classification model.

Every data in the dataset can be represented by their own embedding features $f^E(.)$ which is extracted from the classification model, indicating that they can be mapped to a multidimensional space. In each class, through the calculation of the eigenvalues, we can observe the degree of the dominance of each vector. By taking the largest eigenvalue, the bias-aware feature offers information about the degree of how simply a certain class of data are described. In our design, we select the value oppositely as the feature $BA(.)$ shown in Eq. 1 we called it as maximum component suppression. Lower value implies the oversimplification of feature description, causing overconfidence on the unlabeled set $D_u$. As a result, the bias-aware feature can be served as a signal enabling the agent to observe the distribution of labeled data $D_l$ for switching different strategies. Here, we define bias-aware feature as follow:

$$BA(\phi, D_l) = 1 - \max \lambda f^E(x_w^l_{y=\hat{y}_i})$$

where $BA(.) \in \mathbb{R}^2$ is the feature of bias aware, $\lambda f^E(x_w^l_{y=\hat{y}_i})$ is the set of class-wise eigenvalues of labeled set’s embedding features and this criterion describes how confident can the embedding feature represent the data without main eigenvector.

Uncertainty In order to boost the performance of the classification model $f_\theta$ trained on rough data at the beginning of selecting data, we need to find out hard samples located in ambiguous regions near the decision boundary. Here, we model it by MC-dropout (Gal, Islam, and Ghahramani 2017) which outperforms Shannon entropy. We perturb the model by dropout and compare it with the unperturbed model so as to find out how uncertain is the data. That is, the higher the uncertainty of the data, the more it is worth to be selected. The MC-dropout method is formulated as follow:

$$I(x; \phi) \approx H(x; \phi) - \frac{1}{n} \sum_{i=1}^{n} H(x; \phi^i)$$

where the $H(x; \phi) = -\sum_{i=1}^{L} P(\hat{y}_i|x; \phi)log(P(\hat{y}_i|x; \phi))$, $\hat{y}_i$ is the probability distribution, $\phi$ is the parameters of active model and $\phi^i$ is the parameters with noise by dropout which is done $n$ times.

However, depending merely on information of uncertainty limits the growth of performance resulting by over-confidence, so we need to solve it by disagreement samples.

Disagreement sample learning In order to solve the overconfidence samples, we try to use the concept of QBD to learn from disagreement samples, which are unseen samples and in-class potential uncertain samples clearly defined in Sec. 3.2. To find out unseen sample, inspiring by DAL (Gissin and Shalev-Shwartz 2019), we query samples that far from class-wise labeled set distribution. We formulate the calculation of the distance shown as follow:

$$D(x; \phi, D_l) = \bigcup_{i=1}^{L} Dist(x; \phi, D_{y\neq i})$$

where the diversity feature is defined as the distance between unlabeled data and the labeled set representation of each class distribution. The $Dist(.)$ is defined as follow:

$$Dist(x; \phi, D_{y\neq i}) = \text{norm1}(\frac{(f^E_{\phi}(x) - f^E_{\phi}(x^D_{y=\hat{y}_i}))^2}{2\sigma^2 f^E_{\phi}(x^D_{y=\hat{y}_i})})$$

where the $x$ is input image sample, $\phi$ is model parameters, $f^E_{\phi}(x^D_{y=\hat{y}_i}) \in \mathbb{R}^{L_n}$ is the mean of embedding features in each class of labeled set and $f_n$ is the length of the embedding feature. We have ablation study about labeled set representation in table 1. In Eq. 4 we calculate the distance between the unlabeled data $D_u$ and the labeled data $D_l$ to represent whether data is seen or not for the classification


Figure 4: Off-policy Heapified(compare) policy single selection transition: Here we use memory replay to achieve reward collection efficiently. In every single episode, the agent is required to choose only $K$ images as budget for labeling to the training set $D_l$. In each data query, the agent will go through unlabeled set $D_u$ which have $M$ images, and the certain path of the final winner of the whole comparison (dark blue path shown above in the figure) is the most related reward’s experience. Policy learns from the path and we show up detail of the decision process with agent network in double box.

model $f_\phi$. In addition, we normalize the distance for each class owing that every class distribution is quite different.

On the other hand, searching in-class potential uncertain samples for sampling is quite tricky unless we provide hand-craft features (e.g. SIFT (Lowe 2004), SURF (Bay et al. 2008), HOG (Dalal and Triggs 2005), BoVW (Chandra, Kumar, and Jawahar 2012)) as prior and information of labeled data. To explore unseen case in labeled set $D_l$, we use Eq. 5 to model it. In addition, as to in-class potential uncertain sample which provides a conditional prior, we add a hand-craft feature to describe the image statistic information for the active model $f_\phi$ to explore more efficiently. Finally, we express the bias-aware feature with $D_t$ by Eq. 6 in order to prevent overconfidence which means that in a few classes, misclassification occurs which is caused by low complexity of class features description.

3.3 Heapified Policy

Our policy $\pi_\theta$ is a maximum-heap like pooling based query method, so the action space $A$ is quite large. Thus, to learn experience more efficiently, we adopt off-policy policy gradient method. As shown in Fig. 4, our single episode is limited by budget $K$ and our heapified policy will select the most valuable image from $M$ unlabeled set images. Then, we break the task into as many sub-policies, which only compare two features of images, and the better one advances to the next round. We analyze the time complexity of Monte Carlo experience collection and maximum heapified like sub-policies. The time complexity of maximum heapified collection is $O(logM)$ less than Monte Carlo collection which is $O(M)$. In Monte Carlo sampling method, in order to select the best item, we need to compare pair item $M - 1$ times. On the other hands, maximum heapified collection uses $logM$ times to achieve the goal of the most influential of classification model performance unlabeled data selection. In this setting, even if the action space is reduced, the global information (overview of the whole unlabeled set) still remains.

Sub-Policy model. Our sub policy agent $a = \pi_\theta(s)$ tries to compare which one is better based on two image’s features, $O$ define in Eq. 3 where $a \in \{0, 1\}, s = (O_1, O_2)$. After two comparisons are done, the two winner data will form the next state, noted as the sub transition $T(s_{t+1}|d_{t}^{top}, d_{t}^{bot}, s_{t}^{top}, s_{t}^{bot})$ as shown in Fig. 4. After we find out the best image, it will merge the sub transitions of the winner into a trajectory. Finally, The agent shall maximize their reward. In our application, we will maximize reward of the marginal accuracy (Acc) of classification.

In every single episode, the agent is required to choose only $K$ images as budget for labeling to the training set $D_l$. In each data query, the agent will go through unlabeled set $D_u$ which have $M$ images, and the certain path of the final winner of the whole comparison is the most related reward’s experience. Policy learns from the path and we show up detail of the decision process with agent network in double box.
tion task with prediction model $\phi$ as $r = Acc(D_{\text{val}}, \phi') - Acc(D_{\text{val}}, \phi)$, where $\phi'$ is trained model parameters and the $\phi$ is original parameters before training.

**Offline policy gradient.** The reward collection is not efficient and single collection cost much time by reward designed as the increase of performance. Therefore, we learn from previous sampling reward and decision. Then we compute offline-policy gradient to update model as follow:

$$\nabla_{\theta} \frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{K} \sum_{t=1}^{M} \log \pi_{\theta}(s_{i,j,t}) * r * \text{corr} \quad . \tag{6}$$

where $N$ is episode of game and the $K$ is limited of budget, $M$ is the number of totally unlabeled set images. $\pi_{\theta}(.)$ is now noted as probability estimate. The $\text{corr}$ term is to correct the reward which remained from previous policy action probability. The correction term of reward is noted as $\pi_{\theta}(s_{i,j,t} | a_{i,j,t})$, it will maintain the present behavior if identical to previous experience, where $\pi_{\theta}(.)$ is previous probability estimate, and the $\pi_{\theta}(.)$ is nowstaged probability estimate. The agent will update their gradient direction more stably with previous experience.

### 4 Experiments

We conduct experiments to validate the proposed bias-aware learning to learn policy in cross modalities setting and image duplicated setting. Firstly, in Sec. 4.1, the result of ablation study shows that our method using bias aware feature and mean representation of labeled set as diversity hint obtain the best result with a few labeled data in the beginning and the experiment is in train model from scratch setting. Secondly, in Sec. 4.2, we get better result comparing with other baselines in finetune setting. Finally, we validate the transferability of our query policy across datasets in Sec. 4.3. We report average (15 times) performance of all experiments.

**Implementation detail.** We train classification model LeNet5 (Lecun et al. 1998) with two datasets. One is MNIST (LeCun and Cortes 2010), and the other one is MNIST-M (Ganin and Lempitsky 2015) which blend background with color photos from BSDS500. Firstly, we split MNIST, MNIST-M in three subset - labeled, unlabeled and validation set ($D_t, D_u, D_{val}$), which amounts to (50, 60000, 10000) training pairs with balanced number of class. Secondly, we use Adam optimizer (Kingma and Ba 2015) with learning rate 0.001 to train our policy agent in 800 episodes. Each episode has 10 steps and each step samples 10 images. The discount factor of policy gradient is set as 0.9998. Finally, we use the accuracy to plot a learning curve with the size of images and $\text{mALC}_{\text{norm}} = \frac{\text{ALC}_{\text{norm}} - \text{A}_{\text{rand}}} {\text{A}_{\text{max}} - \text{A}_{\text{rand}}}$, which is mentioned in the active learning challenge (Guyon et al. 2011). Moreover, ALC is the performance of the classification model by proposed query method. $A_{\text{rand}}$ is performance of the classification model by random query. $A_{\text{max}}$ is performance of the classification model by fully $D_u$ with label which will be used in table 1.

| Labeled set Representation | Mean | Median | Mode | Max | Min |
|----------------------------|------|--------|------|-----|-----|
| mALC_{\text{norm}} | 0.207 | 0.139 | 0.148 | 0.058 | 0.079 |

### 4.1 Ablation Study

**Diversity feature.** In the design of the diversity feature, we calculate the distance between the representation of unlabeled set and the labeled set. There are different kinds of statistic method to represent the diversity feature. We compare these methods, including mean, median, mode, minimum and maximum on MNIST with average $\text{ALC}_{\text{norm}}$. We find that mean is best representation of labeled set in feature space.

**Bias aware feature.** We design the bias aware feature to avoid overconfidence condition in query data procedure. In order to simulate the dilemma, we train classification model from scratch with little labeled data. Because of imbalanced data (mode collapse (Pop and Fulop 2018) have mentioned), the effect is more extreme on a small dataset, resulting in overconfidence. As Fig. 5 shown, we can see that heapified active learning w/ bias feature can get better performance than w/o bias feature in the interval from 50 to 100 images. The uncertainty approach-DBAL, due to incomplete data understanding, faces overconfidence in the beginning. Thus, we know the importance of bias aware feature to avoid overconfidence at the beginning of the query procedure.

### 4.2 Compare Previous Works

Here, we compare different types of query methods on MNIST and duplicated MNIST which has many redundant and noise information. From the results, we show that our HAL is outstanding both dataset. Before that, we introduce the baseline methods as following:

![Figure 5: The ablation study of bias aware feature: w/, w/o bias aware comparison. Bias is easily be generated while training from scratch, resulting in uncertainty approach-DBAL will not be useful. Thus, with bias aware feature, overconfidence can be prevented.](image-url)
Figure 6: Figures above are the average performance of our method and other baselines. On the left figure, we can find out that our HAL only needs less than 100 images to achieve over 85% of accuracy compared to other methods on average. On the right figure, even in a repeated and noised dataset, HAL can achieve over 85% of accuracy with less than 75 images; on the contrast, other methods need over 100 images to reach this criterion.

- **Random**: Sample data uniformly from \( D_u \).
- **Entropy** (Shannon 2001): Sample maximum value of chaotic prediction from \( D_u \).
- **DBAL** (Gal, Islam, and Ghahramani 2017): Apply MC-dropout in the model to produce noises, and then query data with Eq. 2 from \( D_u \) with maximum value.
- **K-center** (Sener and Savarese 2018): It will compute the minimum Euclidean distance \( d \) of an unlabeled data by \( k_{center}(x_i) = \min(x_i, x_j) \), where \( x_j \in D_l \). Then, it will query data with the maximum distance.
- **Stream-based policy network** (Fang, Li, and Cohn 2017): Through Deep Q Learning (DQN), the agent learns the strategy of choosing images. With the arrival of every batch of images, the agent will decide if the batch of data is necessary to be added to the training set by observing the feature of the batch with the length of action space \( \text{len}(A) = 2 \). As the budget is exhausted, the selection process will be terminated.

As shown in Fig. 5, our method queries data more efficiently than the other method in the whole training procedure. Instead of the uncertainty based method, they are unstable in the beginning and fall in the overconfidence condition. Specifically, we outperform the stream-based agent on average that it misses many important data in early steps. On the other hand, we create a special dataset to test the ability to perform generally among repeated and noised images.

**Synthetic dataset**: In real world application, there may be a lot of redundant data and make the model bias easily. For example, image data from surveillance camera, it may completely capture the same street view for hours. In this scenario, the capability to avoid duplicate information is essential. Therefore, we create a synthetic dataset - **Duplicate MNIST** with 60000 images. In the set, we have 48000 class-uniformly repeated image (80 percent of the total dataset) with random Gaussian noise. In the right figure of Fig. 6, our method is general enough that it is able to achieve high performance in few amounts of data when encountering repeated and noised images.

### 4.3 Generalization

Our method learns how to query from meta-experience with image spatial texture structure as prior by HoG, so we can adopt the experience in cross-domain setting which is Gray(MNIST) v.s. RGB(MNIST-M) scale and outperform with 5% through querying procedure on average. In this setting, we train the agent in MNIST and directly apply as a query method in MNIST-M. We obtain a better result than training from scratch randomly shown in Fig. 7. In this setting, we realize that our HAL is a general method can adopt query experience to other works that have similar prior.

### 5 Conclusion

We proposed a bias-aware policy network called heapi-fied active learning (HAL), which prevents data sample bias due to overly confident model prediction. Moreover, our policy model trades off the query time complexity and global information by heapified structure in pooling based active learning setting. In addition, in our experiment, HAL outperforms other baseline methods on MNIST dataset and duplicated MNIST. From the results, we can show that our method is able to reach high generalization on different dataset which share similar features.
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