DeepAL: Deep Active Learning in Python

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Abstract

We present DeepAL, a Python library that implements several common strategies for active learning, with a particular emphasis on deep active learning. DeepAL provides a simple and unified framework based on PyTorch that allows users to easily load custom datasets, build custom data handlers, and design custom strategies without much modification of codes. DeepAL is open-source on Github\(^1\) and welcome any contribution.

1. Introduction

Active learning is a popular solution to reduce the expensive cost of labeling [11]. Due to its practical value, many libraries are presented to help people adopt active learning to their applications, such as JCLAL [8] based on Java and libact [12] based on Python. They provide general frameworks for active learning and include some built-in query strategies. However, since they are developed in the earlier years, those libraries are designed for traditional learning approaches, such as support vector machine [2] and random forest [1]. Given that deep learning has gradually become a standard learning approach recently, the demand for an active learning library that is capable of deep neural models is rising. Motivated by this demand, we present DeepAL, a Python library that implements several common strategies for deep active learning. DeepAL provides a simple and unified framework based on PyTorch for pool-based active learning [11] and includes several modules that can be easily extended to custom datasets, custom data handlers, and custom query strategies. We hope that DeepAL can be a useful tool for both practical applications and research purposes.

2. Pool-Based Active Learning

DeepAL Focuses on the pool-based active learning setting [11]. Given a labeled pool \(D_l = \{(x_i, y_i)\}_{i=1}^{N_l}\) and an unlabeled pool \(D_u = \{x_i\}_{i=1}^{N_u}\), a pool-based active learning algorithm first learns an initial classifier \(f^{(0)}\) based on \(D_l\). Next, for each round \(t = 1, 2, ..., T\), the algorithm selects \(n\) examples from \(D_u\) according to a query strategy and queries the corresponding labels of those selected examples. The \(n\) examples are then moved from \(D_u\) to \(D_l\) and the algorithm learns a new classifier \(f^{(t)}\) based the updated \(D_l\). The objective is to design a good query strategy and make \(f^{(0)}, f^{(1)}, f^{(2)}, ..., f^{(T)}\) perform well on the testing set \(D_{test} = \{(x_i, y_i)\}_{i=1}^{M}\).

\(^1\)https://github.com/ej0cl6/deep-active-learning
3. DeepAL

DeepAL consists of several modules to fit the scenario of pool-based active learning.

Data. The Data class maintains the labeled pool $D_l$ and the unlabeled pool $D_u$ as well as the testing set $D_{test}$. Some important attributes are listed as follows.

- `Data.X_train` and `Data.Y_train`: a list of examples and the corresponding labels in $D_l \cup D_u$.
- `Data.Y_test` and `Data.Y_test`: a list of examples and the corresponding labels in the testing set $D_{test}$.
- `Data.labeled_idxs`: a binary numpy array to indicate which examples in `Data.X_train` and `Data.Y_train` are labeled and which are not.
- `Data.handler`: a class inherits `torch.utils.data.Dataset` that pre-processes the data ($X$ and $Y$) and convert them into Tensors. It is supposed to support two functions `Data.handler.__getitem__` and `Data.handler.__len__`.

Net. The Net class defines the architecture of classifier $f$ and the corresponding training parameters. Some important attributes and methods are listed as follows.

- `Net.net`: a class inherits `torch.nn.Module` that specifies the architecture of classifier $f$. It is supposed to support `Net.net.forward` and `Net.net.get_embedding_dim`, where the latter function has to return the size of hidden representations.
- `Net:params`: a dictionary that contains all the parameters for training, such as the number of epochs, the batch size, and the learning rate.
- `Net.train(data)`: a function that specifies the training process. It trains a classifier `Net.clf` from `data`.
- `Net.predict(data)`: a function that uses `Net.clf` to make predictions for `data` and returns the corresponding Tensors.
- `Net.predict_prob(data)`: a function that uses `Net.clf` to make predictions with probabilities for `data` and returns the corresponding Tensors.
- `Net.get_embeddings(data)`: a function that uses `Net.clf` to generate hidden representations for `data` and returns the corresponding Tensors.

Strategy. The Strategy class specifies the details of the query strategy. Some important attributes and methods are listed as follows.

- `Strategy.dataset`: a Data instance that maintains the labeled pool $D_l$ and the unlabeled pool $D_u$ as well as the testing set $D_{test}$.
- `Strategy.net`: a Net instance that specifies the architecture of classifier $f$ and the corresponding training parameters.
- `Strategy.query(n)`: a function that implements the rule to select $n$ examples from the unlabeled pool $D_u$.
- `Strategy.update(query_idxs)`: a function that updates the labeled pool $D_l$ and the unlabeled pool $D_u$ with the given `query_idxs`.
• **Strategy.train()**: a function that updates `Strategy.net` with the current labeled pool $D_l$.

In DeepAL, we implement several common query strategies, including:

- **Random sampling**: randomly select examples from $D_u$.
- **Least confidence** [6]: select examples with least confidence
  $$x^* = \arg \max_x 1 - P(\hat{y}|x),$$
  where $\hat{y}$ is the most probable class label.
- **Margin sampling** [9]: select examples with smallest margins
  $$x^* = \arg \min_x P(\hat{y}_1|x) - P(\hat{y}_2|x),$$
  where $\hat{y}_1$ and $\hat{y}_2$ are the first and second most probable class labels.
- **Entropy sampling** [11]: select examples with largest entropy
  $$x^* = \arg \max_x - \sum_y P(y|x) \log P(y|x).$$

- **Uncertainty sampling with dropout estimation** [4]: select examples with most uncertainties estimated by dropouts. We implement the above three uncertainties: least confidence, smallest margins, and largest entropy.
- **Bayesian active learning disagreement** (BALD) [4]: select examples with largest mutual information between predictions and model posterior.
- **Core-set selection** [10]: select examples from the score-set based on $k$-means and $k$-medians algorithms.
- **Adversarial margin** [3]: select examples with smallest margins approximated by adversarial perturbations. We implement two adversarial methods: basic iterative method [5] and DeepFool [7].

**Usage.** The framework for the whole active learning process is shown by the following pseudo-code:\(^\text{2}\)

```plaintext
1: dataset = Data()
2: net = Net()
3: strategy = Strategy(dataset, net)
4: for $t = 1, 2, 3, \ldots, T$ do
5:   query_idxs = strategy.query(n)
6:   strategy.update(query_idxs)
7:   strategy.train()
8: end for
```

As illustrated by line 4 to line 8, for each iteration, the strategy selects $n$ examples for querying, updates the labeled pool and the unlabeled pool, and train a classifier.

\(^\text{2}\) Please refer to https://github.com/ej0c16/deep-active-learning/blob/master/demo.py for more details.
4. Conclusion

We present DeepAL, a Python library that implements several common strategies for deep active learning. DeepAL provides a simple and unified framework and flexible modules that allow users to easily develop custom active learning strategies. We hope that DeepAL can be a useful tool for both practical applications and research purposes.

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