Active Learning Benchmark

Towards Comparable Active Learning

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Motivation

The DAL result landscape is terrible

Every paper uses different datasets and use-cases

Every paper has a different classification model and training regime

No one-fits-all evaluation metric

Competitor Papers

Some Benchmark papers for DAL exist already:

- Focus on Image Classification
- Focus on best possible classifier performance
  - Data Augmentation
  - Type of Optimizer
  - Semi-Supervised Learning

Main Idea

We focus on the AL algorithms themselves:

- When we find the ”best” algorithm, classification performance will come naturally
- AL is lacking reproducible research, not strong classification models (random/uncertainty sampling does a good job already)
- We incorporate different domains instead of focusing on images
- We reduce the amount of true hyperparameters by design

Theoretical Problems

Some conflicting results from other papers:

- Data augmentations (seemingly) can replace diversity components from AL algorithms (under investigation currently)

Scope

The framework is planned to include

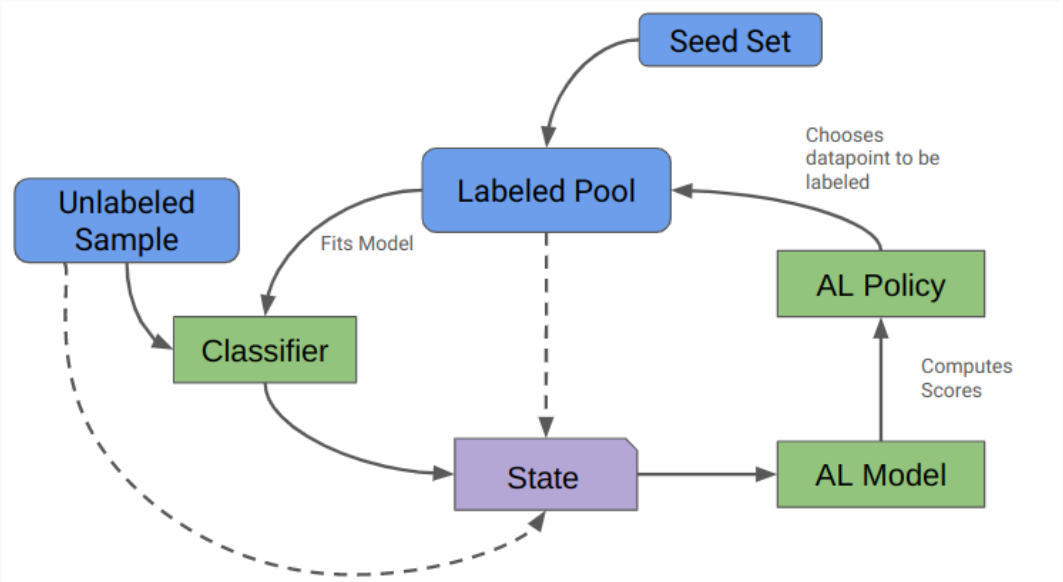
- Three different domains (Tabular, Image, Text)
- SOTA baseline methods
- Preprocessed datasets (train/test split and seed set)
- Tuned classifiers for each dataset
- Set logging and evaluation procedures
- (Single Domain and Domain Transfer use cases)

The framework will **not** include

- Batch Active Learning
- Elaborate Training (Data Augmentation, etc.)

Design Decisions

The AL Cycle


Seed Set
Chooses datapoint to be labeled
Labeled Pool
Unlabeled Sample
Fits Model
AL Policy
Classifier
Computes Scores
State
AL Model

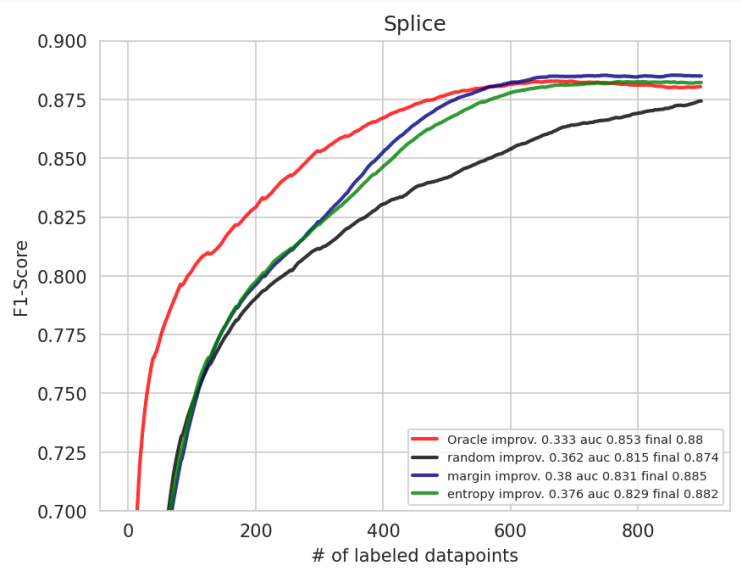
Datasets

Each dataset should be preprocessed - The features are normalized, the target are one-hot encoded and **the seed set should be fixed**

Datasets should be selected by their ”potential”

Each dataset needs an oracle curve that sets an upper bound performance

Dataset Potential



Classifier

The classification model should be governed by the dataset

There is no need to have the same model for every dataset, as long as the model in question is suited well for the data

Simpler models with less dynamic behaviour are better - SOTA performance is not so important

The model needs have tuned hyperparameters for each dataset (full dataset or subset?)

The expectation is that good AL algorithms will also work well on SOTA models

Evaluation Metrics

Multiple options are available

- Accuracy* / F1-Score
- AUC
- Advantage over random sampling*
- Regret from the oracle curve
- Relative performance (0% = random / 100% = oracle)

Cross Validation

AL can cross validate in two ways

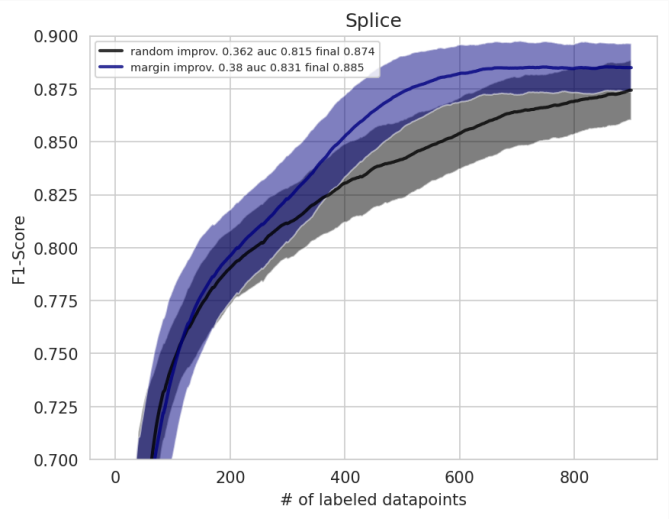
- Changing the seed set
- Changing the presented sub-samples of unlabeled points
- Changing model initialization

Currently, I keep the seed set fixed

Is there value in fixing everything? (Model checkpoints, pre-sampling data*, etc.)

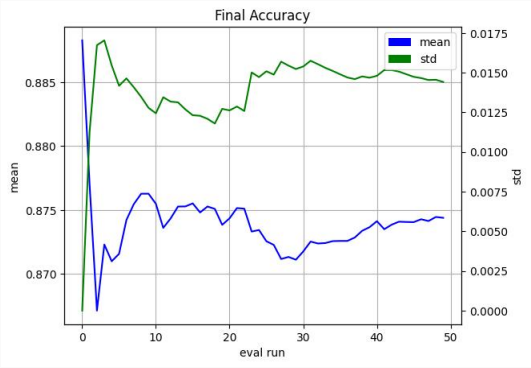
Cross Validation

Splice (Tabular):
Random: 0.874 ± 0.01
Margin: 0.885 ± 0.015
Difference: 0.011

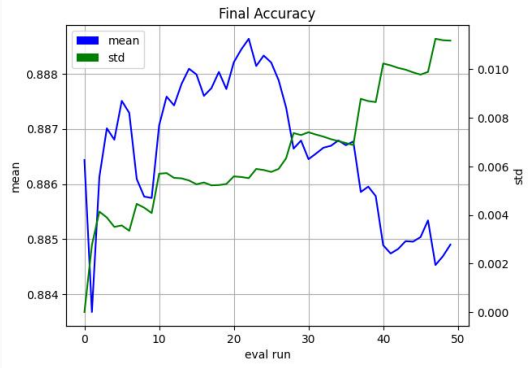


Cross Validation

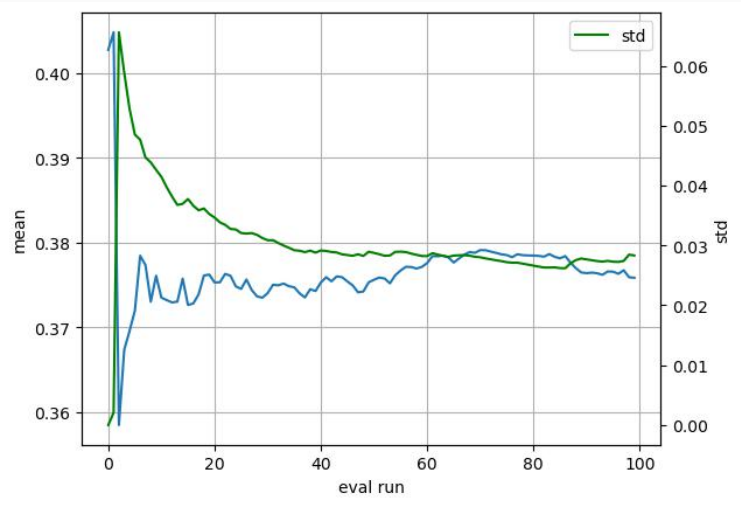
Random Sampling



Uncertainty Sampling



Cross Validation



Hyperparameters

Data HPs are fixed by the dataset (budget, seed set, ...)

Classifier HPs are set with BO per dataset (architecture, learning rate, regularization, ...)

Environment HPs are choosen with respect to the classifiers (training loop, ...)

Each AL agent defines its own state space with the information from the environment

This leaves very few ”true” hyperparameters:

- Unlabeled Sample Size
- # of cross validation trials

Single Domain vs. Transfer

pass

The End

Cheers

Classifier Training

Labeled points are unweighted

Always at least one epoch of training

Aggressive early stopping with patience 0

Adam (NAdam) optimizer, since SGD proves to be too slow (needs more epochs)