Active Learning of Classification Models from Soft-Labeled Groups

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ABSTRACT

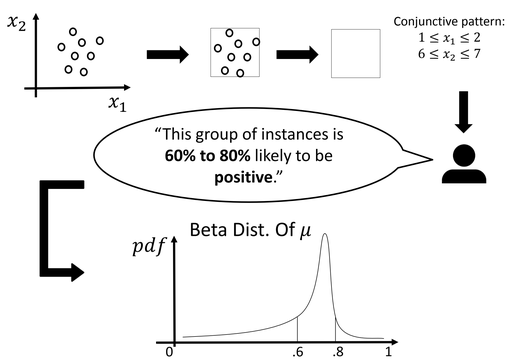
- Challenge: learning classification models from labeled instances often requires huge human annotation efforts.
- Our solution: **actively** learn (instance-based) classification models from (soft) **labeled groups**.
- Our empirical study demonstrates that our method is competitive and can outperform instance-based active learning methods as well as other group- or cluster-based active learning approaches.

MOTIVATION

- Group learning [4,5]: In many real-world situations, it is easier for annotators to provide **one meta-label** on **a set of similar instances** as opposed to annotating individual instance one by one.
  - Electronic health records
  - Image annotation
  - Presidential election results
- Active learning [7]: proper querying strategies can reduce the number of labeled data needed.
- Combining both of the solutions can further reduce human annotation efforts.

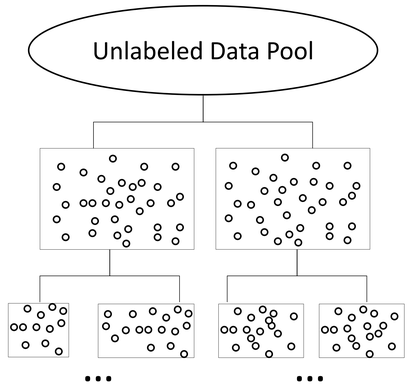
GROUP CONCEPT

- A group is a compact collection of similar instances.
- It is described to humans by using conjunctive patterns over the input space features.
- Annotators assign a **range-based binary label** to the group.
- The range label can be interpreted as a Beta distribution.
  - $P(Group\ is\ positive) = \mu \in [0,1] \sim Beta$



GROUP FORMATION

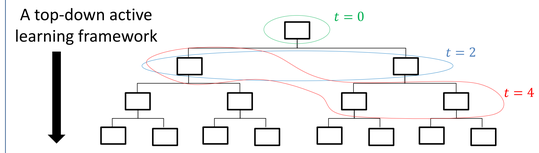
- In practice, groups are not always apparently available.
- Solution: use hierarchical clustering to form groups from general to specific.
- The conjunctive patterns for each group description are learned using a standard decision tree algorithm.



ACTIVE LEARNING FRAMEWORK

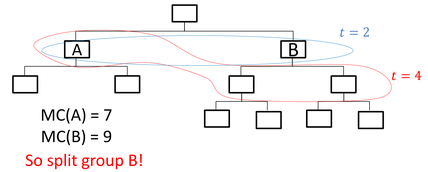
1. Form a hierarchy of groups (unlabeled) by performing hierarchical clustering;
2. Maintain a fringe $F^{(0)} = \{the\ root\ of\ hierarchy\}$;
3. Instantiate an initial classifier with parameters $\boldsymbol{\theta}^{(0)}$;
4. Time $t \leftarrow 0$ is also the number of queries;
5. Repeat :
   i. Actively select a group $G_* \in F^{(t)}$ based on $\boldsymbol{\theta}^{(t)}$;
   ii. Query the labels of G_*'s child groups;
   iii. Replace G_* with its children in the fringe;
      - $F^{(t+\Delta t)} = \{F^{(t)} - G_*\} \cup \{G_*'s\ children\}$.
      - Δt is the number of G_*'s children.
   iv. Retrain the classifier with groups in $F^{(t+\Delta t)}$;
   v. Update $t \leftarrow t + \Delta t$

A top-down active learning framework

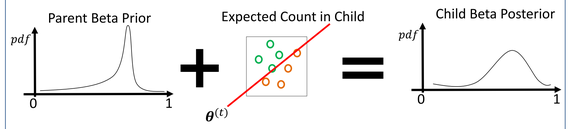


ACTIVE LEARNING STRATEGY

- Maximal expected model change principle [3].
- At each time t, choose the group in current fringe such that if it were split, it would lead to the greatest change to current classifier.



- Use the entire unlabeled data to measure classifier's performance change.
- Essentially we need to **predict** the labels of child groups.
- Method: **Beta Prior** (from parent's label) + **Binomial Counts** (given by classifier) = **Posterior Beta** (child's label predicted)



LEARNING CLASSIFIER FROM GROUPS

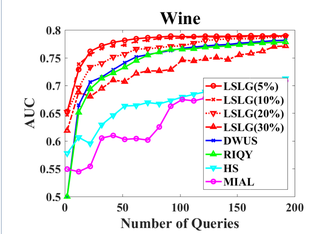
- The learning problem is formulated as a least square regression [4,5] that aims to match (1) the group label given by human with (2) the empirical **averaged** label of all instances in that group estimated by the classifier.
- Suppose at time t, there are N groups $\{G_i\}_{i=1}^N$ in fringe.
  - Each group has n_i instances
  - $n = \sum_{i=1}^N n_i$ is the number of all training instances.
- Each group has a label μ_i following $Beta(a_i, b_i)$.
- Each instance in the group has an estimated μ_{ij} by classifier.
  - $\mu_{ij} = P(the\ j^{th}\ instance\ in\ G_i\ is\ positive|\boldsymbol{\theta})$
- Loss function: $L(\boldsymbol{\theta}) = \sum_{i=1}^N \mathbf{E}_{\mu_i}\{\frac{n_i}{n}(\frac{\sum_j \mu_{ij}}{n_i} - \mu_i)\}^2 + R(\boldsymbol{\theta})$
  - u_i is a given label for group G_i;
  - $\frac{\sum_j \mu_{ij}}{n_i}$ is the averaged instance labels given by model;
  - $R(\boldsymbol{\theta})$ is a regularizing term;
  - $\mathbf{E}_{\mu_i}(\cdot)$ integrates out all possible μ_i.
- The $\boldsymbol{\theta}^*$ that minimizes $L(\boldsymbol{\theta})$ can be solved by:
  - Newton's optimization for simple models;
  - gradient-based method for more complex models.

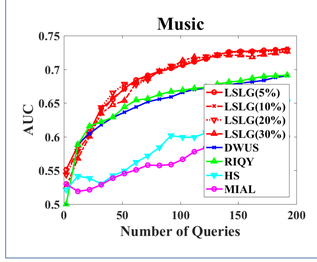
EXPERIMENT SETTING

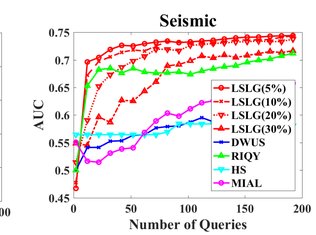
- 3 binary classification datasets from UCI ML repository [1]:
  - **Wine**, which has been used widely;
  - **Music**, which is high-dimensional with 68 features;
  - **Seismic Bump**, which has unbalanced class distribution (7%);
- Active learning methods tested:
  - [7] Density-Weighted Uncertainty Sampling (**DWUS**);
  - [6] **RIQY**, a state-of-the-art group-based active learning approach;
  - [2] Hierarchical Sampling (**HS**);
  - [8] Multi-Instance Active Learning (**MIAL**);
  - Our method: Learning from Soft-Labeled Groups (**LSLG**);
- Group range label simulation:
  - Our group labels are simulated by counting class proportion based on instance labels within each group. The proportion is further expanded to an range label with certain level of precision: 5%, 10%, 20%, 30%.
  - E.g. LSLG(10%) means all the simulated range labels have a fixed interval width = 10%, like '60%~70% positive'.
- The base classifier: Logistic Regression
- Evaluation: We show AUC (Area under ROC curve) of the base classifier on test data for all methods after $k < 200$ queries.

EXPERIMENT RESULTS

- Our methods outperform others when range labels are fairly precise (≤20%).
- For all datasets, the performance of our method gradually drops as the range label uncertainty increases from 5% to 30%, as expected.
- We recommend a robust range width as 20% for future studies.







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