Medical symptom recognition from patient text: An active learning approach for long-tailed multilabel distributions

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**Abstract**

We study the problem of medical symptoms recognition from patient text, for the purposes of gathering pertinent information from the patient (known as history-taking). We introduce an active learning method that leverages underlying structure of a continually refined, learned latent space to select the most informative examples to label. This enables the selection of the most informative examples that progressively increases the coverage on the universe of symptoms via the learned model, despite the long tail in data distribution.

1. Introduction

The COVID-19 pandemic has catalyzed rapid adoption of telehealth *Wosik et al. (2020)*, leading to over 100% increase in virtual urgent care visits and over 4000% increase in virtual non-urgent care visits *Mann et al. (2020)*. A typical virtual visit starts with the patient describing their reason for encounter/ visit (RFE) *WHO (2003)*. Based on the RFE, automated history taking algorithms could gather further information including details about the presenting symptoms, before the patient is finally directed to a chat (video or text) with the practitioners.

This paper focuses on an intermediate implicit step of recognizing the symptoms in the patient’s RFE, as it serves as the backbone for automated history taking. Note that this is related to the task of medical named entity recognition where the goal has been to extract symptoms from the clinical text in electronic health records (c.f. *Baumel et al. (2018)* and references therein). In contrast, we focus on medical entities recognition from the patient text, since patient text (RFEs) are less standardized, and often express symptoms in a colloquial manner. Figure 1 presents some examples RFEs from the dataset we use in our paper.

Learning a model for medical symptom recognition poses a number of challenges: 1) **Access**: As there is no publicly available dataset, any new telehealth platform wanting to build its machine learning solution will need to start with a small set of labeled data points and rapidly increase the scope. This also means that as we increase the number of labeled data points, the system may need to recognize new symptoms that were previously unknown. 2) **Multilabel distribution**: There may be multiple symptoms in a given RFE, and all symptoms need to be extracted to enable automated history taking. 3) **Long-tailed distribution**: Some symptoms are common while multiple symptoms tend to co-occur. This implicitly induces asymmetry and long tail in data distribution (Figure 1). This is compounded by...
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Figure 1: Long-tailed data distribution. Also, shown are example RFEs from the dataset. Note the patient language and co-occurrence of symptoms. Best viewed by zooming into the digital version.

the distribution of patient population on the telehealth platform.

Given these challenges, in this work, we propose a new active learning algorithm for gathering data efficiently. The main intuition for our algorithm is as follows: RFEs form distinct clusters that are medically grounded by underlying health condition. By finding the right balance between selecting points close to cluster centroids and points far from labeled RFEs, we can overcome the problem of long tail distribution. Our experiments show that our model outperforms the state-of-the-art on multi-label classification tasks and can address long-tailed distribution in our dataset. Ablation studies and qualitative analyses shed more light on the advantages of our approach.

2. Method

**Notation:** Let $\mathcal{C}$ be the universe of symptoms. Let $x = [w_1, w_2, \ldots, w_t]$ represent a sequence of words corresponding to a reason for encounter (RFE), and $y \in \mathcal{Y}$ corresponds to a set of labels. A labeled data point is represented by the pair $(x, y)$. Assume access to a labeled set $D_L = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ and an unlabeled set $D_U = \{\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_m\}$.

**Algorithm:** Alg. 1 provides the overview of Active Long-Tailed Learning (ALTL). At each iteration, the objective is to select $b > 1$ unlabeled points from $D_U$ to be labeled by an oracle, so as to minimize the future expected loss of the model after training on the new labeled set.

In the beginning of the model training, we have samples that correspond to a small subset of labels $\mathcal{C}$. In subsequent iterations of training, we want to select data points such that we obtain examples that expand existing labels and discover new ones, despite the data distribution being long-tailed.

**Affinity:** A standard approach is to choose a set of points that cover as much of the latent space of input representation as possible. While methods such as Coreset [Sener and Savarese (2017)], BADGE [Ash et al. (2019)], and VAAL [Sinha et al. (2019)] are tailored to this objective, they can also select data points that are outliers or are close to the boundaries of data representation; this issue is further exacerbated in our setting where the data distribution is long-tailed. In order to address these issues, we leverage the Coreset framework but introduce several key innovations. First, we cluster the latent space of $D_L \cup D_U$ to capture the coherent structure. This facilitates RFEs with different co-occurring symptoms to form distinct clusters (e.g. abdominal pain with a gynecological issue such as menstrual bleeding, vs. abdominal pain with constipation). For this, we use Affinity propagation [Frey and Dueck (2007)]. As an exemplary clustering method based on probability propagation, it does not require the number of clusters to be specified beforehand. This clustering step results in cluster centroids denoted as $r_1, \ldots, r_p \in \mathbb{R}^d$ where $p$ is the number of output clusters.
Algorithm 1 Active Long-Tailed Learning (ALTL)

**Input:** Labeled set \( D_L \), Unlabeled pool \( D_U \), Budget \( b \), Feature extractor \( f(.) \)

1: Initialize \( n = |D_L| \)
2: \( r_1, \ldots, r_p \leftarrow \text{Affinity}(f(D_L \cup D_U)) \)
3: repeat
4: \( u \leftarrow \text{GetDatumToLabel}(D_L, D_U, r_1, \ldots, r_p, f(.)) \)
5: \( y = \text{Oracle}(u) \)
6: \( D_L = D_L \cup \{(u, y)\} \)
7: \( D_U = D_U - \{u\} \)
8: until \( |D_L| = n + b \)
9: return \( D_L \) and \( D_U \)

**GetDatumToLabel** Then, we select data points that explore both new regions of the latent space (and hence introduces previously unseen labels), as well as those that are close to the cluster centroids (captures data density in the latent space). We fold these two properties in our optimization function:

\[
u = \arg \max_{x_u \in D_U} \left( \min_{x_l \in D_L \cup S} \Delta(f(x_u), f(x_l)) \right) - \lambda \min_{r \in \{r_1, \ldots, r_p\}} \Delta(f(x_u), r) \tag{1}\]

Here \( \lambda \) is a hyper-parameter that balances the exploration of new parts of the latent space versus exploiting the established clusters, and \( f(.) \) is the feature extractor. While increasing \( \lambda \) enables selecting more examples near the cluster centroids where data points are concentrated, lowering it encourages exploring new areas in the latent space despite being far from established clusters in the data. As we show in our experiments, this approach is very effective when dealing with long-tailed multilabel distribution of data.

3. Experiments

**Data** We gathered 1232 RFEs from an online telemedicine practice and had medical experts label them with corresponding symptoms. RFEs are limited to 30-300 characters with average length of around 100 characters. We consider a universe of 20 medical symptoms, where these 20 symptoms are made of the most frequently occurring medical findings in patient RFEs. We use 80:20 data split for train and test set, respectively. Data distribution is show in Figure 1.

**Metrics:** F1-score Manning et al. (2008) and Label ranking average precision (LRAP) Tsoumakas et al. (2009).

**Baselines**
1) **Coreset** Sener and Savarese (2017), as discussed in Section 2 is a representation based method that solves the K-Center problem to select points in the latent space. This baseline is the closest algorithm to our proposed method.
2) **Max-entropy** Settles (2009) is the best known uncertainty-based method in Active Learning, that uses the entropy of the model’s output as a measure for uncertainty. Due to similarity in performance (also reported in Sinha et al. (2019)) we do not compare against additional uncertainty-based baselines.
3) **Random** baseline, as the name suggests, randomly selects new data points from the unlabeled data pool following a uniform distribution.
4) **Fully-supervised** baseline is a fully supervised model trained on a completely labeled training data set, and serves as a reference. See Appendix A for more comparisons, including Bayesian methods.

3.1. Main Results

To compare our proposed method with the baselines considered, we set up our experiments to first start with a small set of 10 labeled RFEs and then at each iteration we select a new batch (again of size 10) of unlabeled RFEs, via the acquisition function described in Alg. 1. Then the updated dataset is re-trained, and the next batch of examples are obtained for labeling. The details of the classifier (and hence the representation), and implementation details are in Appendix A.
Figure 2 shows the performance of our model compared to the baselines. We can see that our approach outperforms the baselines. Since we start with only 10 labeled RFEs, many labels in the universe of symptoms do not have associated data samples. Our method is able to identify the previously unseen and unlabeled data points for exploration. In contrast, Coreset suffers from sampling too many outliers or data points too close to the boundaries in the latent space. Such examples are usually less informative than examples close to the centroids of the unexplored data clusters that our method can identify (see Appendix B for visualizations of identified clusters). Max-entropy is not a competitive baseline since in the initial iterations, where many labels are still unexplored, the model’s output is not a good indicator of uncertainty. Comparing against the fully supervised baseline, we see that our method achieves an LRAP score of 85 using only 10% of the labeled data set, as opposed to achieving a LRAP score of 92 when trained on the entire labeled data set.

3.2. Ablation Study

To understand the trade-off between exploring new clusters and exploiting the pre-existing clusters in the latent space, we study the effect of hyperparameter $\lambda$. Figure 2 shows the difference in performance as the function of $\lambda$. When $\lambda$ is very small, our method performs similarly to Coreset as expected, as it does not account for the distance of the selected points from the cluster centroids. On the other hand, choosing a large $\lambda$ makes our method conservative in that it only selects cluster centroids. This is not helpful in the long-run, since cluster centroids of adjacent iterations are usually close to each other and as a result, selecting only centroids is not diverse enough; therefore in this scenario, our method may underperform to Coreset. The optimal choice, in this case, is around 0.1, which results in a good balance.

4. Conclusion

In this paper, we studied the problem of medical symptoms recognition from patient text. We proposed a new active learning method that selects a diverse set of data points based on their latent representation while expanding the coverage on the universe of labels. This method balances selecting examples in the latent space’s undiscovered parts with selecting samples close to cluster centroids. As we showed in our experiments, this can address long-tailed distribution in the dataset and outperform compared baselines in the symptoms recognition task.
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Appendix A. Implementation details

Model architecture: Due to the size of available data sets as well as due to the well documented performance of pre-trained sentence encoders, we use InferSent Conneau et al. (2017) for encoding patient RFE text. Each RFE is embedded in a 4096 dimension vector. In addition to obtaining text embeddings from InferSent, a set of boolean feature vectors that capture the surface of symptoms from patient text are created. These are 256 dimensional embeddings where the presence of a 1 in the kth position indicates the presence of the kth symptom word (e.g. abdominal) in the patient text. Text embeddings are fed into a 2-layer MLP (512 and 256 neurons) with 0.5 dropout. Then the result is concatenated with boolean vectors. Another 2-layer MLP (512 and 128 neurons) with 0.5 dropout is used to generate the logits. The outputs before the last fully-connected layer are used as our main features in our method.

Training: For training the model, we used the multi-label loss function proposed in Mahajan et al. (2018). In this loss function, targets are formed by normalizing (sum to 1) the multi-hot encoded label vector, and then the cross-entropy of the target is computed with respect to the softmax of the model’s output. For optimizing our loss function, we used Adam optimizer with 0.001 learning rate. In the Affinity Propagation algorithm we use euclidean distance and damping factor of 0.5 for clustering. For all experiments we train the model for 200 epochs in each iteration. The results are averaged over 4 runs, and predictions are made with 0.2 margin on the softmax of model’s logits.

Comparison to lookup-based models: Our model significantly outperforms in-house lookup-based methods (label and their synonyms) as it better captures the meaning of the whole text. After being fully trained, our model archives 76% F1-Score which is significantly higher compared to 58% F1-Score for our best rule-based model.

Appendix B. Qualitative Analysis

We further analyze the behavior of our method qualitatively by visualizing the latent space. We visualize the features from the last layer of the fully connected network in our model using TSNE visualization Maaten and Hinton (2008). We also include the clusters that resulted from the Affinity Propagation algorithm as disjoint graphs. Selected, labeled, and unlabeled data points are also depicted using crosses and colored and white dots in our graph. Figure 3 shows the TSNE visualization of the latent space of the model in the first iteration and subsequent iterations as more data points are labeled. In the first iteration, our method selects a diverse set of data points in order to cover as much of the latent space as possible. However, it does not over-sample outlier data points or data points close to the boundaries, although they are attractive choices for the Corseset method. When more data points are already labeled in later iterations, our method continues to discover new clusters and improve upon the existing ones. This experiment shows that our model’s qualitative behaviors are consistent with our hypothesis and expectations.
Figure 3: TSNE visualisation of the latent space of the model and the selected data points by our method in the first iteration (top) and the last one (bottom)
Appendix C. Related Works

The main goal of active learning is to select a set of the most informative examples to be labeled and achieve the highest performance after training the model with the lowest number of data points being labeled. Active learning is a relatively established topic in machine learning, and most of the classic works in active learning can be found in Settles (2009). Active learning methods can be categorized into two main approaches: 1) **Pool-based methods** where examples are selected from a large pool of unlabeled data points; and 2) **Query synthesizing methods** in which the active learning algorithm generates the data points for which it wants to get labels Zhu and Bento (2017) Mahapatra et al. (2018). In this work, we focus on pool-based methods as they appear in many practical applications.

There are three main approaches for pool-based active learning. 1) **Uncertainty approaches**: In these methods, an active learning algorithm selects the examples about which it is most uncertain, i.e., it labels data points that are most challenging for the model to predict. Different methods in this category measure the uncertainty in different ways such as entropy Shannon (1948), variation Freeman (1965) or standard deviation Kendall et al. (2015) of output predictions or distance from the decision boundaries Tong and Koller (2001). Gal et al. (2017) introduced a Bayesian approach called Bayesian Active Learning by Disagreement (BALD), which uses dropout in deep networks to capture the uncertainty. 2) **Representation approaches**: In these approaches, the goal is to cover the latent space of the model and to select a diverse set of data points based on their latent representation. The Core-set Sener and Savarese (2017) method formulates the objective as a core-set selection in the latent space and selects a batch of examples with the highest coverage in the latent representation. 3) **Mixing Uncertainty and Representation**: Additionally, some approaches use both uncertainty and representation for selecting the data points. For example, Yang et al. (2017) adds an uncertainty component to the core-set approach. Ash et al. (2019) select data points in a hallucinated gradient space based on diversity and predictive uncertainty. Also, Sinha et al. (2019) learns the distribution of labeled and unlabeled data points with a Variations Autoencoder (VAE), trains a discriminator for detecting the unlabeled data points based on latent representation and sends the detected data points for annotation. They argue that they can learn both representation and uncertainty at the same time in this way. Our method utilizes the latent representation of the model for selecting a new data point, but it does not rely on the model’s output as we show the predictions are not reliable when the distribution is long-tailed, and some label categories are undiscovered.

While most of the literature focuses on the classification task, a few works also tackle the problem of multi-label classification. Almost all of them use uncertainty as to the criteria for selecting data points. Reyes et al. (2018) proposes a rank aggregation problem for measuring the uncertainty of each instance based on the predictions for all labels. Nakano et al. (2020) employs an ensemble of predictive models and uses the query-by-committee method to measure disagreement and uncertainty. We also further study this problem in the context of a long-tailed distribution dataset with undiscovered label categories, which has not been studied before.