OSLAT: Open Set Label Attention Transformer for Medical Entity Span Extraction

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Abstract

Identifying spans in medical texts that correspond to medical entities is one of the core steps for many healthcare NLP tasks such as ICD coding, medical finding extraction, medical note contextualization, to name a few. Existing entity extraction methods rely on a fixed and limited vocabulary of medical entities and have difficulty with extracting entities represented by disjoint spans. In this paper, we present a new transformer-based architecture called OSLAT, Open Set Label Attention Transformer, that addresses many of the limitations of the previous methods. Our approach uses the label-attention mechanism to implicitly learn spans associated with entities of interest. These entities can be provided as free text, including entities not seen during OSLAT’s training, and the model can extract spans even when they are disjoint. To test the generalizability of our method, we train two separate models on two different datasets, which have very low entity overlap: (1) a public discharge notes dataset from hNLP, and (2) a much more challenging proprietary patient text dataset “Reasons for Encounter” (RFE). We find that OSLAT models trained on either dataset outperform rule-based and fuzzy string matching baselines when applied to the RFE dataset as well as to the portion of hNLP dataset where entities are represented by disjoint spans. Our code can be found at https://github.com/curai/curai-research/tree/main/OSLAT.

Keywords: Medical NLP, Label Attention, Open Set, Disjoint span, Document Level Annotation, Cross-domain Transfer, Contrastive Learning, Document-Level Annotation

1. Introduction

Many natural language processing (NLP) tasks in the healthcare domain such as information retrieval (IR) (Tamine and Goeuriot, 2021), diagnosis coding (Crammer et al., 2007), and conversational agents (Compton et al., 2021; Valmianski et al., 2021) depend on correctly identifying medical entities such as disorders and findings in the text. This has led to a wealth of literature centered on entity recognition in the past decades (Friedman et al., 1995; Chapman et al., 2001; Aronson, 2001; Savova et al., 2010) and many competitions/tasks in both NLP and IR communities (Pestian et al., 2007; Styler et al., 2014; Elhadad et al., 2015; Bethard et al., 2016). However, the problem of entity recognition continues to be largely unsolved. We articulate two main challenges: availability of large amounts of labeled and diverse data (cf. Fries et al. (2021)) and in-the-wild open-set recognition (Prabhu et al., 2019; Mottaghi et al., 2020).

The data challenge comes from existing methods requiring significant amounts of labeled data (Esteva et al., 2019). This labeled data needs to include two parts: (1) spans of entity locations, and (2) entities linked to the spans. Human labeling can be expensive, especially in specialized domains such as medicine, where the annotators require significant domain expertise. To decrease the need for human annotations, different pseudo- or weak-labeling approaches have been proposed (Ratner et al., 2016, 2017). In biomedical
OSLAT: Open Set Label Attention Transformer for Medical Entity Span Extraction

| Entity                              | Text containing the entity                                                                 |
|------------------------------------|------------------------------------------------------------------------------------------|
| knee swelling                       | pain and **swelling in knee**                                                            |
| knee pain                           | **pain and swelling in knee**                                                            |
| cervical lymphadenopathy            | **swollen lymph node on right side of neck**                                             |
| dyspnea                            | been having weird head pressure and anxiety for the past couple weeks also, having to take really deep breaths to catch my breath |

Table 1: For each entity in first column, the second column provides an example text that contains in the entity. We can see that the entity can present as a contiguous-span of text (row 1) or over disjoint-spans (rows 2-3). Also, for the same text, two different entities may share a span (rows 1 and 2). For each (text, entity), we also highlight the text according to the prediction from the proposed model: Brighter the green (best viewed in color), the more confident that the model is that the underlying text is part of describing the entity.

In this paper, we propose an alternative approach for span tagging that allows an open set of entities and is robust to disjoint spans for individual entities. We assume that we are given the entities found in the target text, and use that information to implicitly identify which spans correspond to the provided entities. These “entity presence annotations” can be made with free text, new entities can be added as needed, and entity labels do not need to have any lexical overlap with tokens in the target text. To implicitly learn span information, we propose a new model called Open Set Label Attention Transformer (OSLAT), which removes the typical label-attention transformer requirement of being trained on a fixed universe of labels. We make two new technical contributions. First, we use a transformer-based encoder to not only encode the sentence, but also the labels. Second, we use a novel Label Synonym Supervised Normalized Temperature-Scaled Cross-Entropy (LSS-NT-Xent) loss, an extension of NT-Xent first proposed by Chen et al. (2020), instead of the classification objectives typical to label-attention models.
We test the generalizability of our approach by training on one of two different datasets: a proprietary patient-generated text dataset of “Reasons for Encounter” (RFE) for primary care visits and a dataset with physician-generated text derived from Elhadad et al. (2015) (hNLP). We then test each of the two models on both datasets. Despite significant vocabulary differences between the two datasets, we show that our approach beats rule-based and fuzzy-string-matching baselines even when applied on a dataset the model was not trained on and with entities not previously seen.

Generalizable Insights about Machine Learning in the Context of Healthcare

A large fraction of electronic health records (EHR) data consists of unstructured free text. The goal of many machine learning applications within healthcare is that of extracting useful snippets of information from this free text. This extraction process underlies applications such as search/retrieval, ICD (WHO, 2005) coding, medical findings extraction, and categorization of notes, which in turn can be used to power clinical decision support and help reduce physician clerical load. We can view these extractions as spans (disjoint or contiguous) of text that carry information about underlying entities that we care about.

In this work, we propose a new method for identifying spans in a medical text where a particular entity is mentioned. Our method has three principal advantages when compared to existing approaches: First, it is not limited to a fixed set of entities used during training. This means that the model is useful in practical settings where new labels may emerge (e.g., ‘COVID’) or when recognizing an entity that is not in the training set (e.g., ‘sudden and severe abdominal pain’). Second, the model can identify spans, including disjoint ones, even across different sentences. Often, weak supervision methods use approximate string matching to bootstrap contiguous spans for downstream tasks. Given the proposed model’s competitive performance over these lookup methods, it can serve as an approach to rapidly generate data needed for downstream medical NLP tasks. Third, as we show in this paper, our approach is robust to changes in vocabulary (colloquial patient language or medical expert jargon).

Our work is motivated by a practical need to improve medical entity extraction and, particularly, medical entity span detection, in the context of an existing telehealth medical service. We believe that the improvements listed here make this approach broadly applicable to extended EHR datasets that include not only provider written text but also patient-provider dialogue, which are becoming more prevalent with the rise of telemedicine. More generally, this model can serve as a building block for future development of NLP methods not bound by fixed vocabularies and express in non-contiguous text.

2. Related Work

Span detection in entity recognition: As we discussed in the introduction, there is a vast amount of research in entity recognition (see survey by Pagad and Pradeep (2022) and references therein). Most works treat entity recognition as a structured prediction task to detect entity boundaries (span detection) followed by entity classification within each span. These models assume access to manually-labeled span-level information during training, with more recent approaches bootstrapping these spans through a simple look-up-based approach over medical ontologies. We differ from this line of work in three fundamental ways: First, we assume we know the entity in the text, and the task is to identify the spans in the text that describe the entity. Second, during training, our approach does not require any span information instead the model learns this automatically as part of the learning to relate inputs to the entities. The model's attention score can be used to infer the spans. Third, in comparison to the weak supervision methods that bootstrap labels through look-up-based approaches (cf. Fries et al. (2021)), we compare two variants of these bootstrap methods (rule-based and fuzzy-string-matching) and show that our model has better performance, especially when spans are disjoint.

Learning joint representations (in healthcare): The approach presented in this work is preceded by a copious amount of research on joint learning of multimodal inputs (e.g. joint representations of inputs and labels). Starting with the seminal work of Weston et al. (2011), the field has witnessed tremendous success through the use of attention mechanisms, (Bahdanau et al., 2014; Vaswani et al., 2017). Classifications
models are more expressive by utilizing cross-attention between labels and words to embed both the input text and the label into a joint space (Tang et al., 2015; Wang et al., 2018).

In the context of healthcare, much of the work has been in the context of classification tasks over a fixed label set. Mullenbach et al. (2018) used a convolutional model with label attention (CAML) to predict ICD codes from clinical notes, where a regularization objective was added to encourage the label embedding to be similar to the max-pool of the label’s description embeddings. Vu et al. (2021) applied BiLSTM with label attention for the task of ICD classification from clinical notes, where they propose a hierarchical joint learning scheme to handle highly skewed class distributions. Another convolutional label attention ICD classification approach was proposed by Liu et al. (2021c), where they combined convolutional layers in residual squeeze-and-excite modules (Hu et al., 2018) and applied label attention at every residual block. More recently, label-attention models include transformer architecture. The first application of transformers with label attention to ICD coding was done by Mayya et al. (2021). A similar approach, but framed as a method for fine-tuning the encoder was proposed by Nguyen and Ji (2021), who report improvement in encoder representations of biomedical texts after being trained on a label-attention classification task.

All these tasks focused on the problem of multi-class prediction over a fixed label set. In this paper, we are interested in inferring (disjoint) spans in the input text that maps to an input entity, and we want to do it in the wild with an open set of entities. To the best of our knowledge, we are the first to propose this problem in the open set context. We are also the first, to the best of our knowledge, to use the label-attention (and transformer) model in the context of open-set labels.

3. Approach

We use a label-attention paradigm to implicitly learn spans corresponding to target entities by observing the label-attention values. To achieve this, we propose a new model called Open Set Label Attention Transformer (OSLAT). OSLAT (§ 3.2) modifies the typical label-attention transformer architecture to use the encoder not only to embed the target text, but also the label. Prior to training on the label-attention, we perform a self-alignment pre-training of the encoder similar to the one proposed by SapBERT (Liu et al., 2021a). After pre-training, we perform the label-attention training of OSLAT using a novel loss, Label Synonym Supervised Normalized Temperature-Scaled Cross-Entropy (LSS-NT-Xent). This loss leverages knowledge about the labels derived from UMLS or other vocabularies, enabling supervised contrastive training while maintaining an open set of possible labels. An overview of our two-stage approach is illustrated in Figure 1.

Let’s begin with some notation: There exists a universe of all entities, denoted by $E$. Note, we do not need to explicitly define $E$. During training, we will observe a subset of these entities $E_{\text{seen}}$ and the remaining unobserved (open-set) is $E_{\text{unseen}} = E \setminus E_{\text{seen}}$. We then assume access to a dataset $D_{\text{train}} = \{(x_t, e_t)\}_{t=1}^T$, where $x_t$ is the $t^{th}$ target text and $e_t$ is an entity present in it, with $E_{\text{seen}} = \cup e_t l_{t=1}$. For each entity, $e_t \in E_{\text{seen}}$, we also assume access to its synonyms, obtained from an external source such as UMLS (which we use in this paper). During inference, we are provided with input text-entity pair $(x, e)$ s.t. $e \in E$, this reflects the application of the model in the wild. The goal of this is to identify the spans of text in $x$ that describes $e$.

3.1. Self-Alignment Pretraining on Medical Entities

For OSLAT results presented in this paper we start with the BioBERT (Lee et al., 2020) encoder. In order to decrease representational anisotropy of entity embeddings (Li et al., 2020; Carlsson et al., 2021; Gao et al., 2021; Liu et al., 2021a,b), we perform a self-alignment pretraining (for the change in anisotropy see Figure 2). In particular, for medical entity $e_t \in E_{\text{seen}}$, we obtain its representation $h^{(e_t)}$ by taking the [CLS] token embedding of the last hidden layer of BioBERT. To apply the contrastive loss function, we follow the model architecture described in SimCLR (Chen et al., 2020), where a two-level feed-forward projection head maps the representation $h^{(e_t)}$ from BioBERT into a low-dimension space, before a supervised contrastive
OSLAT: Open Set Label Attention Transformer for Medical Entity Span Extraction

Figure 1: Overview of our proposed two-stage training approach. In the first step, we perform self-alignment pretraining on medical entities and their synonyms. This decreases the anisotropy in encoded entity representations. In the second step, we use the pretrained encoder to align label-text joint representations to that of label synonym-text joint representations. The representations themselves are obtained through label attention. Because in this process, the entity representations are obtained from an encoder, we can handle previously unseen entities (from an open set of entities).

loss, NT-Xent, is applied to the normalized projection output $z_i$ (Khosla et al., 2020; Gao et al., 2021):

$$L_{\text{pre}} = \sum_{i \in B} \frac{-1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(z_i \cdot z_p / \tau)}{\sum_{a \sim E_{\text{seen}}} \exp(z_i \cdot z_a / \tau)}$$

For each entity in batch $B$, the positives $z_p$ are projected representations from the synonym set $P(i)$ of entity $e_i$, with $|P(i)|$ as its cardinality, while the negatives $z_a$ are projected representations from sampled entities from $E_{\text{seen}}$. Finally, hyperparameter $\tau$ denotes the scalar temperature. As the entities are organized into disjoint synonym sets, we apply a stratified sampling strategy for sampling negatives, where we first sample a synonym set and then sample an entity from that set. This ensures that entities with a smaller synonym set do not get under-represented during training. After the self-alignment pretraining, we discard the projection head keeping the fine-tuned encoder. Details on our training procedure can be found in §5.1.

3.2. Label Attention Training

OSLAT supports an open set of labels by jointly encoding labels and target texts into the same subspace. To obtain the representation of the entity spans within the target text, we first encode label $e_t$ and target text $x_t$ with our self-alignment pretrained BioBERT (see §3.1). Specifically, for $(x_t, e_t) \in \mathcal{D}$, the label representation $h(e_t) \in \mathbb{R}^{1 \times d}$ and target text representation $h[x_t] \in \mathbb{R}^{n \times d}$ from the last hidden layer of BioBERT (with hidden size $d$) are used to compute the label-attention score using a variant of the dot-product attention:

$$\alpha^{(x_t, e_t)} = \text{Softmax}(h(e_t)(h[x_t])^T)$$

where the attention score $\alpha^{(x_t, e_t)}$ can be interpreted as the token-wise semantic similarity between the label $e_t$ and the $k$th token of target text $x_t$. Since the [CLS] token for the target text can contain aggregate semantic information about the entire input, we found that the model often resorted to attending solely to the [CLS] token. To mitigate this issue, we remove the [CLS] token from $h[x_t]$ to encourage the model to attend to other portions of the target text. Finally, we compute the entity span representation as a weighted
sum of the target text $h^{(x_t)}$ by the attention scores:

$$c^{(x_t, e_t)} = \sum_{k=1}^{n} \alpha_k^{(x_t, e_t)} h_k^{(x_t)}$$

(3)

To train our model using a variant of NT-Xent which we call Label Synonym Supervised Normalized Temperature-Scaled Cross Entropy (LSS-NT-Xent):

$$\mathcal{L}_{\text{LSS}}(I) = \frac{-1}{|P(t)|} \sum_{p \in P(t)} \log \frac{\sum_{a \sim E_{\text{seen}}} \exp(c^{(x_t, e_t)}, c^{(x_t, p_a)}/\tau)}{\sum_{a \sim E_{\text{seen}}} \exp(c^{(x_t, e_t)}, c^{(x_t, e_a)}/\tau)}$$

(4)

Similarly to the self-alignment pre-training described in § 3.1, we use $e_t$’s synonym set $P(t)$ as positives and randomly sample negatives from the $E_{\text{seen}}$ and their synonyms.

At inference time, we use the attention scores $\alpha^{(x_t, e_t)}$ to predict whether each token of $x_t$ lies in the span of entity $e_t$.

4. Datasets

We are interested in investigating the following empirical questions:

- **Open set entity detection**: Is our approach robust to entities that are unseen during training?
- **Cross-domain transfer**: Is our approach robust to be applied to data that was not used during training (e.g. train on patient written and apply to provider/expert-written text)?
- **Handling disjoint-spans**: Is our approach robust in identifying entity spans that are disjoint?

In order to answer these questions, we build two complementary datasets. The first dataset (§ 4.2) is comprised of texts in which patients describe their health issues (RFE dataset). The second dataset (§ 4.3) is comprised of discharge summary notes written by physicians (hNLP dataset). The train-test split procedure (§ 4.1) of these datasets is itself non-trivial as we need to split both target texts and medical entities such that the test set contains both seen and unseen entities. Finally, we compare the entities in the two datasets in § 4.4.

4.1. Train/Test dataset construction

We start with an intermediate dataset of the form $(x_k, E_k)$ where $x_k$ is the $k^{th}$ input text that has a set $E_k$ of entities to reflect that multiple entities can be in the same input text. Then, $E = \bigcup_k E_k$ is universe of entities, and $p(e)$ is marginal probability of entity $e$ in the dataset.

**Constructing $E_{\text{seen}}, E_{\text{unseen}}$**: For our experiments, we choose 10% of the entities as unseen. We choose these entities randomly from 20%, 40%, and 40% from high, medium, and low marginal probability bins of $p(e)$ so that we capture entities across the spectrum of frequency distribution.

**Train-Test split**: We split the dataset into disjoint sets for training and testing from the perspective of the entity. For each entity $e \in E_{\text{unseen}}$, we associate all pairs $((x_k, e))_{k,e \in E_k}$ to the test set. For each entity $e \in E_{\text{seen}}$, we randomly sample, without replacement, 10% of $((x_k, e))_{k,e \in E_k}$ pairs for the test set and remaining 90% to training set. We ensure that all entities in $E_{\text{seen}}$ have at least five examples in the training set. If not, we first prioritize adding to the training set.

**Span level labels for test set**: We also augment the test set with the spans that correspond to the concept. In particular, an example in test set is of the form $(x, e, \{s_{i,e}\})$ where $\{s_{i,e}\}$ is the set of spans that collectively identify the entity $e$ in the text $x$. In particular, each element in $\{s_{i,e}\}$ encodes the character level beginning and end of the phrase in $x$ that is constituent of $e$.

Thus, $D_{\text{train}} = \{(x_t, e)\}_{t=1}^{|E_{\text{seen}}|}$ where $e \in E_{\text{seen}}$ and $D_{\text{test}} = \{(x_k, e, \{s_{i,e}\})\}_{k=1}^{|E|}$, where $e \in E$.  


4.2. Dataset 1: Reason for Encounter (RFE) dataset

This is a dataset gathered from a telemedicine practice. It contains a labeled subset of 4909 encounters with 4080 patients. The distribution of biological sexes in the dataset is 75% female and 25% male, the distribution of ages is 74% below 30 years old, 20% between 30 and 50 years old, and 6% above 50 years old. This distribution is not a random sample representative of the overall practice’s population, but rather comes from a mixture of random samples drawn from two distinct times, and also from an active learning experiment for a different project.

Patients starting a visit describe their reason for seeking an encounter. The language used in RFEs is more colloquial and less standardized, featuring many disjoint spans for medical entities. We can see some examples in Table 1. Each RFE is labeled by medical experts with corresponding medical findings using UMLS ontology. The RFEs have an average length of 26 words.

We constructed the train-test dataset as outlined in §4.1. In particular, \( |\mathcal{E}_{\text{seen}}| = 450 \) and \( |\mathcal{E}_{\text{unseen}}| = 73 \). This results in roughly 90% of the RFEs to have at least one entity that is seen. 24% of RFEs have at least one entity in \( \mathcal{E}_{\text{unseen}} \) and 10% of RFEs have all their entities in \( \mathcal{E}_{\text{unseen}} \). For more statistics, see Table 2.

For the test set, we also obtained span-level labels from the same pool of medical experts. They were independently shown (RFE, entity) pairs and asked to highlight all the spans of text from which they can deduce the entity. By labeling each pair independently, we also get sub-spans that are shared across multiple concepts. As an example, “pain and swelling on my wrist” has two entities – wrist swelling and wrist pain – and share the same sub-span “wrist” (in this example “wrist pain” is a disjoint span).

4.3. Dataset 2: hNLP dataset

Our second dataset is derived from the training data from the SemEval-2015 Task 14 (Elhadad et al., 2015). In particular, we start with the provided 136 discharge notes and their corresponding medical concepts along with their location spans. We split each discharge note into smaller text chunks using the newline delimiter. We removed chunks that do not have any entities associated with them. This leads to 5508 text chunks with an average length of 69.08 words. We built an initial dataset with text chunks, their entities, and their spans. These entities are UMLS Concept Unique Identifiers (CUIs).

We then constructed the train-test dataset as outlined in §4.1. \( |\mathcal{E}_{\text{seen}}| = 1054 \) and \( |\mathcal{E}_{\text{unseen}}| = 143 \). This results in roughly 90% of the examples having at least one entity that is seen. For more detailed statistics on the dataset see Table 2. For all examples in the test set, we attach the corresponding spans provided in the original dataset. We do not use these spans during training.

|               | Seen          |          | Unseen        |          | Disjoint-Spans |
|---------------|--------------|----------|--------------|----------|----------------|
|               | \( |\mathcal{E}_{\text{seen}}| \) | # Examples | \( |\mathcal{E}_{\text{unseen}}| \) | # Examples | Fraction of examples |
| RFE           | Train        | 450      | 6430         | n/a      | n/a            | unk            |
|               | Test         | 73       | 266          | 66       | 863            | 13%            |
| hNLP          | Train        | 1054     | 4377         | n/a      | n/a            | 5%             |
|               | Test         | 61       | 185          | 143      | 1018           | 7%             |

Table 2: Statistics of dataset used in the experiments. Note, the test set has a lot more unseen entities which facilitates the evaluation of the approach in the wild (open set). Also, during model training, we do not need access to spans, and therefore did not obtain span-level annotations for the RFE training set.

4.4. Dataset comparison

In Table 3, we quantitatively compare the overlap of entities between the datasets and make two observations.
First, there is a significant difference between the entity sets in both datasets (roughly 85% from hNLP to RFE and 69% from RFE to hNLP), although hNLP has twice the number of entities as the RFE dataset. We attribute the difference between the two datasets to their source; while RFE is derived from a telemedicine practice, hNLP is built from doctor’s notes from in-patient settings. This is also evident when we look at the top frequent entities from these two datasets in Table 4 where hNLP focuses on more severe health issues (such as heart-related) that require hospitalization while RFE dataset focuses on non-urgent primary care services. However, they also share entities such as “vomiting.”

Second, only a tiny fraction of unseen entities in one dataset is seen in the other. This gives the assurance that when we evaluate the cross-domain task (§ 5.2) we do not provide undue advantage to the model trained on the other dataset just because these unseen entities are known to the other dataset. Note that we did not intentionally construct the datasets this way and this result is a natural consequence of the significant difference in the vocabulary of the two datasets.

5. Results

5.1. Setup

Training details: For both self-alignment pretraining (§ 3.1) and label attention training (§ 3.2), we use the ADAM optimizer (Kingma and Ba, 2014) with exponential decay after 1/10 of total steps and an effective batch size of 32. For self-alignment pretraining, we train the model for a total of 20 epochs with a learning rate of $2e^{-3}$ and the number of negatives set to 50. For label attention training, we train for a total 5 epochs with a learning rate of $2e^{-4}$ with the number of negatives set to 50. We set temperature $\tau$ to 0.07 based on the settings reported by Khosla et al. (2020).

Prediction task: During inference, we compute the entity-attention scores for the ground-truth entities present in each input text. For experiments on the hHLP dataset (§ 4.3), we compute the average entity-attention scores across all synonym terms associated with each ground-truth entity (identified by a UMLS CUI) as the exact matching synonym is not provided in the annotation. For the RFE dataset (§ 4.2), we instead use the provided synonym term. Since the attention scores are normalized to sum up to 1, we manually set the threshold to be 0.05 during inference. Lastly, we also remove stop-words and punctuation marks from the predictions.

Metric: We use the per-token micro-F1 score as the primary metric for evaluating our models across all experiments. This is done by computing the per-token precision and recall based on the token overlaps between the predicted and ground-truth spans before averaging across all examples. We report the per-token micro-precision and recall performance in the Appendix A.

|       | RFE          | hNLP         |
|-------|--------------|--------------|
|       | Seen | Unseen | Disjoint | Seen | Unseen | Disjoint |
| RFE   | 1.00 | 0.00  | 0.00     | 0.23 | 0.05   | 0.72     |
| Unseen| 0.00 | 1.00  | 0.00     | 0.09 | 0.24   | 0.67     |
| hNLP  | 0.10 | 0.02  | 0.88     | 1.00 | 0.00   | 0.00     |
| Unseen| 0.12 | 0.04  | 0.84     | 0.00 | 1.00   | 0.00     |

Table 3: Comparison of entities overlap between the two datasets. For each dataset (represented by rows), we present the number of entities in the training set (seen) and in the open set (unseen). In the columns corresponding to the other dataset, we provide the distribution of the occurrence of these entities in their seen and unseen concept distribution. The “Disjoint” column corresponds to the proportion of concepts not represented in the other dataset.
OSLAT: Open Set Label Attention Transformer for Medical Entity Span Extraction

| Dataset | Frequent entities                                                                 |
|---------|-----------------------------------------------------------------------------------|
| RFE     | pregnancy (C0549206), headache (C0018681), dysuria (C0013428),                   |
|         | cough (C0010200), abdominal pain (C0235309), nausea (C0027497),                  |
|         | throat pain (C0242429), urinary tract infection (C0042029),                     |
|         | delayed menstruation (C0240322), vaginal pruritus (C0042256),                   |
|         | vaginal spotting (C2979982), fever (C0015967),                                   |
|         | crampy abdominal pain (C0344375), fatigue (C0015672), vomiting (C0042963)      |
| hNLP    | systemic arterial hypertension (C0020538), edema (C0013604),                     |
|         | chest pain (C0008031), coronary artery disease (C1956346), pain (C0030193),     |
|         | dyspnea (C0013404), atrial fibrillation (C0004238),                              |
|         | heart failure (C0018802), nausea (C0027497),                                    |
|         | vomiting (C0042963), bleeding (C0019080),                                      |
|         | intracerebral hemorrhage (C0038454), pneumonia (C0032285),                     |
|         | cyanosis (C0010520), diabetes mellitus (C0011849)                               |

Table 4: The table shows the top 15 frequent entities found in the two datasets. See § 4.4 for details

**Baselines:** We compare against strong baseline methods. The first method, **Rule-based,** is an in-house developed lookup-based approach that uses a sliding window strategy to find maximal matches of text corresponding to the entities and their synonyms. It ignores stop words while doing the match. For the second method, **Fuzzy-Match,** we adopt the fuzzy-string matching from the implementation by RapidFuzz (Bachmann, 2021), where spans with normalized Levenshtein Distance (Levenshtein, 1966) greater than a threshold are extracted for each entity. These two rule-based baselines are particularly strong because they are provided with the target entity. This means that all they have to do is match a known entity or its synonym to a span in the target text. In particular, these baselines have very high precision, since if they can find an entity or its synonym in the target text, then they are essentially guaranteed to have a perfect span extraction.

Lastly, we also compare against the attention scores without the self-alignment pretraining of entity representations, **OSLAT (No Pretrain)** trained on the RFE dataset. We did not see any significant difference when **OSLAT (No Pretrain)** on the hNLP dataset.

**5.2. Results**

Table 5 shows the micro-F1 score from our experiments compared with the three baseline methods, a breakdown that include micro-recall and micro-precision can be found in Appendix A. **OSLAT (RFE)** and **OSLAT (hNLP)** are our models trained respectively on the RFE and hNLP dataset. **OSLAT (No Pretrain)** is a baseline OSLAT trained without the pretraining step (§ 3.1) on the RFE dataset.

**Robustness to open set entity detection** As described in § 4.1, we report the results on both seen and unseen entities (during both stages of training) to evaluate our model’s performance on open set entity detection. Although we see a slight degradation, our model generally performed well for unseen entities. Since the synonym set we train on often contains paraphrases of the same entity (e.g. stuffy nose, clogged nose), we hypothesize that our model learns to interpolate within the entity representation space and generalize to paraphrases for unseen entities based on the semantic knowledge encoded in original BioBERT.

**Cross-domain evaluation** In addition to the generalization of entities, we find that OSLAT also performs well in cross-domain settings. In particular, we were surprised to see that the **OSLAT (RFE)** outperformed all other approaches in three of the four benchmarks, with the only exception being the contiguous-span hNLP examples. It is worth mentioning that most of the single-span entities in hNLP are exact matches with one of the ground-truth entity’s synonyms, making the job easier for rule-based methods. We believe
Table 5: For every approach (in columns 3–7), we evaluate their performance on both datasets, broken down by spans and also examples with seen and unseen entities, we report the Micro-F1 score along with the standard deviation of our models across 5 random seeds. Please see §5.2 for detailed insights. An even more detailed breakdown can be found in Table A.1 of the Appendix. Note that for Rule-Based and Fuzzy Matching baselines we do not report separate seen and unseen values as these methods are provided ground truth entities and their synonyms for all examples.

The superior performance of the OSLAT (RFE) is due to the nature of the training data, since RFE data contains a lot more disjoint spans and implicitly mentioned entities, the model will encounter “harder” examples during training. We, therefore, conclude that training with diverse examples is more important than in-domain examples.

Handling disjoint spans Since medical entities in colloquial language are often mentioned in different locations within the input text (e.g. “I fell on my head, and now it really hurts.”), we separately evaluate our models on subsets of the dataset consisting solely of contiguous and disjoint-span entities. In short, both of our models significantly outperform the baseline methods in the “disjoint-span” subset of both datasets, demonstrating the effectiveness of our model for extracting entities mentioned in multiple disjointed spans. The performance gain is most observed in the RFE dataset, where entities are often implicitly mentioned across the input text. The effectiveness of our approach can be attributed to the independent prediction at each token position, where regardless of the position within the input text, OSLAT is able to extract spans based on semantic similarity with the ground-truth entity representation.

Importance of pretraining Figure 2 shows the anisotropy in the BioBERT representations of medical entities before and after self-alignment pretraining. Consistent with the discussion in §3.1, without pretraining BioBERT presents large embedding anisotropy. Before pretraining, the two overlapping curves demonstrate the inability of the encoder to distinguish between synonyms and randomly sampled entities. After pretraining, the synonyms are well separated from non-synonyms. Further, we can see the performance impact in Table 5, where the model fails to learn the task without self-alignment pretraining of the encoder.

6. Conclusion

We propose a new approach for rapidly creating span annotations in medical texts. This has direct relevance for training many downstream NLP tasks such as ICD coding, medical finding extraction, and conversational
OSLAT: Open Set Label Attention Transformer for Medical Entity Span Extraction

(a) Before self-alignment pretraining

(b) After self-alignment pretraining

Figure 2: Density plot of cosine similarities between 1000 positive (synonymous) and negative (non-synonymous) entity pairs randomly sampled from $\mathcal{E}_{\text{seen}}$ (RFE). Before pretraining the encoder could not differentiate representations of entity synonyms from non-synonyms, after the pretraining there is a dramatic shift fully separating synonyms from non-synonyms.

agent training. In our approach, we rely on entity presence annotations within the text to implicitly find the corresponding spans. In order to support the large domain-specific vocabulary and varied phraseology present in the clinical text, we also propose a new model architecture: Open Set LabelAttention Transformer (OSLAT). OSLAT presents two novelties: (1) it uses the encoder not only to embed the target text but also the entity whose span needs to be extracted, (2) it is trained with a new loss, Label Synonym Supervised Normalized Temperature-Scaled Cross Entropy (LSS-NT-Xent), which allows us to train OSLAT on an open set of medical entities.

We extensively test OSLAT’s generalizability on two datasets with low entity vocabulary overlap. The first dataset is a proprietary corpus of patient-generated “Reasons for Encounter” (RFE). The second dataset is a publicly available corpus of physician-generated in-patient discharge notes from hNLP. We train and evaluate our models on both datasets and also perform the evaluation in a cross-domain scenario. We compare against two strong baselines: a rule-based entity extractor and fuzzy-string matching. We find that OSLAT significantly outperforms both baselines on the patient-generated RFE dataset, and additionally beats the baselines on the subset of hNLP dataset where entity spans are disjoint. This is because unlike rule-based and fuzzy-string matching approaches, OSLAT is able to contextualize the entire input text, even when the entity is implicitly mentioned among multiple disjoint spans.

We believe OSLAT can serve as a building block for many downstream applications. In particular, we can jointly train on LSS-NT-Xent, the loss function proposed in our work, with other learning objectives such as cross-entropy in classification to solve tasks in information retrieval, label bootstrapping, or as an intermediate component of end-to-end systems. A concrete example of IR is to enable physicians to search patient medical records for arbitrarily phrased concepts and find highlights of relevant historical discussions in the EHR.

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Appendix A. Detailed metrics breakdown

In this section, we provide a detailed breakdown of the results from Table 5, where we discuss the recall-precision trade-off between our models and the two baseline methods. From the results in Table A.1, we see that while the RFE trained OSLAT achieved higher recall against both baseline methods, the rule-based model achieved higher precision across all datasets, with near-perfect precision for contiguous span entities. This is expected since the rule-based model has access to the ground-truth entity, the predictions it makes almost always exactly match with the entity or one of its synonyms. On the other hand, OSLAT can extract implicitly mentioned entities and disjoint-spans based on semantic similarity, resulting in a higher recall across all datasets. We leave the exploration of ensembling the two methods as a potential direction for future work. Lastly, it is worth mentioning that the precision and recall trade-off for OSLAT could be manually adjusted by tuning the prediction threshold of the attention scores. However, due to the limited size of our training set, we only report the performance for a fixed threshold (0.05).

| Dataset       | Entities          | Metric (Micro) | OSLAT (RFE) | OSLAT (hNLP) | Rule-Based | Fuzzy |
|---------------|-------------------|----------------|-------------|--------------|------------|-------|
| RFE           | Continuous-Span    | Precision      | 0.69±0.01   | 0.62±0.01    | 0.59±0.01  | -     |
|               |                    | Recall         | 0.65±0.00   | 0.69±0.01    | 0.59±0.01  | -     |
|               | seen               | Precision      | 0.59±0.01   | 0.53±0.01    |            |       |
|               |                    | Recall         | 0.59±0.01   | 0.50±0.01    |            |       |
|               | all                | Precision      | 0.67±0.01   | 0.57±0.01    | 0.98       | 0.90  |
|               |                    | Recall         | 0.64±0.00   | 0.58±0.01    | 0.38       | 0.21  |
| RFE           | Disjoint-Span      | Precision      | 0.61±0.01   | 0.60±0.01    | 0.62±0.02  | -     |
|               |                    | Recall         | 0.51±0.02   | 0.54±0.01    | 0.58±0.01  | -     |
|               | seen               | Precision      | 0.61±0.01   | 0.54±0.01    |            |       |
|               |                    | Recall         | 0.61±0.01   | 0.54±0.01    |            |       |
|               | all                | Precision      | 0.67±0.01   | 0.66±0.02    | 0.53±0.02  | 0.95  |
|               |                    | Recall         | 0.64±0.01   | 0.44±0.01    | 0.12       | 0.12  |
| hNLP          | Continuous-Span    | Precision      | 0.97±0.00   | 0.92±0.01    | 0.52±0.01  | -     |
|               |                    | Recall         | 0.97±0.00   | 0.92±0.01    | 0.88±0.01  | -     |
|               | seen               | Precision      | 0.52±0.01   | 0.61±0.01    |            |       |
|               |                    | Recall         | 0.88±0.01   | 0.90±0.00    |            |       |
|               | all                | Precision      | 0.57±0.01   | 0.61±0.01    | 0.91±0.01  | 0.98  |
|               |                    | Recall         | 0.90±0.01   | 0.90±0.01    | 0.64       | 0.89  |
| hNLP          | Disjoint-Span      | Precision      | 0.47±0.02   | -            | 0.43±0.02  | -     |
|               |                    | Recall         | 0.71±0.02   | -            | 0.45±0.02  | -     |
|               | seen               | Precision      | 0.44±0.02   | 0.45±0.01    |            |       |
|               |                    | Recall         | 0.45±0.02   | 0.47±0.01    |            |       |
|               | all                | Precision      | 0.44±0.02   | 0.45±0.01    | 0.51±0.02  | 0.72  |
|               |                    | Recall         | 0.47±0.01   | 0.47±0.01    | 0.33       | 0.32  |

Table A.1: The breakdown of the micro-precision and recall performance on both datasets. We report the results for both of our models and the two baseline methods along with the standard deviation across 5 random seeds.