Extracting Appointment Spans from Medical Conversations

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Abstract

Extracting structured information from medical conversations can reduce the documentation burden for doctors and help patients follow through with their care plan. In this paper, we introduce a novel task of extracting appointment spans from medical conversations. We frame this task as a sequence tagging problem and focus on extracting spans for appointment reason and time. However, annotating medical conversations is expensive, time-consuming, and requires considerable domain expertise. Hence, we propose to leverage weak supervision approaches, namely incomplete supervision, inaccurate supervision, and a hybrid supervision approach and evaluate both generic and domain-specific, ELMo, and BERT embeddings using sequence tagging models. The best performing model is the domain-specific BERT variant using weak hybrid supervision and obtains an F1 score of 79.32.

1 Introduction

Increased Electronic Health Records (EHR) documentation burden is one of the leading causes for physician burnout (Downing et al., 2018; Collier, 2017). Although EHRs facilitate effective workflow and access to data, several studies have shown that physicians spend more than half of their workday on EHRs (Arndt et al., 2017). This leads to decreased face time with patients and reduced work satisfaction for physicians (Drossman and Ruddy, 2019; Sinsky et al., 2016). For these reasons, there has been growing interest in using machine learning techniques to extract relevant information for a medical record from medical conversations (Lin et al., 2018; Schloss and Konam, 2020).

On the other hand, research shows that approximately 23% of patients do not show up for their doctor appointments (Dantas et al., 2018). Missed appointments have a large impact on hospitals’ ability to provide efficient and effective services (Chandio et al., 2018). Studies in Callen et al. (2012) also show that a significant number of patients miss their lab appointments. Missed lab appointments can put a patient’s health at risk and allow diseases to progress unnoticed (Mookadam et al., 2016). One of the main reasons for no-shows is patient forgetfulness (Ullah et al., 2018). Mookadam et al. (2016) and Perron et al. (2013) show that proactive reminders through text messages, calls, and mobile applications are promising and significantly decrease the missed appointment rates.

In line with the aforementioned value, appointment span extraction from medical conversations can help physicians document the care plan regarding diagnostics (Dx), procedures (Px), follow-ups, and referrals. It can also directly impact a patient’s ability to keep their appointments. In this work, we investigate extracting the appointment reason and time spans from medical conversations as shown in Figure 1. The reason span refers to a phrase that corresponds to Dx, Px, follow-ups and referrals.

Figure 1: An utterance window from a medical conversation annotated with appointment reason and time spans.
The time span refers to a phrase that corresponds to the time of the appointment. To tackle this task, we collected a dataset for both reason and time spans and framed it as a sequence tagging problem. Our contributions include: (i) defining the appointment span extraction task, (ii) describing the annotation methodology for labeling the medical conversations, (iii) investigating weak supervision approaches on sequence tagging models using both generic and domain-specific ELMo and BERT embeddings, and (iv) performing error analysis to gather insights for improving the performance.

3 The Appointment Span Extraction Task

3.1 Corpus Description

Our corpus consists of human-written transcripts of 23k fully-consented and manually de-identified real doctor-patient conversations. Each transcript is annotated with utterance windows where the appointment is discussed. We have obtained a total of 43k utterance windows that discuss appointments. Of the 43k utterance windows, 3.2k utterances windows from 5k conversations are annotated with two types of spans: appointment reason and appointment time (Figure 1). We have also obtained annotations for other span types such as appointment duration and frequency, however due to infrequency of such spans, we have not included these spans in this study.

3.2 Annotation Methodology

Table 1: Examples of annotated spans.

| Span Type | Examples |
|-----------|----------|
| Reason    | follow-up, dermatologist, MRI, chemotherapy, chemo, physical, heart surgery |
| Time      | about a month, every two weeks, in the middle of August, July 2021, before the next appointment |

A team of 15 annotators annotated the dataset. The annotators were highly familiar with medical language and have significant experience in medical transcription and billing. We have distributed 3.2k utterance windows equally among 15 annotators. Each utterance window is doubly-annotated with appointment spans, and the authors resolved any conflicting annotations. We collect the spans of text describing the reason and time for only future appointments. We show examples of reason and time spans in Table 1. Overall, 6860 reason spans and 2012 time spans are annotated, and the average word lengths for reason and time spans are 1.6 and 2.3, respectively.
**Reason span** The reason span captures four types of appointments: follow-ups, referrals, diagnostics, and procedures. Phrases of body parts and substances are also captured if they are mentioned in relation to the appointment reason (e.g., ultrasound of my kidney, surgery for the heart valve). We also annotated the spans where the appointment reason is expressed in informal language (e.g., see you back for follow-ups, let’s do your blood for a blood test).

**Time span** The time span captures the time of an appointment. We also included prepositions (e.g., in two days, at 3 o’clock) and time modifiers (e.g., after a week, every year) in this span. In cases where multiple different time phrases are present for an appointment, annotators were instructed to annotate a time phrase that is confirmed by either patient or doctor, or annotate potentially valid time phrases if the discussion is ambiguous.

Due to the conversational nature, appointment reason and time are often discussed multiple times using the same phrase or a synonymous phrase (e.g., a blood test called FibroTest, Monday or Monday next week). To maintain consistency across different conversations, annotators were instructed to mark all occurrences of the span.

### 3.3 Methods

To account for the limited set of annotations, we employed weak supervision approaches. We specifically used inaccurate supervision, incomplete supervision (Zhou, 2018) and developed a hybrid approach that utilizes both inaccurate and incomplete supervision.

**Inaccurate Supervision** Inaccurate supervision is a scenario where the training labels provided are not always the ground-truth; in other words, the training labels suffer from errors. We take advantage of off-the-shelf tools such as UMLS and spaCy (Honnibal et al., 2020) to automatically annotate reason and time spans. For the reason span, we perform a dictionary lookup in UMLS vocabularies and extract any span with a semantic type belonging to Dx, Px, and body parts. For the time span, we use spaCy’s named entity recognition (NER) model to extract spans belonging to time and date. To reduce the inaccuracies, we included only the utterance windows with at least one reason phrase and one time phrase. Using this approach, we obtained 20k utterance windows with both appointment reason and time spans.

**Incomplete Supervision** Incomplete Supervision refers to a scenario where only a small subset of data has annotated labels. For this scenario, we use 2.5k conversations from manual span annotated corpus conversations, which resulted in 1292 utterance windows.

**Hybrid Supervision** In this approach, we apply both inaccurate and incomplete supervision techniques sequentially. To avoid catastrophic forgetting (McCloskey and Cohen, 1989), the models are first trained with inaccurate supervision and then fine-tuned with incomplete supervision.

We use a 85:15 split of the remaining 1844 manual span annotated utterance windows for testing and validation purposes. To make the test dataset more difficult, we used a weighted sampling technique in which each appointment span is weighted by the inverse probability of it being sampled.

### 4 Models

In this section, we briefly describe our two models that use variants of contextualized embeddings namely, ELMo (Peters et al., 2018) and BERT (Devlin et al., 2018).

#### 4.1 ELMo-based CRF

Our model is a 2-layer BiLSTM network using GloVe word embeddings and a character-based CNN representation trained with CRF loss. Similar to the approach taken in Peters et al. (2018), our model is enhanced by concatenating a weighted average of ELMo embeddings with GloVe and character embeddings. We next describe the two variants of ELMo models we use.

**ELMo** The original ELMo model is pre-trained on generic language corpora using the 1-Billion Words dataset (Chelba et al., 2013).

**BioELMo** BioELMo (Jin et al., 2019) is a biomedical variant of ELMo trained on 10M recent abstracts (2.46B tokens) from PubMed.

#### 4.2 BERT-based classifier

Similar to the approach taken in Devlin et al. (2018), we use a token level classifier instead of a CRF layer and fine-tune variants of the BERT model. We next describe the variants of BERT models we use.
BERT The original BERT model is trained on BooksCorpus (Zhu et al., 2015) and English Wiki.

BioBERT BioBERT (Lee et al., 2019) further pre-trains the BERT-base model on a large corpus of PubMed abstracts containing 4.5B words.

4.3 Experiment details

| Model     | Embedding Size | Learning rate |
|-----------|----------------|---------------|
| ELMo variants | 1024            | 1e-3          |
| BERT variants | 768             | 3e-5          |

Table 2: Experiment configurations for the models.

The experiment configuration for ELMo and BERT variants used in our experiments is shown in Table 2. Both ELMo and BERT variants use an uncased vocabulary. The span labels are represented using the IOB2 tagging scheme (Sang and Veenstra, 1999).

5 Evaluation

To evaluate our models, we measure micro-averaged Precision, Recall, and F1 of reason and time spans on the test dataset (Table 3). Both ELMo and BERT variants performed similarly with inaccurate supervision owing to the noisy nature of the inaccurate supervision. With the incomplete supervision approach, the performance improved considerably, ranging from 49% in ELMo to 60% in BioBERT. Both BioELMo and BioBERT gained more than the ELMo and BERT variants, respectively. However, with hybrid supervision, both the ELMo variants benefited most and achieved similar performance nullifying the advantage of the in-domain pre-training of BioELMo.

On the other hand, the BERT variants showed a minor improvement with hybrid supervision. The BERT variants consistently performed better than ELMo variants, and the domain-specific pre-training has only a minor impact on BERT when compared to ELMo. Overall, the proposed hybrid supervision approach has consistently improved performance across all model variants and the results show that augmenting the training data with inaccurate supervision can improve the performance.

In order to assess performance at each span type, we chose the best performing BioBERT-hybrid model. For both span types precision was lower than recall (Table 4) suggesting a higher percentage of false positives than false negatives.

| Span Type | Precision | Recall | F1  | # Occurrences |
|-----------|-----------|--------|-----|---------------|
| Reason    | 80.52     | 84.27  | 82.36 | 3459 (3687)   |
| Time      | 66.24     | 72.02  | 69.01 | 997 (1163)    |

Table 3: Performance of BioBERT-hybrid model and the number of occurrences of each span type in ground truths and predictions respectively.

6 Error Analysis

| Error Type                      | Reason | Time |
|---------------------------------|--------|------|
| Correct Label - Overlapping Span| 6.83   | 14.61|
| Wrong Label - Correct Span      | 0.08   | 0.08 |
| Wrong Label - Overlapping Span  | 0.13   | 0.77 |
| Complete False Positive         | 13.77  | 23.12|
| Complete False Negative         | 8.03   | 11.41|

Table 5: Percentage of error types on the test set using the BioBERT-hybrid model.

To better understand the errors in predictions, we computed percentages of different types of errors (Table 5). The cases where the model predicted the right label but with an overlapping span (Correct Label-Overlapping Span) are mainly due to inconsistencies in annotations. The primary source of these inconsistencies is when annotators missed annotating a prepositional phrase or a time modifier phrase in the time span. Wrong label errors (Wrong Label - Correct Span, Overlapping Span) are minimal, suggesting that the model distinguishes between the time and reason spans very well.
Complete false positives and false negatives are the significant sources of errors for both reason and time spans and our qualitative analysis suggests that these cases often happen when multiple reason phrases and time phrases are present in the utterance window, but only a subset of them are valid. Because the task actually involves two different aspects, extracting reason and time mentions and spotting their confirmation clues, it may be difficult for the trained system to select exactly the confirmed reason or time mentions without explicitly modeling their relations. The ambiguity due to the oral nature of the conversations also makes it difficult to spot the confirmation clues.

Notably, we observe that the portion of complete false positives for the time span is significantly higher than reason spans. For example, the conversation in Figure 1 discusses several options for the appointment time, but the patient finally settles for Monday. The model often struggles with such cases and also extracts time mentions that are not confirmed. Using SpaCy’s NER, we find that 87% of these errors occurred when multiple time phrases are present, but not all are valid. The model may have difficulty with these cases because they amount to only 21.3% of the manually annotated time spans. Further, the annotated time spans are infrequent by a factor of three than the reason spans. These reasons explain why the F1 score on time span is significantly lower than the reason span.

7 Conclusion

In summary, we defined a novel task of extracting appointment spans from medical conversations, described our annotation methodology, and employed three weak supervision approaches to account for the limited set of annotations. Our proposed hybrid weak supervision approach showed improvement across all our experiments. Finally, our error analysis shows that a significant portion of the errors comes from false positives where the model has difficulty in identifying the correct span when multiple appointment reason or time mentions are present. In future work, we plan to study the data augmentation approaches as well as joint entity and relation extraction approaches to improve performance on difficult examples. We also plan to study the generalization of this work to automatic transcripts, whose transcription error rate may challenge entity detection.

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