# Generating SOAP Notes from Doctor-Patient Conversations

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#### **Abstract**

Following each patient visit, physicians must draft detailed clinical summaries called SOAP notes. Moreover, with electronic health records, these notes must be digitized. For all the benefits of this documentation the process remains onerous, contributing to increasing physician burnout. In a parallel development, patients increasingly record audio from their visits (with consent), often through dedicated apps. In this paper, we present the first study to evaluate complete pipelines for leveraging these transcripts to train machine learning model to generate these notes. We first describe a unique dataset of patient visit records, consisting of transcripts, paired SOAP notes, and annotations marking noteworthy utterances that support each summary sentence. We decompose the problem into extractive and abstractive subtasks, exploring a spectrum of approaches according to how much they demand from each component. Our best performing method first (i) extracts noteworthy utterances via multi-label classification assigns them to summary section(s); (ii) clusters noteworthy utterances on a per-section basis; and (iii) generates the summary sentences by conditioning on the corresponding cluster and the subsection of the SOAP sentence to be generated. Compared to an end-to-end approach that generates the full SOAP note from the full conversation, our approach improves by 7 ROUGE-1 points. Oracle experiments indicate that fixing our generative capabilities, improvements in extraction alone could provide (up to) a further 9 ROUGE point gain.

## 1 Introduction

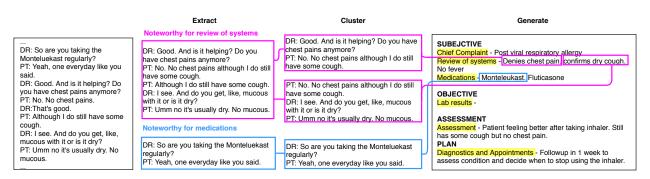


Figure 1: Workflow of our best performing approach involving extraction and clustering of noteworthy conversation utterances followed by abstractive summarization of each cluster (fictitious data)

Electronic health records (EHR) play a crucial role in the short and long-term coordination of patient care, public health, and clinical medical research. A patient's EHR contains various structured and unstructured data documenting their condition, including lab tests, treatments, diagnoses, billing codes, and the free-form and semi-structured notes captured by various providers in the health system. However, populating the data in EHRs places a massive burden on healthcare providers. Studies show that on an average, for every hour

of time that physicians spend seeing patients, they spend about 45 minutes on EHR documentation [Sinsky et al., 2016]. Often, physicians are so overloaded with work that they must complete the documentation outside of work hours, contributing to increased stress and burnout [Gardner et al., 2018]. Additionally, when physicians document visits too long after their conclusion, imperfect recollection may result in non-comprehensive or even erroneous documentation. Hence, automatic systems that improve the efficiency of EHR documentation can potentially mitigate a critical pain point in the medical profession.

After seeing a patient, doctors typically document the encounter in SOAP notes, semi-structured written accounts containing four sections: (S)ubjective information reported by the patient; (O)bjective observations, e.g., lab results; (A)ssessments made by the doctor (typically, the diagnosis); and a (P)lan for future care, including diagnostic tests, medications, treatments, and follow-up protocol. Each section is further divided into subsections giving it a finer substructure. For example, the subjective section contains 9 subsections, e.g., *chief complaint* and *past medical history*. A visit may not have information relevant to each subsection, and thus some of the subsections may be empty. The fraction of times a subsection is populated varies widely: *allergies* is the sparsest (present in about 4% of notes), *chief complaint* is the most frequently observed (present in every note).

In this work, we propose and compare a spectrum of machine learning approaches that leverage transcripts of conversations that take place between physicians and patients during a visit, to automatically generate structured SOAP notes. Our work builds on a unique resource: a corpus consisting of thousands of recorded clinical conversations with associated SOAP notes created by a work force trained in the official style of SOAP note documentation. Compared to common abstractive summarization benchmarks like CNN/Dailymail [Nallapati et al., 2016], Newsroom [Grusky et al., 2018], and AMI meeting corpus [Carletta, 2007], with short summaries (55, 27, and 18 words on average, respectively), our SOAP notes are much longer (320 words on average). The dual challenges of (i) generating coherent summaries much longer than those demanded by traditional benchmark tasks; and (ii) handling specialized medical terminology; make this task especially challenging.

However, our problem also offers useful structure in the form of *additional annotations* that (i) segment each note into 15 subsections (not every subsection features in every note); and (ii) identify, for each sentence in the note, a set of corresponding *supporting utterances* in the conversation. Our proposed summarization algorithms leverage these annotations to achieve better performance on the task.

Decomposing the problem into *extractive* and *abstractive* subtasks, we explore a spectrum of approaches that vary in terms of how they allocate work among the subtasks: (i) the *extraction* module does nothing, placing the full burden of summarization on an end-to-end *abstractive* module; (ii) the extractive module extracts all noteworthy utterances and the decoder is trained only on these utterances; (iii) the extractive model extracts per-section utterances and the decoder generates each subsection, conditioned only on those utterances predicted to support sentences in that subsection; (iv) the extractive module not only extracts per-subsection noteworthy utterances but additionally clusters them—in this approach, the decoder produces a single sentence at a time, each conditioned upon a single cluster of supporting sentences. Notably, our data contains annotations for extraction, allowing us both to directly train the extraction models and to evaluate the decoding modules in an oracle setting (assuming perfect extraction).

Our best-performing model (iv) demands the most of the extractive module. Interestingly given oracle per-section noteworthy utterances, a simple proximity-based clustering heuristic performs nearly as well as the ground-truth groupings by most metrics, even though the ground truth groupings are not always localized. In addition to achieving the highest ROUGE scores, this approach confers some additinoal benefits. For example, it localizes the precise sentences upon which each SOAP note sentence depends, enabling physicians to (i) verify the correctness of each sentence and (ii) to improve the draft by highlighting sentences (vs revising the text directly).

Our best performing model for extraction leverages a hierarchical model in which a pretrained BERT model encodes each sentence and then a bidirectional LSTM classifies each utterance as noteworthy or not

for each subsection (multilabel classification). In the abstractive phase, our best-performing model builds on the pointer-generator model due to See et al. [2017], additionally conditioning on the identity of the subsection to be generated.

In summary, we contribute the following:

- The first pipeline for drafting entire SOAP notes from doctor-patient conversations.
- An exploration of methods of modularizing the task into extractive and an abstractive components, demonstrating the benefits of shifting maximal burden to extraction.
- A rigorous quantitative evaluation of several strong approaches to each subtask.
- A qualitative evaluation of the produced SOAP notes, characterizing the errors that both models make, and the impact of per-section conditioning.

## 2 Related Work

Summarization is a well-studied problem in the field of natural language processing [Nenkova et al., 2011]. Traditionally, more works focused on purely extractive approaches [Erkan and Radev, 2004, Wong et al., 2008, Kågebäck et al., 2014]. Some early abstractive approaches used sentence compression [Filippova, 2010, Berg-Kirkpatrick et al., 2011, Banerjee et al., 2015] or relied on templates to generate summaries [Wang and Cardie, 2013]. Following the advent of neural sequence models [Sutskever et al., 2014], recent approaches have focused on neural generation of abstractive summaries [Rush et al., 2015, Nallapati et al., 2016]. Some gains have been made by leveraging pointer mechanisms [Vinyals et al., 2015] that can copy words from the input, in addition to generating words via the softmax. Pointer-generator approaches have consistently outperformed others by most standard metrics [See et al., 2017, Celikyilmaz et al., 2018].

Many papers address the summary of news articles, due to the wide availability of large public datasets [Chen et al., 2016, Grusky et al., 2018]. In comparison, fewer works summarize conversations, owing to the conparatice paucity of public datasets. A few smaller datasets exist [Carletta, 2007] and some large datasets have been publicly released recently [Gliwa et al., 2019]. Example works in this domain include summarizing conversations between a tourist and a clerk at an information center [Yuan and Yu, 2019], summarizing customer service conversations at a cab company [Liu et al., 2019a], and summarizing business meetings [Wang and Cardie, 2013, Goo and Chen, 2018, Zhu et al., 2020].

A two-step approach of extraction of important content followed by abstractive summarization has been used for summarizing long documents such as scientific papers [Subramanian et al., 2019]. Gehrmann et al. [2018] proposed a modification to the pointer-generator model, where important words are pre-selected from news articles for copying into the summary while generating it. Chen and Bansal [2018] proposed a pipeline where an extractor trained using reinforcement learning is used to select important sentences from a news article and a summary is generated by paraphrasing each sentence. In contrast, our extractive module focuses on clustering together multiple turns of conversation that are related to each other.

Several prior works generate summaries conditioned on a desired topic. Conroy et al. [2006] produce extractive summaries from multiple documents conditioned on the topic in an input query. Krishna and Srinivasan [2018] propose a method to generate multiple summaries of a given news article conditioned on various topics.

Finally, there has also been work on summarizing medical conversations. Lacson et al. [2006] proposed a method for extractive summarization of conversations between patients and nurses. In the most similar related work, Liu et al. [2019b] investigate abstractive summarization of patient-nurse conversation with the aim of capturing 9 predefined symptoms of interest, using a modified pointer-generator model. This

task is similar to generating the *review of systems* subsection of a SOAP note, one of 15 subsections that we investigate.

#### 3 Dataset

Our dataset consists of transcripts from real-life patient-physician visits. For each visit, we have a human-generated transcript of the conversation. The utterances are segmented by speaker and each utterance has a timestamp. The average conversation lasts 9 minutes and 26 seconds and consists of about 1500 spoken words (Figure 2). Along with the conversation, we have a human-drafted SOAP note created by trained, professional annotators. The dataset consists of 6862 visits consisting of 2732 cardiologist visits, 2731 visits for family medicine, 989 interventional cardiologist visits, and 410 internist visits. The dataset is divided into train, validation and test splits of size 6270, 500 and 592 respectively.

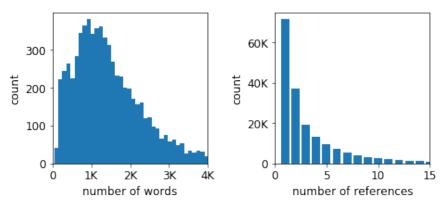
Our annotated SOAP notes contain (up to) 15 subsections, each of which may contain multiple sentences. The subsections vary in length. The *Allergies* subsections is most often empty, while the *Assessment* subsection contains 5.16 sentences on average. The average SOAP note contains 27.47 sentences (Table 1). The different subsections also differ in the style of writing. The *Medications* subsection usually consists of bulleted names of medicines and their dosages, while the *Assessment* subsection typically consists of full English sentences.

Section	Subsection	Mean length	Total mean length
	Family Medical History	0.23	
	Past Surgical History	0.58	
	Review of Systems	3.65	
	Chief Complaint	2.17	
Subjective	Miscellaneous	2.81	
	Allergies	0.06	
	Past Medical History	2.93	
	Social History	0.27	
	Medications	3.74	16.44
Objective	Immunizations	0.11	
Objective	Laboratory and Imaging Results	2.27	2.38
Assessment	Assessment	5.16	5.16
Dlass	Diagnostics and Appointments	1.65	
Plan	Prescriptions and Therapeutics	1.75	3.40
Other	Healthcare Complaints	0.09	0.09

Table 1: Different sections and subsections in a SOAP note in our dataset with mean lengths measured in terms of number of sentences

Each sentence in the SOAP note is also annotated with utterances from the conversation which are supporting evidence for that SOAP note sentence. A sentence in the SOAP note can have one or more supporting utterances, and on an average there are 3.85 supporting utterances per SOAP note sentence. However, the most common number of supporting utterances for a sentence is just one (Figure 2). We refer to supporting utterances as *noteworthy* utterances in other parts of this paper.

Each SOAP note sentence is also tagged with various subsection-specific tags. For example, medications mentioned in the corresponding subsection are annotated with dosage and frequency of use. Similarly,



(a) Number of words per conversation (b) Number of reference utterances per SOAP note sentence

Figure 2: Distribution of number of words in physician-patient conversations and the number of evidence utterances referred by a sentence of a SOAP note

sentences in *Review of Systems* section contain categorical labels describing the symptom being checked and the patient's response mentioned as confirmation or denial. Although we do not use such tags in this work, but they can be useful for future work. In our work we deal with the more granular subsections rather than the coarse sections of SOAP notes. However, we refer to the subsections as 'sections' in the remainder of the work for the sake of simplicity.

## 4 Methods

We detail our four key approaches for generating SOAP notes in Algorithms 1,2,3 and 4. The four algorithms are designed to decompose the summarization problem into two different phases—extractive and abstractive, with each method shifting work among the two phases of the summarization pipeline.

Algorithm 1 takes an end-to-end approach, generating the entire SOAP note from the entire conversation in one shot. Algorithm 2 first predicts all the noteworthy utterances in the conversation (without regard to the associated section) and then generates the entire SOAP note in one shot from only those utterances. Algorithm 3 generates the SOAP note by generating one section at a time, using only the extracted noteworthy utterances that are predicted to be relevant to that section. Algorithm 4 attempts to group together the set of noteworthy utterances associated with each summary sentence. Here, we cluster together section-specific noteworthy utterances, and then generate each section one sentence at a time, conditioning each on the associated cluster of sentences.

Each of these pipelines still leaves open many choices of the specific models to employ for each subtask. We try several different models for each of the subtasks. For the abstractive modules of Algorithm 1 and Algorithm 2, denoted by  $\mathcal{F}_1$  and  $\mathcal{F}_2$  respectively, we use a pointer generator network. The abstractive modules of Algorithm 3 ( $\mathcal{F}_3$ ) and Algorithm 3 ( $\mathcal{F}_4$ ) are modelled as conditioned pointer-generator networks that condition on the section for which the summary is to be generated. We describe these models in the next section.

For the utterance extractor used in Algorithm 2, denoted by  $\mathcal{E}_1$ , we train a logistic regression baseline and a hierarchical LSTM model. Algorithm 3 and Algorithm 4 both use the same extractor denoted by  $\mathcal{E}_2$  that predicts whether a given utterance is noteworthy with respect to each section. For  $\mathcal{E}_2$ , we experiment with logistic regression, a hierarchical LSTM model, and a BERT-LSTM with multi-label output. We describe the architecture of the hierarchical LSTM and BERT-LSTM models in the next section.

## Algorithm 1: FullConversationToFullSummary

 $\mathbf{U} \leftarrow \text{sequence of utterances from conversation}$ 

$$\textbf{N} \leftarrow \mathcal{F}_1(\textbf{U})$$

return N

## Algorithm 2: SupportingUtterancesToFullSummary

 $U \leftarrow$  sequence of utterances from conversation

$$\mathbf{S} \leftarrow \mathcal{E}_1(\mathbf{U})$$

$$\mathbf{N} \leftarrow \mathcal{F}_2(\mathbf{S})$$

return N

#### Algorithm 3: SectionwiseSummaryGeneration

 $U \leftarrow$  sequence of utterances from conversation

 $\mathbf{P} \leftarrow$  sequence of sections in a SOAP note

 $\mathbf{for}\ section \in \mathbf{\textit{P}}\ \mathbf{do}$ 

$$\mathbf{S}_{section} \leftarrow \mathcal{E}_2(\mathbf{U}, section)$$
  
 $\mathbf{N}_{section} \leftarrow \mathcal{F}_3(\mathbf{S}_{section}, section)$ 

end

$$N \leftarrow \bigcup_{\mathit{section} \in P} N_{\mathit{section}}$$

return N

## Algorithm 4: SentencewiseSummaryGeneration

 $U \leftarrow$  sequence of utterances from conversation

 $\mathbf{P} \leftarrow$  sequence of sections in a SOAP note

 $\mathbf{for}\ section \in \mathbf{\textit{P}}\ \mathbf{do}$ 

$$\boldsymbol{S}_{section} \leftarrow \mathcal{E}_2(\boldsymbol{U}, section)$$

$$\mathbf{C}_{section} \leftarrow \mathcal{C}(\mathbf{S}_{section})$$

sort  $C_{section}$  using timestamp of earliest supporting utterance in each cluster

$$N_{section} \leftarrow \phi$$

for 
$$Z_{cluster} \in C_{section}$$
 do

$$\mathbf{S}_{cluster} \leftarrow \mathcal{F}_4(\mathbf{Z}_{cluster}, section)$$
  
 $\mathbf{N}_{section} \leftarrow \mathbf{N}_{section} \cup \mathbf{S}_{cluster}$ 

end

end

$$N \leftarrow \bigcup_{\mathit{section} \in P} N_{\mathit{section}}$$

return N

For the clustering module used in Algorithm 4, denoted as  $\mathcal{C}$ , . For  $\mathcal{C}$  we use a clustering heuristic that groups together supporting utterances whose distance from each other is below a threshold  $\tau$ . Since each cluster necessarily produces one sentence in the SOAP note, having too many or too few clusters can make the SOAP note too long or short respectively. Therefore, the value of the hyperparameter  $\tau$  is tuned on the validation set to produce approximately the same number of clusters over the entire validation data set as present in the ground truth. In the dataset, approximately 38% of clusters of noteworthy utterances are singleton (Figure 2), and among the remaining clusters containing multiple noteworthy utterances, all of the utterances are contiguous in 82% of the cases. Hence this clustering heuristic works quite well. To verify it quantitatively, we performed an experiment where the heuristic is used to cluster the oracle noteworthy utterances for each section, and then the clusters are used to generate the SOAP notes as outlined in Algorithm 4. The performance achieved on all ROUGE metrics was only about 1 point below the highest achievable score (mentioned in Table 2) using oracle cluster annotations .

## 5 Model Architectures

#### 5.1 Pointer-Generator Network

We use the pointer-generator network as proposed by See et al. [2017] for Algorithm 1 and 2. The pointer-generator network embeds the input sequence of words  $\{w_1, w_2, ... w_n\}$  into learnt embeddings  $\{e_1, e_2, ... e_n\}$  via a lookup table. Then these are passed through a bidirectional LSTM encoder to get the input encodings.

$$\{h_1, h_2, ..., h_n\} = \text{BiLSTM}_{\text{enc}}(\{e_1, e_2, ..., e_n\})$$
 (1)

The output is generated word by word in multiple timesteps using an LSTM decoder augmented with an attention mechanism. At each timestep, the state  $s_t$  of the decoder LSTM<sub>dec</sub> is used to calculate an attention distribution  $a^t$  across the input words. The attention distribution is used to take a weighted average of the input encodings to give a context vector  $h_t^*$ , which is then passed through linear layers with softmax activation to generate a distribution  $P_{\text{vocab}}$  over words to be generated next.  $W_h$ ,  $W_s$ ,  $b_{\text{attn}}$ , V', V, b, b' and v are parameters that are learnt.

$$e_i^t = v^T \tanh(W_h h_i + W_s s_t + b_{attn})$$
 (2)

$$a^t = \mathtt{softmax}(e^t)$$
 (3)

$$\boldsymbol{h}_t^* = \sum_{i=1}^n \boldsymbol{a}_i^t \boldsymbol{h}_i \tag{4}$$

$$P_{\text{vocab}} = \text{softmax}(V'(V[s_t; h_t^*] + b) + b')$$
 (5)

While  $P_{\text{vocab}}$  is the probability of generating a new word, the model also calculates a distribution  $P_{\text{copy}}$  over words to be copied from the source text. The probability of copying a word w from the source text at timestep t is given by the aggregate attention received by all occurrences of w in the input.

$$P_{\text{copy}} = \sum_{i=1}^{n} \boldsymbol{a}_{i}^{t} \mathbb{I}(w_{i}, w), \tag{6}$$

where  $\mathbb{I}$  is the indicator function that gives 1 if both its arguments are equal and 0 otherwise. The output of the model is a weighted combination of  $P_{\text{vocab}}$  and  $P_{\text{copy}}$ . The affinity of the model's output towards

generating a new word versus copying a word from the input is given by  $p_{\rm gen}$  computed as in equation 7, where  $w_{\rm s}, w_{\rm h^*}, w_{\rm x}, b_{\rm gen}$  are learnt parameters, and  $x_t$  is the input to LSTM<sub>dec</sub> at time step t, which is a concatenation of  $h_{t-1}^*$  and the word embedding for the previous timestep's output passed through a linear layer. The final output is the word distribution P(w) as given in Equation 8.

$$p_{\text{gen}} = \sigma(\boldsymbol{w}_{\text{h}^*}^T \boldsymbol{h}_t^* + \boldsymbol{w}_{\text{s}}^T \boldsymbol{s}_t + \boldsymbol{w}_{\text{x}}^T \boldsymbol{x}_t + \boldsymbol{b}_{\text{gen}})$$
(7)

$$P(w) = p_{gen}P_{vocab}(w) + (1 - p_{gen})P_{copy}(w)$$
(8)

#### 5.2 Section-conditioned Pointer-Generator Network

We use a modification of pointer-generator network for algorithms 3 and 4, where extra information is input to the network in the form of the section for which the summary is being generated. Let z represent the section for which the summary is being generated. The network uses a new lookup table to embed the section into an embedding  $e^z$ . The section embedding is concatenated to each input word embedding fed into the encoder as given in equation 9. The section embedding is also appended to the inputs of the decoder LSTM in the same fashion.

$$\{h_1, h_2, ..., h_n\} = \text{BiLSTM}_{enc}(\{[e_1; e^z], [e_2; e^z], ...[e_n; e^z]\})$$
 (9)

#### 5.3 Hierarchical LSTM classifier

We use a hierarchical LSTM classifier to classify conversation utterances as noteworthy or not. For algorithm 2, we use it as a binary classifier, and for algorithms 3 and 4, we use it as a multi-label classifier where an utterance can be classified as noteworthy or not with respect to each among the multiple sections of the SOAP note.

Given an input conversation with utterances  $\{u_1, u_2, ..., u_n\}$ , where each utterance is represented by a sequence of words  $u_j = \{w_1, w_2, ..., w_{n_j}\}$ , we first compute a representation  $h_j$  of each utterance  $u_j$ . This is done by embedding the words of each  $u_j$  into embeddings  $\{e_1, e_2, ..., e_{n_j}\}$  using an embedding lookup table. We calculate each utterance's representation  $h^*$  as the meanpooled output of a bidirectional LSTM given the embeddings as the input.

$$\{h_1, h_2, ..., h_{n_i}\} = BiLSTM_{utterance}(\{e_1, e_2, ..., e_{n_i}\})$$
 (10)

$$\boldsymbol{h}^* = \sum_{i=1}^{n_j} \boldsymbol{h}_i \tag{11}$$

Given the representations for the sequence of utterances as  $\{h_1^*, h_2^*, ..., h_n^*\}$ , we pass them again through a bidirectional LSTM to incorporate the context across different utterances before predicting whether each utterance is noteworthy or not. The resulting output representation  $z_i$  for each utterance is passed through a sigmoid-activated linear layer to get the output  $p_i$ . In Algorithm 2, where we are just trying to predict whether an utterance is noteworthy (for any section),  $p_i$  is a scalar. For Algorithms 3 and 4,  $p_i$  is a vector, where  $p_i^j$  represents the probability of it being a noteworthy utterance with respect to the  $j^{th}$  section.

$$\{z_1, z_2, ..., z_n\} = BiLSTM_{context}(\{h_1^*, h_2^*, ..., h_n^*\})$$
 (12)

$$o_i = W_{\mathsf{proj}} z_i \tag{13}$$

$$\boldsymbol{p}_i = \sigma(\boldsymbol{o}_i) \tag{14}$$

#### 5.4 BERT-LSTM Classifier

Finally, we also implement a BERT-LSTM classifier to categorize utterances into different SOAP note sections. Its usage with different summarization algorithms mirrors that of the hierarchical LSTM.

Each token in the utterance is passed through the BERT encoder to obtain a contextualized representation, i.e.,  $[h_{i1}^{\text{BERT}}, h_{i2}^{\text{BERT}}, ..., h_{im}^{\text{BERT}}]$ , where  $h_{ij}$  represents BERT-encoding of  $j^{th}$  token of  $u_i$ . The utterance-level representation is obtained by MEAN pooling the contextualized token embeddings.

$$\boldsymbol{h}_{i}^{\text{BERT}} = \frac{1}{m} \sum_{j=1}^{m} \boldsymbol{h}_{ij}^{\text{BERT}}$$
 (15)

**Side Information:** Apart from encoding the text of an utterance, we also make use of side information like speaker identity and utterance's position in the conversation.

- 1. **Speaker Identity:** Conversations usually involve multiple speakers, each of them playing a specific role in the goal of that interaction. For instance, diagnosis and medications are likely to be narrated by the doctor rather than the patient. We provide this additional signal to allow our model to condition its representations on the speaker of the utterance.
- 2. **Position in Conversation:** Clinical Conversations follow a pattern where SOAP note sections like symptoms, past medical history and chief complaints are more likely to be discussed earlier in the dialog whereas medications and diagnosis are presented in the middle or around the culmination. We include positional information in our model by partitioning all the utterances in a conversation into k equal parts based on their position. For instance, if k = 5 and number of utterances is 20 then initial 4 belongs to  $0^{th}$  partition and the next 4 belongs to  $1^{st}$  partition and so on.

Both signals are mapped to separate d-dimensional embeddings, which are concatenated with the utterance embedding, and learned during training  $\boldsymbol{h}_i^* = [\boldsymbol{h}_i^{\text{BERT}}, \boldsymbol{h}_i^{\text{SPK}}, \boldsymbol{h}_i^{\text{POS}}]$ . The resulting utterance-level feature vectors are passed through a bidirectional LSTM to incorporate context across different utterances. Similar to the hierarchical LSTM, the resulting output representation  $z_i$  is passed through a fully-connected layer followed by a sigmoid layer to get the final logit  $p_i$ .

Domain-specific supervised fine-tuning of BERT encoder has been shown to significantly improve performance in a variety of tasks (Devlin et al. [2018]). Following this, we perform end-to-end fine-tuning of the BERT-LSTM on our training dataset.

#### 5.5 Implementation details

For the hierarchical LSTM classifier, we again have a word embedding size of 128 and both bidirectional LSTMs have a hidden size of 256. For the BERT-LSTM classifier, the BERT embeddings are initialized from bert-base-uncased (768 dimensions). LSTMs in either direction have a hidden-layer of size 512. Speaker and Position (k = 4) information are initialized as 8 and 4 dimensional learnable embedding vectors respectively and the entire model is optimized end-to-end with a learning-rate of 0.001. The pointer-generator models

have a word embedding size of 128, and a hidden size of 256 for both the encoder and the decoder. The section embeddings used in section-conditioned pointer-generator network have 32 dimensions.

Beam search was used to generate the output for both these models with a beam size of 4. For the vanilla pointer-generator model used in Algorithm 1 and 2, we modified the beam search procedure to make sure that all the SOAP note sections are generated in proper order. To do this, we start the beam search procedure by feeding the header of the first section (chief complaint). Whenever the model predicts a section header as next word and it shows up in a beam, we check if it is the next section to be generated and if it is not, we replace it with the correct next section's header. Any end-of-summary tokens generated before all the sections have been produced are also replaced similarly. Note that producing all sections simply means that the headers for each section have to be generated, and a section can be left empty by starting the next section immediately after generating the previous section header.

## 6 Results

## 6.1 Quantitative results

We experimented with two baselines. The first is a random baseline where given a conversation, we output a randomly chosen SOAP note from our training set as the output. We run this experiment 25 times and report the average ROUGE scores obtained. The standard deviation was less than 0.003 for each variant of ROUGE. The second one is an extractive baseline where we present all the noteworthy utterances from the conversation as the SOAP note. We use oracle noteworthy utterances for this baseline to get the best ROUGE scores that can be achieved by having an output that has all the correctly chosen information from the conversation, but is not expressed in the form and language of a SOAP note. Both baselines give similar performance and are vastly outperformed by all algorithms described in Section 4.

We train the abstractive summarization models for algorithms 2, 3 4 with the ground truth noteworthy utterances as inputs. While testing, we have to input predicted noteworthy utterances since we do not know apriori which utterances are noteworthy in a new unseen conversation. However, to get an estimate of the upper bound on the performance we can get when our noteworthy utterance classifiers are perfect, we test our models with oracle noteworthy utterances. We see that all three algorithms that make use of noteworthy utterances outpeform Algorithm 1 which takes an end-to-end approach to generate the full SOAP note from the full conversation. The ROUGE scores increase monotonically from Algorithm 1 to Algorithm 4. The best model using noteworthy utterances improves over Algorithm 1 by around 16, 14 and 23 points on ROUGE-1, ROUGE-2 and ROUGE-L respectively, demonstrating the performance gains that can be made with perfect noteworthy utterance classifiers.

We experiment with four models to predict noteworthy utterances. The first is a logistic regression baseline modeled on TF-IDF transformed bag of words representation of each utterance. We use separate logistic regression models for each section of the SOAP note in Algorithm 3 and Algorithm 4. The second model uses a bidirectional LSTM to encode each utterance as the meanpooled representation of its words, and using it jointly predicts the probabilities of it being a noteworthy utterance for each of the SOAP note sections. These two models make the predictions for each utterance independently and do not take the context present in the sequence of utterances into account. To take the context into account, we use a hierarchical LSTM architecture as descibed in section 5.3. We see that there is a uniform trend in all the classification metrics (Table 3) with the bidirectional LSTM model performing slightly better than logistic regression, and the hierarchical LSTM performing much better than both. This shows that for predicting the noteworthiness of an utterance, it helps to incorporate the context from neighboring utterances.

As expected, the performance on the SOAP note generation task drops when using predicted noteworthy utterances instead of oracle ones(Table 2). When using logistic regression model for extracting noteworthy utterances, we see that Algorithm 2 and 3 no longer do better than Algorithm 1. However, generating the

Method	ROUGE-1	ROUGE-2	ROUGE-L
RANDOM NOTE BASELINE	0.3164	0.1000	0.2239
Oracle Supporting Sentences	0.3225	0.1127	0.2053
FullConversationToFullSummary	0.4894	0.2423	0.3548
SupportingUtterancesToFullSummary (Oracle)	0.5289	0.2692	0.3846
SectionwiseSummaryGeneration (Oracle)	0.5825	0.3294	0.4876
SENTENCEWISESUMMARYGENERATION (ORACLE)	0.6524	0.3891	0.5824
SupportingUtterancesToFullSummary (LR)	0.4750	0.2274	0.3419
SECTIONWISESUMMARYGENERATION (LR)	0.4880	0.2385	0.3562
SENTENCEWISESUMMARYGENERATION (LR)	0.5289	0.2671	0.3799
SupportingUtterancesToFullSummary (LSTM)	0.4929	0.2402	0.3524
SectionwiseSummaryGeneration (LSTM)	0.4926	0.2414	0.3591
SENTENCEWISESUMMARYGENERATION (LSTM)	0.5349	0.2736	0.3860
SupportingUtterancesToFullSummary (HI-LSTM)	0.4972	0.2441	0.3583
SectionwiseSummaryGeneration (HI-LSTM)	0.5119	0.2529	0.3774
SENTENCEWISESUMMARYGENERATION (HI-LSTM)	0.5561	0.2873	0.4072
SectionwiseSummaryGeneration (BERT-LSTM)	0.5222	0.2636	0.3920
$Sentence wise Summary Generation\ (BERT\text{-}LSTM)$	0.5648	0.2960	0.4182

Table 2: ROUGE scores for different methods

SOAP note sentencewise (Algorithm 4) manages to outperform Algorithm 1 even with the relatively poor performance of these noteworthy utterance extractors. Since Algorithms 3 and 4 use exactly same extracted noteworthy utterances, the superior performance of the latter suggests an inherent benefit in generating the SOAP note one sentence at a time. Using the noteworthy utterances extracted by a BERT-LSTM leads to better performance and algorithms 4 achieves the best ROUGE scores outperforming Algorithm 1 by a significant margin including an improvement of about 7 points in ROUGE-1.

The quality of generated summaries varies across different sections of the SOAP note. Sections that are less frequent in the dataset such as *allergies* and *healthcare complaints* have relatively lower ROUGE scores, likely because there is not enough training data to learn from. One notable exception is *immunizations* which occurs sparsely in the dataset but has the highest ROUGE score amongst all sections. This is because it is mostly about patient getting a flu shot (20 out of the 25 times it occurs in the test dataset) and that is what the model almost always generates.

The SOAP notes produced by Algorithm 1 had a lower fraction of novel ngrams (i.e. ngrams that do not occur in the input conversation) compared to Algorithm 4 (Table 5). The fraction of novel ngrams in a summary is used to measure how abstractive it is [Chen and Bansal, 2018, Gehrmann et al., 2018, Wang et al., 2019] and hence this result suggests that Algorithm 4 produces more abstractive summaries than Algorithm 1 which has a higher tendency to copy sequences of words as-is from the conversation.

We observe that Algorithm 1 generates longer outputs - 358 words per SOAP note on an average , compared to Algorithm 4 that generated an average of 250 words per SOAP note. The summaries generated by Algorithm 1 exhibits high degree of repetition in the generated sentences and phrases even after the pointer-generator network was fine-tuned with coverage loss. Both Algorithm 1 and Algorithm 4 perform better on shorter conversations, as measured by ROUGE scores (Figure 3). The difference is more visible for variants of ROUGE comparing longer sequences of text.

Metric	Logistic Regression	LSTM	Hi-LSTM	BERT-LSTM
Accuracy	0.9604	0.9611	0.9650	0.9675
Macro-AUC	0.7814	0.7934	0.9008	0.9086
Macro-F1	0.2952	0.3102	0.3863	0.4075
Macro-Precision	0.3033	0.3229	0.4088	0.4388
Macro-Recall	0.2924	0.3048	0.3719	0.3852
Micro-AUC	0.8732	0.8762	0.9271	0.9343
Micro-F1	0.3127	0.3293	0.3960	0.4106
Micro-Precision	0.3182	0.3326	0.4006	0.4392
Micro-Recall	0.3075	0.3261	0.3916	0.3855

Table 3: Aggregate performance metrics for multilabel classification of supporting utterances across different SOAP note sections

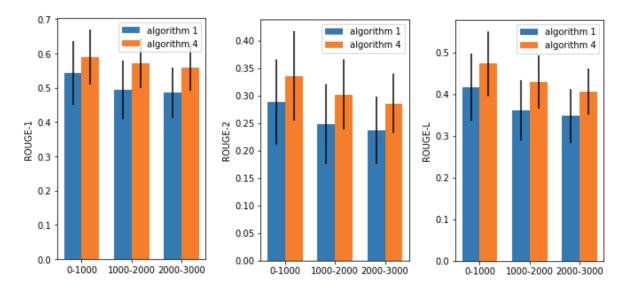


Figure 3: Variation in ROUGE scores averaged over different lengths of input conversation

#### 6.2 Qualitative Analysis

We analysed the SOAP notes generated by reading and comparing them with the input conversation and the ground truth. Due to space constraints, we can not show full conversations and generated SOAP notes here and we direct the reader to the appendix for such an example. However, we do show summaries of smaller noteworthy utterance clusters generated by the abstractive module of Algorithm 4 (Figure 4). The input clusters are taken from the test dataset and obfuscated by changing sensitive data such as symptoms, medications, dosages and lab readings due to privacy concerns.

The models learn to put the correct information in various sections, such as names of medicines in the *Medications* section and lab results and readings in the *Laboratory and Imaging Results* section. But occasionally, there are mistakes where information is put in incorrect sections. For example, information supposed to be in the *review of systems* section is sometimes placed into the *chief complaint* section. In one instance a surgery that was meant to be performed on the patient in future was mentioned in the *past surgical history* section. In one instance, the dosage of a prescribed medicine was reported incorrectly in the SOAP note as 500mg instead of 1000mg. The discrepancy occurred because both of the dosages

Subsection	ROUGE-1	ROUGE-2	ROUGE-L	N	L
chief complaint	0.4105	0.1724	0.3963	592	11.4
review of systems	0.4184	0.1989	0.3883	514	29.2
past medical history	0.4523	0.2459	0.4255	547	17.8
past surgical history	0.4031	0.1680	0.3865	230	10.3
family medical history	0.3521	0.1813	0.3358	72	16.1
social history	0.3831	0.1580	0.3742	97	10.3
medications	0.5414	0.3124	0.5100	549	15.2
allergies	0.1971	0.1048	0.1971	21	8.5
miscellaneous	0.2459	0.0945	0.2306	415	34.4
immunizations	0.5707	0.4618	0.5646	25	7.3
laboratory and imaging results	0.4699	0.2415	0.4452	448	19.3
assessment	0.3390	0.1149	0.2651	570	132.4
diagnostics and appointments	0.4372	0.2489	0.4171	488	17.6
prescriptions and therapeutics	0.3970	0.1748	0.3677	446	18.7
healthcare complaints	0.1811	0.0279	0.1775	43	16.7

Table 4: Average ROUGE scores for each section of SOAP note (N-number of test datapoints with the section populated, L-average number of words in ground truth)

N	1	2	3	5	7	10
Ground truth	0.2409	0.6779	0.8522	0.9501	0.9773	0.9902
Algorithm 4	0.1275	0.4509	0.6522	0.8287	0.9111	0.9653
Algorithm 1	0.0902	0.3579	0.5575	0.7550	0.8514	0.9220

Table 5: Fraction of novel N-grams in the ground truth SOAP note and the outputs of different algorithms with respect to the corresponding conversation

were mentioned in the conversation and the patient was earlier taking the 500mg dose which was changed to 1000mg. We also observed that the model has a tendency to generate incorrect diagnoses because of confusing between conditions with similar words such as high/low blood pressure and weight loss/gain.

The conditioned pointer-generator model used in Algorithm 4 learns what kind information is relevant for each section. Hence, given a cluster of supporting utterances, the model can generate different summaries for multiple sections. For example, given the same supporting utterances discussing the patient's usage of *lisinopril* for low blood pressure, the model generates "low blood pressure" in the *review of systems* section, "lisinopril" in *medications*, and "discussed that lisinopril is a good pill for blood pressure" in the *assessment* section. However, in a scenario where the abstractive summarization model is invoked to generate a summary for a section while feeding in supporting utterances that do not have anything relevant to that section can lead to completely unrelated made-up facts that are not mentioned in the conversation. For example, sometimes the model fabricates information such as saying the patient is a non-smoker in the *social history* section, or that the patient has taken a flu shot in the *immunizations* section. Hence, the performance of the summarization model depends crucially on the ability of the noteworthy utterance extractor used to classify the extracted utterances to the correct section.

Sometimes, the conditioned pointer-generator model sometimes produces new inferred information that is not mentioned in the conversation but is nevertheless correct. One example is the model's ability to predict the diseases that the person has by looking at the medicines being taken. In one instance the

Cluster of utterances	Subsection	Summary
DR That one thing that we can do to reduce risk with that cholesterol is 100 mg metoprolol. DR But I want you on two a day.	Prescriptions and Therapeutics	metoprolol 100 mg twice a day.
DR Um, you don't smoke? PT No. DR Okay.	Review of Systems	denies smoking.
<b>DR</b> Um, the first thing I didn't get was that, um, are	Past Medical History	history of heart disease.
you , you 're on digoxin , right?	Medications	digoxin.
PT Um-hum.	Assessment	the patient is on digoxin.
<b>DR</b> Uh, and have you had any more chest pain? <b>PT</b> I did, yeah, I do.	Review of Systems	confirms chest pain.
<b>DR</b> Uh, and have you had any more chest pain? <b>PT</b> Not really. No.	Review of Systems	denies chest pain.
<b>DR</b> Um, and then let 's just peek at the x-ray on Thursday. <b>PT</b> Okay.	Assessment	discussed with the patient that x-ray is not a visit with a copay or anything like that.
<b>DR</b> Um, and that's just an x-ray. <b>DR</b> It shouldn't be a visit with a copay or anything like that.	Diagnostics and Appointments	x-ray to be done on thursday ( not a visit with a copay or anything like that.
<b>DR</b> This one, this amlodipine that you are taking it's	Chief Complaint	high blood pressure.
a good pill for high blood pressure.  PT Okay	Review of Systems	blood pressure is a bit low.
<b>DR</b> But right now your blood pressure is a bit low. <b>PT</b> Um-hum	Past Medical History	high blood pressure.
<b>DR</b> So I will reduce it to half a pill per day, alright?	Prescriptions and Therapeutics	amlodipine half a pill a day.
DR And nothing like that?	Chief Complaint	leg swelling.
PTI, and, of course, when you break something,	Past Medical History	leg pain.
like I fractured my leg , I don't think that whatever	Medications	patient is on leg.
that feeling is ever goes away completely.	Immunizations	patient had a flu shot in the past.
	Diagnostics and Appointments	the patient will undergo leg surgery.

Figure 4: Noteworthy utterance clusters summarized in different ways for different sections by the abstractive summarization module of Algorithm 4 (obfuscated data)

model generated that the patient has a history of heart disease, although heart disease or even heart was never mentioned in the conversation. We observed that Algorithm 4 used a noteworthy utterance that mentioned that the patient takes the medicine *digoxin*, which is used for heart disease, to generate that line mentioning the disease in the SOAP note. We saw a similar phenomenon where the model generated a past medical history of high cholesterol by seeing that the patient is on *pravastatin*. In another scenario where the supporting utterances reflected the doctor explaining to the patient that he/she has leaky heart valves which are causing shortness of breath, the model put a sentence *diagnostics and appointments* section saying "check valves". This is an undesirable output since the doctor might not have suggested the diagnostic procedure during the visit, but it further suggests that some non-trivial correlations are learnt by the model.

There are some drawbacks of using Algorithm 4. One major drawback is that the current heuristic that we use allows a supporting utterance to be a part of only a single cluster which means that one utterance can participate in the generation of a single SOAP note sentence. However, in the ground truth data, about 5% of the supporting utterances participate in the generation of multiple SOAP note sentences in the same section. Another drawback is that because Algorithm 4 summarizes localized regions of the conversation, it can lead to conflicting information in the SOAP note. In one instance, the model generated both that the patient denied chest pain as well as confirmed chest pain. This happened because the patient was asked

about chest pain twice - once in the beginning to get to know his/her current state, and once as a question about how he/she felt just before experiencing a fall in the past. Since these parts of conversations can lead to noteworthy utterances that are *independently* summarized, such inconsistencies can take place.

## 7 Conclusion

In this work, we presented the first attempt at generating full length SOAP notes for a physician-patient visit by summarizing the transcript of the conversation. We experimented with four different algorithms to generate SOAP notes. They were aimed at dividing the inherent difficulty of summarization between an extractive and and abstractive phase in varying proportions. We showed that the best approach to generate the SOAP note is to use an extractive module that selects noteworthy utterances from the conversation for different sections and clusters related extracted utterances, and then use an abstractive module to generate a one-line summary for each of those clusters while conditioning on the section of the SOAP note being generated. Such a modular approach to SOAP note generation reduces the burden on the abstractive component and not only achieves better ROUGE scores compared to an end-to-end approach of generating full SOAP note from full summary, but also leads to a more interpretable model where every output sentence comes with the noteworthy utterances that were used for its creation. Our results are promising and show that it may indeed be possible to generate long SOAP notes automatically and lighten the burden on doctors, although work remains to ensure factual correctness of the generated note, which is an active area of research in text summarization.

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# **Appendix**

Due to privacy concerns, we can not publish conversations from our dataset and the SOAP notes generated for them. However, we present here an obfuscated conversation from our test dataset, modified by changing sensitive content such as medicines, diseases, dosages (Figure 5). We also present the SOAP notes generated using end-to-end summarization (Algorithm 1) and sentencewise summary generation (Algorithm 4).

Predicted relevant subsections	Conversation utterances
(PT) (A)	DR Okay, so, um, we are going to talk a little bit about being a Metformin candidate .
(CC) (PMH) (A)	DR Um , we have talked about your hemoglobin and the things , what are , so what are the things that , that keep you from , um , from
	managing your anemia well ?
	DR, I know there's a lot of stuff that troubles you.
(M)	PT Snacking and stress eating.
	PT Eating late in the evenings instead of, um, at a reasonable time -
	DR Right.
	PT At night, late.
(M) (A)	PT Poor meal planning.
(PMH) (LIR) (A)	DR Right, and I think that's in the, we can all take a little note for but one of things that really got me worried because your last
	Hemoglobin was really high -
	PT Uh-huh.
(LIR) (A)	DR It was below, it was below 10, and we 've had this consistent pattern and you 've really, I mean, you really have given it an effort and
	I have to give it up to you that you 've been trying and , um , so we 're down to like just a couple of options and so I want to just kind of put
	them before you .
(A) (PT) (Med)	DR I 've got, I 'm, I 'm considering once a day Metformin with you at some point .
(A)	DR Um, I do n't want to use that as a threat.
(A)	DR I do n't want to use it as like a, oh , you 've been a bad patient you deserve to be on Metformin .
(A) (PT)	DR Um, I do have one other option, um, but I want to counsel you that, that Metformin, even if, if we did, we do go to it, it is not a
	punishment.
(A)	DR It is something to kind of get your baseline down to a regular, regular situation and you only have to do it once a day.
(A)	DR Um, and I know that one of the things that we have for anemics is their eating habits .
(A) (PT)	DR And, so , I am proposing as instead of using Metformin this time , um , that we use something called Lipitor for the , for the eating at
(0)	nighttime .
(A)	<b>DR</b> Um, it's supposed to reduce the incidence of having those nighttime cravings so that you can work, you can do your things, you can
(0)	plan a little bit better.
(A)	DR It 's , it's originally for ADHD so some people actually feel a little bit more focused , um , and controlled but it also affects appetite
	centers and so it's supposed to do it for the longer term as opposed to using like a fen phen, um, so, which is short term.  DR So, um, I 'm really hoping with your interest in it and with the coverage hopefully, I know, with your particular plan it should be
	covered and we can get a discount.
(PT)	DR Um, we do it once a day with your other medications , which are actually pretty minor .
(PT) (DA)	DR Um, and then we check you again in eight weeks .
(DA)	PT Okay.
(DA)	DR All right?
(A) (DA)	DR And, so what we do is we say , you know , it should be , we usually will do three months but then eight weeks we should see some
(A) (DA)	difference from today.
	DR We should see some kind of improvement and then we can sort of celebrate that in and of itself, if that's okay with you.
	PT That sounds great.
(DA)	DR Cool, all right well we will plan to meet again in eight weeks .
1-14	PT Okay.
	DR And, uh , and we 'll go from there .
	PT Okay.
	DR Cool, all right , cool .
	2. doc, a g , doc

#### SOAP note produced using Algorithm4

Chief Complaint: anemia .

Past Medical History: anemia .

Medications: metformin .

 $\textbf{Miscellaneous:} \ patient \ has \ snacking \ and \ stress \ eating \ . \ poor \ meal \ planning \ .$ 

Laboratory and Imaging Results: last hemoglobin was really low .

Assessment: patient is going to talk a little bit about being an metformin candidate . discussed that patient is on lipitor for the hemoglobin a1c . the patient will be se en back in 3 months to see some difference .

 $\textbf{Diagnostics and Appointments:} \ follow \ up \ in \ 8 \ weeks \ .$ 

 $\textbf{Prescriptions and Therapeutics:} \ metformin\ candidate\ .\ start\ lipitor\ once\ a\ day\ .\ do\ it\ twice\ a\ day\ .$ 

## SOAP note produced using Algorithm1

 $\textbf{Chief Complaint:} \ \mathsf{metformin} \ \mathsf{candidate} \ . \ \mathsf{anemia} \ .$ 

Past Medical History: anemia . anemia .

Medications: metformin .

Miscellaneous: patient eating late in the evenings instead of a reasonable time at night . snacking and stress eating . snacking and stress eating .

Laboratory and Imaging Results: hemoglobin was low below 10. hemoglobin was low below 10. hemoglobin was low below 10.

Assessment: discussed that the metaformin is not a punishment and it is something to get the baseline down to a regular situation and only have to do it once a day. discussed that it is originally for adhd and some people actually feel a little bit more focused and controlled but it also affects appetite centers and so it is supposed to do it for the longer term as opposed to using a fen phen, which is short term. discussed that it is originally for adhd and some people actually feel a little bit more focused and controlled but it also affects appetite centers and so it is supposed to do it for the longer term as opposed to using a fen phen, which is short term. discussed that it is originally for adhd and some people actually feel a little bit more focused and controlled but it also affects appetite centers. it is supposed to reduce the incidence of having those nighttime cravings so that you can work, you can do your things, you can plan a little bit better. it is supposed to reduce the incidence of having those nighttime cravings so that you can work, you can plan a little bit called lipitor for the eating at nighttime. it is supposed to reduce the incidence of having those nighttime cravings, so one of the things that we have for anemics is their eating habits.

 $\textbf{Diagnostics and Appointments:} \ we \ will \ plan \ to \ meet \ again \ in \ 8 \ weeks \ .$ 

Figure 5: Sample SOAP notes generated for an obfuscated conversation.