ScopeIt: Scoping Task Relevant Sentences in Documents

Vishwas Suryanarayanan∗†  vishwas@cs.ucla.edu  University of California, Los Angeles

Barun Patra∗  bapatra@microsoft.com  Microsoft

Pamela Bhattacharya  pamelabh@microsoft.com  Microsoft

Chala Fufa  chfufa@microsoft.com  Microsoft

Charles Lee  charlle@microsoft.com  Microsoft

ABSTRACT
Intelligent assistants like Cortana, Siri, Alexa, and Google Assistant are trained to parse information when the conversation is synchronous and short; however, for email-based conversational agents, the communication is asynchronous, and often contains information irrelevant to the assistant. This makes it harder for the system to accurately detect intents, extract entities relevant to those intents and thereby perform the desired action. We present a neural model for scoping relevant information for the agent from a large query. We show that when used as a preprocessing step, the model improves performance of both intent detection and entity extraction tasks. We demonstrate the model’s impact on Scheduler - a virtual conversational meeting scheduling assistant that interacts asynchronously with users through email. The model helps the entity extraction and intent detection tasks requisite by Scheduler achieve an average gain of 35% in precision without any drop in recall. Additionally, we demonstrate that the same approach can be used for component level analysis in large documents, such as signature block identification.

CCS CONCEPTS
• Computing methodologies → Natural language processing; Supervised learning by classification; Neural networks.

KEYWORDS
Neural Networks, Natural Language Processing, Information Extraction

1 INTRODUCTION
Intelligent personal digital assistants (IPDA) such as Microsoft Cortana, Amazon Alexa, Apple Siri, and Google Assistant, are becoming increasingly popular. The natural language interface for communicating with these IPDAs often leads to faster task completion, ultimately improving the user’s productivity. A typical interaction with such a digital assistant requires a trigger, often saying the assistant’s name, which will make the assistant pay attention to the user, followed by a short phrase or sentence describing the user’s ask of the digital assistant. Some examples of these conversations are: “Cortana, what is the weather now?”, “Alexa, play next”, “Cortana, turn off Bluetooth”, “Hey Google, take me home”.

Most of these digital assistants however are voice based, communicate synchronously with the user, and only work well with short, targeted directives. On the other hand, there also exist email-based assistants that communicate and provide assistance asynchronously, and hence are not affected by the constraints associated with short queries. Notable examples from the scheduling space are assistants like Cortana from Microsoft Scheduler, or Amy and Andrew from x.ai, or Clara from Clara labs. These assistants require that the meeting organizer add them in the email with the attendees, and delegate the scheduling task to the assistant. In Figure 2, we show one such example of an email that an organizer can send to their virtual assistant. Once the assistant receives the email, the goal is to identify entities of interest for scheduling the meeting. For example, how long the meeting to be scheduled for is, where the meeting location is, which attendees are optional or required in the meeting, what type of meeting is being requested (e.g. lunch, coffee), etc. There are two major challenges of extracting scheduling related entities from large queries (e.g. emails):

- Information for scheduling the meeting could be spread across a long email where most of the content is irrelevant
- Most generic open source entity extraction models are recall-heavy as they often are context independent, and consequently detect entities that are not relevant for scheduling.
Both the aforementioned issues can be mitigated by building models (both feature based and neural) trained on the task at hand. However the models still get confused by the irrelevant information prevalent in the document.

To build accurate models for extracting entities of interest to scheduling (like duration, location, etc.) the assistant needs to identify parts of the email that has the relevant information. On preliminary analysis, we observed that there are two main clusters of relevant sentences in these email documents. The first cluster, similar to the scenarios encountered by voice assistants, contain sentences that directly refer to the assistant's name and provide instruction, e.g. "Cortana, schedule a meeting next week for 45 minutes". The second cluster contains indirect references to the meeting without naming the assistant, e.g. "Hi Ann, it would be great to meet you next week. My assistant will schedule this meeting for us", i.e. even if the sentences in the email do not refer to the assistant directly, there is an expectation that the digital assistant infers entities from these sentences to schedule the meeting.

We model this problem of finding relevant sentences in a large document as a sentence-level binary classification problem, wherein every sentence in the email is either considered to be relevant or irrelevant to the context of scheduling meetings. While we focus on scheduling as an example throughout this paper, we believe our approach would be useful for domains outside of scheduling. For ease of reference, we will henceforth call the model that solves this problem Scopelt. We show that a good performance by Scopelt on the task of identifying relevant sentences in an email boosts the performance of the downstream intent classifiers and entity extractors. Additionally, we show the application of the same model in component level analyses of emails. Signature block identification is an essential part of these component level analyses. We demonstrate that our method can identify signature blocks for signature removal tasks, often required for pre-processing emails for text to speech systems, or for anonymizing email corpora.

To this end, the main contributions of our work are:

- Propose an architecture that can scope out the relevant sentences for the context at hand from a large document.
- Demonstrate the benefits of using Scopelt as a preprocessing step to improve the performance of a suite of downstream intent classifiers and entity detectors for the meeting scheduling task.
- Illustrate that our proposed architecture also performs better than publicly available baselines on the component level.

**Figure 2: A typical email encountered by Scheduler**
tasks like signature detection and generalizes better to real world data.

We first present our approach to the problem of scoping out relevant sentences in Section 2. In Section 3, we describe our experimental setup and introduce the baselines we compare our approach against. We discuss ScopeItAAZs performance in Section 4. We analyze the embedding space induced by ScopeIt in Section 5 to understand why it performs well. In Section 6 we show the effectiveness of using ScopeIt as a preprocessing step on downstream intent classification and entity extraction tasks. Section 7 shows the performance of ScopeIt on the signature detection task. In Section 8 we discuss the related work. Finally, we conclude with Section 9.

2 PROPOSED METHOD

In this section, we outline our approach to the problem of scoping out relevant sentences for Scheduler. Our approach consists of 2 parts: a preprocessing module and a neural model. An incoming email is first passed through the preprocessing module. The preprocessed email is then tokenized, indexed and passed through the neural model to generate a confidence score for each sentence. The model is trained end-to-end with human-labeled gold scores denoting the relevant sentences of the email. We also adopt some data augmentation methods to improve model generalization. Each of these steps is described in detail below:

2.1 Preprocessing Module

The preprocessing step fixes any issues due to improperly decoded text (mojibake characters). Furthermore, since we use the wordpiece tokenizer\(^2\) to tokenize each word into its constituent wordpieces, having raw urls or emails often generates a large number of uninformative wordpieces (e.g. “https://www.kdd.org/calls/view/kdd-2020-call-for-research-papers” generates 34 wordpieces). In order to circumvent this issue, we replace all urls and emails with special tokens (eg: URLTOKEN, EMAILTOKEN). We keep track of the original urls/emails, and invert the token replacement after obtaining the confidence scores from the neural model.

2.2 Neural Model

Our neural model consists of 3 different modules: an intra-sentence aggregator to aggregate information within a sentence, an inter-sentence aggregator to share information across different sentences, and a classifier to predict the final relevance score of each sentence. This allows the model to capture context based on other sentences around it, enabling us to capture document level features. Once we have these contextual sentence embeddings, a final Sigmoid output layer generates the probability of each sentence being relevant:

\[
(f_{s_1}, f_{s_2}, \ldots, f_{s_m}) \leftarrow \text{Seq2SeqEncoder}(e_{s_1}, e_{s_2}, \ldots, e_{s_m})
\]

\[
(p_{s_1}, p_{s_2}, \ldots, p_{s_m}) = (\sigma(f_{s_1}), \sigma(f_{s_2}), \ldots, \sigma(f_{s_m}))
\]

Finally, the model is trained with a binary cross entropy loss using gold annotated relevance scores, i.e. given annotations for the sentences \(Y = \{y_1, y_2, \ldots, y_m\}\):

\[
L = - \sum_{i=1}^{m} y_i \log(p_{s_i}) + (1 - y_i) \log(1 - p_{s_i})
\]

2.3 Data Augmentation

Given that most emails received by Scheduler have some information pertinent to scheduling, we also augment the training data with irrelevant emails (i.e emails not relevant to scheduling). These emails are sampled from the Enron Dataset [6, 13]. Furthermore, we observed that the original dataset had a bias of having relevant information being present at the beginning of the email. In order to account for that bias, we also shuffled passages of text within each email except the salutation and signature, and augment our dataset with the shuffled emails. We do so to ensure that the resulting shuffled emails are not nonsensical.

3 EXPERIMENTS

We show the effectiveness of the model on scoping relevant sentences:

3.1 Dataset and Experimental Setup

We identify relevant sentences from 10000 emails sampled from an internal dataset. We use a standard 80%, 10%, 10% train, validation and test split. During evaluation, any sentence with score > 0.5 is classified as relevant and others are classified as irrelevant. We use the F1 score of the sentence relevance prediction task as the metric of evaluation.

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\(^2\)https://github.com/google/sentencepiece
3.2 Baselines

We compare against the following baselines:

**Seq2Seq Encoder**: This model does not use BERT for generating contextual embeddings. Instead, a standard word-level BiGRU model is used as the sentence encoder to generate sentence embeddings, with the vocabulary set to the top 10,000 most frequently occurring words encountered in the training data. The sentence embeddings are then projected using a feed-forward layer to generate the relevance probabilities.

**No Inter-Sentence Aggregator**: This model uses BERT for generating the contextual embeddings, and then a BiGRU encoder to generate the sentence embeddings. It however does not make use of any inter-sentence aggregator; instead a feed-forward layer directly generates the relevance probabilities.

**BERT with [CLS] only**: This model just uses the [CLS] token of BERT for generating the sentence embedding vector. Note that we don’t fine-tune the BERT model.

**Scopelt Without Data Augmentation**: This is our proposed model (Section 2.2), trained without any data augmentation (Section 2.3).

3.3 Hyperparameters and Training Details

We use the BERT-Base, Multilingual Cased model for generating the contextual embeddings. We do not fine-tune the BERT model for any of the models due to compute constraints. We use a 2 layer BiGRU encoder [5] (hidden dimension of 128) as the Seq2SeqEncoder for the intra-sentence aggregator, and a 2 layer BiGRU (dimension of 128) as the Seq2Seq Encoder for the inter-sentence aggregator. The model was trained with gradient descent for 50 epochs, having a batch size of 4. We used Adam [12] as the optimizer with a learning rate of 0.0001. The learning rate was annealed by a factor of 0.5 if the validation loss failed to improve over 5 epochs. All our models were developed using the AllenNLP framework [11].

| Model                                    | F1 Score |
|------------------------------------------|----------|
| BERT [CLS]                               | 0.81     |
| Seq2Seq Encoder                          | 0.83     |
| No Inter-Sentence Aggregator             | 0.89     |
| Scopelt Without Data Augmentation        | 0.93     |
| Scopelt                                  | **0.94** |

Table 1: Performance for relevance scoping

4 RESULTS

Table 1 shows the performance of Scopelt compared to the baseline models. Since the BERT [CLS] model is not fine-tuned, it does not perform as well as any of the models where the Seq2Seq encoders are trained on the task at hand. Unsurprisingly, the models with BERT augmented embeddings outperform the standard Seq2Seq encoder model substantially. We further observe that the inter-sentence aggregator also improves performance. Finally, the model with data-augmentation outperforms all of the baselines. We believe this is because of two reasons. First, most emails have a prior of being relevant, simply because the user CC’d Cortana. A consequence of this was that the model predicted a few sentences as relevant even though there weren’t any. Augmenting the data with completely irrelevant emails helps overcome that bias.

We also observed that, for most emails, the relevant scope usually was in the beginning of the email. Hence, the baseline models were biased towards scoring the beginning of the email higher than the end, even if the beginning was not particularly relevant. Training with the shuffling data augmentation mitigates the issue.
5 CLUSTERING IN THE EMBEDDING SPACE
Given ScopeIt’s performance, it is natural to ask if the sentence embeddings generated by ScopeIt exhibit any clusters that make semantic sense. On preliminary data analysis, some clusters that we observed were salutations, signature blocks and sentences containing entities associated with scheduling meetings. We hypothesize that similar clusters are observed in the sentence embedding space. To test this hypothesis, we propose the following experiment: given the embedding of a sentence belonging to a certain cluster (hence referred to as the query sentence), retrieve the top k nearest neighbor sentence embeddings3 (NNs) from a set of sentence embeddings generated by ScopeIt. If similar clusters exist in the sentence embedding space, then the sentences associated with the retrieved embeddings should belong in the same cluster as the query sentence.

To generate the set of sentence embeddings, we use the publicly available Enron Dataset [6, 13]. We randomly sample 10000 of the 500000 emails present in the dataset, and generate sentence embeddings for all the emails, obtaining ≈ 100000 sentence embeddings. We then generate a typical email that a user might send containing similar information. We also observe that contextual embeddings generated by ScopeIt exhibit any clusters that make semantic sense. On preliminary data analysis, some clusters that we observed were salutations, signature blocks and sentences containing entities associated with scheduling meetings. We hypothesize that similar clusters are observed in the sentence embedding space. To test this hypothesis, we propose the following experiment: given the embedding of a sentence belonging to a certain cluster (hence referred to as the query sentence), retrieve the top k nearest neighbor sentence embeddings3 (NNs) from a set of sentence embeddings generated by ScopeIt. If similar clusters exist in the sentence embedding space, then the sentences associated with the retrieved embeddings should belong in the same cluster as the query sentence.

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6 IMPROVEMENTS TO DOWNSTREAM TASKS
6.1 Downstream tasks

Our main motivation for developing ScopeIt was the hypothesis that using relevant sentences would improve the performance of downstream tasks in Scheduler. In this section we highlight the impact ScopeIt has on 6 downstream tasks. 5 of these tasks are either associated with detecting an intent related with scheduling a meeting or extracting the necessary entities. All the models that solve these tasks use the scoped message generated by ScopeIt as an input. We also consider the “Non-actionable Emails” task which helps Scheduler identify emails that it should ignore. The models used for each task vary. They can either be context independent regex models, or context aware neural models. For each of these

5 we also retrieve the sentence that generated the embedding as well as the emails containing the sentence. This is done to provide context, since these sentence embeddings also take context into consideration

4https://scikit-learn.org/stable/modules/neighbors.html

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6.1.1 Meeting Type. When Scheduler receives an email and has determined that the email has an intent to schedule a meeting, the Meeting Type task tries to classify the meeting request into one of the broad classes of meeting types as defined by Scheduler. Each of the categories have special meeting properties that help Scheduler populate the meeting details. Some examples of these meeting types defined are Lunch (which constrain the times to schedule), Conference Call (require a Remote Bridge), Phone call etc. Scheduler uses an ensemble of different models to classify the meeting requests into these classes. For this case study, we focus on the model responsible for detecting a call or a conference call intent, which maps to the Phone Call and Conference Call meeting type classes, respectively. The following is an example of an input to the model and its expected response:

Input: “Let us get together on a Team’s call.”
Output: Conference Call Intent

This task is modeled as a multi-label classification task, and we use a context aware deep network to tackle it. We use a model similar to the one proposed in [18]. Specifically, we generate a contextual embedding using BERT for each token in the email. Then, an attention method [1], one for each label, is used to aggregate the embeddings into a document embedding, which is then passed through a sigmoid layer to generate the probability for each label. The entire model is trained end to end by minimizing the negative log likelihood of the gold labels. While using ScopeIt, we only select sentences that occur above a particular threshold (0.01), and feed the concatenation of those sentences as inputs to the model.

6.1.2 Meeting Duration. Scheduler needs to extract the duration for the meeting from the meeting organizer’s email. If there wasn’t a duration entity detected, Scheduler uses the default duration set by the organizer in their meeting preferences. The following is an example of an input to the duration extraction model and its corresponding expected output:

Input: “Cortana, schedule a meeting for 30 minutes.”
Output: 30 minutes.

We use LUIS5 for extracting the duration of a meeting from the meeting requests. LUIS is the Language Understanding Service in Microsoft Azure Cognitive Services that provides natural language intelligence for conversational AI applications [27]. In order to utilize LUIS’s high recall duration extraction model in the context of scheduling meetings, we select sentences scored above 0.01 by ScopeIt, and feed the concatenation of the sentences as the input to LUIS’s duration extraction model.

6.1.3 Meeting Phone Number. When users schedule a phone call, Scheduler needs to extract phone numbers from the organizer

5https://www.luis.ai/home
| Original Email | Query Sentence | Cluster Type | Nearest Neighbors With Surrounding Context |
|---------------|----------------|--------------|------------------------------------------|
| Hey Harry     | @Cortana, schedule a meeting for next week, in Hogsmade. | Hey Harry  | @Cortana, schedule a meeting for next week, in Hogsmade. |
|               | Hey Harry       | Salutation  | Suryanarayanan et al.                      |
|               | @Cortana, schedule a meeting for next week, in Hogsmade. | Date-time availability intent | @Cortana, schedule a meeting for next week, in Hogsmade. |
|               | My phone number is 000-000-0000. | Phone availability intent | My phone number is 000-000-0000. |
| Thanks,     |                |              |                                          |
| Ronald Weasley|                |              |                                          |
|                |                |              |                                          |

Table 2: Nearest Neighbor Analysis on the Enron Dataset. Red denotes the scoped email as predicted by Scopelt. Blue denotes the actual nearest neighbor in the context. Best viewed in color.
or attendee to add to the meeting invite. The following is an example of an input to the phone number extraction model and the corresponding expected output:

**Input:** "Cortana, please schedule a call with Albus. My phone number is +1 000-000-0000. Regards, Gellert Grindelwald"

**Output:** +1 000-000-0000.

We use LUIS for extracting the phone numbers from an email. We extract sentences scored above a threshold of 0.01 by ScopeIt, concatenate the sentences, and feed that as an input to the high recall phone number extraction model.

### 6.1.4 Meeting Location

In order to schedule the meeting at the right location, Scheduler needs to extract the intended location expressed by the organizer. The following is an example of an input to the location extraction model and the expected output:

**Input:** “Cortana, schedule a meeting. Hagrid, let’s meet at Starbucks.”

**Output:** Starbucks

This is modeled as an entity extraction problem and consequently we fine-tune BERT for tagging (similar to the BERT for NER, as done in [8]). We concatenate sentences scored above a certain threshold by ScopeIt and pass it as an input to the model.

### 6.1.5 Meeting Timezone

Users typically express multi timezones in two ways: express time zones by explicitly mentioning timezone abbreviations like “EST”, or implicitly by indicating the city and sometimes the country where the meeting is going to be held. Below is an example of an email, which serves as the input to the high recall timezone extraction model.

**Input:** “Cortana, schedule an online meeting with Ron Weasley next week. Ron is in EST, and I am going to be working from Dublin for that week.”

**Output:** EST, Dublin

By using ScopeIt to filter out sentences that are not relevant to scheduling the meeting, Scheduler is able to leverage recall heavy time zone entity extractors, and city and country extractors to find the right time zones. Scheduler utilizes LUIS for time zone entity extraction and LU (Location Understanding) from Bing to extract cities and countries from the input text. These utterances are subsequently resolved for their time zone offsets.

### 6.1.6 Non-actionable Emails

When Scheduler processes a request, the system might receive emails from meeting participants which are irrelevant to scheduling. For example, after the meeting organizer has sent a request to Cortana, one of the invitees might reply to the email thread with all meeting participants including Cortana saying, “Thanks for setting this up. Look forward to meeting you.” In these cases, there is no action required from Scheduler’s point of view and the email can be safely ignored. Similar to the approach stated in the previous tasks, sentences in the email that are scored above a threshold are extracted and concatenated. If there are no sentences in the email above the relevance threshold, the email is considered irrelevant and is ignored by Scheduler.

### 6.2 Results

Table 3 summarizes the utility of using ScopeIt. For the intent classification and duration extraction tasks, we see an average increment of 0.14 in the accuracy. An interesting observation is that even the context aware neural model benefits strongly (+0.24 accuracy improvement). These findings are in line with those presented in [24, 29], where the authors showed that hierarchically obtained representations often performed better for document classification and that not all parts of the document were relevant for solving a given task.

For the entity extraction models, we observe a strong increase in the precision, with an average increase of 0.35. The context independent models benefit strongly when we strip out the irrelevant parts of the document: as shown in the example in Figure 2, phone numbers extracted by the context independent regex based model are often found in the signature block of the email. A similar behaviour is also observed in the timezone extraction task, where locations in the signature often get picked up as timezones. As hypothesized, once the email is scoped to only the relevant parts, these models get a substantial boost in precision. A similar gain is also observed for the BERT Location extractor.

An interesting observation is that the recall for these extraction models also improves. On further investigation, we found that this

| Task                  | Task Type      | Model Type     | Metric    | Before ScopeIt | After ScopeIt | ∆      |
|-----------------------|----------------|----------------|-----------|----------------|---------------|--------|
| Meeting Type          | Classification| Context Aware  | Accuracy  | 0.72           | 0.96          | +0.24  |
| Non-actionable Emails | Classification| Context Aware  | Accuracy  | N/A            | 0.96          | +0.96  |
| Duration              | Extraction     | Context Independant | Precision | 0.46           | 0.98          | +0.52  |
| Phone Number          | Extraction     | Context Independant | Precision | 0.73           | 0.96          | +0.23  |
| Location              | Extraction     | Context Aware   | Precision | 0.37           | 0.67          | +0.30  |
| Timezone              | Extraction     | Context Independant | Precision | 0.92           | 0.96          | +0.04  |
| Average               |                |                | Accuracy  |               |               | +0.14  |
|                       |                |                | Precision |               |               | +0.35  |
|                       |                |                | Recall    |               |               | +0.02  |

Table 3: A summary of all improvements resulting from the ScopeIt’s preprocessing.
can be attributed to an increase in the true positives. For the BERT Location extraction, this makes sense, since a simplified input allows the model to reason better about the location. For the timezone task, we hypothesize that the LU model has additional heuristics and that the heuristics perform better on the simplified inputs.

Using Scopelt also offers the benefit of making regex models feasible to use. This is especially advantageous since regex-based models have faster inference times and require much less data to build than their neural counterparts.

Finally, Scopelt also helps Scheduler decide between which emails to process and which ones to ignore, which plays a crucial role for an email-based agent. People often use reply-all when interacting with each other even though the email-based agent is on the thread and the content isn’t* relevant to scheduling the meeting. Having Scopelt ensures that those emails are ignored by the agent.

7 SIGNATURE BLOCK DETECTION

As described in Section 5, we observed that sentences with similar semantics were clustered close to each other in the sentence embedding space. We use this observation to apply our model to component detection in email, specifically for signature block identification. In the next section, we show the model’s performance on a publicly available dataset, and show that it outperforms the baseline model. We also hypothesize that the publicly available systems for extracting signatures are not suitable for real-world use-cases, as they are often trained on well structured emails using hand crafted features, and hence are not robust to the variety of writing styles that people employ in the real world. In order to validate this hypothesis, we test the effectiveness of the baseline on our use-case.

7.1 Dataset and Experimental Setup

We use the 20-Newsgroup dataset consisting of emails annotated with signature blocks ([4]). This dataset is publicly available [6]. We use a standard split of 80%, 10% and 10% as the training, validation, and testing splits. In order to validate our hypothesis about the efficacy of the publicly available baseline on our use-case, we annotate 625 emails with signature blocks and then test the performance of the baseline as well as our model (trained on the 20-Newsgroup dataset) on this annotated dataset.

7.2 Baseline

We compare against a publicly available signature detection tool Jangada[4]. Jangada uses a CRF model with handcrafted features, and is trained on the 20-Newsgroup dataset.

| Dataset       | Model | Precision | Recall | Fscore |
|---------------|-------|-----------|--------|--------|
| 20 Newsgroup  | Jangada     | 0.98      | 0.971  | 0.975  |
|               | Scopelt     | 0.992     | 0.999  | 0.996  |
| Manually      | Jangada     | 0.908     | 0.224  | 0.359  |
| Annotated     | Scopelt     | 0.995     | 0.884  | 0.936  |

Table 4: Performance: Jangada Vs Scopelt

7.3 Results on Signature Block Detection

As seen in Table 4, our proposed neural model outperforms Jangada on the 20 Newsgroup dataset. We also validate our hypothesis when we use Jangada for our real world use-case to remove signatures, we observe that while it has a high precision, the recall drops drastically (0.224); making it impractical to use in production. On the other hand, Scopelt, even when trained on 20 Newsgroup, generalizes much better (recall 0.885, fscore: 0.936).

8 RELATED WORK

Our problem of relevance scoping in documents is similar to extractive summarization. Extractive summarization deals with selecting subsets (usually sentences) of a document that succinctly summarizes it. For the case of Scheduler, scoping out the relevant part in an email document is in essence selecting the subset of sentences from the email that accurately summarizes the scheduling intent and specifies the parameters necessary to schedule a meeting correctly. Both traditional feature based methods using word probability, TF-IDF weights, sentence position and sentence length features [3, 10, 16, 25] and recent neural methods [14, 15, 19, 20, 31] have been used for the task of extractive summarization. Liu and Lapata [14] show the benefit of using pretrained language models [8, 9, 22, 23, 30] for the same task. They leverage interval segment embeddings to distinguish multiple sentences within a document and add more positional embeddings (learned during training) in order to overcome the 512 maximum positional embeddings length of the original BERT model. The authors train the entire model end-to-end. However, since our dataset is orders of magnitude smaller than the CNN/Daily Mail dataset (used by the authors for the extractive summarization task), and due to computational constraints (the authors report using 4 GTX 1080 Ti GPUs during training), we adopted a different approach for incorporating these pretrained language models. Specifically we used hierarchical RNNs (similar to the approach in [19, 31]), with the pretrained embeddings forming the embedding layer (See Figure 3); thereby allowing us to encode emails much larger than 512 tokens long. In doing so, as a result of not back-propagating the gradients through these often large pretrained language models, we also observed a speedup during training.

Intent classification and entity extraction tasks in the context of conversational understanding have been studied both in academia and corporate research laboratories [7]. There exists a rich body of research in user intent identification from targeted queries [26]. However, these methods don’t work as well when applied to large documents. We showed that using the right models and the right features improves performance of classification and extraction tasks on large queries. To the best of our knowledge, this is the first work to explore the utility of extractive summarization as a preprocessing step for tackling problems involving large text corpora.

There has been extensive research on the topic of identifying signature blocks and reply lines from an email [2, 4, 17, 28]. [2, 28] present heuristic driven methods for supervised identification of the signature body, while [4] present a CRF based approach for identifying and extracting signature and reply lines from Email. We
showed in Section 7 that our proposed method also works well for removing signatures and also generalizes better.

9 CONCLUSION

In this paper, we proposed a simple method for scoping relevant information within emails and the impact the model had on a suite of tasks that are vital for Scheduler. We also showed our models applicability on the task of Signature Detection. We show that it performs better than existing publicly available baselines and generalizes better on real world use-cases.

A logical next step would be to move from the extractive summarization paradigm presented in this paper to an abstractive one, wherein the model generates the synopsis summarizing the meeting intents and parameters. We hypothesize this would lead to further reduction in errors in the downstream tasks.

In this work we showed that our model works well with emails. Another avenue of future work would be to see if other tasks that process large textual inputs (Eg: document classification, sentiment analysis on large reviews, information extraction from large text corpora) also benefit from our proposed method.

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