Improving Online Forums Summarization via Hierarchical Unified Deep Neural Network

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Abstract—Online discussion forums are prevalent and easily accessible, thus allowing people to share ideas and opinions by posting messages in the discussion threads. Forum threads that significantly grow in length can become difficult for participants, both newcomers and existing, to grasp main ideas. To mitigate this problem, this study aims to create an automatic text summarizer for online forums. We present Hierarchical Unified Deep Neural Network to build sentence and thread representations for the forum summarization. In this scheme, Bi-LSTM derives a representation that comprises information of the whole sentence and whole thread; whereas, CNN captures most informative features with respect to context from sentence and thread. Attention mechanism is applied on top of CNN to further highlight high-level representations that carry important information contributing to a desirable summary. Extensive performance evaluation has been conducted on three datasets, two of which are real-life online forums and one is news dataset. The results reveal that the proposed model outperforms several competitive baselines.

Index Terms—Online Forums Summarization, Social Media Computing, Extractive Summarization, Deep Neural Networks

1 INTRODUCTION

Online discussion forums embody a plethora of information exchanged among people with a common interest. Typically, a discussion thread is initiated by a user posting a message (e.g., question, suggestion, narrative, etc), then other users who are interested in the topic will join the discussion, also by posting their own messages (e.g., answer, relevant experience, new question, etc). The thread that gains popularity can span hundreds of messages, putting burden on both newcomers and current participants as they have to spend extra time to understand or simply to catch up with the discussion so far. An automatic forum summarization method that generates a concise summary is therefore highly desirable.

One simple way to produce a summary is to identify salient sentences and aggregate them. This method naturally aligns with the concept of extractive summarization which involves selecting representative units and concatenating them according to their chronological order. In order to determine saliency of each unit, the context must be taken into account. This factor is critical to any summarization process whether it be an automatic system or a human tasked with selecting sentences from a document to form a summary. As an illustration, if a human is given a thread to extract key sentences from, he/she would first read the thread to grasp contextual information, then select sentences based on that context to compose a summary. On the other hand, if an arbitrary sentence is shown to a human without supplying context of the thread which that sentence belongs to, there would be no clear way of deciding if the sentence should be included in the summary. Previous works [1], [2], [3] have shown that a context information lies within a document structure contributes to a performance improvement of a summarizer. Similar to documents, forum threads also possess a hierarchical structure; in which, words constitute a sentence, sentences constitute a post, and posts constitute a thread.

In this work, we propose a data-driven hierarchical-based approach to summarize online forums. In order to utilize knowledge of the forum structure, the method hierarchically encodes sentences and threads to obtain sentence and thread representations. Meanwhile, an attention mechanism is applied to further place emphasis on salient units. Drawing our inspiration from how humans read, comprehend, and then summarize a document, it led us to a network design that unifies Bidirectional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Network (CNN). In this scheme, Bi-LSTM derives a representation that comprises information of an entire sentence and thread; whereas, CNN captures most informative features. All in all, both networks are utilized with an aim to leverage their individual strength to achieve effective representations, compared to when either one is used. Our extensive experimental results verifies this effectiveness.

The contributions of this study are as follows:

• We propose a hierarchical-based unified neural network [4] which utilizes Bi-LSTM and CNN to obtain representations for summarizing forum threads. The attention mechanism is employed to give weight to important units. Different from previous studies that apply attention directly to individual words and sentences [2], [4], our findings suggest that applying attention to the high-level features extracted by CNN contributes to improvements in the performance.

1. Our code is available at https://github.com/sansiri20/forums_summ.git

—Online Forums Summarization, Social Media Computing, Extractive Summarization, Deep Neural Networks
To demonstrate the advantage of the proposed model, we perform comprehensive empirical study. The results show that the proposed approach significantly outperforms a range of competitive baselines as well as the initial study [4]. This encourages further investigation into the use of the proposed network for text summarization.

We conduct an extensive experiment using different pretrained embeddings (static and contextual) to investigate their effectiveness towards improving the summarization performance.

The remainder of this paper is organized as follows. We review the literature related to automatic summarization in Section 2. The proposed framework is introduced in Section 3. In Section 4, we provide details on the dataset and the experimental configurations for the performance studies, and explain the baselines used in the comparative study to assess the effectiveness of our proposed model. The performance results are analyzed in Section 5. Finally, we draw our conclusions in Section 6.

2 RELATED WORK

In this study, we address the problem of online forums summarization. Therefore, described herein this section are three major strands of research related to this study, including extractive summarization, neural network-based text summarization, and representation learning.

2.1 Extractive Summarization

There are mainly two kinds of methods used in text summarization, namely extractive summarization and abstractive summarization [3]. Owing to its effectiveness and simplicity, the extractive summarization approach has been used extensively. The technique involves segmenting text into units (e.g., sentences, phrases, paragraphs, etc), then concatenating a key subset of these units to derive a final summary. In contrast, the abstractive approach functions similarly to paraphrasing, by which the original units are hardly preserved in the output summary. In this study, we consider the extractive summarization approach and propose a deep classifier to recognize key sentences for the summary.

The extractive approach has been applied to data from various domains such as forum threads [4], online reviews [7], [8], [9], [10], emails [11], group chats [12], [13], meetings [14], [15], microblogs [16], [17], [18], [19], and news [20], [21], [22], [23] just to name a few. In the news domain, articles typically follow a clear pattern where the most important point is at the top of the article, followed by the secondary point, and so forth. We generally do not observe a clear pattern in other domains. For example, a forum thread is participated and written by multiple users; thus, the gist may be contained across different posts – not necessarily at the first sentence or paragraph. Furthermore, these user-generated content (UGC) generally contains noise, misspellings, and informal abbreviations which make choosing sentences for summarization more challenging. In our work, we focus on summarizing content in the forum thread. Given the nature of forum data, it can be framed as a multi-document summarization where these documents are created and posted by different authors.

2.2 Neural Network-based Text Summarization

A large body of research applies neural networks involving RNN [24], CNN [25], along with a combination of both [26], [27] to improve text summarization. For example, Nallapati et al. [24] have proposed a neural-based sequence model entitled SummaRuNNer to produce extractive summaries. A two-layer bidirectional Gated Recurrent Unit (GRU) is applied to derive document representations. The first layer runs at the word level to derive hidden representation of each word in both forward and backward directions. The second layer runs at the sentence level to encode the representations of sentences in the document. Cao et al. [25] have proposed a CNN-based summarization system entitled TCSum to perform multi-document summarization. Adopting transfer learning concept, TCSum demonstrated that the distributed representation projected from text classification model can be shared with the summarization model. The model can achieve state-of-the-art performance without handcrafted features needed.

A unified architecture that combines RNN and CNN for summarization task has shown success in several works. For instance, Singh et al. [26] have proposed Hybrid MemNet, a data-driven end-to-end network for a single-document summarization where CNN is applied to capture latent semantic features and LSTM is applied thereafter to capture an overall representation of the document. The final document representation is generated by concatenating two document embeddings, one from CNN-LSTM and the other from the memory network. Narayan et al. [27] also proposed a unified architecture which frames an extractive summarization problem with a reinforcement learning objective. The architecture involves LSTM and CNN to encode sentences and documents successively. The model learns to rank sentences by training the network in a reinforcement learning framework while optimizing ROUGE evaluation metric.

Several lines of research have taken into account the hierarchical structure of the document [1], [3], [28], [29], [30]. Cheng and Lapata [1] have developed a framework containing a hierarchical document encoder and an attention-based extractor for single-document summarization. The hierarchical information has shown to help derive a meaningful representation of a document. Zhou et al. [3] have proposed an end-to-end neural network framework to generate extractive document summaries. Essentially, the authors have developed a hierarchical encoder via bidirectional Gated Recurrent Unit (BiGRU) which integrates sentence selection strategy into the scoring model, so that the model can jointly learn to score and select sentences.

The usage of an attention mechanism has also proven successful in many applications [31], [32], [33], [34], [35], [36]. For example, Wang and Ling [34] have introduced an attention-based encoder-decoder concept to summarize opinions. The authors have applied LSTM network to generate abstracts, where a latent representation computed from the attention-based encoder is an input to the network. Cao et al. [35] have applied the attention concept to simulate human attentive reading behavior for extractive query-focused summarization. The system called AttSum is proposed and demonstrated to be capable of handling query relevance.
2.3 Representation Learning

Representation learning which aims to acquire representations automatically from the data plays a crucial role in many Natural Language Understanding (NLU) and Natural Language Processing (NLP) models. Particularly, pre-trained word representations are the building blocks of any NLP and NLU models that have shown to improve downstream tasks in many domains such as text classification, machine translation, machine comprehension, among others [38]. Learning high-quality word representations is challenging, and many approaches have been developed to produce pre-trained word embeddings which differ on how they model the semantics and context of the words. word2vec [39], a window-based model, and GloVe (Global Vectors for Word Representation) [40], a count-based model, rely on distributional language hypothesis in order to capture the semantics. FastText [41] is a character-based word representation in which a word is represented as a bag of character n-grams and the final word vector is the sum of these representations. One of the advantages of FastText is the capability of handling out-of-vocabulary words (OOV) – unlike word2vec and GloVe.

Although the classical word embeddings can capture semantic and syntactic characteristics of words to some extent, they fail to capture polysemy and disregard the context in which the word appears. To address the polysemous and context-dependent nature of words, the contextualized word embeddings are proposed. ELMo (Embeddings from Language Models) proposes a deep contextualized word representation in which each representation is a function of the input sentence where the objective function is a bidirectional Language Model (biLM) [42]. The representations are a linear combination of all of the internal layers of the biLM where the weights are learnable for a specific task. BERT (Bidirectional Encoder Representations from Transformers) is another contextualized word representation which is trained on bidirectional transformers by jointly conditioning on both left and right context in all layers [43]. The objective function in BERT is a masked language model where some of the words in the input sentence are randomly masked. FLAIR is contextualized character-level word embedding which models words and context as sequences of characters and is trained on a character-level language model objective [44].

In summary, there are several approaches adopted to learn the word representation in literature which differ in the ways they model meaning and context. The choice of word embeddings for particular NLP tasks is still a matter of experimentation and evaluation. In this study, we experimented with word2vec, FastText, ELMo, and BERT embeddings, by integrating them in an embedding layer of the model. These embeddings initialize vectors of words/sentences present in the forum data.

3 Summarization Model

Our system is tasked with extracting representative sentences from a thread to form a summary, which is naturally well-suited to be formulated as a supervised-learning task. We consider a sentence as an extraction unit due to its succinctness. Let \( s = [s_1, \ldots, s_N] \) be the sentences in a thread and \( l = [l_1, \ldots, l_N] \) be the corresponding labels, where “\( l_i = 1 \)” indicates that the sentence \( s_i \) is part of the summary, and “\( 0 \)” otherwise. Our goal is to find the most probable tag sequence given the thread sentences:

\[
\arg \max_{l \in T} p(l | s)
\]

where \( T \) is the set of all possible tag sequences, and \( p(l | s) = \prod_{i=1}^{N} p(l_i | s) \) where the tag of each sentence is determined independently.

In this section, we elaborate our hierarchical-based framework for multi-document summarization. Inspired by the development of Hierarchical Attention Networks (HAN) [2], [4], the proposed model adopts their concept to construct sentence and thread representations. Two types of neural networks, namely bi-directional recurrent neural network and convolutional neural network, are utilized to maximize capability of the summarizer. In a nutshell, the model is comprised of hierarchical encoders, a neural attention component, and a sentence extractor. The encoders generate the representations based on words and sentences in the forum. The neural attention mechanism pinpoints any meaningful units in the process. Finally, the sentence extractor selects and puts together all the key sentences to produce a summary. In the following, the boldface letters represent vectors and matrices. Words and sentences are denoted by their indices.

3.1 Sentence Encoder

The sentence encoder reads an input sentence as a sequence of word embeddings, then returns a sentence vector as an output. Adopting the pipeline architecture to process data in a streaming manner, a bi-directional recurrent neural network is followed by a convolutional neural network to constitute the sentence encoder. Furthermore, the attention mechanism is employed while generating the sentence vector to give more emphasis on units that contribute more to the meaning of the sentence. This strategy to sentence encoding is illustrated in Figure 1. We elaborate the different network components in the following subsections.

3.1.1 Input Layer

Given that, each thread is a sequence of sentences and each sentence is a sequence of words, let \( s_i = [x_1, \ldots, x_T] \) denote the \( i \)-th sentence and the words are indexed by \( t \in \{1, \ldots, T\} \) where \( T \) denotes the number of words in the sentence. Each word is converted to its corresponding pretrained embedding, and subsequently fed into the bidirectional recurrent neural network.

3.1.2 Bidirectional Recurrent Neural Network layer

We opt for Bidirectional Long Short-Term Memory (BiLSTM) due to its effectiveness as evidenced in previous studies [45]. LSTM contains an input gate \( (i_t) \), a forget gate \( (f_t) \), and an output gate \( (o_t) \) to control the amount of information coming from the previous time-step as well as flowing out in the next time-step. This gating mechanism
accommodates long-term dependencies by allowing the information flow to sustain for a long period of time. Our Bi-LSTM model contains forward pass and backward pass (Eq. 2). The forward hidden representation $\overrightarrow{h_t}$ comprises semantic information from the beginning of the sentence to the current time-step; on the contrary, $\overleftarrow{h_t}$ comprises semantic information from the current time-step to the end of the sentence. Both vectors $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are of dimension $\mathbb{R}^{d_t}$, where $d_t$ is the dimensionality of the hidden state in the word-level Bi-LSTM. Finally, concatenating the two vectors, $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \in \mathbb{R}^{2d_t}$, produces a word representation that carries contextual information of the whole sentence the word being a part of.

$$\overrightarrow{h_t} = \text{LSTM}_1(\overrightarrow{h_{t-1}}, \overrightarrow{x_t})$$  \hspace{1cm} (2)  

$$\overleftarrow{h_t} = \text{LSTM}_2(\overleftarrow{h_{t-1}}, \overleftarrow{x_t})$$  \hspace{1cm} (3)  

### 3.1.3 Convolutional Layer

The convolutional layer is primarily used to capture most informative features. The representation $h_t$ of every word in the sentence $s_t$ is compiled to form a matrix $H^{s_t}$ which is an input to the CNN. Concretely, $H^{s_t} = [h_1, \ldots, h_T]$, where $H^{s_t} \in \mathbb{R}^{T \times d_t}$. The convolutional layer is composed of a set of filters $F$. Each filter $F^p \in \mathbb{R}^{2 \times 2d_t}$, where $p$ denotes filter index, slides across the input with a window of $j$ words to form a feature map $m^p \in \mathbb{R}^{T-j+1}$.

$$m^p = \text{ReLU}(F^p \cdot H^{s_t}_{[a:a+j-1]} + b), a \in [1, T-j+1]$$  \hspace{1cm} (4)  

where $H^{s_t}_{[a:a+j-1]}$ denotes a submatrix of $H^{s_t}$ from row $a$ to row $a + j - 1$; $b \in \mathbb{R}$ is an additive bias. A Rectified Linear Unit (ReLU) is applied element-wise as a nonlinear activation function in our study.

One-dimensional max-pooling operation is then performed to obtain a fixed-length vector. Given that each feature $m^p$ is of length $T-j+1$, a feature map $m^p$ is transformed into a vector of half the length through a 1D max-pooling window of size 2. In other words, only meaningful features per bigram are extracted (Eq. 5). All resultant feature maps are combined into a final representation $C^{s_t} \in \mathbb{R}^{[T-j+1]/2 \times |F|}$ (Eq. 6).

$$f^p = [\max(m^p_{1:2}) \oplus \cdots \oplus \max(m^p_{T-j+1:T-j+1})]$$  \hspace{1cm} (5)  

$$C^{s_t} = [f^1 \oplus \cdots \oplus f^{|F|}]$$  \hspace{1cm} (6)  

### 3.1.4 Attention Layer

In this section, we describe the attention mechanism employed to attend to important units (bigrams) in a sentence. We introduce a trainable vector $u_v$ for all the bigrams to capture “global” bigram saliency. Each vector of $C^{s_t}$, denoted as $C^{v_t}$, is selected through a multiplication operation $C^{v_t}e_v$, where $e_v$ is a standard basis vector containing all zeros except for a one in the $v$-th position. $C^{v_t}$ is projected to a transformed space to generate $u_{s_t}$ (Eq. 7). The inner product $u^T_v \cdot u_{s_t}$ signals the importance of the $v$-th bigram. We convert it to a normalized weight $\alpha_{s_t}$ using a softmax function (Eq. 8). Finally, a weighted sum of representation is computed to obtain a sentence vector $s_t$ (Eq. 9).

$$u_{s_t} = \tanh(W^{s_t}C^{v_t} + b^{s_t})$$  \hspace{1cm} (7)  

$$\alpha_{s_t} = \frac{\exp(u^T_{s_t}u_v)}{\sum_v \exp(u^T_{s_t}u_v)}, 1 \leq v \leq |F|$$  \hspace{1cm} (8)  

$$s_t = \sum_v \alpha_{s_t}C^{v_t}$$  \hspace{1cm} (9)  

### 3.2 Thread Encoder

The thread encoder takes as input a sequence of sentence vectors $d=[s_1, \ldots, s_N]$ previously encoded through the sentence encoder. We choose to index sentences by $i$. The thread encoder has a similar network architecture as the sentence encoder, summarized by Eq. 10-12. Vectors $h_i$ and $\overleftarrow{h_i}$ are of dimension $\mathbb{R}^{d_t}$; thus, $h_i = [h_i, \overleftarrow{h_i}] \in \mathbb{R}^{2d_t}$ where $d_t$ is the dimensionality of the hidden state in the sentence-level Bi-LSTM (Eq. 10-12). A matrix $H^d \in \mathbb{R}^{N \times 2d_t}$ is generated.

![Fig. (1) Illustration of the sentence encoder.](image-url)
Fig. (2) Complete framework of the proposed summarization model.

from \( h_i \) of every sentence in the thread compiled together (Eq. 13).

\[
\begin{align*}
\overrightarrow{h_i} & = \text{LSTM}_3(\overrightarrow{h_{i-1}}, s_i) \\
\overleftarrow{h_i} & = \text{LSTM}_4(\overleftarrow{h_{i-1}}, s_i) \\
h_i & = [\overrightarrow{h_i}, \overleftarrow{h_i}] \\
H^d & = [h_1, \cdots, h_N]
\end{align*}
\] 

(10)  
(11)  
(12)  
(13)

Each feature map is represented by \( m^q \in \mathbb{R}^{N-k+1} \), where \( q \) is a filter index; \( N \) is total number of sentences in the thread; and \( k \) is a filter height (Eq. 14). \( f^q \) is constituted of the max-pooled values of \( m^q \) concatenated together (Eq. 15). The max-pooling window size is 2 representing a pair of consecutive sentences. All resultant max-pooled vectors are combined into a final representation \( C^d \in \mathbb{R}^{\lfloor (N-k+1)/2 \rfloor \times |F|} \) (Eq. 16).

\[
\begin{align*}
m^q & = \text{ReLU}(F^q \cdot H^d_{[a:a+k-1]} + b), a \in [1, N-k+1] \quad (14) \\
f^q & = [\max(m^q_{[1:2]}) \oplus \cdots \oplus \max(m^q_{[N-k:N-k+1]})] \\
C^d & = [f^1 \oplus \cdots \oplus f^{|F|}] \\
\end{align*}
\] 

(15)  
(16)

Each vector of \( C^d \) is denoted by \( C^d_{v'} \) (Eq. 17). The sentence-level attention mechanism introduces a trainable vector \( u_{v'} \) that encodes salient sentence-level content. The thread vector \( d \) is a weighted sum of sentence pairs, where \( \alpha_d \) is a normalized scalar value indicating important sentence pairs in the thread (Eq. 18, 19).

\[
\begin{align*}
u_d & = \tanh(W^d C^d_{v'} + b^d); \\
\alpha_d & = \frac{\exp(u^T_d u_{v'})}{\sum_{v'} \exp(u^T_d u_{v'})}, 1 \leq v' \leq |F| \\
d & = \sum_{v'} \alpha_d C^d_{v'}
\end{align*}
\] 

(17)  
(18)  
(19)

3.3 Output Layer

The vector representation of each sentence is concatenated with its corresponding thread representation to construct the final representation, denoted as \([s_i, d]\). With this, both sentence-level and thread-level context are taken into account for the classification. The learned vector representations are fed into a dense layer of which sigmoid is used as an activation function. Cross-entropy is used to measure the network loss.

3.4 Sentence Extraction

We impose a limit to the number of words in the final summary – at most 20% of total words in the original thread are allowed. In order to extract salient sentences, all sentences are sorted based on saliency scores outputted from the dense layer. Sorted sentences are then iteratively added to the final summary until the compression limit is reached. At last, all the sentences in the final summary are chronologically ordered according to their appearance in the original thread. Since sentences selected by supervised summarization models tend to be redundant [25], we apply an additional constraint to include a sentence in the summary only if it contains at least 50% new bigrams in comparison to all existing bigrams in the final summary. Henceforth, we refer to our approach as Hierarchical Unified Deep Neural Network. A complete framework of the proposed network is illustrated in Figure 2.

4 EXPERIMENT

In this section, we first give a description of the datasets used for experiments, followed by details of how the training set is created. Then, we present experiment configurations along with a list of hyperparameters explored to achieve the best performing model. Next, we provide a brief description of baselines used in our performance study, and subsequently give an introduction to the metrics for evaluating performance of the summarization system.
4.1 Dataset

Since the proposed approach is applicable for multidocument summarization, we perform experiments on news articles in addition to online forums. Three datasets, namely TripAdvisor, Reddit, and Newsroom, are used in our study – the former two were crawled from online forums while the latter is news articles from major publications. Statistics of all datasets is provided in Table 1 and a brief description of each is as follows.

**Trip advisor.** The TripAdvisor forum data were collected by Bhatia et al. [6]. In our study, there are a total of 700 TripAdvisor threads, 100 of which were originally annotated with human summaries by [6], and the additional 600 threads were annotated later by [6]. We held out 100 threads as a development set and reported the performance results on the remaining threads. The development set is mainly used for hyperparameter-tuning purposes as described in Section 4.3. The reference summaries were prepared by having two human annotators generate a summary for each thread. Both annotators were instructed to read a thread, then write a corresponding summary with the length limited within 10% to 25% of the original thread length. The annotators were also encouraged to pick sentences directly from the data.

**Reddit.** Reddit forum data [4] were prepared by Wubben et al. [46]. It contains 242,666 threads in 12,980 subreddits. The size of threads ranges from 5 sentences with a few words per line to over 43,000 sentences. In our study, we utilize threads with a length of at least 10 sentences, since any threads of smaller size no longer requires a summary. The training and test sets contain 66,589 and 17,869 threads respectively, while the development set contains 20,891 threads for hyperparameter-tuning. The reference summaries were prepared by using the number of votes as a factor to select sentences. That is, all sentences are first ranked based on their final votes (No. of upvotes - No. of downvotes), then the ranked sentences are iteratively added into the output list until total words reach the compression ratio (25% of original total words), and finally the selected sentences are ordered according to their chronological order.

**Newsroom.** Newsroom is a summarization dataset contains 1.3 million articles and summaries written by authors and editors in the newsrooms of 38 major publications [47]. It is used for training and evaluating summarization systems. The dataset provides training, development, and test sets. Each set comprises summary objects, where each individual one includes information of article text, its corresponding summary, date, density bin, just to name a few. Density bin represents a factor to select sentences. That is, all sentences are first ranked based on their final votes (No. of upvotes - No. of downvotes), then the ranked sentences are iteratively added into the output list until total words reach the compression ratio (25% of original total words), and finally the selected sentences are ordered according to their chronological order.

4.2 Training Set Creation

In this study, every sentence requires a label to train the deep neural network; therefore, we create a training set where each sentence will be marked as True to indicate a part-of-summary unit, or False to indicate otherwise. First of all, an empty set \( S = \{ \} \) is initialized per thread (or per news article). For each sentence that is not a member of the set, the sentence will be added to the set then measure ROUGE-1 score between the set and the gold summaries; thereafter, the sentence is removed from the set. This process is repeated until one of the following conditions is achieved: 1) the total number of words in the selected sentences has hit the desired compression ratio of 20%, or 2) the ROUGE score of summary cannot be improved any further. Finally, those sentences that are a member of the set are labeled True, while others are labeled False. We utilized the ROUGE 2.0 Java package [55] to evaluate the ROUGE scores that presents the unigram overlap between the selected sentences and the gold summaries [54].

4.3 Model Configuration

The optimum parameters for the proposed model were explored through experimentation. Six-fold cross-validation was used for both tuning and training process. We performed a random search by sampling without replacement over 80% of all possible configurations since the whole configuration space is too large. All hyperparameters are listed in Table 2 [5]. We found the best configuration for the number of Bi-LSTM neurons at sentence encoder to be 200, and at thread encoder to be 100, respectively. For CNN hyperparameters, the best explored number of convolutional layers at sentence and thread levels is 2; and the best number of filters at both levels is 100, where each filter has the size and a stride length of 2. The best explored dropout rate is 0.3, with learning rate of 0.001 and a batch size of 16. Lastly, RMSprop optimizer has shown to best optimize binary cross-entropy loss function in our model.

The training/validation/test split was set to 0.8/0.1/0.1 of all threads. We kept this split ratio fixed in all the experiments and all datasets. To prevent the model from overfitting, we applied early stopping during the training process. This was done by computing an error value of the model on a validation dataset for every epoch and terminating the training if the error value monotonically increased. After obtaining the best configuration, we retrained the model on the union of training and development sets and evaluated

| TABLE (1) Data statistics                  | Trip advisor | Reddit | Newsroom |
|------------------------------------------|--------------|--------|----------|
| Vocabulary                               | 26,422       | 910,941| 894,212  |
| #Threads                                 | 700          | 105,349| 351,910  |
| Avg #sentences                           | 59.41        | 64.99  | 35.57    |
| Max #sentences                           | 144          | 43,486 | 1,559    |
| Avg #words                               | 833.65       | 783.85 | 679.24   |
| Max #words                               | 1,559        | 532,400| 178,463  |
| Avg #words per sentence                  | 14.03        | 11.84  | 16.23    |
For BERT our comparative study: The following unsupervised-learning baselines are used for supervised methods. Detailed descriptions of each baseline shown to give better performances.

4.4 Baselines

We compare the proposed model against unsupervised and supervised methods. Detailed descriptions of each baseline are as follows.

4.4.1 Unsupervised-learning Baselines

The following unsupervised-learning baselines are used for our comparative study:

- ILP [57], a baseline Integer Linear Programming framework implemented by [58].
- SumBasic [59], an approach that assumes words occurring frequently in a document cluster have a higher chance of being included in the summary.
- KL-SUM [60], a method that adds sentences to the summary so long as it decreases the KL Divergence.
- LSA [61], the latent semantic analysis technique to identify semantically important sentences.
- LEXRANK [62], a graph-based summarization approach based on eigenvector centrality.
- MEAD [63], a centroid-based summarization system that scores sentences based on sentence length, centroid, and position.
- Opinosis [64], a graph based algorithm for generating abstractive summaries from large amounts of highly redundant text.
- TextRank [65], a graph-based extractive summarization algorithm which computes similarity among sentences.

4.4.2 Supervised-learning Baselines

We also include traditional supervised-learning methods namely Support Vector Machine (SVM) and LIBLINEAR [66] in our study. Both of which employ the following features: 1) cosine similarity of current sentence to thread centroid, 2) relative sentence position within the thread, 3) the number of words in the sentence excluding stopwords, and 4) max/avg/total TF-IDF scores of the consisting words. The features were designed such that they carry similar information as our proposed model.

4.4.3 Deep Learning Baseline

Neural network methods, including LSTM and CNN, have been used as a deep learning baseline in our study. For LSTM, we implemented a neural network containing a single layer of LSTM to classify sentences in each input thread/news article. For CNN, the sentence classification model proposed by [67] is applied. The input layer was initialized with pre-trained static word embeddings. The network uses features extracted from the convolutional layer for the classification.

In addition, we implemented a variant of HAN, namely hierarchical convolutional neural network (HCNN) which employs CNN rather than LSTM. This allows us to examine the effectiveness of each individual network.

4.5 Evaluation Methods

We report ROUGE-1, ROUGE-2, and ROUGE-L scores along with sentence-level scores for the evaluation. The quantitative values for each method are computed as precision, recall, and F1 measure. Note that we will also refer to ROUGE metrics as R-1, R-2, and R-L for short.

ROUGE-1 and ROUGE-2 are metrics commonly used in the DUC and TAC competitions to evaluate the quality of system summary [68]. Their precision scores are computed as the number of n-grams the system summary has in common with its corresponding human reference summaries divided by total n-grams in the system summary where R-1 and R-2 set n=1 and n=2, respectively. R-1 and R-2 recall scores are calculated the same way except that the number of overlapping n-grams are divided by the total n-grams in the human reference summary. Finally, the F1 score for R-1 and R-2 is the harmonic mean of precision and recall. We use R-1 and R-2 as a means to assess informativeness. ROUGE-L measures the longest common subsequence of words between the sentences in the system summary and the reference summary. The higher the R-L, the more likely that the output summary has n-grams in the same order as the reference summary. In other words, R-L indicates how well the output summary preserves the semantic meaning of the reference summary.

Sentence-level scores report the classification performance of the model. Each sentence is labelled true or false to signify if it is part of the summary. When the label is true in both reference set (actual class) and system set (predicted class), this case is considered true positive. If labelled true
in the reference set yet false in the system set, this case is considered false negative. On the other hand, if labelled true in the system set yet false in the reference set, this case is considered false positive. Finally, a sentence labelled false in both the system set and the reference set is considered true negative. Table 3 presents the confusion matrix.

| Actual Class | Predicted Class | True Positives (TP) | False Positives (FP) | True Negatives (TN) | False Negatives (FN) |
|--------------|-----------------|---------------------|----------------------|---------------------|----------------------|
| True         | False           |                      |                      |                     |                      |
| False        | True            |                      |                      |                     |                      |

Sentence-level precision is the number of true positives divided by the sum of true positives and false positives. Sentence-level recall is the number of true positives divided by the sum of true positives and false negatives. Lastly, sentence-level F1 is the harmonic mean of recall and precision.

5 PERFORMANCE EVALUATION RESULTS AND DISCUSSIONS

Our proposed network is compared against a set of unsupervised and supervised approaches, along with variants of hierarchical methods. In this section, we first discuss the performance of different methods which involve traditional machine learning baselines, non-hierarchical and hierarchical deep learning methods. Then, we explain comparisons, observations, and provide our detailed analysis. After that, extensive ablation studies are presented.

5.1 Comparison with Traditional Machine Learning Baselines

Among the unsupervised-learning baselines in Table 4, the sentence classification results from MEAD demonstrate good performance. MEAD has also been shown to perform well in previous studies such as 69. In this study, MEAD and LexRank are centroid-based, meaning that sentences that contain more words from the cluster centroid are considered to be holding key information, thereby increasing the likelihood of being included in the final summary. A similar pattern in results appears in KL-Sum and LSA. Nonetheless, in terms of ROUGE evaluation as shown in Table 5, they were all outperformed by hierarchical-based deep learning approaches. Opinosis has poor performance since it relies heavily on the redundancy of the data to generate a graph with meaningful paths. To this end, the hierarchical approaches appear to achieve better performance without the need for sophisticated constraint optimization such as in ILP.

Regarding the supervised-learning baselines, according to Table 5, a pattern of high precision and low recall can generally be observed for both SVM and LogReg. The R-1 results reflect that among the sentences classified as True, there are several unigrams overlapping with the reference summaries. However, when evaluating with higher n-grams, the results show that only a few matches exist between the system and the references. Considering the sentence-level scores of the Trip advisor dataset as an example, it can be seen that LogReg has failed to extract representative sentences as evidenced from the 14.50% precision and 12.10% recall, which are the lowest.

The comparison of traditional models against hierarchical-based models has shown that the hierarchical models have better potential in classifying and selecting salient sentences to form a summary. Furthermore, both traditional machine learning baselines possess one disadvantage which is their reliance on a set of features from the feature engineering process. These handcrafted features might not be able to capture all the traits necessary for the models to differentiate between classes.

5.2 Comparison to Non-hierarchical Deep Learning Methods

In general, LSTM outperforms CNN in terms of sentence classification as well as ROUGE evaluation. Particularly for the sentence classification task, LSTM has shown to achieve high precision scores across all datasets. This indicates the importance of the learning of sequential information towards obtaining an effective representation. CNN, although proven to be efficient in previous studies, the results have evidenced that omitting sequential information essentially results in an inferior performance as shown in Table 5.

In terms of ROUGE evaluation, according to Table 6, R-1 and R-2 of both LSTM and CNN baselines are quite competitive compared to the hierarchical-based methods. However, with respect to R-L scores, hierarchical-based models generally have better performance by a significant margin. We observe that, hierarchical models have an advantage over the non-hierarchical deep learning methods in that they also explore hierarchical structure on top of sequential information learned via LSTM or feature extraction learned via CNN.

5.3 Comparison with Hierarchical Attention-based Deep Networks

Of all the hierarchical-based models, we compare the proposed model against the state-of-the-art HAN model to examine whether the proposed architecture contributes to performance gain/loss. We hypothesize that both LSTM and CNN encourage the leverage of long-term and short-term dependencies, which are keys to learning and generating effective representation for the summarizer. We also make a comparison with the hierarchical convolutional neural network (HCNN) to observe the effect of excluding long-term dependencies captured by LSTM.

According to Table 5, the sentence-level score shows that on average the performance of our proposed network is comparative to other hierarchical methods regardless of the choice of embedding. HCNN is generally the most inferior among the three hierarchical models. This demonstrates that LSTM layers play a key role in capturing sequential information which is essential for the system to understand input documents. Without LSTM layers, the system only obtains high-level representation through CNN which is insufficient to generate an effective representation. Using both LSTM and CNN has shown a promising avenue to improve the summarization task.
It is important to note that, when the contextual representation is employed, especially for Reddit and Newsroom datasets, their results have shown high precision yet low recall. This indicates that few sentences are predicted as a part-of-summary sentence; however, most of its predicted labels are correct. Figure 3 illustrates a comparison among hierarchical methods with respect to sentence-level scores across all datasets.

With respect to ROUGE evaluation, Table 6 shows that ROUGE scores for the hierarchical models are promising. Among the hierarchical models, our proposed method outperforms others in all datasets, as displayed in Figure 4 (a) - (i). We present example summaries generated by the hierarchical models in Figure 5. The results indicate that for our proposed model, among all its true-labeled sentences, 46.67% were labeled correctly which is higher than the rest of the hierarchical models.

We also observed the behavior of each hierarchical model in terms of loss that is minimized. Figure 6 (a) - (f) illustrate the training loss of each hierarchical model per fold. We note that for every fold of every model, the objective loss continuously decreases and begins to converge very early on. The average losses across all epochs of HAN, HCNN, and our proposed model are approximately 0.2555, 0.2564, and 0.2466, respectively. More fluctuations also appear in the HCNN curve. Our model converges faster due to its larger model complexity.

5.4 Ablation Study
In this subsection, we discuss our observations from extensive ablation experiments conducted to better understand our model from various aspects.

5.4.1 Model Component Analysis
A comprehensive component analysis is performed by adding different components on top of baseline methods as presented in Table 5. The results reveal that using a model equipped with either CNN or LSTM alone performs poorly across all datasets. This indicates that leveraging the hierarchical structure of an input document to generate a document representation has helped boost the performance. Specifically, the hierarchical structure captures information at both word and sentence levels – word-level representation is learned and subsequently aggregated to form a sentence; likewise, sentence-level representation is learned and subsequently aggregated to form document representation. Among all hierarchical-based models, the ROUGE-L scores of HAN and HCNN are comparative, whereas our proposed model has illustrated an evident performance gain. The shift in improvement is also noticeable (>1%) for Reddit and Newsroom datasets which are larger in size than Trip advisor.

According to Table 5, when comparing results from the proposed model against those from baseline-CNN and baseline-LSTM, the overall improvement is 11.94% for Trip advisor dataset, 14.53% and 24.11% for Reddit dataset, and 4.24% and 9.29% for Newsroom dataset, respectively.

5.4.2 Effect of CNN configurations
Table 7 and 8 show the model performance on different receptive field sizes and different number of convolutional layers, while other parameters remain fixed. It is important to note that when multiple receptive field sizes are used, such as [2,3], an output obtained from each local feature needs to be concatenated first to yield a representation that will be used by a layer following CNN. We observe that the receptive field size of 2 outperforms others across all datasets in both sentence classification and ROUGE evaluation. For Reddit dataset, the decrease in performance is notable. Regarding the number of convolutional layers, we observe that increasing convolutional layers leads to a drop in overall performance. With the number of layers of 6 (highest), the classification performance as well as the output summary quality are the lowest. The CNN part of our proposed model, therefore, applies a receptive field size of 2 and a single convolutional layer.

5.4.3 Representation Learning
In this section, we discuss the impact of different embeddings on the hierarchical models. We report the effect of using static word embeddings versus contextual embeddings. We also concatenate static and contextual embeddings to examine their joint effect on the performance.

We investigate the outputs from the model initialized with only static word embeddings. The results for all...
### Table 4: Sentence-level classification results from all models. Precision (P), Recall (R), and F1 scores (F) are reported in percentage. Variance (±) of F1 scores across all data are also presented.

| Embedding | Method          | Trip advisor | Reddit | Newsroom |
|-----------|----------------|--------------|--------|----------|
|           | Baselines      | P  | R  | F  | P  | R  | F  | P  | R  | F  | P  | R  | F  |
|           | ILP            | 22.60 | 13.60 | 15.60±0.40 | 22.86 | 23.40 | 23.12±0.10 | 16.05 | 20.15 | 17.87±0.10 |
|           | Sum-Basic      | 22.90 | 14.70 | 16.70±0.50 | 22.31 | 17.11 | 19.37±0.20 | 16.57 | 18.52 | 17.49±0.10 |
|           | KL-Sum         | 21.10 | 15.20 | 16.36±0.50 | 23.58 | 17.91 | 20.36±0.10 | 17.28 | 20.74 | 18.83±0.20 |
|           | LSA            | 21.05 | 15.02 | 17.53±0.50 | 23.59 | 17.91 | 20.37±0.10 | 27.64 | 32.34 | 29.81±0.20 |
|           | LexRank        | 21.50 | 14.30 | 16.00±0.50 | 24.69 | 18.17 | 20.94±0.10 | 29.22 | 32.98 | 29.65±0.20 |
|           | MEAD           | 29.20 | 27.80 | 26.80±0.50 | 26.83 | 28.26 | 27.52±0.10 | 25.40 | 41.03 | 31.38±0.10 |
|           | SVM            | 34.30 | 32.70 | 31.40±0.40 | 17.09 | 4.32 | 6.90±0.10 | 27.19 | 14.09 | 18.56±0.30 |
|           | LogReg         | 14.50 | 12.10 | 12.50±0.50 | 5.10 | 0.67 | 1.18±0.30 | 18.43 | 6.22 | 9.30±0.40 |
|           | LSTM           | 43.12 | 38.09 | 40.44±0.03 | 35.02 | 30.85 | 32.27±0.02 | 35.31 | 26.30 | 30.17±0.01 |
|           | CNN            | 35.17 | 23.35 | 28.03±0.03 | 27.91 | 22.61 | 24.98±0.02 | 27.63 | 26.88 | 26.23±0.01 |
| Hierarchical + Static Embedding | w2v | 39.65 | 33.41 | 36.26±0.05 | 27.01 | 29.74 | 28.31±0.02 | 25.80 | 27.33 | 26.55±0.01 |
|           |                | HCNN | 36.37 | 26.78 | 30.84±0.03 | 26.64 | 23.23 | 24.82±0.04 | 23.20 | 31.43 | 26.69±0.03 |
|           |                | Ours | 40.65 | 32.49 | 36.12±0.02 | 27.63 | 30.78 | 29.12±0.04 | 25.40 | 26.65 | 26.01±0.03 |
| FastText  | w2v            | 35.56 | 25.43 | 29.66±0.05 | 27.11 | 28.00 | 27.55±0.03 | 25.90 | 28.52 | 27.15±0.01 |
|           |                | HCNN | 34.97 | 25.56 | 29.53±0.03 | 26.60 | 23.22 | 24.80±0.03 | 22.64 | 28.54 | 25.25±0.02 |
|           |                | Ours | 39.97 | 32.25 | 35.70±0.02 | 29.48 | 20.89 | 24.45±0.03 | 25.32 | 26.81 | 26.04±0.02 |
| Hierarchical + ELMo     | w2v | 39.74 | 33.48 | 36.31±0.01 | 35.60 | 1.98 | 3.74±0.01 | 31.61 | 25.84 | 28.44±0.02 |
|           |                | HCNN | 38.02 | 30.44 | 33.81±0.01 | 36.07 | 5.03 | 8.82±0.01 | 31.22 | 19.22 | 23.79±0.01 |
|           |                | Ours | 40.74 | 36.92 | 38.69±0.02 | 35.49 | 3.75 | 6.79±0.01 | 30.87 | 26.52 | 28.53±0.02 |
| FastText  | w2v            | 38.05 | 30.06 | 33.56±0.01 | 30.78 | 15.69 | 20.79±0.01 | 26.31 | 27.17 | 26.75±0.02 |
|           |                | HCNN | 38.08 | 31.08 | 34.18±0.01 | 33.62 | 2.29 | 4.28±0.01 | 26.57 | 26.07 | 26.32±0.01 |
|           |                | Ours | 38.50 | 32.50 | 35.15±0.01 | 29.33 | 14.60 | 24.50±0.01 | 26.44 | 25.94 | 25.98±0.01 |
| Hierarchical + BERT     | w2v | 37.67 | 29.12 | 32.83±0.02 | 30.35 | 15.59 | 20.42±0.01 | 25.89 | 24.16 | 24.99±0.01 |
|           |                | HCNN | 38.20 | 30.30 | 33.78±0.01 | 34.45 | 3.56 | 6.45±0.01 | 25.79 | 24.22 | 24.98±0.02 |
|           |                | Ours | 38.16 | 31.88 | 34.72±0.01 | 29.61 | 11.63 | 16.70±0.02 | 26.80 | 30.66 | 26.50±0.02 |

### Table 5: Ablation study to investigate the effect of each component in the hierarchical-based models. F1 scores of ROUGE-L are compared (unit in percentage). ✓ indicates the component available in the model. The overall improvement in red and blue are the proposed model performance gain compared to Baseline LSTM and Baseline CNN, respectively.

| Model Component | LSTM | CNN | Hierarchical Attention | Data | Trip advisor | Reddit | Newsroom |
|-----------------|------|-----|------------------------|------|--------------|--------|----------|
| Baseline LSTM   | ✓    | ✓   | ✓                      | Baseline LSTM | 20.07 | 38.81 | 19.87 |
| Baseline CNN    | ✓    | ✓   | ✓                      | Baseline CNN  | 20.07 | 29.23 | 14.82 |
| HAN             | ✓    | ✓   | ✓                      | HAN      | 21.84 | 44.52 | 18.39 |
| HCNN            | ✓    | ✓   | ✓                      | HCNN     | 21.60 | 44.61 | 17.25 |
| Ours            | ✓    | ✓   | ✓                      | Ours     | 32.01 | 53.34 | 24.11 |

Overall Improvement | +11.94 | +14.53 | +4.24 | +11.94 | +24.11 | +9.29 |
### TABLE (6) Summarization results from all models. F1 scores are reported for both sentence-level classification (SL) and ROUGE evaluation (R-1, R-2, R-L). Shaded in gray are best values (in %). Non-shaded values presents loss compared to the best values, also in %.

| Embedding | Method | Trip advisor | Reddit | Newsroom |
|-----------|--------|--------------|--------|----------|
|           |        | K-1 | R-2 | R-L | K-1 | R-2 | R-L | K-1 | R-2 | R-L |
| Baselines |        |     |     |     |     |     |     |     |     |     |
| ILP       |        | 29.30 | 9.90 | 12.80 | 40.85 | 38.96 | 37.84 | 17.45 | 16.89 | 16.05 |
| Sum-Basic |        | 33.10 | 10.40 | 13.70 | 36.66 | 34.72 | 36.63 | 16.28 | 15.63 | 16.31 |
| KL-Sum    |        | 35.50 | 12.30 | 13.40 | 46.87 | 45.23 | 46.78 | 21.10 | 20.53 | 20.96 |
| LSA       |        | 34.20 | 14.50 | 13.60 | 46.85 | 45.24 | 46.88 | 25.29 | 24.80 | 24.41 |
| LexRank   |        | 38.70 | 14.20 | 13.20 | 44.93 | 43.28 | 44.85 | 21.08 | 20.51 | 20.99 |
| MEAD      |        | 38.50 | 15.40 | 22.00 | 44.70 | 46.94 | 47.57 | 20.97 | 22.24 | 22.26 |
| Opinosis  |        | 0.62  | 0.10  | 0.99  | 1.33  | 0.24  | 1.67  | 2.22  | 0.95  | 2.24  |
| TextRank  |        | -     | -     | -     | -     | -     | -     | 24.45 | 10.12 | 20.13 |
| SVM       |        | 24.70 | 10.00 | 25.80 | 6.02  | 2.57  | 7.46  | 17.46 | 17.76 | 25.04 |
| LogReg    |        | 29.40 | 7.80  | 10.30 | 0.73  | 0.34  | 0.92  | 7.21  | 7.35  | 11.23 |
| LSTM      |        | 33.02 | 11.92 | 20.07 | 48.00 | 34.40 | 38.81 | 24.47 | 15.06 | 19.87 |
| CNN       |        | 33.37 | 12.22 | 20.07 | 40.00 | 24.41 | 29.23 | 20.46 | 9.19  | 14.82 |

### TABLE (7) Ablation study to investigate the effect of receptive field size towards the overall performance improvement. F1 scores are reported for both sentence-level classification (SL) and ROUGE evaluation (R-1, R-2, R-L). Shaded in gray are best values (in %). Non-shaded values presents loss compared to the best values, also in %.

| Size       | SL | R-1 | R-2 | R-L | SL | R-1 | R-2 | R-L | SL | R-1 | R-2 | R-L |
|------------|----|-----|-----|-----|----|-----|-----|-----|----|-----|-----|-----|
| Baselines  |    |     |     |     |    |     |     |     |    |     |     |     |
| (2,3)      | 36.12 | 38.13 | 15.51 | 32.01 | 29.12 | 54.67 | 42.84 | 15.54 | 30.01 | 42.84 | 54.67 | 15.54 |
| (2,3,4)    | -2.41 | -2.44 | -1.45 | -1.65 | -8.33 | -10.51 | -14.72 | -11.68 | -2.00 | -2.90 | -1.69 | -2.32 |
| (2,3,4,5)  | -2.64 | -1.97 | -0.97 | -1.23 | -12.33 | -11.03 | -15.06 | -11.86 | -1.15 | -2.76 | -1.56 | -2.24 |

### TABLE (8) Ablation study to investigate the effect of number of convolutional layer(s) towards the overall performance improvement. F1 scores are reported for both sentence-level classification (SL) and ROUGE evaluation (R-1, R-2, R-L). Shaded in gray are best values (in %). Non-shaded values presents loss compared to the best values, also in %.

| Depth     | SL | R-1 | R-2 | R-L | SL | R-1 | R-2 | R-L | SL | R-1 | R-2 | R-L |
|-----------|----|-----|-----|-----|----|-----|-----|-----|----|-----|-----|-----|
| Baselines |    |     |     |     |    |     |     |     |    |     |     |     |
| 1         | 36.12 | 38.13 | 15.51 | 32.01 | 29.12 | 54.67 | 42.84 | 15.54 | 30.01 | 42.84 | 54.67 | 15.54 |
| 2         | -2.02 | -2.11 | -1.11 | -1.17 | -2.01 | -11.07 | -15.59 | -12.17 | -0.97 | -2.98 | -1.72 | -2.49 |
| 3         | -1.28 | -2.36 | -1.39 | -1.57 | -10.33 | -10.68 | -14.69 | -11.68 | -2.30 | -3.15 | -2.13 | -2.70 |
| 4         | -2.03 | -2.30 | -1.10 | -1.42 | -12.04 | -10.86 | -14.87 | -11.72 | -1.64 | -3.04 | -1.87 | -2.39 |
| 5         | -1.80 | -2.48 | -1.51 | -1.75 | -9.97 | -10.82 | -15.08 | -11.80 | -0.94 | -2.84 | -1.66 | -2.31 |
| 6         | -2.34 | -2.14 | -1.10 | -1.15 | -10.55 | -11.27 | -15.39 | -12.23 | -3.07 | -3.37 | -2.29 | -2.80 |
Fig. (4) Comparison of F1-scores among Hierarchical Methods based on ROUGE scores. \textbf{x-axis} denotes types of embeddings; 1=w2v, 2=FastText, 3=ELMo, 4=ELMo+w2v, 5=ELMo+FastText, 6=BERT, 7=BERT+w2v, 8=BERT+FastText. \textbf{y-axis} denotes F1 scores normalized between [0,1]. The bar color blue presents HAN, orange presents HCNN, and gray presents our proposed model. Fig. (4)(a)-(c) are R-1 scores, Fig. (4)(d)-(f) are R-2 scores, and Fig. (4)(g)-(i) are R-L scores.

TABLE (9) Ablation study to investigate the effect of attention mechanism. The results are obtained from the proposed model. \checkmark means the attention mechanism is applied in the model, whereas \xmark is the opposite case.

| Data       | Sentence-level | R-1 | R-2 | R-L |
|------------|----------------|-----|-----|-----|
| Trip advisor | 36.12 | 36.13 | 38.13 | 35.74 | 15.51 | 14.4 |
| Reddit     | 29.12 | 30.33 | 54.67 | 43.55 | 42.84 | 27.30 |
| Newsroom   | 26.01 | 24.14 | 25.56 | 19.73 | 12.41 | 9.20 |

5.4.4 Effect of Attention Mechanism on Selecting Salient Units

We investigate the attention layer to validate whether the attention mechanism aids in selecting representative units. Table 9 shows that, with respect to ROUGE evaluation, when the attention mechanism is incorporated in the model, the performance is improved across all datasets. In particular, for the larger dataset (Reddit and Newsroom), the difference of results between with and without attention is nontrivial. In terms of sentence-level classification, incorporating the attention mechanism does not significantly affect the performance.

It is important to note that the proposed model attends to important bigrams at the word level and contiguous sentence pairs at the sentence level. At the word level, the attention value of each bigram influences the sentence vector to which the bigram belongs. The attention weight is computed according to the relevance of each bigram, given the sentence context. If a sentence contains many bigrams with high attention values, its corresponding sentence vector will potentially contain information about these prominent bigrams. In the sentence level, likewise, the attention values of the sentence pairs influence the resulting thread vector. A high attention value of a sentence pair indicates its importance and relevance towards the thread key concept.
### Model: HAN

1. You could drop your things at the hotel, and then one person could take the car there and park there, and take the train back to town.
2. I would strongly advise NOT to park on the street in Queens, the Bronx or Brooklyn and taking the subway in between, because, frankly, it takes up precious parking spaces from residents.
3. I'm sure your car will be very safe, but it really strikes a nerve with the locals.

#### Accuracy (%)

35.71

### Model: HCNN

1. How about the long-term lots at Newark or JFK?
2. Don’t worry, you’re not the only cheapskate - uh, I mean - person interested in this strategy.
3. I live near a very desirable and strategic subway station in Queens, and you can’t imagine the daily invasion of cars double-parking and cruising for spots at 7 AM.

#### Accuracy (%)

35.29

### Model: Ours

1. Would it be better or even feasible to park outside of Manhattan at a subway and take the subway into town, rather than parking in Manhattan?
2. I live near a very desirable and strategic subway station in Queens, and you can’t imagine the daily invasion of cars double-parking and cruising for spots at 7 AM.

#### Accuracy (%)

46.67

Fig. (5) Example of output summaries generated by each hierarchical model. Presented in **Bold** are correctly labelled sentences. Accuracy value (%) is computed as a ratio of number of correctly labelled sentences out of total sentences selected by the model.
Fig. (6) Plots showing the convergence of training loss per fold. The results from first 20 epochs are displayed since all models have shown to plateau from this point forward.
This attention-weighted sentence pair goes through softmax normalization, from which the output indicates how likely a sentence pair is a key unit for the summary.

Figure 7 illustrates a visualization of words in the example summary. The bigram with high attention weight will be highlighted with a darker shade compared to other bigrams with lower attention. The sentence “I am glad you are so mellow and think that it might be difficult filling up the morning before you get married at noon!” contains two bigrams, namely “glad you” and “are so” which have attention weights of 0.782 and 0.555, respectively. The sentence encoder outputs a weighted sum of the bigrams using normalized attention as weight, and the two aforementioned encoder outputs a weighted sum of the bigrams using normalized weights of 0.782 and 0.555, respectively. The sentence bigrams, namely “are so” and “mellow and think that it might be difficult filling up the morning before you get married at noon!” contains two.

Later in the thread encoder, this sentence has also shown to be in one of the highest sentence pairs ranked by attention weights. Finally, in the final summary, it can be noticed that the majority of sentences (italicized) are those belonging to the example sentence pairs with high ranked weights. Nevertheless, we emphasize that it is not necessarily the case that if a sentence is in a sentence pair with high attention, it will be selected into the final summary. High attention weights only indicate the significance of the constituent unit. In other words, whether or not a sentence is chosen into the summary is determined by the output layer which considers both sentence and thread representations concatenated together. However, it is observed that when sentences belong to sentence pairs with high attention weights, they have a higher chance of being selected into the final thread summary.

6 Conclusions

In this study, we present Hierarchical Unified Deep Neural Network to extractively summarize online forum threads. Our proposed network utilizes two deep neural networks, namely Bi-LSTM and CNN, to obtain representations used to classify whether or not the sentence is summary-worthy. The experimental results on three real-life datasets have demonstrated that the proposed model outperforms the majority of baseline methods.

Our findings confirm the initial hypothesis that the capability of encoders can be enhanced through the proposed architecture. In essence, Bi-LSTM serves a role to capture contextual information, whereas CNN helps to signify prominent units that are keys pertaining to a summary. Together, the strength of both deep neural networks have been leveraged to achieve effective representations.

Finally, we have conducted extensive experiments to investigate the effect of attention mechanism and pretrained embeddings. The results show that applying attention to the high-level features extracted and compressed by CNN, together with the contextual embeddings, provides a promising avenue towards improving the performance of extractive summarization methods.

Acknowledgments

This work was supported by Crystal Photonics, Inc. (Grant 1063271).

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Hi, I have previously posted a topic here tripadvisor.com/ShowTopic-g607963-i5-k1688802 ... We are planning a wedding for October 2015 in Central Park. The time we had thought of was 5pm. This was only because we were worried about how we would fill the day and entertain a party of 10 guests. Obviously, if we were not our wedding day we would be able to fill in some gaps easily in New York! We would ideally like to get married at noon. Any suggestions? I'm sorry, I'm confused - are you planning to get married at 3pm or noon or do you mean get married at noon and eat at 3pm??? I've ready your other post and I'd say you could still do all that and then maybe after the meal go back to your hotel, change and meet up again for cocktails at some nice bars?? Another thought is, seeing as you're in NY, depending on the weather etc would be to travel to a few different places for photos - like Time Sq., or even Top of the Rock - places that are different to what you'd get at home if that makes sense, obviously this would take some planning if you wanted all 10 guests to go too but if not you could do this after dinner before going out for the evening when everyone else has gone home to change etc. If that makes any sense? I am glad you are so mellow and think that it might be difficult filling up the morning before you get married at noon! Since you are getting married in Central Park, what about heading up to the Top of the Rock which has amazing views of the whole park? Bring a map of the park with you so you can figure out from above where the spot is. (Thanks lg1006)

We were originally planning to get married at 3pm, so we wouldn't have as much time to fill after the ceremony. Ideally though, we would like to get married at noon, as long as we have a good plan to fill up the rest of the day. The various places for photo opportunities may be a good option to use up some time between the ceremony and some dinner for the bride and father to the ceremony location, then when the ceremony has finished take some photos within Central Park, then champagne at the Bearwoods & Gedula ride & more photos, then go to a bar for 2 or 3 different locations such as the ones you mentioned. Then at the end of the 3 hour limo service it drops us off at a restaurant for dinner. GreenWhiteBlue - i was talking about filling-up the rest of the day after the wedding ceremony, not the rest of three hours before it. Sorry for the confusion. I think I explained what you're wearing. As in, if you're wearing a full dress for the ceremony, it might be nice to have a back-up outfit so you can change and hit some of the places mentioned above that are iconic of NYC for more photos. Like the Brooklyn Bridge - Times Square, NY Water taxi, Flatiron building etc etc etc if you're wearing a big dress and planning on staying in it (which could damage it). Then maybe a few nice places for drinks afterwards. Like the Rainbow Grill (below the famous Rainbow Room), The View (which overlooks Times Square), Rise Bar at the Ritz Carlton (with views of the Statue of Liberty) Cheers age, Yeah the bride will definitely be wearing her dress all day. I don't think this will stop us visiting a few places though if not sure a limo for transportation. Do you know if children are allowed in the places you mentioned as there will be a baby aged 0.9. I honestly don't know. I'd definitely motivate them first. They all serve food beautifully, you'd imagine kids would be welcome - whether or not you'd have to actually be eating there is another matter. They're all google-able though and should have contact numbers or email addresses so you can ask. (Mention it's your wedding day because if they want you to make a reservation, even for drinks, you might just get something thrown in)

Top 25 bigrams with highest attention weights:
(topic here; 0.993), (I'm sorry; 0.958), (though so; 0.941), (it depends; 0.920), (if we; 0.787), (glad you; 0.782), (full dress; 0.781), (two or; 0.756), (contact them; 0.744), (want you; 0.738), (waiting for; 0.731), (let etc; 0.729), (famous Rainbow; 0.717), (much time; 0.715) (This was; 0.650), (far different; 0.652), (guests aged; 0.644), (because; 0.630), (to the; 0.622), (fill-up; 0.617), (post and; 0.587), (quite easily; 0.584), (our time; 0.572), (so are; 0.555), (good plan; 0.544)

Top 6 sentence pairs ranked by attention weights:
- 0.527
  - Any suggestions?
  - I'm sorry - I'm confused - are you planning to get married at 3pm or noon or do you mean get married at noon and eat at 3pm??!
- 0.511
  - If that makes any sense?
  - I am glad you are so mellow and think that it might be difficult filling up the morning before you get married at noon!
- 0.500
  - I've ready your other post and I'd say you could still do all that and then maybe after the meal go back to your hotel, change and meet up again for cocktails in some nice bars??
  - Another thought is, seeing as you're in NY, depending on the weather etc would be to travel to a few different places for photos - like Time Sq., or even Top of the Rock - places that are different to what you'd get at home if that makes sense, obviously this would take some planning if you wanted all 10 guests to go too but if not you could do this after dinner before going out for the evening when everyone else has gone home to change etc.
- 0.462
  - Thanks lg1006. We were originally planning to get married at 3pm, so we wouldn't have as much time to fill after the ceremony.
  - Ideally though, we would like to get married at noon, as long as we have a good plan to fill up the rest of the day.
- 0.453
  - As in, if you're wearing a full dress for the ceremony, it might be nice to have a back-up outfit so you can change and hit some of the places mentioned above that are iconic of NYC for more photos.
  - Like the Brooklyn Bridge - Times Square, NY Water taxi, Flatiron building etc etc etc.
- 0.443
  - Like the Rainbow Grill (below the famous Rainbow Room), The View (which overlooks Times Square), Rise Bar at the Ritz Carlton (with views of the Statue of Liberty) Cheers age, Yeah the bride will definitely be wearing her dress all day.

Final summary:
Hi, I have previously posted a topic here tripadvisor.com/ShowTopic-g607963-i5-k1688802 ... Any suggestions? I've ready your other post and I'd say you could still do all that and then maybe after the meal go back to your hotel, change and meet up again for cocktails in some nice bars?? Another thought is, seeing as you're in NY, depending on the weather etc would be to travel to a few different places for photos - like Time Sq., or even Top of the Rock - places that are different to what you'd get at home if that makes sense, obviously this would take some planning if you wanted all 10 guests to go too ... but if not you could do this after dinner before going out for the evening when everyone else has gone home to change etc.

Like the Brooklyn Bridge - Times Square, NY Water taxi, Flatiron building etc etc etc.

Cheers age, Yeah the bride will definitely be wearing her dress all day.

(Mention it's your wedding day because if they want you to make a reservation, even for drinks, you might just get something thrown in!)

Fig. (7) Visualization of the generated summary for a forum thread. Top: Relative attention weights for each bigram by the proposed model over an entire thread. Bigrams with a darker highlight present higher importance. The attention values of all bigrams were obtained from word-level attention layer. Bottom: The first row presents a list of top 25 bigrams that are ranked according to their attention values, formatted as a (bigram, attention weights) tuple. The second row presents a list of sentence pairs ranked by attention weights, where the highest weight is 0.527. The bigrams in bold and underlined are those with highest attention weights. The third row presents the final summary which lists all chronologically-ordered extracted sentences. The sentences in italic are those in the top 6 sentence pairs with highest attention weights.
