Neural Extractive Summarization with Side Information

Shashi Narayan  Nikos Papasarantopoulos  Shay B. Cohen  Mirella Lapata
Institute for Language, Cognition and Computation, School of Informatics, University of Edinburgh
{shashi.narayan,nikos.papas}@ed.ac.uk {scohen,mlap}@inf.ed.ac.uk

Abstract

Most extractive summarization methods focus on the main body of the document from which sentences need to be extracted. However, the gist of the document may lie in side information, such as the title and image captions which are often available for newswire articles. We propose to explore side information in the context of single-document extractive summarization. We develop a framework for single-document summarization composed of a hierarchical document encoder and an attention-based extractor with attention over side information. We evaluate our model on a large scale news dataset. We show that extractive summarization with side information consistently outperforms its counterpart that does not use any side information, in terms of both informativeness and fluency.

1 Introduction

Increased access to information and the massive growth in the global news data have led to a growing demand from readers to spot emerging trends, person mentions and the evolution of storylines in the news (Liepins et al. 2017). The vast majority of this news data contains textual documents, driving the need for automatic document summarization systems aiming at acquiring key points in the form of a short summary from one or more documents.

While it is not so challenging for humans to summarize text, automatic summarization systems struggle with producing high quality summaries. Both extractive and abstractive systems have been proposed in recent years. Extractive summarization systems select sentences from the document and assemble them together to often generate a grammatical, fluent and semantically correct summary (Cheng and Lapata 2016; Nallapati, Zhai, and Zhou 2017; Yasunaga et al. 2017). Abstractive summarization systems, on the other hand, aim at building an internal semantic representation and then generate a summary from scratch (Chen et al. 2016; Nallapati et al. 2016; See, Liu, and Manning 2017; Tan and Wan 2017). Despite recent improvements, abstractive systems still struggle to outperform extractive systems. This paper addresses the task of single-document summarization and explores how we can further improve the sentence selection process for extractive summarization.

Most extractive methods often focus on the main body of the document from which sentences are extracted. Traditional methods manually define features which are local in the context of each sentence or a set of sentences which form the body of the document. Such features include sentence position and length (Radev et al. 2004), keywords and the presence of proper nouns (Kupiec, Pedersen, and Chen 1995; Mani 2001), frequency information such as content word frequency, composition functions for estimating sentence importance from word frequency, and the adjustment of frequency weights based on context (Nenkova, Vanderwende, and McKeown 2006) and low-level event-based features describing relationships between important actors in a document (Filatova and Hatzivassiloglou 2004). Sentences are ranked for extraction based on the overlap with features. Recent deep learning methods circumvent hand-engineered features using continuous sentence features. Kågebäck et al. (2014) and Yin and Pei (2015) map sentences to a continuous vector space which is used for similarity measurement to reduce the redundancy in the generated summaries. Cheng and Lapata (2016) and Nallapati, Zhai, and Zhou (2017) use recurrent neural networks to read sequences of sentences to get a document representation which they use to label each sentence for extraction. These methods report state of the art results without using any kind of linguistic annotation.

It is a challenging task to rely only on the main body of the document for extraction cues, as it requires document understanding. Documents in practice often have side information, such as the title, image captions, videos, images and twitter handles, along with the main body of the document. These types of side information are often available for newswire articles. Figure 1 shows an example of a newswire article taken from CNN (CNN.com). It shows the side information such as the title (first block) and the images with their captions (third block) along with the main body of the document (second block). The last block shows a manually written summary of the document in terms of “highlights” to allow readers to quickly gather information on stories. As one can see in this example, gold highlights focus on sentences from the fourth paragraph, i.e., on key events such as the “PM’s resignation”, “bribery scandal and its investigation”, “suicide” and “leaving an important note”. Interestingly, the essence of the article is explicitly or implicitly
In this paper, we develop a general framework for single-document extractive summarization with side information. Given a document $D$ consisting of a sequence of sentences $(s_1, s_2, ..., s_n)$ and a sequence of pieces of side information $(c_1, c_2, ..., c_p)$, we produce a summary $S$ by selecting $m$ sentences from $D$ (where $m < n$). We judge each sentence $s_i$ for its relevance in the summary and label it with $y_i \in \{0, 1\}$ where 1 indicates that $s_i$ should be considered for the summary and 0 otherwise. In this paper, we approach this problem in a supervised setting where we aim to maximize the likelihood of the set of labels $y = (y_1, y_2, ..., y_n)$ given the input document $D$ and model parameters $\theta$:

$$p(y|D; \theta) = \prod_{i=1}^{n} p(y_i|D; \theta)$$

The next section presents our model and discusses how it generates summaries informed with side information.

2 Problem Formulation

In this section we formally define our extractive summarization problem with side information. Given a document $D$ consisting of a sequence of sentences $(s_1, s_2, ..., s_n)$ and a sequence of pieces of side information $(c_1, c_2, ..., c_p)$, we produce a summary $S$ by selecting $m$ sentences from $D$ (where $m < n$). We judge each sentence $s_i$ for its relevance in the summary and label it with $y_i \in \{0, 1\}$ where 1 indicates that $s_i$ should be considered for the summary and 0 otherwise. In this paper, we approach this problem in a supervised setting where we aim to maximize the likelihood of the set of labels $y = (y_1, y_2, ..., y_n)$ given the input document $D$ and model parameters $\theta$:

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3 Summarization with Side Information

Our extractive summarization framework consists of a hierarchical encoder-decoder architecture assembled by recurrent neural networks (RNNs) and convolutional neural networks (CNNs). The main components of our model are a convolutional neural network sentence encoder, a recurrent...
neural network document encoder and an attention-based recurrent neural network sentence extractor. Our model exploits the compositionality of the document. It reflects that a document is built of a meaningful sequence of sentences and each sentence is built of a meaningful sequence of words. With that in mind, we first obtain continuous representations of sentences by applying single-layer convolutional neural networks over sequences of word embeddings and then we rely on a recurrent neural network to compose sequence of sentences to get document embeddings. We model extractive summarization as a sequence labelling problem using a standard encoder-decoder architecture (Sutskever, Vinyals, and Le 2014). First, the encoder reads the sequence of sentences \( s_1, s_2, \ldots, s_n \) in \( D \) and then, the decoder generates a sequence of labels \( y_1, y_2, \ldots, y_n \) labelling each sentence in \( D \). Figure 2 presents the layout of our model. In the following, we explain the main components of our model in detail.

### 3.1 Sentence Encoder

One core component of our hierarchical model is a convolutional sentence encoder which encodes sentences (from the main body and the side information) into continuous representations. CNNs (LeCun et al. 1990) have shown to be very effective in computer vision (Krizhevsky, Sutskever, and Hinton 2012) and in NLP (Collobert et al. 2011). We chose CNNs in our framework for the following reasons. Firstly, single-layer CNNs can be trained effectively and secondly, CNNs have been shown to be effective in identifying salient patterns in the input depending on the task. For example, for the caption generation task (Xu et al. 2015), CNNs successfully identify salient objects in the image for the corresponding words in the caption. We believe that CNNs can similarly identify salient terms, e.g., named-entities and events, in sentences that correlate with the gold summary. This should in turn (i) optimize intermediate document representations in both our document encoder and sentence extractor and (ii) assist the attention mechanism to correlate salient information in the side information and sentences, for extractive summarization.

Our model is a variant of the models presented in Collobert et al. (2011), Kim (2014) and Cheng and Lapata (2016). A sentence \( s \) of length \( k \) in \( D \) is represented as a dense matrix \( W = [w_1, w_2, \ldots, w_k] \in \mathbb{R}^{k \times d} \) where \( w_i \in \mathbb{R}^d \) is the word embedding of the \( i \)th word in \( s \). We apply a temporal narrow convolution by using a kernel filter \( K \in \mathbb{R}^{h \times d} \) of width \( h \) for a window of \( h \) words in \( s \) to produce a new feature. This filter is applied to each possible window of words in \( s \) to produce a feature map

\[
    f = [f_1, f_2, \ldots, f_{k-h+1}] \in \mathbb{R}^{k-h+1}
\]

where \( f_i \) is defined:

\[
    f_i = \text{ReLU}(K \circ W_{i:i+h-1} + b)
\]

where, \( \circ \) is the Hadamard Product followed by a sum over all elements, ReLU is a rectified linear activation \(^3\) and \( b \in \mathbb{R} \) is a bias term. We use the ReLU activation function to accelerate the convergence of stochastic gradient descent compared to sigmoid or tanh functions (Krizhevsky, Sutskever, and Hinton 2012). We then apply max pooling over time (Collobert et al. 2011) over the feature map \( f \) and get \( f_{\text{max}} = \max(f) \) as the feature corresponding to this particular filter \( K \). Max-pooling is followed by local response normalization for better generalization (Krizhevsky, Sutskever, and Hinton 2012). We use multiple kernels \( K_h \) of width \( h \) to compute a list of features \( f^{K_h} \). In addition, we use kernels of varying widths to learn a set of feature lists \( (f^{K_{h_1}}, f^{K_{h_2}}, \ldots) \). We concatenate all feature lists to get the final sentence representation.\(^4\)

The bottom part of Figure 2 briefly presents our convolutional sentence encoder. Kernels of sizes 2 (shown in red)

\(^2\)We tried sentence/paragraph vector (Le and Mikolov 2014) to infer sentence embeddings in advance, but the results were inferior to those presented in this paper with CNNs.

\(^3\)We use a smooth approximation to the rectifier, i.e., the softplus function: \( \text{ReLU}(x) = \ln(1 + e^x) \).

\(^4\)Cheng and Lapata (2016) sum over feature lists to get the final sentence embedding. In contrast, we follow Kim et al. (2016) and concatenate them. This seems to work best in our settings.
and 4 (shown in blue) are applied 3 times each. The max pooling over time operation leads to two feature lists $f_{K_2}$ and $f_{K_3} \in \mathbb{R}^3$. The final sentence embeddings have six dimensions. We use this sentence encoder to get sentence-level representations of the sentences and side information (the title and image captions) of the document $D$.

### 3.2 Document Encoder

The document encoder (shown in Figure 2, top left) composes a sequence of sentences to get a document representation. The sentence extractor, along with attending the side information, crucially exploits the document representation to identify the local and global importance of a sentence in the document to make a decision on whether it should be considered for the summary.

We use a recurrent neural network with Long Short-Term Memory (LSTM) cells to avoid the vanishing gradient problem when training long sequences (Hochreiter and Schmidhuber 1997). Given document $D$ consisting of a sequence of sentences $(s_1, s_2, ..., s_n)$, we follow a common practice and feed sentences in reverse order (Sutskever, Vinyals, and Le 2014; Li, Luong, and Jurafsky 2015; Filippova et al. 2015). This way we make sure that the network does not omit top sentences of the document which are particularly important for summarization (Rush, Chopra, and Weston 2015; Nallapati et al. 2016). At time step $t$, the hidden state $h_t = \text{LSTM}(s_{n-t+1:t}, h_{t-1})$ is updated as:

$$
\begin{bmatrix}
    f_t \\
    i_t \\
    o_t \\
    c_t
\end{bmatrix} =
\begin{bmatrix}
    \sigma \\
    \sigma \\
    \sigma \\
    \tanh
\end{bmatrix} W \cdot
\begin{bmatrix}
    h_{t-1} \\
    s_{n-t+1}
\end{bmatrix}
$$

$$
\begin{align*}
    c_t &= f_t \odot c_{t-1} + i_t \odot c_t \\
    h_t &= o_t \odot \tanh(c_t)
\end{align*}
$$

where the operator $\odot$ denotes element-wise multiplication and $W$ are the learned parameters of the model.

### 3.3 Sentence Extractor

Our sentence extractor (Figure 2, top right) labels each sentence in the document with labels 1 or 0 by implicitly estimating its relevance in the document and by directly attending to the side information for importance cues. It is implemented with another recurrent neural network with LSTM cells and an attention mechanism (Bahdanau, Cho, and Bengio 2014). Our attention mechanism differs from the standard practice of attending intermediate states of the input (encoder). Instead, our extractor attends to the side information in the document for cues. Given a document $D : \{(s_1, s_2, ..., s_n), (c_1, c_2, ..., c_p)\}$, it reads sentences $(s_1, s_2, ..., s_n)$ in order and labels them one by one while attending the side information $(c_1, c_2, ..., c_p)$ consisting of the title and image captions. Given sentence $s_t$ at time step $t$, it returns a probability distribution over labels as:

$$
p(y_t|s_t, D) = \text{softmax}(g(h_t, h'_t))
$$

$$
g(h_t, h'_t) = U_v V_h h_t + W'_h h'_t
$$

$$
h_t = \text{LSTM}(s_t, h_{t-1})
$$

$$
h'_t = \sum_{i=1}^p \alpha(t,i)c_i,
$$

where $\alpha(t,i) = \frac{\exp(h(t,c_i))}{\sum_j \exp(h(t,c_j))}$

where $g(\cdot)$ is a single-layer neural network with parameters $U_v, V_h$ and $W'_h$. $h_t$ is an intermediate RNN state at time step $t$. The dynamic context vector $h'_t$ is essentially the weighted sum of the side information in the document. Figure 2 summarizes our model. For each labelling decision, our network considers the encoded document meaning representation, sentences labeled so far and the side information.

### 3.4 Summary Generation

We rank sentences in the document $D$ by $p(1|s_t, D, \theta)$, the confidence scores assigned by the softmax layer of the sentence extractor and generate a summary $S$ by assembling together the $m$ best ranked sentences.

### 4 Experimental Setup

This section presents our experimental setup for the assessment of our models. We discuss the training and the evaluation dataset. We also explain how we augment existing datasets with side information and describe implementation details to facilitate the replication of our results. We present a brief description of our baseline systems.

#### 4.1 Training and Test data

To train our model, we need documents annotated with sentence importance information, i.e., each sentence in a document is labelled with 1 (summary-worthy) or 0 (not summary-worthy). For our purposes, we used an augmented version of the CNN dataset (Hermann et al. 2015).\footnote{Hermann et al. (2015) have also released the DailyMail dataset, but we do not report our results on this dataset. We found that the script written by Hermann et al. to crawl DailyMail articles mistakenly extracts image captions as part of the main body of the document. As image captions often don’t have sentence boundaries, they blend with the sentences of the document unnaturally. This leads to the production of erroneous summaries.}

Our dataset is an evolved version of the CNN dataset first collected by Svore, Vanderwende, and Burges (2007) for highlight generation. Svore, Vanderwende, and Burges (2007) noticed that CNN articles often come with “story highlights” to allow readers to quickly gather information on stories. They collected a small dataset for evaluation purposes. Woodsend and Lapata (2010) improved on this by collecting 9,000 articles and manually annotating them for sentence extraction. Recently, Hermann et al. (2015) crawled 93K CNN articles to build a large-scale corpus to...
set a benchmark for deep learning methods. Since then, this dataset has been used for single-document summarization (Nallapati et al. 2016; Cheng and Lapata 2016; Nallapati, Zhai, and Zhou 2017; See, Liu, and Manning 2017; Tan and Wan 2017). Cheng and Lapata (2016) annotated this dataset with the Woodsend and Lapata (2010) style gold annotation using a rule-based method judging each sentence for its semantic correspondence to the gold summary. Nallapati, Zhai, and Zhou (2017) automatically extracted ground truth labels such that all positively labeled sentences from an article collectively gives the highest ROUGE score with respect to the gold summary. ROUGE (Lin and Hovy 2003), a recall-oriented metric, is often used to evaluate summarization systems. See Section 5.1 for more details. Nallapati, Zhai, and Zhou (2017) reported comparable results to Cheng and Lapata (2016) with their automatically extracted labels on the DailyMail dataset (Hermann et al. 2015).

In our experiments we annotated the CNN dataset with the Nallapati, Zhai, and Zhou (2017) style annotation. We approach this exponential problem of selecting the best subset of sentences using a greedy approach and add one sentence at a time to the summary such that the ROUGE score of the current summary is the highest with respect to the gold summary. We stop adding new sentences to the summary when the additions do not improve the ROUGE score or the maximum number of sentences in the summary is reached.  

We further augmented this dataset with side information. We used a modified script of Hermann et al. (2015) to extract titles and image captions, and we associated them with the corresponding articles. All articles get associated with their titles. The availability of image captions varies from 0 to 126. For each document, we consider a maximum of 10 image captions. We experimented with various numbers (1, 3, 5, 10 and 20) of image captions on the validation set and found that our model performed best with 10 image captions. We performed mini-batch cross-entropy training with a batch size of 20 documents for 10 training epochs. After each epoch, we evaluated our model on the validation set and chose the best performing model for the test set. We trained our models with the optimizer Adam (Kingma and Ba 2015) with initial learning rate 0.001. Our system is fully implemented in TensorFlow (Abadi et al. 2015).  

4.3 Implementation Details

We used our training data to train word embeddings using the Word2vec skip-gram model (Mikolov et al. 2013) with context window size 6, negative sampling size 10 and hierarchical softmax 1. For known words, word embedding variables were initialized with pre-trained word embeddings of size 200. For unknown words, embeddings were initialized to zero, but optimized during training. All sentences, including titles and image captions, were padded with zeros to a sentence length of 100. For the convolutional sentence encoder, we followed Kim et al. (2016), and used a list of kernels of widths 1 to 7, each with output channel size of 50. This leads the sentence embedding size in our model to be 350. For the recurrent neural network component in document encoder and sentence extractor, we used a single-layered LSTM network with size 600. All input documents were padded with zeros to a maximum document length of 126. For each document, we consider a maximum of 10 image captions. We experimented with various numbers (1, 3, 5, 10 and 20) of image captions on the validation set and found that our model performed best with 10 image captions. We performed mini-batch cross-entropy training with a batch size of 20 documents for 10 training epochs. After each epoch, we evaluated our model on the validation set and chose the best performing model for the test set. We trained our models with the optimizer Adam (Kingma and Ba 2015) with initial learning rate 0.001. Our system is fully implemented in TensorFlow (Abadi et al. 2015).

5 Results and Discussion

We conducted an automatic and a human evaluation. We start this section with an ablation study on the validation set. The best model from this study is chosen for the test set. In the rest of the paper, we refer to our model as SIDE-NET for its ability to exploit side information.

4.2 Comparison Systems

We compared the output of our model against the standard baseline of simply selecting the first three sentences from each document as the summary. We refer to this baseline as LEAD in the rest of the paper.

We also compared our system against the sentence extraction system of Cheng and Lapata (2016).  

The architecture of POINTERNET is closely related to the architecture of SIDE-NET without side information.

Adding side information to POINTERNET is an interesting direction of research but we do not pursue it here. It requires decoding with multiple types of attentions, and this is not the focus of this paper.

We are unable to compare our results to the extractive system of Nallapati, Zhai, and Zhou (2017) because they report their results on the DailyMail dataset and their code is not available. The abstractive systems of Chen et al. (2016) and Tan and Wan (2017) report their results on the CNN dataset, however, their results are not comparable to ours as they report on the full-length F1, variants of ROUGE to evaluate their abstractive summaries. We report ROUGE recall scores which is more appropriate to evaluate our extractive summaries.

Our TensorFlow code is publicly available at https://github.com/shashiongithub/sidenet.
Table 1: Ablation results on the validation set. We report R1, R2, R3, R4, RL and their average (Avg.). The first block of the table presents LEAD and POINTERNET which do not use any side information. LEAD is the baseline system selecting “first” three sentences. POINTERNET is the sentence extraction system of Cheng and Lapata. SİDEİNET is our model. The second and third blocks of the table present different variants of SİDEİNET. We experimented with three types of side information: title (TITLE), image captions (CAPTION) and the first sentence (FS) of the document. The bottom block of the table presents models with more than one type of side information. The best performing model (highlighted in boldface) is used on the test set.

| MODELS         | R1  | R2  | R3  | R4  | RL  | Avg. |
|----------------|-----|-----|-----|-----|-----|------|
| LEAD           | 49.2| 18.9| 9.8 | 6.0 | 43.8| 25.5 |
| POINTERNET     | 53.3| 19.7| 10.4| 6.4 | 47.2| 27.4 |
| SİDEİNET+TITLE | 55.0| 21.6| 11.7| 7.5 | 48.9| 28.9 |
| SİDEİNET+CAPTION| 55.3| 21.3| 11.4| 7.2 | 49.0| 28.8 |
| SİDEİNET+FS    | 54.8| 21.1| 11.3| 7.2 | 48.6| 28.6 |
| Combination Models (SİDEİNET+) |       |     |     |     |     |      |
| TITLE+CAPTION  | 55.4| 21.8| 11.8| 7.5 | 49.2| 29.2 |
| TITLE+FS       | 55.1| 21.6| 11.6| 7.4 | 48.9| 28.9 |
| CAPTION+FS     | 55.3| 21.5| 11.5| 7.3 | 49.0| 28.9 |
| TITLE+CAPTION+FS| 55.4| 21.5| 11.6| 7.4 | 49.1| 29.0 |

Table 2: Final results on the test set. POINTERNET is the sentence extraction system of Cheng and Lapata. SİDEİNET is our best model from Table 1. Best ROUGE score in each block and column is highlighted in boldface.

| MODELS         | R1  | R2  | R3  | R4  | RL  |
|----------------|-----|-----|-----|-----|-----|
| Fixed length: 75b |     |     |     |     |     |
| LEAD           | 20.1| 7.1 | 3.5 | 2.1 | 14.6|
| POINTERNET     | 20.3| 7.2 | 3.5 | 2.2 | 14.8|
| SİDEİNET       | 20.2| 7.1 | 3.4 | 2.0 | 14.6|
| Fixed length: 275b |     |     |     |     |     |
| LEAD           | 39.1| 14.5| 7.6 | 4.7 | 34.6|
| POINTERNET     | 38.6| 13.9| 7.3 | 4.4 | 34.3|
| SİDEİNET       | 39.7| 14.7| 7.9 | 5.0 | 35.2|
| Full length summaries |     |     |     |     |     |
| LEAD           | 49.3| 19.5| 10.7| 6.9 | 43.8|
| POINTERNET     | 51.7| 19.7| 10.6| 6.6 | 45.7|
| SİDEİNET       | 54.2| 21.6| 12.0| 7.9 | 48.1|

5.1 Automatic Evaluation

To automatically assess the quality of our summaries, we used ROUGE (Lin and Hovy 2003), a recall-oriented metric, to compare our model-generated summaries to manually-written highlights.12 Previous work has reported ROUGE-1 (R1) and ROUGE-2 (R2) scores to access informativeness, and ROUGE-L (RL) to access fluency. In addition to R1, R2 and RL, we also report ROUGE-3 (R3) and ROUGE-4 (R4) capturing higher order n-grams overlap to assess informativeness and fluency simultaneously.

We follow Cheng and Lapata and report on both full length (three sentences with the top scores as the summary) and fixed length (first 75 bytes and 275 bytes as the summary) summaries. For full length summaries, our decision of selecting three sentences is guided by the fact that there are 3,111 sentences on average in the gold highlights of the training set. We conduct our ablation study on the validation set with full length ROUGE scores, but we report both fixed and full length ROUGE scores for the test set.

We experimented with two types of side information: title (TITLE) and image captions (CAPTION). In addition, we experimented with the first sentence (FS) of the document as side information. Note that the latter is not strictly speaking side information, it is a sentence in the document. However, we wanted to explore the idea that the first sentence of the document plays a crucial part in generating summaries (Rush, Chopra, and Weston 2015; Nallapati et al. 2016). SİDEİNET with FS acts as a baseline for SİDEİNET with title and image captions.

We report the performance levels of several variants of SİDEİNET on the validation set in Table 1. We also compare them against the LEAD baseline and POINTERNET. These two systems do not use any side information. Interestingly, all the variants of SİDEİNET significantly outperform LEAD and POINTERNET. When the title (TITLE), image captions (CAPTION) and the first sentence (FS) are used separately as side information, SİDEİNET performs best with TITLE as its side information. Our result demonstrates the importance of the title of the document in extractive summarization (Edmundson 1969; Kupiec, Pedersen, and Chen 1995; Mani 2001). The performance with TITLE and CAPTION is better than that with FS. We also tried possible combinations of TITLE, CAPTION and FS. All SİDEİNET models are superior to the ones without any side information. SİDEİNET performs best when TITLE and CAPTION are jointly used as side information (55.4%, 21.8%, 11.8%, 7.5%, and 49.2% for R1, R2, R3, R4, and RL respectively). It is better than the LEAD baseline by 3.7 points on average and than POINTERNET by 1.8 points on average, indicating that side information is useful to identify the gist of the document. We use this model for testing purposes.

Our final results on the test set are shown in Table 2. We present both fixed length (first 75 bytes and 275 bytes) and full length (three highest scoring sentences) ROUGE scores. It turns out that for smaller summaries (75 bytes) fixed length ROUGE scores are better than that with full length summaries for R1, R2, R3, R4, and RL respectively. It is better than the LEAD baseline by 3.7 points on average and than POINTERNET by 1.8 points on average, indicating that side information is useful to identify the gist of the document. We use this model for testing purposes.

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Table 3: Human evaluations: Ranking of various systems. Rank 1st is best and rank 4th, worst. Numbers show the percentage of times a system gets ranked at a certain position.

| Models      | 1st | 2nd | 3rd | 4th |
|-------------|-----|-----|-----|-----|
| LEAD        | 0.15| 0.17| 0.47| 0.21|
| POINTERNet  | 0.16| 0.05| 0.31| 0.48|
| SIDE Net    | 0.28| 0.53| 0.15| 0.04|
| HUMAN       | 0.41| 0.25| 0.07| 0.27|

Figure 3: Summaries produced by various systems for the article shown in Figure 1.

- LEAD: Seoul South Korea’s Prime Minister Lee Wan-koo offered to resign on Monday amid a growing political scandal. Lee will stay in his official role until South Korean President Park Geun-hye accepts his resignation. He has transferred his role of chairing cabinet meetings to the deputy Prime Minister for the time being, according to his office.

- POINTERNet: South Korea’s Prime Minister Lee Wan-koo offered to resign on Monday amid a growing political scandal. Lee will stay in his official role until South Korean President Park Geun-hye accepts his resignation. Lee and seven other politicians with links to the South Korean President are under investigation.

- SIDE Net: South Korea’s Prime Minister Lee Wan-koo offered to resign on Monday amid a growing political scandal. Lee will stay in his official role until South Korean President Park Geun-hye accepts his resignation. Calls for Lee to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul in an apparent suicide on April 9.

- HUMAN: Calls for Lee Wan-koo to resign began after South Korean tycoon Sung Woan-jong was found hanging from a tree in Seoul. Sung, who was under investigation for fraud and bribery, left a note listing names and amounts of cash given to top officials.

Figure 3: Summaries produced by various systems for the article shown in Figure 1.

performs better than POINTERNet by 0.8 points for 275-byte summaries and by 1.9 points for full length summaries, on average for all ROUGE scores.

5.2 Human Evaluation

We complement our automatic evaluation results with human evaluation. We randomly selected 20 articles from the test set. Annotators were presented with a news article and summaries from four different systems. These include the LEAD baseline, POINTERNet, SIDE Net and the human authored highlights. We followed the guidelines in Cheng and Lapata (2016), and asked our participants to rank the summaries from best (1st) to worst (4th) in order of informativeness (does the summary capture important information in the article?) and fluency (is the summary written in well-formed English?). We did not allow any ties, we only sampled articles with non-identical summaries. We assigned this task to five annotators who were proficient English speakers. Each annotator was presented with all 20 articles. The order of summaries to rank was randomized per article. Examples of summaries our subjects ranked are shown in Figure 3.

The results of our human evaluation study are shown in Table 3. We compare our SIDE Net against LEAD, POINTERNet and HUMAN on how frequently each system gets ranked 1st, 2nd and so on, in terms of best-to-worst summaries. As one might imagine, HUMAN gets ranked 1st most of the time (41%). However, it is closely followed by SIDE Net with ranked 1st 28% of the time. In comparison, POINTERNet and LEAD were mostly ranked at 3rd and 4th places. We also carried out pairwise comparisons between all models in Table 3 for their statistical significance using a one-way ANOVA with post-hoc Tukey HSD tests with (p < 0.01). It showed that SIDE Net is significantly better than LEAD and POINTERNet, and it does not differ significantly from HUMAN. On the other hand, POINTERNet does not differ significantly from LEAD and it differs significantly from both SIDE Net and HUMAN. The human evaluation results corroborate our empirical results in Table 1 and Table 2: SIDE Net is better than LEAD and POINTERNet in producing informative and fluent summaries.

Figure 3 shows output summaries from various systems for the article shown in Figure 1. As can be seen, both SIDE Net and POINTERNet were able to select the most relevant sentence for the summary from anywhere in the article, but SIDE Net is better at producing summaries which are close to human authored summaries.

6 Conclusion

In this paper, we developed a neural network framework for single-document extractive summarization with side information. We evaluated our system on the large scale CNN dataset. Our experiments show that side information is useful for extracting salient sentences from the document for the summary. Our framework is very general and it could exploit different types of side information. There are few previous works which improve extractive summarization with external knowledge from third party sources. Svore, Vanderwende, and Burges (2007) included features from news search query logs and Wikipedia entities to summarize CNN articles. Recently, Li et al. (2016) used public posts following a news article to improve automatic summarization. For future work, it would be interesting to use such knowledge as side information in our framework.

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