Neural Sentence Location Prediction for Summarization

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ABSTRACT
A competitive baseline in sentence-level extractive summarization of news articles is the Lead-3 heuristic, where only the first 3 sentences are extracted. The success of this method is due to the tendency for writers to implement progressive elaboration in their work by writing the most important content at the beginning. In this paper, we introduce the Lead-like Recognizer (LeadR) to show how the Lead heuristic can be extended to summarize multi-section documents where it would not usually work well. This is done by introducing a neural model which produces a probability distribution over positions for sentences, so that we can locate sentences with introduction-like qualities. To evaluate the performance of our model, we use the task of summarizing multi-section documents. LeadR outperforms several baselines on this task, including a simple extension of the Lead heuristic designed for the task. Our work suggests that predicted position is a strong feature to use when extracting summaries.

CSCS CONCEPTS
• Information systems → Summarization; • Computing methodologies → Supervised learning by classification; • Computing methodologies → Neural networks;

KEYWORDS
summarization; sentence classification; text embedding; heuristics; neural networks; document coherence

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1 INTRODUCTION
Summarization is an important problem in natural language processing. With information being generated and written about at an increasing pace, more reading is required to keep up. Faced with the problem of no longer being able to read in entirety everything that may be interesting, summarization renders a potential solution for many applications. The goal of informative summaries is to allow users to read a small amount of text while being exposed to the main ideas in a document.

Previous approaches cover the spectrum of techniques from expert knowledge [9], to simple word frequency based approaches [19], to supervised and unsupervised machine learning approaches [4, 5, 23, 25, 31], and even reinforcement learning [29]. These approaches employ an extractive or abstractive strategy. Extractive approaches aim to summarize using extracted spans of text, and abstractive approaches aim to accomplish this by generating novel phrases. Forming useful extractive summaries has proven to be the easier option, but an abstractive summary has the ability to be more concise, by combining the information in multiple sentences or by identifying important concepts not explicitly stated in a document. Excellent views of the wide array of summarization algorithms are provided by Nenkova et al. in [26, 27] and Mani et al in [20].

More recently, deep learning has been explored to perform automatic summarization. In [5] for example, a document is encoded with a convolutional neural network, then decoded with a recurrent neural network (RNN), where the inclusion of a sentence in the summary depends on the degree to which the decoder attends to that sentence. [4] uses a fully recurrent encoder-decoder framework, and the authors use it to directly generate abstractive summaries. To encourage topic coverage of summaries, they focus on adding “distraction” to the encoder and decoder instead of improving local attention mechanisms. Similar to [5] where sentences are classified for summary inclusion are the approaches taken by [23] and [25], where sentences are sequentially read by a RNN and directly classified for summary inclusion. [31] describes an abstractive model aiming to solve common problems of abstractive summarizers, including generating incorrect or inaccurate details and not handling out-of-vocabulary words. This is done with a RNN capable of producing novel text as well as explicitly copying text from the source document. An abstractive model which also uses a RNN and encoder-decoder framework with attention is [29]. Using a novel attention mechanism and by training with both reinforcement and supervised learning, their model achieved state-of-the-art ROUGE scores on the multiple datasets.

Despite the complexity and expressive power of models used in recent approaches, position-based baselines have proven difficult to beat by more than a small margin on the popular CNN/Daily Mail news article dataset. The competitive performance of the Lead heuristic is due to the progressive elaboration present in the writing, so that important and general information is already found at the beginning.

While most of the deep-learning-based summarizers use the CNN/Daily Mail data, partly due to the large volume of the dataset, it is obvious that not all documents are written by trained reporters or contain a single important story. Similarly, not all documents will have the most important information at the very beginning. An increasingly common typifying example is the "listicle" — a list-like
During pregnancy the rectus abdominus, the muscle running down the centre of the abdomen, separates, and leaves a crescent-shaped hole.

No more mummy tummies: Gwyneth Paltrow, left, wore an Agent Provocateur corset following the birth of her son Moses, now seven. Over time, these muscles need to come back together again. Gwyneth Paltrow sported one by Agent Provocateur after the birth of her son Moses, now seven. In April, actress Jessica Alba revealed that she wore corsets after the births of daughters Honor, four, and Haven, one.

Womens-health specialist Jennifer White said: They may also give support to the back, help with posture and encourage the muscles to improve posture and pulling in stomach muscles will make you look thinner, but in terms of losing fat long-term thats still down to exercise and diet. It is likely to be very uncomfortable post-caesarean. I think these corsets help push them together a bit more quickly. Improving posture and pulling in stomach muscles will make you look thinner, but in terms of losing fat long-term thats still down to exercise and diet. Companies who sell corsets and girdles say sales have been increasing for years. Celebrity interest has certainly raised our profile, says Anna Blakey, from medical supplies company MaCom. But its not a gimmick they make sense.

Celebrity interest has certainly raised our profile, says Anna Blakey, from medical supplies company MaCom. But its not a gimmick they make sense. Improving posture and pulling in stomach muscles will make you look thinner, but in terms of losing fat long-term thats still down to exercise and diet. Companies who sell corsets and girdles say sales have been increasing for years. Celebrity interest has certainly raised our profile, says Anna Blakey, from medical supplies company MaCom. But its not a gimmick they make sense.

Figure 1: A news article is analyzed with our neural position model and the predicted position distributions generated by the model is shown for each sentence. White is low probability, red is high probability, and position quantiles are ordered from left to right. The position model considers sentences 2-4, 11, and 12 to be more characteristic of introductory sentences than the actual first two sentences.

article containing many equally important sections. Many documents may also contain a catching but low-information story or adage at the very beginning. In such articles, applying the Lead heuristic may provide a summary indicating what type of information is present, but is unlikely to result in an informative summary of the total document. In documents where the boundaries between sections are not available or are vague, applying Lead to each of the sections individually is also not easily done.

In this paper, we aim to further explore neural-network-based summarization to explicitly consider the guidance of position. In particular the main contributions of this paper are as follows:

1. We create a neural model which produces a probability distribution over positions in the document for a given sentence.
2. We introduce a sentence embedding which can combine pretrained word embeddings to retain word order information while using an embedding dimension independent of sentence length.
3. We introduce the task of summarizing documents with multiple sections.
4. We propose the LeadR summarizer which can be applied to multi-section documents by locating sentences with introduction-like properties.
5. We compare LeadR to several baseline algorithms on the task of summarizing multi-section documents to 10% of their original length. On documents with more than one main topic, LeadR consistently outperforms all models tested against by a full point on ROUGE-2, and about 0.5 points on ROUGE-1 and -L scores.

The remainder of the paper is organized as follows. Section 2 reviews related work on applying heuristics to summarization and the task of predicting sentence position in a document. Section 3 introduces our summarization algorithm, its primary components, and describes how they are combined to extract summaries. In Section 4 we discuss how the dataset was prepared, how our model was trained and optimized, and compare our summarizer to several baselines. This section also includes interesting observations made using the sentence position model. Section 5 concludes the paper and proposes directions for future work.

2 RELATED WORK

2.1 Predicting sentence position

Sentence position has been applied to understanding document structure and coherence. In [18], Logeswaran et al. approach two tasks related to sentence order. The first task is that of determining whether a given sequence of sentences is coherent (i.e. in the correct order) or not. In the second, more difficult problem, they take an unordered set of sentences from an abstract and reorder them. To solve these tasks, they use an end-to-end set-to-sequence RNN framework proposed by [35] and reorder sentences by iteratively choosing among all sentences the one best fit to follow the one last added. This work is in contrast to the more computationally efficient approach we will take where we predict the position information of all sentences in a document at once. True sentence position is often provided as a feature for sentence level extractive summarizers, but to our knowledge, no previous work has been done on explicitly using predicted sentence position in summary extraction.

2.2 Phrase embedding

Many options exist for creating sentence representations suitable for machine learning. Representing sentences as a bag of words
(BoW) is a simple and common approach, but removes word order information of sentences, which is often important for understanding the meaning of sentences. Combining distributed word embeddings [1] is an approach which has been shown to work well for many applications. In [14], the authors explore different methods for combining word embeddings for the purpose of measuring semantic similarity between sentences. They compare combining word embeddings by either using a recursive auto-encoder [33] or simply adding the vectors together, and find that adding vectors consistently performs better. In addition to looking at how word embeddings are combined, they consider choices in the semantic similarity function. They find that a measure based on Euclidean distance performs better than using cosine similarity. For representing short texts such as tweets, [7] considers learning to weight the words when adding their embeddings, and shows that it outperforms other combination methods such as taking the mean or max of the word embeddings. Moving beyond addition, [22] considers combinations of multiplying and adding word embeddings to produce a phrase embedding. Evaluating on a sentence semantic similarity task, they show that multiplying, or a combination of multiplication and addition, outperforms the common addition approach.

3 LEADR SUMMARIZER MODEL

Our summarization model is inspired by the competitive performance of the Lead-3 heuristic on news articles. The reasoning behind the LeadR summarizer is as follows: We know that the Lead-3 heuristic works well for certain single-section documents, so if we can locate sentences in a multi-section document similar to those extracted by Lead in a single-section document, we may be able to form a good summary. To be able to handle very long documents, the summarizer is implemented in a pipeline where each step can be efficiently executed. In Section 3.2 we mention additional benefits to using this pipeline. At a high level, the LeadR summarizer executes the following steps:

1. First, we generate embeddings for each sentence in the document. Refer to Section 3.1.
2. We feed these embeddings into a position model to obtain a probability distribution over positions for each sentence. Refer to Section 3.2.
3. Next, we compare a window of target distributions over the sequence of sentence position distributions to obtain an intro score for each sentence. Refer to Section 3.3.
4. Finally, we iteratively construct a summary by choosing sentences with high intro scores and small overlaps with previously chosen sentences. Refer to Section 3.4.

3.1 Sentence embedding

In this paper, we develop a flexible sentence embedding technique which combines benefits of multiple methods. The new method has the property of producing fixed dimension embeddings similar to BoW on a fixed vocabulary or word embedding addition. The method also retains word order information, a property enjoyed by recurrent models. The intuition behind our embedding is that we are squeezing (or stretching) word embeddings of dimension $d_f$ to fill a matrix of width $R$ and height $d_f$. The word embeddings are blended together across the width to make the embedding less sensitive to exact word ordering and to allow every word to have an influence on the combined embedding even if $R < |S|$. Figure 2 provides a visualization of the embedding technique.

Given the speed of using pretrained word embeddings and the excellent cross-task performance recently reported in [13], we choose to build upon these state-of-the-art fastText word embeddings. The word embeddings are created with a cbow model architecture described in [21], with the addition of a few tricks. These embeddings were shown to form good sentence representations when averaged together.

As the first step in producing sentence embeddings, we apply a random sparse projection to the fastText word embeddings to reduce the dimension from 300 to $d_f = 75$. This value was chosen to balance performance with increased model training and summary extraction speed and reduced memory usage. In addition to the new sentence embedding we define in this section, our model requires the ability to generate simple fastText embeddings for words, sentences (lists of words), and documents (lists of sentences). We use the notation $f\text{txt}(\text{token})$ to represent converting a textual token to its dimensionally reduced fastText embedding, as defined by:

$$
\begin{align*}
\text{fastText word embedding} & \quad \text{if token is a word in fastText vocabulary} \\
\frac{1}{|\text{token}|} \sum_{w \in \text{token}} f\text{txt}(w) & \quad \text{if token is a sentence of |token| words} \\
\frac{1}{|\text{token}|} \sum_{s \in \text{token}} f\text{txt}(s) & \quad \text{if token is a list of |token| sentences}
\end{align*}
$$

Given a sentence $S$ from a document $D$ consisting of words $[w_1, \ldots, w_{|S|}]$, we combine the word embeddings for the sentence to obtain $X^S_D$, the main part of the embedding as follows:

$$
X^S_D[|c|] = \sum_{i=1}^{|S|} \omega(c, i) f\text{txt}(w_i), \text{ for } c \in [1, \ldots, R],
$$

where

$$
\omega(c, i) = \begin{cases} 
1 & \text{if } R = 1 \\
\left(1 - \frac{i - 1}{|S| - 1} - f(i)\right)^\beta & \text{if } R > 1
\end{cases}
$$

and

$$
f(i) = \begin{cases} 
0 & \text{if } |S| = 1 \\
\frac{i - 1}{|S| - 1} & \text{if } |S| > 1
\end{cases}
$$

$R \in \mathbb{N}$ is the spatial resolution of the sentence embedding, $\beta \in \mathbb{R}$ controls the spatial decay in word importance in the combined embedding. The amount of blending between words is inversely proportional to $\beta$, so that when $\beta$ is large, very little blending occurs. When $\beta = 0$ and $R = 1$, the embedding is equivalent to adding together the fastText embeddings. In Sections 4.4, we will

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1. Available online at https://fasttext.cc/docs/en/english-vectors.html.
2. As implemented with default parameters by the Scikit-learn Python package [30].
see that controlling the spatial resolution and amount of word blending allows us to produce better summaries than if the word embeddings were simply averaged.

The second part of the sentence embedding, $X^b_D$, shared by all sentences in $D$, is computed with $f_{txt}(D_{nostops})$, where $D_{nostops}$ is the document with stopwords removed. $X^b_S$ is then flattened into a vector and concatenated with $X^b_D$ to obtain $X_S$. The purpose of $X^b_D$ is to incorporate a global context, shown in [18] to improve performance at sentence ordering.

### 3.2 Neural Position Model

The purpose of the position model is to predict the position in a document of a given sentence. We will implement the position model with a fully connected neural network with a softmax output layer. Instead of predicting a single continuous value for the position of a sentence as the fraction of the way through a document, we frame sentence position prediction as a classification problem. The use of classification was initially motivated by the poor performance of regression models; since the task of position prediction is quite difficult, the models would consistently make predictions very close to 0.5 (middle of the document), thus not much useful information was attained. To convert the task to a classification problem, we aim to determine what quantile of the document a sentence resides in. Notationally, we will refer to the number of quantiles as $Q$. We can interpret the class probabilities behind a prediction as a distribution over positions for a sentence, providing us with a predicted position distribution (PPD). When $Q = 2$ for example, we are predicting whether a sentence is in the first or last half of a document. When $Q = 4$, we are predicting which quarter of the document it is in. In Figure 1, we can see an example of the PPDs for sentences in an article when our model uses $Q = 11$. As we will see in Section 4.4.2, having fine-resolution distributions (i.e. $Q > 2$) is beneficial when locating sentences for a summary.

This neural model will be trained to map the sentence embeddings to one-hot encodings of sentence quantile position. More implementation and evaluation details will be discussed in Section 4.3. Composing the novel sentence embedding method with the position model provides us with the $PosDist$ function which maps a sentence $S$ to its predicted position distribution, a vector of dimension $Q$.

While a summarization model which learns to predict the inclusion of a sentence in a summary given our novel word embedding without generating PPDs is possible, being able to generate and access these PPDs confers multiple benefits, including:

**Cross-task flexibility** Being able to generate the PPDs for a document allows for upstream models to use them for a variety of tasks, akin to pretrained word embeddings.

**Coherence evaluation** As we mention in Section 4.5, PPDs may be used for judging the coherence of a document. For the same reason, they may prove useful for the purpose of segmenting an otherwise unstructured document by topic and into coherent sections, similar to [32] or [8]. PPDs may also be useful for automatic grading of essays as a high level indicator of coherence and structure.

**Insights** In Section 4.5 we will use these PPDs to analyze human written summaries and show how they are unique from sentences typically found in documents.
3.3 Intro Scores

To try solve the difficult problem of determining how characteristic a sentence is of an introductory sentence, we compare the predicted position distributions of the sentence and its successors to a sequence of target distributions. The purpose of the sequence of target distributions is to specify what we consider an archetypal introduction to look like. The sequence of sentences whose PPDs maximizes the cosine similarity with the target distributions should be the most introduction-like. Since we may care more about the similarity of sentences at the start of a sequence than ones at the end, we allow for placing more weight on matching the PPDs near the start of the target distribution. Equation 5 shows how these ideas are combined to produce the final score for each sentence.

\[
\text{Intro}(S_i) = \sum_{j=1}^{T_i} \eta^{j-1} \text{Sim}(\text{PosDist}(S_{i+j}), T_j)
\]

Here, \(S_i\) is the \(i^{th}\) sentence in \(D\), \(T_j\) is the \(j^{th}\) target distribution, \(\eta\) controls the weight decay of sentence similarities. To measure semantic similarity between a PPD and a target distribution, \(\text{Sim}\) (cosine similarity) is used.

3.4 Summary extraction

Instead of building up a summary one sentence at a time, we allow our model to add sentence spans of length \(sl\). If \(sl = 2\) for example, then sentences are added to the summary in contiguous pairs. Having a larger \(sl\) allows for more coherent summaries, and as we will see in Section 4.4.2, can also improve performance. In addition to considering intro scores when constructing a summary, we also consider the semantic overlap of sentence spans chosen by using Maximal Marginal Relevance (MMR) as described in [3]. MMR essentially provides a way of weighting the positive and negative aspects of adding a piece of text to the summary, given what has already been added. A linear combination of the two values is used, with the weight distribution controlled with \(\lambda \in [0, 1]\). In our case, when \(\lambda = 1\), the sentence spans are scored only according to their intro score. When \(\lambda = 0\), spans are scored entirely on their semantic novelty (or added coverage) with respect to previously chosen spans. Carbonell et al. find that an intermediate value for \(\lambda\) is best for the task of generating query-directed summaries. Similar to their work, we use cosine similarity for semantic similarity, but we use averaged fastText embeddings to embed the text and compare sentence spans instead of single sentences. Algorithm 1 shows how we apply MMR for extracting a summary of \(n\) sentences for document \(D\).

4 EXPERIMENTS

In this section, first we will discuss the dataset used and its preparation for the multi-section summarization task. Second, we will look at how our models are trained and tuned. Third, we will compare our LeadR model to several baselines. Finally, interesting results attainable using the neural sentence position model will be presented. All experiments were performed on a machine with an Intel Core i7-6700HQ CPU and 16G RAM. Neural networks were implemented with the Keras Python library [6].

4.1 Data preparation for multi-section summarization

In this paper, we aim to show how neural models can be used to extend the Lead heuristic beyond its typical area of expertise on single-sectioned news articles. To construct a dataset for this task, we start by preparing the CNN/Daily Mail news article dataset constructed by [12], then simulate the more challenging situation of multi-section summarization by concatenating multiple news articles.

For features predictive of sentence location to be learned which may transfer to other datasets, many of the articles in the CNN/Daily Mail dataset require preprocessing to remove unwanted information. Publication meta-information appearing at the beginning of articles could easily be used as an indicator of sentence position without having to consider the remainder of the sentence. Table 1 contains examples of such cases.

Each news article also contains "highlights" which compose the human written summary of the article. These are extracted and will be used during evaluation of summarizers. Our model does not require entity anonymization to be performed on the news articles.

After preprocessing, we end up with over 300,000 articles, with an average of almost 30 sentences/article, and the most common length being 17 sentences. 114 articles which contain zero sentences are not used at any point in the experiments. Human written summaries are an average of 3.8 sentences long and most commonly 4.

To extend this set of articles for multi-section summarization, we simply concatenate random articles together. We refer to a

Algorithm 1: LeadR

Input: document, \(D\), consisting of sentences \(S_1, \ldots, S_{|D|}\)

Input: number of sentences, \(n\), to extract

intro_scores ← list with \(\text{IntroScore}\) for each sentence in \(D\)

potential_span_encs ← list of length \(|D|\)

for \(i\) from 1 to \(|D|\) do

\[\text{potential_span_encs}[i] ← \text{f-txt}([S_1, \ldots, S_{i+sl}])\]

chosen_span_encs ← empty list

summary ← empty set

while \(|\text{summary}\| < \min(n, |D|)\) do

\[\text{index}_{\text{best}} ← 0\]

score\_best ← 0

for \(i\) from 1 to \(|D|\) do

\[
\text{max}\_\text{sim} \leftarrow \max \text{cosine similarity between potential_span_encs}[i] \text{ and all previously chosen spans}
\]

score ← \(\lambda \times \text{intro}\_\text{score}[i] - (1 - \lambda) \times \text{max}\_\text{sim}

if score > score\_best then

\[\text{score}\_\text{best} ← \text{score}\]

\[\text{index}\_\text{best} ← i\]

\[\text{chosen}\_\text{span}\_\text{encs}.\text{append}(\text{potential}\_\text{span}\_\text{encs}[\text{index}\_\text{best}])\]

\[q ← \min(sl, n - |\text{summary}|) = 1\]

\[\text{summary} ← \text{summary} \cup \{S_{\text{index}_\text{best}}, \ldots, S_{\text{index}_\text{best}+q}\}\]

Output: \(\text{summary}\) sentences in original order
document formed by concatenating $M$ single articles as an $MX$-concatenated document. The task of summarizing $IX$ concatenated documents refers to the standard single-article summarization task. For automated evaluation of summaries, we use ROUGE scores [17], which requires ground-truth ("gold") summaries. Each article in the CNN/Daily Mail dataset is accompanied with a short summary, so to extend to the multi-section task we simply concatenate the $M$ summaries together. This concatenated summary is considered the gold summary for the $MX$ concatenated document. Next, we will discuss in more detail how summarization models will be evaluated.

4.2 Evaluation of multi-section summarizers

To evaluate the quality of summaries, we use three ROUGE evaluation metrics [17]: ROUGE-1, which measures the amount of unigram overlap between the gold summaries for an article and the proposed (automatically produced) summary, ROUGE-2, which measures the amount of bigram overlap, and ROUGE-L, based on the longest common subsequence in the gold and automated summary. While ROUGE metrics originally focused only on recall, precision is often taken into account in the form of F1 scores so that summaries which are both informative and sufficiently concise are rewarded. For evaluating newswire summaries, these metrics have been shown to correlate well to human assessments [16]. In this paper, we will use full-length F1 ROUGE variants.

For training, validation, and testing, 50,000 articles are randomly selected from the CNN/Daily Mail dataset, with 80% used for training, 10% for validation, and 10% for testing. The volume of data used is largely limited by the time required to run full-length ROUGE for evaluating the extracted summaries. The evaluation time is especially noticeable in our experiments due to the use of concatenated articles.

To train the neural sentence position model, the original single-section articles are used. Since we have one sample per sentence and 24,000 training articles, we will train on approximately 700,000 samples. For validation of the summarizer, the original 3,000 single-section validation articles are used, as well as 9,000 multi-section articles formed by concatenating 2, 3, and 4 random articles from the validation set.

To evaluate models on the validation set, instead of aiming to maximize a single ROUGE metric, we combine ROUGE -1, -2, and -L scores for several levels of article concatenation. The individual ROUGE scores are combined as follows:

$$\frac{1}{L} \sum_{M=1}^{4} \sum_{type=1,2,L} \text{ROUGE-type(model, MX concatenated docs)}$$

For testing, a process similar to validation set construction is used, except 5X concatenated articles are also included, for a total of 15,000 articles, and the individual ROUGE scores will be reported. In the single-section ($1X$) summarization task, extractively summarizing articles to three sentences is most commonly performed. For the $MX$ concatenated task, we will focus on summarizing documents in $3M$ sentences.

4.3 Training details

To determine our hyperparameters in a tractable way, we perform grid searches on subsets of the hyperparameters. The subsets are chosen to minimize search time and take into account those hyperparameters which might interact non-linearly to influence the final performance. To further reduce training time and decrease the potential for over-fitting, many values are fixed to reasonable settings. A summary of the fixed values is as follows:

**Neural network structure**: We use a fully connected feedforward structure with two hidden layers, Leaky ReLu activation [36] (with $a = 10$), and no regularization.

**Neural network training regime**: The number of epochs is set to 10. Batch size is set to 256. We use the Adam optimizer [15] with most default parameters as supplied by Keras [6]. The learning rate is tuned to avoid over or underfitting on the training set. Training is performed to minimize the cross-entropy of the predicted and true labels.

**Target distributions**: We fix the sequence length of target distributions to 5. To calculate the target distributions for a given $Q$ value, we linearly interpolate between a $Q$-length vector with a 1 in the first dimension and a vector with all values set to $1/Q$. We expect this to be a good approximation of what the introductory PPDs of an archetypal article should be like.

The six sets of tuned hyperparameters are shown in Table 2. Initial values are not applicable to the very first two hyperparameters optimized. The initial value is meant to be a best guess and is used when optimizing other hyperparameters before it itself undergoes optimization. After the hyperparameters in a set are optimized, they are fixed and the next set is optimized. An exploration into how a few hyperparameters affect the validation performance is given in Section 4.4.2.

4.4 Results

4.4.1 Comparison to baseline models. We look at the test performance of four versions of LeadR. The first is the full LeadR algorithm. Second is $\text{LeadR}_{\lambda=1}$, which does not value maximizing coverage and only chooses sentence spans based on intro scores. Third is $\text{LeadR}_{\lambda=0}$, which does not use the intro scores and only

\[ \text{for comparison, in the train/validation/test split of the CNN/Daily Mail dataset prepared by [24], just over 11,400 articles are used for testing.} \]
Table 2: Sets of hyperparameters tuned using grid search. Tested values, initial values, and optimal values are shown for each hyperparameter.

| Parameter | Grid values | Initial value | Best value |
|-----------|-------------|---------------|------------|
| \( R \)   | 1, 2, 3, 4, 5, 6 | - | 5 |
| \( \beta \) | 1, 2, 3, 4, 5, 6 | - | 6 |
| \( Q \)   | 2, 3, 5, 7, 9, 11 | 11 | 11 |
| learning_rate | 3e-3, 1e-3, 3e-4 | 1e-3 | 3e-3 |
| layer_sizes | [20, 5], [100, 25], [200, 50], [1000, 50], [200, 50] | [200, 50] | [100, 25] |
| \( \gamma \) | 0., 0.1, ..., 0.9, 1. | 0.5 | 0.5 |
| \( s_l \) | 1, 2, 3, 4 | 3 | 3 |
| \( \lambda \) | 0, 0.1, ..., 0.9, 1. | 0.8 | 0.7 |

Table 2: Sets of hyperparameters tuned using grid search. Tested values, initial values, and optimal values are shown for each hyperparameter.

maximizes coverage. Fourth is LeadR\_avg which uses word embedding averages instead of our novel position-sensitive sentence embedding. In this paper, we evaluate our models on the novel task of multi-section summarization, thus no previously reported results are directly comparable to this work. However, existing summarization algorithms can be applied to this task. We compare our models to the following baselines:

**Lead** Sentences are extracted in their original order. On the 1X CNN/Daily Mail summarization task, this is a competitive heuristic, especially for 3 extracted sentences.

**Lead\_multi** This method is a naïve extension of Lead. If \( k \) sentences are required for the summary, it will split the document into \( \lfloor k/3 \rfloor \) sections and take the first three sentences from each section until the sentence limit is reached.

**Luhn** This method makes use of both word frequency statistics as well as position of words within sentences to rank them by importance [19].

**SumBasic** This is a method which exclusively makes use of word frequency information [28].

**LSA** This method uses singular value decomposition applied to the term by sentences matrix of a document to identify important concepts [34]. The sentences chosen for summarization are those which best represent these concepts.

**TextRank** This graph based method ranks sentences using an algorithm similar to PageRank [2].

**LexRank** This graph based method aims to capture sentence importance with eigenvector centrality in a weighted edge graph induced by the sentences and their similarity [10].

**KLSum** This method greedily adds sentences to a summary to minimize the KL divergence between the document and summary unigram distributions [11].

Aside from the first two baselines, these models are all implemented in the sumy Python package\(^7\).

Our LeadR model is clearly shown in Table 3 to consistently outperformed all baselines tested against on the multi-section summarization tasks. On the 2X - 5X concatenation tasks, our ROUGE-1, -2, and -L scores are an average of 0.5, 1, and 0.6 points above the next best scores respectively. One immediately evident detail is that the Lead heuristic still outperforms our model on the 1X task. The simple extension of Lead is able to improve upon the performance of Lead by several points on the 2X - 5X tasks and even performs better than or similarly to LSA, TextRank, and KLSum. Of the LeadR variations, LeadR\(_{\lambda=0}\) and LeadR\_avg perform the poorest across all tasks and metrics, suggesting that the use of intro scores and novel sentence embedding are the main contributors to its performance.

4.4.2 Effects of parameter tuning. The effects of several of our model hyperparameters are displayed in Figure 4. In each of the plots, the performance shown is that on the validation set calculated with Equation 6. The performance curves for the hyperparameters are gathered during their tuning. This means, for example, that while \( R \), \( \beta \), and \( Q \) were being optimized, neural networks with hidden layers of sizes [200, 50] were being used, while layers of size [100, 25] were used when optimizing \( \gamma \), \( s_l \), and \( \lambda \). The following observations on the effects of various hyperparameters can be made:

- **\( R \) and \( \beta \)** When one of \( R \) (sentence embedding resolution) or \( \beta \) (inverse word blending) is low, average ROUGE score is low. After both reach about 4, performance seems levels off. Since \( R \) and \( \beta \) are optimized together, the curve values for \( R \) are averages across all values of \( \beta \), and the curve values for \( \beta \) are averages across all values of \( R \).
- **\( Q \)** Having a value for \( Q \) (number of position quantiles in PPDs) at or above 5 seems to be critical to performance.
- **\( \gamma \)** There seems to be a clear optimal value for \( \gamma \) (controls importance decay of sentence PPD similarity with target distributions). The best performance is achieved when the similarity of a sentence PPD to the corresponding target distribution is considered as an important factor.
- **\( \lambda \)** The optimal value for \( \lambda \) (balance of intro score and coverage importance) appears to be around 0.7, and going below that value is more detrimental than increasing it. This indicates that intro score for a sentence is more important than maximizing coverage, but a benefit is achieved by taking it into account.
- **\( s_l \)** The span length used when extracting summaries has a sweet spot at 3. Going above or below it is detrimental.

\(^7\)Available online at https://pypi.python.org/pypi/sumy.
Table 3: Performance of the various models on the multi-section CNN/Daily Mail test set. For all but the 1X task where Lead is best, LeadR consistently outperforms the baselines on ROUGE-1, ROUGE-2 and ROUGE-L.

4.5 Interesting Observations

Ideally, one would like an extractive summarizer to choose sentences most similar to those in a human written summary. However, applying the neural position model to gold summaries reveals why that may be difficult. In Figure 5, we see averaged PPDs for gold summaries of length 4, for the first 5 sentences of news articles, and for the last 5 sentences of news articles. Even though the Lead heuristic performs quite well, the predicted sentence positions at the start of articles are quite different from those in gold summaries. Interestingly, the very first sentence in a gold summary is strongly predicted to be either at the start or the end, with low probabilities in the middle. While the PPDs for gold summaries might seem more characteristic of conclusory sentences, applying a Last-3 heuristic on the 1X summarization task results in very poor performance (ROUGE-1, -2, and -L scores of 13.2, 2.7, and 12.3 respectively). Upon looking at the PPDs for many news articles (the PPDs for five articles are shown in Figure 3), we observe that sentences with high start and end position probabilities are quite rare.

Another interesting observation made with PPDs is how easily the structure of an article may be observed. In the PPD sequence in the bottom left of Figure 3, there seem to be multiple sentence subsequences whose predicted positions shift relatively smoothly from the first to last quantile, akin to small articles embedded within the larger one. When reading these sentence subsequences, the characterization often seems appropriate. This observation suggests that the neural position model could be applied to automatically assess the flow and coherence of documents.

5 CONCLUSIONS

To extend the performance of the Lead-3 heuristic to extract summaries for multi-section documents, we propose the LeadR algorithm which locates sentences with introduction-like properties. This is performed by first using a neural model to predict position distributions of sentences, then choosing those sentences with predicted positions similar to that of introductory sentences. The strength of predicted sentence position as an indicator for summary quality is demonstrated on an augmented version of a common summarization dataset. The importance of the position model is demonstrated by adding over 4, 2, and 4 ROUGE-1, -2, and -L points respectively when compared to the same summarization pipeline which only maximizes coverage of the summary. We also employ a novel sentence embedding which encodes positional information of words while maintaining a constant dimensionality. We demonstrate that this embedding contributes a full ROUGE-2 point and over 2 ROUGE-1 and -L points when summarizing multi-section articles.

This paper leaves many interesting areas for future work. As suggested by [14], optimizing the semantic similarity measures used could increase performance. Other heuristics to build upon could also be used. For example, instead of predicting the location of sentences, the presence of other signals such as key phrases could be
predicted. Similar to training a model to predict sentence location, obvious evidence of the phrases would need to be removed before training. We also briefly mentioned applications of predicted position distributions of sentences including segmenting documents into subsections and estimating coherence for automatic evaluation of writing quality.

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REFERENCES

[1] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. 2003. A neural probabilistic language model. Journal of machine learning research 3, Feb (2003), 1177–1192.
[2] Si Chen, Soroosh Yousefi, and Jie Zhou. 2016. Predicting gold summary sentences. arXiv preprint arXiv:1606.04462 (2016).
[3] Jamie Carbonell and Jade Goldstein. 1998. The use of MMR, diversity-based reranking for reorder documents and producing summaries. In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval. ACM, 335–336.
[4] Qian Chen, Xiaodan Zhu, Zhenhua Ling, Si Wei, and Hui Jiang. 2016. Distraction-based neural networks for document summarization. arXiv preprint arXiv:1603.07252 (2016).
[5] Jianpeng Cheng and Mirella Lapata. 2016. Neural summarization by extracting sentences and words. arXiv preprint arXiv:1603.07252 (2016).
[6] François Chollet et al. 2015. Keras. https://github.com/keras-team/keras. (2015).
[7] Cedric De Boom, Steven Van Cannayt, Thomas Demeester, and Bart Dhoedt. 2016. Representation learning for very short texts using weighted word embedding aggregation. Pattern Recognition Letters 80 (2016), 150–156.
[8] Satya Dharsanaprada, Martin Franz, J Scott McCarley, Kishore Papineni, Salim Roukos, Todd Todd, and W-J Zuo. 2000. Statistical methods for topic segmentation. In Sixth International Conference on Spoken Language Processing.
[9] Harold P Edmundson. 1969. New methods in automatic extracting. Journal of the ACM (JACM) 16, 2 (1969), 264–285.
[10] Günter Erkan and Dagiurum R. Radev. 2004. Lexrank: Graph-based lexical centrality as salience in text summarization. Journal of Artificial Intelligence Research 22 (2004), 457–479.
[11] Aria Haghighi and Lucy Vanderwende. 2009. Exploring content models for multi-document summarization. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics. Association for Computational Linguistics, 362–370.
[12] Karl Moritz Hermann, Tomasz Kociski, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. In Advances in Neural Information Processing Systems. 1693–1701.
[13] Armand Joulin, Édouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of Tricks for Efficient Text Classification. arXiv preprint arXiv:1607.01759 (2016).
[14] Mikael Kägberg, Olof Mogren, Nina Tahmasebi, and Devdatt Dubhashi. 2014. Extractive summarization using continuous vector space models. In Proceedings of the 2nd Workshop on Continuous Vector Space Models and their Compositionality (CVSC). 31–39.
[15] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014).
[16] Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. Text Summarization Branches Out (2004).
[17] Chin-Yew Lin and Eduard Hovy. 2003. Automatic evaluation of summaries using n-gram co-occurrence statistics. In Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology-Volume 1. Association for Computational Linguistics, 71–78.
[18] Lajanugen Logeswaran, Honglak Lee, and Dragomir Radev. 2016. Sentence ordering using recurrent neural networks. arXiv preprint arXiv:1611.02524 (2016).
[19] Hans Peter Luhn. 1958. The automatic creation of literature abstracts. IBM journal of research and development 2, 2 (1958), 159–165.
[20] Indrijeet Mani and Mark T Maybury. 1999. Advances in automatic text summarization. MIT press.
[21] Tomasz Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781 (2013).
[22] Jeff Mitchell and Mirella Lapata. 2008. Vector-based models of semantic composition. proceedings of ACL-08: HLT (2008), 236–244.
[23] Ramesh Nallapati, Feifei Zhai, and Bowen Zhou. 2017. SummaRuNNer: A Recurrent Neural Network Based Sequence Model for Extractive Summarization of Documents. In AAAI. 3075–3081.
[24] Ramesh Nallapati, Bowen Zhou, Cicero dos Santos, Caglar Guelhure, and Bing Xiang. 2016. Abstractive Text Summarization using Sequence-to-sequence RNNs and Beyond. In Proceedings of The 20th SIGKDD Conference on Computational Natural Language Learning, 280–290.
[25] Ramesh Nallapati, Bowen Zhou, and Mingbo Ma. 2016. Classify or select: Neural architectures for extractive document summarization. arXiv preprint arXiv:1611.04244 (2016).
[26] Ani Nenkova and Kathleen McKeown. 2012. A survey of text summarization techniques. In Mining text data. Springer, 43–76.
[27] Ani Nenkova, Kathleen McKeown, et al. 2011. Automatic summarization. Foundations and Trends® in Information Retrieval 5, 2–3 (2011), 103–233.
[28] Ani Nenkova and Lucy Vanderwende. 2005. The impact of frequency on summarization. Microsoft Research, Redmond, Washington, Tech. Rep. MSR-TR-2005-101 (2005).
[29] Romain Paulus, Caiming Xiong, and Richard Socher. 2017. A deep reinforced model for abstractive summarization. arXiv preprint arXiv:1705.04304 (2017).
[30] Fabian Pedregosa, Gael Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. Journal of machine learning research 12, Oct (2011), 2825–2830.
[31] Abigail See, Peter J Liu, and Christopher D Manning. 2017. Get To The Point: Summarization with Pointer-Generator Networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Vol. 1. 1073–1083.
[32] Malcolm Slaney and Dulce Ponceleon. 2001. Hierarchical segmentation using latent semantic indexing in scale space. In Acoustics, Speech, and Signal Processing, 2001. Proceedings.(ICASSP’01). 2001 IEEE International Conference on, Vol. 3. IEEE, 1437–1440.
[33] Richard Socher, Eric H Huang, Jeffrey Pennin, Christopher D Manning, and Andrew Y Ng. 2011. Dynamic pooling and unfolding recursive autoencoders for paraphrase detection. In Advances in neural information processing systems. 801–809.
[34] Josef Steinberger and Karel Jestek. 2004. Using latent semantic analysis in text summarization and summarization evaluation. Proc. ESMI 4 (2004), 93–100.
[35] Oriol Vinyals, Samy Bengio, and Manjunath Kudlur. 2015. Order matters: Sequence to sequence for sets. arXiv preprint arXiv:1511.06391 (2015).
[36] Bing Xu, Naiyan Wang, Tingting Chen, and Mu Li. 2015. Empirical evaluation of rectified activations in convolutional network. arXiv preprint arXiv:1505.00853 (2015).