Abstract

We show that a simple unsupervised masking objective can approach near supervised performance on abstractive multi-document news summarization. Our method trains a state-of-the-art neural summarization model to predict the masked out source document with highest lexical centrality relative to the multi-document group. In experiments on the Multi-News dataset (Fabbri et al., 2019), our masked training objective yields a system that outperforms past unsupervised methods and, in human evaluation, surpasses the best supervised method without requiring access to any ground-truth summaries. Further, we evaluate how different measures of lexical centrality, inspired by past work on extractive summarization, affect final performance.

1 Introduction

Multi-document summarization (MDS) aims to condense and combine information from topically related groups of documents into a single concise yet comprehensive short text. The news domain, where input documents are article clusters of varying size covering the same event, is a common challenge setting for MDS systems (Paul and James, 2004; Owczarzak and Dang, 2011). While most early approaches to the problem focused on extractive methods that select and copy relevant sections from the input documents (Radev et al., 2004; Erkan and Radev, 2004; Mihalcea and Tarau, 2004), advances in neural text generation have increased both performance of and, subsequently, interest in abstractive methods, which generate a summary from scratch conditioned on a combined representation of the encoded source documents.

While large neural systems have seen success on single-document summarization, where human summaries are relatively easy to obtain at scale (Napoles et al., 2012; Hermann et al., 2015), their application to the multi-document task has been restricted by the difficulty of collecting such data—reading and then summarizing a collection of documents is a daunting annotation task. We focus on the task of unsupervised abstractive MDS where the system is only allowed access to input document collections at training time (Chu and Liu, 2019). Similar to older work on unsupervised extractive summarization (Radev et al., 2004; Erkan and Radev, 2004; Mihalcea and Tarau, 2004), we propose an approach that leverages lexical centrality of the document clusters to select a document to mask out and then predict. This allows for any black box discriminative neural abstractive summarization model to be trained without ground-truth summaries by maximizing the likelihood of the masked out document, drawing inspiration from masked language modeling (e.g., BERT (Devlin et al., 2018)). Some recent works have automatically built large-scale, supervised MDS datasets for news (Fabbri et al., 2019) and Wikipedia (Liu et al., 2018). We evaluate our unsupervised method on the news domain using the Multi-News dataset (Fabbri et al., 2019).

2 Masked Document Objective

Typically, neural abstractive single-document and multi-document summarization models consist of an encoder-decoder architecture (Sutskever et al., 2014) discriminatively trained end-to-end to maximize the likelihood of the supervised, ground truth summaries given the input document(s). This can be achieved by minimizing the cross-entropy under the model between the predicted summary’s word sequence and the true summary’s word sequence. In order to adapt discriminative training to an unsupervised multi-document setting, we propose a surrogate objective that maximizes the likelihood of a masked document from each topically-related
cluster of documents as shown in Figure 1. Crucially, this procedure can be applied to any black box neural summarization model including current state-of-the-art approaches normally trained on supervised data.

2.1 Selecting the Best Masking Candidate

In principle, by training a summarizer to predict randomly chosen masked documents in each input collection, we implicitly train the model to predict the centroid of the collection—a feature of successful extractive systems in past work (Radev et al., 2004; Erkan and Radev, 2004; Mihalcea and Tarau, 2004). However, since document collections may themselves be noisy, we hypothesize that the summarization model will receive an improved training signal from documents that are more representative of the cluster topic. By masking the central-most document instead of a random document, we avoid learning to predict diverging documents comprised of irrelevant information. Contrary to auto-encoding based objectives that learn to reconstruct each input document (Chu and Liu, 2019), our objective encourages overlapping information to be used to predict a target document it does not see as input. We discuss overlap metrics in the next subsection and outline the candidate mask selection procedure in Algorithm 1.

2.2 Measuring Document Overlap

Ultimately, since ROUGE, a measure based on n-gram recall, is summarization’s quantitative evaluation measure, we choose to use n-gram recall as our overlap metric too. Due to both its simplicity and effectiveness, n-gram overlap measures have historically been a mainstay for centroid-based extractive approaches (Radev et al., 2004; Erkan and Radev, 2004; Mihalcea and Tarau, 2004), which measure the lexical overlap between documents of the same topic. We empirically investigate using either the unigram or bigram recall between each document in a cluster and the rest of the combined documents in the cluster for the document distance metric, referred to as $O$ in Algorithm 1. The document with the highest score is selected to be masked out and predicted.

3 Related Work

Non-neural unsupervised MDS has been approached from both extractive (Carbonell and Goldstein, 1998; Gillick and Favre, 2009; Haghigi and Vanderwende, 2009) and abstractive (McKeown and Radev, 1995; Radev and McKeown, 1998; Barzilay et al., 1999; Ganesan et al., 2010) angles. At a high level, extractive methods compute a heuristic ranking of source segments and compose them together. Centroid-based extractive summarization ranks a graph representation of the input document(s), where edges are drawn between segments with similar meanings (Radev et al., 2004; Erkan and Radev, 2004; Mihalcea and Tarau, 2004). Instead of computing centroid-based score functions to produce an output, in our approach we will use them to select a masked document candidate as an unsupervised objective for training a neural abstractive summarization system.

Supervised neural abstractive single-document summarization has received increased interest lately (Rush et al., 2015; See et al., 2017; Gehrmann et al., 2018) despite its many shortcomings (Kryściński et al., 2019), such as a reliance on large human-annotated datasets (Napoles et al., 2012; Hermann et al., 2015). Additionally, supervised abstractive MDS models have also been proposed alongside new datasets (Liu and Lapata, 2019; Liu et al., 2018; Fabbri et al., 2019). Our unsupervised masking objective enables us to train any of the above neural methods discriminatively.

![Algorithm 1: Masked candidate selection](image)

| Input: Training set of document clusters $C = \{C_1, \ldots, C_N\}$, pairwise document overlap function $O$ | Output: Masked training set $X', Y'$ |
|---------------------------------------------------------------|----------------------------------|
| for $i \leftarrow 1$ to $N$ do |
| maxScore $\leftarrow 0$ |
| for $k \leftarrow 1$ to $N$ do |
| score $\leftarrow O(C_{ik}, C_i \setminus \{C_{ik}\})$ |
| if score $> maxScore$ then |
| $X'_i \leftarrow C_i \setminus \{C_{ik}\}$; $Y'_i \leftarrow C_{ik}$ |
| maxScore $\leftarrow$ score |
| end if |
| end for |
| end for |
without ground truth summaries.

Research into unsupervised neural abstractive multi-document summarization is scarcer. Lebanoff et al. (2018) and Zhang et al. (2018) transferred single-document summarization models to MDS, which required no supervised multi-document data. Chu and Liu (2019)’s recently proposed MeanSum, which learns to summarize groups of reviews from a mean-pooled document representation via an auto-encoder objective, represents the most related approach to our own method.

4 Experiments

4.1 Dataset

We use the Multi-News dataset for training and evaluation since it contains supervised summaries for over 125k total news articles in 50k multi-document clusters. Following Fabbri et al. (2019), we concatenate each document cluster into a single 500 token mega-document separated by special document separator tokens using the same strategy: for each cluster, the first $500/M$ tokens are added from each of the $M$ documents, with additional tokens being added iteratively thereafter.

Cleaning Most automatically collected summarization datasets are noisy (Krysciński et al., 2019) and Multi-News is no exception. We remove articles less than 100 characters, nonsensical articles containing links to tweets, and duplicated/syndicated articles by thresholding 4-gram overlap. Next, we find and delete repeated phrases like captions by computing $n$-gram similarity between sentences within a document. Finally, we use regular expressions to remove article metadata. This reduces the dataset from 45K / 5.6K / 5.6K train / valid / test clusters to 42K / 5.2K / 5.2K.

4.2 Unsupervised Baselines

We compare to multiple popular unsupervised extractive approaches\(^2\) like Fabbri et al. (2019) along with a recent neural unsupervised approach.

Lede-$k$ We concatenate the first $k$ sentences from each article cluster together to form the summary, which has proven to be a straightforward, but effective baseline for summarization systems (See et al., 2017).

LexRank Erkan and Radev (2004)’s LexRank computes sentence importance via eigenvector centrality in a graph representation of the sentences in each multi-document cluster.

TextRank TextRank (Mihalcea and Tarau, 2004) is another graph-based method that ranks sentences for extraction, originally proposed for single-document summarization.

MMR Maximal Marginal Relevance (Carbonell and Goldstein, 1998) ranks candidate sentences based on a balance between relevance and redundancy. Top-ranked sentences are appended to form an extractive summary.

MeanSum MeanSum\(^3\) is a completely unsupervised method introduced by Chu and Liu (2019) for summarizing Yelp and Amazon reviews. It is trained to simultaneously auto-encode reviews and produce a summary that is semantically similar to the input reviews using their mean-pooled representation. We remove their review rating classifier and adapt it to the Multi-News dataset.

Source Doc with Best Overlap We simply return the source document with the highest bigram overlap (i.e., the document that would be masked out and predicted). This tests how effective our model is at fusing the information between source documents as opposed to just generating a new, separate document on the same topic.

4.3 Neural Abstractive Summ. Model

While any neural multi-document abstractive summarization model could be used (e.g., Liu and Lapata (2019); Liu et al. (2018)), we use the Hierarchical MMR-Attention Pointer-generator network (Hi-MAP) model (Fabbri et al., 2019) because it was developed on the Multi-News dataset.\(^4\) As the name implies, the Hi-MAP model is composed of a hierarchical pointer-generator network that has an additional attention mechanism over MMR-ranked (Carbonell and Goldstein, 1998) input sentences. Thus, sentence-level extractive summarization scores balancing relevancy and redundancy can be effectively combined with a commonly used single document neural summarization model capable of learning when to produce new output or copy from the source vocabulary. We refer the reader to Fabbri et al. (2019) for hyperparameter settings and implementation details.

\(^1\)In practice, we also truncate masked documents to 300 tokens for efficiency.

\(^2\)Methods are configured to output similar length summaries to our system.

\(^3\)https://github.com/sosuperic/MeanSum

\(^4\)https://github.com/Alex-Fabbri/Multi-News
Table 1: Limited-length ROUGE scores at different output lengths on the Multi-News dataset (Fabbri et al., 2019). The outputs from each model were truncated to meet the length requirement. The distribution of output lengths before truncation for each model is shown in the right-hand column. Results are divided into unsupervised baselines, supervised baselines, and our proposed unsupervised masked objective. The best unsupervised result in each column is bolded. Models with ‘≥ 3’ in their name indicate that they were only trained on document collections that contained at least three input documents. ‘Bigram Overlap Src Doc’ is a baseline that simply uses the truncated masking candidate as the output document. ‘Random Src Doc’ selects a random input document.

| Method                        | Output Length: | 100 Words | 150 Words | 200 Words |
|-------------------------------|----------------|-----------|-----------|-----------|
|                               | MeanLen R-1 R-2 | R-1 R-2 | R-1 R-2 | μ len ± σ |
| **Unsupervised Baselines**    |                |           |           |           |
| Bigram Overlap Src Doc        | 37.15 11.39    | 41.02 13.08| 43.29 14.25| 294 ± 26  |
| Random Src Doc                | 37.54 11.33    | 39.68 12.70| 40.81 13.32| 203 ± 71  |
| Lede-3                        | 36.84 11.15    | 39.73 12.14| 40.83 12.54| 212 ± 84  |
| Lede-4                        | 36.95 11.28    | 40.32 12.55| 42.11 13.23| 269 ± 94  |
| Lede-5                        | 36.98 11.34    | 40.47 12.74| 42.56 13.56| 318 ± 98  |
| LexRank                       | 35.30 10.28    | 38.85 11.93| 40.89 12.85| 246 ± 15  |
| TextRank                      | 36.29 11.10    | 39.49 12.44| 41.33 13.23| 244 ± 16  |
| MMR                           | 35.62 9.35     | 39.89 11.48| 42.57 12.91| 237 ± 17  |
| MeanSum                       | 24.88 3.03     | 27.16 3.66 | 28.48 4.06 | 258 ± 129 |
| **Unsupervised Mask Objective**|                |           |           |           |
| Hi-MAP Random                 | 36.12 10.83    | 40.13 12.90| 42.52 14.09| 233 ± 53  |
| Hi-MAP Unigram                | 37.25 11.77    | 41.05 13.61| 43.19 14.61| 243 ± 56  |
| Hi-MAP Bigram                 | 37.21 11.48    | 41.01 13.33| 43.35 14.54| 247 ± 53  |
| Hi-MAP Random ≥ 3             | 36.68 11.15    | 40.58 13.11| 42.47 13.99| 213 ± 46  |
| Hi-MAP Unigram ≥ 3            | 37.03 11.28    | 41.00 13.31| 43.28 14.47| 256 ± 58  |
| Hi-MAP Bigram ≥ 3             | 37.58 11.60    | 41.45 13.63| 43.75 14.82| 247 ± 52  |

5 Results

Automatic Evaluation In Table 1, we report ROUGE-{1, 2} (Lin, 2004) F-scores for hypotheses5 limited to 100, 150, and 200 words to better compare among uncontrollable neural output lengths (pointed out in (Sun et al., 2019)), along with their untruncated average lengths on the test set summaries from the Multi-News dataset. Unsupervised methods are purely unsupervised since we use only the masked source documents for the validation set for early stopping. Since clusters range in size from 2–10 documents in Multi-News, we also experiment with filtering our training set by number of documents per cluster to see if it affects the choice of masks for each unsupervised method. We report on both the full training set and the other with their untruncated average lengths on the test set. While ROUGE-2 performance on ≥ 3 is slightly better for the supervised system, filtering out 2-article clusters gives statistically significant gains between models trained with the unsupervised objective. Allowing the unsupervised objective to choose the article to mask and predict among ≥ 3 articles is clearly important, which is also suggested by the increase in the difference between scores when excluding 2-article clusters from training with a randomly selected masked document and the bigram overlap mask. We perform a paired bootstrap test on ROUGE-{1,2} 200 scores and find that our best method is significantly better than the baselines with (p ≪ 0.05) and not significantly different from the best supervised model on ROUGE-1 (p = 0.1). We attribute MeanSum’s poor performance to it losing supervision from its review rating classifier and the subtle task differences between its original domain (Yelp reviews) and the news domain.

Human Evaluation We ask two native English speaking human annotators to evaluate 50 randomly sampled test document clusters and their summaries shuffled between our best bigram method and MeanSum, and our best method and the best supervised Hi-MAP. Annotators are shown the input documents and either pair of summaries shown above and asked to choose which is best and which is worst (Louviere and Woodworth, 1991) for informativeness, fluency, and non-redundancy, in line with past work (Fabbri et al., 2019). Annotators almost always selected our method over MeanSum. Surprisingly, annotators also ranked our method better than the supervised Hi-MAP system in informativeness (58%) and fluency (53%).

6 Conclusion The unsupervised masking method achieves comparable performance with supervised abstractive summarizers. Further, the masking candidate itself proves to be a simple and performant baseline. Similar masking objectives for long-form text generation might find applications in related domains.

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5We use beam search with beam size 4, block repeated trigrams, and apply a length penalty with α = 0.9 & β = 5 (Wu et al., 2016).
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