# **Abstractive Summarization of** *Reddit* **Posts with Multi-level Memory Networks**

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## Abstract

We address the problem of abstractive summarization in two directions: proposing a novel dataset and a new model. First, we collect Reddit TIFU dataset, consisting of 120K posts from the online discussion forum Reddit. We use such informal crowd-generated posts as text source, because we empirically observe that existing datasets mostly use formal documents as source text such as news articles; thus, they could suffer from some biases that key sentences usually locate at the beginning of the text and favorable summary candidates are already inside the text in nearly exact forms. Such biases can not only be structural clues of which extractive methods better take advantage, but also be obstacles that hinder abstractive methods from learning their text abstraction capability. Second, we propose a novel abstractive summarization model named multi-level memory networks (MMN), equipped with multi-level memory to store the information of text from different levels of abstraction. With quantitative evaluation and user studies via Amazon Mechanical Turk, we show the Reddit TIFU dataset is highly abstractive and the MMN outperforms the stateof-the-art summarization models.

## 1 Introduction

Abstractive summarization methods have been under intensive study, yet they often suffer from inferior performance compared to extractive methods (Allahyari et al., 2017; Nallapati et al., 2017; See et al., 2017). Admittedly, by task definition, abstractive summarization is more challenging than extractive summarization. However, we argue that such inferior performance is partly due to some biases of existing summarization datasets. The source text of most datasets (Over et al., 2007; Hermann et al., 2015; Cohan et al., 2018; Grusky et al., 2018; Narayan et al., 2018a) originates from

formal documents such as news articles and journals, which have some structural patterns of which extractive methods better take advantage.

In formal documents, there could be a strong tendency that key sentences locate at the beginning of the text and favorable summary candidates are already inside the text in similar forms. Hence, summarization methods could generate good summaries by simply memorizing keywords or phrases from particular locations of the text. Moreover, if abstractive methods are trained on these datasets, they may not show much abstraction capability (See et al., 2017), because they are implicitly forced to learn such structural patterns. Grusky et al. (2018) and Narayan et al. (2018a) have recently reported similar extractive bias in existing datasets. They alleviate this bias by collecting articles from diverse news publications or regarding intro sentences as gold summary.

Different from previous approaches, we propose to alleviate such bias issue by changing the source of summarization dataset. We exploit usergenerated posts from the online discussion forum Reddit, especially TIFU subreddit, which are more casual and conversational than news articles. We observe that the source text in Reddit does not follow strict formatting and disallows models to simply rely on locational biases for summarization. Moreover, the passages rarely contain sentences that are nearly identical to the gold summary. Our new large-scale dataset for abstractive summarization named as Reddit TIFU contains 122,933 pairs of an online post as source text and its corresponding long or short summary sentence. These posts are written by many different users, but each pair of post and summary is created by the same user.

Another key contribution of this work is to propose a novel memory network model named *multi-level memory networks* (MMN). Our model is

equipped with multi-level memory networks, storing the information of source text from different levels of abstraction (*i.e.* word-level, sentence-level, paragraph-level and document-level). This design is motivated by that abstractive summarization is highly challenging and requires not only to understand the whole document, but also to find salient words, phrases and sentences. Our model can sequentially read such multiple levels of information to generate a summary sentence.

Most abstractive summarization methods (See et al., 2017; Li et al., 2017; Zhou et al., 2017; Liu et al., 2018; Cohan et al., 2018; Paulus et al., 2018) employ sequence-to-sequence (seq2seq) models (Sutskever et al., 2014) where an RNN encoder embeds an input document and another RNN decodes a summary sentence. Our MMN has two major advantages over seq2seq-based models. First, RNNs accumulate information in a few fixed-length memories at every step regardless of the length of an input sequence, and thus may fail to utilize far-distant information due to vanishing gradient. It is more critical in summarization tasks, since input text is usually very long (>300 words). On the other hand, our convolutional memory explicitly captures long-term information. Second, RNNs cannot build representations of different ranges, since hidden states are sequentially connected over the whole sequence. This still holds even with hierarchical RNNs that can learn multiple levels of representation. In contrast, our model exploits a set of convolution operations with different receptive fields; hence, it can build representations of not only multiple levels but also multiple ranges (e.g. sentences, paragraphs, and the whole document). Our experimental results show that the proposed MMN model improves abstractive summarization performance on both our new Reddit TIFU and Newsroom-Abs benchmark (Grusky et al., 2018); it outperforms several state-of-the-art abstractive models with seq2seq architecture such as (See et al., 2017; Zhou et al., 2017; Li et al., 2017). We evaluate with quantitative language metrics (e.g. perplexity and ROUGE (Lin, 2004)) and user studies via Amazon Mechanical Turk (AMT).

The contributions of this work are as follows.

1. We newly collect a large-scale abstractive summarization dataset named *Reddit TIFU*. As far as we know, our work is the first to use non-news text for summarization data.

- 2. We propose a novel model named *multi-level memory networks* (MMN). To the best of our knowledge, our model is the first attempt to leverage memory networks for the abstractive summarization. We discuss the unique updates of the MMN over existing memory networks in Section 2.
- 3. With quantitative evaluation and user studies via AMT, we show that our model outperforms state-of-the-art abstractive summarization methods on both Reddit TIFU and the Newsroom abstractive subset.

## 2 Related Work

Our work can be uniquely positioned in the context of the following three topics.

Neural Abstractive Summarization. Many deep neural network models have been proposed for abstractive summarization. One of the most dominant architectures is to employ RNN-based seq2seq models with attention mechanism such as (Rush et al., 2015; Chopra et al., 2016; Nallapati et al., 2016; Cohan et al., 2018) In addition, recent advances in deep network research have been promptly adopted for improving abstractive summarization. Some notable examples include the use of variational autoencoders (VAEs) (Miao and Blunsom, 2016; Li et al., 2017), graph-based attention (Tan et al., 2017), pointer-generator models (See et al., 2017), self-attention networks (Liu et al., 2018), reinforcement learning (Paulus et al., 2018; Pasunuru and Bansal, 2018) and contextual agent attention (Celikyilmaz et al., 2018).

Compared to existing neural methods of abstractive summarization, our approach is novel to replace an RNN-based encoder with explicit multi-level convolutional memory. While RNN-based encoders always consider the whole sequence to represent each hidden state, our multi-level memory network exploits convolutions to control the extent of representation in multiple levels of sentences, paragraphs, and the whole text.

Summarization Datasets. Most existing summarization datasets use formal documents as source text. News articles are exploited the most, including in DUC (Over et al., 2007), Gigaword (Napoles et al., 2012), CNN/DailyMail (Nallapati et al., 2016; Hermann et al., 2015), Newsroom (Grusky et al., 2018) and XSum (Narayan et al., 2018a) datasets. Cohan et al. (2018) introduce datasets of academic papers from arXiv

and PubMed. Hu et al. (2015) propose the LC-STS dataset as a collection of Chinese microblog's short text each paired with a summary. However, it selects only formal text posted by verified organizations such as news agencies or government institutions. Compared to previous summarization datasets, our dataset is novel in that it consists of posts from the online forum Reddit.

Rotten Tomatoes and Idebate dataset (Wang and Ling, 2016) use online text as source, but they are relatively small in scale: 3.7K posts of Rotten-Tomatoes vs. 80K posts of TIFU-short as shown in Table 1. Moreover, Rotten Tomatoes use multiple movie reviews written by different users as single source text, and one-sentence consensus made by another professional editor as summary. Thus, each pair of this dataset could be less coherent than our TIFU, in which each pair is written by the same user. The Idebate dataset is collected from short arguments of debates on controversial topics, and thus the text is rather formal. On the other hand, our dataset contains the posts of interesting stories happened in daily life, and thus the text is more unstructured and informal.

**Neural Memory Networks**. Many memory network models have been proposed to improve memorization capability of neural networks. Neural Turing Machines (Graves et al., 2014, 2016) use external memory to solve algorithmic problems such as sorting and graph traversal. Weston et al. (2014) propose one of early memory networks for language question answering (QA); since then, many memory networks have been proposed for QA tasks (Sukhbaatar et al., 2015; Kumar et al., 2016; Miller et al., 2016). Park et al. (2017) propose a convolutional read memory network for personalized image captioning. One of the closest works to ours may be Singh et al. (2017), which use a memory network for text summarization. However, they only deal with extractive summarization by storing embeddings of individual sentences into memory.

Compared to previous memory networks, our MMN has four novel features: (i) building a multi-level memory network that better abstracts multi-level representation of a long document, (ii) employing a dilated convolutional memory write mechanism to correlate adjacent memory cells, (iii) proposing normalized gated tanh units to avoid covariate shift within the network, and (iv) generating an output sequence without RNNs.

## [Short Summary] (16 words)

TIFU by forgetting my chemistry textbook and all of my notes in a city five hours away

#### [Long Summary] (29 words)

**TL;DR** I forgot my chemistry textbook and binder full of notes in Windsor, which is five hour drive away and I am now screwed for the rest of the semester.

#### [Source Text] (282 words)

(...) So the past three days I was at a sporting event in Windsor. I live pretty far from Windsor, around a 5 hour drive. (...) A five hour drive later, I finally got back home. I was ready to start catching up on some homework when I realized I left my binder (which has all of my assignments, homework etc.) in it, and my chemistry textbook back in Windsor.

I also have a math and chem test next week which I am now so completely screwed for. (...)

Figure 1: An example post of the TIFU subreddit.

Dataset	# posts	# words/post	# words/summ
RottenTomatoes	3,731	2124.7 (1747)	22.2 (22)
Idebate	2,259	178.3 (160)	11.4 (10)
TIFU-short	79,949	342.4 (269)	9.33 (8)
TIFU-long	42,984	432.6 (351)	23.0 (21)

Table 1: Statistics of the Reddit TIFU dataset compared to existing opinion summarization corpora, *RottenTomatoes* and *Idebate* (Wang and Ling, 2016). We show average and median (in parentheses) values.

## 3 Reddit TIFU Dataset

We introduce the Reddit TIFU dataset whose key statistics are outlined in Table 1. We crawled all the posts from January 2013 to March 2018. We make two sets of datasets: TIFU-short and TIFUlong, which consist of pairs of source text and its corresponding short and long summary, respectively. We collect data from Reddit, which is a popular discussion forum platform with a large number of subreddits on diverse topics and interests. Specifically, we use the TIFU subreddit, where every post should strictly follow the posting rules, otherwise they are removed. Thanks to the following rules<sup>1</sup>, the posts in this subreddit can be an excellent corpus for abstractive summarization: Rule 3: Posts and titles without context will be removed. Your title must make an attempt to encapsulate the nature of your f\*\*\*up. Rule 11: All posts must end with a TL;DR summary that is descriptive of your  $f^{***up}$  and its consequences. Thus, we regard the body text as source, the title as short summary, and the TL;DR summary as long summary. Fig. 1 shows an example post of the TIFU subreddit.

<sup>1</sup>https://reddit.com/r/tifu/wiki/rules.

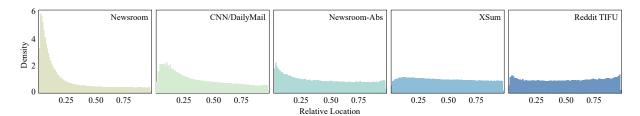


Figure 2: Relative locations of bigrams of gold summary in the source text across different datasets.

	PG		Lead		Ext-Oracle		PG/Lead	PG/Oracle			
Dataset	R-1	R-2	R-L	R-1	R-2	R-L	R-1	R-2	R-L	Ratio (R-L)	Ratio (R-L)
CNN/DM (Nallapati et al., 2016)	36.4	15.7	33.4	39.6	17.7	36.2	54.7	30.4	50.8	0.92x	0.66x
NY Times (Sandhaus, 2008)	44.3	27.4	40.4	31.9	15.9	23.8	52.1	31.6	46.7	1.70x	0.87x
Newsroom (Grusky et al., 2018)	26.0	13.3	22.4	30.5	21.3	28.4	41.4	24.2	39.4	0.79x	0.57x
Newsroom-Abs (Grusky et al., 2018)	14.7	2.2	10.3	13.7	2.4	11.2	29.7	10.5	27.2	0.92x	0.38x
XSum (Narayan et al., 2018a)	29.7	9.2	23.2	16.3	1.6	12.0	29.8	8.8	22.7	1.93x	1.02x
TIFU-short	18.3	6.5	17.9	3.4	0.0	3.3	8.0	0.0	7.7	5.42x	2.32x
TIFU-long	19.0	3.7	15.1	2.8	0.0	2.7	6.8	0.0	6.6	5.59x	2.29x

Table 2: Comparison of ROUGE scores between different datasets (row) and methods (column). PG is a state-of-the-art abstractive summarization method, and Lead and Ext-Oracle are extractive ones. PG/Lead and PG/Oracle are the ROUGE-L ratios of PG with Lead and Ext-Oracle, respectively. We report the numbers for each dataset (row) from the corresponding cited papers.

## 3.1 Preprocessing

We build a separate vocabulary dictionary  $\mathcal{V}$ for each dataset by choosing the most frequent V(=15K) words in the dataset. We do not take OOV words into consideration, since the dictionary with a size of 15K covers about 98% of word frequencies in our dataset. We set the maximum length of a document as 500. We exclude the gold summaries whose lengths are more than 20 and 50 for TIFU-short and TIFU-long, respectively. They amount to about 0.6K posts in both datasets (i.e. less than 1% and 3%). We use these maximum lengths, based on previous datasets (e.g. 8, 31, 56 words on average per summary in Gigaword, DUC, and CNN/DailyMail datasets, respectively). We randomly split the dataset into 95% for training, 5% for test. We defer more details of data preprocessing in the appendix.

## 3.2 Abstractive Properties of Reddit TIFU

We discuss some abstractive characteristics found in Reddit TIFU dataset, compared to existing news article-based summarization dataset.

Weak Lead Bias. Formal documents including news articles tend to be structured to emphasize key information at the beginning of the text. On the other hand, key information in informal online text data are more spread across the text. Fig. 2 plots the density histogram of the relative locations of bigrams of gold summary in the source

text. In the CNN/DailyMail and Newsroom, the bigrams are highly concentrated on the front parts of documents. Contrarily, our Reddit TIFU dataset shows rather uniform distributions across the text.

This characteristic can be also seen from the ROUGE score comparison in Table 2. The Lead baseline simply creates a summary by selecting the first few sentences or words in the document. Thus, a high score of the Lead baseline implicitly indicates a strong lead bias. The Lead scores are the lowest in our TIFU dataset, in which it is more difficult for models to simply take advantage of locational bias for the summary.

Strong Abstractness. Besides the locational bias, news articles tend to contain wrap-up sentences that cover the whole article, and they often have resemblance to its gold summary. Its existence can be measured by the score of the Ext-Oracle baseline, which creates a summary by selecting the sentences with the highest average score of ROUGE-1/2/L. Thus, it can be viewed as an upper bound for extractive models (Narayan et al., 2018a,b; Nallapati et al., 2017). In Table 2, the ROUGE scores of the Ext-Oracle are the lowest in our TIFU dataset. It means that sentences that are similar to gold summary scarcely exist inside the source text in our dataset. This property let the model to be trained to focus on comprehending the entire text instead of simply finding wrap-up sentences.

Finally, PG/Lead and PG/Oracle in Table 2 are the ROUGE-L ratios of PG with Lead and Ext-Oracle, respectively. These metrics can quantify the dataset according to the degree of difficulty for extractive methods and the suitability for abstractive methods, respectively. High scores of the TIFU dataset in both metrics show that it is potentially an excellent benchmark for evaluation of abstractive summarization systems.

## 4 Multi-level Memory Networks (MMN)

Fig. 3 shows the proposed multi-level memory network (MMN) model. The MMN memorizes the source text with a proper representation in the memory and generates a summary sentence one word at a time by extracting relevant information from memory cells in response to previously generated words. The input of the model is a source text  $\{x_i\} = x_1,..,x_N$ , and the output is a sequence of summary words  $\{y_t\} = y_1,...,y_T$ , each of which is a symbol from the dictionary  $\mathcal{V}$ . We below explain the model according to information flow, from source text to summary generation.

## 4.1 Text Embedding

Online posts include lots of morphologically similar words, which should be closely embedded. Thus, we use the fastText (Bojanowski et al., 2016) trained on the Common Crawl corpus, to initialize the word embedding matrix  $\mathbf{W}_{emb}$ . We use the same embedding matrix  $\mathbf{W}_{emb}$  for both source text and output sentences. That is, we represent a source text  $\{x_i\}_{i=1}^N$  in a distributional space as  $\{\mathbf{d}_i^0\}_{i=1}^N$  by  $\mathbf{d}_i^0 = \mathbf{W}_{emb}\mathbf{x}_i$  where  $\mathbf{x}_i$  is a one-hot vector for i-th word in the source text. Likewise, output words  $\{y_t\}_{t=1}^T$  is embedded as  $\{\mathbf{o}_t^0\}_{t=1}^T$ , and  $\mathbf{d}_i^0$  and  $\mathbf{o}_t^0 \in \mathbb{R}^{300}$ .

## 4.2 Construction of Multi-level Memory

As shown in Fig. 3(a), the multi-level memory network takes the source text embedding  $\{\mathbf{d}_i^0\}_{i=1}^N$  as an input, and generates S number of memory tensors  $\{\mathbf{M}_s^{a/c}\}_{s=1}^S$  as output, where superscript a and c denote input and output memory representation, respectively. The multi-level memory network is motivated by that when human understand a document, she does not remember it as a single whole document but ties together several levels of abstraction (e.g. word-level, sentence-level, paragraph-level and document-level). That is, we generate S sets of memory tensors, each of

which associates cells with different numbers of neighboring word embeddings based on the level of abstraction. To build memory slots of such a multi-level memory network, we exploit a multilayer CNN as the write network, where each layer is chosen based on the size of its receptive field.

However, one issue of convolutions is that large receptive fields require many layers or large filters. For example, stacking 6 layers with a filter size of 3 results in a receptive field size of 13, *i.e.* each output depends on 13 input words. In order to increase the receptive field without increasing the computational cost, we exploit the *dilated* convolutions (Yu and Koltun, 2016; Oord et al., 2016a) for the write network.

## Memory Writing with Dilated Convolution.

A dilated convolution is a convolution where the filter is applied over an area larger than its length by skipping input values with a certain gap. More formally, for a 1-D n-length sequence input  $\mathbf{x} \in \mathbb{R}^{n \times 300}$  and a filter  $\mathbf{w}: \{1,...,k\} \to \mathbb{R}^{300}$ , the dilated convolution operation  $\mathcal{F}$  on s elements of a sequence is defined as

$$\mathcal{F}(\mathbf{x}, s) = \sum_{i=1}^{k} \mathbf{w}(i) * \mathbf{x}_{s+d \cdot (i-\lfloor k/2 \rfloor)} + \mathbf{b} \quad (1)$$

where d is the dilation rate, k is the filter size,  $s-d\cdot(i-\lfloor k/2\rfloor)$  accounts for the direction of dilation and  $\mathbf{w}\in\mathbb{R}^{k\times300\times300}$  and  $\mathbf{b}\in\mathbb{R}^{300}$  are the parameters of each convolution filter. With d=1, the dilated convolution reduces to a regular convolution. Using larger dilation enables an output at the top level to represent a wider range of inputs, thus effectively expanding the receptive field.

To given source text embeddings  $\{\mathbf{d}_i^0\}_{i=1}^N$ , we recursively apply a series of dilated convolutions  $F(\mathbf{d}^0) \in \mathbb{R}^{N \times 300}$ . We set the dilation rate to  $d=2^l$ , the kernel size to k=3, and number of convolution layers to L=9. We denote the output of the l-th convolution layer as  $\{\mathbf{d}_i^l\}_{i=1}^N$ .

Normalized Gated Tanh Units. Each convolution is followed by our newly introduced activation of *normalized gated tanh unit* (NGTU), which is illustrated in Fig. 4. The NGTU is an extension of the existing gated tanh units (GTU) (Oord et al., 2016a,b) by applying weight normalization (Salimans and Kingma, 2016) and layer normalization (Ba et al., 2016):

$$\mathrm{GTU}(\mathbf{d}^l) = \tanh(F_f^l(\mathbf{d}^l)) \circ \sigma(F_g^l(\mathbf{d}^l)) \tag{2}$$

$$\mathbf{d}^{l+1} = \text{LayerNorm}(\mathbf{d}^l + \text{GTU}(\mathbf{d}^l))$$
 (3)

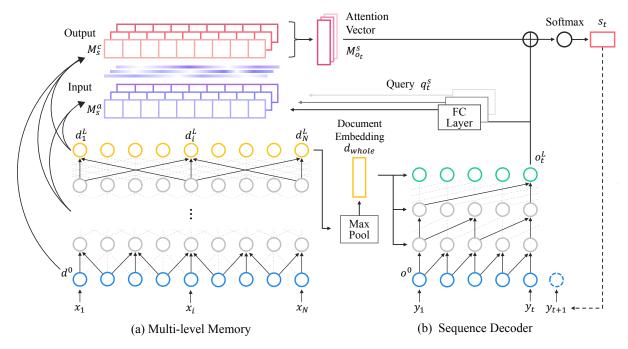


Figure 3: Illustration of the proposed multi-level memory network (MMN) model.

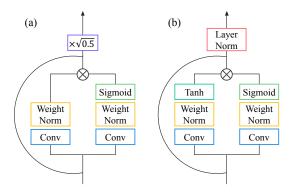


Figure 4: Comparison between (a) the gated linear unit (Gehring et al., 2017) and (b) the proposed normalized gated tanh unit.

where  $\sigma$  is a sigmoid,  $\circ$  is the element-wise multiplication and  $F_f^l$  and  $F_g^l$  denote the filter and gate for l-th layer dilated convolution, respectively.

This mixed normalization structure improves earlier work of Gehring et al. (2017), where they apply weight normalization to the GLU. As in Fig. 4(a), they try to preserve the variance of activations throughout the whole network by scaling the output of residual blocks by  $\sqrt{0.5}$ . However, we observe that this heuristic does not always preserve the variance of activations and does not empirically work well in our dataset. On the other hand, the proposed NGTU not only guarantees preservation of activation variances but also significantly improves the performance.

**Multi-level Memory**. Rather than using only the last layer output of CNNs, we exploit the out-

puts of multiple layers of CNNs to construct S sets of memories. For example, memory constructed from the 4-th layer, whose receptive field is 31, may have sentence-level embeddings, while memory from the 8-th layer, whose receptive field is 511, may have document-level embeddings. We obtain each s-th level memory  $\mathbf{M}_s^{a/c}$  as:

$$\mathbf{M}_{s}^{a} = \mathbf{d}^{\mathbf{m}(s)}, \ \mathbf{M}_{s}^{c} = \mathbf{d}^{\mathbf{m}(s)} + \mathbf{d}^{0}$$
 (4)

Recall that  $\mathbf{M}_s^a$  and  $\mathbf{M}_s^c \in \mathbb{R}^{D \times 300}$  are input and output memory matrix, respectively.  $\mathbf{m}(s)$  indicates an index of convolutional layer used for s-th level memory. For example, if we set S=3 and  $\mathbf{m}=\{3,6,9\}$ , we make three-level memories, each of which uses the output of the 3-rd, 6-th, and 9-th convolution layer, respectively. For output memory representation  $\mathbf{M}_s^c$ , we add the document embedding  $\mathbf{d}^0$  as a skip connection.

## 4.3 State-Based Sequence Generation

We discuss how to predict the next word  $y_{t+1}$  at time step t based on the memory state and previously generated words  $y_{1:t}$ . Fig. 3(b) visualizes the overall procedure of decoding.

We fist apply max-pooling to the output of the last layer the encoder network to build a whole document embedding  $\mathbf{d}_{whole} \in \mathbb{R}^{300}$ :

$$\mathbf{d}_{whole} = \text{maxpool}([\mathbf{d}_1^L; ...; \mathbf{d}_N^L])$$
 (5)

The decoder is designed based on WaveNet (Oord et al., 2016a) that uses a series of causal dilated convolutions, denoted by  $\hat{F}(\mathbf{o}_{1:t}^l) \in \mathbb{R}^{t \times 300}$ . We globally condition  $\mathbf{d}_{whole}$  to obtain embeddings of previously generated words  $\mathbf{o}_{1:t}^l$  as:

$$\mathbf{h}_{f/g}^{l} = \hat{F}_{f/g}^{l}(\mathbf{o}_{1:t}^{l} + \mathbf{W}_{f/g}^{l}\mathbf{d}_{whole})$$
 (6)

$$\mathbf{h}_{a}^{l} = \tanh(\mathbf{h}_{f}^{l}) \circ \sigma(\mathbf{h}_{q}^{l}) \tag{7}$$

$$\mathbf{o}_{1:t}^{l+1} = \text{LayerNorm}(\mathbf{o}_{1:t}^{l} + \mathbf{h}_{a}^{l})$$
 (8)

where  $\mathbf{h}_{f/g}^l$  are the filter and gate hidden state respectively, and learnable parameters are  $\mathbf{W}_f^l$  and  $\mathbf{W}_g^l \in \mathbb{R}^{300 \times 300}$ . We initialize  $\mathbf{o}_t^0 = \mathbf{W}_{emb}\mathbf{y}_t$ . We set the level of the decoder network to L=3 for TIFU-short and L=5 for TIFU-long.

Next, we generate S number of query vectors  $\{\mathbf{q}_t^s\}_{s=1}^S$  at time t to our memory network as

$$\mathbf{q}_t^s = \tanh(\mathbf{W}_q^s \mathbf{o}_t^L + \mathbf{b}_q^s) \tag{9}$$

where  $\mathbf{W}_q^s \in \mathbb{R}^{300 \times 300}$  and  $\mathbf{b}_q^s \in \mathbb{R}^{300}$ .

Each of these query vectors  $\{\mathbf{q}_t^s\}_{s=1}^S$  is fed into the attention function of each level of memory. As in Vaswani et al. (2017), the attention function is

$$\mathbf{M}_{o_t}^s = \operatorname{softmax}(\frac{\mathbf{q}_t^s(\mathbf{M}_s^a)^T}{\sqrt{d_k}})\mathbf{M}_s^c \qquad (10)$$

where we set  $d_k=300$  for the embedding dimension and  $\mathbf{M}_{o_t}^s \in \mathbb{R}^{300}$ .

Next, we obtain the output word probability:

$$\mathbf{s}_t = \operatorname{softmax}(\mathbf{W}_o[\mathbf{M}_{ot}^1; ...; \mathbf{M}_{ot}^S; \mathbf{o}_t^L]) \quad \ (11)$$

where  $\mathbf{W}_o \in \mathbb{R}^{(300 \times (S+1)) \times V}$ .

Finally, we select the word with the highest probability  $y_{t+1} = \operatorname{argmax}_{\mathbf{s} \in \mathcal{V}}(\mathbf{s}_t)$ . Unless  $y_{t+1}$  is an EOS token, we repeat generating the next word by feeding  $y_{t+1}$  into the output convolution layer of Eq.(8). This inference is greedy in that the model creates the best sequence by a sequential search for the best word at each time step.

## 4.4 Training

We use the softmax cross-entropy loss, which minimizes the negative log likelihood from the estimated  $y_t$  to its corresponding target word  $y_{GT,t}$ . However, this likelihood training forces the model to predict extremes (zero or one) to distinguish among the ground truth and alternatives. The label smoothing alleviates this issue by acting as a regularizer that makes the model less confident in

TIFU-short							
Methods	PPL	R-1	R-2	R-L			
seq2seq-att	46.2	18.3	6.4	17.8			
PG (See et al., 2017)	40.9	18.3	6.5	17.9			
SEASS (Zhou et al., 2017)	62.6	18.5	6.4	18.0			
DRGD (Li et al., 2017)	69.2	14.6	3.3	14.2			
Lead-1	n/a	3.4	0.0	3.3			
Best-Match	n/a	8.0	0.0	7.7			
MMN	32.1	20.2	7.4	19.8			
MMN-NoDilated	31.8	19.5	6.8	19.1			
MMN-NoMulti	34.4	19.0	6.1	18.5			
MMN-NoNGTU	40.8	18.6	5.6	18.1			
TIFU-long							
seq2seq-att	180.6	17.3	3.1	14.0			
PG (See et al., 2017)	175.3	16.4	3.0	13.5			
SEASS (Zhou et al., 2017)	387.0	17.5	2.9	13.9			
DRGD (Li et al., 2017)	176.6	16.8	2.0	13.6			
Lead-1	n/a	2.8	0.0	2.7			
Best-Match	n/a	6.8	0.0	6.6			
MMN	114.1	19.0	3.7	15.1			
MMN-NoDilated	124.2	17.6	3.4	14.1			
MMN-NoMulti	124.5	14.0	1.5	11.8			
MMN-NoNGTU	235.4	14.0	2.6	12.1			

Table 3: Summarization results measured by perplexity and ROUGE-1/2/L on the TIFU-short/long dataset.

Newsroom-Abs							
Methods	R-1	R-2	R-L				
Lead-3 (Grusky et al., 2018)	13.7	2.4	11.2				
TextRank (Barrios et al., 2016)	13.5	1.9	10.5				
seq2seq-att	6.2	1.1	5.7				
PG	14.7	2.2	11.4				
MMN	16.1	3.2	13.6				

Table 4: Summarization results measured by ROUGE-1/2/L on the Newsroom-Abs dataset. Except MMN, all numbers are reported results in Grusky et al. (2018).

its prediction. We smooth the target distribution with a uniform prior distribution u (Pereyra et al., 2017; Edunov et al., 2017; Vaswani et al., 2017). Thus, the loss function over the training set  $\mathcal{D}$  is

$$\mathcal{L} = -\sum \log p_{\theta}(\mathbf{y}|\mathbf{x}) - D_{KL}(u||p_{\theta}(\mathbf{y}|\mathbf{x}))$$

We implement label smoothing by modifying the ground truth distribution for word  $y_{GT,t}$  to be  $p(y_{GT,t}) = 1 - \epsilon$  and  $p(y') = \epsilon/\mathcal{V}$  for  $y' \neq y_{GT,t}$  where  $\epsilon$  is a smoothing parameter set to 0.1. Further details can be found in the appendix.

## 5 Experiments

## 5.1 Experimental Setting

**Evaluation Metrics**. We evaluate the summarization performance with two language metrics: perplexity and standard ROUGE scores (Lin, 2004). We remind that lower perplexity and higher ROUGE scores indicate better performance.

**Datasets.** In addition to *Reddit TIFU* dataset, we also evaluate our model on abstractive subset of Newsroom dataset (Grusky et al., 2018), composed of 400K text-summary pairs from diverse 38 major news publications. This subset is a suitable benchmark for evaluation of our model in two aspects. First, it is specialized for abstractive summarization, which meets well the goal of this work. Second, it has a larger vocabulary size (40K) than Reddit TIFU (15K), and thus we can evaluate the learning capability of our model.

Baselines. We compare with three state-of-theart abstractive summarization methods, one basic seq2seq model, two heuristic extractive methods, and variants of our model. We choose PG (See et al., 2017), SEASS (Zhou et al., 2017), DRGD (Li et al., 2017) as the state-of-the-art methods of abstractive summarization. We test the attention based seq2seq model denoted as seq2seq-att (Chopra et al., 2016). As heuristic extractive methods, the Lead-1 uses the first sentence in the text as summary, and the Best-Match takes the sentence with the highest average score of ROUGE-1/2/L with the gold summary in the text. Thus, Best-Match can be viewed as an upper-bound for extractive methods.

We also test variants of our method MMN-\*. To validate the contribution of each component, we exclude one of key components from our model as follows: (i) -NoDilated with conventional convolutions instead, (ii) -NoMulti with no multi-level memory (iii) -NoNGTU with existing gated linear units (Gehring et al., 2017). That is, -NoDilated quantifies the performance improvement by the use of dilated convolution, -NoMulti assesses the effect of using multi-level memory, and -NoNGTU validates the usefulness of our normalized gated tanh unit.

## 5.2 Quantitative Results

Table 3 compares the summarization performance among different methods on the TIFU-short/long dataset. Our model outperforms the state-of-the-art abstractive methods in both ROUGE and perplexity scores. PG utilizes a pointer network to copy words from the source text, but it may not be a good strategy in our dataset, which is more abstractive as discussed in Table 2. SEASS shows strong performance in DUC and Gigaword dataset, in which the source text is a single long sentence and the gold summary is its shorter ver-

	TI	FU-sho	ort	TIFU-long			
vs. Baselines	Win	Lose	Tie	Win	Lose	Tie	
seq2seq-att	43.0	28.3	28.7	32.0	24.0	44.0	
PG	38.7	28.0	33.3	42.3	33.3	24.3	
SEASS	35.7	28.0	36.3	47.0	37.3	15.7	
DRGD	46.7	17.3	15.0	61.0	23.0	16.0	
Gold	27.0	58.0	15.0	22.3	73.7	4.0	

Table 5: AMT results on the TIFU-short/long between our MMN and four baselines and gold summary. We show percentages of responses that turkers vote for our approach over baselines.

sion. Yet, it may not be sufficient to summarize much longer articles of our dataset, even with its second-level representation. DRGD is based on variational autoencoders with latent variables to capture the structural patterns of gold summaries. This idea can be useful for the similarly structured formal documents but may not go well with diverse online text in the TIFU dataset.

These state-of-the-art abstractive methods are not as good as our model, but still perform significantly better than extractive methods. Given that the Best-Match heuristic is an upper-bound for extractive methods, this result implicates that our dataset is highly abstractive, and it is not successful to simply retrieve existing sentences from the source text. Moreover, in other work using different datasets (See et al., 2017; Paulus et al., 2018; Cohan et al., 2018), the performance gaps between abstractive and extractive methods are much smaller, which means too that our dataset is more abstractive than other datasets.

Table 4 compares the summarization performance on the Newsroom-Abs dataset. Our model not only outperforms the state-of-the-art abstractive methods in all the ROUGE scores, but also outperforms extractive methods. These results show that even on formal documents with a large vocabulary size, our multi-level memory is effective especially when the dataset is highly abstractive.

## 5.3 Qualitative Results

We perform two types of qualitative evaluation to complement the limitation of automatic language metrics as summarization evaluation.

User Preferences. We perform Amazon Mechanical Turk (AMT) tests to observe general users' preferences between different algorithms. We randomly sample 100 test examples. At test, we show a source text and two summaries generated by our method and one baseline in a random

#### [Source Text]

(...) I decided to go over to my friends house to a small party at 1 in the morning. I knew my parents would say no so I snuck out of the house. (...) I had been talking to my mom about how sad even hearing the theme song made me. Also she had seen me watching a bunch of sad anime theme songs and tearing up a little so she must have thought I was depressed. When I got home today my mom was practically in tears. (...)

#### [Short Summary]

(Gold) sneaking out of my friends house last night

(Ours) sneaking out of my friends house

(PG) not watching my friends

(SEASS) accidentally spoiling my mom song

#### [Source Text]

(...) Saturday was on my way to a party and this dog was walking in the road. (...) Since it was a holiday I couldn't get her scanned for a chip but she was obviously neglected. Missing fur from flea infestation, (...) Yesterday I was able to go get her scanned for a chip. No chip. So I get ready to take her home and deflea her. (...) Anyway a third party today starts accusing me of stealing (...) and talking about pressing charges. (...)

#### [Long Summary]

(Gold) Saved a dog. Had to give dog back to possible abusers. Being accused of stealing the fucking dog. No good deed goes unpunished.

(Ours) tried to help a dog got a bit and got accused of stealing (seq2seq-att) got accused of being a dog by stealing a \_UNK bit the dog and accused of stealing dog to the police

(SEASS) called a dog a UNK might get charged with UNK

Figure 5: Examples of abstractive summary generated by our model and baselines. In each set, we too show the source text and gold summary.

order. We ask turkers to choose the more relevant one between the two for the source text. We obtain answers from three different turkers for each example. We compare with four abstractive baselines (seq2seq-att, PG, SEASS and DRGD) and the gold summary (Gold).

Table 5 summarizes the results of AMT tests, which validate that human annotators significantly prefer our results to those of baselines. As expected, the gold summary is voted the most.

**Summary Examples.** Fig. 5 shows selected examples of abstractive summarization. Baselines generate summary by mostly focusing on some keywords in the text, while our model produces summary considering both keywords and the whole context thanks to multi-level memory. We present more examples in the appendix.

## 6 Conclusions

We introduced a new dataset *Reddit TIFU* for abstractive summarization using informal online text. We also proposed a novel summarization model named multi-level memory networks

(MMN). With quantitative evaluation and AMT user studies, we showed that the Reddit TIFU dataset is highly abstractive and the proposed MMN model outperforms other state-of-the-art abstractive models. There are several promising future directions that go beyond this work. First, we observe that ROUGE metrics are limited to correctly capture paraphrased summaries, for which a new automatic metric of abstractive summarization may be required. Second, we can explore the data in other online forums such as Quora, Stackoverflow and other subreddits.

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## A Preprocessing of Reddit TIFU Dataset

We build a vocabulary dictionary  $\mathcal{V}$  for each dataset by choosing the most frequent  $V(=15\mathrm{K})$  words in the dataset. We exclude any urls, unicodes and special characters. We lowercase words, and normalize digits to 0. Subreddit names and user ids are replaced with @subreddit and @userid token, respectively. We use markdown² package to strip markdown format, and spacy³ to tokenize words. Common prefixes of summary sentences (e.g. tifu by, tifu-, tl;dr, etc) are trimmed. We do not take OOV words into consideration, since our vocabulary with size 15K covers about 98% of word frequencies in our dataset.

We set the maximum length of document as 500. We exclude the gold summaries whose lengths are more than 20 and 50 for *TIFU-short* and *TIFU-long*, respectively. They amount to about 0.6K posts in both datasets (*i.e.* less than 1% and 3%). We use these maximum lengths, based on previous datasets (*e.g.* 8, 31, 56 words on average per summary in Gigaword, DUC, and CNN/DailyMail datasets, respectively).

Symbol	Description	short	long	N-Abs		
-	Initial learning rate		0.001			
_	Grad clip	0.3				
$d_k$	Embedding dimension	300				
k	Kernel size	3				
d	Dilation rate	$2^l$				
-	# of encoder layers	9	8	10		
-	# of decoder layers	3	5	6		
m	Layers used for memory	${3, 6, 9}$	{4, 8}	${3, 6, 10}$		
$\epsilon$	Smoothing parameter	0.1	0.05	0.05		

Table 6: Model hyperparameters used for experiments on TIFU-short/long and Newsroom-Abs dataset.

## **B** Implementation Details

All the parameters are initialized with the Xavier method (Glorot and Bengio, 2010). We apply the Adam optimizer (Kingma and Ba, 2015) with  $\beta_1=0.9, \beta_2=0.999$  and  $\epsilon=1e-8$ . We apply weight normalization (Salimans and Kingma, 2016) to all layers. We set learning rate to 0.001 and clip gradient at 0.3. At every 4 epochs, we divide learning rate by 10 until it reaches 0.0001. We train our models up to 12 epochs for TIFU-short and 60 epochs for TIFU-long,

Table 6 summarizes the setting of hyperparameters for our model in all experiments on TIFU-short/long and Newsroom-Abs dataset.

## C More Examples

Fig. 6 illustrates selected examples of summary generation. In each set, we show a source text, a gold summary and generated summaries by our method and baselines. In the examples, while baselines generate summary by mostly focusing on some keywords, our model produces summary considering both keywords and the whole context thanks to multi-level memory.

<sup>&</sup>lt;sup>2</sup>https://python-markdown.github.io/.

https://spacy.io.

#### [Source Text]

(...) This weekend I went out and bought myself a motorcycle! I've been planning on buying one this summer and I finally went out and did it. (...) I geared up and went on my way for my first ride. (...) I went all the way back to my house and alas, no phone. So I spent the next 4 hours walking the route to my girlfriends house looking along the side of the road for my phone. These are all back roads to my girlfriends house so I had to really get in the undergrowth to look for my phone. It got dark and I headed home feeling dejected. The next morning my friend came over with my phone! The only damage was a few scuffs to my otterbox. I couldn't believe he found it, and as it turns out it fell off my bike and tumbled onto the side of his driveway. I chalked this up as a win and considered myself lucky. Until yesterday. I woke up with poison ivy all over my body. And when I say all over my body, I mean ALL OVER my body. I have some on my arms, legs, face, and most importantly all over my dick. And the worst spot of them all is on my dick. I have never been so uncomfortable in my life. I must have had some of the oil on my hands and scratched an itch down there. Needless to say I haven't been on my new motorcycle since I've had this and I've been doing as little moving as possible at my job and at home. F\*\*\*.

#### [Short Summary]

(Gold) taking a ride on my new motorcycle

(Ours) buying my new motorcycle

(seq2seq-att) trying to be a good samaritan

(PG) not wearing my cargo helmet

(SEASS) going for a ride

(DRGD) getting my phone stuck

#### [Source Text]

(...) We use an internal messaging application software at work which has been great for communicating with other teammates. A lot of us have started using it to complain about things we are not happy about at work. (...) This leads me to today where just as i am about to go home my manager calls me in to a private meeting looking really upset. Then they mentioned the program name and that they had received an email, and suddenly I realized I had fucked up one of the quirks of this program is that when someone is offline it emails them the message. A recently ex co-worker is still active on the chat for quick questions for the next 2 weeks. They came online so we started having a conversation, then another co-worker walked up to me for a chat who has been having a rough week and complained about our boss. When they finished their rant, I then messaged my ex co-worker that my boss wasn't popular with the staff at the moment as that was the second minor complaint I had heard that week. They had gone offline, so an email was sent to their old work email. Past employees emails get sent to the boss, in case important emails are sent to them. So after the meeting I still have my job. I had an awkward conversation with my boss (...)

#### [Long Summary]

(Gold) message program at work emailed a private message between a past co worker and myself to my boss saying how people where not happy with them

(Ours) sent a message to my boss and now i 'm in a meeting with my boss

(seq2seq-att) i lied about my boss to get my job and now i 'm in a job with a new job

 $(\mbox{\sc PG})$  i got a program that sacked from work and i got sent to a metting by my boss

#### [Source Text]

(...) Later that night, the rest of the family proceeded to play cards and become quite intoxicated. Me, being the little shit that I was, and probably still am, took this opportunity to raid the liquor cooler, and made off with a bottle of wine. I, along with a few other of my underage cousins, ran off to consume our loot. Now, in most situations, this really wouldn't be a that big deal, however, getting drunk at 18 wasn't where my f\*\*\* up occurred. (...) John tells her it'll be okay, that he will smooth talk it over with them, and that she should bring them a bottle of their favorite wine. Well John and Jane are having dinner outside to meet the parents, and when Jane goes to retrieve her gift of wine to John's parents, she discovers the wine is gone. Jane then begins to panic, and starts tearing up the surrounding area looking for it. John's parents have no idea what she's freaking out about, or why John would bring crazy to the family reunion. (...) Jane now slips into complete hysteria, and runs inside to lock herself in the bathroom. (...) The day after, John convinces his parents to try again, and all goes very well, especially since last night's thief is still recovering from his first wine hangover.

#### [Short Summary]

(Gold) stealing a bottle of wine

(Ours) getting drunk and stealing a wine bottle

(seq2seq-att) getting drunk and making a family cry

(PG) ruining my future dinner vacation

(SEASS) accidentally stealing alcohol from my cousin's parent's party

(DRGD) smoking a cigarette

#### [Source Text]

(...) My girlfriend and I have just started to "get a bit more uncomfortable with each other". (...) My curfew for the night had been midnight, however we both got a bit carried away in the beautiful setting (...) I had over extended my curfew by around an hour. This prompted my mother to call me angrily and groggily claiming that she was mad at me. I defended myself by saying that we both fell asleep listening to the docile tones of Steve Harvey on "Family Feud". (...) I sent my girlfriend a text that said something along the lines of "X acts of affection. Comments questions, or complaints?" However upon hitting the send button I noticed that it was heading in the direction of my birth giver. I panicked and luckily managed to put it into airplane mode! (...) I quickly googled "How to prevent texts from sending" and it said to simply delete the text while it was on airplane mode. I did so, and proceeded to turn airplane mode off, however the "always correct Internet" was wrong and I hear my mom receive the text in the next room over. I quickly went into her room to try and crack her phone's code in order to diffuse the bomb (...) I then asked my mother for her phone so that I could "call mine". She reluctantly agreed and I hurriedly rushed to my room. (...)

#### [Long Summary]

(Gold) did some funky stuff with my date

(Ours) accidentally sent an inappropriate text to a girl and then accidentally sent it to my mother's phone and now i'm trouble

**(PG)** tifu by answering an airplane call and accidentally adding my mothers phone and her phone to find out she was sleeping on me

(SEASS) I accidentally sent a text to my mom that I was sending her a text from the UNK bomb

Figure 6: Examples of abstractive summary generated by our model and baselines. In each set, we too show the source text and gold summary.