

Incorporating Copying Mechanism in Sequence-to-Sequence Learning

Jiatao Gu[†] Zhengdong Lu[‡] Hang Li[‡] Victor O.K. Li[†]

[†]Department of Electrical and Electronic Engineering, The University of Hong Kong
 {jiataogu, vli}@eee.hku.hk

[‡]Huawei Noah's Ark Lab, Hong Kong
 {lu.zhengdong, hangli.hl}@huawei.com

Abstract

We address an important problem in sequence-to-sequence (Seq2Seq) learning referred to as copying, in which certain segments in the input sequence are selectively replicated in the output sequence. A similar phenomenon is observable in human language communication. For example, humans tend to repeat entity names or even long phrases in conversation. The challenge with regard to copying in Seq2Seq is that new machinery is needed to decide when to perform the operation. In this paper, we incorporate copying into neural network-based Seq2Seq learning and propose a new model called COPYNET with encoder-decoder structure. COPYNET can nicely integrate the regular way of word generation in the decoder with the new copying mechanism which can choose subsequences in the input sequence and put them at proper places in the output sequence. Our empirical study on both synthetic data sets and real world data sets demonstrates the efficacy of COPYNET. For example, COPYNET can outperform regular RNN-based model with remarkable margins on text summarization tasks.

1 Introduction

Recently, neural network-based sequence-to-sequence learning (Seq2Seq) has achieved remarkable success in various natural language processing (NLP) tasks, including but not limited to Machine Translation (Cho et al., 2014; Bahdanau et al., 2014), Syntactic Parsing (Vinyals et al., 2015b), Text Summarization (Rush et al., 2015) and Dialogue Systems (Vinyals and Le, 2015).

Seq2Seq is essentially an encoder-decoder model, in which the encoder first transforms the input sequence to a certain representation which can then transform the representation into the output sequence. Adding the attention mechanism (Bahdanau et al., 2014) to Seq2Seq, first proposed for automatic alignment in machine translation, has led to significant improvement on the performance of various tasks (Shang et al., 2015; Rush et al., 2015). Different from the canonical encoder-decoder architecture, the attention-based Seq2Seq model revisits the input sequence in its raw form (array of word representations) and dynamically fetches the relevant piece of information based mostly on the feedback from generation of the output sequence.

In this paper, we explore another mechanism important to the human language communication, called the “copying mechanism”. Basically, it refers to the mechanism that locates a certain segment of the input sentence and puts the segment into the output sequence. For example, in the following two dialogue turns we observe different patterns in which some subsequences (colored blue) in the response (R) are copied from the input utterance (I):

I: Hello Jack, my name is Chandralekha.

R: Nice to meet you, Chandralekha.

I: This new guy doesn't perform exactly as we expected.

R: What do you mean by "doesn't perform exactly as we expected"?

Both the canonical encoder-decoder and its variants with attention mechanism rely heavily on the representation of “meaning”, which might not be sufficiently inaccurate in cases in which the system needs to refer to sub-sequences of input like entity names or dates. In contrast, the copying mechanism is closer to the rote memo-

rization in language processing of human being, deserving a different modeling strategy in neural network-based models. We argue that it will benefit many Seq2Seq tasks to have an elegant unified model that can accommodate both understanding and rote memorization. Towards this goal, we propose COPYNET, which is not only capable of the regular generation of words but also the operation of copying appropriate segments of the input sequence. Despite the seemingly “hard” operation of copying, COPYNET can be trained in an end-to-end fashion. Our empirical study on both synthetic datasets and real world datasets demonstrates the efficacy of COPYNET.

2 Background: Neural Models for Sequence-to-sequence Learning

Seq2Seq Learning can be expressed in a probabilistic view as maximizing the likelihood (or some other evaluation metrics (Shen et al., 2015)) of observing the output (target) sequence given an input (source) sequence.

2.1 RNN Encoder-Decoder

RNN-based Encoder-Decoder is successfully applied to real world Seq2Seq tasks, first by Cho et al. (2014) and Sutskever et al. (2014), and then by (Vinyals and Le, 2015; Vinyals et al., 2015a). In the Encoder-Decoder framework, the source sequence $X = [x_1, \dots, x_{T_S}]$ is converted into a fixed length vector \mathbf{c} by the encoder RNN, i.e.

$$\mathbf{h}_t = f(x_t, \mathbf{h}_{t-1}); \quad \mathbf{c} = \phi(\{\mathbf{h}_1, \dots, \mathbf{h}_{T_S}\}) \quad (1)$$

where $\{\mathbf{h}_t\}$ are the RNN states, \mathbf{c} is the so-called context vector, f is the dynamics function, and ϕ summarizes the hidden states, e.g. choosing the last state \mathbf{h}_{T_S} . In practice it is found that gated RNN alternatives such as LSTM (Hochreiter and Schmidhuber, 1997) or GRU (Cho et al., 2014) often perform much better than vanilla ones.

The decoder RNN is to unfold the context vector \mathbf{c} into the target sequence, through the following dynamics and prediction model:

$$\begin{aligned} \mathbf{s}_t &= f(y_{t-1}, \mathbf{s}_{t-1}, \mathbf{c}) \\ p(y_t | y_{<t}, X) &= g(y_{t-1}, \mathbf{s}_t, \mathbf{c}) \end{aligned} \quad (2)$$

where \mathbf{s}_t is the RNN state at time t , y_t is the predicted target symbol at t (through function $g(\cdot)$) with $y_{<t}$ denoting the history $\{y_1, \dots, y_{t-1}\}$. The prediction model is typically a classifier over the vocabulary with, say, 30,000 words.

2.2 The Attention Mechanism

The attention mechanism was first introduced to Seq2Seq (Bahdanau et al., 2014) to release the burden of summarizing the entire source into a fixed-length vector as context. Instead, the attention uses a dynamically changing context \mathbf{c}_t in the decoding process. A natural option (or rather “soft attention”) is to represent \mathbf{c}_t as the weighted sum of the source hidden states, i.e.

$$\mathbf{c}_t = \sum_{\tau=1}^{T_S} \alpha_{t\tau} \mathbf{h}_\tau; \quad \alpha_{t\tau} = \frac{e^{\eta(\mathbf{s}_{t-1}, \mathbf{h}_\tau)}}{\sum_{\tau'} e^{\eta(\mathbf{s}_{t-1}, \mathbf{h}_{\tau'})}} \quad (3)$$

where η is the function that shows the correspondence strength for attention, approximated usually with a multi-layer neural network (DNN). Note that in (Bahdanau et al., 2014) the source sentence is encoded with a Bi-directional RNN, making each hidden state \mathbf{h}_τ aware of the contextual information from both ends.

3 COPYNET

From a cognitive perspective, the copying mechanism is related to rote memorization, requiring less understanding but ensuring high literal fidelity. From a modeling perspective, the copying operations are more rigid and symbolic, making it more difficult than soft attention mechanism to integrate into a fully differentiable neural model. In this section, we present COPYNET, a differentiable Seq2Seq model with “copying mechanism”, which can be trained in an end-to-end fashion with just gradient descent.

3.1 Model Overview

As illustrated in Figure 1, COPYNET is still an encoder-decoder (in a slightly generalized sense). The source sequence is transformed by **Encoder** into representation, which is then read by **Decoder** to generate the target sequence.

Encoder: Same as in (Bahdanau et al., 2014), a bi-directional RNN is used to transform the source sequence into a series of hidden states with equal length, with each hidden state \mathbf{h}_t corresponding to word x_t . This new representation of the source, $\{\mathbf{h}_1, \dots, \mathbf{h}_{T_S}\}$, is considered to be a short-term memory (referred to as \mathbf{M} in the remainder of the paper), which will later be accessed in multiple ways in generating the target sequence (decoding).

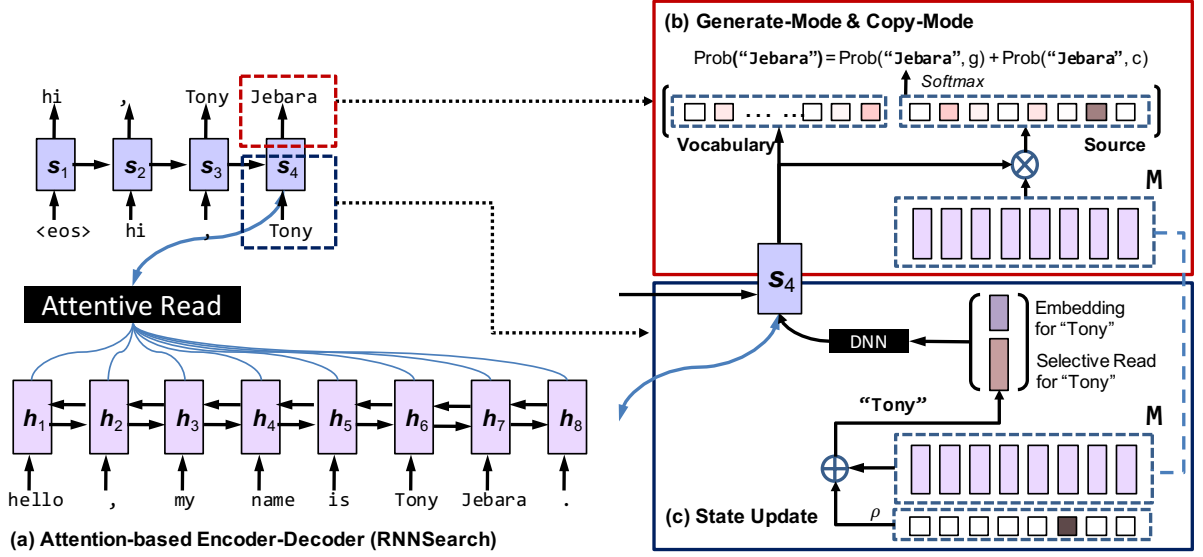


Figure 1: The overall diagram of COPYNET. For simplicity, we omit some links for prediction (see Sections 3.2 for more details).

Decoder: An RNN that reads \mathbf{M} and predicts the target sequence. It is similar with the canonical RNN-decoder in (Bahdanau et al., 2014), with however the following important differences

- **Prediction:** COPYNET predicts words based on a mixed probabilistic model of two modes, namely the **generate-mode** and the **copy-mode**, where the latter picks words from the source sequence (see Section 3.2);
- **State Update:** the predicted word at time $t-1$ is used in updating the state at t , but COPYNET uses not only its word-embedding but also its corresponding location-specific hidden state in \mathbf{M} (if any) (see Section 3.3 for more details);
- **Reading \mathbf{M} :** in addition to the attentive read to \mathbf{M} , COPYNET also has “selective read” to \mathbf{M} , which leads to a powerful hybrid of content-based addressing and location-based addressing (see both Sections 3.3 and 3.4 for more discussion).

3.2 Prediction with Copying and Generation

We assume a vocabulary $\mathcal{V} = \{v_1, \dots, v_N\}$, and use UNK for any out-of-vocabulary (OOV) word. In addition, we have another set of words \mathcal{X} , for all the *unique* words in source sequence $X = \{x_1, \dots, x_{T_S}\}$. Since \mathcal{X} may contain words not in \mathcal{V} , copying sub-sequence in X enables COPYNET to output some OOV words. In a nutshell, the instance-specific vocabulary for source X is $\mathcal{V} \cup \text{UNK} \cup \mathcal{X}$.

Given the decoder RNN state s_t at time t together with \mathbf{M} , the probability of generating any target word y_t , is given by the “mixture” of probabilities as follows

$$p(y_t | s_t, y_{t-1}, \mathbf{c}_t, \mathbf{M}) = p(y_t, g | s_t, y_{t-1}, \mathbf{c}_t, \mathbf{M}) + p(y_t, c | s_t, y_{t-1}, \mathbf{c}_t, \mathbf{M}) \quad (4)$$

where g stands for the generate-mode, and c the copy mode. The probability of the two modes are given respectively by

$$p(y_t, g | \cdot) = \begin{cases} \frac{1}{Z} e^{\psi_g(y_t)}, & y_t \in \mathcal{V} \\ 0, & y_t \in \mathcal{X} \cap \bar{\mathcal{V}} \\ \frac{1}{Z} e^{\psi_g(\text{UNK})}, & y_t \notin \mathcal{V} \cup \mathcal{X} \end{cases} \quad (5)$$

$$p(y_t, c | \cdot) = \begin{cases} \frac{1}{Z} \sum_{j: x_j = y_t} e^{\psi_c(x_j)}, & y_t \in \mathcal{X} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where $\psi_g(\cdot)$ and $\psi_c(\cdot)$ are score functions for generate-mode and copy-mode, respectively, and Z is the normalization term shared by the two modes, $Z = \sum_{v \in \mathcal{V} \cup \{\text{UNK}\}} e^{\psi_g(v)} + \sum_{x \in \mathcal{X}} e^{\psi_c(x)}$. Due to the shared normalization term, the two modes are basically competing through a softmax function (see Figure 1 for an illustration with example), rendering Eq.(4) deviated from the canonical definition of mixture model (McLachlan and Basford, 1988). This is also pictorially illustrated in Figure 2. The score of each mode is calculated:

Generate-Mode: The same scoring function as in the generic RNN encoder-decoder (Bahdanau et

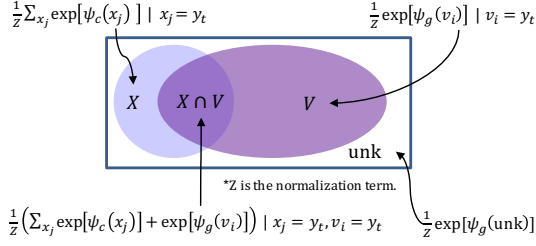


Figure 2: The illustration of the decoding probability $p(y_t | \cdot)$ as a 4-class classifier.

al., 2014) is used, i.e.

$$\psi_g(y_t = v_i) = \mathbf{v}_i^\top \mathbf{W}_o \mathbf{s}_t, \quad v_i \in \mathcal{V} \cup \text{UNK} \quad (7)$$

where $\mathbf{W}_o \in \mathbb{R}^{(N+1) \times d_s}$ and \mathbf{v}_i is the one-hot indicator vector for v_i .

Copy-Mode: The score for “copying” the word x_j is calculated as

$$\psi_c(y_t = x_j) = \sigma \left(\mathbf{h}_j^\top \mathbf{W}_c \right) \mathbf{s}_t, \quad x_j \in \mathcal{X} \quad (8)$$

where $\mathbf{W}_c \in \mathbb{R}^{d_h \times d_s}$, and σ is an activation that is either an identity or a non-linear function such as \tanh . When calculating the copy-mode score, we use the hidden states $\{\mathbf{h}_1, \dots, \mathbf{h}_{T_S}\}$ to “represent” each of the word in the source sequence $\{x_1, \dots, x_{T_S}\}$ since the bi-directional RNN encodes not only the content, but also the location information into the hidden states in \mathbf{M} . The location information is important for copying (see Section 3.4 for related discussion). Note that we sum the probabilities of all x_j equal to y_t in Eq. (6) considering that there may be multiple source symbols for decoding y_t . Naturally we let $p(y_t, c | \cdot) = 0$ if y_t does not appear in the source sequence, and set $p(y_t, g | \cdot) = 0$ when y_t only appears in the source.

3.3 State Update

COPYNET updates each decoding state \mathbf{s}_t with the previous state \mathbf{s}_{t-1} , the previous symbol y_{t-1} and the context vector \mathbf{c}_t following Eq. (2) for the generic attention-based Seq2Seq model. However, there is some minor changes in the $y_{t-1} \rightarrow \mathbf{s}_t$ path for the copying mechanism. More specifically, y_{t-1} will be represented as $[\mathbf{e}(y_{t-1}); \zeta(y_{t-1})]^\top$, where $\mathbf{e}(y_{t-1})$ is the word embedding associated with y_{t-1} , while $\zeta(y_{t-1})$ is the weighted sum of hidden states in \mathbf{M} corresponding to y_t

$$\begin{aligned} \zeta(y_{t-1}) &= \sum_{\tau=1}^{T_S} \rho_{t\tau} \mathbf{h}_\tau \\ \rho_{t\tau} &= \begin{cases} \frac{1}{K} p(x_\tau, \mathbf{c} | \mathbf{s}_{t-1}, \mathbf{M}), & x_\tau = y_{t-1} \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (9)$$

where K is the normalization term which equals $\sum_{\tau': x_{\tau'} = y_{t-1}} p(x_{\tau'}, \mathbf{c} | \mathbf{s}_{t-1}, \mathbf{M})$, considering there may exist multiple positions with y_{t-1} in the source sequence. In practice, $\rho_{t\tau}$ is often concentrated on one location among multiple appearances, indicating the prediction is closely bounded to the location of words.

In a sense $\zeta(y_{t-1})$ performs a type of read to \mathbf{M} similar to the attentive read (resulting \mathbf{c}_t) with however higher precision. In the remainder of this paper, $\zeta(y_{t-1})$ will be referred to as *selective read*. $\zeta(y_{t-1})$ is specifically designed for the copy mode: with its pinpointing precision to the corresponding y_{t-1} , it naturally bears the location of y_{t-1} in the source sequence encoded in the hidden state. As will be discussed more in Section 3.4, this particular design potentially helps copy-mode in covering a consecutive sub-sequence of words. If y_{t-1} is not in the source, we let $\zeta(y_{t-1}) = \mathbf{0}$.

3.4 Hybrid Addressing of M

We hypothesize that COPYNET uses a hybrid strategy for fetching the content in \mathbf{M} , which combines both content-based and location-based addressing. Both addressing strategies are coordinated by the decoder RNN in managing the attentive read and selective read, as well as determining when to enter/quit the copy-mode.

Both the semantics of a word and its location in X will be encoded into the hidden states in \mathbf{M} by a properly trained encoder RNN. Judging from our experiments, the attentive read of COPYNET is driven more by the semantics and language model, therefore capable of traveling more freely on \mathbf{M} , even across a long distance. On the other hand, once COPYNET enters the copy-mode, the selective read of \mathbf{M} is often guided by the location information. As the result, the selective read often takes rigid move and tends to cover consecutive words, including UNKS. Unlike the explicit design for hybrid addressing in Neural Turing Machine (Graves et al., 2014; Kurach et al., 2015), COPYNET is more subtle: it provides the architecture that can facilitate some particular location-based addressing and lets the model figure out the details from the training data for specific tasks.

Location-based Addressing: With the location information in $\{\mathbf{h}_i\}$, the information flow

$$\zeta(y_{t-1}) \xrightarrow{\text{update}} \mathbf{s}_t \xrightarrow{\text{predict}} y_t \xrightarrow{\text{sel. read}} \zeta(y_t)$$

provides a simple way of “moving one step to the right” on X . More specifically, assuming the se-

lective read $\zeta(y_{t-1})$ concentrates on the ℓ^{th} word in X , the state-update operation $\zeta(y_{t-1}) \xrightarrow{\text{update}} s_t$ acts as “location \leftarrow location+1”, making s_t favor the $(\ell+1)^{th}$ word in X in the prediction $s_t \xrightarrow{\text{predict}} y_t$ in copy-mode. This again leads to the selective read $\hat{h}_t \xrightarrow{\text{sel. read}} \zeta(y_t)$ for the state update of the next round.

Handling Out-of-Vocabulary Words Although it is hard to verify the exact addressing strategy as above directly, there is strong evidence from our empirical study. Most saliently, a properly trained COPYNET can copy a fairly long segment full of OOV words, despite the lack of semantic information in its M representation. This provides a natural way to extend the effective vocabulary to include all the words in the source. Although this change is small, it seems quite significant empirically in alleviating the OOV problem. Indeed, for many NLP applications (e.g., text summarization or spoken dialogue system), much of the OOV words on the target side, for example the proper nouns, are essentially the replicates of those on the source side.

4 Learning

Although the copying mechanism uses the “hard” operation to copy from the source and choose to paste them or generate symbols from the vocabulary, COPYNET is fully differentiable and can be optimized in an end-to-end fashion using back-propagation. Given the batches of the source and target sequence $\{X\}_N$ and $\{Y\}_N$, the objectives are to minimize the negative log-likelihood:

$$\mathcal{L} = -\frac{1}{N} \sum_{k=1}^N \sum_{t=1}^T \log \left[p(y_t^{(k)} | y_{<t}^{(k)}, X^{(k)}) \right], \quad (10)$$

where we use superscript to index the instances. Since the tribalistic model for observing any target word is a mixture of generate-mode and copy-mode, there is no need for any additional labels for modes. The network can learn to coordinate the two modes from data. More specifically, if one particular word $y_t^{(k)}$ can be found in the source sequence, the copy-mode will contribute to the mixture model, and the gradient will more or less encourage the copy-mode; otherwise, the copy-mode is discouraged due to the competition from the shared normalization term Z . In practice, in most cases one mode dominates.

5 Experiments

We report our empirical study of COPYNET on the following three tasks with different characteristics

1. A synthetic dataset on with simple patterns;
2. A real-world task on text summarization;
3. A data set for simple single-turn dialogues.

5.1 Synthetic Dataset

Dataset: We first randomly generate transformation rules with 5~20 symbols and variables x & y , e.g.

$$a \ b \ x \ c \ d \ y \ e \ f \rightarrow g \ h \ x \ m,$$

with $\{a \ b \ c \ d \ e \ f \ g \ h \ m\}$ being regular symbols from a vocabulary of size 1,000. As shown in the table below, each rule can further produce a number of instances by replacing the variables with randomly generated subsequences (1~15 symbols) from the same vocabulary. We create five types of rules, including “ $x \rightarrow \emptyset$ ”. The task is to learn to do the Seq2Seq transformation from the training instances. This dataset is designed to study the behavior of COPYNET on handling simple and rigid patterns. Since the string to repeat are random, they can also be viewed as some extreme cases of rote memorization.

Rule-type	Examples (e.g. $x = i \ h \ k$, $y = j \ c$)
$x \rightarrow \emptyset$	$a \ b \ c \ d \ x \ e \ f \rightarrow c \ d \ g$
$x \rightarrow x$	$a \ b \ c \ d \ x \ e \ f \rightarrow c \ d \ x \ g$
$x \rightarrow x \ x$	$a \ b \ c \ d \ x \ e \ f \rightarrow x \ d \ x \ g$
$x \ y \rightarrow x$	$a \ b \ y \ d \ x \ e \ f \rightarrow x \ d \ i \ g$
$x \ y \rightarrow x \ y$	$a \ b \ y \ d \ x \ e \ f \rightarrow x \ d \ y \ g$

Experimental Setting: We select 200 artificial rules from the dataset, and for each rule 200 instances are generated, which will be split into training (50%) and testing (50%). We compare the accuracy of COPYNET and the RNN Encoder-Decoder with (i.e. RNNsearch) or without attention (denoted as Enc-Dec). For a fair comparison, we use bi-directional GRU for encoder and another GRU for decoder for all Seq2Seq models, with hidden layer size = 300 and word embedding dimension = 150. We use bin size = 10 in beam search for testing. The prediction is considered correct only when the generated sequence is exactly the same as the given one.

It is clear from Table 1 that COPYNET significantly outperforms the other two on all rule-types except “ $x \rightarrow \emptyset$ ”, indicating that COPYNET can effectively learn the patterns with variables and accurately replicate rather long subsequence of symbols at the proper places. This is hard to Enc-Dec

Rule-type	$x \rightarrow \emptyset$	$x \rightarrow x$	$x \rightarrow xx$	$xy \rightarrow x$	$xy \rightarrow xy$
Enc-Dec	100	3.3	1.5	2.9	0.0
RNNSearch	99.0	69.4	22.3	40.7	2.6
COPYNET	97.3	93.7	98.3	68.2	77.5

Table 1: The test accuracy (%) on synthetic data.

due to the difficulty of representing a long sequence with very high fidelity. This difficulty can be alleviated with the attention mechanism. However attention alone seems inadequate for handling the case where strict replication is needed.

A closer look (see Figure 3 for example) reveals that the decoder is dominated by copy-mode when moving into the subsequence to replicate, and switch to generate-mode after leaving this area, showing COPYNET can achieve a rather precise coordination of the two modes.

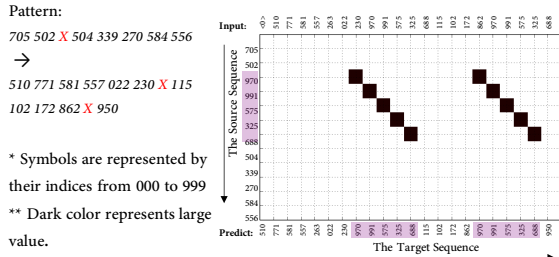


Figure 3: Example output of COPYNET on the synthetic dataset. The heatmap represents the activations of the copy-mode over the input sequence (left) during the decoding process (bottom).

5.2 Text Summarization

Automatic text summarization aims to find a condensed representation which can capture the core meaning of the original document. It has been recently formulated as a Seq2Seq learning problem in (Rush et al., 2015; Hu et al., 2015), which essentially gives *abstractive* summarization since the summary is generated based on a representation of the document. In contrast, *extractive* summarization extracts sentences or phrases from the original text to fuse them into the summaries, therefore making better use of the overall structure of the original document. In a sense, COPYNET for summarization lies somewhere between two categories, since part of output summary is actually extracted from the document (via the copying mechanism), which are fused together possibly with the words from the generate-mode.

Dataset: We evaluate our model on the recently published LCSTS dataset (Hu et al., 2015), a large scale dataset for short text summarization. The

dataset is collected from the news medias on Sina Weibo¹ including pairs of (short news, summary) in Chinese. Shown in Table 2, PART II and III are manually rated for their quality from 1 to 5. Following the setting of (Hu et al., 2015) we use Part I as the training set and the subset of Part III scored from 3 to 5 as testing set.

Dataset	PART I	PART II	PART III
no. of pairs	2,400,591	10,666	1106
no. of score ≥ 3	-	8685	725

Table 2: Some statistics of the LCSTS dataset.

Experimental Setting: We try COPYNET that is based on character (+C) and word (+W). For the word-based variant the word-segmentation is obtained with jieba². We set the vocabulary size to 3,000 (+C) and 10,000 (+W) respectively, which are much smaller than those for models in (Hu et al., 2015). For both variants we set the embedding dimension to 350 and the size of hidden layers to 500. Following (Hu et al., 2015), we evaluate the test performance with the commonly used ROUGE-1, ROUGE-2 and ROUGE-L (Lin, 2004), and compare it against the two models in (Hu et al., 2015), which are essentially canonical Encoder-Decoder and its variant with attention.

Models		ROUGE scores on LCSTS (%)		
		R-1	R-2	R-L
RNN	+C	21.5	8.9	18.6
(Hu et al., 2015)	+W	17.7	8.5	15.8
RNN context	+C	29.9	17.4	27.2
(Hu et al., 2015)	+W	26.8	16.1	24.1
COPYNET	+C	34.4	21.6	31.3
	+W	35.0	22.3	32.0

Table 3: Testing performance of LCSTS, where “RNN” is canonical Enc-Dec, and “RNN context” its attentive variant.

It is clear from Table 3 that COPYNET beats the competitor models with big margin. Hu et al. (2015) reports that the performance of a word-based model is inferior to a character-based one. One possible explanation is that a word-based model, even with a much larger vocabulary (50,000 words in Hu et al. (2015)), still has a large proportion of OOVs due to the large number of entity names in the summary data and the mistakes in word segmentation. COPYNET, with its ability to handle the OOV words with the copying mechanism, performs however slightly better with the word-based variant.

¹www.sina.com

²https://pypi.python.org/pypi/jieba

<p>Input(1): 今天上午9点半, <u>复旦投毒案</u>将在上海二中院<u>公开审理</u>。被害学生<u>黄洋</u>的亲属已从四川抵达上海, <u>其父</u>称待刑事部分结束后, 再提民事赔偿, <u>黄洋</u>92岁的奶奶依然不知情。今年4月, 在复旦上海医学院读研究生的<u>黄洋</u>遭室友<u>林森浩</u>投毒, 不幸身亡。新民网</p> <p>Today 9:30, the Fudan poisoning case will be will on public trial at the Shanghai Second Intermediate Court. The relatives of the murdered student Huang Yang has arrived at Shanghai from Sichuan. His father said that they will start the lawsuit for civil compensation after the criminal section. HuangYang 92-year-old grandmother is still unaware of his death. In April, a graduate student at Fudan University Shanghai Medical College, Huang Yang is allegedly poisoned and killed by his roommate Lin Senhao. Reported by Xinmin</p> <p>Golden: 林森浩投毒案今日开审 92岁奶奶尚不知情 (the case of Lin Senhao poisoning is on trial today, his 92-year-old grandmother is still unaware of this)</p> <p>RNN context: 复旦投毒案: 黄洋遭室友投毒凶手已从四川飞往上海, 父亲命案另有4人被通知家属不治?</p> <p>CopyNet: <u>复旦投毒案</u> 今在沪上公开审理 (the Fudan poisoning case is on public trial today in Shanghai)</p>
<p>Input(2): <u>华谊兄弟</u> (300027) 在昨日收盘后发布公告称, 公司拟以自有资金<u>3.978亿元</u>收购浙江<u>永乐影视</u>股份有限公司若干股东持有的<u>永乐影视</u>51%的股权。对于<u>此项</u>收购, 华谊兄弟<u>董秘</u>胡明昨日表示: “和<u>永乐影视</u>的合并是对华谊兄弟<u>电视剧业务</u>的一个<u>加强</u>。”</p> <p>Huayi Brothers (300027) announced that the company intends to buy with its own fund 397.8 million 51% of Zhejiang Yongle Film LTD's stake owned by a number of shareholders of Yongle Film LTD. For this acquisition, the secretary of the board, Hu Ming, said yesterday: "the merging with Yongle Film is to strengthen Huayi Brothers on TV business".</p> <p>Golden: 华谊兄弟拟收购永乐影视 51% 股权 (Huayi Brothers intends to acquire 51% stake of Zhejiang Yongle Film)</p> <p>RNN context: 华谊兄弟收购永乐影视51%股权: 与永乐影视合并为“和唐”影视合并的“UNK”和“UNK”的区别?</p> <p>CopyNet: <u>华谊兄弟</u>拟<u>3.978亿</u>收购<u>永乐影视</u><u>董秘</u>称<u>加强</u><u>电视剧业务</u> (Huayi Brothers is intended to 397.8 million acquisition of Yongle Film secretaries called to strengthen the TV business)</p>
<p>Input(3): 工厂, 大门紧锁, 约<u>20名工人</u>散坐在<u>树荫下</u>。“我们就是普通工人, 在这里等工资。”其中一人说道。7月4日上午, 记者抵达深圳龙华区清湖路上的深圳<u>愿景光电子</u>有限公司。正如传言一般, <u>愿景光电子</u>倒闭了, 大股东<u>邢毅</u>不知所踪。</p> <p>The door of factory is locked. About 20 workers are scattered to sit under the shade. "We are ordinary workers, waiting for our salary" one of them said. In the morning of July 4th, reporters arrived at Yuanjing Photoelectron Corporation located at Qinghu Road, Longhua District, Shenzhen. Just as the rumor, Yuanjing Photoelectron Corporation is closed down and the big shareholder Xing Yi is missing.</p> <p>Golden: 深圳亿元级LED企业倒闭 烈日下工人苦等老板 (Hundred-million CNY worth LED enterprise is closed down and workers wait for the boss under the scorching sun)</p> <p>RNN context: 深圳“<UNK>”: 深圳<UNK><UNK>, <UNK>, <UNK>, <UNK></p> <p>CopyNet: <u>愿景光电子</u>倒闭 20名工人散坐在树荫下 (Yuanjing Photoelectron Corporation is closed down, 20 workers are scattered to sit under the shade)</p>

Figure 4: Examples of COPYNET on LCSTS compared with RNN context. Word segmentation is applied on the input, where underlined are OOV words. The highlighted words (with different colors) are those words with copy-mode probability higher than the generate-mode. We also provide literal English translation for the document, the golden, and COPYNET, while omitting that for RNN context since the language is broken.

5.2.1 Case Study

We make the following interesting observations about the summary from textscCopyNet (Figure 4, and more in the supplementary material): 1) most words are from copy-mode, but the summary is usually still fluent; 2) COPYNET tends to cover consecutive words in the original document, but it often puts together segments far away from each other, indicating a sophisticated coordination of content-based addressing and location-based addressing; 3) COPYNET handles OOV words really well: it can generate acceptable summary for document with many OOVs, and even the summary itself often contains many OOV words. In contrast, the canonical RNN-based approaches often fail in cases like that.

It is quite intriguing that COPYNET can often find important parts of the document, a behavior with the characteristics of extractive summarization, while it often generate words to “connect” those words, showing its aspect of abstractive summarization.

5.3 Single-turn Dialogue

In this experiment we follow the work on neural dialogue model proposed in (Shang et al., 2015; Vinyals and Le, 2015; Sordoni et al., 2015), and test COPYNET on single-turn dialogue. Basically, the neural model learns to generate a response to

user’s input, from the given (input, response) pairs as training instances.

Dataset: We build a simple dialogue dataset based on the following three instructions:

1. Dialogue instances are collected from Baidu Tieba³ with some coverage of conversations of real life e.g., greeting and sports, etc.
2. Patterns with slots like
 $hi, my\ name\ is\ x \rightarrow hi, x$
are mined from the set, with possibly multiple responding patterns to one input.
3. Similar with the synthetic dataset, we enlarge the dataset by filling the slots with suitable subsequence (e.g. name entities, dates, etc.)

To make the dataset close to the real conversations, we also maintain a certain proportion of instances with the response that 1) do not contain entities or 2) contain entities not in the input.

Experimental Setting: We create two datasets: DS-I and DS-II with slot filling on 173 collected patterns. The main difference between the two datasets is that the filled substrings for training and testing in DS-II have no overlaps, while in DS-I they are sampled from the same pool. For each dataset we use 6,500 instances for training and 1,500 for testing. We compare COPYNET with canonical RNNSearch, both character-based, with the same model configuration in Section 5.1.

³<http://tieba.baidu.com>

Input(1): 我出生在 <u>上海</u> 。 /I was born in Shanghai	Golden: 真巧, 我也来自上海, 老乡啊! /What a coincidence, I also come from Shanghai, we are fellow townsman!
	✗ RNNSearch: 真巧, 我也来自海南, 老乡啊! /What a coincidence, I also come from Hainan, we are fellow townsman!
	○ CopyNet: 真巧, 我也来自 <u>上海</u> , 老乡啊! /What a coincidence, I also come from Shanghai, we are fellow townsman!
Input(2): 今天去爬 <u>黄山</u> 吗? /Shall we climbing Huangshan?	Golden: 去爬泰山吧, 黄山没意思! /Climb Taishan. Huangshan is boring!
	✗ RNNSearch: 去爬长白山吧, 衡山没意思! /Climb Changbaishan, Hengshan is boring!
	○ CopyNet: 去爬 <u>嵩山</u> 吧, <u>黄山</u> 没意思! /Climb Songshan, Huangshan is boring!
Input(3): 你喜 <u>欢</u> 喝 <u>雪碧</u> 还是喜 <u>欢</u> <u>可</u> <u>乐</u> ? /Would you like to drink Sprite or Coke?	Golden: 都不喜欢, 谢谢! /Not at all, thanks!
	✗ RNNSearch: 我喜欢喝蜂蜜! /I like to drink honey!
	○ CopyNet: 我喜 <u>欢</u> 喝 <u>可</u> <u>乐</u> ! /I like to drink coke!

Figure 5: Examples on the testing set of DS-II shown as the input text and golden, with the outputs of RNNSearch and CopyNet. Words in red rectangles are unseen in the training set. The highlighted words (with different colors) are those words with copy-mode probability higher than the generate-mode. Green circles (meaning correct) and red cross (meaning incorrect) are given based on human judgment on whether the response is appropriate.

Models	DS-I (%)		DS-II (%)	
	Top1	Top10	Top1	Top10
RNNSearch	44.1	57.7	13.5	15.9
COPYNET	61.2	71.0	50.5	64.8

Table 4: The decoding accuracy on the two testing sets. Decoding is admitted success only when the answer is found exactly in the Top-K outputs.

We compare COPYNET and RNNSearch on DS-I and DS-II in terms of top-1 and top-10 accuracy (shown in Table 4), estimating respectively the chance of the top-1 or one of top-10 (from beam search) matching the golden. Since there are often many good responses to a input, top-10 accuracy appears to be closer to the real world setting.

As shown in Table 4, COPYNET significantly outperforms RNNsearch, especially on DS-II. It suggests that introducing the copying mechanism helps the dialogue system master the patterns in dialogue and correctly identify the correct parts of input, often proper nouns, to replicate in the response. Since the filled substrings have no overlaps in DS-II, the performance of RNNSearch drops significantly as it cannot handle words unseen in training data. In contrast, the performance of COPYNET only drops slightly as it has learned to fill the slots with the copying mechanism and relies less on the representation of the words.

5.3.1 Case Study

As indicated by the examples in Figure 5, COPYNET accurately replicates the critical segments from the input with the copy-mode, and generates the rest of answers smoothly through the generate-mode. Note that in (2) and (3), the decoding sequence is not exactly the same with the standard one, yet still correct regarding to their meanings. In contrast, although RNNSearch usually generates answers in the right formats, it fails to catch

the critical entities in all three cases because of the difficulty brought by the unseen words.

6 Related Work

Our work is partially inspired by the recent work of Pointer Networks (Vinyals et al., 2015a), in which a pointer mechanism (quite similar with the proposed copying mechanism) is used to predict the output sequence directly from the input. In addition to the difference with ours in application, (Vinyals et al., 2015a) cannot predict outside of the set of input sequence, while COPYNET can naturally combine generating and copying.

COPYNET is also related to the effort to solve the OOV problem in neural machine translation. Luong et al. (2015) introduced a heuristics to post-process the translated sentence using annotations on the source sentence. In contrast COPYNET addresses the OOV problem in a more systemic way with an end-to-end model. However, as COPYNET copies the exact source words as the output, it cannot be directly applied to machine translation.

The copying mechanism can also be viewed as carrying information over to the next stage without any nonlinear transformation. Similar ideas are proposed for training very deep neural networks in (Srivastava et al., 2015; He et al., 2015) for classification tasks, where shortcuts are built between layers for the direct carrying of information.

7 Conclusion and Future Work

We proposed COPYNET to incorporate the copying mechanism into Seq2Seq learning framework. For future work, we will extend this idea to the task where the source and target are in different languages, for example, machine translation.

References

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*.
- Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*.
- Alex Graves, Greg Wayne, and Ivo Danihelka. 2014. Neural turing machines. *arXiv preprint arXiv:1410.5401*.
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2015. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.
- Baotian Hu, Qingcai Chen, and Fangze Zhu. 2015. Lcsts: a large scale chinese short text summarization dataset. *arXiv preprint arXiv:1506.05865*.
- Karol Kurach, Marcin Andrychowicz, and Ilya Sutskever. 2015. Neural random-access machines. *arXiv preprint arXiv:1511.06392*.
- Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In Stan Szpakowicz Marie-Francine Moens, editor, *Text Summarization Branches Out: Proceedings of the ACL-04 Workshop*, pages 74–81, Barcelona, Spain, July. Association for Computational Linguistics.
- Thang Luong, Ilya Sutskever, Quoc Le, Oriol Vinyals, and Wojciech Zaremba. 2015. Addressing the rare word problem in neural machine translation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 11–19, Beijing, China, July. Association for Computational Linguistics.
- Geoffrey J McLachlan and Kaye E Basford. 1988. Mixture models. inference and applications to clustering. *Statistics: Textbooks and Monographs*, New York: Dekker, 1988, 1.
- Alexander M Rush, Sumit Chopra, and Jason Weston. 2015. A neural attention model for abstractive sentence summarization. *arXiv preprint arXiv:1509.00685*.
- Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. Neural responding machine for short-text conversation. *arXiv preprint arXiv:1503.02364*.
- Shiqi Shen, Yong Cheng, Zhongjun He, Wei He, Hua Wu, Maosong Sun, and Yang Liu. 2015. Minimum risk training for neural machine translation. *CoRR*, abs/1512.02433.
- Alessandro Sordani, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. *arXiv preprint arXiv:1506.06714*.
- Rupesh Kumar Srivastava, Klaus Greff, and Jürgen Schmidhuber. 2015. Highway networks. *arXiv preprint arXiv:1505.00387*.
- Ilya Sutskever, Oriol Vinyals, and Quoc VV Le. 2014. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pages 3104–3112.
- Oriol Vinyals and Quoc Le. 2015. A neural conversational model. *arXiv preprint arXiv:1506.05869*.
- Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015a. Pointer networks. In *Advances in Neural Information Processing Systems*, pages 2674–2682.
- Oriol Vinyals, Łukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, and Geoffrey Hinton. 2015b. Grammar as a foreign language. In *Advances in Neural Information Processing Systems*, pages 2755–2763.

<p>Input(5): 1. 掌握技巧 <u>融会贯通</u>; 2. 学会融资; 3. 懂法律; 4. 保持自信; 5. 测试+尝试; 6. 了解客户的需求; 7. 预测+衡量+确保; 8. 做好与各种小bug做斗争的心态; 9. 发现机遇保持 <u>创业</u> 激情。</p> <p>1. master the skills; 2 Learn to finance; 3. understand the law; 4. Be confident; 5. test+ trial; 6. understand the need of customers; 7 forecast+measure+ensure; 8. mentally prepared to fight all kinds of small bugs ; 9 discover opportunities and keep the passion of start-up.</p> <p>Golden: 初次创业者必知的10个技巧 The 10 tips for the first time start-ups</p> <p>RNN context: 6个方法让你创业的6个<UNK>与<UNK>, 你怎么看懂你的创业故事吗? (6家)</p> <p>CopyNet: <u>创业</u> 成功的9个技巧 The 9 tips for success in start-up</p>
<p>Input(6): 9月3日, 总部位于日内瓦的世界经济论坛发布了《2014-2015年全球竞争力报告》, 瑞士连续六年位居榜首, 成为全球最具竞争力的国家, 新加坡和美国分列第一位和第三位。中国排名第28位, 在金砖国家中排名最高。</p> <p>On September 3, the Geneva based World Economic Forum released "The Global Competitiveness Report 2014-2015". Switzerland topped the list for six consecutive years, becoming the world's most competitive country. Singapore and the United States are in the second and third place respectively. China is in the 28th place, ranking highest among the BRIC countries.</p> <p>Golden: 全球竞争力排行榜中国居28位居金砖国家首位 The Global competitiveness ranking list, China is in the 28th place, the highest among BRIC countries.</p> <p>RNN context: 2014-2015年全球竞争力报告: 瑞士连续6年居榜首中国居28位(首/3——访榜首)中国排名第28位</p> <p>CopyNet: 2014-2015年全球竞争力报告: 瑞士居首中国第28 2014-2015 Global Competitiveness Report: Switzerland topped and China the 28th</p>
<p>Input(7): 瑞典媒体日前报道, “按照 <u>购买力平价</u> 的计算方式, 中国 <u>经济总量</u> 29日超过 <u>美国</u>, 成为 <u>世界第一</u>”。专家分析, 其可能是将全年总量除以 <u>365</u> 天得出的 <u>平均值</u>, 但一个国家的经济不可能是 <u>匀速</u> 增长的, 此外, <u>购买力平价</u> 本身也存在 <u>高估</u> 中国的问题。</p> <p>Swedish media recently reported that, "in accordance with the calculation of purchasing power parity, China's GDP exceeded United States on 29th, becoming the first in the world." Expert analyzed, this may be the average over 365 days, but a country's economic growth is not likely to be on the same speed. Moreover, there is problem of over estimate China with PPP itself.</p> <p>Golden: 观察: 中国经济总量29日超美? 专家称“不靠谱” Watch: China's GDP surpasses the United States on the 29th? Experts say "do not believe it"</p> <p>RNN context: 外媒:中国经济总量29日成为世界第一中国经济总量29日超美成世界第一, 但不是中国的“问题”而是“<UNK>”的是福是祸</p> <p>CopyNet: 中国 <u>经济总量</u> 超 <u>美国</u> 成 <u>世界第一</u> China's GDP surpasses the United States, becoming the world's NO.1</p>

Figure 7: Examples 5-7 of COPYNET on LCSTS compared with RNN context. Word segmentation is applied on the input, where underlined are OOV words. The highlighted words (with different colors) are those words with copy-mode probability higher than the generate-mode. We also provide literal English translation for the document, the golden, and COPYNET, while omitting that for RNN context since the language is broken.

A.2 Single-turn Dialogue System

We present more examples of single-turn dialogue results on the testing set of the dialogue dataset, following the same instructions discussed in Section 5.3, comparing COPYNET and RNN encoder as you can see in Figure 8.

Input(1): 我大青岛四季宜人 /Our great Qingdao has a good weather!		Golden: 壮我大青岛~~~ /Our Qingdao is great~~~
	✗ RNNSearch: 壮我大哈尔滨~~~ /Our Harbin is great~~~	
	○ CopyNet: 壮我大青岛~~~ /Our Qingdao is great~~~	
Input(2): 看了昨晚利物浦的比赛了吗? /Did you watch Liverpool's game last night?		Golden: 我这眼睛比裁判都强! /My eyes are stronger than the referee
	○ RNNSearch: 我这眼睛比裁判都强! /My eyes are stronger than the referee	
	○ CopyNet: 昨晚睡觉了没看利物浦怎么样了/I slept last night and I did not see how is Liverpool	
Input(3): 女儿会游泳吗? /Daughter can swim butterfly?		Golden: 我连游泳都不会T^T /I cannot swim at all T^T
	○ RNNSearch: 我连游泳都不会T^T /I cannot swim at all T^T	
	○ CopyNet: 我连游泳都不会T^T /I cannot swim at all T^T	
Input(4): 苏有朋是谁? /Who is Su You Peng?		Golden: 苏有朋是一个男明星。 /Su You Peng is a male star.
	✗ RNNSearch: 吴亦凡是一个男明星。 /Wu Yifan is a male star.	
	✗ CopyNet: 苏有是一个男明星。 /Su You is a male star	

Figure 8: Examples on the testing set of DS-II shown as the input text and golden, with the outputs of RNNSearch and CopyNet. Words in red rectangles are unseen in the training set. The highlighted words (with different colors) are those words with copy-mode probability is higher than the generate-mode. Green circles (meaning correct) and red cross (meaning incorrect) are given based on human judgment whether the response is appropriate.