Incorporating Copying Mechanism in Sequence-to-Sequence Learning

2022 年 4 月 28 日

1 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.

2 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 transforms the representation into the output sequence.

- Adding the attention mechanism (Bah- danau et al., 2014) to Seq2Seq, first proposed for automatic alignment in machine translation, has led to significant improvement on the perfor- mance 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 out- put 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.

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"?

图 1: the human language communication.For example, in the following two dialogue turns we observe differ- ent patterns in which some subsequences (colored blue) in the response (R) are copied from the input utterance (I)

- 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 in- put like entity names or dates.
- In contrast, the copying mechanism is closer to the rote memorization 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 pro- pose 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.

3 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.

3.1 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 $X = [x_1, ..., x_{TS}]$ is converted into a fixed length vector c by the encoder RNN, i.e.

$h_t = f(x_t, h_{t-1}); c = \phi(h_1, h_2, ...h_{TS})$

where h_t are the RNN states, c is the so-called context vector, f is the dynamics function, and ϕ summarizes the hidden states, e.g. choosing the last state h_{TS}. In practice it is found that gated RNN alternatives such as LSTM (Hochreiter and Schmidhuber, 1997) or GRU (Cho et al., 2014) of- ten perform much better than vanilla ones. The decoder RNN is to unfold the context vector c into the target sequence, through the following dynamics and prediction model:

$s_t = f(y_{t-1}, s_{t-1}, c)$

$p(y_t|y_{<t}, X) = g(y_{t-1}, s_t, c)$

where 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 $y_1, ..., y_{t-1}$. The prediction model is typically a classifier over the vocabulary with, say, 30,000 words.

3.2 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 c_t in the decoding process. A natural option (or rather "soft attention") is to represent c_t as the weighted sum of the source hidden states, i.e.

$c_t = \sum_{\tau=1}^{T_s} \alpha_{t\tau} h_\tau;$

$\alpha_{t\tau} = \frac{e^{\eta(s_{t-1}, h_\tau)}}{\sum_{\tau'} e^{\eta(s_{t-1}, h'_\tau)}}$

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 h_τ aware of the contextual information from both ends.

4 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.

4.1 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.

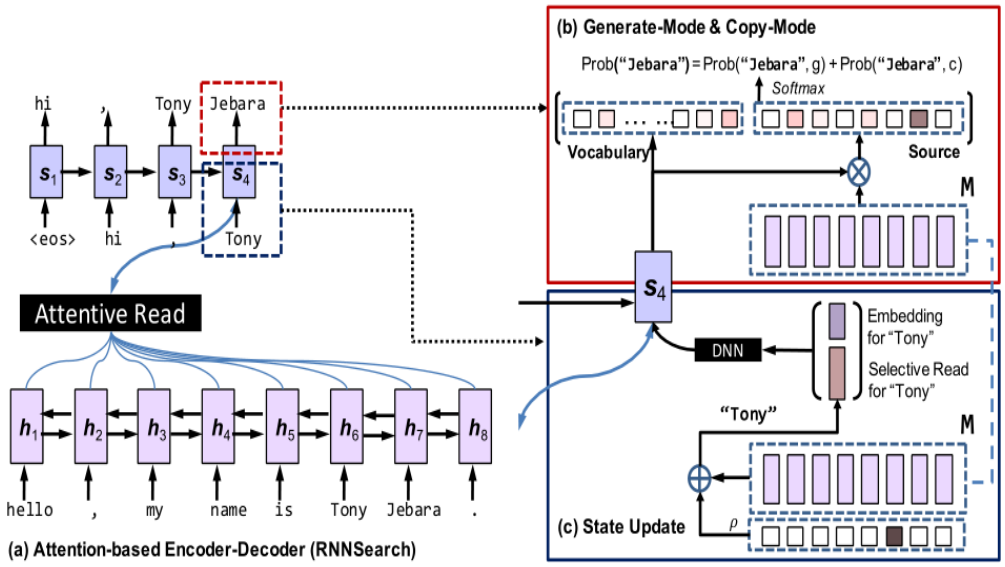


图 2: The overall diagram of COPYNET. For simplicity, we omit some links for prediction (see Sections 3.2 for more details).

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 ht corresponding to word x_t. This new representation of the source, $h1, ..., h_{T_S}$, is considered to be a short-term memory (referred to as M in the remainder of the paper), which will later

be accessed in multiple ways in generating the target sequence (decoding).

Decoder: An RNN that reads M and predicts the target sequence. It is similar with the canoni- cal 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 COPY- NET uses not only its word-embedding but also its corresponding location-specific hid- den state in M (if any) (see Section 3.3 for more details);
- Reading M: in addition to the attentive read to M, COPYNET also has "selective read" to 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).

4.2 Prediction with Copying and Generation

We assume a vocabulary V = v1, ..., vN, and use UNK for any out-of-vocabulary (OOV) word. In addition, we have another set of words χ , for all the unique words in source sequence $X = x1, ..., xTS$. Since χ may contain words not in V, copying sub-sequence in X enables COPY- NET to output some OOV words. In a nutshell, the instance-specific vocabulary for source X is $V \cup UNK \cup \chi$.

Given the decoder RNN state st at time t to- gether with M, the probability of generating any target word y_t, is given by the "mixture" of probabilities as follows

$$p(y_t|s_t, y_{t-1}, c_t, M) = p(y_t, g|s_t, y_{t-1}, c_t, M) + p(y_t, c|s_t, y_{t-1}, c_t, M)$$

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

$$p(y_t, g|.) = \begin{cases} \frac{1}{Z} e^{\psi_g(y_t)} & y_t \in V \\ 0 & y_t \in \chi \cap \bar{V} \\ \frac{1}{Z} e^{\psi_g(UNK)} & y_t \notin V \cup \chi \end{cases}$$

$$p(y_t, c|.) = \begin{cases} \frac{1}{Z} \sum j : x_j = y_t e^{\psi_c(x_j)} & y_t \in V \\ 0 & otherwise \end{cases}$$

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, $Z = \sum v \in V \cup UNK e^{\psi_g(v)} + \sum_{x \in X} e^{\psi_c(x)}$. 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: al., 2014) is used, i.e.

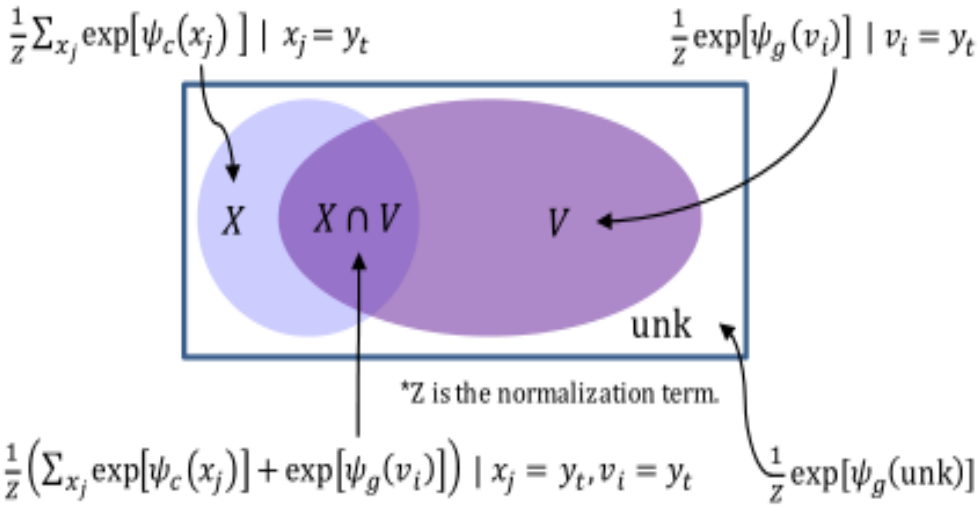


图 3: The illustration of the decoding probability $p(y_t|\cdot)$ as a 4-class classifier.

Generate-Mode: The same scoring function as in the generic RNN encoder-decoder (Bahdanau et al., 2014) is used, i.e.

$\psi_g(y_t = v_i) = {v_i}^T W_o s_t, v_i \in V \cup UNK$

,where $W_o \in R^{(N+1) \times d_s}$ and v_i is the one-hot in dicator vector for v_i.

Copy-Mode: The score for "copying" the word x_j is calculated as $\psi_c(y_t = x_j) = \sigma({h_j}^T W_c) s_t, x_j \in \chi$

where $W_c \in R^{d_h} \times d_s$, 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 $h_1, ..., h_{T_S}$ to "represent" each of the word in the source se- quence $x_1, ..., x_{T_S}$ since the bi-directional RNN encodes not only the content, but also the location information into the hidden states in M. The loca- tion informaton is important for copying (see Sec- tion 3.4 for related discussion). Note that we sum the probabilities of all x_j equal to y_t in Eq. (6) con- sidering 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.

4.3 State Update

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

$$\zeta(y_{t-1}) = \sum_{\tau=1}^{T_s} \rho_{t\tau} h_\tau$$

$$\rho_{t\tau} = \begin{cases} \frac{1}{K} p(x_\tau, c | s_{t-1}, M) & x_\tau = y_{t-1} \\ 0 & otherwise \end{cases}$$

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

In a sense $\zeta(y_{t-1})$ performs a type of read to M similar to the attentive read (resulting 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 cor- responding 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 $\zeta(y_{t-1}) = 0$.

4.4 Hybrid Addressing of M

We hypothesize that COPYNET uses a hybrid strategy for fetching the content in M, which com- bines both content-based and location-based addressing. Both addressing strategies are coordi- nated by the decoder RNN in managing the atten- tive 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 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 M, even across a long distance. On the other hand, once COPYNET enters the copy-mode, the selec- tive read of M is often guided by the location in- formation. As the result, the selective read often takes rigid move and tends to cover consecutive words, including UNKs. Unlike the explicit de- sign for hybrid addressing in Neural Turing Ma- chine (Graves et al., 2014; Kurach et al., 2015), COPYNET is more subtle: it provides the archi- tecture 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 $\{h_i\}$, the information flow $\zeta(y_{t-1})update{\rightarrow}s_tpredict{\rightarrow}y_tsel.read{\rightarrow}\zeta(y_t)$ provides a simple way of "moving one step to the right" on X. More specifically, assuming the selective read ζy_{t-1} concentrates on the l^th word in X, the state-update operation $\zeta(y_{t-1})update{\rightarrow}s_t$ acts as "location $\leftarrow$ location+1" , making st favor the $(l+1)^th$ word in X in the prediction $s_tpredict{\rightarrow}y_t$ in copy-mode. This again leads to the selective read $\hat{h}_tsel.read{\rightarrow}\zeta(y_t)$ for the state up- date 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 infor- mation 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 empiri- cally 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.

5 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:

$L = -\frac{1}{N}\sum_{k=1}^{N}\sum_{t=1}^{T} log[p({y_t}^k|{y_{<t}}^k, X_k)]$

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 en- courage 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.

6 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.

6.1 Synthetic Dataset

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

$abxcdyef \rightarrow ghxm$,

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 num- ber of instances by replacing the variables with randomly generated subsequences (1-15 sym- bols) from the same vocabulary. We create five types of rules, including "x → ". 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.

Experimental Setting: We select 200 artificial rules from the dataset, and for each rule 200 in- stances are generated, which will be split into training (50the 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 test- ing. The prediction is considered correct only when the generated sequence is ex- actly the same as the given one.

It is clear from Table 1 that COPYNET signifi- cantly outperforms the other two on all rule-types except "x → ", indicating that COPYNET can ef- fectively learn the patterns with variables and ac- curately replicate rather long subsequence of sym- bols at the proper places.This is hard to Enc-Dec due to the difficulty of representing a long se- quence with very high fidelity. This difficulty can be alleviated with the attention mechanism. How- ever 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

Rule-type	Examples (e.g. **x** = i h k, **y** = j c)
x → ∅	a b c d **x** e f → c d g
x → **x**	a b c d **x** e f → c d **x** g
x → **x** **x**	a b c d **x** e f → **x** d **x** g
x **y** → **x**	a b **y** d **x** e f → **x** d i g
x **y** → **x** **y**	a b **y** d **x** e f → **x** d **y** g

图 4: data

can achieve a rather precise coordination of the two modes.

6.2 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.

Rule-type	x → ∅	x → x	x → xx	xy → x	xy → 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.

图 5: result

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 and the subset of Part III scored from 3 to 5 as testing set.

Experimental Setting: We try COPYNET that is based on character (+C) and word (+W). For the word-based variant the word-segmentation is ob- tained 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 em- bedding 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.

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-

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.

图 6: TS data

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 en- tity names in the summary data and the mistakes in word segmentation. COPYNET, with its ability to handle the OOV words with the copying mech- anism, performs however slightly better with the word-based variant.

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 ad- dressing; 3) COPYNET handles OOV words really well: it can generate acceptable summary for doc- ument with many OOVs, and even the summary itself often contains many OOV words. In con- trast, the canonical RNN-based approaches often fail in cases like that. It is quite intriguing

图 7: 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.

that COPYNET can often find important parts of the document, a behavior with the characteristics of extractive summa- rization, while it often generate words to "con- nect" those words, showing its aspect of abstractive summarization

6.3 Single-turn Dialogue

图 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 higher than the generate-mode. Green cirles (meaning correct) and red cross (meaning incorrect) are given based on human judgment on whether the response is appropriate.

7 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 ad- dition 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 clas- sification tasks, where shortcuts are built between layers for the direct carrying of information.

8 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.

9 Personal understanding

9.1 Paper structure

9.2 The problem to solve

- the rote memorization; copying mechanism
- out-of-vocabulary (OOV)

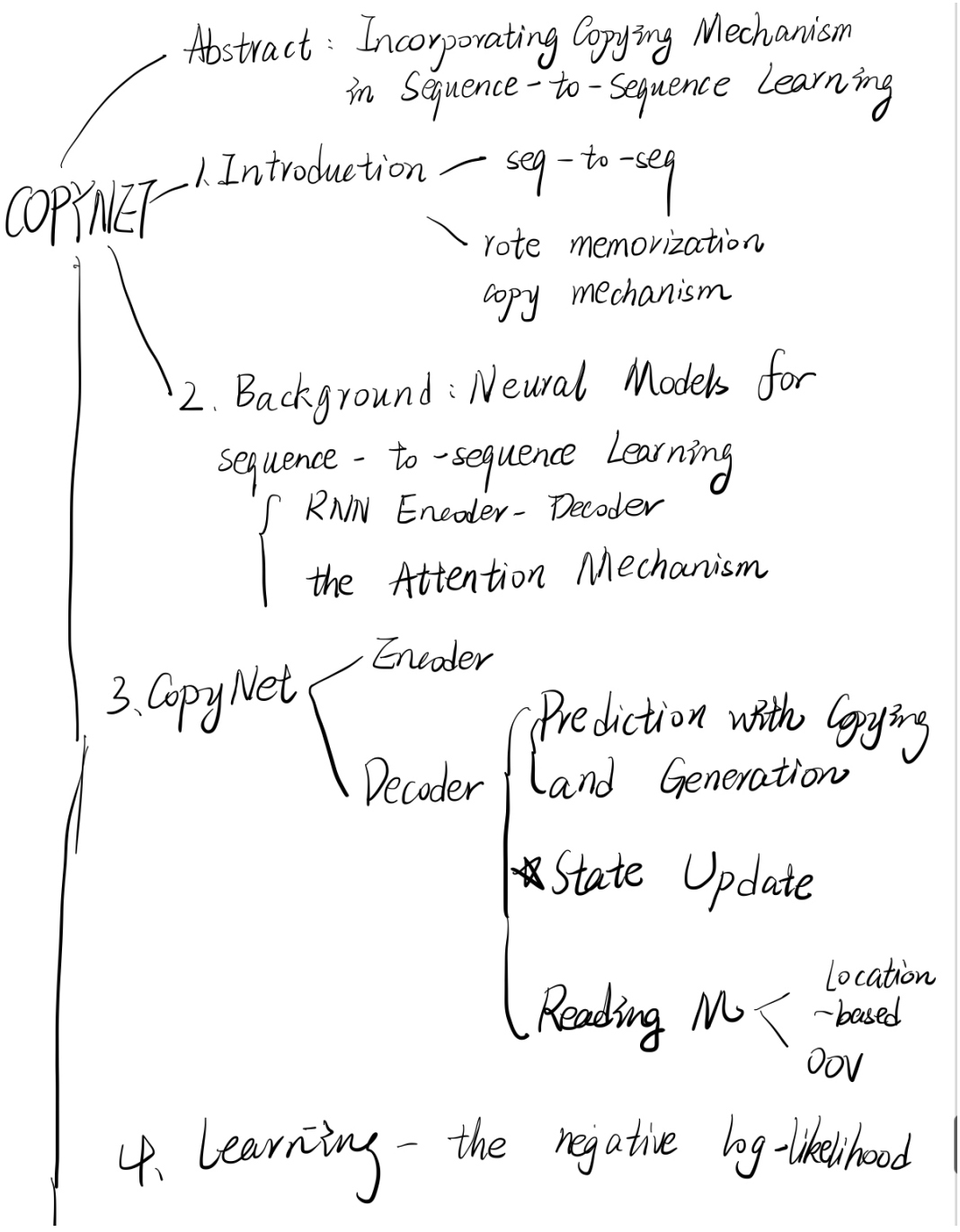


图 9: Paper: COPYNET.

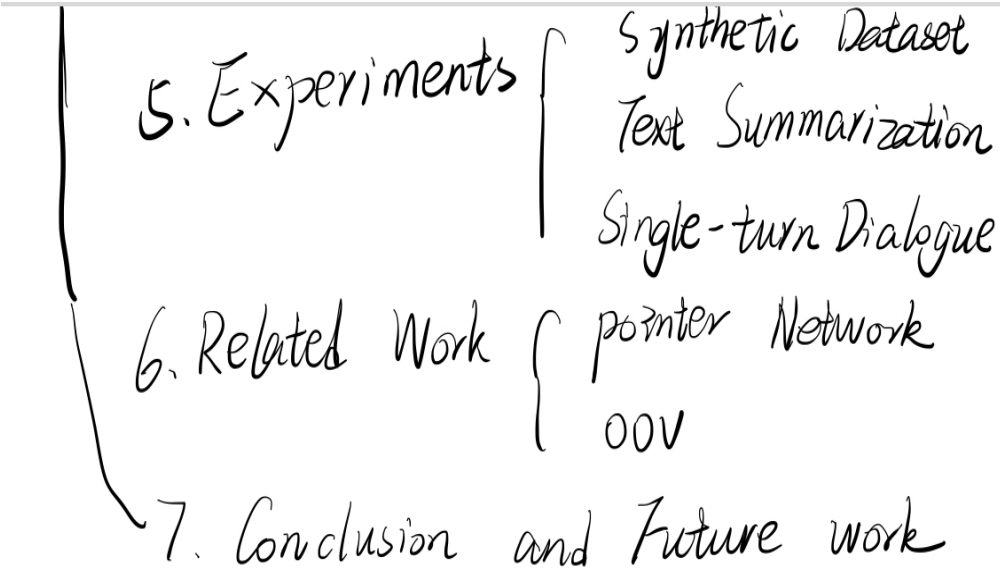


图 10: Paper: COPYNET..

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"?

图 11: the human language communication.For example, in the following two dialogue turns we observe differ- ent patterns in which some subsequences (colored blue) in the response (R) are copied from the input utterance (I)

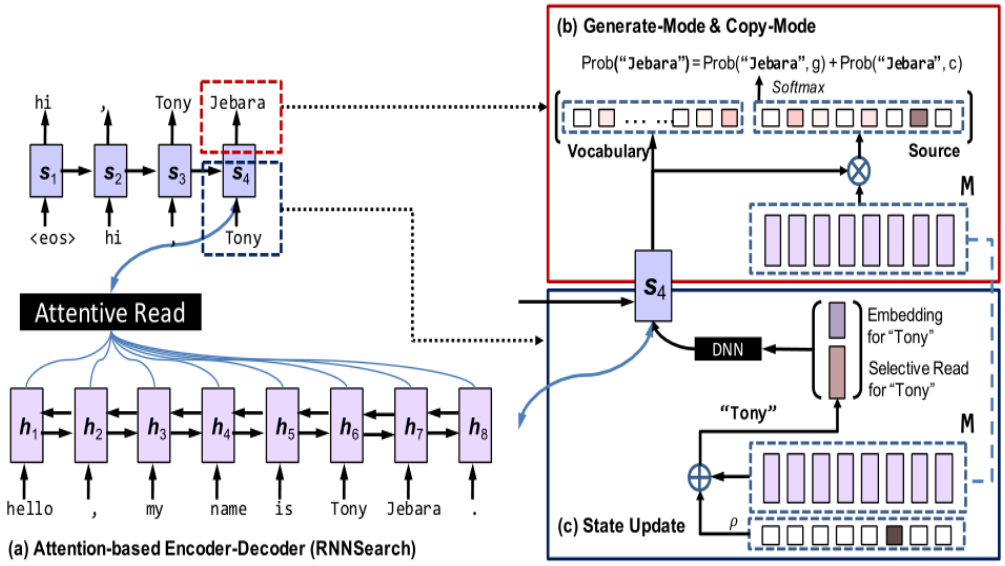


图 12: The overall diagram of COPYNET.

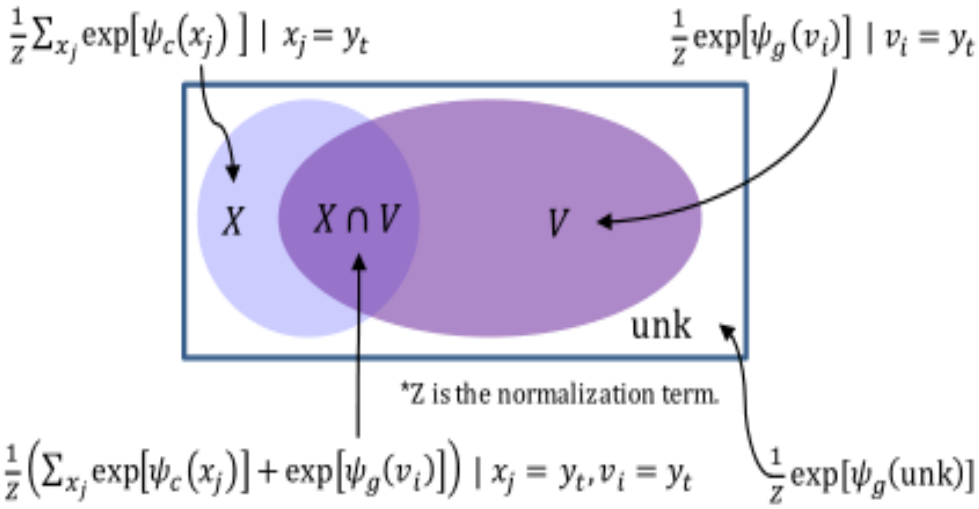
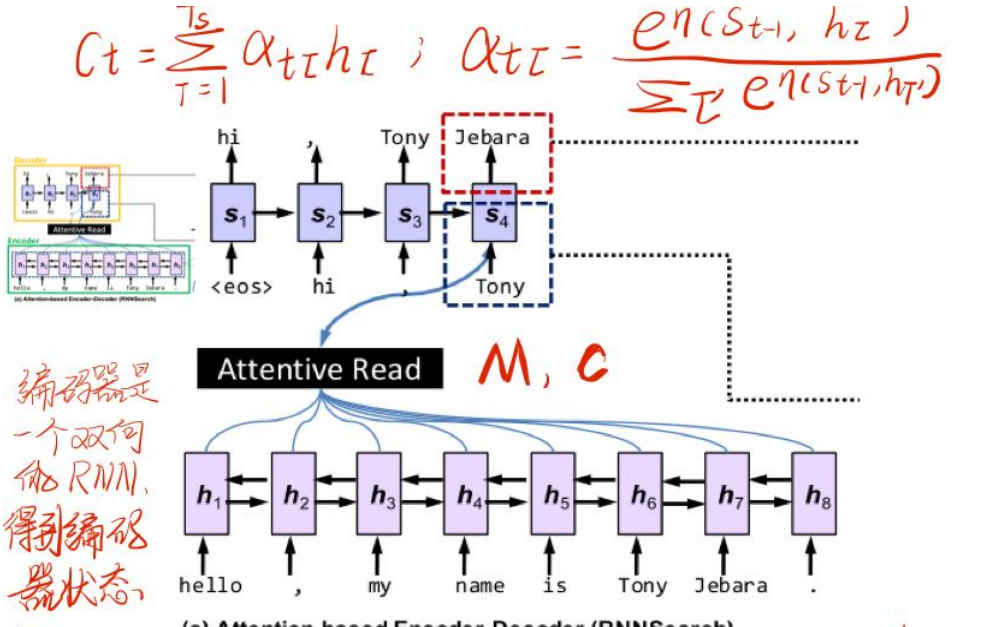


图 13: The illustration of the decoding probability $p(y_t|\cdot)$ as a 4-class classifier.



$$c_t = \sum_{T=1}^{T_S} \alpha_{tT} h_T \; ; \; \alpha_{tT} = \frac{e^{\eta(s_{t-1}, h_T)}}{\sum_{T'} e^{\eta(s_{t-1}, h_{T'})}}$$

编码器是一个双向的 RNN，得到编码器状态，

h_t（h_t 包含了输入句子的语义信息、长期依赖关系，序列位置信息）

$$h_t = f(x_t, h_{t-1}) \; ; \; x_t$$：输入序列的词嵌入

$$c = \phi(\{h_1, \cdots h_{T_S}\})$$；ϕ 是一种概括函数（summarize），将所有的编码器状态整合，比如使用 attention mechanism），整合得到上下文向量 c.（context vector）

所有编码器状态，构成记忆 M.

$s_t = ff(y_{t-1}, s_{t-1})$（不考虑 attention）

$s_t = ff(y_{t-1}, s_{t-1}, c_t)$（加入 attention）

图 14: Attention-based Encoder-Decoder (RNNSearch)

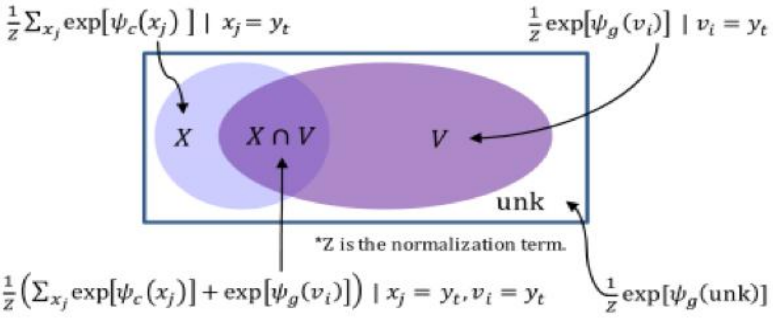
传统 decoder： $S_t = f(y_{t-1}, S_{t-1}, C)$

$P(y_t | y_{<t}, X) = g(y_{t-1}, S_t, C)$

y_{t-1}：t-1 时刻 decoder 的输出

S_{t-1}：t-1 时刻 decoder 的状态。

C： context vector



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

得分称为 score

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

$\psi_g(y_t = v_i) = v_i^T W_o S_t$, $v_i \in V \cup \text{UNK}$

归一化因子

one-hot 向量

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

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

$\psi_c(y_t = v_j) = \sigma(h_j^T W_c) S_t$

h_j^T 是 M 矩阵中的第 j 列（也是 Encoder RNN 中第 j 个词的输出）

σ 是激活函数，本文中 tanh。

图 15: Prediction with Copying and Generation(Generate-Mode & Copy-Mode)

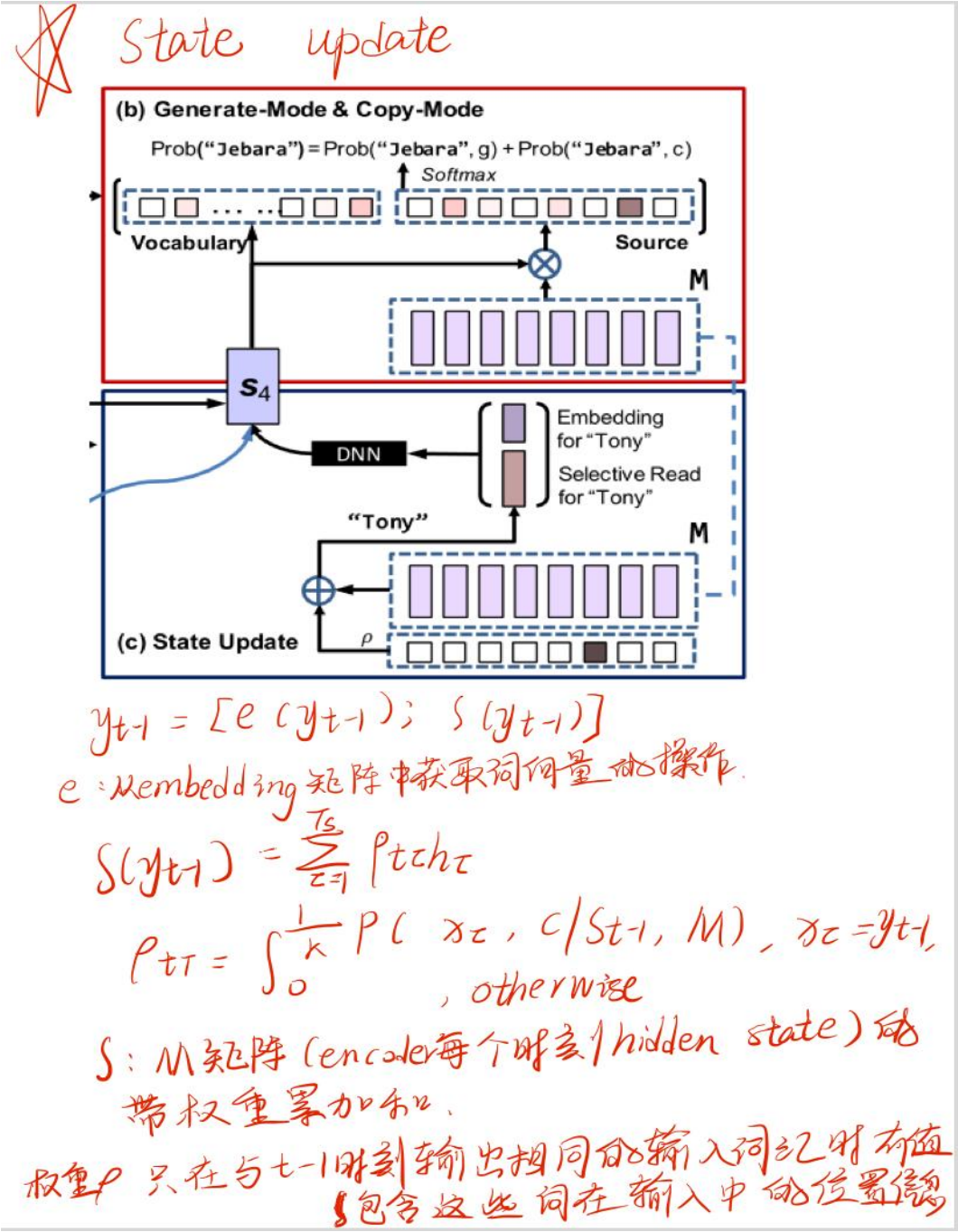


图 16: State update

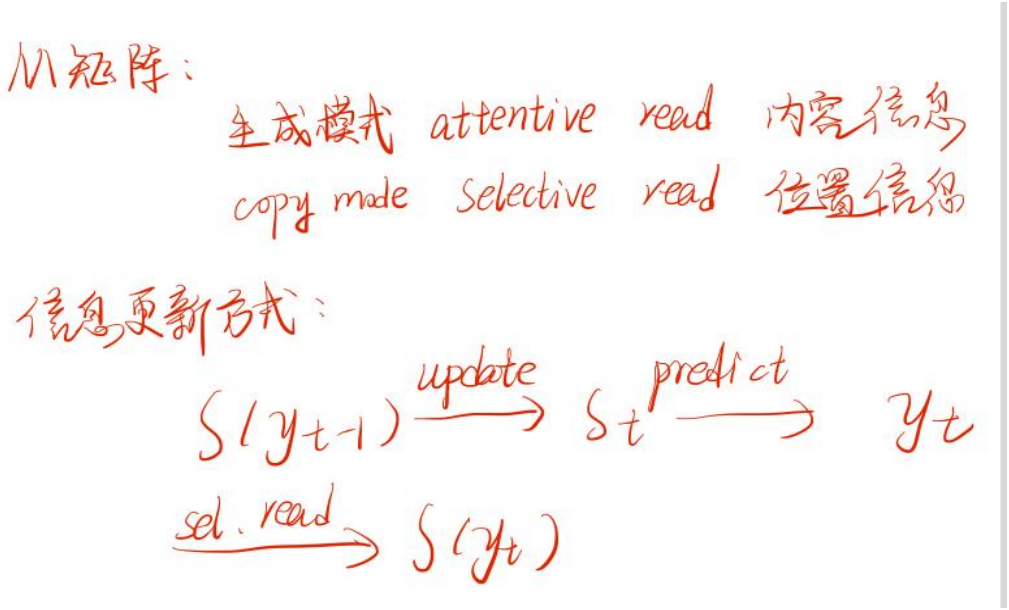


图 17: Hybrid Addressing of M

9.3 The innovation work

9.4 The code analysis

https://github.com/lspvic/CopyNet/blob/master/copynet.py

https://github.com/adamklec/copynet/blob/master/model/copynet_decoder.py

https://github.com/mjc92/CopyNet/blob/master/models/copynet.py

https://github.com/YinpeiDai/Seq2Seq-Models/blob/master/model.py

https://github.com/MultiPath/CopyNet/tree/master/emolga/models