Get To The Point: Summarization with Pointer-Generator Networks

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1 Abstract

- Neural sequence-to-sequence models have provided a viable new approach for ab- stractive text summarization (meaning they are not restricted to simply selecting and rearranging passages from the original text). However, these models have two shortcomings: they are liable to reproduce factual details inaccurately, and they tend to repeat themselves.
- In this work we propose a novel architecture that augments the standard sequence-to-sequence attentional model in two orthogonal ways.
- First,we use a hybrid pointer-generator network that can copy words from the source text via pointing, which aids accurate reproduction of information, while retaining the ability to produce novel words through the generator.
- Second, we use coverage to keep track of what has been summarized, which discourages repetition.
- We apply our model to the CNN Daily Mail summarization task, outperforming the current abstractive state-of-the-art by at least 2 ROUGE points.

2 Introduction

- Summarization is the task of condensing a piece of text to a shorter version that contains the main in- formation from the original. There are two broad approaches to summarization: extractive and ab- stractive. Extractive methods assemble summaries exclusively from passages (usually whole sentences) taken directly from the source text, while abstractive methods may generate novel words and phrases not featured in the source text as a human-written abstract usually does.
- The extractive approach is easier, because copying large chunks of text from the source document ensures baseline levels of grammaticality and accuracy.On the other hand, sophisticated abilities that are crucial to high-quality summarization, such as paraphrasing, generalization, or the incorporation of real-world knowledge, are possible only in an abstractive framework (see Figure 5).
- Due to the difficulty of abstractive summarization, the great majority of past work has been ex- tractive (Kupiec et al., 1995; Paice, 1990; Saggion and Poibeau, 2013). However, the recent success of sequence-to-sequence models (Sutskever et al., 2014), in which recurrent neural networks (RNNs) both read and freely generate text, has made abstractive summarization viable (Chopra et al., 2016; Nallapati et al., 2016; Rush et al.,2015; Zeng et al., 2016). Though these systems are promising,they exhibit undesirable behavior such as inaccurately reproducing factual details, an inability to deal with out-of-vocabulary (OOV) words, and repeating themselves (see Figure 1)
- In this paper we present an architecture that addresses these three issues in the context of multi-sentence summaries. While most recent ab- stractive work has focused on headline genera- tion tasks (reducing one or two sentences to a single headline), we believe that longer-text sum- marization is both more challenging (requiring higher levels of abstraction while avoiding repe- tition) and ultimately more useful. Therefore we apply our model to the recently-introduced CNN/ Daily Mail dataset (Hermann et al., 2015; Nallap- ati et al., 2016), which

Original Text (truncated): lagos, nigeria (cnn) a day after winning nigeria's presidency, ***muhammadu buhari*** told cnn's christiane amanpour that **he plans to aggressively fight corruption that has long plagued nigeria** and go after the root of the nation's unrest. *buhari* said he'll "rapidly give attention" to curbing violence in the northeast part of nigeria, where the terrorist group boko haram operates. by cooperating with neighboring nations chad, cameroon and niger, **he said his administration is confident it will be able to thwart criminals** and others contributing to nigeria's instability. for the first time in nigeria's history, the opposition defeated the ruling party in democratic elections. *buhari* defeated incumbent goodluck jonathan by about 2 million votes, according to nigeria's independent national electoral commission. **the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.**

Baseline Seq2Seq + Attention: UNK UNK says his administration is confident it will be able to **destabilize nigeria's economy**. **UNK** says his administration is confident it will be able to thwart criminals and other **nigerians**. **he says the country has long nigeria and nigeria's economy.**

Pointer-Gen: *muhammadu buhari* says he plans to aggressively fight corruption **in the northeast part of nigeria**. he says he'll "rapidly give attention" to curbing violence **in the northeast part of nigeria**. he says his administration is confident it will be able to thwart criminals.

Pointer-Gen + Coverage: *muhammadu buhari* says he plans to aggressively fight corruption that has long plagued nigeria. he says his administration is confident it will be able to thwart criminals. the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.

图 1: Comparison of output of 3 abstractive summarization models on a news article. The baseline model makes factual errors, a nonsensical sentence and struggles with OOV words muhammadu buhari. The pointer-generator model is accurate but repeats itself. Coverage eliminates repetition. The final summary is composed from several fragments.

contains news articles (39 sentences on average) paired with multi-sentence summaries, and show that we outperform the state- of-the-art abstractive system by at least 2 ROUGE points.

- Our hybrid pointer-generator network facilitates copying words from the source text via point- ing (Vinyals et al., 2015), which improves accuracy and handling of OOV words, while retaining the ability to generate new words. The network,which can be viewed as a balance between extrac- tive and abstractive approaches, is similar to Gu et al.s (2016) CopyNet and Miao and Blunsoms (2016) Forced-Attention Sentence Compression,that were applied to short-text summarization. We propose a novel variant of the coverage vector (Tu et al., 2016) from Neural Machine Translation, which we use to track and control coverage of the source document. We show that coverage is re- markably effective for eliminating repetition.

3 Our Models

In this section we describe (1) our baseline sequence-to-sequence model, (2) our pointer- generator model, and (3) our coverage mechanism that can be added to either of the first two models. The code for our models is available online.1

3.1 Sequence-to-sequence attentional model

Our baseline model is similar to that of Nallapati et al. (2016), and is depicted in Figure 2. The to- kens of the article wi are fed one-by-one into the encoder (a single-layer bidirectional LSTM), pro- ducing a sequence of encoder hidden states h_i. On each step t, the decoder (a single-layer unidirec- tional LSTM) receives the word embedding of the previous word (while training, this is the previous word of the reference summary; at test time it is the previous word emitted by the decoder), and has decoder state s_t. The attention distribution at is calculated as in Bahdanau et al. (2015):

$e_i{}^t = v_T tanh(W_h h_i + W_s s_t + b_a ttn)$

$a_t = softmax(e^t)$

where v, W_h, W_s and b_attn are learnable parame- ters. The attention distribution can be viewed as a probability distribution over the source words, that tells the decoder where to look to produce the next word. Next, the attention distribution is used to produce a weighted sum of the encoder hidden states, known as the context vector ${h_t}^*$:

$${h_t}^* = \sum_i {a_i}^t h_i$$

The context vector, which can be seen as a fixed-size representation of what has been read from the source for this step, is concatenated with the decoder state s_t and fed through two linear layers to produce the vocabulary distribution P_vocab:

$$P_vocab = softmax(V'(V[s_t, {h_t}^*] + b) + b')$$

where V, V', b and b' are learnable parameters. P_vocab is a probability distribution over all words in the vocabulary, and provides us with our final distribution from which to predict words w:

$$P(w) = P_vocab(w)$$

During training, the loss for timestep t is the negative log likelihood of the target word ${w_t}^*$ for that timestep:

$$loss_t = -logP({w_t}^*)$$

and the overall loss for the whole sequence is:

$$loss = \frac{1}{T}\sum_{t=0}^{T} loss_t$$

3.2 Pointer-generator network

Our pointer-generator network is a hybrid between our baseline and a pointer network (Vinyals et al., 2015), as it allows both copying words via pointing, and generating words from a fixed vocabulary. In the pointer-generator model (depicted in Figure3) the attention distribution a_t and context vector ${h_t}^*$ are calculated as in section 2.1. In addition, the generation probability $p_gen \in [0, 1]$ for timestep t is calculated from the context vector ${h_t}^*$, the decoder state s_t and the decoder input x_t:

$$p_gen = \sigma({w_h*}^T {h_t}^* + {w_s}^T s_t + {w_x}^T x_t + b_ptr)$$

where vectors w_h*, w_s, w_x and scalar b_ptr are learn- able parameters and σ is the sigmoid function. Next, p_gen is used as a soft switch to choose be- tween generating a word from the vocabulary by sampling from P_vocab, or copying a word from the input sequence by sampling from the attention dis- tribution a_t. For each document let the extended vocabulary denote the union of the vocabulary, and all words appearing in the source document. We obtain the following probability distribution over the extended vocabulary:

$P(w) = p_genP_vocab(w) + (1 - p_gen) \sum_{i:w_i=w} {a_i}^t$

Note that if w is an out-of-vocabulary (OOV) word, then $P_vocab(w)$ is zero; similarly if w does not appear in the source document, then $\sum_{i:w_i=w} {a_i}^t$ is zero. The ability to produce OOV words is one of the primary advantages of pointer-generator models; by contrast models such as our baseline are restricted to their pre-set vocabulary. The loss function is as described in equations (6) and (7), but with respect to our modified prob- ability distribution P(w) given in equation (9).

3.3 Coverage mechanism

Repetition is a common problem for sequence- to-sequence models (Tu et al., 2016; Mi et al., 2016; Sankaran et al., 2016; Suzuki and Nagata, 2016), and is especially pronounced when gener- ating multi-sentence text (see Figure 1). We adapt the coverage model of Tu et al. (2016) to solve the problem. In our coverage model, we maintain a coverage vector c_t, which is the sum of attention distributions over all previous decoder timesteps:

$c_t = \sum_{t'=0}^{t-1} a_t'$

Intuitively, c_t is a (unnormalized) distribution over the source document words that represents the degree of coverage that those words have received from the attention mechanism so far. Note that c^0 is a zero vector, because on the first timestep, none of the source document has been covered.

The coverage vector is used as extra input to the attention mechanism, changing equation (1) to:

$e_{it} = v^T tanh(W_h h_i + W_s s_t + w_c {c_i}^t + b_a ttn)$

where w_c is a learnable parameter vector of same length as v. This ensures that the attention mecha- nism’ s current decision (choosing where to attend next) is informed by a reminder of its previous decisions (summarized in c_t). This should make it easier for the attention mechanism to avoid re- peatedly attending to the same locations, and thus avoid generating repetitive text.

We find it necessary (see section 5) to addition- ally define a coverage loss to penalize repeatedly attending to the same locations:

$covloss_t = \sum_t min({a_i}^t, {a_i}^t)$

Note that the coverage loss is bounded; in particu- lar $covloss_t \ \sum_i {a_i}^t = 1$. Equation (12) differs from the coverage loss used in Machine Translation. In MT, we assume that there should be a roughly one- to-one translation ratio; accordingly the final cov- erage vector is penalized if it is more or less than 1. Our loss function is more flexible: because sum- marization should not require uniform coverage, we only penalize the overlap between each atten- tion distribution and the coverage so far –prevent- ing repeated attention. Finally, the coverage loss, reweighted by some hyperparameter λ, is added to the primary loss function to yield a new composite loss function:

$loss_t = -logP({w_t}^*) + \lambda \sum_i min({a_i}^t, {c_i}^t)$

4 Related Work

Neural abstractive summarization. Rush et al. (2015) were the first to apply modern neural net- works to abstractive text summarization, achieving state-of-the-art performance on DUC-2004 and Gigaword, two sentence-level summarization datasets. Their approach, which is centered on the attention mechanism, has been augmented with re- current decoders (Chopra et al., 2016), Abstract Meaning Representations (Takase et al., 2016), hi- erarchical networks (Nallapati et al., 2016), vari- ational autoencoders (Miao and Blunsom, 2016), and direct optimization of the performance metric (Ranzato et al., 2016), further improving perfor- mance on those datasets.

However, large-scale datasets for summariza- tion of longer text are rare. Nallapati et al. (2016) adapted the DeepMind question-answering dataset (Hermann et al., 2015) for summarization, result- ing in the CNN/Daily Mail dataset, and provided the first abstractive baselines. The same authors then published a neural extractive approach (Nal- lapati et al., 2017), which uses hierarchical RNNs to select sentences, and found that it significantly outperformed their abstractive result with respect to the ROUGE metric. To our knowledge, these are the only two published results on the full data-set.

Prior to modern neural methods, abstractive summarization received less attention than extrac- tive summarization, but Jing (2000) explored cutting unimportant parts of sentences to create sum- maries, and Cheung and Penn (2014) explore sen- tence fusion using dependency trees.

Pointer-generator networks. The pointer net- work (Vinyals et al., 2015) is a sequence-to- sequence model that uses the soft attention distribution of Bahdanau et al. (2015) to produce an output sequence consisting of elements from

the input sequence. The pointer network has been used to create hybrid approaches for NMT (Gul- cehre et al., 2016), language modeling (Merity et al., 2016), and summarization (Gu et al., 2016; Gulcehre et al., 2016; Miao and Blunsom, 2016; Nallapati et al., 2016; Zeng et al., 2016).

Our approach is close to the Forced-Attention Sentence Compression model of Miao and Blun- som (2016) and the CopyNet model of Gu et al. (2016), with some small differences: (i) We cal- culate an explicit switch probability pgen, whereas Gu et al. induce competition through a shared soft- max function. (ii) We recycle the attention distri- bution to serve as the copy distribution, but Gu et al. use two separate distributions. (iii) When a word appears multiple times in the source text, we sum probability mass from all corresponding parts of the attention distribution, whereas Miao and Blunsom do not. Our reasoning is that (i) calcu- lating an explicit pgen usefully enables us to raise or lower the probability of all generated words or all copy words at once, rather than individually, (ii) the two distributions serve such similar pur- poses that we find our simpler approach suffices, and (iii) we observe that the pointer mechanism often copies a word while attending to multiple oc- currences of it in the source text.

Our approach is considerably different from that of Gulcehre et al. (2016) and Nallapati et al. (2016). Those works train their pointer components to activate only for out-of-vocabulary words or named entities (whereas we allow our model to freely learn when to use the pointer), and they do not mix the probabilities from the copy distribu- tion and the vocabulary distribution. We believe the mixture approach described here is better for abstractive summarization –in section 6 we show that the copy mechanism is vital for accurately reproducing rare but in-vocabulary words, and in section 7.2 we observe that the mixture model en- ables the language model and copy mechanism to work together to perform abstractive copying.

Coverage. Originating from Statistical Ma- chine Translation (Koehn, 2009), coverage was adapted for NMT by Tu et al. (2016) and Mi et al. (2016), who both use a GRU to update the cov- erage vector each step. We find that a simpler approach –summing the attention distributions to obtain the coverage vector –suffices. In this re- spect our approach is similar to Xu et al. (2015), who apply a coverage-like method to image cap-tioning, and Chen et al. (2016), who also incorpo- rate a coverage mechanism (which they call 'dis- traction') as described in equation (11) into neural summarization of longer text. Temporal attention is a related technique that has been applied to NMT (Sankaran et al., 2016) and summarization (Nallapati et al., 2016). In this approach, each attention distribution is di- vided by the sum of the previous, which effec- tively dampens repeated attention. We tried this method but found it too destructive, distorting the signal from the attention mechanism and reducing performance. We hypothesize that an early inter- vention method such as coverage is preferable to a post hoc method such as temporal attention – it is better to inform the attention mechanism to help it make better decisions, than to override its de- cisions altogether. This theory is supported by the large boost that coverage gives our ROUGE scores (see Table 1), compared to the smaller boost given by temporal attention for the same task (Nallapati et al., 2016).

5 Dataset

We use the CNN/Daily Mail dataset (Hermann et al., 2015; Nallapati et al., 2016), which con- tains online news articles (781 tokens on average) paired with multi-sentence summaries (3.75 sen- tences or 56 tokens on average). We used scripts supplied by Nallapati et al. (2016) to obtain the same version of the the data, which has 287,226 training pairs, 13,368 validation pairs and 11,490 test pairs. Both the dataset s published results (Nallapati et al., 2016, 2017) use the anonymized version of the data, which has been pre-processed to replace each named entity, e.g., The United Nations, with its own unique identifier for the exam- ple pair, e.g., @entity5. By contrast, we operate directly on the original text (or non-anonymized version of the data),2 which we believe is the fa- vorable problem to solve because it requires no pre-processing.

6 Experiments

7 Results

8 Discussion

8.0.1 Comparison with extractive systems

It is clear from Table 1 that extractive systems tend to achieve higher ROUGE scores than abstractive, and that the extractive lead-3 baseline is extremely strong (even the best extractive system beats it by only a small margin). We offer two possible ex- planations for these observations.

Firstly, news articles tend to be structured with the most important information at the start; this partially explains the strength of the lead-3 base- line. Indeed, we found that using only the first 400 tokens (about 20 sentences) of the article yielded significantly higher ROUGE scores than using the first 800 tokens.

Secondly, the nature of the task and the ROUGE metric make extractive approaches and the lead- 3 baseline difficult to beat. The choice of con- tent for the reference summaries is quite subjective - sometimes the sentences form a self-contained summary; other times they simply showcase a few interesting details from the article. Given that the articles contain 39 sentences on average, there are many equally valid ways to choose 3 or 4 high- lights in this style. Abstraction introduces even more options (choice of phrasing), further decreasing the likelihood of matching the reference sum- mary. For example, smugglers profit from des- perate migrants is a valid alternative abstractive summary for the first example in Figure 5, but it scores 0 ROUGE with respect to the reference summary. This inflexibility of ROUGE is exac- erbated by only having one reference summary, which has been shown to lower ROUGE’ s relia- bility compared to multiple reference summaries (Lin, 2004a).

Due to the subjectivity of the task and thus the diversity of valid summaries, it seems that ROUGE rewards safe strategies such as select- ing the first-appearing content, or preserving orig- inal phrasing. While the reference summaries do sometimes deviate from these techniques, those deviations are unpredictable enough that the safer strategy obtains higher ROUGE scores on average. This may explain why extractive systems tend to obtain higher ROUGE scores than abstractive, and even extractive systems do not significantly ex- ceed the lead-3 baseline.

To explore this issue further, we evaluated our systems with the METEOR metric, which rewards not only exact word matches, but also matching stems, synonyms and paraphrases (from a pre- defined list). We observe that all our models re- ceive over 1 METEOR point boost by the inclu- sion of stem, synonym and paraphrase matching, indicating that they may be performing some ab- straction. However, we again observe that the lead-3 baseline is not surpassed by our models. It may be that news article style makes the lead- 3 baseline very strong with respect to any metric. We believe that investigating this issue further is an important direction for future work.

8.1 How abstractive is our model?

We have shown that our pointer mechanism makes our abstractive system more reliable, copying fac- tual details correctly more often. But does the ease of copying make our system any less abstractive?

Figure 6 shows that our final model’ s sum- maries contain a much lower rate of novel n-grams (i.e., those that don’ t appear in the article) than the reference summaries, indicating a lower degree of abstraction. Note that the baseline model produces novel n-grams more frequently –however, this statistic includes all the incorrectly copied words, UNK tokens and fabrications alongside the good instances of abstraction.

Figure 6: Although our best model is abstractive, it does not produce novel n-grams (i.e., n-grams that don't appear in the source text) as often as the reference summaries. The baseline model produces more novel n-grams, but many of these are erroneous (see section 7.2).

In particular, Figure 6 shows that our final model copies whole article sentences 35% of the time; by comparison the reference summaries do so only 1.3% of the time. This is a main area for improvement, as we would like our model to move beyond simple sentence extraction. However, we observe that the other 65% encompasses a range of abstractive techniques. Article sentences are trun- cated to form grammatically-correct shorter versions, and new sentences are composed by stitch- ing together fragments. Unnecessary interjections, clauses and parenthesized phrases are sometimes omitted from copied passages. Some of these abil- ities are demonstrated in Figure 1, and the supple- mentary material contains more examples.

Figure 7 shows two examples of more impres- sive abstraction –both with similar structure. The dataset contains many sports stories whose summaries follow the X beat Y hscorei on hdayi template, which may explain why our model is most confidently abstractive on these examples. In general however, our model does not routinely pro- duce summaries like those in Figure 7, and is not close to producing summaries like in Figure 5.

The value of the generation probability pgen also gives a measure of the abstractiveness of our model. During training, pgen starts with a value of about 0.30 then increases, converging to about 0.53 by the end of training. This indicates that the model first learns to mostly copy, then learns to generate about half the time. However at test time, pgen is heavily skewed towards copying, with a mean value of 0.17. The disparity is likely due to the fact that during training, the model re- ceives word-by-word supervision in the form of the reference summary, but at test time it does not. Nonetheless, the generator module is use- ful even when the model is copying. We find that pgen is highest at times of uncertainty such as the beginning of sentences, the join between stitched-together fragments, and when producing periods that truncate a copied sentence. Our mix- ture model allows the network to copy while si- multaneously consulting the language model – en- abling operations like stitching and truncation to be performed with grammaticality. In any case, encouraging the pointer-generator model to write more abstractively, while retaining the accuracy advantages of the pointer module, is an exciting direction for future work.

9 Conclusion

In this work we presented a hybrid pointer- generator architecture with coverage, and showed that it reduces inaccuracies and repetition. We applied our model to a new and challenging long- text dataset, and significantly outperformed the abstractive state-of-the-art result. Our model ex- hibits many abstractive abilities, but attaining higher levels of abstraction remains an open re- search question.

10 Personal understanding

10.1 Paper structure

10.2 The problem to solve

Problem 1: The summaries sometimes reproduce factual details inaccurately (e.g. Germany beat Argentina 3-2). This is especially common for rare or out-of-vocabulary words such as 2-0.

Problem 2: The summaries sometimes repeat themselves (e.g. Germany beat Germany beat Germany beat⋯)

Explanation for Problem 1: The sequence-to-sequence-with-attention model makes it too difficult to copy a word w from the source text. The network must somehow recover the original word after the information has passed through several layers of computation (including mapping w to its word embedding). In particular, if w is a rare word that appeared infrequently during training and therefore has a poor word embedding (i.e. it is clustered with completely unrelated words), then w is, from the perspective of the network, indistinguishable from many other words, thus impossible to reproduce. Even if w has a good word embedding, the network may still have difficulty reproducing the word. For example, RNN summarization systems often replace a name with another name (e.g. Anna → Emily) or a city with another city (e.g. Delhi → Mumbai). This is because the word embeddings for e.g. female names or Indian cities tend to cluster together, which may cause confusion when attempting to reconstruct the original word. In short, this seems like an unnecessarily difficult way to perform a simple operation -copying -that is a fundamental operation in summarization.

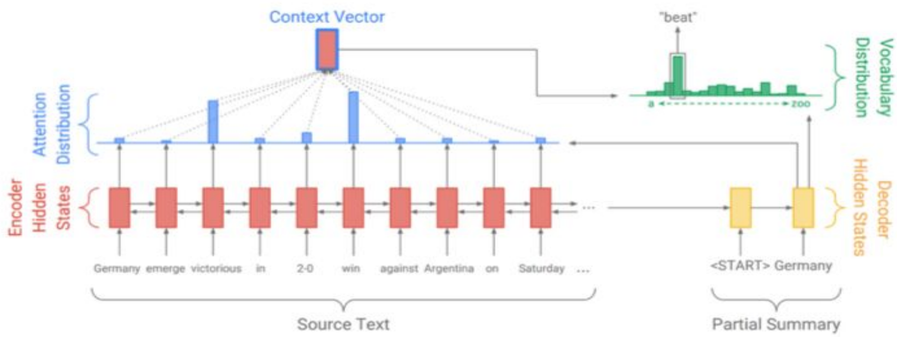
Explanation for Problem 2: Repetition may be caused by the decoder's over-reliance on the decoder input (i.e. previous summary word), rather than storing longer-term information in the decoder state. This can be seen by the fact that a single repeated word commonly triggers an endless repetitive cycle. For example, a single substitution error Germany beat Germany leads to the catastrophic Germany beat Germany beat Germany beat⋯, and not the less-wrong Germany beat Germany 2-0.

10.3 The innovation work

10.4 The code analysis

http://www.abigailsee.com/2017/04/16/taming-rnns-for-better-summarization.html

https://github.com/abisee/pointer-generator



$e_i^t = v^T \tanh(W_h h_i + W_s s_t + b_{attn})$

$a^t = softmax(e^t)$

context vector $h_t^* = \sum_i a_i^t h_i$

$P_{vocab} = softmax(V'(V[s_t, h_t^*] + b) + b')$

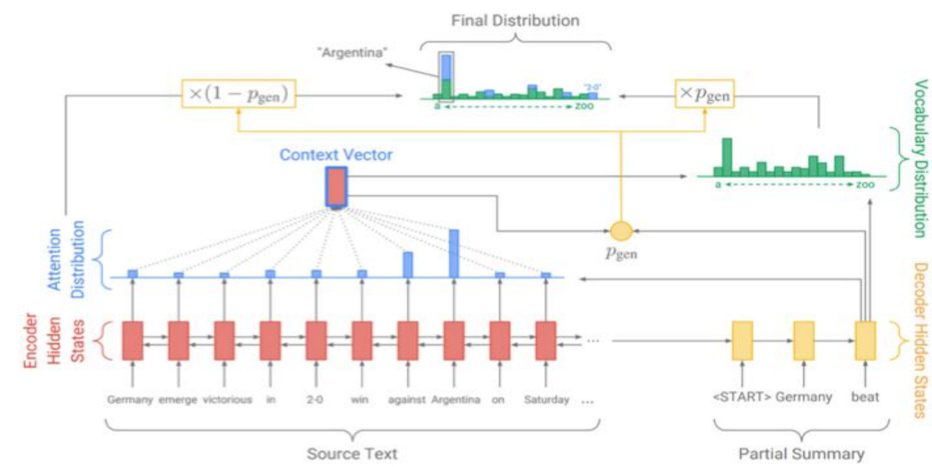
$P(w) = P_{vocab}(w)$

$loss_t = -\log P(w_t^*)$

context vector, a weighted sum of the encoder hidden states.

Finally, the context vector and the decoder hidden state are used to calculate the vocabulary distribution, which is a probability distribution over all the words in a large fixed vocabulary.

图 2: Baseline sequence-to-sequence model with attention. The model may attend to relevant words in the source text to generate novel words, e.g., to produce the novel word beat in the abstractive summary Germany beat Argentina 2-0 the model may attend to the words victorious and win in the source text.



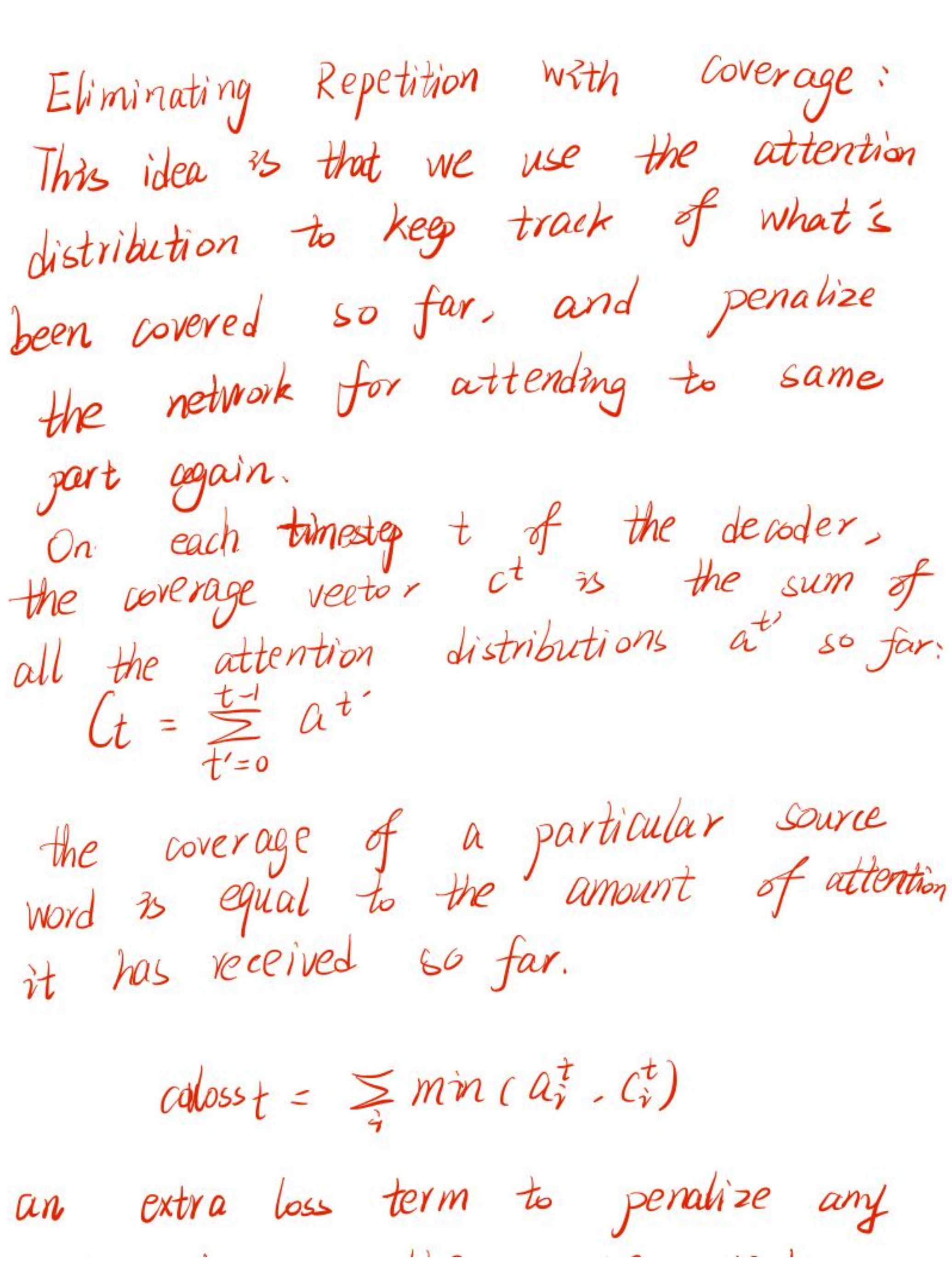
generation probability P_{gen} (This represents the probability of generating a word from the vocabulary, versus copying a word from the source). The P_{gen} is used to weight and com-bine the vocabulary distribution P_{vocab} and the attention distribution a (which we use for pointing to source words w_i) into the final distribution P_{final}:

$$P_{final}(w) = P_{gen} P_{vocab}(w) + (1-P_{gen}) \sum_{i:w_i=w} a_i$$

copy ↑ P_{gen} ↑

extraction (pointing) + abstraction (generating)

图 3: Pointer-generator model. For each decoder timestep a generation probability pgen [0,1] is calculated, which weights the probability of generating words from the vocabulary, versus copying words from the source text. The vocabulary distribution and the attention distribution are weighted and summed to obtain the final distribution, from which we make our prediction. Note that out-of-vocabulary article words such as 2-0 are included in the final distribution. Best viewed in color.



Eliminating Repetition with Coverage:

This idea is that we use the attention distribution to keep track of what's been covered so far, and penalize the network for attending to same part again.

On each timestep t of the decoder, the coverage vector c^t is the sum of all the attention distributions $a^{t'}$ so far:

$$C_t = \sum_{t'=0}^{t-1} a^{t'}$$

the coverage of a particular source word is equal to the amount of attention it has received so far.

$$covloss_t = \sum_i \min(a_i^t, c_i^t)$$

an extra loss term to penalize any

图 4: Coverage mechanism