Abstract
A good neural sequence-to-sequence summarization model should have a strong encoder that can distill and memorize the important information from long input texts so that the decoder can generate salient summaries based on the encoder’s memory. In this paper, we aim to improve the memorization capabilities of the encoder of a pointer-generator model by adding an additional ‘closed-book’ decoder without attention and pointer mechanisms. Such a decoder forces the encoder to be more selective in the information encoded in its memory state because the decoder can’t rely on the extra information provided by the attention and possibly copy modules, and hence improves the entire model. On the CNN/Daily Mail dataset, our 2-decoder model outperforms the baseline significantly in terms of ROUGE and METEOR metrics, for both cross-entropy and reinforced setups (and on human evaluation). Moreover, our model also achieves higher scores in a text-only DUC-2002 generalizability setup. We further present a memory ability test, two saliency metrics, as well as several sanity-check ablations (based on fixed-encoder, gradient-flow cut, and model capacity) to prove that the encoder of our 2-decoder model does in fact learn stronger memory representations than the baseline encoder.

1 Introduction
Text summarization is the task of condensing a long passage to a shorter version that only covers the most salient information from the original text. Extractive summarization models (Jing and McKeown, 2000; Knight and Marcu, 2002; Clarke and Lapata, 2008; Filippova et al., 2015) directly pick words, phrases, and sentences from the source text to form a summary, while an abstractive model generates (samples) words from a fixed-size vocabulary instead of copying from text directly.
ing steps’ hidden states or directly copy words from the source text, instead of relying solely on encoder’s final memory state for all information about the source passage. Recent studies (Rush et al., 2015; Nallapati et al., 2016; Chopra et al., 2016; Zeng et al., 2016; Gu et al., 2016b; Gulcehre et al., 2016; See et al., 2017) have demonstrated success with such seq-attention-seq and pointer models in summarization tasks.

While the advantage of attention and pointer models compared to vanilla sequence-to-sequence models in summarization is well supported by previous studies, these models still struggle to find the most salient information in the source text when generating summaries. This is because summarization, being different from other text-to-text generation tasks (where there is an almost one-to-one correspondence between input and output words, e.g., machine translation), requires the sequence-attention-sequence model to additionally decide where to attend and where to ignore, thus demanding a strong encoder that can determine the importance of different words, phrases, and sentences and flexibly encode salient information in its memory state. To this end, we propose a novel 2-decoder architecture by adding another ‘closed book’ decoder without attention layer to a popular pointer-generator baseline, such that the ‘closed book’ decoder and pointer decoder share an encoder. We argue that this additional ‘closed book’ decoder encourages the encoder to be better at memorizing salient information from the source passage, and hence strengthen the entire model. We provide both intuition and evidence for this argument in the following paragraphs.

Consider the following case. Two students are learning to do summarization from scratch. During training, both students can first scan through the passage once (encoder’s pass). Then student A is allowed to constantly look back (attention) at the passage when writing the summary (similar to a pointer-generator model), while student B has to occasionally write the summary without looking back (similar to our 2-decoder model with a non-attention/copy decoder). During the final test, both students can look at the passage while writing summaries. We argue that student B will write more salient summaries in the test because s/he learns to better distill and memorize important information in the first scan/pass by not looking back at the passage in training.

In terms of back-propagation intuition, during the training of a seq-attention-seq model (e.g., See et al. (2017)), most gradients are back-propagated from the decoder to the encoder’s hidden states through the attention layer. This encourages the encoder to correctly encode salient words at the corresponding encoding steps, but does make sure that this information is not forgotten (overwritten in the memory state) by the encoder afterward. However, for a plain LSTM (closed-book) decoder without attention, its generated gradient flow is back-propagated to the encoder through the memory state, which is the only connection between itself and the encoder, and this, therefore, encourages the encoder to encode only the salient, important information in its memory state. Hence, to achieve this desired effect, we jointly train the two decoders, which share one encoder, by optimizing the weighted sum of their losses. This approximates the training routine of student B because the sole encoder has to perform well for both decoders. During inference, we only employ the pointer decoder due to its copying advantage over the closed-book decoder, similar to the situation of student B being able to refer back to the passage during the test for best performance (but is still trained hard to do well in both situations). Fig. 1 shows an example of our 2-decoder summarizer generating a summary that covers the original passage with more saliency than the baseline model.

Empirically, we test our 2-decoder architecture on the CNN/Daily Mail dataset (Hermann et al., 2015; Nallapati et al., 2016), and our model surpasses the strong pointer-generator baseline significantly on both ROUGE (Lin, 2004) and METEOR (Denkowski and Lavie, 2014) metrics, as well as based on human evaluation. This holds true both for a cross-entropy baseline as well as a stronger, policy-gradient based reinforcement learning setup (Williams, 1992). Moreover, our 2-decoder models (both cross-entropy and reinforced) also achieve reasonable improvements on a test-only generalizability/transfer setup on the DUC-2002 dataset.

We further present a series of numeric and qualitative analysis to understand whether the improvements in these automatic metric scores are in fact due to the enhanced memory and saliency strengths of our encoder. First, by evaluating the representation power of the encoder’s final memory state after reading long passages (w.r.t.
the memory state after reading ground-truth summaries) via a cosine-similarity test, we prove that our 2-decoder model indeed has a stronger encoder with better memory ability. Next, we conduct three sets of ablation studies based on fixed-encoder, gradient-flow cut, and model capacity to show that the stronger encoder is the reason behind the significant improvements in ROUGE and METEOR scores. Finally, we show that summaries generated by our 2-decoder model are qualitatively better than baseline summaries as the former achieved higher scores on two saliency metrics (based on cloze-Q&A blanks and a keyword classifier) than the baseline summaries, while maintaining similar length and better avoiding repetitions. This directly demonstrates our 2-decoder model’s enhanced ability to memorize and recover important information from the input document, which is our main contribution in this paper.

2 Related Work

Extractive and Abstractive Summarization: Early models for automatic text summarization were usually extractive (Jing and McKeown, 2000; Knight and Marcu, 2002; Clarke and Lapata, 2008; Filippova et al., 2015). For abstractive summarization, different early non-neural approaches were applied, based on graphs (Giannakopoulos, 2009; Ganesan et al., 2010), discourse trees (Cheung and Penn, 2014; Wang et al., 2013), and a combination of linguistic compression and topic detection (Zajic et al., 2004). Recent neural-network models have tackled abstractive summarization using methods such as hierarchical encoders and attention, coverage, and distraction (Rush et al., 2015; Chopra et al., 2016; Nallapati et al., 2016; Chen et al., 2016; Takase et al., 2016) as well as various initial large-scale, short-length summarization datasets like DUC-2004 and Gigaword. Nallapati et al. (2016) adapted the CNN/Daily Mail (Hermann et al., 2015) dataset for long-text summarization, and provided an abstractive baseline using attentional sequence-to-sequence model.

Pointer Network for Summarization: Pointer networks (Vinyals et al., 2015) are useful for summarization models because summaries often need to copy/contain a large number of words that have appeared in the source text. This provides the advantages of both extractive and abstractive approaches, and usually includes a gating function to model the distribution for the extended vocabulary including the pre-set vocabulary and words from the source text (Zeng et al., 2016; Nallapati et al., 2016; Gu et al., 2016b; Gulcehre et al., 2016; Miao and Blunsom, 2016). See et al. (2017) used a soft gate to control model’s behavior of copying versus generating. They further applied coverage mechanism and achieved the state-of-the-art results on CNN/Daily Mail dataset.

Memory Enhancement: Some recent works (Wang et al., 2016; Xiong et al., 2018; Gu et al., 2016a) have studied enhancing the memory capacity of sequence-to-sequence models. They studied this problem in Neural Machine Translation by keeping an external memory state analogous to data in the Von Neumann architecture, while the instructions are represented by the sequence-to-sequence model. Our work is novel in that we aim to improve the internal long-term memory of the encoder LSTM by adding a closed-book decoder that has no attention layer, yielding a more efficient internal memory that encodes only important information from the source text, which is crucial for the task of long-document summarization.

Reinforcement Learning: Teacher forcing style maximum likelihood training suffers from exposure bias (Bengio et al., 2015), so recent works instead apply reinforcement learning style policy gradient algorithms (REINFORCE (Williams, 1992)) to directly optimize on metric scores (Henß et al., 2015; Paulus et al., 2018). Reinforced models that employ this method have achieved good results in a number of tasks including image captioning (Liu et al., 2017; Ranzato et al., 2016), machine translation (Bahdanau et al., 2016; Norouzi et al., 2016), and text summarization (Ranzato et al., 2016; Paulus et al., 2018).

3 Models

3.1 Pointer-Generator Baseline

The pointer-generator network proposed in See et al. (2017) can be seen as a hybrid of extractive and abstractive summarization models. At each decoding step, the model can either sample a word from its vocabulary, or copy a word directly from the source passage. This is enabled by the attention mechanism (Bahdanau et al., 2015), which includes a distribution $a_t$ over all encoding steps, and a context vector $c_t$ that is the weighted sum of encoder’s hidden states. The attention mechanism
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vocab = softmax(V2(V1[s_t, c_t] + b_1) + b_2), where V_1, V_2, b_1, b_2 are learnable parameters.

To enable copying out-of-vocabulary words from source text, a pointer similar to Vinyals et al. (2015) is built upon the attention distribution and controlled by the generation probability p_{gen}:

\[ p_{gen}^t = \sigma(U_{cc} c_t + U_{s}s_t + U_{x}x_t + b_{ptr}) \]

\[ P_{attn}(w) = p_{gen}^t P_{vocab}(w) + (1 - p_{gen}^t) \sum_{i: w_i = w} a_i^t \]

where \( U_c, U_s, U_x \) and \( b_{ptr} \) are learnable parameters. \( x_t \) and \( s_t \) are the input token and decoder’s state at \( t \)th decoding step. \( \sigma \) is the sigmoid function. We can see \( p_{gen} \) as a soft gate that controls the model’s behavior of copying from text with attention distribution \( a^t \) versus sampling from vocabulary with generation distribution \( P_{vocab}^t \).

### 3.2 Closed-Book Decoder

As shown in Eqn. 1, the attention distribution \( a_t \) depends on decoder’s hidden state \( s_t \), which is derived from decoder’s memory state \( c_t \). If \( c_t \) does not encode salient information from the source text or encodes too much unimportant information, the decoder will have a hard time to locate relevant encoder states with attention. However, as explained in the introduction, most gradients are back-propagated through attention layer to the encoder’s hidden state \( h_t \), not directly to the final memory state, and thus provide little incentive for the encoder to memorize salient information in \( c_t \).

Therefore, to enhance encoder’s memory, we add a closed-book decoder, which is a unidirectional LSTM decoder without attention/pointer layer. The two decoders share a single encoder and word-embedding matrix, while out-of-vocabulary (OOV) words are simply represented as [UNK] for the closed-book decoder. The entire 2-decoder model is represented in Fig. 2. During training, we optimize the weighted sum of negative log likelihoods from the two decoders:

\[ \mathcal{L}_{XE} = \frac{1}{T} \sum_{t=1}^{T} - ((1 - \gamma) \log P_{attn}(w|x_{1:t}) + \gamma \log P_{cbdec}(w|x_{1:t})) \]

where \( P_{cbdec} \) is the generation probability from the closed-book decoder. The mix ratio \( \gamma \) is tuned on the validation set.

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**Figure 2: Our 2-decoder summarization model with a pointer decoder and a closed-book decoder, both sharing a single encoder (this is during training; next, at inference time, we only employ the memory-enhanced encoder and the pointer decoder).**
3.3 Reinforcement Learning

In the reinforcement learning setting, our summarization model is the policy network that generates words to form a summary. Following Paulus et al. (2018), we use a self-critical policy gradient training algorithm (Rennie et al., 2016; Williams, 1992) for both our baseline and 2-decoder model. For each passage, we sample a summary $y^* = w^*_1:T+1$, and greedily generate a summary $\hat{y} = \hat{w}^*_1:T+1$ by selecting the word with the highest probability at each step. Then these two summaries are fed to a reward function $r$, which is the ROUGE-L scores in our case. The RL loss function is:

$$L_{RL} = \frac{1}{T} \sum_{t=1}^{T} (r(\hat{y}) - r(y^*)) \log P_{\text{atten}}^t(w^*_t+1|w^*_1:t)$$

(3)

where the reward for the greedily-generated summary ($r(\hat{y})$) acts as a baseline to reduce variance. We train our reinforced model using the mixture of Eqn. 3 and Eqn. 2, since Paulus et al. (2018) showed that a pure RL objective would lead to summaries that receive high rewards but are not fluent. The final mixed loss function for RL is:

$$L_{XE+RL} = \lambda L_{RL} + (1-\lambda) L_{XE},$$

where the value of $\lambda$ is tuned on the validation set.

4 Experimental Setup

We evaluate our models mainly on CNN/Daily Mail dataset (Hermann et al., 2015; Nallapati et al., 2016), which is a large-scale, long-paragraph summarization dataset. It has online news articles (781 tokens or ~40 sentences on average) with paired human-generated summaries (56 tokens or 3.75 sentences on average). The entire dataset has 287,226 training pairs, 13,368 validation pairs and 11,490 test pairs. We use the same version of data as See et al. (2017), which is the original text with no preprocessing to replace named entities. We also use DUC-2002, which is also a long-paragraph summarization dataset of news articles. This dataset has 567 articles and 1-2 summaries per article.

All the training details (e.g., vocabulary size, RNN dimension, optimizer, batch size, learning rate, etc.) are provided in the supplementary materials.

5 Results

We first report our evaluation results on CNN/Daily Mail dataset. As shown in Table 1, our 2-decoder model achieves statistically significant improvements on the pointer-generator baseline (pg), with +1.51, +0.74, and +0.96 points advantage in ROUGE-1, ROUGE-2 and ROUGE-L (Lin, 2004), and +1.43 points advantage in METEOR (Denkowski and Lavie, 2014). In the reinforced setting, our 2-decoder model still maintains significant ($p < 0.001$)
different personality traits can vary according to expectations of parents. Different personality traits are also supposedly affected by whether parents have high expectations and how strict they were. The siblings share very different personality traits. The kardashians are a strong example of a large celebrity family where the siblings share very different personality traits. The personality traits are also supposedly affected by whether parents have high expectations and how strict they were.

Reference summary: Mitchell Moffit and Greg Brown from ASAPscience present theories. Different personality traits can vary according to expectations of parents. Beyoncé, Hillary Clinton and J.K. Rowling are all oldest children. The kardashians are a strong example of a large celebrity family where the siblings share very different personality traits. The personality traits are also supposedly affected by whether parents have high expectations and how strict they were.

Table 3: Cosine-similarity between memory states after two forward passes.

| Model                      | Similarity |
|----------------------------|------------|
| pg (baseline)              | 0.817      |
| pg + cbdec (γ = 1/10)      | 0.869      |
| pg + cbdec (γ = 1/50)      | 0.889      |
| pg + cbdec (γ = 1/100)     | 0.872      |
| pg + cbdec (γ = 1/500)     | 0.860      |

Table 5: Human evaluation for our 2-decoder model versus the pointer-generator baseline.

| Model                      | Score |
|----------------------------|-------|
| 2-Decoder Wins             | 49    |
| Pointer-Generator Wins     | 31    |
| Non-distinguishable        | 20    |

Table 4: Human evaluation for our 2-decoder model versus the pointer-generator baseline.

advantage in all metrics over the pointer-generator baseline.

We further add the coverage mechanism as in See et al. (2017) to both baseline and 2-decoder model, and our 2-decoder model (pg + cbdec) again receives significantly higher\(^2\) scores than the original pointer-generator (pg) from See et al. (2017) and our own pg baseline, in all ROUGE and METEOR metrics (see Table 2). In the reinforced setting, our 2-decoder model (RL + pg + cbdec) outperforms our strong RL baseline (RL + pg) by a considerable margin (stat. significance of \(p < 0.001\)). Fig. 1 and Fig. 3 show two examples of our 2-decoder model generating summaries that cover more salient information than those generated by the pointer-generator baseline (see supplementary materials for more example summaries).

We also evaluate our 2-decoder model with coverage on the DUC-2002 test-only generalizability/transfer setup by decoding the entire dataset with our models pre-trained on CNN/Daily Mail, again achieving decent improvements (shown in Table 3) over the single-decoder baseline as well as See et al. (2017), in both a cross-entropy and a reinforcement learning setup.

\(^2\)All our improvements in Table 2 are statistically significant with \(p < 0.001\), and have a 95% ROUGE-significance interval of at most ±0.25.

5.1 Human Evaluation

We also conducted a small-scale human evaluation study by randomly selecting 100 samples from the CNN/DM test set and then asking human annotators to rank the baseline summaries versus the 2-decoder’s summaries (randomly shuffled to anonymize model identity) according to an overall score based on readability (grammar, fluency, coherence) and relevance (saliency, redundancy, correctness). As shown in Table 4, our 2-decoder model outperforms the pointer-generator baseline (stat. significance of \(p < 0.03\)).

6 Analysis

In this section, we present a series of analysis and tests in order to understand the improvements of the 2-decoder models reported in the previous section, and to prove that it fulfills our intuition that the closed-book decoder improves the encoder’s ability to encode salient information in the memory state.

6.1 Memory Similarity Test

To verify our argument that the closed-book decoder improves the encoder’s memory ability, we design a test to numerically evaluate the representation power of encoder’s final memory state. We perform two forward passes for each encoder (2-decoder versus pointer-generator baseline). For the first pass, we feed the entire article to the encoder and collect the final memory state; for the second pass we feed the ground-truth summary to the encoder and collect the final memory state. Then we calculate the cosine similarity between these two memory-state vectors. For an optimal summarization model, its encoder’s memory state after reading the entire article should be highly similar to its memory state after reading the ground truth summary (which contains all the important information), because this shows that when reading a long passage, the model is only encoding important information in its memory and...
forgets the unimportant information. The results in Table 5 show that the encoder of our 2-decoder model achieves significantly ($p < 0.001$) higher article-summary similarity score than the encoder of a pointer-generator baseline. This observation verifies our hypothesis that the closed-book decoder can improve the memory ability of the encoder.

6.2 Ablation Studies and Sanity Check

**Fixed-Encoder Ablation:** Next, we conduct an ablation study in order to prove the qualitative superiority of our 2-decoder model’s encoder to the baseline encoder. To do this, we train two pointer-generators with randomly initialized decoders and word embeddings. For the first model, we restore the pre-trained encoder from our pointer-generator baseline; for the second model, we restore the pre-trained encoder from our 2-decoder model. We then fix the encoder’s parameters for both models during the training, only updating the embeddings and decoders with gradient descent. As shown in the upper half of Table 6, the pointer-generator with our 2-decoder model’s encoder receives significantly higher ($p < 0.001$) scores in ROUGE than the pointer-generator with baseline’s encoder. Since these two models have the exact same structure with only the encoders initialized according to different pre-trained models, the significant improvements in metric scores suggest that our 2-decoder model does have a stronger encoder than the pointer-generator baseline.

**Gradient-Flow-Cut Ablation:** We further design another ablation test to identify how the gradients from the closed-book decoder influence the entire model during training. Fig. 4 demonstrates the forward pass (solid line) and gradient flow (dashed line) between encoder, decoders, and embeddings in our 2-decoder model. As we can see, the closed-book decoder only depends on the word embeddings and encoder. Therefore it can affect the entire model during training by influencing either the encoder or the word-embedding matrix. When we stop the gradient flow between the encoder and closed-book decoder ($\dag$ in Fig. 4), and keep the flow between closed-book decoder and embedding matrix ($\ddag$ in Fig. 4), we observe non-significant improvements in ROUGE compared to the baseline. On the other hand, when we stop the gradient flow at $\ddag$ and keep $\dag$, the improvements are statistically significant ($p < 0.01$) (see the lower half of Table 6). This proves that the gradients back-propagated from closed-book decoder to the encoder can strengthen the entire model, and hence verifies the gradient-flow intuition discussed in introduction (Sec. 1).

**Model Capacity:** To validate and sanity-check that the improvements are the result of the inclusion of our closed-book decoder and not due to some trivial effects of having two decoders or larger model capacity (more parameters), we train a variant of our model with two duplicated (initialized to be different) attention-pointer decoders. We also evaluate a pointer-generator baseline with 2-layer encoder and decoder (pg-2layer) and increase the LSTM hidden dimension and word embedding dimension of the pointer-generator baseline (pg-big) to exceed the total number of parameters of our 2-decoder model (34.5M versus 34.4M parameters). Table 7 shows that neither of these variants can match our 2-decoder model in terms of ROUGE and METEOR scores, and hence proves that the improvements of our model are indeed because of the closed-book decoder rather than due to simply having more parameters.  

**Mixed-loss Ratio Ablation:** We also present eval-

![Figure 4: Solid lines represent the forward pass, and dashed lines represent the gradient flow in back-propagation. For the two ablation tests, we stop the gradient at $\dag$ and $\ddag$ respectively.](image-url)

Table 6: ROUGE F1 scores of ablation studies, evaluated on CNN/Daily Mail validation set.

| Fixed-Encoder Ablation | ROUGE |
|------------------------|-------|
| pg baseline’s encoder  | 37.59 | 16.27 | 34.33 |
| 2-decoder’s encoder    | 38.44 | 16.85 | 35.17 |

| Gradient-Flow-Cut Ablation | ROUGE |
|-----------------------------|-------|
| pg baseline                 | 37.73 | 16.52 | 34.49 |
| stop $\dag$                 | 37.72 | 16.58 | 34.54 |
| stop $\ddag$                | 38.35 | 16.79 | 35.13 |

Footnote: It is also important to point out that our model is not a 2-decoder ensemble, because we use only the pointer decoder during inference. Therefore, the number of parameters used for inference is the same as the pointer-generator baseline.
Table 7: ROUGE F1 and METEOR scores of sanity check ablations, evaluated on CNN/DM validation set.

| Method                  | ROUGE 1 | ROUGE 2 | ROUGE L |
|-------------------------|---------|---------|---------|
| pg baseline             | 37.73   | 16.52   | 34.49   |
| pg + ptrdec             | 37.66   | 16.50   | 34.47   |
| pg-2layer               | 37.92   | 16.48   | 34.62   |
| pg-big                  | 38.03   | 16.71   | 34.84   |
| pg + cbdec              | 38.87   | 16.93   | 35.38   |

Table 8: ROUGE F1 scores on CNN/DM validation set, of 2-decoder models with different values of the closed-book-decoder:pointer-decoder mixed loss ratio.

| Value of γ      | ROUGE 1 | ROUGE 2 | ROUGE L |
|-----------------|---------|---------|---------|
| γ = 0           | 37.73   | 16.52   | 34.49   |
| γ = 1/2         | 38.09   | 16.71   | 34.89   |
| γ = 2/3         | 38.87   | 16.93   | 35.38   |
| γ = 5/6         | 38.21   | 16.69   | 34.81   |
| γ = 10/11       | 37.99   | 16.39   | 34.7    |

Table 9: Saliency scores based on CNN/Daily Mail cloze blank-filling task and a keyword-detection approach (Pasunuru and Bansal, 2018). All models in this table are trained with coverage loss.

| Method                  | Saliency 1 | Saliency 2 |
|-------------------------|------------|------------|
| pg (See17)              | 60.4%      | 27.95%     |
| our pg baseline         | 59.6%      | 28.95%     |
| pg + cbdec              | 62.1%      | 29.97%     |
| RL + pg                 | 62.5%      | 30.17%     |
| RL + pg + cbdec         | 66.2%      | 31.40%     |

Table 10: Percentage of repeated 3, 4, 5-grams and sentences in generated summaries.

| Method                  | 3-gram | 4-gram | 5-gram | sent |
|-------------------------|--------|--------|--------|------|
| pg (baseline)           | 13.20% | 12.32% | 11.60% | 8.39%|
| pg + cbdec              | 9.66%  | 9.02%  | 8.55%  | 6.72%|

6.3 Saliency and Repetition

Finally, we show that our 2-decoder model can make use of this better encoder memory state to summarize more salient information from the source text, as well as to avoid generating unnecessarily lengthy and repeated sentences besides achieving significant improvements on ROUGE and METEOR metrics.

Saliency: To evaluate saliency, we design a keyword-matching test based on the original CNN/Daily Mail cloze blank-filling task (Hermann et al., 2015). Each news article in the dataset is marked with a few cloze-blank keywords that represent salient entities, including names, locations, etc. We count the number of keywords that appear in our generated summaries, and found that the output of our best teacher-forcing model (pg+cbdec with coverage) contains 62.1% of those keywords, while the output provided by See et al. (2017) has only 60.4% covered. Our reinforced 2-decoder model (RL + pg + cbdec) further increases this percentage to 66.2%. The full comparison is shown in the first column of Table 9. We also use the saliency metric in Pasunuru and Bansal (2018), which finds important words detected via a keyword classifier (trained on the SQuAD dataset (Rajpurkar et al., 2016)). The results are shown in the second column of Table 9. Both saliency tests again demonstrate our 2-decoder model’s ability to memorize important information and address them properly in the generated summary. Fig. 1 and Fig. 3 show two examples of summaries generated by our 2-decoder model compared to baseline summaries.

Summary Length: On average, summaries generated by our 2-decoder model have 66.42 words per summary, while the pointer-generator-baseline summaries have 65.88 words per summary (and the same effect holds true for RL models, where there is less than 1-word difference in average length). This shows that our 2-decoder model is able to achieve higher saliency with similar-length summaries (i.e., it is not capturing more salient content simply by generating longer summaries).

Repetition: We observe that our 2-decoder model can generate summaries that are less redundant compared to the baseline, when both models are not trained with coverage mechanism. Table 10 shows the percentage of repeated n-grams/sentences in summaries generated by the pointer-generator baseline and our 2-decoder model.

Abstractiveness: Abstractiveness is another major challenge for current abstractive summarization models other than saliency. Since our baseline is an abstractive model, we measure the percentage of novel n-grams (n=2, 3, 4) in our generated summaries, and find that our 2-decoder model generates 1.8%, 4.8%, 7.6% novel n-grams while
our baseline summaries have 1.6%, 4.4%, 7.1% on the same test set. Even though generating more abstractive summaries is not our focus in this paper, we still show that our improvements in metric and saliency scores are not obtained at the cost of making the model more extractive.

6.4 Discussion: Connection to Multi-Task Learning

Our 2-decoder model somewhat resembles a Multi-Task Learning (MTL) model, in that both try to improve the model with extra knowledge that is not available to the original single-task baseline. While our model uses MTL-style parameter sharing to introduce extra knowledge from the same dataset, traditional Multi-Task Learning usually employs additional/out-of-domain auxiliary tasks/datasets as related knowledge (e.g., translation with 2 language-pairs). Our 2-decoder model is more about how to learn to do a single task from two different points of view, as the pointer decoder is a hybrid of extractive and abstractive summarization models (primary view), and the closed-book decoder is trained for abstractive summarization only (auxiliary view). The two decoders share their encoder and embeddings, which helps enrich the encoder’s final memory state representation.

Moreover, as shown in Sec. 6.2, our 2-decoder model (pg + cbdec) significantly outperforms the 2-duplicate-decoder model (pg + ptrdec) as well as single-decoder models with more layers/parameters, hence proving that our design of the auxiliary view (closed-book decoder doing abstractive summarization) is the reason behind the improved performance, rather than some simplistic effects of having a 2-decoder ensemble or higher #parameters.

7 Conclusion

We presented a 2-decoder sequence-to-sequence architecture for summarization with a closed-book decoder that helps the encoder to better memorize salient information from the source text. On CNN/Daily Mail dataset, our proposed model significantly outperforms the pointer-generator baselines in terms of ROUGE and METEOR scores (in both a cross-entropy (XE) setup and a reinforcement learning (RL) setup). It also achieves improvements in a test-only transfer setup on the DUC-2002 dataset in both XE and RL cases. We further showed that our 2-decoder model indeed has a stronger encoder with better memory capabilities, and can generate summaries with more salient information from the source text. To the best of our knowledge, this is the first work that studies the “representation power” of the encoders final state in an encoder-decoder model. Furthermore, our simple, insightful 2-decoder architecture can also be useful for other tasks that require long-term memory from the encoder, e.g., long-context QA/dialogue and captioning for long videos.

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Supplementary Material

A Coverage Mechanism

See et al. (2017) apply coverage mechanism to the pointer-generator in order to alleviate repetition. They maintain a coverage vector \( c^t \) as the sum of attention distribution over all previous decoding steps \( 1 : t - 1 \). This vector is incorporated in calculating the attention distribution at current step \( t \):

\[
c^t = \sum_{t'=0}^{t-1} a^{t'}
\]

\[
e^t_i = v^T \tanh(W_h h_i + W_s s_t + W_c c^t_i + b_{attt})
\]

where \( W_h, W_s, W_c, b_{attt} \) are learnable parameters. They define the coverage loss and combine it with the primary loss to form a new loss function, which is used to fine-tune a converged pointer-generator model.

\[
\text{loss}_{cov} = \sum_i \min(a^t_i, c^t_i)
\]

\[
L_{total} = \frac{1}{T} \sum_{t=1}^{T} \left( - \log P_{pg}(w|x_{1:t}) + \lambda \text{loss}_{cov} \right)
\]

B Reinforcement Learning

To overcome the exposure bias (Bengio et al., 2015) between training and testing, previous works (Ranzato et al., 2016; Paulus et al., 2018) use reinforcement learning algorithms to directly optimize on metric scores for summarization models. In this setting, the generation of discrete words in a sentence is a sequence of actions. The decision to take what action is based on a Policy Network \( \pi_{\theta} \), which outputs a distribution of all possible actions at that step. In our case, \( \pi_{\theta} \) is simply our summarization model.

The process of generating a summary \( s \) given the source passage \( P \) can be summarized as follows. At each time step \( t \), we sample a discrete action \( w_t \in V \) - word in vocabulary, based on distribution from policy \( \pi_{\theta}(P, s_t) \), where \( s_t = w_{1:t-1} \) is the sequence of actions sampled in previous steps. When we reach the end of the sequence at terminal step \( T \) (end-of-sentence marker is sampled from \( \pi_{\theta} \)), we feed the entire sequence \( s_T = w_{1:T} \) into a reward function and get a reward \( R(w_{1:T}|P) \).

In typical Reinforcement Learning, an agent with policy \( \pi \) receives rewards at intermediate steps while the discount factor is used to balance long-term and short-term rewards. In our task, there is no intermediate rewards, only a final reward at terminal step \( T \). Therefore, the value function of a partial sequence \( c_t = w_{1:t} \) is the expected reward at the terminal step.

\[
V(w_{1:T}|P) = \mathbb{E}_{w_{t+1:T}}[R(w_{1:t}; w_{t+1:T}|P)]
\]

The objective of policy gradient is to maximize the average value starting from the initial state:

\[
J(\theta) = \frac{1}{N} \sum_{n=1}^{N} V(w_0|I)
\]

where \( N \) is the total number of examples in training set. The gradient of \( V(w_0|P) \) is computed as below (Williams, 1992):

\[
\mathbb{E}_{w_{1:T}} \left[ \sum_{t=1}^{T} \nabla_{\theta} \pi_{\theta}(w_{t+1}|w_{1:t}, P) \times Q(w_{1:t}, w_{t+1}|P) \right]
\]

where \( Q(w_{1:t}, w_{t+1}|P) \) is the state-action value for a particular action \( w_{t+1} \) at state \( w_{1:t} \) given source passage \( P \), and should be calculated as follow:

\[
Q(w_{1:t}, w_{t+1}|P) = \mathbb{E}_{w_{t+2:T}}[R(w_{1:t}; w_{t+1}; w_{t+2:T}|P)]
\]

Previous work (Liu et al., 2017) adopts Monte Carlo Rollout to approximate this expectation. Here we simply use the terminal reward \( R(w_{1:T}|P) \) as an estimation with large variance. To compensate for the variance, we use a baseline estimator that doesn’t change the validity of gradients (Williams, 1992). We further follow Paulus et al. (2018) to use the self-critical policy gradient training algorithm (Rennie et al., 2016; Williams, 1992). For each iteration, we sample a summary \( y^* = w^*_{1:T+1} \), and greedily generate a summary \( \hat{y} = \hat{w}^*_{1:T+1} \) by selecting the word with the highest probability at each step. Then these two summaries are fed to a reward function \( r \) that evaluates their closeness to the ground-truth. We choose ROUGE-L scores as the reward function \( r \) as in previous work (Paulus et al., 2018). The RL loss function is as follows:

\[
\mathcal{L}_{RL} = \frac{1}{T} \sum_{t=1}^{T} (r(\hat{y}) - r(y^*)) \log \pi_{\theta}(w^*_{t+1}|w^*_{1:t})
\]
where the reward for the greedily-generated summary ($r(\hat{y})$) acts as a baseline to reduce variance.

C Training Details

We keep most of hyper-parameters and settings the same as in See et al. (2017). We use a bi-directional LSTM of 400 steps for the encoder, and a uni-directional LSTM of 100 steps for both decoders. All of our encoder and decoder LSTMs have hidden dimension of 256, and the word embedding dimension is set to 128. Our pre-set vocabulary has a total of 50k word tokens including special tokens for start, end, and out-of-vocabulary (OOV) signals. The embedding matrix is learned from scratch and shared between the encoder and two decoders.

All of our teacher forcing models reported are trained with Adagrad (Duchi et al., 2011) with learning rate of 0.15 and an initial accumulator value of 0.1. The gradients are clipped to a maximum norm of 2.0. The batch size is set to 16. Our model with closed-book decoder converged in about 200,000 to 240,000 iterations and achieved the best result on the validation set in another 2k~3k iterations with coverage loss added. We restore the best checkpoints (pre-coverage and post-coverage) and apply policy gradient (RL). For this phase of training, we choose Adam optimizer (Kingma and Ba, 2015) because of its time efficiency, and the learning rate is set to 0.000001. The RL-XE mixed-loss ratio ($\lambda$) is set to 0.9984.

D Examples

We provide more example summaries generated by our 2-decoder and pointer-generator baseline (see Fig. 5, Fig. 6, and Fig. 7 on the next page).
**Original Text (truncated):** lionel messi should be fit to play in barcelona's la liga game at celta vigo on sunday despite a scare over a possible foot injury, centre back gerard pique said on wednesday. messi, the top scorer in la liga, did not feature in either of argentina's friendlies during the international break after sustaining a blow to his right foot in last month's `clasico' against real madrid. 'i am optimistic about messi,' i have spoken to him,' pique told reporters at a promotional event. lionel messi -lb- right -rrb- should be available for barcelona 's trip to celta vigo, according to gerard pique. 'i think that he can play at balaidos -lb- celta 's stadium -rrb-,' added the spain international, who came through barca 's youth academy with messi. 'in the end it is up to how he feels during the rest of the week, the medical staff are those who should decide. my feeling is that he will play.' barca's 2-1 win at home to real stretched their lead over their arch rivals at the top of la liga to four points with 10 games left. second-placed real, who host granada on sunday, have stuttered in recent weeks and the 2-1 defeat at the nou camp was their third loss in their last four outings in all competitions.

**Reference summary:**

lionel messi didn't feature in either of Argentina's recent friendlies. messi suffered a foot injury in barcelona's win over real madrid last month. barca sits four points clear of real in la liga with 10 games remaining.

**Pointer-Gen baseline:**

lionel messi should be available for barcelona's trip to celta vigo. the spain international did not feature in either of argentina's friendlies during the international break. messi, the top scorer in la liga, did not feature in either of argentina's friendlies during the international break after sustaining a blow to his right foot in last month's 'clasico' against real madrid. barca's 2-1 win at home to real stretched their lead over their arch rivals at the top of la liga to four points with 10 games.

**Pointer-Gen + closed-book decoder:**

lionel messi should be available for barcelona 's trip to celta vigo. messi, the top scorer in la liga, did not feature in either of argentina's friendlies during the international break after sustaining a blow to his right foot in last month's 'clasico' against real madrid. barca's 2-1 win at home to real stretched their lead over their arch rivals at the top of la liga to four points with 10 games.

Figure 5: The pointer-generator repeats itself (italic) and makes a factual error (red), while the 2-decoder (pointer-generator + closed-book decoder) generates the summary that recovers the salient information (highlighted) in the original text.
a waitress has revealed how the new zealand prime minister had repeatedly given her unwanted attention while she was working at a cafe in auckland frequented by him and his wife. published on the daily blog on wednesday, the anonymous woman has recounted how john key kept playfully pulling her hair despite being told to stop during election time last year. however mr key defended his pranks as 'a bit of banter' and said he had already apologised for his actions, stuff.co.nz reports. a waitress has revealed how the new zealand prime minister had repeatedly given her unwanted attention while she was working at a cafe in auckland frequented by him and his wife bronagh (pictured together). the waitress had reportedly been working at a cafe called rosie (pictured) in parnell, east of auckland. the waitress believed to be working at a cafe called rosie in parnell, east of auckland - wrote about she how made it very clear that she was unimpressed by mr key's gestures. 'he was like the school yard bully tugging on the little girls' hair trying to get a reaction, experiencing that feeling of power over her,' she wrote on the blog. mr key kept being persistent with his hair-pulling antics, despite being told by his wife bronagh to stop. after dealing with the practical jokes over the six months he had visited the cafe, the waitress finally lost her cool...

Reference summary:
amanda bailey, 26, says she doesn't regret going public with her story. the waitress revealed in a blog how john key kept pulling her hair. she wrote that she gained unwanted attention from him last year at a cafe. ms bailey said mr key kept touching her hair despite being told to stop. owners say they were disappointed she never told them of her concerns. they further stated mr key is popular among the cafe staff. the prime minister defended his actions, saying he had already apologised. he also said his pranks were 'all in the context of a bit of banter'. the waitress was working at a cafe called rosie in parnell, east of auckland.

Pointer-Generator baseline:
waitress was working at a cafe in auckland frequented by him and his wife. she was working at a cafe called rosie in parnell, east of auckland. mr key defended his pranks as 'a bit of banter' and said he had already apologised.

Pointer-Generator + closed-book decoder:
waitress has revealed how john key kept playfully pulling her hair despite being told to stop during election time last year. however mr key defended his pranks as 'a bit of banter' and said he had already apologised for his actions, stuff.co.nz reports.

Figure 6: The pointer-generator fails to address the most salient information from the original text, only mentioned a few unimportant points (where the waitress works), while the 2-decoder (pointer-generator + closed-book decoder) generates the summary that recovers the salient information (highlighted) in the original text.
The suicides of five young sailors who served on the same base over two years has unearthed a shocking culture of ice taking, binge drinking, bullying and depression within the Australian navy. The sailors were stationed or had been stationed at the west Australian port of HMAS Stirling off the coast of Rockingham, south of Perth. Their families did not learn of their previous attempts to take their own lives and their drug use until after their deaths, according to ABC’s 7.30 program. Scroll down for video. Stuart Addison was serving on HMAS Stirling off the coast of Western Australia when he took his own life. Five of the sailors who committed suicide had been serving with the Australian navy on HMAS Stirling...

Reference summary:
Five sailors took their own lives while serving on WA’s HMAS Stirling. Suicides happened over two years and some had attempted it before. Stuart Addison’s family didn’t know about his other attempts until his death. It was a similar case for four other families, including Stuart’s close friends. Revelations of ice use, binge drinking and depression have also emerged.

Pointer-Gen baseline:
Stuart Addison was serving on HMAS Stirling off the coast of Western Australia. He was serving on HMAS Stirling off the coast of Rockingham, south of Perth. Their families did not learn of their previous attempts to take their own lives and their drug use until after their deaths.

Pointer-Gen + closed-book decoder:
The suicides of five young sailors who served on the same base over two years has unearthed a shocking culture of ice taking, binge drinking, bullying and depression within the Australian navy. The sailors were stationed at the west Australian port of HMAS Stirling off the coast of Rockingham, south of Perth. Their families did not learn of their previous attempts to take their own lives and their drug use until after their deaths, according to ABC’s 7.30 program.

Figure 7: The pointer-generator (non-coverage) repeats itself (italic), while the 2-decoder (pointer-generator + closed-book decoder) generates the summary that recovers the salient information (highlighted) in the original text as well as the reference summary.