Fast Abstractive Summarization with Reinforce-Selected Sentence Rewriting

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Abstract

Inspired from how humans summarize long documents, we propose an accurate and fast summarization model that first selects salient sentences and then rewrites them abstractively (i.e., compresses and paraphrases) to generate a concise overall summary. We use a novel sentence-level policy gradient method with metric rewards to bridge the non-differentiable computation between these two neural networks in a hierarchical way, while maintaining language fluency. Empirically, we achieve the new state-of-the-art on all metrics on the CNN/Daily Mail dataset. Moreover, by first operating at the sentence-level and then the word-level, we enable *parallel decoding* of our neural generative model that results in substantially faster (10-20x) inference speed as well as 4x faster training speed than previous long-paragraph encoder-decoder models. We also demonstrate the generalization of our model on the test-only DUC-2002 dataset, where we achieve higher scores than a state-of-the-art model.

1 Introduction

The task of document summarization has two main paradigms: extractive and abstractive. The former method directly chooses and outputs the salient sentences (or phrases) in the original document (Jing and McKeown, 2000; Knight and Marcu, 2000; Martins and Smith, 2009; Berg-Kirkpatrick et al., 2011). The latter abstractive approach involves rewriting the summary (Banko et al., 2000; Zajic et al., 2004), and has seen substantial recent gains due to neural sequence-to-sequence models (Chopra et al., 2016; Nallapati et al., 2016; See et al., 2017; Paulus et al., 2017). Abstractive models can be more concise by performing generation from scratch, but they suffer from slow and inaccurate encoding of very long documents, with the attention model being required to look at all encoded words (in long paragraphs) for decoding each generated summary word (slow, one by one sequentially). Abstractive models also suffer from redundancy (repetitions), especially when generating multi-sentence text.

To address both these issues and combine the advantages of both paradigms, we propose a hybrid extractive-abstractive architecture, with policy-based reinforcement learning to bridge together the two networks. Similar to how humans summarize long documents, our model first uses an *extractor agent* to select salient sentences or highlights, and then employs an *abstractor network* to rewrite (i.e., compress and paraphrase) each of these extracted sentences. To overcome the non-differentiable behavior of our extractor and train on available document-summary pairs without saliency label, we next use actor-critic policy gradient with sentence-level metric rewards to connect these two neural networks and to learn sentence saliency. We also avoid common language fluency issues (Paulus et al., 2017) by preventing the policy gradients from affecting the abstractive summarizer's word-level training, which also stabilizes the learning dynamics. Our sentence-level RL takes into account the word-sentence hierarchy, which better models the language structure and makes parallelization possible. Our extractor combines reinforcement learning and pointer networks, which is inspired from Bello et al. (2017)'s attempt to solve the Traveling Salesman Problem. Our abstractor is a simple encoder-aligner-decoder model (with copying) and is trained on pseudo document-summary sentence pairs obtained via simple auto-

matic matching criteria.

Thus, our method incorporates the abstractive paradigm's advantages of concisely rewriting sentences and generating novel words from the full vocabulary, yet it adopts intermediate extractive behavior to improve the overall model's quality, speed, and stability. Instead of encoding and attending to every word in the long input document sequentially, our model adopts a human-inspired *coarse-to-fine* approach that first extracts all the salient sentences and then decodes (rewrites) them (*in parallel*). This also avoids almost all redundancy issues because the model has already chosen non-redundant salient sentences to abstractively summarize (but adding an optional final reranker component does give additional gains by removing the fewer across-sentence repetitions).

Empirically, our approach is the new state-of-the-art on all ROUGE metrics (Lin, 2004) as well as on METEOR (Denkowski and Lavie, 2014) of the CNN/Daily Mail dataset, achieving statistically significant improvements over previous models that use complex long-encoder, copy, and coverage mechanisms (See et al., 2017). The test-only DUC-2002 improvement also shows our model's better generalization than this strong abstractive system. Moreover, our model's training is 4x and inference is more than 20x faster than the previous state-of-the-art. The optional final reranker gives further improvements while maintaining a 7x speedup. In addition, we surpass the popular lead-3 baseline on all ROUGE scores with an abstractive model. This empirically justifies that our RL-guided extractor has learnt sentence saliency, rather than benefiting from simply copying longer sentences. We also show that our model maintains the same level of fluency as a conventional RNN-based model because the reward does not leak to our abstractor's word-level training.[1]

Overall, our contribution is three fold: First we propose a novel sentence-level RL technique for the well-known task of abstractive summarization, effectively utilizing the word-then-sentence hierarchical structure without annotated matching sentence-pairs between the document and ground truth summary. Next, our model achieves the new state-of-the-art on all metrics of multiple versions of a popular summarization dataset (as well as a test-only dataset) both extractively and abstractively, without loss in language fluency. Finally, our parallel decoding results in a significant 10-20x speed-up over previous best neural abstractive summarization system with even better accuracy.

[1]We plan to release our code, best trained models, as well the generated summaries, to foster future research.

2 Model

In this work, we consider the task of summarizing a given long text document into several (ordered) highlights, which are then combined to form a multi-sentence summary. Formally, given a training set of document-summary pairs $\{x_i, y_i\}_{i=1}^N$, our goal is to approximate the function $h : X \rightarrow Y, X = \{x_i\}_{i=1}^N, Y = \{y_i\}_{i=1}^N$ such that $h(x_i) = y_i, 1 \leq i \leq N$. Furthermore, we assume there exists an abstracting function g defined as: $\forall s \in S_i, \exists d \in D_i$ such that $g(d) = s, 1 \leq i \leq N$, where S_i is the set of summary sentences in x_i and D_i the set of document sentences in y_i. i.e., in any given pair of document and summary, every summary sentence can be produced from some document sentence. For simplicity, we omit subscript i in the remainder of the paper. Under this assumption, we can further define another latent function $f : X \rightarrow D^n$ that satisfies $f(x) = \{d_t\}_{j=1}^n$ and $y = h(x) = [g(d_1), g(d_2), \ldots, g(d_n)]$, where $[,]$ denotes sentence concatenation. This latent function f can be seen as an extractor that chooses the salient (ordered) sentences in a given document for the abstracting function g to rewrite. Our overall model consists of these two submodules, the *extractor agent* and the *abstractor network*, to approximate the above-mentioned f and g, respectively.

2.1 Extractor Agent

The extractor agent is designed to model f, which can be thought of as extracting salient sentences from the document. We exploit a hierarchical neural model to learn the sentence representations of the document and a 'selection network' to extract sentences based on their representations.

2.1.1 Hierarchical Sentence Representation

We use a temporal convolutional model (Kim, 2014) to compute r_j, the representation of each individual sentence in the documents. The model details are in the supplementary. To further incorporate global context of the document and capture the long-range semantic dependency between sentences, a bidirectional LSTM-RNN (Hochreiter and Schmidhuber, 1997; Schuster et al., 1997) is applied on the convolutional representation. This

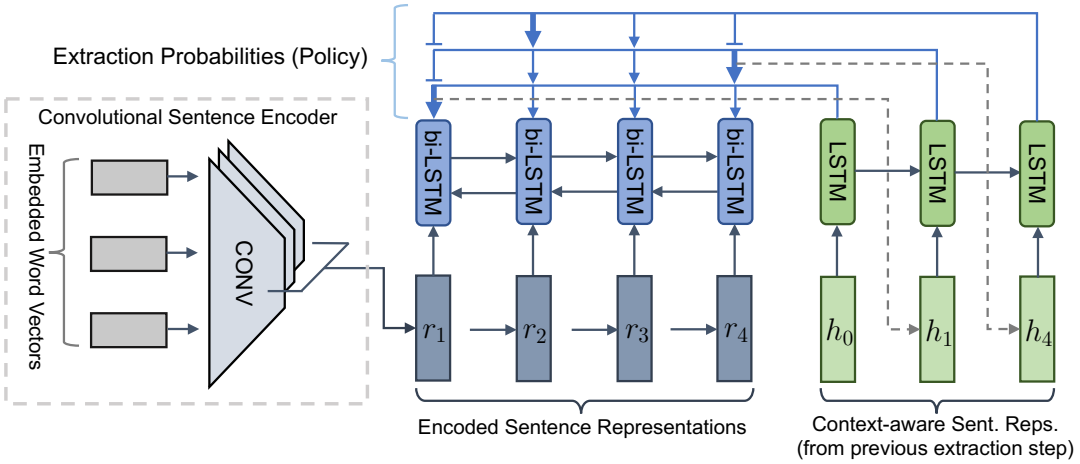

Figure 1: The sentence selection model. The convolutional encoder computes representation r_j for each sentence. The RNN encoder (blue) computes context-aware representation h_j and then the RNN decoder (green) selects sentence j_t at time step t. With j_t selected, h_{j_t} will be fed into the decoder at time $t+1$.

enables learning a strong representation, denoted as h_j for the j-th sentence in the document, that takes into account the context of all previous and future sentences in the same document.

2.1.2 Sentence Selection

Next, to select the extracted sentences based on the above sentence representations, we add another LSTM-RNN to train a *Pointer Network* (Vinyals et al., 2015), to extract sentences recurrently. We calculate the extraction probability by:

$$u_j^t = \begin{cases} v_p^T \tanh(W_{p1} h_j + W_{p2} e_t) & \text{if } j_t \neq j_k \\ & \forall k < t \\ -\infty & \text{otherwise} \end{cases} \quad (1)$$

$$P(j_t | j_1, \ldots, j_{t-1}) = \text{softmax}(u^t) \quad (2)$$

where e_t's are the output of the *glimpse* operation (Vinyals et al., 2016):

$$a_j^t = v_g^T \tanh(W_{g1} h_j + W_{g2} z_t) \quad (3)$$

$$\alpha^t = \text{softmax}(a^t) \quad (4)$$

$$e_t = \sum_j \alpha_j^t W_{g1} h_j \quad (5)$$

In Eqn. 3, z_t is the output of the added LSTM-RNN (shown in green in Fig. 1) which is referred as the *decoder*. All the W's and v's are trainable parameters. At each time step t, the decoder performs a 2-hop attention mechanism: It first attends to h_j's to get a context vector e_t and then attends to h_j's again for the extraction probabilities.[2] This model is essentially classifying all sentences of the document at each extraction step. An illustration of the whole extractor is shown in Fig. 1.

2.2 Abstractor Network

The abstractor network approximates g, which compresses and paraphrases an extracted document sentence to a concise summary sentence. We briefly discuss its architecture here and leave the details in the supplementary. We use the standard encoder-aligner-decoder model (Bahdanau et al., 2014; Luong et al., 2015), popular for several conditioned NL generation tasks. We add a simple copying mechanism[3] to our abstractor to help avoid generation of out-of-vocabulary(OOV) words (See et al., 2017), given the high overlap between the input and output of text summarization.

3 Learning

Given that our extractor performs a non-differentiable *hard* extraction, we apply standard policy gradient methods to bridge the back-propagation and form an end-to-end trainable (stochastic) computation graph. However, simply starting from randomly initialized network to train the whole model in an end-to-end fashion is infeasible. With randomly initialized networks, the extractor would often select sentences that are not relevant, so it would be difficult for the abstractor to learn to abstractively summarize. On the other hand, without a well-trained abstractor the extractor would get noisy reward, which

[2] In Eqn. 1, we zero the extraction prob. of already extracted sentences, a non-diff. op. only done in RL training.

[3] We use *copy mechanism* (originally named *pointer-generator*) to avoid confusion with the *pointer network*.

leads to a bad estimate of policy gradient and a sub-optimal policy. We hence propose optimizing each sub-module separately using maximum-likelihood (ML) objectives: train the extractor to select salient sentences (fit f) and the abstractor to generate shortened summary (fit g). Finally, RL is applied to train the full model end-to-end (fit h).

3.1 Maximum-Likelihood Training for Submodules

Extractor Training: In Sec. 2.1.2, we have formulated our sentence selection as classification. However, most of the summarization datasets are end-to-end document-summary pairs without extraction (saliency) labels of each sentence. Hence, we propose a simple similarity method to provide a 'proxy' target label for the extractor. Similar to the extractive model of Nallapati et al. (2017), for each ground-truth summary sentence, we find the most similar document sentence d_{j_t} by[4]:

$$j_t = \text{argmax}_i(\text{ROUGE-L}_{recall}(d_i, s_t)) \quad (6)$$

Given these proxy training labels, the extractor is then trained to minimize the cross-entropy loss.

Abstractor Training: For the abstractor training, we create training pairs using each of document sentence extracted by Eqn. 6 above for each corresponding summary sentence. The network is trained as an usual sequence-to-sequence model to minimize the cross-entropy loss $L(\theta_{abs}) = -\frac{1}{M}\sum_{m=1}^{M} \log P_{\theta_{abs}}(w_m|w_{1:m-1})$ of the decoder language model at each generation step, where θ_{abs} is the set of trainable parameters of the abstractor and w_m the m^{th} generated word.

3.2 Reinforce-Guided Extraction

Here we explain how policy gradient techniques are applied to optimize the whole model. To make the extractor an RL agent, we can formulate a Markov Decision Process (MDP)[5]: at each extraction step t, the agent observes the current state $c_t = (D, d_{j_{t-1}})$, samples an action $j_t \sim \pi_{\theta_{a,\omega}}(c_t, j) = P(j)$ from Eqn. 2 to extract a document sentence and receive a reward[6]

$$r(t+1) = \text{ROUGE-L}_{F_1}(g(d_{j_t}), s_t) \quad (7)$$

after the abstractor summarizes the extracted sentence d_{j_t}. We denote the trainable parameters of the extractor agent by $\theta = \{\theta_a, \omega\}$ for the decoder and hierarchical encoder respectively. We can then train the extractor with policy-based RL.

The vanilla policy gradient algorithm, REINFORCE (Williams, 1992), is known for high variance. To mitigate this problem we add a critic network with trainable parameters θ_c to predict the state-value function $V^{\pi_{\theta_{a,\omega}}}(c)$. The predicted value of critic $b_{\theta_c,\omega}(c)$ is called the 'baseline', which is used to estimate the *advantage function*: $A^{\pi_\theta}(c, j) = Q^{\pi_{\theta_{a,\omega}}}(c, j) - V^{\pi_{\theta_{a,\omega}}}(c)$ because the total return R_t is an estimate of action-value function $Q(c_t, j_t)$. Instead of maximizing $Q(c_t, j_t)$ as done in REINFORCE, we maximize $A^{\pi_\theta}(c, j)$ with the following policy gradient:

$$\nabla_{\theta_{a,\omega}} J(\theta_a, \omega) = \mathbb{E}[\nabla_{\theta_{a,\omega}} \log \pi_\theta(c, j) A^{\pi_\theta}(c, j)] \quad (8)$$

And the critic is trained to minimize the square loss: $L_c(\theta_c, \omega) = (b_{\theta_c,\omega}(c_t) - R_t)^2$. This is known as the *Advantage Actor-Critic* (A2C), a synchronous variant of A3C (Mnih et al., 2016). For more A2C details, please refer to the supp.

Intuitively, our RL training works as follow: If the extractor chooses a good sentence, after the abstractor rewrites it the ROUGE match would be high and thus the action is encouraged. If a bad sentence is chosen, though the abstractor

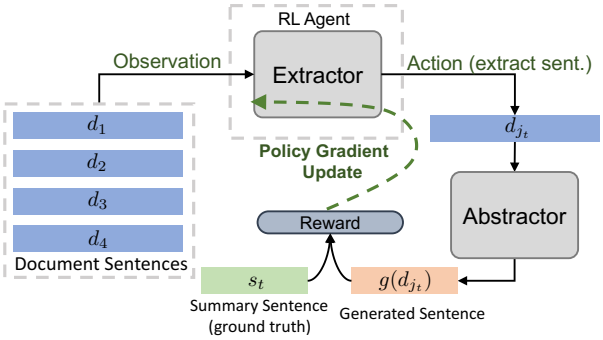

Figure 2: Reinforced training of the extractor (for one extraction step). For simplicity, the critic network is not shown. Note that all d's and s_t are raw sentences, not some vector representations.

[4] Nallapati et al. (2017) also used a similar approach to obtain a proxy label for their extractive model; the main difference is that they chose sentences greedily to get the maximum summary-level ROUGE, whereas we choose sentences based on best individual matches of the sentence-level score to each ground-truth summary sentence (since we need to match exactly 1 document sentence for each GT summary sentence).

[5] Strictly speaking, this is a *Partially Observable Markov Decision Process* (POMDP). We approximate it by MDP by assuming that the RNN hidden state contains all past info.

[6] In Eqn. 6 we use ROUGE-recall because we want the extracted sentence to contain as much information as possible for rewriting. Nevertheless, for Eqn. 7, ROUGE-F_1 is more suitable because the abstractor g is supposed to rewrite the extracted sentence d to be as concise as the ground truth s.

still produce a compressed version of it, the summary would not match the ground truth and the low ROUGE score discourages this action. Our RL with a sentence-level agent is a novel attempt in neural summarization. We use RL as a saliency guide without altering the language model, while previous work applied RL on the word-level, which could be prone to gaming the metric at the cost of language fluency.[7]

3.3 Repetition-Avoiding Reranking

Existing abstractive summarization systems on long documents suffer from generating repeating and redundant words and phrases. To mitigate this issue, See et al. (2017) proposes the coverage mechanism and Paulus et al. (2017) incorporates tri-gram avoidance during beam-search at test-time. Our model without these already performs well because the summary sentences are generated from different document sentences, which naturally avoid redundancy. However, we do get a small further boost to the summary quality by removing a few 'across-sentence' repetitions, via a simple reranking strategy: At sentence-level, we apply the same beam-search tri-gram avoidance (Paulus et al., 2017). We keep all k sentence candidates generated by beam search, where k is the size of the beam. Next, we then rerank all k^n combinations of the n generated summary sentence beams. The summaries are reranked by the number of repeated N-grams, the smaller the better. We also apply the diverse decoding algorithm described in Li et al. (2016) (which has almost no computation overhead) so as to get the above approach to produce useful diverse reranking lists. We show how much the redundancy affects the summarization task in Sec. 6.2.1.

4 Related Work

Early summarization works mostly focused on extractive and compression based methods (Jing and McKeown, 2000; Knight and Marcu, 2000; Clarke and Lapata, 2010; Berg-Kirkpatrick et al., 2011; Filippova et al., 2015). Recent large-sized corpora attracted neural methods for abstractive summarization (Rush et al., 2015; Chopra et al., 2016). Some of the recent success in neural abstractive models include hierarchical attention (Nallapati et al., 2016), coverage (Suzuki and Nagata, 2016; Chen et al., 2016; See et al., 2017), RL based metric optimization (Paulus et al., 2017), graph-based attention (Tan et al., 2017b), and the copy mechanism (Miao and Blunsom, 2016; Gu et al., 2016a; See et al., 2017), which combines extractive and abstractive methods in a *soft* way using attention.

Our model shares some high-level intuition with extract-then-compress methods. Earlier attempts in this paradigm used Hidden Markov Models and rule-based systems (Jing and McKeown, 2000), statistical models based on parse trees (Knight and Marcu, 2000), and integer linear programming based methods (Martins and Smith, 2009; Gillick and Favre, 2009; Clarke and Lapata, 2010; Berg-Kirkpatrick et al., 2011). Recent approaches investigated discourse structure (Louis et al., 2010; Hirao et al., 2013; Kikuchi et al., 2014; Wang et al., 2015), graph cuts (Qian and Liu, 2013), and parse trees (Li et al., 2014; Bing et al., 2015). For neural models, Cheng and Lapata (2016) used a second neural net to select words from an extractor's output. Our abstractor does not merely 'compress' the sentences but generatively produce novel words. Moreover, our RL bridges the extractor and the abstractor for end-to-end training.

Reinforcement learning has been used to optimize the non-differential metrics of language generation and to mitigate exposure bias (Ranzato et al., 2015; Bahdanau et al., 2016). Henß et al. (2015) use Q-learning based RL for extractive summarization. Paulus et al. (2017) use RL policy gradient methods for abstractive summarization, utilizing sequence-level metric rewards with curriculum learning (Ranzato et al., 2015) or weighted ML+RL mixed loss (Paulus et al., 2017) for stability and language fluency. We use sentence-level rewards to optimize the extractor while keeping our ML trained abstractor decoder fixed, so as to achieve the best of both worlds.

Training a neural network to use another fixed network has been investigated in machine translation for better decoding (Gu et al., 2017) and real-time translation (Gu et al., 2016b). They used a fixed pretrained *translator* (similar to our abstractor) and applied policy gradient techniques

[7] During this RL training of the extractor, we keep the abstractor parameters fixed. Because the input sentences for the abstractor are extracted by an intermediate stochastic policy of the extractor, it is impossible to find the correct target summary for the abstractor to fit g with ML objective. Though it is possible to optimize the abstractor with RL (Paulus et al., 2017), in our experiments we found that this does not improve the overall ROUGE, most likely because this RL optimizes at a sentence-level and can add across-sentence redundancy. We achieve SotA results without this abstractor-level RL.

to train another task-specific network. In question answering (QA), Choi et al. (2017) extract sentences and then generate the answer from their vector representations. We instead use the raw selected sentences to employ the copy mechanism; also, we produce multi-sentence summaries instead of just one answer. Another recent work attempted a new coarse-to-fine attention approach on summarization (Ling and Rush, 2017) and found desired sharp focus properties for scaling to larger inputs (though without metric improvements). Lastly, our extractor is inspired by a recent attempt on solving the traveling salesman problem using pointer networks and RL (Bello et al., 2017).

Finally, there are some loosely-related recent works: Zhou et al. (2017) proposed *selective gate* to improve the attention in abstractive summarization. Tan et al. (2017a) uses an *extract-then-synthesis* approach on QA, where an extraction model predicts the important spans in the passage and then another synthesis model generates the final answer. Swayamdipta et al. (2017) attempted cascaded non-recurrent small networks on extractive QA, resulting a scalable, parallelizable model. Fan et al. (2017) added controlling parameters to allow summarization to user preferences of length, style, etc. However, none of these used RL to bridge non-differentiability of neural models.

5 Experimental Setup

We use the CNN/Daily Mail dataset first proposed by Hermann et al. (2015) and then later modified for summarization by Nallapati et al. (2017). Because there are two versions of the dataset, original text and entity anonymized, we show results on both versions of the dataset for a fair comparison to prior works. The experiment runs training and evaluation for each version separately. Despite the fact that the 2 versions have been considered separately by the summarization community as 2 different datasets, we use same hyper-parameter values for both dataset versions to show the generalization of our model. We also show improvements on the DUC-2002 dataset in a *test-only* setup. For more details, please refer to the supplementary.

5.1 Evaluation Metrics

For all the datasets, we evaluate standard ROUGE-1, ROUGE-2, and ROUGE-L (Lin, 2004) on full-length F_1 (with stemming) following previous works (Nallapati et al., 2017; See et al., 2017; Paulus et al., 2017). Following See et al. (2017), we also evaluate on METEOR (Denkowski and Lavie, 2014) for a more thorough analysis.

5.2 Modular Extractive vs. Abstractive

Our hybrid extractive-abstractive approach is capable of both extractive and abstractive (i.e., rewriting every sentence) summarization. The extractor alone performs extractive summarization. To investigate the effect of the recurrent extractor (rnn-ext), we implement a feed-forward extractive baseline ff-ext(details in supp.). It is also possible to apply RL to extractor without using the abstractor (rnn-ext + RL).[8] Benefiting from the high modularity of our model, we can make our summarization system abstractive by simply applying the abstractor on the extracted sentences. Our abstractor rewrites each sentence and generates novel words from a large vocabulary, and hence every word in our overall summary is generated from scratch; making our full model categorized into the abstractive paradigm.[9] We run experiments on separately trained extractor/abstractor (ff-ext + abs, rnn-ext + abs) and the reinforced full model (rnn-ext + abs + RL) as well as the final reranking version (rnn-ext + abs + RL + rerank).

6 Results

For easier comparison, we show separate tables for the original-text vs. anonymized versions (with corresponding previous works in each table) – Table 1 and Table 2, respectively. Overall, our model achieves strong improvements and the new state-of-the-art on both extractive and abstractive settings for both versions of the CNN/DM dataset (with some comparable results on the anonymized version). Moreover, Table 3 shows the generalization of our abstractive system to an out-of-domain test-only setup (DUC-2002), where our model achieves better scores than See et al. (2017).

6.1 Extractive Summarization

In the extractive paradigm, we compare our model with the extractive model from Nallapati et al. (2017) and a strong lead-3 baseline. For producing our summary, we simply concatenate the extracted sentences from the extractors. From Table 2 and

[8] In this case the abstractor function $g(d) = d$.

[9] Note that the CNN/DM dataset does *not* include any extraction label which could have benefited our abstractive full model over previous abstractive models.

Models	ROUGE-1	ROUGE-2	ROUGE-L	METEOR
Extractive Results				
lead-3 (See et al., 2017)	40.34	17.70	36.57	22.21
ff-ext	40.63	18.35	36.82	**22.91**
rnn-ext	40.17	18.11	36.41	22.81
rnn-ext + RL	**41.47**	**18.72**	**37.76**	22.35
Abstractive Results				
See et al. (2017) (w/o coverage)	36.44	15.66	33.42	16.65
See et al. (2017)	39.53	17.28	36.38	18.72
Fan et al. (2017) (controlled)	39.75	17.29	36.54	-
ff-ext + abs	39.30	17.02	36.93	20.05
rnn-ext + abs	38.38	16.12	36.04	19.39
rnn-ext + abs + RL	40.04	17.61	37.59	**21.00**
rnn-ext + abs + RL + rerank	**40.88**	**17.80**	**38.54**	20.38

Table 1: Results on the original, non-anonymized CNN/Daily Mail dataset. Adding RL gives statistically significant improvements for all metrics over non-RL rnn-ext models (and over the state-of-the-art See et al. (2017)) in both extractive and abstractive settings with $p < 0.01$. Adding the extra reranking stage yields statistically significant better results in terms of all ROUGE metrics with $p < 0.01$.

Models	R-1	R-2	R-L
Extractive Results			
lead-3 (Nallapati et al., 2017)	39.20	15.70	35.5
Nallapati et al. (2017)	39.60	16.20	35.30
ff-ext	39.51	**16.85**	35.80
rnn-ext	38.97	16.65	35.32
rnn-ext + RL	**40.13**	16.58	**36.47**
Abstractive Results			
Nallapati et al. (2016)	35.46	13.30	32.65
Fan et al. (2017) (controlled)	38.68	15.40	35.47
Paulus et al. (2017) (ML)	38.30	14.81	35.49
Paulus et al. (2017) (RL+ML)	**39.87**	15.82	36.90
ff-ext + abs	38.73	15.70	36.33
rnn-ext + abs	37.58	14.68	35.24
rnn-ext + abs + RL	38.80	15.66	36.37
rnn-ext + abs + RL + rerank	39.66	**15.85**	**37.34**

Table 2: ROUGE for anonymized CNN/DM.

Table 1, we can see that our feed-forward extractor out-performs the lead-3 baseline, empirically showing that our hierarchical sentence encoding model is capable of extracting salient sentences.[10] The reinforced extractor performs the best, because of the ability to get the summary-level reward and the reduced train-test mismatch of feeding the previous extraction decision. The improvement over lead-3 is consistent across both tables. It also outperforms the previous best neural extractive model (Nallapati et al., 2017).

6.2 Abstractive Summarization

After applying the abstractor, the ff-ext based model still out-performs the rnn-ext model. Both combined models exceeds the pointer-generator model (See et al., 2017) without coverage by a large margin for all metrics, showing the effectiveness of our 2-step hierarchical approach: our method naturally avoids repetition by extracting multiple sentences with different keypoints.

Models	R-1	R-2	R-L
See et al. (2017)	37.22	15.78	33.90
rnn-ext + abs + RL	39.46	17.34	36.72

Table 3: Generalization to DUC-2002.

Moreover, after applying reinforcement learning, our model performs better than the best model of See et al. (2017) and the best ML trained model of Paulus et al. (2017). Our reinforced model outperforms the ML trained rnn-ext + abs baseline with statistical significance of $p < 0.01$ on all metrics for both version of the dataset, indicating the effectiveness of the RL training. Also, rnn-ext + abs + RL is statistically significant better than See et al. (2017) for all metrics with $p < 0.01$.[11] In the supplementary, we show the learning curve of our RL training, where the average reward goes up quickly after the extractor learned the End-of-Extract action and then stabilizes. For all the above models, we use standard greedy decoding and find that it performs well.[12]

6.2.1 Reranking and Redundancy

Although the extract-then-abstract approach inherently will not generate repeating sentences like

[10] We suspect ff-ext outperforms rnn-ext because feed-forward model is easier to optimize in nature and the evaluations (n-gram matching) do not consider sentence ordering.

[11] We calculate statistical significance based on the bootstrap test (Noreen, 1989; Efron and Tibshirani, 1994) with 100K samples. Output of Paulus et al. (2017) is not available so we couldn't test for statistical significance there.

[12] In our MDP formulation, we cannot apply RL on ff-ext due to its historyless nature. It is, however, possible to apply RL naively. We did not do so because we do not want to rely on the ordering assumption (Eqn. 5 in the supp.), though the current metrics are agnostic to sentence ordering. Our rnn-ext therefore is more generalizable in the sense of less assumption and will be easier to adapt to arbitrary metrics.

	Speed	
Models	total time (hr)	words / sec
(See et al., 2017)	12.9	14.8
rnn-ext + abs + RL	0.68	361.3
rnn-ext + abs + RL + rerank	2.00 (1.46 +0.54)	109.8

Table 4: Speed comparison with See et al. (2017).

other neural-decoders do, there might still be across-sentence redundancy because the abstractor is not aware of other extracted sentences when decoding one. Hence, we incorporate an optional reranking strategy described in Sec. 3.3. The improved ROUGE scores indicate that this successfully removes some remaining redundancies and hence produces more concise summaries. Our best abstractive model (rnn-ext + abs + RL + rerank) is clearly superior than the one of See et al. (2017). We are comparable on R-1 and R-2 but a 0.4 point improvement on R-L w.r.t. Paulus et al. (2017).[13]

Several previous works have pointed out that extractive baselines are very difficult to beat (in terms of ROUGE) by an abstractive system (See et al., 2017; Nallapati et al., 2017). Note that our best model is the first abstractive model to report better ROUGE scores than the lead-3 baseline on the original-text CNN/DM dataset. Our extractive experiment serves as a complementary analysis on the effect of RL with extractive systems.

6.3 Speed Comparison

Our two-stage extractive-abstractive hybrid model is not only the SotA on summary quality metrics, but more importantly also gives a significant speed-up in both train and test time over a strong neural abstractive system (See et al., 2017).[14]

Our full model is composed of a extremely fast extractor and a parallelizable abstractor, where the computation bottleneck is on the abstractor, which has to generate summaries with a large vocabulary from scratch.[15] The main advantage of our abstractor at decoding time is that we can first compute all the extracted sentences for the document, and then abstract every sentence concurrently (*in parallel*) to generate the overall summary. In Table 4, we show the substantial test-time speed-up of our model compared to See et al. (2017).[16] We calculate the total decoding time for producing all summaries for the test set.[17] Due to the fact that the main test-time speed bottleneck of RNN language generation model is that the model is constrained to generate one word at a time, the total decoding time is dependent on the number of total words generated; we hence also report the decoded words per second for a fair comparison. Our model without reranking is extremely fast. From Table 4 we can see that we achieve a speed up of 18x in time and 24x in word generation rate. Even after adding the (optional) reranker, we still maintain a 6-7x speed-up (and hence a user can choose to use the reranking component depending on their downstream application's speed requirements).

6.4 Qualitative Analysis

Overall we observe that extractive methods consistently get higher ROUGE F_1 scores over abstractive models. However, abstractive models generate shorter sentences that are more concise. We show examples on how our best model selects sentences and then rewrites them. In the supplementary Table 2, we can see that the abstractor does compress the sentence to be more concise while keeping correct facts. Also, the reranker helps removing redundant information in the second and third summary sentence. We observe that when rewriting longer text, the abstractor would have many facts to choose and this is when the reranker helped avoid redundancy across sentences. We do not observe any fluency issue (Paulus et al., 2017). In the supplementary we empirically show that our models' summaries achieve better/comparable perplexity w.r.t. the ground truth.

7 Conclusion

We proposed a novel sentence-level RL model for abstractive summarization, which makes the model aware of the word-sentence hierarchy. Our model achieved the new state-of-the-art on both CNN/DM versions as well a better generalization on test-only DUC-2002, along with a significant speed-up in training and decoding.

[13] We do not list the scores of their pure RL model because they discussed its bad readability. Moreover, we also report new results from the recent preprint of Fan et al. (2017)–our model achieves better scores over this.

[14] The only publicly available code with a pretrained model for neural summarization which we can test the speed.

[15] The time needed for extractor is negligible w.r.t. the abstractor because it does not require large matrix multiplication like generative model does for every word. Moreover, with convolutional encoder (very efficient with GPU) at word-level made parallelizable by the hierarchical rnn-ext, our model is scalable for very long documents.

[16] For details of training speed-up, please see the supp.

[17] We time the model of See et al. (2017) using beam size of 4 (used for their best-reported scores). Without beam-search, it gets significantly worse ROUGE of 36.62, 15.12, 34.08, so we don't compare speed-ups w.r.t. that version.

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