Abstractive Summarization for Low Resource Data using Domain Transfer and Data Synthesis

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Abstract

Training abstractive summarization models typically requires large amounts of data, which can be a limitation for many domains. In this paper we explore using domain transfer and data synthesis to improve the performance of recent abstractive summarization methods when applied to small corpora of student reflections. First, we explored whether tuning state of the art model trained on newspaper data could boost performance on student reflection data. Evaluations demonstrated that summaries produced by the tuned model achieved higher ROUGE scores compared to model trained on just student reflection data or just newspaper data. The tuned model also achieved higher scores compared to extractive summarization baselines, and additionally was judged to produce more coherent and readable summaries in human evaluations. Second, we explored whether synthesizing summaries of student data could additionally boost performance. We proposed a template-based model to synthesize new data, which when incorporated into training further increased ROUGE scores. Finally, we showed that combining data synthesis with domain transfer achieved higher ROUGE scores compared to only using one of the two approaches.

Introduction

Recently, with the emergence of neural seq2seq models, abstractive summarization methods have seen great performance strides (See, Liu, and Manning 2017; Gehrmann, Deng, and Rush 2018; Paulus, Xiong, and Socher 2018). However, complex neural summarization models with thousands of parameters usually require a large amount of training data. In fact, much of the neural summarization work has been trained and tested in news domains where numerous large datasets exist. For example, the CNN/DailyMail (CNN/DM) (Hermann et al. 2015; Nallapati et al. 2016) and New York Times (NYT) datasets are in the magnitude of 300k and 700k documents, respectively. In contrast, in other domains such as student reflections, summarization datasets are only in the magnitude of tens or hundreds of documents (e.g., (Luo and Litman 2015)). We hypothesize that training

complex neural abstractive summarization models in such domains will not yield good performing models, and we will indeed later show that this is the case for student reflections.

To improve performance in low resource domains, we explore three directions. First, we explore domain transfer for abstractive summarization. While domain transfer is not new, compared to prior summarization studies (Hua and Wang 2017; Keneshloo, Ramakrishnan, and Reddy 2019), our training (news) and tuning (student reflection) domains are quite dissimilar, and the in-domain data is small. Second, we propose a template-based synthesis method to create synthesized summaries, then explore the effect of enriching training data for abstractive summarization using the proposed model compared to a synthesis baseline. Lastly, we combine both directions. Evaluations of neural abstractive summarization method across four student reflection corpora show the utility of all three methods.

Related Work

Abstractive Summarization. Abstractive summarization aims to generate coherent summaries with high readability, and has seen increasing interest and improved performance due to the emergence of seq2seq models (Sutskever, Vinyals, and Le 2014) and attention mechanisms (Bahdanau, Cho, and Bengio 2014). For example, (See, Liu, and Manning 2017), (Paulus, Xiong, and Socher 2018), and (Gehrmann, Deng, and Rush 2018) in addition to using encoder-decoder model with attention, they used pointer networks to solve the out of vocabulary issue, while (See, Liu, and Manning 2017) used coverage mechanism to solve the problem of word repetition. In addition, (Paulus, Xiong, and Socher 2018) and (Chen and Bansal 2018) used reinforcement learning in an end-to-end setting.

To our knowledge, training such neural abstractive summarization models in low resource domains using domain transfer has not been thoroughly explored on domains different than news. For example, (Nallapati et al. 2016) reported the results of training on CNN/DM data while evaluating on DUC data without any tuning. Note that these

two datasets are both in the news domain, and both consist of well written, structured documents. The domain transfer experiments of (Gehrmann, Deng, and Rush 2018) similarly used two different news summarization datasets (CNN/DM and NYT). Our work differs in several ways from these two prior domain transfer efforts. First, our experiments involve two entirely different domains: news and student reflections. Unlike news, student reflection documents lack global structure, are repetitive, and contain many sentence fragments and grammatical mistakes. Second, the prior approaches either trained a part of the model using NYT data while retaining the other part of the model trained only on CNN/DM data (Gehrmann, Deng, and Rush 2018), or didn't perform any tuning at all (Nallapati et al. 2016). In contrast, we do the training in two consecutive phases, pretraining and fine tuning. Finally, (Gehrmann, Deng, and Rush 2018) reported that while training with domain transfer outperformed training only on out-of-domain data, it was not able to beat training only on in-domain data. This is likely because their in and out-of-domain data sizes are comparable, unlike in our case of scarce in-domain data.

In a different approach to abstractive summarization, (Cao et al. 2018) developed a soft template based neural method consisting of an end-to-end deep model for template retrieval, reranking and summary rewriting. While we also develop a template based model, our work differs in both model structure and purpose.

Data Synthesis. Data synthesis for text summarization is underexplored, with most prior work focusing on machine translation, and text normalization. (Zhang, Zhao, and LeCun 2015) proposed doing data augmentation through word replacement, using WordNet (Miller 1998) and vector space similarity, respectively. We will use a WordNet replacement method as a baseline synthesis method in the experiments described below. In contrast, (Fadaee, Bisazza, and Monz 2017) synthesized/augmented data through back-translation and word replacement using language models. (Parida and Motlicek 2019) is another recent work that was done in parallel and is very close to ours. However, in addition to the difference in both our and their model, we think it might be infeasible to back generate student reflections from a human summary, especially an abstractive one.

Reflection Summarization Dataset

Student reflections are comments provided by students in response to a set of instructor prompts. The prompts are directed towards gathering students' feedback on course material. Student reflections are collected directly following each of a set of classroom lectures over a semester. In this paper, the set of reflections for each prompt in each lecture is considered a *student reflection document*. The objective of our work is to provide a comprehensive and meaningful abstractive summary of each student reflection document. Our dataset consists of documents and summaries from four course instantiations: ENGR[1] (Introduction to Materials Sci-

Prompt
Point of Interest (POI): Describe what you found most interesting in today's class.
Student Reflection Document
●Learning about bags was very interesting.   ●Bags as a data type and how flexible they are.   etc...
Reference Summary
Students were interested in ADT Bag, and also its array implementation. Many recognized that it should be resizable, and that the underlying array organization should support that. Others saw that order does not matter in bags. Some thought methods that the bag provides were interesting.

Table 1: Sample data from the CS course.

	CS	ENGR	Stat2015	Stat2016
Lectures	23	26	22	23
Prompts	2	2	2	2
Reflections	26	66	41	44
Summaries	3	1	2	2
Documents	138	52	88	92

Table 2: Dataset summary (n=370 documents).

ence and Engineering), Stat2015 and Stat2016[2] (Statistics for Industrial Engineers, taught in 2015 and 2016, respectively), and CS[3] (Data Structures in Computer Science). All reflections were collected in response to two pedagogically-motivated prompts (Menekse et al. 2011): "Point of Interest (POI): Describe what you found most interesting in today's class" and "Muddiest Point (MP): Describe what was confusing or needed more detail."

For each reflection document, at least one human (either a TA or domain expert) created summaries. Table 1 shows example reference summary produced by one annotator for the CS course. Table 2 summarizes the dataset in terms of number of lectures, number of prompts per lecture, average number of reflections per prompt, and number of abstractive reference summaries for each set of reflections.

Explored Approaches for Limited Resources

To overcome the size issue of the student reflection dataset, we first explore the effect of incorporating **domain transfer** into a recent abstractive summarization model: pointer networks with coverage mechanism (PG-net)(See, Liu, and Manning 2017)[4]. To experiment with domain transfer, the model was pretrained using the CNN/DM dataset, then fine tuned using the student reflection dataset (see the Experiments section). A second approach we ex-

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plore to overcome the lack of reflection data is **data synthesis**. We first propose a template model for synthesizing new data, then investigate the performance impact of using this data when training the summarization model. The proposed model makes use of the nature of datasets such as ours, where the reference summaries tend to be close in structure: humans try to find the major points that students raise, then present the points in a way that marks their relative importance (recall the CS example in Table 1). Our third explored approach is to **combine domain transfer with data synthesis**.

Proposed Template-Based Synthesis Model

Our motivation for using templates for data synthesis is that seq2seq synthesis models (as discussed in related work) tend to generate irrelevant and repeated words (Koehn and Knowles 2017), while templates can produce more coherent and concise output. Also, extracting templates can be done either manually or automatically typically by training a few parameters or even doing no training, then external information in the form of keywords or snippets can be populated into the templates with the help of more sophisticated models. Accordingly, using templates can be very tempting for domains with limited resources such as ours.

Model Structure. The model consists of 4 modules:
1. Template extraction: To convert human summaries into templates, we remove keywords in the summary to leave only non-keywords. We use Rapid Automatic Keyword Extraction (RAKE) (Rose et al. 2010) to identify keywords.
2. Template clustering: Upon converting human summaries into templates, we cluster them into N clusters with the goal of using any template from the same cluster interchangeably. A template is first converted into embeddings using a pre-trained BERT model[5] (Devlin et al. 2018), where template embedding is constructed by average pooling word embeddings. Templates are then clustered using k-medoid.
3. Summary rewriting: An encoder-attention-decoder with pointer network is trained to perform the rewriting task. The model is trained to inject keywords into a template and perform rewriting into a coherent paragraph. The produced rewrites are considered as candidate summaries.
4. Summary selection: After producing candidate summaries, we need to pick the best ones. We argue that the best candidates are those that are coherent and also convey the same meaning as the original human summary. We thus use a hybrid metric to score candidates, where the metric is a weighted sum of two scores and is calculated using Equations 1, 2, and 3. Eq.1 measures coherency using a language model (LM), Eq.2 measures how close a candidate is to a human summary using ROUGE scores, while Eq.3 picks the highest scored N candidates as the final synthetic set.

$$LM_S = (\sum_{w \in CS} log(P(w)))/(len(CS)) \qquad (1)$$

$$R_S = Avg(\sum_{i \in [1,2,l]} R_i(CS, HS)) \qquad (2)$$

$$Score = (\alpha LM_S + \beta R_S)/(\alpha + \beta) \qquad (3)$$

CS and HS are a candidate and human summary. $P(w)$ is the probability of word w using a language model. α, β are weighting parameters. In this work we use $\alpha = \beta = 1$ for all experiments. $R_i(CS, HS)$ is ROUGE-i score between CS and HS for i=1, 2, and l.

Model Training. Before using the synthesis model, some of the constructing modules (rewriting module, scoring LM) need training. To train the rewriting model, we use another dataset consisting of a set of samples, where each sample can be a text snippet (sentence, paragraph, etc.). For each sample, keywords are extracted using RAKE, then removed. The keywords plus the sample with no keywords are then passed to the rewriting model. The training objective of this model is to reconstruct the original sample, which can be seen as trying to inject extracted keywords back into a template.

Model Usage. To use the synthesis model to generate new samples, the set of human summaries are fed to the model, passing the sub-modules in the following order:
1. Human summaries first pass through the template extraction module, converting each summary s_i into template t_i and the corresponding keywords kw_i.
2. Templates are then passed to the clustering module, producing a set of clusters. Each cluster C contains a number of similar templates.
3. For each template t_i and corresponding keywords kw_i from step 1, find the cluster C_i that contains the template t_i, then pass the set of templates within that clusters $\{t_j\} \forall j$, if $t_j \in C_i$ alongside the keywords kw_i to the summary rewriting module. This will produce a set of candidate summaries.
4. The summary selection module scores and selects the highest N candidates as the synthetic summaries.

Experiments

Our experimental designs address the following hypotheses:
Hypothesis 1 (H1) : Training complex abstractive models with limited in-domain or large quantities of out-of-domain data won't be enough to outperform extractive baselines.
Hypothesis 2 (H2) : Domain transfer helps abstractive models even if in-domain and out-of-domain data are very different and the amount of in-domain data is very small.
Hypothesis 3 (H3) : Enriching abstractive training data with synthetic data helps overcome in-domain data scarcity.
Hypothesis 4 (H4) : The proposed template-based synthesis model outperforms a simple word replacement model.
Hypothesis 5 (H5) : Combining domain transfer with data synthesis outperforms using each approach on its own.
Hypothesis 6 (H6) : The synthesis model can be extended to perform reflection summarization directly.

Extractive Baselines (for testing H1). While (See, Liu, and Manning 2017) used Lead-3 as an extractive baseline, in our data sentence order doesn't matter as reflections are independent. We thus use a similar in concept baseline: randomly select N reflections. Since the baseline is random we report the average result of 100 runs. Following (Luo and Litman 2015), we compare results to

Model	Summary
CNN/DM	Internal vs. external version of iteration iterarors i was a bit preoccupied today but seeing merge sort. How typically iterating through a linked list can be very inefficient the implementation of iterators iterators and their effectiveness how iterators can be used.
Student Reflections	Most students found the data of data along with its mean and effectiveness interesting, as well as topics related to sse, their, and different. Students also found different a good topic.
Tuned	Most of students were interested in iterators, the concept of iterators, and quick sort and merge sort. They also found analyzing linked lists in regards to runtime to be interesting.

Human Reference
Most of the students found iterators and linked lists as interesting. Some of them liked merge sort and quick sort. A few of them liked internal vs external iteration and analyzing runtimes of linked lists.

Extracted Keywords
iterators, linked lists, merge sort, quick sort, external iteration, analyzing runtimes

Synthesized Sample
In this lecture students were mainly interested by iterators and linked lists and merge sort . they also liked quick sort, external iteration , and analyzing runtimes.

Table 3: Summaries generated by the three variants of PG-net for the same CS reflection document, and synthetic sample generated by the proposed template model.

MEAD (Radev et al. 2004) and to (Luo and Litman 2015)'s extractive phrase-based model. Since these models extracted 5 phrases as extractive summary, we use N=5 for our three extractive baselines. Additionally we compare to running only the extractive part of Fast-RL.

Domain Transfer (for testing H2, H5). To observe the impact of using out-of-domain (news) data for pretraining to compensate for low resource in-domain (reflection) data, we train 3 variants of PG-net: model training on CNN/DM; model training on reflections; and model training on CNN/DM then tuning using reflections. Table 3 shows example summaries generated by the three variants of PG-net for a CS document. For all experiments where reflections are used for training/tuning, we train using a leave one course out approach (i.e, in each fold, three courses are used for training and the remaining course for testing). If the experiment involves tuning a combined dictionary of CNN/DM and reflections is used to avoid domain mismatch. To tune model parameters, the best number of steps for training, the learning rate, etc., a randomly selected 50% of the training data is used for validation. We choose the parameters that maximize ROUGE scores over this validation set.

To implement PG-net we use OpenNMT (Klein et al. 2017) with the original set of parameters. The out-of-domain model is trained for 100k steps using the CNN/DM dataset. Following base model training, we tune the model by training it using student reflections. The tuning is done by lowering the LR from 0.15 to 0.1 and training the model for additional 500 steps. The in-domain model is trained only using reflections. We use the same model architecture as above and train the model for 20k steps using adagrad and LR of 0.15.

Synthesis Baseline (for testing H3, H4). Following (Zhang, Zhao, and LeCun 2015), we developed a data synthesis baseline using word replacement via WordNet. The baseline iterates over all words in a summary. If word X has N synonyms in WordNet, the model creates N new versions of the summary and corresponding reflections by replacing the word X with each of the N synonyms.

Template Synthesis Model (for testing H4, H5). To synthesize summaries, we use the same leave one course out approach. For each course, we use the data from the other three courses to train the rewriting module and tune the scoring language model. We can also use the summaries from CNN/DM data as additional samples to further train the rewriting module. We then start synthesizing data using that training data as input. First templates are constructed. The templates are then clustered into 8 clusters. We decided to use 8 to avoid clustering templates from POI with MP, as the templates from both prompts would contain very different supporting words. We also wanted to avoid a high level of dissimilarity within each cluster, and allow some diversity. Following the clustering, the rewriting model produces candidate summaries for each human summary. The rewriting model is another PG-net with the same exact parameters. After producing the candidate summaries, a language model is used to score them. The language model is a single layer LSTM language model trained on 36K sentences from Wikipedia and fine tuned using student reflections. In this work we decided to pick only the highest 3 scored candidate summaries as synthetic data, to avoid adding ill-formed summaries to the training data. Since we are adding N synthetic summaries for each set of reflections, that means we are essentially duplicating the size of our original reflection training data by N, which is 3 in our case.[6] Table 3 shows a human summary, the keywords extracted, then the output of injecting keywords in a different template using rewriting.

Template-based Summarization (for testing H6). While the proposed template-based model was intended for data synthesis, with minor modification it can be adapted for summarization itself. Because the modifications introduce few parameters, the model is suitable for small datasets. Recall that for data synthesis, the input to the template method is a summary. Since for summarization the input instead is a set of reflections, we perform keyword extraction over the set of reflections. We then add an extra logistic regression classifier that uses the set of reflections as input and predicts a cluster of templates constructed from other courses. Using the keywords and the predicted cluster of templates, we use the same rewriting model to produce candidate summaries. The last step in the pipeline is scoring. In data synthesis, a reference summary is used for scoring; however, in summarization we don't have such a reference. To score

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[6] We plan to explore the effect of varying N in the future.

the candidate summaries, the model only uses the language model and produces the candidate with the highest score.

Results

ROUGE Evaluation Results. Table 4 presents summarization performance results for the 4 extractive baselines, for the original and proposed variants of PG-net, and finally for template-summarization. Following (See, Liu, and Manning 2017), performance is evaluated using ROUGE (1, 2, and L) (Lin 2004) on F1. The motivation for using domain transfer and data synthesis is our hypothesis (**H1**). Table 4 supports this hypothesis. All ROUGE scores for PG-net that outperform all extractive baselines (in italics) involve tuning and/or use of synthesised data, except for one R-1 (row 18).

As for our second hypothesis (**H2**), table 4 shows that it is a valid one. For PG-net, comparing the CNN/DM out-of-domain and Student Reflection in-domain results in rows (5 and 6) and (17 and 18) with their corresponding tuned results in rows 9 and 21, we see that fine tuning improves R-1, R-2, and R-L for all courses (rows 5, 6, 9 and 17, 18, 21). Qualitatively, the examples presented in Table 3 clearly show that tuning yields a more coherent and relevant summary. Over all courses, the tuned version of PG-net consistently outperforms the best baseline result for each metric (rows 9 vs. 1, 2, 3, 4 and 21 vs. 13, 14, 15, 16) except for R-2 in Stat2016.

To validate our next set of hypothesises (**H3, H4. H5**), we use the synthesized data in two settings: either using it for training (rows 7, 8 and 19, 20) or tuning (rows 10, 11 and 22, 23). Table 4 supports **H4** by showing that the proposed synthesis model outperforms the WordNet baseline in training (rows 7, 8 and 19, 20) except Stat2016, and tuning (10, 11 and 22, 23) over all courses. It also shows that while adding synthetic data from the baseline is not always helpful, adding synthetic data from the template model helps to improve both the training and the tuning process. In both CS and ENGR courses, tuning with synthetic data enhances all ROUGE scores compared to tuning with only the original data. (rows 9 and 11). As for Stat2015, R-1 and R-L improved, while R-2 decreased. For Stat2016, R-2 and R-L improved, and R-1 decreased (rows 21 and 23). Training with both student reflection data and synthetic data compared to training with only student reflection data yields similar improvements, supporting **H3** (rows 6, 8 and 18, 20). While the increase in ROUGE scores is small, our results show that enriching training data with synthetic data can benefit both the training and tuning of other models. In general, the best results are obtained when using data synthesis for both training and tuning (rows 11 and 23), supporting **H5**.

Finally, while the goal of our template model was to synthesize data, using it for summarization is surprisingly competitive, supporting **H6**. We believe that training the model with little data is doable due to the small number of parameters (logistic regression classifier only). While rows 12 and 24 are never the best results, they are close to the best involving tuning. This encourages us to enhance our template model and explore templates not so tailored to our data.

Human Evaluation Results. While automated evaluation metrics like ROUGE measure lexical similarity between machine and human summaries, humans can better measure how coherent and readable a summary is. Our evaluation study investigates whether tuning the PG-net model increases summary coherence, by asking evaluators to select which of three summaries for the same document they like most: the PG-net model trained on CNN/DM; the model trained on student reflections; and finally the model trained on CNN/DM and tuned on student reflections. 20 evaluators were recruited from our institution and asked to each perform 20 annotations. Summaries are presented to evaluators in random order. Evaluators are then asked to select the summary they feel to be most readable and coherent. Unlike ROUGE, which measures the coverage of a generated summary relative to a reference summary, our evaluators don't read the reflections or reference summary. They choose the summary that is most coherent and readable, regardless of the source of the summary. For both courses, the majority of selected summaries were produced by the tuned model (49% for CS and 41% for Stat2015), compared to (31% for CS and 30.9% for Stat2015) for CNN/DM model, and (19.7% for CS and 28.5% for Stat2015) for student reflections model. These results again suggest that domain transfer can remedy the size of in-domain data and improve performance.

Conclusions and Future Work

We explored improving the performance of neural abstractive summarizers when applied to the low resource domain of student reflections using three approaches: domain transfer, data synthesis and the combination of both. For domain transfer, state of the art abstractive summarization model was pretrained using out-of-domain data (CNN/DM), then tuned using in-domain data (student reflections). The process of tuning improved ROUGE scores on the student reflection data, and at the same time produced more readable summaries. To incorporate synthetic data, we proposed a new template based synthesis model to synthesize new summaries. We showed that enriching the training data with this synthesized data can further increase the benefits of using domain transfer / tuning to increase ROUGE scores. We additionally showed that the proposed synthesis model outperformed a word replacement synthesis baseline.

Future plans include trying domain adaptation, enhancing the synthesising process by using other models, further exploring template-based methods, and extending the analysis of the synthesis model to cover other types of data like reviews and opinions.

Acknowledgments

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Summarization Model		R-1	R-2	R-L	R-1	R-2	R-L	Row
		CS			ENGR			
Extractive Baselines	(Luo and Litman 2015)	27.65	6.66	22.76	<u>30.99</u>	<u>8.97</u>	<u>25.38</u>	1
	Mead 5	<u>30.59</u>	<u>8.26</u>	<u>23.78</u>	29.35	7.91	23.12	2
	Random Select 5	26.74	5.89	20.55	26.14	5.35	20.57	3
	Fast-RL (Extractive)	28.95	6.62	22.16	26.6	5.09	21.06	4
PG-net	CNN/DM	29.83	7.10	18.28	29.30	6.95	17.63	5
	Student Reflection	25.90	4.62	17.49	26.14	6.05	20.94	6
	Student Reflection + WordNet Synthetic	27.15	3.13	17.8	28.11	6.11	21.29	7
	Student Reflection + Template Synthetic	26.93	3.49	19.38	29.54	6.96	21.30	8
	Tuned	*37.31*	*10.20*	*24.16*	*38.47*	*13.88*	*27.79*	9
	Tuned + WordNet Synthetic	34.13	7.13	21.96	32.61	7.51	21.72	10
	Tuned + Template Synthetic	***<u>37.88</u>***	***<u>11.01</u>***	***<u>25.30</u>***	***<u>38.98</u>***	***<u>13.97</u>***	***<u>28.65</u>***	11
Summarizing with Template Model		*34.8*	*9.3*	*23.4*	*36.5*	*11.2*	*24.1*	12
Summarization Model		Stat2015			Stat2016			
Extractive Baselines	(Luo and Litman 2015)	<u>28.84</u>	<u>10.15</u>	<u>25.05</u>	<u>32.96</u>	***<u>12.44</u>***	<u>27.90</u>	13
	Mead 5	26.06	8.84	21.28	32.31	12.30	26.27	14
	Random Select 5	23.50	5.88	19.46	23.77	7.63	20.11	15
	Fast-RL (Extractive)	27.49	7.73	22.05	24.59	8.16	20.66	16
PG-net	CNN/DM	27.22	7.62	17.80	30.99	10.01	20.29	17
	Student Reflection	29.29	5.66	20.31	32.10	5.92	22.28	18
	Student Reflection + WordNet Synthetic	26.11	5.26	20.41	31.92	6.14	22.36	19
	Student Reflection + Template Synthetic	29.65	5.42	20.54	32.43	5.96	21.53	20
	Tuned	*38.78*	***<u>12.45</u>***	*26.19*	***<u>41.05</u>***	12.17	28.25	21
	Tuned + WordNet Synthetic	34.65	9.88	24.31	36.58	9.78	24.08	22
	Tuned + Template Synthetic	***<u>39.12</u>***	*12.23*	***<u>26.93</u>***	*40.95*	<u>12.26</u>	***<u>28.51</u>***	23
Summarizing with Template Model		*35.6*	*11.1*	*24.8*	*38.3*	*11.9*	*25.6*	24

Table 4: ROUGE results. *Italics* indicates outperforms baselines. **Boldface** indicates best result over all models. <u>Underlining</u> indicates best result within model group (i.e., Extractive Baselines, PG-net).

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