# **Unsupervised Summarization Re-ranking**

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#### **Abstract**

With the rise of task-specific pre-training objectives, abstractive summarization models like PEGASUS offer appealing zero-shot performance on downstream summarization tasks. However, the performance of such unsupervised models still lags significantly behind their supervised counterparts. Similarly to the supervised setup, we notice a very high variance in quality among summary candidates from these models whereas only one candidate is kept as the summary output. In this paper, we propose to re-rank summary candidates in an unsupervised manner, aiming to close the performance gap between unsupervised and supervised models. proach improves the pre-trained unsupervised PEGASUS by 4.37% to 7.27% relative mean ROUGE across four widely-adopted summarization benchmarks, and achieves relative gains of 7.51% (up to 23.73%) averaged over 30 transfer setups.

# 1 Introduction

Transformer-based encoder-decoder language models have achieved great success in abstractive summarization in the last few years, and produce fluent summaries which can be quite abstractive (Raffel et al., 2019; Lewis et al., 2020; Zhang et al., 2020). These models follow the *pre-train then fine-tune* paradigm: they are first pre-trained with a selfsupervised objective on a large text corpus; then they are fine-tuned on the downstream dataset of interest, using the available supervision, which may be very scarce. Finding a better pre-training objective remains an active research area. Some models like T5 (Raffel et al., 2019) and BART (Lewis et al., 2020) adopt a more general language modeling objective (e.g., masked span generation), while others like PEGASUS (Zhang et al., 2020) or TED (Yang et al., 2020) are pre-trained specifically for the task of summarizing a document. PEGASUS uses salient sentences of the document as a proxy

Generation method	Summary candidate	R-1	R-2	R-L
	First (top beam)	35.47	13.89	31.61
Beam search	Random	34.89	13.46	31.22
Beam search	Minimum	26.64	7.68	23.18
	Maximum (oracle)	42.62	19.76	38.75
	First	34.35	13.02	30.65
Diverse beam search	Random	31.73	11.22	28.4
Diverse beam search	Minimum	21.25	4.45	18.61
	Maximum (oracle)	41.87	19.29	38.22
	First	32.14	11.29	28.66
Nucleus sampling	Random	32.12	11.29	28.64
	Minimum	24.09	6.49	21.19
	Maximum (oracle)	40.19	17.47	36.43

Table 1: **ROUGE results with PEGASUS (unsupervised) on CNN/DM** test set, for three generation methods to produce 20 summary candidates, and four candidate selection strategies.

summary label, while TED leverages the lead bias to get the pseudo-summary target.

Despite the impressive success on supervised abstractive summarization tasks, unsupervised summarization, remains very challenging. The LEAD-3 baseline which simply takes the first three sentences of a document as its summary, remains far ahead of unsupervised approaches on several news summarization datasets (See et al., 2017), especially the popular CNN/DM dataset (Hermann et al., 2015). In fact, it was only improved on by supervised abstractive models not more than five years ago (Narayan et al., 2018). It is expected that a model which has never seen any summarization example would struggle, as summarization is a task that is subjective and complex even for humans (Kryscinski et al., 2019). Since summarization labels are expensive to collect, it is essential to develop models with good zero-shot performance.

Recently, in the supervised setup, second-stage approaches have gathered interest in abstractive summarization research. While the base encoder-decoder model is trained with maximum-likelihood estimation (MLE) to predict each token of the ground-truth summary in an autoregressive manner, second-stage methods work with a global view at the whole sequence level. SimCLS (Liu and Liu,

2021) and SummaReranker (Ravaut et al., 2022a) propose to train another neural model to rank summary candidates generated by decoding methods like beam search (Reddy, 1977) or diverse beam search (Vijayakumar et al., 2016). BRIO (Liu et al., 2022a) bypasses the need for another model, and re-uses the fine-tuned model for another fine-tuning stage in which the model also learns to rank candidates in the correct order. SummaFusion (Ravaut et al., 2022b) encodes each summary candidate separately and decodes into a new, abstractive second-stage summary. Such second-stage methods have improved ROUGE-1 state-of-the-art on CNN/DM by more than 3 points (Liu et al., 2022a).

In this paper, we propose to re-rank summary candidates in the unsupervised setup. Following observations made by second-stage summarization studies (Liu et al., 2021; Ravaut et al., 2022a), we also observe that in the unsupervised setup, there is large variance in performance among summary candidates. In Table 1, the oracle for PEGA-SUS, which is the summary candidate maximizing the ROUGE score with the reference, reaches 42.62 when using beam search with 20 beams on CNN/DM (Hermann et al., 2015). This is in the same range (42-45 ROUGE-1) as the top beam of supervised leading models on this dataset (Lewis et al., 2020; Zhang et al., 2020). This observation implies strong potential motivating our work: with a perfect unsupervised summary re-ranker, one could potentially by-pass supervised fine-tuning.

The main challenge consists in the fact that the re-ranker must also not access any supervision. Our proposed model does not train any neural model, but simply computes features indicative of summary quality to score each summary candidate, some of them also leveraging the source document. We then aggregate these features, and propose several methods to obtain the corresponding coefficients. A final, unique score, weighted average of all features, is used for candidate re-ranking. Our method, named SummScore, is lightweight, fast and easy to use as it is model-free. Since it is purely unsupervised, the re-ranked results can provide more refined self-supervision to the pretrained models, complementing the pre-training with rounds of self-training.

Our contributions in this paper are threefold:

• We propose SummScore, the first system to rerank summarization candidates in an unsupervised setup and in an unsupervised manner.

- We demonstrate the strength of SummScore by consistent performance improvement: +4.37% to +7.27% ROUGE gains over four unsupervised summarization datasets, +7.51% ROUGE gains on average over 30 transfer learning setups.
- Using the re-ranker, we derive an original and effective self-training method which continuously improves the base unsupervised summarization model, reaching a strong 39.49 R-1 on CNN/DM.

#### 2 Related Work

Unsupervised abstractive summarization In unsupervised abstractive summarization, SummAE (Liu et al., 2019a) proposes to auto-encode paragraphs with a sequence-to-sequence model and decode single-sentence summaries from the latent embeddings. SEQ3 (Baziotis et al., 2019) also uses an auto-encoder to compress the input then reconstruct it into a differentiable manner, the encoder output serving as a summary. However, both methods stick to unsupervised sentence summarization. More recent approaches typically rely on large language models being pre-trained, then used in a zero-shot fashion. PEGASUS (Zhang et al., 2020) treats salient sentences as pseudo abstractive targets to build a pre-training objective. TED (Yang et al., 2020) and BART-LB (Zhu et al., 2019) both exploit the lead bias in news articles and take out the first sentences of the document as pseudo summary targets for pre-training. Due to their pretraining objective built for summary generation, these pre-trained models can be directly used for unsupervised summarization. The Summary Loop (Laban et al., 2020) uses reinforcement learning to train a model to fill-in deleted important words from the source document using the summary generated so far, then refines this summary.

Re-ranking in abstractive summarization Second-stage or sequence-level methods are gaining traction recently in *supervised* summarization. Among such methods, re-ranking consists in selecting a better summary candidate out of several of them produced by a base model (which has already been fine-tuned). RefSum (Liu et al., 2021) uses a meta-learning approach to learn how to rank summaries coming from multiple systems. SimCLS (Liu and Liu, 2021) trains a RoBERTa (Liu et al., 2019b) model with a ranking loss to learn how to rank summary candidates generated by a base BART or PEGASUS in their target

metric order. SummaReranker (Ravaut et al., 2022a) also trains a RoBERTa re-ranker, but this time in a multi-label binary classification manner to predict whether each summary candidate maximizes each of the metrics of interest. To avoid using another neural network for re-ranking, BRIO (Liu et al., 2022b) performs a second fine-tuning stage with the re-ranking loss built it in the base summarization system. Each of the four models above improves the SOTA on the CNN/DM benchmark, reaching 47.78 ROUGE-1 for BRIO.

To the best of our knowledge, there is no work on sequence-level unsupervised abstractive summarization. Concurrently to our work, MBRD (Suzgun et al., 2022) proposes to rank generated candidates in several generation tasks using majority voting based on BERTScore (Zhang et al., 2019).

#### 3 Method

# 3.1 Unsupervised Summary Re-ranking

As an unsupervised summarization re-ranking approach, our method assumes access to a zero-shot self-supervised summarization model. We refer to it as the base model  $\mathcal{M}_{base}$ . Given a source document D,  $\mathcal{M}_{base}$  will generate k summary candidates using a generation method to transform model predictions into a natural language summary. A widely used such generation approach is beam search, which maintains k top summary candidates throughout decoding, ranking them with decreasing mean log-probability of the sequence. In the end, practitioners keep the candidate maximizing the log-probability and discard the remaining, whereas we propose to keep  $all\ k$  candidates and re-rank them, following (Ravaut et al., 2022a).

Let  $\mathbb{C}=\{C_1,\ldots,C_k\}$  be the pool of candidates. Our goal in (re-)ranking the candidates is to assign to each of them a score S, such that  $S(C_i)>S(C_j)$  if  $C_i$  is a better candidate than  $C_j$  (for  $1\leq i,j\leq k$ ) according to some summary quality measures. We can then select the candidate maximizing the score as the best output:

$$C_S^* = \underset{C_i \in \mathbb{C}}{\operatorname{arg max}} \left\{ S(C_1), \dots, S(C_k) \right\} \quad (1)$$

Unlike re-ranking in a supervised setup, where one can compute such scores by comparing with the ground truth summary or build models to optimize them (Liu and Liu, 2021; Ravaut et al., 2022a; Liu et al., 2022a), in our unspervised setup, we cannot assume access to the ground truth, which thus excludes scoring the candidate with regards

to it (e.g., using ROUGE). In the following, we describe how we build our unsupervised scoring method (named *SummScore*) following principles assessing the quality of a summary.

## 3.2 Multi-Objective Re-ranking Score

We design our candidate-level SummScore as an aggregation of features, each representing desired properties for a summary. Features either come from the comparison between the summary candidate and the source, or from the candidate itself.

Comparison with the source One evident property of a summary is that it should stick to the source content, and contain as much of the important content as possible. The most straightforward way to measure this consists in using n-gram overlap metrics between the source document and each candidate. We use ROUGE-1 (Lin, 2004), ROUGE-2, and BLEU (Papineni et al., 2002), which form our first set of features:

$$F_{\text{overlap}} = \{\text{R-1}, \text{R-2}, \text{BLEU}\} \tag{2}$$

The above metrics only evaluate n-gram overlap, which can be helpful penalizing summary candidates departing too much from the source, potentially hallucinating. However, they have been shown to not be well suited at evaluating semantic similarity, and might encourage too much copying.

Thus, our next batch of SummScore features consists in model-based metrics explicitly designed to capture semantic similarity between two text items. We explore the use of three metrics: BERTScore (Zhang et al., 2019), BARTScore (Yuan et al., 2021) and BLEURT (Sellam et al., 2020). BERTScore (noted BS) computes token-level cosine similarity between the contextual embeddings of the pretrained BERT (Devlin et al., 2019) of each text item to compare. BARTScore (noted BaS) uses BART (Lewis et al., 2020) token-level log-probabilities from the pre-trained BART to score the generated text. BLEURT (noted BRT) also leverages BERT but extends its pre-training with an additional multitask pre-training on synthetic data. Our next batch of features is:

$$F_{\text{sem}} = \{\text{BS}, \text{BaS}, \text{BRT}\} \tag{3}$$

When each of these metrics is referred to, it is implicit that they are used to compare a summary candidate with the source document (in contrast to the supervised case, comparing with the target).

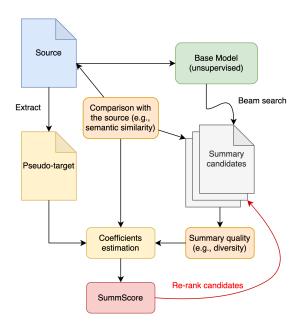


Figure 1: **SummScore (unsupervised) re-ranking** construction. SummScore leverages the source document for semantic similarity comparisons with summary candidates, as well as to extract a pseudo target.

**Summary quality** A good summary should be *diverse*, meaning it should avoid repeated n-grams. We build a summary-level diversity score which measures the proportion of unique n-grams.

$$S_{\text{div}} = \frac{1}{N} \sum_{n=1}^{N} \frac{\text{unique } n\text{-grams}}{\text{total } n\text{-grams}}$$
(4)

We take N=3 in practice.

The summary should not be too short, nor too long. We penalize summaries which deviate a lot from the average summary length on the given dataset. To build a score with increasing values being desirable, we use a smooth inverse of the absolute length difference between the summary candidate and the mean summary length  $\mu_{\rm len}$ .

$$S_{\text{len}} = \frac{1}{\max(1, |\text{length} - \mu_{\text{len}}|)}$$
 (5)

Final Score Our final set of features is:

$$F = F_{\text{overlap}} \cup F_{\text{sem}} \cup \{S_{\text{div}}, S_{\text{len}}\}$$
  
=  $\{F_1, \dots, F_{|F|}\}$  (6)

For data point  $x_i$ , SummScore simply outputs the summary candidate among the set  $\mathbb{C}_i$  maximizing a weighted combination of all features above:

SummScore<sub>$$\theta$$</sub>( $\mathbb{C}_i$ ) =  $\underset{C_i \in \mathbb{C}_i}{\operatorname{arg max}} \sum_{j=1}^{|F|} \theta_j . F_j(\mathbb{C}_i)$  (7)

where we enforce coefficients to be  $\sum\limits_{j=1}^{|F|}\theta_j=1.0$ 

#### 3.3 Coefficients Estimation

SummScore is simply a linear combination of eight features in total. Yet a last crucial question remains: how to estimate the coefficients to assign to each feature? We propose to bootstrap a pseudosummary from the source document. Coefficients are then tuned to maximize the mean of ROUGE-1/2/L between the summary candidate with the highest SummScore (e.g., SummScore output candidate), and the pseudo-target. We compare three approaches to extract pseudo-targets:

- Random-3: As a baseline, we randomly select three sentence from the source document to form a pseudo-target.
- LEAD-3: This consists in the first three sentences of the document. LEAD-3 is a strong baseline for lead-biased news summarization datasets (Hermann et al., 2015; See et al., 2017), and it has even been used as a pseudo-target for summarization pre-training in TED (Yang et al., 2020).
- Salient Sentences: We follow the *gap-sentences generation* idea introduced by PEGASUS pretraining objective (Zhang et al., 2020), and also used by SUPERT (Gao et al., 2020) for unsupervised summarization evaluation. A pseudo-target is constructed with salient sentences, which are defined as the source sentences maximizing the ROUGE with the rest of the document. The top 30% such sentences are extracted to form a pseudo-summary. We experiment with all three standard versions ROUGE-1, ROUGE-2 and ROUGE-L for salient sentences definition, referred to as Salient-R1, Salient-R2 and Salient-RL, respectively.

We emphasize that none of these pseudo-targets definition makes any access to human supervision. Training SummScore amounts to estimating the coefficients  $\theta$  in Eq. (7) using the pseudo-targets:

$$\hat{\theta} = \underset{\theta}{\operatorname{arg\,max}} \sum_{i} \mathcal{R}(\tilde{y_i}, \operatorname{SummScore}_{\theta}(\mathbb{C}_i))$$
 (8)

where  $\mathcal{R}$  is the mean of ROUGE-1, ROUGE-2 and ROUGE-L,  $\mathbb{C}_i$  is the set of candidates predicted by the base model  $\mathcal{M}_{\text{base}}$  for data point  $x_i$ , and  $\tilde{y}_i$  is the pseudo-target. To optimize coefficients, we hill climb with randomness to maximize  $\mathcal{R}$  between the SummScore selected summary candidate, and the pseudo-target. Specifically, we estimate coefficients with stochastic local search on

Dataset	Domain	# E	# Data points		# Words		# Tokens (PEGASUS)		New summary n-grams		
Dataset	Domain	Train	Val	Test	Doc.	Summ.	Doc.	Summ.	1-grams (%)	2-grams (%)	
CNN/DM (Hermann et al., 2015)	News	287113	13334	11490	786.68	55.06	851.53	64.57	12.07	51.05	
XSum (Narayan et al., 2018)	News	204045	11332	11334	430.18	23.19	456.96	26.01	33.98	83.33	
WikiHow (Koupaee and Wang, 2018)	Wikipedia	157304	5600	5580	588.06	62.10	620.52	71.82	29.79	77.45	
SAMSum (Gliwa et al., 2019)	Dialogue	14732	818	819	124.07	23.42	133.07	25.66	33.88	79.02	

Table 2: Statistics on the datasets used for experiments. Doc. is the source document, Summ. the summary.

the validation set in a hierarchical manner: we first tune coefficients for  $F_{overlap}$  and  $F_{sem}$  separately before estimating global coefficients for  $\{F_{overlap}, F_{sem}, S_{div}, S_{len}\}$ . The reason is that  $F_{overlap}$  (resp.  $F_{sem}$ ) is made of metrics capturing the same type of features, and thus can be seen as a single broad feature. Besides, hierarchical estimation dramatically reduces the search space.

Fig. 1 synthesizes the overall SummScore reranking process.

# 4 Experiments

#### 4.1 Setup

We experiment on four popular abstractive summarization datasets, from three different domains:

- CNN-DailyMail (Hermann et al., 2015; See et al., 2017) is made of 93k and 220k articles from the CNN and DailyMail newspapers, respectively. CNN/DM is the most extractive dataset among all the ones we consider.
- **XSum** (Narayan et al., 2018) has 227k articles from the BBC from 2010 to 2017. This is an extreme summarization task, compressing each article into a single abstractive sentence.
- WikiHow (Koupaee and Wang, 2018) contains 168k instruction lists from Wikipedia.
- **SAMSum** (Gliwa et al., 2019) is a dialogue summarization dataset containing 17k conversations. In this dataset, source length is significantly shorter than in the other datasets.

Table 2 gives basic statistics on each dataset.

In practice, to estimate coefficients, we subsample randomly (on datasets other than SAM-Sum) 1,000 from the validation set. To avoid the coefficients optimization to overfit, we cap the random search at 1,000 trials. Evaluation of summaries selected by SummScore is done with the standard ROUGE-1/2/L (Lin, 2004) (using summary-level ROUGE-LS variant for ROUGE-L) and BERTScore (Zhang et al., 2019).

Model	R-1	R-2	R-L	BS	Gain (%)					
	CNN/	DM .								
LEAD-3	40.05	17.48	36.35	87.19	16.01					
PEGASUS (Zhang et al., 2020)	32.90	13.28	29.38	_	_					
PEGASUS - top beam (ours)	35.47	13.89	31.61	86.29	_					
PEGASUS - random (ours)	34.89	13.46	31.22	86.11	-1.67					
SummScore - Random-3	35.92 <sup>†</sup>	14.26 <sup>†</sup>	32.34	86.28	1.96					
SummScore - LEAD-3	$36.92^{\dagger}$	15.03 <sup>†</sup>	33.19 <sup>†</sup>	$86.54^{\dagger}$	5.19					
SummScore - Salient-R1	35.54	14.05	$32.04^{\dagger}$	86.22	0.85					
SummScore - Salient-R2	35.65	14.12	$32.14^{\dagger}$	86.24	1.19					
SummScore - Salient-RL	35.54	14.05	$32.04^{\dagger}$	86.22	0.85					
XSum										
LEAD-3	19.44	2.67	12.39	86.04	0.1					
PEGASUS (Zhang et al., 2020)	19.27	3.00	12.72	_	_					
PEGASUS - top beam (ours)	18.77	2.86	13.85	85.66	_					
PEGASUS - random (ours)	18.58	2.81	13.90	85.29	-1.31					
SummScore - Random-3	19.37 <sup>†</sup>	2.99 <sup>†</sup>	14.52	85.78 <sup>†</sup>	3.89					
SummScore - LEAD-3	$19.62^{\dagger}$	$3.02^{\dagger}$	$14.71^{\dagger}$	$85.92^{\dagger}$	5.24					
SummScore - Salient-R1	18.96	2.88	$14.19^{\dagger}$	85.65	1.52					
SummScore - Salient-R2	$19.13^{\dagger}$	2.96	$14.34^{\dagger}$	85.67	2.62					
SummScore - Salient-RL	19.29 <sup>†</sup>	2.99 <sup>†</sup>	14.48 <sup>†</sup>	85.79 <sup>†</sup>	3.63					
	WikiH	Iow								
LEAD-3	24.38	5.54	15.64	84.89	-4.40					
PEGASUS (Zhang et al., 2020)	22.59	6.10	14.44	_	_					
PEGASUS - top beam (ours)	25.49	5.91	17.99	84.98	_					
PEGASUS - random (ours)	25.39	6.00	18.09	84.82	-0.38					
SummScore - Random-3	26.29 <sup>†</sup>	6.28 <sup>†</sup>	18.78	84.98	3.89					
SummScore - LEAD-3	$26.17^{\dagger}$	$6.19^{\dagger}$	18.69 <sup>†</sup>	84.96	3.16					
SummScore - Salient-R1	$26.37^{\dagger}$	$6.32^{\dagger}$	$18.81^{\dagger}$	84.92	4.25					
SummScore - Salient-R2	$26.40^{\dagger}$	$6.30^{\dagger}$	$18.83^{\dagger}$	84.92	4.37					
SummScore - Salient-RL	26.37 <sup>†</sup>	6.32 <sup>†</sup>	18.81 <sup>†</sup>	84.92	4.31					
	SAMS	Sum								
LEAD-3	30.70	8.95	23.49	86.47	17.80					
PEGASUS - top beam (ours)	26.64	6.32	22.75	86.12	_					
PEGASUS - random (ours)	25.27	5.80	21.78	85.31	-5.26					
SummScore - Random-3	28.09 <sup>†</sup>	7.26 <sup>†</sup>	24.42	86.39	7.27					
SummScore - LEAD-3	$28.22^{\dagger}$	7.16	$24.39^{\dagger}$	$86.41^{\dagger}$	7.27					
SummScore - Salient-R1	$27.89^{\dagger}$	7.08	$24.08^{\dagger}$	86.25	5.98					
SummScore - Salient-R2	$27.93^{\dagger}$	7.04	$24.14^{\dagger}$	86.24	6.09					
SummScore - Salient-RL	$28.01^{\dagger}$	7.08	$24.21^{\dagger}$	86.21	6.46					

Table 3: Unsupervised summarization results with SummScore re-ranking on the four datasets. PEGASUS is decoded with beam search using 20 beams. R-1/2/L denotes ROUGE-1/2/L and BS denotes BERTScore. Gain represents the mean ROUGE relative gain compared to *our PEGASUS baseline*. † marks indicate significantly better results (*p*-value of paired t-test smaller than 0.05). Best results within 0.1 are in bold.

#### 4.2 Unsupervised Summarization

We first apply SummScore to unsupervised summarization using PEGASUS (Zhang et al., 2020) as base model  $\mathcal{M}_{base}$ . Due to its pre-training objective of generating gap-sentences, PEGASUS can directly be applied to the summarization task after pre-training. This is not the case of comparable sequence-to-sequence Transformer-based models T5 (Raffel et al., 2019) and BART (Lewis et al., 2020), which are pre-trained with token spans generation and sequence de-noising, respectively.

We report the LEAD-3 trivial extractive unsuper-

Fine-tuning	Backbone	Candidate	CNN/I	ЭM		XSt	ım		Wikil	How		SAM	Sum	
dataset	Баскоопе	Selection	R-1/R-2/R-L	BS	Gain (%)	R-1/R-2/R-L	BS	Gain (%)	R-1/R-2/R-L	BS	Gain (%)	R-1/R-2/R-L	BS	Gain (%)
	PEGASUS	Top beam SummScore				21.18/3.44/16.53 21.51 <sup>†</sup> /3.49/16.69	85.95 86.05 <sup>†</sup>	1.31	24.53/5.68/18.57 25.87 <sup>†</sup> /6.04 <sup>†</sup> /19.37 <sup>†</sup>	84.87 84.94 <sup>†</sup>	5.10	31.03/9.05/28.21 31.98/9.59/28.78	86.39 86.56	_
CNN/DM	BART	Top beam SummScore				20.32/3.10/15.95 20.61 <sup>†</sup> /3.16/16.21 <sup>†</sup>		- 1.60	26.13/6.03/19.69 26.61 <sup>†</sup> /6.24 <sup>†</sup> /20.01 <sup>†</sup>		_ 1.97	30.78/9.60/28.28 30.77/9.56/28.20	86.81 86.87	-0.02
	BRIO	Top beam SummScore				23.91/5.41/19.51 23.72/5.33/19.38	87.07 87.06	- -0.86	29.67/8.01/22.73 30.08 <sup>†</sup> /8.17/23.01	86.04 86.05	1.39	35.04/13.04/32.42 35.50/13.35/32.85		1.50
	PEGASUS	Top beam SummScore	23.10/8.03/20.18 26.60 <sup>†</sup> /9.47 <sup>†</sup> /23.13 <sup>†</sup>	85.88 86.47 <sup>†</sup>	_ 15.38				15.32/3.54/11.98 19.36 <sup>†</sup> /4.52 <sup>†</sup> /14.27 <sup>†</sup>			23.05/4.75/19.89 26.82 <sup>†</sup> /6.39 <sup>†</sup> /22.91 <sup>†</sup>	87.03 87.39	_
XSum	BART			86.37 86.69 <sup>†</sup>	9.18				18.31/4.30/13.71 20.52 <sup>†</sup> /4.92 <sup>†</sup> /14.94 <sup>†</sup>		11.24	26.92/5.98/22.20 30.03 <sup>†</sup> /7.28 <sup>†</sup> /24.71 <sup>†</sup>		
	BRIO	Top beam SummScore	25.52/8.47/22.08 28.67†/9.82†/24.58†	85.97 86.42 <sup>†</sup>	_				18.39/4.24/13.82 21.94†/5.31†/15.75†			26.69/5.19/22.02 30.10 <sup>†</sup> /7.13 <sup>†</sup> /24.90 <sup>†</sup>		
WikiHow	PEGASUS	Top beam SummScore Top beam	27.55/9.41/24.02 30.49 <sup>†</sup> /10.97 <sup>†</sup> /26.74 <sup>†</sup> 29.39/10.52/25.26	85.20 85.95 <sup>†</sup> 85.87	11.82	28.05/8.40/21.31 28.10/8.33/21.30 23.79/7.19/19.05	87.86 87.92 87.99	-0.05				21.15/3.92/17.46 23.62 <sup>†</sup> /4.84 <sup>†</sup> /19.26 <sup>†</sup> 19.51/4.52/17.29		12.20
	BART		31.30 <sup>†</sup> /11.42 <sup>†</sup> /26.72 <sup>†</sup>	86.21 <sup>†</sup>	6.54	25.57 <sup>†</sup> /7.54 <sup>†</sup> /20.11 <sup>†</sup>	88.18 <sup>†</sup>	6.41				22.48 <sup>†</sup> /5.40/19.63 <sup>†</sup>	87.15	14.80
SAMSum	PEGASUS		$39.15^\dagger / 16.89^\dagger / 35.33^\dagger$			24.30/6.31/18.75 24.10/5.67/18.69	87.41 87.31	-1.52	22.17/5.10/16.29 24.44 <sup>†</sup> /5.78 <sup>†</sup> /18.03 <sup>†</sup>		_ 10.74			
SAMSum	BART	Top beam SummScore	38.40/16.58/35.22 39.24 <sup>†</sup> /17.07 <sup>†</sup> /35.94 <sup>†</sup>	86.93 87.11	2.26	20.78/3.70/15.42 21.22 <sup>†</sup> /3.71/15.79 <sup>†</sup>	86.49 86.59 <sup>†</sup>	2.03	26.00/6.29/19.63 26.35 <sup>†</sup> /6.43/19.91 <sup>†</sup>	84.73 84.75	1.44			
WikiTransf	fer* (Fabbri et al., 2021)	Top beam	39.11/ <b>17.25</b> /35.73	_	_	31.85/10.44/23.75	_	_	_	_	_	_	_	_

Table 4: **Zero-shot transfer results with SummScore re-ranking**, across all twelve transfer directions over the four summarization datasets. Each model is decoded with beam search with 20 beams. **Top beam** refers to the base model performance, while **SummScore** is the candidate re-ranked by SummScore. **R-1/2/L** is ROUGE-1/2/L, **BS** denotes BERTScore, and **Gain** (%) is the relative mean ROUGE improvement compared to the base model performance. † marks indicate significantly better results (*p*-value of paired t-test smaller than 0.05). Best results within 0.1 are in bold. Greyed out cells correspond to the supervised setup, which is excluded. \*WikiTransfer is not directly comparable due to constructing the fine-tuning dataset specifically to optimize transfer to the downstream task.

vised baseline for reference, and candidate selection baselines from Table 1: *top beam* (the standard beam search output), and *random* for a randomly selected beam search candidate.

We show unsupervised summarization results with PEGASUS and 20 beams in Table 3. Across the four datasets, SummScore always improves the top beam score, and the best SummScore version improves mean ROUGE by 4.37% to 7.27% compared to the top beam. We point out that this is achieved without using any human supervision. SummScore - LEAD-3 performs best for the news domain, unsurprisingly. Notably, SummScore -LEAD-3 pushes the model performance above that of LEAD-3 on XSum. However, SummScore -LEAD-3 still trails LEAD-3 itself by 3 ROUGE points on CNN/DM. On WikiHow, SummScore - Salient-R2/RL works the best, yet SummScore fails to improve the BERTScore on this dataset. Surprisingly, SummScore - Random-3 is tied with SummScore - LEAD-3 on SAMSum: we attribute it to the fact that SAMSum source documents are very short (Table 2), and the LEAD-3, Random-3, and entire source document all overlap a lot. Appendix A confirms that SummScore re-ranking always finds a non-trivial candidate selection.

#### 4.3 Zero-Shot Transfer

Next, we investigate SummScore performance in the transfer setup. We perform zero-shot summarization inference followed by SummScore on a target dataset where the base model was fine-tuned on *another* source dataset. As base model, we use three high-performing summarization models: PE-GASUS (Zhang et al., 2020), BART (Lewis et al., 2020), and the recently introduced BRIO (Liu et al., 2022a), which achieves SOTA results on news summarization (CNN/DM & XSum). We use public fine-tuned checkpoints on CNN/DM and XSum, and PEGASUS on WikiHow. We fine-tune ourselves PEGASUS on SAMSum, and BART on WikiHow and SAMSum. Generation and fine-tuning hyper-parameters and results are in Appendix B.

Given the findings from §4.2, we use Summ-Score - LEAD-3 on CNN/DM, XSum, and SAM-Sum, and SummScore - Salient-R2 on WikiHow. We tune coefficients in the same process described in §4.1. To stick to a **no supervision** scenario, we do not apply SummScore on a dataset on the which the base model was fine-tuned, which would fall into the supervised learning use case. We compare SummScore transfer performance on CNN/DM with that of state-of-the-art WikiTransfer (Fabbri et al., 2021), which fine-tunes BART on external data retrieved from Wikipedia before applying the model in zero-shot summarization.

Zero-shot transfer results are displayed in Table 4. SummScore consistently improves transfer performance, with ROUGE gains of 7.51% averaged over 30 setups: +9.43% on CNN/DM, +1.27% on XSum, +9.20% on WikiHow (up to +17.64% average when transferring from XSum) and +9.61% on SAMSum. Notably, on CNN/DM, BART transferred from SAMSum with SummScore improves on the ROUGE-1 and ROUGE-L of SOTA trans-

Dataset	Model	R-1	R-2	R-L	BS
	LEAD-3	40.05	17.48	36.35	87.19
	PEGASUS (Zhang et al., 2020)	32.90	13.28	29.38	_
	Summary Loop 45 (Laban et al., 2020)	37.70	14.80	34.70	_
	TED (Yang et al., 2020)	38.73	16.84	35.40	_
	FAR-RW (Zhang et al., 2022) (SOTA)	40.13	17.00	36.34	_
CNN/DM	PEGASUS (ours)	35.47	13.89	31.61	86.29
	PEGASUS (ours) + SummScore	36.92	15.03	33.19	86.54
	Self-training (1st round)	36.68	14.52	32.72	86.49
	Self-training (1st round) + SummScore	38.75	16.11	34.78	86.88
	Self-training (2nd round)	38.17	15.77	34.25	86.87
	Self-training (2nd round) + SummScore	39.49	16.69	35.61	87.07
	PEGASUS (ours)	18.77	2.86	13.85	85.66
XSum	PEGASUS (ours) + SummScore	19.62	3.02	14.71	85.92
ASuili	Self-training	19.52	2.90	14.48	85.98
	Self-training + SummScore	20.15	2.86	15.05	86.19
	PEGASUS (ours)	25.49	5.91	17.99	84.98
WikiHow	PEGASUS (ours) + SummScore	26.40	6.30	18.83	84.92
WIKIHOW	Self-training	26.23	6.10	18.72	84.91
	Self-training + SummScore	26.53	6.25	19.02	84.92
	PEGASUS (ours)	26.64	6.32	22.75	86.12
SAMSum	PEGASUS (ours) + SummScore	28.22	7.16	24.39	86.41
SAMSUM	Self-training	26.96	6.41	23.40	86.25
	Self-training + SummScore	28.91	7.55	25.54	86.58

Table 5: Unsupervised summarization results with SummScore re-ranking and self-training on the four datasets. On each dataset, we fine-tune PEGASUS with the unsupervised PEGASUS summary candidate which was selected by SummScore as pseudo-target. We apply again SummScore on the output, for further gains. All our PEGASUS models are decoded with beam search with 20 beams. Best results within 0.1 are in bold. We compare to previous work on CNN/DM, although FAR-RW is not directly comparable due to relying on a SOTA unsupervised extractive summarization model.

fer model WikiTransfer (also using a BART backbone), despite WikiTransfer being fine-tuned on data specifically crafted to transfer better to the downstream task. We notice that SummScore helps more when the base model transfers less well, such as from single-sentence summaries XSum.

# 4.4 Self-Training with Unsupervised Paraphrasing

Using the selected summary candidate as a pseudotarget, one can naturally extend SummScore into a self-training summarization objective. Indeed, if  $\gamma$  parametrizes  $\mathcal{M}_{base}$ , we can further train  $\mathcal{M}_{base}$  through the objective:

$$\tilde{\gamma} = \arg\max_{\gamma} \sum_{i} \log \left( p(\text{SummScore}(\mathbb{C}_i) | x_i; \gamma) \right)$$
 (9)

This process can be repeated: if we denote new model weights by  $\gamma^k$ , we can re-apply SummScore and perform another round of self-training, yielding new model weights  $\gamma^{k+1}$ .

We notice that the unsupervised PEGASUS beam search summary candidates, including the one selected by SummScore, are quite extractive (see Appendix C). This could be because the self-supervised gap-sentences are extracts from the source document. To make the pseudo-summaries more abstractive and diverse enough to mitigate the confirmation bias in self-training (Tarvainen and

Use case	PEGASUS	SummScore	Tie	Identical
Unsupervised summarization	11.33 (1.15)	<b>20.67</b> (6.43)	18.00 (6.93)	7
Zero-shot from XSum	5.67 (2.89)	24.00 (2.00)	20.33 (1.53)	4
Self-training (1 round)	16.00(2.65)	<b>17.00</b> (1.73)	17.00 (1.00)	12
Average over all three	11.00 (4.22)	<b>20.56</b> (2.86)	18.44 (1.40)	7.67

Table 6: **Human evaluation on CNN/DM**. Mean number of times out of 50 that each model or a tie is selected as more informative, with standard deviation in parenthesis.

Valpola, 2017), we use the paraphrasing approach proposed in FAR-RW (Zhang et al., 2022). On each dataset, we train a paraphrase model to generate the top n sentences maximizing the mean ROUGE with the top n most salient sentences, conditioning on these salient sentences. This yields an unsupervised, in-domain paraphrase model which we apply to the SummScore pseudo-labels on the training set to make them more abstractive and diverse. We refer to Appendix D for details on the paraphrasing model training, its performance and resulting abstractiveness and diversity levels on pseudo-labels. As the unsupervised process of paraphrasing may harm the pseudo-summary quality, in practice, we apply it to the x% most extractive training data points, where x is among {12.5%, 25%, 50%}. We settle on 25% of training points for CNN/DM, 50% for XSum and WikiHow, and 12.5% on SAMSum, as these provide a good ROUGE/abstractiveness trade-off (see Appendix C).

For each dataset except SAMSum, we randomly subsample 50k data points from the training set and 1k from the validation set to self-train and validate the model, resulting in a self-training process much less computationally expensive than finetuning. We show self-training results on the test sets using PEGASUS as base model in Table 5. Self-training improves unsupervised summarization performance on all datasets, resulting in a selftrained model better than the base model althoug not as performing as SummScore. Notably, reapplying SummScore on the new model after selftraining further improves performance drastically. Besides, paraphrasing self-training pseudo-labels helps maintain some degree of abstractiveness, as seen in Appendix C. On CNN/DM, one round of self-training followed by SummScore brings PE-GASUS performance above that of the Summary Loop, and two rounds to 39.49 R-1, above TED.

# 4.5 Human Evaluation

We conduct a human evaluation, asking participants to indicate which summary is more informative between the unsupervised PEGASUS top beam output, and the new summary, with the option of

Candidate selection		D	ataset		Average
Candidate selection	CNN/DM	XSum	WikiHow	SAMSum	Average
PEGASUS	26.99	11.83	16.46	18.57	18.46
ROUGE-1 with source	26.90	12.03	17.21	19.89	19.01
ROUGE-2 with source	26.98	11.93	17.16	19.62	18.92
BLEU with source	26.90	11.99	17.19	19.94	19.01
BERTScore with source	28.19	12.42	17.11	19.43	19.29
BARTScore with source	28.11	12.23	16.60	19.70	19.16
BLEURT with source	27.45	12.12	16.79	19.69	19.01
Diversity score	25.33	11.36	14.52	15.67	16.72
Length score	27.07	11.67	16.66	18.60	18.50
Plain average	27.75	12.28	16.96	19.73	19.18
Random coefficients	27.75	12.25	16.84	19.72	19.14
SummScore	28.38	12.45	17.18	19.92	19.48

Table 7: **Ablation study**. We isolate each feature of Summ-Score and report its re-ranking performance in unsupervised summarization, using the mean of ROUGE-1/2/L metric. Best results within 0.1 are in bold.

choosing a tie. We perform it on CNN/DM over our three use cases: unsupervised summarization, zero-shot transfer (from XSum), and self-training. Human raters are three volunteer graduate students, with full professional command of English. Results are displayed in Table 6. Although both summaries often overlap significantly (rightmost column), resulting in a high score for the *Tie* option, on average SummScore is strongly preferred over the baseline PEGASUS. We refer to Appendix F for full qualitative unsupervised re-ranking examples.

# 5 Analysis

#### 5.1 Ablation

To better understand the performance gains with SummScore, we perform an ablation study where re-ranking is done with each feature component of SummScore taken individually. Results are shown in Table 7. N-gram overlap with the source features are very strong re-ranking baselines on WikiHow and SAMSum. In fact, ROUGE-1 with the source is slightly better than SummScore on WikiHow. On news datasets, semantic similarity with the source features such as BERTScore are strong baselines. Interestingly, our hand-crafted feature *diversity* has a *negative* contribution when used as standalone reranker. However, when coupled with other features, it can provide a significant improvement, acting as a regularizer and encouraging some diversity.

On average, SummScore performs the best. We also report *Plain average*, a re-ranking baseline consisting in averaging all eight features, and *Random coefficients*, an average of ten re-ranking performed with coefficients drawn randomly with uniform distribution. Both are at least 0.20 ROUGE lower than SummScore, and do not improve on BERTScore, confirming the efficiency of estimating SummScore coefficients through pseudo-labels.

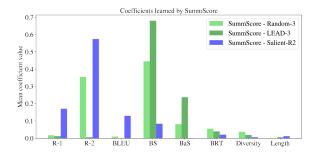


Figure 2: **SummScore coefficients**. We average coefficients over the four datasets. **BS** is BERTScore, **BaS** BARTScore, and **BRT** BLEURT.

We also explore unsupervised summarization re-ranking in other setups: decoding methods diverse beam search (Vijayakumar et al., 2016) and nucleus sampling (Holtzman et al., 2019)); and a number of candidates in {5,10,15,20}. Results are in Appendix E. SummScore re-ranking improves with more candidates, more so with lower baseline (nucleus sampling), and echoing SummaReranker findings (Ravaut et al., 2022a), gains further increase when mixing in several decoding methods.

#### 5.2 Learned Coefficients

We analyze coefficients learned by SummScore in Fig. 2. SummScore - Salient-RL places much more emphasis on n-gram overlap with the source. In contrast, SummScore - LEAD-3 uses a lot semantic similarity features, suggesting that it is able to exploit key semantic content contained in initial source sentences. As a sanity check, we report SummScore - Random-3, which behaves in between the other two variants.

#### 6 Conclusion

We introduced SummScore, the first unsupervised summarization re-ranking system. SummScore does not rely on a neural network: instead, it builds features for each summary candidate, and aggregates them into a final re-ranking score. Feature coefficients are estimated through tuning against a pseudo-label derived from the source document. SummScore significantly improves the performance of the base summarization model, in both unsupervised and zero-shot transfer scenar-SummScore naturally extends into a selftraining objective for summarization, which consistently improves unsupervised summarization performance, achieving close to SOTA results on CNN/DM. SummScore also compares favorable with other baselines on human evaluation results. Lastly, SummScore can readily be enriched with extra features, potentially leading to more gains.

#### Limitations

As a second-stage method, SummScore requires access to a base abstractive summarization model generating summary candidates. Generating up to 20 summary candidates per data point can take a long time, especially on training sets, which is needed for the self-training process. Besides, even though SummScore does not need to train a new neural network, we also need to generate all eight features for each summary candidate once all candidates are generated. This can be time-consuming, especially for model-based semantic similarity features (e.g, BERTScore).

Another limitation lays in the metric used to compare summary candidates with the pseudo-target. We used mean ROUGE, although a model-based semantic similarity metric could be more appropriate. However, it would become much more computationally intensive.

# **Ethics Statement**

Scientific work published at ACL 2023 must comply with the ACL Ethics Policy. We encourage all authors to include an explicit ethics statement on the broader impact of the work, or other ethical considerations after the conclusion but before the references. The ethics statement will not count toward the page limit (8 pages for long, 4 pages for short papers).

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# **A** Overlap with Simple Baselines

Simple Candidate Selection	CNN/DM	XSum	WikiHow	SAMSum
Max R-1 w. source	16.33	21.38	60.36	38.71
Max R-2 w. source	21.45	24.32	66.94	44.93
Max BLEU w. source	16.68	18.92	58.44	38.95
Max BS w. source	43.46	69.98	35.50	58.61
Max BaS w. source	47.15	46.06	13.85	52.50
Max BRT w. source	14.74	13.43	15.75	23.32
Max diversity feature	5.40	5.95	1.45	4.40
Max length feature	11.80	7.46	14.19	13.68
Top beam	15.05	12.85	9.18	30.28
Longest candidate	20.58	22.74	64.43	51.28

Table 8: Overlap with simple re-reranking methods. We report the fraction of test set data points on the which Summ-Score falls back to a trivial summary candidate selection: maximizing one of the input features, picking the top beam, or the longest candidate. All setups are with beam search with 20 candidates, thus a random baseline corresponds to 5%.

We perform a sanity check counting the percentage of time that SummScore falls back to a *trivial* method of re-ranking summary candidates. For each feature described in §3.3, we report the overlap between SummScore and a re-ranking approach consisting in picking the summary candidate maximing this feature. We also report baselines consisting in picking the top beam, and the longest candidate. As seen in Table 8, SummScore never collapses to a dummy summary candidate selection.

# **B** Generation & Fine-Tuning Details

In Table 9, we show generation hyper-parameters used for each dataset to generate beam search summary candidates used in Table 3.

For the transfer setup shown in Table 4, we use as generation hyper-parameters on each target dataset

Dataset	Model	Max source length	Max target length	Length penalty	Trigram blocking
	PEGASUS			0.8	Yes
CNN/DM	BART	1024	128	1.0	Yes
	BRIO			1.0	Yes
	PEGASUS			0.8	Yes
XSum	BART	512	64	1.0	Yes
	BRIO			0.8	Yes
WikiHow	PEGASUS	510	128	0.6	No
WIKIHOW	BART	512	128	1.0	Yes
CAMC	PEGASUS		64	0.8	No
SAMSum	BART	512	04	1.0	Yes

Table 9: **Generation hyper-parameters** for each dataset and model.

the parameters used on that dataset for Table 3. For instance, PEGASUS-XSum, PEGASUS-WikiHow and PEGASUS-SAMSum, when transferred to CNN/DM, are decoded with hyper-parameters of PEGASUS-CNN/DM shown in Table 9.

Dataset	Model	Epochs	Optimizer	Scheduler	LR	BS	LS	Eval steps
WikiHow	BART	15	Adam	none	1e-5	80	0.1	250
SAMSum	PEGASUS	30	Adam	none	1e-4	256	0.1	50
SAMSum	BART	30	Adam	linear	1e-5	80	0.1	50

Table 10: Fine-tuning hyper-parameters

For experiments shown in Table 4, we fine-tune ourselves BART on WikiHow dataset, and PEGA-SUS and BART on SAMSum dataset. Fine-tuning hyper-parameters are shown in Table 10.

We perform early stopping with regards to the mean ROUGE on the validation set. Our BART reaches 44.21/19.31/34.67 ROUGE-1/2/L on WikiHow test set, our PEGASUS 52.33/27.97/44.02 ROUGE-1/2/L on SAMSum test set, and our BART 52.78/28.28/44.08 ROUGE-1/2/L on SAMSum test set.

#### C Abstractiveness Analysis

In Table 12, we show ROUGE results from Table 5 alongside abstractiveness results, as measured per the fraction of novel n-grams in output summaries, for re-ranking and self-training experiments. Maximizing both ROUGE and abstractiveness is notoriously difficult, as easy solutions for abstractiveness optimization can deviate a lot from the source, resulting in a harmed ROUGE score.

The unsupervised PEGASUS (first row) is very extractive and only produces a small fraction of novel n-grams. SummScore selected summaries, despite maximizing a score which maximizes the mean ROUGE with pseudo-labels extracted from the source document, both improve the ROUGE

and the abstractiveness level. However, Summ-Score re-ranking applied to self-trained models tends to reduce their abstractiveness level, although it stays above the level of the baseline PEGASUS. We also confirm that our pseudo-labels for self-training, made of a blend of SummScore selected summaries and selected summaries being paraphrased, maintains high ROUGE while being much more abstractive than the baseline PEGASUS.

#### **D** Paraphrasing Model

For each dataset, we fine-tune BART-large (Lewis et al., 2020) (from the pre-training checkpoint facebook/bart-large in HuggingFace transformers (Wolf et al., 2020)) for paraphrasing. The model is trained to paraphrase blocks of n=3 sentences on CNN/DM, n = 1 sentence on XSum, and n = 2sentences on WikiHow and SAMSum, in line with average summary lengths on these datasets. We train the model with Adafactor (Shazeer and Stern, 2018) for 5 epochs, with effective batch size 32, learning rate 2e-5, and no weight decay nor label smoothing. We evaluate every 500 optimization steps on CNN/DM, XSum, and WikiHow, and every 100 steps on SAMSum. At inference, we use beam search with beam width 5 and length penalty of 1.0, and block repeated trigrams like in (Kryściński et al., 2018).

We track the mean of ROUGE-1, ROUGE-2 and ROUGE-L between the generated paraphrase and target paraphrase on the validation set during training, and perform early stopping. Best mean ROUGE results are shown in Table 11.

Dataset	CNN/DM	XSum	WikiHow	SAMSum
Paraphrasing model	32.88	15.58	20.67	17.44

Table 11: **ROUGE results of the paraphrasing model**, on the validation set of each dataset. We report the mean of ROUGE-1/2/L.

Next, we study the impact of the paraphrasing model on the SummScore pseudo-targets. In Table 13, we compute the mean ROUGE between pseudo-targets and their paraphrase, and analyze the novel n-grams. We point out that we paraphrasing is only applied to the *training* pseudo-labels as the goal of paraphrasing is to encourage the model to learn diversity during self-training, hence Table 13 reporting results on training sets.

On each dataset, the mean ROUGE is above 50.0, indicating that the paraphrased pseudo-labels do not deviate too much from the original pseudo-

			ROU	GE		Abstracti	veness (nev	v n-grams)
Dataset	Model	Mean R	R-1	R-2	R-L	New 1-grams	New 2-grams	New 3-grams
	PEGASUS	26.99	35.47	13.89	31.61	0.19	0.89	2.44
	PEGASUS + SummScore LEAD-3	28.38	36.92	15.03	33.19	0.19	0.94	2.73
	PEGASUS + SummScore LEAD-3 - paraphrasing 100%	22.46	29.72	11.07	26.58	14.01	35.18	44.23
CNIMOM	PEGASUS + SummScore LEAD-3 - paraphrasing 25% (pseudo-labels)	26.85	35.06	13.99	31.49	3.73	9.71	13.36
CNN/DM	PEGASUS self-trained (1st round)	27.98	36.68	14.52	32.72	0.25	0.66	1.84
	PEGASUS self-trained (1st round) + SummScore LEAD-3	29.88	38.75	16.11	34.78	0.10	0.43	1.60
	PEGASUS self-trained (2nd round)	29.40	38.17	15.77	34.25	0.66	1.49	2.61
	PEGASUS self-trained (2nd round) + SummScore LEAD-3	30.59	39.49	16.69	35.61	0.21	0.93	2.15
	PEGASUS	11.83	18.77	2.86	13.85	0.20	0.44	1.16
	PEGASUS + SummScore LEAD-3	12.45	19.62	3.02	14.71	0.19	0.60	2.04
VC	PEGASUS + SummScore LEAD-3 - paraphrasing 100%	12.98	20.19	3.60	15.16	12.94	30.30	37.63
XSum	PEGASUS + SummScore LEAD-3 - paraphrasing 50% (pseudo-labels)	12.75	19.94	3.32	14.97	6.55	15.46	19.87
	PEGASUS self-trained	12.30	19.52	2.90	14.48	0.26	0.66	1.76
	PEGASUS self-trained + SummScore LEAD-3	12.69	20.15	2.86	15.05	0.20	0.80	2.14
	PEGASUS	16.46	25.49	5.91	17.99	0.48	1.12	2.36
	PEGASUS + SummScore R-2	17.17	26.40	6.30	18.83	0.80	2.47	5.05
WikiHow	PEGASUS + SummScore R-2 - paraphrasing 100%	16.99	26.13	6.21	18.62	2.29	7.06	11.50
WIKIHOW	PEGASUS + SummScore R-2 - paraphrasing 50% (pseudo-labels)	17.09	26.28	6.26	18.72	1.55	4.79	8.33
	PEGASUS self-trained	17.02	26.23	6.10	18.72	0.85	1.85	3.76
	PEGASUS self-trained + SummScore R-2	17.27	26.53	6.25	19.02	0.57	1.61	3.82
	PEGASUS	18.57	26.64	6.32	22.75	0.30	1.35	2.81
	PEGASUS + SummScore LEAD-3	19.92	28.22	7.16	24.39	0.54	1.73	3.85
CAMC	PEGASUS + SummScore LEAD-3 - paraphrasing 100%	15.95	22.84	4.14	20.88	15.08	37.45	50.66
SAMSum	PEGASUS + SummScore LEAD-3 - paraphrasing 12.5% (pseudo-labels)	19.33	27.41	6.73	23.84	2.28	5.85	9.29
	PEGASUS self-trained	18.92	26.96	6.41	23.40	0.36	1.51	3.35
	PEGASUS self-trained + SummScore LEAD-3	20.67	28.91	7.55	25.54	0.60	2.18	4.93

Table 12: **ROUGE** and abstractiveness for several models: the unsupervised PEGASUS, re-ranking with SummScore, paraphrasing the resulting pseudo-labels, self-training with the pseudo-labels, then re-ranking self-training outputs with SummScore again. All results are on the test set, and highest numbers within 0.1 are in bold.

Dataset	Mean R	New 1-grams	New 2-grams	New 3-grams
CNN/DM	55.80	17.28	34.58	39.61
XSum	62.13	20.93	34.60	38.59
WikiHow	94.84	2.47	5.93	8.10
SAMSum	50.64	22.52	41.29	52.02

Table 13: **Impact of paraphrasing on the pseudo-targets**. We report mean ROUGE and percentage of novel n-grams between the paraphrased pseudo-targets and the original pseudo-targets, on the *training* set of each dataset since this is the subset that paraphrasing is applied to.

labels and are able to re-write the main content. Besides, there is a high proportion of new n-grams: more than 10% new 1-grams, with the exception of WikiHow on the which the paraphrasing model seems to struggle to rephrase the input.

# **E** Other Summary Candidates Setups

In Table 14, we apply SummScore outside of the standard beam search with 20 beams setup. Results show that SummScore performance continuously improves with more summary candidates, whereas the top beam stays around the same level. Besides, SummScore relative gains are stronger with lower quality decoding methods diverse beam search and nucleus sampling. Lastly, combining 20 summary candidates from each of the three decoding methods.

Decoding	Candidate	# Candidates			
method	Selection	5	10	15	20
Beam search	PEGASUS	26.74	27.00	27.00	26.99
Beam search	SummScore	27.46	28.01	28.33	28.38
Diverse beam search	PEGASUS	26.08	26.08	26.07	26.01
Diverse beam search	SummScore	26.98	27.48	27.76	27.87
Nuclous compling	PEGASUS	23.92	23.95	24.04	24.03
Nucleus sampling	SummScore	26.13	26.57	26.85	27.11
All three methods	SummScore	<b>15</b> 27.87	<b>30</b> 28.35	<b>45</b> 28.34	60 28.59

Table 14: Candidate generation setups. We compare several summary candidates generation setups with PEGASUS on CNN/DM, varying the decoding method and the number of candidates. We report the mean of ROUGE-1/2/L. Best results within 0.1 are in bold.

ods yields a pool of 60 summary candidates, out of the which SummScore re-ranking can improve by an extra +0.21 mean ROUGE the performance compared to re-ranking 20 beam search candidates (28.59 mean ROUGE vs 28.38). Overall, we recommend our default setup of beam search with 20 beams to apply SummScore re-ranking. A greater number of beams becomes difficult to fit into a standard GPU with 16 GB memory.

## **F** Re-ranking Examples

In the following, beam search output (the top beam) is in orange, SummScore selected summary candidate in blue, and oracle candidate(s) in teal.

#### CNN/DM: re-ranking from the unsupervised PEGASUS

Royal Dutch Shell Ple said it . has filed a complaint in federal court in Alaska seeking an . order to remove Greenpeace activists who climbed aboard an oil . rig in the Pacific Ocean bound for the Arctic on Monday in a . protest against Arctic drilling. The environmental group said in a statement its team would . occupy the underside of the main deck of the Polar Pioneer, which is under contract to Shell, and plans to unfurl a banner. with the names of millions of people opposed to Arctic drilling. The group said the activists would not interfere with the . vessel's navigation. Scroll down for video. On the rig: Greenpeace activists scale the Polar Pioneer drill rig in the Pacific Ocean. Map: The activists boarded the rig just 750 miles northwest of Hawaii as it makes its journey to the Arctic . At dawn on Monday, the six, from the USA, Germany, New Zealand, Australia, Sweden and Austria, sped towards the Polar Pioneer in inflatable boats launched from the Greenpeace ship Esperanza Climbers: All Greenpeace activists aboard the rig are experienced climbers and say they don't plan to interfere with the ship's course. 'We're here to highlight that Climbers: All Greenpeace activists aboard the rig are experienced climbers and say they don't plan to interrere with the ship is course. We re here to nignight that in less than 100 days Shell is, going to the Arctic to drill for oil, 32-year-old Johno Smith, one of the six to board the Blue Marlin, the ship carrying the . rig, said in the statement. 'Shell's actions are exploiting the melting ice to increase . a man-made disaster. Climate change is real,' he added. Shell said in an emailed statement that it has met with groups against oil drilling off Alaska's shores and 'respect. views' but condemned the boarding. 'We can confirm that protesters from Greenpeace have. illegally boarded the Polar Pioneer, under contract to Shell, jeopardizing not only the safety of the crew on board, but the . protesters themselves,' Shell said. The move comes just days after the U.S. Interior Department . upheld a 2008 lease sale in the Chukchi Sea off Alaska, moving. Shell a step closer to returning Shell said. The move comes just days after the U.S. Interior Department. Joined a 2008 tasses sale in the Church Sea off Alaska, moving, Shell a step closer to returning to oil and gas exploration in . the Arctic since it suffered mishaps in the region in 2012. The people ye shell: The activists hope they will draw media attention to oil drilling in the Arctic . Reveal a list: Greenpeace activists scale the Polar Pioneer drill rig in the Pacific Ocean to unfurl a banner with the names of millions of people opposed to Arctic drilling. Long haul: The activists used ropes and climbing equipment to scale the 38,000-tonne platform. Many environmentalists oppose offshore energy exploration in . the Arctic, saying that once production begins any oil spill . would be extremely difficult to clean up. Oil industry interests say the Arctic will be important to . the United States' energy security in coming decades when output, from shale formations is expected to wane. Images published by Greenpeace Arctic will be important to . the United States' energy security in coming decades when output, from shale formations is expected to wane. Images published by Greenpeac showed the activists using . climbing gear to move from an inflatable boat onto the Blue . Marlin heavy-lift vessel towing the Pioneer, one of two drill . rigs heading to the region, as it cruised some 750 miles (1,207 . km) northwest of Hawaii. The six activists planned to camp on the 38,000-tonne Polar Pioneer platform, which they boarded using inflatable boats from he Greenpeace vessel 'Esperanza.' Tweeting from the rig: Aliyah Field tweeted she'd love some coffee but that the sunrise over the Pacific is gorgeous even from the side of the oil rig . Many names: Aliyah maybe referring to the list of names the activists will hang showing all the people who are opposed to oil drilling in the arctic. The six — from the United States, Germany, New Zealand, Australia, Sweden and Austria — have supplies for several days and can communicate with the outside world, Greenpeace said. 'We made it! We're on Shell's platform. And we're not alone. Everyone can help turn this into a platform for people power!' tweeted one of the six, Aliyah Field. Johno Smith from New Zealand added: 'We're here to highlight that in less than 100 days Shell is going to the Arctic to drill for oil. 'This pristine environment needs protecting for future generations and all life that will call to home. But instead Shell's actions are exploiting the melting ice to increase a man-made disaster.' A Shell spokeswoman, Kelly op de Weegh, blasted the action. 'We can confirm that protestors from Greenpeace have illegally boarded the 'Polar Pioneer,' under contract to Shell, jeopardizing not only the safety of the crew on board, but the protestors themselves,' she said on Monday. She added: 'Shell has met with oreanizations and individuals who oppose energy exploration offshore Alaska. We respect their views and value the dialogue. 'We will not, however. Shell has met with organizations and individuals who oppose energy exploration offshore Alaska. We respect their views and value the dialogue. We will not, however, condone the illegal tactics employed by Greenpeace. Nor will we allow these stunts to distract from preparations underway to execute a safe and responsible exploration program,' she said in a statement.

		program, suc said in a statement.
Beam #1	Summary	'We're here to highlight that in less than 100 days Shell is.
	Scores	Mean ROUGE: 6.55 (rank 11)    SummScore rank: 20
		'We're here to highlight that in less than 100 days Shell is.' Greenpeace activists boarded the Polar Pioneer drill rig in the Pacific Ocean to unfurl a banner with
D #2	C	the names of millions of people opposed to oil drilling in the Arctic. Greenpeace activists climbed aboard an oil drilling rig off the coast of Alaska on Monday in a
Beam #2	Summary	protest against Shell's plans to drill for oil in Arctic waters, the environmental group said in a statement. The group said the activists would not interfere with the
		vessel's navigation, but the company said it had filed a complaint in federal court in Alaska seeking an order to remove the activists.
	Scores	Mean ROUGE: 43.17 (rank 3) ∥ SummScore rank: 2
		'We're here to highlight that in less than 100 days Shell is.' Greenpeace activists boarded the Polar Pioneer drill rig in the Pacific Ocean to unfurl a banner with the
Beam #3	Cummour	names of millions of people opposed to oil drilling in the Arctic. Greenpeace activists climbed aboard an oil drilling rig off the coast of Alaska on Monday in a protest
Bealii #3	Summary	against Shell's plans to drill for oil in Arctic waters, the environmental group said in a statement. The group said the activists would not interfere with the ship's
		navigation, but the company said it had filed a complaint in federal court in Alaska seeking an order to remove the activists.
	Scores	Mean ROUGE: 42.85 (rank 4)    SummScore rank: 1 (SummScore output)
		'We're here to highlight that in less than 100 days Shell is.' Greenpeace activists boarded the Polar Pioneer drill rig in the Pacific Ocean to unfurl a banner with the names
Beam #4	Summary	of millions of people opposed to oil drilling in the Arctic. Greenpeace activists climbed aboard an oil drilling rig off the coast of Alaska on Monday in a protest against Shell's
Deam #4	Summary	plans to drill for oil in Arctic waters, the environmental group said in a statement. The group said the activists would not interfere with the vessel's navigation, but the company
		said it had filed a complaint in federal court in Alaska seeking an order to remove the activists from
	Scores	Mean ROUGE: 43.59 (rank 2) ∥ SummScore rank: 12
		'We're here to highlight that in less than 100 days Shell is.' Greenpeace activists boarded the Polar Pioneer drill rig in the Pacific Ocean to unfurl a banner with the names
Beam #10	Summary	of millions of people opposed to oil drilling in the Arctic. Greenpeace activists climbed aboard an oil drilling rig off the coast of Alaska on Monday in a protest against
Beam #10	Summary	Shell's plans to drill for oil in Arctic waters, the environmental group said in a statement. The group said the activists would not interfere with the vessel's navigation,
		but the company said it had filed a complaint in federal court in Alaska seeking an order to remove them from the
	Scores	Mean ROUGE: 43.91 (rank 1)    SummScore rank: 6

Table 15: SummScore re-ranking applied to the unsupervised PEGASUS with beam search on CNN/DM.

Shell has filed a complaint in federal court in Alaska seeking an order to remove Greenpeace activists who climbed aboard an oil rig in the Pacific The environmental group said in a statement its team would occupy the underside of the main deck of the Polar Pioneer.

The six activists are camping on the 38,000-tonne Polar Pioneer platform, which they boarded using inflatable boats from the Greenpeace vessel 'Esperanza'

'We made it! We're on Shell's platform. And we're not alone. Everyone can help turn this into a platform for people power!' tweeted Aliyah Field

Source

Reference

#### CNN/DM: re-ranking from the PEGASUS trained on WikiHow Assault: Dr Sahar Hussain attacked two Tube workers because she didn't want to miss the last train home. A GP attacked two Tube workers while screaming 'I'm a doctor' because she did not want to miss the last train home on a Friday night. Dr Sahar Hussain, 53, panicked when she was unable to get through the gates at Leicester Square station, and started ranting at staff. She denied assaulting the two workers, saying she was worried about being stranded on her own in central London because she is a Muslim woman. But Hussain has now been found guilty and ordered to pay a total of £2,250 in fines, compensation and court costs - and she could face disciplinary action from the General Medical Council. In video footage captured on her own mobile phone, Hussain could be heard to shout: 'I'm a doctor actually, I work for the NHS. I'm a doctor. Get me through the gate, I'm going to miss my train.' City of London Magistrates' Court heard Hussain arrived at the station around 11.30pm on June 20 last year, trying to get home to Woodford Green after socialising with friends in the West End. When she was refused entry by the automatic gates, she demanded that ticket seller Malcolm Shaw let her through before lashing out at his colleague Indira Ramsaroop, who was trying to help. Hussain, originally from Iraq, screamed and shouted at Mrs Ramsaroop as she thrust a camera phone into her face before grabbing her by the arm. The 24-year-old Transport for London worker was then chased by the doctor as she tried to flee to the control room, bumping her head on the way. In the video on Hussain's phone she was heard shouting: 'This woman is on something, she's not sober is she? You're in work and you're not sober. Get me through the gate.' During the scuffle Hussain, a mother of one who helps train GPs at two universities, also grabbed Mr Shaw by the arms, leaving him with scratches. Mrs Ramsaroop was close to tears in court as she told how she had to take almost two weeks off work following the incident, adding: 'I had a lot of sleepless nights. It had an impact on myself with customers when I came back to work. 'I have felt very let down to have been threatened and been running away in my place of work. It actually affected me for a very long time and I got quite ill just at the worrying and Source fear. Row: The assault took place on a Friday night at Leicester Square station in central London. Hussain admitted losing her temper, telling the court: 'I'm very sorry about the way I expressed myself with my agitation and frustration.' District Judge Quentin Purdy found her guilty of two counts of assault by beating, saying: 'The evidence is overwhelming. You completely lost your self-control. 'Unusually for the sort of incident this court regularly deals with, there is no hint of intoxication in any way. 'But the explanation is there. You were anxious about missing the last train, concerned about being late for work or unable to work the next day, cultural embarrassment by being left in London as married Muslim woman. It was completely out of character, but as we have all seen, you acted in an unpleasant and hysterical fashion towards numerous members of staff. He said she had subjected Mrs Ramsaroop to 'completely unjustified violence', as well as 'humiliation' for falsely suggesting she was intoxicated at work. The judge added: 'You have lost a great deal by your lack of self-control. Your good name is now lost with these two convictions for assault.' Hussain was fined £500 for each assault and ordered her to pay £500 compensation to Mrs Ramsaroop, £200 to Mr Shaw, £500 prosecution costs and a £50 victim surcharge. Try to get through the gate because you didn't want to miss the last train home. Attack the workers because you didn't want to miss the last train home. Beam #1 Summary Scores Mean ROUGE: 13.80 (rank 6) || SummScore rank: 17 Tell the court she was worried about being stranded on her own in central London because she is a Muslim woman. Describe to the court how she screamed: 'I'm a doctor, get me through the gate.' Beam #2 Summary through the gate. Mean ROUGE: 40.97 (rank 2) || SummScore rank: 2 Tell the court she was worried about being stranded on her own in central London because she is a Muslim woman. Describe to the court how she screamed: 'Get me through the Scores Beam #3 Summary gate, get me through the gate. Mean ROUGE: 39.29 (rank 4) || SummScore rank: 10 Try to get through the gate because you don't want to miss the last train home. Attack the workers because you didn't want to miss the last train home. Beam #4 Summary Scores Mean ROUGE: 13.80 (rank 6) || SummScore rank: 18 Tell the court she was worried about being stranded on her own in central London because she is a Muslim woman. Describe to the court how she screamed: 'I'm a doctor, Beam #10 Summary Scores Mean ROUGE: 40.97 (rank 2) || SummScore rank: 1 (SummScore output) Tell the court she was worried about being stranded on her own in central London because she is a Muslim woman. Describe to the court how she screamed: 'I'm a doctor, Beam #14 Summary Scores Mean ROUGE: 42.04 (rank 1) || SummScore rank: 9 Shell has filed a complaint in federal court in Alaska seeking an order to remove Greenpeace activists who climbed aboard an oil rig in the Pacific. The environmental group said in a statement its team would occupy the underside of the main deck of the Polar Pioneer. Reference The six activists are camping on the 38,000-tonne Polar Pioneer platform, which they boarded using inflatable boats from the Greenpeace vessel 'Esperanza' 'We made it! We're on Shell's platform. And we're not alone. Everyone can help turn this into a platform for people power!' tweeted Aliyah Field

Table 16: SummScore re-ranking applied to the **PEGASUS fine-tuned on WikiHow** with beam search on **CNN/DM**.

#### CNN/DM: re-ranking from the self-trained PEGASUS

Grandparents have pleaded for the safe return to Australia of two young children whose mother took them from Melbourne to the Islamic State capital in Syria. Former Melbourne woman Dullel Kassab fled to Raqqa in Syria with her children last year, and she regularly boasts on Twitter that her four-year-old daughte

and two-year-old son sleep with toy guns next to their beds and her daughter likes watching IS videos of 'Muslims killing bad ppl.' The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border last year, The Herald Sun reported. Former Melbourne woman Dullel Kassab fled to Raqqa in Syria from Melbourne with her children last year. Kassab posts pictures to Twitter of airstrikes hitting blocks away from their Raqqa apartment. 'We miss the children a lot. Their safety and religion has been compromised and we are deeply worried but unable to do anything about it, a family spokesman told the Herald Sun. 'We pray they come back but it does not look good.' Kassab's Twitter paints a picture of their life in the city the terrorist group IS have made their headquarters, where the children cannot go to school and airstrikes hit blocks away from their apartment. The 28-year-old has a new husband, as the Islamic State does not permit unmarried foreign women to stay in Raqqa. In social media posts she boasts about her children's distaste for Kuffar (non-believers). A photo of another airstrike a day later. The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border last year. On her Twitter account she boasts about her children's distaste for Kuffar (non-believers) 'My 4y/o encouraging her little bro to eat his eggs – "C'mon eat ur eggs so u can be big & strong & fight the Kuffar!" Allah yehmikum! [sic]' she wrote in December. '#Awkward Just asked my 4yo wat she wants 2 watch.. "Muslims killing bad ppl" (i.e. #IS vids obv not beheading ones) LOL [sic], she wrote in October. Kassab has also complained the 12 to 17-year-olds are now regarded as children when 'in the past they were warriors'. And during the Sydney Lindt café siege in December last year she sent a series of tweets joking that it was exciting. 'This is the most excitement Sydney has seen since the 2000 Olympics!' she posted. Kassab also posts pictures of the Islamic State capital - including this of a 'double rainbow' And during the Sydney Lindt café siege last year Kassab sent a series of tweets joking that it was 'exciting' 'I guess attack the coffee shop wasn't a bad idea, It's a long night... One needs caffeine and chocolate!! [sic]' Kassab also posts pictures of the Islamic State capital, and of Nutella and Twix and Snickers chocolate bars with the caption: 'Im really appreciating #globalization right about now! #SimplePleasures Another reason to love #IS [sic].' The 28-year-old's father Jalal Kassab said he was worried about his grandchildren living in a war zone, but said the threat of imprisonment made it difficult for his daughter to return to Australia. 'I know she wants to come back and we are trying everything we can to bring her back,' Mr Kassab told the Herald Sun. Another former Melbourne woman Zehra Duman last month shared a series of propaganda pictures she says shows her 'five star jihad' lifestyle . In photographs posted to a Twitter several women are pictured standing under an Islamic State flag, reclining against a clean white BMW M5 and wielding machine guns . In one tweet, Duman said: 'US + Australia, how does it feel that all 5 of us were born n raised in your lands, & now here thirsty for ur blood?'
The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border ck but it does not look good.' Kassab's Twitter paints a picture of their life in the city the terrorist group IS have made their the children cannot go to school and airstrikes hit blocks away from their apartmen Mean ROUGE: 14.89 (rank 4) || SummScore rank: 6 'We pray they come back but it does not look good.' Kassab's Twitter paints a picture of their life in the city the terrorist group IS have made their headquarters, where the children cannot go to school and airstrikes hit blocks away from their apartment. The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border last year. Mean ROUGE: 14.89 (rank 4) || SummScore rank: 11 The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border last year, The Herald Sun reported. 'We pray they come back but it does not look good.' Kassab's Twitter paints a picture of their life in the city the terrorist group IS have made their headquarters, where the children cannot go to school and airstrikes hit blocks away from their apartment. Mean ROUGE: 14.41 (rank 6) || SummScore rank: 5

We pray they come back but it does not look good. Kassab's Twitter paints a picture of their life in the city the terrorist group IS have made their headquarters. where the children cannot go to school and airstrikes hit blocks away from their apartment. 'My 4y/o encouraging her little bro to eat his eggs ' 'C' mon eat ur eggs Beam #4 Summary so u can be big & strong & fight the Kuffar!' Allah yehmikum! Mean ROUGE: 9.92 (rank 10) || SummScore rank: 13 Former Melbourne woman Dullel Kassab fled to Raqqa in Syria with her children last year, and she regularly boasts on Twitter that her four-year-old daughter and

two-year-old son sleep with toy guns next to their beds and her daughter likes watching IS videos of 'Muslims killing bad ppl.' The children's paternal grandparents say they are worried Kassab, 28, is 'brainwashing' the children, after their father was killed near the Syria-Turkey border last year.

Mean ROUGE: 57.48 (rank 1) || SummScore rank: 1 (SummScore output)

Grandparents have pleaded for the safe return of two children in Syria .

Former Melbourne woman Dullel Kassab fled to Raqqa in Syria with her four-year-old daughter and two-year-old son last year .

She said her daughter likes watching IS videos of 'Muslims killing bad ppl'

Table 17: Self-trained PEGASUS with beam search on CNN/DM.

Source

Scores

Beam #2 Summary

Scores

Beam #3 Summary

Scores

Scores

Beam #9 Summary Scores

Reference

		XSum: re-ranking from the unsupervised PEGASUS
		Acting Taoiseach Enda Kenny of Fine Gael and Micheál Martin of Fianna Fáil hope to avoid a second election. Mr Martin has said his party will facilitate a minority
		government, but will not support a programme for government. Water charges are one of the main sticking points to reaching agreement. A commission to consider the
Source		future of national water utility Irish Water is one of the proposals being considered. Fianna Fáil want to see the immediate removal of water charges, but Fine Gael
		see a role for them. Following the election, almost two months ago, Fine Gael had 50 seats, Fianna Fáil 44, Sinn Féin 23 and the Labour Party got seven. But no party
		was able to form a majority government and TDs have so far failed to elect a taoiseach.
Beam #1	Summary	Fianna Fil want to see the immediate removal of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 8.77 (rank 5)    SummScore rank: 14
Beam #2	Summary	Following the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.06 (rank 9)    SummScore rank: 6
Beam #3	Summary	Acting Taoiseach Enda Kenny of Fine Gael and Michel Martin of Fianna Fil hope to avoid a second election.
	Scores	Mean ROUGE: 7.02 (rank 7)    SummScore rank: 15
Beam #4	Summary	After the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.06 (rank 9)    SummScore rank: 7
Beam #5	Summary	The election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.20 (rank 8)    SummScore rank: 12
		A commission to consider the future of national water utility Irish Water is one of the proposals being considered. Fianna Fil want to see the immediate removal
Beam #6	Summary	of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 10.53 (rank 4)    SummScore rank: 4
		Mr Martin has said his party will facilitate a minority government, but will not support a programme for government. Fianna Fil want to see the immediate removal
Beam #7	Summary	of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 17.63 (rank 3)    SummScore rank: 2
Beam #8	Summary	following the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.06 (rank 9)    SummScore rank: 8
Beam #9	Summary	Follow the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.06 (rank 9)    SummScore rank: 13
Beam #10	Summary	During the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven.
	Scores	Mean ROUGE: 6.06 (rank 9)    SummScore rank: 9
Beam #11	Summary	acting Taoiseach Enda Kenny of Fine Gael and Michel Martin of Fianna Fil hope to avoid a second election.
	Scores	Mean ROUGE: 7.02 (rank 7)    SummScore rank: 20
Beam #12	Summary	Fianna Fil wants to see the immediate removal of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 8.77 (rank 5)    SummScore rank: 16
		Mr Martin has said his party will facilitate a minority government, but will not support a programme for government. Fianna Fil want to see the immediate
Beam #13	Summary	removal of water charges, but Fine Gael see a role for them. However, no party was able to form a majority government and TDs have so far failed
	Scores	Mean ROUGE: 19.28 (rank 2)    SummScore rank: 1 (SummScore output)
Beam #14	Summary	While Fianna Fil want to see the immediate removal of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 8.55 (rank 6)    SummScore rank: 19
Beam #15	Summary	Fianna Fil wanted to see the immediate removal of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 8.77 (rank 5)    SummScore rank: 17
Beam #16		Mr Martin has said his party will facilitate a minority government, but will not support a programme for government.
	Scores	Mean ROUGE: 21.25 (rank 1)    SummScore rank: 10
Beam #17	Summary	Fianna Fil hope to see the immediate removal of water charges, but Fine Gael see a role for them.
	Scores	Mean ROUGE: 8.77 (rank 5)    SummScore rank: 18
		Mr Martin has said his party will facilitate a minority government, but will not support a programme for government. Fianna Fil want to see the immediate
Beam #18	Summary	removal of water charges, but Fine Gael see a role for them. However, no party was able to form a majority government and TDs so far failed to
	Scores	Mean ROUGE: 19.28 (rank 2)    SummScore rank: 3
Beam #19		Following the election, almost two months ago, Fine Gael had 50 seats, Fianna Fil 44, Sinn Féin 23 and the Labour Party got seven
	Scores	Mean ROUGE: 6.06 (rank xx)    SummScore rank: 11
		Mr Martin has said his party will facilitate a minority government, but will not support a programme for government. Fianna Fil want to see the immediate
Beam #20	Summary	removal of water charges, but Fine Gael see a role for them. However, no party was able to form a majority government and TDs will so far failed
	Scores	Mean ROUGE: 19.28 (rank 2)   SummScore rank: 5

 $\label{thm:core} \mbox{Table 18: SummScore re-ranking applied to the } \mbox{\bf unsupervised PEGASUS} \mbox{ with beam search on } \mbox{\bf XSum}.$ 

		XSum: re-ranking from the BART trained on WikiHow
		Cardiff narrowly missed out on the Championship play-offs last term, finishing eighth in the table. But under new head coach Paul Trollope, Pilkington thinks the Welsh side are capable of better. "We fell just short [last season] and we were all really disappointed with that. We felt we had the squad to get in the play-offs definitely," he said. "It's going to be a tough season again, just like it was last year, but hopefully we can be right up there come the end of the season." Pilkington, 28, scored Cardiff's first goal in their 4-0 friendly win at Shrewsbury on Saturday. The Republic of Ireland international played in attack,
Source		having moved from the wing to a central forward role last season. Pilkington made the transition under former Cardiff boss Russell Slade, who was replaced by Trollope in May. Trollope had been working under Slade before then, and Pilkington believes that smooth transition has helped the Bluebirds in their preparations for the new campaign. "The gaffer was working with us last season so we know how he works," he added. "We know what he's about and we know we have to be on our toes all the time. "He's come in and changed a few things. It's been good up to now so hopefully we can carry on working really well."
Beam #1	Summary	Aim to improve on last season's finish., Expect a tough season.
Beam #2	Scores	Mean ROUGE: 5.13 (rank 11)    SummScore rank: 12  Aim to improve on last season's finish, Pilkington believes the Bluebirds are capable of reaching the play-offs.
Beam #3	Scores Summary Scores	Mean ROUGE: 24.63 (rank 2)    SummScore rank: 5 Aim to improve on last season's finish., Believe the Bluebirds have the squad to get back up the table.  Mean ROUGE: 17.89 (rank 7)    SummScore rank: 6
Beam #4	Summary	Reach the play-offs again.  Mean ROUGE: 7.02 (rank 10)    SummScore rank: 18
Beam #5	Summary	Aim to improve on last season's finish.,Pilkington believes the Bluebirds have the squad to get back up the table.  Mean ROUGE: 23.20 (rank 4)    SummScore rank: 1 (SummScore output)
Beam #6	Summary	Aim to improve on last season's finish, Pilkington believes the Bluebirds have the squad to reach the play-offs.  Mean ROUGE: 23.90 (rank 3)    SummScore rank: 2
Beam #7	Summary	Expect to improve on last season's finish.,Pilkington believes the Bluebirds have the squad to get back up the table.  Mean ROUGE: 23.20 (rank 4)    SummScore rank: 3
Beam #8	Summary	Aim to improve on last season's finish. Pilkington believes the Bluebirds have the squad to challenge for promotion.  Mean ROUGE: 41.06 (rank 1)    SummScore rank: 7
Beam #9	Summary	Acim to improve on last season's finish, Pilkington believes the Bluebirds are capable of reaching the play-offs again.  Mean ROUGE: 23.90 (rank 3)    SummScore rank: 4
Beam #10		Aim to improve on last season's finish., Believe in the squad.
Beam #11	Summary	Mean ROUGE: 12.82 (rank 9)    SummScore rank: 9  Aim to improve on last season's finish, Expect a tough season again.
Beam #12	-	Mean ROUGE: 4,94 (rank 12)    SummScore rank: 8  Āim to improve on last season's finish, Believe in the squad.
Beam #13	Scores Summary Scores	Mean ROUGE: 12.82 (rank 9)    SummScore rank: 11  Aim to improve on last season's finish., Expect to challenge for promotion again.  Mean ROUGE: 21.79 (rank 6)    SummScore rank: 16
Beam #14		Prepare for a tough season.  Mean ROUGE: 14.04 (rank 8)    SummScore rank: 13
Beam #15	Summary	Aim to improve on last season's finish., Believe in the squad.  Mean ROUGE: 12.82 (rank 9)    SummScore rank: 10
Beam #16		Prepare for a tough season.  Mean ROUGE: 14 04 (rank 8)    SummScore rank: 14
Beam #17		Aim to improve on last season's finish., Expect to challenge for promotion.  Mean ROUGE: 22.62 (rank 5)    SummScore rank: 17
Beam #18		Mean ROUGE: 2.20 (talk 5)   summScore rank: 17 Prepare for a tough season.  Mean ROUGE: 14.04 (rank 8)    SummScore rank: 15
Beam #19	Summary	Prepare for another tough season.
Beam #20	Scores Summary Scores	Mean ROUGE: 14.04 (rank 8)    SummScore rank: 20 Prepare for another tough season. Mean ROUGE: 14.04 (rank 8)    SummScore rank: 19
Reference	Scores	Cardiff City forward Anthony Pilkington believes the Bluebirds can challenge for promotion this season.

Table 19: SummScore re-ranking applied to the **BART fine-tuned on WikiHow** with beam search on **XSum**.

		XSum: re-ranking from the self-trained PEGASUS
		In a statement seen by the BBC, his wife said he had been out drinking with another man in the city of Yangon on Friday night before his death. The Foreign
		Office said it was investigating the death of a British national and was providing support to the victim's family. News agency AFP quoted police as saying the
Source		dead man was a 47-year-old who had suffered wounds to his head and chest. According to reports, the man - who had been working at an international school -
		was found dead at an apartment in Yangon, previously known as Rangoon. The Foreign Office says it is working with local authorities in Myanmar, formerly Burma,
		to determine what happened.
Beam #1	Summary	The Foreign Office said it was investigating the death of a British national and was providing support to the victim's family.
	Scores	Mean ROUGE: 13.07 (rank 10)    SummScore rank: 3
Beam #2	Summary	In a statement seen by the BBC, his wife said he had been out drinking with another man in the city of Yangon on Friday night before his death.
	Scores	Mean ROUGE: 10.85 (rank 12)    SummScore rank: 4
Beam #3	Summary	According to reports, the man - who had been working at an international school - was found dead at an apartment in Yangon, previously known as Rangoon.
	Scores	Mean ROUGE: 20.61 (rank 8)    SummScore rank: 7
Beam #4	Summary	The man, who has not been named, was found dead at an apartment in Yangon, Myanmar, on Saturday.
	Scores	Mean ROUGE: 31.39 (rank 1)    SummScore rank: 14
Beam #5	Summary	The man, who has not been named, was found dead at an apartment in Yangon, formerly known as Rangoon, on Saturday.
	Scores	Mean ROUGE: 24.88 (rank 6)    SummScore rank: 12
Beam #6	Summary	According to reports, the man - who had been working at an international school - was found dead at an apartment in Yangon, formerly known as Rangoon.
	Scores	Mean ROUGE: 20.61 (rank 8)    SummScore rank: 5
Beam #7	Summary	The man, who has not been named, was found dead at an apartment in Yangon, previously known as Rangoon.
	Scores	Mean ROUGE: 26.39 (rank 4)    SummScore rank: 1 (SummScore output)
Beam #8	Summary	The man, who has not been named, was found dead at an apartment in Yangon, formerly known as Rangoon.
	Scores	Mean ROUGE: 26.39 (rank 4)    SummScore rank: 2
Beam #9	Summary	The man, who has not been named, was found dead at an apartment in Yangon, previously known as Rangoon, on Saturday.
	Scores	Mean ROUGE: 24.88 (rank 6)    SummScore rank: 11
Beam #10		The Foreign Office said it was working with local authorities in Myanmar, formerly Burma, to determine what happened.
	Scores	Mean ROUGE: 12.64 (rank 11)    SummScore rank: 10
Beam #11		The Foreign Office says it is working with local authorities in Myanmar, formerly Burma, to determine what happened.
	Scores	Mean ROUGE: 12.64 (rank 11)    SummScore rank: 11
Beam #12		The man, who has not been named, was found dead at an apartment in Yangon, formerly Burma, on Saturday.
	Scores	Mean ROUGE: 26.39 (rank 4)    SummScore rank: 18
Beam #13		Media playback is unsupported on your device 11 August 2015 Last updated at 08:00 BST The Foreign Office said it was investigating the death of a British national in the city of Yangon.
B57	Scores	Mean ROUGE: 9.78 (rank 13)    SummScore rank: 19  Media playback is unsupported on your device 11 August 2015 Last updated at 08:00 BST The man, who has not been named, was found dead at an apartment in Yangon.
Beam #14		
Beam #15	Scores	Mean ROUGE: 19.33 (rank 9)    SummScore rank: 20  The man, who has not been named, was found dead at an apartment in Yangon, the capital of Myanmar, on Saturday.
Beam #15		
Beam #16	Scores	Mean ROUGE: 28.69 (rank 2)    SummScore rank: 16  According to reports, the man - who had been working at an international school - was found dead at an apartment in Yangon, previously known as Burma.
Beam #16		
Beam #17	Scores	Mean ROUGE: 20.61 (rank 8)    SummScore rank: 15  The man, who has not been named, was found dead at an apartment in the city of Yangon on Saturday.
Beam #1/	Summary	The man, who has not been namened, was found dead at an apartment in the city of Yangon on Saturday.  Mean ROUGE: 25.61 (rank 5)    SummScore rank: 13
Beam #18	Summary	Mean NOCHE: 2501 (fails 3) if Sulminscole rains. 15 The Foreign Office said the man, who has not been named, was found dead at an apartment in Yangon, previously known as Rangoon.
Beam #18		
Beam #19	Scores	Mean ROUGE: 23.53 (rank 7)    SummScore rank: 9  The Foreign Office said the man, who has not been named, was found dead at an apartment in Yangon, formerly known as Rangoon.
Deam #19	Summary	The Foreign Uffice said the man, who has not been named, was found dead at an apartment in Yangon, formerly known as Kangoon.  Mean ROUGE: 23.53 (rank 7) II SummScore rank: 8  Mean ROUGE: 23.53 (rank 7) II SummScore rank: 8
Beam #20	Summary	Mean ROUGE: 23.53 (rank 7)    SummScore rank: 8 The man, who has not been named, was found dead at an apartment in Yangon on Saturday.
Deam #20	Summary	The man, who has not been namened, was found dead at an apartment in Yangon on Saturday.  Mean ROUGE: 28.11 (rank 3)    SummScore rank: 17  Mean ROUGE: 28.11 (rank 3)    SummScore rank: 17
	Scores	
Reference		A British man believed to be a teacher has been found dead in Myanmar.

Table 20: Self-trained PEGASUS with beam search on XSum.

		WikiHow: re-ranking from the unsupervised PEGASUS
Source		On your scanner tool, set the PPI (Pixel per inch) to 350 so that it will create a high-quality image.; , Click on the program's shortcut icon on your desktop or programs list to launch it. Wait until the program starts. Any version will do, but the latest one is better because they have additional useful functions. , On the Menu bar located at the top of the screen, go to File and click "Open." Locate the image, select it, then click "Open.", To change it, go to "Image" on the Menu bar then click "Mode" and choose "RGB." To turn your scanned image fully grayscale, just in case you didn't change it on your scanner setting and the image has traces of colors, change the Adjustment, under "Image" on the Menu bar, into "Black and White." , On the Layer panel on the palette dock located at the bottom left of the screen, create a new layer by clicking a small paper-like icon beside the folder icon. , Change the layer name to "Skin" as this will be the first part of the image that you will add a color to . Press "B" on your keyboard or get the Brush tool on the toolbar located at the left side of the screen. The icon is a brush. , Pick a nice skin tone color on the Swatches, which are also on the Palette dock. You may also set the foreground color to get more colors on the Toolbar, below the Zoom Tool, which is the two square that indicates as foreground and background color. A skin tone color is the lightest Orange or Yellow Orange. , Drag and move your mouse to the skin tone of your image. To avoid misplacing the colors, use the Zoom tool or simply press CTRL + Z. Use the Eraser tool, which is also located on the toolbar, to delete some misplaced part; but change the Brush Preset, which is on the Palette Dock, and choose "Soft Round" so it will create pixelated color when you erase them. , Once you're done with the skin, repeat Steps 1 to 6 with other parts of the body. For example, if you want to color the clothes, add a layer and rename the layer "Clothes." After renaming, proceed with selecting the right tool and
Beam #1	Summary	To many also set the foreground color to get more colors on the Toolbar, below the Zoom Tool, which is the two square that indicates as foreground and background color.
	Scores	Mean ROUGE: 13.01 (rank 7)    SummScore rank: 20
Beam #2	Summary	, On your scanner tool, set the PPI (Pixel per inch) to 350 so that it will create a high-quality image:,, Click on the program's shortcut icon on your desktop or programs list to launch it., To change it, go to "Image" on the Menu bar then click "Mode" and choose "RGB." To turn your scanned image fully grayscale, just in case you didn't change it on your scanner setting and the image has traces of colors, change the Adjustment, under "Image"—on the Palette dock located at the bottom left of the screen—into "
	Scores	Mean ROUGE: 23.18 (rank 1) Il SummScore rank: 2
Beam #3	Summary	On your scanner tool, set the PPI (Pixel per inch) to 350 so that it will create a high-quality image;. Click on the program's shortcut icon on your desktop or programs list to launch it., To change it, go to "Image" on the Menu bar then click "Mode" and choose "RGB." To turn your scanned image fully grayscale, just in case you didn't change it on your scanner setting and the image has traces of colors, change the Adjustment, under "Image"—on the Palette dock located at the bottom left of the screen, into "
	Scores	Mean ROUGE: 23.18 (rank 1)    SummScore rank: 5
Beam #4	Summary	, On your scanner tool, set the PPI (Pixel per inch) to 350 so that it will create a high-quality image;; Click on the program's shortcut icon on your desktop or programs list to launch it., To change it, go to "Image" on the Menu bar then click "Mode" and choose "RGB." To turn your scanned image fully grayscale, just in case you didn't change it on your scanner setting and the image has traces of colors, change the Adjustment, under "Image"—on the menu bar, into "Black and White.",On the
	Scores	Mean ROUGE: 21.05 (rank 5)    SummScore rank: 11
· :		, On your scanner tool, set the PPI (Pixel per inch) to 350 so that it will create a high-quality image.;, Click on the program's shortcut icon on your desktop or programs
Beam #11	Summary	list to launch it., To change it, go to "Image" on the Menu bar then click "Mode" and choose "RGB." To turn your scanned image fully grayscale, just in case you didn't change it on your scanner setting and the image has traces of colors, change the Adjustment, under "Image"—on the Palette dock located at the bottom left of the screen—and choose
	Scores	Mean ROUGE: 22.71 (rank 3)    SummScore rank: 1 (SummScore output)
Reference		Negotiators from Ireland's two biggest parties are to meet for a final effort to form a minority government.

Table 21: SummScore re-ranking applied to the unsupervised PEGASUS with beam search on WikiHow.

		WikiHow: re-ranking from the PEGASUS trained on CNN/DM
Source		Gently stabilize it by holding it steady with one or both hands. Pet your cat and talk to it in a soothing voice to calm and reassure it. If your cat resists you or is prone to scratching, then wrap your cat in the towel so that just its head is sticking out. Once your cat is calm, place your non-dominant hand on top of your cat's head in front of its ears. Wrap your fingers around the bottom of its cheekbones for leverage., This should cause your cat's mouth to open involuntarily. Pick up the pill with your other hand. Hold the pill between your index finger and thumb. Then place your middle or ring finger on the lower molars to keep its jaw open. Do not place your finger on top of the canine tooth, i.e., the sharp fang, to keep its jaw open. If your cat will not open its mouth, then you will need to pry it open. Do this using the middle finger of the same hand holding the pill. Place your middle finger over the small incisor teeth in the front of your cat's mouth at the bottom. Then apply gentle pressure to push your cat's jaw open. Do the pill as far back as you can on your cat's tongue, i.e., the base of the tongue. Or, use your index finger and thumb to push the pill over the back of your cat's tongue. If you do it this way, you must do it quickly to prevent your fingers from getting bitten. Alternatively, you can use a pill syringe to place the pill at the base of your cat's tongue. This way you can avoid having to put your fingers in your cat's mouth. Coat the pill with butter to make swallowing it easier. Once you have placed the pill at the base of its tongue, use your hands to keep its mouth closed by applying gentle pressure. Also re-position your cat's head so that it is level instead of tilted back; this will make it easier for your cat to swallow the pill. Gently rub your cat's throat or blow in its nose to encourage it to swallow the pill. Try not to let your cat go until the pil lis swallowed. Place a drop of water on its nose. If your cat licks the water off, then this means that it has swallow
Beam #1	Summary	Pet your cat and talk to it in a soothing voice to calm and reassure it. If your cat resists you or is prone to scratching, then wrap your cat in a towel so that just its head is sticking out.
	Scores	Mean ROUGE: 17.17 (rank 8)    SummScore rank: 12
Beam #2	Summary Scores	Pet your cat and talk to it in a soothing voice to calm and reassure it. If your cat resists you or is prone to scratching, then wrap your cat in the towel so that just its head is sticking out.  Mean ROUGE: 18.78 (rank 6)    SummScore rank: 8
Beam #3	Summary	Pet your cat and talk to it in a soothing voice to calm and reassure it. If your cat resists you or is prone to scratching, then wrap your cat in a towel so that just its head is sticking out.  Mean ROUGE: 17.17 (rank 8)    SummScore rank: 11
Beam #4	Summary	Pet your cat and talk to it in a soothing voice to calm and reassure it, gently stabilize it by holding it steady with one or both hands. Rub your cat's throat or blow in its nose to encourage it to swallow the pill.
	Scores	Mean ROUGE: 18.68 (rank 7)    SummScore rank: 7
Beam #5	Summary	Pet your cat and talk to it in a soothing voice to calm and reassure it. Wrap your fingers around the bottom of its cheekbones for leverage. Alternatively, you can use a pill syringe to place the pill at the base of your cat's tongue.
	Scores	Mean ROUGE: 26.93 (rank 3)    SummScore rank: 1 (SummScore output)
Beam #14	Summary	If your cat resists you or is prone to scratching, then wrap your cat in a towel so that just its head is sticking out. Alternatively, you can use a pill syringe to place the pill at the base of your cat's tongue.
	Scores	Mean ROUGE: 30.74 (rank 1)    SummScore rank: 2
Reference		Negotiators from Ireland's two biggest parties are to meet for a final effort to form a minority government.
Reference		regulators from from a two diggest parties are to meet for a final effort to form a fillibility government.

Table 22: SummScore re-ranking applied to the **PEGASUS fine-tuned on CNN/DM** with beam search on **Wiki-How**.

		WikiHow: re-ranking from the self-trained PEGASUS
Source		Talking in private will help you feel less nervous and more comfortable about asking for help.It will also give your teacher more time to help you because they aren't trying to teach at the same time. For example, you could say, "When you have time later today, could we talk about a problem I'm having?" If you're afraid to approach your teacher, put a note on their chair. The note could say, "Can we talk later about something personal? Thanks, Mark." You could also send your teacher an email or message letting them know you would like to ask their help with a personal issue., Sometimes teachers will try to offer advice on what you should do, when all you wanted was for them to listen. If you let your teacher know how they can help, it will make it easier for them to give you the help you want and need. Think about what kind of help you want. Ask yourself, "Do I want her to listen, to give me advice, or to do something about the problem?" Tell your teacher how they can help. For example, "Can you help me come up with ways to make more friends?" If you don't know how you want your teacher to help, you it's okay for you to say that, too. Try saying, "I need your help with a problem, but I don't know what kind of help I need." Also, being honest will help your teacher figure out the right way to help you. The more truthful information your teacher has about what is going on, the more they will be able to help. If you are afraid you will get in trouble, then say that. You could say, "I need your help with something but I'm scared I'll get in trouble." If you are asking for help, but also trying not to get someone else in trouble, you could leave out names, but still be honest about what is going on. For example, "My friend is thinking about cheating on a test and I need advice on how to stop them from doing something so stupid."
Beam #1	Summary	You could say, "I need your help with something but I'm scared I'll get in trouble." If you are asking for help, but also trying not to get someone else in trouble, you could leave out names, but still be honest about what is going on. For example, "My friend is thinking about cheating on a test and I need advice on how to stop them from doing something so stupid."
	Scores	Mean ROUGE: 22.54 (rank 14)    SummScore rank: 14
Beam #2	Summary	Think about what kind of help you want. You could say, "I need your help with something but I'm scared I'll get in trouble." If you are asking for help, but also trying not to get someone else in trouble, you could leave out names, but still be honest about what is going on. If you're afraid to approach your teacher, put a note on their chair.
	Scores	Mean ROUGE: 30.92 (rank 7)    SummScore rank: 18
Beam #3	Summary	For example, you could say, "When you have time later today, could we talk about a problem I'm having?" If you're afraid to approach your teacher, put a note on their chair. Try saying, "I need your help with a problem, but I don't know what kind of help I need.", Also, being honest will help your teacher figure out the right way to help you.
	Scores	Mean ROUGE: 29.41 (rank 9)    SummScore rank: 15
Beam #4	Summary	Think about what kind of help you want. You could say, "I need your help with something but I'm scared I'll get in trouble." If you are asking for help, but also trying not to get someone else in trouble, you could leave out names, but still be honest about what is going on.
	Scores	Mean ROUGE: 28.40 (rank 10)    SummScore rank: 20
Beam #19	Summary	For example, you could say, "When you have time later today, could we talk about a problem I'm having?" If you're afraid to approach your teacher, put a note on their chair. Try saying, "I need your help with a problem, but I don't know what kind of help I need.", Also, being honest will help your teacher figure out the right way to help you. The more truthful information your teacher has about what is going on, the more they will be able to help
	Scores	Mean ROUGE: 35.08 (rank 1)    SummScore rank; 2
Beam #20	Summary	Think about what kind of help you want. You could say, "I need your help with something but I'm scared I'll get in trouble." If you are asking for help, but also trying not to get someone else in trouble, you could leave out names, but still be honest about what is going on. If you're afraid to approach your teacher, put a note on their chair.
	•	It will also give your teacher more time to help you because they aren't trying to teach at the same time
	Scores	Mean ROUGE: 34.51 (rank 2) ∥ SummScore rank: 1 (SummScore output)
Reference		Negotiators from Ireland's two biggest parties are to meet for a final effort to form a minority government.

Table 23: Self-trained PEGASUS with beam search on WikiHow.

		SAMSum: re-ranking from the unsupervised PEGASUS
		Mike: dude, wendy has grown prettier
		Dave: <laughing><laughing><thumb_up></thumb_up></laughing></laughing>
		Mike: <love><love></love></love>
		Dave: i know right?
		Mike: yeah, since she came from Houston, she looks like an angel
		Dave: i'll have to hit on her soon
Source		Mike: haha, stay off, i hear Jerry is her lover
		Dave: really <sad> Mike: yeah</sad>
		Dave: since when
		Mike: haha, i dont know, but you can push your luck
		Dave: haha, i will
		Mike: slink> good luck
		Dave: yeah, ill need it
Beam #1	Summary	Mike: dude, wendy has grown prettier Dave: Mike: Dave: i know right?
	Scores	Mean ROUGE: 19.73 (rank 3) ∥ SummScore rank: 19
Beam #2	Summary	Mike: guy, wendy has grown prettier Dave: Mike: Dave: i know right?
	Scores	Mean ROUGE: 19.73 (rank 3)    SummScore rank: 20
Beam #3	Summary	Mike: Yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Dount #5	-	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 2
Beam #4	Summary	Mike: uh, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
	Caaras	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push Mean ROUGE: 22.31 (rank 2)    SummScore rank: 11
	Scores	Mike: sure, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #5	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 13
		Mike:yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #6	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 6
Beam #7	C	Mike: yes, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
beam #/	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 10
Beam #8	Summary	Mike: Yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Dealli #0	-	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you can put
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 1 (SummScore output)
Beam #9	Summary	Mike: uh, yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
	C	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike is haha, i dont know, but you
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 18  Mike: obviously, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #10	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 15
		Mike: uh, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #11	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you can put
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 9
D #12		Mike: sure, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #12	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you can put
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 12
Beam #13	Summary	Mike: uh, yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Deam #15	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you
	Scores	Mean ROUGE: 22.64 (rank 1)    SummScore rank: 5
Beam #14	Summary	Mike: yes, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
	-	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you can pu
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 8  Mike: no, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #15	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 17
		Mike:yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #16	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you can pu
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 4
		Mike: cool, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #17	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 14
Doom #10		Mike: Yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #18	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i dont know, but you can push
	Scores	Mean ROUGE: 22.31 (rank 2)    SummScore rank: 7
Ream #10		Mike: uh, yeah, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Beam #19	Summary	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike: hahaha, i dont know, but you
	Scores	Mean ROUGE: 22.64 (rank 1)    SummScore rank: 3
Beam #20	Summary	Mike: uh, since she came from Houston, she looks like an angel Dave: i'll have to hit on her soon
Deuiii 174U	-	Mike: haha, stay off, i hear Jerry is her lover Dave: really Mike: yeah Dave: since when Mike:haha, i don't know, but you
	Scores	Mean ROUGE: 22.64 (rank 1)    SummScore rank: 16
Reference		Mike and Dave notice Wendy got prettier. Dave wants to hit on her, but she's with Jerry. He'll try anyway.

Table 24: SummScore re-ranking applied to the **unsupervised PEGASUS** with beam search on **SAMSum**.

		SAMSum: re-ranking from the PEGASUS trained on XSum
		Mia: God, he keeps talking about the stupid wall
		Jennifer: I think he's just senile
		Karine: unfortunately it's much more
		Karine: this populist strategy to scare people with a minority
		Karine: and then present himself as the only savior
		Peter: Karine is right, I think he's not as senile and stupid as we would like to believe Mia: so it's even worse - he's pure evil
		Peter: possibly yes
		Karine: I really think so, because it's not only about politics anymore
Source		Karine: he is destroying the Earth
Source		Karine: trying to shake the world's order
		Jennifer: but he's also quite stupid Jennifer: and the dangerous thing is his self confidence
		Jennifer: he's persistence
		Jennifer: and ignorance
		Karine: but we have a chance to change it
		Karine: maybe Trump will be over soon?
		Mia: we will see
		Mia: but we should do anything to win the next elections
6 <u>-</u>		Karine: everything!
Beam #1	Summary	In our series of letters from British schoolchildren, Mia, Jennifer and Karine give their views on US President Donald Trump.
	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 18
Beam #2	Summary	In our series of letters from British children, Mia, Jennifer and Karine give their views on US President Donald Trump.
D 42 - ·	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 17
Beam #3	Summary	All images are copyrighted.
D	Scores	Mean ROUGE: 00.00 (rank 7)    SummScore rank: 20  In our series of letters from British children, Mia, Jennifer and Karine tell us what they think about US President Donald Trump.
Beam #4	Summary Scores	Mean ROUGE: 21.65 (rank 6)    SummScore rank: 6
Beam #5		In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think about Donald Trump.
Beam #5	Summary	
D #6	Scores	Mean ROUGE: 36.19 (rank 2)    SummScore rank: 5 In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think about US President Donald Trump.
Beam #6	-	
Beam #7	Scores	Mean ROUGE: 33.89 (rank 3)    SummScore rank: 5 In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think of Donald Trump.
beam #/	Summary Scores	Mean ROUGE: 36.19 (rank 2)    SummScore rank: 10
Beam #8	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think of US President Donald Trump.
DCaiii πο	Scores	Mean ROUGE: 33.89 (rank 3)    SummScore rank: 11
Beam #9	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter give their views on US President Donald Trump.
DCaiii π7	Scores	Mean ROUGE: 36.19 (rank 2)    SummScore rank: 16
Ream #10	Summary	In our series of letters from British children, Mia, Jennifer and Karine tell us what they think about Donald Trump.
Deam #10	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 3
Beam #11	Summary	In our series of letters from British schoolchildren, Mia, Jennifer and Karine give their views on Donald Trump.
Dealii #11	Scores	Mean ROUGE: 24.89 (rank 4)    SummScore rank: 19
Beam #12	Summary	In our series of letters from British children, Mia, Jennifer and Karine tell us what they think of Donald Trump.
Deam #12	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 9
Beam #13		In our series of letters from British schoolchildren, Mia, Jennifer and Karine tell us what they think of Donald Trump.
	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 13
Beam #14	Summary	In our series of letters from British schoolchildren, Mia, Jennifer and Karine tell us what they think about Donald Trump.
	Scores	Mean ROUGE: 23.16 (rank 5)    SummScore rank: 8
Beam #15		In our series of letters from British children, Mia, Jennifer and Karine give their views on Donald Trump.
	Scores	Mean ROUGE: 24.89 (rank 4)    SummScore rank: 15
Beam #16	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter give their views on Donald Trump.
	Scores	Mean ROUGE: 38.83 (rank 1)    SummScore rank; 14
Beam #17	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think of Donald Trump's presidency.
	Scores	Mean ROUGE: 33.89 (rank 3)    SummScore rank: 7
Beam #18	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us what they think about Donald Trump's presidency.
	Scores	Mean ROUGE: 33.89 (rank 3)    SummScore rank: 2
Beam #19	Summary	n our series of letters from British children, Mia, Jennifer, Karine and Peter give their views on US President Donald Trump's presiden
	Scores	Mean ROUGE: 33.89 (rank 3)    SummScore rank: 12
Beam #20	Summary	In our series of letters from British children, Mia, Jennifer, Karine and Peter tell us why they think Donald Trump is a fool.
	Scores	Mean ROUGE: 33.89 (rank 3) ∥ SummScore rank: 1 (SummScore output)
Reference		Mia, Jennifer, Karine and Peter do not like Trump.

Table 25: SummScore re-ranking applied to the **PEGASUS transferred from XSum** with beam search on SAM-Sum.

		SAMSum: re-ranking from the self-trained PEGASUS
		Louis: Hey, hows your day? :D
		Cheryl: Okaaay I guess
		Louis: Aha, someone's feeling a bit down, am I right?
		Cheryl: yea, sort of
		Louis: Go on, tell me what happened
		Cheryl: I just had an argument with my mom Louis: Jesus what again
		Cheryl: I forgot to close the window when I was leaving home!
		Louis: And that's it?
Source		Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything;/
		Louis: not a good idea, babe
		Cheryl: I knoooow
		Louis: Was it really bad?
		Cheryl: I suppose yea, she kicked me out xd Louis: WHAT
		Cheryl: I mean I don't have to move right now, but she gave me time till the end of the year
		Louis: I'm sorry
		Cheryl: Naah, don't be, I believe it's for good. I couldn't stand her anyway xD
Beam #1	Summary	Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything /
Jeann #1	•	Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad?
	Scores	Mean ROUGE: 12.15 (rank 8)    SummScore rank: 8
Beam #2	Summary	Cheryl: no, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything :/ Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad?
	Scores	Mean ROUGE: 12.15 (rank 8)    SummScore rank: 10
		Cheryl: Ya know, wouldn't be that bad, but I got angry, started screaming and everything ;/
Beam #3	Summary	Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad?
	Scores	Mean ROUGE: 12.73 (rank 7) ∥ SummScore rank: 18
3eam #4	Summary	Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything ;/
Jean #4		Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad? Cheryl:
	Scores	Mean ROUGE: 11.97 (rank 9)    SummScore rank: 9
Beam #5	Summary	Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything :/ Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad? Cheryl
	Scores	Mean ROUGE: 11.97 (rank 9)    SummScore rank: 11
		Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything:/
Beam #6	Summary	Louis: not a good idea, babe Cheryl: i knoooow Louis: Was it really bad?
	Scores	Mean ROUGE: 12.15 (rank 8)    SummScore rank: 16
Beam #7	Summary	Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything :/
Jeann π /		Louis: not a good idea, babe Cheryl:I knoooow Louis: Was it really bad?
	Scores	Mean ROUGE: 12.15 (rank 8)    SummScore rank: 15
Beam #8	Summary	Cheryl: D Cheryl: Okaaay I guess Louis: Aha, someone's feeling a bit down, am I right? Cheryl: yea, sort of  Louis: Go on, tell me what happened Cheryl: Ijust had an argument with my mom
	Scores	Mean ROUGE: 17.23 (rank 5)    SummScore rank: 5
		Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything ;/
Beam #9	Summary	Louis: not a good idea, babe Cheryl: I knoooow; Louis: Was it really bad?
	Scores	Mean ROUGE: 12.15 (rank 8)    SummScore rank: 12
Beam #10	Summary	Cheryl: yea, sort of Louis: Go on, tell me what happened Cheryl: Ijust had an argument with my mom
		Louis: Jesus what again Chery): I forgot to close the window when I was leaving home!
	Scores	Mean ROUGE: 29.19 (rank 1)    SummScore rank: 17
Beam #11	Summary	Cheryl: yea, sort of Louis: Go on, tell me what happened Cheryl: Ijust had an argument with my mom Louis: Jesus what again Cheryl:I forgot to close the window when I was leaving home! Louis: And that's it?
	Scores	Louis, Joseph Main again Carly II, 10 gord to toke the window which I was tearing home: Louis, And that s it:  Mean ROUGE: 29.00 (rank 2)    SummScore rank: 7
		:D Cheryl: Okaaay I guess Louis: Aha, someone's feeling a bit down, am I right? Cheryl: yea, sort of
3eam #12	Summary	Louis: Go on, tell me what happened Cheryl: Ijust had an argument with my mom
	Scores	Mean ROUGE: 17.48 (rank 4)    SummScore rank: 1 (SummScore output)
Beam #13	Summary	:D Cheryl: Okaaay I guess Louis: Aha, someone's feeling a bit down, am I right? Cheryl: yea, sort of
	•	Louis: Go on, tell me what happened Cheryl: Ijust had an argument with my mom Louis
	Scores	Mean ROUGE: 17.23 (rank 5)    SummScore rank: 2  Cheryl: yea, sort of Louis: Go on, tell me what happened Cheryl: Ljust had an argument with my mom
Beam #14	Summary	Louis: Jesus what again Cheryl: I forgot to close the window when I was leaving home! Louis: And that's it?
	Scores	Mean ROUGE: 29,00 (rank 2)    SummScore rank: 6
		Cheryl: No, not only Ya know, wouldn't be that bad, but I got angry, started screaming and everything :/
Beam #15	Summary	Louis: not a good idea, babe Cheryl: I knoooow Louis: Was it really bad? Louis: Go on.
	Scores	Mean ROUGE: 11.62 (rank 10) ∥ SummScore rank: 14
3eam #16	Summary	Cheryl: :D Cheryl: Okaaay I guess Louis: Aha, someone's feeling a bit down, am I right?
	•	Louis: Go on, tell me what happened Cheryl: Iju st had an argument with my mom Louis: Jesus what again Cheryl:
	Scores	Mean ROUGE: 16.04 (rank 6)    SummScore rank: 4  D Cheryl: Okaaay I guess Louis: Aha, someone's feeling a bit down, am I right? Cheryl: yea, sort of
Beam #17	Summary	Louis: Go on, tell me what happened Cheryl: Ljust had an argument with my mom Louis:
	Scores	Louis. Go on, en me what inappened criefly ijugs had an argument with my mon Louis.  Mean ROUGE: 17.23 (rank 5)    SummScore rank: 3
Beam #18	Summary	Cheryl: Naah, don't be, I believe it's for good. I couldn't stand her anyway xD
	Scores	Mean ROUGE: 5.23 (rank 11)    SummScore rank: 19
200m #10		Cheryl: Ok, I suppose yea, she kicked me out xd Louis: WHAT Cheryl: I mean I don't have to move right now, but she gave me time till the end of the year
Beam #19	Summary	Louis: I'm sorry Cheryl: Naah, don'
	Scores	Mean ROUGE: 28.10 (rank 3)    SummScore rank: 13
Beam #20		Cheryl: Hi Louis Louis: Hi Cheryl, how are you?
	Scores	Mean ROUGE: 3.17 (rank 12)    SummScore rank: 20

Table 26: Self-trained PEGASUS with beam search on SAMSum.