SummaReranker: A Multi-Task Mixture-of-Experts Re-ranking Framework for Abstractive Summarization

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Abstract

Sequence-to-sequence neural networks have recently achieved great success in abstractive summarization, especially with the trend of fine-tuning large pre-trained language models on the downstream dataset. These models are typically decoded with beam search to generate a unique summary. However, the search space is very large, and due to exposure bias, such decoding is not optimal. In this paper, we show that it is possible to directly train a second-stage model performing *re-ranking* on a set of summary candidates. Our mixture-of-experts SummaReranker learns to select a better candidate and systematically improves the performance of the base model. With a base PEGASUS, we push ROUGE scores by 5.44% on CNN-DailyMail (47.16 ROUGE-1), 1.31% on XSum (48.12 ROUGE-1) and 9.34% on Reddit TIFU (29.83 ROUGE-1), reaching a new state-of-the-art [1].

1 Introduction

In recent years, sequence-to-sequence neural models have enabled great progress in abstractive summarization. In the news domain, they have surpassed the strong LEAD-3 extractive baseline. Initially models like the Pointer-Generator (See et al., 2017) were trained from scratch, but with the rise of transfer learning since BERT (Devlin et al., 2019), leading approaches typically fine-tune a base pre-trained model that either follows a general text generation training objective like T5 (Raffel et al., 2019), BART (Lewis et al., 2020), ERNIE (Zhang et al., 2019b) and ProphetNet (Qi et al., 2021), or an objective specifically tailored for summarization like in PEGASUS (Zhang et al., 2020).

Most of these sequence-to-sequence models are history-based, where an output sequence is represented as a sequence of decisions and the probability of the sequence is computed as a product of decision probabilities. This is also known as the auto-regressive factorization. To transform the sequence of probabilities into summaries, beam search is commonly used. While auto-regressive decoding with beam search is simple and has many advantages, it can be difficult to encode global constraints such as grammaticality, coherence and factual consistency within this framework, properties that are believed to be useful in discriminating among candidate outputs. If the model starts decoding in a bad direction, mistakes might propagate, carry over the mistake of previous tokens to the generation of new ones, and the model has no way to know that it should adjust the decoding. Furthermore, these models are typically trained with teacher forcing (Williams and Zipser, 1989), which leads to an inherent discrepancy between training time and inference time known as the exposure bias problem (Bengio et al., 2015; Sun and Li, 2021).

Decoding methods	# Summary candidates	R-1	R-2	R-L	BS	BaS
Beam search (top beam)	1	44.23	21.48	41.21	87.39	-2.78
Beam search	15	51.06	27.74	48.05	88.50	-2.48
Diverse beam search	15	**54.30**	**30.02**	**51.33**	**88.97**	**-2.40**
Top-k sampling	15	52.31	27.41	49.17	88.64	-2.56
Top-p sampling	15	53.52	28.88	50.46	88.87	-2.46
All four methods above	60	**57.70**	**33.77**	**54.72**	**89.58**	**-2.25**

Table 1: Oracle scores for four popular decoding methods and five summarization evaluation measures for a base PEGASUS model on CNN/DM. **R-1/2/L** denotes ROUGE-1/2/L, **BS** and **BaS** denote BERTScore and BARTScore, respectively.

Decoding methods such as beam search maintain a list of top-k best candidates, and output a single best one. In the case of beam search, candidates are sorted by decreasing log-probability, and the last $(k-1)$ hypotheses are discarded. However, these $(k-1)$ other hypotheses often contain considerably better sequences in terms of different evaluation measures. This observation holds over other decoding methods: diverse beam search (Vijayakumar et al., 2016), top-k sampling (Fan et al., 2018) and top-p sampling (Holtzman et al., 2019). In Table 1, we illustrate this phenomenon

[1] We will share the code and model checkpoints at <url>

with the *oracle* scores for four popular decoding methods and five measures on the CNN-DailyMail (Hermann et al., 2015) dataset with a PEGASUS model. The oracle ROUGE-1 scores are up to 10 points higher (+22.8%) than the top beam baseline. Moreover, oracle gains significantly increase when mixing several generation methods together, reaching an improvement of more than 13 ROUGE-1 points (+30.5%). Such a gap is larger than the progress made by research in the whole field of neural abstractive summarization in the last five years (Nallapati et al., 2016; Dou et al., 2021). This suggests that current abstractive models are not exploited to their full capacity, calling for better methods to generate and identify the best summary candidate.

Given this assessment, in this work we investigate whether it is possible to train a *second-stage* summarization model which learns to select the best summary among a set of candidates obtained from a base model and with a decoding process, which itself can potentially involve a set of decoding methods (e.g., beam search variants). This way, the model would recover the gap that separates it with the oracle. This raises the question of what makes a summary candidate the *optimal* summary? Admittedly, summarization has been an underconstrained task and its evaluation is complex and remains an active research area (Kryscinski et al., 2019; Fabbri et al., 2021; Koto et al., 2021). To build a flexible approach, we use a multi-task learning framework based on a mixture-of-experts architecture in order to optimize *jointly* over several measures.

To design a robust re-ranker, we systematically explore the dimensions of summary re-ranking: base model, decoding process, and evaluation measure. Our system, named *SummaReranker*, is flexible and multi-task: it can be trained with any set of evaluation metrics. It is considerably less computationnally expensive to train than the single-stage summarization models that it is plugged on. We apply our system across three different datasets {CNN-DailyMail, XSum, Reddit TIFU} and two base models {PEGASUS, BART}. Optimizing ROUGE metrics leads to performance improvements from 1.31% to 9.34% depending on the dataset. It outperforms recently proposed second-stage summarization approaches RefSum (Liu et al., 2021) and SimCLS (Liu and Liu, 2021) and sets a new state-of-the-art on CNN-DailyMail and XSum (Narayan et al., 2018). We present extensive quantitative results coupled with a qualitative human evaluation.

2 Related Work

Re-ranking has been adopted in several branches of NLP. In syntactic parsing, Collins and Koo (2005) were the first to employ a re-ranker on the outputs of a base parser, followed by Charniak and Johnson (2005), who used a Maximum Entropy re-ranker. Passage re-ranking is used as the first stage of question-answering systems, to retrieve relevant passages where the answer might lay (Kratzwald and Feuerriegel, 2018; Nogueira and Cho, 2019). Some recent question-answering models also propose to perform answer re-ranking, to refine the answer selection (Kratzwald et al., 2019; Iyer et al., 2021). Re-ranking has also been used in neural machine translation. Checkpoint reranking (Pandramish and Sharma, 2020) generates several translation candidates with multiple model checkpoints, based on the observation (similar to the one we made in §1) that the oracle across checkpoints is of higher quality than just the last checkpoint. Bhattacharyya et al. (2021) use an energy-based model on top of BERT to select translation candidates with higher BLEU score.

In abstractive summarization, second-stage approaches such as re-ranking remain underexplored. Recently, RefSum (Liu et al., 2021) defined a second-stage summarization framework which helps address the problem of the train-test distribution mismatch in second-stage models. With a base GSum model (Dou et al., 2021), the authors reach a 46.18 state-of-the-art ROUGE-1 on CNN-DailyMail. In SimCLS (Liu and Liu, 2021), the authors train a second-stage model with contrastive learning, using a ranking loss to select the best summary candidate from a pool of 16 diverse beam search candidates, reaching 46.67 ROUGE-1 on CNN-DailyMail. Our approach differs from RefSum and SimCLS in terms of model architecture and loss function, as well as summary candidate generation process. In contrast with RefSum, we use a single base model, but mix several decoding methods, as our goal is single-model improvement. Unlike SimCLS, we do not use a ranking loss, but directly model the probability that a summary candidate is the best one. To the best of our knowledge, we are the first ones to propose a *multi-task* re-ranking system for abstractive summarization.

This enables practitioners to leverage the literature in automatic abstractive summarization evaluation (Lin, 2004; Zhang et al., 2019a; Zhao et al., 2019a; Yuan et al., 2021).

3 Model

3.1 Re-ranking Framework

Our approach follows the paradigm of second-stage models. Specifically, given a source document S, a base model B, and a set of decoding methods $\mathbb{D}$, we get a pool of m summary candidates $\mathbb{C} = \{C_1, \ldots, C_m\}$. Given an evaluation metric μ in a set of metrics $\mathbb{M}$, we get associated scores for each candidates $\mathbb{S}_\mu = \{\mu(C_1), \ldots, \mu(C_m)\}$. Our goal is to train a model f_θ parameterized by θ to explicitly identify the best summary candidate C_μ^* according to the metric, which is given by:

$$C_\mu^* = \underset{C_i \in \mathbb{C}}{\arg\max} \; \{\mu(C_1), \ldots, \mu(C_m)\} \tag{1}$$

We frame this problem as a binary classification: C_μ^* is the positive candidate, while other candidates are treated as negative. For a metric μ, the re-ranker f_θ is trained with a binary cross-entropy loss:

$$\mathcal{L}_\mu = -y_i \log p_\theta^\mu(C_i) - (1 - y_i) \log(1 - p_\theta^\mu(C_i)) \tag{2}$$

where $y_i = 1$ if $C_i = C_\mu^*$, otherwise $y_i = 0$.

To optimize for N different metrics $\mathbb{M} = \{\mu_1, \ldots, \mu_N\}$ simultaneously, we have a separate prediction head (tower) for each and we minimize the average over metric losses defined as:

$$\mathcal{L} = \frac{1}{N} \sum_{\mu \in \mathbb{M}} \mathcal{L}_\mu \tag{3}$$

3.2 Model Architecture

We first need to get a good representation of the summary candidate. To use contextual information, we concatenate the source with the candidate, separating the two with a special token: `[CLS] Source [SEP] Candidate`, and pass it to a pre-trained language model. In all experiments, we use RoBERTa-large (Liu et al., 2019) as encoder. Concatenating the source with the candidate enables RoBERTa to perform cross-attention between the two, which finds parts of the source relevant to the summary candidate. We take the `[CLS]` representation from RoBERTa's last layer, and feed it to a multi-layer perceptron (MLP).

Once we have a joint representation of the source with the candidate (noted $\boldsymbol{x}$), we perform multi-task learning in order to optimize for the desired metrics.

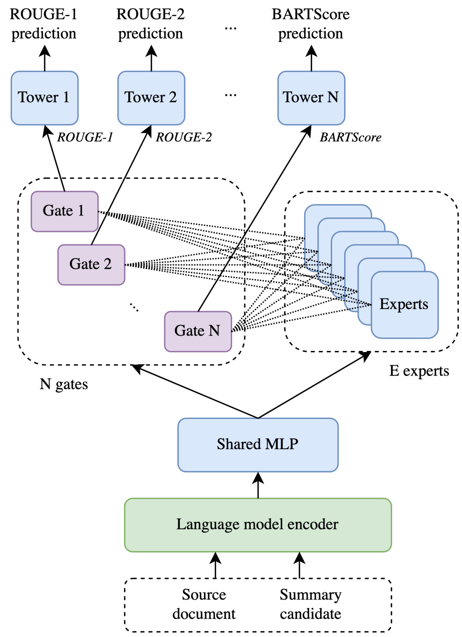

Figure 1: SummaReranker model architecture, optimizing N metrics. The summarization metrics here (*ROUGE-1*, *ROUGE-2*, ..., *BARTScore*) are displayed as examples.

Since metrics are different, yet may be strongly correlated (e.g., ROUGE variants), we adopt a mixture-of-experts (MoE) architecture. In particular, we follow the sparse MoE approach (Shazeer et al., 2017), which introduces experts dropout. To adapt it to multi-task training, we use the multi-gate approach proposed in Zhao et al. (2019b). Given E experts $\mathcal{E}_1, \ldots, \mathcal{E}_E$ and N prediction towers $\mathcal{T}_1, \ldots, \mathcal{T}_N$, the prediction for an input summary representation $\boldsymbol{x}$ for a metric μ indexed by $k \in \{1, \ldots, N\}$ is:

$$f_\theta^k(\boldsymbol{x}) = \mathcal{T}_k\Big(\sum_{i=1}^{E} \text{softmax}(\boldsymbol{W}_k \boldsymbol{x})_{(i)} \mathcal{E}_i(\boldsymbol{x})\Big) \tag{4}$$

where $\boldsymbol{W}_k$ is the weight matrix associated with gate k. The corresponding prediction probability is:

$$p_\theta^\mu = \text{sigmoid}(f_\theta^k(\boldsymbol{x})) \tag{5}$$

Experts are shared across all tasks, and through the softmax gates the model learns how much weight to assign to each expert for each task.

Our SummaReranker model architecture is shown in Fig. 1. In practice, the shared bottom MLP consists in two fully-connected layers with ReLU activation (Glorot et al., 2011). Each expert $\mathcal{E}_i$ is a also a two-layer MLP with ReLU, and each prediction tower $\mathcal{T}_k$ is a single-layer MLP. We set the number E of experts to be equal to twice the number of tasks (N), and the experts dropout to 50%, so that the effective number of experts being used during training matches N.

3.3 Tackling Training and Inference Gap

Second-stage learning approaches may suffer from an inherent distribution bias. Indeed, the base model has a different output distribution on the training set than on the validation and test sets. Thus, it is ineffective to train a second-stage model on the training set outputs of the base model.

To resolve this distribution shift, we split the training set into two equal parts, and fine-tune a pre-trained model on each half. Then, to build a training set for the re-ranker, we infer with each model on the half that it was not trained on. At testing time, we face two options:

- **Base setup**: in this setup, we infer on the test set with *one of the two base models trained on half the training set*, then apply the re-ranker. Since the base models are trained on less data (i.e., half of the original training data), their performance on the test set worsens. However, we will show that SummaReranker brings improvements which more than compensate this performance drop.
- **Transfer setup**: this setup consists in applying SummaReranker on top of a base model *trained on the whole training set*. Note that SummaReranker is still trained in the same fashion as before. There could be a distribution mismatch in this setting, since SummaReranker needs to rank summary candidates of a potentially higher quality (generated by a model trained on full data) than the summaries that it was trained on (generated by a model trained on half data). Nevertheless, SummaReranker still transfers well and considerably improves the performance of the base model in this setup.

If $\mathbb{D}$ is made of multiple decoding methods $\{\delta_1, ..., \delta_j\}$, each producing several candidates, the overall candidate set may be large, slowing down inference. Thus, to explore lower-resource inference, we separate the sets of decoding methods $\mathbb{D}_{\text{train}}$ and $\mathbb{D}_{\text{test}}$ used for training and inference, respectively, and enforce that $\mathbb{D}_{\text{test}} \subset \mathbb{D}_{\text{train}}$.

4 Experiments

4.1 Scope & Datasets

Throughout our experiments, we vary all the three dimensions of our re-ranking framework: the base model, the set of decoding methods $\mathbb{D}$ and the set of scoring metrics $\mathbb{M}$.

	R-1	**R-2**	**R-L**	**BS**	**BaS**
R-1	1.000	0.884	0.977	0.858	0.662
R-2	0.884	1.000	0.910	0.833	0.665
R-L	0.977	0.910	1.000	0.855	0.669
BS	0.858	0.833	0.855	1.000	0.682
BaS	0.662	0.665	0.669	0.682	1.000

Table 2: Pearson correlation coefficient between the five evaluation metrics {R-1, R-2, R-L, BS, BaS} for a base PEGASUS decoded with beam search on CNN/DM. **R-1/2/L** denotes ROUGE-1/2/L, **BS** and **BaS** denote BERTScore and BARTScore, respectively.

As base models, we use PEGASUS (Zhang et al., 2020) and BART (Lewis et al., 2020), each one in their large version, as they are leading summarization models with publicly available checkpoints. We obtain pre-trained and fine-tuned checkpoints from the HuggingFace library (Wolf et al., 2020).

For decoding methods ($\mathbb{D}$), we experiment with beam search (referred to as 1), diverse beam search (2), top-k sampling (3) and top-p sampling (4). For each decoding method employed, we set the number of candidates to 15, as it is close to the maximum which could fit in a standard 11GB RAM GPU when doing generation with PEGASUS-large.

As set of metrics, we first use ROUGE (Lin and Hovy, 2003), in its commonly used three flavours of ROUGE-1 (noted *R-1*), ROUGE-2 (noted *R-2*) and ROUGE-L (noted *R-L*) for summarization evaluation. We also leverage recently introduced model based evaluation methods BERTScore (noted *BS*) (Zhang et al., 2019a) and BARTScore (noted *BaS*) (Yuan et al., 2021), which both rely on contextual word embeddings from pre-trained language models. Thus, our total set of metrics is $\mathbb{M}$ = {R-1, R-2, R-L, BS, BaS}. We display correlation between each pair of this set of metrics on Table 2. Notably, R-1 and R-L are strongly correlated (Pearson correlation score of 0.977), while BARTScore is the least correlated to other metrics, suggesting that it captures aspects complementary to the other four.

We train SummaReranker on the following datasets, covering multiple domains:

- **CNN-DailyMail** (Hermann et al., 2015) contains 93k and 220k articles from the CNN and DailyMail newspapers, respectively. We use the non anonymized version from (See et al., 2017).
- **XSum** (Narayan et al., 2018) contains 227k articles from the BBC for years 2010 - 2017. While

Dataset	Domain	# Data points			# Words	
		Train	Val	Test	Doc.	Summ.
CNN/DM	News	287,113	13,368	11,490	766.56	54.78
XSum	News	204,045	11,332	11,334	414.51	22.96
Reddit TIFU	Social media	33,704	4,213	4,222	385.59	20.59

Table 3: Statistics of the three datasets.

also in the news domain, XSum is by design significantly more abstractive than CNN/DM and is made of single-sentence summaries.

- **Reddit TIFU** (Kim et al., 2019) contains 120k posts from the popular online Reddit forum. As in other summarization works (Zhang et al., 2020), we use the TIFU-long subset, containing 37k posts. As there is no official split, we build a random 80:10:10 split for training:validation:test.

We refer to Table 3 for statistics on each dataset.

4.2 Training & Inference Details

To help the model better discriminate between candidates, we found that sampling was useful. Specifically, during training, we rank candidates by decreasing sum of normalized scores for the evaluation metrics and keep the top m_{top} and bottom m_{bottom} candidates. Thus, training time varies in $\mathcal{O}(m_{\text{top}} + m_{\text{bottom}})$, while inference is in $\mathcal{O}(m)$ as we need to score each candidate. In practice, we found that taking $m_{\text{top}} = 1$ and $m_{\text{bottom}} = 1$ performed well, on top of decreasing the training time. This enables us to scale to 15 summary candidates from four decoding methods, totalling 60 summary candidates per source document.

We train SummaReranker for five epochs. We use the Adafactor optimizer (Shazeer and Stern, 2018), with maximum learning rate 1e-5, warming up the learning rate linearly over the first 5% training steps. Training on CNN/DM takes four days on a single RTX 2080 Ti GPU.

For inference, we need to output a single candidate. After getting predicted probabilities across each metric $\mu \in \mathbb{M}$, we output the candidate maximizing the sum of predicted probabilities. Note that relaxing inference to allow for a different best candidate for each metric would improve performance, but is not practical. We perform inference with the model checkpoint maximizing the sum of the scores for the metrics on the validation set.

4.3 Base Setup Results

First, we investigate how our model performs in the base setup described in §3. We apply SummaReranker on top of PEGASUS and BART models

Model	Model stage	Decoding methods ($\mathbb{D}$)	R-1	R-2	R-L	Gain (%)
PEGASUS - 1st half	1	{1}	42.23	19.62	38.90	_
PEGASUS - 1st half	1	{2}	42.50	19.75	39.55	_
PEGASUS - 2nd half	1	{1}	42.46	19.95	39.19	_
PEGASUS - 2nd half	1	{2}	42.75	19.93	**39.86**	_
BART - 1st half	1	{1}	42.79	20.25	39.66	_
BART - 1st half	1	{2}	40.70	18.99	37.88	_
BART - 2nd half	1	{1}	**42.93**	**20.36**	39.73	_
BART - 2nd half	1	{2}	41.93	19.79	39.06	_
PEGASUS - 1st half + SR	2	{1}	44.02	20.97	40.68	5.23
PEGASUS - 1st half + SR	2	{2}	**45.66**	21.31	42.51	7.61
PEGASUS - 2nd half + SR	2	{1}	44.11	21.08	40.82	4.57
PEGASUS - 2nd half + SR	2	{2}	45.73	21.31	**42.62**	6.94
BART - 1st half + SR	2	{1}	44.23	21.23	41.09	3.94
BART - 1st half + SR	2	{2}	45.05	21.47	42.12	11.65
BART - 2nd half + SR	2	{1}	44.51	21.52	41.29	4.44
BART - 2nd half + SR	2	{2}	45.61	**21.78**	**42.62**	9.32
PEGASUS - 1st half + SR	2	{1, 2}	46.12	21.97	42.84	9.36
PEGASUS - 2nd half + SR	2	{1, 2}	**46.19**	22.02	**42.92**	8.70
BART - 1st half + SR	2	{1, 2}	45.76	22.14	42.71	7.99
BART - 2nd half + SR	2	{1, 2}	45.96	**22.18**	42.88	7.98

Table 4: Base setup results for SummaReranker applied to PEGASUS and BART on the CNN/DM dataset. SR refers to SummaReranker. Best scores for each type of model are in bold. **Gain** represents the mean relative gain over {R-1, R-2, R-L} over the best decoding method.

which we fine-tuned on 50% of the training dataset. For each model, we decode using beam search (1) and diverse beam search (2). The former performs better for BART, while the latter is better for PEGASUS. We then apply SummaReranker optimized jointly for R-1, R-2, and R-L on top of the best of the two base models, for each decoding method and also when using both decoding methods. Results are shown in Table 4.

SummaReranker improves a base PEGASUS by 4.57% to 7.21% with 15 candidates, and 8.70% to 9.36% with 30 candidates. With BART, SummaReranker improves by 3.94% to 11.65% with 15 candidates, and 7.98% with 30 candidates. When using several decoding methods, we compare the re-ranker performance with the best baseline among decoding methods. Notably, with SummaReranker, PEGASUS and BART models trained on 50% of the training set now surpass their counterparts trained on *the whole* training set, achieving 46.19/22.02/42.92 R-1/2/L for PEGASUS, 45.96/22.18/42.88 R-1/2/L for BART. This is better than GSum (Dou et al., 2021), the best summarization model on CNN/DM (Table 5).

4.4 Transfer Setup Results

Next, we look at how SummaReranker performs in the transfer setup. That means, we apply it on top of PEGASUS and BART models fine-tuned on the entire dataset, using public checkpoints. We also include R3F (Aghajanyan et al., 2020) and GSum (Dou et al., 2021) in our single-stage model comparison. In terms of second-stage approaches,

Model	Model stage	Decoding methods $\mathbb{D}_{train}$	$\mathbb{D}_{test}$	m	Optimized Metrics ($\mathbb{M}$)	Evaluation metrics R-1	R-2	R-L	BS	BaS	Gain (%)
PEGASUS (Zhang et al., 2020)	1	{1}	{1}	8	_	44.16	21.56	41.30	_	_	_
PEGASUS - *our setup*	1	{1}	{1}	15	_	44.23	21.48	41.21	87.39	-2.78	_
PEGASUS - *our setup*	1	{2}	{2}	15	_	44.56	20.90	41.58	87.36	-2.81	_
BART (Lewis et al., 2020)	1	{1}	{1}	5	_	44.16	21.28	40.90	_	_	_
BART - *our setup*	1	{1}	{1}	15	_	43.28	20.44	40.06	87.78	-2.48	_
BART - *our setup*	1	{2}	{2}	15	_	44.48	21.21	41.60	**88.11**	**-2.33**	_
BART + R3F (Aghajanyan et al., 2020)	1	{1}	{1}	5	_	44.38	21.53	41.17	_	_	_
GSum (Dou et al., 2021)	1	{1}	{1}	4	_	**45.94**	**22.32**	**42.48**	_	_	_
GSum + RefSum (Liu et al., 2021)	2	{1}	{1}	4	_	46.18	22.36	42.91	_	_	_
BART + SimCLS (Liu and Liu, 2021)	2	{2}	{2}	16	_	46.67	22.15	43.54	66.14	_	_
PEGASUS + SR	2	{1}	{1}	15	{R-1, R-2, R-L}	45.56†	22.23†	42.46†	87.60†	-2.74†	3.18
PEGASUS + SR	2	{2}	{2}	15	{R-1, R-2, R-L}	**46.86**†	22.01†	**43.59**†	87.66†	-2.73†	5.10
PEGASUS + SR	2	{1, 2}	{1}	15	{R-1, R-2, R-L}	46.13†	**22.61**†	42.94†	87.67†	-2.72†	4.59
PEGASUS + SR	2	{1, 2}	{2}	15	{R-1, R-2, R-L}	46.83†	21.88†	43.55†	87.63†	-2.74†	4.84
BART + SR	2	{1}	{1}	15	{R-1, R-2, R-L}	44.60†	21.38†	41.36†	88.03†	-2.40†	3.63
BART + SR	2	{2}	{2}	15	{R-1, R-2, R-L}	46.47†	22.17†	43.45†	88.43†	-2.19†	4.48
BART + SR	2	{1, 2}	{1}	15	{R-1, R-2, R-L}	45.08†	21.79†	41.85†	88.13†	-2.37†	5.08
BART + SR	2	{1, 2}	{2}	15	{R-1, R-2, R-L}	46.50†	22.15†	43.50†	**88.45**†	**-2.18**†	4.51
PEGASUS + SR (**new SOTA**)	2	{1, 2}	{1, 2}	30	{R-1, R-2, R-L}	**47.16**†	**22.55**†	**43.87**†	87.74†	-2.71†	**5.44**
PEGASUS + SR	2	{1, 2}	{1, 2}	30	{BS, BaS}	45.00†	20.90	41.93†	87.56†	-2.55†	4.23
PEGASUS + SR	2	{1, 2}	{1, 2}	30	{R-1, R-2, R-L, BS, BaS}	46.59†	22.41†	43.45†	87.77†	-2.58†	4.39
BART + SR	2	{1, 2}	{1, 2}	30	{R-1, R-2, R-L}	46.62†	22.39†	43.59†	**88.47**†	-2.18†	5.05
BART + SR	2	{1, 2}	{1, 2}	30	{BS, BaS}	44.90†	20.85	42.03†	88.28†	**-2.05**†	6.11
BART + SR	2	{1, 2}	{1, 2}	30	{R-1, R-2, R-L, BS, BaS}	45.96†	21.79†	43.01†	88.44†	-2.09†	4.03
PEGASUS + SR	2	{1, 2, 3, 4}	{1, 2, 3, 4}	60	{R-1, R-2, R-L}	**47.04**†	**22.32**†	**43.72**†	**87.69**†	**-2.74**†	_

Table 5: Transfer setup results on CNN/DM. SR refers to SummaReranker, m refers to the number of summary candidates, **BS** and **BaS** to BERTScore and BARTScore, respectively. Best scores for each type of model (single stage, second-stage) are in bold. † marks are results significantly better than the base model counterpart among metrics that SummaReranker was optimized for. Results for optimized metrics are shaded. **Gain** represents the mean relative gain over optimized metrics.

we compare SummaReranker with RefSum (Liu et al., 2021) and SimCLS (Liu and Liu, 2021). Note that SummaReranker is trained as usual, on the outputs of two base models trained on 50%.

Results on the CNN/DM dataset are shown in Table 5. We first optimize for ROUGE metric {R-1, R-2, R-L} with multi-task training. With a single decoding method and 15 summary candidates, SummaReranker places PEGASUS and BART on par with SimCLS. With two decoding methods, PEGASUS + SummaReranker sets a new state of the art on CNN/DM with 47.16 R-1, 22.55 R-2 and 43.87 R-L, corresponding to gains of 2.60/1.65/2.29 R-1/2/L or +5.44% from our diverse beam search baseline (and +3.00/1.99/2.57 R-1/2/L from the PEGASUS paper). As expected, the relative gains in this transfer setup are lower. Next, we optimize model-based metrics, and note the difficulty in improving BERTScore, compared to BARTScore. Optimizing jointly ROUGE and model-based metrics improves all metrics, but does not match the results when training only ROUGE. Interestingly, performance gains saturate when adding two extra decoding methods (top-k and top-p sampling), despite gains in the oracle scores observed in Table 1. We note that performance could be further improved with a GSum base model.

To assert statistical significance of performance gains, we perform a t-test between SummaReranker scores and scores from the base model with *each* of the decoding methods, and mark with † results where the p-value is smaller than 0.05 for *all* decoding methods. We also show experts utilization (obtained with softmax weights from the gates) for the model optimized on all five metrics in Fig. 2. Notably, some experts specialize in certain metrics (for instance, expert 0 on R-2 and expert 4 on R-L).

Then, we apply SummaReranker on XSum and Reddit TIFU, as shown in Table 6. We train SummaReranker using the three ROUGE metrics $\mathbb{M}$ = {R-1, R-2, R-L} as objective, and $\mathbb{D}$ = {beam search, diverse beam search} to generate the candidates. With beam search candidates, we push the state-of-the-art to 48.12 R-1, 24.95 R-2 and 40.00 R-L on XSum (+1.31%). On Reddit TIFU, we improve a base PEGASUS from 26.28 R-1 to 29.83 R-1 (+9.34% average ROUGE), a base BART from 27.42 R-1 to 28.99 R-1 (+4.22% average ROUGE).

4.5 Ranking Evaluation

Beyond the qualities of summaries selected by our re-ranker, we investigate the performance of re-ranking itself with rank-based evaluation measures. A perfect re-ranker should systematically single out the best summary from the rest. To evaluate how SummaReranker ranks the best summary, we compute the best summary candidate recall at different thresholds. For a single best summary candidate among m candidates, the recall at k for a ran-

Model	Model stage	$\mathbb{D}_{\text{train}}$	$\mathbb{D}_{\text{test}}$	m	XSum R-1	XSum R-2	XSum R-L	XSum BS	XSum BaS	XSum Gain (%)	Reddit TIFU R-1	Reddit TIFU R-2	Reddit TIFU R-L	Reddit TIFU BS	Reddit TIFU BaS	Reddit TIFU Gain (%)
PEGASUS (Zhang et al., 2020)	1	{1}	{1}	8	47.21	24.56	39.25	_	_	_	*26.63*	*9.01*	*21.60*	_	_	_
PEGASUS - *our setup*	1	{1}	{1}	15	**47.33**	**24.75**	**39.43**	**92.01**	**-1.92**	_	26.28	9.01	21.52	87.34	**-3.46**	_
PEGASUS - *our setup*	1	{2}	{2}	15	46.78	23.77	38.70	91.94	-2.00	_	25.67	8.07	20.97	87.47	-3.48	_
BART (Lewis et al., 2020)	1	{1}	{1}	5	45.14	22.27	37.25	_	_	_	_	_	_	_	_	_
BART - *our setup*	1	{1}	{1}	15	45.24	22.28	37.21	91.58	-1.97	_	**27.42**	**9.53**	**22.10**	87.43	-3.78	_
BART - *our setup*	1	{2}	{2}	15	44.15	20.84	35.88	91.51	-2.08	_	25.43	8.27	20.79	**87.48**	-4.19	_
BART + R3F (Aghajanyan et al., 2020)	1	{1}	{1}	5	_	_	_	_	_	_	*30.31*	*10.98*	*24.74*	_	_	_
GSum + RefSum (Liu et al., 2021)	2	{1}	{1}	4	47.45	24.55	39.41	_	_	_	_	_	_	_	_	_
PEGASUS + SimCLS (Liu and Liu, 2021)	2	{2}	{2}	16	47.61	24.57	39.44	69.81	_	_	_	_	_	_	_	_
PEGASUS + SR (**new XSum SOTA**)	2	{1, 2}	{1}	15	**48.12**†	**24.95**	**40.00**†	**92.14**†	**-1.90**†	**1.31**	**29.57**†	9.70†	**23.29**†	87.63†	**-3.34**†	9.47
PEGASUS + SR	2	{1, 2}	{2}	15	47.04	23.27	38.55	91.98	-2.01	-0.65	28.71†	8.73†	22.79†	**87.84**†	-3.42†	9.57
BART + SR	2	{1, 2}	{1}	15	45.79†	22.17	37.31	91.69†	-1.97	0.33	28.99†	**9.82**	22.96†	87.53	-3.78	4.22
BART + SR	2	{1, 2}	{2}	15	44.39	20.35	35.66	91.51	-2.16	-0.81	28.04†	8.66	22.41†	87.73†	-3.91†	7.59
PEGASUS + SR (**best Reddit TIFU score**)	2	{1, 2}	{1, 2}	30	**47.72**	**24.16**	**39.42**	**92.10**†	**-1.94**	-0.53	**29.83**†	**9.50**†	**23.47**†	**87.81**†	**-3.33**†	**9.34**
BART + SR	2	{1, 2}	{1, 2}	30	45.32	21.46	36.64	91.64	-2.04	-1.68	28.92†	9.16	22.87†	87.70†	-3.83†	1.69

Table 6: Transfer setup results on XSum and Reddit TIFU. SR refers to SummaReranker, m refers to the number of summary candidates, **BS** and **BaS** to BERTScore and BARTScore, respectively. Best scores for each type of model (single stage, second-stage) are in bold. † marks are results significantly better than the base model counterpart among metrics that SummaReranker was optimized for. Results for optimized metrics are shaded. **Gain** represents the mean relative gain over optimized metrics. Reddit TIFU results in italic are not directly comparable due to a different data split.

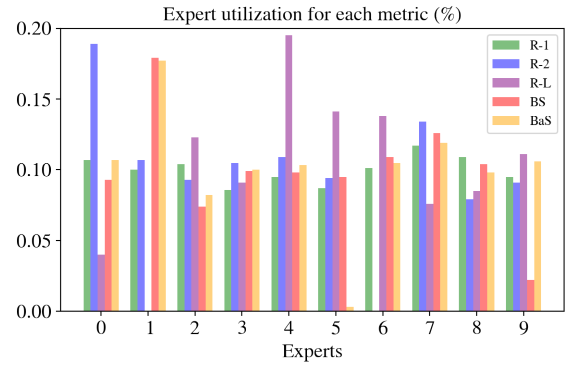

Figure 2: Expert utilization for a base PEGASUS with SummaReranker optimized with {R-1, R-2, R-L, BS, BaS} on CNN/DM, with 10 experts and 50% expert dropout.

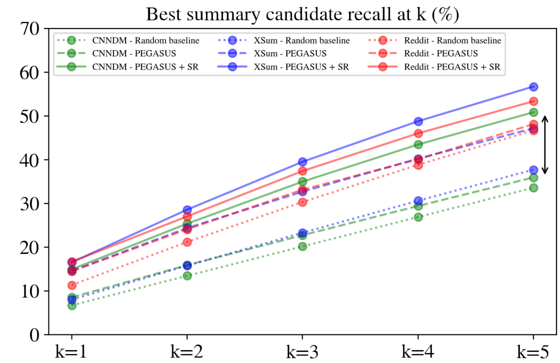

Figure 3: Best summary candidate recall with 15 diverse beam search candidates for PEGASUS. SR denotes SummaReranker. Dotted lines are random baselines, and dashed lines correspond to base models.

dom uniform ranking baseline is simply given by: $R@k = \frac{k}{m}$. However, with the decoding methods under study, there may be multiple best summary candidates maximizing the sum of evaluation measures. This can happen with ROUGE metrics when two summary candidates only differ by a few words. In this case, the best candidate recall at threshold k for the random uniform ranking baseline is given by:

$$R@k = \frac{\binom{m}{m_{\text{best}}} - \binom{m-k}{m_{\text{best}}}}{\binom{m}{m_{\text{best}}}} \quad (6)$$

where m_{best} is the number of best (maximizing the sum of metrics) summary candidates.

In Fig. 3, we see that PEGASUS with diverse beam search ranking of summary candidates (dashed lines) is not significantly better than the corresponding random baseline from eq. (6) (dotted lines) on CNN/DM and Reddit. However, it improves on it on XSum. On all three datasets, SummaReranker (solid lines) significantly pushes the recall at all thresholds. We note +14.90 absolute recall@5 improvement on CNN/DM (50.84 versus 35.94, represented by the black arrow), +9.54 on XSum and +5.23 on Reddit TIFU.

4.6 Qualitative Evaluation

Lastly, we demonstrate that re-ranking improvements in quantitative metrics also translate to qualitatively better summaries. Fig. 4 shows an example of summary selected by SummaReranker, alongside its source document, ground-truth (reference) summary and output from the base model. SummaReranker is able to include a whole sentence which was missed by the base summary. We refer to Appendix G for full re-ranking examples.

We also conduct a human evaluation. We asked three different humans to evaluate 50 randomly sampled test summaries for each dataset. Human raters were graduate students with professional English proficiency (TOEFL scores above 100 out of 120). Humans were shown the source document alongside the top beam search summary from PEGASUS, and SummaReranker's summary, and were asked to choose which one they believe is

Source document: CPRE president Sir Andrew Motion, who is demanding a national clean-up. Council chiefs were condemned last night after claiming it was too dangerous to collect the roadside litter blighting Britain. Winchester Council in Hampshire said its annual clean-up of roads around the city had been hit by new Health and Safety Executive rules designed to protect litter-pickers from traffic. But the HSE denied tightening rules – and said councils were 'over-interpreting' legislation. Last night, former Poet Laureate Sir Andrew Motion, now president of the Campaign to Protect Rural England, accused town hall bosses and the Highways Agency of ruining the countryside by failing to remove rubbish. He said: 'Every day, people tell us that they are disgusted, angry and ashamed of the state of England's roads. 'Nobody wants to drive through our beautiful countryside or approach a vibrant city, heralded only by discarded rubbish.' Although laws to fine people who throw litter from vehicles were now in place, their implementation had been delayed by 'shameful time-wasting', Sir Andrew said. 'Without funding to tackle the problem, I fear our roads will become corridors of waste,' he added. Highways England – the Government-owned company launched last week to replace the Highways Agency – is required to keep the motorway network clean, but responsibility for clearing A-roads and trunk routes is divided between the agency and councils [...]

Reference: Winchester Council in Hampshire claimed annual clean-up hit by new rules. But the Health and Safety Executive denied tightening rules and added that councils were 'over-interpreting' legislation. Poet Laureate Sir Andrew Motion accused town hall bosses and Highways Agency of ruining the countryside by failing to remove rubbish.

Base PEGASUS summary: Council chiefs condemned for claiming it was too dangerous to collect litter. Winchester Council said its annual clean-up had been hit by new rules. Health and Safety Executive denied tightening rules and said councils were 'over-interpreting' legislation.

SummaReranker summary: Winchester Council said its annual clean-up had been hit by new rules. Health and Safety Executive said councils were 'over-interpreting' legislation. Sir Andrew Motion accused town hall bosses and Highways Agency of ruining countryside by failing to remove rubbish.

Figure 4: Example of a summary generated by SummaReranker trained for {R-1, R-2, R-L} on CNN/DM.

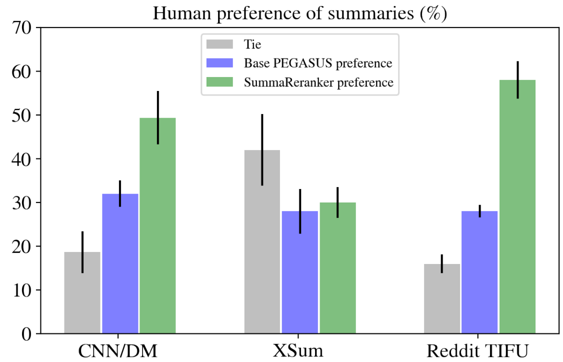

Figure 5: Human evaluation results on all three datasets. Black vertical bars are standard deviation across human raters.

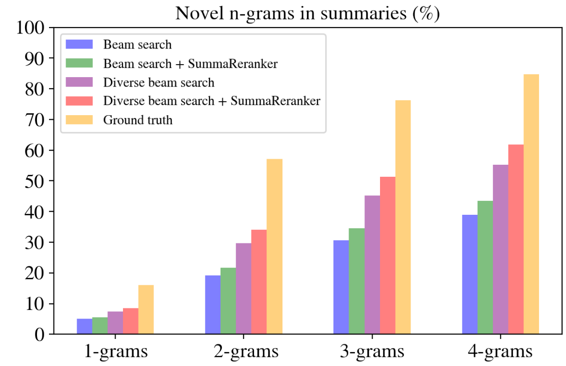

Figure 6: Novel n-grams with a base PEGASUS model on CNN/DM.

more faithful, with the option of choosing a tie. The latter is relevant since - in some cases - the base summary and the re-ranked one are very similar or identical. In Fig. 5, we see that on average, humans are more likely to pick the SummaReranker candidate over the base one.

5 Discussion

Abstractiveness Given that we are not modifying the base model nor its training procedure, we analyze whether our re-ranking system favors more abstractive candidates. In Fig. 6, we display the percentage of novel n-grams for n in {1,2,3,4}, for a base PEGASUS with beam search and diverse beam search decoding, and when adding SummaReranker in both cases. As first raised in (See et al., 2017), summary candidates are much less abstractive than ground truth summaries on CNN/DM. Yet, our re-ranker selects more abstractive candidates. With diverse beam search, which is already more abstractive than beam search, the re-ranker selects even more abstractive summaries. This observation also holds on Reddit TIFU, while XSum summary candidates are already almost as abstractive as the ground truth (see appendix E).

Further Work To encode the source jointly with the summary candidate, we need to truncate the source to a fixed number of tokens. Thus, we are limited by the maximum context window of the language model encoder (512 in the case of RoBERTa-large). Applying SummaReranker to long-document summarization, such as scientific articles summarization (Cohan et al., 2018) would need a different encoder, capable of modeling a long amplitude of source-candidate interactions. In §3, we weighted metric-dependent losses uniformly. We leave to further work the exploration of more complex weight balancing or multi-task learning objectives (Lin et al., 2019).

6 Conclusion

We introduced SummaReranker, the first multi-task re-ranking framework for abstractive summarization. Using the source, our model predicts which summary candidate maximizes each of the evaluation metrics optimized for. SummaReranker works well across different datasets, models, decoding methods and evaluation metrics. Summaries selected by SummaReranker improve the ROUGE state-of-the-art on CNN/DM and XSum. In addition, we also show that summaries selected by SummaRerankder are more abstractive and more favored by human evaluators.

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A Hyper Parameters

Dataset	Model	Learning rate	Num of epochs	Optimizer	Batch size	Label smoothing	Mixed precision	Max source tokens	Max summary tokens
CNN/DM	PEGASUS	5e-5	10	Adafactor	256	0.1	No	1024	128
	BART	3e-5	10	Adam	80	0.1	Yes	1024	128
XSum	PEGASUS	5e-5	10	Adafactor	256	0.1	No	512	64
	BART	3e-5	10	Adam	80	0.1	Yes	512	64
Reddit TIFU	PEGASUS	1e-4	15	Adafactor	256	0.1	No	512	128
	BART	3e-5	15	Adam	80	0.1	Yes	512	128

Table 7: Hyper-parameters for fine-tuning the base models.

Dataset	Model	Max source tokens	Max summary tokens	Length penalty	Repetition penalty	Trigram blocking
CNN/DM	PEGASUS	1024	128	0.8	1.0	No
	BART	1024	128	0.8	1.0	No
XSum	PEGASUS	512	64	0.8	1.0	Yes
	BART	512	64	0.8	1.0	Yes
Reddit TIFU	PEGASUS	512	128	0.6	1.0	Yes
	BART	512	128	1.0	1.0	Yes

Table 8: Hyper-parameters for the summary candidates generation with the base models.

B Oracle Scores

Decoding methods	# Summary candidates	R-1	R-2	R-L	BS	BaS
Beam search (top beam)	1	47.33	24.75	39.43	92.01	-1.92
Beam search	15	56.07	33.80	48.33	93.19	-1.82
Diverse beam search	15	**57.82**	**35.28**	**50.95**	**93.65**	**-1.63**
Top-k sampling	15	55.57	32.54	48.35	93.18	-1.86
Top-p sampling	15	56.74	33.94	49.60	93.40	-1.77
All four above	60	**62.30**	**40.84**	**55.92**	**94.24**	**-1.48**

Table 9: Oracle scores for four popular decoding methods and five summarization evaluation measures for a base PEGASUS model on XSum.

Decoding methods	# Summary candidates	R-1	R-2	R-L	BS	BaS
Beam search (top beam)	1	26.28	9.01	21.52	87.34	-3.46
Beam search	15	36.08	14.93	29.70	88.64	-2.89
Diverse beam search	15	36.70	15.22	**30.88**	**89.08**	**-2.81**
Top-k sampling	15	36.76	14.37	29.49	88.53	-3.14
Top-p sampling	15	**37.54**	**15.24**	30.50	88.69	-3.03
All four above	60	**43.25**	**20.70**	**36.41**	**89.71**	**-2.58**

Table 10: Oracle scores for four popular decoding methods and five summarization evaluation measures for a base PEGASUS model on Reddit TIFU.

C Metrics Correlation

	R-1	R-2	R-L	BS	BaS
R-1	1.000	0.888	0.905	0.850	0.657
R-2	0.888	1.000	0.911	0.790	0.628
R-L	0.905	0.911	1.000	0.847	0.620
BS	0.850	0.790	0.847	1.000	0.690
BaS	0.657	0.628	0.620	0.690	1.000

Table 11: Pearson correlation coefficient between the five evaluation metrics {R-1, R-2, R-L, BS, BaS} for a base PEGASUS decoded with beam search on XSum.

	R-1	R-2	R-L	BS	BaS
R-1	1.000	0.806	0.927	0.766	0.600
R-2	0.806	1.000	0.856	0.679	0.524
R-L	0.927	0.856	1.000	0.768	0.564
BS	0.766	0.679	0.768	1.000	0.646
BaS	0.600	0.524	0.564	0.656	1.000

Table 12: Pearson correlation coefficient between the five evaluation metrics {R-1, R-2, R-L, BS, BaS} for a base PEGASUS decoded with beam search on Reddit TIFU.

D Recall Curves

Threshold k	**k=1**	**k=2**	**k=3**	**k=4**	**k=5**
CNN-DailyMail - Random baseline	6.75	13.49	20.20	26.91	33.60
CNN-DailyMail - PEGASUS	8.57	15.93	22.76	29.43	35.94
CNN-DailyMail - PEGASUS + SummaReranker	14.97	25.40	35.00	43.46	50.84
XSum - Random baseline	8.05	15.81	23.33	30.62	37.72
XSum - PEGASUS	14.60	24.40	32.70	40.23	47.17
XSum - PEGASUS + SummaReranker	16.57	28.60	39.53	48.78	56.71
Reddit TIFU - Random baseline	11.39	21.22	30.35	38.83	46.70
Reddit TIFU - PEGASUS	14.54	24.11	33.16	40.10	48.11
Reddit TIFU - PEGASUS + SummaReranker	16.70	27.07	37.42	46.02	53.34

Table 13: Values of recall curves plotted in Fig. 3.

E Human Evaluation

	Tie		**Base model**		**SummaReranker**	
	Mean	Std	Mean	Std	Mean	Std
CNN/DM	18.67	9.50	32.00	6.00	49.33	12.20
XSum	42.00	16.33	28.00	10.20	30.00	7.12
Reddit TIFU	16.00	4.32	28.00	2.82	58.00	4.32

Table 14: Numbers of the human evaluation in Fig. 5.

F Abstractiveness

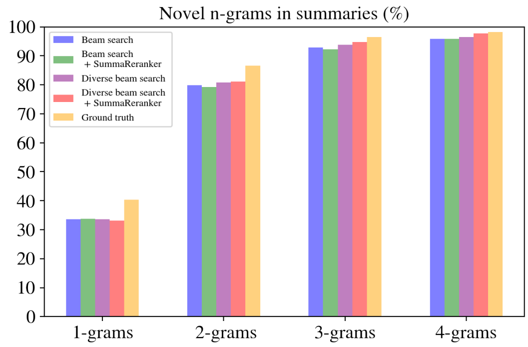

Figure 7: Novel n-grams with a base PEGASUS model on XSum.

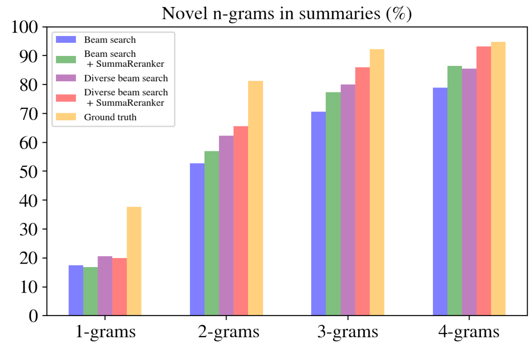

Figure 8: Novel n-grams with a base PEGASUS model on Reddit TIFU.

G Re-ranking Examples

CNN/DM		
Source		Is this confirmation that Angel Di Maria is happy as a Manchester United player? The 27-year-old has endured a mixed start to his United career on-and-off the pitch since joining the club last summer - which has included an attempted burglary at his family home in Cheshire back in February. The midfielder has been linked with a move away from Old Trafford as a result, but speculation about his future could be squashed following his latest tattoo. Angel Di Maria (left) has a new No 7 tattoo which stands out among others on his left arm . Di Maria wears the No 7 shirt at Manchester United following his £60million from Real Madrid last summer. A new picture has been revealed on Twitter of Di Maria's latest piece of body art - the number seven which stands out strongly among others on his left arm. United's club record £60million signing of course adorns the No 7 shirt at the Red Devils - so could his latest tattoo suggest he's committed to Louis van Gaal's side for the long haul? However, before United fans get too carried away it must be noted that the former Real Madrid star does also wear the No 7 jersey for Argentina too. As well as adorning the No 7 shirt at United, 27-year-old (right) also wears that number for Argentina too.
Beam #1	Summary	Angel Di Maria has revealed his latest tattoo on Twitter. The 27-year-old has the No 7 shirt at Manchester United on his left arm. The Argentine has endured a mixed start to his United career. He has been linked with a move away from Old Trafford as a result.
	Reference scores	R-1: 38.6364, R-2: 18.6047, R-L: 34.0909 // Rank: 15
	Re-ranking	SummaReranker score: 0.1577 // SummaReranker score rank: 15
Beam #2	Summary	Angel Di Maria has a new tattoo of the No 7 shirt at Manchester United. The 27-year-old has endured a mixed start to his United career. The midfielder has been linked with a move away from Old Trafford. Di Maria also wears the No 7shirt for Argentina too.
	Reference scores	R-1: 59.0909, R-2: 34.8837, R-L: 56.8182 // Rank: 5
	Re-ranking	SummaReranker score: 0.3905 // SummaReranker rank: 6
Beam #3	Summary	Angel Di Maria has had a new No 7 tattoo on his left arm. The number stands out strongly among others on his arm. The 27-year-old joined Manchester United for a club record £60million last summer. Di Maria also wears the No 7 shirt for Argentina.
	Reference scores	R-1: 61.1765, R-2: 33.7349, R-L: 58.8235 // Rank: 4
	Re-ranking	SummaReranker score: 0.4447 // SummaReranker rank: 5
Beam #4	Summary	Manchester United's record signing has a new No 7 tattoo on his left arm. Angel Di Maria wears the number seven shirt at Old Trafford. The 27-year-old has endured a mixed start to his United career. He has been linked with a move away from Old Trafford as a result.
	Reference scores	R-1: 37.7778, R-2: 15.9091, R-L: 37.7778 // Rank: 14
	Re-ranking	SummaReranker score: 0.2528 // SummaReranker score: 10
Beam #5	Summary	Angel di Maria's latest tattoo shows him with the No 7 shirt at Manchester United. The 27-year-old has endured a mixed start to his United career. The midfielder has been linked with a move away from Old Trafford. Di Maria joined United for a club record £60million from Real Madrid.
	Reference scores	R-1: 53.3333, R-2: 27.2727, R-L: 48.8889 // Rank: 10
	Re-ranking	SummaReranker score: 0.2377 // SummaReranker rank: 12
Beam #6	Summary	Argentina star Angel Di Maria has a new No 7 tattoo on his left arm. The number stands out strongly among others on his arm. Di Maria joined Manchester United for a club record £60million last summe$. The 27-year-old does also wear the No 7 shirt for Argentina too.
	Reference scores	R-1: 61.3636, R-2: 37.2093, R-L: 59.0909 // Rank: 2
	Re-ranking	SummaReranker score: 0.3058 // SummaReranker rank: 8
Beam #7	Summary	Manchester United's Angel Di Maria has had a new No 7 tattoo on his left arm. The 27-year-old's latest body art was revealed on Twitter. Di Maria wears the No 7 shirt at Old Trafford following his £60million move from Real Madrid last summer.
	Reference scores	R-1: 56.4706, R-2: 31.3253, R-L: 47.0588 // Rank: 8
	Re-ranking	SummaReranker score: 0.8853 // SummaReranker rank: 2
Beam #8	Summary	The Manchester United star has revealed his latest tattoo on Twitter. Angel Di Maria has been linked with a move away from Old Trafford in recent weeks. Di Maria wears the No 7 shirt at United following his £60million move from Real Madrid last summer.
	Reference scores	R-1: 48.7805, R-2: 25.0000, R-L: 43.9024 // Rank: 12
	Re-ranking	SummaReranker score: 0.2473 // SummaReranker rank: 11
Beam #9	Summary	**Manchester United's Angel Di Maria has had a new No 7 tattoo on his left arm. The 27-year-old's latest body art was revealed on Twitter. Di Maria wears the No 7 shirt at Old Trafford following his £60million move from Real Madrid last summer. The Argentine also wears the number for Argentina too.**
	Reference scores	R-1: 61.7021, R-2: 34.7826, R-L: 53.1915 // Rank: 6
	Re-ranking	**SummaReranker score: 0.9135 // SummaReranker rank: 1**
Beam #10	Summary	The Manchester United star has revealed his latest tattoo on Twitter. Angel Di Maria has been linked with a move away from Old Trafford in recent weeks. Di Maria wears the No 7 shirt at United following his £60million move from Real Madrid last summer. The Argentine also wears the number for Argentina too.
	Reference scores	R-1: 54.9451, R-2: 29.2135, R-L: 50.5495 // Rank: 9
	Re-ranking	SummaReranker score: 0.1829 // SummaReranker rank: 14
Beam #11	Summary	Man Utd star Angel Di Maria has revealed his latest tattoo on Twitter. The 27-year-old has the No 7 shirt at Manchester United on his left arm. Di Maria joined United for a club record £60million from Real Madrid last summer. The Argentine also wears the No 7 shirt for Argentina too.
	Reference scores	R-1: 68.1319, R-2: 40.4494, R-L: 61.5385 // Rank: 1
	Re-ranking	SummaReranker score: 0.3383 // SummaReranker rank: 7
Beam #12	Summary	Manchester United star Angel Di Maria has had a new No 7 tattoo. The number stands out strongly among others on his left arm. Di Maria wears the No 7 shirt at Old Trafford following his £60million move. The Argentine also wears the number for his country too.
	Reference scores	R-1: 54.1176, R-2: 24.0964, R-L: 42.3529 // Rank: 11
	Re-ranking	SummaReranker score: 0.2172 // SummaReranker rank: 13
Beam #13	Summary	Manchester United midfielder Angel Di Maria has a new tattoo of the No 7 shirt at the club on his left arm. The 27-year-old has endured a mixed start to his United career on-and-off the pitch since joining the club last summer. Di Maria has been linked with a move away from Old Trafford as a result.
	Reference scores	R-1: 40.8163, R-2: 20.8333, R-L: 36.7347 // Rank: 13
	Re-ranking	SummaReranker score: 0.2782 // SummaReranker rank: 9
Beam #14	Summary	Angel Di Maria has revealed his latest tattoo on Twitter. The 27-year-old has the number seven inked on his left arm. Di Maria joined Manchester United for a club record £60million last summer. The Argentine also wears the No 7 shirt for Argentina.
	Reference scores	R-1: 58.5366, R-2: 35.0000, R-L: 56.0976 // Rank: 7
	Re-ranking	SummaReranker score: 0.7447 // SummaReranker rank: 3
Beam #15	Summary	Angel di Maria has a new No 7 tattoo on his left arm. The number seven is among others on his left arm. The 27-year-old wears the No 7 shirt at Manchester United. Di Maria joined United for a club record £60million from Real Madrid last summer.
	Reference scores	R-1: 62.7907, R-2: 33.3333, R-L: 58.1395 // Rank: 3
	Re-ranking	SummaReranker score: 0.4988 // SummaReranker rank: 4
Reference		Angel di Maria joined Manchester United from Real Madrid for £60million. Di Maria took the No 7 shirt upon his arrival at the English giants. 27-year-old also wears the No 7 jersey for Argentina too.

Table 15: Diverse beam search summary candidates of a base PEGASUS and their ground truth and SummaReranker re-ranking scores on CNN/DM.

		XSum
Source		Female officers will be able to wear a headscarf under their caps or berets, provided it is plain and is the same colour as the uniform. Headscarf bans on university campuses and state institutions - except for the judiciary, military and police - have also been lifted in recent years. The garment has been controversial in Turkey for years. Secularists regard it as a symbol of religious conservatism. Since the 1920s, Turkey has had a secular constitution with no state religion. The opposition have accused President Recep Tayyip Erdogan and his Islamist-rooted Justice and Development Party (AKP) of trying to reinterpret secularism. However, public debate has also evolved to accept the hijab as an expression of individual liberties, correspondents say. No strong opposition has been voiced against this latest move. President Erdogan has long embraced Turks' right to express their religious beliefs openly, but he says he is committed to secularism. In 2010, the country's universities abandoned an official ban on Muslim headscarves. Three years later, women were allowed to wear headscarves in state institutions - with the exception of the judiciary, military and police. That year, four MPs wore headscarves in parliament. Most people in Turkey are Sunni Muslims.
Beam #1	Summary	The Turkish authorities have lifted a ban on female police officers wearing headscarves.
	Reference scores	R-1: 50.0000, R-2: 27.2727, R-L: 41.6667 // Rank: 11
	Re-ranking	SummaReranker score: 0.6553 // SummaReranker rank: 12
Beam #2	Summary	Turkey has lifted a ban on female police officers wearing headscarves, the interior ministry says.
	Reference scores	R-1: 61.5385, R-2: 41.6667, R-L: 61.5385 // Rank: 2
	Re-ranking	SummaReranker score: 0.8562 // SummaReranker rank: 2
Beam #3	Summary	The Turkish authorities have lifted a ban on female police officers wearing headscarves, state media report.
	Reference scores	R-1: 53.8462, R-2: 25.0000, R-L: 53.8462 // Rank: 8
	Re-ranking	SummaReranker score: 0.5605 // SummaReranker rank: 1
Beam #4	Summary	Turkey has lifted its ban on female police officers wearing headscarves, the interior ministry says.
	Reference scores	R-1: 53.8462, R-2: 25.0000, R-L: 53.8462 // Rank: 8
	Re-ranking	SummaReranker score: 0.7049 // SummaReranker rank: 9
Beam #5	Summary	The Turkish government has lifted a ban on female police officers wearing headscarves.
	Reference scores	R-1: 58.3333, R-2: 36.3636, R-L: 50.0000 // Rank: 5
	Re-ranking	SummaReranker score: 0.7104 // SummaReranker rank: 8
Beam #6	Summary	The Turkish authorities have lifted a ban on police officers wearing headscarves.
	Reference scores	R-1: 52.1739, R-2: 28.5714, R-L: 43.4783 // Rank: 10
	Re-ranking	SummaReranker score: 0.7503 // SummaReranker rank: 7
Beam #7	Summary	**Turkey has lifted a ban on female police officers wearing headscarves.**
	Reference scores	R-1: 63.6364, R-2: 50.0000, R-L: 63.6364 // Rank: 1
	Re-ranking	**SummaReranker score: 0.9019 // SummaReranker rank: 1**
Beam #8	Summary	Turkey's police force has lifted its ban on female officers wearing headscarves.
	Reference scores	R-1: 50.0000, R-2: 18.1818, R-L: 50.0000 // Rank: 12
	Re-ranking	SummaReranker score: 0.6919 // SummaReranker rank: 10
Beam #9	Summary	Turkey's police force has lifted a ban on female officers wearing headscarves.
	Reference scores	R-1: 58.3333, R-2: 36.3636, R-L: 58.3333 // Rank: 4
	Re-ranking	SummaReranker score: 0.8103 // SummaReranker rank: 5
Beam #10	Summary	Turkey's police force has lifted its ban on female officers wearing headscarves, officials say.
	Reference scores	R-1: 46.1538, R-2: 16.6667, R-L: 46.1538 // Rank: 13
	Re-ranking	SummaReranker score: 0.5066 // SummaReranker rank: 15
Beam #11	Summary	The Turkish government has lifted a ban on female police officers wearing headscarves, state media report.
	Reference scores	R-1: 51.8519, R-2: 32.0000, R-L: 44.4444 // Rank: 9
	Re-ranking	SummaReranker score: 0.6522 // SummaReranker rank: 13
Beam #12	Summary	Turkey's police force has lifted a ban on female officers wearing headscarves, state media report.
	Reference scores	R-1: 51.8519, R-2: 32.0000, R-L: 51.8519 // Rank: 7
	Re-ranking	SummaReranker score: 0.7819 // SummaReranker rank: 6
Beam #13	Summary	Turkey has lifted its ban on female police officers wearing headscarves.
	Reference scores	R-1: 54.5455, R-2: 30.0000, R-L: 54.5455 // Rank: 6
	Re-ranking	SummaReranker score: 0.8140 // SummaReranker rank: 4
Beam #14	Summary	Turkey has lifted a ban on female police officers wearing headscarves, the interior ministry has said.
	Reference scores	R-1: 59.2593, R-2: 40.0000, R-L: 59.2593 // Rank: 3
	Re-ranking	SummaReranker score: 0.8298 // SummaReranker rank: 3
Beam #15	Summary	Turkey's police force has lifted its ban on female officers wearing headscarves, state media report.
	Reference scores	R-1: 44.4444, R-2: 16.0000, R-L: 44.4444 // Rank: 15
	Re-ranking	SummaReranker score: 0.6728 // SummaReranker rank: 11
Reference		Turkey has lifted a ban on police women wearing the Islamic headscarf.

Table 16: Beam search summary candidates of a base PEGASUS and their ground truth and SummaReranker re-ranking scores on XSum.

Reddit TIFU		
Source		here's my reconstruction of the fuck-up: during the visa application, i'm sifting through pages and pages of documentation with 15 tabs open on my browser and i arrive at a page with the title english requirement. it says something like "here's a list of approved test providers and you have to score a minimum cefr level of b1 to meet the english requirement." as someone who has taken many english exams such as toefl, ielts and pearson, i wonder what the hell a cefr level is, how come i've never heard of this and start popping new pages. turns out you have to score that much from ielts or this much from pearson or that much from other exams. cool. i'm thinking, currently i have 2 valid ielts exams that meet the criteria and a pearson's from which i've scored 90/90, sweet! i'll just submit pearson's and done. so i pay 2000aud and get an appointment, submit my documents and come back home. "hey wifey, it was really easy, let's do the same for you and get it done quickly." pay another 2000aud and my wife submits her application. 3 days after my submission, i get an e-mail saying a decision has been made, yay? more like nay, refused because we don't accept pearson's. 2 days later, wife gets refuses as well because we refused your husband. 2000 down the drain, luckily they are refunding the healthcare extras. turns out i failed to go back to that webpage and click on the link to get access to the most ridiculous list of approved english tests. there's not a mention of pearson, what's more, it doesn't have idp melbourne so my ielts exams are useless as well. on the plus side, i learn there are other ways to meet the requirement. if you have a diploma from an australian uni, just submit your diploma and you're good to go? why didn't you give me a call or send me an email and say "hey, you made a mistake silly" and i'd be like here's my diploma or something, wtf is refusing? this will stick to our international travel cv like a fucking bug. plus, i had to ask my future employer for another certificate, which takes another two weeks and makes me look like an idiot. then i'll have to submit another application, pay another 4000 and yada yada. A bit of background: we are turkish citizens living in australia as permanent residents obtained by using the same pearson's test. i'm working as a post-doctoral researcher and hopefully starting another post-doctoral position in scotland, not giving up!
Beam #1	Summary	i didn't go back to the page that says you have to score a cefr level of b1 to meet the english requirement.
	Reference scores	R-1: 4.4444, R-2: 0.0000, R-L: 4.4444 // Rank: 12
	Re-ranking	SummaReranker score: 0.8117 // SummaReranker rank: 12
Beam #2	Summary	i'm an idiot.
	Reference scores	R-1: 0.0000, R-2: 0.0000, R-L: 0.0000 // Rank: 15
	Re-ranking	SummaReranker score: 0.0612 // SummaReranker rank: 15
Beam #3	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement.
	Reference scores	R-1: 4.3478, R-2: 0.0000, R-L: 4.3478 // Rank: 13
	Re-ranking	SummaReranker score: 0.7396 // SummaReranker rank: 14
Beam #4	Summary	i didn't go back to the page that says you have to score a cefr level of b1 to meet the english requirement
	Reference scores	R-1: 4.4444, R-2: 0.0000, R-L: 4.4444 // Rank: 11
	Re-ranking	SummaReranker score: 0.7940 // SummaReranker rank: 13
Beam #5	Summary	i didn't go back to the page where i found out i had to score a minimum cefr level of b1 to meet the english requirement.
	Reference scores	R-1: 4.1667, R-2: 0.0000, R-L: 4.1667 // Rank: 14
	Re-ranking	SummaReranker score: 0.8320 // SummaReranker rank: 11
Beam #6	Summary	i didn't go back to the page that says you have to score a cefr level of b1 to meet the english requirement and now i'm stuck in australia.
	Reference scores	R-1: 7.6923, R-2: 0.0000, R-L: 7.6923 // Rank: 7
	Re-ranking	SummaReranker score: 0.8954 // SummaReranker rank: 5
Beam #7	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement and now i'm stuck in australia.
	Reference scores	R-1: 7.5472, R-2: 0.0000, R-L: 7.5472 // Rank: 8
	Re-ranking	SummaReranker score: 0.8890 // SummaReranker rank: 8
Beam #8	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement and now i'm stuck in a foreign country.
	Reference scores	R-1: 7.2727, R-2: 0.0000, R-L: 7.2727 // Rank: 10
	Re-ranking	SummaReranker score: 0.8889 // SummaReranker rank: 9
Beam #9	Summary	i didn't go back to the page that says you have to score a cefr level of b1 to meet the english requirement on my visa application and now i'm stuck in australia.
	Reference scores	R-1: 7.2727, R-2: 0.0000, R-L: 7.2727 // Rank: 10
	Re-ranking	SummaReranker score: 0.8941 // SummaReranker rank: 7
Beam #10	Summary	**i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement on my visa application and now i'm stuck in australia.**
	Reference scores	R-1: 21.4286, R-2: 3.7037, R-L: 17.8571 // Rank: 1
	Re-ranking	**SummaReranker score: 0.9052 // SummaReranker rank: 1**
Beam #11	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement on my visa application and now i'm stuck in australia.
	Reference scores	R-1: 21.0526, R-2: 3.6364, R-L: 17.5439 // Rank: 2
	Re-ranking	SummaReranker score: 0.9045 // SummaReranker rank: 2
Beam #12	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement and now i'll have to submit another application, pay 4000 and look like an idiot.
	Reference scores	R-1: 12.9032, R-2: 0.0000, R-L: 12.9032 // Rank: 6
	Re-ranking	SummaReranker score: 0.8861 // SummaReranker ran: 10
Beam #13	Summary	i didn't go back to the page that says you have to score a cefr level of b1 to meet the english requirement and now i'm going to have to submit another application and pay 4000.
	Reference scores	R-1: 13.5593, R-2: 0.0000, R-L: 13.5593 // Rank: 3
	Re-ranking	SummaReranker score: 0.8994 // SummaReranker rank: 3
Beam #14	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement and now i'm going to have to submit another application and pay 4000.
	Reference scores	R-1: 13.3333, R-2: 0.0000, R-L: 13.3333 // Rank: 4
	Re-ranking	SummaReranker score: 0.8947 // SummaReranker rank: 6
Beam #15	Summary	i didn't go back to the page that says you have to score a minimum cefr level of b1 to meet the english requirement and now i'm going to have to submit another application and pay 4000 dollars.
	Reference scores	R-1: 13.1148, R-2: 0.0000, R-L: 13.1148 // Rank: 5
	Re-ranking	SummaReranker score: 0.8964 // SummaReranker rank: 4
Reference		made a silly mistake and got refused on 2x tier 2 uk visa applications for me and my partner costing 2000aud.

Table 17: Beam search summary candidates of a base PEGASUS and their ground truth and SummaReranker re-ranking scores on Reddit TIFU.