

# Effect of fine-tuning Beam Search and Length Penalty on Abstractive Text Summarization with PEGASUS

Jeyabarani Seenivasagam

UC Berkeley School of Information  
ksjeyabarani@berkeley.edu

Jasdeep Basra

UC Berkeley School of Information  
jbasra@berkeley.edu

## Abstract

Abstractive-Summarization is the automatic generation of text to paraphrase the source text. It has an advantage over Extractive-Summarization methods because it can reduce redundancy and provide more coherent summaries similar to a summarization made by human. In this paper, we study the effect of the fine-tuning the beam search hyper-parameters during evaluation time using the recently released PEGASUS model for Abstractive Summarization (Zhang et al., 2019). We evaluate the model using ROUGE, BLEU, Length and Repetition metrics, as well as the Extractive Fragment Coverage and Density metrics as described by Grusky et al (Grusky et al., 2018).

## 1 Introduction

Automatic text summarization is generally categorized into two approaches abstractive and extractive. Extractive summaries identify the sentences that contain the main ideas and extract phrases from the original text. On the other hand, abstractive summaries result from the generation of new text that highlight and convey the main ideas.

Text summarization models for domain specific use are still not very common since most "current research on abstractive summarization focuses primarily on the genre of news", making it difficult to summarize other types of text such as social media posts (Syed et al., 2019). Additionally, now during the pandemic, there is an increasing need for models that can perform in biomedical contexts (Gigoli et al., 2018).

We use a large pre-trained model *PEGASUS Pre-training with Extracted Gap-sentences for Abstractive Summarization* released by Google(Liu and Zhao, 2020). We intend to study

the effects of using domain specific fine-tuned models on cross-domain data-sets to see how to generalize an out-of-box model by changing the hyper-parameters at evaluation time. We have picked six of the same data-sets used in PEGASUS across different domains such as social media posts, biomedical articles, news articles, U.S. State Bills, and Emails.

We hypothesize that we could get a better quality text summary using a state-of-art pre-trained - fine-tuned architecture such as PEGASUS while setting the evaluation hyper-parameter on beam search and length-penalty to a bigger value.

## 2 Background

Traditionally, abstractive text summarization used Attentional Encoder-Decoder Recurrent Neural Networks. These sequence-to-sequence networks map input sequences to output sequences. While effective, they were difficult to parallelize across large amounts of data (Nallapati et al., 2016). Transformers provided an alternative approach by focusing on the attention mechanism or self-attention (Vaswani et al., 2017). Transformers are able to achieve "state of the art performance" and have become ubiquitous (Wu et al., 2020). Thus, Transformers have formed the basis of many large pre-trained language models such BERT, GPT, and others that can be used in a wide array of tasks and fine tuned via transfer learning. Pre-trained models such as BERT are of great value to researchers and enable more practical use cases for text summarizing but allowing very short training periods and moderate computing resources to achieve state-of-the-art performance in a wide array of tasks including text generation. Indeed, "Pre-trained language models have recently emerged as a key technology for achieving impressive gains in a wide variety of natural language tasks" (Liu and Lapata, 2019). GPT-3 and PEGASUS have emerged recently as powerful pre-

trained models. Though, GPT-3 is still not publicly available yet, which is why we focus on PEGASUS for our study.

PEGASUS, that is used in this study has reported state-of-art performance on several different scores for abstractive text summarization. PEGASUS uses a Transformer encoder-decoder model combined with a supervised objective called *gap-sentence generation* (Liu and Zhao, 2020). Their work primarily focuses on the pre-training objectives and they have presented their results on twelve different data-sets for text summarization. According to the Google team, prior models that used "self-supervised objectives in pre-training were somewhat agnostic to downstream applications." Since the model is trained specifically for the task of abstractive text summarization, we believe it will be more effective than other pre-trained models.

### 3 Methods

In our work, we focus on studying the effects of tuning the hyper-parameters during the evaluation time, namely beam search and length penalty (beam  $\alpha$ ).

**Data Set and Models:** We use vocabulary, pre-trained PEGASUS model (pegasus\_ckpt) and fine-tuned models on domain-specific datasets: (CNN/Daily Mail News - cnn\_dailymail, News newser.com - multi\_news, Emails - aeslc, US State Bills - billsum, social media posts from reddit\_tifu , a subreddit of the social media site Reddit - fu, and Scientific papers - pubmed) and their corresponding Tensorflow text-summarization data-sets for our experiments.

**Design:** We picked a set of 100 text articles from each domain specific data-set to evaluate. We then evaluate the test samples on:

- baseline (PEGASUS check-point)
- fine-tuned model on the same domain data-set (e.g. CNNDailyMail test data on fine-tuned CNN model checkpoint)
- fine-tuned model across domains (e.g. CNNDailyMail test data on fine-tuned multi-news model, CNNDailyMail test data on fine-tuned billsum model, etc...)

We repeat this experiment by changing the beam-size and beam  $\alpha$  for the following combinations:

- Beam Size 1 and beam  $\alpha$  0.5
- Beam Size 5 and beam  $\alpha$  0.5
- Beam Size 10 and beam  $\alpha$  0.1
- Beam Size 10 and beam  $\alpha$  0.5
- Beam Size 10 and beam  $\alpha$  0.9

We investigate the effects of these values under different metrics for text summarization.

**Evaluation:** We evaluate our model with a robust method for automatic scoring of the results including ROUGE and other metrics which have been widely used to evaluate the quality of abstractive text summaries (Zopf et al., 2018). Comprehensively, we will use the following metrics for analysis:

- Recall scores, Precision score, f1-scores for:
  - ROUGE1
  - ROUGE2
  - ROUGEL
  - ROUGESum
- Coverage and Density
- Length score used to compare target and prediction lengths
- Repetition Evaluation of Generated Sequences

### 4 Results

#### Coverage and Density

We calculate the Extractive Fragment Coverage and Density metrics. The coverage measure is the extent to which a summary is derivative of a text. The density is how well the word sequence of a summary can be described as a series of extractions of the text.(Grusky et al., 2018)

In the general case, setting the evaluation hyper-parameters for beam search and length-penalty to higher values give the best results.

For models fine-tuned on a larger body of text such as in the news domain (cnn daily mail and multi news ), government bills and published research articles, higher beam search value and higher length-penalty clearly works best in terms of coverage and density . The same is true when validating larger text on fine-tuned models on any domains.

On the other hand, for models fine-tuned on shorter text such as email (aesic) and reddit (redditt.tifu - short), shorter beam search value clearly performs better in terms of coverage when tested using data-sets across different domains.

This study shows that the hyper-parameters used for beam search and length-penalty during validation shows a correlation on the coverage metrics for shorter vs longer body of text used during fine-tuning. We suspect that the attention heads learn differently when trained on shorter vs longer length of text. This could be a future extension of research from this work.

## ROUGE

Precision: Generally, the summarization task:

- performs better with higher beam search value keeping length-penalty a constant
- performs better with lower length-penalty keeping beam search a constant

Recall:

- performs better with lower beam search value keeping length-penalty a constant
- performs better with higher length-penalty keeping beam search a constant

## Repetition Evaluation of Generated Sequences

It is the ratio for n-gram based consecutive repeating sub-sequences. We consider the repetition score for predicted text. The lower the score, the better. Generally, the summarization task:

- performs better with higher beam search value keeping length-penalty a constant
- performs better with lower length-penalty keeping beam search a constant

## Length scorer to compare targets and prediction lengths

char value of 10, word value of 5, and relative value of 0.1 are used.

Generally, the summarization task:

- performs better with lower beam search value keeping length-penalty a constant
- performs better with higher length-penalty keeping beam search a constant

The detailed results of our experiments and investigation are in the tables of Appendix 2.

## 5 Conclusion

We examined the impact of altering the hyper-parameters Beam Search and Length Penalty under various metrics including ROUGE, BLEU, Coverage and Density, Length and Repetition met-

rics. We notice that when the parameter Beam size increases, ROUGE-Precision, Repetition Score, and the Coverage and Density metrics all improve, while ROUGE-Recall and Length Score have diminished results. For the Length-Penalty beam  $\alpha$ , as it increases, ROUGE-Recall, Length Score, and the Coverage and Density metrics improve, while ROUGE-Precision and Repetition Score have weaker results.

We would have liked to recruit human raters as an additional metric for a qualitative review, but due to time and resource constraints we could not. This could be used in further research to achieve greater confidence or variation in the results presented here. Further research could be done in other datasets and with a wider range of parameters.

## References

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## **Appendix 1 - Data sources and model check-points:**

### **Data Set Sources:**

1. [https://www.tensorflow.org/datasets/catalog/cnn\\_dailymail](https://www.tensorflow.org/datasets/catalog/cnn_dailymail)
2. [https://www.tensorflow.org/datasets/catalog/multi\\_news](https://www.tensorflow.org/datasets/catalog/multi_news)
3. <https://www.tensorflow.org/datasets/catalog/aeslc>
4. <https://www.tensorflow.org/datasets/catalog/billsum>
5. [https://www.tensorflow.org/datasets/catalog/reddit\\_tifu](https://www.tensorflow.org/datasets/catalog/reddit_tifu)
6. [https://www.tensorflow.org/datasets/catalog/scientific\\_papers#scientific\\_paperspubmed](https://www.tensorflow.org/datasets/catalog/scientific_papers#scientific_paperspubmed)

### **Model Checkpoints:**

1. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt](https://console.cloud.google.com/storage/browser/pegasus_ckpt)
2. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/cnn\\_dailymail](https://console.cloud.google.com/storage/browser/pegasus_ckpt/cnn_dailymail)
3. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/multi\\_news](https://console.cloud.google.com/storage/browser/pegasus_ckpt/multi_news)
4. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/aeslc](https://console.cloud.google.com/storage/browser/pegasus_ckpt/aeslc)
5. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/billsum](https://console.cloud.google.com/storage/browser/pegasus_ckpt/billsum)
6. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/reddit\\_tifu](https://console.cloud.google.com/storage/browser/pegasus_ckpt/reddit_tifu)
7. [https://console.cloud.google.com/storage/browser/pegasus\\_ckpt/pubmed](https://console.cloud.google.com/storage/browser/pegasus_ckpt/pubmed)

## **Appendix 2 - Tables and Figures:**









Figure 5: REGS1 (Repetition Evaluation of Generated Sequences): Comparison of validation results on cross-domain trained models

A	B	C	D	E	F	G
Model	Testset	beamsearch_1_α_0.5 (target predicted)	beamsearch_5_α_0.5 (target predicted)	beamsearch_10_α_0.5 (target predicted)	beamsearch_10_α_0.1 (target predicted)	beamsearch_10_α_0.9 (target predicted)
base	cnn	0.2705   0.4295	0.27   0.4018	0.2694   0.396	0.2697   0.3941	0.27   0.4078
base	multi_news	0.3857   0.7612	0.385   0.5168	0.3851   0.4757	0.3856   0.3867	0.3849   0.5189
base	billsum	0.4525   0.9073	0.4539   0.8387	0.4526   0.8184	0.4533   0.6925	0.453   0.8972
base	pubmed	0.544   0.7875	0.5437   0.6696	0.5441   0.613	0.5434   0.4576	0.5441   0.7647
base	reddit_tifu	0.1291   0.371	0.1297   0.3665	0.1299   0.353	0.1294   0.3361	0.1293   0.3587
base	aeslc	0.0079   0.1026	0.0079   0.0893	0.0084   0.0859	0.0085   0.0839	0.0079   0.0871
cnn	cnn	0.2695   0.3213	0.2693   0.2275	0.2697   0.2453	0.2701   0.1817	0.2699   0.295
cnn	multi_news	0.385   0.3131	0.3853   0.2544	0.3849   0.2447	0.3853   0.1619	0.3852   0.3381
cnn	billsum	0.4529   0.5085	0.4543   0.2256	0.4528   0.2258	0.452   0.1318	0.4541   0.4645
cnn	pubmed	0.5433   0.4116	0.5441   0.2388	0.5443   0.2383	0.5435   0.1086	0.544   0.3831
cnn	reddit_tifu	0.1293   0.4173	0.1291   0.2625	0.1291   0.2413	0.1309   0.1237	0.1296   0.3997
cnn	aeslc	0.0078   0.184	0.0084   0.1007	0.0079   0.1016	0.0084   0.061	0.0079   0.1207
multi_news	cnn	0.2695   0.3814	0.2695   0.3535	0.2698   0.3463	0.2692   0.3467	0.2701   0.3513
multi_news	multi_news	0.3854   0.4704	0.385   0.425	0.3853   0.4173	0.3852   0.4104	0.3855   0.4345
multi_news	billsum	0.4543   0.6005	0.4541   0.5936	0.4522   0.5957	0.4536   0.5921	0.4527   0.6113
multi_news	pubmed	0.5439   0.5754	0.5441   0.5779	0.5432   0.598	0.5441   0.5975	0.5446   0.6047
multi_news	reddit_tifu	0.1303   0.4359	0.1298   0.4211	0.1294   0.4153	0.1302   0.4159	0.1291   0.4197
multi_news	aeslc	0.0078   0.1654	0.0084   0.1578	0.0084   0.1489	0.0084   0.1492	0.0079   0.1484
billsum	cnn	0.2689   0.404	0.27   0.3246	0.2701   0.3335	0.2699   0.2724	0.2694   0.5687
billsum	multi_news	0.3853   0.4522	0.385   0.402	0.3849   0.3589	0.385   0.3191	0.3856   0.6068
billsum	billsum	0.4523   0.5368	0.4523   0.4743	0.4522   0.4189	0.453   0.3692	0.4531   0.4643
billsum	pubmed	0.5437   0.467	0.544   0.4262	0.5442   0.432	0.5441   0.4203	0.544   0.6119
billsum	reddit_tifu	0.1286   0.3956	0.1303   0.3122	0.13   0.2878	0.1301   0.2438	0.1289   0.545
billsum	aeslc	0.0084   0.2412	0.0079   0.1592	0.0079   0.1413	0.0084   0.1375	0.0079   0.1597
pubmed	cnn	0.2698   0.6919	0.2697   0.627	0.2697   0.6031	0.2698   0.5814	0.2701   0.7033
pubmed	multi_news	0.3849   0.7748	0.3853   0.6904	0.3853   0.6616	0.3849   0.5699	0.3854   0.8761
pubmed	billsum	0.452   0.8053	0.4528   0.7863	0.4531   0.7965	0.4528   0.7716	0.4522   0.8804
pubmed	pubmed	0.5444   0.6132	0.5444   0.5591	0.5446   0.5469	0.5437   0.5263	0.5444   0.5675
pubmed	reddit_tifu	0.1297   0.5976	0.13   0.4888	0.1299   0.4892	0.1296   0.4252	0.1301   0.601
pubmed	aeslc	0.0079   0.3295	0.0079   0.2509	0.0079   0.2571	0.0079   0.259	0.0084   0.258
reddit_tifu	cnn	0.2699   0.1744	0.2688   0.1574	0.2693   0.155	0.2696   0.0754	0.269   0.4088
reddit_tifu	multi_news	0.3849   0.566	0.385   0.2095	0.3852   0.2432	0.3852   0.0339	N/A
reddit_tifu	billsum	0.453   0.7803	0.4544   0.6456	0.4538   0.7495	0.4535   0.1928	0.4538   0.9722
reddit_tifu	pubmed	0.5438   0.3746	0.5445   0.4049	0.5436   0.3765	0.5441   0.2422	0.544   0.8442
reddit_tifu	reddit_tifu	0.1307   0.1676	0.1296   0.1111	0.1298   0.0913	0.1295   0.084	0.1291   0.2595
reddit_tifu	aeslc	0.0078   0.1191	0.0084   0.068	0.0079   0.0763	0.0079   0.0138	0.0079   0.1941
aeslc	cnn	0.2702   0.0377	0.2699   0.0448	0.2694   0.0664	0.2693   0.0417	0.2695   0.1154
aeslc	multi_news	0.3851   0.0178	0.3856   0.0182	0.3852   0.0171	0.3844   0.0062	0.3856   0.0938
aeslc	billsum	0.4534   0.0255	0.4535   0.0055	0.4539   0.01	0.4531   0.0129	0.4537   0.0399
aeslc	pubmed	0.5433   0.0231	0.5436   0.0321	0.5443   0.0108	0.5445   0.01	0.5443   0.2039
aeslc	reddit_tifu	0.1296   0.011	0.1305   0.03	0.13   0.03	0.13   0.02	0.1289   0.0617
aeslc	aeslc	0.0079   0.0086	0.0084   0.0061	0.0079   0.0076	0.0078   0.0061	0.0079   0.0081

Figure 6: REGS2 (Repetition Evaluation of Generated Sequences): Comparison of validation results on cross-domain trained models

<b>Model</b>	<b>Testset</b>	<b>beamsearch_1_α_0.5 (target predicted)</b>	<b>beamsearch_5_α_0.5 (target predicted)</b>	<b>beamsearch_10_α_0.5 (target predicted)</b>	<b>beamsearch_10_α_0.1 (target predicted)</b>	<b>beamsearch_10_α_0.9 (target predicted)</b>
base	cnn	0.0169   0.2243	0.0172   0.1958	0.0172   0.1812	0.0173   0.1956	0.017   0.1891
base	multi_news	0.0491   0.6723	0.049   0.3255	0.049   0.2672	0.0489   0.1798	0.049   0.3113
base	billsum	0.1202   0.8501	0.1202   0.7568	0.1205   0.7456	0.1206   0.585	0.1199   0.854
base	pubmed	0.1354   0.6575	0.1356   0.481	0.136   0.3894	0.135   0.2136	0.1359   0.6026
base	reddit_tifu	0.0115   0.0977	0.0121   0.0813	0.0119   0.0709	0.0121   0.0654	0.012   0.0692
base	aeslc	0.0   0.0127	0.0   0.0199	0.0   0.0247	0.0   0.0242	0.0   0.0255
cnn	cnn	0.0172   0.0454	0.0171   0.0186	0.017   0.0168	0.017   0.0131	0.017   0.028
cnn	multi_news	0.0491   0.049	0.0491   0.0232	0.0491   0.0188	0.0491   0.0057	0.0489   0.063
cnn	billsum	0.1204   0.1971	0.1207   0.051	0.1203   0.056	0.1199   0.0157	0.1204   0.1556
cnn	pubmed	0.1357   0.1007	0.1356   0.0347	0.1355   0.0464	0.1354   0.0082	0.1352   0.081
cnn	reddit_tifu	0.0119   0.094	0.0116   0.0495	0.0119   0.0461	0.0121   0.0096	0.0121   0.0674
cnn	aeslc	0.0   0.0346	0.0   0.0107	0.0   0.0098	0.0   0.0067	0.0   0.0099
multi_news	cnn	0.017   0.0608	0.017   0.0563	0.0171   0.0572	0.0172   0.0562	0.0172   0.057
multi_news	multi_news	0.0491   0.118	0.0489   0.0979	0.0491   0.0902	0.0491   0.0873	0.049   0.105
multi_news	billsum	0.1203   0.2528	0.1196   0.2755	0.1195   0.2966	0.1199   0.2942	0.1209   0.3192
multi_news	pubmed	0.1354   0.2071	0.1355   0.2513	0.135   0.2756	0.1348   0.2755	0.1354   0.2839
multi_news	reddit_tifu	0.0122   0.0978	0.012   0.1234	0.0121   0.1316	0.0123   0.1304	0.0118   0.1351
multi_news	aeslc	0.0   0.0138	0.0   0.0198	0.0   0.0171	0.0   0.0171	0.0   0.0171
billsum	cnn	0.0169   0.1858	0.017   0.1647	0.0172   0.1874	0.0172   0.1203	0.0171   0.4326
billsum	multi_news	0.049   0.2051	0.0489   0.2104	0.0489   0.193	0.0487   0.1622	0.0491   0.4577
billsum	billsum	0.1196   0.1983	0.1199   0.1541	0.1198   0.124	0.1207   0.1075	0.1196   0.1574
billsum	pubmed	0.1353   0.1725	0.1347   0.1331	0.1358   0.1501	0.1355   0.1319	0.1352   0.3739
billsum	reddit_tifu	0.0119   0.1712	0.0121   0.1412	0.0122   0.1341	0.0122   0.0901	0.0118   0.3766
billsum	aeslc	0.0   0.0983	0.0   0.0531	0.0   0.0376	0.0   0.038	0.0   0.0394
pubmed	cnn	0.0171   0.4101	0.017   0.3702	0.017   0.3894	0.0173   0.35	0.0171   0.5057
pubmed	multi_news	0.049   0.5693	0.049   0.493	0.0491   0.4584	0.0489   0.3332	0.0489   0.7724
pubmed	billsum	0.12   0.5925	0.1205   0.5936	0.12   0.6132	0.1198   0.5634	0.1202   0.7483
pubmed	pubmed	0.1353   0.2322	0.1355   0.1561	0.1351   0.1459	0.1353   0.1345	0.1349   0.1674
pubmed	reddit_tifu	0.0118   0.285	0.0121   0.199	0.012   0.226	0.012   0.1535	0.012   0.3115
pubmed	aeslc	0.0   0.1002	0.0   0.0674	0.0   0.0854	0.0   0.0857	0.0   0.084
reddit_tifu	cnn	0.0168   0.045	0.017   0.0489	0.017   0.0426	0.0169   0.0175	0.0171   0.2917
reddit_tifu	multi_news	0.0492   0.5006	0.0491   0.1819	0.0489   0.2133	0.0493   0.02	N/A
reddit_tifu	billsum	0.1205   0.6902	0.1198   0.5229	0.1195   0.6547	0.1201   0.082	0.1205   0.9476
reddit_tifu	pubmed	0.1355   0.1956	0.1355   0.2592	0.1353   0.2149	0.1351   0.103	0.1356   0.7483
reddit_tifu	reddit_tifu	0.012   0.0278	0.0119   0.0206	0.0121   0.0075	0.0118   0.0076	0.012   0.1568
reddit_tifu	aeslc	0.0   0.0512	0.0   0.0412	0.0   0.0524	0.0   0.0	0.0   0.1229
aeslc	cnn	0.017   0.0194	0.0171   0.028	0.0171   0.038	0.0171   0.0222	0.017   0.088
aeslc	multi_news	0.049   0.001	0.0491   0.0099	0.049   0.01	0.049   0.0	0.049   0.0874
aeslc	billsum	0.12   0.0073	0.1198   0.0014	0.1197   0.01	0.1204   0.01	0.1203   0.0293
aeslc	pubmed	0.1355   0.009	0.1352   0.0162	0.1351   0.0	0.1356   0.0	0.1349   0.1872
aeslc	reddit_tifu	0.0118   0.006	0.0117   0.03	0.0119   0.03	0.0122   0.02	0.0118   0.06
aeslc	aeslc	0.0   0.0	0.0   0.0	0.0   0.0	0.0   0.0	0.0   0.0

Figure 7: REGS3 (Repetition Evaluation of Generated Sequences): Comparison of validation results on cross-domain trained models

<b>Model</b>	<b>Testset</b>	<b>beamsearch_1_α_0.5 (target predicted)</b>	<b>beamsearch_5_α_0.5 (target predicted)</b>	<b>beamsearch_10_α_0.5 (target predicted)</b>	<b>beamsearch_10_α_0.1 (target predicted)</b>	<b>beamsearch_10_α_0.9 (target predicted)</b>
base	cnn	0.0023   0.1851	0.0023   0.1619	0.0023   0.1476	0.0023   0.1599	0.0023   0.1494
base	multi_news	0.0086   0.6547	0.0085   0.2953	0.0086   0.2414	0.0085   0.1529	0.0085   0.2836
base	billsum	0.0498   0.8146	0.0497   0.7273	0.0494   0.7193	0.0496   0.5513	0.0493   0.8328
base	pubmed	0.0482   0.6247	0.0485   0.4413	0.0483   0.356	0.0481   0.1768	0.0482   0.5696
base	reddit_tifu	0.0035   0.0669	0.0034   0.0504	0.0033   0.0398	0.0033   0.0361	0.0031   0.0389
base	aeslc	0.0   0.0036	0.0   0.0123	0.0   0.0193	0.0   0.0213	0.0   0.0193
cnn	cnn	0.0023   0.0111	0.0021   0.0027	0.0023   0.0023	0.0023   0.0025	0.0023   0.0054
cnn	multi_news	0.0086   0.0146	0.0086   0.0057	0.0087   0.0031	0.0086   0.0004	0.0085   0.0333
cnn	billsum	0.0497   0.1215	0.0497   0.0269	0.0501   0.0313	0.0498   0.0079	0.0495   0.0938
cnn	pubmed	0.0485   0.0418	0.0483   0.0133	0.0485   0.0233	0.0484   0.0026	0.0479   0.037
cnn	reddit_tifu	0.0031   0.0473	0.0033   0.0274	0.0031   0.026	0.0035   0.0017	0.0031   0.0275
cnn	aeslc	0.0   0.0159	0.0   0.0024	0.0   0.0024	0.0   0.0014	0.0   0.0031
multi_news	cnn	0.0023   0.0159	0.0023   0.0205	0.0023   0.0193	0.0023   0.0187	0.0023   0.0196
multi_news	multi_news	0.0087   0.0518	0.0087   0.0445	0.0086   0.0391	0.0086   0.0377	0.0086   0.049
multi_news	billsum	0.0498   0.1423	0.0494   0.1798	0.0496   0.2103	0.0493   0.2068	0.0498   0.2297
multi_news	pubmed	0.0482   0.1013	0.048   0.1489	0.0479   0.1717	0.048   0.1709	0.0485   0.1817
multi_news	reddit_tifu	0.0035   0.0386	0.0031   0.0754	0.0035   0.0827	0.0035   0.0837	0.0035   0.0868
multi_news	aeslc	0.0   0.003	0.0   0.0124	0.0   0.0059	0.0   0.0053	0.0   0.0051
billsum	cnn	0.0022   0.1337	0.0023   0.1344	0.0023   0.1563	0.0023   0.0922	0.0022   0.3902
billsum	multi_news	0.0086   0.142	0.0086   0.1705	0.0084   0.1557	0.0086   0.1281	0.0086   0.4145
billsum	billsum	0.0495   0.1037	0.0493   0.076	0.0495   0.0587	0.0494   0.0525	0.0499   0.0825
billsum	pubmed	0.0484   0.1179	0.048   0.0945	0.0487   0.1105	0.0479   0.0914	0.0484   0.316
billsum	reddit_tifu	0.0033   0.1209	0.0035   0.101	0.0031   0.1061	0.0035   0.0581	0.0031   0.3241
billsum	aeslc	0.0   0.059	0.0   0.0314	0.0   0.0197	0.0   0.0191	0.0   0.0202
pubmed	cnn	0.0023   0.3134	0.0023   0.2988	0.0022   0.3289	0.0023   0.285	0.0023   0.4483
pubmed	multi_news	0.0084   0.4831	0.0087   0.4387	0.0086   0.4045	0.0086   0.2716	0.0086   0.7282
pubmed	billsum	0.05   0.4848	0.0496   0.512	0.0493   0.5415	0.0495   0.4874	0.0495   0.6828
pubmed	pubmed	0.0479   0.1224	0.048   0.0725	0.0481   0.0658	0.0484   0.0598	0.0487   0.0814
pubmed	reddit_tifu	0.0031   0.1964	0.0034   0.1427	0.0031   0.1741	0.0035   0.1056	0.0031   0.2549
pubmed	aeslc	0.0   0.0451	0.0   0.0398	0.0   0.0533	0.0   0.0534	0.0   0.052
reddit_tifu	cnn	0.0024   0.0377	0.0023   0.0346	0.0023   0.0165	0.0023   0.0014	0.0023   0.2791
reddit_tifu	multi_news	0.0086   0.4986	0.0086   0.1797	0.0086   0.2103	0.0086   0.02	N/A
reddit_tifu	billsum	0.0498   0.6674	0.0495   0.5118	0.0494   0.6506	0.0498   0.0821	0.0492   0.9434
reddit_tifu	pubmed	0.0482   0.1605	0.0482   0.2362	0.0481   0.1943	0.0482   0.0734	0.0485   0.7254
reddit_tifu	reddit_tifu	0.0033   0.0126	0.0031   0.0168	0.0031   0.0012	0.0031   0.0012	0.0035   0.1459
reddit_tifu	aeslc	0.0   0.0377	0.0   0.04	0.0   0.05	0.0   0.0	0.0   0.1215
aeslc	cnn	0.0022   0.0192	0.0023   0.0269	0.0023   0.0369	0.0023   0.02	0.0022   0.085
aeslc	multi_news	0.0085   0.0	0.0086   0.0099	0.0088   0.01	0.0086   0.0	0.0085   0.0875
aeslc	billsum	0.0499   0.0029	0.0492   0.0	0.0493   0.01	0.0491   0.01	0.0495   0.0288
aeslc	pubmed	0.0482   0.0067	0.0482   0.0095	0.0483   0.0	0.0484   0.0	0.0484   0.1811
aeslc	reddit_tifu	0.0035   0.005	0.0031   0.02	0.0035   0.02	0.0033   0.01	0.0031   0.06
aeslc	aeslc	0.0   0.0	0.0   0.0	0.0   0.0	0.0   0.0	0.0   0.0

Figure 8: REGSTCR (Repetition Evaluation of Generated Sequences): Comparison of validation results on cross-domain trained models

A	B	C	D	E	F	G
Model	Testset	beamsearch_1_α_0.5 (target predicted)	beamsearch_5_α_0.5 (target predicted)	beamsearch_10_α_0.5 (target predicted)	beamsearch_10_α_0.1 (target predicted)	beamsearch_10_α_0.9 (target predicted)
base	cnn	0.2705   0.4295	0.27   0.4018	0.2694   0.396	0.2697   0.3941	0.27   0.4078
base	multi_news	0.3857   0.7612	0.385   0.5168	0.3851   0.4757	0.3856   0.3867	0.3849   0.5189
base	billsum	0.4525   0.9073	0.4539   0.8387	0.4526   0.8184	0.4533   0.6925	0.453   0.8972
base	pubmed	0.544   0.7875	0.5437   0.6696	0.5441   0.613	0.5434   0.4576	0.5441   0.7647
base	reddit_tifu	0.1291   0.371	0.1297   0.3665	0.1299   0.353	0.1294   0.3361	0.1293   0.3587
base	aeslc	0.0079   0.1026	0.0079   0.0893	0.0084   0.0859	0.0085   0.0839	0.0079   0.0871
cnn	cnn	0.2695   0.3213	0.2693   0.2275	0.2697   0.2453	0.2701   0.1817	0.2699   0.295
cnn	multi_news	0.385   0.3131	0.3853   0.2544	0.3849   0.2447	0.3853   0.1619	0.3852   0.3381
cnn	billsum	0.4529   0.5085	0.4543   0.2256	0.4528   0.2258	0.452   0.1318	0.4541   0.4645
cnn	pubmed	0.5433   0.4116	0.5441   0.2388	0.5443   0.2383	0.5435   0.1086	0.544   0.3831
cnn	reddit_tifu	0.1293   0.4173	0.1291   0.2625	0.1291   0.2413	0.1309   0.1237	0.1296   0.3997
cnn	aeslc	0.0078   0.184	0.0084   0.1007	0.0079   0.1016	0.0084   0.061	0.0079   0.1207
multi_news	cnn	0.2695   0.3814	0.2695   0.3535	0.2698   0.3463	0.2692   0.3467	0.2701   0.3513
multi_news	multi_news	0.3854   0.4704	0.385   0.425	0.3853   0.4173	0.3852   0.4104	0.3855   0.4345
multi_news	billsum	0.4543   0.6005	0.4541   0.5936	0.4522   0.5957	0.4536   0.5921	0.4527   0.6113
multi_news	pubmed	0.5439   0.5754	0.5441   0.5779	0.5432   0.598	0.5441   0.5975	0.5446   0.6047
multi_news	reddit_tifu	0.1303   0.4359	0.1298   0.4211	0.1294   0.4153	0.1302   0.4159	0.1291   0.4197
multi_news	aeslc	0.0078   0.1654	0.0084   0.1578	0.0084   0.1489	0.0084   0.1492	0.0079   0.1484
billsum	cnn	0.2689   0.404	0.27   0.3246	0.2701   0.3335	0.2699   0.2724	0.2694   0.5687
billsum	multi_news	0.3853   0.4522	0.385   0.402	0.3849   0.3589	0.385   0.3191	0.3856   0.6068
billsum	billsum	0.4523   0.5368	0.4523   0.4743	0.4522   0.4189	0.453   0.3692	0.4531   0.4643
billsum	pubmed	0.5437   0.467	0.544   0.4262	0.5442   0.432	0.5441   0.4203	0.544   0.6119
billsum	reddit_tifu	0.1286   0.3956	0.1303   0.3122	0.13   0.2878	0.1301   0.2438	0.1289   0.545
billsum	aeslc	0.0084   0.2412	0.0079   0.1592	0.0079   0.1413	0.0084   0.1375	0.0079   0.1597
pubmed	cnn	0.2698   0.6919	0.2697   0.627	0.2697   0.6031	0.2698   0.5814	0.2701   0.7033
pubmed	multi_news	0.3849   0.7748	0.3853   0.6904	0.3853   0.6616	0.3849   0.5699	0.3854   0.8761
pubmed	billsum	0.452   0.8053	0.4528   0.7863	0.4531   0.7965	0.4528   0.7716	0.4522   0.8804
pubmed	pubmed	0.5444   0.6132	0.5444   0.5591	0.5446   0.5469	0.5437   0.5263	0.5444   0.5675
pubmed	reddit_tifu	0.1297   0.5976	0.13   0.4888	0.1299   0.4892	0.1296   0.4252	0.1301   0.601
pubmed	aeslc	0.0079   0.3295	0.0079   0.2509	0.0079   0.2571	0.0079   0.259	0.0084   0.258
reddit_tifu	cnn	0.2699   0.1744	0.2688   0.1574	0.2693   0.155	0.2696   0.0754	0.269   0.4088
reddit_tifu	multi_news	0.3849   0.566	0.385   0.2095	0.3852   0.2432	0.3852   0.0339	N/A
reddit_tifu	billsum	0.453   0.7803	0.4544   0.6456	0.4538   0.7495	0.4535   0.1928	0.4538   0.9722
reddit_tifu	pubmed	0.5438   0.3746	0.5445   0.4049	0.5436   0.3765	0.5441   0.2422	0.544   0.8442
reddit_tifu	reddit_tifu	0.1307   0.1676	0.1296   0.1111	0.1298   0.0913	0.1295   0.084	0.1291   0.2595
reddit_tifu	aeslc	0.0078   0.1191	0.0084   0.068	0.0079   0.0763	0.0079   0.0138	0.0079   0.1941
aeslc	cnn	0.2702   0.0377	0.2699   0.0448	0.2694   0.0664	0.2693   0.0417	0.2695   0.1154
aeslc	multi_news	0.3851   0.0178	0.3856   0.0182	0.3852   0.0171	0.3844   0.0062	0.3856   0.0938
aeslc	billsum	0.4534   0.0255	0.4535   0.0055	0.4539   0.01	0.4531   0.0129	0.4537   0.0399
aeslc	pubmed	0.5433   0.0231	0.5436   0.0321	0.5443   0.0108	0.5445   0.01	0.5443   0.2039
aeslc	reddit_tifu	0.1296   0.011	0.1305   0.03	0.13   0.03	0.13   0.02	0.1289   0.0617
aeslc	aeslc	0.0079   0.0086	0.0084   0.0061	0.0079   0.0076	0.0078   0.0061	0.0079   0.0081

Figure 9: BLUE: Comparison of validation results  
on cross-domain trained models

Model	Testset	beamsearch_1_α_0.5	beamsearch_5_α_0.5	beamsearch_10_α_0.5	beamsearch_10_α_0.1	beamsearch_10_α_0.9
base	cnn	7.434	8.1764	8.3794	8.4174	8.215
base	multi_news	3.0505	3.8242	3.7505	2.84	4.1654
base	billsum	2.1748	2.7755	2.7239	2.64	2.9896
base	pubmed	2.8936	3.2114	3.076	1.9833	4.2745
base	reddit_tifu	2.2867	2.3226	2.3191	2.332	2.3029
base	aeslc	2.4254	2.2997	2.3694	2.2275	2.3575
cnn	cnn	14.425	13.5281	12.6422	10.9263	14.1885
cnn	multi_news	1.4331	0.8877	0.8849	0.2527	2.8845
cnn	billsum	4.807	1.7625	1.6234	1.0079	5.0149
cnn	pubmed	3.0847	0.8838	0.7238	0.4212	3.0419
cnn	reddit_tifu	2.5296	3.0526	2.9692	3.5678	1.844
cnn	aeslc	2.1683	2.4368	2.3011	3.0219	2.3166
multi_news	cnn	4.8318	5.5219	4.9069	4.9295	4.8171
multi_news	multi_news	13.1772	13.3808	12.9807	12.7873	13.9081
multi_news	billsum	2.4333	3.4515	4.6368	4.5674	4.7414
multi_news	pubmed	2.1454	2.9982	3.2318	3.2428	3.187
multi_news	reddit_tifu	1.2127	1.1168	1.1832	1.1702	1.1706
multi_news	aeslc	0.8117	0.8761	1.1026	1.1053	1.1108
billsum	cnn	4.4674	4.3165	4.2582	3.905	5.0225
billsum	multi_news	1.3953	0.9606	0.4871	0.4204	1.7915
billsum	billsum	30.7906	31.2473	27.8634	23.9812	31.5621
billsum	pubmed	1.3346	1.0063	0.8648	0.7406	1.4382
billsum	reddit_tifu	1.7808	2.0054	2.1638	2.122	1.6097
billsum	aeslc	2.4126	2.7003	2.9178	3.0232	2.718
pubmed	cnn	1.6289	2.0017	2.2508	2.344	2.0577
pubmed	multi_news	1.0348	0.5395	0.4521	0.3129	1.0146
pubmed	billsum	1.5974	1.6522	1.4588	1.446	1.5245
pubmed	pubmed	15.7253	15.6704	15.2355	14.5062	15.6786
pubmed	reddit_tifu	1.6866	2.1389	2.2229	2.5322	1.583
pubmed	aeslc	1.0905	1.1474	1.1467	1.1387	1.1413
reddit_tifu	cnn	4.4702	4.6138	5.5171	3.2821	6.5069
reddit_tifu	multi_news	0.124	0.0486	0.0495	0.0111 N/A	
reddit_tifu	billsum	1.0198	0.6335	0.5655	0.3296	0.7137
reddit_tifu	pubmed	1.0674	1.2786	1.4398	0.651	5.9314
reddit_tifu	reddit_tifu	6.4737	6.1387	5.8654	5.76	4.9569
reddit_tifu	aeslc	1.8399	1.7689	2.0162	1.6595	2.7744
aeslc	cnn	0.5478	0.9124	0.7178	0.2832	1.2466
aeslc	multi_news	0.0015	0.0009	0.0016	0	0.0888
aeslc	billsum	0.2093	0.1697	0.172	0.1698	0.2223
aeslc	pubmed	0.0039	0.005	0	0	0.1576
aeslc	reddit_tifu	0.7613	0.5248	0.5542	0.431	0.7563
aeslc	aeslc	12.6212	13.1251	12.9268	11.9428	13.4071



Figure 11: Length Scorer word: Comparison of validation results on cross-domain trained models

<b>Model</b>	<b>Testset</b>	<b>beamsearch_1_α_0.5 (target predicted relative)</b>	<b>beamsearch_5_α_0.5 (target predicted relative)</b>	<b>beamsearch_10_α_0.5 (target predicted relative)</b>	<b>beamsearch_10_α_0.1 (target predicted relative)</b>	<b>beamsearch_10_α_0.01 (target predicted relative)</b>
base	cnn	51.68   75.71   1.5779	51.65   70.41   1.4732	51.73   71.875   1.5057	51.575   66.405   1.4167	51.685   71.875   1.5057
base	multi_news	184.315   141.605   0.7974	184.385   100.87   0.5803	184.38   98.11   0.5635	184.34   73.435   0.4357	184.3   129.64   0.4357
base	billsum	129.54   162.23   2.048	129.02   112.755   1.4882	129.11   103.115   1.3328	129.465   48.45   0.5943	129.64   129.64   0.5943
base	pubmed	156.285   136.065   0.9896	156.065   93.63   0.6622	156.38   86.13   0.6279	155.835   55.41   0.4218	156.41   156.41   0.4218
base	reddit_tifu	20.18   67.92   4.4569	20.115   65.295   4.3109	20.14   64.565   4.2617	20.15   60.585   4.039	20.25   62.11   4.039
base	aeslc	4.29   17.47   5.4749	4.28   15.74   4.9701	4.29   15.01   4.7066	4.3   14.885   4.7156	4.29   14.885   4.7156
cnn	cnn	51.81   58.45   1.1851	51.63   41.4   0.8322	51.585   43.495   0.8912	51.74   30.86   0.641	51.715   61.715   0.641
cnn	multi_news	184.325   55.695   0.3172	183.995   45.81   0.2635	184.065   46.28   0.263	184.27   30.845   0.1746	184.35   184.35   0.1746
cnn	billsum	129.515   59.415   0.7663	129.49   24.255   0.2898	129.35   22.79   0.2759	129.355   15.72   0.1923	129.25   129.25   0.1923
cnn	pubmed	156.315   58.515   0.4346	156.15   29.745   0.2352	155.79   29.15   0.2396	156.17   18.18   0.1395	156.59   156.59   0.1395
cnn	reddit_tifu	20.2   68.63   4.8161	20.115   37.305   2.3986	20.21   35.115   2.8613	20.13   21.465   1.3861	20.1   86.1   1.3861
cnn	aeslc	4.28   24.81   7.8608	4.28   18.175   6.0586	4.28   18.33   6.1235	4.27   14.53   4.7118	4.29   20.1   4.7118
multi_news	cnn	51.77   101.16   2.1482	51.7   94.895   2.016	51.635   94.24   2.0117	51.705   93.735   2.0052	51.71   96.71   2.0052
multi_news	multi_news	184.255   172.275   0.955	184.38   160.235   0.8862	184.23   155.475   0.8648	184.16   148.875   0.826	184.15   184.15   0.826
multi_news	billsum	129.34   192.695   2.4537	129.46   179.625   2.2877	129.215   176.35   2.3269	128.845   175.525   2.3322	129.21   129.21   2.3322
multi_news	pubmed	156.22   199.435   1.5187	156.265   192.39   1.4654	156.175   191.465   1.4208	156.12   190.805   1.4232	155.97   155.97   1.4232
multi_news	reddit_tifu	20.21   103.79   7.5298	20.195   98.68   7.145	20.15   95.97   6.9665	20.22   95.39   6.8185	20.135   20.135   6.8185
multi_news	aeslc	4.28   27.65   8.9317	4.3   26.47   8.5218	4.28   26.54   8.6099	4.27   26.55   8.6052	4.29   26.55   8.6052
billsum	cnn	51.715   60.375   1.2563	51.565   42.155   0.8838	51.66   39.06   0.8375	51.64   34.555   0.739	51.62   60.375   0.739
billsum	multi_news	184.2   89.83   0.5225	184.21   52.765   0.3027	184.225   45.11   0.2674	184.205   40.59   0.2405	184.2   184.2   0.2405
billsum	billsum	129.55   153.89   1.5579	129.64   117.315   1.1861	128.885   96.285   1.0258	129.84   82.135   0.8735	129.365   129.365   0.8735
billsum	pubmed	156.47   78.11   0.5887	155.76   60.38   0.457	156.235   60.94   0.4754	156.245   56.01   0.4383	156.075   156.075   0.4383
billsum	reddit_tifu	20.17   48.33   3.1382	20.1   29.105   2.2168	20.15   27.99   2.0119	20.15   24.595   1.835	20.145   20.145   1.835
billsum	aeslc	4.285   21.965   7.125	4.29   18.39   5.8343	4.28   17.385   5.771	4.28   16.655   5.3529	4.29   18.39   5.3529
pubmed	cnn	51.615   93.515   2.0163	51.58   66.615   1.4428	51.7   65.625   1.4121	51.61   58.445   1.2561	51.6   84.355   1.2561
pubmed	multi_news	184.245   150.705   0.8749	184.145   104.16   0.6058	184.135   95.99   0.5431	184.34   68.495   0.3917	184.355   184.355   0.3917
pubmed	billsum	128.98   163.085   2.0936	128.845   129.165   1.6207	129.5   127.97   1.5182	129.405   113.175   1.3577	129.515   129.515   1.3577
pubmed	pubmed	156.22   161.93   1.1322	156.105   149.15   1.0197	156.01   145.12   1.0034	156.275   136.4   0.9307	156.155   156.155   0.9307
pubmed	reddit_tifu	20.115   80.64   5.5781	20.175   58.42   4.2213	20.09   57.95   4.2779	20.22   45.485   3.22	20.135   20.135   3.22
pubmed	aeslc	4.3   25.4   8.2452	4.29   25.27   8.0682	4.29   24.49   7.8305	4.29   24.47   7.8687	4.29   24.47   7.8687
reddit_tifu	cnn	51.705   22.61   0.4747	51.71   24.015   0.5402	51.645   25.955   0.5695	51.685   13.96   0.3049	51.61   54.075   0.3049
reddit_tifu	multi_news	184.435   73.355   0.4374	184.17   28.18   0.1567	184.485   33.565   0.1826	184.455   3.95   0.0219	N/A
reddit_tifu	billsum	129.63   97.175   1.1085	128.87   71.065   0.9121	129.01   88.085   0.9953	129.515   6.26   0.0762	129.515   129.515   0.0762
reddit_tifu	pubmed	155.76   50.34   0.4128	156.405   54.32   0.4106	156.36   52.53   0.4018	156.195   24.23   0.1818	156.085   156.085   0.1818
reddit_tifu	reddit_tifu	20.11   19.03   1.3798	20.205   15.34   0.9847	20.2   13.53   0.8757	20.175   12.705   0.8337	20.18   32.11   0.8337
reddit_tifu	aeslc	4.32   11.17   3.553	4.29   6.59   2.0353	4.29   7.11   2.2098	4.29   4.0   1.304	4.3   12.7   1.304
aeslc	cnn	51.675   9.48   0.2088	51.67   7.935   0.1711	51.63   8.555   0.1848	51.655   3.65   0.0792	51.7   15.65   0.0792
aeslc	multi_news	184.3   6.49   0.0376	184.26   6.455   0.035	184.14   6.13   0.033	184.12   3.09   0.0184	184.285   184.285   0.0184
aeslc	billsum	129.695   5.69   0.0656	129.52   3.16   0.0412	129.28   3.07   0.0428	129.48   2.635   0.0385	129.31   129.31   0.0385
aeslc	pubmed	156.375   5.82   0.0433	156.08   6.21   0.0394	156.225   3.27   0.0239	156.13   2.94   0.0218	156.395   156.395   0.0218
aeslc	reddit_tifu	20.21   2.8   0.207	20.13   3.74   0.3201	20.1   3.86   0.3264	20.24   2.06   0.1437	20.19   8.1   0.1437
aeslc	aeslc	4.295   4.12   1.1896	4.28   3.6   1.0031	4.295   3.645   1.0093	4.28   3.29   0.9056	4.29   3.8   0.9056