

# Improving Zero and Few-Shot Abstractive Summarization with Intermediate Fine-tuning and Data Augmentation

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## Abstract

Models pretrained with self-supervised objectives on large text corpora achieve state-of-the-art performance on text summarization tasks. However, these models are typically fine-tuned on hundreds of thousands of data points, an infeasible requirement when applying summarization to new, niche domains. In this work, we introduce a general method, called WikiTransfer, for fine-tuning pretrained models for summarization in an unsupervised, dataset-specific manner which makes use of characteristics of the target dataset such as the length and abstractiveness of the desired summaries. We achieve state-of-the-art, zero-shot abstractive summarization performance on the CNN-DailyMail dataset and demonstrate the effectiveness of our approach on three additional, diverse datasets. The models fine-tuned in this unsupervised manner are more robust to noisy data and also achieve better few-shot performance using 10 and 100 training examples. We perform ablation studies on the effect of the components of our unsupervised fine-tuning data and analyze the performance of these models in few-shot scenarios along with data augmentation techniques using both automatic and human evaluation.

## 1 Introduction

Automatic text summarization aims to distill the most salient content of a given text in a compact form. Recent advances in summarization have been driven by the availability of large-scale datasets such as the CNN-DailyMail (CNNDM) corpus (Nallapati et al., 2016) and the New York Times corpus (Sandhaus, 2008) as well as by the introduction of large pretrained models such as BART (Lewis et al., 2019) and Pegasus (Zhang et al., 2019), in some cases resulting in summaries which are even favored over the human-written reference summaries. Fine-tuning such models, however, typically requires a large corpus of labeled summaries,

and creating data for every domain is infeasible and highly costly. Thus, the ability to transfer large pretrained models to new domains with only a small amount of data is necessary, especially as such models make their way into production environments.

Unsupervised summarization approaches include autoencoders to mirror the information compression inherent in summarization (Baziotsis et al., 2019; Chu and Liu, 2019; Bražinskas et al., 2020b) as well as large-scale pretraining for domain-specific adaptation (Yang et al., 2020). However, little work has focused on domain adaptation in summarization. Wang et al. (2019) examine domain adaptation for extractive summarization. Hua and Wang (2017) showed that summarization models have difficulty generating text in the style of the target domain, while more recently, Zhang et al. (2019) report strong performance of pretrained models when trained in few-shot settings and (Bražinskas et al., 2020a) fine-tune dataset-specific components of a model for few-shot learning. We aim to build off of recent work in pretrained models and improve unsupervised and few-shot summarization by encoding characteristics of the target summarization dataset in unsupervised, intermediate fine-tuning data.

In one view, summarization can be seen as a function of several sub-functions, called sub-aspects, which determine the output form. Jung et al. (2019) define three subaspects for summarization, position, importance, and diversity, and study how these subaspects manifest themselves in summarization corpora and model outputs. For example, a common subaspect for the CNNDM dataset is position; earlier sentences tend to give a good summary. Inspired by this view of summarization as subaspects, we aim to encode subaspects of a target dataset into unlabeled data to allow a model fine-tuned on this data to learn characteris-

tics of the target dataset to improve zero-shot and few-shot transfer of the model. In our work, we focus on the subaspects of *extractive diversity*, as determined by how well an extractive model performs on the data, *compression ratio* between the source document and summary, and, in the case of CNNDM, the *lead bias*. We assume knowledge of the target dataset such as the size of input documents, the size of the desired summaries, and the extent to which the summary is abstractive, all of which are prior knowledge if the task is to be well defined. We encode this knowledge into Wikipedia article data by extracting summaries of the desired output length and filtering examples based on the desired level of abstraction.

Our contributions are the following: 1) We introduce a method, called WikiTransfer, to create pseudo-summaries with subaspects of the target dataset which can be used as unlabeled data for intermediate fine-tuning 2) We show that this method improves zero-shot domain transfer over transfer from other domains, achieving state-of-the-art unsupervised abstractive summarization performance on the CNNDM dataset while generalizing to other domains, and we perform extensive ablation studies on the factors influencing zero-shot performance 3) We demonstrate additional improvements in transferring our WikiTransfer models in the few shot setting and analyze differences in performance when using data augmentation techniques on datasets with different level of extractiveness.

## 2 Related Work

While advances have been made in neural techniques for summarization due in part to large datasets, less work has focused on domain adaptation of such methods for summarization in the zero and few-shot settings. Wang et al. (2019) examine domain adaptation, but in extractive summarization. Hua and Wang (2017) examine domain adaptation between opinion and news summarization, observing that models trained on one domain and applied to another domain can capture relevant content but differ in style in generating the summary.

Bražinskas et al. (2020a) introduce plug-in networks, small finetune-able layers added to a larger model that aims to reproduce characteristics of the target dataset as seen in a small set of labeled examples. In contrast, we aim to encode the characteristics of our target dataset, such as extractiveness and compression, a priori in the intermediate

training phase for better adaptation. In other work, Lebanoff et al. (2018) adapt a single-document summarization model to the multi-document setting, while Zhu et al. (2019) use the references from Wikipedia data for downstream query-based summarization, similar to the task of Wikipedia paragraph generation as defined in Liu et al. (2019).

Several approaches for unsupervised summarization have made use of variational autoencoders (Baziotis et al., 2019; Chu and Liu, 2019; Bražinskas et al., 2020b). Zhou and Rush (2019) makes use of pretrained language models for unsupervised text summarization by aligning the coverage of the generated summary to the source document. Laban et al. (2020) train an unsupervised summarization model by guiding the model with reinforcement learning rewards. In another line of work, extractive models such as TextRank, (Mihalcea and Tarau, 2004), LexRank (Erkan and Radev, 2004), and more recently PacSum (Zheng and Lapata, 2019), aim to use graph centrality in order to extract important sentences for a document.

The power of pretrained models for few-shot transfer was shown in Zhang et al. (2019). Our work focuses on the zero-shot case as well as the transferability of models fine-tuned on given datasets across multiple datasets, rather than just the transferability of a single pre-trained model. The closest work to ours for zero-shot transfer is Yang et al. (2020), which makes use of the lead-bias in news articles to pretrain an unsupervised model on a large dataset of news articles. Our approach, however, focuses on fine-tuning an already pretrained model specific for the task of summarization on a downstream dataset and shows the generalizability of such fine-tuning across domains. BART (Lewis et al., 2020) is a pretrained denoising autoencoder and achieved state-of-the-art performance when fine-tuned on summarization tasks at the time. In this work, we use BART as our base pretrained model but in future work will experiment with intermediate fine-tuning and few-shot transfer with other pretrained models.

## 3 Methods

In this section, we introduce our methods to improve zero and few-shot abstractive summarization.

Let  $x = \{x_1, x_2, \dots, x_t, \dots, x_n\}$  be a source document with  $n$  words and  $N$  sentences, where  $x_i$  represents the  $i$ -th word in  $x$ . It could also be represented as  $\{s_1, s_2, \dots, s_t, \dots, s_N\}$ , where  $s_t$  rep-

resents the  $t$ -th sentence in  $x$ . The corresponding target summary  $y$  contains  $m$  words and  $M$  sentences, and  $y_t$  denotes the  $t$ -th token of  $y$ .

Standard training minimizes the negative log-likelihood loss using supervised teacher forcing (Williams and Zipser, 1989), which we label  $L_{sup}$ :

$$L_{sup}(x, y) = - \sum_{i=1}^m \log(f(y_t|y_{0:t-1}, x, \theta)) \quad (1)$$

where  $f(\cdot|\cdot, \theta)$  represents the distribution among the vocabulary predicted by our model with parameter  $\theta$ .  $\theta$  will be ignored for the following equations for simplicity.

### 3.1 Intermediate Fine-tuning

We propose a method for fine-tuning pretrained models using unsupervised Wikipedia data. To create data for this intermediate fine-tuning, we assume knowledge of characteristics of the target dataset such as the average length of input documents, the average summary length and the general bin of whether the summaries desired are very abstractive or very extractive. Such specifications are necessary a priori so that the summarization problem is not underconstrained (Kryściński et al., 2019). Assume that we want a summary of  $M$  sentences from source documents of  $N$  sentences on average. Assume that we know approximately how well an oracle extractive model performs on the target dataset, as defined as bins of extractive oracle ROUGE scores ranging from extremely abstractive (ROUGE oracle 10-30), more abstractive (ROUGE oracle 20-30), more extractive (ROUGE oracle 30-50), and extremely extractive (ROUGE oracle 40-60). We then iterate the following procedure on all Wikipedia articles available in a Wikipedia dump: We remove the first  $M$  sentences from the Wikipedia article for use as a summary. Then, we select the  $M$  sentences in the remaining article with the highest individual ROUGE scores against the pseudo summary and calculate the ROUGE score between those  $M$  sentences joint and the pseudo summary, which amounts to a greedy upper bound of the performance of an extractive model on this example. The example will be kept if this ROUGE score falls into the general range of the extractive oracle of the target dataset defined previously and otherwise discarded. We use knowledge of how abstractive a dataset is as a type of summary style which an end-user would know ahead of time. We

filter the data points from Wikipedia, so that only those which fall into the bin for a given dataset are used for fine-tuning. For datasets that are extremely abstractive, such examples may be hard to find, so we remove high-ROUGE sentences from the input until the desired ROUGE oracle score is reached. From here on we refer to data created through this process as **WikiTransfer**. We then fine-tune a pre-trained model on this dataset-specific WikiTransfer data to transfer to a target domain.

### 3.2 Data Augmentation via Round-Trip Translation

In addition to fine-tuning on WikiTransfer data for zero-shot domain transfer, we test the ability of our model to transfer when we have few examples and whether data augmentation further improves these results. In few-shot fine-tuning, we conduct data augmentation to reduce brute-force memorization and introduce a regularization effect. Specifically, we perform round-trip translation (Yu et al., 2018) to generate paraphrases of both the source documents and summaries. Given a dataset of size  $N$ , we translate the source and target sentence-wise into a non-English language and keep the top  $k$  beam hypotheses from beam search as output. We then do likewise for the backtranslation to English. This results in  $N + (N * k^2)$  total data points.

### 3.3 Data Augmentation Consistency

While data augmentation may introduce a regularization effect, naively training with augmented data does not necessarily account for noise introduced in the augmented examples. To balance learning from the examples while not overfitting to the small number of supervised samples, the model must learn to be robust to small changes in input examples. We thus investigate the effect of using a consistency loss for few-shot training by building off of ideas in Unsupervised Data Augmentation (UDA) (Xie et al., 2019). In our formulation, the output distribution given an augmented example should not diverge much from the distribution given the original document with teacher forcing so that the model learns to be resilient to small perturbations. Let  $\hat{x}$  be a paraphrase of input document  $x$  generated via round-trip translation as described in the previous section. In addition to the supervised loss  $L_{sup}(x, y)$ , we introduce another loss

$L_{cons}(x, \hat{x}, y)$ :

$$\sum_{t=1}^m KL(f(\cdot | y_{0:t-1}, x) || f(\cdot | y_{0:t-1}, \hat{x})) \quad (2)$$

where  $KL$  is the KL divergence, which penalizes the loss if the probability distribution of the output using the original input is far from the distribution using the round-trip translated input document. As in Xie et al. (2019), the gradient does not backpropagate through the model for the distribution of the original input while it does propagate through to the round-trip translated input. As a result, the total loss  $L'$  for training with consistency is:

$$L'(x, \hat{x}, y) = L_{sup}(x, y) + \lambda L_{cons}(x, \hat{x}, y) \quad (3)$$

We note that the original formulation of UDA enforces consistency in a semi-supervised framework. We also experimented with this setup using unlabeled examples from the target dataset with pseudo labels (for teacher forcing) generated by a model trained on the associated few-shot subset, although this approach is very sensitive to the quality of the pseudo labels (see appendix).

## 4 Experimental Settings

In this section, we describe our experimental settings for data usage, intermediate finetuning, as well as zero-shot and few-shot domain transfer.

**Datasets:** We experiment with four datasets, CNN-NDM, XSum (Narayan et al., 2018), Reddit\_tifu (Reddit) (Kim et al., 2018), and BigPatent (Sharma et al., 2019). The datasets were chosen as they all differ in their abstractiveness, output length (ranging from one sentence in XSum to on average four sentences in BigPatent), and cover multiple domains from news (CNNDM and XSum) to social media (Reddit) to patent documents (BigPatent) to show the generalizability of our results.

**Model Selection and Metric:** For the experiments which follow, we first choose the model with the best zero-shot performance on a given domain. We test the zero-shot performance from all four domains onto every other domain. For models from our WikiTransfer subset, we choose the best model based on performance on an unsupervised validation subset. We found that fine-tuning the model longer did not result in performance gains in few-shot transfer, and the checkpoints chosen were typically fine-tuned from 2 to 5 epochs.

Results from ablation studies for the WikiTransfer subset are shown on the validation set of that given target dataset. Unless otherwise stated, all results reported are **ROUGE-1**, **ROUGE-2**, and **ROUGE-L**. We run all few-shot transfer experiments on five subsets of supervised data, as we found results may vary from run to run, and the reported numbers, unless zero-shot, are the average of the top three results of the five runs. The 10 data point sets are subsets of the 100 data point sets.

**Data Augmentation Parameters:** For data augmentation via round-trip translation, we use a beam size of 10 and  $k$  of 10 on German and Russian translation models; fairseq provides bidirectional pretrained translation models (Edunov et al., 2018) from WMT19 (Ng et al., 2019) for these language pairs. For both 10 and 100 data points, we use a  $k$  of 10, resulting in 2010 and 20100 total data points. We label the model fine-tuned on these settings 10-aug and 100-aug. For consistency loss, we make use of the same augmented data.

**Model Hyperparameters:** We use the fairseq codebase (Ott et al., 2019) for our experiments. Our base abstractive text summarization model is BART (Lewis et al., 2019), a pretrained denoising autoencoder that builds off of the sequence-to-sequence transformer of Vaswani et al. (2017). We fine-tune BART using a polynomial decay learning rate scheduler using the Adam optimizer (Kingma and Ba, 2015). We mainly vary the learning-rate scheduler, warm-up updates, and total updates. As in the previous few-shot summarization work (Zhang et al., 2019) and work in unsupervised machine translation (Lample and Conneau, 2019), we make use of the validation set for early stopping based on the validation loss. We used the following learning rates, warmup updates and total parameters based on an examination of the validation curves in initial experiments: 10: (25, 100, 3e-5) 10-aug: (20, 200, 3e-5), 100 (20, 200, 3e-5), 100-aug: (200, 1000, 1e-5). For consistency loss experiments, we use the  $\lambda$  value of .5 for experiments with 100 data points and  $\lambda$  of 0.1 for experiments with 10 data points. See the appendix for additional training details.

## 5 Zero-shot Transfer Results

In this section, we compare transferring from a BART model fine-tuned on WikiTransfer data to one transferred from summarization datasets in terms of zero-shot performance. We also show

ablations of different choices for WikiTransfer fine-tuning data across the CNNDM and XSum datasets. Each of the datasets falls into a different extractive bin, ranging from the most extractive CNNDM dataset to the more abstractive XSum; we discuss these settings further in the appendix.

### 5.1 Zero-shot Transfer Comparison

We fine-tune BART on WikiTransfer data for each of the four datasets described above and also fine-tune a model on the fully-supervised datasets. We compare the zero-shot performance of transferring from WikiTransfer against the best zero-shot transfer performance from another dataset, as well as the current state-of-the-art fully-supervised results, in Table 1. We see that zero-shot transfer from WikiTransfer data outperforms transfer from other datasets in terms of ROUGE-1. We also experimented with training a model on data combined from multiple datasets; we leave one dataset out and train on the others and then test in a zero-shot setting. This setting, however, did not give improved results (except for BigPatent transfer, where the zero-shot transfer increases to 34.36 from 33.57 in ROUGE-1, still lower than our WikiTransfer model), so for the experiments which follow we use the best performing single-domain transfer model. Note that the difference in performance for our supervised BigPatent results from BART likely is due to differences in capacity and training batch size when compared to the current state-of-the-art Pegasus Large model (Zhang et al., 2019). Our result on BigPatent is comparable to that of the Pegasus Base model (Zhang et al., 2019).

Additionally, in Table 2 we compare the zero-shot performance of our model to the state-of-the-art unsupervised abstractive model on CNNDM, as this dataset has seen the most comparison in unsupervised summarization literature of the datasets in our study. We outperform the recently-introduced TED model (Yang et al., 2020) which was specifically motivated for the news domain, showing the generalizability of our approach.

### 5.2 Ablation Studies on WikiTransfer Data

We conduct ablation studies to determine what effect the characteristics of our intermediate fine-tuning data have on downstream zero-shot performance. We perform these ablation studies on CNNDM and XSum to show the effect on both ends of the extractive and abstractive dataset spectrum.

Target Dataset	SOTA full dataset	WikiTransfer	Transfer (Best)
CNNDM	44.17 (44.16)	39.11	36.81 (from Reddit)
XSum	47.21 (45.14)	31.85	24.04 (from Reddit)
Reddit	32.76	21.47	21.37 (from CNNDM)
BigPatent	53.63 (43.34)	35.58	33.57 (from CNNDM)

Table 1: Comparison of ROUGE-1 zero-shot transfer performance from dataset-specific WikiTransfer vs. transfer from another dataset. The best-performing zero-shot model is shown the right column in parentheses. We show the state-of-the-art supervised performance on that dataset and in parentheses the performance of our BART model trained on that dataset.

Model	ROUGE-1/2/L
WikiTransfer	<b>39.11/17.25/35.73</b>
TED (Yang et al., 2020)	38.73/16.84/35.40

Table 2: A comparison of our approach to the unsupervised pretraining of Yang et al. (2020), showing the superior performance and generalizability of our approach versus the TED model, which focused on only the news domain.

Ablation	CNNDM	XSum
LR=3e-6	40.14/17.71/36.66	27.60/8.62/20.93
LR=3e-5	39.73/16.94/36.24	31.80/10.46/23.66
LR=3e-6, No-bin	39.11/16.98/35.66	22.78/5.66/17.16
LR=3e-6, bin, M=1	37.45/14.72/32.52	27.60/8.62/20.93
LR=3e-6, bin, M=3	40.14/17.71/36.66	27.98/9.59/23.11

Table 3: Ablation studies on the effect of learning rate, the use of extractive bin for data filtering and the choice of M in intermediate fine-tuning on ROUGE performance on CNNDM and XSum validation sets.

**Effect of learning rate in intermediate fine-tuning:** We examine the extent to which overfitting to the unsupervised WikiTransfer data occurs by examining the effect of the learning rate in intermediate fine-tuning on zero-shot transfer performance. We finetune the models on the CNNDM and XSum WikiTransfer data respectively each with a maximum learning rate of 3e-6 and 3e-5. Results are shown in Table 3. Using a smaller learning rate in intermediate fine-tuning improves results on CNNDM, but not on XSum, likely due to the simple extractive and lead bias objective which can easily overfit during fine-tuning, as opposed to the abstractive object in the XSum WikiTransfer data. We see a similar trend with the effect of dataset size. For datasets other than CNNDM, we use a learning rate of 3e-5 in intermediate fine-tuning.  
**Effect of extractive oracle bin use and the choice of M:** We tested whether using the extractive bin to filter examples in the unsupervised data affected zero-shot transfer. For this ablation experiment, we used the first M sentences from the

Wikipedia article as the summary and the remaining N as the source, but do not filter examples according to how extractive they are. From Table 3, we see that the extractive bin has a very noticeable effect on transfer results for XSum and a moderate effect on CNNDM. This is to be expected, as the model otherwise is missing information about XSum’s distinctive output style.

We examined how the choice of M affected performance. We set  $M = 1$  for CNNDM and  $M = 3$  for XSum and filtered examples in a similar way based on the extractive bin of the target dataset. We see that the choice of M has a large impact on CNNDM performance but no decrease on XSum. This result, combined with the effect of filtering examples based on extractive bin, gives insight into the importance of the subaspect of abstractiveness over compression for XSum performance.

**Effect of intermediate pretraining dataset size:** We examined the effect of the size of the Wiki-Transfer data on downstream performance. For this experiment, we take a single subset of 10k unsupervised data points as validation data and then vary the amount of data used for training for 10k, 100k, 250k, and 400k examples. Results are shown in Table 4. We see a general increase with the addition of more data, although smaller increases after 100k data points and even a decrease in 250k on XSum, likely due to noise variation. When compared to XSum, we see that the performance with 10k data points on CNNDM is already much closer to the best performance. We believe that this is due to the highly extractive nature of CNNDM. Such an objective is especially easy for a model such as BART to learn, as it is pretrained as a denoising autoencoder. For XSum, we see a noticeable improvement from 10k to 100k examples. We suspect that the abstractive objective is harder for the model to learn with small datasets. As we add more examples, we do not see a noticeable improvement. Such observations agree with our observation of the effect of learning rate and the CNNDM objective being easier for the model to overfit to and learn. For the remaining experiments, we use 400k data points since this worked well in initial experiments.

**Effect of summary sentence choice:** The first M sentences of a given Wikipedia article were chosen as this introduction intuitively form a coherent summary of the article. We examine the effect of choosing the first sentences compared to choosing based

Intermediate Dataset Size	CNNDM	XSum
10k	39.48/17.79/36.3	21.59/4.85/16.28
100k	39.92/17.65/36.5	31.52/10.86/23.94
250k	40.10/17.70/36.62	31.39/10.27/23.43
400k	40.14/17.71/36.66	31.80/10.46/23.66

Table 4: A comparison of the effect of dataset size of the unsupervised intermediate fine-tuning data on the zero-shot transfer ROUGE performance.

Target Dataset	First M Sents	IND-ORIG	IND-ORIG-P
CNNDM	40.14/17.71/36.66	37.62/15.15/34.21	37.85/15.32/34.39
XSum	31.80/10.46/23.66	29.95/9.37/21.78	30.22/9.79/23.23

Table 5: A comparison of the effect of summary sentence choice for WikiTransfer on zero-shot transfer.

on other criteria. As an alternative, we pick the sentences with the highest self-ROUGE (ROUGE score of a sentence when using all other sentences as the reference summary) in a greedy fashion (the equivalent of the **IND-ORIG** settings in Zhang et al. (2019)). As in Zhang et al. (2019), we use ROUGE-1 F1 for this setting. The sentences chosen under this heuristic consistently corresponded to those which were longest, and the resulting summaries were hence longer. Thus, we also experimented with choosing important sentences by using ROUGE-1 Precision **IND-ORIG-P**. The comparison of these methods is shown in Table 5. We see that the choice of the summary sentence has a noticeable impact on performance. We hypothesize that the coherence lost in the summaries is especially important for the longer CNNDM summaries. Using important sentences other than the first sentence likely adds more diversity in the data, and finding a balance between coherence and output style is an interesting direction for additional work (Christensen et al., 2013).

**Effect of lead bias on CNNDM fine-tuning:** We examined the effect of selecting the M sentences greedily chosen for calculating the extractive oracle and inserting them at the beginning of the unsupervised source document versus leaving them in place for CNNDM. This insertion is meant to mirror the lead bias present in the dataset. This had a slight impact on performance (40.14 vs 39.74 without this bias), and thus we keep the lead bias.

**Wikipedia vs target domain unlabeled data:** While Wikipedia is a natural source of unlabeled data, we tested whether creating unsupervised data from unlabeled in-domain data improved results. We performed the same dataset creation treating the source data of the target domain as we did the Wikipedia data. This resulted in about 60k exam-

ples for CNNDM and 200k examples for XSum. Fine-tuning on this data, however, resulted in a performance of about 38.08 R1 (vs 39.11 on WikiTransfer data) for CNNDM and 25.83 R1 (vs 31.85 on WikiTransfer data) for XSum. The removal of the first sentences may remove too much information in the case of CNNDM, while for XSum, which already has an initial sentence headline removed as the summary, the first sentence may not constitute a very good summary of the remainder of the document. Wikipedia data often contains multi-paragraph introductions; thus the removal of the first few sentences may still leave a pyramid-structured document with coherent informative content placed at the front. This result supports the emphasis on learning the subspects of the target domain over simply in-domain training. An analysis of the output of intermediate fine-tuning on CNNDM revealed that the output was more abstractive, due to information present in the summary not being directly stated in the source, than fine-tuning on Wikipedia. We also experimented with further in-domain pretraining of the denoising autoencoder objective before zero-shot transfer, but this did not result in consistent improvements across datasets.

## 6 Few-Shot Transfer Results

We examine whether the improvements in zero-shot transfer also carry over to the few-shot setting as well as the effect of data augmentation techniques. The results of our experiments with varying training data sizes and augmentation methods for all 4 datasets are shown in Table 6 and appendix.

**10 and 100-shot performance with round-trip translation augmentation:** We see that in few-shot settings without data augmentation or consistency training our model outperforms transferring from another domain or vanilla BART. We see in transfer to Reddit that despite similar zero shot performance with transfer from CNNDM, there is a more sizeable gap with 10-shot transfer, which suggests that our intermediate fine-tuning does more closely align the BART model with the target domain. Furthermore, when training on augmented data from round-trip translation, we see the best performance in transfer from WikiTransfer in all cases except BART transfer to CNNDM on 10-aug, which is likely due to the autoencoder pretraining objective of BART which biases it towards copying and lead bias, allowing it to perform well in applications to CNNDM. We see improvements

Target Dataset		CNNDM		
Transfer from	WikiTransfer	Reddit	BART	
<b>0</b>	<b>39.11/17.25/35.73</b>	36.81/14.18/32.62	35.98/15.10/32.97	
<b>10</b>	<b>39.10/16.98/35.84</b>	38.26/16.34/34.76	38.55/16.56/34.97	
10-aug	39.39/16.92/36.00	39.12/16.90/35.44	<b>39.78/17.11/36.38</b>	
10-cons	<b>39.16/16.96/35.92</b>	38.99/16.83/35.43	38.98/16.68/35.41	
<b>100</b>	<b>40.55/18.01/37.03</b>	40.13/17.88/36.67	40.14/17.88/36.62	
100-aug	<b>42.08/18.93/38.83</b>	40.94/18.52/37.00	40.47/18.18/37.07	
100-cons	41.12/18.34/37.51	40.84/18.09/37.28	<b>41.36/18.59/37.77</b>	
Target Dataset		XSum		
Transfer from	WikiTransfer	Reddit	BART	
<b>0</b>	<b>31.85/10.44/23.75</b>	24.04/6.43/18.99	19.87/2.75/15.66	
<b>10</b>	<b>34.95/12.61/26.58</b>	30.69/10.22/23.29	22.45/5.94/17.23	
10-aug	<b>34.98/12.73/26.79</b>	31.03/10.23/23.29	26.10/8.19/20.18	
10-cons	<b>35.17/12.76/26.80</b>	31.25/10.54/23.73	28.28/9.13/21.61	
<b>100</b>	<b>36.92/14.09/28.44</b>	34.17/12.64/26.37	35.17/13.29/27.20	
100-aug	<b>36.87/14.18/28.62</b>	31.75/11.12/24.49	28.85/9.46/22.28	
100-cons	<b>37.26/14.20/28.85</b>	36.14/13.65/27.97	36.65/14.05/28.57	
Target Dataset		Reddit		
Transfer from	WikiTransfer	CNNDM	BART	
<b>0</b>	<b>21.47/4.10/17.62</b>	21.37/ <b>4.14/17.76</b>	18.66/2.90/15.33	
<b>10</b>	<b>27.88/7.62/22.09</b>	26.55/6.83/21.29	19.37/3.51/15.72	
10-aug	<b>28.07/7.70/22.47</b>	26.88/6.95/21.46	21.39/4.57/17.22	
10-cons	<b>28.42/7.88/22.32</b>	27.20/7.14/21.67	20.42/3.97/16.45	
<b>100</b>	<b>29.87/8.93/23.31</b>	28.90/8.42/22.56	29.66/8.88/23.12	
100-aug	<b>30.54/9.24/24.31</b>	29.28/8.51/23.28	28.96/8.39/22.80	
100-cons	30.56/9.22/24.38	<b>30.78/9.45/24.14</b>	<b>30.78/9.22/23.32</b>	
Target Dataset		BigPatent		
Transfer from	WikiTransfer	CNNDM	BART	
<b>0</b>	<b>35.58/10.91/31.53</b>	33.57/9.34/25.76	32.56/9.64/29.27	
<b>10</b>	<b>37.06/11.58/32.37</b>	35.76/10.62/30.63	34.48/10.76/30.56	
10-aug	<b>37.73/12.40/32.89</b>	36.83/11.33/30.95	36.11/11.40/32.04	
10-cons	<b>37.64/12.24/33.05</b>	36.11/10.84/30.64	33.99/10.48/30.45	
<b>100</b>	<b>39.61/13.53/33.86</b>	39.35/13.03/ <b>33.88</b>	39.06/13.04/33.61	
100-aug	<b>40.95/14.05/35.03</b>	38.88/12.69/32.88	38.77/12.88/33.55	
100-cons	<b>39.87/13.76/34.32</b>	39.74/13.45/ <b>34.49</b>	39.46/13.37/34.28	

Table 6: A comparison of transfer results across datasets, training dataset size, data augmentation techniques, showing the generalizable and robust performance of our models transferred from WikiTransfer.

when training with augmented data in 10-example cases and 3/4 100-example cases for WikiTransfer. Less improvement is seen in the 100-aug setting when transferring from BART or another domain. We hypothesize that the noise present in the larger augmented dataset causes this occasional performance drop, while the WikiTransfer models appear more robust to potential noise. Interestingly, for transfer from BART and another domain 100-aug only improves on CNNDM, the most extractive dataset, while the largest drop in performance from augmented data occurs on XSum. This XSum performance drop may be caused by the high compression in the XSum summaries which leaves less room for noisy output when compared to the longer CNNDM and BigPatent summaries which may still preserve the main meaning of the original summary better despite backtranslation noise. In 3/4 cases, 100-aug with WikiTransfer results in the best performance, only several points away from the state-of-the-art supervised performance in Table 1.

**Transfer with Consistency Training:** We find contrasting trends with the added consistency loss

Target Dataset	CNNDM		XSum	
	Relevance	Consistency	Relevance	Consistency
0	4.37	4.71	3.75*	3.75
10-aug	4.31	4.76	3.77*	4.10
100-aug	4.25	4.86	4.00	4.04
Full supervision	4.31	4.86	4.11	3.98

Table 7: Summary relevance and factual consistency across CNNDM and XSum datasets with varying amounts of training data. All results except those with an asterisks do not differ in a statistically significant way (p-value of 0.05) from the full supervision score.

compared to data augmentation via round-trip translation. We note the most sizeable improvements in the more abstractive cases of XSum and Reddit. We hypothesize that the consistency loss promotes better abstraction as the model learns to be invariant to noise which does not change the meaning of the text, and is thus equipped with a better notion of paraphrasing. The consistency loss allows for better training of vanilla BART as well as in general better transfer from other domains than without consistency loss. The loss likely provides a regularization factor which prevents the models from overfitting to the supervised examples. As the WikiTransfer model is already more closely tuned to the target domain, this regularization may not make as large of a difference. This aligns with our observation of WikiTransfer models being more robust to noisy backtranslated data on XSum and Reddit. Transfer to Reddit shows similar results across models for consistency loss with 100 examples (better ROUGE-L for WikiTransfer, better ROUGE-1/2 for Reddit); vanilla BART’s strong performance at 100 examples suggests that the information provided in this subset is sufficient for good performance, thus diminishing the gains from the head-start the WikiTransfer model provides in zero and 10-shot transfer. We leave aspects of the consistency training such as the role of the quality of the round-trip translation data and its relation to the transfer domain to future work.

### 6.1 Human Quality Assessment

We examine how the improved performance from WikiTransfer manifests itself in qualitative annotations when varying the amount of training data. We collect human judgment annotations for two of the four quality dimensions studied in Kryściński et al. (2019); Fabbri et al. (2020), namely consistency and relevance. Consistency is defined as the factual alignment between the summary and the summarized source text, while relevance is defined

as the selection of important content; only relevant information should be included in the summary. We did not include fluency as a dimension as an initial inspection of the data found fluency to be of very high quality, and we did not include coherence due to our inclusion of single-sentence XSum summaries where coherence is not a factor. We randomly select 50 examples per dataset and collect the model output from the best-performing zero-shot, 10-aug, 100-aug, and fully supervised models on CNNDM and XSum. The annotator sees the source article and randomly-ordered output from the four models rates the summaries for relevance and consistency on a Likert from 1-5, with 5 being the best score. We averaged the score of two native English-speaking annotators on each example and then across examples, and found moderate and strong annotator correlations for relevance and consistency, respectively. Results are shown in Table 7. For CNNDM, we see an increase in consistency as more training data is added but not a statistically significant difference (using a Student’s t-test with a p-value of 0.05) between 100 and full supervision for any of the relevance or consistency results. We see that the relevance of the full model does not outperform the others, likely because the model output was more concise and was judged as not including source information, while the zero-shot output more closely resembles the lead-three bias, and is longer, so was judged as more informative. For XSum, we see that relevance improves noticeably as more training data is used. We see varied results for consistency, although without statistically significant differences. This fluctuation in scores may be due to the transition of the model from using knowledge from pretraining in its output versus knowledge from the target dataset obtained during fine-tuning, which we discuss in the appendix.

## 7 Conclusion

We show improved performance when fine-tuning pretrained models on dataset-specific unsupervised data on both zero and few-shot transfer experiments. We also demonstrate the benefits and drawbacks of data augmentation and consistency training techniques. For future work, we plan to incorporate additional subaspects into the intermediate fine-tuning data such as redundancy, diversity, and more explicitly token overlap. We also plan to expand our experiments across more domains and compare other pretrained models for transfer.

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## A Appendix

### A.1 Comparison to previous work

We show a comparison of our best-performing WikitTransfer few-shot results with those from [Zhang et al. \(2019\)](#) in Table 8. Note that the Reddit dataset does not have a predefined subset so this comparison is not exact. Also, the Pegasus numbers were obtained by a single run as opposed to our average of the best three over 5 subsets. We show large improvements with our few-shot approach compared to previous numbers, except for the 100-shot experiment on XSum. The XSum dataset has the highest overlap with the Pegasus pretraining dataset of all datasets explored in [Zhang et al. \(2019\)](#), although that work states that the effect of removing this overlap does not affect the full-dataset performance. We hope that this comparison promotes future benchmarking of few-shot results.

### A.2 Sample Summary Outputs

We include an example of model output summaries on the XSum dataset in Table 9. The example serves to demonstrate how output style varies as the amount of training data is increased and how the source of pretraining or fine-tuning data affects this style and model hallucinations. The source document does not state the first name of Ms. Jones, yet every model output, and the gold target, gives her one. For zero and 10-aug, the model outputs Lorraine Jones, likely still under the influence of BART Wikipedia pretraining, as there is a Wikipedia article on the Welsh politician Ruth Lorraine Jones (although it does not appear in our intermediate fine-tuning subset). The zero and 10-aug also most resemble Wikipedia introduction sentences; although the output is compact and abstractive like an XSum target sentence, the "X is Y" format of Wikipedia appears. We see at 100-aug examples that the model output is stylistically already much like that of the fully-supervised output and gold summary. This stylistic change is also reflected in the change in hallucination; the use of Rachel Jones is likely caused by the appearance of the name of a minister Rachel Haves in an article on Welsh politics found in the 100-aug subset. The model at this point is already fitting strongly to the target domain. For the fully supervised output, we see the use of Carwyn Jones, which does not match the gender of Ms Jones but which is found 1090 times in the training source documents. Caroline Jones, the actual person in question, only appears 21 times in the

training set. This phenomenon points to two interesting research directions for future work, how to properly preserve world knowledge from pretraining and improvement faithfulness to the source text in knowing when to insert world knowledge.

### A.3 Semi-supervised UDA experiments

We experimented with the original formulation of UDA in a semi-supervised setting. In this framework, the label (summary) outputted by the model for an augmented example should be the same as the label of the original document on unlabeled examples. Let  $x_U$  be an unsupervised source document from the target dataset other than our supervised few-shot examples. Let  $\hat{x}_U$  be a paraphrase of input  $x_U$  generated via round-trip translation as in our above data augmentation experiments. To apply teacher forcing, we require a label  $y_U$ , which we obtain for each model by applying the model fine-tuned on the analogous few-shot subset. In addition to the supervised loss  $L_{sup}(x, y)$ , we thus introduce another loss  $L_{uda}(x_U, \hat{x}_U, y_U) =:$

$$\sum_{t=1}^m KL(f(\cdot|y_{U0:t-1}, x_U) || f(\cdot|y_{U0:t-1}, \hat{x}_U)) \quad (4)$$

In practice, for an epoch, we iterate through the supervised examples with loss  $L_{sup}$  followed by iterating over the unsupervised examples  $L_{uda}$ . We sampled 1k unlabeled data points for 10-UDA experiments and 3k unlabeled data points for 100-UDA. Results of initial experiments are shown in Table 10. We find that the performance of the UDA models is very dependent on the quality of the pseudo-labels generated. We chose the model trained on the first data subset of the 5 runs to generate the pseudo-labels and if this model had higher performance then this model likely performed better in UDA. As a result, as the quality of the pseudo-labels improves with 100-shot training the UDA performance improves and is more comparable to the unaugmented performance in 6.

### A.4 Additional Training Setting Details

We found that full-precision floating-point gave slightly better, and more stable, results, so we report full-precision floating-point numbers. We set a maximum tokens-per-batch of 1024 and use gradient accumulation with an update frequency of 8 for all experiments with 10 data points, and 32 for 10-aug as well as all experiments with 100 (+ augmented) data points. For CNNDM 10 examples,

Target Dataset	WikiTransfer			Pegasus (Zhang et al., 2019)		
# training samples	0	10	100	0	10	100
CNNNDM	39.11/17.25/35.73	39.39/16.92/36.00	42.08/18.93/38.83	32.90/13.28/29.38	37.25/15.84/33.49	40.28/18.21/37.03
XSum	31.85/10.44/23.75	35.17/12.76/26.80	37.26/14.20/28.85	19.27/3.00/12.72	19.39/3.45/14.02/	39.07/16.44/31.27
Reddit	21.47/4.10/17.62	28.42/7.88/22.32	30.56/9.22/24.38	14.66/3.06/10.17	15.36/2.91/10.76	16.64/4.09/12.92
BigPatent	35.58/10.91/31.53	37.73/12.40/32.89	40.95/14.05/35.03	25.61/6.56/17.42	28.87/8.30/19.71	33.52/10.82/22.87

Table 8: A comparison of zero and few-shot performance between our best-performing WikiTransfer model (-aug in the case of CNNNDM and BigPatent and -cons for XSum and Reddit) and the zero and few-shot results reported in Zhang et al. (2019).

<b>Source Document:</b> Ms Jones told BBC Radio Wales she did not want to give up being an AM to go to Brussels to replace Nathan Gill, UKIP Wales leader. Mr Gill has been told by the UKIP assembly group and the UKIP party chairman Steve Crowther to stop "double-jobbing" as an AM and MEP. Mr Gill said those making such calls were doing it out of "malice". "We've got Brexit now and I think that, possibly, it may be best to leave that role unfilled," Ms Jones told the Good Morning Wales programme. "I'm surprised I've not been formally asked what I'd like to do." Ms Jones, the South Wales West AM, is one of two people who could take up the role of UKIP Wales MEP if Mr Gill made it vacant - the other being South Wales East AM David Rowlands...
<b>0:</b> Lorraine Jones is a Welsh Labour Party Member of the Welsh Assembly for South Wales West.
<b>10-aug:</b> Lorraine Jones is a Welsh Labour member of the Welsh Assembly for South Wales West.
<b>100-aug:</b> Wales Assembly Member for South Wales West Rachel Jones says she has not been formally asked to become a UKIP MEP.
<b>Full supervision:</b> First Minister Carwyn Jones has said she is "surprised" she has not been asked to become a UKIP MEP.
<b>Gold Summary:</b> UKIP's Welsh MEP post may be better left unfilled as a result of Brexit , party AM Caroline Jones has said .

Table 9: An example of WikiTransfer model output across dataset size used in fine-tuning, illustrating how model output style and hallucinated entities differ as the model moves from Wikipedia pretraining as a source of knowledge to the target dataset. Text not stated in the source document is highlighted in red.

Target Dataset	CNNNDM		
Transfer from	WikiTransfer	Reddit	BART
10-UDA	39.51/17.2/35.93	38.86/16.83/35.26	37.81/16.82/34.64
<b>Target Dataset</b>			
Transfer from	XSum		
10-UDA	35.09/12.86/26.94	29.34/9.56/22.6	19.75/3.19/15.09
<b>Target Dataset</b>			
Transfer from	Reddit		
10-UDA	27.6/7.19/22.37	25.21/5.96/20.63	20.9/4.16/16.82
<b>Target Dataset</b>			
Transfer from	BigPatent		
10-UDA	36.58/11.45/32.29	33.77/9.45/29.19	32.32/10.0/28.98

Table 10: Results from experiments using the original formulation of UDA Xie et al. (2019) on 10 examples.

we found it necessary to use a smaller learning rate (3e-6) to avoid immediate overfitting. We per-

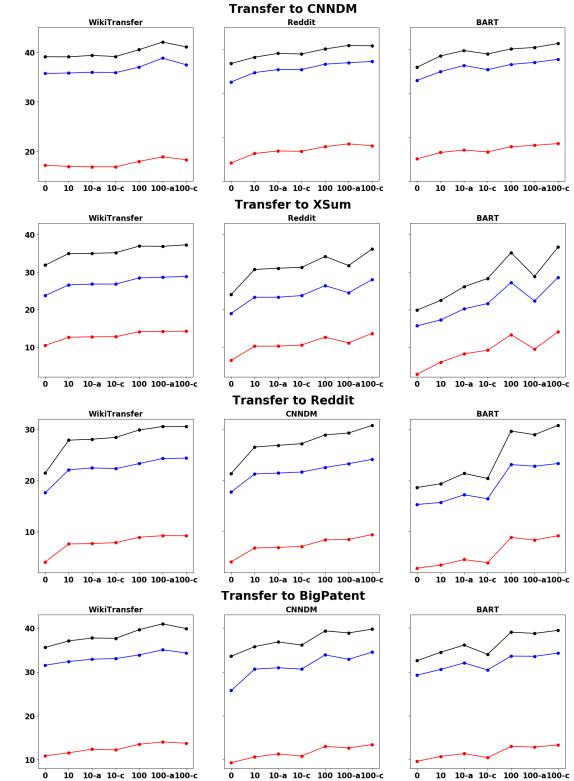


Figure 1: ROUGE-1, ROUGE-2, and ROUGE-L scores across datasets, training dataset size, data augmentation (\*-a), and consistency loss (\*-c) showing the generalizable and robust performance of our models transferred from WikiTransfer.

form validation after each model update, as the models typically converge in under 50 iterations. For the 100-aug setting, we begin validation checking after 50 iterations as the models typically converged around 100 iterations. We train with label-smoothed cross-entropy (Szegedy et al., 2016) loss for few-shot transfer. We found that models can be sensitive to the choice of hyperparameters in the few-shot settings, hence the averaging over 5 subsets to reduce variation. While we did not observe large differences in preliminary experiments on varying the size of this validation set, we leave the task of training without, or with very little, validation data for future work.

We use the statistics from the original papers to determine the extractive bin of the dataset except for the case of Reddit; upon seeing the strong zero-shot performance of the CNNDM, we investigated the extractive oracle of the Reddit dataset and found it to be much higher (about 31 R) than that stated in the original paper. We select the first M sentences for the pseudo-summaries from Wikipedia except in the case of Reddit, where we choose the IND-ORIG setting; this did not result in a difference in zero-shot performance but upon a qualitative inspection of the output we found the IND-ORIG to be less biased towards Wikipedia style with the coherence of the summaries not being an issue.