The diverse demands of different summarization tasks and their high annotation costs are driving a need for few-shot summarization. However, despite the emergence of many summarization tasks and datasets, the current training paradigm for few-shot summarization systems ignores potentially shareable knowledge in heterogeneous datasets. To this end, we propose UNISUMM, a unified few-shot summarization model pre-trained with multiple summarization tasks and can be prefix-tuned to excel at any few-shot summarization datasets. Meanwhile, to better evaluate few-shot summarization systems, under the principles of diversity and robustness, we assemble and publicize a new benchmark SUMM-ZOO. It consists of 8 diverse summarization tasks with multiple sets of few-shot samples for each task, covering both monologue and dialogue domains. Experimental results and ablation studies show that UNISUMM outperforms strong baseline systems by a large margin across all tasks in SUMM-ZOO under both automatic and human evaluations. We release our code and benchmark at https://github.com/microsoft/UniSumm.

1 Introduction

The task of text summarization is to generate a concise summary that conveys the key information of the input text (Liu et al., 2019; Huang et al., 2020). Encouraged by the success of summarizers based on large pre-trained language models (PLMs) (Liu and Lapata, 2019; Yang et al., 2020; Lewis et al., 2020; Zhang et al., 2020; Yu et al., 2022), various summarization tasks have been proposed to meet different practical demands, such as comprehending different input (like news (Fabbri et al., 2019) and paragraphs (Perez-Beltrachini and Lapata, 2021)). However, annotating gold summaries for each newly-proposed summarization task can be costly (Sen et al., 2008). Therefore, few-shot summarization, the task of building a model for a specific summarization scenario using very limited ground-truth data (Chen and Shuai, 2021), has gained increasing attention from the research community (Bražinskas et al., 2020; Fabbri et al., 2021; Logan IV et al., 2022; Liu et al., 2022).

Pre-trained models such as PEGASUS (Zhang et al., 2020) and BART (Lewis et al., 2020) have established strong baselines on many few-shot natural language generation tasks, including summarization. Li and Liang (2021) find that it is possible to quickly adapt a pre-trained model to new tasks by adding and updating a small set of extra parameters (called prefix) while keeping other parameters frozen. And this prefix-tuning method is especially helpful to improve few-shot learning results. However, previous study (Ghazvininejad et al., 2021) shows that prefix-tuning can be less stable, and sometimes underperforms standard fine-tuning for few-shot text summarization.

Several studies try to improve prefix-tuning by...
designing more sophisticated prefixes (Ghazvininejad et al., 2021; Liu et al., 2022). However, they ignore the fact that PLMs themselves can have limited summarization knowledge due to the salient gap between pre-training objectives (e.g., language modeling) and summarization objectives (Aribandi et al., 2021). In addition, despite the growing number of summarization tasks proposed every year, existing work tends to directly fine-tune or prefix-tune PLMs when facing a new task (Chen and Yang, 2021; Chen et al., 2022a; Fang et al., 2022; Li and Liang, 2021). Intuitively, existing summarization datasets can provide relevant knowledge to newly-proposed summarization tasks, and therefore be beneficial to the new summarization tasks, especially under the few-shot scenario.

We aim to address these issues by proposing a unified few-shot summarization framework (UniSUMM). The idea is to combine multi-task pre-training on existing summarization datasets with few-shot prefix-tuning. To this end, we first build a multi-task model based on a backbone Transformer-based language model and equip it with task-specific prefix vectors, and then continually pre-train the multi-task model on diverse summarization datasets, where we optimize the summarization model together with task-specific prefixes and also a universal prefix. Using prefixes in multi-task pre-training stage leads to two advantages: First, the mixture of shared summarization parameters and unique task-specific parameters conforms with the principle of multi-task learning, helping these tasks to optimize each other without bringing much noise (Ruder, 2017). Second, task-specific prefix can be replaced or tuned to serve as a knob for our second stage of prefix-tuning on individual few-shot tasks.

When facing an unseen few-shot summarization task, we freeze the multi-task learned backbone model and use the universal prefix as initialization for prefix-tuning on the target task. To further avoid negative transfer between distant tasks, we introduce an asymmetrical weight decay strategy in pre-training to allow the backbone model to update slower and learn the general summarization knowledge while letting prefixes update faster and learn more task-specific knowledge. The resulting system, UniSUMM, is a single model that can be easily prefix-tuned to excel at various few-shot summarization tasks.

The lack of a benchmark for fair comparison between systems has been a major obstacle for few-shot summarization research. Previous studies either focus on one type of data, e.g., news summarization (Ghazvininejad et al., 2021), or train their systems on non-public few-shot samples. Because few-shot models can be very sensitive to training data, the selection of different few-shot samples in different papers can lead to ambiguous comparisons (also known as Sample Selection Bias (Cortes et al., 2008)). To address these issues, we assemble and publicize a new few-shot summarization benchmark, SUMMZOO, following two principles, namely diversity of tasks and robustness of evaluation. SUMMZOO collects summarization data from 8 existing datasets covering both monologue and dialogue texts. These tasks are diverse in terms of domain (news, academic papers, meetings, etc.), format (single-document and multi-document) and length on both source and target sides. For a more robust evaluation, for each task, SUMMZOO provides 5 different (randomly sampled) few-shot training sets, and requires all systems to report their averaged results. Finally, SUMMZOO includes both 10-shot and 100-shot settings.

We compare UniSUMM against several strong baselines on SUMMZOO and conduct thorough ablation studies. Experimental results of automatic and human evaluations show that UniSUMM outperforms all baselines by a large margin across all sub-tasks under both 10-shot and 100-shot settings. Additionally, UniSUMM is empirically found to be more stable and robust when facing different few-shot samples. Analysis shows that combining multi-task pre-training and few-shot prefix-tuning is essential to the performance of UniSUMM and other techniques like universal prefix and asymmetrical weight decay can all improve its generalization ability. We release our code and benchmark at https://github.com/microsoft/UniSumm.

2 Method

Following Chen and Shuai (2021), the task of few-shot text summarization is defined as: For an unseen target summarization task \( u \), few-shot text summarization is to generate a summary \( Y \), given an input text \( X \), by learning from a limited number \( k \) (\( k \leq 100 \) typically) of labeled training instances of \( u \), with the help of general knowledge \( K \).

The overall framework of UniSUMM is shown in Figure 2. It consists of 2 phases: 1) Learn-
as shown in Figure 2 (a), in the first stage, we take a Transformer-based pre-trained language model $M$ as the summarization model, parameterized by $θ$. We further pre-train this model on a set of popular summarization datasets (e.g., \textit{CNNDM}, \textit{PubMed}, and \textit{XWiki}) to learn general summarization knowledge. For each task $t$, we inject task-specific encoder ($P_{t}^{e}$) and decoder ($P_{t}^{d}$) prefix vectors $P_{t} = [P_{t}^{e}; P_{t}^{d}]$ into the model, parameterized by $θ_{p_{t}}$. The prefix vectors are prepended to each Transformer layer of $M$ as additional key and value vectors (Li and Liang, 2021).

For all pre-training tasks, given input text $X$, the multi-task optimization objective is to minimize the negative log-likelihood of generating the target summary $Y = \{y_{1}, y_{2}, \ldots, y|Y|\}$:

$$L(θ, θ_{p_{t}}) = \sum_{i} \log P(y_{0}|X, y_{1}, \ldots, y_{i-1})$$ (1)

In the multi-task pre-training stage, we optimize $θ$ and $θ_{p_{t}}$ together.

2.2 Prefix-Tuning for Few-Shot Summarization

Through multi-task pre-training, we obtain the UNISUMM model with diverse summarization knowledge. As shown in Figure 2 (b), for an unseen summarization task $u$ (for example, \textit{Wikihow} or \textit{MultiNews}), given only $k$ training samples, we conduct prefix-tuning (Li and Liang, 2021) on the UNISUMM model. A new-task prefix $P_{t} = [P_{u}^{e}; P_{u}^{d}]$ is created, parameterized by $θ_{p_{u}}$, which can be either initialized randomly or from a prefix of pre-training tasks. We then freeze the parameters $θ$ of the shared summarization model and only tune $θ_{p_{u}}$ via the objective defined in Equation 1. By doing this, we are capable of maximizing the learned summarization knowledge in UNISUMM and also avoid over-fitting the model to very few samples.

2.3 Universal Prefix for Few-shot Initialization

Empirically, given a target task, initializing new-task prefix from the most related pre-training tasks can be helpful. However, for a brand new task, selecting meta tasks can be a complicated process, which requires large efforts of feature engineering (Chen and Shuai, 2021). Therefore, during multi-task pre-training, we also pre-train a universal prefix, which can be used as a stable initialization for few-shot prefix-tuning.

In particular, during multi-task pre-training (§ 2.1), we initialize a universal encoder and decoder prefix vector $P^{*} = [P_{en}^{*}; P_{de}^{*}]$, parameterized by $θ_{p^{*}}$. For each training instance from task $t$, it has a 15% probability to be coupled with this universal prefix vector instead of its task-specific prefix $P_{t}$. The parameters $θ_{p^{*}}$ are optimized together with $θ$. Then in prefix-tuning, we use this universal vector as initialization for the unseen task parameter $θ_{p_{u}}$ (§ 2.2).
| Type             | Domain        | Dataset     | Testset Size | Avg. D/S Length |
|------------------|---------------|-------------|--------------|-----------------|
| Monologue        |               |             |              |                 |
| Multi-doc        | News          | MultiNews   | 5,622        | 2,103/264       |
| Extreme          |               | XSum        | 11,334       | 431/20          |
| Single-doc       | Scientific Paper | ArXiv    | 6,440        | 4,938/220       |
| Single-doc       | Instructions  | WikiHow     | 6,000        | 580/62          |
| Single-doc       | Online Forum  | Reddit-TIFU | 4,208        | 433/23          |
| Dialogue         |               |             |              |                 |
| Single-doc       | Online Chit-chat | SAMSum  | 819          | 94/28           |
| Single-doc       | Real-life     | DIALOGSUM   | 500          | 131/24          |
| Query-based      | Meeting       | QMSum       | 279          | 1,310/65        |

Table 1: Summary of tasks in SUMMZOO. We report the size of testset here. “Avg. D/S length” stands for “averaged document/summary token length”. For QMSum, we concatenate the query and gold span as input.

2.4 Asymmetrical Weight Decay

A potential problem in multi-task learning is negative transfer among different tasks. To alleviate this, inspired by previous work (Evgeniou and Pontil, 2004; Bengio, 2012; Liu et al., 2019), we set different weight decay regularizations on different parameters of UniSUMM. Specifically, we separate optimizers of the prefixes and the summarization model in pre-training. We assign a lower weight decay value $d_p = 0.01$ on the prefix optimizer, enabling the prefixes to flexibly learn task-specific knowledge, and a higher weight decay value $d_l = 0.05$ on the summarization model optimizer, enforcing it to learn broader generalization across different tasks.

3 The SUMMZOO Benchmark

We propose the SUMMZOO dataset for better benchmarking few-shot summarization. The construction of SUMMZOO is based on two principles, namely diversity and robustness.

Diversity of Tasks As a major goal, we ensure that SUMMZOO includes a diverse of different summarization tasks, covering multiple domains, text styles and compression ratios. Thus, we carefully select 8 summarization tasks including monologue/dialogue texts and single/multi-document summarization tasks. Their domains also span in an assorted set such as news, scientific papers, instructions, online forums and meetings.

Robustness of Evaluation Our second goal is to ensure that experiments on SUMMZOO can be compared with each other in a robust manner. Meanwhile, we want to reduce randomness from the different selections of few-shot training samples. Therefore, for each summarization task, we provide 5 sets of few-shot training samples, and we ask all models to train on these 5 sets respectively and report the averaged results and standard deviations. We also formulate two few-shot training settings with the number of shots $k$ set to 10 or 100, where the first can be considered as a more extreme low-resource scenario while the second is a more commonly tested setting.

The final SUMMZOO benchmark consists of the following summarization tasks:

- **MultiNews** (Fabbrì et al., 2019) is a large-scale multi-document summarization dataset. The task is to generate a summary given multiple news articles.
- **XSum** (Narayan et al., 2018) is an extreme text summarization dataset. Given a news article, the task is to generate a one-sentence summary.
- **Reddit-TIFU** (Kim et al., 2019) is a social post summarization dataset. The task is to generate a summary given multiple news articles.
- **ArXiv** (Cohan et al., 2018) is a long scientific paper summarization dataset collected from ArXiv, including articles of multiple domains, such as physics, computer science, etc.
- **WikiHow** (Koupaee and Wang, 2018) is a large-scale instruction summarization dataset. The task is to generate a short summary given the multiple-step instruction.
- **SAMSum** (Gliwa et al., 2019) is a written conversation summarization dataset for Messenger-style chit-chats. Both dialogue and summary are annotated by experts.

1 We categorize it into single document summarization task because the posts of each input are from the same user, centering one event.
Table 2: Statistics of multi-task pre-training data. We combine 7 summarization tasks. Raw size is the number of input and output pairs of raw datasets. Sampled size is the size of balanced data that are actually used in multi-task pre-training.

| Dataset        | Raw Size | Sampled Size |
|----------------|----------|--------------|
| CNNDM          | 287,227  | 287,227      |
| BillSum        | 23,455   | 113,694      |
| PubMed         | 119,924  | 119,924      |
| GovReport      | 19,466   | 105,114      |
| MediaSum       | 463,596  | 100,000      |
| SummScreen     | 22,588   | 67,764       |
| XWikis         | 280,000  | 100,000      |
| Total          | –        | 893,723      |

**DIALOGSUM** (Chen et al., 2021) is a real-life scenario dialogue summarization dataset that covers a wide range of daily life dialogues, including diverse task-oriented dialogues. The testset of DIALOGSUM provides three reference summaries for each dialogue, we report the averaged results.

**QMSum** (Zhong et al., 2021) is a query-based meeting summarization dataset that is derived from Augmented Multi-party Interaction (AMI) corpus (Kraaij et al., 2005), the International Computer Science Institute (ICSI) (Shriberg et al., 2004) and Committee Meetings. The task is to generate a summary given a meeting and a query.

Table 1 summarizes the statistics of sub-datasets in SUMMZOO.

### 4 Experimental Setup

#### 4.1 Training Datasets

For multi-task pre-training (§ 2.1), we combine the following summarization datasets:

**CNNDM** (Nallapati et al., 2016) is a large news summarization dataset that contains articles and paired human annotated summaries from CNN and Daily Mail.

**BillSum** (Kornilova and Eidelman, 2019) consists of the US Congressional and California state bills, and summaries written by Legislative Counsel.

**PubMed** (Cohan et al., 2018) contains large long scientific articles and human labeled abstracts. Compared with ArXiv, which contains data from multiple domains, PubMed dataset focuses on the biomedical field.

**GovReport** (Huang et al., 2021) consists of long reports and summaries from government research agencies.

**MediaSum** (Zhu et al., 2021) is an interview summarization dataset that contains 463.6k transcripts and summaries from NPR and CNN.

**SummScreen** (Chen et al., 2022a) consists of long TV series transcripts and human written recaps.

**XWikis** (Perez-Beltrachini and Lapata, 2021) is a cross-lingual summarization dataset that contains Wikipedia articles and leading paragraphs in multiple languages. We only use the English data that have paired documents and summaries.

To balance the training data size of different datasets, we perform down-sampling on over-sized datasets and up-sampling on low-resource datasets respectively. The statistics of resulting data for pre-training are shown in Table 2.

#### 4.2 Implementation Details

We use BART-large (Lewis et al., 2020) to initialize the summarization model of UNISUMM. All experiments are conducted on NVIDIA A100 GPUs with PyTorch 1.11. The max input length and target length are set to 2,048 and 400. For multi-task pre-training, we initialize from BART-large, and train the model on 16 GPUs with 300,000 steps, batch size of 32, learning rate of 1.5e-5, and warm-up with 4,000 steps. For few-shot tuning, we prefix-tune the model on 4 GPUs with 100 and 1000 steps for 10-shot and 100-shot, respectively, with batch size of 32, learning rate of 1.5e-4, and warm-up with 10% of the training steps. For XSum, the training steps are set to 10 and 100 for 10-shot and 100-shot, respectively, while other configurations are unchanged.

#### 4.3 Baseline Models

We compare UNISUMM against the following strong few-shot summarization baselines:

**PEGASUS** (Zhang et al., 2020) is a large pre-trained encoder-decoder model, which is particularly designed for text summarization. The model is trained using the gap sentence generation task. We use PEGASUS\textsubscript{LARGE} (C4+HugeNews) for comparison, which improves upon the results reported in the original paper.

**BART** (Lewis et al., 2020) is a pre-trained encoder-decoder language model using self-denosing tasks. We compare with the BART-
large model with two tuning strategies on few-shot summarization tasks, namely standard fine-tuning (BART-FT) and prefix-tuning (BART-PT). In BART-PT, the prefix vector is added in the same way as UniSUMM.

**MultiBART** is a variant of BART-large. Similar to UniSUMM, it is also multi-task pre-trained on the same data but without prefixes. And it can also be fine-tuned or prefix-tuned to fit few-shot summarization tasks. We only show the results of prefix-tuned MultiBART because we find fine-tuning the entire MultiBART model always leads to worse performance in few-shot setting. This strong baseline can be considered as an indicator to verify the effectiveness of using prefixes in both multi-task pre-training and few-shot tuning.

We use ROUGE (Lin, 2004) for automatic evaluation, which evaluates the $n$-gram overlap in the model-generated summary against the reference summary. We report $F$-1 scores of ROUGE-1 (R1), ROUGE-2 (R2) and ROUGE-L (RL). As described, SUMZOO requires models to report averaged results over 5 sets of different few-shot samples.

### 5 Results

#### 5.1 Main Results

The main results are shown in Table 3. First, compared with PEGASUS, UniSUMM outperforms it across all tasks except 100-shots XSum, and shows the best averaged scores in both 10-shots and 100-shots settings. We also find that 10-shot UniSUMM can outperform 100-shot PEGASUS on MultiNews, Arxiv and QMSum by a large margin, suggesting that UniSUMM can benefit from diverse training data and effectively adapt indirect knowledge to unseen tasks. It is notable that although the foundation BART model is inferior to PEGASUS, BART-based UniSUMM can still outperform PEGASUS with the learned summarization knowledge. Overall, UniSUMM surpasses both BART-FT and BART-PT by a large margin on all tasks in all settings, which suggests that the equipment of multi-task learning can substantially improve model performance on few-shot summarization tasks, in particular in the 10-shot setting.

UniSUMM also outperforms MultiBART by a large margin, especially in the 10-shot setting (Avg. 14.96 R1, 1.14 R2 and 1.51 RL improvements). Considering that MultiBART is multi-task pre-trained on the exact same data as UniSUMM does, and its main difference from UniSUMM is whether

| Task | PEGASUS | BART-FT | BART-PT | MultiBART | UNISUMM |
|------|---------|---------|---------|-----------|---------|
| MN   | 39.12   | 11.15   | 19.44   | 38.29     | 10.05   |
|      | 10.05   | 19.44   | 38.29   | 11.15     | 22.05   |
| WH   | 40.76   | 12.78   | 20.56   | 42.65     | 13.27   |
|      | 13.27   | 20.56   | 42.65   | 12.78     | 20.56   |
| DS   | 20.55   | 3.98    | 14.80   | 24.89     | 6.42    |
|      | 6.42    | 14.80   | 24.89   | 3.98      | 14.80   |
| SS   | 100.00  | 0.00    | 0.00    | 100.00    | 0.00    |
|      | 0.00    | 0.00    | 100.00  | 0.00      | 0.00    |
| Average | 36.94 | 12.22   | 26.79   | 32.66     | 9.67    |
|      | 9.67    | 26.79   | 32.66   | 12.22     | 26.79   |

Table 3: Main results of PEGASUS, BART-FT, BART-PT, MultiBART and UniSUMM on the SUMMZOO benchmark. MN, WH, DS and SS are abbreviations of MultiNews, WikiHow, DIALOGS and SAMSum. Best results on each sub-dataset are in bold. All models are trained on the same 5 sets of few-shot samples and we report their averaged ROUGE scores. The bottom block presents the averaged results of all 8 sub-tasks in SUMMZOO.
The sample selection bias (Cortes et al., 2008) has been a major problem for few-shot tasks, where the model performance is strongly correlated with the selection of few-shot samples. And a sound system should be robust when taking different few-shot samples. To demonstrate the robustness and stability of different few-shot summarization models, Table 4 shows standard deviations of ROUGE scores on those 5 different sets of few-shot samples provided in SUMMZO. Overall, the standard deviations of UNISUMM are lower than all other baselines on most tasks in both settings, suggesting that UNISUMM is most stable and robust when facing different few-shot samples. Also, MultiBART outperforms BART-PT and shows better averaged results compared with PEGASUS in the 100-shot, showing that reusing related summarization datasets is valuable. However, it can still be unstable in the 10-shot setting. In contrast, UNISUMM shows the least averaged standard deviations across all tasks in both settings. This suggests the superiority and necessity of two-phrase training with prefixes in the UNISUMM framework.

| Task       | PEGASUS | BART-PT | MultiBART | UNISUMM |
|------------|---------|---------|-----------|---------|
|            | D_{R1}  | D_{R2}  | D_{RL}    | D_{R1}  | D_{R2}  | D_{RL}    | D_{R1}  | D_{R2}  | D_{RL}    |
| MultiNews  | 0.83    | 0.31    | 0.31      | 0.83    | 0.31    | 0.31      | 0.83    | 0.31    | 0.31      |
| XSum       | 1.04    | 0.37    | 0.23      | 1.04    | 0.37    | 0.23      | 1.04    | 0.37    | 0.23      |
| Arxiv      | 0.27    | 0.28    | 0.30      | 0.27    | 0.28    | 0.30      | 0.27    | 0.28    | 0.30      |
| WikiHow    | 1.60    | 0.54    | 1.05      | 1.60    | 0.54    | 1.05      | 1.60    | 0.54    | 1.05      |
| Reddit     | 1.20    | 0.49    | 0.29      | 1.20    | 0.49    | 0.29      | 1.20    | 0.49    | 0.29      |
| DIALOGSUM  | 0.96    | 0.68    | 0.65      | 0.96    | 0.68    | 0.65      | 0.96    | 0.68    | 0.65      |
| SAMSum     | 1.58    | 1.44    | 1.19      | 1.58    | 1.44    | 1.19      | 1.58    | 1.44    | 1.19      |
| QMSum      | 0.75    | 0.45    | 0.36      | 0.75    | 0.45    | 0.36      | 0.75    | 0.45    | 0.36      |
| Average    | 1.16    | 0.62    | 0.74      | 1.16    | 0.62    | 0.74      | 1.16    | 0.62    | 0.74      |

Table 4: Comparison of model robustness towards different few-shot samples. We report the standard deviations of R1, R2 and RL mean the standard deviations of R1, R2 and RL, respectively. Lower standard deviation indicates the model is more robust towards different few-shot samples. The bottom block presents the averaged results of all 8 sub-tasks.
We compare three strategies, namely initializing the prefix randomly (15%) picked by all tasks during multi-task pre-training (§ 2.3). In Table 6, we show the ablation study of using different prefix initialization can potentially be continually improved by learning more indirect knowledge.

The results in Table 5 show that when extending the multi-task pre-training datasets from 3 to 7, UNISUMM achieves better results on multiple datasets. For example, taking MultiNews and XSum as target tasks, 7-Task UNISUMM outperforms 3-Task UNISUMM in both 10-shot and 100-shot settings. It suggests that 7-Task UNISUMM can still benefit from GovReport, XWikis, SummScreen and BillSum for news summarization tasks. On average, the ROUGE-1 score improves by 1.00 for the 10-shots setting and 0.54 for the 100-shots setting. This shows that negative transfer is minor in UNISUMM and also suggests that by training UNISUMM on even more datasets, its generalization can potentially be continually improved by learning more indirect knowledge.

5.3.2 Different Prefix Initializations

UNISUMM is equipped with a universal prefix that was randomly (15%) picked by all tasks during multi-task pre-training (§ 2.3). In Table 6, we show the ablation study of using different prefix initialization strategies in few-shot prefix-tuning. Due to space limitation, we only show ROUGE-2 scores. We compare three strategies, namely initialized the prefix randomly, using CNNDM prefix or using universal prefix. The CNNDM prefix is selected to be compared here because it is considered as a general summarization task and has been proved helpful to many other tasks, such as SAMSUM (Gliwa et al., 2019).

We can see that using universal prefix yields the best results on most tasks. Also, universal prefix is particularly useful for the 10-shot setting, bringing 0.23 improvement for R2 score. In addition, we find that using task-specific prefix (CNNDM) shows the worst performance on some tasks, such as QMSum and ArXiv, and has the lowest average score. This can be explained by that the task-specific prefix stores abundant task specific knowledge, which however can be harmful to unseen target tasks, especially when the target task is very different from the pre-training task.

5.3.3 Influence of Weight Decay

In Section 2.4, we design a separated weight decay strategy to circumvent negative transfer in multi-task learning. In Table 7, we examine whether the combination of different weight decay rates ($d_p$ for prefixes and $d_l$ for the summarization model) is beneficial. Specifically, we report ROUGE-2 scores on SUMMZOO with different combinations of weight decay rates. We can see that the model performs the best with $d_p = 0.05$ and $d_l = 0.01$. And this asymmetrical weight decay is especially helpful to 10-shot XSum, which is more distinct from pre-training summarization tasks and relies more on general summarization knowledge.
MultiNews & R2 & 15.50 & 15.71 & 15.74 & 15.64 & 13.39 & 13.26 & 13.38 & 13.89 & 12.07 & 12.02 & 12.09 & 13.97 \\
Arxiv & 10 & 15.50 & 15.71 & 15.82 & 15.86 & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 15.47 & 15.60 & 15.64 & & 11.81 & 11.72 & 11.73 & & & & \\
XSum & 10 & 6.52 & 6.41 & 7.20 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 6.32 & 6.17 & 6.23 & & 11.81 & 11.72 & 11.73 & & & & \\
Axiv & 10 & 9.48 & 9.37 & 9.35 & & 11.81 & 11.72 & 11.73 & & & & \\
& 100 & 11.50 & 11.65 & 11.64 & & 11.81 & 11.72 & 11.73 & & & & \\
WH & 10 & 5.72 & 5.55 & 5.60 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 6.17 & 6.23 & 6.17 & & 11.81 & 11.72 & 11.73 & & & & \\
Reddit & 10 & 13.39 & 13.26 & 13.38 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 15.71 & 15.74 & 15.64 & & 11.81 & 11.72 & 11.73 & & & & \\
DS & 10 & 18.55 & 18.38 & 18.53 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 20.93 & 20.96 & 20.65 & & 11.81 & 11.72 & 11.73 & & & & \\
SS & 10 & 12.06 & 12.04 & 12.12 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 13.40 & 13.73 & 13.89 & & 11.81 & 11.72 & 11.73 & & & & \\
QMSum & 10 & 12.07 & 11.90 & 12.09 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 13.95 & 13.96 & 13.97 & & 11.81 & 11.72 & 11.73 & & & & \\
Average & 10 & 15.32 & 15.00 & 15.19 & & 11.57 & 11.30 & 11.36 & & & & \\
& 100 & 15.47 & 15.82 & 15.86 & & 11.81 & 11.72 & 11.73 & & & & \\

Table 7: Results of UniSUM using different combinations of weight decay rates for multi-task training. $P_{0.01}$ indicates the weight decay rate for prefix parameters is 0.01 and $L_{0.01}$ indicates the weight decay rate for LM parameters is 0.01.

Table 8: Human evaluation for 100-shot PEGASUS, BART-PT, UniSUM and gold summaries, respectively. F. Coh. Con. and R. stand for Fluency, Coherence, Consistency and Relevance, respectively.

| Summary | QMSum | MultiNews |
|---------|-------|-----------|
| PEGASUS | 4.43  | 4.07      |
| BART-PT | 4.37  | 3.83      |
| UniSUM  | 4.90  | 4.47      |
| Gold    | 4.86  | 5.00      |

Table 8: Human evaluation for 100-shot PEGASUS, BART-PT, UniSUM and gold summaries on QMSum and MultiNews, respectively. F. Coh. Con. and R. stand for Fluency, Coherence, Consistency and Relevance, respectively.

6 Human Evaluation

To better understand the outputs of different few-shot summarization systems, following Kryscinski et al. (2020), we conduct a human evaluation from four dimensions: Fluency evaluates the quality of individual generated sentences, including grammar, word order, etc; Coherence evaluates the collective quality of generated summaries; Relevance evaluates the importance of information in the generated summaries and; Consistency evaluates the factual alignment of the generated summary against the input document. We select 30 samples from MultiNews and QMSum, respectively, covering both monologue and dialogue texts. Then, for each sample, we ask a judge, who has experience in human evaluation for summarization tasks, to give scores from 1 to 5 (higher score indicates better quality) along each evaluation dimension for the outputs of 100-shot PEGASUS, BART-PT, UniSUM and gold summaries, respectively. In total, we have 240 summaries to evaluate and the averaged results are reported in Table 8.

It is noticeable that UniSUM outperforms PEGASUS and BART-PT on both datasets regarding all dimensions. In detail, UniSUM achieves higher fluency score than gold summaries on QMSum and comparable score on MultiNews, suggesting that UniSUM can generate very fluent sentences which can be comparable with human annotated summaries. A challenge of QMSum is that models are asked to generate summaries centring the input queries. Thus, Relevance is a very important metric for this task. However, Relevance sees very low score for PEGASUS (3.26) and BART-PT (2.83), suggesting they are weak in extracting relevant information based on user queries. In contrast, UniSUM achieves much higher score (3.93).

7 Case Study

We qualitatively demonstrate the advantages of UniSUM (100-shots) using cases from QMSum and MultiNews, respectively. As shown in Table 9, compared with gold summary, although UniSUM generated summary is longer, it is highly relevant to the query. And UniSUM properly rephrases the key utterance from the source meeting into an objective description. In contrast, the summary generated by PEGASUS misses important contents and contains irrelevant sentences compared with UniSUM and human annotation. This evidence shows that UniSUM successfully learns important characters of query-based meeting summarization task with only 100 samples.

As shown in Table 10, we see that the UniSUM generates a summary with similar events and faithful descriptions compared with the gold summary. However, PEGASUS generated summary contains factual errors (“... was last seen in a package shipped to the us from belgium.”) while the summary generated by UniSUM (“... unearthed ... shipment from belgium to newark”) is consistent with the gold summary and input (“... turned up ... shipped from belgium.”). This shows that UniSUM has the ability to collect important information from multiple news reports and generate high-quality summaries, which is a task that the model has never seen during multi-task pre-
what did barry hughes think about draft changes to cps guidance when talking about the divergence between the law in england and wales? suzy davies am: thank you. i was going to ask this question later, but i think it fits in. i’ve forgotten what i was going to ask; this is terrible. oh no, that’s right obviously, this act is on a particular trajectory at the moment, and it’s due to be introduced before the end of this assembly. do you think it would be better for us as scrutinisers of this act if we could see the draft changes to cps guidance on the public interest test before we make our final decision? barry hughes: i honestly don’t think that would necessarily be helpful. i’ve had some discussions with kwame, who would have an involvement in this. ...

PEGASUS

barry hughes thought it would be better for the members to see the draft changes to cps guidance on the public interest test before making their final decision. he added that they would need to work that up as they went along, and it would be a risk of putting the cart before the horse.

UNI SUMM

barry hughes thought that the draft changes to cps guidance would not necessarily be helpful. he thought that they would simply want to take the present public interest factors set out very clearly in the code for crown prosecutors, and provide a degree of detail around those that relates more specifically to the issues that they were discussing. so, it would be taking principles of generality and according them a degree of specificity, and they’d need to work that up as they go along.

Gold

barry hughes thought draft changes to cps guidance would not necessarily be helpful to the scrutinisers, and simply wanted to take the present interest factors. barry thought they needed to work for the principles of generality and a degree of specificity.

Table 9: Case study (a): Gold and generated summaries by 100-shot PEGASUS and UNI SUMM on QMSum, respectively. The bold is the query.

training.

Both cases suggest that compared with other systems, UNI SUMM generated summaries are more fluent, readable and reliable, which is consistent with the high Fluency, Coherence and Consistency scores in Section 6, showing the potential of using UNI SUMM in real applications. We show more case studies in Appendix A.

8 Related Work

Few-shot Summarization A critical challenge for neural summarization models is that they are data-hungry and require large-scale annotated article-summary pairs to perform well. To alleviate the data sparsity issue, Fabbri et al. (2021) extract characteristics of the target dataset and build pseudo summaries out of the Wikipedia corpus. Small plug-in networks (Bražinskas et al., 2020) are injected into the larger language models to predict the properties of the target dataset with only a small amount of labeled instances. The few-shot challenge of summarization has also been explored in the cross-lingual setting (Bai et al., 2021; Chen et al., 2022b). Compared with them, UNI SUMM can effectively make use of data from related tasks, and thus is free of building large pseudo data and more efficient when used for a novel task.

To close the gap between pre-training and fine-tuning, Yu et al. (2021) propose a second stage of pre-training before fine-tuning with large-scale generative models. Although transfer learning methods make use of external data, one still needs to carefully select source domains and tasks to avoid negative transfer (Wang et al., 2019; Gururangan et al., 2020; Pilault et al., 2020; Bai et al., 2022). In contrast UNI SUMM can be easily prefix-tuned to any target tasks without the effort of selecting relevant data. To our knowledge, we are the first to combine prefix-tuning and multi-task learning for few-shot summarization, showing very positive results.

Existing few-shot summarization evaluation suffers from two data-related problems. First, previous studies usually focus on only one type of summarization tasks in their experiments (Bražinskas et al., 2020; Zhang et al., 2020; Fabbri et al., 2021; Khalman et al., 2021). For example, Fabbri et al. (2019) and Zhang et al. (2020) experiment only on monologue datasets while Khalman et al. (2021) experiment only on dialogue datasets. Thus, it is difficult to evaluate their generalization ability. Second, the few-shot settings and selections of few-shot samples are miscellaneous, which makes evaluations from different research papers not comparable with each other (Cortes et al., 2008). Therefore, in this work, we propose the SUMMZOO dataset for better benchmarking future research on few-shot summarization. To our knowledge, SUMMZOO is the first public few-shot summarization benchmark that covers a set of diverse summarization tasks.
paris (ap) the pompidou centre in paris hopes to display a long-vanished picasso painting in may, now that it has been recovered by u.s. customs authorities. this undated photo provided by the united states department of justice, shows a cubist painting entitled the hairdresser pablo picasso. authorities say the painting worth millions of dollars was ... ill a stolen picasso worth millions of dollars was shipped to the u.s. in a package that described it as a $37 "art craft " but it will soon be on its way back to france...

a century-old picasso painting missing from paris for more than a decade resurfaced in the united states – a 1911 cubist painting worth millions of dollars has been recovered after being mysteriously transported from france to the us nearly a decade ago. the pablo picasso painting, titled la coiffeuse, was reported missing from a pompidou storeroom in paris in 2001 and was last seen in a package shipped to the us from belgium, the ap reports. federal prosecutors in brooklyn filed papers thursday to seize the painting, which was hidden in a climate-controlled storage facility in queens, ny, and will soon be returned to france, reports the new york times. the center for art recovery in paris says it hopes to have the painting back in may, at a time when the cultural world is reeling from islamic state videos showing the destruction of statues in iraq. "this is a true comfort for us at a time when the cultural world is reeling from islamic state video showing the destruction of statues in iraq," says alain seban, the director of the pompidou centre in paris. "it is a work of art that represents the genius of pablo picasso and was bequeathed to us in 2001 by the master of france’s national museum."

a stolen picasso worth millions of dollars was shipped to the u.s. in a package of justice, shows a cubist painting entitled the hairdresser by pablo picasso. authorities say the painting worth $2 million was recovered by u.s. customs authorities. this undated photo provided by the united states department of commerce shows the painting. federal investigators seized the painting in a climate-controlled storage facility in queens, ny, and will soon be returned to france, the u.s. attorney for the eastern district of new york said in a statement. the painting, titled "la coiffeuse," was bequeathed to the national museums of france in 1998. the pompidou director alain seban said in a statement friday that he hopes the work can be exhibited again publicly in may. no arrests have been made in the case.

a picasso painting that was found to have vanished from a paris museum more than a decade ago has turned up 2014 in the us, in a package shipped from belgium. its papers identified it as a $37 "art craft/toy" and also included the line "joyeux noel," or merry christmas, the new york times reports. a man named "robert" attempted to send the package to a climate-controlled warehouse in queens, ny, in december, but custom officials at the port of newark seized what turned out to be picasso’s 1911 la coiffeuse (the hairdresser). french museum officials traveled to new york last month and confirmed the find is indeed the missing picasso work, which the centre georges pompidou realized was missing from its storerooms in 2001 following a loan request; it was then valued at more than $2.5 million. court documents don’t specify whether the sender or would-be recipient have been identified, nbc news reports, but "a lost treasure has been found," us attorney loretta lynch said in a statement. she filed a civil complaint yesterday that will have the painting returned to france. the painting, titled "la coiffeuse," was bequeathed to the national museums of france in 1998. the pompidou director alain seban said in a statement friday that he hopes the work can be exhibited again publicly in may. no arrests have been made in the case.

Table 10: Case study (b): Gold and generated summaries by 100-shot PEGASUS and UniSUMM on MultiNews, respectively. "|||" separates different reports in the input.

### Table 10: Case study (b)

| MultiNews | Input text | Summary |
|-----------|------------|---------|
| **PARIS (AP)** | **The Pompidou Centre in Paris hopes to display a long-vanished Picasso painting in May, now that it has been recovered by U.S. customs authorities. This undated photo provided by the United States Department of Justice, shows a cubist painting entitled the hairdresser Pablo Picasso. Authorities say the painting worth millions of dollars was...** | "a stolen Picasso worth millions of dollars was shipped to the U.S. in a package that described it as a $37 "art craft" but it will soon be on its way back to France..." |
| **PEGASUS** | **A 1911 cubist painting worth millions of dollars has been recovered after being mysteriously transported from France to the U.S nearly a decade ago. The Pablo Picasso painting, titled La Coiffeuse, was reported missing from a Pompidou storeroom in Paris in 2001 and was last seen in a package shipped to the U.S from Belgium, the AP reports. Federal prosecutors in Brooklyn filed papers Thursday to seize the painting, which was hidden in a climate-controlled storage facility in Queens, NY, and will soon be returned to France, reports the New York Times. The Center for Art Recovery in Paris says it hopes to have the painting back in May, at a time when the cultural world is reeling from Islamic State videos showing the destruction of statues in Iraq. "This is a true comfort for us at a time when the cultural world is reeling from Islamic State video showing the destruction of statues in Iraq," says Alain Seban, the Director of the Pompidou Centre in Paris. "It is a work of art that represents the genius of Pablo Picasso and was bequeathed to us in 2001 by the master of France's national museum."** | "A century-old Picasso painting missing from Paris for more than a decade resurfaced in the United States – a 1911 cubist painting worth millions of dollars has been recovered after being mysteriously transported from France to the U.S nearly a decade ago. The Pablo Picasso painting, titled La Coiffeuse, was reported missing from a Pompidou storeroom in Paris in 2001 and was last seen in a package shipped to the U.S from Belgium, the AP reports. Federal prosecutors in Brooklyn filed papers Thursday to seize the painting, which was hidden in a climate-controlled storage facility in Queens, NY, and will soon be returned to France, reports the New York Times. The Center for Art Recovery in Paris says it hopes to have the painting back in May, at a time when the cultural world is reeling from Islamic State videos showing the destruction of statues in Iraq. "This is a true comfort for us at a time when the cultural world is reeling from Islamic State video showing the destruction of statues in Iraq," says Alain Seban, the Director of the Pompidou Centre in Paris. "It is a work of art that represents the genius of Pablo Picasso and was bequeathed to us in 2001 by the master of France’s national museum."** |
| **UNISUMM** | **A stolen Picasso painting worth millions of dollars was shipped to the U.S in a package of Justice, shows a cubist painting entitled the hairdresser by Pablo Picasso. Authorities say the painting worth $2 million was recovered by U.S. customs authorities. This undated photo provided by the United States Department of Commerce shows the painting. Federal investigators seized the painting in a climate-controlled storage facility in Queens, NY, and will soon be returned to France, the U.S. Attorney for the Eastern District of New York said in a statement. The painting, titled "La Coiffeuse," was bequeathed to the National Museums of France in 1998. The Pompidou Director Alain Seban said in a statement Friday that he hopes the work can be exhibited again publicly in May. No arrests have been made in the case.** | "A stolen Picasso painting worth millions of dollars was shipped to the U.S in a package of Justice, shows a cubist painting entitled the hairdresser by Pablo Picasso. Authorities say the painting worth $2 million was recovered by U.S. customs authorities. This undated photo provided by the United States Department of Commerce shows the painting. Federal investigators seized the painting in a climate-controlled storage facility in Queens, NY, and will soon be returned to France, the U.S. Attorney for the Eastern District of New York said in a statement. The painting, titled "La Coiffeuse," was bequeathed to the National Museums of France in 1998. The Pompidou Director Alain Seban said in a statement Friday that he hopes the work can be exhibited again publicly in May. No arrests have been made in the case.** |
| **Gold** | **A Picasso painting that was found to have vanished from a Paris museum more than a decade ago has turned up 2014 in the U.S, in a package shipped from Belgium. Its papers identified it as a $37 "art craft/toy" and also included the line "Joyeux Noel," or Merry Christmas, the New York Times reports. A man named "Robert" attempted to send the package to a climate-controlled warehouse in Queens, NY, in December, but custom officials at the port of Newark seized what turned out to be Picasso's 1911 La Coiffeuse (the hairdresser). French museum officials traveled to New York last month and confirmed the find is indeed the missing Picasso work, which the Centre Georges Pompidou realized was missing from its storerooms in 2001 following a loan request; it was then valued at more than $2.5 million. Court documents don’t specify whether the sender or would-be recipient have been identified, NBC News reports, but "a lost treasure has been found," U.S. Attorney Loretta Lynch said in a statement. She filed a civil complaint yesterday that will have the painting returned to France. The painting, titled "La Coiffeuse," was bequeathed to the National Museums of France in 1998. The Pompidou Director Alain Seban said in a statement Friday that he hopes the work can be exhibited again publicly in May. No arrests have been made in the case.** | "A Picasso painting that was found to have vanished from a Paris museum more than a decade ago has turned up 2014 in the U.S, in a package shipped from Belgium. Its papers identified it as a $37 "art craft/toy" and also included the line "Joyeux Noel," or Merry Christmas, the New York Times reports. A man named "Robert" attempted to send the package to a climate-controlled warehouse in Queens, NY, in December, but custom officials at the port of Newark seized what turned out to be Picasso's 1911 La Coiffeuse (the hairdresser). French museum officials traveled to New York last month and confirmed the find is indeed the missing Picasso work, which the Centre Georges Pompidou realized was missing from its storerooms in 2001 following a loan request; it was then valued at more than $2.5 million. Court documents don’t specify whether the sender or would-be recipient have been identified, NBC News reports, but "a lost treasure has been found," U.S. Attorney Loretta Lynch said in a statement. She filed a civil complaint yesterday that will have the painting returned to France. The painting, titled "La Coiffeuse," was bequeathed to the National Museums of France in 1998. The Pompidou Director Alain Seban said in a statement Friday that he hopes the work can be exhibited again publicly in May. No arrests have been made in the case.** |

### Prompt Learning for Text Generation

The idea of prompt learning is first proposed in GPT-3 (Brown et al., 2020), where it aims to guide a large language model to do different tasks without further fine-tuning by prepending task-related examples to the input. Prefix-tuning extends this idea from discrete tokens to continuous vectors (Li and Liang, 2021). It adds continuous embeddings (prefixes) to each Transformer layer as external value and key vectors. During training, only prefixes are updated while the other parameters are unchanged. To further simplify prompt-tuning, Lester et al. (2021) only prepend tunable tokens to the encoder input, and keep all other parameters frozen. Logan IV et al. (2022) and Gu et al. (2022) propose to use pre-training to boost the low performance for few-shot learning. Compared with them, we are interested in few-shot summarization and we propose to use multi-task prefix-tuning as an effective strategy to make use of data from related tasks to improve the performance of diverse target tasks, which suits real-life scenarios.

### 9 Conclusion

We introduced UniSUMM, a novel few-shot summarization system that can be easily prefix-tuned to excel at and generalize on a diverse of summarization tasks. The major idea is a combination of multi-task learning and prefix-tuning by jointly training the prefixes and the summarizer on multi-
We thank Dan Iter, Hiteshi Sharma, Zicheng Liu, Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Sen Yang and Leyang Cui for their proofreading and valuable feedback.

Acknowledgements

We thank Dan Iter, Hiteshi Sharma, Zicheng Liu, Sen Yang and Leyang Cui for their proofreading and valuable feedback.

Copyright, Citation and Ethical Consideration

The copyright of individual datasets in SUMMZOO belongs to the original authors. The usage license of each dataset also applies to SUMMZOO. To ensure fair credit, when using SUMMZOO for evaluation, please also cite original papers where individual datasets are introduced.

Pre-training and fine-tuning summarization data studied in this paper are mostly publicly available, otherwise we will provide links to the access application. Although filtering has been conducted in building the original datasets, some contents can contain uncomfortable descriptions, e.g., news coverage of violent crimes and events.

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A More Case Studies

We present more cases to demonstrate the performance of 100-shot UniSUMM in Table 11 (ArXiv, DIALOGSUM and SAMSum) and Table 12 (WikiHow, Xsum and Reddit). Overall, UniSUMM is capable of generating very fluent, relevant, faithful and human-like summaries on diverse unseen tasks. This verifies UniSUMM’s great generalization ability in the few-shot scenario.
Table 11: Case study (c): Gold and generated summaries by 100-shot PEGASUS and UniSUMM on ArXiv, DIALOGSUM and SAMSum, respectively.
before folding the letter, make sure that the address on the inside of the letter matches with the one that you have written or printed on the envelope. this will help avoid any mixups. don’t forget to check that you’ve signed the letter. make sure that the text is facing up and towards you. this is your last chance to proofread and double check that you haven’t forgotten anything. for example, have you dated the letter? are there any spelling or grammar mistakes? . take the bottom of the letter and fold it so that it is about half an inch (about 1 cm) from the top of the page. you can place the envelope underneath the letter to use as a guide. make sure that when you have folded the letter up, it is small enough to fit inside the envelope. use a ruler to make the crease nice and sharp. you can do this by holding a ruler sideways and using the thin edge. slide the edge of the ruler along the letter on the creases so they are nice and flat. you will now take the right part of the letter and fold it about one third of the way in. line up the top and bottom edges of the letter and then crease the fold. take the other side of the letter and fold it one third of the way in. this will be the same thing that you did with the right side. line up the top and bottom of the edges so they are perfectly straight before creasing. the last crease you made should go into the bottom of the envelope first. place it so that the folds face the backside of the envelope. this will make it easy for your recipient to find where to begin unfolding the letter.

PEGASUS

check that the address on the inside of the letter matches the text of the letter to make sure that the address on the inside of the letter matches with the one on the page. make sure that the text matches with the one on the inside of the letter. make sure that the envelope is flat on the inside. crease the folded side of the letter.

UNI SUMM

take the top of the letter and fold it so that it is about half an inch (about 1 cm) from the top of the page. place the envelope underneath the letter. make sure that the envelope is flat on the inside. crease the folded side of the letter.

Gold

take the top of the letter and fold it so that it is about half an inch (about 1 cm) from the top of the page. place the envelope underneath the letter. make sure that the envelope is flat on the inside. crease the folded side of the letter.

XSum

the prime minister has been accused of “ side-stepping ” questions about a submarine-launched nuclear-capable missile which misfired during a test.

PEGASUS

the sunday times says the missile veered off course during a test in june last year - weeks before the commons voted to spend 40bn renewing trident . questioned by andrew marr, the pm refused to say four times if she had known about the test ahead of the vote. the snp’s nicola sturgeon called for a ’ full disclosure ’ of what happened. according to the sunday times, an unarmed trident ii d5 missile veered off in the wrong direction towards the us - instead of towards africa - when it was launched from a british submarine off the coast of florida . in july - days after mrs may had become prime minister - mps voted overwhelmingly in favour of replacing trident. during the debate, mrs may told mps it would be “ an act of gross irresponsibility ” for the uk to abandon its nuclear weapons. mps backed its renewal by 472 votes to 117. however, all 52 snp mps voted against it - as did labour leader jeremy corbyn. when asked on the bbc’s andrew marr show whether she had known then that a misfire had happened, mrs may said: “ i have absolute faith in our trident missiles. ” when i made that speech in the house of commons, what we were talking about was whether or not we should renew our trident. ” she was asked a further three times - but did not answer the questions. the minister of defence did not give details of the test process but said it had been a success. scottish first minister, mrs sturgeon - a long-standing opponent of trident, whose submarines are based at faslane, on the river clyde - said the apparent misfire was a “ hugely serious issue ”. she tweeted: “ there should be full disclosure of what happened, who knew what/when, and why the house of commons wasn’t told. ” meanwhile, mr corbyn said the reports called for “ a serious discussion ” .

UNI SUMM

a nuclear missile launched a british submarine failed during a test, according to a report in the sunday times.

Gold

theresa may is coming under pressure to say whether she knew about a reported misfire of the uk’s nuclear weapons system before a crucial commons vote.

Reddit

tifu making lunch. made myself a lush sandwich for lunch today. smoked ham, cheddar cheese, a dash of bbq sauce on thick cut wholemeal bread. popped it in a small tupperware box, for freshness. i found some bn type biscuits in the cupboard, so i pop them in the box on top of my sandwiches. think nothing of it. eventually lunch time comes around. i discover, to my horror, that the biscuits have absorbed the moisture from the sandwich. and now i have a dried out sandwich and soggy biscuits

PEGASUS

made a luch sandwich for lunch, only to have it ruined by soggy biscuits. i’m completely fucked.

UNI SUMM

made a big sandwich, with cheddar cheese, bbq sauce and bn type biscuits. popped them in a tupperware box, and discover they’ve dried out

Gold

don’t put your sandwich and biscuits in same box, unless you like dry bread and soggy biscuits.

Table 12: Case study (d): Gold and generated summaries by 100-shot PEGASUS and UNI SUMM on WikiHow, XSum and Reddit, respectively.