# **Exploring Domain Shift in Extractive Text Summarization**

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## Abstract

Although domain shift has been well explored in many NLP applications, it still has received little attention in the domain of extractive text summarization. As a result, the model is underutilizing the nature of the training data due to ignoring the difference in the distribution of training sets and shows poor generalization on the unseen domain. With the above limitation in mind, in this paper, we first extend the conventional definition of the domain from categories into data sources for the text summarization task. Then we re-purpose a multidomain summarization dataset and verify how the gap between different domains influences the performance of neural summarization models. Furthermore, we investigate four learning strategies and examine their abilities to deal with the domain shift problem. Experimental results on three different settings show their different characteristics in our new testbed.

Our source code including *BERT-based*, *meta-learning* methods for multi-domain summarization learning and the re-purposed dataset MULTI-SUM will be available on our project: http://pfliu.com/TransferSum/.

## 1 Introduction

Text summarization has been an important research topic due to its widespread applications. Existing research works for summarization mainly revolve around the exploration of neural architectures (Cheng and Lapata, 2016; Nallapati et al., 2017) and design of training constraints (Paulus et al., 2017; Wu and Hu, 2018). Apart from these, several works try to integrate document characteristics (e.g. domain) to enhance the model performance (Haghighi and Vanderwende, 2009; Cheung and Penn, 2013a; Cao et al., 2017; Isonuma et al., 2017;

Wang et al., 2018; Narayan et al., 2018a) or make interpretable analysis towards existing neural summarization models (Zhong et al., 2019).

Despite their success, only a few literature (Cheung and Penn, 2013b; Hua and Wang, 2017) probes into the exact influence domain can bring, while none of them investigates the problem of domain shift, which has been well explored in many other NLP tasks. This absence poses some challenges for current neural summarization models: 1) How will the domain shift exactly affect the performance of existing neural architectures? 2) How to take better advantage of the domain information to improve the performance for current models? 3) Whenever a new model is built which can perform well on its test set, it should also be employed to unseen domains to make sure that it learns something useful for summarization, instead of overfitting its source domains.

The most important reason for the lack of approaches that deal with domain shift might lay in the unawareness of different domain definitions in text summarization. Most literature limits the concept of the domain into the document categories or latent topics and uses it as the extra loss (Cao et al., 2017; Isonuma et al., 2017) or feature embeddings (Wang et al., 2018; Narayan et al., 2018a). This definition presumes that category information will affect how summaries should be formulated. However, such information may not always be obtained easily and accurately. Among the most popular five summarization datasets, only two of them have this information and only one can be used for training. Besides, the semantic categories do not have a clear

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<sup>&</sup>lt;sup>1</sup> The five datasets are DUC, Gigward(Napoles et al., 2012), CNN/Daily Mail(Hermann et al., 2015), The New York Times Annotated Corpus (NYT)(Sandhaus, 2008) and Newsroom(Grusky et al., 2018). Only DUC and NYT are annotated with document categories, and DUC is designed only for competition test.

definition.<sup>2</sup> Both of these prevent previous work from the full use of domains in existing datasets or building a new multi-domain dataset that not only can be used for multi-domain learning but also is easy to explore domain connection across datasets.

In this paper, we focus on the extractive summarization and demonstrate that news publications can cause data distribution differences, which means that they can also be defined as domains. Based on this, we re-purpose a multi-domain summarization dataset MULTI-SUM and further explore the issue of domain shift.

Methodologically, we employ four types of models with their characteristics under different settings. The first model is inspired by the *joint training* strategy, and the second one builds the connection between large-scale pre-trained models and multi-domain learning. The third model directly constructs a domain-aware model by introducing domain type information explicitly. Lastly, we additionally explore the effectiveness of meta-learning methods to get better generalization. By analyzing their performance under IN-DOMAIN, OUT-OF-DOMAIN, and CROSS-DATASET, we provide a preliminary guideline in Section 5.2 for future research in multi-domain learning of summarization tasks.

Our contributions can be summarized as follows:

- We analyze the limitation of the current domain definition in summarization tasks and extend it into article publications. We then repurpose a dataset MULTI-SUM to provide a sufficient multi-domain testbed (IN-DOMAIN and OUT-OF-DOMAIN).
- To the best of our knowledge, this is the first work that introduces domain shift to text summarization. We also demonstrate how domain shift affects the current system by designing a verification experiment.
- Instead of pursuing a unified model, we aim to analyze how different choices of model designs influence the generalization ability of dealing with the domain shift problem, shedding light on the practical challenges and provide a set of guidelines for future researchers.

## 2 Domains in Text Summarization

In this section, we first describe similar concepts used as the domain in summarization tasks. Then

we extend the definition into article sources and verify its rationality through several indicators that illustrate the data distribution on our re-purposed multi-domain summarization dataset.

#### 2.1 Common Domain Definition

Although a domain is often defined by the content category of a text (Li and Zong, 2008; Blitzer et al., 2007) or image (Saenko et al., 2010), the initial motivation for a domain is a metadata attribute which is used in order to divide the data into parts with different distributions (Joshi et al., 2012).

For text summarization, the differences between data distribution are often attributed to the document categories, such as sports or business, or the latent topics within articles, which can be caught by classical topic models like Latent Dirichlet Allocation (LDA) (Blei et al., 2003). Although previous works have shown that taking consideration of those distribution differences can improve summarization models performance (Isonuma et al., 2017; Wang et al., 2018), few related them with the concept of the domain and investigated the summarization tasks from a perspective of multi-domain learning. <sup>3</sup>

#### 2.2 Publications as Domain

In this paper, we extend the concept into the article sources, which can be easily obtained and clearly defined<sup>4</sup>.

Three Measures We assume that the publications of news may also affect data distribution and thus influence the summarization styles. In order to verify our hypothesis, we make use of three indicators (Coverage, Density and Compression) defined by Grusky et al. (2018) to measure the overlap and compression between the (document, summary) pair. The coverage and the density are the word and the longest common subsequence (LCS) overlaps, respectively. The compression is the length ratio between the document and the summary.

**Two Baselines** We also calculate two strong summarization baselines for each publication. The

<sup>&</sup>lt;sup>2</sup> For example, "Dining and Wine" in NYT refers to "Food and Drink" in DUC 2002.

<sup>&</sup>lt;sup>3</sup> Hua and Wang (2017) studied domain adaptation between news stories and opinion articles from NYT. However, their model was just trained in a single domain and was adapted to another, which was different from our multidomain training and evaluation settings.

<sup>&</sup>lt;sup>4</sup> Most existing benchmark datasets are a mixture of multiple publications with the idea of collecting a larger amount of data, such as CNN/DailyMail, Gigward and Newsroom.

	Statistics			Measures			Lead			Ext-Oralce		
	Train	Valid	Test	Cov.	Den.	Comp.	R-1	R-2	R-L	R-1	R-2	R-L
FN	78,760	8,423	8,392	0.90	16.18	35.58	40.30	33.90	38.74	73.61	65.53	71.50
CNN	43,466	4,563	4,619	0.85	12.46	38.28	35.56	25.60	33.25	59.99	46.66	56.64
MA	31,896	3,414	3,316	0.84	6.66	28.93	29.38	19.15	27.17	55.35	40.97	51.97
NYT	152,959	16,488	16,620	0.85	9.19	42.30	28.24	16.62	25.20	52.25	36.14	47.73
WTP	95,379	9,939	10,072	0.76	6.04	63.52	20.75	10.57	18.56	43.00	27.14	39.48
Avg	80,492	8,565	8,604	0.84	10.11	41.72	29.70	19.74	27.30	55.32	41.28	51.72
NYDN	55,653	6,057	5,904	0.93	14.57	21.25	45.25	37.69	43.64	74.05	64.84	72.13
WSJ	49,967	5,449	5,462	0.80	8.45	23.64	35.21	23.70	32.26	57.21	43.08	53.31
USAT	44,919	4,628	4,781	0.78	6.35	31.17	25.11	15.52	23.03	47.22	33.43	44.05
TG	58,057	6,376	6,273	0.80	2.75	40.35	21.66	8.02	18.24	41.23	21.56	35.90
TIME	42,200	4,761	4,702	0.75	4.87	47.67	19.80	10.83	17.94	41.37	26.04	37.87
Avg	50,159	5,454	5,424	0.81	7.40	32.81	29.90	19.54	27.48	52.79	38.33	49.20

Table 1: The statistics of the MULTI-SUM dataset. Three measures refer to COVERAGE, DENSITY and COMPRESSION respectively. LEAD and EXT-ORACLE are two common baselines for summarization. All measures and baselines are calculated on the test set of the corresponding publication. The top five publication are used as source domains for training and the bottom ones are viewed as OUT-OF-DOMAIN.

LEAD baseline concatenates the first few sentences as the summary and calculates its ROUGE score. This baseline shows the lead bias of the dataset, which is an essential factor in news articles. The EXT-ORACLE baseline evaluates the performance of the ground truth labels and can be viewed as the upper bound of the extractive summarization models (Nallapati et al., 2017; Narayan et al., 2018a).

MULTI-SUM The recently proposed dataset Newsroom (Grusky et al., 2018) is used, which was scraped from 38 major news publications. We select top ten publications (NYTimes, Washington-Post, FoxNews, TheGuardian, NYDailyNews, WSJ, USAToday, CNN, Time and Mashable) and process them in the way of See et al. (2017). To obtain the ground truth labels for extractive summarization task, we follow the greedy approach introduced by Nallapati et al. (2017). Finally, we randomly divide ten domains into two groups, one for training and the other for test. We call this re-purposed subset of Newsroom MULTI-SUM to indicate it is specially designed for multi-domain learning in summarization tasks.

From Table 1, we can find that data from those news publications vary in indicators that are closely relevant to summarization. This means that (document, summary) pairs from different publications will have unique summarization formation, and models might need to learn different semantic features for different publications. Furthermore, we follow the simple experiment by Torralba et al.

(2011) to train a classifier for the top five domains. A simple classification model with GloVe initializing words can also achieve 74.84% accuracy (the chance is 20%), which ensures us that there is a built-in bias in each publication. Therefore, it is reasonable to view one publication as a domain and use our multi-publication MULTI-SUM as a multi-domain dataset.

# 3 Analytical Experiment for Domain Shift

Domain shift refers to the phenomenon that a model trained on one domain performs poorly on a different domain(Saenko et al., 2010; Gopalan et al., 2011). To clearly verify the existence of domain shift in the text summarization, we design a simple experiment on MULTI-SUM dataset.

Concretely, we take turns choosing one domain and use its training data to train the basic model. Then, we use the testing data of the remaining domains to evaluate the model with the automatic metric ROUGE (Lin and Hovy, 2003)

**Basic Model** Like a few recent approaches, we define extractive summarization as a sequence labeling task. Formally, given a document S consisting of n sentences  $s_1, \dots, s_n$ , the summaries are extracted by predicting a sequence of label  $Y = y_1, \dots, y_n$  ( $y_i \in \{0, 1\}$ ) for the document, where  $y_i = 1$  represents the i-th sentence in the document should be included in the summaries.

<sup>&</sup>lt;sup>5</sup>ROUGE-2 and ROUGE-L show similar trends and their results are attached in Appendix.

	FN	CNN	MA	NYT	WTP	NYDN	WSJ	USAT	TG	TIME
FN	48.84	-1.23	-1.76	-0.70	-0.27	-2.29	-0.31	-0.57	-0.27	-0.02
CNN	-0.92	41.22	-1.93	-1.49	-1.01	-3.83	-0.55	-1.00	-0.80	-0.06
MA	-2.59	-6.62	35.19	-1.37	-1.45	-5.11	-0.25	-1.54	-0.17	-0.71
NYT	-3.13	-4.46	-2.41	29.65	-0.97	-3.95	-0.33	-1.16	-0.17	-0.86
WTP	-1.92	-3.03	-2.00	-0.61	23.01	-3.28	-0.43	-0.57	-0.01	-0.28
NYDN	-1.96	-2.31	-1.91	-0.57	-0.53	51.36	-0.41	-1.20	-0.36	-0.05
WSJ	-4.66	-7.07	-3.10	-1.04	-1.57	-6.37	38.60	-1.71	-0.58	-1.00
USAT	-2.04	-3.55	-2.56	-2.77	-1.86	-6.09	-0.92	29.11	-0.68	-1.27
TG	-5.47	-8.63	-3.50	-1.50	-1.74	-5.82	-1.43	-2.19	23.93	-1.66
TIME	-0.82	-3.05	-1.64	-1.36	-1.06	-4.65	-0.47	-1.05	-0.24	21.90

Table 2: Results (Matrix V) of the verification experiment based on the MULTI-SUM dataset. The ROUGE-1 scores  $^5$  of the model which is trained and tested on the same domain  $R_{ii}$  are shown on the diagonal line. It is regarded as benchmark scores. The other cells  $V_{ij} = R_{ij} - R_{jj}, i \neq j$ , which represents that for the same test domain j, how many improvements we obtained when we switch from training domain i to j. Positive values are higher than the benchmark, and negative values are less than the benchmark.

In this paper, we implement a simple but powerful model based on the encoder-decoder architecture. We choose CNN as the sentence encoder following prior works (Chen and Bansal, 2018) and employ the popular modular Transformer (Vaswani et al., 2017) as the document encoder. The detailed settings are described in Section 5.1.

**Results** From Table 2, we find that the values are negative except the diagonal, which indicates models trained and tested on the same domain show the great advantage to those trained on other domains. The significant performance drops demonstrate that the domain shift problem is quite serious in extractive summarization tasks, and thus pose challenges to current well-performed models, which are trained and evaluated particularly under the strong hypothesis: training and test data instances are drawn from the identical data distribution. Motivated by this vulnerability, we investigate the domain shift problem under both multi-domain training and evaluation settings.

## 4 Multi-domain Summarization

With the above observations in mind, we are seeking an approach which can alleviate the domain shift problem effectively in text summarization. Specifically, the model should not only perform well on source domains where it is trained on, but also show advantage on the unseen target domains. This involves the tasks of multi-domain learning and domain adaptation. Here, we begin with several simple approaches for multi-domain summarization based on multi-domain learning.

## 4.1 Four Learning Strategies

To facilitate the following description, we first set up mathematical notations. Assuming that there are K related domains, we refer to  $D_k$  as a dataset with  $N_k$  samples for domain k.  $D_k = \{(S_i^{(k)}, Y_i^{(k)})\}_{i=1}^{N_k}$ , where  $S_i^{(k)}$  and  $Y_i^{(k)}$  represent a sequence of sentences and the corresponding label sequence from a document of domain k, respectively. The goal is to estimate the conditional probability P(Y|S) by utilizing the complementarities among different domains.

 $\mathbf{Model}_{Base}^{I}$  This is a simple but effective model for multi-domain learning, in which all domains are aggregated together and will be further used for training a set of shared parameters. Notably, domains in this model are not explicitly informed of their differences.

Therefore, the loss function of each domain can be written as:

$$\mathcal{L}_{I}^{(k)} = L(\text{BASIC}(\mathbf{S}^{(k)}, \theta^{(s)}), \mathbf{Y}^{(k)}) \tag{1}$$

where BASIC denotes our CNN-Transformer encoder framework (As described in Section 3).  $\theta^{(s)}$  means that all domains share the same parameters.

Analysis: The above model benefits from the *joint training* strategy, which can allow a monolithic model to learn shared features from different domains. However, it is not sufficient to alleviate the domain shift problem, because two potential limitations remain: 1) The joint model is not aware of the differences across domains, which would lead to poor performance on in-task evaluation since some task-specific features shared by other tasks. 2) Negative transferring might happened on new domains. Next, we will study three different approaches to address the above problems.

 $\mathbf{Model}_{BERT}^{II}$  More recently, unsupervised pretraining has achieved massive success in NLP community (Devlin et al., 2018; Peters et al., 2018), which usually provides tremendous external knowledge. However, there are few works on building the connection between large-scale pre-trained models and multi-domain learning. In this model, we explore how the external knowledge unsupervised pre-trained models bring can contribute to multidomain learning and new domain adaption <sup>6</sup>.

We achieve this by pre-training our basic model  $Model_{Base}^{I}$  with BERT (Devlin et al., 2018), which is one of the most successful learning frameworks. Then we investigate if BERT can provide domain information and bring the model good domain adaptability. To avoid introducing new structures, we use the feature-based BERT with its parameters fixed.

**Analysis:** This model instructs the processing of multi-domain learning by utilizing external pretrained knowledge. Another perspective is to address this problem algorithmically.

 $\mathbf{Model}_{Tag}^{III}$  The domain type can also be introduced directly as a feature vector, which can augment learned representations with domain-aware

Specifically, each domain tag  $C^{(k)}$  will be embedded into a low dimensional real-valued vector and then be concatenated with sentence embedding  $\mathbf{s_i^{(k)}}.$  The loss function can be formulated as:

$$\mathcal{L}_{III}^{(k)} = L(\text{BASIC}(\mathbf{S}^{(k)}, C^{(k)}, \theta^{(s)}), \mathbf{Y}^{(k)})$$
 (2)

It is worth noting that, on unseen domains, the information of real domain tags is not available. Thus we design a domain tag ' $\mathfrak{X}$ ' for unknown domains and randomly relabeled examples with it during training. Since the real tag of the data tagged with 'X' may be any source domain, this embedding will force the model to learn the shared features and makes it more adaptive to unseen domains. In the experiment, this improves the performance on both source domains and target domains.

Analysis: This domain-aware model makes it possible to learn domain-specific features, while it still suffers from the negative transfer problem since private and shared features are entangled in shared space (Bousmalis et al., 2016; Liu et al., 2017). Specifically, each domain has permission to

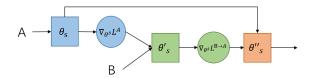


Figure 1: The gradient update mechanism of the meta learning strategy of Model $_{Meta}^{IV}$ .

modify shared parameters, which makes it easier to update parameters along different directions.

 $\mathbf{Model}_{Meta}^{IV}$  In order to overcome the above limitations, we try to bridge the communication gap between different domains when updating shared parameters via meta-learning (Finn et al., 2017; Li et al., 2017; Liu and Huang, 2018).

Here, the introduced communicating protocol claims that each domain should tell others what its updating details (gradients) are. Through its different updating behaviors of different domains can be more consistent.

Formally, given a main domain A and an auxiliary domain B, the model will first compute the gradients of A  $\nabla_{\theta} \mathcal{L}^A$  with regard to the model parameters  $\theta$ . Then the model will be updated with the gradients and calculate the gradients of B.

Our objective is to produce maximal perfor-

mance on sample 
$$(S^{(B)}, Y^{(B)})$$
:
$$\mathcal{L}^{A \leftarrow B} = \min_{\theta} L(S^{(B)}, Y^{(B)}, \nabla_{\theta} \mathcal{L}^{A}) \quad (3$$

So, the loss function for each domain can be finally written as:

$$\mathcal{L}_{IV}^{(k)} = \gamma \mathcal{L}^{(k)} + (1 - \gamma) \sum_{j \neq k} \mathcal{L}^{k \leftarrow j}$$
 (4)

where  $\gamma$  ( $0 \le \gamma \le 1$ ) is the weight coefficient and  $\mathcal{L}$  can be instantiated as  $\mathcal{L}_I$  (Eqn. 1),  $\mathcal{L}_{II}$  or  $\mathcal{L}_{III}$ (Eqn. 2).

Analysis: To address the multi-domain learning task and the adaptation to new domains,  $\mathsf{Model}^{II}_{BERT}, \mathsf{Model}^{III}_{Tag}, \mathsf{Model}^{IV}_{Meta}$  take different angles. Specifically,  $Model_{BERT}^{II}$  utilizes a largescale pre-trained model while  $Model_{Tag}^{III}$  proposes to introduce domain type information explicitly. Lastly,  $Model_{Meta}^{IV}$  is designed to update parameters more consistently, by adjusting the gradient direction of the main domain A with the auxiliary domain B during training. This mechanism indeed purifies the shared feature space via filtering out the domain-specific features which only benefit A.

<sup>&</sup>lt;sup>6</sup>Concurrent with our work, Radford et al. (2019) also apply pre-trained language model to a wide range of NLP tasks in a zero-shot setting. We will discuss the differences in the related work section.

## 5 Experiment

We investigate the effectiveness of the above four strategies under three evaluation settings: IN-DOMAIN, OUT-OF-DOMAIN and CROSS-DATASET. These settings make it possible to explicitly evaluate models both on the quality of domain-aware text representation and on their adaptation ability to derive reasonable representations in unfamiliar domains.

### 5.1 Experiment Setup

We perform our experiments mainly on our multi-domain MULTI-SUM dataset. Source domains are defined as the first five domains (IN-DOMAIN) in Table 1 and the other domains (OUT-OF-DOMAIN) are totally invisible during training. The evaluation under the IN-DOMAIN setting tests the model ability to learn different domain distribution on a multi-domain set and later OUT-OF-DOMAIN investigates how models perform on unseen domains. We further make use of CNN/DailyMail as a CROSS-DATASET evaluation environment to provide a larger distribution gap.

We use  $\operatorname{Model}^{I}_{Basic}$  as a baseline model, build  $\operatorname{Model}^{II}_{BERT}$  with feature-based BERT and  $\operatorname{Model}^{III}_{Tag}$  with domain embedding on it. We further develop  $\operatorname{Model}^{III}_{Tag}$  as the instantiation of  $\operatorname{Model}^{IV}_{Meta}$ . For the detailed dataset statistics, model settings and hyper-parameters, the reader can refer to Appendix.

#### **5.2** Quantitative Results

We compare our models by ROUGE-1 scores in Table 3. Note that we select two sentences for MULTI-SUM domains and three sentences for CNN/Daily Mail due to the different average lengths of reference summaries.

 $\mathbf{Model}_{Basic}^{I}$  vs  $\mathbf{Model}_{Tag}^{III}$  From Table 3, we observe that the domain-aware model outperforms the monolithic model under both IN-DOMAIN and OUT-OF-DOMAIN settings. The significant improvement of IN-DOMAIN demonstrates domain information is effective for summarization models trained on multiple domains. Meanwhile, the superior performance on OUT-OF-DOMAIN further illustrates that, the awareness of domain difference also benefits under the zero-shot setting. This might suggest that the domain-aware model could capture domain-specific features by domain tags and have learned domain-invariant features at the same time, which can be transferred to unseen domains.

Domains	$Model^I_{Basic}$	$Model^{II}_{BERT}$	$Model_{Tag}^{III}$	$Model^{IV}_{Meta}$			
In-domain Setting							
FN	49.13	49.70	49.54	49.06			
CNN	41.84	41.59	42.14	41.73			
MA	35.40	36.46	35.51	34.85			
NYT	30.68	31.92	30.70	30.20			
WTP	23.88	24.47	24.02	23.51			
Average	34.24	35.04	34.40	33.95			
OUT-OF-DOMAIN SETTING							
NTDN	48.62	49.37	49.44	49.47			
WSJ	38.55	39.63	39.00	38.93			
USAT	28.85	29.57	29.09	28.99			
TG	24.15	24.89	24.10	24.18			
TIME	21.67	22.45	22.20	22.12			
$\overline{Average}$	32.78	33.68	33.17	33.24			
$\Delta R$	1.47 ↓	1.35 ↓	1.24 ↓	0.71 ↓			
CROSS-DATASET SETTING							
CNN/DM	40.11	39.82	40.28	40.30			

Table 3: Rouge-1 performance of our four learning strategies on the MULTI-SUM dataset.  $\Delta R = |Rouge(\text{IN-DOMAIN}) - Rouge(\text{OUT-OF-DOMAIN})|$ . A smaller  $\Delta R$  indicates corresponding model has a better generalization ability. Bold numbers are the best results, and red ones indicate the minimum performance gap between source and target domains. The grey rows show the models' average performance under three evaluation settings.

 $\mathbf{Model}_{Basic}^{I}$   $\mathbf{vs}$   $\mathbf{Model}_{Meta}^{IV}$  Despite a little drop under IN-DOMAIN setting, the narrowed performance gap, as shown in  $\Delta R$  of Table 3, indicates  $\mathbf{Model}_{Meta}^{IV}$  has better generalization ability as a compensation. The performance decline mainly lies in the more consistent way to update parameters, which purifies shared feature space at the expense of filtering out some domain-specific features. The excellent results under CROSS-DATASET settings further suggest the meta-learning strategy successfully improve the model transferability not only among the domains of MULTI-SUM but also across different datasets.

**Model** $_{BERT}^{II}$  Supported by the smaller  $\Delta R$  compared with Model $_{Base}^{I}$ , we can draw the conclusion that BERT shows some domain generalization ability  $^{7}$  within MULTI-SUM. However, this ability is inferior to Model $_{Tag}^{III}$  and Model $_{Meta}^{IV}$ , which further leads to the worse performance on CROSS-DATASET. Thus we cannot attribute its success in MULTI-SUM to the ability to address multidomain learning nor domain adaptation. Instead,

 $<sup>^{7}\</sup>mathrm{We}$  give a specific experiment and analyze why Model  $^{II}_{BERT}$  with BERT can achieve domain generalization in Appendix.

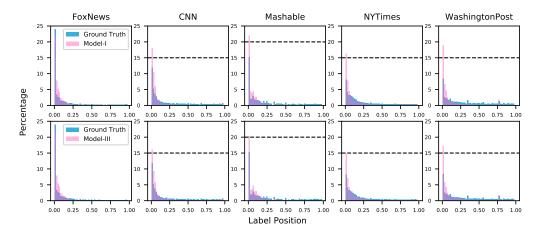


Figure 2: Relative position of selected sentence in the original document across five source domains. We overlap the ground truth labels with the model results in order to highlight the differences. The two rows correspond to Model-I and Model-III in Section 4.

Model	R-1	R-2	R-L
Lead-3 (See et al., 2017)	40.34	17.70	36.57
Narayan et al. (2018b)	40.00	18.20	36.60
Zhang et al. (2018)	41.05	18.77	37.54
Chen and Bansal (2018)	41.47	18.72	37.76
Dong et al. (2018)	41.50	18.70	37.60
Zhou et al. (2018)	<b>41.59</b>	<b>19.01</b>	<b>37.98</b>
Our basic model Basic model + Tag Basic model + Meta Basic model + BERT Basic model + BERT + Tag	41.33	18.83	37.65
	0.13↑	0.05↑	0.10↑
	0.07↓	0.02↓	0.05↓
	0.93↑	0.90↑	0.97↑
	0.97↑	0.93↑	1.01↑

Table 4: Comparison between our strategies with other extractive summarization models on non-anonymized CNN/Daily Mail provided by See et al. (2017). The red up-arrows indicate performance improvement over our base model, and the green down-arrows denote the degradation.

we suppose the vast external knowledge of BERT provides its superior ability for feature extraction. That causes  $\mathrm{Model}_{BERT}^{II}$  to overfit MULTI-SUM and perform excellently across all domains, but fails on the more different dataset CNN/Daily Mail.

This observation also suggests that although unsupervised pre-trained models are powerful enough (Radford et al., 2019), still, it can not take place the role of supervised learning methods (i.e.  $\mathrm{Model}_{Tag}^{III}$  and  $\mathrm{Model}_{Meta}^{IV}$ ), which is designed specifically for addressing multi-domain learning and new domain adaptation.

Analysis of Different Model Choices To summarize, Model $_{Tag}^{III}$  is a simple and efficient method, which can achieve good performance under indomain setting and shows certain generalization ability on the unseen domain. Model $_{Meta}^{IV}$  shows

the best generalization ability at the cost of relatively lower in-domain performance. Therefore, using  $\mathrm{Model}_{Meta}^{IV}$  is not a good choice if in-domain performance matters for end users.  $\mathrm{Model}_{BERT}^{II}$  can achieve the best performance under in-domain settings at expense of training time and shows worse generalization ability than  $\mathrm{Model}_{Meta}^{IV}$ . If the training time is not an issue,  $\mathrm{Model}_{BERT}^{IV}$  could be a good supplement for other methods.

## 5.3 Results on CNN/DailyMail

Inspired by such observations, we further employ our four learning strategies to the mainstream summarization dataset CNN/DailyMail (See et al., 2017), which also includes two different data sources: CNN and DailyMail. We use the publication as the domain and train our models on its 28w training set. As Table 4 shows, our basic model has comparable performance with other extractive summarization models. Besides, the publication tags can improve ROUGE scores significantly by 0.13 points in ROUGE-1 and the meta learning strategy does not show many advantages when dealing with in-domain examples, what we have expected. BERT with tags achieves the best performance, although the performance increment is not as much as what publication tags bring to the basic model, which we suppose that BERT itself has contained some degree of domain information.

#### 5.4 Qualitative Analysis

We furthermore design several experiments to probe into some potential factors that might contribute to the superior performance of domainaware models over the monolithic basic model.

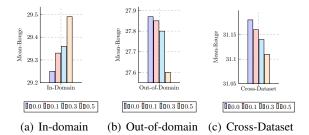


Figure 3: Loss weight coefficients  $\gamma$  for Model-IV. The y-axis is the mean score of ROUGE-1, ROUGE-2 and ROUGE-L and different bins correspond to different  $\gamma$  values.

**Label Position** Sentence position is a well known and powerful feature, especially for extractive summarization (Kedzie et al., 2018)  $^8$ . We compare the relative position of sentences selected by our models with the ground truth labels on source domains to investigate how well these models fit the distribution and whether they can distinguish between domains. We select the most representative models  $Model^{III}_{Base}$  and  $Model^{III}_{Tag}$  illustrated in Figure 2  $^9$ .

The percentage of the first sentence on FoxNews is significantly higher than others: (1) Unaware of different domains,  $Model_{Base}^{I}$  learns a similar distribution for all domains and is seriously affected by this extreme distribution. In its density histogram, the probability of the first sentence being selected is much higher than the ground truth on the other four domains. (2) Compared with  $Model_{Base}^{I}$ , domain-aware models are more robust by learning different relative distributions for different domains.  $Model_{Tag}^{III}$  constrains the extreme trend especially obviously on CNN and Mashable.

Weight  $\gamma$  for  $\mathbf{Model}_{Meta}^{IV}$  We investigate several  $\gamma$  to further probe into the performance of  $\mathbf{Model}_{Meta}^{IV}$ . In Eqn. 4,  $\gamma$  is the weight coefficient of main domain A. When  $\gamma=0$ , the model ignores A and focuses on the auxiliary domain B and when  $\gamma=1$  it is trained only on the loss of main domain A (the same as the instantiation  $\mathbf{Model}_{Tag}^{III}$ ). As Figure 3 shows, with the increase of  $\gamma$ , the Rouge scores rise on IN-DOMAIN while decline on OUT-OF-DOMAIN and CROSS-DATASET. The performances under IN-DOMAIN settings prove that

the import of the auxiliary domain hurts the model ability to learn domain-specific features. However, results under both OUT-OF-DOMAIN and CROSS-DATASET settings indicate the loss of B, which is informed of A's gradient information, helps the model to learn more general features, thus improving the generalization ability.

## 6 Related Work

We briefly outline connections and differences to the following related lines of research.

Domains in Summarization There have been several works in summarization exploring the concepts of domains. Cheung and Penn (2013b) explored domain-specific knowledge and associated it as template information. Hua and Wang (2017) investigated domain adaptation in abstractive summarization and found the content selection is transferable to a new domain. Gehrmann et al. (2018) trained a selection mask for abstractive summarization and proved it has excellent adaptability. However, previous works just investigated models trained on a single domain and did not explore multi-domain learning in summarization.

Multi-domain Learning (MDL) & Domain Adaptation (DA) We focus on the testbed that requires both training and evaluating performance on a set of domains. Therefore, we care about two questions: 1) how to learn a model when the training set contains multiple domains – involving MDL. 2) how to adapt the multi-domain model to new domains – involving DA. Beyond the investigation of some effective approaches like existing works, we have first verified how domain shift influences the summarization tasks.

Semi-supervised Pre-training for Zero-shot Transfer It has a long history of fine-tuning downstream tasks with supervised or unsupervised pre-trained models (Le and Mikolov, 2014; Devlin et al., 2018; Peters et al., 2018). However, there is a rising interest in applying large-scale pre-trained models to zero-shot transfer learning (Radford et al., 2019). Different from the above works, we focus on addressing domain shift and generalization problem. One of our explored methods is semi-supervised pre-training, which combines supervised and unsupervised approaches to achieve zero-shot transfer.

<sup>&</sup>lt;sup>8</sup>We plot the density histogram of the relative locations of ground truth labels for both source and target domains and attach it in Appendix. Compared with Table 2, we can find that the relative position of ground truth labels is closely related to ROUGE performance of the basic model.

<sup>&</sup>lt;sup>9</sup>The whole picture in the Appendix illustrates the four models performance.

## 7 Conclusion

In this paper, we explore publication in the context of the domain and investigate the domain shift problem in summarization. When verified its existence, we propose to build a multi-domain testbed for summarization that requires both training and measuring performance on a set of domains. Under these new settings, we propose four learning schemes to give a preliminary explore in characteristics of different learning strategies when dealing with multi-domain summarization tasks.

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