Neural Label Search for Zero-Shot Multi-Lingual Extractive Summarization

Ruipeng Jia[1,2]*, **Xingxing Zhang**[3]†, **Yanan Cao**[1,2]†, **Shi Wang**[4], **Zheng Lin**[1,2] and **Furu Wei**[3]
[1]Institute of Information Engineering, Chinese Academy of Sciences
[2]School of Cyber Security, University of Chinese Academy of Sciences
[3]Microsoft Research Asia
[4]Institute of Computing Technology, Chinese Academy of Sciences
[1,2]{jiaruipeng,caoyanan,linzheng}@iie.ac.cn
[3]{xizhang,fuwei}@microsoft.com, [4]wangshi@ict.ac.cn

Abstract

In zero-shot multilingual extractive text summarization, a model is typically trained on English summarization dataset and then applied on summarization datasets of other languages. Given English gold summaries and documents, sentence-level labels for extractive summarization are usually generated using heuristics. However, these monolingual labels created on English datasets may not be optimal on datasets of other languages, for that there is the syntactic or semantic discrepancy between different languages. In this way, it is possible to translate the English dataset to other languages and obtain different sets of labels again using heuristics. To fully leverage the information of these different sets of labels, we propose NLSSum (**N**eural **L**abel **S**earch for **Sum**marization), which jointly learns hierarchical weights for these different sets of labels together with our summarization model. We conduct multilingual zero-shot summarization experiments on MLSUM and WikiLingua datasets, and we achieve state-of-the-art results using both human and automatic evaluations across these two datasets.

1 Introduction

The zero-shot multilingual tasks, which aim to transfer models learned on a high-resource language (e.g., English) to a relatively low-resource language (e.g., Turkish) without further training, are challenging (Ruder et al., 2019). Recently, large pre-trained multilingual transformers such as M-BERT (Devlin et al., 2019), XLM (Lample and Conneau, 2019), and XLM-R (Conneau et al., 2020) have shown remarkable performance on zero-shot multilingual natural language understanding tasks. During pre-training, these transformer models project representations of different languages into the same vector space, which makes the transfer learning across different languages easier during fine-tuning (Gong et al., 2021). In zero-shot extractive summarization, we train an extractive model (based on a pre-trained multilingual transformer) on English summarization dataset, which selects important sentences in English documents. Then, we apply this trained model to documents of a different language (i.e., extracting sentences of documents in another language). In this paper, we aim to enhance the zero-shot capabilities of multilingual sentence-level extractive summarization.

Sentence (English, Label 1): *He was never charged in* that Caribbean Nation. **Reference Summary (English):** *He was* arrested twice, but *never charged in* Natalee Holloway's disappearance.
Translated Sentence (German, Label 0): *Er* wurde jedoch *nie* in dieser karibischen Nation *angeklagt*. **Translated Reference Summary (German):** Beim Verschwinden von Natalee Holloway wurde *er* zweimal verhaftet, aber *nie angeklagt*.

Table 1: Monolingual Bias for Different Languages.

In text summarization, most datasets only contain human-written *abstractive* summaries as ground truth. We need to transform these datasets into *extractive* ones. Thus, a greedy heuristic algorithm (Nallapati et al., 2017) is employed to add one sentence at a time to the candidate extracted summary set, by maximizing the ROUGE (Lin, 2004) between candidate summary set and the gold summary. This process stops when none of the remaining sentences in the document can increase the ROUGE anymore. These selected sentences are labelled as one and all the other sentences labeled as zero. While the labels obtained from this greedy algorithm are monolingual-oriented and may not be suitable for multilingual transfer. For the example in Table 1, the English sentence is quite likely to be selected as a summary sentence, since it greatly overlaps with the English reference (high ROUGE). While when the document and the summary are translated into German, the ROUGE between the sentence and the summary is significantly lower

* Work done during the first author's internship at Microsoft Research Asia.
† Corresponding authors

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(fewer n-gram overlap). Then, another sentence will be selected as substitution. The greedy algorithm yields different labels on the English data and the translated data and these labels may complement for each other. We define this discrepancy as *monolingual label bias*, and it is the key to further improve the performance of zero-shot multilingual summarization.

To address the above problem, we design a method to create multiple sets of labels with different machine translation methods according to the English summarization dataset, and we employ NLSSum (**N**eural **L**abel **S**earch for **Sum**marization) to search suitable weights for these labels in different sets. Specially, in NLSSum, we try to search the hierarchical weights (sentence-level and set-level) for these labels with two neural weight predictors and these label weights are used to train our summarization model. During training, the two neural weight predictors are jointly trained with the summarization model. NLSSum is used only during training and during inference, we simply apply the trained summarization model to documents in another language.

Experimental results demonstrate the effectiveness of NLSSum, which significantly outperforms original XLMR by 2.25 ROUGE-L score on MLSUM (Scialom et al., 2020). The human evaluation also shows that our model is better compared to other models. To sum up, our contributions in this work are as follows:

- To the best of our knowledge, it is the first work that studies the *monolingual label bias* problem in zero-shot multilingual extractive summarization.

- We introduce the multilingual label generation algorithm (Section 3.5) to improve the performance of multilingual zero-shot models. Meanwhile, we propose the NLSSum architecture (Section 3.6) to search suitable weights for different label sets.

- Extensive experiments are conducted with detailed analysis, and the results across different datasets demonstrate the superior performance on multilingual datasets. In MLSUM, the zero-shot performance on Russian is even close to its supervised counterpart.

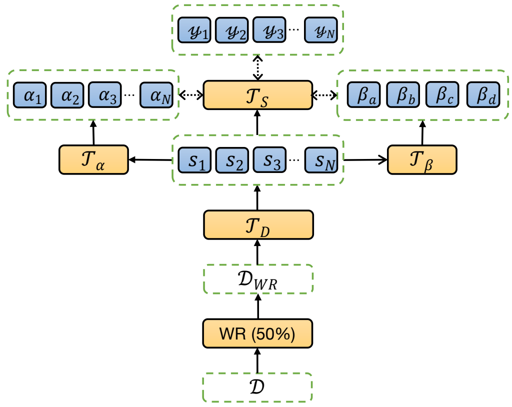


Figure 1: Overview of NLSSum. The input English document is argumented by 50% word replacement and the output is supervised by multilingual labels.

2 Related Work

There has been a surge of research on multilingual pretrained models, such as multilingual BERT (Devlin et al., 2019), XLM (Lample and Conneau, 2019) and XLM-RoBERTa (Conneau et al., 2020). For multilingual summarization, the summarize-then-translate and translate-then-summarize are widely used approaches in prior studies Lim et al. (2004). There is another effective multi-lingual data augmentation, a method that replaces a segment of the input text with its translation in another language (Singh et al., 2019). On the other hand, large-scale multilingual summarization datasets have been introduced (Scialom et al., 2020; Ladhak et al., 2020), which enable new research directions for the multilingual summarization. Nikolov and Hahnloser (2020) applies an alignment approach to collect large-scale parallel resources for low-resource domains and languages. In this paper, we aim to advance the multilingual zero-shot transferability, by training extractive summarization on English and inferring on other languages.

3 Methodology

3.1 Problem Definition

Let $\mathcal{D} = (s_1, s_2, ..., s_N)$ denotes a document with N sentences, where $s_i = (w_1^i, w_2^i, ..., w_{|s_i|}^i)$ is a sentence in $\mathcal{D}$ with $|s_i|$ words. $\mathcal{S}$ is the human-written summary. Extractive summarization can be considered as a sequence labeling task that assigns a label $y_i \in \{0, 1\}$ to each sentence s_i, where $y_i = 1$ indicates the i-th sentence should be included in the extracted summary. The gold labels of sentences in $\mathcal{D}$ are obtained from ($\mathcal{D}$, $\mathcal{S}$) by the

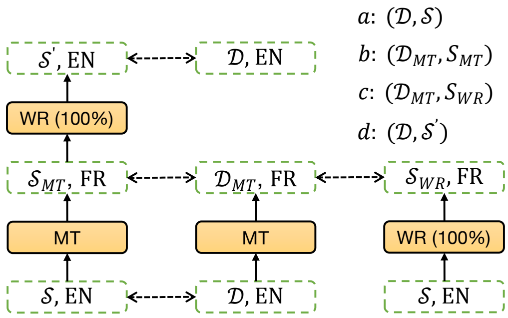


Figure 2: Four Sets of Multilingual Label. 'EN' is the symbol of English and 'FR' is for the foreign language.

greedy heuristic algorithm (Nallapati et al., 2017), which adds one sentence at a time to the extracted summary, skipping some sentences to maximize the ROUGE score of $\mathcal{S}$ and the extracted sentences. In multi-lingual zero-shot setting, the summarization model is trained on English dataset and is finally applied on documents of other languages.

3.2 Neural Extractive Summarizer

Our sentence encoder builds upon the recently proposed XLMR (Conneau et al., 2020) architecture, which is based on the deep bidirectional Transformer (Vaswani et al., 2017) and has achieved state-of-the-art performance in many multilingual zero-shot understanding tasks. Our extractive model is composed of a sentence-level Transformer $\mathcal{T}_S$ (initialized with XLMR) and a document-level Transformer $\mathcal{T}_D$ (a two-layer Transformer).

For each sentence s_i in the input document $\mathcal{D}$, $\mathcal{T}_S$ is applied to obtain a contextual representation for each word w_j^i:

$$[\mathbf{u}_1^1, \mathbf{u}_2^1, ..., \mathbf{u}_{|s_N|}^N] = \mathcal{T}_S([w_1^1, w_2^1, ..., w_{|s_N|}^N]) \quad (1)$$

Similar to Liu and Lapata (2019), the representation of a sentence s_i is acquired by taking the representation of the first token in the sentence $\mathbf{u}_1^i$. The document-level Transformer $\mathcal{T}_D$ (a two-layer inter-sentence Transformer), which is stacked to $\mathcal{T}_S$, takes s_i as input and yields a contextual representation $\mathbf{v}_i$ for each sentence. We intend this process to further captures the sentence-level features for extractive summarization:

$$[\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_N] = \mathcal{T}_D([\mathbf{u}_1^1, \mathbf{u}_1^2, ..., \mathbf{u}_1^N]) \quad (2)$$

For sentence s_i, the final output prediction of the extractive model $\hat{y}_i$ (i.e., the probability of being selected as summary) is obtained through a linear and a sigmoid classifier layer:

$$\hat{y}_i = \sigma(\mathbf{W}_o \mathbf{v}_i + b_o) \quad (3)$$

where $\mathbf{W}_o$ and b_o are the weight matrix and bias term. Next we introduce how we obtain the neural labels for model training.

3.3 Overview of Neural Label Search

The training and inference of our NLSSum model includes five steps as follows.

(I) **Multilingual Data Augmentation**: This step aims to enhance the multilingual transfer capability of our extractive model and alleviate the discrepancy between training (on English) and inference (on unseen languages).

(II) **Multilingual Label Generation**: The extractive model is supervised by multilingual label, which consists of four sets of labels, according to different strategies.

(III) **Neural Label Search**: In this step, we design the hierarchical sentence-level and set-level weights for labels of different strategies. The final weights are calculated with a weighted average and assigned to corresponding sentences.

(IV) **Fine-Tuning**: We fine-tune our extractive model the augmented English document (generated in Step I) with supervision from the weighted multilingual labels (generated in Step III), as shown in Figure 1.

(V) **Zero-Shot**: We apply the model fine-tuned on English data (Step IV) to extract sentences on documents of the target language.

3.4 Multilingual Data Augmentation

In the training process, only the raw English documents and its paired summary labels are available. We use the following two methods for multilingual data argumentation of English documents, which we intend the model to align its English representations with representations in other languages.

Word Replacement (WR) Similar to Qin et al. (2020), we enhance multilingual transferability by constructing *Word Replacement* data in multiple languages *dynamically*. Let FR denote a foreign language. Specifically, a set of words are randomly chosen in raw English documents and replaced with words in FR using the bilingual dictionary MUSE (Conneau et al., 2018). This approach can in some degree align the replaced word representations in FR with their English counterpart by mixing with the English context.

Machine Translation (MT) The above augmentation method is applied *dynamically* during training, and *Machine Translation* yet is another offline strategy to augment data. First, we translate documents and their paired summaries from English into the target language FR using the MarianMT system[1] (Junczys-Dowmunt et al., 2018). Then, the labels are generated on the translated data with the same greedy algorithm as on English data. Finally, the extractive model is fine-tuned on the translated documents with the supervision of new labels, and inferred on the original FR document.

Unfortunately, the performance of machine translation is instable with the noise or error propagation (Wan et al., 2010). Therefore, we choose the word replacement method here to enhance the input document and the argumented document is served as the input of our extractive model. Note that we do use both the word replacement and machine translation methods to generate multilingual labels (see the next section).

3.5 Multilingual Labels

Given an English article $\mathcal{D}$ and its summary $\mathcal{S}$, we can obtain its extractive labels using the greedy algorithm introduced in Section 3.1.

Label Set U_a Let $U_a = \texttt{GetPosLabel}(\mathcal{D}, \mathcal{S})$ denote the indices of sentences with positive labels, where $\texttt{GetPosLabel}(\mathcal{D}, \mathcal{S})$ returns the indices of positive labeled sentences in the original English document $\mathcal{D}$ using the greedy algorithm. The labels created on English data $(\mathcal{D}, \mathcal{S})$ may not be optimal in multilingual settings (inference on a different language). As shown in Figure 2, we therefore create yet another three label sets using the WR and MT methods introduced earlier to simulate the multilingual scenario during inference time.

Label Set U_b To create labels based foreign language (FR) data, we translate both the English document $\mathcal{D}$ and its summary $\mathcal{S}$ to FR using the MT method in Section 3.4, resulting $\mathcal{D}_{MT}$ and $\mathcal{S}_{MT}$ (also see Figure 2). Again by using the greedy algorithm, we obtain the indices of sentences with positive labels $U_b = \texttt{GetPosLabel}(\mathcal{D}_{MT}, \mathcal{S}_{MT})$.

Label Set U_c Label set U_c is also based on FR data. To make label set U_c different from U_b, we translate $\mathcal{D}$ to $\mathcal{D}_{MT}$ using the MT method, while we translate $\mathcal{S}$ to $\mathcal{S}_{WR}$ using the WR method (we do 100% word replacement) with the EN-FR dictionary. The resulting label set $U_c = \texttt{GetPosLabel}(\mathcal{D}_{MT}, \mathcal{S}_{WR})$.

Label Set U_d Label set U_d is based on English data. The idea is to create a paraphrased English summary $\mathcal{S}'$ using the back translation technology. We first translate $\mathcal{S}$ to $\mathcal{S}_{MT}$ using MT method and translate $\mathcal{S}_{MT}$ back to English $\mathcal{S}'$ using the WR method (100% word replacement). We use different *translation* method for forward and backward translations to maximize the different between $\mathcal{S}$ and $\mathcal{S}'$. Finally, $U_d = \texttt{GetPosLabel}(\mathcal{D}, \mathcal{S}')$.

Note that there are also many other possible strategies for creating multilingual labels and we only use these four strategies above as examples to study the potential of multilingual labels. Intuitively, the contributions of these four label sets for multilingual transferability are different, and the MT and WR translation methods may introduce translation errors, which result noisy labels. Therefore, we introduce the *Neural Label Search* in the next section to find suitable weights for these multilingual labels.

3.6 Neural Label Search

In this section, we assign a weight for each sentence in a document and the weight will be used as the supervision to train our extractive model. Note that the weight is a multiplication of a sentence level weight and a label set level weight. Let $\mathcal{T}_\alpha$ denote the sentence level weight predictor and $\mathcal{T}_\beta$ the set level weight predictor. The implementation of $\mathcal{T}_\alpha(\cdot) = \sigma(g(\mathcal{T'}_\alpha(\cdot)))$ is a two-layer transformer model $\mathcal{T'}_\alpha(\cdot)$ followed by a linear layer $g(\cdot)$ and a sigmoid function. The implementation of $\mathcal{T}_\beta$ is the same as $\mathcal{T}_\alpha$, but with different parameters.

The predictor $\mathcal{T}_\alpha$ transforms sentence representations (see Equation (1) for obtaining $\mathbf{u}_j^i$) to probabilities $\alpha_i \in [0, 1]$ as follows:

$$
\begin{aligned}
&[\hat{\alpha_1}, \hat{\alpha_2}, ..., \hat{\alpha_N}] = \mathcal{T}_\alpha([\mathbf{u}_1^1, \mathbf{u}_1^2, ..., \mathbf{u}_1^N]) \\
&\alpha_i = \begin{cases} \hat{\alpha_i}, & \text{if } i \in U \\ 0, & \text{otherwise} \end{cases}
\end{aligned}
\tag{4}
$$

[1]https://github.com/marian-nmt/marian

where $U = U_a \cup U_b \cup U_c \cup U_d$. Note that we only predict weights for sentences with non-zero labels, since we believe that these sentences, which are the minority, are more informative than zero-label sentences.

The computation of $\mathcal{T}_\beta$ is similar, but we first do a mean pooling over sentences in each label set.

$$[\beta_a, \beta_b, \beta_c, \beta_d] = \mathcal{T}_\beta([\frac{\sum\limits_{i \in U_a} \mathbf{u}_1^i}{n_a}, \frac{\sum\limits_{i \in U_b} \mathbf{u}_1^i}{n_b}, \frac{\sum\limits_{i \in U_c} \mathbf{u}_1^i}{n_c}, \frac{\sum\limits_{i \in U_d} \mathbf{u}_1^i}{n_d}])$$

where n_a, n_b, n_c, n_d are sizes of the four label sets.

The final weight l_i for sentence s_i is 0 when $i \notin U$ (i does not belong to any label set). Otherwise, the computation of l_i is as follows.

$$l_i = \alpha_i * \frac{\sum_{j \in \{a,b,c,d\}} \beta_j^i}{m_i} \tag{5}$$

where if $i \in U_j$, β_j^i is β_j, else β_j^i is 0 and m_i is the number of label sets containing i. Note that one sentence may belong to multiple label sets, so we normalize its β_j^i weights in Equation (5).

Weight Normalization In this paper, we only calculate the multilingual weights for multilingual labels, in which the corresponding sentences are all selected as summary sentences by different document-summary pairs, as shown in the Figure 2. The label weights l_i are used to train our summarization model, whose output $\hat{y}_i$ is through a sigmoid function (Equation 3). $\hat{y}_i > 0.5$ means sentence s_i could be selected as in summary. Therefore, when $i \in U$, we rescale l_i to $[0.5, 1.0]$:

$$l_i = \frac{l_i - l_{min}}{2 * (l_{max} - l_{min})} + 0.5 \tag{6}$$

where l_{max} and l_{min} are the maximum and minimum value of l_i, when $i \in U$.

3.7 Training and Zero-shot Inference

In this section, we present how we train our extractive model as well as the two weight predictors $\mathcal{T}_\alpha$ and $\mathcal{T}_\beta$. Note that we train the components above jointly. We train the extractive model using both the English labels y^a (created using the greedy algorithm) as well as the label weights generated in Section 3.6. To train $\mathcal{T}_\alpha$, we use binary labels y^α, where in one document, $y_i^\alpha = 1$ when $i \in U$, otherwise $y_i^\alpha = 0$. To train $\mathcal{T}_\beta$, we again use binary labels y^β, but these labels are on set level rather than sentence level. Defining positive examples for $\mathcal{T}_\beta$ is straight-forward and we set $y_q^\beta = 1$ when $q \in \{U_a, U_b, U_c, U_d\}$ (each label set corresponds to one positive example). For negative examples in one particular document, we randomly sample three sentence indices from sentences with zero labels as one negative example. We finally make the numbers of positive and negative examples for $\mathcal{T}_\beta$ close to 1:1.

Datasets	# Docs (Train / Val / Test)
CNN/DM, English	287,227 / 13,368 / 11,490
MLSUM, German	220,887 / 11,394 / 10,701
MLSUM, Spanish	266,367 / 10,358 / 13,920
MLSUM, French	392,876 / 16,059 / 15,828
MLSUM, Russian	25,556 / 750 / 757
MLSUM, Turkish	249,277 / 11,565 / 12,775
WikiLingua, English	99,020 / 13,823 / 28,614
WikiLingua, German	40,839 / 5,833 / 11,669
WikiLingua, Spanish	79,212 / 11,316 / 22,632
WikiLingua, French	44,556 / 6,364 / 12,731

Table 2: Data Statistics: CNN/Daily Mail, MLSUM and WikiLingua.

The final loss is a sum of the four losses above:

$$\begin{aligned} \mathcal{L} = & CE(\hat{y}, y^a) + CE(\hat{y}, l) + \\ & CE(\alpha, y^\alpha) + CE(\beta, y^\beta) \end{aligned} \tag{7}$$

where CE is the cross entropy loss; l is the weighted multilingual label (Section 3.6); y^a, y^α, and y^β are the binary labels for the supervision of $\hat{y}$, α, and β. Specifically, $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_N]$ and $\beta = [\beta_a, \beta_b, \beta_c, \beta_d]$ (just as Equation 4 and 5).

During the zero-shot inference, we simply apply the model trained on the English dataset using the objectives above to other languages.

4 Experiments

4.1 Datasets

MLSUM & CNN/DM MLSUM is the first large-scale multilingual summarization dataset (Scialom et al., 2020), which is obtained from online newspapers and contains 1.5M+ document/summary pairs in five different languages, namely, French(Fr), German(De), Spanish(Es), Russian(Ru), and Turkish(Tr). The English dataset is the popular CNN/Daily mail (CNN/DM) dataset (Hermann et al., 2015). Our model is trained on CNN/DM.

WikiLingua A large-scale, cross-lingual dataset for abstractive summarization (Ladhak et al., 2020). The dataset includes 770K article and summary

Models	MLSUM De	Es	Fr	Ru	Tr	avg
Oracle*	52.30	35.78	37.69	29.80	45.78	40.27
Lead-2*	33.09	13.70	19.69	5.94	28.90	20.26
Supervised						
Pointer-Generator	35.08	17.67	23.58	5.71	32.59	22.99
mBERTSum-Gen	42.01	20.44	25.09	9.48	32.94	25.99
XLMRSum*	41.28	21.99	24.12	10.44	33.29	26.22
MARGE (Train One)	42.60	22.31	25.91	10.85	36.09	27.55
MARGE (Train All)	42.77	22.72	25.79	11.03	35.90	27.64
Zero-Shot						
MARGE	30.01	17.81	19.39	8.67	29.39	21.05
mBERTSum*	17.36	17.27	19.64	8.37	19.30	16.39
XLMRSum*	32.05	19.49	22.20	8.70	27.64	22.02
XLMRSum-MT* w/ U_a	29.34	21.14	23.82	8.68	24.23	21.44
XLMRSum-MT* w/ U_b	29.70	21.18	23.62	9.37	24.27	21.63
XLMRSum-WR*	32.37	21.03	23.67	9.34	30.10	23.30
NLSSum-Sep*	34.21	**21.24**	**23.92**	10.09	**31.68**	24.23
NLSSum*	**34.95**	21.20	23.59	**10.13**	31.49	**24.27**

Table 3: ROUGE-L on MLSUM dataset. * means extractive models, and others are abstractive models.

pairs in 18 languages from WikiHow[2]. Our training setting is identical to that of MLSUM, our extractive model is trained on the English data and inferred on other three languages (French, German, Spanish). MLSUM and WikiLingua are described in detail in Table 2.

4.2 Evaluation

Similar to Liu and Lapata (2019), we also select the top three sentences as the summary, with Trigram Blocking to reduce redundancy. Following Scialom et al. (2020), we report the F1 ROUGE-L score of NLSSum with a full Python implemented ROUGE metric[3], which calculates the overlap lexical units between extracted sentences and ground-truth. Following Lin (2004), to assess the significance of the results, we applied bootstrap resampling technique (Davison and Hinkley, 1997) to estimate 95% confidence intervals for every correlation computation.

4.3 Implementation

Our implementation is based on Pytorch (Paszke et al., 2019) and transformers. The pre-trained model employed in NLSSum is `XLMR-Large`. We train NLSSum on one Tesla V100 GPU for 100,000 steps (2 days) with a batch size of 4 and gradient accumulation every two steps. Adam with $\beta_1 = 0.9, \beta_2 = 0.999$ is used as optimizer. The learning rate is linearly increased from 0 to $1e-4$ in the first 2,500 steps (warming-up) and linearly decreased thereafter. For the source document data augmentation, we use a 0.5 word replacement rate

[2] https://www.wikihow.com
[3] https://github.com/pltrdy/rouge

Models	WikiLingua De	Es	Fr	avg
Oracle	30.81	36.52	34.64	33.99
Lead-3	16.32	19.78	18.40	18.17
mBERTSum	18.83	22.49	20.91	20.74
XLMRSum	22.10	26.73	25.06	24.63
XLMRSum-MT	21.92	26.41	24.75	24.36
XLMRSum-WR	22.20	26.78	25.10	24.69
NLSSum	**22.45**	**26.98**	**25.34**	**24.92**

Table 4: Zero-Shot ROUGE-L Results of WikiLingua

with a bilingual dictionary (Conneau et al., 2018).

4.4 Models in Comparison

Oracle sentences are extracted by the greedy algorithm introduced in Section 3.1. **Lead-K** is a simple baseline to choose the first k sentences in a document as its summary. We use $k = 2$ on MLSUM and $k = 3$ on WikiLingua, which lead to the best results. **Pointer-Generator** augments the standard Seq2Seq model with copy and coverage mechanisms (See et al., 2017). **mBERTSum-Gen** is based on the multilingual version BERT (mBERT; Devlin et al. 2019) and it is extended to do generation with a unified masking method in UniLM (Dong et al., 2019). **MARGE** is a pre-trained seq2seq model learned with an unsupervised multilingual paraphrasing objective (Lewis et al., 2020). **mBERTSum**, **XLMRSum**, **XLMRSum-MT** and **XLMRSum-WR** are all extractive models described in Section 3.2 and their sentence encoders are either initialized from `mBERT` or `XLMR-Large`. They are all trained on the Enlgish dataset. XLMRSum-MT is trained on the English training data argumented with machine translation. While XLMRSum-WR is trained on the English training data argumented with bilingual dictionary word replacement.

5 Result & Analysis

ROUGE Results on MLSUM Table 3 shows results on MLSUM. The first block presents the Oracle upper bound and the Lead-2 baseline, while the second block includes the supervised summarization results. Results of Pointer-Generator, mBERTSum-Gen are reported in Scialom et al. (2020), while results of MARGE are reported in Lewis et al. (2020). The results of MARGE training on all languages jointly (Train All) are slightly better than its counterpart when training on each language separately (Train One). While we see a different trend with other models. Comparing ex-

Models	1st	2nd	3rd	4th	MeanR
mBERTSum	0.07	0.25	0.31	0.37	2.98
XLMRSum	0.16	0.28	0.27	0.29	2.69
NLSSum	0.28	0.32	0.2	0.2	2.32
Oracle	0.49	0.15	0.22	0.14	2.01

Table 5: Human Evaluation on MLSUM, German

tractive models against abstractive models in the supervised setting, the abstractive paradigm is still the better choice.

We present the zero-shot results in the third block. All models are trained on the Enlgish summarization dataset and infered on dataset of other languages. With a decent multi-lingual pre-trained model, the extractive XLMRSum performs better than the abstractive MARGE, which demonstrates the superiority of extractive approaches in zero-shot summarization. When applying machine translation based (XLMRSum-MT) and multi-lingual word replacement based (XLMRSum-WR) data argumentation method to XLMR (see Section 3.4), we obtain further improvements. With MT based argumentation method (XLMRSum-MT), we could re-generate extractive labels using the translated doucments and summaries (the U_b setting). We do observe that the re-generated labels could slightly improve the results, but the resulting XLMRSum-MT is still worse than XLMRSum and XLMRSum-WR. With the neural label search method, NLSSum-Sep outperforms all models in comparison. For faster feedback, we train a separate model for each language in XLMRSum-MT and XLMRSum-WR and NLSSum-Sep (models for different languages can be trained in parallel), which is to do data argumentation only to one target language. In our final model NLSSum, we train one model for all languages (we do data argumentation from English to all target languages) and we observe that the results of NLSSum-Sep and NLSSum are similar. Compared with the original XLMRSum, NLSSum achieves 2.27 improvements on the average R-L score, which is a remarkable margin in summarization. It indicates that our multilingual neural label search method significantly improves the multilingual zero-shot transferability. The differences between NLSSum and other models in comparison except NLSSum-Sep are significant ($p < 0.05$). Specifically, the performance XLMRSum-MT is worse than that of XLMRSum. For more in-depth analysis, we note that: 1) As the input of a model, the translation-based documents are prone to the error propagation, therefore, we should avoid to encode these noise documents. 2) Fortunately, our multilingual label only applies the translation method when converting document/summary pair into labels, instead of encoding.

Models	MLSUM De	Es	Fr	Ru	Tr	avg
XLMRSum	30.35	20.67	22.85	9.39	31.55	22.81
NLSSum w/o $\mathcal{T}_\beta$	33.13	21.21	23.09	9.72	**32.68**	23.97
NLSSum	**33.51**	**21.74**	**24.10**	**9.91**	32.58	**24.37**
Train with Different Label Sets						
XLMRSum-WR w/ U_a	**32.09**	**21.04**	**23.33**	9.69	**32.04**	**23.58**
XLMRSum-WR w/ U_b	30.39	20.71	23.17	**9.83**	31.37	23.05
XLMRSum-WR w/ U_c	29.66	20.64	22.96	9.32	31.63	22.76
XLMRSum-WR w/ U_d	30.22	20.16	22.90	9.61	31.90	21.78
Train with All Label Sets and with Fixed Weights						
XLMRSum-WR, w=0.6	32.12	**21.05**	23.30	9.31	32.51	23.65
XLMRSum-WR, w=0.7	32.46	20.73	**23.67**	**9.77**	32.72	23.82
XLMRSum-WR, w=0.8	**32.86**	20.98	23.42	9.64	**32.93**	**23.91**
XLMRSum-WR, w=0.9	32.41	20.48	23.27	9.57	32.63	23.65
Train with Different Replacement Rates						
NLSSum w/ 0.45	33.09	21.75	24.13	9.84	32.42	24.25
NLSSum w/ 0.50	33.43	21.78	**24.17**	**9.99**	32.31	24.34
NLSSum w/ 0.55	**33.51**	21.74	24.10	9.91	**32.58**	**24.37**
NLSSum w/ 0.60	33.50	**21.81**	23.98	9.86	32.32	24.29

Table 6: Ablation Study, Zero-Shot ROUGE-L Results on Validation Dataset of MLSUM

ROUGE Results on WikiLingua To further evaluate the performance of NLSSum, we design additional zero-shot experiments for all our extractive models on WikiLingua. These models are trained on English and inferred on other three languages. The results are in Table 4. We observe that our NLSSum still performs better than all the other extractive models. Meanwhile, compared with the results on MLSUM, the improvement on WikiLingua is not remarkable. Probably because the documents and summaries in WikiLingua are a series of how-to steps, which are more platitudinous than news summarization.

5.1 Ablation Studies

To investigate the influence of each components in NLSSum, we conduct experiments on the validation set of MLSUM and the results are in Table 6. In neural label search, we have two weight predictors, the sentence level predictors $\mathcal{T}_\alpha$ and the label set level predictor $\mathcal{T}_\beta$ (Section 3.6). We can see from the first block of Table 6 that without $\mathcal{T}_\beta$, the result of NLSSum drops. NLSSum leverages four label sets (U_a, U_b, U_c and U_d) to train $\mathcal{T}_\alpha$ and $\mathcal{T}_\beta$. In the second block, we study the effect of each label set separately (note that XLMRSum-WR is the backbone of NLSSum and we therefore build label set baselines upon it). U_a works best overall. However, U_b is better on Russian compared to

b	c \ d	0.7	0.8
0.7	0.7	32.46	32.51
	0.8	32.33	32.49
0.8	0.7	32.94	**33.03**
	0.8	32.62	32.86

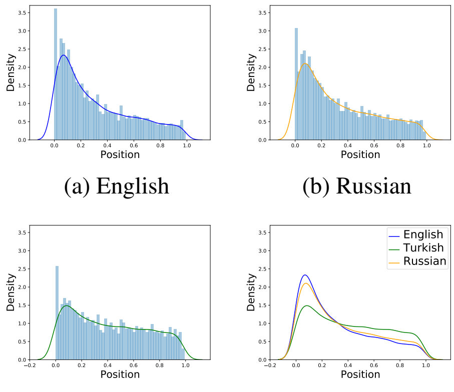
Table 7: ROUGE-L Results for Different Weights

U_a, which indicates these different label sets can compensate for each other. Not surprisingly, using one label set performs worse than NLSSum. In the third block, we use all the label sets, but we use *fixed weights* instead of using weight predicted from neural label search[4]. We can see using multiple label sets can improve variants with only one label set, but there is still a gap to NLSSum, which learns these weights for each sentence automatically. It is also possible to use different weights for different label sets. To make the number of experiments tractable, we conduct experiments on German only and search weight around our optimal value (i.e., 0.8). Results are in Table 7. There is slight gain by using different weights, but the result is still worse than NLSSum. In the last block, we train NLSSum with different word replacement rates. We observe that 55% is the best choice for the bilingual dictionary word replacement and the word replacement rate is not sensitive. In practice, we set the rate to 50% directly instead of tuning it, in order to make the our experiments in *true* zero-shot settings (Perez et al., 2021).

5.2 Human Evaluation

The human evaluation is important for summarization tasks, since the ROUGE can only determine the textual representation overlapping. In this subsection, we design the ranking experiment (Cheng and Lapata, 2016) with system outputs of different systems on the German test set of MLSUM. First, we randomly select 20 samples from the test set of German. Then, we extract summary sentences from the original document with four mBERTSum, XLMRSum, NLSSum, and Oracle. Third, we translate the document and summaries into English by Machine Translation. Finally, the human participants are presented with one translated English document and a list of corresponding translated summaries produced by different approaches. Each

[4] *Fixed weight* means a fixed weight for label sets U_b, U_c and U_d, instead of the label search in Section 3.6. Weight of original English labels U_a is set to 1.0, since the second block shows the quality of U_a is the highest.



(a) English (b) Russian (c) Turkish (d) Comparison

Figure 3: Density of Summary Sentences in CNN/DM

example is reviewed by five different participants separately. Participants are requested to rank these summaries by taking the importance and redundancy into account. To measure the quality of MT System, we first translate the English document into German and then back-translate it into English. We observed that there are almost no changes in meanings between the original English documents and the back-translated English documents. We therefore conclude the German to English translation quality is acceptable. As shown in Table 5, NLSSum is ranked 1st 28% of the time and considered best in the extractive models except for Oracle.

5.3 Monolingual Label Bias

In Figure 3, we calculate the positions of oracle sentence and plot the kernel density[5]. Specically, we translate the test set of CNN/DM from English into Turkish and Russian, and re-calculate the oracle labels for each language. Then, we collect all of the oracle sentences and keep its relative positions. It is obvious that: 1) The oracle sentences of English are mainly located in the head of document, and the Russian takes the second place, and then the Turkish. That is why the Turkish achieves more improvement than Russian, by comparing the results of NLSSum and XLMRSum in the in Part III of Table 3. 2) Multilingual labels pay more attention to the latter sentences, which is more suitable in multilingual summarization.

6 Conclusion

We first study the monolingual label bias, that when translate the (document, summary) from English

[5] https://en.wikipedia.org/wiki/Kernel_density_estimation

into other language, the re-converted labels will change along with the transformation of textual representation. Then we propose NLSSum to improve the performance of multilingual zero-shot extractive summarization, by introducing multilingual labels. Finally, the summarization model is trained on English with the weighted multilingual labels and achieves great improvement on other languages.

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