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

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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 (Neural Label Search for Summarization), 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.

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.

Table 1: Monolingual Bias for Different Languages.

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

\begin{itemize}
\item Work done during the first author’s internship at Microsoft Research Asia.
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\end{itemize}
(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 (Neural Label Search for Summarization) to search suitable weights for these labels in different sets. Specifically, 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 \(D = (s_1, s_2, ..., s_N)\) denotes a document with \(N\) sentences, where \(s_i = (w_1^i, w_2^i, ..., w_{|s_i|}^i)\) is a sentence in \(D\) with \(|s_i|\) words. \(S\) 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 \(D\) are obtained from \((D, S)\) by the
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 $S$ 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 $T_S$ (initialized with XLMR) and a document-level Transformer $T_D$ (a two-layer Transformer).

For each sentence $s_i$ in the input document $D$, $T_S$ is applied to obtain a contextual representation for each word $w_j$:

$$[u_1^i, u_2^i, ..., u_N^{i[S_N]}] = T_S([w_1, w_2, ..., w_N^{[S_N]}])$$

(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 $u_1^i$. The document-level Transformer $T_D$ (a two-layer inter-sentence Transformer), which is stacked to $T_S$, takes $s_i$ as input and yields a contextual representation $v_i$ for each sentence. We intend this process to further captures the sentence-level features for extractive summarization:

$$[v_1, v_2, ..., v_N] = T_D([u_1^1, u_2^1, ..., u_N^1])$$

(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:

$$\hat{y}_i = \sigma(W_o v_i + b_o)$$

(3)

where $W_o$ 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 transferability 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\(^\text{1}\) (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 \(D\) and its summary \(S\), we can obtain its extractive labels using the greedy algorithm introduced in Section 3.1.

**Label Set \(U_a\)** Let \(U_a = \text{GetPosLabel}(D, S)\) denote the indices of sentences with positive labels, where \(\text{GetPosLabel}(D, S)\) returns the indices of positive labeled sentences in the original English document \(D\) using the greedy algorithm. The labels created on English data \((D, S)\) 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 \(D\) and its summary \(S\) to FR using the MT method in Section 3.4, resulting \(D_{MT}\) and \(S_{MT}\) (also see Figure 2). Again by using the greedy algorithm, we obtain the indices of sentences with positive labels \(U_b = \text{GetPosLabel}(D_{MT}, S_{MT})\).

**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 \(D\) to \(D_{MT}\) using the MT method, while we translate \(S\) to \(S_{WR}\) using the WR method (we do 100% word replacement) with the EN-FR dictionary. The resulting label set \(U_c = \text{GetPosLabel}(D_{MT}, S_{WR})\).

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

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 \(T_{\alpha}\) denote the sentence level weight predictor and \(T_{\beta}\) the set level weight predictor. The implementation of \(T_{\alpha}(\cdot) = \sigma(g(T'_{\alpha}(\cdot)))\) is a two-layer transformer model \(T'_{\alpha}(\cdot)\) followed by a linear layer \(g(\cdot)\) and a sigmoid function. The implementation of \(T_{\beta}\) is the same as \(T_{\alpha}\), but with different parameters.

The predictor \(T_{\alpha}\) transforms sentence representations (see Equation (1) for obtaining \(u_i^j\)) to probabilities \(\alpha_i \in [0, 1]\) as follows:

\[
[\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_N] = T_{\alpha}([u_1^1, u_1^2, ..., u_N^N])
\]

\[
\alpha_i = \begin{cases} 
\hat{\alpha}_i, & \text{if } i \in U \\
0, & \text{otherwise}
\end{cases}
\]
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 \( T_\beta \) is similar, but we first do a mean pooling over sentences in each label set.

\[
[\beta_a, \beta_b, \beta_c, \beta_d] = T_\beta(l) = \left[ \frac{\sum_{i \in U_a} u_i^l}{n_a}, \frac{\sum_{i \in U_b} u_i^l}{n_b}, \frac{\sum_{i \in U_c} u_i^l}{n_c}, \frac{\sum_{i \in U_d} u_i^l}{n_d} \right]
\]

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.

\[
l_i = \alpha_i \times \frac{\sum_{j \in \{a,b,c,d\}} \beta_j}{m_i} \tag{5}
\]

where if \( i \in U_j \), \( \beta_j \) is \( \beta_j \), else \( \beta_j \) 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 \( \beta_j \) 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). \( y_i > 0.5 \) means sentence \( s_i \) could be selected as in summary. Therefore, when \( i \in U \), we rescale \( l_i \) to \([0.5, 1.0] \):

\[
l_i = \frac{l_i - l_{\text{min}}}{2 \times (l_{\text{max}} - l_{\text{min}})} + 0.5 \tag{6}
\]

where \( l_{\text{max}} \) and \( l_{\text{min}} \) 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 \( T_\alpha \) and \( T_\beta \). 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 \( T_\alpha \), we use binary labels \( y^a \), where in one document, \( y^a_i = 1 \) when \( i \in U \), otherwise \( y^a_i = 0 \). To train \( T_\beta \), we again use binary labels \( y^\beta \), but these labels are on set level rather than sentence level. Defining positive examples for \( T_\beta \) 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 \( T_\beta \) close to 1:1. The final loss is a sum of the four losses above:

\[
\mathcal{L} = CE(\hat{y}, y^a) + CE(\hat{y}, l) + CE(\alpha, y^\alpha) + CE(\beta, y^\beta) \tag{7}
\]

where \( CE \) is the cross entropy loss; \( l \) is the weighted multilingual label (Section 3.6); \( y^a, y^\alpha, y^\beta \) are binary labels for the supervision of \( \hat{y}, \alpha, \beta \). 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.

| 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            | 25,566 / 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 3: ROUGE-L on MLSUM dataset. * means extractive models, and others are abstractive models.

# 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 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 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, XLMR-Sum, 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 English 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-

### Table 3: Zero-Shot ROUGE-L Results of WikiLingua

| Models            | De   | Es   | Fr   | Ru   | Tr   | avg   |
|-------------------|------|------|------|------|------|-------|
| Oracle            | 30.81| 35.52| 34.64| 36.80| 36.30| 33.99 |
| Lead-3            | 16.32| 19.78| 18.40| 16.94| 16.70| 18.17 |
| mBERTSum          | 18.83| 22.49| 20.91| 19.94| 21.28| 20.74 |
| XLMRSum           | 22.10| 26.73| 25.06| 24.63| 24.63| 24.63 |
| XLMRSum-MT        | 21.92| 26.41| 24.75| 24.36| 24.36| 24.36 |
| XLMRSum-WR        | 22.20| 26.78| 25.10| 24.69| 24.69| 24.69 |
| NLSSum            | 22.45| 26.98| 25.34| 24.92| 24.92| 24.92 |

**Table 4: ROUGE-L on MLSUM dataset.**

| Models            | 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 | 10.13| 9.50  |
| mBERTSum          | 42.01| 20.44| 25.09| 9.48 | 32.94| 25.99 |
| XLMSum*           | 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 |

\(^{3}\)https://www.wikihow.com

\(^{3}\)https://github.com/pltrdy/rouge
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 English summarization dataset and inferred 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 documents 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 XLMR-

### Table 5: Human Evaluation on MLSUM, German

| Models   | 1st | 2nd | 3rd | 4th | Mean R |
|----------|-----|-----|-----|-----|--------|
| 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 6: Ablation Study, Zero-Shot ROUGE-L Results on Validation Dataset of MLSUM

| Models                  | De | Es | Fr | Ru | Tr | avg |
|-------------------------|----|----|----|----|----|-----|
| XLMRSum                 | 30.35| 20.67| 22.85| 9.39| 31.55| 22.81 |
| XLMRSum w/o $T_{\beta}$| 33.13| 21.21| 23.09| 9.72| 32.68| 23.97 |
| NLSSum $T_{\alpha}$     | 33.51| 21.74| 24.10| 9.91| 32.58| 24.37 |

Table 5: Human Evaluation on MLSUM, German

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

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.

**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 $T_{\alpha}$ and the label set level predictor $T_{\beta}$ (Section 3.6). We can see from the first block of Table 6 that without $T_{\beta}$, the result of NLSSum drops. NLSSum leverages four label sets ($U_a$, $U_b$, $U_c$, and $U_d$) to train $T_{\alpha}$ and $T_{\beta}$. 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
Table 7: ROUGE-L Results for Different Weights

| Position | English | Russian | Turkish |
|----------|---------|---------|---------|
| 0.0      | 0.0     | 0.0     | 0.0     |
| 0.5      | 0.0     | 0.0     | 0.0     |
| 1.0      | 0.0     | 0.0     | 0.0     |
| 1.5      | 0.0     | 0.0     | 0.0     |
| 2.0      | 0.0     | 0.0     | 0.0     |
| 2.5      | 0.0     | 0.0     | 0.0     |
| 3.0      | 0.0     | 0.0     | 0.0     |
| 3.5      | 0.0     | 0.0     | 0.0     |

Figure 3: Density of Summary Sentences in CNN/DM

5.3 Monolingual Label Bias

In Figure 3, we calculate the positions of oracle sentence and plot the kernel density. Specifically, 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
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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