Zero-shot Cross-lingual Alignment for Embedding Initialization

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Abstract

For multilingual training, we present CrossInit, an initialization method that initializes embeddings into similar geometrical structures across languages in an unsupervised manner. CrossInit leverages a common cognitive linguistic mechanism, Zipf's law, which indicates that similar concepts across languages have similar word ranks or frequencies in their monolingual corpora. Instead of considering point-to-point alignments based on ranks, CrossInit considers the same span of consecutive ranks in each language as the Positive pairs for alignment, while others out of the span are used as Negative pairs. CrossInit then employs Contrastive Learning to iteratively refine randomly initialized embeddings for similar geometrical structures across languages. Our experiments on Unsupervised NMT, XNLI, and MLQA showed significant gains in low-resource and dissimilar languages after applying CrossInit.

1 Introduction

Zipf's law suggests that words with similar meanings and senses in different languages may have similar word ranks in their monolingual corpus [1]. In multilingual training, the starting point is how Zipf's law reflects on the multilingual corpus we use. To observe this from an inspiring experiment, we considered a bilingual model by computing the word ranks on en and de Wikipedia dumps† [2]. Then, we downloaded conception mappings from CLLD (List et al., 2022)† to understand the correspondence between word ranks and conceptions, where conception mappings associate words to conceptions or semantics, e.g., "Etwas" (de), "Wenig" (de), "bit", and "little" are associated with the same

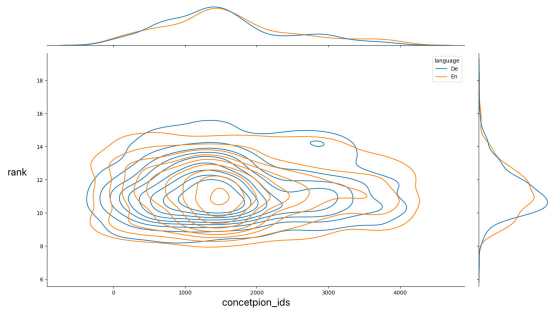

Figure 1: Correlation of word ranks and conceptions. We map words to conceptions via conception mappings from CLLD (List et al., 2022)†.

ID 2949, and the shared conception is "A LITTLE". Our results, presented in Figure 1, demostrated similar patterns across en and de. In conclusion, as supported by the literature (Zipf, 1949, 2013; Divjak and Caldwell-Harris, 2019), languages are motivated by common cognitive mechanisms to form similar structural patterns across languages, thus conforming to Zipf's law.

One idea we can derive from Zipf's law is how to align words in different languages without training, e.g., aligning words in initialization. However, directly aligning words across languages based on word ranks is still a challenge because it is impossible to use point-to-point alignments based on word ranks in practice. On multilingual corpus, although we use a shared vocabulary for all the languages, each language has a different local vocabulary, and words with similar concepts and meanings only have similar ranks (not identical) in the language, as observed in Figure 1. To address challenges, we can approximately separate totally irrelevant words or word ranks to some extend. Intuitively, we can consider Positive pairs between relevant spans of consecutive word ranks and Negative pairs between irrelevant ones. In this way, the multilingual model is encouraged to understand possible and impossible alignments between words across languages.

[1] Suppose f is the frequency of a word in the corpus and r is the rank. Zipf's law indicates $f = \frac{k}{r^\beta}$, where k and β are constants for the corpus. For instance, according to Wikipedia word frequency †, the English word "the" ($r = 1$) has a similar meaning to the German word "der" ($r = 1$).

[2] Sources, scripts, and tools marked with † are listed in Table 8. Source code will be publicly available.

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We present a method to take into account cross-lingual self-supervision for alignments in the embedding initialization phase. In a multilingual embedding space, there are two types of alignments: *1)* absolute and *2)* geometrical. The absolute alignment is based on language-agnostic word embeddings (Artetxe et al., 2017; Lample et al., 2018a), while geometrical alignments preserve language characteristics based on a similar geometric spatial structure across languages (Vulić et al., 2020). Our idea aligns Positive pairs and separate Negative pairs for similar geometrical structures that reflect on similar manifold patterns across languages. In other words, work ranks on monolingual corpus implicitly work as pivots or anchors for alignments across languages.

Another motivation comes from self-inference multilingual models (Ai and Fang, 2023b). Existing works have shown that a pre-trained multilingual model can infer translations for input words, where translations and input words have similar word ranks or frequencies on their monolingual corpora. If the model is more likely to understand words with similar ranks across languages as cross-lingual transferable entries, we can align these words in the initialization phase to provide meta-learning supervision.

In this work, we present CrossInit, a method to iteratively initialize an embedding space for a multilingual model before formal training or pre-training on a multilingual corpus. In each initialization step, according to word ranks in each language, we randomly sample a span of consecutive ranks and use all words (embeddings) in this span across languages for Positive pairs. In contrast, we create Negative pairs between words inside and outside of this span across languages. We show the idea in Figure 2. We experimented with Contrastive Learning to train these Positive and Negative pairs in each initialization step, but we believe there is a significant potential for the development of new alternatives. Our experimental results demonstrated that CrossInit can improve results in low-resource and dissimilar languages on unsupervised NMT, XNLI, and MLQA. We summarize contributions and findings as follows:

- We introduce CrossInit, an initialization method that aligns embeddings across languages for similar geometrical structures in an unsupervised manner.
- Previous works like (K et al., 2020) have provided some evidence that word frequencies alone do not contain enough information for cross-lingual learning. However, we found that words with similar frequencies might help the model in forming a similar structure across languages.
- CrossInit shows a long-term impact throughout multilingual training as it can predict a possible structure of the embedding space for cross-lingual transfer during the initialization phase.
- In experiments, CrossInit improved zero-shot cross-lingual transfer in multilingual training for low-resource and dissimilar languages.

2 Cross-lingual Initialization

CrossInit aims to iteratively initialize random embeddings using Contrastive Learning. Instead of standard initialization, CrossInit can be run before any multilingual pre-training for downstream tasks.

2.1 Step 1: Sorting

CrossInit requires a multilingual vocabulary across languages and word ranks based on their frequencies/counts in each language. To obtain these resouces, we first sample sentences from all the monolingual corpora with the temperature strategy (Lample and Conneau, 2019) to learn BPE codes and the multilingual vocabulary. Next, we count the occurrences of each word on each monolingual corpus and sort word counts in descending order. For our implementation,

- we used the multilingual vocabulary and the tokenizer of the target model. For example, in our experiments with XLM (Lample and Conneau, 2019), we use the multilingual vocabulary and the corresponding tokenizer of XLM.
- we collected word counts from the monolingual Wikipedia.

2.2 Step 2: Pairing

When createing Positive and Negative pairs, we randomly sample a span of consecutive ranks. We then create Positive pairs using words in this span across languages and Negative pairs using words inside and outside of this span. Suppose the span width is n, the language id is L_i, the word ranks

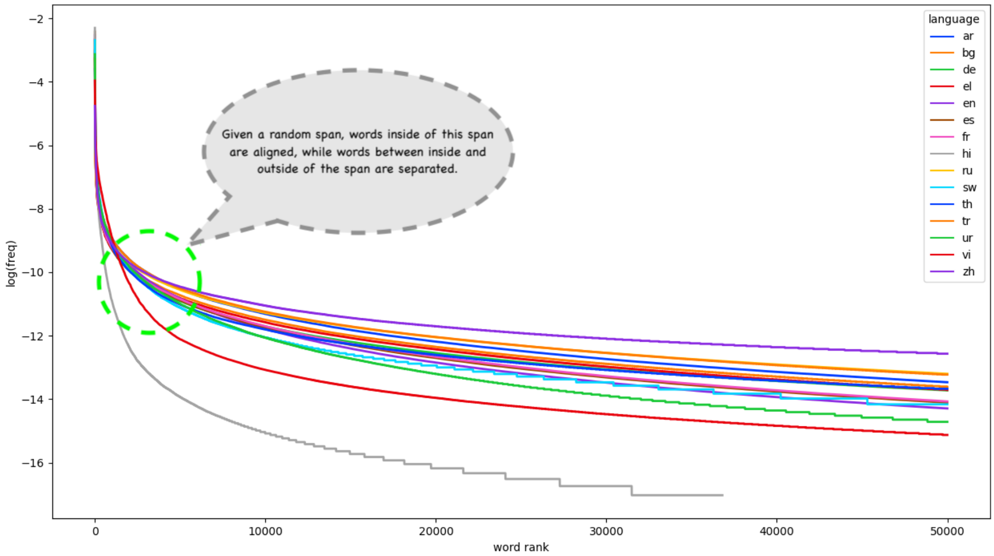


Figure 2: Example of CrossInit in each training step. We assign labels 1 and 0 to Positive and Negative pairs, respectively. Then, we leverage Supervised Contrastive Learning (SCL) to train embeddings from these pairs. We suggest frequent words in creating Positive pairs because frequencies across languages differ significantly in long tails.

for each language are V^{L_i}, and a random rank is k. We zip pairs:

- **Positive**: $\forall i, j : \{V^{L_i}_{span}, V^{L_j}_{span}\}$
- **Negative**: $\forall i, j : \{V^{L_i}_{span}, V^{L_j}_{\notin span}\}$

where $V^{L_i}_k$ stands for the word with rank k in V^{L_i}, $span$ is a span of consecutive ranks $[(k - n/2), \ldots, (k + n/2)]$. In our experiments, we considered a quite dev experiments to find the key hyperparameter n. We will discuss this later.

2.3 Step 3: Contrastive Learning

We randomly initialize all embeddings for the multilingual vocabulary. Then, in each CrossInit step, we run **Step 2: Pairing** to acquire Positive and Negative pairs for Contrastive Learning. We compute dot products between paired embeddings in Positive and Negative pairs, respectively. Then, we classify the two dot products with labels $\{1, 0\}$ (Positive and Negative). Formally, we have an initialization objective:

$$\begin{aligned}\mathcal{L}_{CrossInit} = &-\log P(1|E_{V^{L_i}_{span}} E^T_{V^{L_j}_{span}}) \\ &-\log P(0|E_{V^{L_i}_{span}} E^T_{V^{L_j}_{\notin span}}),\end{aligned} \quad (1)$$

where $E_{V^{L_i}_{span}} = \frac{1}{n}\sum_k^{V^{L_i}_{span}} E_{V^{L_i}_k}$, $E_{V^{L_j}_{span}} = \frac{1}{n}\sum_k^{V^{L_j}_{span}} E_{V^{L_j}_k}$, and $E_{V^{L_j}_{\notin span}} = \frac{1}{|V^{L_j}_{\notin span}|}\sum_k^{V^{L_j}_{\notin span}} E_{V^{L_j}_k}$. In this Contrastive Learning for initialization, we randomly select the span center k in **Step 2: Pairing** for different spans and i and j for different languages. We refine embeddings until the flatness of $\mathcal{L}_{CrossInit}$.

3 Analysis and Discussion

3.1 Setup

To analyze CrossInit quickly, we configured an XLM model (Lample and Conneau, 2019) and made 3 significant modifications:

- trained the model on 3 languages $\{En, De, Hi\}$.
- adjusted the number of layers to 3.
- ran CrossInit for the randomly initialized embeddings.

Any other settings are identical to the XLM model. In this scenario, the model is not overly parameterized for these three languages so that unsupervised cross-lingual transfer could succeed. Additionally,

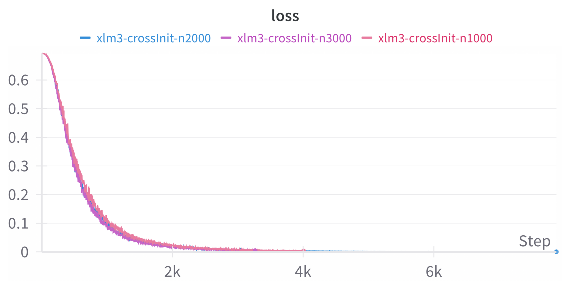


Figure 3: $\mathcal{L}_{CrossInit}$ with different span width.

Hi is distant from $\{En, De\}$, which can verify the effectiveness for distant and low-resource languages. We used Adam optimizer with learning rate $1e-4$ for CrossInit. We marked these settings as **XLM-tiny-3** in our work.

3.2 Hyper-parameter

In **Step 2: Pairing**, there are two important hyperparameters. The first one is the random bound of the span center k. As shown in Figure 2, we observed that word frequencies are divergent and not ideally comparable in the long tail area. Therefore, in our experiments, we only considered the first 20k most frequent words in each language as candidates for Positive pairs, i.e., words ranked between 1 and 20k in each language. This means that CrossInit does not consider words in the long tail area for Positive pairs. Those words contribute to over 80% of total word frequency in the training corpus. Note that Negative pairs still use all the ranks. The second one is the width of span n in Eq. 1. We experimented with 3 settings *span* $= \{1000, 2000, 3000\}$ for $\mathcal{L}_{CrossInit}$. As shown in Figure 3, we found that $\mathcal{L}_{CrossInit}$ become flat for all settings.

3.3 Type of Initialized Alignment

We examined the type of cross-lingual alignment CrossInit initializes in an unsupervised manner. We demonstrated PCA visualizations in Figure 4. We found that compared to Random initialization, CrossInit successfully formed some consistent patterns across languages, showing different distributions while sharing a similar geographic structure. Note that for shared tokens, we randomly choose colors for the scattered points. We observed that CrossInit was inclined to move shared tokens into a dense area.

3.4 Cross-lingual Analogy Test

Ai and Fang (2023a) used the classic analogy test: "English: *King* - *Man* + *Woman* = *Queen* and German: *König*-*Mann*+*Frau* = *Königin*" to observe cross-lingual analogical phenomenon. We show the results of 3 runs in Table 1. Compared to Random initialization, CrossInit obtains positive scores for mixed languages *multi*, indicating potential for kickstarting cross-lingual transferability. This test tells us that CrossInit might improve cross-lingual transferability due to cross-lingual analogy.

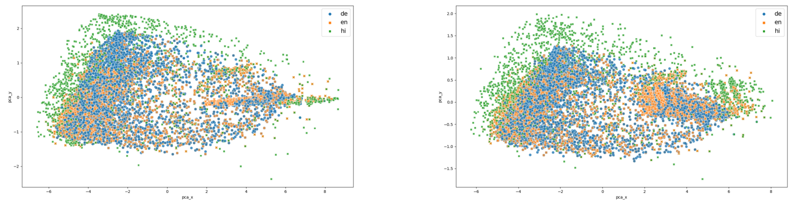
In addition to the above toy example, we developed more cross-lingual analogy tests using statements from mLAMA (Kassner et al., 2021). Specifically, mLAMA offers triples in the form of (object, relation, subject), e.g., (Paris, capital, France). Similar to the toy example, we created analogy tests in the form of $object_{lang1} - subject_{lang1} + subject_{lang2} = object_{lang2}$. As shown in Table 2, we observed that CrossInit can initialize cross-lingual analogy information.

3.5 Fast XNLI Experiment

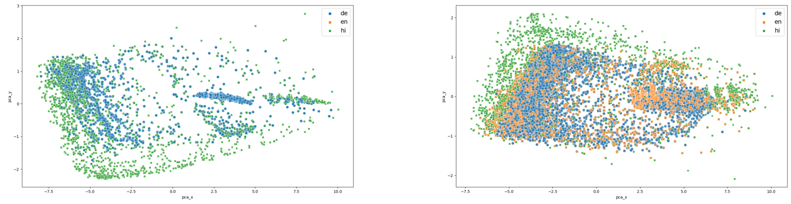
So far we have analyzed CrossInit from the perspective of cross-lingual alignments. Before applying it to standard multilingual experiments, we conducted an analysis of XNLI. We pre-trained XLM-tiny-3 for 200k steps with batch size 64 on Wikipedia dumps. We used Adam optimizer with a learning rate $1e-4$. For temperature sampling (Lample and Conneau, 2019), we set $\alpha = 0.7$. After pre-training, we evaluated XLM-tiny-3 on the XNLI dataset with zero-shot settings (only fine-tuning on the English dataset). We ran experiments *3 times* and showed the average results in Table 3. Due to the small size of the model and language diversities (i.e., Hi is distant), the model is difficult to learn zero-shot cross-lingual transferability in zero-shot settings because of "the curse of multilinguality" (Conneau et al., 2020). However, we still observe significant gains for the distant and low-resource language in all settings, which means the gain is agnostic to shared tokens. We attribute to a similar geometric structure CrossInit forms in initialization across languages. *We skip the introduction of both XLM and XNLI here and will introduce them properly in §Experiment.*

3.6 Predictable Structure and Lifetime Effect

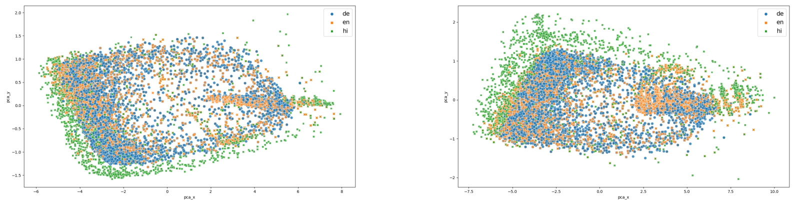
Recall that, in §Introduction, we justify our motivation of CrossInit from cognitive mechanisms and



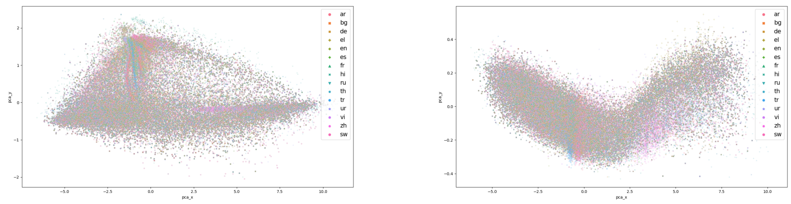
(a) XLM-3-tiny, span1000 vs after multilingual pre-training.



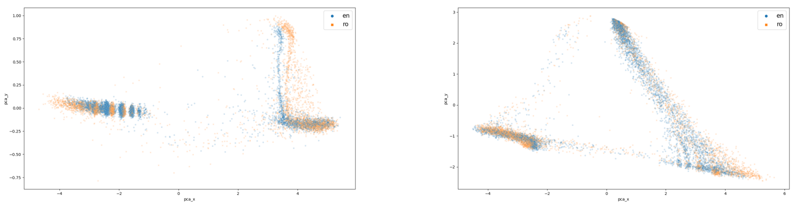
(b) XLM-3-tiny, span2000 vs after multilingual pre-training.



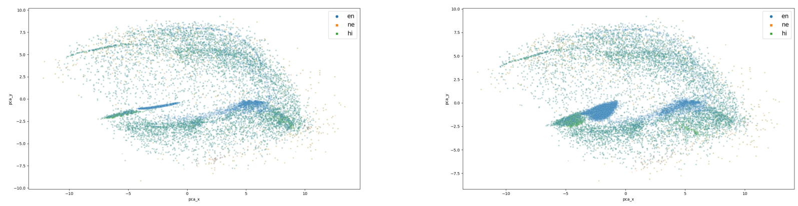
(c) XLM-3-tiny, span3000 vs after multilingual pre-training.



(d) XLM vs after multilingual pre-training.



(e) Bi-mBART-enro vs after multilingual pre-training.



(f) mBART-ennehi vs after multilingual pre-training.

Figure 4: PCA visualization for "CrossInit vs After Multilingual Pre-training". CrossInit is derived from the fact that languages are motivated by common cognitive mechanisms and results in Zipf's law with similar structural patterns, as reported in the literature (Zipf, 1949, 2013; Divjak and Caldwell-Harris, 2019). This is might be main reason that CrossInit predicts a possible structure of the embedding space for multilinguality and shows a long-term effect from beginning to ending.

X	cos (X , Queen)				cos(X , Königin)			
	Random	span=1000	span=2000	span=3000	Random	span=1000	span=2000	span=3000
mono: King-Man+Woman	0.00	0.90	0.90	0.93	-0.04	0.92	0.93	0.91
mono: König-Mann+Frau	-0.05	0.93	0.96	0.95	0.24	0.92	0.93	0.91
multi: King-Man+Frau	-0.08	0.85	0.85	0.91	-0.10	0.92	0.93	0.93
multi: King-Mann+Woman	0.04	0.97	0.98	0.96	0.24	0.91	0.91	0.89
multi: King-Mann+Frau	-0.05	0.96	0.97	0.96	0.16	0.92	0.93	0.91
multi: König-Man+Woman	0.00	87	0.87	0.92	0.04	0.92	0.93	0.92
multi: König-Man+Frau	-0.09	-0.78	0.80	0.89	-0.03	0.89	0.91	0.93
multi: König-Mann+Woman	0.04	0.96	0.98	0.96	0.32	0.91	0.92	0.90

Table 1: Word analogy: King - Man + Woman = Queen (German: König-Mann+Frau = Königin).

CrossInit	Lang1, 2=En, De	Lang1, 2=En, Hi	Lang1, 2=Hi, En	avg.
span=1000	0.601	0.222	0.258	0.360
span=2000	0.599	0.221	0.262	0.360
span=3000	0.613	0.233	0.265	0.370

Table 2: Word analogy from mLAMA statements. We create analogy tests in the form of $object_{lang1} - subject_{lang1} + subject_{lang2} = object_{lang2}$ from triples (object, relation, subject) in 3 languages . .

CrossInit	en	de	hi	avg.
Random initialization	71.01	51.08	38.22	53.40
span1000	71.57	52.15	39.80	54.50
span2000	71.45	53.05	41.09	55.20
span3000	71.49	52.53	42.07	55.36

Table 3: Fast XNLI Experiment. Results are reported by averaging 3 runs.

statistics on Wikipedia. However, if sufficient corpora are avaliable in training, the effectiveness of well-organized embeddings in initialization might be washed out due to extensive mappings between these trainable embeddings throughout training. There is an interesting question: *Can we predict a possible structure for the embedding space?* To answer this question, we compared the embedding space at CrossInit with the one after multilingual training. The idea is, if the two structures are similar, it is possible to predict an optimal structure for embeddings at initialization. To set up experiments, we considered XLM (encoder based) and mBART (encoder-decoder based). Figure 4 demonstrates the contrast between "CrossInit" and "After Multilingual Training", showing that the embedding space keeps its shape throughout training. This suggests that CrossInit has a lifetime effect and predicts a possible structure of the embedding space for all the languages at initialization.

4 Experiment

Our analysis including fast XNLI experiments show the effectiveness of CrossInit. In scaled experiments, we transfer our findings from our small setup to larger scale settings.

4.1 Multilingual Task

XNLI We experimented with the cross-lingual classification task on XNLI † (Conneau et al., 2018) including all 15 languages to test the general cross-lingual capabilities our method could impact. The model was only fine-tuned on the En NLI dataset for English classification, aiming at making zero-shot classification for other languages.

MLQA We experimented with MLQA† (Lewis et al., 2020) for a cross-lingual question-answering task. Given a question and a passage containing the answers, the goal is to predict the answer text span in the passage. This task involves identifying the answer to a question as a span in the corresponding paragraph. The evaluation data for English and 6 other languages are obtained by automatically mining target language sentences that are parallel to sentences in English from Wikipedia, crowd-sourcing annotations in English, and translating the question and aligning the answer spans in the target languages. Similar to XNLI, the model is fine-tuned on the English dataset and makes zero-shot predictions for other languages.

Unsupervised NMT UNMT (Lample and Conneau, 2019; Lample et al., 2018b; Liu et al., 2020) tackles bilingual translation (Bahdanau et al., 2015; Vaswani et al., 2017) on non-parallel bilingual corpora without access to any parallel sentence. In the pre-training phase, UNMT is trained on monolingual corpor with the objective of MLM for the two languages. During the training phase, on-the-fly back-translation (Sennrich et al., 2016) performs to generate synthetic parallel sentences that can be used for training of translation as NMT (neural machine translation) is trained on genuine parallel sentences in a supervised manner.

4.2 Model and dataset cards

We use pre-configured models, the corresponding tokenizers, and trainings datasets from Huggingface, showing in Table 4 .

	Model Card
XLM	facebook/xlm-mlm-xnli15-1024
mBART	facebook/mbart-large-en-ro
Wiki	wikimedia/wikipedia (version: 20231101)
CC	cc100
wmt16	wmt/wmt16
XNLI	facebook/xnli
MLQA	facebook/mlqa
FLoRes	facebook/flores

Table 4: List of model cards.

4.3 Multilingual Training with CrossInit

Following the previous work, we set up identical XLM and mBART using the model cards and the same corpora. We randomly initialize these models and utilize our CrossInit to embeddings. For pre-training, we used the Adam optimizer (Kingma and Ba, 2015) with hyperparameters $\beta_1 = 0.9$,$\beta_2 = 0.99$, $\epsilon = 10^{-6}$,$lr = 1e - 4$, and learning warm-up step 30k. We set dropout regularization with a drop rate $rate = 0.1$. We processed 18k tokens per training step. We trained the model until no improvements were observed in dev sets.

5 Result

5.1 XNLI

Setup and Fine-tuning After multilingual training with CrossInit, we fine-tuned the models on the English NLI dataset with mini-batch size 8. We used Adam optimizer (Kingma and Ba, 2015) with $lr = 5e - 6$. Categorical cross-entropy were employed with three labels: entailment, contradiction, and neutral. Following fine-tuning, we made zero-shot predictions for the other 14 languages.

Performance We report the result in Table 5. Our method consistently improves baseline models by 2.1% (Avg). As discussed in previous models (Conneau et al., 2018; K et al., 2020; Wu and Dredze, 2019; Pires et al., 2019; Dufter and Schütze, 2020), multilinguality is essential for this task. Then, we confirm the effectiveness of CrossInit in improving multilinguality for cross-lingual transfer. Additionally, the result is consistent with our fast experiment on XNLI as we observe more gains $\approx$ 8% in low-resource and dissimilar languages than rich-resource languages $\approx$ 2.5%. In this way, CrossInit is suitable for low-resource and dissimilar languages, which improve the fairness of multilingual models in the consideration of all the languages.

5.2 MLQA

Setup and Fine-tuning The setup is similar to the experiment on XNLI. We used Adam optimizer (Kingma and Ba, 2015) with $lr = 5e-5$ and linear decay of lr. Meanwhile, as suggested, we fine-tuned the model on the SQuAD v1.1 (Rajpurkar et al., 2016) dataset and then made zero-shot predictions for the 7 languages of MLQA.

Performance In Table 6, CrossInit substantially improves the overall performance (Avg) in terms of both F1 and EM metrics by 3 % and 2 %, respectively. In addition, CrossInit yields more improvements for low-resource and dissimilar languages, which is consistent with fast experiments and XNLI. Meanwhile, answers across languages are most likely to consist of analogous nouns and terms with similar frequencies in Wikipedia. CrossInit can prompt similar embeddings for them at initialization because of the dot products between Positive pairs. This could be observed from our word analogy tests. Finally, analogous words across different languages help the training process.

5.3 UNMT

Setup and Training We considered 2 language families. Specifically, we considered low-resource language pairs $Ro \leftrightarrow En$ on *newstest2016*. Meanwhile, we shared the FLoRes† (Guzmán et al., 2019) task to evaluate a dissimilar language pair $Ne \leftrightarrow English$ (Nepali). In the translation training phase, we used Adam optimizer (Kingma and Ba, 2015) with parameters $\beta_1 = 0.9$,$\beta_2 = 0.997$, $\epsilon = e - 9$, $warm\_up = 8000$ and $lr = 7e - 4$ (Vaswani et al., 2017). We set dropout regularization with a drop rate $rate = 0.1$ and label smoothing with $gamma = 0.1$ (Mezzini, 2018). On-the-fly back-translation (Sennrich et al., 2016) (the inference mode of the model) performed to generate synthetic parallel sentences that can be used for translation training as NMT (neural machine translation) is trained on genuine parallel sentences in a supervised manner. We reported BLEU computed by *scareBLEU*† with default rules.

Performance In Table 7, we report *sacreBleu* † to compare with mBART (Liu et al., 2020). Given Ne's extremely low resources, we use its similar language Hi in our multilingual training. We observed that CrossInit improves low-resource and dissimilar languages significantly. The findings

Model	en	fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur	Avg
XLM Conneau et al. (2018)	73.7	67.7	68.7	67.7	68.9	67.9	65.4	64.2	64.8	66.4	64.1	65.8	64.1	55.7	58.4	65.6
mBERT (Devlin et al., 2019)	81.4		74.3	70.5					62.1			63.8			58.3	
XLM ⋆	83.1	76.4	76.3	74.2	73.1	74.0	73.1	67.6	68.3	71.1	69.1	71.6	65.6	64.5	63.3	71.4
+ CrossInit	83.2	77.3	76.8	74.8	73.9	75.0	73.9	70.9	70.8	73.4	71.4	73.9	69.3	68.8	67.8	73.5

Table 5: Performance of cross-lingual classification on XNLI. During multilingual training, models are initialized by CrossInit and trained on 15 languages. ⋆ denotes models we reimplement with model cards.

Model	en	es	de	ar	hi	vi	zh	Avg
(Lewis et al., 2020)	80.2 / 67.4							
mBERT	77.7 / 65.2	64.3 / 46.6	57.9 / 44.3	45.7 / 29.8	43.8 / 29.7	57.1 / 38.6	57.5 / 37.3	57.7 / 41.6
XLM	74.9 / 62.4	68.0 / 49.8	62.2 / 47.6	54.8 / 36.3	48.8 / 27.3	61.4 / 41.8	61.1 / 39.6	61.6 / 43.5
+CrossInit	75.9 / 64.1	70.8 / 50.4	64.7 / 48.1	57.5 / 39.1	51.5 / 29.4	64.5 / 42.5	63.9 / 41.2	63.8 / 45.1

Table 6: Performance of cross-lingual question answering on MLQA. We report the F1 and EM (exact match) scores for zero-shot prediction. During multilingual training, models are initialized by CrossInit and trained on 15 languages.

of this experiment align with other experiments conducted in this work. CrossInit initializes geometrical alignments and multilingual analogies, helping the model preserve language characteristics based on a similar geometric spatial structure across languages (Vulić et al., 2020). As a result, we suspect that translation might be more fluent due to the initialized language characteristics and dependencies of each language.

6 Related Work and Other Inspiration

Structural Similarity and Zipf's Law Zipf's law (Zipf, 1949, 2013; Søgaard, 2020) indicates that words or phrases appear with different frequencies, and one may suggest analogical words or phrases appear with relatively similar frequencies in other languages. In multilingual training, Wu et al. (2020); K et al. (2020); Pires et al. (2019); K et al. (2020); Sinha et al. (2021) study structural information and find that structural similarities across languages are essential for multilinguality, where in this paper, structural similarities refer to similar ranks as Zipf's law indicated. Another interesting work is from Ai and Fang (2023a). They use translation pairs to show that phrases with similar meanings have similar (not identical) frequencies in comparable corpora. In our work, we consider spans of word ranks to alleviate the non-identical problem reported by (Ai and Fang, 2023a) with Contrastive Learning. Moreover, Artetxe et al. (2020) show that monolingual models trained individually on monolingual corpora eventually result in a similar structure including the embedding space. In our case, due to Positive and Negative pairs used for Contrastive Learning, embeddings are refined to a similar geometric structure in the embedding space across languages.

6.1 Intuition from V-structure Dependency

Multilingual training with the MLM objective (Devlin et al., 2019; Lample and Conneau, 2019) usually forms a vocabulary that covers shared tokens across 1+ languages. This v-structure dependency is explored and leveraged in different perspectives including multilingual BOW (Ai and Fang, 2023b), information theory (Chi et al., 2021), language domain adaptation (Ai and Fang, 2022), and data augmentation processes (Krishnan et al., 2021; Chaudhary et al., 2020; Tarunesh et al., 2021). In this work, we follow this line but concentrate on initialization. Meanwhile, tokens do not have to be shared as the information bottleneck principle pushes cross-lingual structural similarity into isomorphic representations (Chi et al., 2021), which have similar bridge effects as the anchor points. In our idea, we do not rely on shared tokens but consider a span with similar ranks across languages to initialize a geometrical structure with Contrastive Learning. Our analysis shows that the initialized geometrical structure can be retained from beginning to end in multilingual training.

6.2 Pre-trained Embeddings for Initialization

Qi et al. (2018) shows an effective initialization from pre-trained embeddings for downstream multilingual tasks. (Dufter and Schütze, 2020; Ai and Fang, 2023b) considers pre-trained embeddings in initialization for multilingual training with the MLM objective. We share the same goal. Compared to those existing works, which consider embedding similarity, CrossInit uses word ranks as implicit signals to align and refine embeddings.

Language pair	$Ro \leftrightarrow En$		$Ne \leftrightarrow En$	
mBART25	30.5	35.0	10.0 (+cc25)	4.4 (+cc25)
bi-mBART $\star$	31.5	32.9	2.3 (+Hi)	0.5 (+Hi)
bi-mBART + CrossInit	32.2	36.3	4.2 (+Hi)	2.1 (+Hi)

Table 7: Performance of UNMT. During multilingual training, models are initialized by CrossInit and trained on monolingual corpora in paired languages. Given Ne's extremely low resources, we use its similar language Hi in our multilingual training (+Hi). $\star$ denotes models we reimplement with model cards. +cc25 stands for using cc25 corpora.

Another interesting line is initializing embeddings for transfer learning (Minixhofer et al., 2022; Kim et al., 2019), where new embeddings are properly initialized in order to be merged with pre-trained embeddings. In contrast, we focus on initializing embeddings before training. However, CrossInit might be further explored for a similar application.

7 Conclusion

In this work, we present CrossInit, an initialization method to arrange embeddings into similar geometric structures in an unsupervised manner. CrossInit is based on Zipf's law, a common cognitive mechanism, that indicates similar concepts across languages have similar word ranks or frequencies in their monolingual corpora. To alleviate non-identical ranks across languages, CrossInit considers a span of consecutive ranks in each language as the Positive pairs for alignment while others out of the span are Negative pairs.CrossInit further employs Contrastive Learning for Positive and Negative pairs to refine embeddings. In our analysis, we observed that CrossInit can predict a possible structure of the embedding space for cross-lingual transfer and show a long-term effect over the course of multilingual training. In our experiments on UNMT, XNLI, and MLQA, we observed significant gains in low-resource languages and dissimilar languages after applying CrossInit.

8 Limitation

We did not conduct experiments on incomparable corpora. Incomparable corpora across languages might have different domains, which results in significant differences in word ranks as Zipf's law might be satisfied only for similar domains in practice. This might limit the scope of our method. However, multilingual models are commonly pre-trained on comparable corpora, e.g., Wikipedia and CC.

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Table 8: Links of source.

Item	Links
WMT 2016	http://www.statmt.org/wmt16/translation-task.html
XTREME	https://github.com/google-research/xtreme
fastBPE	https://github.com/glample/fastBPE
MUSE	https://github.com/facebookresearch/MUSE
Cambridge Dictionary	https://dictionary.cambridge.org/
SemEval'17	https://alt.qcri.org/semeval2017/task2/
WikiExtractor	https://github.com/attardi/wikiextractor
PyThaiNLP	https://github.com/PyThaiNLP/pythainlp
Stanford Word Segmenter	https://nlp.stanford.edu/software/segmenter.html
Tensor2Tensor	https://github.com/tensorflow
HuggingFace	https://huggingface.co
ORPUS, Wikipedia v1.0	https://opus.nlpl.eu
Wiktionary:Frequency lists	https://en.wiktionary.org/wiki/Wiktionary:Frequency_lists

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