

ZhichunRoad at SemEval-2022 Task 2: Adversarial Training and Contrastive Learning for Multiword Representations

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Abstract

This paper presents our contribution to the SemEval-2022 Task 2: Multilingual Idiomaticity Detection and Sentence Embedding. We explore the impact of three different pre-trained multilingual language models in the SubTaskA, By enhancing the model generalization and robustness, we use exponential moving average (EMA) method and the adversarial attack strategy. In the SubTaskB, we add an efficient cross-attention module to exchange information with the other sentence. We jointly train the model with contrastive objective and employ a momentum contrast to enlarge the number of negative pairs. Additionally, we use the alignment and uniformity properties to measure the quality of sentence embeddings. Our approach obtained competitive results and ranked among the top-10 systems in both subtasks. We release the source code and pre-trained models associated with this work.¹

1 Introduction

In recent years, the pretrained models have been widely used and playing a vital role in the natural language processing tasks. The success of language models relies on huge amounts of unlabeled data and the useful representation layers that are designed to draw on information from the surrounding context (Devlin et al., 2018; Nedumpozhi-[mana and Kelleher, 2021](#)). However, more recent studies show that even state-of-the-art pre-trained contextual models (e.g. BERT) cannot accurately represent idiomatic expressions (Yu and Ettinger, 2020; Garcia et al., 2021). One reason for this is that many expressions can be used both literally or idiomatically. Specifically, the size of vocabulary can't increase indefinitely, which makes representing idiomatic phrases particularly challenging (Shwartz, 2021; Tayyar Madabushi et al., 2021). Idioms occur in almost all languages, to

SubTask	Train	Dev	Test	Desc
zero-shot	4492	740	763	binary classification
one-shot	4632	740	763	
pre-train	24498	2000	3827	semantic text similarity
fine-tune	6573	2182	2263	

Table 1: The statistics of datasets.

distinguish whether an expression has an idiomatic sense would leverage both cross-lingual models and multiword expressions (MWEs). The SemEval 2022 Task 2(2021) is aimed at detecting and representing MWEs and presents a novel multilingual dataset across English, Portuguese and Galician. And this task consists of two different subtasks to evaluate the model's ability to identify and capture idiomaticity.

Our contributions can be summarized as follows: 1) We choose three transformer-based language models from XTREM Leaderboard (Hu et al., 2020), and compare the effectiveness of MBERT_{base} (Devlin et al., 2018), XLM-R_{base} (Conneau et al., 2020) and InfoXLM_{base} (Chi et al., 2021). 2) We adopt the exponential moving average method (EMA) and adversarial training strategy to improve the model's generalization and robustness. We achieve considerably performance gain of 4.9%, 7.1% over the baseline solution, and ranked top-6 in the zero-shot and one-shot settings. 3) With fine-tuning on the supervised target datasets, we use cross-attention module and jointly train the model with an extra contrastive loss layer on top of the BERT encoder. Our approach achieves a 2.6%, 9.9% improvement compared to the baseline solution, and ranked top-3 in the pre-train and fine-tune settings.

Moreover, we find that the adversarial training can achieve good performance with setting the appropriate minibatch size. In the SubTaskB, we

¹<https://github.com/cuixuange>

show that jointly training regularizes the sentence embeddings’ anisotropic space to be more uniform but also suffers a degeneration in alignment slightly. The trade off between the alignment and uniformity (Wang and Isola, 2020) indicates that perfect alignment and perfect uniformity are likely hard to simultaneously achieve in practice.

2 Background

SemEval-2022 Task 2 provides two subtasks. In Subtask A, there is a binary classification task aimed at determining whether a sentence contains an idiomatic expression. The sample of the dataset consists of previous sentence, target sentence, next sentence and MWE. The target sentence contains the potentially idiomatic MWE, and the label of 0 indicates "Idiomatic" and the label of 1 indicates "non-idiomatic". Our model receives the context sentences as input in the zero-shot setting, and receives the target sentence with adding the MWE as an additional feature in the one-shot setting. This is based on the results presented in the dataset paper (Tayyar Madabushi et al., 2021).

In SubtaskB, there is a novel task which requires the model to output the correct Semantic Text Similarity (STS) scores. The task is designed to test a model’s ability to generate sentence embeddings that accurately represent sentences regardless of whether or not they contain idiomatic expressions. When evaluating the trained model, we first obtain the sentence embeddings, then we calculate the spearman correlation between the cosine similarity scores of sentence embeddings and the human-annotated gold labels. The statistics of the corpus are shown in Table 1. Our team participated in both subtasks, and the next section will introduce an overview of our system.

3 System Overview

We focus on comparing the impact of different training techniques that adopted in our system. In this section, we first present the BERT-like text encoder, then we introduce several strategies for improving models’ robustness. Finally, we talk about the design of cross-attention module and the jointly training way of incorporating supervised signals and unsupervised signals.

3.1 Transformer-based Models

In the zero-shot and one-shot settings, we compare several pre-trained multilingual language models

from XTREME Leaderboard² as the text encoder. The models shown below are also available on the hugging-face website³.

M-BERT_{base}, the bert-base-multilingual-cased model is pretrained on the top 104 languages with the Wikipedia dataset, and consists of 12-layer, 768-hidden, 12-heads, 109M parameters and a shared vocabulary size of 110000 (Devlin et al., 2018).

XLM-R_{base}, the xlm-roberta-base model consists of 100 languages and pretrained with filtered CommonCrawl dataset, and consists of 12-layer, 768-hidden, 12-heads, 270M parameters and a shared vocabulary size of 250002 (Conneau et al., 2020).

InfoXLM_{base}, we use the "microsoft/infoclm-base" model containing 94 languages and pre-trained with CCNet dataset, and has the same configurations of XLM-R and a shared vocabulary size of 250002 (Chi et al., 2021).

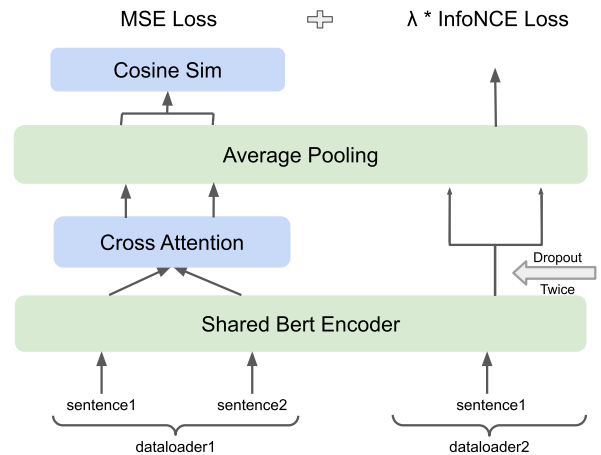


Figure 1: Incorporating supervised and unsupervised signals. MSE Loss: the mean squared error, InfoNCE Loss: the contrastive objective.

3.2 Training Procedures

There are two ways of enhancing the model generalization and robustness.

Exponential Moving Average Our model uses EMA to smooth the trained parameters. Evaluations that use averaged parameters sometimes produce significantly better results than the final trained values. Formally, we define the smoothed variables and trained variables as θ_s and θ_t , EMA decay weight as η . After each training step, we update θ_s by:

$$\theta_s \leftarrow \eta\theta_s + (1 - \eta)\theta_t \quad (1)$$

²<https://sites.research.google/xtreme>

³<https://huggingface.co/models>

SubTask	Model	ALL Data	Idiom Data	STS Data
pre-train	mbert _{base}	67.90	21.87	81.82
	mbert _{base} [◇]	70.58	27.18	81.09
	mbert _{base} [♣]	71.34	26.98	80.42
fine-tune	mbert _{base}	66.29	34.59	54.29
	mbert _{base} [◇]	76.16	29.95	46.49
	mbert _{base} [♣]	77.84	45.79	50.65

Table 2: Performance of Our Approach on the Sentence Representation Task. We report the spearman correlation $\times 100$ on the test sets, \diamond : jointly train the model with the contrastive objective, \clubsuit : jointly train the model with the cross attention module and the contrastive objective.

Before evaluating, we assign θ_s to the variables of our model. And then we restore these variables before continuing training.

Adversarial Training Recently, adversarial attack has been widely applied in computer vision and natural language processing (Yan et al., 2021). Many works use it during fine-tuning, because computing adversarial perturbations relies on supervised signals. We explore the influence of adversarial training strategies with different minibatch size, and compare the FGSM (Goodfellow et al., 2015), PGD (Madry et al., 2019), FREELB (Zhu et al., 2020) and SMART (Jiang et al., 2020) methods in the zero-shot and one-shot settings. It works by augmenting the input with a small perturbation that maximizes the adversarial loss:

$$\min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[\max_{\Delta x \in \Omega} L(x + \Delta x, y; \theta) \right] \quad (2)$$

where the \mathcal{D} is dataset, x is input, y is the gold label, θ is the model paramters, $L(x, y; \theta)$ is the sample loss and Δx is the perturbation. In our experiments, we adopt SMART method in zero-shot setting, and FREELB method in one-shot setting. These choices are based on actual performance.

3.3 Sentence Representation

Reimers and Gurevych (2019) proposes a siamese architecture with a shared BERT encoder to compute the sentence representations for each input text. By making use of unlabeled texts, SimCSE (Gao et al., 2021) proposes an unsupervised contrastive learning method to alleviate the collapse issue of BERT. Compared to unsupervised SimCSE, we use extra supervised signals during training. Our approach is mainly inspired by ConSERT (Yan et al., 2021) and EsimCSE (Wu et al., 2021). As shown in Figure 1, there are two major objectives

and an extra cross-attention module to exchange information with the token-wise embeddings.

$$\mathcal{L}_{\text{joint}} = \mathcal{L}_{\text{mse}} + \lambda \mathcal{L}_{\text{con}} \quad (3)$$

, the λ is a hyparameter to balance two objectives. \mathcal{L}_{mse} is Mean Squared Error, \mathcal{L}_{con} is Contrastive Loss.

During training, each data point is trained to find out its counterpart among $(N - 1)$ from in-batch negative samples and the queue of data samples. The samples in the queue are progressively replaced (He et al., 2019).

$$\ell_i = -\log \frac{e^{\text{sim}(\mathbf{h}_i, \mathbf{h}_i^+)/\tau}}{\sum_{j=1}^N e^{\text{sim}(\mathbf{h}_i, \mathbf{h}_j^+)/\tau} + \sum_{q=1}^Q e^{\text{sim}(\mathbf{h}_i, \mathbf{h}_q^+)/\tau}} \quad (4)$$

The h_* is the sentence representation, where h_i and h_i^+ are semantically related. The h_q^+ denotes a sentence embedding in the momentum-updated queue. And the Q is the size of the queue, $\text{sim}(h_1, h_2)$ is the cosine similarity scores of sentence representations, τ is a temperature hyperparameter. In the end, we average the all N \mathcal{L}_i losses to calculate the contrastive loss \mathcal{L}_{con} .

4 Experiments

4.1 Settings

We use InfoXLM_{base} (Chi et al., 2021) as the text encoder, the EMA decay weight is set to 0.999, the learning rate is set to 2e-5 with warmup ratio over 10% in the SubTaskA. We compare the impact of minibatch size $\in \{16, 32, 64\}$ with different adversarial training strategies. By default, We set ε to 1.0 in FGM, set K steps to 3 in PGD, FREELB and SMART. That means calculate 3 steps in the adversarial attack. We adopt λ as 0.5 and μ as 0.2 to smooth the logits and embeddings

SubTask	Model	Dev	Test
zero-shot	mbert _{base}	70.46	68.71
	infxlm _{base} \diamond	76.43	73.67
one-shot	mbert _{base}	84.77	86.91
	infxlm _{base} \clubsuit	91.80	94.07

Table 3: Performance of Our Approach on the Idiomaticity Detection Task. We report the F1 Score $\times 100$ on the dev and test sets, \diamond : set bathsize to 16 and use SMART, \clubsuit : set bathsize to 32 and use FREELB.

Method	Dev
M-Bert _{base}	70.46
InfoXLM _{base}	73.10
+EMA	75.75
+SMART	76.43

Table 4: The effect of different strategies and keep accumulating from top to bottom. We report the dev-F1 Score $\times 100$ in zero-shot setting..

in the SMART method (Jiang et al., 2020). We use SMART method and batches of size 16 in zero-shot setting, FREELB method and batches of size 32 in one-shot setting.

In the SubTaskB, we use M-BERT_{base} (Devlin et al., 2018) as the text encoder, set batch size to 32 and set warmup ratio to 10%. During the jointly training, λ is set to 0.15 and τ is set to 0.05 that used in the \mathcal{L}_{con} . We use the dev set of STS-B and ASSIN2 to tune the hyperparameters and evaluate the model every 250 steps during training. The best checkpoint is saved for testing, we further discuss the results of our experiments in the subsequent section.

4.2 Main Results

Our submitted results were evaluated on F1 Score in SubTaskA, and spearman correlation in SubTaskB. We jointly train the model with contrastive objective and the supervised signals on the Semantic Text Similarity dataset, including STS-Benchmark and ASSIN2 datasets. We compare several pre-trained models as the text encoder and different training methods, as described in Section 3. The main results shown in Table 2 and Table 3.

As shown in Table 3, we achieve a performance gain of 4.9%, 7.1% over the baseline solution by finetuning the InfoXLM_{base} model with using

EMA method and adversarial training. In the Table 2, our approach achieves a 2.6%, 9.9% improvement compared to the baseline solution that indicates the usefulness of the cross-attention module and jointly training way. In the next section, we study the effect of different strategies.

5 Ablation Studies

5.1 Effect of Pretrained Models

We investigate the impact of adopting different multi-lingual models in the zero-shot setting. In the Figure 2, we show the results of different language models fine-tuning in 50 epochs. We find that the best f1 score on validation dataset is provided by InfoXLM_{base} (Chi et al., 2021).

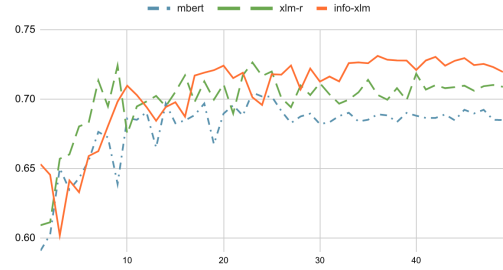


Figure 2: The fine-tuning of multi-lingual language models. We report the dev-F1 Score in zero-shot setting.

5.2 Effect of Training Techniques

As shown in Figure 3, we set bath size to 16 and use 0.999 as the EMA decay weight to obtain the best score. In the zero-shot and one-shot settings, we find that the performance is extremely sensitive to the batch size. And with the benefit of smoothing performance, using the EMA method can improve the model robustness when evaluating the trained model.

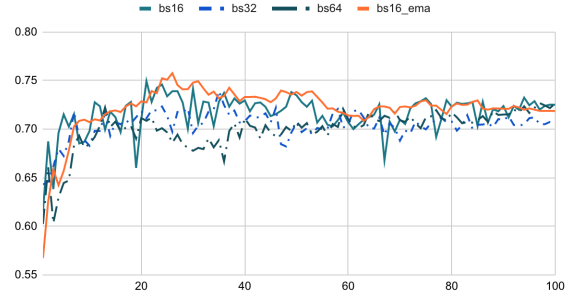


Figure 3: The batch size with EMA method. We report the dev-F1 Score in zero-shot setting.

The experimental results of adversarial training are presented in Figure 4. We set the size of mini-batch to 16 and use SMART in the zero-shot setting,

Method	Dev
M-Bert _{base}	78.93
+CrossAttention	79.74
+InfoNCE	79.85
+MoCo	80.14

Table 5: The effect of different strategies on the STS-Test dataset. We report the spearman correlation $\times 100$ in pre-train setting.

and the batch size is set to 32 and use FREELB as adversarial attack in one-shot setting. We observe that the SMART and FREELB strategies have better performance than FGM and PGD strategies.

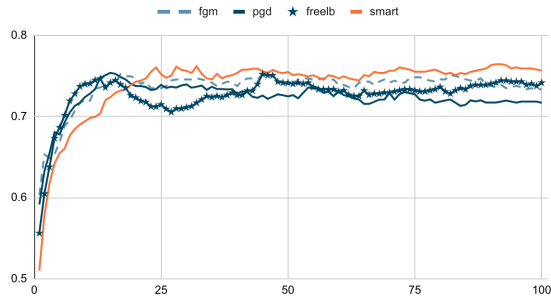


Figure 4: The performance of different adversarial attack strategies. We report the dev-F1 Score in zero-shot setting.

As presented in Table 4, we explore the impact of InfoXLM_{base} model, smaller batch size, EMA method and adversarial training. These strategies can effectively improve the performance of our approach.

5.3 Effect of Contrastive Learning

In this section, we investigate the contrastive learning how to further improve the performance of sentence representations. As shown in Table 5, we use contrastive learning as unsupervised signals which yields a substantial improvement on the STS-Test dataset. We also use an extra cross-attention layer to achieve a 0.8%, 1.2% improvement in the pre-train and fine-tune settings. The cross attention idea is inspired by Reimers and Gurevych (2019), the paper shows that the Cross-Encoder achieves better performances than Bi-Encoders.

In general, models which have both better alignment and uniformity obtain better sentence representations, confirming the findings in Wang and Isola (2020). We also evaluate these metrics to measure the quality of learned embeddings, including alignment of the positive pairs and uniformity

of the whole representation space. We calculate uniformity on the STS-B and ASSIN2 datasets, and alignment from the positive pairs that have the gold label more than or equal to the number 4.

As shown in Figure 5, we also find that: 1) Though pre-trained embeddings have good alignment, their uniformity is poor, e.g. M-Bert_{base}. 2) Unsupervised SimCSE_{base} (Gao et al., 2021) has better uniformity of pre-trained embeddings than M-Bert_{base}. 3) Jointly training regularizes the sentence embeddings’ anisotropic space to be more uniform than others, but also suffers a degeneration in alignment slightly. 4) The trade off between the alignment and uniformity indicates that perfect alignment and perfect uniformity are likely hard to simultaneously achieve in practice.

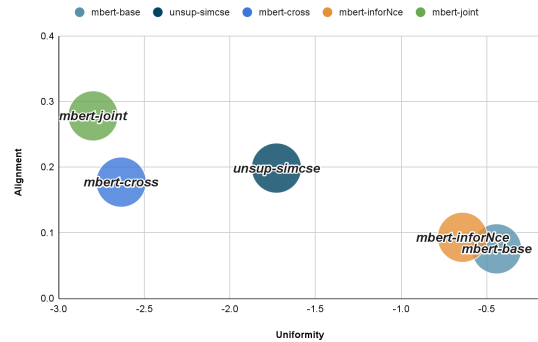


Figure 5: The alignment and uniformity of different pre-trained models. The closer to the origin of the coordinate axis, the better sentence representations.

6 Conclusion and Future Work

In this work, we provide an overview of the combined approach to detect and represent multiword expressions. We use InfoXLM_{base} model as the text encoder and enhance the model generalization and robustness with exponential moving average (EMA) method and the adversarial attack strategy in the SubTaskA. In the SubTaskB, experimental results show that the cross-attention module and the contrastive learning task can considerably improve the performance. Finally, we analyze the alignment and uniformity properties to measure the quality of sentence embeddings.

Future work of our system includes: 1) Using the larger pretrained language models, such as M-BERT_{large}, InfoXLM_{large}. 2) Adopting other data augmentation, including Token-Shuffle, Token-Cutoff and Mix-Up.

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