

High Lights

Subtask A=Text Classification

Our approach:

EMA + Adversarial Training

Subtask B=Sentence Embedding

Our approach:

Sentence-Bert + Cross-Attention
+ Contrastive Learning

Rank 12th In the SubA, Zero-Shot

Rank 4th In the SubA, One-Shot

Rank 4th In the SubB, Pretrain

Rank 4th In the SubB, Finetune

Paper:

https://github.com/cuixuage/SemEval2022-Task2/blob/main/semEval_2022_task2.pdf

Code:

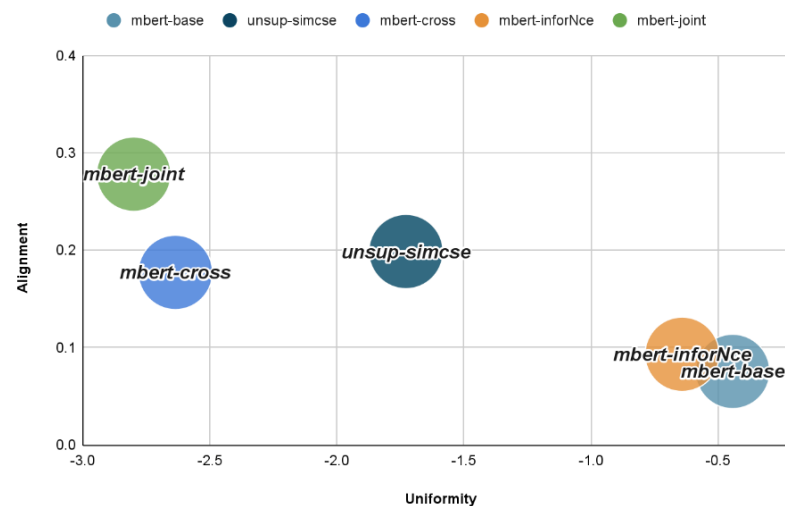
<https://github.com/cuixuage/SemEval2022-Task2>

Adversarial Training and Contrastive Learning for Multiword Representations

In the SubTaskA, we use InfoXLM as text encoder and exponential moving average (EMA) method and the adversarial attack strategy.

In the SubTaskB, we add an cross-attention module, contrastive objective and employ a momentum contrast.

Additionally, we use the alignment and uniformity properties to measure the quality of sentence embeddings.



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., 2020).

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

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 ℓ_i losses to calculate the contrastive loss \mathcal{C}_{con} .

