CBERTdp

Clustering BERT Embeddings for Classification in Sentiment Analysis via Dot Product

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Objective

Enhaning the efficiency of Sentiment Analysis

- By redistributing the tasks laid upon neural networks
- While maintaining a good accuracy

How?

Employing **K-means clustering** and the **dot product**

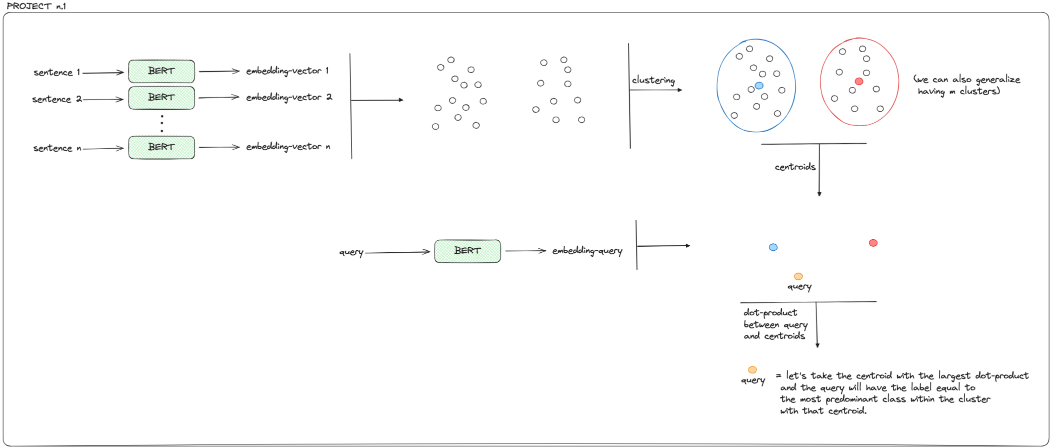
- Clustering BERT [2] embeddings
- Classification via dot product between centroids and new embedding
- *Three approaches*
  - Each of different complexity to increase the accuracy step-wise
- Can be extended to other classification problems

Which are the related studies?

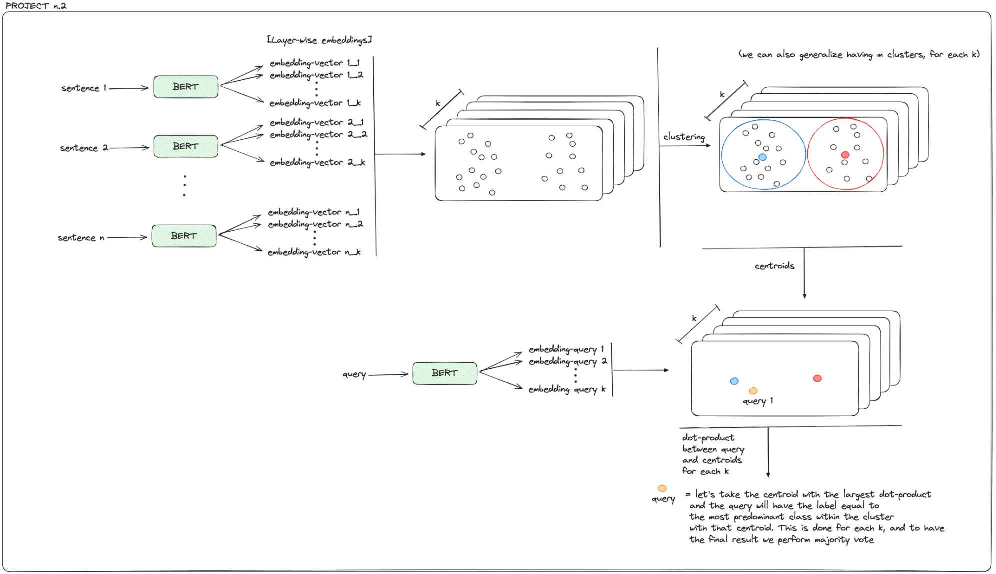
Clustering BERT embedding is not a new idea, indeed much research has been conducted in this field:

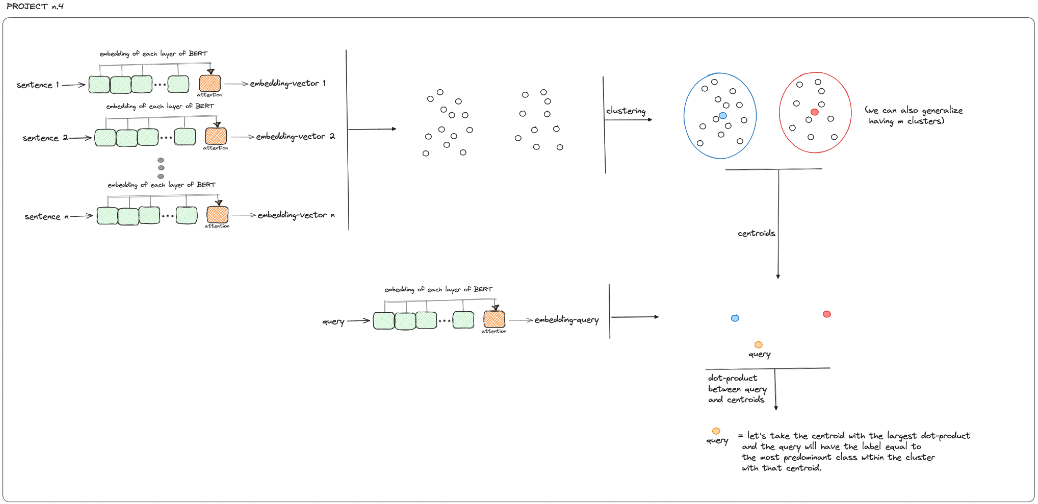
- Power of contextualized word embedding [8]
- Benchmarks for combination of different embeddings and clustering algorithm [10]
- BERT $\rightarrow$ UMAP $\rightarrow$ HDBSCAN [4]
- Embedding into LDA [3]
- Topic modelling and prototype selection [7] [5] [1]
- Prototype-Selection [11]

Project N.1 - Main Approach



Project N.2 - Layer Wise




PROJECT n.4
embedding of each layer of BERT
sentence 1
attention
embedding-vector 1
sentence 2
embedding-vector 2
sentence n
embedding-vector n
clustering
(we can also generalize having m clusters)
centroids
query
embedding-query
dot-product between query and centroids
= let's take the centroid with the largest dot-product and the query will have the label equal to the most predominant class within the cluster with that centroid.

Experiments I

- **Google Colaboratory Pro +** using Tesla T4
- **Pytorch** and **HuggingFace** as deep learning libraries
- **FAISS** [6] library for the implementation of K-Means on the GPU
- **Datasets** are all available on HuggingFace and have positive and negative labels
  - *IMDb*[1]*:* movie reviews
  - *Stanford Sentiment Treebank*[2]*:* movie reviews
  - *Yelp Polarity Review Dataset*[3]*:* yelp reviews

[1] https://huggingface.co/datasets/imdb
[2] https://huggingface.co/datasets/sst2
[3] https://huggingface.co/datasets/yelp_polarity

Experiments II

- **Confidence measure** to assess the cluster goodness/purity [11]
- **Performance evaluation:**
  - Accuracy Score
  - F1-score
- **Comparison with baseline:**
  - *Naive:* predict the most common class
  - *Random choice*
  - *Machine learning:* SSM, Naive Bayes, Logistic Regression and KNN
- **Competitors:** multiple combinations of BERT plus one the following additional module: Linear layer, LSTM and GRU, the last two both uni and bidirectional
- **Training parameters:** 100 epochs, CrossEntropyLoss and AdamW, learning rate to $2e-5$, early stopping strategy on loss (after 20 epochs)

Application Workflow

Three main steps of our approaches

1. **Saving Pre-trained BERT Embedding:**
   - Get the Layer-Wise embedding and store them in a separate *.npy* file
   - Done for each dataset saving the *training*, *validation* and *test* embedding
2. **Select Embeddings:**
   - **Main Approach** CLS from the last BERT layer
   - **Layer-Wise**
     1. Concatenation of the CLS token of all layer
     2. Mean of the CLS token of all layer
   - **Layer-Aggregation**
     - Same embeddings as the first variation of Layer-Wise
     - Embedding fed into a Multi-Head Self Attention layer
3. **Clustering with K-Means and Save Results**

- **Layer-Aggregation** outperforms its counterparts across all evaluation metrics
- Underperformance of the **Layer-Wise** approach
- Choice of dataset does not significantly influence the results

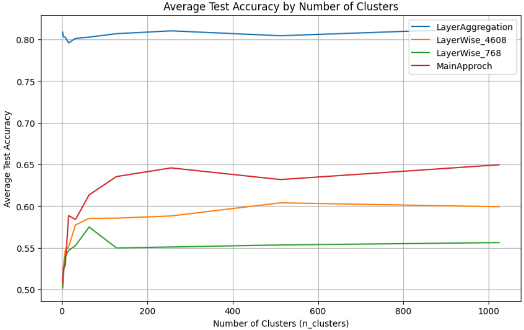


Figure 1: Mean accuracy for each of the separate methods we propose.

- **Layer-Aggregation** matches the baselines
- **Logistic Regression** outperforms it
- Remaining approaches fall short of the Machine Learning baselines performance
- **Competitors** outpace our approaches (higher accuracy)

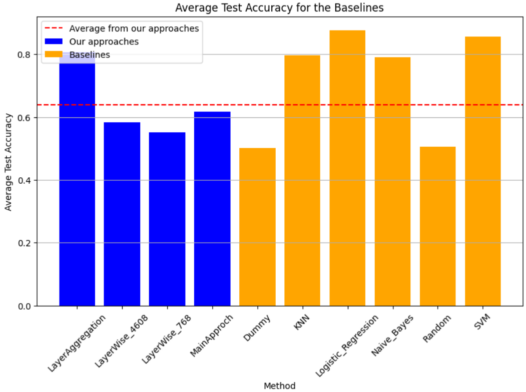


Figure 2: Mean accuracy in comparison with the baselines

- **KNN** and **SVM** have higher computational demands than our approaches (by elapsed time)
- **Logistic Regression** outperforms our own approaches
- **Competitor** models outperform our own approaches (different usage of GPU)
- For our own approaches approx. more computational costs with increasing accuracy

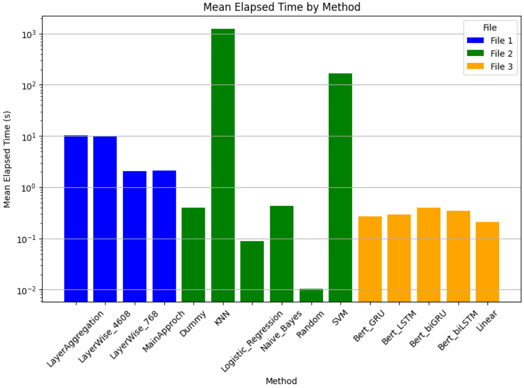


Figure 3: Average elapsed time scaled logarithmically

- Results of IMDb dataset
- $\#$ clusters $k = 128$, as optimal k on average
- No evidence of a clear pattern. However, $m = 8$ gives good results
- We can generally observe only 6% of the closest clusters in terms of dot-products
- To find the **best result** for a given *dataset* and a given *number of clusters*, the **choice of** m **is important**

Figure 4: Variation of the accuracy in test, varying the top-m clusters

method	dataset	n_cls	top_k	t_acc	f1	conf	s_el
MA	imdb	1024	64	0.741	0.738	0.548	6.622
MA	sst2	1024	1	0.687	0.686	0.473	0.222
MA	y_p	256	32	0.735	0.722	0.558	2.784
LW_9216	imdb	1024	32	0.687	0.688	0.471	92.658
LW_9216	sst2	1024	1	0.627	0.624	0.354	3.297
LW_9216	y_p	1024	32	0.757	0.756	0.506	145.846
LW_768	imdb	1024	512	0.614	0.608	0.451	6.622
LW_768	sst2	1024	64	0.634	0.629	0.348	0.225
LW_768	y_p	256	1	0.634	0.631	0.401	2.698
LA	imdb	512	16	0.826	0.826	0.743	41.882
LA	sst2	4	2	0.509	0.338	0.695	0.025
LA	y_p	512	256	0.913	0.913	0.802	53.749

- BERT pre-trained model results

method	dataset	n_cls	top_k	t_acc	f1	conf	s_el
MA	imdb	1024	64	0.678	0.672	0.544	7.647
MA	sst2	1024	1	0.581	0.522	0.523	0.224
MA	y_p	256	32	0.789	0.787	0.581	2.755
LW_4608	imdb	1024	32	0.626	0.621	0.416	34.575
LW_4608	sst2	1024	1	0.569	0.558	0.384	1.18
LW_4608	y_p	1024	32	0.573	0.492	0.456	53.831
LW_768	imdb	1024	512	0.601	0.59	0.405	6.51
LW_768	sst2	1024	64	0.565	0.501	0.375	0.22
LW_768	y_p	256	1	0.526	0.405	0.391	2.795
LA	imdb	128	4	0.5	0.334	0.066	5.03
LA	sst2	4	2	0.688	0.666	0.703	0.016
LA	y_p	512	256	0.89	0.89	0.793	26.999

- DistilBERT pre-trained model results

method	dataset	n_cls	top_k	t_acc	f1	conf	s_el
MA	imdb	1024	64	0.53	0.502	0.201	0.527
MA	sst2	1024	1	0.528	0.528	0.171	0.011
LW_9216	imdb	1024	32	0.535	0.528	0.235	0.487
LW_9216	sst2	1024	1	0.516	0.514	0.17	0.011
LW_768	imdb	1024	512	0.544	0.54	0.239	0.619
LW_768	sst2	1024	64	0.509	0.338	0.168	0.019
LA	imdb	128	4	0.811	0.811	0.139	0.243
LA	sst2	4	2	0.509	0.338	0.179	0.008

Table 1: Results using PCA on pre-trained BERT

- $PCA(\phi(\text{sentence})) = \vec{v} \in \mathbb{R}^2$
- Results are still good, losing approximately only 10% from the initial dimensionality
- Speed up in computational terms
- *yelp_polarity* dataset is excluded

Conclusion

- **CBERTdp**: new approach for sentiment analysis classification
- The method is composed essentially by two simple but powerful points:
  - Bidirectional transformer model
  - Dot-product
- **Results**: the results of our approach in terms of accuracy are not up to the level of the competitors and are similar to the baseline
- **Hyper-parameters**: k for the number of clusters and m for the top-m clusters after the dot-product
- **Property**: simplicity
- **New directions**:
  - Testing new centroid-based clustering algorithms
  - Finding representatives more suited to the problem for each cluster
  - Improve the embeddings
  - Extending the approach to n different sentiments

Thank You for your Attention!

The project code is available at this link, or you can scan the following QrCode

[1] Ercan Atagün, Bengisu Hartoka, and Ahmet Albayrak. "Topic Modeling Using LDA and BERT Techniques: Teknofest Example". In: *2021 6th International Conference on Computer Science and Engineering (UBMK)*. 2021, pp. 660–664. DOI: 10.1109/UBMK52708.2021.9558988.

[2] Jacob Devlin et al. *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. 2019. arXiv: 1810.04805 [cs.CL].

[3] Adji B. Dieng, Francisco J. R. Ruiz, and David M. Blei. *Topic Modeling in Embedding Spaces*. 2019. arXiv: 1907.04907 [cs.IR].

[4] Anton Eklund and Mona Forsman. "Topic Modeling by Clustering Language Model Embeddings: Human Validation on an Industry Dataset". In: *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: Industry Track*. Ed. by Yunyao Li and Angeliki Lazaridou. Abu Dhabi, UAE: Association for Computational Linguistics, Dec. 2022. DOI: 10.18653/v1/2022.emnlp-industry.65. URL: https://aclanthology.org/2022.emnlp-industry.65.

[5] Maarten Grootendorst. *BERTopic: Neural topic modeling with a class-based TF-IDF procedure*. 2022. arXiv: 2203.05794 [cs.CL].

[6] Jeff Johnson, Matthijs Douze, and Hervé Jégou. "Billion-scale similarity search with GPUs". In: *IEEE Transactions on Big Data* 7.3 (2019), pp. 535–547.

[7] Sarojadevi Palani, Prabhu Rajagopal, and Sidharth Pancholi. *T-BERT – Model for Sentiment Analysis of Micro-blogs Integrating Topic Model and BERT*. 2021. arXiv: 2106.01097 [cs.CL].

[8] Nils Reimers et al. *Classification and Clustering of Arguments with Contextualized Word Embeddings*. 2019. arXiv: 1906.09821 [cs.CL].

[9] Victor Sanh et al. *DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter*. 2020. arXiv: 1910.01108 [cs.CL].

[10] Suzanna Sia, Ayush Dalmia, and Sabrina J. Mielke. *Tired of Topic Models? Clusters of Pretrained Word Embeddings Make for Fast and Good Topics too!* 2020. arXiv: 2004.14914 [cs.CL].

[11] Sebastiano Vascon et al. *Using Dominant Sets for k-NN Prototype Selection*. 2013. DOI: 10.1007/978-3-642-41184-7_14. URL: https://link.springer.com/chapter/10.1007/978-3-642-41184-7_14.