Abstract

Current state-of-the-art approaches to text classification typically leverage BERT-style Transformer models with a softmax classifier, jointly fine-tuned to predict class labels of a target task. In this paper, we instead propose an alternative training objective in which we learn task-specific embeddings of text: our proposed objective learns embeddings such that all texts that share the same target class label should be close together in the embedding space, while all others should be far apart. This allows us to replace the softmax classifier with a more interpretable \( k \)-nearest-neighbor classification approach. In a series of experiments, we show that this yields a number of interesting benefits: (1) The resulting order induced by distances in the embedding space can be used to directly explain classification decisions. (2) This facilitates qualitative inspection of the training data, helping us to better understand the problem space and identify labelling quality issues. (3) The learned distances to some degree generalize to unseen classes, allowing us to incrementally add new classes without retraining the model. We present extensive experiments which show that the benefits of ante-hoc explainability and incremental learning come at no cost in overall classification accuracy, thus pointing to practical applicability of our proposed approach.

1 Introduction

Text classification is the classic NLP problem of predicting the appropriate class labels for a given textual document from a pre-defined set of classes. It is used for various applications such as sentiment analysis (Rosenthal et al., 2017), spam detection (Jindal and Liu, 2007) or automatic document categorization (Zhang et al., 2015). The current state-of-the-art approach leverages BERT-style language models together with a softmax classifier (Devlin et al., 2019; Wang et al., 2019). The language model is fine-tuned using a task’s training data to produce a vector representation of a given text, typically retrieved from the [CLS] token of the language model. This representation is trained such that a simultaneously trained softmax classifier projects it into a distribution over class label probabilities.

In this work, we explore a complementary path to address the text classification problem which we argue, yields significant advantages in terms of explainability and incremental learning, while giving similar results in terms of classification accuracy. **Task-specific similarity of texts.** We propose to view text classification as a task-specific text-text similarity problem. In other words, we assume that if two textual documents share the same class label, then they are semantically similar in the context of this particular task. To illustrate, consider the following two sentences from a question type classification task:

- **Which one of the Great Lakes is entirely within U.S. territory?**
- **What arch can you see from the Place de la Concorde?**

These two sentences seemingly have little in common in terms of semantics\(^1\). However, they both share the same label in a specific downstream task (namely LOC, indicating a question that requires a location name as answer) and so could be argued to be similar when considering only the semantics of the target task.

Based on this observation, we propose a training objective called Class-driven Embedding Alignment (CEA). The main idea is to learn embeddings that maximize the similarity between two textual documents if they share the same class label, and minimize it if they do not. This builds

\(^{1}\)In fact, when embedded with a generic STS model stsb-roberta-base (Reimers and Gurevych) we find only a cosine similarity of 0.28 between their embeddings.
on recent work in learning representations for semantic textual similarity (STS) using Siamese networks (Reimers and Gurevych, 2019), but with the difference that we aim to learn task-specific embeddings instead of broad semantic representations. We illustrate the difference between the two paradigms in Figure 1 showing a TSNE plot of an embedding space learned for general semantics (1a) vs. one learned for task-specific representations of semantics (1b).

**Advantages for text classification.** We show that such a task-specific embedding space can directly be used for text classification and that this yields a number of desirable properties:

1. We show that task-specific embeddings can be employed in a \( k \)-nearest-neighbor (kNN) approach to classify texts based on their similarity to training data points. As kNN is an instance of example-based learning, this allows ante-hoc explanations of the classification results: each classification decision is based on the identified nearest neighbors from the training data and thus is explained in a human-readable way.

2. This facilitates qualitative exploration of training data to better understand the problem space and to identify labeling quality issues in the training data. For instance, our example TSNE plot in Figure 1b reveals that task-specific embeddings mostly form clusters conforming to their class labels, but not entirely (note the subclusters and the pockets of differently colored data points). As we show in Section 4, exploration reveals pockets of wrongly labeled data points in the training data of some tasks, as well as other anomalies.

3. Finally, the proposed formulation is also effective for incremental learning approaches in which more labeled data points are added after training. We show that the similarities in the learned embedding space partially generalize even to new class labels, allowing us to add new classes without retraining.

We present extensive quantitative and qualitative experiments over 6 datasets from various text classification tasks that indicate our formulation yields these properties with no hit in overall classification accuracy. Based on these results, we conclude our proposed approach to be a viable alternative with many benefits over standard softmax classifier-based approaches.

## 2 Method

We formulate the text classification problem as an application-specific text-text similarity problem. In the following, we would use the terms sentence and document interchangeably to refer to a particular text input to be classified. Formally, we aim to learn a function:

\[
f : \text{text} \rightarrow \mathbb{R}^d
\]

\[
f(\text{text}) \approx f(\text{text}^+) \quad \text{if } f(\text{text}) \neq f(\text{text}^-)
\]

where, \( \text{text}^+ \) is another document which shares the same class as that of \( \text{text} \), and \( \text{text}^- \) is one which does not; \( \approx \) (or \( \neq \)) denote equality (or inequality) in terms of some similarity metric. In other words, we aim to learn a text encoder which embeds a textual document in a \( d \)-dimensional vector space. In this space, documents that share the same class should be close to each other, and the ones from different classes should be further apart.
2.1 Sampling for CEA Training

To train task-specific embeddings with CEA, we require input pairs (e.g., \((text, text^+)\), \((text, text^-)\)) as shown in Equation 1. Since with \(n\) labelled samples in the corpus the number of pairs grows quadratically, we sample pairs from this set of \(\frac{n(n-1)}{2}\) possible combinations over epochs, where each epoch consists of \(n\) steps as shown in Algorithm 1. Specifically, for every text document, we pick a positive sample document \(text^+\) with equal probability from all other documents in the training set that share the same class as of text document. Similarly, we pick a negative sample \(text^-\) from the pool of all documents that belong to different classes than that of text document. We repeat this sampling process for all the documents in an epoch, resulting in \(2n\) document pairs. Note that as we sample the pairs randomly, in each epoch different positive, and negative examples might be picked for a particular document.

2.2 CEA Training

We use a Siamese architecture for CEA training as shown in Figure 2. It uses a pre-trained BERT as the text encoder, and the weights for both the BERT towers are tied. We consider every positive sample pair \((text, text^+)\) to have a target label of 1, conversely negative sample pair \((text, text^-)\) has target label of 0. The network takes a sample pair as input, makes a forward pass through the BERT stack for both the input documents, and yields the sub-token level encoded representations from the final layer of the stack.

Deriving a document representation. There exist several strategies to derive document-level representations from BERT-style language models, such as using the representation at the [CLS] token or performing mean or max pooling over all subtoken representations. Reimers and Gurevych showed the effect of different pooling mechanisms and found mean pooling to yield best results for their tasks. However, as we are primarily interested in performing text classification over documents with potentially widely varying lengths, we follow current practice in using the [CLS] token representation of the final output layer as document embedding.

Loss calculation. For each embedded input pair, we compute the MeanSquaredError (MSE) between their CosineSimilarity value \(\hat{y}\) and the target value \(y\):

\[
\hat{y} = \text{CosineSimilarity}(CLS_A, CLS_B) \\
loss = \text{MeanSquaredError}(y, \hat{y})
\]  

The target value \(y\) is either 1 or 0 depending on if both the inputs share the same class or not. This objective thus pushes documents with the same labels to be close together in the embedding space (high cosine similarity) and all others far apart.

2.3 Nearest Neighbor Classification

After training CEA, we perform classification for unseen documents using a \(k\)-nearest neighbor approach. This requires us to first encode all documents in the training data with the task-specific CEA model, yielding \(n \times d\)-dimensional embeddings. We normalize these embeddings with the respective \(L2\) norms to obtain unit-norms, and store all embeddings in a look-up index.

For inference, we encode a given data point with the CEA model and normalize the resulting embedding to have unit-norm. We fetch \(k\) nearest points in the look-up index in terms of \(L2\) distance, and consider the majority class label as the predicted class for the document under test.

Inference speed. The inference time of \(k\)NN is theoretically linear with respect to the size of the

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Algorithm 1: Sampling for CEA training.

| Input: | Labelled documents \(\{(text_i, label_i) | i \in [1, n]\}\) |
|---|---|
| Output: | Positive and negative sample pairs |
| samples \(\leftarrow\) | \{\} |
| for \(i \leftarrow 1\) to \(n\) do |
| text \(\leftarrow text_i\); |
| text\(^+\) \(\leftarrow\) \(U\{\{text_i, \forall j | label_i = label_j\}\}; |
| text\(^-\) \(\leftarrow\) \(U\{\{text_i, \forall j | label_i \neq label_j\}\}; |
| samples \(\leftarrow\) samples \(\cup\) \((\text{text, text\(^+\)}, 1)\); |
| samples \(\leftarrow\) samples \(\cup\) \((\text{text, text\(^-\)}, 0)\); |
| end |
| return samples |

Figure 2: Siamese architecture for Class-driven Embedding Alignment (CEA) training.
lookup index. In practice, it is possible to accelerate the look-up using efficient algorithms such as Ball Tree (Omohundro, 1989), parallelization and approximate NN methods (Johnson et al., 2017).

3 Evaluation of Classification Accuracy

In this first round of evaluation, we investigate whether (1) our proposed approach combining CEA, and \( k \)NN classification comes at a cost of accuracy compared to state-of-the-art approaches, and (2) whether CEA can additionally be used in combination with traditional softmax-classifier instead of \( k \)NN. In Section 4, we examine CEA further, regarding the postulated advantages i.e., better interpretability and incremental learning.

3.1 Datasets

We consider six widely used datasets in English from three domains, formally released with training and test splits (cf Table 1). In all cases, we consider a random subset (10\%) from the training as the development set. We use identical splits for all evaluated models and baselines. The original test set remains untouched and is used as-is for evaluation.

**Question type detection.** TREC is a corpus annotated with coarse and fine-grained question types (Li and Roth, 2002). There are 50 fine-grained question types (TREC-50) that each belong to one of 6 coarse-grained categories (TREC-6). The two layers of annotations allow us to investigate whether CEA uncovers structure beyond the class labels it is trained with.

**Sentiment analysis.** Two popular review datasets, on movies (IMDb), and restaurants (YELP-FULL). They are annotated with coarse (binary positive/negative), and fine-grained 5-class sentiment labels (Zhang et al., 2015; Maas et al., 2011) respectively. Documents are longer in general here.

**Topic detection.** Two commonly used topic classification datasets, namely Wikipedia-based (DBPEDIA) and news articles (AGNEWS), with 14 and 4 topic labels respectively (Zhang et al., 2015).

3.2 Proposed Model and Ablations

For each dataset, we start with a pre-trained BERT\(_{\text{base}}\) model (110M parameters), and perform our proposed CEA training as described in Section 2 using AdamW optimization (Loshchilov and Hutter, 2018), a batch size of \( 16^2 \) and a learning rate of \( 2e-5 \) for 20 epochs. We follow Reimers and Gurevych (2019) and perform model selection based on Spearman Correlation between \( \hat{y}, y \) on held-out development set.

**CEA-based classification.** We show the use of CEA model in three following methods:

1. **CEA + \( k \)NN:** Our proposed model uses \( k \)NN classification as described in Section 2.3. To find the optimal \( k \) for each dataset, we perform a hyper-parameter search for \( k \) within the range \([1 \text{ -- } 100]\), and select the best \( k \) using accuracy on the development split. Unseen documents are classified with majority voting over the \( k \) nearest neighbors.

2. **CEA + Softmax:** An ablation where instead of \( k \)NN classification, we add a softmax-classifier to the trained CEA model and fine-tune all model parameters on the target task using cross-entropy loss, as typically done in text classification. The purpose is to evaluate whether CEA provides a good initialization of model parameters for the standard text classification approach.

3. **CEA (frozen) + Softmax:** Another ablation that fits a softmax-classifier, but freezes all weights in the CEA model. We perform this experiment to determine if it can be directly used to learn a softmax classifier.

3.3 Baselines

We compare against the following baseline approaches based on the same BERT\(_{\text{base}}\) model

4. **S-BERT (frozen) + Softmax** (Reimers and Gurevych, 2019) is a BERT model trained on STS and NLI to capture generic semantic textual similarity. We use the pre-trained model\(^3\) released by the authors. As recommended, we

\[ \text{Dataset} \quad \text{Type} \quad \text{#class} \quad \text{#train / #test} \quad \text{#words} \]

| Dataset          | Type    | #class | #train / #test | #words |
|------------------|---------|--------|----------------|--------|
| TREC-6 (2002)    | Question| 6      | 5.5k / 500     | 11     |
| TREC-50 (2002)   | Question| 50     | 5.5k / 500     | 11     |
| IMDb (2011)      | Sentiment| 2      | 25k / 25k      | 190    |
| YELP-FULL (2015) | Sentiment| 5      | 650k / 50k     | 136    |
| AGNEWS (2015)    | Topic   | 4      | 120k / 7.6k    | 37     |
| DBPEDIA (2015)   | Topic   | 14     | 560k / 70k     | 49     |

\[ \text{Table 1: Dataset statistics.} \]

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\(^3\)huggingface.co/sentence-transformers/bert-base-nli-stsb-mean-tokens
use the mean-pooled embedding as the document representation and train a softmax classifier on top in this method. This lets us compare our task-specific representations against general semantic representations.

5. **BERT + Softmax** (Devlin et al., 2019): In this, we fine-tune BERT\textsubscript{base} directly on the task, together with a standard softmax classifier. This experiment benchmarks how well the traditional text classification approach fares with ours.

All model variants with softmax classifier are fine-tuned for 20 epochs using batch-size of 32, and learning rate of 3e-6. Model selection is performed on development data accuracy. We implement the variants using: **Sentence-Transformer** for CEA training (Reimers and Gurevych, 2019), **Flair** for fine tuning (Akbik et al., 2019), and **FAISS** for kNN look-up (Johnson et al., 2017).

### 3.4 Model Accuracy Results

For all models and datasets, we report accuracy on the held-out test set. Since Transformer models are known for their high variance (Dodge et al., 2020; Halder et al., 2020; Mosbach et al., 2021) we train 3 independent models with controlled random seeds, and report the mean and standard deviation. The results are presented in Table 2.

We observe that our CEA approach performs competitively with other variants. In 5 out of 6 datasets, CEA based models are able to outperform the Sentence-BERT, and BERT fine-tuned models. Unsurprisingly, the improvement is nominal as the underlying model (thus number of learnable parameters in the Transformer stack), as well as the ground-truth data used for training are exactly the same. Although Sentence-BERT model is pre-trained on supervised tasks such as STS, NLI, and in general is reported in the literature to be able to capture semantic similarity well, for downstream text classification tasks, these generic sense of similarity is not effective as evident from the results.

Our proposed CEA approach conditions the embedding space well to show strong classification performance. CEA embeddings can be seamlessly used in conjunction with a softmax classifier on top (CEA + Softmax, CEA (f) + Softmax), as well as with a $k$-nearest neighbour lookup (CEA + kNN).

We observe that we are able to obtain the best results when fine-tune the CEA obtained model further with a softmax classifier on top (CEA + Softmax). This is expected since, it has additional learnable parameters. In case of YELP-FULL, the BERT fine tuned model achieves the best results, closely followed by our CEA variants. From these observations, we conclude that CEA indeed provides a viable mechanism to train text classification model with strong performance on a range of tasks.

### 3.5 Inference Speed of CEA

With our proposed CEA + kNN approach, two major operations take place for each input document i.e., (i) computing the [CLS] token’s embedding from the Transformer stack; (ii) retrieving the $k$ most similar points in nearest neighbor index to perform majority voting. We present the average running time (total time/number of test points) in a batch inference setting on Nvidia V100 GPUs in Table 3. We observe that the inference is reasonably fast with average running time being less than 10ms for all the datasets. In general, the running time appears to depend mostly on the average length of the documents rather than the number of indexed points.

**Table 2: Results on text classification datasets. Our CEA variants outperform other baselines with no additional data used during training across the board (except YELP-FULL).**

| Methods          | TREC-6     | TREC-50    | IMDB       | DBPEDIA   | AGNEWS    | YELP-FULL  |
|------------------|------------|------------|------------|-----------|-----------|------------|
| 1. CEA + kNN     | 0.9706±.0049 | 0.8980±.0028 | 0.9314±.0005 | 0.9932±.0000 | 0.9366±.0013 | 0.6916±.0009 |
| 2. CEA + Softmax | 0.9680±.0028 | 0.9093±.0049 | 0.9344±.0006 | 0.9930±.0001 | 0.9387±.0007 | 0.6955±.0001 |
| 3. CEA (f) + Softmax | 0.9653±.0033 | 0.8840±.0090 | 0.9329±.0012 | 0.9920±.0001 | 0.9352±.0007 | 0.6890±.0017 |
| 4. S-BERT (f) + Softmax | 0.8286±.0002 | 0.7120±.0000 | 0.8719±.0004 | 0.9788±.0004 | 0.8891±.0006 | 0.5831±.0003 |
| 5. BERT + Softmax | 0.9626±.0038 | 0.9013±.0041 | 0.9286±.0012 | 0.9919±.0002 | 0.9362±.0002 | 0.6972±.0005 |

**Table 3: Inference speed of CEA based text classification.**
4 Evaluation of Interpretability and Incrementality

In this section, we answer important claims regarding the useful properties of CEA embeddings, we made in Section 1.

4.1 Transparency in Classification Process

Our training objective of bringing documents with the same class label closer in the embedding space, helps the $k$-NN classifier to rely on the neighbor sentences to achieve strong performance. We perform a qualitative study with the retrieved nearest neighbors, and obtain some interesting insights. A few case studies where our CEA + $k$-NN method’s predictions differ from the ground-truth labels, are presented in Table 4 for TREC-6.

First, we observe that the retrieved neighbor sentences indeed share similarity in the context of the downstream task i.e., question type detection. We believe these nearest points can be considered as a form of justification of the model prediction. As shown in Table 4a, the test document “What is the sales tax in Minnesota?” is classified as “NUM” by our model. Looking at the supporting justifications retrieved, it is hard to argue why this classification is incorrect. Second, this can also help in making corrections in the labelled corpus. As one can just take a note of such cases, and make corrections in the corpus. Another such example is provided in Table 4b. Here, not only the ground-truth label “ENTY” for the document “What is the electrical output in Madrid, Spain?” is questionable, but the retrieved nearest neighbors highlight that there are duplicates in this formally released dataset. Both of these observations depict an interesting, and useful artifact of our model, that it points at such anomalies in a labelled corpus by design, which could be a time-consuming exercise to spot otherwise.

Figure 3: Incremental Learning capabilities of CEA when more labelled data is made available to an already trained model.

4.2 Incremental Learning Capabilities

Our proposed method uses $k$-nearest neighbor search which is a lazy classification approach. It decouples the final prediction from the training step, and allows one to just add more knowledge in form of labelled examples in the search index. This introduces a significant advantage for human-in-the-loop oriented systems, where newly labelled data arrives periodically. Traditionally, it would require a full-fledged model training loop to utilize the additional labelled data, which might be expensive in terms of time and compute resources. In the following two experiments, we show that once our CEA model is trained on part of the corpus, it would allow one to incrementally add more labelled data into the index, and still get comparable performance with respect to a model trained from scratch on all the data points.

Introducing more data incrementally. To simulate the incremental data arrival scenario, we train CEA models with $x\%$ of all the labelled documents available in the training corpus. We vary $x$ between $[5, 10, 20, ..., 60]$ and note the accuracy on the en-
tire test set for TREC-6 corpus, at all stages as shown in Figure 3. We ensure that all the classes appear at least once in training for all \( x \). It is clear from Table 2 that the Sentence-BERT is not effective in this setting. Therefore we do not display it in Figure 3 since with 60% of training data it reaches accuracy of only 0.75. Once we add the rest \((100 - x)\)% labelled documents to the index, denoted by CEA + \( k \)-NN (index++), we observe a boost in the performance compared to both CEA + \( k \)-NN, and fine-tuned BERT variant. The accuracy of CEA + \( k \)-NN at small values of \( x \) is quite close (within 3 – 4%) to what a model would achieve if trained on 100% of the available data, denoted by CEA + \( k \)-NN (Full), and BERT (Full). Unsurprisingly, the improvement subsides as we move beyond \( x \geq 50\% \).

**Introducing a new class.** In this setting, we study a common use-case where the classification need evolves with time e.g., more classes are introduced at some point into a dataset. We simulate this by hiding a class completely during training the CEA model. During inference, we encode the labelled documents from the new class, and just add their embeddings into the \( k \)-nearest neighbour index like earlier. We present the F1-scores of all individual classes, and overall accuracy on the entire test set in following three settings in Table 5: i) **Held-out:** The class is completely hidden during training, and inference; (ii) **Index++:** The class is hidden during training, but added onto the \( k \)-NN lookup index for inference; (iii) **Full:** CEA is trained with the full corpus with all classes. Note that, the variants with softmax classifier do not offer this flexibility.

We observe that CEA indeed shows strong evidence of handling a new class well without requiring any weight updates. The accuracy it yields after extending the index is comparable to a model trained on entire training data \((0.9620 \text{ vs} \ 0.9720, 0.9168 \text{ vs} \ 0.9356, 0.9900 \text{ vs} \ 0.9932 \text{ for TREC-6, AGNEWS, DBPEDIA respectively})\). We spot some interesting interactions between the classes in this study by observing the ones where there is a large change in F1-score after extending the index (denoted by ↑ beside). For TREC-6, we find that all the documents belonging to “ABBRR”, conflates “DESC”. We find this consistent with the intuitive notion of these two classes. For AGNEWS, introduction of “World” impacts “Business”, and “SciTech” the most. Similarly, in DBPEDIA, the newly introduced class “Company” nudges the FI-

![Figure 4: TSNE plot of CEA embeddings for training samples in TREC corpus, coloured according to labels as in a) TREC-6, and b) TREC-50. CEA learns to keep the documents belonging to the sub-classes nearby without explicit supervision.](image)

score of “Plant”, “Artist”, “Building” by absolute improvements of 0.12, 0.09, 0.10 respectively. Our further investigation reveals that there is labelling anomaly in the “Plant” class (presented in the appendix for the interested readers).

**Introducing sub-classes.** An existing class might need to be further divided into multiple sub-classes (Wohlwend et al., 2019) with time. The TREC corpus lets us study the effect of such scenario. In TREC-6 version, all the questions are annotated with 1 out of 6 possible types, whereas in TREC-50, the same questions are further divided into 50 categories. To investigate, how our proposed CEA mechanism would work there, we first train a CEA model on TREC-6, but during inference we use fine-grained labels from TREC-50 and perform majority voting on them. We observe that CEA yields an impressive accuracy of 0.846 in this task.

We analyze the embeddings learned by the CEA model to better understand this classification performance in Figure 4\(^4\). We present the 2d TSNE plots of the CEA embeddings after training on TREC-6 in Figure 4a. On the right (4b), we color the same points according to TREC-50 classes. Interestingly we observe that, CEA is able to cluster the fine-grained classes together without explicit supervision. This can be explained by the desirable property of CEA i.e., it learns the task-specific similarity between texts, however still pays attention to the syntactic similarity (Table 4a).

**Note on alternative objectives:** We have explored other metric learning approaches for training CEA, such as contrastive loss for pair classification (Hadsell et al., 2006), and triplet ranking loss (Hermans et al., 2017). However, our regression based objective yielded the best results, and interpretability of nearest neighbors in our experiments.

\(^4\)enlarged Figure, and full report is provided in appendix.
5 Related Works

Similarity learning. We build on the work of similarity learning of Reimers and Gurevych which showed that Siamese architectures could be leveraged to capture general semantic similarity across texts. Metric learning based approaches (Weinberger and Saul, 2009) were used for few-shot text classification (Wohlwend et al., 2019) both in Euclidean and hyperbolic space, and for image class prototype meta-learning (Snell et al., 2017).

Nearest neighbour approaches. Nearest Neighbour has seen applications in NLP in the recent past for sequence labelling (Wiseman and Stratos, 2019; Sogaard, 2011; Chen and Chen, 2019; Zhang et al., 2020), as well as language modelling (Khandelwal et al., 2020) and question answering (Kassner and Schütze, 2020). Perhaps the closest ours is work of Wallace et al. where they apply Deep k-Nearest Neighbors (Papernot and McDaniel, 2018) for text classification. However, they focus on developing reliable uncertainty estimates with simpler neural models such as CNN (Kim, 2014), and BiLSTM (Sun et al., 2017). We believe ours is the first work to benchmark larger Transformer based models in conjunction with Nearest Neighbour lookup on a wide range of text classification tasks.

Explainability in text classification. Majority of work related to explainability (or interpretability) of text classification models based on neural networks uses post-hoc mechanisms e.g., saliency or attention weights (Jain and Wallace, 2019; Wiegrefe and Pinter, 2019) to attribute part of input to a specific prediction (Linzen et al., 2018). Our approach is orthogonal to this line of work, as it is based on nearest neighbour classification, which uses ante-hoc principles (Sokol and Flach, 2020) by design, such as majority voting for prediction.

6 Conclusion

In this work, we considered text classification as a task-specific text similarity problem. To this end, we proposed Class-driven Embedding Alignment, a training mechanism that brings text documents with the same class label closer in embedding space, and pushes others further apart. We trained a large Transformer model with our proposed approach. We showed the embeddings produced by our model can be used in multiple ways to perform accurate text classification, with a softmax classifier or non-parametric methods such as k-nearest neighbor search. Finally, we presented interesting properties of CEA model, that can be leveraged for introducing transparency in the text classification process, as well as imbues flexibility by incrementally adding new data without expensive model updates with quantitative results and qualitative visualizations of the learned embeddings. In the future, we would like to explore how this nearest neighbour based approach can be extended for other forms of NLU tasks such as textual entailment detection, multi-label text classification where the relationship between documents are more complex.
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A Appendix

| Dataset    | $k$ | Validation Accuracy |
|------------|-----|---------------------|
| TREC-6     | 6   | 0.9706              |
| TREC-50    | 3   | 0.9047              |
| AGNews     | 11  | 0.9767              |
| IMDB       | 21  | 0.9712              |
| DBPedia    | 13  | 0.9926              |
| YELP-FULL  | 95  | 0.6832              |

Table 6: Validation Accuracy for $k$-nearest neighbour search as found during hyper-parameter search within $[1 - 100]$ with step size of 1.

| Dataset    | CEA | Fine Tuning | NN (inference) |
|------------|-----|-------------|-----------------|
| TREC-6     | 32  | 64          | 128             |
| TREC-50    | 32  | 64          | 128             |
| IMDB       | 16  | 64          | 128             |
| DBPedia    | 16  | 64          | 128             |
| AGNews     | 16  | 64          | 128             |
| Yelp-full  | 16  | 32          | 128             |

Table 7: Batch-sizes used for different datasets.

Figure 5: (Enlarged Figure 4) TSNE plot of CEA embeddings for training samples in TREC corpus, coloured according to labels as in a) TREC-6, and b) TREC-50. CEA learns to keep the documents belonging to the sub-classes nearby without explicit supervision, since it is only trained with TREC-6.
|        | precision | recall  | f1-score | support |
|--------|-----------|---------|----------|---------|
| ABBR:abb | 1.00000  | 1.00000 | 1.00000  | 1       |
| ABBR:exp | 0.58333  | 0.67500 | 0.70000  | 8       |
| DESC:def | 0.92857  | 0.95122 | 0.93976  | 123     |
| DESC:desc | 1.00000  | 0.85714 | 0.92308  | 7       |
| DESC:method | 1.00000 | 1.00000 | 1.00000  | 2       |
| DESC:reason | 1.00000  | 0.83333 | 0.90909  | 6       |
| ENTITY:animal | 0.81250  | 0.81250 | 0.81250  | 16      |
| ENTITY:body | 1.00000  | 0.50000 | 0.66667  | 2       |
| ENTITY:color | 1.00000  | 1.00000 | 1.00000  | 10      |
| ENTITY:cremat | 0.00000  | 0.00000 | 0.00000  | 0       |
| ENTITY:currency | 1.00000 | 0.83333 | 0.90909  | 6       |
| ENTITY:dismed | 0.00000  | 0.00000 | 0.00000  | 2       |
| ENTITY:event | 0.66667  | 1.00000 | 0.80000  | 2       |
| ENTITY:food | 0.25000  | 0.25000 | 0.25000  | 4       |
| ENTITY:instru | 1.00000  | 1.00000 | 1.00000  | 1       |
| ENTITY:lang | 1.00000  | 1.00000 | 1.00000  | 2       |
| ENTITY:other | 0.42857  | 0.25000 | 0.31579  | 12      |
| ENTITY:plant | 0.50000  | 0.40000 | 0.44444  | 5       |
| ENTITY:product | 0.40000  | 0.50000 | 0.44444  | 4       |
| ENTITY:sport | 1.00000  | 1.00000 | 1.00000  | 1       |
| ENTITY:substance | 0.75000  | 0.60000 | 0.66667  | 15      |
| ENTITY:technology | 1.00000 | 1.00000 | 1.00000  | 1       |
| ENTITY:terminology | 0.42857  | 0.42857 | 0.42857  | 7       |
| ENTITY:vehicle | 0.60000  | 0.75000 | 0.66667  | 4       |
| ENTITY:word | 0.00000  | 0.00000 | 0.00000  | 0       |
| HUM:desc | 1.00000  | 1.00000 | 1.00000  | 3       |
| HUM:en | 0.66667  | 0.66667 | 0.66667  | 6       |
| HUM:ind | 0.96429  | 0.98182 | 0.97297  | 55      |
| HUM:client | 0.00000  | 0.00000 | 0.00000  | 0       |
| LOC:city | 0.87500  | 0.77778 | 0.82333  | 18      |
| LOC:country | 0.37500  | 1.00000 | 0.54545  | 3       |
| LOC:mount | 0.66667  | 0.66667 | 0.66667  | 3       |
| LOC:other | 0.87778  | 0.86000 | 0.86869  | 50      |
| LOC:state | 1.00000  | 0.71429 | 0.83333  | 7       |
| NUM:count | 0.72727  | 0.86868 | 0.80000  | 9       |
| NUM:date | 0.97917  | 1.00000 | 0.98947  | 47      |
| NUM:dist | 0.86667  | 0.81250 | 0.83871  | 16      |
| NUM:money | 1.00000  | 1.00000 | 1.00000  | 3       |
| NUM:other | 0.61538  | 0.66667 | 0.64000  | 12      |
| NUM:percent | 0.75000  | 1.00000 | 0.85714  | 3       |
| NUM:period | 0.80000  | 1.00000 | 0.88889  | 8       |
| NUM:speed | 0.80000  | 0.66667 | 0.72727  | 6       |
| NUM:temp | 1.00000  | 0.20000 | 0.33333  | 5       |
| NUM:volsizes | 0.00000  | 0.00000 | 0.00000  | 0       |
| NUM:weight | 0.75000  | 0.75000 | 0.75000  | 4       |

**accuracy**: 0.84600 **500**

**macro avg**: 0.71249 0.69985 0.69064 **500**

**weighted avg**: 0.85433 0.84600 0.84342 **500**

Figure 6: Full classification report for all 50 classes for the TREC-6 to TREC-50 transfer experiment.
Table 8: Nearest Neighbours for a test document in DBPEDIA dataset when a new class “Company” is added to the index. Note that, all the nearest neighbours indeed are similar. However, they carry the wrong ground-truth labels, affecting the final prediction according to majority voting.