Graph neural networks have triggered a resurgence of graph-based text classification methods, defining today’s state of the art. We show that a simple multi-layer perceptron (MLP) using a Bag of Words (BoW) outperforms the recent graph-based models TextGCN and HeteGCN in an inductive text classification setting and is comparable with HyperGAT in single-label classification. We also run our own experiments on multi-label classification, where the simple MLP outperforms the recent sequential-based gMLP and aMLP models. Moreover, we fine-tune a sequence-based BERT and a lightweight DistilBERT model, which both outperform all models on both single-label and multi-label settings in most datasets. These results question the importance of synthetic graphs used in modern text classifiers. In terms of parameters, DistilBERT is still twice as large as our BoW-based wide MLP, while graph-based models like TextGCN require setting up an $O(N^2)$ graph, where $N$ is the vocabulary plus corpus size.

1 Introduction

Topical text classification is the task of assigning a category (text categorization) or multiple class labels (multi-label text classification) to a text unit such as a document, a social media posting, or a news article. Research on text classification is a very active field as just the sheer amount of new methods in recent surveys shows (Bayer et al., 2021; Li et al., 2020; Zhou et al., 2020c; Kowsari et al., 2019; Kadhim, 2019).

There are approaches based on a Bag of Words (BoW) that perform text classification purely on the basis of a multiset of tokens. Among them are Deep Averaging Networks (DAN) (Iyyer et al., 2015), a deep Multi-Layer Perceptron (MLP) model with $n$ layers that relies on averaging the BoW, Simple Word Embedding Models (SWEM) (Shen et al., 2018) that explores different pooling strategies for pretrained word embeddings, and fastText (Bojanowski et al., 2017), which uses a linear layer on top of pretrained word embeddings. These models count the occurrence of all tokens in the input sequence, while disregarding word position and order, and then rely on word embeddings and fully connected feedforward layer(s). We call these BoW-based models.

There is the well-known Transformer (Vaswani et al., 2017) universe with models such as BERT (Devlin et al., 2019) and its size-reduced variants such as DistilBERT (Sanh et al., 2019). Here, the input is a (fixed-length) sequence of tokens, which is then fed into multiple layers of self-attention. Lightweight versions such as DistilBERT and others (Tay et al., 2020; Fournier et al., 2021) use less parameters but operate on the same type of input. Recently a new family of models emerged (Tolstikhin et al., 2021; Liu et al., 2021a) which also utilize sequence-based input tokens, with an MLP-based, recurrent-free architecture. These models offer a simpler alternative to self-attention modules and convolutional layers for cross-token interaction, while achieving comparable results on both vision and natural language processing (NLP) tasks. Together with recurrent models such as LSTMs, we call these sequence-based models.

Among the most popular recent methods for text classification are graph-based models such as using a graph convolutional network for text classification (TextGCN) (Yao et al., 2019). TextGCN first induces a synthetic word-document co-occurrence graph over the corpus and subsequently applies a graph neural network (GNN) to perform the classification task. Besides TextGCN, there are follow-up works like HeteGCN (Ragesh et al., 2021), TensorGCN (Liu et al., 2020b), and HyperGAT (Ding et al., 2020), which we collectively call graph-based models.
Graphs are also found in the form of a hierarchy among the classes. A structural encoder is used for modeling hierarchical label relations and a text encoder is used to extract textual features from the text. Additional information can be passed to the structural encoder to enhance the label structural features, e.g., HiAGM (Zhou et al., 2020a) uses prior probabilities of label dependencies to enhance label features. Label and textual features can be combined in several ways, as shown by the HiAGM variants HiAGM-LA and HiAGM-TP. There is also the possibility to utilize weakly-supervised training where the model is learned over the hierarchy of the classes without using the actual document labels. An example of such a weakly supervised approach is TaxoClass (Shen et al., 2021). In this work, we focus on supervised methods and experiment with HiAGM as a top-performing hierarchical text classification method and leave weakly-supervised training for future work. We call this group of methods the hierarchy-based models.

In this paper, we hypothesize that text classification can be very well conducted by simple but effective BoW-based models. We assume that this hypothesis holds true for both single-label text classification as well as multi-label text classification. We investigate the research question in three steps: First, we conduct an in-depth analysis of the literature. We review the key research in the field of modern and classical machine learning methods for topical text classification. From this analysis, we derive the different families of methods, the established benchmark datasets, and identify the top performing methods. We decide for which models we report numbers from the literature and which models we run on our own. Overall, we compare 18 different methods from the families of BoW-based models (8 methods), sequence-based models (5 methods), and graph-based models (5 methods) on single label classification, and 6 different methods (1 BoW-based, 4 sequence-based, 1 hierarchical) on multi-label classification. We run our own experiments for 7 of these methods on 5 single-label text classification datasets, while we report the results from the literature for the remaining methods. For multi-label text classification we used 7 datasets for our experiments.

The results are surprising: our own BoW-based MLP, called the WideMLP, with only one wide hidden layer, outperforms many of the recent graph-based models for inductive single-label text classification (Yao et al., 2019; Liu et al., 2020b; Ragesh et al., 2021). Although single-label classification is a relatively simple downstream task, the new MLP-based sequence models without pretraining under-performed most other models. That underlines another strength of the BoW-based MLPs, the lack of need for costly task-agnostic pretraining. Moreover, we did not find any reported scores for BERT-based methods from the sequence-based family. The only exception is the work by Sun et al. (2019), who fine tuned BERT for text classification but used different datasets. To fill this gap, we fine-tuned our own BERT (Devlin et al., 2019) and DistilBERT (Sanh et al., 2019). These models set a new state of the art. In multi-label text-classification, we observe a similar trend: The BoW-based MLP achieves a strong performance and outperforms the recent gMLP/aMLP models. Again, the fine-tuned BERT and DistilBERT models achieved the state of the art. Although the hierarchical HiAGM model results are only a few percent behind BERT and DistilBERT, it is important to note that this model uses additional information about the labels, namely the hierarchy. This requires additional memory, which lead to out-of-memory errors for large datasets, while all other models were able to run on the same infrastructure.

On a meta-level, our study shows that MLPs have largely been ignored as competitor methods in experiments. It seems as if MLPs have been forgotten as baseline in the literature, which instead is focusing mostly on other advanced Deep Learning architectures. Considering strong baselines is, however, an important means to argue about true scientific advancement (Shen et al., 2018; Dacrema et al., 2019). Simple models are also often preferred in industry due to lower operational and maintenance costs.

Below, we introduce our methodology and results from the literature study. Subsequently, we introduce the families of models in Section 3. Thereafter, we describe the experimental procedure in Section 4. We present the results of our experiments in Section 5 and discuss our findings in Section 6, before we conclude. This work is based on our ACL 2022 paper by Galke and Scherp (2022). It extends this work by experimenting with more methods and adding multi-label text classification. The latter also resulted in adding a method from the family of hierarchy-based models to the paper since
multi-label text classification often comes with a hierarchical structure among the classes.

2 Literature on Topical Text Classification

Methodology In a first step, we have analyzed recent surveys on text categorization and multi-label text classification and comparison studies (Tarekegn et al., 2021; Bayer et al., 2021; Li et al., 2020; Zhou et al., 2020c; Qaraei et al., 2020; Liu et al., 2020a; Kowsari et al., 2019; Kadhim, 2019; Mai et al., 2018a; Galke et al., 2017a; Zhang et al., 2016). These cover the range from shallow to deep classification models. The existing works consider both single- and multi-label text classification. Second, we have screened for literature in key NLP and AI venues. Finally, we have complemented our search by checking results and papers on paperswithcode.com. On the basis of this input, we have determined the families of methods and benchmark datasets (see Table 2). We focus our analysis on identifying models per family showing strong performance and select the methods to include in our study. For all models, we have verified that the same train-test split is used. We check whether modified versions of the datasets have been used (e.g., less classes), to avoid bias and wrongfully giving advantages.

BoW-based Models Classical machine learning models that operate on a BoW-based input are extensively discussed in two surveys (Kowsari et al., 2019; Kadhim, 2019) and other comparison studies (Galke et al., 2017a). Iyyer et al. (2015) proposed DAN, which combine word embeddings and deep feedforward networks. It is an MLP with 1-6 hidden layers, non-linear activation, dropout, and AdaGrad as optimization method. The results suggest to use pretrained embeddings such as GloVe (Pennington et al., 2014) over a randomly initialized neural bag of-words (Kalchbrenner et al., 2014) as input. In fastText (Bojanowski et al., 2017; Joulin et al., 2017) a linear layer on top of pretrained embeddings is used for classification. Furthermore, Shen et al. (2018) explore embedding pooling variants and find that SWEM can rival approaches based on recurrent (RNN) and convolutional neural networks (CNN). We consider fastText, SWEM, and a DAN-like deeper MLP in our comparison.

Note that those approaches that rely on logistic regression on top of pretrained word embeddings, e.g., fastText, share a similar architecture as an MLP with one hidden layer. However, the standard training protocol involves pretraining the word embedding on large amounts of unlabeled text and then freezing the word embeddings while training the logistic regression (Mikolov et al., 2013).

Sequence models: RNN and CNN Recurrent neural networks (RNN) are a natural choice for any NLP task. However, it turned out to be challenging to find numbers reported on text categorization in the literature that can be used as references. The bidirectional LSTM with two-dimensional max pooling BLSTM-2DCNN (Zhou et al., 2016) has been applied on a stripped-down to 4 classes version of the 20ng dataset. Thus, the high score of 96.5 reported for 4ng cannot be compared with papers applied on the full 20ng dataset. Also Text-RCNN (Lai et al., 2015), a model combining recurrence and convolution uses only the 4 major categories in the 20ng dataset. The results of Text-RCNN are identical with BLSTM-2DCNN. For the MR dataset, BLSTM-2DCNN provides no information on the specific split of the dataset. RNN-Capsule (Wang et al., 2018) is a sentiment analysis method reaching an accuracy of 83.8 on the MR dataset, but with a different train-test split. Lyu and Liu (2020) combine a 2D-CNN with bidirectional RNN. Another work applying a combination of a convolutional layer and an LSTM layer is by Wang et al. (2019b). The authors experiment with five English and two Chinese datasets, which are not in the set of representative datasets we identified. The authors report that their approach outperforms existing models like fastText on two of the five English datasets and both Chinese datasets.

Sequence models: Transformers Surprisingly, only few works consider Transformer models for topical text classification. A recent work shows that BERT outperforms classic TF-IDF BoW approaches on English, Chinese, and Portuguese text classification datasets (González-Carvajal and Garrido-Merchán, 2020). Another work has compared different fine-tuning strategies for text classification with BERT including multi-task objectives and few-shot learning tasks (Sun et al., 2019). We have not found any results of transformer-based models reported on those text categorization datasets that are commonly used in the graph-based approaches.
Therefore, we fine-tune BERT (Devlin et al., 2019) and DistilBERT (Sanh et al., 2019) on those datasets ourselves. BERT is a large pretrained language model on the basis of Transformers. DistilBERT (Sanh et al., 2019) is a distilled version of BERT with 40% reduced parameters while retaining 97% of BERT’s language understanding capabilities. TinyBERT (Jiao et al., 2020) and MobileBERT (Sun et al., 2020) would be similarly suitable alternatives, among others. We chose DistilBERT because it can be fine-tuned independently from the BERT teacher. Its inference times are 60% faster than BERT, which makes it easier to use in settings with limited resources.

Sequence models: MLP-based Models

Convolutional Neural Networks and attention-based networks became the go-to models in the past years for both computer vision and NLP tasks. More recently, researchers at Google introduced a new family of models, which discard these architectural advancements, and are based purely on an MLP architecture. The first of these models, MLP-Mixer (Tolstikhin et al., 2021) was developed for vision tasks. It divides the input image into a sequence of non-overlapping patches, which is then fed through blocks of MLPs consisting of channel-mixing and token-mixing layers. Following this, a more general alternative was introduced as a replacement for NLP-Transformer models, called the gMLP (Liu et al., 2021a). This model replaces the attention unit in the basic blocks of a network with a special gating unit, called the Spatial Gating Unit (SGU). Inside this layer, cross-token interactions are achieved with the use of an element-wise multiplication between the hidden-representation $Z$ and a linear projection of $Z$. Formally this layer is described as:

$$s(Z) = Z \circ f_{W,b}(Z)$$

The authors also experimented with different setups for the SGU, and found it most effective to split the hidden layer before the gating function into two equal parts $(Z_1, Z_2)$ along the channel dimension. Inside the SGU, $Z_1$ is multiplied by the linear projection of $Z_2$.

$$s(Z) = Z_1 \circ f_{W,b}(Z_2)$$

While they found that it is possible to achieve similar performance as BERT by replacing self-attention with these gating units, on some tasks gMLP was still outperformed by BERT. The authors hypothesized that the presence of self-attention can be advantageous depending on the tasks (i.e., cross-sentence alignment). Therefore, they attached a tiny attention unit (single-head with size 64) to the gating. This improvement substantially increased the performance of the model, and is referred to as $aMLP$.

Graph-based Models

Using graphs induced from text for the task of text categorization has a long history in the community. An early work is the term co-occurrence graph of the KeyGraph algorithm (Ohsawa et al., 1998). The graph is split into segments, representing the key concepts in the document. Co-occurrence graphs have also been used for automatic keyword extraction such as in the influential early work RAKE on automatic keyword extraction method (Rose et al., 2010) and can be also used for classification (Zhang et al., 2021).

Modern approaches exploit this idea in combination with graph neural networks (GNN) (Hamilton, 2020). Examples of GNN-based methods operating on a word-document co-occurrence graph are TextGCN (Yao et al., 2019) and its successor TensorGCN (Liu et al., 2020b) as well as HeteGCN (Ragesh et al., 2021), HyperGAT (Ding et al., 2020), and DADGNN (Liu et al., 2020b). We briefly discuss these models: In TextGCN, the authors set up a graph based on word-word connections given by window-based pointwise mutual information and word-document TF-IDF scores. They use a one-hot encoding as node features and apply a two-layer graph convolutional network (Kipf and Welling, 2017) on the graph to carry out the node classification task. HeteGCN combines ideas from Predictive Text Embedding (Tang et al., 2015) and TextGCN and split the adjacency matrix into its word-document and word-word submatrices and fuse the different layers’ representations when required. TensorGCN uses multiple ways of converting text data into graph data including a semantic graph created with an LSTM, a syntactic graph created by dependency parsing, and a sequential graph based on word co-occurrence. HyperGAT extended the idea of text-induced graphs for text classification to hypergraphs. The model uses graph attention and two kinds of hyperedges. Sequential hyperedges represent the relation between sentences and their words. Semantic hyperedges for word-word connections are derived from topic models (Blei et al., 2003). Finally, DADGNN
is a graph-based approach that uses attention diffusion and decoupling techniques to tackle oversmoothing of the GNN and to build deeper models.

In TextGCN’s original transductive formulation, the entire graph including the test set needs to be known for training. This may be prohibitive in practical applications as each batch of new documents would require retraining the model. When these methods are adapted for inductive learning, where the test set is unseen, they achieve notably lower scores (Ragesh et al., 2021). GNNs for text classification use corpus statistics, e.g., pointwise mutual information (PMI), to connect related words in a graph (Yao et al., 2019). When these were omitted, the GNNs would collapse to bag-of-words MLPs. Thus, GNNs have access to more information than BoW-MLPs. GloVe (Pennington et al., 2014) also captures PMI corpus statistics, which is why we include an MLP on GloVe input representations.

Hierarchy-based Models Hierarchical text classification is a subclass of text classification, sometimes also referred to as Hierarchical text classification (HMTC). In HMTC (Shen et al., 2021; Zhou et al., 2020a), the taxonomic hierarchy of labels is usually modeled as a tree or a directed acyclic graph. Thus, the goal of HMTC is to predict multiple labels, which corresponds to one or more nodes in the hierarchy.

Following Shen et al. (Shen et al., 2021), there are two main approaches of hierarchical text classification, local and global methods. In local approaches, a single classifier is used for each node or level in the hierarchy (Wehrmann et al., 2018; Shimura et al., 2018; Huang et al., 2019; Chang et al., 2019; Banerjee et al., 2019). These approaches aim to learn from parent nodes in case of data imbalance of children nodes. In the global approach, a single multilabel classifier is used for the given text.

As Zhou et al. (2020a) proposed, HiAGM is a hierarchical text classification model that uses label hierarchy information as directed graphs and utilizes prior probabilities of label dependencies to model label dependencies using hierarchy-aware structure encoders. Another recent model is TaxoClass (Shen et al., 2021), a weakly-supervised HMTC framework. Their framework consists of four steps. First, the document-class similarities are calculated with a textual entailment model. Afterwards, the core document core classes are identified and a taxonomy-enhanced classifier is trained. Last, the classifier is generalized with a multi-label self-training. In their experiments, the authors compare TaxoClass to different weakly-supervised and semi-supervised models on two datasets (Amazon-531, DBPedia-298). Since TaxoClass only uses class descriptive names in the text as training data, it is not comparable with our supervised models.

Additionally, in the beginning of 2021 a number of hierarchical label-based attention models were published like HLAN (Dong et al., 2021), LAHCN (Zhang et al., 2020), and (Liu et al., 2021b). Some papers also worth mentioning are Meng et al. (2018); Xiao et al. (2019) and Yin et al. (2019). Those are not included due to lack of common use of datasets and reporting of different F1-scores.

Summary From our literature survey, we see that most recent methods are based on graphs. BoW-based methods are hardly found in experiments, while, likewise surprisingly, Transformer-based sequence models are extremely scarce in the literature on topical text classification. The recent surveys on text categorization and multi-label text classification include both classical and Deep Learning models, but none considered a simple MLP except for the inclusion of DAN (Iyyer et al., 2015) in Li et al. (2020). Finally, we note that most surveys are considering single-label text classification. While there are some comparison studies on multi-label classification, it is clearly underrepresented.

3 Model Families for Text Classification

We formally introduce the families of models for text classification, namely the BoW-based, sequence-based, graph-based, and hierarchy-based models. Table 1 summarizes the key properties of the approaches: whether they require a synthetic graph, whether word position is reflected in the model, whether the model can deal with arbitrary length text, and whether the model is capable of inductive learning.

Between single- and multi-label classification, the models only differ in their loss function. We use categorical cross-entropy as loss function for the single-label case. For multi-label classification, we use binary cross-entropy.

3.1 BoW-based Text Classification

Under pure BoW-based text classification, we denote approaches that are not order-aware and operate only on the multiset of words from the input document. Given paired training examples
We consider RNNs, LSTMs, Transformers, and their successors HeteGCN, TensorGCN, HyperGAT, DADGNN, as well as simplified GCN (SGC) (Wu et al., 2019). We do not run our own experiments with pure BoW, TF-IDF weighted, and averaged GloVe input representations. We also use a two hidden layers WideMLP-2. We list the numbers for fastText, SWEM, and logistic regression from Ding et al. (2020) in our comparison.

For multi-label classification, the BoW-based model considers multiple class labels. Instead of using arg max(\hat{y}) to decide on a label, a binary sigmoid output per label and a threshold \( \lambda \) is applied to decide whether the output is accepted. Zhang and Zhou (2014) and Tsoumakas and Katakis (2009) suggest a threshold of \( \lambda = .5 \). This fits the output range of the sigmoid function (0,1), where 0.5 is the inflection point in the middle of the interval. However, in pre-experiments, Galke et al. (2017a) found that \( \lambda = .2 \) is a better threshold than \( \lambda = .5 \) for multi-label classification with many classes. Thus, for multi-label classification with the Wide-MLP model, we use a fixed threshold of \( \lambda = .2 \).

### 3.3 Graph-based Text Classification

Graph-based text classification approaches first set up a synthetic graph on the basis of the text corpus \( \mathcal{D} \) in the form of an adjacency matrix \( \hat{A} := \text{make-graph}(\mathcal{D}) \). For instance, in TextGCN the graph is set up in two parts: word-word connections modeled by pointwise mutual information and word-document edges resemble that the word occurs in the document. Then, a parameterized function \( f^\theta(\hat{A}) \) is learned that uses the graph as input, where \( X \) are the node features. The graph is composed of word and document nodes, each receiving its own embedding (by setting \( X = I \)). In inductive learning, however, there is no embedding of the test documents. Note that the graph-based approaches from the current literature such as TextGCN also disregard word order, similar to the BoW-based models described above. A detailed discussion of the connection between TextGCN and MLP is provided in the Appendix B.

We consider top performing graph-based models from the literature, namely TextGCN along with its successors HeteGCN, TensorGCN, HyperGAT, DADGNN, as well as simplified GCN (SGC) (Wu et al., 2019). We do not run our own experiments for the graph-based models but rely on the original token’s position is associated with an embedding vector that is added to the token embedding at input level. In the recent gMLP model, the positional information is only encoded in the spatial gating unit that model the sequence of the input units.

For the sequence-based models, we run our own experiments with a pretrained BERT and DistilBERT, while we train our gMLP and aMLP models from scratch. We also include the scores of a pretrained LSTM from Ding et al. (2020) for comparison. In the multi-label case, we use the same thresholding setup as described before, i.e., a threshold of \( \lambda = .5 \).

### Table 1: Properties of text classification approaches. Graph-based models that rely on having access to unlabeled test documents such as TextGCN and TensorGCN are not capable of inductive learning without modifications.

| Model                  | Synthetic Graph | Position-Aware | Arbitrary Length | Inductive |
|------------------------|-----------------|----------------|------------------|-----------|
| Bag-of-Words           | No              | No             | Yes              | Yes       |
| Graph: TextGCN         | Yes             | No             | Yes              | No        |
| Graph: TensorGCN       | Yes             | Yes            | Yes              | No        |
| Graph: HeteGCN/HyperGAT| Yes             | No             | Yes              | Yes       |
| Sequence: RNN/CNN      | No              | Yes            | No               | Yes       |
| Sequence: BERT/DistilBERT| No             | Yes            | No               | Yes       |
| Sequence: gMLP/aMLP    | No              | Yes            | No               | Yes       |

\((x, y) \in \mathcal{D}\), each consisting of a bag-of-words \( x \in \mathbb{R}^{n_{voc}} \) and a class label \( y \in \mathcal{Y} \), the goal is to learn a generalizable function \( \hat{y} = f^\theta_{(BoW)}(x) \) with parameters \( \theta \) such that \( \arg\max(\hat{y}) \) preferably equals the true label \( y \) for input \( x \).

As BoW-based model, we consider a one hidden layer WideMLP (i.e., two layers in total). We experiment with pure BoW, TF-IDF weighted, and averaged GloVe input representations. We also use a two hidden layers WideMLP-2. We list the numbers for fastText, SWEM, and logistic regression from Ding et al. (2020) in our comparison.

For multi-label classification, the BoW-based model considers multiple class labels. Instead of using \( \arg\max(\hat{y}) \) to decide on a label, a binary sigmoid output per label and a threshold \( \lambda \) is applied to decide whether the output is accepted. Zhang and Zhou (2014) and Tsoumakas and Katakis (2009) suggest a threshold of \( \lambda = .5 \). This fits the output range of the sigmoid function (0,1), where 0.5 is the inflection point in the middle of the interval. However, in pre-experiments, Galke et al. (2017a) found that \( \lambda = .2 \) is a better threshold than \( \lambda = .5 \) for multi-label classification with many classes. Thus, for multi-label classification with the Wide-MLP model, we use a fixed threshold of \( \lambda = .2 \).

### 3.2 Sequence-based Text Classification

We consider RNNs, LSTMs, Transformers, and the variations of gMLP models as sequence-based models. These models are aware of the order of the words in the input text in the sense that they are able to exploit word order information. Thus, the key difference to the BoW-based and graph-based models is that the word order is reflected by sequence-based model. The model signature is \( \hat{y} = f^\theta_{(sequence)}(x_1, x_2, \ldots, x_k) \), where \( k \) is the (maximum) sequence length.

Word position can be also modeled by a dedicated positional encoding. For instance, in BERT a
work and extensive studies by Ding et al. (2020) and Ragesh et al. (2021).

3.4 Hierarchy-based Text Classification

For the hierarchy-based text classification, we use HiAGM, which uses a GNN-based encoder to obtain each class’s representation. HiAGM-LA is a multi-label attention model that uses an inductive approach. At the same time, HiAGM-TP is a text feature propagation model that uses a deductive approach to extract hierarchy-aware text features. In the architecture variants they also used Tree-LSTM and GCN as structure encoders for aggregating node information. We use their best-performing variant HiAGM-TP with GCN as structure encoder, which was tested on four datasets RCV1-V2, RCV1-V2-R, WOS, and NYT, keeping the rest of the hyperparameters the same as the original paper.

4 Experimental Apparatus

4.1 Datasets

Single-label Datasets  We use the same datasets and train-test split as in TextGCN (Yao et al., 2019). Those datasets are 20ng, R8, R52, ohsumed, and MR. Twenty Newsgroups (20ng)1 contains long posts categorized into 20 newsgroups. The mean sequence length is 551 words with a standard deviation (SD) of 2,047. R8 and R52 are subsets of the R21578 news dataset with 8 and 52 classes, respectively. The mean sequence length and SD is 119 ± 128 words for R8, and 126 ± 133 words for R52. Ohsumed2 is a corpus of medical abstracts from the MEDLINE database that are categorized into diseases (one per abstract). The mean sequence length is 285 ± 123 words. Movie Reviews (MR)3 (Pang and Lee, 2005), split by Tang et al. (2015), is a binary sentiment analysis dataset on sentence level (mean sequence length and SD: 25 ± 11). Table 2 shows the dataset characteristics. The label distribution of each single-label dataset is shown in Appendix E.

Multi-label Datasets  Table 3 shows the characteristics of the multi-label datasets. Reuters-21578 (R21578) (Bache and Lichman, 2013) is a popular dataset for multi-label classification. It is a collection of documents that appeared on Reuters newswire in 1987. We use the train-test split from NLTK4. The labels in R21578 are not hierarchical organized. EconBiz (Mai et al., 2018b) is a dataset, which contains documents with titles of a meta-data export as well as documents with titles and full-text from the ZBW - Leibniz Information Centre for Economics in 2017. EconBiz does not provide a specific train or test set, but the samples are split into eleven parts. Parts 0 to 9 correspond to the samples that have a full-text, while part 10 contains to all other samples containing only the titles of documents. This special organization of the dataset is due to the research question addressed by Mai et al. (2018b), which is about to compare text classification using full-text versus only employing the titles. In order to accommodate this dataset in our experiments, we use the titles for training and the parts with the full-text documents for testing. GoEmotions is a corpus of comments extracted from Reddit, with human annotations to 27 emotion categories. We use the same train-test split as in GoEmotions (Demszky et al., 2020). GoEmotions is not providing a hierarchical label structure. Amazon-531 (McAuley and Leskovec, 2013) contains 49,145 product reviews and a three-level class taxonomy consisting of 531 classes. DBPedia-298 (Lehmann et al., 2015) includes 245,832 Wikipedia articles and a three-level class taxonomy with 298 classes. For Amazon-531 and DBPedia-298, we use the same train-test split as in TaxoClass (Shen et al., 2021). NYT AC (Sandhaus, 2008) contains New York Times articles written between 1987 and 2007. We use the train-validation-test split from HiAGM (Zhou et al., 2020a). RCV1-V2 is a newer version of the R21578 dataset containing a significantly larger amount of manually categorized newswire stories. For RCV1-V2, we use the train-test split proposed in Lewis et al. (2004).

Table 2: Characteristics of text classification datasets

| Dataset | N     | #Train | #Test | #Classes |
|---------|-------|--------|-------|----------|
| 20ng    | 18,846| 11,314 | 7,532 | 20        |
| R8      | 7,674 | 5,485  | 2,189 | 8         |
| R52     | 9,100 | 6,532  | 2,568 | 52        |
| ohsumed | 7,400 | 3,357  | 4,043 | 23        |
| MR      | 10,662| 7,108  | 3,554 | 2         |

1http://qwone.com/~jason/20Newsgroups/  
2http://disi.unitn.it/moschitti/corpora.htm  
3https://www.cs.cornell.edu/people/pabo/movie-review-data/  
4https://www.nltk.org/book/ch02.html
train set as validation set for each dataset. The label distribution of each multi-label dataset and the number of labels per document of each multi-label dataset is shown in Appendix E.

4.2 Inductive and Transductive Setups

We distinguish between a transductive and an inductive setup for topical text classification. In the transductive setup, as used in TextGCN, the test documents are visible and actually used for the preprocessing step. In the inductive setting, the test documents remain unseen until test time (i.e., they are not available for preprocessing). We report the scores of the graph-based models for both setups from the literature, where available. BoW-based and sequence-based models are inherently inductive. Ragesh et al. (2021) have evaluated a variant of TextGCN that is capable of inductive learning, which we include in our results, too.

4.3 Procedure and Hyperparameter Settings

We have extracted accuracy scores from the literature according to our systematic selection from Section 2. Below, we provide a detailed description of the procedure for the models that we have run ourselves. We borrow the tokenization strategy from BERT (Devlin et al., 2019) along with its uncased vocabulary. The tokenizer relies primarily on WordPiece (Wu et al., 2016) for a high coverage while maintaining a small vocabulary.

Hyperparameters for the Single-label Case

**Training WideMLP:** Our WideMLP has one hidden layer with 1,024 rectified linear units (one input-to-hidden and one hidden-to-output layer). We apply dropout after each hidden layer, notably also after the initial embedding layer. Only for GloVe+WideMLP, neither dropout nor ReLU is applied to the frozen pretrained embeddings but only on subsequent layers. The variant WideMLP-2 has two ReLU-activated hidden layers (three layers in total) with 1,024 hidden units each. While this might be overparameterized for single-label text classification tasks with few classes, we rely on recent findings that overparameterization leads to better generalization (Neyshabur et al., 2018; Nakkiran et al., 2020). In pre-experiments, we realized that MLPs are not very sensitive to hyperparameter choices. Therefore, we optimize cross-entropy with Adam (Kingma and Ba, 2015) and its default learning rate of $10^{-3}$, a linearly decaying learning rate schedule and train for a high amount of steps (Nakkiran et al., 2020) (we use 100 epochs) with small batch sizes (we use 16) for sufficient stochasticity, along with a dropout ratio of 0.5.

**Training gMLP/aMLP:** We took the gMLP/aMLP architecture design from the original paper (Liu et al., 2021a). Similar to the BERT models, there is an initial embedding layer, followed by 18 gMLP blocks with a token sequence length of 512. Layer normalization and a GeLU activation function is applied between the blocks. For the aMLP version, we attach a single-head attention module to the spatial gating unit with a size of 64. Furthermore, we truncate all inputs to 512 tokens, use the Adam optimizer with a fixed learning rate of $10^{-4}$, and run the training for 100 epochs with a batch size of 32.

**Fine-tuning BERT:** For BERT and DistilBERT, we fine-tune for 10 epochs with a linearly decaying learning rate of $5 \cdot 10^{-5}$ and an effective batch size of 128 via gradient accumulation of 8 x 16 batches. We truncate all inputs to 512 tokens. To isolate the influence of word order on BERT’s performance, we conduct two further ablations. First, we set all position embeddings to zero and disable their gradient (BERT w/o pos ids). By doing this, we force BERT to operate on a bag-of-words without any notion of word order or position. Second, we shuffle each sequence to augment the training data. We use this augmentation strategy to increase the number of training examples by a factor of two (BERT w/ shuffle augment).

Hyperparameters for the Multi-label Case

**Training WideMLP:** For the multi-label classifier WideMLP, we use a manual search for setting hyperparameters. We use a TF-IDF input representation, 100 epochs, and a fixed learning rate of $10^{-1}$ for all datasets. We scale the batch size with the dataset size to reduce training time. For the smaller datasets (R21578, GoEmotions, Amazon-531, NYT AC, RCV1-V2), we use a batch size of 8. For DBPedia-298, the batch size is 32 and for EconBiz, we use a batch size of 256. In pre-experiments, we tested different thresholds from $\lambda = .5$ to $\lambda = .1$ (.1 steps) and experienced similar results reported in Galke et al. (2017a), where $\lambda = .2$ achieved the best results.

**Training gMLP/aMLP:** For the multi-label setup, we use the same architecture as described in the single label setup. Pre-experiments on the R21578 dataset showed the best learning-rate to be $10^{-4}$. The use of different learning-rate schedulers (linear
decaying, reduce on plateau) was investigated, but we found the best results with a fixed, non-decaying learning rate. We train for 300 epochs with a batch-size of 32 across all datasets, with the exemption of Econbiz where due to the greater size of the dataset we scale down our epoch count to 50 and increase the batch size to 64. We collect results with a threshold of $\lambda = .2$ and $\lambda = .5$ and find the latter to be better performing.

Fine-tuning BERT: For BERT and DistilBERT, we use a manual search to find the best hyperparameters, and the same hyperparameters were chosen for the two models. We used the R21578 dataset for pre-experiments. In practice, it has been observed that when using a larger batch, the model’s quality, as evaluated by its ability to generalize, degrades (Zhou et al., 2020b). We observed in pre-experiments, that the results of BERT and DistilBERT are best with smaller batch size. After trying different learning rates and batch sizes, we used a linearly decaying learning rate of $5 \cdot 10^{-5}$ with a batch size of 4 across all the datasets.

We use a fixed threshold of $\lambda = .5$ as a result of the pre-experiments. We select the number of training epochs based on minimum validation loss. We fine-tune for 5 and 15 epochs. Instead of using 10 epochs as in the single-label training case, we fixed 15 epochs for multi-label training. DBPedia-298 and GoEmotions had best results with 5 epochs that the validation loss increases as epochs increase. We truncate all inputs to 512 tokens.

Training HiAGM: For hierarchical multi-label classification, we used HiAGM-TP, which was the best performing variant of HiAGM with GCN as a structural encoder. We used the hyperparameters given in the original study (Zhou et al., 2020a). We used a batch size of 64 with a learning rate of 0.0001 and a decay of 1.0 across all datasets for the training process. We experimented with a threshold of $\lambda = .5$ to $\lambda = .2$ and found that 0.5 was the best value.

4.4 Measures

We report accuracy as evaluation metric for the single-label datasets. Note, accuracy is equivalent to Micro-F1 in single-label classification (see Appendix C). We repeat all experiments five times with different random initialization of the parameters and report the mean and standard deviation of these five runs.

For the multi-label measure, we follow the approach in Galke et al. (2017b) and report a sample-based F1 measure. We choose this sample-based evaluation measure because it reflects the classification quality of each document separately. The sample-based F1-measure is calculated by the harmonic mean of precision and recall for each example individually and then these scores are averaged.

5 Results

5.1 Single-label Text Classification

Table 4 shows the accuracy scores for the single-label text classification models on the five datasets. All graph-based models in the transductive setting show similar accuracy scores (maximum difference is 2 points). As expected, the scores decrease in the inductive setting up to a point where they are matched or even outperformed by our WideMLP.

In the inductive setting, the WideMLP models perform best among the BoW models, in particular, TFIDF+WideMLP and WideMLP on an unweighted BoW. The best-performing graph-based model is HyperGAT, yet DADGNN has a slight advantage on R8, R52, and MR. For the sequence-based models, BERT attains the highest scores, closely followed by DistilBERT.

The sequential MLP-based models show a poor performance, only outperforming the weaker baseline models, such as Logistic Regression, pre-trained LSTM and TextGCN, on the R21578 dataset. The inclusion of the single-head attention layers in the aMLP increased the accuracy scores.

| Dataset    | N   | #Train  | #Test  | Split Ratio | #Classes | Avg. #classes per sample |
|------------|-----|---------|--------|-------------|----------|--------------------------|
| R21578     | 10,788 | 7,769   | 3,019  | 72:18       | 90       | 1.24                     |
| EconBiz    | 1,064,634 | 994,015 | 70,619 | 93:7        | 5,661    | 4.36                     |
| GoEmotions | 48,837 | 43,410  | 5,427  | 89:11       | 28       | 1.18                     |
| Amazon-531 | 49,145 | 29,487  | 19,658 | 60:40       | 531      | 3                        |
| DBPedia-298| 245,832| 196,665 | 49,197 | 80:20       | 298      | 3                        |
| NYT AC     | 36,471 | 29,179  | 7,292  | 80:20       | 166      | 7.58                     |
| RCV1-V2    | 804,414| 23,149  | 781,265| 3:97        | 103      | 3.24                     |
Table 4: Mean accuracy and standard deviation over five runs on the single-label text classification datasets. Column “Provenance” reports the source.

| Inductive Setting | 20ng | R8  | R52 | ohsumed | MR  | Provenance |
|-------------------|------|-----|-----|---------|-----|------------|
| BoW-Models        |      |     |     |         |     |            |
| Log. Regression   | 83.70| 93.33| 90.65| 61.14   | 76.28| Ragesh et al. (2021) |
| SWEM              | 85.16 (0.29) | 95.32 (0.26) | 92.94 (0.24) | 63.12 (0.55) | 76.65 (0.63) | Ding et al. (2020) |
| fastText          | 79.38 (0.30) | 96.13 (0.21) | 92.81 (0.09) | 57.70 (0.49) | 75.14 (0.20) | Ding et al. (2020) |
| TF-IDF + WideMLP  | 84.20 (0.16) | 97.08 (0.16) | 93.67 (0.23) | 66.06 (0.29) | 76.32 (0.17) | own experiment |
| WideMLP           | 83.31 (0.22) | 97.27 (0.12) | 93.89 (0.16) | 63.95 (0.13) | 76.72 (0.26) | own experiment |
| WideMLP-2         | 81.02 (0.23) | 96.61 (1.22) | 93.98 (0.23) | 61.71 (0.33) | 75.91 (0.51) | own experiment |
| GloVe+WideMLP     | 76.80 (0.11) | 96.44 (0.08) | 93.58 (0.06) | 61.36 (0.22) | 75.96 (0.17) | own experiment |
| GloVe+WideMLP-2   | 76.33 (0.18) | 96.50 (0.14) | 93.19 (0.11) | 61.65 (0.27) | 75.72 (0.45) | own experiment |

| Graph-based Models |      |     |     |         |     |            |
| TextGCN           | 80.88 (0.54) | 94.00 (0.40) | 89.39 (0.38) | 56.32 (1.36) | 74.60 (0.43) | Ragesh et al. (2021) |
| HeteGCN           | 84.59 (0.14) | 97.17 (0.33) | 93.89 (0.45) | 63.79 (0.80) | 75.62 (0.26) | Ragesh et al. (2021) |
| HyperGAT          | 86.62 (0.16) | 97.07 (0.23) | 94.98 (0.27) | 69.90 (0.34) | 78.32 (0.27) | Ragesh et al. (2021) |
| DADGNN            | —     | 98.15 (0.16) | 95.16 (0.22) | —     | 78.64 (0.29) | Liu et al. (2021c) |

| Sequence-based Models |      |     |     |         |     |            |
| LSTM w/ pretrain    | 75.43 (1.72) | 96.09 (0.19) | 90.48 (0.86) | 51.10 (1.50) | 77.33 (0.89) | Ding et al. (2020) |
| DistilBERT          | 86.24 (0.26) | 97.89 (0.15) | 95.34 (0.08) | 69.08 (0.60) | 85.10 (0.33) | own experiment |
| BERT                | 87.21 (0.18) | 98.03 (0.24) | 96.17 (0.33) | 71.46 (0.54) | 86.31 (0.38) | own experiment |
| BERT w/o pos emb    | 81.47 (0.49) | 97.39 (0.20) | 94.70 (0.27) | 65.18 (1.53) | 80.35 (0.20) | own experiment |
| BERT w/ shuffle augment | 86.46 (0.42) | 98.07 (0.21) | 96.48 (0.18) | 70.94 (0.60) | 86.23 (0.33) | own experiment |
| gMLP w/o pretraining | 86.62 (1.66) | 94.46 (0.41) | 91.27 (0.09) | 39.58 (0.77) | 66.24 (0.37) | own experiment |
| aMLP w/o pretraining | 72.14 (1.07) | 95.40 (0.20) | 91.77 (0.11) | 49.29 (1.13) | 66.67 (0.35) | own experiment |

| Transductive Setting | 20ng | R8  | R52 | ohsumed | MR  | Provenance |
|---------------------|------|-----|-----|---------|-----|------------|
| Graph-based Models  |      |     |     |         |     |            |
| TextGCN             | 86.34 | 97.07 | 93.56 | 68.36   | 76.74 | Yao et al. (2019) |
| SGC                 | 88.5 (0.1) | 97.2 (0.1) | 94.0 (0.2) | 68.5 (0.3) | 75.9 (0.3) | Wu et al. (2019) |
| TensorGCN           | 87.74 | 98.04 | 95.05 | 70.11   | 77.91 | Liu et al. (2020b) |
| HeteGCN             | 87.15 (0.15) | 97.24 (0.51) | 94.35 (0.25) | 68.11 (0.70) | 76.71 (0.33) | Ragesh et al. (2021) |

by 0.5-10 points compared to the standard gMLP model.

The strong performance of WideMLP rivals all graph-based techniques reported in the literature, in particular, the recently published graph-inducing methods. MLP only falls behind HyperGAT, which relies on topic models to set up the graph. Another observation is that 1 hidden layer (but wide) is sufficient for the tasks, as the scores for MLP variants with 2 hidden layers are lower. We further observe that both pure BoW and TF-IDF weighted BoW lead to better results than approaches that exploit pretrained word embeddings such as GloVe-MLP, fastText, and SWEM.

With its immense pretraining, BERT yields the overall highest scores, closely followed by DistilBERT. DistilBERT outperforms HyperGAT by 7 points on the MR dataset while being on par on the others. BERT outperforms the strongest graph-based competitor, HyperGAT, by 8 points on MR, 1.5 points on ohsumed, 1 point on R52 and R8, and 0.5 points on 20ng.

Our results further show that removing positional embeddings from BERT does decrease the scores notably (5-6 accuracy points on 20ng, ohsumed, and MR), but BERT w/o positional embeddings still achieves scores that are comparable to WideMLP. Augmenting the data with shuffled sequences has led to neither a consistent decrease nor increase in performance.

5.2 Multi-label Text Classification

Table 5 shows the F1-samples measure for the multi-label text classification models on the 7 datasets. Overall, the sequence-based models BERT and DistilBERT perform best on most of the multi-label datasets, outperforming the other models by up to 15 points on GoEmotions. BERT and DistilBERT are only falling behind the other models on EconBiz, where the large number of classes has to be taken into account. Between BERT and DistilBERT, the F1-samples scores are similar (maximum difference 2 Points, except 4 Points on EconBiz). The next best model is the hierarchical model of HiAGM. The additional hierarchical label information give HiAGM overall good results, especially on Amazon-531, where HiAGM outperforms WideMLP by 7 points and is
Table 5: F1-Samples on the multi-label text classification datasets. Column “Provenance” reports the source. Blank numbers mean that the referenced paper did not report results on a dataset. “-” indicates that HiAGM could not produce results, because of the not hierarchical structured dataset. “OOM” denotes that the model ran out-of-memory. For our experiments the results are based on one run. Galke et al. (2017a) and Mai et al. (2018b) collected the F1-Samples score over ten folds of cross-validation.

| Inductive Setting | R21578 | RCV1-V2 | EconBiz | Amazon | DBPedia | NYT | GoEmotions | Provenance |
|-------------------|--------|---------|---------|--------|---------|-----|-------------|------------|
| **MLP**           | 0.85   | 0.519   | 0.457   | 0.569  |         |     |             |            |
| **MLP**           | 0.88   | 0.82    | 0.45    | 0.80   | 0.95    | 0.75 | 0.40        | Galke et al. (2017a) |
| WideMLP           | 0.85   | 0.79    | 0.40    | 0.83   | 0.95    | 0.72 | 0.44        | Mai et al. (2018b)  |
| gMLP w/o pr.      | 0.85   | 0.77    | 0.42    | 0.82   | 0.95    | 0.70 | 0.47        | own experiment   |
| aMLP w/o pr.      | 0.93   | 0.88    | 0.43    | 0.89   | 0.98    | 0.80 | 0.55        | own experiment   |
| BERT              | 0.92   | 0.87    | 0.39    | 0.87   | 0.98    | 0.79 | 0.55        | own experiment   |
| DistilBERT        | -      | 0.85    | OOM     | 0.87   | 0.96    | 0.75 | -           | own experiment   |

only 2 points behind BERT. HiAGM is closely followed by our WideMLP model. WideMLP is equal or outperforming the sequential MLP-based models on most datasets (R21578, RCV1-V2, EconBiz, DBPedia-298, NYT AC), only falling behind gMLP and aMLP on Amazon-531 and GoEmotions. On the sentiment prediction task in GoEmotions, the WideMLP performs worst among the models (15 points behind BERT/DistilBERT). However, the WideMLP performs best on EconBiz. The score is comparable with the results reported in Mai et al. (2018b), although having a different train-test dataset setup. The sequence-based models of gMLP and aMLP outperform DistilBERT (gMLP by 4 points and aMLP by 6 points). Both gMLP and aMLP show similar results (maximum difference of 3 points). Similar to the single-label results, BERT yields overall the highest scores, followed by DistilBERT.

5.3 Parameter Count of Models

Table 6 lists the parameter counts of the models used in our experiments. The parameter counts are the same for the multi-label and single-label setups and are estimated based on small class numbers. In the case of datasets with a large number of classes, the parameter count of the models increases uniformly. Even though the MLP is fully-connected on top of a bag-of-words with the dimensionality of the vocabulary size, it has only half of the parameters as DistilBERT, and a quarter of the parameters of BERT. Using TF-IDF does not change the number of model parameters. The new MLP-based models are larger than WideMLP models, but still less than half the size of BERT. Due to the high vocabulary size, GloVe-based models have a high number of parameters, but the majority of those is frozen, i.e., does not get gradient updates during training. HiAGM consists of two smaller models, the text encoder and the structural label encoder. The former has a constant parameter count across different datasets while in the later, the parameter count varies according to the number of labels present in the dataset.

| Model                  | #parameters |
|------------------------|-------------|
| WideMLP                | 31.3M       |
| WideMLP-2              | 32.3M       |
| GloVe+WideMLP          | 575.2M (frozen) + 0.3M |
| GloVe+WideMLP-2        | 575.2M (frozen) + 1.3M |
| DistilBERT             | 66M         |
| BERT                   | 110M        |
| gMLP                   | 48.5M       |
| aMLP                   | 51.4M       |
| HiAGM                  | 53.9M       |

6 Discussion

We discuss the results of our single- and multi-label text classification experiments separately, before we reflect on similarities and differences between the results for the two different tasks.

6.1 Single-label Case

Key Insights. Our experiments show that our MLP models using BoW outperform the recent graph-based models TextGCN and HeteGCN in an inductive text classification setting. Furthermore, the MLP models are comparable to HyperGAT. The new sequential MLP-based models without

---

5Using different train-test split with full-text training data
6Using different modality: both train and test on only title data
pretraining show an inferior performance to most models, being only comparable to Logistic Regression, pretrained LSTM and TextGCN on some datasets. The inclusion of tiny attention shows a significant performance increase across all datasets, but aMLP is still far behind the fine-tuned DistilBERT and BERT models which set the new state of the art. This result is important for two reasons: First, the strong performance of a pure BoW-MLP questions the added value of synthetic graphs in models like TextGCN to the topical text classification task. Only HyperGAT, which uses the expensive Latent Dirichlet Allocation for computing the graph, slightly outperforms our BoW-WideMLP in two out of five datasets. Thus, we argue that using strong baseline models for text classification is important to assess the true scientific advancement (Dacrema et al., 2019).

Second, in contrast to conventional wisdom (Iyyer et al., 2015), we find that pretrained embeddings, e.g., GloVe, can have a detrimental effect when compared to using an MLP with one wide hidden layer. Such an MLP circumvents the bottleneck of the small dimensionality of word embeddings and has a higher capacity. Furthermore, we experiment with more hidden layers (see WideMLP-2), but do not observe any improvement when the single hidden layer is sufficiently wide. A possible explanation is that already a single hidden layer is sufficient to approximate any compact function to an arbitrary degree of accuracy depending on the width of the hidden layer (Cybenko, 1989).

Finally, a new state-of-the-art is set by the transformer model BERT, which is not very surprising. The attention mechanism of (standard) Transformers is quadratic in the sequence length, which leads to slower processing of long sequences. With larger batches, the speed of the MLP could be increased even further.

**Detailed Discussion of Results** Graph-based models come with high training costs, as not only the graph has to be first computed, but also a GNN has to be trained. For standard GNN methods, the whole graph has to fit into the GPU memory and mini-batching is nontrivial, but possible with dedicated sampling techniques for GNNs (Fey et al., 2021). Furthermore, the original TextGCN is inherently transductive, i.e., it has to be retrained whenever new documents appear. Strictly transductive models are effectively useless in practice (Lu et al., 2019) except for applications, in which a partially labeled corpus needs to be fully annotated. However, recent extensions such as HeteGCN, HyperGAT, and DADGNN already relax this constraint and enable inductive learning. Nevertheless, word-document graphs require $O(N^2)$ space, where $N$ is the number of documents plus the vocabulary size, which is a hurdle for large-scale applications.

There are also tasks where the natural structure of the graph data provides more information than the mere text, e.g., citations networks or connections in social graphs. In such cases, the performance of graph neural networks is the state of the art (Kipf and Welling, 2017; Veličković et al., 2018) and are superior to MLPs that use only the node features and not the graph structure (Shchur et al., 2018). GNNs also find application in various NLP tasks, other than classification (Wu et al., 2021).

An interesting factor is the ability of the models to capture word order. BoW models disregard word order entirely and yield good results, but still fall behind order-aware Transformer models. In an extensive study, Conneau et al. (2018) have shown that memorizing the word content (which words appear at all) is most indicative of downstream task performance. Sinha et al. (2021) have experimented with pretraining BERT by disabling word order during pretraining and show that it makes surprisingly little difference for fine-tuning. In their study, word order is preserved during fine-tuning. In our experiments, we have conducted complementary experiments: we have used a BERT model that is pretrained with word order, but we have deactivated the position encoding during fine-tuning. Our results show that there is a notable drop in performance but the model does not fail completely.

Although gMLP and aMLP utilize the positional information of the inputs, without pretraining it fails to outperform even the Bow-based simple MLP. This highlights the need of task-agnostic pretraining in sequence models and the cost-benefit of using simpler models trained from scratch on less complex downstream tasks, such as single-label text classification.

Other NLP tasks such as question answering (Rajpurkar et al., 2016) or natural language inference (Wang et al., 2019a) can also be regarded as text classification on a technical level. Here, the positional information of the sequence is more important than for pure topical text classification. One can expect that BoW-based models perform worse than sequence-based models.
**Generalizability**  We expect that similar observations would be made on other text classification datasets because we have already covered a range of different characteristics: long and short texts, topical classification (20ng, R5, R52, and Ohsumed) and sentiment prediction (MR) in the domains of forum postings, news, movie reviews, and medical abstracts. Our results are in line with those from other fields, who have reported a resurgence of MLPs. For example, in business prediction, an MLP baseline outperforms various other Deep Learning models (Venugopal et al., 2021; Yedida et al., 2021). In computer vision, Tolstikhin et al. (2021) and Melas-Kyriazi (2021) proposed attention-free MLP models are on par with the Vision Transformer (Dosovitskiy et al., 2021). In NLP, the introduction of the pretrained sequential MLP-based models Liu et al. (2021a) show similar results, while acknowledging that a small attention module is necessary for some tasks. Our experiments also showed that not unlike other sequence models, without pretraining the results of gMLP and aMLP are subpar.

6.2 Multi-label Case

**Key Insights**  Although we observed relatively small differences in F1-Samples scores between Transformers-based and MLP-based models, BERT and DistilBERT still outperformed the other models in all datasets, except for EconBiz. The reason for the strong performance of Transformer models could be the large-scale pretraining and the multi-head self-attention layers in the architecture (Liu et al., 2021a).

In the multi-label case, the presence of single-head attention layers in aMLP did not lead to a consistent performance upgrade compared to gMLP. While on the EconBiz and GoEmotions datasets attention increased the F1-Samples score by a few percent, on other datasets the performance was the same, or even less than that of gMLP.

HiAGM’s performance is comparable with that of DistilBERT and BERT. However, HiAGM cannot be used with the R21578 and GoEmotions datasets, because they have no label hierarchies. Additionally, it is not used with EconBiz, because HiAGM utilizes a GCN as a structure encoder which limits its capacity to process datasets with large number of classes due to high memory requirements. In our experiments, HiAGM applied on the EconBiz dataset was the only model that ran into an out-of-memory. We used for all experiments the same NVIDIA A100 HGX GPUs with 40 GB of RAM.

WideMLP proved to be a strong baseline in the multi-label setup as well, achieving comparable performance to the Transformers and HiAGM.

**Detailed Discussion of Results**  We found similar patterns in F1-Samples scores across datasets. In all models, EconBiz gave the lowest F1-Samples, and DBPedia-298 had the best results. EconBiz is by far the largest dataset, having 10-times more documents and classes than the second largest dataset. Also, the label distribution of EconBiz is very imbalanced (see Appendix E). This makes it difficult to correctly predict labels. In contrast to EconBiz, in DBPedia-298 every document has 3 labels (see Figure 3 in Appendix E). This fixed number of labels with less imbalanced data indicates the good results on DBPedia-298 compared to EconBiz. RCV1-V2 is an outlier based on the train-test split compared to the other used datasets. RCV1-V2 uses only 30% of the dataset for training compared to around 80% for the other datasets (see Table 3). However, this did not effect the F1-Samples scores and the detected pattern stayed the same. The only dataset where the WideMLP results are the worst out of all the models used, is the GoEmotions. Despite having a similar average class count per sample as R21578, the WideMLP achieves only a F1-Samples score of 0.4 compared to 0.88 on R21578. This may be due to the fact that GoEmotions is a sentiment prediction instead of topical classification.

**Generalizability**  With the multi-label datasets we cover a wide range of different characteristics: full-text and titles (EconBiz), topical classification (R21578, RCV1-V2, Amazon-531, DBPedia-298, NYT AC), and sentiment prediction (GoEmotions). The characteristics are used in different domains like forum posts, news, product reviews. So, we expect similar results on other text classification datasets.

6.3 Reflection on Single- vs. Multi-label Case

Our results show a generally better performance on single-label text-classification compared to the multi-label cases. This can be explained by different reasons: First, the multi-label datasets are greater in size with much more imbalanced distributions. The ground truth label count also changes between samples across all multi-label datasets,
with the exception of DBPedia-298. In the latter dataset, each sample has exactly 3 labels, which makes the prediction task easier. Lastly, for multi-label classification an additional hyperparameter is added with the class-thresholding. Using a global threshold is not the most optimized method for maximizing inference performance.

The trend between the models used for both tasks remains the same. The best results are achieved through the fine-tuned Transformer models, while WideMLP gives comparable and sometimes better performance than many other recent models. Our results show that WideMLP can be considered a strong baseline for both single and multi-label classification tasks.

Another trend can be found by looking at the sentiment prediction dataset results. In the single-label setups, BERT outperforms the WideMLP on the MR dataset with the largest margin compared to other datasets. This same trend exists for the GoEmotions dataset in the multi-label case, where WideMLP achieves the worst performance across all models, and the highest margin compared to BERT between datasets. This shows that BoW-based MLP models might be at disadvantage in sentiment prediction compared to sequence-based models.

6.4 Threats to Validity

We acknowledge that the experimental datasets are limited to English. While word order is important in the English language, it is notable that methods that discard word order still work well for topical text classification. Another possible bias is the comparability of the results. However, we carefully checked all relevant parameters such as the train/test split, the number of classes in the datasets, if datasets have been pre-processed in such a way that, e.g., makes a task easier like reducing the number of classes, the training procedure, and the reported evaluation metrics. In addition, we run some further efficiency analyses reported in Appendix D. We made sure to report numbers for the parameter count and a measure for the speed other than FLOPs, as recommended by Dehghani et al. (2021). Since runtime is heavily dependent on training parameters such as batch size, we complement this with asymptotic complexity.

Without a publicly available pretrained gMLP model our experiments were restricted to training the new MLP-based models from scratch. Task-agnostic pretraining has been a staple part of generalist models like BERT. Therefore, it would be interesting to use a pretrained gMLP in our experiments when it becomes available.

6.5 Practical Impact and Future Work

Our study has an immediate impact on practitioners who seek to employ robust text classification models in research projects and in industrial operational environments. Furthermore, we advocate to use an MLP baseline in future text classification research, for which we provide concrete guidelines in Appendix A.

Regarding the multi-label text classification task, future work could be to expand on the compared methods with more hierarchy-based models. Techniques to learn threshold values for each class independently (Pellegrini and Masquelier, 2021; Bénédict et al., 2021) could further improve our results. For the sequence based models, it would be interesting to compare the addition of end-task-aware training during pre-training to using fine-tuning after pretraining (Dery et al., 2021). Another interesting yet challenging setting would be few-shot classification (Brown et al., 2020).

7 Conclusion

We argue that a wide multi-layer perceptron enhanced with today’s best practices should be considered as a strong baseline for text classification tasks. In fact, the experiments show that our WideMLP is oftentimes on-par or even better than recently proposed models that synthesize a graph structure from the text. Although the WideMLP models are more robust in single-label classification, their performance in multi-label case is still comparable to state-of-the-art methods, making them good candidates for baseline even in more complex classification setups.

The source code is available: https://github.com/drndr/project_ds_textclass

References

K. Bache and M. Lichman. 2013. UCI machine learning repository.
Siddhartha Banerjee, Cem Akkaya, Francisco Perez-Sorrosal, and Kostas Tsiontouliakis. 2019. Hierarchical transfer learning for multi-label text classification. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.
Markus Bayer, Marc-André Kaufhold, and Christian Reuter. 2021. A survey on data augmentation for text classification. CoRR, abs/2107.03158.

Gabriel Bénédict, Vincent Koops, Daan Odijk, and Maarten de Rijke. 2021. sigmoidf1: A smooth f1 score surrogate loss for multilabel classification. arXiv preprint arXiv:2108.10566.

David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent dirichlet allocation. J. Mach. Learn. Res., 3:993–1022.

Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov. 2017. Enriching word vectors with subword information. Trans. Assoc. Comput. Linguistics, 5:135–146.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, During Wu, Noahfan Wu, Vic Wu, Jiaxin Pan, Weiwei Xu, Juan Zhang, Saicheng Zhang, Mo Elmore, Alex Hennessy, Brian Patro, Jeffrey Lu, Weizheng Chen, Huanan Xu, Wei Liao, Stan Zhang, Wilson Or, Chenan Bai, Yong Zhang, Stan Rudich, Jared Passon, Shengzhong Qian, Rex Panetta,泡洁, Wei Li, Kai Li, Yelong Shen,ユーコ, Zhicong Liu, Ping Huang, Jason Wei, Di Wu, Xiaoxiao Hu, Wei Li, Yuan contraction, Ewen Chung, Jiaxin Ji, Wei Li, Yiding Zhang, Xiaohan Li, Yuan Zhang, and Yanqi Zhou. 2020. Language models are few-shot learners. In NeurIPS.

Weí-Cheng Chang, Hsiang-Fu Yu, Kai Zhong, Yiming Yang, and Inderjit S. Dhillon. 2019. X-bert: extreme multi-label text classification with using bidirectional encoder representations from transformers. arXiv: Learning.

Alexis Conneau, Germán Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. 2018. What you can cram into a single $&!#*$ vector: Probing sentence embeddings for linguistic properties. In ACL (1), pages 2126–2136. ACL.

George Cybenko. 1989. Approximation by superpositions of a sigmoidal function. Math. Control. Signals Syst., 2(4):303–314.

Maurizio Ferrari Dacrema, Paolo Cremonesi, and Dietmar Jannach. 2019. Are we really making much progress? A worrying analysis of recent neural recommendation approaches. In RecSys, pages 101–109. ACM.

Mostafa Dehghani, Anurag Arnab, Lucas Beyer, Ashish Vaswani, and Yi Tay. 2021. The efficiency misnomer. CoRR, abs/2110.12894.

Dorottya Demszky, Dana Movshovitz-Attias, Jeong-woo Ko, Alan Cowen, Gaurav Nemade, and Su-jith Ravi. 2020. GoEmotions: A Dataset of Fine-Grained Emotions. In 58th Annual Meeting of the Association for Computational Linguistics (ACL).

Lucio M Dery, Paul Michel, Ameet Talwalkar, and Graham Neubig. 2021. Should we be pre-training? an argument for end-task aware training as an alternative. arXiv preprint arXiv:2109.07437.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT (1), pages 4171–4186. ACL.

Kaize Ding, Jianling Wang, Jundong Li, Dingcheng Li, and Huan Liu. 2020. Be more with less: Hypergraph attention networks for inductive text classification. In EMNLP (1), pages 4927–4936. ACL.

Hang Dong, Víctor Suárez-Paniagua, William Whiteley, and Honghan Wu. 2021. Explainable automated coding of clinical notes using hierarchical label-wise attention networks and label embedding initialisation.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An image is worth 16x16 words: Transformers for image recognition at scale. In ICLR.

Mathias Fey, Jan Eric Lenssen, Frank Weichert, and Jure Leskovec. 2021. Gnautoscale: Scalable and expressive graph neural networks via historical embeddings. In ICML, volume 139 of Proceedings of Machine Learning Research, pages 3294–3304. PMLR.

Qquentin Fournier, Gaëtan Marceau Caron, and Daniel Aloise. 2021. A practical survey on faster and lighter transformers. CoRR, abs/2103.14636.

Lucas Galke, Florian Mai, Alan Schelten, Dennis Brunsch, and Ansar Scherp. 2017a. Using titles vs. full-text as source for automated semantic document annotation. In K-CAP, pages 20:1–20:4. ACM.

Lucas Galke, Florian Mai, Alan Schelten, Dennis Brunsch, and Ansar Scherp. 2017b. Using titles vs. full-text as source for automated semantic document annotation. In Proceedings of the Knowledge Capture Conference, K-CAP 2017, New York, NY, USA. Association for Computing Machinery.

Lucas Galke and Ansar Scherp. 2022. Bag-of-words vs. graph vs. sequence in text classification: Questioning the necessity of text-graphs and the surprising strength of a wide MLP. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics.

Santiago González-Carvajal and Eduardo C. Garrido-Merchán. 2020. Comparing BERT against traditional machine learning text classification. CoRR, abs/2005.13012.
William L. Hamilton. 2020. *Graph Representation Learning*.

Wei Huang, Enhong Chen, Qi Liu, Yuying Chen, Zai Huang, Yang Liu, Zhou Zhao, Dan Zhang, and Shijin Wang. 2019. *Hierarchical multi-label text classification: An attention-based recurrent network approach*. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, CIKM ’19, page 1051–1060, New York, NY, USA. Association for Computing Machinery.

Mohit Iyyer, Varun Manjunatha, Jordan L. Boyd-Graber, and Hal Daumé III. 2015. Deep unordered composition rivals syntactic methods for text classification. In *ACL (1)*, pages 1681–1691. ACL.

Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. 2020. Tinybert: Distilling BERT for natural language understanding. In *EMNLP (Findings)*, volume EMNLP 2020 of *Findings of ACL*, pages 4163–4174. Association for Computational Linguistics.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2017. Bag of tricks for efficient text classification. In *EACL (2)*, pages 427–431. ACL.

Ammar Ismael Kadhim. 2019. Survey on supervised machine learning techniques for automatic text classification. *Artif. Intell. Rev.*, 52(1):273–292.

Nal Kalchbrenner, Edward Grefenstette, and Phil Blunsom. 2014. A convolutional neural network for modelling sentences. In *ACL (1)*, pages 655–665. ACL.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *ICLR (Poster)*.

Thomas N. Kipf and Max Welling. 2017. Semi-supervised classification with graph convolutional networks. In *ICLR (Poster)*. OpenReview.net.

Kamran Kowsari, Kiana Jafari Meimandi, Mojtaba Heidarysafa, Sanjana Mendu, Laura E. Barnes, and Donald E. Brown. 2019. Text classification algorithms: A survey. *Inf.*, 10(4):150.

Siwei Lai, Liheng Xu, Kang Liu, and Jun Zhao. 2015. Recurrent convolutional neural networks for text classification. In *AAAI*, pages 2267–2273. AAAI Press.

Jens Lehmann, Robert Isele, Max Jakob, Anja Jentzsch, Dimitris Kontokostas, Pablo N. Mendes, Sebastian Hellmann, Mohamed Morsey, Patrick van Kleef, Sören Auer, and Christian Bizer. 2015. Dbpedia - a large-scale, multilingual knowledge base extracted from wikipedia. *Semantic Web*, 6:167–195.

David D. Lewis, Yiming Yang, Tony G. Rose, and Fan Li. 2004. Rcv1: A new benchmark collection for text categorization research. *J. Mach. Learn. Res.*, 5:361–397.

Qian Li, Hao Peng, Jianxin Li, Congying Xia, Renyu Yang, Lichao Sun, Philip S. Yu, and Lifang He. 2020. A survey on text classification: From shallow to deep learning. *CoRR*, abs/2008.00364.

Hanxiao Liu, Zihang Dai, David R. So, and Quoc V. Le. 2021a. Pay attention to MLPs. *CoRR*, abs/2105.08050.

Hui Liu, Danqing Zhang, Bing Yin, and Xiaodan Zhu. 2021b. Improving pretrained models for zero-shot multi-label text classification through reinforced label hierarchy reasoning. *arXiv preprint arXiv:2104.01666*.

Weiwei Liu, Xiaobo Shen, Haobo Wang, and Ivor W. Tsang. 2020a. *The emerging trends of multi-label learning*. *CoRR*, abs/2011.11197.

Xien Liu, Xinxin You, Xiao Zhang, Ji Wu, and Ping Lv. 2020b. Tensor graph convolutional networks for text classification. In *AAAI*, pages 8409–8416. AAAI Press.

Yonghao Liu, Renchu Guan, Fausto Giunchiglia, Yanchun Liang, and Xiaoju Ye. 2021c. Deep attention diffusion graph neural networks for text classification. In *EMNLP (1)*, pages 8142–8152. Association for Computational Linguistics.

Haonan Lu, Seth H. Huang, Tian Ye, and Xiuyan Guo. 2019. Graph star net for generalized multi-task learning. *CoRR*, abs/1906.12330.

Shengfei Lyu and Jiaqi Liu. 2020. Combine convolution with recurrent networks for text classification. *CoRR*, abs/2006.15795.

Florian Mai, Lukas Galke, and Ansgar Scherp. 2018a. Using deep learning for title-based semantic subject indexing to reach competitive performance to full-text. In *JCDL*, pages 169–178. ACM.

Florian Mai, Lukas Galke, and Ansgar Scherp. 2018b. Using deep learning for title-based semantic subject indexing to reach competitive performance to full-text. pages 169–178.

Julian McAuley and Jure Leskovec. 2013. Hidden factors and hidden topics: Understanding rating dimensions with review text. In *Proceedings of the 7th ACM Conference on Recommender Systems*, RecSys ’13, page 165–172, New York, NY, USA. Association for Computing Machinery.

Luke Melas-Kyriazi. 2021. Do you even need attention? A stack of feed-forward layers does surprisingly well on imagenet. *CoRR*, abs/2105.02723.

Yu Meng, Jianming Shen, Chao Zhang, and Jiawei Han. 2018. Weakly-supervised hierarchical text classification. *CoRR*, abs/1812.11270.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Gregory S. Corrado, and Jeffrey Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information
Yi Tay, Mostafa Dehghani, Dara Bahri, and Donald Metzler. 2020. Efficient transformers: A survey. CoRR, abs/2009.06732.

Ilya O Tolstikhin, Neil Houlsby, Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Thomas Unterthiner, Jessica Yung, Andreas Steiner, Daniel Keysers, Jakob Uszkoreit, et al. 2021. MLP-Mixer: An all-MLP architecture for vision. Advances in Neural Information Processing Systems, 34.

Grigoris Tsoumakas and Ioannis Katakis. 2009. Multi-label classification: An overview. International Journal of Data Mining and Business Intelligence, 1:1–13.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS, pages 5998–6008.

Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph attention networks. International Conference on Learning Representations.

Ishwar Venugopal, Jessica Töllich, Michael Fairbank, and Ansgar Scherp. 2021. A comparison of deep-learning methods for analysing and predicting business processes. In IJCNN. IEEE.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019a. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In ICLR (Poster). OpenReview.net.

Ruishuang Wang, Zhao Li, Jian Cao, Tong Chen, and Lei Wang. 2019b. Convolutional recurrent neural networks for text classification. In IJCNN, pages 1–6. IEEE.

Yequan Wang, Aixin Sun, Jialong Han, Ying Liu, and Xiaoyan Zhu. 2018. Sentiment analysis by capsules. In WWW, pages 1165–1174. ACM.

Jonatas Wehrmann, Ricardo Cerri, and Rodrigo Barros. 2018. Hierarchical multi-label classification networks. In International Conference on Machine Learning, pages 5075–5084. PMLR.

Felix Wu, Amsauri H. Souza Jr, Tianyi Zhang, Christopher Fifty, Tao Yu, and Kilian Q. Weinberger. 2019. Simplifying graph convolutional networks. In ICML, volume 97 of Proceedings of Machine Learning Research, pages 6861–6871. PMLR.

Lingfei Wu, Yu Chen, Kai Shen, Xiaojie Guo, Hanming Gao, Shucheng Li, Jian Pei, and Bo Long. 2021. Graph neural networks for natural language processing: A survey. CoRR, abs/2106.06090.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideo Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. CoRR, abs/1609.08144.

Huiru Xiao, Xin Liu, and Yangqiu Song. 2019. Efficient path prediction for semi-supervised and weakly supervised hierarchical text classification. CoRR, abs/1902.09347.

Liang Yao, Chengsheng Mao, and Yuan Luo. 2019. Graph convolutional networks for text classification. In AAAI, pages 7370–7377. AAAI Press.

Rahul Yadita, Xueqi Yang, and Tim Menzies. 2021. When SIMPLE is better than complex: A case study on deep learning for predicting Bugzilla issue close time. CoRR, abs/2101.06319.

Wenpeng Yin, Jamaal Hay, and Dan Roth. 2019. Benchmarking zero-shot text classification:Datasets, evaluation and entailment approach. CoRR, abs/1909.00161.

Dell Zhang, Jun Wang, Emine Yilmaz, Xiaoleng Wang, and Yuxin Zhou. 2016. Bayesian performance comparison of text classifiers. In SIGIR, pages 15–24. ACM.

Lu Zhang, Jiandong Ding, Yi Xu, Yingyao Liu, and Shuigeng Zhou. 2021. Weakly-supervised text classification based on keyword graph. In EMNLP (1), pages 2803–2813. Association for Computational Linguistics.

Min-Ling Zhang and Zhi-Hua Zhou. 2014. A review on multi-label learning algorithms. IEEE Transactions on Knowledge and Data Engineering, 26(8):1819–1837.

Xinyi Zhang, Jiahao Xu, Charlie Soh, and Lihui Chen. 2020. LA-HCN: label-based attention for hierarchical multi-label textclassification neural network. CoRR, abs/2009.10938.

Jie Zhou, Chunping Ma, Dingkun Long, Guangwei Xu, Ning Ding, Haoyu Zhang, Pengjun Xie, and Gongshen Liu. 2020a. Hierarchy-aware global model for hierarchical text classification. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1106–1117. Online. Association for Computational Linguistics.

Pan Zhou, Jiashi Feng, Chao Ma, Caiming Xiong, Steven Chu Hong Hoi, and Weinan E. 2020b. Towards theoretically understanding why sgd generalizes better than adam in deep learning. In Advances in Neural Information Processing Systems, volume 33, pages 21285–21296. Curran Associates, Inc.
Appendix

A Practical Guidelines for Designing a WideMLP

On the basis of our results, we provide recommendations for designing a WideMLP baseline.

Tokenization We recommend using modern subword tokenizers such as BERT-like WordPiece or SentencePiece that yield a high coverage while needing a relatively small vocabulary.

Input Representation In contrast to conventional wisdom (Iyyer et al., 2015), we find that pretrained embeddings, e.g., GloVe, can have a detrimental effect when compared to using an MLP with one wide hidden layer. Such an MLP circumvents the bottleneck of the small dimensionality of word embeddings and has a higher capacity.

Depth vs. Width In text classification, width seems more important than depth. We recommend to use a single, wide hidden layer, i.e., one input-to-hidden and one hidden-to-output layer, e.g., with 1,024 hidden units and ReLU activation. While this might be overparameterized for single-label text classification tasks with few classes, we rely on recent findings that overparameterization leads to better generalization (Neyshabur et al., 2018; Nakkiran et al., 2020).

We further motivate the choice of using wide layers with results from multi-label text classification (Galke et al., 2017a), which has shown that MLP outperforms all tested classical baselines such as SVMs, k-Nearest Neighbors, and logistic regression. Follow-up work by Mai et al. (2018a) found that also CNN and LSTM do not substantially improve over the wide MLP.

Having a fully-connected layer on-top of a bag-of-words leads to a high number of learnable parameters. Still, the wide first input-to-hidden layer can be implemented efficiently by using an embedding layer followed by aggregation, which avoids large matrix multiplications. See also the runtime measurements reported for single-label text classification in Appendix D.

In our experiments, we did not observe any improvement with more hidden layers (WideMLP-2), as suggested by Iyyer et al. (2015), but it might help for other, more challenging, datasets.

Optimization and Regularization We seek to find an optimization strategy that does not
require dataset-specific hyperparameter tuning. This comprises optimizing cross-entropy with Adam (Kingma and Ba, 2015) and default learning rate $10^{-3}$, a linearly decaying learning rate schedule and training for a high amount of steps (Nakkiran et al., 2020) (we use 100 epochs) with small batch sizes (we use 16) for sufficient stochasticity. For regularization during this prolonged training, we suggest to use a high dropout ratio of 0.5 (Srivastava et al., 2014). Regarding initialization, we rely on framework defaults, i.e., $N(0, 1)$ for the initial embedding layer and random uniform $U(-\sqrt{d_{\text{input}}}, \sqrt{d_{\text{output}}})$ for subsequent layers’ weight and bias parameters.

B Connection between BoW-MLP and TextGCN

TextGCN uses the PMI matrix to set up edge weights for word-word connections. A single layer TextGCN is a BoW-MLP, except for the document embedding. The one-hop neighbors are words which are aggregated after a nonlinear transform. The basic GCN equation $H = \sigma(AWX)$ reveals that the order of transformation and neighborhood aggregation is irrelevant. The document embedding implies that TextGCN is a semisupervised technique. Truly new documents, as in inductive learning scenarios, would need a special treatment such as using an all zero embedding vector.

A two-layer MLP can be characterized by the equation $\hat{y} = W^{(2)}\sigma(W^{(1)}x + b^{(1)}) + b^{(2)}$. On bag-of-words inputs, the first layer $W^{(1)}x + b^{(1)}$ can be replaced by an equivalent embedding layer with weighting (e.g., TF-IDF or length normalization) being applied during aggregation of the embedding vectors.

The first layer of TextGCN is equivalent to aggregating embedding vectors. A standard GCN layer with shared weights has the form (assuming self-loops have been inserted)

$$h_i = \sum_{j \in N(i)} a_{ij} W^{(1)} x_j + b^{(1)}$$

Now in TextGCN node features are given by the identity, such that $x_j$ is one-hot. Then we can rewrite the first layer of Text-GCN as an aggregation of embeddings $E$. We gain

$$h_i = \sum_{j \in N(i)} a_{ij} E_j$$

as $Wx + b$ may again be replaced by an embedding matrix if applied to one hot vectors $x$. Now $E$ contains two types of embedding vectors: word embeddings and document embeddings corresponding to word nodes and document nodes. We see that the first layer of TextGCN is essentially an aggregation of word embeddings plus the document embedding. Only with a second layer, TextGCN considers the embedding of other documents whose words are connected to the present documents’ words.

C Equivalence of Micro-F1 and Accuracy in Multiclass Classification

In multiclass classification, we have a single true label for each instance and the predictions are constrained to a single prediction per instance. As a consequence, the measures accuracy and Micro-F1 coincide to the same formula.

Micro-F1 aggregates true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) globally. It can be expressed as:

$$\text{Micro-F1} = \frac{2 \sum_c TP_c}{2 \sum_c TP_c + \sum_c FP_c + \sum_c FN_c},$$

where $c$ iterates over all classes.

While the accuracy can be expressed as:

$$\text{Acc} = \frac{\sum_c TP_c + \sum_c TN_c}{\sum_c TP_c + \sum_c TN_c + \sum_c FP_c + \sum_c FN_c}.$$

In multiclass classification, every true positive is also a true negative for all other classes. When summing those up over the entire dataset, we obtain

$$\sum_c TP_c = \sum_c TN_c.$$

Thus, we can rewrite

$$2 \sum_c TP_c = 2 \sum_c TP_c + \sum_c TN_c$$

and see that the Micro-F1 and accuracy are equivalent in the multiclass (a.k.a. single-label) case.

D Runtime Performance of the Single-label Models

For the single-label case, we collected the runtime performance of our models, averaged over five times. We provide the total running times in Table 7 as observed while conducting the experiments on a single NVIDIA A100-SXM4-40GB.
card. All WideMLP variants are an order of magnitude faster than DistilBERT when considering the average runtime per epoch. DistilBERT is twice as fast as the original BERT. The transformers are only faster than BoW models on the MR dataset. This is because the sequences in the MR dataset are much shorter and less $O(L^2)$ attention weights have to be computed. The average runtime of the sequential MLP-based models is significantly longer than both the WideMLP and Transformer models. The additional single-head attention modules in the aMLP model resulted in an approximately 10% increase in average runtime compared to the gMLP model.
Table 7: Total runtime (training+inference). Average of five runs rounded to minutes.

| Model                  | #epochs | 20ng  | R8   | R52  | ohsumed | MR   |
|------------------------|---------|-------|------|------|---------|------|
| WideMLP                | 100     | 7min  | 3min | 4min | 3min    | 4min |
| TF-IDF+WideMLP         | 100     | 9min  | 4min | 4min | 3min    | 4min |
| WideMLP-2              | 100     | 9min  | 5min | 5min | 3min    | 6min |
| GloVe+WideMLP          | 100     | 6min  | 3min | 4min | 3min    | 4min |
| GloVe+WideMLP-2        | 100     | 6min  | 4min | 4min | 3min    | 4min |
| gMLP                   | 100     | 189min| 55min| 67min| 45min   | 56min|
| aMLP                   | 100     | 203min| 63min| 78min| 50min   | 66min|
| DistilBERT             | 10      | 8min  | 4min | 5min | 3min    | 1min |
| BERT                   | 10      | 15min | 7min | 8min | 5min    | 2min |
Figure 1: Label distribution of single-label datasets.

(a) Label distribution of 20ng
(b) Label distribution of MR
(c) Label distribution of R8
(d) Label distribution of R52
(e) Label distribution of ohsumed
Figure 2: Label distribution of multi-label datasets.

(a) Label distribution of R21578
(b) Label distribution of Econbiz
(c) Label distribution of NYT AC
(d) Label distribution of GoEmotions
(e) Label distribution of DBPedia-298
Figure 3: Number of labels per document in the multi-label datasets.

(a) R21578

(b) GoEmotions

(c) Econbiz
(d) NYT AC

(e) DBPedia-298

(f) Amazon-531

(g) RCV1-v2