Abstract

Pre-trained word embeddings encode general word semantics and lexical regularities of natural language, and have proven useful across many NLP tasks, including word sense disambiguation, machine translation, and sentiment analysis, to name a few. In supervised tasks such as multiclass text classification (the focus of this article) it seems appealing to enhance word representations with ad-hoc embeddings that encode task-specific information. We propose (supervised) word-class embeddings (WCEs), and show that, when concatenated to (unsupervised) pre-trained word embeddings, they substantially facilitate the training of deep-learning models in multiclass classification by topic. We show empirical evidence that WCEs yield a consistent improvement in multiclass classification accuracy, using four popular neural architectures and six widely used and publicly available datasets for multiclass text classification. Our code that implements WCEs is publicly available at https://github.com/AlexMoreo/word-class-embeddings.

Keywords Word-Class Embeddings, Word embeddings, Distributional hypothesis, Multiclass text classification

1 Introduction

Recent advances in deep learning have led to important improvements in many NLP tasks that deal with the semantic analysis of text, including word sense disambiguation, machine translation, summarization, question answering, and sentiment analysis (see [17, 43], for an overview). At the heart of the neural approach to the semantics of text lies the concept of word embedding (a.k.a. continuous or distributed representation) – [9, 52], a dense representation of a word's meaning in a vector space where the semantic similarity of words is embodied in the notion of distance between vectors.

Word embeddings can either be initialized randomly and allowed to evolve along the rest of the model parameters, or be initialized from pre-trained word embeddings obtained offline by scanning massive amounts of textual data. This latter approach is generally preferred, since pre-trained embeddings encode an effective prior that embodies our general-purpose knowledge of the semantics of words, and that can be successfully transferred to (and eventually fine-tuned for) specific application contexts and downstream tasks [24].

Approaches to generate word embeddings typically rely on the distributional hypothesis, according to which words that tend to occur in similar contexts tend to have similar meanings [30]. Different realizations of this hypothesis were initially based on context-counting approaches [11, 14, 20, 61] and later based on context-predicting approaches [29, 52, 57]. Context-counting approaches collect frequencies of word co-occurrence and typically involve some form of matrix factorization to obtain the final word representations [20]. Conversely, in context-predicting approaches the word representations constitute the parameters of a model trained to predict some distributional property of the data. As an example, word2vec’s skip-gram with negative sampling method (SGNS – [52]) tries to guess the surrounding words from the observation of the central word in a sliding context window.
While the relative desirability of one paradigm over the other was once the subject of debate [6], it has later been argued that the two approaches simply embody different ways of pursuing what is essentially the same objective [44], and that differences in performance are mainly explainable in terms of hyperparameter settings and design choices [45]. It has been proven that the optimum of the objective function that SGNS (a context-predicting method) seeks to optimize can directly be attained by a context-counting method called shifted positive pointwise mutual information (SPPMI – [44]). This seems to suggest that SPPMI (and context-counting approaches in general) should be preferred to SGNS (and to context-predicting approaches in general). However, there are practical reasons why the opposite is the case. The main drawback of context-counting methods is the fact that they need to work with the entire co-occurrence matrix, something that becomes impractical when large quantities of text are involved. This problem does not harm neural supervised learning approaches, though, which are inherently incremental when adopting stochastic optimization (a standard practice nowadays). For this reason, the neural approach is currently the dominant one in modern distributional semantics.

1.1 Word-Class Embeddings

Through the lens of the downstream task, the pre-trained word embeddings that all these methods generate are unsupervised, in the sense that they capture how terms are distributed in general language use, in a way which is completely independent of (and thus not optimized for) the downstream task. However, in supervised tasks such as text classification (the focus of this work), it seems reasonable to imbue the word representations with supervised information that is available during training. In this article we propose word-class embeddings (WCEs), a form of supervised embeddings of words specifically designed for multiclass text classification, that directly model the interactions between terms and class labels.

A related intuition has been explored before in the context of text classification [13, 29, 67, 70] by jointly modelling word embeddings and label embeddings in a common vector space as part of the optimization procedure. Arguably, the best-known among the methods based on this intuition is fastText [13, 29], a variant of word2vec’s continuous bag-of-words method (CBOW – see Section 2.1) that substitutes the target central word that CBOW seeks to predict, with a token representing one of the document’s labels. The result is a method that jointly models words and labels as vectors, by recasting labels as new terms and simply applying the distributional hypothesis anew.

We follow a different approach from those explored before by confining the supervised embeddings in a dedicated vector space, so that they can then be concatenated with any unsupervised pre-trained representations. The resulting embedding matrix can be used as the building block of any neural architecture. Our method does not involve any optimization procedure but operates directly on the co-occurrence counters. In a way, the method we propose might be regarded as the context-counting counterpart of (the context-predicting) fastText for word-class distributions, just like SPPMI stands to SGNS for word-word distributions [44]. Note that the disadvantage of context-counting approaches with respect to context-predicting ones that we have discussed before (i.e., the need to work with the entire, potentially huge co-occurrence matrix) does not arise here, since the amount of labelled documents one typically has in text classification applications is limited, and working with the co-occurrence matrix is thus unproblematic.

We show empirically that extending the pre-trained unsupervised word embeddings with our task-specific supervised WCEs substantially facilitates the training of neural classifiers, and yields consistent improvements in multiclass classification performance across six widely used and publicly available text classification datasets, and four popular neural architectures (including fastText). Experiments also show that our word-class embeddings can be computed very quickly.

The rest of this article is structured as follows. In Section 2 we thoroughly review related work. We explain the method in Section 3 while Section 4 reports the experimental evaluation we have conducted. Section 5 tackles a few advanced topics related to WCEs, while Section 6 concludes, pointing at possible avenues for future work.

2 Related Work

In this section we turn to review relevant related work on word embeddings (Section 2.1), label embeddings (Section 2.2), and neural approaches to text classification that exploit either word or label embeddings (Section 2.3).

2.1 Word Embeddings

Although the term word embedding owns its popularity to the neural approach, the very first attempts to generate distributed representations arose in the realm of context-counting approaches. Arguably, the best-known one is Latent
Semantic Analysis (LSA – [20]), a method that obtains r-dimensional representations of words by factoring (via singular value decomposition – SVD) a term-by-context co-occurrence matrix, and retaining the r eigenvectors with the highest eigenvalue. Positive Pointwise Mutual Information (PPMI – [44]) takes the positive part of PMI as applied to the counters of the matrix, before decomposing it. We explore PPMI as an alternative to our method in Section 4.8.

Latent Dirichlet Allocation (LDA – [11]) is a generative statistical model that assumes each document to be a mixture of latent topics. Although LDA ends up building a matrix that models the strength of the association of words with topics (something very similar in spirit to our goal), it does not use supervision; instead, our WCEs are supervised (i.e., they use the class label information along with the co-occurrence matrix), and require no optimization.

Most context-counting approaches suffer from the fact that the co-occurrence matrix has to be explicitly allocated in memory. In an attempt to overcome this limitation, Random Indexing (RI – [37, 61]) iteratively constructs an approximation of the co-occurrence matrix by accumulating nearly-orthogonal random indexes for terms and getting rid of the factorization. However, RI is generally outperformed by neural methods such as word2vec and GloVe (explained below) when large quantities of text are available for training [62].

The neural approach to distributional semantics started with [9], and gathered momentum with word2vec [52], a method based on a two-layer neural network trained to predict the words in the context of a central word (skip-gram – SG) or the center word from the words in a (sliding) context window (continuous bag-of-words – CBOW). Input and output terms are represented as one-hot vectors, and the first layer acts as a lookup table indexing the word embeddings (the layer parameters). word2vec owns part of its success to hierarchical softmax and negative sampling [51], that permitted to dramatically speed up their computation, thus allowing the method to scale to massive amounts of textual data. GloVe is another popular method for generating embeddings, that has proven superior to word2vec in various tasks [57]. GloVe learns the word vectors that better reconstruct the probabilities of co-occurrence between pairs of terms as estimated via their dot product. Both word2vec and GloVe have been used to generate large sets of embeddings that have later been made publicly available. We use both sets of pre-trained vectors in the experiments of Section 4.

2.2 Label Embeddings

A primitive form of label embedding is to be found in distributed output codes for single-label multiclass classification problems[4]. The idea is to assign a different (binary) “codeword” of length \( m' \) to each of the \( m \) classes, with \( m' < m \), and then learn \( m' \) binary predictors (one for each binary bit in the codeframe), instead of \( m \) predictors (one for each class). The actual class to be returned is the class with the closest codeword (in terms of Hamming distance) to the predicted binary string. These distributed codes were said to be “meaningful” if each bit was meant to encode one particular aspect of the label [63], e.g., when guessing the correct digit represented in an image of a handwritten digit, the meaning of one bit in the codeframe could be “the image contains a horizontal line”, while the meaning of another could be “the image contains a closed curve”. [22] obtained improved results by redefining codewords as error-correcting codes, a type of distributed output codes with constraints. Error-correcting codes allow the classifier to recover the correct label in spite of some binary misclassifications, though at the expense of involving more binary learners and sacrificing the meaning of each of them. Note that, although these early attempts reflect some semantic structure of the labels, they do so to a very limited extent.

Label embeddings have later proven useful in large sparse multilabel classification (sometimes called extreme multilabel classification), i.e., in classification scenarios characterized by large sets of classes and where each item typically belongs to only a few classes [3, 10, 33, 48, 72, 77]. The general idea is to reduce the high-dimensional and sparse label matrix by means of an encoding function, so that a learner can be then trained to predict low-dimensional label vectors, that are ultimately mapped back to the original sparse label space via a decoding function. In this context, [33] used compressed sensing as the encoding function, and applied sparse reconstruction techniques for the decoding function. The encoding function was defined as a random projection, and was thus not learned from data. [8] and [72] proposed instead to learn the parameters of the projection matrix, while other approaches, such as the one of [48], assumed the encoding function to be implicit, and directly attempted to learn a code matrix and a decoding function. Other approaches, such as that of [77], frame the problem as a (linear) low-rank approximation, or as a (non-linear) manifold

\[ \text{Pointwise Mutual Information (PMI)} \text{ is defined as } \text{PMI}(t_i, c_j) = \log \frac{Pr(t_i, c_j)}{Pr(t_i)Pr(c_j)}, \text{ where } Pr(t_i, c_j) \text{ is the joint probability of term } t_i \text{ and context } c_j. \text{ And } Pr(t_i) \text{ and } Pr(c_j) \text{ are the marginal probabilities of the term and context, respectively. PMI takes the positive part of PMI, i.e., } \text{PPMI}(t_i, c_j) = \max\{0, \text{PMI}(t_i, c_j)\}. \]

\[ \text{Given a set of classes } \mathcal{C} = \{c_1, \ldots, c_m\}, \text{ a classification problem is said to be multiclass if } m > 2; \text{ it is said to be single-label if each item always belongs to exactly one class; it is said to be multilabel if each item can belong to any number (i.e., 0, 1, or more than 1) of classes in } \mathcal{C}. \]
learning of the sparse label matrix \cite{10}. The ultimate goal that all these works pursue is to bypass the cost of training a classifier for each binary label.

A considerable body of research on label embeddings has then emerged which was aimed at dealing with the difficulty of obtaining labeled data for specific domains, especially in the realm of “zero-shot” classification of images \cite{1, 2, 56}. For instance, ConvSE \cite{56} maps image embeddings, as produced by a convolutional classifier trained on ImageNet, to the word embedding space representing the class labels (as produced by SGNS trained on Wikipedia). \cite{2} propose Structured Joint Embeddings, investigating different mechanisms to produce label embeddings from supervised attributes (hand-coded vectors accounting for aspects describing the label – much like the “meaningful” distributed output codes mentioned above), hierarchical dependencies between labels (as mined from ontologies such as WordNet), and unsupervised sources of text data (such as Wikipedia). Labels are embedded into complementary vector spaces, and a compatibility function, within the structured support vector machine (SSVM) framework, is then trained to maximize the matching with embedded images from the same class.

For the unsupervised representation of labels, bag-of-words and other distributional semantic models (GloVe and word2vec) have been investigated. \cite{59} tackle the problem of text recognition, and similarly rely on SSVM. The goal is to identify the correct word from an image containing it. Words are thus taken as labels, and these labels are embedded in a vector space governed by lexical (instead of semantic) similarity.

\section{Neural Text Classification}

Text classification (TC) is a supervised learning task in which a model is trained to predict labels for unseen documents from the observation of labelled documents. Unlike traditional machine learning approaches to TC which represented documents thorough sparse vectors of lexical features \cite{35, 71}, the neural approach to TC builds on top of distributed representations for words and documents. Popular architectures routinely adopted in neural TC include convolutional neural networks (CNNs – \cite{17, 38, 42}), recurrent neural networks (RNNs – \cite{41, 60}), recursive deep models (RDMs – \cite{42}), and attention models (ATTNs – \cite{49, 69}). The training strategy is common across all these architectures: they first generate a document representation and they then connect it directly to the labels during training; words in documents are only connected to labels indirectly.

Different models have been proposed that instead leverage the training labels directly at the word level \cite{13, 29, 67, 70}. \cite{67} proposed Predictive Text Embeddings (PTEs), a type of embeddings that rely on a heterogeneous text network consisting of three bipartite graphs, each of which models one particular type of co-occurrence: word-word, word-document, and word-label. An embedding is then generated for each vertex in the graph, and documents are represented by averaging the embeddings of the vertices corresponding to the words they contain. However, the embeddings of the vertices corresponding to the labels are not used directly by the classifier, but only concur in the generation of the word embeddings.

\cite{29} and \cite{13} proposed fastText, a variant of the CBOW architecture for text classification that generates both word embeddings and label embeddings. fastText seeks to predict one of the document’s labels (instead of the central word) and incorporates further tricks (e.g., n-gram features, sub-word information) to further improve efficiency. As a variant of CBOW, and similarly to PTEs, fastText represents a document as a simple average of word embeddings. \cite{70} proposed a model called Label Embedding Attentive Model (LEAM), which jointly embeds words and labels in the same latent space. Text representations in LEAM are conditioned on the compatibility between words and labels according to an attention model. The label-embedding attentive model allows LEAM to go beyond simply averaging word embeddings (as, e.g., PTE and fastText do), and to weight differently the contribution of the word embeddings in a non-linear fashion. Once words and labels are embedded in a common vector space, word-label compatibility is measured via cosine similarity. Our method instead models these compatibilities directly, without generating intermediate embeddings for words or labels.

A differentiating aspect of our method is that it keeps the modelling of word-class interactions separate from the original word embedding. Word-class correlations are confined in a dedicated vector space, whose vectors enhance (by concatenation) the unsupervised representations. The net effect is an embedding matrix that is better suited to classification, and imposes no restriction to the network architecture using it.

\footnote{While \cite{59} dub “word-label embeddings” their word representations, this is just to emphasize that words are the target variables, which indicates that the meaning they attribute to the term “word-label embedding” is very different from our notion of WCE.}
3 Method

Let \( \mathcal{C} = \{ c_1, \ldots, c_m \} \) be the classification scheme (a.k.a. codeframe). We consider multiclass classifiers \( h : \mathcal{D} \rightarrow \{0, 1\}^m \), mapping documents from a domain \( \mathcal{D} \) into vectors of \( m \) binary class labels. (The label vector contains a single 1 in single-label multiclass classification \((m > 2)\) and in binary classification \((m = 2)\), and any combination of 0’s and 1’s in multilabel multiclass classification.) We are interested in equipping the classifiers with continuous distributed representations of words, i.e., with an embedding function \( E : V \rightarrow \mathbb{R}^r \) (sometimes called the lookup table, and often presented simply as a matrix \( E \)) mapping terms in the vocabulary \( V \) (the set containing any desired textual feature, e.g., words, stems, word n-grams, or any such surface form of interest) into a dense \( r \)-dimensional vector space. Most methods based on distributional semantics learn the mapping \( E \) on the basis of how terms are distributed in an external corpus \( \mathcal{D}' \) of textual data (sometimes huge, and sometimes unrelated to the domain \( \mathcal{D} \)). We instead investigate task-specific mappings, i.e., mappings specific to the domain \( \mathcal{D} \) and codeframe \( \mathcal{C} \), based on how terms are distributed across classes.

We define the word-class embedding \( E(t_i) \in \mathbb{R}^r \) of term \( t_i \) with respect to codeframe \( \mathcal{C} \) as

\[
E(t_i) = \psi(\eta(t_i, c_1), \ldots, \eta(t_i, c_m)) \in \mathbb{R}^r
\]  

(1)

where \( \eta : V \times \mathcal{C} \rightarrow \mathbb{R} \) is a real-valued function that quantifies the correlation between term \( t_i \in V \) and class \( c_j \in \mathcal{C} \), and where \( \psi : \mathbb{R}^m \rightarrow \mathbb{R}^r \) is any projection function mapping vectors of class-conditional priors into an \( r \)-dimensional embedding space. (More details on both \( \eta \) and \( \psi \) later on.) The value of \( \eta(t_i, c_j) \) can be estimated from a training set of labelled documents \( L = \{(x_k, y_k)\}_{k=1}^n \), with \( x_k \) the \( k \)-th training document and \( y_k \in \{0, 1\}^m \) the binary vector indicating the class labels attributed to \( x_k \). We make the default assumption that the same training set \( L \) is also used by the supervised learning algorithm for generating the classifier \( h \).

We now detail the embedding generation process using matrix notation. First, we map set \( L \) into a matrix \( X \in \mathbb{R}^{n \times v} \), where \( v = |V| \) is the vocabulary length, and where \( X \) consists of the vectorial representations of the documents in \( L \) according to a weighted (e.g., tfidf, or BM25) “bag-of-words” feature model. Note that the step of mapping \( L \) into \( X \) is specific to the WCE generation procedure, and imposes no restrictions on the supervised learning method to be used, which may instead rely on a different mechanism for representing documents. Similarly, we create a document-class binary matrix \( Y \in \{0, 1\}^{n \times m} \), consisting of the \( n \) binary vectors \( y_k \in \{0, 1\}^m \). We generate a word-class matrix \( A \in \mathbb{R}^{v \times m} \) as

\[
A = X^\top Y
\]  

(2)

where \( X^\top \) denotes the matrix \( X \) with L1-normalized columns. Element \( a_{ij} \) of matrix \( A \) thus represents the correlation between the \( i \)-th feature and the \( j \)-th class across the \( n \) labelled documents, as quantified by the dot product.

We may expect a randomly chosen term to show no a priori significant correlation with a randomly chosen class label. We thus want to choose as our \( \eta \) function one that is centered at the expected correlation value (i.e., the value of correlation that may simply be explained by chance). In other words, we want \( \eta \) to return positive (resp., negative) values whenever the presence of \( t_i \) brings stronger (resp., weaker) evidence that the document is in \( c_j \) than this expected value, and close to 0 when the presence of \( t_i \) brings no significant evidence about the presence of \( c_j \). A natural way to fulfill this requirement is through standardizing. We thus (independently) standardize each of the \( m \) dimensions of \( A \) so that the resulting matrix \( S \) is such that the distribution of the elements in its columns has zero mean and unit variance, i.e.,

\[
s_{ij} \leftarrow z_j(a_{ij}) = \frac{a_{ij} - \bar{\mu}_j}{\sigma_j}
\]  

(3)

where \( z_j \) denotes the function that returns standard scores (a.k.a. z-scores) for column \( j \) (i.e., for the random variable which takes on values \( \{a_{1j}, \ldots, a_{vj}\} \)), with sample mean

\[
\bar{\mu}_j = \frac{1}{v} \sum_{i=1}^v a_{ij}
\]  

(4)

and sample standard deviation

\[
\sigma_j = \sqrt{\frac{1}{v-1} \sum_{i=1}^v (a_{ij} - \bar{\mu}_j)^2}
\]  

(5)

\[5\] It is worth recalling that the bag-of-words model tends to produce matrices that are highly sparse. Many software packages take advantage of this sparsity in order to compute matrix multiplication efficiently, at a cost that, in practice, falls far below the asymptotic bound \( O(vnm) \). We discuss empirical computational complexity issues in Section 5.
Note that the resulting random variable which takes on values \( \{s_{ij}, \ldots, s_{ij}\} \) is unbiased with respect to the feature prevalence of \( t_i \) and the prevalence of class \( c_j \). The reason is that the feature prevalence has been factored out after the L1 normalization of the columns of \( X \), while the class prevalence has become a constant factor for each column in \( A \), and is thus implicitly factored out during standardizing.

Function \( \eta \) is thus

\[
\eta(t_i, c_j) = z_j(t_i^\top c_j)
\]

where \( t_i \in \mathbb{R}^n \) is the L1-normalized column vector of weighted values for term \( t_i \) in \( X \) and \( c_j \in \mathbb{R}^n \) is the binary column vector of class \( c_j \) in \( Y \). In Section 4.8 we experiment with functions alternative to the dot product as the instantiation of function \( \eta \), including ones that, unlike the dot product, pay equal attention to positive and negative correlation.

There are additional motivations behind the use of standardizing. On one hand, the zero-mean property establishes the zero-vector as a natural choice for any possible future term not encountered at training time, since the zero-vector would indicate that the term shows no a priori correlation to any of the classes. (Further considerations regarding the treatment of out-of-vocabulary terms are discussed in Section 4.11.) On the other hand, unit variance guarantees that all classes contribute approximately equally to the representation, which reinforces the possibility that the downstream classifier performs well on all classes.

For the moment being, let us simply define the projector \( \psi \) in Equation 1 to be the identity function (thus forcing \( r \) to be equal to \( m \); we will come back to this in Section 3.1); then \( S \) is the resulting WCE matrix. Arranged in rows are the WCEs, that encode how each word is distributed across the classes in the codeframe. The WCE matrix \( S \) can finally be concatenated with any other pre-trained word embedding matrix \( U \) (as those produced by, e.g., \text{GloVe} or \text{word2vec}) to define the embedding matrix \( E \).

### 3.1 Large Codeframes

The necessity of dealing with large codeframes could easily cause the optimization of neural models relying on WCEs to become intractable. The reason is that, in many applications of text classification, hundreds of thousands of features are generated, and the newly added WCEs lie on a (dense) vector space with as many dimensions as classes in the codeframe. In such cases we might want \( \psi \) to implement a dimensionality reduction technique, thus mapping \( m \)-dimensional vectors into an \( r \)-dimensional space, with \( r < m \).

In this work we assume \( \psi \) to be implemented via principal component analysis (PCA), in order to replace \( S \) with a low-rank approximation of it. In the experiments of Section 4.1 when dealing with codeframes with \( m > 300 \) we choose to retain only the 300 principal components with the largest eigenvalues (i.e., those explaining the largest variance); in the literature, 300 is indeed a popular choice for the size of word embeddings. (Somehow abusing notation, and when clear from context, we will use symbol \( S \) to either denote \( S \) or its low-rank approximation, assuming the application of PCA to be implicit whenever \( m > 300 \).)

Alternative ways for implementing \( \psi \) might be found in the class of label-embedding approaches from the extreme multilabel text classification literature [10, 33, 77] already discussed in Section 2.2 or more generally in dimensionality reduction techniques [5, 68].

### 3.2 Regularization

WCEs inject a task-specific pressure into the representation mechanism that might compromise the data-generating process of training and test documents, since, unlike when using pre-trained embeddings, terms from the training documents have played a role in the generation of WCEs. Indeed, during preliminary experiments we observed that models operating with a concatenation of WCEs and pre-trained word-embeddings tend to incur a much lower training loss than those using pre-trained word-embeddings only, but the former tend to perform substantially worse on unseen data (more details on this in Section 4.6). This case of overfitting makes evident the need for properly regularizing the model.

In order to perform regularization, we apply a variant of dropout [65] to the embedding layer. Dropout consists of zeroing random activations in order to prevent nodes from co-adapting. Since dropout is only applied in the training phase, the activation values are scaled by \((1 - p)^{-1}\) during training, with \( p \) the drop probability, in order to keep the expected activation consistent with the test phase.

We only apply dropout to the WCEs, and keep the unsupervised embeddings untouched (there is no reason to believe the unsupervised embeddings fit more the training documents than the unseen documents). Let \( E = [U \oplus S] \in \mathbb{R}^{u \times (q+1)} \) represent the entire embedding layer, consisting of the concatenation (here denoted by the \( \oplus \) operator) of
the unsupervised $q$-dimensional matrix $U$ and the supervised $r$-dimensional matrix $S$. In order to bring to bear correct expected activations during test, we compute the scaling at training time as

$$D(E) = \frac{[U \oplus (1 - p) \cdot d(S)]}{1 - \frac{q}{q+r}}$$

(7)

where $d$ indicates dropout and $D$ indicates supervised dropout.

4 Experiments

In this section we turn to describing the experiments that we have carried out in order to quantify the contribution of WCEs to multiclass text classification. In order to make all the experiments discussed in this paper fully reproducible, we make available at https://github.com/AlexMoreo/word-class-embeddings the code that implements our method and all the baselines used in this work.

4.1 Datasets

In our experiments we use the following six publicly available datasets:

- **REUTERS-21578** is a popular multilabel dataset which consists of a set of 12,902 news stories, partitioned (according to the “ModApt” split we adopt) into a training set of 9,603 documents and a test set of 3,299 documents. In our experiments we restrict our attention to the 115 classes with at least one positive training example. This dataset presents cases of severe imbalance, with many classes containing fewer than 5 positive examples.

- **20NEWSGROUPS** is a single-label test collection of approximately 20,000 posts on Usenet discussion groups, nearly evenly partitioned across 20 different newsgroups (classes). In this article we use the “harder” version of the dataset, i.e., the one from which all metadata (headers, footers, and quotes) have been removed.

- **OHSUMED** [31] is a dataset consisting of a set of MEDLINE documents spanning the years from 1987 to 1991. Each entry consists of summary information relative to a paper published on one of 270 medical journals. The available fields are title, abstract, MeSH indexing terms, author, source, and publication type. Following [35], we restrict our experiments to the set of 23 cardiovascular disease classes, and we use the 34,389 documents of year 1991 that have at least one of these 23 classes. Since no standard training/test split has been proposed in the literature we randomly partition the set into a part used for training (70% of the documents) and a part used for testing (the other 30%).

- **RCV1-v2** is a dataset comprising 804,414 news stories published by Reuters from Aug 20, 1996, to Aug 19, 1997; for text classification purposes it is traditionally split into a training set consisting of the (chronologically) first 23,149 documents (the ones written in Aug 1996), and a test set consisting of the last 781,265 documents (the ones written from Sep 1996 onwards). In our experiments we use this dataset in its entirety, and stick to the standard training/test split described above. RCV1-v2 is multilabel, i.e., a document may belong to several classes at the same time. Of the 103 classes of which its “Topic” hierarchy consists, in our experiments we have restricted our attention to the 101 classes with at least one positive training example. This dataset is the one with the largest test set in our experiments.

- **JRC-ACQUIS** (version 3.0) is a collection of legislative texts of European Union law written between the 1950s and 2006. JRC-ACQUIS is publicly available for research purposes, and covers 22 official
European languages. We restrict our attention to the English subset, which consists of 20,370 documents. For our experiments, we consider the 13,137 documents written in the [1950, 2005] interval as the training set, and leave the remaining 7,233 documents written in 2006 as the test set. The dataset is multilabel and is labelled according to the EuroVoc thesaurus. We focus on the 2,706 classes with at least one positive element in the training set. This dataset is the one with the largest codeframe in our experiments.

- WIPO-GAMMA is a test collection of patent documents.\(^1\) Documents are labelled according to the International Patent Classification (IPC) taxonomy, covering patents and patent applications in all areas of technology. We focus on the single-label version labelled at the subclass level in the IPC hierarchy. For our experiments, we extract the abstract field of the documents (thus discarding the list of inventors, list of applicant companies, claims, and the long description), and follow the train/test split made available by the WIPO organization. The dataset contains a total of 1,118,299 documents, of which 896,363 (80%) is used as the training set, and the remaining 221,936 (20%) are used for test. This dataset is the one with the largest training set in our experiments.

Details of these datasets are given in Table 1. Note that the datasets chosen cover a broad spectrum of experimental conditions, including single-label and multilabel scenarios, a number of classes ranging from tens (20NEWSGROUPS) to thousands (JRC-AQUIS), a number of documents from small (REUTERS-21578) to very large (WIPO-GAMMA), from well balanced datasets (20NEWSGROUPS) to severely imbalanced ones (e.g., RCV1-v2), etc. Note also that the first four datasets (REUTERS-21578, 20NEWSGROUPS, OHSUMED, RCV1-v2) are probably the most popular datasets in text classification research; together with the fact that they are all publicly available, this guarantees a high level of comparability (and interpretability) to our results. In this work we restrict our attention to text classification by topic, and leave other dimensions (e.g., classification by sentiment) for future work (see also the discussion in Section 4.2).

We pre-process text by using the default analyzer available in the scikit-learn framework\(^2\) (which applies lower-casing, stop word removal, punctuation removal), and by masking numbers with a dedicated token. For the computation of the WCEs, we retain all terms (unigrams) appearing at least 5 times in the training set. However, in experiments involving pre-trained embeddings we also consider those out-of-vocabulary (OOV) terms for which a pre-trained embedding exists; these terms are represented by the zero vector in the WCE space (see Section 3). This is a major advantage of also using pre-trained embeddings, which allow neural models to also make sense (at testing time) of terms unseen at training time if they have anyway been encountered during the pre-training phase (see Section 4.11 for more on this).

### 4.2 Evaluation Measures

As the effectiveness measure we use \(F_1\), the harmonic mean of precision (\(\pi\)) and recall (\(\rho\)), defined as \(F_1 = (2\pi\rho)/(\pi + \rho) = (2TP)/(2TP + FP + FN)\), where TP, FP, FN, are the numbers of true positives, false positives, false negatives, from the binary contingency table. We take \(F_1 = 1\) when \(TP = FP = FN = 0\), since the classifier has correctly classified all examples as negative.

---

\(^1\) [https://www.wipo.int/classifications/ipc/en/ITsupport/Categorization/dataset/]

\(^2\) [http://scikit-learn.org/]

| Dataset       | Type | # Classes | # Train docs | # Test docs | Total # of docs | Vocabulary | OOV | # Words | Prev(mean) | Prev(std) | Prev(min) | Prev(max) |
|---------------|------|-----------|--------------|-------------|----------------|------------|-----|--------|-----------|-----------|-----------|-----------|
| REUTERS-21578 | ML   | 115       | 9,603        | 3,299       | 12,902        | 8,250      | 24,094 | 1.7M   | 83.9      | 314.3     | 1         | 2,577     |
| 20NEWSGROUPS  | SL   | 20        | 11,314       | 7,532       | 18,846        | 17,184     | 112,594 | 3.5M   | 56.7      | 377       | 600       |
| OHSUMED       | ML   | 25        | 24,061       | 10,328      | 34,389        | 18,238     | 44,062 | 1,151  | 56.8      | 101       | 7         | 1,523.6   |
| RCV1-v2       | ML   | 101       | 25,149       | 781,265     | 804,414       | 24,816     | 384,327 | 188.1M | 709.9     | 1,417.2   | 1         | 10,282    |
| JRC-AQUIS     | ML   | 2,706     | 13,137       | 7,233       | 20,370        | 21,109     | 141,800 | 28.3M  | 25.7      | 58.6      | 2         | 1,131     |
| WIPO-GAMMA    | SL   | 613       | 896,363      | 221,936     | 1,118,299     | 114,802    | 395,270 | 471.8M | 1,462.3   | 945.6     | 1         | 63,655    |
|               |      |           |              |             |               |            |       |        |           |           |           |           |

Table 1: Details of the datasets we use in this research. Column “Type” indicates whether the classification is multilabel (ML) or single-label (SL). Column “Vocabulary” shows the number of terms occurring at least 5 times in the training set. This dataset is the one with the largest codeframe in our experiments.
As defined above, $F_1$ is a measure for binary classification only. For multiclass classification, we average $F_1$ across all the classes of a given codeframe by computing both micro-averaged $F_1$ (denoted by $F_1^\mu$) and macro-averaged $F_1$ (denoted by $F_1^M$). $F_1^\mu$ is obtained by (i) computing the class-specific values $TP_j$, $FP_j$, and $FN_j$, (ii) obtaining $TP$ as the sum of the $TP_j$'s (same for $FP$ and $FN$), and then applying the $F_1$ formula. $F_1^M$ is obtained by first computing the class-specific $F_1$ values and then averaging them across the classes.

4.3 Supervised Learners for Classifier Training

We test the contribution of WCEs to text classification using a “traditional” (i.e., non-neural), high-performance learner (support vector machines), a well-known, deep learning-based library for text classification (fastText), and three popular architectures based on deep neural networks (convolutional neural networks, long-short term memory networks, and attention models).

For each such system we explore different variants, corresponding to different ways of instantiating the embedding matrix $E$. As the pre-trained embeddings we use the biggest set of GloVe vectors made available, and consisting of 2.2M 300-dimensional word embeddings generated from a text corpus of 840 billion tokens.[17] (In Section 4.9 we report results of using word2vec embeddings instead of GloVe embeddings.) The variants we explore are the following:

Random: randomly initialized trainable embeddings (their dimensionality is optimized from the range \{50, 200, 300\} on a validation set).

GloVe(static): static pre-trained GloVe embeddings.

GloVe(trainable): trainable vectors initialized with pre-trained GloVe embeddings.

GloVe+Random: trainable embeddings initialized as the concatenation of pre-trained GloVe embeddings and random embeddings. The random embeddings are chosen to have the same dimensionality as WCEs. This configuration serves for control purposes, in order to ensure that any possible relative improvement brought about by the use of WCEs cannot merely be attributed to the presence of more parameters in the embedding layer.

GloVe+WCEs(static): static concatenations of pre-trained GloVe embeddings and WCEs.

GloVe+WCEs(trainable): trainable embeddings initialized with the concatenation of pre-trained GloVe embeddings and WCEs.

We perform hyperparameter search via grid-search on the validation set, independently for each combination of type (dataset, architecture, variant).

The hyperparameters to be optimized are dependent on the architecture, and are explained in the sections below.

4.3.1 Support Vector Machines

The problem of training a classifier via SVMs with unsymmetric costs is stated as the empirical risk minimization problem \[18,55\]

\[
\minimize \quad \frac{1}{2}\|w\|^2 + C_+ \sum_{k=1}^n \xi_k[y_k = +1] + C_- \sum_{k=1}^n \xi_k[y_k = -1]
\]

\[
\text{over:} \quad w, b, \xi_1, \ldots, \xi_n
\]

\[
\text{subject to:} \quad \forall_{k=1}^n : y_k(w \cdot x_k + b) \geq 1 - \xi_k \quad \forall_{k=1}^n : \xi_k > 0
\]

where $w$ and $b$ are the parameters (hyperplane and bias) of the separation functional, $\xi_k$ are the slack variables for the labelled examples $(x_k, y_k)$, $[\cdot]$ is the indicator function that returns 1 if its argument is true and 0 if it is false, and $C_+$ and $C_-$ are two hyperparameters that control the trade-off between training error and margin for positive and negative examples, respectively. It is convenient to factor $C_+$ and $C_-$ as $C_+ = CJ_+$ and $C_- = CJ_-$, so that the unsymmetric cost factors are confined to two dedicated hyperparameters, with $J_+$ (resp., $J_-$) controlling the amount by which training error on positive examples (resp., negative examples) outweighs error on the negatives (resp., positives). We follow [55] and set the cost factors so that the ratio $J_+/J_-$ equals the ratio $N/P$ between the

\[\text{http://nlp.stanford.edu/data/glove.840B.300d.zip}\]

\[\text{We generate the validation set by randomly sampling 20\% of the training set, with a maximum of 20,000 documents; the rest is taken to be the training set proper. We keep the training/validation split consistent across all methods.}\]

\[\text{Note that, consistently with [18,55], in this formulation we assume the class labels $y_k$ to be in \{-1, +1\}, while in Section 3 we had assumed them to be in \{0, 1\}; the difference is, of course, unproblematic.}\]
number \( N \) of negative training examples and the number \( P \) of positive training examples. The trade-off between training error and margin, now confined to \( C \), becomes the only hyperparameter we tune. Note that, while in other application fields the kernel to employ is considered an important parameter to optimize, in text classification it is customary to employ the linear kernel, since there are theoretical arguments for its optimality in these contexts.\(^{19}\); we thus use the linear kernel without further ado.

Although the application of SVMs to text classification dates back to \cite{23, 35}, SVMs are still considered among the strongest baselines for text classification.\(^{19}\) Having set the unsymmetric cost factors, the most influential hyperparameter for SVMs is \( C \). We choose the best value for \( C \) from the set \( \{10^{-3}, 10^{-2}, \ldots, 10^3\} \) by performing 5-fold cross-validation on the full set of labelled documents (i.e., the training set proper plus the validation set); we perform the optimization of \( C \) independently for each class.\(^{20}\) In the experiments of this paper we use the implementation of SVMs available in scikit-learn.\(^{21}\) We leave the rest of the parameters set to their default values.

Since SVMs do not cater for word embedding fine-tuning, we only report experiments involving sets of static embeddings. Specifically, for SVMs we report the following experiments:

**SVM-tfidf**: a SVM-based classifier trained on the tfidf matrix \( X \) defined in Section\(^5\)

**SVM-GloVe**: a SVM-based classifier trained on the projection \( UX \), with \( U \) the pre-trained GloVe embeddings;

**SVM-GloVe+WCEs**: a SVM-based classifier trained on the projection \( XE \), with \( E = [U \oplus S] \) the concatenation of pre-trained GloVe embeddings and WCEs.

### 4.3.2 fastText

We report experiments for fastText \cite{13, 29}, which we have already discussed in Sections\(^{1.1} \text{ and } 2.3\).

We select hyperparameters via grid-search optimization on the validation set. Following \cite{13, 29}, we let the learning rate vary in \( \{0.05, 0.1, 0.25, 0.5\} \) and the number of epochs in \( \{5, 10\} \). Some of our datasets (20NEWSGROUPS, JRC-AQUIS, OHSUMED, and REUTERS-21578) are comparatively smaller than those tested in the original article; in those cases we let the number of epochs vary on \( \{5, 50, 100, 200\} \) (we observed drastic improvements when using 100 or 200 epochs, but no further improvement when going beyond 200).

In our experiments we only consider the case in which fastText operates with unigram features. While fastText has been found to deliver better results when using bigrams, the adoption of bigrams would likely lead to similar improvements for the rest of the methods being compared \cite{21}, and might only blur the purpose of this comparison.

For fastText we only report experiments involving sets of trainable vectors (combinations Random, GloVe(trainable), GloVe+Random, and GloVe+WCEs(trainable)), since fastText is implicitly a method for learning embeddings, and thus does not cater for static vectors. In the case of GloVe+WCEs(trainable), we do not apply supervised dropout, since we stick to the official implementation.\(^{22}\)

### 4.3.3 Deep-Learning Architectures

Since our goal is to quantify the relative improvement (if any) brought about by concatenating WCEs to pre-trained embeddings, we adopt the most general and simple formulation for each of our three deep-learning architectures, and leave the exploration of more sophisticated models for future research.

Let \((x_k, y_k)\) be a training instance, with \( x = [t_{1k}, \ldots, t_{lk}] \) a document consisting of a sequence of \( l \) terms (padded where necessary) labelled with \( y_k \in \{0, 1\}^m \). Let \( E \in \mathbb{R}^u \times \mathbb{R}^r \) be the embedding matrix, containing \( u \times r \)-dimensional word embeddings \( e_i \in \mathbb{R}^r \) (where embeddings may either be initialized randomly, using pre-trained embeddings, or concatenations of pre-trained and supervised embeddings). All the tested architectures use an embedding layer as the

\[^{18}\text{In scikit-learn this is achieved by setting } J_+ = n/\left( mP \right) \text{ and } J_- = n/\left( mN \right), \text{ and corresponds to setting the parameter } \text{class_weight} \text{ to "balanced".}\]

\[^{19}\text{Somewhat surprisingly, though, several relevant related works where SVMs are used as baselines (see, e.g., } \cite{29, 33, 9} \text{ do not report the details of how, if at all, they tune the SVM hyperparameters.}\]

\[^{20}\text{Using } k \text{-fold cross-validation } (k-\text{FCV}) \text{ on the full set of labelled documents is a more expensive, but stronger, way of doing parameter optimization than using a single split between a training set and a validation set, because } k-\text{FCV } \text{performs } k \text{ such splits. We here use } k-\text{FCV } \text{for SVMs and single-split optimization for all the other deep learning -based architectures because it is realistic to do so, i.e., because SVMs are computationally cheap enough for us to be able to afford } k-\text{FCV}, \text{ while neural architectures are not.}\]

\[^{21}\text{This implementation relies on liblinear. See } \text{https://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html } \text{for further details.}\]

\[^{22}\text{https://fasttext.cc/}\]
first layer on the network, which transforms every input document \( x_k \) into \( x_k = [E(t_{1k}), \ldots, E(t_{lk})] \), where \( E(t_{ik}) \) is the word embedding in \( E \) for term \( t_{ik} \). Different models implement different transformations

\[
o_k = N(x_k; \Theta)
\]

(8)
of the input (as defined below) parameterized by \( \Theta \), with \( o_k \) denoting the document embedding of \( x_k \). Finally, \( o_k \) is mapped into the space of label outputs by

\[
y_k = f(o_k \cdot W + b)
\]

(9)
where \( W \) and \( b \) are the parameters (weight and bias) of an affine transformation, \( f \) is a non-linear function, instantiated as the softmax function for single-label problems or as the sigmoid function for multilabel problems, and \( y_k \in [0, 1]^m \) is a vector of \( m \) predicted posterior probabilities, one for each class. The full set of model parameters to optimize is thus \( \Theta' = [\Theta; W, b] \).

We initialize the model parameters using the Xavier uniform method described in [27]. We then train the model by backpropagating the errors, where error is computed as the cross-entropy loss (in the single-label case) or as the binary cross-entropy loss (in the multilabel case). We carry out optimization via stochastic gradient descent with the Adam update rule [40]. We set the learning rate to 1e-3 and the batch size to 100 documents, dynamically padding the sequences to \( l = \min \{500, l_{\text{max}}\} \), where \( l_{\text{max}} \) is the length of the longest document within the batch.

We train the models for a maximum of 200 epochs, but we apply early stopping whenever 10 consecutive training epochs do not yield any improvement in the validation set in terms of \( F_1^M \). An epoch consists of a full pass over all the training documents. Since WIPO-GAMMA is one order of magnitude larger than the other datasets, we consider an epoch to be over after 30,000 documents (300 batches) have been processed. We dump the model parameters whenever the value of \( F_1^M \) on the validation set improves. When the training epochs are over, we restore the best model parameters and perform one final training epoch on the validation set.

We consider the following network architectures as alternative implementations of the transformation \( N \) of Equation 8.

**Convolutional Neural Networks.** Convolutional Neural Networks (CNN) are a special type of neural models particularly suited for computer vision, that apply convolved filters which are robust to position-invariant patterns. In text-related applications [17, 38] a convolution is the result of the application of a linear filter to a matrix consisting of the \( w \) word embeddings corresponding to the words that appear in a sliding window of length \( w \), in order to produce a feature map.

A convolutional layer typically contains and applies many filters, each of which is followed by a non-linear activation function (typically: the rectified linear unit \( \text{ReLU}(x) = \max\{0, x\} \), which is the one we use here) and a max-pooling operation that takes the maximum value for each filter. The result is a thus a vector with as many features as there are filters.

We consider one single convolutional layer [42] with \( \gamma \) output channels for each window length \( w \in \{3, 5, 7\} \) (i.e., \( 3\gamma \) output channels in total), where \( \gamma \) is a hyperparameter to be optimized on a validation set. We let \( \gamma \) vary in the range \( \{64, 128, 256, 512\} \). The final representation is a vector \( o_k \in \mathbb{R}^{3\gamma} \), which concatenates all convolved outputs, followed by the application of a dropout operator.

**Long-Short Term Memory Networks.** Recurrent Neural Networks (RNNs – [41, 60]) are a family of network architectures specially devised for processing sequential data. RNNs apply the same computation to each input in the sequence. The internal state \( h_{ik} \) at time \( i \) is defined recursively as \( h_{ik} = f(h_{i-1k}, E(t_{ik}); \Theta) \), with \( E(t_{ik}) \) the embedding of term \( t_{ik} \) and \( \Theta \) parameterizing the recurrent function. The model is trained by Backpropagation Through Time (BPTT) via unfolding the recursive computation and sharing the parameters \( \Theta \) across all time steps. In this work we adopt the well-known Long-Short Term Memory (LSTM) [22] as the recurrent cell. We apply gradient clipping at \( ±0.1 \) in order to avoid exploding gradients. The size \( \gamma \) of the hidden state is a hyperparameter of the model, to be optimized on a validation set from the range \( \{256, 512, 1024, 2048\} \). The output \( o_k \in \mathbb{R}^{\gamma} \) is the final state \( h_{lk} \) produced by the LSTM.

**Attention Models.** Attention models (ATTNs) implement criteria that enable the model to weight differently (i.e., to pay different attention to) the contribution of intermediate factors in certain computations. Although attention mechanisms by their own [69] constitute nowadays an entire family of deep neural models, called transformers [21, 58, 75], we focus on a simpler formulation, called soft-scaled dot-product attention mechanism [49].

This attention mechanism takes all hidden states \( H_k = [h_{1k}, \ldots, h_{lk}] \) produced by a RNN (we use the LSTM here as well) and the document embedding \( o_k = h_{lk} \), and computes a vector of attention weights over all intermediate states,
Table 2: Classification performance in terms of $F_1^M$. Boldface indicates the best absolute result for each dataset, and greyed-out cells indicate the best result locally to a specific neural architecture. Symbols † and †† indicate the methods, if any, whose performance is not statistically significantly different with respect to the best result obtained by any neural approach according to a two-tailed t-test at confidence level $\alpha = 0.05$ and $\alpha = 0.005$, respectively.

\[
a_k = \text{softmax}(\mathbf{a}_k^T \mathbf{H}_k)
\]

and produces a new output $\mathbf{o}' \in \mathbb{R}^\gamma$ as a weighted sum

\[
\mathbf{o}'_k = \sum_{a_{ik} \in a_k} a_{ik} \mathbf{h}_{ik}
\]

As for LSTM, for the hidden layer $\gamma$ we choose the size from the range \{256, 512, 1024, 2048\} that performs best on the validation set.

4.4 Results

Tables 2 and 3 report the $F_1^M$ and $F_1^\gamma$ results we have obtained. Since neural architectures use a random initialization of the parameters, our results for them are averages across 10 runs. (SVMs are deterministic and thus excluded from the test of statistical significance, which requires the repetition of random trials.)

Various facts emerge from these results. First, beating well-optimized “traditional” baselines, such as SVM-$\text{tfidf}$, is not easy (especially in terms of $F_1^M$). This has already been noticed in past literature \cite{71}, and has recently stimulated debate \cite{47,73}. For SVMs, our results for 20NEWSGROUPS and REUTERS-21578 are in line with those reported for \cite{47}. These authors found that the adoption of more sophisticated supervised representations helps SVMs to improve over simple tfidf features in 20NEWSGROUPS but not on REUTERS-21578, and argued that in this latter case a considerably high accuracy is achievable by simply using a handful of highly correlated terms for each class (something that is already well represented in a bag-of-words model). Notwithstanding this, we should observe that SVMs, in their standard formulation, do not scale to very large training sets; as a result, we were unable to train them on WIPO-GAMMA.
Concerning neural approaches, a method equipped with WCEs either turns out to be the best performer, or is comparable (in a statistically significant sense) to the best performer, both in terms of $F_1^M$ and $F_1^H$, and for all datasets. Concatenating GloVe embeddings and WCEs almost always yields superior performance with respect to only using GloVe embeddings, both for static and trainable pre-trained embeddings, across all models (this applies also to SVMs). On average across all six datasets and neural models, GloVe+WCEs (static) shows a relative improvement of +7.42% and +3.30% over GloVe (static) in terms of $F_1^M$ and $F_1^H$, respectively. In a similar way, the relative improvement of GloVe+WCEs (trainable) with respect to GloVe (trainable) amounts to +6.66% and +4.42% on average in terms of $F_1^M$ and $F_1^H$, respectively. In all cases except $F_1^H$ for the static case, the differences in performance, as averaged across methods and datasets, are statistically significant at $\alpha = 0.05$.

The superiority of the models also equipped with WCEs cannot be merely explained by the higher number of parameters in their embedding layer. By inspecting the execution logs, we found out that approximately 50% of the times the best hyperparameters chosen by the variants with WCEs were consistent with those chosen by the same variant without them. In such cases, the GloVe+WCEs (trainable) setting contains exactly the same number of trainable parameters as the corresponding GloVe+Random variants, yet it performs better (with relative average improvements of +6.19% and +4.40% in $F_1^M$ and $F_1^H$, respectively, and with statistical significance at $\alpha = 0.05$). For other approximately 40% of the times, the model selected when using WCEs happened to be comparatively smaller than when not using them, and only in the remaining 10% of the cases the variants using WCEs turned out to be larger.

Fine-tuning embeddings (GloVe (trainable) and GloVe+WCEs (trainable)) has proven consistently superior to keeping them static (GloVe (static) and GloVe+WCEs (static)) when using the CNN architecture, but not necessarily for LSTM or ATTN.

### 4.5 Learning Curves

In this section we look at the learning curves for the three deep learning architectures when equipped with different types of embeddings. For the sake of clarity, we choose to plot only three representative variants: Random,
GloVe(static) and GloVe+WCEs(static) (that, for simplicity, we here simply denote by GloVe and GloVe+WCEs). Unless specified differently, these plots and all the subsequent ones are generated with the same, fixed hyperparameters for all variants, i.e., 250 channels for CNN and 512 hidden nodes for LSTM and ATTN, a supervised dropout probability of 0.5 for GloVe+WCEs, and 200 dimensions for random embeddings; we run 100 training epochs and deactivate early stop. For these experiments we choose RCV1-v2, since it is arguably the most widely adopted benchmark in the literature of text classification by topic. (In similar experiments that we have run on other datasets we have verified similar trends.)

Figure 1 shows a grid of plots that visualize learning curves as a function of the number of epochs for RCV1-v2. The first and second rows display (the logarithm of) the training and validation loss, respectively, while the third and fourth rows display the values of $F_1^M$ and $F_1^P$, respectively, on the validation set. Columns correspond, from left to right, to the CNN, LSTM, and ATTN architectures.

There are a few observations that we can make from these plots. Networks with random embeddings have more parameters to tune than networks which rely on static pre-trained embeddings (since the latter are fixed, and thus are not trainable parameters), and thus lower the training loss faster than the rest. Notwithstanding this, the validation loss is always higher for them than that of GloVe and GloVe+WCEs, which shows that the presence of random embeddings brings about a tendency to overfit the training data. This tendency to generate overfitting is well countered by the variants that use static pre-trained embeddings. The knowledge incorporated in GloVe embeddings is generic and thus consistent for validation documents as well.

We can also observe that the use of WCEs eases parameter optimization across the three architectures tested. That is, models equipped with WCEs reach promising regions of the parameter space faster (i.e., in fewer epochs) than those not using them.

However, since models relying exclusively on pre-trained embeddings are anyway connected to class labels through the loss function, it is legitimate to wonder what is the real contribution of WCEs to the supervised learning task. Clearly, WCEs are not bringing any new information to the model, since they are computed using the very same amount of information the learner has when training a classifier (this is in contrast to pre-trained embeddings, which are learnt from external data). We conjecture that this has to do with the way WCEs inject supervised information from the bottom (word level) and the top (document level), instead of only from the top, which may favour the gradient flow. In other words, WCEs may not really be adding any new information, but are handling the available class label information in a more efficient way.

It is worth noting that WCEs model the correlations between words and labels globally (at the dataset level) and not locally (at the batch level). Global word-class dependencies remain reachable to batched optimization only in the long term. The same principle, according to which the word-class distributions are mined globally beforehand, and later serve the purpose of a model prior, was already used in [54] (more details are given in Section 5.1).

4.6 The Importance of Regularization

WCEs directly inject into the model information from the label distribution as available in the training set. This might somehow compromise the generalization capability of the classifier when dealing with future unseen data, for the reasons discussed at the beginning of Section 3.2. During preliminary experiments we observed that this is indeed the case, and that there is thus a need for properly regularizing the model.

Figure 2 shows the effect of supervised dropout (which, as explained in Section 3.2, is the device we use performing regularization) at varying drop probability rates for the GloVe+WCEs configuration. In the last two rows of this figure we plot $F_1^M$ and $F_1^P$ as directly computed on the test set of RCV1-v2 every 10 epochs (last two columns). The rationale behind showing the values of effectiveness on the test set (instead of on the validation set, as in Figure 1) is to better illustrate the effect of regularization when dealing with unseen data: as observed in Section 4.1, news stories in the RCV1-v2 test set are from a disjoint time window with respect to those in the training set, which is not true for validation documents, which are randomly drawn from the original training set.

We can observe that applying no regularization at all ($p = 0.0$) yields a faster minimization of the training loss, but also results in poorer generalization on unseen data. The model generalizes better for $p > 0.0$; setting $p = 0.5$ actually yields the best results. Of course, in general the optimal value for $p$ has to be explored on a validation set in a case-by-case fashion, but we have observed the setting $p = 0.5$ to generally entail, across all methods and datasets, a good tradeoff between loss minimization in training and performance on validation/test data (this is indeed in agreement with general considerations regarding dropout as reported in the literature).
4.7 Execution Times

Table 4 reports the average time each method takes to complete a full training and test run. All timings are recorded on the same machine, equipped with a 12-core processor Intel Core i7-4930K at 3.40GHz with 32 GB of RAM and an Nvidia GeForce GTX 1080, under Ubuntu 16.04 (LTS). Note that SVMs and fastText run on CPU, while CNN, LSTM, and ATTN (in our own implementation based on PyTorch\(^2\)) run on GPU. We do not clock model selection, i.e., the times reported correspond to the execution time of the model with already optimized hyperparameters\(^2\). In the interest of brevity, for each neural architecture we only report times for GloVe(trainable), and GloVe+WCEs(trainable) variants.

SVMs with tfidf features typically rank as the fastest method. When learning from dense representations SVMs become slower, though. Since SVMs run one optimization problem for each class, execution times drastically grow in JRC-ACQUIS (whose codeframe consists of 2,706 classes). The combination of these two factors (dense representations and large codeframes) may further penalize execution times for SVMs, as shown in the experiment running SVM-GloVe and SVM-GloVe+WCEs on JRC-ACQUIS. The rest of the models instead run one simple optimization for

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\(^2\)https://pytorch.org/

\(^2\)The total time of computation to execute all 10 runs for all variants amounts to 37d 14h 52m (this is without considering model selection, which by itself requires 15d 10h 22m).
all classes at once. No clear pattern emerges as to which among GloVe and GloVe+WCEs is faster. This means that the benefits in classification accuracy brought about by enlarging the dimensionality of the embedding space with word-class features does not necessarily entail a penalization in terms of running times; convergence times remain in any case governed by the stochastic nature of backpropagation. Finally, even if fastText does not implement any early-stopping policy, it still stands out as the fastest neural approach by a large margin, and is sometimes even comparable to SVMs. In particular, the two running times that stand out are those regarding fastText-GloVe+WCEs on 20Newsgroups and OHSUMED. In both cases, these low training times are due to the fact that, as resulting from hyperparameter optimization, only 5 training epochs are required, instead of the 200 epochs that are required for fastText-GloVe.

Table 5 reports the time it takes to create the WCEs, which can be broken down into two components, i.e., (i) the time needed to generate matrix $X$ (which encodes the bag-of-words model with tfidf weighting), and (ii) the time needed to subsequently generate matrix $S$ (which contains the WCEs). Most of the total time is accounted for by the generation of matrix $X$ (1st row of Table 5); the computational cost of generating the WCEs from matrix $X$ is almost negligible (2nd row of Table 5), and typically represents less than 10% of the total time. The higher times clocked for JRC-Acquis and WIPO-Gamma are due to the application of PCA, which is not necessary for the other datasets (see Section 3.2). The total times (last row of Table 5) are, in all cases, much smaller than the times needed for optimizing the models, that are shown in Table 4.
4.8 Other Measures of Correlation

In this section we explore other correlation measures as alternative ways for computing the WCEs. In other words, we explore alternatives to the use of the dot product for instantiating the $\eta$ function of Equation 6. For this, we use well-known functions from information theory or statistics that have been routinely used for feature selection purposes in text classification, including Positive Pointwise Mutual Information (PPMI – see Footnote 2), Information Gain (IG), and Chi-square ($\chi^2$). In preliminary experiments we had carried out using these functions we had indeed found that standardizing the resulting matrix $A$ (Equation 2) improves accuracy. We thus report the results of using as the $\eta$ function one that also performs standardizing, e.g., $\eta_{\chi^2}(t_i, c_j) = z_j(\chi^2(t_i, c_j))$ (similarly for PPMI and IG).

Figure 3 compares the classification performance, in terms of $F_M^1$, of the dot product (as originally used in Equation 2, and here abbreviated as “Dot”) against PPMI, IG, and $\chi^2$. As can be observed from Figure 3 “Dot” is almost always superior to all other functions, or at least comparable to the best-performing function, across all datasets and network architectures. Other functions behave irregularly across experiments; for example, PPMI seems to be the most competitive method for WIPO-GAMMA, but is a weak one in REUTERS-21578 (this applies to all architectures) and JRC-ACQUIS (in CNN and LSTM).

We conjecture that the superiority of the dot product partly depends on its ability to take non-binary (in our case: tfidf) weights into account, while PPMI, IG, and $\chi^2$ only consider binary presence/absence indicators. Additionally, the

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25Though most traditional functions used for feature selection can only use presence/absence, other metrics exist that work with weighted scores, e.g., the Fisher score. In initial experiments not described in this paper we have indeed tried to use the Fisher score, but we have eventually given up, due to the fact that (a) its computation is very slow, and (b) the classification accuracy
Figure 3: Classification accuracy (in terms of $F_1^M$) resulting from the use of measures of correlation alternative to the one (“Dot”) that we use for generating WCEs.
dot product only leverages positive correlations (this is also true for PPMI), and is thus much faster than other methods that compute negative correlations at intermediate steps, as is the case of IG and $\chi^2$. The reason is that our tfidf matrix $X$ and the label matrix $Y$ (see Equation 2) are highly sparse; many machine learning software packages (including the ones we use) do cater for the presence of sparse matrices, and thus do not explicitly represent zero values, causing any operation involving non-zero values to substantially increase computation times. For example, it takes 20s to compute matrix $S$ for Reuters-21578 when using $\chi^2$, while the same only takes 0.04s when using the dot product (see Table 5).

4.9 Different Pre-trained Embeddings

Up to now, we have tested the performance of WCEs as an extension of GloVe vectors. It might be interesting to check how well WCEs could perform when concatenated to pre-trained vectors other than those generated by GloVe.

Table 4 shows the results of experiments in which WCEs are concatenated to word2vec pre-trained embeddings. The results show that the improvements brought about by WCEs for word2vec are similar to those reported for GloVe. It thus seems reasonable to believe that the use of WCEs is beneficial in general, and independently of the particular set of pre-trained embeddings under consideration.

One question that still remains open is how much effort it might require to pair WCEs with differently characterized embeddings, such as contextualized vector representations, subword representations, character-based embeddings, or high-dimensional sparse representations. We plan to answer these questions in future research.

4.10 Visualizing WCEs

In this section we try to gain an understanding on how terms represented by WCEs are topologically distributed in the embedding space, and how WCEs alter the distribution of pre-trained embeddings once they are concatenated to them. To do so we use Embedding Projector, a publicly available tool for data visualization based on the t-distributed Stochastic Neighbor Embedding (t-SNE) technique and which allows to map word embeddings onto a 2-dimensional space. We use its default parameters (perplexity=18 and learning rate=10) and perform 1,000 iterations. We only represent 5,000 terms, in order to get a clearer visualization; the terms we select are the most predictive ones (as quantified via information gain) for each class, following a “round robin” policy which selects the same number of highly predictive terms for each class. We assign different colours to the classes, and colour each embedding according to the class for which it was selected. For this experiment we choose 20NewsGroups (the dataset with fewest classes), with the aim of keeping the colour coding simple enough, thus maximizing visual clarity.

Figure 5 shows the distribution of GloVe vectors. The top part shows that, to some extent, some word clusters seem to correlate with some classes. This was to be expected, since terms relevant to a given class tend to be semantically related to each other. The enlarged region (bottom) shows how GloVe succeeds at producing meaningful local structures containing smaller clusters of semantically interrelated words, e.g., {“diet”, “dietary”, “vitamin”}, or {“doctor”, “medical”, “hospital”}, within class sci.med.

Figure 6 shows the distribution of WCEs for the very same terms represented in Figure 5. The visualization shows almost perfect word clusters for classes (top). This should come at no surprise, since the WCEs explicitly encode class structure. As a counterpart, local semantics within clusters vanishes (bottom), given that WCEs disregard word-word interactions. For example, for certain pairs of words (e.g., {“attacking”, “attacks”}, {“terror”, “terrorism”}), the two words happen to lie far from each other within the cluster for class talk.politics.mideast.

Figure 7 shows the distribution of the concatenation of GloVe vectors and WCEs for the very same terms of Figures 5 and 6. This representation brings together the best of the two worlds. Globally, a neat class structure emerges, as imposed by the WCEs (top). Locally, clusters exhibit a meaningful inner structure, thanks to GloVe vectors (bottom). As an example, relevant words for class sci.space organize in smaller clusters such as {“moon”, “earth”, “lunar”} and {“allen”, “grifin”, “dani”}.

that we have observed is not much different from what can be obtained with the other functions mentioned above, and is often intermediate between the best and the worst recorded values.

26 Available at https://code.google.com/archive/p/word2vec/
27 https://projector.tensorflow.org/
Figure 4: Classification accuracy resulting from the use of GloVe embeddings or word2vec embeddings, with or without concatenated WCEs.
4.11 Can we Learn WCEs for Out-of-Vocabulary Terms?

In contrast to unsupervised word embeddings, WCEs are inherently task-dependent, and thus heavily rely on the distribution of the terms in the training set. This means that, for any word encountered at testing time that was not observed during training, the corresponding WCE will be a vector of zeroes (or a randomly initialized vector), and this could harm performance. This is yet another manifestation of the well-known problem of out-of-vocabulary (OOV) terms, which represents an active area of research in the field of word embeddings [26].
Classifiers that make use of pre-trained embeddings do have a chance to make sense of OOV terms (i.e., terms not encountered at classifier training time). When (as is usually the case) pre-trained embeddings are generated from huge quantities of text, an OOV term is fairly likely to have a corresponding pre-trained embedding. If this is the case, what is learnt during classifier training is thus related to this term too, inasmuch as its pre-trained embedding is at least partly aligned with the embeddings of some terms encountered during classifier training.

In this section we cope with the problem of WCEs for OOV terms. Our idea is to predict the WCE for an OOV term from its pre-trained embedding (when available), on the grounds that semantically similar terms (as observed in general language use) can be expected to exhibit similar class-conditional distributions.
We frame the problem of generating the WCE for an OOV term as a multivariate regression task.\footnote{Another technique for solving this problem is \textit{Latent Semantic Imputation} \cite{76}. This method allows filling the missing representation in a vector space (in our case: the space of WCEs) by analyzing the neighborhood of the term representation in another vector space (in our case: the space of unsupervised embeddings) via techniques inspired by manifold learning.} As from Section 3, let $E = [U \oplus S]$ be the embedding matrix, where rows $e_i = [u_i \oplus s_i]$ are the embeddings, consisting of a concatenation of a pre-trained embedding $u_i$ and a WCE $s_i$. We train a two-layered feed-forward network (in the experiments we use 64 units in the hidden layer, ReLU activation, and 0.5 dropout) to predict the WCE $s_i \in S$ from the pre-trained embedding $u_i \in U$, using the terms in the vocabulary as the training examples. We adopt Mean Square Error (MSE)
as the loss criterion. Once trained, and once an OOV term is encountered, the regressor is asked to generate the WCE for it, provided this term has a pre-trained embedding.

We have run experiments, using RCV1-v2 as the dataset and all the five learners of Section 4.3 in which we compare the accuracy of two different configurations: (i) a configuration in which the WCEs of an OOV term is a vector of zeros (which is the setting we have used so far), and (ii) a configuration in which the WCEs of an OOV term has been predicted from the pre-trained embedding of the term, using all the non-OOV terms as training examples.

Unfortunately, the differences in classification accuracy between the two configurations turned out to be barely discernible; in the interest of brevity, we thus omit to plot them out explicitly. The likely reason of this result is that, while RCV1-v2 contains no less than 384,327 OOV terms, occurring 2,073,278 times in the test set, these represent only 2.16% of the total number of term occurrences, which means that their impact on classification accuracy is minimal.

However, in a qualitative (although somehow “anecdotal”) evaluation we have verified that the predicted WCEs for OOV terms look meaningful. In order to do this, we looked for OOV terms whose predicted WCE displays a large correlation with some class, i.e., whose WCE is such that the value for some of its features is high. Some interesting examples of such OOV terms include “astronauts”, “invincible”, “battlefields”, “indiscriminate” for class GDEF (which is about armed forces, defence policy, and defence budget); “windfarm” for class GENV (about environment, pollution, conservation, green issues); “pneumatic” and “prostatectomy” for class GHEA (dealing with health and diseases).

We also found many misspelled terms whose predicted WCE displays a large correlation with some class, e.g., “selling” and “exchang” for classes C311 (domestic markets, sales and imports) and C312 (external markets and exports); “emploment” for class C41 (all management issues); “manufatures” for class E12 (monetary/economic policy and intervention, interest rates), among others. This is interesting, because the ability to make sense of misspelled terms is important for many text management applications. Incidentally, these findings also speak about the ability of GloVe to model rare terms.

Surprisingly, we have also found new correlations for non-English terms, like Spanish terms “aseguradora” (insurer) for class E121 (money supply), and “mantenimiento” (maintenance) for class E313 (inventories and stocks of manufacturing raw materials).

5 Discussion

5.1 Term Semantics: From Unsupervised to Supervised

In Section 1.1 we have touched upon the connections between WCEs and fastText, and argued that the two methods are the supervised counterparts of SPPMI and word2vec, respectively. These are just the most recent examples of a trend, in the field of extracting term semantics from data for text classification purposes, that over the years has seen a move from unsupervised to supervised techniques.

The first interesting example of this trend is that of term clustering. In the ’90s, term clustering was advocated, among others, as a means to implement dimensionality reduction for text classification purposes, according to the idea that clusters of semantically related terms, instead of individual terms, would serve as features. While standard unsupervised techniques were initially used [46], the field slowly moved to using supervised ones, such as distributional clustering by class distribution (DCCD) [4, 7]. While unsupervised term clustering has the simple goal of grouping together semantically related terms, DCCD has the goal of grouping together terms that are discriminative for the same classes; as such, it constitutes a technique for building special-purpose term clusters, i.e., ones that are to be used for text classification only, and only for the specific codeframe on which they have been trained.

The second interesting example is that of term weighting. In text classification, and also in other tasks such as text search and text clustering, term weighting serves the purpose of emphasizing the importance of terms that are deemed to be more important in describing the semantics of the documents they occur in. While standard unsupervised techniques were initially used [74], supervised term weighting (STW) techniques later started to gain prominence [19], based on the notion that the terms that should weigh more in representing a document are not the ones that are rarest in the collection, but the ones which are most correlated with the labels of interest. As in the case of DCCD, STW techniques leverage the class labels of the training documents, and generate document representations that have a special-purpose nature, i.e., should be used only for the specific text classification task on which they have been trained. The notion of STW is brought one step further in learning to weight [54], where the STW function is not given but is learnt from data.
5.2 Known Limitations

In this article we have focused our attention on multiclass classification by topic. Other classification scenarios remain unexplored. Two important such scenarios include (i) simple binary classification, and (ii) classification by dimensions other than topic, such as, e.g., sentiment classification (an active area of research where deep learning is already showing interesting results [78]).

In their current form, WCEs are not suitable for binary classification. The reason is that, since the dimensionality of WCEs is the number \( m \) of classes in the codeframe of interest, in binary classification the dimensionality of WCEs would be 1, which indicates that WCEs would convey very little information to the classification process. One possible strategy to counter this problem might be based on increasing the number of classes artificially. A possible approach to do so might gain inspiration from the structural learning framework [3]. This strategy would consist of adding new classes that account for the presence or absence of certain highly predictive terms for the task (i.e., adding to \( Y \) new columns corresponding to binary versions of columns in \( X \) for highly predictive terms), and then computing the WCEs across them (a similar intuition has been explored in [53]). However, preliminary experiments we have conducted along this vein are still inconclusive.

In addition to this, WCEs depend on the training set prevalences of the classes in the codeframe. This might compromise their contribution to tasks characterized by the presence of prior probability shift, i.e., by the fact that the prevalence of a class in the training data is substantially different from the prevalence of the same class in the unseen data. This might yield WCEs detrimental for tasks such as text quantification [28], which indeed target scenarios characterized by prior probability shift.

6 Conclusions

In this article we have presented word-class embeddings (WCEs), i.e., distributed representations of words specifically designed for multiclass text classification. The hypothesis underlying the present study is that the class-conditional distributions of a term defines a fingerprint that might help to refine its pre-trained representation for applications of multiclass text classification. The extensive empirical evaluation we have conducted indeed confirms this hypothesis.

WCEs are easy and quick to compute. Word-class embeddings are meant to expand, and not modify, pre-trained word representations that model general language usage. Although this implies adding some parameters to the model, we have seen that this additional cost is negligible in practice; they contribute to the classification task far more than they complicate the model.

We have investigated, also with the aid of a visualization tool, how these new embeddings alter the topology of the embedding space when WCEs are concatenated to embeddings pre-trained on generic, unlabelled text corpora. Our findings suggest that the new representation adds global class structure while preserving local word semantics, and is thus better suited for the classification task.

Unsupervised word embeddings are known to encode a mixture of the senses of polysemous terms [15]. We think WCEs indirectly help to disambiguate relevant domain-dependent terms. The word-class distribution might uncover the meaning of a term prevalent in the domain of interest, thus leaving a domain-specific mark on the resulting representation. This information might be thought of as a form of task-dependent word bias, which reframes the general-purpose word meaning through the lens of the codeframe of interest.

In future work we will try to provide solutions for the limitations discussed in Section 5.2. Other directions worth exploring would be that of modelling, in sentiment classification contexts, the sentiment prior of words across different domains (e.g., reviews of books, music, films, kitchen appliances, etc.), thus producing word-sentiment embeddings with as many dimensions as there are source domains available. This would hopefully help in cross-domain sentiment classification tasks [12, 53]. It should similarly be interesting to investigate the implications of this idea on multi-task learning [16], where each task might contribute with a dedicated task-specific embedding to the representation for other tasks.

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