Hierarchical models vs. transfer learning for document-level sentiment classification

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Abstract
Documents are composed of smaller pieces – paragraphs, sentences, and tokens – that have complex relationships between one another. Sentiment classification models that take into account the structure inherent in these documents have a theoretical advantage over those that do not. At the same time, transfer learning models based on language model pretraining have shown promise for document classification. However, these two paradigms have not been systematically compared and it is not clear under which circumstances one approach is better than the other. In this work we empirically compare hierarchical models and transfer learning for document-level sentiment classification. We show that non-trivial hierarchical models outperform previous baselines and transfer learning on document-level sentiment classification in five languages.

1 Introduction
The inherent structure found in documents – paragraphs, sentences, and tokens – and their interdependence is vital to document-level sentiment, as rhetorical devices and anaphora relationships disperse the sentiment signal across the various sub-components (Yang and Cardie, 2014). This also means that not all sub-components contribute equally towards identifying the overall polarity of a document (Yu and Hatzivassiloglou, 2003; Pang and Lee, 2004) and models that are able to take these relationships into account should theoretically perform better.

Recently, two divergent research directions have shown promise for document-classification: on the one hand, transfer learning (Peters et al., 2018; Howard and Ruder, 2018; Devlin et al., 2019) and on the other hand hierarchical modeling (Xiao and Cho, 2016; Conneau et al., 2017; Yang et al., 2016). Transfer learning (in its current form) attempts to take advantage of large amounts of unlabeled text in order to improve contextualized representations of tokens, while ignoring the structure of documents. Hierarchical models, on the other hand, attempt to take document structure into account by first building up representations for sentences and then aggregating them to create document representations.

While the two approaches are complementary in the sense that one could use pretrained LMs for transfer-learning also for hierarchical models, we here focus on isolating their relative strengths and weaknesses. In this paper we empirically show that methods which explicitly incorporate the structure of documents outperform those that do not and further examine the influence of data characteristics such as document length and size of training data on the choice of architecture. Finally, we release the code to reproduce the results from our study.\(^1\)

2 Background and related work
Document-level sentiment classification is a fundamental task in natural language processing and has a long tradition. Although there are document representation approaches which are more linguistically motivated, such as Rhetorical Structure Theory (Mann and Thompson, 2009), or centering (Grosz and Sidner, 1986; Grosz et al., 1995) these are not currently competitive with state-of-the-art approaches. In this section, we will review two current paradigms towards improving document-level classification: hierarchical models and transfer learning.

Hierarchical models Hierarchical approaches to document classification aim to model the relationship between sub-components in a document by

\(^1\)https://github.com/ltgoslo/hier_vs_typology
encoding first tokens, then sentences, and aggregating their representations in some way to create a full document representation which can be used for classification.

The first work on hierarchical models for text classification was based on CNNs, either by stacking CNN layers (Zhang et al., 2015; Conneau et al., 2017) or by using a single RNN to aggregate the output of the convolutional layers (Xiao and Cho, 2016). The performance of these models depends largely on the characteristics of the data, e.g., number of classes or dataset size, as these authors have conflicting findings on how many layers are optimal.

Hierarchical models can also be based solely on RNNs. Yang et al. (2016) propose a hierarchical model that uses an attention mechanism (Bahdanau et al., 2015) at both sentence- and document-level in order to attend to the most salient information, given the task. This model has shown promise for sentiment analysis and topic classification (Yang et al., 2016), as well as classification of social media texts for e-health (Ive et al., 2018).

Transfer learning Transfer learning approaches, on the other hand, attempt to improve contextualized word representations, specifically by pretraining with a language modelling objective (Peters et al., 2018; Devlin et al., 2019; Chang et al., 2019; Wang et al., 2019). Howard and Ruder (2018) pretrain a state-of-the-art LM (Merity et al., 2018) and introduce a number of improvements to the fine-tuning procedures. They demonstrate that this approach is able to make better use of later supervision.

These approaches have shown promise for several document classification tasks, thanks largely to the availability of unannotated text and the size of the models used. However, these models have not been tested extensively on large documents.

### 3 Data

We perform experiments on document-level sentiment datasets in five languages: English, French, German, Japanese, and Norwegian. For the first four, we use the Amazon Customer Reviews datasets, a 5-class sentiment dataset with labels \( L \in \{1, 2, 3, 4, 5\} \) stars.\(^2\) Although the full corpora are much larger, due to preprocessing requirements and in the interest of having similar sized data for all languages, we create a subcorpus \( D \) by sampling 50,000 documents for each language without regarding domain, finally splitting these into test/dev/train splits of 35,000/5,000/10,000 documents. Each document is sentence split and tokenized using UDPipe (Straka and Straková, 2017) and stored in CoNLL-U format. For Norwegian, we use the NoReC corpus 2.0, which is a 6-class task with labels \( L \in \{1, 2, 3, 4, 5, 6\} \) ratings. It differs from version 1.0 (Velldal et al., 2018) in that it has more training examples. Table 2 shows the statistics for each dataset.

|       | \( |D| \) | \( |L| \) | T. | S. | T./S. | \( |V| \) |
|-------|-------|-------|-----|----|------|-------|
| Fr    | 50k   | 5     | 81  | 6.3| 12.9 | 100k  |
| De    | 50k   | 5     | 77  | 3.9| 20.1 | 156k  |
| En    | 50k   | 5     | 114 | 8.0| 14.3 | 109k  |
| Ja    | 50k   | 5     | 365 | 13.2| 27.7 | 251k  |
| No    | 43k   | 6     | 463 | 27.8| 16.7 | 564k  |

Table 1: Statistics \((|D| = \text{number of documents}, |L| = \text{number of labels}, T. = \text{average number of tokens per document}, S. = \text{average number of sentences per document}, T./S. = \text{average sentence length in tokens}, |V| = \text{vocabulary size})\) for sentiment datasets.

4 Experimental Setup

The main research questions we seek to address in this section are: for document-level sentiment classification, are there systematic performance differences between language model pretraining or hierarchical modeling, and do any of these approaches offer improvements over baseline models that do not have these characteristics. Further, we investigate how performance is affected by several relevant data characteristics.

#### 4.1 Models

We start by briefly summarizing the architectures.

**Bow**: We train a linear SVM implemented in sklearn (Pedregosa et al., 2011) on bag-of-words representations and tune the \( C \) parameter on the development set.

**CNN**: CNNs are known to be strong baselines for document-level classification (Kim, 2014). We implement a CNN in AllenNLP (Gardner et al., 2017) with filter sizes \( F \in \{2, 3, 4, 5\} \), with 100 filters...
per size and max pooling before a fully connected layer. The 300-dimensional word embeddings are randomly initialized and updated during training.

**Universal Language Model Fine-Tuning (ULMFiT):** We use the AWD-LSTM architecture (Merity et al., 2018) and pretrain on Wikipedia data (or Common Crawl in the case of Norwegian) taken from the CONLL 2017 shared task (Zeman et al., 2017). The data was sentence and word tokenized using UDPipe (Straka and Straková, 2017) and we perform no further preprocessing steps. We use between 14 and 18.7 million tokens (for No and Ja respectively) to pretrain the language model and choose the best model after pretraining for 100 epochs as determined by perplexity on the development set.

We then fine-tune the language models on the target domain, using slanted triangular learning rate schedule and finally fine-tune the models to the sentiment task using discriminative training proposed in Howard and Ruder (2018). All experiments were performed using fastai (Howard et al., 2018).

**Hierarchical CNN (HCNN):** The Hierarchical CNN uses filters $F_{\text{sent}} \in \{2, 3, 4, 5\}$ and $F_{\text{doc}} \in \{2, 3\}$, with 100 filters per size and max pooling before a fully connected layer to create sentence and document-level representations respectively. The 300-dimensional word embeddings are randomly initialized and updated during training.

**Hierarchical Attention Network (HAN):** Hierarchical Attention Networks (Yang et al., 2016) have shown promise for document-level tasks. We use Gated Recurrent Units (Cho et al., 2014, GRUs) as our encoders, dot product attention, and randomly initialize sentence and document vectors. The 300-dimensional word embeddings are randomly initialized and updated during training.

### 4.2 Results

Table 2 shows the accuracy ($F_1$ results are similar) of the five models for each of the five languages as well as the average across all. The BOW model performs well across all experiments, achieving an average 64.2 accuracy, and ties HAN for the best performance on the German dataset (73.2). The CNN performs worse than the BOW across all experiments except Japanese (an average loss of 1.2 percentage points (pp)). ULMFiT performs better than BOW on Norwegian and Japanese (0.1 / 3.1 pp), but 0.4 pp worse overall. This seems to contradict previous findings (Howard and Ruder, 2018), but can be a result of smaller training data for the original language model objective.

Regarding the hierarchical models, the HCNN performs on par with the flat CNN (avg. 63.6), while the HAN model is the best on three of five experiments (72.1 En, 61.4 No, 73.2 De) and the best overall (avg. 66.4). This seems to indicate that while it is useful to explicitly model hierarchical structure using the HAN model, the HCNN is not as well suited to the task.

### 5 Analysis

Although it is clear that HAN is the best model overall, we would also like to know how the models differ with respect to data characteristics.

#### 5.1 Removing non-evaluative sentences

In order to classify the polarity of a document, one might assume that all relevant information should be contained in the evaluative (i.e. sentiment-bearing) sentences. One could reason that, while non-evaluative sentences are important for information and coherence purposes, they should not help with this specific task, and can possibly act as distractors, leading models to make incorrect predictions.

Early approaches to sentiment analysis often took a pipeline approach, where they first filtered out objective sentences and then performed sentiment analysis on the remaining subjective ones (Yu and Hatzivassiloglou, 2003; Pang and Lee, 2004; Wilson, 2008). More recently, these pipeline approaches have been abandoned under the assumption that current models can learn to differentiate relevant information in a data-driven manner.

We test this assumption on NoReC, as it contains polarity annotations at document-level and

|        | En | No | Fr | De | Ja | Avg. |
|--------|----|----|----|----|----|------|
| BOW    | 71.1 | 55.6 | 63.3 | 73.2 | 60.6 | 64.2 |
| CNN    | 68.1 | 52.8 | 63.4 | 72.4 | 61.1 | 63.6 |
| ULMFiT | 69.4 | 55.7 | 60.8 | 69.3 | 63.7 | 63.8 |
| HCNN   | 68.3 | 55.7 | 61.9 | 71.2 | 61.0 | 63.6 |
| HAN    | **72.1** | **61.4** | **63.2** | **73.2** | **61.9** | **66.4** |

Table 2: Accuracy of non-hierarchical (BOW, CNN, ULMFiT) and hierarchical (HCNN, HAN) models on document-level sentiment datasets.
Table 3: Accuracy of models on NoReC with evaluative-only sentences.

|       | BOW | CNN | ULMFiT | HCNN | HAN |
|-------|-----|-----|--------|------|-----|
| Full  | 55.6| 52.8| 55.7   | 55.7 | 61.4|
| Eval  | 54.5| 47.7| 34.6   | 55.0 | 57.5|

Annotations for evaluativity at sentence-level for a subset of the full dataset (Mæhlum et al., 2019), allowing us to train a sentence-level model to predict whether a sentence is evaluative or not. The lack of such in-domain sentence-level evaluativity annotated data precludes such experiments for the Amazon datasets. We remove any sentences which the evaluative model classifies as non-evaluative, and train and test the document-level sentiment models on the evaluative data (Eval).

Table 3 shows that all models perform worse when removing non-evaluative sentences (0.7 – 21.1 loss in accuracy) and this is in particular evident for ULMFiT where we observe a notable drop in performance.

5.2 Simulated low-resource settings

In this section we compare transfer and hierarchical models in a simulated low-resource setting, where there are only a few training examples. A priori, one might expect that transfer learning should perform better, given the use of additional unlabeled data.

We compute learning curves by training models (except HCNN due to runtime) on NoReC (same results on the other data) using between 64 to 30,000 labeled documents. Development and test data are kept the same. Figure 1 indicates that the models have the same relative ranking with as few as 64 training examples as they do with 30,000. This suggests that hierarchical models are preferable even in low-resource scenarios.

5.3 Effect of document length

Although most documents in the datasets are multi-sentence, they are not all of the same length. Therefore, we ask ourselves: do any of these models perform significantly better than other models on shorter/longer documents?

Figure 2 shows the accuracy of HAN and ULMFiT across the five languages on test documents, where the x-axis denotes sentence lengths (from 1 to 50), keeping those lengths that have more than 25 examples in order to avoid spurious results. It is clear that HAN performs much better than ULMFiT on longer documents (|d| > 25), with Pearson ranked correlation of 0.41 (p < 0.01).

6 Conclusion

We have compared hierarchical and transfer learning models for document-level sentiment classification for five different languages and have shown that hierarchical attention networks tend to outperform other approaches. The effect is particularly strong for longer documents. We also found that hierarchical models outperform transfer learning...
approaches even in low-resource scenarios, contrary to expectation.

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