A Systematic Comparison of Architectures for Document-Level Sentiment Classification

Jeremy Barnes, Vinit Ravishankar, Lilja Øvrelid, and Erik Velldal
University of Oslo
Department of Informatics
{jeremycb,vinitr,liljao,erikve}@ifi.uio.no

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 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 flat, hierarchical, and transfer learning models for document-level sentiment classification in five languages. We show that the choice of model depends on data attributes and that hierarchical models perform similar to transfer learning, even in low-resource settings.

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.

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...
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) over both sentence- and document-level GRU-based sequence encoders 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, to the best of our knowledge, 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 1 shows the statistics for each dataset.

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

Table 1: Statistics (\( |D| \) = number of documents, \( |L| \) = number of labels, T. = average number of tokens per document, S. = average number of sentences per document, T./S. = average sentence length in tokens, \( |V| \) = 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 flat, hierarchical, and LM-pretrained models, and do any of these approaches offer consistent improvements? Further, we investigate how performance is affected by several relevant data characteristics. Besides testing on the original data, we also test on documents where the order of the sentences is shuffled (shuffled), to determine sensitivity to sentence order.

4.1 Models
We start by briefly summarizing the architectures. For all flat and hierarchical models, we use 200-dimensional randomly initialized embeddings that are updated during training, implemented in AllenNLP (Gardner et al., 2017). The flat and hierarchical models use randomly initialized word (sentence) embeddings that are updated during training. Unless stated otherwise, all models are trained for

\(^2\)https://s3.amazonaws.com/amazon-reviews-pds/readme.html
50 epochs with a patience of 5 with Adam, and the best model is chosen using accuracy on the dev set.

**BOW:** We train a linear SVM implemented in sklearn (Pedregosa et al., 2011) on bag-of-words vectors learned from the train set 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 with filter sizes \( F \in \{2, 3, 4, 5\} \), with 50 filters per size and max pooling before a fully connected layer with a hidden size of 50.

**AN:** We use bidirectional Gated Recurrent Units (Cho et al., 2014, GRU) with dot product attention as a document encoder and a hidden size of 50.

**Hierarchical CNN (HCNN):** The Hierarchical CNN uses filters \( F_{sent} \in \{2, 3, 4, 5\} \) and \( F_{doc} \in \{2, 3\} \), with 50 filters per size and max pooling before a fully connected layer to create sentence and document-level representations respectively. The output size for both layers is 50 dimensions.

**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, with dot product attention.

**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).

**Multilingual BERT (mBERT):** The multilingual BERT model is a transformer model (Vaswani et al., 2017) which has been pretrained on masked-language and next sentence prediction tasks (Devlin et al., 2019). We use the cased model which was trained on Wikipedia dumps from 104 languages. We use the [CLS] token for prediction and fine-tune the model for 20 epochs, and test the model with the best performance on the dev set.

### Table 2: Accuracy of flat (BOW, AN, CNN), hierarchical (HCNN, HAN), and transfer (ULMFIT, mBERT) models on document-level sentiment datasets († denotes statistically significant difference (\( p < 0.01 \)) when compared to the second best model. Bold numbers are the best model for each dataset, red numbers indicate poorer performance (in percentage points) when the sentence order is shuffled, while blue numbers indicate better results when shuffled.

|        | 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 |
| shuffled | 6.0 | 6.1 | 9.3 | 11.8| 8.2 | 8.3  |
| AN     | 71.9| 58.1| 63.9| 74.3| 62.1| 66.1 |
| shuffled | 0.1 | 0.1 | 0.0 | 0.0 | 0.6 | 0.5  |
| HCN    | 68.3| 55.7| 61.9| 71.2| 61.0| 63.6 |
| shuffled | 0.3 | 0.1 | 0.2 | 0.1 | 0.2 | 0.0  |
| HAN    | 72.1| 61.4 | 63.2| 73.2| 61.9| 66.4 |
| shuffled | 0.6 | 1.9 | 0.4 | 0.0 | 0.3 | 0.7  |
| ULMFiT | 69.4| 55.7| 60.8| 69.3| 63.7| 63.8 |
| shuffled | 0.1 | 15.8| 0.3 | 0.0 | 0.4 | 3.3  |
| mBERT  | 73.4| 54.4| 65.6 | 74.6 | 56.3 | 64.9 |
| shuffled | 0.7 | 8.0 | 0.5 | 0.8 | 0.4 | 2.0  |

### 4.2 Results

Table 2 shows the accuracy (\( F_1 \) results are similar) of the seven models for all five languages and their average, as well as statistical significance\(^3\). The BOW model performs well across all experiments, achieving an average 64.2 accuracy, and ties HAN 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 \( \text{pp} \)). AN has the second best overall performance (66.4).

Regarding the hierarchical models, the HCNN performs on par with the flat CNN (avg. 63.6), while the HAN model is the best on Norwegian (61.4) 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.

\(^3\)We calculate statistical significance with approximate randomization testing (Yeh, 2000) with 10000 runs.
ULMFiT performs better than BOW on Norwegian and Japanese (0.1 / 3.1 pp), but 0.4 pp worse overall. MBERT is the best model on English, French, and German (73.4, 65.6, 74.6 respectively), but performs poorly on Norwegian (54.4) and Japanese (56.3).

Shuffling the test data hurt 22 of 30 experiments and had the highest impact on the Norwegian and Japanese data – an average drop of 5.6 pp – both of which have the longest documents. The CNN seems most sensitive to sentence order, losing 8.3 pp overall, followed by ULMFiT 3.3 and MBERT 2.0. Surprisingly, the hierarchical models are more robust to changes in sentence order.

5 Analysis

In this section we analyze what effects the number of training examples and document length has on the classifiers.

5.1 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 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 nearly same relative ranking with as few as 64 training examples as they do with 30,000, with the exception of MBERT. Surprisingly, even for low data scenarios, hierarchical modeling is as beneficial as transfer learning.

5.2 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 MBERT across the five languages on test documents, where the x-axis denotes document lengths (from 1 to 50), keeping those lengths that have more than 25 examples in order to avoid spurious results. Although MBERT performs better on short documents, HAN performs much better than MBERT on longer documents ($|d| > 10$), with Pearson ranked correlation of 0.41 ($p < 0.01$). This trend also holds when comparing HAN and AN. Hierarchical modeling, therefore, increases robustness to document length.

6 Conclusion

We have compared flat, hierarchical, and transfer learning models for document-level sentiment classification for five different languages and have shown that the best model depends on characteristics of your data. We also found that hierarchical models perform similar to transfer learning approaches even in low-resource scenarios, contrary to expectation.

Acknowledgements

This work has been carried out as part of the SANT project (Sentiment Analysis for Norwegian Text), funded by the Research Council of Norway (grant number 270908).

References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In Proceedings of the Third International Conference on Learning Representations (ICLR).

Ming-Wei Chang, Kristina Toutanova, Kenton Lee, and Jacob Devlin. 2019. Language model pre-training for hierarchical document representations. CoRR, abs/1901.09128.
Figure 2: HAN outperforms mBERT across different document lengths as determined by number of sentences per document. The scatter plot shows the accuracy on individual sentence counts (each color represents a dataset, and the markers represent the two models) while the bar plots show the mean accuracy of HAN and mBERT respectively on 5 sentence-length bins.

Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder–decoder for statistical machine translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, Doha, Qatar.

Alexis Conneau, Holger Schwenk, Loïc Barrault, and Yann Lecun. 2017. Very deep convolutional networks for text classification. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics, pages 1107–1116, Valencia, Spain.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson F. Liu, Matthew Peters, Michael Schmitz, and Luke S. Zettlemoyer. 2017. AllenNLP: A deep semantic natural language processing platform.

Barbara J. Grosz and Candace L. Sidner. 1986. Attention, intentions, and the structure of discourse. Computational Linguistics, 12(3):175–204.

Jeremy Howard and Sebastian Ruder. 2018. Universal language model fine-tuning for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 328–339, Melbourne, Australia. Association for Computational Linguistics.

Jeremy Howard et al. 2018. fastai. https://github.com/fastai/fastai.

Julia Ive, George Gkotsis, Rina Dutta, Robert Stewart, and Sumithra Velupillai. 2018. Hierarchical neural model with attention mechanisms for the classification of social media text related to mental health. In Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic, pages 69–77, New Orleans, LA. Association for Computational Linguistics.

Yoon Kim. 2014. Convolutional Neural Networks for Sentence Classification. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, pages 1746–1751, Doha, Qatar.

William C. Mann and Sandra A. Thompson. 2009. Rhetorical structure theory: Toward a functional theory of text organization. Text - Interdisciplinary Journal for the Study of Discourse, 8(3):243–281.

Stephen Merity, Nitish Shirish Keskar, and Richard Socher. 2018. Regularizing and optimizing LSTM language models. In International Conference on Learning Representations.

Bo Pang and Lillian Lee. 2004. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics (ACL-04), pages 271–278, Barcelona, Spain.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.
Milan Straka and Jana Straková. 2017. Tokenizing, POS tagging, lemmatizing and parsing UD 2.0 with UDPipe. In Proceedings of the CoNLL 2017 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies, Vancouver, Canada.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, Advances in Neural Information Processing Systems 30, pages 5998–6008. Curran Associates, Inc.

Erik Velldal, Lilja Øvrelid, Cathrine Stadsnes Eivind Alexander Bergem, Samia Touileb, and Fredrik Jørgensen. 2018. NoReC: The Norwegian Review Corpus. In Proceedings of the 11th edition of the Language Resources and Evaluation Conference, pages 4186–4191, Miyazaki, Japan.

Alex Wang, Jan Hula, Patrick Xia, Raghavendra Pappagari, R. Thomas McCoy, Roma Patel, Najoung Kim, Ian Tenney, Yinghui Huang, Katherine Yu, Shuning Jin, Berlin Chen, Benjamin Van Durme, Edouard Grave, Ellie Pavlick, and Samuel R. Bowman. 2019. Can you tell me how to get past sesame street? sentence-level pretraining beyond language modeling. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4465–4476, Florence, Italy. Association for Computational Linguistics.

Yijun Xiao and Kyunghyun Cho. 2016. Efficient character-level document classification by combining convolution and recurrent layers. CoRR, abs/1602.00367.

Bishan Yang and Claire Cardie. 2014. Context-aware learning for sentence-level sentiment analysis with posterior regularization. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 325–335, Baltimore, Maryland. Association for Computational Linguistics.

Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. 2016. Hierarchical attention networks for document classification. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1480–1489, San Diego, California. Association for Computational Linguistics.

Alexander Yeh. 2000. More accurate tests for the statistical significance of result differences. In COLING 2000 Volume 2: The 18th International Conference on Computational Linguistics.