Annotating Norwegian Language Varieties on Twitter for Part-of-Speech
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Abstract
Norwegian Twitter data poses an interesting challenge for Natural Language Processing (NLP) tasks. These texts are difficult for models trained on standardized text in one of the two Norwegian written forms (Bokmål and Nynorsk), as they contain both the typical variation of social media text, as well as a large amount of dialectal variety. In this paper we present a novel Norwegian Twitter dataset annotated with POS-tags. We show that models trained on Universal Dependency (UD) data perform worse when evaluated against this dataset, and that models trained on Bokmål generally perform better than those trained on Nynorsk. We also see that performance on dialectal tweets is comparable to the written standards for some models. Finally we perform a detailed analysis of the errors that models commonly make on this data.

1 Introduction
Norwegian Twitter data poses an interesting challenge for Natural Language Processing (NLP) tasks. Not only do these data represent a set of noisy, user-generated texts with the kinds of orthographic variation common on social media, but also because there is a considerable number of tweets written in dialectal Norwegian. These dialectal variants are quite common and add another level of difficulty for NLP models trained on clean data in one of the two Norwegian written forms (Bokmål or Nynorsk).

Barnes et al. (2021) compiled a dataset of tweets classified according to whether they are written in primarily Bokmål, Nynorsk, or a dialect of Norwegian. We build upon this work by annotating a subset for Part-of-Speech (POS). We investigate to what extent available Norwegian POS tagging models, that were trained on Bokmål and Nynorsk Universal Dependency data (Nivre et al., 2020), perform on this Twitter dataset.

To this end, we use five POS models: three off-the-shelf models, and two developed for the purpose of this work. Each of these models was trained on either a dataset of Bokmål or Nynorsk texts. We explore the performance of each model in terms of accuracy, and investigate which standardized written form can be used as training data and yield good results for non-standardized dialectal texts.

The main contributions of this work are:
- we annotate a moderately sized Twitter dataset with POS labels and include metadata related to which language variety it belongs (Bokmål, Nynorsk, Dialect, or Mixed),
- we perform a detailed error analysis of common model errors specific to our Twitter data,
- we include our insights into the annotation process for POS tagging of non-standardized written forms,
- we release two spaCy models built on top of a Norwegian BERT model.

2 Background
Johannessen (1990) outlined a system for automatic morphosyntactic analysis of Norwegian nouns in the framework of Koskenniemi (1983). This was among the first systems, if not even the very first, that automatically assigned Norwegian texts any morphological information. The first widely used tagger, however, was developed within the Taggerprosjekt¹ and came to be known as the Oslo-Bergen Tagger² (OBT). Rather than continuing and expanding the system of Johannessen (1990), OBT was implemented in the framework of Karlsson (1990). OBT was initially a rule-based Constraint Grammar tagger for Norwegian Bokmål.

¹The project ran from April 1996 to December 1998.
²https://github.com/noklesta/The-Oslo-Bergen-Tagger
Later, both support for Norwegian Nynorsk and a statistical disambiguation component were added (Johannessen et al., 2012). But one drawback of OBT is that it is made for written, edited text, and therefore might not scale well to sources that are not standardised.

Extending tagger coverage to spoken Norwegian dialect transcription, on the other hand, was the objective of both Nøklestad and Søfteland (2007) and Kåsen et al. (2019). Both sampled data either from the Norwegian part of the Nordic Dialect Corpus (NDC, Johannessen et al. (2009)) or the Language Infrastructure made Accessible (LIA) Corpus. Annotations are found in the respective treebanks of the corpora and are accounted for in Øvrelid et al. (2018) and Kåsen et al. (2022).

Besides Norwegian, there is a large amount of work on the difficulty of processing noisy data from social media (Xu et al., 2015), including the difficulty of POS tagging on social media (Albogamy and Ramasy, 2015), with dialectal variation (Jørgensen et al., 2015), or whether lexical normalisation is helpful (van der Goot et al., 2017). However, Norwegian currently lacks any of these studies.

3 Data

Resources for evaluating NLP pipeline tasks for Norwegian are scarce. The only dataset available for standard NLP tasks such as POS tagging, lemmatization, and parsing is the Norwegian Dependency Treebank (NDT, Solberg (2013), Solberg et al. (2014)) that has been converted to the Universal Dependencies standard (Øvrelid and Hohle, 2016). There is, however, a notable exception when it comes to transcribed spoken dialectal data, where the LIA and NDC treebanks as mentioned above are available with annotations for POS tags, morphological features, lemmas, and dependency-style syntax. Despite this, the transcribed texts in the LIA and NDC corpora do not share the same characteristics as the Twitter data. Twitter contains spelling errors and emoji, along with mentions and hashtags. We observe that although our Twitter data contains some characteristics of spoken Norwegian, such as subjectless sentences as in 1, which is otherwise within the spelling norms, the spelling conventions differ from those of LIA and NDC, making it difficult to directly compare the data.

(1) Kommer nok hjem snart.
Comes probably home soon.
‘(Unspecified) probably comes home soon.’

In LIA and NDC, all transcriptions are done according to a Norwegian-based semi-phonetic standard (Hagen et al., 2015), with strict marking of vowel quantity, palatalization, retroflexion, and more. We see that writers on Twitter do not conform to any specific spelling norm when writing in their own or another dialect. This means that although not all dialectal traits from a dialect are faithfully preserved, this still leads to much dialectal variation in the Twitter data, as things that could have had a common spelling is spelled according to the author’s own preference. Especially phonetic differences are often not indicated on Twitter. Because of this, we needed a separate dataset that could be used to evaluate how various systems for Norwegian POS-tagging work on dialectal text as it is found on real data from social media platforms.

We sampled a balanced subset of the dataset introduced by Barnes et al. (2021), who developed to develop a dialect classifier for Norwegian tweets, with the aim to be able to further investigate issues related to dealing with dialectal data on Twitter. This subset includes a selection of 38 tweets in Bokmål, 31 tweets in Nynorsk, and 35 in dialects, which comprises their full test set. We acknowledge that the size of the dataset is small. The POS-tagged dataset is subject to restrictions due to it containing personal information, but is available upon request.

3.1 Norwegian Dialects

Norwegian is considered to have four main dialect groups based on four different traits. This has been a controversial matter and the four-way divide essentially follows Christiansen (1954). There are also recent proponents of a two-way divide (Skjekkeland, 1997). The four-way distinctions have a Northern, Middle, Western, and Eastern group, whereas the two-way divide only operates with a Western and Eastern group. But these distinctions are made with traits from the spoken language. And, as Mæhlum and Røyneland (2012, p. 29) point out, there is a discrepancy between how dialectologists and lay people classify dialects. What sort of dialectal traits Twitter users choose to

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3https://tekstlab.uio.no/LIA/korpus.html
4Emoji has recently gained some interest in the linguistic literature (see https://ling.auf.net/lingbuzz/005981)
include may therefore lead to a different kind of di-
vide than one can find in the dialectology literature.
That being said, Venås (1990) shows that there has
been a long tradition of writing in dialect, where
the oldest text in Venås (1990) dates back to 1525.

3.2 POS Annotations
The texts from the test set were annotated using the
Universal Dependencies POS tagset. The tweets
were tokenized with NLTK’s tokenizer (Bird et al.,
2009) and split into sentences manually. The NLTK
tokenizer was chosen over other tokenizers as our
preliminary testing on our Twitter dataset shows
that it performs better on noisy Norwegian data.
The tokenized data was then pre-annotated with
Stanza’s Bokmål tokenizer to alleviate the annota-
tion task. The remaining task was to correct each
POS-tag for these pre-annotated sentences. One
annotator annotated the whole test set, while two
other annotators annotated two separate subsets
of the dataset to give an indication of how robust
the annotations were. All three annotators were
trained in linguistics and language technology, and
are native Norwegian speakers. An overview of
the distribution of each POS-tag for each written
form is reported in table 1. We see that the percent-
wise distribution of POS-tags is similar in Bok-
mål, Nynorsk and All, but that the PRON tag is
somewhat more frequent than the VERB tag in the
Dialect tweets. This could be due to the fact that
some dialectal tweets only appear as dialectal due
to specific dialectal pronouns.

3.3 Inter-Annotator Agreement
The inter-annotator score for the full doubly-
annotated test set, using Cohen’s $\kappa$, was 0.87, in-
dicating quite high agreement. Looking at the spe-
cific categories, we see that the agreement was 0.92
for Bokmål, 0.83 for Nynorsk, and 0.88 for dialec-
tal tweets. No specific error patterns are observed
that would account for the difference in scores, but
all annotators have more familiarity with the Bok-
mål variant. One common point of disagreement
across all is the copula verb å være ‘to be’, which
according to the UD guidelines should be tagged
as AUX. This was commonly tagged as VERB by
one of the annotators. There is also some disagree-
ment when it comes to words such as opp ‘up’, and
ned ‘down’, which can be tagged both as adverbs
(ADV), adpositions (ADP), and verbal particles.
Since there is no tag for verbal particles in UD,
the annotators had to choose between the other two.
Cases of disagreement were solved by discussing
tags where one or more annotators disagreed.
4 Experiments

We test several models trained on available Norwegian UD datasets on our Twitter data. Specifically, we compare OBT, Stanza, UDPipe 2.0, a simple BiLSTM model, as well as training our own spaCy models.

Both Stanza (Qi et al., 2020) and UDPipe 2.0 (Straka, 2018) use a BiLSTM which takes features from 1) pre-trained word embeddings, 2) a trainable frequent word embedding that is randomly initialized before training, and 3) character-level LSTM features. While UDPipe only uses a softmax layer for classification, Stanza instead uses a biaffine classifier to ensure consistency between the UPOS and XPOS predictions.

The BiLSTM model we use is a simplified version of the models used in UDPipe and Stanza. The model does not take any pre-trained word embeddings as features, but rather uses the vocabulary of the dataset it is trained on to create the embeddings. The model uses a linear layer for classification.

The spaCy models are newly trained during the present work, and will be released publicly in the near future. Since spaCy is a fully configurable and trainable pipeline, we used the Norwegian BERT model described in (Kummervold et al., 2021) with a shared embedding layer for a tagger, morphologizer, and trainable lemmatizer in an effort to optimize the tagger task.

5 Results and Discussion

Table 2 gives an overview of the accuracy on the Twitter test set using our five models trained on either Bokmål or Nynorsk data. Note that due to their small number, we do not include the mixed category by itself, but these tweets are included in the ALL column. On our twitter Bokmål test set, the best model is the UDPipe Bokmål model, which achieves 89.6 accuracy. Generally, the models trained on the UD Bokmål data are consistently better than the Nynorsk versions on this data (an average of 26.5 percentage points (pp)). Interestingly, the same is not true for the Twitter Nynorsk data. One may assume that models trained on the Nynorsk UD data would always perform better, but in fact, the best performing model is the spaCy model trained on Bokmål (85.7 acc) and on average, the models trained on UD Bokmål perform 4.9 pp worse.

Finally, on the dialectal Twitter data, the spaCy Bokmål model once again performs best (83.3). Again training on the Bokmål data generally performs 12.8 pp better than training on Nynorsk data. This may be due to the subset of dialectal tweets, as a manual inspection showed a large number of tweets from Central and Northern dialects, which share more features with Bokmål. A larger number of tweets from Western and Southern dialects could potentially change this. At the same time, however, it seems clear that the spaCy Bokmål model performs quite well on all the Twitter test data (85.8 acc), so it may simply be a stronger model.

5.1 Error Analysis

We note that the models struggle with features that are typical of the noisy Twitter data containing several misspellings. One concrete example is å, which in normative writing most likely refers to the identically spelled infinitive marker å ‘to’. However, as dialectal writing is much more relaxed, alternative spellings create new homographs that need to be dealt with. We see that some cases of ‘â’ refer to the conjunction og ‘and’, which in many dialects is homophonous with å. We also note that many of the errors come from erroneously tagging pronouns as other word classes, such as INTJ, PART, or NOUN. One reason why there are many errors of this type might simply be because these are frequent indicators of dialect. Barnes et al. (2021) show that certain pronouns such as æ and mæ (both ‘I’) are highly correlated with dialectal tweets. They are in some cases the only dialectal indicator in a tweet. Finally, we observe that there are problems with annotating enclitic elements and words that should have been written separately, or conversely, with compound words that have been split. The two latter problems are not exclusive to dialects, but are common in informal writing. Enclitic elements, such as the enclitic negation (‘kke, ’kje, ’che, etc.) and enclitic pronouns such as ‘n ‘he, him’ and ’a ‘she, her’ are sometimes added after words, and sometimes without any punctuation, and there are no tokenizers that the authors are aware of that can correctly separate out these enclitic elements. For example, a spelling like ekkje, ‘is not’, which is the copula e with the enclitic negation adverb kke ‘not’ written as one word, has this issue. The same happens with other words that according to the norm should be written as two words, such as i dag ‘today’, being written as idag. This leads to tokens with multiple possible POS-tags. In these cases the annotators would consider what
Table 2: Accuracy on our Twitter test set using five different models trained on either Bokmål or Nynorsk datasets.

| Model                   | Bokmål | Nynorsk | Dialect | All |
|-------------------------|--------|---------|---------|-----|
| OBT Bokmål              | 77.8   | -       | 62.3    | -   |
| OBT Nynorsk             | -      | 73.1    | 57.3    | -   |
| BiLSTM_UD Bokmål        | 80.5   | 63.8    | 63.4    | 70.2|
| BiLSTM_UD Nynorsk       | 62.3   | 76.2    | 56.7    | 64.6|
| BiLSTM_UD Nynorsk_LIA  | 47.6   | 56.2    | 43.9    | 48.9|
| Stanza Bokmål           | 86.6   | 67.5    | 69.5    | 75.4|
| Stanza Nynorsk          | 45.8   | 82.8    | 52.0    | 58.1|
| UDPipe Bokmål           | 89.6   | 76.1    | 72.9    | 80.4|
| UDPipe Nynorsk          | 74.4   | 82.9    | 63.2    | 73.2|
| spaCy Bokmål            | 87.9   | 85.7    | 83.3    | 85.8|
| spaCy Nynorsk           | 62.5   | 83.2    | 65.0    | 69.6|

6 Conclusion

In this paper, we have introduced the first dataset of Norwegian tweets annotated for Part-of-Speech, that also include the metadata for the language variety of each tweet (Bokmål, Nynorsk, Dialect, or Mixed). We tested several POS taggers trained on UD data and show that, for our Twitter data, it is generally better to train on the UD Bokmål data, even if testing on Nynorsk or Dialect. Our detailed error analysis showed that the models generally have problems with dialectal pronouns and unfamiliar compounds. Finally, we release the newly trained spaCy models, and make our annotated data available on request, in order to enable the reproduction of our results.

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References

Fahad Albogamy and Allan Ramasy. 2015. Towards POS tagging for Arabic tweets. In Proceedings of the Workshop on Noisy User-generated Text, pages 167–171, Beijing, China. Association for Computational Linguistics.

Jeremy Barnes, Petter Mæhlum, and Samia Touileb. 2021. NorDial: A preliminary corpus of written Norwegian dialect use. In Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa), pages 445–451, Reykjavik, Iceland (Online). Linköping University Electronic Press, Sweden.

Steven Bird, Ewan Klein, and Edward Loper. 2009. Natural language processing with Python: analyzing text with the natural language toolkit. "O'Reilly Media, Inc.".

Hallfrid Christiansen. 1954. Hovedinndelingen av norske dialektér, volume 1954. Bymålslaget Oslo.

Kristin Hagen, Live Håberg, Eirik Olsen, and Ashild Søfteland. 2015. Transkripsjonsretningslinje for LIA. Technical report, Technical report.

Janne B. Johannessen. 1990. Automatisk morfologisk analyse og syntese. Novus forlag, Oslo.

Janne B. Johannessen, Kristin Hagen, André Lynum, and Anders Nøklestad. 2012. Exploring Newspaper Language: Using the web to create and investigate a large corpus of modern Norwegian. Studies in Corpus Linguistics, 49:51.

Janne B. Johannessen, Joel Priestley, Kristin Hagen, Tor Anders Åfarli, and Øystein Alexander Vangsnes. 2009. The Nordic Dialect Corpus—an advanced research tool. In Proceedings of the 17th norder conference of computational linguistics (nodalida 2009), pages 73–80.

Anna Jørgensen, Dirk Hovy, and Anders Søgaard. 2015. Challenges of studying and processing dialects in social media. In Proceedings of the Workshop on Noisy
User-generated Text, pages 9–18, Beijing, China. Association for Computational Linguistics.

Fred Karlsson. 1990. Constraint grammar as a framework for parsing running text. In COLING 1990 Volume 3: Papers presented to the 13th International Conference on Computational Linguistics.

Andre Kåsen, Kristin Hagen, Anders Nøklestad, and Joel Priestley. 2019. Tagging a Norwegian dialect corpus. In Linköping Electronic Conference Proceedings, pages 350–355. Linköping University Electronic Press.

Andre Kåsen, Kristin Hagen, Anders Nøklestad, Joel Priestly, Per Erik Solberg, and Dag Tryge Truslew Haug. 2022. The Norwegian Dialect Corpus Treebank. In Proceedings of the Language Resources and Evaluation Conference, pages 4827–4832, Marseille, France. European Language Resources Association.

Kimmo Koskenniemi. 1983. Two-level morphology: A general computational model for word-form recognition and production, volume 11. University of Helsinki, Department of General Linguistics Helsinki, Finland.

Per E Kummervold, Javier De la Rosa, Freddy Wetjen, and Svein Arne Brygjefjeld. 2021. Operationalizing a National Digital Library: The Case for a Norwegian Transformer Model. In Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa), pages 20–29.

Brit Mehlum and Unn Røyneland. 2012. Det norske dialektlandskapet: innføring i studiet av dialektar. Cappelen Damm akademisk.

Joakim Nivre, Marie-Catherine de Marneffe, Filip Ginter, Jan Hajič, Christopher D. Manning, Sampo Pyysalo, Sebastian Schuster, Francis Tyers, and Daniel Zeman. 2020. Universal Dependencies v2: An evergrowing multilingual treebank collection. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 4034–4043, Marseille, France. European Language Resources Association.

Anders Nøklestad and Åshild Softedland. 2007. Tagging a Norwegian speech corpus. In Proceedings of the 16th Nordic Conference of Computational Linguistics (NODALIDA 2007), pages 245–248.

Lilja Øvrelid and Petter Hohle. 2016. Universal dependencies for Norwegian. In Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), pages 1579–1585.

Lilja Øvrelid, Andre Kåsen, Kristin Hagen, Anders Nøklestad, Per Erik Solberg, and Janne B. Johannessen. 2018. The LIA treebank of spoken Norwegian dialects. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018).

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A python natural language processing toolkit for many human languages. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 101–108, Online. Association for Computational Linguistics.

Martin Skjekkeland. 1997. Dei norske dialektane: tradisjonelle særdrag i jamføring med skriftmåla. Høyskoleforl.

Per Erik Solberg. 2013. Building gold-standard treebanks for Norwegian. In Proceedings of the 19th Nordic Conference of Computational Linguistics (NODALIDA 2013), pages 459–464.

Per Erik Solberg, Arne Skjerholt, Lilja Øvrelid, Kristin Hagen, and Janne Bondi Johannessen. 2014. The Norwegian dependency treebank. In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), pages 789–795, Reykjavik, Iceland. European Language Resources Association (ELRA).

Milan Straka. 2018. UDPipe 2.0 prototype at CoNLL 2018 UD shared task. In Proceedings of the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies, pages 197–207, Brussels, Belgium. Association for Computational Linguistics.

Rob van der Goot, Barbara Plank, and Malvina Nissim. 2017. To normalize, or not to normalize: The impact of normalization on part-of-speech tagging. In Proceedings of the 3rd Workshop on Noisy User-generated Text, pages 31–39, Copenhagen, Denmark. Association for Computational Linguistics.

Kjell Venås. 1990. Den fyrste morgonblånen: tekster på norsk frå dansketida. Novus forlag.

Wei Xu, Bo Han, and Alan Ritter, editors. 2015. Proceedings of the Workshop on Noisy User-generated Text. Association for Computational Linguistics, Beijing, China.