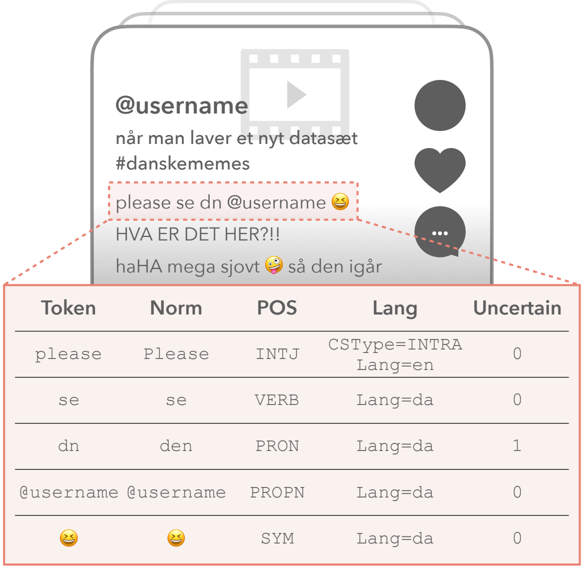
DanTok: Domain Beats Language for Danish Social Media POS Tagging

Kia Kirstein Hansen, Maria Barrett, Max Müller-Eberstein, Cathrine Damgaard,
Trine Naja Eriksen, Rob van der Goot
IT University of Copenhagen
`[kiah, mbarrett, mamy, catd, trer, robv]@itu.dk`

Abstract

Language from social media remains challenging to process automatically, especially for non-English languages. In this work, we introduce the first linguistically annotated dataset for TikTok comments and the first Danish social media dataset with part-of-speech annotation. Additionally, we supply annotations for normalization, code-switching, and annotator uncertainty. As transferring models to such a highly specialized domain is non-trivial, we conduct an extensive study into which source data and modeling decisions most impact the performance. Surprisingly, transferring from in-domain data, even from a different language, outperforms in-language, out-of-domain training. These benefits nonetheless rely on the underlying language models having been at least partially pre-trained on data from the target language. Using our additional annotation layers, we analyze how normalization, code-switching, and human uncertainty affect the tagging accuracy.



@username
når man laver et nyt datasæt
#danskememes

please se dn @username 😆
HVA ER DET HER?!!
haHA mega sjovt 🤪 så den igår

Token	Norm	POS	Lang	Uncertain

please	Please	INTJ	CSType=INTRA
			Lang=en
				0

se	se	VERB	Lang=da	0
dn	den	PRON	Lang=da	1
@username	@username	PROPN	Lang=da	0
😆	😆	SYM	Lang=da	0

Figure 1: DanTok annotation layers for a fabricated example comment.

1 Introduction

Language data from social media offer unique insights into how communities use language to communicate in a natural, spontaneous setting, using a highly domain-specific vocabulary. This domain is, however, also subject to frequent changes, high noise, and variability, making it difficult to process (Eisenstein, 2013) both for high (Gimpel et al., 2011; Derczynski et al., 2013) and especially for lower-resourced languages (Kaji and Kitsuregawa, 2014; Albogamy and Ramasy, 2015; Singh et al., 2018; Mæhlum et al., 2022). To better understand and improve how to target such a highly specialized domain, we present the first linguistically annotated dataset of contemporary Danish social media from TikTok, a relatively new platform focused on short videos. The Danish Dependency Treebank (Kromann et al., 2003) from the PAROLE Corpus (Bilgram and Keson, 1998), and its Universal Dependencies (UD) conversion (Johannsen et al., 2015) is the primary part-of-speech (POS) resource for Danish (Kirkedal et al., 2019). However, it contains well-edited text only.

We present not only the first Danish social media dataset with POS annotation, but, to the best of our knowledge, also the first linguistic exploration of TikTok language in any language. The dataset contains annotation for POS, normalization, code-switching and annotator uncertainty (Figure 1). It further prioritizes quality over quantity, covering over 8k tokens, which have been manually verified to ensure relevance, correctness, and privacy.

It has been shown that training language models on the target domain can be used for cross-domain

Code available at: github.com/kkirsteinhansen/dantok. Data is available upon request (contact `robv@itu.dk`).

learning (Gururangan et al., 2020; Barbieri et al., 2022). In this work, we aim to tease apart the effect of the pre-training data of the language model and the source of the annotated training data for the target task. For this purpose, we contribute: ① DanTok, the first linguistically annotated dataset of TikTok comments and the first Danish POS-annotated social media dataset; ② An extensive study of transfer learning targeting this highly specialized domain; ③ An in-depth analysis investigating the unique features of this new domain, and how specific data/model properties help boost transfer performance.

2 DanTok

2.1 Collection

The social media platform TikTok shows a continuous, personalized feed of short videos on various topics. Users may respond to these videos using likes and/or comments. In 2022, the number of Danish users of age ≥ 18 was estimated to be 1.14M. This is substantial compared to the total population in Denmark (5.8M), as well as, e.g., the number of Danish Twitter users (est. 685k).[1] It is challenging to gather data from TikTok in a reproducible way due to algorithmically populated user feeds as well as the inability to filter videos by language. To increase reproducibility, we browsed videos directly by hashtag while logged out. We selected 15 Danish hashtags (Appendix B.1) where videos were determined to be predominantly in Danish.

Filtering and Deduplication We applied automatic filtering to maximize data diversity relative to the dataset size while reducing annotation workload. Using the Aspell dictionary for Danish (Aspell, 2019), we removed non-Danish comments while retaining interesting token variations using a removal threshold of $< 10\%$ or $> 60\%$ OOV (out-of-vocabulary) tokens per comment. As comments often have a high degree of repetitiveness (e.g., "wow", "woow!!"), we deduplicated them by iteratively merging the two most similar comments, keeping only one, until there were no more pairs with a similarity greater than a threshold t. Similarity was measured using the normalized Levenshtein distance, and we retained the comment with a higher total similarity to all other comments (i.e., the more prototypical one). To determine the best threshold, we conducted a sweep over $t \in (0.0; 1.0)$ in 0.05 increments (see also Appendix B.2), and chose $t = 0.60$, as this set retained a relatively high diversity while accounting for the downstream, manual filtering of irrelevant comments down to our target of annotating 8k tokens.

2.2 Annotation

The data was tokenized using the `NLTK TweetTokenizer` (Bird et al., 2009) with manual post-correction. We replaced usernames with *@username*, and manually filtered out comments containing personal information. After two rounds of annotation[2], we reached a Fleiss' κ score of 96.05. As the remaining disagreements were mainly ambiguities and accidental mistakes, we annotated the remainder of the dataset once, with the following layers:

POS We followed the UD 2.11 guidelines and the social media-specific suggestions by Sanguinetti et al. (2020). Where possible, we annotated the intended meaning of a token given its use in context, e.g., in "Would you like a 🍺?", 🍺 is a `NOUN`. Tokens that imitate pronunciation were tagged as `INTJ`. *Den*, *det* and *de*, which may function as articles or pronouns, were tagged as `DET` only when followed by an adjective.

Normalization Given that we annotated the intended meaning of a token, we additionally decided to annotate for lexical normalization. We followed the format and guidelines of MultiLexNorm (van der Goot et al., 2021a): URLs and interjections were not normalized, and splits and merges were included in the annotations. Merging of tokens that had erroneously been written as multiple words is indicated in the normalization column of the last word, as compound words in Danish adopt the part-of-speech (POS) of the final word. For tokens that were split, an overall POS tag was given to this token alongside individual tags for the tokens resulting from the splitting.

Code-Switching Code-switching is indicated with language and type. The type is either `INTER` (full sentence), `INTRA` (individual tokens) or `MIXED` (a lemma from one language with inflection from another language) as described by

[1] https://datareportal.com/reports/digital-2022-denmark

[2] See Appendix A for information about the annotators.

	Langs	Train-sources	Type	Train-size	Architecture	Params	%Unk.	Subw. ratio	Reference
LLM									
DANISH-BERT-botxo	DA	web, wiki, subtitles	-D+L	10gb	Bert-base	111M	0.15	1.28	github.com/certainlyio/nordic_bert
RØBÆRTA-base-danish	DA	web		?	Roberta-base	125M	0.00	1.58	hf.co/DDSC/roberta-base-danish
ÆLÆCTRA-danish-small-cased	DA	legal, social, web, wiki, news		1,045M words	Electra-small	14M	0.04	1.39	github.com/MalteHB/-l-ctra
BERTWEET-Base	EN	social	+D-L	850M tweets	Roberta-base	135M	0.10	1.65	Nguyen et al. (2020)
BERTWEET-Large	EN	social		850M tweets	Roberta-large	355M	0.00	1.90	Nguyen et al. (2020)
TWITTER-ROBerta-base	EN	social		58M tweets	Roberta-base	125M	0.00	1.90	Barbieri et al. (2020)
TWITTER-XLM-roberta-base	30+	social	+D-L	198M tweets	XLM-r base	278M	0.01	1.45	Barbieri et al. (2022)
BERNICE	66	social		2.5B tweets	Roberta-base	278M	0.00	1.44	DeLucia et al. (2022)
TWHIN-bert-large	100+	social		7.5B tweets	new	561M	0.01	1.45	Zhang et al. (2022)
TREEBANK									
LINES	EN	fiction, nonfiction, spoken	-D-L	57,372 words					Ahrenberg (2015)
TWEEBANK2	EN	social	+D-L	24,753 words					Liu et al. (2018)
DDT	DA	fiction, nonfiction, spoken, news	-D+L	80,378 words					Johannsen et al. (2015)

Table 1: An overview of the used language models and POS fine-tuning sets. %Unk. is the percentage of unknown subwords in our development data; Subw. ratio is the average amount of subwords per word. Capitalized name parts are handles.

	COMMENTS	TOKENS	TYPES	TTR
Dev	429	4,000	1,520	0.38
Test	430	4,028	1,519	0.38
Total	859	8,028	2,512	0.31

Table 2: DanTok dataset statistics. TTR is type-token ratio.

Sanguinetti et al. (2020). We used the Danish dictionary[3] for cross-referencing, as many originally English words are now considered Danish.

Certainty Following Bassignana and Plank (2022), the annotator's certainty of a POS tag was annotated as either 0 (certain) or 1 (uncertain).

2.3 DanTok Statistics

Our final dataset consists of 8,028 tokens and 2,512 unique types (Table 2). A comparative POS tag distribution is given in Appendix C. In DanTok, we observe that 16.66% of the tokens required normalization, 5.03% were code-switched (all to English), and 5.12% had annotation uncertainty. Overall, these annotation layers allow us to investigate how Danish is used on contemporary internet platforms with respect to syntax, and how sociolinguistic factors such as code-switching can impact downstream performance.

3 Experiments

3.1 Setup

For a highly specialized dataset such as DanTok, transfer learning is key, as there is no training data matching the domain and language. We therefore investigated 36 combinations of in/out-of-domain (+D/-D)[4] and in/out-of-language (+L/-L)[5] training data and large language models (LLMs). We selected English as the -L transfer language due to dataset and language model availability. All experiments were replicated on the normalized version of DanTok. The Danish LLMs are trained on web data, including some forum data, but none are explicitly optimized for social media. The LLMs and training sets used in our experiments are given in Table 1. All the models consist of an LLM encoder plus a linear layer for POS labeling (both fully finetuned) and are implemented in MaChAmp v0.4 (van der Goot et al., 2021b) using default hyperparameters with the development data for model selection. To avoid overfitting on DanTok, we use the transfer data's development set for model selection (Artetxe et al., 2020).

3.2 Results

Our main results are given in Table 3. Unsurprisingly, the combination of in-domain, in-language (+D+L) training data and LLMs results in the best overall performance. In general, having in-language data is more beneficial than in-domain data; however, when training on a single dataset, the in-domain English dataset (+D-L) leads to surprisingly high performance with the multilingual language models, even outperforming all scores obtained with the Danish training data (-D+L). One reason for this could be the relatively high frequency of code-switched tokens (5%). Inter-

[3] https://dsn.dk/ordboeger/retskrivningsordbogen/

[4] +D: social media data, -D: data from other domains.

[5] +L: trained on Danish, -L: trained on other languages.

	Model \ Data	-D-L LinES	+D-L TwB	-D+L DDT	+D-L + -D+L TwB+DDT
-D-L	DANISH-BERT	44.02	49.60	77.98	84.08
	RØBÆRTA	58.43	60.82	70.17	78.72
	ÆLÆCTRA	49.50	63.30	74.20	84.95
+D-L	BERTWEET-B	27.80	38.00	67.90	79.47
	BERTWEET-L	25.92	36.55	67.40	81.50
	TWITTER-ROB	25.02	37.30	64.05	79.40
+D+L	TWITTER-XLM	67.58	77.15	72.15	83.28
	BERNICE	70.45	78.22	72.95	83.28
	TWHIN	69.30	81.38	72.65	**85.92**

Table 3: POS tagging accuracy on the DanTok development set using combinations of in/out-of-domain (+D/-D) and in/out-of-language (+L/-L) models and training data, plus a concatenation covering +D and +L.

	Model \ Data	-D-L LinES	+D-L TwB	-D+L DDT	+D-L + -D+L TwB+DDT
-D+L	DANISH-BERT	42.69	48.12	80.19	85.75
	RØBÆRTA	60.79	63.48	73.80	82.36
	ÆLÆCTRA	50.87	61.69	78.48	88.45
+D-L	BERTWEET-B	28.24	38.48	70.88	82.83
	BERTWEET-L	27.46	37.48	70.98	85.35
	TWITTER-ROB	25.75	38.13	68.76	84.19
+D+L	TWITTER-XLM	69.85	80.12	75.16	86.26
	BERNICE	72.01	80.27	75.61	85.15
	TWHIN	70.95	83.09	75.33	**88.80**

Table 4: POS tagging accuracy on the normalized DanTok development set using combinations of in/out-of-domain (+D/-D) and in/out-of-language (+L/-L) models and training data.

estingly, model size (see Table 1) is not a good predictor of performance: Although the largest model, TWHIN, obtains the highest score overall, it requires large amounts of pre-training data and a specialized pre-training objective based on rich social engagements (Zhang et al., 2022). Meanwhile, ÆLÆCTRA's performance is very close, despite being 41 times smaller. Given these results, we conclude that the best strategy for obtaining a high-quality tagger would be to use domain-specific models when available (even if multilingual) and use in-domain fine-tuning data even if in another language (+ in-language if available).

Table 4 shows that using normalized data gives a consistent boost of 2–5 % points across all setups, with only a few exceptions. Furthermore, performance varies less compared to the non-normalized data (Table 3).

LLM	-NORM	+NORM
TWHIN	86.05	88.18
ÆLÆCTRA	85.80	88.55

Table 5: Results on the DanTok test set of our two best models trained on TWEEBANK and DDT.

On Test Data TWHIN performs similarly on the development and test data. After normalization, the smaller ÆLÆCTRA model outperforms TWHIN slightly (Table 5).

4 Analysis

4.1 Subword Analysis

The Subword ratio (Table 1) does not show a clear correlation with performance, so we qualitatively evaluate the subword segmentation of the two best-performing models, TWHIN and ÆLÆCTRA. Surprisingly, we find that the multilingual model (TWHIN) seems more capable of interpreting inflection suffixes than the Danish model. It correctly splits morphemes indicating definiteness, plurality, or adverbial status, which the Danish model sometimes fails to do. Examples of this are *batterier* ("batteries") split into *batteri-er* ("batteri-es") and *dårligt* ("badly") split into *dårlig-t* ("bad-ly") only by the multilingual model, whereas the Danish model does not split these tokens at all.

4.2 Stratified Analysis

We explore the accuracy on different subsets of the development set according to our additional annotation layers (Table 6). We observe that the models, perhaps unsurprisingly, struggle more with tokens that were normalized, as well as tokens that annotators were also uncertain of. For code-switched tokens, we observe a large performance drop for the in-language LLM (ÆLÆCTRA) despite fine-tuning on English in-domain data. Surprisingly, the multilingual model, likewise fine-tuned on Danish and English in-domain data, also struggles with code-switched tokens.

4.3 Qualitative Error Analysis

The most frequent tag confusions for the best ÆLÆCTRA model are given in Figure 2. TWHIN follows a similar pattern. Over half of the errors made by each tagger on the original data are shared with the other tagger. Some of the errors

LLM	POS CERTAINTY			NORMALIZED			IN FINE-TUNE VOCAB			CODE-SWITCHED		
	n	-	+	n	-	+	n	-	+	n	-	+
TWHIN	203	62.1	87.2	3,338	88.9	70.8	1,234	83.3	87.1	3,808	86.3	78.1
ÆLÆCTRA		58.6	86.4		88.6	66.8		83.1	85.8		86.1	62.5

Table 6: Stratified accuracy on the 4,000-token dev set of the two best models trained on TWEEBANK and DDT. n is the number of tokens in the - category, e.g., 1,234 words were not seen during fine-tuning.

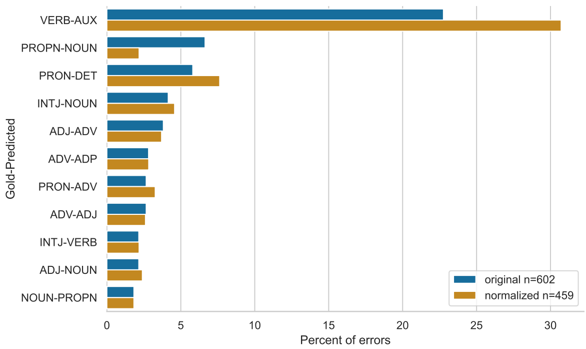


Figure 2: The 11 most frequent tag confusions for the ÆLÆCTRA model.

are caused by erroneous annotations in DanTok. The most frequent error types can be categorized as follows:

VERB vs. AUX In DanTok, the present tense of the copula verb *være* ("to be") has been labeled VERB when it is the only verb in the sentence. However, the models prefer the tag AUX in 91.6% and 85.0% of cases, respectively. This seems to be in line with the UPOS guidelines and is likely a result of the annotation of *er* in the DDT training set; here, 78.85% of *er* tokens have been tagged as AUX (the remaining being tagged as VERB).

Pronoun Confusions Tokens that may be multiple parts of speech confuse the taggers. The most frequent issue is PRON and DET confusion, which is arguably non-trivial in Danish[6]. PRON and ADV confusion is also prevalent; e.g., the token *der* can be either a relative PRON, the preliminary subject "there", or an ADV of place. In the erroneous predictions, *der* is generally tagged as ADV.

Proper Noun Inconsistencies Orthographic variations in social media language throw off the models. For example, names written in lowercase are often tagged as NOUN rather than PROPN. On the normalized data, PROPN (gold) → NOUN errors decreased by 75% for ÆLÆCTRA and 62% for TWHIN. Likewise, when capitalized names are used in context, the models labeled them as PROPN, whereas we annotated the syntactical use of the token, e.g., *filming a TikTok*/NOUN.

ADV vs. ADP These are errors made on tokens like *af* ("of, off") and *for* ("for, too") which may function as both prepositions and adverbs[7]. In a few cases, the models do not recognize when *for* is used as an adverb of degree.

ADJ vs. ADV For adjectives that end in *-t*, the models seem to prefer the ADV tag. While *-t* can indicate an adverb, it may also indicate the gender of an adjective. The token *her* ("here"), an adverb, also poses a challenge when it occurs before a noun, e.g. *den her bog* ("this book"). In such cases, the models seem to prefer the erroneous tag sequence *den*/DET ***her*/ADJ** *bog*/NOUN.

Interjection Confusions Tokens that are meant to imitate pronunciation have been labeled as INTJ in DanTok, but the models seem to prefer a more concrete labeling[8]. The models also prefer INTJ for tokens with character repetition, whereas we tagged these tokens according to their presumed intended function.

5 Conclusion

We presented DanTok, the first linguistically annotated TikTok dataset and the first Danish social media dataset with POS annotation. We conducted an extensive analysis of how to best transfer to a highly specialized domain in a mid-resource language, and we demonstrated that LLMs benefit from common approaches such as normalization, while struggling with the same cases as the human annotators. Simultaneously, our results show that although in-language data and models form the basis for high performance, in-domain data, even from another language, should not be neglected in order to achieve state-of-the-art results.

[6] Consider, e.g., ***den*/PRON** *bog*/NOUN vs. ***den*/DET** *gamle*/ADJ *bog*/NOUN ("**that** book" vs. "**the** old book").

[7] *For* may also be used as a conjunction.

[8] E.g., "It's *nuclear*, not *nucular*," should be tagged as if it said *nuclear* twice.

Acknowledgments

We would like to thank the members of NLPnorth, MaiNLP Lab and the anonymous reviewers for their feedback. This project has been supported by the Pioneer Centre for Artificial Intelligence. Maria Barrett is supported by a research grant (34437) from VILLUM FONDEN. Max Müller-Eberstein is supported by the Danmarks Frie Forskningsfond (DFF) Sapere Aude grant 9063-00077B.

References

Lars Ahrenberg. 2015. Converting an English-Swedish parallel treebank to Universal Dependencies. In *Proceedings of the Third International Conference on Dependency Linguistics (Depling 2015)*, pages 10–19, Uppsala, Sweden. Uppsala University, Uppsala, Sweden.

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.

Mikel Artetxe, Sebastian Ruder, Dani Yogatama, Gorka Labaka, and Eneko Agirre. 2020. A call for more rigor in unsupervised cross-lingual learning. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7375–7388, Online. Association for Computational Linguistics.

GNU Aspell. 2019. GNU Aspell. `http://aspell.net/`. Version da-1.6.36-11-0.

Francesco Barbieri, Jose Camacho-Collados, Luis Espinosa Anke, and Leonardo Neves. 2020. TweetEval: Unified benchmark and comparative evaluation for tweet classification. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1644–1650, Online. Association for Computational Linguistics.

Francesco Barbieri, Luis Espinosa Anke, and Jose Camacho-Collados. 2022. XLM-T: Multilingual language models in Twitter for sentiment analysis and beyond. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 258–266, Marseille, France. European Language Resources Association.

Elisa Bassignana and Barbara Plank. 2022. CrossRE: A cross-domain dataset for relation extraction. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 3592–3604, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Emily M. Bender and Batya Friedman. 2018. Data statements for natural language processing: Toward mitigating system bias and enabling better science. *Transactions of the Association for Computational Linguistics*, 6:587–604.

Thomas Bilgram and Britt Keson. 1998. The construction of a tagged Danish corpus. In *Proceedings of the 11th Nordic Conference of Computational Linguistics (NODALIDA 1998)*, pages 129–139, Copenhagen, Denmark. Center for Sprogteknologi, University of Copenhagen, Denmark.

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

Alexandra DeLucia, Shijie Wu, Aaron Mueller, Carlos Aguirre, Philip Resnik, and Mark Dredze. 2022. Bernice: A multilingual pre-trained encoder for Twitter. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 6191–6205, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Leon Derczynski, Alan Ritter, Sam Clark, and Kalina Bontcheva. 2013. Twitter part-of-speech tagging for all: Overcoming sparse and noisy data. In *Proceedings of the International Conference Recent Advances in Natural Language Processing RANLP 2013*, pages 198–206, Hissar, Bulgaria. INCOMA Ltd. Shoumen, BULGARIA.

Jacob Eisenstein. 2013. What to do about bad language on the internet. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 359–369, Atlanta, Georgia. Association for Computational Linguistics.

Kevin Gimpel, Nathan Schneider, Brendan O'Connor, Dipanjan Das, Daniel Mills, Jacob Eisenstein, Michael Heilman, Dani Yogatama, Jeffrey Flanigan, and Noah A. Smith. 2011. Part-of-speech tagging for Twitter: Annotation, features, and experiments. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 42–47, Portland, Oregon, USA. Association for Computational Linguistics.

Rob van der Goot, Alan Ramponi, Arkaitz Zubiaga, Barbara Plank, Benjamin Muller, Iñaki San Vicente Roncal, Nikola Ljubešić, Özlem Çetinoğlu, Rahmad Mahendra, Talha Çolakoğlu, Timothy Baldwin, Tommaso Caselli, and Wladimir Sidorenko. 2021a. MultiLexNorm: A shared task on multilingual lexical normalization. In *Proceedings of the 2021 EMNLP Workshop W-NUT: The Seventh Workshop on Noisy User-generated Text*, pages 493–509. Association for Computational Linguistics.

Rob van der Goot, Ahmet Üstün, Alan Ramponi, Ibrahim Sharaf, and Barbara Plank. 2021b. Massive choice, ample tasks (MaChAmp): A toolkit for multi-task learning in NLP. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*, pages 176–197, Online. Association for Computational Linguistics.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. 2020. Don't stop pretraining: Adapt language models to domains and tasks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8342–8360, Online. Association for Computational Linguistics.

Anders Johannsen, Héctor Martínez Alonso, and Barbara Plank. 2015. Universal Dependencies for Danish. In *International Workshop on Treebanks and Linguistic Theories (TLT14)*, page 157.

Nobuhiro Kaji and Masaru Kitsuregawa. 2014. Accurate word segmentation and POS tagging for Japanese microblogs: Corpus annotation and joint modeling with lexical normalization. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 99–109, Doha, Qatar. Association for Computational Linguistics.

Andreas Kirkedal, Barbara Plank, Leon Derczynski, and Natalie Schluter. 2019. The lacunae of Danish natural language processing. In *Proceedings of the 22nd Nordic Conference on Computational Linguistics*, pages 356–362, Turku, Finland. Linköping University Electronic Press.

Matthias T Kromann, Line Mikkelsen, and Stine Kern Lynge. 2003. Danish Dependency Treebank. In *Proc. TLT*, pages 217–220. Citeseer.

Yijia Liu, Yi Zhu, Wanxiang Che, Bing Qin, Nathan Schneider, and Noah A. Smith. 2018. Parsing tweets into Universal Dependencies. 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 965–975, New Orleans, Louisiana. Association for Computational Linguistics.

Petter Mæhlum, Andre Kåsen, Samia Touileb, and Jeremy Barnes. 2022. Annotating Norwegian language varieties on Twitter for part-of-speech. In *Proceedings of the Ninth Workshop on NLP for Similar Languages, Varieties and Dialects*, pages 64–69, Gyeongju, Republic of Korea. Association for Computational Linguistics.

Dat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pre-trained language model for English tweets. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 9–14, Online. Association for Computational Linguistics.

Manuela Sanguinetti, Cristina Bosco, Lauren Cassidy, Özlem Çetinoğlu, Alessandra Teresa Cignarella, Teresa Lynn, Ines Rehbein, Josef Ruppenhofer, Djamé Seddah, and Amir Zeldes. 2020. Treebanking user-generated content: A proposal for a unified representation in Universal Dependencies. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 5240–5250, Marseille, France. European Language Resources Association.

Kushagra Singh, Indira Sen, and Ponnurangam Kumaraguru. 2018. A Twitter corpus for Hindi-English code mixed POS tagging. In *Proceedings of the Sixth International Workshop on Natural Language Processing for Social Media*, pages 12–17, Melbourne, Australia. Association for Computational Linguistics.

Xinyang Zhang, Yury Malkov, Omar Florez, Serim Park, Brian McWilliams, Jiawei Han, and Ahmed El-Kishky. 2022. Twhin-bert: A socially-enriched pre-trained language model for multilingual tweet representations. *arXiv preprint arXiv:2209.07562*.

Appendix

A Data Statement

The following dataset characteristics are outlined following Bender and Friedman (2018):

A. CURATION RATIONALE This dataset aims to provide high-quality, linguistically annotated data from contemporary Danish social media, in order to allow for analyses of how language use is evolving in these specialized domains, and how NLP methods can best be adapted to these changes.

B. LANGUAGE VARIETY The data consists of comments from TikTok videos collected in January 2023. The language covered is manually verified Danish (da-DK) with code-switching to English (en), and orthographic variations specific to the social media domain.

C. SPEAKER DEMOGRAPHIC Nothing specific is known about speaker demographics, as the data was scraped from 75 videos spanning different topics.

D. ANNOTATOR DEMOGRAPHIC Three Master's students, all native Danish speakers, one with previous experience in dataset creation for POS tagging. The annotators were paid for their efforts.

E. SPEECH SITUATION Comments under TikTok videos represent informal, written language produced largely spontaneously with the intent to address the video creator or express an opinion to other viewers.

F. TEXT CHARACTERISTICS The text contains domain-specific terms and abbreviations, some degree of typographical and orthographic errors as well as occasional ellipsis of sentence subject. Code-switching to English makes up 5% of tokens in the full dataset (development + test), though the dataset contains several additional tokens that exist with the same meaning in both English and Danish, e.g., *shit* and *like*.

G. RECORDING QUALITY N/A

H. OTHER N/A

I. PROVENANCE APPENDIX N/A

B Data Collection Details

B.1 Hashtags

Videos from the following 15 hashtags were scraped during data collection:

- #børn ("children")
- #danskememes ("Danish memes")
- #danskhumor ("Danish humor")
- #glædeligjul ("merry Christmas")
- #godtnytår ("happy new year")
- #gørdetselv ("do it yourself")
- #landsholdet ("the national team")
- #madlavning ("cooking")
- #mitarbejde ("my job")
- #morgenrutine ("morning routine")
- #parforhold ("relationships")
- #selvtak ("you're welcome")
- #sommerprojekt ("summer project")
- #tobiasrahim ("Tobias Rahim")
- #træning ("workout")

B.2 Deduplication Details

Figure 3 plots the number of tokens and their token-type ratios (TTR) after applying merge deduplication (Section 2.1) with threshold t.

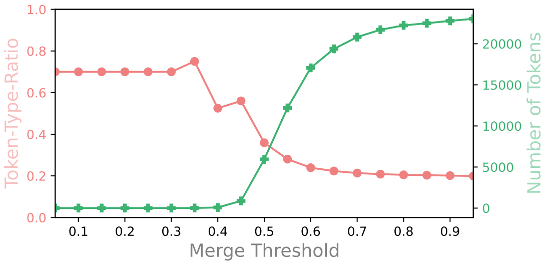


Figure 3: Deduplication using varying merge thresholds. A low t merges all comments into one, a high t contains more tokens and less token-type diversity.

C POS Tag Distribution

Figure 4 presents an overview of the POS tag distribution in DanTok compared to the English LinES, Tweebank2 and DDT.

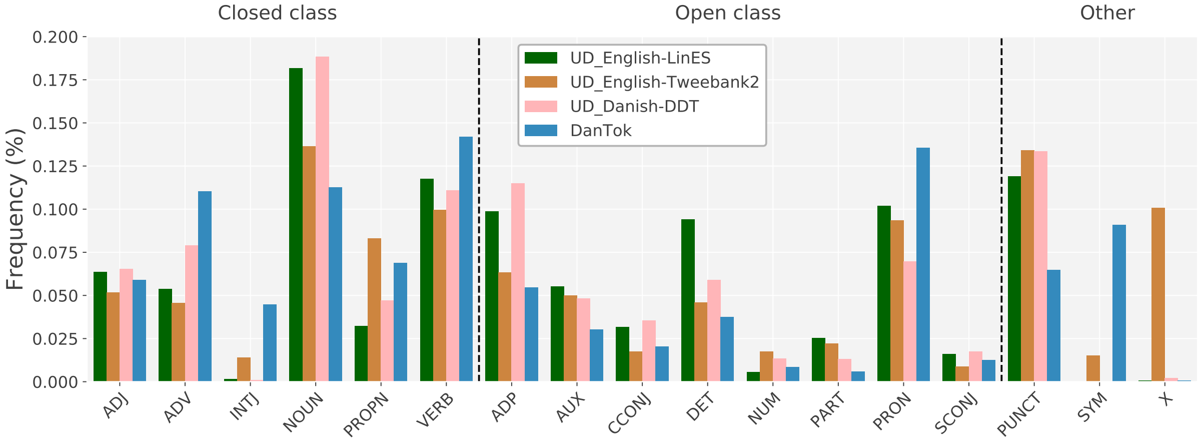


Figure 4: POS tag distribution in DanTok compared to the treebanks used for fine-tuning in Section 3.