DACy: A Unified Framework for Danish NLP

Kenneth C. Enevoldsen
Interacting Minds Centre &
Center for Humanities Computing Aarhus
Aarhus University
Jens Chr. Skous Vej 4, Building 1483, 3rd floor
Denmark, 8000 Aarhus C
kenneth.enevoldsen@cas.au.dk

Lasse Hansen
Department of Clinical Medicine &
Center for Humanities Computing Aarhus
Aarhus University
Jens Chr. Skous Vej 4, Building 1483, 3rd floor
Denmark, 8000 Aarhus C
lasse.hansen@clin.au.dk

Kristoffer L. Nielbo
Interacting Minds Centre &
Center for Humanities Computing Aarhus
Aarhus University
Jens Chr. Skous Vej 4, Building 1483, 3rd floor
Denmark, 8000 Aarhus C
kln@cas.au.dk

ABSTRACT

Danish natural language processing (NLP) has in recent years obtained considerable improvements with the addition of multiple new datasets and models. However, at present, there is no coherent framework for applying state-of-the-art models for Danish. We present DaCy: a unified framework for Danish NLP built on SpaCy. DaCy uses efficient multitask models which obtain state-of-the-art performance on named entity recognition, part-of-speech tagging, and dependency parsing. DaCy contains tools for easy integration of existing models such as for polarity, emotion, or subjectivity detection. In addition, we conduct a series of tests for biases and robustness of Danish NLP pipelines through augmentation of the test set of DaNE. DaCy large compares favorably and is especially robust to long input lengths and spelling variations and errors. All models except DaCy large display significant biases related to ethnicity while only Polyglot shows a significant gender bias. We argue that for languages with limited benchmark sets, data augmentation can be particularly useful for obtaining more realistic and fine-grained performance estimates. We provide a series of augmenters as a first step towards a more thorough evaluation of language models for low and medium resource languages and encourage further development.

Keywords Natural Language Processing · Low-resource NLP · Data Augmentation · Danish NLP

1 Introduction

Danish Natural Language Processing (NLP) has seen a recent rise in resources with the introduction of the Danish Gigaword Corpus (Derczynski et al., 2021), curated lists of Natural Language Processing (NLP) tools by DaNLP (Brogaard Pauli et al., 2021) and sprogteknoledi,dk, and at least five pretrained neural language models (Højmark-Bertelsen, 2021; Møllerhøj, 2019; Tamini-Sarnikowski, 2020). Datasets and models are available for most common tasks such as Named Entity Recognition (NER), Part-of-Speech (POS) tagging, dependency parsing, sentiment analysis, and coreference resolution (Brogaard Pauli et al., 2021; “Sprogteknoledi,dk”, 2021). However, no coherent, efficient and state-of-the-art framework exists for all fundamental NLP tasks. Models are developed and distributed as disjoint projects and often require diverging package versions and have idiosyncratic APIs. These factors complicate workflows and hamper further developments.
1.1 DaCy

With this motivation we present DaCy: an efficient end-to-end framework for Danish NLP with state-of-the-art performance on POS, NER and dependency parsing. DaCy fills the gap in Danish NLP by providing a consistent interface that is easily extendable and able to integrate other models. DaCy is built on SpaCy v.3 which comes with a range of advantages: the framework is optimized, user-friendly, and well-documented. DaCy includes three fine-tuned language models: DaCy small, based on a Danish Electra (14M parameters) (Højmark-Bertelsen, 2021); DaCy medium, based on the Danish BERT (110M parameters) (Møllerhøj, 2019); and DaCy large, based on the multilingual XLM-Roberta (550M parameters) (Conneau et al., 2020). All models have been fine-tuned to do POS tagging, NER, and dependency parsing in a single forward pass, which increases the efficiency of the model and allows for larger models at the same computational cost.

Besides models fine-tuned for DaCy, the package includes convenient wrappers to add other models to the pipeline. For instance, Danish models for detecting polarity, emotion, and subjectivity classification can be added in a single line of code, and any HuggingFace Transformers (Wolf et al., 2020) model trained for sentence classification can be conveniently wrapped and included in the pipeline using utility functions. With this functionality, DaCy aims at being a unified framework for Danish NLP. All functionality is well-documented and covered by tutorials.¹

1.2 Robustness & Evaluation

Fine-tuned language models are commonly evaluated by testing performance on a gold-standard benchmark dataset. The most commonly used benchmark for Danish is the DaNE dataset (Hvingelby et al., 2020), which consists of the Danish Dependency Treebank (Johannsen et al., 2015), additionally tagged for NER. For languages with few benchmarks datasets, such as Danish, the performance stability and generalizability can not be reliably estimated (Ribeiro et al., 2020). For instance, the text included in DaNE was collected in the years 1983–1992 from both written and spoken domains (Hvingelby et al., 2020). Given the change of languages over time and the addition of new textual domains such as social media, this dataset is unlikely to be representative of the contemporary domains of application. For instance, models might not be sufficiently exposed to e.g. abbreviated names, spelling errors, or non-standard casing to correctly and robustly classify them. In this sense, the performance obtained on DaNE is unlikely to hold for real-world use cases.

To provide an additional layer of validation, we propose evaluating models on augmented gold-standard data. Data augmentation entails generating new data by slightly modifying existing data points (Feng et al., 2021). Data augmentation techniques such as rotation and cropping are widely used in computer vision to reduce overfitting (Shorten & Khoshgoftaar, 2019), and are becoming increasingly common in NLP (Chen et al., 2021). The complex syntactic and semantic structure of text complicates the task of finding useful augmentations, but simple manipulations such as synonym replacement and random character swaps and deletions have been found to be particularly useful for supervised learning in low-resource settings (Wei & Zou, 2019).

Although data augmentation is most commonly used for increasing the amount of training data, it can just as well be used for evaluation purposes (Ribeiro et al., 2020). By augmenting a gold-standard dataset, we can evaluate model performance when exposed to data that more closely mimics real-life settings by adding spelling errors, more diverse names, or other manipulations. In section 2.2, we introduce a series of augmentations and evaluate the performance of Danish NLP pipelines on them.

The contributions of this paper are three-fold. 1) We introduce new state-of-art models for Danish dependency parsing, NER and POS. 2) We introduce the DaCy Python library as a unified framework for state-of-the-art NLP in Danish. 3) We evaluate Danish NLP pipelines using data augmentation and provide directions for future model development.

2 Methods

2.1 Training

To train the candidate models for DaCy, all publicly available language models for Danish were fine-tuned on the DaNE corpus (Hvingelby et al., 2020) using SpaCy 3.0.3 (Honnibal et al., 2020). The models include 2 Danish ELECTRAs (Clark et al., 2020; Højmark-Bertelsen, 2021; Tamini-Sarnikowski, 2020), the Danish ConvBERT (Jiang et al., 2021; Tamini-Sarnikowski, 2020), the Danish BERT (Devlin et al., 2019; Møllerhøj, 2019), and the multilingual XLM-Roberta Large (Conneau et al., 2020). All models were trained with an input length of 10 sentences until convergence using similar hyperparameters on a Quadro RTX 8000 GPU. Adam was used as optimizer with hyperparameters $\beta_1 = 0.9$.

¹See: https://centre-for-humanities-computing.github.io/DaCy/
and $\beta_2 = 0.999$. Further, L2 normalization with $\alpha = 0.01$ and gradient clipping with $c = 1.0$ was employed. For increased efficiency, all models were trained with a multi-task objective (Caruana, 1997; Ruder, 2017) on NER, POS, and dependency parsing. This allows the training of larger models at the same computational cost, but it is unlikely that multi-task training at this scale improves performance (Aghajanyan et al., 2021; Raffel et al., 2020).

Table 1 shows the performance of all fine-tuned models evaluated on DaNE’s test set. The three best performing models in each size category, XLM-Roberta, DaBERT, and Ælæctra Cased are included in DaCy as the large, medium and small, respectively. In line with previous findings (Brown et al., 2020; Radford et al., 2019; Raffel et al., 2020), larger models tend to perform better with XLM-Roberta obtaining the best performance across the board.

### Table 1: Performance of models finetuned for DaCy. Highest scores are in bold and second highest is underlined. WPS indicates words pr. second.

| Framework   | Model          | POS Accuracy | PER | LOC | ORG | MISC | Avg. F1 | UAS | LAS | Speed |
|-------------|----------------|--------------|-----|-----|-----|------|---------|-----|-----|-------|
| DaCy large  | XLM-Roberta    | 98.39        | 95.53 | 83.90 | 77.82 | 80.16 | 85.20   | 90.59 | 88  | 4311  |
| DaCy medium | DaBERT         | 97.93        | 89.62 | 83.09 | 67.35 | 70.69 | 78.47   | 87.88 | 85  | 8335  |
| DaCy small  | Ælæctra Cased | 97.69        | 87.36 | 81.95 | 63.83 | 70.68 | 76.55   | 86.45 | 83  | 10671 |
| DaELECTRA   |                | 97.40        | 82.80 | 77.39 | 63.01 | 66.95 | 73.16   | 85.20 | 82  | 9855  |
| DaConvBERT  |                | 97.23        | 85.08 | 78.26 | 61.76 | 66.93 | 73.77   | 84.61 | 81  | 10029 |

2. **Evaluation**

To evaluate the robustness of DaCy and other Danish NLP pipelines, we assessed their performance on multiple augmented version of the DaNE test set. All Danish models are trained on the DaNE corpus which consists of a mix of textual data of both spoken and written origin from the years 1983–1992 (Hvingelby et al., 2020), with the exception of Polyglot which is trained on entities extracted from Wikipedia (Al-Rfou’ et al., 2013). As a consequence, the training data is rarely representative of the domain in which the models will be applied. For example, social media, contemporary news media, and historical texts have domain specific characteristics such as non-standard casing, a higher degree of typos, use of hashtags, and historic spelling such as upper-cased nouns (Baldwin, 2012; Farzindar & Inkpen, 2015; Tahmasebi, 2018). While it is infeasible to test the models on all possible domains, some of these characteristics can be modelled using data augmentation which can provide practitioners with an estimate of the potential shortcomings of the model. Further, data augmentation can be used to estimate biases against protected groups such as gender and ethnicity.

The augmenters developed for this paper are designed in accordance with the SpaCy framework, and are thus not necessarily tied to DaCy or Danish in particular and can be used both during model validation and training. Comprehensive tutorials are provided on the DaCy Github repository.

We tested small, medium, and large SpaCy (Honnibal et al., 2020) and DaCy models, Stanza (Qi et al., 2020), Polyglot (Al-Rfou’ et al., 2013), NERDA (Kjeldgaard, 2020), Flair (Akbik et al., 2019), and DaNLP’s BERT (Brogaard Pauli et al., 2021) on the DaNE test set augmented with the following augmenters:

1. Keystroke augmentation: substitute 2%, 5%, or 15% of characters with a neighbouring character on a Danish QWERTY keyboard.
2. ÆØÅ augmentation: substitute æ/Æ with ae/Ae, ø/Ø with oe/Oe, and å/Å with aa/Aa to simulate some historic text variations in Danish.
3. Lower-case augmentation: convert all text to lower-case.

For a full list of models and training configurations see the config files on Github: [https://github.com/centre-for-humanities-computing/DaCy/tree/main/training](https://github.com/centre-for-humanities-computing/DaCy/tree/main/training)
Table 2: Performance of Danish NLP pipelines. Wall Time is the time taken by the model to go through the DaNE test set without augmentation. Stanza uses the spacy-stanza implementation. The speed of the DaNLP model is reported as provided by the framework, which does not utilize batch input. However, given the model size it can be expected to reach speeds comparable to DaCy medium. Empty cells indicates that the framework does not include the specific model.

| Model     | POS Accuracy | NER F1 | Dependency Parsing F1 | Wall Time |
|-----------|--------------|--------|-----------------------|-----------|
| DaCy large | 98.37        | 93.33  | 84.88                 | 84.39     |
| DaCy medium | 98.15       | 89.86  | 83.96                 | 80.16     |
| DaCy small | 97.75        | 87.98  | 79.23                 | 64.7      |
| DaNLP BERT | 92.27        | 83.90  | 71.13                 | 72.84     |
| Flair     | 97.80        | 92.60  | 84.82                 | 70.49     |
| NERDA     | 92.35        | 81.52  | 65.96                 | 72.41     |
| Polyglot  | 76.26        | 79.25  | 68.06                 | 40.69     |
| SpaCy large | 96.30       | 86.17  | 84.16                 | 56.67     |
| SpaCy medium | 95.71      | 84.55  | 77.29                 | 63.25     |
| SpaCy small | 94.80       | 78.92  | 69.04                 | 53.49     |
| Stanza    | 97.62        | 83.84  | 78.34                 |            |

4. Spacing augmentation: randomly remove 5% of all whitespace.

5. Name augmentations:
   (a) Substitute all names (PER entities) with randomly sampled Danish names, respecting first and last names.
   (b) Substitute all names with randomly sampled names of Muslim origin used in Denmark (Meldgaard, 2005), respecting first and last names.
   (c) Substitute all names with sampled Danish male names, respecting first and last names.
   (d) Substitute all names with sampled Danish female names, respecting first and last names.
   (e) Abbreviate all first names to the first character including a full stop.

The stochastic augmentations, i.e. name and keystroke augmentations, were repeated 20 times.

Previous evaluations of Danish NLP tools have used the gold-standard tokens instead of using a tokenization module. While this allows for easier comparison of the specific modules it inflates the performance metrics of the models and is unlikely to reflect the metric of interest, namely, the performance during application. All models were tested using both their own tokenizer (if they have one) and the SpaCy tokenizer for Danish. The performance reported in section 3 uses the best performing tokenization module for each pipeline. For all models except Stanza and Polyglot this was found to be the SpaCy tokenizer.

### 3 Results

Table 2 shows the overall performance of Danish NLP frameworks on POS, NER, and dependency parsing on the un-augmented DaNE test set. DaCy large obtains a new state-of-the-art on all tasks, most notably on NER and dependency parsing. Regardless of model, performance for POS is stable around 98% accuracy. POS tagging has long been at this level, and obtaining greater accuracy has been argued to require updates to the training data rather than new architectures (Manning, 2011).

Tables 3 to 5 shows a detailed performance breakdown of the models on NER, POS, and dependency parsing on the augmented data described in section 2.2. Overall, spelling variations and abbreviated first names consistently reduce performance of all models on all tasks. Even simple replacements of æ, ø, and å lead to performance degradation. In general, larger models handle augmentations better than small models with DaCy large performing the best on all augmentations with the exception of lower-casing. DaCy medium, DaNLP’s BERT, and NERDA are based on the uncased Danish BERT (Møllerhøj, 2019), and are consequently not affected by casing. The BiLSTM-based models (Stanza and Flair) perform competitively under augmentations and are only consistently outperformed by DaCy large.

On NER specifically, all models with the exception of DaCy large obtain significantly worse performance on Muslim names as compared to Danish names. The robustness of DaCy large likely stems from the multilingual pre-training.

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3In our experiments, several of the Danish models performed worse using their own tokenizer.
Table 3: NER performance of Danish NLP pipelines reported as average F1 scores excluding the MISC category. Best scores are marked bold and second best are underlined. * denotes that the result is significantly different from the baseline using a significance threshold of 0.05 with Bonferroni correction for multiple comparisons. Danish names is considered the baseline for the augmentation of Muslim, female, and male names. Values in parentheses denote the standard deviation. NERDA limits input size to 128 wordpieces which leads to truncation on long input sizes and high rates of keystroke errors.

| Model          | Baseline | Æøå | Lowercase | Input Length | Names | Abbreviated |
|----------------|----------|------|-----------|--------------|-------|-------------|
| DaCy large     | 85.6     | 83.5 | 69.7      | 86.5         | 86.5  | 80.1        |
| DaCy medium    | 79.7     | 73.1 | 79.5      | 80.9         | 80.4  | 76.3        |
| DaCy small     | 77.0     | 74.7 | 48.0      | 77.0         | 78.2  | 69.4        |
| DaNLP BERT     | 83.2     | 78.6 | 83.1      | 78.6         | 61.9  | 78.1        |
| Flair          | 81.1     | 80.2 | 24.4      | 81.0         | 80.9  | 74.9        |
| NERDA          | 80.9     | 74.8 | 80.7      | 73.7         | 53.8  | 76.4        |
| Polyglot       | 65.3     | 61.4 | 55.3      | 64.8         | 64.2  | 40.2        |
| SpaCy large    | 78.6     | 75.4 | 5.7       | 78.8         | 78.8  | 78.0        |
| SpaCy medium   | 76.0     | 74.7 | 9.7       | 76.5         | 76.8  | 76.0        |
| SpaCy small    | 68.6     | 66.9 | 4.8       | 68.0         | 68.0  | 63.8        |

Table 4: POS performance of Danish NLP pipelines reported as accuracy. Best scores are marked bold and second best are underlined. * denotes that the result is significantly different from baseline using a significance threshold of 0.05 with Bonferroni correction for multiple comparisons. Values in parentheses denote the standard deviation. NERDA limits input size to 128 wordpieces which leads to truncation on long input sizes and with a high degree of keystroke errors.

| Model          | Baseline | Æøå | Lowercase | Input Length | Names | Keystroke Errors |
|----------------|----------|------|-----------|--------------|-------|------------------|
| DaCy large     | 98.4     | 97.5 | 95.5      | 98.5         | 98.4  | 95.5 (0.2)*      |
| DaCy medium    | 98.2     | 96.5 | 98.1      | 97.8         | 97.9  | 93.6 (0.3)*      |
| DaCy small     | 97.7     | 95.4 | 95.4      | 97.6         | 97.7  | 93.1 (0.2)*      |
| Flair          | 97.8     | 95.0 | 95.0      | 97.7         | 97.7  | 94.7 (0.2)*      |
| Polyglot       | 76.3     | 71.6 | 75.6      | 75.7         | 75.6  | 71.7 (0.2)*      |
| SpaCy large    | 96.3     | 92.4 | 91.5      | 96.3         | 96.3  | 91.5 (0.2)*      |
| SpaCy medium   | 95.7     | 92.4 | 91.6      | 95.8         | 95.7  | 91.0 (0.3)*      |
| SpaCy small    | 94.8     | 90.5 | 90.3      | 94.8         | 94.8  | 90.7 (0.2)*      |
| Stanza         | 97.6     | 96.1 | 95.4      | 97.7         | 97.7  | 94.8 (0.2)*      |
Table 5: Dependency parsing performance of Danish NLP pipelines reported as LAS. Best scores are marked bold and second best are underlined. * denotes that the result is significantly different from baseline using a significance threshold of 0.05 with Bonferroni correction for multiple comparisons. Values in parentheses denote the standard deviation.

| Model       | Baseline | Åøå | Lowercase | Input Length | Keystroke Errors |
|-------------|----------|-----|-----------|--------------|------------------|
|             |          |     |           | 5 sentences  | 10 sentences     |
| DaCy large  | 88.4     | 86.2| 87.0      | 88.3         | 88.3             |
| DaCy medium | 86.7     | 84.6| 86.6      | 85.4         | 85.3             |
| DaCy small  | 84.0     | 79.0| 82.7      | 83.5         | 83.0             |
| SpaCy large | 78.0     | 71.0| 74.0      | 77.6         | 77.6             |
| SpaCy medium| 77.7     | 71.2| 73.8      | 77.4         | 77.4             |
| SpaCy small | 74.0     | 65.9| 70.4      | 74.1         | 74.1             |
| Stanza      | 83.8     | 80.2| 82.5      | 83.9         | 83.9             |

and the model size. Similarly, DaCy small is robust to spelling errors and outperforms larger models such as DaNLP’s BERT and NERDA, this is likely due to its well-curated training data (Derczynski et al., 2021). DaNLP’s BERT and NERDA models were found to severely under-perform if given longer input lengths. DaCy’s models consistently perform slightly better with more context, but are not vulnerable to shorter input. Lastly, as expected, the lack of casing is especially detrimental for NER for the cased models, most notably Flair, the SpaCy models, DaCy large and DaCy small.

4 Discussion

This paper has introduced the DaCy models and presented a thorough evaluation of Danish NLP models on a battery of augmentations. DaCy models achieve state-of-the-art performance on Danish NER, POS, and dependency parsing, and are robust to augmentations such as keystroke errors, name changes, and lowercasing. The results from training DaCy underline three well-known trends in deep learning and NLP, 1) larger models tend to perform better, 2) higher quality pre-training data leads to better models, as illustrated by the superior performance of Ælæctra compared to DaELECTRA, and 3) multilingual models perform competitively with monolingual models (Brown et al., 2020; Raffel et al., 2020; Xue et al., 2021).

Our experiments with multiple augmenters revealed different patterns of strengths and weaknesses across Danish NLP models. In general, larger models tend to be more robust to data augmentations. Several models are highly sensitive to casing, which limits their usefulness on certain domains. Evaluating models on augmented data provides a more holistic and realistic estimate of the expected performance, and can reveal in which use cases one model might be more useful than another. For example, it might be better to use DaCy medium on social media as opposed to DaCy large as its performance is not affected by casing.

The purpose of the data augmentation experiments was to evaluate the robustness of Danish models and to open a discussion on how to present new models going forward. As more models are developed for low and medium resource languages, properly evaluating them becomes vital for securing robustness, transparency, and effectiveness despite limited benchmark sets. We do not posit data augmentation as the only solution, but demonstrate that it can effectively reveal performance differences on important factors such as casing, spelling errors, and biases related to protected groups. As researchers, we bear the responsibility for releasing adequately tested and robust models into the world. With the increasing ease of deployment, users must be made aware of the level of performance they can realistically expect to achieve on their problem, and when to choose one model over another. Social media researchers should know that certain models are sensitive to casing, historians should know that some models handle old text variations such as ae, oe, aa poorly, and lawyers should be aware that models might not be able to identify abbreviated names as effectively. In this regard, transparency and openness as to when and how models fail are crucial measures to report. Such evaluation requires the development of infrastructure and tools, but is fast and easy to conduct once in place. For instance, it only takes 8 minutes to test DaCy large on all augmented datasets including bootstrapping. As part of the DaCy library, we provide several augmenters and utility functions for evaluation that integrate with SpaCy and encourage new NLP models to use and expand upon them. For the continued development of low and medium resource NLP in a direction that is beneficial for practitioners, it is vital to conduct more thorough evaluation of new models. We
suggestions these augmenters not as an evaluation standard, but as preliminary guiding principles for future development of NLP models for low and medium resource languages in particular.

### Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| NER          | Named Entity Recognition |
| NLP          | Natural Language Processing |
| POS          | Part-of-Speech |

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