NLPre: a revised approach towards language-centric benchmarking of Natural Language Preprocessing systems

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Abstract

With the advancements of transformer-based architectures, we observe the rise of natural language preprocessing (NLPre) tools capable of solving preliminary NLP tasks (e.g. tokenisation, part-of-speech tagging, dependency parsing, or morphological analysis) without any external linguistic guidance. It is arduous to compare novel solutions to well-entrenched preprocessing toolkits, relying on rule-based morphological analysers or dictionaries. Aware of the shortcomings of existing NLPre evaluation approaches, we investigate a novel method of reliable and fair evaluation and performance reporting. Inspired by the GLUE benchmark, the proposed language-centric benchmarking system enables comprehensive ongoing evaluation of multiple NLPre tools, while credibly tracking their performance. The prototype application is configured for Polish and integrated with the thoroughly assembled NLPre-PL benchmark. Based on this benchmark, we conduct an extensive evaluation of a variety of Polish NLPre systems. To facilitate the construction of benchmarking environments for other languages, e.g. NLPre-GA for Irish or NLPre-ZH for Chinese, we ensure full customization of the publicly released source code of the benchmarking system. The links to all the resources (deployed platforms, source code, trained models, datasets etc.) can be found on the project website: https://sites.google.com/view/nlpre-benchmark.

Keywords: benchmarking, leaderboard, segmentation, POS tagging, dependency parsing, Polish

Introduction and related works

Morphosyntactic features predicted by part-ofspeech (POS) taggers and dependency parsers underlie various downstream tasks, including but not limited to sentiment analysis (Sun et al., 2019), relation extraction (Zhang et al., 2018; Vashishth et al., 2018; Guo et al., 2019), semantic role labelling (Wang et al., 2019; Kasai et al., 2019), question answering (Khashabi et al., 2018), or machine translation (Chen et al., 2017; Zhang et al., 2019). These underlying tasks may therefore be referred to as natural language preprocessing (NLPre) tasks, as they precede the advanced NLP tasks. Since the quality of morphosyntactic predictions has a crucial impact on the performance of downstream tasks (Sachan et al., 2021), it is prudent to employ the best existing NLPre tools to predict the proper linguistic features. We are equipped with various NLPre methods, ranging from rule-based tools with hand-crafted grammars (e.g. Crouch et al., 2011), through statistical systems (e.g. Nivre, 2009; Mc-Donald et al., 2005; Straka et al., 2016), neural systems supported by pre-trained language models (e.g. Qi et al., 2020; Nguyen et al., 2021a) to large language models (LLM Ouyang et al., 2022).

In the context of intrinsically evaluating NLPre tools and reporting their performance, a variety of approaches have been proposed, e.g. shared task, performance table, and progress repository. The main goal of a *shared task* is to comprehensively evaluate participating systems on the re-

leased datasets using the carefully defined evaluation methodology. Numerous NLPre shared tasks have been organised so far (e.g. Buchholz and Marsi, 2006; Seddah et al., 2013; Zeman et al., 2017, 2018), and they undoubtedly boosted the development of NLPre. While widely favoured, shared tasks are questionable as a complete and up-todate source of knowledge about NLPre progress. First, they scrutinise only solutions propounded in the current contest and do not include systems participating in the previous editions or possible future ones. Second, as shared tasks are organised sporadically, their results are not revised and may quickly become outdated. Certainly, the datasets released for shared tasks can be reused in experiments involving novel tools. The results of such experiments can be reported in independent scientific publications. Nonetheless, these publications are widely scattered, lacking a centralised platform for systematically tracking the ongoing NLPre progress with respect to a particular language.

The results of a new or upgraded NLPre tool are typically reported in *performance tables* (e.g. Stanza¹ or Trankit²). Such tables provide information about the quality of the tool in preprocessing a set of languages. The performance tables, however, often lack comparison with other systems trained for these particular languages. Additionally, as NL-

¹https://stanfordnlp.github.io/stanza/performance.html (UD v2.8)

²https://trankit.readthedocs.io/en/latest/performance. html#universal-dependencies-v2-5 (UD v2.5)

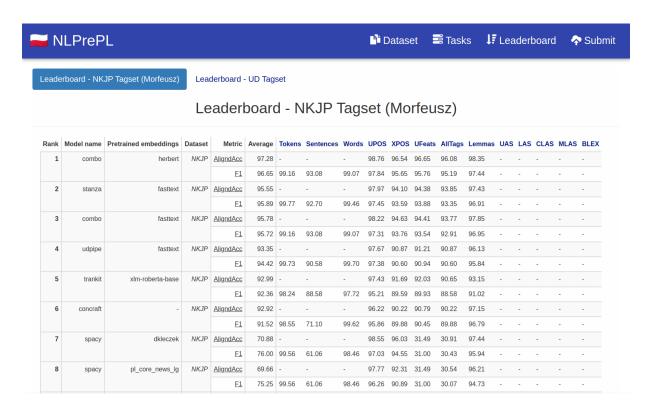


Figure 1: Screenshot of the NLPre-PL leaderboard.

Pre systems may be trained on different dataset releases (e.g. of Universal Dependencies), comparing their performance tables is not conclusive.

Information about trends and progress in NLP research is usually collected in public repositories such as Papers with Code³ or NLP-progress⁴. These repositories contain a repertoire of datasets for common NLP tasks, e.g. dependency parsing and POS tagging, and rankings of models trained and tested on these datasets. They are open to contributing new datasets and results, which, to ensure their credibility, originate from published and linked scientific papers. However, cutting-edge yet unpublished results of a new or upgraded NLPre system are not eligible to report. NLPre tasks are accompanied by datasets mostly in English, raising the problem of language unrepresentation of the repositories. Last but not least, the Papers with Code repository is prone to abuse. After logging in, one can add new results and link them with irrelevant papers as well as edit existing results. The fraudulent results are publicised immediately.

Despite yielding valuable information about the progress in NLPre, the mentioned evaluation approaches also reveal shortcomings, e.g. outdated and incomplete outcomes, lack of cross-system comparison, disregarding some systems, risk of result manipulation and absence of a language-centring perspective.

Following standard procedures in NLP research, we propose to robustly and fairly evaluate NLPre tools using the benchmarking method that allows for the evaluation of NLP models' performance and progress. NLP benchmarks are coupled with leaderboards that report and update model performance on the benchmark tasks, e.g. GLUE (Wang et al., 2018), XTREME (Hu et al., 2020), GEM (Gehrmann et al., 2021). The conventional benchmarking approach may be dynamically enhanced, exemplified by the *Dynabench* platform (Kiela et al., 2021), which enables users to augment the benchmark data by inputting custom examples. This humanand-model-in-the-loop benchmarking scenario appears promising for NLU tasks. Nevertheless, it may not be effective in the case of NLPre, as annotating credible examples of syntactic trees or morphological features requires expert knowledge. Finding multiple experts among casual users can be a serious obstacle, we thus implement our system in tune with the standard benchmarking method.

To our knowledge, benchmarking hasn't been used to rank NLPre systems, even if it is valuable and desired by the community creating treebanks or designing advanced NLP pipelines. Our NLPre benchmarking approach fills this gap. The proposed online benchmarking system automatically assesses submitted predictions of NLPre systems and publishes their performance ranking on a public scoreboard (see Section 2.2). The system is language-centric and tagset-agnostic, enables comprehensive and credible evaluation and consti-

³https://paperswithcode.com

⁴http://nlpprogress.com

tutes an up-to-date source of information on NLPre progress for a particular language. Unlike similar platforms, e.g. Codalab (Pavao et al., 2022), the NL-Pre benchmarking system is fully configurable and easy to set up, allowing users to establish an evaluation environment for any language. Additionally, it can be self-hosted, making it convenient for developers and researchers working with a particular language to have it accessible on a local server.

To justify the use of the benchmarking technique for NLPre tasks, we conduct empirical research in a challenging scenario with Polish as an example language. In the case of Polish, one dominant hurdle arises - the discrepancies between different tagsets, annotation schemes and datasets utilised for training disparate systems preclude their direct comparison. We thus standardise the training and evaluation of NLPre systems on a new performance benchmark for Polish, hereafter NLPre-PL (see Section 3). It consists of a predefined set of NLPre tasks and reformulated versions of existing Polish datasets. Section 4 outlines our robust and reliable evaluation of the selected NLPre systems on the NLPre-PL benchmark. According to our knowledge, no evaluation experiments have been carried out in Polish to compare the performance of off-the-shelf LLMs, neural NLPre systems and established tagging disambiguators due to the lack of a coherent evaluation environment.

This work makes a tripartite contribution encompassing novelty, research, and development underpinned by an open-source ethos. (1) We propose a novel language-oriented benchmarking approach to evaluate and rank NLPre systems. (2) We conduct a scientific evaluation of the proposed approach in the non-trivial Polish language scenario on the assembled NLPre-PL benchmark. (3) We publish online benchmarking platforms for three distinct languages: Polish⁵, Chinese⁶, and Irish⁷, and release the benchmarking system's source code as open-source.

2. NLPre benchmarking

2.1. Research concept

In this study, we introduce a novel adaptation of the benchmarking approach to NLPre. The primary objective is to establish an automated and credible method for evaluating NLPre systems against a provided benchmark and continuously updating their performance ranking on a publicly accessible scoreboard. More specifically, predictions for the benchmark test sets output by NLPre systems and submitted to the benchmarking system are automatically compared against the publicly undisclosed reference dataset. This method effectively prevents result manipulation and ensures fairness of the final assessment. The second important methodological assumption is to enable the ongoing evaluation of new or upgraded NLPre systems to guarantee up-to-date and complete ranking. Consequently, the leaderboard can serve as a reliable point of reference for NLPre system developers.

Based on these assumptions, we design and implement the language-centric and tagset-agnostic benchmarking system that enables comprehensive and credible evaluation, constitutes an up-to-date source of information on NLPre progress, and is fully configurable to facilitate building benchmarking systems for multiple languages.

2.2. Online benchmarking system

The benchmarking system comprises three main parts: a data repository, a submission and evaluation system, and a leaderboard. The data repository provides descriptions of NLPre tasks, datasets, and evaluation metrics, as well as links to the datasets.

The model submission and evaluation system allows the researchers to evaluate a new model by submitting its predictions for the test sets of raw sentences. It is mandatory to upload predictions for all provided test sets for a given tagset; however, it is possible to participate in an evaluation for only one tagset and only for a selected range of tasks.

The leaderboard is a tabular display of the performance of all submissions with their results for each dataset and tagset. The results for the evaluated model and its rank are displayed in the leaderboard provided the submitter confirms their publication.

The benchmarking system is implemented as a web-based application in Python using Django framework. This framework allows quite an easy implementation of MVC design pattern. Moreover, it offers access to the administrator panel, which can be very useful in the custom configuration of the benchmark. The submission scores are stored in a local SQLite database and the submissions are stored in .zip files in a designated directory. The results from the leaderboard are conveniently accessible via an API.

2.3. Configuration

We acknowledge the need to configure similar evaluation environments for other languages to promote linguistic diversity within the worldwide NLP community and to support local NLP communities working on a particular language. To ensure that, we publish a .yaml file that enables easy management of datasets, tagset, and metrics included in the benchmark. The content of all subpages can be

⁵https://nlpre-pl.clarin-pl.eu

⁶https://nlpre-zh.clarin-pl.eu

⁷https://nlpre-ga.clarin-pl.eu

modified using a WYSIWYG editor within the application. This setting ensures quite a low entry level for setting up the platform, with minimal changes required.

As a standard feature, we include pre-defined descriptions for the prevalent NLPre tasks. Those can be modified via either configuration files or the administrator panel. Additionally, we supply a default evaluation script, but users are free to provide their own customised code.

To show the capabilities of the benchmarking system, we set up a prototype for Polish (Figure 1). NLPre-PL is described in detail in Section 3. To support our claim that the system is language agnostic, we set up NLPre-GA for Irish and NLPre-ZH for Chinese. The choice of those languages is not arbitrary; our objective is to demonstrate the capability of the platform in evaluating diverse languages, including those based on non-Latin scripts. In setting up said benchmarking systems we use existing UDv2.9 treebanks: UD Chinese-GSD (Shen et al., 2019) and UD_Irish-IDT (Lynn et al., 2015) and available up-to-date models, trained on these treebanks. The selection of models mirrors the criteria applied in this work regarding the evaluation of Polish, that is: COMBO, Stanza, SpaCy, UDPipe, and Trankit. If the specific model is not available for UDv2.9, we train it from scratch on the datasets linked above.

3. NLPre-PL benchmark

3.1. Datasets

	Ni	PDB-UD	
POS	Morfeusz	UD	
DEP	n/a	n/a	UD
Format	TEI / DAG	CoNLL-X / -U	CoNLL-U
# tokens		350K	
# sentences	8	22K	
Avg. t/s		14.2	15.8
	NLP	re-PL	
Split	byName	byType	original
# train	984K	978K	282K
# dev	110K	112K	35K
# test	122K	125K	34K

Table 1: Summary of source datasets (NKJP1M and PDB-UD) and NLPre-PL Datasets (in tokens). Explanations: POS – the part-of-speech tagset; DEP – the dependency schema; $Avg.\ t/s$ – the average number of tokens per sentence.

NKJP1M (Przepiórkowski et al., 2018) The NKJP1M subcorpus of the Polish National Corpus (Przepiórkowski et al., 2012) is manually annotated according to the NKJP tagset (Szałkiewicz and Przepiórkowski, 2012) and afterwards modified in line with the Morfeusz tagset (Woliński, 2019). This

balanced subset of thematic- and genre-diverse texts and transcriptions is used to train Polish POS taggers. NKJP1M is maintained in two formats: TEI⁸ and DAG.⁹ These two formats are accepted by older NLPre tools but not modern ones. We thus convert NKJP1M to the CoNLL-X format (Buchholz and Marsi, 2006) preserving the original segmentation, POS tags and morphological features (i.e. the Morfeusz tagset), and to the CoNLL-U format¹⁰ with UD tags, Morfeusz tags (*XPOS*) and UD morphological features.

Since there is no generally accepted split of NKJP1M into training, development and testing subsets, we uniformly divide NKJP1M in all formats (i.e. DAG, TEI, CoNLL-X and CoNLL-U) pursuant to the formulated splitting heuristics. Each document in the subcorpus contains multiple paragraphs of continuous textual data. To avoid possible information leakage, we treat each such paragraph as an indivisible unit. To ensure that the subsets include paragraphs of varying length, we investigate the distribution over the number of segments in each paragraph. Since it is akin to Gaussian distribution, we decide to not exclude any data, and we divide the paragraphs into K = 10 buckets of roughly similar size and then sample from them with respective ratios of 0.8:0.1:0.1 (corresponding to train, dev, and test subsets). This data selection technique assures similar distribution of segments number per paragraph in three subsets, hereafter byName. For creating our second split, hereafter by Type, we consider the type of document a paragraph belongs to. We first group paragraphs into categories equal to the document types, and then we repeat the above-mentioned procedure per category (see the summary of NKJP1M and data splits in Table 1). PDB-UD (Wróblewska, 2018) Polish Dependency Bank is the largest collection of Polish sentences manually annotated with dependency trees and afterwards converted into UD representations in line with the UD annotation schema (de Marneffe et al., 2021). PDB-UD slightly correlates with NKJP1M, i.e., a subset of the PDB-UD sentences comes from NKJP1M, and the language-specific tags (XPOS) in PDB-UD match the Morfeusz tagset. PDB-UD is typically used to train NLPre systems for Polish. In NLPre-PL, we use the original PDB-UD data without any modifications and its standard split (see the statistical summary of PDB-UD in Table 1).

3.2. Tasks

The complete set of NLPre tasks was originally curated for evaluating language systems in the CoNLL shared task 2018 (Zeman et al., 2018). These tasks

⁸http://nlp.ipipan.waw.pl/TEI4NKJP.

⁹https://github.com/kawu/concraft-pl#data-format

¹⁰https://universaldependencies.org/format.html

mainly focus on preliminary text processing, such as tokenisation or divulging morphosyntactic features. We follow the CoNLL task choice and include all these tasks in NLPre-PL.

Segmentation A segmentation task consists in splitting texts into sentences (Sentences), orthographic tokens (Tokens), and syntactic words (Words), the latter being the basic units of morphosyntactic analysis. Segmentation is not a trivial task. In some languages, an orthographic token may be recognised as a multi-word token (multiword for short) combining multiple syntactic words, e.g. in Polish, the token spalibyśmy (Eng. we would sleep) consists of the past participle spali (Eng. slept), the conditional marker by (Eng. would) and the mobile inflection śmy. Since the consistent model of segmentation into words and sentences was used in NKJP1M and PDB-UD, we maintain this data segmentation in NLPre-PL. It is also worth mentioning that the CoNLL format (but not TEI and DAG) allows for annotating orthographic tokens; thus, they are included in the NLPre-PL benchmark.

Tagging A tagging task is the process of identifying parts of speech (i.e. POS tagging) and possibly morphological features (i.e. morphological analysis) of words. It follows a predefined POS tagset. As mentioned in Section 3.1, two tagsets are used in the NLPre-PL datasets: Morfeusz and UD.

Lemmatisation Lemmatisation involves predicting canonical forms of syntactic words. Canonical forms are conventionally established identifiers of lexemes (i.e. sets of inflectionally related syntactic words). Since Polish is a fusional language with a large number of inflected words, lemmatisation is an important task, albeit not trivial, e.g. the lemma of *kluczy* can be either the infinitive κμυςχής (Eng. *to weave*) or the noun κμυςς (Eng. *a key*).

Dependency parsing Dependency parsing is the process of automatically predicting the syntactic structure of an input sentence. A dependency structure is a labelled directed tree with nodes corresponding to syntactic words and edges between these words specifying dependency relations.

4. Evaluation

4.1. Evaluation methodology

To maintain the de facto standard to NLPre evaluation, we apply the evaluation measures defined for the CoNLL 2018 shared task and implemented in the official evaluation script.¹¹ In particular, we focus on F1 and *AlignedAccuracy*, which is similar to F1 but does not consider possible misalignments in tokens, words, or sentences.

In our evaluation process, we follow default training procedures suggested by the authors of the evaluated systems, i.e. we do not conduct any optimal hyperparameter search in favour of leaving the recommended model configuration as-is. We also do not further fine-tune selected models.

4.2. Evaluated systems

Based on the NLPre-PL benchmark, we evaluate both well-rooted rule-based disambiguation methods and modern systems based on neural network architectures to enable an informative and thorough comparison of different approaches. We use the most up-to-date versions of available tools at the time of conducting experiments: (1) pipelines of separate tools (Concraft-pl, UDPipe), (2) systems integrating separate models for NLPre tasks (spaCy, Stanza, Trankit), (3) end-to-end systems with a model for all NLPre tasks (COMBO), and large language model GPT-3.5.

Concraft-pl (Waszczuk, 2012; Waszczuk et al., 2018) ¹² is a system for joint morphosyntactic disambiguation and segmentation. ¹³ It uses Morfeusz morphological analyser (Woliński, 2014; Kieraś and Woliński, 2017) to extract morphological and segmentation equivocates and then disambiguates them using the conditional random fields model. We train the Concraft-pl models with default parameters.

UDPipe (Straka and Straková, 2017) is a language-agnostic trainable NLPre pipeline.¹⁴ Depending on the task, it uses recurrent neural networks (Graves and Schmidhuber, 2005) in segmentation and tokenization, the average perceptron in tagging and lemmatization, a rule-based approach in multi-word splitting, and a transition-based neural dependency parser. We train the UDPipe models with the default parameters. The dependency parser is trained with the Polish *fastText* embeddings (Grave et al., 2018).

SpaCy (Montani and Honnibal, 2022) is an NLP Python library shipped with pretrained pipelines and word vectors for multiple languages.¹⁵ It also supports training the models for tagging and parsing, inter alia. We use spaCy to train pipelines for morphosyntactic analysis with: feed-forward network-

¹¹https://universaldependencies.org/conll18/conll18_ud_eval.py

¹²Polish is a fusional language for which a two-stage tagging procedure is typically applied: first, a rule-based morphological analyser outputs all morphological interpretations of individual tokens, and then a tagging disambiguator selects the most likely one for each token. The tools implemented in accordance with this procedure are still imminent.

¹³ https://github.com/kawu/concraft-pl (v2.0)

¹⁴ https://ufal.mff.cuni.cz/udpipe (v1)

¹⁵https://github.com/explosion/spaCy (v3.4.1)

Model / Task	Average	Tokens	Sentences	Words	UPOS	XPOS	UFeats	AllTags	Lemmas	Tok/s CPU	Tok/s GPU
concraft	91.61	98.56	71.33	99.64	95.88	90.04	90.59	90.04	96.79	111	_
udpipe + fT	94.43	99.75	90.51	99.73	97.36	90.64	90.97	90.64	95.86	2365	2181
combo + fT	95.75	99.12	93.33	99.04	97.25	93.82	93.61	92.98	96.90	458	822
combo + H	96.67	99.12	93.33	99.04	97.80	95.66	95.75	95.20	97.42	241	722
stanza + fT	95.89	99.76	92.70	99.45	97.43	93.57	93.90	93.36	96.94	933	2379
spacy + pl	75.38	99.56	61.85	98.46	96.30	90.97	31.03	30.14	94.77	3252	8407
spacy + fT	75.15	99.56	61.85	98.46	95.89	89.93	31.03	30.08	94.43	3134	8063
spacy + P	76.12	99.56	61.85	98.46	97.02	94.60	31.03	30.46	95.98	1571	5367
trankit + R	92.59	98.37	89.39	97.84	95.36	89.74	90.05	88.73	91.19	287	541

Table 2: Results (F1 scores) and inference time (the number of tokens processed per second) of benchmarking the selected NLPre systems on the Morfeusz tagset averaged by the datasets (byName and byType). The systems are grouped into non-neural and neural by a double horizontal line. Embeddings used in the models are: R - xlm-RoBERTa-base, fT - fastText, P - Polbert, pl - pl-core-news-lg, H - HerBERT.

Model / Task	Average	Tokens	Sentences	Words	UPOS	XPOS	UFeats	AllTags	Lemmas	Tok/s CPU	Tok/s GPU
udpipe + fT	92.30	99.79	92.44	99.78	97.33	89.97	90.37	89.35	95.23	1977	1848
combo + fT	94.04	99.18	94.29	98.77	96.64	93.30	93.48	91.97	96.53	471	844
combo + H	95.51	99.21	94.29	98.77	97.57	95.33	95.61	94.54	97.13	254	733
stanza + fT	94.25	99.77	93.92	99.43	97.33	92.88	92.90	91.63	96.60	910	2262
spacy + pl	88.39	99.58	65.05	98.47	96.36	90.95	91.22	89.65	93.62	2495	5403
spacy + fT	87.68	99.58	65.05	98.47	95.79	89.77	90.05	88.37	93.37	2484	4533
spacy + P	90.70	99.58	65.05	98.47	97.26	94.68	94.84	94.09	94.89	1376	4207
trankit + R	92.91	98.88	92.44	98.52	96.50	91.74	91.91	90.21	90.47	319	593

Table 3: Results (F1 scores) and inference time (tokens per second) of benchmarking the selected NLPre systems on the UD tagset averaged by the datasets (byName, byType, and PDB-UD). The systems are grouped into non-neural and neural by a double horizontal line (Concraft is not included because it does not allow data in the UD tagset) Embeddings used in the models are: R - xIm-RoBERTa-base, fT - fastText, P - Polbert, pI - pI-core-news-lg, H - HerBERT.

Task / model	udpipe + fT	combo + fT	combo + H	stanza + fT	spacy + fT	spacy + pl	spacy + P	trankit + R	GPT-3.5
Avg. F1 on PDB-UD	88.16	90.46	93.37	92.10	83.03	84.21	87.98	94.03	50.95
Tokens	99.86	99.35	99.40	99.86	99.65	99.65	99.65	99.90	98.08
Sentences	95.90	96.22	96.22	96.83	71.46	71.46	71.46	98.51	89.81
Words	99.84	98.22	98.22	99.42	98.51	98.51	98.51	99.89	96.96
UPOS	97.28	95.34	97.31	97.64	95.62	96.49	97.54	99.07	64.07
XPOS	88.57	92.03	94.92	93.17	88.57	90.14	94.35	96.18	41.32
UFeats	89.07	92.21	95.23	93.22	88.79	90.42	94.52	96.34	41.88
AllTags	88.02	90.41	94.29	92.15	87.00	88.71	93.85	95.57	35.65
Lemmas	94.29	95.37	96.38	95.77	91.72	91.69	93.77	88.98	64.77
UAS	86.68	88.49	91.31	91.09	80.91	82.15	88.08	95.79	35.57
LAS	83.01	86.19	89.98	88.83	72.24	73.60	80.33	94.24	26.58
CLAS	79.53	84.14	89.03	86.90	73.72	75.71	80.50	93.00	29.06
MLAS	69.53	76.64	84.77	79.90	63.57	66.90	75.75	87.79	11.81
BLEX	74.49	81.34	86.77	82.53	67.64	69.29	75.48	77.18	26.86
Avg. F1 on NKJP1M	94.37	95.84	96.59	95.33	90.01	90.49	92.06	92.36	NA

Table 4: Results of benchmarking the selected NLPre systems on the smaller PDB-UD dataset. The last row with the mean F1 scores of the models trained on larger NKJP1M data is for reference. Embeddings used in the models are: R - xlm-RoBERTa-base, fT - fastText, P - Polbert, pl - pl-core-news-lg, H - HerBERT. The results of GPT-3.5 are greyed out due to their exclusion from display on the leaderboard.

based text encoders with static embeddings (fast-Text and pl-core-news-lg) or transformer-based encoders with the Polbert embeddings (Kłeczek, 2021), taggers (linear layers with softmax activation on top of the encoders), and transition-based parsers.

Stanza (Qi et al., 2020) is a language-agnostic, fully neural toolkit offering a modular pipeline for tokenization, multi-word token expansion, lemmatization, tagging, and dependency parsing. ¹⁶ It mainly uses recurrent neural networks (Graves and Schmidhuber, 2005) as a base architecture and external word embeddings (*fastText*). Each module reuses the basic architecture.

Trankit (Nguyen et al., 2021b) uses a multilingual pre-trained transformer-based language model, XLM-Roberta (Conneau et al., 2019) as the text encoder which is then shared across pipelines for different languages.¹⁷ The resulting model is jointly trained on 90 UD treebanks with a separate adapter (Pfeiffer et al., 2020a,b) for each treebank. Trankit uses a wordpiece-based splitter to exploit contextual information.

COMBO (Rybak and Wróblewska, 2018; Klimaszewski and Wróblewska, 2021) is a fully neural language-independent NLPre system¹⁸ integrated with the LAMBO tokeniser (Przybyła, 2022). It is an end-to-end system with jointly trained modules for tagging, parsing, and lemmatisation. We train the COMBO models with the pre-trained word embeddings – *fastText* and *HerBERT* (Mroczkowski et al., 2021).

GPT-3.5 (Brown et al., 2020) is a large language model, notable for its outstanding performance in NLU tasks. It is a fined-tuned version of the GPT-3 model. GPT-3.5's architecture is based on a transformer neural network with 12 stacks of decoders blocks with multi-head attention blocks.

For segmentation tasks, we train modules integrated with the tested NLPre systems. The only aberration is in spaCy, where poor segmentation results of the dependency module¹⁹ forced us to use an out-of-the-box sentenciser available in spaCy.

For each model, we initialise training with possibly the most prominent and congruent embedding model available. Virtually all models are capable of fully capitalising from that addition, apart from Concraft and UDPipe. The first does not use embeddings at all, and the latter uses them only for dependency parsing training. If embeddings based

on BERT architecture are feasible to use, we select their *base* versions. This ensures fairness of comparison between NLPre systems, as not all of them support BERT-*large* embeddings.

4.3. Results

Impact of system architecture We assess the quality of the selected NLPre systems contingent on the NLPre-PL benchmark. In Polish (and most other languages), non-neural NLPre tools are currently not widely developed. We evaluate two of them: Concraft and UDPipe. Although they do not use neural network algorithms to train models, their quality does not significantly differ from the best tested neural systems, especially in terms of segmentation, which UDPipe performs best (*Words*) or second-best (*Sentences*) (see Tables 2 and 3). We cannot unequivocally say that the system architecture has a decisive influence on the results, as spaCy models, even transformer-based, output the lowest quality.

Impact of tagset selection We compare systems trained and tested on data adjusted to two tagsets - the Morfeusz tagset (see Table 2) and the UD tagset (see Table 3). The average scores indicate that only COMBO performs better on Morfeusz-annotated data than on UD data. The performance of Trankit, UDPipe, and Stanza slightly decreases on Morfeusz data. Notably, all spaCy models trained on this dataset record a significant quality drop mainly due to poorly performed morphological analysis, i.e. UFeats values (and thus also the low AllTags values, i.e., matching between UPOS, XPOS, and UFeats). Regarding segmentation, UPOS and XPOS tagging, and lemmatisation, the tagset selection does not negatively affect the results, and the systems perform comparably.

Impact of the size of training data Intuitively, the size of the training data affects the prediction quality. Considering the data size factor, we compare the average F1 scores of the NLPre systems trained on NKJP1M (see the last row in Table 4) and on PDB-UD (see Table 4), which is two orders of magnitude smaller. The results confirm our intuitive assumptions – there is a difference of 6.21 between the mean F1 scores obtained by the systems trained on the smaller PDB-UD (avg. F1 of 88.16) and those trained on the larger NKJP1M (avg. F1 of 94.37).

When comparing the performance of individual systems on the smaller PDB-UD dataset, Trankit turns out to be the undisputed winner in all tasks except lemmatisation. However, considering the average performance of all tasks, COMBO and Stanza perform the best.

¹⁶https://github.com/stanfordnlp/stanza (v1.4.0)

¹⁷https://github.com/nlp-uoregon/trankit (v1.1.1)

¹⁸https://gitlab.clarin-pl.eu/syntactic-tools/combo (v1.0.5)

¹⁹Dependency parsing module is responsible for sentence segmentation in the spaCy implementation.

In alignment with contemporary developments on zero-shot learning, we test the predictive capabilities of GPT-3.5 acquired via the prompting technique (Brown et al., 2020). Despite comprehensive instructions along with the UD tree examples in the prompt, the results are highly unsatisfactory. An error analysis has revealed that 1) the GPT model modifies the input texts (e.g. adds elided words, alters the word's declension and conjugation, leading also to non-existent words); 2) while parsing questions, it answers them or returns information that they cannot be answered; 3) it replaces Polish words with their foreign equivalents; 4) it outputs graphs with cycles, thus not adhering to UD trees. Even for GPTs, achieving UD-compliant morphosyntactic analysis is challenging when they lack access to training examples. GPT-3.5's results are not included in the leaderboard.

Impact of split heuristics As outlined in Section 3.1, NKJP1M has no official split into train, dev, and test subsets. Since intuitively, the type of document can affect text processing, we propose two alternative splits, i.e. *byName* and *byType*. We compare the F1 scores for these two splits to verify this hypothesis. For the *byName* split, the average F1 for tasks and systems is 90.69, and for the *byType* split, it is 90.56. The difference is negligible, indicating that the document type, and hence the text domain, does not affect the quality of the NLPre tasks. Based on this outcome, we arbitrarily choose the more balanced *byType* split as binding in the final NLPre-PL benchmarking system. The detailed results of all experiments are in Appendix 6.2.

Inference time In the context of benchmarking, quality is a fundamental factor. In our case, the best average F1 scores are achieved by COMBO and Stanza, far ahead of spaCy and Concraft. The second crucial issue is the processing time of the evaluated NLPre systems, especially their inference time. ²⁰ We calculate the times in which the systems tokenise, tag and lemmatise the input text. ²¹ The exception is COMBO with the mandatory parsing module that cannot be disabled. Therefore, its calculations include the parsing time as well. The inference time, corresponding to the number of tokens processed per second, is provided in the last two columns of Tables 2 and 3. On CPU, the fastest systems are spaCy and UDPipe, and the slowest

is Concraft. Other systems process one order of magnitude fewer tokens per second than the top ones. On GPU, spaCy is the undisputed winner, followed by Stanza, UDPipe, COMBO and Trankit.

Correlation analysis We conduct a statistical analysis to capture meaningful relations between the performance and the model types, the used embeddings, or the datasets. To check whether the performance of a given model on a given tagset allows us to expect similar relationships between the scores on another tagset, we calculate a correlation matrix of vectors composed of the F1 scores for various tasks, i.e. $\vec{v} = [Tokens, Sentences, Words, UPOS, XPOS, Lemmas]$, averaged over embeddings and datasets (see Figure 2). The vectors are calculated for a pair $(tagset_i, model_j)$. To maintain comparability, we exclude PDB-UD from the study as it does not appear in the Morfeusz tagset.

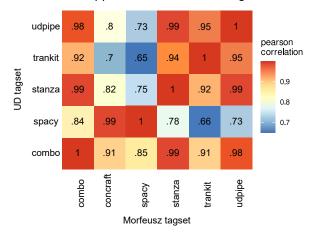


Figure 2: Pearson correlation coefficients between vectors of F1 scores on *Tokens*, *Sentences*, *Words*, *UPOS*, *XPOS*, *Lemmas* tasks averaged over datasets (excluding PDB-UD) and embeddings.

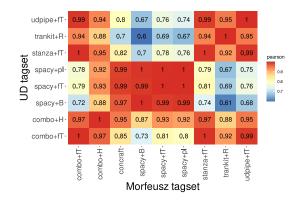


Figure 3: Pearson correlation coefficients between vectors of F1 scores on *Tokens*, *Sentences*, *Words*, *UPOS*, *XPOS*, *Lemmas* tasks averaged over datasets (excluding PDB-UD).

Pearson's correlation r suggests that the results are linearly proportional for the same mod-

²⁰We share a conviction favoured in the NLP community that the training time is slightly less requisite than the inference time since models are trained only once but then constantly reused for predictions. We thus provide inference times.

²¹We run tests uniformly on CPU – Intel Xeon Platinum 8268 processor (1 node with 12 cores), and GPU – 2x Tesla V100-SXM2. The machines used to train the models are listed in Appendix 6.1.

els and different tagsets, which we conclude from the values close to 1 at the intersection of $(model_i, tagset_{UD})$ and $(model_i, tagset_{NKJP})$. Even though correlation coefficients are generally high (i.e. $r \in [0.90, 0.99]$) for most pairs $(model_i, tagset_{UD})$ and $(model_j, tagset_{NKJP})$, there are noticeable lower values for spaCy, i.e. $r \in [0.66, 0.78]$. We hypothesise that this is due to the non-linear rate of changes between the scores, as all Spearman correlation coefficients exceed 0.89 (i.e. $\rho > 0.89$).

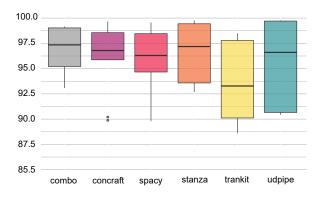


Figure 4: Dispersion of model performance measured by F1 on the Morfeusz tagset and *Sentences*, *Words*, *UPOS*, *XPOS*, and *Lemmas* tasks.

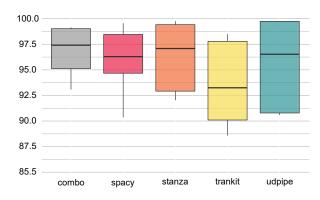


Figure 5: Dispersion of model performance measured by F1 on the UD tagset and *Sentences*, *Words*, *UPOS*, *XPOS*, and *Lemmas* tasks.

The results of a more granular analysis of Pearson's r between vectors of F1 scores for triples (tagset_i, model_j, embeddings_k), averaged over datasets, show a strong correlation for the same models, regardless of the tagset and the embedding (see Figure 3). Hence, if a change in the tagset or embedding causes an increase in one task, a proportional increase in remaining tasks is expected.

Boxplot charts (see Figures 4 and 5) determine the stability of the model results for a given tagset regardless of dataset and embedding. One box shows the scattering of F1 scores for *Tokens*, *Sentences*, *Words*, *UPOS*, *XPOS*, and *Lemmas* tasks. The shortest COMBO's box indicates a relatively similar performance of the model across tasks for each triplet (COMBO, *embedding*_j, *dataset*_k).

5. Conclusions

In this work, we propose a revised approach to NLPre evaluation via benchmarking. This is motivated by the widespread use of the benchmarking technique in other NLP fields on par with the shortcomings of existing NLPre evaluation solutions.

We implement said NLPre benchmarking approach as the online system that evaluates the submitted outcome of an NLPre system and updates the associated leaderboard with the results after the submitter's approval. The benchmarking system is designed to rank NLPre tools available for a given language in a trustworthy environment.

The endeavour of defining and enhancing the system's capabilities is conducted concurrently with the effort to create the NLPre benchmark for Polish that encompasses numerous factors, such as tasks not required in English or diverse tagsets. The NLPre-PL benchmark consists of the predefined NLPre tasks, coupled with two reformulated datasets. The NLPre-PL benchmark, therefore, sets the standard for evaluating the performance of the NLPre tools for Polish, which represents a derivative yet important outcome of our research.

In addition to integration into the benchmarking system, NLPre-PL is used to conduct empirical experiments. We perform a robust and extensive comparison of different NLPre methods, including the classical non-neural tools and the modern neural network-based techniques. The results of these experiments on datasets in two tagsets are discussed in detail. The experiments confirm our assumptions that modern architectures obtain better results. Because NLP is a discipline undergoing rapid progress, new NLPre solutions, e.g. multilingual or zero-shot, can be expected in the coming years. These new solutions can be easily tested and compared with the tools evaluated so far in our benchmarking system.

Finally, we release the open-source code of the benchmarking system in hopes that this endeavour could be replicated for other languages. To expedite this process, we ensure that the system is fully configurable and language- and tagset-agnostic. The NLPre system, configured for a specified language, can be self-hosted on a chosen server, and the results from the leaderboard are conveniently accessible via an API. We see a potential future application of our system to the UD repository, where for 141 languages, there are currently 245 tree-banks with supposedly discrepant versions of the UD tagset.

6. Appendices

6.1. Infrastructure used

We train the models using several types of computational nodes at our disposal, including NVIDIA V100 32GB, NVIDIA GeForce RTX 2080 8GB, NVIDIA GeForce 3070 8GB and Intel Xeon E5-2697 processor. Since we do not perform hyperparameter tuning, this should not impact our results.

6.2. Further results of experiments

Herein, we present a comprehensive depiction of our experimental findings as they are displayed on the NLPre-PL leaderboard.

In Table 5, we present the full results of the evaluation of the selected models on the Morfeuszbased datasets *byName* and *byType*. These results are provided for all available tasks that can be performed on the above-mentioned datasets. As NKJP1M datasets contain no syntantic trees, it is thus impossible to test the dependency parsing task that rely on these trees and measure *UAS*, *LAS*, *CLAS*, *MLAS* and *BLEX*.

In Table 6, we present the results of the evaluation of the selected models on the UD-based datasets *byName*, *byType*, and *PDB*. This table contains the results of segmentation, tagging, and lemmatization tasks. Table 7 is a continuation of Table 6 and it contains the results for the same tagset and dataset on the dependency parsing task.

Model / Task	Dataset	Scores	Average	Tokens	Sentences	Words	UPOS	XPOS	UFeats	AllTags	Lemmas
combo	bN	AA	97.31	-	-	-	98.74	96.63	96.70	96.15	98.36
+ H	bN	F1	96.68	99.07	93.57	99.01	97.76	95.67	95.74	95.20	97.39
	bT	AA	97.28	-	-	-	98.76	96.54	96.65	96.08	98.35
	bT	F1	96.65	99.16	93.08	99.07	97.84	95.65	95.76	95.19	97.44
stanza	bN	AA	95.58	-	-	-	97.97	94.09	94.44	93.89	97.51
+ fT	bΝ	F1	95.88	99.75	92.69	99.43	97.41	93.55	93.91	93.36	96.96
	bT	AA	95.55	-	-	-	97.97	94.10	94.38	93.85	97.43
	bT	F1	95.89	99.77	92.70	99.46	97.45	93.59	93.88	93.35	96.9
combo	bN	AA	95.87	-	-	-	98.15	94.81	94.60	93.97	97.80
+ fT	bN	F1	95.78	99.07	93.57	99.01	97.18	93.87	93.67	93.04	96.84
	bT	AA	95.78	-	-	-	98.22	94.63	94.41	93.77	97.85
	bT	F1	95.72	99.16	93.08	99.07	97.31	93.76	93.54	92.91	96.95
udpipe	bN	AA	93.34	-	-	-	97.57	90.90	91.22	90.90	96.12
+ fT	bΝ	F1	94.44	99.77	90.43	99.75	97.33	90.68	90.99	90.68	95.88
	bT	AA	93.35	-	-	-	97.67	90.87	91.21	90.87	96.13
	bT	F1	94.42	99.73	90.58	99.70	97.38	90.60	90.94	90.60	95.84
trankit	bN	AA	93.06	-	-	-	97.49	91.77	92.05	90.73	93.25
+ R	bN	F1	92.81	98.50	90.19	97.96	95.50	89.89	90.17	88.88	91.35
	bT	AA	92.99	-	-	- -	97.43	91.69	92.03	90.65	93.15
	bT	F1	92.36	98.24	88.58	97.72	95.21	89.59	89.93	88.58	91.02
concraft	bN	AA	93.09	-	-	-	96.24	90.51	91.05	90.51	97.13
	bN	F1	91.70	98.56	71.55	99.65	95.90	90.20	90.73	90.20	96.79
	bT	AA	92.92	-		- -	96.22	90.22	90.79	90.22	97.15
	bT	F1	91.52	98.55	71.10	99.62	95.86	89.88	90.45	89.88	96.79
spacy	bN	AA	70.94	-	-	-	98.54	96.12	31.54	30.96	97.52
+ <i>P</i>	bN	F1	76.23	99.56	62.64	98.45	97.01	94.64	31.05	30.48	96.01
	bT	AA	70.88	-	-	-	98.55	96.03	31.49	30.91	97.44
	bT	F1	76.00	99.56	61.06	98.46	97.03	94.55	31.00	30.43	95.94
spacy	bN	AA	69.77	-	-	-	97.86	92.47	31.54	30.68	96.30
+ pl	bN	F1	75.51	99.56	62.64	98.45	96.34	91.04	31.05	30.21	94.81
	bT	AA	69.66	-	-	-	97.77	92.31	31.49	30.54	96.21
	bT	F1	75.25	99.56	61.06	98.46	96.26	90.89	31.00	30.07	94.73
spacy	bN	AA	69.39	-	-	-	97.42	91.48	31.54	30.61	95.89
+ fT	bN	F1	75.28	99.56	62.64	98.45	95.92	90.06	31.05	30.13	94.40
	bT	AA	69.29	-	-	-	97.35	91.20	31.49	30.49	95.94
	bT	F1	75.02	99.56	61.06	98.46	95.85	89.79	31.00	30.02	94.46

Table 5: Benchmark results for the Morfeusz tagset performed on two datasets: NKJP-byType (bT) and NKJP-byName (bN); AA – Aligned Accuracy; F1 – F1 score. Embeddings used in the models are: R – xlm-RoBERTa-base, fT – fastText, P – Polbert-base, pI – pl-core-news-lg, H – HerBERT.

Model / Task	Dataset	Scores	Average	Tokens	Sentences	Words	UPOS	XPOS	UFeats	AllTags	Lemmas
combo + H	bN bN	AA F1	97.18 96.59	99.07	- 93.57	- 99.01	98.63 97.65	96.45 95.50	96.77 95.81	95.60 94.66	98.42 97.45
	bT	AA	97.17	-	-	-	98.66	96.46	96.70	95.57	98.48
	bT PDB	F1 AA	96.58 93.62	99.15	93.08	99.07	97.75 99.07	95.56 96.65	95.80 96.96	94.68 96.00	97.57 98.13
	PDB	F1	93.37	99.40	96.22	98.22	97.31	94.92	95.23	94.29	96.38
stanza + fT	bN bN	AA F1	94.66 95.20	99.70	92.03	- 99.40	97.67 97.08	93.11 92.55	93.13 92.56	91.73 91.17	97.68 97.09
+ //	bT	AA	94.82	-	-	-	97.78	93.42	93.41	92.05	97.45
	bT	F1	95.46	99.76	92.89	99.47	97.26	92.93	92.91	91.56	96.93
	PDB PDB	AA F1	90.60 92.10	99.86	96.83	99.42	98.21 97.64	93.71 93.17	93.76 93.22	92.69 92.15	96.32 95.77
combo	bN	AA	95.93	-	-	-	98.20	94.79	95.01	93.59	98.04
+ fT	bN bT	F1 AA	95.82 96.00	99.07	93.57	99.01	97.22 98.28	93.86 94.88	94.07 95.05	92.67 93.69	97.07 98.07
	bT	F1	95.85	99.13	93.08	99.07	97.37	94.00	94.17	92.83	97.16
	PDB PDB	AA F1	89.77 90.46	- 99.35	- 96.22	- 98.22	97.07 95.34	93.70 92.03	93.88 92.21	92.05 90.41	97.11 95.37
 trankit	bN		92.68	55.55	50.22		97.31	91.56	91.72	89.51	93.30
+ R	bN	F1	92.57	98.49	90.24	97.95	95.32	89.68	89.84	87.68	91.39
	bT bT	AA F1	92.58 92.12	- 98.24	- 88.58	- 97.73	97.32 95.11	91.43 89.36	91.62 89.55	89.40 87.37	93.15 91.04
	PDB	AA	92.51	-	-	-	99.18	96.28	96.44	95.68	89.08
	PDB	F1	94.03	99.90	98.51	99.89	99.07	96.18	96.34	95.57	88.98
udpipe + fT	bN bN	AA F1	93.20 94.39	- 99.75	90.82	- 99.74	97.61 97.36	90.91 90.68	91.27 91.03	90.29 90.06	95.94 95.70
	bT	AA	93.17	-	-	-	97.59	90.88	91.24	90.20	95.94
	bT PDB	F1 AA	94.35 85.14	99.77	90.59	99.76	97.35 97.43	90.65 88.71	91.02 89.21	89.98 88.16	95.70 94.44
	PDB	F1	88.16	99.86	95.90	99.84	97.28	88.57	89.07	88.02	94.29
spacy	bN	AA	96.82	-	-	-	98.63	96.37	96.50	95.72	96.87
+ <i>P</i>	bN bT	F1 AA	92.15 96.83	99.56	62.64	98.45	97.10 98.67	94.88 96.30	95.00 96.48	94.23 95.68	95.37 97.02
	bT	F1	91.97	99.54	61.06	98.46	97.15	94.82	94.99	94.20	95.52
	PDB PDB	AA F1	87.45 87.98	- 99.65	- 71.46	- 98.51	99.02 97.54	95.77 94.35	95.95 94.52	95.27 93.85	95.19 93.77
spacy	bN	AA	94.27	<u> </u> -	<u>-</u>	-	97.77	92.82	93.12	91.58	96.05
+ pl	bN bT	F1 AA	90.59 94.24	99.56	62.64	98.45	96.25 97.84	91.38 92.75	91.68 93.01	90.16 91.50	94.56 96.10
	bT	F1	94.24	99.54	61.06	98.46	96.34	92.75	93.01	90.09	96.10
	PDB	AA	82.58	-	-	-	97.95	91.50	91.79	90.05	93.07
	PDB	F1	84.21	99.65	71.46	98.51	96.49	90.14	90.42	88.71	91.69
spacy + fT	bN bN	AA F1	93.47 90.10	99.56	- 62.64	98.45	97.34 95.83	91.83 90.40	92.17 90.74	90.48 89.07	95.56 94.07
	bT	AA	93.49	-	-	-	97.44	91.77	92.03	90.42	95.79
	bT PDB	F1 AA	89.91 81.07	99.54	61.06 -	98.46 -	95.93 97.06	90.35 89.91	90.62 90.13	89.03 88.31	94.32 93.10
	PDB	F1	83.03	99.65	71.46	98.51	95.62	88.57	88.79	87.00	91.72

Table 6: Benchmark results for the UD tagset performed on three datasets: NKJP-byType (bT), NKJP-byName (bN), and PDB-UD (PDB) for segmentation, tagging and lemmatization tasks; AA – Aligned Accuracy; F1 – F1 score. Embeddings used in the models are: R – xlm-RoBERTa-base, fT – fastText, P – Polbert-base, pl – pl-core-news-lg, H – HerBERT-base.

Model / Task	Dataset	Scores	Average	UAS	LAS	CLAS	MLAS	BLEX
combo + H	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 93.62 93.37	- - - - 92.97 91.31	- - - - 91.61 89.98	- - - - 90.47 89.03	- - - - 86.15 84.77	88.18 86.77
stanza + fT	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 90.60 92.10	- - - - 91.62 91.09	- - - - 89.34 88.83	- - - - 87.25 86.90	- - - - 80.22 79.90	82.87 82.53
combo + fT	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 89.77 90.46	- - - - 90.10 88.49	- - - - 87.76 86.19	- - - - 85.49 84.14	- - - - 77.88 76.64	82.65 81.34
trankit + R	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 92.51 94.03	- - - - 95.89 95.79	- - - - 94.34 94.24	- - - - 93.10 93.00	- - - - 87.88 87.79	77.26 77.18
udpipe + fT	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 85.14 88.16	- - - - 86.82 86.68	- - - - 83.14 83.01	- - - - 79.52 79.53	- - - - 69.52 69.53	74.48 74.49
spacy + P	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 87.45 87.98	- - - - 89.41 88.08	- - - - 81.54 80.33	- - - - 77.23 80.50	- - - - 72.67 75.75	72.41 75.48
spacy + pl	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	- - - - 82.58 84.21	- - - - 83.39 82.15	- - - - 74.71 73.60	- - - - 72.66 75.71	- - - - 64.21 66.90	66.50 69.29
spacy + fT	bN bN bT bT PDB PDB	AA F1 AA F1 AA F1	81.07 83.03	- - - - 82.13 80.91	- - - - 73.33 72.24	- - - - 70.76 73.72	- - - - 61.02 63.57	64.93 67.64

Table 7: Benchmark results for the UD tagset performed on three datasets: NKJP-byType (bT), NKJP-byName (bN), and PDB-UD (PDB) for the dependency parsing task; AA – Aligned Accuracy; F1 – F1 score. Embeddings used in the models are: R – xlm-RoBERTa-base, fT – fastText, P – Polbert-base, pl – pl-core-news-lg, H – HerBERT.

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