Optimizing a PoS Tag Set for Dependency Parsing

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Abstract

Abstraction ensues.

1 Introduction

PoS tagging is an important preprocessing step for many NLP tasks, such as dependency parsing (Nivre et al., 2007; Hajič et al., 2009), named entity recognition (Tjong Kim Sang and De Meulder, 2003) and sentiment analysis (Wilson et al., 2009). Whereas much effort has gone into the development of PoS-taggers, to the effect that this task is often considered more or less a solved task, considerably less effort has been devoted to the empirical evaluation of the PoS tag sets themselves. Error analysis of PoS-taggers indicate that, whereas tagger improvement though means of learning algorithm or feature engineering seems to have reached something of a plateau, linguistic assessment of the distinctions made by the PoS tag set may be a venue worth investigating further (Manning, 2011). Clearly, the utility of a PoS tag set is tightly coupled with the downstream task for which it is performed. Even so, PoS tag sets are usually employed in a "one size fits all" fashion, regardless of the requirements posed by the task which makes use of this information.

It is well known that syntactic parsing often benefits from quite fine-grained morphological distinctions (Zhang and Nivre, 2011; Seeker and Kuhn, 2013). Morphology interacts with syntax though phenomena such as agreement and case marking and incorporating information on morphological properties of words can therefore often improved parsing performance. However, in a realistic setting where the aim is to automatically parse raw text, the generation of morphological information will often require a separate step of morphological analysis that can be quite costly.

In this paper, we optimize a Norwegian PoS tag set for the task of data-driven dependency parsing. We show that the introduction of morphological distinctions not present in the original tag set, whilst compromising tagger accuracy, actually leads to significantly improved parsing accuracy. In a set of experiments, various morphological distinctions are introduced and evaluated both intrinsically, i.e. in terms of PoS-tagging accuracy, and extrinsically, in terms of parsing accuracy. Our results show that the introduction of morphological distinctions not present in the original tag set, whilst compromising tagger accuracy, actually leads to significantly improved parsing accuracy. This optimization allows us to bypass the additional step of morphological analysis, framing the whole preprocessing problem as a simple tagging The article is structured as follows. We start out by reviewing previous work on tag set evaluation in Section 2 and Section 3 provides an overview of the treebank used for experimentation. Section 4 describes the experimental setup used in our work and Section 5 goes on to provide the results from our optimization experiments. Finally, Section 7 summarizes our main findings and discusses some avenues for future work.

2 Previous/Related work

There has been little previous work dedicated specifically to extrinsic evaluation of the effects of PoS tag sets on downstream applications. There has, however, been some work that evaluates the effects of PoS tag set granularity on PoS tagging. This includes investigation of the effects of PoS tag sets on tagging of Swedish (Megyesi, 2001; Megyesi, 2002) and English (MacKinlay, 2005).

(Megyesi, 2001; Megyesi, 2002) trained and evaluated a range of PoS taggers on

the Stockholm-Umeå Corpus (SUC) (Gustafson-Capková and Hartmann, 2006), annotated with a tag set based on a Swedish version of PAROLE tags totaling 139 tags. Furthermore, they investigated the effects of tag set size on tagging by mapping the original tag set into smaller subsets designed for parsing. They argue that a tag set with complete morphological tags may not be necessary for all NLP applications, for instance syntactic parsing. They found that the smallest tag set comprising 26 tags yields the lowest tagger error rate. However, for some of the taggers, augmenting the tag set with more linguistically informative tags may actually lead to a drop in error rate. They argue that this shows that the size of the tag set as well as the type of information in the tags are crucial factors for tagger performance. However/unfortunately, they do not report results of parsing with the various PoS tag sets.

Similarly, MacKinlay (2005) investigated the effects of PoS tag sets on tagger performance in English, specifically the Wall Street Journal portion of Penn Treebank (Marcus et al., 1993). They mapped the original tag set of Penn Treebank to more fine-grained tag sets using linguistic insight to investigate whether additional linguistic information included in finer-grained tags could assist the tagger. Experimenting with both lexically and syntactically conditioned modifications such as distinguishing between count nouns and noncount nouns and between transitive and intransitive verbs, they found that more fine-grained tag sets rarely led to improvements in tagger accuracy; the most successful modification yielded an improvement in tagger accuracy of 0.05 percentage points.

Transition/overgang her ...

3 Data

3.1 The Norwegian Dependency Treebank

We used the newly developed Norwegian Dependency Treebank (NDT) (Solberg et al., 2014), the first publicly available treebank for Norwegian. It was developed at the National Library of Norway in collaboration with the University of Oslo, and contains manual syntactic and morphological annotation. The treebank contains data from both varieties of Norwegian; 311 000 tokens of Bokmål and 303 000 tokens of Nynorsk. The annotated texts are mostly newspaper text, but also include government reports, parliament transcripts and ex-

Tag	Description
adj	Adjective
adv	Adverb
det	Determiner
inf-merke	Infinitive marker
interj	Interjection
konj	Conjunction
prep	Preposition
pron	Pronoun
sbu	Subordinate conjunction
subst	Noun
ukjent	Unknown (foreign word)
verb	Verb

Table 1: Overview of the PoS tag set of NDT.

cerpts from blogs. The annotation process of the treebank was supported by the Oslo-Bergen Tagger (Hagen et al., 2000) and then manually corrected by annotators.

Morphological Annotation The morphological annotation and PoS tag set of NDT follows the Oslo-Bergen Tagger (Hagen et al., 2000; Solberg, 2013), which in turn is largely based on the work of Faarlund et al. (1997). The tag set consists of 12 morphosyntactic PoS tags, with 7 additional tags for punctuation and symbols. The tag set is thus rather coarse-grained, with broad categories such as subst (noun) and verb (verb). The PoS tags are complemented by a large set of morphological features, providing information about morphological properties such as definiteness, number and tense. These features are used in our tag set modifications, where the coarse PoS tag of relevant tokens are concatenated with one or more of these features to include more linguistic information in the tags.

Syntactic Annotation The syntactic annotation choices in NDT are largely based on the Norwegian Reference Grammar (Faarlund et al., 1997). The annotation choices are outlined in Table 2, taken from/courtesy of Solberg et al. (2014), providing overview of the analyses of syntactic constructions that often distinguish dependency treebanks, such as coordination and the treatment of auxiliary and main verbs. The set of dependency relations comprises 29 dependency relations, including ADV (adverbial), SUBJ (subject) and KOORD (coordination).

Head	Dependent
Preposition	Prepositional complement
Finite verb	Complementizer
First conjunct	Subsequent conjuncts
Finite auxiliary	Lexical/main verb
Noun	Determiner

Table 2: Annotation choices in NDT.

4 Experimental Setup

In preparation to conducting our experiments with linguistically motivated tag set modifications, a concrete setup for the experiments needed to be established, which is presented in the following.

Data Set Split As there was no standardized data set split of NDT due to its very recent development, we needed to establish a data set split (training/development/test). Our data set split of the treebank follows the standard 80-10-10 (training/development/test) split and will be distributed with the treebank and proposed as the new standard(?). In creating the data set split, care has been taken to preserve contiguous texts in the various data sets while keeping the split balanced in terms of genre (and source). Our proposed data set split was used in the Norwegian contribution to the Universal Dependencies project (Øvrelid and Hohle, 2016). The split will be made available at a companion website.

Tagger For our experiments with tag set modifications, we wanted a PoS tagger both reasonably fast and accurate. There is often a trade-off between the two factors/considerations, as the most accurate taggers tend to suffer in terms of speed due to their complexity. However, a tagger that achieves both close to state-of-the-art accuracy as well as very high speed is TnT (Brants, 2000). The fact that TnT was used for evaluating the universal tag set (Petrov et al., 2012), served as another good indication of TnT being appropriate for our task. The sum of these factors led to TnT being the tagger of choice for our experiments.

Parser In choosing a syntactic parser for our experiments, we considered previous work on dependency parsing of Norwegian, specifically that of (Solberg et al., 2014). They found the Mate parser (Bohnet, 2010) to be the most successful parser for the parsing of NDT. Furthermore, recent dependency parser comparisons (Choi et al.,

2015) showed that Mate performed very well on parsing of English, beating a range of contemporary state-of-the-art parsers.

Tag Set Mapping In order to carrying out the tag set modifications, we created a mapping that maps the relevant existing tags to new, more fine-grained tags including more relevant morphological features for the applicable tokens. A given tag set modification involves specifying a tag and one or more features to be concatenated with said tag for all applicable tokens, i.e., tokens that are assigned said tag and contains the set of features in its morphological features.

Baseline It is common practice to compare the performance of PoS taggers to a pre-computed baseline for an initial point of comparison. For PoS tagging, a commonly used baseline is the Most Frequent Tag (MFT) baseline, which we use in our experiments. This involves labeling each word with the tag it was assigned most frequently in the training. All unknown words, i.e., words not seen in the training data, are assigned the tag most frequently assigned to words seen only once in the training. Unknown and infrequent words have in common that they rarely occur, and we might therefore expect them to have similar properties.

Tags & Features As we seek to quantify the effects of PoS tagging in a realistic setting, we want to run the parser on automatically assigned PoS tags. For the training of the parser, however, we have two options: using either gold standard or automatically assigned tags. In order to settle on a configuration, we conducted experiments with gold standard and automatically assigned tags to see how they differ with respect to performance. The results of our experiments reveal that the combination of training and testing on automatic tags is superior to training on gold standard tags and testing on automatic tags. Consequently, the parser was both trained and tested on automatically assigned tags in our experiments.

We removed any morphological features in order to simulate a realistic setting. Moreover, it is crucial that we remove these features when working with automatically assigned tags, as the features is still gold standard. For instance, if a verb token is erroneously tagged as a noun, we could potentially have a noun token with verbal features such as tense, which markedly obfuscates

the training and parsing. Another important aspect is that we want to isolate the effect of PoS tags, necessitating the exclusion of morphological features.

5 Tag Set Optimization/Experiments

With more fine-grained linguistically motivated distinctions, we increase the linguistic information represented in the tags, which may assist the tagger in disambiguating ambiguous and unknown words, which in turn may aid the parser in recognizing and generalizing syntactic patterns. However, the addition of more linguistic information to the tags and thus a more fine-grained tag set will most likely lead to a drop in tagger accuracy, due to the increase in complexity. The best tagging does not necessarily lead to the best parse, and it is therefore interesting to investigate how the tag set modifications may affect the interplay between tagging and parsing.

5.1 Tag Set Experiments

We modified the tags for nouns, verbs, adjectives, determiners and pronouns in NDT by appending selected sets of morphological features to each tag in order to increase the linguistic information expressed by the tags. For each tag, we first experimented with each of the features in isolation before employing various combinations of them. We based our choices of combinations on how promising the features are and what we deem worth investigating in terms of linguistic utility, in order to see how the features might interact.

Nouns In Norwegian, nouns are assigned gender (feminine, masculine, neuter), definiteness (indefinite or definite) and number (singular or plural). There is agreement in gender, definiteness and number between nouns and their modifiers (adjectives and determiners).

Verbs Verbs are inflected for tense (infinitive, present, preterite, past perfect) in Norwegian and can additionally take on mood (imperative, indicative) and voice (active or passive).

Adjectives Adjectives agree with the noun they modify in terms of gender, number and definiteness in Norwegian.

Determiners Like adjectives, determiners in Norwegian agree with the noun they modify in terms of gender, number and definiteness.

Pronouns Pronouns in Norwegian include personal, reciprocal, reflexive and interrogative. They can exhibit gender, number and person. Personal pronouns have case (accusative or nominative).

6 Optimized Pipeline

7 Summary/Conclusion and Future Work

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400	Category	Feature(s)	MFT	Accuracy	LAS	UAS
401	Baseline	_	94.14%	97.47%	87.01%	90.19%
402	Noun	Type, case & definiteness	89.61%	97.05%	88.81%	91.73%
403	Verb	Finiteness	93.72%	97.35%	87.30%	90.43%
403	Adjective	Degree	94.13%	97.41%	87.29%	90.44%
104	Determiner	Definiteness	94.13%	97.49%	87.30%	90.42%
405	Pronoun	Type & case	94.12%	97.51%	87.30%	90.41%

Table 3: Results of tagging and parsing with the most successful tag set modification for each category.

Mitchell Marcus, Beatrice Santorino, and Mary Ann Marcinkiewicz. 1993. Building A Large Annotated Corpus of English: The Penn Treebank. Technical report, University of Philadelphia, Philadelphia, PA, USA.

Tag	Description		
adj komp	Comparative adjective	Вeá	
adj pos	Positive adjective	i	
adj sup	Superlative adjective	C	
det be	Definite determiner	6	
det ub	Indefinite determiner	1	
pron pers	Personal pronoun		
pron pers akk	Personal pronoun, accusative I	Beá	
pron pers nom	Personal pronoun, nominative	S	
pron refl	Reflexive pronoun	t	
pron res	Reciprocal pronoun	S	
pron sp	Interrogative pronoun		
subst appell	Common noun J	loa!	
subst appell be	Common noun, definite	Ι	
subst appell be gen	Common noun, definite, genitive	3	
subst appell ub	Common noun, indefinite	Ċ	
subst appell ub gen	Common noun, indefinite, genitiv	e 6	
subst prop	Proper noun		
subst prop gen	Proper noun, genitive	Slav	
verb fin	Finite verb	A	
verb infin	Nonfinite verb	_ 6	

Table 4: Overview of the optimized tag set.

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Tag set	MFT	Accuracy	LAS	UAS
Original	94.14%	97.47%	87.01%	90.19%
Full	85.12%	93.46%	87.13%	90.32%
Optimized	89.20%	96.85%	88.87%	91.78%

Table 5: Results of tagging and parsing with the optimized tag set, compared to the initial tag sets.

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