Abstract

In principle, the design of transition-based dependency parsers makes it possible to experiment with any general-purpose classifier without other changes to the parsing algorithm. In practice, however, it often takes substantial software engineering to bridge between the different representations used by two software packages. Here we present extensions to MaltParser that allow the drop-in use of any classifier conforming to the interface of the Weka machine learning package, a wrapper for the TiMBL memory-based learner to this interface, and experiments on multilingual dependency parsing with a variety of classifiers. While earlier work had suggested that memory-based learners might be a good choice for low-resource parsing scenarios, we cannot support that hypothesis in this work. We observed that support-vector machines give better parsing performance than MaltParser’s default SVM and linear classifiers for small training sets. We had considered the hypothesis, as suggested by earlier work using several general-purpose classifiers for the same NLP task (Banko and Brill, 2001), that a memory-based learner would provide better parsing accuracy than MaltParser’s default SVM and linear classifiers for small training sets, but our experiments with the default TiMBL settings do not support that hypothesis. Instead, we found that, absent any particular parameter tuning, SVMs gave us the best parsing accuracy for all of our experimental settings, for each of the four languages in our experiments.

2 Transition-Based Dependency Parsing

Transition-based dependency parsers such as MaltParser (Nivre et al., 2006a) are popular for a number of attractive features. First, in their deterministic variety, they operate in linear time in the length of the input sentence, so are comparatively fast when compared with graph-based or chart-parsing methods, which operate in polynomial time (Küberl et al., 2009). Secondly, transition-based methods give state-of-the-art parsing accuracy in many settings: in the recent CoNLL shared tasks on multi-lingual dependency parsing, many of the top-ranking systems were based on transition-based algorithms, and often used MaltParser specifically (Buchholz and Marsi, 2006; Nivre et al., 2007). Of additional interest is that transition-based parsing algorithms have an isolated classification task and can make use of general-purpose machine learners to address it. Thus the user of the parser may experiment with different classification algorithms or parameters.
While keeping the rest of the parsing system fixed.

Deterministic transition-based dependency parsers come in several varieties, but in general, they make a single pass over an input sentence, token by token, and build a dependency structure as the result of a bounded-length series of decisions. At each point in the processing of a sentence, the parser is said to be in a given configuration, and it must choose which possible transition to make in order to proceed to the next configuration: eventually, the parser makes its way from the initial configuration to a final one, in which all of the words in the sentence have been processed. This parsing approach is analogous to the shift-reduce parsing that one might use in a constituency parsing setting (Küber et al., 2009).

Typically, in the initial configuration, an input sentence has been loaded into a buffer $B$, and there is an empty stack $S$, which will have tokens pushed on to it and popped off in the subsequent transitions. Along the way, dependency arcs are formed between words on the front of the buffer and the top of the stack, and these are added to $A$, the set of current arcs, which, in the final configuration, constitutes the dependency parse of the sentence.

There are several possible “transition systems” that can be used with transition-based dependency parsing, each of which provides a different set of transition operations for proceeding through the configurations in the derivation of a particular parse. Many, but not all, transition systems derive only projective dependency trees, which is to say that for any directed arc $(w_i, r, w_j)$ (an arc from word $w_i$ to word $w_j$ with dependency relation $r$), all of the words between $w_i$ and $w_j$ are also either dependents of $w_i$ or transitively dependent on it. Thus for projective trees, dependency relations describe contiguous regions where all of the words share the same head, not unlike the constituents that one might see in a constituency parsing task.

A transition system for projective dependency trees should be both sound and complete with respect to the set of projective dependency trees; this is to say that every output that can be produced by the transition system is in fact a valid projective dependency tree (soundness), and that every projective dependency tree can be produced by some sequence of transitions from the transition system (completeness). The soundness and completeness proofs for several transition systems are provided in (Nivre, 2008). A baseline transition system with only three operations (left-arc, right-arc, and shift) is described in (Küber et al., 2009); these three transitions are sufficient to produce any projective dependency tree. The intuition for the completeness proof is also provided in the book: an algorithm is provided to map from any projective dependency tree to a sequence of these three transitions, and therefore a transition sequence exists such that any particular projective tree could be produced by this transition system.

We have yet to describe the process of how the parsing algorithm decides which transition to take, out of all possible transitions from the current configuration. Given an oracle, a parser could make optimal decisions about how to best proceed to the correct parse; in practice, supervised machine learning techniques are used to simulate an oracle.

The parser has a classifier that has been trained to predict, for a given configuration, what the best available transition is. The training data for these classifiers is produced from a dependency treebank using an algorithm like the one mentioned previously, mapping from parses of sentences to sequences of (configuration, transition) pairs. Features are then extracted from the configurations, and the classifier is trained to predict the transitions, given the features. Commonly used features include the forms, part-of-speech tags, and dependency relations associated with the top word of the stack or next upcoming word from the buffer, though other variations are possible.

While the techniques described so far only produce projective trees, it is often useful, in describing the syntax of natural languages, to allow non-projective dependency structures with crossing arcs. Many of the non-projective structures are familiar from the constituency-parsing world as those that cause difficulties for context-free grammars. For example, in English, topicalization or wh-pronouns (in the case of questions) often make the object of a verb appear outside of a contiguous range with the rest of the dependents of the verb. Non-projective structures are also common in languages with more free word order.

There are at least three different ways to produce non-projective dependency trees with a transition-based parser. One could use a different transition system with extra operations that produce non-projective trees by moving words from the stack back on to the buffer, as described in
Kübler et al., 2009), or one could use a modified parsing algorithm like that of Covington, which makes use of more than one stack (Covington, 2001). Alternatively, one could use a “pseudo-projective” approach, where the non-projective structures are converted to projective ones and annotated in the dependency labels during a preprocessing step. Then at parse time, the classifier will hopefully predict the enriched labels when generating projective trees; these labels include enough information to reconstruct the non-projective trees. This approach is very effective in practice, and was used for many of the winning CoNLL-X shared task entries (Buchholz and Marsi, 2006).

In this work, we are concerned with Nivre’s Arc-Eager transition system, initially described in (Nivre, 2003), which has the operations shift, left-arc, right-arc, and reduce. The arc-creating operations are parameterized by some dependency relation \( r \) from the set of possible dependency relations \( R \), which varies according to the task or treebank in question. The Arc-Eager transition system, without modifications, produces only projective dependency trees, but can be used with pseudo-projective parsing. Arc-Eager modifies earlier systems that did not have a separate reduce operation, and would eliminate words from the buffer immediately upon attaching them to their heads, if they appeared to the right of the head. The Arc-Eager system adds the the reduce operation and thus permits transition sequences in which appropriate arcs can be created eagerly, with the dependent word being used in subsequent arcs as well, since its right-arc operation does not eliminate the dependent word.

3 MaltParser

MaltParser is a popular package for transition-based dependency parsing, developed by Hall, Nilsson and Nivre. MaltParser comes with implementations of several (nine, as of the current version) transition systems for dependency parsing; the default is Nivre’s Arc-Eager system. MaltParser also comes with transition systems that can produce non-projective trees, and pre- and post-processors for pseudo-projective parsing.

For learning to make transition decisions, MaltParser is packaged with two classifier libraries, LIBSVM (Chang and Lin, 2011) and LIBLINEAR (Fan et al., 2008). These packages provide a variety of classification techniques, including support vector machines with various kernels, linear support vector machines, and logistic regression. Each of these classifiers has tunable parameters, such as the type of kernel used for SVMs, or regularization options for logistic regression. MaltParser uses SVMs with a polynomial kernel by default; this was the kernel used by the MaltParser team during both of the CoNLL multilingual dependency parsing shared tasks. In earlier versions of MaltParser, memory-based learning with TiMBL was also supported (Nivre et al., 2004), although this has been removed in the post-1.0 versions of the system, which are implemented in Java. Previous to version 1.0, MaltParser was written in C.

MaltParser seems to have been designed with generality and extensibility in mind; it has has an internal API for integrating arbitrary classifiers, and much of the program logic has been pushed into separate XML files and expressed declaratively. However, large portions of the MaltParser code are specific to LIBSVM and LIBLINEAR, and no documentation about how to add more classifier libraries is provided, so researchers who wish to experiment with other classifiers have a significant software engineering task ahead of them.

4 Weka

Weka (Hall et al., 2009) is a popular machine learning toolkit for Java, freely available online. It includes implementations of a variety of machine learning algorithms, and each algorithm for a given task – classification, clustering, etc. – follows a common interface. Weka can be used either as a stand-alone application or as a library for other JVM programs, and for any given task or data set, Weka makes it convenient to experiment with different machine learners and parameters for those learners. Several third-party machine learning packages also include wrappers for the Weka interface, allowing them to be plugged in to any application using the Weka standard. This variety and generality makes it seem like a natural fit with transition-based dependency parsing; we would like to make it possible to try any classification algorithm as a component of a parsing
system.

One caveat about machine learners included with Weka is that they are not necessarily high-performance, particularly when compared with the implementations of the same algorithms from special-purpose packages such as LIBSVM and LIBLINEAR; while it was easy, from a performance standpoint, to use the decision-tree and Naive Bayes classifiers from Weka, we could not get any parses to succeed using Weka’s logistic regression classifier, due to performance problems that will be discussed later. But Weka contains dozens of other classifiers, and some of them may be perfectly suitable for parsing with MaltParser.

5 The CoNLL-X Shared Task

In the 2006 CoNLL-X shared task on multilingual dependency parsing (Buchholz and Marsi, 2006), participants built dependency parsing systems capable of handling many languages, ideally with the same parsing algorithm and the same machine learners, although perhaps with different parameter settings per language. The evaluation was carried out over thirteen different languages, from a variety of language families, although one (Bulgarian) was optional. The training data made available to the participants contained some non-projective structures, as did the gold standard parses for the testing data, though the systems were not strictly required to produce non-projective parses.

The CoNLL dependency format (Buchholz and Marsi, 2006) has become a standard for dependency parsers. CoNLL-formatted parse trees separately describe each token of a sentence, and can include raw and lemmatized versions of each word, coarse- and fine-grained part of speech tags, additional lexical features, the head of the token, and token’s dependency relation to the head. The lexical features present vary for each language, but they might include information like number, gender, and case. In practice, these features do not seem to be used by working parsers – MaltParser comes with feature sets that make use of in parts of speech, dependency relations, and the surface forms of words.

The participants presented systems based on a variety of techniques, but the best systems used either transition-based dependency parsing or graph-based strategies like those of McDonald’s MSTParser (McDonald et al., 2005). Among the transition-based systems, the highest-scoring parsers used pseudo-projective strategies, deterministic parsing algorithms, and support vector machines with polynomial kernels.

6 Experiments

To evaluate a variety of classifiers, we replicated the CoNLL-X (2006) shared tasks on multilingual dependency parsing. In the interests of reproducibility and frugality, here we ran experiments on the languages with freely available treebanks. Out of the thirteen languages in the evaluation, this leaves Danish, Dutch, Portuguese and Swedish.

We did almost no parameter tuning or feature engineering, save making sure that the task could be run in 8 gigabytes of RAM. We used a feature set already present in MaltParser – the one used for parsing with the Arc-Eager transition system and LIBSVM – and default settings for each software package to get an initial sense for each classifier’s behavior. There are almost certainly classifier settings and feature sets that would provide better parsing accuracy, but finding those is left to interested parties in the future.

Additionally, we did not use pseudo-projective post-processing, since the goal of the experiments was simply to compare the available classifiers. The best CoNLL-X entries performed rather better than the parsers trained in these experiments, and this is due in part to their handling of non-projective structures, which is described in (Nivre et al., 2006b).

We also generated learning curves for the parsing task, varying the amount of training data given to the classifiers in increments of a thousand sentences, from one thousand sentences, up to eleven thousand, which was roughly the entire training set for two of the four languages. For Danish, however, the training set was only 5190 sentences long, so the experiments for that language cut off at six repetitions, and for Portuguese, the training set contains 9071 sentences, so the tenth and eleventh iterations were the same. In all cases, we show the labeled attachment score curves in Figure 1. The unlabeled attachment scores varied similarly, and of course were higher; some of these are given in Figure 4. In Figure 2 we also show the best available CoNLL-X labeled attach-
Figure 1: LAS learning curves for the four languages and various classifiers.

Figure 2: Labeled attachment score for the various languages and classifiers, at the maximum training corpus size, with the winning CoNLL-X scores, for comparison.
We report results for six different classifiers, which are listed in Figure 3. Three of the classification approaches that we tested, LIBSVM with a polynomial kernel, LIBLINEAR’s linear support vector machines, and LIBLINEAR’s logistic regression (also known as a “Maximum Entropy” classifier), are available by default with MaltParser. The remaining three made use of the malt-libweka interface; J48 decision trees and the Naive Bayes classifier are familiar algorithms that have implementations in Weka. The TiMBL memory-based learner also made use of the malt-libweka interface, through a new wrapper that was implemented for these experiments.

Looking at the results, we see that, in all cases, the SVM classifiers outperform the other classifiers, typically followed by logistic regression, decision trees, and TiMBL. Perhaps unsurprisingly, Naive Bayes does not give good parsing results on these tasks, and gave the worst performance for all settings; the features in a parsing task are not mutually independent. At a few points in the learning curves, logistic regression is met or outperformed by TiMBL or decision trees, but at all of the points along the curves, the SVM classifiers perform several LAS points better than the next-best classifier.

We did observe, however, that across all four languages, the linear SVMs outperformed the polynomial-kernel SVMs when trained with the smallest corpora. Also, in parsing Swedish, the linear SVMs were consistently slightly better than the polynomial-kernel ones. The higher performance of the linear SVM on the smaller data sets could be explained by its higher bias, which is to say that, while it is less able to express complex hypotheses in higher-dimensional spaces, this makes it less likely to over-fit small training sets, so the result is not entirely surprising.

Our confidence that the implementation of malt-libweka is basically correct, and not the source of the lower performance of the other classifiers, stems from comparing the performance of the J48 and TiMBL classifiers with that of the linear regression setting for LIBLINEAR; they had very comparable performance with one of the major modes of operation for LIBLINEAR, in some cases equalling or outperforming it. It seems that support vector machines are simply a good choice for parsing tasks.

7 Software

One contribution of this work is a reusable package, malt-libweka, which is freely available online. malt-libweka itself is a library that works with MaltParser; its repository includes scripts that can be used to reproduce the results in this paper, or could be easily modified to do further parsing experiments on treebanks in the CoNLL format.

While MaltParser is open-source and designed for extensibility, the development of malt-libweka took non-trivial software engineering effort, largely due to a lack of documentation of the internals of MaltParser, which was perhaps not implemented with the convenience of third-party developers in mind. While MaltParser apparently has a plugin system, both mentioned in the online documentation and present in the source code, it was non-obvious how to use it, and we could not find examples of it being used in practice. Whether or not the plugin system is in a usable state, MaltParser’s source tree definitely contains substantial amounts of “dead code” with misleading names. Particularly, while the “LibSvm” and “LibLinear” classes are instrumental in MaltParser’s interfaces to the corresponding machine learning packages, MaltParser also contains the classes “Libsvm” and “Liblinear”– note the capitalization differences. The latter two seem to be entirely vestigial, and not called in the current version.

Hopefully the use of malt-libweka will save future developers from having to delve too much into the source of MaltParser when they would like to experiment with MaltParser and different classifiers. With malt-libweka, users need only adapt their machine learners to the interface used in Weka; a straightforward example of this is provided in the maltparser.TimblClassifier class. For this use case, the only required methods in the interface are buildClassifier and classifyInstance, which, respectively, train a classifier given a set of training instances and return a predicted class for a given instance. The existing MaltParser code, coupled with malt-libweka, handle the rest of the process, including extracting the relevant features from parse configurations and then making those features available.
### Figure 3: The six different classifiers used in experiments.

| label   | description                                                                 |
|---------|-----------------------------------------------------------------------------|
| libsvm  | LIBSVM: polynomial kernel (default for MaltParser)                          |
| linearsvm | LIBLINEAR: linear SVM                                                       |
| logistic | LIBLINEAR: logistic regression                                               |
| j48     | malt-libweka with Weka’s J48 decision tree classifier                       |
| timbl   | malt-libweka with our new Weka wrapper for TimBL                            |
| naivebayes | malt-libweka with Weka’s NaiveBayes classifier                          |

### Figure 4: Scores for different classifiers (rounded, as a percentage), on each of the four languages, Danish, Dutch, Portuguese, and Swedish. The designation (sm) is for the smallest training set that was tried with the given language, and (lg) indicates the largest. In all cells of the table, the first number is the LAS, and the second is the UAS.

| classifier | da (sm) | nl (sm) | pt (sm) | sv (sm) | da (lg) | nl (lg) | pt (lg) | sv (lg) |
|------------|---------|---------|---------|---------|---------|---------|---------|---------|
| libsvm     | 75, 81  | 54, 59  | 79, 84  | 73, 81  | 81, 86  | 69, 72  | 84, 80  | 83, 89  |
| linearsvm  | 77, 84  | 55, 62  | 79, 86  | 75, 84  | 81, 86  | 68, 72  | 83, 88  | 83, 89  |
| logistic   | 71, 79  | 50, 57  | 77, 83  | 69, 78  | 77, 83  | 64, 68  | 80, 84  | 76, 84  |
| j48        | 67, 75  | 50, 58  | 74, 81  | 65, 74  | 74, 82  | 63, 68  | 79, 85  | 76, 84  |
| timbl      | 68, 76  | 51, 58  | 72, 80  | 63, 75  | 76, 83  | 64, 68  | 78, 85  | 73, 82  |
| naivebayes | 58, 66  | 44, 52  | 68, 75  | 57, 64  | 62, 69  | 54, 58  | 71, 77  | 63, 69  |

7.1 Implementing the TiMBL-Weka Interface

TiMBL, described in detail in [Daelemans et al., 2010], is a package for memory-based learning, and is freely available online[^1]. As a lazy learner, TiMBL’s training process consists of storing all of the examples that it is given for use at classification time, where the values of the features of these examples could be treated in a symbolic, nominal way, or as numbers over which there is an ordering or a distance. At an implementation level, the TiMBL classifier can be run as a server with the timblserver package, making it possible to interface with TiMBL from a program written in any language that has a networking library.

In implementing the Weka wrapper for TiMBL, we had to implement the code for training time, and for classification time. For the code for the training procedure, we serialize all of the training instances to a file readable by the TiMBL software, which uses, roughly, a CSV format. Then, when it is time to parse, we need to be able to classify new instances, so the Java program opens a connection to the timblserver – which must be started by some external program, in this case the scripts that manage the parsing experiments – and serializes a new instance then sends it across the network. Then TiMBL sends back its classification result, and we must, on the Java side, reinterpret the result as a number for MaltParser’s consumption. The implementation of the Weka wrapper for TiMBL took roughly 100 lines of Java, most of which manages the network connection.

8 Discussion

An issue that we encountered during development was that we had to maintain the meaning of the representations used internally by MaltParser, when they were passed to Weka classifiers. At an early stage of processing, MaltParser builds several vocabularies, mapping from tokens and the provided lexical features (POS tags, etc) to integers, so that the system need not pass around large strings. So sensibly, both at training time and at parsing time, the classifiers called by MaltParser are presented with integers rather than strings. These should not be treated as anything other than unique identifiers, but it would be fairly easy for a programmer to allow a classifier trained on these numbers to interpret them as ordinal numbers or take distances over them. But during early development of the system, we made exactly this mis-

[^1]: [http://ilk.uvt.nl/timbl/]
take; we discovered the problem when inspecting the decision trees learned by Weka’s J48 classifier, which was making comparisons with a less-than operator. J48 is a Java reimplementation of the C4.5 algorithm (Quinlan, 1993), which will try to do comparisons over ordinal numbers given the opportunity. With this in mind, we made Weka interpret the features passed to it as nominal features – although they are still represented as numbers – which prevents order-based comparisons.

However, the logistic regression algorithm, in a mathematical sense, is defined in terms of distances over numbers. If the Weka implementation is given nominal attributes, it will binarize them into a larger number of binary attributes. In this process, an attribute that has \( n \) possible values is transformed into \( n \) different binary attributes. So for many features passed to the learner during the parsing task, there are many thousands of possible values. If we consider the feature “which word is on the top of the stack”, any word in the vocabulary could appear.

During development, we ran across a few surprising performance problems. The binarization code in Weka is much less efficient than it could be, and while trying to parse some of the smaller datasets, the system would run out of memory during binarization, even when given 8 gigabytes of RAM. This seemed surmountable, so we implemented a more efficient version of feature binarization (maltlibweka.FastBinarizer), in hopes that this would let us experiment with Weka’s logistic regression. But the training times for Weka’s Logistic class ended up being unbearably long and prohibitively memory-intensive when given large numbers of binary features, so we also tried a few approaches for feature selection, though were not successful in this regard. In the end, we gave up on Weka’s logistic regression implementation, although we had hoped to compare it to the one in LIBLINEAR.

So while any given classifier may not perform well in terms of parsing accuracy, or even computational efficiency – as we have seen in the course of this work – malt-libweka makes it straightforward to try new classifiers and new parameters for those classifiers on parsing tasks. And to adapt a new classifier to work with Weka and thus malt-libweka, the programmer need only provide a method that trains the classifier given a set of training instances and another that classifies a given instance after training, barring mishaps with the classifier not scaling well to the parsing task.

9 Conclusions and Future Work

We have introduced extensions to MaltParser that enable experimentation with different classifiers for transition-based dependency parsing, making such experiments straightforward in practice, when previously they were only straightforward in theory. We have also presented experiments with six classifiers for a standard multilingual dependency parsing task, including varying the size of the training set. We were not able to support the hypothesis that memory-based learners provide better parsing accuracy than support-vector machines in low-resource settings; in fact, for settings with small training sets as well as those with comparatively large ones, support vector machines continue to perform the best out of the approaches considered. Our results also suggest that for small training sets, linear support vector machines are a good choice.

There may well be classifiers, or parameter settings for the algorithms, that learn better parsers for training sets of these sizes for these languages. There may also be better feature sets, perhaps making use of agreement information for morphologically rich languages, and those with more free word order. Finding out which parameters and which settings is, however, left to future work. Hopefully malt-libweka will make these experiments easy to carry out.

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