IllinoisSL: A JAVA Library for Structured Prediction

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Abstract

ILLINOISL is a Java library for learning structured prediction models. It supports structured Support Vector Machines and structured Perceptron. The library consists of a core learning module and several applications, which can be executed from command-lines. Documentation is provided to guide users. In comparison to other structured learning libraries, ILLINOISL is efficient, general, and easy to use.

1. Introduction

Structured prediction models have been widely used in several fields, ranging from natural language processing, computer vision, and bioinformatics. To make structured prediction more accessible to practitioners, we present ILLINOISL, a Java library for implementing structured prediction models. Our library supports fast parallelizable variants of commonly used models like Structured Support Vector Machines (SSVM) and Structured Perceptron (SP), allowing users to use multiple cores to train models more efficiently. Experiments on part-of-speech (POS) tagging show that models implemented in ILLINOISL achieve the same level of performance as SVM\textsuperscript{struct}, a well-known C++ implementation of Structured SVM, in one-sixth of its training time. To the best of our knowledge, ILLINOISL is the first fully self-contained structured learning library in Java. The library is released under NCSA licence\footnote{http://opensource.org/licenses/NCSA} providing freedom for using and modifying the software.

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| Task               | $x$     | $y$     | INF/Solver | Feature/Generator |
|-------------------|---------|---------|------------|-------------------|
| POS Tagging       | sentence| tag     | Viterbi    | Emission and Transition Features |
| Dependency Parsing| sentence| dependency| Chu-Liu-Edmonds | Edge features |
| Cost-Sensitive Multiclass | document | document category | argmax | document features |

Table 1: Examples of applications implemented in the library.

ILLINOISL provides a generic interface for building algorithms to learn from data. A developer only needs to define the input and the output structures, and specify the underlying model and inference algorithm (see Sec. 3). Then, the parameters of the model can be estimated by the learning algorithms provided by library. The generality of our interface allows users to switch seamlessly between several learning algorithms.

The library and documentation are available at [http://cogcomp.cs.illinois.edu/page/software_view/illinois-sl](http://cogcomp.cs.illinois.edu/page/software_view/illinois-sl).

2. Structured Prediction Models

This section introduces the notation and briefly describes the learning algorithms. We are given a set of training data $D = \{x_i, y_i\}_{i=1}^l$, where instances $x_i \in X$ are annotated with structured outputs $y_i \in Y_i$, and $Y_i$ is a set of feasible structures for the $i^{th}$ instance.

Structured SVM (Taskar et al., 2004; Tsochantaridis et al., 2005) learns a weight vector $w \in \mathbb{R}^n$ by solving the following optimization problem:

$$
\min_{w, \xi} \quad \frac{1}{2} w^T w + C \sum_i \xi_i^2 \quad \text{s.t.} \quad w^T \Phi(x_i, y_i) - w^T \Phi(x_i, y) \geq \Delta(y_i, y) - \xi_i, \quad \forall i, y \in Y_i. \quad (1)
$$

where $\Phi(x, y)$ is a feature vector extracted from both input $x$ and output $y$. The constraints in (1) force the model to assign higher score to the correct output structure $y_i$ than to others. $\xi_i$ is a slack variable and we use $L^2$ loss to penalize the violation in the objective function (1). ILLINOISL supports two algorithms to solve (1), a dual coordinate descent method (DCD) (Chang et al., 2010; Chang and Yih, 2013) and a parallel DCD algorithm, DEMI-DCD (Chang et al., 2013).

ILLINOISL also provides an implementation of Structured Perceptron (Collins, 2002). At each step, Structured Perceptron updates the model using one training instance $(x_i, y_i)$ by $\hat{y} \leftarrow \arg\max_{y \in Y_i} w^T \phi(x_i, y)$, $w \leftarrow w + \eta(\phi(x_i, y_i) - \phi(x_i, \hat{y}))$, where $\eta$ is a learning rate. Our implementation includes the averaging trick introduced in Daumé III (2006).

3. IllinoisSL Library

We provide command-line tools to allow users to quickly learn a model for problems with common structures, such as linear-chain, ranking, or a dependency tree.

The user can also implement a custom structured prediction model through the library interface. We describe how to do the latter below.
Library Interface. IllinoisSL requires users to implement the following classes:

- **IInstance**: the input \( x \) (e.g., sentence in POS tagging).
- **IStructure**: the output structure \( y \) (e.g., tag sequence in POS tagging).
- **AbstractFeatureGenerator**: contains a function FeatureGenerator to extract features \( \phi(x, y) \) from an example pair \( (x, y) \).
- **AbstractInfSolver**: provides a method for solving inference \( \arg \max_y w^T \phi(x_i, y) \) and for loss-augmented inference \( \arg \max_y w^T \phi(x_i, y) + \Delta(y, y_i) \), and a method for evaluating the loss \( \Delta(y, y_i) \). For example, in POS tagging, this class will include implementations of a viterbi decoder and the hamming loss, respectively.

Once these classes are implemented, the user can seamlessly switch between different learning algorithms.

Ready-To-Use Implementations. The IllinoisSL package contains implementations of several common NLP tasks including a sequential tagger, a cost-sensitive multiclass classifier, and an MST dependency parser. Table ?? shows the implementation details of these learners. These implementations provide users with the ability to easily train a model for common problems using the command lines, and also serve as examples for using the library. The README file provides the details of how to use the library.

Documentation. IllinoisSL comes with detailed documentations, including JAVA API, command-line usage, and a tutorial. The tutorial provides a step-by-step instructions for building a POS tagger in 350 lines of JAVA code. Users can post their comments and questions about the package to illinois-ml-nlp-users@cs.uiuc.edu.

4. Comparison

To show that IllinoisSL-based implementation of common NLP systems is on par with other structured learning libraries, we compare IllinoisSL with SVMstruct\(^2\) and Seqlearn\(^3\).

\(^2\)http://www.cs.cornell.edu/people/tj/svm_light/svm_struct.html
\(^3\)https://github.com/larsmans/seqlearn
on a Part-of-speech (POS) tagging problem. We follow the settings in Chang et al. (2013) and conduct experiments on the English Penn Treebank bank (PTB) (Marcus et al.). SVMstruct solves an L1-loss structured SVM problem using a cutting-plane method (Joachims et al., 2009). Seqlearn implemented a structured Perceptron algorithm for the sequential tagging problem. For ILLINOISSL, we use 16 CPU cores to train the structured SVM model. Default parameters are used. Figure 1a shows the accuracy along training time of each model with default parameters. Despite being a general-purpose package, ILLINOISSL is more efficient than others.

We also implemented a minimum spanning tree based dependency parser using ILLINOISSL API. The implementation was done in less than 1000 lines of code, with a few hours of coding effort. Figure 1b shows the performance of our system in accuracy of head words (i.e., unlabeled attachment score). ILLINOISSL is competitive with MSTParser, a popular implementation of dependency parser.

References

K.-W. Chang, V. Srikumar, and D. Roth. Multi-core structural SVM training. In ECML, 2013.

M. Chang and W. Yih. Dual coordinate descent algorithms for efficient large margin structural learning. TACL, 2013.

M. Chang, V. Srikumar, D. Goldwasser, and D. Roth. Structured output learning with indirect supervision. In ICML, 2010.

M. Collins. Discriminative training methods for hidden Markov models: Theory and experiments with perceptron algorithms. In EMNLP, 2002.

H. Daumé III. Practical Structured Learning Techniques for Natural Language Processing. PhD thesis, University of Southern California, 2006.

T. Joachims, T. Finley, and Chun-Nam Yu. Cutting-plane training of structural SVMs. Machine Learning, 2009.

M. P. Marcus, B. Santorini, and M. A. Marcinkiewicz. Building a large annotated corpus of english: The penn treebank. Computational Linguistics.

A. C. Müller and S. Behnke. pystruct - learning structured prediction in Python. JMLR, 2014.

B. Taskar, C. Guestrin, and D. Koller. Max-margin markov networks. In NIPS, 2004.

I. Tsochantaridis, T. Joachims, T. Hofmann, and Y. Altun. Large margin methods for structured and interdependent output variables. JMLR, 2005.

4. We do not compare with pyStruct (Müller and Behnke, 2014) because their package does not support sparse vectors. When representing the features using dense vector, pyStruct suffers from large memory usage and computing time.

5. Note that different learning packages using different training objectives. Therefore, the accuracy performances are slightly different.

6. http://www.seas.upenn.edu/ strctlrn/MSTParser/MSTParser.html