An Empirical Evaluation of Sequence-Tagging Trainers

P. Balamurugan\textsuperscript{1}, Shirish Shevade\textsuperscript{1}, S. Sundararajan\textsuperscript{2}, and S. S. Keerthi\textsuperscript{3}

\textsuperscript{1}Computer Science and Automation, Indian Institute of Science, Bangalore, India.
\textsuperscript{2}Microsoft Research, Bangalore, India.
\textsuperscript{3}Cloud and Information Services Lab, Microsoft Corporation, Mountain View, CA, USA.

Abstract The task of assigning label sequences to a set of observed sequences is common in computational linguistics. Several models for sequence labeling have been proposed over the last few years. Here, we focus on discriminative models for sequence labeling. Many batch and online (updating model parameters after visiting each example) learning algorithms have been proposed in the literature. On large datasets, online algorithms are preferred as batch learning methods are slow. These online algorithms were designed to solve either a primal or a dual problem. However, there has been no systematic comparison of these algorithms in terms of their speed, generalization performance (accuracy/likelihood) and their ability to achieve steady state generalization performance fast. With this aim, we compare different algorithms and make recommendations, useful for a practitioner.

We conclude that the selection of an algorithm for sequence labeling depends on the evaluation criterion used and its implementation simplicity.

1 Introduction

In conventional classification learning, the aim is to learn a function which assigns discrete (scalar) labels to unseen objects, given a set of already labeled training set examples. There exist tasks in computational linguistics or bioinformatics, which are often described as mappings from input sequences to output sequences. As an example, in computational linguistics, such tasks include part-of-speech (POS) tagging, named entity recognition (NER) and shallow parsing (Sha and Pereira, 2003).

In this work, we focus on discriminative models for sequence learning. Lafferty et al. (2001) introduced conditional random fields (CRFs), an undirected graphical model that models \( p(y|x) \) directly, and proposed to use iterative scaling algorithms for CRF training. Subsequently, Sha and Pereira (2003) demonstrated that preconditioned conjugate gradient or limited-memory quasi-Newton (L-BFGS) methods offer significant training speed advantages over iterative scaling. These batch algorithms were found to be very slow on large sequence labeling problems. On a benchmark data set with about 35,000 examples and 18 million features, L-BFGS method for CRF training required about five days on a reasonably fast machine to design a classifier. Therefore, in this work, we consider online algorithms where model parameters are updated after visiting each example. Note that, though some of the algorithms discussed here are fundamentally batch algorithms, they have an online feel and are reasonably fast.

Many real world prediction problems can be posed as structured prediction problems, where the output is a structured object like a sequence or a tree or a graph. Large margin methods like support vector machines (SVMs) have shown much promise for
structured output learning (Tschantaridis et al., 2005). In recent years, several learning algorithms have been proposed to solve the structured prediction problems involving sequence labeling. Some prominent methods among them include stochastic gradient descent (SGD) algorithm for CRFs (Bottou, 2011), Sequential Minimal Optimization (SMO) (Taskar et al., 2003), Cutting Plane method (Joachims et al., 2009), Sequential Dual Method (SDM) (Balamurugan et al., 2011), exponentiated gradient (EG) methods (Collins et al., 2008) for max-margin Markov networks (also called Structural SVMs) and structured perceptron (Collins, 2002). These methods assume exact inference, which is often computationally expensive. Huang et al. (2012a) proposed the variants of perceptron, called “violation-fixing perceptrons”, which use a violation (approximate inference) in each update. It is important to note that all these algorithms (except the structured perceptron algorithm) solve either a primal problem or a dual problem. It will be therefore interesting to compare these algorithms in terms of their speed and generalization performance achieved by the resulting model. Nguyen and Guo (2007) compared some prominent algorithms for sequence labeling. However, as pointed out in (Keerthi and Sundararajan, 2007), this comparison employed different internal feature functions and therefore the comparison was not fair. In the case of sequence labeling, to the best of our knowledge, there has been no systematic comparison of models obtained by using different algorithms, which solve either a primal or a dual problem and use the same set of feature functions. We believe that, this evaluation will be useful for practitioners and help them choose an appropriate method for sequence labeling depending upon the requirement.

Contributions: This work is motivated by the need to compare different sequence labeling algorithms systematically on real-world data sets and make recommendations about the algorithm selection. We consider two types of convex loss functions and compare methods which solve the regularized loss minimization problem (either the primal problem or its equivalent dual). The loss functions used are: a) A variant of the hinge loss function used in large-margin classification problems, and b) the negative log-likelihood function (used in CRFs). In particular, we compare i) stochastic gradient descent (SGD) method for CRF to solve the primal problem for regularized loss function (b), ii) Cutting Plane (CP) method to solve the dual problem of regularized loss function (a), iii) Sequential Dual Method (SDM) (which can be used to solve the dual problems obtained using either of the loss functions), and iv) Averaged Structured Perceptron Algorithm (which does not use any objective function). On a number of experiments carried out on large-scale real-world data sets, we observed that the sequential dual method for SVMs and stochastic gradient descent methods should be preferred if test set accuracy and likelihood are respectively the evaluation criteria. Further, the averaged structured perceptron algorithm does achieve comparable test set accuracy, if not test set likelihood. This is despite the fact that it does not optimize any objective function!

The paper is organized as follows. The following section briefly describes different sequence learning algorithms used in this work. The details of various experiments performed on large data sets and their results are given in Section 3. Our recommendations are presented in Section 4.

2 Sequence Learning Algorithms

In this section, we describe various sequence learning algorithms used in this work. We assume that a training set $S$ of input-output sequence pairs is available. Let $S = \{ (x_i, y_i) \}_{i=1}^{n}$ where $x_i \in \mathcal{X}$ and $y_i \in \mathcal{Y}$ for every $i$. The goal is to learn a discriminant function $g : \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$ over the training set $S$ from which prediction for a input $x$ is
given by
\[ h(x) = \arg\max_{y \in \mathcal{Y}} g(x, y). \]

For sequence labeling problems, the \( \arg\max \) computation in the above equation can be done using dynamic programming like the Viterbi algorithm. If an input sequence and the corresponding output sequence are of length \( L \), and each individual label of the output sequence can take values from the set \( \Sigma \), then the sequence labeling problem can be considered as a multi-class classification problem with \( |\Sigma|^L \) classes. This demonstrates that the cardinality of \( \mathcal{Y} \) grows exponentially with the size of \( x \). In this work, we assume that \( g(x, y) \) takes the form of a linear function,
\[ g(x, y) = w^T f(x, y) \]
where \( w \) is a parameter vector and \( f(x, y) \) is a feature vector relating input \( x \) and \( y \).

Using a variant of the hinge loss function, the sequence learning problem can be posed as an extension of multi-class SVM problem as follows (Crammer and Singer, 2001):
\[
\min_w \xi \lambda \frac{1}{2} \| w \|^2 + \sum_i \xi_i \\
\text{s.t. } w^T \Delta f_i(y) \geq l_i(y) - \xi_i \forall i, y
\]
where \( \Delta f_i(y) = f(x_i, y_i) - f(x_i, y) \) and \( \lambda > 0 \) is a regularization parameter. \( l_i(y) \) in (1) is a loss function that quantifies the loss associated with predicting \( y \) instead of the correct output \( y_i \). In sequence learning problems, a natural choice for the loss function is the Hamming distance,
\[ l_i(y) = \sum_{j=1}^{L} I(y_j \neq y_j^i) \]

where \( I(\cdot) \) is the indicator function and \( y = (y^1, y^2, \ldots, y^L) \). By defining the conditional distribution,
\[
p(y|x; w) = \frac{e^{w^T f(x, y)}}{Z_x}
\]
where \( Z_x = \sum_{y'} e^{w^T f(x, y')} \) is the partition function and using the negative log-likelihood function, the parameter \( w \) can be learned by solving the following unconstrained optimization problem:
\[
\min_w \lambda \frac{1}{2} \| w \|^2 - \sum_i \log p(y_i|x_i; w)
\]
where \( \lambda > 0 \) is a regularization parameter. CRF training (batch algorithm) involves solving the problem (3) in batch mode. Note that both the problems (1) and (3) are convex programming problems and the optimal solution \( w \) can be used for making the prediction for a specific input \( x \) as \( \arg\max_{y \in \mathcal{Y}} w^T f(x, y) \).

We note that a variety of techniques have been developed in the literature to solve large scale sequence learning problems. These include bundle method (Teo et al., 2007).
fast Newton-CG method for batch learning of CRFs (Tsuboi et al., 2011), SGD and block coordinate methods for $L_1$ regularized and elastic-net CRFs (Lavergne et al., 2010), stochastic meta-descent method (Vishwanathan et al., 2006), stochastic block coordinate Frank-Wolfe optimization (Lacoste-Julien et al., 2013), dual coordinate ascent method (Martins et al., 2010) and excessive gap reduction technique (Zhang et al., 2011). The number of dual variables for the problems (1) and (3) is exponentially large and techniques which use marginal variables (which are polynomial in number and from which dual variables can be easily derived) were also proposed in the literature. These techniques include exponentiated gradient method (Collins et al., 2008) and sequential minimal optimization algorithm (Taskar et al., 2003). It will be difficult to compare every method proposed in the literature. Therefore, in this work, we restrict ourselves to algorithms which are simple, easy to implement from a practitioner’s viewpoint and solve the problems (1) and (3) or their dual problems directly.

Recently, adaptive-rate and parameter-free variants of SGD have also been proposed for binary classification tasks in (Duchi et al., 2011) and (Schaul et al., 2012). While a simple SGD chooses the learning rate to be $\frac{1}{t}$, $t$ being the number of iterations, adaptive-rate variant of SGD (Duchi et al., 2011) updates the learning rate for each component of the model parameter $w$ by incorporating gradient-information from the past iterations. However, tuning is required to find an initial choice of the learning rate. Schaul et al. (2012) propose to automatically choose the learning rate based on a second-order approximation of the loss function at a particular component of $w$, thus eliminating the need to tune the learning rate altogether. However, making the learning rate automatically-tuned or adaptable, comes at an added cost of computing the second order information or book-keeping gradient information, thus increasing the iteration complexity of the basic SGD. Moreover, the results given in (Schaul et al., 2012) show that the generalization performance achieved by the basic SGD is comparable and sometimes better than that achieved by the adaptive-rate and parameter-free variants of SGD. Hence, we resort to the basic SGD method with averaging (Bottou, 2011), in our experiments.

In the following, we give a brief description of the algorithms used to solve the problems (1) and (3) and compared in this work.

2.1 Cutting Plane Method (CP)

Joachims et al. (2009) proposed an equivalent formulation of the problem (1), given by (4) and presented a cutting-plane algorithm, which is significantly fast on large scale problems. It was shown that the dual problem of (4) has a sparse solution (that is, the number of non-zero dual variables is small at optimality).

$$\min_{w, \xi} \frac{\lambda}{2} \|w\|^2 + \xi$$

s.t. $\frac{1}{n}w^T \sum_{i=1}^n \Delta f_i(y) \geq \frac{1}{n} \sum_{i=1}^n l_i(y) - \xi, \forall \{y_1, \ldots, y_n\} \in Y^n$ (4)

Even for large data sets, the size of the quadratic programs that need to be solved was observed to be very small (as the number of violated constraints was very small) and therefore, the method achieved considerable speed-up. We note that the bundle method presented in (Teo et al., 2007) is similar to the cutting-plane algorithm and therefore, we do not use it for comparison.
2.2 Sequential Dual Method for Structural SVMs (SVM-SDM)

Balamurugan et al. (2011) suggested the use of sequential dual method (SDM) to solve the dual problem of (1).

\[
\begin{align*}
\min \frac{1}{2\lambda} \| \sum_{i,y} \alpha_i(y) \Delta f_i(y) \|^2 - \sum_{i,y} \alpha_i(y) l_i(y) \\
\text{s.t.} \sum_y \alpha_i(y) = 1 \forall i, \alpha_i(y) \geq 0 \forall i, y
\end{align*}
\]

(5)

The method makes repeated passes over the training data set and optimizes the dual variables associated with one example at a time, until some stopping condition is satisfied. Note that the number of dual variables in (5) is exponentially large for every example \(i\). However, at optimality, very few of the dual variables are strictly positive. This fact was used to develop a fast and efficient algorithm to solve the dual problem (5). Some heuristics were also proposed to make the sequential dual method more efficient. This method was found to be an order of magnitude faster than the cutting-plane method on many sequence-learning data sets (Balamurugan et al., 2011).

2.3 Averaged Stochastic Gradient Descent Method for CRF (CRF-ASGD)

Gradient based online methods like stochastic gradient descent (SGD) can be used to solve the CRF primal problem (3) (Bottou, 2011). The SGD method is fast and is quite useful when the training data size is large. It operates by visiting each example and updating the parameter \(w\) through a simple update step. For example, at iteration \(t\), using a single training example (say \(x_i\)), the following simple update rule is used:

\[
w_{t+1} = w_t - \gamma_t (\lambda w_t + f(x_i, y_i) - E_{p(y|x_i)} f(x_i, y))
\]

(6)

where \(\gamma_t\) is a learning rate parameter (typically set to \(\frac{1}{t+1}\)). The expectation term, \(E_{p(y|x_i)} f(x_i, y)\) is calculated with respect to the conditional probability (2). This is usually done using a forward-backward algorithm (Lafferty et al., 2001). The SGD method, though simple, requires multiple passes over the data before it converges to the optimal solution. To overcome this difficulty, Xu (2011) proposed a method which averages the parameter \(w\). An average parameter \(\bar{w}\) is maintained and updated at every iteration,

\[
\bar{w}_{t+1} = \frac{t}{t+1} w_t + \frac{1}{t+1} w_{t+1}.
\]

(7)

This method, called averaged SGD (ASGD), has been demonstrated to make reasonable progress in the objective function in the initial few iterations. A thorny issue with online methods like SGD or ASGD methods is the choice of the initial learning rate, \(\gamma_0\). With an improper choice, the methods might become very slow on large data sets. Choosing a suitable \(\gamma_0\) involves taking a random sample of the data set initially and performing SGD or ASGD updates on this selected sample using different learning rate values and then choosing the best learning rate as the rate which gives maximum decrease in the objective function. Having determined the initial learning rate \(\gamma_0\), the method then proceeds in the normal fashion on the entire training set.

2.4 Sequential Dual Method for CRF (CRF-SDM)

Inspired by the speed-up achieved by SVM-SDM over state-of-the-art methods, we implemented a sequential dual method to solve the dual of the CRF primal problem (3).
Memisevic (2006) and Yu et al. (2011) proposed to solve the dual of (3) for multi-class classification problems. These methods cannot be directly used for sequence learning problems as the number of dual variables is exponentially large for such problems. Further, the resulting model at optimality is not sparse. That is, all the possible sequences are used to define the parameter vector,

$$\mathbf{w}(\alpha) = \frac{1}{\lambda} \sum_{i,y} \alpha_i(y) \Delta f_i(y)$$

(8)

when the following dual problem of (3) is solved:

$$\begin{align*}
\min & \quad \frac{1}{2\lambda} ||\mathbf{w}(\alpha)||^2 + \sum_{i,y} \alpha_i(y) \log \alpha_i(y) \\
\text{s.t.} & \quad \sum_{y} \alpha_i(y) = 1 \quad \forall \ i, \quad \alpha_i(y) \geq 0 \quad \forall \ i, \ y 
\end{align*}$$

(9)

One way to alleviate this problem is to assume that \( \alpha_i(y) \leq \eta \) for many \( y \in \mathcal{Y} \) corresponding to every example \( i \), where \( \eta \) is very small (say, \( 10^{-18} \)) and solve the dual problem with respect to the sequences in the set, \( V_i = \{ y : \alpha_i(y) > \eta \} \) using SMO-type algorithm with the modified Newton method illustrated in (Yu et al., 2011). Note that the CRF-SDM method finds only an approximate solution to (9) because of the practical limitation on the size of the set \( V_i \). Our experiments presented in the next section, clearly indicate that on many data sets, such an approximate solution is sufficient to obtain a comparable generalization performance.

2.5 Averaged Structured Perceptron (AvStructPerc)

Perceptron algorithm for binary classification is simple and does not use any objective function. Collins (2002) proposed the perceptron algorithm for structural learning. After randomly initializing the weight vector \( \mathbf{w} \), the algorithm makes repeated passes over the training data set (visiting one example at a time), until some stopping condition is satisfied. In every pass, after visiting an example \((x_i, y_i)\), the following update rule is used if the current weight vector fails to predict the desired label \( y_i^* \):

$$\mathbf{w} := \mathbf{w} + \eta (f(x_i, y_i) - f(x_i, y^*))$$

(10)

where \( y^* = \arg \max_y \mathbf{w}^T f(x_i, y) \) and \( \eta (> 0) \) is the learning rate parameter. Collins (2002) also proposed a simple refinement to the perceptron algorithm. Defining \( w^{t,i}_j \) to be the value of the \( j \)-th parameter after the \( i \)-th training example has been visited in pass \( t \) over the training data, the average parameter \( \mathbf{w}_{avg} \) is defined as,

$$\mathbf{w}_{avg,j} = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{n} w^{t,i}_j / (nT) \quad \forall \ j = 1, \ldots, d$$

(11)

where \( d \) denotes the dimension of the parameter vector \( \mathbf{w} \). In our implementation, we adopted a very efficient way of updating \( \mathbf{w}_{avg} \). It was observed that the use of this refined algorithm gave better generalization performance (Collins, 2002).

In our experiments, we observed that the value of \( \eta \) is crucial to get good generalization performance and therefore, preferred to choose it using the procedure similar to that used in the SGD method. Since the averaged structured perceptron algorithm does not optimize any objective function, the learning rate which resulted in the least error on the remaining training set was chosen.

We give details of experimental evaluation in the next section.
Table 1: Summary of data sets. \( n \), \( n_{val} \) and \( n_{test} \) denote the sizes of the training, validation and test data respectively, \( d \) is the input dimension, \( k \) denotes the number of alphabets and \( N \) is the feature vector dimension.

| Data set    | \( n \) | \( n_{val} \) | \( n_{test} \) | \( d \)    | \( k \) | \( N \)     |
|-------------|--------|---------------|---------------|-----------|-------|-----------|
| BioCreative  | 6000   | 1500          | 5000          | 102409    | 3     | 307236    |
| BioNLP      | 14836  | 3710          | 3856          | 513932    | 11    | 565373    |
| CoNLL       | 14987  | 3684          | 3466          | 651041    | 8     | 520839    |
| dataPOS     | 39832  | 2416          | 1700          | 258299    | 45    | 1162548   |
| WSJPOS      | 28424  | 7107          | 1681          | 446147    | 42    | 18739938  |

3 Experiments and Discussion

In this section we compare different sequence learning algorithms, mentioned in Section 2, on five benchmark data sets:

- Wall Street Journal POS (WSJPOS) \cite{Marcus1993}
- BioNLP \cite{Kim2004}
- BioCreative \cite{Hirschman2005}
- CoNLL \cite{Sang2003} and
- dataPOS \cite{Huang2012b}.

The characteristics of these data sets are summarized in Table 1. In all our experiments, the feature vector \( f(x, y) \) was constructed using the combination of first order and token-independent second order feature functions \cite{Keerthi2007}. For the first order feature function, we aggregated the \( d \) dimensional feature vector over the nodes for each label. The second order functions used are independent of the tokens, but capture the dependencies between the labels of two neighboring nodes. In this case, the dimension \( N \) of the feature vector is \( k^2 + dk \). The value of the hyper-parameter \( \lambda \) was set to 10 and 1 respectively for the problems (1) and (3). To compare the test likelihood achieved by batch CRF with that obtained by the models trained using online algorithms, limited memory BFGS method (CRF-LBFGS) was used in the batch mode. To get an idea about the steady state generalization performance of the resulting models trained using online algorithms, the algorithms were run for a large number of iterations. Test set accuracy (for large-margin related methods) and likelihood (for CRF related methods) were used as performance measures to compare different algorithms. Validation set performance was calculated at the end of every iteration; this time was not counted for CPU time calculations. An algorithm could be stopped if there is no significant improvement in the validation set performance. This stopping criterion was used for all the methods. This condition is represented by a black square on each graph in Figures 1-5. The computation of \( \arg \max_y w(\alpha)^T f(x_i, y) \) and similar terms was performed using the Viterbi algorithm. All experiments were run on a 2.4GHz Intel Xeon processor with 16GB of shared main memory under Linux. The plots in Figures 1-5 depict the performance of different algorithms. The results are summarized in Table 2.

Generalization Performance (Test Set Accuracy): The left panel of Figures 1-5 shows the behaviour of test set accuracy of the resulting models, as a function of CPU.
time. From these plots, it is evident that the SVM-SDM method achieves the steady state performance much faster than other methods. The difference is significant especially for large data sets like dataPOS and WSJPOS (Figure 4 and Figure 5, left panel). It is worth noting that the performance of the averaged structured perceptron is comparable with SVM-SDM on BioCreative and CoNLL data sets (Figure 1 and Figure 3). On large data sets, however, it showed degrading behaviour as iterations progressed (Figures 4-5). The averaged structured perceptron has this overfitting/overtraining issue that is bothersome. The methods which solve the problem or its dual were not found to be suitable if test set accuracy is used as a performance measure. The main reason is that these methods are designed to maximize the likelihood. On the other hand, methods like CRF-ASGD perform better if test set likelihood is used as a performance measure. We now discuss this.

Table 2: Comparison of various algorithms at the point of termination based on validation set performance. Acc - Accuracy, ANLL - Average Negative Log-likelihood. The best and the second best results are highlighted in boldface and italic style respectively.

| Dataset     | Algorithm     | Time (sec) | Test Acc(%) | Test ANLL |
|-------------|---------------|------------|-------------|-----------|
| BioCreative | AvStructPerc  | 4.84       | 98.67       | 7800      |
|             | SVM-SDM       | 7.27       | 98.73       | 21820     |
|             | CP            | 31.17      | 98.72       | 16420     |
|             | CRF-SDM       | 20.95      | 98.6        | 5053      |
|             | CRF-ASGD      | 15.16      | 98.38       | 5491      |
|             | CRF-LBFGS     | 270.8      | 98.58       | 4667      |
| BioNLP      | AvStructPerc  | 39.23      | 98.01       | 210600    |
|             | SVM-SDM       | 36.93      | 97.72       | 56170     |
|             | CP            | 369.7      | 97.86       | 28730     |
|             | CRF-SDM       | 138.5      | 97.75       | 6920      |
|             | CRF-ASGD      | 151.7      | 97.77       | 6522      |
|             | CRF-LBFGS     | 8850       | 97.76       | 6439      |
| CoNLL       | AvStructPerc  | 34.69      | 95.8        | 51330     |
|             | SVM-SDM       | 26.85      | 95.8        | 37060     |
|             | CP            | 158.4      | 95.38       | 34020     |
|             | CRF-SDM       | 45.11      | 95.31       | 6297      |
|             | CRF-ASGD      | 79.02      | 95.51       | 5877      |
|             | CRF-LBFGS     | 1350       | 95.51       | 5765      |
| dataPOS     | AvStructPerc  | 415.3      | 97.14       | 8256      |
|             | SVM-SDM       | 235.2      | 97.36       | 84900     |
|             | CP            | 808.7      | 97.05       | 68310     |
|             | CRF-SDM       | 1446       | 97.27       | 6511      |
|             | CRF-ASGD      | 8497       | 97.29       | 4261      |
|             | CRF-LBFGS     | 609600     | 97.28       | 4215      |
| WSJPOS      | AvStructPerc  | 250.6      | 96.46       | 5576      |
|             | SVM-SDM       | 128.8      | 96.6        | 627900    |
|             | CP            | 870.7      | 96.23       | 511200    |
|             | CRF-SDM       | 1620       | 96.56       | 6363      |
|             | CRF-ASGD      | 4391       | 96.57       | 3954      |
|             | CRF-LBFGS     | 463700     | 96.5        | 3953      |
Generalization Performance (Test Set Likelihood): The behaviour of test set likelihood as a function of CPU time, is depicted in the right panel of Figures 1-5. Note that the methods CRF-ASGD and CRF-LBFGS (batch algorithm) optimize the training set likelihood directly by solving problem (3). On the other hand, the sequential dual method for CRFs (CRF-SDM) solves the dual problem of (3). From the results in Table 2, we see that the CRF-LBFGS method, though slow, gave the best test likelihood value among all the methods compared. While the performance of CRF-SDM and CRF-ASGD was comparable on three data sets, the CRF-ASGD method clearly outperformed the CRF-SDM method on large data sets like dataPOS and WSJPOS. This is mainly due to the large number of alphabets ($k$ in Table 1) in these data sets. This results in a large number of possible output sequences for every example. Since the CRF-SDM method assumes that, only those sequences in the set $V_i$ have a non-zero value of the dual variable, and the set $V_i$ cannot accommodate all possible sequences associated with example $i$, the vector $w(\alpha)$ in (8) cannot be accurately determined. This results in degradation of performance of CRF-SDM, especially on those data sets where the number of alphabets is large.

Test likelihood performance of CP and SVM-SDM methods was not good compared to other methods, as these methods were mainly designed to solve the dual problems obtained using a variant of the hinge loss function. On the other hand, the averaged structured perceptron, which does not optimize any objective function, performed better than these methods on all the data sets except BioNLP and CoNLL. The averaged structured perceptron algorithm is simple, easy to implement, fast and gives reasonable test accuracy and likelihood performance. However, it does begin to overfit eventually, as is evident from Figures 1-5. Some key observations, made in this Section, are summarized in Table 4.

Sensitivity to hyper-parameter selection: For the Structural SVM and CRF model design, the effect of hyper-parameter selection on the test set performance was studied by conducting the following experiment. The hyper-parameter $\lambda$ (in (1) or (3)) was varied from $10^{-3}$ to $10^{3}$ and the test set accuracy and likelihood values were noted. The results are reported in Table 3. It is clear from this table that the variation in test accuracy was not large for Structural SVM over different values of $\lambda$. On the other hand, test likelihood values varied significantly over a range of $\lambda$ values, when CRF was used. We however note that, for most of the data sets, $\lambda = 10$ was an optimal choice for Structural SVMs (with accuracy as a measure) and the corresponding choice for CRF was $\lambda = 1$ (with likelihood as a measure). These optimal choices of hyper-parameters were used in all our experiments.

4 Conclusion and Recommendations

In this work, we have done a systematic comparison of different sequence labeling algorithms in terms of their speed, ability to reach a good generalization performance (accuracy and likelihood) fast, and ability to maintain best generalization performance at the end. Based on experimental results on real-world benchmark data sets, we recommend that a dual method like SVM-SDM which solves the dual of (1) is preferred if test accuracy is the evaluation criterion. The averaged structured perceptron yields good test accuracy; however it has an overfitting issue that is bothersome. On the other hand, the CRF-ASGD method should be preferred if likelihood is the criterion.
Table 3: Sensitivity of Structural SVM and CRF to $\lambda$. ANLL - Average Negative Log-likelihood. (Not given for Structural SVM as one does not expect any pattern there.) The best results are highlighted in boldface style.

| Dataset   | $\lambda$ | Test Accuracy (%) | Test ANLL |
|-----------|------------|-------------------|-----------|
|           |            | Struct SVM (SDM)  | CRF (ASGD) | CRF (ASGD) |
| BioCreative| 10$^3$     | 97.27             | 94.17     | 15186     |
|           | 10$^2$     | 98.07             | 97.01     | 9278      |
|           | 10         | 98.76             | 98.16     | 6070      |
|           | 1          | **98.77**         | 98.5      | 4894      |
|           | 10$^{-1}$  | 98.36             | 98.57     | 4275      |
|           | 10$^{-2}$  | 98.07             | 98.57     | **4707**  |
|           | 10$^{-3}$  | 97.47             | 98.57     | 4707      |
| BioNLP    | 10$^3$     | 96.46             | 91.6      | 21105     |
|           | 10$^2$     | 97.83             | 96.07     | 10752     |
|           | 10         | **98.15**         | 97.45     | 7115      |
|           | 1          | 98.02             | 97.82     | **6189**  |
|           | 10$^{-1}$  | 97.56             | 97.88     | 6452      |
|           | 10$^{-2}$  | 97.29             | 97.88     | 6550      |
|           | 10$^{-3}$  | 96.5              | 97.88     | 6553      |
| CoNLL     | 10$^3$     | 91.75             | 89.57     | 12763     |
|           | 10$^2$     | 93.94             | 92.01     | 9076      |
|           | 10         | **95.81**         | 94.6      | 6680      |
|           | 1          | 95.6              | 95.54     | **5630**  |
|           | 10$^{-1}$  | 94.75             | 95.74     | 5659      |
|           | 10$^{-2}$  | 94.03             | 95.75     | 5715      |
|           | 10$^{-3}$  | 92.59             | 95.75     | 5716      |
| dataPOS   | 10$^3$     | 95.1              | 90.7      | 25560     |
|           | 10$^2$     | 96.7              | 95.79     | 9989      |
|           | 10         | **97.36**         | 97.05     | 5358      |
|           | 1          | 97.04             | 97.27     | **4273**  |
|           | 10$^{-1}$  | 96.17             | 97.13     | 5142      |
|           | 10$^{-2}$  | 95.01             | 96.99     | 6670      |
|           | 10$^{-3}$  | 94.5              | 96.99     | 6770      |
| WSJPOS    | 10$^3$     | 93.4              | 87.87     | 21964     |
|           | 10$^2$     | 95.88             | 94.36     | 8933      |
|           | 10         | **96.59**         | 96.31     | 4769      |
|           | 1          | 96.25             | 96.53     | **3939**  |
|           | 10$^{-1}$  | 95.56             | 96.42     | 4544      |
|           | 10$^{-2}$  | 95.01             | 96.35     | 5159      |
|           | 10$^{-3}$  | 93.7              | 96.35     | 5188      |
Table 4: **Generalization performance characteristics of various algorithms**

| Ability to reach best test set accuracy fast | AvgStrPerc | SVM-SDM | CP | CRF-SDM | CRF-SGD | CRF-LBFGS |
|-----------------------------------------------|------------|--------|----|--------|---------|-----------|
| ✓                                             | ✓          | ✗      | ✗  | ✗      | ✗       | ✗         |
| Ability to reach best test set likelihood fast | ✗          | ✗      | ✗  | ✗      | ✓       | ✓         |
| Ability to maintain best test set accuracy    | ✗          | ✓      | ✓  | ✓      | ✓       | ✓         |
| Ability to maintain best test set likelihood  | ✗          | ✗      | ✗  | ✓      | ✓       | ✓         |
Figure 1: Comparison of Test Accuracy and Test Likelihood for BioCreative dataset. The plots in rows 2 and 3 are zoomed versions to clearly see certain behaviour in the initial and final stages respectively.
Figure 2: Comparison of Test Accuracy and Test Likelihood for BioNLP dataset. The plots in rows 2 and 3 are zoomed versions to clearly see certain behaviour in the initial and final stages respectively.
Figure 3: Comparison of Test Accuracy and Test Likelihood for dataCoNLL2003 dataset. The plots in rows 2 and 3 are zoomed versions to clearly see certain behaviour in the initial and final stages respectively.
Figure 4: Comparison of Test Accuracy and Test Likelihood for dataPOS dataset. The plots in rows 2 and 3 are zoomed versions to clearly see certain behaviour in the initial and final stages respectively.
| CRF−SDM | CRF−ASGD | CRF−LBFGS | SVM−SDM | CP | AvStructPerc |
|---------|----------|-----------|---------|----|--------------|
| Test Accuracy% | CPU Time(sec) | Test Log Likelihood |
| 95 | 10^2 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 95.2 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 95.4 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 95.6 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 95.8 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 96 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 96.2 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 96.4 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 96.6 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| 96.8 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |

Figure 5: Comparison of Test Accuracy and Test Likelihood for WSJPOS dataset. The plots in rows 2 and 3 are zoomed versions to clearly see certain behaviour in the initial and final stages respectively.
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