Adversarial Structured Prediction for Multivariate Measures

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Abstract
Many predicted structured objects (e.g., sequences, matchings, trees) are evaluated using the F-score, alignment error rate (AER), or other multivariate performance measures. Since inductively optimizing these measures using training data is typically computationally difficult, empirical risk minimization of surrogate losses is employed, using, e.g., the hinge loss for (structured) support vector machines. These approximations often introduce a mismatch between the learner’s objective and the desired application performance, leading to inconsistency. We take a different approach: adversarially approximate training data while optimizing the exact F-score or AER. Structured predictions under this formulation result from solving zero-sum games between a predictor seeking the best performance and an adversary seeking to approximate the training data labels in limited ways based on structural relationships between the variables in a manner that maximizes expected multivariate loss. This generalizes previous methods for adversarially optimizing multivariate performance measures without structure (Wang et al., 2015) and adversarial structured prediction with chain structures and decomposable losses (Li et al., 2016). We investigate how these games can be solved efficiently using both exact and approximate methods.

1 INTRODUCTION
Supervised structured prediction methods are prevalently used to predict sequences, alignments, or trees, for natural language processing (NLP) tasks (Manning and Schütze, 1999; Lafferty et al., 2001; Och and Ney, 2003; Taskar et al., 2005c; Jurafsky and Martin, 2008; Finkel et al., 2008; Haghighi et al., 2009). Unfortunately, inductively optimizing the precision, recall, F-score, alignment error rate (AER), or other multivariate evaluation measures of interest is intractable due to having many local optima—even for the simple 0-1 loss (Hoffgen et al., 1995) and the structured prediction extension: Hamming loss.

Existing approaches bypass these intractabilities by replacing the performance measure with a convex surrogate loss function for which optimization is tractable. This can be viewed as approximating the loss function and employing the exact training data. Minimizing the multivariate conditional logarithmic loss yields conditional random fields (CRFs) (Lafferty et al., 2001), and minimizing the structured hinge loss yields (structured) support vector machines (SVM) (Tsochantaridis et al., 2004). The latter method can integrate different multivariate performance measures into the hinge loss. However, the mismatch that using a hinge loss approximation introduces degrades predictive performance in both theory (i.e., inconsistency (Liu, 2007)) and practice.

We approach the task of structured predictions with multivariate performance measures by adversarially approximating the training data and using the exact evaluation measure in two important NLP tasks: named entity recognition evaluated using the F-score (§2.1) and word alignment evaluated using alignment error rate (§2.2). Our approach (§3) takes the form of a zero-sum game between a predictor player seeking label predictions that minimize expected multivariate loss and an adversary seeking to approximate the training data labels in limited ways based on structural relationships between the variables in a manner that maximizes expected multivariate loss. This generalizes previous methods for adversarially optimizing multivariate performance measures without structure (Wang et al., 2015) and adversarial structured prediction with chain structures and decomposable losses (Li et al., 2016). We investigate how these games can be solved efficiently using both exact and approximate methods.

Preliminary work. Under review by AISTATS 2018. Do not distribute.
2 BACKGROUND

Many important evaluation measures are multivariate, meaning they cannot be additively constructed by separately evaluating on each predicted variable. We focus on two measures: F-score and alignment error rate (AER) used in named entity recognition and word alignment tasks. We review these tasks before discussing existing methods for addressing them.

2.1 Named Entity Recognition

Identifying all occurrences of a type of entity in a sentence is often needed for natural language processing. Accuracy is often an inappropriate measure due to the relative infrequency of these occurrences. Instead, the F-score is commonly evaluated in named entity recognition (NER) (Finkel et al., 2005; Kim et al., 2003) and coreference resolution (Raghunathan et al., 2010; Lee et al., 2013) tasks. It is the harmonic mean of precision and recall of class c based on predicted vector \( \hat{y} \) evaluated against ground truth vector \( y \):

\[
F_c(\hat{y}, y) = \frac{2(1 y_{c=1} \cdot 1 y_{c=1})}{|1 y_{c=1}| + |1 y_{c=1}|},
\]

where \( 1 y_{c=1} \) is the binary vector that represents the occurrences of \( c \) in the gold standard sequence. \( 1 y_{c=1} \) is the binary vector that represents the existence of \( c \) in the proposed sequence \( \hat{y} \).

Leveraging sequential structure improves performance in named entity recognition tasks (Finkel et al., 2005). This has previously been accomplished using conditional random fields (Lafferty et al., 2001) (2.3). We seek a learning method that is better aligned with the F-score evaluation measure in this paper.

2.2 Word Alignment

Determining how words align between translated sentences is another important natural language processing task. The alignment error rate (AER) is a common evaluation measure for assessing machine translation quality (Cherry and Lin, 2006; Haghighi et al., 2009; Dyer et al., 2013; Kocisky et al., 2014). It generalizes the F-score for settings with more than binary-valued tags (Och and Ney, 2000). For example, an alignment task may contain three different kinds of tags between each pair of source and target words: a sure tag (S) for unambiguous alignments, a possible tag (P) for alignments that might exist or not, and a negative tag (N) for alignments that are neither S nor P. For a gold standard sequence of alignments \( y \), and a proposed sequence of alignments \( \hat{y} \) from the system under evaluation, AER is defined as:

\[
AER(\hat{y}, y) = 1 - \frac{1 y_{a=1} \cdot 1 y_{a=1} + 1 y_{a=1} \cdot 1 y_{a=1}}{|1 y_{a=1}| + |1 y_{a=1}|},
\]

where \( A \) is the proposed positive tag. \( S \) alignments are also considered to be \( P \) alignments (\( S \subseteq P \)) in this measure and it is evaluated accordingly. Figure 1 shows an example alignment task for an English-French translation.

![Figure 1: The gold standard sequence alignment (top) between English words \( e_i \) and French words \( f_j \) and the proposed sequence alignment \( a \) (bottom) with AER of \( \frac{1}{2} \). Each complete alignment can be represented in sequence form as \( SNNNNNN \ldots NPSP \) and \( ANNNNNN \ldots NNNAP \) for \( (e_1, f_1), (e_1, f_2), \ldots, (e_1, f_8), (e_2, f_1), \ldots, (e_5, f_8) \) of the gold standard and proposed sequence alignments. Negative tags (N) are omitted in the figure for clarity.](image-url)

2.3 Empirical Risk Minimization Approaches

In addition to being inherently multivariate, many key evaluation measures are also not concave (corresponding losses are non-convex). This makes it challenging to maximize these measures (or perform empirical risk minimization (ERM) for complementary loss functions): \( \max_{\theta} \mathbb{E}_{y,x} \cdot \hat{p}_0(y,x) \cdot \mathbb{E}_{y,x} \cdot \hat{p}_0(y,x) \cdot [\text{score}(Y, X)] \) for training data distribution \( \hat{p}_0(y,x) \) and predictive distribution \( \hat{p}_0(y|x) \). Even the univariate prediction accuracy (zero-one loss) is a non-concave (non-convex) function of standard prediction model parameters, leading to an NP-hard optimization problem (Hoffgen et al., 1995). Instead, surrogates performance loss measures that upper bound the 0-1 loss/Hamming loss are employed: logistic regression and conditional random fields (CRFs) (Lafferty et al., 2001)

\[
\hat{p}_0(y|x) = \frac{e^{\sum_{i} \theta \cdot \Phi(y_{i-1}, y_{i}, x_{i})}}{\sum_{y} e^{\sum_{i} \theta \cdot \Phi(y_{i-1}, y_{i}, x_{i})}}, \quad \text{where:} \quad \theta = \arg \min_{\theta} \mathbb{E}_{X, Y} \cdot \hat{p}_0(Y|X) \cdot [\log \hat{p}_0(Y|X)]
\]

—minimize the logarithmic loss (maximizing likelihood); the (structured) support vector machine
We present a generalized adversarial formulation (Eq. (5)) for prediction tasks with both multivariate performance measures and structured properties relating the predicted variables. We review a general constraint generation method for solving the resulting game problems efficiently (Eq. (6)) and establish its applicability to the AER performance measure over matchings (Eq. (7)), more restrictive bipartite matching (Eq. (8)), and F-measure with chain constraints (Eq. (9)).

### 3.1 Adversarial Game Formulation

We construct structured predictors for specific performance measures by taking an adversarial philosophy with respect to inductive uncertainty. For a particular performance measure, we seek the predictor that is robust to the worst-case label approximation that still matches structural properties measured on training data or other structural constraints on the predicted variables from the domain. Mathematically, this takes the form of a zero-sum game (von Neumann and Morgenstern, 1947) between two players: player $Y$ who maximizes the expected score between the two players’ structured choices, and player $\hat{Y}$ who approximates the training data in a manner that minimizes the expected score while also residing within the constraint set $\Xi$, which is defined as:

$$
E_{X \sim \rho, Y \sim \rho} \left[ \Phi(X, Y) \right] = E_{Y \sim \rho} \left[ \Phi(X, Y) \right]:
$$

(5)

$$
\max_{\rho} \min_{\Phi} E_{X \sim \rho, Y \sim \rho} \left[ \Phi(X, Y) \right] = \max_{\theta} \left\{ E_{Y \sim \rho} \left[ \psi(X, Y) \right] \right\},
$$

(6)

where the parameters $\theta$ for the Lagrangian term $\psi(x, y) = \theta \cdot \Phi(x, y)$ are a learned weight vector, and $\Phi(x, y)$ are the features characterizing the relationship between $x$ and $\hat{y}$.

For example, the score matrix (Eq. (5)) for the $(1-AER)$ game for a simple setting with one source word $e1$ and two target words $(f1, f2)$ from Figure 2 is extended to $S'_{x, y'}$, as shown in Table 1 with Lagrangian terms, $\psi(y)$, that enforce the constraint requirement, $P(y|x) \in \Xi$, by motivating the adversary to produce features that are similar to those of the training data set. The predictor chooses (a distribution of) $\{A, N\}$ tags for the pair of edges, while the adversary chooses (a distribution of) $\{S, P, N\}$ tags that also resides within the set $\Xi$. This corresponds to the game in Eq. (6), which can be expressed as a linear program. Estimating game parameters $\theta$ is a convex optimization problem, which can be solved using existing convex optimization methods (e.g., AdaDelta, L-BFGS).

Table 1: The $(1-AER)$ game matrix $S'_{x, y'}$.

|       | NN | NA | AN | AA |
|-------|----|----|----|----|
| NN    | 1 - $\psi(NN)$ | 0 - $\psi(NN)$ | 0 - $\psi(NN)$ | 0 - $\psi(NN)$ |
| NP    | 1 - $\psi(NP)$ | 1 - $\psi(NP)$ | 0 - $\psi(NP)$ | 0 - $\psi(NP)$ |
| NS    | 0 - $\psi(NS)$ | 1 - $\psi(NS)$ | 0 - $\psi(NS)$ | 1 - $\psi(NS)$ |
| PN    | 1 - $\psi(PN)$ | 0 - $\psi(PN)$ | 1 - $\psi(PN)$ | 1 - $\psi(PN)$ |
| PP    | 1 - $\psi(PP)$ | 1 - $\psi(PP)$ | 1 - $\psi(PP)$ | 1 - $\psi(PP)$ |
| PS    | 0 - $\psi(PS)$ | 0 - $\psi(PS)$ | 0 - $\psi(PS)$ | 0 - $\psi(PS)$ |
| SN    | 0 - $\psi(SN)$ | 0 - $\psi(SN)$ | 0 - $\psi(SN)$ | 0 - $\psi(SN)$ |
| SP    | 0 - $\psi(SP)$ | 0 - $\psi(SP)$ | 0 - $\psi(SP)$ | 0 - $\psi(SP)$ |
| SS    | 0 - $\psi(SS)$ | 0 - $\psi(SS)$ | 0 - $\psi(SS)$ | 0 - $\psi(SS)$ |

One key advantage of the adversarial approach over structured prediction methods based on the hinge loss is its Fisher consistency guarantee (Li et al., 2016). Given the full data distribution, $P(y|x)$, and an arbitrarily rich feature representation, the adversary is constrained by the set $\Xi$ to exactly match the conditional distribution of the data, $P(y|x) = P(y|x)$. Equation (6) then reduces to:

$$
\max_{P(y|x)} E_{X \sim \rho, Y \sim \rho} \left[ \text{score}(\hat{Y}, Y) \right],
$$

(7)
which is the optimizer of the evaluation measure, score(\(\hat{y}, y\)), on the full distribution of data.

### 3.2 Double Oracle Method

Unfortunately, the games for these multivariate settings grow exponentially in size with the number of variables. For example, the 1 - \(1 \cdot 1\) game for the sequence alignment task of Figure [1] has 5·8 word pairs, yielding 3^5·8 sequence choices for the adversary, 5·8 sequence choices for the predictor player, and a game size of (2·3)^5·8 \(\approx 1.3 \cdot 10^{31}\). Thus, explicitly constructing and solving the game matrix is computationally impractical even for small alignment tasks.

We use the double oracle method [McMahan et al., 2003] to obtain the equilibrium solution to the adversarial prediction game without explicitly constructing the game matrix. It iteratively adds a new sequence (for one player at a time) in response to the opponent’s current equilibrium distribution over sequences obtained from solving a zero-sum game with the sets of current sequences. This continues until adding more sequences no longer benefits either player, guaranteeing a Nash equilibrium for the original game.

The double oracle game solver is a central component of the our approach. Its returned equilibrium distributions are used to compute the gradients needed for learning the model parameters, \(\theta\). The zero-sum game solver used as a sub-routine of the double oracle method is implemented using linear programming [Ferguson, 2014], with different linear program solvers available [Optimization, 2014]. The key remaining problem—a required subroutine of the double oracle method—is to efficiently find each player’s best response:

\[
\hat{y}^* = \arg\max_{\hat{y}} \mathbb{E}_{Y|X\sim P}[\text{score}(\hat{y}, Y) - \psi(Y)], \tag{8}
\]

\[
\hat{y}^* = \arg\min_{\hat{y}} \mathbb{E}_{Y|X\sim P}[\text{score}(\hat{Y}, y) - \psi(\hat{y})]. \tag{9}
\]

The difficulty depends on both the loss function being considered and the constraints imposed on the adversary. We efficiently solve this best response problem under structured constraints for alignment error rate and F-score with chain structured constraints in the next sections.

### 3.3 Best Response for Alignment Error Rate

Under our approach for 1 - \(1 \cdot 1\), the two players are: \(y \in Y\), which adversarially approximates the gold standard alignment distribution; and \(a \in A\), which maximizes 1 - \(1 \cdot 1\) (hence, minimizes \(1 \cdot 1\)). where \(A\) and \(Y\) are the domain of \(a\) with a distribution \(Q(\hat{a})\), and \(y\) with a distribution \(Q(y)\) respectively. For a sequence of alignments of length \(n\), the objective of finding the best responses \(a^*\) (Eq. (8)) and \(y^*\) (Eq. (9)) are:

\[
a^* = \arg\max_{a \in A} \sum_{y \in (0, S)^n} q(y) [1 - AER(a, y) - \psi(y)], \tag{10}
\]

\[
y^* = \arg\min_{y \in Y} \sum_{a \in (0, A)^n} q(a) [1 - AER(a, y) - \psi(y)]. \tag{11}
\]

We focus first on the adversary’s best response (Equation (10)), which must incorporate the Lagrangian potential term, \(\psi(y)\). For the choice of alignment \(y^*\), we separate the choices among all possible numbers of \(S\) tags, \(k = 0, \ldots, n\), for the alignment sequence of length \(n\), and denote these sets as \(Y^{(k)}\). The best choice of a certain \(k\) is rewritten as follows, where \(a_i\) is the natural shorthand of the indicator function \(I(a_i = A)\), and \(y_{i*} = I(y_i = S), y_{ri} = I(y_i = P, y_i \neq S)\); the number of \(A\) tags in the alignment is \(\alpha = \sum_{i=1}^{n} a_i:\n
\[
y^{(k)}* = \arg\min_{y \in Y^{(k)}} \sum_{a \in (0, A)^n} q(a) \left( \sum_{i=1}^{n} a_i (2a_i y_{i*} + a_i y_{ri}) - \sum_{i=1}^{n} \psi_i(y_i) \right) = \arg\min_{y \in Y^{(k)}} \sum_{a \in (0, A)^n} q(a) \left( \sum_{i=1}^{n} a_i (2a_i y_{i*} + y_{ri}) - \psi_i(y_{i*}) - \psi_i(y_{ri}) \right) = \arg\min_{y \in Y^{(k)}} \sum_{i=1}^{n} a_i 2 \sum_{a = 1}^{n} \left( \frac{2a_i y_{i*} - \psi_i(y_{i*})}{\alpha + k} \right) + \sum_{i=1}^{n} y_{ri} \sum_{a = 1}^{n} \frac{q(a)}{\alpha + k} - \psi_i(y_{ri}) \tag{12}
\]

\[
\hat{y}_{isk} - f_{rik} \]

Here, in Equation (12), \(q_i\) is the marginal probability that alignment \(a\) has \(|a_s| = \alpha\) and \(a_i = S\) (i.e., the number of \(S\) tags equals to \(\alpha\), and the \(i\)-th position is \(S\)). We separate the Lagrangian potential \(\psi\) into two terms: \(\psi(S)\) for \(S\) tags, \(\psi(P)\) for \(P\) tags that are not also \(S\) tags. To get the permutation that minimizes this equation, for \(tag S\) at position \(i\) we pay \(f_{isk}\), for \(tag P\) we pay \(f_{rik}\), and for \(tag N\) we pay 0. Without the \(y \in Y^{(k)}\) constraint, to compute the minimum, all that we need to do is finding the smallest of these three terms for each \(i\). With the constraint, we have to set exactly \(k\) tags to \(S\), so we choose the \(k\) positions where the \(f_{isk}\) cost exceeds the best alternative, \(\min(f_{isk}, 0)\), by as little as possible. Thus, we sort \(f_{isk} - \min(f_{isk}, 0)\) in ascending order, set the top \(k\) positions to \(S\), \(P\), or \(N\) accordingly. The detailed algorithm is shown as Algorithm [A].

The best response for the AER minimizer is simpler to obtain since the Lagrangian terms \(\psi(y)\) are invariant to the choice of alignment \(a^*\). The approach of [Dembczynski et al., 2011] can be used after replacing \(F = P \times W\) with \(F = Q_S W_S + Q_P W_P\), where matrix \(Q_S\) is the marginal probability for \(S\) tag, \(Q_P\) is for \(P\) tag, and permutation matrices \(W_S, W_P\) for \(S\) and \(P\) respectively, where each element (with index \(i, k\)) in the matrix \(w_{ik}^S = \frac{2}{1+\frac{1}{k}}\), and \(w_{ik}^P = \frac{1}{1+\frac{1}{k-1}}\).

### 3.4 Best Response for Bipartite Matching

Following [Taskar et al., 2005b]'s modeling of the AER task as a maximum weighted bipartite matching prob-
The best response should be found efficiently: encode the linear-chain structure information in the Chain structures permit two types of features: unimodal and bigram. We consider the F-score

\[ F = 2PW - D \]

Exact Best Responses:

Let using additive cost-sensitive losses (Cormen et al., 2001), we develop a bipartite best response for our adversarial problem. The best responses are:

\[ a^* = \arg \max_{a \in A} \sum_{y \in \{0,1\}^n} q(y) \sum_{i} \left[ 1 - C(a_i, y_i) - \psi(y_i) \right], \]

\[ y^* = \arg \min_{y \in \mathcal{Y}} \sum_{a \in \{0,1\}^n} q(a) \sum_{i} \left[ 1 - C(a_i, y_i) - \psi(y_i) \right], \]

where each \( a \) or \( y \) must also be a valid bipartite matching, and \( C(\cdot, \cdot) \) is a cost function. The best responses can be computed using widely used maximum weight bipartite matching algorithms (Lawler, 2001) by incorporating Lagrangian potentials and expected losses as edge weights and an integer linear program exactly using the integral solution of a linear program relaxation.

3.5 Best Response for Linear-chain F-score

Exact Best Responses: We consider the F-score for a particular class \( C \) and define two players in the zero-sum game: player \( Y \) makes predictions that maximizes F-score, and player \( Y \) adversarially approximates the evaluation distribution. For each set of adversarial sequences \( Y \), and its distribution \( P(\hat{Y}) \), the best response should be found efficiently:

\[ y^* = \arg \max_{\hat{y} \in \mathcal{Y}} \sum_{\hat{y}} p(\hat{y}) [F_{\hat{y}}(\hat{y}, \hat{y}) - \psi(\hat{y})] \]

(13)

\[ y^* = \arg \min_{\hat{y} \in \mathcal{Y}} \sum_{\hat{y}} p(\hat{y}) [F_{\hat{y}}(\hat{y}, \hat{y}) - \psi(\hat{y})] \]

(14)

Chain structures permit two types of features: unigram \( \Phi^{u}(x_t, y_t) \), and bigram \( \Phi^{b}(x_t, y_{t-1}, y_t) \). We encode the linear-chain structure information in the weight vectors (i.e., Lagrange multipliers in Equation (14)). For example, suppose we have \( m \) classes

\[ C_t \in \mathcal{C} = \{C_1, ..., C_m\} \]

in the dataset. Then each distinct consecutive pair of classes \( (C_{t-1}, C_t) \) has its own weight vector \( \theta(\cdot|C_{t-1}, C_t) \), for a total number of pairs and weight vectors \( m^2 \). An optional START tag can be added in front of a sequence, forming \( m \) additional pairs \((START, C_t)\) (and corresponding weight vectors). Besides these pair vectors that accommodate bigram features, each class also has a separate weight vector \( \theta(\cdot|C_t) \) for unigram features in our model. So in total, we use \( m \) unigram feature vectors, and \( m^2 + m \) bigram feature vectors to capture the linear chain information.

From Equation (13), we can see that the Lagrange potentials \( \psi(\cdot) \) are related to the choice of \( \hat{y} \) only, and because the binary nature of the F-score of a specific target class (Jurak and Martim, 2008), the GFM algorithm (Dembczynski et al., 2011) can be applied directly to the binarized sequences for the target.

For the adversary's best response, we rewrite Equation (14) for a particular target class \( C \) by considering the total number of target class in \( \hat{y} \) and \( \hat{y} \) sequence.
as $\hat{k}$ and $\bar{k}$ respectively, as follows:

$$
y^* = \arg \min_{y \in \mathcal{Y}} \sum_i p(y) \left\{ \frac{2}{k + \bar{k}} \right\},
$$

$$
\sum_{i=1}^{n} \left[ \psi^w(\hat{y}_i) + \psi^b(\hat{y}_{i-1}, \bar{y}_i) \right],
$$

$$
y^{(k)*} = \arg \min_{y \in \mathcal{Y}(k)} \sum_{i=1}^{n} \left\{ \sum_j p(y) \left[ \frac{\psi^w(\hat{y}_j) - \psi^b(\hat{y}_{i-1}, \bar{y}_i)}{k + \bar{k}} \right] \right\},
$$

$$
= \arg \max_{y \in \mathcal{Y}(k)} \sum_{i=1}^{n} \left\{ \psi^w(\hat{y}_i) + \psi^b(\hat{y}_{i-1}, \bar{y}_i) - \sum_{k=1}^{n} \frac{2p^w_{y}}{k + \bar{k}} \right\},
$$

where $\hat{y}_C = I(\hat{y}_t = C)$, $\bar{y}_C = I(\bar{y}_t = C)$, $\hat{k} = \sum_{i=1}^{n} \hat{y}_C$, $\bar{k} = \sum_{i=1}^{n} \bar{y}_C$, and $p^w_C$ is the marginal probability that $|\hat{y}_C| = \hat{k}$ and $y_t = C$.

The difficulty of solving Eq. (15) comes from the Lagrange potential term $[\psi^w(\hat{y}_i) + \psi^b(\hat{y}_{i-1}, \bar{y}_i)]$ in the linear-chain structure. To solve this problem efficiently, we propose a dynamic programming algorithm, for the particular class $C$, Linear-Chain F-score Minimizer (LCFM) in Algorithm 2. The MSUM subroutine computes the sum in Equation (15) via a backward pass with the following recurrence relation for $k$ instances of class $C$ tags in sequence $y$:

$$
\beta^w(c_{t-1}, t, r) = \begin{cases} 
0 & t = 0 \\
\max_{c_t} \{ \beta^w(c_t, t+1, r - I(c_t = C)) \} & t > 0 \\
+\psi(c_{t-1}, c_t) - f_{t,k} \times I(c_t = C) & t = 0 
\end{cases},
$$

Looping through subroutines of MSUM for each of the $n$ values of $k$, i.e., number of target tags in the best response sequence, can be accomplished in $O(n^2)$ time, which characterizes the overall complexity of the algorithm.

Approximate Best Responses: To overcome this cubic complexity, we employ an approximation method for F-score over the linear-chain structure using the cost sensitive approach proposed by Parambath et al. (2014). For different costs of false negatives chosen as $\delta_+ \in \{2 - w, w \in \{0.1, 0.2, \ldots, 1\}\}$ against false positive cost of $\delta_- \in \{w, w \in \{0.1, 0.2, \ldots, 1\}\}$, we find the best response over the linear chain by a Viterbi forward pass in $O(nm^2)$, i.e for the adversary we compute:

$$
\alpha^w(c_t) = \begin{cases} 
0 & t = 0 \\
\max_{c_{t-1}} \{ \alpha^w(c_{t-1}) + \psi(c_{t-1}, c_t) \} & t > 0 \\
+I(c_t = C)(1 - P^C)\delta^w + I(c_t \neq C)P^C\delta^w & t = 0 
\end{cases},
$$

where $P_t^C$ is the marginal probability that $y_t = C$.

The algorithm finds the approximated best response by calling the dynamic programming subroutine for different values of $w$ and chooses the sequence with the lowest F-score a posteriori. For the maximizer player, in absence of Lagrangian potentials, choosing the best tag at each position becomes an independent binary decision (target vs. non-target tag) which can be accomplished in $O(n)$. We transform the range of Lagrangian potentials in $[10]$ to $[-1, 1]$ in order to better match the range of cost terms.

4 EXPERIMENTS AND RESULTS

We evaluate our approach against a maximum margin structured prediction model / SSVM (Taskar et al., 2005c) for alignment error rate and conditional random field (CRF) for linear-chain F-score. Since the maximum margin method’s implementation is not available, we implemented it ourselves following the algorithm description (Taskar et al., 2005a-c,b). We use the Stanford Named Entity Recognizer’s CRF implementation (Finkel et al., 2005) in our experiments.

We use the NAACL 2003 Hansards data (Mihalcea and Pedersen, 2003) for the AER task. It contains 1,470,000 unlabeled sentence pairs, 447 labeled pairs, and a separate validation set of 37 labeled pairs. We experiment with translation from English to French, following the same setting as Taskar et al. (2005c) and Cherry and Lin (2006). We use first 100 English-French sentence pairs from the original labeled data as training examples, the remaining 347 sentence pairs as test examples, and the same 37 validation pairs as validation examples. Since the features described in Taskar et al. (2005c) are not available, we duplicate them with our best efforts.1

We train the maximum margin structured model (SSVM), and our adversarial approach (ADV) with maximum weight bipartite matching (ADVskip), and without bipartite matching constraints for AER (ADVaer) using those features extracted from the training data set. Also, following the same setting as Taskar et al. (2005c), we include GIZA++’s unsupervised prediction from the $1^5H$ training scheme (Och and Ney, 2003) as an additional feature. We select $\ell_2$ regularization values using performance on the validation data set.

The performances of models on validation and test data sets are shown in Table 2. ADVaer outper-
Table 2: AER of different models.

| Model  | Valid | Test  |
|--------|-------|-------|
| SSVM   | 13.98%| 13.34%|
| MPG_{bip} | 15.82%| 14.52%|
| MPG_{aer} | 6.97% | 7.28% |

Table 3: \( F_1 \) scores of CRF and MPG_{\hat{f}_1} on ‘testa’ (top) and ‘testb’ (bottom).

| Dataset          | testa          | testb          |
|------------------|----------------|----------------|
|                  | CRF            | \( \text{ADV}_{\hat{f}_1} \) | \( \text{ADV}^+_\text{aer} \) |
| conll_{300}      |                |                |                |
| PER              | 17.88          | 29.64          | 29.64          |
| LOC              | 30.94          | 47.40          | 47.40          |
| ORG              | 7.19           | 15.74          | 15.74          |
| MISC             | 16.22          | 19.51          | 19.51          |
| conll_{1000}     |                |                |                |
| PER              | 78.68          | 85.42          | 85.42          |
| LOC              | 80.00          | 78.63          | 78.63          |
| ORG              | 58.24          | 59.39          | 59.39          |
| MISC             | 62.30          | 67.08          | 67.08          |
| conll_{3000}     |                |                |                |
| PER              | 85.72          | 88.97          | 88.97          |
| LOC              | 85.74          | 85.38          | 85.38          |
| ORG              | 75.69          | 76.34          | 76.34          |
| MISC             | 78.82          | 81.04          | 81.04          |

forms all other model, which demonstrates the effectiveness of better aligning the predictor to the performance measure of interest. Comparing \( \text{ADV}_{\text{bip}} \) against \( \text{ADV}_{\text{aer}} \) shows the advantage of modeling AER more directly without as strong exclusivity restrictions on the edges over modeling the alignment problem as a maximum weight bipartite matching.

In the comparison to the CRF model, we use the well known CoNLL-2003 English data set (Kim et al., 2003). We consider each sentence as one sequence example, and create three different sizes of subsets from the CoNLL-2003 data for our experiments, to demonstrate the benefit that adversarially optimizing \( F_1 \) can bring, with respect to the training data size. The first data set contains the first 300 sentences from ‘train,’ 300 sentences from ‘testa,’ and 300 sentences from ‘testb.’ The second data set contains 1000 (\( \times 3 \)) sentences, and the last contains 3000 (\( \times 3 \)) sentences. Features are extracted exact the same as Stanford NER with the first-order CRF configuration. The number of features in each data set is 31979, 67513, and 166737 respectively.

We evaluate the \( F_1 \) score of \( \text{ADV}_{\hat{f}_1} \) on each data set. The performances of both the CRF model and the \( \text{ADV}_{\hat{f}_1} \) model can be found in Table 3. \( \text{ADV}_{\hat{f}_1} \) works better for all NER tags than CRF on the 300 sentences data sets. On 1000 and 3000 sentences data sets, \( \text{ADV}_{\hat{f}_1} \) achieves better \( F_1 \) scores for all tags except ‘LOC’, for which CRF shows better results. The results suggest that optimizing \( F_1 \) directly can reduce the need for using larger data set.

We train \( \text{ADV}^+_\text{aer} \) using our faster approximation method for best response (§3.5). This facilitates more efficient training by an order of magnitude. Solving the game by this approximation yields same best single strategy as using exact method in Algorithm 2, 92% \( \pm \) 3 of the time with 99% confidence level. Figure 3 shows the efficiency of this method for solving the game for longer sequences using double oracle. We still use the exact method for prediction at test time. The results in Table 3 suggest no penalty in final test scores.

![Figure 3: Comparison of double oracle performance using exact best response (LCFM Algorithm 2) and the alternative approximation method on different lengths of the sequence.](Figure3.png)

5 CONCLUSION & FUTURE WORK

This paper generalized adversarial prediction methods to structured prediction tasks with multivariate performance measures. We investigated the benefits of
this approach by addressing two key NLP tasks: word alignment evaluated using the alignment error rate and named entity recognition using chain structures evaluated using the F-score. The algorithms for finding the best response for each task are described in detail. In our future work, we plan to further extend adversarial prediction to other tasks of interest in NLP and computer vision. Also, we plan to further study and characterize the multivariate performance measures that can be efficiently optimized within the adversarial prediction framework, and explore the effectiveness of approximation during constraint generation.

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