Optimizing Multivariate Performance Measures for Learning Relation Extraction Models

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June 16, 2015
Outline

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Max-margin method for Optimizing Multi-variate Performance Measures

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Relation Extraction

*Xerox Corporation is an American multinational company headquartered in Norwalk, Connecticut. On May 21, 2009, it was announced that Ursula Burns would be the CEO of Xerox.*
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Contains(Norwalk, Connecticut)
CEO(Xerox Corp., Ursula Burns)
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Traditionally: *supervised* learning

Limitations: not scalable (expensive and time consuming to create labeled data)
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Traditionally: *supervised* learning
Limitations: not scalable (expensive and time consuming to create labeled data)
Can we leverage already existing high quality databases (e.g. Freebase) to learn good relation extractors?
Distant Supervision for Relation Extraction

Mintz et al. (2009)

<table>
<thead>
<tr>
<th>Knowledge base</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$</td>
</tr>
<tr>
<td>BornIn</td>
</tr>
<tr>
<td>PresidentOf</td>
</tr>
</tbody>
</table>

Sentences

- *Barack Obama* was born in Honolulu, Hawaii, *United States*.
- *Obama* left *United States* this *Saturday* for a *UN summit in Geneva*.
- *President Obama* defended his administrations’ collection of phone records in the *U.S.*
Distant Supervision based Relation Extraction

Mintz et al. (2009)

<table>
<thead>
<tr>
<th>Knowledge base</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ r ]</td>
</tr>
<tr>
<td>BornIn Barack Obama</td>
</tr>
<tr>
<td>PresidentOf Barack Obama</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sentences</th>
<th>Latent Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barack Obama was born in Honolulu, Hawaii, United States.</td>
<td>BornIn</td>
</tr>
<tr>
<td>Obama left United States this Saturday for a UN summit in Geneva.</td>
<td>none</td>
</tr>
<tr>
<td>President Obama defended his administrations’ collection of phone records in the U.S.</td>
<td>PresidentOf</td>
</tr>
</tbody>
</table>
Multiple instance, multiple label

Riedel et al. (2010); Hoffmann et al. (2011); Surdeanu et al. (2012)

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(Barack Obama, United States) BORNIN

President Obama, United States PRESIDENTOF
Motivation

In existing approaches, model parameters are often learnt by optimizing performance measures (e.g.: conditional log-likelihood, error rate)
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- However, these are not directly related to evaluation measures (e.g.: F1-score, area under ROC curve)
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- However, these are not directly related to evaluation measures (e.g.: F1-score, area under ROC curve)
- **Training Objective ⇬ Evaluation Measure**
Motivation (cont.)

- Can we train better models by directly optimizing task specific performance measures while allowing latent variables to adapt their values
Motivation (cont.)

- Can we train better models by directly optimizing task specific performance measures while allowing latent variables to adapt their values
- Further, can we provide a knob in the training algorithm to favor precision more than recall
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  - That contain latent variables
  - Optimize performance measures that are non-linear (e.g. $F_\beta$)
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- Outline of our approach: Interleaves concave-convex procedure (CCCP) with dual decomposition
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  - CCCP: used to populate latent variables
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  - Dual decomposition: factorizes the hard optimization problem (during training) into independent sub-problems
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- Outline of our approach: Interleaves concave-convex procedure (CCCP) with dual decomposition
  - CCCP: used to populate latent variables
  - Dual decomposition: factorizes the hard optimization problem (during training) into independent sub-problems
  - We present linear programming (LP) and local search methods to solve the sub-problems
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Figure: Graphical model instantiated for entity pair \( x := (\text{Barack Obama, United States}) \)
Preliminaries

One data-point

- $x$: entity pair
- $y$: relation labels
- $h$: latent mention labels
Optimizing Multivariate Performance Measures for Learning Relation Extraction Models

Preliminaries

*one data-point*

- $x$: entity pair
- $y$: relation labels
- $h$: latent mention labels

$(x_1, y_1, h_1)$

$(x_2, y_2, h_2)$

$(x_3, y_3, h_3)$

$\cdots$

$(X, Y, H) :$

*Set of all points in the training dataset*

$(x_n, y_n, h_n)$
Structured Prediction Learning

Goal: To find $w \in \mathbb{R}^d$ that minimizes risk

$$R_{f_w}^\Delta := \Delta \left( \left( f_w(x_1), \ldots, f_w(x_N) \right), \left( y_1, \ldots, y_N \right) \right)$$
Structured Prediction Learning

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$$R_{f_w}^\Delta := \Delta\left(\left(f_w(x_1), \ldots, f_w(x_N)\right), \left(y_1, \ldots, y_N\right)\right)$$

- Most large margin learning algorithms assume that loss is decomposable. So $R_{f_w}^\Delta$ is simplified to,

$$R_{f_w}^\Delta := \sum_{i=1}^{N} \delta(f_w(x), y)$$
Structured Prediction Learning

- Goal: To find $\mathbf{w} \in \mathbb{R}^d$ that minimizes risk

$$R^\Delta_{f_w} := \Delta \left( (f_w(x_1), \ldots, f_w(x_N)), (y_1, \ldots, y_N) \right)$$

- Most large margin learning algorithms assume that loss is decomposable. So $R^\Delta_{f_w}$ is simplified to,

$$R^\Delta_{f_w} := \sum_{i=1}^{N} \delta(f_w(x), y)$$

- However, for non-decomposable loss functions like $-F_1$, $\Delta$ cannot be expressed in terms of $\delta$
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Multi-variate Structured Prediction

- In decomposable structure prediction task, our aim is to learn $\mathbf{w} \in \mathbb{R}^d$ such that for a new entity pair $\mathbf{x}$, we can find:
Multi-variate Structured Prediction

In decomposable structure prediction task, our aim is to learn $w \in \mathbb{R}^d$ such that for a new entity pair $x$, we can find:

$$f_w(x) := \arg \max_y \max_h w \cdot \Phi(x, h, y)$$
Multi-variate Structured Prediction

- In decomposable structure prediction task, our aim is to learn \( \mathbf{w} \in \mathbb{R}^d \) such that for a new entity pair \( \mathbf{x} \), we can find:

\[
f_{\mathbf{w}}(\mathbf{x}) := \arg \max_y \max_h \mathbf{w} \cdot \Phi(\mathbf{x}, h, y)
\]

- Instead of learning a mapping function from an individual instance to its label, we learn a mapping from all instances to their labels.
Multi-variate Structured Prediction

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$$f_w(x) := \arg \max_w \max_y w \cdot \Phi(x, h, y)$$

- Instead of learning a mapping function from an individual instance to its label, we learn a mapping from all instances to their labels.

- We define the best labeling using the following linear discriminant function:

$$f(X) := \arg \max_{Y' \in \mathcal{Y}} \max_{H \in \mathcal{H}} \left\{ w \cdot \Psi(X, H, Y') \right\}$$

where $\Psi(X, H, Y') := \sum_{i=1}^{N} \Phi(x_i, h_i, y'_i)$
Training Objective

Based on margin re-scaling formulation of structured prediction problems, our training objective is:

$$\min_w \frac{1}{2} \|w\|_2^2 + C \max_{y_1', \ldots, y_N'} \left\{ \Delta \left( (y_1, \ldots, y_N), (y_1', \ldots, y_N') \right) + \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y_i') - \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y_i) \right\}$$
Training Objective

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\[
\begin{align*}
\min_w & \frac{1}{2} \|w\|_2^2 + C \max_{y'_1, \ldots, y'_N} \left\{ \Delta \left( (y_1, \ldots, y_N), (y'_1, \ldots, y'_N) \right) \right. \\
& \left. + \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y'_i) - \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y_i) \right\}
\end{align*}
\]

- The above objective is non-convex since it is the difference of two convex functions
Convex-concave Procedure (CCCP)

- Refer to Yuille and Rangarajan (2001) and Sriperumbudur and Lanckriet (2012)
- CCCP is a special example of Majorization-Minimization (class of) algorithm(s)
- Elaborate Convergence proof for constrained version by Sriperumbudur and Lanckriet (2012) using Zangwill’s global convergence framework

Training Objective

$$\min_w \frac{1}{2}\|w\|^2 + C \max_{y_1, \ldots, y_N} \left\{ \Delta \left( (y_1, \ldots, y_N), (y'_1, \ldots, y'_N) \right) \right\}$$

+ $$\sum_{i=1}^{N} \max_h w \cdot \Phi(x_i, h, y'_i) - \sum_{i=1}^{N} \max_h w \cdot \Phi(x_i, h, y_i)$$

Algorithm 1: The Training Algorithm

1: procedure OPT-LATENT SVM(X, Y)
2: Initialize $w^{(0)}$ and set $t = 0$
3: repeat
4: for $i := 1$ to $N$ do
5: Conic Step
6: Update $w$
Convex-concave Procedure (CCCP)

The Training Objective

\[
\min_w \frac{1}{2} \|w\|^2 + C \max_{y'_1, \ldots, y'_N} \left\{ \Delta \left( (y_1, \ldots, y_N), (y'_1, \ldots, y'_N) \right) + \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y'_i) - \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y_i) \right\}
\]

Algorithm 1: The Training Algorithm

1: procedure OPT-LATENT SVM(X, Y)
2: Initialize \( w^{(0)} \) and set \( t = 0 \)
3: repeat
4: \hspace{1em} for \( i := 1 \) to \( N \) do
5: \hspace{2em} \( h^*_i := \arg \max_h w^{(t)} \cdot \Phi(x_i, h, y_i) \)
6: \hspace{1em} Convex Step:
7: \hspace{1.5em} Given the best assignment of latent variables,
8: \hspace{1.5em} Solve for \( w \) (via cutting plane algorithm)
9: \hspace{1em} until some stopping condition is met
10: return \( w^{(t)} \)

**Figure**: CCCP Algorithm
Convex-concave Procedure (CCCP)

Training Objective

\[
\min_w \frac{1}{2} \|w\|^2 + C \max_{y'_1, \ldots, y'_N} \left\{ \Delta((y_1, \ldots, y_N), (y'_1, \ldots, y'_N)) \right. \\
+ \sum_{i=1}^{N} \max_h w \cdot \Phi(x_i, h, y'_i) - \sum_{i=1}^{N} \max_h w \cdot \Phi(x_i, h, y_i) \left. \right\}
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1: procedure OPT-LATENTSVM(X, Y)
2: Initialize \( w^{(0)} \) and set \( t = 0 \)
3: repeat
4:     for \( i := 1 \) to \( N \) do
5:         \( h^*_i := \arg \max_h w^{(t)} \cdot \Phi(x_i, h, y_i) \)
6:     \( h^* := \text{optSVM}(X, H^*, Y) \)
7:     \( t := t + 1 \)
8: until some stopping condition is met
9: return \( w^{(t)} \)

**Figure:** CCCP Algorithm
Convex Step: Loss Augmented Inference

- Convex step (via cutting plane) to find the best \( w \)
Convex Step: Loss Augmented Inference

- Convex step (via cutting plane) to find the best $w$
- Involves solving the following “loss-augmented inference”

$$
\max_{y'_1, \ldots, y'_N} \Delta\left( (y_1, \ldots, y_N), (y'_1, \ldots, y'_N) \right) \\
+ \sum_{i=1}^{N} \max_h w \cdot \Phi(x_i, h, y'_i)
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Convex Step: Loss Augmented Inference

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$$

- We employ dual decomposition to decouple the two terms and efficiently find an approximate solution
Dual Decomposition

$$\max_{y_1', \ldots, y_N'} \Delta \left( (y_1, \ldots, y_N), (y_1', \ldots, y_N') \right) + \sum_{i=1}^{N} \max_{h} w \cdot \Phi(x_i, h, y'_i)$$
Dual Decomposition

\[
\max_{y'_1, \ldots, y'_N} \quad \Delta \left( (y_1, \ldots, y_N), (y'_1, \ldots, y'_N) \right) \\
+ \sum_{i=1}^{N} \max_{h} w \cdot \Phi(x_i, h, y'_i)
\]

subject to

\[
\forall i \in \{1, \ldots, N\}, \forall \ell \in \{1, \ldots, L\}, \quad y'_{i,\ell} = y''_{i,\ell}
\]
Dual Decomposition (cont.)

After forming lagrangian, the dual objective function is derived as:

\[
L(\Lambda) := \max_{\mathbf{Y}, \mathbf{Y}'} \Delta(\mathbf{Y}, \mathbf{Y}') + \sum_i \sum_{\ell} \lambda_i(\ell) y_{i,\ell} + \sum_{i=1}^{N} \max_{\mathbf{Y}''} \left( \max_h \mathbf{w} \cdot \Phi(\mathbf{x}_i, h, y_{i'',\ell}) - \sum_i \sum_{\ell} \lambda_i(\ell) y_{i,\ell} \right) \]

\[\rightarrow \quad \text{“loss-lagrangian”} \]

\[\rightarrow \quad \text{“model-lagrangian”} \]
After forming lagrangian, the dual objective function is derived as:

\[
L(\Lambda) := \max_{Y'} \Delta(Y, Y') + \sum_i \sum_\ell \lambda_i(\ell) y_{i,\ell} + \max_{Y''} \sum_{i=1}^N \max_h w \cdot \Phi(x_i, h, y''_{i,\ell}) - \sum_i \sum_\ell \lambda_i(\ell) y''_{i,\ell}
\]

Since \( L(\Lambda) \) is an upper-bound on the original loss-augmented inference, we find the tightest upper-bound as an approximate solution: \( \min_{\Lambda} L(\Lambda) \)

This is solved via sub-gradient descent method
Optimization of the Dual - Multivariate Loss

$$Y'_* := \arg \max_{Y'} \Delta(Y, Y') + \sum_i \sum_\ell \lambda_i^{(t-1)}(\ell)y'_{i,\ell}$$
Optimization of the Dual - Multivariate Loss

\[
Y'_* := \arg \max_{Y'} \Delta(Y, Y') + \sum_i \sum_\ell \lambda_i^{(t-1)}(\ell) y'_{i,\ell}
\]

- Optimizing the multivariate loss is also a hard problem since we have search over entire space of \(Y' \in Y\) (exponential)
Optimization of the Dual - Multivariate Loss

\[ Y_* := \arg \max_{Y'} \Delta(Y, Y') + \sum_i \sum_\ell \lambda_i^{(t-1)}(\ell) y_{i,\ell} \]

- Optimizing the multivariate loss is also a hard problem since we have search over entire space of \( Y' \in \mathcal{Y} \) (exponential).
- However, loss term can be expressed in terms of aggregate statistics over \( Y' \) (false positives (FPs) and false negatives (FNs)).
Optimizing the multivariate loss is also a hard problem since we have search over entire space of $Y' \in \mathcal{Y}$ (exponential).

However, loss term can be expressed in terms of aggregate statistics over $Y'$ (false positives (FPs) and false negatives (FNs)).

Since FPs and FNs are integral it can take finite values which can be represented on a two-dimensional grid and efficiently searched via a local search algorithm.
Local Search Algorithm

Figure: Local Search Algorithm : An Illustration
Optimization of the Dual - Model Lagrangian

\[ Y_*^{''} := \arg \max_{Y^{''}} \sum_{i=1}^{N} \max_{h} \mathbf{w} \cdot \Phi(x_i, h, y_i^{''}) \]

\[ - \sum_{i} \sum_{\ell} \lambda_i^{(t-1)}(\ell)y_{i,\ell}^{''} \]
Optimization of the Dual - Model Lagrangian

\[ Y'':= \arg \max_{Y''} \sum_{i=1}^{N} \max_{h} w \cdot \Phi(x_i, h, y_i'') \]

\[ - \sum_{i} \sum_{\ell} \lambda_i^{(t-1)}(\ell) y_i'', \ell \]

▶ This problem is as difficult as the MAP inference in the underlying graphical model (NP-hard for loopy graphs)
Optimization of the Dual - Model Lagrangian

\[ Y''_* := \arg \max_{Y''} \sum_{i=1}^{N} \max_{h} w \cdot \Phi(x_i, h, y''_i) \]

\[- \sum_{i} \sum_{\ell} \lambda_i^{(t-1)}(\ell)y''_{i,\ell} \]

- This problem is as difficult as the MAP inference in the underlying graphical model (NP-hard for loopy graphs)
- We use ILP formulations (relaxed to LP) to solve this
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Experimental Setup

- Dataset: We used the benchmark dataset created by Riedel et al. (2010)

$$F_\beta := \frac{\beta \cdot \text{Precision} + \text{Recall}}{\beta + 1}$$
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- Baseline: Hoffmann et. al.’s (2011) state-of-the-art distantly supervised relation extractor
Experimental Setup

- Dataset: We used the benchmark dataset created by Riedel et. al. (2010)
- Baseline: Hoffmann et. al.'s (2011) state-of-the-art distantly supervised relation extractor
- Our approaches:
  - Max-margin which optimizes simple decomposable (Hamming) loss
  - Max-margin which optimizes non-decomposable $-F_\beta$ loss

\[
F_\beta := \frac{1}{\beta \text{Precision} + \frac{1-\beta}{\text{Recall}}}
\]
Training on sub-samples of data

Figure: Experiments on 10% Riedel datasets.
Tuning towards Precision/Recall

Figure: Weighting of Precision and Recall ($\beta = 0.833$)
Accuracies on the entire dataset

Figure: Overall accuracies Riedel dataset
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- Our approach is general and can be applied to other latent variable models in NLP.
Conclusion

- Described a novel max-margin approach to optimize non-linear performance measures, such as $F_\beta$, in distant supervision of information extraction models
- Our approach is general and can be applied to other latent variable models in NLP
- Our approach involves solving the hard-optimization problem in learning by interleaving Concave-Convex Procedure with dual decomposition
Conclusion

Under several conditions, we have shown our technique outperforms very strong baselines, and results in up to 8.5% improvement in $F_1$-score.
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- Under several conditions, we have shown our technique outperforms very strong baselines, and results in up to 8.5% improvement in $F_1$-score
- For future work:
  - Maximize other performance measures, such as area under the curve, for information extraction models
  - Explore our approach for other latent variable models in NLP, such as those in machine translation
Acknowledgements

- National ICT Australia (NICTA) for their generous funding, as part of the Machine Learning Collaborative Research Projects.
- Xerox Research Centre India (XRCI) for their generous student travel grant.
Conclusion

Thank You!

*Code present at:*  
https://github.com/ajaynagesh/lsvm_relationextraction
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