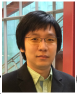
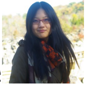
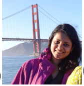
Hands-on Learning to Search for ~~Structured~~ Joint Prediction

Kai-Wei Chang  @UIUC->MSR-NE

Hal Daume , He He , Sudha Rao  @UMaryland

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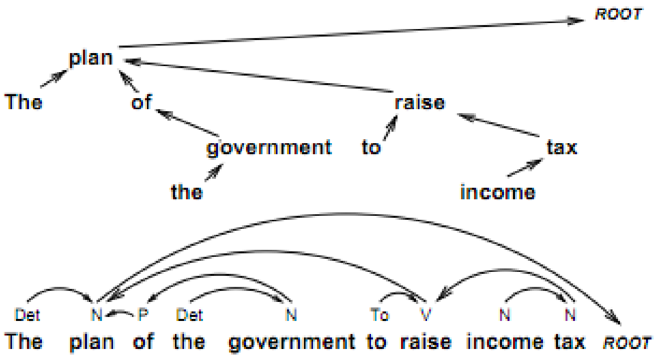
http://tinyurl.com/naacl15l2s

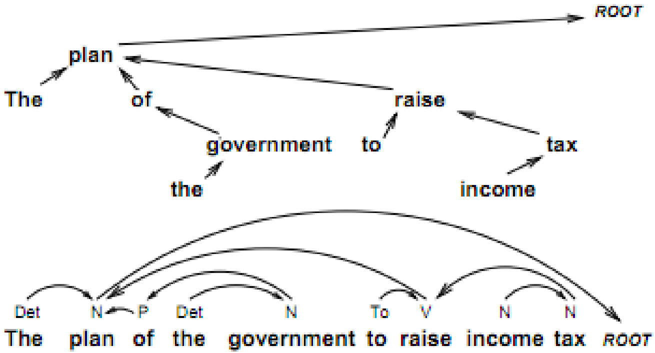
NAACL, May 31

The Problem: Joint Prediction



How? Other answers

The Problem: Joint Prediction



How? Other answers

1. Each prediction is independent.

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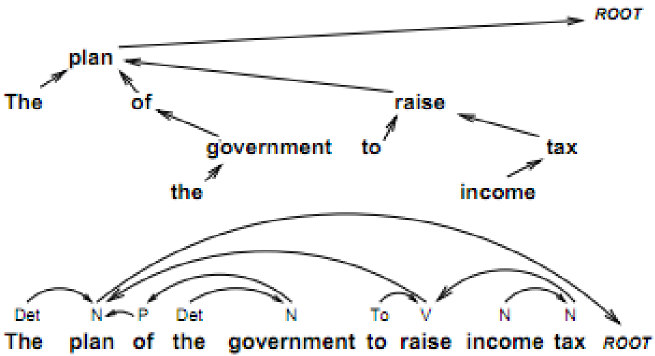

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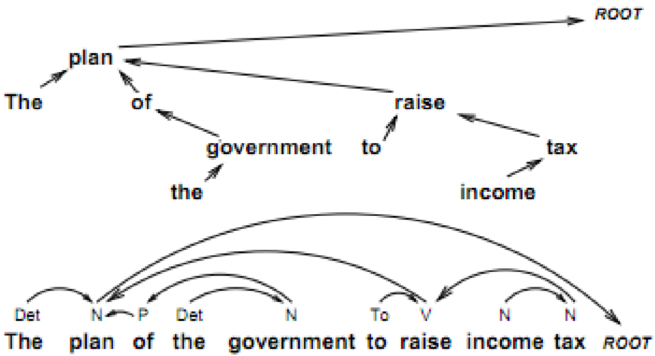

How? Other answers

1. Each prediction is independent.
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3. Assume tractable graphical model, optimize.

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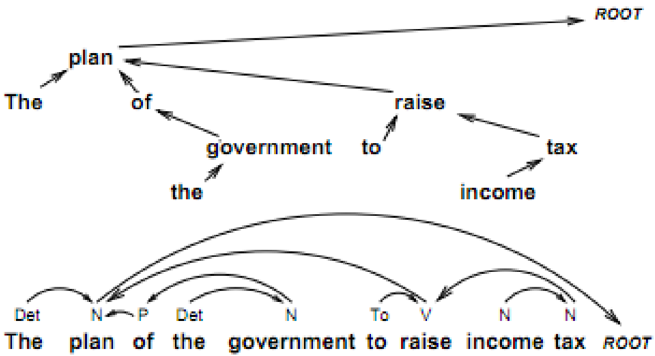

How? Other answers

1. Each prediction is independent.
2. Multitask learning.
3. Assume tractable graphical model, optimize.
4. Hand-crafted approaches.

What makes a good solution?

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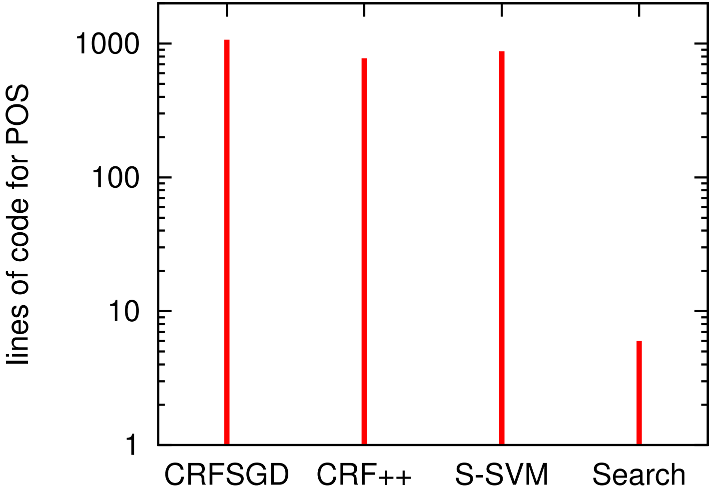
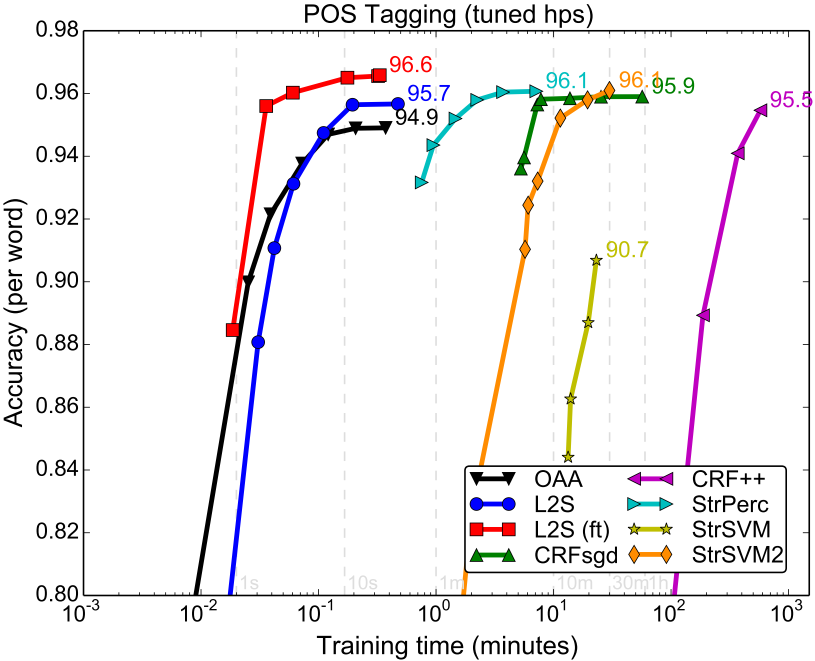
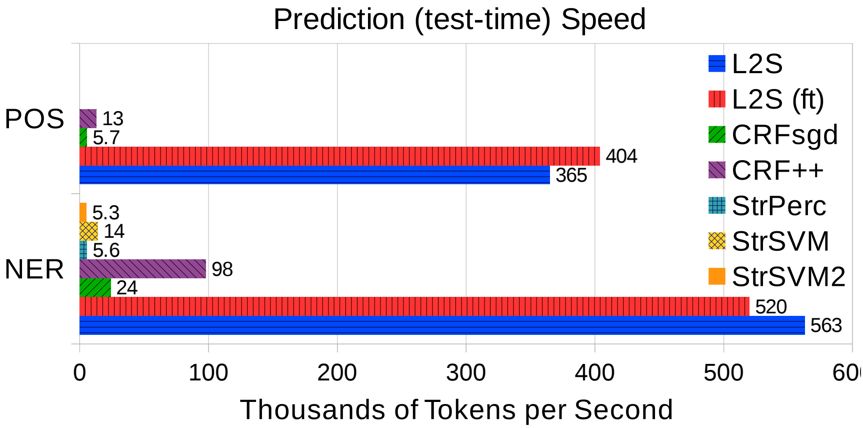
3. Train speed. Debug/development productivity + maximum data input.
4. Test speed. Application efficiency

A program complexity comparison




POS Tagging (tuned hps)
Accuracy (per word)
Training time (minutes)
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0.80
10^{-3}
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}
1s
10s
1m
10m
30m
1h
96.6
95.7
94.9
96.1
96.1
95.9
95.5
90.7
OAA
L2S
L2S (ft)
CRFsgd
CRF++
StrPerc
StrSVM
StrSVM2



Prediction (test-time) Speed
POS
NER
13
5.7
404
365
5.3
14
5.6
98
24
520
563
L2S
L2S (ft)
CRFsgd
CRF++
StrPerc
StrSVM
StrSVM2
0
100
200
300
400
500
600
Thousands of Tokens per Second

The Plan

1. Part 1
   1. Machine Learning + Vowpal Wabbit Background
      1. Input format
      2. One-against-all Multiclass
      3. Regression
   2. Joint prediction by Imitation Learning
   3. Joint Prediction by Learning to Search
2. Part 2: Hands-on.
   Let's solve Named Entity Recognition.

Part of Speech Tagging

wget `http://bit.ly/1FVkLEK`

Part of Speech Tagging

wget http://bit.ly/1FVkLEK
unzip 1FVkLEK

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wget http://bit.ly/1FVkLEK

unzip 1FVkLEK

less wsj.train.vw

```
1 |w Despite
2 |w continuing
3 |w problems
1 |w in
4 |w its
5 |w newsprint
5 |w business
```

In general:

label |Namespace Feature

An approach: One-Against-All (OAA)

Create k binary problems, one per class.
For class i predict "Is the label i or not?"

$$(x, y) \longmapsto \begin{cases} (x, \mathbf{1}(y = 1)) \\ (x, \mathbf{1}(y = 2)) \\ \ldots \\ (x, \mathbf{1}(y = k)) \end{cases}$$

Then reduce to regression.

vw --oaa 45 wsj.train.vw

vw --oaa 45 wsj.train.vw

Key ideas:

1. Hashing: avoid dictionaries for simplicity/speed.
2. Online Learning: quick optimization.
3. Progressive Validation: test one ahead of train for unbiased perf.

Cost-sensitive multiclass classification

Distribution D over $X \times [0,1]^k$, where a vector in $[0,1]^k$ specifies the cost of each of the k choices.

Find a classifier $h : X \to \{1, \ldots, k\}$ minimizing the expected cost

$$\text{cost}(c, D) = \mathbf{E}_{(x,c)\sim D}[c_{h(x)}].$$

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1. Is this packet {normal,error,attack}?
2. A key primitive for learning to search.

Use in VW

Label information via sparse vector.

A test example:

|Namespace Feature

A test example with only classes 1,2,4 valid:

1: 2: 4: |Namespace Feature

A training example with only classes 1,2,4 valid:

1:0.4 2:3.1 4:2.2 |Namespace Feature

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Methods:

–csoaa k cost-sensitive OAA prediction. $O(k)$ time.

–csoaa_ldf Label-dependent features OAA.

–wap_ldf LDF Weighted-all-pairs.

The reduction to regression

wget http://bit.ly/1EvYlm9
tar -xvzf 1EvYlm9
zless VW_raw/rcv1.train.raw.txt.gz

The reduction to regression

```
wget http://bit.ly/1EvYlm9
tar -xvzf 1EvYlm9
zless VW_raw/rcv1.train.raw.txt.gz
1 | tuesday year million short compan ...
-1 | econom stock rate month year invest ...
...
```

The reduction to regression

wget `http://bit.ly/1EvYlm9`
tar -xvzf 1EvYlm9
zless VW_raw/rcv1.train.raw.txt.gz
1 | tuesday year million short compan ...
-1 | econom stock rate month year invest ...
...

```
vw -c rcv1.train.raw.txt -b 22 --ngram 2
--skips 4 -l 0.25 --binary
```

generates good solution.

Linear Learning

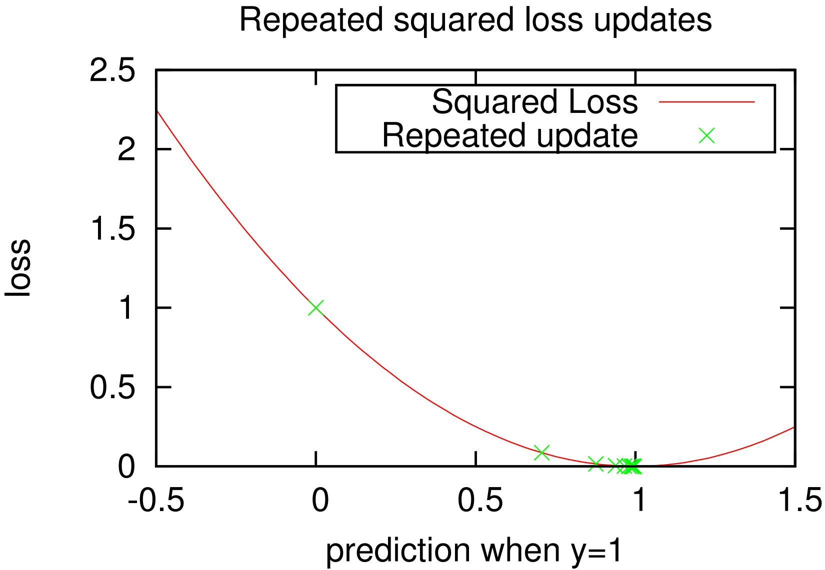
Features: a vector $x \in \mathbb{R}^n$
Label: $y \in \mathbb{R}$
Goal: Learn $w \in \mathbb{R}^n$ such that $\hat{y}_w(x) = \sum_i w_i x_i$ is close to y.

Online Linear Learning

Start with $\forall i: \quad w_i = 0$

Repeatedly:

1. Get features $x \in \mathbb{R}^n$.
2. Make linear prediction $\hat{y}_w(x) = \sum_i w_i x_i$.
3. Observe label $y \in \mathbb{R}$.
4. Update weights so $\hat{y}_w(x)$ is closer to y.
   Example: $w_i \leftarrow w_i + \eta(y - \hat{y})x_i$.



Repeated squared loss updates
Squared Loss
Repeated update
loss
2.5
2
1.5
1
0.5
0
-0.5
0
0.5
1
1.5
prediction when y=1

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