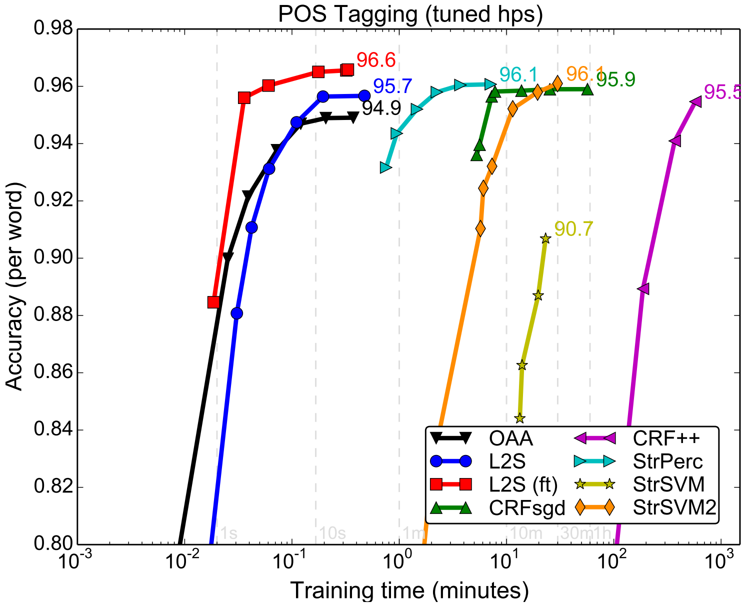
Outline

1. Empirics
2. Analysis
3. Programming
4. Others and Issues

What part of speech are the words?



A demonstration

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

...

A demonstration

1 |w Despite
2 |w continuing
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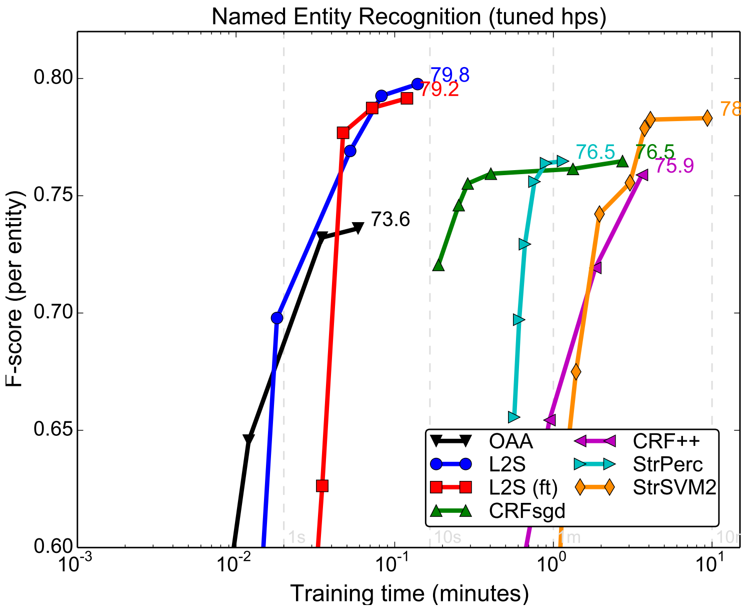
...

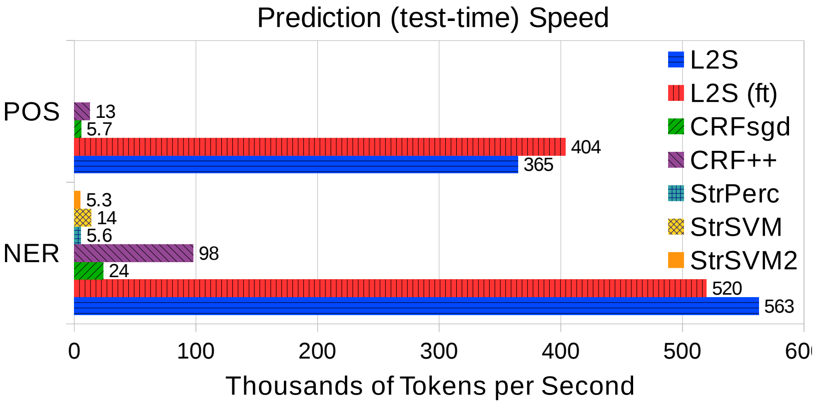
vw -b 24 -d wsj.train.vw -c –search_task sequence –search 45 –search_alpha 1e-8 –search_neighbor_features -1:w,1:w –affix -1w,+1w -f foo.reg

vw -t -i foo.reg wsj.test.vw

Is this word a name or not?



How fast in evaluation?



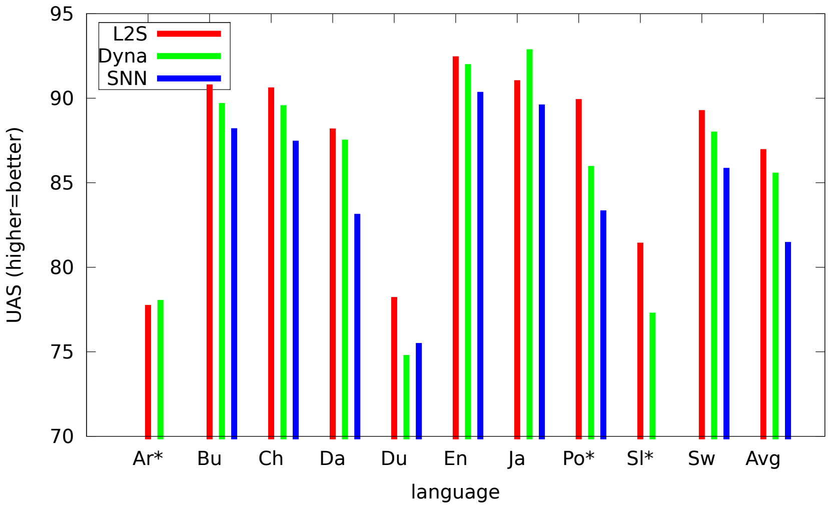
Entity Relation

Goal: find the Entities and then find their Relations

Method	Entity F1	Relation F1	Train Time
Structured SVM	88.00	50.04	300 seconds
L2S	92.51	52.03	13 seconds

L2S uses ~100 LOC.

Find dependency structure of sentences.



L2S uses ~300 LOC.

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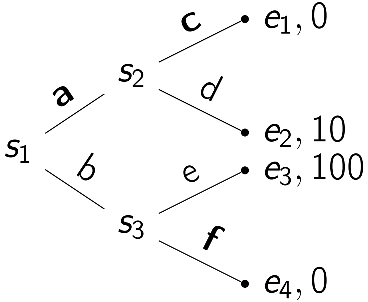
Effect of Roll-in and Roll-out Policies

roll-out $\rightarrow$ $\downarrow$ roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	.		



Effect of Roll-in and Roll-out Policies

roll-out → ↓ roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	.		

Theorem

Roll-in with ref:

0 *cost-sensitive regret* $\Rightarrow$ *unbounded joint regret*

Effect of Roll-in and Roll-out Policies

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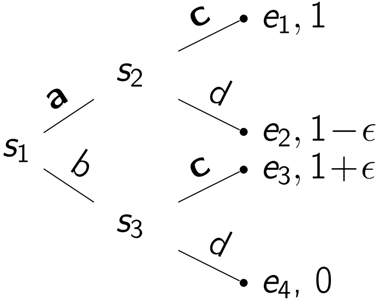
Learned	Consistent No local opt		



Effect of Roll-in and Roll-out Policies

roll-out → ↓ roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt		

Theorem

Roll-out with Ref:

0 *cost-sensitive regret* ⇒ 0 *joint regret*

(but not local optimality)

Effect of Roll-in and Roll-out Policies

roll-out → ↓ roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt		Reinf. L.

Theorem

Ignore Ref:
$\Rightarrow$ *Equivalent to reinforcement learning.*

Effect of Roll-in and Roll-out Policies

roll-out → ↓ roll-in	Reference	Half-n-half	Learned
Reference	Inconsistent		
Learned	Consistent No local opt	Consistent Local Opt	Reinf. L.

Theorem

Roll-out with $p = 0.5$ Ref and $p = 0.5$ Learned:
0 *cost-sensitive regret* $\Rightarrow 0$ *joint regret* $+$ *locally optimal*

AggreVaTe Regret Decomposition

π^{ref} = reference policy
$\bar{\pi}$ = stochastic average learned policy
$J(\pi)$ = expected loss of π.

Theorem

$J(\bar{\pi}) - J(\pi^{ref}) \leq$

AggreVaTe Regret Decomposition

π^{ref} = reference policy
$\bar{\pi}$ = stochastic average learned policy
$J(\pi)$ = expected loss of π.

Theorem

$$J(\bar{\pi}) - J(\pi^{ref}) \leq T\mathbb{E}_{n,t}\mathbb{E}_{x\sim D^t_{\hat{\pi}_n}}\left[Q^{\pi^{ref}}(x,\hat{\pi}_n) - Q^{\pi^{ref}}(x,\pi^{ref})\right]$$

T = number of steps
$\hat{\pi}_n$ = nth learned policy
$D^t_{\hat{\pi}_n}$ = distribution over x at time t induced by $\hat{\pi}_n$
$Q^{\pi}(x,\pi')$ = loss of π' at x then π to finish

Proof

For all π let π^t play π for rounds $1 \ldots t$ then play π^{ref} for rounds $t+1 \ldots T$. So $\pi^T = \pi$ and $\pi^0 = \pi^{\text{ref}}$

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$J(\pi) - J(\pi^{\text{ref}})$

$\quad = \sum_{t=1}^{T} J(\pi^t) - J(\pi^{t-1})$ (Telescoping sum)

Proof

For all π let π^t play π for rounds $1 \ldots t$ then play π^{ref} for rounds $t+1 \ldots T$. So $\pi^T = \pi$ and $\pi^0 = \pi^{\text{ref}}$

$$
\begin{aligned}
&J(\pi) - J(\pi^{\text{ref}}) \\
&\quad = \textstyle\sum_{t=1}^{T} J(\pi^t) - J(\pi^{t-1}) \text{ (Telescoping sum)} \\
&\quad = \textstyle\sum_{t=1}^{T} \mathbb{E}_{x \sim D_\pi^t} \left[Q^{\pi^{\text{ref}}}(x, \pi) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right]
\end{aligned}
$$

since for all π, t, $J(\pi) = \mathbb{E}_{x \sim D_\pi^t} Q^{\pi}(x, \pi)$

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Proof

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So $J(\bar{\pi}) - J(\pi^{\text{ref}})$

$$= T \mathbb{E}_{t,n} \mathbb{E}_{x \sim D_{\hat{\pi}_n}^t} \left[Q^{\pi^{\text{ref}}}(x, \hat{\pi}_n) - Q^{\pi^{\text{ref}}}(x, \pi^{\text{ref}}) \right]$$

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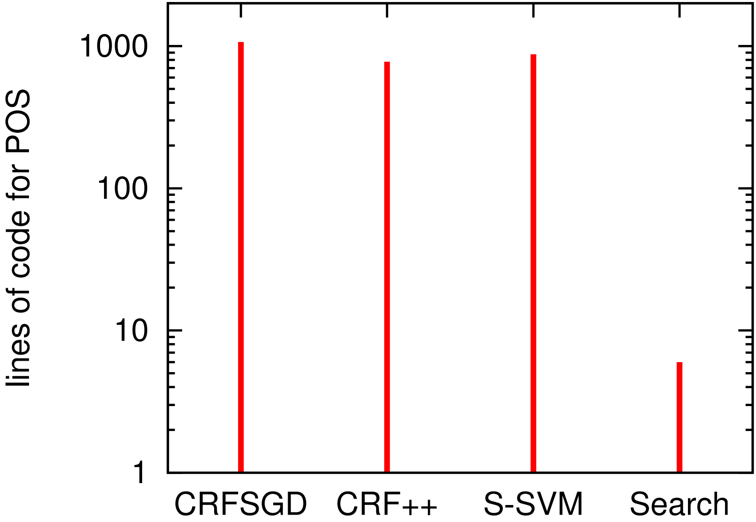
Lines of Code



How?

Sequential_RUN(*examples*)

for $i = 1$ **to** len(*examples*) **do**
    prediction $\leftarrow$ **predict**(*examples*[i], *examples*[i] . *label*)
    loss(*prediction* $\neq$ *examples*[i] . *label*)
end for

How?

Sequential_RUN(*examples*)

```
for i = 1 to len(examples) do
    prediction ← predict(examples[i], examples[i].label)
    loss(prediction ≠ examples[i].label)
end for
```

Decoder + loss + reference advice

RunParser(*sentence*)

stack $S \leftarrow \{\textbf{Root}\}$
buffer $B \leftarrow$ [words in sentence]
arcs $A \leftarrow \emptyset$
while $B \neq \emptyset$ or $|S| > 1$ **do**
    ValidActs $\leftarrow$ GetValidActions(S, B)
    features $\leftarrow$ GetFeat(S, B, A)
    ref $\leftarrow$ GetGoldAction(S, B)
    action $\leftarrow$ **predict**(features, ref, ValidActs)
    $S, B, A \leftarrow$ Transition$(S, B, A,$ action$)$
end while
loss$(A[w] \neq A^*[w], \forall w \in$ sentence$)$
return output

Program/Search equivalence

Theorem: Every algorithm which:

1. Always terminates.
2. Takes as input relevant feature information X.
3. Make $0+$ calls to predict.
4. Reports loss on termination.

defines a search space, and such an algorithm exists for every search space.

It even works in Python

```
def _run(self, sentence):
    output = []
    for n in range(len(sentence)):
        pos,word = sentence[n]
        with self.vw.example('w': [word],
              'p': [prev_word]) as ex:
          pred = self.sch.predict(examples=ex,
                    my_tag=n+1, oracle=pos,
                    condition=[(n,'p'), (n-1, 'q')])
          output.append(pred)
    return output
```

Bugs you cannot have

1. Never train/test mismatch.

Bugs you cannot have

1. Never train/test mismatch.
2. Never unexplained slow.

Bugs you cannot have

1. Never train/test mismatch.
2. Never unexplained slow.
3. Never fail to compensate for cascading failure.

Outline

1. Empirics
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4. Others and Issues
    1. Families of algorithms.
    2. What's missing from learning to search?

Imitation Learning

Use perceptron-like update when learned deviates from gold standard.

- **Inc. P.** Collins & Roark, ACL 2004.
- **LaSo** Daume III & Marcu, ICML 2005.
- **Local** Liang et al, ACL 2006.
- **Beam P.** Xu et al., JMLR 2009.
- **Inexact** Huang et al, NAACL 2012.

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Train a classifier to mimic an expert's behavior

DAgger	Ross et al., AIStats 2011.
Dyna O	Goldberg et al., TACL 2014.

Learning to Search

When the reference policy is optimal

Searn Daume III et al., MLJ 2009.

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Code in Vowpal Wabbit `http://hunch.net/~vw`

Inverse Reinforcement Learning

Given observed expert behavior, infer the underlying reward function the expert seems to be optimizing

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Ng & Russell, ICML 2000

for apprenticeship learning

Apprent. Abbeel & Ng, ICML 2004

Maxmar. Ratliff et al., NIPS 2005

MaxEnt Ziebart et al., AAAI 2008

What's missing? Automatic Search order

Learning to search $\simeq$ dependency $+$ search order.
Graphical models "work" given dependencies only.

What's missing? The reference policy

A good reference policy is often nonobvious... yet critical to performance.

What's missing?
Efficient Cost-Sensitive Learning

When choosing 1-of-k things, $O(k)$ time is not exciting for machine translation.

What's missing? GPU fun

Vision often requires a GPU. Can that be done?

How to optimize discrete joint loss?

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1. Programming complexity.

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How to optimize discrete joint loss?

1. Programming complexity. Most complex problems addressed independently—too complex to do otherwise.
2. Prediction accuracy. It had better work well.
3. Train speed. Debug/development productivity + maximum data input.
4. Test speed. Application efficiency