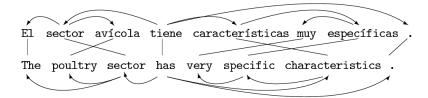
# Dependency Grammar Induction via Bitext Projection Constraints

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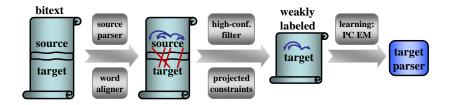
May 11, 2009

#### Overview



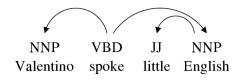
- Goal: Automate creation of linguistic resources
- Method: Use parallel corpora to bootstrap parser learning

#### Overview



Require most projected dependencies be exhibited in learned parses

## Generative Model



$$p_{\theta}(x,y) = \theta_{root(VBD)}$$

$$\cdot \theta_{continue(VBD,right,false)} \cdot \theta_{child(VBD,right,NNP)}$$

$$\cdot \theta_{stop(VBD,right,true)} \cdot \theta_{stop(NNP,right,false)}$$

$$\cdot \theta_{continue(VBD,left,false)} \cdot \theta_{continue(NNP,left,false)}$$

$$\cdot \theta_{child(VBD,left,NNP)} \cdot \theta_{child(NNP,left,JJ)}$$

$$\cdot \theta_{stop(NNP,right,false)} \cdot \theta_{stop(VBD,left,true)}$$

$$\cdot \theta_{stop(JJ,right,false)} \cdot \theta_{stop(JJ,left,false)}$$

$$\cdot \theta_{stop(NNP,left,false)} \cdot \theta_{stop(NNP,left,true)}$$

### Discriminative Model

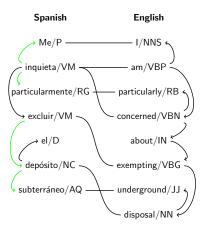
$$p_{ heta}(\mathbf{y}\mid\mathbf{x}) \propto \prod_{y\in\mathbf{y}} e^{ heta\cdot\phi(y,\mathbf{x})}$$

Example feature vector  $\phi$ 

```
\vdots\\ \mathbf{1}(\mathsf{child}\text{-POS} = \mathsf{D},\, \mathsf{child}\text{-word} = \mathsf{el},\, \mathsf{parent}\text{-POS} = \mathsf{NC})\\ \mathbf{1}(\mathsf{child}\text{-POS} = \mathsf{D},\, \mathsf{between}\text{-POS} = \mathsf{AQ},\, \mathsf{parent}\text{-POS} = \mathsf{NC})\\ \mathbf{1}(\mathsf{pre}\text{-child}\text{-POS} = \mathsf{VM},\, \mathsf{child}\text{-POS} = \mathsf{D},\, \mathsf{parent}\text{-POS} = \mathsf{NC})\\ \mathbf{1}(\mathsf{child}\text{-POS} = \mathsf{D},\, \mathsf{parent}\text{-POS} = \mathsf{NC})\\ \mathbf{1}(\mathsf{child}\text{-POS} = \mathsf{D},\, \mathsf{parent}\text{-POS} = \mathsf{VM})\\ \vdots
```

# **Expectation Maximization**

## Constrained EM



- $E_a[f(x,y)] \geq c$
- f(x,y) = # of projected dependencies realized in parse y
- $\mathbf{c} = \mathbf{c}$  lower limit on feature expectation



## Constrained EM

#### E-Step

$$\underset{q(y) \in \mathcal{Q}(x)}{\operatorname{arg \, min}} \, \operatorname{KL}(q(y) \parallel p_{\theta^t}(y \mid x))$$

#### M-Step

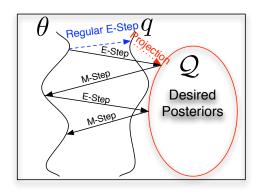
$$\arg\max_{\theta} E_X[q(y)\log p_{\theta}(x,y)]$$

- $\mathbf{x} =$  words and POS tags, y = dependency parse
- ullet  $\theta = \mathsf{model}$  parameters
- $\bullet$  f = a feature, c = lower limit on feature expectation

J. Graca, K. Ganchev, B. Taskar. EM and Posterior Constraints, 2008.



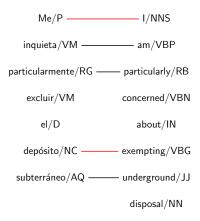
## Constrained EM



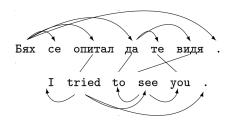
**Objective**: 
$$\arg \max_{\theta} \left( L(\theta) - E_X[KL(Q(x) || p_{\theta}(y | x))] \right)$$

# Alignment Pre-Processing

- Corpora Bulgarian subtitles, Spanish Europarl
- Remove alignments if POS don't belong to same category



# Corrective Rules for Bulgarian



- "da" should dominate words until next verb, and adopt their children
- Auxiliary verb should be parent of main verb
- Similar rules for 5 more words like "da"

## Corrective Rules for Spanish





- Main verb should be parent of auxiliary verb
- First element in adjective-noun or noun-adjective pair should be parent of other, and adopt other's children

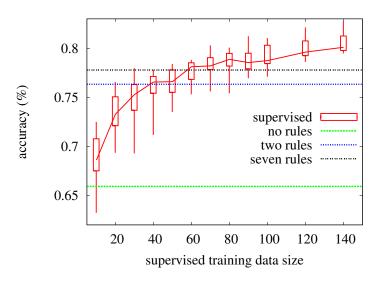
### No Rules Results

Constraint: In expectation, at least 70% of projected dependencies must appear in Bulgarian/Spanish parses.

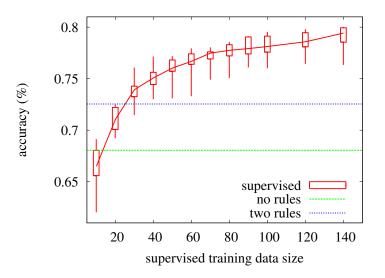
Language	Link-left	Gener.	Discrim.
Bulgarian	33.8 %	61.9%	65.9%
Spanish	27.9 %	55.6%	68.1%

- Train sets: 10k parallel sentences of length  $\leq$  20
- Test sets: CoNLL train, sentences of length  $\leq 10$

# Bulgarian Discriminative Results



# Spanish Discriminative Results



# Top Bulgarian Errors

child POS			parent POS	
	acc(%)	errors		errors
N	75.1	1839	N/V	1078
Ρ	70.2	1223	V/V	607
V	84.4	1004	R/V	533
R	79.0	678	V/N	482

- V verb, N noun, P pronoun, R preposition, T particle
- Accuracies are by child or parent truth/guess POS tag

# Related Work on Spanish

#### Hwa et. al.

- Special projection for each of one-to-many, many-to-one, and many-to-many alignments
- Filtered sentences where
  - < 30% of words aligned</p>
  - one-to-many alignment was too unbalanced
- Used extensive set of language-specific rules (only 37% accuracy before rules)

Best performance  $\approx 72\%$  for both methods (though corpora differ)

Hwa et. al. Bootstrapping Parsers via Syntactic Projection across Parallel Texts, 2004

#### Conclusion

- Equivalent of supervised methods with limited training data
- Using constrained EM allows for
  - Fewer language-specific rules
  - Learning from partial projected parses
- Further improvement by adding more complex constraints?
  - Grandparent or other long-range chains
  - Surface length for a particular POS tag

