Structured Learning for Taxonomy Induction with Belief Propagation

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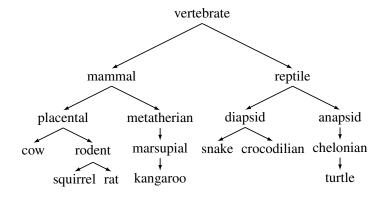




A Lexical Taxonomy



Captures types and categories via hypernymy



Current resources incomplete, unavailable, time-intensive





Automatically build taxonomy trees

Widdows (2003), Snow et al. (2006), Yang and Callan (2009), Poon and Domnigos (2010), Fountain and Lapata (2012), Kozareva and Hovy (2010), Navigli et al. (2011)



Outline



Structured inference (during both learning and decoding) and learned semantic features on links and siblings

Supervised learning: train on one part of WordNet (e.g., food) and test on a new part (e.g., animals)

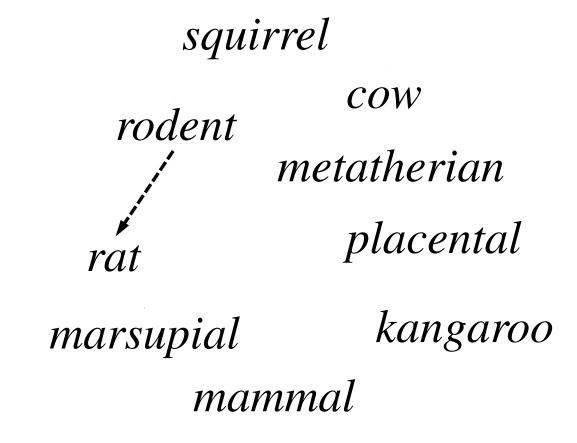
Train
$$\cap$$
 Test $= \emptyset$

No repeated words!!! → Cannot use lexicalized features; need surface and external Web features



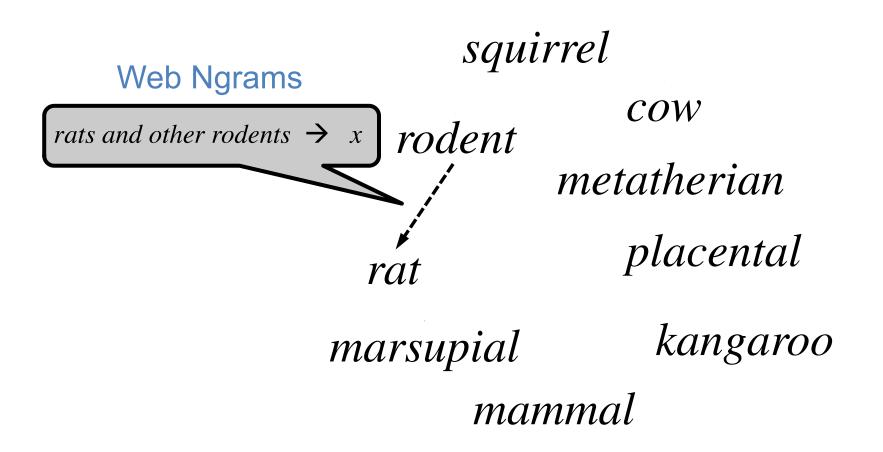


▶ For a particular set of terms $x = \{x_1, x_2, \dots, x_n\}$





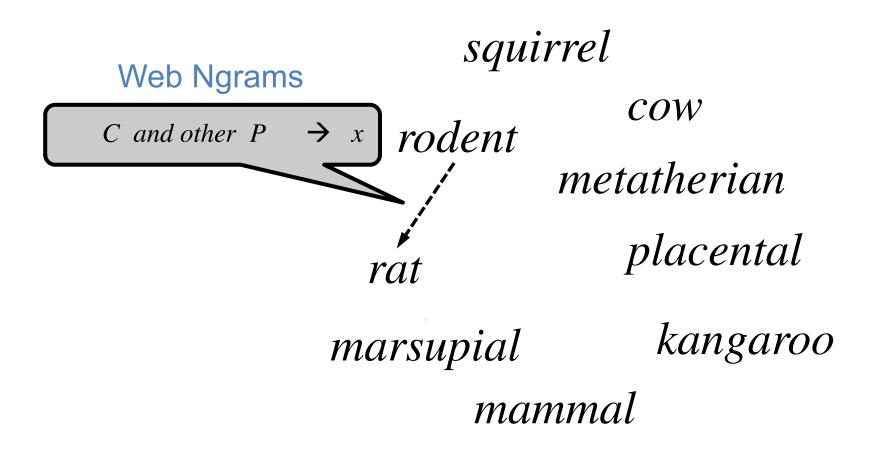






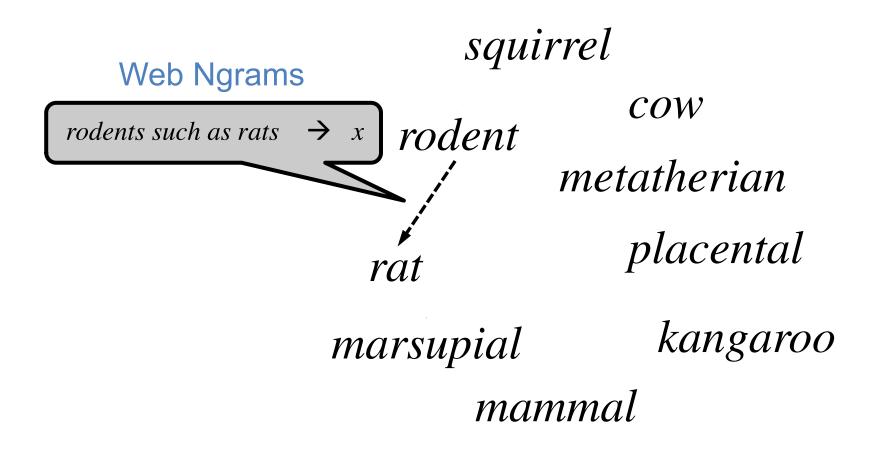


Hearst, 1992





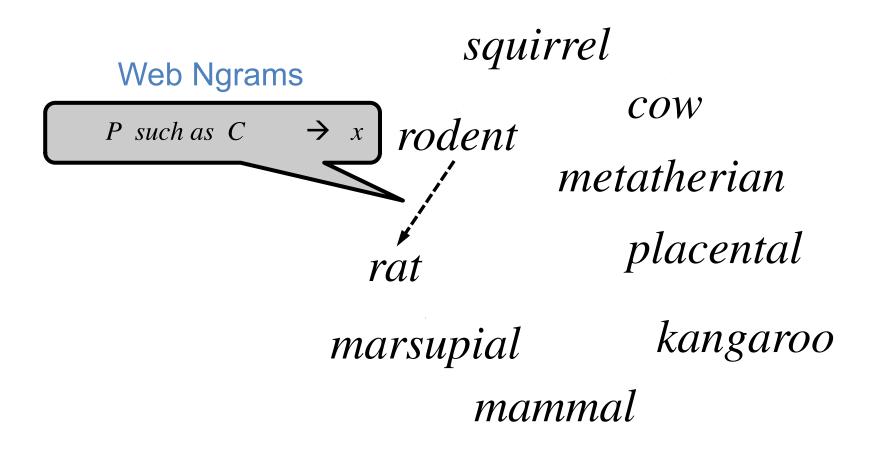






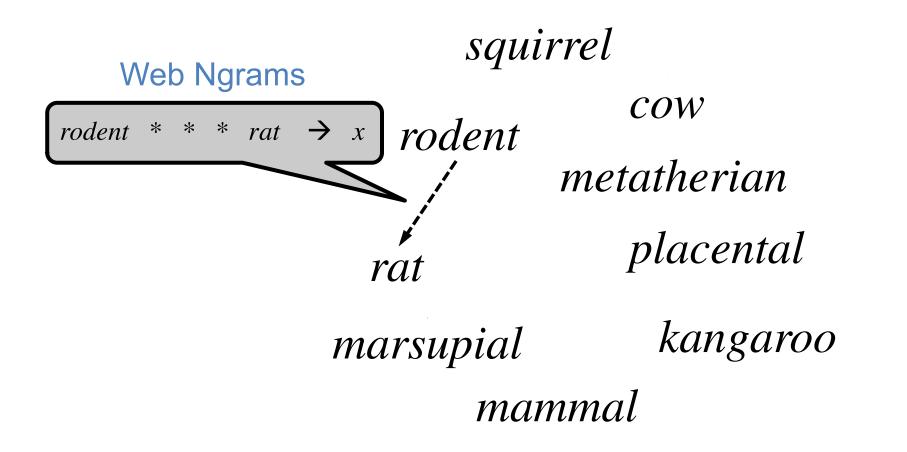


Hearst, 1992



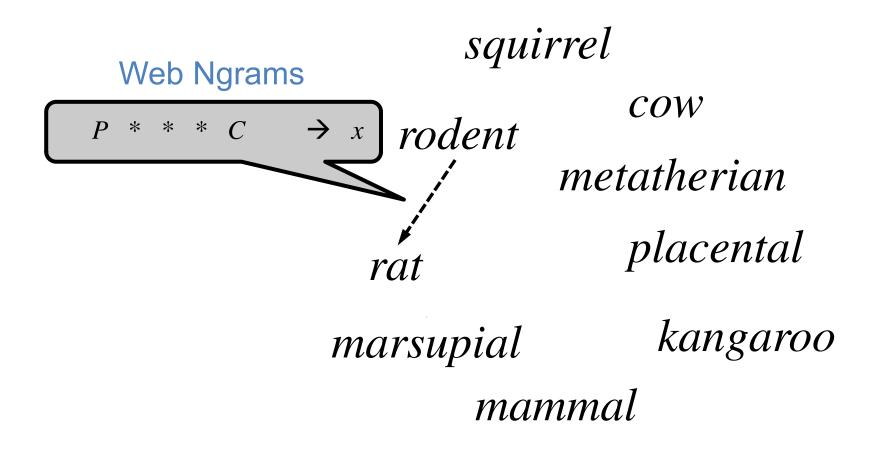














Surface Features



▶ Capitalization: $(ISCAPS(x_j), ISCAPS(x_i))$

▶ Ends-with: ENDSWITH (x_j, x_i)

E.g.,
$$varphi$$
 nut bee salad $varphi$, $varphi$, $varphi$ chestnut honeybee potato salad

Contains, LCS, Suffix-match, Length-difference



Semantic Features



▶ Web *n*-gram Patterns and Counts



Web Ngrams

$P w_1 w_2 w_3 C$	$\boldsymbol{\mathcal{X}}$
$w_1 P w_2 w_3 C$	\mathcal{X}
$\stackrel{\cdots}{P} w_1 w_2 C w_3$	$\boldsymbol{\mathcal{X}}$
$\stackrel{\cdots}{P} w_1 w_2 C$	$\boldsymbol{\mathcal{X}}$



Semantic Features



Web n-gram Patterns and Counts



Web Ngrams

C and other P	1329
P (C and	539
P such as C	388
P > C	222
C is a P	164
P, especially C	388

Individual count, Unary patterns, Pattern order



Semantic Features



Wikipedia abstracts (for longer terms)



The Rhode Island Red is a breed of chicken (Gallus gallus domesticus). They are ...

... Department of Justice (DOJ), ... is the U.S. federal executive department ...

The Gulf Stream, together with its northern ... swift Atlantic ocean current that ...

Features on Presence, Min-distance, and Patterns

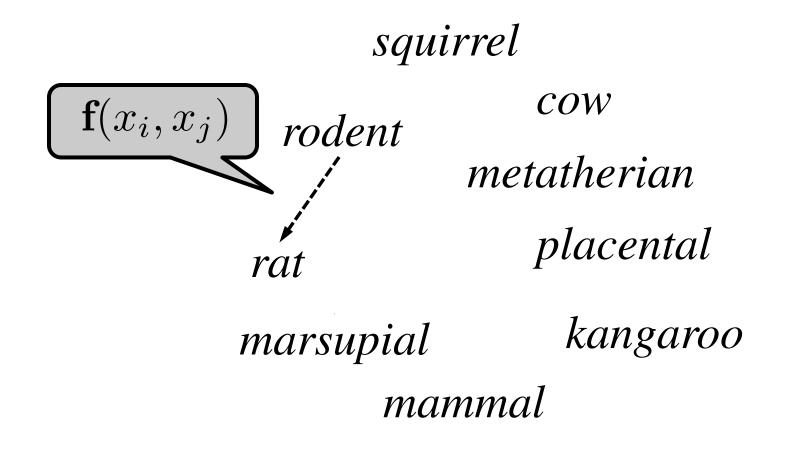


Structured Taxonomy Induction



Hearst, 1992

▶ Each edge fires features with score $s(y_{ij}) = \mathbf{w} \cdot \mathbf{f}(x_i, x_j)$

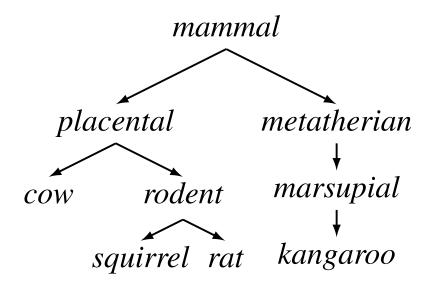




Edge-factorization



▶ Chu-Liu-Edmonds: MST $\hat{\boldsymbol{y}} = \operatorname*{argmax}_{\boldsymbol{y} \in \mathcal{Y}(\boldsymbol{x})} \Big\{ \sum_{y_{ij} \in \boldsymbol{y}} s(y_{ij}) \Big\}$



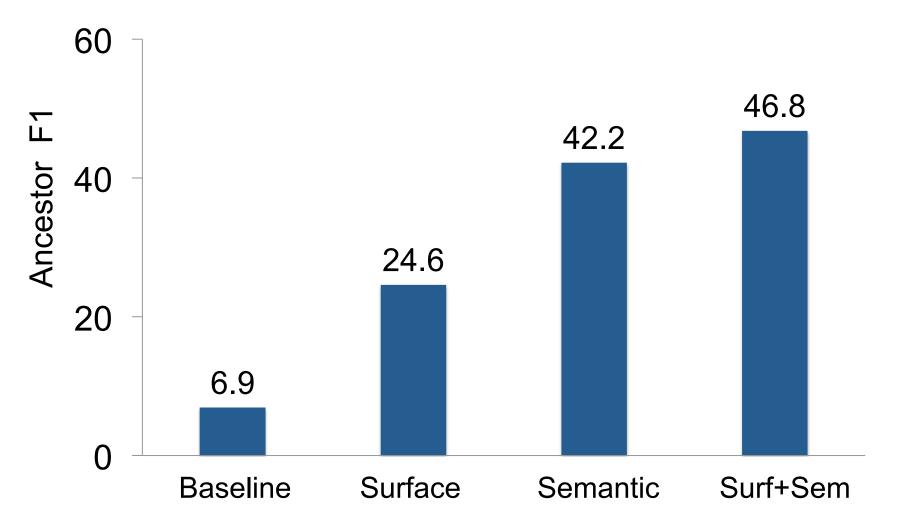
Weights learned using standard gradient descent



Results: 1st Order



Setup: Train on a WordNet portion and reproduce the rest

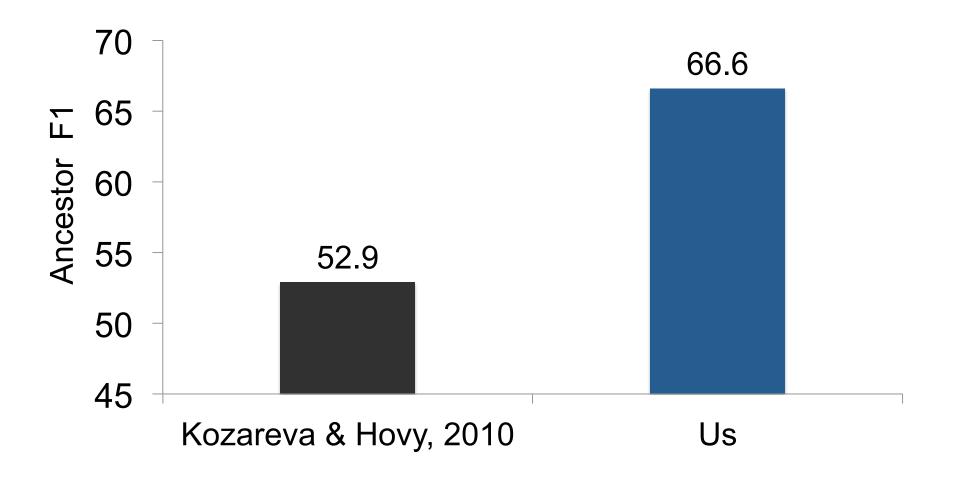




Comparison Results



Setup: Train on a WordNet portion and reproduce the rest





Analysis: Learned Edge Features



Hearst, 1992

High-weight edge pattern examples

```
C and other P> P > CC , P ofC is a PC , a PP , including CC or other PP ( CC : a PC , american PC - like PC , the P
```

rats and other rodents



Analysis: Learned Edge Features



Hearst, 1992

High-weight edge pattern examples

```
C and other P > P > C
C, P of C is a P
C, a P P, including C
C or other P P C
C: a P C
C, american P
C - like P C, the P
```

electronics > *office electronics* > *shredders*



Analysis: Learned Edge Features



Hearst, 1992

High-weight edge pattern examples

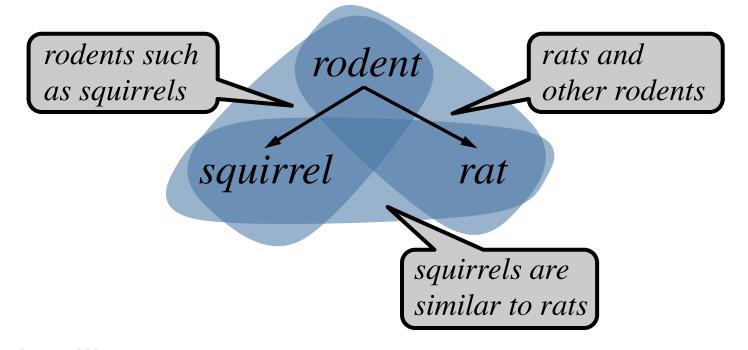
```
C and other P > P > C
C, P of C is a P
C, a P P, including C
C or other P P C
C: a P C, american P
C - like P C, the P
```

Michael Jackson, American singer

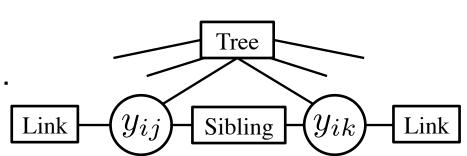


Higher Order (Siblinghood)





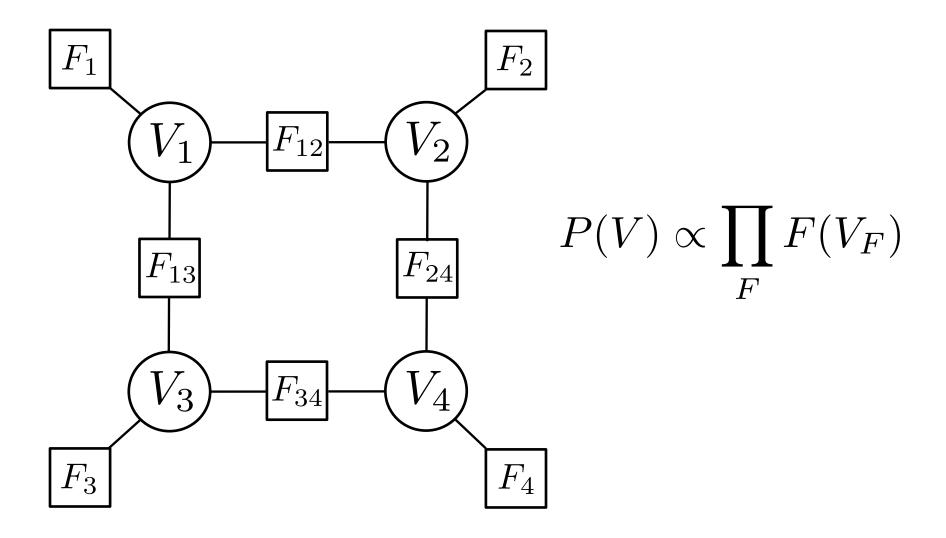
NP-hard!!
Use factor graphs and loopy belief propagation...





Factor Graph Formulation







Factor Graph Formulation



lacksquare Given the input term set $oldsymbol{x} = \{x_1, x_2, \dots, x_n\}$, we want

$$P(oldsymbol{y}|oldsymbol{x}) \propto \prod_F \phi_F(oldsymbol{y})$$

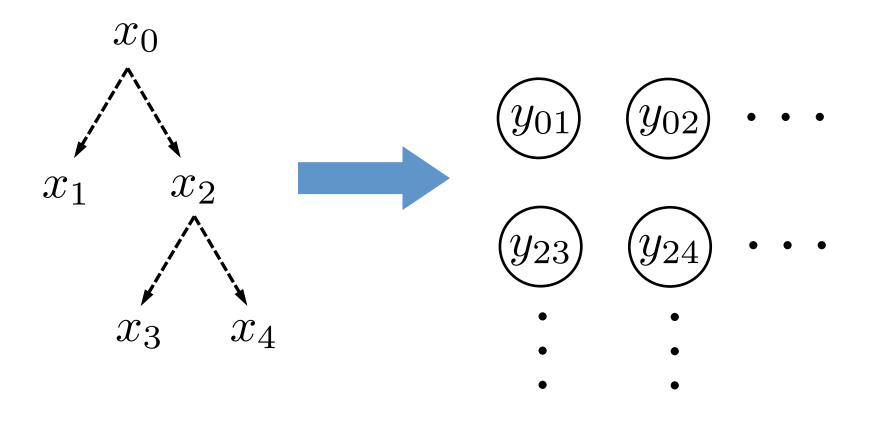
lacktriangle Each potential taxonomy edge $x_i
ightarrow x_j$ is a variable y_{ij}





Variables







Edge Factors



$$\phi_{E_{ij}}(y_{ij}) = \begin{cases} \exp(\mathbf{w} \cdot \mathbf{f}(x_i, x_j)) & y_{ij} = \text{ON} \\ \exp(0) = 1 & y_{ij} = \text{OFF} \end{cases}$$



y_{n1} y_{n2} y_{n2} y_{n2} y_{n2} y_{n2} y_{n2} y_{n3} y_{n2} y_{n3} y_{n3} y_{n3} y_{n3} y_{n3} y_{n3} y_{n3} y_{n3} y_{n3}



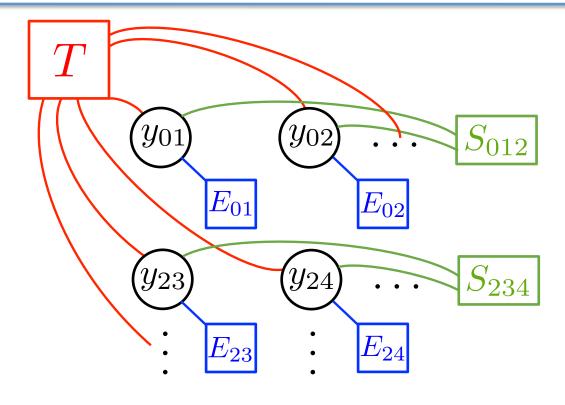
$$y_{01}$$
 y_{02} ... S_{012}
 E_{01} E_{02}
 y_{23} y_{24} ... S_{234}
 E_{23} E_{24}

$$\phi_{S_{ijk}}(y_{ij}, y_{ik}) = \begin{cases} \exp(\mathbf{w} \cdot \mathbf{f}(x_i, x_j, x_k)) & y_{ij} = y_{ik} = \text{ON} \\ 1 & \text{otherwise} \end{cases}$$



Tree Factor





$$\phi_T(\boldsymbol{y}) = \begin{cases} 1 & \boldsymbol{y} \text{ forms a legal taxonomy tree} \\ 0 & \text{otherwise} \end{cases}$$



Model Score



$$P(\boldsymbol{y}|\boldsymbol{x}) \propto \prod_{F} \phi_F(\boldsymbol{y}) \propto egin{cases} \exp(\mathbf{w} \cdot \mathbf{f}(\boldsymbol{y})) & \boldsymbol{y} \text{ is a tree} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{f}(oldsymbol{y}) = \sum_{\substack{i,j \ y_{ij} = \mathrm{ON}}} \mathbf{f}(x_i,x_j) + \sum_{\substack{i,j,k \ y_{ij} = y_{ik} = \mathrm{ON}}} \mathbf{f}(x_i,x_j,x_k)$$
Edge features Sibling features



Inference



- 2 main inference tasks:
 - learn w (expected feature counts)
 - decode (select a taxonomy tree)

Each needs marginals of edges and triples being ON

One natural way to compute marginals in factor graph: Belief Propagation (MacKay, 2003)



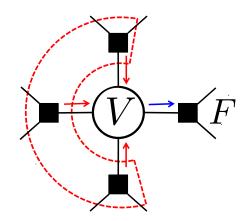
Inference: Belief Propagation



Smith and Eisner, 2008; Burkett and Klein, 2012 (tutorial); Gormley and Eisner, 2014 (tutorial)

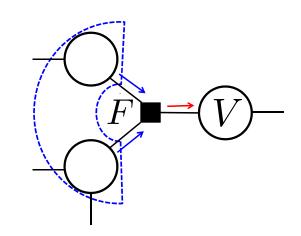
Message from variables to factors:

$$m_{V \to F}(v) \propto \prod_{F' \in N(V) \setminus \{F\}} m_{F' \to V}(v)$$



Message from factors to variables:

$$m_{F \to V}(v) \propto \sum_{\mathcal{X}_F, \mathcal{X}_F[V] = v} \phi_F(\mathcal{X}_F) \prod_{V' \to F} m_{V' \to F}(\mathcal{X}_F[V'])$$





Inference: Belief Propagation

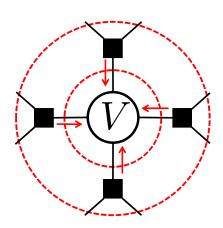


Smith and Eisner, 2008; Burkett and Klein, 2012 (tutorial); Gormley and Eisner, 2014 (tutorial)

- Messages from tree factor exponentially slow!
 - $\rightarrow O(n^3)$ Matrix Tree Theorem (Tutte, 1984)

Marginal beliefs:

$$b_V(v) \propto \prod_{F \in N(V)} m_{F \to V}(v)$$



Loopy belief propagation (sibling factors introduce cycles)



Learning



Gradient-based maximum likelihood training to learn w

Run loopy BP to get approximate marginals

Compute expected feature counts and gradients

 Plug into any gradient optimizer – we use AdaGrad (Duchi et al., 2011)



Decoding



Smith and Eisner, 2008

After learning w, run BP again to get marginal beliefs

Set edge-scores = belief-odds-ratio =
$$\frac{b_{Y_{ij}}(\text{on})}{b_{Y_{ij}}(\text{off})}$$

Run MST algorithm to get minimum Bayes risk tree

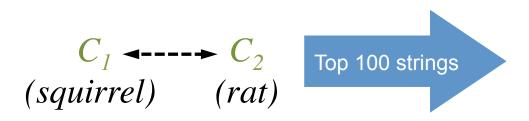


Sibling Features



- lacksquare Consider each potential sibling pair (x_j,x_k) in factor S_{ijk}
- Fire similar Web n-gram and Wikipedia features

Web Ngrams

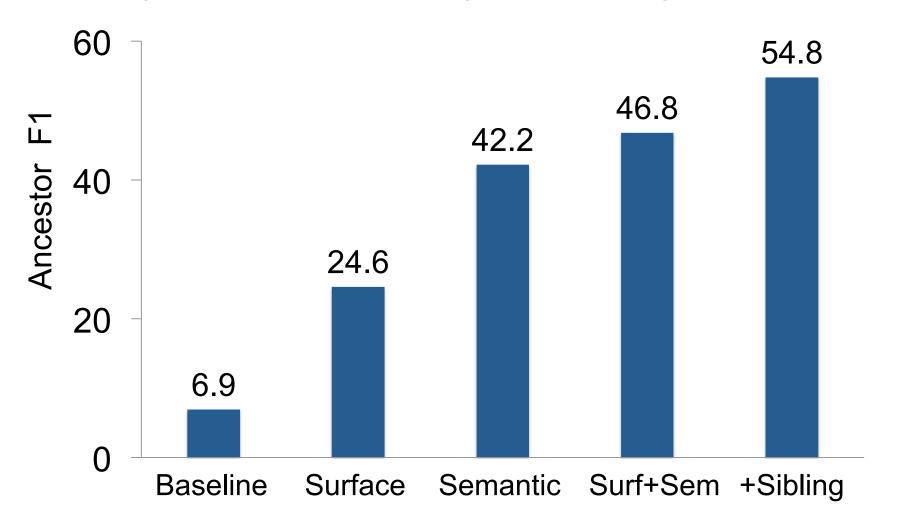




Results: Adding Siblings



Setup: Train on a WordNet portion and reproduce the rest





Analysis: Learned Sibling Features



High-weight sibling pattern examples

 C_1 and C_2 C_1 or C_2 of , C_1 , C_2 and the C_1/C_2 C_1 , C_2 (C_1 and / or C_2 either C_1 or C_2 $< s > C_1$ and $C_2 < / s >$



Conclusion



- Structured learning for taxonomy induction
- No lexicalized features possible, so learned external pattern features from Web n-grams and Wikipedia
- Incorporated sibling information via 2nd order factors and loopy BP
- Strong improvements on WordNet corpora

Thank you!





Questions?