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Advanced Graph-Based Parsing Techniques

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Based on previous tutorials with Ryan McDonald

Overall Plan

1. Basic notions of dependency grammar and dependency parsing
2. Graph-based and transition-based dependency parsing
3. Advanced graph-based parsing techniques
4. Advanced transition-based parsing techniques
5. Neural network techniques in dependency parsing
6. Multilingual parsing from raw text to universal dependencies

Plan for this Lecture

- Projective parsing
  - Exact higher-order parsing
  - Approximations
- Non-projective parsing
  - NP-completeness
  - Exact higher-order parsing
  - Approximations

Graph-Based Parsing Trade-Off

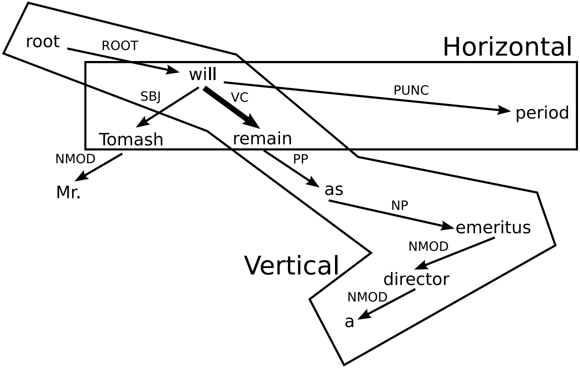
[McDonald and Nivre 2007]

- Learning and inference are global
  - Decoding guaranteed to find highest scoring tree
  - Training algorithms use global structure learning
- But this is only possible with local feature factorizations
  - Must limit context statistical model can look at
  - Results in bad 'easy' decisions

The major question in graph-based parsing has been how to increase scope of features to larger subgraphs, without making inference intractable.

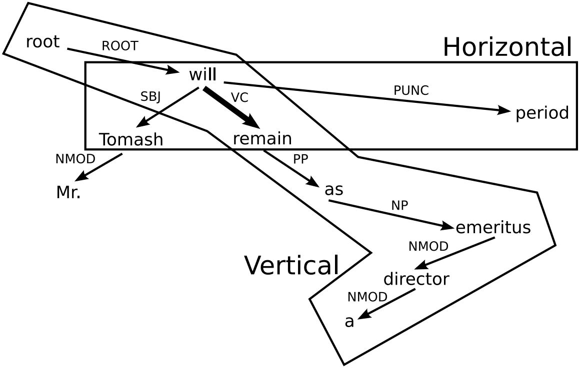
Higher-Order Parsing

- Two main dimensions of higher-order features
  - Vertical: e.g., "remain" is the grandparent of "emeritus"
  - Horizontal: e.g., "remain" is first child of "will"



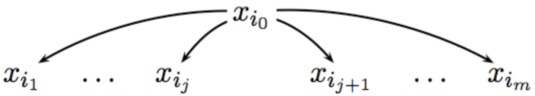
Higher-Order Projective Parsing

- Easy – just modify the chart
- Usually asymptotic increase with each order modeled
- But we have a bag of tricks that help



2nd-Order Horizontal Projective Parsing

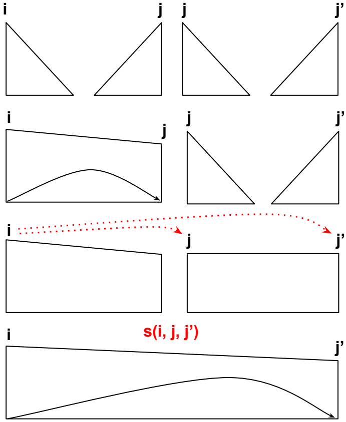
- Score factors by pairs of horizontally adjacent arcs
- Often called sibling dependencies
- $s(i, j, j') =$ score of adjacent arcs $x_i \rightarrow x_j$ and $x_i \rightarrow x_{j'}$



$$
\begin{aligned}
s(T) &= \sum_{(i,j):(i,j')\in A} s(i, j, j') \\
&= \ldots + s(i_0, i_1, i_2) + s(i_0, i_2, i_3) + \ldots + s(i_0, i_{j-1}, i_j) + \\
&\quad s(i_0, i_{j+1}, i_{j+2}) + \ldots + s(i_0, i_{m-1}, i_m) + \ldots
\end{aligned}
$$

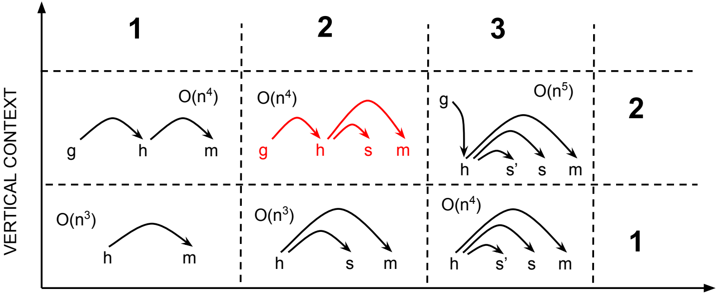
2nd-Order Horizontal Projective Parsing

- Add a sibling chart item to get to $O(n^3)$



Higher-Order Projective Parsing

- People played this game since 2006
  - McDonald and Pereira [2006] (2nd-order sibling)
  - Carreras [2007] (2nd-order sibling and grandparent)
  - Koo and Collins [2010] (3rd-order grand-sibling and tri-sibling)
  - Ma and Zhao [2012] (4th-order grand-tri-sibling+)



Exact Higher-Order Projective Parsing

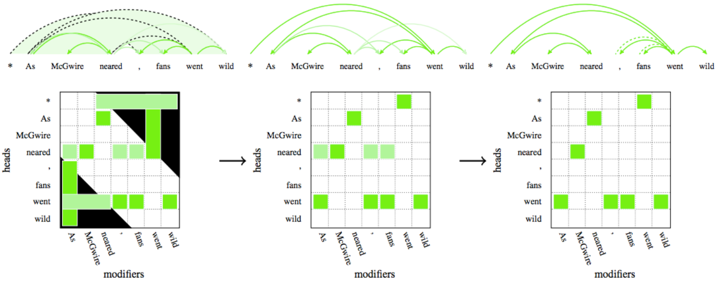
- Can be done via chart augmentation
- But there are drawbacks
  - $O(n^4)$, $O(n^5)$, ... is just too slow
  - Every type of higher order feature requires specialized chart items and combination rules

Exact Higher-Order Projective Parsing

- Can be done via chart augmentation
- But there are drawbacks
  - $O(n^4)$, $O(n^5)$, ... is just too slow
  - Every type of higher order feature requires specialized chart items and combination rules
- Led to research on approximations
  - Bohnet [2010]: feature hashing, parallelization
  - Koo and Collins [2010]: first-order marginal probabilities
  - Bergsma and Cherry [2010]: classifier arc filtering
  - Cascades
    - Rush and Petrov [2012]: structured prediction cascades
    - He et al. [2013]: dynamic feature selection
  - Zhang and McDonald [2012], Zhang et al. [2013]: cube-pruning

Structured Prediction Cascades

[Rush and Petrov 2012]

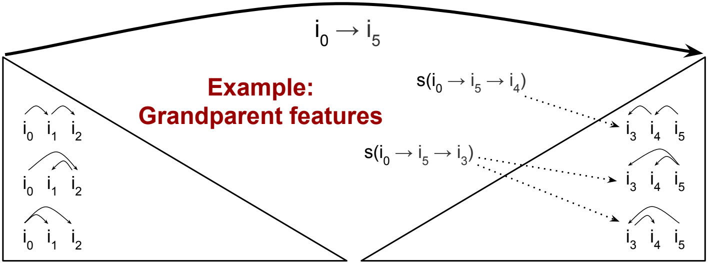


- Weiss et al. [2010]: train level n w.r.t. to level $n + 1$
- Vine-parsing allows linear first stage [Dreyer et al. 2006]
- 100X+ faster than unpruned 3rd-order model with small accuracy loss (93.3$\rightarrow$93.1) [Rush and Petrov 2012]

Cube Pruning

[Zhang and McDonald 2012, Zhang et al. 2013]

- Keep Eisner $O(n^3)$ as back bone
- Use chart item k-best lists to score higher order features



- Always $O(n^3)$ asymptotically
- No specialized chart parsing algorithms

Projective Parsing Summary

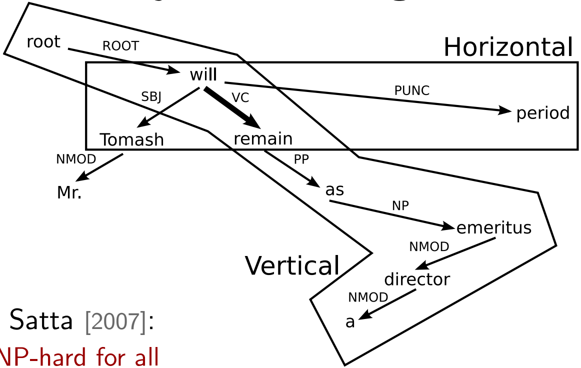
- Can augment chart (dynamic program) to increase scope of features but comes at complexity cost
- Solution: use pruning approximations

	En-UAS	Zh-UAS
1st order exact	91.8	84.4
2nd order exact	92.4	86.6
3rd order exact*	93.0	86.8
4th order exact†	93.4	87.4
struct. pred. casc.‡	93.1	–
cube-pruning⋆	93.5	87.9

* [Koo and Collins 2010], † [Ma and Zhao 2012], ‡ [Rush and Petrov 2012], ⋆ [Zhang et al. 2013]

Cube-pruning is 2x slower than structured prediction cascades and 5x faster than third-order

Higher-Order Non-Projective Parsing



- McDonald and Satta [2007]:
  - Parsing is NP-hard for all higher-order features
  - Horizontal, vertical, valency, etc.
  - Even seemingly simple arc features like "Is this the only modifier" result in intractability

What to do?

What to do?

- Exact non-projective parsing
  - Integer Linear Programming
    [Riedel and Clarke 2006, Martins et al. 2009]
  - Intractable in general, but efficient optimizers exact
  - Higher order parsing: asymptotic increase in constraint set size

What to do?

- Exact non-projective parsing
  - Integer Linear Programming [Riedel and Clarke 2006, Martins et al. 2009]
  - Intractable in general, but efficient optimizers exact
  - Higher order parsing: asymptotic increase in constraint set size
- Approximations (some return optimal in practice)
  - Approximate inference: $T^* = \text{argmax}_{T \in G_x} \; s(T)$
    - Post-processing [McDonald and Pereira 2006], [Hall and Novák 2005], [Hall 2007]
    - Dual Decomposition
    - Belief Propagation [Smith and Eisner 2008]
    - LP relaxations [Riedel et al. 2012]
    - Sampling [Nakagawa 2007]
  - Approximate search space: $T^* = \text{argmax}_{T \in G_x} \; s(T)$
    - Mildly non-projective structures

Dual Decomposition

- Assume a 2nd-order sibling model:

$$s(T) = \sum_{(i,j):(i,j')\in A} s(i,j,j')$$

$$T^* = \operatorname*{argmax}_T s(T)$$

- Computing T* is hard, so let us try something simpler:

$$s(D_i) = \sum_{(i,j):(i,j')\in A} s(i,j,j')$$

$$D_i^* \operatorname*{argmax}_{D_i} s(D_i)$$

- The highest scoring sequence of dependents for each word x_i can be computed in $O(n)$ time using a semi-Markov model

Dual Decomposition

- For each word x_i, find D_i^*:

ROOT What did economic news have little effect on

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Dual Decomposition

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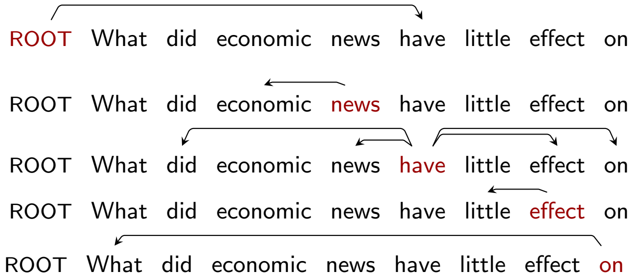

put it together

Dual Decomposition

- Why does this not work? No tree constraint!

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put it together

ROOT What did economic news have little effect on

Dual Decomposition

- First-order $O(n^2)$ model with tree constraint exists
  - MST algorithm [Chu and Liu 1965, Edmonds 1967]
- Second-order $O(n^3)$ model without tree constraint exists
  - The $O(n^3)$ sibling decoding algorithm

Dual Decomposition

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- Second-order $O(n^3)$ model without tree constraint exists
  - The $O(n^3)$ sibling decoding algorithm
- Dual Decomposition [Koo et al. 2010]
  - Add components for each feature
    - Independently calculate each efficiently
    - Tie together with agreement constraints (penalties)

Dual Decomposition

- For a sentence $x = x_1 \ldots x_n$, let:

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  - $s_{1o}(T)$ be the first-order score of a tree T
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- Define structural variables
  - $t_{1o}(i,j) = 1$ if $(i,j) \in T_{1o}$, 0 otherwise
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- What we really want to find is

$$T = \underset{T \in G_x}{\text{argmax}} \; s_{1o}(T) + s_{so}(T)$$

Dual Decomposition

- For a sentence $x = x_1 \dots x_n$, let:
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  - $t_{1o}(i,j) = 1$ if $(i,j) \in T_{1o}$, 0 otherwise
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- This is equivalent to:

$$(T, G) = \underset{T \in G_x, G \in G_x}{\text{argmax}} \; s_{1o}(T) + s_{so}(G)$$

$$\text{s.t. } t_{1o}(i,j) = g_{2o}(i,j), \; \forall \; i,j \leq n$$

Dual Decomposition

$$(T, G) = \underset{T \in G_x, G \in G_x}{\operatorname{argmax}} s_{1o}(T) + s_{so}(G), \text{ s.t. } t_{1o}(i,j) = g_{2o}(i,j)$$

Algorithm sketch

Dual Decomposition

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Algorithm sketch

for $k = 1$ to K

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Algorithm sketch

for $k = 1$ to K

1. $T_{1o} = \text{argmax}_{T \in G_x} s_{1o}(T) - p$ *// first-order decoding*

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If K is reached, return T_{1o} from last iteration

Dual Decomposition

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4. else Update penalties p and go to 1

What are the penalties p?

Dual Decomposition

- Let $p(i, j) = t_{1o}(i, j) - g_{2o}(i, j)$
- p is the set of all penalties $p(i, j)$

Dual Decomposition

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- p is the set of all penalties $p(i,j)$
- We rewrite the decoding objectives as:

$$T_{1o} = \operatorname*{argmax}_{T \in G_x} \; s_{1o}(T) - \sum_{i,j} p(i,j) \times t_{1o}(i,j)$$

$$G_{2o} = \operatorname*{argmax}_{G \in G_x} \; s_{2o}(G) + \sum_{i,j} p(i,j) \times g_{2o}(i,j)$$

- Reward trees/graphs that agree with other model

Dual Decomposition

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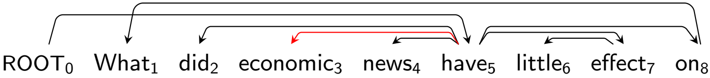
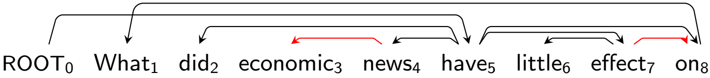
- Reward trees/graphs that agree with other model
- Since t_{1o} and g_{2o} are arc-factored indicator variables, we can easily include in decoding
- $s(i,j) = s(i,j) - p(i,j)$ for first-order model

Dual Decomposition – 1-iter Example

First-order



Second-order sibling



penalties: $p(5,3) = 1,\ p(4,3) = -1,\ p(7,8) = -1$

first-order: $s_{1o}(5,3) \mathrel{-}= 1,\ s_{1o}(4,3) \mathrel{+}= 1,\ s_{1o}(7,8) \mathrel{+}= 1$

second-order: $s_{2o}(5,*,3) \mathrel{+}= 1,\ s_{2o}(4,*,3) \mathrel{-}= 1,\ s_{2o}(7,*,8) \mathrel{-}= 1$

*Indicates any sibling, even null if it is first left/right modifier.

Dual Decomposition

$$\text{Goal}: (T, G) = \underset{T \in G_x, G \in G_x}{\text{argmax}} \; s_{1o}(T) + s_{so}(G), \text{ s.t. } t_{1o}(i,j) = g_{2o}(i,j)$$

for $k = 1$ to K

1. $T_{1o} = \text{argmax}_{T \in G_x} \, s_{1o}(T) - p$ // *first-order decoding*
2. $G_{2o} = \text{argmax}_{G \in G_x} \, s_{2o}(T) + p$ // *second-order decoding*
3. if $t_{1o}(i,j) = g_{2o}(i,j), \forall \, i, j$, return T_{1o}
4. else Update penalties p and go to 1

- Penalties push scores towards agreement
- Theorem: If for any k, line 3 holds, then decoding is optimal

Dual Decomposition

- Koo et al. [2010]: grandparents, grand-sibling, tri-siblings
- Martins et al. [2011, 2013]: arbitrary siblings, head bigrams

	UAS
1st order	90.52
2nd order	91.85
3rd order	92.41

[Martins et al. 2013]

Mildly Non-Projective Structures

- Dual decomposition approximates search over entire space
  - $T = \textcolor{red}{\text{argmax}}_{T \in G_x} s(T)$

Mildly Non-Projective Structures

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- Another approach is to restrict search space
  - $T = \operatorname{argmax}_{T \in G_x} s(T)$
    1. Allow efficient decoding
    2. Still cover all linguistically plausible structures

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- Another approach is to restrict search space
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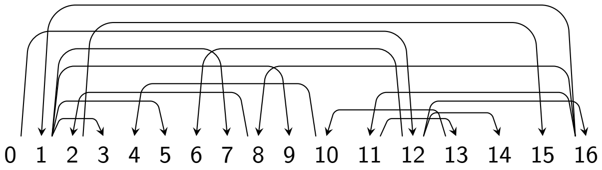
    1. Allow efficient decoding
    2. Still cover all linguistically plausible structures
- Do we really care about scoring such structures?



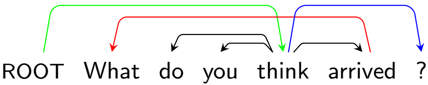
Mildly Non-Projective Structures

- Well-nested block-degree 2 [Bodirsky et al. 2005]
  - LTAG-like algorithms: $O(n^7)^*$ [Gómez-Rodríguez et al. 2011]
  - $+$ 1-inherit: $O(n^6)$ [Pitler et al. 2012]
    - Empirical coverage identical to well-nested block-degree 2
  - $+$ Head-split: $O(n^6)$ [Satta and Kuhlmann 2013]
    - Empirical coverage similar to well-nested block-degree 2
  - $+$ Head-split $+$ 1-inherit: $O(n^5)$ [Satta and Kuhlmann 2013]
- Gap Minding Trees: $O(n^5)$ [Pitler et al. 2012]
- 1-Endpoint-Crossing: $O(n^4)$ [Pitler et al. 2013]

*All run-times are for first-order parsing

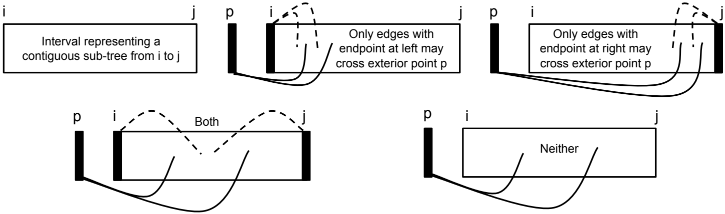
1-Endpoint-Crossing [Pitler et al. 2013]

- An arc A, is 1-endpoint-crossing iff all arcs A' that cross A have a common endpoint p
- An endpoint p is either a head or a modifier in an arc
- E.g., (arrived, What) is crossed by (ROOT,think) and (think,?), both have endpoint 'think'



1-Endpoint-Crossing

- Can we design an algorithm that parses all and only 1-endpoint-crossing trees?
- Pitler et al. [2013] provides the solution
- Pitler's algorithm works by defining 5 types of intervals



- Location of exterior point, direction of arcs, etc, controlled via variables, similar to Eisner [1996] projective formulation

1-Endpoint-Crossing

- On CoNLL-X data sets [Buchholz and Marsi 2006]

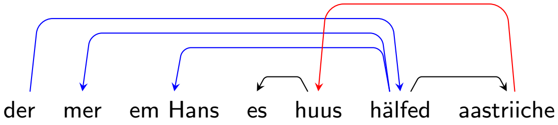
Class	Tree coverage	Run-time
Projective	80.8	$O(n^3)$
Well-nested block-degree 2	98.4	$O(n^7)$
Gap-Minding	95.1	$O(n^5)$
1-Endpoint-Crossing	98.5	$O(n^4)$

[Pitler et al. 2013]

Macro average over Arabic, Czech, Danish, Dutch, Portuguese

1-Endpoint-Crossing

- Good empirical coverage and low run-time
- Can be linguistically motivated [Pitler et al. 2013]



- Phrase-impenetrability condition (PIC) [Chomsky 1998]
  - Only head and edge words of phrase accessible to sentence
  - Long-distance elements leave chain of traces at clause edges
  - Pitler et al. [2013] conjecture: PIC implies 1-endpoint-crossing

1-Endpoint-Crossing

- Pitler [2014]: 1-endpoint-crossing + third-order
  - Merge of Pitler et al. [2013] and Koo and Collins [2010]
  - Searches 1-endpoint-crossing trees
  - Scores higher-order features when no crossing arc present
  - $O(n^4)$ – identical to third-order projective!
  - Significant improvements in accuracy

Coming Up Next

1. Basic notions of dependency grammar and dependency parsing
2. Graph-based and transition-based dependency parsing
3. Advanced graph-based parsing techniques
4. Advanced transition-based parsing techniques
5. Neural network techniques in dependency parsing
6. Multilingual parsing from raw text to universal dependencies

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