# CS388: Natural Language Processing

## Lecture 12: Dependency I


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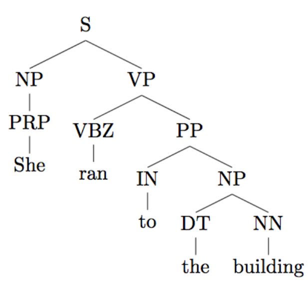
## Administrivia

- Project 1 graded, discussion at end of lecture
- Mini 2 due tonight
- Final project proposals due next Tuesday

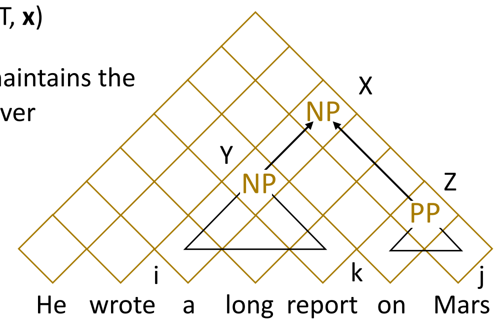
## Recall: Constituency

- Tree-structured syntactic analyses of sentences
- Nonterminals (NP, VP, etc.) as well as POS tags (bottom layer)
- Structured is defined by a CFG




## Recall: CKY

- Find argmax P(T|**x**) = argmax P(T, **x**)
- Dynamic programming: chart maintains the best way of building symbol X over span (i, j)
- Loop over all split points k, apply rules X -> Y Z to build X in every possible way




Cocke-Kasami-Younger

# Recall: Top-down Parsing

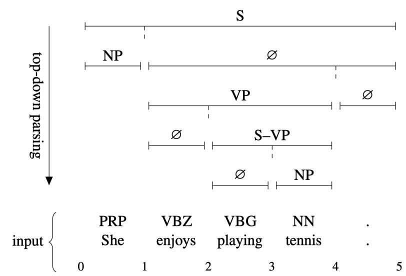
- Can score split points and also labels
- Dynamic programming version:

$$s_{\text{best}}(i,j) = \max_{\ell,k}\left[s_{\text{label}}(i,j,\ell) + \tilde{s}_{\text{split}}(i,k,j)\right]$$

(best way of building *i* and *j* involves maxing over split point and a *single* label)

- Greedy top-down version: at each stage, predict split point *k* and label *l*

$$(\widehat{\ell},\widehat{k}) = \operatorname*{argmax}_{\ell,k}\left[s_{\text{label}}(i,j,\ell) + s_{\text{split}}(i,k,j)\right]$$



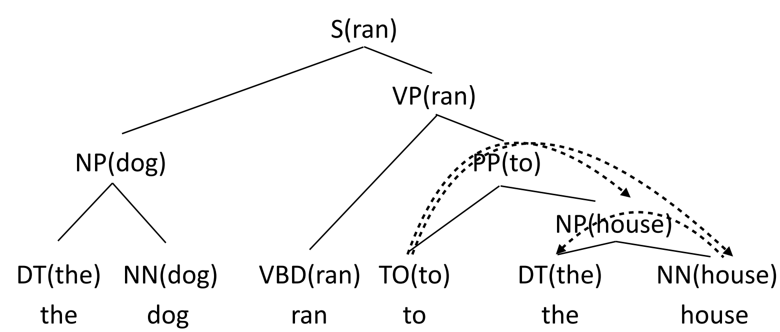

(a) Execution of the top-down parsing algorithm.

# Outline

- Dependency representation, contrast with constituency
- Projectivity
- Graph-based dependency parsers

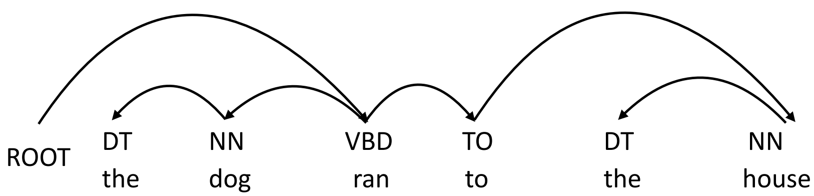
# Dependency Representation

# Lexicalized Parsing



# Dependency Parsing

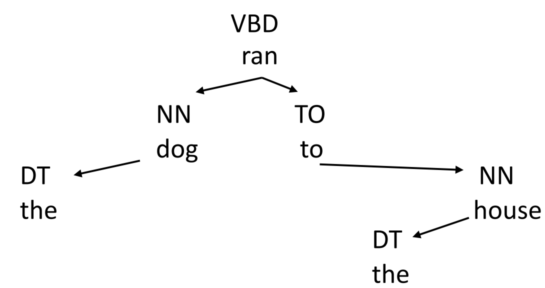
- Dependency syntax: syntactic structure is defined by these arcs
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph




- POS tags same as before, usually run a tagger first as preprocessing

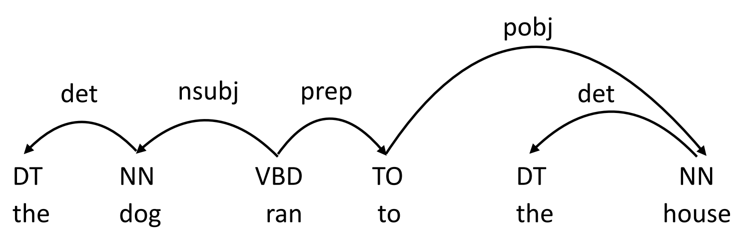
# Dependency Parsing

- Still a notion of hierarchy! Subtrees often align with constituents



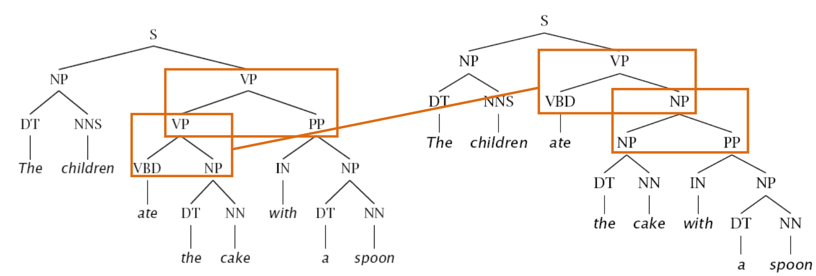

# Dependency Parsing

- Can label dependencies according to syntactic function
- Major source of ambiguity is in the structure, so we focus on that more (labeling separately with a classifier works pretty well)




# Dependency vs. Constituency: PP Attachment

- Constituency: several rule productions need to change



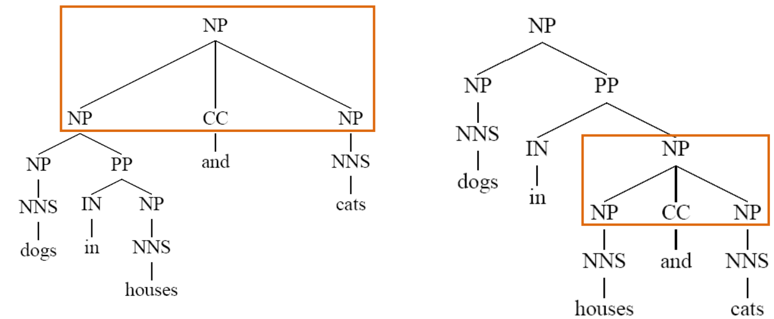
## Dependency vs. Constituency: PP Attachment

- Dependency: one word (with) assigned a different parent


- More predicate-argument focused view of syntax
- "What's the main verb of the sentence? What is its subject and object?" — easier to answer under dependency parsing

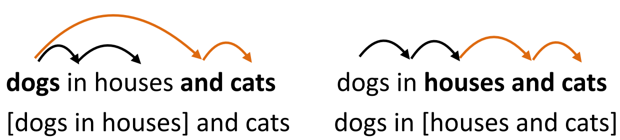
## Dependency vs. Constituency: Coordination

- Constituency: ternary rule NP -> NP CC NP




## Dependency vs. Constituency: Coordination

- Dependency: first item is the head

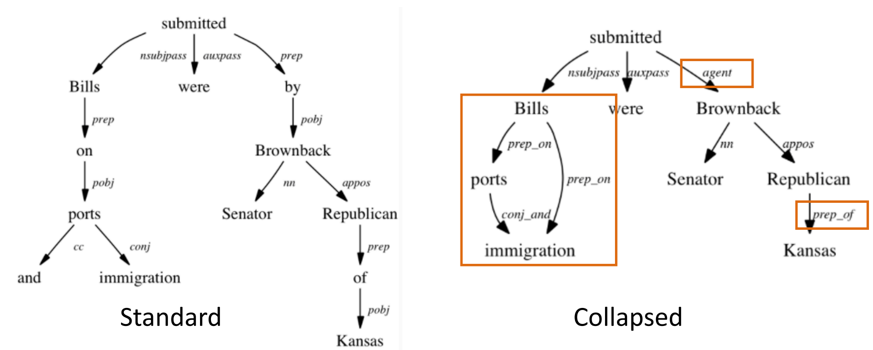



- Coordination is decomposed across a few arcs as opposed to being a single rule production as in constituency
- Can also choose *and* to be the head
- In both cases, headword doesn't really represent the phrase — constituency representation makes more sense

## Stanford Dependencies

- Designed to be practically useful for relation extraction

Bills on ports and immigration were submitted by Senator Brownback, Republican of Kansas

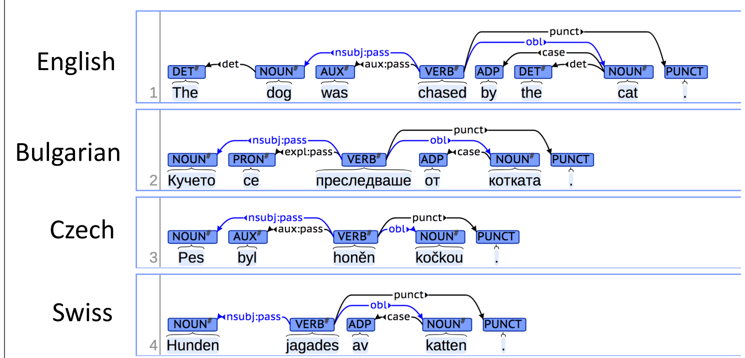


# Dependency vs. Constituency

- Dependency is often more useful in practice (models predicate argument structure)
- Slightly different representational choices:
  - PP attachment is better modeled under dependency
  - Coordination is better modeled under constituency
- Dependency parsers are easier to build: no "grammar engineering", no unaries, easier to get structured discriminative models working well
- Dependency parsers are usually faster
- Dependencies are more universal cross-lingually

# Universal Dependencies

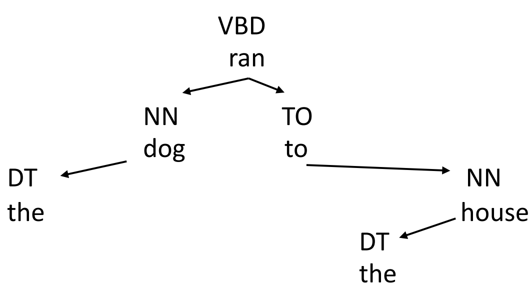
- Annotate dependencies with the same representation in many languages




http://universaldependencies.org/

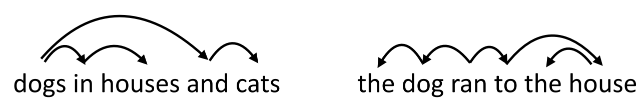
# Projectivity

- Any subtree is a contiguous span of the sentence <-> tree is *projective*

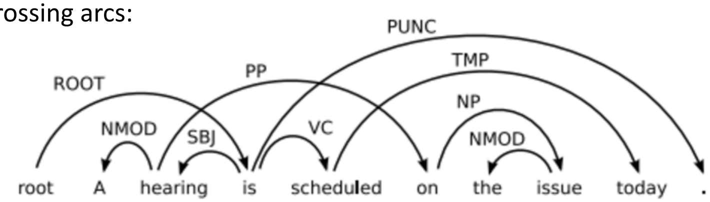



# Projectivity

- Projective <-> no "crossing" arcs

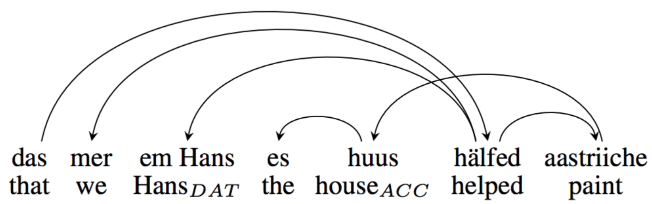



- Crossing arcs:




credit: Language Log

## Projectivity in other languages




- Swiss German example
- (Swiss German also has famous non-context-free constructions)

credit: Pitler et al. (2013)

## Projectivity

- Number of trees produceable under different formalisms

| | Arabic | Czech | Danish |
|---|---|---|---|
| Projective | 1297 (88.8) | 55872 (76.8) | 4379 (84.4) |
| Sentences | 1460 | 72703 | 5190 |

- Many trees in other languages are nonprojective

Pitler et al. (2013)

## Projectivity

- Number of trees produceable under different formalisms

| | Arabic | Czech | Danish |
|---|---|---|---|
| 1-Endpoint-Crossing | 1457 (99.8) | 71810 (98.8) | 5144 (99.1) |
| Well-nested, block degree 2 | 1458 (99.9) | 72321 (99.5) | 5175 (99.7) |
| Gap-Minding | 1394 (95.5) | 70695 (97.2) | 4985 (96.1) |
| Projective | 1297 (88.8) | 55872 (76.8) | 4379 (84.4) |
| Sentences | 1460 | 72703 | 5190 |

- Many trees in other languages are nonprojective
- Some other formalisms (that are harder to parse in), most useful one is 1-Endpoint-Crossing

Pitler et al. (2013)

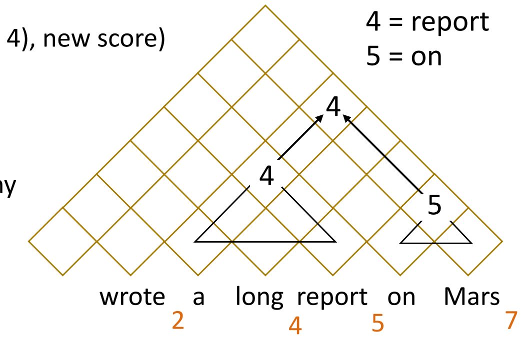
## Graph-Based Parsing

## Defining Dependency Graphs

- Words in sentence **x**, tree T is a collection of directed edges (parent(i), i) for each word i
  - Parsing = identify parent(i) for each word
  - Each word has exactly one parent. Edges must form a projective tree
- Log-linear CRF (discriminative): $P(T|\mathbf{x}) = \exp\left(\sum_i w^\top f(i, \mathrm{parent}(i), \mathbf{x})\right)$
- Example of a feature = I[head=*to* & modifier=*house*] (more in a few slides)

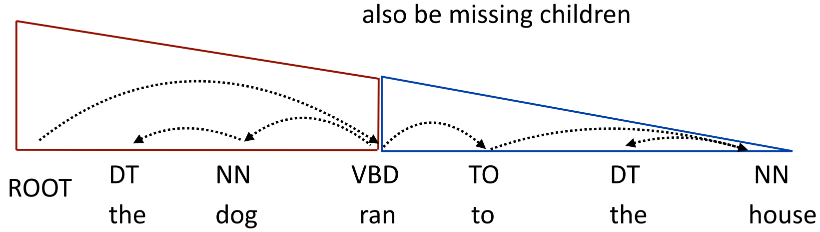

## Generalizing CKY

- DP chart with three dimensions: start, end, and head, start <= head < end
- new score = chart(2, 5, 4) + chart(5, 7, 5) + edge score(4 -> 5)
- score(2, 7, 4) = max(score(2, 7, 4), new score)
- Time complexity of this?
- Many *spurious derivations*: can build the same tree in many ways...need a better algorithm



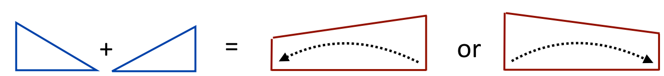

## Eisner's Algorithm: O(n³)

- Cubic-time algorithm
- Maintain two dynamic programming charts with dimension [n, n, 2]:
  - Complete items: head is at "tall end", may be missing children on tall side
  - Incomplete items: arc from "tall" to "short" end, word on short end may also be missing children

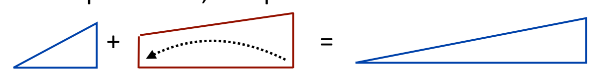



## Eisner's Algorithm: O(n³)

- Complete item: all children are attached, head is at the "tall end"
- Incomplete item: arc from "tall end" to "short end", may still expect children
- Take two adjacent complete items, add arc and build incomplete item



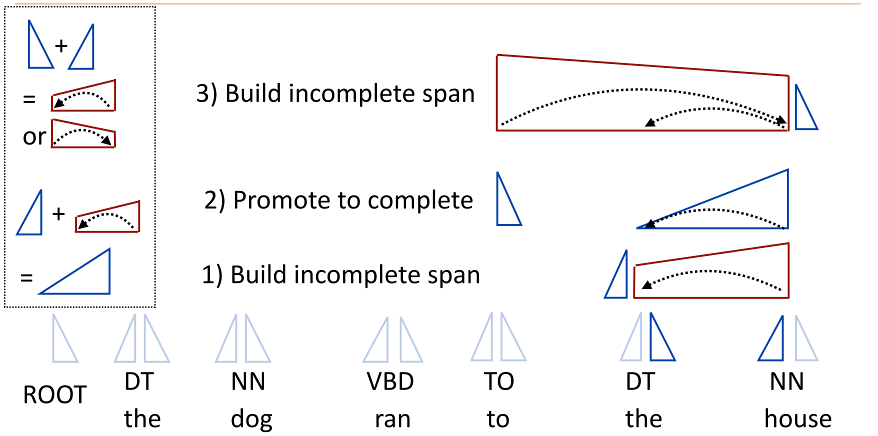

- Take an incomplete item, complete it



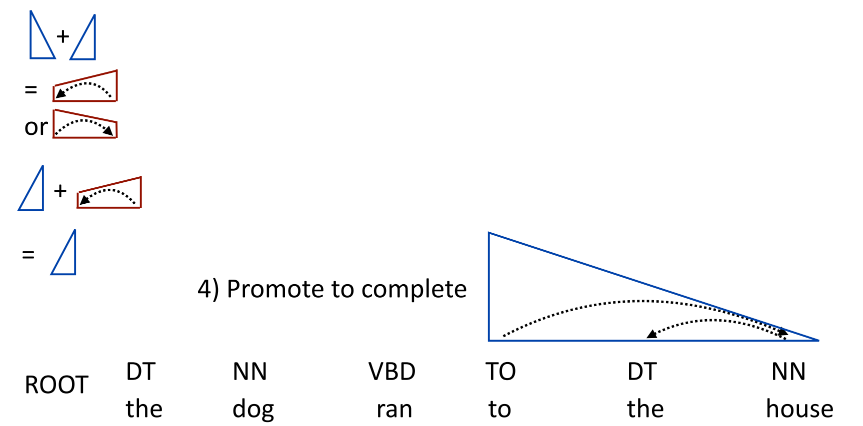

(other case is symmetric)

ROOT DT the NN dog VBD ran TO to DT the NN house

## Eisner's Algorithm: O(n³)

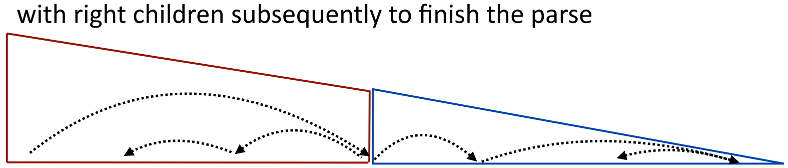



## Eisner's Algorithm: O(n³)

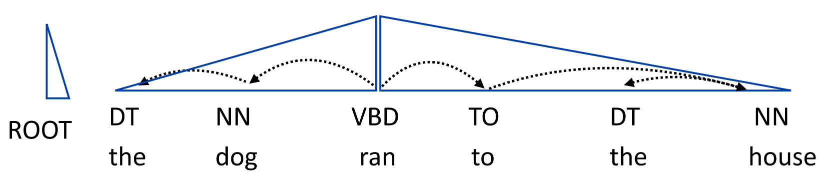



## Eisner's Algorithm: O(n³)

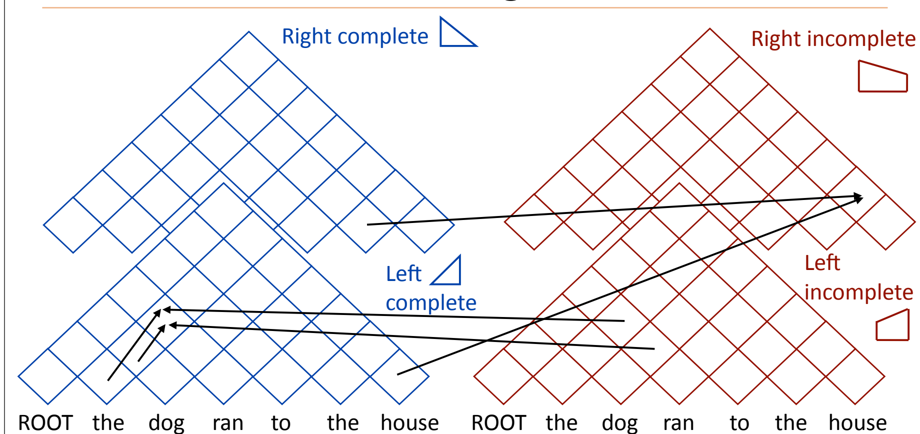
- Attaching to ROOT makes an incomplete item with left children, attaches with right children subsequently to finish the parse



- We've built left children and right children of *ran* as complete items



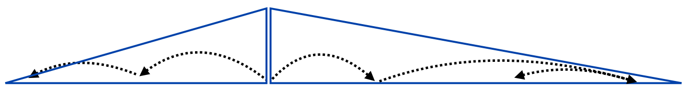

## Eisner's Algorithm



## Eisner's Algorithm

- Eisner's algorithm doesn't have split point ambiguities like CKY does
- Left and right children are built independently, heads are edges of spans
- Charts are n x n x 2 because we need to track arc direction / left vs right

Eisner:



$n^5$

| ROOT | DT | NN | VBD | TO | DT | NN |
|---|---|---|---|---|---|---|
| | the | dog | ran | to | the | house |

## Building Systems

- Can implement decoding and marginal computation using Eisner's algorithm to max/sum over projective trees
- Conceptually the same as inference/learning for sequential CRFs for NER, can also use margin-based methods

## Features in Graph-Based Parsing

- Dynamic program exposes the parent and child indices

$f(i, \mathrm{parent}(i), \mathbf{x})$

| ROOT | DT | NN | VBD | TO | DT | NN |
|---|---|---|---|---|---|---|
| | the | dog | ran | to | the | house |

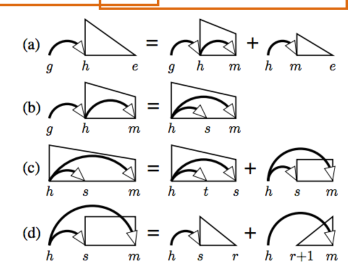
- McDonald et al. (2005) — conjunctions of parent and child words + POS, POS of words in between, POS of surrounding words
  - HEAD=TO & MOD=NN
  - HEAD=TO & MOD=house
  - HEAD=TO & MOD-1=the
  - ARC_CROSSES=DT

## Higher-Order Parsing

| ROOT | DT | NN | VBD | TO | DT | NN |
|---|---|---|---|---|---|---|
| | the | dog | ran | to | the | house |

$f(i, \mathrm{parent}(i), \mathrm{parent}(\mathrm{parent}(i)), \mathbf{x})$

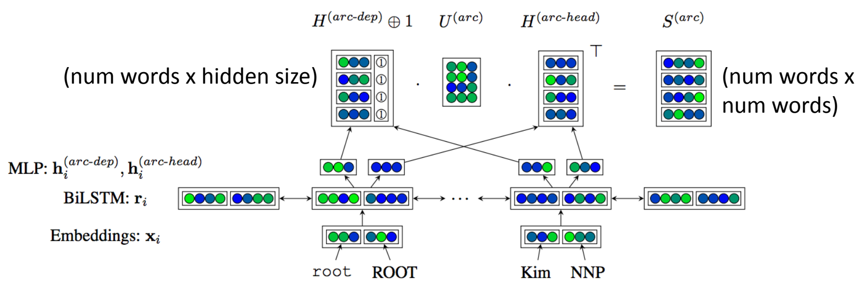
- Track additional state during parsing so we can look at "grandparents" (and siblings). $O(n^4)$ dynamic program or use approximate search




Koo and Collins (2009)

# Biaffine Neural Parsing

- Neural CRFs for dependency parsing: let *c* = LSTM embedding of *i*, *p* = LSTM embedding of parent(*i*). *score*(*i*, parent(*i*), **x**) = $p^{\mathsf{T}}Uc$




LSTM looks at words and POS

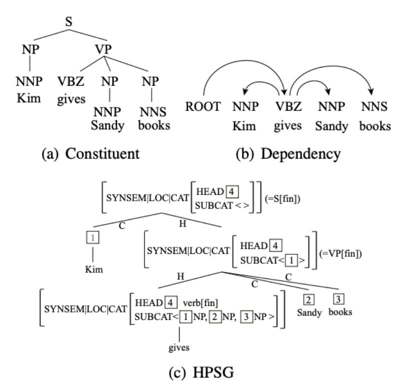
Dozat and Manning (2017)

# Evaluating Dependency Parsing

- UAS: unlabeled attachment score. Accuracy of choosing each word's parent (*n* decisions per sentence)
- LAS: additionally consider label for each edge
- Log-linear CRF parser, decoding with Eisner algorithm: 91 UAS
- Higher-order features from Koo parser: 93 UAS
- Best English results with neural CRFs (Dozat and Manning): 95-96 UAS

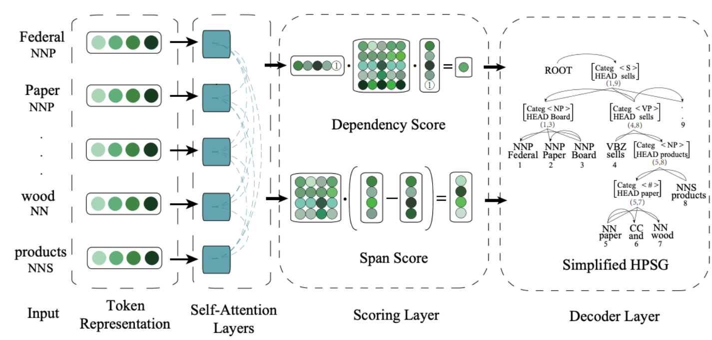
# HPSG

- Head-driven phrase structure grammar (HPSG): very complex grammar formalism which annotates large feature structures over tree
- Very little work on HPSG in NLP




Pollard and Sag (1994), Zhou and Zhao (2019)

# Parsing with "HPSG"




- Joint model of constituency and dependency combining ideas from Dozat + Manning and Stern et al.

Zhou and Zhao (2019)

## Parsing with "HPSG"

- Slightly stronger results than Dozat + Manning, significantly better results on Chinese

| Model | English | | Chinese | |
|---|---|---|---|---|
| | UAS | LAS | UAS | LAS |
| Chen and Manning (2014) | 91.8 | 89.6 | 83.9 | 82.4 |
| Andor et al. (2016) | 94.61 | 92.79 | - | - |
| Zhang et al. (2016) | 93.42 | 91.29 | 87.65 | 86.17 |
| Cheng et al. (2016) | 94.10 | 91.49 | 88.1 | 85.7 |
| Kuncoro et al. (2016) | 94.26 | 92.06 | 88.87 | 87.30 |
| Ma and Hovy (2017) | 94.88 | 92.98 | 89.05 | 87.74 |
| Dozat and Manning (2017) | 95.74 | 94.08 | 89.30 | 88.23 |
| Li et al. (2018a) | 94.11 | 92.08 | 88.78 | 86.23 |
| Ma et al. (2018) | 95.87 | 94.19 | 90.59 | **89.29** |
| Our (Division) | 94.32 | 93.09 | 89.14 | 87.31 |
| Our (Joint) | **96.09** | **94.68** | **91.21** | 89.15 |
| Our (Division*) | - | - | 91.69 | 90.54 |
| Our (Joint*) | - | - | 93.24 | 91.95 |

Zhou and Zhao (2019)

## Takeaways

- Dependency formalism provides an alternative to constituency, particularly useful in how portable it is across languages
- Dependency parsing also has efficient dynamic programs for inference
- CRFs + neural CRFs (again) work well

## Proj 1 Results

Jiaming Chen: 82.46 F1

Po-Yi Chen: 82.02 F1

Ting-Yu Yen: 81.57 F1

Prakhar Singh: 81.54 F1

All others <81

- WordPair features, larger window for POS tag extraction ([-2, 2])
- Also larger window and data shuffling in between epochs
- Unregularized Adagrad worked best
- City gazetteer, generic date recognizer