CS388: Natural Language Processing
Lecture 11: Dependency Parsing I

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Administrivia

- Project 1 graded by Tuesday

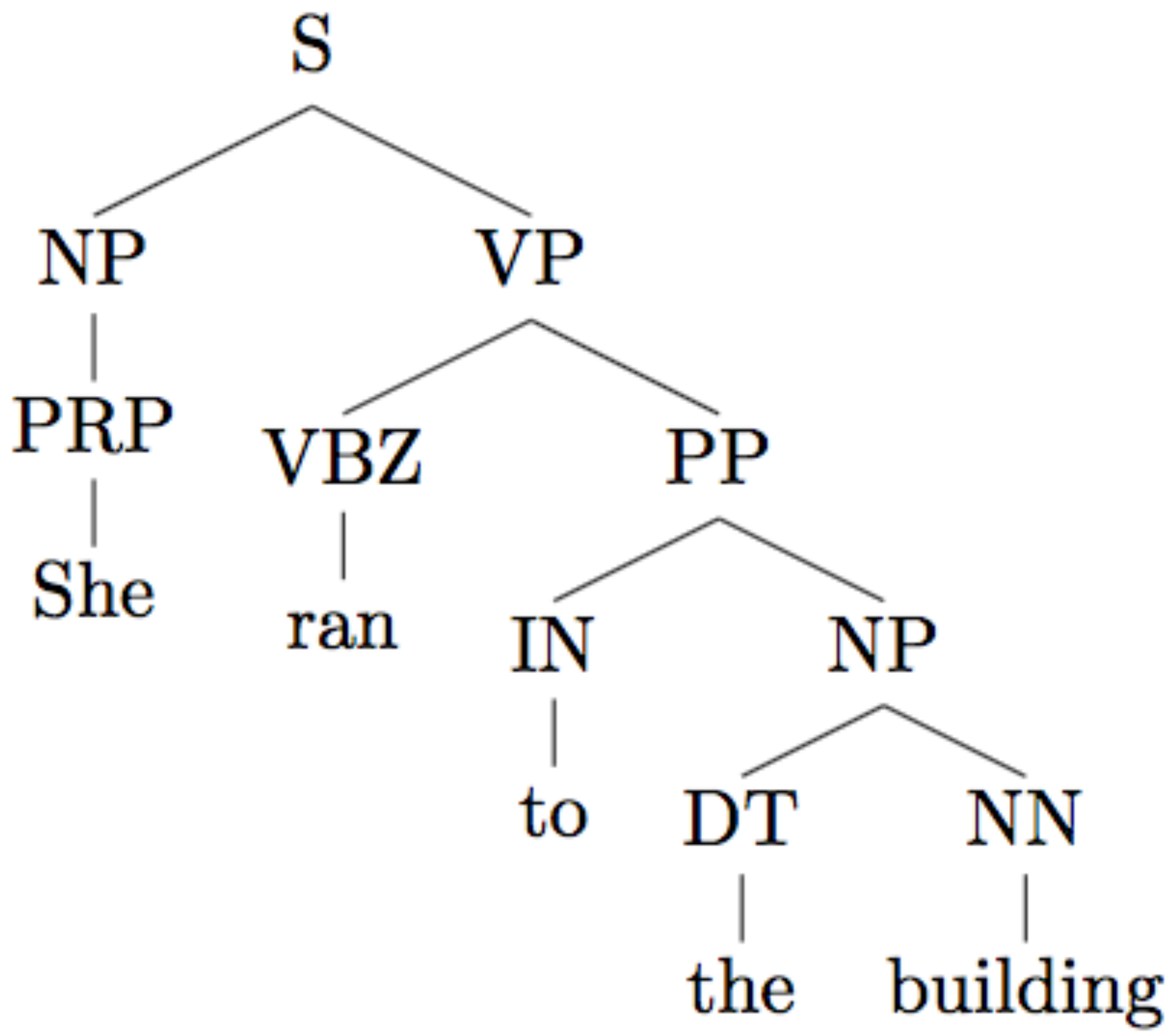
- Survey results:
  - Some annoyances from projects: slow debugging/training, etc.
    - If you have comments on the code, please send them to me (either anonymously or non-anonymously)
  - Bit rate
  - Clearer slides/notation

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

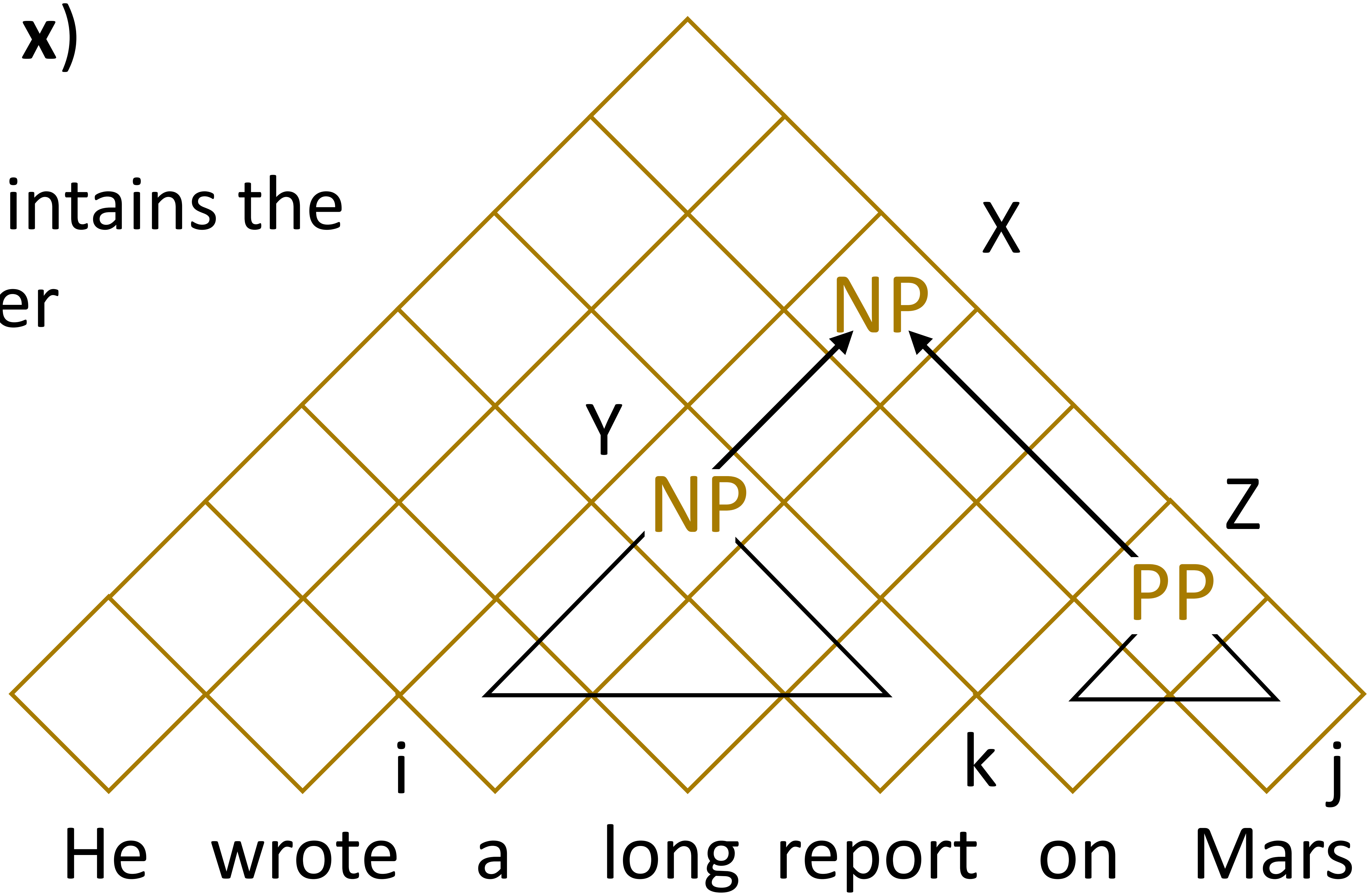


Recall: CKY

- 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



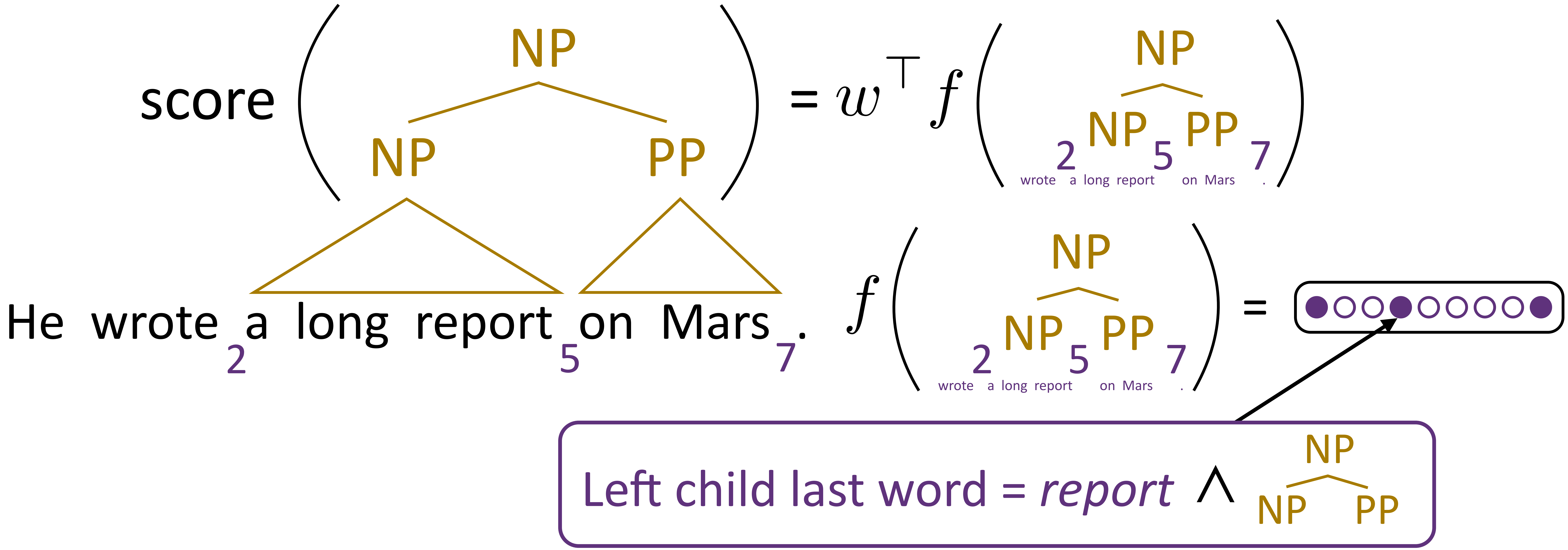
Cocke-Kasami-Younger

Outline

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

Discriminative Parsers

CRF Parsing

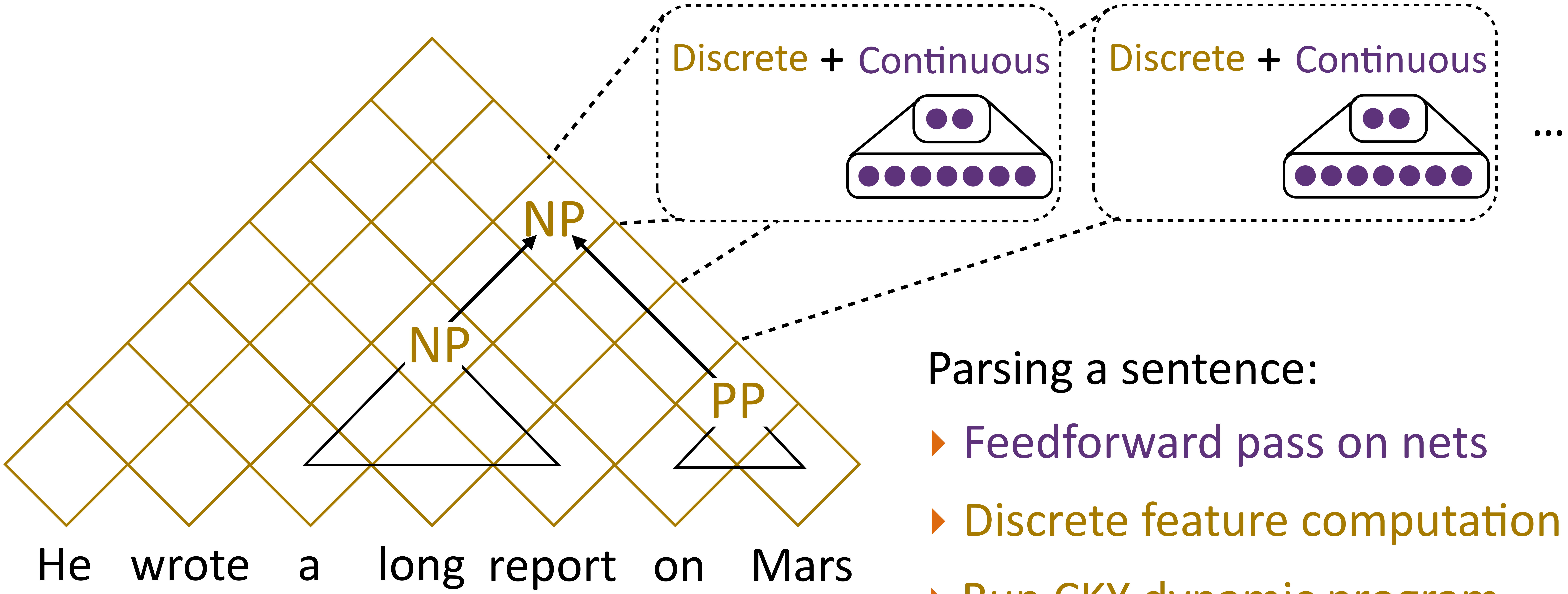


- Can learn that we *report* [PP], which is common due to *reporting on* things
- Can “neuralize” this as well like neural CRFs for NER

Taskar et al. (2004)
Hall, Durrett, and Klein (2014)
Durrett and Klein (2015)

Joint Discrete and Continuous Parsing

- Chart remains discrete!



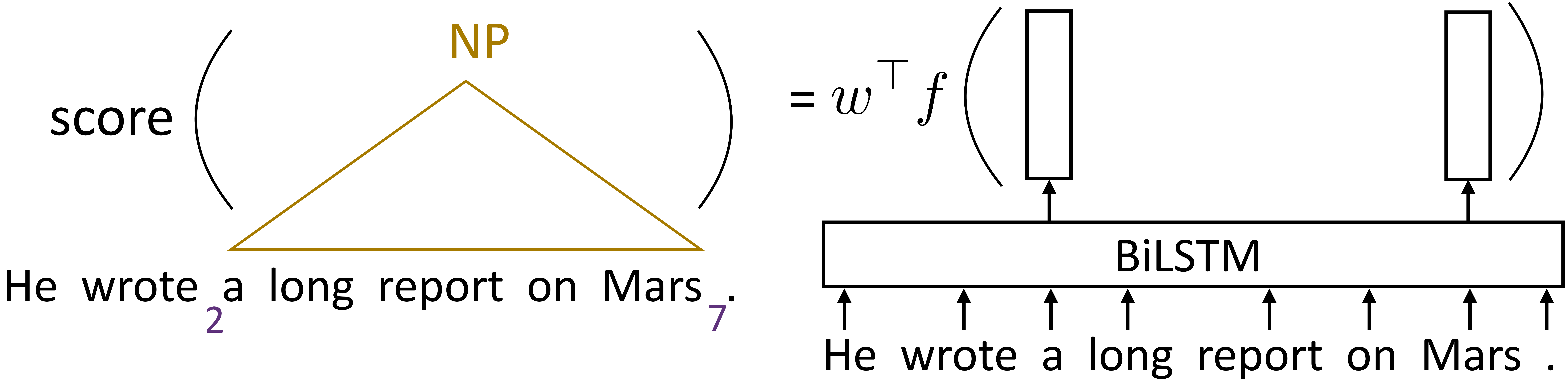
Parsing a sentence:

- Feedforward pass on nets
- Discrete feature computation
- Run CKY dynamic program

Durrett and Klein (ACL 2015)

Neural CRF Parsing

- Simpler version: score *constituents* rather than rule applications

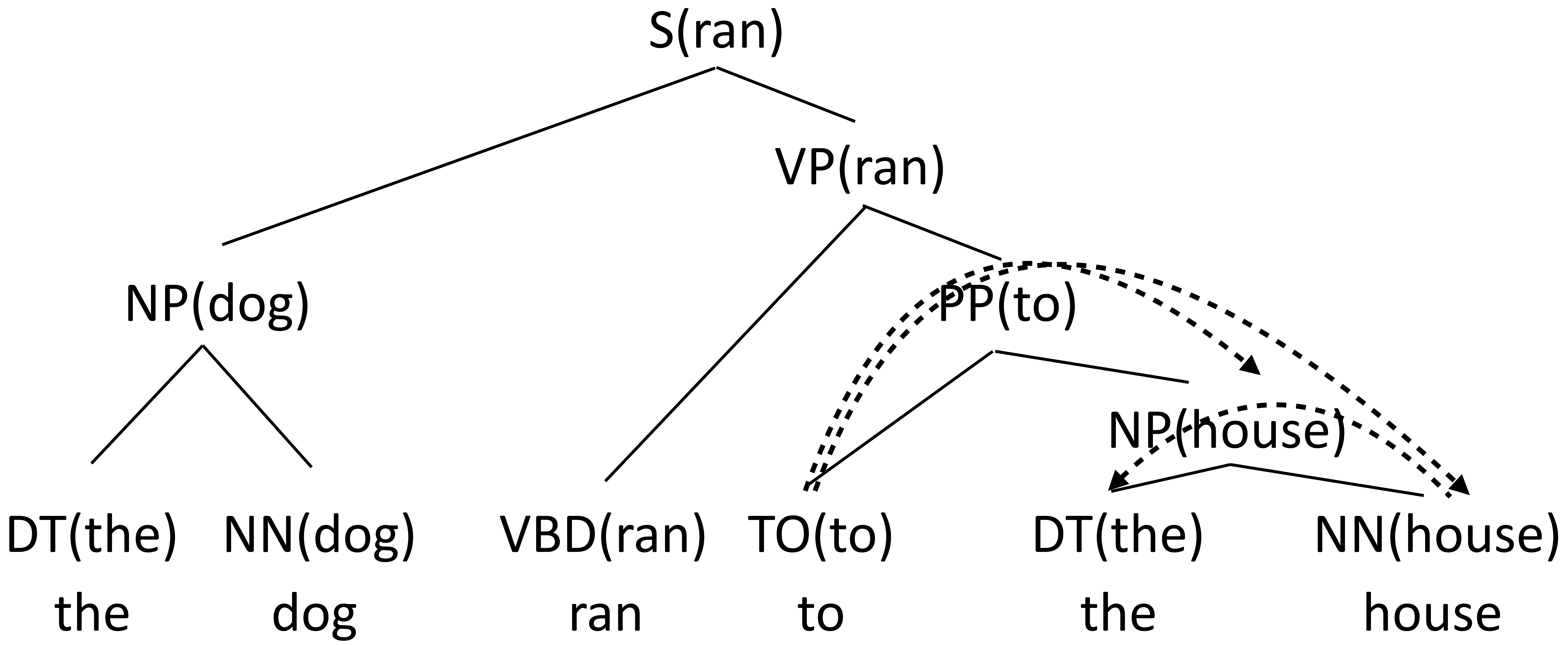


- Use BiLSTMs to compute embeddings of each word, embeddings at edge of span characterize that span
- 91-93 F1, 95 F1 with ELMo (SOTA). Great on other langs too!

Stern et al. (2017), Kitaev et al. (2018)

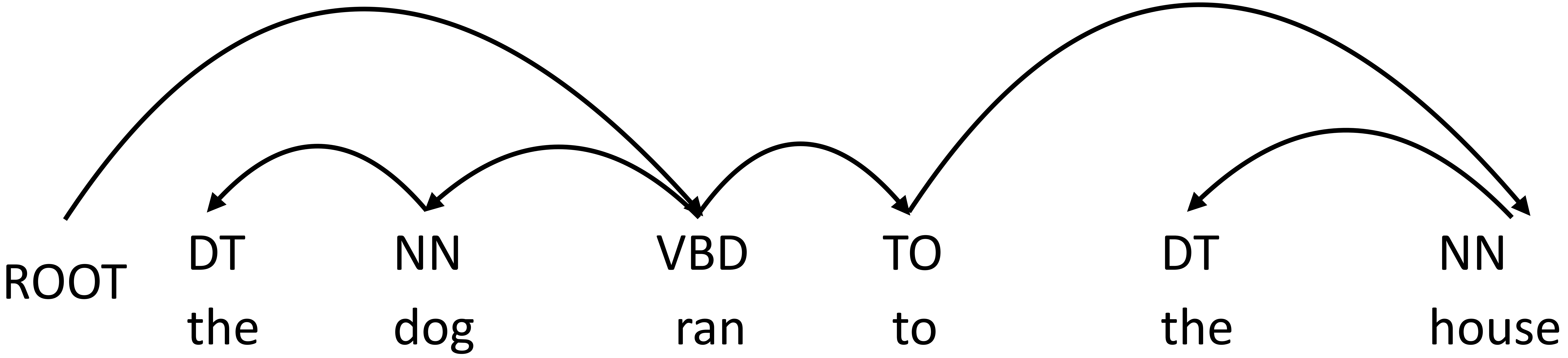
Dependency Representation

Lexicalized Parsing



Dependency Parsing

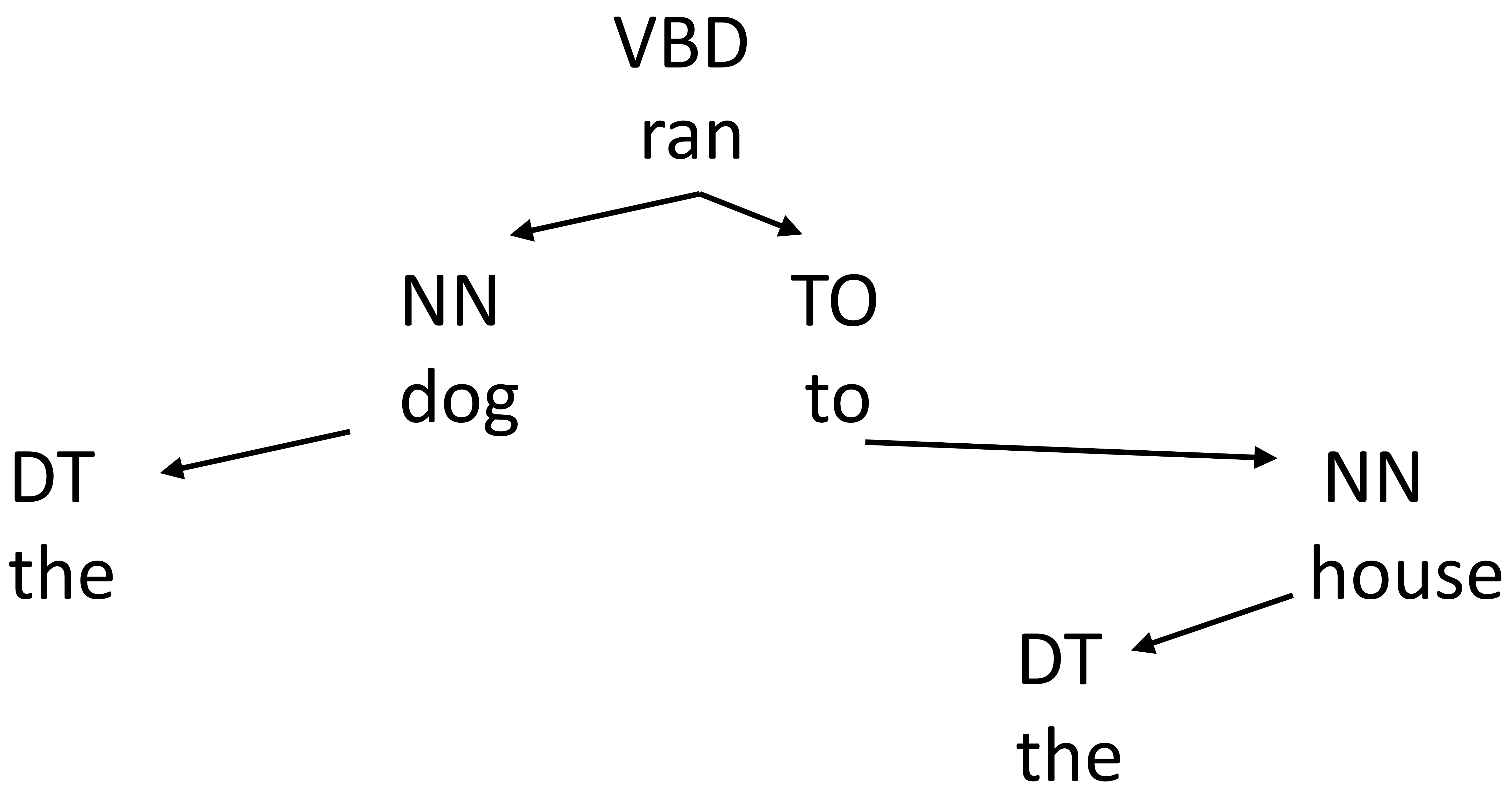
- Dependency syntax: syntactic structure is defined by these arcs
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph



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

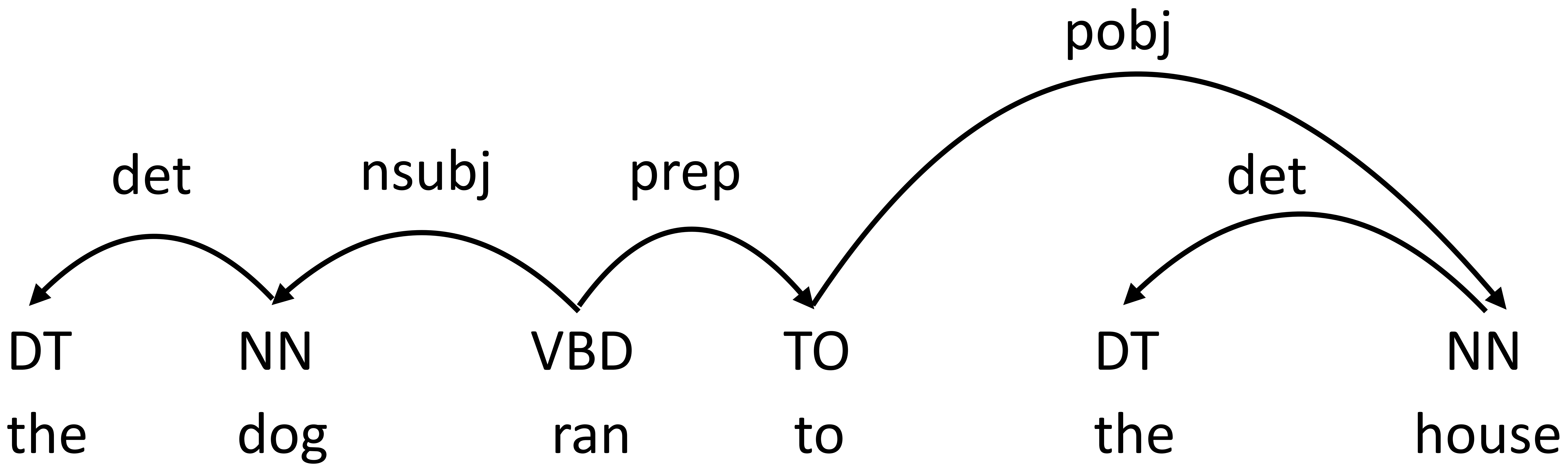
Dependency Parsing

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



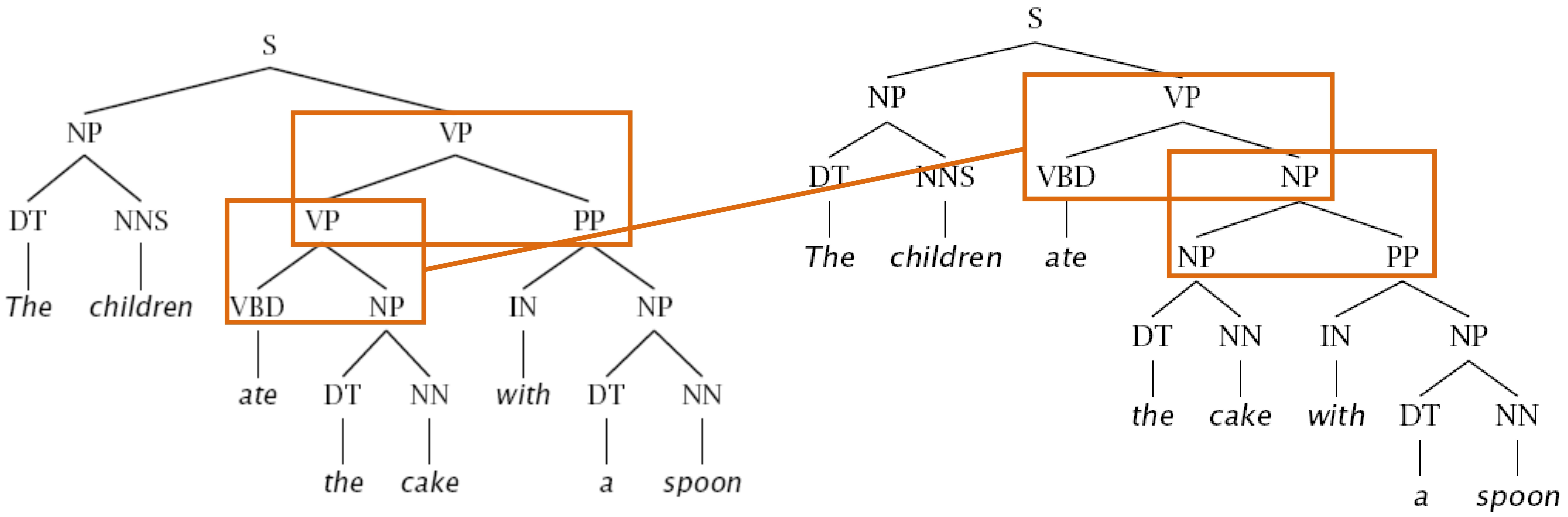
Dependency Parsing

- 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

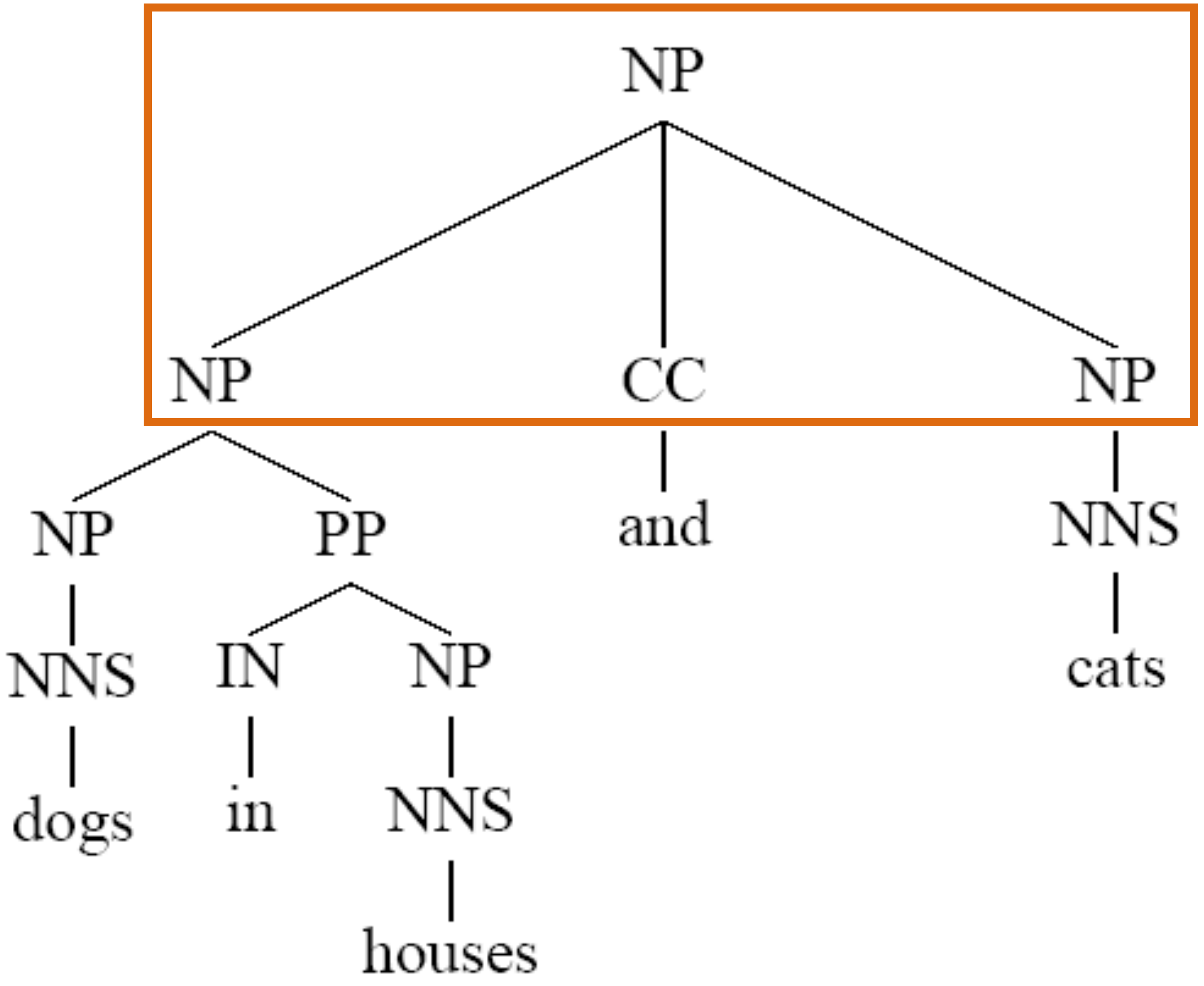
- Dependency: one word (with) assigned a different parent

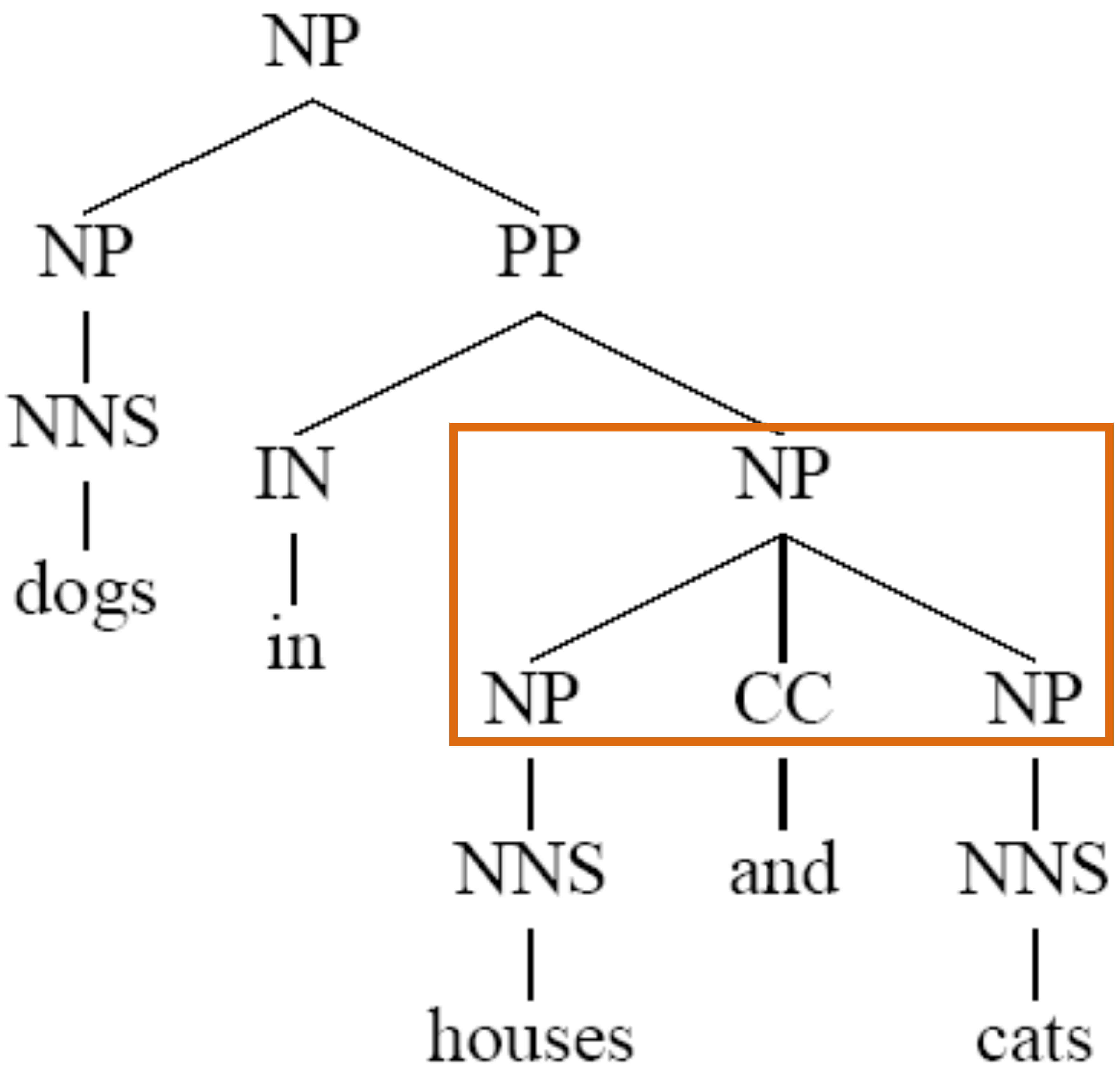
the children ate the cake with a spoon

- 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

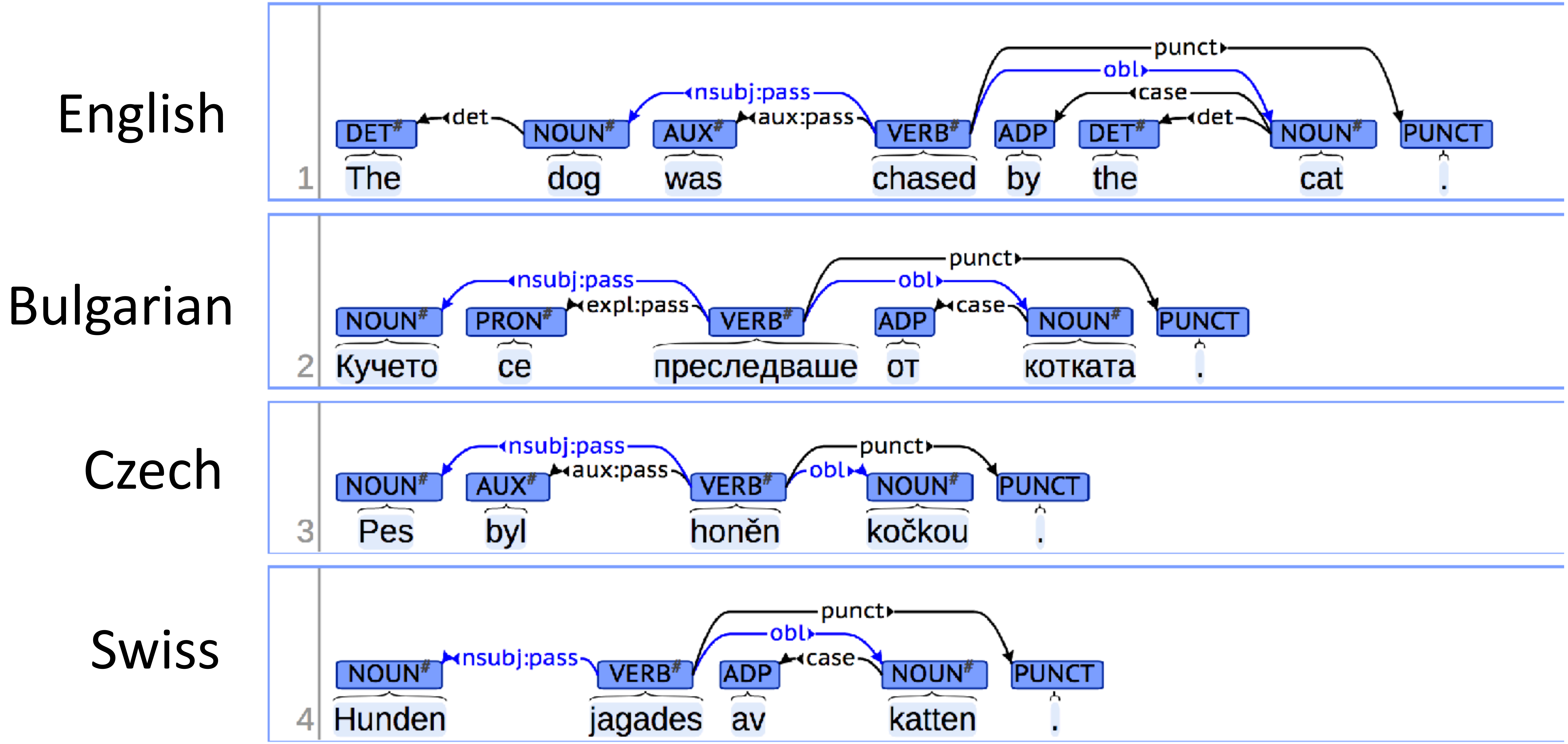
dogs in houses **and cats**   dogs in **houses and cats**

[dogs in houses] and cats   dogs in [houses and cats]

- 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

Universal Dependencies

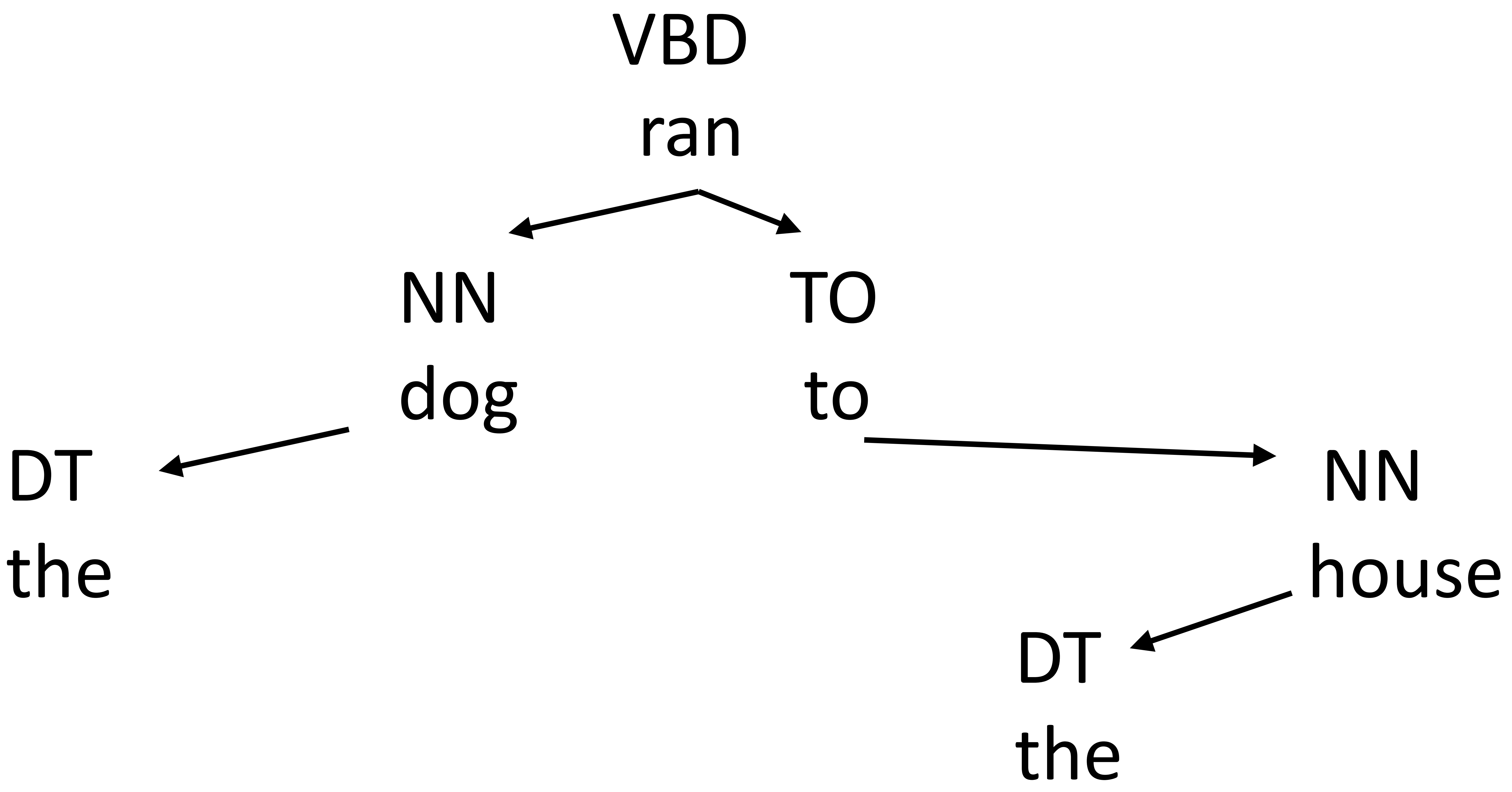
- Annotate dependencies with the same representation in many languages



http://universaldependencies.org/

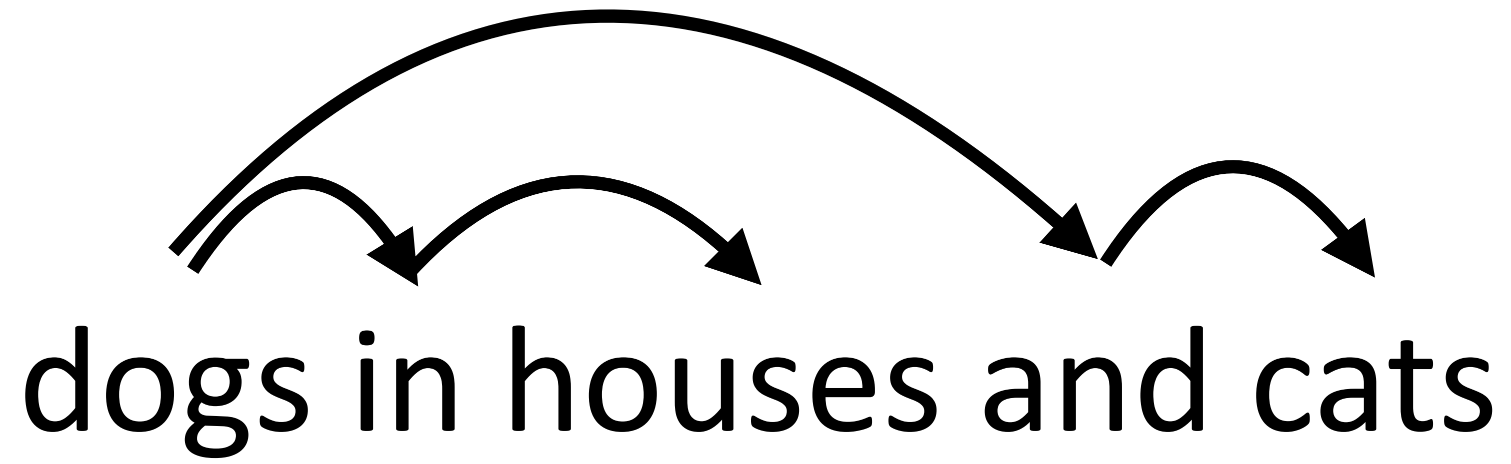
Projectivity

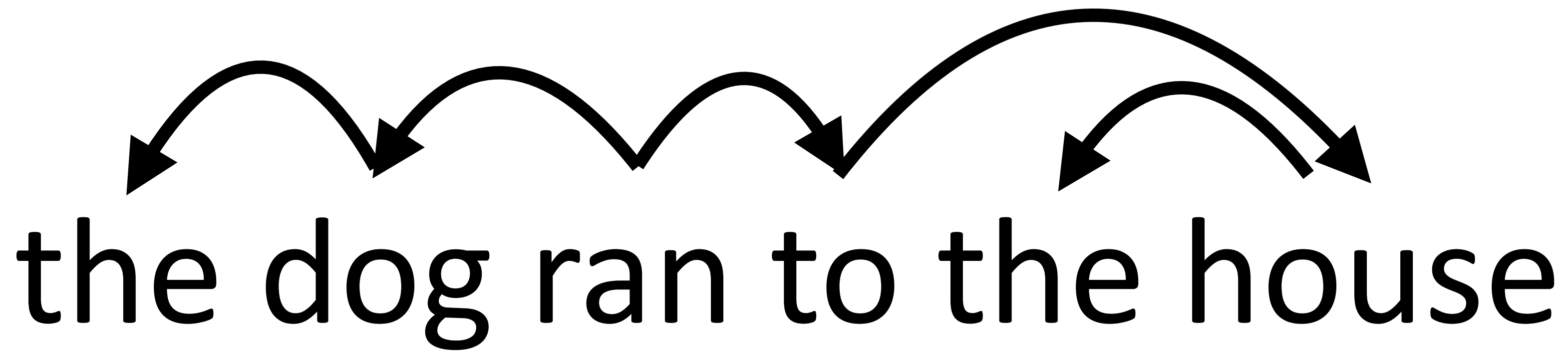
- Any subtree is a contiguous span of the sentence <-> tree is *projective*



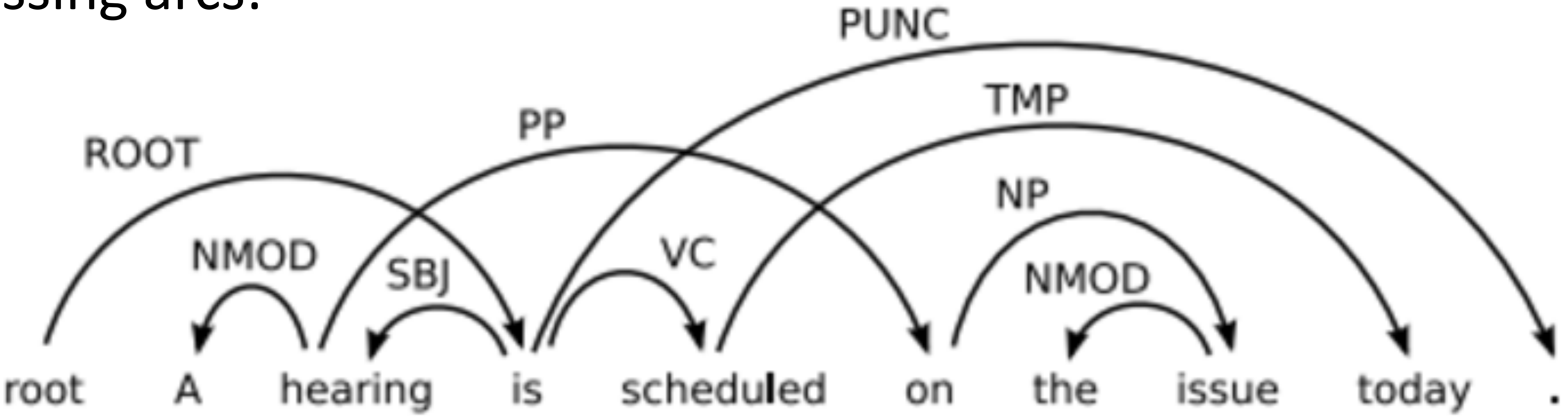
Projectivity

- Projective <-> no “crossing” arcs



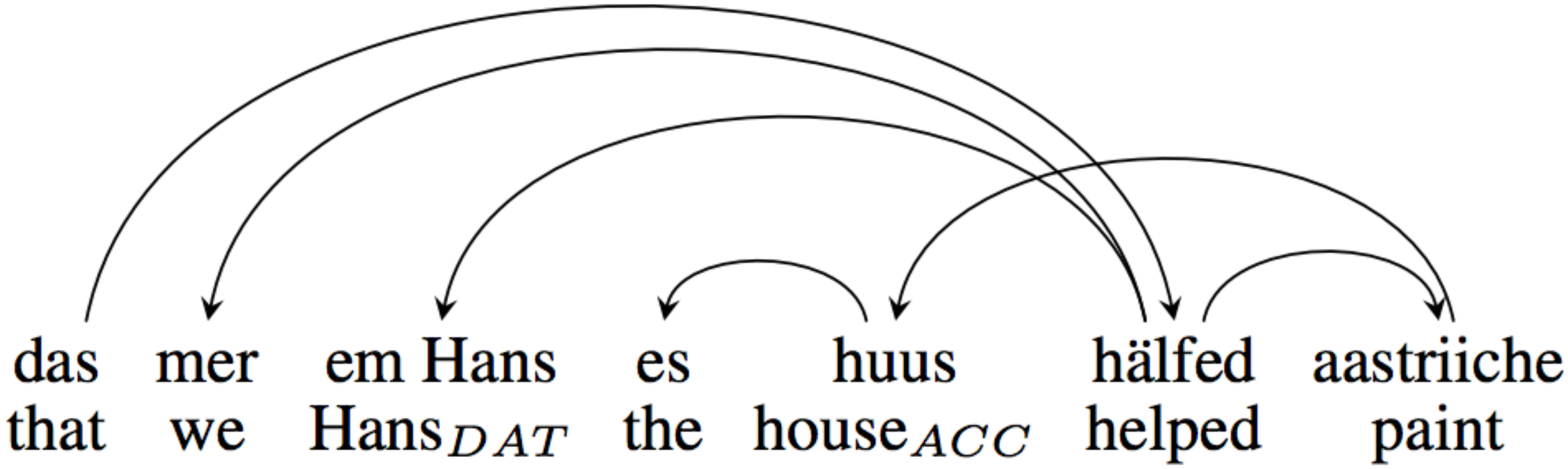


- Crossing arcs:



credit: Language Log

Projectivity in other languages



- Swiss-German 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

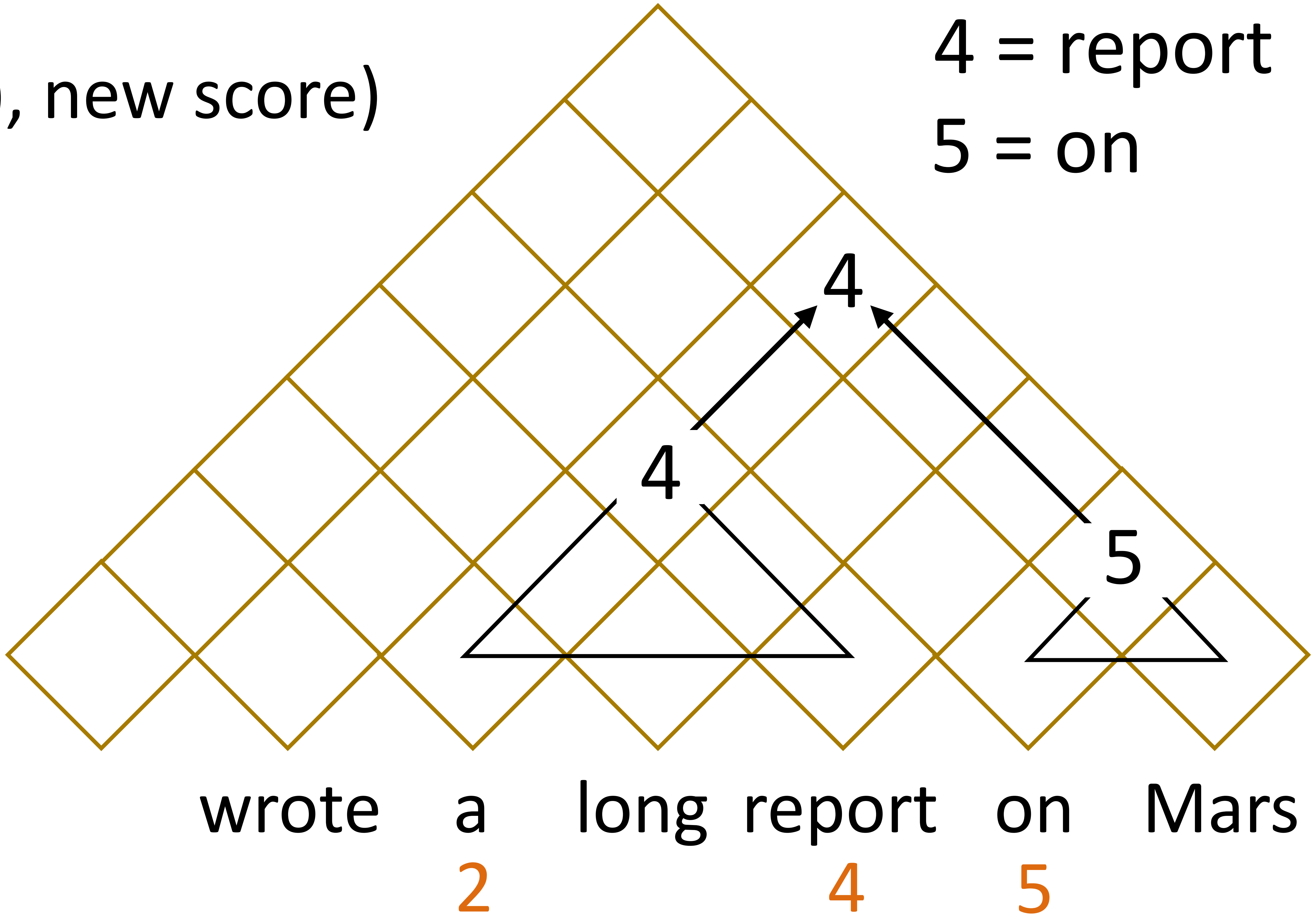
Defining Dependency Graphs

- 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)

ROOT the dog ran $\boxed{\text{to}}$ the $\boxed{\text{house}}$

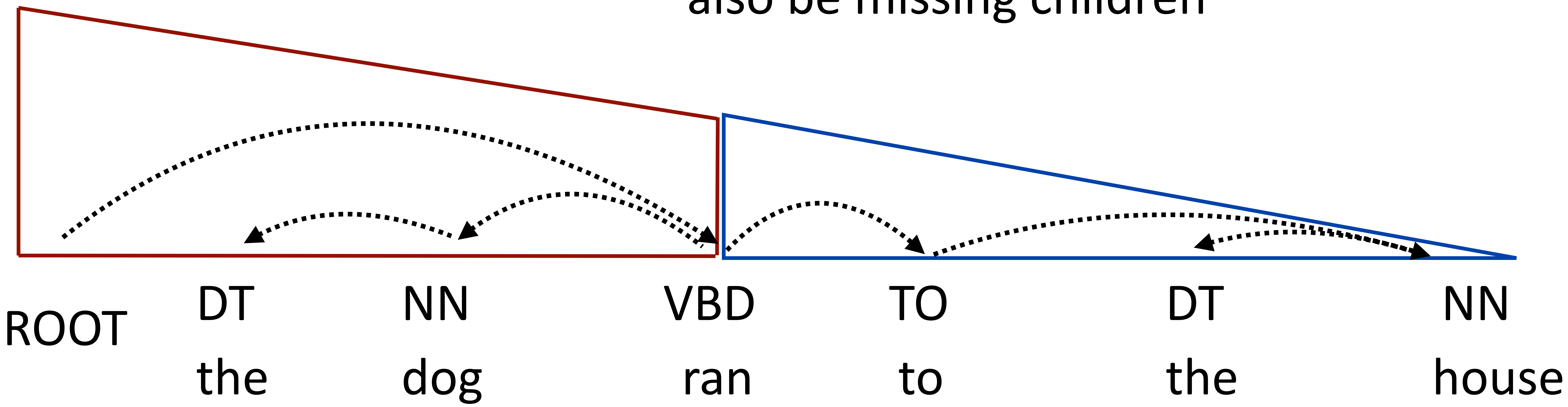
Generalizing CKY

- Score matrix with three dimensions: start, end, and head, start <= head < end
- new score = score(2, 5, 4) + score(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: $O(n^3)$

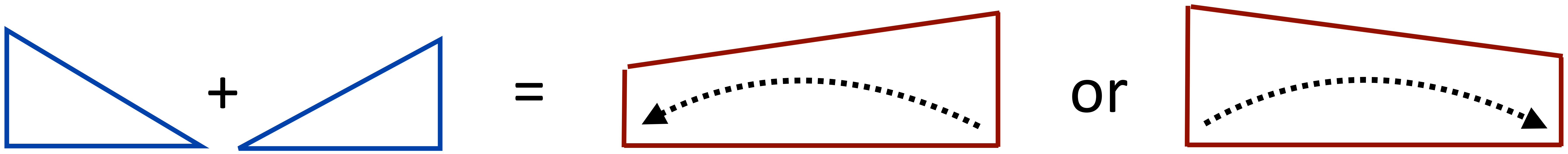
- Cubic-time algorithm
- Maintain two dynamic programming charts with dimension [n, n, 2]:
  - Complete items: head is at "tall end", may be missing children on tall side
  - Incomplete items: arc from "tall" to "short" end, word on short end may also be missing children



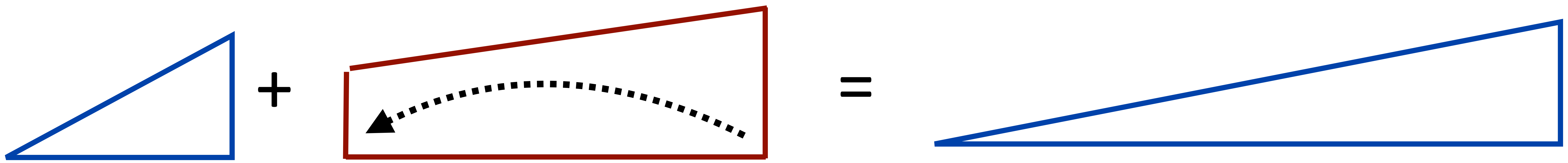
Eisner's Algorithm: $O(n^3)$

- 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



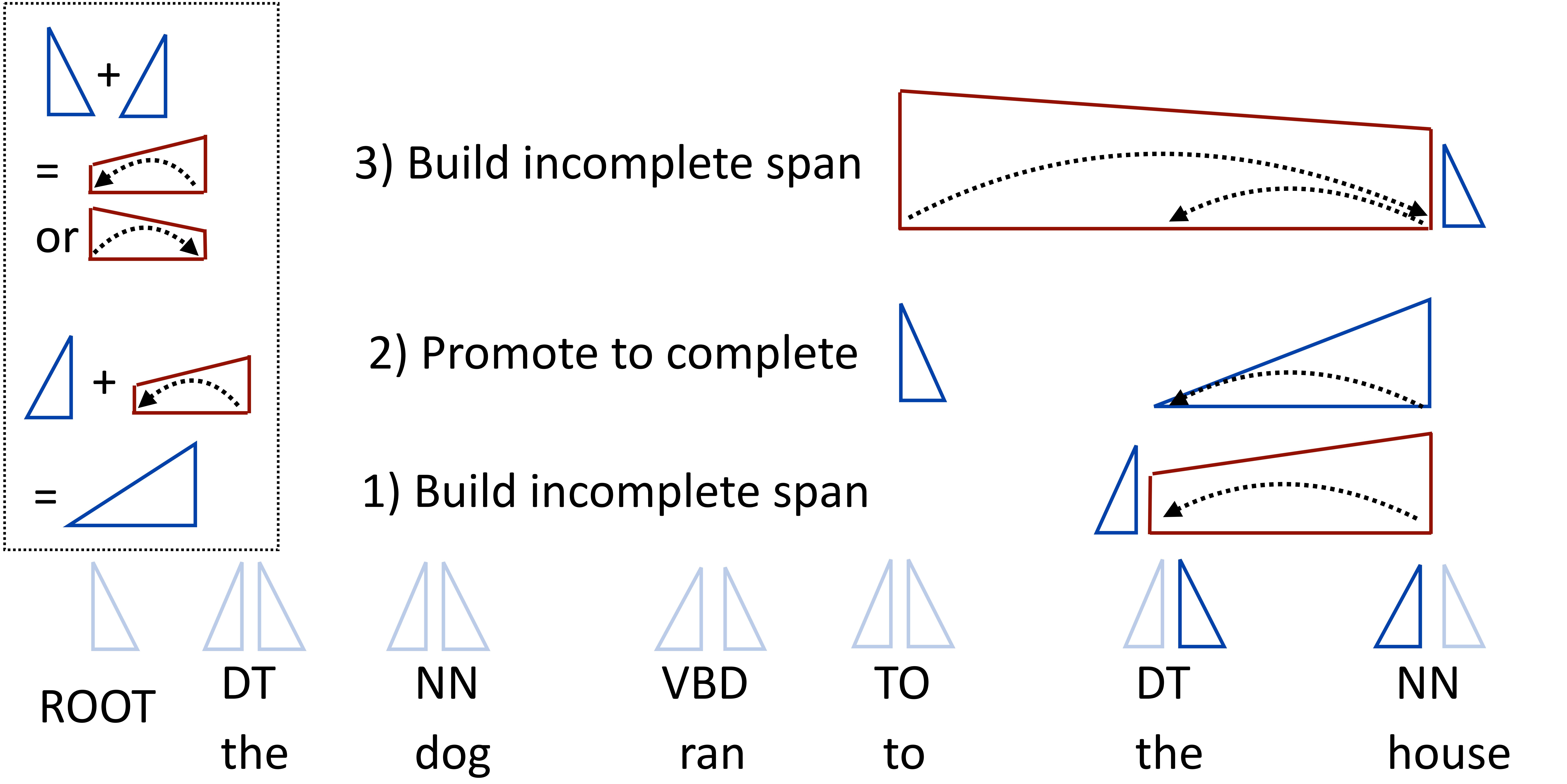
- Take an incomplete item, complete it



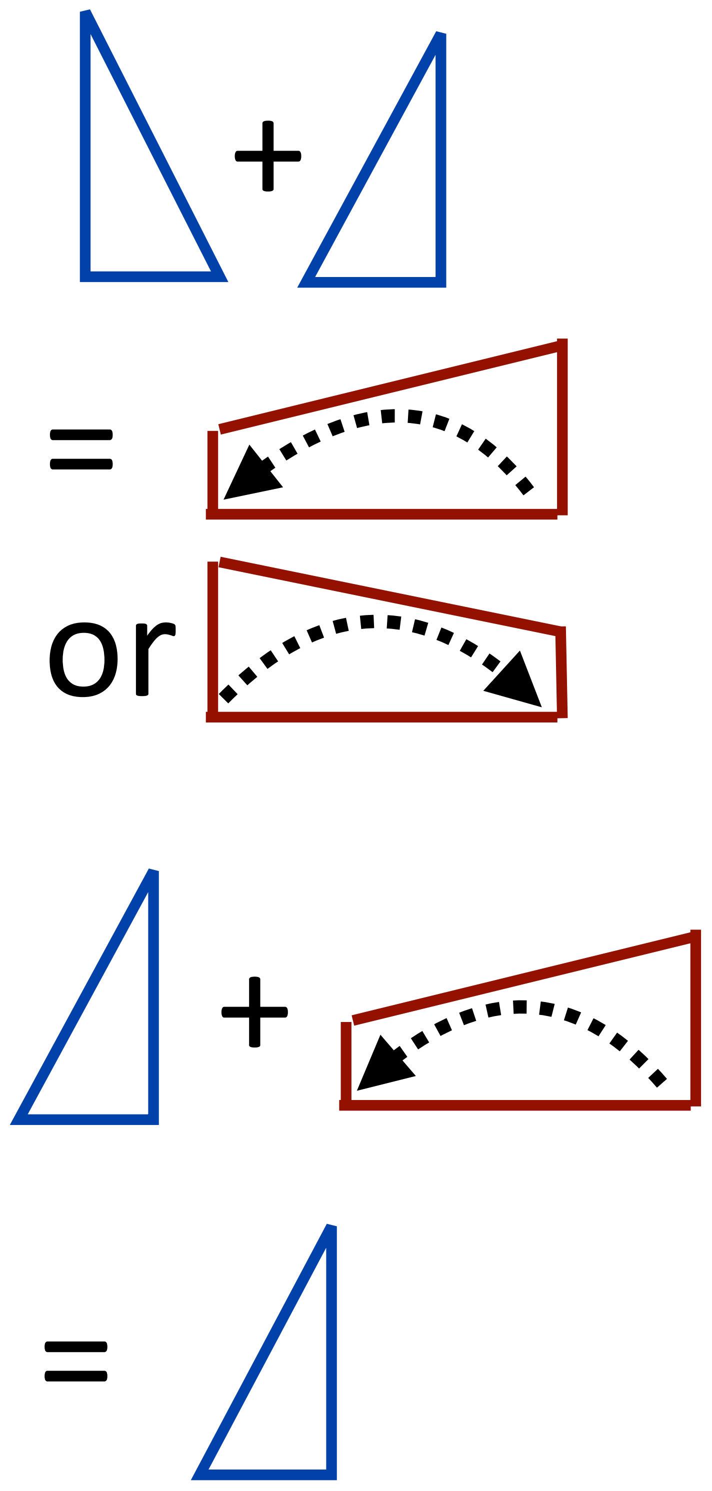
(other case is symmetric)

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

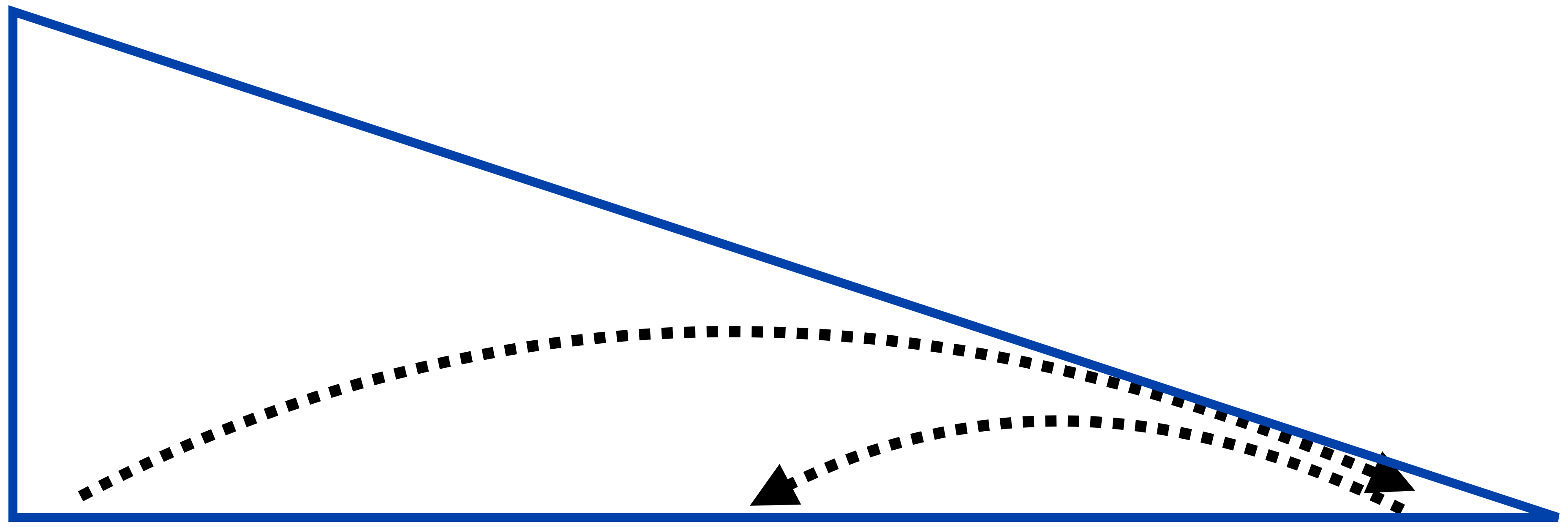
Eisner's Algorithm: $O(n^3)$



Eisner's Algorithm: $O(n^3)$



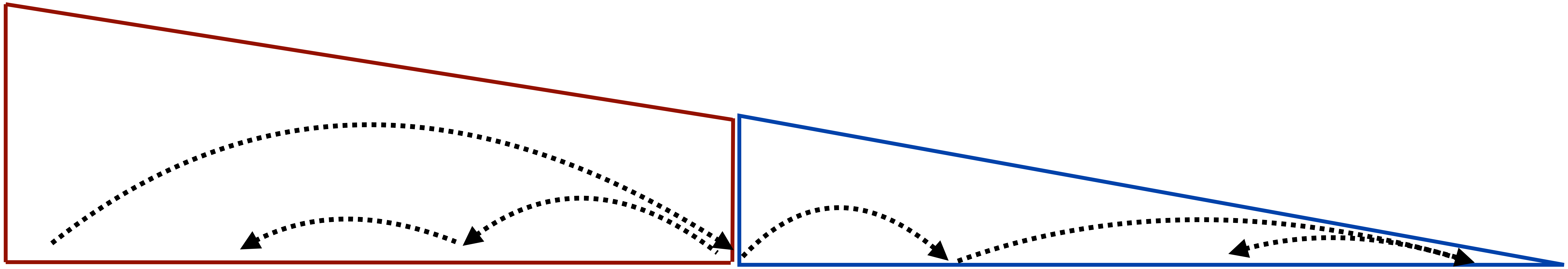
4) Promote to complete



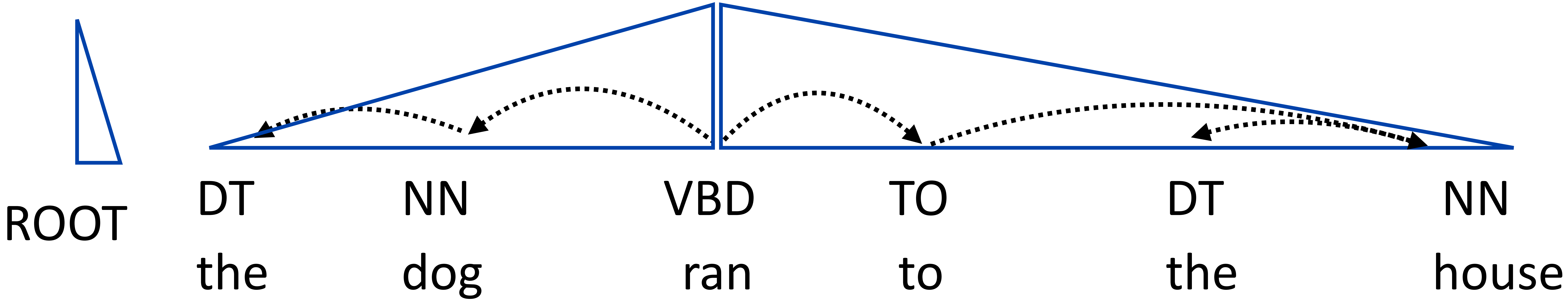
ROOT	DT	NN	VBD	TO	DT	NN
	the	dog	ran	to	the	house

Eisner’s Algorithm: $O(n^3)$

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

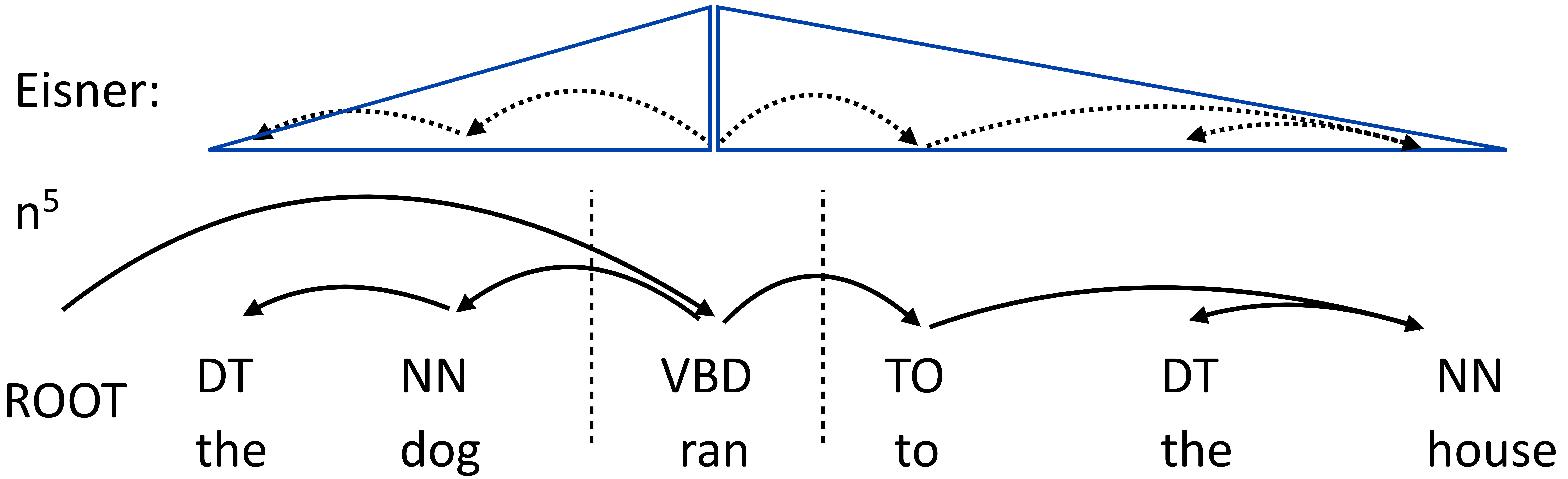


- We’ve built left children and right children of *ran* as complete items



Eisner’s Algorithm

- Eisner’s algorithm 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



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

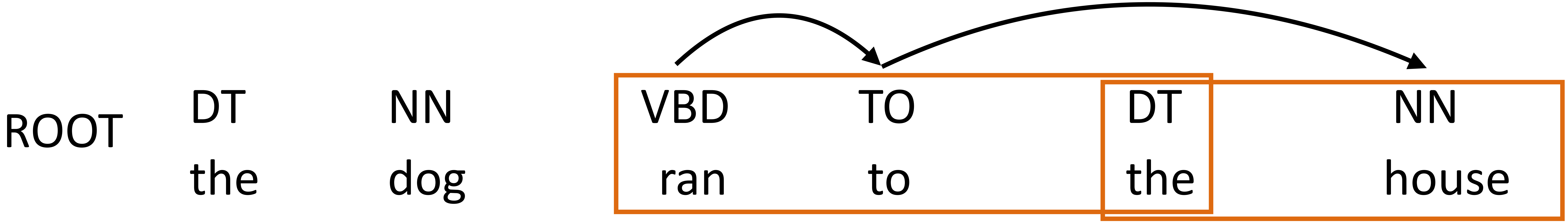
- Dynamic program exposes the parent and child indices

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

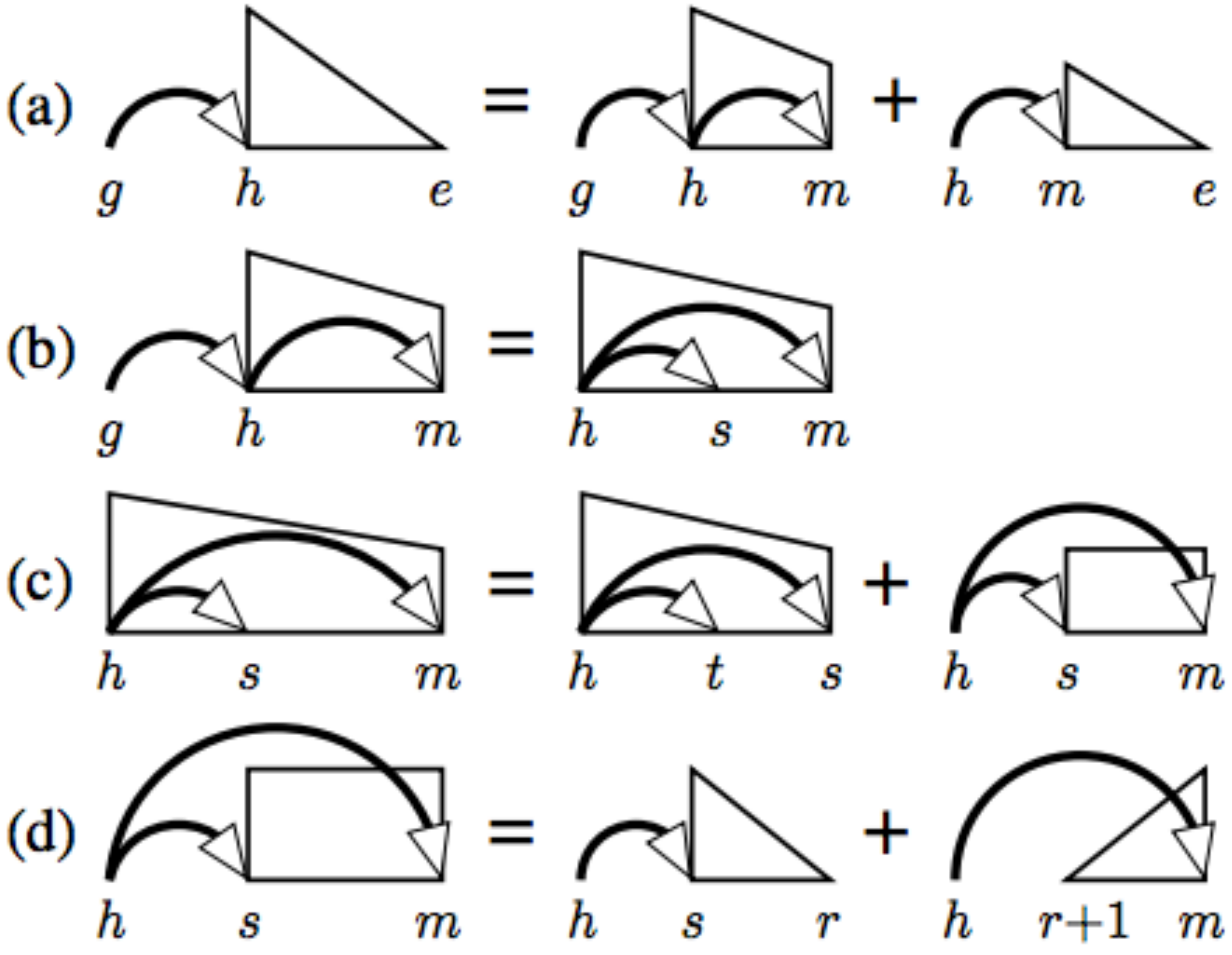
ROOT	DT	NN	VBD	TO	DT	NN
	the	dog	ran	to	the	house

- 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



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



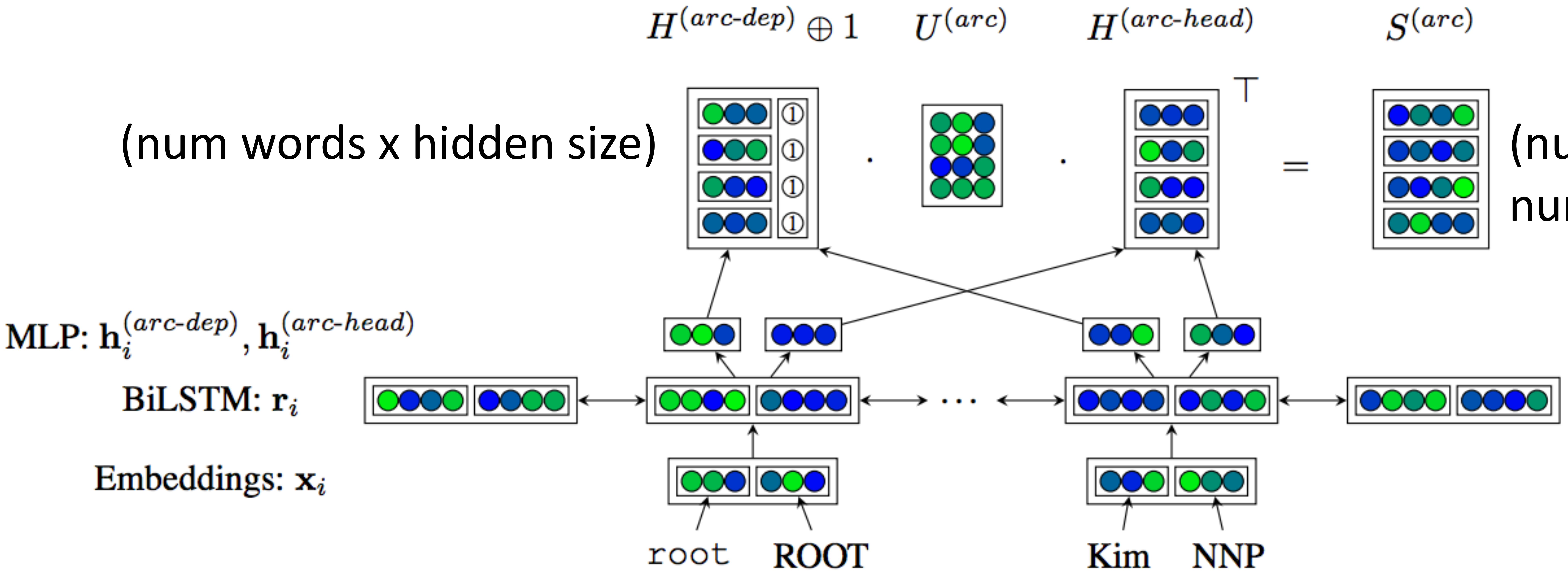
- Track additional state during parsing so we can look at "grandparents" (and siblings). $O(n^4)$ dynamic program or use approximate search

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^TUc

(num words x hidden size)



(num words x num words)

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: 95-96 UAS

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