# Dependency Grammars and Parsers

Deep Processing for NLP
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January 27, 2016

# Roadmap

- PCFGs: Reranking
- Dependency Grammars
  - Definition
  - Motivation:
    - Limitations of Context-Free Grammars
- Dependency Parsing
  - By conversion to CFG
  - By Graph-based models
  - By transition-based parsing

# Reranking

- Issue: Locality
  - PCFG probabilities associated with rewrite rules
  - Context-free grammars
  - Approaches create new rules incorporating context:
    - Parent annotation, Markovization, lexicalization
  - Other problems:
    - Increase rules, sparseness
- Need approach that incorporates broader, global info

# Discriminative Parse Reranking

- General approach:
  - Parse using (L)PCFG
  - Obtain top-N parses
  - Re-rank top-N parses using better features

- Discriminative reranking
  - Use arbitrary features in reranker (MaxEnt)
    - E.g. right-branching-ness, speaker identity, conjunctive parallelism, fragment frequency, etc

# Reranking Effectiveness

- How can reranking improve?
  - N-best includes the correct parse
- Estimate maximum improvement
  - **Oracle** parse selection
    - Selects correct parse from N-best
      - If it appears
- E.g. Collins parser (2000)
  - Base accuracy: 0.897
  - Oracle accuracy on 50-best: 0.968
- Discriminative reranking: 0.917

# Dependency Parsing

# Dependency Grammar

- CFGs:
  - Phrase-structure grammars
  - Focus on modeling constituent structure
- Dependency grammars:
  - Syntactic structure described in terms of
    - Words
    - Syntactic/Semantic relations between words

# Dependency Parse

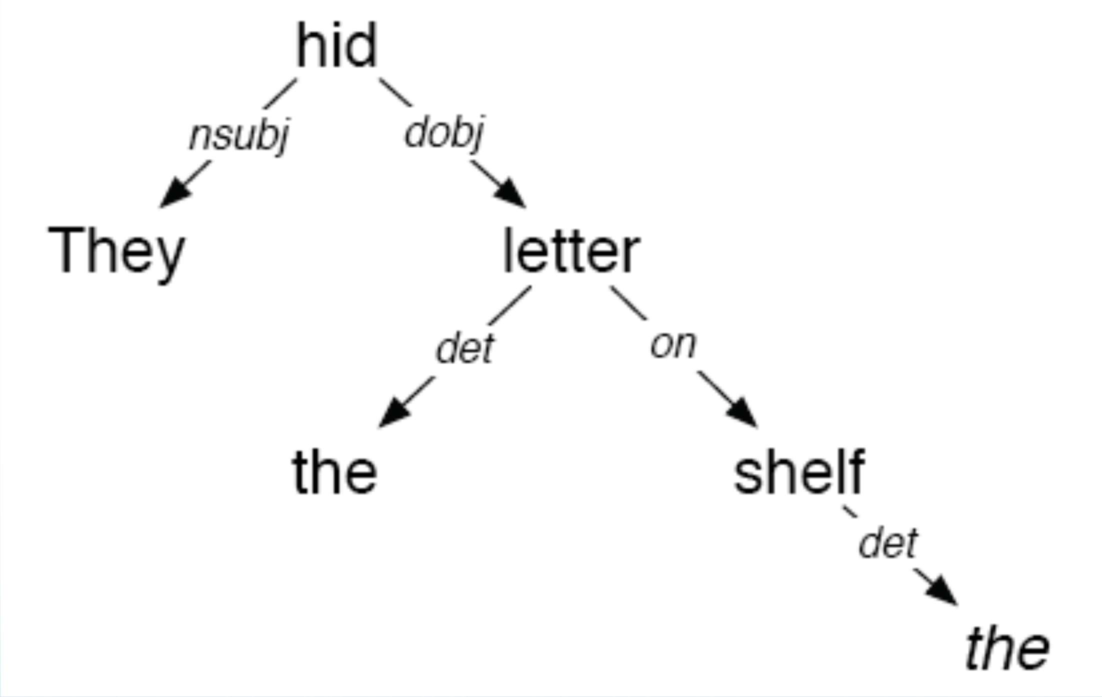
- A dependency parse is a tree, where
  - Nodes correspond to words in utterance
  - Edges between nodes represent dependency relations
    - Relations may be labeled (or not)

# Dependency Relations

| Argument Dependencies | Description |
|---|---|
| **nsubj** | nominal subject |
| **csubj** | clausal subject |
| **dobj** | direct object |
| **iobj** | indirect object |
| **pobj** | object of preposition |
| **Modifier Dependencies** | **Description** |
| **tmod** | temporal modifier |
| **appos** | appositional modifier |
| **det** | determiner |
| **prep** | prepositional modifier |

# Dependency Parse Example

- They hid the letter on the shelf



# Why Dependency Grammar?

- More natural representation for many tasks
  - Clear encapsulation of predicate-argument structure
    - Phrase structure may obscure, e.g. wh-movement
  - Good match for question-answering, relation extraction
    - Who did what to whom
    - Build on parallelism of relations between question/relation specifications and answer sentences

# Why Dependency Grammar?

- Easier handling of flexible or free word order

  - How does CFG handle variations in word order?
    - Adds extra phrases structure rules for alternatives
      - Minor issue in English, explosive in other langs

  - What about dependency grammar?
    - No difference: link represents relation
    - Abstracts away from surface word order

# Why Dependency Grammar?

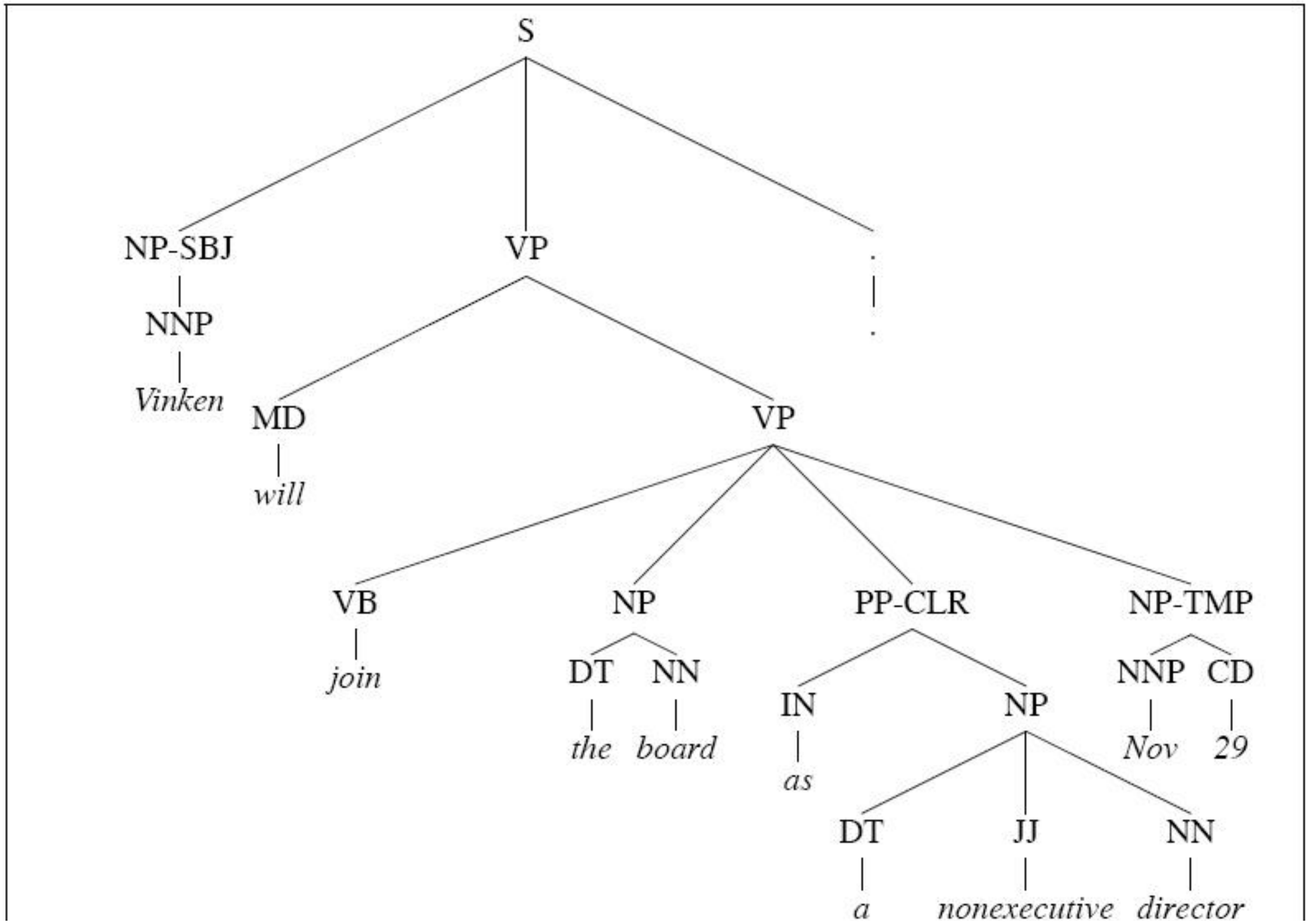
- Natural efficiencies:
  - CFG: Must derive full trees of many non-terminals
  - Dependency parsing:
    - For each word, must identify
      - Syntactic head, h
      - Dependency label, d
    - Inherently lexicalized
      - Strong constraints hold between pairs of words

# Summary

- Dependency grammar balances complexity and expressiveness
  - Sufficiently expressive to capture predicate-argument structure
  - Sufficiently constrained to allow efficient parsing

# Conversion

- Can convert phrase structure to dependency trees
  - Unlabeled dependencies
- Algorithm:
  - Identify all head children in PS tree
  - Make head of each non-head-child depend on head of head-child



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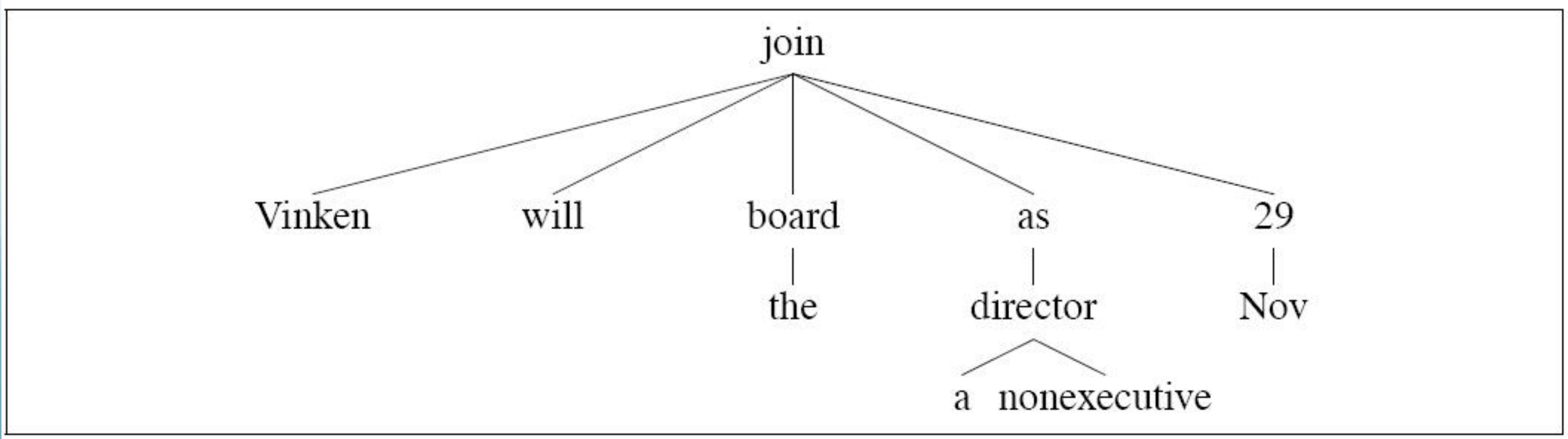

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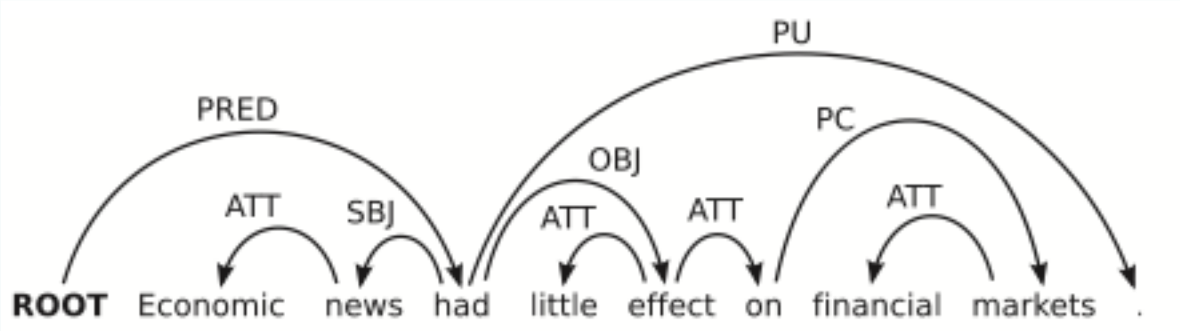
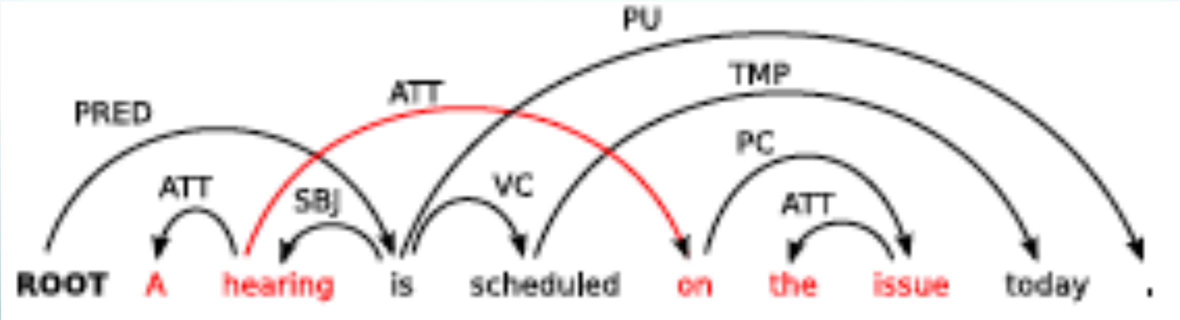
# Dependency Parsing

- Three main strategies:
  - Convert dependency trees to PS trees
    - Parse using standard algorithms $O(n^3)$
  - Employ graph-based optimization
    - Weights learned by machine learning
  - Shift-reduce approaches based on current word/state
    - Attachment based on machine learning

# Parsing by PS Conversion

- Can map any projective dependency tree to PS tree
  - Non-terminals indexed by words
    - "Projective": no crossing dependency arcs for ordered words



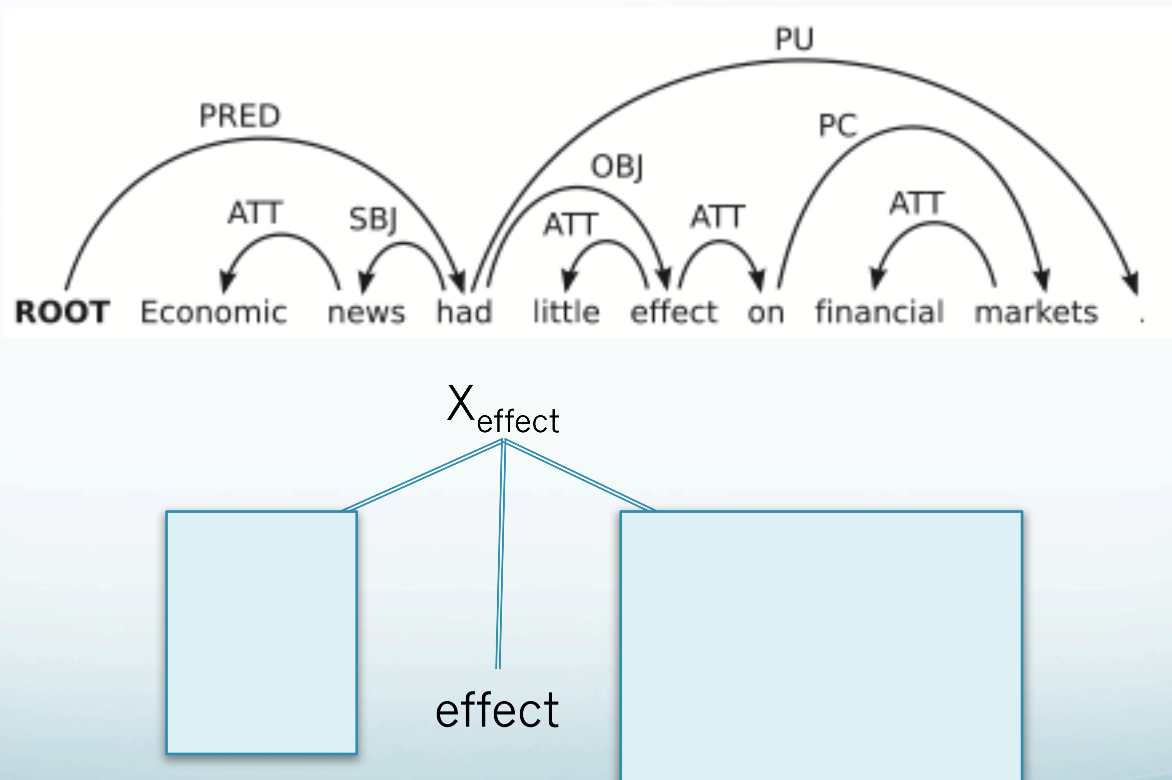



# Dep to PS Tree Conversion

- For each node *w* with outgoing arcs,
  - Convert the subtree *w* and its dependents $t_1,..,t_n$ to
  - New subtree rooted at $X_w$ with child *w* and
    - Subtrees at $t_1,..,t_n$ in the original sentence order

# Dep to PS Tree Conversion

E.g., for ‘effect’



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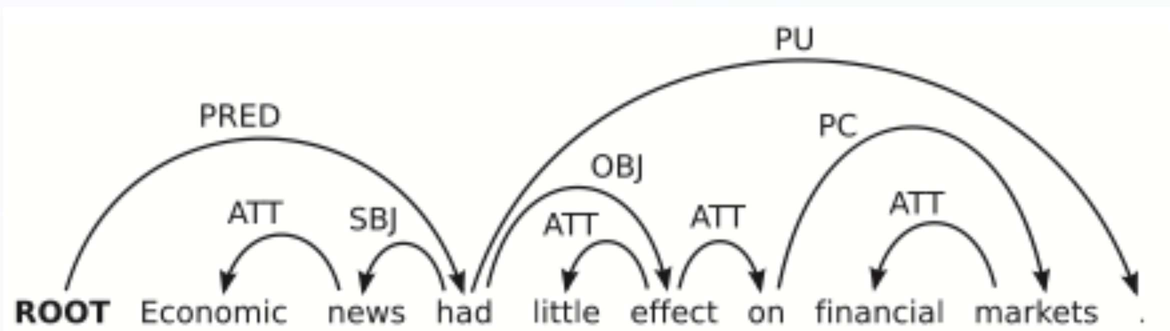
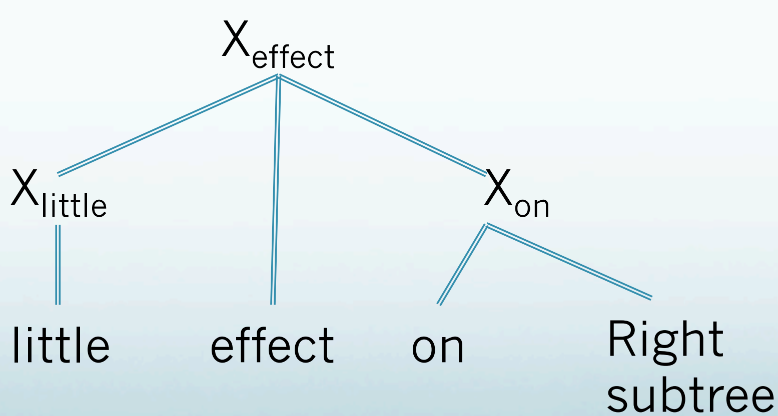
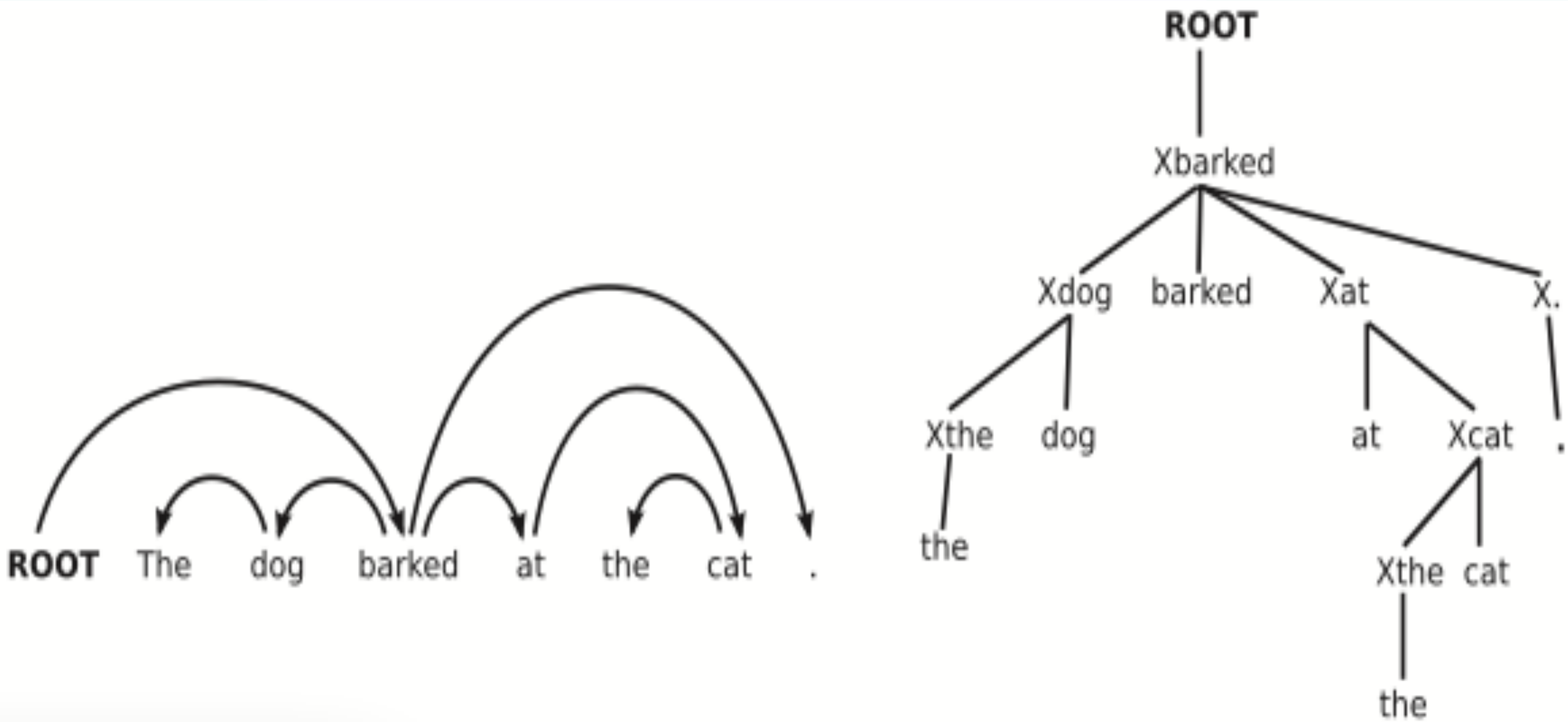


# PS to Dep Tree Conversion

- What about the dependency labels?
  - Attach labels to non-terminals associated with non-heads
  - E.g. $X_{little} \rightarrow X_{little:nmod}$
- Doesn't create typical PS trees
  - Does create fully lexicalized, context-free trees
    - Also labeled
- Can be parsed with any standard CFG parser
  - E.g. CKY, Earley

# Full Example Trees




Example from J. Moore, 2013

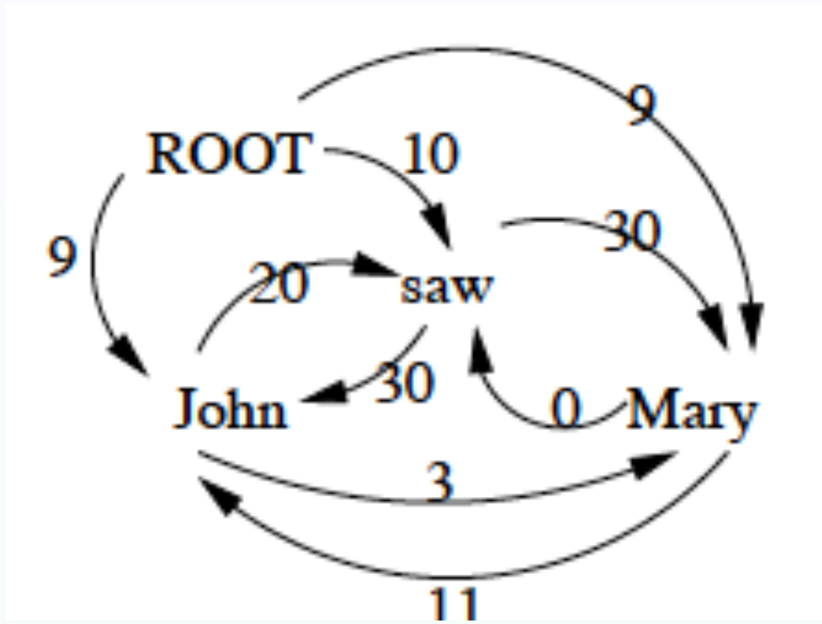
# Graph-based Dependency Parsing

- Goal: Find the highest scoring dependency tree T for sentence S
  - If S is unambiguous, T is the correct parse.
  - If S is ambiguous, T is the highest scoring parse.
- Where do scores come from?
  - Weights on dependency edges by machine learning
  - Learned from large dependency treebank
- Where are the grammar rules?
  - There aren't any; data-driven processing

# Graph-based Dependency Parsing

- Map dependency parsing to maximum spanning tree
- Idea:
  - Build initial graph: fully connected
    - Nodes: words in sentence to parse
    - Edges: Directed edges between all words
      - + Edges from ROOT to all words
  - Identify maximum spanning tree
    - Tree s.t. all nodes are connected
    - Select such tree with highest weight
    - Arc-factored model: Weights depend on end nodes & link
      - Weight of tree is sum of participating arcs

# Initial Tree




- Sentence: John saw Mary (McDonald et al, 2005)
  - All words connected; ROOT only has outgoing arcs

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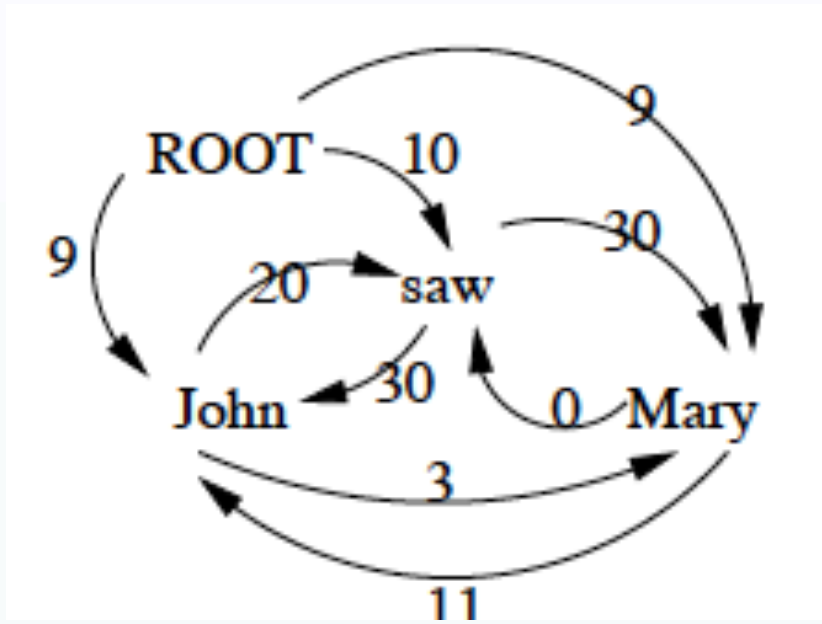


- Sentence: John saw Mary (McDonald et al, 2005)
  - All words connected; ROOT only has outgoing arcs
- Goal: Remove arcs to create a tree covering all words
  - Resulting tree is dependency parse

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    - “Contract” the cycle: Treat it as a single vertex
    - Recalculate weights into/out of the new vertex
    - Recursively do MST algorithm on resulting graph
- Running time: naïve: $O(n^3)$; Tarjan: $O(n^2)$
  - Applicable to non-projective graphs