Dependency Parsing & Feature-based Parsing

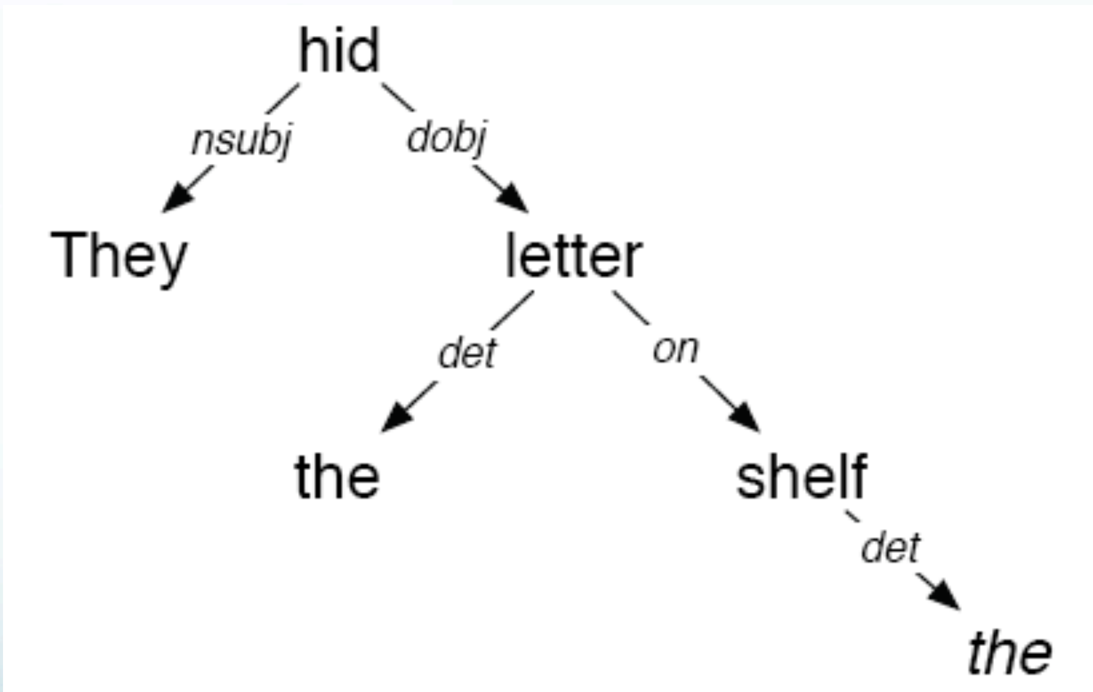
Ling571
Deep Processing Techniques for NLP
February 2, 2015

Roadmap

- Dependency parsing
  - Graph-based dependency parsing
    - Maximum spanning tree
    - CLE Algorithm
    - Learning weights
- Feature-based parsing
  - Motivation
  - Features
  - Unification

Dependency Parse Example

- They hid the letter on the shelf



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  - There aren't any; data-driven processing

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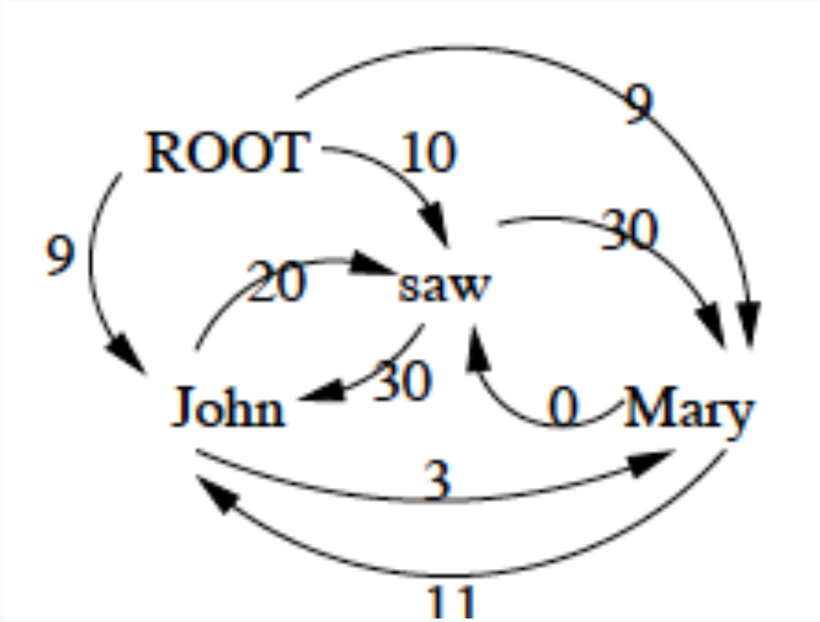
    - Arc-factored model: Weights depend on end nodes & link
      - Weight of tree is sum of participating arcs

Initial Tree



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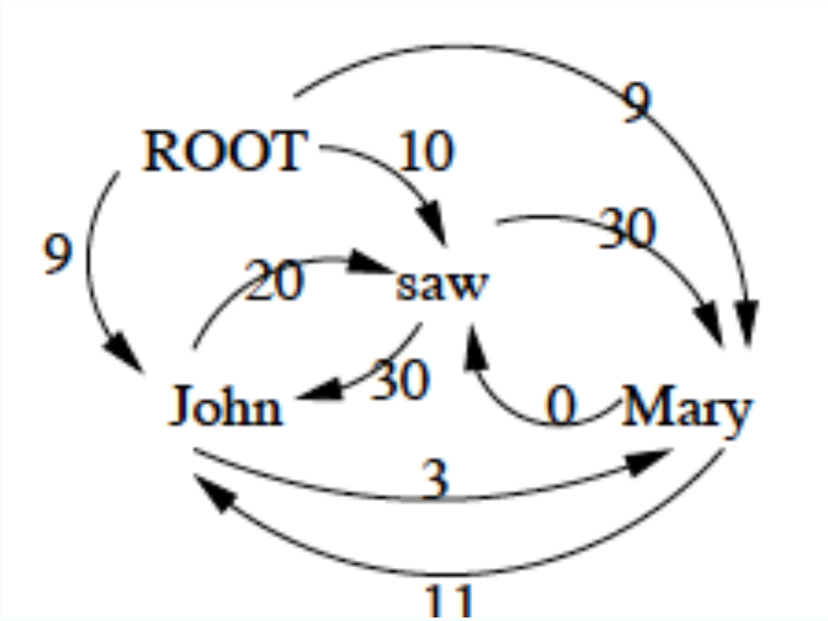

- Sentence: John saw Mary (McDonald et al, 2005)
  - All words connected; ROOT only has outgoing arcs
- Goal: Remove arcs to create a tree covering all words
  - Resulting tree is dependency parse

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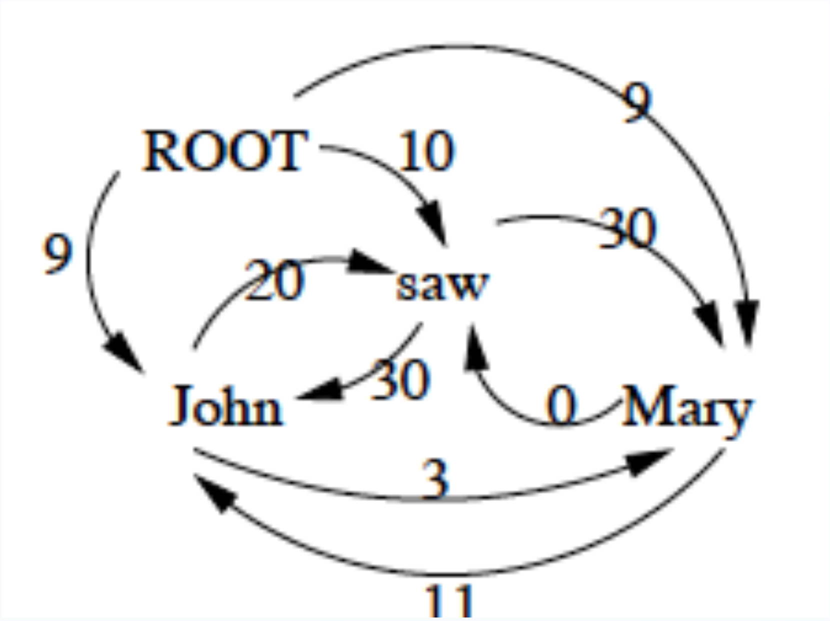
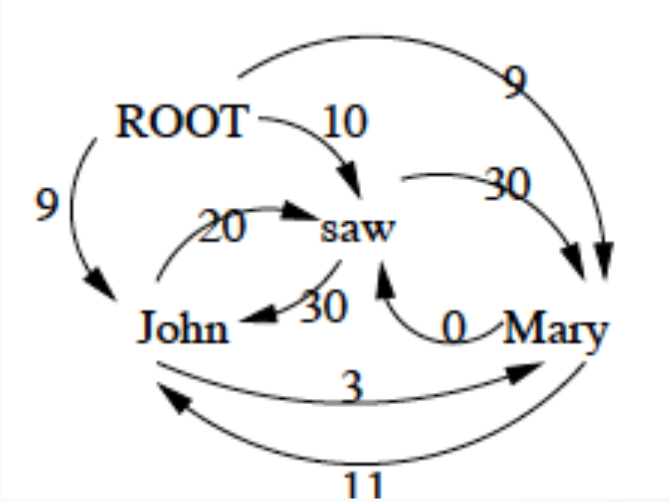
    - Recalculate weights into/out of the new vertex
    - Recursively do MST algorithm on resulting graph
- Running time: naïve: $O(n^3)$; Tarjan: $O(n^2)$
  - Applicable to non-projective graphs

Initial Tree



CLE: Step 1

- Find maximum incoming arcs



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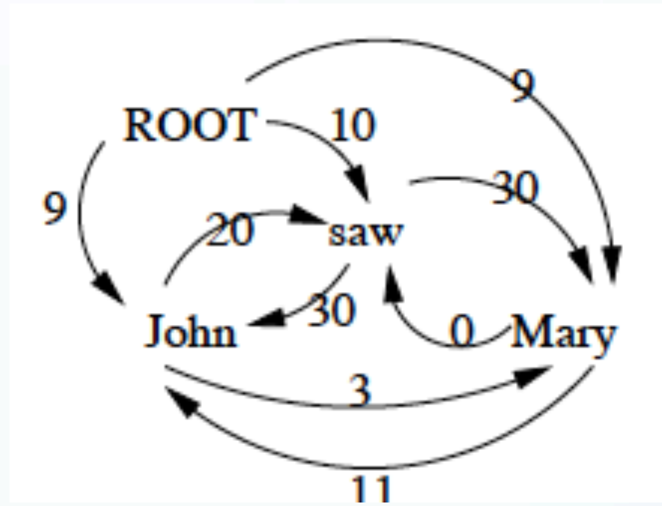

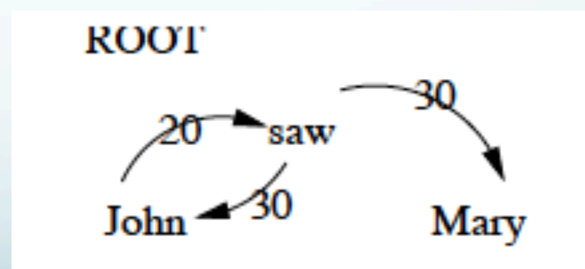

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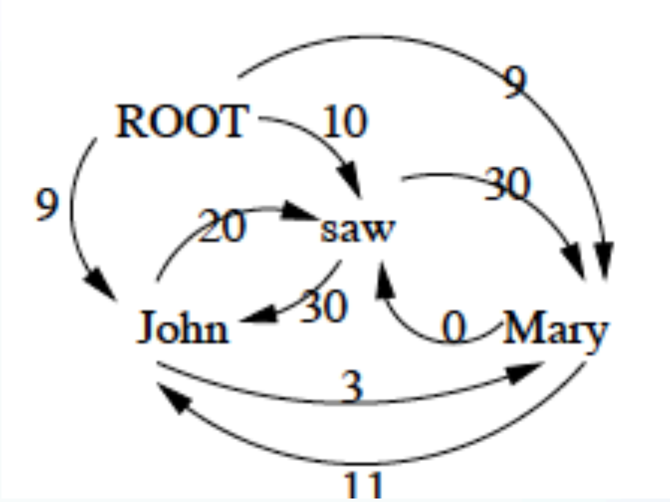

- Is the result a tree?
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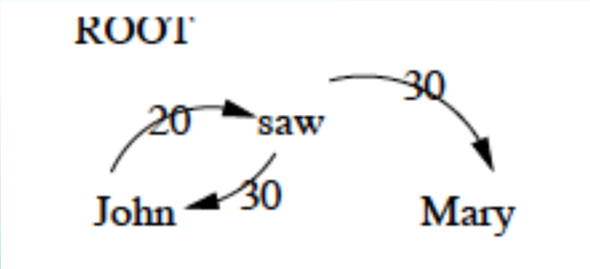

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CLE: Step 1

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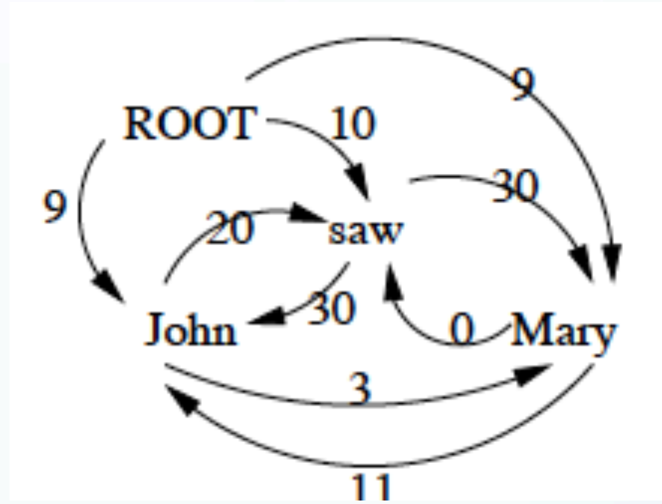
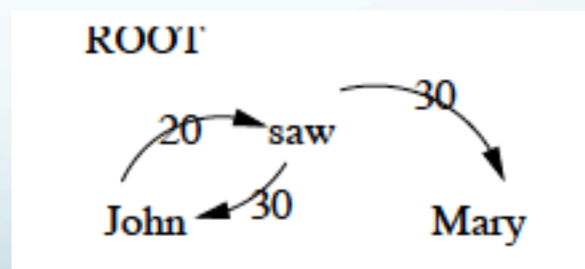
    - No
  - Is there a cycle?
    - Yes, John/saw





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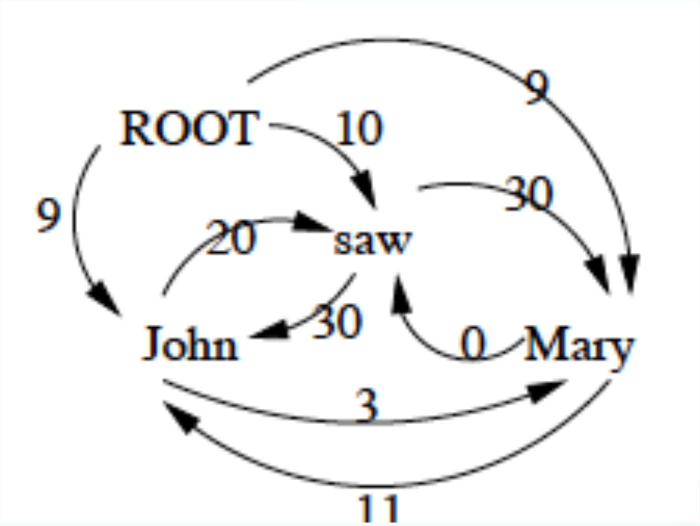

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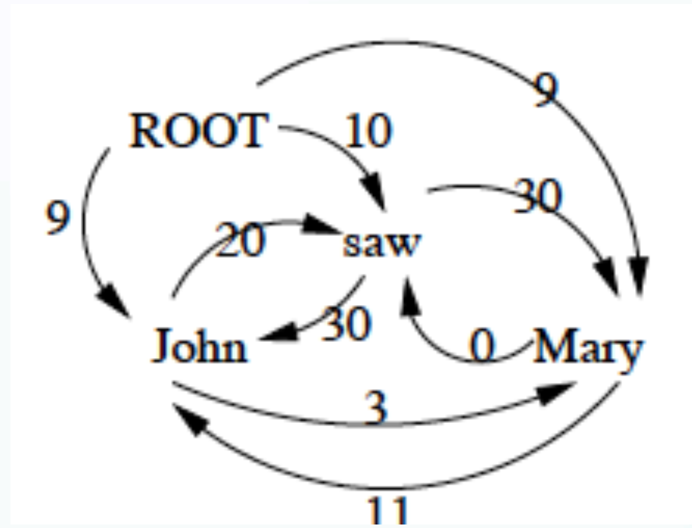
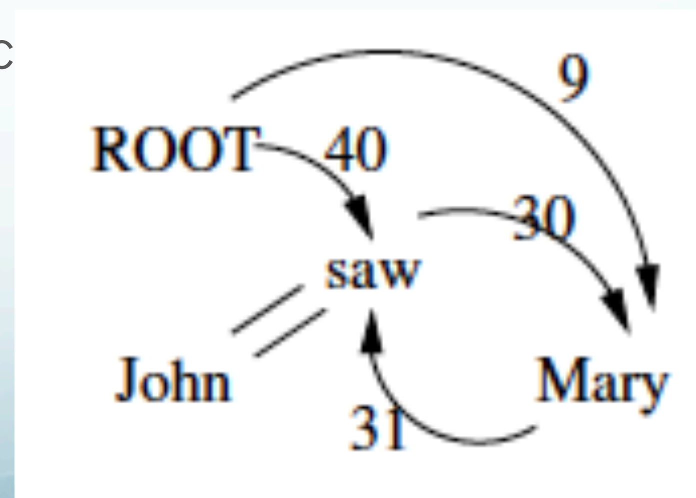
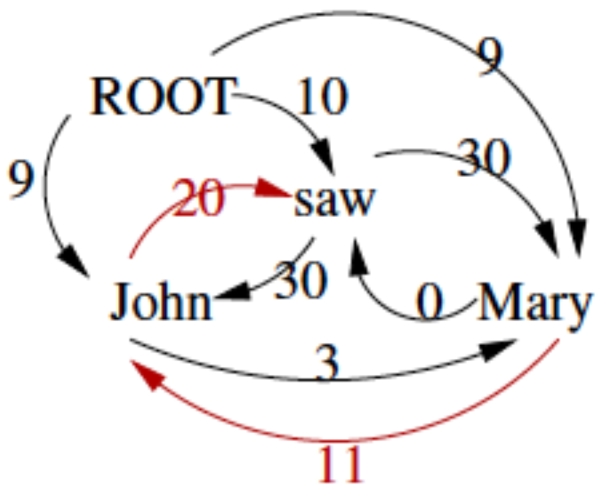
  - Calculate weights in & out as:
    - Maximum based on internal arcs
    - and original nodes
- Recurse

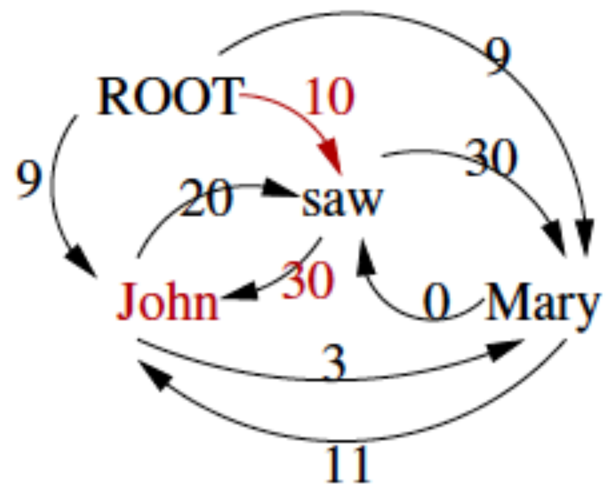




Calculating Graph



s(Mary, C) 11+20 = 31



s(ROOT, C) 10+30 = 40

CLE: Recursive Step

- In new graph, find graph of
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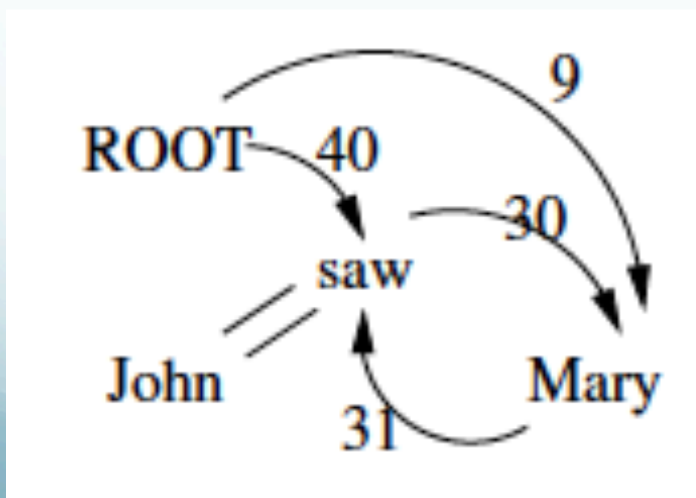

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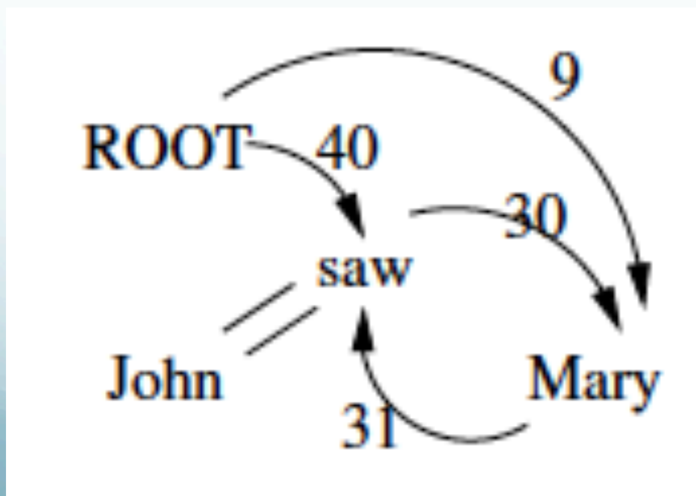
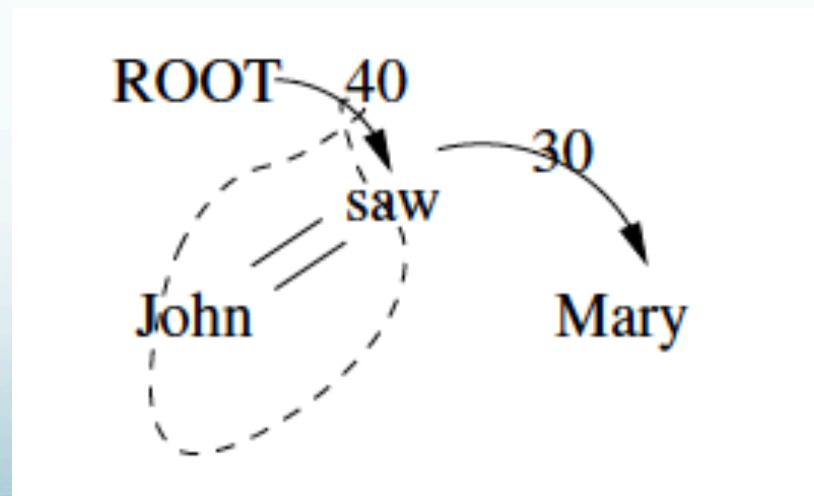
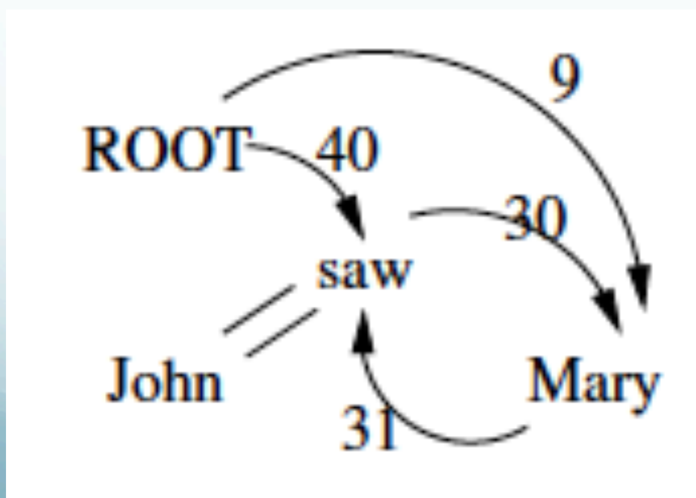
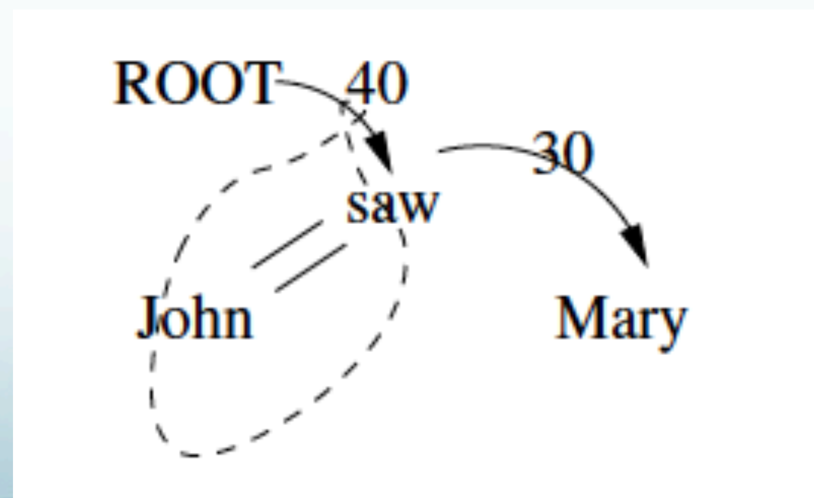




CLE: Recursive Step

- In new graph, find graph of
  - Max weight incoming arc for each word
- Is it a tree? Yes!
  - MST, but must recover internal arcs ➔ parse





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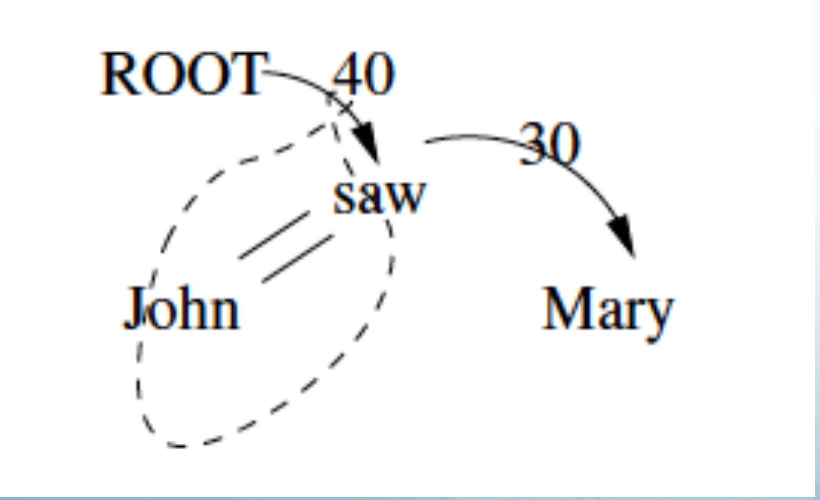
- Found maximum spanning tree
  - Need to 'pop' collapsed nodes
- Expand "ROOT → John+saw" = 40



CLE: Recovering Graph

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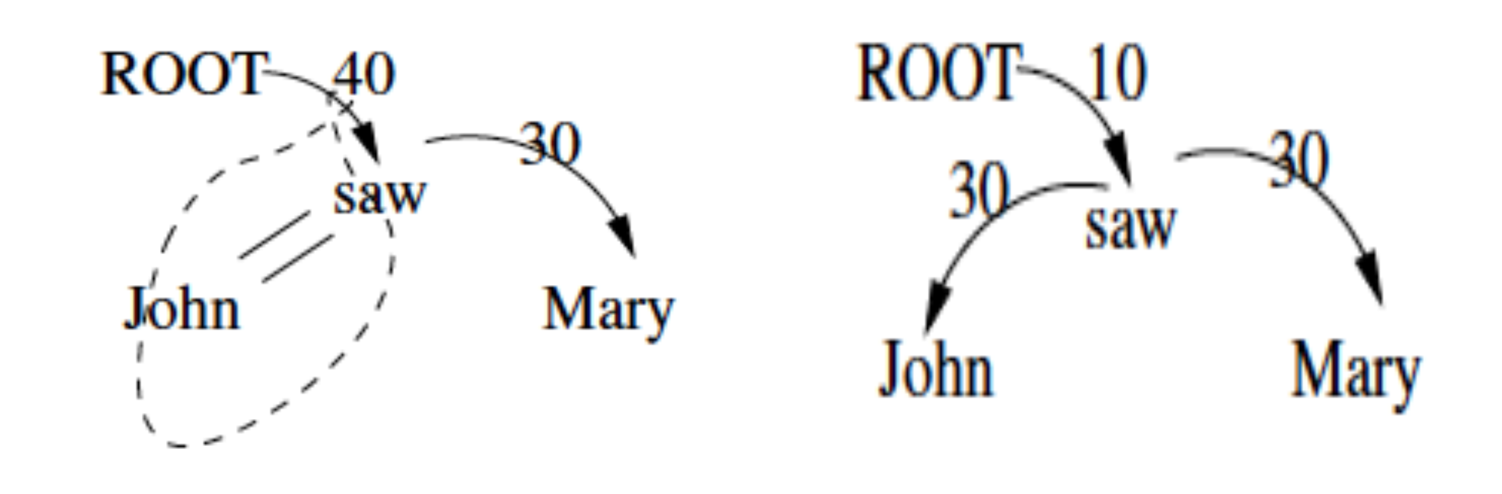
- MST and complete dependency parse



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- Operates on vector of local features

Features for Learning Weights

- Simple categorical features for (w_i, L, w_j) including:
  - Identity of w_i (or char 5-gram prefix), POS of w_i
  - Identity of w_j (or char 5-gram prefix), POS of w_j
  - Label of L, direction of L
  - Sequence of POS tags b/t w_i, w_j
  - Number of words b/t w_i, w_j
  - POS tag of w_{i-1}, POS tag of w_{i+1}
  - POS tag of w_{j-1}, POS tag of w_{j+1}
- Features conjoined with direction of attachment and distance b/t words

Dependency Parsing

- Dependency grammars:
  - Compactly represent pred-arg structure
  - Lexicalized, localized
  - Natural handling of flexible word order
- Dependency parsing:
  - Conversion to phrase structure trees
  - Graph-based parsing (MST), efficient non-proj $O(n^2)$
  - Transition-based parser
    - MALTparser: very efficient $O(n)$
      - Optimizes local decisions based on many rich features

Features

Roadmap

- Features: Motivation
  - Constraint & compactness
- Features
  - Definitions & representations
- Unification
- Application of features in the grammar
  - Agreement, subcategorization
- Parsing with features & unification
  - Augmenting the Earley parser, unification parsing
- Extensions: Types, inheritance, etc
- Conclusion

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  - Violate agreement (number), subcategorization

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  - Explosive!, loses key generalizations

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  - E.g. Agreement
    - Number, person, gender, etc
- Augment CF rules with feature constraints
  - Develop mechanism to enforce consistency
  - Elegant, compact, rich representation

Feature Representations

- Fundamentally, Attribute-Value pairs
  - Values may be symbols or feature structures
    - Feature path: list of features in structure to value
    - “Reentrant feature structures”: share some struct
  - Represented as
    - Attribute-value matrix (AVM), or
    - Directed acyclic graph (DAG)

AVM

$$\begin{bmatrix} \text{NUMBER} & \text{PL} \end{bmatrix}$$

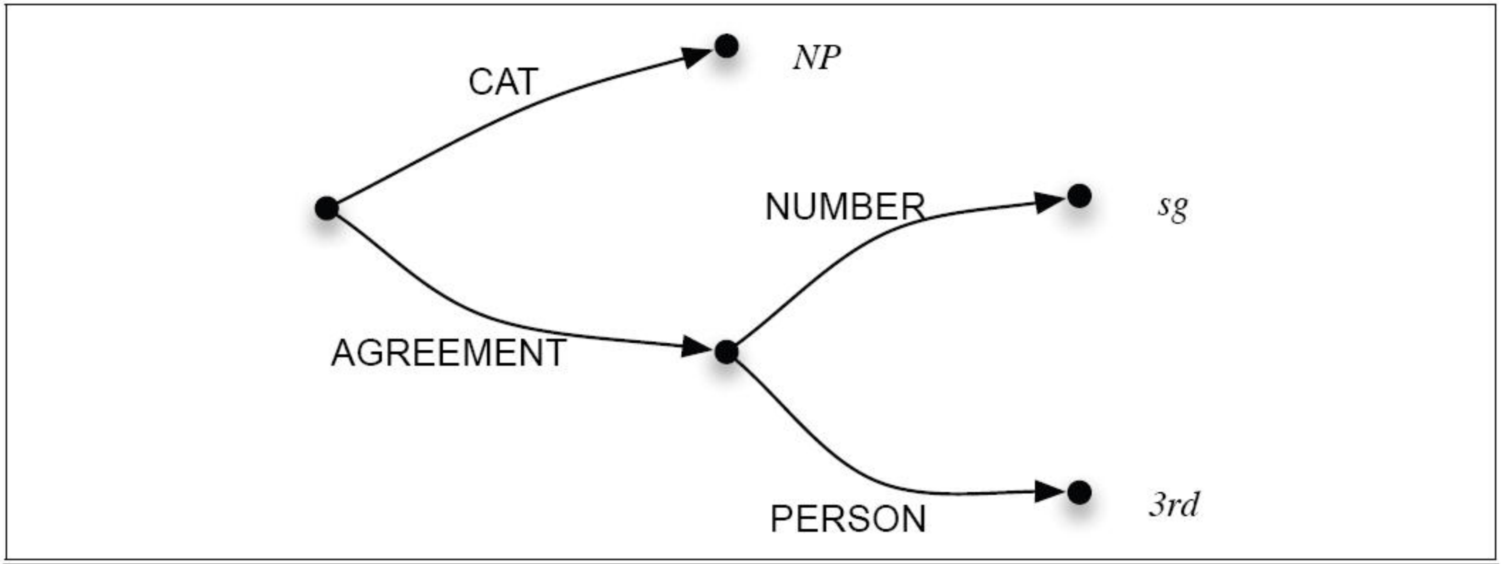
$$\begin{bmatrix} \text{PERSON} & 3 \end{bmatrix}$$

$$\begin{bmatrix} \text{NUMBER} & \text{PL} \\ \text{PERSON} & 3 \end{bmatrix}$$

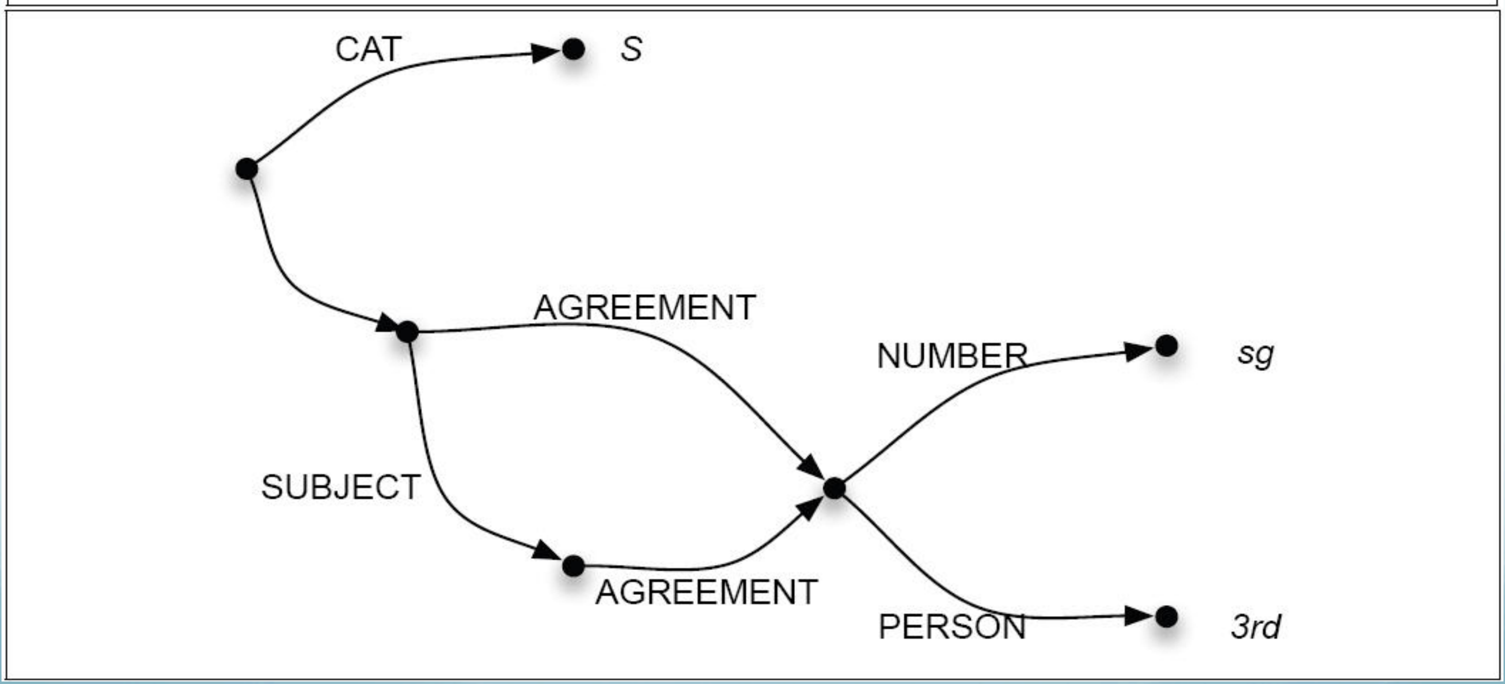
$$\begin{bmatrix} \text{CAT} & \text{NP} \\ \text{NUMBER} & \text{PL} \\ \text{PERSON} & 3 \end{bmatrix}$$

$$\begin{bmatrix} \text{CAT} & \text{NP} \\ \text{AGREEMENT} & \begin{bmatrix} \text{NUMBER} & \text{PL} \\ \text{PERSON} & 3 \end{bmatrix} \end{bmatrix}$$

$$\begin{bmatrix} \text{CAT} & \text{S} \\ \text{HEAD} & \begin{bmatrix} \text{AGREEM'T} & \boxed{1} \begin{bmatrix} \text{NUMBER} & \text{PL} \\ \text{PERSON} & 3 \end{bmatrix} \\ \text{SUBJECT} & \begin{bmatrix} \text{AGREEMENT} & \boxed{1} \end{bmatrix} \end{bmatrix} \end{bmatrix}$$



CAT
NP
NUMBER
sg
AGREEMENT
PERSON
3rd



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Unification

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- Two structures can unify if
  - Feature structures are identical
    - Result in same structure
  - Feature structures match where both have values, differ in missing or underspecified
    - Resulting structure incorporates constraints of both

Subsumption

- Relation between feature structures
  - Less specific f.s. subsumes more specific f.s.
  - F.s. F subsumes f.s. G iff
    - For every feature x in F, F(x) subsumes G(x)
    - For all paths p and q in F s.t. F(p)=F(q), G(p)=G(q)

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- Examples:
  - A: [Number SG], B: [Person 3]
  - C:[Number SG]
    - [Person 3]
  - A subsumes C; B subsumes C; B,A don't subsume
    - Partial order on f.s.

Unification Examples

- Identical
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  - [Person 3]
- Mismatched
  - [Number SG] U [Number PL] → Fails!

More Unification Examples

$$\begin{pmatrix} \text{AGREEMENT} & [1] \\ \text{SUBJECT} & \begin{pmatrix} \text{AGREEMENT} & [1] \end{pmatrix} \end{pmatrix} \quad \text{U}$$

$$\begin{pmatrix} \text{SUBJECT} & \begin{pmatrix} \text{AGREEMENT} & \begin{pmatrix} \text{PERSON} & 3 \\ \text{NUMBER} & \text{SG} \end{pmatrix} \end{pmatrix} \end{pmatrix} \quad =$$

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Features in CFGs: Agreement

- Goal:
  - Support agreement of NP/VP, Det Nominal
- Approach:
  - Augment CFG rules with features
  - Employ head features
    - Each phrase: VP, NP has head
      - Head: child that provides features to phrase
        - Associates grammatical role with word
        - VP – V; NP – Nom, etc

Agreement with Heads and Features

VP → Verb NP
<VP HEAD> = <Verb HEAD>

NP → Det Nominal
<NP HEAD> = <Nominal HEAD>
<Det HEAD AGREEMENT> = <Nominal HEAD AGREEMENT>

Nominal → Noun
<Nominal HEAD> = <Noun HEAD>

Noun → flights
<Noun HEAD AGREEMENT NUMBER> = PL

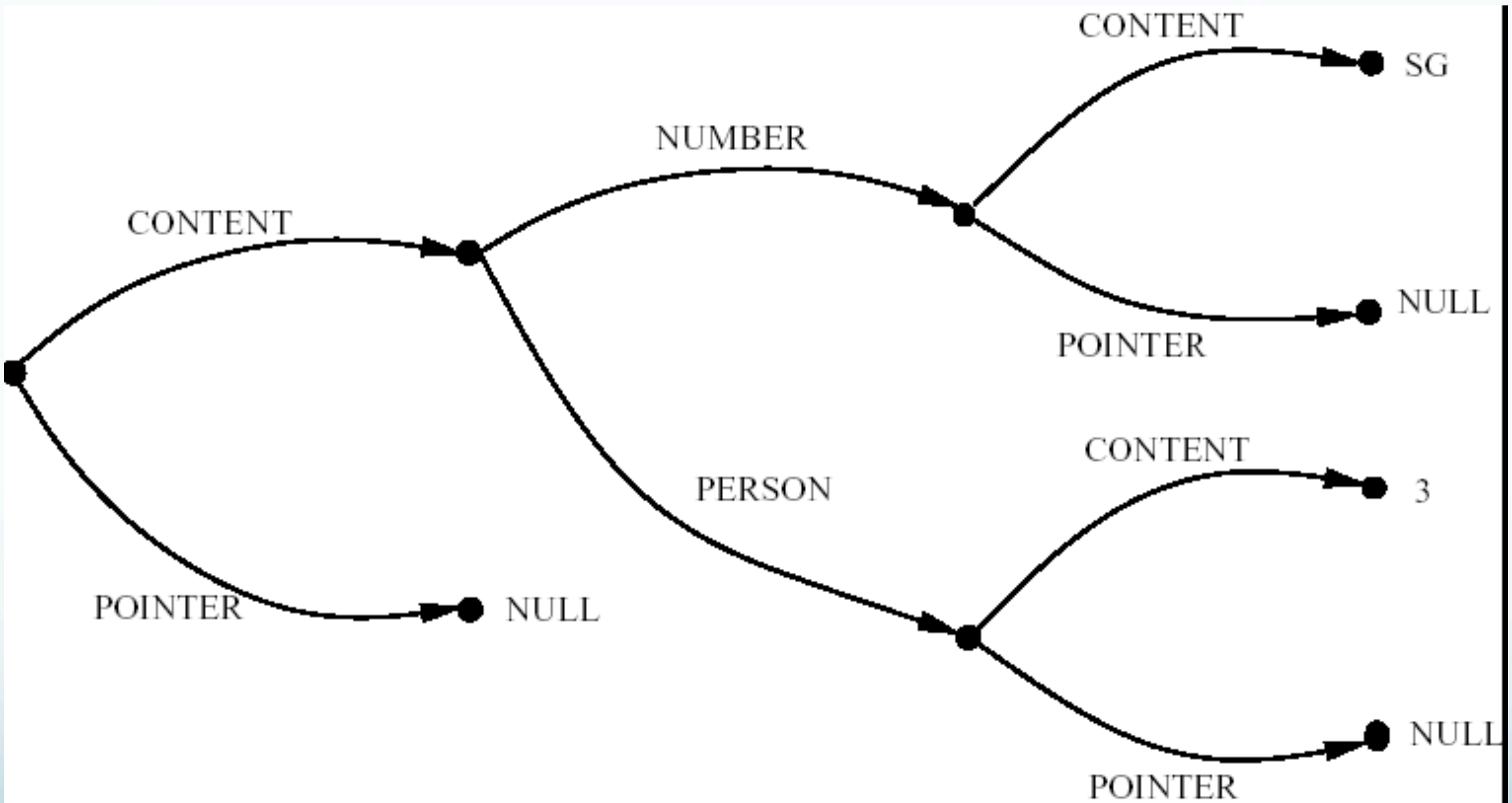
Verb → serves
<Verb HEAD AGREEMENT NUMBER> = SG
<Verb HEAD AGREEMENT PERSON> = 3

Feature Applications

- Subcategorization:
  - Verb-Argument constraints
    - Number, type, characteristics of args (e.g. animate)
    - Also adjectives, nouns
- Long distance dependencies
  - E.g. filler-gap relations in wh-questions, rel

Implementing Unification

- Data Structure:
  - Extension of the DAG representation
  - Each f.s. has a content field and a pointer field
    - If pointer field is null, content field has the f.s.
    - If pointer field is non-null, it points to actual f.s.



$$\begin{pmatrix} \text{NUMBER} & \\ & \text{SG} \\ \text{PERSON} & \\ & 3 \end{pmatrix}$$

Implementing Unification: II

- Algorithm:
  - Operates on pairs of feature structures
    - Order independent, destructive
  - If fs1 is null, point to fs2
  - If fs2 is null, point to fs1
  - If both are identical, point fs1 to fs2, return fs2
    - Subsequent updates will update both
  - If non-identical atomic values, fail!

Implementing Unification: III

- If non-identical, complex structures
  - Recursively traverse all features of fs2
  - If feature in fs2 is missing in fs1
    - Add to fs1 with value null
  - If all unify, point fs2 to fs1 and return fs1

Example

$$\begin{bmatrix} \text{AGREEMENT [1]} & \begin{bmatrix} \text{NUMBER} & \text{SG} \end{bmatrix} \\ \text{SUBJECT} & \begin{bmatrix} \text{AGREEMENT [1]} \end{bmatrix} \end{bmatrix} \text{ U}$$

$$\begin{bmatrix} \text{SUBJECT} & \begin{bmatrix} \text{AGREEMENT} & \begin{bmatrix} \text{PERSON} & 3 \end{bmatrix} \end{bmatrix} \end{bmatrix}$$

[AGREEMENT [1]] U [AGREEMENT [PERSON 3]]

[NUMBER SG] U [PERSON 3]

[NUMBER SG] U [PERSON 3]
[PERSON NULL]

Unification and the Earley Parser

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- Actually pretty straightforward
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  - Augment state (chart entries) with DAG
    - Prediction adds DAG from rule
    - Completion applies unification (on copies)
      - Adds entry only if current DAG is NOT subsumed

Conclusion

- Features allow encoding of constraints
  - Enables compact representation of rules
  - Supports natural generalizations

- Unification ensures compatibility of features
  - Integrates easily with existing parsing mech.

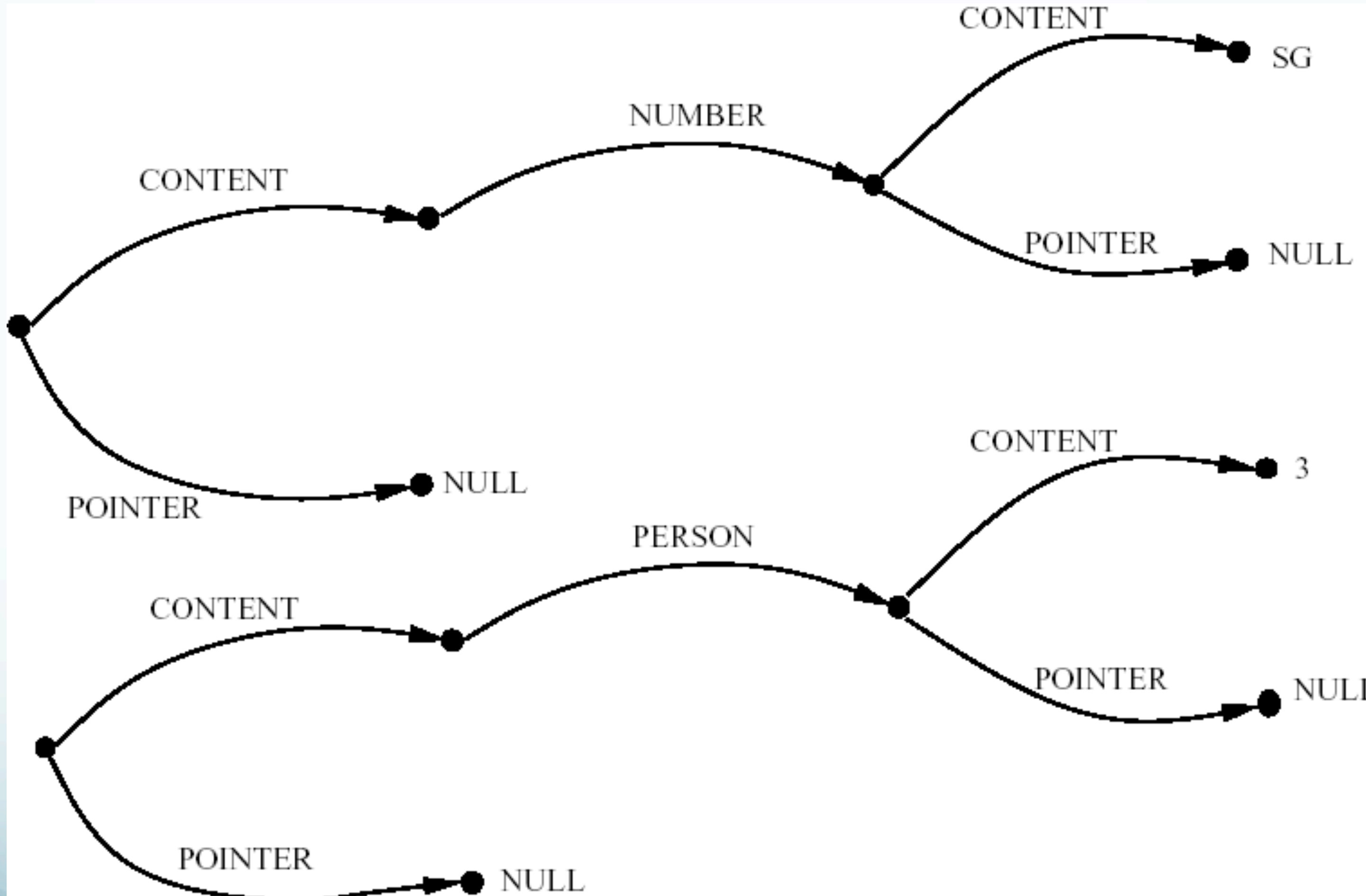
- Many unification-based grammatical theories

Unification Parsing

- Abstracts over categories
  - S-> NP VP =>
    - X0 -> X1 X2; <X0 cat> = S; <X1 cat>=NP;
    - <X2 cat>=VP
  - Conjunction:
    - X0->X1 and X2; <X1 cat> =<X2 cat>;
    - <X0 cat>=<X1 cat>
- Issue: Completer depends on categories
- Solution: Completer looks for DAGs which unify with the just-completed state's DAG

Extensions

- Types and inheritance
  - Issue: generalization across feature structures
    - E.g. many variants of agreement
      - More or less specific: 3rd vs sg vs 3rdsg
  - Approach: Type hierarchy
    - Simple atomic types match literally
    - Multiple inheritance hierarchy
      - Unification of subtypes is most general type that is more specific than two input types
    - Complex types encode legal features, etc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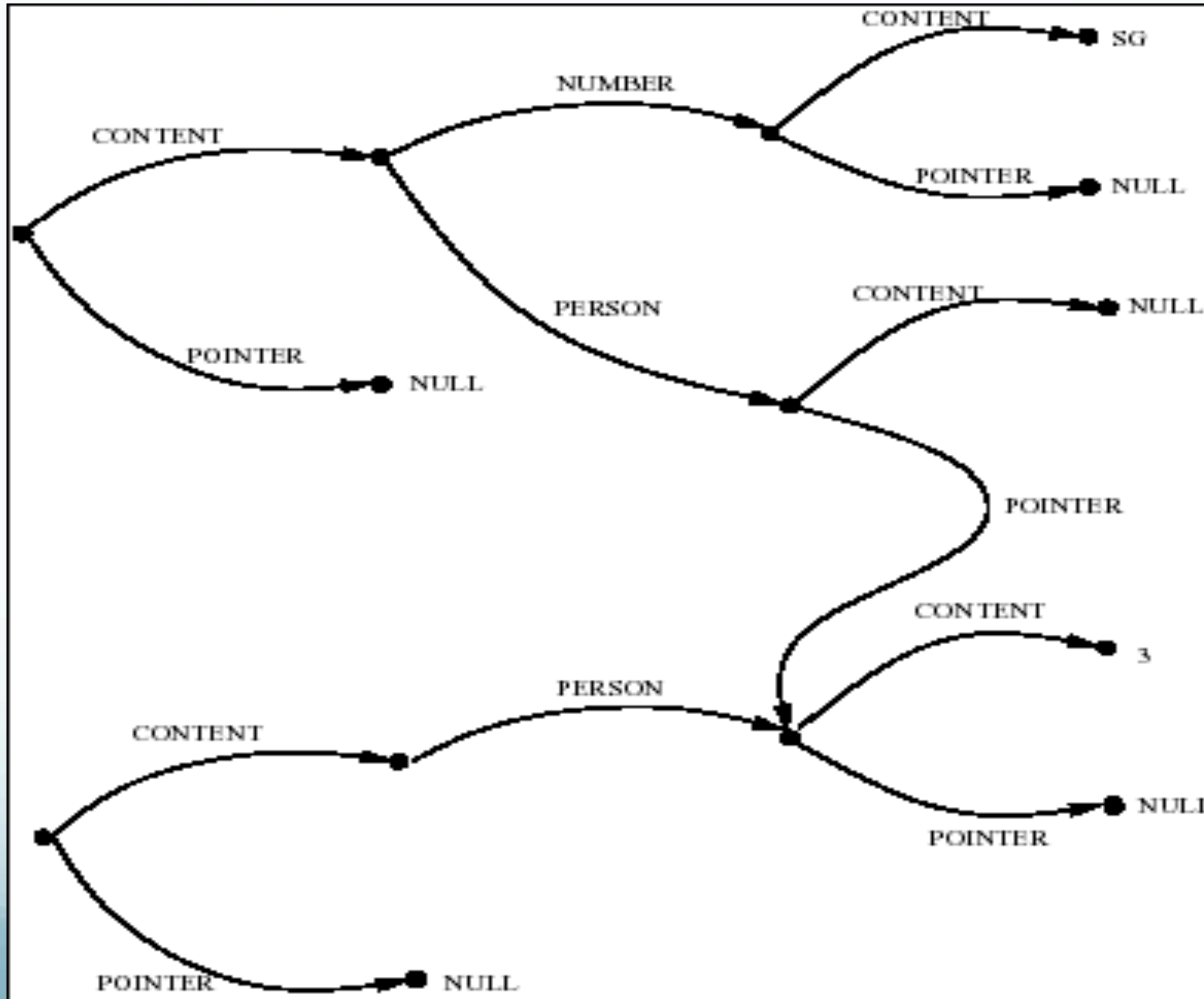
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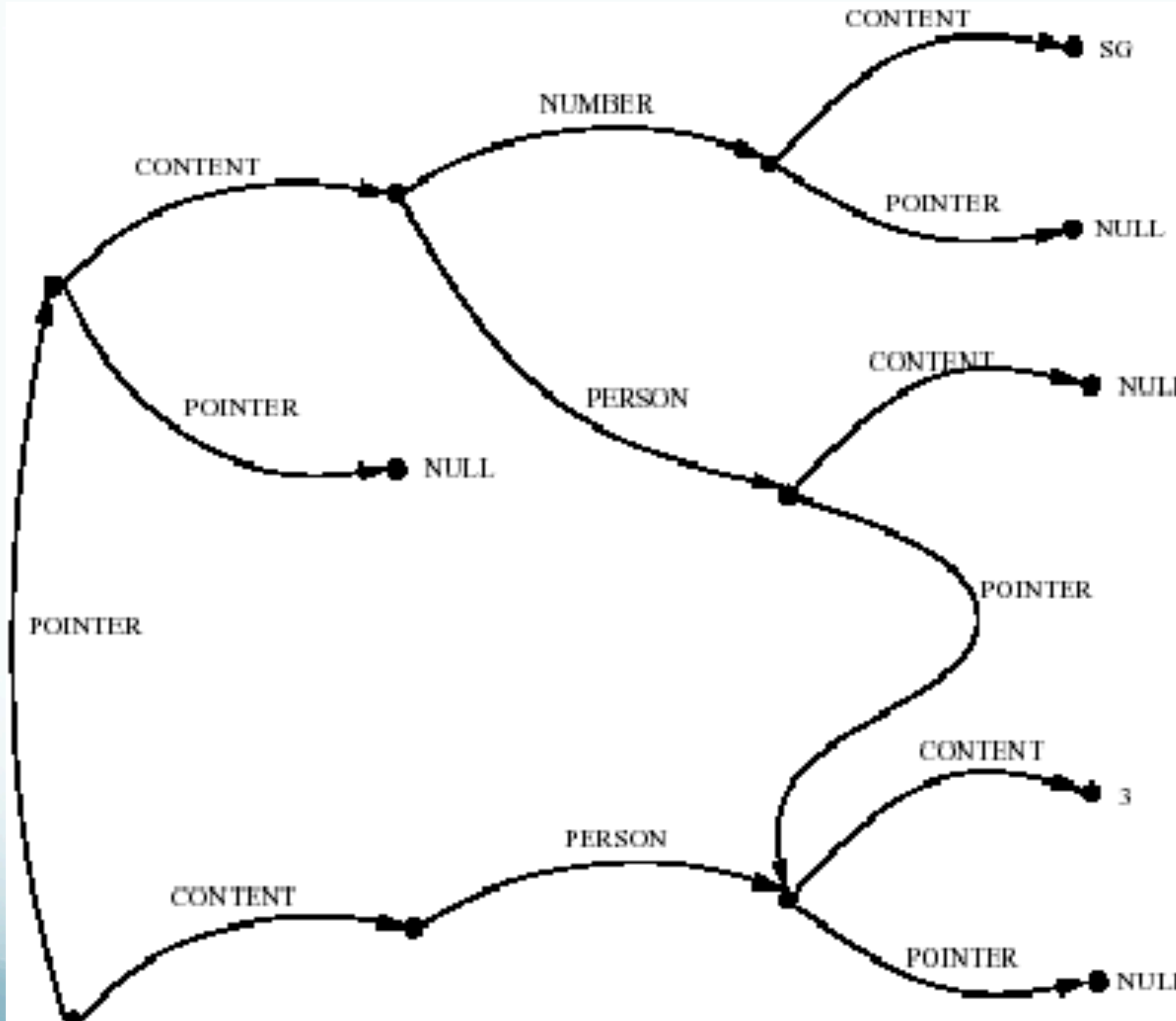
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