# &

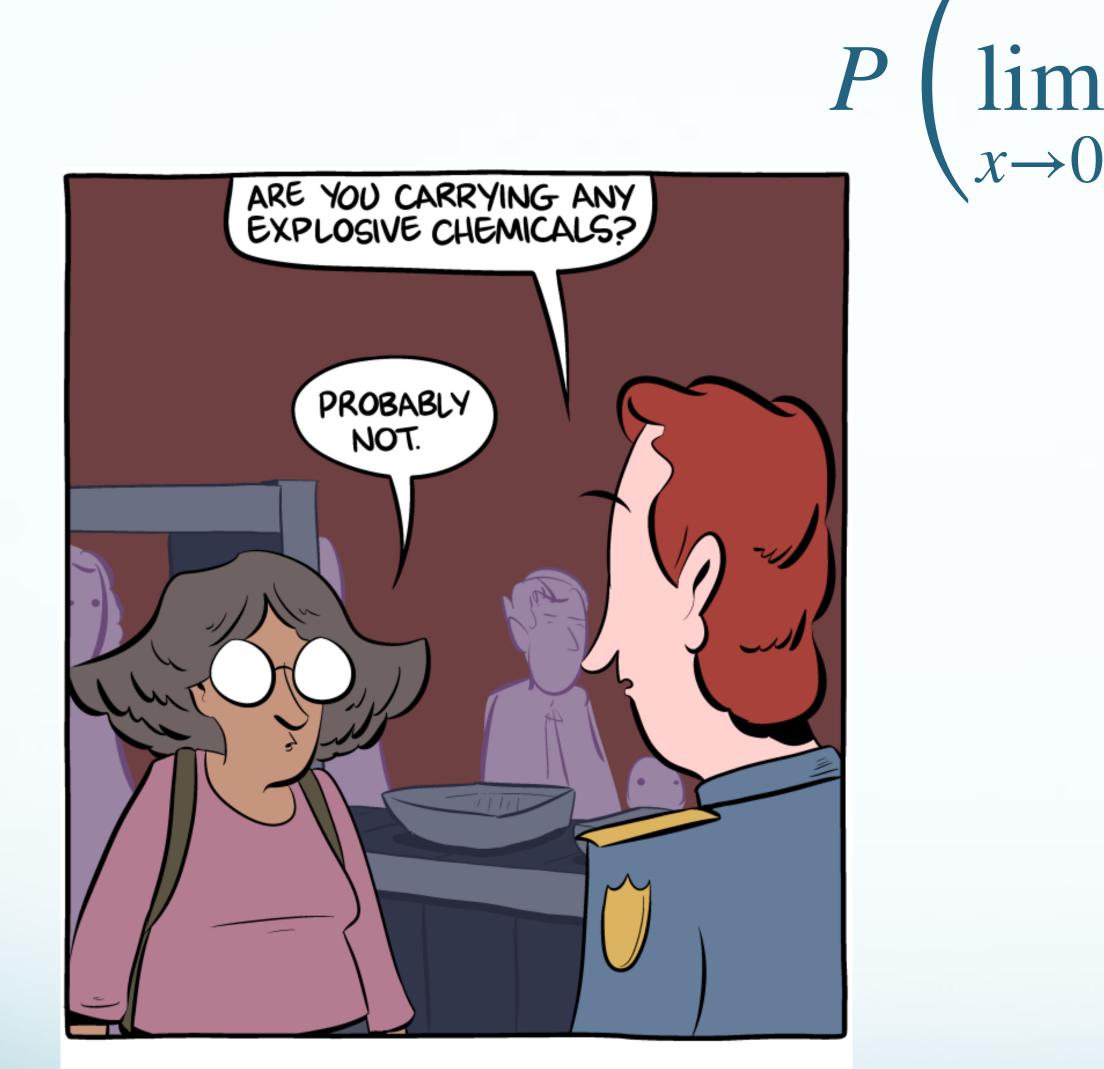
# **Dependency Parsing** Feature-based Parsing

Ling 571 — Deep Processing Techniques for NLP October 22, 2018 Ryan Georgi









Fun Fact: No statistician has ever been on an airplane.

Source: Saturday Morning Breakfast Cereal

 $P\left(\lim_{x\to 0}\frac{x}{n}\right)\neq P(0)$ 

#### $P(ADJ \rightarrow \text{`brillig'}) = 1.2 \times 10^{-342}$ (Think "Jabberwocky")

#### $P(ADJ \rightarrow \text{'brilliger'}) \neq 0$ ...l just used it!

Input query:

"Is 'brilliger' an adjective?"

Parser with OOV handling:

"Err... probably not?"





-



HW #4 Follow-up





# HW #4 Follow-up: OOV Handling

- As we discussed previously, you will find OOV tokens
- Sometimes this as as simple as case-sensitivity:

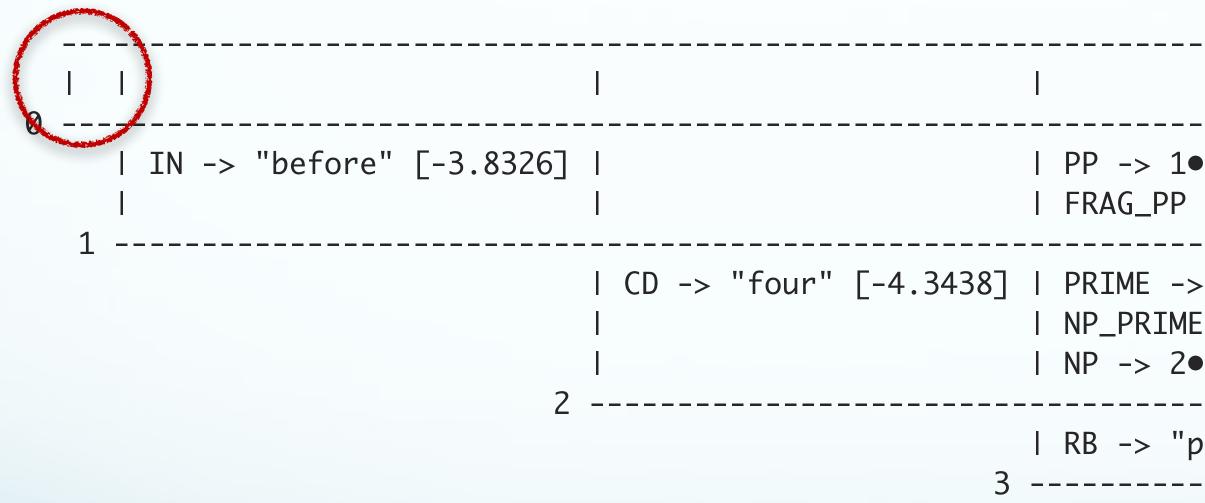






### OOV: Cas

#### Sentence #23: "Arriving before four p.m.



"arriving" is in our grammar, but not "Arriving"



se Sensitiv	ty			
<b>9 9</b>				
•IN•2 2•NP•4 [-13.9845] -> 1•IN•2 2•NP•4 [-13.1613]			4●PUNC●5 [-19. _PP●4 4●PUNC●5	
> 2•CD•3 3•RB•4 [-10.3372] E -> 2•CD•3 3•RB•4 [-10.2784] •CD•3 3•RB•4 [-8.9233]		> 2●NP●4	4●PUNC●5 [-11.	4025]
o.m" [-1.1144]				
4		·> "." [-	-0.3396]	

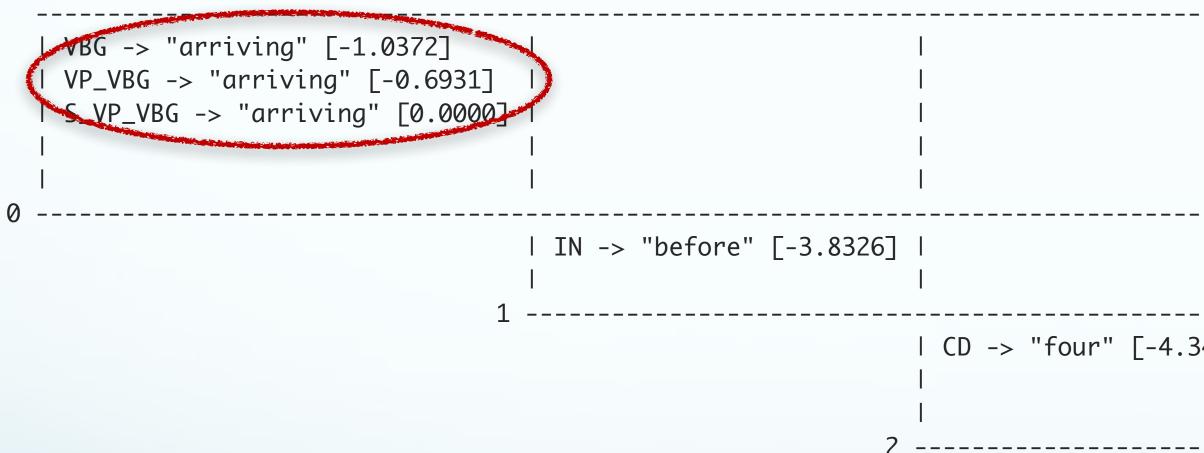






## **OOV: Case Sensitivity**

#### Sentence #23: "Arriving before four p.m ."





<pre>  PRIME -&gt; 0•VBG•1 1•PP•4 [-19.6776]   VP_PRIME -&gt; 0•VBG•1 1•PP•4 [-18.0049]   VP -&gt; 0•VBG•1 1•PP•4 [-17.6629]   FRAG_VP -&gt; 0•VBG•1 1•PP•4 [-16.2257]   FRAG_VP_PRIME -&gt; 0•VBG•1 1•PP•4 [-15.869</pre>	TOP -> 0•FRAG_VP•4 4•PUNC•5 [-2:   TOP -> 0•VP•4 4•PUNC•5 [-20.150:   
PP -> 1●IN●2 2●NP●4 [-13.9845]   FRAG_PP -> 1●IN●2 2●NP●4 [-13.1613]	TOP -> 1●PP●4 4●PUNC●5 [-19.4677   TOP -> 1●FRAG_PP●4 4●PUNC●5 [-18
3438]   PRIME -> 2•CD•3 3•RB•4 [-10.3372]   NP_PRIME -> 2•CD•3 3•RB•4 [-10.2784]   NP -> 2•CD•3 3•RB•4 [-8.9233]	TOP -> 2●NP●4 4●PUNC●5 [-11.4025   
RB -> "p.m" [-1.1144]	
J	PUNC -> "." [-0.3396] 4







# HW #4 Follow-up: OOV Handling

#### • Propose some number of N most likely tags at runtime...







"Show me Ground transportation in Denver during weekdays ." — No "during"!

	FRAG_NP_PRIME $\rightarrow$ 2FRAG_NP_PRIME 4 PP 6[-21.810] FRAG_NP $\rightarrow$ 2FRAG_NP_PRIME 4 PP 6[-20.858]			
	NP_PRIME $\rightarrow$ 3 NN 4 PP 6[-16.296] PRIME $\rightarrow$ 3 NN 4 PP 6[-15.949]			
IN → "in" [-2.4018]	PP → 4 IN 5 NP_NNP 6[-7.505] FRAG_PP → 4 IN 5NP_NNP 6 [-6.828]			
5	NNP $\rightarrow$ "Denver" [-4.4002] NP_NNP $\rightarrow$ "Denver" [-3.3280]			
	6			
		7	NNS $\rightarrow$ "weekdays" [-5.5759] NP_NNS $\rightarrow$ "weekdays" [-3.7257]	TOP → 7NP_NNS 8PUNC 9[-11.00
			8	PUNC → "." [-0.3396]



9

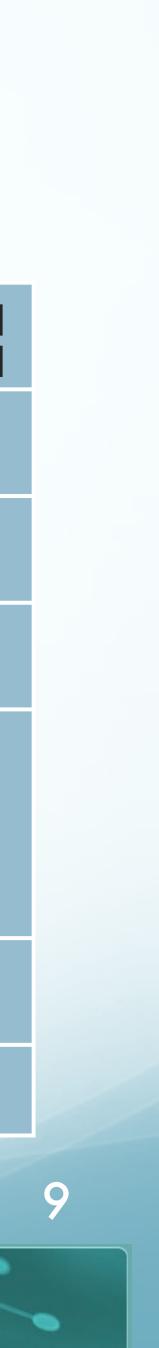




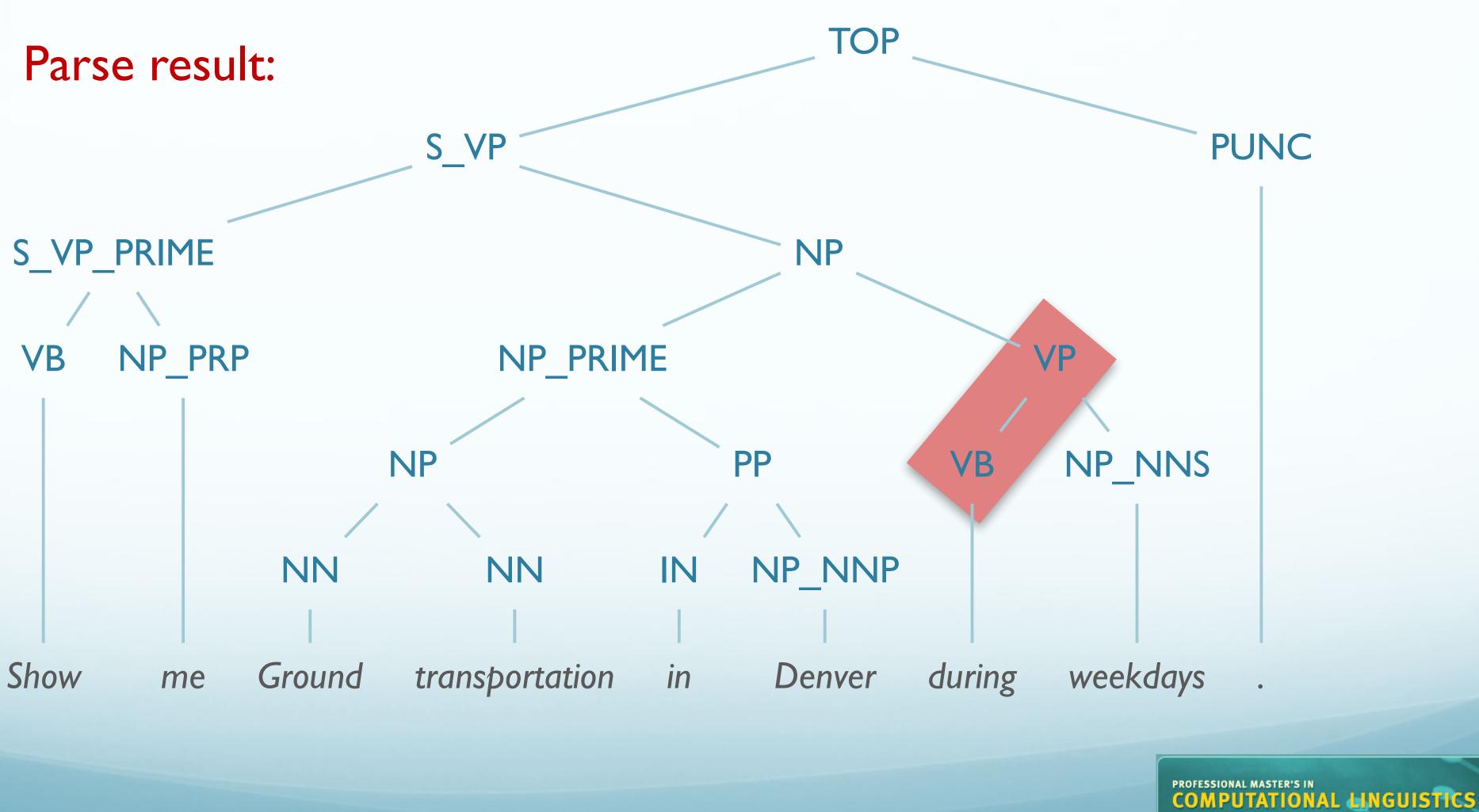


$FRAG\_NP\_PRIME \rightarrow \dots$ $FRAG\_NP \rightarrow \dots$	$FRAG\_NP\_PRIME \rightarrow \dots$ $FRAG\_NP \rightarrow \dots$	$FRAG\_NP \rightarrow \dots$ $FRAG\_NP \rightarrow \dots$	TOP $\rightarrow$ 2FRAG_NP 8 PUNC 9[-34.939] TOP $\rightarrow$ 2FRAG_NP 8 PUNC 9[-34.006]
NP_PRIME $\rightarrow \dots$ PRIME $\rightarrow \dots$	PRIME $\rightarrow$ 3 NN 4PP 7 [-17.145] QP $\rightarrow$ 3 PRIME 6CD 7 [-15.930]	NP $\rightarrow$ 3 PRIME 7NNS 8 [-26.542] NP $\rightarrow$ 3 QP 7 NNS 8 [-26.398]	TOP $\rightarrow$ 3NP 8PUNC 9[-29.022] TOP $\rightarrow$ 3NP 8PUNC 9[-28.877]
$PP \rightarrow \dots$ $FRAG\_PP \rightarrow \dots$	$PP \rightarrow 4 \text{ IN 5 NP 7[-8.701]}$ $FRAG\_PP \rightarrow 4 \text{ IN 5NP 7 [-7.878]}$	PP → 4 IN 5 NP 8[-19.056] FRAG_PP → 4 IN 5NP 8 [-18.233]	TOP $\rightarrow$ 4PP 8PUNC 9[-24.540] TOP $\rightarrow$ 4FRAG_PP 8 PUNC 9[-23.716]
NNP $\rightarrow$ "Denver" [-4.4002] NP_NNP $\rightarrow$ "Denver" [-3.3280]	NP_PRIME $\rightarrow$ 5NNP 6 NNP 7[-6.110] NP $\rightarrow$ 5 NNP 6NNP 7 [-5.070]	NP $\rightarrow$ 5 NP 7 NNS 8 [-17.330] NP $\rightarrow$ 5NP_PRIME 7 NNS 8 [-15.426]	TOP $\rightarrow$ 5NP 8PUNC 9[-19.809] TOP $\rightarrow$ 5NP 8PUNC 9[-17.905]
6	NNP → "during" [1.0000] NN → "during" [1.0000] NP_NNP → "during" [1.0000] VB → "during" [1.0000] CD → "during" [1.0000]	VP → 6 VB 7NP_NNS 8[-8.922] S_VP → 6 VB 7NP_NNS 8[-6.611]	TOP → 6VP 8PUNC 9[-11.410] TOP → 6S_VP 8PUNC 9[-9.176]
	7	NNS $\rightarrow$ "weekdays" [-5.5759] NP_NNS $\rightarrow$ "weekdays" [-3.7257]	TOP $\rightarrow$ 7NP_NNS 8 PUNC 9[-11.001]
		8	PUNC → "." [-0.3396]



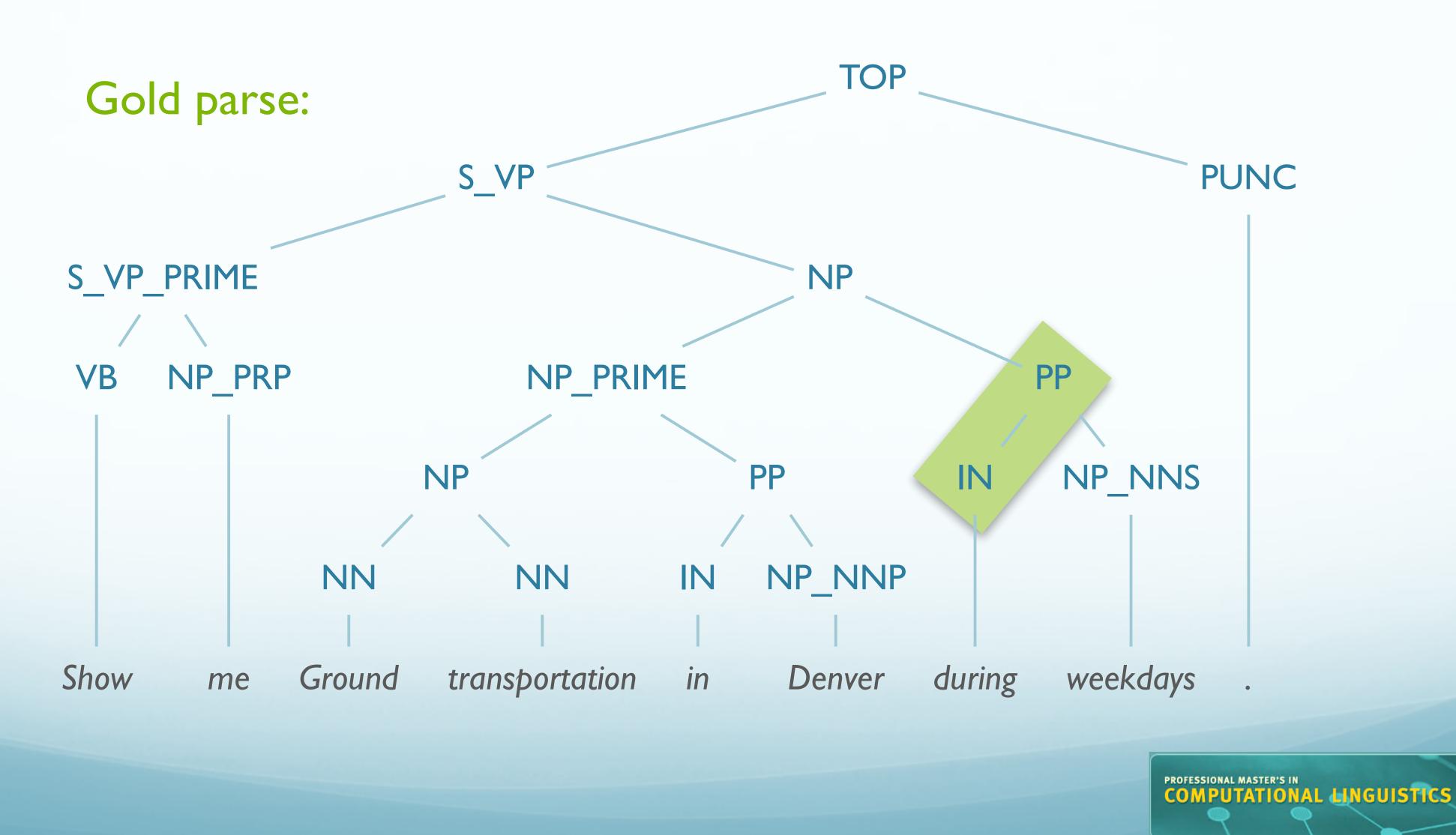


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Problems with this approach?





# Handling OOV

#### • Option #I:

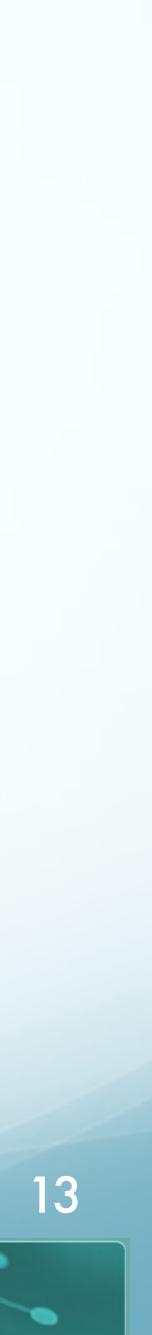
- Choose subset of training data vocab to be hidden
- Hidden words replaced by <UNK>
- Run induction as usual, but some words are now '<UNK>'

#### • **Option #2:**

- Replace first occurrence of every word with <UNK>
- (See J&M 2<sup>nd</sup> ed 4.3.2 <u>3rd ed, 3.3.1</u>)







# Problems with These Approaches?

#### **Option #I**

- May sample "closed-class" words
- Closed-class words are disproportionately more common
  - .: Approximation will be worse the more data there is, because Zipf

#### • **Option #2**

- **Con**: Requires a lot more data
- **Pros**: Samples from all word classes
  - Will only count closed-class words once







# HW #4 Extra Credit Opportunity

#### • Up to 10 points:

- Design an OOV treatment for handling treebank training data that:
  - I. Uses <UNK> token sampling
  - 2. Is smart about open vs. closed-class words
- You can modify reference code for HW #4.









### Other Announcements





# Other Announcements

#### • HW #2

#### • Expect grades by EOD

#### • HW #3

#### • By Wednesday, most likely.









### Dependency Parsing

#### • Transition-based Parsing

- Feature-based Parsing
  - Motivation
  - Features
  - Unification



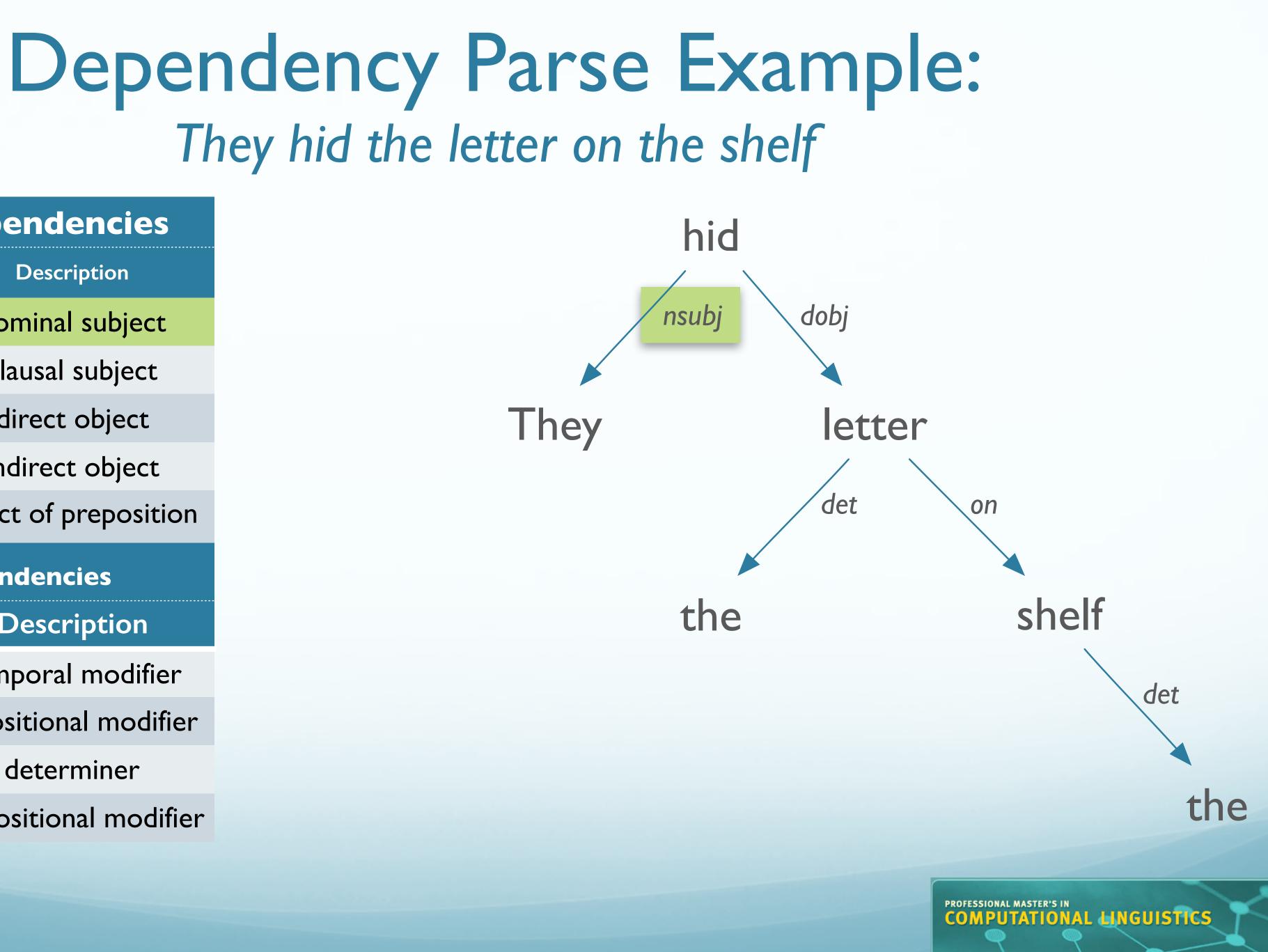
# Today



#### **Argument Dependencies**

Abbreviation	Description
nsubj	nominal subject
csubj	clausal subject
dobj	direct object
iobj	indirect object
pobj	object of preposition
Modifier	Dependencies
Modifier Abbreviation	<b>Dependencies</b> Description
	-
Abbreviation	Description
Abbreviation tmod	Description temporal modifier

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# Transition-Based Parsing

- Parsing defined in terms of sequence of transitions
- Alternative methods for learning/decoding
  - Most common model: Greedy classification-based approach
  - Very efficient: O(n)
- Best-known implementations:
  - Nivre's MALTParser
    - Nivre et al (2006); Nivre & Hall (2007)









# Transition-Based Parsing

- A transition-based system for dependency parsing is:
  - A set of configurations C
  - A set of transitions between configurations
  - A transition function between configurations
  - An initialization function (for  $C_0$ )
  - A set of terminal configurations ("end states")







# Configurations

- A configuration for a sentence x is the triple  $(\Sigma, B, A)$ :
- $\Sigma$  is a stack with elements corresponding to the nodes (words + ROOT) in x
- B (aka the buffer) is a list of nodes in x
- A is the set of dependency arcs in the analysis so far,
  - $(w_i, L, w_j)$ , where  $w_x$  is a node in x and L is a dependency label







### Transitions

- Transitions convert one configuration to another
  - $C_i = t(C_i 1)$ , where t is the transition
- Dependency graph for a sent:
  - The set of arcs resulting from a sequence of transitions
- The parse of the sentence is that resulting from the initial state through the sequence of transitions to a legal terminal state







# Dependencies -> Transitions

- To parse a sentence, we need the sequence of transitions that derives it
- How can we determine sequence of transitions, given a parse?
- This is defining our **oracle** function:
  - How to take a parse and translate it into a series of transitions







# Dependencies -> Transitions

- Many different oracles:
  - Nivre's arc-standard
  - <u>Nivre's arc-eager</u>
  - Non-projectivity with <u>Attardi's</u>

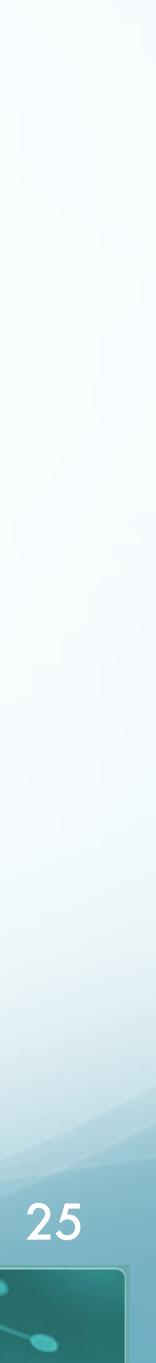
• Generally:

. . .

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- Use oracle to identify gold transitions
- Train classifier to predict best transition in new config





## Nivre's Arc-Standard Oracle

- Words:  $w_1, \ldots, w_n$ 
  - $\boldsymbol{w}_0 = \mathrm{ROOT}$
- Initialization:
  - Stack =  $[w_0]$ ; Buffer =  $[w_1, \dots, w_n]$ ; Arcs =  $\emptyset$
- Termination:
  - Stack =  $\sigma$ ; Buffer= []; Arcs = A
    - for any  $\sigma$  and A





### Nivre's Arc-Standard Oracle

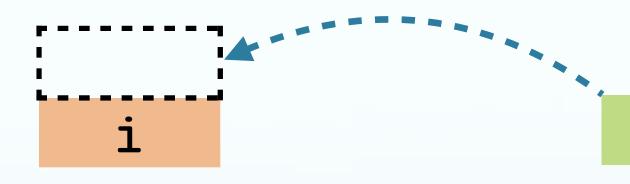
- Transitions are one of three:
  - Shift
  - Left-Arc
  - Right-Arc





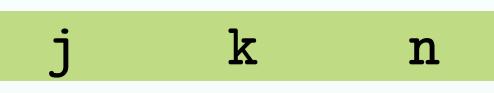
# Transitions: Shift

### • Shift first element of buffer to top of stack. ● [i][j,k,n][] → [i,j][k,...,n][]



### Stack





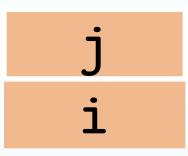
### Buffer

Arcs



# Transitions: Shift

### • Shift first element of buffer to top of stack. ● [i][j,k,n][] → [i,j][k,...,n][]









### Buffer





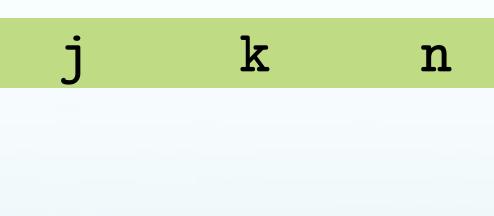
### Transitions: Left-Arc

- Add arc from first element of buffer j to element at top of stack i with dependency label 1
  - Pop i from stack.
  - [i] [j,k,n]  $A \rightarrow$  [i] [k,...,n]  $A \cup$  [(j,l,i)]

i

### Stack





Buffer

Arcs



### Transitions: Left-Arc

- Add arc from first element of buffer j to element at top of stack i with dependency label 1
  - Pop i from stack.
  - [i] [j,k,n]  $A \rightarrow$  [i] [k,...,n]  $A \cup$  [(j,l,i)]

Stack





Arcs

(j,l,i)



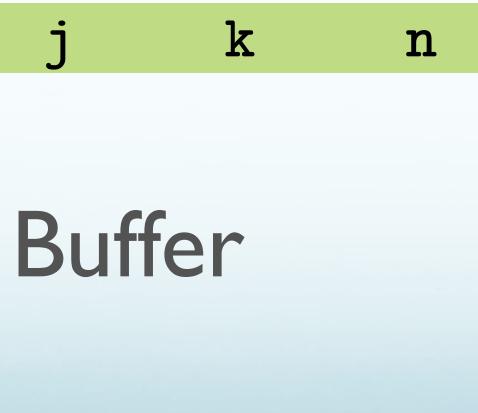
# Transitions: Right-Arc

- Add arc from top of stack i to first element of buffer j with dependency label 1
  - Replace j with i as front of buffer; pop j from stack.
  - [i] [j,k,n]  $A \rightarrow$  [i] [k,...,n]  $A \cup$  [(j,l,i)]













# Transitions: Right-Arc

- Add arc from top of stack i to first element of buffer j with dependency label 1
  - Replace j with i as front of buffer; pop j from stack.
  - [i] [j,k,n]  $A \rightarrow$  [i] [k,...,n]  $A \cup$  [(j,l,i)]













# Transitions: Right-Arc

- Add arc from top of stack i to first element of buffer j with dependency label 1
  - Replace j with i as front of buffer; pop j from stack.
  - [i] [j,k,n]  $A \rightarrow$  [i] [k,...,n]  $A \cup$  [(j,l,i)]









Arcs

(i,l,j)



# Training Process

- Each step of the algorithm is a decision point between the three states
- - (Reduce to a classification problem)
- We start with:
  - A treebank
  - An *oracle* process for guiding the transitions



• We want to train a model to decide between the three options at each step

• A discriminative learner to relate the transition to features of the current configuration





# Training Process, Formally:

 $(\Sigma, B, A)$ 

1) 
$$c \leftarrow c_{\theta}(S)$$
  
2) while c is not terminal  
3)  $t \leftarrow o(c) + Choose the (o)$   
4)  $c \leftarrow t(c) + Move to the ne
5) return  $G_c$$ 



)ptimal transition for the config *c* ext configuration





# Testing Process, Formally:

 $(\Sigma, B, A)$ 

1) 
$$c \leftarrow c_{\theta}(S)$$
  
2) while c is not terminal  
3)  $t \leftarrow \lambda_c(c)$  # Choose the tra  
4)  $c \leftarrow t(c)$  # Move to the ne  
5) return  $G_c$ 



ensition given model parameters at c ext configuration





# Representing Configurations with Features

#### • Address

- Locate a given word:
  - By position in stack
  - By position in buffer
  - By attachment to a word in buffer

#### • Attributes

- Identity of word
- Iemma for word
- POS tag of word

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# Example: (Ballesteros et al 2015)

Action	Stack	Buffer
	[ROOT]	[They told him a story]
Shift	[ROOT, They]	[told him a story]
Left-Arc (subj)	[ROOT, told]	[him a story]
Shift	[ROOT, told, him]	[a story]
Right-Arc (iobj)	[ROOT, told]	[a story]
Shift	[ROOT, told, a]	[story]
Shift	[ROOT,told, a, story]	[]
Left-Arc (Det)	[ROOT, told, story]	[]
Right-Arc (dobj)	[ROOT, told]	[]
Right-Arc (root)	[ROOT]	[]
subj	h (iobj)	det
They	told him	a story

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### Transition-Based Parsing Summary

• Shift-Reduce paradigm, bottom-up approach

#### • Pros:

- Single pass, O(n) complexity
- Reduce parsing to classification problem; easy to introduce new features

#### • Cons:

- Only makes local decisions, may not find global optimum
- Does not handle non-projective trees without hacks
  - e.g. transforming nonprojective trees to projective in training data; reconverting after







### Other Notes

- ... is this a parser?
  - No, not really!
  - Transforms problem into sequence labeling task, of a sort.
    - e.g. (SH, LA, SH, RA, SH, SH, LA, RA)
    - Sequence score is sum of transition scores
- Classifier: Any
  - Originally, SVMs
  - Currently: NNs + LSTMs
  - State-of-the-art: UAS: 92.5%; LAS: 90.5%

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### **Dependency Parsing:** Summary

- 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

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# Roadmap

- Dependency Parsing
  - Transition-based Parsing

#### • Feature-based Parsing

- Motivation
- Features
- Unification







### Feature-Based Parsing







#### • $S \rightarrow NPVP$

• They run.

• He runs.

#### But...

- \*They runs
- \* He run
- \* He disappeared the flight

Violate agreement (number/person), subcategorization



### Constraints & Compactness





# Enforcing Constraints with CFG Rules

• Agreement

- $S \rightarrow NP_{sg+3p}VP_{sg+3p}$
- $S \rightarrow NP_{pl+3p}VP_{pl+3p}$

• Subcategorization:

•  $VP \rightarrow V_{\text{transitive}} NP$ 

- $VP \rightarrow V_{intransitive}$
- $VP \rightarrow V_{ditransitive} NP NP$

• Explosive, and loses key generalizations





- Need compact, general constraint
- $S \rightarrow NPVP$  [iff NP and VP agree]

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- How can we describe agreement & subcategory?
  - Decompose into elementary features that must be consistent
    - e.g. Agreement on number, person, gender, etc
- Augment CF rules with feature constraints
  - Develop mechanism to enforce consistency
  - Elegant, compact, rich representation

### Feature Grammars





### Feature Representations

- Fundamentally Attribute-Value pairs
  - Values may be symbols or feature structures
  - Feature path: list of features in structure to value
  - "Reentrant feature structure" sharing a structure
- Represented as
  - Attribute-Value Matrix (AVM)
  - Directed Acyclic Graph (DAG)







# Attribute-Value Matrices (AVMs)



# $\begin{bmatrix} \mathsf{ATTRIBUTE}_1 & \mathsf{value}_1 \\ \mathsf{ATTRIBUTE}_2 & \mathsf{value}_2 \end{bmatrix}$ $\vdots$ $\underbrace{\mathsf{ATTRIBUTE}_n & \mathsf{value}_n \end{bmatrix}$





CAT



# NUMBER PL PERSON 3

CAT S

**(B)** 

NP CAT NUMBER PL PERSON 3

**(D)** 

**(C)** 

HEAD





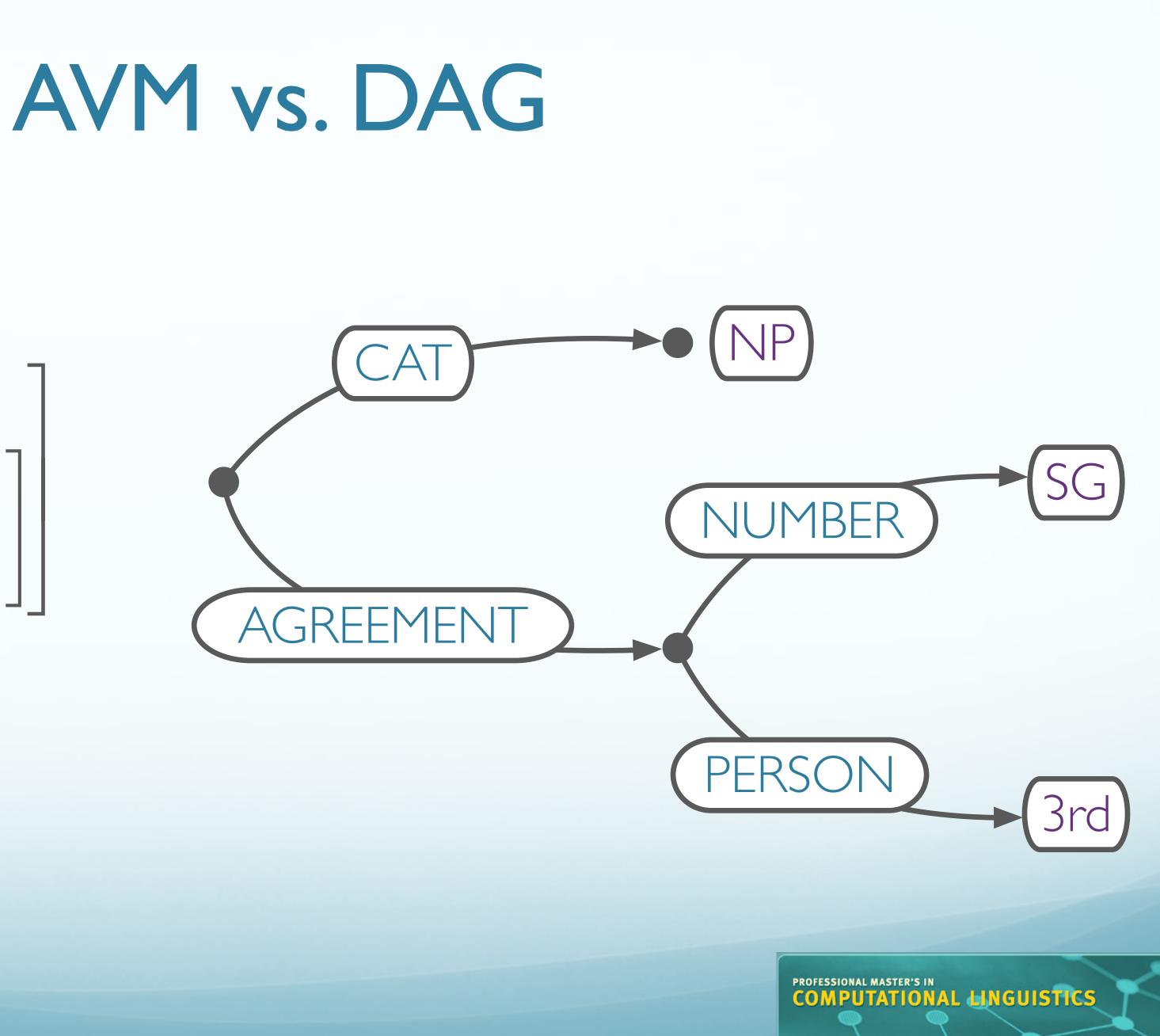
NP NUMBER PL PERSON 3 AGREEMENT

#### NUMBER PL AGREEMENT 1 PERSON 3 AGREEMENT SUBJEC

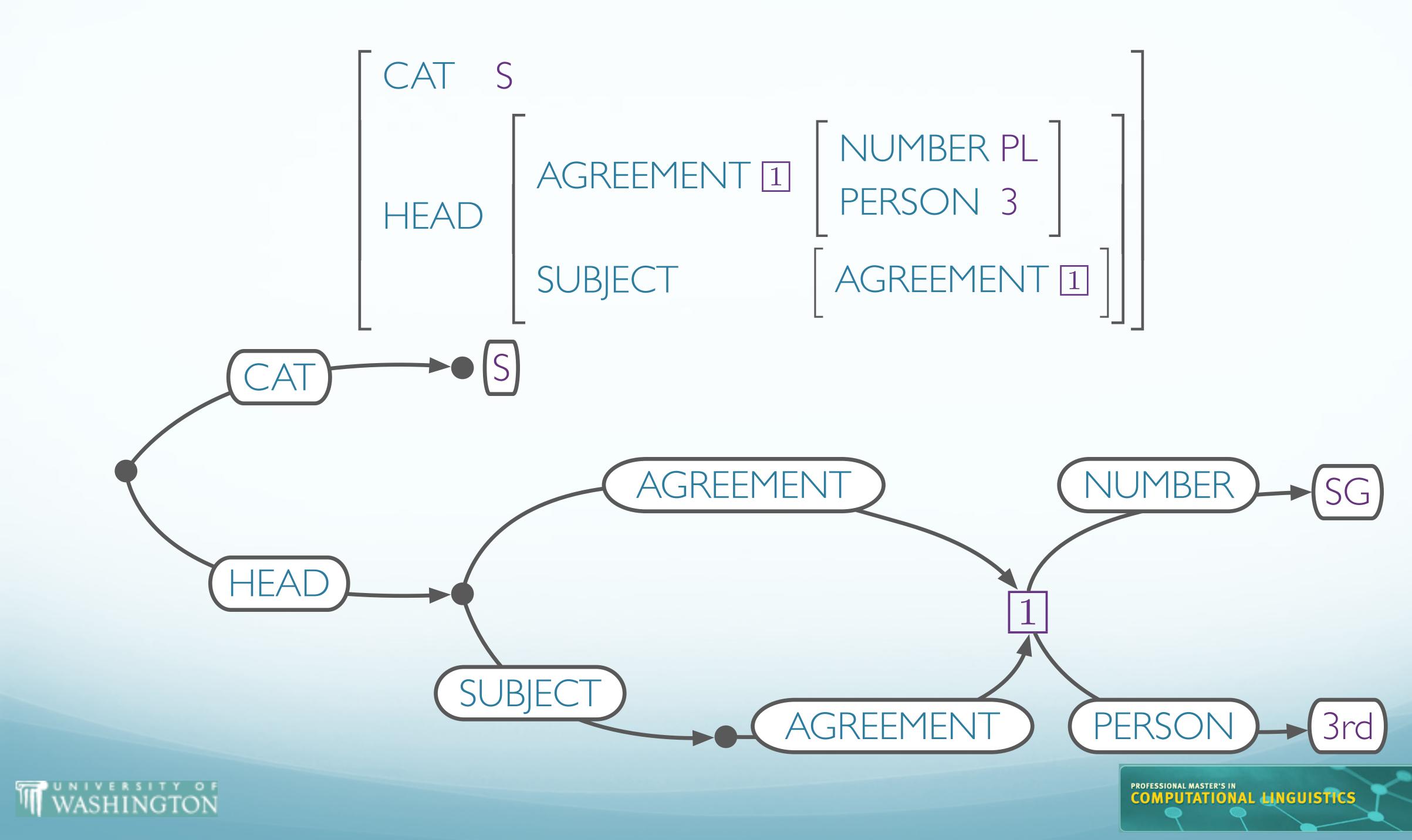


#### CAT NP NUMBER PL AGREEMENT PERSON 3











# Using Feature Structures

- Feature Structures provide formalism to specify constraints
- ... but how to apply the constraints?
- Unification







# Unification:

- Two key roles:
  - Merge compatible feature structures
  - Reject incompatible feature structures
- Two structures can unify if:
  - Feature structures *match* where both have values
  - Feature structures differ only where one value is missing or underspecified
    - Missing or underspecified values are filled with constraints of other
- Result of unification incorporates constraints of both







### Subsumption

- Less specific feature structure *subsumes* more specific feature structure
- FS F subsubmes FS 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)
- Examples:
  - $A = \begin{bmatrix} NUMBER SG \end{bmatrix}$   $B = \begin{bmatrix} PERSON 3 \end{bmatrix}$  A subsumes C C = NUMBER SG PERSON 3





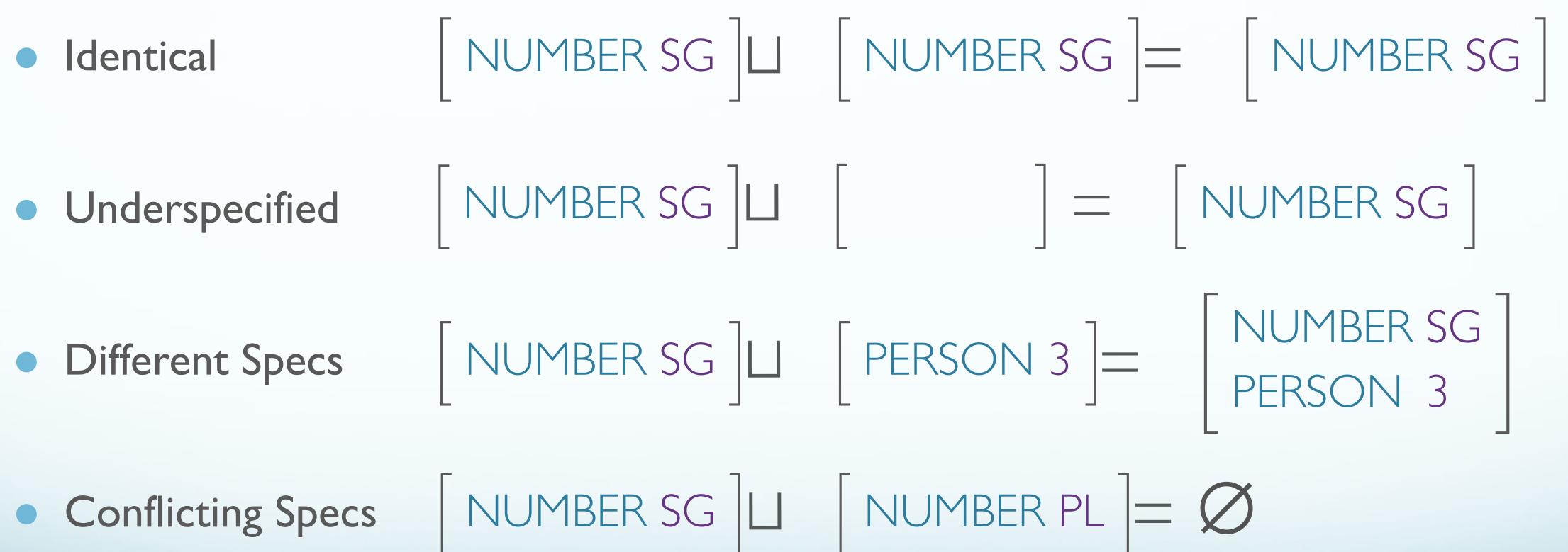
• B subsumes C **B** & A don't subsume



# Unification Examples

- Identical







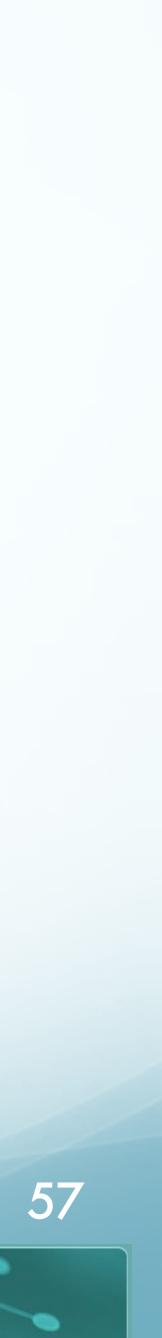
# Larger Unification Example



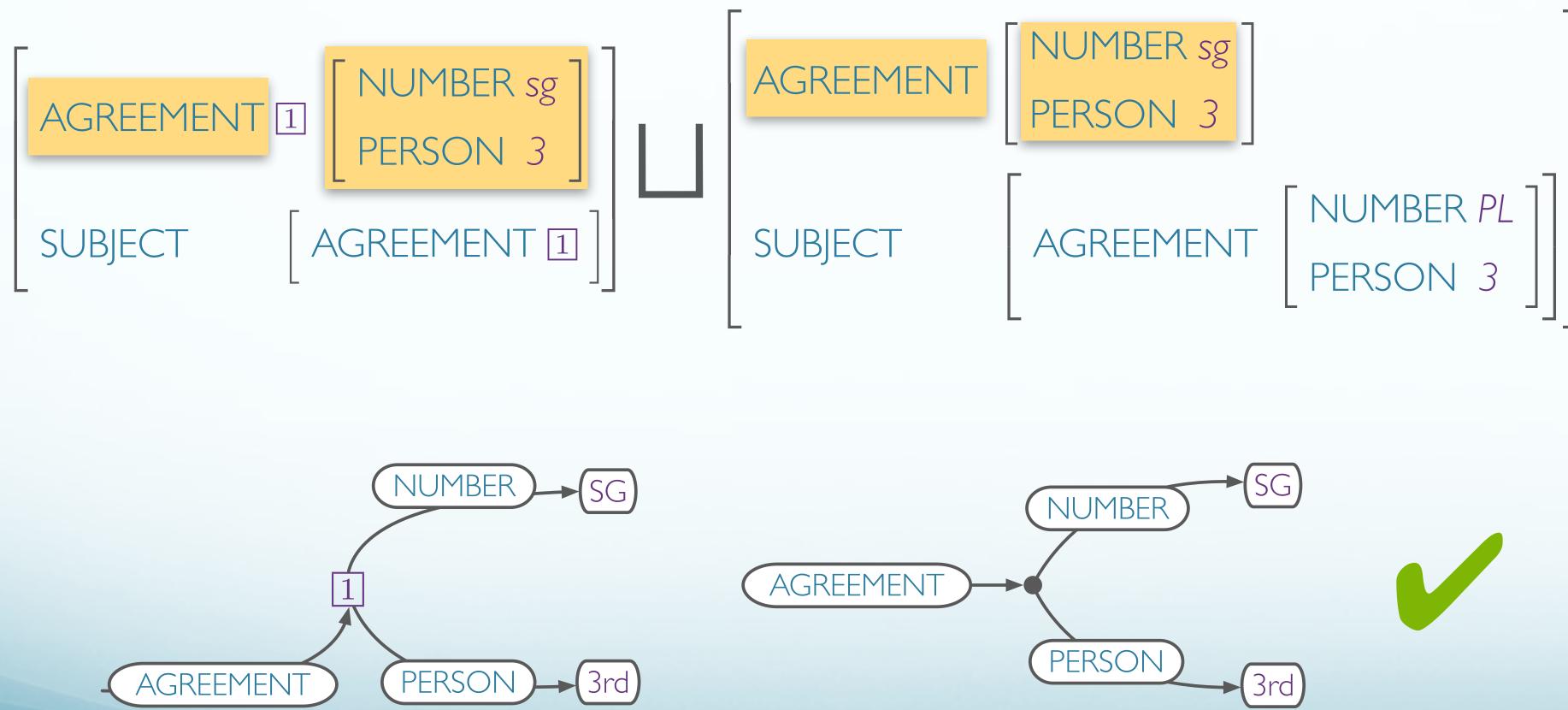


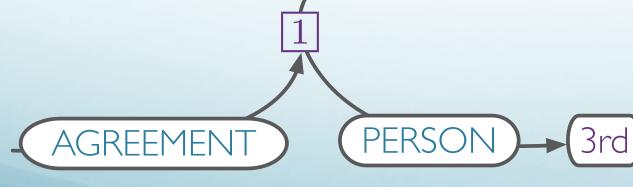






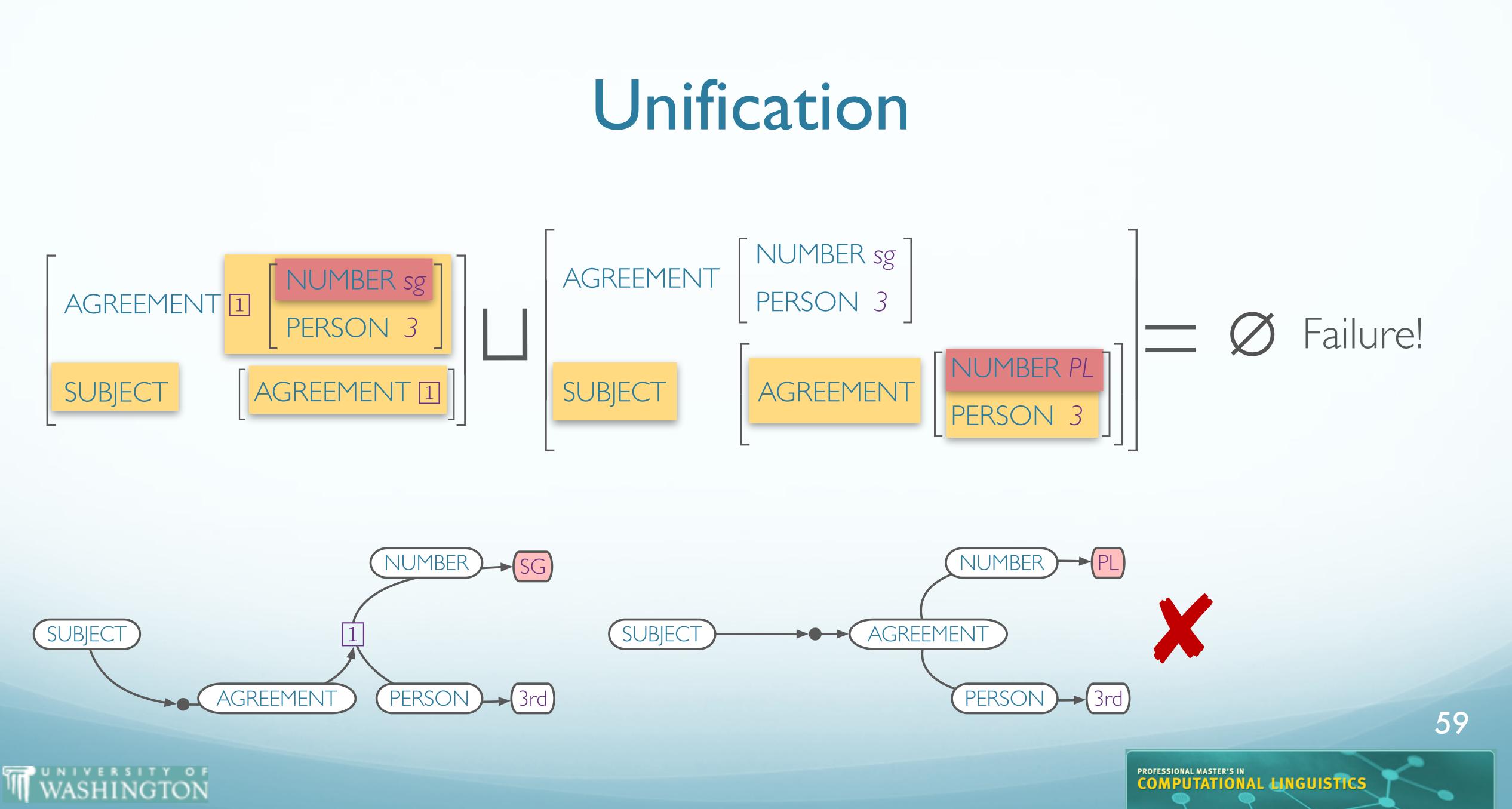
# **One More Unification Example**





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# Rule Representation

# • $\beta \rightarrow \beta_1 \dots \beta_n$

•  $Pron \rightarrow \text{'he'}$ 

#### $\langle PRON | AGREEMENT | PERSON \rangle = 3rd$





#### $\{set of constraints\}$ $\langle \beta_i feature path \rangle = Atomic value | \langle \beta_j feature path \rangle$

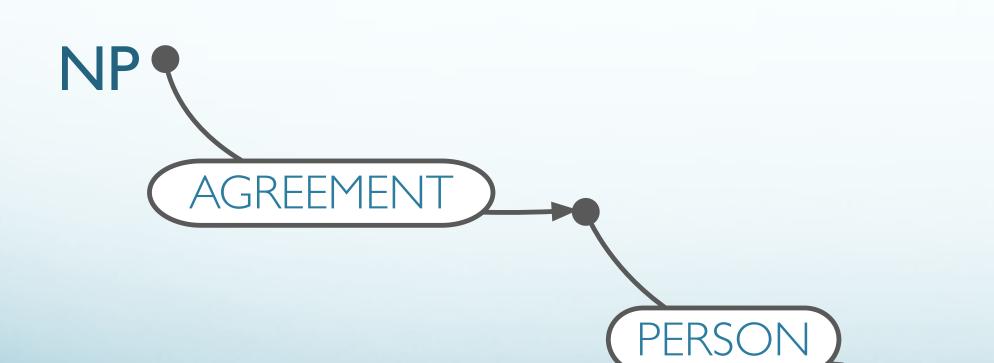




# Rule Representation

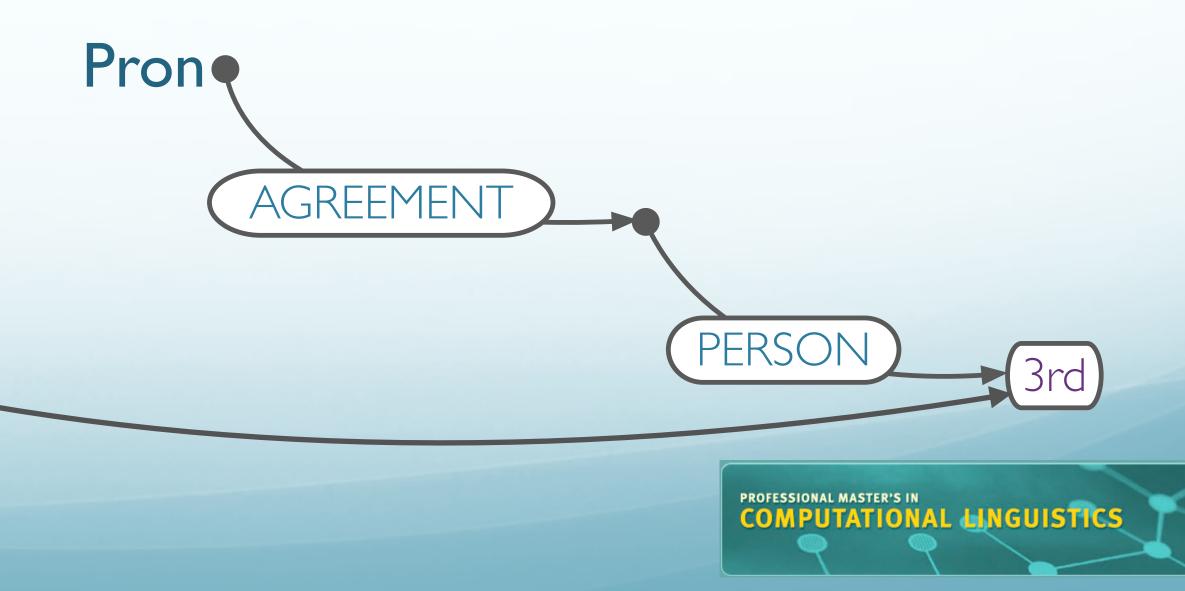
#### • $\beta \to \beta_1 \dots \beta_n$ {set of constraints} $\langle \beta_i \text{ feature period} \rangle$

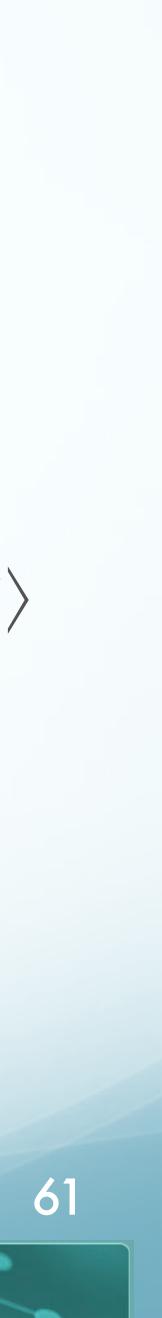
#### • $NP \rightarrow Pron$ $\langle NP \text{ Agreement Person} \rangle = \langle Pron \text{ Agreement Person} \rangle$





 $\langle \beta_i \text{feature path} \rangle = \text{Atomic value} | \langle \beta_j \text{feature path} \rangle$ 





Agreement with Heads and Features •  $\beta \rightarrow \beta_1 \dots \beta_n$  $\{set of constraints\}$   $\langle \beta_i feature path \rangle = Atomic value | \langle \beta_j feature path \rangle$ 

S 
ightarrow NP VP $\langle NP \text{ AGREEMENT} \rangle = \langle VP \text{ AGREEMENT} \rangle$ 

#### $S ightarrow Aux \ NP \ VP$

 $\langle Aux \text{ AGREEMENT} \rangle = \langle NP \text{ AGREEMENT} \rangle$ 

NP 
ightarrow Det Nominal

 $\langle Det \text{AGREEMENT} \rangle = \langle Nominal \text{AGREEMENT} \rangle$  $\langle NP \text{ AGREEMENT} \rangle = \langle Nominal \text{ AGREEMENT} \rangle$ 

 $Aux \rightarrow does$  $\langle AUX \text{ AGREEMENT NUMBER} \rangle = sg$  $\langle NP | AGREEMENT | PERSON \rangle = 3rd$ WASHINGTON

 $Det \rightarrow this$  $\langle Det \text{ AGREEMENT NUMBER} \rangle = sg$ 

 $Det \rightarrow these$  $\langle Det \text{ AGREEMENT NUMBER} 
angle = pl$ 

 $Verb \rightarrow serve$  $\langle Verb | AGREEMENT | NUMBER \rangle = pl$ 

 $Noun \rightarrow flight$  $\langle Noun | AGREEMENT | NUMBER \rangle = sg$ 





HW #5

PROFESSIONAL MASTER'S IN COMPUTATIONAL LINGUISTICS



### 

### Goals

- Explore the role of features in implementing linguistic constraints.
- Identify some of the challenges in building compact constraints to define a precise grammar.
- Apply feature-based grammars to perform grammar checking.







#### Tasks

- Build a Feature-Based Grammar
  - We will focus on the building of the grammar itself you may use NLTK's nltk.parse.FeatureEarleyChartParser or similar.







# Simple Feature Grammars

#### • $S \rightarrow NPVP$







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- N[NUM=pl] -> 'dogs' | 'girls' | 'cars' | 'children'
- N[NUM=sg] -> 'dog' | 'girl' | 'car' | 'child'
- Det[NUM=pl] -> 'these' | 'all'
- Det[NUM=sg] -> 'this' | 'every'
- NP[NUM=?n]  $\rightarrow$  Det[NUM=?n] N[NUM=?n]
- NP[NUM=?n]  $\rightarrow$  PropN[NUM=?n]
- NP[NUM=?n]  $\rightarrow$  N[NUM=?n]
- S  $\rightarrow$  NP[NUM=?n] VP[NUM=?n]

### Simple Feature Grammars



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(S[] (NP[NUM='sg'])(PropN[NUM='sg'] Kim)) (VP[NUM='sg', TENSE='pres'] (TV[NUM='sg', TENSE='pres'] likes)

>>> cp = load\_parser('grammars/book\_grammars/ feat0.fcfg') >>> for tree in cp.parse(tokens): print(tree) • • •

# Parsing with Features

(NP[NUM='pl'] (N[NUM='pl'] children)))



# Feature Applications

- Subcategorization
  - Verb-Argument constraints
    - Number, type, characteristics of args
      - e.g. is the subject animate?
      - Also adjectives, nouns
- Long-distance dependencies
  - e.g. filler-gap relations in wh-questions





# Morphosyntactic Features

- Grammtical feature that influences morphological or syntactic behavior
  - English:
    - Number:
      - Dog, dogs
    - Person:
      - am; are; is
    - Case:
      - I / me; he / him; etc.







### Semantic Features

- E.g.:
  - ?The rocks slept.
- Many proposed:
  - Animacy: +/-
  - Gender: masculine, feminine, neuter
  - Human: +/-
  - Adult: +/-
  - Liquid: +/-

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• Grammatical features that influence semantic (meaning) behavior of associated units





# Aspect (J&M 17.4.2)

- The climber [hiked] [for six hours].
- The climber [hiked] [on Saturday].
- The climber [reached the summit] [on Saturday].
- \*The climber [reached the summit] [for six hours].

- Contrast:
  - Achievement (in an instant) vs activity (for a time)



