

# MURI Year 2 Meeting

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# Syntactic Annotation Without Pain?

Noah Smith (CMU)  
with Chris Dyer (CMU)  
& Jason Baldridge (UT)

# The Penn Treebank Approach

- \$millions, 5 years
- One specific genre/dialect: 1980s *WSJ*!
- Methodologically hard to replicate
- Annotate *everything* ...
  - Even though some parts are highly predictable.
  - And “everything” ain’t what it used to be!
  - Today, many people are “rebanking” ...
- Licensing (data owned by Murdoch)

# Syntax Annotation Attempt #1

- (Jason already told you about this)
- Phrase structure analysis, with heads:
  - Kinyarwanda (KGMC): 2,900 tokens
  - Malagasy (news): 2,300 tokens
- Great for exploring phenomena and *evaluating* text analyzers
  - ... not *building* analyzers.

# New Solution

- Allow *partial* annotation of the most important phenomena.
- Represent:
  - chunks (contiguous and non-contiguous)
  - dependencies among tokens, chunks
  - empty nodes
  - explicit “can’t be bothered” annotations
- Intuitive, flexible text-based interface and interpreter for annotation
  - Less reliance on expertise

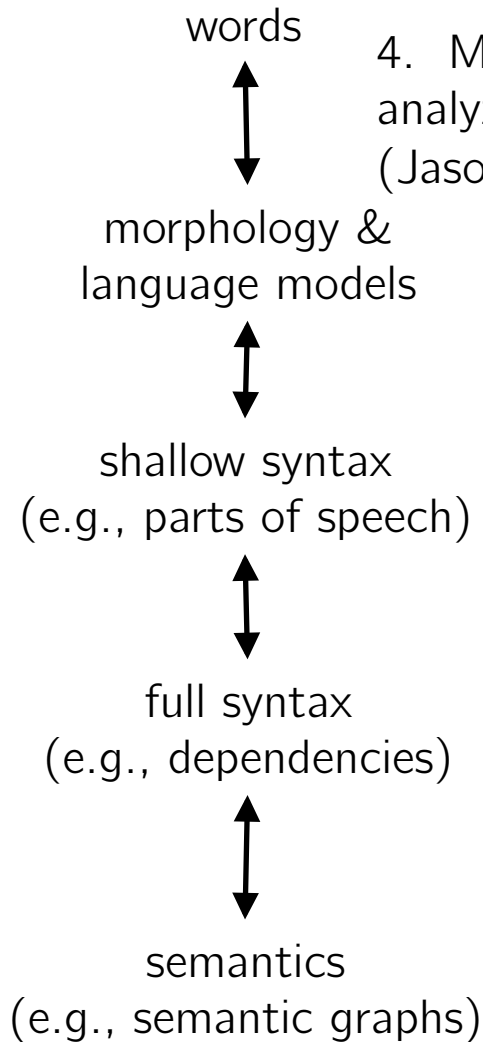
***Twice-as-large dataset annotated in 3 weeks  
(vs. 3-4 months)***

# Graph Fragment Language

Chris: what it looks like

Jason: what we've done with it

# Building Blocks



4. Marrying knowledge and learning for analyzing and predicting words  
(Jason Mielens, UT; Chris Dyer, CMU)

2. Type annotation for efficient prior POS knowledge use  
(Dan Garrette, UT)

**3. Multilingual guidance for parser transfer  
(Noah Smith, CMU; Zach Hynes, MIT)**

1. Synchronous hyperedge replacement grammars for efficient semantic analysis & generation (David Chiang, USC/ISI)



# Text Analysis Transfer with Non-Parallel Multilingual Guidance



Shay Cohen    CMU → Columbia University

Dipanjan Das    CMU → Google Research

Noah Smith    Carnegie Mellon University



# Multilingual Transfer

using parallel data

no parallel data

**(hard)**

joint learning  
for multiple  
languages

supervision in  
helper  
language(s)

joint learning  
for multiple  
languages

**supervision in  
helper  
language(s)**

Snyder et al. (2009)

Naseem et al. (2010)

Yarowsky and Ngai (2001)

Xi and Hwa (2005)

Zeman and Resnik (2008)

Smith and Eisner (2009)

Das and Petrov (2011)

McDonald et al. (2011)

Cohen and Smith (2009)

Berg-Kirkpatrick and  
Klein (2010)

***this work:***

**Cohen et al.  
(2011)**

**Naseem et al.  
(2012)**

# Mixture Approach

**Annotated** data in  
helper languages

+

**Unlabeled** data in  
Portuguese

=

**Portuguese  
parameters**

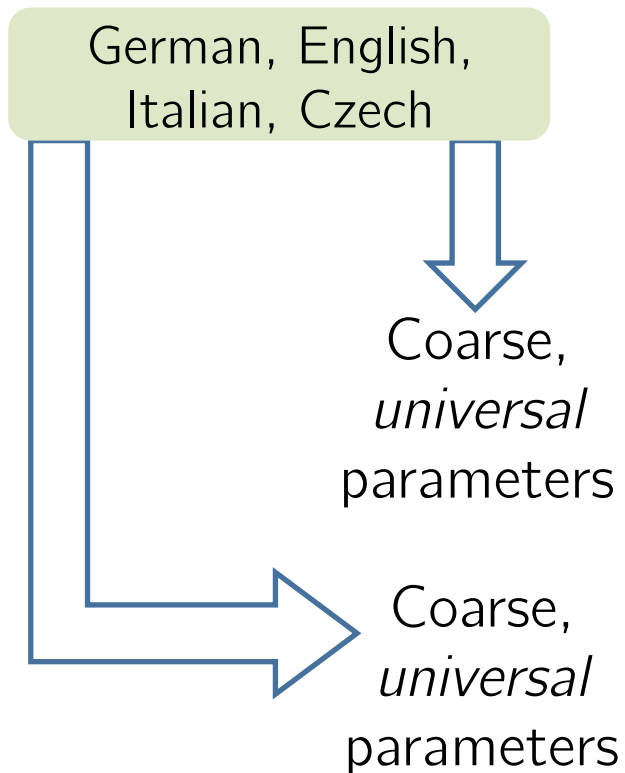
German, English,  
Italian, Czech

# Mixture Approach

**Annotated** data in  
helper languages +

**Unlabeled** data in  
Portuguese =

**Portuguese  
parameters**



# Technique in a Nutshell

**Annotated** data in  
helper languages

+

**Unlabeled** data in  
Portuguese

=

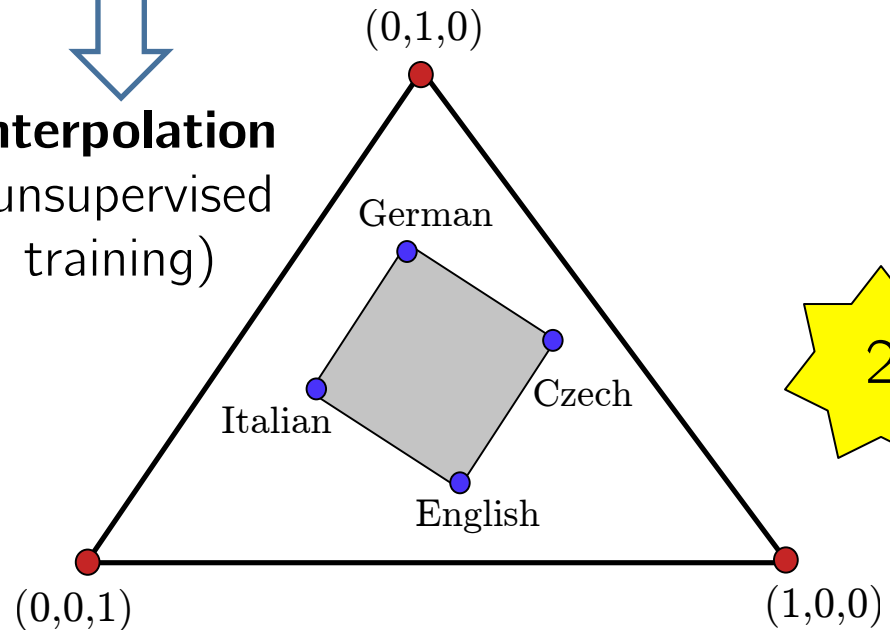
**Portuguese  
parameters**

German, English,  
Italian, Czech

Coarse,  
*universal*  
parameters

Coarse,  
*universal*  
parameters

**Interpolation**  
(unsupervised  
training)



# Mixture Approach

**Annotated** data in  
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+

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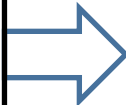
=

**Portuguese  
parameters**

German, English,  
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Coarse,  
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**Interpolation**  
(unsupervised  
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*coarse* parameters of Portuguese



# Mixture Approach

**Annotated** data in  
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=

**Portuguese  
parameters**

German, English,  
Italian, Czech



**Monolingual** unsupervised training in Portuguese

Coarse-to-fine  
expansion  
and initialization



*coarse* parameters of Portuguese

# Mixture Approach

**Annotated** data

+

**Unlabeled** data in  
Portuguese

=

**Portuguese  
parameters**

German, English,  
Italian, Czech



**Monolingual** unsupervised training in Portuguese



# Results: Part-of-Speech Tagging

				<b>our results</b>		
				Direct Gradient (DG)	Uniform + DG	Mixture + DG
<b>Number of Languages with Best Results</b>				2 (Portuguese, Danish)	2 (Turkish, Bulgarian)	<b>6</b>
<b>Average Accuracy</b>				40.6	41.0	<b>43.3</b>

(without tag dictionary)

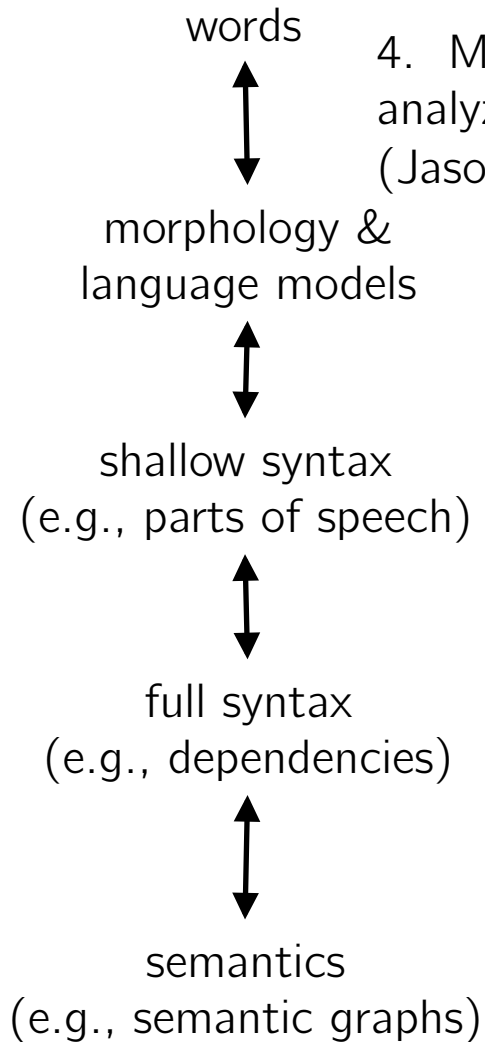


# Results: Dependency Parsing

	EM	PR	PGI	Uniform	Mixture	Uniform + EM	Mixture + EM
Number of Languages with Best Results	0	2 (Turkish, Slovene)	0	3 (Bulgarian, Swedish, Dutch)	1 (Danish)	1 (Greek)	3 (Portuguese, Japanese, Spanish)
Average Accuracy	41.4	50.2*	53.6*	61.6	<b>62.2</b>	61.5	62.1

**our results**

# Building Blocks



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(David Chiang, USC/ISI)



# Tree-to-Tree Translation with Quasi-Synchronous Phrase Dependency Grammars



Kevin Gimpel

CMU → Toyota Technological Institute at Chicago

*Advisor/presenter:* Noah Smith (CMU)

*Committee:* Jaime Carbonell (CMU),  
David Chiang (USC/ISI)

# Phrase Dependency



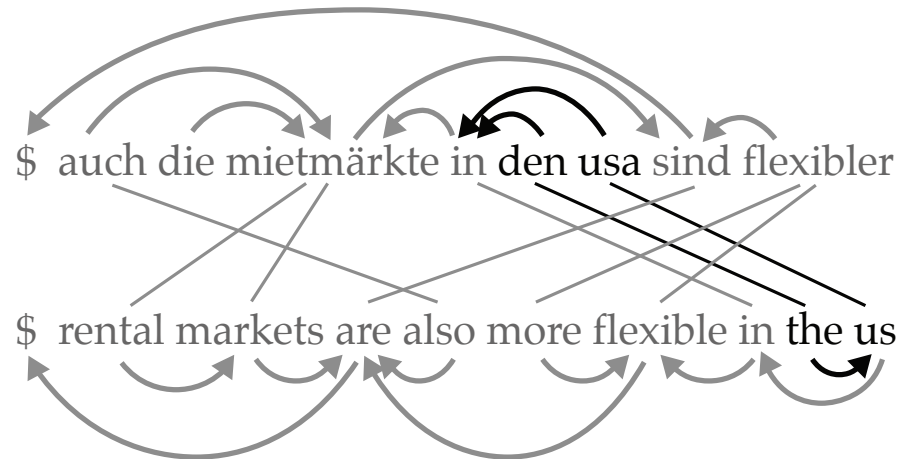
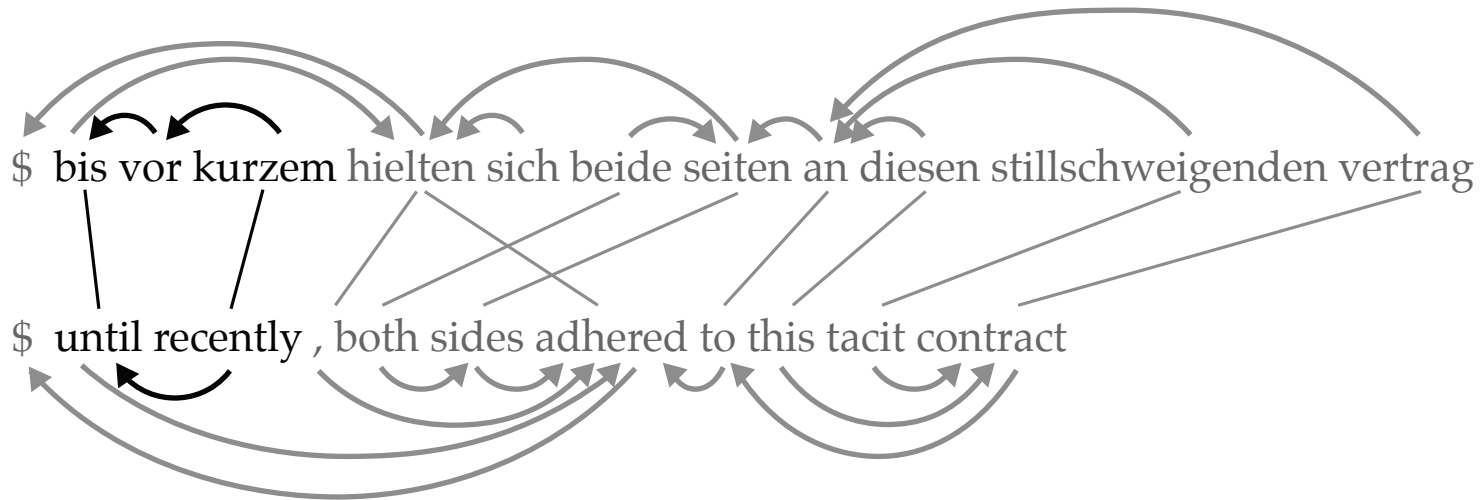
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# Syntactic Divergence in Real Data



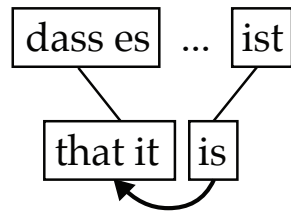
# Problems & Solutions

- Lexical dependencies align in many complex ways.
  - “Bigger” dependency rules on *phrases*.
- Across languages, dependency parsing ranges from pretty okay to nonexistent.
  - Source-side syntax is *optional*.
  - We explored *unsupervised parsing* as a stand-in.
- Flexible formalism → expensive decoding!
  - Coarse-to-fine strategy (key advance over 2011).

# Example Extracted Rules

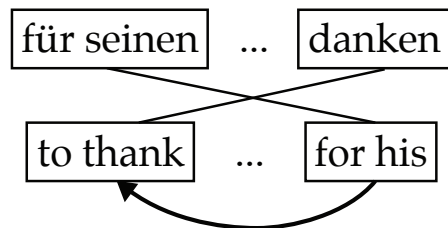
(a) ich meine deshalb , dass es eine frage der geeigneten methodik ist .

i think that it is consequently a question of the appropriate methodologies .



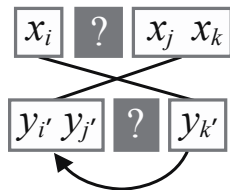
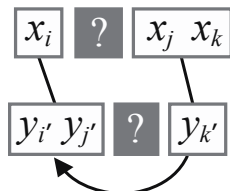
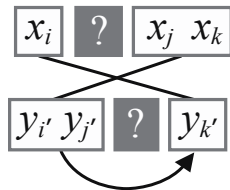
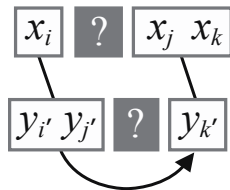
(b) abschließend möchte ich herrn langen herzlich für seinen bericht danken ,...

finally , mr president , i would like to thank mr langen warmly for his report ,...

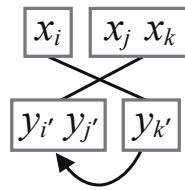
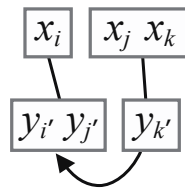
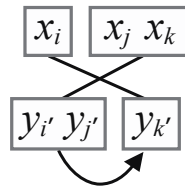
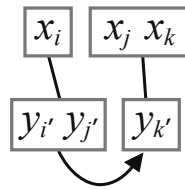


# String-to-Tree Configurations

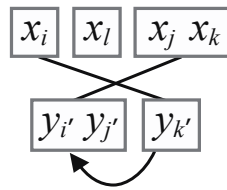
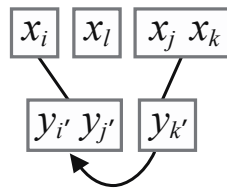
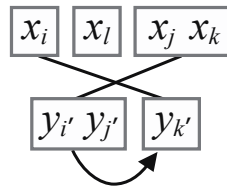
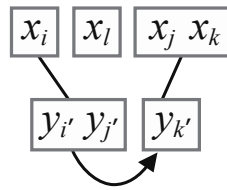
coarse configurations  
(only direction  
and orientation)



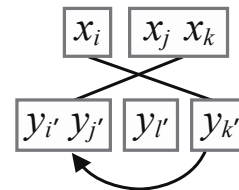
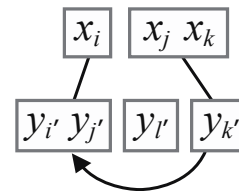
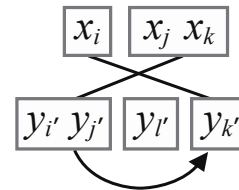
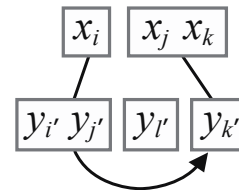
no gaps



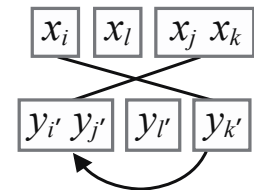
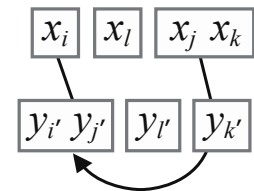
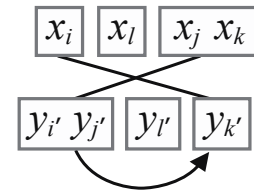
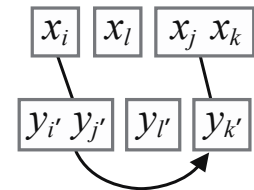
source gap



target gap



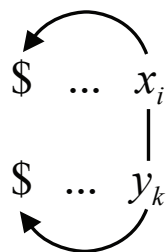
source and  
target gaps



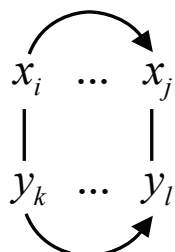


# Tree-to-Tree Configurations

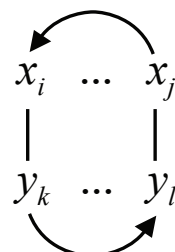
root-root



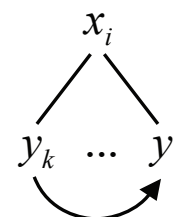
parent-child



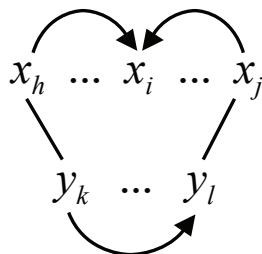
child-parent



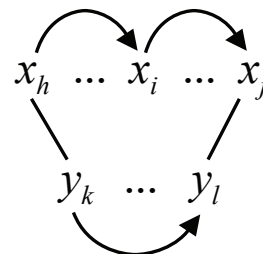
same-node



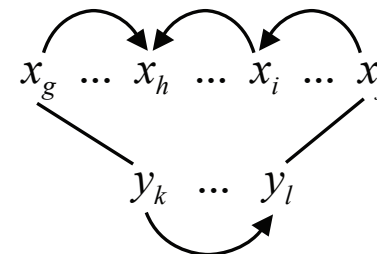
siblings



grandparent-grandchild

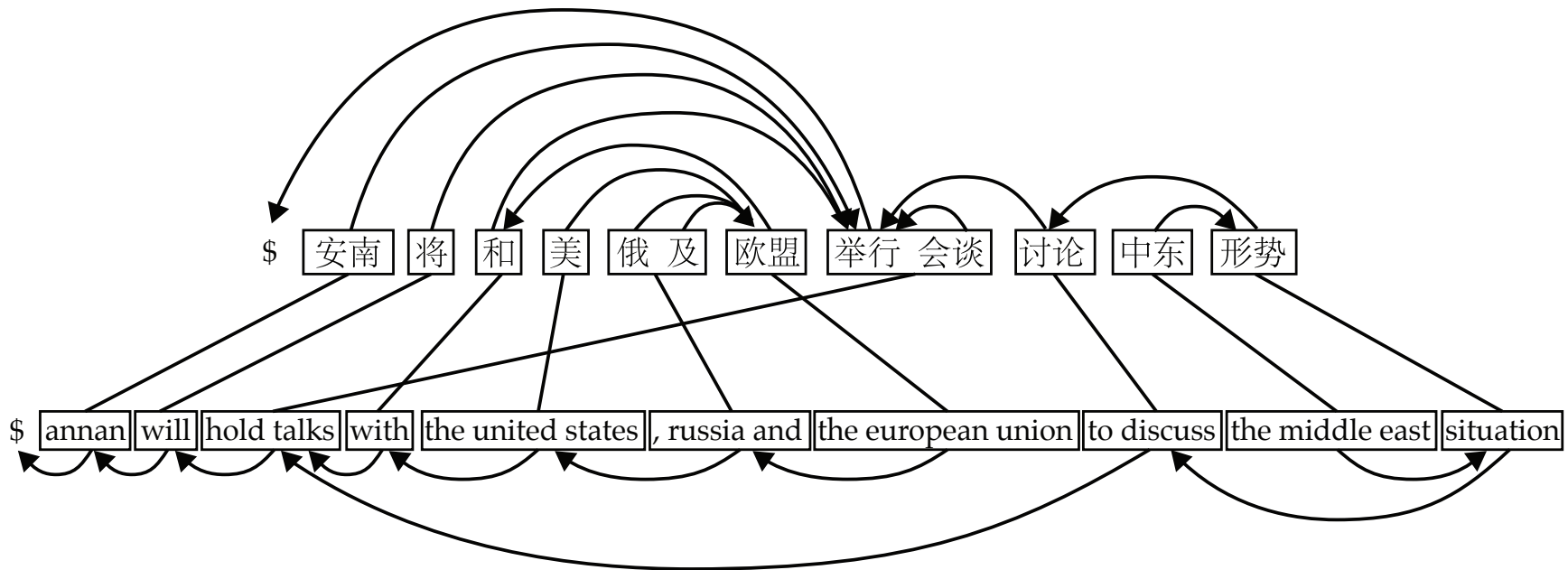


c-command



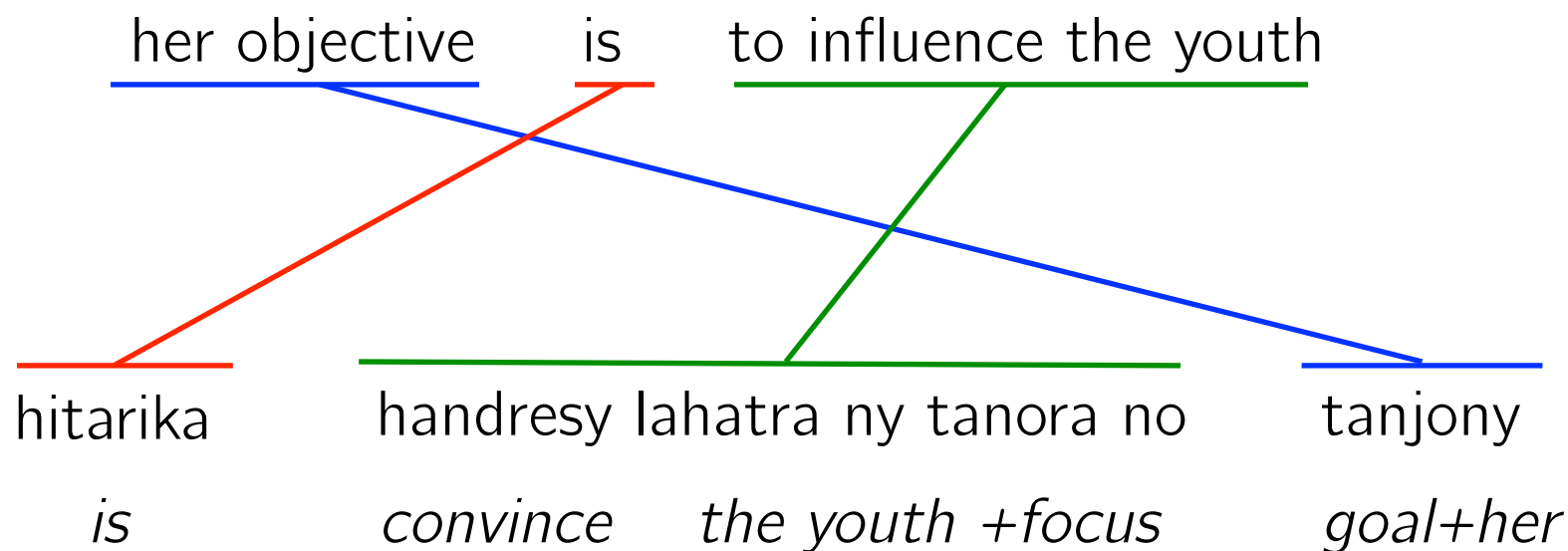
Credit: D. Smith and Eisner (2006)

# Example Derivation Structure



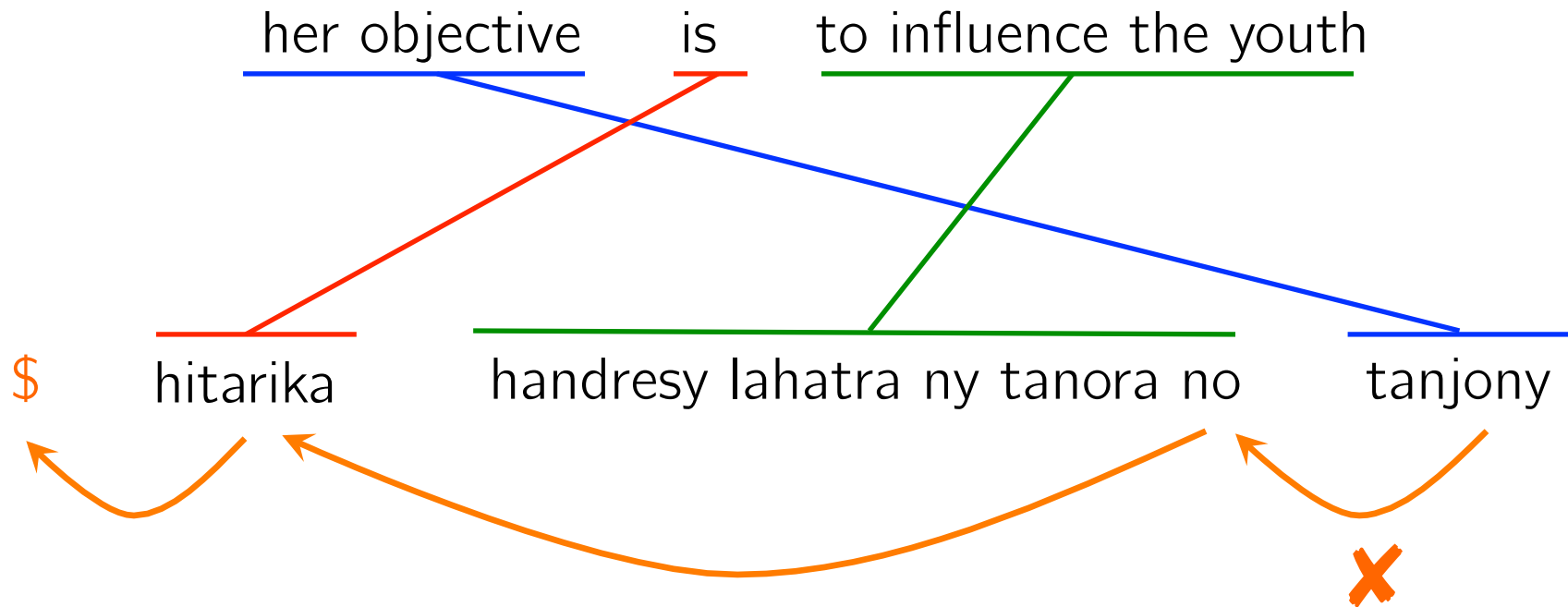
**references:** annan to hold talks with us , russia and eu over situation in middle east  
annan will discuss middle east situation with u.s. , russia and european union  
annan to discuss mideast situation with us , russia and eu  
annan to meeting the us , russia and eu to discuss middle east crisis

# An English-Malagasy Example



S O V → O V S

# Unsupervised Dependencies



# Results: English→Malagasy

<b>System</b>	<b>%BLEU (test)</b>
Moses (stack size = 200)	15.05
Moses (stack size = 500)	15.08
QPDG	<b>15.54</b>

# Lessons & Future

- ✓ QPDG: syntax + phrases can work together for better MT, even in syntax-hostile scenarios
- Use improved POS tagger (UT) and dependency parser (MIT) developed in year 2!
- Model morphology in the language model (Jason Mielens and Chris Dyer's talk this morning) and translation model (Waleed Ammar's talk later)