# CS388: Natural Language Processing Lecture 24: Multilinguality + Morphology



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## Administrivia

- Final project presentations next week
  - See Canvas announcement for who is presenting when
  - Can be "work in progress", but there should be at least preliminary results
  - Final reports due on December 14; no slip days
- Project 2 graded; average = 19.0



# Dealing with other languages

- Other languages present some problems not seen in English at all!
- Many algorithms so far have been developed for English
  - Some structures like constituency parsing don't make sense for other languages
  - Neural methods are typically tuned to English-scale resources, may not be the best for other languages where less data is available
- Question:
  - 1) What other phenomena / challenges do we need to solve?
  - 2) How can we leverage existing resources to do better in other languages without just annotating massive data?



## This Lecture

- Morphology: effects and challenges
- Morphology tasks: analysis, inflection, word segmentation
- Cross-lingual tagging and parsing

# Morphology

# What is morphology?

- Study of how words form
- Derivational morphology: create a new *lexeme* from a base estrange (v) => estrangement (n)
   become (v) => unbecoming (adj)
  - May not be totally regular: enflame => inflammable
- Inflectional morphology: word is inflected based on its context I become / she becomes
  - Mostly applies to verbs and nouns



# Morphological Inflection

In English: larrive you arrive

he/she/it arrives

[X] arrived

we arrive you arrive

they arrive

In French:

			singular		plural			
		first second		third	first	second	third	
indicative		je (j')	tu	il, elle	nous	vous	ils, elles	
	present	arrive	arrives	arrive	arrivons	arrivez	arrivent	
	present	/a.ʁiv/	/a.ĸiv/	/a.ĸiv/	/a.ĸi.vɔ̯/	/a.ʁi.ve/	/a.ĸiv/	
	imperfect	arrivais	arrivais	arrivait	arrivions	arriviez	arrivaient	
	imperiect	/a.ʁi.vɛ/	/a.ĸi.vɛ/	\ari.Λε\	/a.ĸi.vjɔ̃/	/a.ʁi.vje/	/a.κi.νε/	
(simple	past historic <sup>2</sup>	arrivai	arrivas	arriva	arrivâmes	arrivâtes	arrivèrent	
tenses)		/a.ʁi.vɛ/	/a.ʁi.va/	/a.ʁi.va/	/a.ʁi.vam/	/a.ʁi.vat/	/a.ri.vɛr/	
	future	arriverai	arriveras	arrivera	arriverons	arriverez	arriveront	
		\arkirake\	/a.ri.vra/	/a.ĸi.vĸa/	\ari.\R2\	/a.ri.vre/	/ari.vrɔ̯/	
	conditional	arriverais	arriverais	arriverait	arriverions	arriveriez	arriveraient	
	Conditional	/a.κi.νκε/	\ari.ΛRε\	\ari.ΛRε\	/ari.vəri)2/	/a.ĸi.və.ĸje/	/ari.vrs/	



# Morphological Inflection

#### In Spanish:

			singular		plural			
			2nd person	3rd person	1st person	2nd person	3rd person	
		yo	tú vos	él/ella/ello usted	nosotros nosotras	vosotros vosotras	ellos/ellas ustedes	
	present	llego	llegas <sup>tú</sup> llegás <sup>vos</sup>	llega	llegamos	llegáis	llegan	
indicative	imperfect	llegaba	llegabas	llegaba	llegábamos	llegabais	llegaban	
	preterite	llegué	llegaste	llegó	llegamos	llegasteis	llegaron	
	future	llegaré	llegarás	llegará	llegaremos	llegaréis	llegarán	
	conditional	llegaría	llegarías	llegaría	llegaríamos	llegaríais	llegarían	



### Noun Inflection

Not just verbs either; gender, number, case complicate things

Declension of Kind [hide ▲]								
	singular				plural			
	indef.	def.	noun	def.	noun			
nominative	ein	das	Kind	die	Kinder			
genitive	eines	des	Kindes, Kinds	der	Kinder			
dative	einem	dem	Kind, Kinde <sup>1</sup>	den	Kindern			
accusative	ein	das	Kind	die	Kinder			

- Nominative: I/he/she, accusative: me/him/her, genitive: mine/his/hers
- Dative: merged with accusative in English, shows recipient of something I taught the children <=> Ich unterrichte die Kinder I give the children a book <=> Ich gebe den Kindern ein Buch



# Irregular Inflection

- Common words are often irregular
  - lam/you are/she is
  - Je suis / tu es / elle est
  - Yo soy / usted está / ella es
- However, less common words typically fall into some regular paradigm — these are somewhat predictable



# Agglutinating Langauges

Finnish/Turkish/
Hungarian (FinnoUgric): what a
preposition would
do in English is
instead part of the
verb

		active	passive				
1st		nalata					
long	1st <sup>2</sup>	halatakseen					
2nd	inessive <sup>1</sup>	halatessa	halattaessa				
ZIIU	instructive	halaten	_				
	inessive	halaamassa	_				
	elative	halaamasta	_				
3rd	illative	halaamaan	_				
Siu	adessive	halaamalla	_				
	abessive	halaamatta	_				
	instructive	halaaman	halattaman				
4th partitive		halaaminen					
		halaamista					
5th <sup>2</sup>		halaamaisillaan					

eivispie halannee positive oile halamus oils halamus olisi halannut ete pisi nalameet distance she hadow okas halanneet ed only with a possessive coding this is the term for the territories on organizational throughouse plants

illative: "into" adessive: "on"

▶ Many possible forms — and in newswire data, only a few are observed



# Morphologically-Rich Languages

- Many languages spoken all over the world have much richer morphology than English (Chinese is the main exception)
  - CoNLL 2006 / 2007: dependency parsing + morphological analyses for ~15 mostly Indo-European languages
  - ▶ SPMRL shared tasks (2013-2014): Syntactic Parsing of Morphologically-Rich Languages
- Word piece / byte-pair encoding models for MT are pretty good at handling these if there's enough data



# Morphologically-Rich Languages



#### Linguistic Fundamentals for Natural Language Processing

100 Essentials from Morphology and Syntax

Emily M. Bender

Great resources for challenging your assumptions about language and for understanding multilingual models!

Synthesis Lectures on Human Language Technologies

Graeme Hirst, Series Editor

# Morphological Analysis/Inflection



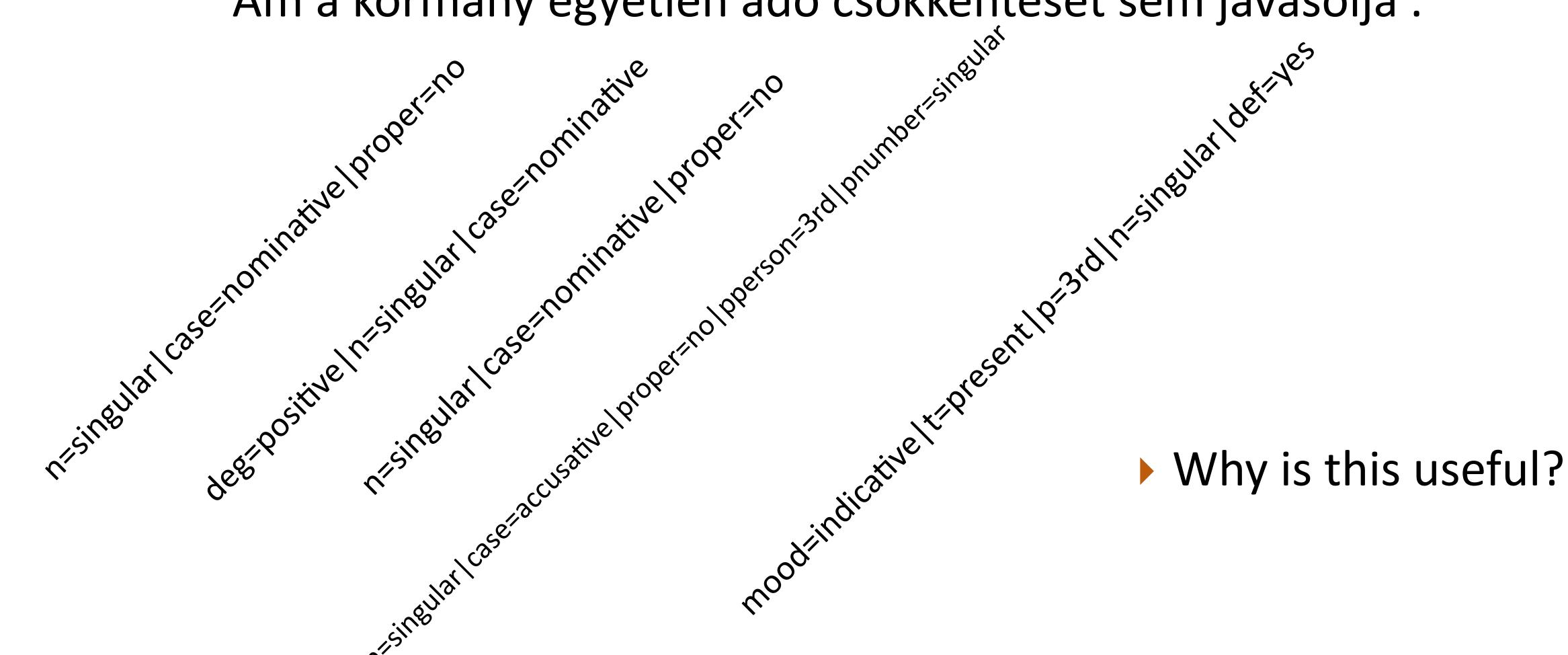
# Morphological Analysis

- In English, not that many word forms, lexical features on words and word vectors are pretty effective
- In other languages, \*lots\* more unseen words! Affects parsing, translation, ...
- When we're building systems, we probably want to know base form + morphological features explicitly
- ▶ How to do this kind of morphological analysis?



# Morphological Analysis

But the government does not recommend reducing taxes. Ám a kormány egyetlen adó csökkentését sem javasolja.





# Morphological Analysis

- Given a word, need to recognize what its morphological features are
- Basic approach:
  - Lexicon: tells you what possibilities are
  - Analyzer: statistical model that disambiguates
- Models are largely CRF-like: score morphological features in context
- Lots of work on Arabic inflection (high amounts of ambiguity)



# Predicting Inflection

- Other direction: given base form + features, inflect the word
  - ▶ Hard for unknown words need models that generalize

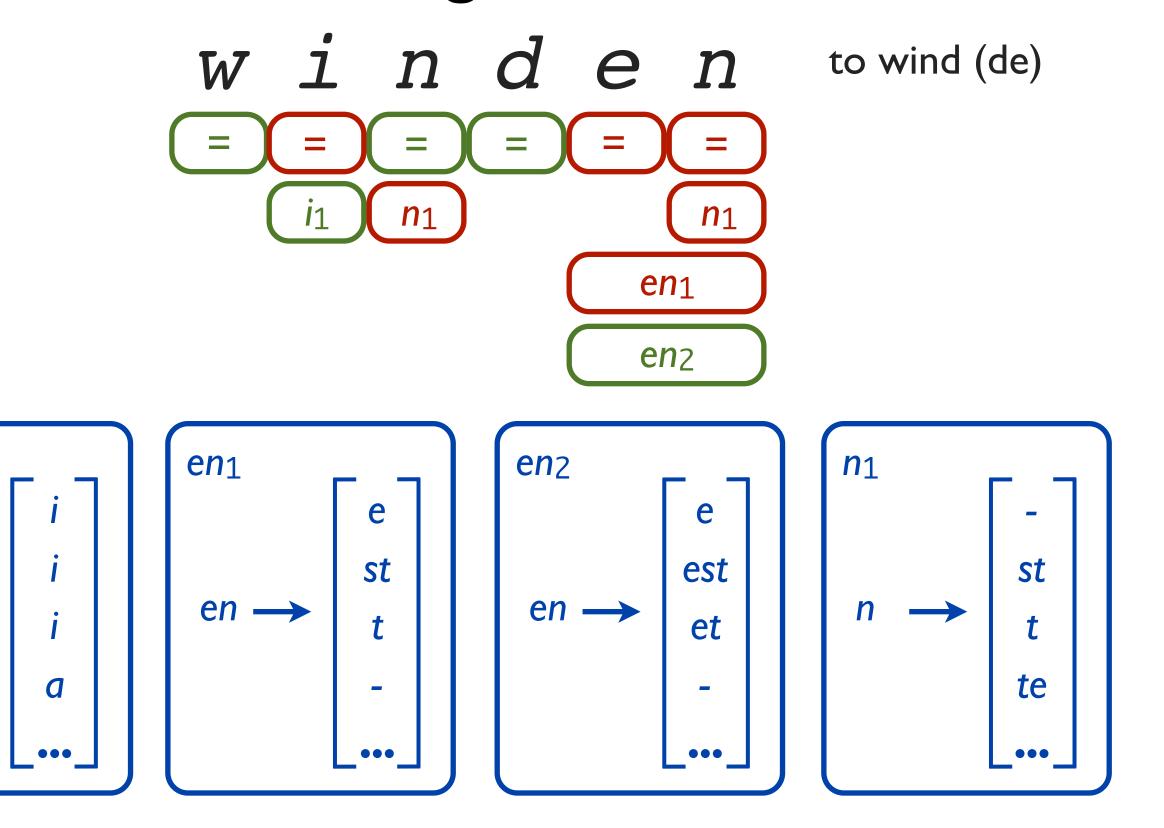


	infinitive		winden					
pres	esent participle windend							
pas	st participle		gewunden					
	auxiliary		haben					
	indic	ative		subju	nctive			
	ich winde	wir <b>winden</b>		ich winde	wir <b>winden</b>			
present	du windest	ihr windet	i	du windest	ihr windet			
	er windet	sie <b>winden</b>		er winde	sie <b>winden</b>			
	ich wand	wir wanden		ich wände	wir wänden			
preterite	du wandest	ihr wandet	ii	du wändest	ihr wändet			
	er wand	sie wanden		er wände	sie wänden			
imperative	winde (du)	windet (ihr)						



# Predicting Inflection

- Other direction: given base form + features, inflect the word
  - ▶ Hard for unknown words need models that generalize
- Take a bunch of existing verbs from Wiktionary, extract these change rules using character alignments
- Train a CRF with character ngram context features to learn where to apply them

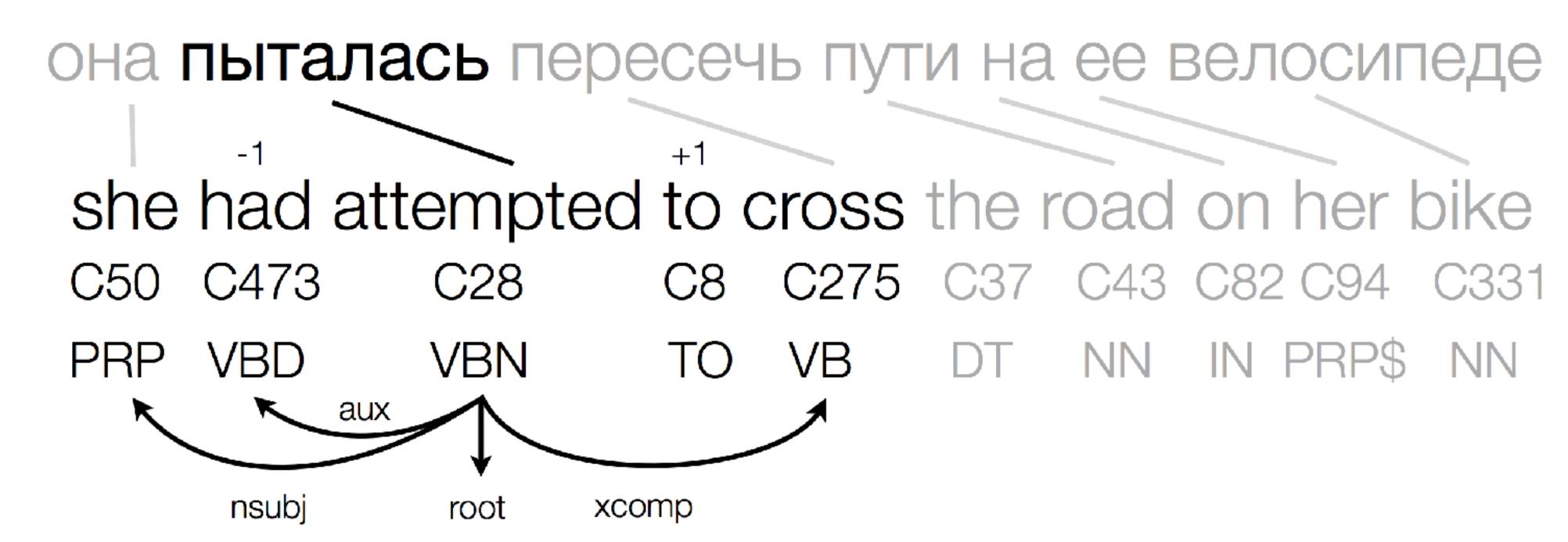


Durrett and DeNero (2013)



## Morphological Reinflection

σ:пытаться\_V + μ:mis-sfm-e



- Machine translation where phrase table is defined in terms of lemmas
- "Translate-and-inflect": translate into uninflected words and predict inflection based on source side

Chahuneau et al. (2013)

# Word Segmentation



# Morpheme Segmentation

- Can we do something unsupervised rather than these complicated analyses?
- unbecoming => un+becom+ing we should be able to recognize these common pieces and split them off
- How do weo do this?



# Morpheme Segmentation

- Simple probabilistic model  $\operatorname{Cost}(\operatorname{Source\ text}) = \sum_{\operatorname{morph\ tokens}} -\log p(m_i)$
- $p(m_i) = count(token)/count(all tokens)$
- Train with EM: E-step involves estimating best segmentation with Viterbi, M-step: collect token counts
- allowed expected need needed all+owe+d expe+cted n+e+ed ne+ed+ed E0
- M0: ed has count 3 all+ow+ed expect+ed ne+ed ne+ed+ed E1
- Some heuristics: reject rare morphemes, one-letter morphemes
- Doesn't handle stem changes: becoming => becom + ing

Creutz and Lagus (2002)



# Chinese Word Segmentation

- Some languages including Chinese are totally untokenized
- LSTMs over character embeddings / character bigram embeddings to predict word boundaries
- Having the right segmentation can help machine translation

```
冬天 (winter), 能 (can) 穿 (wear) 多少 (amount) 穿 (wear) 多少 (amount); 夏天 (summer), 能 (can) 穿 (wear) 多 (more) 少 (little) 穿 (wear) 多 (more) 少 (little)。
```

Without the word "夏天 (summer)" or "冬天 (winter)", it is difficult to segment the phrase "能 穿多少穿多少".

- separating nouns and pre-modifying adjectives: 高血压 (high blood pressure)
  - → 高(high) 血压(blood pressure)
- separating compound nouns:
   内政部 (Department of Internal Affairs)
   → 内政(Internal Affairs) 部(Department).

Chen et al. (2015)

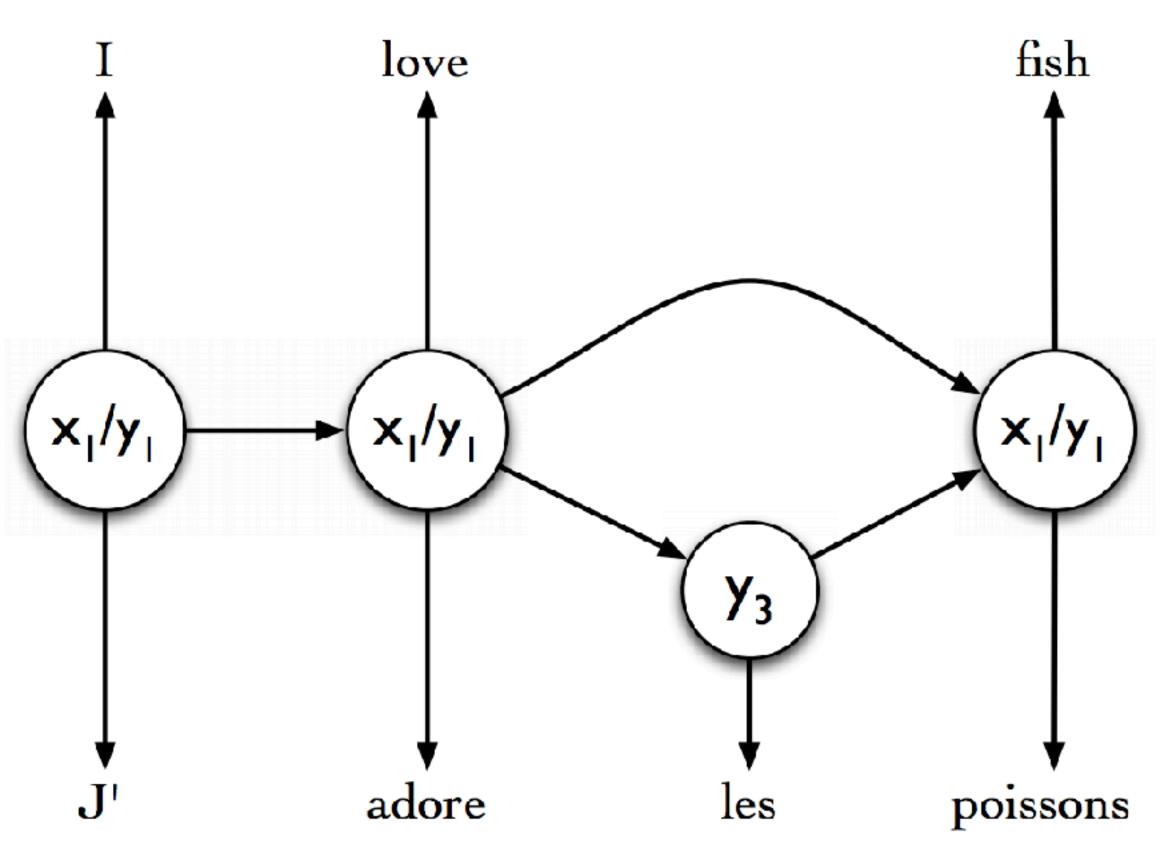
# Cross-Lingual Tagging and Parsing



Multilingual POS induction

 Generative model of two languages simultaneously, joint alignment + tag learning

Complex generative model, requires Gibbs sampling for inference





▶ We have resources for languages like English — can we use these more directly?

```
N V PR DT ADJ
I like it a lot

Je l' aime beaucoup
N PR V ??
```

- Tag with English tagger, project across bitext, train French tagger?
- Can do something smarter



N V PR DT ADJ like it a lot

Je l' aime beaucoup

Form a graph of trigrams, use these to propagate knowledge about tags

#### **Algorithm 1** Bilingual POS Induction

Require: Parallel English and foreign language data  $\mathcal{D}^e$  and  $\mathcal{D}^f$ , unlabeled foreign training data  $\Gamma^f$ ; English tagger.

Ensure:  $\Theta^f$ , a set of parameters learned using a constrained unsupervised model (§5).

 $\begin{cases} 1: \ \mathcal{D}^{e \leftrightarrow f} \leftarrow \text{word-align-bitext}(\mathcal{D}^e, \mathcal{D}^f) \\ 2: \ \widehat{\mathcal{D}^e} \leftarrow \text{pos-tag-supervised}(\mathcal{D}^e) \\ 3: \ \mathcal{A} \leftarrow \text{extract-alignments}(\mathcal{D}^{e \leftrightarrow f}, \widehat{\mathcal{D}^e}) \end{cases}$ 

4:  $G \leftarrow construct-graph(\Gamma^f, \mathcal{D}^f, \mathcal{A})$ 5:  $\tilde{G} \leftarrow graph-propagate(G)$ 6:  $\Delta \leftarrow extract-word-constraints(\tilde{G})$ 

7:  $\Theta^f \leftarrow \mathsf{pos\text{-}induce\text{-}constrained}(\widehat{\Gamma^f}, \Delta)$ 

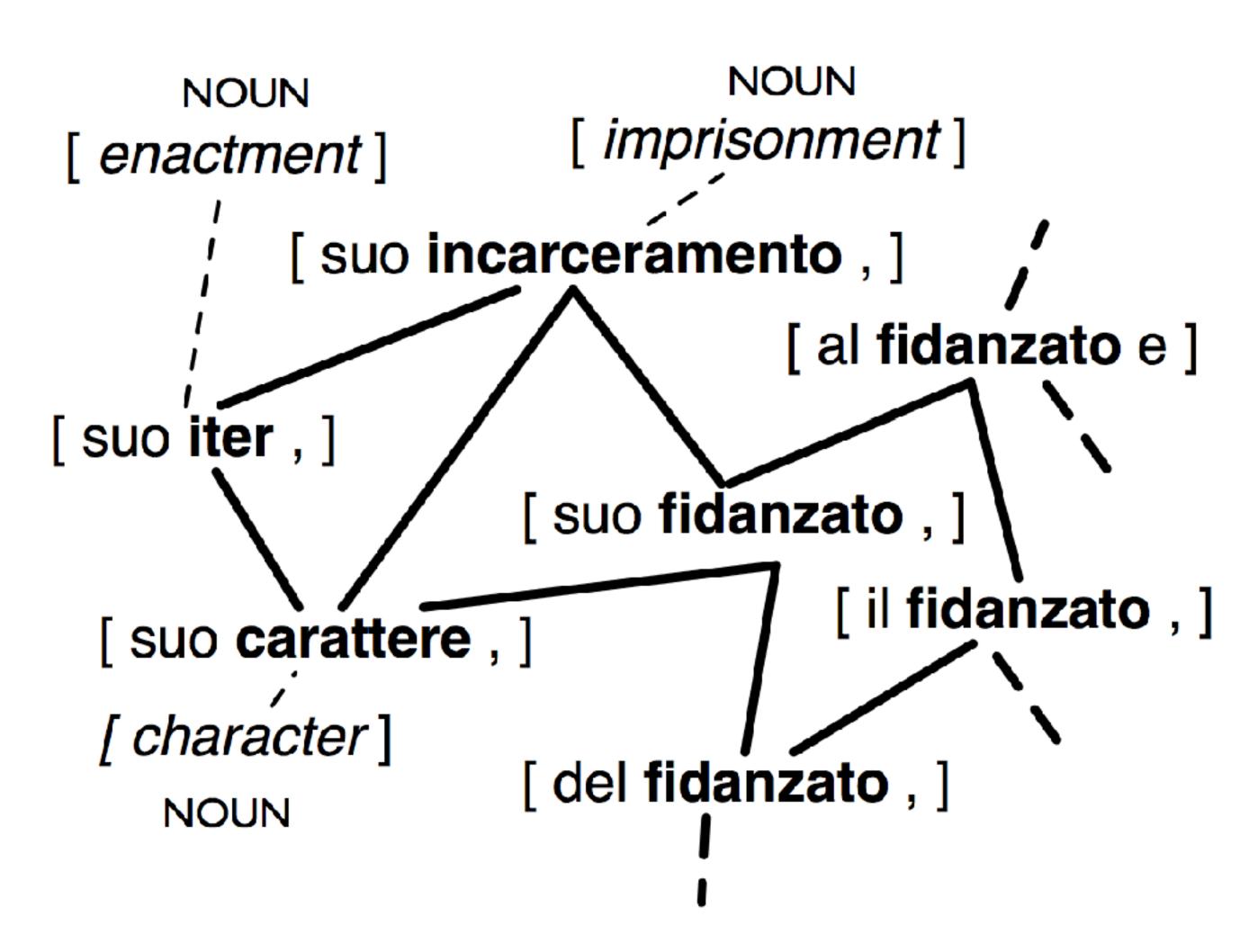
8: Return  $\Theta^f$ 



Das and Petrov (2011) I **like** it love it he **loves** it she loves it edge weights based on alignments (middle word ' adore un peu must be aligned) l' aime beaucoup l' adore beaucoup edge weights based on similarity of contexts these trigrams occur in

▶ Each node is associated with a distribution over tags, label propagation updates these using the graph





Das and Petrov (2011)



- Label propagation: encourages nodes with higher-weight edges between them to have similar tags
- ▶ Take these trigrams and treat them as "soft training examples" and learn an HMM tagger
- Prune to only keep tags above some probability to get the lexicon (valid tag-word pairs)



	Model	Danish	Dutch	German	Greek	Italian	Portuguese	Spanish	Swedish	Avg
	EM-HMM	68.7	57.0	75.9	65.8	63.7	62.9	71.5	68.4	66.7
baselines	Feature-HMM	69.1	65.1	81.3	71.8	68.1	78.4	80.2	<b>70.</b> 1	73.0
	Projection	73.6	77.0	83.2	79.3	79.7	82.6	80.1	74.7	78.8
our annroach	No LP	79.0	78.8	82.4	76.3	84.8	87.0	82.8	79.4	81.3
our approach	With LP	83.2	<b>79.5</b>	82.8	<b>82.5</b>	86.8	<b>87.9</b>	84.2	80.5	83.4
oracles	TB Dictionary	93.1	94.7	93.5	96.6	96.4	94.0	95.8	85.5	93.7
oracies	Supervised	96.9	94.9	98.2	97.8	95.8	97.2	96.8	94.8	96.6

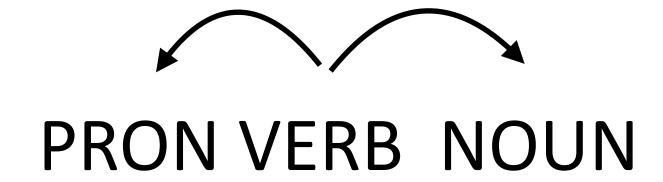
- ► EM-HMM/feature HMM: unsupervised methods with a greedy mapping from learned tags to gold tags
- Projection: project tags across bitext to make pseudogold corpus, train on that

Das and Petrov (2011)



# Cross-Lingual Parsing

- Now that we can POS tag other languages, can we parse them too?
- Direct transfer: train a parser over POS sequences in one language, then apply it to another language

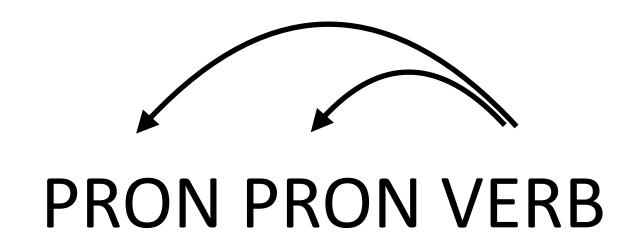


I like tomatoes



PRON VERB PRON

I like them



Je les aime

Even though we've never seen this sequence in English and don't know the words, we can still figure it out

McDonald et al. (2011)



# Cross-Lingual Parsing

	best-source		avg-source	gold	l-POS	pred-POS	
	source	gold-POS	gold-POS	multi-dir.	multi-proj.	multi-dir.	multi-proj.
da	it	48.6	46.3	48.9	49.5	46.2	47.5
de	n1	55.8	48.9	56.7	56.6	51.7	52.0
el	en	63.9	51.7	60.1	65.1	58.5	63.0
es	it	68.4	53.2	64.2	64.5	55.6	56.5
it	pt	69.1	58.5	64.1	65.0	56.8	58.9
nl	el	62.1	49.9	55.8	65.7	54.3	64.4
pt	it	74.8	61.6	74.0	75.6	67.7	70.3
sv	pt	66.8	54.8	65.3	68.0	58.3	62.1
avg		63.7	51.6	61.1	63.8	56.1	59.3

- Multi-dir: transfer a parser trained on several source treebanks to the target language
- Multi-proj: more complex annotation projection approach



# Cross-Lingual Embeddings

- Learn a shared multilingual embedding space so *any* neural system can transfer over
- multiCluster: use bilingual dictionaries to form clusters of words that are translations of one another, replace corpora with cluster IDs, train "monolingual" embeddings over all these corpora
- multiCCA: "project" all other languages into English
  - ▶ CCA: learn a projection of aligned data points into a shared space



# Cross-Lingual Embeddings

Task	multiCluster	multiCCA
dependency parsing	48.4 [72.1]	<b>48.8</b> [69.3]
doc. classification	90.3 [52.3]	91.6 [52.6]
mono. wordsim	14.9 [71.0]	43.0 [71.0]
cross. wordsim	12.8 [78.2]	66.8 [78.2]
word translation	30.0 [38.9]	<b>83.6</b> [31.8]

Word vectors work pretty well at "intrinsic" tasks, some improvement on things like document classification and dependency parsing as well



### Where are we now?

- Universal dependencies: treebanks (+ tags) for 70+ languages
- Many languages are still small, so projection techniques may still help
- More corpora in other languages, less and less reliance on structured tools like parsers, and pretraining on unlabeled data means that performance on other languages is better than ever
- ▶ BERT has pretrained multilingual models that seem to work pretty well (trained on a whole bunch of languages)

# Takeaways

- Many languages have richer morphology than English and pose distinct challenges
- Problems: how to analyze rich morphology, how to generate with it
- Can leverage resources for English using bitexts

Next time: wrapup + ethics of NLP