Multilinguality

Dealing with other languages

- Other languages present some problems not seen in English at all!
- Some of our algorithms have been specified to 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

- Morphological richness: 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 become**s**

  - Mostly applies to verbs and nouns

Morphological Inflection

- In English: I arrive 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
(simple tenses)	present	arrive /a.ʁiv/	arrives /a.ʁiv/	arrive /a.ʁiv/	arrivons /a.ʁi.vɔ̃/	arrivez /a.ʁi.ve/	arrivent /a.ʁiv/
	imperfect	arrivais /a.ʁi.vɛ/	arrivais /a.ʁi.vɛ/	arrivait /a.ʁi.vɛ/	arrivions /a.ʁi.vjɔ̃/	arriviez /a.ʁi.vje/	arrivaient /a.ʁi.vɛ/
	past historic[2]	arrivai /a.ʁi.vɛ/	arrivas /a.ʁi.va/	arriva /a.ʁi.va/	arrivâmes /a.ʁi.vam/	arrivâtes /a.ʁi.vat/	arrivèrent /a.ʁi.vɛʁ/
	future	arriverai /a.ʁi.vʁɛ/	arriveras /a.ʁi.vʁa/	arrivera /a.ʁi.vʁa/	arriverons /a.ʁi.vʁɔ̃/	arriverez /a.ʁi.vʁe/	arriveront /a.ʁi.vʁɔ̃/
	conditional	arriverais /a.ʁi.vʁɛ/	arriverais /a.ʁi.vʁɛ/	arriverait /a.ʁi.vʁɛ/	arriverions /a.ʁi.və.ʁjɔ̃/	arriveriez /a.ʁi.və.ʁje/	arriveraient /a.ʁi.vʁɛ/

Morphological Inflection

- In Spanish:

		singular			plural		
		1st person	2nd person	3rd person	1st person	2nd person	3rd person
indicative		yo	tú vos	él/ella/ello usted	nosotros nosotras	vosotros vosotras	ellos/ellas ustedes
	present	llego	llegas tú llegás vos	llega	llegamos	llegáis	llegan
	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[1]	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

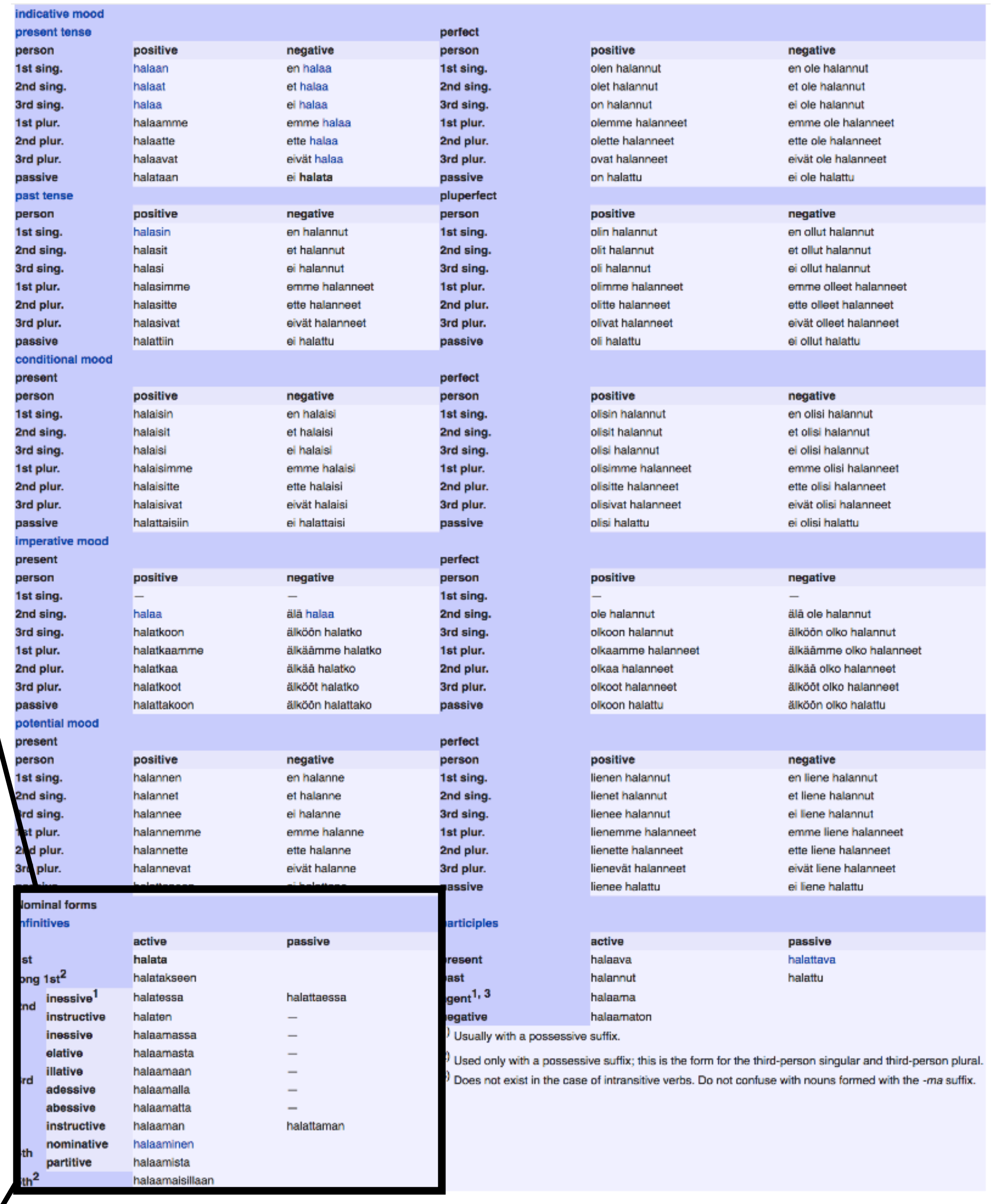
Irregular Inflection

- Common words are often irregular
  - I am / you are / she is
  - Je suis / tu es / elle est
  - Soy / está / es
- Less common words typically fall into some regular *paradigm* — these are somewhat predictable

Agglutinating Langauges

- Finnish/Hungarian (Finno-Ugric), also Turkish: what a preposition would do in English is instead part of the verb

		active	passive
1st		halata	
long 1st[2]		halatakseen	
2nd	inessive[1]	halatessa	halattaessa
	instructive	halaten	—
3rd	inessive	halaamassa	—
	elative	halaamasta	—
	illative	halaamaan	—
	adessive	halaamalla	—
	abessive	halaamatta	—
	instructive	halaaman	halattaman
4th	nominative	halaaminen	
	partitive	halaamista	
5th[2]		halaamaisillaan	



halata: “hug”

illative: “into”

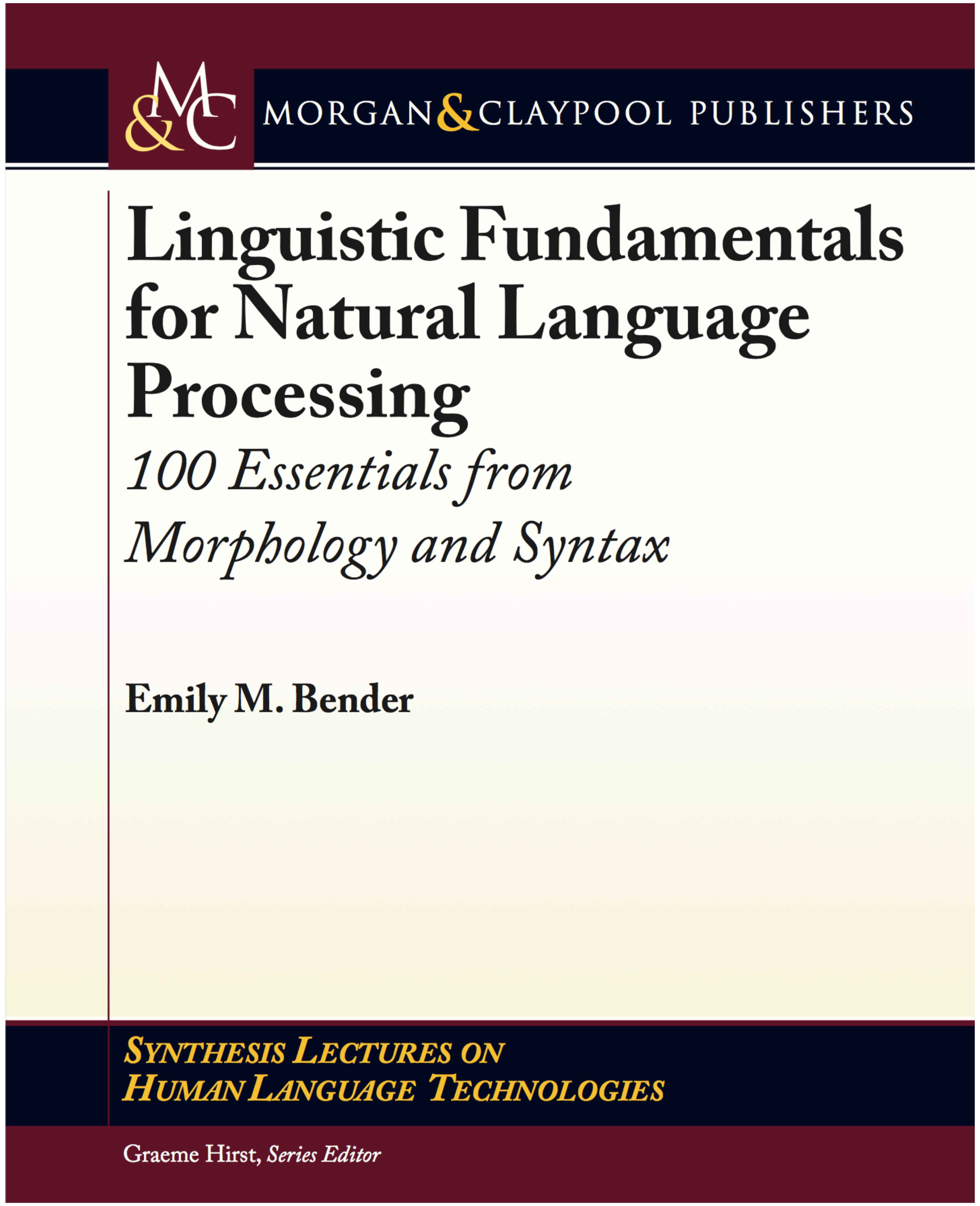
adessive: “on”

- 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
  - 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



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

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 .

n=singular|case=nominative|proper=no

deg=positive|n=singular|case=nominative

n=singular|case=nominative|proper=no

n=singular|case=accusative|proper=no|pperson=3rd|pnumber=singular

mood=indicative|t=present|p=3rd|n=singular|def=yes

Morphological Analysis

- Given a word in context, need to predict what its morphological features are
- Basic approach: combines two modules:
  - Lexicon: tells you what possibilities are for the word
  - 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

- Inflection: given base form + features, inflect the word
- Hard for unknown words — need models that generalize

w i n d e n →

conjugation of winden [hide ▲]

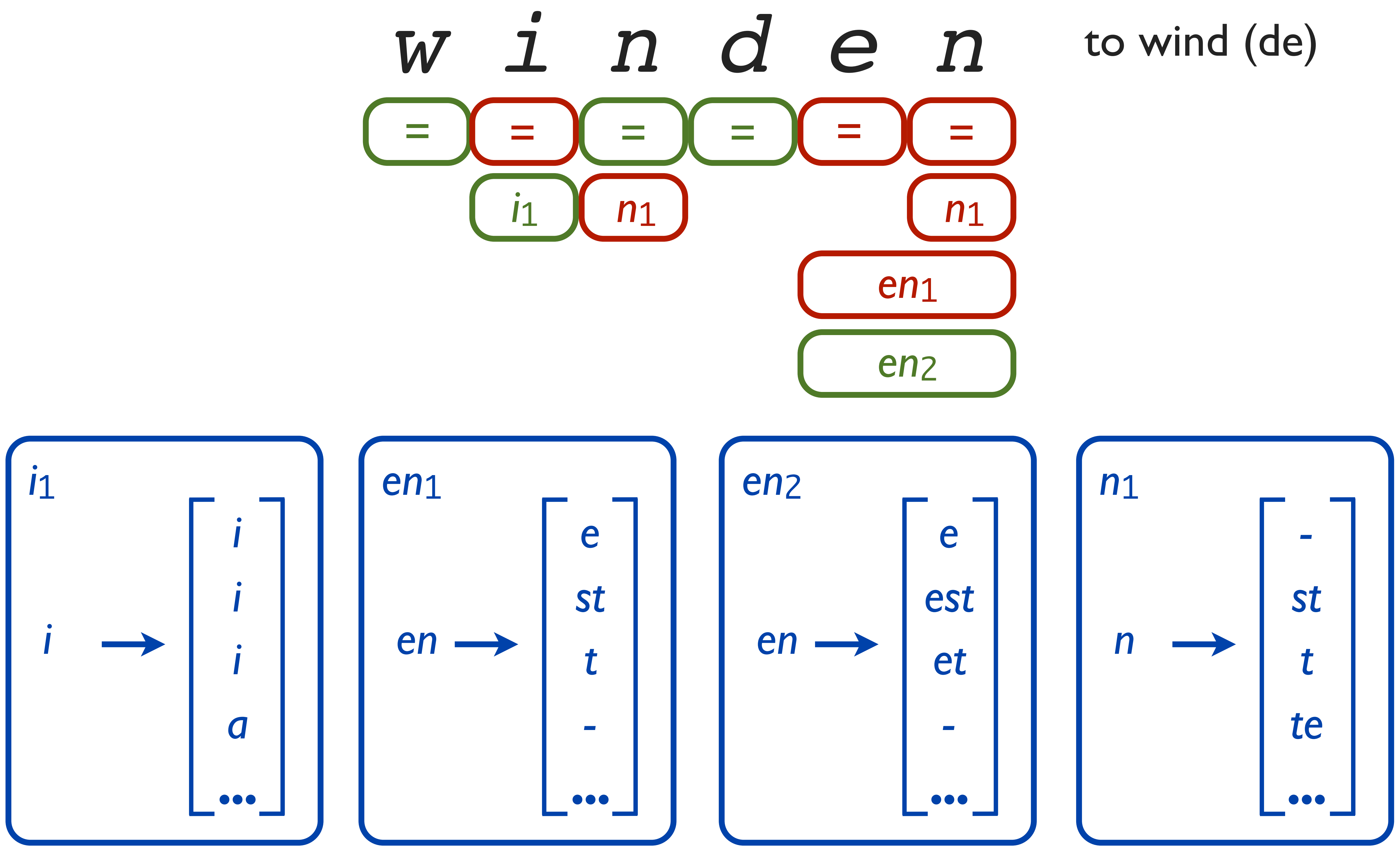
infinitive	winden				
present participle	windend				
past participle	gewunden				
auxiliary	haben				
	indicative			**subjunctive**	
present	ich winde	wir **winden**	**i**	ich winde	wir **winden**
	du windest	ihr windet		du windest	ihr windet
	er windet	sie **winden**		er winde	sie **winden**
preterite	ich wand	wir wanden	**ii**	ich wände	wir wänden
	du wandest	ihr wandet		du wändest	ihr wändet
	er wand	sie wanden		er wände	sie wänden
imperative	winde (du)	windet (ihr)			

composed forms of winden [show ▼]

Durrett and DeNero (2013)

Predicting Inflection

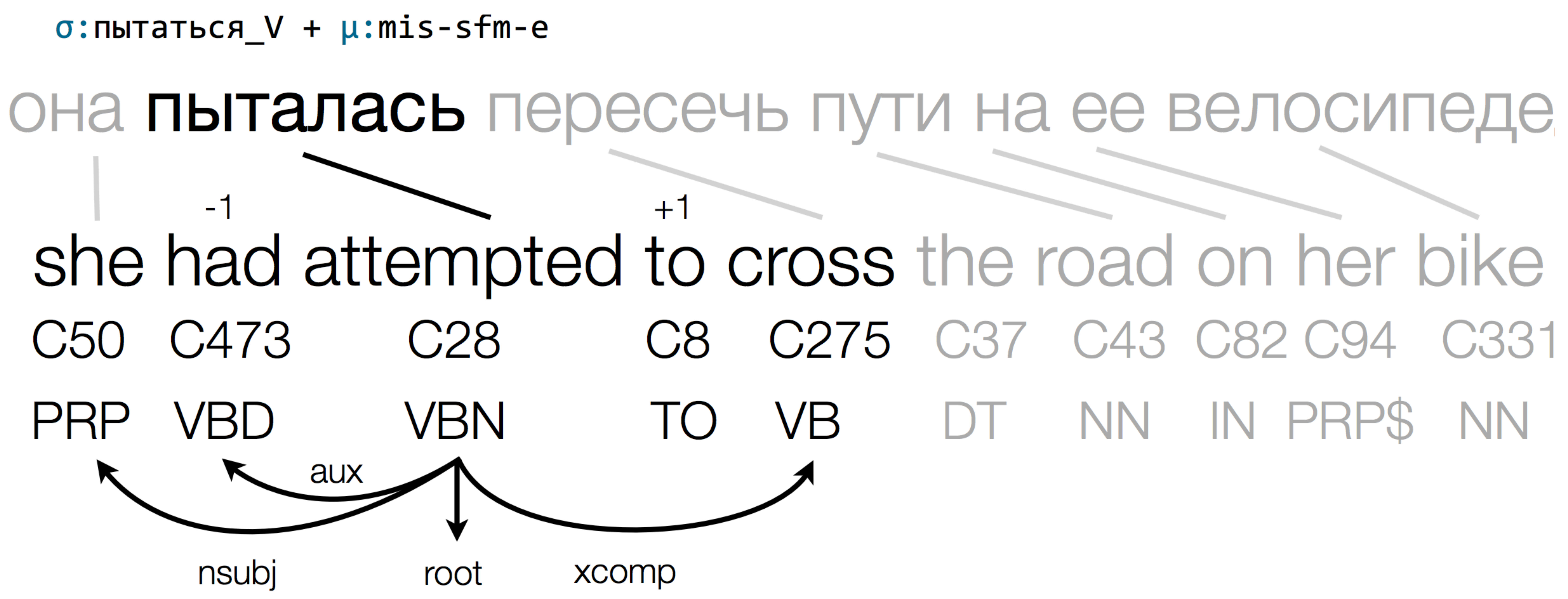
- Inflection: given base form + features, inflect the word
- Hard for unknown words — need models that generalize
- Take a bunch of existing verbs from Wiktionary, extract these change rules using character alignments



Change describes how *i* changes for 1st person sg, 2nd person sg, …

Durrett and DeNero (2013)

Morphological Reinflection



- 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 we do this?

Creutz and Lagus (2002)

Morpheme Segmentation

- Simple probabilistic model $\text{Cost}(\text{Source text}) = \sum_{\text{morph tokens}} -\log p(m_i)$
- $p(m_i)$ = 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".

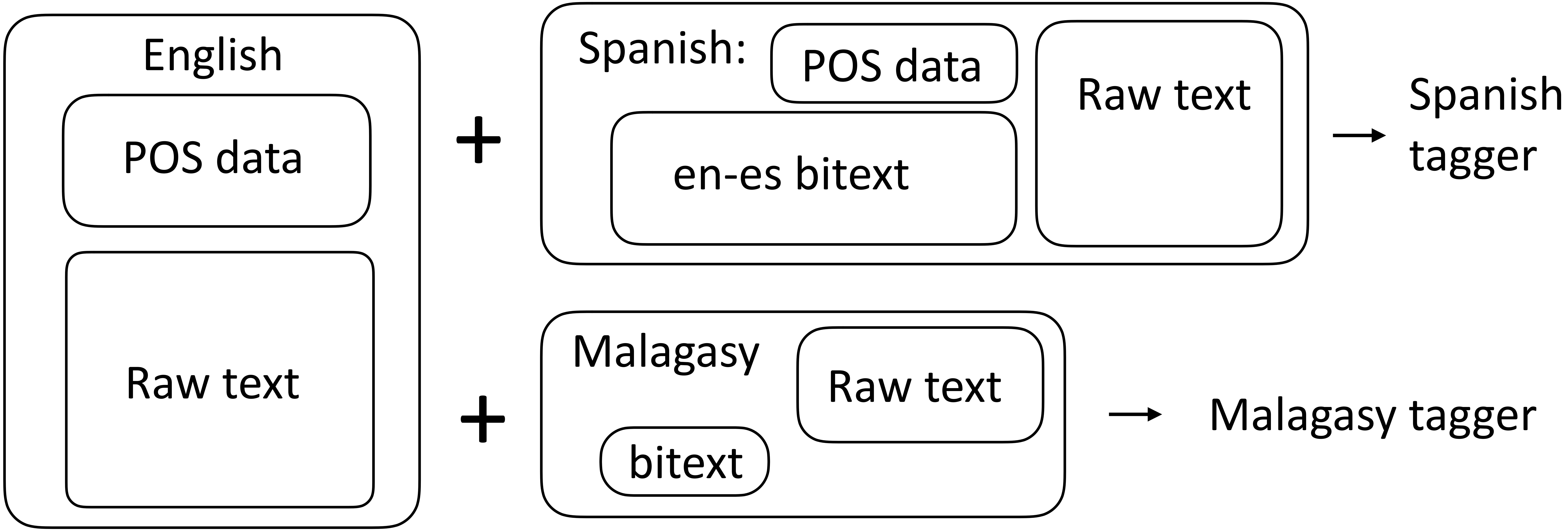
- separating nouns and pre-modifying adjectives:
  高血压 (*high blood pressure*)
  → 高(*high*) 血压(*blood pressure*)
- separating compound nouns:
  内政部 (*Department of Internal Affairs*)
  → 内政(*Internal Affairs*) 部(*Department*).

Chen et al. (2015)

Cross-Lingual Tagging and Parsing

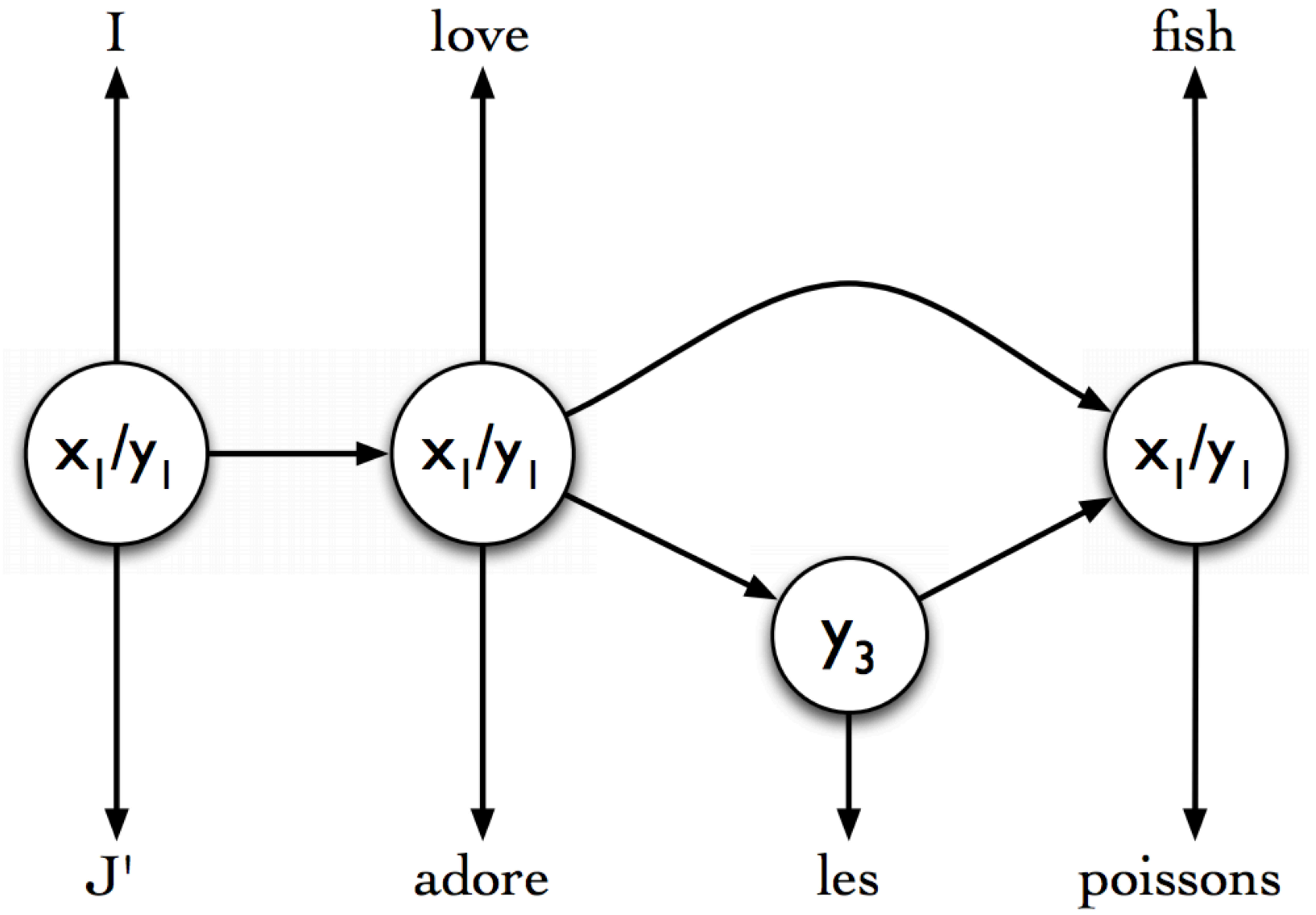
Cross-Lingual Tagging

- Labeling POS datasets is expensive
- Can we transfer annotation from *high-resource* languages (English, etc.) to *low-resource* languages?



Cross-Lingual Tagging

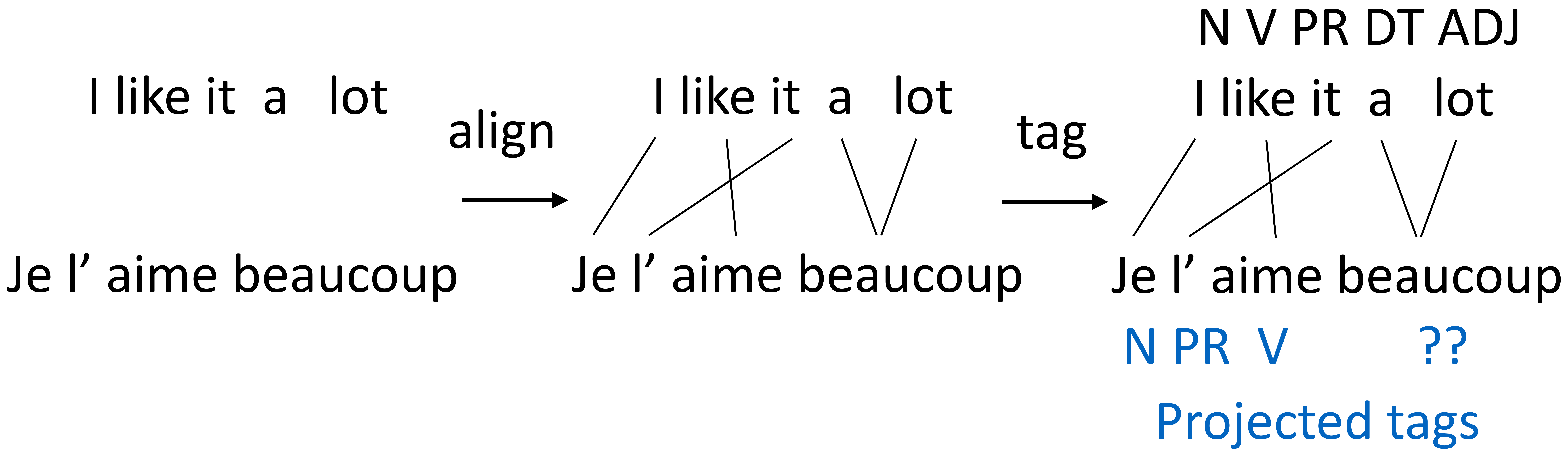
- Multilingual POS induction
- Generative model of two languages simultaneously, joint alignment + tag learning
- Complex generative model, requires Gibbs sampling for inference



Snyder et al. (2008)

Cross-Lingual Tagging

- Rather than doing unsupervised learning, can we use supervised learning in combination with alignments?



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

Das and Petrov (2011)

Cross-Lingual Tagging

Das and Petrov (2011)

I **like** it

I **love** it

he **loves** it

she **loves** it

edge weights based on alignments (middle word must be aligned)

l' **aime** beaucoup

l' **adore** un peu

l' **adore** beaucoup

edge weights based on similarity of contexts these trigrams occur in

- Add links between words in similar contexts on each side. Can help resolve words that otherwise would be tricky

Cross-Lingual Tagging

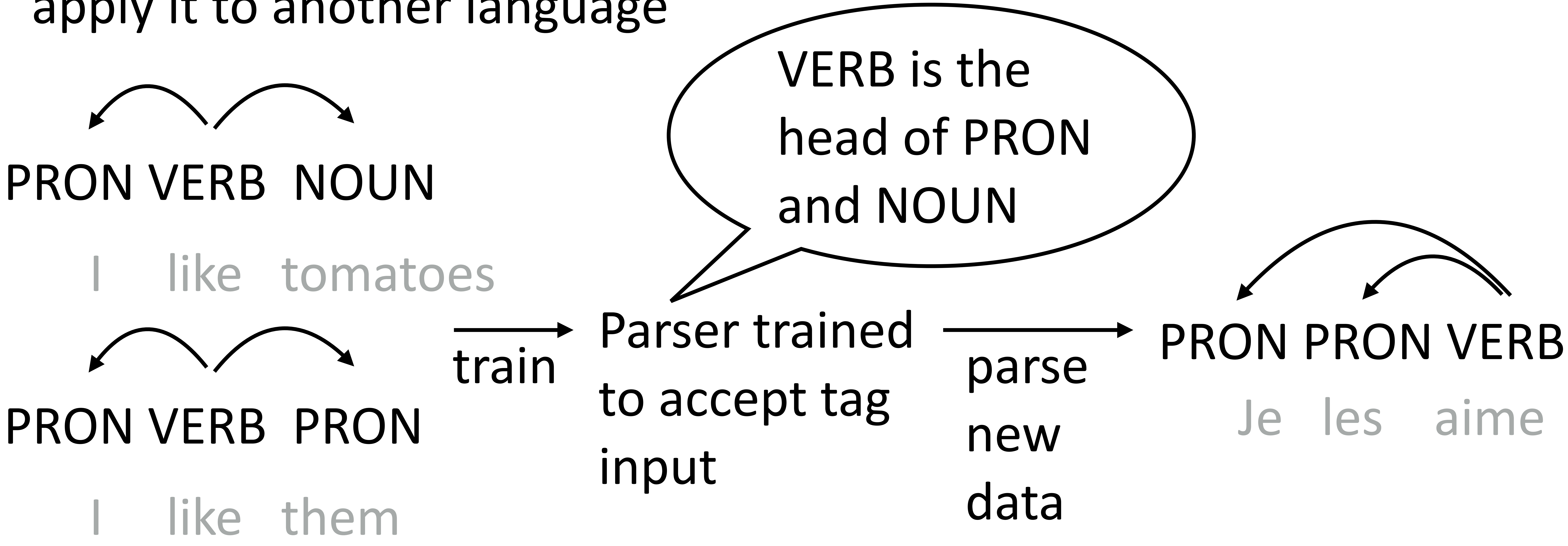
	Model	Danish	Dutch	German	Greek	Italian	Portuguese	Spanish	Swedish	Avg
baselines	EM-HMM	68.7	57.0	75.9	65.8	63.7	62.9	71.5	68.4	66.7
	Feature-HMM	69.1	65.1	81.3	71.8	68.1	78.4	80.2	70.1	73.0
	Projection	73.6	77.0	83.2	79.3	79.7	82.6	80.1	74.7	78.8
our approach	No LP	79.0	78.8	82.4	76.3	84.8	87.0	82.8	79.4	81.3
	With LP	**83.2**	**79.5**	82.8	**82.5**	**86.8**	**87.9**	**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*
	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
- LP: add monolingual connections and run “label propagation”

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



McDonald et al. (2011)

Cross-Lingual Parsing

	best-source		avg-source	gold-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	nl	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

McDonald et al. (2011)

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

I do it	I = Je = 1, le = it = 2, fais = do = 3	1 3 2
Je le fais		1 2 3

Ammar et al. (2016)

Cross-Lingual Embeddings

Task	multiCluster	multiCCA
dependency parsing	48.4 [**72.1**]	**48.8** [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**]	**83.6** [31.8]

- CCA = canonical correlation analysis
- Word vectors work pretty well at "intrinsic" tasks, some improvement on things like document classification and dependency parsing as well

Ammar et al. (2016)

Where are we now?

- Universal dependencies: treebanks (+ tags) for 70+ languages
- Many languages are still small, so projection techniques may still help
- More corpora are getting annotated 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 + discussion of ethics