



Recap: BERT



Announcements

- ▶ FP check-in due today, will be returned soon
- ▶ A4 back today, A5 back soon
- ▶ eCIS evaluations: please fill these out

Multilinguality



Dealing with other languages

- ▶ Other languages present some challenges 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?



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

Morphology



- ▶ Study of how words form
- ▶ Derivational morphology: create a new *lexeme* from a base
 - estrane (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



- 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	arrives	arrive	arrivons	arrivez	arrivent
		/a.ʁiv/	/a.ʁiv/	/a.ʁiv/	/a.ʁi.vɔ̃/	/a.ʁi.vɛ/	/a.ʁiv/
	imperfect	arrivais	arrivais	arrivait	arrivions	arriviez	arrivaient
		/a.ʁi.vɛ/	/a.ʁi.vɛ/	/a.ʁi.vɛ/	/a.ʁi.vjɔ̃/	/a.ʁi.vjɛ/	/a.ʁi.vɛ/
	past historic ²	arrivai	arrivas	arriva	arrivâmes	arrivâtes	arrivèrent
		/a.ʁi.vɛ/	/a.ʁi.va/	/a.ʁi.va/	/a.ʁi.vam/	/a.ʁi.vat/	/a.ʁi.vɛs/
	future	arriverai	arriveras	arrivera	arriverons	arriverez	arriveront
		/a.ʁi.vʁɛ/	/a.ʁi.vʁa/	/a.ʁi.vʁa/	/a.ʁi.vʁɔ̃/	/a.ʁi.vʁɛ/	/a.ʁi.vʁɔ̃/
conditional	arriverais	arriverais	arriverait	arriverions	arriveriez	arriveraient	
	/a.ʁi.vʁɛ/	/a.ʁi.vʁɛ/	/a.ʁi.vʁɛ/	/a.ʁi.və.ʁijɔ̃/	/a.ʁi.və.ʁjɛ/	/a.ʁi.vʁɛ/	



Morphological Inflection

- In Spanish:

		singular			plural		
		1st person	2nd person	3rd person	1st person	2nd person	3rd person
		yo	tú vos	él/ella/ello usted	nosotros nosotras	vosotros vosotras	ellos/ellas ustedes
indicative	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	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 Languages

- 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 instructive halaten inessive halaamassa elative halaamasta illative halaamaan adessive halaamalla abessive halaamatta instructive halaaman nominative halaaminen partitive halaamista	halattaessa — — — — — halattaman
3rd		
4th		
5th ²	halaamaisillaan	

illative: “into”

adessive: “on”

halata: “hug”

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

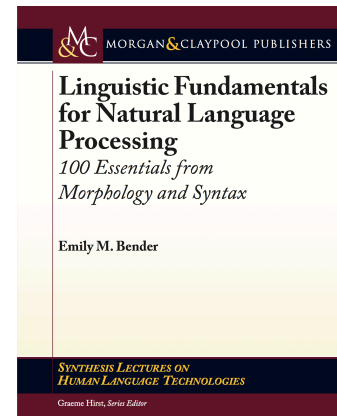


Morphologically-Rich Languages

- ▶ 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, lexical features on words and word vectors are pretty effective
- ▶ In other languages, **lots** more unseen words due to rich morphology! 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: Hungarian

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 | person=3rd | number=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)



Morphological Inflection

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

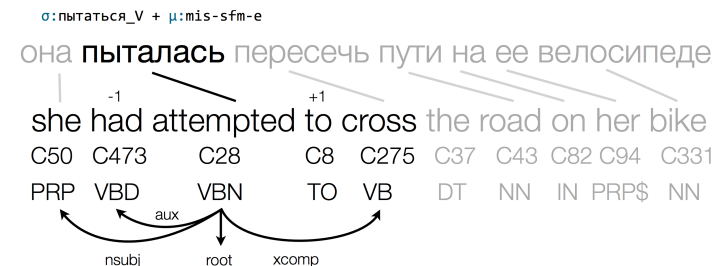
w i n d e n →

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)



Morphological Inflection



- 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)



Chinese Word Segmentation

- 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:
民政部 (*Department of Internal Affairs*)
→ 内政(*Internal Affairs*) 部(*Department*).

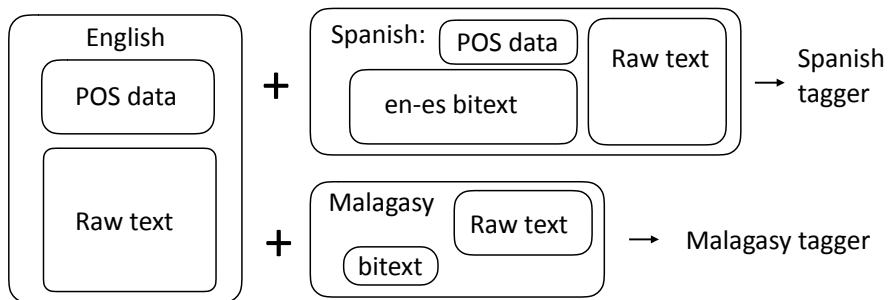
Chen et al. (2015)

Cross-Lingual Tagging and Parsing



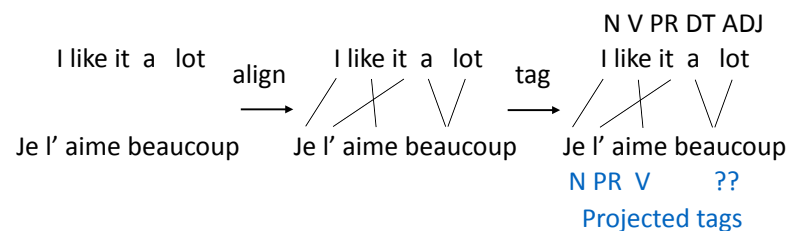
Cross-Lingual Tagging

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



Cross-Lingual Tagging

- Can we leverage word alignment here?



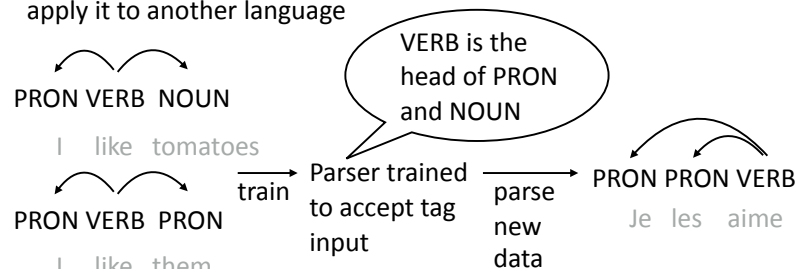
- Tag with English tagger, project across bitext, train French tagger?
Works pretty well

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

	source	best-source	avg-source	gold-POS		pred-POS	
		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 Word Representations



Multilingual Embeddings

- Input: corpora in many languages. Output: embeddings where similar words *in different languages* have similar embeddings

I have an apple
47 24 18 427

J' ai des oranges
47 24 89 1981

ID: 24
ai have

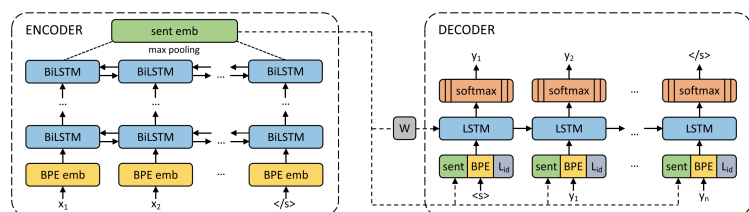
ID: 47
I Je J'

- 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
- Works okay but not all that well

Ammar et al. (2016)



Multilingual Sentence Embeddings



- Form BPE vocabulary over all corpora (50k merges); will include characters from every script
 - Take a bunch of bitexts and train an MT model between a bunch of language pairs with shared parameters, use W as sentence embeddings
- Artetxe et al. (2019)



Multilingual Sentence Embeddings

		EN	EN → XX													
			fr	es	de	el	bg	ru	tr	ar	vi	th	zh	hi	sw	ur
Zero-Shot Transfer, one NLI system for all languages:																
Conneau et al. (2018b)	X-BiLSTM	73.7	67.7	68.7	67.7	68.9	67.9	65.4	64.2	64.8	66.4	64.1	65.8	64.1	55.7	58.4
	X-CBOW	64.5	60.3	60.7	61.0	60.5	60.4	57.8	58.7	57.5	58.8	56.9	58.8	56.3	50.4	52.2
	Transformer	<u>81.4</u>	—	<u>74.3</u>	70.5	—	—	—	—	62.1	—	—	63.8	—	—	58.3
Proposed method	BiLSTM	73.9	71.9	72.9	72.6	72.8	74.2	72.1	69.7	71.4	72.0	69.2	71.4	65.5	62.2	61.0

- Train a system for NLI (entailment/neutral/contradiction of a sentence pair) on English and evaluate on other languages

Artetxe et al. (2019)



Multilingual BERT

- Take top 104 Wikipedias, train BERT on all of them simultaneously
- What does this look like?

Beethoven may have proposed unsuccessfully to Therese Malfatti, the supposed dedicatee of "Für Elise"; his status as a commoner may again have interfered with those plans.

当人们在马尔法蒂身后发现这部小曲的手稿时，便误认为上面写的是“Für Elise”（即《给爱丽丝》）[51]。

Китай (официально — Китайская Нарóдная Респу́блика, сокращённо — КНР; кит. trad. 中華人民共和國, упр. 中华人民共和国, пиньинь: Zhōnghuá Rénmín

Devlin et al. (2019)



Multilingual BERT: Results

Fine-tuning \ Eval	EN	DE	NL	ES	Fine-tuning \ Eval	EN	DE	ES	IT
EN	90.70	69.74	77.36	73.59	EN	96.82	89.40	85.91	91.60
DE	73.83	82.00	76.25	70.03	DE	83.99	93.99	86.32	88.39
NL	65.46	65.68	89.86	72.10	ES	81.64	88.87	96.71	93.71
ES	65.38	59.40	64.39	87.18	IT	86.79	87.82	91.28	98.11

Table 1: NER F1 results on the CoNLL data.

Table 2: POS accuracy on a subset of UD languages.

- Can transfer BERT directly across languages with some success
- ...but this evaluation is on languages that all share an alphabet

Pires et al. (2019)



Multilingual BERT: Results

	HI	UR		EN	BG	JA
HI	97.1	85.9	EN	96.8	87.1	49.4
UR	91.1	93.8	BG	82.2	98.9	51.6
			JA	57.4	67.2	96.5

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

- ▶ Urdu (Arabic script) => Hindi (Devanagari). Transfers well despite different alphabets!
- ▶ Japanese => English: different script and very different syntax

Pires et al. (2019)



Scaling Up: XLM-R

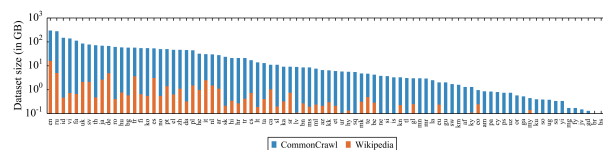


Figure 1: Amount of data in GiB (log-scale) for the 88 languages that appear in both the Wiki-100 corpus used for mBERT and XLM-100, and the CC-100 used for XLM-R. CC-100 increases the amount of data by several orders of magnitude, in particular for low-resource languages.

- ▶ Larger “Common Crawl” dataset, better performance than mBERT
- ▶ Low-resource languages benefit from training on other languages
- ▶ High-resource languages see a small performance hit, but not much

Conneau et al. (2019)



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
- ▶ Multilingual models seem to be working better and better — but still many challenges for low-resource settings



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