Massively Multilingual Neural Grapheme-to-Phoneme Conversion

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Outline

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Grapheme-to-Phoneme Conversion

Convert orthography to pronunciation

- Graphemes: the abstract units of writing
- Phonemes: the abstract units of sound
- Figure out the relationship

Problem: scaling down to low resource languages

Figure: "Just sound it out..."

Grapheme-to-Phoneme Conversion

How do you build a system for a low resource language?

- Rule-based systems need language-specific expertise, which you don't have
- Statistical systems need annotated data, which you don't have

This seems intractable, but...

Idea

Train a single system for all languages

- A handful of scripts (Latin, Cyrillic, Arabic) cover most languages
- Spelling rules are similar cross-linguistically:
  English: <real> = /ɹiəl/
  Spanish: <real> = /real/
  German: <real> = /ʁeal/
  Brazilian Portuguese: <real> = /xeaw/
- Solve the data sparsity problem by letting low resource languages learn from high resource data

But traditional models can't take advantage of these similarities

- /ɹ/ and /ʁ/ are just different phonemes
- Solve it with a sequence-to-sequence model: details next section

Outline

Architecture

Fairly vanilla sequence-to-sequence model

- Basically OpenNMT (Klein et al., 2017) defaults, but with smaller embeddings and layers
- Global attention
- Bidirectional LSTM encoder
- Completely character-level
- Language indicated with token (Johnson et al., 2016) or language embedding (Östling & Tiedemann, 2017) on source side

The key point:

- Grapheme and phoneme embeddings are shared across all languages
- This captures our intuition: a grapheme usually mean similar things in different languages

Experiments

Dataset

- Deri & Knight (2016)'s corpus scraped from Wiktionary, cleaned to conform to Phoible (Moran et al., 2014).
- 311 languages to train, 507 to test
- We limit to 9000 words per language
- Evaluation on high and low resource subsets of test data

Training

- Stochastic Gradient Descent
- 64 words per mini-batch

Baseline

- Deri & Knight's system
- WFST models for high resource languages adapted for low resource languages
- Linguistic knowledge guides adaptation

Evaluation Metrics

- Phoneme Error Rate (PER): the Levenshtein distance between predicted and gold standard phoneme sequences, divided by the length of the gold length.
- Word Error Rate (WER): percentage of words in which the predicted and gold phoneme sequences do not match.
- Word Error Rate at 100 (WER 100): the percentage of words for which none of the first 100 guesses is correct.

Metrics are averaged across languages, weighting all equally

Results

Model	WER	WER 100	PER
wFST w/ adaptation	88.04	69.80	48.01
seq2seq w/ LangID feature	**71.94**	**40.69**	**35.38**
seq2seq w/ LangID token	74.10	43.23	37.85
seq2seq w/o LangID	83.65	47.13	51.87

Table: Results on the 229 language 'adapted' set, a mix of high- and low-resource languages. More details: (Peters et al., 2017)

But is there a benefit over a monolingually-trained network?

Results

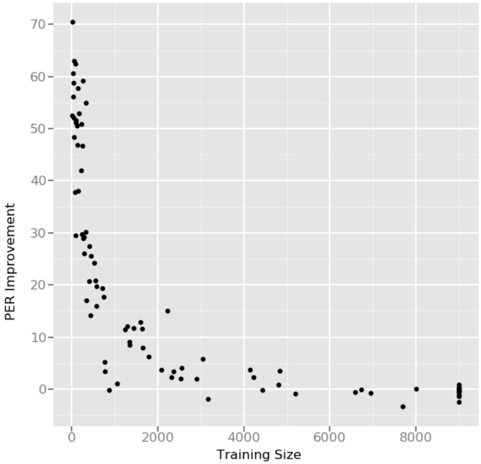
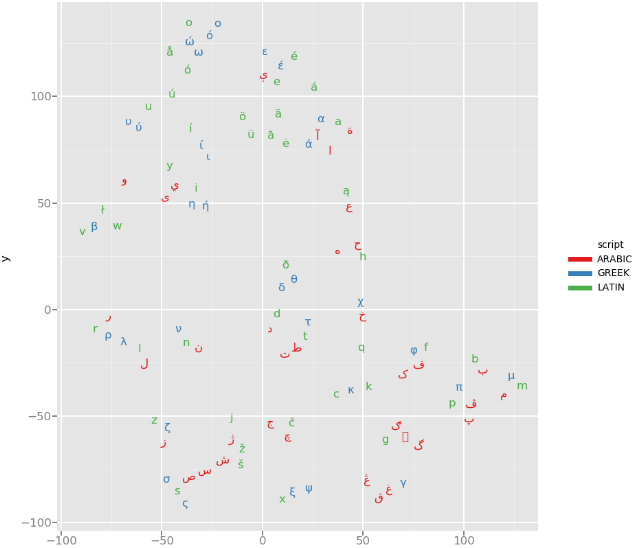
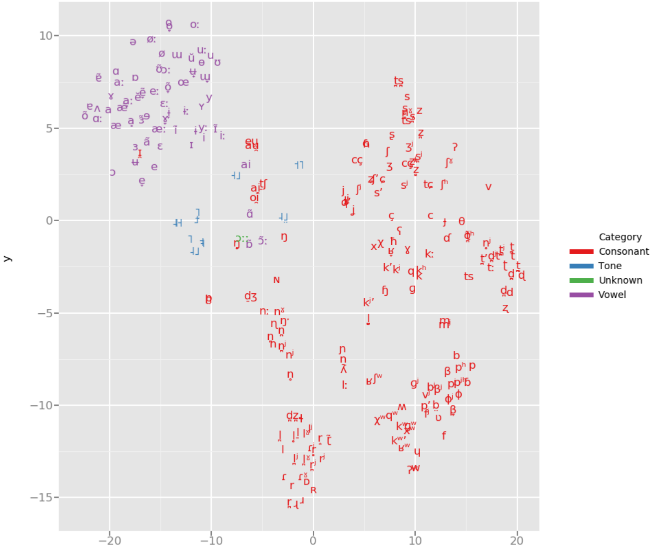


Figure: Training Size vs. Improvement over monolingual NN

Grapheme Embeddings



Phoneme Embeddings



Example Output

Identifying the language has a big effect on the system output

Language	**Pronunciation**
English	dʒuːæɪs
German	jʊtsə
Spanish	xwiθe̞
Italian	dʒuitʃe
Portuguese	ʒwisĩ
Turkish	ʒʊɪd̪ʒɛ
Arabic	juːis

Table: Pronunciations of ‘juice’ learned by the model

Outline

Data Cleaning

How do you clean multilingual data consistently?

- Different phonetic features matter in different languages
- Suprasegmentals matter
- How do you evaluate data cleaning (see Hixon et al., 2011)?

segment	consonantal	trill	anterior	distributed
ɹ	-	-	-	+
r	+	+	+	-

segment	consonantal	lateral	anterior	distributed
ɹ	-	-	-	+
l	+	+	+	-

Figure: ɹ is the same distance from l as from r

Linguistic Knowledge

How do we encode things we know that we can't get from the data?

- Great results for Serbo-Croat-Bosnian (tons of data in corpus)
- Much worse for Serbian, Croat, Bosnian (much less)

One possibility: directly use typology as extra input (Tsvetkov et al., 2016)

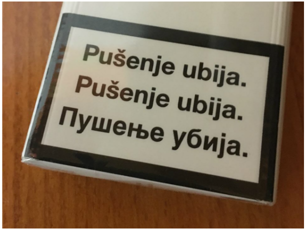


Figure: "Multilingual" labeling

Other Ideas

Multilinguality

- Output softmax layer gives probability distribution over union of all phoneme inventories
- For any language, most of these phonemes are a priori impossible
- Language-specific softmax?

Attention

- Little reordering in g2p, alignments close to one-to-one
- Local or monotonic attention?

Jointly learn phoneme-to-grapheme

- Doubles training data
- Enables zero-shot transliteration

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