

Cross-language mapping for small-vocabulary ASR in under-resourced languages: Investigating the impact of source language choice

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Small-vocabulary recognition: Why & how

Cross-language pronunciation mapping

The Salaam method (Qiao et al. 2010)

Our contribution: Impact of source language choice

Data & method

Experimental results

Conclusions

Ongoing & future work

Goal: Enable non-experts to quickly develop basic speech-driven applications in any Under-Resourced Language (URL)

- ▶ Training/adapting recognizer takes data, expertise
- ▶ Many applications use ≤ 100 terms (e.g. Bali et al. 2013)

Strategy: Use **existing** HRL recognizer for small-vocab recognition in URLs (Sherwani 2009; Qiao et al. 2010)

Key: Mapped pronunciation lexicon

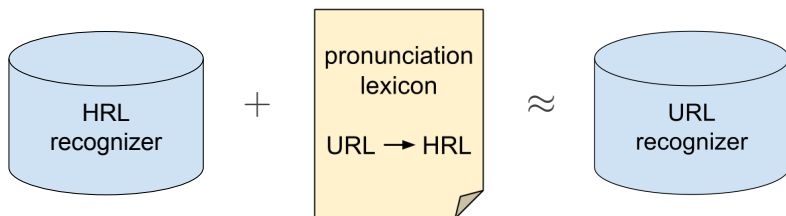
Terms in target lg. (URL) → Pronunciations in source lg. (HRL)

Yoruba		English
<i>igba</i>	<i>ig^hba</i>	→ <i>igbə</i> <i>ibə</i> ...?

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The Salaam Method (Qiao et al. 2010)

- ▶ Requires ≥ 1 sample per term (a few minutes of audio)
- ▶ Mimics phone decoding
- ▶ “Super-wildcard” recognition grammar:

$$term \rightarrow \{ * | * * | * ** \}_0^{10}$$

(* = any source-language phoneme)

- ▶ Iterative training algorithm finds confidence-ranked matches

$$igba \rightarrow ibæə, ibʌə, ibɛə, \dots$$

- ▶ Accuracy: $\approx 80\text{-}98\%$ for ≤ 50 terms

Hypothesis

More phoneme overlap between source/target languages →
Easier pronunciation-mapping → Higher recognition accuracy

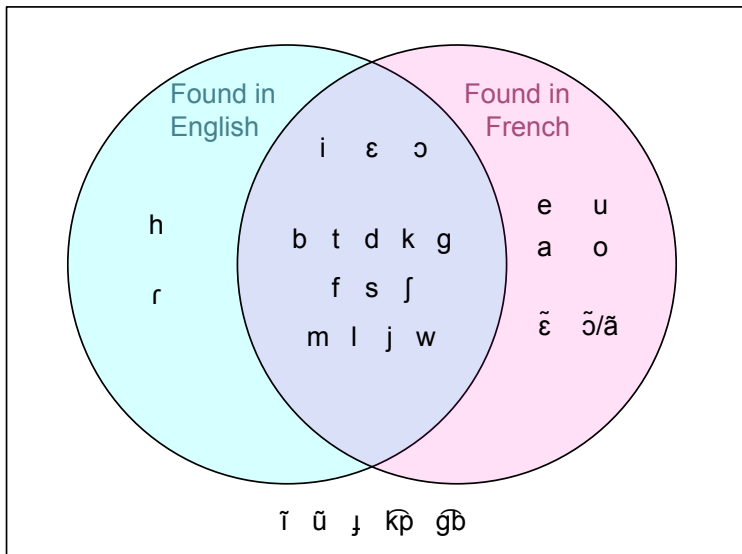
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Experiment

- ▶ Target language: Yoruba
- ▶ Source languages: English (US), French (France)

Phonemic segments of Yoruba



Data

- ▶ 25 Yoruba terms (subset of Qiao et al. 2010 dataset)
- ▶ 5 samples/term from 2 speakers (1 male, 1 female)
- ▶ Telephone quality (8 kHz)

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Method

- ▶ Generate Fr./En. lexicons with Salaam (Qiao et al. 2010)
 - Microsoft Speech Platform (msdn.microsoft.com/library/hh361572)
 - 1, 3, and 5 pronunciations per term

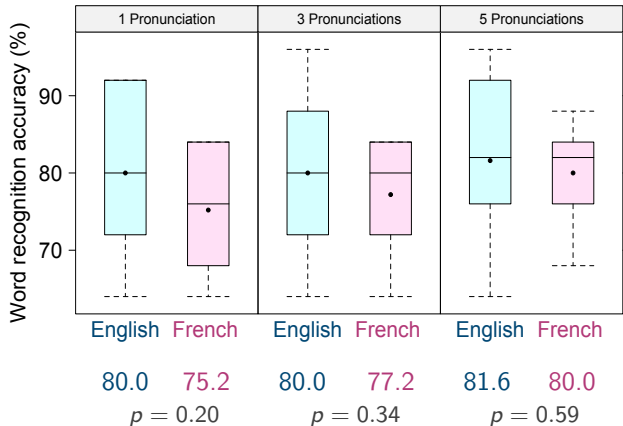
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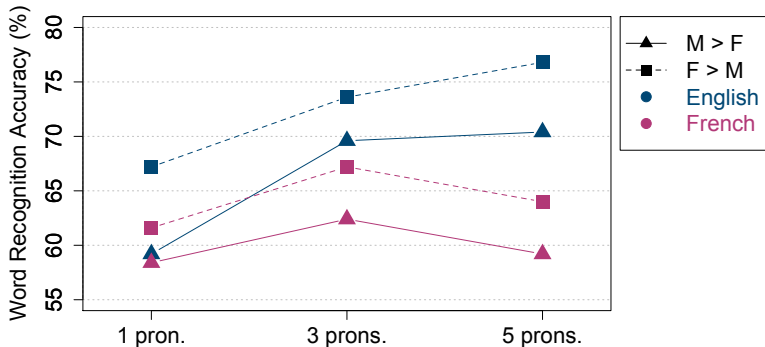
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 - Microsoft Speech Platform (msdn.microsoft.com/library/hh361572)
 - 1, 3, and 5 pronunciations per term
- ▶ Compare mean word recognition accuracy
 - Same-speaker: Leave-one-out
 - Cross-speaker: Train M > Test F; F>M
 - *t*-tests for significance ($\alpha = 0.05$)

Same-speaker accuracy



Cross-Speaker Accuracy



En. mean 63.2

Fr. mean 60.0

 $p (* \leq .05)$ 0.41

71.6

64.8

0.04*

73.6

61.6

0.04*

Accuracy by word type (**nasal**)

	English	French
Best	duro	ogba
	ogba	iba
	shii	mejo
	ogoji	ogoji
	mesan	lehin
	beeni	tunse
	:	:
	iba	mesan
	igba	ookan
	ogorun	sun
	meta	meji
	sun	bere
	meji	igba
Worst		

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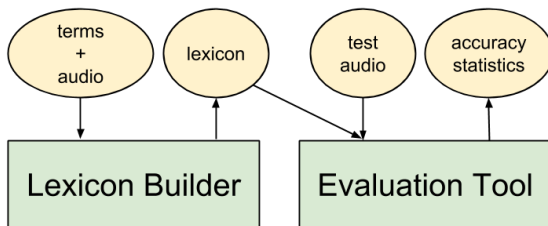
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Possible explanations:

- ▶ Source languages may be too similar w.r.t. target language
- ▶ Better metric needed for evaluating source-target match
- ▶ Baseline recognizer accuracy may play a role

lex4all: Pronunciation **Lexicons for Any Low-resource Language** (Vakil et al. 2014)



<http://lex4all.github.io/lex4all>

Planned experiments:

- ▶ More source-target language pairs
- ▶ Discriminative training (Chan and Rosenfeld 2012)
- ▶ Algorithm modifications

- ▶ K. Bali, S. Sitaram, S. Cuendet, and I. Medhi. “A Hindi speech recognizer for an agricultural video search application”. In: *ACM DEV*. 2013.
- ▶ H. Y. Chan and R. Rosenfeld. “Discriminative pronunciation learning for speech recognition for resource scarce languages”. In: *ACM DEV*. 2012.
- ▶ F. Qiao, J. Sherwani, and R. Rosenfeld. “Small-vocabulary speech recognition for resource-scarce languages”. In: *ACM DEV*. 2010.
- ▶ J. Sherwani. “Speech interfaces for information access by low literate users”. PhD thesis. Carnegie Mellon University, 2009.
- ▶ A. Vakil, M. Paulus, A. Palmer, and M. Regneri. “lex4all: A language-independent tool for building and evaluating pronunciation lexicons for small-vocabulary speech recognition”. In: *ACL 2014: System Demonstrations*. 2014.

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