SPEECH RECOGNITION AND KEYWORD SPOTTING PERFORMANCE ANALYSIS ACROSS LANGUAGES

Jake Vasilakes, Haipeng Wang, Anton Ragni, Mark Gales, and Kate Knill

Cambridge University Engineering Department

{jav39,hw443,ar527,mjfg,kate.knill}@eng.cam.ac.uk

1 INTRODUCTION

- Cross-lingual performance analysis
  - Expect variation across languages due to, e.g.
    - vocabulary size
    - number of phones
  - Observe unexpected variations
    - How can we improve models?
- Performance prediction
  - Primary: keyword spotting (KWS)
  - Secondary: automatic speech recognition (ASR)
- Estimate quantity of data required to achieve target performance
- Carried out within the IARPA Babel Program
  - Automatic speech recognition (ASR) and keyword spotting (KWS) for low-resource languages

2 PERFORMANCE METRICS

- KWS: Maximum Term Weighted Value (MTWV)

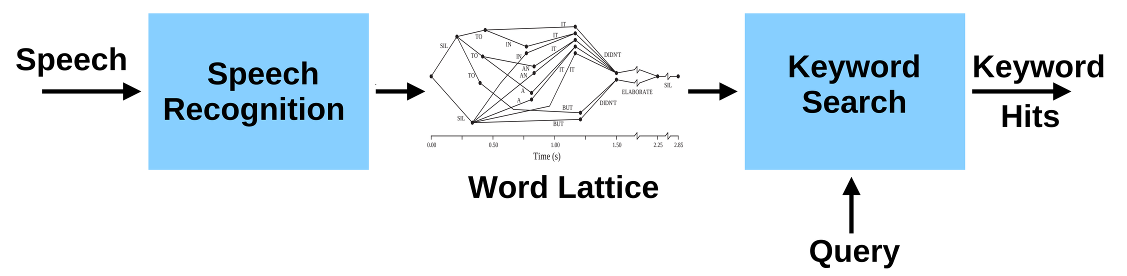
$$\text{MTWV} = \max_{\theta}\{1-(P_{\mathtt{miss}}(\theta)+\beta P_{\mathtt{FA}}(\theta))\}$$

  - where $\beta \approx 1000$
- ASR: Token Error Rate (TER)
- Root grapheme error rate (GER)
  - Represents grapheme confusability
  - Root grapheme: grapheme without unicode attributes

Char	Unicode description	Root grapheme	Grapheme
ı	LATIN SMALL LETTER I	G6	G6;D2D3D6

  - Computation
    - Maximum-likelihood, speaker independent, GMM system with PLP features
    - Weakened LM
    - Computed over training data

3 SYSTEM DESCRIPTION



- Data
  - 80h transcribed audio data
  - Conversational telephone speech
  - Language models built from transcriptions
- ASR
  - Root graphemic lexica
  - Joint decoding of Tandem and Hybrid systems
  - Single decode using combination of log-likelihoods
- KWS
  - Word lattices from output of ASR joint decoder
  - Query represented as a WFSA
  - IV query: composed with word lattice
  - OOV query: composed with grapheme lattice

4 ANALYSIS FRAMEWORK

- Examined correlation of attributes with performance
- Performed over 11 languages from the Babel project

Language	Script	Family	#Phones	$\lvert V\rvert (10^3)$
Cebuano	Latin	Austronesian	28	15.7
Kurmanji Kurdish		Iranian	37	14.9
Lithuanian		Balto-Slavic	60	32.1
Swahili		Niger-Congo	38	24.9
Tagalog		Austronesian	48	23.7
Tok Pisin		Creole	37	6.5
Zulu		Niger-Congo	47	60.9
Kazakh	Non-Latin	Altaic	61	23.3
Pashto		Iranian	44	21.0
Tamil		Dravidian	34	57.8
Telugu		Dravidian	50	36.9

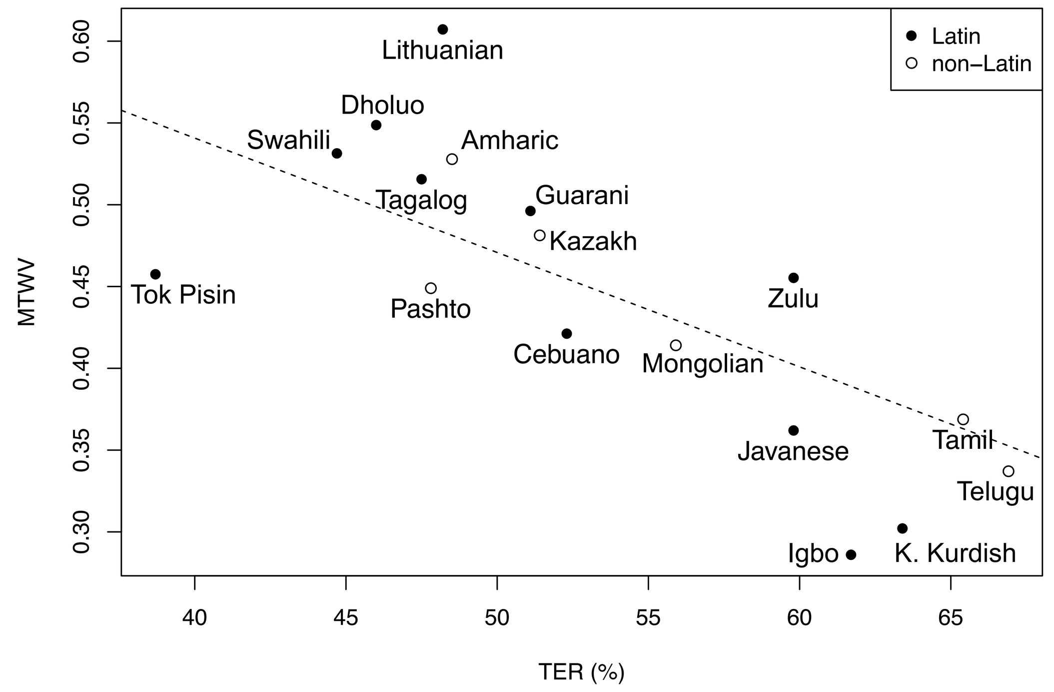
- 3 groups of attributes investigated

Linguistic	# Graphemes # Phones
Data	Signal-noise ratio (SNR) Mean opinion score (MOS) Vocabulary size # Frames
Model	Language model perplexity % out-of-vocabulary terms for ASR Root grapheme error rate (GER)

  - TER also investigated with respect to MTWV
  - Pearson's correlation (PCC) measured between each attribute and both TER and MTWV

5 ANALYSIS

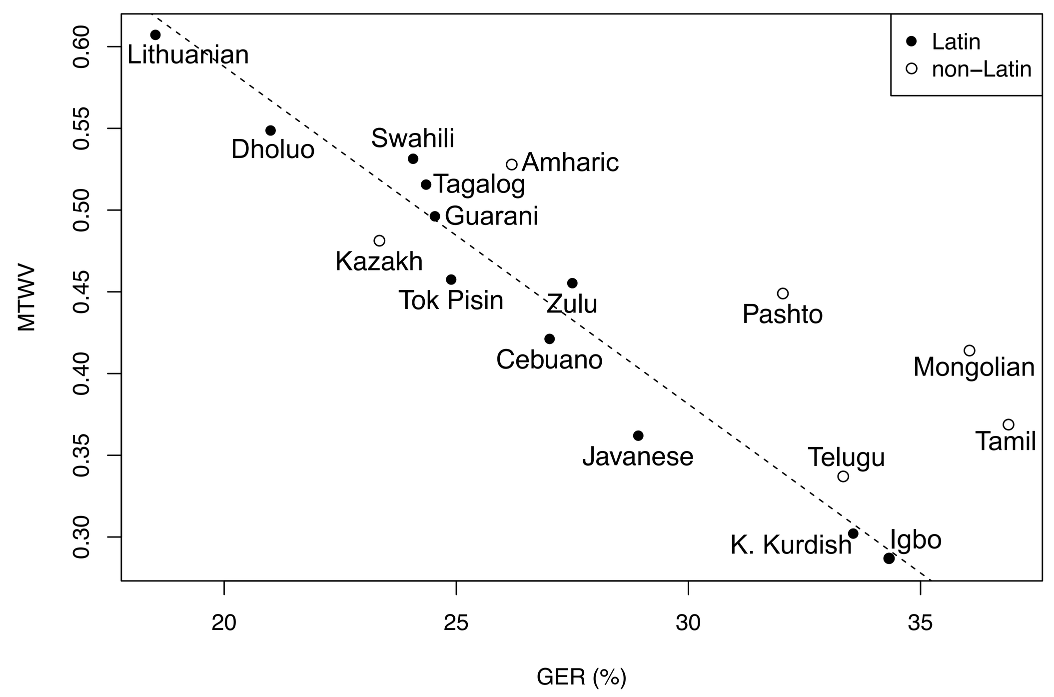
- TER against MTWV
  - PCC $= -.730$
  - But some languages do not behave as expected.
  - e.g. Lithuanian, Tok Pisin



- Other attributes
  - Most attributes were at best weakly correlated with performance
  - GER strongly correlated to MTWV

Script	PCC	
	MTWV	TER
Latin	$-.972$	$.684$
All	$-.887$	$.722$

  - TER correlation also shows possibility of prediction
- GER against MTWV
  - Lithuanian and Tok Pisin are no longer outliers
  - Non-Latin script outliers due to difference in grapheme set?



6 PREDICTIONS

- Predicted TER and MTWV
  - 6 held-out Babel languages
- Linear regression
  - GER as independent variable
  - MTWV predictions: Latin script languages only
  - Regression equations:

$$\mathtt{TER} = 19.68 + 1.21 \times \mathtt{GER}$$

$$\mathtt{MTWV} = 1.00063 - 0.02065 \times \mathtt{GER}$$

- Predictions well approximate observed values!

Language	%GER	%TER		MTWV	
		pred	obs	pred	obs
Dholuo	20.9	≈45	46.0	≈0.57	0.549
Guarani	24.5	≈49	51.1	≈0.50	0.496
Igbo	34.3	≈61	61.7	≈0.29	0.286
Javanese	28.5	≈54	59.8	≈0.41	0.362
Amharic†	25.6	≈51	48.5	≈0.47	0.528
Mongolian†	35.3	≈62	55.9	≈0.27	0.414

† Non-Latin script

7 CONCLUSIONS

- Variation in ASR and KWS performance across languages
  - Even given same system configuration
- Linguistic, data, and model attributes investigated
  - Most weakly correlated with performance
- Root grapheme error rate (GER)
  - Available at early stage of the system build
  - Strong correlation with MTWV
  - Correlated with TER
  - Able to predict performance for Latin script languages

LANGUAGE RELEASES

Cebuano (301) IARPA-babel301b-v1.0b; Kurmanji Kurdish (205) IARPA-babel205b-v1.0a; Lithuanian (304) IARPA-babel304b-v1.0b; Swahili (202) IARPA-babel202b-v1.0d; Tagalog (106) IARPA-babel106-v0.2g; Tok Pisin (207) IARPA-babel207b-v1.0a; Zulu (206) IARPA-babel206b-v0.1e; Kazakh (302) IARPA-babel302b-v1.0a; Pashto (104) IARPA-babel104b-v0.4bY; Tamil (204) IARPA-babel204b-v1.1b; Telugu (303) IARPA-babel303b-v1.0a;Dholuo(403) IARPA-babel403b-v1.0b;Guarani(305) IARPA-babel305b-v1.0b;Igbo(306) IARPA-babel306b-v2.0c;Javanese(402) IARPA-babel402b-v1.0a;Amharic(307) IARPA-babel307b-v1.0b;Mongolian(401) IARPA-babel401b-v2.0b;

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