Aalto system for the 2017 Arabic multi-genre broadcast challenge

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MGB CHALLENGE

The challenge

- Arabic MGB-3 transcription challenge: build a speech-to-text system for transcribing Egyptian Arabic.
- Arabic MGB-2 (re-run): transcription system for Modern Standard Arabic (MSA).
- Audio data: 1200 hrs MSA + 6 hrs Egyptian Arabic. LM data: 121M tokens.

Results

	MGB-3		MGB-2	
	Dev.	Eval.	Dev.	Eval.
Primary	**28.2**	**29.3**	**14.8**	**13.2**
Contr. 1 (char)	31.8	31.3	16.3	14.4
Contr. 2 (sub-17k)	31.3	30.5	15.9	14.0
Contr. 3 (word)	31.3	31.2	16.3	14.3

TOP-3

	MGB-3		MGB-2
	MR-WER	AV-WER	WER
Aalto	**29.3**	**37.5**	**13.2**
NDSC-THUEE	32.5	40.7	14.5
JHU	32.8	40.7	16.0

Why did we succeed

- Effective acoustic model adaptation.
- Use of multiple different lexical units (words, subwords, characters).
- Wide variety of tools (Kaldi, Morfessor, TheanoLM, VariKN).

Acoustic modeling

Organizer's baseline -

- The provided baseline was a model trained on the MGB-2 data. The acoustic model was a Time-Delay Neural Network (**TDNN**) trained on all MSA data, without any filtering.
- The language model was a **3-gram** trained on the provided background text corpus.
- For acoustic modeling and decoding **Kaldi** was used, for language modeling **SRILM**.

Aalto baseline relative improvement +11%

Our baseline was the same as the organizer's, except for

- We used only data with high confidence for GMM training.
- All provided training data was **automatically cleaned and segmented** using standard Kaldi scripts. This resulted in **1022 hours** of cleaned data.
- The language model was a small **varigram** model trained with the **VariKN** toolkit.

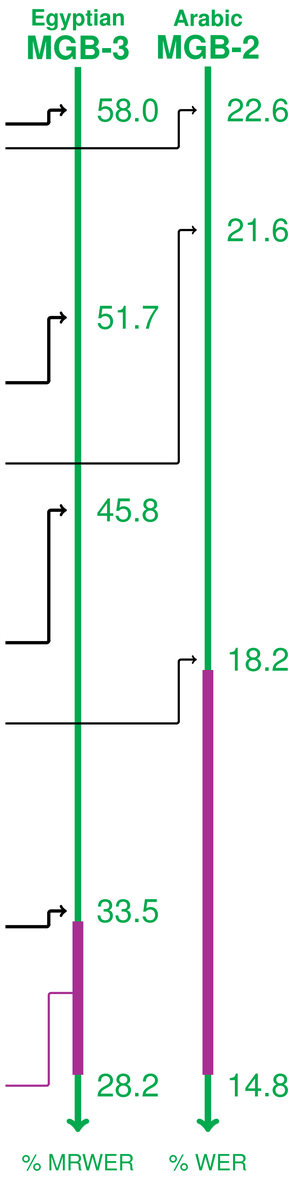
RNN acoustic model +11.4%

- We experimented with different recurrent and non-recurrent architectures.
- Bidirectional long short-term models combined with regular TDNN layers (**TDNN-BLSTM**) gave the best results. This model had 3 TDNN layers (1024 units) and 3 BLSTM layers in both directions (256 units).
- We used WER on the MGB-2 development set as the stopping criterion.

Dialect adapted Acoustic model +26.7%

- We used our best TDNN-BLSTM model and **adapted** with a simple procedure.
- The Egyptian data was used to continue training the model for a small number of epochs. Same parameters were used as for the last regular training iteration.
- We used MRWER on the MGB-3 development set as the stopping criterion.

Scale of language modeling improvements in the next column.



Language / lexical modeling

Interpolation and Rescoring +2.8%

- Besides a small language model on the background text data, we also trained bigger models on the background data, as well as separate models on the transcriptions of the MGB-2 and MGB-3 training sets.
- We **interpolated** these n-gram models, with the interpolation weight optimized for the respective development sets.
- We **rescored** the first-pass results with the larger interpolated language model.

Subwords -0.1%

- Instead of words as units, we also tried **subwords** (trained with **Morfessor**) and **characters** as language modeling units.
- Subwords reduce the vocabulary size while increasing the coverage of the language, as unseen words can be constructed.
- For MGB-3 this did not give an immediate improvement, but in combination with later steps, it did improve over word models.

Recurrent Neural Network Language Model +4.5%

- We build Recurrent Neural Network Language Models (**RNNLM**) with the **TheanoLM** toolkit.
- Our models were **LSTM** models with a projection layer (300/200 units), a hidden layer (1500/1000 units) and a highway layer (1500/1000 units) with a *tanh* activation function (units for subwords/words). The models were trained with Adagrad.
- We rescored the lattices and interpolated them with the n-gram lattices.

System combination +9.9%

- Different systems were built, including TDNN-LSTM and TDNN-BLSTM acoustic models, and models with various lexical units and boundary marking methods.
- Systems were combined and decoded using Minimum Bayesian Risk (**MBR-decoding**).
- In total 40 systems were used.