Unified Simplified Grapheme Acoustic Modeling for Medieval Latin LVCSR

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What is the problem with Latin speech recognition?

- Latin is not spoken natively
- There is no available speech database, and it is resource-heavy to create one
- Many variants/dialects exists, and we can only make guesses about the pronunciation
- The pronunciation mainly depends on
  - the **era** of the read text
  - the **georaphical region** where the text originates from
  - the **native language** of the speaker

Text data

Regions of origin: Kingdom of Bohemia (CZ), Kingdom of Hungary (HU), Kingdom of Poland (PL)

- In-domain data (Monasterium): medieval charters (HU), 480k/35k token/type
- Background data (Latin Library): historical texts, 1.3M/115k token/type

Speech data

- CZ: 76 hours
- HU: 567 hours (G2P) or 112 hours (grapheme and USG)
- PL: 31 hours
- RO: 35 hours

Spelling variants

jam	→	iam
judex		iudex
gracia		gratia

Test data

- Independent medieval charters
- Region of read text: CZ, HU, PL
- Native language of test speakers: CZ, HU, PL, SK

Perplexity measures on test

Table 1: Perplexity/OOV rate

	Text region			
Corpus	CZ	HU	PL	All
Monasterium	551	82	3130	671
Latin Library	3266	3549	2305	4303
Interpolated	924	82	2288	953

Language model

- 3-gram language model
- Kneser-Ney smoothing
- Interpolating the two corpora
- SRILM [2]

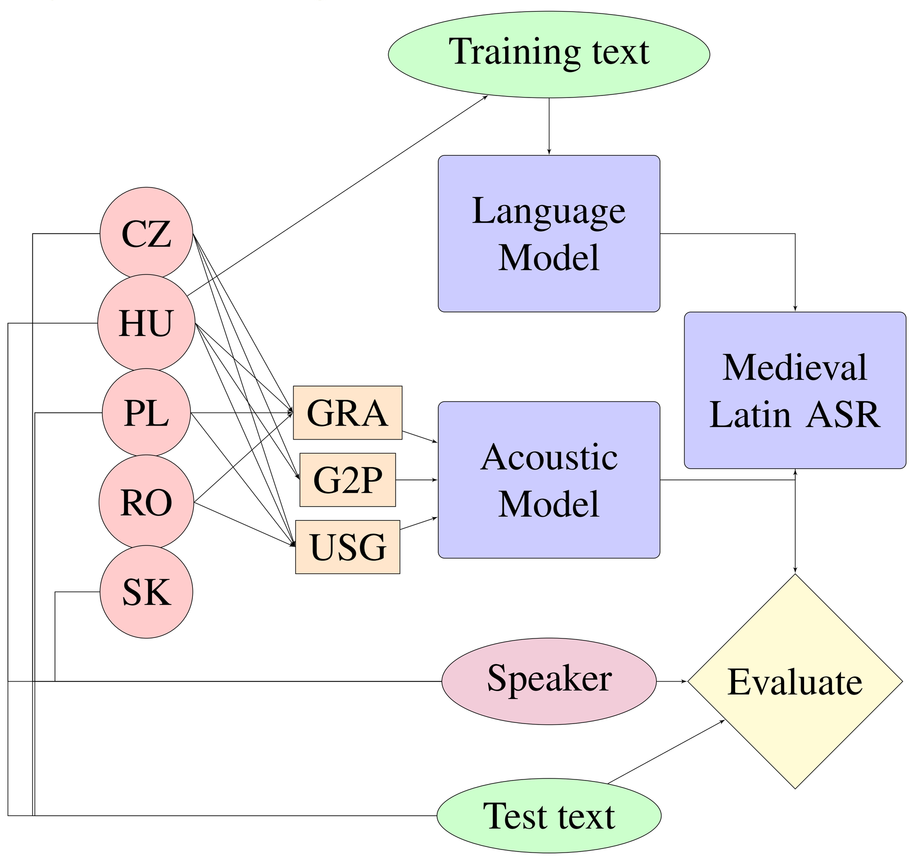
Dimensions of data

- **Region of training text**: HU, mixed
- **Speech data**: CZ, HU, PL, RO
- **Model type**: grapheme, G2P, USG
- **Native language of test speakers**: CZ, HU, PL, SK
- **Region of test text**: CZ, HU, PL

Acoustic model

- Mel-Frequency Cepstrum + Energy features were used with Linear Discriminant Analysis (LDA) + Maximum Likelihood Linear Transformation (MLLT), with a splice context of ± 4 frames, 10 ms of frame shift.
- 9×40 dimensional spliced up feature vectors served as input to the feed-forward, 6 hidden-layer neural network with p-norm [1] activation function.
- Prior to DNN training, a Gaussian Mixture Model (GMM) pre-training was performed.
- Clustering and Regression Tree (CART) [1] was applied to obtain acrossword context dependent shared state phone (or graph) models and their time alignment.
- The number of senones (and so the size of the DNN softmax output layer) was between 7.000 and 11.000 depending on the nature of the training data.
- The size of the hidden layers was kept constantly on 2.000.
- A minibatch size of 512, an initial learning rate of 0.1, and final learning rate of 0.01 was applied in 20 epochs using the Kaldi toolkit [1].

System diagram



GRA: baseline grapheme model
G2P: grapheme-to-phoneme model
USG: Unified Simplified Grapheme model

Figure 1: Medieval Latin Speech Recognizer

Baseline Grapheme Model

- All graphemes are trained
- Only those grapheme models are retained that are part of the Latin alphabet, e.g.
  - keeping model of r
  - throwing away model of $\check{r}$

Table 2: Word Error Rate (WER[%]) results for monolingual grapheme-based acoustic models of Czech, Hungarian, Polish and Romanian (CZ, HU, PL, RO).

	Speaker				
AM Language	CZ	HU	PL	SK	$\sum$
CZ	53.6	73.8	62.9	45.7	59.0
HU	33.7	28.6	47.1	29.1	**34.6**
PL	65.0	67.6	46.4	51.1	57.5
RO	53.6	69.1	44.7	43.8	52.8

Knowledge-based grapheme-to-phoneme (G2P) mapping

Figure 2: Latin digraph context-insensitive rewrite rules and context-sensitive rewrite rules.
V: vowel, VP: palatal vowel, ^VP: everything but a palatal vowel, C: consonant, $*$: zero or any, ^: beginning of word, $[\hat{\ } stx]$: not s, t or x.

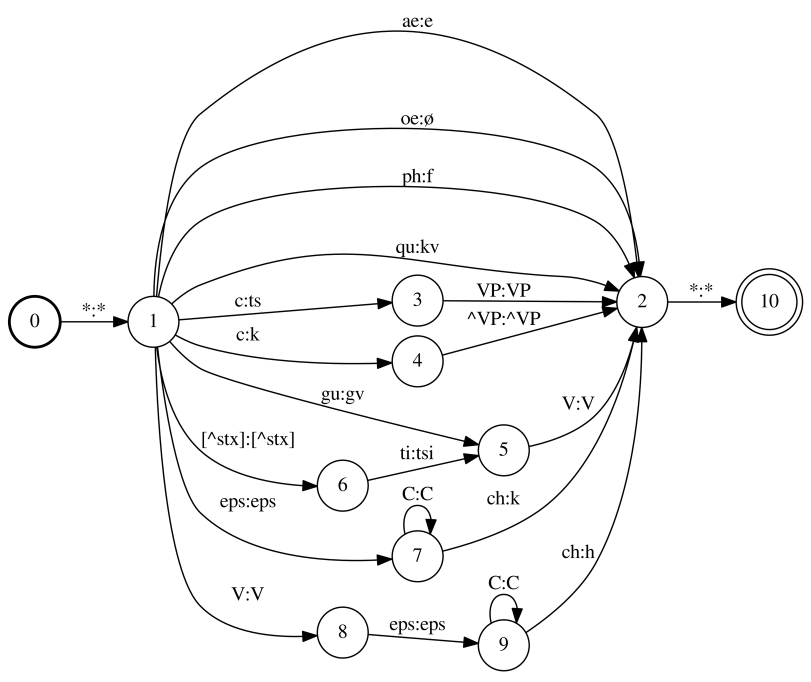


Table 3: WER[%] for Czech-Latin source-target G2P model. Acoustic model training set: 76 hours.

	Latin Test Text			
Speaker	CZ	HU	PL	$\sum$
CZ	43.8	28.2	49.1	40.4
HU	48.7	40.0	58.7	49.1
PL	53.3	18.2	53.2	41.6
SK	30.3	30.0	44.0	34.8
$\sum$	43.9	28.9	50.8	41.2

Table 4: WER[%] for Hungarian-Latin source-target G2P model. Acoustic model training set: 567 hours.

	Latin Test Text			
Speaker	CZ	HU	PL	$\sum$
CZ	19.4	**6.4**	28.0	17.9
HU	25.0	25.4	20.2	23.5
PL	28.9	15.4	41.3	28.5
SK	20.4	**9.1**	22.9	17.5
$\sum$	22.6	12.5	28.1	**21.1**

Unified Simplified Grapheme (USG) Model

- Utilizing many available language resources in the hopes that statistical variations help generalizing over different pronunciations

Table 5: Simplification examples for the unified model.

Language	CZ	HU	PL	RO
Orthographic form	řekl	őz	miś	apă
USG transcription	rekl	oz	mis	apa

Table 6: WER[%] for all the three-language USG models.

	Speaker				
AM Language	CZ	HU	PL	SK	$\sum$
CZ+HU+PL	28.2	28.2	27.7	22.4	26.6
CZ+HU+RO	23.3	21.4	23.9	19.2	**21.9**
CZ+PL+RO	24.6	33.1	25.6	19.8	25.8
HU+PL+RO	24.8	21.5	25.7	20.7	23.2

Table 7: WER[%] for USG model of Czech, Hungarian, Polish and Romanian (CZ+HU+PL+RO).

	Latin Test Text			
Speaker	CZ	HU	PL	$\sum$
CZ	20.4	11.8	30.7	21.0
HU	21.1	14.6	25.7	20.5
PL	23.0	**10.0**	33.0	22.0
SK	14.5	12.7	24.8	17.3
$\sum$	19.9	12.2	29.0	**20.4**

Conclusions

- Knowledge-based G2P modeling is good, but time consuming and restricted
- Four-language USG modeling is the best
  - It is able to generalize over different speaker test sets

References

[1] Povey, D., Ghoshal, A., Boulianne, G., Burget, L., Glembek, O., Goel, N., Hannemann, M., Motlicek, P., Qian, Y., Schwarz, P., Silovsky, J., Stemmer, G., Vesely, K.: The kaldi speech recognition toolkit. In: IEEE 2011 Workshop on Automatic Speech Recognition and Understanding. IEEE Signal Processing Society (2011)

[2] Stolcke, A.: Srilm – an extensible language modeling toolkit. In: In Proceedings of the 7th International Conference on Spoken Language Processing (ICSLP). pp. 901–904 (2002)