# Unified Simplified Grapheme Acoustic Modeling for Medieval Latin LVCSR

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## Motivation

- Digitizing medieval charters when optical character recognition in not sufficient

## Challenges

- 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

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

## Speech data

- CZ: 76 hours
- HU:
  - G2P model: 567 hours
  - GRA and USG models: 112 hours
- PL: 31 hours
- RO: 35 hours

## Spelling variants

| | |
|---|---|
| jam | iam |
| judex | iudex |
| gracia | gratia |

## Test data

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

## Language model

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

## Acoustic model

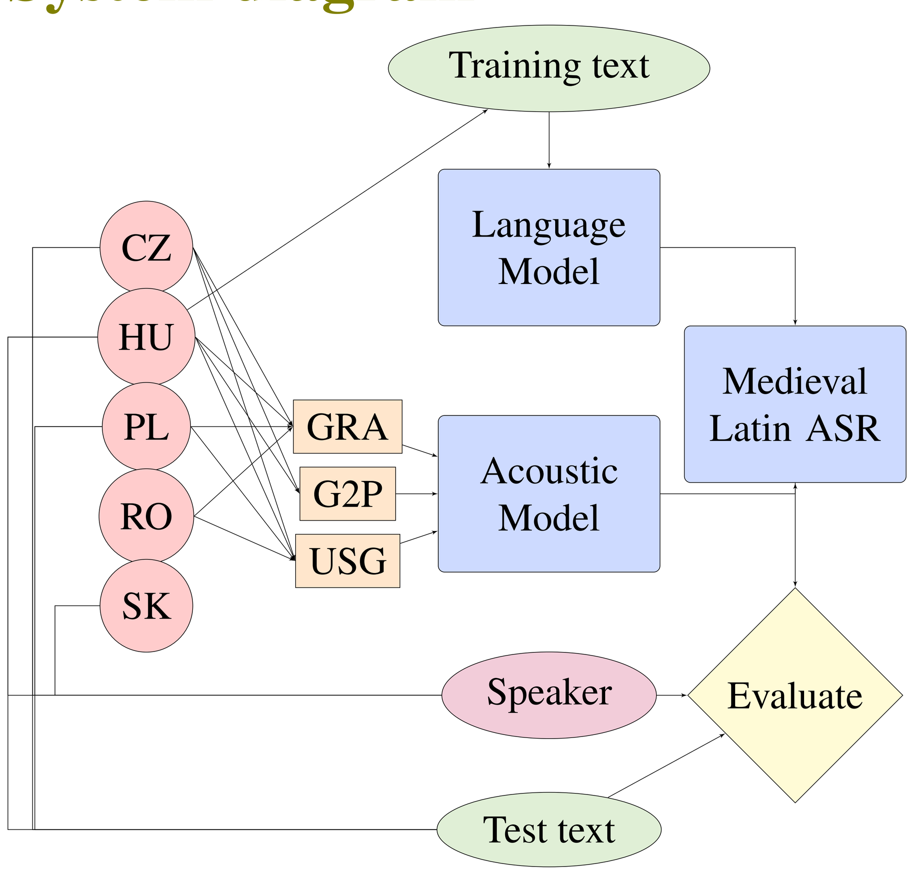
- 6-hidden-layer DNN
- 2000 neurons per layer
- p-norm activation function
- 7000-11000 senones (softmax size)
- Kaldi toolkit [1]

## Perplexity measures on test

Table 1: Perplexity/OOV rate (%)

| | Text region | | | |
|---|---|---|---|---|
| Corpus | CZ | HU | PL | All |
| Monasterium | 551/11.8 | **82/0.9** | 3130/18.3 | 479/10.5 |
| Latin Library | 3266/7.8 | 3549/1.6 | 2305/5.5 | 2992/9.7 |
| Interpolated | 924/3.9 | **82/0.9** | 2288/5.5 | 672/3.5 |

## System diagram




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

Figure 1: Medieval Latin Speech Recognizer

## Dimensions of data

- **Region of training text**: Kingdom of Hungary (HU), mixed
- **Region of test text origin**: Kingdom of Bohemia (CZ), Kingdom of Hungary (HU), Kingdom of Poland (PL)
- **Speech data**: Czech (CZ), Hungarian (HU), Polish (PL), Romanian (RO)
- **Native language of test speakers**: CZ, HU, PL, Slovak (SK)
- **Model type**: GRA, G2P, USG

## 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 ř

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, ˆVP: everything but a palatal vowel, C: consonant, $*$: zero or any, ˆ: beginning of word, $[\hat{\ } stx]$: not s, t or x.

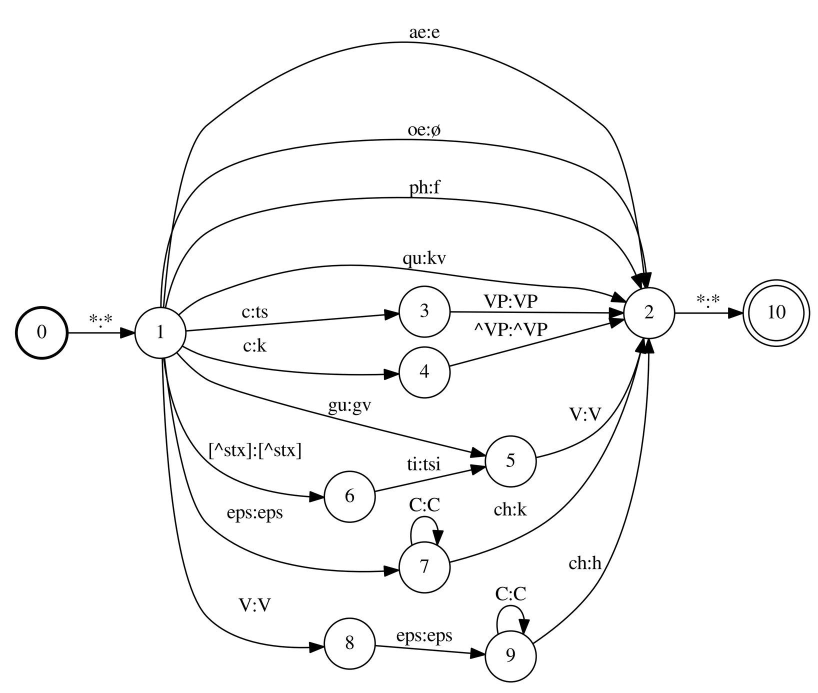


Table 3: WER[%] for Czech-Latin source-target G2P model. Acoustic model training set: 76 hours.

| | 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)