Quantifying the Role of Textual Predictability in Automatic Speech Recognition

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What is textual predictability?

- Given *only* part of a transcription, how easy or hard it is to guess the rest.
- Such guesswork is the role of the language model (LM).
- The acoustic model (AM) models whatever is left.
- The textual predictability of transcript $y = y_1, y_2, \ldots, y_L$ may be estimated with the Negative Log Likelihood (NLL) an external LM Q assigns it:

$$H_y = -\frac{1}{L} \log Q(y).$$

Colourless green [redacted] sleep furiously

Why quantify it's role?

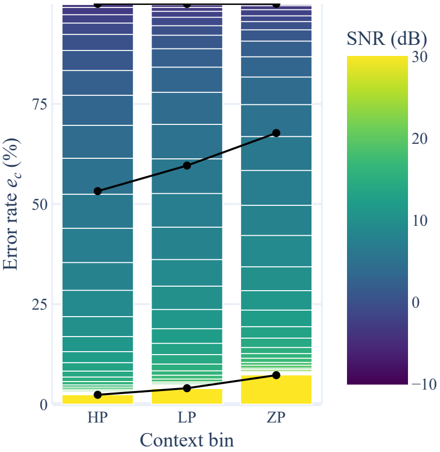
- Recent Automatic Speech Recognition (ASR) thinks it should have a very big role.
    - *E.g.* LLM-style ASR, contextual biasing, aggressive LM fusion...
- Is focusing on LMs enough?
    - The poor performance of ASR on African American English (AAE) was blamed on bad AMs, not LMs [1].
- An easy-to-compute number solves disputes and offers paths forward.

Error rates as a function of NLL

- Previous work focuses on an *absolute* relationship between H_y and e.
- Parametrized by $a, b \in \mathbb{R}^+$, they follow a power law [2]:

$$e_y = b \exp(aH_y).$$

- Fit depends on "acoustic conditions" [2].
  - a increases and b decreases with Signal-to-Noise Ratio (SNR).



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Can we do better?

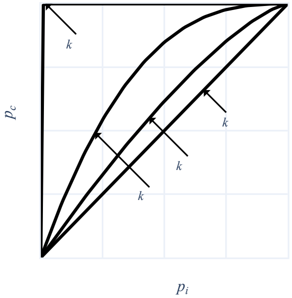
- ASR performance depends on *more* than textual predictability.
- Instead, we compare error rates e_i and e_c of less and more predictable utterances.
- Then the difference is due to predictability.

Relative improvements and k

- The relationship can be modelled with constant exponent $k \geq 1$ [3]:

$$e_c = e_i^k \text{ or } p_c = 1 - (1 - p_i)^k.$$

- k should increase with:
  - *greater predictability* of H_c, and/or
  - *greater reliance* on predictability.



Human subjects experiments

- The k model was verified for human listeners [3]:
  - Test utterances were partitioned into Zero, Low, and High Predictability (ZP, LP, and HP) bins.
  - Utterance i was drawn from the ZP bin; c from either LP or HP.
  - $k \approx 1.38$ between ZP-LP, but $k \approx 2.72$ between ZP-HP.
  - k was robust to adjustments of SNR (and thus error rates).
- k also increases with age [4].

The recipe

To do the same for ASR, we need to pick:

1. the corpora to draw utterances from,
2. an LM Q to bin utterances by predictability, and
3. our ASR systems to be subjects.

The corpora

- LibriSpeech [5] is our in-domain corpus.
  - Presumed standard/mainstream American English.
  - All ASR systems and LMs are trained on it.
  - Convenience and ecological validity.
  - Tested on dev-clean (LS-C) and dev-other (LS-O) partitions.
- CORAAL [6] is our out-of-domain corpus.
  - Regional AAE corpus from earlier studies [1], [7].
  - Tested on Rochester (CL-R) and Princeville (CL-P) partitions.
- **If ASR under-utilizes LMs on CORAAL, k should decrease.**

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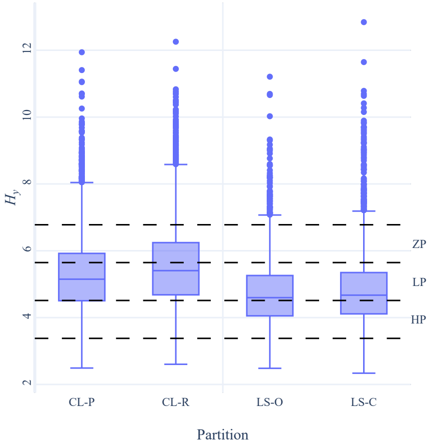
The language model

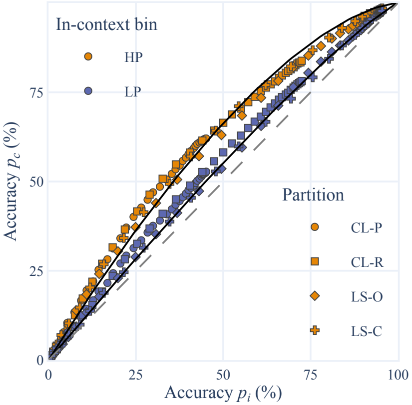
- Compared LMs from Kaldi *s5* recipe [8].
- Took RNN-LM as Q because it had the lowest average NLL.
- Used LS-C partition to make three equal intervals for ZP, LP, and HP bins.
- k **should be higher on ZP-HP pair than on ZP-LP pair.**

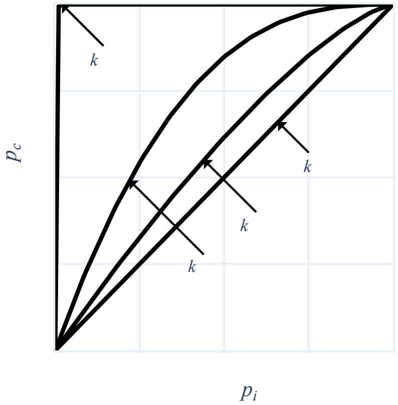


The ASR systems

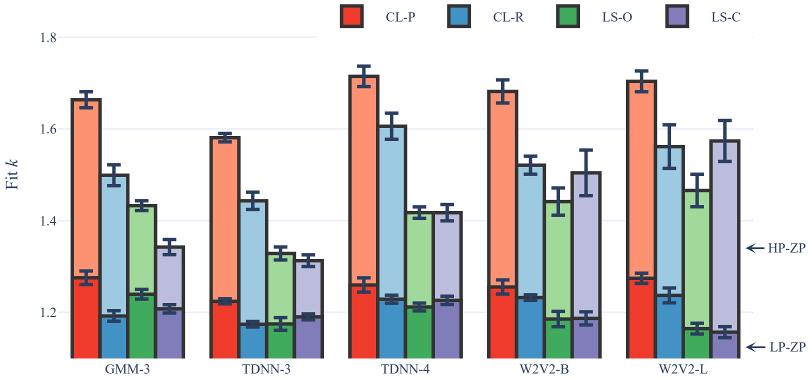
- Tested ASR systems from *s5* with explicit LMs:
  - GMM-3 = Gaussian Mixture Model + 3-gram, and
  - TDNN-{3,4} = Time-Delay Neural Network + {3,4}-gram.
- Tested E2E ASR systems with implicit LMs [9]:
  - W2V2-B = Wav2Vec 2-Base (smaller, LibriSpeech only), and
  - W2V2-L = Wav2Vec 2-Large (bigger, + LibriLight [10]).
- k **should increase with more sophisticated LMs.**

Plotting k


In-context bin
HP
LP
Partition
CL-P
CL-R
LS-O
LS-C
Accuracy p_c (%)
Accuracy p_i (%)
0
25
50
75
100


k
k
k
k
k
p_c
p_i

Fit k



- k reliably increases on ZP-HP comparisons.
- k reliably decreases on 3-gram-based models.
  - Less reliably: W2V2-L $>$ W2V2-B $>$ TDNN-4.
- k reliably increases on CORAAL data.

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Discussion

- k captures *main* effects of textual predictability on error rates.
- Models with fancy LMs rely more on textual predictability.
- Evidence that poor AAE performance is not due to LM under-utilization.
  - k *may* increase, but certainly not *decrease*.
- $k \approx \frac{\log e_c}{\log e_i}$ can substitute for fit.
  - k stabilizes as $e \to 0$.

Thank you!

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Repo + slides:

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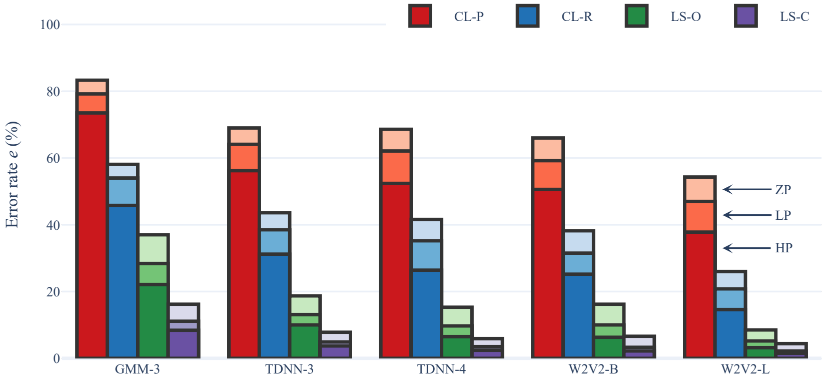
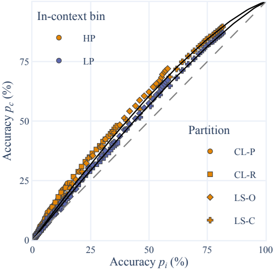
Error rates



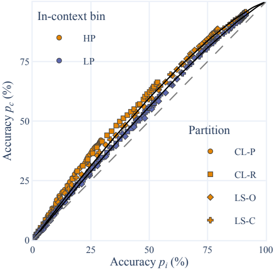
- Error rates decrease with more sophisticated LMs.
- Error rates decrease with increasing predictability.
- Error rates increase on CORAAL.

Regression plots

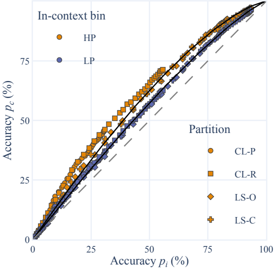
GMM-3



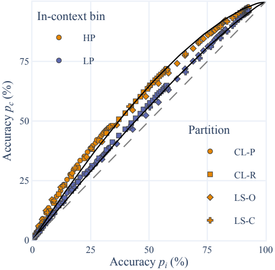
TDNN-3



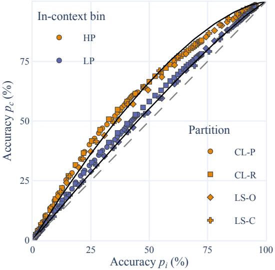
TDNN-4



W2V2-B



W2V2-L



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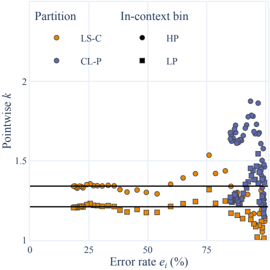
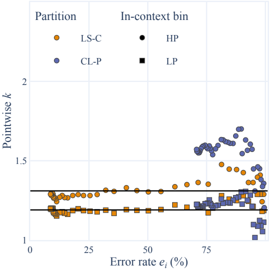
Point-wise estimates

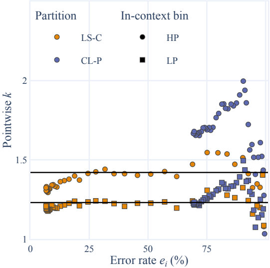
GMM-3



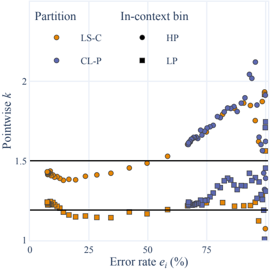
TDNN-3



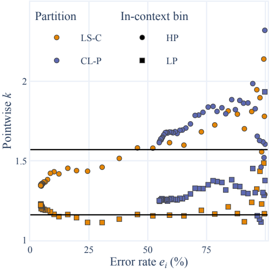
TDNN-4



W2V2-B



W2V2-L



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Looking forward

- Like with humans, k increases as a function of e [4], [11].
- Plenty of other models, settings to explore.
- Other forms of "predictability."

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References I

[1] Allison Koenecke, Andrew Nam, Emily Lake, et al. "Racial disparities in automated speech recognition". In: *Proceedings of the National Academy of Sciences* 117.14 (Apr. 2020), pp. 7684–7689. DOI: 10.1073/pnas.1915768117. (Visited on 12/20/2022).

[2] Dietrich Klakow and Jochen Peters. "Testing the correlation of word error rate and perplexity". In: *Speech Communication* 38.1 (2002), pp. 19–28. ISSN: 0167-6393. DOI: 10.1016/S0167-6393(01)00041-3.

[3] Arthur Boothroyd and Susan Nittrouer. "Mathematical treatment of context effects in phoneme and word recognition". In: *JASA* 84.1 (July 1988), pp. 101–114. ISSN: 0001-4966. DOI: 10.1121/1.396976.

[4] Susan Nittrouer and Arthur Boothroyd. "Context effects in phoneme and word recognition by young children and older adults". In: *JASA* 87.6 (June 1990), pp. 2705–2715. ISSN: 0001-4966. DOI: 10.1121/1.399061. (Visited on 02/13/2024).

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References II

[5] Vassil Panayotov, Guoguo Chen, Daniel Povey, et al. "Librispeech: An ASR corpus based on public domain audio books". In: *ICASSP*. 2015, pp. 5206–5210. ISBN: 2379-190X. DOI: 10.1109/ICASSP.2015.7178964.

[6] Tyler Kendall and Charlie Farrington. *The corpus of regional African American language*. 2023. DOI: 10.7264/1ad5-6t35.

[7] Joshua L. Martin and Kevin Tang. "Understanding racial disparities in automatic speech recognition: The case of habitual "be"". In: *Proc. Interspeech 2020*. 2020, pp. 626–630. DOI: 10.21437/Interspeech.2020-2893.

[8] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, et al. "The Kaldi speech recognition toolkit". In: *ASRU*. Hilton Waikoloa Village, Big Island, Hawaii, US: IEEE Signal Processing Society, 2011.

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References III

[9] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, et al. "wav2vec 2.0: A framework for self-supervised learning of speech representations". In: *NeurIPS*. Ed. by H. Larochelle, M. Ranzato, R. Hadsell, et al. Vol. 33. Curran Associates, Inc., 2020, pp. 12449–12460.

[10] J. Kahn, M. Rivière, W. Zheng, et al. "Libri-light: A benchmark for ASR with limited or no supervision". In: *ICASSP*. 2020, pp. 7669–7673. DOI: 10.1109/ICASSP40776.2020.9052942.

[11] Adelbert W. Bronkhorst, Thomas Brand, and Kirsten Wagener. "Evaluation of context effects in sentence recognition". In: *JASA* 111.6 (June 2002), pp. 2874–2886. ISSN: 0001-4966. DOI: 10.1121/1.1458025. (Visited on 02/02/2024).

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