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Evaluating Whisper for Sociolinguistic Data Transcription

IVACS conference| University of Cambridge
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01 Introduction

01 ASR Performance

… the higher the audio quality

… the more structured the speech

… the more 'standard' the speech

… the less speakers involved

… the better

sociolinguistic speech data

(Jurafsky and Martin 2023: 331)

01 OpenAI Whisper

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OpenAI

Radford et al. 2022

- End-to-end transformer architecture with encoder and decoder blocks
- trained on 680,000 hours of speech via unsupervised learning
- multilingual in 96 languages
- machine translation to English possible

Python script
whisper_to_textgrid.py
(Weilinghoff 2023)

01 OpenAI Whisper

- different models available

Size	Parameters	English-only model	Multilingual model	Required VRAM	Relative speed
tiny	39 M	`tiny.en`	`tiny`	~1 GB	~32x
base	74 M	`base.en`	`base`	~1 GB	~16x
small	244 M	`small.en`	`small`	~2 GB	~6x
medium	769 M	`medium.en`	`medium`	~5 GB	~2x
large	1550 M	N/A	`large`	~10 GB	1x

01 Previous research

"Speech is easier to recognize if the speaker is speaking the same dialect or variety that the system was trained on" (Jurafsky and Martin 2023: 331)

- ASR bias towards
  → non-native speakers (e.g. Knill et al. 2018; Graham and Roll 2024)
  → regional accents (Tatman 2017; Markl 2022)
  → racial minority groups (Koenecke et al. 2020)

- influence of gender
  → better Youtube captions for male speakers (Tatman 2017)
  → better performance for female speakers (Adda-Decker and Lamel 2005; Goldwater et al. 2010)

01 Previous research

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Whisper evaluation: **(Graham and Roll 2024)**

- L1 varieties: → best performance on L1 North American English
  → worse performance on British and Australian accents
  (some L2 Swedish and German accents better than some British accents; e.g. Leeds)
- worse performance on L2 varieties overall; higher English experience and pronunciation accuracy lead to better ASR performance
- worse performance on male speakers
- worse performance on spontaneous speech

01 Research aims and research questions

→ identify strengths/weaknesses of Whisper for sociolinguistic data transcription

→ integrate Whisper efficiently in sociolinguistic data transcription workflows

RQ1 What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

RQ2 Which variables have a **significant influence on ASR performance**?

RQ3 How does **Whisper compare with trained human transcribers** in terms of accuracy and speed?

02 Data and Method

To be published.

02 Data and Method

To be published.

02 Data and Method

To be published.

02 Data and Method

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To be published.

02 Data and Method

To be published.

03 Findings

03 Findings

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RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

Results to be published.

03 Findings

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RQ2 Which variables have a **significant influence on ASR performance**?

Results to be published.

03 Findings

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RQ2

Which variables have a **significant influence on ASR performance**?

Results to be published.

03 Findings

RQ2

Which variables have a **significant influence on ASR performance**?

Results to be published.

03 Findings

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RQ3

How does **Whisper compare with trained human transcribers** in terms of accuracy and speed?

Results to be published.

04 Discussion

04 Discussion

Results to be published.

04 Discussion - timestamps

Results to be published.

04 Discussion - timestamps

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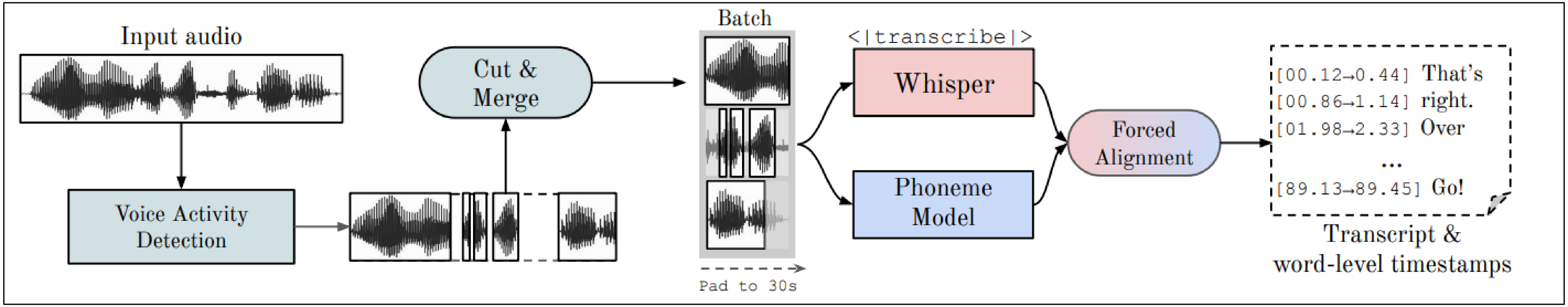
→ WhisperX (Bain et al. 2023)



(Bain et al. 2023: 1)

04 Discussion - timestamps

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Results to be published.

04 Discussion - timestamps

Results to be published.

04 Discussion – speaker diarization

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Results to be published.

04 Discussion – speaker diarization

Results to be published.

05 Conclusion

05 Conclusion and References

RQ1

What is the **transcription accuracy** of different Whisper models for the corpora ICE Nigeria & ICE Scotland?

Results to be published.

05 Conclusion and References

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RQ2 Which variables have a **significant influence on ASR performance**?

Results to be published.

05 Conclusion and References

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RQ3

How does **Whisper compare with trained human transcribers** in terms of accuracy and speed?

Results to be published.

05 Conclusion and References

NEXT STEPS

Results to be published.

References

References

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Adda-Decker, M., and Lamel, L. (2005). “Do speech recognizers prefer female speakers?,” in *Proceedings of INTERSPEECH*, Lisbon, Portugal (International Speech Communication Association, Baixas, France).

Armstrong, R. (2024). *werpy - Word Error Rate for Python* [Computer software]. https://github.com/analyticsinmotion/werpy

Ashraf, M. (2023). *Speaker Diarization Using OpenAI Whisper*. [Computer software]. https://github. com/MahmoudAshraf97/whisper-diarization

Baevski,. , Zhou, Y., Mohamed, A. & Auli, M. (2020). “wav2vec 2.0: A framework for self-supervised learning of speech representations,” *NeurIPS*, vol. 33, pp. 12449–12460.

Bain, M., Huh, J., Han, T. & Zisserman, A. (2023). *WhisperX: Time-Accurate Speech Transcription of Long-Form Audio*. https://www.robots.ox.ac.uk/~vgg/publications/2023/Bain23/bain23.pdf

Boersma, P., & Weenink, D. (2019). Praat: doing phonetics by computer (Version 6.1.08) [Computer software]. http://www.praat.org/

Desplanques, B., Thienpondt, J. & Demuynck, K. (2020). *ECAPA-TDNN: Emphasized Channel Attention, Propagation and Aggregation in TDNN Based Speaker Verification.* https://arxiv.org/pdf/2005.07143.pdf

Goldwater, S., Jurafsky, D., & Manning, C. (2010). “Which words are hard to recognize? prosodic, lexical, and disfluency factors that increase speech recognition error rates,” *Speech Communication* 52(3), 181–200.

Graham, C. & Roll, N. (2024). Evaluating OpenAI's Whisper ASR: Performance analysis across diverse accents and speaker traits. *The Journal of the Acoustical Society of America*. https://doi.org/10.1121/10.0024876

Hirschle, J. (2022). *Deep Natural Language Processing. Einstieg in Word Embedding, Sequence-to-Sequence Modelle und Transformer mit Python*. Munich: Hanser Publishing.

IBM (2022). Watson Speech to Text. [Software]. Retrieved from: https://www.ibm.com/cloud/watson-speech-to-text [Date of access: 25 Nov. 2022].

Jurafsky, D. & Martin, J. H. (2023). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition.* https://web.stanford.edu/~jurafsky/slp3/ed3book_jan72023.pdf

References

Kisler, T., Reichel, U. D., & Schiel, F. (2017). Multilingual processing of speech via web services. *Computer Speech & Language*, *45*, 326–347.

Klein, G. (2023). *faster-whisper*. [Computer software]. https://github.com/guillaumekln/faster-whisper

Knill, K., Gales, M., Kyriakopoulos, K., Malinin, A., Ragni, A., Wang, Y., and Caines, A. (2018). "Impact of ASR performance on free speaking language assessment," in *Proceedings of Interspeech 2018*, Hyderabad, India (International Speech Communication Association, Baixas, France), pp. 1641–1645.

Koenecke, A., Nam, A., Lake, E., Nudell, J., Quartey, M., Mengesha, Z., Toups, C., Rickford, J. R., Jurafsky, D., and Goel, S. (2020). "Racial disparities in automated speech recognition," *Proc. Natl. Acad. Sci. U.S.A*. 117(14), 7684–7689.

Markl, N. (2022). "Language variation and algorithmic bias: Understanding algorithmic bias in British English automatic speech recognition," in *Proceedings of 2022 5th ACM Conference on Fairness, Accountability, and Transparency* (FAccT 2022), June 21–24, Seoul (Association for Computing Machinery, New York), pp. 521–534.

Python Software Foundation. (2021). *Python* (Version 3.9) [Computer software]. http://www.python.org

Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C. & Sutskever, I. (2022): Robust Speech Recognition via Large-Scale Weak Supervision. https://arxiv.org/abs/2212.04356

Schützler, O., Gut, U., & Fuchs, R. (2017). New perspectives on Scottish Standard English: Introducing the Scottish component of the International Corpus of English. In S. Hancil & J. C. Beal (Eds.), *Perspectives on Northern Englishes* (pp. 273–302). Mouton de Gruyter.

Tatman, R., and Kasten, C. (2017). "Effects of talker dialect, gender and race on accuracy of Bing speech and YouTube automatic captions," in *Proceedings of Interspeech, Stockholm, Sweden* (International Speech Communication Association, Baixas, France), pp. 934–938.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. & Polosukhin, I. (2017). Attention Is All You Need. https://arxiv.org/pdf/1706.03762.pdf

Weilinghoff, A. (2023): whisper_to_textgrid+eaf.py (Version 1.0) [Source code]. https://www.andreas-weilinghoff.com/#code

Wunder, Eva-Maria & Voormann, Holger & Gut, Ulrike. (2008). "The ICE Nigeria corpus project: Creating an open, rich and accurate corpus." *International Computer Archive of Modern and Medieval English (ICAME) Journal*, 34, pp. 78-88.

Yu, D., Deng, L. (2015). *Automatic Speech Recognition: A Deep Learning Approach*. London: Springer Publishing.

Thank you very much for your attention!

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