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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

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

02 Data and Method

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RQ1

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

ICE Nigeria (Wunder et al. 2008)

- postcolonial outer-circle variety
- compilation 2007-2013
- manually transcribed spoken component

Extraction:
- 60 sound files | 12 speech categories

→ 13:05:47 hours | 94,499 words

ICE Scotland (Schützler et al. 2017)

- inner-circle variety (not GA or SSBE)
- compilation 2014-2020
- manually transcribed spoken component (time-aligned)

Extraction:
- 60 sound files | 12 speech categories

→ 11:50:31 hours | 111,418 words

02 Data and Method

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corpus	file_name	file_duration	word_count
ICE Nigeria	bdis_01	00:12:47	2143
ICE Nigeria	bdis_02	00:07:46	1165
ICE Nigeria	bdis_03	00:03:23	587
ICE Nigeria	bdis_04	00:07:58	1296
ICE Nigeria	bdis_05	00:01:16	201
ICE Nigeria	bnew_01	00:05:24	555
ICE Nigeria	bnew_02	00:09:07	1143
ICE Nigeria	bnew_03	00:16:27	1473
ICE Nigeria	bnew_04	00:15:24	1231
ICE Nigeria	bnew_05	00:12:54	887
ICE Nigeria	btal_01	00:08:17	1056
ICE Nigeria	btal_02	00:02:51	503
ICE Nigeria	btal_03	00:01:46	193
ICE Nigeria	btal_04	00:08:59	1198
ICE Nigeria	btal_05	00:04:28	708
ICE Nigeria	leg_02	00:23:27	3979
ICE Nigeria	leg_04	00:15:59	2352
ICE Nigeria	leg_11	00:06:19	1212
ICE Nigeria	leg_08	00:02:44	586
ICE Nigeria	leg_09	00:03:59	790
ICE Nigeria	nbtal_01	00:16:55	1536
ICE Nigeria	nbtal_02	00:06:11	521
ICE Nigeria	nbtal_03	00:21:40	2346
ICE Nigeria	nbtal_04	00:26:56	3409
ICE Nigeria	nbtal_05	00:19:25	2391
ICE Nigeria	parl_01	00:07:53	1069
ICE Nigeria	parl_02	00:07:47	1089
ICE Nigeria	parl_03	00:11:16	1350
ICE Nigeria	parl_04	00:16:21	2012
ICE Nigeria	parl_05	00:12:06	2327
…	…	…	…

corpus	file_name	file_duration	word_count
ICE Scotland	bdis_01 (s1)	00:08:53	470
ICE Scotland	bdis_02	00:20:45	3030
ICE Scotland	bdis_03	00:06:00	1115
ICE Scotland	bdis_04	00:13:58	2964
ICE Scotland	bdis_05	00:11:56	2914
ICE Scotland	bnew_01	00:02:14	159
ICE Scotland	bnew_02 (s1)	00:02:48	93
ICE Scotland	bnew_03 (s1)	00:01:39	96
ICE Scotland	bnew_04 (s1)	00:03:36	179
ICE Scotland	bnew_05	00:01:47	305
ICE Scotland	btal_01	00:02:37	415
ICE Scotland	btal_02	00:02:34	453
ICE Scotland	btal_03	00:03:24	473
ICE Scotland	btal_04	00:02:52	379
ICE Scotland	btal_05	00:07:51	934
ICE Scotland	leg_01	00:19:08	2033
ICE Scotland	leg_02	00:22:32	2168
ICE Scotland	leg_03	00:02:29	324
ICE Scotland	leg_04	00:10:39	1333
ICE Scotland	leg_05	00:05:04	713
ICE Scotland	nbtal_01	00:21:55	3040
ICE Scotland	nbtal_02	00:30:00	4835
ICE Scotland	nbtal_03	00:11:17	1739
ICE Scotland	nbtal_04	00:04:45	713
ICE Scotland	nbtal_05	00:02:31	387
ICE Scotland	parl_01	00:20:54	3782
ICE Scotland	parl_02	00:20:09	3427
ICE Scotland	parl_03	00:11:31	1776
ICE Scotland	parl_04	00:25:21	4178
ICE Scotland	parl_05	00:36:08	5900
…	…	…	…

→ different varieties
→ different file sizes
→ different speech forms
→ monologues and dialogues
→ different speaker groups
→ different quality

02 Data and Method

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

- retrieval of audio files and reference transcriptions (→ plain .txt)
- re-transcription of files with Whisper models (tiny, base, small, medium, large_v2, large_v3) via AMD EPYC 7402 processor

- normalization and comparison of manual reference transcription and Whisper transcriptions via **Word Error Rate (WER)** using werpy library (Armstrong 2024) via Python script

$$WER = \frac{S + D + I}{N}$$

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

- annotation for metadata (corpus, text category, model, sound quality, speaker number, gender, file duration)

- following approach of Graham and Roll (2024):

→ linear mixed effects modelling of WER with lme4 (Bates et al. 2015) and lmerTest (Kuznetsova et al. 2017) packages in R (R core team 2024)

RANDOM FACTORS	TYPE	LEVELS
sound file	categorical	120 individual sound files
FIXED FACTORS	**TYPE**	**LEVELS**
corpus	categorical	ICE Nigeria, ICE Scotland
text category	categorical	bdis, bnew, btal, btran, com, cr, dem, leg, les, nbtal, parl, unsp
model	categorical	tiny, base, small, medium, large_v2, large_v3
quality_2	categorical	okay, bad
speaker number binary	categorical	mono, poly
gender	categorical	female, male, mixed
file duration (min)	numerical	1-48

02 Data and Method

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

- subset of dataset (24 files) re-transcribed by human transcribers
→ trained student assistants (Bachelor's degree in English studies)
→ close tracking of working time

- subset transcribed with Whisper models via laptop (Processor: AMD Ryzen 7 Pro 6850 U with Radeon Graphics (2.70 GHz), RAM: 32 GB, OS: Windows 11, 64 bit) via Python script
→ automated tracking of working time

- normalization and comparison of human and Whisper transcripts in terms of accuracy (**WER**) and speed (**working time/file duration**)

03 Findings

03 Findings

RQ1

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

Results to be published.

03 Findings

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

Results to be published.

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03 Findings

RQ3

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

Results to be published.

04 Discussion

04 Discussion

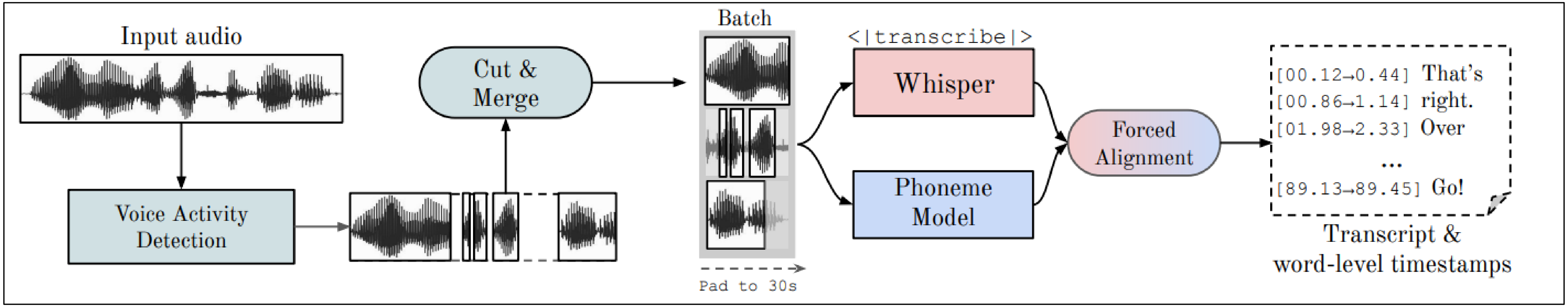
Results to be published.

04 Discussion - timestamps

Results to be published.

04 Discussion - timestamps

→ **WhisperX (Bain et al. 2023)**



(Bain et al. 2023: 1)

04 Discussion - timestamps

Results to be published.

04 Discussion - timestamps

Results to be published.

04 Discussion – speaker diarization

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

RQ2

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

Results to be published.

05 Conclusion and References

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.

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