SlideAVSR: A Dataset of Paper Explanation Videos for Audio-Visual Speech Recognition

Anonymous ACL submission

Abstract

Audio-visual speech recognition (AVSR) is a multimodal extension of automatic speech recognition (ASR), using video as a complement to audio. In AVSR, considerable efforts have been directed at datasets for facial features such as lip-readings, while they often fall short in evaluating the image comprehension capabilities in broader contexts. In this paper, we construct **SlideAVSR**, an AVSR dataset using scientific paper explanation videos. SlideAVSR provides a new benchmark where models transcribe speech utterances with texts on the slides on the presentation recordings. As technical terminologies that are frequent in paper explanations are notoriously challenging to transcribe without reference texts, our SlideAVSR dataset spotlights a new aspect of AVSR problems. As a simple yet effective baseline, we propose DocWhisper, an AVSR model that can refer to textual information from slides, and confirm its effectiveness on SlideAVSR.

1 Introduction

Research on multimodal models capable of handling multiple types of data, such as language, images, videos, and audio simultaneously, has garnered significant attention. An example is audio-visual speech recognition (AVSR), a multimodal extension of automatic speech recognition (ASR), using video as a complement to audio. Most previous studies in AVSR have been conducted with the aim of improving accuracy on lip reading datasets (Afouras et al., 2018a,b). While models built in these studies (Shi et al., 2022; Pan et al., 2022; Haliassos et al., 2023) demonstrate high performance on lip reading data, their applicability to other types of videos remains limited.

In this paper, we aim to evaluate the image comprehension capabilities of AVSR models across a broader spectrum of visual contents than facial features. To achieve this, we construct SlideAVSR, an AVSR dataset that contains various technical terms that are notoriously challenging to transcribe without referring to textual information on slides. Specifically, we collect scientific paper explanation videos from YouTube, apply data refinement procedures with several custom filters, and perform data partitioning considering the speakers' accents.

Furthermore, we propose DocWhisper, a simple yet effective AVSR baseline that can efficiently refer to the content of slides using optical character recognition (OCR). In experiments utilizing SlideAVSR, DocWhisper demonstrated a performance improvement of up to 14.3% compared to Whisper (Radford et al., 2022), which relies solely on audio input. Additionally, to address the long-tail problem in OCR results, we introduce FQ Ranker, which calculates word ranks based on the frequency of word occurrences, and we evaluate its effectiveness integrated with DocWhisper.

2 Related Work

Compared to the efforts that have been made on lip reading datasets (Chung et al., 2017; Chung and Zisserman, 2017a,b; Afouras et al., 2018a,b; Shillingford et al., 2019), AVSR datasets in other types of videos remain scarce. To our knowledge, VisSpeech (Gabeur et al., 2022) and the audio-visual diarization benchmark in the Ego4D challenge (Jain et al., 2023) are the only AVSR datasets not centered around lip reading. VisSpeech is constructed from a subset of the instructional video dataset HowTo100M (Miech et al., 2019), where the visual stream and speech audio are semantically related. The audiovisual diarization benchmark in the Ego4D challenge consists of 585 egocentric video clips. It is imperative to build more diverse benchmark datasets to evaluate the image comprehension capabilities of AVSR models.

In the context of extending Whisper to an AVSR model, Peng et al. (2023) employed CLIP (Radford et al., 2021) to transform the input visual stream into word sequences, which were then utilized as

prompts for Whisper. They reported that this approach enhances the zero-shot performance on VisSpeech. In this study, we employ OCR to create prompts and implement fine-tuning to improve performance rather than using zero-shot prompting.

3 SlideAVSR: Dataset Construction

In this study, we construct SlideAVSR, an AVSR dataset based on scientific paper explanation videos incorporating various technical terms, making accurate transcription difficult without referring to the slides. Based on JTubeSpeech (Takamichi et al., 2021), a framework for building audio corpora from YouTube videos, we implement several custom filters to target videos, thereby applying high-precision data refinement. This section describes the construction flow of SlideAVSR. Figure 1 illustrates the flow.

3.1 Data Collection

Creating search queries. We first collect videos with search queries that are related to top conferences in the field of artificial intelligence. We create queries in the format {Conference} {Year} {Form}. The list of target conferences is provided in Appendix A. Considering the increased prevalence of online conferences since COVID-19, we focus on the years 2020 to 2023. The forms include "paper", "workshop", and "talk". An example search query is "ACL 2023 paper".

Obtaining videos with subtitles. Using the search queries, we retrieve video IDs with subtitles and download them.[1] To ensure data quality, only videos with manual subtitles are considered. Additionally, we set the following criteria:

- Duration between 5 and 20 minutes (videos that are too short or too long are less likely to be paper explanation videos).
- Video format: MP4, 720P, H264.
- Audio format: single-channel, 16bit, 16kHz.

3.2 Filtering

We curate several filters to remove videos that are not paper explanations or do not include slides.

ChatGPT filter. We provide the videos' description for ChatGPT[2] to confirm the following:

- This video is an explanation of a paper.
- The description is written in English.

[1] https://github.com/yt-dlp/yt-dlp
[2] https://openai.com/product

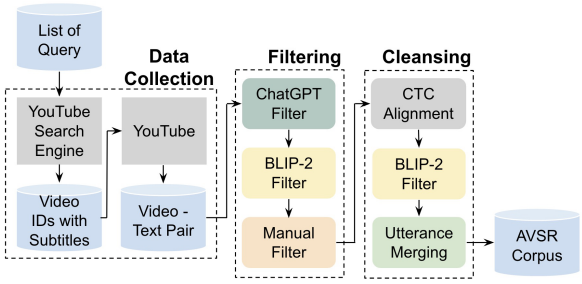


Figure 1: Construction flow of SlideAVSR.

We perform three times of generation, and if "Yes" is outputted at least once, we adopt the video; otherwise, we discard it. We show the details of the model and prompt in Appendix B.

BLIP-2 filter for videos. We capture screenshots at the beginning, end, and three quartile points in the timeline for each video, and then present these screenshots to the vision language model BLIP-2 (Li et al., 2023) to verify the following:

- This image is a screenshot, not a photo.
- This image is a part of slides.

We perform generation for each screenshot, and if "Yes" is outputted at least once, we adopt the video; otherwise, we discard it. We show the details of the model and prompt in Appendix B.

Manual filter. We conduct manual checks to remove inappropriate videos that are not excluded by the automatic filters, including:

- Videos rarely showing slides.
- Videos unrelated to paper explanations, such as conference openings.

3.3 Cleansing

We implement audio-subtitle alignment, exclude utterances that do not correspond to slides, and merge short utterances for data cleansing.

CTC alignment. Due to the inaccuracy in the timing of subtitles, we implement audio-subtitle alignment and scoring using CTC segmentation (Kürzinger et al., 2020). We set the threshold to -7 and exclude utterances with lower scores. The details of the model are shown in Appendix B.

BLIP-2 filter for utterances. We capture screenshots at the midpoint of each utterance, followed by filtering using BLIP-2. Three generations are conducted for each screenshot, and if "Yes" is outputted at least once, we adopt the utterance; otherwise, we discard it. The employed prompt is identical to the BLIP-2 filter in Section 3.2.

	#videos	#speakers	#utterances	#hours
Train	195	172	15,803	29.26
Dev	20	20	1,515	3.08
TestA	15	15	1,034	2.21
TestB	15	13	1,111	1.90
Total	245	220	19,463	36.45

Table 1: Statistics of SlideAVSR.

Merging utterances. Subtitles created by video authors occasionally exhibit unnatural segmentation, resulting in exceedingly brief spans. Utilizing the audio segments obtained through CTC segmentation, we implement a merging process, combining two consecutive utterances into a single entity if the end time of the preceding utterance aligns with the start time of the subsequent one and their cumulative duration does not exceed 15 seconds. This procedure significantly enhanced Whisper's ASR performance by approximately 20%.

3.4 Data Partitioning

Previous studies (Meyer et al., 2020; Javed et al., 2023; DiChristofano et al., 2023) have suggested that the performance of ASR systems significantly varies depending on the speaker's accent[3]. Based on the hypothesis that visual information contributes to the recognition of challenging accents, we ask native English speakers to classify the speakers' accents in SlideAVSR and perform dataset partitioning. We partition the dataset into Train, Dev, and TestA, reserving a smaller yet significant TestB subset for South Asian English (SAE) accents. During partitioning, we have ensured that the same speaker did not belong to multiple partitions. Additionally, videos with machine-generated audio were manually excluded by the annotators.

Through the construction flow, we produced an AVSR dataset of around 36 hours from 245 videos. We show the statistics of the dataset in Table 1.

4 Experiments

4.1 Approaches

DocWhisper processes the input video stream through an OCR module, extracting textual information into word sequences, which are then provided to Whisper as prompts for fine-tuning and inference. While Peng et al. (2023) employed prompts derived from CLIP in zero-shot learning, our preliminary experiments did not reveal a performance improvement in zero-shot learning on SlideAVSR. Given that Whisper's pre-training (Radford et al., 2022) did not use prompts, we speculate that Whisper loses robustness when it faces diverse prompts.

[3]The term "accent" in this paper refers to comprehensive prosodic information, including accent, intonation, tone, etc.

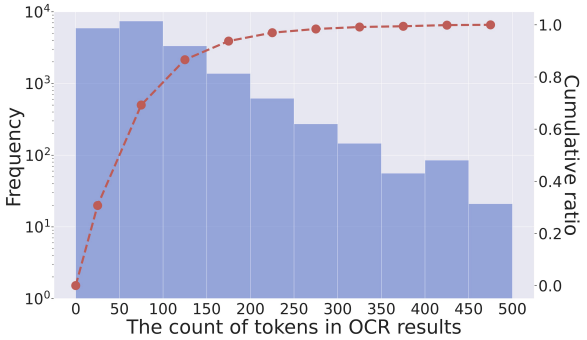


Figure 2: Frequency distribution of the number of words in OCR results. While samples with over 500 words are present, they are omitted for brevity.

We show the frequency distribution of the number of words in OCR results in Figure 2. The distribution is long-tail, which means that only 70% of the samples can be covered even if we include 100 words in the prompts[4]. To address this issue, we propose FQ Ranker, which calculates word ranks based on the frequency of word occurrences. Given the demonstrated high correlation between word frequency and familiarity as shown in previous studies (Coltheart, 1981; Tanaka-Ishii, 2021), increasing the rank of less frequent and more challenging words is expected to enhance the information content of prompts.

4.2 Implement Details

We used Whisper large-v3[5] as a base model and Word Error Rate (WER) for evaluation. In the case of DocWhisper, we captured screenshots at the midpoint of each utterance, fed them into the OCR module, and used the recognized text as the prompts to Whisper. We use Google Cloud Vision API[6] for OCR. The prompts were presented to the model as word sequences, such as "word 1, word 2, ..., word n". FQ Ranker utilized word frequency counts obtained from the English Wikipedia as of April 2023 and sorted the OCR results in ascending order based on word frequency. We conducted experiments with different maximum word counts for prompts ($K \in \{25, 50, 75, 100\}$) and with or without FQ Ranker. More implementation details are provided in Appendix C.

[4]Whisper typically assigns a maximum length of 224 to prompts, making inputs with over 100 words challenging.

[5]https://huggingface.co/openai/whisper-large-v3

[6]https://cloud.google.com/vision

Type	Example
Technical term	W Hyp: we select quantum ~~adhering~~ 2 and nxt as representative of pos protocols
(41%)	D Hyp: we select quantum ethereum 2 and nxt as representative of pos protocols
Inflection	W Hyp: manual ~~transcript~~ we call this setting supervised things we have paired data
(28%)	D Hyp: manual transcripts we call this setting supervised things we have paired data
Mishearing	W Hyp: we can also perform other tasks like ~~normal~~ view synthesis
(24%)	D Hyp: we can also perform other tasks like novel view synthesis
Name	W Hyp: this is a work done at ibm research with ~~gilmoseci chileo~~ and irina ~~rich~~
(7%)	D Hyp: this is a work done at ibm research with guillermo cecchi and irina rish

Table 2: Error types and examples that are substitution errors in Whisper (W) but correct in DocWhisper (D).

Model	Modality	Fine-tune	K^a	TestA	TestB
Whisper	A	✗	0	8.23	11.18
		✔		8.07	11.25
DocWhisper	A + V	✔	25	7.35	10.82
+ FQ Ranker				7.42	10.59
DocWhisper	A + V	✔	50	7.08	10.43
+ FQ Ranker				7.26	10.35
DocWhisper	A + V	✔	75	7.02	10.04
+ FQ Ranker				7.26	10.29
DocWhisper	A + V	✔	100	**6.91**	**10.01**
+ FQ Ranker				7.04	10.22

[a]Indicating maximum word counts for prompts.

Table 3: Quantitative evaluation (WER) on SlideAVSR.

4.3 Results

We show the results of quantitative evaluations for Whisper and DocWhisper in Table 3. In both models, the scores of the TestB set, consisting of videos with SAE accents, were inferior to the scores of the TestA set, indicating that Whisper struggles with rare accents. With fine-tuning, Whisper demonstrated a 1.9% improvement on the TestA set. However, no notable improvement was observed for the TestB set. Despite the presence of videos with SAE accents in the training data, their limited quantity was deemed insufficient to address the challenges posed by difficult accents.

Compared to the fine-tuned Whisper, DocWhisper exhibited a maximum improvement of 14.3% on TestA and 11% on TestB. We gather that referring to textual information on slides can significantly improve speech recognition performance on SlideAVSR. We also found that as the maximum word count of prompts increased, the performance improved, indicating that maximizing information content contributes to performance enhancement.

FQ Ranker improved the scores on TestB when the maximum word count of prompts was set to 25; however, this advantage was reversed when the maximum word count exceeded 50. Details provided in Section 4.4 indicate that transcriptions corrected by DocWhisper do not exclusively consist of technical terms, which suggests the potential for misinterpretation even in words with high familiarity. We also speculate that sorting words based on word frequency disrupts the ordered contextual information, thus increasing the difficulty of Whisper's decoder, which is a language model, to refer to the textual information on the slides.

4.4 Analysis of Specific Examples

Among Whisper's errors (deletions, substitutions, and insertions), DocWhisper corrected substitution errors the most. To delve into the details, we collected 100 instances that are substitution errors in Whisper but correct in DocWhisper and categorized them into four groups: technical term, inflection, mishearing, and name. While the anticipated large proportion (41%) of technical terms was observed, noteworthy percentages were also found for inflection (28%) and mishearing (24%). Many words with high familiarity could result in lower ranks when sorting based on word frequency, potentially causing a decline in the performance of FQ Ranker. We show the error types and specific examples in Table 2 and more details in Appendix D.

5 Conclusion and Future Work

We constructed an AVSR dataset, SlideAVSR, by utilizing paper explanation videos. We proposed DocWhisper, which leverages OCR to refer to slide content. We verified the effectiveness of DocWhisper on SlideAVSR and conducted a detailed analysis. Additionally, we introduced FQ Ranker, which calculates word ranks based on word frequency, and evaluated its performance on DocWhisper.

In the future, we plan to continually refine OCR-based methods and aim to construct an end-to-end AVSR model that is not dependent on OCR. Furthermore, we intend to build a benchmark that allows a comprehensive evaluation of the image comprehension capabilities of AVSR models by incorporating diverse types of videos, such as sports commentary, gaming commentary, cooking videos, and more. Ultimately, we aim to construct a foundation model for AVSR that exhibits high performance across diverse video inputs.

Limitations

In comparison to mainstream AVSR datasets, SlideAVSR exhibits a notably limited number of speakers. This may lead to data imbalance and create obstacles to the model's training process. In addition, due to our focused collection of scientific paper explanation videos related to artificial intelligence, imbalances may have emerged in terms of speaker nationality, age, and gender.

In Section 3.4, we attempted to classify speakers' accents by collaborating with native English speakers. However, the task of assigning precise labels to every video was impeded by the complexity of distinguishing certain speakers' accents. As a result, we selectively picked out videos with South Asian English accents, leaving the remainder unlabeled. Ideally, each data split should exhibit a comparable distribution of accents, but this was unattainable due to the aforementioned challenges.

Ethical Considerations

In adherence to the terms of use and copyright policies governing the YouTube platform, we collected data exclusively from publicly available videos. We acknowledge the potential presence of sensitive information in our dataset, such as personal names and portraits. To prioritize privacy and responsible data sharing, we plan to release OCR results and public video URLs instead of raw video files. Furthermore, the release of our dataset will be strictly limited to research purposes.

References

Triantafyllos Afouras, Joon Son Chung, Andrew Senior, Oriol Vinyals, and Andrew Zisserman. 2018a. Deep audio-visual speech recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(12):8717–8727.

Triantafyllos Afouras, Joon Son Chung, and Andrew Zisserman. 2018b. Lrs3-ted: a large-scale dataset for visual speech recognition.

Joon Son Chung, Andrew Senior, Oriol Vinyals, and Andrew Zisserman. 2017. Lip reading sentences in the wild. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3444–3453.

Joon Son Chung and Andrew Zisserman. 2017a. Lip reading in profile.

Joon Son Chung and Andrew Zisserman. 2017b. Lip reading in the wild. In *Computer Vision – ACCV 2016*, pages 87–103, Cham. Springer International Publishing.

Max Coltheart. 1981. The mrc psycholinguistic database. *The Quarterly Journal of Experimental Psychology Section A*, 33(4):497–505.

Alex DiChristofano, Henry Shuster, Shefali Chandra, and Neal Patwari. 2023. Global performance disparities between english-language accents in automatic speech recognition.

Valentin Gabeur, Paul Hongsuck Seo, Arsha Nagrani, Chen Sun, Karteek Alahari, and Cordelia Schmid. 2022. Avatar: Unconstrained audiovisual speech recognition.

Alexandros Haliassos, Pingchuan Ma, Rodrigo Mira, Stavros Petridis, and Maja Pantic. 2023. Jointly learning visual and auditory speech representations from raw data. In *The Eleventh International Conference on Learning Representations*.

Suyog Jain, Rohit Girdhar, Andrew Westbury, and et al. 2023. Ego4d challenge 2023. Https://ego4d-data.org/docs/challenge/.

Tahir Javed, Sakshi Joshi, Vignesh Nagarajan, Sai Sundaresan, Janki Nawale, Abhigyan Raman, Kaushal Bhogale, Pratyush Kumar, and Mitesh M. Khapra. 2023. Svarah: Evaluating english asr systems on indian accents.

Ludwig Kürzinger, Dominik Winkelbauer, Lujun Li, Tobias Watzel, and Gerhard Rigoll. 2020. Ctc-segmentation of large corpora for german end-to-end speech recognition. In *International Conference on Speech and Computer*, pages 267–278. Springer.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. 2023. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. In *ICML*.

Ilya Loshchilov and Frank Hutter. 2019. Decoupled weight decay regularization.

Josh Meyer, Lindy Rauchenstein, Joshua D. Eisenberg, and Nicholas Howell. 2020. Artie bias corpus: An open dataset for detecting demographic bias in speech applications. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 6462–6468, Marseille, France. European Language Resources Association.

Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. 2019. HowTo100M: Learning a Text-Video Embedding by Watching Hundred Million Narrated Video Clips. In *ICCV*.

Xichen Pan, Peiyu Chen, Yichen Gong, Helong Zhou, Xinbing Wang, and Zhouhan Lin. 2022. Leveraging unimodal self-supervised learning for multimodal audio-visual speech recognition. In *Proceedings of the 60th Annual Meeting of the Association for*

Computational Linguistics (Volume 1: Long Papers), pages 4491–4503, Dublin, Ireland. Association for Computational Linguistics.

Puyuan Peng, Brian Yan, Shinji Watanabe, and David Harwath. 2023. Prompting the hidden talent of web-scale speech models for zero-shot task generalization. In *Interspeech*.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2022. Robust speech recognition via large-scale weak supervision.

Bowen Shi, Wei-Ning Hsu, Kushal Lakhotia, and Abdelrahman Mohamed. 2022. Learning audio-visual speech representation by masked multimodal cluster prediction. *arXiv preprint arXiv:2201.02184*.

Brendan Shillingford, Yannis Assael, Matthew W. Hoffman, Thomas Paine, Cían Hughes, Utsav Prabhu, Hank Liao, Hasim Sak, Kanishka Rao, Lorrayne Bennett, Marie Mulville, Misha Denil, Ben Coppin, Ben Laurie, Andrew Senior, and Nando de Freitas. 2019. Large-scale visual speech recognition. In *Proc. Interspeech 2019*, pages 4135–4139.

Shinnosuke Takamichi, Ludwig Kürzinger, Takaaki Saeki, Sayaka Shiota, and Shinji Watanabe. 2021. Jtubespeech: corpus of japanese speech collected from youtube for speech recognition and speaker verification.

Kumiko Tanaka-Ishii. 2021. *Statistical Universals of Language*. Springer Cham.

A The list of target conferences used in data collection

We show our target conferences in Table 4.

Topic	Conference
NLP	ACL, NAACL, EMNLP
CV	CVPR, ICCV, ECCV
Speech	INTERSPEECH, ICASSP
AI	AAAI, IJCAI
ML	ICLR, ICML, NeurIPS
Data Mining	KDD, WSDM, WWW
Database	SIGMOD, VLDB, ICDE
IR	SIGIR
HCI	CHI

Table 4: Target conferences.

B Models and prompts used in data filtering and cleansing

We introduce the details of the models and prompts employed in the ChatGPT filter, BLIP-2 filter, and CTC alignment as described in Section 3.2 and 3.3.

ChatGPT filter. We used gpt-3.5-turbo. The prompt we used is shown in Table 5.

Here is a description of a YouTube video: {DESCRIPTION} Using the description, check whether the video meets the following criteria. - This video is a presentation video of a research paper. - The description is written in English. Attention, you can only answer 'Yes' or 'No' and you can only answer one time.

Table 5: Prompt for ChatGPT filter.

BLIP-2 filter. We used blip2-flan-t5-xl[7]. The prompt we used is shown in Table 6.

Question: This image is a screenshot of a video, check whether the image meets the following criteria. - It is a screen-sharing, not a photo shoot. - It is a part of a slide for a research presentation. Attention, you can only answer 'Yes' or 'No' and you can only answer one time. Answer:

Table 6: Prompt for BLIP-2 filter.

CTC alignment. We used kamo-naoyuki_wsj[8] and ESPnet implemenations[9].

[7] https://huggingface.co/Salesforce/blip2-flan-t5-xl
[8] https://huggingface.co/espnet/kamo-naoyuki_wsj
[9] https://github.com/espnet/espnet

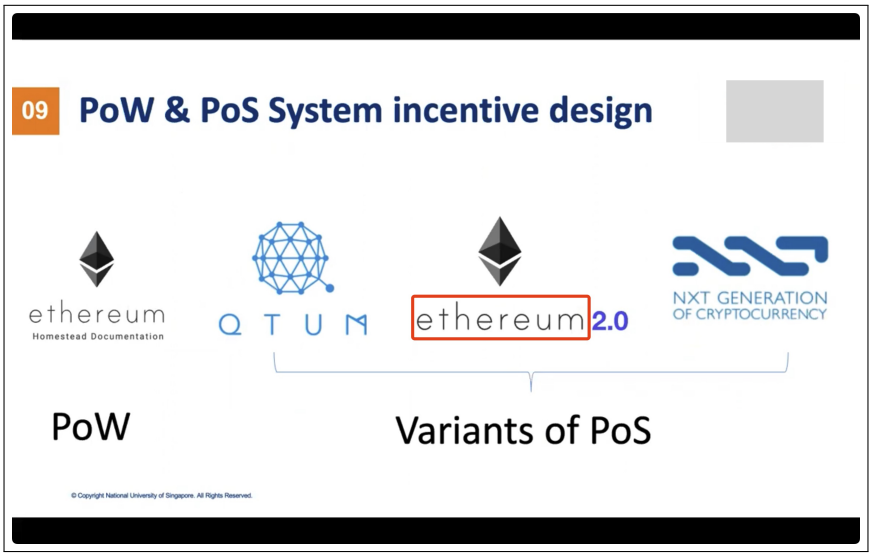
C Implement details

We fine-tuned both Whisper and DocWhisper using AdamW (Loshchilov and Hutter, 2019) with a learning rate of 2e-5, and we linearly warmed up the learning rate over 1,000 steps. The batch size was set to 16. Training was conducted for 10 epochs, and the checkpoint with the best performance on the Dev set was used for evaluation. Additionally, training was performed with three different seed values, and the average was computed. We performed text normalization[10] for evaluation. All experiments were conducted on a single NVIDIA A100 (40G) GPU.

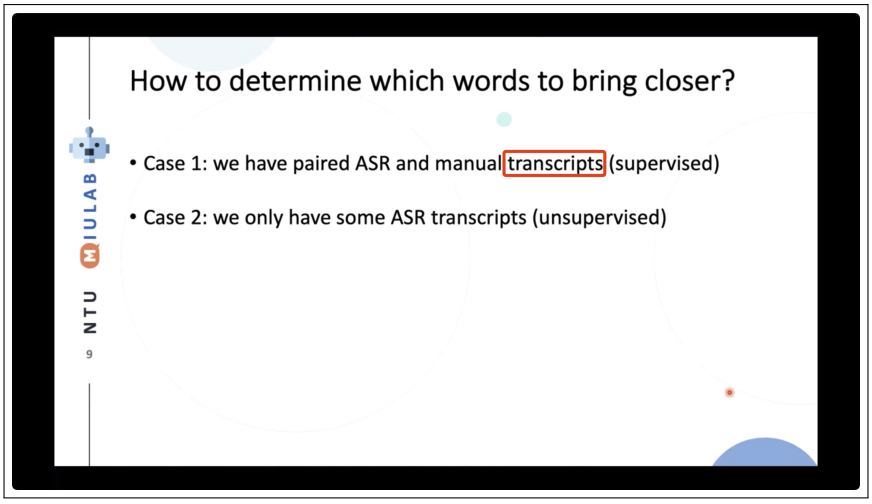
D Specific examples

The corresponding screenshots to Table 2 are shown below, and the parts referred to in the correction are circled in red.

All the variations from the same lexical element, such as plural nouns, conjugated verbs, and third-person singular verbs, were classified as inflection. If the label and prediction are not from the same lexical element, we classified the error as technical terms, mishearing, and names, respectively.

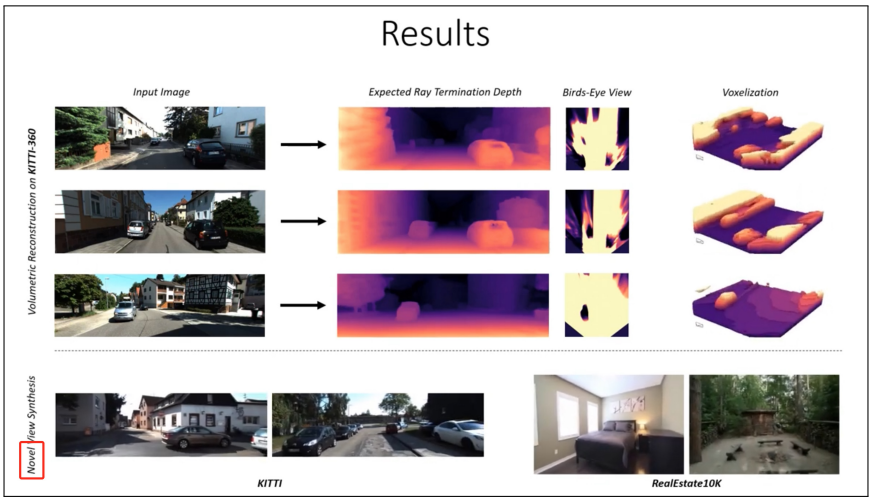


https://www.youtube.com/watch?v=eepUV9NJxFs



https://www.youtube.com/watch?v=dvUutyo72R4

[10] https://github.com/openai/whisper



https://www.youtube.com/watch?v=0VGKPmomrR8

https://www.youtube.com/watch?v=CQBdQz1bmls