Automatic Speech Recognition Datasets in Cantonese Language:
A Survey and a New Dataset

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Abstract
Automatic speech recognition (ASR) on low resource languages improves access of linguistic minorities to technological advantages provided by Artificial Intelligence (AI). In this paper, we address a problem of data scarcity of Hong Kong Cantonese language by creating a new Cantonese dataset. Our dataset, Multi-Domain Cantonese Corpus (MDCC), consists of 73.6 hours of clean read speech paired with transcripts, collected from Cantonese audiobooks from Hong Kong. It combines philosophy, politics, education, culture, lifestyle and family domains, covering a wide range of topics. We also review all existing Cantonese datasets and perform experiments on the two biggest datasets (MDCC and Common Voice zh-HK). We analyze the existing datasets according to their speech type, data source, total size and availability. The results of experiments conducted with Fairseq S2T Transformer, a state-of-the-art ASR model, show the effectiveness of our dataset. In addition, we create a powerful and robust Cantonese ASR model by applying multi-dataset learning on MDCC and Common Voice zh-HK.

Keywords: Speech Corpus, Hong Kong Cantonese, Automatic Speech Recognition System

1. Introduction
Automatic speech recognition (ASR) system aims to take the audio as an input and convert it into the text (Malik et al., 2021). Due to a popularization of deep learning, ASR technology has grown rapidly and has led to a significant improvement in recognizing many languages. For instance, ASR systems in English language (Zhang et al., 2020; Xu et al., 2021; Baevski et al., 2020) have been able to achieve below 2% WER on LibriSpeech corpus. Similar trend is also observed in research on Chinese ASR (Li et al., 2019; Winata et al., 2020a; Zhang et al., 2020), exemplified by the improvement of ASR model performance on Aishell-1 (Bu et al., 2017) corpus from 18.7% CER down to 6.84% CER within just 2 years. However, many languages (e.g., Gujarati, Hindi, Bengali, Amharic and Cantonese), including code-switching, are still lacking resources and the performance of ASR systems in these languages are unsatisfactory (Winata et al., 2021; Khare et al., 2021; Lovenia et al., 2021). Therefore, many adaptability methods in ASR have also been introduced and have shown promising results (Wang et al., 2021; Lin and Chen, 2020; Winata et al., 2020b; Winata et al., 2020c). Many of these achievements are due to the utilization of the most recent deep neural network architectures and high-performance parallel computing graphic cards. However, as deep learning techniques require big amount of training data, creation of ASR datasets is essential for model’s performance. Moreover, creating a speech recognition corpus accelerates the development of the ASR system in corresponding languages.

Although around 88.9% of Hong Kong’s population are native Cantonese speakers, the Cantonese language is still struggling with a shortage of resources for building ASR systems. We present the most important speech resources in Cantonese in Table 1 From the analysis of a speech type used for building the dataset, data source, as well as a total size and availability of the dataset, we assess that not all of them are suitable to build robust ASR systems. To fill this research gap, we introduce a multi-domain Cantonese ASR read corpus called Multi-Domain Cantonese Corpus (MDCC) for the ASR research in Cantonese language. Our corpus consists of 73.6 hours of clean read speech collected from various Hong Kong Cantonese audiobook sources. It contains philosophy, politics, education, culture, lifestyle, and family domains covering a wider range of topics than most of the other corpora. In addition, we perform experiments using a state-of-the-art ASR framework, Fairseq S2T Transformer (Wang et al., 2021), on the two of the largest available datasets (MDCC and Common Voice zh-HK). The model achieves 10.15% CER on the test set of our corpus, which indicates the effectiveness of our dataset. We also use the joint training to create a more powerful and robust model for the Cantonese ASR system.

Contributions of our study to the field are threefold:
- We review existing Cantonese ASR datasets and thoroughly analyze them from different perspectives (e.g., speech type, data source, total size and availability).

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https://github.com/HLTCHKUST/cantonese-asr
| Name                   | Speech Type | Data source          | Size [hours] | Availability |
|------------------------|-------------|----------------------|--------------|--------------|
| HKCAC [Leung and Law, 2001] | Spont.      | Phone-in programs    | 8.1          | Non-Public   |
| HKCanCor [Luke and Wong, 2015] | Spont.      | Chat                 | 30.0         | Cvasi-Public |
| HKCC (Chin, 2015)       | Spont.      | Movie                | 35.0         | Cvasi-Public |
| CantoMap [Winterstein et al., 2020] | Read       | MapTask              | 12.8         | Public       |
| Common Voice zh-HK [Ardila et al., 2019] | Read       | Wikipedia            | 96.0         | Public       |
| MDCC (Ours)             | Read        | Audiobook            | 73.6         | Public       |

Table 1: Hong Kong Cantonese ASR corpus

- We propose a new dataset named MDCC for the ASR research in Cantonese language, which consists of 73.6 hours of clean read speech and covers a wide range of topics.
- We evaluate our dataset and another available Cantonese ASR dataset (Common Voice zh-HK) by using a state-of-the-art ASR model (Fairseq S2T Transformer). Furthermore, we apply multi-dataset learning approaches on the above two datasets to create a powerful and robust model for the Cantonese ASR. Multi-dataset learning boosted the model’s performance on both datasets. The results support the claim on effectiveness of our dataset.

2. Cantonese ASR Datasets

As shown in Table 1, we have listed the most important previous works on Cantonese ASR corpora and analyzed them from speech type, data source, data size and availability.

HKCAC  The Hong Kong Cantonese Adult Language Corpus (HKCAC) is created from the phone-in programs and forums’ spontaneous speech records on the radio in Hong Kong. It has 8.1 hours of recording time and the transcripts that contain approximately 170,000 characters. The HKCAC dataset is inaccessible as there is no website, link, or any other information provided for retrieving the dataset.

HKCanCor  The Hong Kong Cantonese Corpus (HKCanCor) is built based on spontaneous chat records. The participants were recruited for arranged recording sessions for two- or three-party chats. Later, an additional set of recordings was obtained from radio chat shows. The corpus consists of 30.0 hours of the recording time, with each sample 10 minutes long. After the transcription, the corpus contains around 180,000 word tokens. The transcripts of HKCanCor dataset can be accessed from the official website, but no audio data is provided.

HKCC  The Corpus of Mid-20th Century Hong Kong Cantonese (HKCC) is constructed based on Cantonese films from Hong Kong in the 1950s and 1960s. HKCC has two phases and we only introduce the first phase corpus since the second phase’s report is not released. There are 21 movies in the first phase corpus, and each movie is about 100 minutes. The corpus has in total about 200,000 character tokens. The details of the HKCC dataset can be found on their official website, but cannot be retrieved due to limited access control.

CantoMap  Hong Kong Cantonese MapTask Corpus (CantoMap) aims to provide a Cantonese corpus for the ASR research and also involves several controlled elicitation tasks related to the phonology and semantics of Cantonese. A design of the corpus follows a general setup used for the HCRC MapTask corpus [Anderson et al., 1991]. The corpus includes a total of 12.8 hours of recordings and transcripts of forty speakers. The CantoMap dataset is publicly available in the GitHub repository.

Common Voice zh-HK  The Common Voice zh-HK corpus is a massively-multilingual collection of transcribed speech which is collected and validated via Mozilla’s Common Voice initiative. The speakers are required to read sentences from Wikipedia and the annotators verify each sentence. We use 96.0 hour split of verified Cantonese utterances in our experiments. The detailed data statistics are shown in Section 5. The dataset is available on the Common Voice website. Thus, although each of these corpora has its own advantages, not all of them are suitable for developing Cantonese ASR systems. The data size of all of these corpora except Common Voice zh-HK is not large enough for data-intensive ASR model fine-tuning. Furthermore, even for Common Voice zh-HK, the empirical experiments based on recent deep learning models are limited. To fill this research gap, we propose the MDCC to enrich resources of ASR datasets in Cantonese. Furthermore, we implement the state-of-the-art ASR model and report the model’s performance on Common Voice zh-HK and MDCC datasets.

3. Corpus Creation

This section describes the creation of our Multi-Domain Cantonese Corpus (MDCC). We first introduce the approach to collect and pre-process the Cantonese audiobooks and then present the methods to annotate transcripts.

2http://compling.hss.ntu.edu.sg/hkcancor/
3http://202.45.36.235/hkcc/
4https://github.com/gwinterstein/CantoMap
5https://commonvoice.mozilla.org/zh-HK/datasets
### 3.1. Audiobooks Collection

The speech corpus of MDCC is collected from Hong Kong Cantonese audiobook sources. The corpus contains various audiobooks covering different topics (e.g., philosophy, politics, education, culture, lifestyle and family). Most of the books are in the literary form of Cantonese. However, some of them are written in a formal written form of Cantonese that is never used as a spoken language, and therefore not applicable to ASR systems. To remove these books, we hire native Cantonese speakers to check all the audiobooks, and to filter them out manually.

Every piece of the downloaded audiobook varies from 40 minutes to 2 hours, which does not fit the optimal size for ASR systems. Therefore, we apply a voice activate detection (VAD) tool to convert the original audio pieces into shorter audio utterances. The VAD tool can classify a piece of audio data as being voiced or unvoiced, we consequently split the original audio samples by unvoiced parts. After separating, we get 83,275 audio utterances with a total corpus size of 73.6 hours.

### 3.2. Annotation

To ensure cost-efficiency with optimal quality, we annotate all the utterances in two phases. We first conduct an automatic annotation with Google Cloud Speech-to-Text API and then improve the automatic transcripts’ quality by hiring native Cantonese speakers to correct them manually.

Google Cloud Speech-to-Text. Google Cloud Speech-to-Text is an API that converts speech into text and it is powered by Google’s AI technologies. We apply this API to produce the initial transcripts of the utterances. More specifically, we use the default model with the language set to Hong Kong Cantonese (yue-Hant-HK). The API returns a transcript with a confidence score for each utterance. These automatically generated transcripts accelerate the hand-correction process significantly.

**Proofreading of the Transcription.** Since Google Cloud Speech-to-Text is not entirely accurate and there are some errors in the automatically generated transcripts, we hire native Cantonese speakers to hand-correct the transcripts generated from Google Cloud Speech-to-Text. During proofreading, the annotators are required to adjust the transcripts and take notes for each utterance according to our guidelines. As shown in Table 2, we made a list of words that the annotators needed to pay attention to. The words listed in the unified writing mean they share the same semantics, and we replace them with a unified word. There are also many words listed in the important words section, which means the annotators need to focus more on these words and annotate them accurately. One type of important words are question particles indicating interrogative sentences in Cantonese. Table 3 shows samples of question particles that annotators need to focus on.

In addition, the annotators needed to follow the following guideline when taking notes: 1) If the audio contained pure music, the annotators needed to mark the label: (music) in the file name of its transcript. 2) If the utterance contained one or several sentences with background music or noise, the annotators had to mark the label: (music) before each sentence in the transcript. 3) For the uncertain words, the annotators used {} symbols to enclose them. For example: (来自何方) • 我是(何人)。For the English transcriptions or Arabic numerals, annotators needed to do the following: 1) Capitalization of the first word of each complete English sentence. 2) Capitalization of proper nouns (e.g., names of people, countries and regions) 3) Besides the exceptional cases listed above, all the other common English words were lowercased. 4) A space should not be added between common acronyms such as CCTV, VIP, etc. For unusual

### Table 3: Several representative sentences from the MDCC dataset.

| Words | Meaning |
|-------|---------|
| 呢、係、係 - (Question particle) | 那、是、似 |
| 呢個係 | 是呢個 | 呢個係 | 是呢個 |
| 後 | Later | After | Afterward |
| 咪 | Some | A few | Several |
| 係 | And |
| 併 | Combine |
| 徵 | Recruit | Ask for |
| 還 | About |
| 過程 | Process |
| 盡 | - As soon as possible |
| 部份 | Partially |
| 咪樣 | So | Such | Like this |
| 嘴觸 | Actually |
| 其實 | Actually |
| 讀書 | Study |

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6[https://cloud.google.com/speech-to-text/]
Table 4: Breakdown of the train, validation, and test splits in MDCC dataset concerning number of samples, gender, and the duration of the utterances.

| Gender  | # Sample | Duration (hr) |
|---------|----------|---------------|
|         | Train    | Valid | Test | Total | Train | Valid | Test | Total |
| Female  | 29,224   | 2,541 | 5,606| 37,371| 28.67 | 2.52  | 5.39 | 36.58 |
| Male    | 35,896   | 3,122 | 6,886| 45,904| 28.86 | 2.54  | 5.61 | 37.01 |
| Total   | 65,120   | 5,663 | 12,492| 83,275| 57.53 | 5.05  | 11.01| 73.59 |

4. MDCC: Multi-Domain Cantonese Corpus

In this section, we analyze our Multi-Domain Cantonese Corpus (MDCC) from different perspectives, including data statistics, domain analysis and text analysis.

4.1. Data Statistics

The MDCC consists of 73.6 hours of Cantonese scripted speech from the Cantonese native speakers with a balanced gender ratio, that includes 50.29% male and 49.71% female voice talents. The corpus is divided into 83,275 audio files, each containing one utterance. The MDCC includes a total number of 998,366 Cantonese characters, with each utterance being approximately 11.99 characters long. As shown in Figure 2, the length of each utterance varies from a single character to as many as 80 characters. 89.85% of the utterances are less than 23 characters, and the number of utterances decreases rapidly as the length of the utterance increases. Few utterances reach a length of more than 50 characters.

In terms of the duration of each utterance, all of them last between 0.22 to 15.0 seconds. Moreover, the average duration of the utterance is 3.18 seconds. As we can see in Figure 3, the duration distribution is balanced and most of the utterances are between one to nine seconds. Meanwhile, the duration distribution is mainly aligned with the length distribution since longer utterances take more time for the speaker to read.

Figure 1: Gender split of the training, validation and test sets per hour of the recorded audio.

Figure 2: Distribution of the number of character per utterance in the MDCC corpus.

Figure 3: Distribution of the duration (in seconds) per utterance in our MDCC corpus.
### Table 5: The statistics of the MDCC dataset vocabulary: top 10 high-frequency unigrams, bigrams and trigrams.

| Top | Character/Unigram | Bigram | Trigram |
|-----|-------------------|--------|---------|
| 1   | 嘢 - is / are     | 但係 - but | 嘢時候 - the time of |
| 2   | 一 - one          | 一個 - one | 呢一個 - this one |
| 3   | 係 - am / is / are | 亦都 - and / also / as well | 更懂得 - more clear / understand better |
| 4   | 佢 - he / she / it | 同理 - with | 同著作 - same book |
| 5   | 我 - I / me       | 佢哋 - they / them | 自己嘅 - myself / my own |
| 6   | 有 - have / has   | 我哋 - we / us | 嘢學生 - the student of |
| 7   | 人 - person / people | 啠様 - like this | 唔能夠 - cannot / unable to |
| 8   | 噱 - no           | 就係 - that is / just like | 中國人 - Chinese |
| 9   | 個 - pieces       | 學生 - student | 小王子 - little prince |
| 10  | 好 - yes / good   | 裏面 - inside | 呢一種 - this kind |

### 4.2. Domain Analysis

To create a general, natural and commonplace conversation ASR system, we choose a wide range of audiobook sources for the dataset. As a result, our MDCC dataset covers multiple domains, including philosophy, politics, education, culture, and lifestyle. We hire a native Cantonese speaker to read and annotate the domain for each audiobook. Figure 4 provides a summary of domain distribution in the corpus. Furthermore, the domain of each sentence follows the domain of the audiobook that the sentence belongs to.

Since an audiobook can cover multiple domains, the sum of sentences in each domain is greater than the total number of sentences in the MDCC dataset. Culture and lifestyle domains have the most utterances in our dataset, which shows that the content of our dataset is reflecting people’s daily lives. Besides culture and lifestyle, the philosophy domain also includes many utterances. It is worth explaining that the philosophy here mainly refers to the self-help literature. Politics, education and family domains have less data but still are considered essential topics of the MDCC. We believe that this domain analysis can help the research community to better understand the semantic distribution of our dataset.

### 4.3. Common Phrases in MDCC

After a thorough analysis we calculated a total of 998,366 Cantonese characters in the MDCC dataset. Their distribution is depicted in Figure 5. In order to have an explicit understanding of the common phrases in the MDCC, we report the top 10 most common n-grams in Table 5. A small portion of the characters appears much more frequently than the rest from the statistics. In detail, 14.56% of the characters in the MDCC is made up of the 10 most common characters. Meanwhile, there is also a large number of characters that appear less than 10 times in the corpus, which also reflects the diversity of the text in our dataset and complying with the Zipf’s law (Yu et al., 2018).

### Figure 4: The distribution of domains of utterances in the MDCC dataset. Each utterance can belong to more than the one domain, hence the total number of utterances per domain is bigger than the real total number per utterance.

### Figure 5: The distribution of log character frequency in the MDCC dataset.

### 5. Cantonese ASR using Fairseq S2T Transformer

In this section, we introduce the Fairseq S2T Transformer (Wang et al., 2020; Ott et al., 2019) model and conduct experiments on the MDCC and Common Voice zh-HK datasets. We also apply multi-dataset learning
approaches to further improve the model’s performance.

5.1. Fairseq S2T Transformer
The reasons for choosing Fairseq S2T Transformer are twofold: 1) Fairseq S2T Transformer model can achieve start-of-the-art performance on LibriSpeech, the de-facto standard ASR benchmark. 2) It is friendly for training custom models for ASR, and we can easily adapt the model to Cantonese. Based on the original transformer architecture (Vaswani et al., 2017), Fairseq S2T Transformer proposed to add convolutional layers to the encoder (Mohamed et al., 2019), which is the optimal way for processing audio data in the form of log mel filterbanks. We use the S2T Transformer XS version for all the experiments to implement the models.

5.2. Datasets
We conduct experiments on the two largest Cantonese datasets (MDCC and Common Voice zh-HK) for a better comparison, and jointly train them to see how the performance of the dataset improves if we double its size. The splits of the Common Voice zh-HK dataset follow the same ratio of our MDCC dataset, which is 80% for training, 10% for validation and 10% for testing. The detailed information of these two datasets is shown in Table 6. In addition, the audio files were downsampled to the frequency of 16kHz, with 32-bit depth. For follow-up experiments, we join MDCC and Common Voice zh-HK datasets into one and apply multi-dataset training approach. We hope that it can improve the model’s performance in the cross dataset setting and increase the robustness of the model.

5.3. Implementation Details
Data pre-processing. We implemented spectral augmentation (SpecAugment), a state-of-the-art audio data augmentation method, that is implemented by masking certain frequency and time values on the spectrogram (Park et al., 2019). We use SpecAugment for the Common Voice zh-HK baseline where it shows an improvement in overall results. Furthermore, we apply cepstral mean and variance normalisation (CMVN) for all the utterances (Strand and Egeberg, 2004). In Fairseq S2T, pre-processed audio can be used directly or stored in a form of .npy files, the latter is the way in which we store features extracted from Cantonese datasets to achieve a faster training. For tokenization of the transcribed data, we use SentencePiece tokenizer (Kudo and Richardson, 2018) with the unigram subword tokenization (Kudo, 2018) and 8,000-word vocabulary. The vocabulary covers 99.95% of the characters in MDCC dataset (the default coverage for character-based languages).

Hyper-parameters. We use the off-the-shelf Fairseq S2T Transformer XS model, which consists of a 6-layer encoder and a 3-layer decoder with a multi-head attention mechanism with 4 attention heads. For objective function, we apply a cross entropy loss with 0.1 label smoothing. The models were trained on 4 GPUs with the mini-batch size of 32. We have used the default settings of SpecAugment provided in the S2T bundle: frequency masking width parameter F is set to 27, the number of time and frequency masks is set to 1, with the upper bound of time masking width of 1, finally the time masking width parameter T is set to 100. In our experiments the applied SpecAugment policy does not include time warping.

Evaluation Metric. The models are evaluated on separated test sets, as is shown in Table 6. For the evaluation we average the performance of last 10 checkpoints of the model using a beam search with the beam size 8. Since the transcribed language is character based, we use Character Error Rate (CER) rather than word error rate (WER) as an evaluation metric (Wang et al., 2013). The CER is calculated by adding the number of substituted, inserted and deleted characters together and dividing them by the total character count of the reference.

5.4. Results and Analysis
The CER returned by S2T Transformer XS on the MDCC and Common Voice zh-HK datasets is comparable (10.15% and 8.69% CER respectively), possibly due to the similarities in domains and the size of datasets themselves. We discovered, however, that the datasets react differently to spectral augmentation. While SpecAugment hindered the training of the model trained on the MDCC dataset, it did not influence the model trained on Common Voice zh-HK dataset. Similarly the training on the combined dataset was hindered by adding spectral augmentation. In joint dataset we have originally shuffled the training data, but such model did not converge. We conjecture that if we mix the datasets in the same batch, the model cannot reach an optimal direction of gradient descent. The model benefited however from ordering two datasets such that utterances from the MDCC were featured first and the ones from Common Voice zh-HK afterwards, following the theory that modelling long span word dependencies depends on the ordering of training data (Vazhenina and Markov, 2014). This decision was based on the fact that the MDCC data is cleaner, shorter and therefore easier to learn than the Common Voice zh-HK dataset.

The CER returned by the model trained on the joint dataset shows improvement in results of both datasets and a large improvement in the out-of-domain testing scenario. Even though datasets used by us are the largest among other Cantonese ASR datasets, they are still much smaller compared with more comprehensive datasets.

### Table 6: The statistics of the MDCC and Common Voice zh-HK datasets

| Datasets              | # train | # val  | # test  | # Total |
|-----------------------|---------|--------|---------|---------|
| MDCC (ours)           | 65,120  | 5,663  | 12,492  | 83,275  |
| Common Voice zh-HK    | 65,437  | 4,089  | 12,269  | 81,795  |

| Evaluation Metric     |         |
|-----------------------|---------|
| Character Error Rate (CER) | 10.15%  |
| WER                    | 8.69%   |
such as LibriSpeech. Each of the Cantonese datasets contains less than 100 h of speech while LibriSpeech alone contains 960 h of English audio (Panayotov et al. 2015). Thus combining both datasets is a natural step in creating strong Cantonese baselines of data-dependant deep learning models.

6. Conclusion and Future Work

In this paper, we review most of the previous works on Cantonese ASR corpora and thoughtfully analyze them. Moreover, we propose a new dataset named MDCC for the ASR research in the Cantonese language, which consists of 73.6 hours of clean read speech. We evaluate our dataset and compare it with Common Voice zh-HK dataset using Fairseq S2T Transformer model and confirm that the results indicate the effectiveness of our proposed dataset. Our model trained on joint data outperforms Wav2Vec2-Large model on Cantonese dataset. [3] For the future work we plan to collect data from more audiobooks to enrich our dataset. In addition, we will gather Cantonese ASR corpus from different sources such as meetings and movies. Another future work direction includes performing more experiments that combine performance of the MDCC dataset with multilingual datasets. We believe that our dataset and analysis can pave the way for future research works on the Cantonese ASR task and other low resource languages.

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