Audio Super-Resolution to Unlock the World's Languages for Natural Language Processing

Wesley Maa, Palo Alto Senior High School

1.0 ABSTRACT

Approximately 6,500 languages are spoken around the world today, but speech recognition platforms using natural language processing (NLP) focus on only seven key languages: English, Chinese, Urdu, Farsi, Arabic, French, and Spanish. As a result, 99.9% of the world's languages are increasingly being marginalized, as NLP platforms become more entrenched in our daily lives. NLP research has historically focused on the above seven languages because high-quality voice datasets for the rest of the world's languages are generally more difficult to obtain. The datasets that are available are often recorded in low-bitrate formats and require significant preprocessing before they can be used to train NLP platforms. My project aims to develop a convolutional neural network (CNN) pipeline to implement an audio generation technique called bandwidth extension (aka "super-resolution"). Super-resolution transforms low-bitrate audio data into high-bitrate audio data that is then suitable for NLP. This project will be the first time a CNN is trained on a real-world voice dataset collected from phone calls into a customer-service call center in Southeast Asia, including multiple languages with multiple simultaneous speakers. By adapting CNNs to implement super-resolution on voice recordings, my project's long-term goal is to make NLP accessible to all of the world's spoken languages.

2.0 MOTIVATION AND APPROACH

NLP plays a vital role in our everyday lives, from voice-based user interfaces for computing to chatbots and language translation. However, the development of NLP has been far from equitable, as the majority of research has centered around only a handful of languages, particularly English. The development of modern NLP pipelines has been a challenge for the vast majority of the world's less popular languages because voice datasets are scarce and often require a significant amount of augmentation work that can be prohibitively expensive and time-consuming.

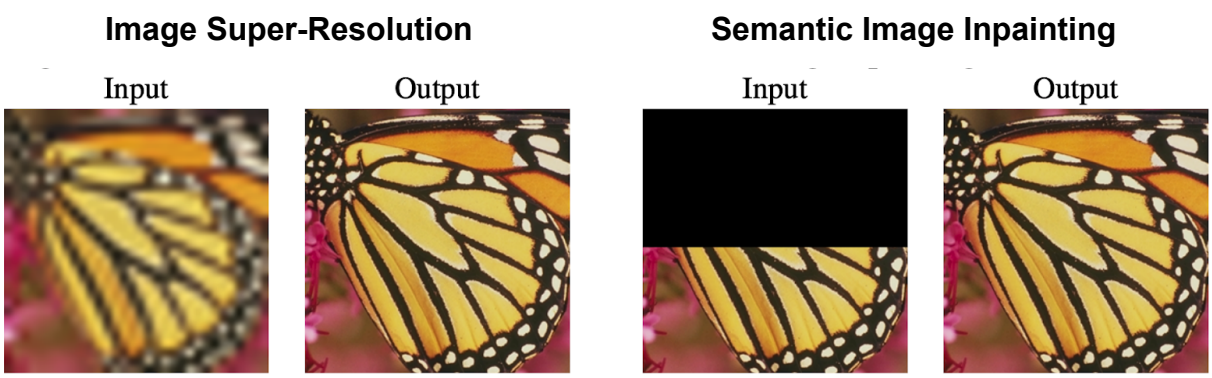
For example, one commonly used NLP pipeline is Google's Bidirectional Encoder Representations from Transformers (BERT), which reports support for the top 100 languages in the world. However, the actual training of the system has only been performed on less than 20 languages because of the lack of high-quality training datasets (Romano, 2020). Other common NLP systems, including the Natural Language Toolkit (NLTK), have similar limitations.

In developing countries, customer call center recordings made over cellular or telephony networks are typically one of the most broadly available voice datasets. However, these datasets are generally unsuitable for training NLP pipelines because of their low-bitrate encoding and poor quality. This is because the vast majority of voice communications systems are based on traditional telephony standards developed in the 1950s, which limit the information bandwidth for voice communications to 300-3,400Hz. However, everyday conversational speech typically ranges from 0-8,000Hz, while the human ear can hear frequencies up to 20kHz. As a result, the audio codecs used in our phone networks encode voice calls at bitrates between 4-8kbps and capture less than

25% of the information generated by the human voice. This is why telephone conversations are less clear and more muffled than face-to-face conversations. To address this issue, telecommunication networks are increasingly upgrading their infrastructure to support high definition (HD) stereo-audio voice, which encodes at 12-40kbps using codecs like Adaptive Multi-Rate Wideband (AMR-WB). However, most mobile handsets, particularly those most often used in developing countries, do not support HD voice because of its added costs. Because the vast majority of voice calls remain encoded in low 4-8kbps bitrate data and contain a significant amount of background noise, these datasets have not been used for developing NLP pipelines for the longtail of the world's 6,500 languages. Audio super-resolution unlocks these datasets for NLP by recreating HD voice in software without the need to upgrade mobile phones or network infrastructure.

To implement super-resolution on voice recordings, I've taken inspiration from the field of image analysis, where bandwidth extension is the process of constructing high-resolution images from low-resolution data. Before the availability of neural networks, this was accomplished through specific image processing algorithms like edge and focal detection. However, with the introduction of CNNs, bandwidth extension techniques for images have been developed that no longer require domain-specific algorithms. CNNs are a class of deep neural networks that are highly computationally efficient for computer vision tasks, including image and object recognition. Figure 1 provides an example of what CNNs can accomplish in image super-resolution (Dong et al., 2016) (Kim et al., 2016) (Lai et al., 2017) and semantic image inpainting to predict masked regions in an image (Pathak et al., 2016) (Yeh et al., 2017).

Figure 1: Example of Image Bandwidth Extension (Lim et al., 2018)



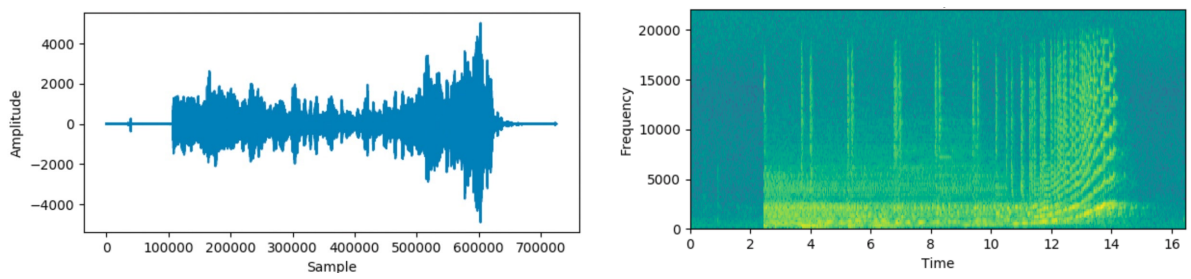
Similarly, in the field of audio analysis, bandwidth extension (aka “super-resolution”) is the process of reconstructing a high-bitrate audio stream from a low-quality, low-bitrate audio recording. Audio super-resolution has historically depended on traditional digital signal processing techniques for upsampling. This required a significant amount of domain-specific expertise and was difficult to generalize. With CNNs, however, these conventional audio processing techniques are no longer needed. Instead, this project will first convert audio data into spectrogram images and then process these spectrograms through a standard CNN developed for image analysis to achieve super-resolution. The resulting spectrograms are then converted back to high-bitrate audio data.

A spectrogram of an audio signal plots the frequency distribution of an audio signal (y-axis) over time (x-axis) and is an elegant way to capture audio data as an image. Different colors indicate the amplitude or strength of each frequency. Each vertical “slice” of a spectrogram is essentially the frequency spectrum at an instant in time. In Figure 2, the time-domain representation of an audio signal provides a sense of

loudness over time but very little information about its frequency content. For comparison, the spectrogram of an audio file displays its frequency strength over time.

Figure 2: Decomposition of Audio Data (Doshi & Rosewell, 2021)

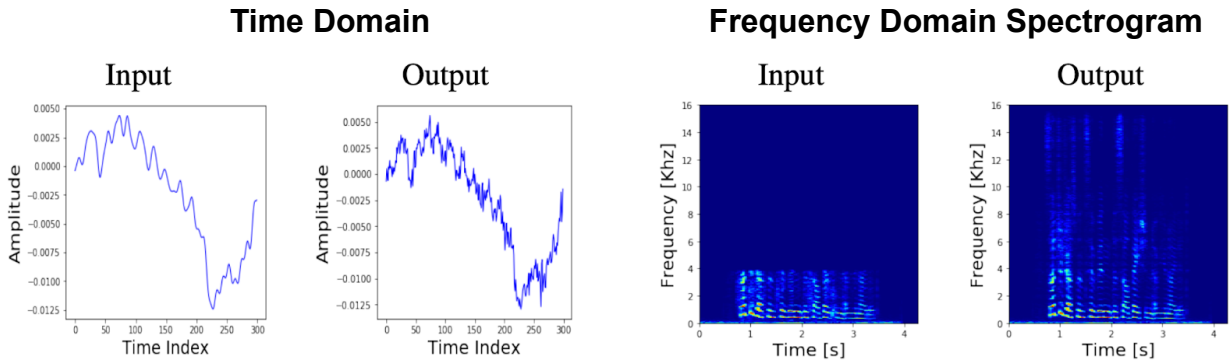
Time Domain **Frequency Domain (Spectrogram)**



3.0 PROJECT LOGISTICS AND ORGANIZATION

For my project, I will apply a CNN pipeline developed for image super-resolution to spectrograms of voice recordings to increase its sampling rate and frequency content. The CNN will be trained on pairs of low and high-bitrate voice recordings, where the low-bitrate input will be a telephone voice recording encoded at 4kbps, and the high-bitrate output will be a 4x upsampled reconstruction of the original voice recording at 16kbps. Figure 3 illustrates a comparison between a low-bitrate audio input and a high-bitrate audio output from current CNNs for audio super-resolution (e.g., AudioUNet, AudioEDSR, and AudioUNetGAN). While these CNNs have been available for general audio recordings, this project will focus on the specific application of training CNNs on voice recordings for NLP.

Figure 3: Super-resolution on audio data (Lim et al., 2018)

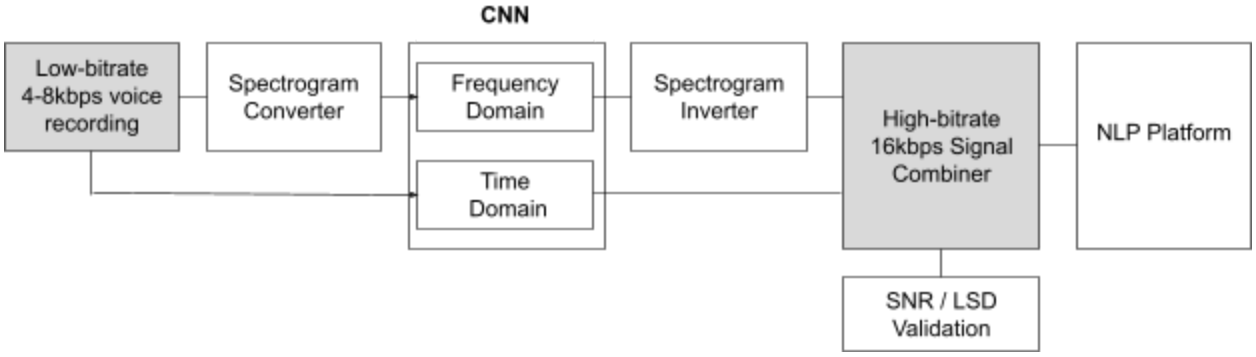


For the training dataset, I will be using recorded voice data collected from a customer service call center that operates across eight different countries in Southeast Asia (“GRAB” dataset). This dataset is ideal for this project because Southeast Asia is home to over 1,000 distinct native languages. This dataset contains over 364k hours of customer support calls across multiple languages in Southeast Asia and provides an extensive library of low-bitrate voice recordings. All voice calls are recorded at 4kbps, with a smaller subset recorded at 8-16kbps for use in the training process. This project will focus on assessing upsampling ratios of 2-4x to 8-16kbps.

This project will also implement a CNN on both the frequency and time domains of low-bitrate voice recordings to compare the validation accuracy of the two approaches because the two domains address very different problems. Audio super-resolution in the time domain is analogous to image super-resolution, which maps audio data from low-bitrate to high-bitrate. In contrast, super-resolution in the frequency domain is analogous to semantic inpainting (i.e., given a particular set of low-frequency components in a spectrogram, reconstruct the high-frequency components). To exploit the best of both worlds, I plan to implement and compare voice super-resolution in both the time and frequency domains.

To evaluate the quality of the output voice audio, I will use two different metrics: signal-to-noise ratio (SNR) and log-spectral distance (LSD). The SNR function compares the CNN output against a high-resolution reference and calculates the proportion of the output voice that is useful information in decibels. While SNR is simple to implement, there may be potential drawbacks, particularly when low-bitrate signals have significant background noise. To address this, I will also compare model outputs using LSD, which computes the amount of distortion present in the frequency spectra of a signal. Figure 4 summarizes the overall CNN pipeline for this project.

Figure 4. Summary of Voice Super-Resolution CNN Pipeline



Over the past 12 months, I've successfully implemented a CNN pipeline for image semantic segmentation as part of an internship with the AI Lab at the National University of Singapore (NUS). In this project, I implemented a UNet architecture in PyTorch to train a supervised multi-class CNN. The NLP project proposed in this paper builds upon my prior work at NUS and extends the CNN to perform super-resolution for voice audio. To prepare for this project, I've read several research papers (cited in the reference) to understand state-of-the-art CNNs for image super-resolution. Key milestones and their timelines for the remaining components of this project include:

Date	Milestone
February 29, 2022	Implement AudioUNET on the VCTK dataset (Dong et al.), a commonly used reference, to create a starting benchmark
March 31, 2022	Train CNN on GRAB datasets using a time-domain model and assess SNR and LSD metrics
April 30, 2022	Train CNN on GRAB datasets using a frequency-domain model and assess SNR and LSD metrics

Three key risks to this project have been identified, including:

1. Training artifacts from real-world datasets. This will be the first time a CNN is trained on a real-world voice dataset collected from customer-service call center recordings in Southeast Asia. Because of the poor quality of cellular networks and mobile handsets in Southeast Asia, this dataset contains significant noise and audio artifacts that may impact the accuracy of the CNN pipeline. To mitigate this risk, I may implement pre-processing filters to cleanse the dataset prior to use.
2. Combining time domain and frequency domain outputs. Time-domain and frequency-domain analysis address different aspects of bandwidth extension. Improving model accuracy will likely require a combination of both methods, and I continue to research an appropriate algorithm to merge the two approaches.
3. LSD and SNR metrics. LSD and SNR metrics may result in high model scores but still produce high-bitrate voice audio that sounds artificial. To address this limitation, this project will likely also evaluate model outputs using a mean opinion score (MOS), whereby a group of people is asked to rate the overall

quality of the voice outputs on a standardized scale. As a subjective metric, MOS measures how well a generative voice sounds, rather than just the accuracy.

My goal in applying to the MIT THINK program is to find mentors who can help advise on addressing the above key risks, particularly on 1) domain-specific audio pre-processing techniques, 2) the best algorithms to merge time-domain and frequency-domain model outputs, and 3) best practices for model and dataset tuning for CNNs. All three of these areas are skills that I will need to develop to complete this project.

Because this project is purely computational, I expect to complete all three milestones on a desktop PC. However, once this project transitions to training on GRAB datasets, the project may migrate to a cloud service using Amazon EC2 P3 instances to run the underlying CNN workloads. Funding for this project will go towards purchasing an Nvidia RTX 3080 GPU graphics card and potentially for EC2 credits.

Table 1. Project Budget

Item	Total Cost	Link
Nvidia RTX 3080 GPU graphics card	$699.99	https://www.bestbuy.com/site/nvidia-geforce-rtx-3080-10gb-gddr6x-pci-express-4-0-graphics-card-titanium-and-black/6429440.p?skuId=6429440
EC2 P3	$300 (100 hours at $3/hour)	https://aws.amazon.com/ec2/instance-types/p3/
Total	$1,000	

4.0 PERSONAL INTEREST

I've had an opportunity to live overseas for over 13 years as my family moved across Asia. During this time, I studied various languages, including Bahasa for more than two years in Indonesia and Japanese for eight years in Japan. I've also had an opportunity to immerse myself in the various dialects of Southeast Asia, including those in Singapore, Thailand, and Malaysia. Living abroad, I've developed a fascination for linguistics and its intersection with computer science. It is particularly eye-opening to see the large gap in access to NLP that exists between developed versus developing countries. This gap will only widen with time, as modern machine learning pipelines essentially skip developing countries altogether.

Cognitive science has shown that language, grammar, and vocabulary profoundly influence how we think. As a result, when NLP is limited to only a handful of languages, we implicitly program those selected languages' societal norms and biases into our digital platforms. By making NLP available to all of the world's spoken languages, my goal is to bring the benefits of NLP to all spoken languages and help reduce the implicit biases in our computing platforms.

Works Cited

Dong, C., Change Loy, C., He, K., & Tang, X. (2016). Image super-resolution using deep convolutional networks. *IEEE Trans. Pattern Anal. Mach. Intell.*, *38*(2), 295–307.

Doshi, K., & Rosewell, J. (2021). *Audio Deep Learning Made Simple (Part 1): State-of-the-Art Techniques*. Towards Data Science. Retrieved December 20,

2021, from https://towardsdatascience.com/audio-deep-learning-made-simple-part-1-state-of-the-art-techniques-da1d3dff2504

Kim, J., Kwon Lee, J., & Mu Lee, K. (2016). Accurate image super-resolution using very deep convolutional networks. *The IEEE Conference on Computer Vision and Pattern Recognition*, *CVPR Oral*.

Lai, W.-S., Huang, J.-B., Ahuja, N., & Yang, M.-H. (2017). Deep laplacian pyramid networks for fast and accurate super-resolution. *IEEE Conference on Computer Vision and Pattern Recognition*.

Lim, T. Y., Yeh, R., Xu, Y., Do, M., & Hasegawa-Johnson, M. (2018). Time-Frequency Networks for Audio Super-Resolution. *IEEE International Conference on Acoustics, Speech and Signal Processing*, 646-650. 10.1109/ICASSP.2018.8462049

Pathak, D., Krahenbuhl, P., Donahue, J., Darrell, T., & Efros, A. (2016). Context encoders: Feature learning by inpainting. *Computer Vision and Pattern Recognition*.

Romano, S. (2020, June 20). *Multilingual Transformers*. Multilingual Transformers. https://towardsdatascience.com/multilingual-transformers-ae917b36034d

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. *CoRR*.

Yamagishi, J. (2012). *English multi-speaker corpus for cstr voice cloning toolkit*. http://homepages.inf.ed.ac.uk/jyamagis/page3/page58/page58.html

Yeh, R., Chen, C., Yian Lim, T., Alexander G, S., Hasegawa-Johnson, M., & Do, M. N. (2017). Semantic image inpainting with deep generative models. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*.