Domain Specific Text-to-Speech with Machine Learning

PlaneEnglish

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BACKGROUND

PlaneEnglish develops training solutions for pilots, including ARSim, an aviation radio simulation app. ARSim allows pilots to practice communicating with Air Traffic Control (ATC) using interactive lessons. **Our goal** is to find a way to generate speech that sounds more like an air traffic controller voice than a typical voice for ARSim.

We used the following approach:

1. Research existing text-to-speech models that fit our needs
2. Find ATC data for training and develop tools for formatting
3. Train model with our aviation-specific dataset
4. Evaluate performance and make necessary adjustments

OVERVIEW OF NEURAL TEXT-TO-SPEECH

Recent models vary in scope and can accomplish tasks in end-to-end processes

- Process starts with input text which is converted to phonemes and finally to waveform audio
- We focused on Tacotron2 and FastSpeech2 which are acoustic models
- These models are recent enough to offer performance benefits but established enough to have a strong support community

MACHINE LEARNING FOR TEXT-TO-SPEECH

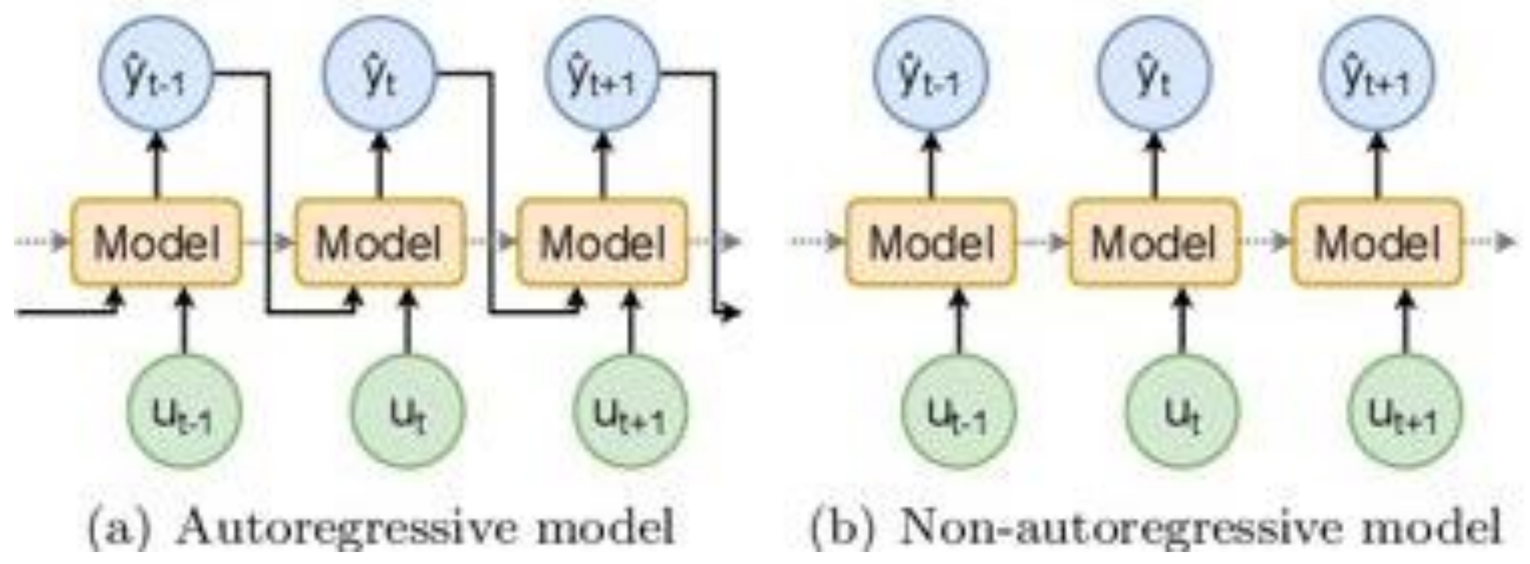
Data Collection and Training on Domain Specific Data

- The LJSpeech dataset links audio data to corresponding transcripts
- Developed tools to convert both the audio and text data into the LJSpeech format

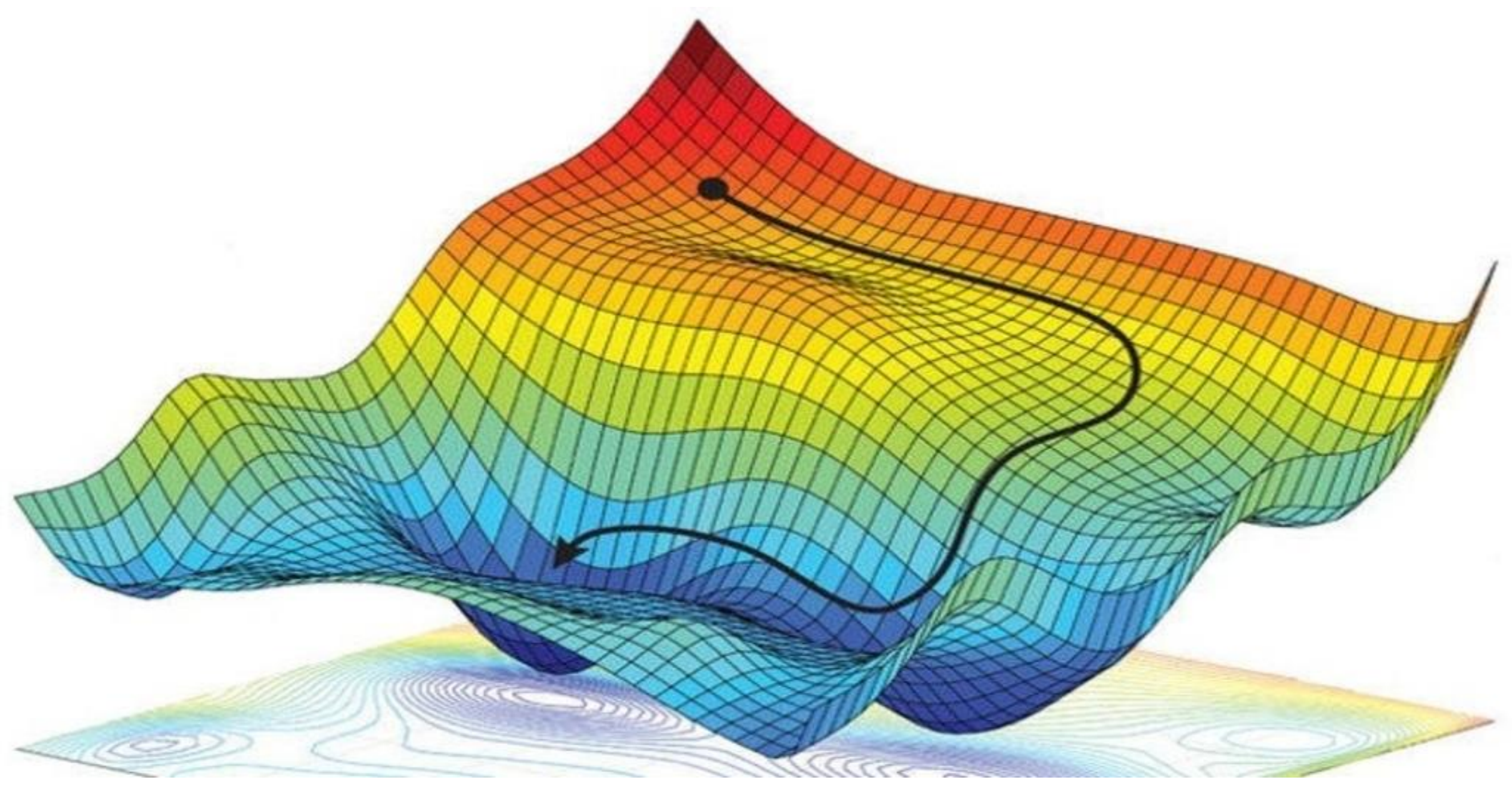
Training Process and Improving Performance

- Trained Tacotron2 model using ATC data with around 1,100 samples
- Model struggled initially, but by adjusting some parameters and giving the model more time to train, noticeable improvements were made
- We noticed that performance eventually plateaued, possibly due to the model exhausting all of the training examples in our dataset, which is relatively small for a TTS dataset (more on this in Future Goals)

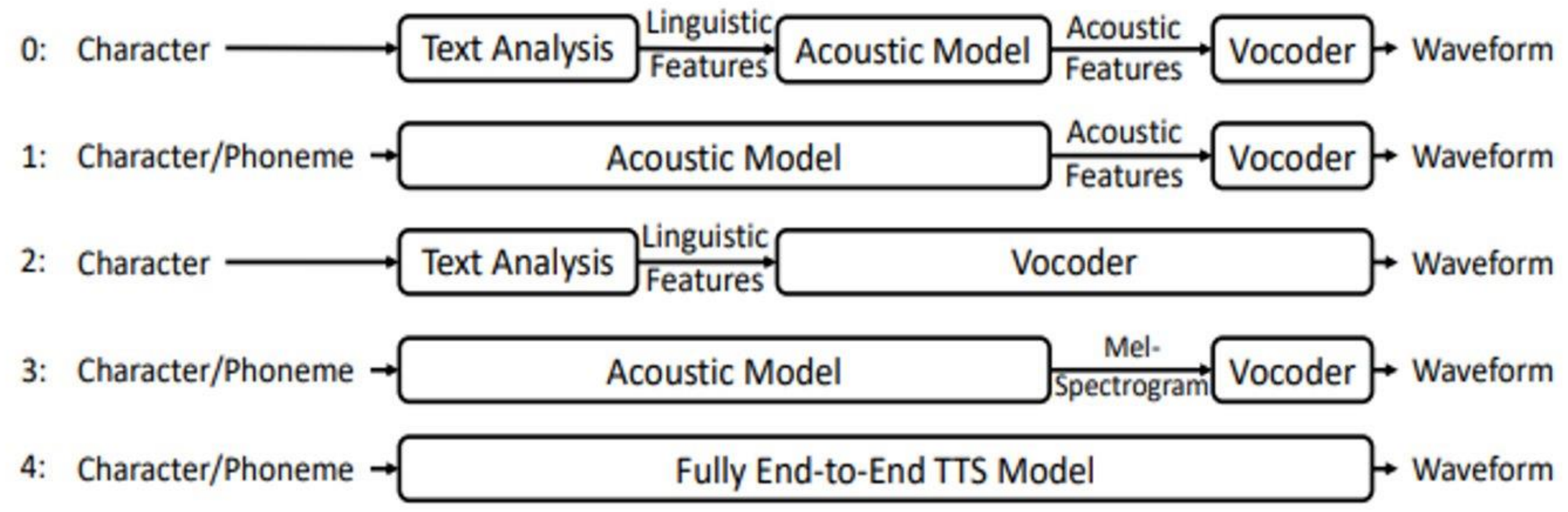
Examples of a recurrent neural network, which tracks its previous state to have a short-term sense of "memory."



A neural network tries to minimize its "loss," which is a function of its error with respect to its weights and biases. Sometimes the loss can converge at a local minimum.



Some types of text-to-speech models and their scopes; we went with acoustic models, which offer flexibility and lots of available documentation



RESULTS AND OPTIMIZATION

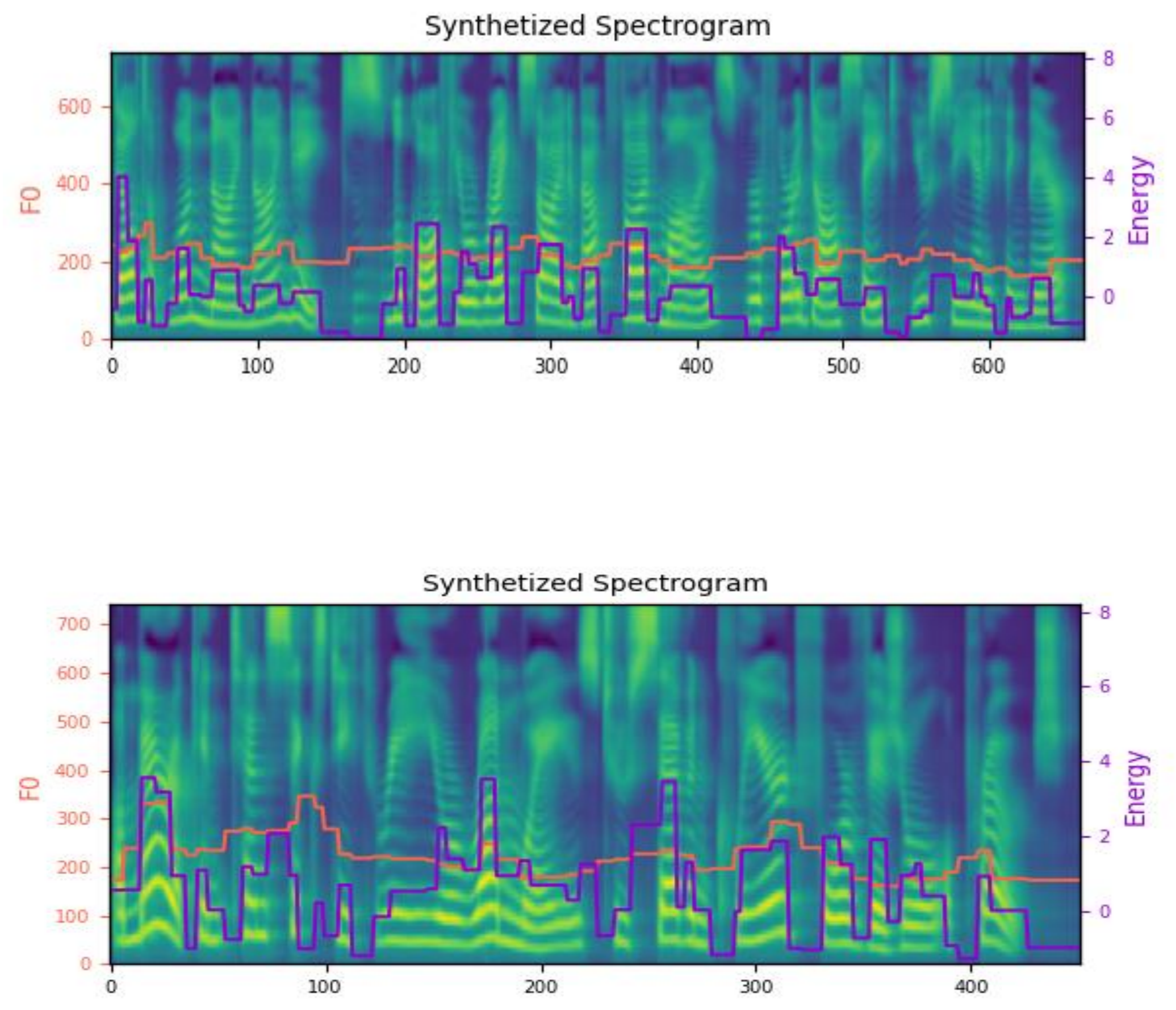
Evaluating Performance

- Model uses an error function (or a loss function) to judge how far it is from desired output
- Helpful for training, but can't capture subjective changes in voice audio quality

Generated Samples

- We tested our trained model with several sample phrases specific to aviation
- Improvements in key areas, such as a voice that sounds closer to an air traffic controller, as well as some typical noises in ATC communication
- Changing parameters helped improve some aspects of speech, but performance limited by dataset size

Example spectrogram outputs from the FastSpeech2 model, which is then used by a vocoder to generate waveform audio



REFERENCES AND AKNOWLEDGEMENT

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ONGOING EFFORTS AND FUTURE GOALS

Optimizing Response Time

- Apply our domain specific data to the FastSpeech2 model which generates audio much faster than Tacotron2
- The goal is to generate speech quickly enough for use in a simulation

Measuring Voice Quality

- Neither loss or subjective evaluation fully capture output quality
- Developing a framework based on existing ATC fluency standards could achieve this
- ICAO language proficiency accounts for words per minute, filler words, other factors

Data Collection

- A larger dataset could help the model continue to improve
- A standard dataset for neural TTS, the LJSpeech dataset, has about 25 hours of training data
- Our model has shown improvements with only 2 hours of data, so looking for more is worthwhile

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