Speaker Accent Classification with Deep Learning

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IFT 6390: Fondements de l'apprentissage machine

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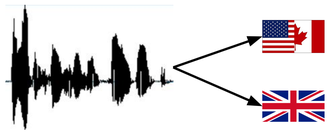
The Task

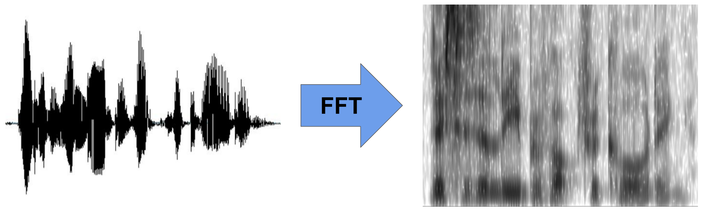


- Classify spoken audio as North American (NA) or British (UK) English.
- Useful for separating data input to ASR pipelines.

Two clean spoken corpora for training/testing:

1. **Librispeech.** NA; 5.5 hours; 40 speakers.
2. **Librit.** UK; 7 hours; 27 speakers.

Feature Extraction



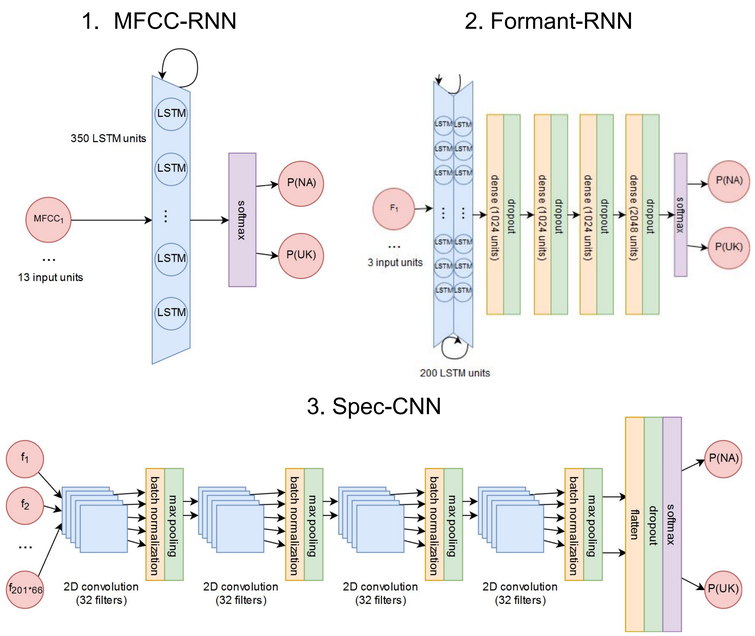
Three types of features extracted:

1. **MFCCs**. Standard in speech processing; modelled on the human ear. Apply Mel filterbank on power spectrum, then DCT.
   Result: Sequence of 13 coefficients per time slice.

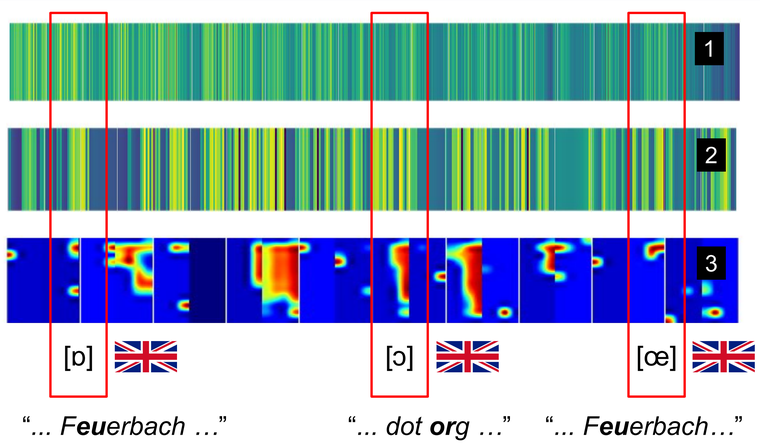
2. **Formants**. First three resonant frequencies of voiced sounds that may correlate with accent; modelled on linguistics knowledge.
   Result: Sequence of 3 frequencies per time slice.

3. **Raw spectrogram**. Frequency, amplitude, and time values after FFT needed to generate above figure; modelled on raw signals.
   Result: Concatenation of 201 amplitude-frequency pairs per time slice.

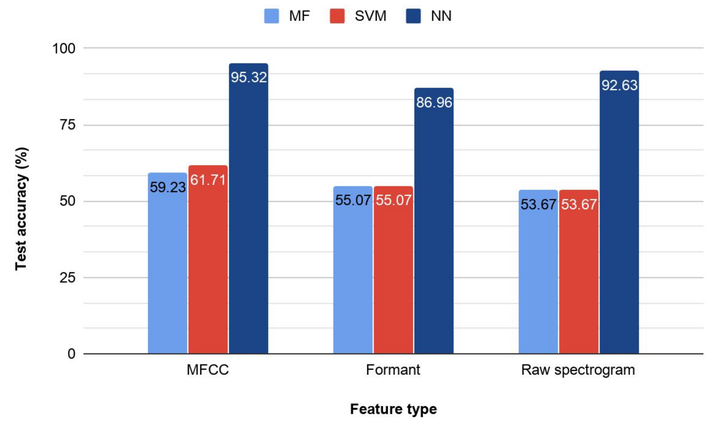
Proposed Networks



Learned Representations



Results



- All three networks outperform MF and SVM baselines.
- MFCC-RNN performs best due to context access and sufficient feature complexity.
- Spec-CNN performs well due to high feature complexity, but might be hindered by noisy signal and lack of context. More data and computational power may project long-run performance beyond MFCC-RNN.
- Formant-RNN performs most poorly due to insufficient feature complexity and limitation to voiced frames, but benefits from context access and feature interpretability.

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