Distinguish Sound With Machine Learning.

Urban Sound Classification

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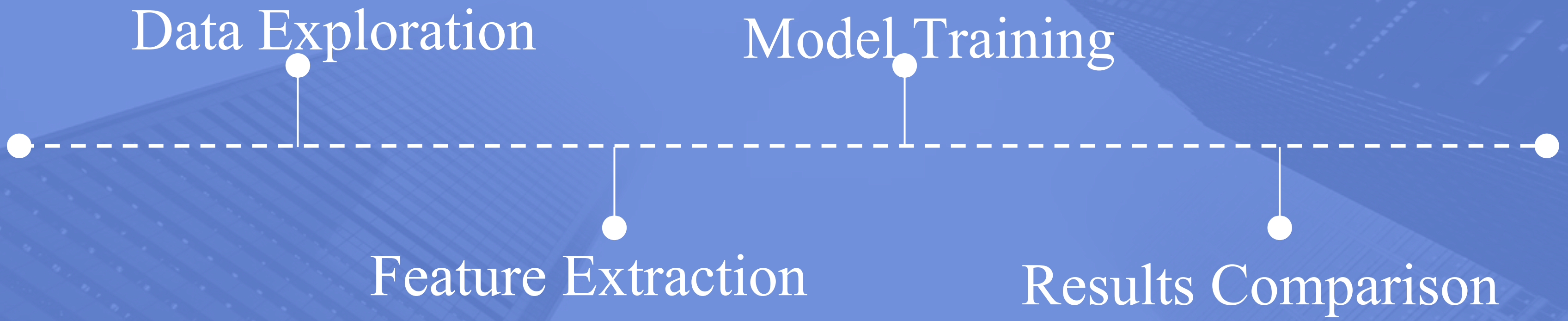
OVERVIEW

- **Background:** exposed to different sounds every day
- **Goal:** to classify sounds automatically
- **Challenge:** compared to image, feature extraction for sound is not quite straightforward

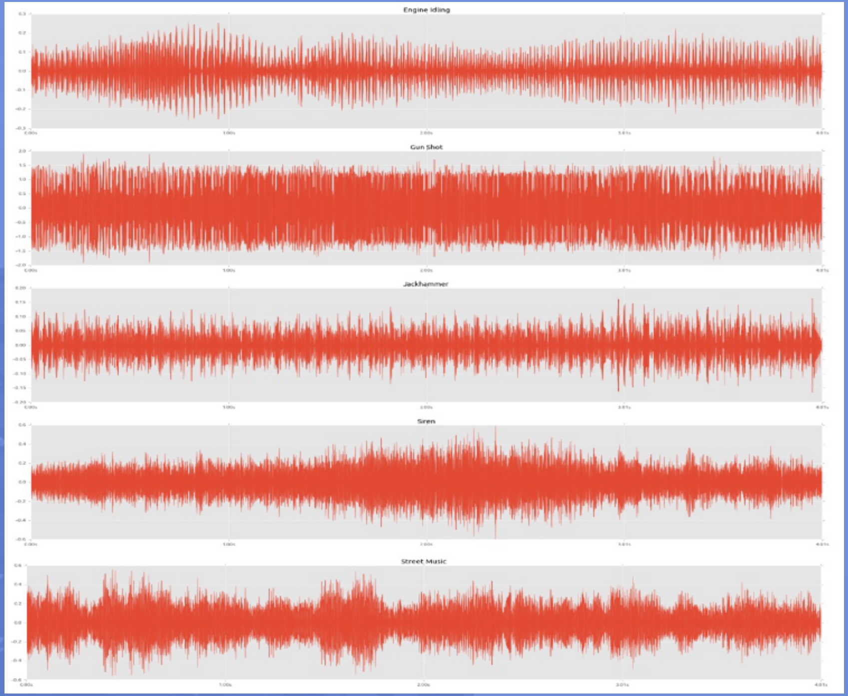
OUR PROCESS FOLLOWS:

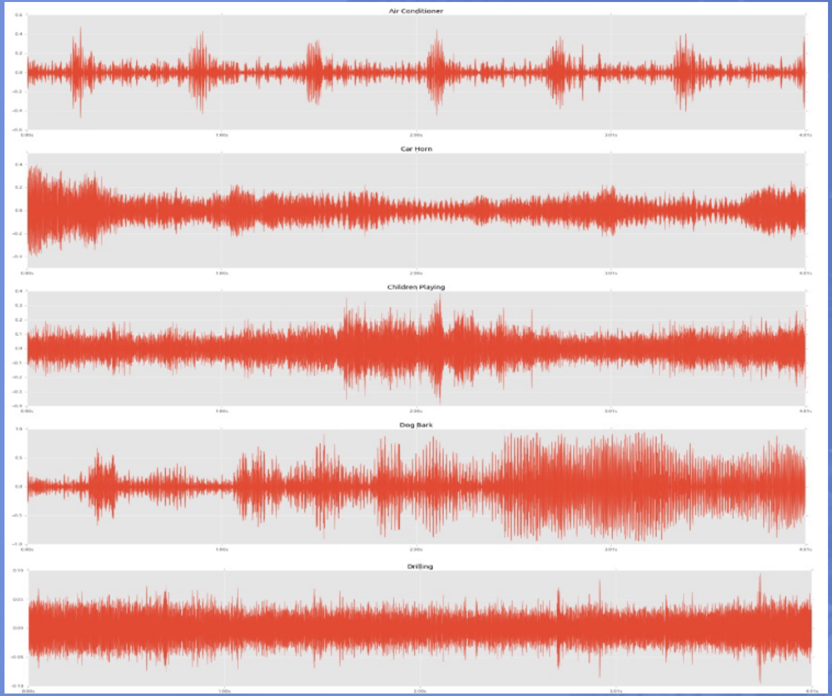


Data

1. **Source:** Urban Sound Dataset
2. **Size:** 1302 labeled sound recordings
3. **Format:** each recording is a wav file
4. **Content:** 10 classes of sounds (air_conditioner, car_horn, children_playing, dog_bark, drilling, enginge_idling, gun_shot, jackhammer, siren, and street_music)
5. **Usage:** 30% of the data is regarded as test data

Waveplot


Engine Idling
Gun Shot
Jackhammer
Siren
Street Music


Air Conditioner
Car Horn
Children Playing
Dog Bark
Drilling

Feature Extraction

Tool: Librosa library in Python

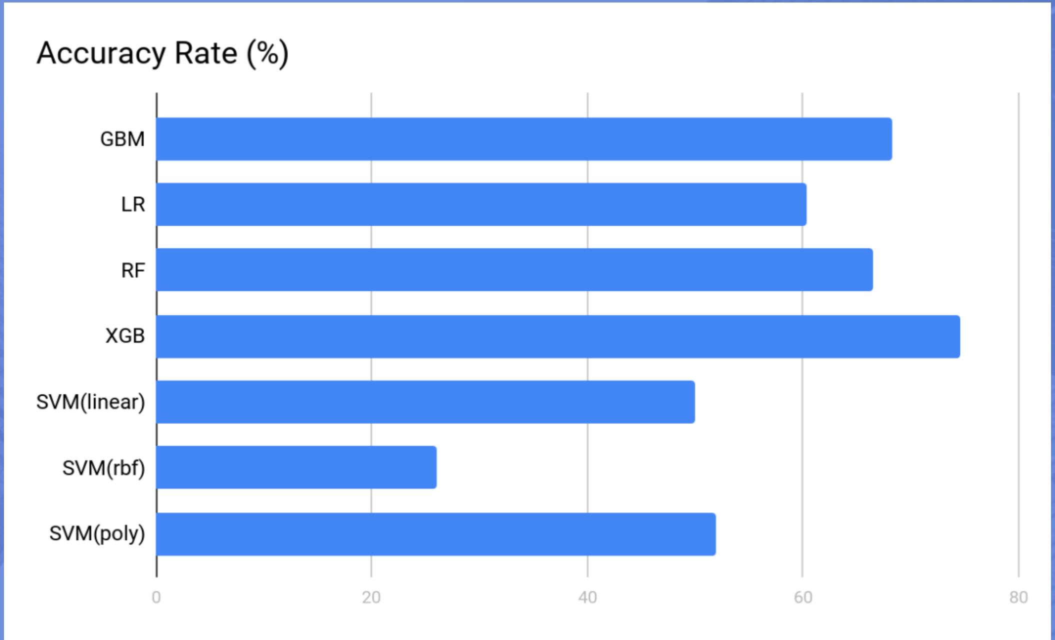
Methods:

- **melspectro gram:** Compute a Mel-scaled power
- **mfcc**: Mel-frequency cepstral coefficients
- **chorma-stft**: chromagram from a waveform/power spectrogram
- **spectral_contras**t: Compute spectral contrast, using method
- **tonnetz:** Computes the tonal centroid features (tonnetz)

Output: Matrix of 1102 rows, 193 columns

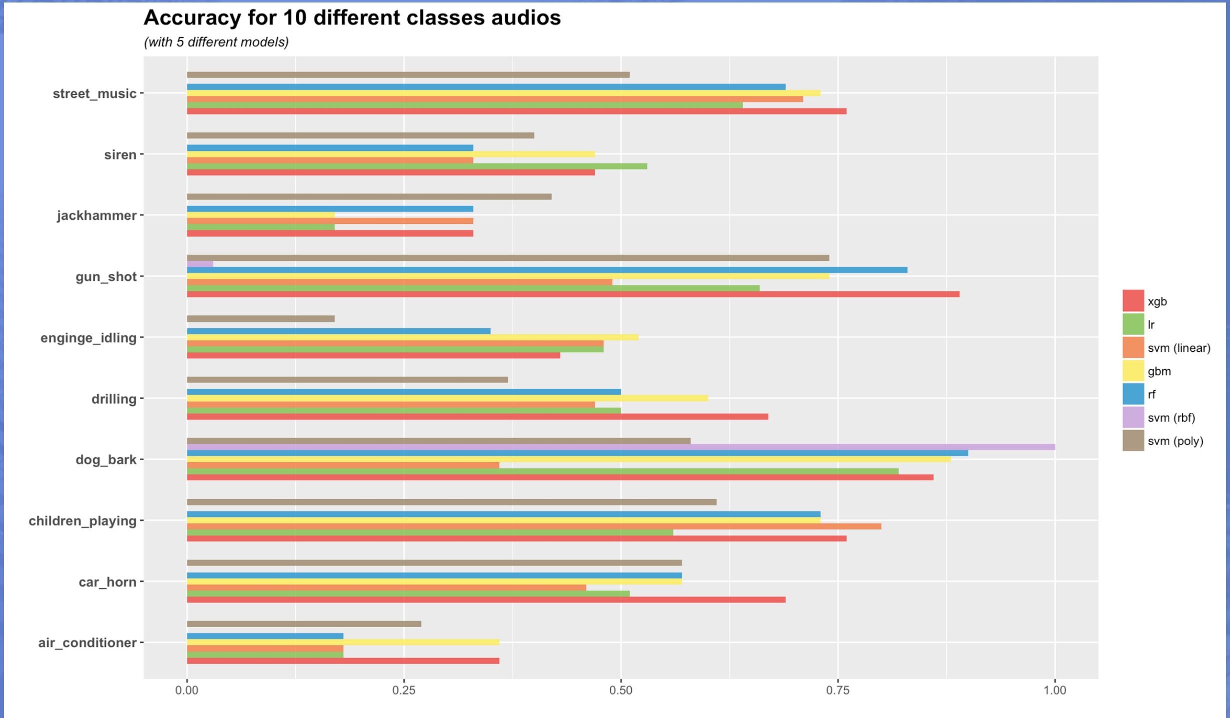
Model Comparison

Accuracy Rate:



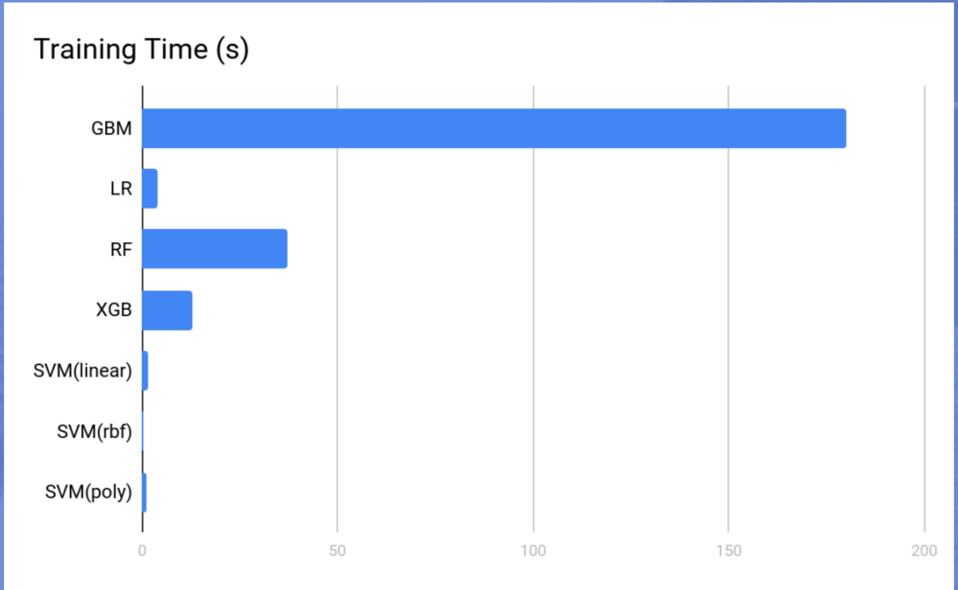
Model Comparison

Accuracy for Each Class:



Model Comparison

Length of Training Time:



Model Comparison

Model	Accuracy Rate (%)	Training Time(s)
GBM	68.28	1200
LR	60.42	3.96
RF	66.47	37.09
XGB	74.61	13
SVM (linear)	50	1.62
SVM (rbf)	26	0.43
SVM (poly)	52	1

Improvements

- Use a larger dataset on the official website which contains more than 8000 audio records with these 10 different classes. Intuitively, more data available, more accurate for model performs.
- Set up a more complex CNN with at least 10 layers, and with some other techniques, such as adding zero-padding or dropout layer to classify those audios.
- Try to use different combinations within those five kinds of features we extracted. We have assumed that perhaps some kinds of the features are much more outstanding than others. So why not try to ignore those "unuseful" features, at some points, reduce dimensions, and train the model on the subset of the features. The result could be exciting, or not.
- Try to extract other kinds of features.

THANKS

Any questions?

You can find our projects at
https://github.com/TZstatsADS/fall2017-project5-grp4