DISTINGUISHING MOTORCYCLE NOISE BY MAKE

Kawasaki

HARLEY-DAVIDSON MOTOR CYCLES

Purpose: Eventual enforcement aid

Exploration and proof of concept for future expansion

- Effectively distinguish motorcycle hardware

- Use a variety of conditions and equipment

- Only use short audio clips

Purpose: Eventual app for cheap enforcement aid

Exploration and proof of concept for future expansion

- Disproportionately benefit disadvantaged

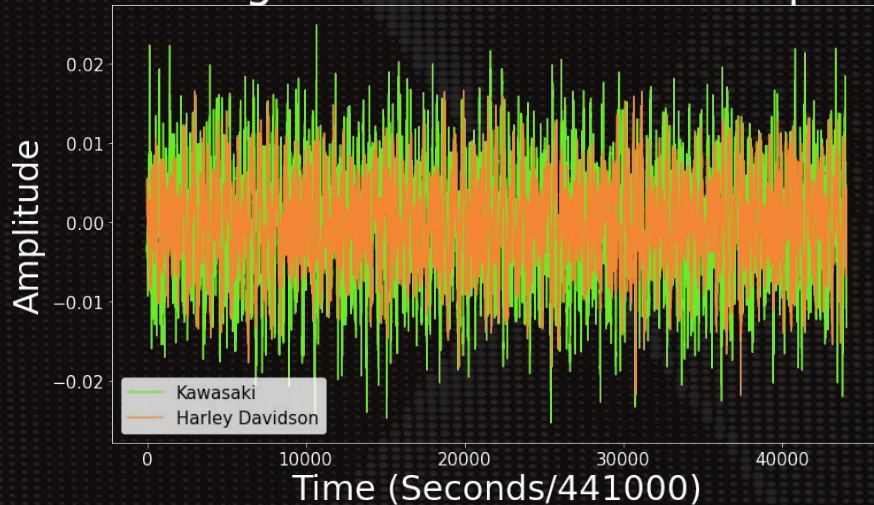- Low cost, especially in officer labor

Data Collection

YouTube as source
- Variety of exhaust hardware
- Variety of recording equipment
- Variety of circumstances

- "[make]+motorcycle+exhaust+sound"

- Top 80 video URLs in each search

- Extract audio

Averaged Raw 1 Second Samples
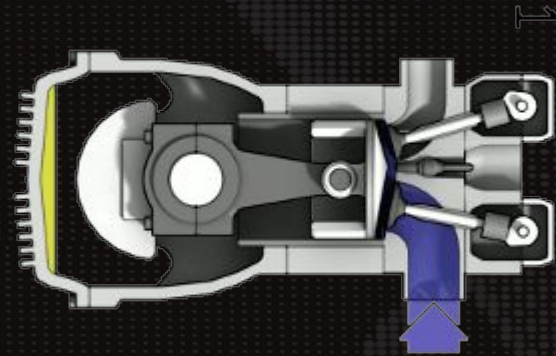
Cleaning and Feature Engineering

Account for:

- Engine RPM

- Doppler Effect

- Other sound content

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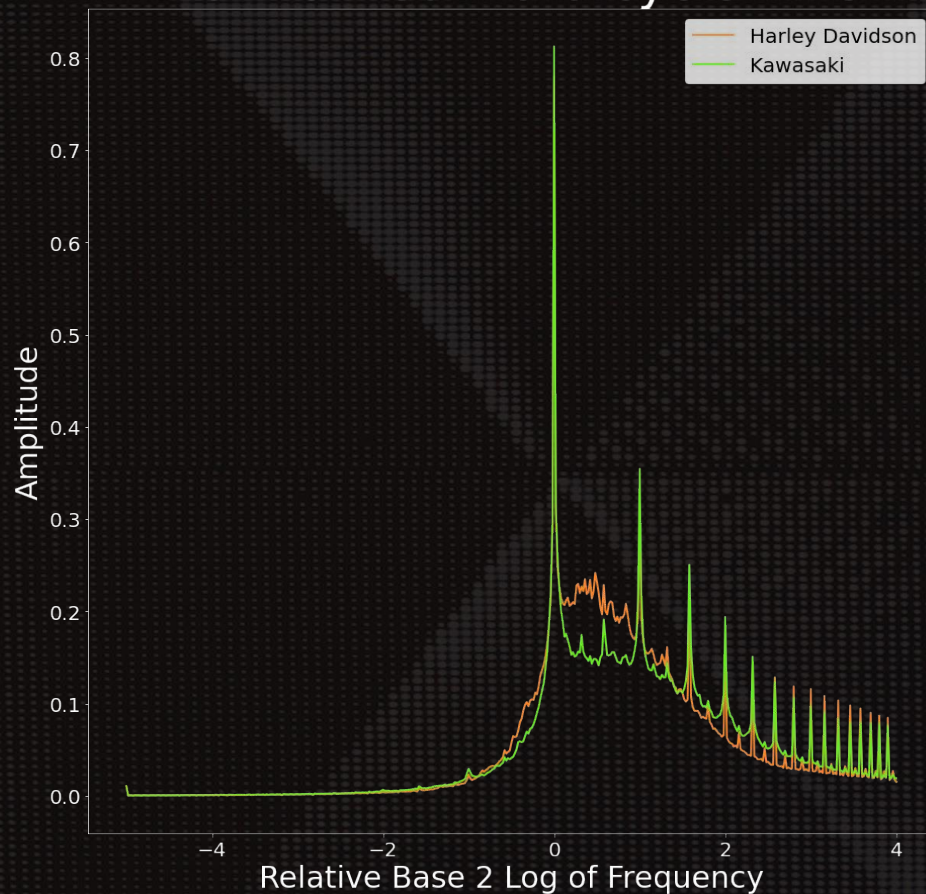
- Doppler Effect

- Other sound content

$$f = \left(\frac{c \pm v_{\mathrm{r}}}{c \pm v_{\mathrm{s}}} \right) f_0$$

Strategies:

- Fast Fourier Transform (FFT)

- Log of frequency

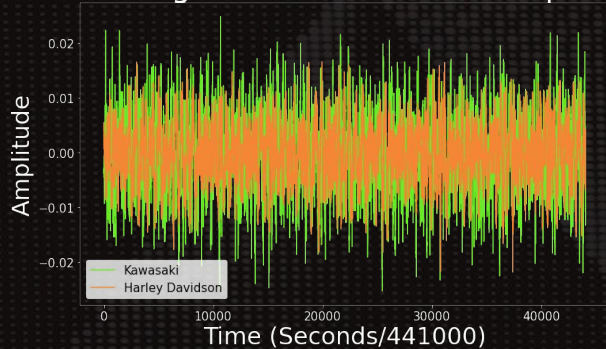- Normalize

- Drop outliers

Normalized Motorcycle FFTs

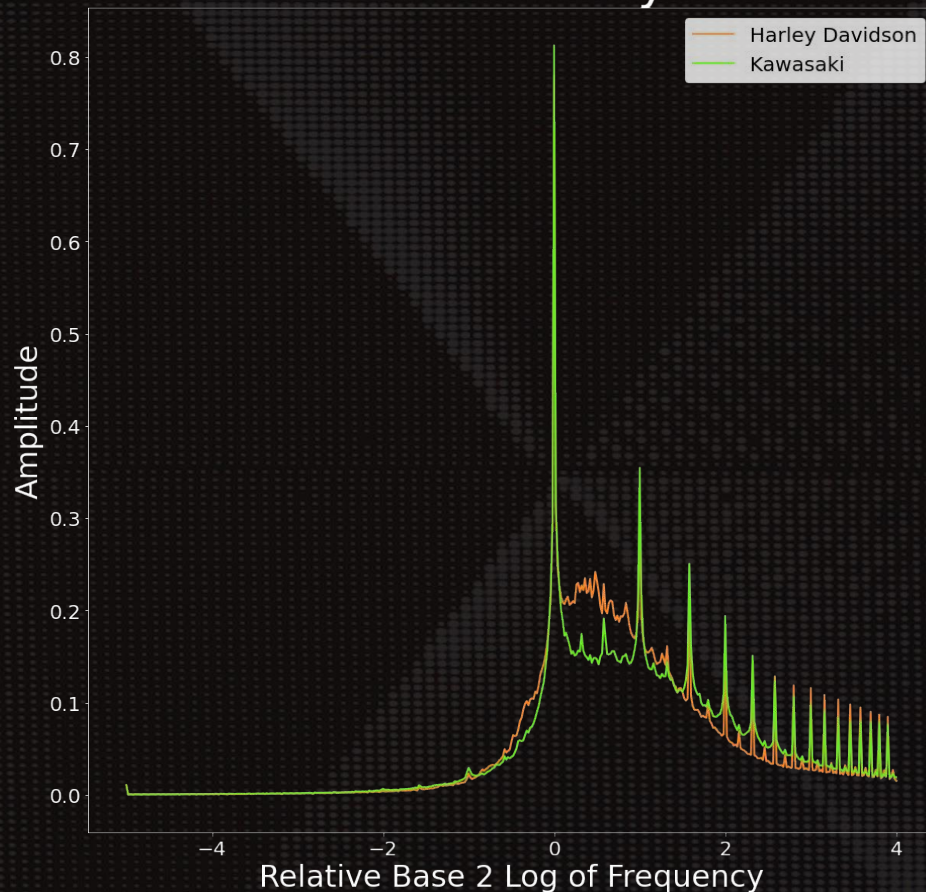# Strategies:

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- Normalize

- Drop outliers
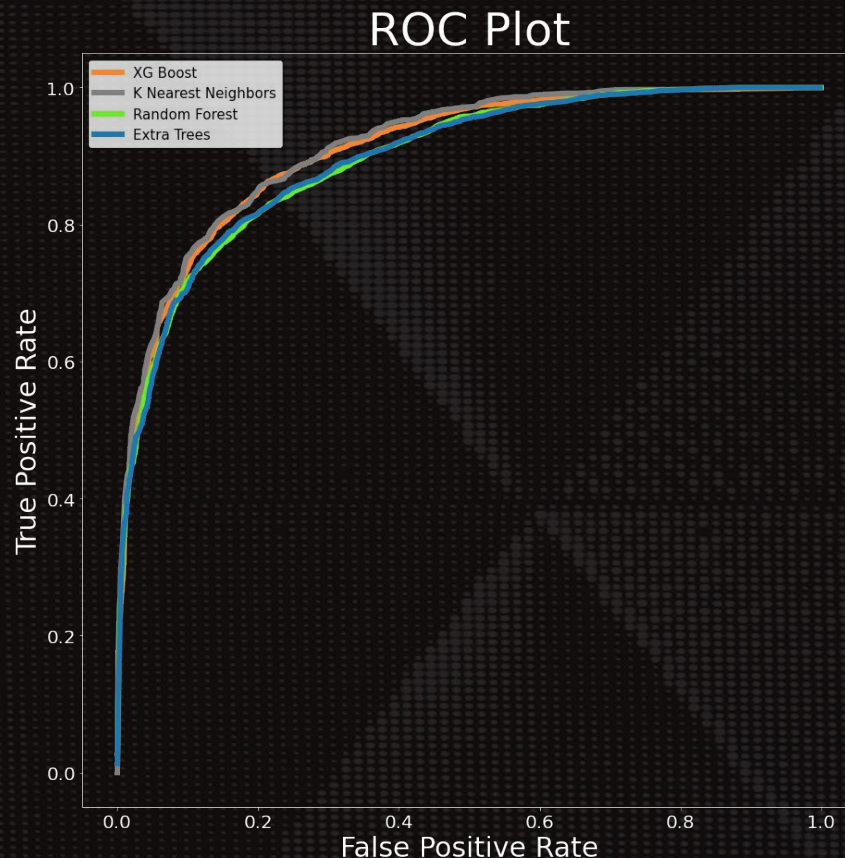
Averaged Raw 1 Second Samples

Normalized Motorcycle FFTs

Models

- XG Boost, KNN, Random Forest, and Extra Trees

- Similar ROC AUC and F1

- Narrow the field

- Similar results on test set:
  - Harley Davidson F1 ~ 0.84
  - Kawasaki F1 ~ 0.79
  - Accuracy ~ 0.82

- One final test

ROC Plot

Final Results

- 30 new videos

- Clean and split

- Remove outliers
  - Some manual work

- Run models and compare
  - Classes fairly balanced in dataset and results

91.6% Accuracy

1 second clips with Random Forest

91.9% Accuracy

1 second clips with XG Boost

95% Accuracy

5 second clips with XG Boost

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Future Work

- Adapt techniques to target illegal exhaust
- Add other vehicles, like trucks
- Develop hardware and further machine learning
- Real world application
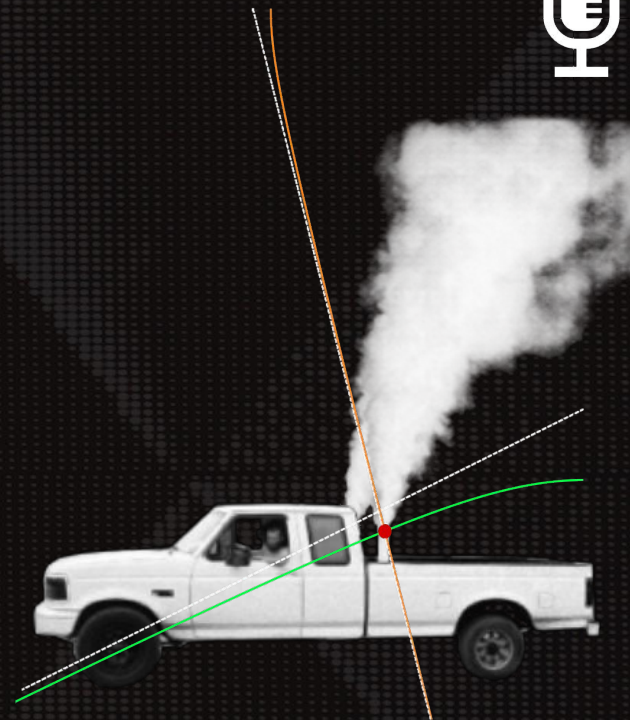
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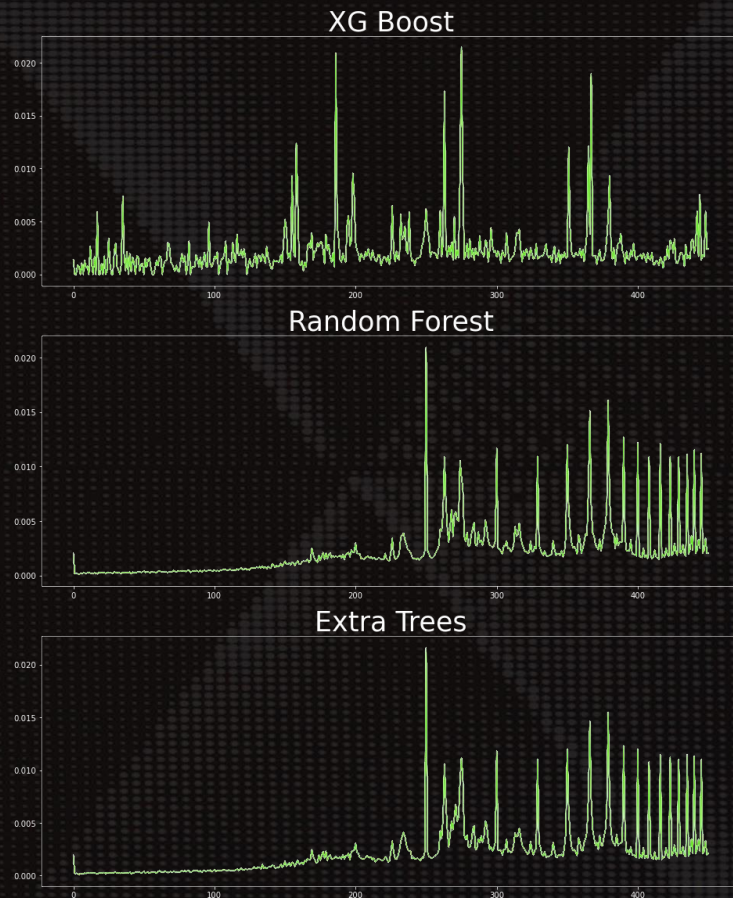- Real world application

Thank you!

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Linkedin
Email
GitHub

Appendix

I wondered why these feature importance plots were so different for XG Boost compared to the other two models, so I also plotted them along with the average Harley/Kawasaki difference by frequency on the next page.

XG Boost

Random Forest

Extra Trees

Feature Importance and FFTs

Significantly different reported feature importance:
- Random Forest and Extra Trees follow shape of the average sounds
- XG Boost has weird spikes at lower frequencies
- Is it good machine learning or overfitting?

Tests on entirely new data assured me that it's very unlikely due to XG Boost picking up on low frequency artifacts of the recording equipment in the original video set.
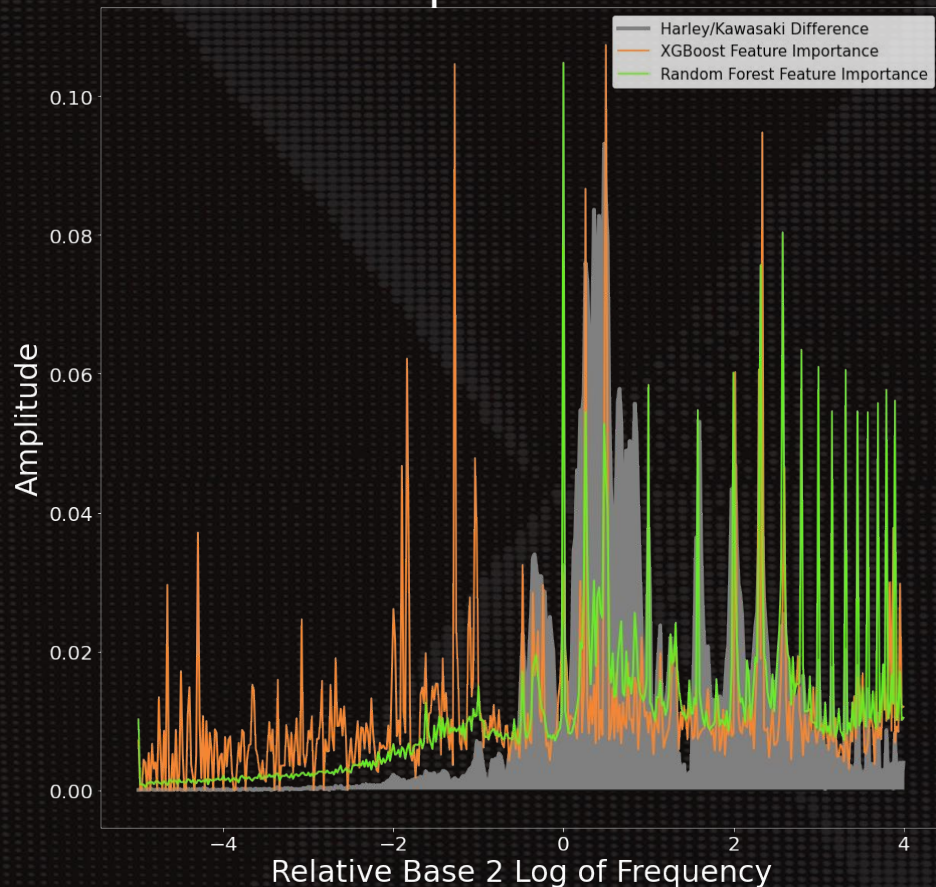
Note on Manual Editing

Significant sections of audio files were removed from the final test set manually. Investigation into the content was spurred by low model performance, but all sections removed were not actually motorcycle noise at all, but people talking, insects, music, or silence. Care was taken to leave all sections in which a motorcycle was present and not being drowned out by other noise.

Such manual editing of the original training set may have further increased the model's performance, if many similar sections of audio were present in them. But they were not manually aurally inspected at all.

Results on Test Set

		K Nearest Neighbors	Random Forest	XG Boost	Extra Trees
Harley Davidson	**Precision**	0.82	0.81	0.84	0.81
	Recall	0.87	0.86	0.86	0.86
	F1	0.85	0.83	0.85	0.83
Kawasaki	**Precision**	0.82	0.8	0.81	0.8
	Recall	0.77	0.73	0.79	0.74
	F1	0.79	0.76	0.8	0.77

Acknowledgements