DISTINGUISHING MOTORCYCLE NOISE BY MAKE

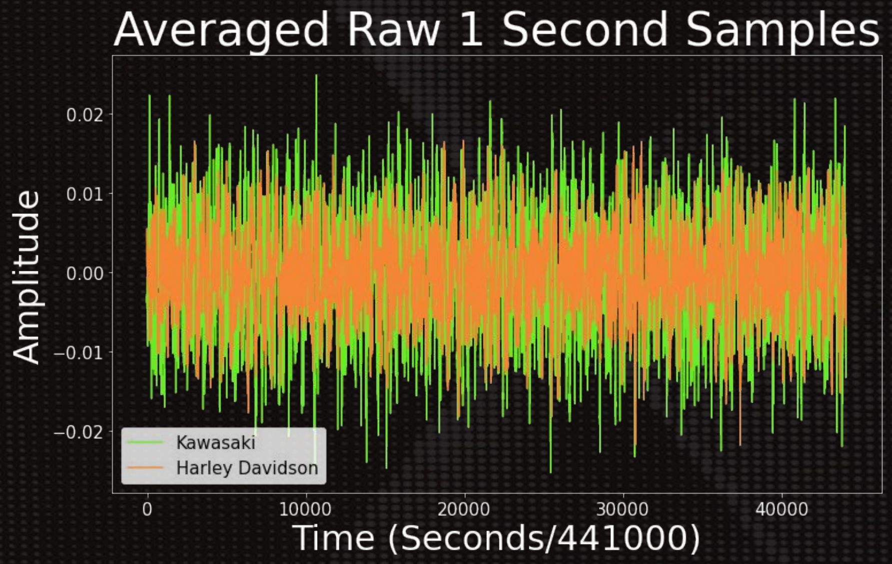
Purpose: Eventual app for cheap enforcement aid

Exploration and proof of concept for future expansion

- Effectively distinguish motorcycle hardware
- Use a variety of conditions and equipment
- Only use short audio clips

Data Collection

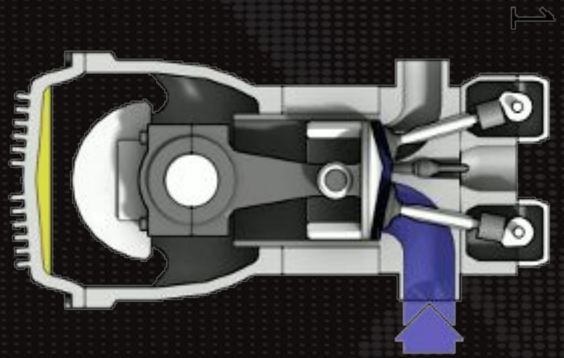
- YouTube as source
  - Variety of exhaust hardware
  - Variety of recording equipment
  - Variety of circumstances
- “[make]+motorcycle+exhaust+sound”
- Top 80 video URLs in each search
- Extract audio



Cleaning and Feature Engineering

Account for:

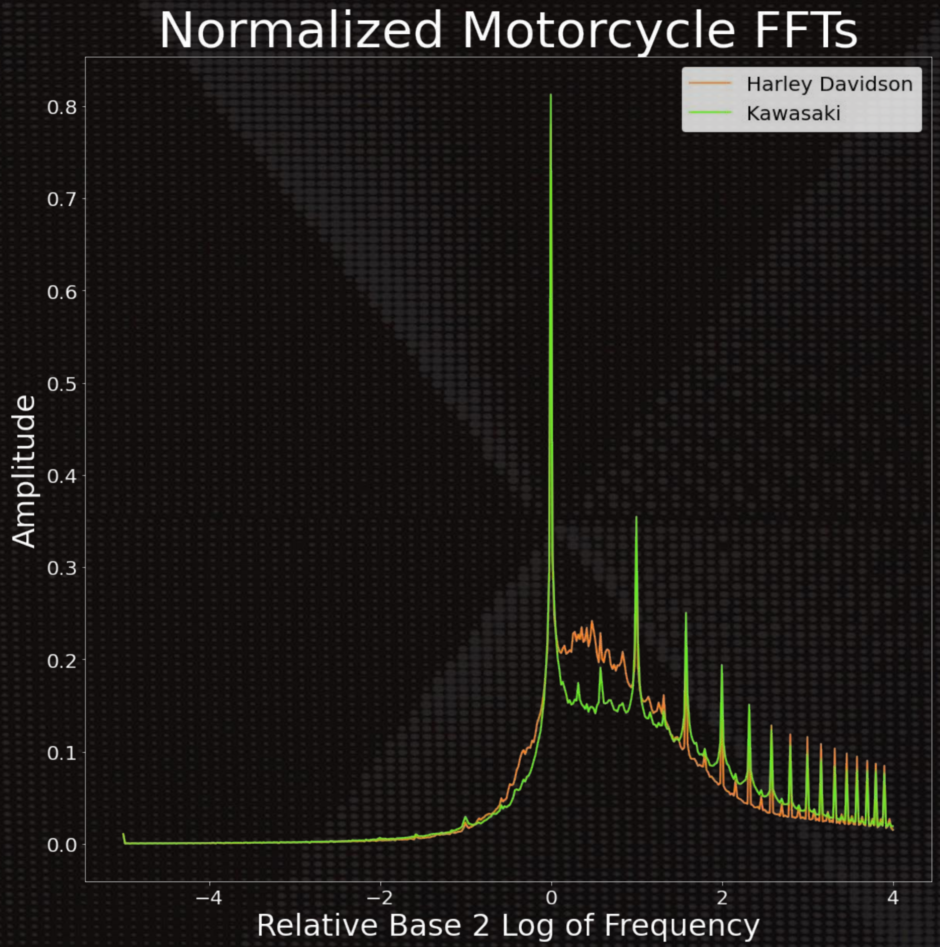
- Engine RPM
- Doppler Effect
- Other sound content



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

Strategies:

- Fast Fourier Transform (FFT)
- Log of frequency
- Normalize
- Drop outliers



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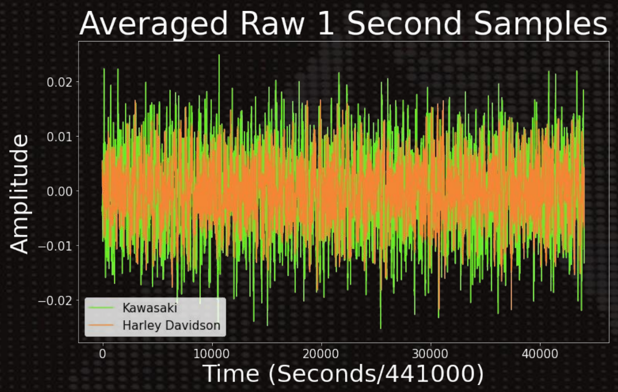
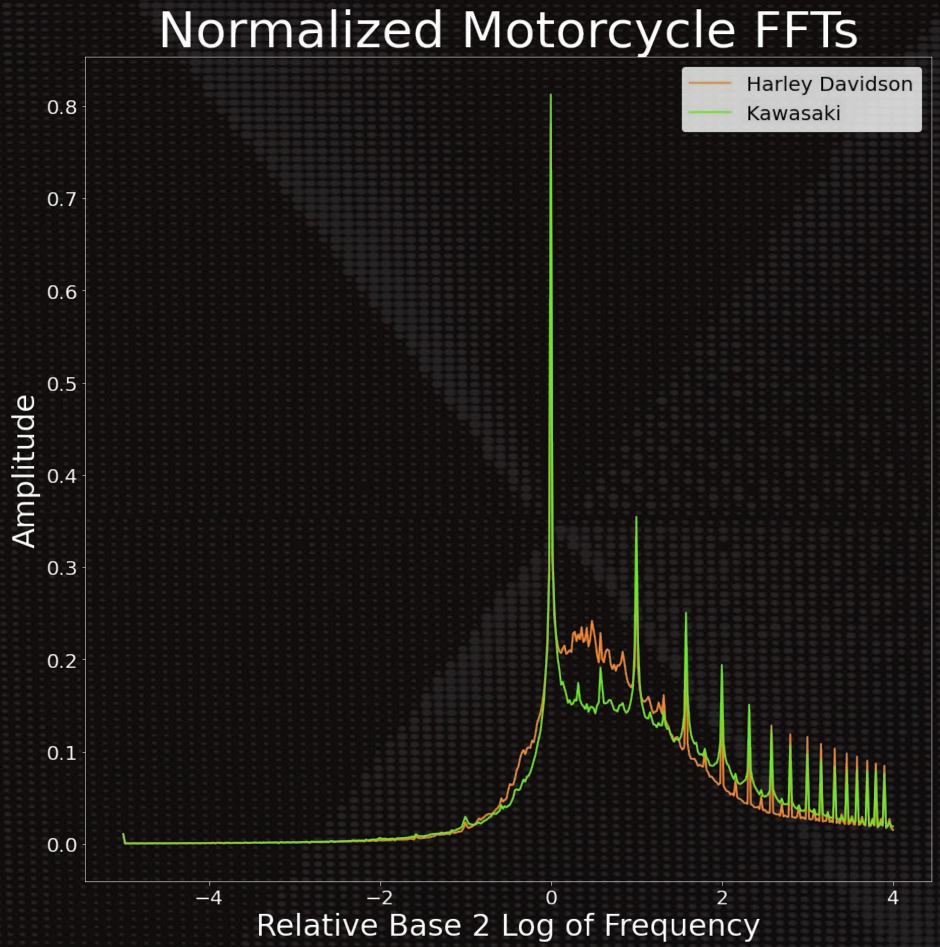
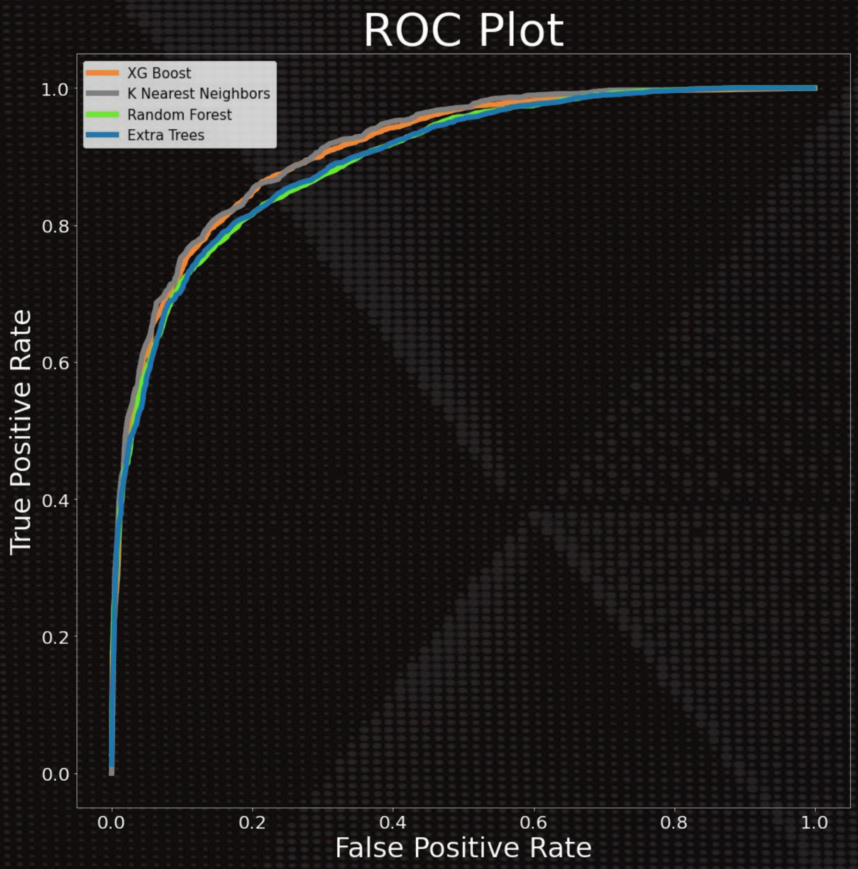




Models

- 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



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
  - May require different data sources
- Develop app for law enforcement
- Add trucks

Thank you!

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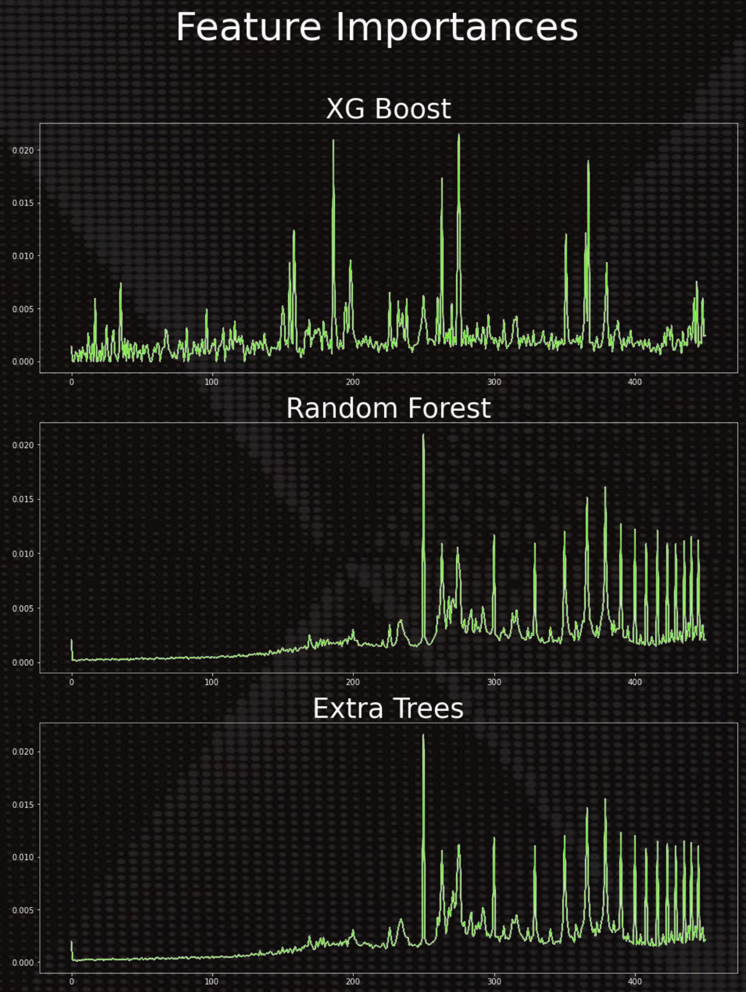
[GitHub]

Appendix

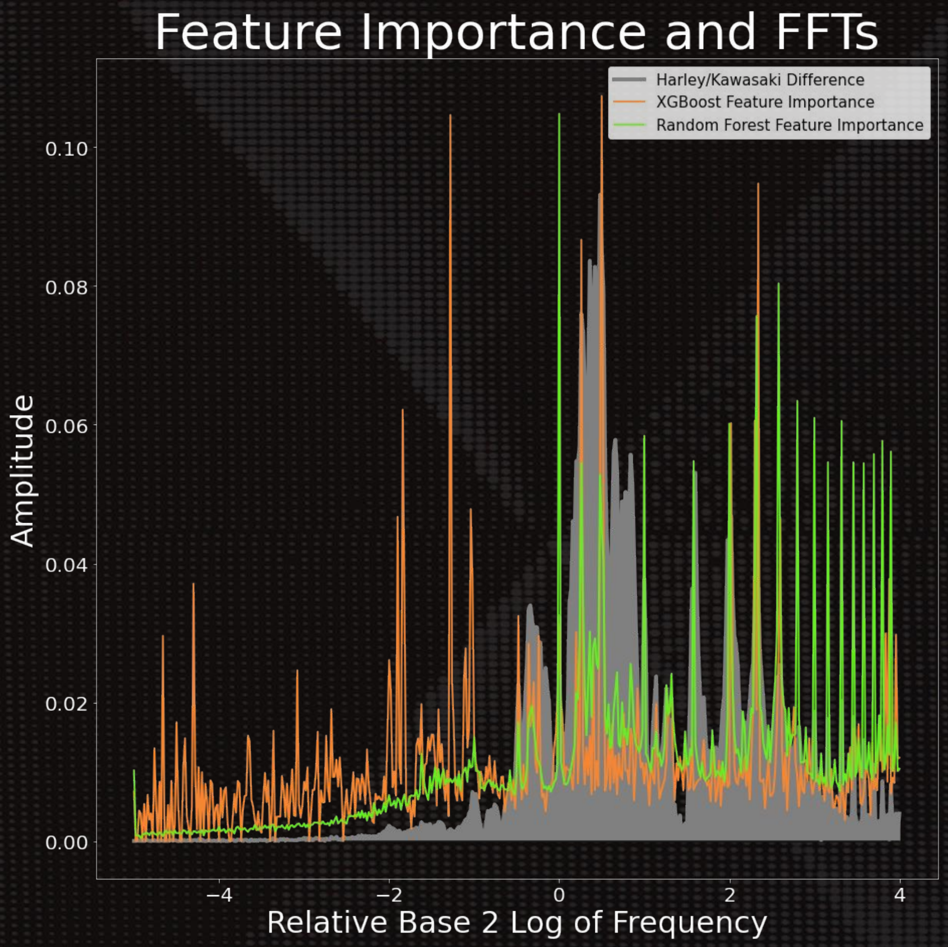
I wondered why these feature importance plots were so different for XG Boost compared to the other two models, so I also plotted them along with the average Harley/Kawasaki difference by frequency on the next page.



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

Sound data: www.youtube.com
Images: Kawasaki, Harley Davidson, Wikipedia