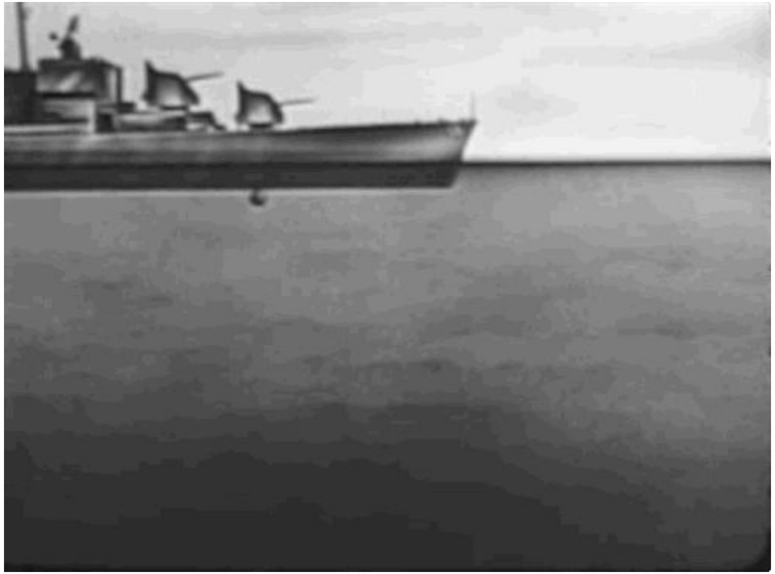
Classifying Undersea Sonar Targets

By Shivesh Mehrotra, Shayaan Subzwari, and Richard Hausman

The Problem: How do we identify Sonar Targets?

- Previous studies relied on human classification of sonar targets
- Although it is easy to see if an object is present on sonar it is hard to tell what the object
- The study we attempted to replicate took a neural network approach to the to problem and was able to achieve 90.4% accuracy



Hypothesis

- Human subjects have been able to differentiate the pings returned with 82% to 97% accuracy
- Furthermore multi-layered neural networks have also been able to successfully classify sonar signals
- **Thus we predict that there are differentiable frequencies between rocks and metal cylinder targets that our ML implementation will be able to identify**

Time and Frequency

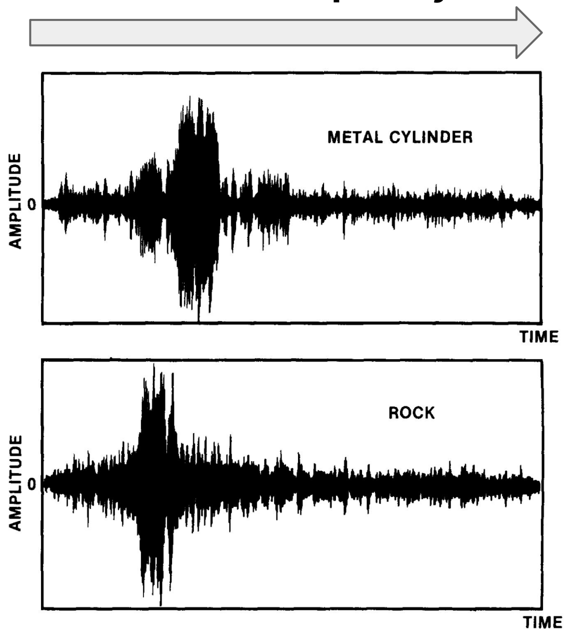
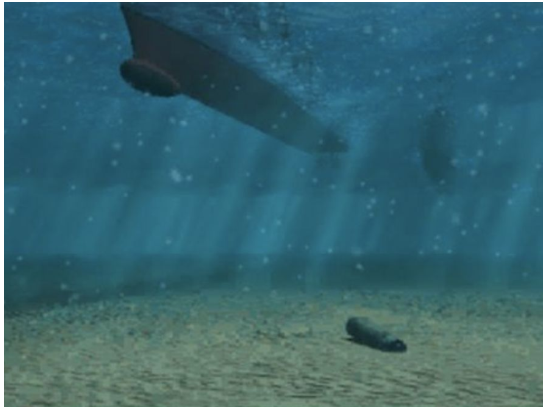


FIGURE 2. Amplitude displays of a typical return from the cylinder and the rock as a function of time.

Data Information

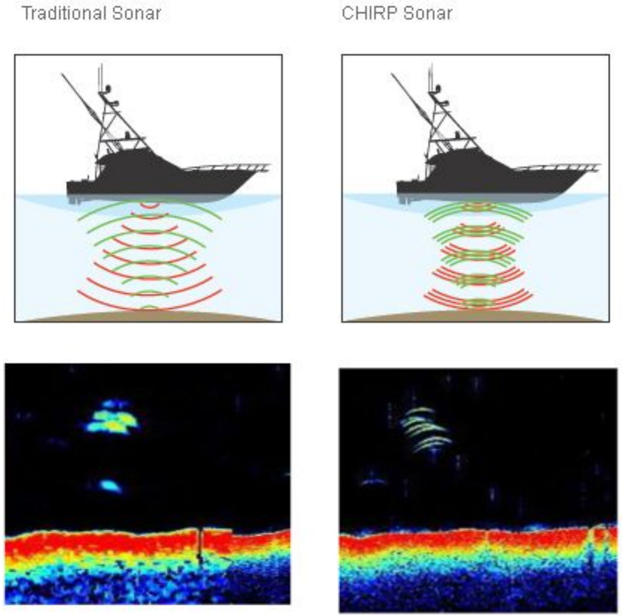
- Sonar data from a metal cylinder and a cylindrically shaped rock, both on the ocean floor
- Targets were of comparable size (5ft)
- Sonar measurements were taken at a distance of 10 meters
- For each of 60 FM frequencies, aspect angles spanned 90 degrees for the cylinders and 180 degrees for the rocks



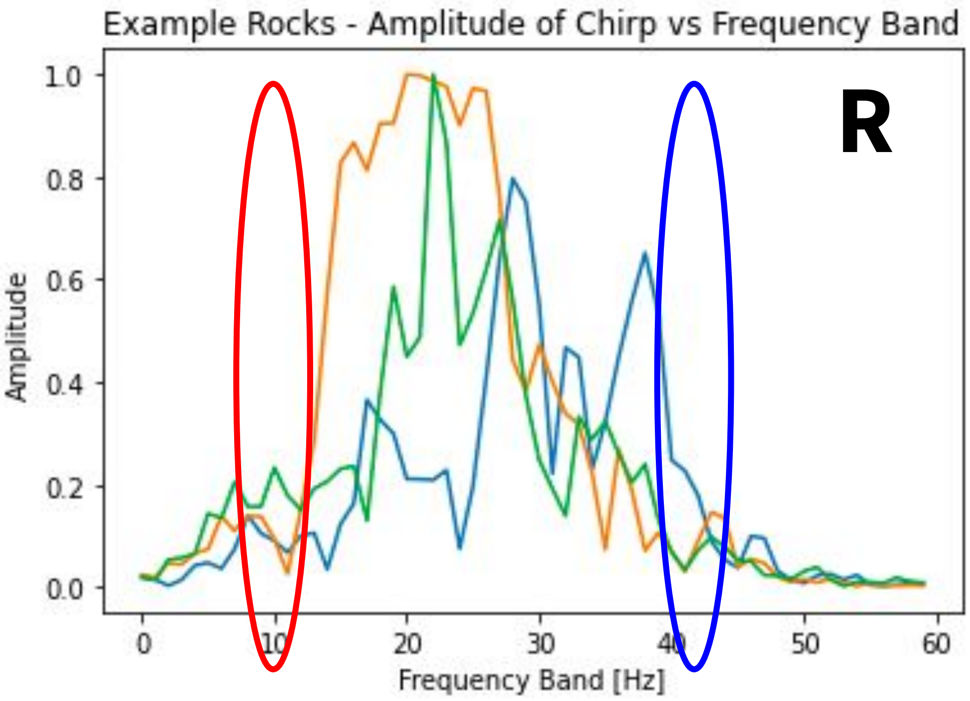
Mk-56 Bottom Mine

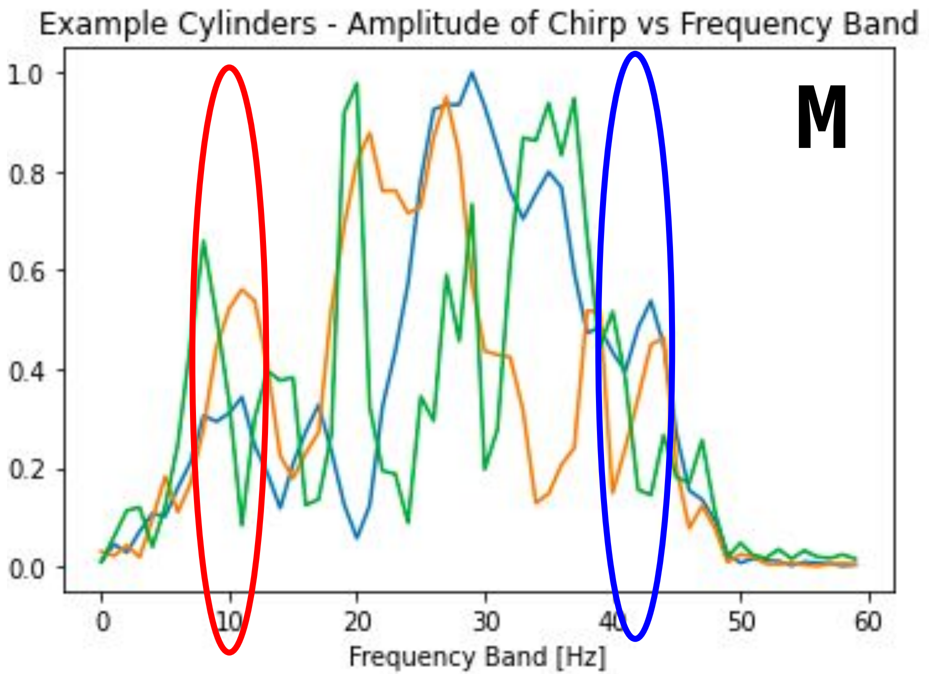
Data Information (Continued)

- In total 208 data samples were collected
    - 97 of which were rock returns
    - 111 of which were cylinder returns
- The data was preprocessed based on previous experiments with human listeners
- The data was pre-cleaned and processed for use
- Additional information can be found at: DGorman, R. P., and Sejnowski, T. J. (1988). "Analysis of Hidden Units in a Layered Network Trained to Classify Sonar Targets" in Neural Networks, Vol. 1, pp. 75-89.

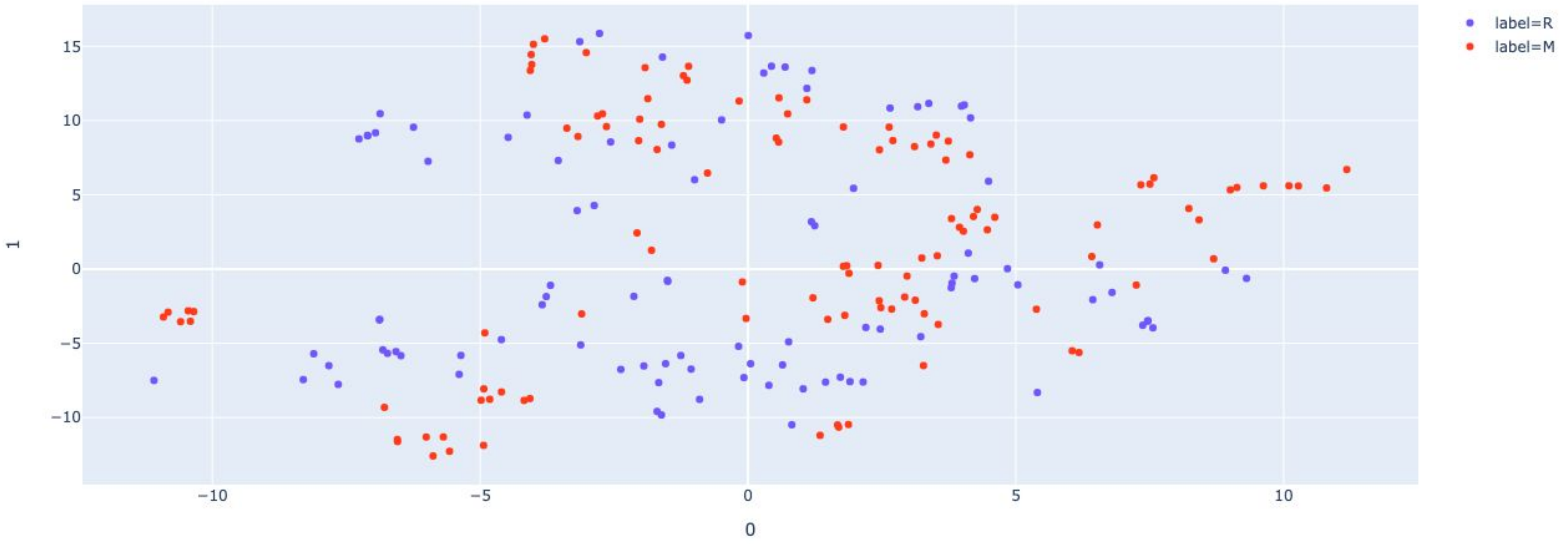


INITIAL VISUALIZATION: REPRESENTATIVE SAMPLES



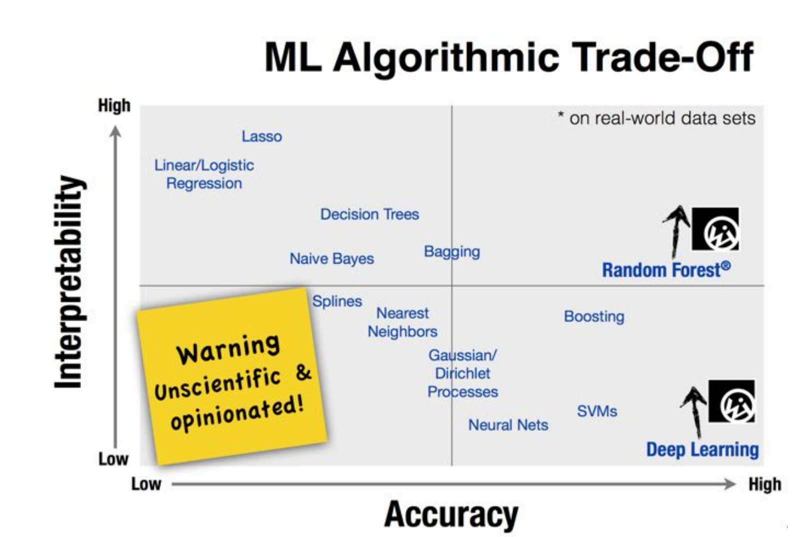


INITIAL VISUALIZATION: T-SNE

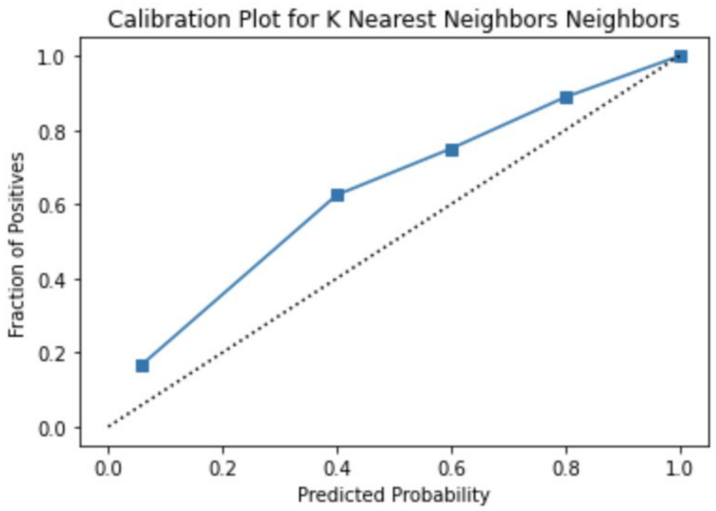


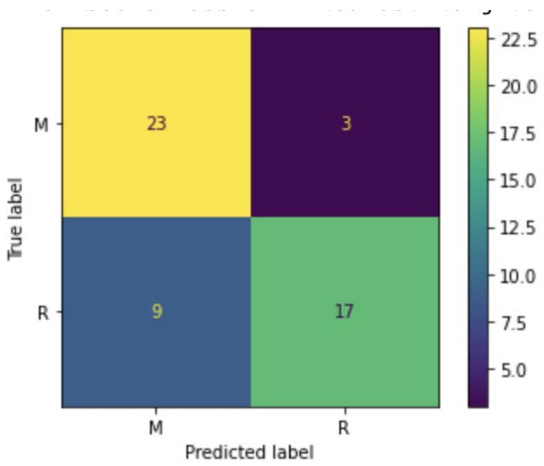
Approach and Methods

- Our approach was to use multiple classification models and assess both their precision, calibration and accuracy
- The models we assessed were KNN, SVM, Random Forest, and Logistic Regression
- Standard train/test split across models
  - **Multiple trials**, consistent results



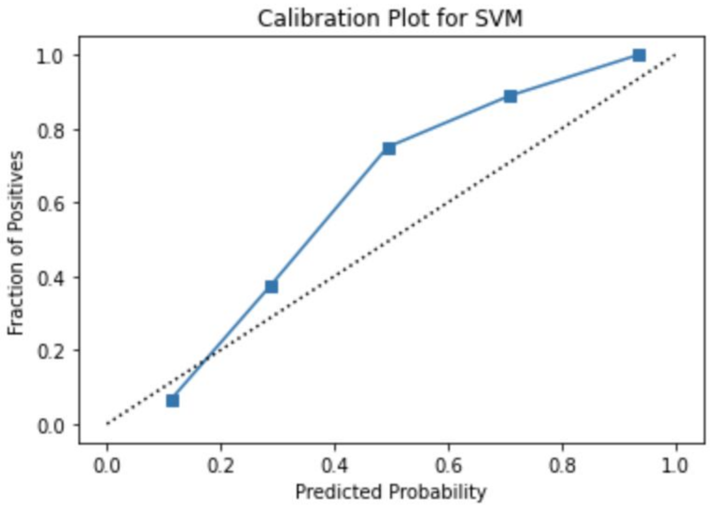
K Nearest Neighbors Classification

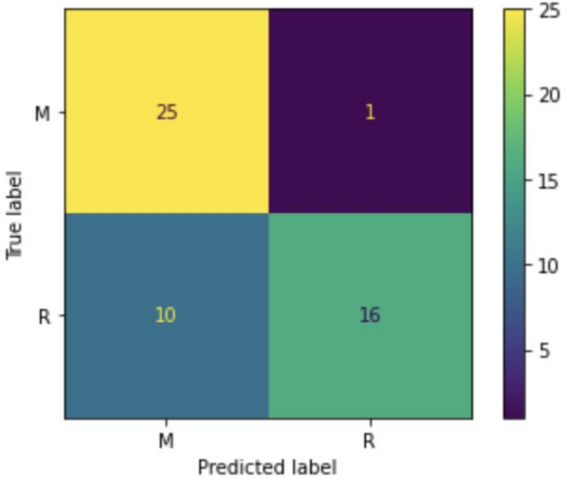




- Accuracy of K Nearest Neighbors Neighbors Classifier : 77%
- Precision of K Nearest Neighbors Neighbors for Class R: 85%
- Precision of K Nearest Neighbors Neighbors for Class M : 72%
- Brier score loss of K Nearest Neighbors Neighbors: 0.1538
- In the paper, KNN **achieved an accuracy of 82.7%**

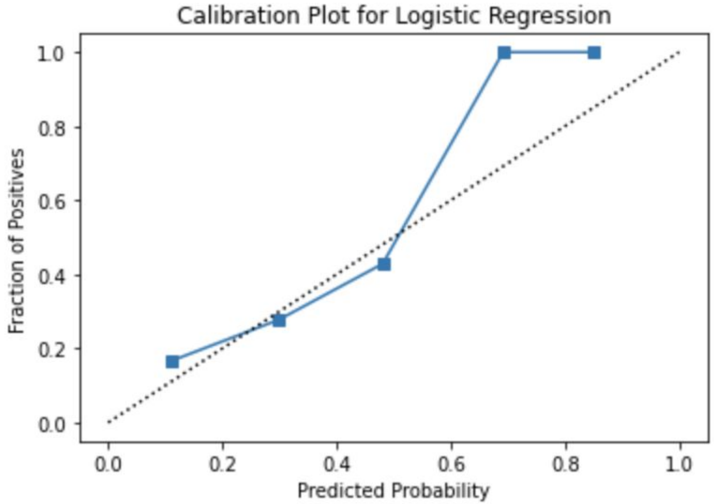
Support Vector Machine Classification

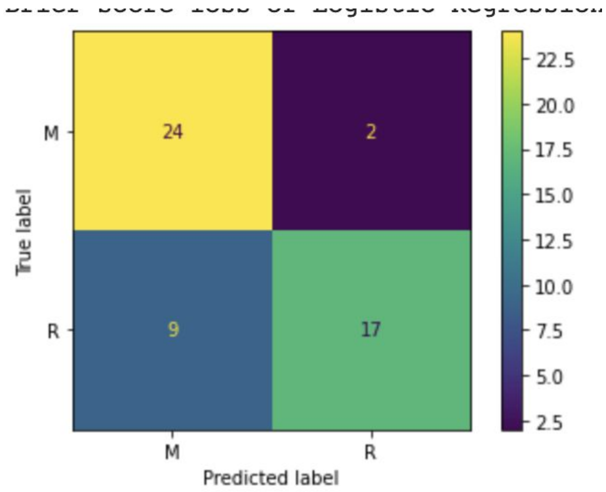




- Accuracy of SVM : 78.8%
- Precision of SVM for Class R : 94%
- Precision of SVM for Class M : 71.4%
- Brier score loss of SVM: 0.14098

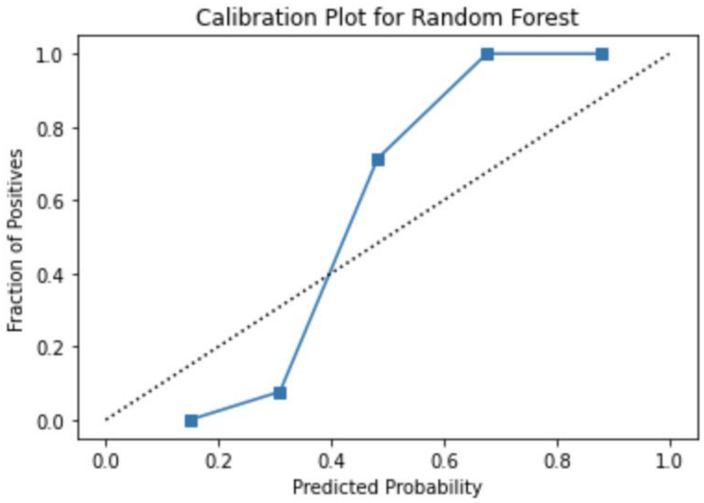
Logistic Regression Classification

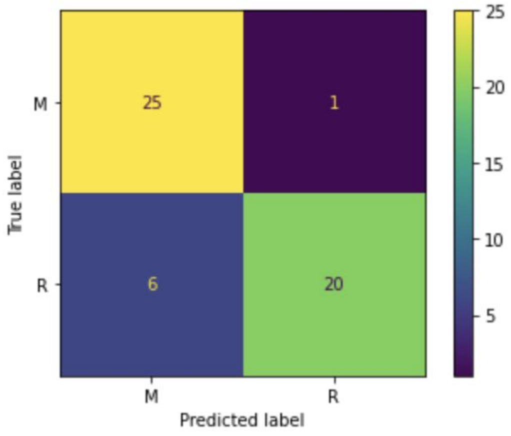




- Accuracy of Logistic Regression : 78.8%
- Precision of Logistic Regression for Class R : 89.5%
- Precision of Logistic Regression for Class M : 73%
- Brier score loss of Logistic Regression: 0.16897

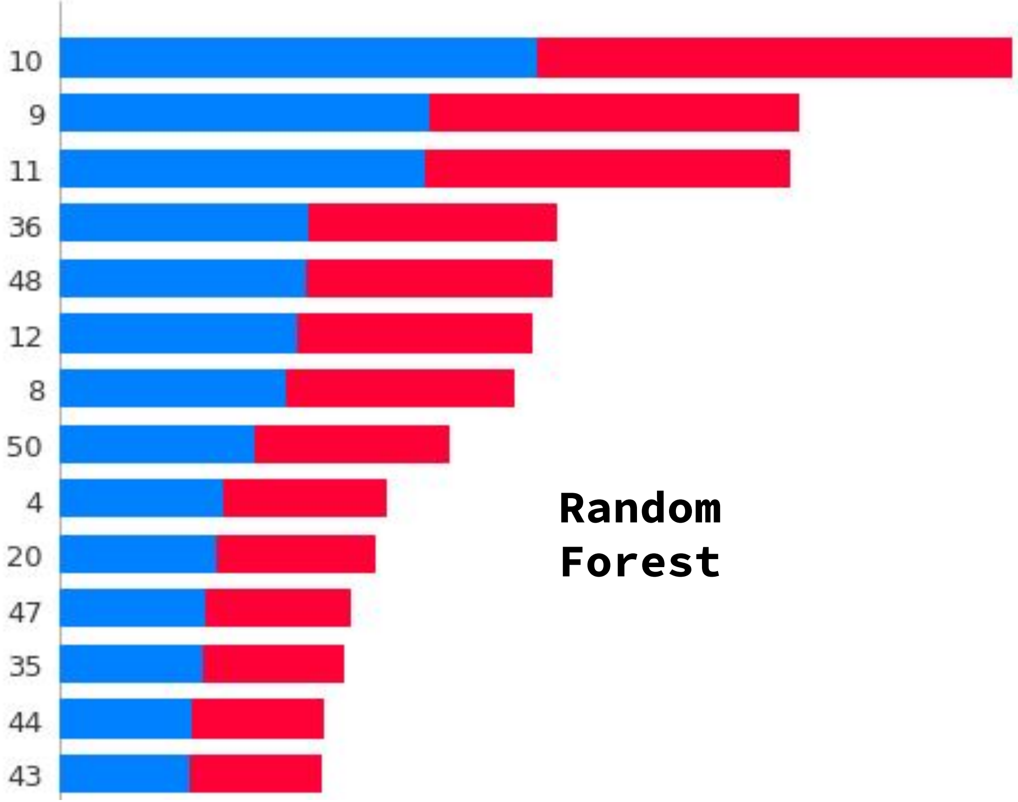
Final Model Choice: Random Forest Classification





- Accuracy of Random Forest : 86.5%
- Precision of Random Forest for Class R : 95.2%
- Precision of Random Forest for Class M : 80.6%
- Brier score loss of Random Forest: 0.11806

Interpreting the Most Significant Features: Shapley

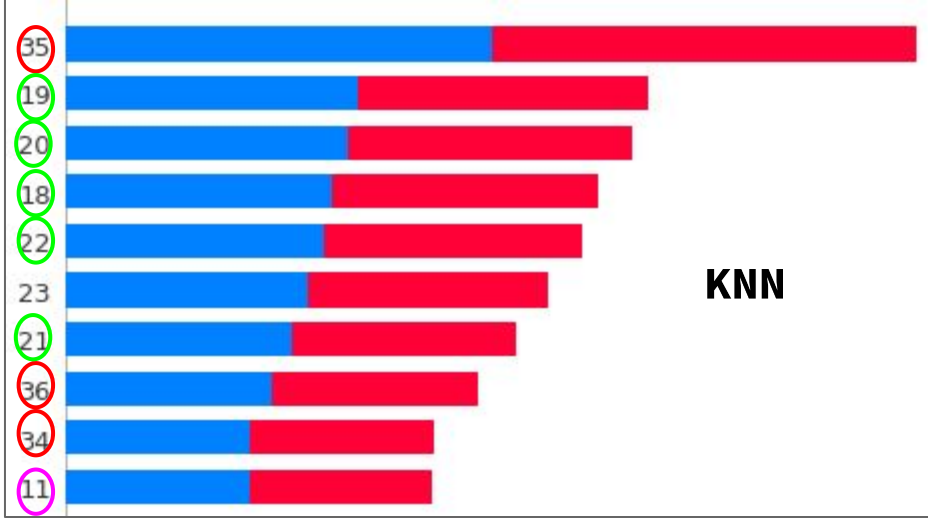


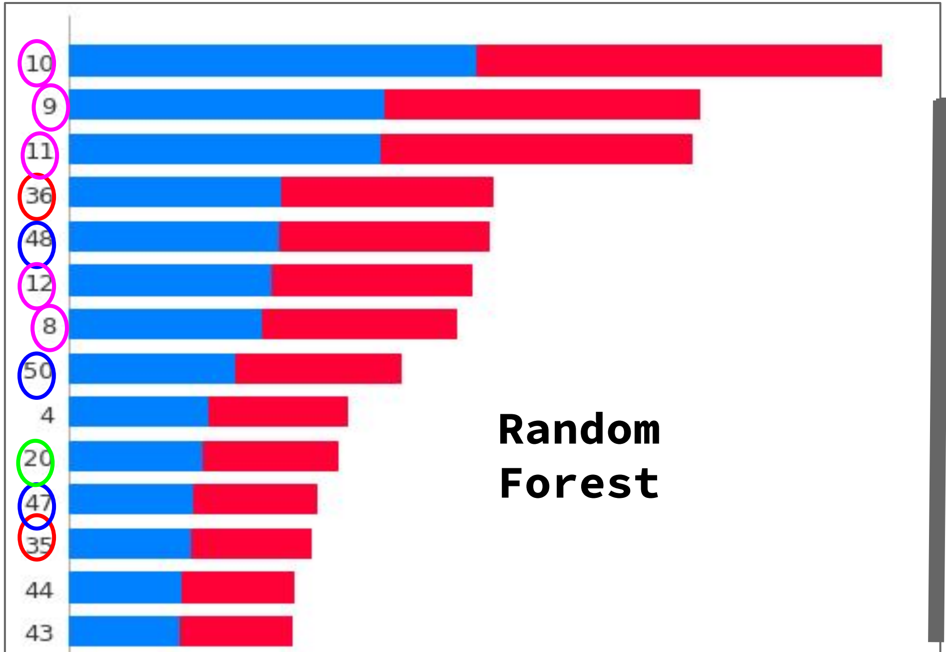
Four main bands of "Key" frequencies

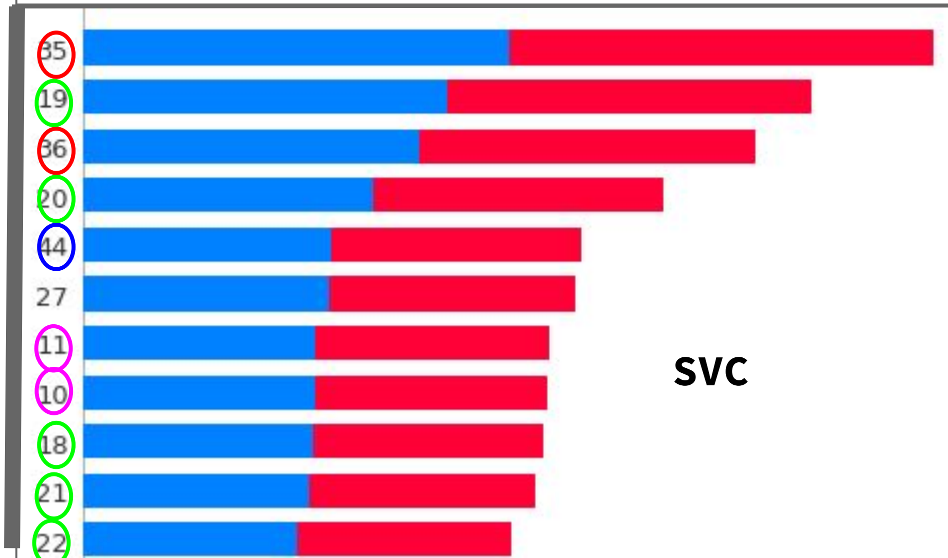
- 9-12
- 18-22
- 34-36
- 45-50

Shapley Consensus

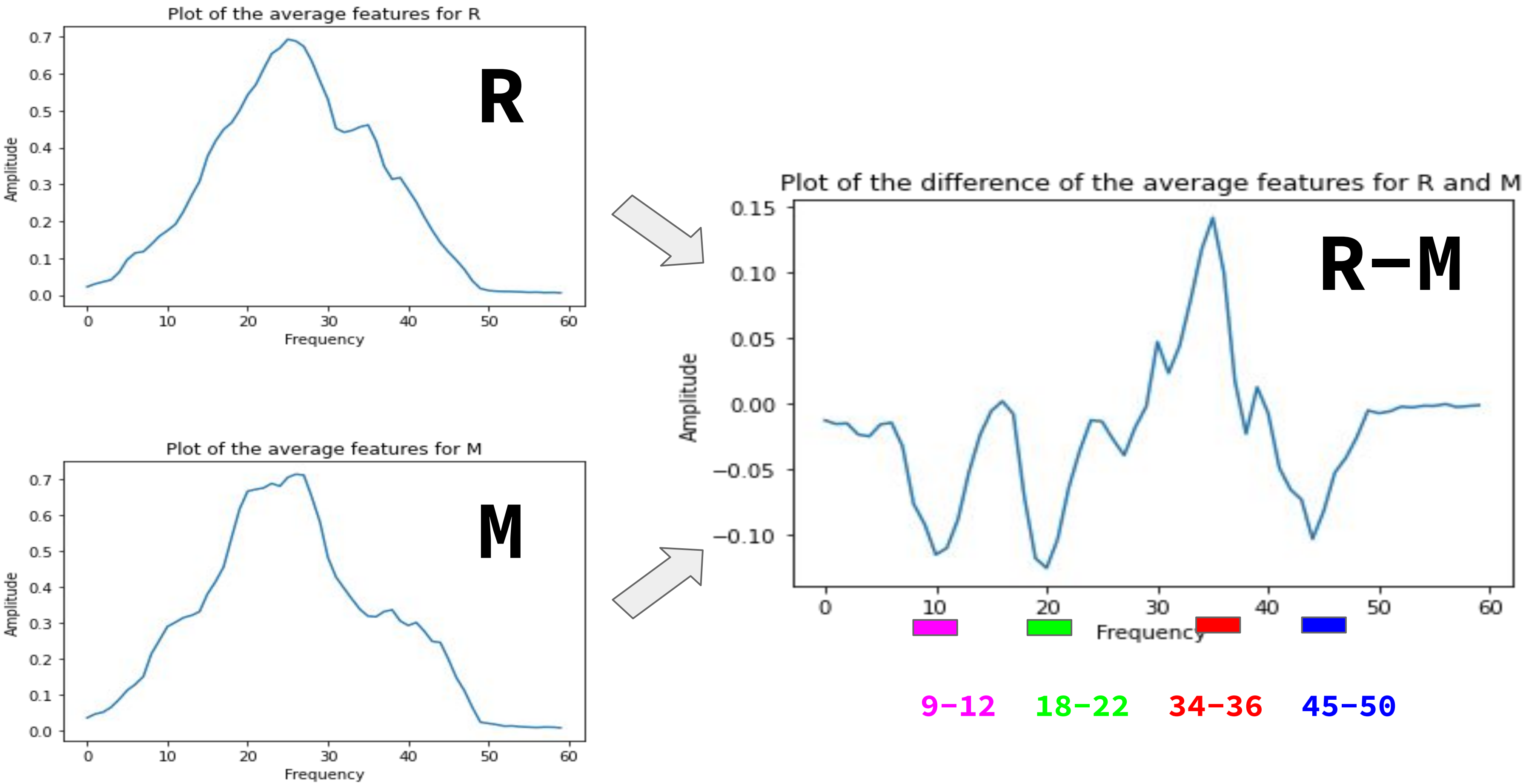
- 9-12
- 18-22
- 34-36
- 45-50







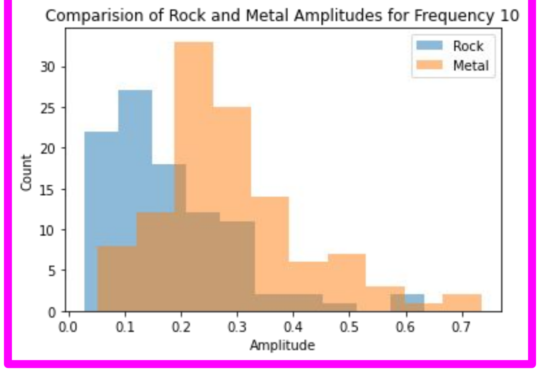
Visualizing the Most Impactful Frequencies

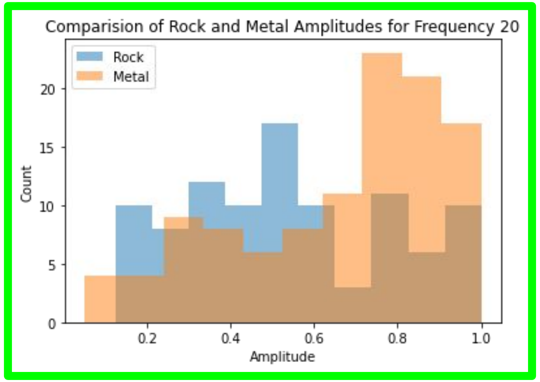


Visualizing the Most Impactful Frequencies

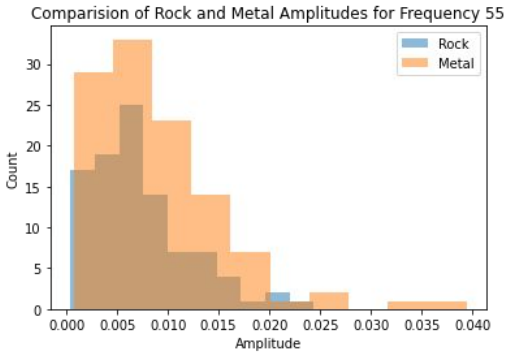
Shapley analysis, differences in mean amplitudes by frequencies, and visualizations of the distributions of candidate “key frequencies” all support our hypothesis

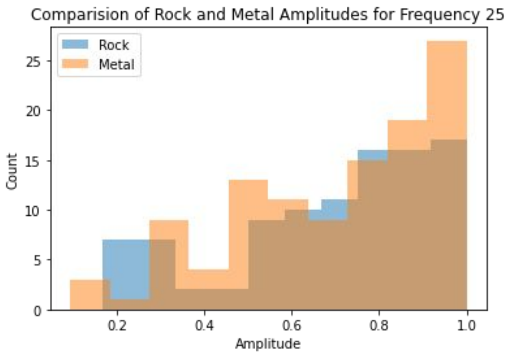
IMPORTANT





USELESS





Interpretation

- A random forest classifier can effectively distinguish between rocks and metals using sonar, with approximately 86% accuracy.
  - On-par with human performance (82% - 97%).
  - More interpretability than a Neural Network
- The four “key” frequency bands we identified give the most disparate/detectable difference between rocks and metals.