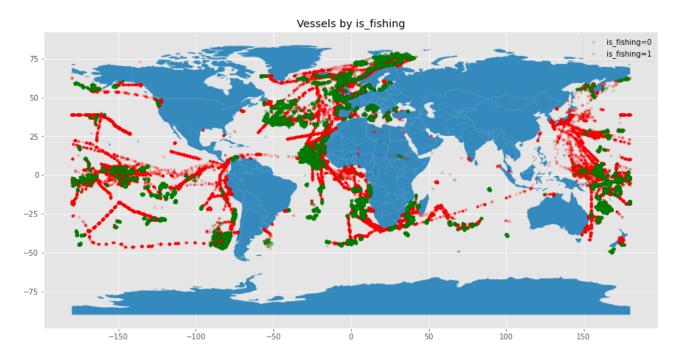


Build a classifier to identify whether a vessel is fishing. Ultimate goal is to create a classifier that can be used by policymakers, regulators, and other stakeholders involved with preservation of ocean resources to identify vessels that are fishing.



# **Repository Contents**

- README.md
- 2. notebook.ipynb jupyter notebook containing all code and modeling
- 3. /datasets directory housing all datasets that were not too large to be uploaded
- 4. tide\_api\_call.ipynb separate notebook that pulls in ocean depth based on lat, lon inputs. Ultimately wasn't used as computation time was too large.
- 5. notebook.pdf pdf version of jupyter notebook
- 6. presentation.pdf non-technical presentation
- 7. repo.pdf pdf version of github repo
- 8. /readme\_imgs directory housing all images used in this file

# **Project Objectives**

Build a classifier to predict whether a vessel is engaged in fishing activity in context of providing policymakers, regulators, and other ocean resource stakeholders a tool to identify vessels that are fishing. Follow CRISP-DM machine learning process to explore dataset, prepare data for modeling, modeling, and post-model evaluation. Main performance metrics focused on were accuracy and recall as our dataset is not very sensitive to producing false positives.

#### **Overview of the Process:**

Following CRISP-DM, the process outlined within notebook.ipynb follows 5 key steps, including:

- 1. Business Understanding: Outlines facts and requirements of the project.
- 2. Data Understanding: focused on unpacking data available and leveraged throughout classification tasks. Section will focus on the distribution of our data, and highlighting relationships between target and predictors.
- 3. Data Preparation: further preprocessing of our data to prepare for modeling.
  Includes separating validation sets, handling missing values, and encoding certain columns
- 4. Modeling: this section iteratively trains a number of machine learning models, specifically using Decision Trees, Random Forests, XGBoost, and Neural Networks.
- 5. Evaluation: Final / optimal model is selected and final performance metrics of final model are discussed and evaluated. Focused primarily on accuracy and recall as performance metrics.

# **Findings & Recommendations**

The best performing model identified was a tuned random forest model. Final model scores:

## Accuracy:

Training Set: 0.9380431102584359

Testing Set: 0.9298294680905873

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## Precision:

Training Set: 0.8991085516328288

Testing Set: 0.8908070007765366

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## Recall:

Training Set: 0.973149879055936

Testing Set: 0.9640883084979152

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## F1 Score:

Training Set: 0.9346651764925026

Testing Set: 0.9260000931402226

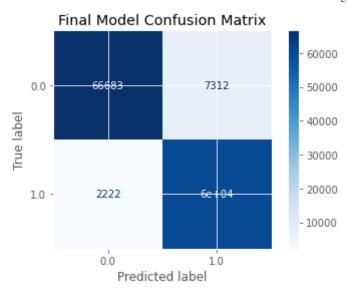
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### ROC AUC:

Training Set: 0.9409182901449071

Test Set: 0.9326354104149147

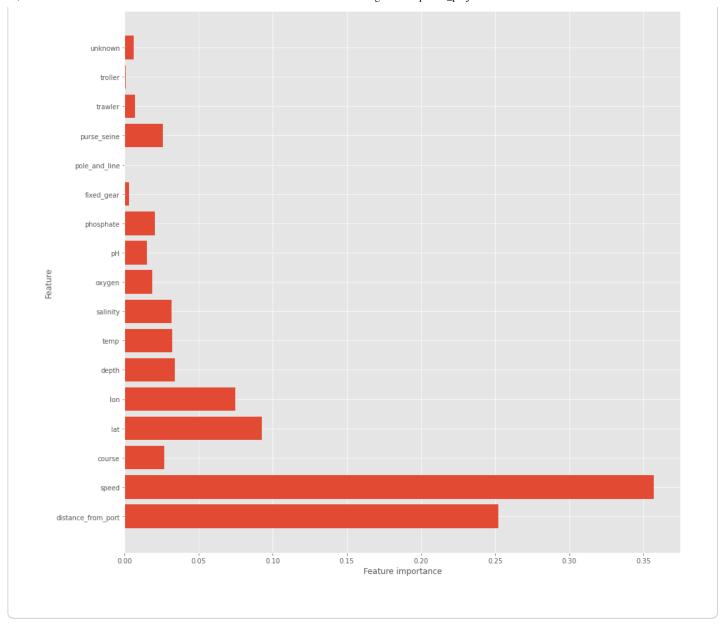
Looking at the confusion matrix for the final model, we can see that there are far more false positives than false negatives, as indicated by the number in the upper right quadrant vs. lower left quadrant. We are more interested in a strong recall, and therefore are not too worried with the level of false positives generated given the end applications.



The top 6 most important features to our model were:

- 1. speed
- 2. distance\_from\_port
- 3. lat
- 4. lon
- 5. depth
- 6. temp

When looking to identify a vessel that is fishing or not, these features will be most important to have as inputs.



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Jupyter Notebook 100.0%