



Mine detection using Sonar

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ABSTRACT

- The problem is to predict metal or rock objects from sonar return data.
- Each pattern is a set of 60 numbers in the range 0.0 to 1.0.
- Each number represents the energy within a particular frequency band, integrated over a certain period of time.
- The label associated with each record contains the letter R if the object is a rock and M if it is a mine (metal cylinder).
- **Data Set description:** The numbers in the features are in increasing order of aspect angle, but they do not encode the angle directly.
- In this project we aim to compare the algorithms and deduce which is optimal for classification.



OVERVIEW

- First step is to understand the dataset. That is deduce the type, description, class distribution.
- Second we do data visualization: Unimodal and Multimodal
- Next we prepare the data i.e. Data Preparation by Setting Baseline using linear and non-linear models (unscaled and scaled features separately). We then tune KNN and SVM and compare the algorithms.
- We later model using Ensemble algorithms (combination of multiple algorithm)
- Make classification using Final model (SVC)



SVC

Support Vectors Classifier tries to find the best hyperplane to separate the different classes by maximizing the distance between sample points and the hyperplane. kernel parameters selects the type of hyperplane used to separate the data. Using 'linear' will use a linear hyperplane (a line in the case of 2D data). 'rbf' and 'poly' uses a non linear hyper-plane. gamma is a parameter for non linear hyperplanes. The higher the gamma value it tries to exactly fit the training data set. C is the penalty parameter of the error term. It controls the trade off between smooth decision boundary and classifying the training points correctly.

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