Reimplementation: Source localization in an Ocean Waveguide Using Supervised Machine Learning

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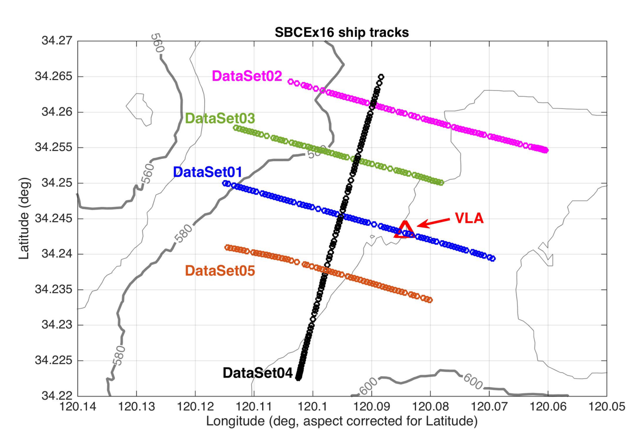
Predicting

Source localization is significant to underwater surveillance, detecting, and tracking. Compared to matched-field processing, machine learning methods are needed for some complicated and changing environment. The sound pressure is preprocessed to a normalized sample covariance matrix as input. Three machine learning methods, support vector machines (SVM), Feed-forward neural networks (FNN), and random forests (RF), are implemented to address the range estimation. The performance of each method is evaluated by mean absolute percentage error (MAPE), and SVM gives the best result with an average of 0.037 in all datasets.

Data



Five Ship Tracks

The shipping noise data was collected from the signal of R/V New Horizon. Figure 1 shows the dataset geometrically, with the vertical linear array (VLA) indicated as a red triangle. The five ship tracks shown in five colors are used for estimation, and each dataset includes both training and test data with different time ranges.

Feature

The received pressure phase and amplitude is preprocessed to a normalized sample covariance matrix (SCM). Since there are more than 7,000 features in each dataset, Principal Component Analysis (PCA) is used to reduce the dimension of feature space, which significantly helps decrease the computation time and improve the performance of each model. Principal components are chosen such that it will retain 90% of the original variance of data.

Model 1 - FNN

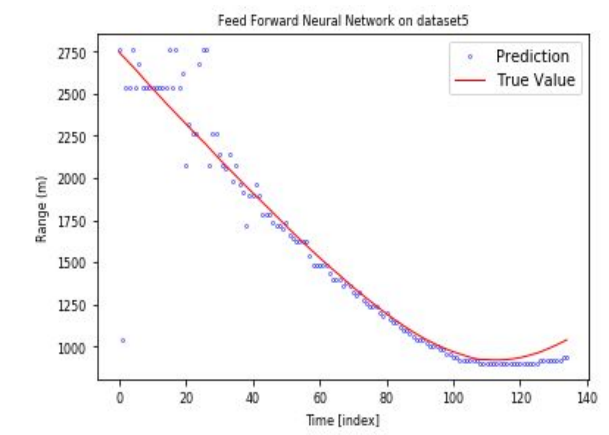
Feed-forward neural network is a form of deep neural network where data flow through the network in one direction. The equation for the output of each layer can be described as:

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)},\ j = 1, 2, \cdots, M$$

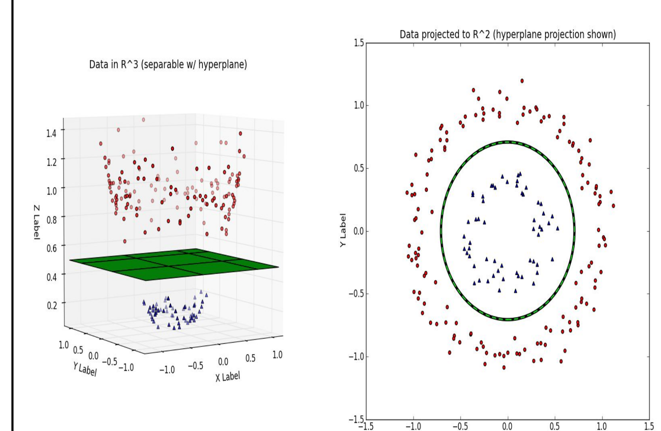
Where x is the input and w is the weight matrix that we need to learn for that layer through training. In our project we will be using rectified linear

FNN-Continued

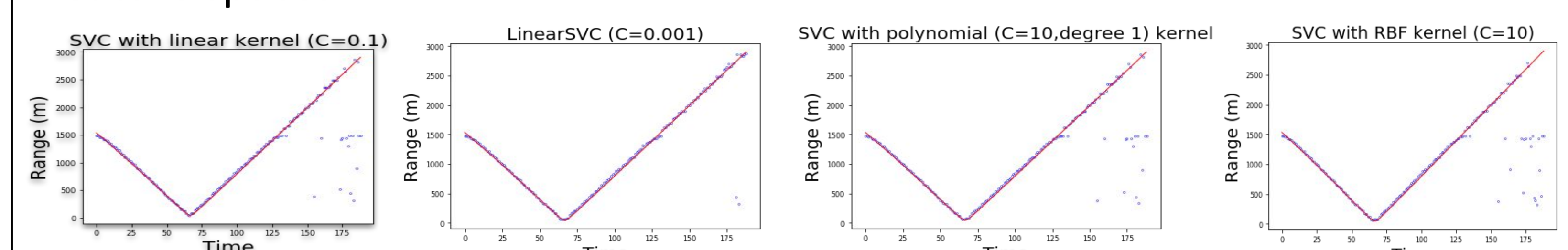
units which has the advantage of no gradient vanishing problem. Our neural network consists of three layers with 64, 128, 256 hidden units respectively. The graph shows the result on one set of dataset.



Model 2 - SVM



In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.



MAPE: 9.28% | **MAPE: 5.76%** | MAPE: 9.13% | MAPE: 10.75%

Model 3 - RF

Random Forest (RF) consists of Classification and Regression Trees (CART), a conditional weighted method which only uses important features to do the classification. Gini impurity is chosen as the metric to split the root:

$$Gini(f) = \sum_{i=1}^{J} f_i(1 - f_i), \quad i = 1, 2, ..., J$$

where J is the number of classes and f_i is the portion of data which belongs to class i. The dataset keeps splitting based on Gini index until all the nodes cannot be splitted any more or a specific threshold is reached. To avoid overfitting problem, training sample of N classes is take at random but with replacement. Each tree is grown to the largest extent possible and there is no pruning. The outcome is

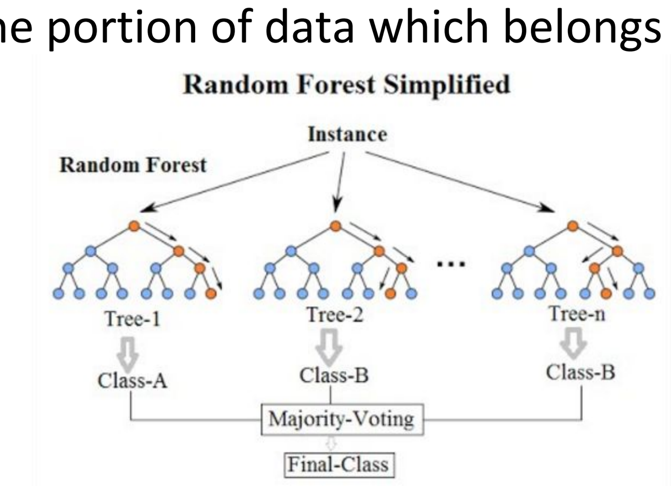
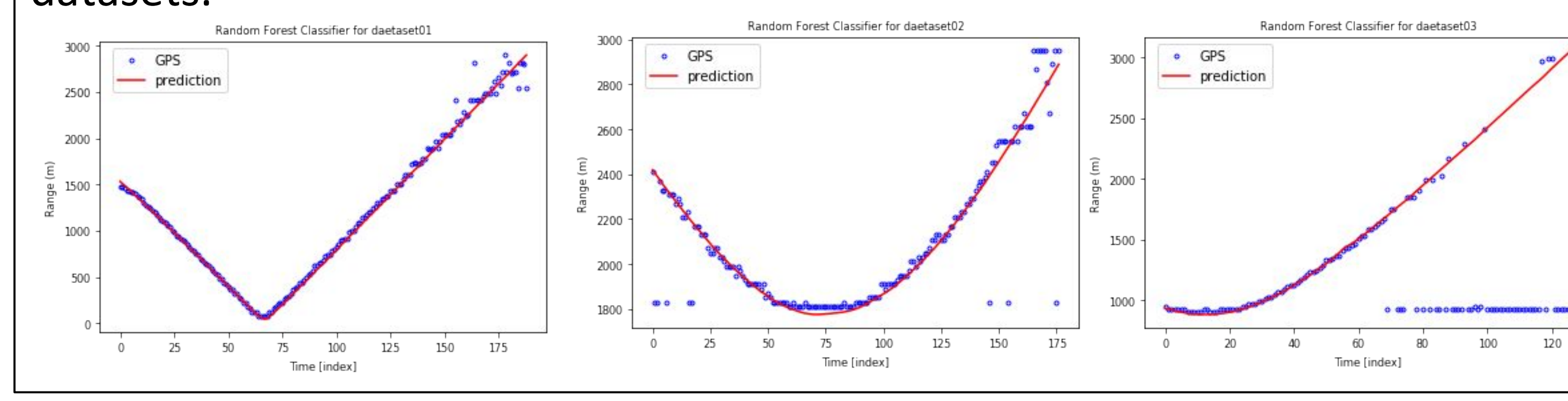


Illustration of RF

RF-Continued

determined by the majority votes for classification problem and the average for regression problem. The following graphs show RF result on first three datasets.



Results

Table 1 quantitatively compares all three models. In order to keep the consistency, the same preprocessed data which retains 90% of the original variance of data is used as input. FNN performs really well, SVM gives the best results on all datasets with specific kernel type.

	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
FNN	0.25314	0.02332	0.05580	0.06038	0.04843
SVM	0.0498 (Linear SVC)	0.03754 (Linear SVC)	0.02640 (Linear SVC)	0.01764 (RBF Kernel)	0.05400 (Linear SVC)
RF	0.05688	0.02334	0.21644	0.05994	0.27771

Table 1. Comparison of MAPE

Discussion

By comparing the methods in the results section, SVM outperforms the comparison with its smallest average MAPE. We obtained similar MAPE of the first two datasets as the reference paper did, which is as expected. RF gives a relatively high MAPE in dataset 03 and dataset 05, and the reason is still unknown since we tried all different RF parameters. In addition, all the three statistical models have better performance on classifying data from the classes containing more than one training samples, which indicate the necessity of big data in machine learning.

Future

In this paper, there are limited amount of data and five tracks are trained and tested as five independent datasets. In the future, we are going to combine all five dataset as one big training set to see how these three models work. In addition, we have started to experiment with using RNN to capture the temporal information of the data, in the future we would like to develop upon this a little more.

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