Data Analytics 2 - Product Type Sales Prediction

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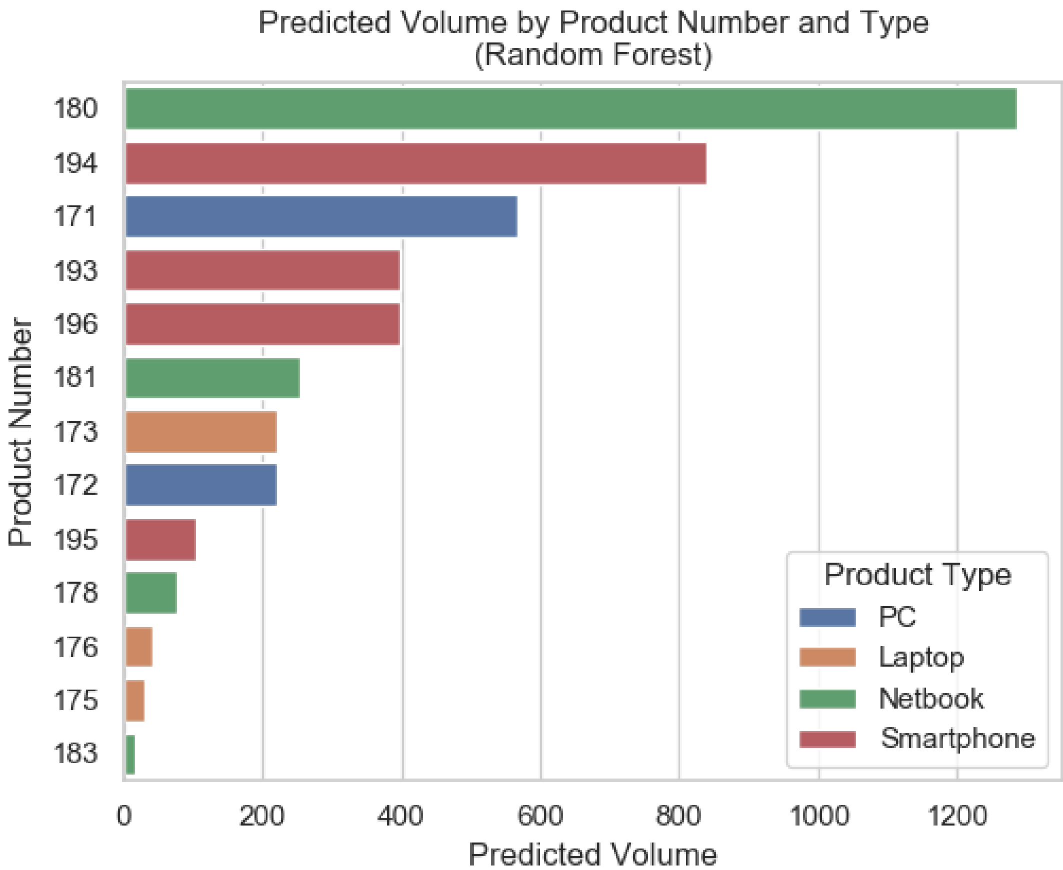
Version Number	**Changes**	**Date**
0.9	Basic layout	02.09.2019
1.0	Finished Report	03.09.2019

Predicted Sales for New Laptops, Smartphones, Netbooks

We predicted the sales volume for future products in the categories Laptops, PCs, Smartphones and Netbooks. Below are the predicted volumes. One of the Netbooks looks like a clear winner, but if we concentrate on the categories we see that our new smartphones were predicted to perform well all around except for product 195.

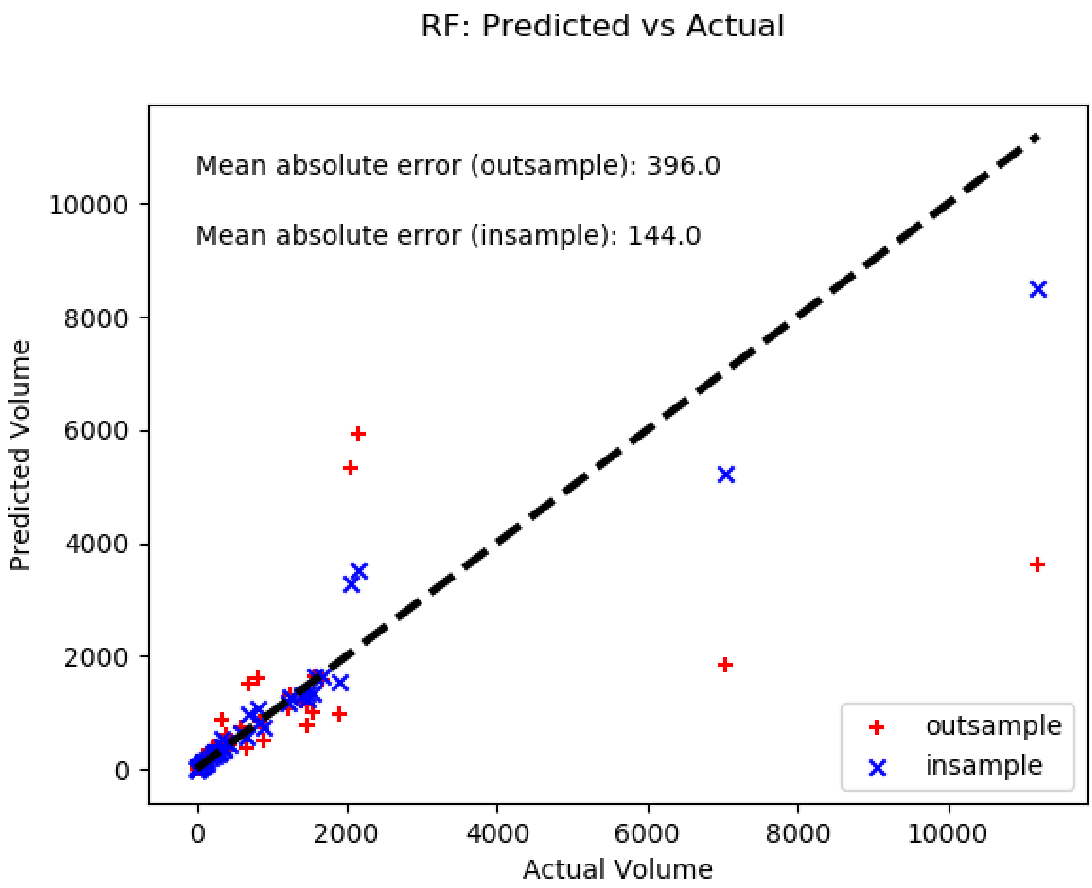


Selected Model and It's Performance

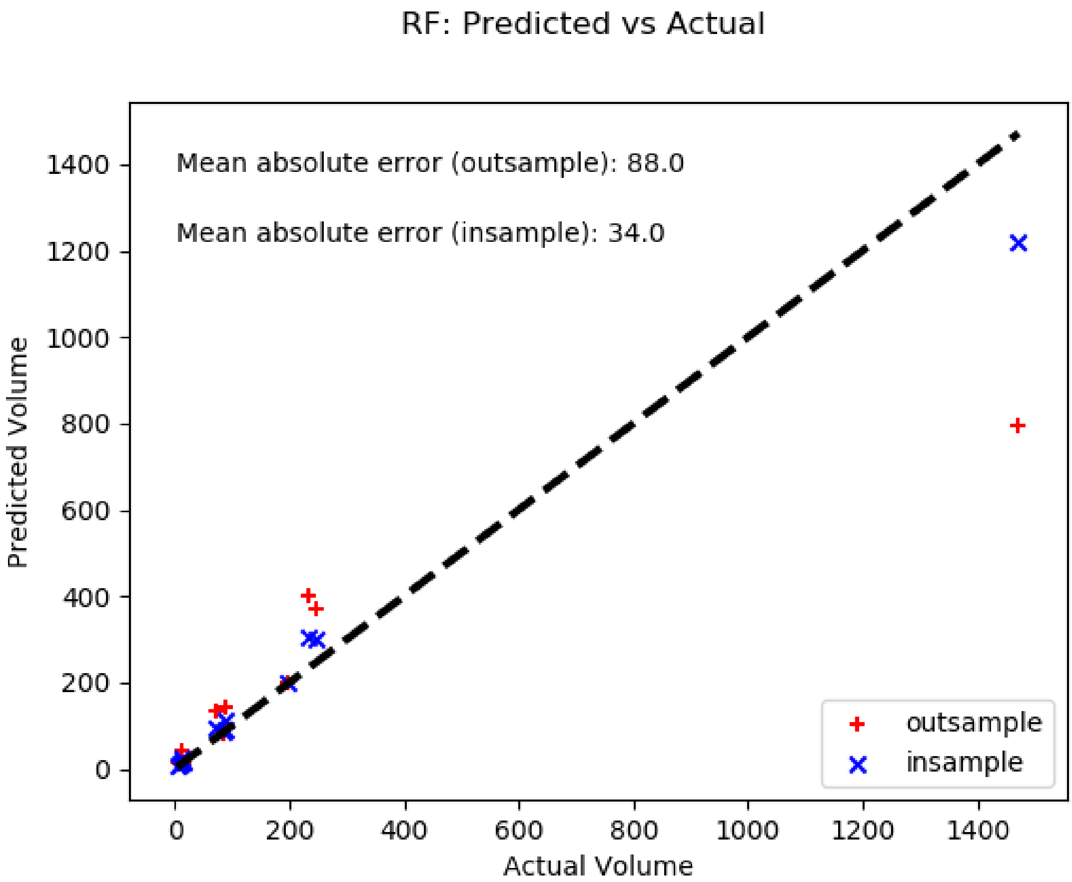
The model that was used to create these predictions was a Random Forest Model. The model was trained using all the data in training set, except for the Extended Warranties.

This means that we used product categories as different from our categories of interest as Printer Supplies and accessories.

Below are the predictions for volume in the training set. Included in the graph are both the predictions made from by training with the whole dataset and the predicting the values with this model (insample) and predictions made by training the model without the observation that was predicted (outsample). The more reliable measure of the models actual predictive power is the outsample error. We can see that the model is not very good with products that have actual sales volumes of over 2000 and this is particularly true for the outsample predictions. We also see that the outsample error is over twice that of the insample error. This means that despite our efforts there is substantial overfitting of the model to the train dataset.

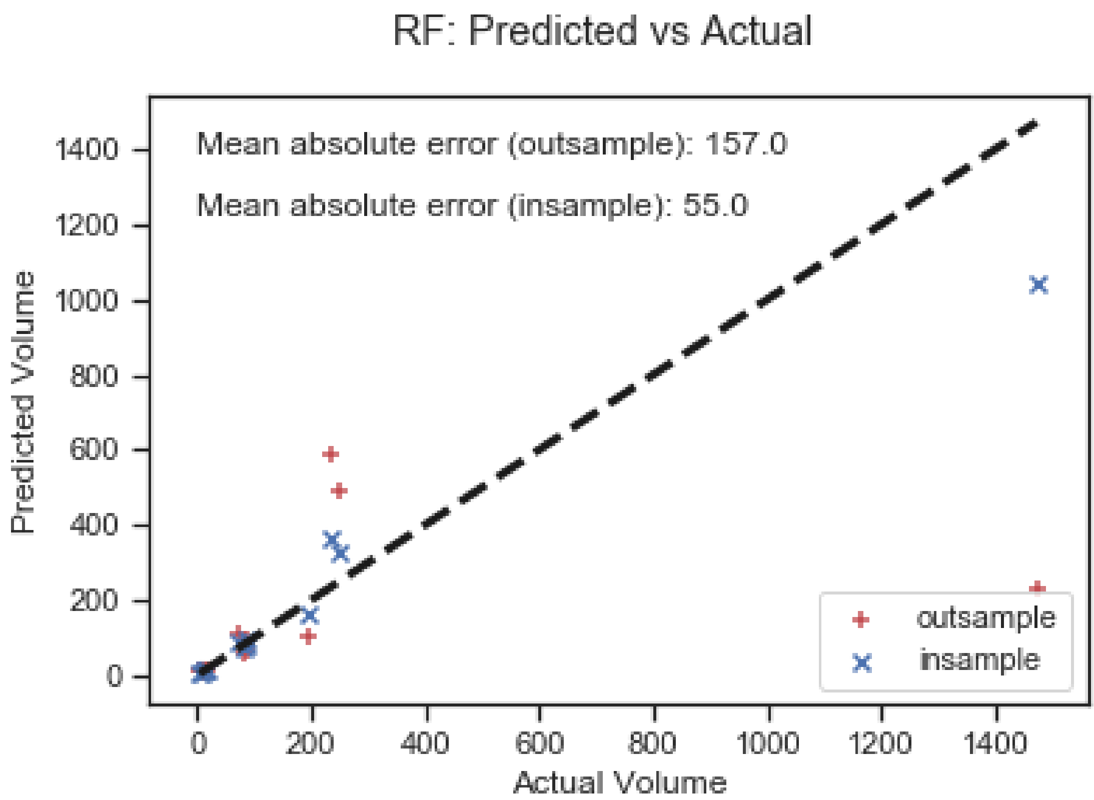


As we in the end interested only in the models accuracy to in predicting the volumes of PCs, Laptops, Smartphones and Netbooks, below is the same graph as before, but now only showing products of these categories:



The model seems to actually work quite good in this case, but we see the same problems of overfitting and poor performance when the number of sales is high.

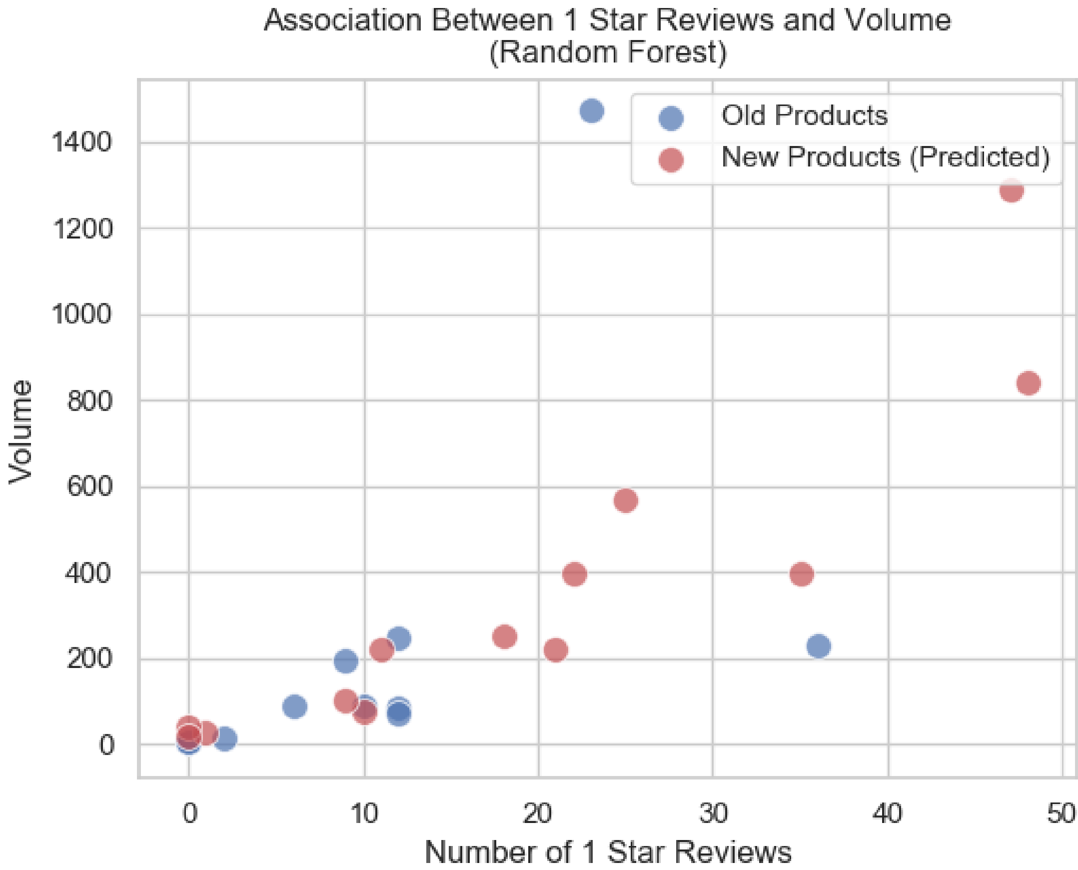
Out of curiosity we also tried to train the model on just Smartphones, PCs, Laptops and Smartphones. This did not work out well. Even though conceptually it makes sense to use similar products for predictions, the amount of data that we have was so small that the model is very unreliable. Below is the familiar plot of the model predicting just product from our categories of interest:

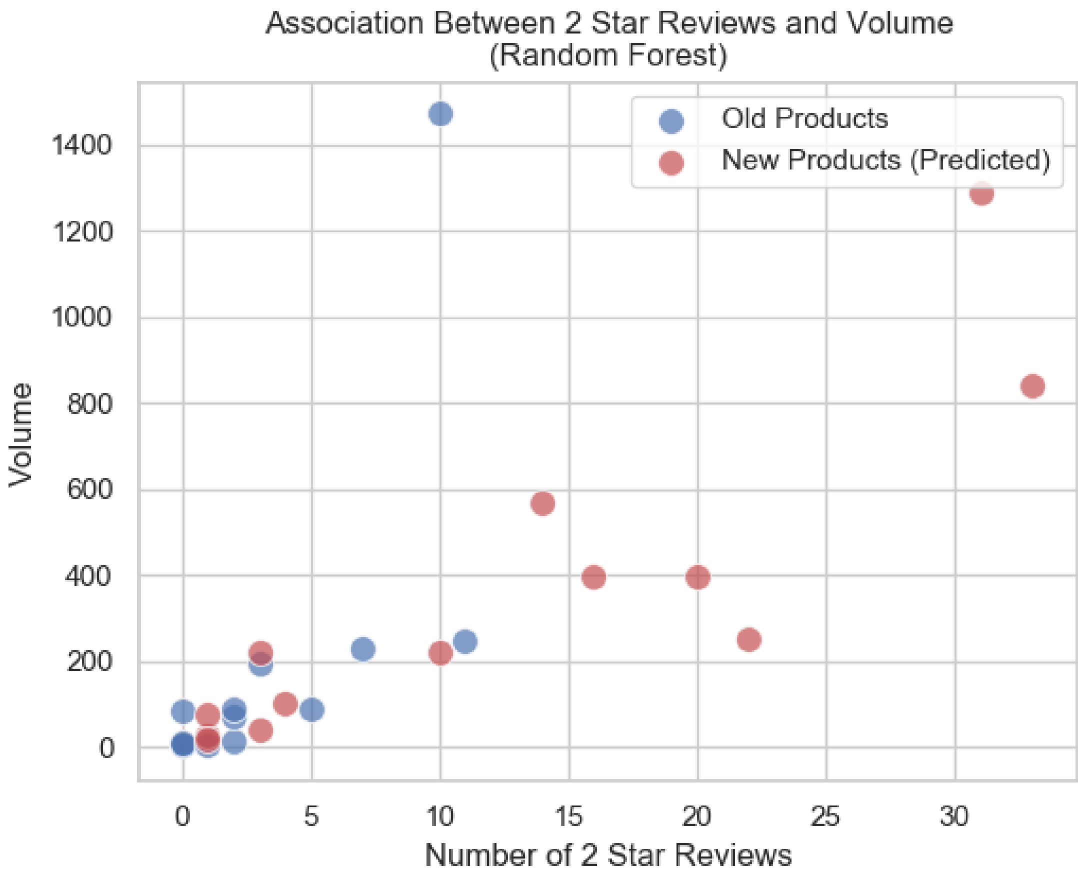


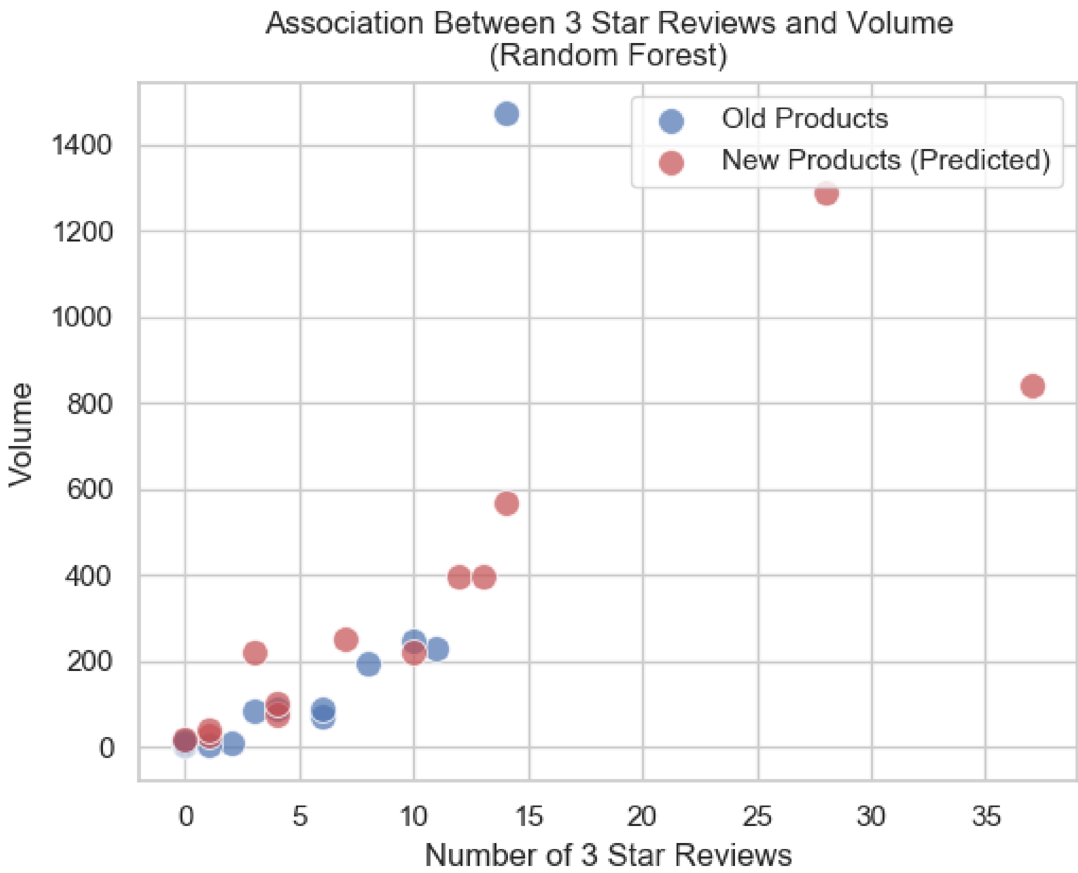
Relation of Reviews to Sales Volume

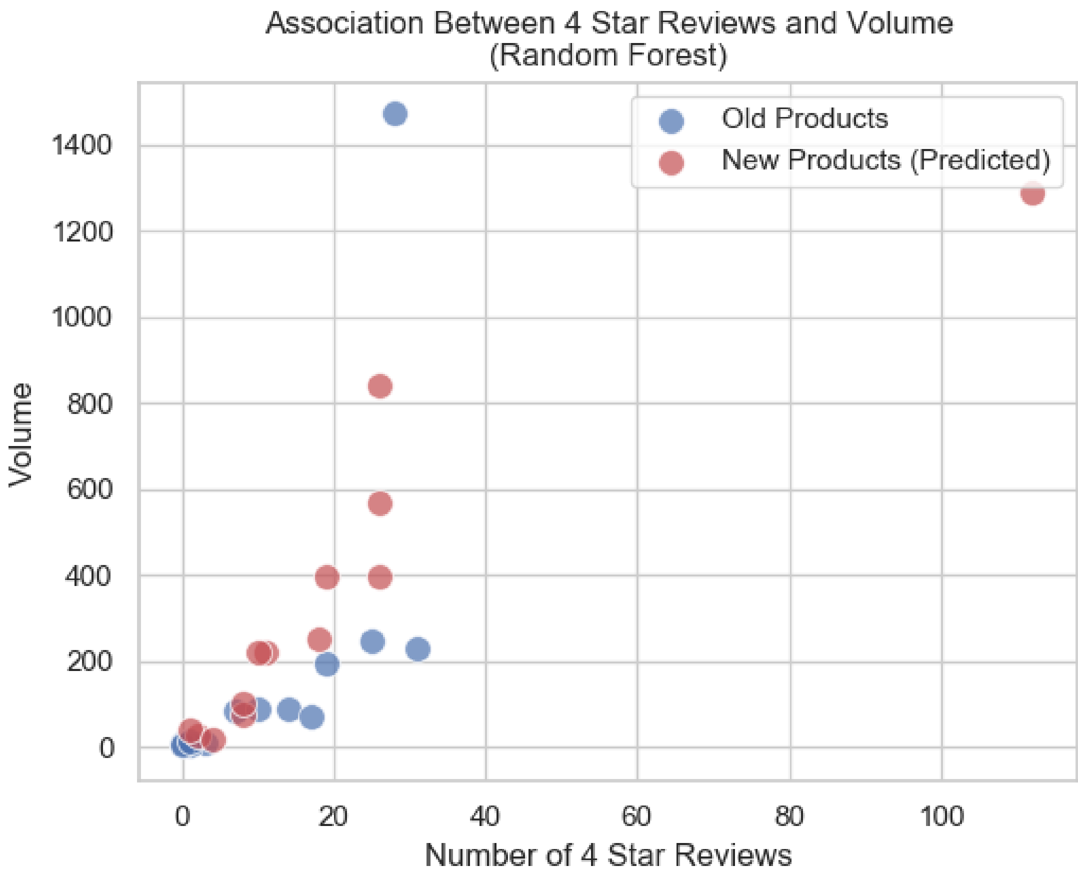
On top of predicting with the model. We were asked to analyse the relation of the reviews the to the sales volume. To do this we combined all the laptops, smartphones, PCs and Netbooks from both the training data and the new products. Because the new products did of course not have a sales volume, we used our predictions for these. We also did not use all the review columns for our model as this made the model less accurate. The review columns that were dropped were 5 star reviews and negative service reviews. 5 star reviews were dropped because they had a perfect correlation with the volume and as this is almost impossible in real life, the column was dropped as faulty. The negative service reviews were dropped because they did not make the model any more accurate after we added positive service reviews. These reviews seem to provide almost identical information.

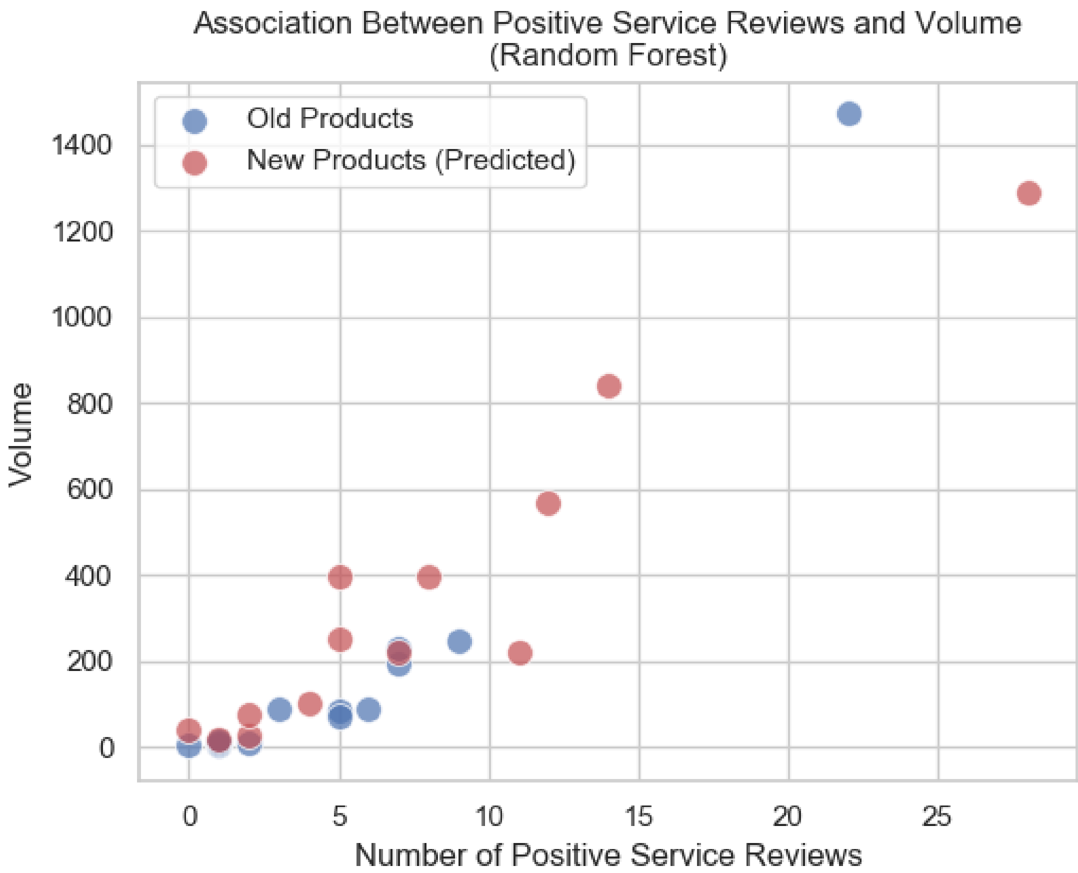
Here are the graphs for the relationship of the number of reviews to sales volume:


Association Between 1 Star Reviews and Volume
(Random Forest)
Old Products
New Products (Predicted)
Volume
1400
1200
1000
800
600
400
200
0
0
10
20
30
40
50
Number of 1 Star Reviews


Association Between 2 Star Reviews and Volume
(Random Forest)
Old Products
New Products (Predicted)
1400
1200
1000
800
600
400
200
0
Volume
0
5
10
15
20
25
30
Number of 2 Star Reviews


Association Between 3 Star Reviews and Volume
(Random Forest)
Old Products
New Products (Predicted)
Volume
1400
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30
35
Number of 3 Star Reviews

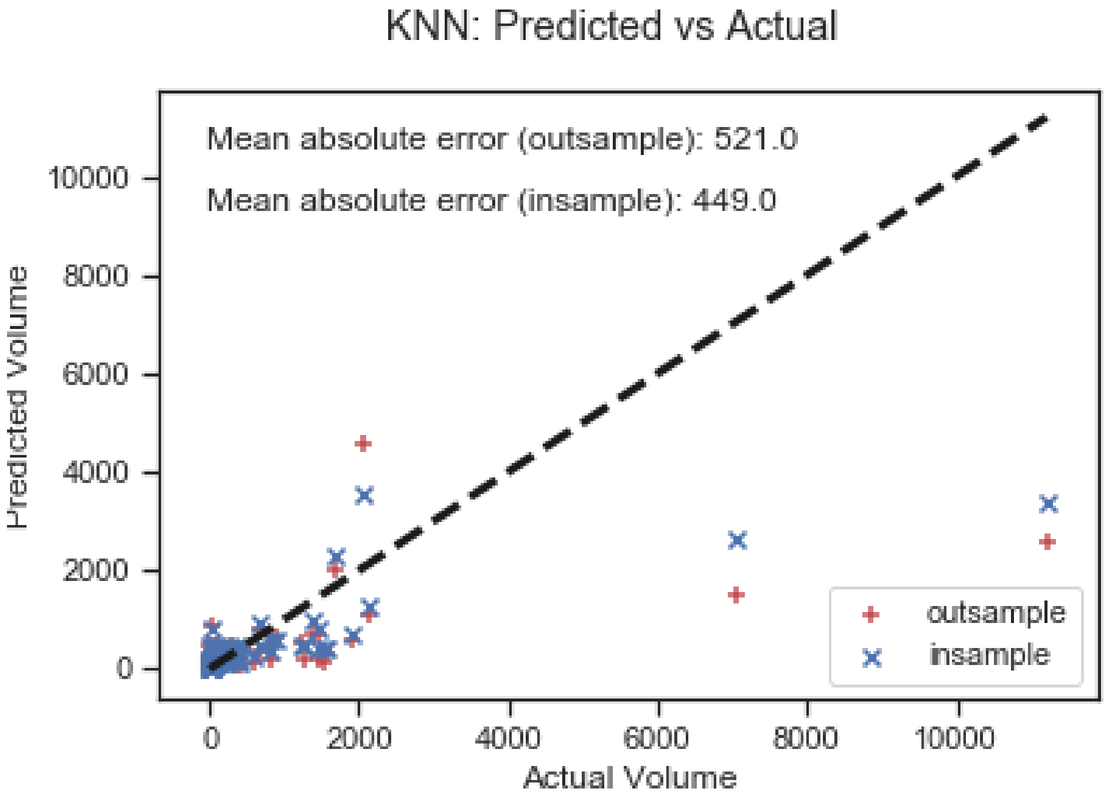

Association Between 4 Star Reviews and Volume
(Random Forest)
Old Products
New Products (Predicted)
Volume
1400
1200
1000
800
600
400
200
0
0
20
40
60
80
100
Number of 4 Star Reviews

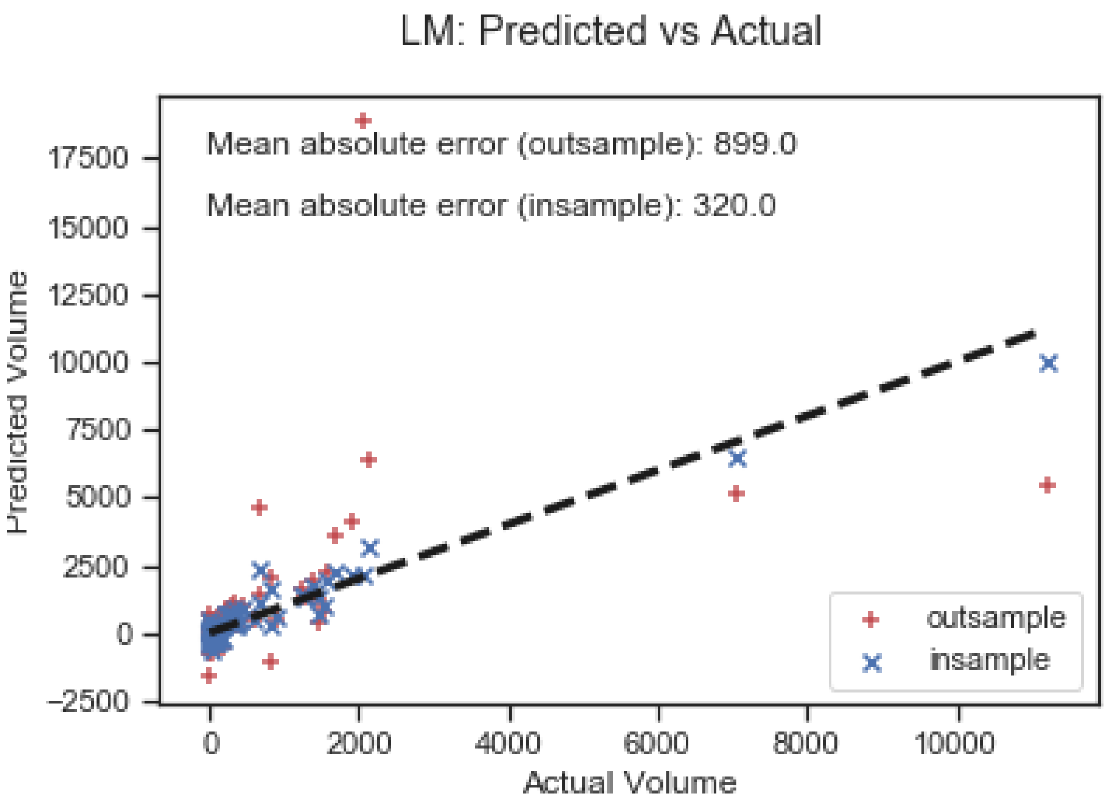


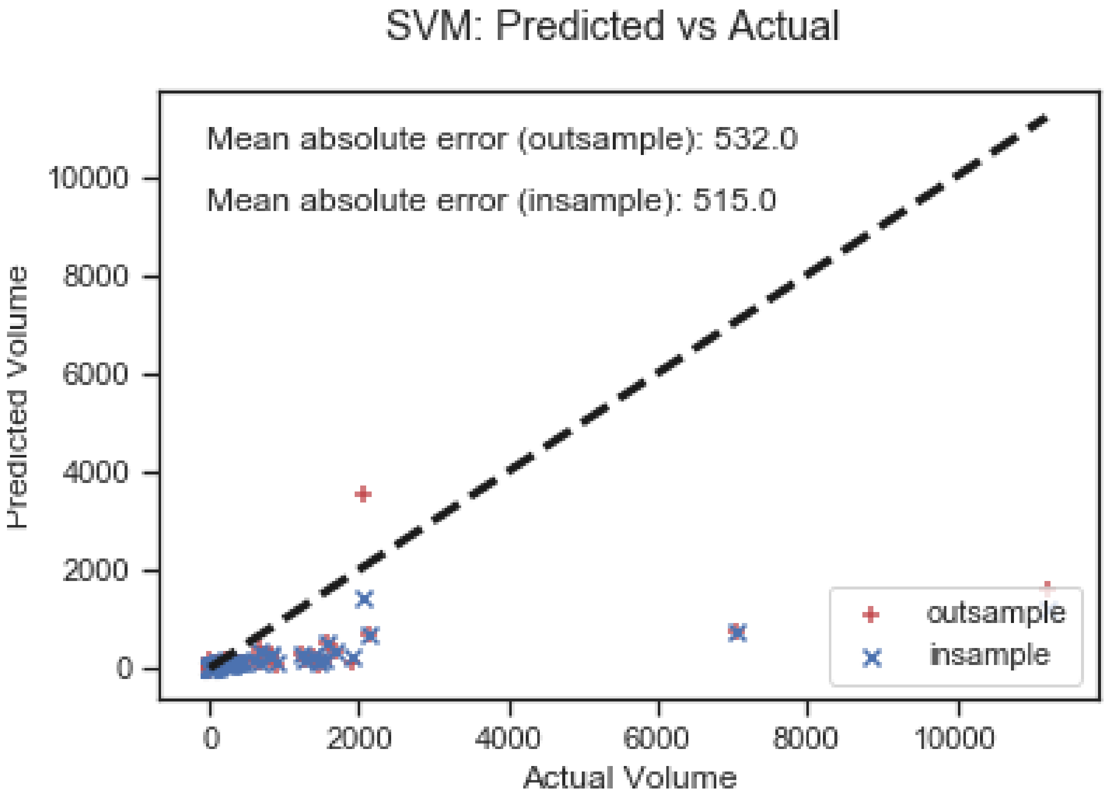
We can see that the relation is always positive so more reviews in itself are related to larger sales amount even for low reviews. This relationship can be seen in both the actual data volume and the predicted volume. It seems that the most import information about the reviews is just their number and not their message.

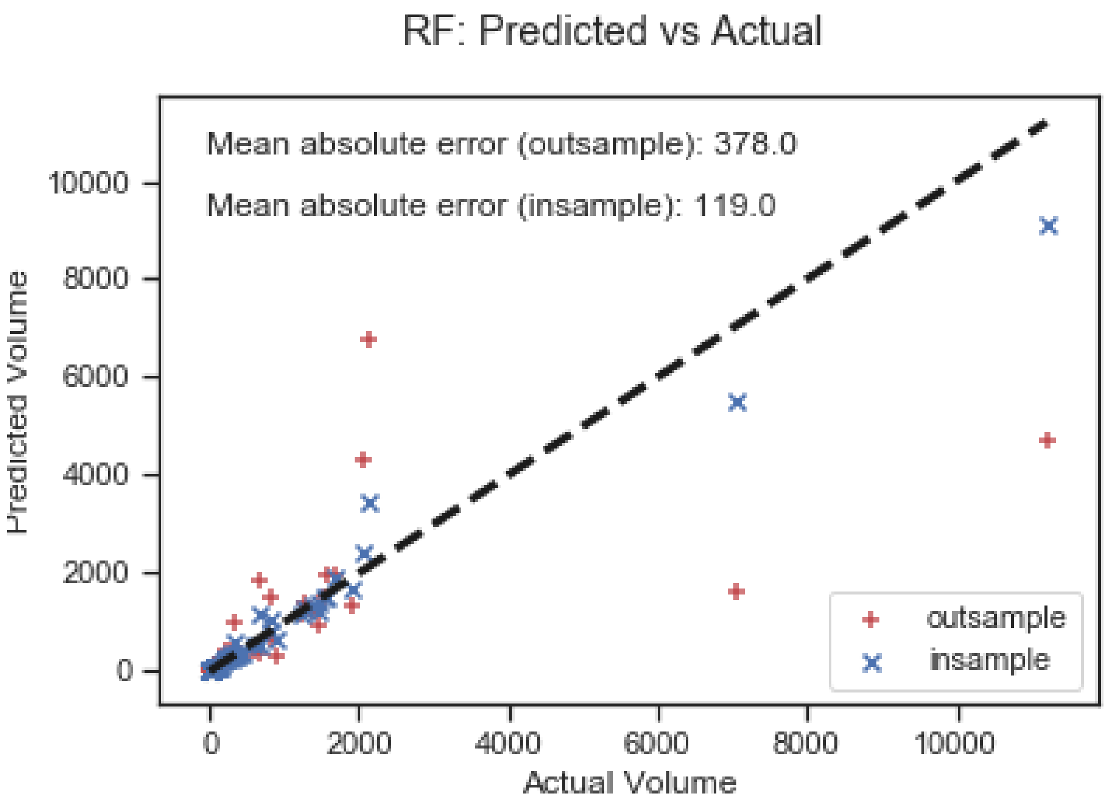
Model Comparison and Performance

Four models were considered for the predictions: K-nearest Neighbors (KNN) Linear models, Support Vector Machines (SVM) and Random Forest. Below are graphs of their performance without hyperparameter optimization and feature selection.


KNN: Predicted vs Actual
Mean absolute error (outsample): 521.0
Mean absolute error (insample): 449.0
Predicted Volume
Actual Volume
outsample
insample
0
2000
4000
6000
8000
10000

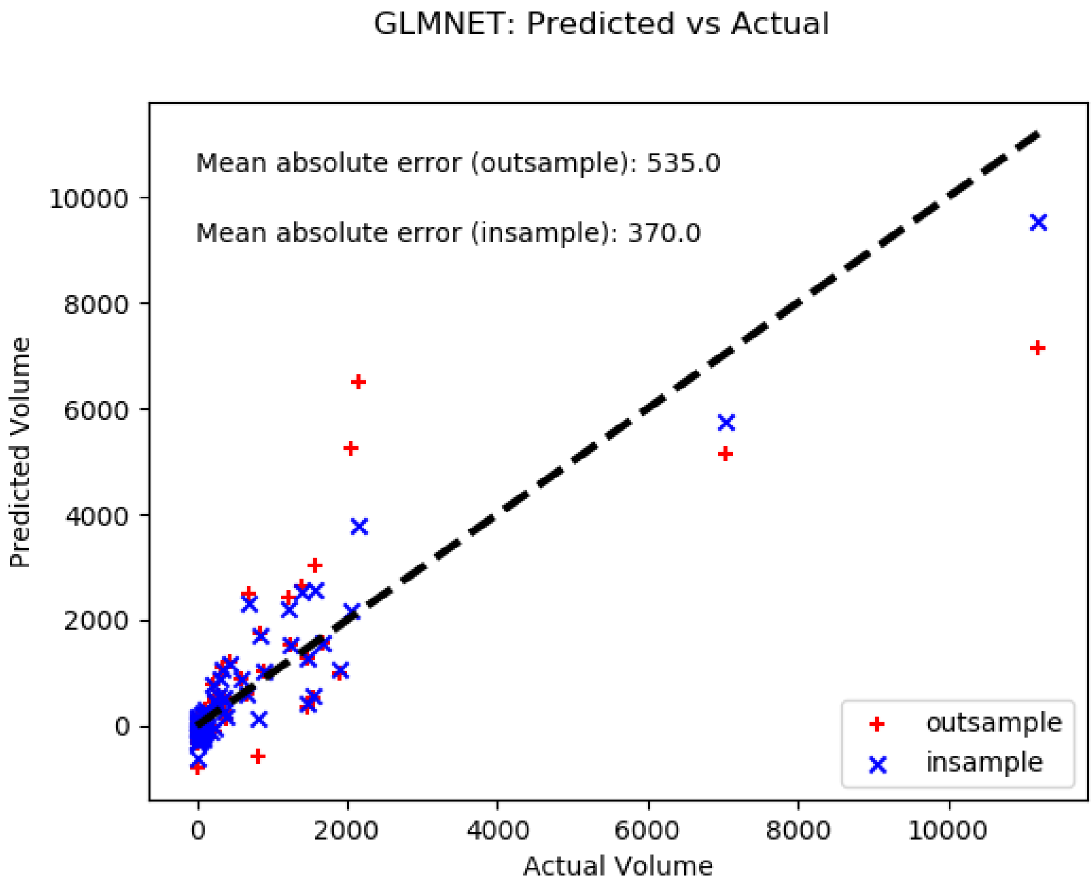

LM: Predicted vs Actual
Mean absolute error (outsample): 899.0
Mean absolute error (insample): 320.0
Predicted Volume
Actual Volume
outsample
insample
17500
15000
12500
10000
7500
5000
2500
0
−2500
0
2000
4000
6000
8000
10000


SVM: Predicted vs Actual
Mean absolute error (outsample): 532.0
Mean absolute error (insample): 515.0
outsample
insample
Predicted Volume
Actual Volume
0
2000
4000
6000
8000
10000

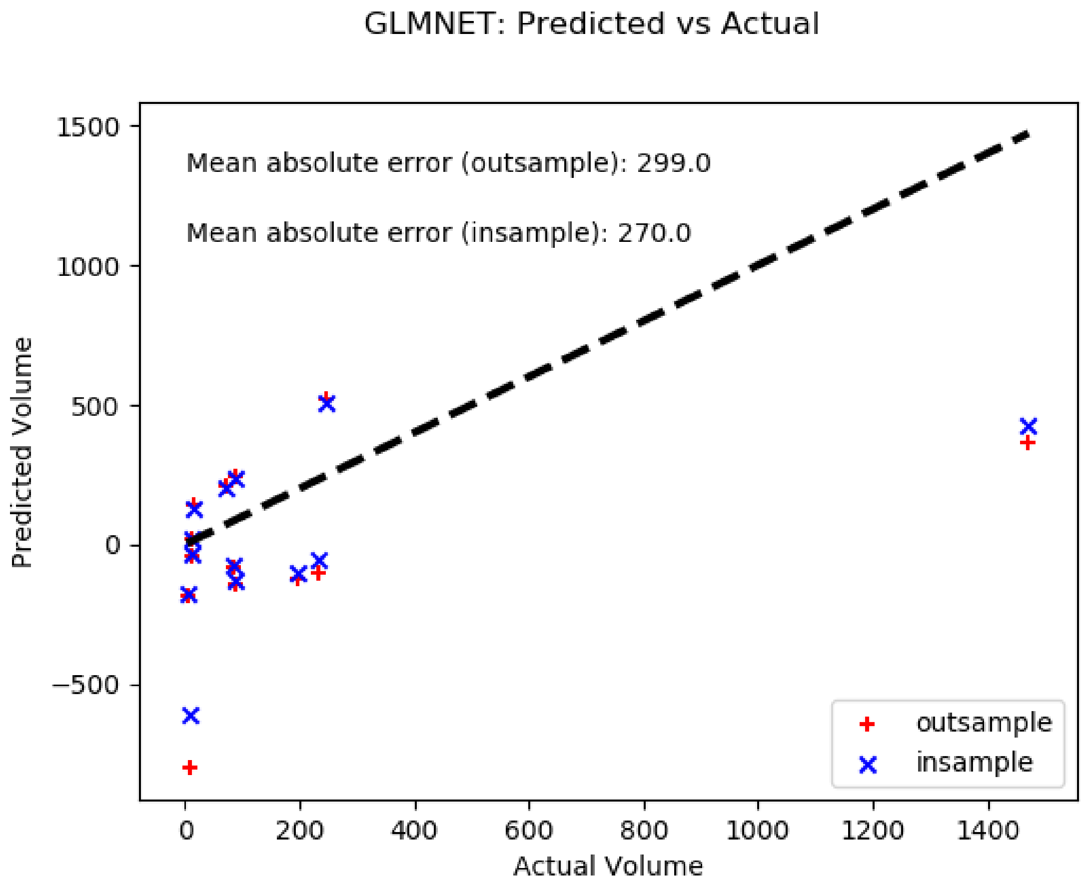


We can see that the random forest performed clearly the best, even though it was clearly overfitting. SVM and KNN did not have the overfitting problem, but were overall less accurate.

From these investigations KNN and SVM were dropped as their accuracy was less than Random Forest and their interpretability is not very good. Linear models were kept for further investigations although their results were the worst, because it was thought that model could be improved much with regularization and that its interpretability could prove interesting. This was not to prove so as even with two steps of feature selection with a separate linear model and applying L1 and L2 regularization with GLMNET model, the performance remained poor. Further problem with the linear model was that it was prone to give predictions for volume that were below 0. This is almost and unavoidable problem for linear models when training data includes volumes that are already very close to zero or even zero. Below you can see the graph of the performance of the best linear model that we produced:



Finally here are the results when limit predictions to the product of our categories of interest:


GLMNET: Predicted vs Actual
Mean absolute error (outsample): 299.0
Mean absolute error (insample): 270.0
Predicted Volume
Actual Volume
1500
1000
500
0
−500
0
200
400
600
800
1000
1200
1400
outsample
insample