Predicting SA Bond Prices Using PCA & SVMs

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Introduction

In the South African financial industry it has become very important to be able to model and predict changes in interest rates as this impacts inflation levels and individuals' spending abilities. One of the main drivers of interest rates are bond prices as exists an inverse relationship between bond prices and interest rates. In this paper we analyze how PCA and SVM methods succeed in describing the dynamics of South African bond market prices at different points in time ,especially in the proximity of major marker events.

This study aims to identify the main underlying factors that are responsible for driving South African bond prices and hence interest movements using PCA . We will then proceed to predicting bond prices using SVMs for regression problems.

Moreover this analysis will be specifically made with the focus being on two periods where the South African financial market experienced volatility and extreme market stress. The first period will be 2008-2009 which is known to be the Global Financial Crisis(GFC) period which took a toll on individuals and institutions around the world, South Africa included. The second period will be 2015 which is called Nenegate in the financial industry causing havoc in the financial industry. Therefore this study further aims to identify the main drivers of bond price factors during these two periods and predict future bond prices during extreme market stress.

Data and Preliminary Data Analysis

The data series studied in this paper are daily-frequency observations from bond market data; the data is daily sampled closing price data and runs from 1994 to 2017. This data was purchased from INET-BFA for academic use . The data consists of bonds with different maturities and types namely ALBI, 1 to 3 years bonds, 3 to 7 years, 7 to 12 years, over 12 years and GOVI. Data for the Global Financial crisis (2008-2009) and Nene-gate (2015) period will be considered .

Applying PCA to SA Monthly Bond Data

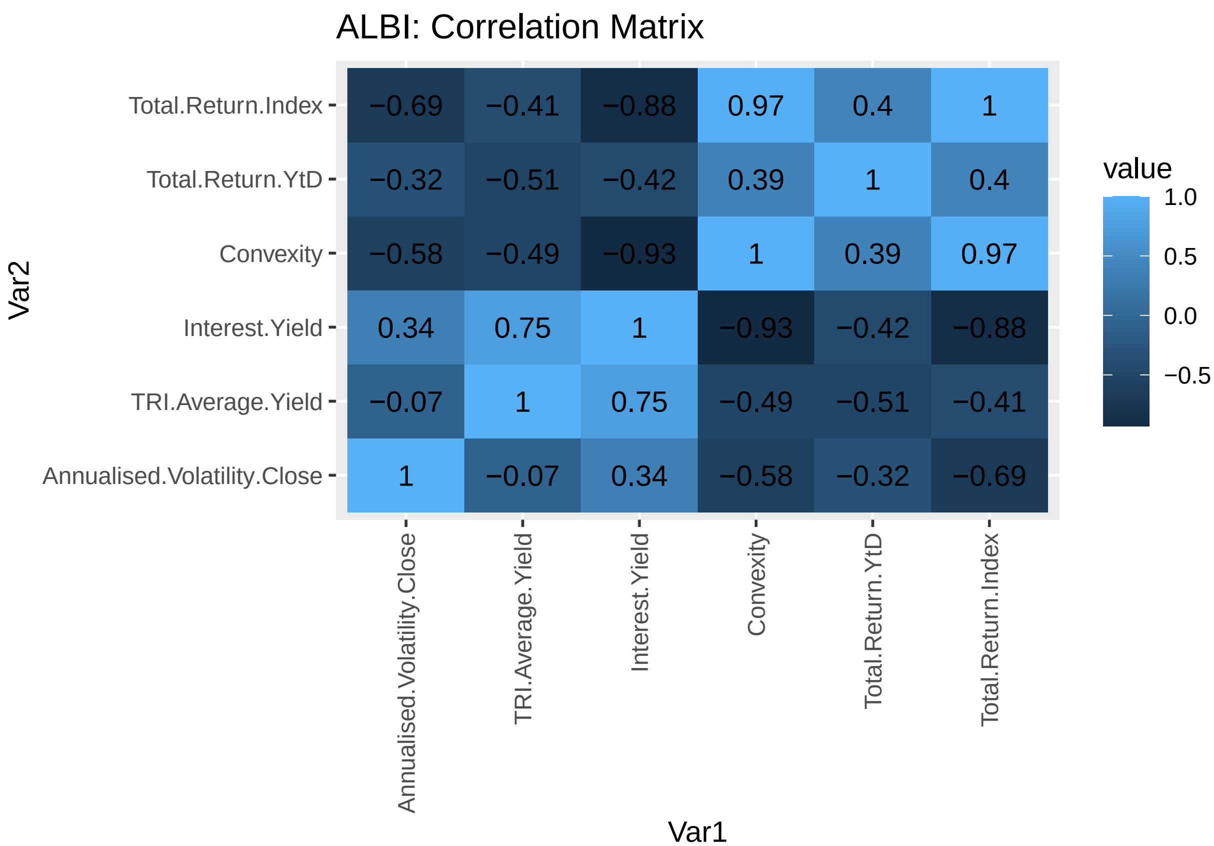
Background

PCA is mainly used for dimension reduction where given a high-dimensional data i.e. information on multiple variables for a set of n observations, we wish to find a low-dimensional representation of the data that will retain most of the information in the original data. This "information" is captured by the variance-covariance matrix. Essentially PCA is a method for explaining the variance-covariance structure of a set of variables through a few linear combination of these variables . The aims behind PCA are variance decomposition and data reduction.

Using the SA Monthly Bond Data we will be performing PCA as it is a tractable and easy-to-implement method for extracting bond price factors from observed data

Prior to applying PCA to these returns series, it is important to determine whether PCA is in fact a meaningful procedure given the properties of the data. Since PCA seeks to replace the set of unordered and correlated input variables with a smaller set of ordered and uncorrelated projections of the input variables we plot the correlation matrix of the bond types below to assess the correlation between the different variables:

PCA will help identify hidden patterns in the data sets by reducing the dimensionality of the data . This is useful when the variables within the dataset are highly correlated , indicating redundancy in the data. Furthermore when interpreting the correlation matrix below we note the multi-collinearity. There is high correlation between the predictor variables i.e. the correlation between Total Return Index and Convexity is 0.97 while Interest Yield and Convexity has a correlation of -0.93 etc.



The table below shows that the first principal component has high values for Convexity, Interest Yield and Total Return Index which indicates that this principal component describes the most variation in these variables. Similarly the second principal component (PC2) has a high value for Annualised Volatility Close, which indicates that this principal component places most of its emphasis on annualised volatility.

The table below shows the total variance in the ALBI data set explained by each component. From the results we observe the following:

- PC1 explains 63.65% of the total variance in the ALBI data set
- PC2 explains 20.29% of the total variance in the ALBI data set
- PC3 explains 12.68% of the total variance in the ALBI data set
- PC4 explains 2.9% of the total variance in the ALBI data set
- PC5 explains 0.35% of the total variance in the ALBI data set

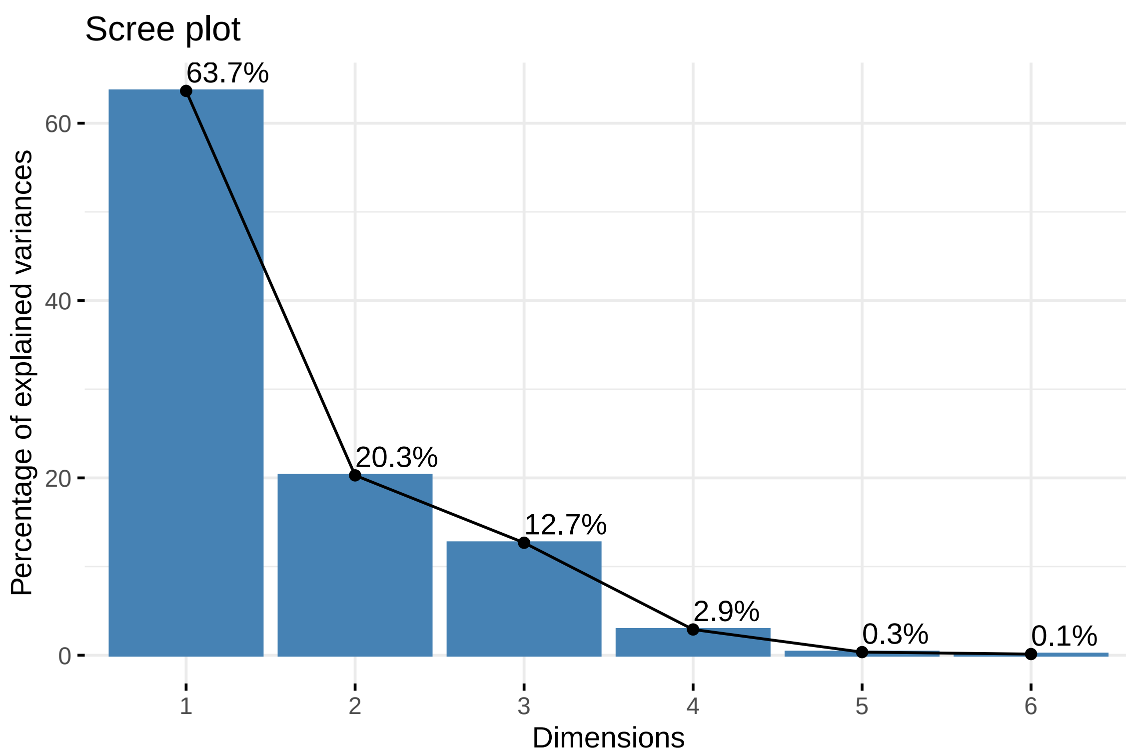
Thus, the first two principal components explain a majority of the total variance (83.94%) in the data.

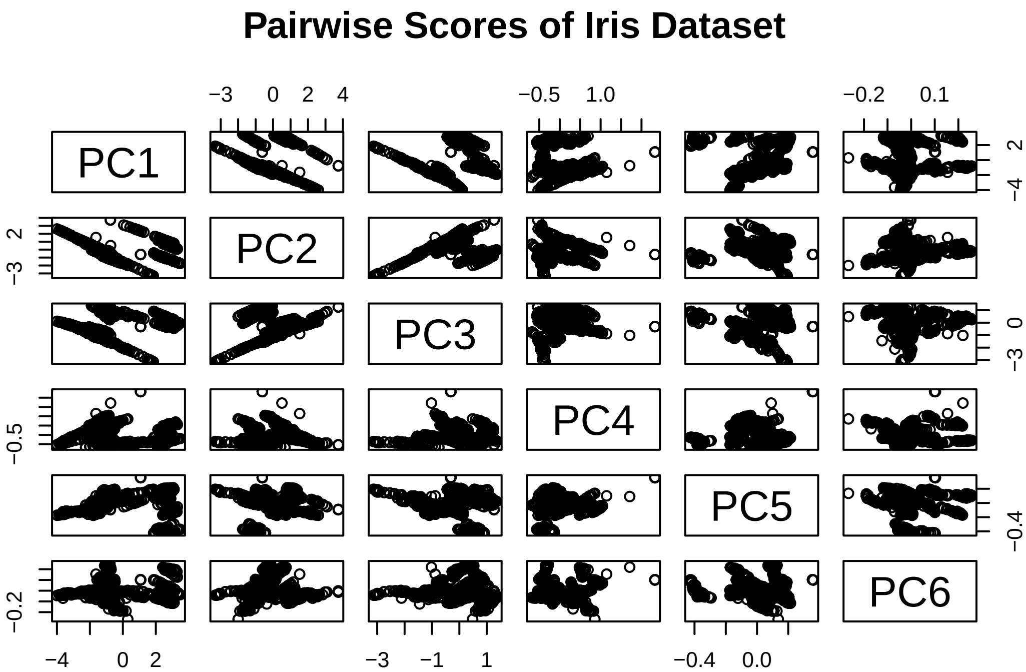
Variable Name	PC1	PC2	PC3	PC4	PC5	PC6
Annualised.Volatility	-0.305	-0.649	0.300	-0.602	-0.125	-0.132
TRI.Average.Yield	-0.332	0.648	-0.0366	-0.623	0.0626	0.278
Interest.Yield	-0.481	0.177	-0.302	0.095	-0.093	-0.792
Convexity	0.488	0.127	0.241	-0.289	0.619	-0.468
Total.Return.YtD	0.303	-0.239	-0.856	-0.337	0.021	0.046
Total.Return.Index	0.484	0.232	0.156	-0.207	-0.766	-0.236

Importance of components table:

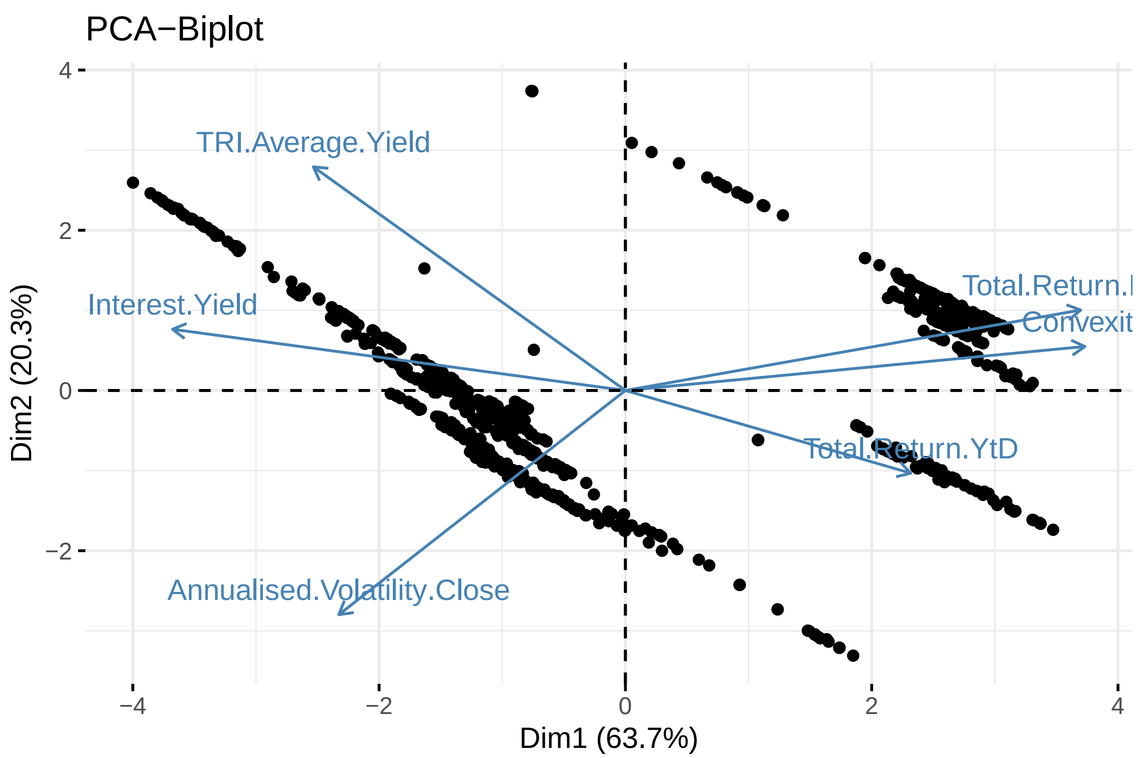
Statistic	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviation	1.954	1.103	0.872	0.417	0.145	0.088
Proportion of Variance	0.637	0.203	0.127	0.029	0.004	0.001
Cumulative Proportion	0.637	0.839	0.966	0.995	0.999	1.000

Additionally by observing the scree plot below we note that the first two principal components are the ideal number of components to retain as they explain 83.94% of the variation in the ALBI data set.





The biplot below projects each of the observations in the data set onto a scatterplot that uses the first and second principal components as the axes. From the plot we can see each of the 6 variables represented in a simple two-dimensional space.



Although PCA is good for dimension reduction SVM offers added advantages in handling high-dimensional data, flexibility with kernels, probabilistic interpretation and finding optimal hyperplanes. We look at the SVM for regression problems below.

Applying SVM to SA Monthly Bond Data

Background

Support vector machines (SVMs) are a group of supervised machine-learning models that can be used for classification and regression. It will seek an optimal hyperplane for separating two classes in a multidimensional space.SVMs are commonly used for classification problems.

SVMs solve binary classification problems by formulating them as convex optimization problems (Vapnik 1998). The optimization problem entails finding the maximum margin separating the hyperplane, while correctly classifying as many training points as possible. SVMs represent this optimal hyperplane with support vectors.

SVM implements a learning algorithm, useful for recognizing subtle patterns in complex data sets. The algorithm performs discriminative classification learning by example to predict the classifications of previously unseen data.

Equally the regression problem (SVR) is a generalization of the classification problem we seek to find a good fitting hyperplane in a kernel-induced feature space that will have good generalization performance using the original features.

In this case we will be using the radial basis (RBF) kernel function

$$\exp(-\gamma * |u-v|^2)$$

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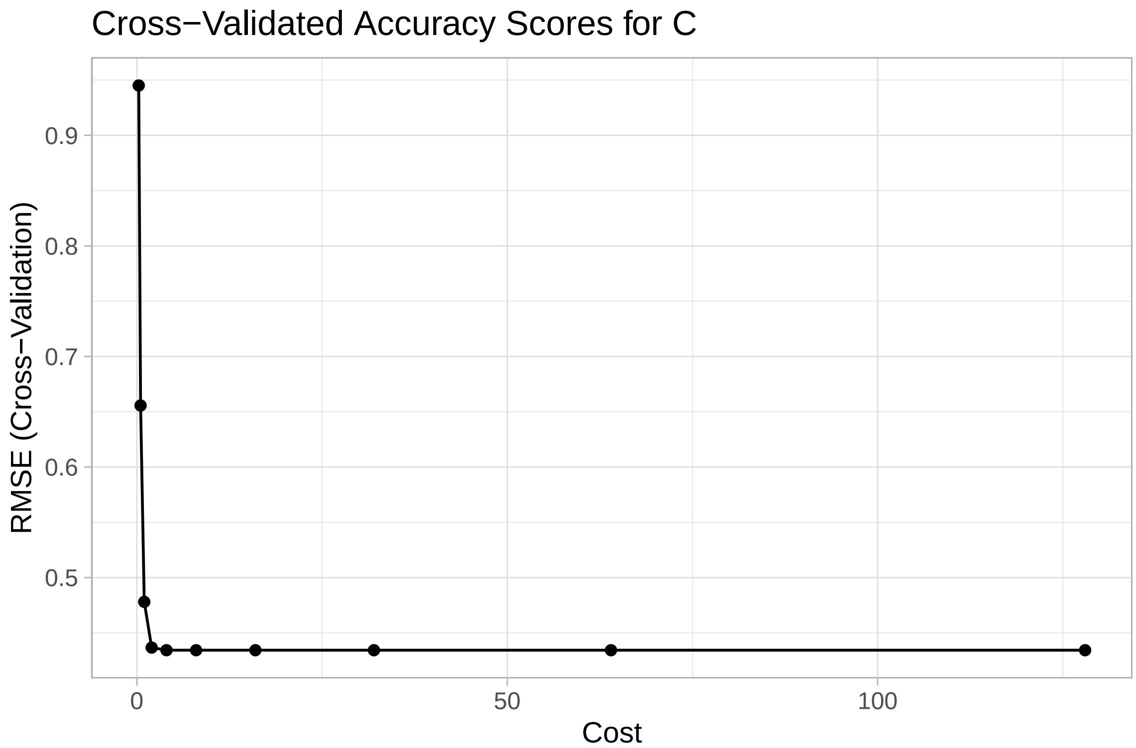
We start by splitting the data into training (80%) and test (20%) set .

Hyperparameters Tuning

The radial basis kernel function has two hyperparameters: σ and C.

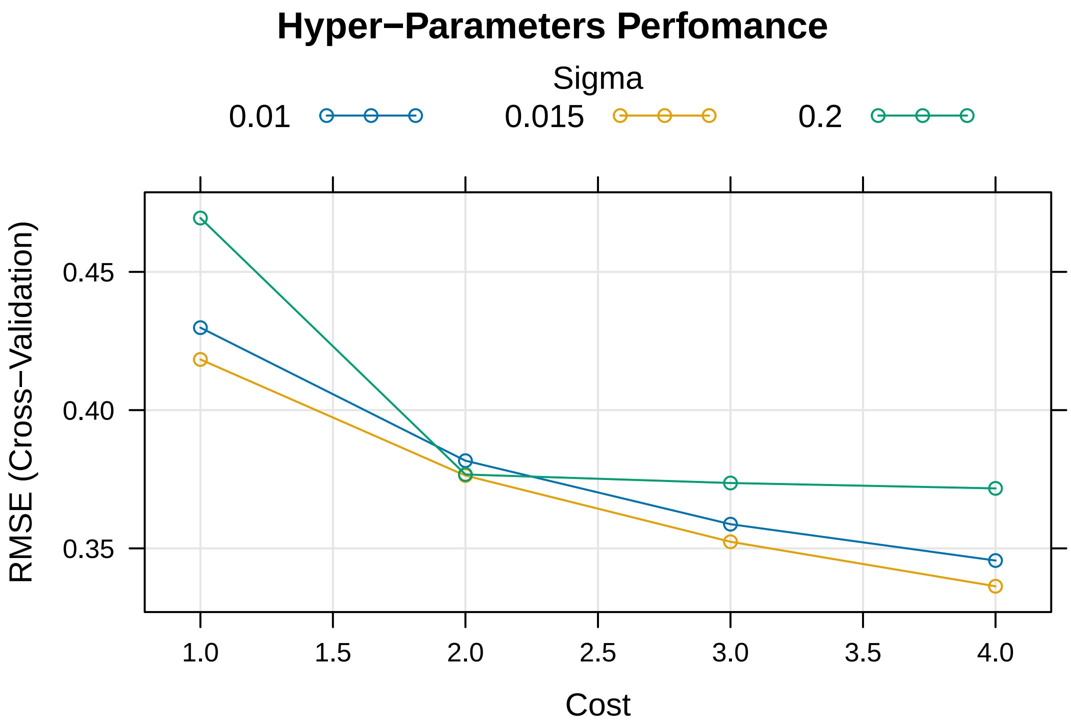
To find the optimal cost function we tune and train an SVM using the radial basis kernel function with autotuning for the σ parameter and 10-fold CV. Plotting the results , we see that smaller values of the cost parameter ($C = 4$) provide better cross-validated scored for the training data.



sigma	C	RMSE	R-Squared	MAE	RMSESD	MAESD
1.035429	0.25	0.9786468	0.9697924	0.4750558	0.4716834	0.041128893
1.035429	0.50	0.7045730	0.9855278	0.3980675	0.3176670	0.018766332
1.035429	1.00	0.5062893	0.9939991	0.3375884	0.1417483	0.004116280
1.035429	2.00	0.4546562	0.9949938	0.3251104	0.1307317	0.003404929
1.035429	4.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627
1.035429	8.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627
1.035429	16.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627
1.035429	32.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627
1.035429	64.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627
1.035429	128.00	0.4524946	0.9946100	0.3317725	0.1221181	0.002960627

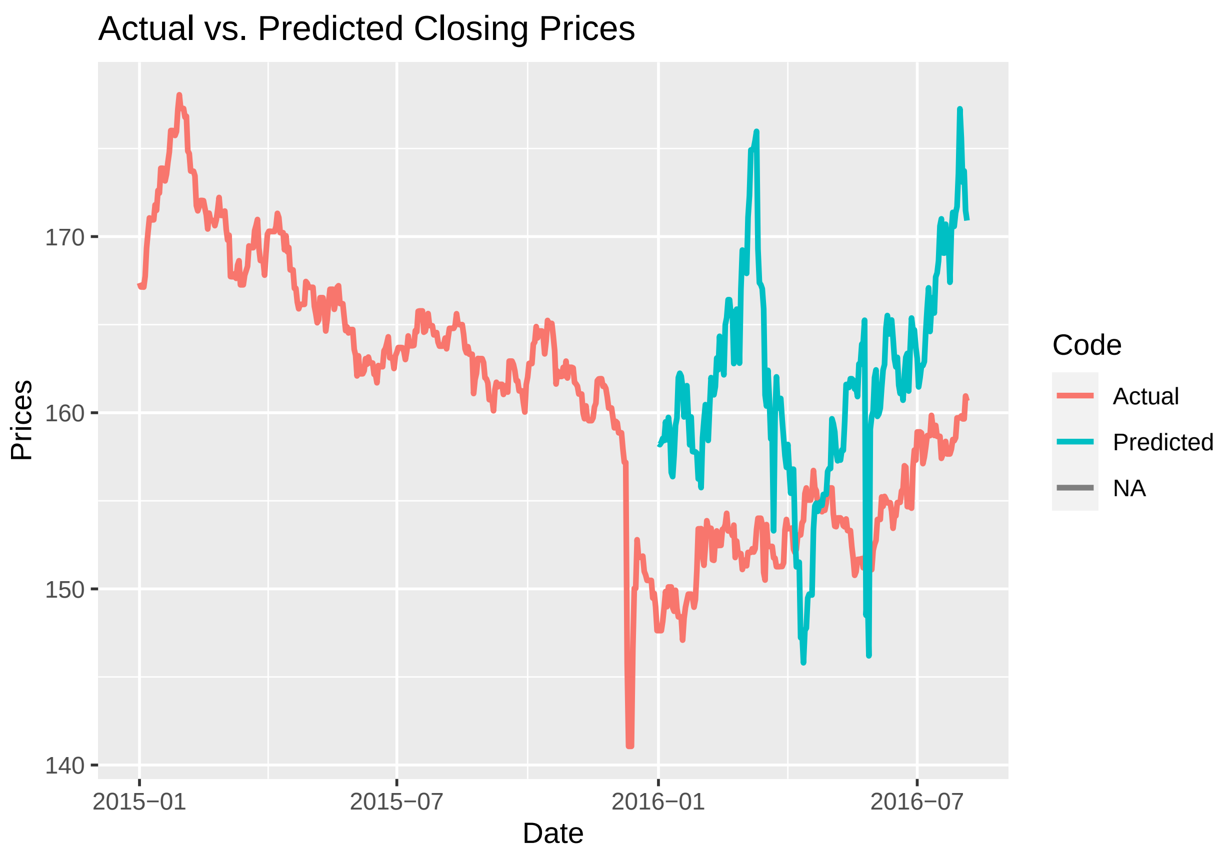
For σ we will provide a range of values for σ which return good results when using the radial basis SVM.

The final values used for the model were $\sigma = 0.015$ and $C = 4$ From the graph below we see that the optimal parameter for σ is 0.015 as it is the line that minimises the root mean square error (RMSE).



Predictions

Using the SVM for regression , we plot the predicted prices and contrast them with the actual prices . As evident in the graph below SVM for regression does not do an adequate job at accurately predicting future prices in volatile market environments .


Actual vs. Predicted Closing Prices
Prices
170
160
150
140
2015−01
2015−07
2016−01
2016−07
Date
Code
Actual
Predicted
NA