Project 4: Face Social Traits and Political Election Analysis by SVM

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Part1: Face Social Traits Classification (or Regression)

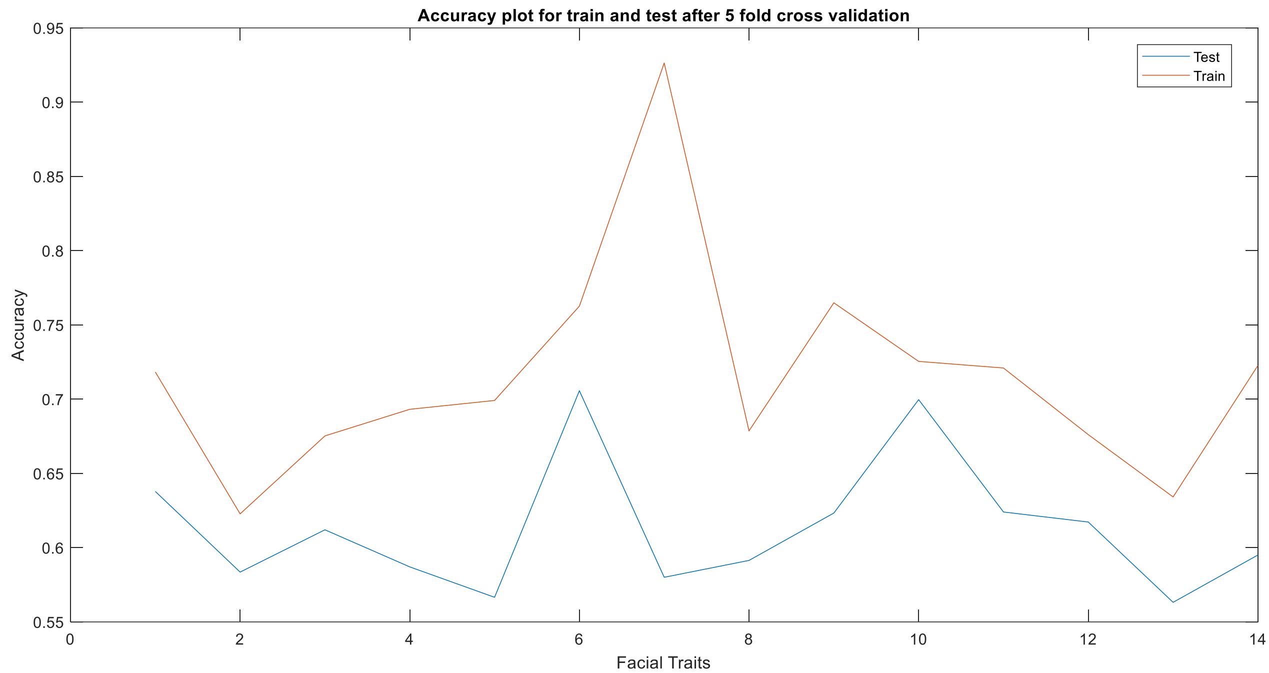
1.1 Classification by Landmarks

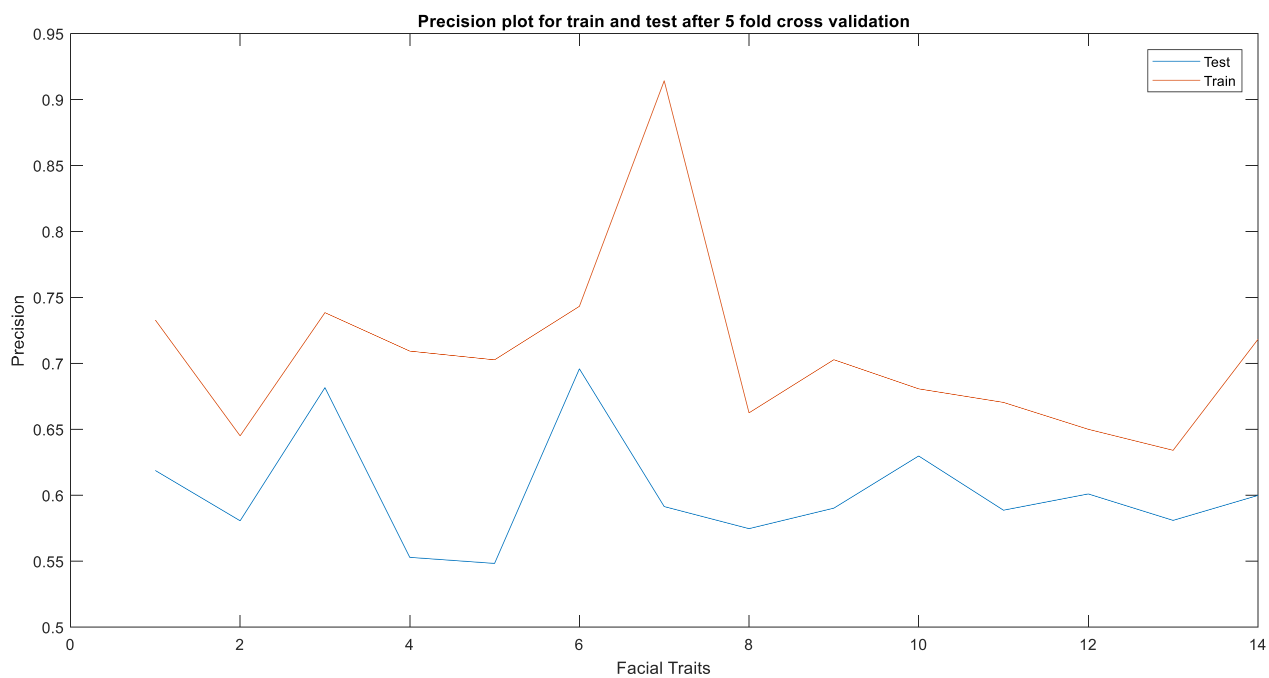
For the 491 images given in the part-I dataset, facial landmarks extracted from the images are used as features. There are a total of 80 landmark points provided for each image in the dataset. The annotations are read from the trait_annotation file. The models are trained seperately for each of the 14 facial traits. Epsilon-SVR with RBF kernel is used for training all the models. Though the model outputs real valued scores, accuracy and precisions are calculated by performing thresholding on both the predicted and groundtruth values at zero. The values greater than 0 are considered to be belonging to class-1 and the negative values to class-2.

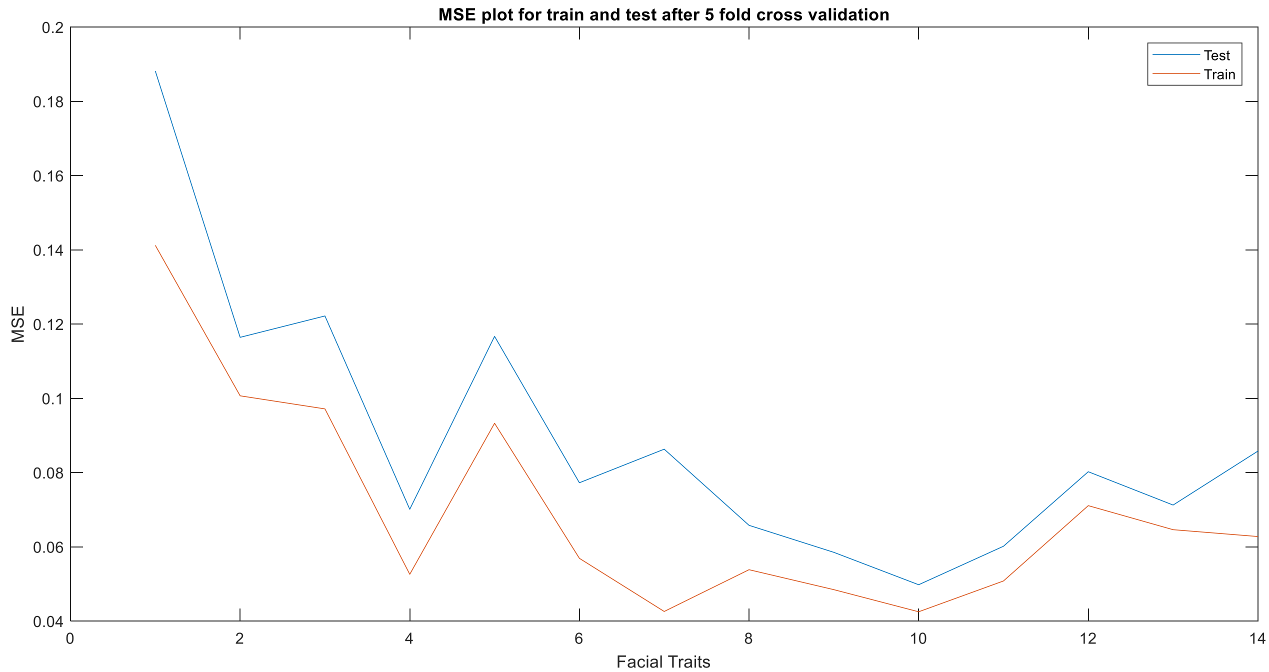
The optimal parameters for the models C, gamma and epsilon are estimated by performing the grid search over a number of different values. The values for the parameters are chosen by minimizing the training mean square error of the model. The estimated parameters for the 14 models corresponding to 14 traits are used while training and testing. These values are also displayed in the table below. As the dataset is not divided into training and testing, 5-fold cross validation has been performed to report the average accuracies and precisions. The data is divided into five parts, four for training the model and the remaining one for testing the model. This is repeated for five times choosing a different part each time for testing. Average accuracy, Average Precision and Average Mean Square error obtained after performing 5-fold cross validation for all the 14 models are plotted for both training and testing phases.

Optimal Parameters of models for all the 14 facial Traits

Traits	C	Gamma	Epsilon
Old	8	0.007813	0.03125
Masculine	512	3.05E-05	0.125
Babyfaced	2048	3.05E-05	0.125
Competent	0.125	0.125	0.125
Attractive	0.125	0.125	0.125
Energetic	8	0.007813	0.125
Well-groomed	0.125	0.5	0.03125
Intelligent	0.5	0.03125	0.125
Honest	2	0.007813	0.007813
Generous	32	0.000488	0.007813
Trustworthy	32	0.000488	0.001953
Confident	0.125	0.03125	0.125
Rich	0.5	0.007813	0.125
Dominant	8	0.007813	0.125


Accuracy plot for train and test after 5 fold cross validation
Test
Train
Accuracy
Facial Traits
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
0
2
4
6
8
10
12
14


Precision plot for train and test after 5 fold cross validation
Test
Train
Precision
Facial Traits
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
0.5
0
2
4
6
8
10
12
14



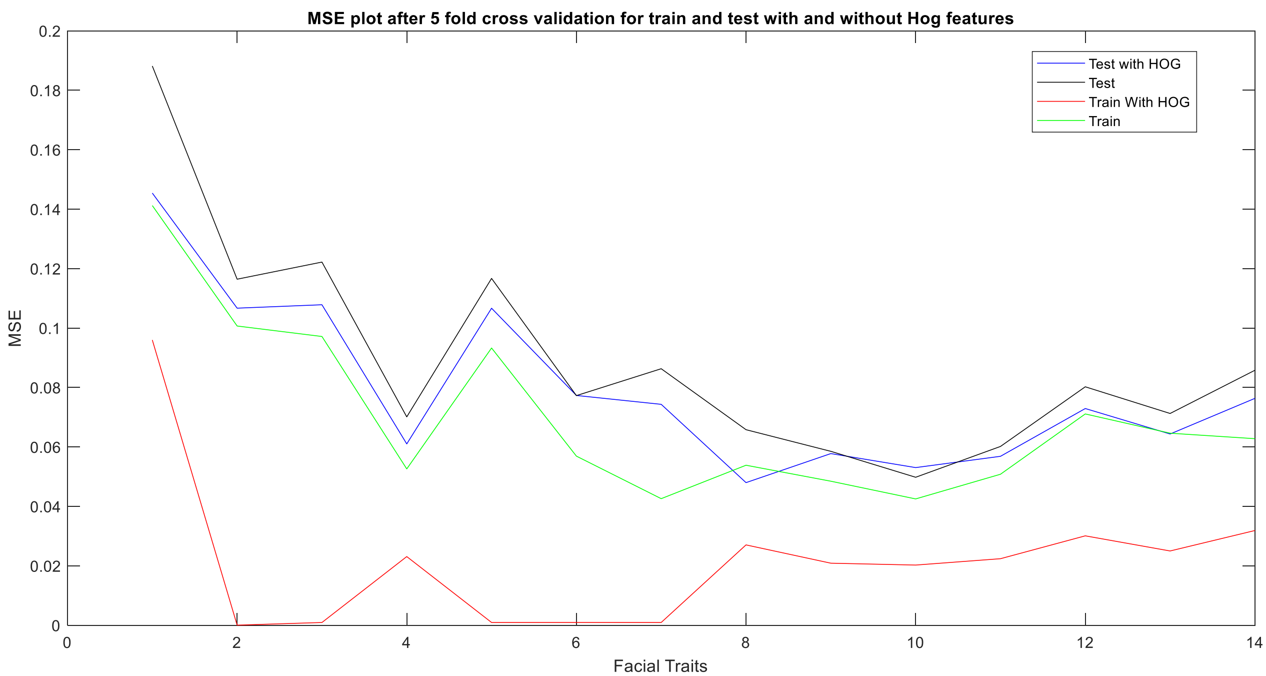
Understandably, all the models have training accuracies and precision values better than testing values. Mean square error for training is less compared to testing which shows the models are performing well in sample compared to out sample data. There are different values set for the parameters C, gamma and epsilon which are estimated by reducing the mean square error while training the model corresponding to each trait. The value of C effectively controls the overfitting of the models to noise present in the training data.

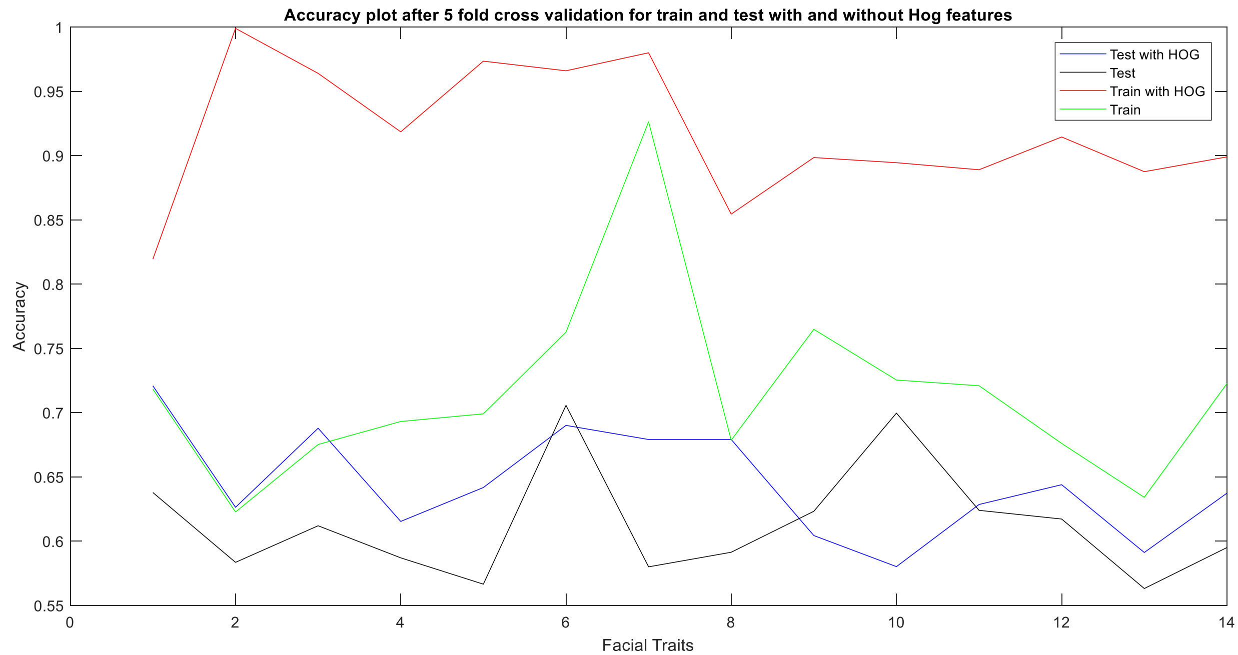
1.2 Classification by Rich Features

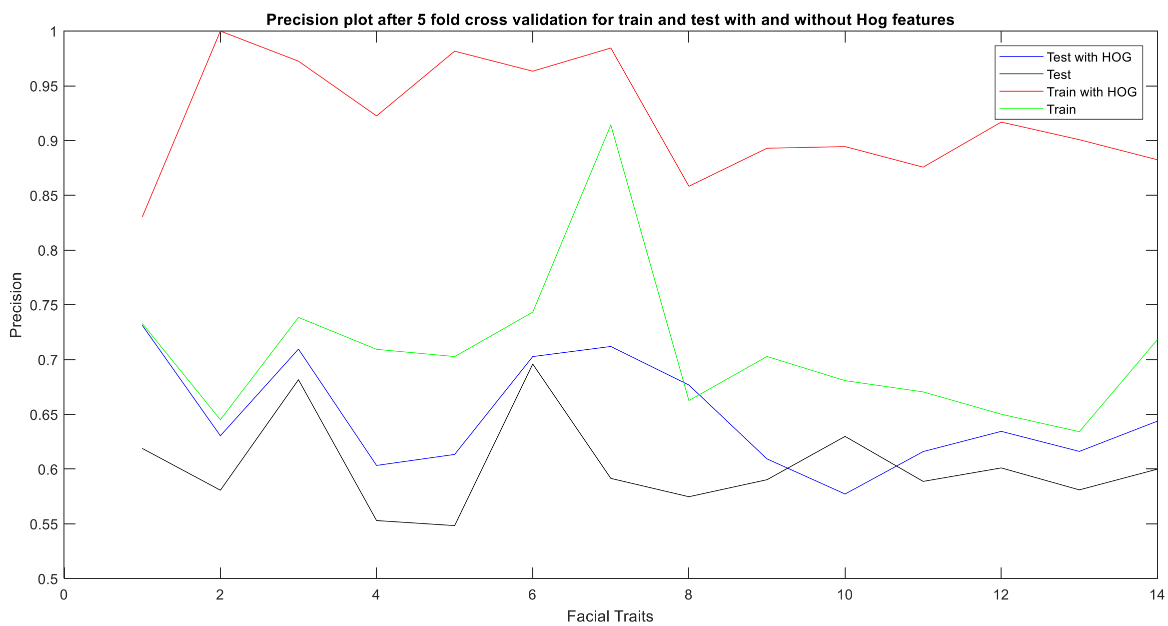
In this part, HOG (histogram of oriented gradient) features are included along with the facial landmarks of 491 images in the part-I dataset. The same procedure is repeated for estimating the model parameters by grid search and for obtaining the accuracy and precision values. Again, SVM models are trained with RBF kernel. Average accuracy, Average Precision and Average Mean Square error obtained after performing 5-fold cross validation for all the 14 models are plotted for both training and testing phases. Each plot shows four different curves with colors.

Blue curves show the test data performance of the model after adding HOG features.
Black curves show the test data performance of the model before adding HOG features.
Red curves show the training data performance of the model after adding HOG features.
Green curves show the training data performance of the model after adding HOG features.

The reported figures show the effectiveness of extracting rich features from images. With the inclusion of HOG features, we can observe that the accuracy and precision are significantly improved compared to the case where only facial landmarks are used. The rise in the values could be attributed to the fact that the models are able to learn effectively with the rich features and leading to better performances. The Mean square error plot clearly indicates that the error is minimized in the case of HOG features training compared to the case where the HOG features are not added. In every curve, we see that the training case is better than testing. Both training and testing are better in every aspect with the addition of HOG features compared to the case where only facial landmarks are used.







<u>Optimal Parameters of models for all the 14 facial Traits after including HOG features</u>

	C	**Gamma**	**Epsilon**
Old	16	3.05E-05	0.03125
Masculine	16	9.77E-04	0.001953

Babyfaced	16	9.77E-04	0.03125
Competent	1	0.000976563	0.001953
Attractive	16	0.000976563	0.03125
Energetic	16	0.000976563	0.03125
Well-groomed	16	0.000976563	0.03125
Intelligent	16	3.05E-05	0.03125
Honest	1	0.000976563	0.03125
Generous	1	0.000976563	0.03125
Trustworthy	1	0.000976563	0.03125
Confident	1	0.000976563	0.03125
Rich	1	0.000976563	0.03125
Dominant	1	0.000976563	0.03125

Part2: Election Outcome Prediction

2.1 Direct Prediction by Rich Features

The main objective of this part is to predict the election outcome from the features used before (facial landmarks and HOG features). Vote differences for 58 pairs of candidates ran for senator and 56 pairs of candidates ran for governor are provided as labels for training the models. Separate models for governor dataset and senator dataset are trained. While training the models, FA – FB is used as feature for the first instance and FB – FA is used as feature vector for the second instance. The vote difference label for the first instance is the positive value of the actual vote difference and the label for the second instance is the negative value of the actual vote difference for the candidate pair A and B. After performing this preprocessing, models are trained on the data. Epsilon-SVR with RBF kernel is used for training. As the dataset is not divided into training and testing parts, 5-fold cross validation has been performed to report the average accuracies. Best parameters for the model C, gamma and epsilon are estimated by performing the grid search over a number of different values. The values for the parameters are chosen by minimizing the training mean square error of the model.

For Governor:

Estimated values of the Parameters (RBF-kernel):
C = 128, gamma = 3.051757812500000e-05, epsilon = 0.001953125000000

Average Test accuracy after 5-fold cross validation: 0.6909

Average Train accuracy after 5-fold cross validation: 1

Kernel	Test Accuracy	Train Accuracy	C	gamma	epsilon
RBF	0.6909	1	128	3.0518e-05	0.00195

For Senator:
Estimated values of the Parameters (RBF-kernel):
C = 2048, gamma = 3.051757812500000e-05, epsilon = 0.001953125000000

Average Test accuracy after 5-fold cross validation: 0.5564

Average Train accuracy after 5-fold cross validation: 0.9914

Kernel	Test Accuracy	Train Accuracy	C	gamma	epsilon
RBF	0.5564	0.9914	2048	3.0518e-05	0.00195

The accuracy values are considerably high which signifies the process of extracting rich features from facial traits for election outcome prediction. The results also show that the facial traits are correlated to election outcomes and could be predicted with reasonable accuracies.

2.2 Prediction by Face Social Traits

Here, a two-layer-model is constructed in which we take each facial image and project it in a 14-dimensional attribute space using the models we trained in part 1 and the second layer performs binary classification of the election outcome in the obtained feature space. So, given a pair of politician images, the architecture first projects the image into a 14 dimensional space represented by their facial traits. Using the facial traits, the model in the second layer of the architecture would be able to predict the election outcome or the winning candidate. For projecting the image into a 14 dimension space, I have utilized the models trained in the first part. The image features (along with HOG features) are extracted from each facial image in Governor and Senator datasets. These features are fed to the trained 14 models in the previous part which results in a 14 dimensional feature vector for each image. The 14 dimensional feature vector obtained for each image is used as features for training a new Epsilon SVR model with RBF kernel and also linear kernel in the second layer. While training the models, FA – FB is used as feature for the first instance and FB – FA is used as feature vector for the second instance. The vote difference label for the first instance is the positive value of the actual vote difference and the label for the second instance is the negative value of the actual vote difference for the candidate pair A and B. Best parameters for the model C, gamma and epsilon are estimated by performing the grid search over a number of different values. The values for the parameters are chosen by minimizing the training mean square error of the model.

The average testing and training accuracies after 5-fold cross validation on **governor** dataset are given in the table below.

Kernel	Test Accuracy	Train Accuracy	C	gamma	epsilon
Linear	0.6364	0.7311	0.0625	----	0.0020
RBF	0.5818	0.6622	16384	3.0518e-05	0.0625

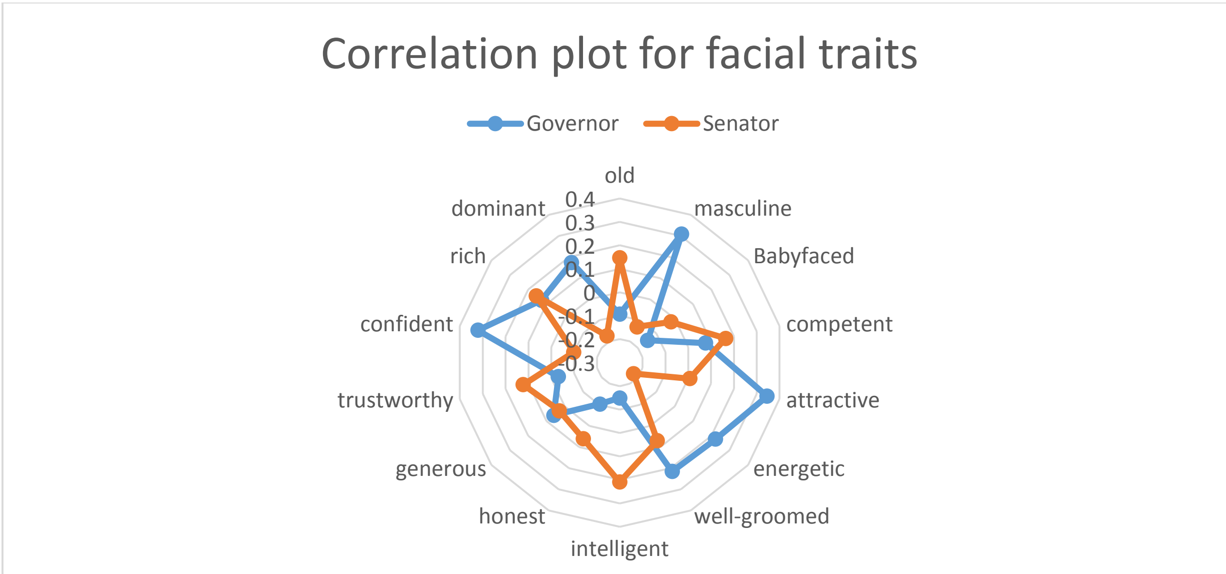
The average testing and training accuracies after 5-fold cross validation on **senator** dataset are given in the table below.

Kernel	Test Accuracy	Train Accuracy	C	gamma	epsilon
Linear	0.6109	0.6668	0.0039	----	0.0313
RBF	0.6109	1	2048	8	3.0518e-05

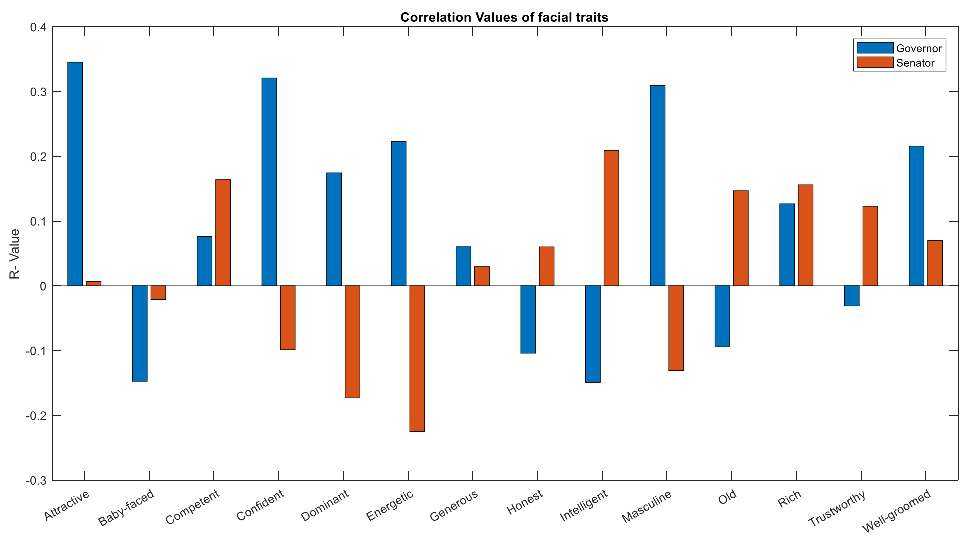
Linear kernel does not have a gamma parameter and other effective estimates of the parameters are shown in the table below. The accuracies obtained now are more coherent as the model is explainable because we know what features we are using here which is not the case previously. The model with the new features provides more flexibility in analyzing the outputs.

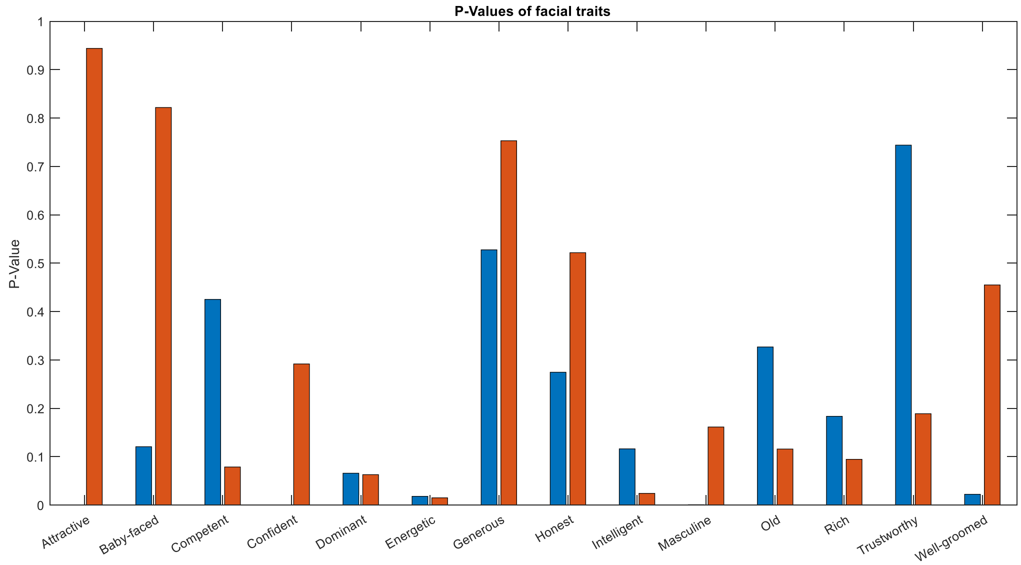
2.3 Analysis of Results

The correlation values of facial traits with election outcome are drawn here. From the correlation plots, we can infer some interesting characteristics regarding the election outcome. Attractive, masculine and confident looking governors have more chance at winning the election. Well-groomed and energetic looks do play a vital role and helps governors to attract votes. However, Baby faced and old facial traits reduce governor chances at election. Also, not being intelligent and honest too helps governors as depicted by the bar graph below. The case with senators is quite opposite. Intelligence and age favors positively for senators unlike governors. Competent and Trustworthy looks along with rich facial traits increases the chances of senators for winning. Energetic and Masculine looks do not favor senators as they do for governors. Confident and Dominant looks also disfavor the election outcome for senators. This is a very interesting idea which deals with predicting the election outcome from facial features. From the correlation matrix shown among the facial traits for governor, confident and dominant traits have a higher correlation and also the traits trustworthy and generosity are highly correlated. From the above analysis, we can infer that the correlated traits act in the same direction (favor or disfavor) of the election outcome for the candidates.



Bar Graph for correlation values:





Correlation among facial traits for governor:

1													
0.13569	1												
-0.49607	-0.31787	1											
0.267642	0.030134	-0.39274	1										
-0.38392	0.424436	0.250162	0.221428	1									
-0.5324	0.152921	0.117942	0.171466	0.56476	1								
-0.2273	0.23137	0.156096	0.400822	0.612074	0.319654	1							
0.296793	-0.36112	-0.42149	0.734736	-0.14913	-0.09918	0.062193	1						
0.101925	-0.38415	0.178905	0.410926	0.064492	-0.12985	0.040075	0.524817	1					
0.183732	-0.2342	0.167662	0.259044	0.109262	0.013983	-0.04126	0.308268	0.748115	1				
0.258594	-0.36757	0.012726	0.437277	-0.03262	-0.10418	0.037507	0.563829	0.846413	0.825222	1			
-0.1566	0.555419	-0.16725	0.294787	0.615842	0.698565	0.433283	-0.08343	-0.20714	0.064359	-0.09619	1		
0.399721	0.232247	-0.29752	0.531195	0.34772	0.063702	0.471688	0.325903	-0.01273	0.133281	0.144386	0.485345	1	
0.150083	0.741144	-0.2309	0.0095	0.351795	0.203958	0.240216	-0.41701	-0.57028	-0.37605	-0.5032	0.546102	0.338838	1