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Pattern Recognition and Machine Learning

Facial Social Traits and Political Election Analysis by SVM

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This project aims at studying the social attributes of human faces using Support Vector Machines.

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1 INTRODUCTION

1.1 PROJECT BRIEF

This project aims at studying the social attributes of human faces using Support Vector Machines. The goal of this project is 1) to train classifiers that can automatically infer the perceived human traits from facial photographs and 2) to apply the model to analyze the outcomes of real-world political elections. A set of face images of US politicians is collected, and in some cases we have a pair of images for the two competing candidates running for public offices: Congressmen, Senators or Governors.

Multiple models are built using the provided images as well as the corresponding annotations. The data set is described below.

1.2 DATASET

The dataset includes a total of 491 frontal faces in size of 250x250 pixels. They are carefully selected so that the facial expression has been filtered out. The clothes have been removed as well. Mechanical Turk is deployed to obtain the human judgments on the perceived trait dimensions. The geometric feature of the images, landmark of human faces, is also provided. The dimensions include: *Old, Masculine, Baby-faced, Competent, Attractive, Energetic, Well-groomed, Intelligent, Honest, Generous, Trustworthy, Confident, Rich, Dominant.*

The testing data include 112 governor faces and 116 senator faces, their corresponding landmark key points and their votes. A trick is applied for binary classifier. Each senator’s feature has been deducted with each other so that the classifier can handle who wins according to the vote difference.

1.3 SUPPORT VECTOR MACHINE

Support Vector Machine algorithm has been adopted in classifying the given data. The feature used can be categorized into geometric and appearance. An example image is shown below. The support vector machine is implemented by the *libsvm* package. The code is initially written in C and deployed by MATLAB. Most of the data processing is done by MATLAB.

Figure 1-1: Example Image of Landmark Points and Face

Another part of the data is pre-computed landmarks and actual voting share differences.

1.4 HISTOGRAM OF GRADIENT FEATURES

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. An example of HOG is shown below. HOG is extracted by the provided C++ code.

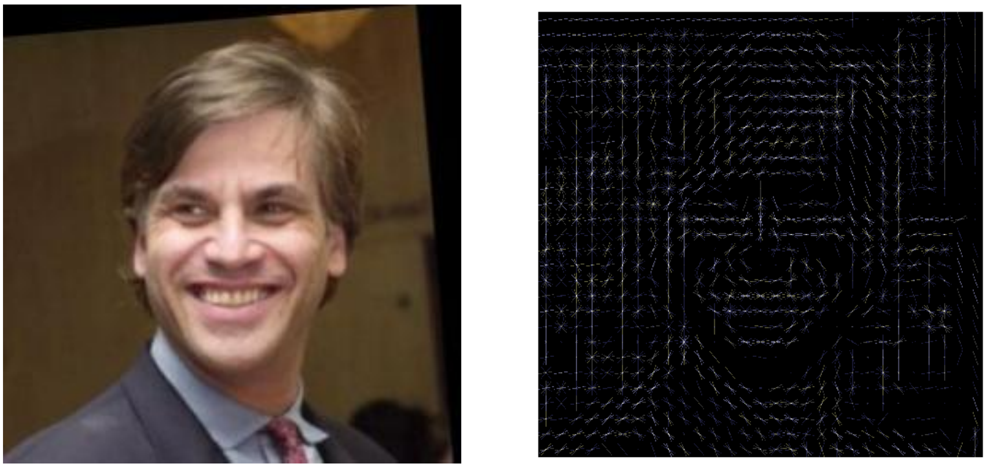


Figure 1-2: Demonstration of HOG Left is Original Image and Right is HOG

2 FACIAL SOCIAL TRAITS CLASSIFICATION (OR REGRESSION)

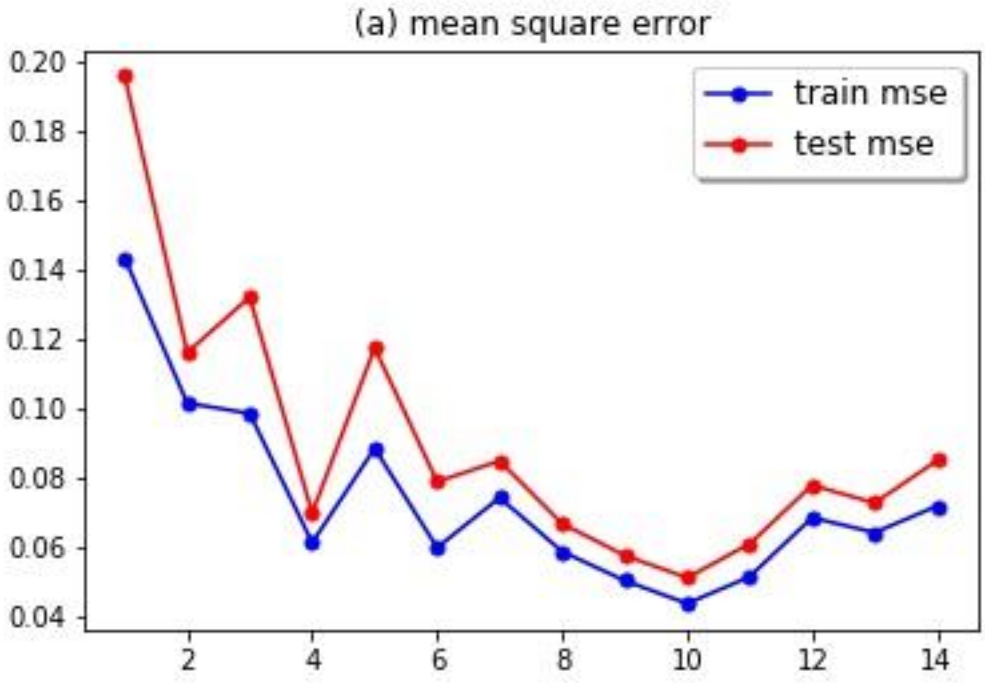
The model training process is done with several different settings. The best model is selected from the various settings. Details of settings are shown in the following table.

Features Used for Training	**Trait Annotation Presentations**	
Landmark Points Only	Binary 1 / -1	Real Values
Landmark Points + HOG Features	Binary 1 / -1	Real Values

Table 2-1 Table of Various Model Settings

2.1 CLASSIFICATION BY LANDMARKS

The provided facial landmarks are used to train 14 SVM and SVR models, which stand for 14 different facial traits. K-fold cross validation is preferred to search for best parameters from the training data. In this project, a 5-fold cross validation is performed. Their MSE, Accuracy and Precision are showed in the following figure.



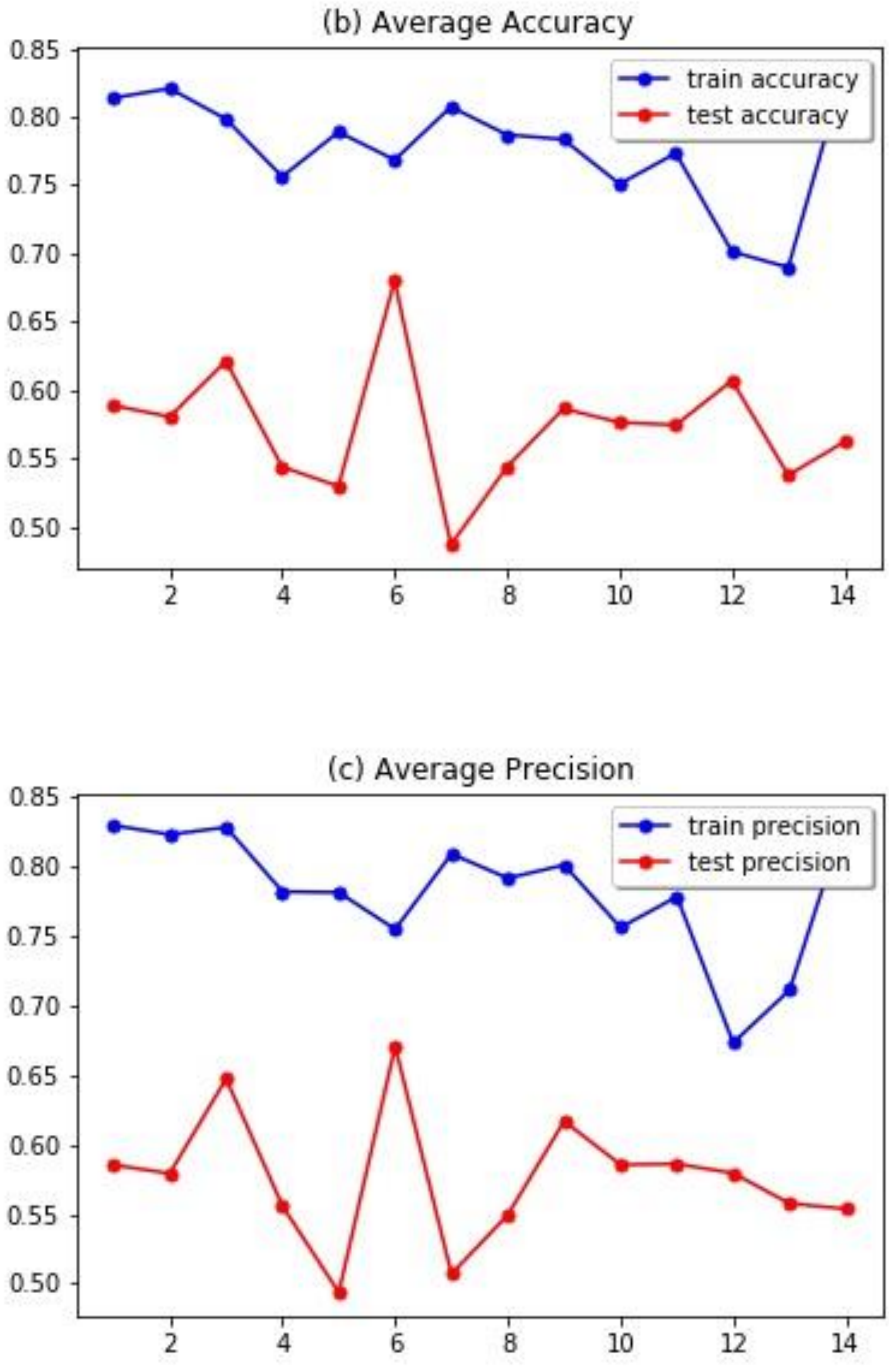


Figure 2-1: Training and Testing results only using landmarks as features

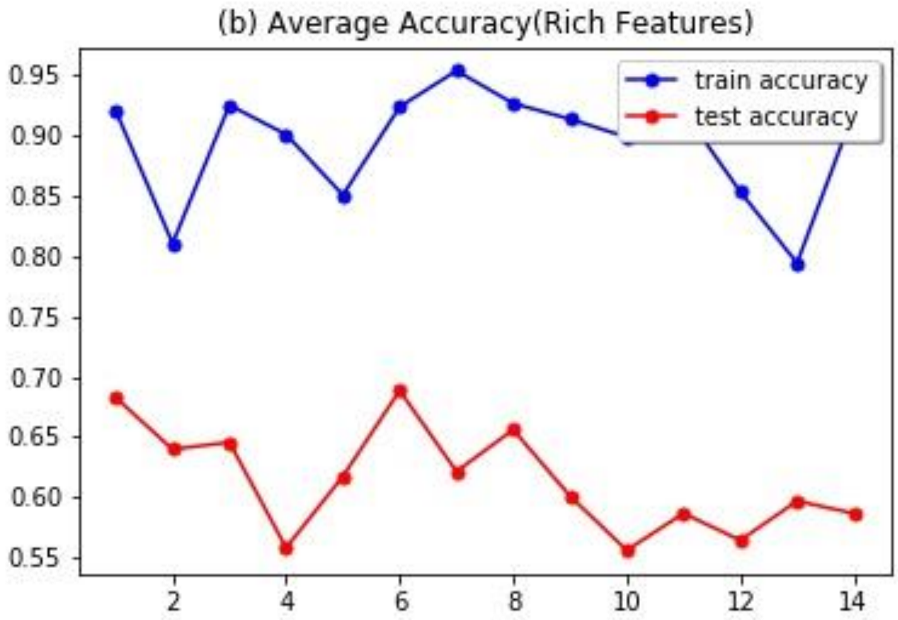
The LIBSVM parameters of the 14 models are listed in the following table：

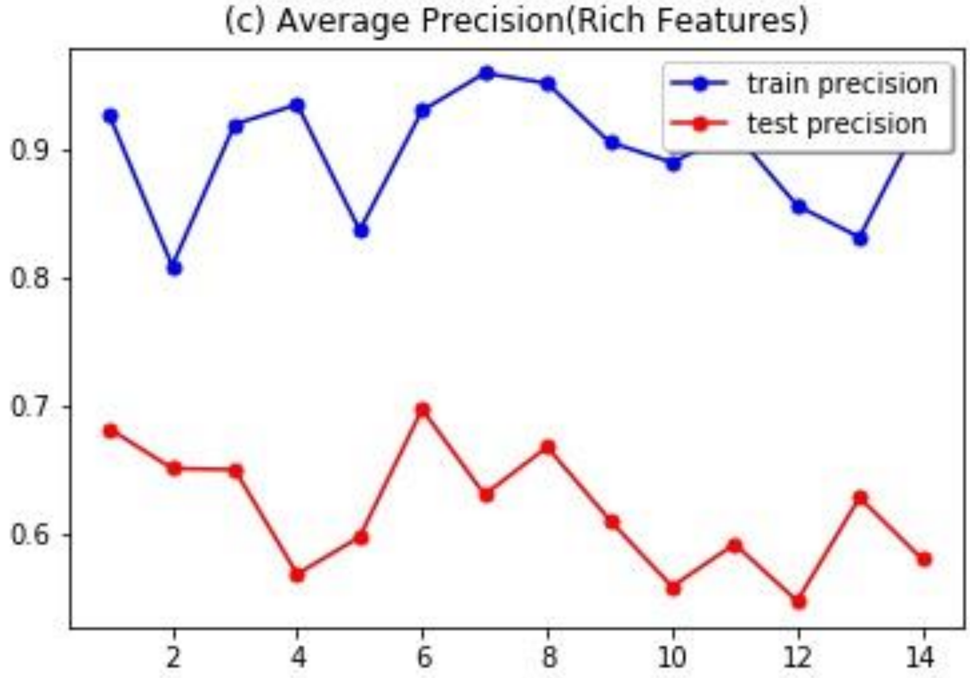
SVR Model	C	Gamma	Epsilon
Old	4.64159	0.01	0.1
Masculine	12.9155	0.001	0.1
Baby-faced	0.59948	0.1	0.1
Competent	0.07743	0.1	0.001
Attractive	0.07743	0.1	0.1
Energetic	1.66810	0.01	0.1
Well-groomed	0.01	0.1	0.1
Intelligent	12.9155	0.001	0.1
Honest	0.59948	0.01	0.01
Generous	12.9155	0.001	0.001
Trustworthy	12.9155	0.001	0.001
Confident	4.64159	0.001	0.1
Rich	1.66810	0.01	0.001
Dominant	35.9381	0.001	0.1

Table 2-2 LIBSVM Parameters of 14 SVR Models

2.2 CLASSIFICATION BY RICH FEATURES

This part is to extract richer visual features (appearance) from the images. Here, we include the HoG (histogram of oriented gradient) features in addition to the landmarks. Of course， you can add more features, like Haar-like features. But here we just use the HoG features.





Method	Old	Mascl.	Baby-face	Compe-tent	Attract.	Ener-getic	Well-groom	Intelli-gent	Honest	Gene-rous	Trust-wrt	Confi-dent	Rich	Domi-nant	Mean
LDK	0.589	0.580	0.621	0.544	0.530	0.680	0.487	0.544	0.586	0.576	0.574	0.607	0.538	0.562	0.573
LDK+HOG	0.682	0.651	0.650	0.569	0.598	0.697	0.631	0.668	0.611	0.559	0.592	0.548	0.629	0.580	0.620

Table 2-2 Accuracy of trait prediction of trained models

The comparison shows that the rich features will have higher accuracy than using only landmarks. But the accuracy increase is still not that obvious, only from 57.3% to 62.0%.

The LIBSVM parameters of the 14 models are listed in the following table：

SVR Model	C	Gamma	Epsilon
Old	4.64159	0.01	0.1
Masculine	12.9155	0.001	0.1
Baby-faced	0.59948	0.1	0.1
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Confident	4.64159	0.001	0.1
Rich	1.66810	0.01	0.001
Dominant	35.9381	0.001	0.1

Table 2-3 LIBSVM Parameters of 14 SVR Models

3 Prediction of Election Result Based on Social Attributes

3.1 Direct Prediction by Rich Features

The same features that are developed in section 1.2 are used to train a classifier to classify the election outcome. The average accuracies on training data and testing data are as follows:

	Training		Testing	
Election	Senator	Governor	Senator	Governor
Average Accuracy	0.9673	0.9405	0.5089	0.5089

Table 3-1 Table of Predicted Election Outcome

We can see that the accuracies on testing data are really high, but the accuracies on testing data are almost equal to 0.5 which is equivalent to the random guess. A better prediction model should be addressed later.

Here we use the support vector regression model and the parameters of the two models are listed in the following table: :

SVR Model	**C**	**Gamma**	**Epsilon**
Governor	0.1000	0.001	0.0000001
Senator	0.3163	0.001	0.0001

Table 3-2 LIBSVM Parameters of the Election Prediction Models

3.2 PREDICTION BY FACE SOCIAL TRAITS

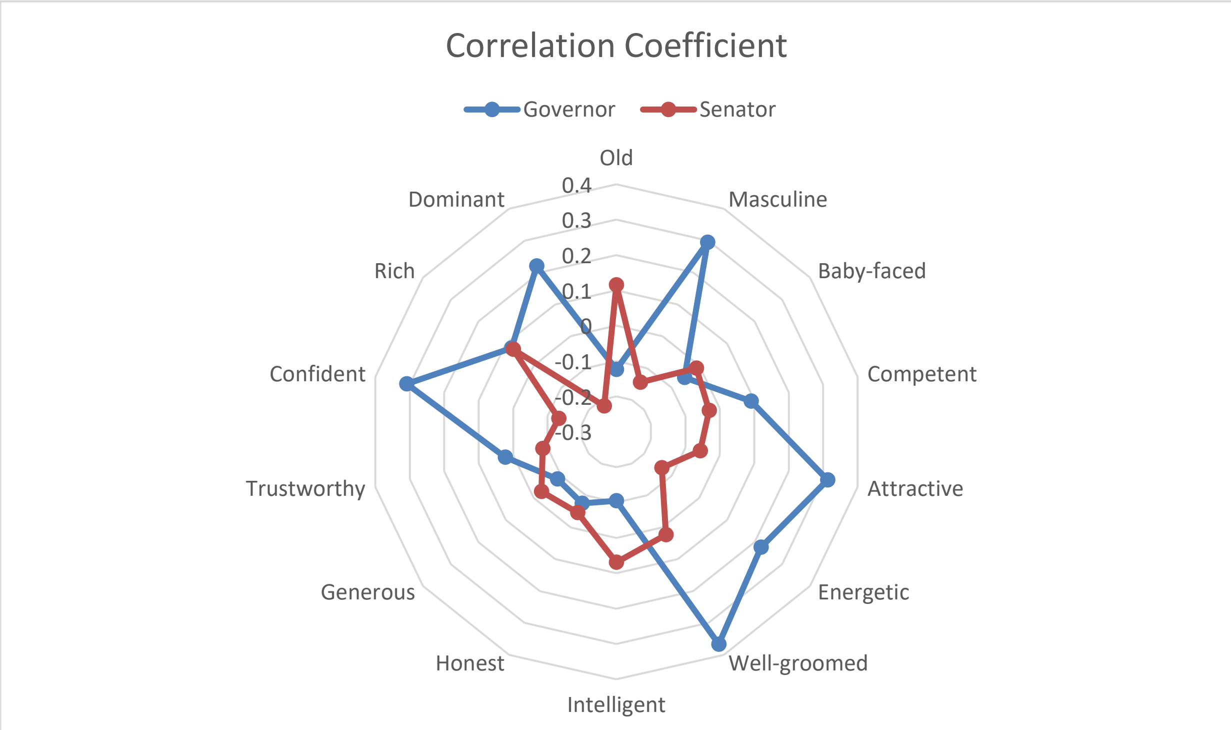
A two-layer-model is used here, where we first project each facial image in a 14-dimensional attribute space and second perform binary classification of the election outcome in the obtained feature space. Specially, we need to apply the classifiers that we trained in the section 1.2 to each politician's image and collect all the outputs of 14 classifiers (use real-valued confidence instead of label). Treat those outputs in 14 categories as a new feature vector that represents the image.

Since each race comprises two candidates, a simple trick is to define a pair of politicians as one data point by subtracting a trait feature vector A from another vector B, and train a binary classifier: $F_{AB} = F_A - F_B$. Do not include a bias term. Then we can again train SVM classifiers using these new feature vectors.

	Training		Testing	
Election	Senator	Governor	Senator	Governor
Average Accuracy	0.8146	0.7183	0.5333	0.5867

3.3 Correlation of Each Traits on Election Win

The correlation of each trait on election win is shown in the following chart:



4 Analysis and Conclusion

The result shows great classification result on senators and governors in terms of predicting their winning. The result is surprisingly better than that of the paper, *Automated Facial Trait Judgment and Election Outcome Prediction: Social Dimensions of Face*. Notice that in this project, only HOG feature is used based on the K-fold cross validation result. In addition, the project categories traits into binary class rather than ranking. A linear kernel is applied in this project. The above mentioned difference may result in the possible outcomes in terms of prediction accuracy.