Project 3 Face Social Traits and Political Election Analysis by SVM

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Part 1: Face Social Traits Classification (or Regression)

1.1 Classification by Landmarks

In this part, we first load the annotation file and the landmark file. Then we use libsvmtrain to train 14 models for each attribute dimension using the provided facial landmarks as features and corresponding 14 trait matrices. Here, we perform 10-fold cross-validation to train and test the given data. The average accuracies and precisions are shown in Table 1. We can find that compared with training data and test data, the accuracies and precisions of training are almost all higher than the testing data, but the differences are not very large. It's sensible that our model can satisfy the basic requirement, but the accuracies and precisions still need to improve. After that, we choose the LIBSVM parameters using grid search. The search ranges are $\mathrm{C}: [2^{-7}, 2^{7}], \gamma: [2^{-19}, 2^{-5}], \varepsilon: [2^{-11}, 2^{1}]$. The chosen parameters are shown in Table 2.

Table 1. Average accuracies and precisions for 14 models

Trait Models	Average Accuracies		Average Precisions	
	Train	Test	Train	Test
1	0.7068	0.6132	0.7165	0.5798
2	0.7187	0.6178	0.7378	0.6455
3	0.7096	0.6547	0.7567	0.7128
4	0.7552	0.6342	0.6943	0.5743
5	0.7004	0.5998	0.7412	0.5276
6	0.7380	0.7289	0.7378	0.7265
7	0.7073	0.5902	0.7534	0.5698
8	0.6821	0.5967	0.6954	0.5575
9	0.7165	0.6107	0.7068	0.6023
10	0.7242	0.6165	0.7245	0.6101
11	0.6753	0.5643	0.6542	0.5567
12	0.6847	0.5745	0.6578	0.5801
13	0.6856	0.5942	0.6833	0.5865
14	0.6689	0.6063	0.6754	0.6235

Table 2. the chosen LIBSVM parameters for 14 models

Trait Models	C	γ	ε
1	2^{3}	2^{-17}	2^{-5}
2	2^{-1}	2^{-13}	2^{-3}
3	2^{1}	2^{-15}	2^{-3}
4	2^{-3}	2^{-11}	2^{-5}
5	2^{3}	2^{-15}	2^{-5}
6	2^{1}	2^{-15}	2^{-3}
7	2^{-5}	2^{-11}	2^{-3}
8	2^{1}	2^{-15}	2^{-3}
9	2^{-3}	2^{-13}	2^{-7}
10	2^{-1}	2^{-15}	2^{-5}
11	2^{-3}	2^{-13}	2^{-3}
12	2^{-1}	2^{-13}	2^{-3}
13	2^{1}	2^{-17}	2^{-9}
14	2^{1}	2^{-15}	2^{-5}

1.2 Classification by Rich Features

In this part, we extract richer visual features (appearance) from the images, and then use two combined features to train and test the given dataset. Finally, we compare the results with those in the previous part.

(1) Average accuracies and precisions on training and testing data for each of the 14 models

With the same strategy, we get the average accuracies and precisions for 14 models as below:

Table 3. Average accuracies and precisions for 14 models (HoG + face landmarks)

Trait Models	Average Accuracies		Average Precisions	
	Train	Test	Train	Test
1	0.8517	0.6970	0.9313	0.6943
2	0.9476	0.6357	0.8722	0.6457
3	0.8920	0.7125	0.8082	0.7107
4	0.7953	0.6235	0.8794	0.6224
5	0.9045	0.6189	0.8921	0.6023
6	0.9026	0.6792	0.7737	0.6778
7	0.9157	0.6793	0.8321	0.6782
8	0.8024	0.6598	0.8501	0.6771
9	0.7258	0.6211	0.7112	0.6136
10	0.8364	0.6034	0.7823	0.5994
11	0.8964	0.6342	0.8334	0.6361

12	0.8273	0.5983	0.9261	0.5994
13	0.8733	0.5952	0.7889	0.6335
14	0.9204	0.6098	0.6991	0.6249

(2) The LIBSVM parameters of the 14 models

We set the search ranges as $C: [2^{-3}, 2^{7}], \gamma: [2^{-19}, 2^{-5}], \varepsilon: [2^{-9}, 2^{1}]$. Then we can get the LIBSVM parameters for 14 models as below:

Table 4. the chosen LIBSVM parameters for 14 models ((HoG + face landmarks))

Trait Models	C	γ	ε
1	2^{1}	2^{-7}	2^{-5}
2	2^{1}	2^{-7}	2^{-7}
3	2^{1}	2^{-9}	2^{-3}
4	2^{3}	2^{-9}	2^{-5}
5	2^{-1}	2^{-7}	2^{-5}
6	2^{3}	2^{-11}	2^{-3}
7	2^{1}	2^{-11}	2^{-5}
8	2^{3}	2^{-13}	2^{-3}
9	2^{5}	2^{-13}	2^{-7}
10	2^{5}	2^{-15}	2^{-5}
11	2^{7}	2^{-15}	2^{-3}
12	2^{-1}	2^{-7}	2^{-3}
13	2^{1}	2^{-11}	2^{-3}
14	2^{1}	2^{-9}	2^{-5}

(3) The names of the features we used: we combine HoG features with face landmarks features.

(4) Comparison to classification by landmarks (1.1)

From the Table 3, we can find that the general trends are similar to that in the previous part. The average accuracies and precisions of training data are higher than those of testing data. After adding in HoG features, the values of four measurements are increased a little. For example, in 2.1, the average accuracies of training data distribute most around 0.7. While now the accuracies distribute most around 0.8 to 0.9. It indicates that feature combination (rich features and landmarks features) helps to classify data.

Part 2: Election Outcome Prediction

2.1 Direct Prediction by Rich Features

In this part, we also use HoG features and face landmarks features to train and test dataset. We set the search range as $C: [2^{-15}, 2^{15}]$, and then do the 10-fold cross-validation. Below are the results:

Table 5. Average accuracies on training and testing data, and the chosen model parameters

Dataset	Average Accuracies		Model parameter
	Train	Test	C
Governors	0.7187	0.6231	2^3
Senators	0.8973	0.6345	2^6

From the above table, we find that the general trends are similar to that in the previous part. The training accuracies are in average higher than the testing accuracies.

2.2 Prediction by Face Social Traits

In this part, we use a two-layer model. First, we project each facial image in a 14-dimensional attribute space. Then, we perform binary classification of the election outcome in the obtained feature space. We apply the classifiers trained in section 1.2 to each politician's image and collect all the outputs of 14 classifiers (use real-valued confidence). We treat these outputs in 14 categories as a new feature vector that represents the image.

Here, we use a trick during classification. Since each race comprises two candidates, we can 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: $F_{AB} = F_A - F_B$. To avoid involving biased terms, we calculate both F_{AB} and F_{BA}. We set the search range as $C: [2^{-15}, 2^{15}]$ and then do the 10-fold cross-validation. Below are the results:

Table 6. Average accuracies on training and testing data, and the chosen model parameters

Dataset	Average Accuracies		Model parameter
	Train	Test	C
Governors	0.6434	0.5502	2^9
Senators	0.6889	0.5536	2^5

From the above table, we find that the general trends are similar to that in the previous part. The training accuracies are in average higher than the testing accuracies. Compared with the results in the previous part, we find that the accuracies are actually lower, but still better than chance.

2.3 Analysis of Results

To show the correlations between the facial attributes and the election outcomes, we calculate each of facial attributes $F_{win} - F_{lose}$ and voting difference for both governors and senators. Below are the results:

Table 7. Correlations between facial attributes and the election outcomes

Trait Models	Governors	Senators
1	0.1202	0.5335
2	0.4651	0.1314
3	0.4120	0.6481
4	0.5374	0.5453
5	0.7702	0.2805
6	0.6915	0.9812
7	0.9283	0.8705
8	0.3516	0.9568
9	0.1871	0.6701
10	0.1372	0.8502
11	0.2421	0.6904
12	0.4965	0.6403
13	0.4901	0.4865
14	0.3624	0.1772

In the above table, the larger the value is, the stronger the relation is. For governors, the election outcomes are positively related to trait 7 (well-groomed), trait 5 (Attractive), trait 6 (Energetic), and trait 4 (Competent). While for senators, the election outcomes are more related to trait 6 (Energetic), trait 8 (Intelligent), trait 7 (well-groomed), trait 10 (Generous), etc. For these two groups, we can see that well-groomed and energetic are two most important traits for a politician to success in an election. It's intuitive because these two traits are direct and would be the most common first impressions when we meet a strange person.