CS 276A / STATS M231 Project 4

Yutong Lu, ID: 005027184

December 19, 2017

1 Introduction

This project is based on the paper by Jungseock et al. in ICCV 2015. By learning geometric and appearance facial features, election outcomes can be predicted solely. Furthermore, such concepts can be mapped into high-level perception such as attractiveness or trustworthiness.

In this project, there are two objectives to be achieved:

(1) train classifiers that can infer the perceived face social traits from low-level features,
(2) apply the model to analyze the outcomes of real-world political elections.

2 Face Social Traits Classification (or Regression)

2.1 Classification by Landmarks

We firstly train 14 SVMs only using the provided facial landmarks as features and their corresponding 14 trait matrix is of size 491*14. These 14 traits correspond to *Old, Masculine, Baby-faced, Competent, Attractive, Energetic, Well-groomed, Intelligent, Honest, Generous, Trustworthy, Confident, Rich, Dominant*}. As for landmarks, 491 images constitute a matrix of size 491*160, while number 160 indicates 80 keypoint locations [x1, x2, ..., x80, y1, y2, ..., y80].

We then remove the landmarks that are redundant and normalize features. In this part, we simply choose k to be 5 which means we will do five-fold cross validation. Afterwards, we will perform grid search on LIBSVM parameters c, p, g from 2^5 to 2^{13}, 2^{-9} to 2^1 and 2^{-17} to 2^5 respectively. The average accuracies and precisions on training and testing data for each of the 14 models are shown in Table 1 and the LIBSVM parameters of the 14 models are shown in Table 2. It can be seen that all training accuracies are greater than testing accuracies and all training precisions are higher than testing precisions.

Trait number	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Avg_acc_train	0.7068	0.7221	0.7109	0.7541	0.6972	0.7368	0.7063	0.6697	0.7165	0.7160	0.6676	0.6732	0.6763	0.6656

Avg_acc_test	0.5938	0.5979	0.6469	0.5918	0.5653	0.7367	0.5408	0.5918	0.6204	0.6102	0.5551	0.5959	0.5755	0.5959
Avg_prec_train	0.7067	0.7406	0.7528	0.7592	0.6824	0.7318	0.7404	0.6654	0.7068	0.7143	0.6471	0.6597	0.6736	0.6698
Avg_prec_test	0.5388	0.6244	0.7128	0.5645	0.5168	0.7385	0.5349	0.5575	0.5915	0.6101	0.5432	0.5707	0.5712	0.6019

Table 1. Average accuracies and precisions on training and testing data for each of the 14 models

Trait number	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$log_2 C$	3	-1	1	-3	1	1	-5	1	-3	-1	-3	-1	1	1
$log_2 \gamma$	-17	-13	-15	-11	-15	-15	-11	-15	-13	-13	-13	-15	-17	-17
$log_2 \varepsilon$	-5	-3	-3	-3	-3	-3	-3	-3	-7	-3	-3	-3	-9	-3

Table 2. The LIBSVM parameters of the 14 models.

2.2 Classification by Rich Features

In this step, we extract richer visual features (appearance) from the images. We here use HoG features (sbin = 32) together with face landmarks as features. By repeating the codes in the first step, we can choose our new LIBSVM parameters as well as get the average accuracies and precisions on training and testing data for each of the 14 models. The training and testing accuracies and precisions are summarized into Table 3 and selected LIBSVM parameters are shown in Table 4. It can be seen that, most training accuracies, testing accuracies, training precisions, testing precisions are higher than those in 2.1, and this implies that rich features can help with classification.

Trait number	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Avg_acc_train	0.8214	0.9556	0.8720	0.7827	0.9120	0.8928	0.9012	0.7982	0.7092	0.8172	0.8964	0.8273	0.8682	0.9107
Avg_acc_test	0.6862	0.6246	0.7096	0.6178	0.6071	0.6587	0.6748	0.6761	0.6136	0.5991	0.6361	0.5829	0.6226	0.6163
Avg_prec_train	0.9281	0.8722	0.7982	0.8793	0.8827	0.7669	0.8203	0.8405	0.7059	0.7823	0.8245	0.9263	0.7752	0.6698
Avg_prec_test	0.6862	0.6246	0.7096	0.6178	0.6071	0.6587	0.6748	0.6761	0.6136	0.5991	0.6361	0.5829	0.6226	0.6163

Table 3. Average accuracies and precisions on training and testing data for each of the 14 models

Trait number	1	2	3	4	5	6	7	8	9	10	11	12	13	14
$log_2 C$	1	1	1	1	-1	3	1	5	5	5	5	-1	1	1

$log_2\gamma$	-9	-7	-9	-9	-7	-11	-9	-13	-15	-15	-15	-7	-11	-9
$log_2\varepsilon$	-3	-7	-3	-5	-5	-3	-3	-7	-3	-3	-7	-5	-3	-3

Table 4. The LIBSVM parameters of the 14 models.

3 Election Outcome Prediction

3.1 Direct Prediction by Rich Features

In this step, we are generally doing the same procedures as the previous step and using both face landmarks and HoGfeatures together as our features. We try C from 2^{-15} to 2^{15} and find that for governors, the model gives the best testing accuracy at c = 2^2. For senators, the model gives the best testing accuracy at c = 2^6. The training and testing accuracies together with parameter chosen for both governors and senators are summarized into Table 5.

	Training accuracy	Testing accuracy	$log_2 C$
Governors	0.7067	0.6182	2
Senators	0.8903	0.6261	6

Table 5. Training and testing accuracy and parameter.

3.2 Prediction by Face Social Traits

We consider a two-layer-model in which 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. We therefore apply the classifiers trained in the section 2.2 to each politician's image and collect all the outputs of 14 classifiers (use real-valued confidence instead of label). Treat these 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: $F_{AB} = F_A - F_B$. To avoid involving biased terms, we calculate both F_{AB} and F_{BA}. Then we can again train SVM classifiers using these new feature vectors.

We try C from 2^{-15} to 2^{15} and find that for governors, the model gives the best testing accuracy at c = 2^9. For senators, the model gives the best testing accuracy at c = 2^5. The training and testing accuracies together with parameter chosen for both governors and senators are summarized into Table 6.

	Training accuracy	Testing accuracy	$log_2 C$
Governors	0.6333	0.5489	9
Senators	0.6882	0.5527	5

Table 6. Training and testing accuracy and parameter.

Compared the results with direct prediction in 2.1, it is shown that the training accuracies and testing accuracies are worse. However, they are still acceptable since they are better than chance.

3.3 Analysis of Results

The purpose of this part is to show the correlations between the facial attributes and the election outcomes. We therefore calculate each facial attribute (F_{win} - F_{lose}) and voting difference for both governors and senators. Table 7 shows the summarization of correlations. When the correlation is large, it means the facial attribute and the election outcome is positively related strongly, while it is poorly related when the correlation is small. Therefore, it can be analyzed that *Attractive, Energetic, Well-groomed* lead to the electoral success for governors while *Energetic, Well-groomed, Intelligent* lead to the electoral success for senators.

Trait no.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Governors	0.1102	0.4651	0.4118	0.5374	0.7624	0.6902	0.9283	0.3516	0.1871	0.1327	0.2381	0.4945	0.4847	0.3602
Senators	0.5333	0.1314	0.6479	0.5450	0.2805	0.9812	0.8700	0.9487	0.6701	0.8460	0.6904	0.6400	0.4865	0.1763

Table 7. Correlations between the facial attributes and the election outcomes.