Motivation

Last election results are very interesting, and several states have surprising result . Most of the media had the wrong prectication. Moreover, in the last few years, the western countries have had several elections that have unexpected results too. We want to know if the same social values exist among western countries that would influence the election results.

Problem

Can we use the data under following categories: Economics, Political affiliation (also known as political party), and Background or Social Media - to train a model which can use to predict the election results? Does the western world have similar social values that affect the elections? Is there a correlation between the results of elections and economics, background, or social media?

We expect it is complicated project which involves a lot of features, data collecting, and pre-processing. We expect that our model can give us some idea about people's preferences on the candidates and their raised issues. If our model can also work on other western countries, then we may be able to conclude that the social values are same among some countries.

This problem is a classification problem, where the election results are the target.

Proposed Solution

We want to use our data to see if we can create a model to predict whether or not the republican candidate will win the election. We randomly picked Republican, our choice has nothing to do with our own affiliations. We are separating the election into only Republican and Democratic. A description of all our desired attributes/features is at the end of the document.

We want to use SVM to create our model because the data is not linearly separable. It has more dependent features. We will also be using other classification algorithms to compare.

Methodology

We tested our dataset using different classifiers (i.e. Perceptron, Decision Tree, KNN, Logistic Regression, SVM, and SGD) and compare their results.

We performed our tests without dimension reductions by changing different parameters, followed by the same tests by using dimension reduction techniques through modifying number of components.

For each test, we tested different classifiers on our data. The parameters were changed for the first three tests. We didn't use any dimension reduction techniques for those first three tests.

According to our notes from class,

> The Fisher's propose is used to maximize the distance between the mean of each class and minimize the spreading within the class itself. Thus, we come up with two measures: the within-class and the between-class. However, this formulation is only possible if we assume that the dataset has a Normal distribution.

As you will see in the results section, our results shows a decrease in performance when using LDA. This means that the distribution of our data is primarily non-Gaussian.

To validate our model, we tried to get data from France as its governing system is similar to the United States. However, the data was scarce and we did not find enough of our feature or instances. We settled on just analyzing the United States.

Preprocessing Data

We had to find all our data for the US. We decided on the features before we actually found the data, so we spent much time searching. Our data needed to be for each state, for each election year. They also needed to include the election result for that state. The data was gathered in a separated state, so they had to be combined. This can be seen in transform_data.py, with the original datasets being in datasets/.

Results

Our result data is stored in the directory results/. The file cross_valid_results.docx contains a second set of results used, ran separately, used as cross validation data. You may also refer to that file when analyzing results. The subdirectory `Tests With Parameters/` contains the parameters beside the result.

Our Runtime showed PCA to be the fastest in running time, while LDA was the slowest. KNN also had one of the quickest runtimes. You can see this in `results/runtimes.txt`

Test1

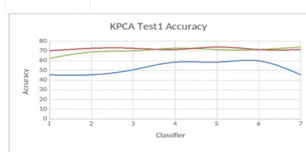
Parameters

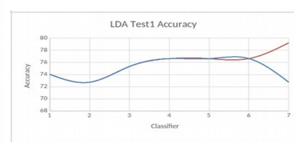
```
per = Perceptron(n_iter=50, eta0=.1, random_state=1)

clf_entropy = DecisionTreeClassifier(criterion="entropy", random_state=1, max\_depth=5, min_samples_leaf=3)

knnn = KNeighborsClassifier(n_neighbors=9, metric='euclidean')#how did i choose

logreg = LogisticRegression(multi_class='auto')

clf1 = svm.SVC(kernel="linear", random_state=1, C=1)

clf2 = svm.SVC(gamma='scale', C = 1.0)

sgd = linear_model.SGDClassifier(max_iter=100, tol=1e-3)
```

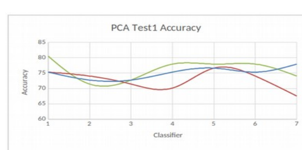
Results

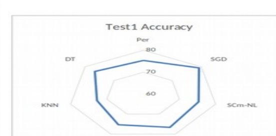
Key

ID	Classifier
1	Perceptron
2	Decision Tree
3	KNN
4	LR
5	SVM-L
6	SCm-NL
7	SGD









Test2

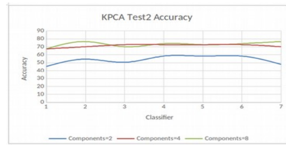
Parameters

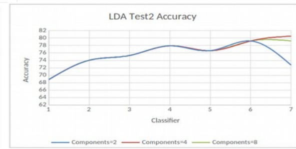
```
per = Perceptron(n_iter=100, eta0=.1,
random_state=1)

clf_entropy =
DecisionTreeClassifier(criterion="entropy",
random_state=1, max_depth=10,
min_samples_leaf=5)

knnn = KNeighborsClassifier(n_neighbors=9,
weights='uniform', algorithm='auto',
leaf_size=30)

logreg =
LogisticRegression(warm_start=True,
n_jobs=5, max_iter=100, C=2)

clf1 = svm.SVC(kernel="linear",
random_state=1, C=2, degree=3,
class_weight='balanced')

clf2 = svm.SVC(gamma='scale', C=2,
degree=3, class_weight='balanced')

sgd =
linear_model.SGDClassifier(max_iter=100,
tol=1e-3, alpha=0.0002, shuffle=True)
```

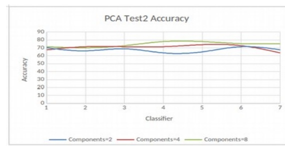
Results

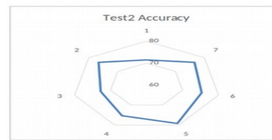
Key

ID	Classifier
1	Perceptron
2	Decision Tree
3	KNN
4	LR
5	SVM-L
6	SCm-NL
7	SGD









Test3:

Parameters

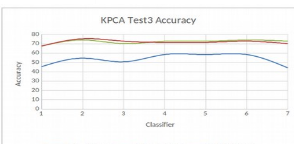
```
per = Perceptron(n_iter=100, eta0=.2,
random_state=1)

clf_entropy =
DecisionTreeClassifier(criterion="entropy",
random_state=1, max_depth=15,
min_samples_leaf=10)

knnn = KNeighborsClassifier(n_neighbors=9,
weights='uniform', algorithm='auto',
leaf_size=50)

logreg =
LogisticRegression(warm_start=True,
n_jobs=10, max_iter=200, C=5)

clf1 = svm.SVC(kernel="linear",
random_state=1, C=5, degree=5,
class_weight='balanced')
```

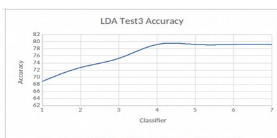
```
clf2 = svm.SVC(gamma='scale', C=5, degree=5, class_weight='balanced')

sgd = linear_model.SGDClassifier(max_iter=200, tol=1e-3, alpha=0.0004, shuffle=False)
```

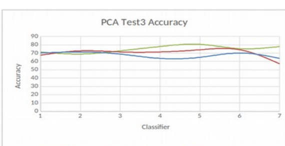
Results

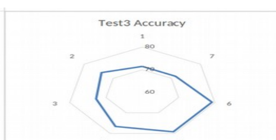
Key

ID	Classifier
1	Perceptron
2	Decision Tree
3	KNN
4	LR
5	SVM-L
6	SCm-NL
7	SGD









Appendix

USA Dataset Shape and Definitions

Features	Description
year	Election year
state	State name
hs_grad	At least HS graduate (%)
bachelors	At least college graduate (%)
adv_degree	Obtained advanced degree
	(%)
median_household_income	Median household income
rep_spending	Republican candidate spending
dem_spending	Democrat candidate spending
inflation_rate	Inflation rate that year
poverty_rate	Poverty rate that year
stock_change	NASDAQ Index (end_year - start_year)
unemployment_rate	Unemployment rate that year
perc_urban	Percentage urban population
rep_sen	Percentage senators that are republican
rep_house	Percentage representatives that are republican
campaign_fund	Campaign spending for republican (% from total)
rep_legis	Percentage of republican legislators in the state
stateGDP	Ratio of Average GDP and Average GDP of Country

Analysis

Our highest accuracy was 79.22%, and the minimum accuracy was 71.43%, as seen from our results. We used the PCA method on all three tests; the highest accuracy was 80.52%, and the lowest, 57.14%. We used the LDA method for all three tests, the highest accuracy was 80.52%, and the lowest was 68.83. We then used Kernel PCA (KCPA) and got 76.62% for our highest accuracy, and 44.16% for our lowest.

Datasets

Poverty rate in France from 2000 to 2015 https://www.statista.com/statistics/460446/poverty-rate-france/

Unemployment rate in France from 2005 to 2015

https://www.statista.com/statistics/459862/unemployment-rate-france/

Average annual wages in France from 2000 to 2015

https://www.statista.com/statistics/416204/average-annual-wages-france-y-on-y-in-euros/

inflation rate France

https://knoema.com/atlas/France/Inflation-rate

France Stock Exchange

https://www.macrotrends.net/2596/cac-40-index-france-historical-chart-data

Share of the urban population in France from 2005 to 2015

https://www.statista.com/statistics/466415/share-urban-population-france/

France GDP

https://countryeconomy.com/gdp/france?year=2015

USA Election Campaign Spending

https://www.huffingtonpost.com/entry/56-years-of-presidential-campaign-spending-how-2016_us_5820bf9ce4b0334571e09fc1

USA Inflation Rate

https://www.inflation.eu/inflation-rates/united-states/historic-inflation/cpi-inflation-united-states.aspx

USA Stock Market Performance %

https://www.macrotrends.net/1320/nasdaq-historical-chart

USA Unemployment Rate

https://data.bls.gov/map/MapToolServlet

USA Poverty Rate

https://www.statista.com/search/?q=poverty+rate&language=0&p=1