Project 2

In [1]:
```
# Load libraries
import pandas as pd
import numpy
from sklearn import linear_model
from sklearn.model_selection import train_test_split, KFold, cross_val_s
core
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
import statsmodels.formula.api as smf
from math import sqrt
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
import plotly.figure_factory as ff

import csv
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn.cluster import KMeans, DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# get merged data
data_mergedtrain = pd.read_csv("merged_train.csv")
data_mergedtrain.head(3)
```

Out[2]:

	State	County	FIPS	Total Population	Percent White, not Hispanic or Latino	Percent Black, not Hispanic or Latino	Percent Hispanic or Latino	Percent Foreign Born	Percent Female	Pe A
0	AZ	apache	4001	72346	18.571863	0.486551	5.947806	1.719515	50.598513	45.8
1	AZ	cochise	4003	128177	56.299492	3.714395	34.403208	11.458374	49.069646	37.9
2	AZ	coconino	4005	138064	54.619597	1.342855	13.711033	4.825298	50.581614	48.9

Task 01: (5 pts.) Partition the merged dataset into a training set and a validation set using the holdout method or the cross-validation method. How did you partition the dataset?

In [3]:
```
#task 1: Partition the merged dataset into a training set and a validati
on set using the holdout method.
#creating a training and validation set
x_train,x_val,y_train,y_val = train_test_split(data_mergedtrain[['Total
 Population',
                                                                    'Pe
rcent White, not Hispanic or Latino',
                                                                     'P
ercent Black, not Hispanic or Latino',
                                                                     'P
ercent Hispanic or Latino','Percent Foreign Born',
                                                                     'P
ercent Female', 'Percent Age 29 and Under',
                                                                     'P
ercent Age 65 and Older', 'Median Household Income',
                                                                     'P
ercent Unemployed', 'Percent Less than High School Degree',
                                                                     'P
ercent Less than Bachelor\'s Degree', 'Percent Rural']],
                                                    data_mergedtrain[['De
mocratic','Republican','Party']],test_size=0.25,random_state =0)
```

Task 02: (5 pts.) Standardize the training set and the validation set.

In [4]:
```
#task 2:  Standardize the training set and the validation set
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_val_scaled = scaler.transform(x_val)
```

Task 03: (25 pts.) Build a linear regression model to predict the number of votes cast for the Democratic party in each county. Consider multiple combinations of predictor variables. Compute evaluation metrics for the validation set and report your results. What is the best performing linear regression model? What is the performance of the model? How did you select the variables of the model? • Repeat this task for the number of votes cast for the Republican party in each county.

In [5]:
```
#task 3

#LINEAR REGRESSIONfor democratic party
LR_model = linear_model.LinearRegression().fit(X=x_train_scaled[:,[0,1,2
,4,6,8,10,11,12]], y=y_train['Democratic'])

print()
print("Coefficients:")
print(LR_model.coef_)

print()
print("Intercept:")
print(LR_model.intercept_)
```

```
Coefficients:
[ 69908.65505722   1830.37860438   2307.30051784   2503.35963873
  -3766.69710289   1289.34667978   2692.06881351 -10326.83277279
   -171.67702553]

Intercept:
27569.373883928565
```

In [6]:
```
#task 3: evaluating the validation set for democratic party for LINEAR R
EGRESSION

LR_predicted = LR_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,12]])

R_squared = LR_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y=y_
val['Democratic'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Democratic'], LR_predict
ed))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.8857920013007843
Adjusted R squared
0.8826414358194266
Root Mean Square
13691.515239455384
```

In [7]:
```
#task 3: prediction for democratic using RIDGE REGRESSION

RIDGE_model = linear_model.Ridge(alpha = 1).fit(X=x_train_scaled[:,[0,1,
2,4,6,8,10,11,12]], y=y_train['Democratic'])
print('Coefficient ',RIDGE_model.coef_)
print()
print()
print('Intercept',RIDGE_model.intercept_)
```

```
Coefficient  [ 69786.00776921   1826.73380191   2326.82743807   2572.80
986389
  -3766.48461727   1285.17188978   2639.8540446  -10298.01716379
   -196.3968742 ]


Intercept 27569.373883928565
```

In [8]:
```
#task 3: evaluating the validation set for democratic party for RIDGE RE
GRESSION
RIDGE_predicted = RIDGE_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,
12]])

R_squared = RIDGE_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y
=y_val['Democratic'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Democratic'], RIDGE_pred
icted))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.8858242606170862
Adjusted R squared
0.8826745850479024
Root Mean Square
13689.581442700883
```

In [9]:
```
#task 3: prediction for democratic using LASSO REGRESSION
LASSO_model = linear_model.Lasso(alpha = 1).fit(X=x_train_scaled[:,[0,1,
2,4,6,8,10,11,12]], y=y_train['Democratic'])
print(LASSO_model.coef_)
print(LASSO_model.intercept_)
```

```
[ 69908.32365572   1824.93653144   2305.36232366   2502.38141147
  -3765.03732921   1288.18104901   2686.71459064 -10324.4038706
   -169.89839456]
27569.373883928565
```

In [10]:
```
#task 3: evaluating the validation set for democratic party for LASSO RE
GRESSION

LASSO_predicted = LASSO_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,
12]])

R_squared = LASSO_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y
=y_val['Democratic'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Democratic'], LASSO_pred
icted))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.885827604553271
Adjusted R squared
0.8826780212306027
Root Mean Square
13689.380973572459
```

In [11]:
```
#task 3

#LINEAR REGRESSIONfor republican party
LR_model = linear_model.LinearRegression().fit(X=x_train_scaled[:,[0,1,2
,4,6,8,10,11,12]], y=y_train['Republican'])

print()
print("Coefficients:")
print(LR_model.coef_)

print()
print("Intercept:")
print(LR_model.intercept_)
```

```
Coefficients:
[45223.82585833   282.41260658 -3604.73112339 -6344.826117
 -3239.76470254  4435.59710529  4011.74489074 -3360.34316285
 -6116.22628287]

Intercept:
21546.910714285706
```

In [12]:
```
#task 3: evaluating the validation set for republican party for LINEAR R
EGRESSION

LR_predicted = LR_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,12]])

R_squared = LR_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y=y_
val['Republican'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Republican'], LR_predict
ed))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.692376200465559
Adjusted R squared
0.6838900266852985
Root Mean Square
16175.406414309417
```

In [13]:
```
#task 3: prediction for republican using RIDGE REGRESSION

RIDGE_model = linear_model.Ridge(alpha = 1).fit(X=x_train_scaled[:,[0,1,
2,4,6,8,10,11,12]], y=y_train['Republican'])
print('Coefficient ',RIDGE_model.coef_)
print()
print()
print('Intercept',RIDGE_model.intercept_)
```

```
Coefficient  [45135.50346327   302.07150389 -3573.90740717 -6255.855596
1
 -3227.36233277  4413.50220457  3957.34616431 -3344.33816617
 -6108.28947836]


Intercept 21546.910714285706
```

In [14]:
```
#task 3: evaluating the validation set for republican party for RIDGE RE
GRESSION
RIDGE_predicted = RIDGE_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,
12]])

R_squared = RIDGE_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y
=y_val['Republican'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Republican'], RIDGE_pred
icted))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.6924864462917757
Adjusted R squared
0.6840033137756867
Root Mean Square
16172.507693782147
```

In [15]:
```
#task 3: prediction for republican party using LASSO REGRESSION
LASSO_model = linear_model.Lasso(alpha = 1).fit(X=x_train_scaled[:,[0,1,
2,4,6,8,10,11,12]], y=y_train['Republican'])
print(LASSO_model.coef_)
print(LASSO_model.intercept_)
```

```
[45221.18172144   282.31670392 -3601.97820678 -6337.17498069
 -3236.69791681  4432.94338974  4002.8747436  -3355.36219685
 -6112.76456802]
21546.910714285706
```

In [16]:
```
#task 3: evaluating the validation set for republicab party for LASSO RE
GRESSION

LASSO_predicted = LASSO_model.predict(x_val_scaled[:,[0,1,2,4,6,8,10,11,
12]])

R_squared = LASSO_model.score(X=x_val_scaled[:,[0,1,2,4,6,8,10,11,12]],y
=y_val['Republican'])
print('R sqaured')
print(R_squared)

Adjusted_R_squared = 1-(((1-R_squared)*(len(x_val_scaled)-1))/(len(x_val
_scaled)-9))
print('Adjusted R squared')
print( Adjusted_R_squared)

RootMeanSquare = sqrt(mean_squared_error(y_val['Republican'], LASSO_pred
icted))
print('Root Mean Square')
print(RootMeanSquare)
```

```
R sqaured
0.6923897725320423
Adjusted R squared
0.6839039731536158
Root Mean Square
16175.049588678503
```

Task 04: (25 pts.) Build a classification model to classify each county as Democratic or Republican. Consider at least two different classification techniques with multiple combinations of parameters and multiple combinations of variables. Compute evaluation metrics for the validation set and report your results. What is the best performing classification model? What is the performance of the model? How did you select the parameters of the model? How did you select the variables of the model?

In [17]:
```
# Decision Tree Classifier - Select best parameters

# create pipeline with StandardScaler and DecisionTreeClassifier
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('dectree', DecisionTreeClassifier())
])

# set the possible parameter values for DecisionTreeClassifier
params = {'dectree__criterion' : ['entropy', 'gini'] , 'dectree__random_
state' : range(0,11)}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train, y_train['Party'])
print("Decision Tree Classifier")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val)
dectree_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", dectree_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
Decision Tree Classifier
Best score found by GridSearchCV :  0.619369138416728
Parameters of the Best score :  {'dectree__criterion': 'entropy', 'dect
ree__random_state': 1}

Confusion matrix on validation set:
 [[192  30]
 [ 31  46]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.7959866220735786
Error  of validation set:  0.20401337792642138
Precision  of validation set:  [0.86098655 0.60526316]
Recall of validation set:  [0.86486486 0.5974026 ]
F1_score of validation set: [0.86292135 0.60130719]
```

In [18]:
```
# Decision Tree Classifier by filtering the variables

# set the filtered variables which we want to use to build the model.
variables = ['Total Population',
        'Percent White, not Hispanic or Latino', 'Percent Black, not His
panic or Latino', 'Percent Hispanic or Latino',
        'Percent Foreign Born', 'Percent Female',
        'Median Household Income', 'Percent Unemployed', 'Percent Less t
han High School Degree',
        'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# create pipeline with StandardScaler and DecisionTreeClassifier
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('dectree', DecisionTreeClassifier())
])

# set the possible parameter values for DecisionTreeClassifier
params = {'dectree__criterion' : ['entropy', 'gini'] , 'dectree__random_
state' : range(0,11)}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train[variables], y_train['Party'])
print("Decision Tree Classifier with filtered variables")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val[variables])
dectree_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", dectree_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
Decision Tree Classifier with filtered variables
Best score found by GridSearchCV :  0.5894992980825718
Parameters of the Best score :  {'dectree__criterion': 'entropy', 'dect
ree__random_state': 7}

Confusion matrix on validation set:
 [[192  30]
 [ 27  50]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.8093645484949833
Error  of validation set:  0.1906354515050167
Precision  of validation set:  [0.87671233 0.625     ]
Recall of validation set:  [0.86486486 0.64935065]
F1_score of validation set: [0.8707483  0.63694268]
```

In [19]:
```
# K Nearest Neighbors Classifier - Select best parameters

# create pipeline with StandardScaler and KNeighborsClassifier
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('knn', KNeighborsClassifier())
])

# set the possible parameter values for KNeighborsClassifier
params = {'knn__n_neighbors' : range(1,31)}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train, y_train['Party'])
print("K Nearest Neighbors Classifier")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val)
knn_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", knn_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
K Nearest Neighbors Classifier
Best score found by GridSearchCV :  0.6488895674315595
Parameters of the Best score :  {'knn__n_neighbors': 5}

Confusion matrix on validation set:
 [[206  16]
 [ 45  32]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.7959866220735786
Error  of validation set:  0.20401337792642138
Precision  of validation set:  [0.82071713 0.66666667]
Recall of validation set:  [0.92792793 0.41558442]
F1_score of validation set: [0.87103594 0.512     ]
```

In [20]:

```
# K Nearest Neighbors Classifier by filtering the variables

# set the filtered variables which we want to use to build the model.
variables = ['Total Population',
         'Percent Black, not Hispanic or Latino', 'Percent Hispanic or La
tino',
         'Percent Foreign Born', 'Percent Female',  'Percent Age 65 and O
lder',
         'Median Household Income', 'Percent Unemployed', 'Percent Less t
han High School Degree',
         'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# create pipeline with StandardScaler and KNeighborsClassifier
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('knn', KNeighborsClassifier())
])

# set the possible parameter values for KNeighborsClassifier
params = {'knn__n_neighbors' : range(1,31)}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train[variables], y_train['Party'])
print("K Nearest Neighbors Classifier with filtered variables")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val[variables])
knn_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", knn_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
K Nearest Neighbors Classifier with filtered variables
Best score found by GridSearchCV :  0.6219982896115672
Parameters of the Best score :  {'knn__n_neighbors': 5}

Confusion matrix on validation set:
 [[207  15]
 [ 39  38]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.8193979933110368
Error  of validation set:  0.1806020066889632
Precision  of validation set:  [0.84146341 0.71698113]
Recall of validation set:  [0.93243243 0.49350649]
F1_score of validation set: [0.88461538 0.58461538]
```

In [21]:
```
# SVM Classifier - Select best parameters

# create pipeline with StandardScaler and SVC
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC())
])

# set the possible parameter values for SVC
params = {'svc__kernel':['linear','rbf','poly']}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train, y_train['Party'])
print("SVM Classifier")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val)
svm_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", svm_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set:  ", accuracy)
print("Error  of validation set:  ", error)
print("Precision  of validation set:  ", precision)
print("Recall of validation set:  ", recall)
print("F1_score of validation set:",F1_score)
```

```
SVM Classifier
Best score found by GridSearchCV :  0.6353200382676392
Parameters of the Best score :  {'svc__kernel': 'rbf'}

Confusion matrix on validation set:
 [[216   6]
 [ 37  40]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.8561872909698997
Error  of validation set:  0.14381270903010035
Precision  of validation set:  [0.85375494 0.86956522]
Recall of validation set:  [0.97297297 0.51948052]
F1_score of validation set: [0.90947368 0.6504065 ]
```

In [22]:
```
# SVM Classifier by filtering the variables

# set the filtered variables which we want to use to build the model.
variables = ['Total Population',
        'Percent Black, not Hispanic or Latino', 'Percent Hispanic or La
tino',
        'Percent Foreign Born', 'Percent Female', 'Percent Age 29 and Un
der', 'Percent Age 65 and Older',
        'Median Household Income', 'Percent Unemployed', 'Percent Less t
han High School Degree',
        'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# create pipeline with StandardScaler and SVC
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC())
])

# set the possible parameter values for SVC
params = {'svc__kernel':['linear','rbf','poly']}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train[variables], y_train['Party'])
print("SVM Classifier with filtered variables")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val[variables])
svm_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred)
print("\nConfusion matrix on validation set:\n", svm_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
SVM Classifier with filtered variables
Best score found by GridSearchCV :  0.644910926535622
Parameters of the Best score :  {'svc__kernel': 'rbf'}

Confusion matrix on validation set:
 [[215   7]
 [ 36  41]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.8561872909698997
Error  of validation set:  0.14381270903010035
Precision  of validation set:  [0.85657371 0.85416667]
Recall of validation set:  [0.96846847 0.53246753]
F1_score of validation set: [0.90909091 0.656     ]
```

In [23]:
```
# Random forest classifier

# set the filtered variables which we want to use to build the model.
variables = ['Total Population',
        'Percent White, not Hispanic or Latino', 'Percent Black, not His
panic or Latino', 'Percent Hispanic or Latino',
        'Percent Foreign Born', 'Percent Female', 'Percent Age 29 and Un
der', 'Percent Age 65 and Older',
        'Median Household Income',  'Percent Less than High School Degre
e',
        'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# create pipeline with StandardScaler and RandomForestClassifier
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('randforest', RandomForestClassifier())
])

# set the possible parameter values for RandomForestClassifier
params = {'randforest__n_estimators' : [10],
          'randforest__criterion': ['entropy'],
          'randforest__random_state' : [0]}

# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
gridsearch = GridSearchCV(estimator = pipe, param_grid = params, cv = 10
, scoring = 'f1')
gridsearch.fit(x_train[variables], y_train['Party'])
print("Random forest classifier")
print("Best score found by GridSearchCV : ", gridsearch.best_score_)
print("Parameters of the Best score : ", gridsearch.best_params_)

# use the model on validation set to predict the values of Party
y_pred = gridsearch.predict(x_val[variables])
randforest_conf_matrix = metrics.confusion_matrix(y_val['Party'], y_pred
)
print("\nConfusion matrix on validation set:\n", randforest_conf_matrix)

# evaluate the model on the predicted values of Party on validation set
accuracy = metrics.accuracy_score(y_val['Party'], y_pred)
error = 1 - accuracy
precision = metrics.precision_score(y_val['Party'], y_pred, average = No
ne)
recall = metrics.recall_score(y_val['Party'], y_pred, average = None)
F1_score = metrics.f1_score(y_val['Party'], y_pred, average = None)
print("\nEvaluation metrics using best parameters on the validation set
 : ")
print("\nAccuracy of validation set: ", accuracy)
print("Error  of validation set: ", error)
print("Precision  of validation set: ", precision)
print("Recall of validation set: ", recall)
print("F1_score of validation set:",F1_score)
```

```
Random forest classifier
Best score found by GridSearchCV :  0.6274414676622195
Parameters of the Best score :  {'randforest__criterion': 'entropy', 'r
andforest__n_estimators': 10, 'randforest__random_state': 0}

Confusion matrix on validation set:
 [[211  11]
 [ 37  40]]

Evaluation metrics using best parameters on the validation set :

Accuracy of validation set:  0.8394648829431438
Error  of validation set:  0.1605351170568562
Precision  of validation set:  [0.85080645 0.78431373]
Recall of validation set:  [0.95045045 0.51948052]
F1_score of validation set: [0.89787234 0.625     ]
```

Task 05: (25 pts.) Build a clustering model to cluster the counties. Consider at least two different clustering techniques with multiple combinations of parameters and multiple combinations of variables. Compute unsupervised and supervised evaluation metrics for the validation set with the party of the counties (Democratic or Republican) as the true cluster and report your results. What is the best performing clustering model? What is the performance of the model? How did you select the parameters of model? How did you select the variables of the model?

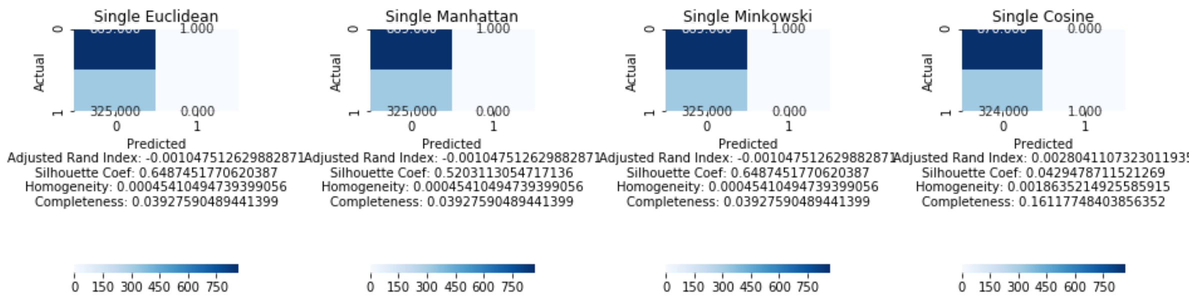
In [24]:
```
# Partition the dataset into attributes and true clusters (Democratic/Re
publican)
X_Clusters = data_mergedtrain[['Total Population',
                      'Percent White, not Hispanic or Latino',
                      'Percent Black, not Hispanic or Latino',
                      'Percent Hispanic or Latino','Percent Foreign Bor
n',
                      'Percent Female', 'Percent Age 29 and Under',
                      'Percent Age 65 and Older', 'Median Household Inco
me',
                      'Percent Unemployed', 'Percent Less than High Scho
ol Degree',
                      'Percent Less than Bachelor\'s Degree', 'Percent R
ural']]
                      #'Democratic','Republican']]
Y_Clusters = data_mergedtrain['Party']
```

In [25]:
```
scalerClusters = StandardScaler()
scalerClusters.fit(X_Clusters)
X_scaledClusters = scalerClusters.transform(X_Clusters)

##Function to plot contingency matrixes
def plotClusters(title_arr,cont_matrix, rand_i,  sil_h, hom, compl):
    fig, ax = plt.subplots(1,len(cont_matrix) ,figsize=(15,15))
    plt.subplots_adjust(
                    wspace = 0.8,  # the amount of width reserved for sp
ace between subplots,
                                   # expressed as a fraction of the avera
ge axis width
                    hspace = 0.2)  # the amount of height reserved for s
pace between subplots,
                                   # expressed as a fraction of the avera
ge axis height)
#     print(ax[0][0])
#     print("\n\n___\n")
#     print(ax[1][0])
    index = 0
    for tmp in ax :
        tmp.title.set_text(title_arr[index])
        sns.heatmap(cont_matrix[index], annot = True, fmt = ".3f", squar
e = True, cmap = plt.cm.Blues, ax=tmp, cbar_kws = dict(orientation ='hor
izontal',use_gridspec=False))
        tmp.set_xlabel( 'Predicted\n' + 'Adjusted Rand Index: ' + str(ra
nd_i[index]) + '\nSilhouette Coef: ' + str(sil_h[index])
                      + '\nHomogeneity: ' + str(hom[index]) + '\nComple
teness: ' + str(compl[index]) )
        tmp.set_ylabel('Actual')
        index = index + 1
#     index = 0
#     for tmp in ax[1]:
#         print(tmp)
#         tmp.table(cellText=[title_arr[i:i+1] for i in  range(0, len(ti
tle_arr), 1)], cellColours=None, cellLoc='right', colWidths=None, rowLab
els=None,
#                   rowColours=None, rowLoc='left', colLabels=None, colC
olours=None, colLoc='center', loc='bottom', bbox=None, edges='closed'
 )
#         #index = index + 1
```

Hierarchical Single

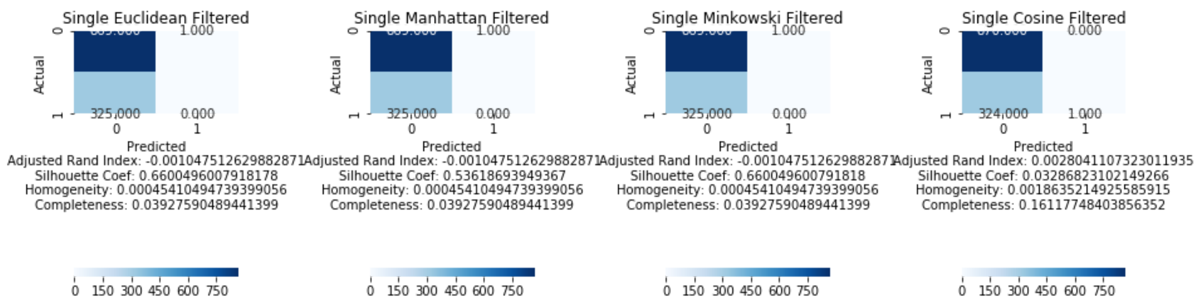
In [26]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Single - Euclidean (All Variables)
clustering = linkage(X_scaledClusters, method='single', metric = 'euclid
ean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Euclidean")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Single - Manhattan (All Variables)
clustering = linkage(X_scaledClusters, method='single', metric = 'citybl
ock')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Manhattan")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Single - Minkowski (All Variables)
clustering = linkage(X_scaledClusters, method='single', metric = 'minkow
ski')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Minkowski")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
```

```
))

#Hierarchical Single - Cosine (All Variables)
clustering = linkage(X_scaledClusters, method='single', metric = 'cosin
e')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Cosine")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



In [27]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []
var = ['Total Population',
        'Percent Black, not Hispanic or Latino', 'Percent Hispanic or La
tino',
        'Percent Foreign Born', 'Percent Female', 'Percent Age 29 and Un
der', 'Percent Age 65 and Older',
        'Median Household Income', 'Percent Unemployed', 'Percent Less t
han High School Degree',
        'Percent Less than Bachelor\'s Degree', 'Percent Rural']

scalerClustersFiltered = StandardScaler()
scalerClustersFiltered.fit(X_Clusters[var])
x_scaled_filtered = scalerClustersFiltered.transform(X_Clusters[var])

#Hierarchical Single - Euclidean (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='single', metric = 'eucli
dean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Euclidean Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Single - Manhattan (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='single', metric = 'cityb
lock')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Manhattan Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Single - Minkowski (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='single', metric = 'minko
wski')
```

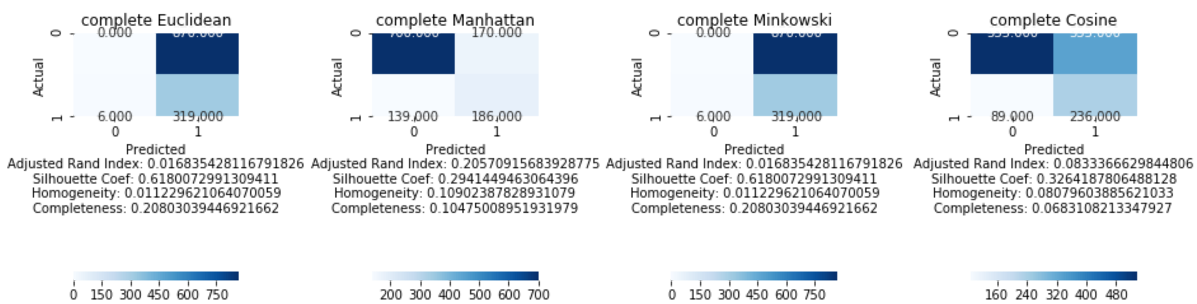
```
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Minkowski Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Single - Cosine (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='single', metric = 'cosin
e')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("Single Cosine Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



Hierarchical Complete

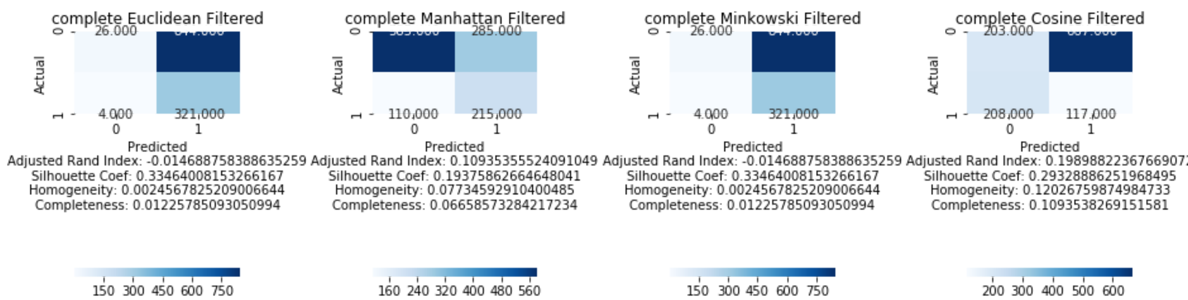
In [28]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Complete - Euclidean (All Variables)
clustering = linkage(X_scaledClusters, method='complete', metric = 'eucl
idean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Euclidean")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Complete - Manhattan (All Variables)
clustering = linkage(X_scaledClusters, method='complete', metric = 'city
block')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Manhattan")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Complete - Minkowski (All Variables)
clustering = linkage(X_scaledClusters, method='complete', metric = 'mink
owski')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Minkowski")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
```

```
))

#Hierarchical Complete - Cosine (All Variables)
clustering = linkage(X_scaledClusters, method='complete', metric = 'cosi
ne')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Cosine")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



In [29]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Complete - Euclidean (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='complete', metric = 'euc
lidean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Euclidean Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Complete - Manhattan (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='complete', metric = 'cit
yblock')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Manhattan Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Complete - Minkowski (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='complete', metric = 'min
kowski')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Minkowski Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
```

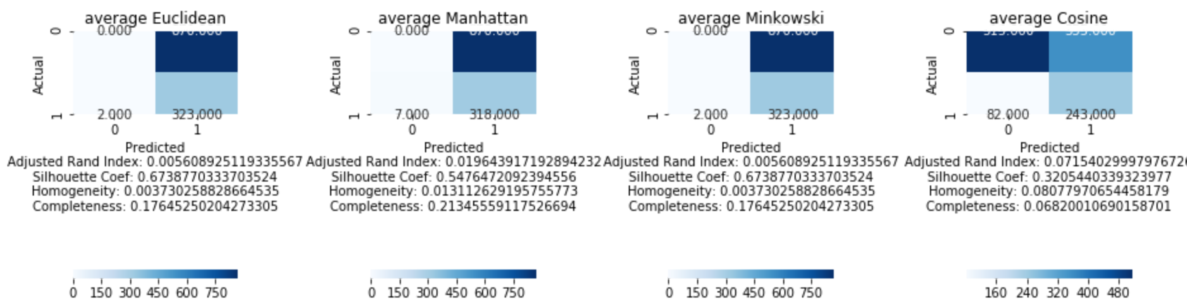
```
))

#Hierarchical Complete - Cosine (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='complete', metric = 'cos
ine')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("complete Cosine Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



Hierarchical Average

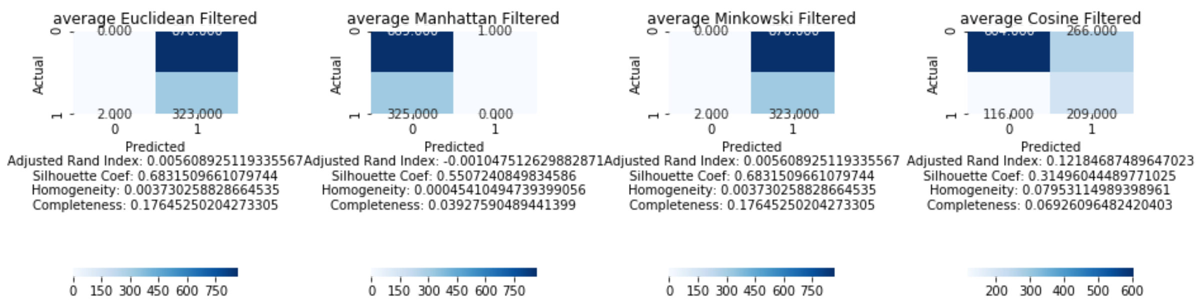
In [30]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Average - Euclidean (All Variables)
clustering = linkage(X_scaledClusters, method='average', metric = 'eucli
dean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Euclidean")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Average - Manhattan (All Variables)
clustering = linkage(X_scaledClusters, method='average', metric = 'cityb
lock')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Manhattan")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Average - Minkowski (All Variables)
clustering = linkage(X_scaledClusters, method='average', metric = 'minko
wski')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Minkowski")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
```

```
))

#Hierarchical Average - Cosine (All Variables)
clustering = linkage(X_scaledClusters, method='average', metric = 'cosin
e')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Cosine")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



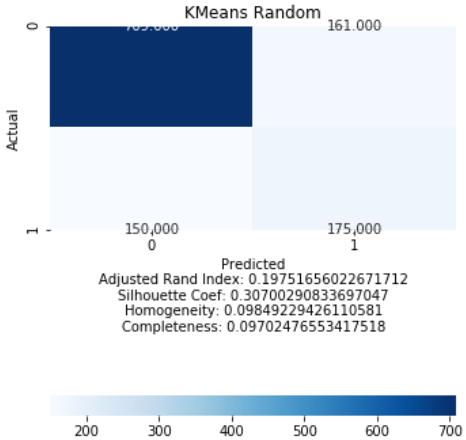
In [31]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#Hierarchical Average - Euclidean (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='average', metric = 'eucl
idean')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Euclidean Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Average - Manhattan (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='average', metric = 'city
block')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cityblock')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Manhattan Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#Hierarchical Average - Minkowski (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='average', metric = 'mink
owski')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='minkowski')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Minkowski Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
```

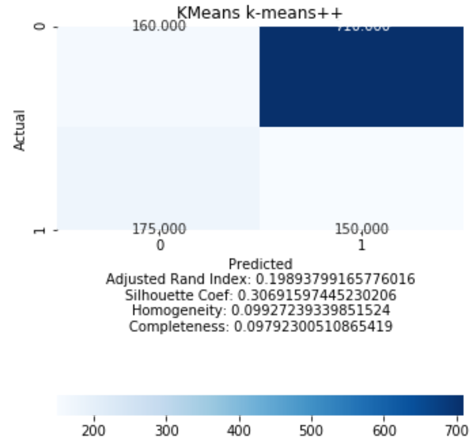
```
))


#Hierarchical Average - Minkowski (Filtered Variables)
clustering = linkage(x_scaled_filtered, method='average', metric = 'cosi
ne')
clusters = fcluster(clustering, 2, criterion = 'maxclust')
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='cosine')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("average Cosine Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```



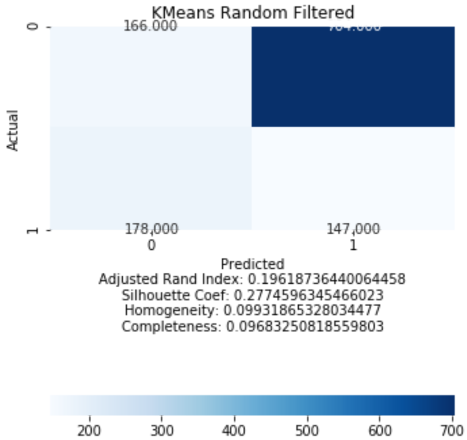
K-Means

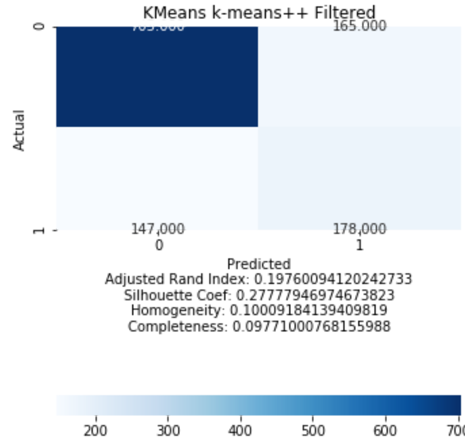
In [32]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#KMeans
clustering = KMeans(n_clusters = 2, init ='random', n_init = 10, random_
state = 0).fit(X_scaledClusters)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans Random")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

clustering = KMeans(n_clusters = 2, init ='k-means++', n_init = 10, rand
om_state = 0).fit(X_scaledClusters)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans k-means++")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```


KMeans Random
161.000
150.000
175.000
Actual
Predicted
Adjusted Rand Index: 0.19751656022671712
Silhouette Coef: 0.30700290833697047
Homogeneity: 0.09849229426110581
Completeness: 0.09702476553417518
200
300
400
500
600
700


KMeans k-means++
160.000
175.000
150.000
Actual
Predicted
Adjusted Rand Index: 0.19893799165776016
Silhouette Coef: 0.30691597445230206
Homogeneity: 0.09927239339851524
Completeness: 0.09792300510865419
200
300
400
500
600
700

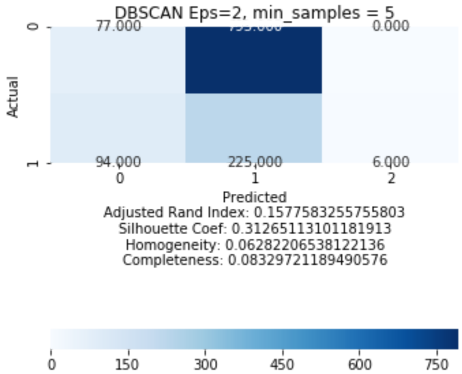
In [33]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#KMeans Filtered
clustering = KMeans(n_clusters = 2, init ='random', n_init = 10, random_
state = 0).fit(x_scaled_filtered)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans Random Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#KMEANS Filtered
clustering = KMeans(n_clusters = 2, init ='k-means++', n_init = 10, rand
om_state = 0).fit(x_scaled_filtered)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("KMeans k-means++ Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```

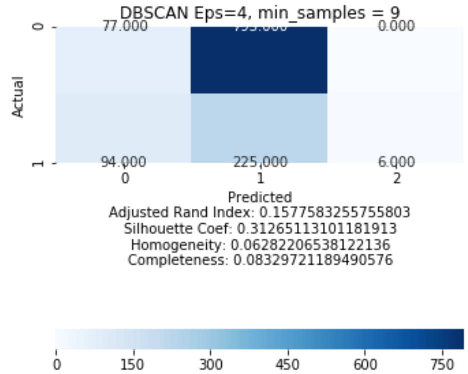

KMeans Random Filtered
166.000
178.000
147.000
0
1
Actual
Predicted
Adjusted Rand Index: 0.19618736440064458
Silhouette Coef: 0.2774596345466023
Homogeneity: 0.09931865328034477
Completeness: 0.09683250818559803
200
300
400
500
600
700


KMeans k-means++ Filtered
165.000
147.000
178.000
0
1
Actual
Predicted
Adjusted Rand Index: 0.19760094120242733
Silhouette Coef: 0.27777946974673823
Homogeneity: 0.10009184139409819
Completeness: 0.09771000768155988
200
300
400
500
600
700

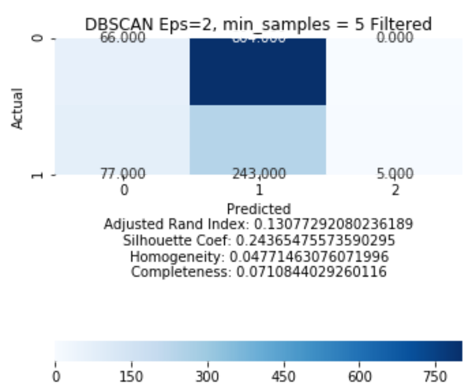
DBSCAN

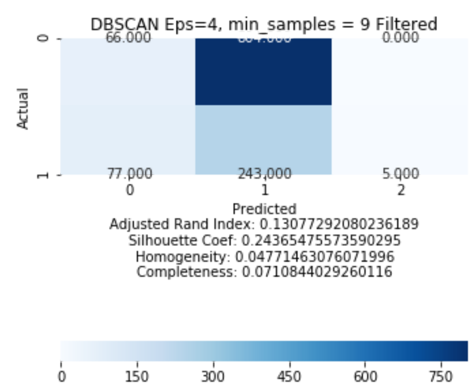
In [34]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#DBSCAN
clustering = DBSCAN(eps = 2, min_samples = 5, metric = 'euclidean').fit(
X_scaledClusters)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("DBSCAN Eps=2, min_samples = 5")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#DBSCAN
clustering = DBSCAN(eps = 2, min_samples = 5, metric = 'euclidean').fit(
X_scaledClusters)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaledClusters, clus
ters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("DBSCAN Eps=4, min_samples = 9")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))


plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```


DBSCAN Eps=2, min_samples = 5
77.000
0.000
94.000
225.000
6.000
Actual
0
1
0
1
2
Predicted
Adjusted Rand Index: 0.1577583255755803
Silhouette Coef: 0.31265113101181913
Homogeneity: 0.06282206538122136
Completeness: 0.08329721189490576
0
150
300
450
600
750


DBSCAN Eps=4, min_samples = 9
77.000
0.000
94.000
225.000
6.000
Actual
0
1
0
1
2
Predicted
Adjusted Rand Index: 0.1577583255755803
Silhouette Coef: 0.31265113101181913
Homogeneity: 0.06282206538122136
Completeness: 0.08329721189490576
0
150
300
450
600
750

In [35]:
```
titles = []
cont_matrix_arr = []
sil_h_arr = []
adj_rand_i_arr = []
homog_arr = []
completeness_arr = []

#DBSCAN Filtered
clustering = DBSCAN(eps = 2, min_samples = 5, metric = 'euclidean').fit(
x_scaled_filtered)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("DBSCAN Eps=2, min_samples = 5 Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))

#DBSCAN Filtered
clustering = DBSCAN(eps = 2, min_samples = 5, metric = 'euclidean').fit(
x_scaled_filtered)
clusters = clustering.labels_
cont_matrix = metrics.cluster.contingency_matrix(Y_Clusters, clusters)
adjusted_rand_index = metrics.adjusted_rand_score(Y_Clusters, clusters)
silhouette_coefficient = metrics.silhouette_score(x_scaled_filtered, clu
sters, metric='euclidean')
#print([adjusted_rand_index, silhouette_coefficient])
titles.append("DBSCAN Eps=4, min_samples = 9 Filtered")
cont_matrix_arr.append(cont_matrix)
sil_h_arr.append(silhouette_coefficient)
adj_rand_i_arr.append(adjusted_rand_index)
homog_arr.append(metrics.homogeneity_score(Y_Clusters, clusters) )
completeness_arr.append(metrics.completeness_score(Y_Clusters, clusters
))


plotClusters(titles,cont_matrix_arr,adj_rand_i_arr, sil_h_arr,homog_arr,
completeness_arr)
```





True Clusters

In [36]:
```
silhouette_coefficient = metrics.silhouette_score(X_Clusters, Y_Clusters
, metric='euclidean')
print(silhouette_coefficient)
```

```
0.41499612317195983
```

Task 06: (10 pts.) Create a map of Democratic counties and Republican counties using the counties' FIPS codes and Python's Plotly library (plot.ly/python/county-choropleth/). Compare with the map of Democratic counties and Republican counties created in Project 01. What conclusions do you make from the plots?

In [37]:
```
columns = x_train.columns
x_train_scaled_df = pd.DataFrame(x_train_scaled, columns=columns)
x_val_scaled_df = pd.DataFrame(x_val_scaled, columns=columns)
x = data_mergedtrain.iloc[:, 2:16]
y = data_mergedtrain[['Democratic','Republican','Party']]
```

In [38]:
```
# Predict Party values for all the merged data using the best classifier

# variables selected for classifier
variables = ['Total Population',
        'Percent White, not Hispanic or Latino', 'Percent Black, not His
panic or Latino', 'Percent Hispanic or Latino',
        'Percent Foreign Born', 'Percent Female', 'Percent Age 29 and Un
der', 'Percent Age 65 and Older',
        'Median Household Income', 'Percent Unemployed', 'Percent Less t
han High School Degree',
        'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# standaridize the entire merged data
scaler = StandardScaler()
columns = x_train[variables].columns
scaler.fit(x_train[variables])
x_train_scaled = scaler.transform(x_train[variables])
x_merged_scaled = scaler.transform(x[variables])

# using the best classifier(SVC) to predict Party for the entire merged
 data
classifier = SVC(kernel = 'rbf')
classifier.fit(x_train_scaled, y_train['Party'])

y_pred_party = classifier.predict(x_merged_scaled)
svm_conf_matrix = metrics.confusion_matrix(y['Party'], y_pred_party)
print("\nConfusion matrix:\n", svm_conf_matrix)

# evaluation of the above classifier used to predict Party for the entir
e merged data
accuracy = metrics.accuracy_score(y['Party'], y_pred_party)
error = 1 - accuracy
precision = metrics.precision_score(y['Party'], y_pred_party, average =
None)
recall = metrics.recall_score(y['Party'], y_pred_party, average = None)
F1_score = metrics.f1_score(y['Party'], y_pred_party, average = None)
print("\nAccuracy: ", accuracy)
print("Error: ", error)
print("Precision: ", precision)
print("Recall: ", recall)
print("F1_score:",F1_score)

# new dataframe(X_merged_predicted) with know Party values and predicted
Party values
X_merged_predicted = pd.DataFrame(x)

X_merged_predicted['Party'] = y['Party']
X_merged_predicted['Party_pred'] = y_pred_party
X_merged_predicted.head(5)
```

```
Confusion matrix:
 [[844  26]
 [140 185]]

Accuracy:  0.8610878661087866
Error:  0.13891213389121337
Precision:  [0.85772358 0.87677725]
Recall:  [0.97011494 0.56923077]
F1_score: [0.91046386 0.69029851]
```

Out[38]:

	FIPS	Total Population	Percent White, not Hispanic or Latino	Percent Black, not Hispanic or Latino	Percent Hispanic or Latino	Percent Foreign Born	Percent Female	Percent Age 29 and Under	Percent Age 65 and Older
0	4001	72346	18.571863	0.486551	5.947806	1.719515	50.598513	45.854643	13.322091
1	4003	128177	56.299492	3.714395	34.403208	11.458374	49.069646	37.902276	19.756275
2	4005	138064	54.619597	1.342855	13.711033	4.825298	50.581614	48.946141	10.873943
3	4007	53179	63.222325	0.552850	18.548675	4.249798	50.296170	32.238290	26.397638
4	4009	37529	51.461536	1.811932	32.097844	4.385942	46.313518	46.393456	12.315809

In [43]:
```
# Map of democratic and republican counties using Party from the merged
 set (Project1)

fips1 = data_mergedtrain['FIPS'].tolist()
values = data_mergedtrain['Party'].tolist()
colorscale = ['rgb(244,109,67)', 'rgb(49,54,149)']
fig1 = ff.create_choropleth(
    colorscale=colorscale,
    fips=fips1, values=values,
    title='Counties by Democratic/Republican',
    legend_title='1 = Democratic Counties, 0 = Republican Counties'
)
fig1.layout.template = None
fig1.show(sort=True)
```

In [40]:
```
# Map of democratic and republican counties using Party_pred predicted u
sing the best classifier(SVM)

fips2 = X_merged_predicted['FIPS'].tolist()
pred_values = X_merged_predicted['Party_pred'].tolist()
colorscale = ['rgb(244,109,67)', 'rgb(49,54,149)']
fig2 = ff.create_choropleth(
    colorscale=colorscale,
    fips=fips2, values=pred_values,
    title='Counties by Democratic/Republican',
    legend_title='1 = Democratic Counties, 0 = Republican Counties'
)
fig2.layout.template = None
fig2.show(sort=True)
```

Task 07: (5 pts.) Use your best performing regression and classification models to predict the number of votes cast for the Democratic party in each county, the number of votes cast for the Republican party in each county, and the party (Democratic or Republican) of each county for the test dataset (demographics_test.csv). Save the output in a single CSV file. For the expected format of the output, see sample_output.csv.

In [41]:
```
data_test = pd.read_csv("demographics_test.csv")
data_test.head(3)

x_test = data_test[['Total Population',
                                                                                    'Pe
rcent White, not Hispanic or Latino',
                                                                                     'P
ercent Black, not Hispanic or Latino',
                                                                                     'P
ercent Hispanic or Latino','Percent Foreign Born',
                                                                                     'P
ercent Female', 'Percent Age 29 and Under',
                                                                                     'P
ercent Age 65 and Older', 'Median Household Income',
                                                                                     'P
ercent Unemployed', 'Percent Less than High School Degree',
                                                                                     'P
ercent Less than Bachelor\'s Degree', 'Percent Rural']]

#select variables
# variables = ['Total Population',
#          'Percent Black, not Hispanic or Latino', 'Percent Hispanic or
 Latino',
#          'Percent Foreign Born', 'Percent Female', 'Percent Age 29 and
 Under', 'Percent Age 65 and Older',
#          'Median Household Income', 'Percent Unemployed', 'Percent Less
than High School Degree',
#          'Percent Less than Bachelor\'s Degree', 'Percent Rural']

# SVM Classifier - Select best parameters
# create pipeline with StandardScaler and SVC
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC())
])
# set the possible parameter values for SVC
params = {'svc__kernel':['linear','rbf','poly']}
# use GridSearchCV to standardize the data and build a model with parame
ters that give best score
bestClassification = GridSearchCV(estimator = pipe, param_grid = params,
cv = 10, scoring = 'f1')
bestClassification.fit(x_train, y_train['Party'])
#print(bestClassification.best_params_)
party_predClass = bestClassification.predict(x_test)



x_test_scaled = scaler.transform(x_test)
LASSO_modelDem = linear_model.Lasso(alpha = 1).fit(X=x_train_scaled[:,[0
,1,2,4,6,8,10,11,12]], y=y_train['Democratic'])
LASSO_DemVotes = LASSO_modelDem.predict(x_test_scaled[:,[0,1,2,4,6,8,10,
11,12]])

RIDGE_modelRep = linear_model.Ridge(alpha = 1).fit(X=x_train_scaled[:,[0
,1,2,4,6,8,10,11,12]], y=y_train['Republican'])
RIDGE_RepVotes = RIDGE_modelRep.predict(x_test_scaled[:,[0,1,2,4,6,8,10,
```

```
11,12]])

results  = pd.DataFrame({'State':data_test['State'] ,'County':data_test[
'County'] ,'Democratic': LASSO_DemVotes, 'Republican': RIDGE_RepVotes,'P
arty':party_predClass }, columns=['State','County', 'Democratic', 'Repub
lican', 'Party'])
#print(results.head())

numeric_results= results._get_numeric_data()
numeric_results[numeric_results < 0] = 0
#print(results.head())


import os, errno
try:
    os.remove('classifier_results.csv')
except OSError:
    pass

with open('classifier_results.csv', 'w') as file:
    filewriter = csv.writer(file, delimiter=',',quotechar='|', quoting=c
sv.QUOTE_MINIMAL)
    filewriter.writerow(['State', 'County','Democratic', 'Republican',
'Party'])
    for index, row in results.iterrows():
        filewriter.writerow([row['State'],row['County'], row['Democrati
c'], row['Republican'], row['Party']])
```

In [ ]: