BostonMarathonChallenge_Project

September 2, 2019

[404]:
```
url = 'https://www.xxx'
```

0.0.1 Unsupervised Learning Challenge Build your own NLP model

For this challenge, you will need to choose a corpus of data from nltk or another source that includes categories you can predict and create an analysis pipeline that includes the following steps:

1. Data cleaning / processing / language parsing

2. Create features using two different NLP methods: For example, BoW vs tf-idf.
3. Use the features to fit supervised learning models for each feature set to predict the category outcomes.
4. Assess your models using cross-validation and determine whether one model performed better.
5. Pick one of the models and try to increase accuracy by at least 5 percentage points.

Write up your report in a Jupyter notebook. Be sure to explicitly justify the choices you make throughout, and submit it below.

0.0.2 Questions that need answering:

1. What question are you trying to solve (or prove wrong) ?
   Clustering for the Boston Marathon 2013 dataset.
2. What kind of data do you have? -> describe the source.. __Race results data, de-identified data from the race including:
   1. Age
   2. Gender
   3. Race times at intervals by 5k: 5k, 10k, 15k, 20k, half, 25k, 30k, 35k, 40k, and overall(finishing time).
   4. Division place
   5. Overall finishing place__
3. Do some EDA, plots
4. What's missing from the data and how do you deal with it?
   Nothing is really missing from the dataset.

5. How can you add, change, or remove features to get more out of your data?
   I added a new feature, called sustainer. A sustainer is a runner that maintains their xk mile pace standard deviation at or below 0.02. Basically at whatever speed they run, if they can be in the top 2% lowest standard deviation of runners, then they are a sustainer.

0.0.3 Test Report

Stuff 1 blah blah blah.

Stuff 2 Blah blah blah.

Stuff 3: Blah blah blah again

Key Learning. Blah blah blah again

[405]:
```
# Constants
max_iterations          = 10            # set it to > 0 for determining the␣
 ↪features inportance
random_state            = 57
rows_in_training_set    = 10000
rows_in_test_set        = 200000
test_size               = 0.10
train_size              = 0.90
rfc_test_size           = 50000
rfc_train_size          = 5000
sample_size             = 10
run_CountVectorizer     = False
run_TfidfVectorizer     = True
BegTimeStampNewlines    = 3
EndTimeStampNewlines    = 3
EndTimeStamp            = '\n'*EndTimeStampNewlines+'End'
BegTimeStamp            = 'End'+'\n'*BegTimeStampNewlines
SustainerSTDDEVLimit    = 0.020

num_clusters = 3
target_column = 'overall_scaled'
xcolumnname = 'racestd'
```

[406]:
```
# Controls
flag_to_run_rf = False
flag_to_plot_them = False
flag_to_run_correlation_matrix = False
flag_to_run_features_importance = False
flag_to_run_gradient_boosting  = False
flag_to_run_linear_regression  = False
flag_to_run_logistic_regression = False
flag_to_run_lasso_regression = False
flag_to_run_ridge_regression = False
```

```
flag_to_run_svc = False
flag_to_run_vectorizer_nb = False
flag_to_run_sentiment_analyzer = False
flag_to_run_affinity_propagation = True
flag_to_run_kmeans = True
flag_to_run_mean_shift = True
flag_to_run_spectral_clustering = True
flag_to_run_elbow_plot = True

debug = False
```

[407]:
```
import pandas as pd
import numpy as np
import scipy
import matplotlib.pyplot as plt

%matplotlib inline

import chardet
import datetime
from sklearn import datasets, ensemble, metrics, linear_model
from sklearn.utils import shuffle
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
import time, sys
import seaborn as sns
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.svm import SVC
import statsmodels.api as sm
from sklearn.linear_model import LogisticRegression
from sklearn import linear_model
from sklearn.model_selection import cross_val_predict, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import MinMaxScaler, normalize
from IPython.display import Markdown, display
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.decomposition import PCA
from sklearn import metrics
from sklearn.metrics import pairwise_distances, mean_squared_error
from sklearn.cluster import AffinityPropagation, KMeans, MeanShift,␣
 ↪estimate_bandwidth, SpectralClustering
from scipy.spatial.distance import cdist
```

[408]:
```
# add this to a dictionary
# Constants
max_iterations          = 10            # set it to > 0 for determining the␣
 ↪features inportance
random_state            = 57
test_size               = 0.10
```

```
train_size              = 0.90

begin_string = '\n'*3+'Begin'
end_string = 'End'+'\n'*3

# Regression/Classification control
Regression = False

print("Regression = {}".format(Regression))
```

```
Regression = False
```

[409]:
```
# Display preferences.
%matplotlib inline
pd.options.display.float_format = '{:.3f}'.format
pd.set_option('display.max_rows', 1000)
pd.set_option('display.max_row', 1000)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

[410]:
```
def plot_time_to_complete():
    objects = ('BernoulliNB', 'MultinomialNB', 'Logistic Regression')
    y_pos = np.arange(len(objects))
    performance = [18,17,32]

    plt.bar(y_pos, performance, align='center', alpha=0.5)
    plt.xticks(y_pos, objects)
    plt.ylabel('Time in Minutes')
    plt.title('Yelp Sentiment Analysis Time to Complete')

    plt.show()
```

[411]:
```
def file_stuff():

#     global df
    path = "../../../../"
    filename = "Datafiles/bostonmarathon/results/2013/results.csv"
    print("fullfilename = {}".format(path+filename))
    df = pd.read_csv(path+filename)
    print("There are {} rows in this file.".format(df.shape[0]))
    return df
```

[412]:
```
def dataset_cleanup(df):
    # data Cleanup

#     global X, y

    df['gender_int'] = np.where(df['gender'] == 'M', 1, 0).astype(float)
```

```
    df['bib_int'] = df['bib'].replace(to_replace=r'[W|F]', value='-',␣
↪regex=True).astype(int)
    kcolumns = ['5k', '10k', '20k', '25k', '30k', '35k', '40k', 'half']
    for kcol in kcolumns:
        df[kcol] = np.where(df[kcol] == '-', 0, df[kcol])
        df[kcol] = df[kcol].astype(float)
    df['5kpace']   = df['5k']/5.0
    df['10kpace']  = df['10k']/10.0
    df['20kpace']  = df['20k']/20.0
    df['halfpace'] = df['half']/21.095
    df['25kpace']  = df['25k']/25.0
    df['30kpace']  = df['30k']/30.0
    df['35kpace']  = df['35k']/35.0
    df['40kpace']  = df['40k']/40.0
    df['officialpace'] = df['official']/42.19
    # df['raceavg'] = ,axis=0).mean()
    df['racestd'] =␣
↪df[['5kpace','10kpace','20kpace','halfpace','25kpace','30kpace','35kpace','40kpace','offici
↪std(axis=1)
    df['raceavg'] =␣
↪df[['5kpace','10kpace','20kpace','halfpace','25kpace','30kpace','35kpace','40kpace','offici
↪mean(axis=1)
#     X = df[['age', 'gender_int','genderdiv', 'country',␣
↪'official','racestd','raceavg']]
#     X = pd.get_dummies(X)

    df.drop('ctz', axis=1, inplace=True)
    df.drop('state',axis=1, inplace=True)
    # these are the 2% sustainers.  They can be running at any pace, but they␣
↪are consistent!
    df['sustainer'] = np.where(df['racestd'] <= SustainerSTDDEVLimit, 1, 0).
↪astype(float) # they sustained their pace very well for the race
    scaler = MinMaxScaler()

    scaler.fit(df[['age']])
    df['age_scaled'] = scaler.transform(df[['age']]).astype(float)

    scaler.fit(df[['overall']])
    df['overall_scaled'] = scaler.transform(df[['overall']]).astype(float)

    scaler.fit(df[['pace']])
    df['pace_scaled'] = scaler.transform(df[['pace']])

    scaler.fit(df[['official']])
    df['official_scaled'] = scaler.transform(df[['official']]).astype(float)
```

```
    display('columns are now', df.columns)
#     df = fcn_MinMaxScaler(df, 'age', 'age_scaled')
#     df = fcn_MinMaxScaler(df, 'official', 'official_scaled')
    X = df[['age_scaled', 'sustainer', 'gender_int', 'racestd']]
#     X = pd.get_dummies(X)


    display("df columns cpt 92310: ", df.columns)

    global target_column, xcolumnname, ycolumnname

#     target_column = 'overall_scaled'
#     xcolumnname = 'age_scaled'
    ycolumnname = target_column

    y = df[target_column]
    printFormatted("target, y column is {}".format(target_column))

    if debug == True:
        print_timestamp("X and y variables created")

    printFormatted('we have cleaned up the dataframe.')
    display_column_names('df values', df)
    display_column_names('X values', X)
    return df, X, y
```

[413]:
```
def printFormatted(string):
    newline = '\n'
    display(Markdown(string))
    write_to_logfile(string+newline)
```

[414]:
```
def fcn_MinMaxScaler(dataframe, orig_column, new_column):
    display("cp 1: In fcn_MinMaxScaler.  shape is:", dataframe.shape)
    scaler = MinMaxScaler()
    scaler.fit(dataframe[['{}'.format(orig_column)]])
    dataframe[['{}'.format(new_column)]] = scaler.transform(dataframe['{}'.
 ↪format(orig_column)])
    display("cp 2: In fcn_MinMaxScaler.  shape is:", dataframe.shape)

    return dataframe
```

[415]:
```
def plot_facet():
    g = sns.FacetGrid(data=df, col='stars')
    g.map(plt.hist, 'message_length', bins=50)
```

[416]:
```
def write_to_logfile(message, mdformat=''):
    bufsize = 0
    with open('TestResults.md', 'a+') as the_file:
        the_file.write('{} {}'.format(mdformat, message))
```

[417]:
```
def plot_model_accuracy():
    objects = ('BernoulliNB', 'MultinomialNB', 'Logistic Regression')
    y_pos = np.arange(len(objects))
    performance = [75.81,85.98,91.08]

    plt.bar(y_pos, performance, align='center', alpha=0.5)
    plt.xticks(y_pos, objects)
    plt.ylabel('Accuracy Percent')
    plt.title('Yelp Sentiment Analysis Accuracy')

    plt.show()
```

[418]:
```
def print_timestamp(displaytext):
    import sys
    import datetime
    datetime_now = str(datetime.datetime.now())
    printFormatted("{:19.19}: In: {} {} ".format(datetime_now, sys._getframe(1).
 ↪f_code.co_name, displaytext))
```

[419]:
```
def return_current_datetime():
    datetime_now = str(datetime.datetime.now())
    return datetime_now
```

[420]:
```
# def printFormatted(string):
#     display(Markdown(string))
```

[421]:
```
def data_demographics(dataframe, num_rows):

    display("dataframe.isnull().sum()", dataframe.isnull().sum())

    display("dataframe.columns\n", dataframe.columns)
    display("dataframe.head({})\n".format(num_rows), dataframe.head(num_rows))

    display("dataframe.sample({})\n".format(num_rows), dataframe.
 ↪sample(num_rows))
    display("dataframe.dtypes\n", dataframe.dtypes)
    display("dataframe.describe()\n", dataframe.describe())
```

[422]:
```
def plot_them():
    for column in X_train.columns:
#        plt.hist(X_train[column]*100, bins=40)
        plt.scatter(y_train, X_train[column]*100)
        plt.xlabel(column)
        plt.show()
```

[423]:
```
def rfc_and_feature_importances(rf):     # Here we are using Random Forest␣
 ↪classifier method to determine the top 30 features.

    X_train, X_test, y_train, y_test = train_test_split(X, y,␣
 ↪test_size=test_size, train_size=train_size)
```

```
    ## Fit the model on your training data.
    rf.fit(X_train, y_train)

    ## And score it on your testing data.
    rf.score(X_test, y_test)

    feature_importance = rf.feature_importances_

    # Make importances relative to max importance.
    feature_importance = 100.0 * (feature_importance / feature_importance.max())
    sorted_idx = np.argsort(feature_importance)
    cols=X.columns[sorted_idx].tolist()
    cols=cols[::-1]
    pos = np.arange(sorted_idx.shape[0]) + .5
    plt.subplot(1, 2, 2)
    plt.barh(pos, feature_importance[sorted_idx], align='center')
    plt.yticks(pos, X.columns[sorted_idx])
    plt.xlabel('Relative Importance')
    plt.title('Variable Importance')
    plt.show()
#     print("We are returning these columns {}".format(cols))
    return cols[:30] # return it sorted
```

[424]:
```
def run_features_importance(rf,n):
# Here we will return the feature importances
    all_feature_important_columns = []

    for i in range(1,n):
        print_timestamp('running rfc iteration {} features importance for {}␣
 ↪times'.format(i,n))
        columns2 = rfc_and_feature_importances(rf)
#         columns2.extend('{}'.format(i))
        all_feature_important_columns = all_feature_important_columns + columns2
    #     print("all_feature_import_columns={}".
 ↪format(all_feature_important_columns))

    print("\nBOD:\nall_feature_important_columns = {}\nEOD".
 ↪format(sorted(all_feature_important_columns)))
    for feature in set(all_feature_important_columns):
        print_timestamp("the NOC of feature {} in all_feature_important_columns␣
 ↪is {}".format(feature, all_feature_important_columns.count(feature)))
```

[425]:
```
def run_correlation_matrix():

    print_timestamp('Begin'+'\n'*3)

    # Setup the correlation matrix.
```

```
    corrmat = X.corr()
    print(corrmat)

    # Set up the subplots
    f, ax = plt.subplots(figsize=(12, 9))

    # Let's draw the heatmap using seaborn.
    sns.heatmap(corrmat, vmax=.6, square=True)
    plt.show()

    print_timestamp('\n'*3+'End')
```

[426]:
```
def data_characteristics():

    printFormatted("#### Columns used in the dataset")
    display(df.columns)

    print("\n\n")
    printFormatted("#### Describe of the df dataset")
    display(df.describe())

    print("\n\n")
    printFormatted("#### Sample of 10 from the dataset")
    display(df.sample(sample_size))

    print("\n\n")
    printFormatted("#### Number of nulls in X")
    display(X.isnull().sum())
    print("\n\n\n")
```

[427]:
```
def training_test_set(X, y):
#     global X_train, X_test, y_train, y_test
    # Let's fit it with the RFC training set
    X_train, X_test, y_train, y_test = train_test_split(X, y,␣
 ↪test_size=test_size, train_size=train_size, random_state=0)
    print("train_size = {}, X_train is {}, and y_train is {}".
 ↪format(train_size, len(X_train), len(y_train)))
    print("test_size  = {}, X_test  is {}, and y_test is {}".format(test_size,␣
 ↪len(X_test), len(y_test)))

    return X_train, X_test, y_train, y_test
```

[428]:
```
def run_rf(rf):
    print_timestamp('Begin run_rf part 1')

    ## Fit the model on your training data.
    rf.fit(X_train, y_train)
```

```
    ## Let's score it with the training data set
    train_score = rf.score(X_train, y_train)
    print("Training score = {}".format(train_score))

    ## Let's score it with the test data set
    test_score = rf.score(X_test, y_test)

    print("Test score = {}".format(test_score))
    #Let's run cross validate score with the training data set
#     cross_val_score(rf, X_train, y_train, cv=5)

    print_timestamp('End run_rfr part 1')
```

[429]:
```
def run_BernoulliNB(data, target):

    # Our data is binary / boolean, so we're importing the Bernoulli classifier.

    # Instantiate our model and store it in a new variable.
    bnb = BernoulliNB()

    # Fit our model to the data.
    bnb.fit(data, target)

    # Classify, storing the result in a new variable.
    y_pred = bnb.predict(data)

    # Display our results.
    print("Number of mislabeled points out of a total {} points : {}".format(
        data.shape[0],
        (target != y_pred).sum()
    ))

     ## Let's score it with the test data set
    test_score = bnb.score(data, target)

    print("Test score = {}".format(test_score))
```

[430]:
```
def sentiment_analyzer(path, parameters, classifier, tfidf_parms):
    # path A = the old path
    # path B = the new path, no CountVectorizer at all


# run block of code and catch warnings

    if debug == True:
        print_timestamp(BegTimeStamp+" running with path={}".format(path))

    global vectorized
```

```python
vectorized = True

pipeline_array = []

if path == "A":
    if classifier == 'bnb':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   BernoulliNB(**parameters))
        ]))
    elif classifier == 'svc':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   SVC(kernel = 'linear', **parameters))
        ]))
    elif classifier == 'mlb':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   MultinomialNB(**parameters))
        ]))
    elif classifier == 'logit':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   LogisticRegression(**parameters))
        ]))
    elif classifier == 'rfc':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   ensemble.RandomForestClassifier(**parameters))
        ]))

elif path == "B":
    if classifier == 'bnb':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   BernoulliNB(**parameters))
        ]))
    elif classifier == 'svc':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   SVC(kernel = 'linear', **parameters))
        ]))
    elif classifier == 'mlb':
        pipeline_array.append(Pipeline([
            ('tfidf', TfidfVectorizer(**tfidf_parms)),
            ('clf',   MultinomialNB(**parameters))
        ]))
```

```
        elif classifier == 'logit':
            pipeline_array.append(Pipeline([
                ('tfidf', TfidfVectorizer()),
                ('clf',   LogisticRegression(**parameters))
            ]))
        elif classifier == 'rfc':
            pipeline_array.append(Pipeline([
                ('tfidf', TfidfVectorizer(**tfidf_parms)),
                ('clf',   ensemble.RandomForestClassifier(**parameters))
            ]))

    pipe = pipeline_array[0]

    try:
        vect_name_list = str(pipe.named_steps['vect']).split('(')
        vect_name = "vect = {}, ".format(vect_name_list[0])
    except:
        vect_name = ''

    classifier_name_list=str(pipe.named_steps['clf']).split('(')
    classifier_name=classifier_name_list[0]
    tfidf_name_list = str(pipe.named_steps['tfidf']).split('(')
    if len(tfidf_name_list) > 0:
        tfidf_name = tfidf_name_list[0]
    else:
        tfidf_name = ''

    printFormatted("####  Now running with: {} tfidf={} and clf={}␣
↪{}\nparameters={} \n\n tfidf_parms={}".format( vect_name,
                                                                                ␣
↪                 tfidf_name,
                                                                                ␣
↪                 classifier_name,
                                                                                ␣
↪                 return_current_datetime(),
                                                                                ␣
↪                 parameters,
                                                                                ␣
↪                 tfidf_parms
                                                                                ␣
↪                 ))
    pipe.fit(X_train, y_train)

    y_pred_class  = pipe.predict(X_test)
    y_pred_class2 = pipe.predict(X_train)
```

```
    metrics_test_score =  metrics.accuracy_score(y_test, y_pred_class)
    metrics_train_score = metrics.accuracy_score(y_train, y_pred_class2)

    printFormatted('###  Metrics test accuracy score = {:.2%} with {}'.
↪format(metrics_test_score, classifier_name))
    printFormatted('###  Metrics train accuracy score = {:.2%} with {}'.
↪format(metrics_train_score, classifier_name))

    if debug == True:
        printFormatted("Steps information: {}".format(pipe.steps))
        print_timestamp("Finished running pipeline with:\n{}: ".
↪format(classifier_name))

    return y_test, y_pred_class

    print_timestamp(EndTimeStamp)
```

Let's try predicting with gradient boosting classification

[431]:
```
def run_gradient_boosting():

    print_timestamp('Begin')

    clf = ensemble.GradientBoostingClassifier(**params)

    #Let's run cross validate score with the training data set
    cross_val_score(clf, X_train, y_train, cv=5)

    loss_function = 'deviance' # could be exponential
    depth_value = 8
    params = {'n_estimators': 500,
              'max_depth': 8,
              'loss_function': loss_function,
              'max_leaf_nodes': depth_value, # 8 worked best...
              'min_samples_leaf': depth_value * 3
              ,'random_state' : random_state
             }

    clf.fit(X_train, y_train)

    predict_train = clf.predict(X_train)
    predict_test = clf.predict(X_test)

    print_timestamp('End')
```

[432]:
```
def run_svc():

    print_timestamp('\n'*3+'Begin run_svc')
```

```
    # Let's do a linear Support Vector Classifier
    print_timestamp('Running SVC(kernel=linear')
    svm = SVC(kernel = 'linear')

    # Let's fit the training model
    print_timestamp('Running svm.fit')
    svm.fit(X_train, y_train)

    # Let's score the training set
    print_timestamp('Running svm.score for the training set')
    svm.score(X_train, y_train)

    # Let's score the test set
    print_timestamp('Running svm.fit for the test set')
    svm.score(X_test, y_test)

    print_timestamp('\n'*3+'End run_svc')
```

[433]:
```
def run_logistic_regression():
    print_timestamp('\n'*3+'Begin')

    lr = LogisticRegression(C=1e20, solver='lbfgs', max_iter=1000)

    print_timestamp('Running lr.fit for the training set')
    lr.fit(X_train, y_train)

    print_timestamp('Running lr.fit for the training set')
    print('\nR-squared simple model training set yields:')
    print(lr.score(X_train, y_train))
    print("here comes the test set")
    lrscore = lr.score(X_test, y_test)
    printFormatted("###  Logistic Regression score={:.2%}".format(lrscore))

    print_timestamp('\n'*3+'End')
```

[434]:
```
def run_linear_regression():

    print_timestamp('\n'*3+'Begin')

    regr = linear_model.LinearRegression()

    print_timestamp('Running regr.fit for the training set')
    regr.fit(X_train, y_train)

    print("\nCoeffecients: \n", regr.coef_)
    print("\nIntercept: \n", regr.intercept_)
    print("\nR-squared for training data set:")
```

```
    print(regr.score(X_train, y_train))

    print("\nR-squared for test data set:")
    print(regr.score(X_test, y_test))

    print_timestamp('End run_linear_regression.\n\n')

    print_timestamp('\n'*3+'End')
```

[435]:
```
def run_ridge_regression():
    # Fitting a ridge regression model. Alpha is the regularization
    # parameter (usually called lambda). As alpha gets larger, parameter
    # shrinkage grows more pronounced. Note that by convention, the
    # intercept is not regularized. Since we standardized the data
    # earlier, the intercept should be equal to zero and can be dropped.
    print_timestamp('\n'*3+'Begin')

    ridgeregr = linear_model.Ridge(alpha=10, fit_intercept=False)
    ridgeregr.fit(X_train, y_train)
    print(ridgeregr.score(X_train, y_train))

    print_timestamp('\n'*3+'End')
```

[436]:
```
def run_affinity_propagation(data, target):

    print_timestamp('\n'*3+'starting AffinityPropagation')

    print_timestamp('\n'*3+'Begin')

    ap = AffinityPropagation()
#     ap = AffinityPropagation(damping=0.5,
#                              max_iter=200,
#                              convergence_iter=15,
#                              copy=True,
#                              preference=None,
#                              affinity='euclidean',
#                              verbose=False)

    model = ap.fit(data)
    pred = ap.predict(data)

    Z = merge_predict_and_cluster(data, target, pred) # let's merge the data␣
 ↪dataframe, prediction, and the cluster

    # Pull the number of clusters and cluster assignments for each data point.
    cluster_centers_indices = ap.cluster_centers_indices_
    n_clusters_ = len(cluster_centers_indices)
    labels = ap.labels_
```

```
    print('Estimated number of clusters: {}'.format(n_clusters_))

    labels = model.labels_

    print("from run_affinity_propagation {}".format(metrics.
 ↪silhouette_score(data, labels, metric='euclidean')))

    print_timestamp('\n'*3+'finished with AffinityPropagation')

    return Z, n_clusters_
```

[437]:
```
def run_kmeans(data, target, K):

    print_timestamp('\n'*3+'Begin')
    print("running with number of clusters = {}".format(K))
    km = KMeans(n_clusters=K, random_state=42)

#     pred = KMeans(n_clusters=K, random_state=42).fit_predict(data)
    pred = km.fit_predict(data)
#     Z = pd.DataFrame()
    Z = merge_predict_and_cluster(data, target, pred) # let's merge the data␣
 ↪dataframe, prediction, and the cluster
#     Z = pd.merge(data, pd.DataFrame(pred), left_index=True, right_index=True)
#     display_column_names('first Z values', Z)
#     Z.rename(columns={Z.columns[-1]: 'cluster'}, inplace=True)
#     display_column_names('second Z values', Z)
#     Z = pd.merge(Z, target, left_index=True, right_index=True)
#     display_column_names('third Z values', Z)
#     print("z columns are {}".format(Z.columns))

    if debug == True:
        print("the shape of Kmeans_pred is {}, and the shape of X is {}, and␣
 ↪the shape of Z is {}".format(pred.shape,
                                                                             ␣
 ↪                      data.shape,
                                                                             ␣
 ↪                      Z.shape))
        display(Z.head(100))
        display_column_names('Z below values', Z)

        count = Z.groupby(['cluster']).count()
        display("Z: Count by clusters are this:\n", count)

    return Z

    print_timestamp('\n'*3+'End')
```

[438]:
```python
def merge_predict_and_cluster(dataframe, target, predict):
    Z = pd.merge(dataframe, target, left_index=True, right_index=True)
    Z = pd.merge(Z, pd.DataFrame(predict), left_index=True, right_index=True)
    Z.rename(columns={Z.columns[-1]: 'cluster'}, inplace=True)

    return Z
```

[439]:
```python
def run_spectral_clustering(data, target, K):
    display_dataframe_shape('entering run_spectral_clustering, data has shape␣
↪of:', data)
    display_dataframe_shape('entering run_spectral_clustering, target has shape␣
↪of:', target)
    print_timestamp('\n'*3+'Begin')

#     for clusternum in range(2, K):
    print_timestamp("Running spectral_clustering with {} clusters.".format(K))
    n_clusters=K

    # Declare and fit the model.
    sc = SpectralClustering(n_clusters=K)
    sc.fit(data)

    #Predicted clusters.
    predict=sc.fit_predict(data)

    Z = merge_predict_and_cluster(data, target, predict) # let's merge the data␣
↪dataframe, prediction, and the cluster

    if debug == True:
        display_dataframe_shape('in run_spectral_clustering, Z has shape of:',␣
↪Z)
        display_dataframe_shape('in run_spectral_clustering, target has shape␣
↪of:', target)
        display("the datatypes of Z are", Z.dtypes)

#     plt.scatter(Z['cluster'], Z[target_column], c=Z['cluster'])
#     plt.show()

    labels = sc.labels_
    print("from spectral clustering {}".format(metrics.silhouette_score(data,␣
↪labels, metric='euclidean')))

#     print('Comparing the assigned categories to the ones in the data:')
#     print(pd.crosstab(target,predict))

    print_timestamp('\n'*3+'End')
```

```
    return Z
```

[440]:
```
def do_the_elbow(X):
    printFormatted("## We are plotting the elbow method!")
    # calculate distortion for a range of number of cluster
    distortions = []
    for i in range(1, 11):
        km = KMeans(
            n_clusters=i, init='random',
            n_init=10, max_iter=300,
            tol=1e-04, random_state=0
        )
        km.fit(X)
        distortions.append(km.inertia_)

    # plot
    plt.plot(range(1, 11), distortions, marker='o')
    plt.xlabel('Number of clusters')
    plt.ylabel('Distortion')
    plt.show()
```

[441]:
```
def plot_it_clusters(dataframe, xvalue, yvalue, title):

    if debug == True:
        display_dataframe_shape('entry received in plot_it_clusters', dataframe)
        display(dataframe.dtypes)

    data_demographics(dataframe, 10)

    plt.rcParams['figure.figsize'] = [xvalue, yvalue]
    plt.xlabel(xcolumnname)
    plt.ylabel(ycolumnname)

    df0 = dataframe[dataframe.cluster == 0]
    df1 = dataframe[dataframe.cluster == 1]
    df2 = dataframe[dataframe.cluster == 2]
    df3 = dataframe[dataframe.cluster == 3]
    df4 = dataframe[dataframe.cluster == 4]
    df5 = dataframe[dataframe.cluster == 5]

    plt.scatter(df0[xcolumnname], df0[ycolumnname], color='green')
    plt.scatter(df1[xcolumnname], df1[ycolumnname], color='red')
    plt.scatter(df2[xcolumnname], df2[ycolumnname], color='blue')
    plt.scatter(df3[xcolumnname], df3[ycolumnname], color='black')
    plt.scatter(df4[xcolumnname], df4[ycolumnname], color='magenta')
    plt.scatter(df5[xcolumnname], df5[ycolumnname], color='orange')
    plt.title(title)
    plt.show()
```

```
#     plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:
 ↪,1],color='purple',marker='*',label='centroid')

#     if type == 'KMeans':
#         plt.xlabel('Age')
#         plt.ylabel('Income ($)')
#         plt.legend()
#         plt.scatter(km.cluster_centers[:,0],
#                     km.cluster_centers[:,1],
#                     marker = '*',
#                     label = 'centroid')
```

[442]:
```
def run_mean_shift(data, target):

    print_timestamp('\n'*3+'Begin')

    X_train = data

    # Here we set the bandwidth. This function automatically derives a␣
 ↪bandwidth
    # number based on an inspection of the distances among points in the data.
    bandwidth = estimate_bandwidth(X_train, quantile=0.2, n_samples=500)

    # Declare and fit the model.
    ms = MeanShift(bandwidth=bandwidth, bin_seeding=True)
    if debug == True:
        display_dataframe_shape('this is the shape of data coming into␣
 ↪run_mean_shift', data)
    ms.fit(data)

    if debug == True:
        display_dataframe_shape('this is the shape of target coming into␣
 ↪run_mean_shift', target)
    pred = ms.predict(data)
    if debug == True:
        display_dataframe_shape('this is the shape of pred after predict in␣
 ↪run_mean_shift', data)

    Z = merge_predict_and_cluster(data, target, pred) # let's merge the data␣
 ↪dataframe, prediction, and the cluster

    # Extract cluster assignments for each data point.
    labels = ms.labels_

    print("from mean shift {}".format(metrics.silhouette_score(data, labels,␣
 ↪metric='euclidean')))
```

```
    # Coordinates of the cluster centers.
    cluster_centers = ms.cluster_centers_

    # Count our clusters.
    n_clusters_ = len(np.unique(labels))

    print("Number of estimated clusters: {}".format(n_clusters_))

    print_timestamp('\n'*3+'End')

    return Z, n_clusters_
```

[443]:
```
def vectorizer_nb(type_of_vectorizer):

    print_timestamp(BegTimeStamp)

    # 1. import and instantiate CountVectorizer (with the default parameters)

    # 2. instantiate CountVectorizer (vectorizer)

#     X = df.message
#     y = df.sentiment_label

    # split X and y into training and testing sets
    # by default, it splits 75% training and 25% test
    # random_state=1 for reproducibility

#     X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)

    # 3. fit & transform
    if type_of_vectorizer == 'Count':
        print("We are running with CountVectorizer")
        vectorizer = CountVectorizer()
        vectorizer.fit(X_train)
        vectorizer_method = 'CountVectorizer'
    elif type_of_vectorizer == 'Tfidf':
        print("We are running with TfidfVectorizer")
        vectorizer = TfidfVectorizer()
        vectorizer.fit_transform(X_train)
        vectorizer_method = 'TfidfVectorizer'

    # 4. transform training data
    X_train_dtm = vectorizer.transform(X_train)

    # equivalently: combine fit and transform into a single step
    # this is faster and what most people would do
```

```
    X_train_dtm = vectorizer.fit_transform(X_train)

    # 4. transform testing data (using fitted vocabulary) into a document-term␣
↪matrix
    X_test_dtm = vectorizer.transform(X_test)

    # 1. import

    # 2. instantiate a Multinomial Naive Bayes model
    nb = MultinomialNB()

    # 3. train the model
    # using X_train_dtm (timing it with an IPython "magic command")

    nb.fit(X_train_dtm, y_train)


    # 4. make class predictions for X_test_dtm
    y_pred_class = nb.predict(X_test_dtm)

    # calculate accuracy of class predictions

    met_test_score = metrics.accuracy_score(y_test, y_pred_class)
    printFormatted('###  With {} vectorizer, the metrics accuracy score = {:.
↪2%}'.format(vectorizer_method,
                                                                                ␣
↪          met_test_score))

    print_timestamp(EndTimeStamp)
```

[444]:
```
def display_column_names(label, df):
    display("Label: {}: Column names are:".format(label), df.columns)
```

[445]:
```
def display_dataframe_shape(label, df):
    display("Label: {}: Dataframe shape is:".format(label), df.shape)
```

[446]:
```
def run_it(X_train, X_test, y_train, y_test, y):

#     file_stuff()

#     data_cleanup()

    print_timestamp('\n'*3+'Begin')

    if Regression == True:
        print_timestamp("We are running with a Regression model")
    elif Regression == False:
        print_timestamp("We are running with a Classifier model")
```

```
    else:
        print_timestamp("We have failed to set the Regression variable")
        sys.exit(main())


if flag_to_plot_them == True:
    plot_them()

if flag_to_run_features_importance == True:

    number_of_features_to_consider = 50
    params = {'n_estimators': 100}

    if Regression == True:
        print_timestamp('We are running RandomForestRegressor')
        rf = ensemble.RandomForestRegressor(**params)

    else:
        print_timestamp('We are running RandomForestClassifier')
        rf = ensemble.RandomForestClassifier(**params)

    run_features_importance(rf, number_of_features_to_consider)

if flag_to_run_correlation_matrix == True:
    run_correlation_matrix()

if flag_to_run_rf == True:
    #     params = {}
    params = {'n_estimators': 100}

    if Regression == True:
        rf = ensemble.RandomForestRegressor(**params)
        print_timestamp('We are running RandomForestRegressor')
    else:
        rf = ensemble.RandomForestClassifier(**params)
        print_timestamp('We are running RandomForestClassifier')

    run_rf(rf)

if flag_to_run_gradient_boosting  == True:
    run_gradient_boosting()

if flag_to_run_linear_regression  == True:
    run_linear_regression()

if flag_to_run_logistic_regression == True:
    run_logistic_regression()
```

```python
    if flag_to_run_svc == True:
        run_svc()

    if flag_to_run_ridge_regression == True:
        run_ridge_regression()

    if flag_to_run_vectorizer_nb == True:
        for vectorizer_iterator in ['Count', 'Tfidf']:
            vectorizer_nb(vectorizer_iterator)

    if flag_to_run_kmeans == True:
        method = KMeans(
                  n_clusters=num_clusters
#                  ,random_state=42
#                  ,init='random'
#                  ,n_init=10
#                  ,max_iter=300
#                  ,tol=1e-04
        )
        df1 = run_kmeans(X_train, y_train, num_clusters)
        plot_it_clusters(df1, xvalue=16, yvalue=16, title="KMeans with number␣
↪of clusters = {}".format(num_clusters))
        display("next plot please")

    if flag_to_run_affinity_propagation == True:
        display_column_names('columns of X_train going into␣
↪affinity_propagation: ', X_train)
        df2, ap_num_clusters = run_affinity_propagation(X_train, y_train)
        plot_it_clusters(df2, xvalue=16, yvalue=16, title="Affinity Propagation␣
↪with number of clusters = {}".format(ap_num_clusters))

    if flag_to_run_mean_shift == True:
        df3, mean_shift_num_clusters = run_mean_shift(X_train, y_train)
        plot_it_clusters(df3, xvalue=16, yvalue=16, title="Mean Shift with␣
↪number of clusters = {}".format(mean_shift_num_clusters))

    if flag_to_run_spectral_clustering == True:
        df4 = run_spectral_clustering(X_train, y_train, K=num_clusters)
        plot_it_clusters(df4, xvalue=16, yvalue=16,title="Spectral clustering␣
↪with number of clusters = {}".format(num_clusters) )

    print_timestamp('End'+'\n'*3)
```

[447]:

```python
def main(entry_point):

    if entry_point == 0:
```

```
        print_timestamp("Starting main()")
        df = file_stuff()
        data_demographics(df, 5)
        display_column_names('post data_demographics of df', df)
        df, X, y = dataset_cleanup(df)
        display_column_names('post dataset_cleanup on X', X)
        data_demographics(df, 5)
        display_column_names('post data_demographics on X #2', X)
#         make_X_and_Y()
        X_train, X_test, y_train, y_test = training_test_set(X, y)
        display_column_names('after training_test_set: columns of X_train going␣
 ↪into affinity_propagation: ', X_train)
#         data_characteristics()
#         plot_time_to_complete()
#         plot_model_accuracy()
#         plot_facet()

    if flag_to_run_elbow_plot == True:    do_the_elbow(X)
    run_it(X_train, X_test, y_train, y_test, y)

    print_timestamp("Ending main()")
```

[448]:
```
main(0)
```

2019-07-25 23:22:55: In: main Starting main()

```
fullfilename = ../../../../Datafiles/bostonmarathon/results/2013/results.csv
There are 16164 rows in this file.

'dataframe.isnull().sum()'


25k              0
age              0
name             0
division         0
10k              0
gender           0
half             0
official         0
bib              0
ctz          15407
country          0
overall          0
pace             0
state         1463
30k              0
5k               0
genderdiv        0
```

```
20k              0
35k              0
city             1
40k              0
dtype: int64
```

```
'dataframe.columns\n'
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'ctz', 'co
```

```
'dataframe.head(5)\n'
```

```
     25k  age               name  division    10k gender   half  official bib  ctz country  ove
0  49.87   28   Cassidy, Josh R.         9  18.18      M  40.93    90.900  W1  NaN     CAN
1  77.27   30      Korir, Wesley         5  30.90      M  64.90   132.500   1  NaN     KEN
2  77.23   23     Desisa, Lelisa         1  30.90      M  64.92   130.370   2  NaN     ETH
3  50.50   32  Fearnley, Kurt H.         5  18.73      M  42.00    88.430  W2  NaN     AUS
4  48.75   39     Hokinoue, Kota         3  18.18      M  40.57    87.220  W3  NaN     JPN
```

```
'dataframe.sample(5)\n'
```

```
         25k  age                    name  division    10k gender    half  official    bib  ctz
7162  121.72   34   Anderson, Rebecca J.      3348  47.58      F  101.25   235.550   8676  NaN
133    85.67   27       Madut, Thomas G.        53  33.60      M   71.92   149.000    150  NaN
5523  109.72   55         Anderson, Nate       102  44.83      M   92.75   197.420   6697  NaN
9782  122.00   38  St. Clair, Suzanne W.      2051  47.75      F  102.27   216.170  11870  NaN
7437  121.45   56      Walls, Richard S.       557  47.68      M  102.15   223.350   9012  NaN
```

```
'dataframe.dtypes\n'
```

```
25k           object
age            int64
name          object
division       int64
10k           object
gender        object
half          object
official     float64
bib           object
ctz           object
country       object
```

```
overall        int64
pace         float64
state         object
30k           object
5k            object
genderdiv      int64
20k           object
35k           object
city          object
40k           object
dtype: object
```

```
'dataframe.describe()\n'
```

```
            age  division  official   overall      pace  genderdiv
count 16164.000 16164.000 16164.000 16164.000 16164.000  16164.000
mean     41.638  1100.967   208.159  8429.373     7.947   4351.685
std      10.351   942.115    23.744  5052.024     0.906   2772.398
min      18.000     1.000    85.530     1.000     3.270      1.000
25%      34.000   363.000   191.727  4061.750     7.320   2032.750
50%      42.000   842.000   209.225  8247.500     7.980   4113.500
75%      49.000  1560.000   225.230 12662.250     8.600   6316.000
max      80.000  3834.000   284.230 17598.000    10.850  10648.000
```

```
'Label: post data_demographics of df: Column names are:'
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'ctz', 'co
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:334:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by MinMaxScaler.
  return self.partial_fit(X, y)
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:334:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by MinMaxScaler.
  return self.partial_fit(X, y)
```

```
'columns are now'
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'country'
```

```
'df columns cpt 92310: '
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'country'
```

target, y column is overall_scaled
we have cleaned up the dataframe.

```
'Label: df values: Column names are:'
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'country'
```

```
'Label: X values: Column names are:'
```

```
Index(['age_scaled', 'sustainer', 'gender_int', 'racestd'], dtype='object')
```

```
'Label: post dataset_cleanup on X: Column names are:'
```

```
Index(['age_scaled', 'sustainer', 'gender_int', 'racestd'], dtype='object')
```

```
'dataframe.isnull().sum()'
```

```
25k           0
age           0
name          0
division      0
10k           0
gender        0
half          0
official      0
bib           0
country       0
overall       0
pace          0
30k           0
5k            0
genderdiv     0
20k           0
35k           0
city          1
40k           0
gender_int    0
bib_int       0
5kpace        0
```

```
10kpace          0
20kpace          0
halfpace         0
25kpace          0
30kpace          0
35kpace          0
40kpace          0
officialpace     0
racestd          0
raceavg          0
sustainer        0
age_scaled       0
overall_scaled   0
pace_scaled      0
official_scaled  0
dtype: int64
```

```
'dataframe.columns\n'
```

```
Index(['25k', 'age', 'name', 'division', '10k', 'gender', 'half', 'official', 'bib', 'country'
```

```
'dataframe.head(5)\n'
```

```
     25k  age               name  division    10k gender   half  official bib country  overall
0 49.870   28   Cassidy, Josh R.         9 18.180      M 40.930    90.900  W1     CAN        9
1 77.270   30      Korir, Wesley         5 30.900      M 64.900   132.500   1     KEN        5
2 77.230   23     Desisa, Lelisa         1 30.900      M 64.920   130.370   2     ETH        1
3 50.500   32  Fearnley, Kurt H.         5 18.730      M 42.000    88.430  W2     AUS        5
4 48.750   39     Hokinoue, Kota         3 18.180      M 40.570    87.220  W3     JPN        3
```

```
'dataframe.sample(5)\n'
```

```
          25k  age                    name  division    10k gender    half  official   bib cou
15742 133.000   50         Moses, Julie K.       401 51.700      F 111.280   239.480 19713
179    92.480   22  O'Connell, Thomas P II      2343 35.930      M  76.880   192.580   205
11432 123.830   26     Venturelli, Gina M.      2226 49.620      F 104.120   218.080 13919
16157 141.080   61             Cortes, Dora        25 57.820      F 118.970   237.480 20834
895    98.570   50        Hrynowski, E. J.        12 39.350      M  83.220   167.870  1119
```

```
'dataframe.dtypes\n'
```

```
25k                float64
age                  int64
name                object
division             int64
10k                float64
gender              object
half               float64
official           float64
bib                 object
country             object
overall              int64
pace               float64
30k                float64
5k                 float64
genderdiv            int64
20k                float64
35k                float64
city                object
40k                float64
gender_int         float64
bib_int              int64
5kpace             float64
10kpace            float64
20kpace            float64
halfpace           float64
25kpace            float64
30kpace            float64
35kpace            float64
40kpace            float64
officialpace       float64
racestd            float64
raceavg            float64
sustainer          float64
age_scaled         float64
overall_scaled     float64
pace_scaled        float64
official_scaled    float64
dtype: object
```

```
'dataframe.describe()\n'
```

```
            25k       age  division       10k      half  official   overall      pace       30k
count 16164.000 16164.000 16164.000 16164.000 16164.000 16164.000 16164.000 16164.000 16164.000
mean    118.036    41.638  1100.967    46.655    99.133   208.159  8429.373     7.947   143.425
std      13.423    10.351   942.115     5.254    10.965    23.744  5052.024     0.906    16.345
min       0.000    18.000     1.000     0.000     0.000    85.530     1.000     3.270     0.000
```

```
25%      108.900    34.000   363.000    43.200    91.530    191.727  4061.750     7.320    132.17
50%      119.150    42.000   842.000    47.170   100.080    209.225  8247.500     7.980    144.70
75%      127.320    49.000  1560.000    50.280   106.850    225.230 12662.250     8.600    154.78
max      163.620    80.000  3834.000    66.680   138.670    284.230 17598.000    10.850    195.87
```

```
'Label: post data_demographics on X #2: Column names are:'
```

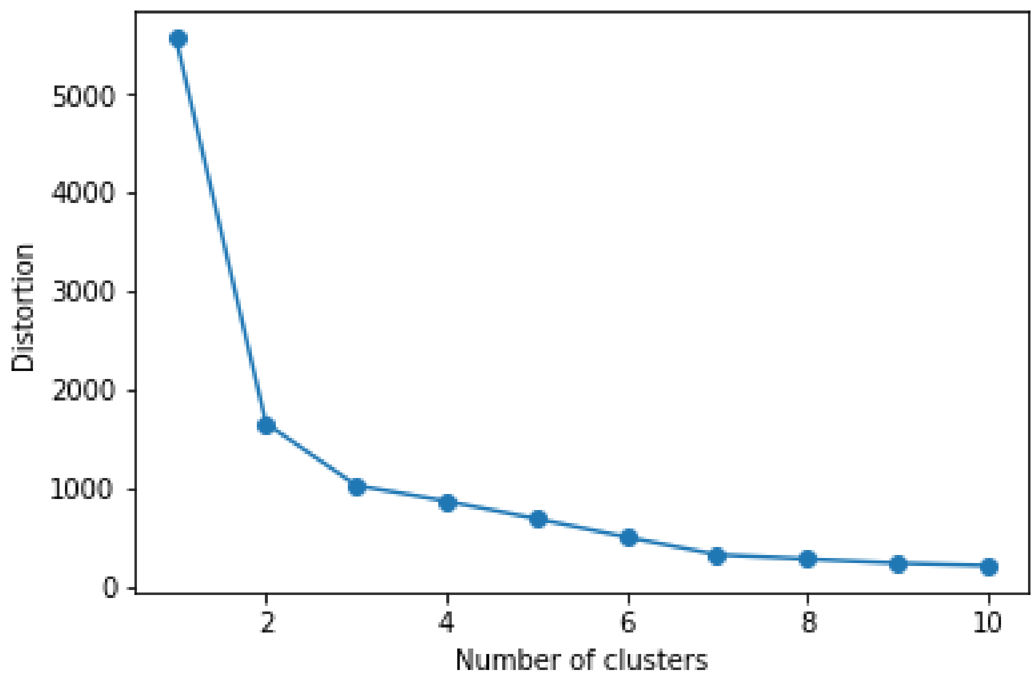
```
Index(['age_scaled', 'sustainer', 'gender_int', 'racestd'], dtype='object')
```

```
train_size = 0.9, X_train is 14547, and y_train is 14547
test_size  = 0.1, X_test  is 1617, and y_test is 1617
```

```
'Label: after training_test_set: columns of X_train going into affinity_propagation: : Column n
```

```
Index(['age_scaled', 'sustainer', 'gender_int', 'racestd'], dtype='object')
```

0.1 We are plotting the elbow method!

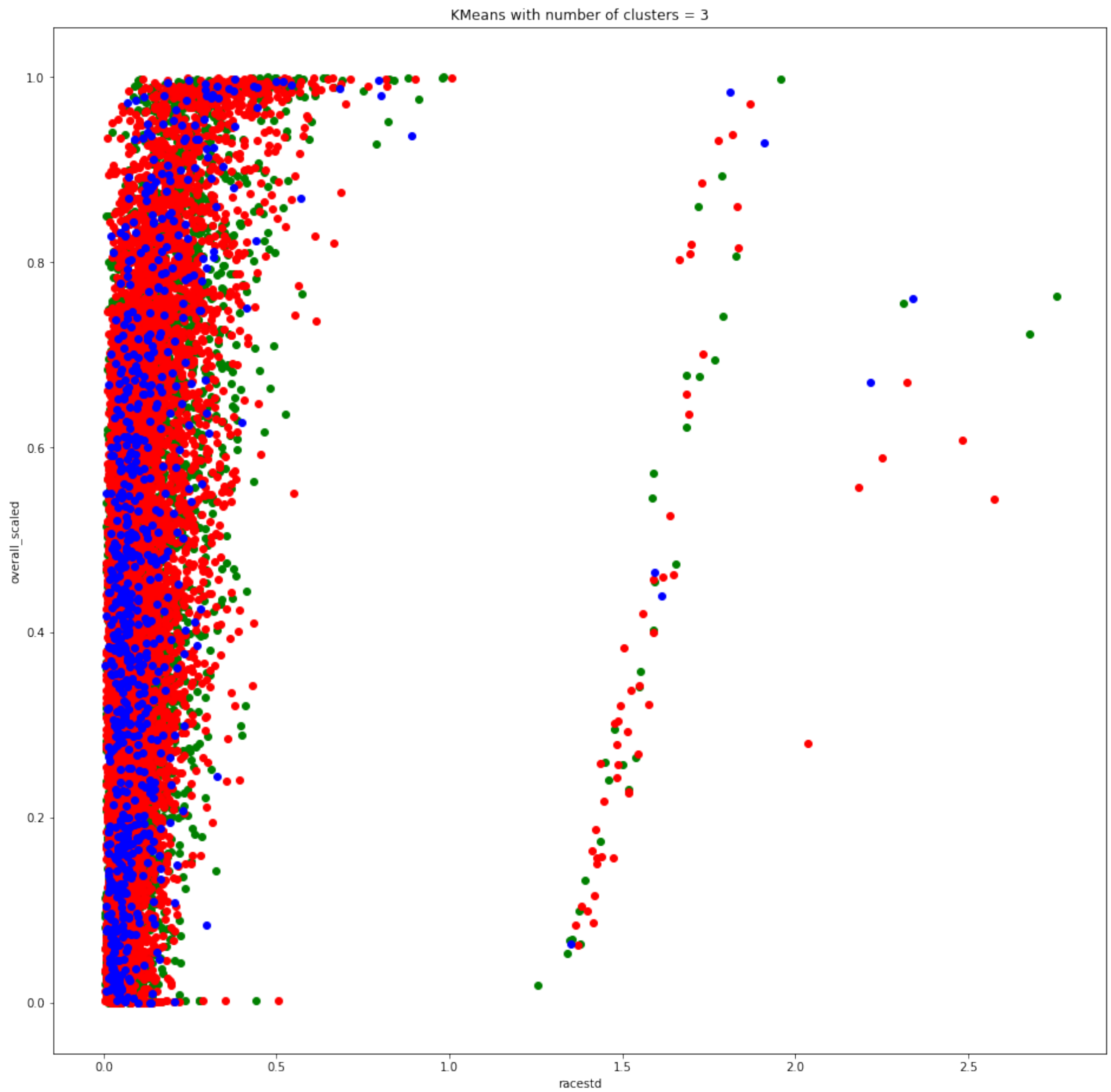


2019-07-25 23:22:57: In: run_it
Begin
2019-07-25 23:22:57: In: run_it We are running with a Classifier model
2019-07-25 23:22:57: In: run_kmeans
Begin

```
running with number of clusters = 3

'dataframe.isnull().sum()'


age_scaled        0
sustainer         0
gender_int        0
racestd           0
overall_scaled    0
cluster           0
dtype: int64


'dataframe.columns\n'


Index(['age_scaled', 'sustainer', 'gender_int', 'racestd', 'overall_scaled', 'cluster'], dtype=


'dataframe.head(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
6260        0.565      0.000       1.000    0.129           0.458        1
10551       0.613      0.000       1.000    0.049           0.557        0
2327        0.097      0.000       1.000    0.309           0.656        0
13087       0.177      0.000       1.000    0.126           0.937        1
8747        0.435      0.000       1.000    0.222           0.945        0
4313        0.500      0.000       1.000    0.028           0.181        0
5463        0.323      0.000       1.000    0.230           0.562        0
10232       0.468      0.000       0.000    0.119           0.585        0
7808        0.452      0.000       1.000    0.064           0.248        1
6497        0.371      0.000       1.000    0.126           0.705        1


'dataframe.sample(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
3366        0.194      1.000       1.000    0.014           0.113        0
12036       0.677      0.000       1.000    0.075           0.570        1
6540        0.355      0.000       1.000    0.151           0.348        2
7452        0.452      0.000       1.000    0.101           0.450        2
2238        0.274      0.000       1.000    0.113           0.151        1
2635        0.226      1.000       1.000    0.012           0.071        1
2972        0.484      0.000       1.000    0.138           0.602        0
14544       0.484      0.000       0.000    0.102           0.560        1
2719        0.419      0.000       1.000    0.124           0.243        0
909         0.145      0.000       1.000    0.211           0.135        1
```

```
'dataframe.dtypes\n'


age_scaled        float64
sustainer         float64
gender_int        float64
racestd           float64
overall_scaled    float64
cluster             int32
dtype: object


'dataframe.describe()\n'
```

	age_scaled	sustainer	gender_int	racestd	overall_scaled	cluster
count	13107.000	13107.000	13107.000	13107.000	13107.000	13107.000
mean	0.364	0.057	0.645	0.123	0.439	0.671
std	0.162	0.232	0.478	0.165	0.273	0.573
min	0.000	0.000	0.000	0.003	0.000	0.000
25%	0.242	0.000	0.000	0.045	0.208	0.000
50%	0.371	0.000	1.000	0.083	0.419	1.000
75%	0.484	0.000	1.000	0.149	0.648	1.000
max	0.919	1.000	1.000	2.756	1.000	2.000




```
'next plot please'

'Label: columns of X_train going into affinity_propagation: : Column names are:'

Index(['age_scaled', 'sustainer', 'gender_int', 'racestd'], dtype='object')
```

2019-07-25 23:22:58: In: run_affinity_propagation
starting AffinityPropagation
2019-07-25 23:22:58: In: run_affinity_propagation
Begin

```
Estimated number of clusters: 7625
from run_affinity_propagation 0.11268298691068244
```

2019-07-25 23:35:29: In: run_affinity_propagation
finished with AffinityPropagation

```
'dataframe.isnull().sum()'


age_scaled        0
sustainer         0
gender_int        0
racestd           0
overall_scaled    0
cluster           0
dtype: int64


'dataframe.columns\n'


Index(['age_scaled', 'sustainer', 'gender_int', 'racestd', 'overall_scaled', 'cluster'], dtype=


'dataframe.head(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
6260        0.565      0.000       1.000    0.129           0.458     5421
10551       0.613      0.000       1.000    0.049           0.557     5601
2327        0.097      0.000       1.000    0.309           0.656     1242
13087       0.177      0.000       1.000    0.126           0.937     6884
8747        0.435      0.000       1.000    0.222           0.945     4624
4313        0.500      0.000       1.000    0.028           0.181     2285
5463        0.323      0.000       1.000    0.230           0.562     2921
10232       0.468      0.000       0.000    0.119           0.585     5433
7808        0.452      0.000       1.000    0.064           0.248     4138
6497        0.371      0.000       1.000    0.126           0.705     1431


'dataframe.sample(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
13848       0.290      0.000       0.000    0.033           0.537     7267
7118        0.645      0.000       1.000    0.239           0.492      187
6082        0.419      0.000       1.000    0.074           0.364     3233
14123       0.597      0.000       1.000    0.171           0.754     7409
7073        0.516      0.000       1.000    0.058           0.331     4977
```

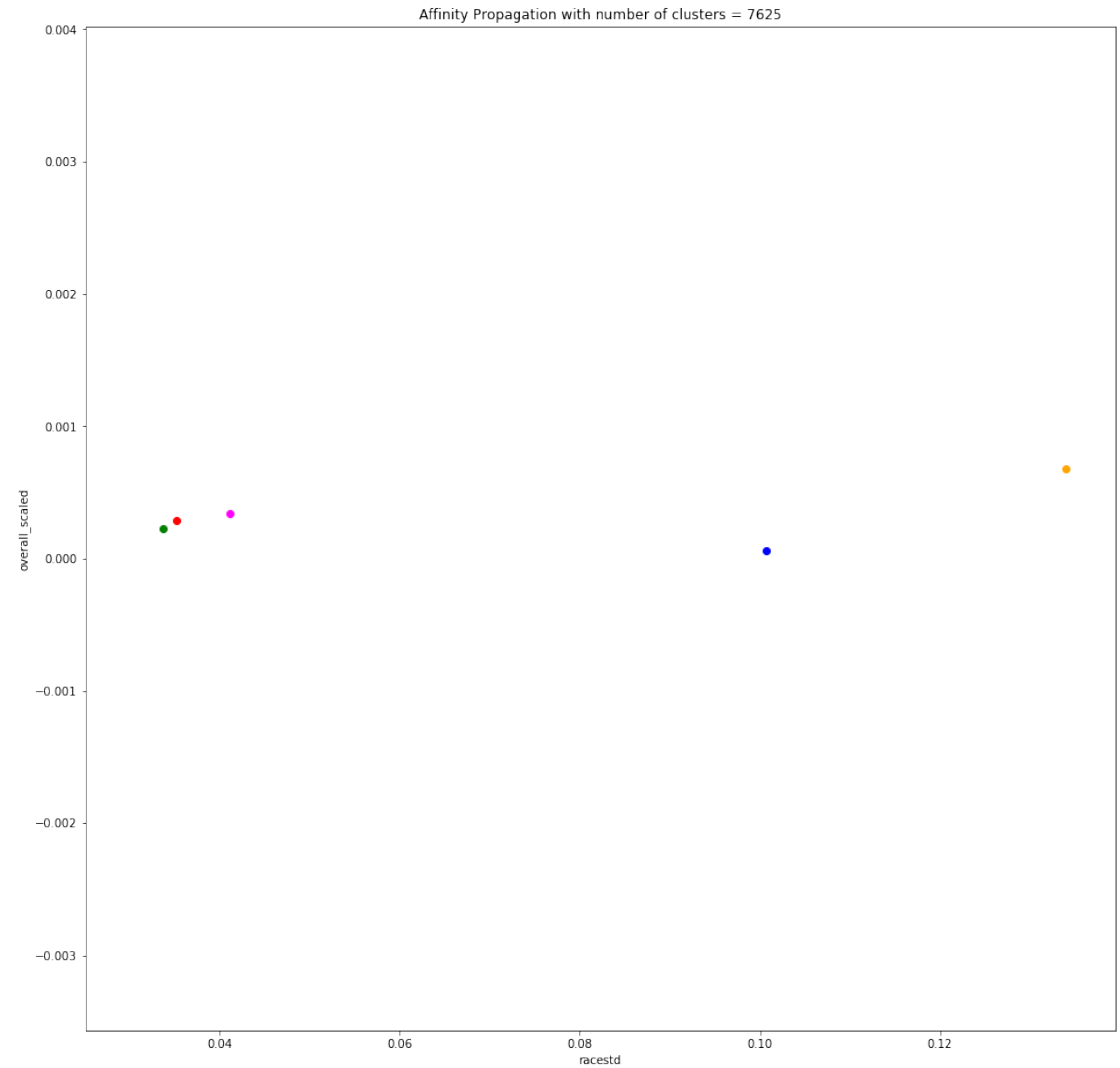
```
9789         0.355      0.000        0.000    0.116             0.533     4734
7421         0.065      0.000        1.000    0.046             0.378     3949
3871         0.210      0.000        1.000    0.063             0.175     2055
770          0.129      0.000        1.000    0.039             0.015     3757
1299         0.242      1.000        1.000    0.011             0.076     5922
```

```
'dataframe.dtypes\n'
```

```
age_scaled        float64
sustainer         float64
gender_int        float64
racestd           float64
overall_scaled    float64
cluster             int64
dtype: object
```

```
'dataframe.describe()\n'
```

```
       age_scaled  sustainer  gender_int   racestd  overall_scaled   cluster
count   13107.000  13107.000   13107.000 13107.000       13107.000 13107.000
mean        0.364      0.057       0.645     0.123           0.439  3605.407
std         0.162      0.232       0.478     0.165           0.273  2171.660
min         0.000      0.000       0.000     0.003           0.000     0.000
25%         0.242      0.000       0.000     0.045           0.208  1698.500
50%         0.371      0.000       1.000     0.083           0.419  3732.000
75%         0.484      0.000       1.000     0.149           0.648  5296.500
max         0.919      1.000       1.000     2.756           1.000  7624.000
```



2019-07-25 23:35:30: In: run_mean_shift
Begin

```
from mean shift 0.7359724125900627
Number of estimated clusters: 11
```

2019-07-25 23:35:33: In: run_mean_shift
End

```
'dataframe.isnull().sum()'


age_scaled        0
sustainer         0
gender_int        0
racestd           0
```

```
overall_scaled    0
cluster           0
dtype: int64
```

```
'dataframe.columns\n'
```

```
Index(['age_scaled', 'sustainer', 'gender_int', 'racestd', 'overall_scaled', 'cluster'], dtype=
```

```
'dataframe.head(10)\n'
```

```
       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
6260        0.565      0.000       1.000    0.129           0.458        0
10551       0.613      0.000       1.000    0.049           0.557        1
2327        0.097      0.000       1.000    0.309           0.656        1
13087       0.177      0.000       1.000    0.126           0.937        0
8747        0.435      0.000       1.000    0.222           0.945        1
4313        0.500      0.000       1.000    0.028           0.181        1
5463        0.323      0.000       1.000    0.230           0.562        1
10232       0.468      0.000       0.000    0.119           0.585        1
7808        0.452      0.000       1.000    0.064           0.248        0
6497        0.371      0.000       1.000    0.126           0.705        0
```

```
'dataframe.sample(10)\n'
```

```
       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
12243       0.210      0.000       0.000    0.162           0.720        0
9601        0.629      0.000       1.000    0.052           0.388        2
1328        0.419      0.000       1.000    0.031           0.063        1
13866       0.468      0.000       0.000    0.082           0.654        4
8247        0.548      0.000       1.000    0.025           0.271        1
7378        0.516      0.000       1.000    0.044           0.309        1
7635        0.516      0.000       1.000    0.100           0.407        0
12871       0.097      0.000       0.000    0.056           0.570        0
99          0.161      0.000       1.000    0.070           0.002        0
4305        0.306      0.000       1.000    0.043           0.250        0
```

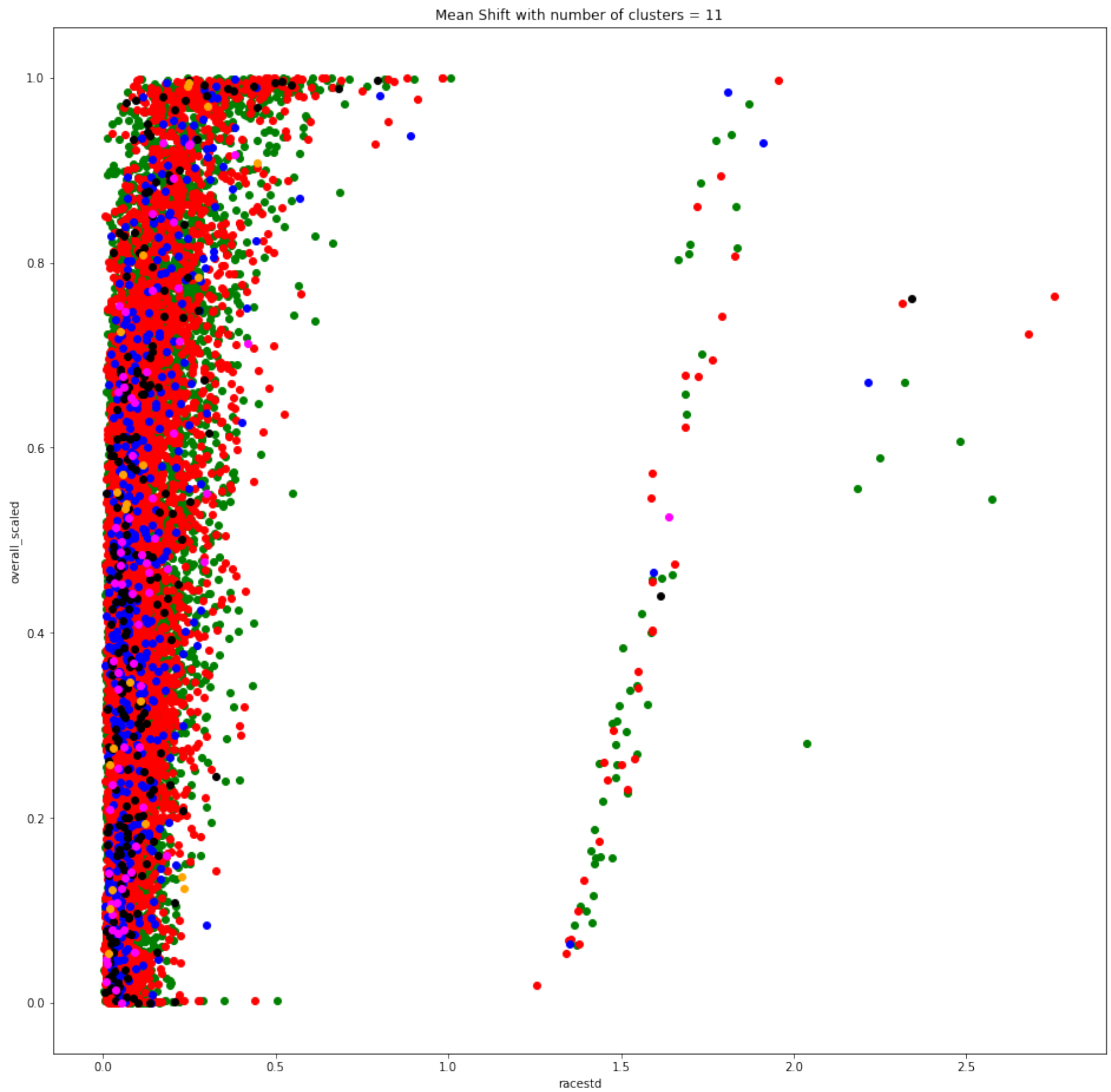
```
'dataframe.dtypes\n'
```

```
age_scaled        float64
sustainer         float64
gender_int        float64
```

```
racestd           float64
overall_scaled    float64
cluster             int64
dtype: object
```

```
'dataframe.describe()\n'
```

	age_scaled	sustainer	gender_int	racestd	overall_scaled	cluster
count	13107.000	13107.000	13107.000	13107.000	13107.000	13107.000
mean	0.364	0.057	0.645	0.123	0.439	0.547
std	0.162	0.232	0.478	0.165	0.273	0.782
min	0.000	0.000	0.000	0.003	0.000	0.000
25%	0.242	0.000	0.000	0.045	0.208	0.000
50%	0.371	0.000	1.000	0.083	0.419	0.000
75%	0.484	0.000	1.000	0.149	0.648	1.000
max	0.919	1.000	1.000	2.756	1.000	10.000




```
'Label: entering run_spectral_clustering, data has shape of:: Dataframe shape is:'

(14547, 4)

'Label: entering run_spectral_clustering, target has shape of:: Dataframe shape is:'

(14547,)
```

2019-07-25 23:35:34: In: run_spectral_clustering
Begin
2019-07-25 23:35:34: In: run_spectral_clustering Running spectral_clustering with 3 clusters.

```
from spectral clustering 0.7531897945637207
```

2019-07-25 23:37:02: In: run_spectral_clustering
End

```
'dataframe.isnull().sum()'


age_scaled        0
sustainer         0
gender_int        0
racestd           0
overall_scaled    0
cluster           0
dtype: int64


'dataframe.columns\n'


Index(['age_scaled', 'sustainer', 'gender_int', 'racestd', 'overall_scaled', 'cluster'], dtype=


'dataframe.head(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
6260        0.565      0.000       1.000    0.129           0.458        0
10551       0.613      0.000       1.000    0.049           0.557        2
2327        0.097      0.000       1.000    0.309           0.656        2
13087       0.177      0.000       1.000    0.126           0.937        0
8747        0.435      0.000       1.000    0.222           0.945        2
4313        0.500      0.000       1.000    0.028           0.181        2
5463        0.323      0.000       1.000    0.230           0.562        2
10232       0.468      0.000       0.000    0.119           0.585        2
7808        0.452      0.000       1.000    0.064           0.248        0
6497        0.371      0.000       1.000    0.126           0.705        0


'dataframe.sample(10)\n'


       age_scaled  sustainer  gender_int  racestd  overall_scaled  cluster
4175        0.597      0.000       1.000    0.204           0.523        2
4671        0.290      0.000       1.000    0.087           0.208        0
14179       0.419      0.000       0.000    0.042           0.678        2
8402        0.484      0.000       0.000    0.392           0.918        0
14158       0.613      0.000       1.000    0.249           0.995        2
8751        0.500      1.000       1.000    0.017           0.208        0
```

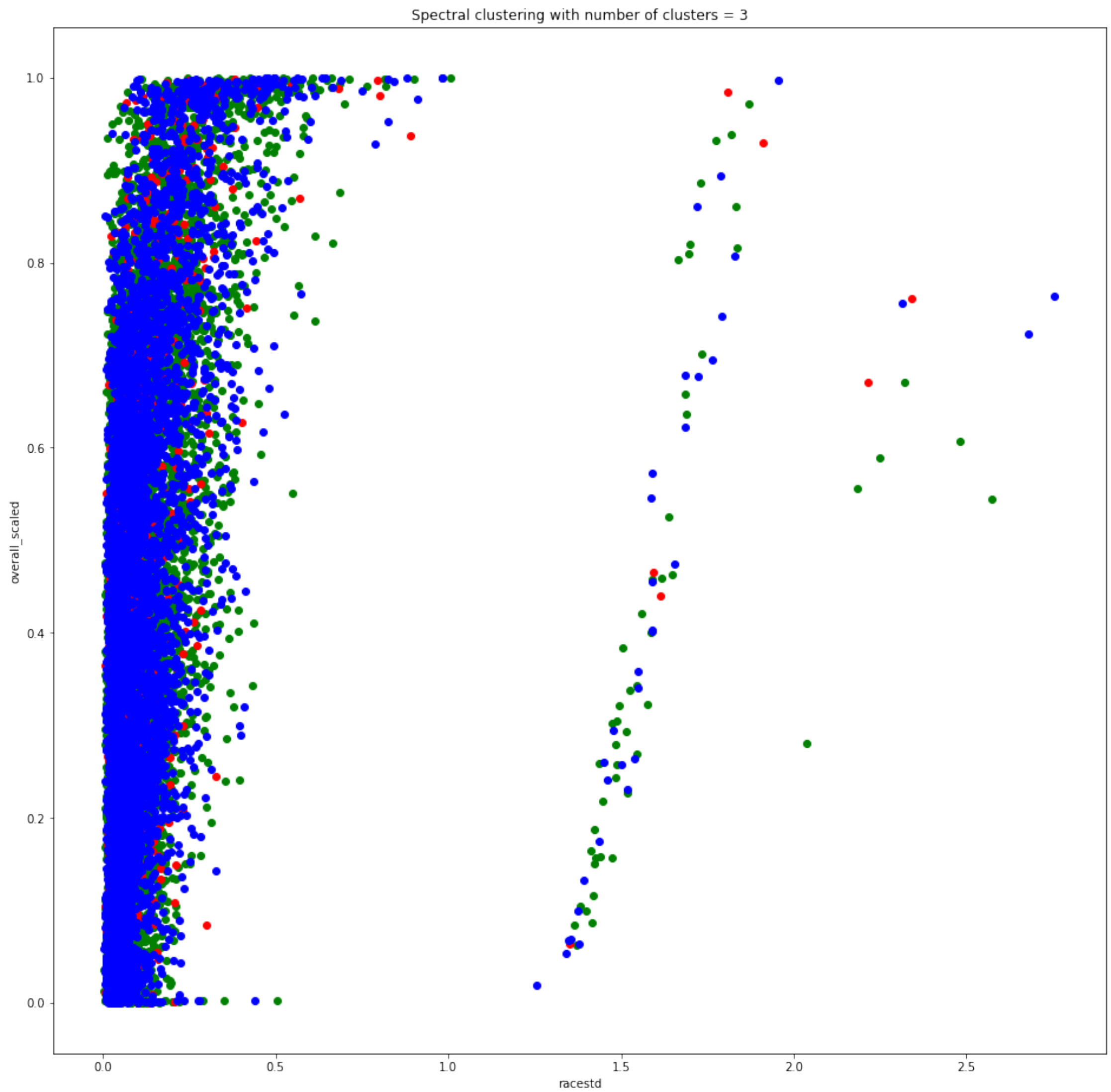
```
1938         0.468       0.000        1.000    0.024             0.206         2
11113        0.468       0.000        0.000    0.200             0.662         0
11380        0.210       0.000        0.000    0.029             0.574         0
7436         0.323       0.000        0.000    0.096             0.378         2
```

```
'dataframe.dtypes\n'
```

```
age_scaled        float64
sustainer         float64
gender_int        float64
racestd           float64
overall_scaled    float64
cluster             int32
dtype: object
```

```
'dataframe.describe()\n'
```

```
       age_scaled  sustainer  gender_int   racestd  overall_scaled   cluster
count   13107.000  13107.000   13107.000 13107.000       13107.000 13107.000
mean        0.364      0.057       0.645     0.123           0.439     0.820
std         0.162      0.232       0.478     0.165           0.273     0.956
min         0.000      0.000       0.000     0.003           0.000     0.000
25%         0.242      0.000       0.000     0.045           0.208     0.000
50%         0.371      0.000       1.000     0.083           0.419     0.000
75%         0.484      0.000       1.000     0.149           0.648     2.000
max         0.919      1.000       1.000     2.756           1.000     2.000
```



2019-07-25 23:37:02: In: run_it End
2019-07-25 23:37:02: In: main Ending main()

[ ]: