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Assigment 3

Brief overview of assignment

perform a penalized (regularized) logistic (multinomial) regression fit using ridge regression, with the model parameters obtained by batch gradient descent. Your predictions will be based on K=5 continental ancestries (African, European, East Asian, Oceanian, or Native American). Ridge regression will permit you to provide parameter shrinkage (tuning parameter λ=0) to mitigate overfitting. The tuning parameter λ will be chosen using five-fold cross validation, and the best- fit model parameters will be inferred on the training dataset conditional on an optimal tuning parameter. This trained model will be used to make predictions on new test data points

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Import Packages

Import packages for manipulating data

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import matplotlib.mlab as mlab
import math
import csv
import random
%matplotlib inline
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
import math

```

Import packages for splitting data

```
from sklearn.model_selection import train_test_split, cross_val_score, KFold,
from sklearn.model_selection import GridSearchCV

```

Import packages for modeling data

```
# Import models:
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression as linearR_Model, Ridge  as
from sklearn.linear_model import RidgeCV

```

```
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import ElasticNetCV

from sklearn.linear_model import LogisticRegression


from sklearn.exceptions import ConvergenceWarning
#from sklearn.utils._testing import ignore_warnings
import warnings
warnings.filterwarnings('ignore', category=ConvergenceWarning) # To filter out
warnings.filterwarnings('ignore', category=UserWarning)
from itertools import product

```

Import packages for Scaling and Centering data

```
from sklearn.preprocessing import StandardScaler
```

Import packages for Measuring Model Perormance

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.metrics import make_scorer
```

Data Processing

Import Data

Traing Dataset

```
Train_dataset = pd.read_csv ('TrainingData_N183_p10.csv')
Train_dataset.head(3)
```

PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8

```
1 # What are the datatypes of each observation:
2 print(Train_dataset.dtypes)
3 # Shape of my data
4 print('The size of our data are: ',Train_dataset.shape)
```

```
PC1         float64
PC2         float64
PC3         float64
PC4         float64
PC5         float64
PC6         float64
PC7         float64
PC8         float64
PC9         float64
PC10        float64
Ancestry     object
dtype: object
The size of our data are:  (183, 11)
```

```
1 print('Training Dataset Missing Values: \n',Train_dataset.isnull().sum())
2
```

```
Training Dataset Missing Values: 
 PC1        0
PC2        0
PC3        0
PC4        0
PC5        0
PC6        0
PC7        0
PC8        0
PC9        0
PC10       0
Ancestry   0
dtype: int64
```

Test Dataset

```
1 Test_dataset = pd.read_csv ('TestData_N111_p10.csv')
2 Test_dataset.head(3)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
0	2.517683	5.464283	9.067873	-4.965928	-0.741937	0.039785	0.573279	-0.216918	2.45
1	6.077012	1.032867	-5.795883	-3.490064	-0.600204	-0.120803	1.243767	1.821390	-1.17
2	1.016945	-2.913299	0.907702	1.233580	-1.983452	1.605964	2.674998	-0.732921	-2.15

```
# What are the datatypes of each observation:
print(Test_dataset.dtypes)
# Shape of my data
print('The size of our data are: ',Test_dataset.shape)
```

```
PC1         float64
PC2         float64
PC3         float64
PC4         float64
PC5         float64
PC6         float64
PC7         float64
PC8         float64
PC9         float64
PC10        float64
Ancestry     object
dtype: object
The size of our data are:  (111, 11)
```

```
# Are there any null or missing values
print('Test Dataset Missing Values: \n',Test_dataset.isnull().sum())
```

```
Test Dataset Missing Values: 
 PC1        0
PC2        0
PC3        0
PC4        0
PC5        0
PC6        0
PC7        0
PC8        0
PC9        0
PC10       0
Ancestry   0
dtype: int64
```

Lets change the categorical values

```
# recode the categories
Training_Class = Train_dataset['Ancestry'].unique().tolist()
Test_Class = Test_dataset['Ancestry'].unique().tolist()
num_features = len(Training_Class)


print("Unique Values for Train Ancestry: ", Training_Class)
print("Unique Values for Test Ancestry: ", Test_Class)

```

```
Unique Values for Train Ancestry:  ['African', 'European', 'EastAsian', 'Oceanian', 'Na
Unique Values for Test Ancestry:  ['Unknown', 'Mexican', 'AfricanAmerican']
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
Train_dataset['Ancestry_Encoded'] = le.fit_transform(Train_dataset.iloc[:,-1:]
Test_dataset['Ancestry_Encoded'] = le.fit_transform(Test_dataset.iloc[:,-1:])
```

```
Train_dataset.head(3)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
0	-10.901171	0.798743	-1.143301	-1.070960	11.856396	-2.265965	4.536405	1.519959	-2.:
1	-9.990054	1.416821	-0.729626	-0.443621	10.418594	0.443514	2.640659	-4.637746	3.:
2	-9.345388	2.913054	-0.921421	0.029173	10.672615	-2.052552	5.140476	-1.451096	0.4

Create Predictor and Target numpy array

```
# Target:
Y_Train= Train_dataset['Ancestry_Encoded'].to_numpy()
Y_Test= Test_dataset['Ancestry_Encoded'].to_numpy()
Y_Train.shape
```

```
(183,)
```

```
# Convert the Pandas dataframe to numpy ndarray for computational improvement
X_Train = Train_dataset.iloc[:,:-2].to_numpy()
X_Test = Test_dataset.iloc[:,:-2].to_numpy()

print(type(X_Train), X_Train[:1], "Shape = ", X_Train.shape)
```

```
<class 'numpy.ndarray'> [[-10.90117144   0.79874334  -1.14330096  -1.07096001  11.85639
   -2.2659654    4.5364047    1.51995913  -2.21429419  -0.67127393]] Shape =  (183, 10)
```

Create a Normalize copy of variables

```
# Create Standarizing ObjectPackages:
standardization = StandardScaler()

# Strandardize
```

```
n_observations = len(Train_dataset)
variables = Train_dataset.columns


# Standardize the Predictors (X)
X_Train = standardization.fit_transform(X_Train)

# Add a constanct to the predictor matrix
#X_Train = np.column_stack((np.ones(n_observations),X_Train))


# Save the original M and Std of the original data. Used for unstandardize
original_means = standardization.mean_

# we chanced standardization.std_ to standardization.var_**.5
originanal_stds = standardization.var_**.5


print("observations :", n_observations)
print("variables :", variables[:2])
print('original_means :', original_means)
print('originanal_stds :', originanal_stds)



```

```
observations : 183
variables : Index(['PC1', 'PC2'], dtype='object')
original_means : [ 1.40487976e+00  2.02293488e+00  1.91271130e-03  1.02811502e-01
  2.43929372e-01  2.93901516e-01  4.37620184e-02 -1.85769325e-01
  1.03879526e-01 -4.17198356e-02]
originanal_stds : [4.8993287  3.47654999 3.90903976 3.149965   2.14032401 1.77048761
 1.58593444 1.50391174 1.58141009 0.97706561]
```

Split Data:

let's first split it into train and test part

X_train, X_out_sample, y_train, y_out_sample = train_test_split(Xst, y_Centered, test_size=0.40, random_state=101) # Training and testing split

X_validation, X_test, y_validation, y_test = train_test_split(X_out_sample, y_out_sample, test_size=0.50, random_state=101) # Validation and test split

Print Data size

print ("Train dataset sample size: {}".format(len(X_train))) print ("Validation dataset sample size: {}".format(len(X_validation))) print ("Test dataset sample size: {}".format(len(X_test)))

Regression Model

Define our learning rates

```
# Define my tuning parameter values λ:

learning_rates_λ = [1.e-04, 1.e-03, 1.e-02, 1.e-01, 1.e+00, 1.e+01, 1.e+02, 1.
print(learning_rates_λ)

# learning rate
α =  1e-4

# K-folds
k = 5


# Itterations
n_iters = 10000

```

```
[0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100.0, 1000.0, 10000.0]
```

Create the Regression Objects

LogisticRegression Library

```
# LogisticRegression
from sklearn.linear_model import LogisticRegression
Library_LogisticRegression = LogisticRegression(max_iter = 10000, multi_clas

```

Deliverable 7.1

> Deliverable 1: Illustrate the effect of the tuning parameter on the inferred ridge regression coefficients by generating five plots (one for each of the K=5 ancestry classes) of 10 lines (one for each of the p=10 features), with the y-axis as $\beta\ jk$, j=1,2,...,10 for the graph of class k, and x-axis the corresponding log-scaled tuning parameter value log10(λ) that 7 generated the particular $\beta\ jk$. Label both axes in all five plots. Without the log scaling of the tuning parameter, the plot will look distorted.

LogisticRegression with Library

```
Lβ_per_λ=[] # set empty list

# Evaluate tuning parameters with LogisticRegression penalty
for tuning_param in learning_rates_λ:
        Library_LogisticRegression = LogisticRegression(max_iter = 10000, mult
        Library_LogisticRegression.fit(X_Train, Y_Train)
        c = np.array(Library_LogisticRegression.coef_)
       # c = np.append(tuning_param,c)
        Lβ_per_λ.append(Library_LogisticRegression.coef_)
#         print(c)

```

```
Lβ_per_λ[0]
```

```
array([[-5.99624844e-03,  2.96117039e-04, -8.73802214e-04,
        -2.04099800e-04,  1.39486513e-03, -5.71819264e-04,
        -5.20972427e-04,  1.07976342e-04,  1.04013395e-03,
        -6.51753379e-04],
       [ 3.17782901e-03,  3.20405131e-03, -2.75595421e-04,
         7.25605495e-03, -5.20324070e-04, -9.23717795e-04,
        -9.90076526e-05,  7.45094436e-04,  4.01783544e-04,
        -1.52613597e-03],
       [ 1.95202263e-04, -6.24913113e-03,  9.13687544e-04,
        -4.18520330e-04, -5.83513899e-04,  3.02492530e-03,
         7.84272369e-04, -2.65956521e-03, -1.24063618e-03,
        -4.04365901e-04],
       [ 2.28441492e-03, -5.37970381e-04, -4.83132244e-03,
        -3.44509733e-03, -1.70996181e-04, -1.31009775e-03,
        -9.47052680e-05,  1.90245786e-03,  5.30506344e-04,
         3.67778162e-03],
       [ 3.38802248e-04,  3.28693316e-03,  5.06703253e-03,
        -3.18833750e-03, -1.20030982e-04, -2.19290489e-04,
        -6.95870212e-05, -9.59634295e-05, -7.31787661e-04,
        -1.09552637e-03]])
```

```
# Loop throught the betas, by class generated by each lamda
temp_df = []
for l in range(np.array(Lβ_per_λ).shape[0]):
```

```
    for c in range(np.array(Lβ_per_λ).shape[1]):
        temp_df.append(np.append(Lβ_per_λ[l][c],(learning_rates_λ[l],c)))
```

```
TunnedLβ_df=pd.DataFrame(np.array(temp_df))
TunnedLβ_df.columns=['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8', '
#TunnedLβ_df['Class_Name'] = TunnedLβ_df['Class_Name'].apply(lambda x: Trainir
TunnedLβ_df.head(10)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
0	-0.005996	0.000296	-0.000874	-0.000204	0.001395	-0.000572	-0.000521	0.000108	0.0
1	0.003178	0.003204	-0.000276	0.007256	-0.000520	-0.000924	-0.000099	0.000745	0.0
2	0.000195	-0.006249	0.000914	-0.000419	-0.000584	0.003025	0.000784	-0.002660	-0.0
3	0.002284	-0.000538	-0.004831	-0.003445	-0.000171	-0.001310	-0.000095	0.001902	0.0
4	0.000339	0.003287	0.005067	-0.003188	-0.000120	-0.000219	-0.000070	-0.000096	-0.0
5	-0.058225	0.002975	-0.008652	-0.001678	0.013273	-0.005503	-0.005145	0.001171	0.0
6	0.030222	0.029984	-0.002905	0.068954	-0.004819	-0.008493	-0.000758	0.006758	0.0
7	0.002223	-0.059828	0.008914	-0.003635	-0.005770	0.028374	0.007473	-0.024838	-0.0
8	0.022178	-0.004906	-0.046279	-0.032885	-0.001479	-0.012364	-0.000878	0.017768	0.0
9	0.003602	0.031775	0.048922	-0.030756	-0.001205	-0.002014	-0.000692	-0.000860	-0.0

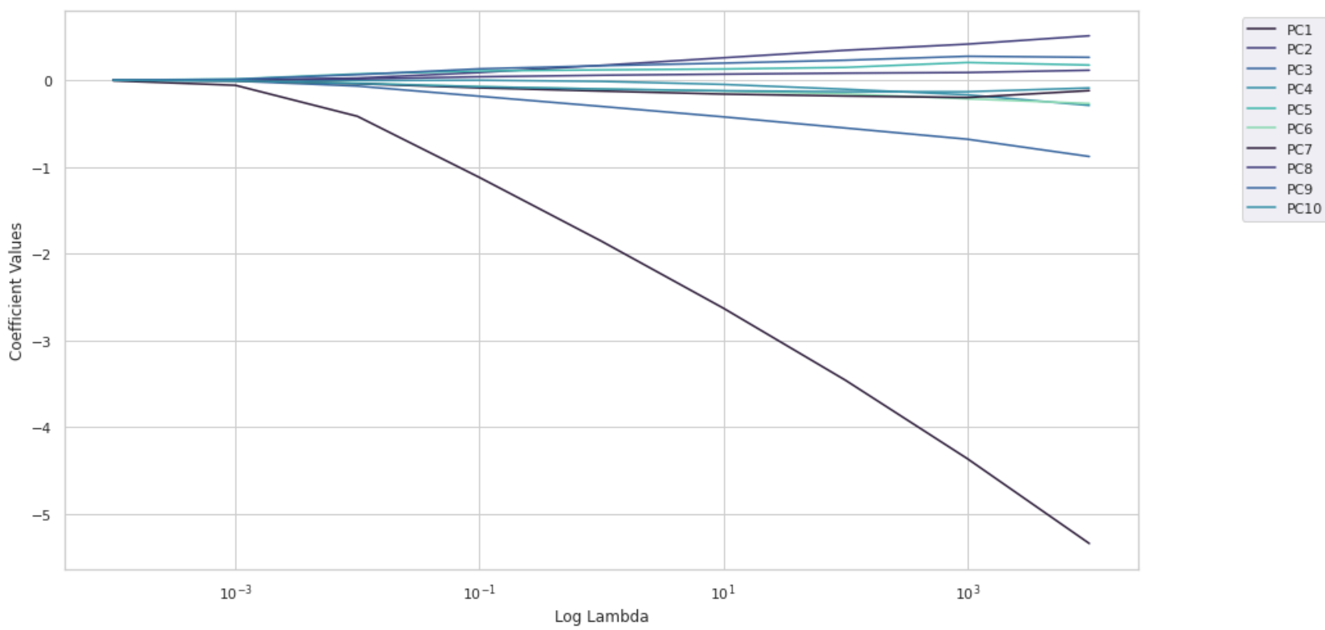
```
Training_Class
```

```
['African', 'European', 'EastAsian', 'Oceanian', 'NativeAmerican']
```

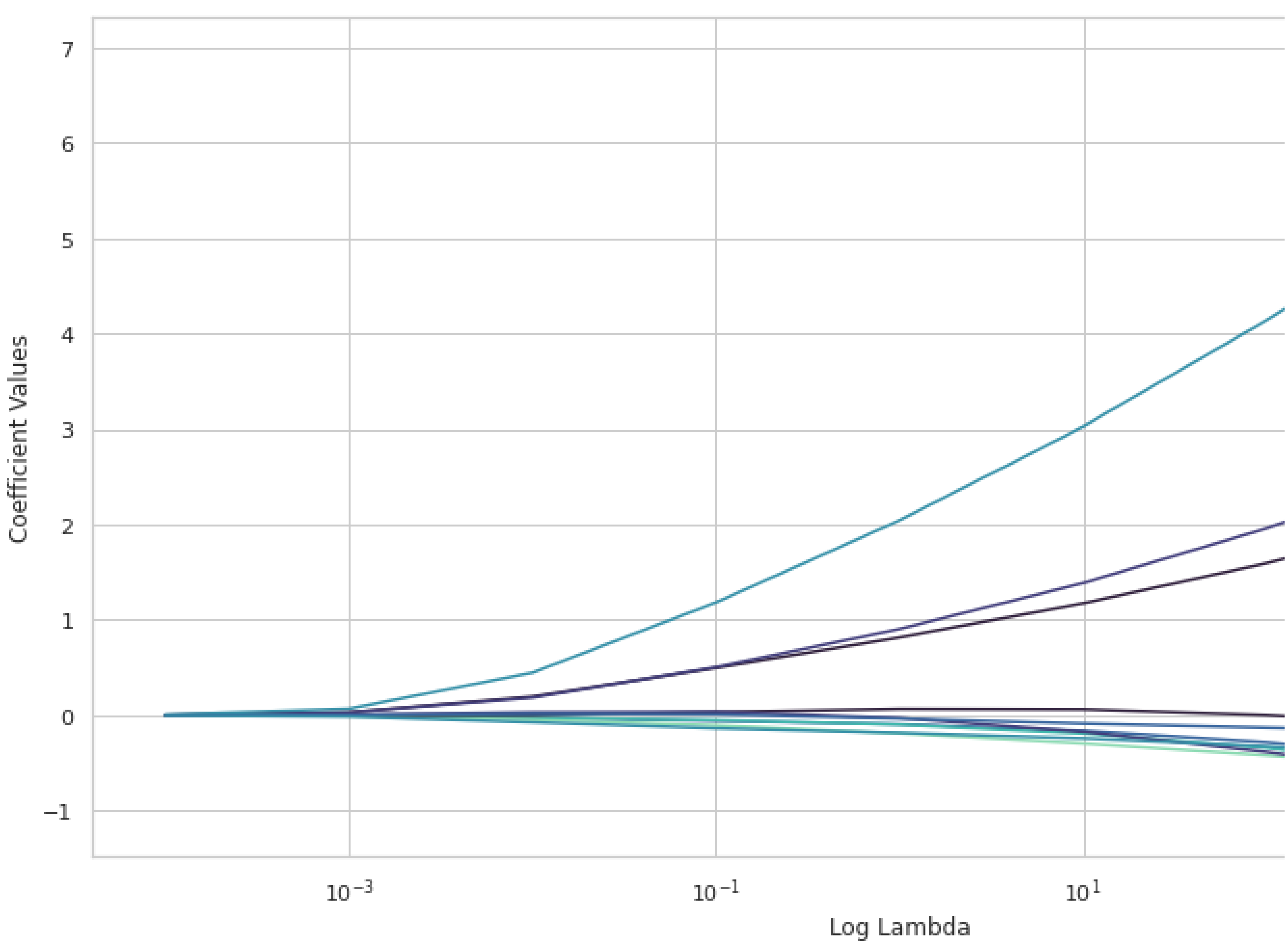
```
TunnedLβ_df[TunnedLβ_df.Class.eq(0)]
```

```
# Plot tuning parameter on the inferred ridge regression coefficients
sns.set(rc = {'figure.figsize':(15,8)})
for i, c in enumerate(Training_Class):
    sns.set_theme(style="whitegrid")
    sns.set_palette("mako")
    for j in range(1, 1 + X_Train.shape[1]):
        sns.lineplot( x =  TunnedLβ_df[TunnedLβ_df.Class.eq(i)]['Lambda'], y =
        sns.set()
    plt.xscale('log')
    plt.legend(bbox_to_anchor=(1.09, 1), loc='upper left')
    plt.xlabel('Log Lambda')
    plt.ylabel('Coefficient Values')
    plt.suptitle('Inferred Ridge Regression Coefficient Tuning Parameters of'
    plt.show()

```

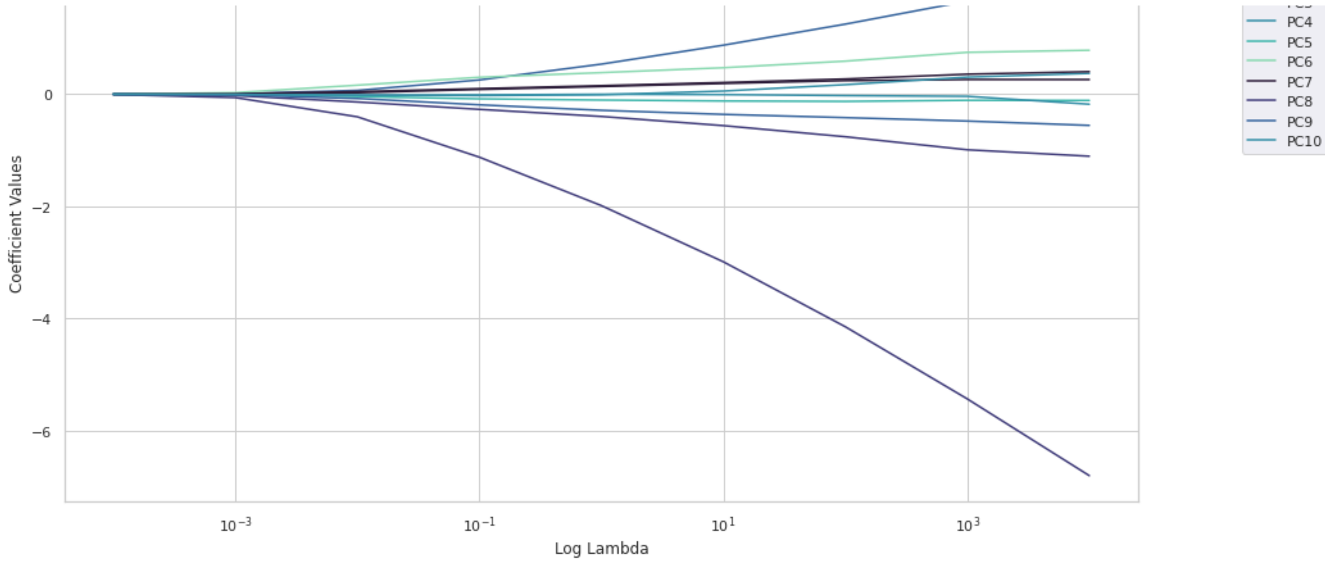
Inferred Ridge Regression Coefficient Tuning Parameters of African Class



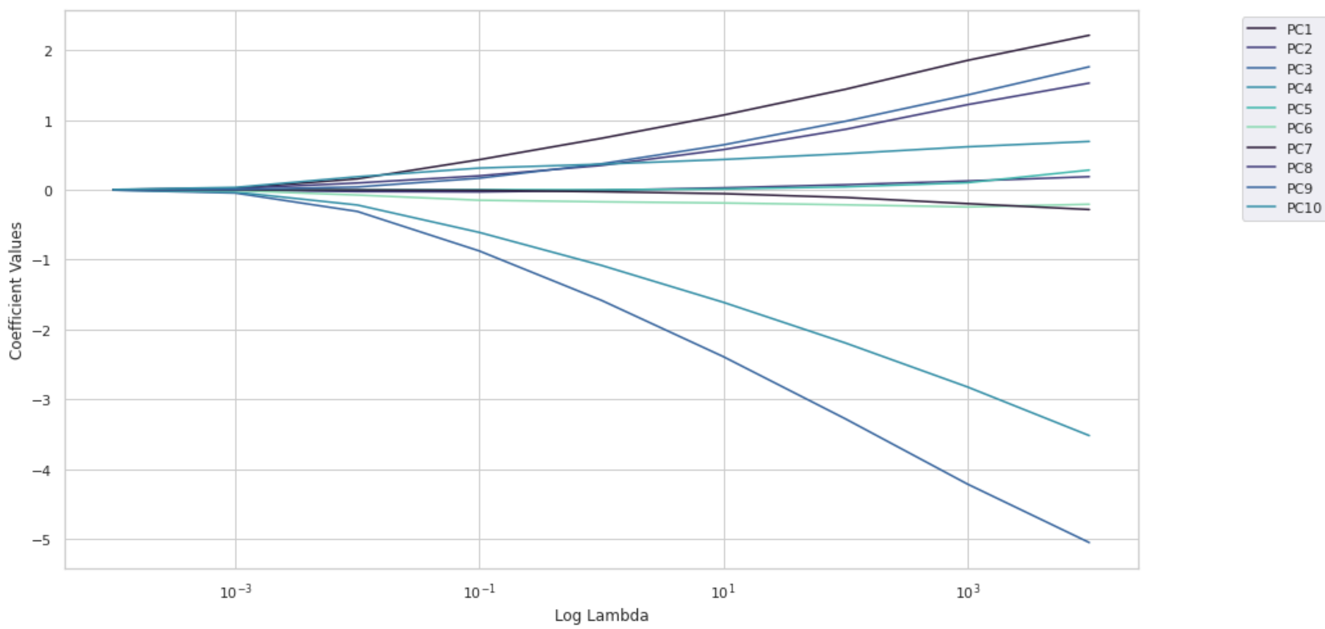
Inferred Ridge Regression Coefficient Tuning Parameters of Europea



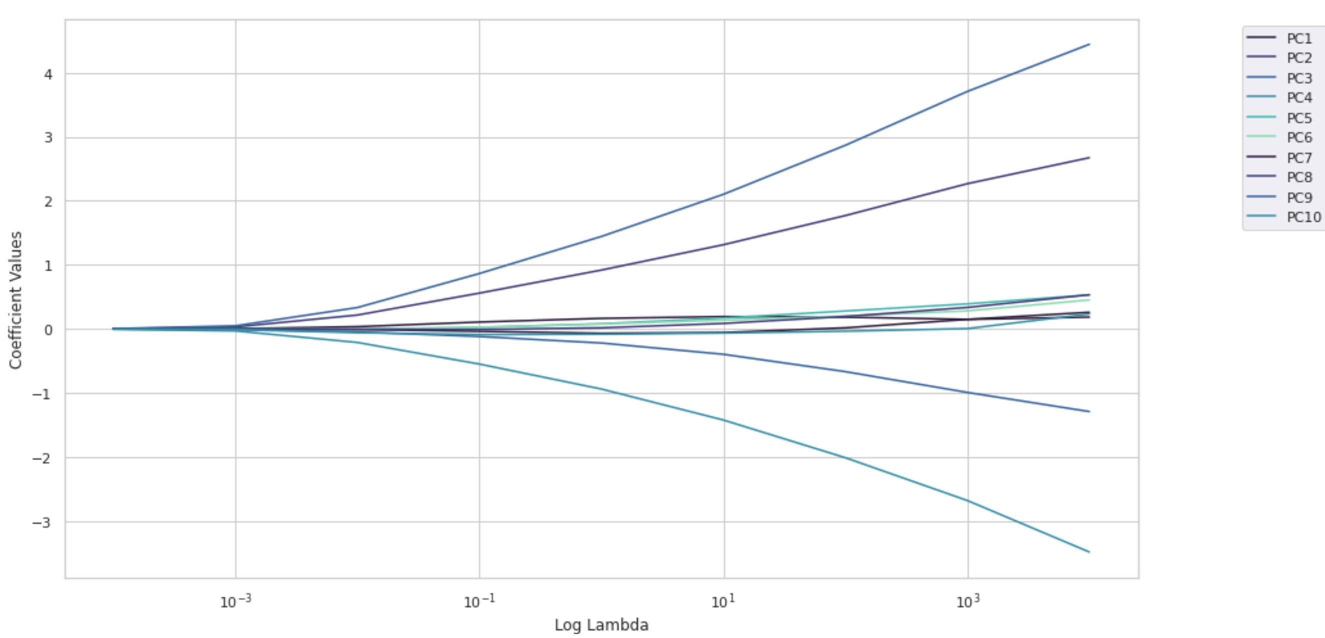
Inferred Ridge Regression Coefficient Tuning Parameters of EastAsian Class



Inferred Ridge Regression Coefficient Tuning Parameters of Oceanian Class



Inferred Ridge Regression Coefficient Tuning Parameters of NativeAmerican Class



Deliverable 7.2

Illustrate the effect of the tuning parameter on the cross validation error by generating a plot with the y-axis as CV(5) error, and the x-axis the corresponding log-scaled tuning parameter value log10(λ) that generated the particular CV(5) error. Label both axes in the plot. Without the log scaling of the tuning parameter λ, the plots will look distorted.

CV Elastic Net with Library

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

#Define the model
Library_LogisticRegression·=·LogisticRegression(max_iter·=·10000,·multi_clas


# Create the Kfold:
cv_iterator = KFold(n_splits = 5, shuffle=True, random_state=101)

cv_score = cross_val_score(Library_LogisticRegression, X_Train, Y_Train, cv=
print (cv_score)
print ('Cv score: mean %0.3f std %0.3f' % (np.mean(cv_score), np.std(cv_scor


```

```
[-0. -0. -0. -0. -0.]
Cv score: mean 0.000 std 0.000
```

```
# define grid
Parm_grid = dict()
Parm_grid['C'] = learning_rates_λ
Parm_grid
```

```
{'C': [0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100.0, 1000.0, 10000.0]}
```

```
# Lets define search
GsearchCV = GridSearchCV(estimator = Library_LogisticRegression, param_grid =
GsearchCV.fit(X_Train, Y_Train)


```

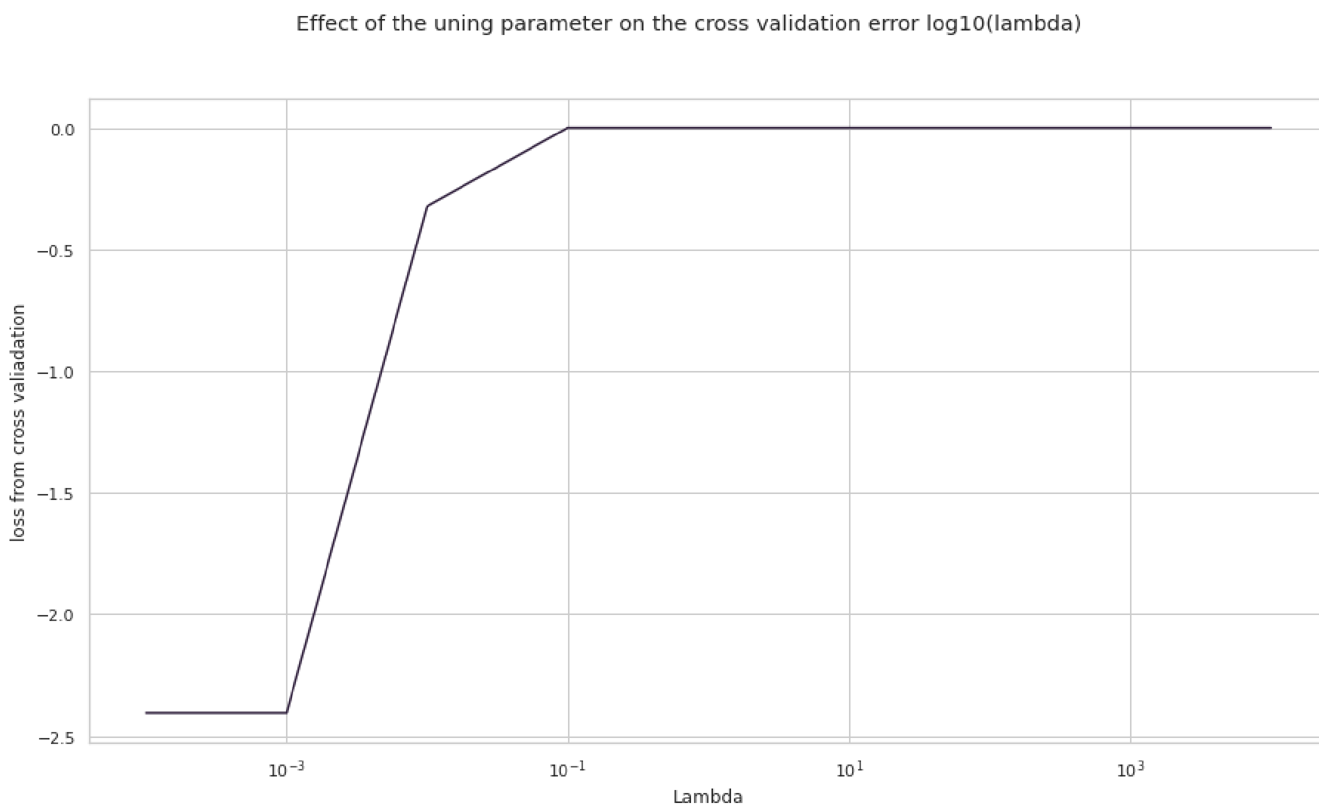
```
GridSearchCV(cv=KFold(n_splits=5, random_state=101, shuffle=True),
             estimator=LogisticRegression(max_iter=10000,
                                          multi_class='multinomial'),
             n_jobs=1,
             param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100.0,
                               1000.0, 10000.0]},
             scoring='neg_mean_squared_error')
```

```
GCV_df = pd.concat([pd.DataFrame(GsearchCV.cv_results_["params"]),pd.DataFrame
#GCV_df.index=GCV_df['alpha']
GCV_df.rename(columns={"C": "learning_rates_λ"}, inplace=True)

GCV_df
```

	learning_rates_λ	mean_test_score
0	0.0001	-2.404354
1	0.0010	-2.404354
2	0.0100	-0.322222
3	0.1000	0.000000
4	1.0000	0.000000
5	10.0000	0.000000
6	100.0000	0.000000
7	1000.0000	0.000000
8	10000.0000	0.000000

```

sns.set_theme(style="whitegrid")
sns.set_palette("mako")


plt.plot(GCV_df["learning_rates_λ"] , GCV_df["mean_test_score"])


```

```
sns.set_palette("mako")
sns.set()


plt.suptitle('Effect of the uning parameter on the cross validation error log1
plt.xscale('log')
plt.xlabel('Lambda')
plt.ylabel('loss from cross valiadation')
plt.show()
```



Deliverable 7.3

Indicate the value of λ that generated the smallest CV(5) error

Smallest CV with Library

```
print ('Best: ',GsearchCV.best_params_)
```

```
print ('Best CV mean squared error: %0.3f' % np.abs(GsearchCV.best_score_))
```

```
Best:  {'C': 0.1}
Best CV mean squared error: 0.000
```

```
GCV_df.sort_values(by=['mean_test_score'], ascending=False)[:1]

```

	learning_rates_λ	mean_test_score
3	0.1	0.0

```
# Alternative: sklearn.linear_model.ElasticNetCV
from sklearn.linear_model import LogisticRegressionCV

auto_LR = LogisticRegressionCV(Cs = learning_rates_λ, cv=5, max_iter = 10000,
auto_LR.fit(X_Train, Y_Train)
#print ('Best alpha: %0.5f' % auto_LR.alpha_)
print ('Best 𝜆: ' , auto_LR.C_)
```

```
Best 𝜆:  [0.1 0.1 0.1 0.1 0.1]
```

Deliverable 7.4

Given the optimal λ, retrain your model on the entire dataset of N=183 observations to obtain an estimate of the $(p+1)\times K$ model parameter matrix as $\hat{\mathbf{B}}$ and make predictions of the probability for each of the K=5 classes for the 111 test individuals located in TestData_N111_p10.csv. That is, for class k, compute $p_k(X;\hat{\mathbf{B}})=\exp(\hat{\beta}_{0k}+\sum_{j=1}^{p} X_j\hat{\beta}_{jk}) / \sum\exp(\hat{\beta}_{0\ell}+\sum_{j=1}^{p} X_j\hat{\beta}_{j\ell})$

- for each of the 111 test samples X, and also predict the most probable ancestry label as
  - $\hat{Y}(X)=\arg\max_{k\in\{1,2,\ldots,K\}} p_k(X;\hat{\mathbf{B}})$
- Report all six values (probability for each of the K=5 classes and the most probable ancestry label) for all 111 test individuals.

Tunned with best λ with Library

```
Library_LogisticRegression_best= LogisticRegression(max_iter = 10000, multi_
Library_LogisticRegression_best.fit( X_Train, Y_Train )

y_predM_best = Library_LogisticRegression_best.predict(X_Test)
print ("Betas= ", np.mean(Library_LogisticRegression_best.coef_, 0))


```

```
Betas=  [ 1.97064587e-16  1.11022302e-16 -4.44089210e-17  0.00000000e+00
 -5.41233725e-17 -6.03683770e-17 -1.94289029e-17  2.25514052e-17
 -4.99600361e-17  4.99600361e-17]
```

```
yhat = Library_LogisticRegression_best.predict_proba(X_Test)
# summarize the predicted probabilities
print('Predicted Probabilities: %s' % yhat[0])
```

```
Predicted Probabilities: [2.65398539e-08 4.07623241e-07 4.19578741e-08 3.58579025e-08
 9.99999488e-01]
```

```
ŷ_test = Library_LogisticRegression_best.predict_proba(X_Test)
ŷ_test[:3]
```

```
array([[2.65398539e-08, 4.07623241e-07, 4.19578741e-08, 3.58579025e-08,
        9.99999488e-01],
       [3.42825046e-08, 3.12778397e-05, 2.56848531e-06, 9.99964053e-01,
        2.06669173e-06],
       [3.56852016e-04, 2.09402026e-02, 9.76706428e-01, 7.64024238e-04,
        1.23249309e-03]])
```

```
Y_class = Library_LogisticRegression_best.predict(X_Test)
Y_class
```

```
array([4, 3, 2, 0, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2, 1,
       3, 3, 3, 3, 3, 1, 3, 2, 2, 2, 3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 2, 2, 2, 3, 3, 3, 3, 4, 3, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0])
```

```
# Re-lable feature headers and add new class prediction index column
new_colNames = ['{}_Probability'.format(c_name) for c_name in Training_Class]
new_colNames
```

```
['African_Probability',
 'European_Probability',
 'EastAsian_Probability',
 'Oceanian_Probability',
 'NativeAmerican_Probability',
 'ClassPredInd']
```

```
# Implemnt index array of probabilities
i_prob = np.concatenate((ŷ_test, Y_class[:, None]), 1)
```

```
# Create New dataframe for probality indeces
df2 = pd.DataFrame(i_prob, columns = new_colNames)
```

```
3 df2
```

	African_Probability	European_Probability	EastAsian_Probability	Oceanian_Probab
0	2.653985e-08	4.076232e-07	4.195787e-08	3.58579
1	3.428250e-08	3.127784e-05	2.568485e-06	9.99964
2	3.568520e-04	2.094020e-02	9.767064e-01	7.64024
3	9.999789e-01	4.743223e-08	7.266109e-08	9.39932
4	4.452492e-08	9.999914e-01	4.315461e-08	7.71225
...	...	...	...	
106	9.999990e-01	4.436773e-08	4.735975e-08	6.70330
107	9.997505e-01	1.521141e-05	1.925700e-04	6.56598
108	9.999776e-01	2.305937e-06	1.045074e-06	9.33498
109	9.997518e-01	1.508667e-06	4.464774e-05	1.36007
110	9.905429e-01	8.528121e-03	6.604245e-04	1.17113

111 rows × 6 columns

```
1 # Concat dependant Ancestory features to dataframe
2 dep_preds = pd.concat([Test_dataset['Ancestry'], df2], axis = 1)
```

```
1 # Add new
2 dep_preds['ClassPredName'] = dep_preds['ClassPredInd'].apply(lambda x: Trainin
```

```
1 # Validate Probability predictions dataframe
2 dep_preds.head()
```

	Ancestry	African_Probability	European_Probability	EastAsian_Probability	Oceanian
0	Unknown	2.653985e-08	4.076232e-07	4.195787e-08	
1	Unknown	3.428250e-08	3.127784e-05	2.568485e-06	
2	Unknown	3.568520e-04	2.094020e-02	9.767064e-01	
3	Unknown	9.999789e-01	4.743223e-08	7.266109e-08	
4	Unknown	4.452492e-08	9.999914e-01	4.315461e-08	

```
1 # Slice prediction and set new feature vector column variable
2 prob_1 = dep_preds.loc[:, 'Ancestry':'NativeAmerican_Probability']
```

```
# Unpivot convert dataFrame to long format
prob_2 = pd.melt(prob_1, id_vars = ['Ancestry'], var_name = 'Ancestry_Predicti
```

```
# Test for true probability
prob_2['Ancestry_Predictions'] = prob_2['Ancestry_Predictions'].apply(lambda x
```

```
# Validate dataframe
prob_2.head(5)
```

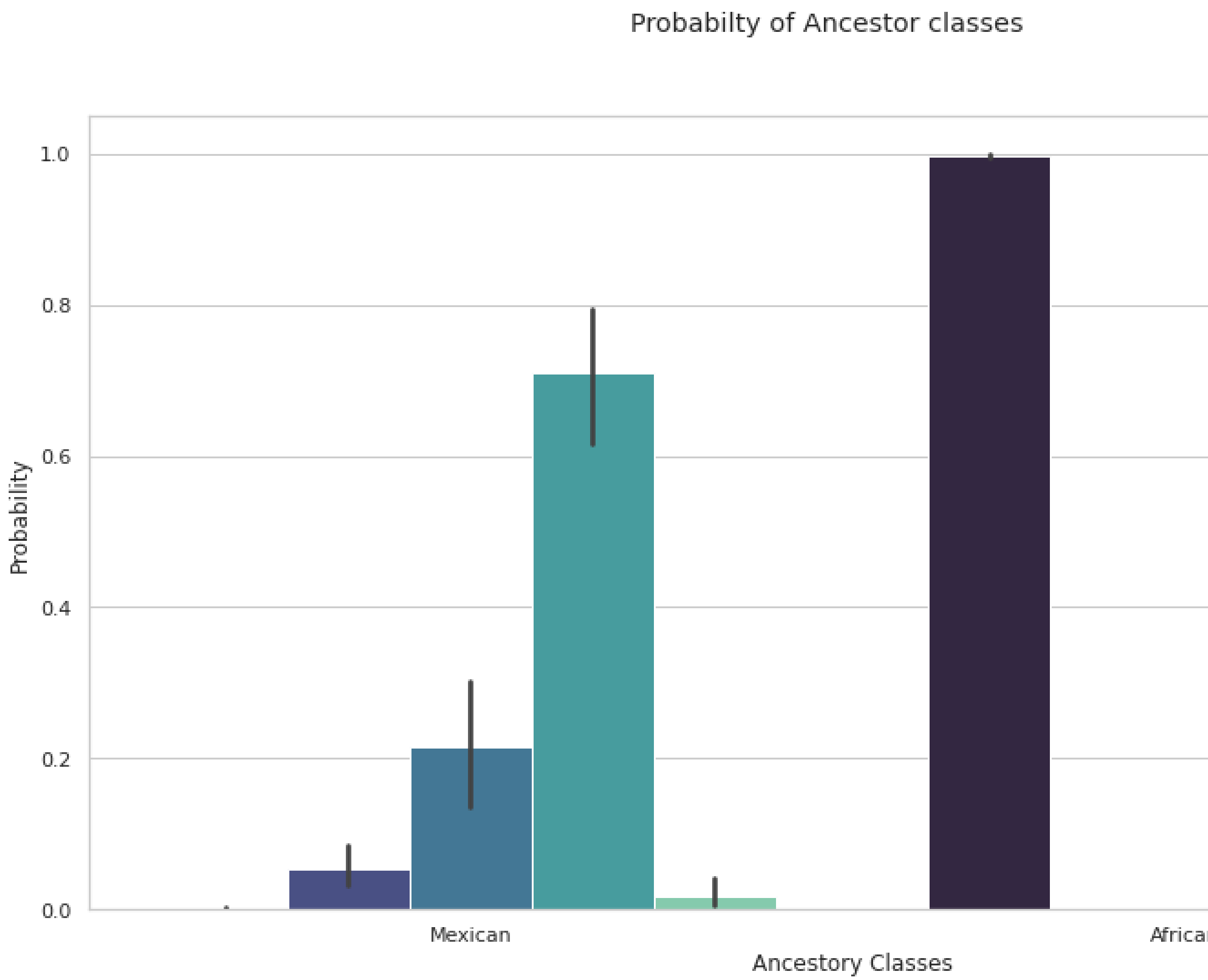
	Ancestry	Ancestry_Predictions	Probability
0	Unknown	African_	2.653985e-08
1	Unknown	African_	3.428250e-08
2	Unknown	African_	3.568520e-04
3	Unknown	African_	9.999789e-01
4	Unknown	African_	4.452492e-08

```
# Validate dataframe features
print('Describe Columns:=', prob_2.columns, '\n')
print('Data Index values:=', prob_2.index, '\n')
print('Describe data:=', prob_2.describe(), '\n')
```

```
Describe Columns:= Index(['Ancestry', 'Ancestry_Predictions', 'Probability'], dtype='ob

Data Index values:= RangeIndex(start=0, stop=555, step=1)

Describe data:=         Probability
count  5.550000e+02
mean   2.000000e-01
std    3.713757e-01
min    1.157843e-08
25%    2.527892e-05
50%    9.045926e-04
75%    9.444702e-02
max    9.999995e-01
```

```
# Plot Probality prediction matrix
sns.set(rc = {'figure.figsize':(15,8)})
sns.set_theme(style="whitegrid")
fig, ax = plt.subplots()
sns.barplot(data = prob_2[prob_2['Ancestry'] != 'Unknown'],color = 'r', x =
plt.xlabel('Ancestory Classes')
plt.ylabel('Probability')
plt.suptitle('Probabilty of Ancestor classes')
```

```
#plt.savefig("Assignment3_Deliverable4.png")
plt.show()
```



Deliverable 7.5

How do the class label probabilities differ for the Mexican and African American samples when compared to the class label probabilities for the unknown samples? Are these class probabilities telling us something about recent history? Explain why these class probabilities are reasonable with respect to knowledge of recent history?

- In comparison to the class label probabilities for the unknown samples, those with unknown ancestry show a probability close to or equal to one while the other classes show a probability close to zero or less than one. African American samples showed similar results. The model assigned high probabilities to the African ancestry class for each of these