**Facial Recognition in the United States and its influence on Asian and Latinx**

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CS156: Machine Learning for Science and Profit

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# Facial Recognition in the United States and its influence on Asian and Latinx

## Problem Definition

Machine Learning technology has benefited a lot of people in the world, but this is not the case that happens every day. Although this technology is based on a complicated mathematical algorithm that seems objective, this is not true (Fawcett, 2020).

Although the United States is a melting pot of different cultures and racial backgrounds, population-wise it is not well-balanced because the majority of the population is white. The population is followed by black, Hispanic, Asian, etc but the ratio is not equal. Most American companies want to avoid any potential bias that their technology and this report explores why current algorithms failed especially against Asian Americans.

## Solution Specification

The report used a couple of different approaches to this problem: Logistic Regression, LDA, 2D-PCA, 3D-PCA, and repeating this algorithm based on different ratios of the racial datasets. By trying multiple algorithms and different ratios of the racial dataset, this report analyzes in which cases the machine is mostly unbiased. However, this report gives a starting point to think about the problem but does not include the ultimate solution because someone's racial background could be complicated, and sometimes the input dataset is biased. For example, some dataset includes mislabelled data such as putting a person of more than one race into one single category. The best way to collect data is to ask people and let them voluntarily put their data under such categories they want to or make categories if needed. Again, this report explores the potential solutions by trying different approaches.

**Testing and Analysis**

Most of the classification methods worked pretty well when they are performed within the majority groups (Black and White); however, most of them reported poorly when the dataset is made up of minority groups (Asian and Latinx).[1]

*Table 1. Testing Accuracy of different algorithms. For 3D-PCA, Well-Spread is better than clustered because it shows that the data is differentiable.*

| | Linear Regression | 2D-PCA | 3D-PCA | LDA |
|---|---|---|---|---|
| Minority Group | 0.55 | 0.57 | Clustered | 0.53 |
| Majority Group | 0.80 | 0.82 | Well-Spread | 0.85 |

As Table 1 shows, the classification algorithms work well in the majority group but work poorly in the minority group. The reason behind this is the skin tone by the RGB color code cannot differentiate between Asians and Latinx while there is a huge difference in RGB color code between blacks and whites. This is one potential reason that people in minority groups feel they could have been more mislabeled than the majority of the group. Of course, the engineers did not mean to but since the result is like the above, they should come up with a different approach that can look fairer for everyone.

One approach that the engineers can take is trying two different datasets. One includes the data of different racial backgrounds equally and another one includes the data of different racial backgrounds based on the population ratio. The current U.S. population is approximately

[1] The majority group and the minority group here are based on the public facial dataset. Black and Whites are labeled as majority group here because the online data includes their data relatively more than Asian and Hispanic.

60% of whites, 12% of blacks, 18% of Latinx, and 5% of Asians. Therefore, the following experiment uses this ratio to redefine minority groups differently from the above, and Asians are labeled as a minority group.

*Table 2. Testing Accuracy of different algorithms with different ratios. For 3D-PCA, Well-Spread is better than clustered because it shows that the data is differentiable.*

| | Linear Regression | 2D-PCA | 3D-PCA | LDA |
|---|---|---|---|---|
| Equal Ratio (25% for all) | 0.72 | 0.57 | Well-Spread | 0.62 |
| Population Ratio (60%, 12%, 18%, 5%) | 0.62 | 0.78 | Clustered | 0.62 |

Compare to the table 1, both of these approaches result the better accuracies. Therefore, rather than simply trying to classify within the same racial backgrounds, it is better to mix up the dataset with different racial backgrounds as much as possible. To interpret the data above, for equal ratio, Linear Regression, 3D-PCA, and LDA performed well. Therefore, it is recommended if the engineers try to use one of these approaches, they want to form a dataset equally. However, it is hard to collect the data with an equal ratio because, in reality, the dataset will naturally follow the population ratio. When the companies collect the data from their users, it makes sense if their data follows the population; therefore, for these situations, it is recommended to use 2D-PCA as reported in table 2.

**Further Research**

Even though most of the countries on the globe approached the past pandemic, there are still a number of people who wear masks. For some facial recognition cases, such as Apple's

FaceID, the users prefer to keep their mask on rather than put it down for a second and put it back. This study can be implicated again with the dataset of people wearing masks or cropped images that only include from eyes to forehead to find what is the best approach or ratio in the dataset to perform the best.

## References

Fawcett, A. (2020). Understanding racial bias in machine learning algorithms. Educative: Interactive Courses for Software Developers. https://www.educative.io/blog/racial-bias-machine-learning-algorithms

KFF. (2020, October 28). Population Distribution by Race/Ethnicity. https://www.kff.org/other/state-indicator/distribution-by-raceethnicity/?currentTimeframe=0&sortModel=%7B%22colId%22%3A%22Location%22%2C%22sort%22%3A%22asc%22%7D

University of Massachusetts, Amherst. (n.d.). *Labeled Faces in the Wild Home*. http://vis-www.cs.umass.edu/lfw/number_11.html

# CS156 Final Assignment Code Appendix

## Code Experiment Starts Here

```
# Importing libraries
from glob import glob
from PIL import Image
from resizeimage import resizeimage
from sklearn.model_selection import train_test_split
from sklearn import decomposition
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import classification_report

# create paths for all images
asian_images = glob('Asian/*')
black_images = glob('Black/*')
latinx_images = glob('Latinx/*')
white_images = glob('White/*')
ratio_images = glob('Ratio/*')
equal_ratio_images = glob('Equal/*')

asian = []
black = []
latinx = []
white = []
ratio = []
equal = []

dim = [64, 64]


# for each image path
for path in asian_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            asian.append(np.array(cover).flatten())
```

```
# for each image path
for path in black_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            black.append(np.array(cover).flatten())

# for each image path
for path in latinx_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            latinx.append(np.array(cover).flatten())

# for each image path
for path in white_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            white.append(np.array(cover).flatten())

for path in ratio_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
```

```
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            ratio.append(np.array(cover).flatten())

for path in equal_ratio_images:
    # open it as a read file in binary mode
    with open(path, 'r+b') as f:
        # open it as an image
        with Image.open(f) as image:
            # convert image to RGB
            image = image.convert('RGB')
            # resize the image to be more manageable
            cover = resizeimage.resize_cover(image, dim)
            # flatten the matrix to an array and append it to all
flattened images
            equal.append(np.array(cover).flatten())

asian = np.asarray(asian)
black = np.asarray(black)
latinx = np.asarray(latinx)
white = np.asarray(white)
ratio = np.asarray(ratio)
equal = np.asarray(equal)
```

## Analysis between Asian and Latinx

```
X = np.concatenate((asian, latinx))
Y = np.concatenate((np.zeros(len(asian)), np.ones(len(latinx))))
print(X.shape, Y.shape)


fig, axes = plt.subplots(10,10,figsize=(9,9),
subplot_kw={'xticks':[], 'yticks':[]},
gridspec_kw=dict(hspace=0.01, wspace=0.01))
for i, ax in enumerate(axes.flat):
    ax.imshow(X[i].reshape(dim[0], dim[1], 3))
```

```
(200, 12288) (200,)
```

```
# Data Set Split
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=0.2, shuffle=True)
```

## Simple Logistic Regression Classifier

```
clf = LogisticRegression(max_iter = 500)
clf.fit(X_train, Y_train)

LogisticRegression(max_iter=500)

predictions = clf.predict(X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        77
```

```
         1.0       1.00      1.00      1.00        83

    accuracy                           1.00       160
   macro avg       1.00      1.00      1.00       160
weighted avg       1.00      1.00      1.00       160
```

This reports the 1.00 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate.

```
predictions = clf.predict(X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.57      0.57      0.57        21
         1.0       0.53      0.53      0.53        19

    accuracy                           0.55        40
   macro avg       0.55      0.55      0.55        40
weighted avg       0.55      0.55      0.55        40
```

This reports the 0.55 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is NOT accurate. This is expected since now we can differentiate Asians and Latinx.

## PCA Reduction and Classification

```
pca = decomposition.PCA(.9)
pca.fit(X_train)

fig, axes = plt.subplots(3, 3,figsize=(9,9),
 subplot_kw={'xticks':[], 'yticks':[]},
 gridspec_kw=dict(hspace=0.01, wspace=0.01))

# Eigen Vectors
print("Showing 9 out of %s eigenvectors" % len(pca.components_))
for i, ax in enumerate(axes.flat):
    ax.imshow((pca.components_[i].reshape(dim[0], dim[1],
3)*255).astype(np.uint8))
```

```
Showing 9 out of 54 eigenvectors
```

```
transformed_inputs = pca.transform(X)
rescaled_inputs = pca.inverse_transform(transformed_inputs)

fig, axes = plt.subplots(10,10,figsize=(9,9), subplot_kw={'xticks':[],
'yticks':[]},
                         gridspec_kw=dict(hspace=0.01, wspace=0.01))
# Plot images
for i, ax in enumerate(axes.flat):
    ax.imshow((rescaled_inputs[i].reshape(dim[0], dim[1],
3)).astype(np.uint8))
```

```
clf_PCA = LogisticRegression(max_iter = 500)
PCA_X_train = pca.transform(X_train)
PCA_X_test = pca.transform(X_test)
clf_PCA.fit(PCA_X_train, Y_train)
```

```
LogisticRegression(max_iter=500)
```

```
PCA_predictions = clf_PCA.predict(PCA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, PCA_predictions))
```

```
Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        77
         1.0       1.00      1.00      1.00        83

    accuracy                           1.00       160
```

```
   macro avg       1.00      1.00      1.00       160
weighted avg       1.00      1.00      1.00       160
```

This reports the 1.00 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate.

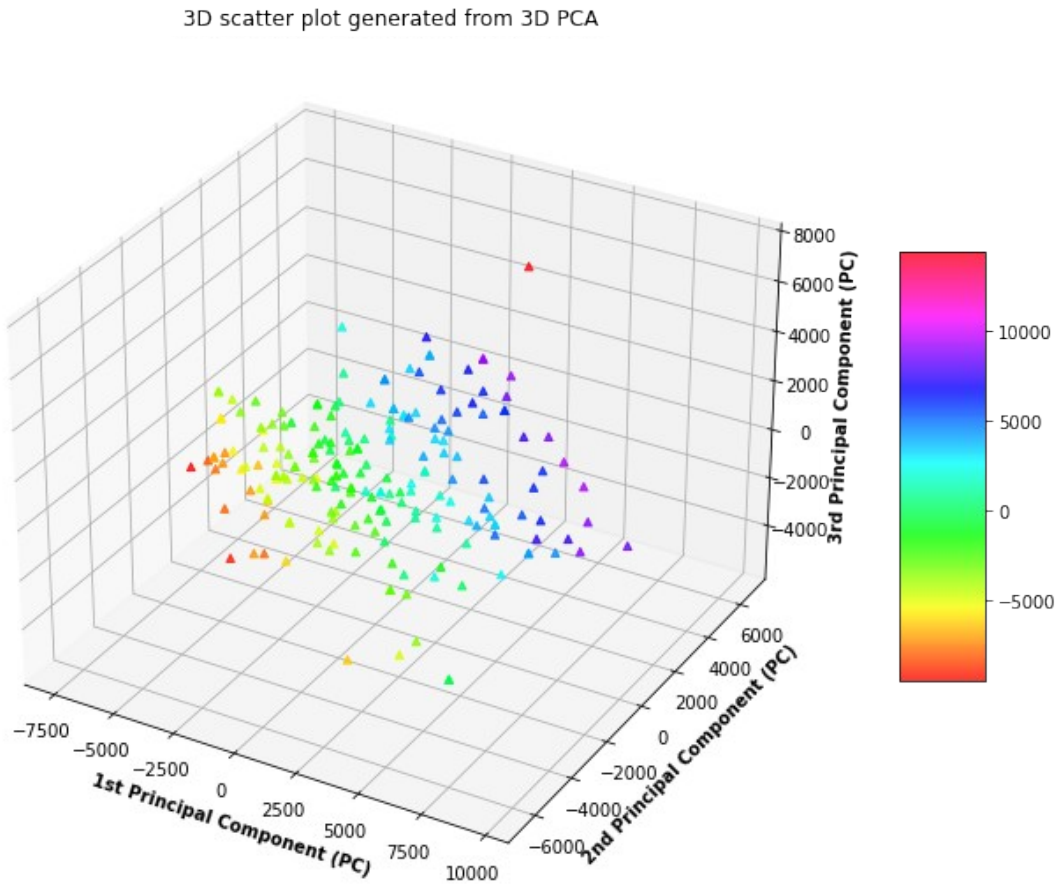
```
PCA_predictions = clf_PCA.predict(PCA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, PCA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.60      0.57      0.59        21
         1.0       0.55      0.58      0.56        19

    accuracy                           0.57        40
   macro avg       0.57      0.58      0.57        40
weighted avg       0.58      0.57      0.58        40
```

This reports the 0.58 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is NOT accurate. This is expected since now we can differentiate Asians and Latinx.

```
# PCA but 3D
import numpy as np
from sklearn.decomposition import PCA
PCA3D = PCA(n_components=3)
PCA3D.fit(X)

# Transfrom images to PCA
X_3D = PCA3D.transform(X)

# Transpose PCA array
ThreeD_ARR = X_3D.T

fig = plt.figure(figsize = (16, 9))
ax_3d = plt.axes(projection = "3d")
ax_3d.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.3,
        alpha = 0.2)
my_cmap = plt.get_cmap('hsv')

plot_3d = ax_3d.scatter3D(ThreeD_ARR[0], ThreeD_ARR[1], ThreeD_ARR[2],
                    alpha = 0.8,
                    c = (ThreeD_ARR[0] + ThreeD_ARR[1] +
ThreeD_ARR[2]),
                    cmap = my_cmap,
```

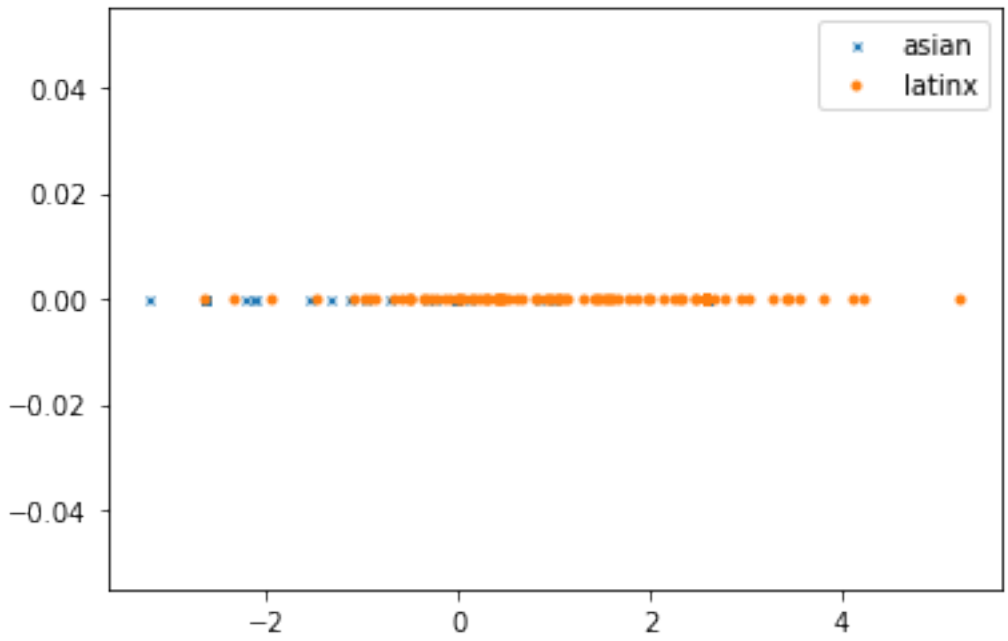
```
                    marker ='^')

plt.title("3D scatter plot generated from 3D PCA")
ax_3d.set_xlabel('1st Principal Component (PC)', fontweight ='bold')
ax_3d.set_ylabel('2nd Principal Component (PC)', fontweight ='bold')
ax_3d.set_zlabel('3rd Principal Component (PC)', fontweight ='bold')
fig.colorbar(plot_3d, ax = ax_3d, shrink = 0.5, aspect = 5)
plt.show()
```




## LDA Reduction and Classification

```
# LDA to reduce it down to 1D
lda = LinearDiscriminantAnalysis(n_components=1)
lda.fit(X_train, Y_train)

transformed_asian = lda.transform(asian)
transformed_latinx = lda.transform(latinx)

plt.plot(transformed_asian, [0 for _ in
range(len(transformed_asian))], 'x', markersize=3, label='asian')
plt.plot(transformed_latinx, [0 for _ in
range(len(transformed_latinx))], 'o', markersize=3, label='latinx')
```

```
plt.legend()
plt.show()
```




```
LDA_X_train = lda.transform(X_train)
LDA_X_test = lda.transform(X_test)

clf_LDA = LogisticRegression(max_iter = 500)
clf_LDA.fit(LDA_X_train, Y_train)

LogisticRegression(max_iter=500)

LDA_predictions = clf_LDA.predict(LDA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, LDA_predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      0.82      0.90        79
         1.0       0.85      1.00      0.92        81

    accuracy                           0.91       160
   macro avg       0.93      0.91      0.91       160
weighted avg       0.93      0.91      0.91       160
```

This reports the 0.91 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate. This is expected since now we verifies that the classification works so now almost fully distinguish Asians and Latinx based on the trained model.

```
LDA_predictions = clf_LDA.predict(LDA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, LDA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.55      0.52      0.54        21
         1.0       0.50      0.53      0.51        19

    accuracy                           0.53        40
   macro avg       0.53      0.53      0.52        40
weighted avg       0.53      0.53      0.53        40
```

This reports the 0.53 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is NOT accurate. This is NOT expected since the trained model had good accuracy but we don't get it from test sets. I think 80% of data is an overfitting.

## Analysis between black and whites

```
X = np.concatenate((black, white))
Y = np.concatenate((np.zeros(len(black)), np.ones(len(white))))
print(X.shape, Y.shape)
```

```
fig, axes = plt.subplots(10,10,figsize=(9,9),
subplot_kw={'xticks':[], 'yticks':[]},
gridspec_kw=dict(hspace=0.01, wspace=0.01))
for i, ax in enumerate(axes.flat):
    ax.imshow(X[i].reshape(dim[0], dim[1], 3))
```

```
(200, 12288) (200,)
```

```
# Data Set Split
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=0.2, shuffle=True)

clf = LogisticRegression(max_iter = 500)
clf.fit(X_train, Y_train)

LogisticRegression(max_iter=500)

predictions = clf.predict(X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        77
         1.0       1.00      1.00      1.00        83
```

```
    accuracy                           1.00       160
   macro avg       1.00      1.00      1.00       160
weighted avg       1.00      1.00      1.00       160
```

```
predictions = clf.predict(X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, predictions))
```

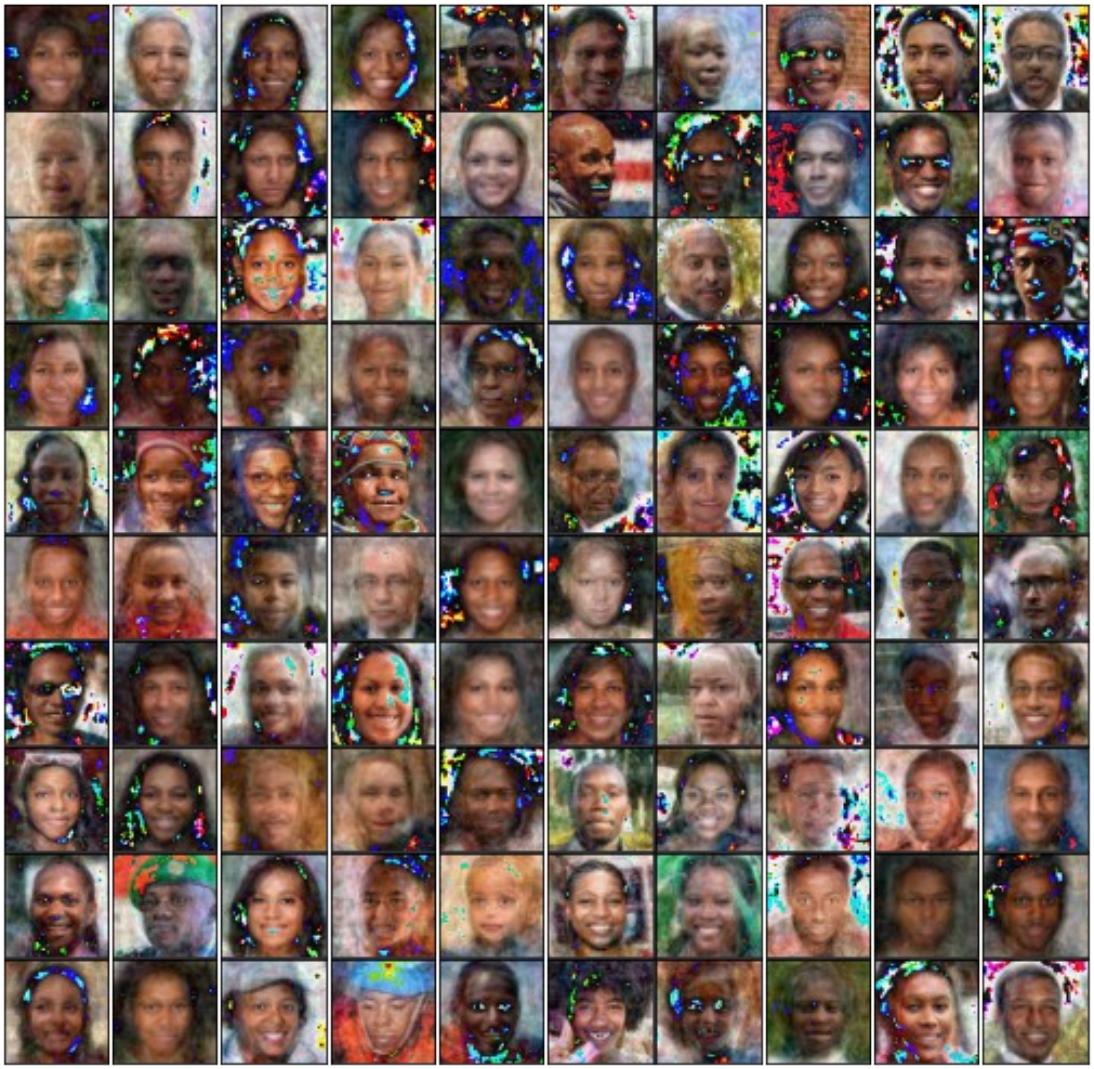
```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.86      0.78      0.82        23
         1.0       0.74      0.82      0.78        17

    accuracy                           0.80        40
   macro avg       0.80      0.80      0.80        40
weighted avg       0.81      0.80      0.80        40
```

This reports the 0.80 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate. This is expected since now we verifies that the classification works so now almost fully distinguish blacks and whites based on the trained model.

```
pca = decomposition.PCA(.9)
pca.fit(X_train)

fig, axes = plt.subplots(3, 3,figsize=(9,9),
 subplot_kw={'xticks':[], 'yticks':[]},
 gridspec_kw=dict(hspace=0.01, wspace=0.01))

# Eigen Vectors
print("Showing 9 out of %s eigenvectors" % len(pca.components_))
for i, ax in enumerate(axes.flat):
    ax.imshow((pca.components_[i].reshape(dim[0], dim[1],
3)*255).astype(np.uint8))
```

```
Showing 9 out of 58 eigenvectors
```

```
transformed_inputs = pca.transform(X)
rescaled_inputs = pca.inverse_transform(transformed_inputs)

fig, axes = plt.subplots(10,10,figsize=(9,9), subplot_kw={'xticks':[],
'yticks':[]},
                         gridspec_kw=dict(hspace=0.01, wspace=0.01))
# Plot images
for i, ax in enumerate(axes.flat):
    ax.imshow((rescaled_inputs[i].reshape(dim[0], dim[1],
3)).astype(np.uint8))
```



```
clf_PCA = LogisticRegression(max_iter = 500)
PCA_X_train = pca.transform(X_train)
PCA_X_test = pca.transform(X_test)
clf_PCA.fit(PCA_X_train, Y_train)
```

```
LogisticRegression(max_iter=500)
```

```
PCA_predictions = clf_PCA.predict(PCA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, PCA_predictions))
```

```
Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00        79
         1.0       1.00      1.00      1.00        81

    accuracy                           1.00       160
```

```
   macro avg       1.00      1.00      1.00       160
weighted avg       1.00      1.00      1.00       160
```

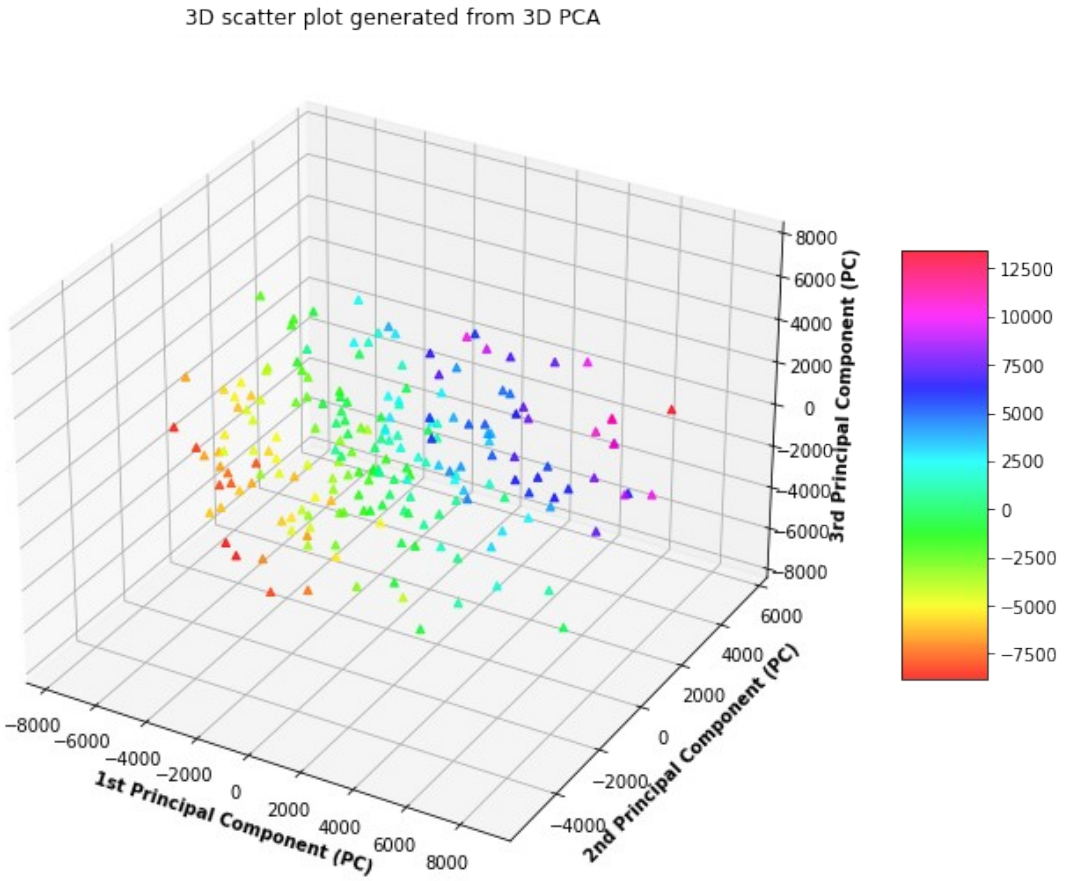
```
PCA_predictions = clf_PCA.predict(PCA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, PCA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.89      0.76      0.82        21
         1.0       0.77      0.89      0.83        19

    accuracy                           0.82        40
   macro avg       0.83      0.83      0.82        40
weighted avg       0.83      0.82      0.82        40
```

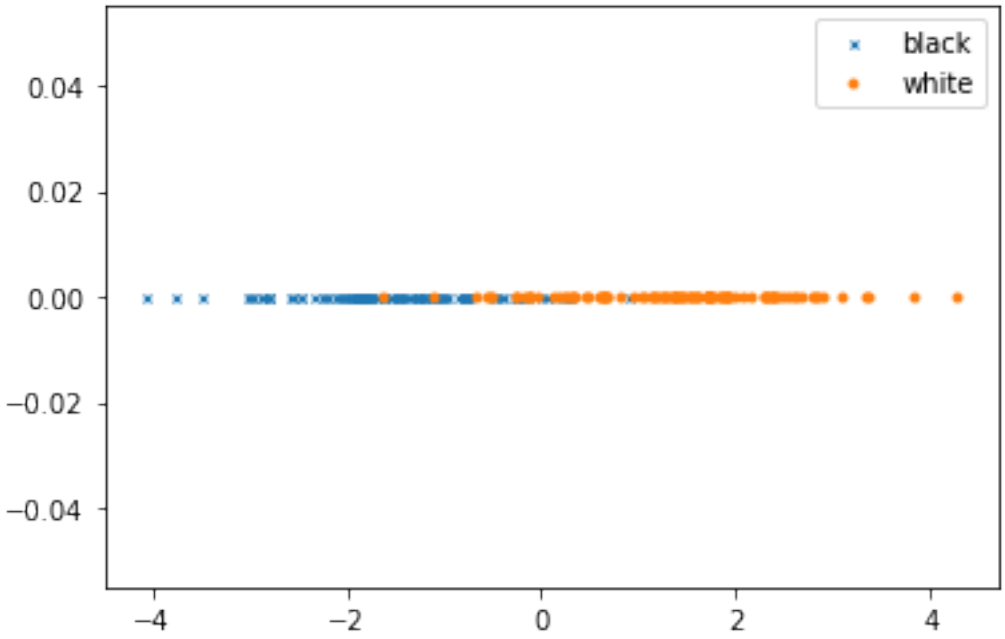
This reports the 0.82 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate. This is expected since now we verifies that the classification works so now almost fully distinguish blacks and whites based on the trained model.

```
# PCA but 3D
import numpy as np
from sklearn.decomposition import PCA
PCA3D = PCA(n_components=3)
PCA3D.fit(X)

# Transfrom images to PCA
X_3D = PCA3D.transform(X)

# Transpose PCA array
ThreeD_ARR = X_3D.T

fig = plt.figure(figsize = (16, 9))
ax_3d = plt.axes(projection = "3d")
ax_3d.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.3,
        alpha = 0.2)
my_cmap = plt.get_cmap('hsv')

plot_3d = ax_3d.scatter3D(ThreeD_ARR[0], ThreeD_ARR[1], ThreeD_ARR[2],
                    alpha = 0.8,
                    c = (ThreeD_ARR[0] + ThreeD_ARR[1] +
ThreeD_ARR[2]),
                    cmap = my_cmap,
                    marker ='^')
```

```
plt.title("3D scatter plot generated from 3D PCA")
ax_3d.set_xlabel('1st Principal Component (PC)', fontweight ='bold')
ax_3d.set_ylabel('2nd Principal Component (PC)', fontweight ='bold')
ax_3d.set_zlabel('3rd Principal Component (PC)', fontweight ='bold')
fig.colorbar(plot_3d, ax = ax_3d, shrink = 0.5, aspect = 5)
plt.show()
```




```
# LDA to reduce it down to 1D
lda = LinearDiscriminantAnalysis(n_components=1)
lda.fit(X_train, Y_train)

transformed_black = lda.transform(black)
transformed_white = lda.transform(white)

plt.plot(transformed_black, [0 for _ in
range(len(transformed_black))], 'x', markersize=3, label='black')
plt.plot(transformed_white, [0 for _ in
range(len(transformed_white))], 'o', markersize=3, label='white')
plt.legend()
plt.show()
```




```
LDA_X_train = lda.transform(X_train)
LDA_X_test = lda.transform(X_test)

clf_LDA = LogisticRegression(max_iter = 500)
clf_LDA.fit(LDA_X_train, Y_train)

LogisticRegression(max_iter=500)

LDA_predictions = clf_LDA.predict(LDA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, LDA_predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.91      0.95      0.93        79
         1.0       0.95      0.91      0.93        81

    accuracy                           0.93       160
   macro avg       0.93      0.93      0.93       160
weighted avg       0.93      0.93      0.93       160


LDA_predictions = clf_LDA.predict(LDA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, LDA_predictions))

Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.89      0.81      0.85        21
```

```
         1.0       0.81      0.89      0.85        19

    accuracy                           0.85        40
   macro avg       0.85      0.85      0.85        40
weighted avg       0.85      0.85      0.85        40
```

This reports the 0.85 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate. This is expected since now we verifies that the classification works so now almost fully distinguish blacks and whites based on the trained model.

## Asian American facial recognition based on Ratio Population of the United States

```
X = np.concatenate((asian, ratio))
Y = np.concatenate((np.zeros(len(asian)), np.ones(len(ratio))))
print(X.shape, Y.shape)
```

```
fig, axes = plt.subplots(10,10,figsize=(9,9),
subplot_kw={'xticks':[], 'yticks':[]},
gridspec_kw=dict(hspace=0.01, wspace=0.01))
for i, ax in enumerate(axes.flat):
    ax.imshow(X[i].reshape(dim[0], dim[1], 3))
```

```
(200, 12288) (200,)
```

```
# Data Set Split
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=0.2, shuffle=True)

clf = LogisticRegression(max_iter = 500)
clf.fit(X_train, Y_train)

LogisticRegression(max_iter=500)

predictions = clf.predict(X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.94      0.99      0.96        75
         1.0       0.99      0.94      0.96        85
```

```
    accuracy                           0.96       160
   macro avg       0.96      0.96      0.96       160
weighted avg       0.96      0.96      0.96       160
```

```
predictions = clf.predict(X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, predictions))
```

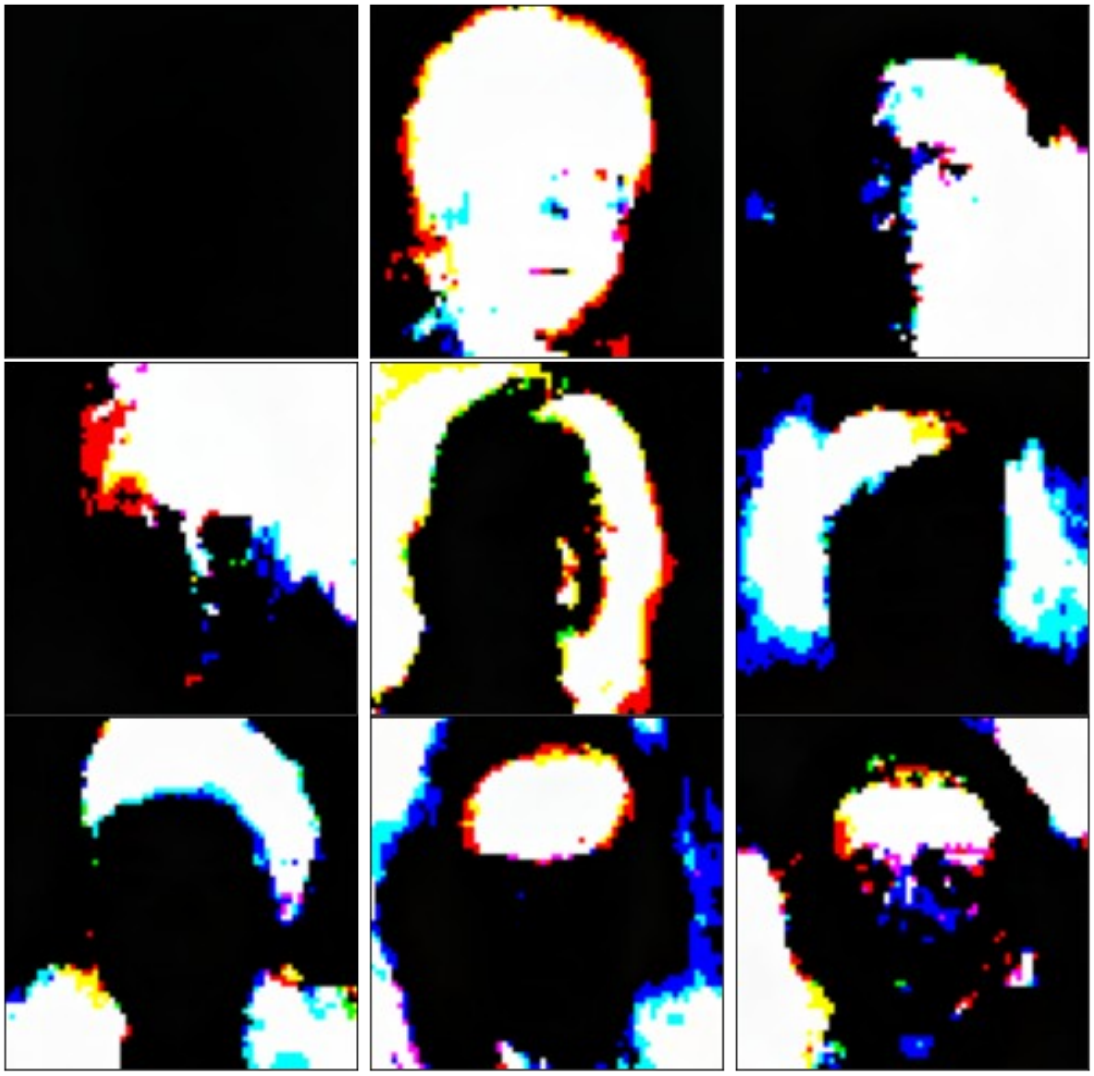
```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.85      0.68      0.76        25
         1.0       0.60      0.80      0.69        15

    accuracy                           0.73        40
   macro avg       0.72      0.74      0.72        40
weighted avg       0.76      0.72      0.73        40
```

This reports the 0.72 of f1 score. The score is significantly dropped based on the analysis had only with Asians.

```
pca = decomposition.PCA(.9)
pca.fit(X_train)
```

```
fig, axes = plt.subplots(3, 3,figsize=(9,9),
 subplot_kw={'xticks':[], 'yticks':[]},
 gridspec_kw=dict(hspace=0.01, wspace=0.01))

# Eigen Vectors
print("Showing 9 out of %s eigenvectors" % len(pca.components_))
for i, ax in enumerate(axes.flat):
    ax.imshow((pca.components_[i].reshape(dim[0], dim[1],
3)*255).astype(np.uint8))
```

```
Showing 9 out of 59 eigenvectors
```



```
transformed_inputs = pca.transform(X)
rescaled_inputs = pca.inverse_transform(transformed_inputs)

fig, axes = plt.subplots(10,10,figsize=(9,9), subplot_kw={'xticks':[],
'yticks':[]},
            gridspec_kw=dict(hspace=0.01, wspace=0.01))
# Plot images
for i, ax in enumerate(axes.flat):
    ax.imshow((rescaled_inputs[i].reshape(dim[0], dim[1],
3)).astype(np.uint8))
```

```
clf_PCA = LogisticRegression(max_iter = 500)
PCA_X_train = pca.transform(X_train)
PCA_X_test = pca.transform(X_test)
clf_PCA.fit(PCA_X_train, Y_train)
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning:
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
```

```
regression
  n_iter_i = _check_optimize_result(

LogisticRegression(max_iter=500)
```

```
PCA_predictions = clf_PCA.predict(PCA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, PCA_predictions))
```

```
Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.86      0.93      0.90        75
         1.0       0.94      0.87      0.90        85

    accuracy                           0.90       160
   macro avg       0.90      0.90      0.90       160
weighted avg       0.90      0.90      0.90       160
```

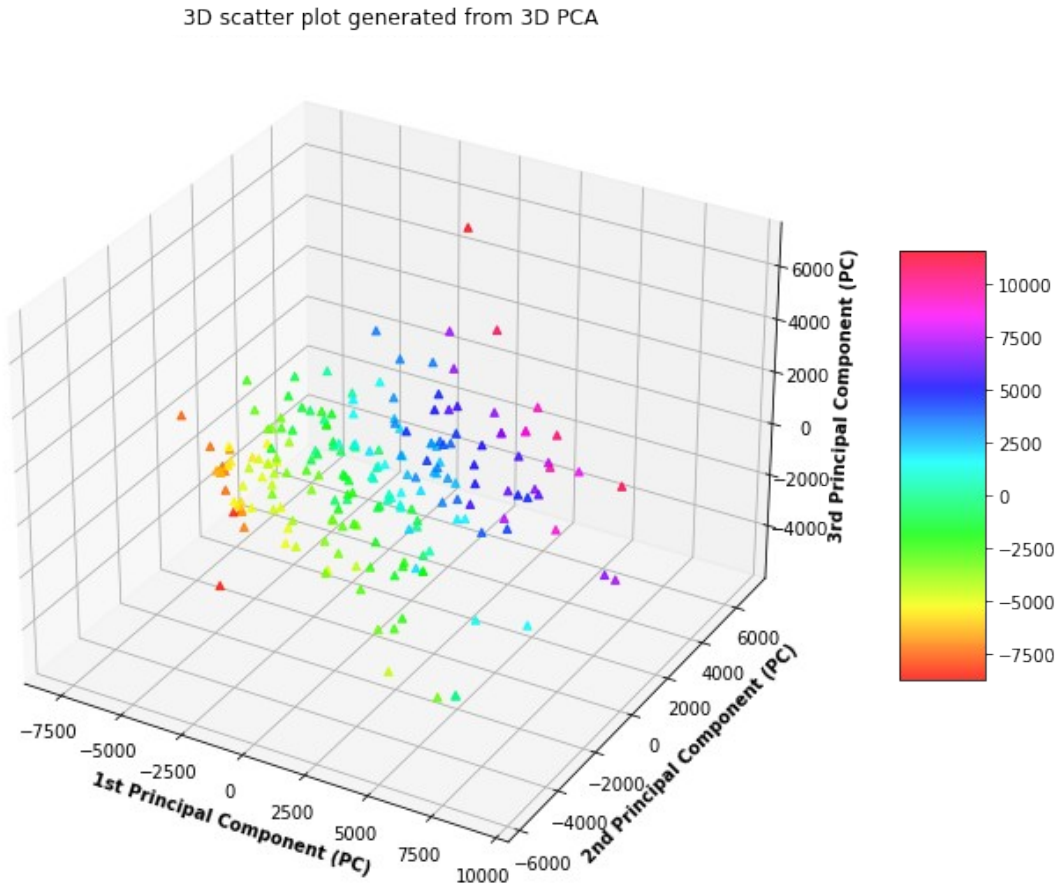
```
PCA_predictions = clf_PCA.predict(PCA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, PCA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.70      0.56      0.62        25
         1.0       0.45      0.60      0.51        15

    accuracy                           0.57        40
   macro avg       0.57      0.58      0.57        40
weighted avg       0.61      0.57      0.58        40
```

This reports the 0.57 of f1 score. The accuracy is significantly dropped down.

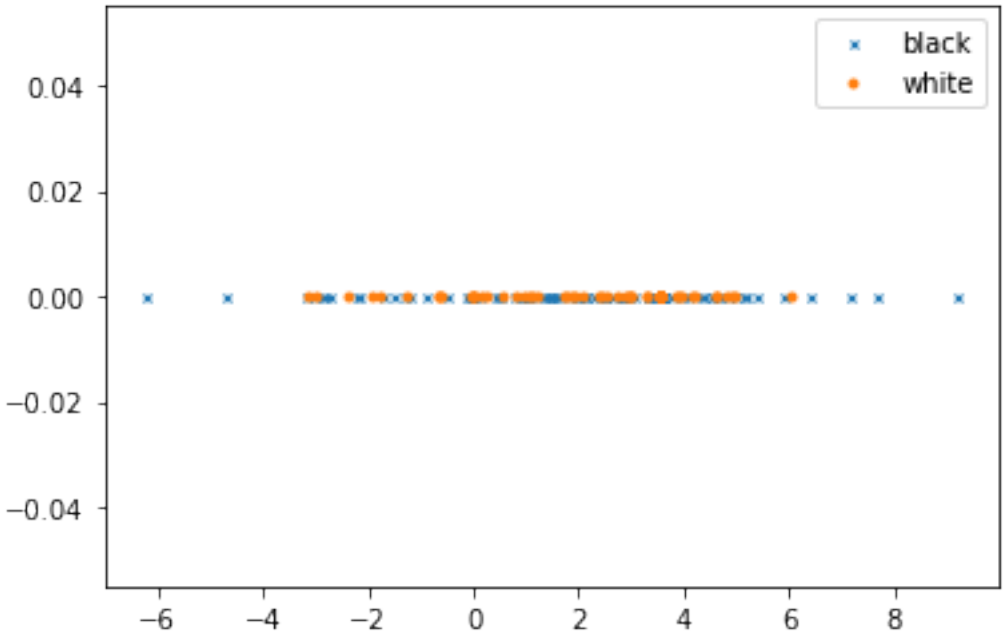
```
# PCA but 3D
import numpy as np
from sklearn.decomposition import PCA
PCA3D = PCA(n_components=3)
PCA3D.fit(X)

# Transfrom images to PCA
X_3D = PCA3D.transform(X)

# Transpose PCA array
ThreeD_ARR = X_3D.T

fig = plt.figure(figsize = (16, 9))
ax_3d = plt.axes(projection = "3d")
```

```
ax_3d.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.3,
        alpha = 0.2)
my_cmap = plt.get_cmap('hsv')

plot_3d = ax_3d.scatter3D(ThreeD_ARR[0], ThreeD_ARR[1], ThreeD_ARR[2],
                    alpha = 0.8,
                    c = (ThreeD_ARR[0] + ThreeD_ARR[1] +
ThreeD_ARR[2]),
                    cmap = my_cmap,
                    marker ='^')

plt.title("3D scatter plot generated from 3D PCA")
ax_3d.set_xlabel('1st Principal Component (PC)', fontweight ='bold')
ax_3d.set_ylabel('2nd Principal Component (PC)', fontweight ='bold')
ax_3d.set_zlabel('3rd Principal Component (PC)', fontweight ='bold')
fig.colorbar(plot_3d, ax = ax_3d, shrink = 0.5, aspect = 5)
plt.show()
```




```
# LDA to reduce it down to 1D
lda = LinearDiscriminantAnalysis(n_components=1)
lda.fit(X_train, Y_train)
```

```
transformed_black = lda.transform(black)
transformed_white = lda.transform(white)

plt.plot(transformed_black, [0 for _ in
range(len(transformed_black))], 'x', markersize=3, label='black')
plt.plot(transformed_white, [0 for _ in
range(len(transformed_white))], 'o', markersize=3, label='white')
plt.legend()
plt.show()
```




```
LDA_X_train = lda.transform(X_train)
LDA_X_test = lda.transform(X_test)

clf_LDA = LogisticRegression(max_iter = 500)
clf_LDA.fit(LDA_X_train, Y_train)

LogisticRegression(max_iter=500)

LDA_predictions = clf_LDA.predict(LDA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, LDA_predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       1.00      0.92      0.96        75
         1.0       0.93      1.00      0.97        85

    accuracy                           0.96       160
   macro avg       0.97      0.96      0.96       160
```

```
weighted avg       0.96      0.96      0.96       160
```

```
LDA_predictions = clf_LDA.predict(LDA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, LDA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.75      0.60      0.67        25
         1.0       0.50      0.67      0.57        15

    accuracy                           0.62        40
   macro avg       0.62      0.63      0.62        40
weighted avg       0.66      0.62      0.63        40
```

This reports the 0.62 of f1 score. The accuracy is significantly dropped down.

## Asian Recognition in Fair Ratio

```
X = np.concatenate((asian, equal))
Y = np.concatenate((np.zeros(len(asian)), np.ones(len(equal))))
print(X.shape, Y.shape)
```

```
fig, axes = plt.subplots(10,10,figsize=(9,9),
subplot_kw={'xticks':[], 'yticks':[]},
gridspec_kw=dict(hspace=0.01, wspace=0.01))
for i, ax in enumerate(axes.flat):
    ax.imshow(X[i].reshape(dim[0], dim[1], 3))
```

```
(200, 12288) (200,)
```

```
# Data Set Split
(X_train, X_test, Y_train, Y_test) = train_test_split(X, Y,
test_size=0.2, shuffle=True)
```

## Simple Logistic Regression Classifier

```
clf = LogisticRegression(max_iter = 500)
clf.fit(X_train, Y_train)

LogisticRegression(max_iter=500)

predictions = clf.predict(X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.87      0.93      0.90        81
```

```
         1.0       0.92      0.86      0.89        79

    accuracy                           0.89       160
   macro avg       0.90      0.89      0.89       160
weighted avg       0.90      0.89      0.89       160
```

This reports the 0.97 of f1 score. F1 score is the harmonic mean of precision and recall; therfore, this shows that the prediction is accurate.

```
predictions = clf.predict(X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.61      0.58      0.59        19
         1.0       0.64      0.67      0.65        21

    accuracy                           0.62        40
   macro avg       0.62      0.62      0.62        40
weighted avg       0.62      0.62      0.62        40
```

This reports the 0.62 of f1 score. The accuracy is significantly dropped down.

## PCA Reduction and Classification

```
pca = decomposition.PCA(.9)
pca.fit(X_train)

fig, axes = plt.subplots(3, 3,figsize=(9,9),
 subplot_kw={'xticks':[], 'yticks':[]},
 gridspec_kw=dict(hspace=0.01, wspace=0.01))

# Eigen Vectors
print("Showing 9 out of %s eigenvectors" % len(pca.components_))
for i, ax in enumerate(axes.flat):
    ax.imshow((pca.components_[i].reshape(dim[0], dim[1],
3)*255).astype(np.uint8))
```

```
Showing 9 out of 53 eigenvectors
```

```
transformed_inputs = pca.transform(X)
rescaled_inputs = pca.inverse_transform(transformed_inputs)

fig, axes = plt.subplots(10,10,figsize=(9,9), subplot_kw={'xticks':[],
'yticks':[]},
                         gridspec_kw=dict(hspace=0.01, wspace=0.01))
# Plot images
for i, ax in enumerate(axes.flat):
    ax.imshow((rescaled_inputs[i].reshape(dim[0], dim[1],
3)).astype(np.uint8))
```

```
clf_PCA = LogisticRegression(max_iter = 500)
PCA_X_train = pca.transform(X_train)
PCA_X_test = pca.transform(X_test)
clf_PCA.fit(PCA_X_train, Y_train)
```

```
LogisticRegression(max_iter=500)
```

```
PCA_predictions = clf_PCA.predict(PCA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, PCA_predictions))
```

```
Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.76      0.84      0.80        81
         1.0       0.82      0.73      0.77        79

    accuracy                           0.79       160
```

```
   macro avg       0.79      0.79      0.79       160
weighted avg       0.79      0.79      0.79       160
```

This reports the 0.79 of f1 score. It is slightly better than ratio population of the United States.

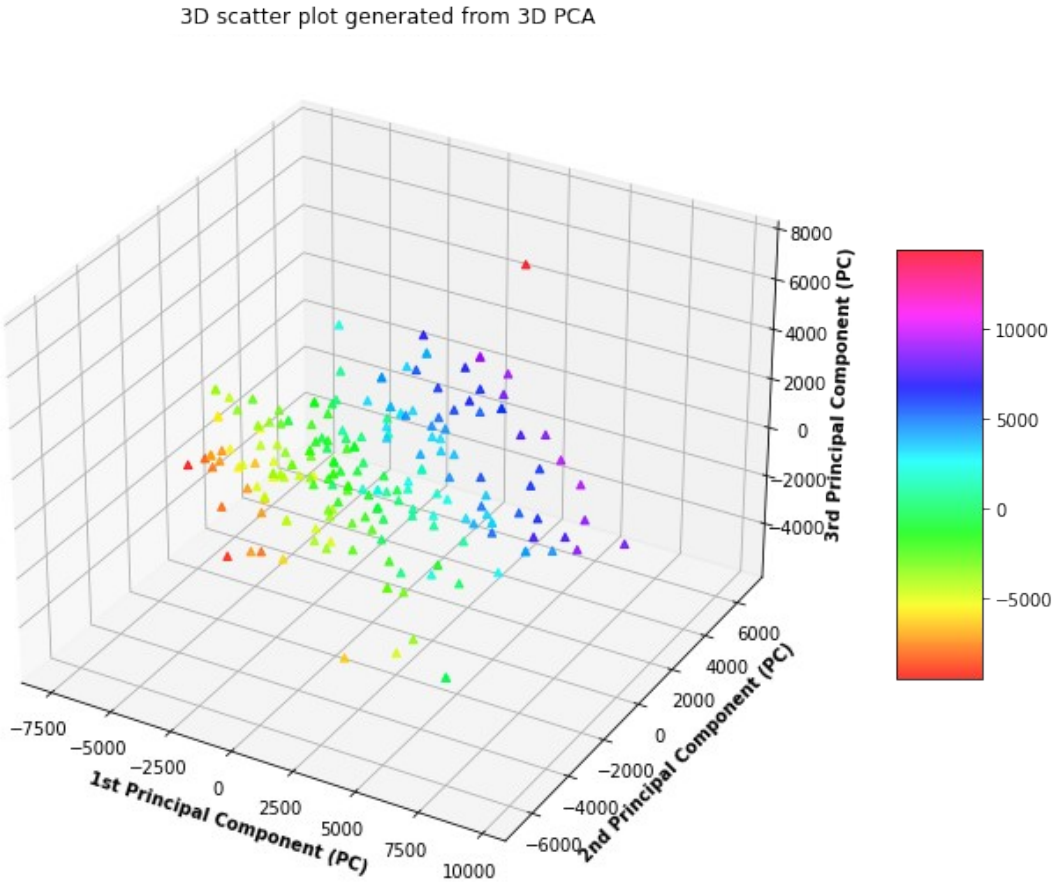
```
PCA_predictions = clf_PCA.predict(PCA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, PCA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.81      0.68      0.74        19
         1.0       0.75      0.86      0.80        21

    accuracy                           0.78        40
   macro avg       0.78      0.77      0.77        40
weighted avg       0.78      0.78      0.77        40
```

This reports the 0.78 of f1 score. It is slightly better than ratio population of the United States.

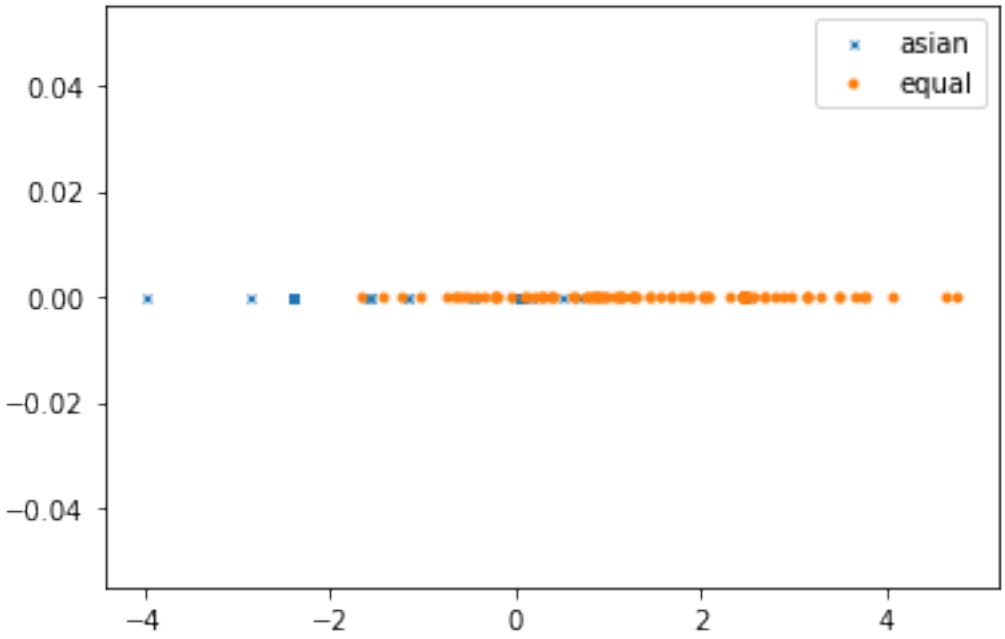
```
# PCA but 3D
import numpy as np
from sklearn.decomposition import PCA
PCA3D = PCA(n_components=3)
PCA3D.fit(X)

# Transfrom images to PCA
X_3D = PCA3D.transform(X)

# Transpose PCA array
ThreeD_ARR = X_3D.T

fig = plt.figure(figsize = (16, 9))
ax_3d = plt.axes(projection = "3d")
ax_3d.grid(visible = True, color ='grey',
        linestyle ='-.', linewidth = 0.3,
        alpha = 0.2)
my_cmap = plt.get_cmap('hsv')

plot_3d = ax_3d.scatter3D(ThreeD_ARR[0], ThreeD_ARR[1], ThreeD_ARR[2],
                    alpha = 0.8,
                    c = (ThreeD_ARR[0] + ThreeD_ARR[1] +
ThreeD_ARR[2]),
                    cmap = my_cmap,
                    marker ='^')
```

```
plt.title("3D scatter plot generated from 3D PCA")
ax_3d.set_xlabel('1st Principal Component (PC)', fontweight ='bold')
ax_3d.set_ylabel('2nd Principal Component (PC)', fontweight ='bold')
ax_3d.set_zlabel('3rd Principal Component (PC)', fontweight ='bold')
fig.colorbar(plot_3d, ax = ax_3d, shrink = 0.5, aspect = 5)
plt.show()
```




## LDA Reduction and Classification

```
# LDA to reduce it down to 1D
lda = LinearDiscriminantAnalysis(n_components=1)
lda.fit(X_train, Y_train)

transformed_asian = lda.transform(asian)
transformed_equal = lda.transform(latinx)

plt.plot(transformed_asian, [0 for _ in
range(len(transformed_asian))], 'x', markersize=3, label='asian')
plt.plot(transformed_equal, [0 for _ in
range(len(transformed_equal))], 'o', markersize=3, label='equal')
plt.legend()
plt.show()
```




```
LDA_X_train = lda.transform(X_train)
LDA_X_test = lda.transform(X_test)

clf_LDA = LogisticRegression(max_iter = 500)
clf_LDA.fit(LDA_X_train, Y_train)

LogisticRegression(max_iter=500)

LDA_predictions = clf_LDA.predict(LDA_X_train)
print("Classification Report on Training Data")
print(classification_report(Y_train, LDA_predictions))

Classification Report on Training Data
              precision    recall  f1-score   support

         0.0       0.83      1.00      0.91        81
         1.0       1.00      0.78      0.88        79

    accuracy                           0.89       160
   macro avg       0.91      0.89      0.89       160
weighted avg       0.91      0.89      0.89       160
```

This reports the 0.89 of f1 score. It is much better than ratio population of the United States.

```
LDA_predictions = clf_LDA.predict(LDA_X_test)
print("Classification Report on Testing Data")
print(classification_report(Y_test, LDA_predictions))
```

```
Classification Report on Testing Data
              precision    recall  f1-score   support

         0.0       0.62      0.53      0.57        19
         1.0       0.62      0.71      0.67        21

    accuracy                           0.62        40
   macro avg       0.62      0.62      0.62        40
weighted avg       0.62      0.62      0.62        40
```

This reports the 0.62 of f1 score. The accuracy dropped down than the previous analyses.