Expt No.: 2
Date: 15/03/2021

Name: Swaranjana Nayak
Reg. No.: 19BCE0977

EXPERIMENT 2

Aim:
To perform statistical analysis(such as multivariate analysis) on Climate Change Dataset - Global Temperature Dataset.

1. Importing Libraries

Code:
```
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import copy
%matplotlib inline
```

2. Reading dataset CSV file and NaN values handling

Code:
```
gt = pd.read_csv('GlobalTemperatures.csv')
gt.dropna(inplace = True)
gt.head()
```

Output:

Out[2]:

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandMaxTemperatureUncertainty	LandMinTemperature	LandMi
1200	1850-01-01	0.749	1.105	8.242	1.738	-3.206	
1201	1850-02-01	3.071	1.275	9.970	3.007	-2.291	
1202	1850-03-01	4.954	0.955	10.347	2.401	-1.905	
1203	1850-04-01	7.217	0.665	12.934	1.004	1.018	
1204	1850-05-01	10.004	0.617	15.655	2.406	3.811	

3. Dataset Information and Columns

Code:
```
print(gt.isnull().sum())
```

Output:
```
dt                                   0
LandAverageTemperature               0
LandAverageTemperatureUncertainty    0
LandMaxTemperature                   0
```

```
LandMaxTemperatureUncertainty                0
LandMinTemperature                           0
LandMinTemperatureUncertainty                0
LandAndOceanAverageTemperature               0
LandAndOceanAverageTemperatureUncertainty    0
dtype: int64
```

Code:

```
gt.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1992 entries, 1200 to 3191
Data columns (total 9 columns):
 #   Column                                     Non-Null Count  Dtype  
---  ------                                     --------------  -----  
 0   dt                                         1992 non-null   object 
 1   LandAverageTemperature                     1992 non-null   float64
 2   LandAverageTemperatureUncertainty          1992 non-null   float64
 3   LandMaxTemperature                         1992 non-null   float64
 4   LandMaxTemperatureUncertainty              1992 non-null   float64
 5   LandMinTemperature                         1992 non-null   float64
 6   LandMinTemperatureUncertainty              1992 non-null   float64
 7   LandAndOceanAverageTemperature             1992 non-null   float64
 8   LandAndOceanAverageTemperatureUncertainty  1992 non-null   float64
dtypes: float64(8), object(1)
memory usage: 155.6+ KB
```

Code:

```
columns = gt.columns
columns
```

Output:

```
Index(['dt', 'LandAverageTemperature', 'LandAverageTemperatureUncertainty',
       'LandMaxTemperature', 'LandMaxTemperatureUncertainty',
       'LandMinTemperature', 'LandMinTemperatureUncertainty',
       'LandAndOceanAverageTemperature',
       'LandAndOceanAverageTemperatureUncertainty'],
      dtype='object')
```

4. Covariance Matrix (Without Scaling)

Code:

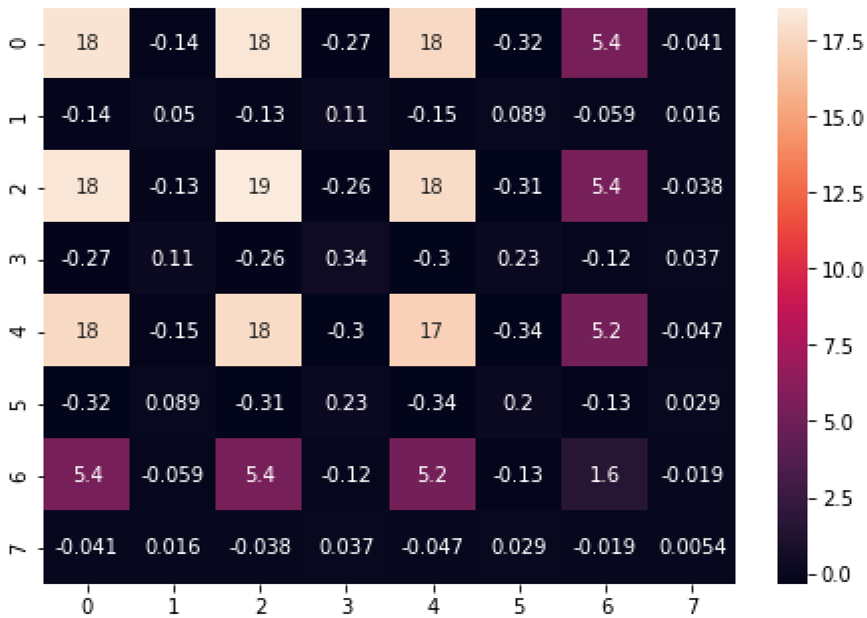
```
def covariance(a, b):
    if len(a) != len(b):
        return

    a_mean = np.mean(a)
    b_mean = np.mean(b)

    sum = 0
    for i in range(0, len(a)):
        sum += ((a[i] - a_mean) * (b[i] - b_mean))

    return sum/(len(a)-1)
```

```
# this covariance is calculated without scaling the dataset
# but nan values have been dropped

cov_gt = np.zeros((8, 8), dtype = float)
x = 0
arr = np.array(gt[columns[1:]]).transpose()
# print(len(arr[0]))
for col1 in arr:
    y = 0
    for col2 in arr:
        cov_gt[x][y] = covariance(col1, col2)
        y += 1
    x += 1

print(cov_gt) # == np.cov(arr))
print("\n")
print(np.cov(arr))

fig = plt.figure()
ax = fig.add_axes([0, 0, 1, 1])
sns.heatmap(pd.DataFrame(cov_gt), annot=True)
fig.savefig('covariance_heatmap_scratch.png', bbox_inches = 'tight')
```

Output:

```
[[ 1.81748118e+01 -1.36699347e-01  1.82955323e+01 -2.69670225e-01
   1.76393578e+01 -3.18273449e-01  5.36687949e+00 -4.12259185e-02]
 [-1.36699347e-01  5.01892292e-02 -1.28316115e-01  1.13270297e-01
  -1.53681120e-01  8.87657928e-02 -5.93726202e-02  1.60306914e-02]
 [ 1.82955323e+01 -1.28316115e-01  1.85724709e+01 -2.64779168e-01
   1.77917613e+01 -3.07457662e-01  5.40215576e+00 -3.82338955e-02]
 [-2.69670225e-01  1.13270297e-01 -2.64779168e-01  3.40125690e-01
  -2.98722006e-01  2.25874580e-01 -1.21412400e-01  3.69260475e-02]
 [ 1.76393578e+01 -1.53681120e-01  1.77917613e+01 -2.98722006e-01
   1.72709672e+01 -3.43721021e-01  5.22292154e+00 -4.73801407e-02]
 [-3.18273449e-01  8.87657928e-02 -3.07457662e-01  2.25874580e-01
  -3.43721021e-01  1.98771377e-01 -1.25960453e-01  2.88728675e-02]
 [ 5.36687949e+00 -5.93726202e-02  5.40215576e+00 -1.21412400e-01
   5.22292154e+00 -1.25960453e-01  1.62331286e+00 -1.90392615e-02]
 [-4.12259185e-02  1.60306914e-02 -3.82338955e-02  3.69260475e-02
  -4.73801407e-02  2.88728675e-02 -1.90392615e-02  5.41501655e-03]]


[[ 1.81748118e+01 -1.36699347e-01  1.82955323e+01 -2.69670225e-01
   1.76393578e+01 -3.18273449e-01  5.36687949e+00 -4.12259185e-02]
 [-1.36699347e-01  5.01892292e-02 -1.28316115e-01  1.13270297e-01
  -1.53681120e-01  8.87657928e-02 -5.93726202e-02  1.60306914e-02]
 [ 1.82955323e+01 -1.28316115e-01  1.85724709e+01 -2.64779168e-01
   1.77917613e+01 -3.07457662e-01  5.40215576e+00 -3.82338955e-02]
 [-2.69670225e-01  1.13270297e-01 -2.64779168e-01  3.40125690e-01
  -2.98722006e-01  2.25874580e-01 -1.21412400e-01  3.69260475e-02]
 [ 1.76393578e+01 -1.53681120e-01  1.77917613e+01 -2.98722006e-01
   1.72709672e+01 -3.43721021e-01  5.22292154e+00 -4.73801407e-02]
 [-3.18273449e-01  8.87657928e-02 -3.07457662e-01  2.25874580e-01
  -3.43721021e-01  1.98771377e-01 -1.25960453e-01  2.88728675e-02]
 [ 5.36687949e+00 -5.93726202e-02  5.40215576e+00 -1.21412400e-01
   5.22292154e+00 -1.25960453e-01  1.62331286e+00 -1.90392615e-02]
```

```
[-4.12259185e-02  1.60306914e-02 -3.82338955e-02  3.69260475e-02
 -4.73801407e-02  2.88728675e-02 -1.90392615e-02  5.41501655e-03]]
```



5. Correlation Matrix

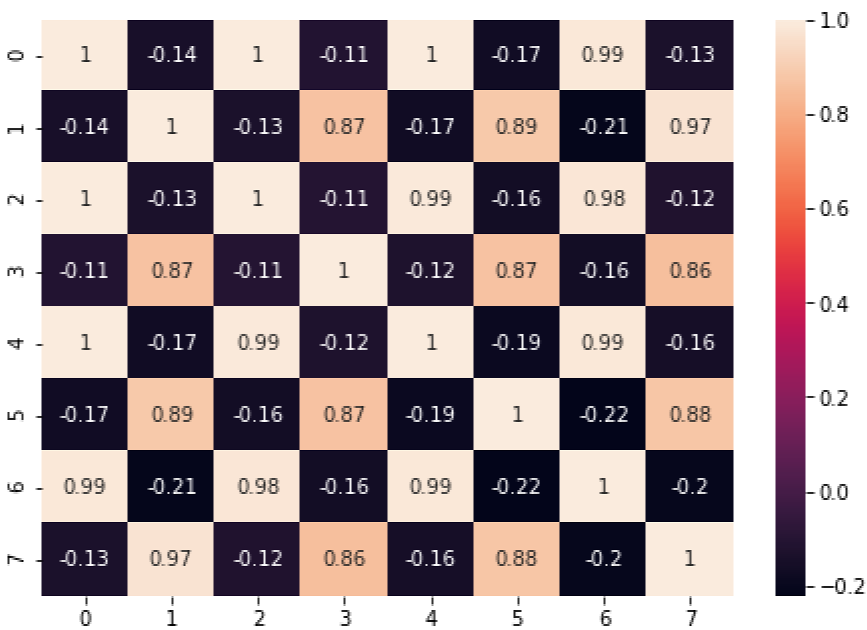
Code:

```
def correlation(a, b):
    c = covariance(a, b)
    std_a = np.std(a)
    std_b = np.std(b)
    corrn = c/(std_a * std_b)
    return corrn

corr_gt = np.zeros((8, 8), dtype = float)
x = 0
arr = np.array(gt[columns[1:]]).transpose()
# print(len(arr[0]))
for col1 in arr:
    y = 0
    for col2 in arr:
        corr_gt[x][y] = correlation(col1, col2)
        y += 1
    x += 1

print(corr_gt) # == np.cov(arr))
print("\n")
print(np.array(gt[columns[1:]].corr()))

fig = plt.figure()
ax = fig.add_axes([0, 0, 1, 1])
sns.heatmap(pd.DataFrame(corr_gt), annot=True)
fig.savefig('correlation_heatmap_scratch.png', bbox_inches = 'tight')
```

Output:

```
[[ 1.00050226 -0.14320042  0.99630732 -0.10851665  0.99611058 -0.16753541
   0.98856184 -0.13147814]
 [-0.14320042  1.00050226 -0.13297168  0.86737946 -0.16514864  0.88916329
  -0.20811238  0.97289321]
 [ 0.99630732 -0.13297168  1.00050226 -0.10540163  0.99390264 -0.16010011
   0.98434926 -0.12062349]
 [-0.10851665  0.86737946 -0.10540163  1.00050226 -0.12331254  0.86913811
  -0.16347837  0.86085754]
 [ 0.99611058 -0.16514864  0.99390264 -0.12331254  1.00050226 -0.18560468
   0.98689769 -0.15500874]
 [-0.16753541  0.88916329 -0.16010011  0.86913811 -0.18560468  1.00050226
  -0.22185757  0.88050368]
 [ 0.98856184 -0.20811238  0.98434926 -0.16347837  0.98689769 -0.22185757
   1.00050226 -0.20317355]
 [-0.13147814  0.97289321 -0.12062349  0.86085754 -0.15500874  0.88050368
  -0.20317355  1.00050226]]
```

```
[[ 1.         -0.14312853  0.99580716 -0.10846218  0.99561052 -0.1674513
   0.98806558 -0.13141214]
 [-0.14312853  1.         -0.13290493  0.86694403 -0.16506573  0.88871692
  -0.2080079   0.97240481]
 [ 0.99580716 -0.13290493  1.         -0.10534872  0.99340369 -0.16001974
   0.98385511 -0.12056294]
 [-0.10846218  0.86694403 -0.10534872  1.         -0.12325064  0.86870179
  -0.1633963   0.86042538]
 [ 0.99561052 -0.16506573  0.99340369 -0.12325064  1.         -0.1855115
   0.98640226 -0.15493093]
 [-0.1674513   0.88871692 -0.16001974  0.86870179 -0.1855115   1.
  -0.22174619  0.88006166]
 [ 0.98806558 -0.2080079   0.98385511 -0.1633963   0.98640226 -0.22174619
   1.         -0.20307155]
 [-0.13141214  0.97240481 -0.12056294  0.86042538 -0.15493093  0.88006166
  -0.20307155  1.        ]]
```



6. Principle Component Analysis

Code:

```
from sklearn.preprocessing import StandardScaler
gt_sdt = StandardScaler().fit_transform(gt[columns[1:]])
gt_scaled                                                                    =
pd.DataFrame(StandardScaler().fit_transform(gt[columns[1:]]))
gt_scaled

gt_arr = np.array(gt[columns[1:]])
mean = np.mean(gt_arr, axis=0)
mean
#nan values are ignored with sklearn so we can do the same

features = gt_sdt.T
cov_matrix = np.cov(features)
c = pd.DataFrame(cov_matrix)

fig = plt.figure()
ax = fig.add_axes([0, 0, 1, 1])
sns.heatmap(c, annot=True)
fig.savefig('covariance_heatmap.png', bbox_inches = 'tight')

values, vectors = np.linalg.eig(cov_matrix)
print(values)
print("\n")
print(vectors)

max_abs_idx = np.argmax(np.abs(vectors), axis=0)
# print(max_abs_idx)
signs = np.sign(vectors[max_abs_idx, range(vectors.shape[0])])
# print(signs)
vectors = vectors*signs[np.newaxis,:]
# print(vectors)
vectors = vectors.T
print(vectors)

explained_variances = []
for i in range(len(values)):
    explained_variances.append(values[i] / np.sum(values))

print(np.sum(explained_variances), "\n", explained_variances)

projected_1 = gt_scaled.dot(vectors.T[0])
projected_2 = gt_scaled.dot(vectors.T[1])
res = pd.DataFrame(projected_1, columns=["PC1"])
res["PC2"] = projected_2
res["Date"] = gt['dt']
res.head()
```

```
fig = plt.figure(figsize=(20, 10))
axes = fig.add_axes([0, 0, 1, 1])
sns.scatterplot(res['PC1'], res['PC2'], ax = axes)
fig.savefig('PCA_plot.png')
```

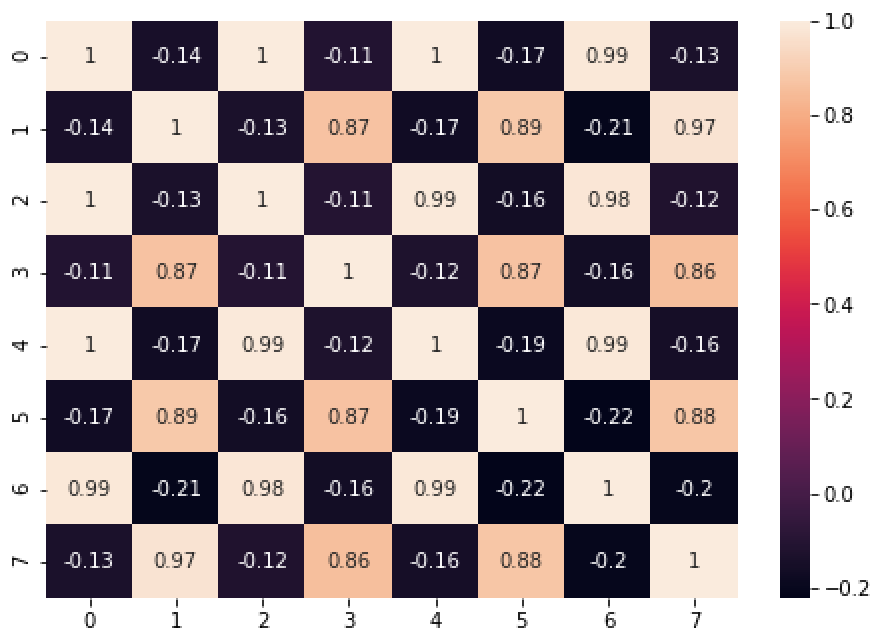
Output:

In [9]:
```
from sklearn.preprocessing import StandardScaler
gt_sdt = StandardScaler().fit_transform(gt[columns[1:]])
gt_scaled = pd.DataFrame(StandardScaler().fit_transform(gt[columns[1:]]))
gt_scaled
```

Out[9]:

	0	1	2	3	4	5	6	7
0	-1.835373	3.698376	-1.417803	2.157970	-1.431984	5.362379	-1.868124	3.241448
1	-1.290574	4.457395	-1.016735	4.334431	-1.211756	2.672385	-1.275396	3.880310
2	-0.848775	3.028653	-0.929234	3.295081	-1.118852	2.194513	-0.918190	2.888035
3	-0.317819	1.733856	-0.328792	0.899087	-0.415327	2.012786	-0.428307	1.882167
4	0.336081	1.519544	0.302750	3.303656	0.256909	2.053170	0.231151	1.637496
...	...	...	...	...	...	...	...	...
1987	1.450784	-0.913782	1.473460	-0.634212	1.507032	-0.587466	1.865665	-0.972322
1988	1.038782	-0.882528	1.043148	-0.671944	1.072353	-0.455098	1.441728	-0.958730
1989	0.523077	-0.779837	0.487269	-0.721682	0.598924	-0.710860	0.845860	-0.904358
1990	-0.267140	-0.703935	-0.338541	-0.663369	-0.141185	-0.731052	0.030959	-0.890766
1991	-0.716447	-0.788767	-0.841500	-0.558748	-0.591268	-0.746757	-0.344304	-0.904358

1992 rows × 8 columns



Eigenvalues:
```
[4.46651682e+00 3.18347024e+00 1.77453809e-01 1.25237144e-01
 2.83359905e-02 1.41197901e-02 3.17441376e-03 5.70987045e-03]
```

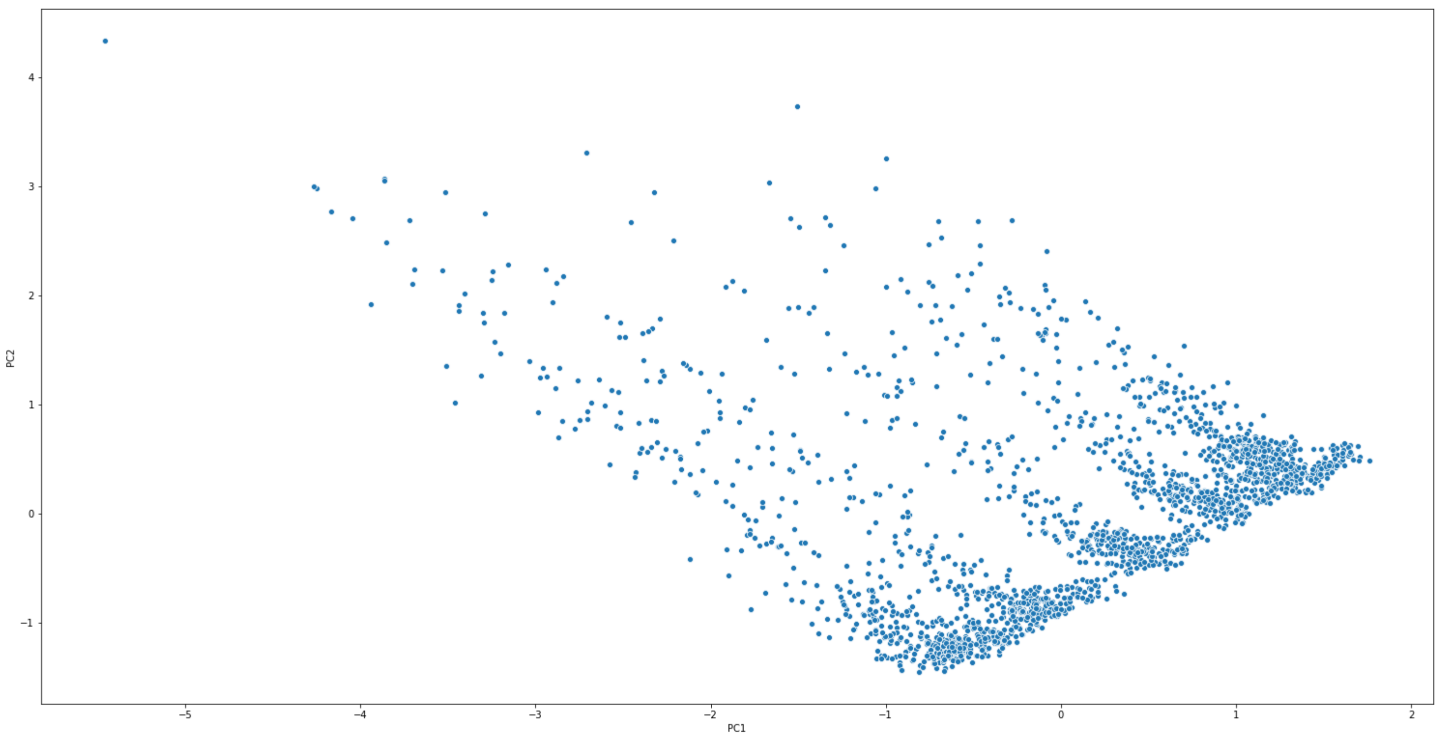
Eigenvectors:
```
[[-3.88372578e-01 -3.19054038e-01  2.01405721e-02 -5.66399735e-04
  -6.47629246e-02  1.32165675e-01 -8.51609009e-01  8.08647040e-03]
 [ 3.15770271e-01 -3.97734760e-01  4.43170938e-01  1.25497688e-01
   7.13414434e-01  1.43846268e-01 -1.65687360e-02 -4.42959816e-03]
```

```
 [-3.85583349e-01 -3.22374208e-01  5.41976212e-02 -1.14395136e-02
  -1.02485868e-01  3.24679898e-01  3.49335574e-01 -7.11601274e-01]
 [ 2.92740257e-01 -3.95545763e-01 -6.90870158e-01  5.28252697e-01
  -1.58131824e-02  8.70233926e-03  2.25824450e-04 -3.41813592e-02]
 [-3.93463236e-01 -3.08970319e-01 -1.51996359e-02  4.55192278e-03
  -4.88713428e-02  3.57743364e-01  3.60706627e-01  6.99281260e-01]
 [ 3.16978937e-01 -3.77225813e-01 -2.78418184e-01 -8.23470327e-01
  -3.62137787e-02  1.65555572e-02 -3.92425707e-03  2.01284623e-03]
 [-4.03612418e-01 -2.86447544e-01 -4.93704194e-02 -3.46052614e-02
   2.25333093e-01 -8.24301453e-01  1.45250595e-01  8.01469359e-03]
 [ 3.11275683e-01 -3.99769727e-01  4.92716721e-01  1.60457508e-01
  -6.49320684e-01 -2.20500413e-01  3.50681032e-02  5.75124395e-02]]
```

Explained Variances:

```
1.0
 [0.55803432420026, 0.39773401439058115, 0.02217059074192478, 0.015646784210716462,
0.003540220694728631, 0.0017640877331766233, 0.0003966025220495761,
0.0007133755065627644]
```

The first two account for 94% of explained variance. We can take those two features for our reduced feature dataset (for example). We don't really need dimensionality reduction in this dataset because all features are meaningful



7. Linear Discriminant Analysis

LDA is a type of Linear combination, a mathematical process using various data items and applying a function to that site to separately analyze multiple classes of objects or items.

Following Fisher's Linear discriminant, linear discriminant analysis can be useful in areas like image recognition and predictive analysis in marketing.

The fundamental idea of linear combinations goes back as far as the 1960s with the Altman Z-scores for bankruptcy and other predictive constructs. Now LDA helps in preventative data for more than two classes, when Logistics Regression is not sufficient. The linear Discriminant analysis takes the mean value for each class and considers variants to make predictions assuming a Gaussian distribution.

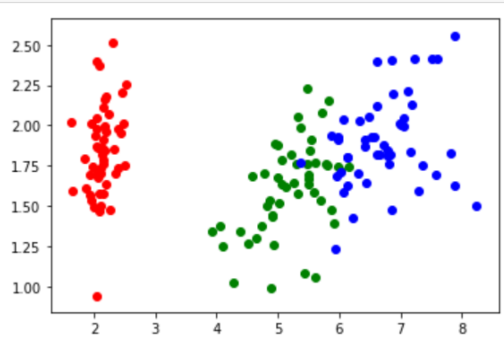
Maximizing the component axes for class-separation.

Since the taken project dataset doesn't have classes, we'll apply LDA on Iris dataset.

Code:
```
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris

data = load_iris()
X, y = data.data, data.target
X_train, X_test, Y_train, Y_test = train_test_split(X, y,
test_size=0.2)

height, width = X_train.shape
unique_classes = np.unique(Y_train)
num_classes = len(unique_classes)

scatter_t = np.cov(X_train.T)*(height - 1)
scatter_w = 0
for i in range(num_classes):
    class_items = np.flatnonzero(Y_train == unique_classes[i])
        scatter_w = scatter_w + np.cov(X_train[class_items].T) *
(len(class_items)-1)

scatter_b = scatter_t - scatter_w
_, eig_vectors =
np.linalg.eigh(np.linalg.pinv(scatter_w).dot(scatter_b))
print(eig_vectors.shape)
pc = X.dot(eig_vectors[:,::-1][:,:3])
print(pc.shape)

colors = ['r','g','b']
labels = np.unique(y)
for color, label in zip(colors, labels):
    class_data = pc[np.flatnonzero(y==label)]
    plt.scatter(class_data[:,0],class_data[:,1],c=color)
```

Output:

```
In [42]: colors = ['r','g','b']
         labels = np.unique(y)
         for color, label in zip(colors, labels):
             class_data = pc[np.flatnonzero(y==label)]
             plt.scatter(class_data[:,0],class_data[:,1],c=color)
```



8. Multivariate Linear Regression

Code:

```
features = gt_sdt.T
cov_matrix = np.cov(features)
c = pd.DataFrame(cov_matrix)
c.columns = columns[1:]

#How does landmaxtemtperature, landmintemperature,
LandAndOceanAverageTemperature affect landAaveragetemperature?
#Multivariate linear regression

mlr = pd.DataFrame(gt[columns[1:9:2]])
mlrcolumns = mlr.columns

X = mlr[mlrcolumns[1:]]
Y = mlr[mlrcolumns[0]]

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)

def cost_function(X, Y, B):
    m = len(Y)
    J = np.sum((X.dot(B) - Y) ** 2)/(2 * m)
    return J

def batch_gradient_descent(X, Y, B, alpha, iterations):
    cost_history = [0] * iterations
    m = len(Y)

    for iteration in range(iterations):
         #print(iteration)
         # Hypothesis Values
        h = X.dot(B)
         # Difference b/w Hypothesis and Actual Y
        loss = h - Y
         # Gradient Calculation
        gradient = X.T.dot(loss) / m
         # Changing Values of B using Gradient
        B = B - alpha * gradient
         # New Cost Value
        cost = cost_function(X, Y, B)
        cost_history[iteration] = cost

    return B, cost_history

m = 1500
f = 3
```

```
X_train = X[:m,:f]
X_train = np.c_[np.ones(len(X_train),dtype='int64'),X_train]
y_train = y[:m]
X_test = X[m:,:f]
X_test = np.c_[np.ones(len(X_test),dtype='int64'),X_test]
y_test = y[m:]
# X_train

# Initial Coefficients
B = np.zeros(X_train.shape[1])
alpha = 0.005
iter_ = 2000
newB,  cost_history  =  batch_gradient_descent(X_train,  y_train,  B,
alpha, iter_)

y_ = (X_test)*(newB)
y_ = np.sum(y_, axis = 1)

def r2(y_,y):
    sst = np.sum((y-y.mean())**2)
    ssr = np.sum((y_-y)**2)
    r2 = 1-(ssr/sst)
    return(r2)

r2(y_, y_test) #99% accuracy is pretty good
```

Output:

```
In [51]: #How does landmaxtemtperature, landmintemperature, LandAndOceanAverageTemperature affect landAaveragetemperature?
         #Multivariate linear regression

         mlr = pd.DataFrame(gt[columns[1:9:2]])
         mlrcolumns = mlr.columns
         mlr
```

Out[51]:

	LandAverageTemperature	LandMaxTemperature	LandMinTemperature	LandAndOceanAverageTemperature
1200	0.749	8.242	-3.206	12.833
1201	3.071	9.970	-2.291	13.588
1202	4.954	10.347	-1.905	14.043
1203	7.217	12.934	1.018	14.667
1204	10.004	15.655	3.811	15.507
...	...	...	...	...
3187	14.755	20.699	9.005	17.589
3188	12.999	18.845	7.199	17.049
3189	10.801	16.450	5.232	16.290
3190	7.433	12.892	2.157	15.252
3191	5.518	10.725	0.287	14.774

1992 rows × 4 columns

After testing, accuracy:

```
In [102]: r2(y_, y_test) #99% accuracy is pretty good

Out[102]: 0.9940195657979105
```