In [1]: # Library Imports import numpy as np import matplotlib.pyplot as plt import seaborn as sns import pandas as pd In [2]: # Dataset Imports data = pd.read csv('Lab1-Data.csv') data.head(10) Out[2]: job\_category race\_ethnicity gender count percentage All workers White 268883 41.257252 Male 1 All workers White Female 105560 16.197065 2 2.686417 All workers Black\_or\_African American Male 17508 3 All workers Black\_or\_African American Female 11479 1.761331 4 All workers Asian Male 125347 19.233171 5 All workers Asian Female 58049 8.907005 6 All workers Hispanic\_or\_Latino 32201 4.940903 Male 7 All workers Hispanic\_or\_Latino Female 15512 2.380152 Male 8 All workers 454813 69.786244 9 All workers Female 196910 30.213756 In [3]: # Viewing Dataset Statistically data.describe() Out[3]: count percentage count 44.000000 44.000000 75269.954545 27.084140 mean 133360.750559 std 31.904184 53.000000 0.427075 min 25% 3452.250000 2.320972 50% 16510.000000 15.423271 75% 91864.500000 39.309757 651723.000000 100.000000 max In [4]: # dropping duplicate values data = data.drop\_duplicates() data Out[4]: job\_category race\_ethnicity gender count percentage 0 All workers White 268883 41.257252 Male 1 All workers White Female 105560 16.197065 2 All workers 17508 2.686417 Black\_or\_African American Male 3 Black\_or\_African American **Female** 11479 1.761331 All workers 4 All workers 125347 19.233171 Asian Male 5 58049 8.907005 All workers Asian Female 6 All workers Hispanic\_or\_Latino 32201 4.940903 Male 7 All workers 15512 2.380152 Hispanic\_or\_Latino Female 8 All workers 454813 69.786244 ΑII Male 9 All workers ΑII Female 196910 30.213756 10 All workers 651723 100.000000 Totals Both Executives 11 White Male 7282 58.678485 Female 12 Executives White 1818 14.649476 13 Executives Black\_or\_African American Male 120 0.966962 14 Executives Black\_or\_African American 0.427075 Female 53 15 Executives Asian 2023 16.301370 Male Executives Female 4.500000 16 Asian 556 17 Executives Hispanic\_or\_Latino Male 266 2.143433 18 Female 103 0.829976 Executives Hispanic\_or\_Latino 19 Executives ΑII Male 9824 79.161966 20 Executives 2586 20.838034 ΑII Female 21 Executives Totals Both 12410 100.000000 22 White 48311 46.479253 Managers Male 23 Managers White Female 18935 18.217065 24 Managers Black\_or\_African American 1.515283 Male 1575 978 25 Managers Black\_or\_African American Female 0.940918 26 Managers Asian Male 18563 17.859170 27 Asian 8084 7.777489 Managers Female 28 Managers Hispanic\_or\_Latino 3741 3.599157 Male 29 Managers Hispanic\_or\_Latino Female 1642 1.579742 30 70.738207 Managers Male 73526 ΑII 31 Managers ΑII Female 30415 29.261793 32 Managers Totals Both 103941 100.000000 33 Professionals White Male 133311 38.660592 White Female 47505 13.776593 34 Professionals Black\_or\_African American 6301 1.827309 35 Professionals Male 36 Professionals Black\_or\_African American Female 3756 1.089251 37 Professionals Asian Male 89365 25.916120 39902 11.571700 38 Professionals Asian Female 39 Hispanic\_or\_Latino 11820 3.427836 Professionals Male Hispanic\_or\_Latino 1.604587 Professionals Female 5533 40 41 Professionals Male 245461 71.184430 99363 28.815570 42 Professionals ΑII Female 43 Professionals **Totals** Both 344824 100.000000 In [5]: # Checking the null values data.isnull() Out[5]: job\_category race\_ethnicity gender count percentage 0 False False False False False False False 2 False False False False False 3 False False False False False 4 False False False False False 5 False False False False False 6 False False False False False 7 False False False False False 8 False False False False False 9 False False False False False 10 False False False False False False False False False 11 False 12 False False False False False 13 False False False False False 14 False False False False False 15 False False False False False 16 False False False False False 17 False False False False False 18 False False False False False 19 False False False False False 20 False False False False False 21 False False False False False 22 False False False False False 23 False False False False False 24 False False False False False 25 False False False False False 26 False False False False False False False False 27 False False 28 False False False False False 29 False False False False False 30 False False False False False 31 False False False False False 32 False False False False False 33 False False False False False 34 False False False False False 35 False False False False False 36 False False False False False 37 False False False False False 38 False False False False False 39 False False False False False 40 False False False False False 41 False False False False False 42 False In [6]: # Statistically checking the missing values data.isnull().sum() Out[6]: job\_category race ethnicity gender 0 count 0 percentage dtype: int64 In [7]: data.dropna(how='any',inplace=True) Splitting the Data In [8]: # Splitting dataset X = data[['job category', 'count', "percentage"]].values Y = data['gender'].values Z = data['race\_ethnicity'].values print(X) print(Y) print(Z) [['All workers' 268883 41.25725193] ['All workers' 105560 16.19706532] ['All workers' 17508 2.686417389] ['All workers' 11479 1.761331118] ['All workers' 125347 19.23317115] ['All workers' 58049 8.90700497] ['All workers' 32201 4.940902807] ['All workers' 15512 2.380152304] ['All workers' 454813 69.78624354] ['All workers' 196910 30.21375646] ['All workers' 651723 100.0] ['Executives' 7282 58.67848509] ['Executives' 1818 14.64947623] ['Executives' 120 0.966962127] ['Executives' 53 0.42707494] ['Executives' 2023 16.30136986] ['Executives' 556 4.5] ['Executives' 266 2.143432716] ['Executives' 103 0.829975826] ['Executives' 9824 79.16196616] ['Executives' 2586 20.83803384] ['Executives' 12410 100.0] ['Managers' 48311 46.47925265] ['Managers' 18935 18.21706545] ['Managers' 1575 1.515282708] ['Managers' 978 0.940918406] ['Managers' 18563 17.85917011] ['Managers' 8084 7.777489152] ['Managers' 3741 3.599157214] ['Managers' 1642 1.579742354] ['Managers' 73526 70.73820725] ['Managers' 30415 29.26179275] ['Managers' 103941 100.0] ['Professionals' 133311 38.66059207] ['Professionals' 47505 13.77659328] ['Professionals' 6301 1.827309004] ['Professionals' 3756 1.089251328] ['Professionals' 89365 25.91611953] ['Professionals' 39902 11.57170035] ['Professionals' 11820 3.427835649] ['Professionals' 5533 1.604586688] ['Professionals' 245461 71.18443032] ['Professionals' 99363 28.81556968] ['Professionals' 344824 100.0]] ['Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Both' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Both' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Both' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Male' 'Female' 'Both'] ['White' 'White' 'Black\_or\_African American' 'Black\_or\_African American' 'Asian' 'Asian' 'Hispanic\_or\_Latino' 'Hispanic\_or\_Latino' 'All' 'All' 'Totals' 'White' 'White' 'Black\_or\_African American' 'Black\_or\_African American' 'Asian' 'Asian' 'Hispanic\_or\_Latino' 'Hispanic or Latino' 'All' 'All' 'Totals' 'White' 'White' 'Black or African American' 'Black or African American' 'Asian' 'Asian' 'Hispanic\_or\_Latino' 'Hispanic\_or\_Latino' 'All' 'All' 'Totals' 'White' 'White' 'Black\_or\_African American' 'Black\_or\_African American' 'Asian' 'Asian' 'Hispanic\_or\_Latino' 'Hispanic\_or\_Latino' 'All' 'All' 'Totals'] Categorical Data Encodding In [9]: # Handling Categorical Data from sklearn.compose import ColumnTransformer from sklearn.preprocessing import OneHotEncoder from sklearn.preprocessing import LabelEncoder le = LabelEncoder() ct = ColumnTransformer(transformers=[('enconder', OneHotEncoder(), [0])], remainder='passthrough') In [10]: # One-Hot Encoding Categorical Data X = np.array(ct.fit transform(X)) print(X) [[1.0 0.0 0.0 0.0 268883 41.25725193] [1.0 0.0 0.0 0.0 105560 16.19706532] [1.0 0.0 0.0 0.0 17508 2.686417389] [1.0 0.0 0.0 0.0 11479 1.761331118] [1.0 0.0 0.0 0.0 125347 19.23317115] [1.0 0.0 0.0 0.0 58049 8.90700497] [1.0 0.0 0.0 0.0 32201 4.940902807] [1.0 0.0 0.0 0.0 15512 2.380152304] [1.0 0.0 0.0 0.0 454813 69.78624354] [1.0 0.0 0.0 0.0 196910 30.21375646] [1.0 0.0 0.0 0.0 651723 100.0] [0.0 1.0 0.0 0.0 7282 58.67848509] [0.0 1.0 0.0 0.0 1818 14.64947623] [0.0 1.0 0.0 0.0 120 0.966962127] [0.0 1.0 0.0 0.0 53 0.42707494] [0.0 1.0 0.0 0.0 2023 16.30136986] [0.0 1.0 0.0 0.0 556 4.5] [0.0 1.0 0.0 0.0 266 2.143432716] [0.0 1.0 0.0 0.0 103 0.829975826] [0.0 1.0 0.0 0.0 9824 79.16196616] [0.0 1.0 0.0 0.0 2586 20.83803384] [0.0 1.0 0.0 0.0 12410 100.0] [0.0 0.0 1.0 0.0 48311 46.47925265] [0.0 0.0 1.0 0.0 18935 18.21706545] [0.0 0.0 1.0 0.0 1575 1.515282708] [0.0 0.0 1.0 0.0 978 0.940918406] [0.0 0.0 1.0 0.0 18563 17.85917011] [0.0 0.0 1.0 0.0 8084 7.777489152] [0.0 0.0 1.0 0.0 3741 3.599157214] [0.0 0.0 1.0 0.0 1642 1.579742354] [0.0 0.0 1.0 0.0 73526 70.73820725] [0.0 0.0 1.0 0.0 30415 29.26179275] [0.0 0.0 1.0 0.0 103941 100.0] [0.0 0.0 0.0 1.0 133311 38.66059207] [0.0 0.0 0.0 1.0 47505 13.77659328] [0.0 0.0 0.0 1.0 6301 1.827309004] [0.0 0.0 0.0 1.0 3756 1.089251328] [0.0 0.0 0.0 1.0 89365 25.91611953] [0.0 0.0 0.0 1.0 39902 11.57170035] [0.0 0.0 0.0 1.0 11820 3.427835649] [0.0 0.0 0.0 1.0 5533 1.604586688] [0.0 0.0 0.0 1.0 245461 71.18443032] [0.0 0.0 0.0 1.0 99363 28.81556968] [0.0 0.0 0.0 1.0 344824 100.0]] In [11]: Y = le.fit transform(Y)print(Y)  $[2 \ 1 \ 2 \$ 2 1 2 1 2 1 0] In [12]:  $Z = le.fit_transform(Z)$ print(Z) [5 5 2 2 1 1 3 3 0 0 4 5 5 2 2 1 1 3 3 0 0 4 5 5 2 2 1 1 3 3 0 0 4 5 5 2 2 1 1 3 3 0 0 4 5 5 2 2 1 1 3 3 0 0 4] Splitting into Test and Train In [13]: from sklearn.model\_selection import train\_test\_split In [14]: # Splitting Test and Train Data on Y as dependent data X\_train, X\_test, Y\_train, Y\_test = train\_test\_split(X, Y, test\_size=0.2, random\_state=2) In [15]: # Splitting Test and Train Data on Z as dependent data X\_train, X\_test, Z\_train, Z\_test = train\_test\_split(X, Z, test\_size=0.2, random\_state=2) In [16]: print(X\_train) print(Y\_train) print(Z\_train) print(X\_test) print(Y\_test) print(Z\_test) [[0.0 0.0 0.0 1.0 11820 3.427835649] [0.0 0.0 1.0 0.0 18935 18.21706545] [0.0 0.0 0.0 1.0 245461 71.18443032] [0.0 0.0 1.0 0.0 8084 7.777489152] [0.0 0.0 1.0 0.0 978 0.940918406] [0.0 1.0 0.0 0.0 1818 14.64947623] [0.0 1.0 0.0 0.0 266 2.143432716] [1.0 0.0 0.0 0.0 105560 16.19706532] [0.0 0.0 0.0 1.0 344824 100.0] [0.0 0.0 1.0 0.0 1575 1.515282708] [0.0 0.0 1.0 0.0 103941 100.0] [0.0 1.0 0.0 0.0 9824 79.16196616] [0.0 0.0 0.0 1.0 3756 1.089251328] [1.0 0.0 0.0 0.0 651723 100.0] [1.0 0.0 0.0 0.0 125347 19.23317115] [1.0 0.0 0.0 0.0 32201 4.940902807] [1.0 0.0 0.0 0.0 11479 1.761331118] [0.0 0.0 0.0 1.0 89365 25.91611953] [1.0 0.0 0.0 0.0 58049 8.90700497] [0.0 0.0 1.0 0.0 73526 70.73820725] [0.0 0.0 1.0 0.0 3741 3.599157214] [0.0 1.0 0.0 0.0 2586 20.83803384] [0.0 0.0 1.0 0.0 18563 17.85917011] [0.0 0.0 0.0 1.0 6301 1.827309004] [0.0 1.0 0.0 0.0 12410 100.0] [0.0 0.0 0.0 1.0 39902 11.57170035] [0.0 0.0 1.0 0.0 30415 29.26179275] [0.0 0.0 0.0 1.0 47505 13.77659328] [1.0 0.0 0.0 0.0 15512 2.380152304] [0.0 1.0 0.0 0.0 7282 58.67848509] [0.0 1.0 0.0 0.0 103 0.829975826] [0.0 0.0 1.0 0.0 48311 46.47925265] [1.0 0.0 0.0 0.0 454813 69.78624354] [0.0 1.0 0.0 0.0 2023 16.30136986] [0.0 0.0 0.0 1.0 5533 1.604586688]]  $[ 3 \ 5 \ 0 \ 1 \ 2 \ 5 \ 3 \ 5 \ 4 \ 2 \ 4 \ 0 \ 2 \ 4 \ 1 \ 3 \ 2 \ 1 \ 1 \ 0 \ 3 \ 0 \ 1 \ 2 \ 4 \ 1 \ 0 \ 5 \ 3 \ 5 \ 3 \ 5 \ 0 \ 1 \ 3 ]$ [[0.0 0.0 1.0 0.0 1642 1.579742354] [0.0 0.0 0.0 1.0 133311 38.66059207] [0.0 1.0 0.0 0.0 53 0.42707494] [1.0 0.0 0.0 0.0 196910 30.21375646] [0.0 0.0 0.0 1.0 99363 28.81556968] [1.0 0.0 0.0 0.0 268883 41.25725193] [1.0 0.0 0.0 0.0 17508 2.686417389] [0.0 1.0 0.0 0.0 556 4.5] [0.0 1.0 0.0 0.0 120 0.966962127]] [1 2 1 1 1 2 2 1 2] [3 5 2 0 0 5 2 1 2] Standardization In [17]: from sklearn.preprocessing import StandardScaler sc = StandardScaler() In [18]: X\_train[:, 5:] = sc.fit\_transform(X\_train[:, 5:]) In [19]: print(X\_test) [[0.0 0.0 1.0 0.0 1642 1.579742354] [0.0 0.0 0.0 1.0 133311 38.66059207] [0.0 1.0 0.0 0.0 53 0.42707494] [1.0 0.0 0.0 0.0 196910 30.21375646] [0.0 0.0 0.0 1.0 99363 28.81556968] [1.0 0.0 0.0 0.0 268883 41.25725193] [1.0 0.0 0.0 0.0 17508 2.686417389] [0.0 1.0 0.0 0.0 556 4.5] [0.0 1.0 0.0 0.0 120 0.966962127]] In [20]: print(X\_train) [[0.0 0.0 0.0 1.0 11820 -0.7795949892757811] [0.0 0.0 1.0 0.0 18935 -0.342214376417952] [0.0 0.0 0.0 1.0 245461 1.2242565500625042]  $[0.0 \ 0.0 \ 1.0 \ 0.0 \ 8084 \ -0.6509571805149282]$ [0.0 0.0 1.0 0.0 978 -0.8531437408001161] [0.0 1.0 0.0 0.0 1818 -0.44772320821412] [0.0 1.0 0.0 0.0 266 -0.8175802629885438] [1.0 0.0 0.0 0.0 105560 -0.40195439714388287] [0.0 0.0 0.0 1.0 344824 2.076455866461907] [0.0 0.0 1.0 0.0 1575 -0.83615733827661] [0.0 0.0 1.0 0.0 103941 2.076455866461907] [0.0 1.0 0.0 0.0 9824 1.460186315286557] [0.0 0.0 0.0 1.0 3756 -0.8487569035405473] [1.0 0.0 0.0 0.0 651723 2.076455866461907] [1.0 0.0 0.0 0.0 125347 -0.31216379638272373] [1.0 0.0 0.0 0.0 32201 -0.7348471389978479] [1.0 0.0 0.0 0.0 11479 -0.8288806372038322] [0.0 0.0 0.0 1.0 89365 -0.11452050477980388] [1.0 0.0 0.0 0.0 58049 -0.6175525795075081] [0.0 0.0 1.0 0.0 73526 1.2110598303919027] [0.0 0.0 1.0 0.0 3741 -0.774528279778144] [0.0 1.0 0.0 0.0 2586 -0.2647011606437482] [0.0 0.0 1.0 0.0 18563 -0.35279886832554114] [0.0 0.0 0.0 1.0 6301 -0.8269293896674803] [0.0 1.0 0.0 0.0 12410 2.076455866461907] [0.0 0.0 0.0 1.0 39902 -0.538746170109162] [0.0 0.0 1.0 0.0 30415 -0.015574675749093906] [0.0 0.0 0.0 1.0 47505 -0.47353808057470326] [1.0 0.0 0.0 0.0 15512 -0.8105794549770345] [0.0 1.0 0.0 0.0 7282 0.8544024019652187] [0.0 1.0 0.0 0.0 103 -0.8564247861476669] [0.0 0.0 1.0 0.0 48311 0.4936190594383802] [1.0 0.0 0.0 0.0 454813 1.182906202616773] [0.0 1.0 0.0 0.0 2023 -0.3988696669555691] [0.0 0.0 0.0 1.0 5533 -0.8335162386366273]] In [ ]: In [ ]: In [ ]: In [ ]: In [ ]: