IST 718

Final Project Report

Professor Lando

Amanda Norwood

In [219…
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from scipy import stats
import seaborn as sns
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
```

In [120…
```
# Read in files
education = pd.read_csv('EducationalData.csv')
medianearnings = pd.read_csv('MedianEarningsbyIndustry.csv')
occupations = pd.read_csv('Occupations.csv')
homeprice = pd.read_excel('AvgHomePricebyZip.xlsx')
crime = pd.read_csv('crimes_with_zipcodes.csv')
```

In [121…
```
crime.head()
```

Out[121]:

	Unnamed: 0	DR_NO	Date Rptd	DATE OCC	TIME OCC	AREA	AREA NAME	Rpt Dist No	Part 1-2	Crm Cd	...
0	0	10304468	1/8/2020 0:00	1/8/2020 0:00	2230	3	Southwest	377	2	624	...
1	1	190101086	1/2/2020 0:00	1/1/2020 0:00	330	1	Central	163	2	624	...
2	2	200110444	4/14/2020 0:00	2/13/2020 0:00	1200	1	Central	155	2	845	...
3	3	191501505	1/1/2020 0:00	1/1/2020 0:00	1730	15	N Hollywood	1543	2	745	...
4	4	191921269	1/1/2020 0:00	1/1/2020 0:00	415	19	Mission	1998	2	740	...

5 rows × 31 columns

In [122…

```
# clean education
education['Group'].unique()
#education[education['Group'] == 'Preschool']
education = education.drop(['ID Group','ID Year','ID State','State','Age Range'
education = education[~education['Group'].isin(['Preschool','Primary Education'
```

In [123…

```
education.head(5)
```

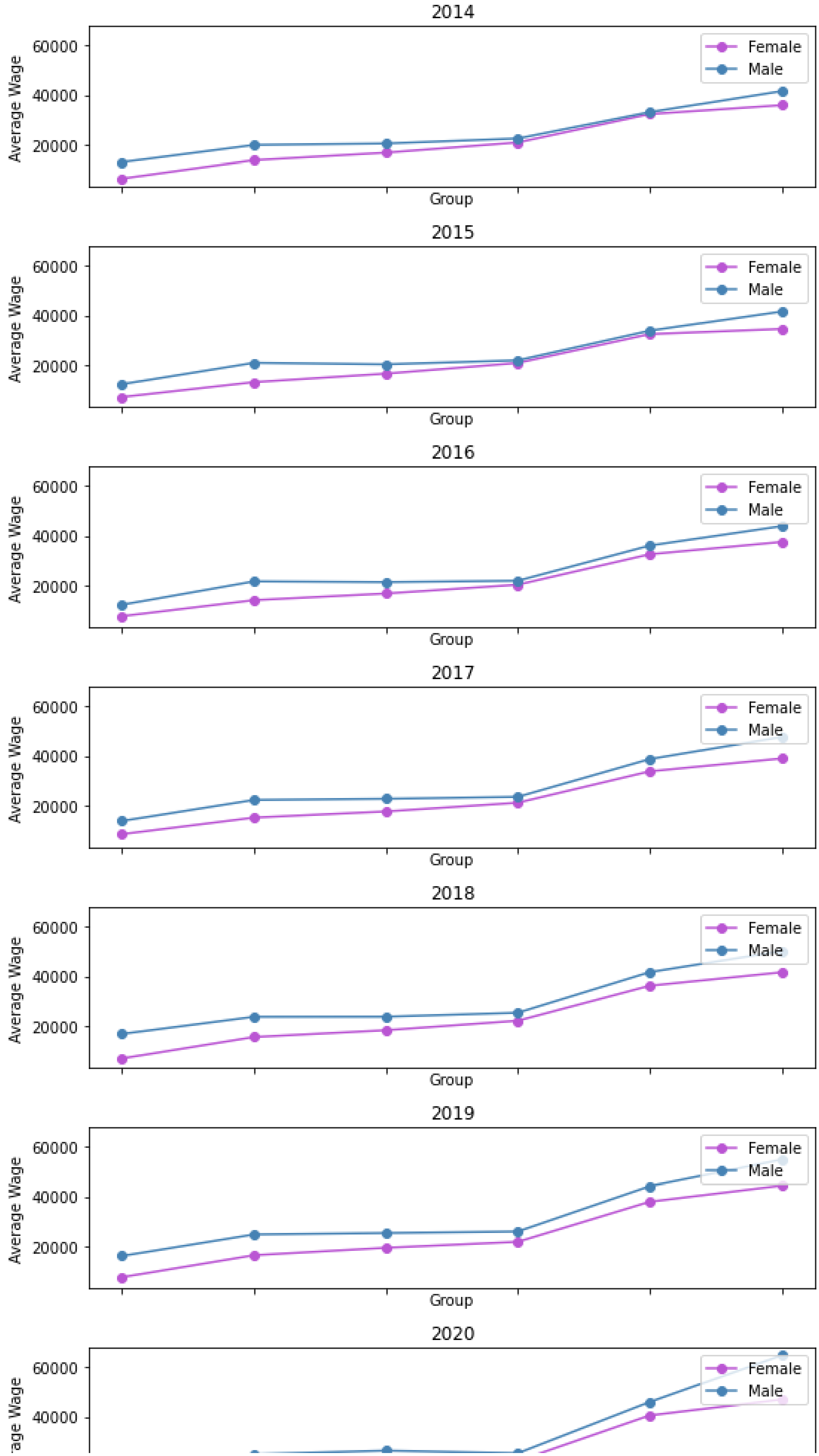
Out[123]:

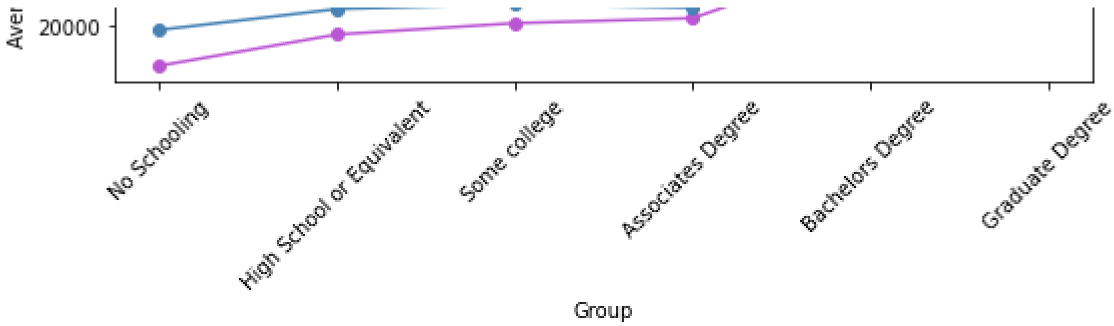
	ID Gender	Gender	Group	Year	Total Population	Total Population MOE Appx	Average Wage	Average Wage Appx MOE	G
0	2	Female	Associates Degree	2020	1161339	4012.757389	22279.847898	2835.671997	
1	2	Female	Bachelors Degree	2020	2994902	7539.885565	40526.050930	2986.719653	
2	2	Female	Graduate Degree	2020	1747439	3818.350081	46913.297071	6708.984104	
3	2	Female	High School or Equivalent	2020	2695919	6122.901609	17423.896492	2326.322214	
4	2	Female	No Schooling	2020	393477	1192.915610	8094.061415	7463.503355	

In [124…

```
## Education/salary graph

df = education
years = sorted(df['Year'].unique())

# least to greatest
sorted_groups = df.groupby('Group')['Average Wage'].mean().sort_values().index

# subplot for each year
fig, axs = plt.subplots(len(years), figsize=(8, 16), sharex=True, sharey=True)
colors = ['mediumorchid', 'steelblue']
```

```
for i, year in enumerate(years):
    year_data = df[df['Year'] == year]

    groups = year_data['Group'].unique()
    x = range(len(groups))
    y_female = []
    y_male = []

    for group in sorted_groups:
        group_data = year_data[year_data['Group'] == group]
        female_wage = group_data[group_data['Gender'] == 'Female']['Average Wag
        male_wage = group_data[group_data['Gender'] == 'Male']['Average Wage']
        y_female.append(female_wage.iloc[0] if len(female_wage) > 0 else 0)
        y_male.append(male_wage.iloc[0] if len(male_wage) > 0 else 0)

    axs[i].plot(x, y_female, marker='o', label='Female', color=colors[0])
    axs[i].plot(x, y_male, marker='o', label='Male', color=colors[1])
    axs[i].set_title(str(year))
    axs[i].set_xlabel('Group')
    axs[i].set_ylabel('Average Wage')

    axs[i].legend(['Female', 'Male'], loc='upper right')

    axs[i].set_xticks(range(len(groups)))
    axs[i].set_xticklabels(sorted_groups, rotation=45)

plt.tight_layout()
plt.show()
```


2014
Average Wage
60000
40000
20000
Group
Female
Male
2015
Average Wage
60000
40000
20000
Group
Female
Male
2016
Average Wage
60000
40000
20000
Group
Female
Male
2017
Average Wage
60000
40000
20000
Group
Female
Male
2018
Average Wage
60000
40000
20000
Group
Female
Male
2019
Average Wage
60000
40000
20000
Group
Female
Male
2020
60000
40000
Female
Male



In [125…
```
education.head()

education = education.drop(['ID Gender','Group ID'],axis=1)
```

In [126…
```
## Linear Regression Model
## with t-test
data = education.copy()

features = ['Gender', 'Group', 'Average Wage']

# drop missing values
data = data.dropna(subset=features)

degree_types = data['Group'].unique()  # Define the degree types

grouped_data = data.groupby(['Gender', 'Group'])['Average Wage']
mean_salary = grouped_data.mean()

# repeat over each degree type
for degree_type in degree_types:
    print('Degree Type:', degree_type)
    print('-------------------------')

    degree_data = data[data['Group'] == degree_type]

    grouped_data = degree_data.groupby('Gender')['Average Wage']
    mean_salary = grouped_data.mean()
    gender_comparison = stats.ttest_ind(
        grouped_data.get_group('Female'), grouped_data.get_group('Male')
    )

    print('Mean Salary by Gender:')
    print(mean_salary)
    print('\nGender Comparison (T-test):')
    print(gender_comparison)
    print('-------------------------\n')

X = pd.get_dummies(data[['Gender', 'Group']])
y = data['Average Wage']

# split data (train/test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon

# create linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
```

```
mse = mean_squared_error(y_test, y_pred)
r_squared = model.score(X_test, y_test)

print('\nModel Evaluation:')
print('Mean Squared Error:', mse)
print('R-squared:', r_squared)

# coefficients
coefficients = pd.DataFrame({'Feature': X.columns, 'Coefficient': model.coef_})

# drop Gender_ and Group_
coefficients['Feature'] = coefficients['Feature'].str.replace('Gender_', '').st

print('\nModel Coefficients:')
print(coefficients)
```

```
Degree Type: Associates Degree
-------------------------
Mean Salary by Gender:
Gender
Female    21384.414883
Male      23822.578809
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-3.377996679033909, pvalue=0.005488449053525724)
-------------------------

Degree Type: Bachelors Degree
-------------------------
Mean Salary by Gender:
Gender
Female    35094.598669
Male      39037.161290
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-1.746972648298837, pvalue=0.10616067403281738)
-------------------------

Degree Type: Graduate Degree
-------------------------
Mean Salary by Gender:
Gender
Female    39954.886160
Male      49111.416991
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-2.545162364074069, pvalue=0.025693269159943754)
-------------------------

Degree Type: High School or Equivalent
-------------------------
Mean Salary by Gender:
Gender
Female    15147.611610
Male      22639.501755
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-8.010718098658623, pvalue=3.7087029194387112e-06)
-------------------------

Degree Type: No Schooling
-------------------------
Mean Salary by Gender:
Gender
Female     7562.072757
Male      14792.420880
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-7.326049463030802, pvalue=9.14663233716475e-06)
-------------------------
```

```
Degree Type: Some college
-------------------------
Mean Salary by Gender:
Gender
Female    18080.886248
Male      22949.213131
Name: Average Wage, dtype: float64

Gender Comparison (T-test):
Ttest_indResult(statistic=-4.506548927122742, pvalue=0.0007184166430933483)
-------------------------


Model Evaluation:
Mean Squared Error: 6576135.54597255
R-squared: 0.9237853627121437

Model Coefficients:
                     Feature   Coefficient
0                     Female  -3013.872550
1                       Male   3013.872550
2          Associates Degree  -3876.491451
3           Bachelors Degree  11639.872295
4            Graduate Degree  18714.332994
5  High School or Equivalent  -6537.676511
6               No Schooling -14524.976605
7               Some college  -5415.060722
```

In [127…

```
## breakdown coeffcinets

coefficients_sorted = coefficients.set_index('Feature').loc[coefficients['Featu
features_sorted = coefficients_sorted.index
coefficients_sorted = coefficients_sorted['Coefficient']

coefficients_sorted
```

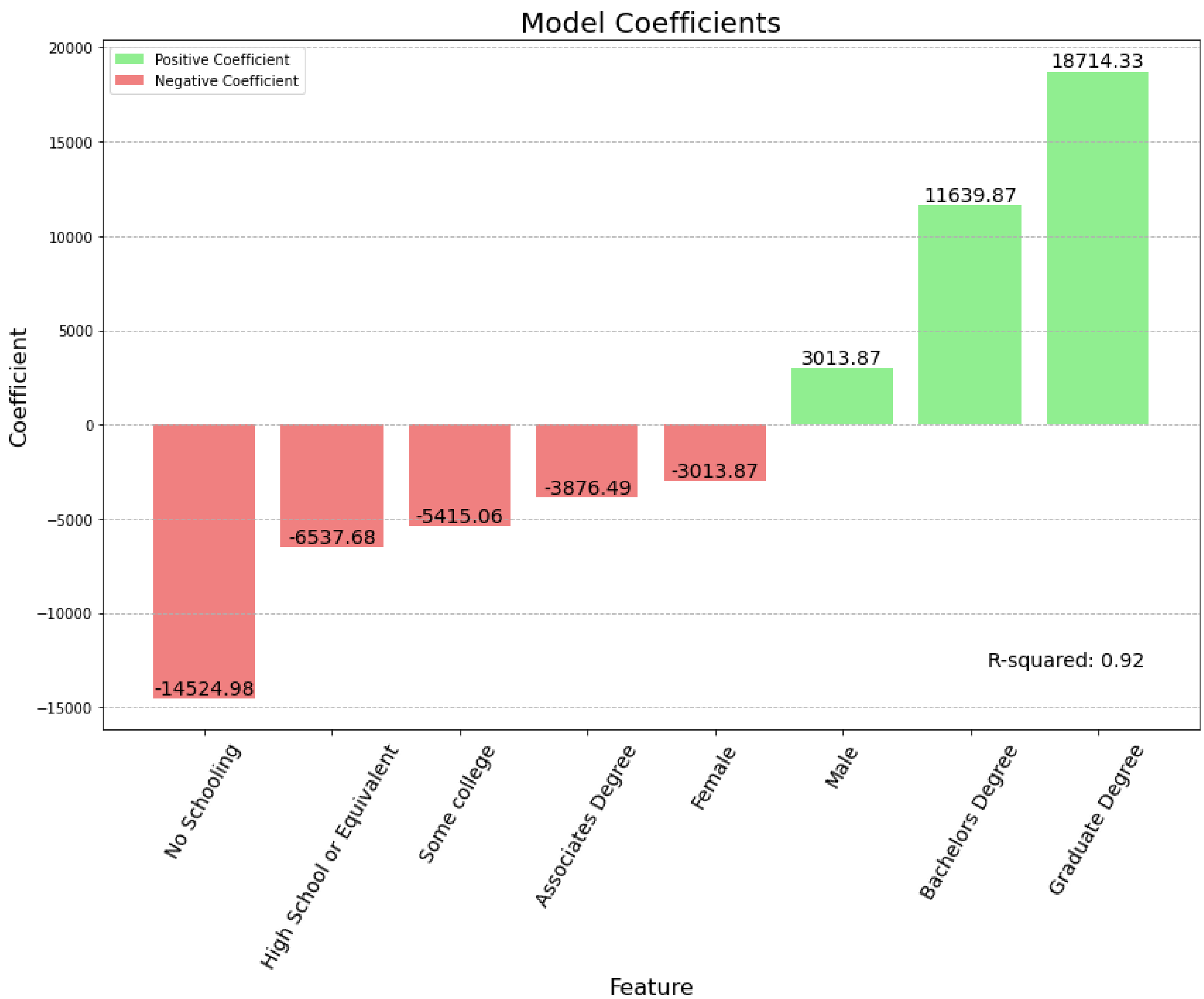
Out[127]:

```
Feature
No Schooling                -14524.976605
High School or Equivalent    -6537.676511
Some college                 -5415.060722
Associates Degree            -3876.491451
Female                       -3013.872550
Male                          3013.872550
Bachelors Degree             11639.872295
Graduate Degree              18714.332994
Name: Coefficient, dtype: float64
```

In [128…

```
# plot the coefficients
colors_sorted = ['lightcoral' if coef < 0 else 'lightgreen' for coef in coeffic

plt.figure(figsize=(12, 10))
bars = plt.bar(range(len(features_sorted)), coefficients_sorted, color=colors_s
plt.xticks(range(len(features_sorted)), features_sorted, rotation=60, fontsize=
plt.xlabel('Feature', fontsize=16)
plt.ylabel('Coefficient', fontsize=16)
plt.title('Model Coefficients', fontsize=20)
positive_bar = plt.bar(0, 0, color='lightgreen', label='Positive Coefficient')
negative_bar = plt.bar(0, 0, color='lightcoral', label='Negative Coefficient')
plt.legend(handles=[positive_bar, negative_bar])
plt.grid(axis='y', linestyle='--')
```

```
for i, bar in enumerate(bars):
    height = bar.get_height()
    coef = coefficients_sorted[i]
    feature = features_sorted[i]
    plt.text(bar.get_x() + bar.get_width() / 2, height, round(coef, 2), ha='cer

#include r squared too
r_squared = model.score(X_test, y_test)
plt.text(0.95, 0.1, f'R-squared: {r_squared:.2f}', ha='right', va='center', tra

plt.tight_layout()
plt.show()
```



Mean Salary by Gender and Education: group breakdown

Gender Comparision (T-Test): there is statistical significance between the average salaries between male and female. --> t-statistic value of -3.38: indicates difference in salary. t-test is used to measure the difference between sample means of two groups. --> p-value of 0.05: difference between genders is statistically significant

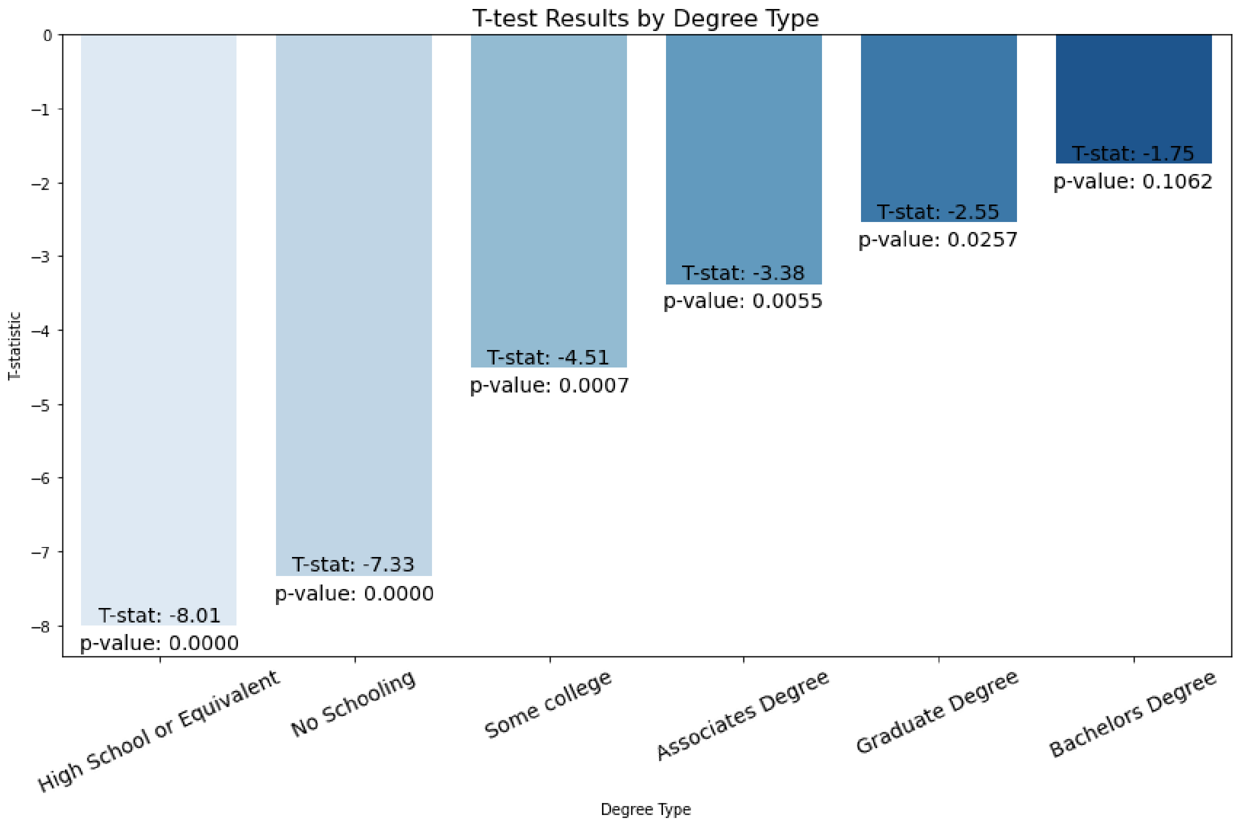
Model Evaluation: --> MSE: avg squared difference between the actual and predicted salaries. Maybe this is a little high? --> R Sq: 0.92. model explains 92% of the variance in the average salary

Model Coefficients: --> Male/Female: the coefficients signify that males have higher salaries compared to women. --> Education groups: coefficients show the different education levels with 'No Schooling' as the most negative and 'Graduate Degree' as positive.

In [129…

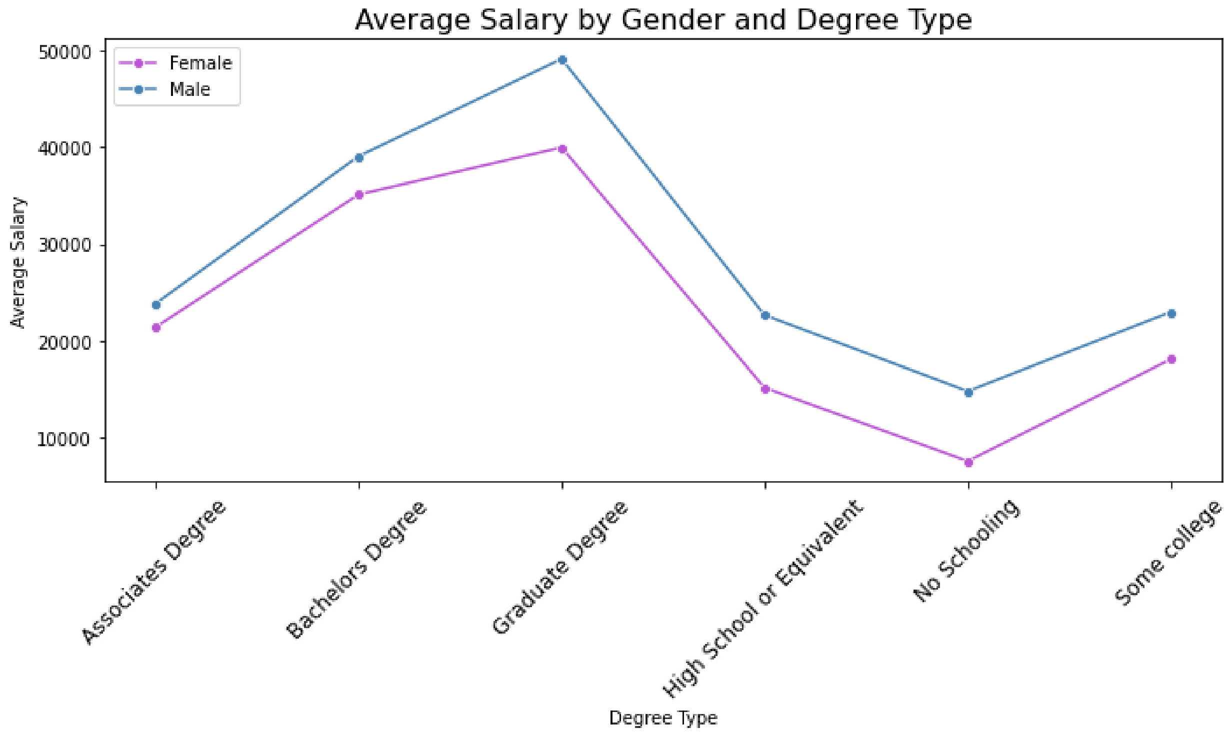
```
# using same data to graph the t-test results
# and the salary comparison between genders by education
data = education.copy()
features = ['Gender', 'Group', 'Average Wage']

# drop missing values
data = data.dropna(subset=features)
degree_types = data['Group'].unique()
# gotta put results somewhere...
degree_type_labels = []
t_stats = []
p_values = []
average_salary_female = []
average_salary_male = []

# repeat over each degree type
for degree_type in degree_types:
    degree_data = data[data['Group'] == degree_type]

    grouped_data = degree_data.groupby('Gender')['Average Wage']

    groups = degree_data['Gender'].unique()
    for i in range(len(groups)):
        for j in range(i + 1, len(groups)):
            gender1 = groups[i]
            gender2 = groups[j]
            t_stat, p_value = stats.ttest_ind(grouped_data.get_group(gender1),

            degree_type_labels.append(degree_type)
            t_stats.append(t_stat)
            p_values.append(p_value)

            # Append average salary by gender to lists
            average_salary_female.append(grouped_data.get_group(gender1).mean()
            average_salary_male.append(grouped_data.get_group(gender2).mean())

results_df = pd.DataFrame({
    'Degree Type': degree_type_labels,
    'T-statistic': t_stats,
    'p-value': p_values,
    'Average Salary (Female)': average_salary_female,
    'Average Salary (Male)': average_salary_male
})

results_df = results_df.sort_values('T-statistic')

# Plotting the results
plt.figure(figsize=(12, 8))
sns.barplot(x='Degree Type', y='T-statistic', data=results_df, palette='Blues')
plt.ylabel('T-statistic')
plt.xticks(rotation=25, fontsize=14)
plt.xlabel('Degree Type')
plt.title('T-test Results by Degree Type', fontsize=16)
```

```
# Add p-value to the plot
for i, row in enumerate(results_df.iterrows()):
    plt.text(i, row[1]['T-statistic'], f'T-stat: {row[1]["T-statistic"]:.2f}',
    plt.text(i, row[1]['T-statistic'] - 0.1, f'p-value: {row[1]["p-value"]:.4f}

plt.tight_layout()
plt.show()
```



In [130…

```
# avg salary by gender
plt.figure(figsize=(10, 6))
sns.lineplot(x=degree_type_labels, y=average_salary_female, marker='o', color='
sns.lineplot(x=degree_type_labels, y=average_salary_male, marker='o', color='st
plt.ylabel('Average Salary')
plt.xticks(rotation=45,fontsize=12)
plt.xlabel('Degree Type')
plt.title('Average Salary by Gender and Degree Type',fontsize=16)
plt.legend(loc='upper left')
plt.tight_layout()
plt.show()
```



In [131…
```
educationYOY = education[['Gender','Group','Year','Average Wage']]
educationpred = educationYOY.copy()
```

In [132…
```
educationpred.head()
```

Out[132]:

	Gender	Group	Year	Average Wage
0	Female	Associates Degree	2020	22279.847898
1	Female	Bachelors Degree	2020	40526.050930
2	Female	Graduate Degree	2020	46913.297071
3	Female	High School or Equivalent	2020	17423.896492
4	Female	No Schooling	2020	8094.061415

In [133…
```
educationpred
```

Out[133]:

	Gender	Group	Year	Average Wage
0	Female	Associates Degree	2020	22279.847898
1	Female	Bachelors Degree	2020	40526.050930
2	Female	Graduate Degree	2020	46913.297071
3	Female	High School or Equivalent	2020	17423.896492
4	Female	No Schooling	2020	8094.061415
...	...	...	...	...
118	Male	Bachelors Degree	2014	33065.569399
119	Male	Graduate Degree	2014	41476.414373
120	Male	High School or Equivalent	2014	19938.661416
121	Male	No Schooling	2014	13090.641410
125	Male	Some college	2014	20510.301437

84 rows × 4 columns

In [134…

```
educationpred
```

Out[134]:

	Gender	Group	Year	Average Wage
0	Female	Associates Degree	2020	22279.847898
1	Female	Bachelors Degree	2020	40526.050930
2	Female	Graduate Degree	2020	46913.297071
3	Female	High School or Equivalent	2020	17423.896492
4	Female	No Schooling	2020	8094.061415
...	...	...	...	...
118	Male	Bachelors Degree	2014	33065.569399
119	Male	Graduate Degree	2014	41476.414373
120	Male	High School or Equivalent	2014	19938.661416
121	Male	No Schooling	2014	13090.641410
125	Male	Some college	2014	20510.301437

84 rows × 4 columns

In [135…

```
# Linear Regression to predict incomes for 2021-2023

data = educationpred.copy()
features = ['Gender', 'Group', 'Year']
target = 'Average Wage'
numerical_features = []
categorical_features = []
for feature in features:
    if data[feature].dtype == 'object':
        categorical_features.append(feature)
```

```
    else:
        numerical_features.append(feature)
preprocessing = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ])

# split the data into training and test
X = data[features]
y = data[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon

model = LinearRegression()

pipeline = Pipeline(steps=[
    ('preprocessing', preprocessing),
    ('model', model)
])
# train the model
pipeline.fit(X_train, y_train)
# predict average wage
years = range(2021, 2024)
categories = data['Group'].unique()
genders = data['Gender'].unique()
predicted_data = []
for year in years:
    for category in categories:
        for gender in genders:
            new_data = pd.DataFrame({
                'Gender': [gender],
                'Group': [category],
                'Year': [year]
            })
            new_data_processed = pipeline.named_steps['preprocessing'].transfor

            predicted_wage = pipeline.named_steps['model'].predict(new_data_pro
            predicted_data.append({
                'Gender': gender,
                'Group': category,
                'Year': year,
                'Average Wage': predicted_wage
            })

predicted_df = pd.DataFrame(predicted_data)

# combine the predicted data to the original dataset
salaryprediction = pd.concat([data, predicted_df], ignore_index=True)
salaryprediction = salaryprediction.sort_values('Year')
salaryprediction
```

Out[135]:

	Gender	Group	Year	Average Wage
83	Male	Some college	2014	20510.301437
82	Male	No Schooling	2014	13090.641410
81	Male	High School or Equivalent	2014	19938.661416
80	Male	Graduate Degree	2014	41476.414373
79	Male	Bachelors Degree	2014	33065.569399
...	...	...	...	...
109	Male	Associates Degree	2023	33720.204412
108	Female	Associates Degree	2023	27840.268767
118	Female	Some college	2023	25724.898144
112	Female	Graduate Degree	2023	49737.610074
119	Male	Some college	2023	31604.833789

120 rows × 4 columns

In [136…

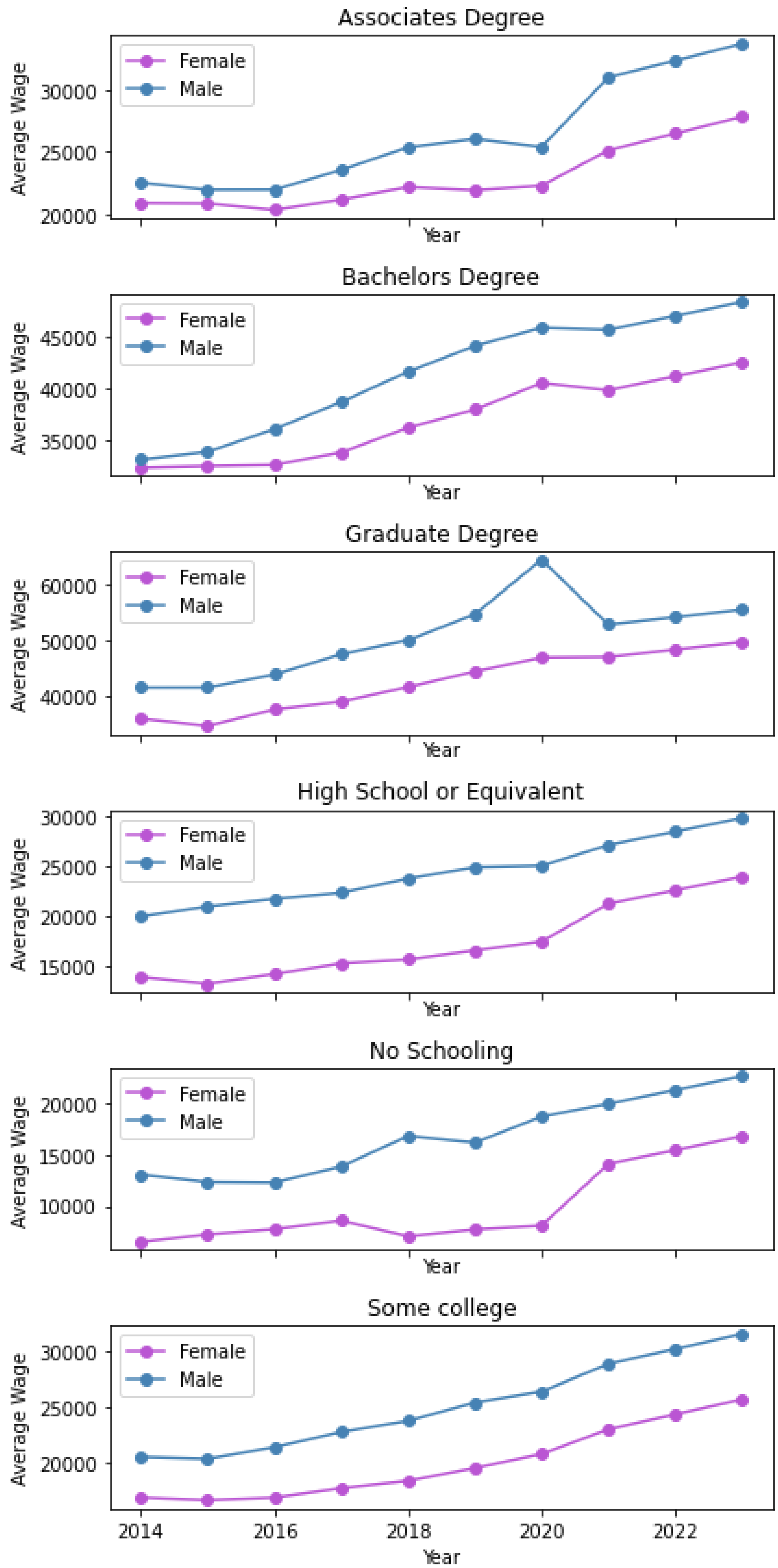
```
salaryprediction['Year'].unique()
```

Out[136]:

```
array([2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023])
```

In [137…

```
# graph the predicted salary

grouped_data = salaryprediction.groupby(['Year', 'Gender', 'Group']).mean().res

# subplot for each degree
groups = grouped_data['Group'].unique()
fig, axs = plt.subplots(len(groups), figsize=(6, 2 * len(groups)), sharex=True)

for i, group in enumerate(groups):
    group_data = grouped_data[grouped_data['Group'] == group]

    for gender in ['Female', 'Male']:
        gender_data = group_data[group_data['Gender'] == gender]
        years = gender_data['Year']
        wages = gender_data['Average Wage']

        color = 'mediumorchid' if gender == 'Female' else 'steelblue'  # Set co

        axs[i].plot(years, wages, marker='o', label=gender, color=color)

    axs[i].set_title(group)
    axs[i].set_xlabel('Year')
    axs[i].set_ylabel('Average Wage')
    axs[i].legend()

plt.tight_layout()
plt.show()
```



In [138…

```
# prep to graph YOY change
educationYOY = salaryprediction[['Gender','Group','Year','Average Wage']]

df = educationYOY
df['Year'] = pd.to_datetime(df['Year'], format='%Y')
df.sort_values(['Year', 'Group'], inplace=True)
```

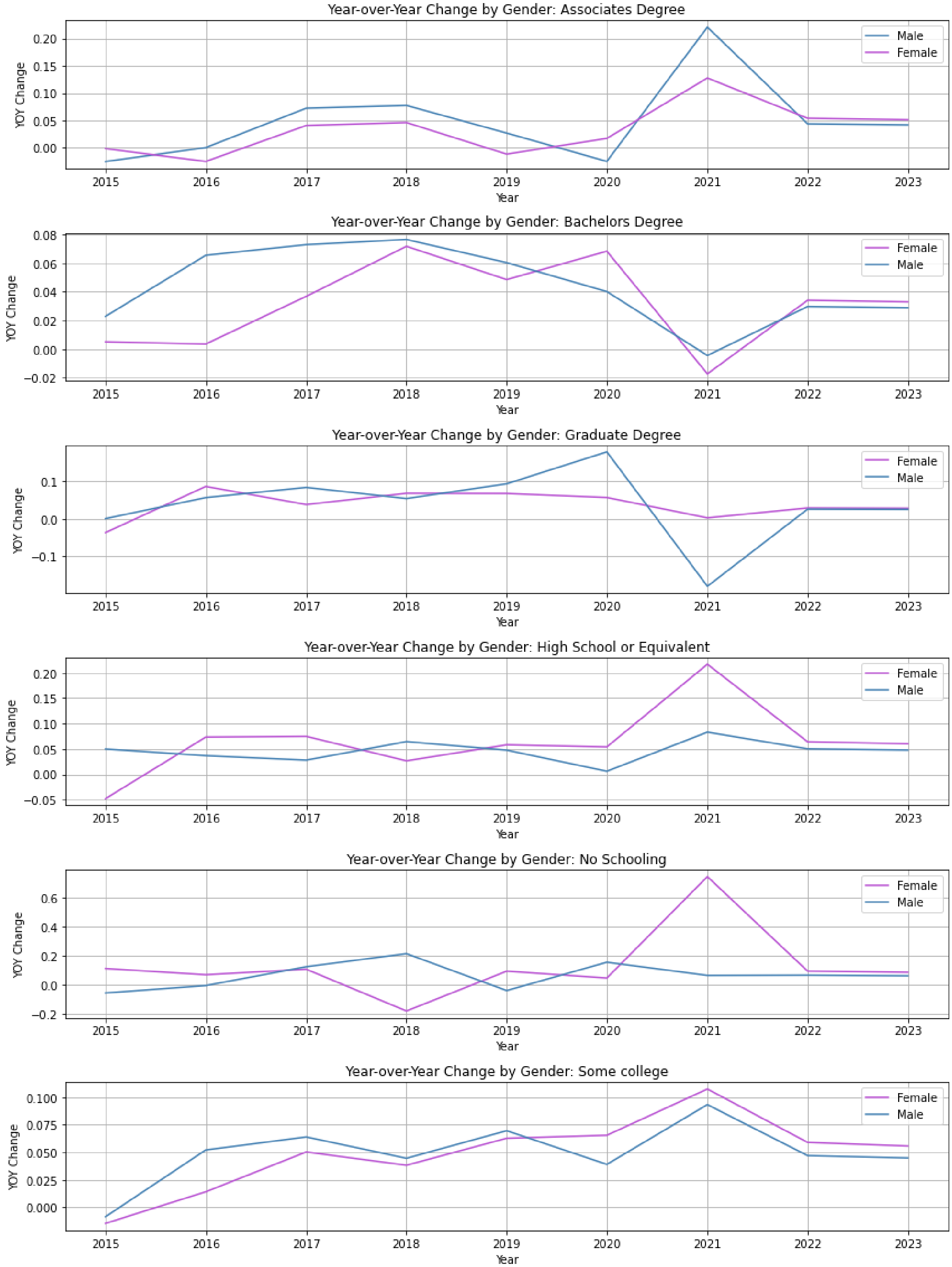
```
# calculate YOY change
df['YOY Change'] = df.groupby(['Gender', 'Group'])['Average Wage'].pct_change()
# drop na values since the first year will be null
df.dropna(subset=['YOY Change'], inplace=True)
df.head(1)
```

Out[138]:

	Gender	Group	Year	Average Wage	YOY Change
72	Male	Associates Degree	2015-01-01	21945.152606	-0.025178

In [227…

```
# showing the YOY change
groups = df['Group'].unique()
group_data = {}

for group in groups:
    group_data[group] = df[df['Group'] == group]

# Define colors for female and male
colors = {'Female': 'mediumorchid', 'Male': 'steelblue'}

# Plotting
fig, axs = plt.subplots(len(groups), figsize=(12, 16))

for i, group in enumerate(groups):
    data = group_data[group]
    ax = axs[i]
    genders = data['Gender'].unique()

    for gender in genders:
        gender_data = data[data['Gender'] == gender]
        color = colors[gender]  # Get the color based on gender
        ax.plot(gender_data['Year'], gender_data['YOY Change'], label=gender, c

    ax.set_xlabel('Year')
    ax.set_ylabel('YOY Change')
    ax.set_title(f'Year-over-Year Change by Gender: {group}')
    ax.legend()
    ax.grid(True)

plt.tight_layout()
plt.show()
```



In [140…
```
education['Year'].unique()
```

Out[140]:
```
array([2020, 2019, 2018, 2017, 2016, 2015, 2014])
```

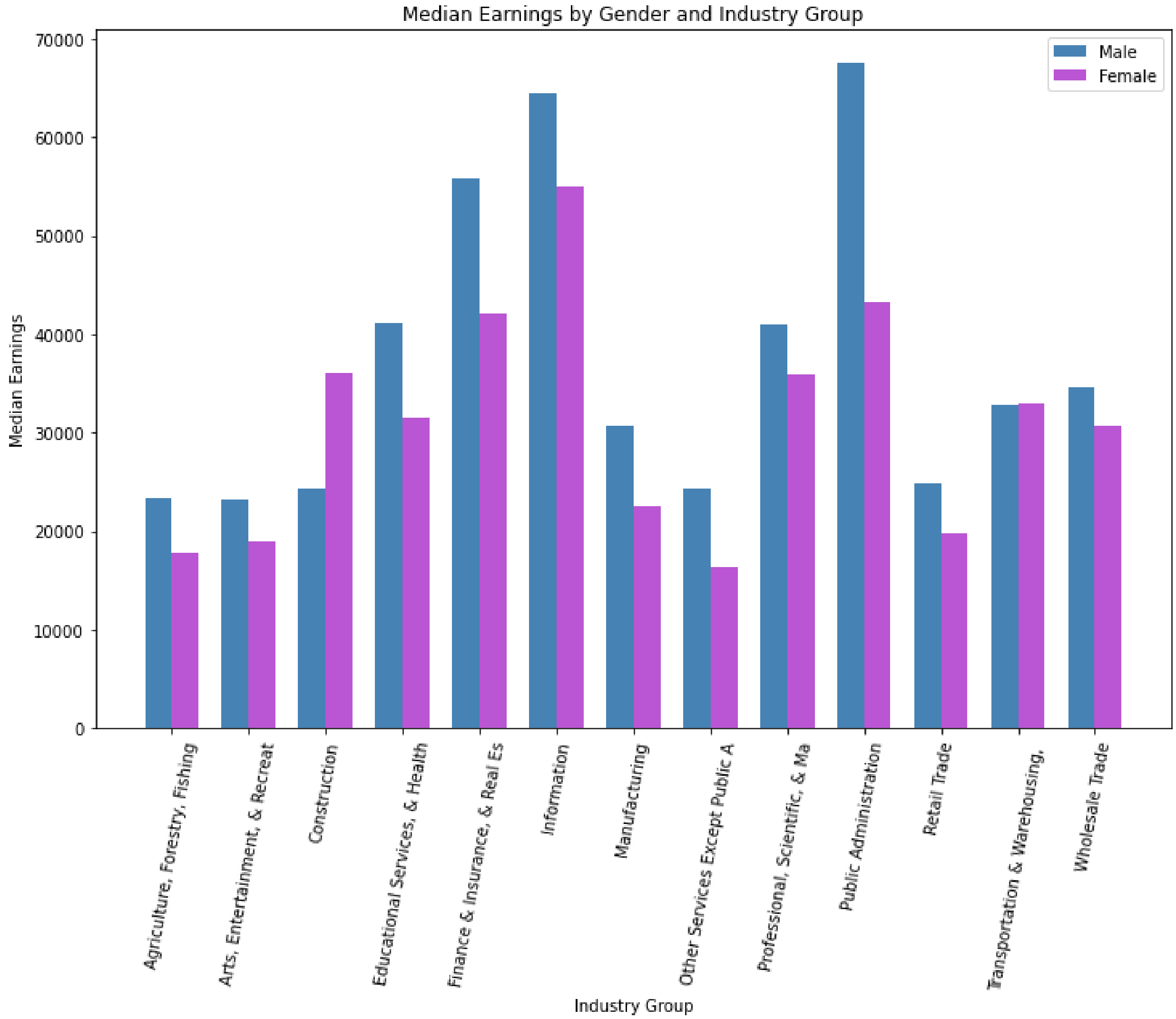
In [141…
```
medianearnings.head()

medianearnings = medianearnings.drop(['ID Year','ID Geography','Geography','Slu
```

In [142…
```
medianearnings.head()
```

Out[142]:

	ID Gender	Gender	ID Industry Group	Industry Group	Year	Median Earnings by Industry and Gender	Median Earnings by Industry and Gender Moe
0	0	Male	1	Agriculture, Forestry, Fishing & Hunting, & Mi...	2020	27462	5706
1	0	Male	2	Construction	2020	31123	358
2	0	Male	3	Manufacturing	2020	39168	1360
3	0	Male	4	Wholesale Trade	2020	40638	1416
4	0	Male	5	Retail Trade	2020	28440	991

In [143…
```
# median earnings
grouped_df = medianearnings.groupby(['Gender', 'Industry Group'])['Median Earni

industry_groups = grouped_df['Industry Group'].unique()
# width
bar_width = 0.35

# positions for the bars
male_positions = np.arange(len(industry_groups))
female_positions = male_positions + bar_width

plt.figure(figsize=(12, 8))
# Subset male/female
male_data = grouped_df[grouped_df['Gender'] == 'Male']
female_data = grouped_df[grouped_df['Gender'] == 'Female']

# plot the median earnings for males & females
plt.bar(male_positions, male_data['Median Earnings by Industry and Gender'], wi
plt.bar(female_positions, female_data['Median Earnings by Industry and Gender']

plt.xticks(male_positions + bar_width / 2, [label[:30] for label in industry_gr
plt.xlabel('Industry Group')
plt.ylabel('Median Earnings')
plt.title('Median Earnings by Gender and Industry Group')
plt.legend()

plt.show()
```



In [144…
```
list(industry_groups)
```

Out[144]:
```
['Agriculture, Forestry, Fishing & Hunting, & Mining',
 'Arts, Entertainment, & Recreation, & Accommodations & Food Services',
 'Construction',
 'Educational Services, & Health Care & Social Assistance',
 'Finance & Insurance, & Real Estate & Rental & Leasing',
 'Information',
 'Manufacturing',
 'Other Services Except Public Administration',
 'Professional, Scientific, & Management, & Administrative & Waste Management
Services',
 'Public Administration',
 'Retail Trade',
 'Transportation & Warehousing, & Utilities',
 'Wholesale Trade']
```

In [145…
```
occupations['Year'].unique()
```

Out[145]:
```
array([2020, 2019, 2018, 2017, 2016, 2015, 2014, 2013])
```

In [146…
```
occupations.head()
occupations = occupations.drop(['ID Year','ID State','State','ID Geography','Ge
```

In [147…
```
occupations.head()
```

Out[147]:

	ID Group	Group	ID Subgroup	Subgroup	ID Occupation	Occupation	Year	Workforce by Occupation and Gender
0	0	Management, Business, Science, & Arts Occupations	0	Management, Business, & Financial Occupations	0	Management Occupations	2020	201655
1	0	Management, Business, Science, & Arts Occupations	0	Management, Business, & Financial Occupations	1	Business & Financial Operations Occupations	2020	108938
2	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	2	Computer & Mathematical Occupations	2020	50906
3	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	3	Architecture & Engineering Occupations	2020	28250
4	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	4	Life, Physical, & Social Science Occupations	2020	17003

In [149…
```
homeprice = homeprice.rename(columns={'2023*': 2023})
homeprice.describe()
```

Out[149]:

	Zip Code	2023	2022	2021	2020	201
count	275.000000	2.680000e+02	2.740000e+02	2.750000e+02	2.750000e+02	2.750000e+0
mean	90911.978182	1.116389e+06	1.150845e+06	1.085190e+06	9.744483e+05	8.990159e+0
std	844.428887	6.975024e+05	7.203652e+05	6.773029e+05	5.983871e+05	5.636030e+0
min	90001.000000	3.536390e+05	3.665310e+05	3.444270e+05	2.894420e+05	2.634590e+0
25%	90226.000000	7.195190e+05	7.421698e+05	7.016110e+05	6.375905e+05	5.847410e+0
50%	90746.000000	8.747265e+05	9.019995e+05	8.527020e+05	7.744530e+05	7.120740e+0
75%	91374.000000	1.286105e+06	1.324968e+06	1.242047e+06	1.114240e+06	1.018949e+0
max	93591.000000	5.867635e+06	5.947918e+06	5.565130e+06	4.814363e+06	4.501657e+0

In [150…
```
crime.head()
crime = crime.drop(['DR_NO','AREA','Premis Cd','Weapon Used Cd','Rpt Dist No','
```

In [151…
```
crime.head()
```

Out[151]:

	Unnamed: 0	Date Rptd	DATE OCC	TIME OCC	AREA NAME	Crm Cd Desc	Vict Age	Vict Sex	Vict Descent	Pr
0	0	1/8/2020 0:00	1/8/2020 0:00	2230	Southwest	BATTERY - SIMPLE ASSAULT	36	F	B	
1	1	1/2/2020 0:00	1/1/2020 0:00	330	Central	BATTERY - SIMPLE ASSAULT	25	M	H	
2	2	4/14/2020 0:00	2/13/2020 0:00	1200	Central	SEX OFFENDER REGISTRANT OUT OF COMPLIANCE	0	X	X	
3	3	1/1/2020 0:00	1/1/2020 0:00	1730	N Hollywood	VANDALISM - MISDEAMEANOR ($399 OR UNDER)	76	F	W	M (AF
4	4	1/1/2020 0:00	1/1/2020 0:00	415	Mission	VANDALISM - FELONY ($400 & OVER, ALL CHURCH VA...	31	X	X	

In [152…
```
crime['Weapon Desc'].unique()
```

Out[152]:
```
array(['STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)',
       'UNKNOWN WEAPON/OTHER WEAPON', nan, 'ROCK/THROWN OBJECT',
       'VERBAL THREAT', 'FOLDING KNIFE', 'BLUNT INSTRUMENT', 'BOTTLE',
       'SEMI-AUTOMATIC PISTOL', 'CLUB/BAT', 'OTHER CUTTING INSTRUMENT',
       'HAND GUN', 'PHYSICAL PRESENCE', 'VEHICLE', 'SCISSORS', 'STICK',
       'MACHETE', 'OTHER KNIFE', 'SHOTGUN', 'ICE PICK',
       'KNIFE WITH BLADE 6INCHES OR LESS', 'FIRE', 'GLASS',
       'SIMULATED GUN', 'KNIFE WITH BLADE OVER 6 INCHES IN LENGTH',
       'DEMAND NOTE', 'BOMB THREAT', 'PIPE/METAL PIPE', 'UNKNOWN FIREARM',
       'MACE/PEPPER SPRAY', 'HAMMER', 'RAZOR', 'OTHER FIREARM',
       'BELT FLAILING INSTRUMENT/CHAIN',
       'UNKNOWN TYPE CUTTING INSTRUMENT', 'SCREWDRIVER', 'KITCHEN KNIFE',
       'AIR PISTOL/REVOLVER/RIFLE/BB GUN', 'BRASS KNUCKLES', 'REVOLVER',
       'SWITCH BLADE', 'STUN GUN', 'AXE', 'RIFLE',
       'ASSAULT WEAPON/UZI/AK47/ETC', 'ANTIQUE FIREARM', 'FIXED OBJECT',
       'SEMI-AUTOMATIC RIFLE', 'CAUSTIC CHEMICAL/POISON', 'TIRE IRON',
       'MARTIAL ARTS WEAPONS', 'CONCRETE BLOCK/BRICK', 'BOARD',
       'DIRK/DAGGER', 'TOY GUN', 'MAC-11 SEMIAUTOMATIC ASSAULT WEAPON',
       'EXPLOXIVE DEVICE',
       'HECKLER & KOCH 93 SEMIAUTOMATIC ASSAULT RIFLE',
       'SAWED OFF RIFLE/SHOTGUN', 'DOG/ANIMAL (SIC ANIMAL ON)', 'SYRINGE',
       'SCALDING LIQUID', 'RAZOR BLADE', 'CLEAVER', 'ROPE/LIGATURE',
       'BOW AND ARROW', 'AUTOMATIC WEAPON/SUB-MACHINE GUN',
       'LIQUOR/DRUGS', 'SWORD', 'M1-1 SEMIAUTOMATIC ASSAULT RIFLE',
       'STARTER PISTOL/REVOLVER', 'MAC-10 SEMIAUTOMATIC ASSAULT WEAPON',
       'BOWIE KNIFE', 'STRAIGHT RAZOR', 'BLACKJACK', 'RELIC FIREARM',
       'HECKLER & KOCH 91 SEMIAUTOMATIC ASSAULT RIFLE',
       'UZI SEMIAUTOMATIC ASSAULT RIFLE',
       'UNK TYPE SEMIAUTOMATIC ASSAULT RIFLE',
       'M-14 SEMIAUTOMATIC ASSAULT RIFLE'], dtype=object)
```

In [153…
```
crime['zipcode'].unique()
```

Out[153]:
```
array(['90037', '90014', '90013', '91607', '91402', '90017', '90012',
       '91342', '90015', '91340', '90851', '90710', '91411', '91405',
       '91316', '91356', '90027', '90086', '90049', '90071', '90035',
       '90048', '91401', '90074', '90025', '90292', '90057', '90044',
       '90031', '90033', '90227', '90034', '90021', '90016', '90003',
       '90028', '90066', '90007', '90036', '90062', '90731', '90079',
       '90002', '91352', '90212', '90210', '91406', '90042', '90043',
       '90029', '90059', '90272', '90032', '90732', '90064', '90019',
       '91335', '90004', '90026', '90006', '90038', '91306', '90024',
       '90744', '90039', '91324', '91344', '90005', '90023', '90001',
       '90291', '90046', '91605', '90008', '90011', '91403', '90041',
       '90230', '91436', '90501', '91343', '91423', '90018', '90068',
       '90065', '90020', '90063', '91328', '90010', '91331', '90248',
       '90047', '90077', '90067', '91606', '91601', '91303', '90094',
       '90045', '90247', '91040', '91345', '90061', '90095', '91326',
       '91030', '90089', 'California', '91604', '91364', '91602', '90505',
       '90073', '91325', '91307', '91108', '90250', '90232', '90058',
       '90405', '91504', '90404', '91330', '90009', '91204', '90052',
       '91608', '60031', '90053', '90293', '91311', '90096', '90502',
       '90040', '90275', '13359', '90717', '91367', '90305', '90813',
       '91506', '90810', '90733', '90745', '90211', '91304', '91042',
       '91505', '90245', '91206', '90402', '91365', '90069', '90504',
       '91371', '91522', '90201', '90301', '91312', '91515', '90734',
       '90272-3002', '91201', '90296', '91105', '91205', '90403', '91210',
       '91203', '90304', '90278', '90302', '90831', '90081', '91803',
       '90056', '91214', '90260', '90290', '90303', '90280', '91355',
       '90265', '91302', '90255'], dtype=object)
```

In [154…
```
crime.dtypes
# Drop California
crime = crime.drop(crime[crime['zipcode'] == 'California'].index)
crime = crime.drop(crime[crime['zipcode'] == '90272-3002'].index)
crime['zipcode'] = crime['zipcode'].astype(int)
```

In [155…
```
crime['Weapon Desc'].unique()
```

Out[155]:
```
array(['STRONG-ARM (HANDS, FIST, FEET OR BODILY FORCE)',
       'UNKNOWN WEAPON/OTHER WEAPON', nan, 'ROCK/THROWN OBJECT',
       'VERBAL THREAT', 'FOLDING KNIFE', 'BLUNT INSTRUMENT', 'BOTTLE',
       'SEMI-AUTOMATIC PISTOL', 'CLUB/BAT', 'OTHER CUTTING INSTRUMENT',
       'HAND GUN', 'PHYSICAL PRESENCE', 'VEHICLE', 'SCISSORS', 'STICK',
       'MACHETE', 'OTHER KNIFE', 'SHOTGUN', 'ICE PICK',
       'KNIFE WITH BLADE 6INCHES OR LESS', 'FIRE', 'GLASS',
       'SIMULATED GUN', 'KNIFE WITH BLADE OVER 6 INCHES IN LENGTH',
       'DEMAND NOTE', 'BOMB THREAT', 'PIPE/METAL PIPE', 'UNKNOWN FIREARM',
       'MACE/PEPPER SPRAY', 'HAMMER', 'RAZOR', 'OTHER FIREARM',
       'BELT FLAILING INSTRUMENT/CHAIN',
       'UNKNOWN TYPE CUTTING INSTRUMENT', 'SCREWDRIVER', 'KITCHEN KNIFE',
       'AIR PISTOL/REVOLVER/RIFLE/BB GUN', 'BRASS KNUCKLES', 'REVOLVER',
       'SWITCH BLADE', 'STUN GUN', 'AXE', 'RIFLE',
       'ASSAULT WEAPON/UZI/AK47/ETC', 'ANTIQUE FIREARM', 'FIXED OBJECT',
       'SEMI-AUTOMATIC RIFLE', 'CAUSTIC CHEMICAL/POISON', 'TIRE IRON',
       'MARTIAL ARTS WEAPONS', 'CONCRETE BLOCK/BRICK', 'BOARD',
       'DIRK/DAGGER', 'TOY GUN', 'MAC-11 SEMIAUTOMATIC ASSAULT WEAPON',
       'EXPLOXIVE DEVICE',
       'HECKLER & KOCH 93 SEMIAUTOMATIC ASSAULT RIFLE',
       'SAWED OFF RIFLE/SHOTGUN', 'DOG/ANIMAL (SIC ANIMAL ON)', 'SYRINGE',
       'SCALDING LIQUID', 'RAZOR BLADE', 'CLEAVER', 'ROPE/LIGATURE',
       'BOW AND ARROW', 'AUTOMATIC WEAPON/SUB-MACHINE GUN',
       'LIQUOR/DRUGS', 'SWORD', 'M1-1 SEMIAUTOMATIC ASSAULT RIFLE',
       'STARTER PISTOL/REVOLVER', 'MAC-10 SEMIAUTOMATIC ASSAULT WEAPON',
       'BOWIE KNIFE', 'STRAIGHT RAZOR', 'BLACKJACK', 'RELIC FIREARM',
       'HECKLER & KOCH 91 SEMIAUTOMATIC ASSAULT RIFLE',
       'UZI SEMIAUTOMATIC ASSAULT RIFLE',
       'UNK TYPE SEMIAUTOMATIC ASSAULT RIFLE',
       'M-14 SEMIAUTOMATIC ASSAULT RIFLE'], dtype=object)
```

In [156…
```
# Create binary 'weapon' column
crime['weapon'] = crime['Weapon Desc'].notnull().astype(int)

crime['weapon'].fillna(0, inplace=True)
```

In [157…
```
crime[['weapon','zipcode']].head()
```

Out[157]:

	weapon	zipcode
0	1	90037
1	1	90014
2	0	90013
3	0	91607
4	0	91402

In [173…

```
# count of total number of rows and number of 1's (yes, weapons)

weaponcount = crime.groupby('zipcode')['weapon'].agg(['sum', 'size'])

weaponcount.columns = ['Total_Weapons', 'Total_Crimes']

weaponcount['WeaponRatio'] = round(weaponcount['Total_Weapons']/ weaponcount['T

weaponcount
```

Out[173]:

zipcode	Total_Weapons	Total_Crimes	WeaponRatio
13359	126	666	0.19
60031	38	127	0.30
90001	1297	2740	0.47
90002	3918	8247	0.48
90003	8551	16562	0.52
...	...	...	...
91605	2508	7905	0.32
91606	2187	7083	0.31
91607	850	4120	0.21
91608	272	870	0.31
91803	3	4	0.75

183 rows × 3 columns

In [174…

```
weaponcount = weaponcount.reset_index()
```

In [175…

```
weaponcount.sort_values(by='WeaponRatio',ascending=True)
```

Out[175]:

	zipcode	Total_Weapons	Total_Crimes	WeaponRatio
135	91302	0	1	0.00
104	90403	0	8	0.00
87	90260	0	1	0.00
69	90081	0	2	0.00
91	90278	2	22	0.09
...	...	...	...	...
127	91108	11	19	0.58
88	90265	3	5	0.60
182	91803	3	4	0.75
92	90280	7	8	0.88
86	90255	2	2	1.00

183 rows × 4 columns

In [176…

```
test = weaponcount['Total_Crimes'].sum()
test2 = weaponcount['Total_Weapons'].sum()
weaponcount['CrimeRelFreq'] = round(weaponcount['Total_Crimes'] / test,3)
weaponcount['WeaponRelFreq'] = round(weaponcount['Total_Weapons'] / test2,3)
```

In [177…

```
weaponcount['WeaponRatio'] = round(weaponcount['WeaponRatio'] * 100, 2)
weaponcount['CrimeRelFreq'] = round(weaponcount['CrimeRelFreq'] * 100, 2)
weaponcount['WeaponRelFreq'] = round(weaponcount['WeaponRelFreq'] * 100, 2)
```

In [178…

```
weaponcount.sort_values(by='WeaponRelFreq',ascending=False)
```

Out[178]:

	zipcode	Total_Weapons	Total_Crimes	WeaponRatio	CrimeRelFreq	WeaponRelFreq
43	90044	9276	18779	49.0	2.6	3.8
4	90003	8551	16562	52.0	2.3	3.5
28	90028	7630	17553	43.0	2.5	3.1
36	90037	6316	13344	47.0	1.9	2.6
12	90011	6304	14519	43.0	2.0	2.6
...	...	...	...	...	...	...
112	90717	91	283	32.0	0.0	0.0
109	90504	19	59	32.0	0.0	0.0
106	90405	30	133	23.0	0.0	0.0
105	90404	28	102	27.0	0.0	0.0
182	91803	3	4	75.0	0.0	0.0

183 rows × 6 columns

In [185…

```
homeclean = homeprice.merge(weaponcount, left_on='Zip Code',right_on='zipcode')
homeclean = homeclean.drop('zipcode', axis=1)
homeclean.head()
```

Out[185]:

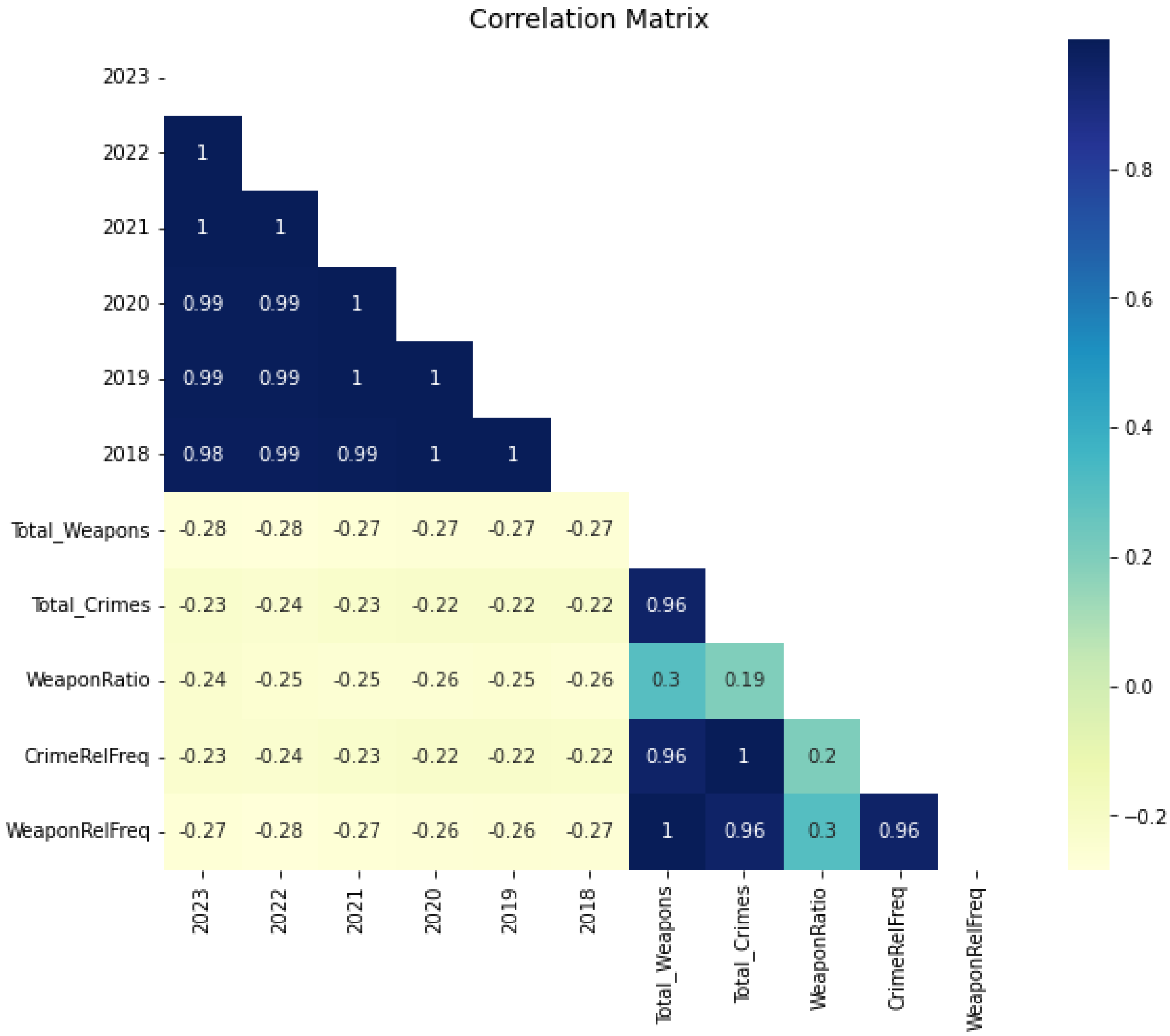
	Zip Code	City / Community	2023	2022	2021	2020	2019	2018	Tota
0	90001	Los Angeles (South Los Angeles), Florence-Graham	540635.0	555034.0	508199	465268	425927	404863	
1	90002	Los Angeles (Southeast Los Angeles, Watts)	539102.0	552950.0	518364	463726	421153	398477	
2	90003	Los Angeles (South Los Angeles, Southeast Los ...	558141.0	577163.0	542654	480137	435456	413903	
3	90004	Los Angeles (Hancock Park, Rampart Village, Vi...	1767062.0	1824797.0	1722525	1578331	1453209	1477493	
4	90005	Los Angeles (Hancock Park, Koreatown, Wilshire...	1791046.0	1880689.0	1774383	1602551	1487273	1504952	

In [186…

```
corr = homeclean.copy()
corr.drop('Zip Code', axis=1, inplace=True)

corr = corr.corr()

plt.figure(figsize=(10,8))

mask = np.triu(np.ones_like(corr, dtype=bool))

sns.heatmap(corr, mask = mask,annot=True,cmap='YlGnBu')
plt.title('Correlation Matrix',fontsize=14)
```

Out[186]:

```
Text(0.5, 1.0, 'Correlation Matrix')
```



In [187…

```
occupations.head()
```

Out[187]:

	ID Group	Group	ID Subgroup	Subgroup	ID Occupation	Occupation	Year	Workforce by Occupation and Gender
0	0	Management, Business, Science, & Arts Occupations	0	Management, Business, & Financial Occupations	0	Management Occupations	2020	201655
1	0	Management, Business, Science, & Arts Occupations	0	Management, Business, & Financial Occupations	1	Business & Financial Operations Occupations	2020	108938
2	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	2	Computer & Mathematical Occupations	2020	50906
3	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	3	Architecture & Engineering Occupations	2020	28250
4	0	Management, Business, Science, & Arts Occupations	1	Computer, Engineering, & Science Occupations	4	Life, Physical, & Social Science Occupations	2020	17003

In [188…
```
occup = occupations[['Year','Occupation','Median Earnings']]
occup = occup.loc[occup['Year'] == 2020]
#occup = occup.groupby(['Year','Occupation'])['Median Earnings'].mean()
```

In [189…
```
occup = pd.DataFrame(data=occup)
occup['Occupation'] = occup['Occupation'].str.replace(' Occupations', '')
```

In [190…
```
medianearnings.head(3)
```

Out[190]:

	ID Gender	Gender	ID Industry Group	Industry Group	Year	Median Earnings by Industry and Gender	Median Earnings by Industry and Gender Moe
0	0	Male	1	Agriculture, Forestry, Fishing & Hunting, & Mi...	2020	27462	5706
1	0	Male	2	Construction	2020	31123	358
2	0	Male	3	Manufacturing	2020	39168	1360

In [191…
```
data_2020 = medianearnings[medianearnings['Year'] == 2020]

average_salary_by_group = data_2020.groupby('Industry Group')['Median Earnings
```

```
avg_sal = pd.DataFrame(average_salary_by_group)
average_salary_by_group
```

Out[191]:

```
Industry Group
Agriculture, Forestry, Fishing & Hunting, & Mining
24075.0
Arts, Entertainment, & Recreation, & Accommodations & Food Services
24684.0
Construction
36365.5
Educational Services, & Health Care & Social Assistance
41376.0
Finance & Insurance, & Real Estate & Rental & Leasing
58793.5
Information
69996.0
Manufacturing
34134.5
Other Services Except Public Administration
25240.0
Professional, Scientific, & Management, & Administrative & Waste Management Se
rvices    47194.5
Public Administration
58136.0
Retail Trade
25604.0
Transportation & Warehousing, & Utilities
34134.0
Wholesale Trade
38159.5
Name: Median Earnings by Industry and Gender, dtype: float64
```

In [192…

```
average_salary_data = pd.DataFrame({
    'Year': ['2020'] * len(average_salary_by_group),  # Repeat '2020' for the l
    'Occupation': average_salary_by_group.index,
    'Median Earnings': average_salary_by_group.values
})
average_salary_data
```

Out[192]:

	Year	Occupation	Median Earnings
0	2020	Agriculture, Forestry, Fishing & Hunting, & Mi...	24075.0
1	2020	Arts, Entertainment, & Recreation, & Accommoda...	24684.0
2	2020	Construction	36365.5
3	2020	Educational Services, & Health Care & Social A...	41376.0
4	2020	Finance & Insurance, & Real Estate & Rental & ...	58793.5
5	2020	Information	69996.0
6	2020	Manufacturing	34134.5
7	2020	Other Services Except Public Administration	25240.0
8	2020	Professional, Scientific, & Management, & Admi...	47194.5
9	2020	Public Administration	58136.0
10	2020	Retail Trade	25604.0
11	2020	Transportation & Warehousing, & Utilities	34134.0
12	2020	Wholesale Trade	38159.5

In [193…

```
combined_data = pd.concat([average_salary_data, occup], ignore_index=True)
combined_data
```

Out[193]:

	Year	Occupation	Median Earnings
0	2020	Agriculture, Forestry, Fishing & Hunting, & Mi...	24075.0
1	2020	Arts, Entertainment, & Recreation, & Accommoda...	24684.0
2	2020	Construction	36365.5
3	2020	Educational Services, & Health Care & Social A...	41376.0
4	2020	Finance & Insurance, & Real Estate & Rental & ...	58793.5
5	2020	Information	69996.0
6	2020	Manufacturing	34134.5
7	2020	Other Services Except Public Administration	25240.0
8	2020	Professional, Scientific, & Management, & Admi...	47194.5
9	2020	Public Administration	58136.0
10	2020	Retail Trade	25604.0
11	2020	Transportation & Warehousing, & Utilities	34134.0
12	2020	Wholesale Trade	38159.5
13	2020	Management	147944.0
14	2020	Business & Financial Operations	136895.0
15	2020	Computer & Mathematical	151426.0
16	2020	Architecture & Engineering	161213.0
17	2020	Life, Physical, & Social Science	123577.0
18	2020	Community & Social Service	88535.0
19	2020	Legal	215184.0
20	2020	Education Instruction, & Library	78961.0
21	2020	Arts, Design, Entertainment, Sports, & Media	114414.0
22	2020	Health Diagnosing & Treating Practitioners & O...	180900.0
23	2020	Health Technologists & Technicians	90323.0
24	2020	Healthcare Support	45194.0
25	2020	Food Preparation & Serving Related	42938.0
26	2020	Building & Grounds Cleaning & Maintenance	42718.0
27	2020	Personal Care & Service	45091.0
28	2020	Fire Fighting & Prevention, & Other Protective...	52540.0
29	2020	Law Enforcement Workers Including Supervisors	151404.0
30	2020	Sales & Related	60297.0
31	2020	Office & Administrative Support	68740.0
32	2020	Farming, Fishing, & Forestry	41622.0
33	2020	Construction & Extraction	70138.0
34	2020	Installation, Maintenance, & Repair	82002.0

	Year	Occupation	Median Earnings
35	2020	Production	52665.0
36	2020	Transportation	57396.0

In [194…

```
sorteddata = combined_data.sort_values(by='Median Earnings', ascending=False)
sorteddata
```

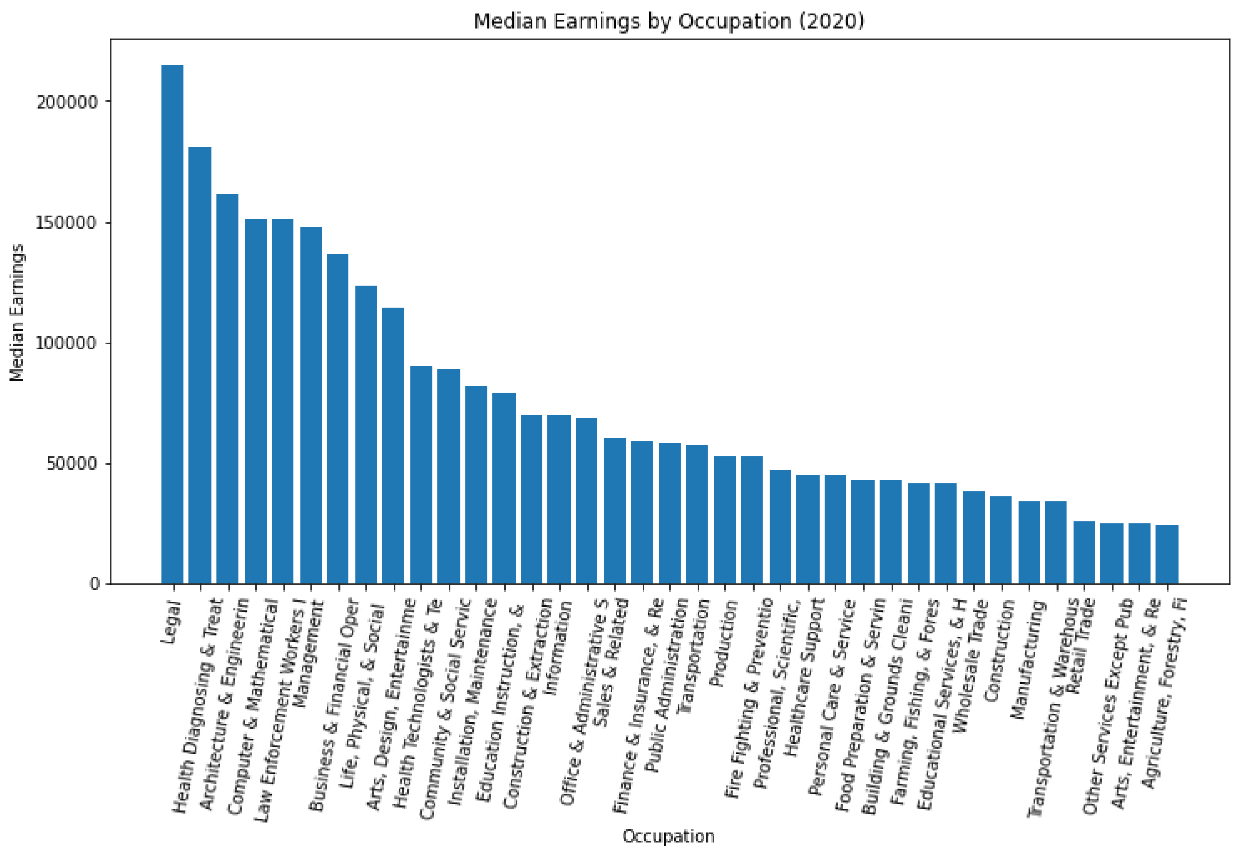
Out[194]:

	Year	Occupation	Median Earnings
19	2020	Legal	215184.0
22	2020	Health Diagnosing & Treating Practitioners & O...	180900.0
16	2020	Architecture & Engineering	161213.0
15	2020	Computer & Mathematical	151426.0
29	2020	Law Enforcement Workers Including Supervisors	151404.0
13	2020	Management	147944.0
14	2020	Business & Financial Operations	136895.0
17	2020	Life, Physical, & Social Science	123577.0
21	2020	Arts, Design, Entertainment, Sports, & Media	114414.0
23	2020	Health Technologists & Technicians	90323.0
18	2020	Community & Social Service	88535.0
34	2020	Installation, Maintenance, & Repair	82002.0
20	2020	Education Instruction, & Library	78961.0
33	2020	Construction & Extraction	70138.0
5	2020	Information	69996.0
31	2020	Office & Administrative Support	68740.0
30	2020	Sales & Related	60297.0
4	2020	Finance & Insurance, & Real Estate & Rental & ...	58793.5
9	2020	Public Administration	58136.0
36	2020	Transportation	57396.0
35	2020	Production	52665.0
28	2020	Fire Fighting & Prevention, & Other Protective...	52540.0
8	2020	Professional, Scientific, & Management, & Admi...	47194.5
24	2020	Healthcare Support	45194.0
27	2020	Personal Care & Service	45091.0
25	2020	Food Preparation & Serving Related	42938.0
26	2020	Building & Grounds Cleaning & Maintenance	42718.0
32	2020	Farming, Fishing, & Forestry	41622.0
3	2020	Educational Services, & Health Care & Social A...	41376.0
12	2020	Wholesale Trade	38159.5
2	2020	Construction	36365.5
6	2020	Manufacturing	34134.5
11	2020	Transportation & Warehousing, & Utilities	34134.0
10	2020	Retail Trade	25604.0
7	2020	Other Services Except Public Administration	25240.0

	Year	Occupation	Median Earnings
1	2020	Arts, Entertainment, & Recreation, & Accommoda...	24684.0
0	2020	Agriculture, Forestry, Fishing & Hunting, & Mi...	24075.0

In [211…

```
sorteddata = combined_data.sort_values(by='Median Earnings', ascending=False)
plt.figure(figsize=(12, 6))
plt.bar(sorteddata['Occupation'], sorteddata['Median Earnings'])
plt.xticks(rotation=80)
plt.xticks(range(len(sorteddata['Occupation'])), [label[:25] for label in sorte
plt.xlabel('Occupation')
plt.ylabel('Median Earnings')
plt.title('Median Earnings by Occupation (2020)')
plt.show()
```



In [196…

```
occup['3x'] = occup['Median Earnings'] * 3
occup['4x'] = occup['Median Earnings'] * 4
occup['5x'] = occup['Median Earnings'] * 5
```

In [197…

```
occup.sort_values(by='Median Earnings')
```

Out[197]:

	Year	Occupation	Median Earnings	3x	4x	5x
19	2020	Farming, Fishing, & Forestry	41622	124866	166488	208110
13	2020	Building & Grounds Cleaning & Maintenance	42718	128154	170872	213590
12	2020	Food Preparation & Serving Related	42938	128814	171752	214690
14	2020	Personal Care & Service	45091	135273	180364	225455
11	2020	Healthcare Support	45194	135582	180776	225970
15	2020	Fire Fighting & Prevention, & Other Protective...	52540	157620	210160	262700
22	2020	Production	52665	157995	210660	263325
23	2020	Transportation	57396	172188	229584	286980
17	2020	Sales & Related	60297	180891	241188	301485
18	2020	Office & Administrative Support	68740	206220	274960	343700
20	2020	Construction & Extraction	70138	210414	280552	350690
7	2020	Education Instruction, & Library	78961	236883	315844	394805
21	2020	Installation, Maintenance, & Repair	82002	246006	328008	410010
5	2020	Community & Social Service	88535	265605	354140	442675
10	2020	Health Technologists & Technicians	90323	270969	361292	451615
8	2020	Arts, Design, Entertainment, Sports, & Media	114414	343242	457656	572070
4	2020	Life, Physical, & Social Science	123577	370731	494308	617885
1	2020	Business & Financial Operations	136895	410685	547580	684475
0	2020	Management	147944	443832	591776	739720
16	2020	Law Enforcement Workers Including Supervisors	151404	454212	605616	757020
2	2020	Computer & Mathematical	151426	454278	605704	757130
3	2020	Architecture & Engineering	161213	483639	644852	806065
9	2020	Health Diagnosing & Treating Practitioners & O...	180900	542700	723600	904500
6	2020	Legal	215184	645552	860736	1075920

In [198…

```
homeclean.sort_values(by=2020)
```

Out[198]:

	Zip Code	City / Community	2023	2022	2021	2020	2019	201
1	90002	Los Angeles (Southeast Los Angeles, Watts)	539102.0	552950.0	518364	463726	421153	39847
0	90001	Los Angeles (South Los Angeles), Florence-Graham	540635.0	555034.0	508199	465268	425927	40486
49	90059	Los Angeles (Southeast Los Angeles, Watts), Wi...	548066.0	563478.0	528218	471088	427050	40292
2	90003	Los Angeles (South Los Angeles, Southeast Los ...	558141.0	577163.0	542654	480137	435456	41390
48	90058	Los Angeles (Southeast Los Angeles), Vernon	543413.0	570248.0	520095	493648	449495	43785
...	...	...	...	...	...	...	...	...
64	90212	Beverly Hills	3340912.0	3498279.0	3392942	3082636	2891801	292483
45	90049	Los Angeles (Bel Air Estates, Brentwood)	3541400.0	3674210.0	3466405	3100872	2847689	292947
74	90272	Los Angeles (Castellemare, Pacific Highlands, ...	3739165.0	3877633.0	3520191	3146729	2970935	299474
87	90402	Santa Monica	4679317.0	4859649.0	4527167	4166743	3939767	402100
62	90210	Beverly Hills	5867635.0	5947918.0	5565130	4814363	4501657	407376

155 rows × 13 columns

In [203…

```
zip_code_occupation_mapping = {}

for index, occ_row in occup.iterrows():
    occupation = occ_row['Occupation']
    median_earnings = occ_row['Median Earnings']
    affordability_3x = occ_row['3x']
    affordability_4x = occ_row['4x']
    affordability_5x = occ_row['5x']

    for index, row in homeclean.iterrows():
        zip_code = row['Zip Code']
        housing_cost = row[2020]

        if housing_cost >= median_earnings and housing_cost <= affordability_3x
            zip_code_occupation_mapping[zip_code] = occupation

results = []

for zip_code, occupation in zip_code_occupation_mapping.items():
    city_community = homeclean[homeclean['Zip Code'] == zip_code]['City / Commu
    result = {
```

```
        'Zip Code': zip_code,
        'City / Community': city_community,
        'Occupation': occupation,
        'Affordability Based on 3x Salary': 'Yes' if occupation in zip_code_occ
    }
    results.append(result)

df3x = pd.DataFrame(results)
df3x.head(1)
```

Out[203]:

	Zip Code	City / Community	Occupation	Affordability Based on 3x Salary
0	90001	Los Angeles (South Los Angeles), Florence-Graham	Health Diagnosing & Treating Practitioners & O...	Yes

occupation_count = df5x['Occupation'].value_counts() print(occupation_count)

In [202…

```
zip_code_occupation_mapping = {}

for index, occ_row in occup.iterrows():
    occupation = occ_row['Occupation']
    median_earnings = occ_row['Median Earnings']
    affordability_3x = occ_row['3x']
    affordability_4x = occ_row['4x']
    affordability_5x = occ_row['5x']

    for index, row in homeclean.iterrows():
        zip_code = row['Zip Code']
        housing_cost = row[2020]

        if housing_cost >= median_earnings and housing_cost <= affordability_3x
            zip_code_occupation_mapping[zip_code] = occupation

results = []
cannot_afford_professions = set(occup['Occupation'])  # Set of all professions

for zip_code, occupation in zip_code_occupation_mapping.items():
    city_community = homeclean[homeclean['Zip Code'] == zip_code]['City / Commu
    result = {
        'Zip Code': zip_code,
        'City / Community': city_community,
        'Occupation': occupation,
        'Affordability Based on 3x Salary': 'Yes' if occupation in zip_code_occ
    }
    results.append(result)
    cannot_afford_professions.discard(occupation)  # Remove the profession from

df3x = pd.DataFrame(results)
df3x
```

Out[202]:

	Zip Code	City / Community	Occupation	Affordability Based on 3x Salary
0	90001	Los Angeles (South Los Angeles), Florence-Graham	Health Diagnosing & Treating Practitioners & O...	Yes
1	90002	Los Angeles (Southeast Los Angeles, Watts)	Health Diagnosing & Treating Practitioners & O...	Yes
2	90003	Los Angeles (South Los Angeles, Southeast Los ...	Health Diagnosing & Treating Practitioners & O...	Yes
3	90059	Los Angeles (Southeast Los Angeles, Watts), Wi...	Health Diagnosing & Treating Practitioners & O...	Yes
4	90011	Los Angeles (Southeast Los Angeles)	Health Diagnosing & Treating Practitioners & O...	Yes
5	90013	Los Angeles (Downtown Central, Downtown Fashio...	Legal	Yes
6	90014	Los Angeles (Downtown Historic Core, Arts Dist...	Health Diagnosing & Treating Practitioners & O...	Yes
7	90023	Los Angeles (Boyle Heights), Commerce, East Lo...	Health Diagnosing & Treating Practitioners & O...	Yes
8	90033	Los Angeles (Boyle Heights)	Legal	Yes
9	90037	Los Angeles (South Los Angeles)	Legal	Yes
10	90040	Commerce	Health Diagnosing & Treating Practitioners & O...	Yes
11	90044	Athens, Los Angeles (South Los Angeles)	Health Diagnosing & Treating Practitioners & O...	Yes
12	90047	Los Angeles (South Los Angeles)	Legal	Yes
13	90058	Los Angeles (Southeast Los Angeles), Vernon	Health Diagnosing & Treating Practitioners & O...	Yes
14	90061	Los Angeles (South Los Angeles)	Health Diagnosing & Treating Practitioners & O...	Yes
15	90062	Los Angeles (South Los Angeles)	Legal	Yes
16	90063	City Terrace, Los Angeles (Boyle Heights)	Legal	Yes
17	90201	Bell, Bell Gardens, Cudahy	Health Diagnosing & Treating Practitioners & O...	Yes
18	90255	Huntington Park, Walnut Park	Legal	Yes
19	90280	South Gate	Legal	Yes

	Zip Code	City / Community	Occupation	Affordability Based on 3x Salary
20	90301	Inglewood	Legal	Yes
21	90304	Inglewood, Lennox	Legal	Yes
22	90502	Torrance, West Carson	Legal	Yes
23	90744	Los Angeles (Wilmington)	Legal	Yes
24	90745	Carson	Legal	Yes
25	90810	Carson, Long Beach	Legal	Yes
26	90813	Long Beach	Health Diagnosing & Treating Practitioners & O...	Yes
27	91331	Los Angeles (Arleta, Hansen Hills, Pacoima)	Legal	Yes
28	91340	San Fernando, Los Angeles (Mission Hills, Paco...	Legal	Yes
29	91402	Los Angeles (Panorama City)	Legal	Yes

In [204…
```
cannot_afford_professions = pd.DataFrame(cannot_afford_professions)
cannot_afford_professions.columns = ['Professions that cannot afford a home on
cannot_afford_professions
```

Out[204]:

	Professions that cannot afford a home on a single salary:
0	Business & Financial Operations
1	Fire Fighting & Prevention, & Other Protective...
2	Computer & Mathematical
3	Law Enforcement Workers Including Supervisors
4	Food Preparation & Serving Related
5	Office & Administrative Support
6	Construction & Extraction
7	Personal Care & Service
8	Production
9	Installation, Maintenance, & Repair
10	Management
11	Farming, Fishing, & Forestry
12	Arts, Design, Entertainment, Sports, & Media
13	Health Technologists & Technicians
14	Sales & Related
15	Education Instruction, & Library
16	Architecture & Engineering
17	Building & Grounds Cleaning & Maintenance
18	Transportation
19	Community & Social Service
20	Healthcare Support
21	Life, Physical, & Social Science

In [205…

```
matched_professions = df3x[df3x['Affordability Based on 3x Salary'] == 'Yes']
matched_professions = matched_professions[['Occupation']]
matched_professions = pd.DataFrame(matched_professions['Occupation'].unique())
matched_professions.columns = ['Professions that can afford a home on a single
matched_professions
```

Out[205]:

	Professions that can afford a home on a single salary:
0	Health Diagnosing & Treating Practitioners & O...
1	Legal

In [206…

```
# alls zips
all_zip_codes = set(homeclean['Zip Code'])

# unmatched zips
unmatched_zip_codes = all_zip_codes.difference(zip_code_occupation_mapping.keys
```

```
matched_results = []
unmatched_results = []

for zip_code, occupation in zip_code_occupation_mapping.items():
    row = homeclean[homeclean['Zip Code'] == zip_code].iloc[0]
    result = {
        'Zip Code': zip_code,
        'City / Community': row['City / Community'],
        'Occupation': occupation,
        'Affordability Based on 3x Salary': 'Yes',
        '2020': row[2020],
        'Total_Weapons': row['Total_Weapons'],
        'Total_Crimes': row['Total_Crimes'],
        'WeaponRatio': row['WeaponRatio'],
        'CrimeRelFreq': row['CrimeRelFreq'],
        'WeaponRelFreq': row['WeaponRelFreq']
    }
    matched_results.append(result)

df_matched = pd.DataFrame(matched_results)

for zip_code in unmatched_zip_codes:
    row = homeclean[homeclean['Zip Code'] == zip_code].iloc[0]
    result = {
        'Zip Code': zip_code,
        'City / Community': row['City / Community'],
        'Occupation': 'Not Matched',
        'Affordability Based on 3x Salary': 'No',
        '2020': row[2020],
        'Total_Weapons': row['Total_Weapons'],
        'Total_Crimes': row['Total_Crimes'],
        'WeaponRatio': row['WeaponRatio'],
        'CrimeRelFreq': row['CrimeRelFreq'],
        'WeaponRelFreq': row['WeaponRelFreq']
    }
    unmatched_results.append(result)

df_unmatched = pd.DataFrame(unmatched_results)

#print("Professions that cannot afford a home in L.A. County on a single salary
#print(list(cannot_afford_professions))
#print("\nMatched zip codes and city/community with full details:")
#print(df_matched)
#print("\nUnmatched zip codes and city/community with full details:")
#print(df_unmatched)
```

In [ ]:

```
print("\nMatched zip codes and city/community with full details:")
df_matched
print("\nUnmatched zip codes and city/community with full details:")
df_unmatched
```

In [213…

```
average_matched = df_matched[['2020', 'Total_Weapons', 'Total_Crimes', 'WeaponR
average_unmatched = df_unmatched[['2020', 'Total_Weapons', 'Total_Crimes', 'Wea

average_matched = average_matched.rename(index={'2020': 'Home Price'})
average_unmatched = average_unmatched.rename(index={'2020': 'Home Price'})

average_matched['Home Price'] = '${:,.2f}'.format(average_matched['Home Price']
average_unmatched['Home Price'] = '${:,.2f}'.format(average_unmatched['Home Pri
```

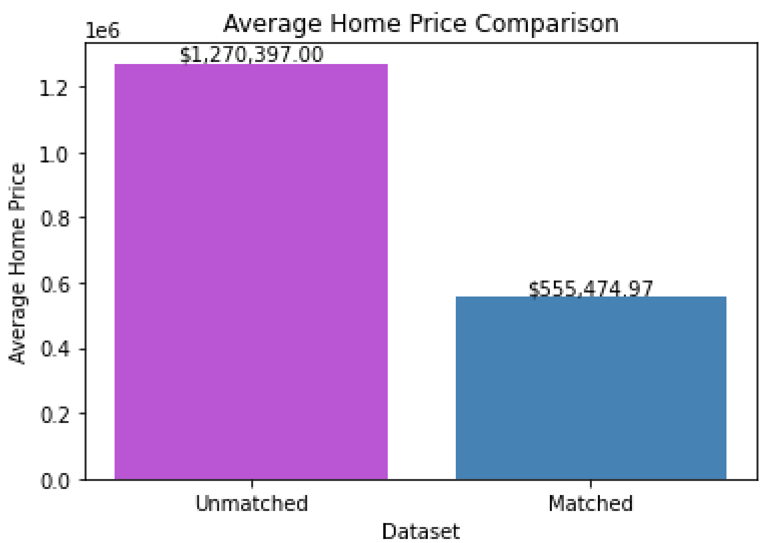
```python
average_combined = pd.DataFrame({'Avg Matched': average_matched, 'Avg Unmatched

average_combined
```

Out[213]:

	Avg Matched	Avg Unmatched
Home Price	$555,474.97	$1,270,397.00
Total_Weapons	2496.43	1310.16
Total_Crimes	5651.23	4132.39
WeaponRatio	44.03	29.62

In [214…

```python
average_home_price_matched = df_matched['2020'].mean()
average_home_price_unmatched = df_unmatched['2020'].mean()

labels = ['Unmatched', 'Matched']
values = [average_home_price_unmatched, average_home_price_matched]

colors = ['mediumorchid','steelblue']

sns.set_palette(colors)

plt.bar(labels, values, color=colors)

for i, v in enumerate(values):
    plt.text(i, v, str('${:,.2f}'.format(v)), ha='center', va='bottom')

plt.xlabel('Dataset')
plt.ylabel('Average Home Price')
plt.title('Average Home Price Comparison')

plt.show()
```



In [ ]:

```python
df_unmatched.head(2)
```

In [217…

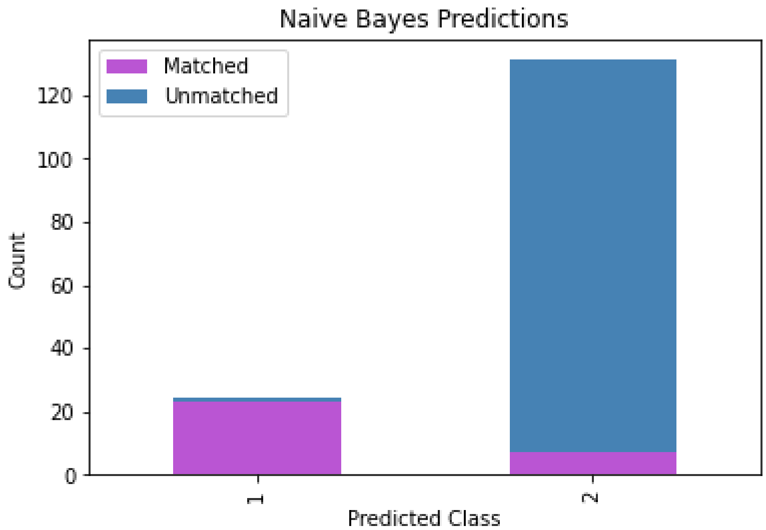
```python
# Naive bayes analysis

df_matched = df_matched.drop(["City / Community", "Occupation","Affordability I
df_unmatched = df_unmatched.drop(["City / Community", "Occupation","Affordabili
```

```
# combine the matched and unmatched datasets and create labels
df_matched['Label'] = 1  #   1 to df_matched
df_unmatched['Label'] = 2  # 2 to df_unmatched
combined_data = pd.concat([df_matched, df_unmatched], ignore_index=True)

# split the combined data into features (X) and labels (y)
X = combined_data.drop('Label', axis=1)
y = combined_data['Label']

classifier = GaussianNB()
classifier.fit(X, y)
predictions = classifier.predict(X)
accuracy = accuracy_score(y, predictions)

df_matched_predictions = predictions[combined_data['Label'] == 1]
df_unmatched_predictions = predictions[combined_data['Label'] == 2]

print("Accuracy:", accuracy)
print("df_matched Predictions:", df_matched_predictions)
print("df_unmatched Predictions:", df_unmatched_predictions)
```

```
Accuracy: 0.9483870967741935
df_matched Predictions: [2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1 2 1 2
1 2 2]
df_unmatched Predictions: [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```

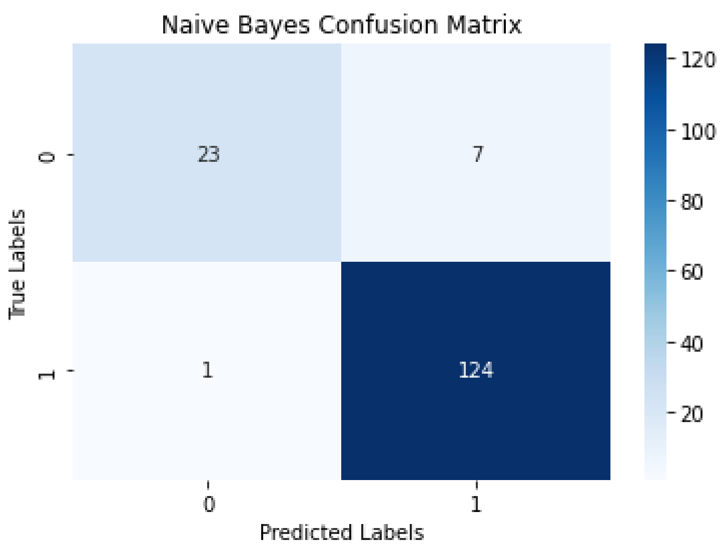
In [218…

```
df_matched_predictions = pd.Series(df_matched_predictions)
df_unmatched_predictions = pd.Series(df_unmatched_predictions)

matched_counts = df_matched_predictions.value_counts()
unmatched_counts = df_unmatched_predictions.value_counts()

predictions_counts = pd.DataFrame({'Matched': matched_counts, 'Unmatched': unma

predictions_counts.plot(kind='bar', stacked=True)
plt.xlabel('Predicted Class')
plt.ylabel('Count')
plt.title('Naive Bayes Predictions')
plt.legend()
plt.show()
```



In [220…

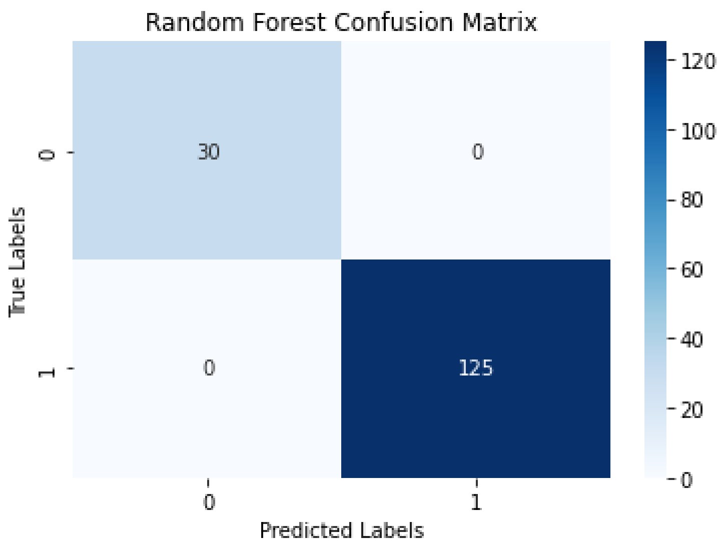
```
conf_matrix = confusion_matrix(y, predictions)

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')

# Add labels, title, and axis ticks
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Naive Bayes Confusion Matrix')

plt.show()
```



In [221…

```
#df_matched = df_matched.drop(["City / Community", "Occupation","Affordability
#df_unmatched = df_unmatched.drop(["City / Community", "Occupation","Affordabil

# combine the matched and unmatched datasets and create labels
df_matched['Label'] = 1  #   1 to df_matched
df_unmatched['Label'] = 2  # 2 to df_unmatched
combined_data = pd.concat([df_matched, df_unmatched], ignore_index=True)

# split the combined data into features (X) and labels (y)
X = combined_data.drop('Label', axis=1)
y = combined_data['Label']

classifier = RandomForestClassifier()
```

```
classifier.fit(X, y)
predictions = classifier.predict(X)

conf_matrix = confusion_matrix(y, predictions)

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')

plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Random Forest Confusion Matrix')

plt.show()
accuracy = accuracy_score(y, predictions)
print("Accuracy:", accuracy)
```



Accuracy: 1.0

In [222…

```
weapon_unmatched = df_unmatched['Total_Weapons'].values
crime_unmatched = df_unmatched['Total_Crimes'].values

weapon_matched = df_matched['Total_Weapons'].values
crime_matched = df_matched['Total_Crimes'].values

mean_weapon_unmatched = np.mean(weapon_unmatched)
std_weapon_unmatched = np.std(weapon_unmatched)
mean_crime_unmatched = np.mean(crime_unmatched)
std_crime_unmatched = np.std(crime_unmatched)

mean_weapon_matched = np.mean(weapon_matched)
std_weapon_matched = np.std(weapon_matched)
mean_crime_matched = np.mean(crime_matched)
std_crime_matched = np.std(crime_matched)

print("Unmatched Dataset:")
print("Mean Weapons:", mean_weapon_unmatched)
print("Standard Deviation Weapons:", std_weapon_unmatched)
print("Mean Crimes:", mean_crime_unmatched)
print("Standard Deviation Crimes:", std_crime_unmatched)

print("\nMatched Dataset:")
print("Mean Weapons:", mean_weapon_matched)
print("Standard Deviation Weapons:", std_weapon_matched)
```

```
print("Mean Crimes:", mean_crime_matched)
print("Standard Deviation Crimes:", std_crime_matched)
```

```
Unmatched Dataset:
Mean Weapons: 1310.16
Standard Deviation Weapons: 1373.1998042528262
Mean Crimes: 4132.392
Standard Deviation Crimes: 3723.4927214023123

Matched Dataset:
Mean Weapons: 2496.4333333333334
Standard Deviation Weapons: 2578.919653438022
Mean Crimes: 5651.233333333334
Standard Deviation Crimes: 5425.104623773526
```

In [223…

```
# plot descriptive statistics
weapon_labels = ['Unmatched', 'Matched']
mean_weapons = [mean_weapon_unmatched, mean_weapon_matched]
std_weapons = [std_weapon_unmatched, std_weapon_matched]

crime_labels = ['Unmatched', 'Matched']
mean_crimes = [mean_crime_unmatched, mean_crime_matched]
std_crimes = [std_crime_unmatched, std_crime_matched]

colors = ['mediumorchid', 'steelblue']

sns.set_palette(colors)

fig, axs = plt.subplots(2, 2, figsize=(10, 8))

sns.barplot(x=weapon_labels, y=mean_weapons, ax=axs[0, 0])
axs[0, 0].set_xlabel('Dataset')
axs[0, 0].set_ylabel('Mean Weapons')
axs[0, 0].set_title('Mean Weapons Comparison')
axs[0, 0].set_xticklabels(weapon_labels)  # Set x-axis tick labels

for i, v in enumerate(mean_weapons):
    axs[0, 0].annotate(str(round(v, 2)), (i, v), ha='center', va='bottom')

sns.barplot(x=weapon_labels, y=std_weapons, ax=axs[0, 1])
axs[0, 1].set_xlabel('Dataset')
axs[0, 1].set_ylabel('Standard Deviation Weapons')
axs[0, 1].set_title('Standard Deviation Weapons Comparison')
axs[0, 1].set_xticklabels(weapon_labels)  # Set x-axis tick labels

for i, v in enumerate(std_weapons):
    axs[0, 1].annotate(str(round(v, 2)), (i, v), ha='center', va='bottom')

sns.barplot(x=crime_labels, y=mean_crimes, ax=axs[1, 0])
axs[1, 0].set_xlabel('Dataset')
axs[1, 0].set_ylabel('Mean Crimes')
axs[1, 0].set_title('Mean Crimes Comparison')
axs[1, 0].set_xticklabels(crime_labels)  # Set x-axis tick labels

for i, v in enumerate(mean_crimes):
    axs[1, 0].annotate(str(round(v, 2)), (i, v), ha='center', va='bottom')

sns.barplot(x=crime_labels, y=std_crimes, ax=axs[1, 1])
axs[1, 1].set_xlabel('Dataset')
axs[1, 1].set_ylabel('Standard Deviation Crimes')
```

```
axs[1, 1].set_title('Standard Deviation Crimes Comparison')
axs[1, 1].set_xticklabels(crime_labels)  # Set x-axis tick labels

for i, v in enumerate(std_crimes):
    axs[1, 1].annotate(str(round(v, 2)), (i, v), ha='center', va='bottom')

plt.tight_layout()

plt.show()
```