Learning from data Assignment

April 10, 2024

```
[14]: import pandas as ol
      import csv
      import math
      import numpy as np
      from scipy import stats
      import matplotlib.pyplot as plt
[15]: with open(r"C:\Users\Laptop\OneDrive\Documents\Shopping_data.csv", 'r') as f:
       csv reader = csv.reader(f, delimiter=";")
       data_list = [row for row in csv_reader if row]
      column_names = data_list[0]
      df = ol.DataFrame(data_list[1:], columns=column_names)
      print(df)
      #Notes
      #This data is used in a supermarket
      #This dataset is based on a supermarket where consumer's gender, annual income_
       ⇒are recorded into the dataset.
      #The spending score(1 to 100) is base on how much the consumer spends on \Box
       ⇔groceries in the supermarket.
      #In this dataset there are 88 males and 112 females and with the statistics \Box
       →recorded, the bar graph in the workbook shows
      #that females have a higher spending score as opposed to the male.
      #In the workbook the lowest value in the dataset is 1 which is a male and the
       ⇔highest is 99 which is female.
      #What the dataset is trying to show is that females in the data do more L
       shopping in the supermarket as there are more females than males
      #and the sum of the spending score is higher than males.
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	CustomerID	Genre	Age	Annual	Income	(k\$)	Spending	Score	(1-100)
0	1	Male	19			15			39
1	2	Male	21			15			81
2	3	Female	20			16			6
3	4	Female	23			16			77
4	5	Female	31			17			40
	•••				•••				
195	196	Female	35			120			79
196	197	Female	45			126			28

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    197
    198
    Male 32
    126
    74

    198
    199
    Male 32
    137
    18

    199
    200
    Male 30
    137
    83
```

[200 rows x 6 columns]

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[16]: #Mean
     sum_age = ol.to_numeric(df['Age'].str.replace(',', ''), errors='coerce').sum()
     sum_income = ol.to_numeric(df['Annual Income (k$)'].str.replace(',', ''),__
      ⇔errors='coerce').sum()
     sum_spendscore = ol.to_numeric(df['Spending Score (1-100)'].str.replace(',',__
      count_age = ol.to_numeric(df['Age'].str.replace(',', ''), errors='coerce').
      ⇔count()
     count_income = ol.to_numeric(df['Annual Income (k$)'].str.replace(',', ''),__
      ⇔errors='coerce').count()
     count_spendscore = ol.to_numeric(df['Spending Score (1-100)'].str.replace(',',_u
      mean_age = sum_age / count_age
     mean_income = sum_income / count_income
     mean_spendscore = sum_spendscore / count_spendscore
     print("Mean Age ", mean_age)
     print("Mean Income ", mean_income)
     print("Mean Spending Score ", mean_spendscore)
```

Mean Age 38.85
Mean Income 60.56
Mean Spending Score 50.2

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[30]: #Median
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median_income = df_sorted['Annual Income (k$)'].iloc[median_index]
      median_spendscore = df_sorted['Spending Score (1-100)'].iloc[median_index]
      print("Median Age:", median_age)
      print("Median Income:", median_income)
      print("Median Spend Score:", median_spendscore)
     Median Age: 36
     Median Income: 85
     Median Spend Score: 75
[31]: #Mode.
      df[['Age', 'Annual Income (k$)']] = df[['Age', 'Annual Income (k$)']].apply(ol.
       →to_numeric, errors='coerce')
      value_counts = {}
      for col in df.columns:
        value_counts[col] = df[col].value_counts().sort_values(ascending=False)
      modes = []
      for col, counts in value counts.items():
       modes.append(counts.index[0])
      #print("Mode Age:", modes[0])
      #print("Mode Income:", modes[1])
      print("Mode Spending Score:", modes[2])
     Mode Spending Score: 32
[32]: #Geometric Mean of Spending Score
      df[['Age', 'Annual Income (k$)']] = df[['Age', 'Annual Income (k$)']].apply(ol.
      →to_numeric, errors='coerce')
      product = 1
      for score in df['Spending Score (1-100)']:
          product *= score
      geometric_mean_score = math.exp(math.log(product)/ len(df))
      print("Geometric Mean of Spending Score:", geometric_mean_score)
     Geometric Mean of Spending Score: 39.921161228635
[33]: #80th Percentile
      df[['Age', 'Annual Income (k$)']] = df[['Age', 'Annual Income (k$)']].apply(ol.
       ⇔to_numeric, errors='coerce')
      income80th = df['Annual Income (k$)'].quantile(0.8)
      score80th = df['Spending Score (1-100)'].quantile(0.8)
```

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print("80th Percentile of Annual Income (k$):", income80th)
      print("80th Percentile of Spending Score:", score80th)
     80th Percentile of Annual Income (k$): 78.2000000000002
     80th Percentile of Spending Score: 75.0
[34]: #Third Quartile
      income75th = df['Annual Income (k$)'].quantile(0.75)
      score75th = df['Spending Score (1-100)'].quantile(0.75)
      print("Third Quartile of Annual Income (k$):", income75th)
      print("Third Quartile of Spending Score:", score75th)
     Third Quartile of Annual Income (k$): 78.0
     Third Quartile of Spending Score: 73.0
[35]: #First Quartile
      income25th = df['Annual Income (k$)'].quantile(0.25)
      score25th = df['Spending Score (1-100)'].quantile(0.25)
      print("First Quartile of Annual Income (k$):", income25th)
      print("First Quartile of Spending Score:", score25th)
     First Quartile of Annual Income (k$): 41.5
     First Quartile of Spending Score: 34.75
[36]: #Range
      min_age= df['Age'].min()
      max_age= df['Age'].max()
      range_age = max_age - min_age + 1
      min_income= df['Annual Income (k$)'].min()
      max_income= df['Annual Income (k$)'].max()
      range_income = max_income - min_income + 1
      min score= df['Spending Score (1-100)'].min()
      max_score= df['Spending Score (1-100)'].max()
      range_score = max_score - min_score + 1
      print("Range of age: ", range_age)
      print("Range of income: ", range_income)
      print("Range of spending Score: ", range_score)
     Range of age: 53
     Range of income: 123
     Range of spending Score: 99
[37]: #Interquartile range
      iqr_income = income75th - income25th
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iqr_score = score75th - score25th

print("Interquartile range of Annual Income:", iqr_income)
print("Interquartile range of Spending Score:", iqr_score)
```

Interquartile range of Annual Income: 36.5
Interquartile range of Spending Score: 38.25

Population variance of Age: 194.1575 Population variance of Spending Score: 663.52

Standard deviation Age: 13.934041050606963 Standard deviation Income: 26.19897707926781 Standard deviation Spending Score: 25.7588819633151

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[40]: #Coefficient of variation
      income_array = df['Annual Income (k$)'].to_numpy()
      income_filtered = income_array[~np.isnan(income_array)]
      if len(income_filtered) > 0:
          cv_income = stats.variation(income_filtered)
          print("Coefficient of Variation of Annual Income (k$):", cv_income)
      else:
          print("Cannot calculate CV: All values in 'Annual Income (k$)' are missing ∪
       →or NaN")
     Coefficient of Variation of Annual Income (k$): 0.43261190685713025
[41]: #Weighted Mean
      weighted_mean_amount = 0
      total_weight = 0
      for i in range(len(df)):
          income_numeric = ol.to_numeric(df.loc[i, 'Annual Income (k$)'],__
       ⇔errors='coerce')
          customer_id_numeric = ol.to_numeric(df.loc[i, 'CustomerID'],__
       ⇔errors='coerce') # No comma replacement needed
          weighted_mean_amount += income_numeric * customer_id_numeric
          total weight += customer id numeric
      print("Weighted mean is:", total_weight/20100)
     Weighted mean is: 1.0
[42]: #z-Score of lowest value
      z_score = (min_score- mean_spendscore)/ standard_deviation_score
      print("Z-score of the lowest value:", z_score)
     Z-score of the lowest value: -1.9100207870073291
[43]: #Outliers
      lower_score= score25th - 1.5 * iqr_score
      upper_score= score25th + 1.5 * iqr_score
      lower income= income25th - 1.5 * igr income
      upper_income= income75th + 1.5 * iqr_income
```

```
print("Upper fence (Annual income):", upper_income)
print("Lower fence (Annual income):", lower_income)

print("Upper fence (Spending Score):", upper_score)
print("Lower fence (Spending Score):", lower_score)

Upper fence (Annual income): 132.75
Lower fence (Annual income): -13.25
Upper fence (Spending Score): 92.125
Lower fence (Spending Score): -22.625

[44]: #Covariance
import numpy as np

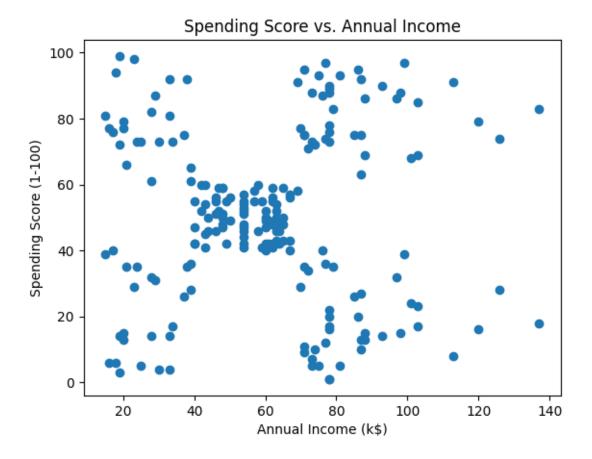
income_array = df['Annual Income (k$)'].to_numpy()
spending_array = df['Spending Score (1-100)'].to_numpy()
covariance = np.cov(income_array, spending_array)[0][1]

covariance_matrix = np.cov(income_array, spending_array)
print("Covariance between Annual Income and Spending Score:", covariance)
```

Covariance between Annual Income and Spending Score: 6.716582914572865

Correlation coefficient between Annual Income and Spending Score:

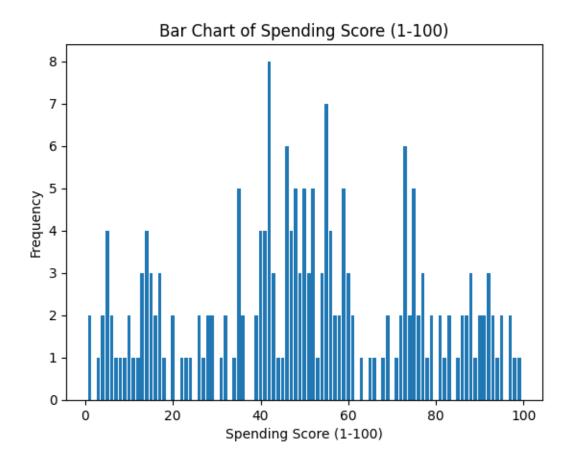
0.009902848094037497



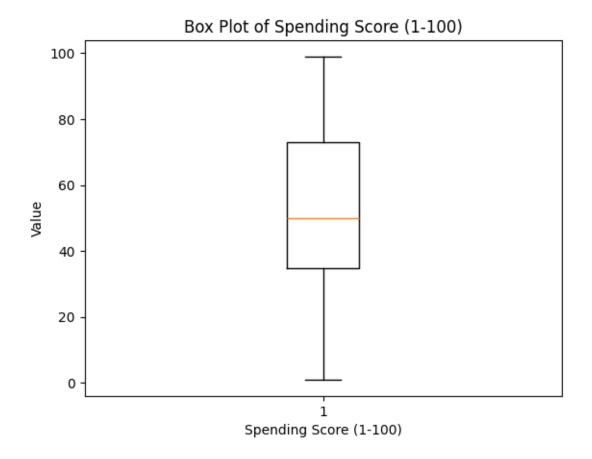
```
[46]: #Chebyshev's theorem
      df = df.apply(ol.to_numeric, errors='coerce')
      k = 1
      means = df.mean()
      squared_deviations = df.sub(means, axis=0).pow(2)
      population_variances = squared_deviations.mean(axis=0)
      chebyshev_proportions = 1 - 1 / (k**2)
      print("Chebyshev's Theorem (", k, " standard deviations):")
      for col, mean in means.items():
        variance = population_variances[col]
        std_dev = np.sqrt(variance)
       proportion = 1 - 1 / (k**2)
       print(f" Column: {col}")
                    Minimum Proportion Within {k} Std Devs: {proportion:.2f}")
        print(f"
                    Expected Range: {mean:.2f} +/- {k * std_dev:.2f}")
```

Chebyshev's Theorem (1 standard deviations):
Column: CustomerID
Minimum Proportion Within 1 Std Devs: 0.00

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Expected Range: 100.50 +/- nan
       Column: Genre
         Minimum Proportion Within 1 Std Devs: 0.00
         Expected Range: nan +/- nan
       Column: Age
         Minimum Proportion Within 1 Std Devs: 0.00
         Expected Range: 38.85 +/- nan
       Column: Annual Income (k$)
         Minimum Proportion Within 1 Std Devs: 0.00
         Expected Range: 60.56 +/- nan
       Column: Spending Score (1-100)
         Minimum Proportion Within 1 Std Devs: 0.00
         Expected Range: 50.20 +/- nan
       Column:
         Minimum Proportion Within 1 Std Devs: 0.00
         Expected Range: nan +/- nan
[46]: #Bar Chart
      column_to_analyze = 'Spending Score (1-100)'
      plt.bar(df[column_to_analyze].value_counts().index, df['Spending Score (1-100)'__
       →].value_counts().values)
      plt.xlabel(column_to_analyze)
      plt.ylabel('Frequency')
      plt.title('Bar Chart of ' + column_to_analyze)
      plt.show()
```

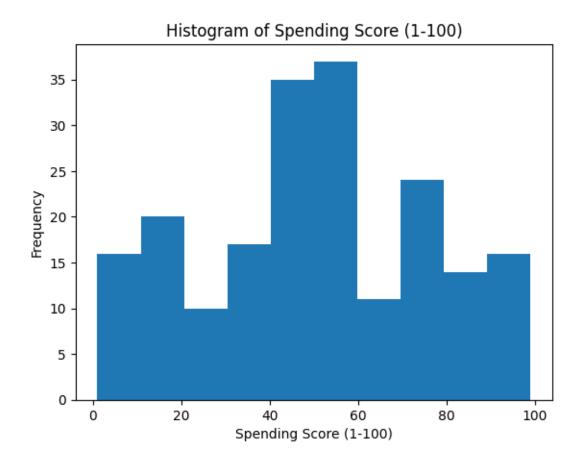


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[48]: #Box plot
plt.boxplot(df[column_to_analyze])
plt.xlabel(column_to_analyze)
plt.ylabel('Value')
plt.title('Box Plot of ' + column_to_analyze)
plt.show()
```



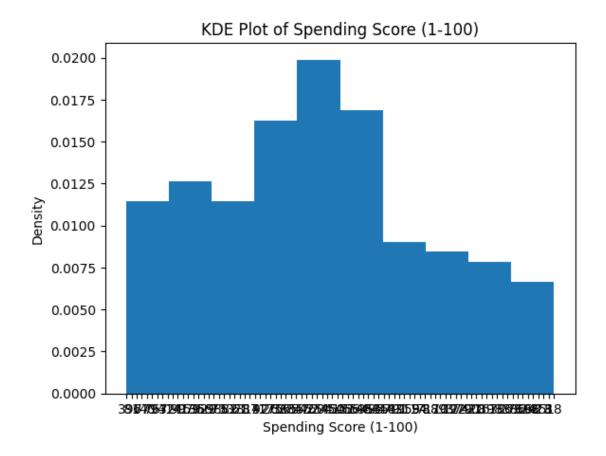
```
[49]: #Histogram
plt.hist(df[column_to_analyze])
plt.xlabel(column_to_analyze)
plt.ylabel('Frequency')
plt.title('Histogram of ' + column_to_analyze)
plt.show()

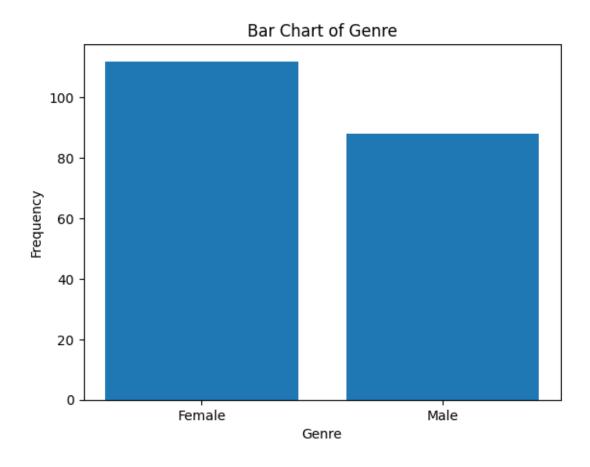
#In the histogram graph it shows that the most spending score in a supermarket
→is between 40 to 60.
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[59]: #KDE plot graph

plt.hist(df[column_to_analyze], density=True)
plt.xlabel(column_to_analyze)
plt.ylabel('Density')
plt.title('KDE Plot of ' + column_to_analyze)
plt.show()
```





[58]: #Reflection

#My thoughts on this assignment have shown me that my knowledge of Python is \rightarrow still lacking,

#as I struggled when using the descriptive statistics on the dataset and trying \rightarrow to make the code run properly without errors.

#Using descriptive statistics on a large dataset can have challenges because $_$ $_$ when you use methods such as variance or coefficient you have to ensure that $_$ $_$ the results make sense,

#I think it shows that picking a dataset to work with is important because the \rightarrow dataset chosen can work well with python but not so much with excel as \rightarrow python can work with different data types.

#When using Python, it is easier to create custom functions compared to Excel, \Box and Python is much better to use when you have a large dataset to work with.

#I would use Python when working with a large dataset rather than Excel and \neg Python work well with diverse datasets.

#For Excel I would use it for a very simple dataset otherwise for data that is $\underline{\ }$ $\underline{\ }$ more complex I would use Python.

#Another difficulty I found when using Python was integrating graphs into the \neg notebook.

[]: