Lab 4: Data Visualization and EDA

CPE232 Data Models

1. Load all Superstore datasets.

Note: The same datasets used in Lab 3

```
In [50]: import pandas as pd
  import matplotlib.pyplot as plt
  import seaborn as sns
  import numpy as np
  import plotly.express as px
```

```
In [51]: # Write your code here
    ss_order = pd.read_csv('./sources/Superstore/superstore_order.csv')
    ss_people = pd.read_csv('./sources/Superstore/superstore_people.csv')
    ss_return = pd.read_csv('./sources/Superstore/superstore_return.csv')
```

2. Determine shape of each dataset (print out the results as well).

```
In [52]: # Write your code here
    print(f"SuperStore Order's shape >> {ss_order.shape}")
    print(f"SuperStore People's shape >> {ss_people.shape}")
    print(f"SuperStore Return's shape >> {ss_return.shape}")

SuperStore Order's shape >> (8880, 21)
SuperStore People's shape >> (4, 2)
SuperStore Return's shape >> (296, 2)
```

3. Show information of the dataset.

```
In [53]: # Write your code here
ss_order.info()
```

```
<class 'pandas.core.frame.DataFrame'>
         RangeIndex: 8880 entries, 0 to 8879
         Data columns (total 21 columns):
             Column Non-Null Count Dtype
         --- -----
                              -----
          0 Row ID 8880 non-null int64
1 Order ID 8880 non-null object
          2 Order Date 8880 non-null object
3 Ship Date 8880 non-null object
4 Ship Mode 8880 non-null object
          5 Customer ID 8880 non-null object
          6 Customer Name 8880 non-null object
             Segment 8880 non-null object
Country 8880 non-null object
          7
          8 Country
         9 City 8880 non-null object
10 State 8880 non-null object
11 Postal Code 8880 non-null int64
         12 Region 8880 non-null object
13 Product ID 8880 non-null object
14 Category 8880 non-null object
15 Sub-Category 8880 non-null object
          16 Product Name 8880 non-null object
          17 Sales 8880 non-null float64
         18 Quantity 8880 non-null int64
19 Discount 8880 non-null float64
20 Profit 8880 non-null float64
         dtypes: float64(3), int64(3), object(15)
         memory usage: 1.4+ MB
In [54]: ss_people.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 4 entries, 0 to 3
         Data columns (total 2 columns):
          # Column Non-Null Count Dtype
              -----
             Person 4 non-null
                                       object
              Region 4 non-null
          1
                                         object
         dtypes: object(2)
         memory usage: 196.0+ bytes
In [55]: ss_return.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 296 entries, 0 to 295
         Data columns (total 2 columns):
          # Column Non-Null Count Dtype
         --- ----- ------
              Returned 296 non-null
          0
                                            object
              Order ID 296 non-null object
          1
         dtypes: object(2)
         memory usage: 4.8+ KB
```

4. Are there any missing values? If so, in which column?

Ans: There are no missing values in any column of any DataFrame because the Non-Null Count matches the maximum number of entries.

5.

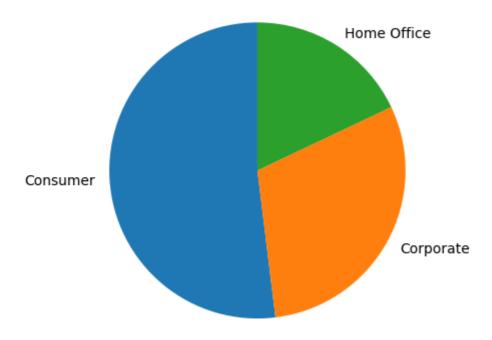
- 5.2 List unique segments and their corresponding count
- 5.3 Create a pie chart to demonstrate unique segments and their count
- 5.4 Briefly describe what could be interpreted from this pie chart

Note: please create additional cells to answer 5.2 - 5.3

```
In [56]: # Write your code here (5.1)
         print(ss_order['Segment'].unique())
        ['Consumer' 'Corporate' 'Home Office']
In [57]: # Write your code here (5.2)
         segment_count = ss_order['Segment'].value_counts()
         print(segment_count)
        Segment
       Consumer
                     4613
        Corporate
                     2673
       Home Office
                     1594
       Name: count, dtype: int64
In [58]: # Write your code here (5.3)
         plt.pie(segment_count, labels = segment_count.index, startangle=90)
         plt.title('Ratio of order per segment')
         plt.show
```

Out[58]: <function matplotlib.pyplot.show(close=None, block=None)>

Ratio of order per segment



Answer for the question 5.4

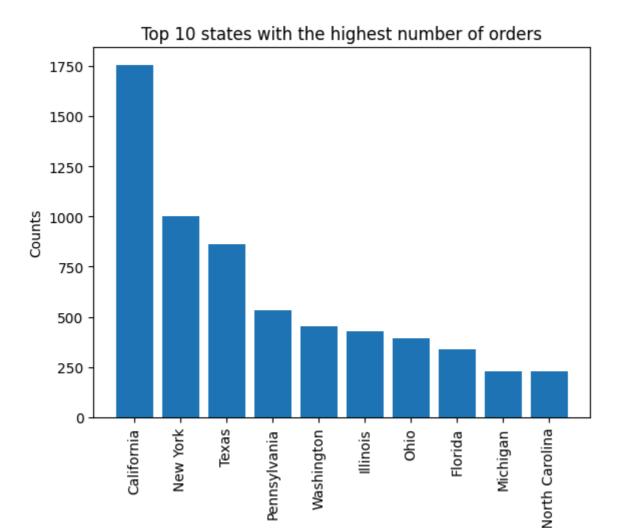
Ans: From the pie chart, we can observe that the number of consumers segment was more than 50% in the superstore, making it the largest segment, followed by corporate and home office in descending order.

- 6.1 List unique states
- 6.2 List top-10 unique states and their corresponding count
- 6.3 Create a bar chart (vertical) to demonstrate the count of top-10 unique states
- 6.4 Based on 6.2, also include the total sales of these states (show your result as a dataframe)
- 6.5 Using the result from 6.4, if you were the owner of this superstore, what information could be interpreted from this result?

Note: please create additional cells to answer 6.2 - 6.4

```
In [59]: # Write your code here (6.1)
         print(ss_order['State'].unique())
        ['Kentucky' 'California' 'Florida' 'North Carolina' 'Washington' 'Texas'
         'Wisconsin' 'Utah' 'Nebraska' 'Pennsylvania' 'Illinois' 'Minnesota'
         'Michigan' 'Delaware' 'Indiana' 'New York' 'Arizona' 'Virginia'
         'Tennessee' 'Alabama' 'South Carolina' 'Oregon' 'Colorado' 'Iowa' 'Ohio'
         'Missouri' 'Oklahoma' 'New Mexico' 'Louisiana' 'Connecticut' 'New Jersey'
         'Massachusetts' 'Georgia' 'Nevada' 'Rhode Island' 'Mississippi'
         'Arkansas' 'Montana' 'New Hampshire' 'Maryland' 'District of Columbia'
         'Kansas' 'Vermont' 'Maine' 'South Dakota' 'Idaho' 'North Dakota'
         'Wyoming' 'West Virginia']
In [60]: # Write your code here (6.2)
         state_count = ss_order['State'].value_counts()
         state_count[:10]
Out[60]: State
         California
                           1754
         New York
                           1001
         Texas
                           860
                         531
         Pennsylvania
         Washington
                          452
         Illinois
                           427
         Ohio
                            396
         Florida
                           339
         Michigan
                            230
         North Carolina
                            229
         Name: count, dtype: int64
In [61]: # Write your code here (6.3)
         plt.bar(state_count[:10].index, state_count[:10])
         plt.title('Top 10 states with the highest number of orders')
         plt.xlabel('States')
         plt.ylabel('Counts')
         plt.xticks(rotation = 90)
         plt.show
```

Out[61]: <function matplotlib.pyplot.show(close=None, block=None)>



```
In [62]: # Write your code here (6.4)
total_sales_by_state = ss_order.groupby('State')['Sales'].sum().loc[state_count[:10].ind
total_sales_by_state
```

States

Out[62]:	State	
	California	399195.4555
	New York	274866.8190
	Texas	147855.0282
	Pennsylvania	103852.5210
	Washington	124497.7780
	Illinois	71456.1780
	Ohio	67924.2140
	Florida	84083.0880
	Michigan	62147.6960
	North Carolina	49962.1580
	Name: Sales, dtype	e: float64

Answer for the question 6.5

Ans: From the results, I observe that California had the highest total sales, while North Carolina had the lowest, which seemed to correlate with the number of orders. On the other hand, Pennsylvania, which had more orders than Washington, showed lower total sales. Additionally, Florida had significantly higher total sales compared to states with similar number of orders

7.

- 7.2 Create a bar chart (horizontal) to demonstrate the proportion of these categories
- 7.3 Compute the ratio of these categories in percentage and print the results

Note: please create additional cells to answer 7.2 - 7.3

```
In [63]: # Write your code here (7.1)
    print(ss_order['Category'].unique())

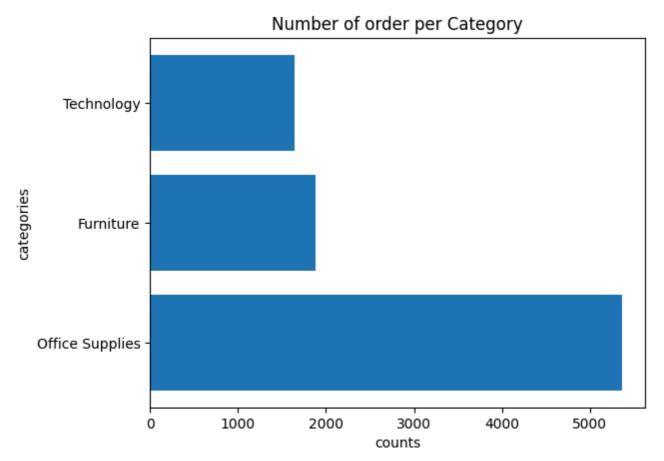
['Furniture' 'Office Supplies' 'Technology']

In [64]: # Write your code here (7.2)
    categories_count = ss_order['Category'].value_counts()

    plt.barh(categories_count.index, categories_count)
    plt.title('Number of order per Category')
    plt.xlabel('counts')
    plt.ylabel('categories')

    plt.show
```

Out[64]: <function matplotlib.pyplot.show(close=None, block=None)>



```
In [65]: # Write your code here (7.3)
    categories_ratio = categories_count / categories_count.sum() * 100
    categories_ratio
```

Out[65]: Category
Office Supplies 60.360360
Furniture 21.171171
Technology 18.468468
Name: count, dtype: float64

8. Update the type of all columns that contain dates to *datetime* and show information after an update.

```
In [66]: # write your code here
          ss_order['Order Date'] = pd.to_datetime(ss_order['Order Date'], format="%d/%m/%Y")
          ss_order['Ship Date'] = pd.to_datetime(ss_order['Ship Date'], format="%d/%m/%Y")
          ss_order.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 8880 entries, 0 to 8879
         Data columns (total 21 columns):
             Column Non-Null Count Dtype
                             -----
         ---
             ----
          0 Row ID
                            8880 non-null int64
          1 Order ID
                             8880 non-null object
         2 Order Date 8880 non-null datetime64[ns]
3 Ship Date 8880 non-null datetime64[ns]
4 Ship Mode 8880 non-null object
         5 Customer ID 8880 non-null object
          6 Customer Name 8880 non-null object
          7 Segment 8880 non-null object
          8 Country
                             8880 non-null object
         9 City 8880 non-null object 10 State 8880 non-null object
          11 Postal Code 8880 non-null int64
         12 Region 8880 non-null object
13 Product ID 8880 non-null object
14 Category 8880 non-null object
          15 Sub-Category 8880 non-null object
         16 Product Name 8880 non-null object
         17 Sales 8880 non-null float64
18 Quantity 8880 non-null int64
19 Discount 8880 non-null float64
20 Profit 8880 non-null float64
         dtypes: datetime64[ns](2), float64(3), int64(3), object(13)
         memory usage: 1.4+ MB
```

9. Create a new column "Processing time day" to show number of days taken to ship an order and show your result in a dataframe format.

Hint: The duration starts as soon as the item has been ordered and ends once the order has successfully shipped.

```
In [67]: # write your code here
    ss_order['Processing time day'] = ss_order['Ship Date'] - ss_order['Order Date']
    ss_order['Processing time day']
```

```
Out[67]: 0
                3 days
                3 days
                4 days
         2
         3
                7 days
                7 days
         8875
               6 days
         8876
               6 days
         8877
                6 days
         8878
                6 days
         8879
                2 days
         Name: Processing time day, Length: 8880, dtype: timedelta64[ns]
```

10. Based on the result in 9.

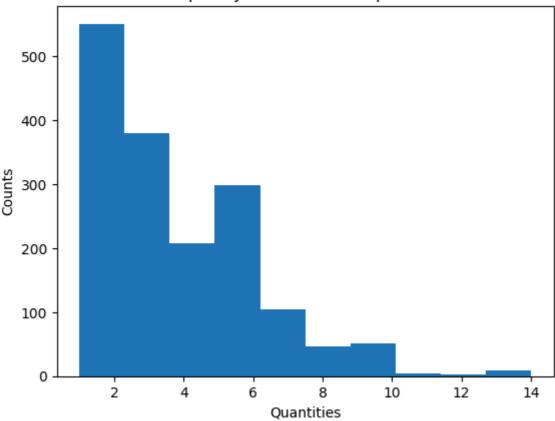
- 10.1 How many orders are there that take more than 5 days to process?
- 10.2 Show the top 5 rows (expected output should contain these columns: Order ID, Order Date, Ship Date, Processing time day, Quantity)
- 10.3 Plot the histogram based on the column Quantity

Note: please create additional cells to answer 10.2 - 10.3

```
In [68]:
         # Write your code here (10.1)
         long_shipping = ss_order[ss_order['Processing time day'].dt.days > 5]
         long_shipping.shape[0]
Out[68]: 1656
In [69]: # Write your code here (10.2)
         long_shipping.head(5)[['Order ID', 'Order Date', 'Ship Date', 'Processing time day', 'Qu
Out[69]:
                    Order ID Order Date
                                          Ship Date Processing time day Quantity
           3 US-2015-108966 2015-10-11 2015-10-18
                                                                              5
                                                                7 days
           4 US-2015-108966 2015-10-11 2015-10-18
                                                                7 days
                                                                              2
          16 CA-2014-105893 2014-11-11 2014-11-18
                                                                              6
                                                                7 days
          53 CA-2016-105816 2016-12-11 2016-12-17
                                                                              7
                                                                6 days
                                                                              5
          54 CA-2016-105816 2016-12-11 2016-12-17
                                                                6 days
In [70]: # Write your code here (10.3)
         plt.hist(long shipping.Quantity)
         plt.title('Frequency distribution of quantities')
         plt.xlabel('Quantities')
         plt.ylabel('Counts')
         plt.show
```

Out[70]: <function matplotlib.pyplot.show(close=None, block=None)>

Frequency distribution of quantities



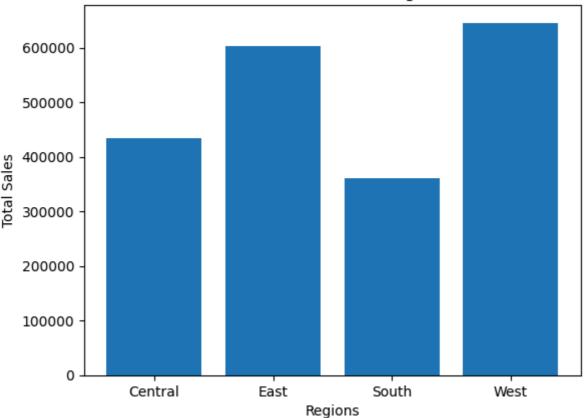
- 11. Total sales compare across different regions
- 11.1 Create a bar chart to visualize.

```
In [71]: # Write your code here (11.1)
total_sales_by_regions = ss_order.groupby('Region')['Sales'].sum()

plt.bar(total_sales_by_regions.index, total_sales_by_regions)
plt.title('Total Sales of each Region')
plt.xlabel('Regions')
plt.ylabel('Total Sales')
plt.show
```

Out[71]: <function matplotlib.pyplot.show(close=None, block=None)>

Total Sales of each Region



• 11.2 How do total sales compare across different regions? Explain in as much detail as possible.

Ans: The bar chart indicates that the West region achieved the highest total sales, followed by the East and Central regions, respectively. The South region recorded the lowest total sales among all regions.

12. Which states have the highest number of returns? Use a horizontal bar chart.

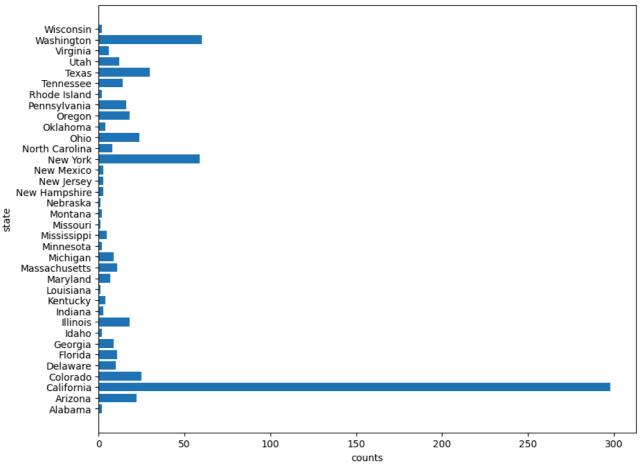
Ans: California clearly got the highest number of returns.

Out[72]: Text(0, 0.5, 'state')

```
In [72]: # Write your code here (12)
    order_return = ss_return.merge(ss_order, on='Order ID', how='inner')
    return_by_state = order_return.groupby('State')['Returned'].count()

plt.figure(figsize=(10, 8))
    plt.barh(return_by_state.index, return_by_state)
    plt.title('Number of Returned in each State')
    plt.xlabel('counts')
    plt.ylabel('state')
```

Number of Returned in each State

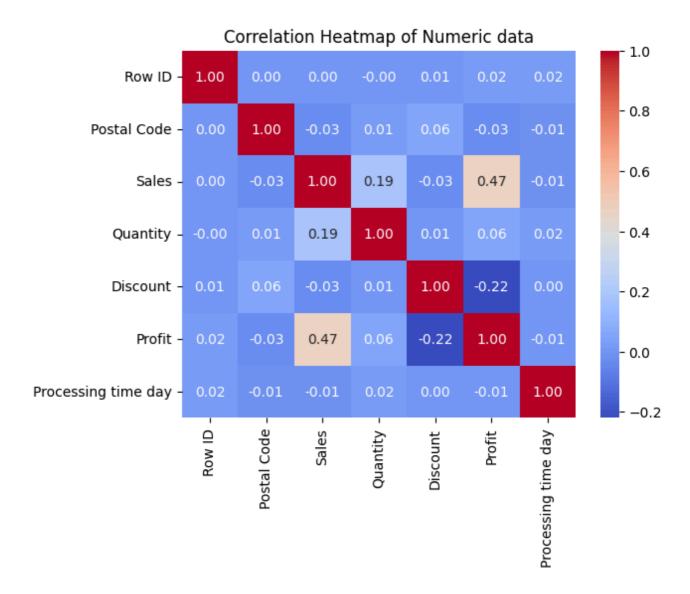


13. What is the correlation between numerical variables in the superstore_order dataset? Use a heatmap *Hint: Use seaborn to create a heatmap :)*

```
In [73]: # Write your code here (13)
    numeric_data = ss_order.select_dtypes(include=['number'])

correlate_data = numeric_data.corr()

plt.title('Correlation Heatmap of Numeric data')
    sns.heatmap(correlate_data, annot=True, cmap='coolwarm', fmt='.2f')
    plt.show()
```



- 14. Create a USA State-Level Choropleth Map to visualize total sales per state.
- The darkest color represents the highest total sales.
- The lightest color represents the lowest total sales.
- Use a continuous gradient scale (e.g., dark blue to light blue, dark red to light red, or any custom gradient of your choice).

Hint: Use plotly.express

```
In [74]:
          us_state = {
              "Alabama": "AL",
              "Alaska": "AK",
              "Arizona": "AZ",
              "Arkansas": "AR",
              "California": "CA",
              "Colorado": "CO",
              "Connecticut": "CT",
              "Delaware": "DE",
              "Florida": "FL",
              "Georgia": "GA",
              "Hawaii": "HI",
              "Idaho": "ID",
              "Illinois": "IL",
              "Indiana": "IN",
              "Iowa": "IA",
              "Kansas": "KS"
              "Kentucky": "KY",
```

```
"Louisiana": "LA",
              "Maine": "ME",
              "Maryland": "MD",
              "Massachusetts": "MA",
              "Michigan": "MI"
              "Minnesota": "MN"
              "Mississippi": "MS",
              "Missouri": "MO",
              "Montana": "MT",
              "Nebraska": "NE",
              "Nevada": "NV",
              "New Hampshire": "NH",
              "New Jersey": "NJ",
              "New Mexico": "NM",
              "New York": "NY",
              "North Carolina": "NC",
              "North Dakota": "ND",
              "Ohio": "OH",
              "Oklahoma": "OK",
              "Oregon": "OR",
              "Pennsylvania": "PA",
              "Rhode Island": "RI",
              "South Carolina": "SC",
              "South Dakota": "SD",
              "Tennessee": "TN",
              "Texas": "TX",
              "Utah": "UT",
              "Vermont": "VT"
              "Virginia": "VA",
              "Washington": "WA",
              "West Virginia": "WV",
              "Wisconsin": "WI",
              "Wyoming": "WY",
              "District of Columbia": "DC",
              "American Samoa": "AS",
              "Guam": "GU",
              "Northern Mariana Islands": "MP",
              "Puerto Rico": "PR",
              "United States Minor Outlying Islands": "UM",
             "Virgin Islands, U.S.": "VI",
In [75]: # Write your code here (14)
         ss_order['State Code'] = ss_order['State'].map(us_state)
         total_sales_by_state = ss_order.groupby('State Code')['Sales'].sum().reset_index()
         fig = px.choropleth(
```

```
In [75]: # Write your code here (14)
ss_order['State Code'] = ss_order['State'].map(us_state)

total_sales_by_state = ss_order.groupby('State Code')['Sales'].sum().reset_index()

fig = px.choropleth(
    total_sales_by_state,
    locations="State Code",
    locationmode="USA-states",
    color="Sales",
    color_continuous_scale="Reds",
    title="Total Sales Per State (USA)",
    scope="usa"
)

fig.show()
```

- 14.2 Answer the following questions:
 - 1. Which state has the highest total sales?

- 2. How do sales anomalies affect the gradient color shading on the map?
- 3. If you change the color scale, does it impact readability? Why or why not?

Ans:

- 1. California.
- 2. Exceptionally high total sales, such as in California, can cause other states to appear in lighter shades of red, making it difficult to observe differences among them.
- 3. Yes, using a color scale that accurately reflects the data values can effectively highlight variations and patterns, making the visualization more informative and easier to interpret. In other ways we can using log transform to make it cleary differences.

```
In [76]: # using Log scale
ss_order['State Code'] = ss_order['State'].map(us_state)

total_sales_by_state = ss_order.groupby('State Code')['Sales'].sum().reset_index()
total_sales_by_state['Log Sales'] = np.log1p(total_sales_by_state['Sales'])

fig = px.choropleth(
    total_sales_by_state,
    locations="State Code",
    locationmode="USA-states",
    color="Log Sales",
    color_continuous_scale="Reds",
    title="Total Sales Per State (USA) - Log Scale",
    scope="usa"
)

fig.show()
```

15. Create a box plot to compare the different shipping modes based on total profit.

```
In [77]: #Write your code here (15)
fig = px.box(ss_order, x='Ship Mode', y='Profit', title='Distrubution of profit per ship fig.show()
```

15.2 Which shipping mode has the highest median profit?

Ans: Second Class, which got 9.7608

[BONUS 20 pts] Determine the percentage of customers who:

- B1)returned the product once
- B2) returned the product at least once
- B3) never returned the product
- Finally, Plot a comparison of B2 and B3

Note: please create additional cells to answer the above points

```
In [78]: total_customer = len(ss_order['Customer ID'].unique())
total_customer
```

```
In [79]: return_order = ss_order.merge(ss_return, on='Order ID', how='left').fillna('No')
          return_order['Returned'] = return_order['Returned'].apply(lambda x: 1 if x == 'Yes' else
         costumer_return_counts = return_order.groupby('Customer ID')['Returned'].sum()
         costumer_return_counts
Out[79]: Customer ID
          AA-10315
          AA-10375
                     0
          AA-10480
                     0
          AA-10645
                     1
          AB-10015
          XP-21865
          YC-21895
                     1
          YS-21880
          ZC-21910
                     4
          ZD-21925
                      3
          Name: Returned, Length: 789, dtype: int64
In [80]: # Write your code here B1
         num_customer_returned_once = costumer_return_counts[costumer_return_counts == 1].count()
         print(f'B1) Percentage of customers who returned the product once : {num_customer_return
        B1) Percentage of customers who returned the product once : 7.858048162230672 %
In [81]: # Write your code here B2
         num_customer_returned_least_once = costumer_return_counts[costumer_return_counts >= 1].c
         print(f'B2) Percentage of customers who returned the product at least once : {num_custom
        B2) Percentage of customers who returned the product at least once : 28.13688212927757 %
In [82]: # Write your code here B3
         num_customer_never_returned = costumer_return_counts[costumer_return_counts == 0].count(
         print(f'B3) Percentage of customers who never returned the product : {num_customer_never
        B3) Percentage of customers who never returned the product : 71.86311787072243 %
         costumer return counts = [num customer returned least once, num customer never returned]
In [83]:
         label = ['Atleast Once', 'Never']
         plt.pie(costumer_return_counts, labels=label, startangle=90)
         plt.title('Ratio of returned')
         plt.show
Out[83]: <function matplotlib.pyplot.show(close=None, block=None)>
```

Ratio of returned

