Teclov_Plotting_Categorical_Data

March 24, 2020

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1 Plotting Categorical Data

In this section, we will: - Plot distributions of data across categorical variables - Plot aggregate/summary statistics across categorical variables

1.1 Plotting Distributions Across Categories

We have seen how to plot distributions of data. Often, the distributions reveal new information when you plot them across categorical variables.

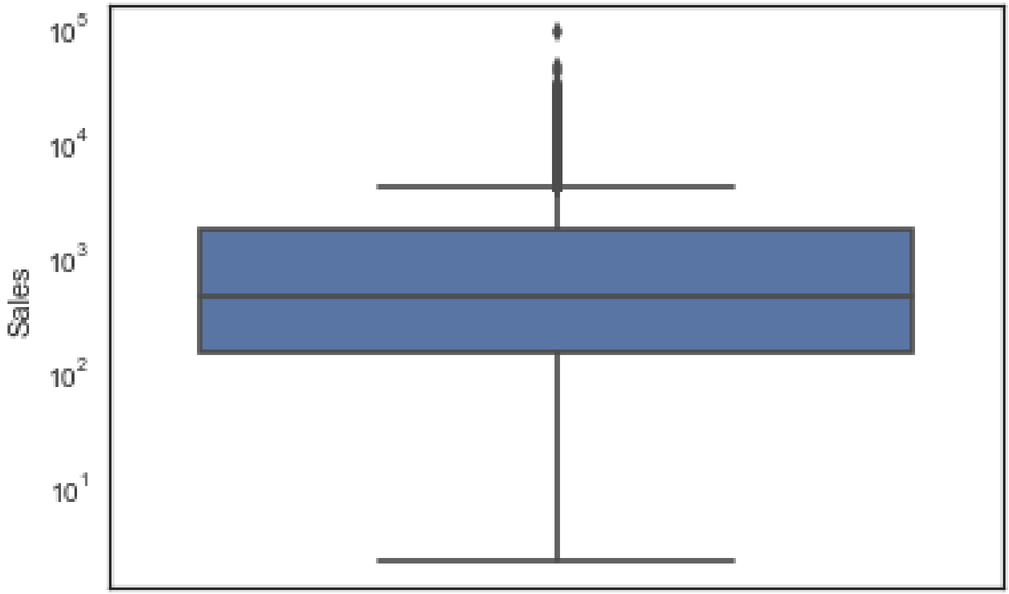
Let's see some examples.

[1]:
```
# loading libraries and reading the data
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# set seaborn theme if you prefer
sns.set(style="white")

# read data
market_df = pd.read_csv("./global_sales_data/market_fact.csv")
customer_df = pd.read_csv("./global_sales_data/cust_dimen.csv")
product_df = pd.read_csv("./global_sales_data/prod_dimen.csv")
shipping_df = pd.read_csv("./global_sales_data/shipping_dimen.csv")
orders_df = pd.read_csv("./global_sales_data/orders_dimen.csv")
```

1.1.1 Boxplots

We had created simple boxplots such as the ones shown below. Now, let's plot multiple boxplots and see what they can tell us the distribution of variables across categories.

[2]:
```python
# boxplot of a variable
sns.boxplot(y=market_df['Sales'])
plt.yscale('log')
plt.show()
```



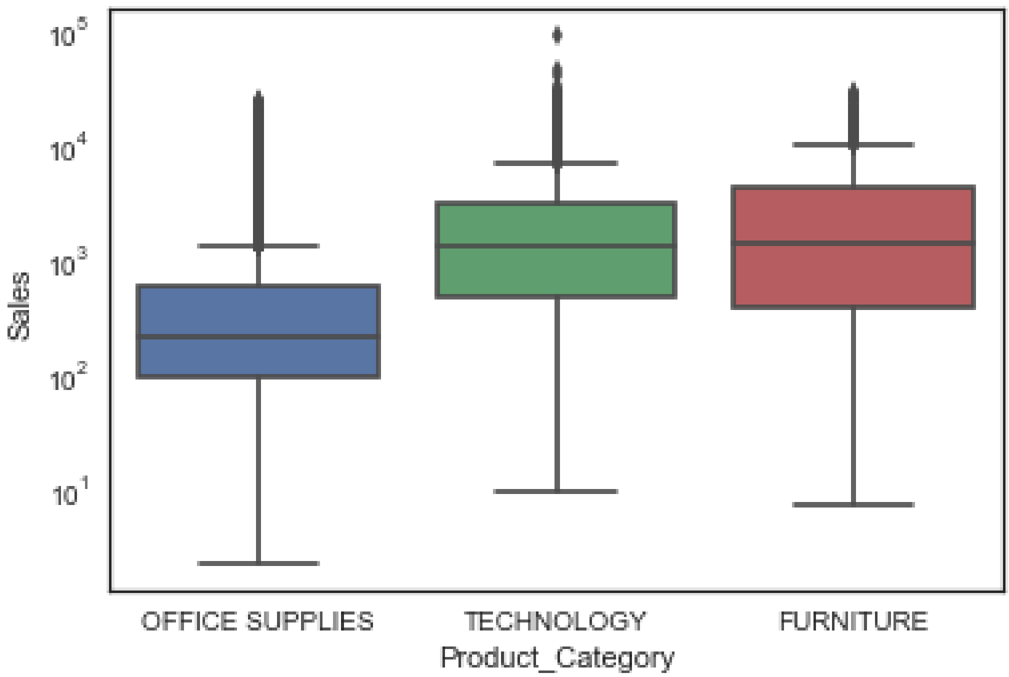
Now, let's say you want to **compare the (distribution of) sales of various product categories**. Let's first merge the product data into the main dataframe.

[3]:
```python
# merge the dataframe to add a categorical variable
df = pd.merge(market_df, product_df, how='inner', on='Prod_id')
df.head()
```

[3]:
```
     Ord_id  Prod_id   Ship_id    Cust_id   Sales  Discount  Order_Quantity  \
0  Ord_5446  Prod_16  SHP_7609  Cust_1818  136.81      0.01              23
1  Ord_2978  Prod_16  SHP_4112  Cust_1088  305.05      0.04              27
2  Ord_5484  Prod_16  SHP_7663  Cust_1820  322.82      0.05              35
3  Ord_3730  Prod_16  SHP_5175  Cust_1314  459.08      0.04              34
4  Ord_4143  Prod_16  SHP_5771  Cust_1417  207.21      0.06              24

   Profit  Shipping_Cost  Product_Base_Margin Product_Category  \
0  -30.51           3.60                 0.56  OFFICE SUPPLIES
1   23.12           3.37                 0.57  OFFICE SUPPLIES
2  -17.58           3.98                 0.56  OFFICE SUPPLIES
3   61.57           3.14                 0.60  OFFICE SUPPLIES
4  -78.64           6.14                 0.59  OFFICE SUPPLIES

          Product_Sub_Category
```

```
0    SCISSORS, RULERS AND TRIMMERS
1    SCISSORS, RULERS AND TRIMMERS
2    SCISSORS, RULERS AND TRIMMERS
3    SCISSORS, RULERS AND TRIMMERS
4    SCISSORS, RULERS AND TRIMMERS
```

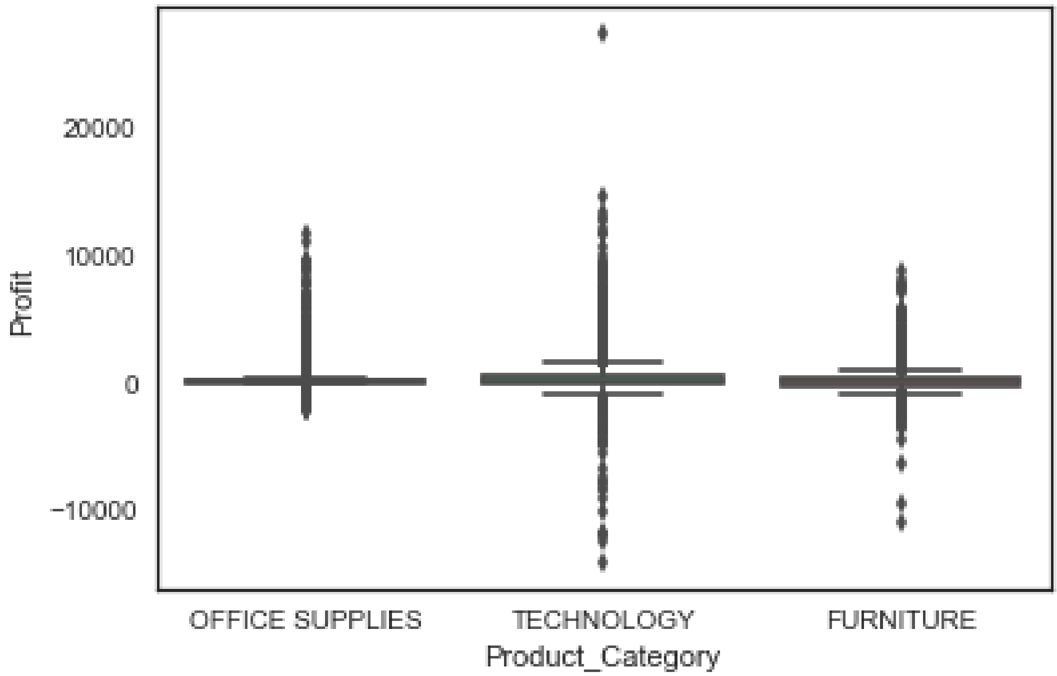
[4]:
```
# boxplot of a variable across various product categories
sns.boxplot(x='Product_Category', y='Sales', data=df)
plt.yscale('log')
plt.show()
```



So this tells you that the sales of office supplies are, on an average, lower than the other two categories. The sales of technology and furniture categories seem much better. Note that each order can have multiple units of products sold, so Sales being higher/lower may be due to price per unit or the number of units.

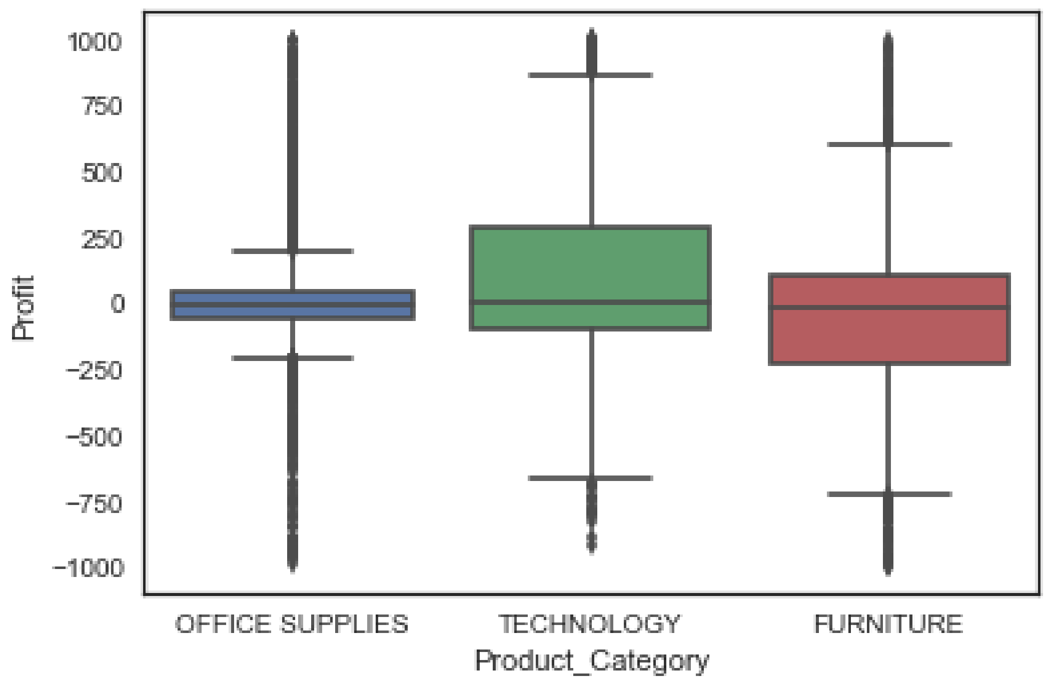
Let's now plot the other important variable - Profit.

[5]:
```
# boxplot of a variable across various product categories
sns.boxplot(x='Product_Category', y='Profit', data=df)
plt.show()
```



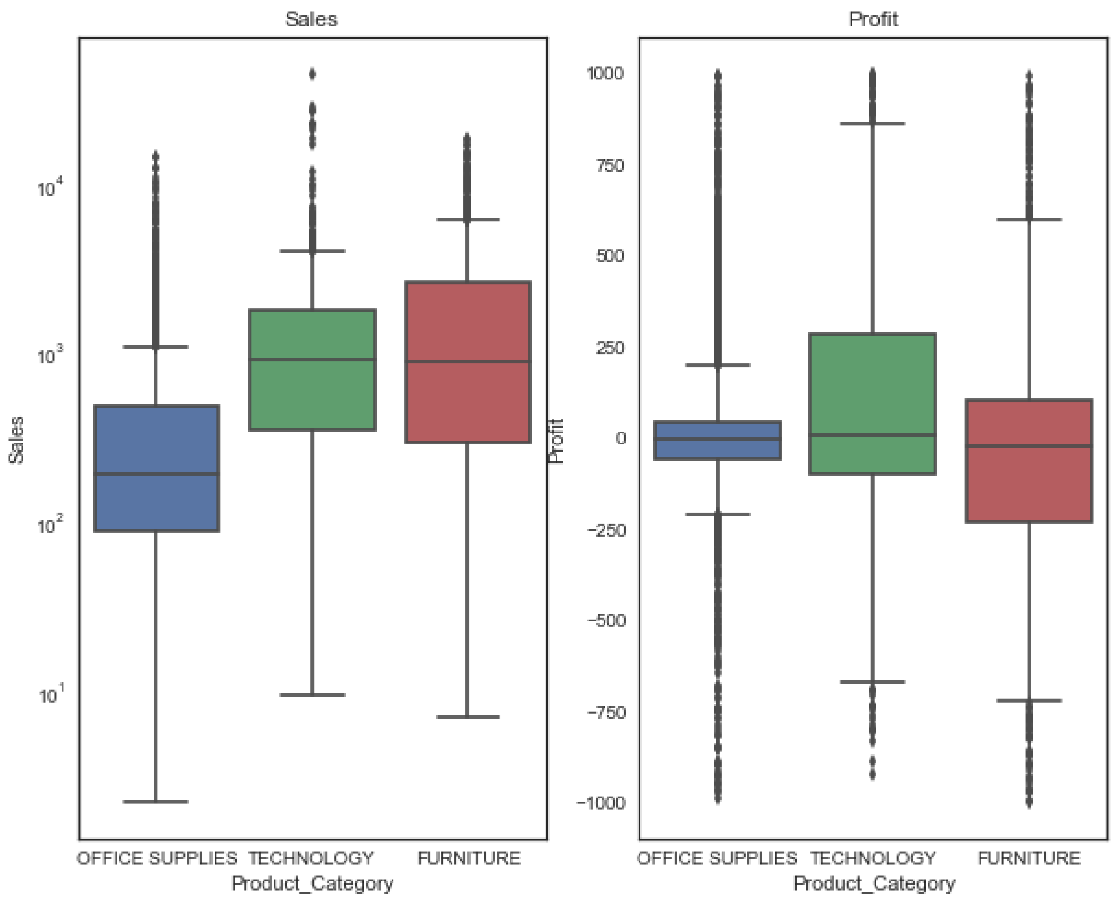
Profit clearly has some *outliers* due to which the boxplots are unreadable. Let's remove some extreme values from Profit (for the purpose of visualisation) and try plotting.

[6]:
```
df = df[(df.Profit<1000) & (df.Profit>-1000)]

# boxplot of a variable across various product categories
sns.boxplot(x='Product_Category', y='Profit', data=df)
plt.show()
```



You can see that though the category 'Technology' has better sales numbers than others, it is also the one where the **most loss making transactions** happen. You can drill further down into this.

[7]:
```
# adjust figure size
plt.figure(figsize=(10, 8))

# subplot 1: Sales
plt.subplot(1, 2, 1)
sns.boxplot(x='Product_Category', y='Sales', data=df)
plt.title("Sales")
plt.yscale('log')

# subplot 2: Profit
plt.subplot(1, 2, 2)
sns.boxplot(x='Product_Category', y='Profit', data=df)
plt.title("Profit")

plt.show()
```



Now that we've compared Sales and Profits across product categories, let's drill down further and do the same across **another categorical variable** - Customer_Segment.

We'll need to add the customer-related attributes (dimensions) to this dataframe.

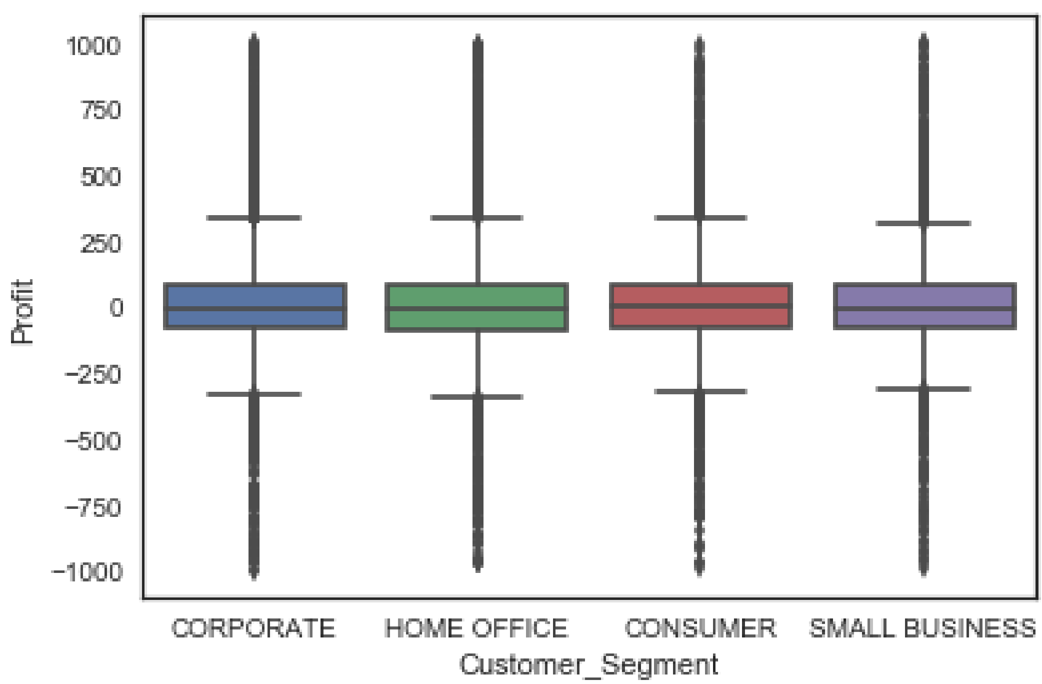
[8]:
```python
# merging with customers df
df = pd.merge(df, customer_df, how='inner', on='Cust_id')
df.head()
```

[8]:
```
     Ord_id  Prod_id   Ship_id     Cust_id    Sales  Discount  Order_Quantity  \
0  Ord_5446  Prod_16  SHP_7609  Cust_1818   136.81      0.01              23
1  Ord_5406  Prod_13  SHP_7549  Cust_1818    42.27      0.01              13
2  Ord_5456   Prod_6  SHP_7625  Cust_1818  2337.89      0.09              43
3  Ord_5446   Prod_6  SHP_7608  Cust_1818   164.02      0.03              23
4  Ord_2978  Prod_16  SHP_4112  Cust_1088   305.05      0.04              27

   Profit  Shipping_Cost  Product_Base_Margin Product_Category  \
0  -30.51           3.60                 0.56  OFFICE SUPPLIES
1    4.56           0.93                 0.54  OFFICE SUPPLIES
2  729.34          14.30                 0.37  OFFICE SUPPLIES
```

```
3  -47.64          6.15                    0.37  OFFICE SUPPLIES
4   23.12          3.37                    0.57  OFFICE SUPPLIES

              Product_Sub_Category  Customer_Name Province   Region  \
0  SCISSORS, RULERS AND TRIMMERS  AARON BERGMAN  ALBERTA     WEST
1            PENS & ART SUPPLIES  AARON BERGMAN  ALBERTA     WEST
2                          PAPER  AARON BERGMAN  ALBERTA     WEST
3                          PAPER  AARON BERGMAN  ALBERTA     WEST
4  SCISSORS, RULERS AND TRIMMERS  AARON HAWKINS  ONTARIO  ONTARIO

  Customer_Segment
0        CORPORATE
1        CORPORATE
2        CORPORATE
3        CORPORATE
4      HOME OFFICE
```

[9]:

```
# boxplot of a variable across various product categories
sns.boxplot(x='Customer_Segment', y='Profit', data=df)
plt.show()
```

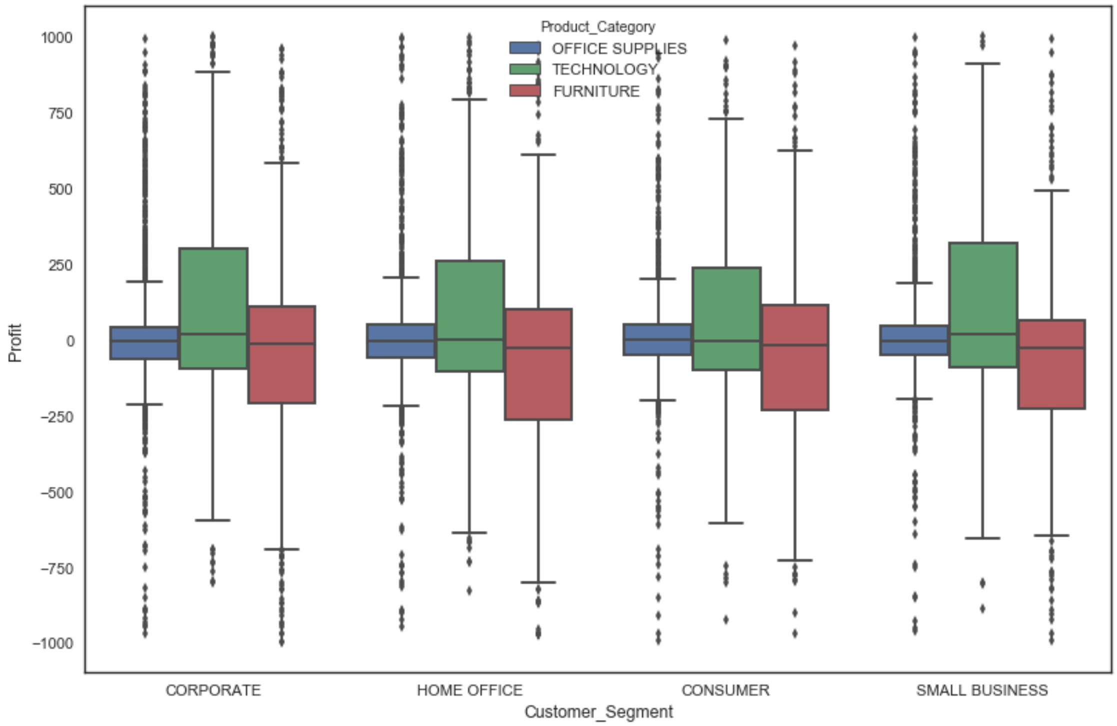


You can **visualise the distribution across two categorical variables** using the hue= argument.

[10]:

```
# set figure size for larger figure
plt.figure(num=None, figsize=(12, 8), dpi=80, facecolor='w', edgecolor='k')
```

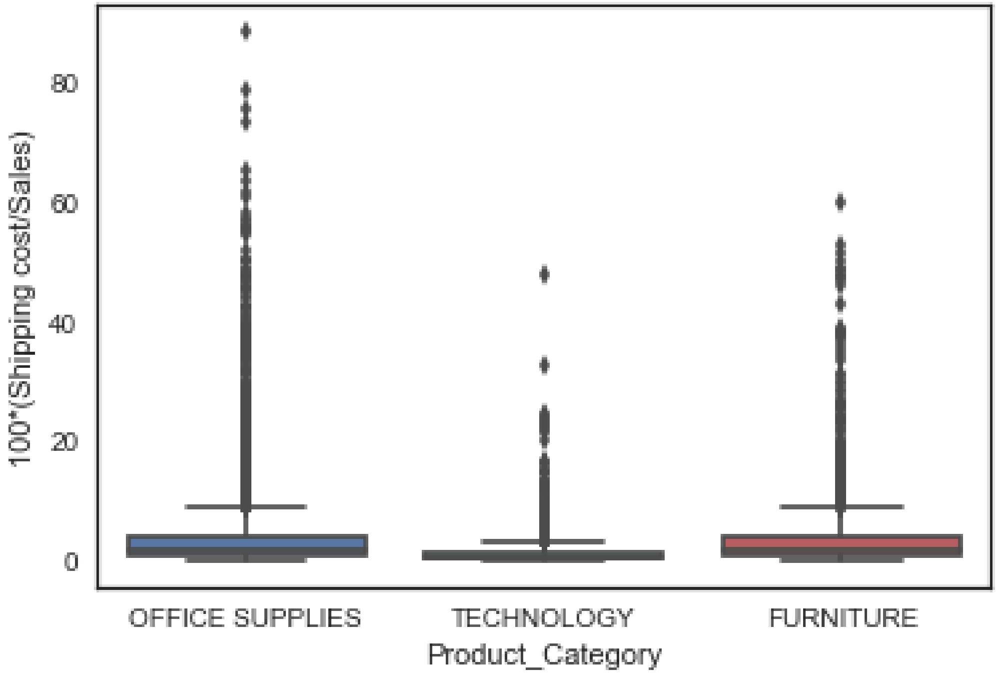
```
# specify hue="categorical_variable"
sns.boxplot(x='Customer_Segment', y='Profit', hue="Product_Category", data=df)
plt.show()
```



Across all customer segments, the product category `Technology` seems to be doing fairly well, though `Furniture` is incurring losses across all segments.

Now say you are curious to know why certain orders are making huge losses. One of your hypothesis is that the *shipping cost is too high in some orders*. You can **plot derived variables** as well, such as *shipping cost as percentage of sales amount*.

[11]:
```
# plot shipping cost as percentage of Sales amount
sns.boxplot(x=df['Product_Category'], y=100*df['Shipping_Cost']/df['Sales'])
plt.ylabel("100*(Shipping cost/Sales)")
plt.show()
```



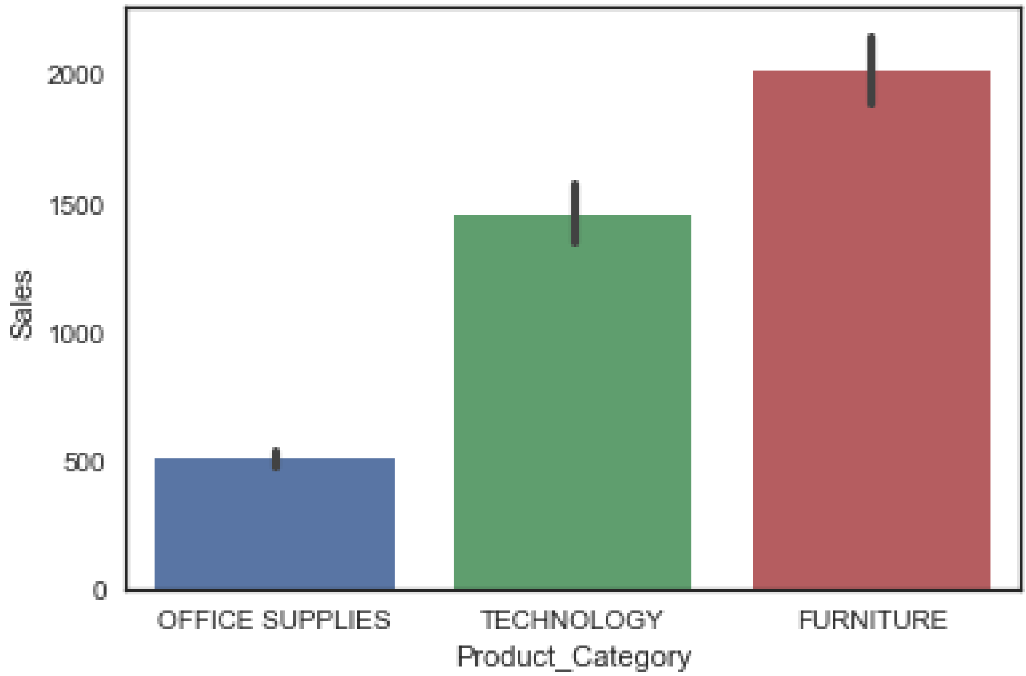
1.2 Plotting Aggregated Values across Categories

1.2.1 Bar Plots - Mean, Median and Count Plots

Bar plots are used to **display aggregated values** of a variable, rather than entire distributions. This is especially useful when you have a lot of data which is difficult to visualise in a single figure.

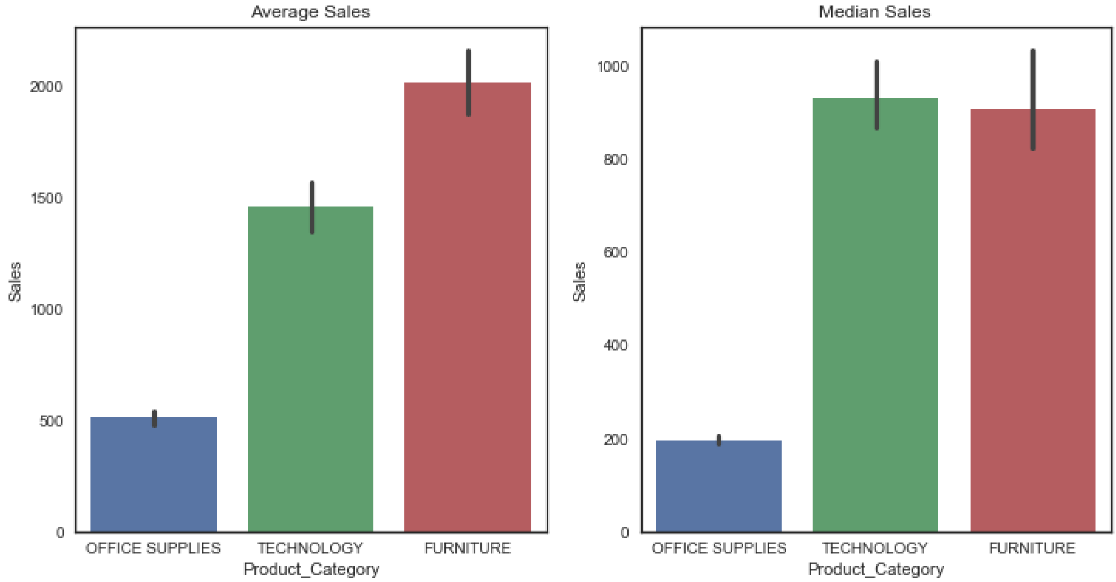
For example, say you want to visualise and *compare the average Sales across Product Categories*. The `sns.barplot()` function can be used to do that.

[12]:
```
# bar plot with default statistic=mean
sns.barplot(x='Product_Category', y='Sales', data=df)
plt.show()
```



Note that, **by default, seaborn plots the mean value across categories**, though you can plot the count, median, sum etc. Also, barplot computes and shows the confidence interval of the mean as well.

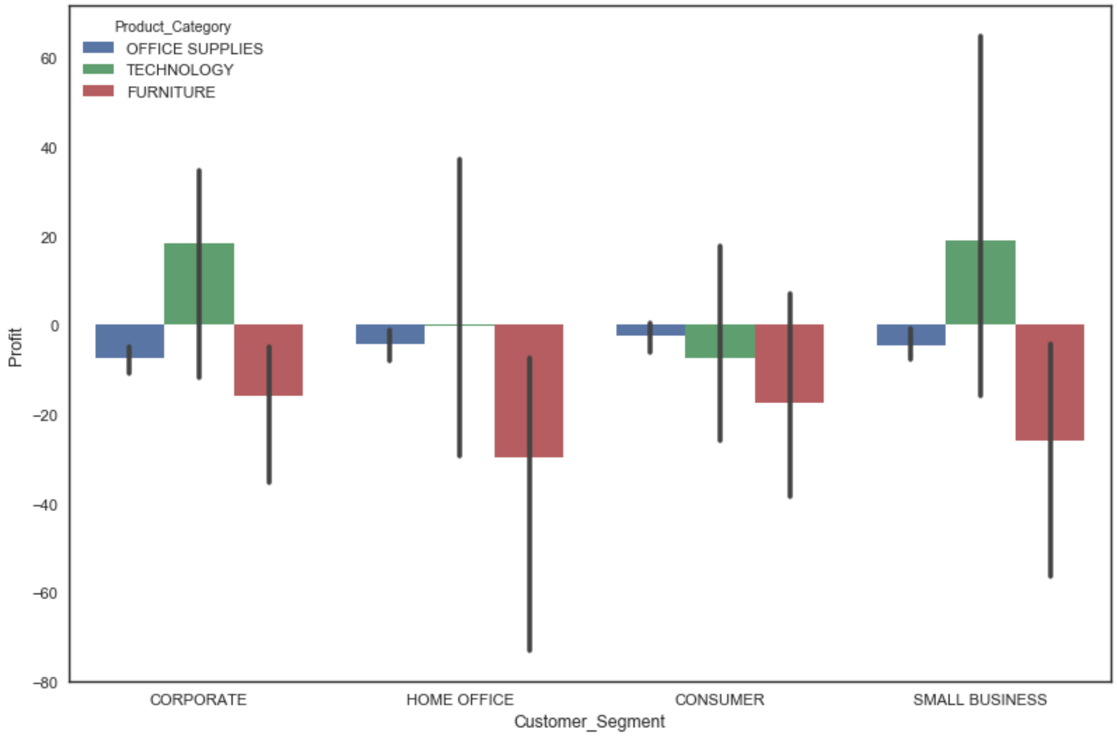
[13]:
```
# Create 2 subplots for mean and median respectively

# increase figure size
plt.figure(figsize=(12, 6))

# subplot 1: statistic=mean
plt.subplot(1, 2, 1)
sns.barplot(x='Product_Category', y='Sales', data=df)
plt.title("Average Sales")

# subplot 2: statistic=median
plt.subplot(1, 2, 2)
sns.barplot(x='Product_Category', y='Sales', data=df, estimator=np.median)
plt.title("Median Sales")

plt.show()
```



Look at that! The mean and median sales across the product categories tell different stories. This is because of some outliers (extreme values) in the `Furniture` category, distorting the value of the mean.

You can add another categorical variable in the plot.

[14]:
```
# set figure size for larger figure
plt.figure(num=None, figsize=(12, 8), dpi=80, facecolor='w', edgecolor='k')

# specify hue="categorical_variable"
sns.barplot(x='Customer_Segment', y='Profit', hue="Product_Category", data=df,␣
 ↪estimator=np.median)
plt.show()
```

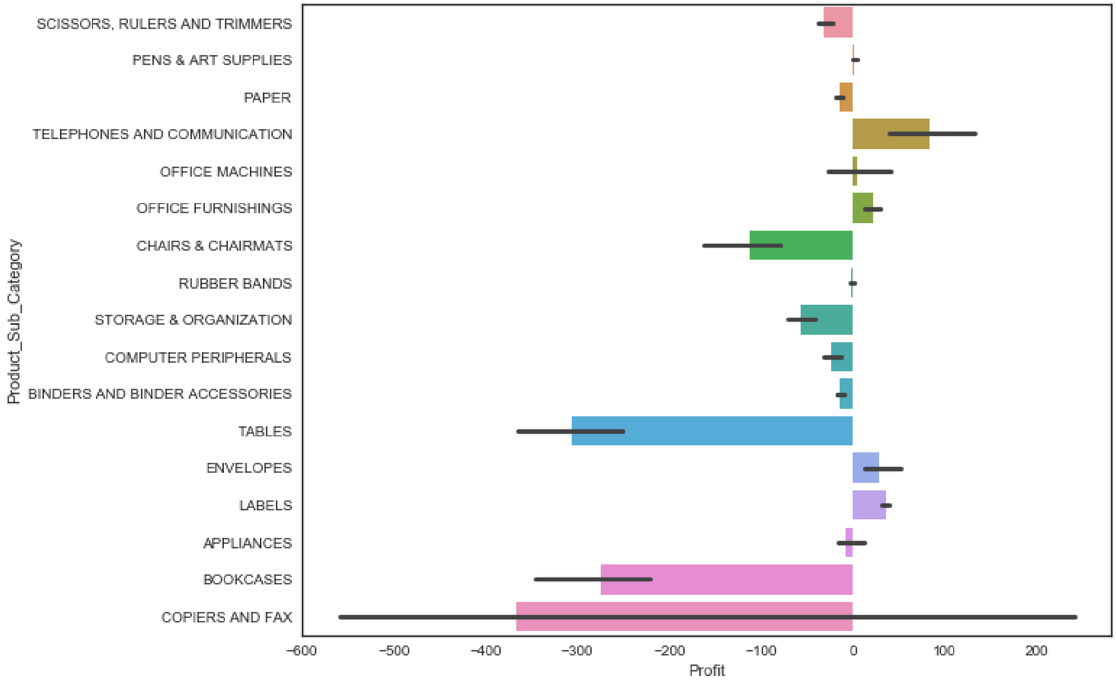


The plot neatly shows the median profit across product categories and customer segments. It says that: - On an average, only Technology products in Small Business and Corporate (customer) categories are profitable. - Furniture is incurring losses across all Customer Segments

Compare this to the boxplot we had created above - though the bar plots contains 'lesser information' than the boxplot, it is more revealing.

When you want to visualise having a large number of categories, it is helpful to plot the categories across the y-axis. Let's now *drill down into product sub categories.*

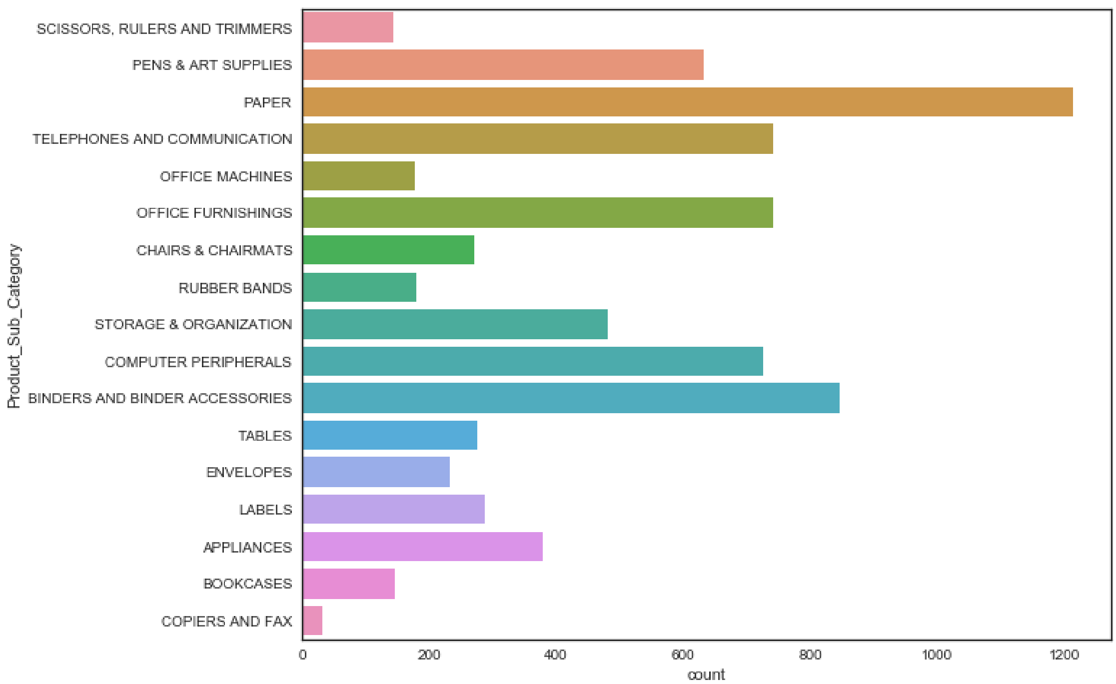
[15]:
```
# Plotting categorical variable across the y-axis
plt.figure(figsize=(10, 8))
sns.barplot(x='Profit', y="Product_Sub_Category", data=df, estimator=np.median)
plt.show()
```



The plot clearly shows which sub categories are incurring the heaviest losses - Copiers and Fax, Tables, Chairs and Chairmats are the most loss making categories.

You can also plot the **count of the observations** across categorical variables using `sns.countplot()`.

[16]:
```
# Plotting count across a categorical variable
plt.figure(figsize=(10, 8))
sns.countplot(y="Product_Sub_Category", data=df)
plt.show()
```



Note the most loss making category - Copiers and Fax - has a very few number of orders.

In the next section, we will see how to plot Time Series data.

1.3 Additional Stuff on Plotting Categorical Variables

1. Seaborn official tutorial on categorical variables