

# Final Project - Grocery store sales analysis-Copy1

August 27, 2024

```
[1]: pip install --upgrade pandas numpy openpyxl  
pip install --upgrade numpy statsmodels
```

```
Requirement already up-to-date: pandas in ./opt/anaconda3/lib/python3.8/site-  
packages (2.0.3)  
Requirement already up-to-date: numpy in ./opt/anaconda3/lib/python3.8/site-  
packages (1.24.4)  
Requirement already up-to-date: openpyxl in ./opt/anaconda3/lib/python3.8/site-  
packages (3.1.5)  
Requirement already satisfied, skipping upgrade: tzdata>=2022.1 in  
./opt/anaconda3/lib/python3.8/site-packages (from pandas) (2023.4)  
Requirement already satisfied, skipping upgrade: python-dateutil>=2.8.2 in  
./opt/anaconda3/lib/python3.8/site-packages (from pandas) (2.9.0.post0)  
Requirement already satisfied, skipping upgrade: pytz>=2020.1 in  
./opt/anaconda3/lib/python3.8/site-packages (from pandas) (2020.1)  
Requirement already satisfied, skipping upgrade: et-xmlfile in  
./opt/anaconda3/lib/python3.8/site-packages (from openpyxl) (1.0.1)  
Requirement already satisfied, skipping upgrade: six>=1.5 in  
./opt/anaconda3/lib/python3.8/site-packages (from python-  
dateutil>=2.8.2->pandas) (1.15.0)  
Note: you may need to restart the kernel to use updated packages.
```

```
[1]: import math  
import matplotlib.pyplot as plt  
import numpy as np  
import pandas as pd  
import random  
import re  
import scipy  
from scipy.stats import norm  
from scipy import stats as st  
import seaborn as sns  
import statsmodels.api as sm
```

# 1 Preliminary data analysis

```
[2]: path_to_file = 'Grocery Database.xlsx'
df = pd.read_excel(path_to_file)
```

## Data shape overview

```
[18]: df.shape
print(f'The set contains {df.shape[0]} rows and {df.shape[1]} columns.')
```

The set contains 50447 rows and 32 columns.

Let us review the data types in the dataset

```
[19]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50447 entries, 0 to 50446
Data columns (total 32 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Receipt Number                        50447 non-null  object
1   Date                                50447 non-null  datetime64[ns]
2   Year                                50447 non-null  int64
3   Month                               50447 non-null  int64
4   Time                                50447 non-null  object
5   Mobile Number                        50447 non-null  int64
6   Membership ID                       50447 non-null  object
7   Loyalty Card Points                 50447 non-null  int64
8   Age                                  50447 non-null  int64
9   Gender                              50447 non-null  object
10  City                                50447 non-null  object
11  Country                             50447 non-null  object
12  Category                            50447 non-null  object
13  Sub_Category                       50447 non-null  object
14  Items                              50447 non-null  object
15  Brand                              50447 non-null  object
16  Description                         50447 non-null  object
17  Price                              50447 non-null  float64
18  QTY                                50447 non-null  int64
19  DISC                              50447 non-null  float64
20  Amount                             50447 non-null  float64
21  Net Bill Amount                    50447 non-null  float64
22  GST                                50447 non-null  float64
23  Gross Bill Amount                  50447 non-null  float64
24  Payment Mode                       50447 non-null  object
25  Bank Name                          50447 non-null  object
26  % Profit Margin                    50447 non-null  float64
27  % Operating Cost                   50447 non-null  float64
```

```

28 % Product Cost      50447 non-null float64
29 Profit Margin      50447 non-null float64
30 Operating Cost      50447 non-null float64
31 Product Cost        50447 non-null float64
dtypes: datetime64[ns](1), float64(12), int64(6), object(13)
memory usage: 12.3+ MB

```

Let us check whether the data set has missing values

```
[20]: df.isna().sum()
```

```

[20]: Receipt Number      0
      Date                0
      Year                0
      Month               0
      Time                0
      Mobile Number       0
      Membership ID       0
      Loyalty Card Points 0
      Age                 0
      Gender              0
      City                0
      Country             0
      Category            0
      Sub_Category        0
      Items               0
      Brand               0
      Description         0
      Price               0
      QTY                 0
      DISC                0
      Amount              0
      Net Bill Amount     0
      GST                 0
      Gross Bill Amount   0
      Payment Mode        0
      Bank Name           0
      % Profit Margin     0
      % Operating Cost    0
      % Product Cost      0
      Profit Margin       0
      Operating Cost      0
      Product Cost        0
dtype: int64

```

There are no missing values in the data set.

## 2 Main part of data analysis

1: What is the most common way of payment among costumers?

```
[21]: df['Payment Mode'].value_counts()
```

```
[21]: Payment Mode
Card      17149
Wallet    16867
Cash      16431
Name: count, dtype: int64
```

**Conclusion:** We can see that the most popular way of payment among customer is card.

**Business idea:** One can develop a mobile app that allows customers to make contactless payments. This could include features like order-ahead and curbside pickup, creating a convenient and safe shopping experience.

2: What are the most commonly purchased product categories?

```
[22]: df.rename(columns = {'Receipt Number':'Receipt_Number'}, inplace = True)
df.groupby(['Category']).Receipt_Number.count()
```

```
[22]: Category
Bakery & Breakfast      6770
Beauty                 5205
Beverages              2208
Choco, Snacks, Sweets  3019
Dairy, Chilled & Eggs  3381
Frozen                 6393
Fruit & Vegetable      4370
Health                 1008
Household              1881
Kitchen & Dining       2552
Meat & Seafood         2149
Mother & Baby          2064
Party Supplies        1836
Pet Care              3465
Rice & Cooking Essentials 2432
Wines, Beers & Spirits  1714
Name: Receipt_Number, dtype: int64
```

**Conclusion:** One sees that the “Bakery and breakfast” is the most purchased category.

**Business ideas:** 1. Gourmet Breakfast Delivery Service: Create a business that specializes in delivering gourmet breakfast options to people’s homes or offices.

2. Healthy Breakfast Subscription Box: Develop a subscription box service that delivers healthy breakfast options to subscribers each month. Include items like granola, yogurt, whole-grain muffins, and fresh fruits.

### 3: What is the average price for the categories?

```
[15]: df.groupby(['Category']).Price.mean()
```

```
[15]: Category
Bakery & Breakfast      5.222038
Beauty                 10.063051
Beverages              8.297360
Choco, Snacks, Sweets  5.770414
Dairy, Chilled & Eggs  6.900683
Frozen                 7.692615
Fruit & Vegetable       5.570590
Health                 13.693046
Household              8.855045
Kitchen & Dining        3.753100
Meat & Seafood          11.947627
Mother & Baby           11.869695
Party Supplies         4.641950
Pet Care               6.976049
Rice & Cooking Essentials 3.507113
Wines, Beers & Spirits  13.282456
Name: Price, dtype: float64
```

**Conclusion:** The highest price is in the “Health” category.

**Business idea:** Beauty Tech: Invest in beauty technology, such as AI-powered skincare analysis or virtual makeup try-on apps. You could provide these services to consumers, helping them find the right products for their skin type and tone.

### 4: What are the top-selling products in terms of quantity sold or revenue generated?

```
[25]: df.rename(columns = {'Profit Margin':'Profit_Margin'}, inplace = True)
df.groupby('Items').Amount.mean().idxmax()
```

```
[25]: 'Bollinger Pink platted moscato rose'
```

### 5: What is the top-selling product category in terms of quantity sold or revenue generated?

```
[26]: df.groupby('Sub_Category').Amount.mean().idxmax()
```

```
[26]: 'Champagne & Spakling Wine'
```

**Conclusion (4,5):** One can see that Bollinger Pink platted moscato rose is the product that generstes the highest revenue. Also, one can see that Champagne & Sparkling Wine is the top-selling producct category.

**Business ideas:** 1.Wine Subscription Service: Launch a subscription service specializing in premium rosé wines, including Bollinger Pink platted moscato Rosé.

2. Wine Tasting Tours: If you're located in a wine-producing region, consider offering wine tasting tours that focus on rosé wines, including a tasting of Bollinger Pink Platted Moscato Rosé. Create unique and immersive experiences by partnering with local wineries for tours and tastings.

#### 6: Who buy more in the “Frozen” category: men or women?

```
[29]: gender_counts = df[df['Category'] == 'Frozen']['Gender'].value_counts()
      print(gender_counts)
```

```
Gender
Female    5401
Male       992
Name: count, dtype: int64
```

**Conclusion:** There less of male customers in the “Frozen” category.

**Business idea:** Product Placement and Store Layout: Adjust the store layout to prominently display frozen food items that are popular among men. Placing these products in areas that men frequently visit can increase their visibility and encourage more purchases.

#### 7: At which category do we have the most expensive purchase?

```
[47]: df.groupby('Membership ID').Price.mean().idxmax()
      df.loc[df['Membership ID'] == 'MIDSG0094'].Category
```

```
[47]: 32676    Mother & Baby
      Name: Category, dtype: object
```

**Conclusion:** We have the most expensive purchase in the category: “Mother & Baby”.

**Business idea:** Baby Shower Planning Services: Offer event planning services for baby showers, gender reveal parties, and other related celebrations. Create memorable experiences for expectant parents and their friends and family.

#### 8: At what city customers have the highest average bill?

```
[76]: df.groupby('City').Amount.mean()
```

```
[76]: City
      Bedok          11.054826
      Jakarta       11.310233
      Kuala Lumpur   11.262599
      Manila         10.822900
      Woodlands      11.732765
      Name: Amount, dtype: float64
```

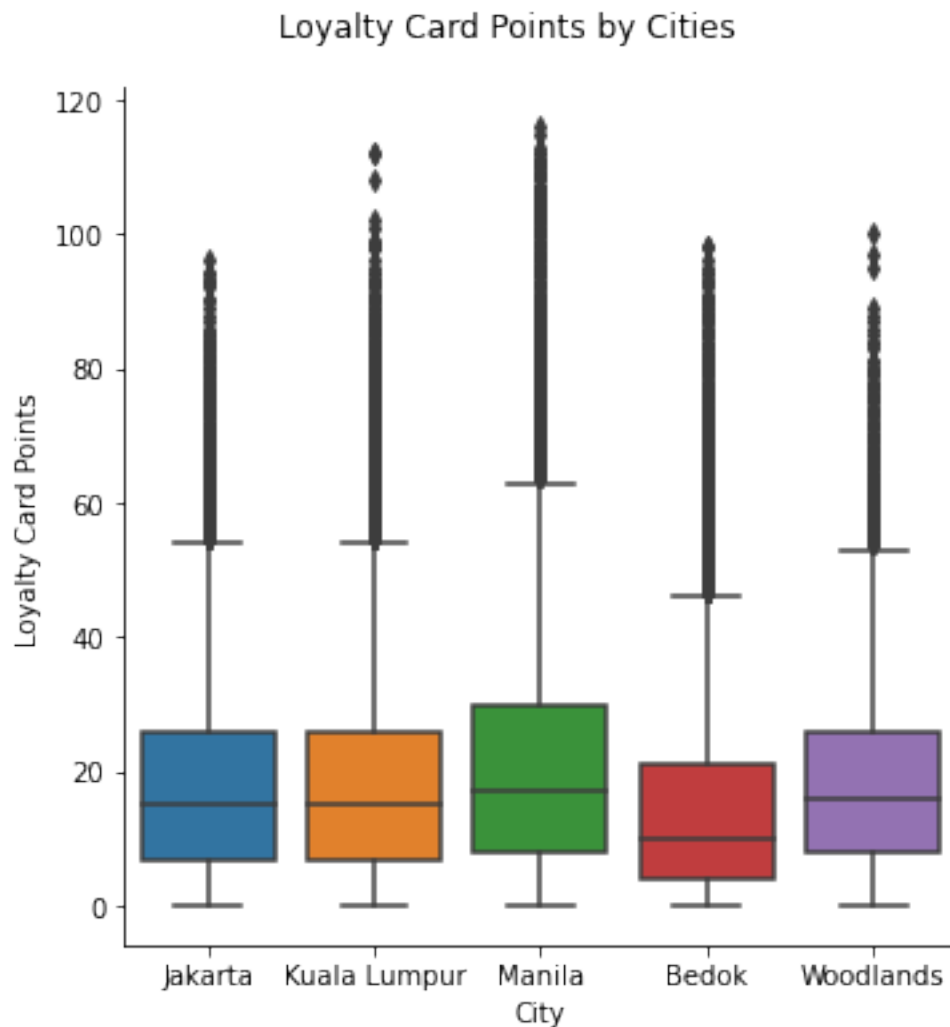
**Conclusion:** In Woodlands customers have the highest average bill.

**Business idea:** Exclusive Cooking Classes: Organize exclusive cooking classes and workshops that teach customers how to prepare gourmet meals using premium ingredients. Collaborate with renowned chefs or culinary experts to provide a unique and educational experience. Offer classes in-person and online to reach a wider audience.

10: At what city people have the lowest level of loyalty card points?

```
[19]: plot = sns.catplot(data = df, x="City", y="Loyalty Card Points", kind="box")
      plot.fig.suptitle("Loyalty Card Points by Cities", y=1.05)
      plot
```

```
[19]: <seaborn.axisgrid.FacetGrid at 0x7fbf63af4580>
```



**Conclusion:** In Bedock people have the lowest level of loyalty card points.

**Business idea:** Loyalty Point Boost Program: Create a loyalty point boosting program specifically for Bedeck grocery stores.

Let us create a pivot table

```
[9]: age_pivot = df.pivot_table(index='Age', columns='City', values='Amount',aggfunc='sum')
age_pivot.head()
```

```
[9]: City      Bedok      Jakarta  Kuala Lumpur      Manila  Woodlands
Age
15      2784.5174  2793.6930      1979.3798  2684.6992  1231.9019
16      3723.5775  1839.1363      4214.1807  3890.7314  2529.8478
17      3601.8660  2530.0170      5495.0694  4463.0577  1619.7760
18      4770.9461  3918.6245      4049.1765  3696.5842  2151.6184
19      2830.9589  4447.4399      8208.4761  2224.9030   860.2747
```

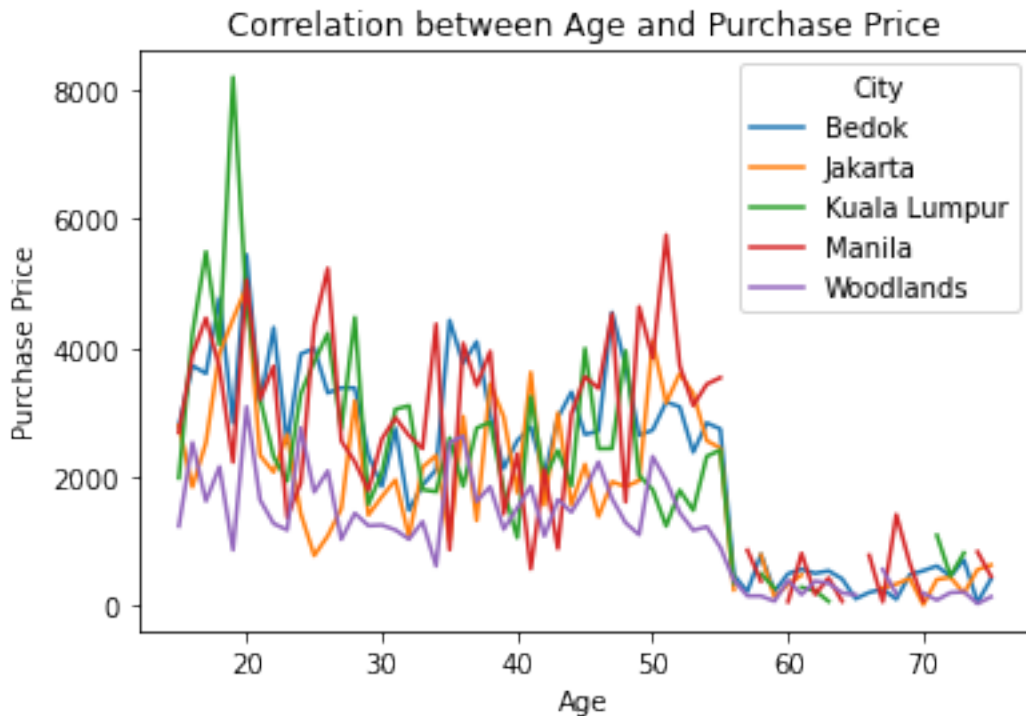
11: What is the corelation between age and purchase price for every city?

```
[16]: ap = age_pivot.plot()

ap.set_xlabel("Age")
ap.set_ylabel("Purchase Price")

ap.set_title("Correlation between Age and Purchase Price")
```

```
[16]: Text(0.5, 1.0, 'Correlation between Age and Purchase Price')
```

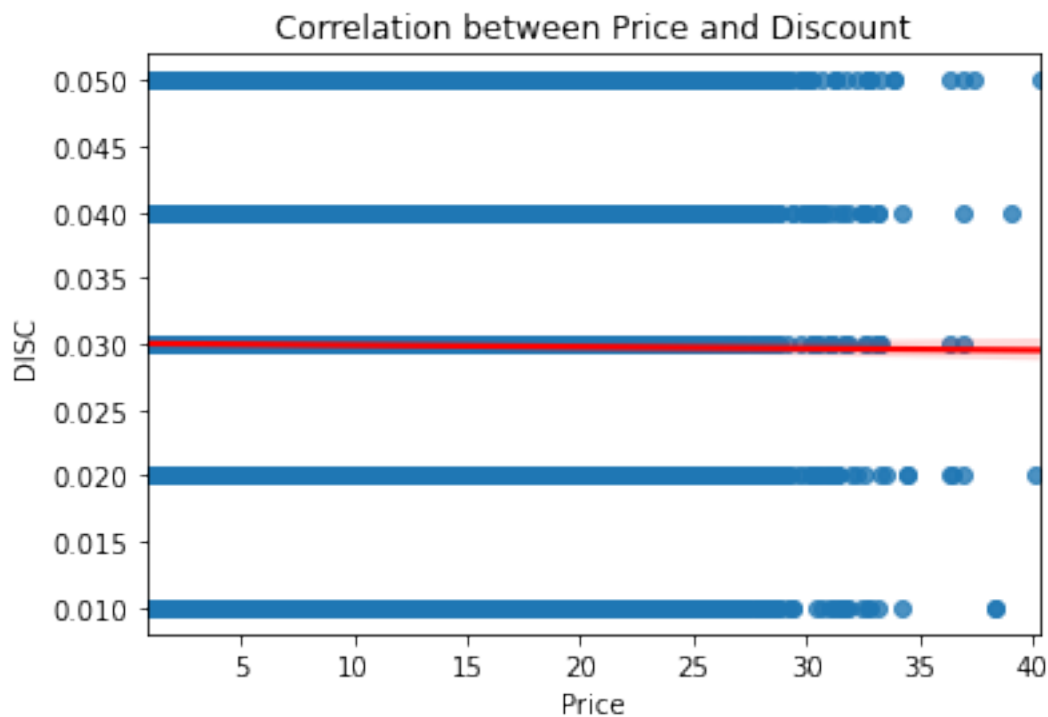




**Conclusion:** one sees that in Kuala Lumpur people around 20 make the most expensive purchases. That look suspicious and takes needs some additional reserch to be done.

### 13: Is there any correlation between Price and Discount?

```
[25]: sns.regplot(
        data = df,
        x = 'Price', y='DISC', line_kws = {'color': 'red'}
    );
plt.title("Correlation between Price and Discount")
plt.show()
```



**Conclusion:** There is a direct correlation between Price and Discount. No outliers.

Let us create another pivot table

```
[34]: gender_pivot = df.pivot_table(index='Gender', columns='City',
    ↪ values='Amount',aggfunc = 'sum')
gender_pivot.head()
```

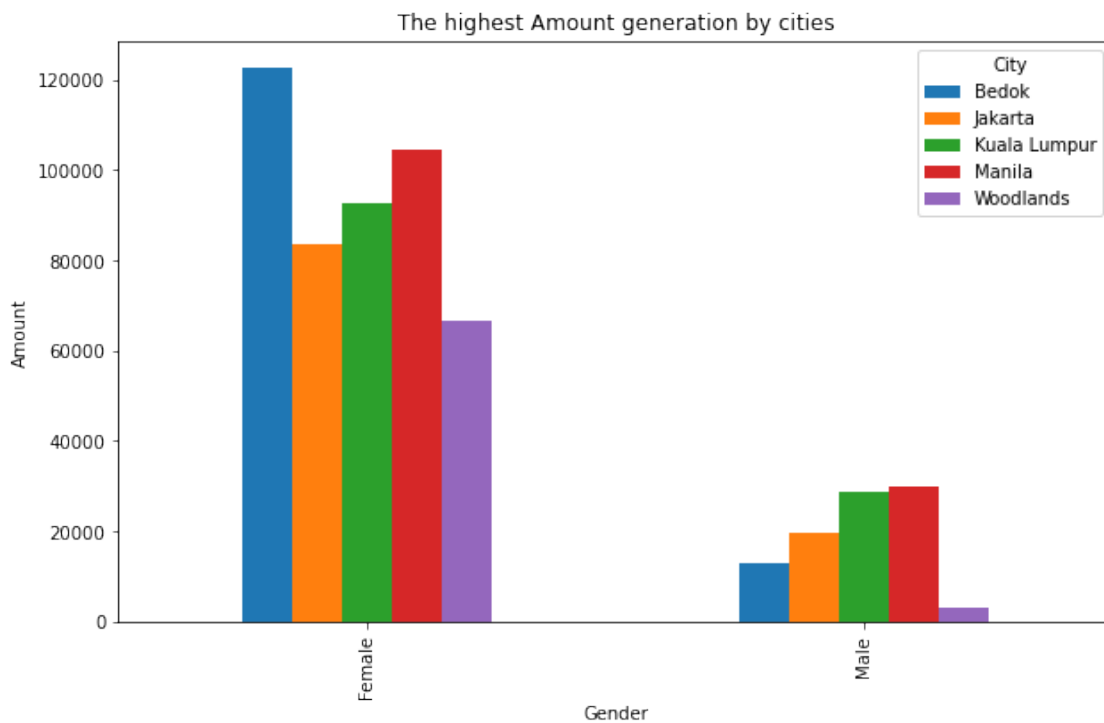
```
[34]: City          Bedok      Jakarta  Kuala Lumpur      Manila  Woodlands
Gender
Female  122601.1731  83361.1450    92527.7172  104309.6095  66404.0654
Male    13063.6490   19652.4567    28691.6373   29677.8889   3100.8349
```

### 14: At what city do female customers generate the highest Amount?

```
[35]: ax = gender_pivot.plot.bar(figsize=(10,6));
ax.set_title("The highest Amount generation by cities")
ax.set_ylabel("Amount")
ax.show()
```

```
-----
AttributeError                                Traceback (most recent call last)
<ipython-input-35-1a481d89051c> in <module>
      2 ax.set_title("The highest Amount generation by cities")
      3 ax.set_ylabel("Amount")
----> 4 ax.show()

AttributeError: 'AxesSubplot' object has no attribute 'show'
```



**Conclusion:** in Bedok female customers generate the highest Amount

**Business ideas:** 1.Inventory and Stocking: If female customers in Bedok prefer specific products, the business can optimize its inventory and stocking decisions. It can ensure that the products favored by this demographic are well-stocked and readily available.

2.Feedback and Surveys: To gain deeper insights into why female customers in Bedok are spending more, the business can conduct surveys or gather feedback. This information can help refine strategies and offerings.

**15: What are the average pre-tax checks for each subcategory in the beauty and care**

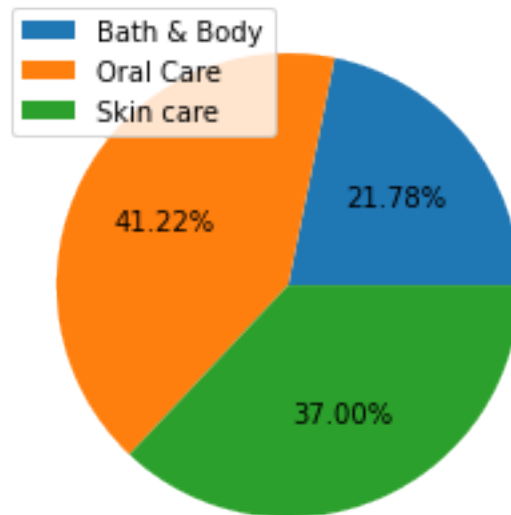
category? Let's create a pie chart and review the structure

```
[7]: beauty_net_bill = df[df['Category'] == 'Beauty'].groupby('Sub_Category')['Net_Bill Amount'].sum()
beauty_net_bill
```

```
[7]: Sub_Category
Bath & Body      84351.7905
Oral Care       159649.8545
skin care       143328.2248
Name: Net Bill Amount, dtype: float64
```

```
[9]: plt.pie(beauty_net_bill, autopct = '%1.2f%')
plt.title('Structure of Beauty category goods')
plt.legend(labels = ['Bath & Body', 'Oral Care', 'Skin care']);
```

Structure of Beauty category goods



**Conclusion:** The oral care goods have the highest pre-tax checks.