dgdzba8zg

April 3, 2024

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

import warnings
warnings.filterwarnings('ignore')

plt.style.use('fivethirtyeight')
%matplotlib inline
```

[5]:
```
df = pd.read_csv('/content/Train.csv')
df
```

[5]:
```
          ID Warehouse_block Mode_of_Shipment  Customer_care_calls  \
0          1               D           Flight                    4
1          2               F           Flight                    4
2          3               A           Flight                    2
3          4               B           Flight                    3
4          5               C           Flight                    2
…        …               …                …                    …
10994  10995               A             Ship                    4
10995  10996               B             Ship                    4
10996  10997               C             Ship                    5
10997  10998               F             Ship                    5
10998  10999               D             Ship                    2

       Customer_rating  Cost_of_the_Product  Prior_purchases  \
0                    2                  177                3
1                    5                  216                2
2                    2                  183                4
3                    3                  176                4
4                    2                  184                3
…                  …                  …              …
10994                1                  252                5
10995                1                  232                5
```

```
10996                4                242                5
10997                2                223                6
10998                5                155                5

      Product_importance Gender  Discount_offered  Weight_in_gms  \
0                    low      F                44           1233
1                    low      M                59           3088
2                    low      M                48           3374
3                 medium      M                10           1177
4                 medium      F                46           2484
…                    …      …               …            …
10994             medium      F                 1           1538
10995             medium      F                 6           1247
10996                low      F                 4           1155
10997             medium      M                 2           1210
10998                low      F                 6           1639

       Reached.on.Time_Y.N
0                        1
1                        1
2                        1
3                        1
4                        1
…                      …
10994                    1
10995                    0
10996                    0
10997                    0
10998                    0

[10999 rows x 12 columns]
```

[6]:
```python
df.head()
```

[6]:
```
   ID Warehouse_block Mode_of_Shipment  Customer_care_calls  Customer_rating  \
0   1               D           Flight                    4                2
1   2               F           Flight                    4                5
2   3               A           Flight                    2                2
3   4               B           Flight                    3                3
4   5               C           Flight                    2                2

   Cost_of_the_Product  Prior_purchases Product_importance Gender  \
0                  177                3                low      F
1                  216                2                low      M
2                  183                4                low      M
3                  176                4             medium      M
4                  184                3             medium      F
```

```
   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
3                10           1177                    1
4                46           2484                    1
```

[7]:
```python
df.shape
```

[7]:
```
(10999, 12)
```

[8]:
```python
df.describe()
```

[8]:
```
                ID  Customer_care_calls  Customer_rating  Cost_of_the_Product  \
count  10999.00000         10999.000000     10999.000000         10999.000000
mean    5500.00000             4.054459         2.990545           210.196836
std     3175.28214             1.141490         1.413603            48.063272
min        1.00000             2.000000         1.000000            96.000000
25%     2750.50000             3.000000         2.000000           169.000000
50%     5500.00000             4.000000         3.000000           214.000000
75%     8249.50000             5.000000         4.000000           251.000000
max    10999.00000             7.000000         5.000000           310.000000

       Prior_purchases  Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
count     10999.000000      10999.000000   10999.000000         10999.000000
mean          3.567597         13.373216    3634.016729             0.596691
std           1.522860         16.205527    1635.377251             0.490584
min           2.000000          1.000000    1001.000000             0.000000
25%           3.000000          4.000000    1839.500000             0.000000
50%           3.000000          7.000000    4149.000000             1.000000
75%           4.000000         10.000000    5050.000000             1.000000
max          10.000000         65.000000    7846.000000             1.000000
```

[9]:
```python
df.info()
```

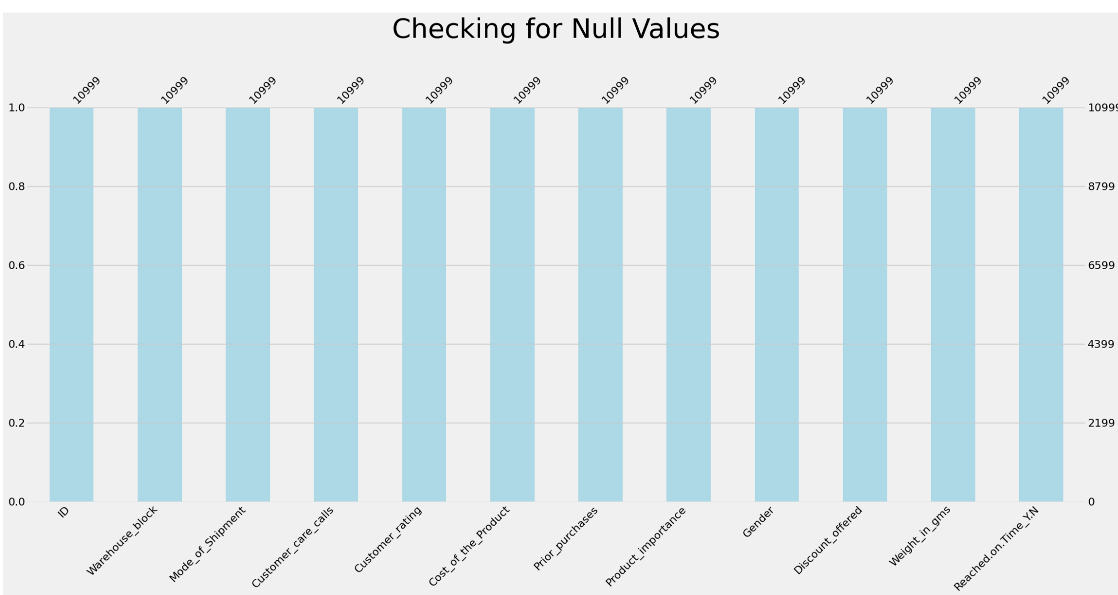
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10999 entries, 0 to 10998
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   10999 non-null  int64
 1   Warehouse_block      10999 non-null  object
 2   Mode_of_Shipment     10999 non-null  object
 3   Customer_care_calls  10999 non-null  int64
 4   Customer_rating      10999 non-null  int64
 5   Cost_of_the_Product  10999 non-null  int64
```

 6   Prior_purchases   10999 non-null int64
 7   Product_importance   10999 non-null object
 8   Gender   10999 non-null object
 9   Discount_offered   10999 non-null int64
 10 Weight_in_gms   10999 non-null int64
 11 Reached.on.Time_Y.N 10999 non-null int64
dtypes: int64(8), object(4)
memory usage: 1.0+ MB

[10]:
```
df.isna().sum()
```

[10]:
```
ID                     0
Warehouse_block        0
Mode_of_Shipment       0
Customer_care_calls    0
Customer_rating        0
Cost_of_the_Product    0
Prior_purchases        0
Product_importance     0
Gender                 0
Discount_offered       0
Weight_in_gms          0
Reached.on.Time_Y.N    0
dtype: int64
```

[11]:
```
# checking for null values using missingno module
import missingno as msno
msno.bar(df, color = 'lightblue')
plt.title('Checking for Null Values\n', fontsize = 40)
plt.show()
```



[12]:
```python
# dropping unwanted column using drop method

df.drop('ID', axis = 1, inplace = True)
df.head()
```

[12]:
```
  Warehouse_block Mode_of_Shipment  Customer_care_calls  Customer_rating  \
0               D           Flight                    4                2
1               F           Flight                    4                5
2               A           Flight                    2                2
3               B           Flight                    3                3
4               C           Flight                    2                2

   Cost_of_the_Product  Prior_purchases Product_importance Gender  \
0                  177                3                low      F
1                  216                2                low      M
2                  183                4                low      M
3                  176                4             medium      M
4                  184                3             medium      F

   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
3                10           1177                    1
4                46           2484                    1
```

[13]:
```python
# heatmap of the data for checking the correlation between the features and␣
↪target column.
plt.figure(figsize = (18, 7))
sns.heatmap(df.corr(), annot = True, fmt = '0.2f', annot_kws = {'size' : 15},␣
↪linewidth = 5, linecolor = 'orange')
plt.show()
```

Conclusions from Correlation matrix :-

```
Discount Offered have high positive correlation with Reached on Time or Not of 40%.
Weights in gram have negative correlation with Reached on Time or Not -27%.
Discount Offered and weights in grams have negative correlation -38%.
Customer care calls and weights in grams havenegative correlation -28%.
Customer care calls and cost of the product have positive correlation of 32%.
Prior Purchases and Customer care calls have slightly positive correlation.
```

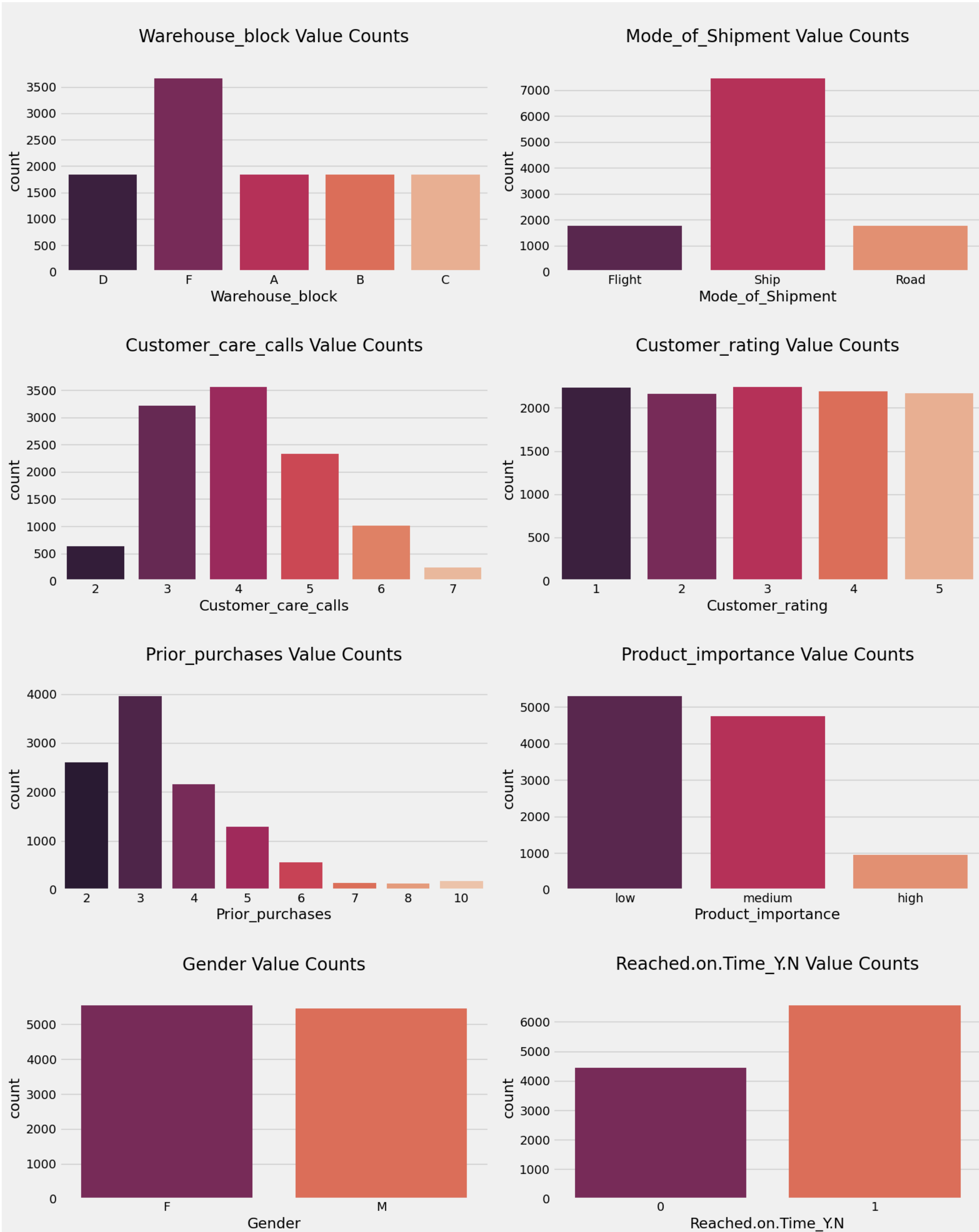
[14]:
```
df.head()
```

[14]:
```
  Warehouse_block Mode_of_Shipment  Customer_care_calls  Customer_rating  \
0               D           Flight                    4                2
1               F           Flight                    4                5
2               A           Flight                    2                2
3               B           Flight                    3                3
4               C           Flight                    2                2

   Cost_of_the_Product  Prior_purchases Product_importance Gender  \
0                  177                3                low      F
1                  216                2                low      M
2                  183                4                low      M
3                  176                4             medium      M
4                  184                3             medium      F

   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
```

3	10	1177	1
4	46	2484	1

Exploratory Data Analysis (EDA)

[15]:
```
# here by these plots we are lookin at the counts of each categories in the␣
↪categorical columns
# creating a list of categorical coumns
cols = ['Warehouse_block', 'Mode_of_Shipment', 'Customer_care_calls',␣
↪'Customer_rating',
        'Prior_purchases', 'Product_importance', 'Gender', 'Reached.on.Time_Y.
↪N']
plt.figure(figsize = (16, 20))
plotnumber = 1


for i in range(len(cols)):
    if plotnumber <= 8:
        ax = plt.subplot(4, 2, plotnumber)
        sns.countplot(x = cols[i], data = df, ax = ax, palette='rocket')
        plt.title(f"\n{cols[i]} Value Counts\n", fontsize = 20)

    plotnumber += 1

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



From the above plots, we can conclude following:-

```
Warehouse block F have has more values than all other Warehouse blocks.
In mode of shipment columns we can clearly see that ship delivers the most of products to the
Most of the customers calls 3 or 4 times to the customer care centers.
Customer Ratings does not have much variation.
```

```
Most of the customers have 3 prior purchases.
We can say that mopst of the products are of low Importance.
Gender Column doesn't have much variance.
More products doesn't reach on time than products reached on time.
```

Exploring relation of categorical columns with reached on time or not

[16]:
```
# creating a list of categorical coumns

object_columns = df.select_dtypes(include = ['object'])
object_columns.head()
```

[16]:

	Warehouse_block	Mode_of_Shipment	Product_importance	Gender
0	D	Flight	low	F
1	F	Flight	low	M
2	A	Flight	low	M
3	B	Flight	medium	M
4	C	Flight	medium	F

[17]:
```
warehouse = object_columns['Warehouse_block'].value_counts().reset_index()
warehouse.columns = ['warehouse', 'value_counts']
warehouse
```

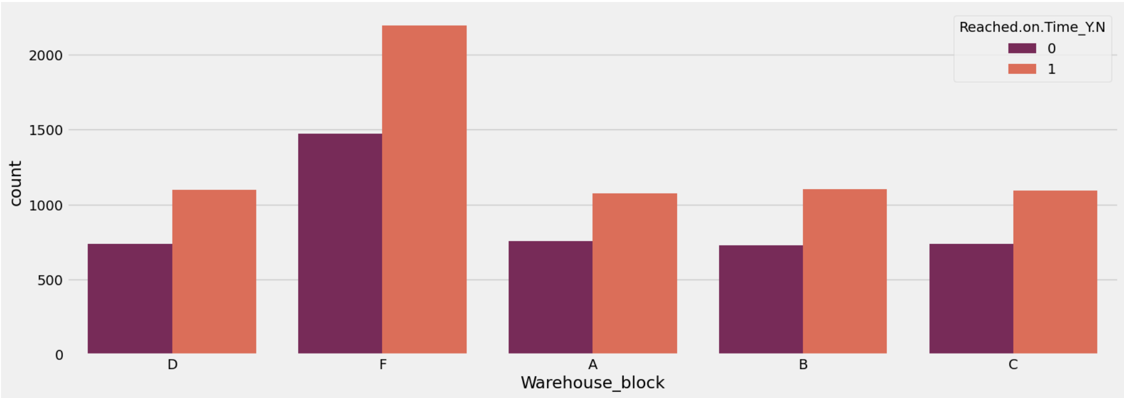
[17]:

	warehouse	value_counts
0	F	3666
1	D	1834
2	A	1833
3	B	1833
4	C	1833

Ware_house block

[18]:
```
fig = px.pie(warehouse, names = 'warehouse', values = 'value_counts',
             color_discrete_sequence = px.colors.sequential.matter_r, width =␣
 ↪650, height = 400,
             hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

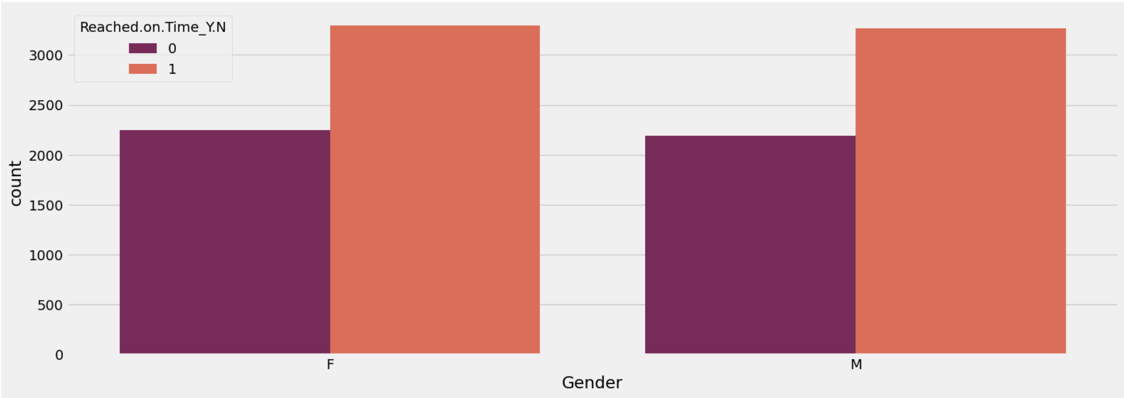
[19]:
```
# making a countplot of warehouse column and see the effect of Reached on time␣
 ↪or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x='Warehouse_block', hue = 'Reached.on.Time_Y.N', data = df,␣
 ↪palette='rocket')
plt.show()
```



gender

[20]:
```
gender = object_columns['Gender'].value_counts().reset_index()
gender.columns = ['Gender', 'value_counts']
fig = px.pie(gender, names = 'Gender', values = 'value_counts',␣
 ↪color_discrete_sequence =
             px.colors.sequential.Darkmint_r, width = 650, height = 400, hole =␣
 ↪0.5)
fig.update_traces(textinfo = 'percent+label')
```

[21]:
```
plt.figure(figsize = (17, 6))
sns.countplot(x='Gender', hue = 'Reached.on.Time_Y.N', data = df,␣
 ↪palette='rocket')
plt.show()
```

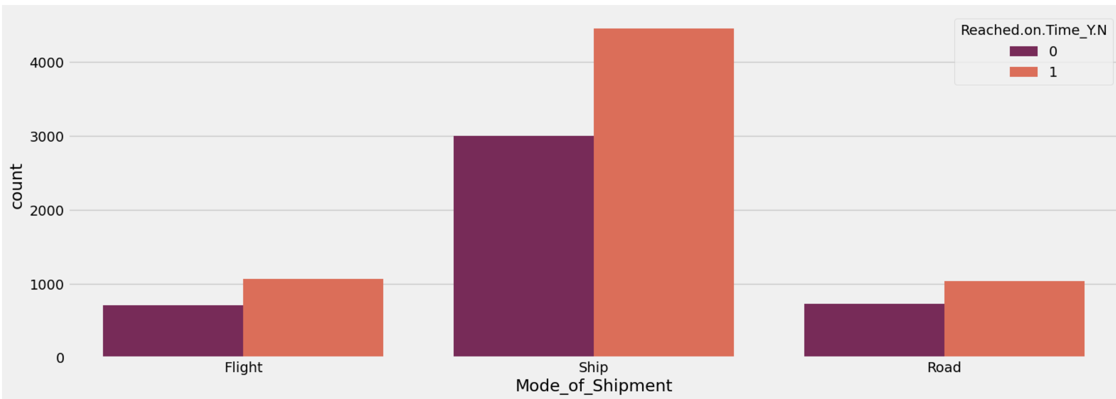


Mode_of_Shipment

[22]:
```
mode = object_columns['Mode_of_Shipment'].value_counts().reset_index()
mode.columns = ['Mode_of_Shipment', 'value_counts']
```

```
fig = px.pie(mode, names = 'Mode_of_Shipment', values = 'value_counts',␣
↪color_discrete_sequence =
            px.colors.sequential.Darkmint_r, width = 650, height = 400, hole =␣
↪0.5)
fig.update_traces(textinfo = 'percent+label')
```

[23]:
```
# making a countplot of mode of shipment column and see the effect of Reached␣
↪on time or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x = 'Mode_of_Shipment', hue = 'Reached.on.Time_Y.N', data = df,␣
↪palette='rocket')
plt.show()
```

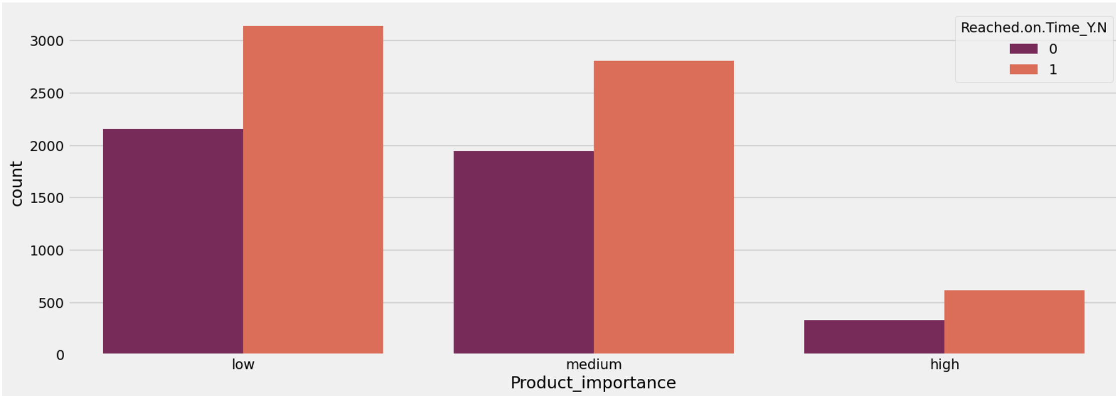


Product_importance

[24]:
```
# looking at the product importance column and what are the categories present␣
↪in it

product_imp = object_columns['Product_importance'].value_counts().reset_index()
product_imp.columns = ['Product_importance', 'value_counts']
fig = px.pie(product_imp, names = 'Product_importance', values = 'value_counts',
             color_discrete_sequence = px.colors.sequential.Darkmint_r, width =␣
↪650, height = 400,
             hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

[25]:
```
# making a countplot of product importance column and see the effect of Reached␣
↪on time or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x='Product_importance', hue = 'Reached.on.Time_Y.N', data = df,␣
↪palette='rocket')
```

```
plt.show()
```



Exploring relation of continuous columns with reached on time or not

[26]:
```
integer_columns = df.select_dtypes(include = ['int64'])
integer_columns.head()
```

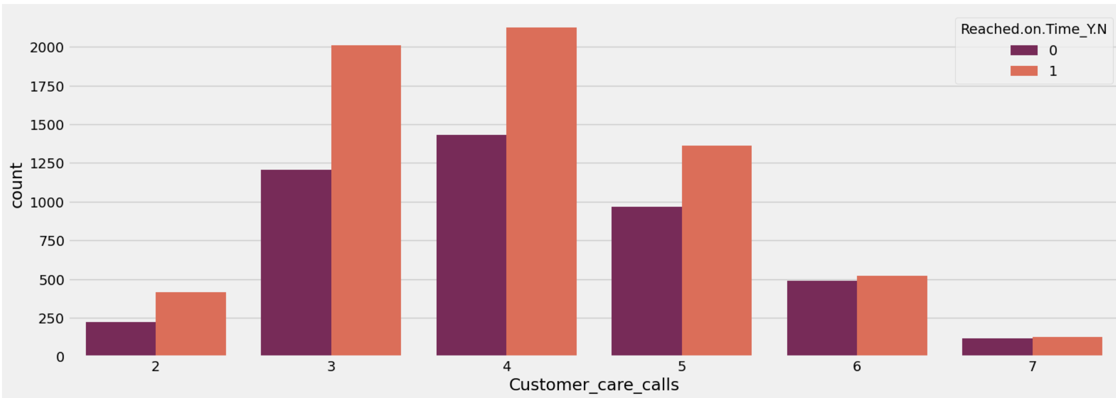
[26]:
```
   Customer_care_calls  Customer_rating  Cost_of_the_Product  Prior_purchases  \
0                    4                2                  177                3
1                    4                5                  216                2
2                    2                2                  183                4
3                    3                3                  176                4
4                    2                2                  184                3

   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
3                10           1177                    1
4                46           2484                    1
```

Customer_care calls

[27]:
```
# looking at the customer care calls column and what are the categories present␣
↪in it

customer_care = integer_columns['Customer_care_calls'].value_counts().
↪reset_index()
customer_care.columns = ['Customer_care_calls', 'value_counts']
fig = px.pie(customer_care, names = 'Customer_care_calls', values =␣
↪'value_counts',
             color_discrete_sequence = px.colors.sequential.matter_r, width =␣
↪650, height = 400,
```

```
            hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

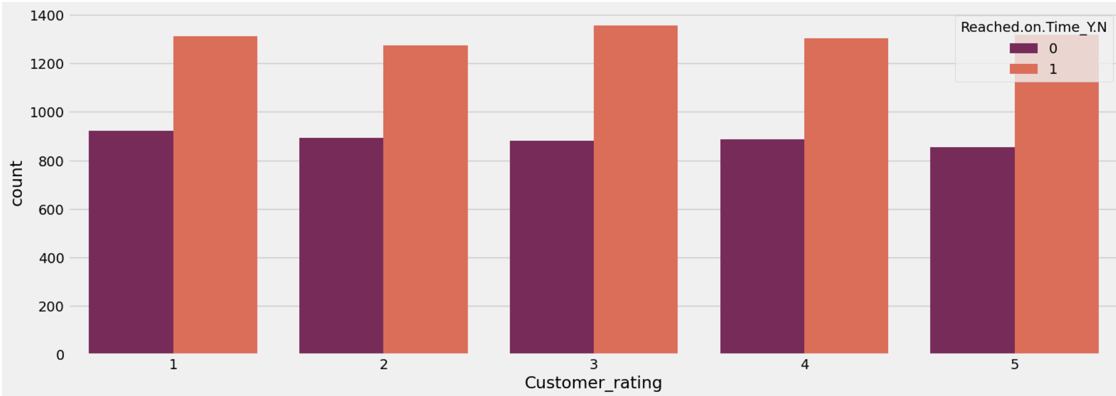
[28]:
```
# making a countplot of customer care calls column and see the effect of␣
↪Reached on time or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x = 'Customer_care_calls', hue = 'Reached.on.Time_Y.N', data =␣
↪df, palette='rocket')
plt.show()
```



Customer_rating

[29]:
```
# looking at the customer ratings column and what are the categories present in␣
↪it

customer_ratings = integer_columns['Customer_rating'].value_counts().
↪reset_index()
customer_ratings.columns = ['Customer_rating', 'value_counts']
fig = px.pie(customer_ratings, names = 'Customer_rating', values =␣
↪'value_counts',
             color_discrete_sequence = px.colors.sequential.matter_r, width =␣
↪650, height = 400,
            hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

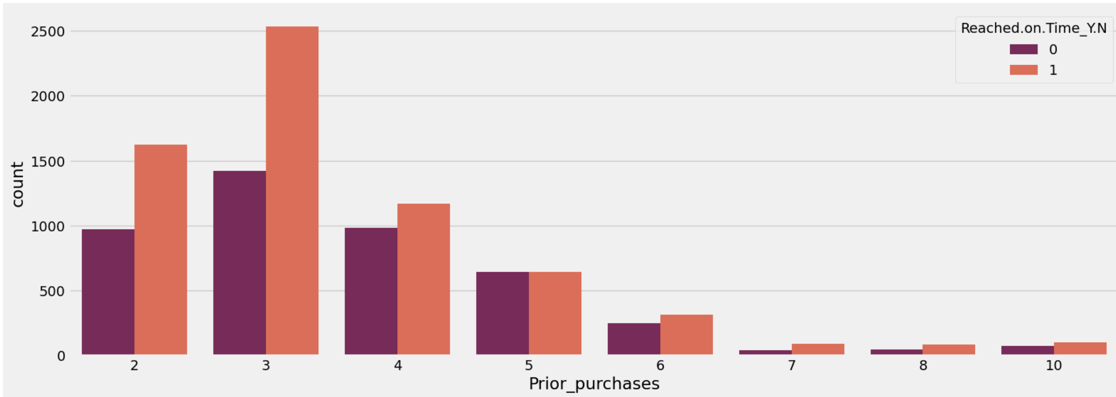
[30]:
```
# making a countplot of customer ratings calls column and see the effect of␣
↪Reached on time or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x ='Customer_rating', hue = 'Reached.on.Time_Y.N', data = df,␣
↪palette='rocket')
plt.show()
```



Prior_purchases

[31]:
```
# looking at the prior purchases column and what are the categories present in
↪it

prior_purchases = integer_columns['Prior_purchases'].value_counts().
↪reset_index()
prior_purchases.columns = ['Prior_purchases', 'value_counts']
fig = px.pie(prior_purchases, names = 'Prior_purchases', values =
↪'value_counts',
             color_discrete_sequence = px.colors.sequential.matter_r, width =
↪650, height = 400,
            hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

[32]:
```
# making a countplot of prior purchases column and see the effect of Reached on
↪time or not on the warehouse column.

plt.figure(figsize = (17, 6))
sns.countplot(x='Prior_purchases', hue = 'Reached.on.Time_Y.N', data = df,
↪palette='rocket')
plt.show()
```

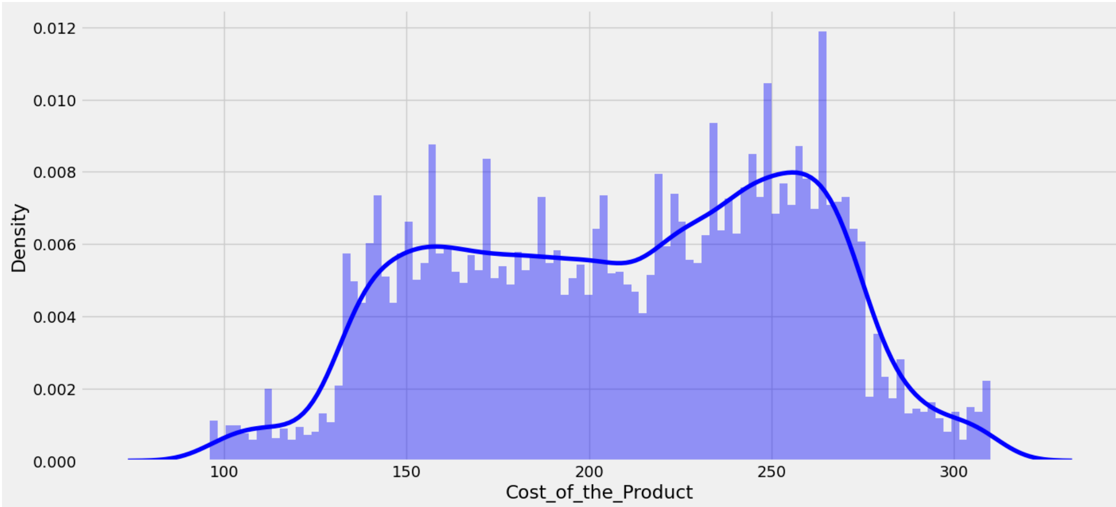


Reached.on.Time

[33]:
```
# looking at the reached on time or not column and what are the categories␣
↪present in it

reached_on_time_y_n = integer_columns['Reached.on.Time_Y.N'].value_counts().
↪reset_index()
reached_on_time_y_n.columns = ['Reached.on.Time_Y.N', 'value_counts']
fig = px.pie(reached_on_time_y_n, names = 'Reached.on.Time_Y.N', values =␣
↪'value_counts',
             color_discrete_sequence = px.colors.sequential.Darkmint_r, width =␣
↪650, height = 400,
            hole = 0.5)
fig.update_traces(textinfo = 'percent+label')
```

Cost of the product

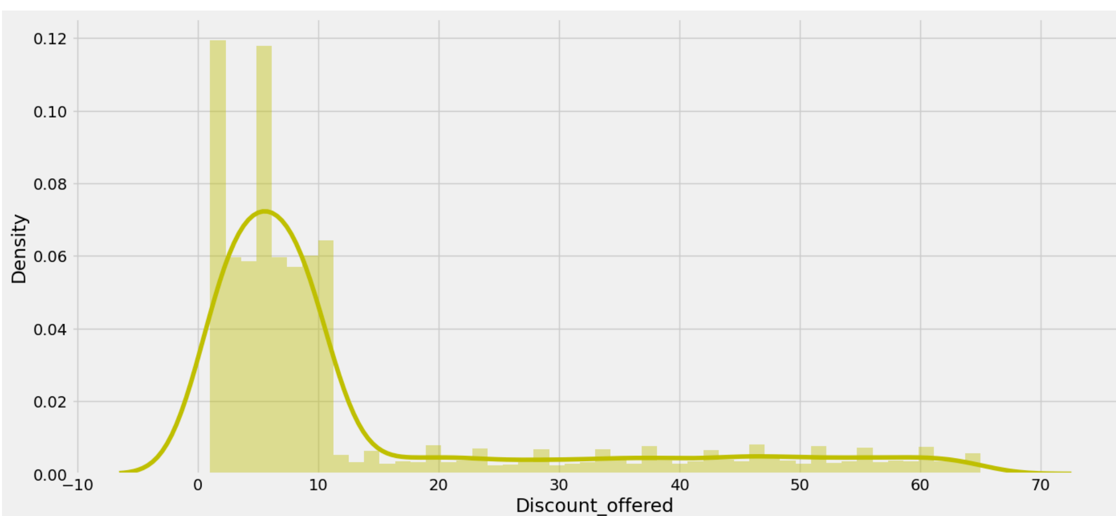
[34]:
```
# making a distplot of cost of the product column

plt.figure(figsize = (15, 7))
ax = sns.distplot(df['Cost_of_the_Product'], bins = 100, color = 'b')

plt.show()
```




```
[35]: # looking at the relation between cost of the product and whether the product␣
      ↪reached on time or not using boxplot

      px.box(data_frame = df, x = 'Reached.on.Time_Y.N', y = 'Cost_of_the_Product',
             color = 'Reached.on.Time_Y.N', template = 'plotly_dark')
```

Discount_offered

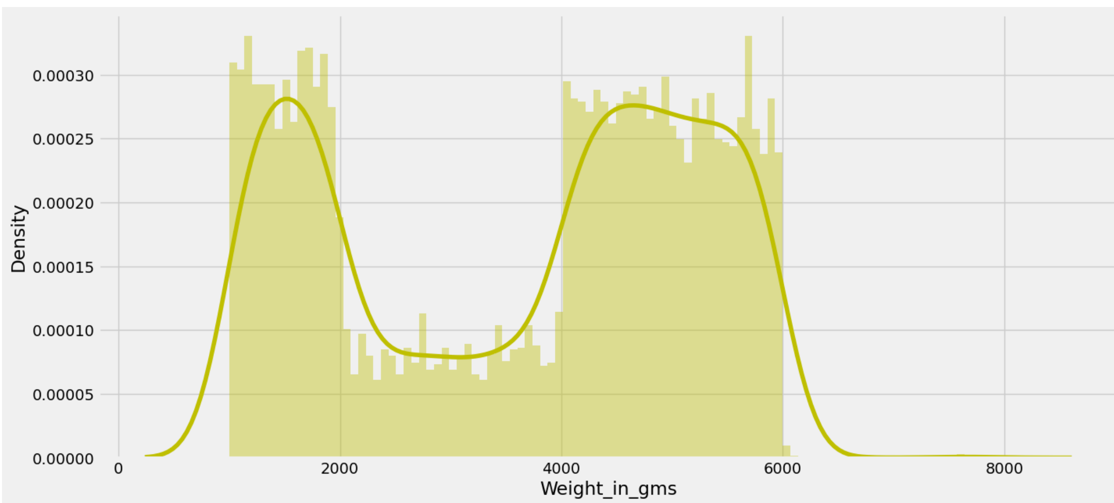
```
[36]: # making a distplot of discount offered column

      plt.figure(figsize = (15, 7))
      ax = sns.distplot(df['Discount_offered'], color = 'y')

      plt.show()
```



[37]:
```
# looking at the relation between discount offered and whether the product␣
↪reached on time or not using boxplot

px.box(data_frame = df, x = 'Reached.on.Time_Y.N', y = 'Discount_offered',
       color = 'Reached.on.Time_Y.N', template = 'plotly_dark')
```

Weight_in_gms

[38]:
```
# making a distplot of weights in gram column

plt.figure(figsize = (15, 7))
ax = sns.distplot(df['Weight_in_gms'], bins = 100, color = 'y')

plt.show()
```



[39]:
```
# looking at the relation between weights in grams and whether the product␣
↪reached on time or not using boxplot\

px.box(data_frame = df, x = 'Reached.on.Time_Y.N', y = 'Weight_in_gms',
       color = 'Reached.on.Time_Y.N', template = 'plotly_dark')
```

Which type of warehouse contains most weights ?

[51]:
```
ware_block_weight = df.groupby(['Warehouse_block'])['Weight_in_gms'].sum()
ware_block_weight.reset_index()
```

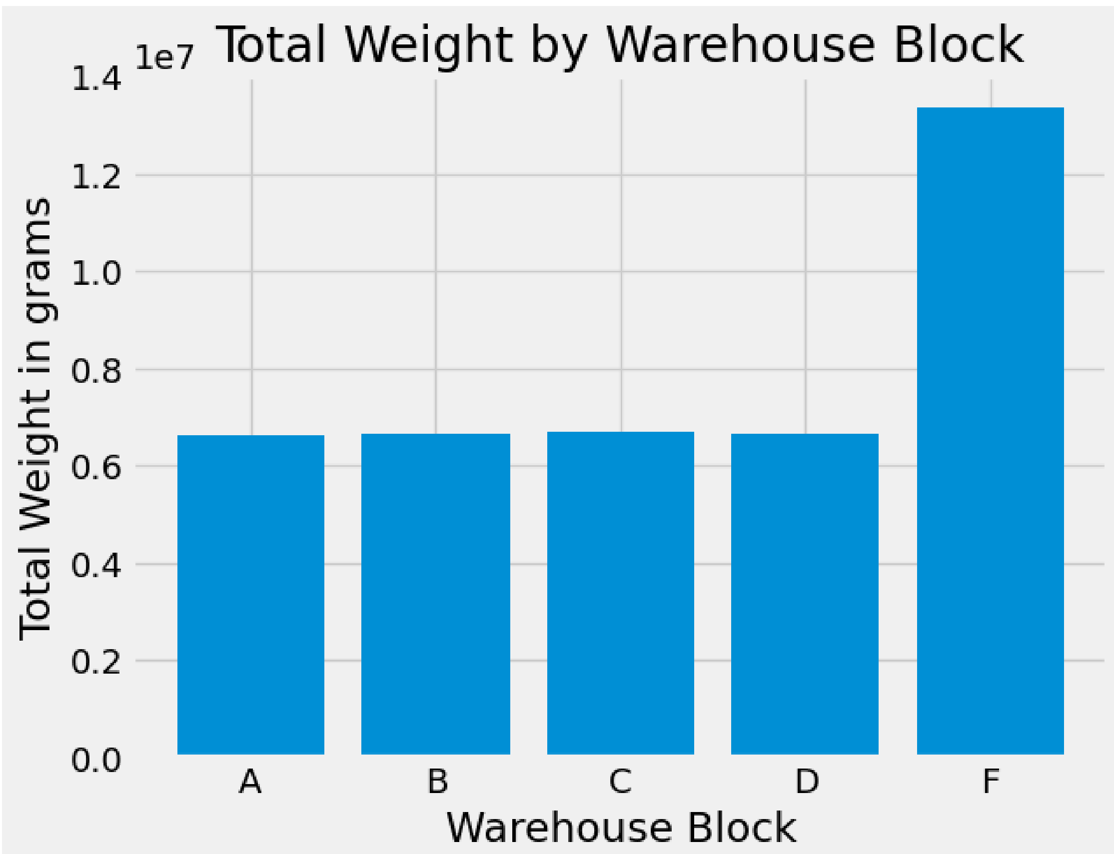
[51]:

	Warehouse_block	Weight_in_gms
0	A	6627118
1	B	6664240

```
2              C       6674560
3              D       6655305
4              F      13349327
```

[55]:
```python
# checking which type of warehouse contains the most weights

plt.bar(ware_block_weight.index, ware_block_weight.values)
plt.xlabel('Warehouse Block')
plt.ylabel('Total Weight in grams')
plt.title('Total Weight by Warehouse Block')
```

[55]:
```
Text(0.5, 1.0, 'Total Weight by Warehouse Block')
```



[54]:
```python
px.histogram(data_frame = df, x = 'Weight_in_gms', nbins = 100, color =␣
↪'Warehouse_block',
             marginal = 'box', template = 'plotly_dark')
```

From above plots we can conclude that warehouse F conatins the most weights.

1 Which mode of shipmemnt carries most weights ?

[57]:
```
#  creating a dataframe of mode of shipment and weights in gram columns

shipment_mode_weight = df.groupby(['Mode_of_Shipment'])['Weight_in_gms'].sum().
  ↪reset_index()
shipment_mode_weight
```

[57]:

	Mode_of_Shipment	Weight_in_gms
0	Flight	6449405
1	Road	6423209
2	Ship	27097936

[58]:
```
# checking which type of shipments carries the most weights

px.histogram(data_frame = df, x = 'Weight_in_gms', nbins = 100, color =␣
  ↪'Mode_of_Shipment',
             marginal = 'box', template = 'plotly_dark')
```

Ship is the mode of shipment throuh which most of the products were delivered

2 Effect of Warehouse on Cost of Product

[59]:
```
# creating a dataframe of warehouse block and cost of the product columns

warehouse_weight = df.groupby(['Warehouse_block'])['Cost_of_the_Product'].sum().
  ↪reset_index()
warehouse_weight
```

[59]:

	Warehouse_block	Cost_of_the_Product
0	A	382671
1	B	388888
2	C	387114
3	D	386805
4	F	766477

[60]:
```
# checking whether or not the warehouse block effects the cost of the product

px.histogram(data_frame = df, x = 'Cost_of_the_Product', nbins = 100, color =␣
  ↪'Warehouse_block',
             marginal = 'box', template = 'plotly_dark')
```

Products from warehouse F have the high costs.

Does Mode of Shipment effect Cost of Product ?

[63]:
```
# creating a dataframe of mode of shipment and cost of the product columns

mode_shipment_cost = df.groupby(['Mode_of_Shipment'])['Cost_of_the_Product'].
↪sum().reset_index()
mode_shipment_cost
```

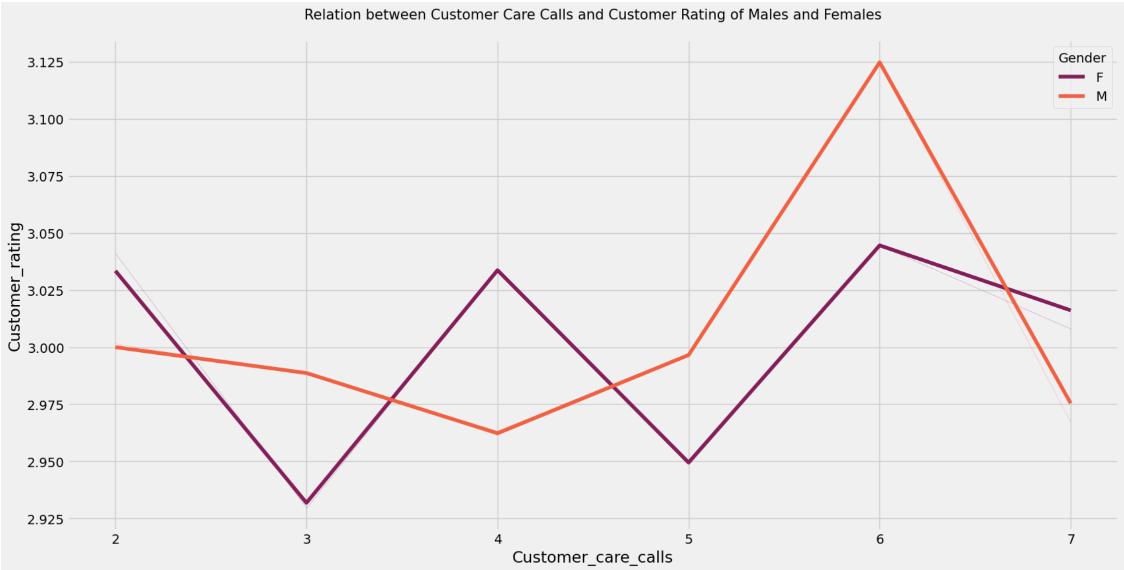
[63]:

	Mode_of_Shipment	Cost_of_the_Product
0	Flight	371938
1	Road	370437
2	Ship	1569580

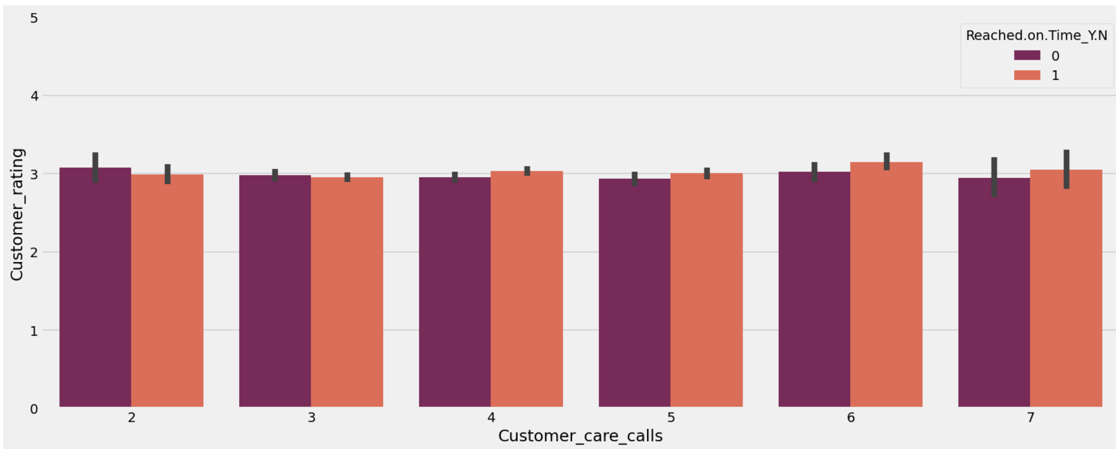
[62]:
```
# checking whether or not the mode of shipment effects the cost of the product

px.histogram(data_frame = df, x = 'Cost_of_the_Product', nbins = 100, color =␣
↪'Mode_of_Shipment',
             marginal = 'box', template = 'plotly_dark')
```

Does Customer calls effect Ratings ?

[68]:
```
plt.figure(figsize = (18, 9))
sns.lineplot(x = 'Customer_care_calls', y = 'Customer_rating', hue = 'Gender',␣
↪data = df,
             palette = 'rocket', ci = 0)
plt.title('Relation between Customer Care Calls and Customer Rating of Males␣
↪and Females\n',
          fontsize = 15)
plt.show()
```

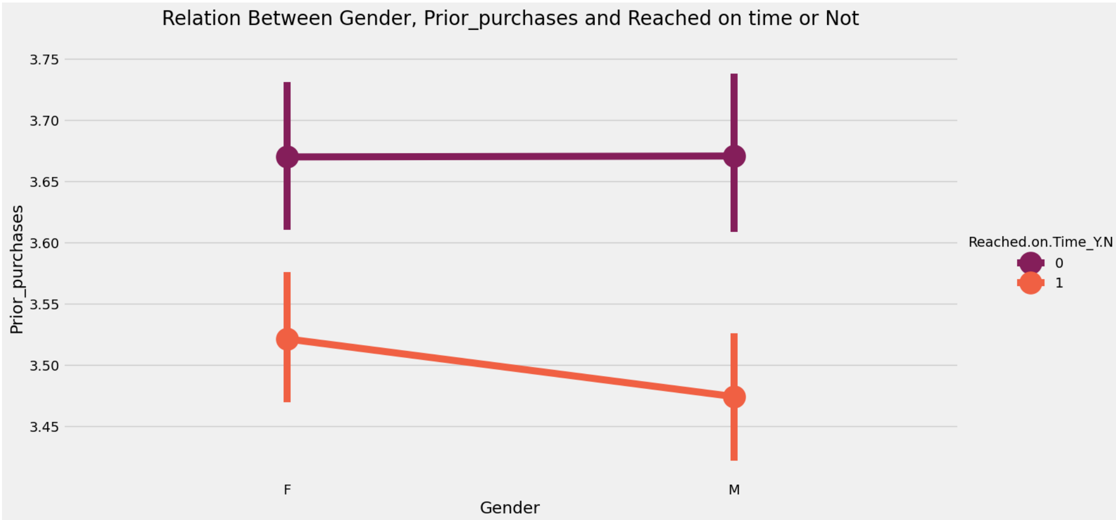


[69]:
```
# checking the relation between customer care calls, customer ratings and␣
↪whether or not the product will reach on time.

plt.figure(figsize = (18, 7))
sns.barplot(x = 'Customer_care_calls', y = 'Customer_rating', hue = 'Reached.on.
↪Time_Y.N', data = df, palette = 'rocket')
plt.ylim(0, 5)
plt.show()
```



Relation Between Gender, Prior_purchases and Reached on time or Not

[70]:
```
# making a lineplot to check the relation between gender, prior purchases and␣
↪reached on time or not

sns.catplot(x = 'Gender', y = 'Prior_purchases', hue = 'Reached.on.Time_Y.N',␣
↪data = df, kind = 'point', height = 7, aspect = 2,
            palette = 'rocket')
plt.title('Relation Between Gender, Prior_purchases and Reached on time or␣
↪Not\n', fontsize = 20)
plt.show()
```



Relation Prior_purchases and Discount Offered and reached on time or not

[71]:
```
# making boxplot between prior purchases and discount offered to see that is␣
↪there any relation between them.

px.box(x = 'Prior_purchases', y = 'Discount_offered', data_frame = df, color =␣
↪'Prior_purchases', template = 'plotly_dark')
```

[72]:
```
# making boxplot between prior purchases, weights in gram and whether or not␣
↪the product will reach on time or not
# to see that is there any relation between them.

px.box(x = 'Prior_purchases', y = 'Weight_in_gms', data_frame = df, color =␣
↪'Reached.on.Time_Y.N', template = 'plotly_dark')
```

[73]:
```
# making boxplot between customer care calls, weights in gram and whether or␣
↪not the product will reach on time or not
# to see that is there any relation between them.

px.box(x = 'Customer_care_calls', y = 'Weight_in_gms', data_frame = df, color =␣
↪'Reached.on.Time_Y.N', template = 'plotly_dark')
```

[74]:
```
# making boxplot between customer care calls, cost of product and whether or␣
↪not the product will reach on time or not
# to see that is there any relation between them.

px.box(x = 'Customer_care_calls', y = 'Cost_of_the_Product', data_frame = df,␣
↪color = 'Reached.on.Time_Y.N',
       template = 'plotly_dark')
```

Customer calls were more when the cost of product is high.

Now lets check the relation between cost of the product and the discount offered and the relation with whether or not the product will reach on time¶

[75]:
```
# creating scatter plot to see the relation between cost of the product and the discount offered and the relation with
# whether or not th product will reach on time

plt.figure(figsize = (15, 7))
sns.scatterplot(x='Discount_offered', y='Cost_of_the_Product', data=df, hue='Reached.on.Time_Y.N')

plt.show()
```

3 Categorical Variable Encoding

[76]:
```
df['Warehouse_block'] = df['Warehouse_block'].map({'A' : 0, 'B': 1, 'C': 2, 'D': 3, 'F': 4})
df['Mode_of_Shipment'] = df['Mode_of_Shipment'].map({'Flight' : 0, 'Ship': 1, 'Road': 2})
df['Product_importance'] = df['Product_importance'].map({'low' : 0, 'medium': 1, 'high': 2})
df['Gender'] = df['Gender'].apply(lambda val: 1 if val == 'M' else 0)
```

[77]:
```
df.head()
```

[77]:
```
   Warehouse_block  Mode_of_Shipment  Customer_care_calls  Customer_rating  \
0                3                 0                    4                2
```

```
1               4               0                 4             5
2               0               0                 2             2
3               1               0                 3             2
4               2               0                 2             2

   Cost_of_the_Product  Prior_purchases  Product_importance  Gender  \
0                  177                3                   0       0
1                  216                2                   0       1
2                  183                4                   0       1
3                  176                4                   1       1
4                  184                3                   1       0

   Discount_offered  Weight_in_gms  Reached.on.Time_Y.N
0                44           1233                    1
1                59           3088                    1
2                48           3374                    1
3                10           1177                    1
4                46           2484                    1
```

[78]:
```
#  creating features and label

X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

[79]:
```
# spilting our data into training and test data

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,␣
↪random_state = 0)
```

[80]:
```
# Scaling the data using standardscaler

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

4 Now the data is preprocessed, and is ready to used to make predictions using machine learning models

[ ]:
```

```