Porter

September 27, 2023

1 Problem Statement

1.1 1. Import the data and understand the structure of the data:

1.1.1 Usual exploratory analysis steps like checking the structure & characteristics of the dataset

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
sns.set(style="darkgrid")

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor

import torch
import torchvision
import torch.nn as nn
from torch.utils.data import DataLoader,Dataset, random_split

from tqdm import tqdm_notebook as tqdm
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
df = pd.read_csv("dataset.csv")
df.head()
```

[2]:
```
   market_id          created_at actual_delivery_time  \
0        1.0  2015-02-06 22:24:17  2015-02-06 23:27:16
1        2.0  2015-02-10 21:49:25  2015-02-10 22:56:29
2        3.0  2015-01-22 20:39:28  2015-01-22 21:09:09
3        3.0  2015-02-03 21:21:45  2015-02-03 22:13:00
4        3.0  2015-02-15 02:40:36  2015-02-15 03:20:26
```

```
                          store_id store_primary_category  order_protocol  \
0  df263d996281d984952c07998dc54358               american             1.0
1  f0ade77b43923b38237db569b016ba25                mexican             2.0
2  f0ade77b43923b38237db569b016ba25                    NaN             1.0
3  f0ade77b43923b38237db569b016ba25                    NaN             1.0
4  f0ade77b43923b38237db569b016ba25                    NaN             1.0

   total_items  subtotal  num_distinct_items  min_item_price  max_item_price  \
0            4      3441                   4             557            1239
1            1      1900                   1            1400            1400
2            1      1900                   1            1900            1900
3            6      6900                   5             600            1800
4            3      3900                   3            1100            1600

   total_onshift_partners  total_busy_partners  total_outstanding_orders
0                    33.0                 14.0                      21.0
1                     1.0                  2.0                       2.0
2                     1.0                  0.0                       0.0
3                     1.0                  1.0                       2.0
4                     6.0                  6.0                       9.0
```

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 197428 entries, 0 to 197427
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   market_id                 196441 non-null  float64
 1   created_at                197428 non-null  object
 2   actual_delivery_time      197421 non-null  object
 3   store_id                  197428 non-null  object
 4   store_primary_category    192668 non-null  object
 5   order_protocol            196433 non-null  float64
 6   total_items               197428 non-null  int64
 7   subtotal                  197428 non-null  int64
 8   num_distinct_items        197428 non-null  int64
 9   min_item_price            197428 non-null  int64
 10  max_item_price            197428 non-null  int64
 11  total_onshift_partners    181166 non-null  float64
 12  total_busy_partners       181166 non-null  float64
 13  total_outstanding_orders  181166 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 21.1+ MB
```

[4]:
```
df.columns
```

[4]:
```
Index(['market_id', 'created_at', 'actual_delivery_time', 'store_id',
       'store_primary_category', 'order_protocol', 'total_items', 'subtotal',
       'num_distinct_items', 'min_item_price', 'max_item_price',
       'total_onshift_partners', 'total_busy_partners',
       'total_outstanding_orders'],
      dtype='object')
```

[5]:
```
df.describe()
```

[5]:
```
           market_id  order_protocol    total_items       subtotal  \
count  196441.000000   196433.000000  197428.000000  197428.000000
mean        2.978706        2.882352       3.196391    2682.331402
std         1.524867        1.503771       2.666546    1823.093688
min         1.000000        1.000000       1.000000       0.000000
25%         2.000000        1.000000       2.000000    1400.000000
50%         3.000000        3.000000       3.000000    2200.000000
75%         4.000000        4.000000       4.000000    3395.000000
max         6.000000        7.000000     411.000000   27100.000000

       num_distinct_items  min_item_price  max_item_price  \
count       197428.000000   197428.000000   197428.000000
mean             2.670791      686.218470     1159.588630
std              1.630255      522.038648      558.411377
min              1.000000      -86.000000        0.000000
25%              1.000000      299.000000      800.000000
50%              2.000000      595.000000     1095.000000
75%              3.000000      949.000000     1395.000000
max             20.000000    14700.000000    14700.000000

       total_onshift_partners  total_busy_partners  total_outstanding_orders
count           181166.000000        181166.000000             181166.000000
mean                44.808093            41.739747                 58.050065
std                 34.526783            32.145733                 52.661830
min                 -4.000000            -5.000000                 -6.000000
25%                 17.000000            15.000000                 17.000000
50%                 37.000000            34.000000                 41.000000
75%                 65.000000            62.000000                 85.000000
max                171.000000           154.000000                285.000000
```

[6]:
```
df.describe(include="object")
```

[6]:
```
                 created_at actual_delivery_time  \
count                197428               197421
unique               180985               178110
top     2015-02-11 19:50:43  2015-02-11 20:40:45
freq                      6                    5
```

```
                                   store_id store_primary_category
count                                197428                 192668
unique                                 6743                     74
top     d43ab110ab2489d6b9b2caa394bf920f               american
freq                                    937                  19399
```

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

[7]:
```
(197428, 14)
```

1.2 2. Data preprocessing

1. Cleaning of data

- Convert created_at column datatype to datetime
- Convert actual_delivery_time to datetime format

[8]:
```
df["created_at"] = pd.to_datetime(df["created_at"])
df["actual_delivery_time"] = pd.to_datetime(df["actual_delivery_time"])
```

[9]:
```
df.isnull().sum()
```

[9]:
```
market_id                     987
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
dtype: int64
```

2. Feature engineering: Creating the target column

[10]:
```
df["delivery_time"] = (df["actual_delivery_time"]-df["created_at"]).dt.
 ↪total_seconds()/60
df["created_hour"] = df["created_at"].dt.hour
df["day_of_week"] = df["created_at"].dt.day_of_week
```

1.3 3. Handling null values

[11]:
```
df.isnull().sum()
```

[11]:
```
market_id                     987
created_at                      0
actual_delivery_time            7
store_id                        0
store_primary_category       4760
order_protocol                995
total_items                     0
subtotal                        0
num_distinct_items              0
min_item_price                  0
max_item_price                  0
total_onshift_partners      16262
total_busy_partners         16262
total_outstanding_orders    16262
delivery_time                   7
created_hour                    0
day_of_week                     0
dtype: int64
```

- we can import null values for the column store__primary__category with reference values
- Remaining we have filled with values:0
- Continuous variable will be filled with median values

[12]:
```
values = {}
for i in df["store_id"]:
    if i not in values:
        dict = {}
        for j in df[df["store_id"] == i]["store_primary_category"]:
            if j in dict:
                dict[j] += 1
            dict[j] = 1
        values[i] = max(dict, key= lambda x: dict[x])
df["store_primary_category"] = df.apply(lambda x: values[x["store_id"]] if␣
 ↪x["store_primary_category"] != x["store_primary_category"] else␣
 ↪x["store_primary_category"],axis=1)
df["store_primary_category"] = df["store_primary_category"].fillna(0)
```

[13]:
```
df["order_protocol"] = df["order_protocol"].fillna(df["order_protocol"].
 ↪median())
df["total_onshift_partners"] = df["total_onshift_partners"].
 ↪fillna(df["total_onshift_partners"].median())
df["total_busy_partners"] = df["total_busy_partners"].
 ↪fillna(df["total_busy_partners"].median())
```

```
df["total_outstanding_orders"] = df["total_outstanding_orders"].
 ↪fillna(df["total_outstanding_orders"].median())
df["market_id"] = df["market_id"].fillna(0)
```

[14]:
```
df.dropna(inplace=True)
```

1.4 4. Encoding categorical columns

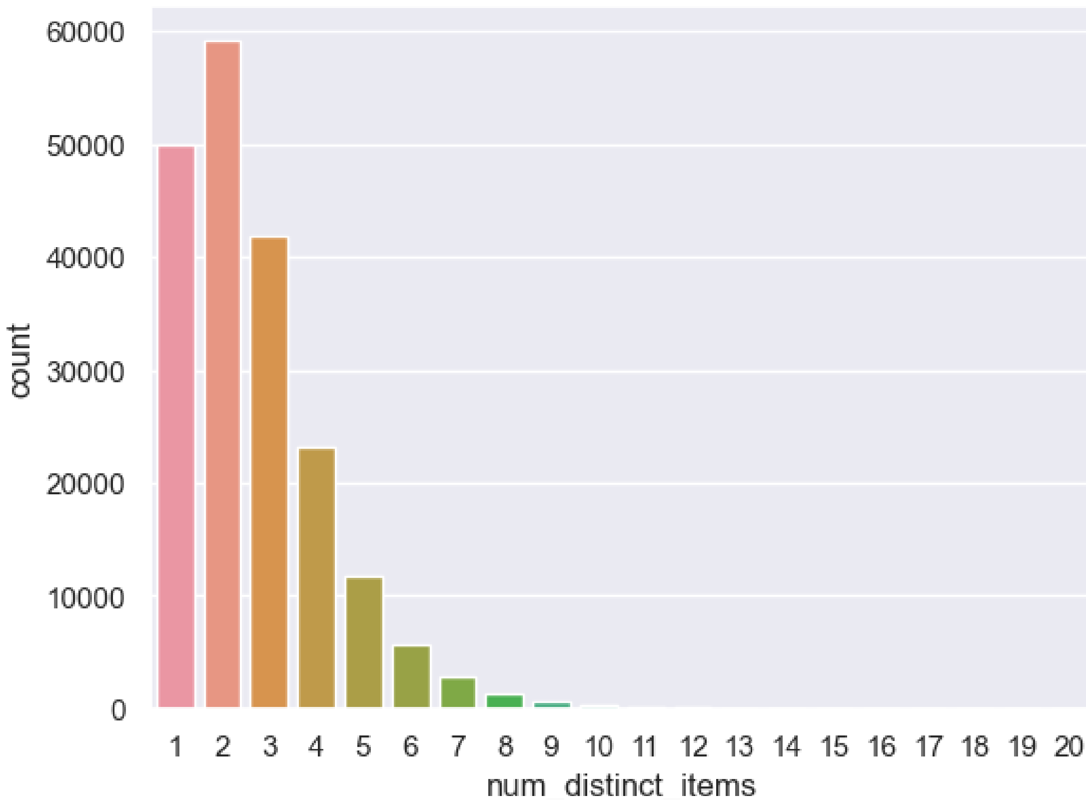
[15]:
```
val = {}
for i, value in enumerate(df["store_primary_category"].unique()):
    if i < 17:
        val[value] = i+1
    elif i == 16 and value == 0:
        val[value] = 0
    else:
        val[value] = i
val[0] = 0
df["store_primary_category"].replace(val,inplace=True)
```

1.5 5. Data visualization and cleaning

1. Visualize various columns for better understanding Countplots, scatterplots

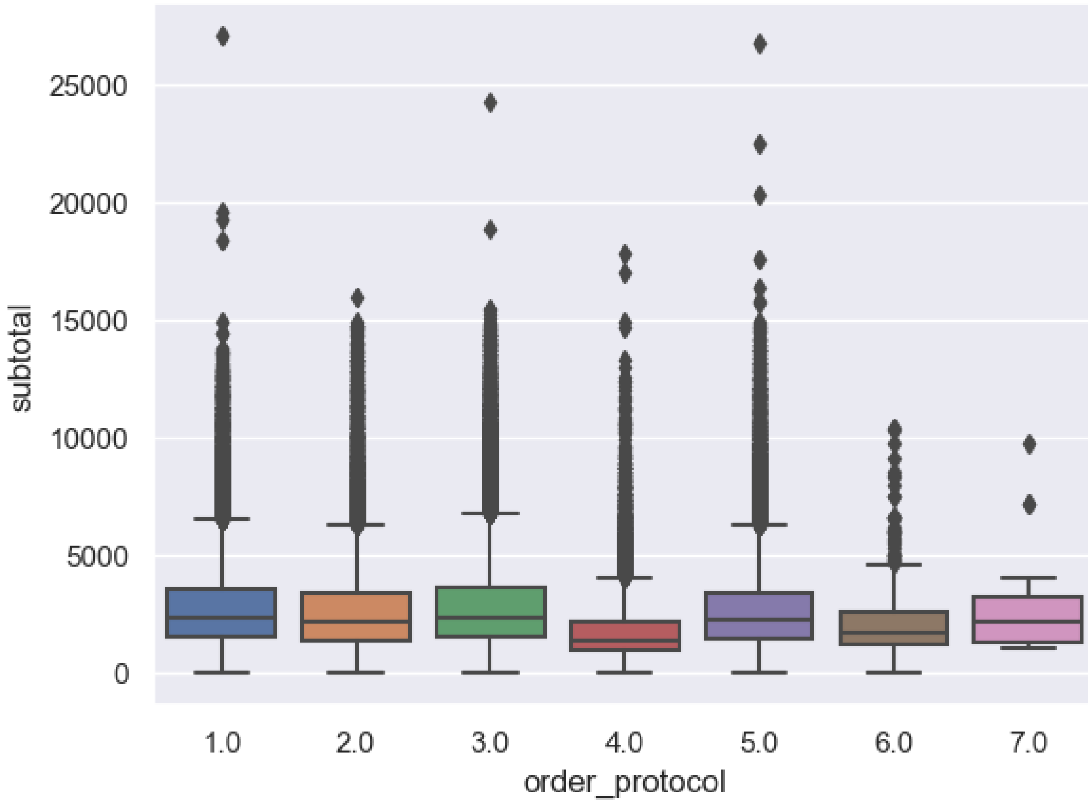
[17]:
```
sns.countplot(data=df,x="num_distinct_items")
```

[17]: <Axes: xlabel='num_distinct_items', ylabel='count'>



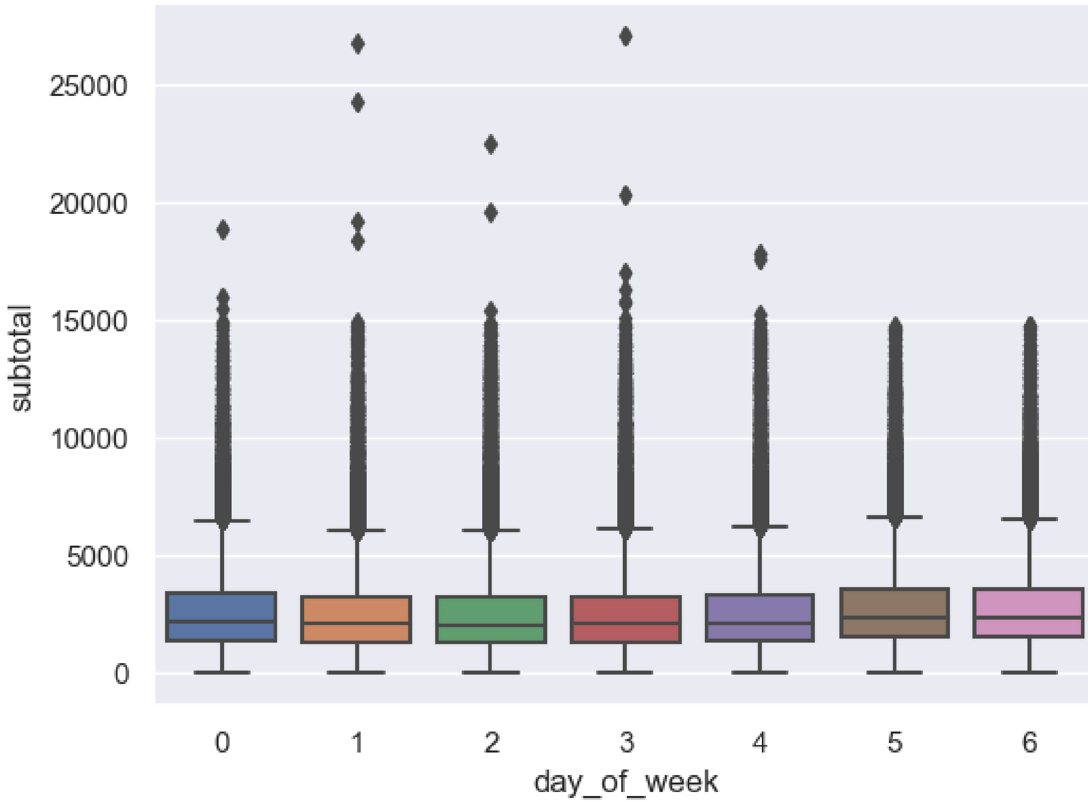
[18]:
```
sns.boxplot(data= df ,x ="order_protocol",y= "subtotal")
```

[18]: <Axes: xlabel='order_protocol', ylabel='subtotal'>




```
[19]: sns.boxplot(data= df ,x ="day_of_week",y= "subtotal")
```

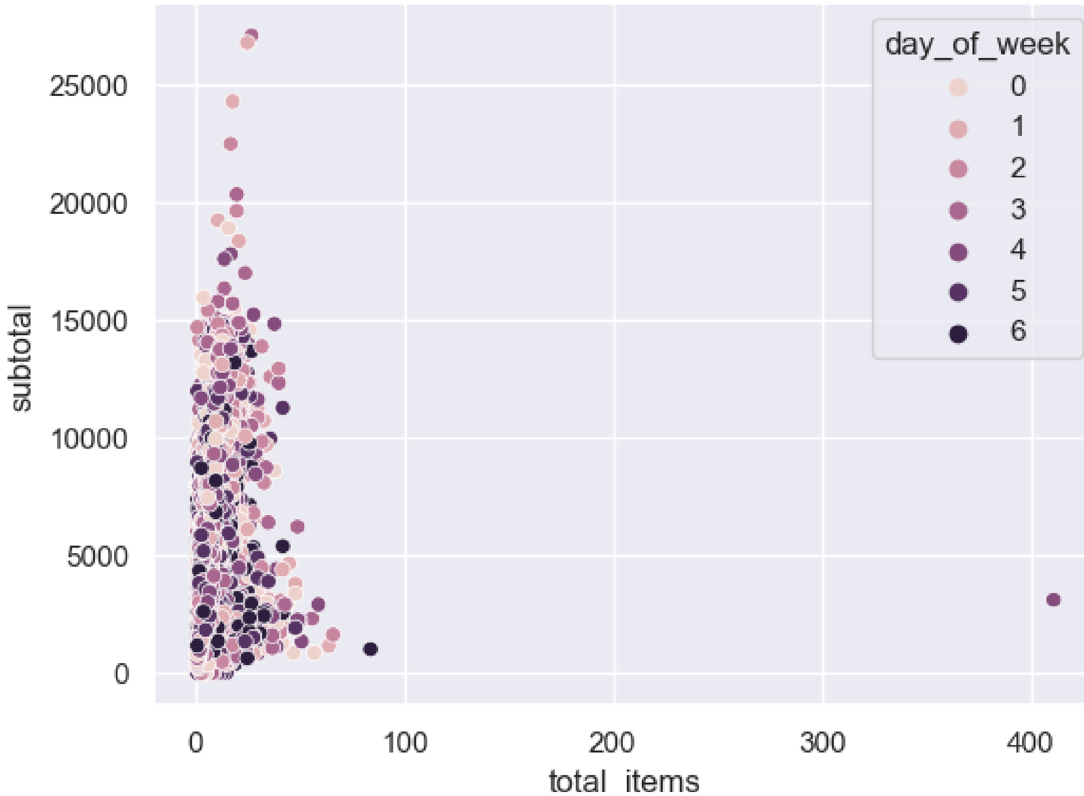
```
[19]: <Axes: xlabel='day_of_week', ylabel='subtotal'>
```



[20]:
```
fig = px.scatter(df,x ="total_items",y=
    "subtotal",color="day_of_week",size="max_item_price")
fig.show()
```

[21]:
```
sns.scatterplot(data= df ,x ="total_items",y= "subtotal",hue="day_of_week")
```

[21]: `<Axes: xlabel='total_items', ylabel='subtotal'>`

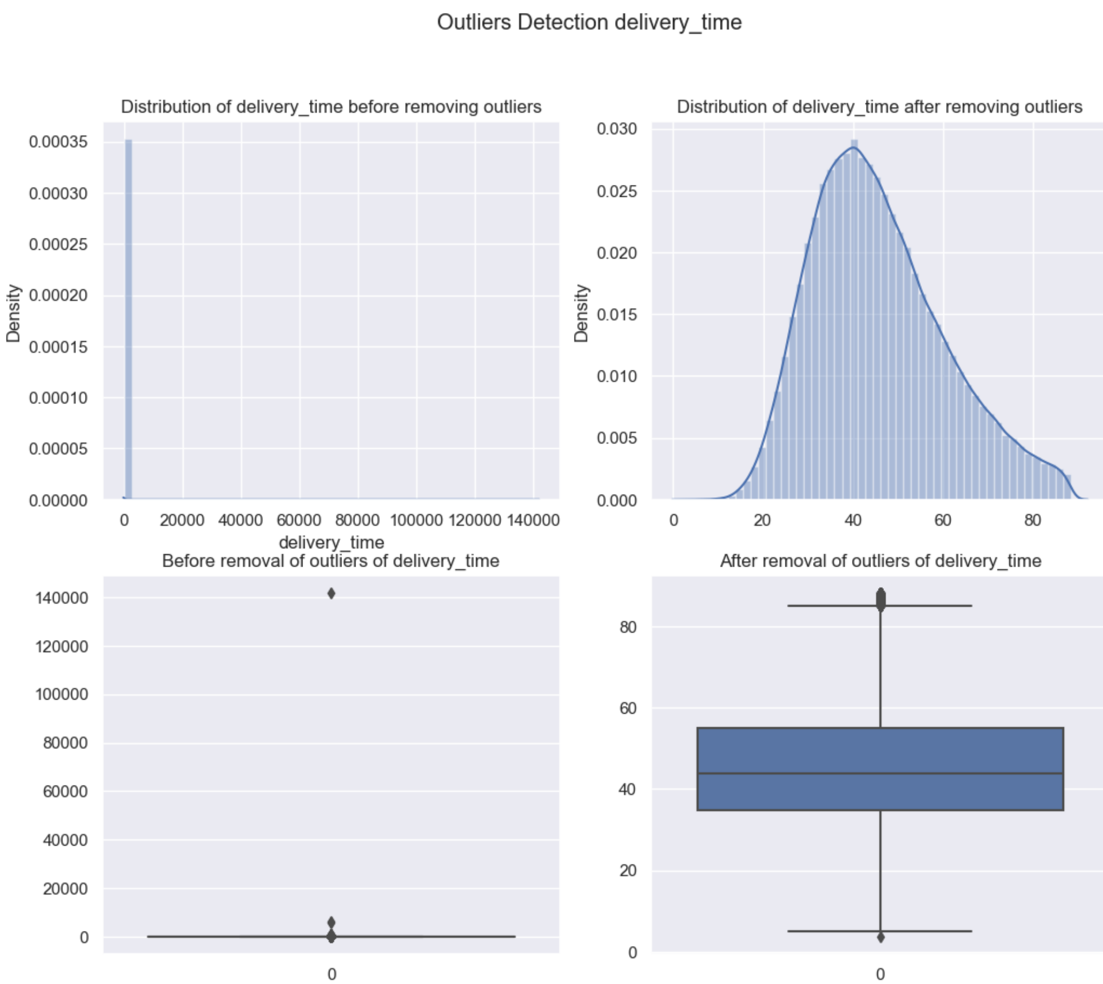


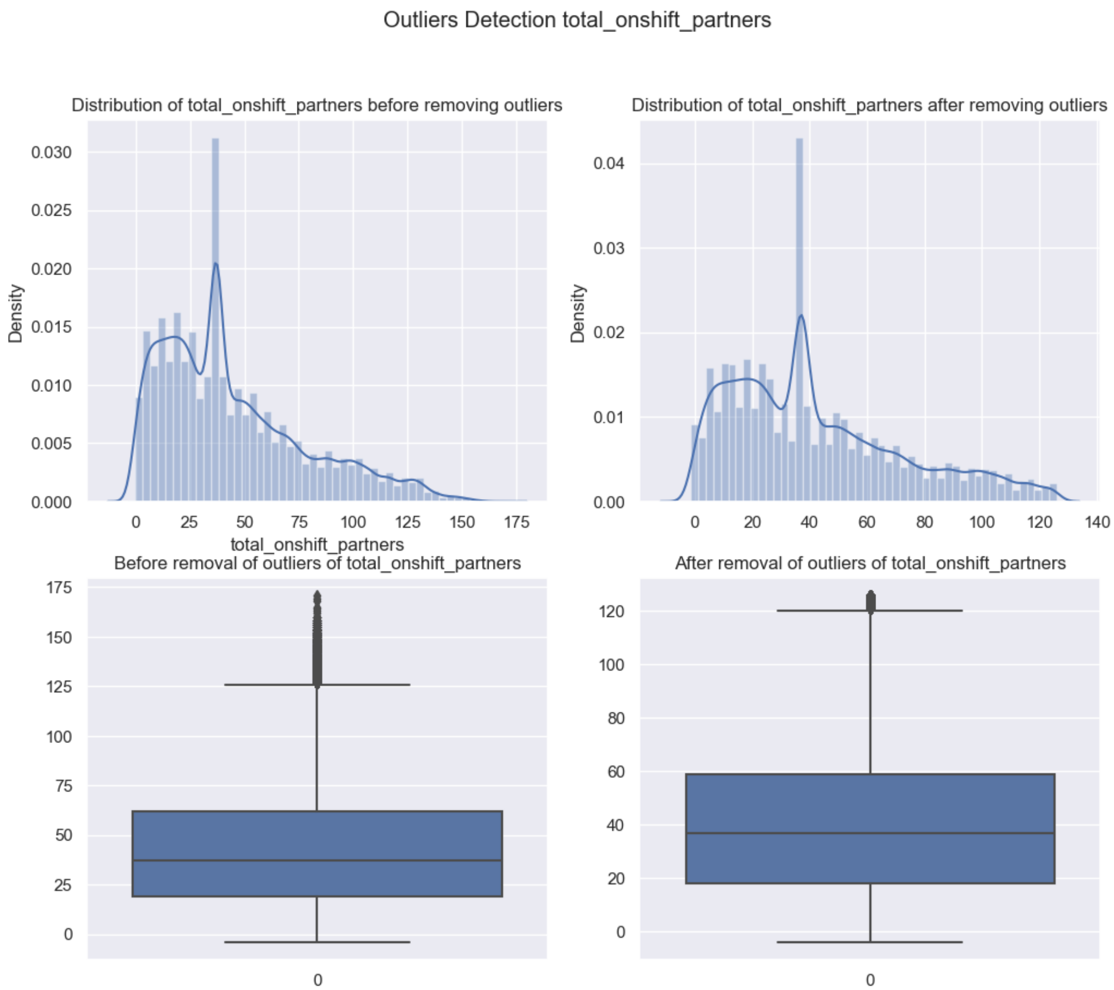
[22]:
```
fig = px.pie(df, values='subtotal', names='day_of_week',title="Percentile of␣
↪subtotal in day of week",color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_traces(textposition='inside', textinfo='percent+label')
fig.show()
```

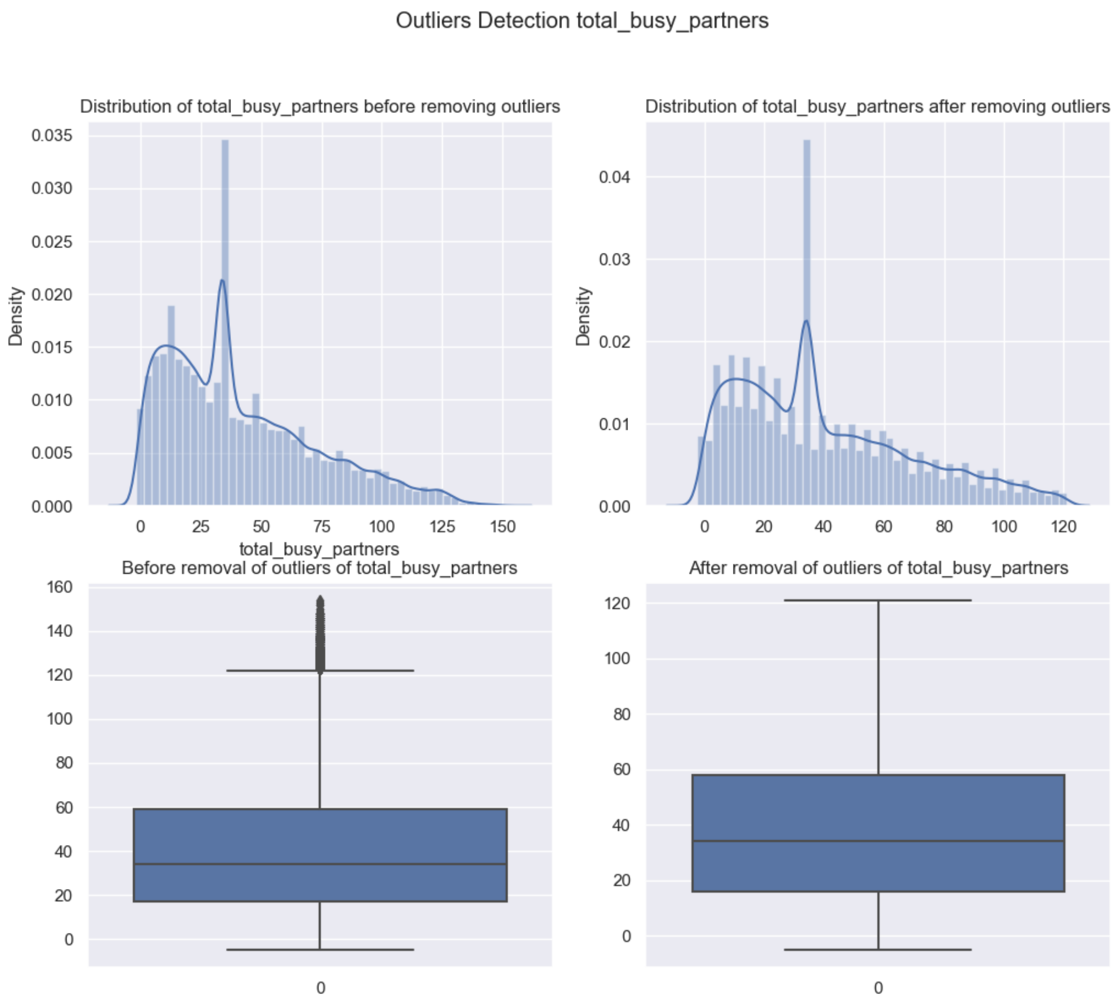
1.6 6. Check if the data contains outliers

[23]:
```
numerical_variable = ["delivery_time"        ,"total_onshift_partners",␣
↪"total_busy_partners","total_outstanding_orders","min_item_price","max_item_price","subtota
for i in range(len(numerical_variable)):
    col = numerical_variable[i]

    upper = df[col].quantile(.75)
    lower = df[col].quantile(.25)
    iqr = upper - lower
    upper_limit = upper + 1.5 * iqr
    lower_limit = lower - 1.5 * iqr

    #Non_outlier data
    non_outlier_data = np.array(df[(df[col] < upper_limit) & (df[col] >␣
↪lower_limit)][col]).reshape(1,-1)
```

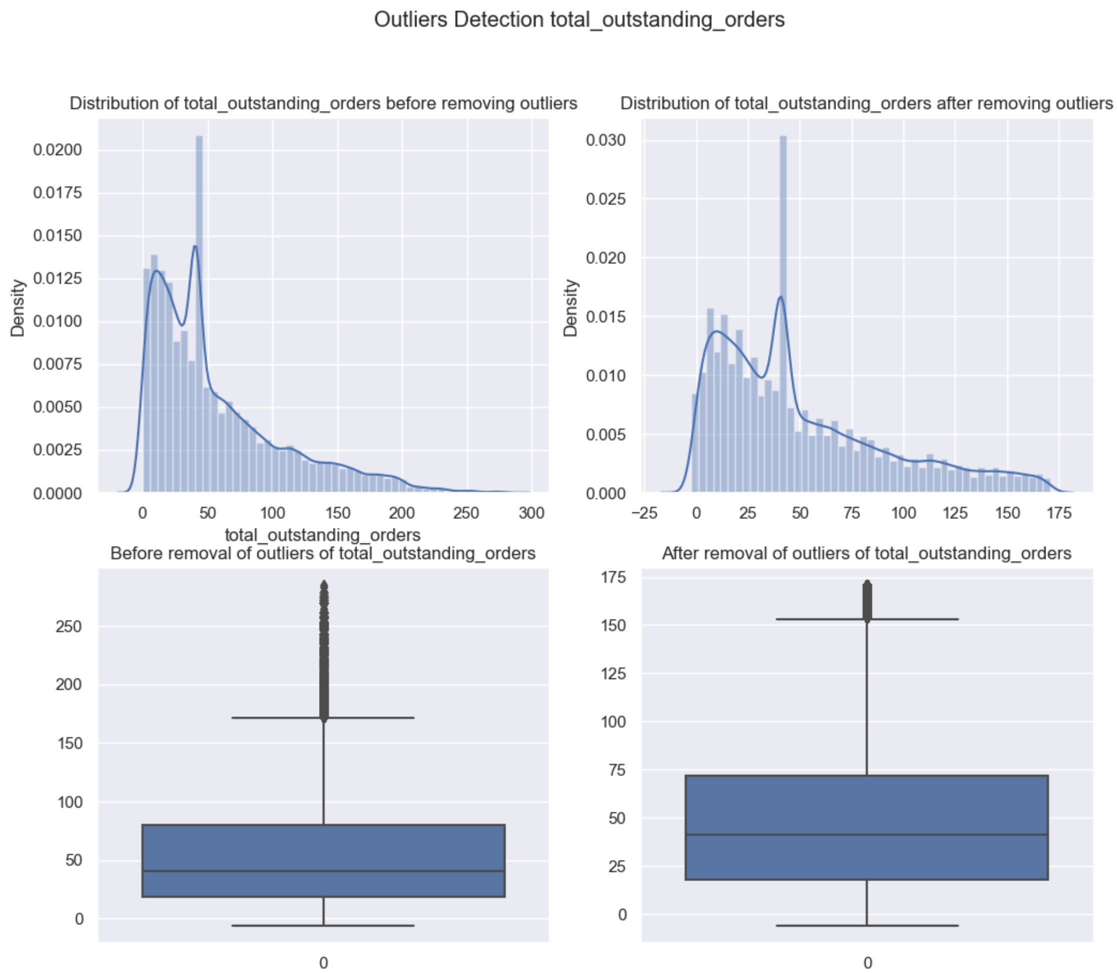
```python
# Even though we have filtered outliers based on IQR range
# But data still have outliers values, this can be ignorable

fig, axes = plt.subplots(2,2, figsize=(12,10))
fig.suptitle(f"Outliers Detection {numerical_variable[i]}")
sns.distplot(ax = axes[0,0],a=df[numerical_variable[i]])
axes[0,0].set_title(f"Distribution of {numerical_variable[i]} before removing outliers")
sns.distplot(ax = axes[0,1],a=non_outlier_data)
axes[0,1].set_title(f"Distribution of {numerical_variable[i]} after removing outliers")
sns.boxplot(ax = axes[1,0],data = df[numerical_variable[i]])
axes[1,0].set_title(f"Before removal of outliers of {numerical_variable[i]}")
sns.boxplot(ax = axes[1,1],data=non_outlier_data)
axes[1,1].set_title(f"After removal of outliers of {numerical_variable[i]}")

plt.show()
```



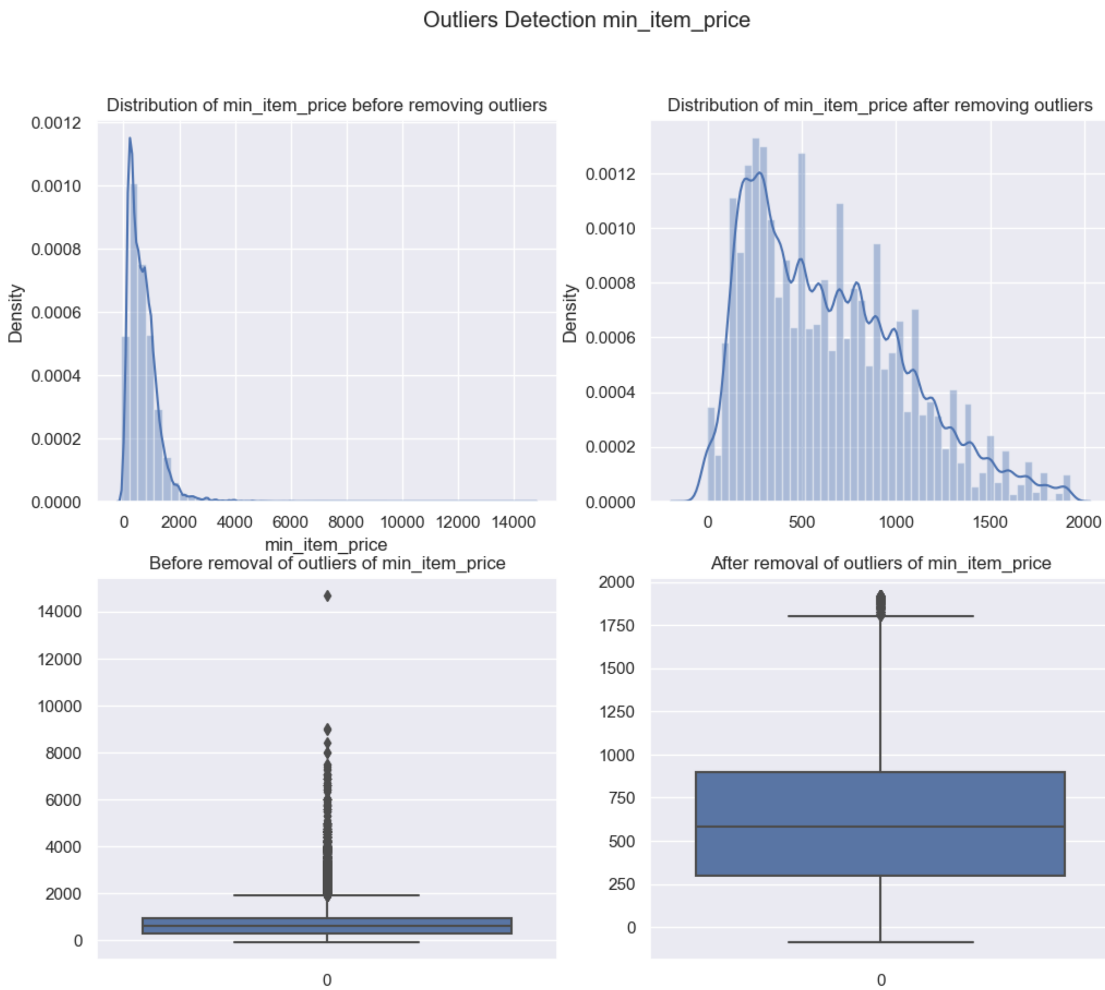

Outliers Detection total_onshift_partners
Distribution of total_onshift_partners before removing outliers
Distribution of total_onshift_partners after removing outliers
Density
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0 25 50 75 100 125 150 175
total_onshift_partners
0.04
0.03
0.02
0.01
0.00
0 20 40 60 80 100 120 140
Before removal of outliers of total_onshift_partners
After removal of outliers of total_onshift_partners
175 150 125 100 75 50 25 0
120 100 80 60 40 20 0
0

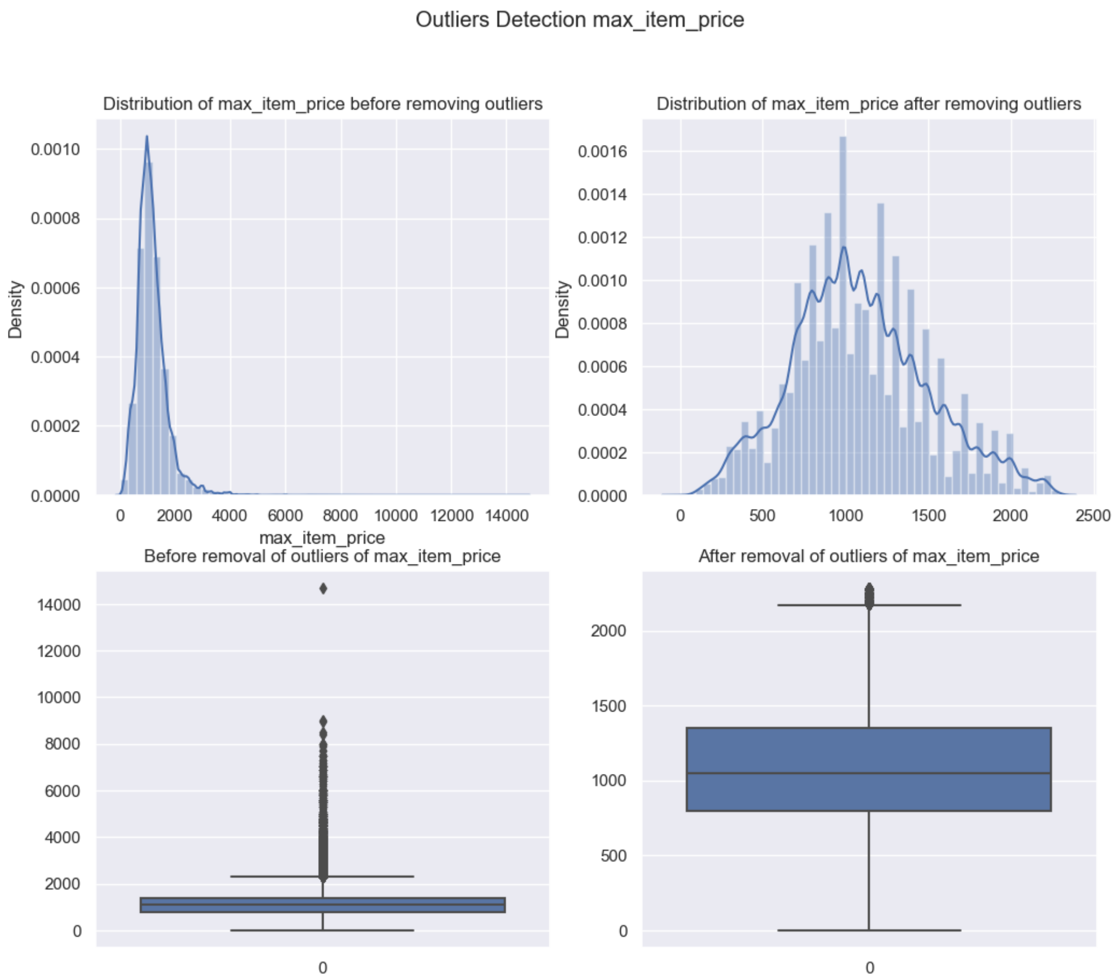


Outliers Detection total_busy_partners
Distribution of total_busy_partners before removing outliers
Distribution of total_busy_partners after removing outliers
Density
total_busy_partners
Before removal of outliers of total_busy_partners
After removal of outliers of total_busy_partners

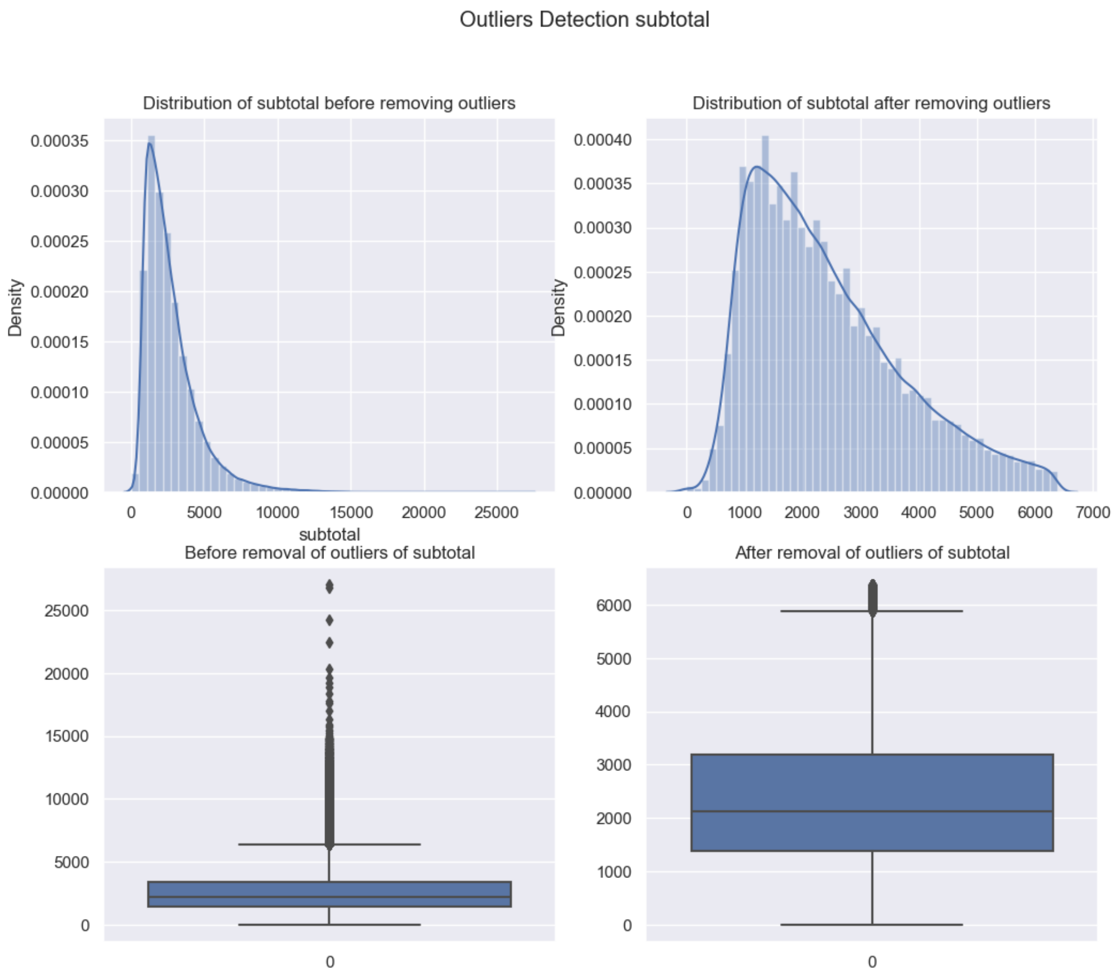


Outliers Detection total_outstanding_orders
Distribution of total_outstanding_orders before removing outliers
Distribution of total_outstanding_orders after removing outliers
Density
0.0200
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
0
50
100
150
200
250
300
total_outstanding_orders
0.030
0.025
0.020
0.015
0.010
0.005
0.000
−25
0
25
50
75
100
125
150
175
Before removal of outliers of total_outstanding_orders
After removal of outliers of total_outstanding_orders
250
200
150
100
50
0
175
150
125
100
75
50
25
0


Outliers Detection min_item_price
Distribution of min_item_price before removing outliers
Density
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
2000
4000
6000
8000
10000
12000
14000
min_item_price
Distribution of min_item_price after removing outliers
Density
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
0
500
1000
1500
2000
Before removal of outliers of min_item_price
14000
12000
10000
8000
6000
4000
2000
0
0
After removal of outliers of min_item_price
2000
1750
1500
1250
1000
750
500
250
0
0



Outliers Detection max_item_price
Distribution of max_item_price before removing outliers
Distribution of max_item_price after removing outliers
Density
max_item_price
Before removal of outliers of max_item_price
After removal of outliers of max_item_price




```
[24]: non_outlier = df
      numerical_variable = ["delivery_time"        ,"total_onshift_partners",␣
       ↪"total_busy_partners","total_outstanding_orders","min_item_price","max_item_price","subtota
      for i in range(len(numerical_variable)):
          col = numerical_variable[i]

          upper = df[col].quantile(.75)
          lower = df[col].quantile(.25)
          iqr = upper - lower
          upper_limit = upper + 1.5 * iqr
          lower_limit = lower - 1.5 * iqr
          non_outlier = non_outlier[(non_outlier[col] < upper_limit) &␣
       ↪(non_outlier[col] > lower_limit)]
```

```
[25]: fig = px.histogram(non_outlier,x="delivery_time")
      fig.show()
```

1.7 7. Split the data in train and test

[40]:
```
encoded_df = pd.get_dummies(data=non_outlier,columns=["market_id",␣
 ↪"order_protocol"])
```

[41]:
```
x = encoded_df.
 ↪drop(["created_at","actual_delivery_time","store_id","delivery_time"],axis=1)
y = encoded_df.delivery_time.values
feature_list = list(x.columns)
x = x.values
```

[42]:
```
xtrain,xtest,ytrain,ytest = train_test_split(x,y,train_size=0.8)
print(xtrain.shape)
print(xtest.shape)
print(ytrain.shape)
print(ytest.shape)
```

```
(132852, 25)
(33213, 25)
(132852,)
(33213,)
```

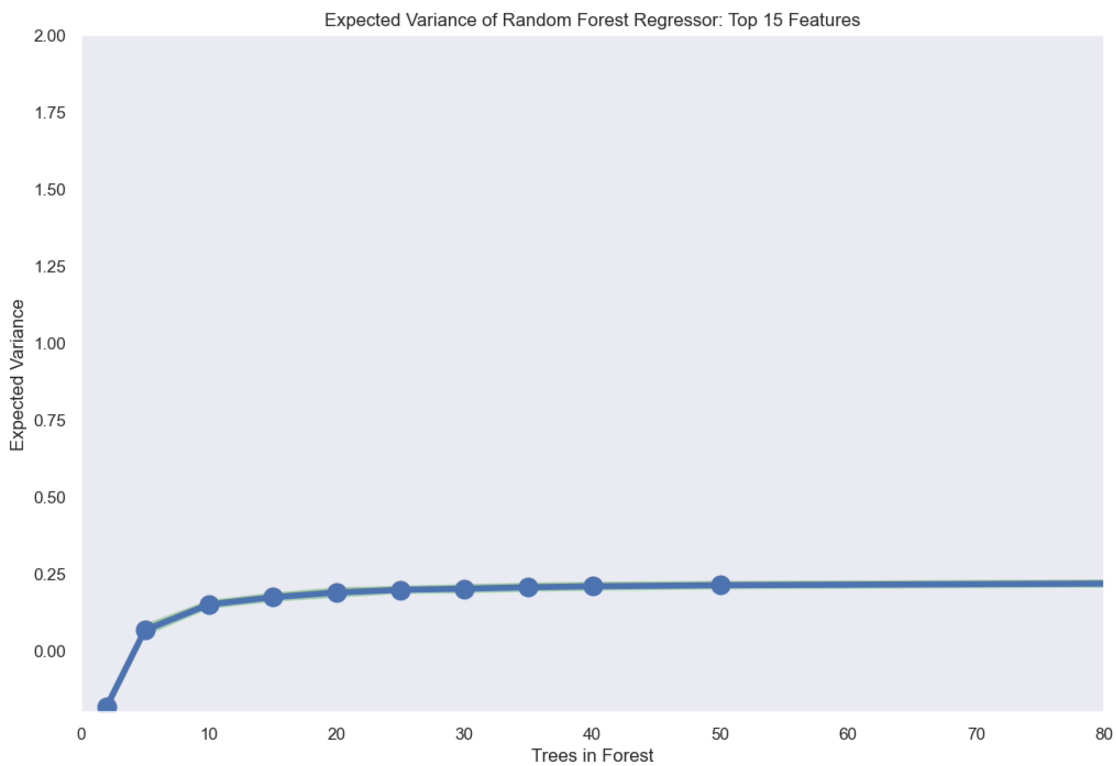
[43]:
```
sc = StandardScaler()
xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
```

- Initialize the model
- Checking on which parameter our model gives high accuracy with cross val score
- Hyper parameter tuning of estimators in our model

[104]:
```
estimators = [2, 5, 10, 15, 20, 25, 30, 35, 40,50,100,250,500,1000]
mean_rfrs = []
std_rfrs_upper = []
std_rfrs_lower = []
np.random.seed(11111)
# for each number of estimators, fit the model and find the results for 8-fold␣
 ↪cross validation
for i in tqdm(estimators):
    model = RandomForestRegressor(n_estimators=i,max_depth=None,n_jobs=-1)
    scores_rfr = cross_val_score(model,xtrain,ytrain,cv=10)
    mean_rfrs.append(scores_rfr.mean())
    std_rfrs_upper.append(scores_rfr.mean()+scores_rfr.std()*2) # for error␣
 ↪plotting
    std_rfrs_lower.append(scores_rfr.mean()-scores_rfr.std()*2)

fig = plt.figure(figsize=(12,8))
ax = fig.add_subplot(111)
ax.plot(estimators,mean_rfrs,marker='o',
```

```
        linewidth=4,markersize=12)
ax.fill_between(estimators,std_rfrs_lower,std_rfrs_upper,
                facecolor='green',alpha=0.3,interpolate=True)
ax.set_ylim([-.2,2])
ax.set_xlim([0,80])
plt.title('Expected Variance of Random Forest Regressor: Top 15 Features')
plt.ylabel('Expected Variance')
plt.xlabel('Trees in Forest')
plt.grid()
plt.show()
```

```
0%|          | 0/14 [00:00<?, ?it/s]
```



[44]:
```
model = RandomForestRegressor(n_estimators=100,max_depth=None,n_jobs=-1)
model.fit(xtrain,ytrain)
```

[44]:
```
RandomForestRegressor(n_jobs=-1)
```

[45]:
```
predictions = model.predict(xtest)
# Calculate the absolute errors
errors = abs(predictions - ytest)
# Print out the mean absolute error (mae)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

```
from sklearn.metrics import mean_squared_error
from math import sqrt

# Print out the mean sqrt error (mae)
rms = sqrt(mean_squared_error(ytest,predictions))
print('Mean Absolute Error:', round(rms,2), 'degrees.')
print("Model_score:", round(model.score(xtest,ytest)*100,2))
```

```
Mean Absolute Error: 10.15 degrees.
Mean Absolute Error: 12.83 degrees.
Model_score: 22.6
```

[46]:
```
importances = list(model.feature_importances_)
# List of tuples with variable and importance
feature_importances = [(feature, importance) for feature, importance in␣
 ↪zip(feature_list, importances)]
# Sort the feature importances by most important first
feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse␣
 ↪= True)
# Print out the feature and importances
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in␣
 ↪feature_importances];
```

```
Variable: subtotal             Importance: 0.13916637466118653
Variable: total_outstanding_orders Importance: 0.11547586521776786
Variable: total_onshift_partners Importance: 0.10450167955135141
Variable: max_item_price       Importance: 0.10118971362490316
Variable: min_item_price       Importance: 0.09906593307162753
Variable: created_hour         Importance: 0.09263100736649003
Variable: store_primary_category Importance: 0.08131575944038652
Variable: total_busy_partners  Importance: 0.06823811149594594
Variable: day_of_week          Importance: 0.058289869423938455
Variable: total_items          Importance: 0.022980077631556517
Variable: num_distinct_items   Importance: 0.022521108103350115
Variable: order_protocol_1.0   Importance: 0.01207773060006196
Variable: order_protocol_5.0   Importance: 0.011488254016547312
Variable: market_id_1.0        Importance: 0.010602594347092344
Variable: order_protocol_3.0   Importance: 0.01040906335932855
Variable: order_protocol_4.0   Importance: 0.008811458900249668
Variable: order_protocol_2.0   Importance: 0.008787190110898253
Variable: market_id_3.0        Importance: 0.00848928976019423
Variable: market_id_2.0        Importance: 0.006656891251951355
Variable: market_id_4.0        Importance: 0.006451744080486935
Variable: market_id_5.0        Importance: 0.004761664338699768
Variable: order_protocol_6.0   Importance: 0.002680587867175718
Variable: market_id_6.0        Importance: 0.002205818215303086
Variable: market_id_0.0        Importance: 0.001189895025306218
Variable: order_protocol_7.0   Importance: 1.2318538200510637e-05
```

1.8 10. Scaling the data for neural networks.

[47]:
```
x = encoded_df.
  ↪drop(["created_at","actual_delivery_time","store_id","delivery_time"],axis=1).
  ↪values
y = encoded_df.delivery_time.values
```

[48]:
```
x = np.array(torch.nn.functional.normalize(torch.tensor(x)))
```

[49]:
```
class MyDataset(Dataset):
    def __init__(self, data, target):
        self.data = torch.from_numpy(data).float()
        self.target = torch.from_numpy(target).float()

    def __getitem__(self, index):
        x = self.data[index]
        y = self.target[index]


        return x, y

    def __len__(self):
        return len(self.data)

batch = 128
dataset = MyDataset(x,y)
train,valid = random_split(dataset,[int(0.8*len(dataset)),int(0.
  ↪2*len(dataset))])
train_loader = DataLoader(train,batch_size=batch,shuffle=True,drop_last=True)
valid_loader = DataLoader(valid,batch_size=batch,shuffle=False,drop_last=True)
```

- Simple neural network with very few layers and high learning rate == 0.01
- We didn't implement regularization or droupout techniques in first neural network

[50]:
```
class Linear(nn.Module):
    def __init__(self) -> None:
        super().__init__()
        self.Linear1 = nn.Sequential(
            nn.Linear(3200,256),
            nn.Tanh()
        )
        self.Linear2 = nn.Sequential(
            nn.Linear(256,128),
            nn.ReLU()
        )
        self.Linear3 = nn.Sequential(
            nn.Linear(128,1)
        )
```

```
    def forward(self,x):
        x = x.flatten()
        out = self.Linear1(x)
        out = self.Linear2(out)
        out = self.Linear3(out)
        return out
```

[51]:

```
device = "cuda" if torch.cuda.is_available() else "cpu"
def training_loop(epochs,model,loss,optim,train,val):
    history = []
    for epoch in tqdm(range(epochs)):
        running_loss = []
        for data,target in train:
            data,target = data.to(device), target.to(device)
            out = model(data)
            train_loss = loss(out,target)
            train_loss.backward()
            optim.step()
            optim.zero_grad()
            running_loss.append(train_loss)
        with torch.no_grad():
            model.eval()
            val_running_loss = []
            for val_data,val_target in val:
                val_data, val_target = val_data.to(device),val_target.to(device)
                val_out = model(val_data)
                val_loss = loss(val_out,val_target)
            val_running_loss.append(val_loss)

        print(f"Train_loss: {torch.tensor(running_loss).mean()} Val_loss :␣
 ↪{torch.tensor(val_running_loss).mean()}")
        history.append({"Train_loss":torch.tensor(running_loss).mean(),
                        "Val_loss":torch.tensor(val_running_loss).mean()})
    return history

model = Linear()
model.to(device)
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(params=model.parameters(),lr=0.001)
hist =␣
 ↪training_loop(epochs=10,model=model,loss=criterion,optim=optimizer,train=train_loader,val=v
```

```
  0%|          | 0/10 [00:00<?, ?it/s]

Train_loss: 244.56289672851562 Val_loss : 183.87179565429688
Train_loss: 211.4013214111328 Val_loss : 184.38873291015625
Train_loss: 211.2703094482422 Val_loss : 182.8123321533203
Train_loss: 211.49888610839844 Val_loss : 183.68630981445312
```

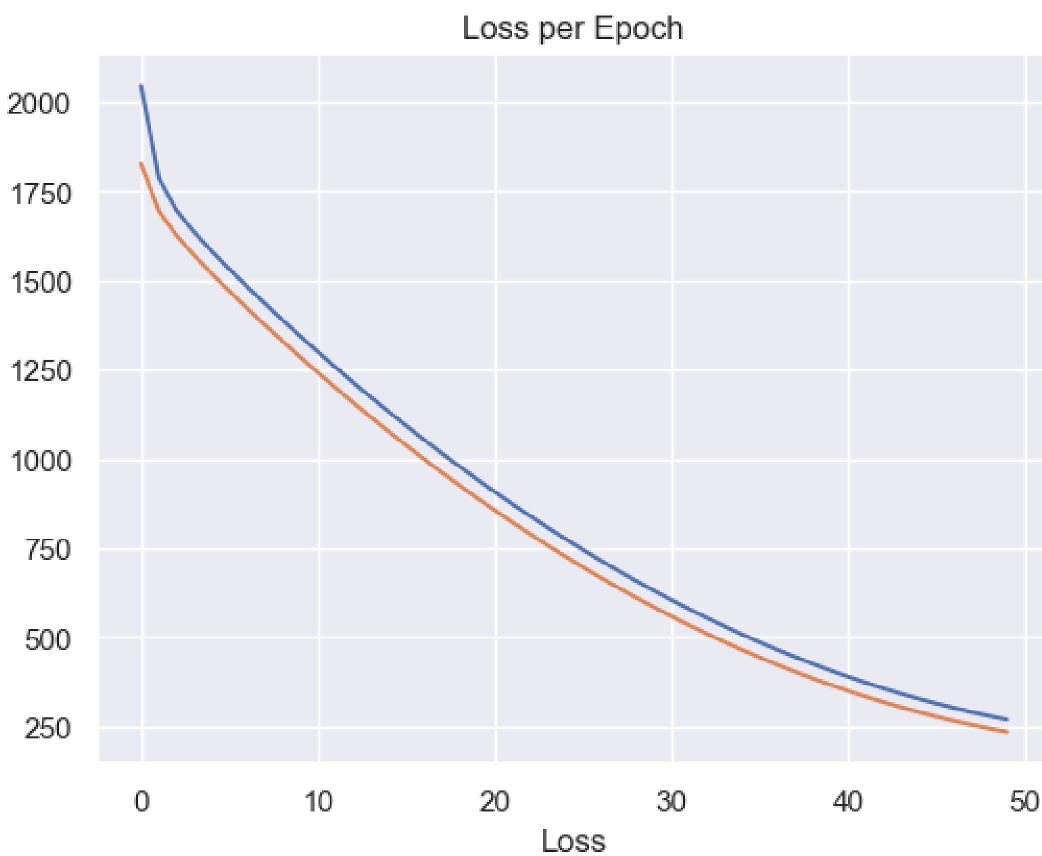
```
Train_loss: 211.68275451660156 Val_loss : 183.5328369140625
Train_loss: 211.38339233398438 Val_loss : 182.9574737548828
Train_loss: 211.50244140625 Val_loss : 183.0537109375
Train_loss: 211.41168212890625 Val_loss : 184.91192626953125
Train_loss: 211.3821258544922 Val_loss : 183.31280517578125
Train_loss: 211.47715759277344 Val_loss : 182.8291778564453
```

[60]:

```
loss = []
val_loss = []
for i in hist:
    loss.append(i["Train_loss"])
    val_loss.append(i["Val_loss"])
plt.plot(loss)
plt.plot(val_loss)
plt.xlabel("Epochs")
plt.xlabel("Loss")
plt.title("Loss per Epoch")

# Simple model with very high rate doesn't give smooth loss and gradient
# Even model is overfitting with training data and valid data not fitting to␣
 ↪model well
```

[60]:

```
Text(0.5, 1.0, 'Loss per Epoch')
```



- Impoved model loss and prevents overfitting by using regularization
- used low learning rate for not exploding gradients

[53]:
```
class Linear1(nn.Module):
    def __init__(self) -> None:
        super().__init__()
        self.Linear1 = nn.Sequential(
            nn.Dropout(0.5),
            nn.Linear(3200,256),
            nn.Tanh()
        )
        self.Linear2 = nn.Sequential(
            nn.Dropout(0.5),
            nn.Linear(256,128),
            nn.Tanh()
        )
        self.Linear3 = nn.Sequential(
            nn.Dropout(0.5),
            nn.Linear(128,64),
            nn.Tanh()
        )
        self.Linear4 = nn.Sequential(
            nn.Linear(64,1)
        )
    def forward(self,x):
        x = x.flatten()
        out = self.Linear1(x)
        out = self.Linear2(out)
        out = self.Linear3(out)
        out = self.Linear4(out)
        return out
```

[59]:
```
model = Linear1()
model.to(device)
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(params=model.parameters(),lr=0.
 ↪00001,weight_decay=1e-5)
hist =␣
 ↪training_loop(epochs=50,model=model,loss=criterion,optim=optimizer,train=train_loader,val=v
```

```
  0%|          | 0/50 [00:00<?, ?it/s]

Train_loss: 2046.27001953125 Val_loss : 1828.04833984375
Train_loss: 1787.8150634765625 Val_loss : 1695.2904052734375
Train_loss: 1697.3505859375 Val_loss : 1627.220458984375
Train_loss: 1636.264892578125 Val_loss : 1571.291259765625
```

```
Train_loss: 1582.4930419921875 Val_loss : 1519.7386474609375
Train_loss: 1532.175048828125 Val_loss : 1470.4638671875
Train_loss: 1483.2584228515625 Val_loss : 1422.713623046875
Train_loss: 1436.116943359375 Val_loss : 1376.1741943359375
Train_loss: 1389.950927734375 Val_loss : 1330.69140625
Train_loss: 1344.789306640625 Val_loss : 1286.223876953125
Train_loss: 1300.699951171875 Val_loss : 1242.6744384765625
Train_loss: 1257.4268798828125 Val_loss : 1200.0751953125
Train_loss: 1214.9481201171875 Val_loss : 1158.3682861328125
Train_loss: 1173.5977783203125 Val_loss : 1117.5411376953125
Train_loss: 1133.25537109375 Val_loss : 1077.6309814453125
Train_loss: 1093.4569091796875 Val_loss : 1038.627197265625
Train_loss: 1054.798828125 Val_loss : 1000.5048217773438
Train_loss: 1016.904296875 Val_loss : 963.2529296875
Train_loss: 980.08349609375 Val_loss : 926.918701171875
Train_loss: 943.9052734375 Val_loss : 891.4522094726562
Train_loss: 908.6734619140625 Val_loss : 856.885498046875
Train_loss: 874.3501586914062 Val_loss : 823.1751708984375
Train_loss: 840.864990234375 Val_loss : 790.4002075195312
Train_loss: 808.5171508789062 Val_loss : 758.4989013671875
Train_loss: 776.7161865234375 Val_loss : 727.4442138671875
Train_loss: 746.0045776367188 Val_loss : 697.30712890625
Train_loss: 716.2274780273438 Val_loss : 668.0344848632812
Train_loss: 687.0953979492188 Val_loss : 639.6525268554688
Train_loss: 658.9866333007812 Val_loss : 612.126708984375
Train_loss: 631.7889404296875 Val_loss : 585.51123046875
Train_loss: 605.3800048828125 Val_loss : 559.7791748046875
Train_loss: 580.0735473632812 Val_loss : 534.9437255859375
Train_loss: 555.4015502929688 Val_loss : 510.9331359863281
Train_loss: 531.7611083984375 Val_loss : 487.84710693359375
Train_loss: 508.86175537109375 Val_loss : 465.58544921875
Train_loss: 486.8695983886719 Val_loss : 444.23382568359375
Train_loss: 465.7298278808594 Val_loss : 423.75445556640625
Train_loss: 445.60186767578125 Val_loss : 404.1435546875
Train_loss: 426.326416015625 Val_loss : 385.3473815917969
Train_loss: 407.79150390625 Val_loss : 367.4773254394531
Train_loss: 390.1742248535156 Val_loss : 350.470947265625
Train_loss: 373.3810729980469 Val_loss : 334.3054504394531
Train_loss: 357.50592041015625 Val_loss : 319.0343322753906
Train_loss: 342.46502685546875 Val_loss : 304.5960693359375
Train_loss: 328.3179931640625 Val_loss : 291.0166320800781
Train_loss: 314.97406005859375 Val_loss : 278.28192138671875
Train_loss: 302.4841003417969 Val_loss : 266.4073486328125
Train_loss: 290.9043273925781 Val_loss : 255.36671447753906
Train_loss: 280.21484375 Val_loss : 245.16456604003906
Train_loss: 270.2618103027344 Val_loss : 235.81402587890625
```

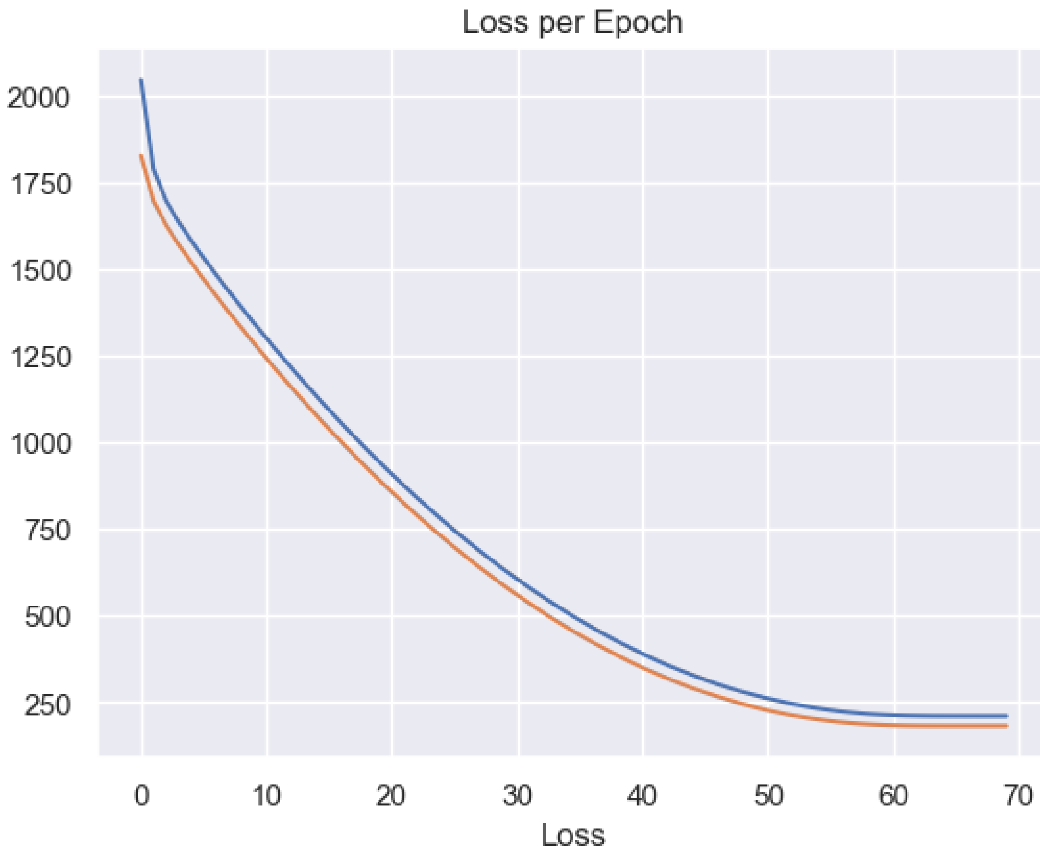
[64]:
```
hist =
 ↪training_loop(epochs=10,model=model,loss=criterion,optim=optimizer,train=train_loader,val=v
```

```
  0%|          | 0/10 [00:00<?, ?it/s]

Train_loss: 213.14898681640625 Val_loss : 184.29605102539062
Train_loss: 211.9913330078125 Val_loss : 183.52081298828125
Train_loss: 211.40158081054688 Val_loss : 183.09776306152344
Train_loss: 210.96311950683594 Val_loss : 182.90313720703125
Train_loss: 210.85438537597656 Val_loss : 182.8314971923828
Train_loss: 210.77992248535156 Val_loss : 182.81326293945312
Train_loss: 210.72235107421875 Val_loss : 182.81387329101562
Train_loss: 210.67251586914062 Val_loss : 182.81727600097656
Train_loss: 210.6506805419922 Val_loss : 182.8208770751953
Train_loss: 210.6818084716797 Val_loss : 182.8221435546875
```

[ ]:
```
loss = []
val_loss = []
```

[65]:
```
for i in hist:
    loss.append(i["Train_loss"])
    val_loss.append(i["Val_loss"])
plt.plot(loss)
plt.plot(val_loss)
plt.xlabel("Epochs")
plt.xlabel("Loss")
plt.title("Loss per Epoch")
```

[65]: Text(0.5, 1.0, 'Loss per Epoch')


Loss per Epoch
2000
1750
1500
1250
1000
750
500
250
0
10
20
30
40
50
60
70
Loss