Problem Statement

- Porter is India's Largest Marketplace for Intra-City Logistics. Leader in the country's $40 billion intra-city logistics market, Porter strives to improve the lives of 1,50,000+ driver-partners by providing them with consistent earning & independence. Currently, the company has serviced 5+ million customers
- Porter works with a wide range of restaurants for delivering their items directly to the people.
- Porter has a number of delivery partners available for delivering the food, from various restaurants and wants to get an estimated delivery time that it can provide the customers on the basis of what they are ordering, from where and also the delivery partners.
- This dataset has the required data to train a regression model that will do the delivery time estimation, based on all those features

Data Dictionary

Each row in this file corresponds to one unique delivery. Each column corresponds to a feature as explained below.

- market_id : integer id for the market where the restaurant lies
- created_at : the timestamp at which the order was placed
- actual_delivery_time : the timestamp when the order was delivered
- store_primary_category : category for the restaurant
- order_protocol : integer code value for order protocol(how the order was placed ie: through porter, call to restaurant, pre booked, third part etc)
- total_items subtotal : final price of the order
- num_distinct_items : the number of distinct items in the order
- min_item_price : price of the cheapest item in the order
- max_item_price : price of the costliest item in order
- total_onshift_partners : number of delivery partners on duty at the time order was placed
- total_busy_partners : number of delivery partners attending to other tasks
- total_outstanding_orders : total number of orders to be fulfilled at the moment

Understanding and Cleaning the Data

In [1]:

```
# Importing Required Libraries.

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler,OneHotEncoder,OneHotEncoder,OrdinalEncode
from sklearn.model_selection import cross_validate,GridSearchCV,train_test_split
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor
from sklearn.metrics import mean_squared_error as mse, mean_absolute_error as mae, mean_ak
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

```python
from tensorflow.keras.utils import plot_model
from tensorflow.keras.layers import BatchNormalization
```

In [2]:
```python
# Importing the Dataset
df=pd.read_csv('/content/dataset.csv')
df.head(3)
```

Out[2]:

	market_id	created_at	actual_delivery_time	store_id	store_primary_category	order_prc
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	american	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	mexican	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	NaN	

In [3]:
```python
# Since the column names are lengthy, therefore renaming to shorter names.

original_column_names = df.columns
new_column_names = ['m_id','created','delivered','storeId','storeCat','orderType','totalIt
                    'distinctItems','minItemPrice','maxItemPrice','onshift_P','busy_P','ou

column_names_mapping = dict(zip(original_column_names,new_column_names))
df.rename(columns=column_names_mapping,inplace=True)
df.head(3)
```

Out[3]:

	m_id	created	delivered	storeId	storeCat	orderType	totalItems	subtotal	distinctI
0	1.0	2015-02-06 22:24:17	2015-02-06 23:27:16	df263d996281d984952c07998dc54358	american	1.0	4	3441	
1	2.0	2015-02-10 21:49:25	2015-02-10 22:56:29	f0ade77b43923b38237db569b016ba25	mexican	2.0	1	1900	
2	3.0	2015-01-22 20:39:28	2015-01-22 21:09:09	f0ade77b43923b38237db569b016ba25	NaN	1.0	1	1900	

In [4]:
```python
# Shape of the Dataset.
df.shape
```

Out[4]:
```
(197428, 14)
```

In [5]:
```python
# Checking for duplicate records.
df.duplicated().sum()
```

Out[5]:
```
0
```

In [6]:
```python
# Checking for Missing values percentage in descending order.
np.round(df.isna().mean()*100,3).sort_values(ascending=False)
```

Out[6]:
```
onshift_P            8.237
busy_P               8.237
outstandingOrders    8.237
storeCat             2.411
orderType            0.504
m_id                 0.500
delivered            0.004
created              0.000
storeId              0.000
totalItems           0.000
subtotal             0.000
distinctItems        0.000
minItemPrice         0.000
maxItemPrice         0.000
dtype: float64
```

- "onshift_P", "busy_P" and "outstandingOrders" have a lot of missing values.
- "storeCat", "m_id", "orderType" and "delivered" also has some missing values.
- Number of delivery partners available on duty at the time order was placed seems to be an important variable to determine delivery time.
- Number of delivery partners attending to other tasks is also an important variable to determine delivery time. If more delivery partners are busy, it implies there would be fewer delivery partners available at that particular moment.
- Total number of orders to be fulfilled at the moment is also another important variable to determine delivery time. More the number of oustanding orders, more would be the time taken to deliver the order.

In [7]:
```
# Checking if "onshift_P", "busy_P" and "outstandingOrders" have missing values for the sa

onshift_P_set=list(df[df['onshift_P'].isna()].index)
busy_P_set=list(df[df['busy_P'].isna()].index)
outstandingOrders_set=list(df[df['outstandingOrders'].isna()].index)

print('Check for Same Records:',(onshift_P_set==busy_P_set) & (busy_P_set==outstandingOrde
# All the records are the same for missing values of "onshift_P", "busy_P" and "outstandi
# We can drop these records safely.

df=df[~df['onshift_P'].isna()].reset_index(drop=True)
```

```
Check for Same Records: True
```

In [8]:
```
# Lets check for missing values again for other remaining columns.

display(np.round(df[["storeCat", "m_id","orderType","delivered"]].isna().mean()*100,3))

# "storeCat", "m_id" and "orderType" still has some missing values.
# We can drop these records as the missing value percentage is small.

df=df[~(df['storeCat'].isna() | df['m_id'].isna() | df['orderType'].isna() | df['delivered
```

```
storeCat     2.327
m_id         0.507
orderType    0.506
delivered    0.004
dtype: float64
```

In [9]:
```
# Checking the data types of the variables.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 176248 entries, 0 to 176247
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   m_id               176248 non-null  float64
 1   created            176248 non-null  object 
 2   delivered          176248 non-null  object 
 3   storeId            176248 non-null  object 
 4   storeCat           176248 non-null  object 
 5   orderType          176248 non-null  float64
 6   totalItems         176248 non-null  int64  
 7   subtotal           176248 non-null  int64  
 8   distinctItems      176248 non-null  int64  
 9   minItemPrice       176248 non-null  int64  
 10  maxItemPrice       176248 non-null  int64  
 11  onshift_P          176248 non-null  float64
 12  busy_P             176248 non-null  float64
 13  outstandingOrders  176248 non-null  float64
dtypes: float64(5), int64(5), object(4)
memory usage: 18.8+ MB
```

- "created" and "delivered" columns are not of datetime data_type.
- Need to convert "m_id", "orderType", "onshift_P", "busy_P" and "outstandingOrders" to integer data_type.

In [10]:

```
for column in ["created","delivered"]:
    df[column]=pd.to_datetime(df[column])

for column in ["m_id", "orderType", "onshift_P", "busy_P","outstandingOrders"]:
    df[column]=df[column].astype('int64')
```

In [11]:

```
# Checking for number of unique values of each variable.
for column in df.columns:
    print(column,':',df[column].nunique())
```

```
m_id : 6
created : 163082
delivered : 160686
storeId : 5645
storeCat : 73
orderType : 7
totalItems : 54
subtotal : 8189
distinctItems : 20
minItemPrice : 2251
maxItemPrice : 2586
onshift_P : 172
busy_P : 158
outstandingOrders : 281
```

- Need to encode "storeId". We can also maybe drop "storeId" since it has lot many categories.
- Need to encode "storeCat" after checking for similar categories having small variation in spellings.

In [12]:

```
# Checking for unique categories of "storeCat" variable.

df['storeCat'].unique()

# Seems like there aren't categories where there are spelling fluctuations. We have total
```

Out[12]:

```
array(['american', 'mexican', 'indian', 'italian', 'sandwich', 'thai',
       'cafe', 'salad', 'pizza', 'chinese', 'singaporean', 'burger',
       'mediterranean', 'japanese', 'greek', 'catering', 'filipino',
```

```
'convenience-store', 'other', 'vegan', 'asian', 'barbecue',
'breakfast', 'fast', 'dessert', 'smoothie', 'seafood',
'vietnamese', 'cajun', 'steak', 'middle-eastern', 'persian',
'nepalese', 'korean', 'sushi', 'latin-american', 'chocolate',
'burmese', 'hawaiian', 'british', 'pasta', 'alcohol', 'vegetarian',
'dim-sum', 'peruvian', 'turkish', 'ethiopian', 'bubble-tea',
'german', 'french', 'caribbean', 'gluten-free', 'comfort-food',
'gastropub', 'afghan', 'pakistani', 'moroccan', 'tapas',
'malaysian', 'soup', 'brazilian', 'european', 'cheese', 'african',
'argentine', 'kosher', 'irish', 'spanish', 'russian', 'southern',
'lebanese', 'belgian', 'alcohol-plus-food'], dtype=object)
```

Feature Engineering

We can create few new features such as

- 1) Delivery_Time
- 2) Hour at which order was placed
- 3) Day of the week

In [13]:
```
# Creating the above mentioned features.

df['delivery_time']=(df['delivered']-df['created']).apply(lambda x : np.round(x.seconds/6(
df['hour']=(df['created'].dt.hour).astype('int64')
df['day']=(df['created'].dt.dayofweek).astype('int64')

# Dropping columns - "created" and "delivered"
df.drop(columns=["created","delivered"],inplace=True)
```

Descriptive Statistics

In [14]:
```
# Numerical Columns.
df.describe().T
```

Out[14]:

	count	mean	std	min	25%	50%	75%	max
m_id	176248.0	2.743747	1.330911	1.00	2.00	2.00	4.00	6.00
orderType	176248.0	2.911687	1.512920	1.00	1.00	3.00	4.00	7.00
totalItems	176248.0	3.204592	2.673899	1.00	2.00	3.00	4.00	411.00
subtotal	176248.0	2696.498939	1828.922584	0.00	1408.00	2221.00	3407.00	26800.00
distinctItems	176248.0	2.674589	1.625558	1.00	1.00	2.00	3.00	20.00
minItemPrice	176248.0	684.937730	519.911425	-86.00	299.00	595.00	942.00	14700.00
maxItemPrice	176248.0	1159.886994	560.784510	0.00	799.00	1095.00	1395.00	14700.00
onshift_P	176248.0	44.905276	34.529394	-4.00	17.00	37.00	65.00	171.00
busy_P	176248.0	41.845434	32.154573	-5.00	15.00	35.00	62.00	154.00
outstandingOrders	176248.0	58.206800	52.708344	-6.00	17.00	41.00	85.00	285.00
delivery_time	176248.0	47.707011	19.632589	1.68	35.08	44.37	56.37	1221.37
hour	176248.0	8.493872	8.681474	0.00	2.00	3.00	19.00	23.00
day	176248.0	3.221563	2.041332	0.00	1.00	3.00	5.00	6.00

In [15]:

```
# Observation - "minItemPrice", "onshift_P", "busy_P" and "outstandingOrders" have some ne
# We can remove these records.

df=df[(df['minItemPrice']>0) & (df['onshift_P']>=0) & (df['busy_P']>=0) & (df['outstanding
```

In [16]:

```
# Object Columns.
df.describe(include='object').T
```

Out[16]:

	count	unique	top	freq
storeId	173978	5634	d43ab110ab2489d6b9b2caa394bf920f	926
storeCat	173978	73	american	18085

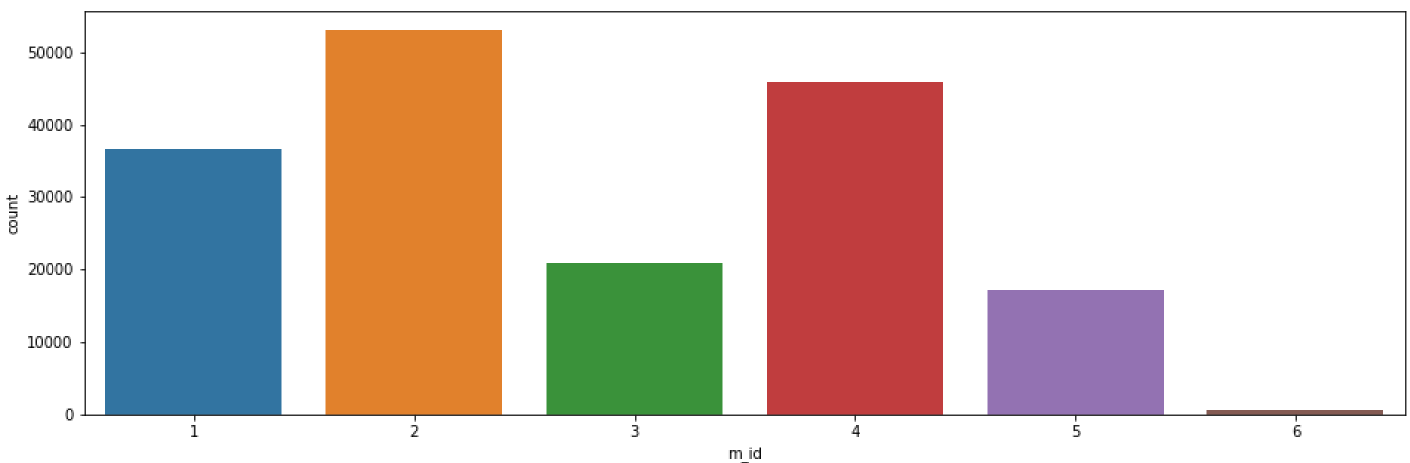
EDA

1) Distribution of Market_Place.

In [17]:

```
temp=pd.DataFrame(np.round(df['m_id'].value_counts(normalize=True)*100,2).sort_index())
display(temp.rename(columns={'m_id':'Percentage'}).T)

plt.figure(figsize=(16,5))
sns.countplot(data=df,x='m_id')
plt.show()
```

	1	2	3	4	5	6
Percentage	21.0	30.46	11.97	26.39	9.82	0.36



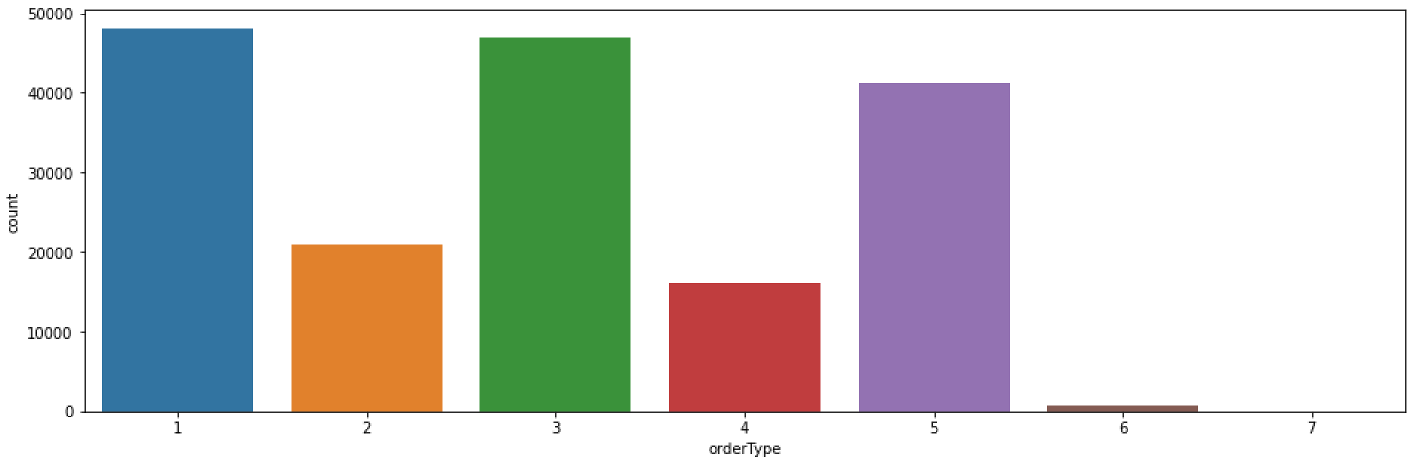
Observation - Most of the orders were placed from market_place 2,4 and 1.

2) Distribution of Order_Type.

In [18]:

```
# order_type : integer code for how the order was placed - through porter, call to restau

temp=pd.DataFrame(np.round(df['orderType'].value_counts(normalize=True)*100,2).sort_index
display(temp.rename(columns={'orderType':'Percentage'}).T)

plt.figure(figsize=(16,5))
sns.countplot(data=df,x='orderType')
plt.show()
```

	1	2	3	4	5	6	7
Percentage	27.64	12.0	27.02	9.3	23.65	0.39	0.01

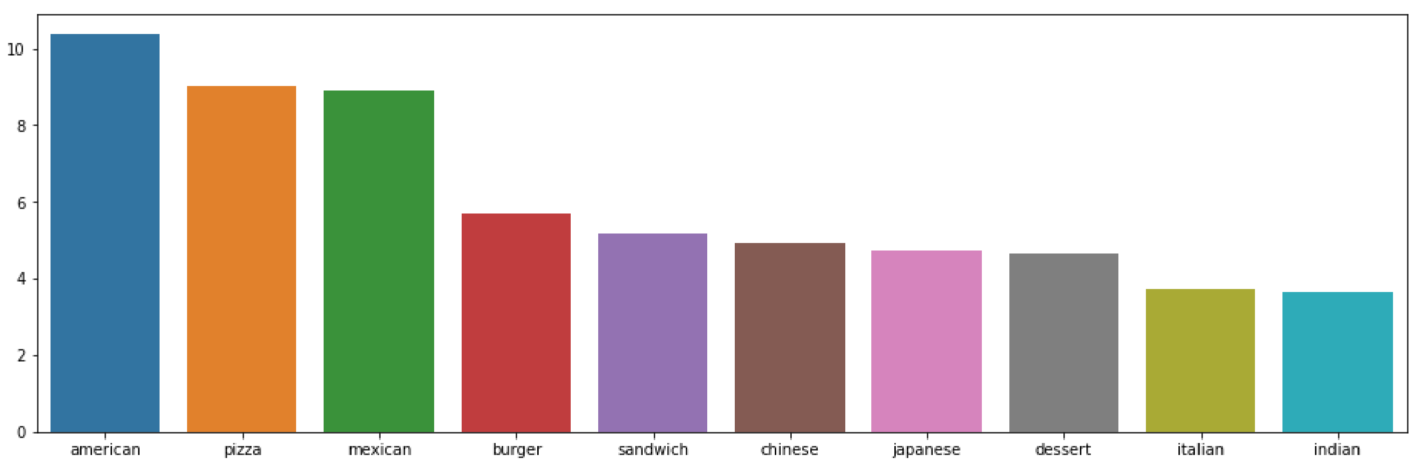


Observation - Most of the orders were placed through order_type 1,3 and 5.

3) Distribution of Store_Category for top 10 categories.

In [19]:
```
temp=pd.DataFrame(np.round(df['storeCat'].value_counts(normalize=True)*100,2)).sort_values
display(temp.rename(columns={'storeCat':'Percentage'}).T)

plt.figure(figsize=(16,5))
sns.barplot(x=temp.index,y=temp.values.flatten())
plt.show()
```

	american	pizza	mexican	burger	sandwich	chinese	japanese	dessert	italian	indian
Percentage	10.39	9.02	8.89	5.69	5.17	4.91	4.71	4.63	3.74	3.66

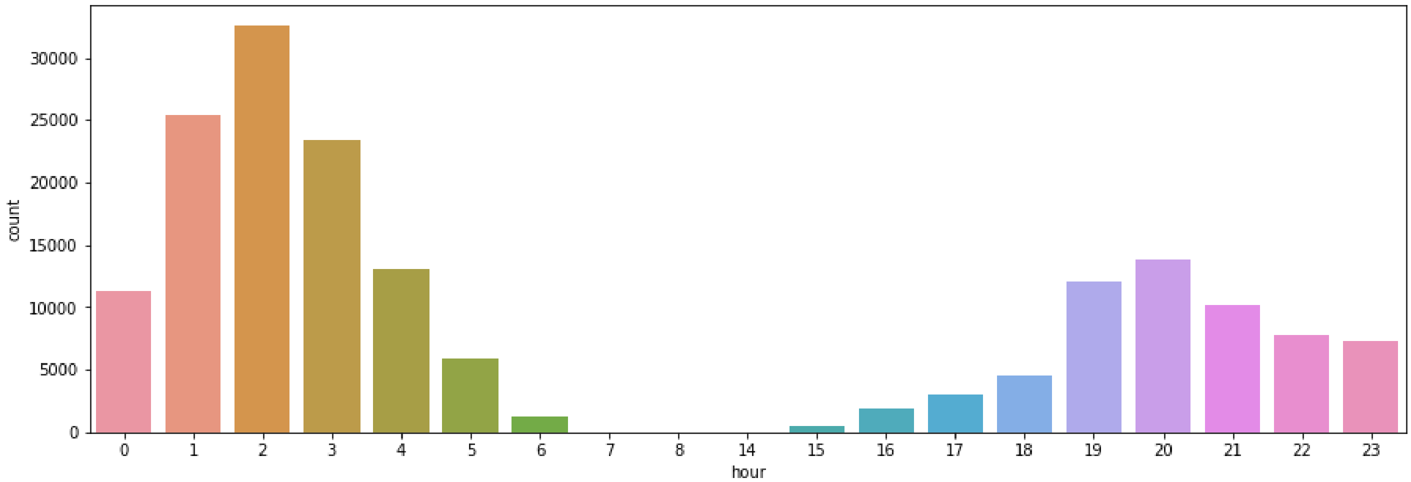


Observation - The top Store_Categories are "american", "pizza" and "mexican".

4) Distribution of Hour.

In [20]:
```
temp=pd.DataFrame(np.round(df['hour'].value_counts(normalize=True)*100,2).sort_index())
display(temp.rename(columns={'hour':'Percentage'}).T)

plt.figure(figsize=(15,5))
sns.countplot(data=df,x='hour')
plt.show()
```

	0	1	2	3	4	5	6	7	8	14	15	16	17	18	19	20	21	22
Percentage	6.51	14.64	18.73	13.47	7.5	3.41	0.68	0.01	0.0	0.02	0.28	1.1	1.73	2.59	6.93	7.97	5.83	4.46

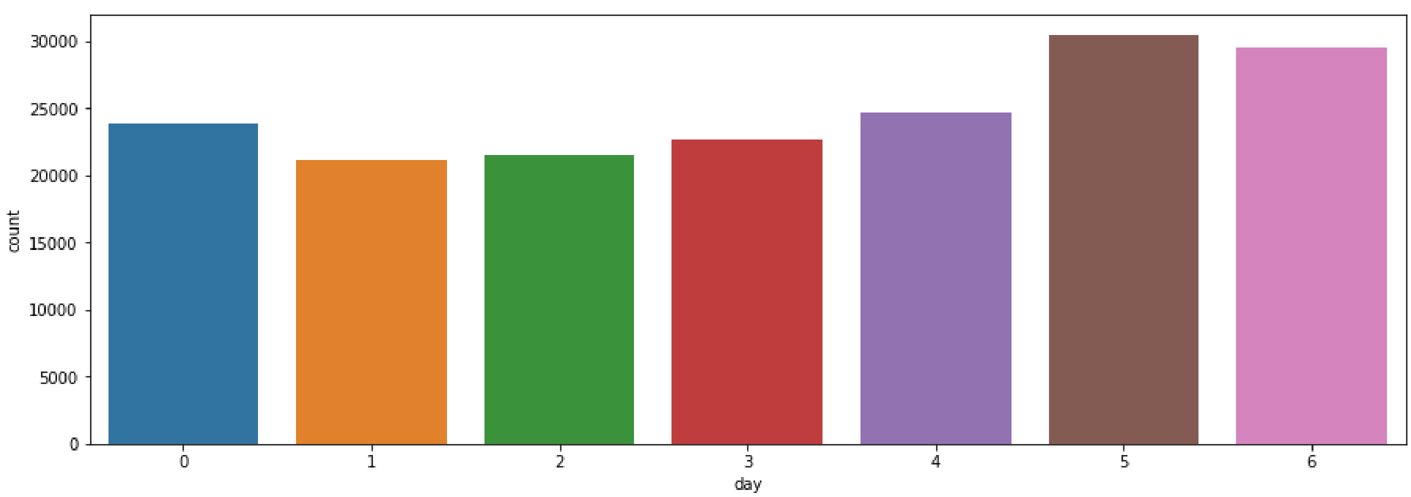


Observation - There is a huge fall in orders_placed between 6 and 15 hours.

5) Distribution of Day.

In [21]:
```
temp=pd.DataFrame(np.round(df['day'].value_counts(normalize=True)*100,2).sort_index())
display(temp.rename(columns={'day':'Percentage'}).T)

plt.figure(figsize=(15,5))
sns.countplot(data=df,x='day')
plt.show()
```

	0	1	2	3	4	5	6
Percentage	13.74	12.18	12.36	13.05	14.2	17.51	16.96

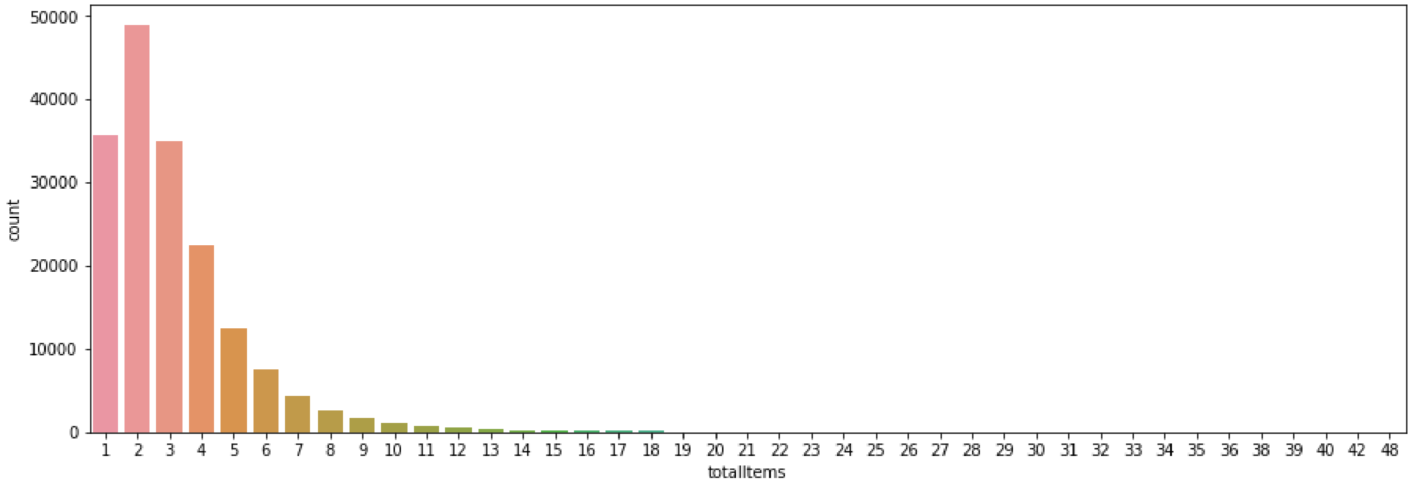


Observation - Highest number of orders were placed on weekends(5-Saturday,6-Sunday).

6) Distribution of Total_Items.

In [22]:
```
temp=pd.DataFrame(np.round(df['totalItems'].value_counts(normalize=True)*100,2).sort_index
display(temp.rename(columns={'totalItems':'Percentage'}).T)

plt.figure(figsize=(15,5))
sns.countplot(data=df,x='totalItems')
plt.show()
```

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Percentage	20.54	28.13	20.09	12.89	7.14	4.37	2.51	1.5	0.91	0.6	0.38	0.31	0.16	0.13	0.09	0.06	0.05	0.04



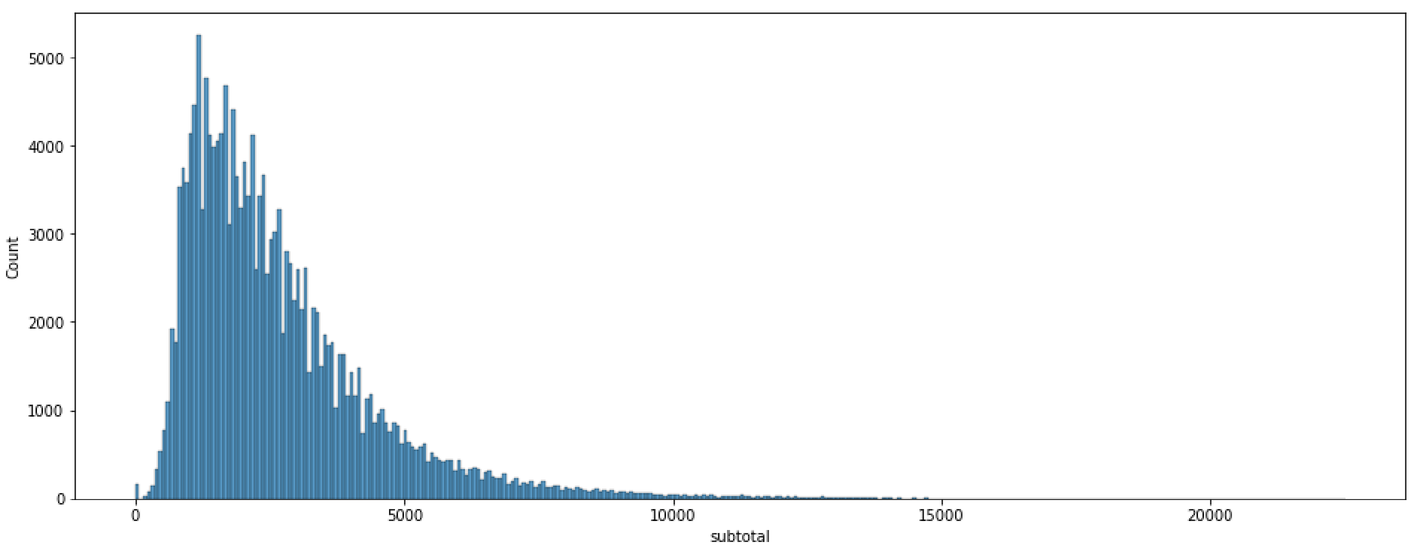
In [23]:

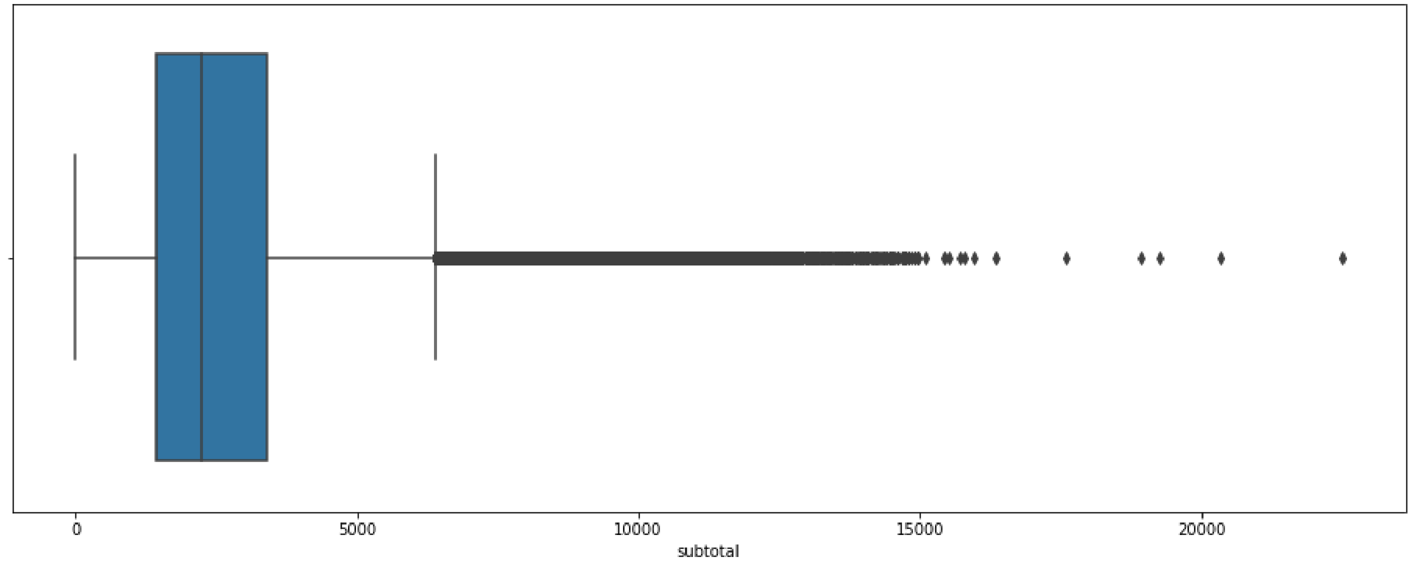
```
# Observation - Orders having total_items more than 20 are very few. We can remove these i
df=df[df['totalItems']<=20].reset_index(drop=True)
```

7) Distribution of SubTotal.

In [24]:

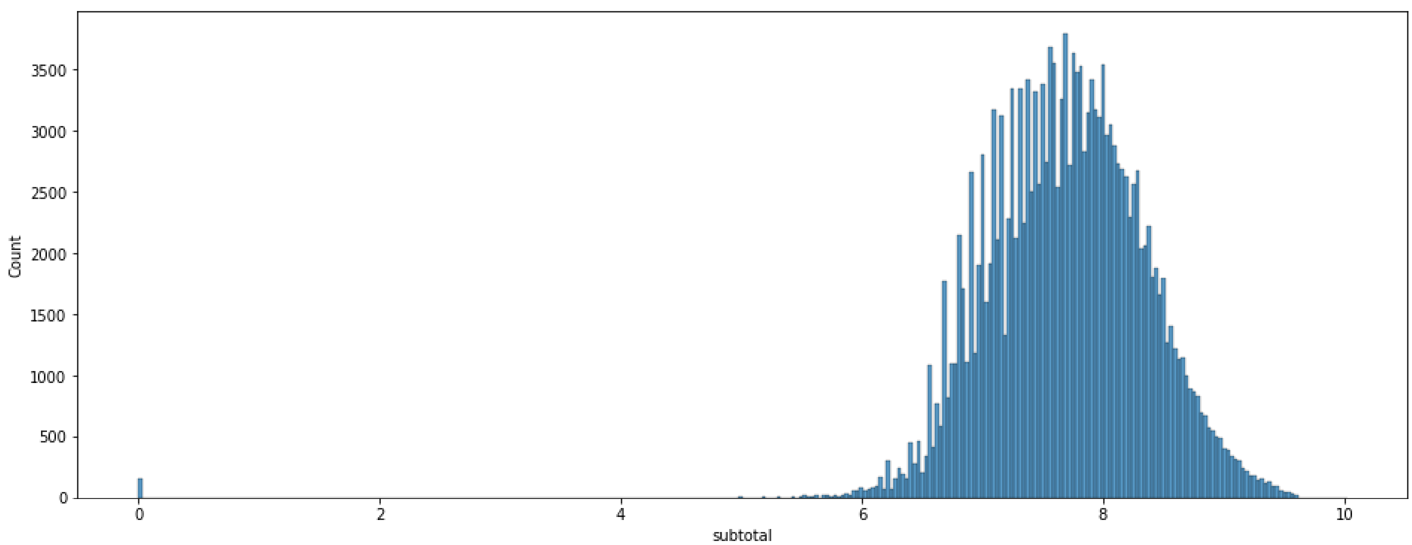
```
plt.figure(figsize=(16,6))
sns.histplot(data=df,x='subtotal')
plt.show()

plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='subtotal')
plt.show()
```





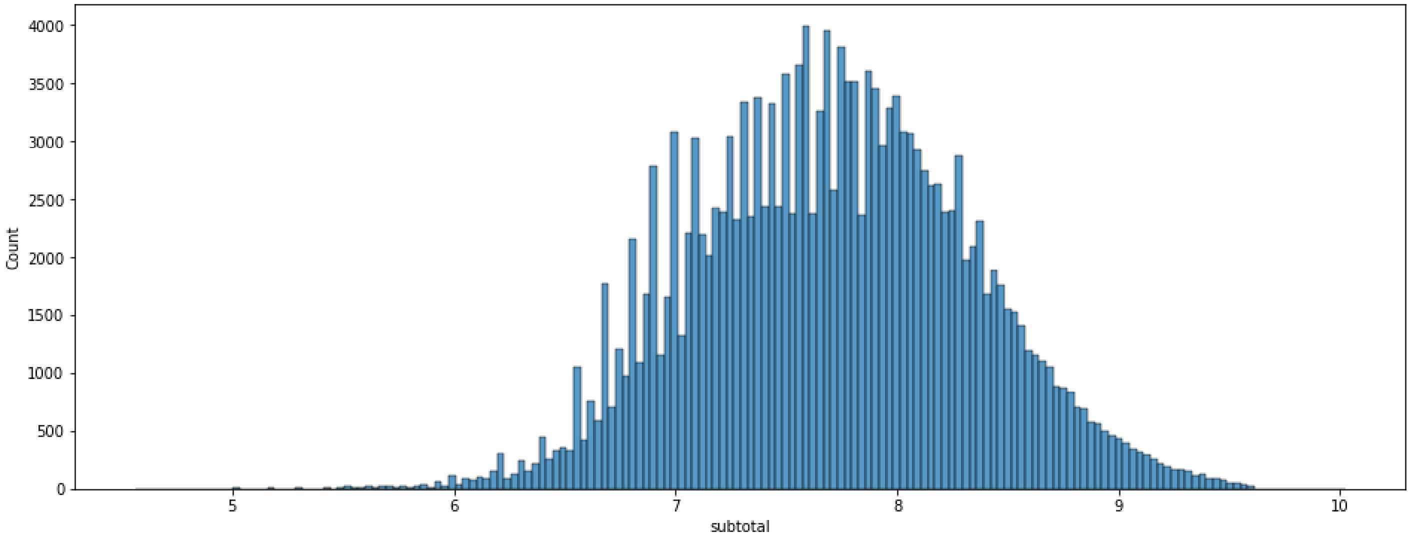
In [25]:

```
# Observation - Data is heavily Right Skewed.
# There are big outliers as large as 2,00,000. We can try doing Log tranformation.

df['subtotal']=np.log(df['subtotal']+1)

plt.figure(figsize=(16,6))
sns.histplot(data=df,x='subtotal')
plt.show()

# There are few outliers on the left at value 0. We can remove them.
df=df[df['subtotal']>0].reset_index(drop=True)
```



In [26]:

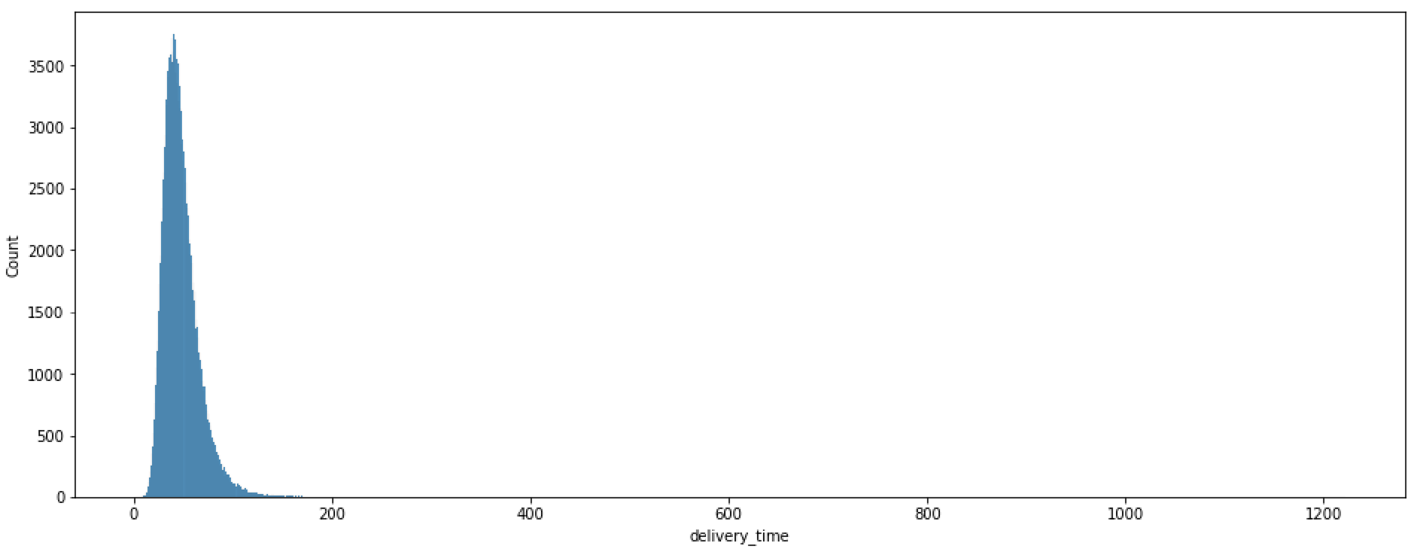
```
# Histogram after Transformation and removing Outliers.

plt.figure(figsize=(16,6))
sns.histplot(data=df,x='subtotal')
plt.show()
```

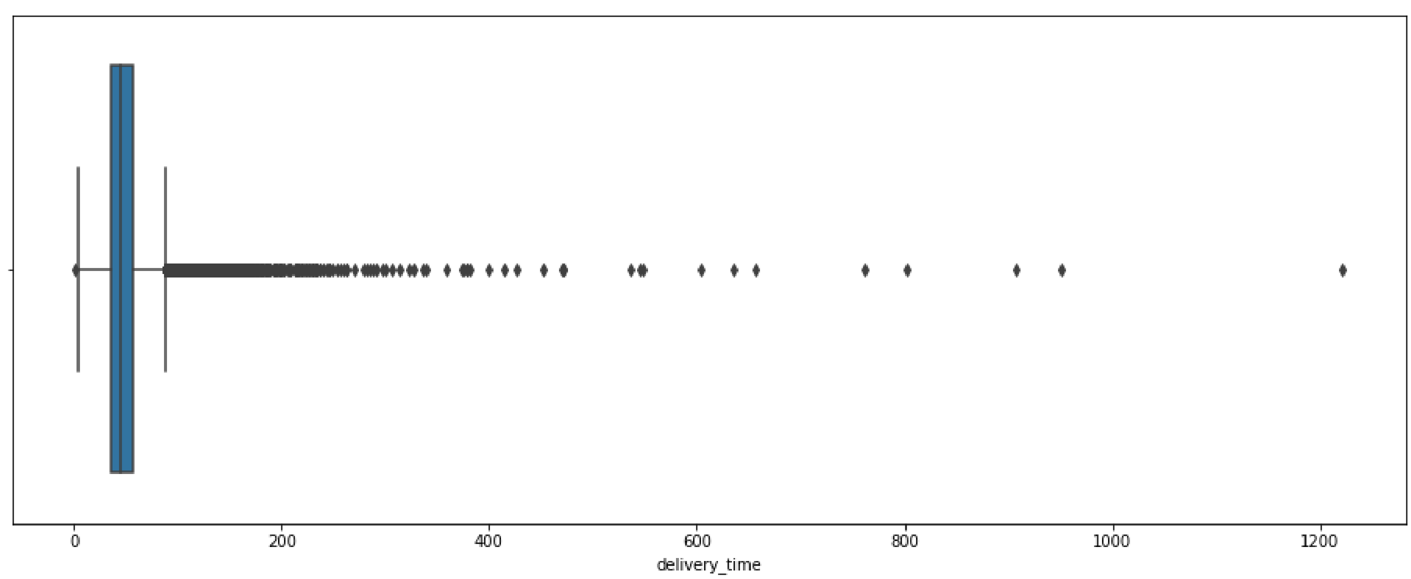


8) Distribution of Delivery_Time.

In [27]:

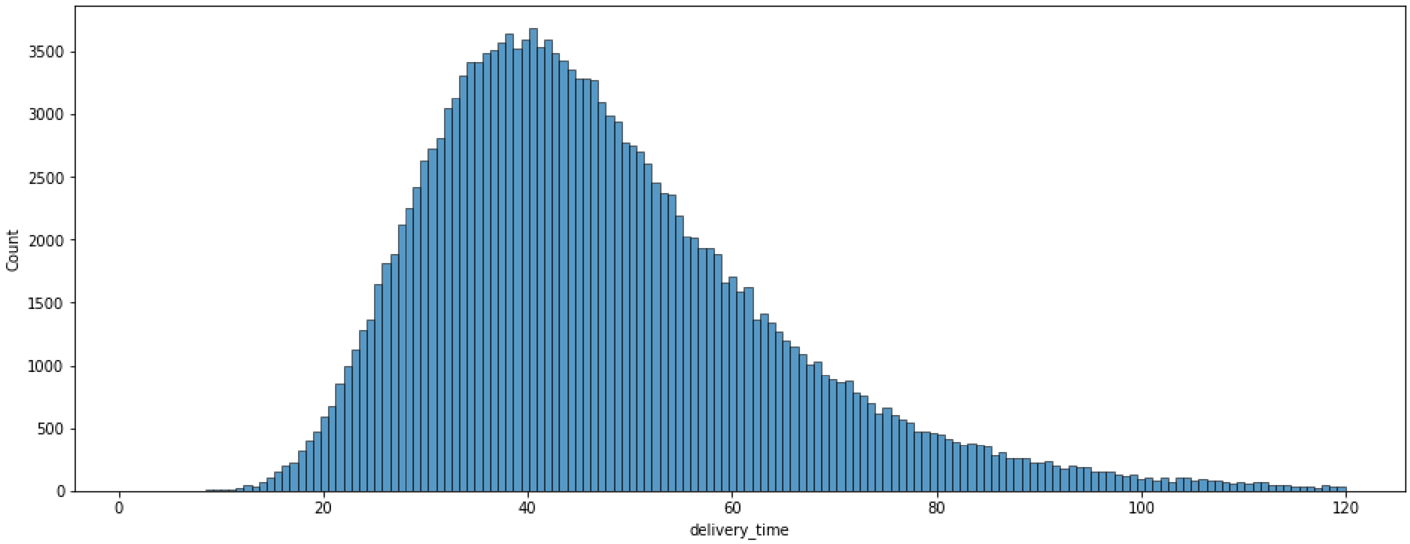
```
plt.figure(figsize=(16,6))
sns.histplot(data=df,x='delivery_time')
plt.show()

plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='delivery_time')
plt.show()
```





In [28]:

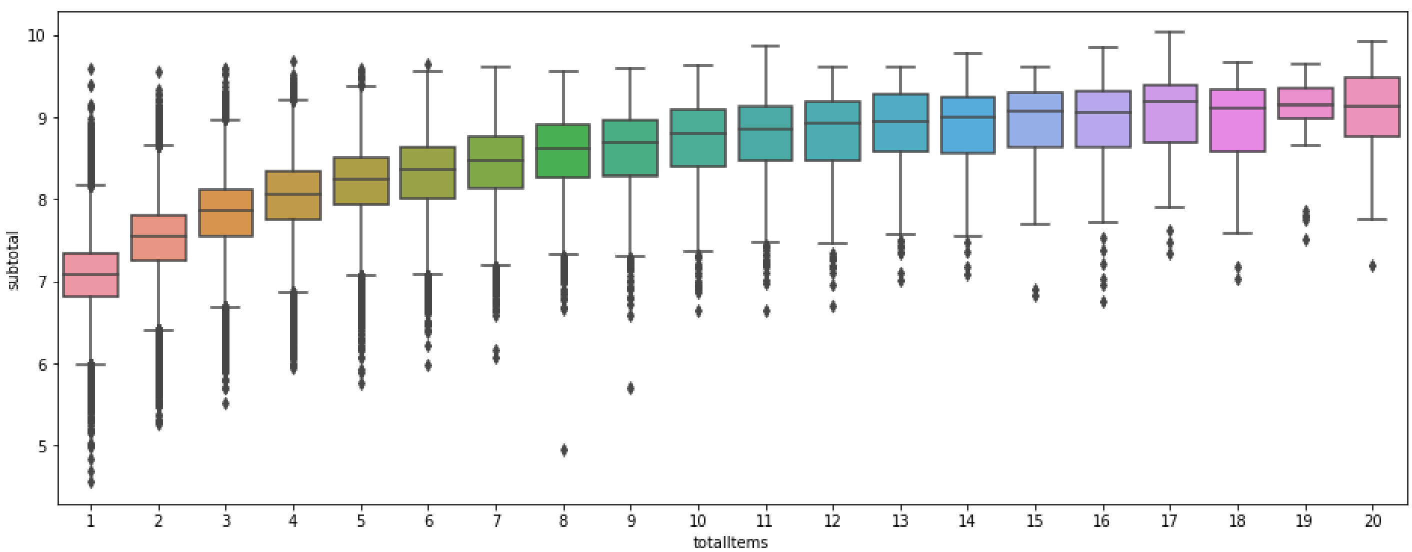
```
# Observation - Data is heavily Right Skewed and there are big outliers.
# Delivery_time more than 2 hours doesn't seem reasonable.We can remove records which have

df=df[df['delivery_time']<=120].reset_index(drop=True)

plt.figure(figsize=(16,6))
sns.histplot(data=df,x='delivery_time')
plt.show()
```



9) Distribution of Total_Items vs Subtotal.

In [29]:

```
plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='totalItems',y='subtotal')
plt.show()
```

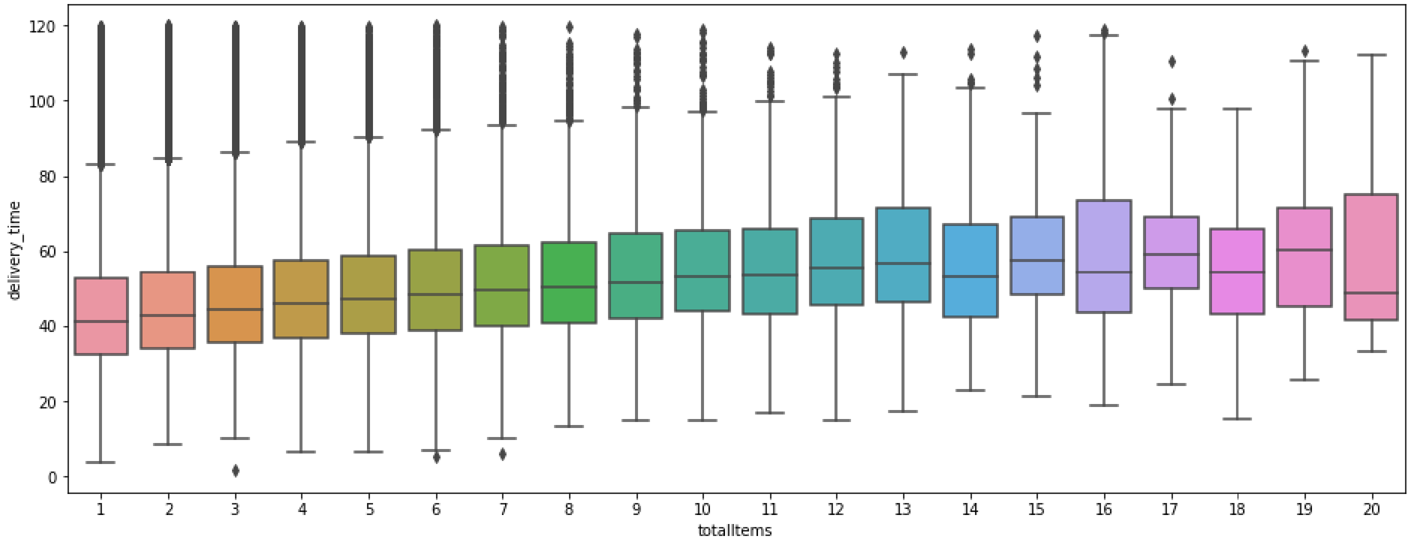


Observation - With increase in total_items, median subtotal is also increasing.

10) Distribution of total_items vs delivery_time.

In [30]:

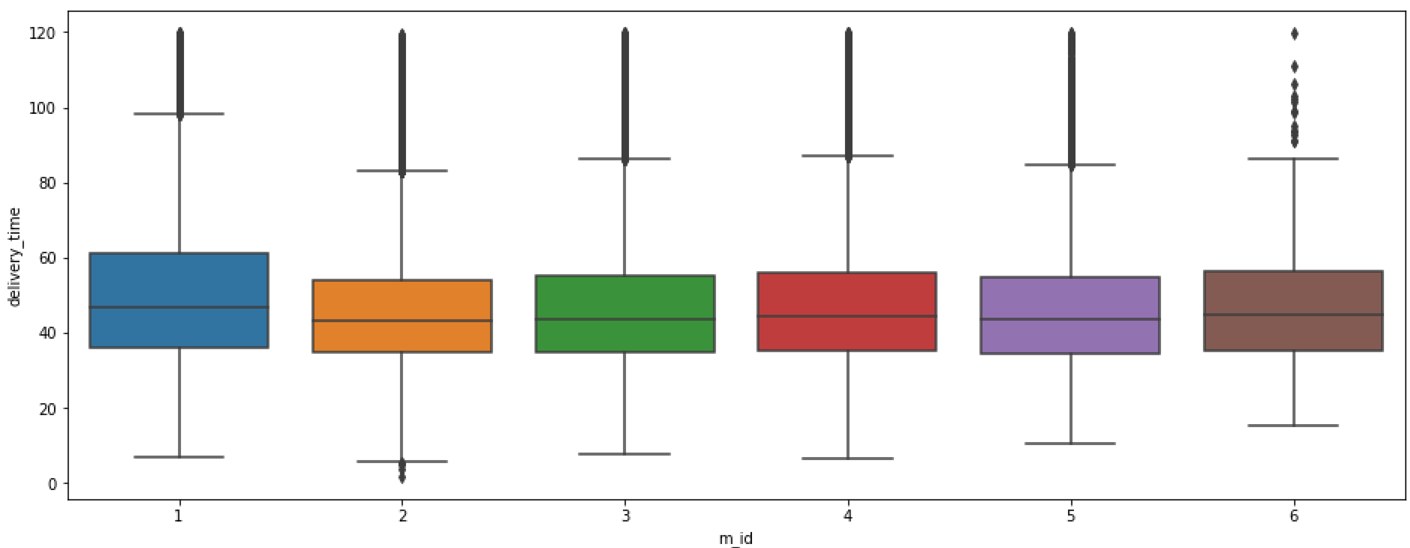
```
plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='totalItems',y='delivery_time')
plt.show()
```



11) Distribution of Market_Id vs delivery_time.

In [31]:

```
plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='m_id',y='delivery_time')
plt.show()
```



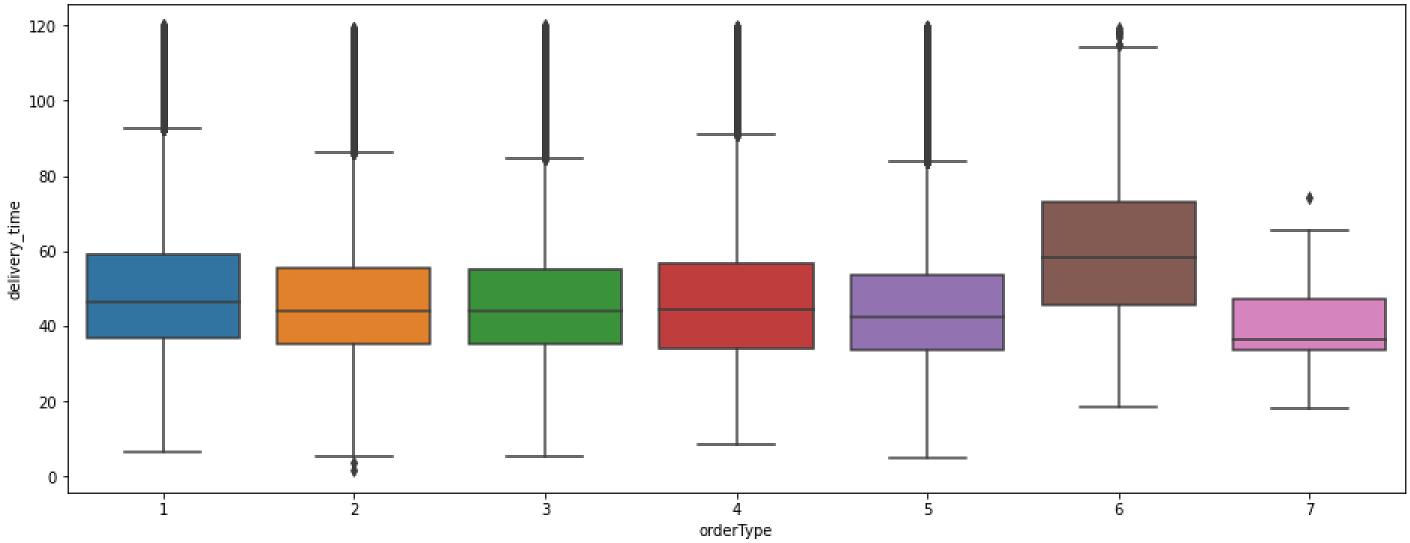
In [32]:

```
# Median_Delivery time for the different markets are almost the same, except market_id 1.
```

12) Distribution of order_type vs delivery_time.

In [33]:

```
plt.figure(figsize=(16,6))
sns.boxplot(data=df,x='orderType',y='delivery_time')
plt.show()
```



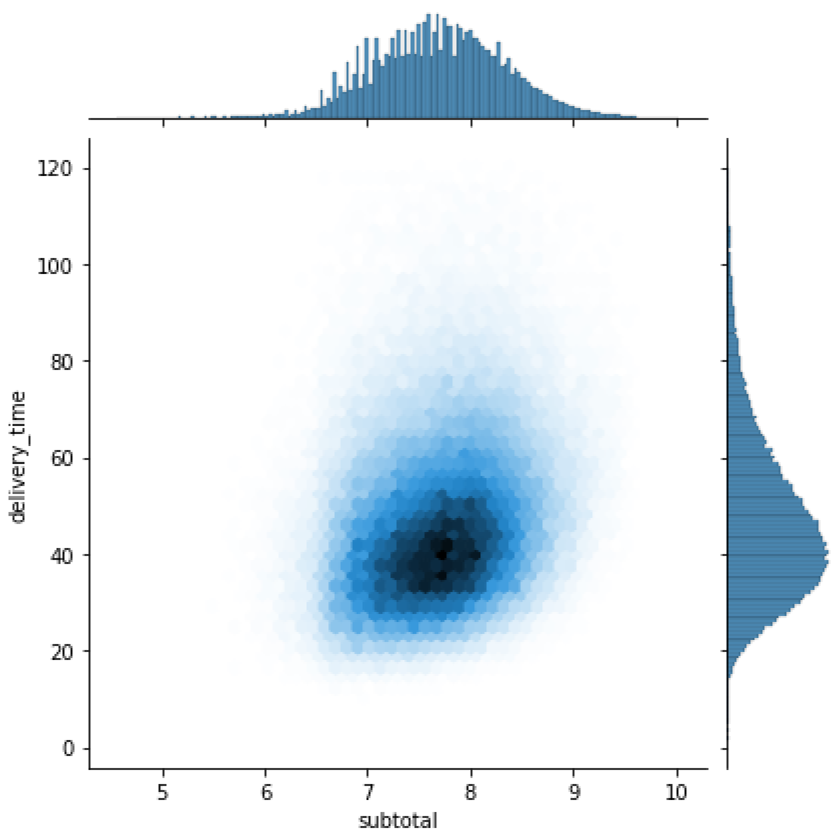
In [34]:

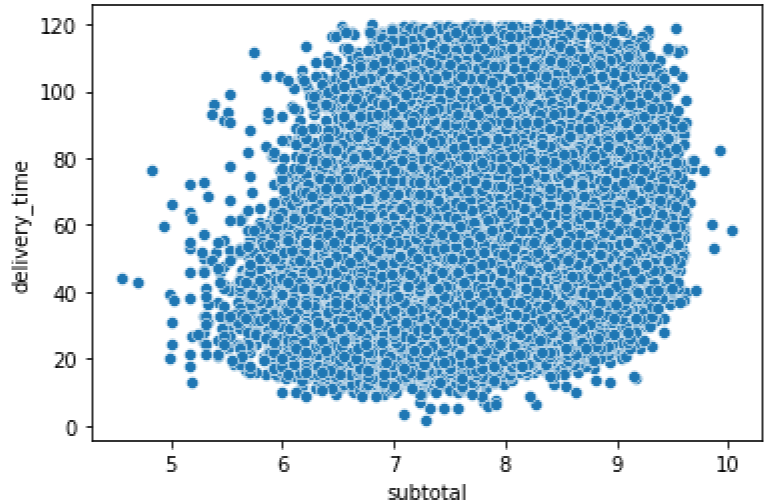
```
# Median_Delivery time for the different order_types are almost the same, except order_typ
```

13) Distribution of delivery_time vs subtotal.

In [35]:

```
sns.jointplot(data=df,x='subtotal',y='delivery_time',kind='hex')
plt.show()
sns.scatterplot(data=df,x='subtotal',y='delivery_time')
plt.show()
```





Observation - We don't see a pattern between subtotal and delivery_time.

Final Sanity Check

In [36]:
```
# We can drop "storeId" column because of the large number of categories, which can lead t
df.drop(columns=['storeId'],inplace=True)
```

In [37]:
```
df.head()
```

Out[37]:

	m_id	storeCat	orderType	totalItems	subtotal	distinctItems	minItemPrice	maxItemPrice	onshift_P	busy_P	c
0	1	american	1	4	8.143808	4	557	1239	33	14	
1	2	mexican	2	1	7.550135	1	1400	1400	1	2	
2	2	indian	3	4	8.470521	3	820	1604	8	6	
3	1	italian	1	1	7.330405	1	1525	1525	5	6	
4	1	italian	1	2	8.194506	2	1425	2195	5	5	

In [38]:
```
df.shape
```

Out[38]:
```
(172737, 14)
```

In [39]:
```
df.isna().sum()
```

Out[39]:
```
m_id                0
storeCat            0
orderType           0
totalItems          0
subtotal            0
distinctItems       0
minItemPrice        0
maxItemPrice        0
onshift_P           0
busy_P              0
outstandingOrders   0
delivery_time       0
hour                0
```

```
day                         0
dtype: int64
```

In [40]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 172737 entries, 0 to 172736
Data columns (total 14 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   m_id               172737 non-null  int64  
 1   storeCat           172737 non-null  object 
 2   orderType          172737 non-null  int64  
 3   totalItems         172737 non-null  int64  
 4   subtotal           172737 non-null  float64
 5   distinctItems      172737 non-null  int64  
 6   minItemPrice       172737 non-null  int64  
 7   maxItemPrice       172737 non-null  int64  
 8   onshift_P          172737 non-null  int64  
 9   busy_P             172737 non-null  int64  
 10  outstandingOrders  172737 non-null  int64  
 11  delivery_time      172737 non-null  float64
 12  hour               172737 non-null  int64  
 13  day                172737 non-null  int64  
dtypes: float64(2), int64(11), object(1)
memory usage: 18.5+ MB
```

Encoding

Need to One_Hot_Encode:

- "storeCat"
- "orderType"
- "hour"
- "day"

In [41]:

```
# For tree based models, we should not do OHE for categorical features. We can therefore u

df_tree=df.copy()
ordinal=OrdinalEncoder(dtype='int64')
ordinal_transformed=ordinal.fit_transform(df_tree[['storeCat']])
df_tree['storeCat']=ordinal_transformed
```

Train_Test Split

In [96]:

```
# Keeping 10% data for test_date to report an unbiased estimate.

X=df_tree.drop(columns=['delivery_time'])
y=df_tree['delivery_time']
X_train_dev,X_test,y_train_dev,y_test=train_test_split(X,y,test_size=0.1,random_state=1)
```

In [97]:

```
print('X_train_dev Size:',X_train_dev.shape)
print('X_test Size:',X_test.shape)
```

```
X_train_dev Size: (155463, 13)
X_test Size: (17274, 13)
```

Model 1 - Random Forests

In [44]:
```
def evaluate(y_actual,y_pred):

    mape_score = mape(y_actual,y_pred,)
    mse_score = mse(y_actual,y_pred)
    mae_score = mae(y_actual,y_pred)

    print('Model Performance')
    print('MAPE',round(mape_score,2))
    print('MSE',round(mse_score,2))
    print('MAE',round(mae_score,2))
```

In [99]:
```
param_grid = {'max_depth': [20,30,40,50]}
rf_model = RandomForestRegressor()

grid_search = GridSearchCV(estimator = rf_model, param_grid = param_grid, cv = 2, n_jobs =
grid_search.fit(X_train_dev, y_train_dev)

y_pred=grid_search.predict(X_test)
evaluate(y_test,y_pred)
```

```
/usr/local/lib/python3.8/dist-packages/joblib/externals/loky/process_executor.py:700: User
Warning: A worker stopped while some jobs were given to the executor. This can be caused b
y a too short worker timeout or by a memory leak.
  warnings.warn(
Model Performance
MAPE 0.26
MSE 203.71
MAE 10.89
```

Model 2 - GBDT

In [49]:
```
param_grid = {'max_depth': [10,15,20,25]}
rf_model = GradientBoostingRegressor()

grid_search = GridSearchCV(estimator = rf_model, param_grid = param_grid, cv = 2, n_jobs =
grid_search.fit(X_train_dev, y_train_dev)

y_pred=grid_search.predict(X_test)
evaluate(y_test,y_pred)
```

```
Model Performance
MAPE 0.25
MSE 192.26
MAE 10.55
```

Model 3 - Neural Networks

Encoding

Need to One_Hot_Encode:

- "storeCat"
- "orderType"
- "hour"

- "day"

In [51]:
```
# For Neural Networks, we should do OneHotEncoding for categorical features.

df_nn=df.copy()
ohe=OneHotEncoder(drop='first',sparse=False,dtype='int64')
ohe_transformed=ohe.fit_transform(df_nn[['storeCat','orderType','hour','day']])
df_nn.drop(columns=['storeCat','orderType','hour','day'],inplace=True)
temp=pd.DataFrame(data=ohe_transformed,columns=ohe.get_feature_names_out())
df_nn=pd.concat((df_nn,temp),axis=1)
```

Train_Test Split

In [52]:
```
# Keeping 10% data for test_date to report an unbiased estimate.

X=df_nn.drop(columns=['delivery_time'])
y=df_nn['delivery_time']
X_train_dev,X_test,y_train_dev,y_test=train_test_split(X,y,test_size=0.1,random_state=1)
```

In [53]:
```
print('X_train_dev Size:',X_train_dev.shape)
print('X_test Size:',X_test.shape)
```

```
X_train_dev Size: (155463, 110)
X_test Size: (17274, 110)
```

In [54]:
```
print('y_train_dev Size:',y_train_dev.shape)
print('y_test Size:',y_test.shape)
```

```
y_train_dev Size: (155463,)
y_test Size: (17274,)
```

Scaling

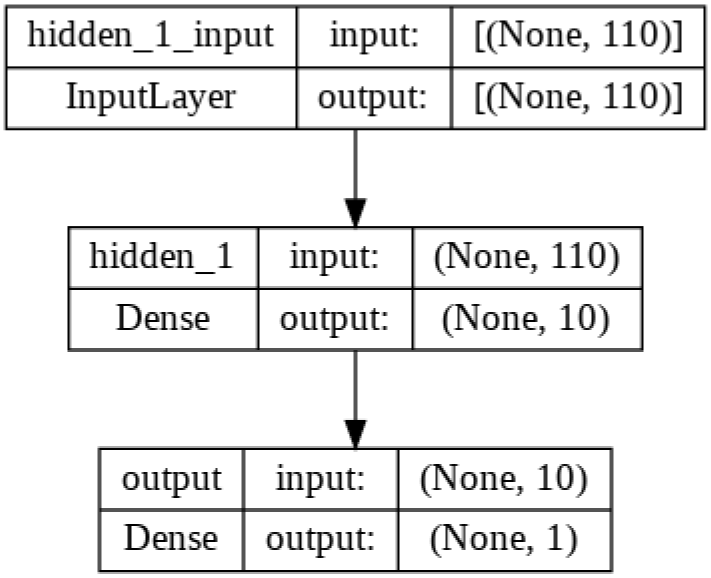
In [55]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_dev = scaler.fit_transform(X_train_dev)
X_test = scaler.transform(X_test)


# Creating a simple neural network
```

NN_Model 1 - Creating a simple neural network

In [56]:
```
model = Sequential([
                    Dense(10, activation="relu",input_shape=(110,), name="hidden_1"), #Hid
                    Dense(1, activation="linear",name="output") #Output Layer has 1 neuro
])

model.compile(
    optimizer = 'sgd',
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=10, batch_size=256, validation_split=0.
```

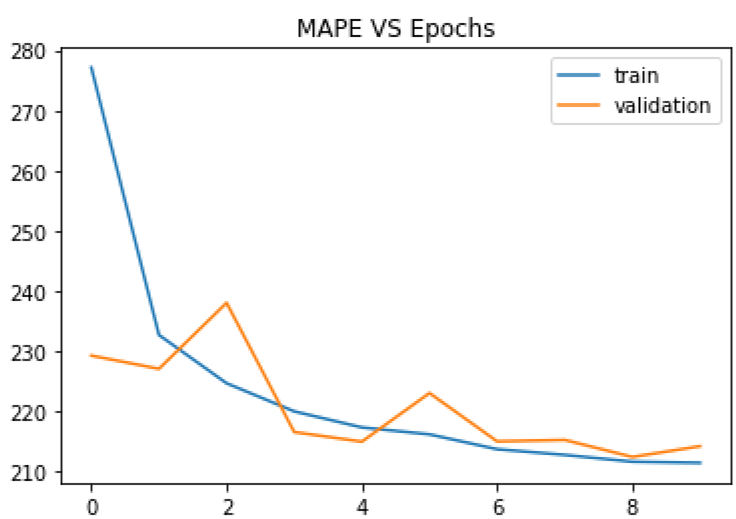
```
In [57]: plot_model(model,
             to_file='model.png',
             show_shapes=True, show_layer_names=True)
```

Out[57]:




```
In [58]: def plot(history):

           epochs = history.epoch
           loss = history.history["loss"]
           val_loss = history.history["val_loss"]

           plt.plot(epochs, loss, label="train")
           plt.plot(epochs, val_loss, label="validation")
           plt.legend()
           plt.title("MAPE VS Epochs")
           plt.show()
```

```
In [59]: plot(history)
```



NN_Model 2 - Using Adam Optimizer and More number of Neurons in Hidden Layer

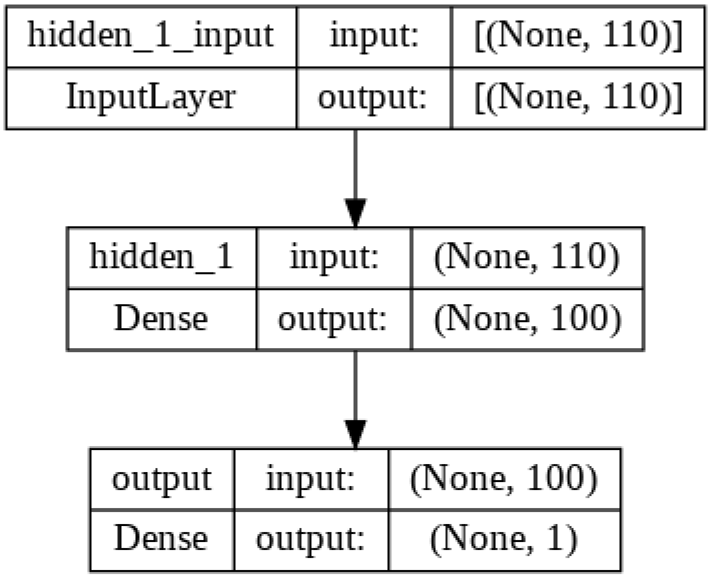
```
In [60]: model = Sequential([
                                         Dense(100, activation="relu",input_shape=(110,), name="hidden_1"), #H
                                         Dense(1, activation="linear",name="output") #Output Layer has 1 neuro
```

```
])

model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=10, batch_size=256, validation_split=0.
```

In [61]:

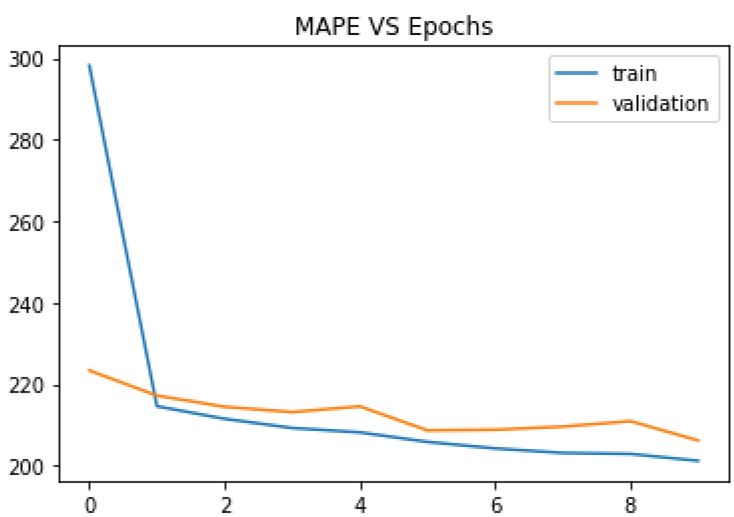
```
plot_model(model,
    to_file='model.png',
    show_shapes=True, show_layer_names=True)
```

Out[61]:



In [62]:

```
plot(history)
```



NN_Model 3 - Using More Hidden Layers

In [66]:

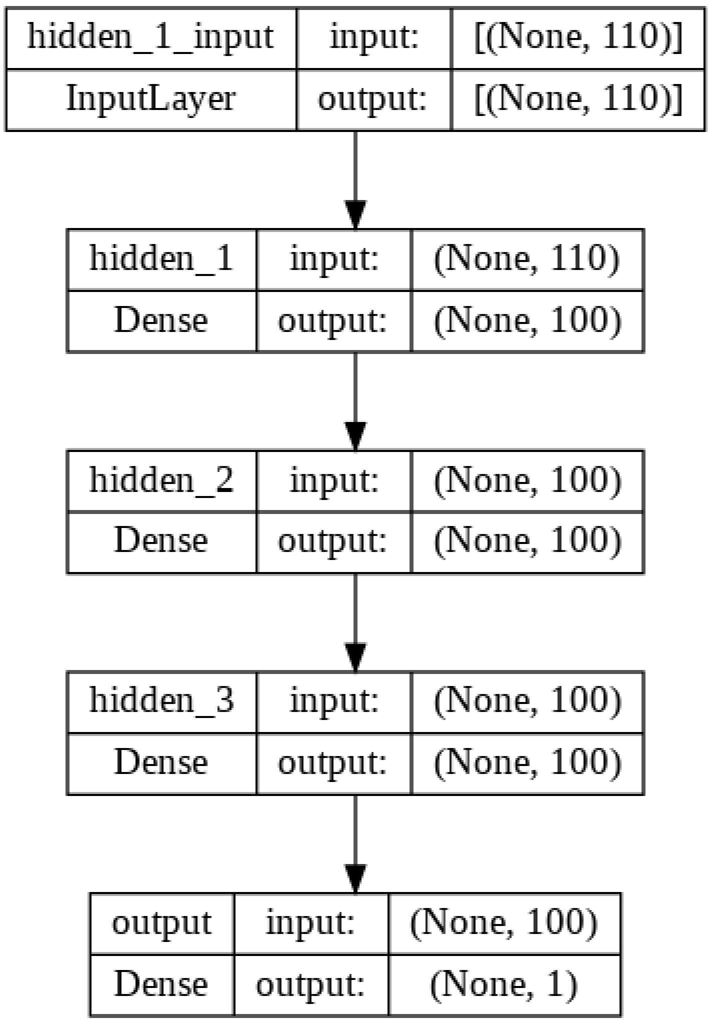
```
model = Sequential([
                    Dense(100, activation="relu",input_shape=(110,), name="hidden_1"), #F
                    Dense(100, activation="relu",name="hidden_2"), #Second Hidden Layer ha
                    Dense(100, activation="relu",name="hidden_3"), #Thied Hidden Layer has
                    Dense(1, activation="linear",name="output") #Output Layer has 1 neuro
])
```

```
model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=10, batch_size=256, validation_split=0.
```

In [67]:

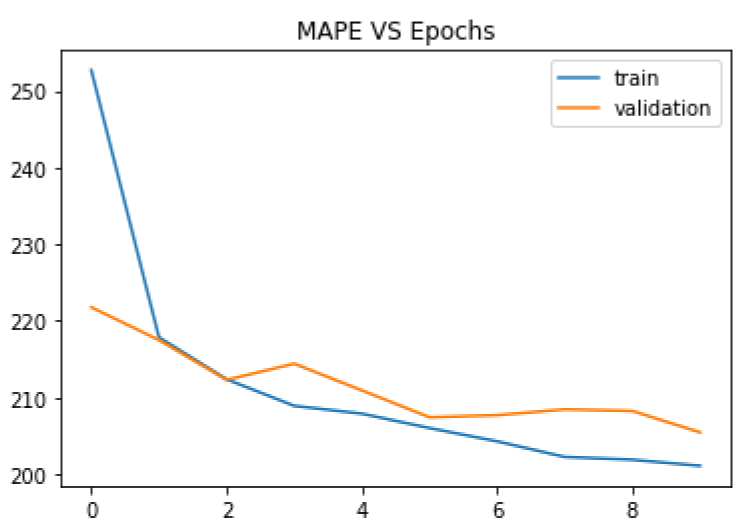
```
plot_model(model,
    to_file='model.png',
    show_shapes=True, show_layer_names=True)
```

Out[67]:



In [68]:

```
plot(history)
```



NN_Model 4 - Using Batch Normalization

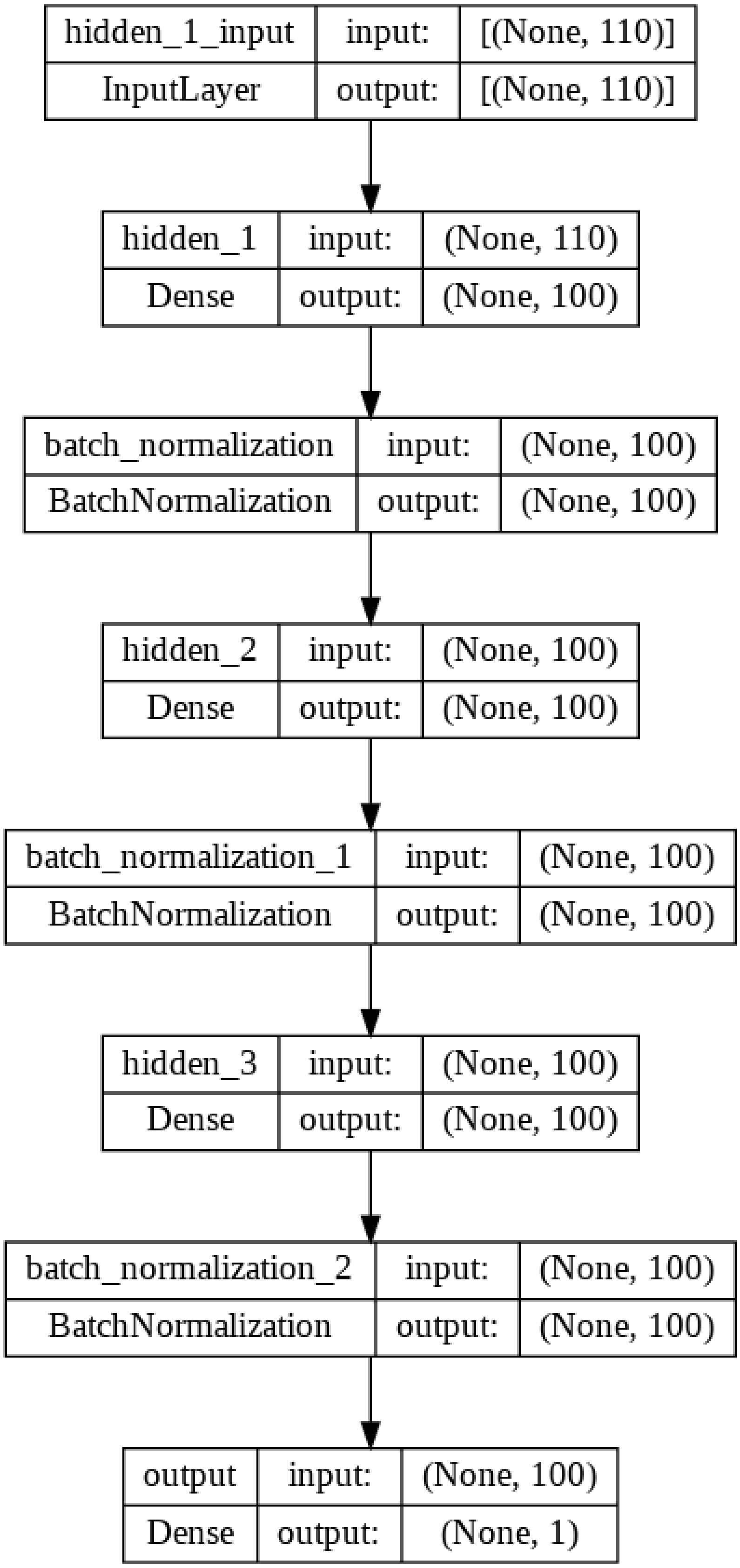
In [70]:

```
model = Sequential([
                    Dense(100, activation="relu",input_shape=(110,), name="hidden_1"), #Fi
                    BatchNormalization(),
                    Dense(100, activation="relu",name="hidden_2"), #Second Hidden Layer ha
                    BatchNormalization(),
                    Dense(100, activation="relu",name="hidden_3"), #Thied Hidden Layer has
                    BatchNormalization(),
                    Dense(1, activation="linear",name="output") #Output Layer has 1 neuron
])

model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=10, batch_size=256, validation_split=0.
```

In [71]:

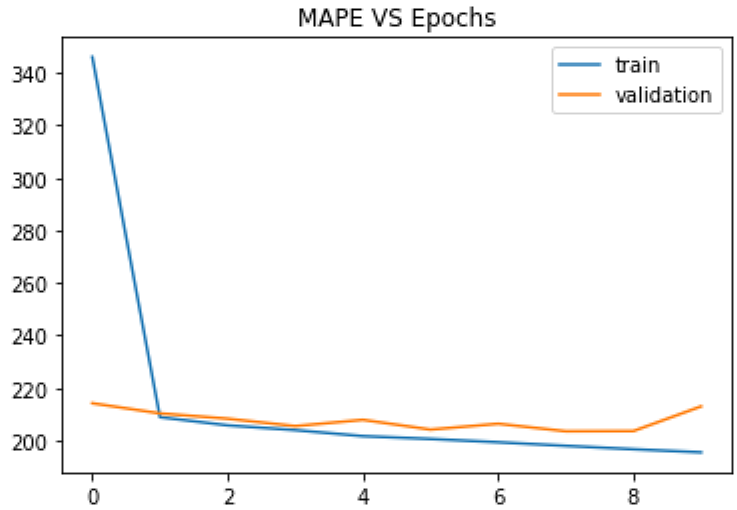
```
plot_model(model,
    to_file='model.png',
    show_shapes=True, show_layer_names=True)
```

Out[71]:



In [72]:

```
plot(history)
```

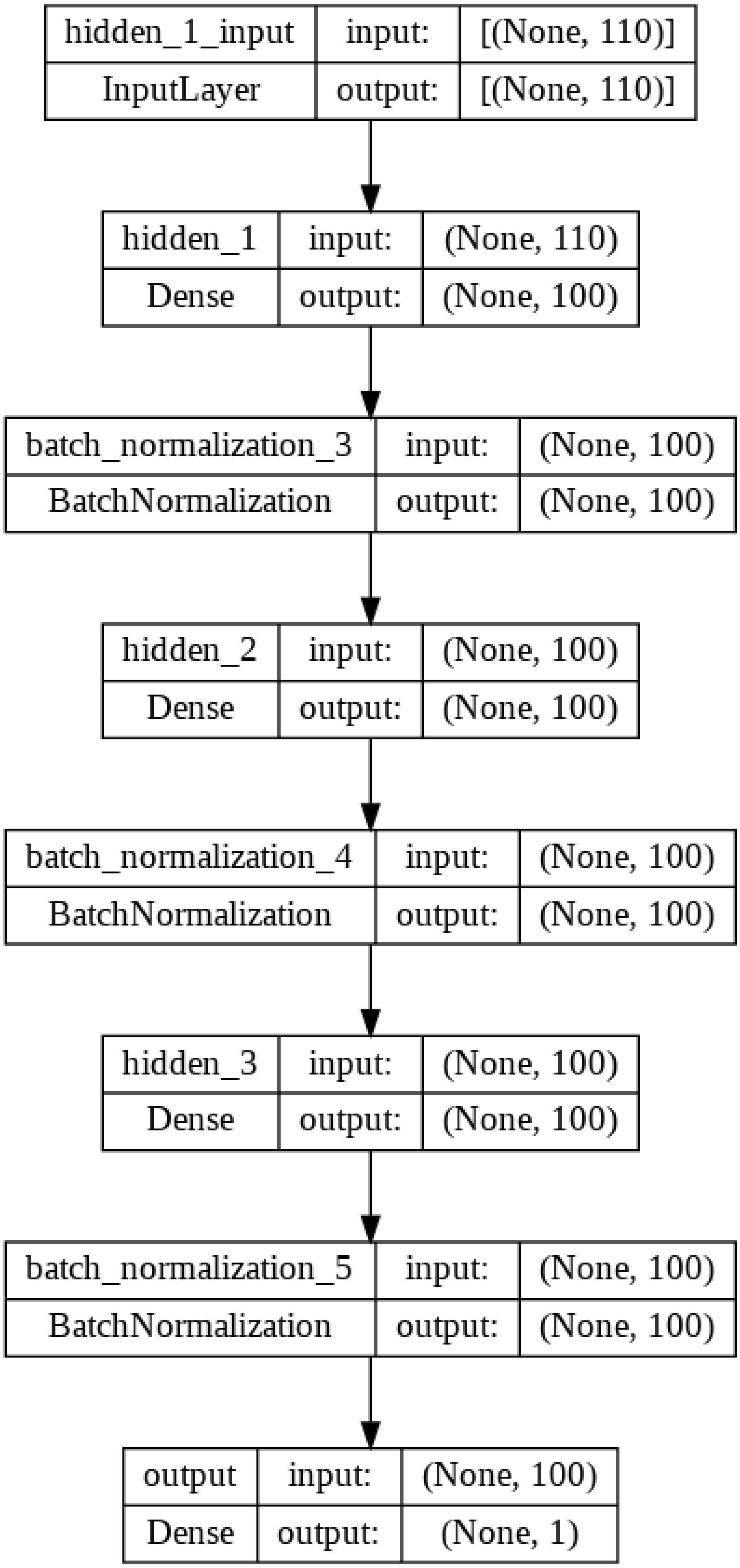


NN_Model 5 - Increasing Number of Epochs

In [73]:
```
model = Sequential([
                    Dense(100, activation="relu",input_shape=(110,), name="hidden_1"), #Fi
                    BatchNormalization(),
                    Dense(100, activation="relu",name="hidden_2"), #Second Hidden Layer ha
                    BatchNormalization(),
                    Dense(100, activation="relu", name="hidden_3"), #Thied Hidden Layer ha
                    BatchNormalization(),
                    Dense(1, activation="linear",name="output") #Output Layer has 1 neuron
])

model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=50, batch_size=256, validation_split=0.
```

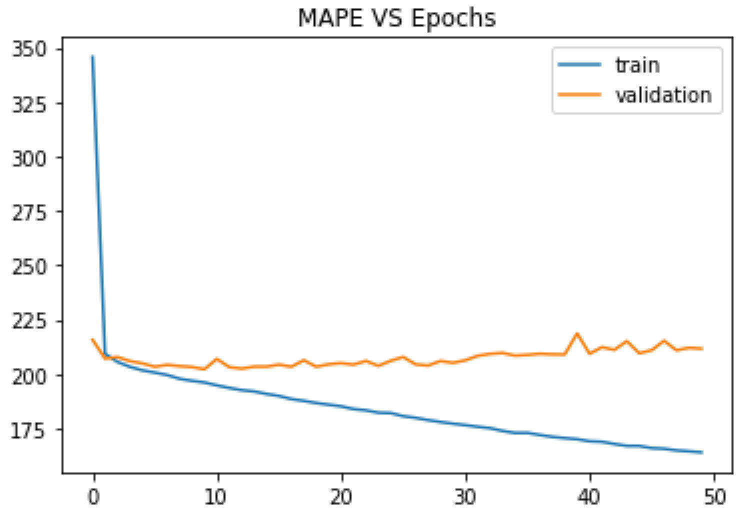
In [74]:
```
plot_model(model,
    to_file='model.png',
    show_shapes=True, show_layer_names=True)
```

Out[74]:



In [75]:

```
plot(history)
```



NN_Model 6 - Using Regulazition

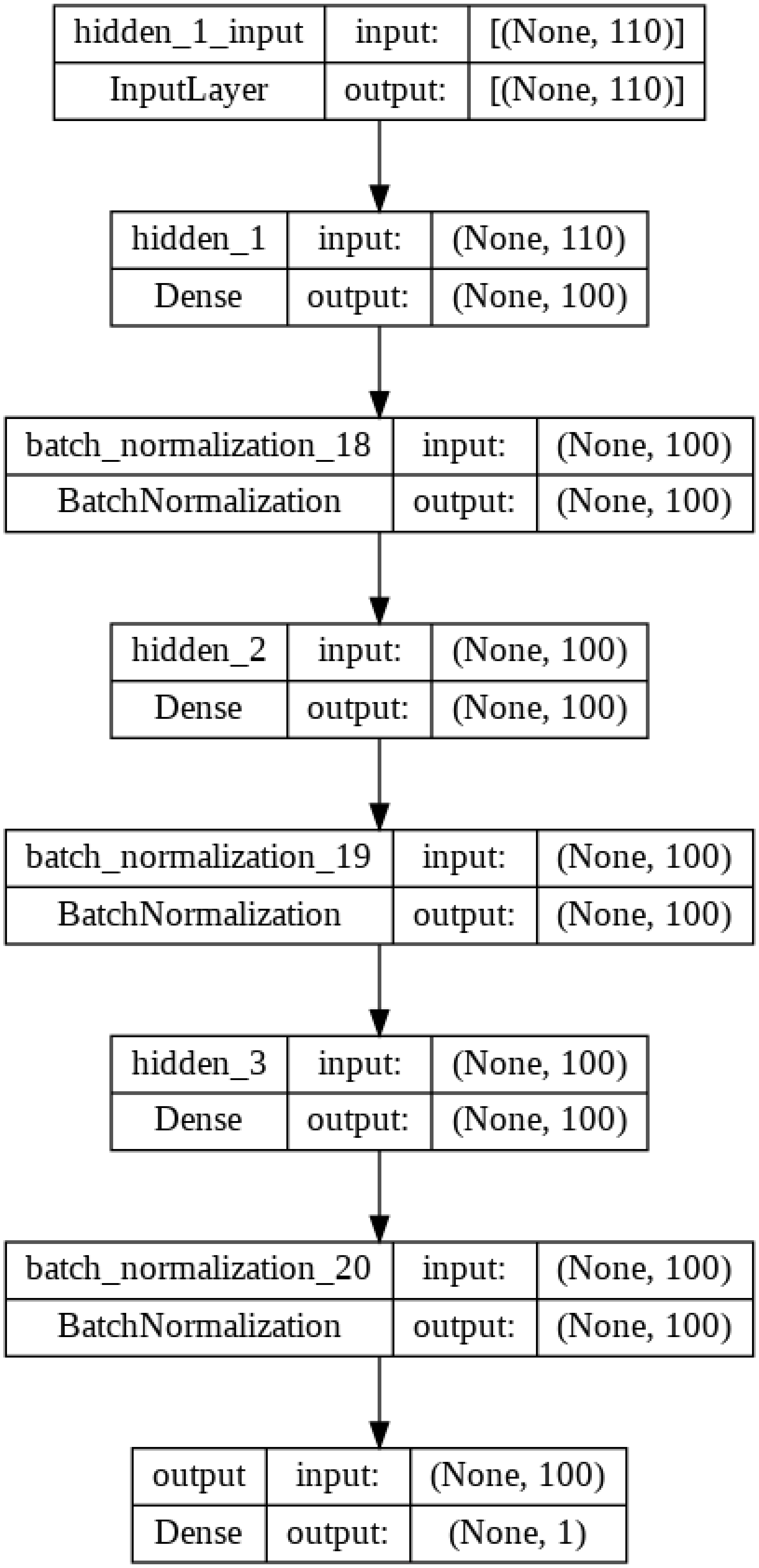
In [89]:

```
L2Reg = tf.keras.regularizers.L2(l2=1e-2)
model = Sequential([
          Dense(100, activation="relu",input_shape=(110,), name="hidden_1",kernel_regulari
          BatchNormalization(),
          Dense(100, activation="relu",input_shape=(110,), name="hidden_2",kernel_regulari
          BatchNormalization(),
          Dense(100, activation="relu",input_shape=(110,), name="hidden_3",kernel_regulari
          BatchNormalization(),
          Dense(1, activation="linear",name="output") #Output Layer has 1 neuron which pre
])

model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=40, batch_size=256, validation_split=0.
```

In [90]:

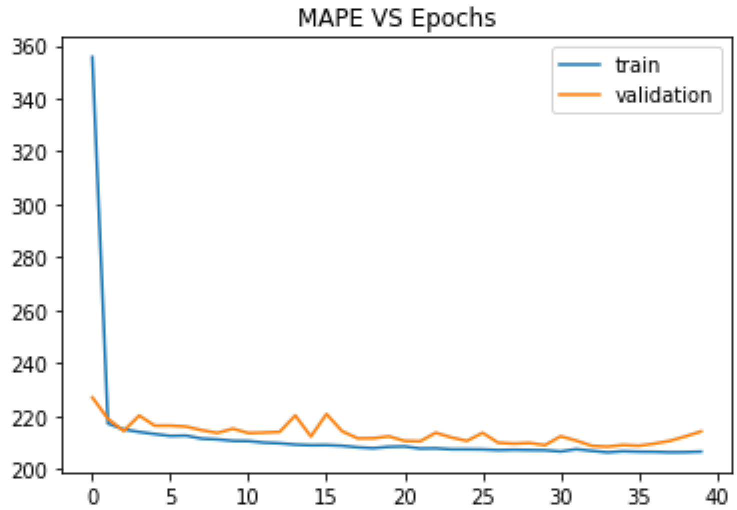
```
plot_model(model,
    to_file='model.png',
    show_shapes=True, show_layer_names=True)
```

Out[90]:



In [91]:

```
plot(history)
```



Comparing the results of neural network and random forest

In [93]:

```
# Building a NN model with 32 epochs as inferred from above graph.

L2Reg = tf.keras.regularizers.L2(l2=1e-2)
model = Sequential([
          Dense(100, activation="relu",input_shape=(110,), name="hidden_1",kernel_regulari
          BatchNormalization(),
          Dense(100, activation="relu",input_shape=(110,), name="hidden_2",kernel_regulari
          BatchNormalization(),
          Dense(100, activation="relu",input_shape=(110,), name="hidden_3",kernel_regulari
          BatchNormalization(),
          Dense(1, activation="linear",name="output") #Output Layer has 1 neuron which pre
])

model.compile(
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.01),
    loss = "mean_squared_error",
    metrics = ["mape"])

history=model.fit(X_train_dev, y_train_dev, epochs=32, batch_size=256, validation_split=0.
```

In [94]:

```
y_pred=model.predict(X_test)
print('Using Neural Network')
evaluate(y_test,y_pred)
```

```
540/540 [==============================] - 1s 2ms/step
Using Neural Network
Model Performance
MAPE 0.24
MSE 201.91
MAE 10.68
```

In [100…

```
y_pred=grid_search.predict(X_test)
print('Using RF')
evaluate(y_test,y_pred)
```

```
Using RF
Model Performance
MAPE 0.26
MSE 203.71
MAE 10.89
```

In [98]:

```
y_pred=grid_search.predict(X_test)
print('Using GBDT')
evaluate(y_test,y_pred)
```

```
Using GBDT
Model Performance
MAPE 0.25
MSE 192.26
MAE 10.55
```

Observation - NN is giving slightly better performance than both GBDT and RF.

Questions:

- Defining the problem statements and where can this and modifications of this be used? Need to predict delivery time of delivery riders. This can be used by Zomato and Swiggy.
- List 3 functions the pandas datetime provides with one line explanation. Extracting hour, month and subtracting dates functionality.
- Short note on datetime, timedelta, time span (period) data represented in date/time format is denoted by datetime. timedelta denotes the different between 2 datetime values. time span is the period between dates.
- Why do we need to check for outliers in our data? So that existing outliers do not create a problem for the ML model to identify the right trend.
- Name 3 outlier removal methods? - IQR Method, Isolation Forest, LOF
- What classical machine learning methods can we use other than random forest for regression? DT, Linear Regression, GBDT
- Why is scaling required for neural networks? To bring the scale of the different features to same level for smoother gradient descent.
- Briefly explain your choice of optimizer. ADAM optimizer because it has both Momentum and RMS Prop for smoother gradient descent..
- Which activation function did you use and why? Relu in hidden units for non-linearity and linear for output layer for predicting continuous values.
- Why does a neural network perform well on a large dataset? With more data, NNs tend to perform better.

In [ ]: