porter-neural-networks-regression

April 18, 2024

`Porter: Neural Networks Regression By Ratnesh Kumar`

Context:

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

[12]:
```python
import pandas as pd
df=pd.read_csv('/content/sample_data/Porterdataset.csv')
df.head()
```

[12]:
```
   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
```

Defining problem statement, importing the data and data structure analysis (10 points)

PROBLEM STATEMENT: 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 esimation, based on all those features

[13]:
```python
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
```

[14]:
```
df.isna().sum()
```

[14]:
```
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
```

[15]:
```
print('NAN in total_onshift_partners :
 ↪',(len(df['total_onshift_partners'])-df['total_onshift_partners'].isna().
 ↪sum())/len(df['total_onshift_partners'])*100)
df.drop(['total_onshift_partners'],inplace=True,axis=1)
print('NAN in total_busy_partners :
 ↪',(len(df['total_busy_partners'])-df['total_busy_partners'].isna().sum())/
 ↪len(df['total_busy_partners'])*100)
df.drop(['total_busy_partners'],inplace=True,axis=1)
print('NAN in total_outstanding_orders :
 ↪',(len(df['total_outstanding_orders'])-df['total_outstanding_orders'].isna().
 ↪sum())/len(df['total_outstanding_orders'])*100)
df.drop(['total_outstanding_orders'],inplace=True,axis=1)
```

```
df.head()
```

```
NAN in total_onshift_partners : 91.7630731203274
NAN in total_busy_partners : 91.7630731203274
NAN in total_outstanding_orders : 91.7630731203274
```

[15]:

```
   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
```

** Data preprocessing and feature engineering (30 points)

- Data cleaning
- Null value handling
- Creating the target column (time taken for delivery) from order timestamp and delivery timestamp
- Getting hour and day of the week
- Encoding categorical column

**

[16]:

```
df['store_primary_category'].value_counts()
df['store_primary_category'].fillna('Other',inplace=True)
df['market_id'].value_counts()
df['market_id'].fillna('0.0',inplace=True)
df['order_protocol'].value_counts()
df['order_protocol'].fillna('0.0',inplace=True)
df.dropna(subset=['actual_delivery_time'],inplace=True)
df.isna().sum()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 197421 entries, 0 to 197427
Data columns (total 11 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   market_id               197421 non-null  object
 1   created_at              197421 non-null  object
 2   actual_delivery_time    197421 non-null  object
 3   store_id                197421 non-null  object
 4   store_primary_category  197421 non-null  object
 5   order_protocol          197421 non-null  object
 6   total_items             197421 non-null  int64
 7   subtotal                197421 non-null  int64
 8   num_distinct_items      197421 non-null  int64
 9   min_item_price          197421 non-null  int64
 10  max_item_price          197421 non-null  int64
dtypes: int64(5), object(6)
memory usage: 18.1+ MB
```

[17]:
```
#Categorical columns
cat_col = [col for col in df.columns if df[col].dtype == 'object']
print('Categorical columns :',cat_col)
# Numerical columns
num_col = [col for col in df.columns if df[col].dtype != 'object']
print('Numerical columns :',num_col)
df[cat_col].nunique()
```

```
Categorical columns : ['market_id', 'created_at', 'actual_delivery_time',
'store_id', 'store_primary_category', 'order_protocol']
Numerical columns : ['total_items', 'subtotal', 'num_distinct_items',
'min_item_price', 'max_item_price']
```

[17]:
```
market_id                      7
created_at                180981
actual_delivery_time      178110
store_id                    6743
store_primary_category        75
order_protocol                 8
dtype: int64
```

[18]:
```
df['actual_delivery_time']=df['actual_delivery_time'].astype('datetime64[ns]')
df['created_at']=df['created_at'].astype('datetime64[ns]')
df['Time_taken_for_delivery']= (df['actual_delivery_time']-df['created_at'])/pd.
 ↪Timedelta('60s')
df['hour']=df['created_at'].dt.hour
df['day']=df['created_at'].dt.dayofweek
```

Dropping the Column that are no longer required

[19]:
```
df.drop(['created_at','actual_delivery_time','store_id'],axis=1,inplace=True)
```

[20]:
```
df['store_primary_category']=df['store_primary_category'].astype('category').
↪cat.codes

df.head()
```

[20]:
```
   market_id  store_primary_category order_protocol  total_items  subtotal  \
0        1.0                       5            1.0            4      3441
1        2.0                      48            2.0            1      1900
2        3.0                       0            1.0            1      1900
3        3.0                       0            1.0            6      6900
4        3.0                       0            1.0            3      3900

   num_distinct_items  min_item_price  max_item_price  \
0                   4             557            1239
1                   1            1400            1400
2                   1            1900            1900
3                   5             600            1800
4                   3            1100            1600

   Time_taken_for_delivery  hour  day
0                62.983333    22    4
1                67.066667    21    1
2                29.683333    20    3
3                51.250000    21    1
4                39.833333     2    6
```

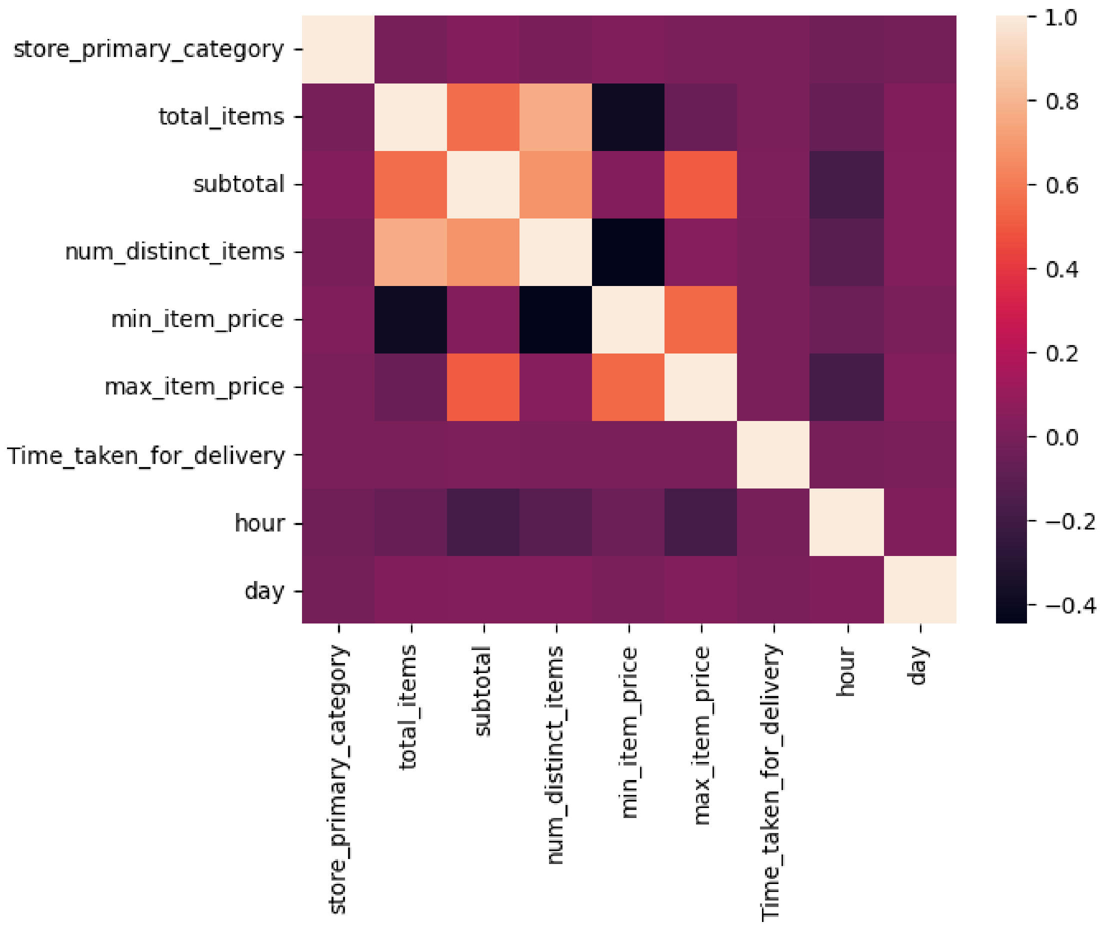
Data visualization and cleaning (20 points)

- Visualization for various features
- Check for outliers
- Remove outliers
- Compare plots and results

[21]:
```
import seaborn as sns
import matplotlib.pyplot as plt
sns.heatmap(df.corr())
```

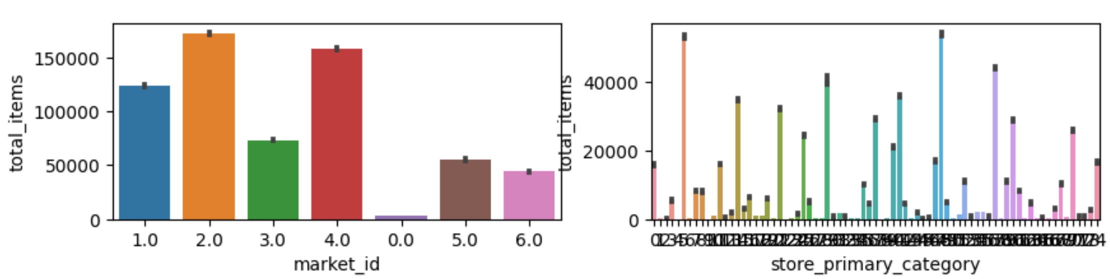
```
<ipython-input-21-fbcf84b297f6>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sns.heatmap(df.corr())
```

[21]:
```
<Axes: >
```



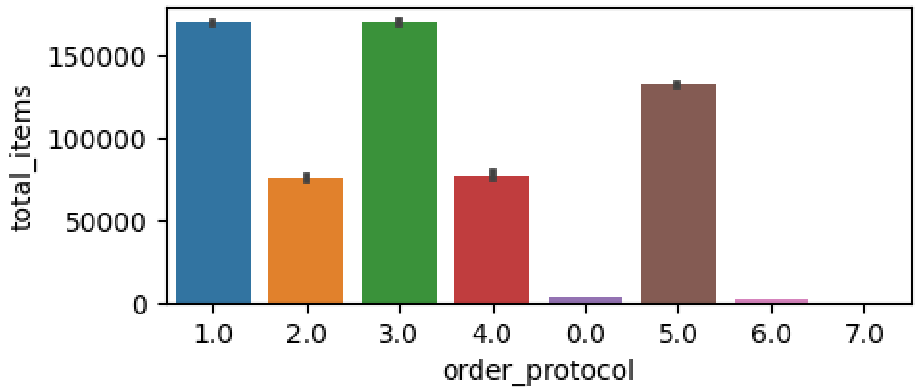
[22]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10,2))
plt.subplot(1,2,1)
sns.barplot(y='total_items',x='market_id',data=df,estimator='sum')
plt.subplot(1,2,2)
sns.barplot(y='total_items',x='store_primary_category',data=df,estimator='sum')
```

[22]: <Axes: xlabel='store_primary_category', ylabel='total_items'>



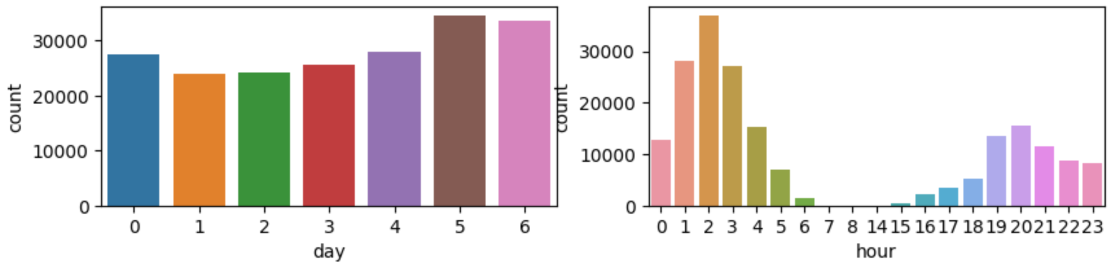
[23]:
```
plt.figure(figsize=(5,2))
sns.barplot(y='total_items',x='order_protocol',data=df,estimator='sum')
```

[23]: <Axes: xlabel='order_protocol', ylabel='total_items'>



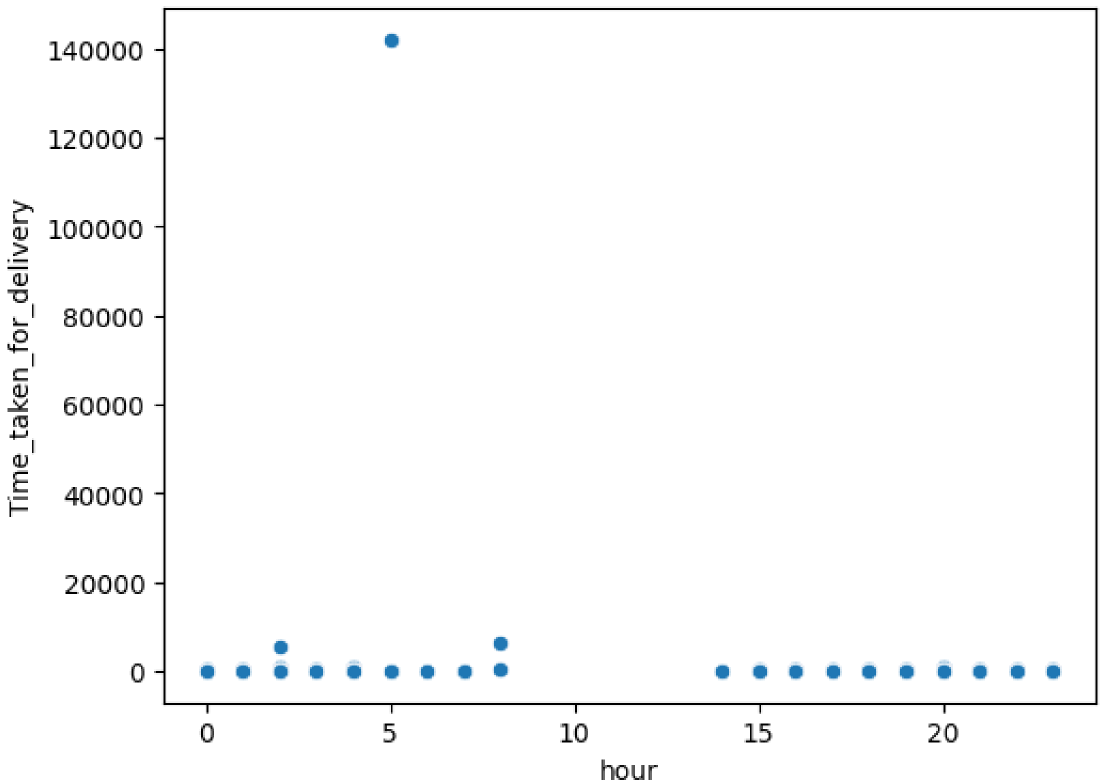
[24]:
```
plt.figure(figsize=(10,2))
plt.subplot(121)
sns.countplot(x=df['day'])
plt.subplot(122)
sns.countplot(x=df['hour'])
```

[24]: <Axes: xlabel='hour', ylabel='count'>



[25]:
```
sns.scatterplot(x='hour',y='Time_taken_for_delivery',data=df)
```

[25]: <Axes: xlabel='hour', ylabel='Time_taken_for_delivery'>



[25]:

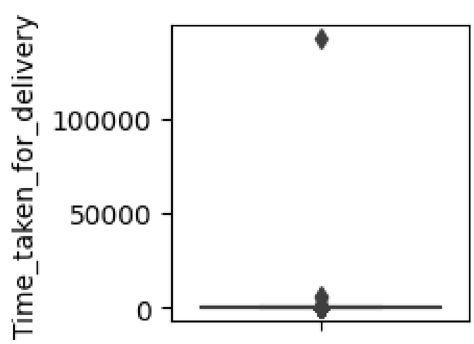
```

```

No Collinearity

Detecting Outliers

[27]:

```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(2,2))
sns.boxplot(y='Time_taken_for_delivery',data=df)
plt.xticks(rotation=90);
plt.show()
```

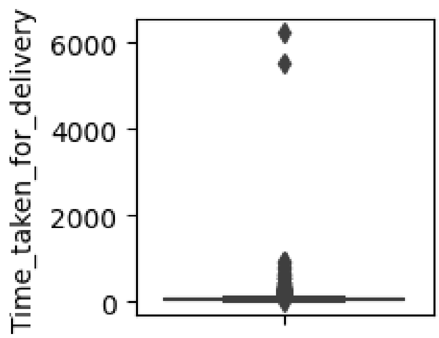


Removing Outliers

[28]:
```
import numpy as np
print((df.loc[df['Time_taken_for_delivery'] >400].shape[0] / df.shape[0]) * 100)
df.drop(index=df.loc[df['Time_taken_for_delivery'] >400].index[0],inplace=True)
```

0.009624102805679234

[29]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(2,2))
sns.boxplot(y='Time_taken_for_delivery',data=df)
plt.xticks(rotation=90);
plt.show()
```



Model training with random forest (10 points)

- Data splitting
- Random forest regression

[33]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
y=df['Time_taken_for_delivery']
x=df.drop(['Time_taken_for_delivery'],axis=1)
X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.
  ↪2,random_state=42)
regressor=RandomForestRegressor()
regressor.fit(X_train,y_train)
```

[33]: RandomForestRegressor()

[40]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
prediction=regressor.predict(X_test)
```

```
mse=mean_squared_error(y_test,prediction)
rmse=mse**.5
print("mse : ",mse)
print("rmse : ",rmse)
mae=mean_absolute_error(y_test,prediction)
print("mase : ",mae)
mape=np.mean(np.abs((y_test - prediction)/y_test))*100
print("mape : ",mape)

r2_score(y_test,prediction)
```

```
mse :  1298.7022878370515
rmse :  36.037512231521355
mase :  12.831212676817074
mape :  29.537370372638787
```

[40]:
```
0.018423261039891337
```

Regression with neural networks (30 points)

- Data scaling
- Defining NN architecture
- Trying different combinations and hyperparameters
- Model training
- Comparing results with random forest

[41]:
```
#Scalling the data to feed before neural network

from sklearn import preprocessing
scaler=preprocessing.MinMaxScaler()
x_scaled=scaler.fit_transform(x)
X_train,X_test,y_train,y_test=train_test_split(x_scaled,y,test_size=0.
↪2,random_state=42)
```

We will build a simple neural network to train our regression model it is a sequential model with two layers,

we have kept the number of nodes in the first layers equal to the number of input columns, and for the subsequent layers 32, 32, which can we changed or experimented with

the activation for the layers is kept as relu because it is a great non linear activation function that works for most cases, we could have used leaky relu if we see gradient vanishing.

the last layer has one node because it will give the single result that is our delivery time and the activation function for that should be linear

[74]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

```
model=Sequential()
model.add(Dense(11,kernel_initializer='normal',activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(1,activation='linear'))
model.compile(loss='mse',optimizer='Adam',metrics=['mse','mae'])
history=model.
 ↪fit(X_train,y_train,epochs=10,batch_size=512,verbose=1,validation_split=0.2)
```

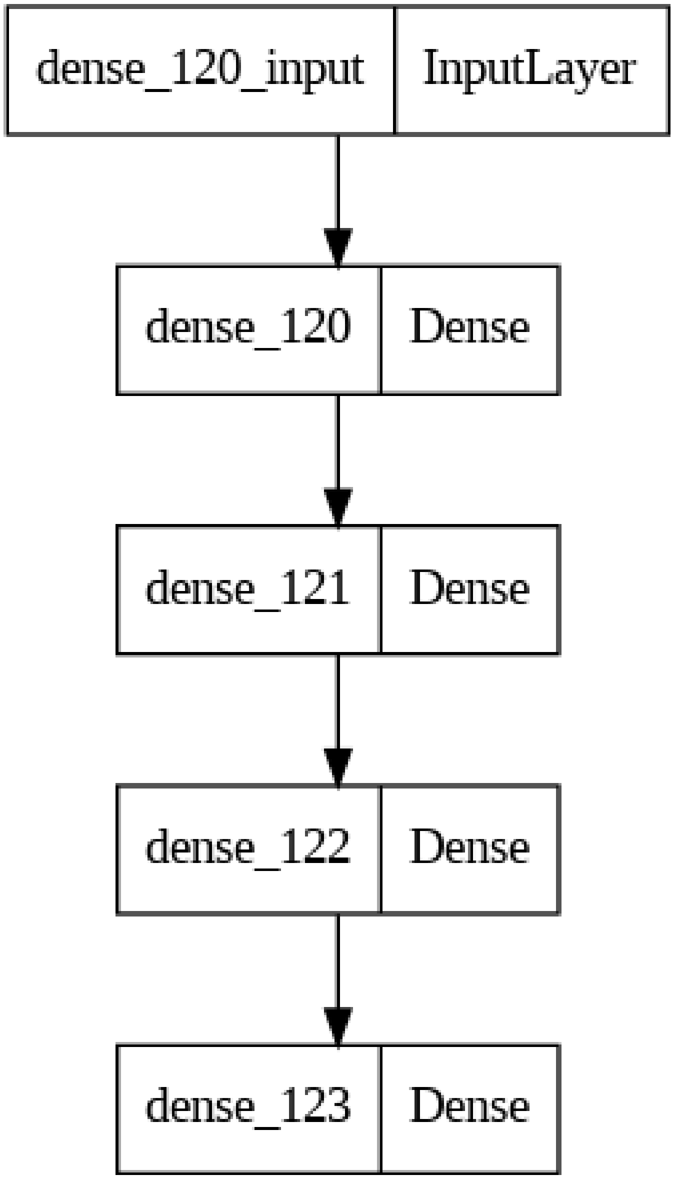
```
Epoch 1/10
247/247 [==============================] - 3s 6ms/step - loss: 1250.7706 - mse:
1250.7706 - mae: 27.2805 - val_loss: 1368.2872 - val_mse: 1368.2872 - val_mae:
14.8899
Epoch 2/10
247/247 [==============================] - 1s 4ms/step - loss: 422.8232 - mse:
422.8232 - mae: 14.2876 - val_loss: 1322.7933 - val_mse: 1322.7933 - val_mae:
13.9953
Epoch 3/10
247/247 [==============================] - 1s 4ms/step - loss: 390.1947 - mse:
390.1947 - mae: 13.6241 - val_loss: 1297.1119 - val_mse: 1297.1119 - val_mae:
13.4820
Epoch 4/10
247/247 [==============================] - 1s 4ms/step - loss: 373.6034 - mse:
373.6034 - mae: 13.2969 - val_loss: 1285.8724 - val_mse: 1285.8724 - val_mae:
13.3453
Epoch 5/10
247/247 [==============================] - 1s 4ms/step - loss: 368.1090 - mse:
368.1090 - mae: 13.2022 - val_loss: 1283.5146 - val_mse: 1283.5146 - val_mae:
13.3899
Epoch 6/10
247/247 [==============================] - 1s 3ms/step - loss: 366.8733 - mse:
366.8733 - mae: 13.1980 - val_loss: 1282.6769 - val_mse: 1282.6769 - val_mae:
13.2896
Epoch 7/10
247/247 [==============================] - 1s 3ms/step - loss: 366.4678 - mse:
366.4678 - mae: 13.1877 - val_loss: 1283.0757 - val_mse: 1283.0757 - val_mae:
13.4240
Epoch 8/10
247/247 [==============================] - 1s 3ms/step - loss: 366.3302 - mse:
366.3302 - mae: 13.1955 - val_loss: 1283.0736 - val_mse: 1283.0736 - val_mae:
13.1529
Epoch 9/10
247/247 [==============================] - 1s 3ms/step - loss: 366.1603 - mse:
366.1603 - mae: 13.1877 - val_loss: 1282.5369 - val_mse: 1282.5369 - val_mae:
13.2340
Epoch 10/10
```

```
247/247 [==============================] - 1s 3ms/step - loss: 366.2173 - mse:
366.2173 - mae: 13.1884 - val_loss: 1283.1187 - val_mse: 1283.1187 - val_mae:
13.1472
```

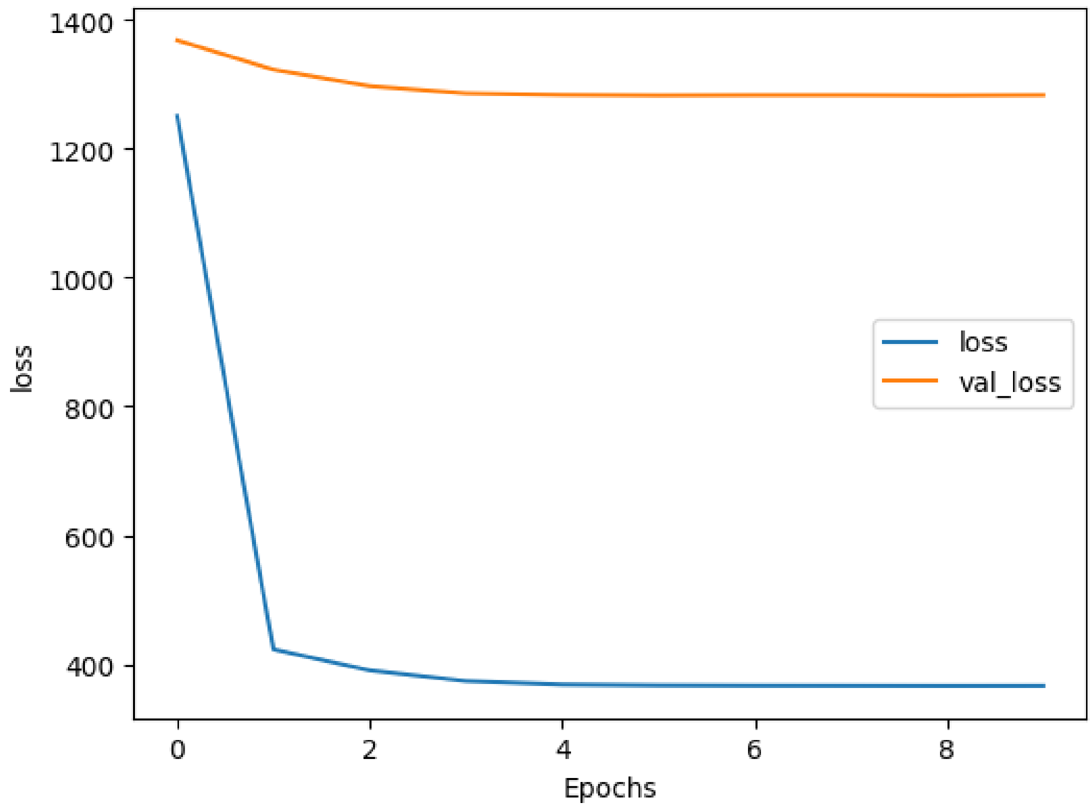
[75]:
```
model.summary()
from tensorflow.keras.utils import plot_model
plot_model(model)
```

```
Model: "sequential_26"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_120 (Dense)           (None, 11)                121

 dense_121 (Dense)           (None, 32)                384

 dense_122 (Dense)           (None, 32)                1056

 dense_123 (Dense)           (None, 1)                 33

=================================================================
Total params: 1594 (6.23 KB)
Trainable params: 1594 (6.23 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[75]:



[78]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel("Epochs")
plt.ylabel('loss')
plt.legend(['loss','val_loss'])
plt.show()
```



[84]:
```
print('r2_score:',r2_score(y_test, model.predict(X_test)))
mse = mean_squared_error(y_test, model.predict(X_test))
rmse = mse**.5
print("mse : ",mse)
print("rmse : ",rmse)
print("errors for neural net")
mae = mean_absolute_error(y_test, model.predict(X_test))
print("mae : ",mae)
```

```
1234/1234 [==============================] - 4s 3ms/step
r2_score: 0.01630627602202872
1234/1234 [==============================] - 2s 2ms/step
mse :  1301.5032234917896
rmse :  36.07635269108824
errors for neural net
1234/1234 [==============================] - 2s 1ms/step
mae :  13.135253871507697
```

[85]:
```
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, model.predict(X_test))
```

```
1234/1234 [==============================] - 3s 2ms/step
```

[85]: 0.29956791711312275

```
[ ]:
```