forecast-product-demand-with-lstm

March 7, 2024

0.1 Data Preparation

[1]:
```
# import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import statistics
import math

#for LSTM model
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout

# ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

```
2024-03-07 19:13:30.850750: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

[2]:
```
# read data
data = pd.read_csv("Historical Product Demand.csv")
data
```

[2]:

	Product_Code	Warehouse	Product_Category	Date	Order_Demand
0	Product_0993	Whse_J	Category_028	2012/7/27	100
1	Product_0979	Whse_J	Category_028	2012/1/19	500
2	Product_0979	Whse_J	Category_028	2012/2/3	500
3	Product_0979	Whse_J	Category_028	2012/2/9	500
4	Product_0979	Whse_J	Category_028	2012/3/2	500
…	…	…	…	…	…

```
1048570  Product_1791    Whse_J     Category_006  2016/4/27        1000
1048571  Product_1974    Whse_J     Category_006  2016/4/27           1
1048572  Product_1787    Whse_J     Category_006  2016/4/28        2500
1048573  Product_0901    Whse_J     Category_023  2016/10/7          50
1048574  Product_0704    Whse_J     Category_001  2016/6/27           4

[1048575 rows x 5 columns]
```

[3]:
```python
# rename the columns
data.rename(columns = {'Product_Code': 'ProductCode',
                       'Product_Category': 'ProductCategory',
                       'Order_Demand': 'OrderDemand'}, inplace = True)
data.head()
```

[3]:
```
   ProductCode Warehouse ProductCategory       Date OrderDemand
0  Product_0993    Whse_J    Category_028  2012/7/27         100
1  Product_0979    Whse_J    Category_028  2012/1/19         500
2  Product_0979    Whse_J    Category_028   2012/2/3         500
3  Product_0979    Whse_J    Category_028   2012/2/9         500
4  Product_0979    Whse_J    Category_028   2012/3/2         500
```

[4]:
```python
# check the null data
data.isnull().sum()
```

[4]:
```
ProductCode            0
Warehouse              0
ProductCategory        0
Date               11239
OrderDemand            0
dtype: int64
```

[5]:
```python
# drop the missing values
data.dropna(inplace=True)

# check the null data again
data.isnull().sum()
```

[5]:
```
ProductCode        0
Warehouse          0
ProductCategory    0
Date               0
OrderDemand        0
dtype: int64
```

[6]:
```python
# sort the data berdasarkan kolom tanggal
data.sort_values('Date', ignore_index=True, inplace=True)
data.head()
```

[6]:

```
     ProductCode Warehouse ProductCategory        Date OrderDemand
0   Product_0965    Whse_A    Category_006    2011/1/8           2
1   Product_0412    Whse_S    Category_007  2011/10/20         (2)
2   Product_0125    Whse_S    Category_011  2011/10/20         (2)
3   Product_0642    Whse_C    Category_019  2011/10/31           3
4   Product_2137    Whse_S    Category_009  2011/11/18        (25)
```

[7]:

```
# ada tanda () di kolom OrderDemand
data['OrderDemand'] = data['OrderDemand'].str.replace('(',"")
data['OrderDemand'] = data['OrderDemand'].str.replace(')',"")

# Mengubah tipe data menjadi integer
data['OrderDemand'] = data['OrderDemand'].astype('int64')
```

[33]:

```
# creating Year, Month, Day field for further analysis

# Mengubah tipe data menjadi datetime
from datetime import datetime as dt

data['Date']= pd.to_datetime(data['Date'])

# create Year, Month, Day columns
data['Year'] = data["Date"].dt.year
data['Month'] = data["Date"].dt.month
data['Day'] = data["Date"].dt.day

data['Year'] = data['Year'].astype(str)
```

0.2 Exploratory Data Analysis and Data Visualization

[27]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1037336 entries, 0 to 1037335
Data columns (total 8 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   ProductCode      1037336 non-null  object
 1   Warehouse        1037336 non-null  object
 2   ProductCategory  1037336 non-null  object
 3   Date             1037336 non-null  datetime64[ns]
 4   OrderDemand      1037336 non-null  int64
 5   Year             1037336 non-null  int32
 6   Month            1037336 non-null  int32
 7   Day              1037336 non-null  int32
dtypes: datetime64[ns](1), int32(3), int64(1), object(3)
memory usage: 51.4+ MB
```

[28]:
```
data["OrderDemand"].describe()
```

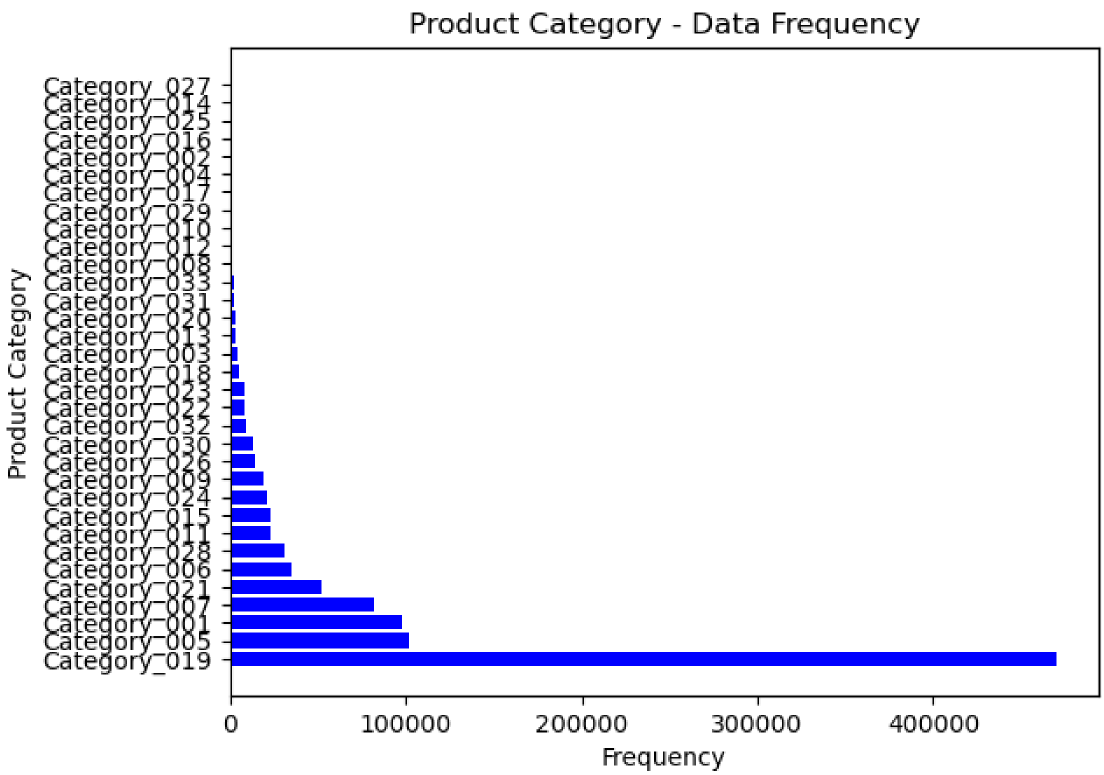
[28]:
```
count    1.037336e+06
mean     4.949384e+03
std      2.907344e+04
min      0.000000e+00
25%      2.000000e+01
50%      3.000000e+02
75%      2.000000e+03
max      4.000000e+06
Name: OrderDemand, dtype: float64
```

[29]:
```
# information about categorical variables
data[["ProductCode", "Warehouse", "ProductCategory"]].describe()
```

[29]:

	ProductCode	Warehouse	ProductCategory
count	1037336	1037336	1037336
unique	2160	4	33
top	Product_1359	Whse_J	Category_019
freq	16936	764447	470266

[14]:
```
# Jumlah data berdasarkan product category
plt.figure()
plt.barh(data["ProductCategory"].value_counts().index, data["ProductCategory"].
 ↪value_counts(), color = "b")
plt.xlabel("Frequency")
plt.ylabel("Product Category")
plt.title("Product Category - Data Frequency")
plt.show()
print(f"Number of ProductCategory \n{data['ProductCategory'].value_counts()}")
```

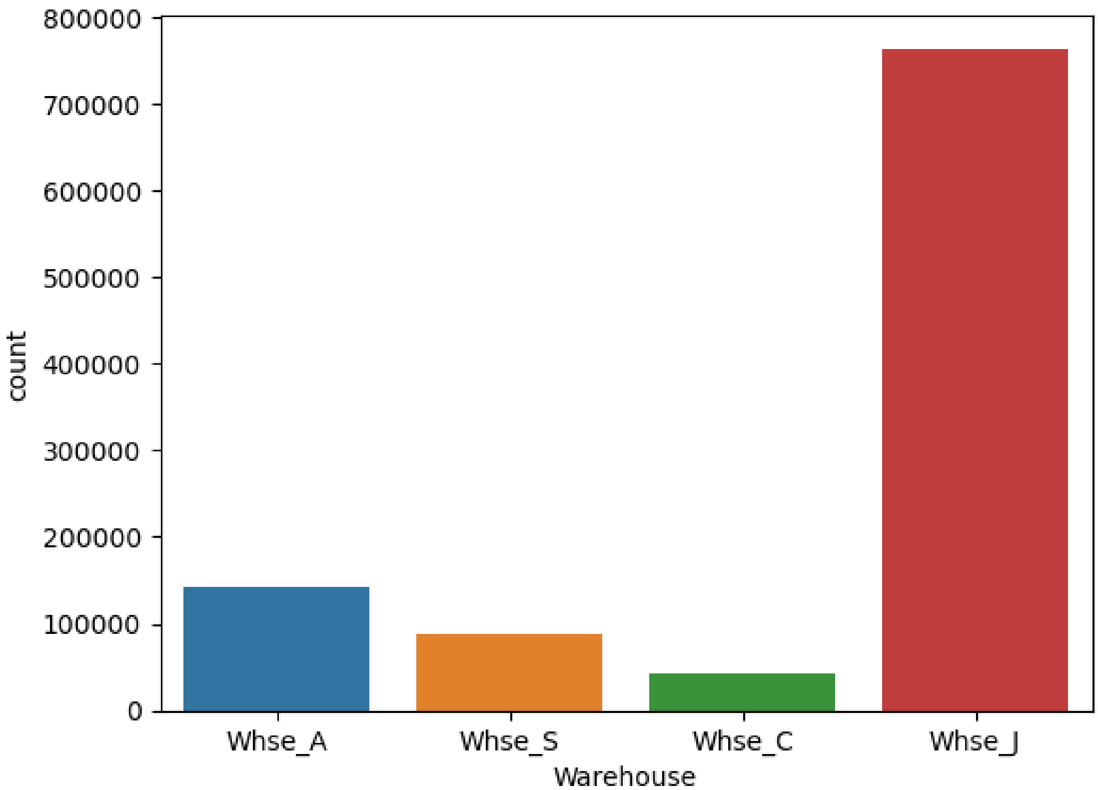



```
Number of ProductCategory
ProductCategory
Category_019    470266
Category_005    101627
Category_001     97787
Category_007     82402
Category_021     52008
Category_006     35552
Category_028     31012
Category_011     23208
Category_015     22954
Category_024     20885
Category_009     19738
Category_026     14771
Category_030     12997
Category_032      9296
Category_022      8657
Category_023      7899
Category_018      5239
Category_003      4189
Category_013      3743
Category_020      3490
```

```
Category_031      2268
Category_033      1849
Category_008      1560
Category_012      1147
Category_010       976
Category_029       671
Category_017       615
Category_004       329
Category_002        77
Category_016        37
Category_025        35
Category_014        26
Category_027        26
Name: count, dtype: int64
```

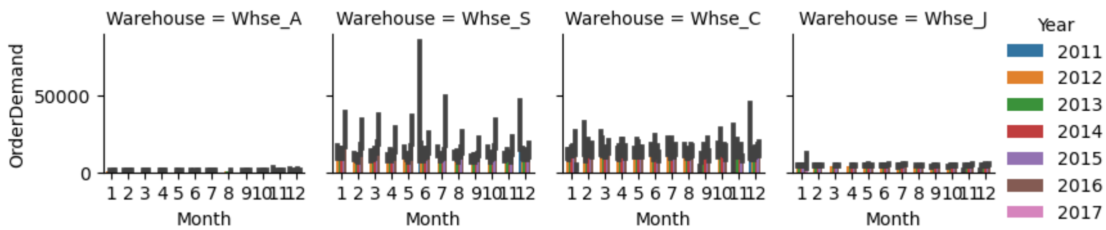
[30]:

```
# Jumlah data berdasarkan Warehouse
sns.countplot(x="Warehouse", data=data)
plt.xticks(rotation = 0)
plt.show()
print(f"Number of samples according to Warehouse \n{data['Warehouse'].
 ↪value_counts()}")
```

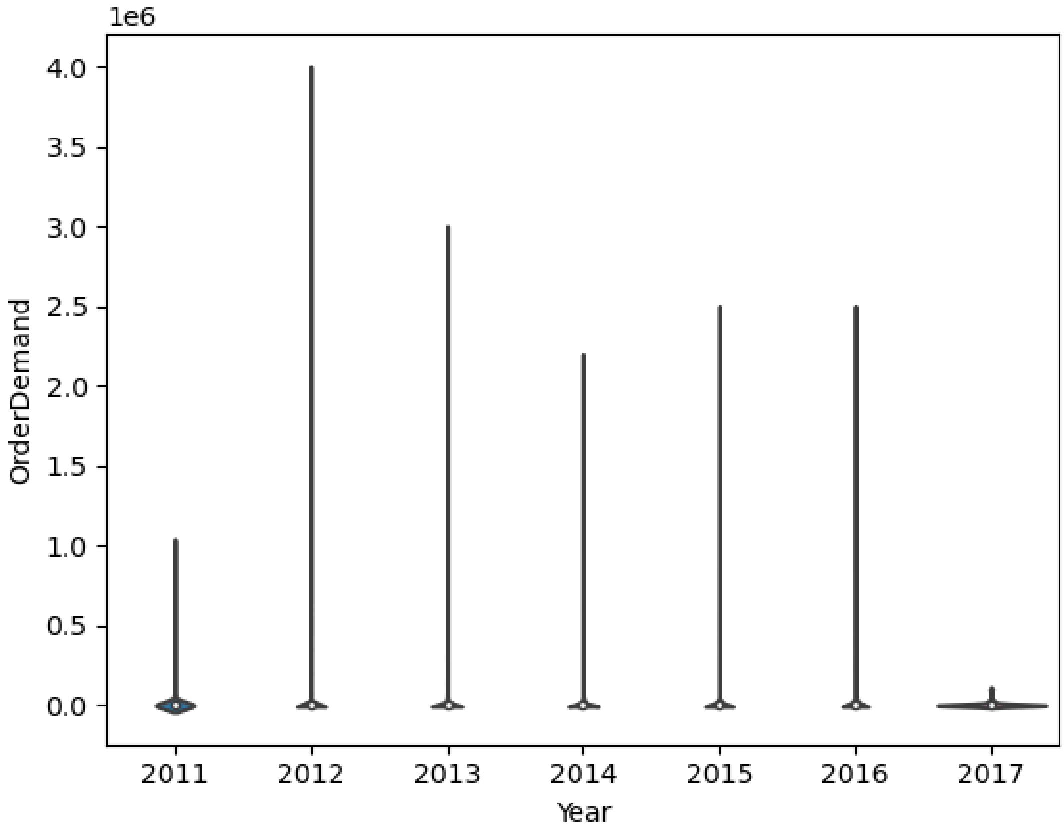


```
Number of samples according to Warehouse
Warehouse
Whse_J    764447
Whse_A    142335
Whse_S     88200
Whse_C     42354
Name: count, dtype: int64
```

[34]:
```
sns.catplot(x="Month", y="OrderDemand",  hue="Year", col="Warehouse",
            data=data, kind="bar", height=2)
plt.show()
```

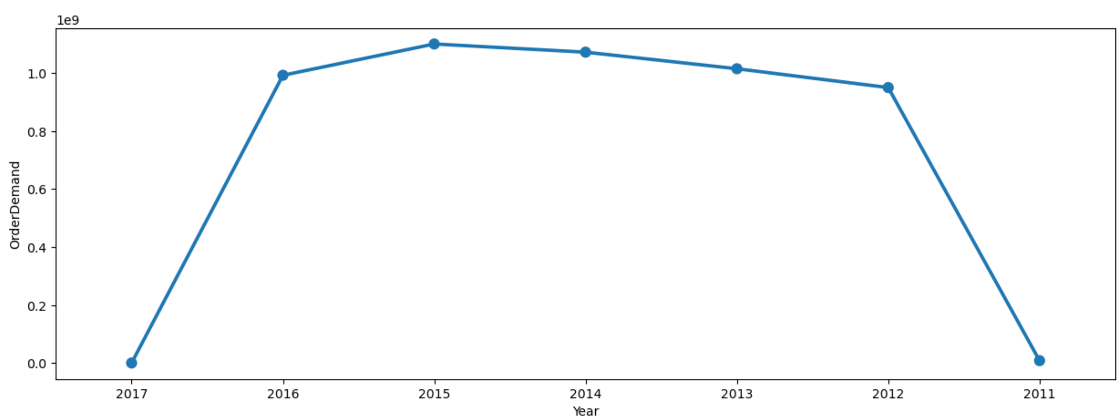


[35]:
```
sns.violinplot(x="Year", y="OrderDemand", data=data)
plt.show()
```

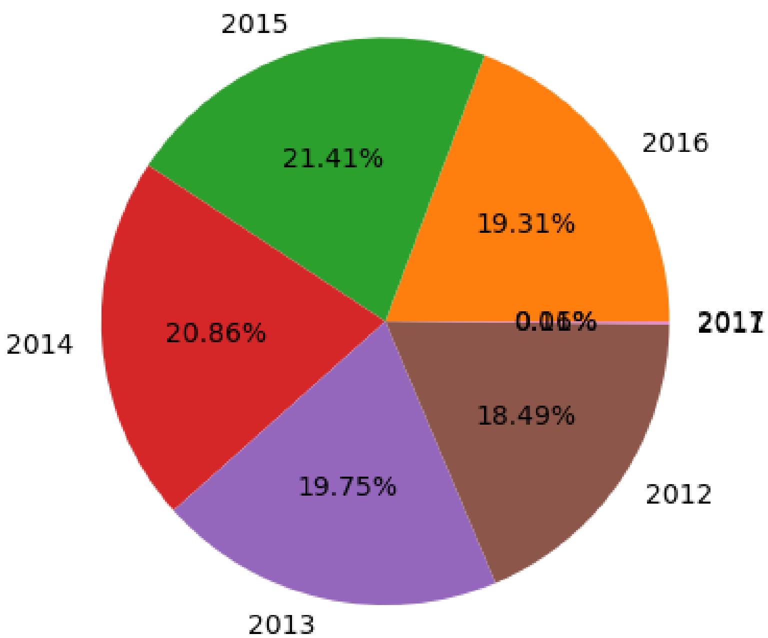


Yearly Analysis

[36]:
```
df = data[['OrderDemand', 'Year']].groupby(["Year"]).sum().reset_index().
    ↪sort_values(by='Year', ascending=False)
f, ax=plt.subplots(figsize=(15, 5))
sns.pointplot(x='Year', y='OrderDemand', data=df)
plt.show()
```



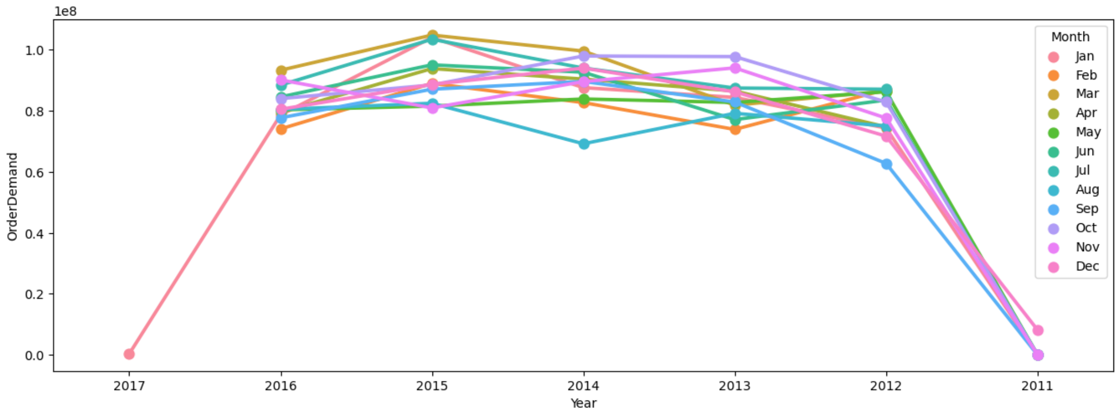
[38]:
```
# plot pie chart persentase order demand
plt.pie(df['OrderDemand'], labels=df['Year'].unique(), autopct='%1.2f%%')
plt.show()
```



Monthly Analysis

[39]:
```
temp_data = data.copy()
temp_data.Month.replace([1,2,3,4,5,6,7,8,9,10,11,12], ['Jan', 'Feb', 'Mar',␣
↪'Apr', 'May',
                                                        'Jun', 'Jul', 'Aug',␣
↪'Sep', 'Oct', 'Nov', 'Dec'], inplace=True)
df = temp_data[['OrderDemand',
                'Month', 'Year',]].groupby(["Year",
                                            "Month"]).sum().reset_index().
↪sort_values(by=['Year',
                                                                            ␣
↪          'Month'], ascending=False)
f, ax=plt.subplots(figsize=(15, 5))
sns.pointplot(x='Year', y='OrderDemand', data=df, hue='Month',␣
↪hue_order=['Jan', 'Feb', 'Mar', 'Apr', 'May',
```

```python
↪'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.show()
```



[40]:
```python
# Monthly pivot table
df = (df.pivot(index='Year', columns='Month', values='OrderDemand'))
df = df.loc[:, ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep',␣
↪'Oct', 'Nov', 'Dec']]
df
```

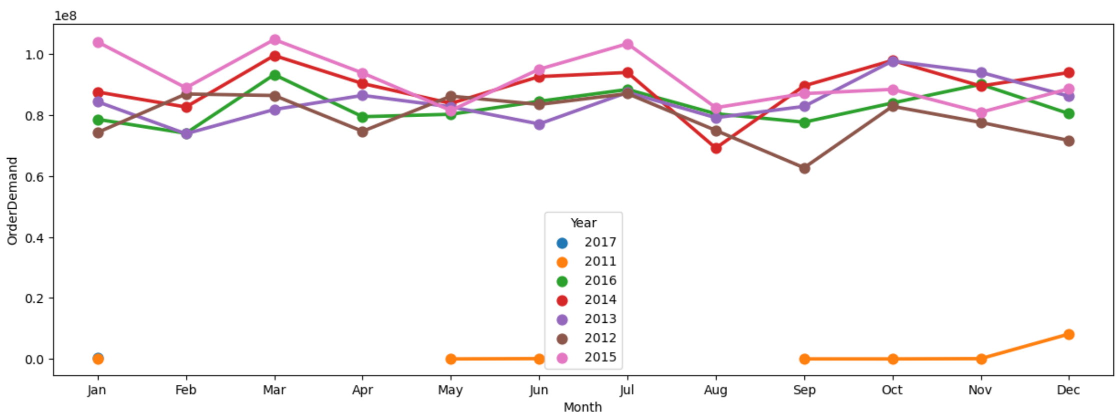
[40]:
```
Month          Jan         Feb          Mar         Apr         May  \
Year
2011           2.0         NaN          NaN         NaN       108.0
2012    74331037.0  86951780.0   86463212.0  74714053.0  86246051.0
2013    84399001.0  73899741.0   81857480.0  86489453.0  82735797.0
2014    87593983.0  82688430.0   99580627.0  90391888.0  83876775.0
2015   104028474.0  88991822.0  104825197.0  93842250.0  81540033.0
2016    78627619.0  74065041.0   93303910.0  79503364.0  80299593.0
2017      294967.0         NaN          NaN         NaN         NaN

Month         Jun          Jul         Aug         Sep         Oct  \
Year
2011      92000.0          NaN         NaN      6728.0         7.0
2012   83521679.0   87071567.0  75003241.0  62748329.0  82891675.0
2013   77115902.0   87469057.0  79181220.0  82882856.0  97773582.0
2014   92655892.0   94023350.0  69199733.0  89629088.0  97963491.0
2015   95074257.0  103449803.0  82468895.0  87080162.0  88477211.0
2016   84553011.0   88439936.0  80471772.0  77698896.0  84000757.0
2017          NaN          NaN         NaN         NaN         NaN

Month         Nov         Dec
Year
```

```
2011      86524.0   8178525.0
2012   77618687.0  71698680.0
2013   94072859.0  86210974.0
2014   89572680.0  94002430.0
2015   80944042.0  88676245.0
2016   90128568.0  80497932.0
2017          NaN         NaN
```

[41]:
```python
custom_dict = {'Jan':0, 'Feb':1, 'Mar':2, 'Apr':3, 'May':4, 'Jun':5,
               'Jul':6, 'Aug':7, 'Sep':8, 'Oct':9, 'Nov':10, 'Dec':11}
temp_data = data.copy()
temp_data.Month.replace([1,2,3,4,5,6,7,8,9,10,11,12], ['Jan', 'Feb', 'Mar',␣
 ↪'Apr', 'May',
                                                               'Jun', 'Jul',␣
 ↪'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], inplace=True)
df = temp_data[["OrderDemand", 'Month', 'Year']].groupby(["Year",
                                                  "Month"]).sum().reset_index().
 ↪sort_values(by=['Year',
                                                                             ␣
 ↪                   'Month'], ascending=True)
df = df.iloc[df['Month'].map(custom_dict).argsort()]
f, ax=plt.subplots(figsize=(15, 5))
sns.pointplot(x='Month', y="OrderDemand", data=df, hue="Year")
plt.show()
```



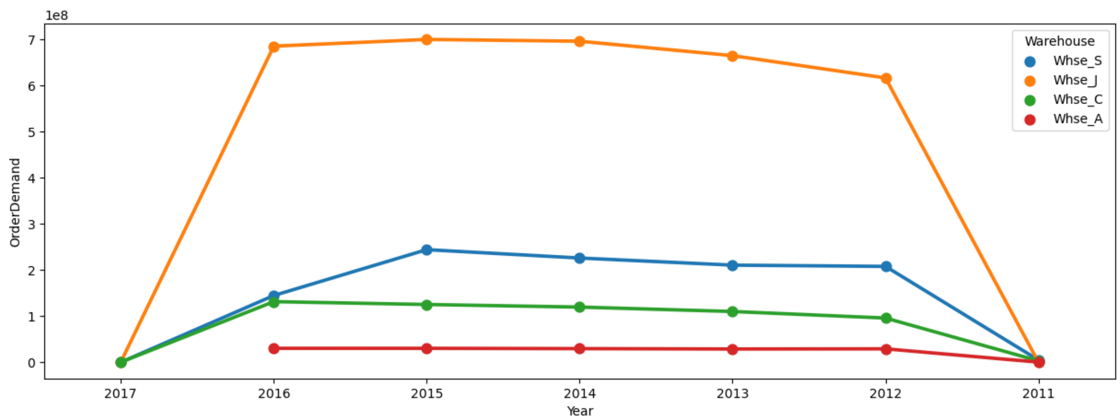
[42]:
```python
# Statistical information about monthly data
df.describe()
```

[42]:
```
        OrderDemand
count  6.800000e+01
mean   7.550256e+07
std    2.852781e+07
```

```
min      2.000000e+00
25%      7.749299e+07
50%      8.369923e+07
75%      8.913704e+07
max      1.048252e+08
```

Warehouse Based Analysis

[43]:
```
df = data[["OrderDemand", 'Year', 'Warehouse']].groupby(["Year",
                                                          "Warehouse"]).sum().
 ↪reset_index().sort_values(by=['Warehouse','Year'], ascending=False)
f, ax=plt.subplots(figsize=(15, 5))
sns.pointplot(x='Year', y="OrderDemand", data=df, hue="Warehouse")
plt.show()
```



[44]:
```
df = (df.pivot(index='Year', columns='Warehouse', values='OrderDemand'))
df
```

[44]:

Warehouse	Whse_A	Whse_C	Whse_J	Whse_S
Year				
2011	230881.0	3031847.0	198547.0	4902619.0
2012	29048000.0	95823181.0	616560449.0	207828361.0
2013	28696890.0	110035879.0	664781670.0	210573483.0
2014	29507380.0	119583036.0	696130811.0	225957140.0
2015	30167990.0	125188986.0	699932604.0	244108811.0
2016	30226290.0	131373097.0	685336996.0	144654016.0
2017	NaN	35378.0	259319.0	270.0

[46]:
```
df.describe()
```

[46]:

Warehouse	Whse_A	Whse_C	Whse_J	Whse_S
count	6.000000e+00	7.000000e+00	7.000000e+00	7.000000e+00

```
mean      2.464624e+07  8.358163e+07  4.804572e+08  1.482892e+08
std       1.197623e+07  5.719735e+07  3.292411e+08  1.042437e+08
min       2.308810e+05  3.537800e+04  1.985470e+05  2.700000e+02
25%       2.878467e+07  4.942751e+07  3.084099e+08  7.477832e+07
50%       2.927769e+07  1.100359e+08  6.647817e+08  2.078284e+08
75%       3.000284e+07  1.223860e+08  6.907339e+08  2.182653e+08
max       3.022629e+07  1.313731e+08  6.999326e+08  2.441088e+08
```

Product Category Based Analysis

[47]:

```
df = data[["OrderDemand",
           'ProductCategory', 'Warehouse']].groupby(["ProductCategory",
                                                     "Warehouse"]).sum().
 ↪reset_index().sort_values(by=['OrderDemand'],
                                                                        ␣
 ↪                  ascending=False)
df = df.pivot(index='ProductCategory', columns='Warehouse',␣
 ↪values='OrderDemand')
df
```

[47]:

```
Warehouse              Whse_A        Whse_C        Whse_J        Whse_S
ProductCategory
Category_001           1749.0       60106.0  1.623054e+06       72564.0
Category_002              NaN           NaN           NaN         628.0
Category_003         131607.0           NaN  3.926700e+04      222076.0
Category_004              NaN           NaN           NaN       99046.0
Category_005        1124300.0    12528700.0  1.289245e+08    57097050.0
Category_006       11613427.0    33131500.0  3.187667e+08    42059693.0
Category_007        2839680.0     7179524.0  1.121572e+08     6515085.0
Category_008           1903.0         317.0  1.534800e+04           NaN
Category_009         920903.0      251031.0  4.464690e+05     2163738.0
Category_010          12610.0           NaN  4.364000e+03        5580.0
Category_011          10360.0       63989.0  1.927557e+06      890936.0
Category_012           8926.0       14776.0  1.558800e+04       30716.0
Category_013          54931.0           NaN  8.557000e+04      169117.0
Category_014              NaN           NaN           NaN         100.0
Category_015          97983.0      112538.0  4.249710e+05      199013.0
Category_016            148.0           NaN           NaN       16702.0
Category_017          47658.0           NaN  1.443000e+03         356.0
Category_018          22935.0           NaN  1.105700e+04       12031.0
Category_019      106355439.0   521898473.0  2.739563e+09   872342758.0
Category_020              NaN      483735.0           NaN     1910078.0
Category_021        1190584.0      362485.0  1.892041e+06     1035460.0
Category_022         102670.0           NaN  6.859800e+04      434783.0
Category_023          45471.0     1640950.0  4.670830e+05     1184220.0
Category_024         154549.0      212478.0  3.551580e+05      335132.0
Category_025              NaN           NaN           NaN      486000.0
```

Category_026	85900.0	NaN	1.344020e+05	61694.0
Category_027	103.0	NaN	NaN	NaN
Category_028	23019635.0	NaN	1.274485e+07	13290870.0
Category_029	23979.0	NaN	NaN	NaN
Category_030	NaN	5702900.0	5.349550e+05	34728700.0
Category_031	9981.0	NaN	3.041000e+03	NaN
Category_032	NaN	1427902.0	3.845720e+05	2660574.0
Category_033	NaN	NaN	4.261000e+07	NaN

0.3 Forecast the Order Demand with LSTM Model

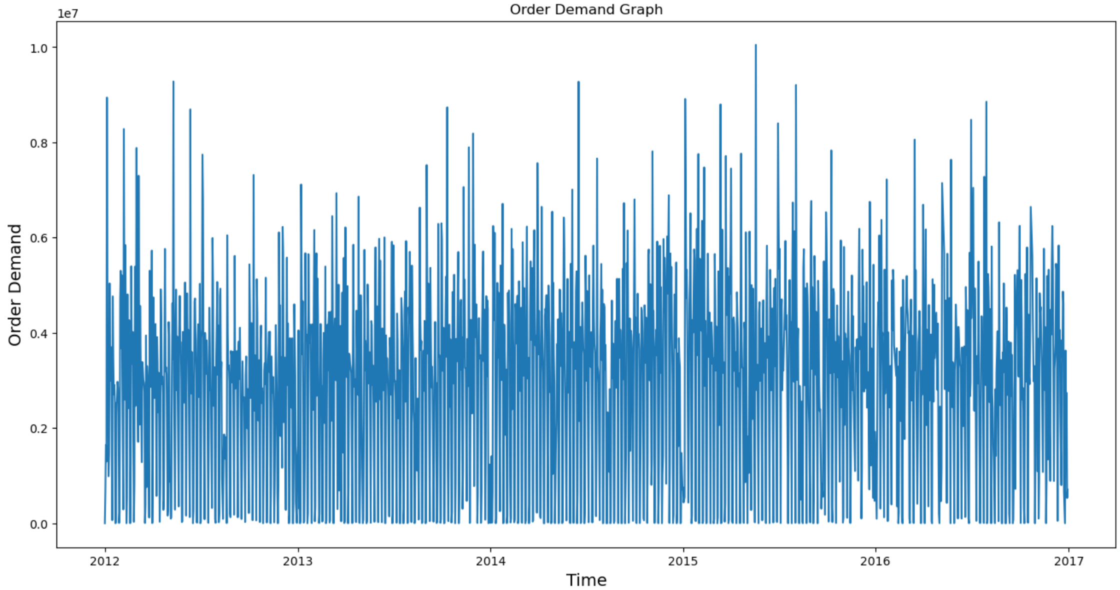
[49]:
```
# data yg digunakan tahun 2012 sampai tahun 2016
df = data[(data['Date']>='2012-01-01') & (data['Date']<='2016-12-31')].
    ↪sort_values('Date', ascending=True)
df = df.groupby('Date')['OrderDemand'].sum().reset_index()
df
```

[49]:

	Date	OrderDemand
0	2012-01-01	2
1	2012-01-02	680277
2	2012-01-03	1645257
3	2012-01-04	1295861
4	2012-01-05	8941774
…	…	…
1676	2016-12-26	3628370
1677	2016-12-27	1674226
1678	2016-12-28	2740302
1679	2016-12-29	530487
1680	2016-12-30	702950

[1681 rows x 2 columns]

[50]:
```
# Grafik order demand
plt.figure(figsize=(16, 8))
plt.title("Order Demand Graph")
plt.plot(df["Date"], df["OrderDemand"])
plt.xlabel("Time", fontsize=14,)
plt.ylabel("Order Demand", fontsize=14)
plt.show()
```



[52]:
```
# Membuat data baru dengan hanya kolom OrderDemand
orderD = df.filter(["OrderDemand"])
# Convert the dataframe to a np array
orderD_array = orderD.values

train_close_len = math.ceil(len(orderD_array) * 0.8)
train_close_len
```

[52]: 1345

[53]:
```
# Normalize the data
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(orderD_array)
scaled_data
```

[53]:
```
array([[1.99031453e-07],
       [6.76982600e-02],
       [1.63728946e-01],
       …,
       [2.72703145e-01],
       [5.27917993e-02],
       [6.99545800e-02]])
```

[54]:
```
# Create the training dataset
train_data = scaled_data[0 : train_close_len, :]
# Create X_train and y_train
X_train = []
```

```
y_train = []
for i in range(60, len(train_data)):
    X_train.append(train_data[i - 60 : i, 0])
    y_train.append(train_data[i, 0])
    if i <= 60:
        print(X_train)
        print(y_train)
```

```
[array([1.99031453e-07, 6.76982600e-02, 1.63728946e-01, 1.28958549e-01,
       8.89847137e-01, 4.36947184e-01, 9.82368500e-02, 1.43570443e-01,
       5.01388891e-01, 3.30568853e-01, 2.98325061e-01, 3.68113549e-01,
       6.39388544e-03, 4.74326585e-01, 3.44696702e-01, 2.69870529e-01,
       2.89035666e-01, 2.55127374e-01, 1.99031453e-05, 1.34953277e-03,
       2.51593073e-01, 2.53474816e-01, 2.95791390e-01, 2.81800375e-01,
       2.26411613e-01, 6.16997505e-04, 2.32949398e-02, 4.68048834e-01,
       5.27871021e-01, 3.66383269e-01, 5.18157490e-01, 3.13818067e-01,
       2.88706070e-02, 8.24073013e-01, 4.73426465e-01, 2.58256546e-01,
       5.81354156e-01, 3.14602052e-01, 9.95157266e-05, 5.74927232e-02,
       4.78518585e-01, 2.40411486e-01, 3.48965828e-01, 4.24549316e-01,
       2.88825090e-01, 1.69176735e-04, 1.26577138e-01, 5.37255155e-01,
       3.60979068e-01, 3.33127004e-01, 3.99856478e-01, 1.72541561e-01,
       2.98547180e-03, 8.14840741e-02, 5.36301397e-01, 2.45390755e-01,
       3.38598080e-01, 7.84473616e-01, 3.67118093e-01, 1.70085413e-01])]
[0.7264143498493282]
```

[55]:
```
#  make X_train and y_train np array
X_train, y_train = np.array(X_train), np.array(y_train)
```

[56]:
```
# reshape the data
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_train.shape
```

[56]: (1285, 60, 1)

[57]:
```
# create the testing dataset
test_data = scaled_data[train_close_len - 60 : , :]
# create X_test and y_test
X_test = []
y_test = df.iloc[train_close_len : , :]
for i in range(60, len(test_data)):
    X_test.append(test_data[i - 60 : i, 0])
```

[58]:
```
# convert the test data to a np array and reshape the test data
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

0.4 Build a LSTM Model

[59]:
```
# Build the LSTM Model
model = Sequential()

model.add(LSTM(units=512, return_sequences=True, activation='relu',␣
↪input_shape=(X_train.shape[1], 1)))


model.add(LSTM(units=256, activation='relu', return_sequences=False))


model.add(Dense(units=1))
```

```
2024-03-07 20:14:14.501906: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

[60]:
```
# compile the LSTM model
model.compile(optimizer="Adam", loss="mean_squared_error", metrics=['mae'])
```

[61]:
```
# train the LSTM model
model.fit(X_train, y_train,
          epochs=3,
          batch_size=100,
          verbose=1)
```

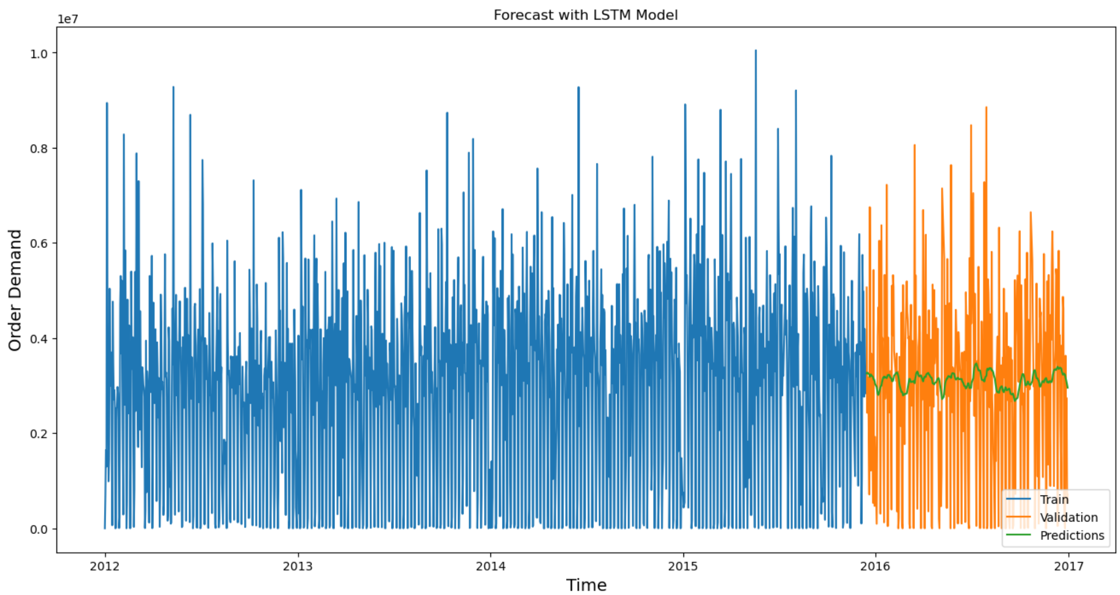
```
Epoch 1/3
13/13 [==============================] - 27s 2s/step - loss: 0.0560 - mae:
0.1944
Epoch 2/3
13/13 [==============================] - 22s 2s/step - loss: 0.0426 - mae:
0.1662
Epoch 3/3
13/13 [==============================] - 20s 2s/step - loss: 0.0409 - mae:
0.1632
```

[61]:
```
<keras.callbacks.History at 0x7f83a59a20d0>
```

[62]:
```
# predict with LSTM model
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(predictions)
```

```
11/11 [==============================] - 4s 297ms/step
```

[63]:
```python
# plot the data
train = orderD[:train_close_len]
valid = orderD[train_close_len:]
valid["Predictions"] = predictions
#visualize the data
plt.figure(figsize=(16, 8))
plt.title("Forecast with LSTM Model")
plt.xlabel("Time", fontsize=14)
plt.ylabel("Order Demand", fontsize=14)
plt.plot(df["Date"][:train_close_len], train["OrderDemand"])
plt.plot(df["Date"][train_close_len:], valid[["OrderDemand", "Predictions"]])
plt.legend(["Train", "Validation", "Predictions"], loc="lower right")
plt.show()
```



0.5 Build an Optimized LSTM Model

[64]:
```python
# change the parameters of first LSTM model and build the Optimized LSTM Model
optimized_model = Sequential()

optimized_model.add(LSTM(512, activation='relu', return_sequences=True,␣
 ↪input_shape=(X_train.shape[1], 1)))

optimized_model.add(LSTM(256, activation='relu', return_sequences=False))

optimized_model.add(Dense(128))

optimized_model.add(Dense(64))
```

```
optimized_model.add(Dense(32))

optimized_model.add(Dense(1))
```

[66]:

```
# compile the model
optimized_model.compile(optimizer="Adam", loss="mean_squared_error",␣
 ↪metrics=['mae'])
```

[67]:

```
# train the optimized model
optimized_model.fit(X_train, y_train,
          batch_size=32,
          epochs=20,
          verbose=1)
```

```
Epoch 1/20
41/41 [==============================] - 43s 927ms/step - loss: 0.0450 - mae:
0.1719
Epoch 2/20
41/41 [==============================] - 36s 866ms/step - loss: 0.0406 - mae:
0.1626
Epoch 3/20
41/41 [==============================] - 40s 973ms/step - loss: 0.0404 - mae:
0.1627
Epoch 4/20
41/41 [==============================] - 37s 893ms/step - loss: 0.0405 - mae:
0.1631
Epoch 5/20
41/41 [==============================] - 42s 1s/step - loss: 0.0393 - mae:
0.1600
Epoch 6/20
41/41 [==============================] - 45s 1s/step - loss: 0.0402 - mae:
0.1626
Epoch 7/20
41/41 [==============================] - 51s 1s/step - loss: 0.0376 - mae:
0.1573
Epoch 8/20
41/41 [==============================] - 41s 996ms/step - loss: 0.0357 - mae:
0.1528
Epoch 9/20
41/41 [==============================] - 43s 1s/step - loss: 0.0359 - mae:
0.1542
Epoch 10/20
41/41 [==============================] - 41s 1s/step - loss: 0.0345 - mae:
0.1494
Epoch 11/20
41/41 [==============================] - 48s 1s/step - loss: 0.0357 - mae:
```

```
0.1542
Epoch 12/20
41/41 [==============================] - 41s 979ms/step - loss: 0.0318 - mae:
0.1421
Epoch 13/20
41/41 [==============================] - 42s 1s/step - loss: 0.0304 - mae:
0.1389
Epoch 14/20
41/41 [==============================] - 42s 1000ms/step - loss: 0.0298 - mae:
0.1375
Epoch 15/20
41/41 [==============================] - 40s 962ms/step - loss: 0.0310 - mae:
0.1404
Epoch 16/20
41/41 [==============================] - 36s 880ms/step - loss: 0.0290 - mae:
0.1345
Epoch 17/20
41/41 [==============================] - 42s 1s/step - loss: 0.0288 - mae:
0.1337
Epoch 18/20
41/41 [==============================] - 43s 1s/step - loss: 0.0276 - mae:
0.1302
Epoch 19/20
41/41 [==============================] - 45s 1s/step - loss: 0.0270 - mae:
0.1294
Epoch 20/20
41/41 [==============================] - 39s 955ms/step - loss: 0.0270 - mae:
0.1270
```

[67]: <keras.callbacks.History at 0x7f837ac2ce50>

[68]:
```
# Predict with optimized LSTM model
o_predictions = optimized_model.predict(X_test)
o_predictions = scaler.inverse_transform(o_predictions)
```

```
11/11 [==============================] - 5s 260ms/step
```

[69]:
```
# plot the data
train = orderD[:train_close_len]
valid = orderD[train_close_len:]
valid["Predictions"] = o_predictions
#visualize the data
plt.figure(figsize=(16, 8))
plt.title("Forecast with Optimized LSTM Model")
plt.xlabel("Time", fontsize=14)
plt.ylabel("Order Demand", fontsize=14)
plt.plot(df["Date"][:train_close_len], train["OrderDemand"])
plt.plot(df["Date"][train_close_len:], valid[["OrderDemand", "Predictions"]])
```

```
plt.legend(["Train", "Validation", "Predictions"], loc="upper right")
plt.show()
```