Prediction of the quantity of taxi orders in time

Content

Project Description

Taxi company wants to understand what time is the highest and lowest drivers load for the optimization of the cost and increase of the drivers in a peak drivers load time. Based on the provided historical data from the company (taxi orders in airports) it's required to predict the quantity of the orders in next hour.

Main tasks are:

1. Load the data and perform resampling to 1 hour.
2. Perform the data Analysis.
3. Train the models with different hypreparameters. The test sample shall be equal to 10% of all data.
4. Test the best model and draw a conclusion.
5. RMSE score on the best model shall not exceed 48.

Data import and overview

Import of required libraries

In [1]:
```
import pandas as pd
import numpy as np
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import TimeSeriesSplit

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

Data import, overview, resampling equal to 1 hour

In [2]:
```
data = pd.read_csv('taxi.csv',index_col = [0], parse_dates = [0])
```

In [3]:
```
data = data.sort_index()
```

In [4]:
```
data.head()
```

Out[4]:

	num_orders
datetime	
2018-03-01 00:00:00	9
2018-03-01 00:10:00	14
2018-03-01 00:20:00	28
2018-03-01 00:30:00	20
2018-03-01 00:40:00	32

In [5]:
```
data = data.resample('1H').sum()
```

In [6]:
```
data.head()
```

Out[6]:

	num_orders
datetime	
2018-03-01 00:00:00	124
2018-03-01 01:00:00	85
2018-03-01 02:00:00	71
2018-03-01 03:00:00	66
2018-03-01 04:00:00	43

Data Analysis

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4416 entries, 2018-03-01 00:00:00 to 2018-08-31 23:00:00
Freq: H
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   num_orders  4416 non-null   int64
dtypes: int64(1)
memory usage: 69.0 KB
```

In [8]:
```
data.describe()
```

Out[8]:

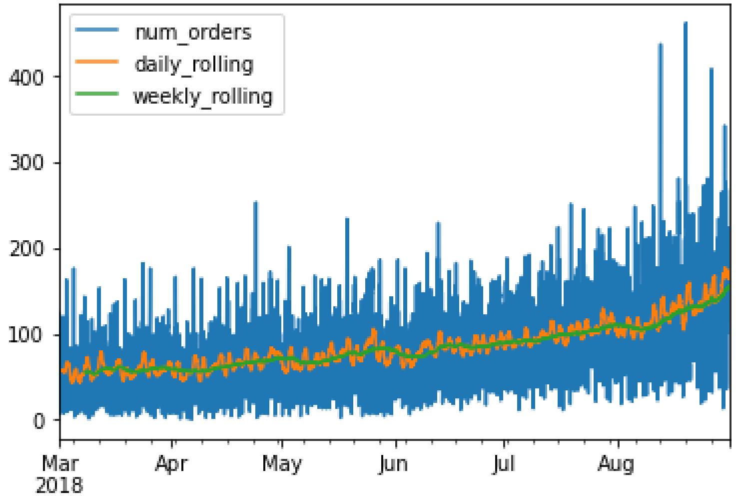
	num_orders
count	4416.000000
mean	84.422781
std	45.023853
min	0.000000
25%	54.000000
50%	78.000000
75%	107.000000
max	462.000000

Plotting of graphs: destribution of orders, weekly and daily flatterned

In [9]:

```
temp_data = data.copy()
temp_data['daily_rolling'] = temp_data.rolling(24).mean()
temp_data['weekly_rolling'] = temp_data['num_orders'].rolling(172).mean()
temp_data.plot()
```

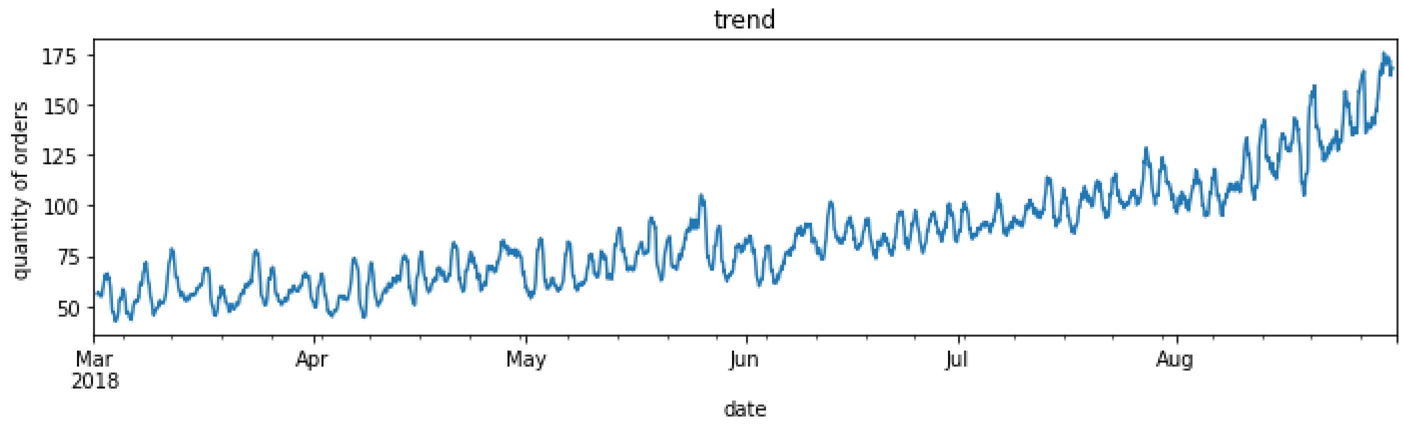
Out[9]: <AxesSubplot:xlabel='datetime'>

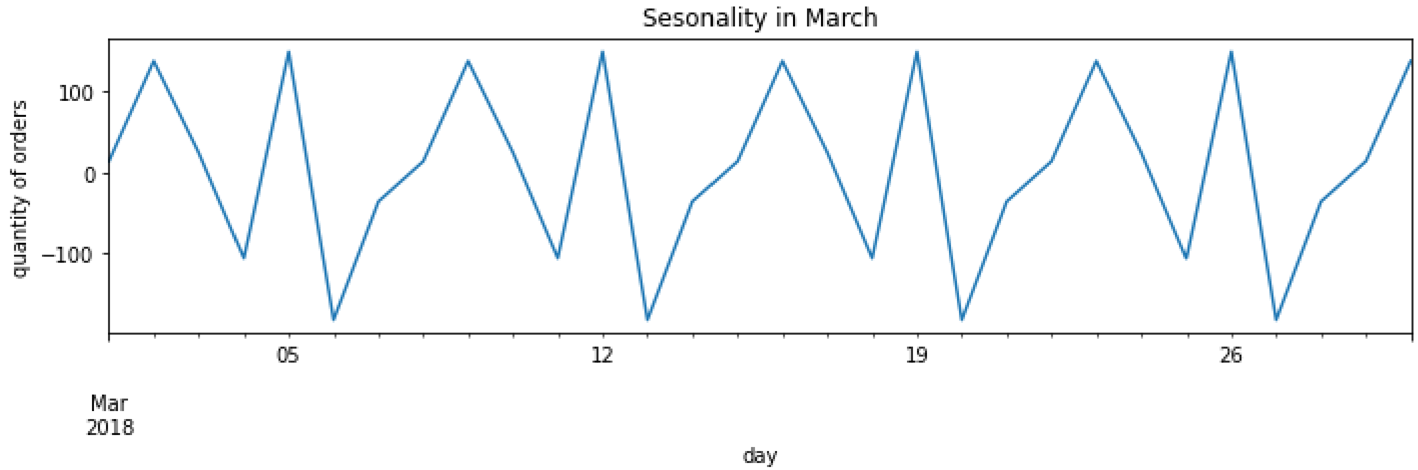


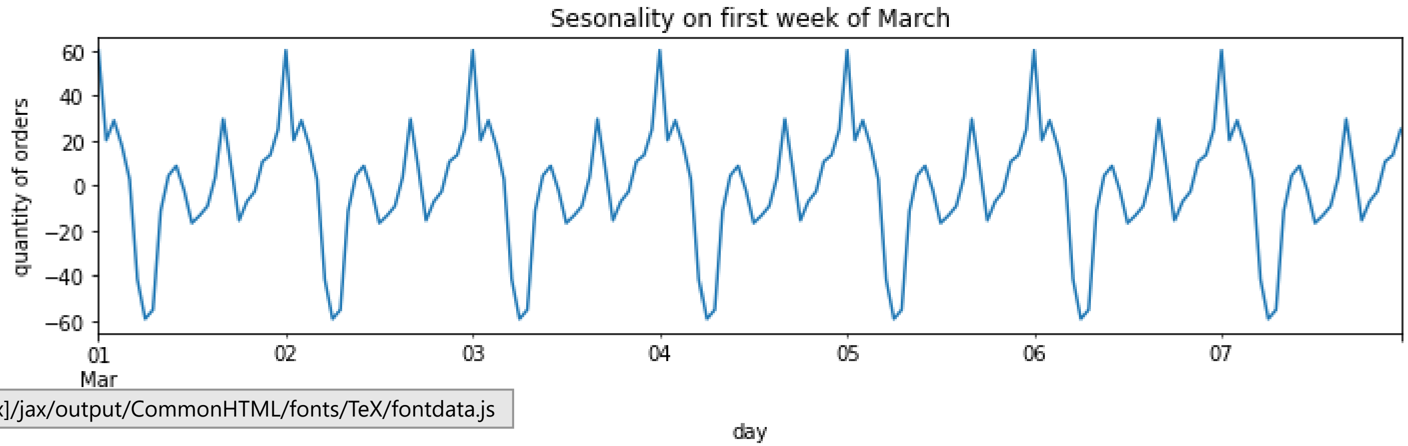
Trend and seasonality graphs plotting

In [10]:
```
decomposed_data = seasonal_decompose(data)
decomposed_data_szn = seasonal_decompose(data.resample('1D').sum())
```

In [11]:
```
plt.figure(figsize =(10,10))
plt.subplot(311)
decomposed_data.trend.plot(ax=plt.gca())
plt.title('trend')
plt.ylabel('quantity of orders')
plt.xlabel('date')

plt.subplot(312)
decomposed_data_szn.seasonal.head(30).plot(ax=plt.gca())
plt.title('Sesonality in March')
plt.ylabel('quantity of orders')
plt.xlabel('day')

plt.subplot(313)
decomposed_data.seasonal.head(168).plot(ax=plt.gca())
plt.title('Sesonality on first week of March')
plt.ylabel('quantity of orders')
plt.xlabel('day')

plt.tight_layout()
```


trend
quantity of orders
175
150
125
100
75
50
Mar
2018
Apr
May
Jun
Jul
Aug
date


Sesonality in March
quantity of orders
100
0
−100
05
12
19
26
Mar
2018
day


Sesonality on first week of March
quantity of orders
60
40
20
0
−20
−40
−60
01
Mar
02
03
04
05
06
07
day

Conclusion:

- Based on the analysis we see that demand on the taxi has slow growth from March to end of August.
- On the seasonal March graph we see increase of demand in the middle of the week and on weekends.
- On the season graph of first week of march we see that the highest demand is in the second half of the day and the lowest demand is the night.

Models training

Features extracting

In [12]:
```
data['year'] = data.index.year
```

In [13]:
```
data['month'] = data.index.month
```

In [14]:
```
data['day'] = data.index.day
```

In [15]:
```
data['dayofweek'] = data.index.dayofweek
```

In [16]:
```
data['hour'] = data.index.hour
```

In [17]:
```
# function for adding the required qunatity of columns using shift method
def rol_lag(df,lag_num,rol_qty):
    df['rolling_mean'] = df['num_orders'].shift().rolling(rol_qty+1).mean()
    lag = 1
    for i in range(lag_num):
        df['lag'+str(lag)] = df['num_orders'].shift(i)
        lag+=1
    return(df)
```

In [18]:
```
data_set = rol_lag(data,3,5)
data_set = data_set.dropna()
data_set.head(10)
```

Out[18]:

datetime	num_orders	year	month	day	dayofweek	hour	rolling_mean	lag1	lag2	lag3
2018-03-01 06:00:00	12	2018	3	1	3	6	65.833333	12	6.0	43.0
2018-03-01 07:00:00	15	2018	3	1	3	7	47.166667	15	12.0	6.0
2018-03-01 08:00:00	34	2018	3	1	3	8	35.500000	34	15.0	12.0
2018-03-01 09:00:00	69	2018	3	1	3	9	29.333333	69	34.0	15.0
2018-03-01 10:00:00	64	2018	3	1	3	10	29.833333	64	69.0	34.0
2018-03-01 11:00:00	96	2018	3	1	3	11	33.333333	96	64.0	69.0
2018-03-01 12:00:00	30	2018	3	1	3	12	48.333333	30	96.0	64.0
2018-03-01 13:00:00	32	2018	3	1	3	13	51.333333	32	30.0	96.0
2018-03-01 14:00:00	48	2018	3	1	3	14	54.166667	48	32.0	30.0
2018-03-01 15:00:00	66	2018	3	1	3	15	56.500000	66	48.0	32.0

In [19]:
```
train, test = train_test_split(data_set, shuffle = False, test_size = 0.1)
```

In [20]:
```
train, valid = train_test_split(train, shuffle = False, test_size = 0.2)
```

In [21]:
```
train_target = train['num_orders']
train_features = train.drop('num_orders', axis = 1)
```

In [22]:
```
valid_target = valid['num_orders']
valid_features = valid.drop('num_orders', axis = 1)
```

In [23]:
```
test_target = test['num_orders']
test_features = test.drop('num_orders', axis = 1)
```

Logistic regression training

In [24]:
```
LR_model = LogisticRegression(random_state=0)
```

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

```
rget)
```

Out[25]:
```
▾ LogisticRegression
LogisticRegression(random_state=0)
```

In [26]:
```
LR_predictions = LR_model.predict(valid_features)
```

In [27]:
```
RMSE_LR = mean_squared_error(valid_target,LR_predictions,squared= False)
```

In [28]:
```
RMSE_LR
```

Out[28]:
```
32.28852920756703
```

Random forest training

In [29]:
```
n_estimators = [int(x) for x in np.linspace(start = 10, stop = 100, num = 10)]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(10, 30, num = 10)]
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 4]
bootstrap = [True, False]
```

In [30]:
```
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

In [31]:
```
RF = RandomForestRegressor()
```

In [32]:
```
tscv = TimeSeriesSplit(max_train_size = 5, test_size=1)
```

In [33]:
```
RF_model = RandomizedSearchCV(estimator = RF, param_distributions = random_grid, random_state=42, cv=tscv)
```

In [34]:
```
RF_model.fit(train_features,train_target)
```

Out[34]:

```
RandomizedSearchCV
estimator: RandomForestRegressor
RandomForestRegressor
```

In [35]:

```
RF_predictions = RF_model.predict(valid_features)
```

In [36]:

```
RMSE_RF = mean_squared_error(valid_target,RF_predictions,squared= False)
```

In [37]:

```
RMSE_RF
```

Out[37]:

```
13.172828459572049
```

Models testing

selection of best model:

In [38]:

```
list = [LR_model,RF_model]
```

In [39]:

```
result_df = pd.DataFrame(list,columns = ['model'])
```

In [40]:

```
prediction = []
test_rmse =[]
for i in range(len(list)):
    prediction.append(result_df['model'][i].predict(test_features))
    test_rmse.append(mean_squared_error(test_target,result_df['model'][i].predict(test_features),squared = False))

result_df['prediction'] = prediction
result_df['RMSE'] = test_rmse
```

In [41]:

```
result_df.sort_values(by = 'RMSE')
```

Out[41]:

	model	prediction	RMSE
1	RandomizedSearchCV(cv=TimeSeriesSplit(gap=0, m...	[157.66814285714284, 145.987, 148.755492063492...	29.591714
0	LogisticRegression(random_state=0)	[129, 118, 129, 110, 146, 76, 115, 110, 129, 1...	58.060274

In [42]:
```
best_result = result_df['RMSE'].min()
```

In [43]:
```
best_model = result_df[result_df['RMSE'] == best_result]
```

In [44]:
```
best_model
```

Out[44]:

	model	prediction	RMSE
1	RandomizedSearchCV(cv=TimeSeriesSplit(gap=0, m...	[157.66814285714284, 145.987, 148.755492063492...	29.591714

Conclusion

1) Best RMSE score has random forest model with hyperparameters tuning;

2) required score RMSE < 48 successfully achieved