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 samplpe 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

Имортируем необходимые библиотеки

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")
```

Импортируем данные, ознакомимся с ними и проводеме ресэмплинг с периодом в 1 час

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]:

datetime	num_orders
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]:

datetime	num_orders
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()
```

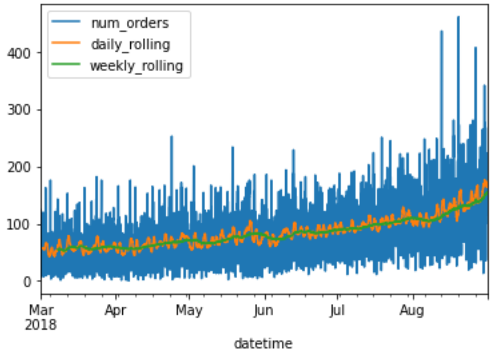
Out[8]:

	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'>

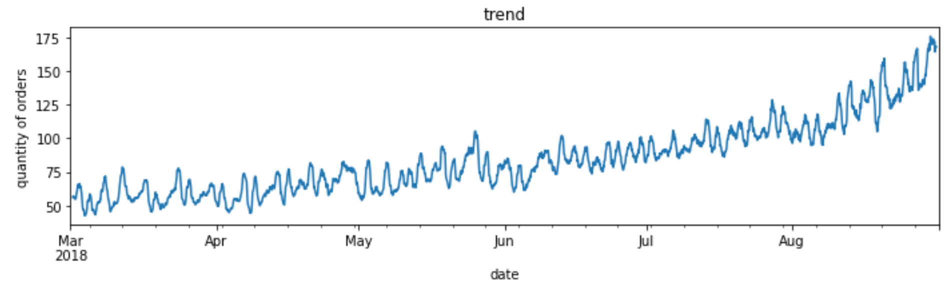


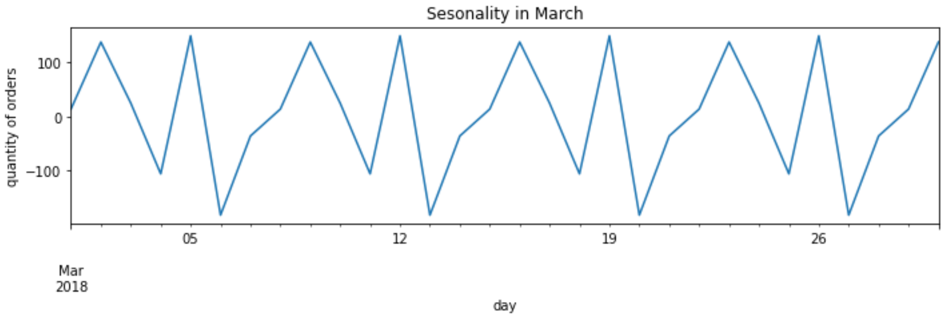
Trend and seasonality graphs plotting

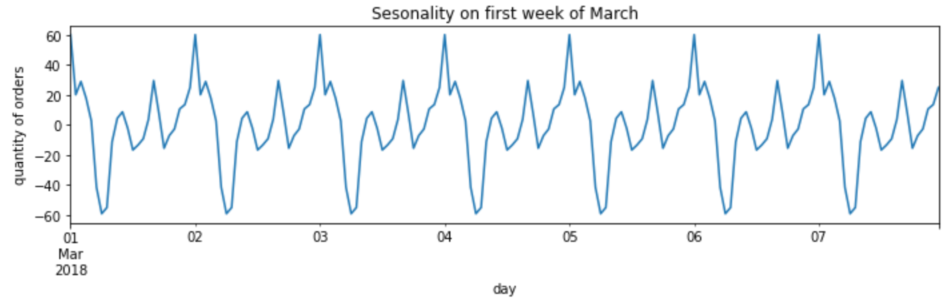
In [10]:
```
decomposed_data = seasonal_decompose(data)
decomposed_data_szn = seasonal_decompose(data.resample('1D').sum())
```

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()
```







Conclsuion:

- Based on the analysis we see that deamnd on the taxi has slow groth 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]:
```python
data['month'] = data.index.month
```

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

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

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

In [17]:
```python
# 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]:
```python
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]:
```python
train, test = train_test_split(data_set, shuffle = False, test_size = 0.1)
```

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

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

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

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

Logistic regression training

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

In [25]:
```python
LR_model.fit(train_features,train_target)
```

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

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

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

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

Out[28]: 32.28852920756703

Random forest training

In [29]:
```python
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]:
```python
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]:
```python
RF = RandomForestRegressor()
```

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

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

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

Out[34]:
```
RandomizedSearchCV
estimator: RandomForestRegressor
RandomForestRegressor
```

In [35]:
```python
RF_predictions = RF_model.predict(valid_features)
```

In [36]:
```python
RMSE_RF = mean_squared_error(valid_target,RF_predictions,squared= False)
```

In [37]:
```python
RMSE_RF
```

Out[37]: 13.172828459572049

Models testing

selection of best model:

In [38]:
```python
list = [LR_model,RF_model]
```

In [39]:
```python
result_df = pd.DataFrame(list,columns = ['model'])
```

In [40]:
```python
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]:
```python
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]:
```python
best_result = result_df['RMSE'].min()
```

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

In [44]:
```python
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 sccessfully achieved