A0218869J–HaojunGao

September 15, 2020

1 Individual Assignment 2

1.0.1 (Due on Sep 8 11:59PM on LumiNUS)

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1.1 Problem 1 (GrabWheels)

Towards the smart nation initiative, the Government of Singapore has encouraged sustainable and smart mobility solutions such as recent scooter vehicle sharing (e.g., GrabWheels). Launched in the late 2018, GrabWheels rolled out around 30 parking locations in NUS Kent Ridge campus. For more details, please see http://news.nus.edu.sg/press-releases/new-e-scooter-sharing-service and https://www.grab.com/sg/wheels/. A group of DBA5106 students is working on a project in the design and operations of GrabWheels at NUS campus, e.g., where to set up the parking locations and how many scooters to place at each location. Please answer the following questions.

a) Suppose GrabWheels wants to improve its service quality by optimizing parking locations and calculating the optimal number of scooters at each location. Please suggest what information would help and what data GrabWheels needs to be collected. [2 pts] There are two ways to improve the service quality: - optimize the infrustructure location(optimizing parking locations) - solve the relocation optimization problem(cope with the problem caused by demand imbalance)

Therefore, from the data type point of view, both spatial data and time series time will be helpful. And if we look at the data source, shared scooter vehicle usage data(taking the vehicle as a unit can avoid the use of user data and reduce the collection of user data) and other sort of data that can affect user behavior could useful. - Infrustracture Information - Parking locations - Number of trips that were taken each location each day - Scooter Vehicle Trip Dataset - vehicle ID - trip starting time - trip end time - trip start location - trip end location - Weather Dataset - Temperature: basic indicator - Precipitation: an indicator of whether rain or not - Wind speed: an indicator of whether suitable for taking scooter - Date-related Dataset - holiday - etc. - Spatial Dataset - Topographic features of parking locations - Distance from the nearest parking location - etc.

b) By Sep 2019, GrabWheels has collected 2-month data (you specified in part a) from its operating 30 locations. To forecast the demand for new locations, e.g., COM2, briefly discuss which data mining task should be performed and what additional data sets should be collected, if any. [2 pts] Data Mining Task

- We could define the problem as a regression problem.
- Forecast objective is the average daily demand of a specific parking location. We could use the 2-month data mentioned above to form the variable(average demand of the parking location). And use spatial data as features to train the model.
- The collected data could be divided into train, validate and test set to model and evaluate.

Additional Data Sets

- As for the additional data sets, the relevant feature data of those new locations await predicted also need to be collected.

c) Following part (b), briefly discuss how GrabWheels can forecast the demand scooter sharing at new locations, using your proposed approach. Please identify which steps are the process of data mining (DM), or the use of the results of data mining (Use). [2 pts] According to the model proposed in the previous question, we basically use the geographical characteristics to predict the use demand of this location. The basic idea is that the inherent characteristics of a place will determine,to a great extent, the demand of the scooter in this place.

For example:

- if this place is close to the bus station or MRT, the demand for scooter may be great.
- If this location is close to the giant company, the demand for scooter may also be great.
- However,if the other/nearest parking location is far away, then one may not use scooter as the transportation.

Process of Data Mining

- Find the feasible locations as a new parking locations.
- Collect the geographical features of existing parking locations and feasible locations.
- Use the existing location data to train and evaluate the model.
- Predict the average demand of the new locations

Knowledge Discovery and Decision Making

- The prediction results could be used as evidence to support or influence the company's decision.
- The feature importance could also perform as an application for knowledge discovery, such like which feature is most relevant to the use of scooters.

d) Discuss what challenges GrabWheels may face and how data analytics can help improve its operations. [2 pts] There are still many tough situations that challenge GrabWheels and also threaten their services, and demand imbalance is the most critical one among them. To a large extent, bike sharing systems are used for one-way trips, and such a trend leads toinappropriate bike distribution in time and space. Consider the scenario: - Many people choose to ride to this place using the scooter, but few rides away from this place. That will cause the scooter to pile up, and the utilization rate drops sharply. - Conversely, if many want to ride away meanwhile few people ride over here, this condition also results in an unsatisfactory service and leads to the low revenue.

To tackle this dilemma, the redistribution of bikes over stations is required. The straightforward strategy is to predict the real-time demand(hourly), rather than the average need of the parking location. Then turn the problem into a path optimization problem: how to relocate the scooter using the least human resources and finance cost.

- The first step to optimize the relocation of scooters in the system is to be able to predict the number of scooters in a particular parking location at particular time, which can be done through the use of machine learning algorithms.

e) If you are evaluating the market expansion plan of GrabWheels, e.g., whether it should cover certain regions, describe what data you would like to collect and how you would like to collect and analyze them for such an evaluation? [2 pts] When it comes to making an expansion plan, model could be level up to the region level, instead of location level. It consists on predicting the total demand of scooters in the region, both returning and renting. This model could provide general information on the number of scooter demand in a particular zones, where it is not necessary to know exactly the decision of the parking location selection.

Region level information is needed to construct the model. Such like, region area, prosperity of the region, region population, age composition of the population, etc.

Same as the above model, we could use the operation performance of the known regions to train the model and predict the performance of the unknown region. And we could use the model results to decide which region could be a target region that needs to be covered in the future.

1.2 Problem 2 (Blue Bikes)

A renowned consulting firm MSBA & Company is currently analyzing the trip data of Blue Bikes (originally Hubway) in Boston. Blue Bikes (https://www.bluebikes.com/) is a public bike share system that operates in the Greater Boston area.

We are interested in exploring the bike share operations from the data available on https://www.bluebikes.com/system-data. We will utilize the "Bluebikes trip history data" as well as "the list of GPS coordinates and number of docks for each station" available on the website.

Please download and analyze the data to answer the following questions. [Note: (1) the unzipped "201906-bluebikes-tripdata.zip" has a wrong file name (with correct data inside); (2) you can add extension ".csv" to the unzipped "201907-bluebikes-tripdata" file]

1. Provide the line chart of monthly trips from 2015-06 to 2020-05. [2 pts]

[1]:
```
import sys
import matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
sys.path.append(
    r'D:\OneDrive\Programming\documents_python\NUS␣
↪Courses\DBA5106\Course-DBA5106\assignment\IndividualAssignment2')
```

[3]:
```
from utils.logger import logger
from utils.config import PROCESSED_DATA_DIR
from utils.data_porter import read_from_csv
```

[4]:
```
tripdata_df = read_from_csv('tripdata.csv', PROCESSED_DATA_DIR,
                            parse_dates=['starttime', 'stoptime'])
```

[5]:
```
tripdata_df.dtypes
```

[5]:
```
tripduration                 int64
starttime           datetime64[ns]
stoptime            datetime64[ns]
start station id             int64
end station id               int64
bikeid                       int64
birth year                   int64
gender                     float64
usertype_id                  int64
dtype: object
```

[6]:
```
tripdata_df['month'] = tripdata_df['starttime'].dt.to_period(
    'M').dt.strftime("%Y-%m")
```

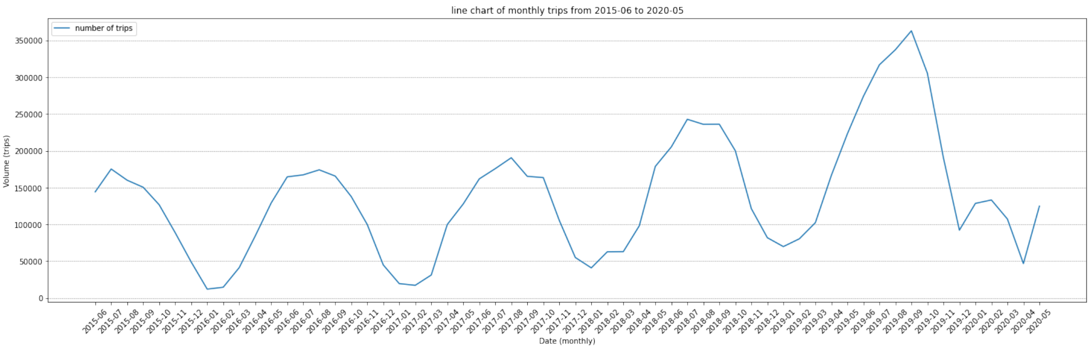
[7]:
```
tripdata_df.head(2)
```

[7]:
```
   tripduration           starttime            stoptime  start station id  \
0           211 2015-06-01 00:07:07 2015-06-01 00:10:39                88
1           834 2015-06-01 00:13:48 2015-06-01 00:27:43                 5

   end station id  bikeid  birth year  gender  usertype_id    month
0              96     546           0     0.0            1  2015-06
1              12     487        1986     1.0            1  2015-06
```

[8]:
```
month_trip = tripdata_df['month'].value_counts().sort_index()
```

[74]:
```
x = month_trip.index.tolist()
y = month_trip.tolist()
```

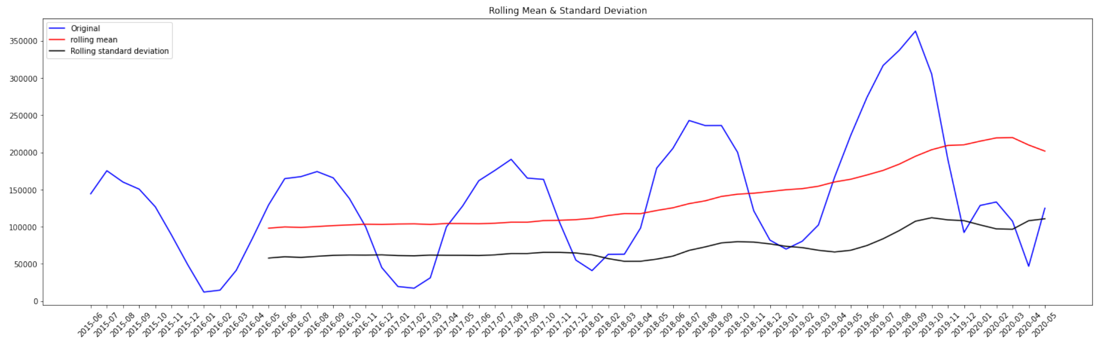
[10]:
```
# month_trip.plot()
fig, ax = plt.subplots(figsize=(25, 7))
ax.plot(x, y, label='number of trips')
ax.set(xlabel='Date (monthly)', ylabel='Volume (trips)',
       title='line chart of monthly trips from 2015-06 to 2020-05')

plt.grid(axis='y', color='grey', linestyle='--', linewidth=0.5)

# You can specify a rotation for the tick labels in degrees or with keywords.
plt.xticks(rotation='45')
plt.legend(loc='upper left')
plt.show()
```



2. Discuss any observed patterns, e.g., trend, seasonality, and shocks. Support your argument with necessary data, if possible. [2 pts]

[11]:
```python
def plot_stationarity(timeseries):
    '''Plot Rolling Mean & Standard Deviation'''
    x = timeseries.index.tolist()

    # One year is used as a window, and the value of each time t is replaced by the mean of the previous 12 months (including itself)
    # and the standard deviation is the same.
    rolmean = timeseries.rolling(window=12).mean()
    rolstd = timeseries.rolling(window=12).std()

    # plot rolling statistics:
    plt.subplots(figsize=(25, 7))
    plt.plot(x, timeseries.tolist(), color='blue', label='Original')
    plt.plot(x, rolmean.tolist(), color='red', label='rolling mean')
    plt.plot(x, rolstd.tolist(), color='black',
             label='Rolling standard deviation')

    plt.xticks(rotation='45')
    plt.legend(loc='upper left')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show()
```

[12]:
```python
plot_stationarity(month_trip)
```



Through the above picture, we can clearly find that - The use of vehicles has a clear upward trend (until the beginning of 2020) - There is yearly seasonality (the peak is from July to September, and the trough is from November to next year February)

Check the Stationarity of time series data. Judging that the data is stable is often based on several statistics that are constant for time: - Constant mean - Constant variance - Time independent autocovariance

[13]:
```python
from statsmodels.tsa.stattools import adfuller
```

[14]:
```python
def test_stationarity(timeseries):
    '''Dickey-Fuller test'''

    print('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    # The output value of #dftest is Test Statistic, p-value, the number of lags, the number of observations used
    # and the critical value under each confidence level.
    dfoutput = pd.Series(dftest[0:4],
                         index=['Test Statistic', 'p-value', '#Lags Used', 'Number of Observations Used'])
    for key, value in dftest[4].items():
        dfoutput['Critical value (%s)' % key] = value

    print(dfoutput)
```

[15]:
```python
test_stationarity(month_trip)
```

```
Results of Dickey-Fuller Test:
Test Statistic                  0.758357
p-value                         0.990933
#Lags Used                     10.000000
Number of Observations Used    49.000000
Critical value (1%)            -3.571472
Critical value (5%)            -2.922629
```

```
Critical value (10%)          -2.599336
dtype: float64
```

The null hypothesis of the Augmented Dickey-Fuller is that there is a unit root, with the alternative that there is no unit root. If the pvalue is above a critical size, then we cannot reject that there is a unit root.(from statsmodel official documentation)

- p-value
  - The p value is the evidence against a null hypothesis. The smaller the p-value, the stronger the evidence that you should reject the null hypothesis. In this case, the p-value is 0.99 which is a strong evidence that the null hypothesis can not be reject. In other words, the ADF test result shows that **there is a unit root**.
  - Nonstationarity can lead to spurious regression, which is an apparent relationship between variables that are not related in reality.
- Critical values for the test statistic at the 1 %, 5 %, and 10 % levels. Based on MacKinnon (2010).
  - The ADF test statistic value is greater than the critical value under each significant level, this result also means: the series is not stationary.

Note that: The ADF test does not prove nonstationarity; it fails to prove stationarity.

[16]:
```
# log transform data to make data stationary on variance
month_trip_log = np.log10(month_trip)
# Difference data to make data stationary on mean (remove trend)
month_trip_stationary = month_trip_log.diff(periods=1)[1:]
```

[17]:
```
test_stationarity(month_trip_stationary)
```

```
Results of Dickey-Fuller Test:
Test Statistic                -5.703544e+00
p-value                        7.579024e-07
#Lags Used                     1.000000e+01
Number of Observations Used    4.800000e+01
Critical value (1%)           -3.574589e+00
Critical value (5%)           -2.923954e+00
Critical value (10%)          -2.600039e+00
dtype: float64
```

Difference log transform data to make data stationary on both mean and variance:

- **p-value**

  In this case, the p-value is almost zero which is a strong evidence that the null hypothesis can be reject. In other words, the ADF test result shows that **there isn't a unit root**.

- **Critical values for the test statistic**

  The ADF test statistic value is not greater than the critical value under each significant level, this result also means: the series is stationary.

3. Implement the following forecasting methods to forecast the monthly trips from 2019-06 to 2020-05. (Note that, when forecasting for month t+1, the history from 2015-06 up to month t are available.)

a. Provide your forecasts using a 3-month moving average. [1 pts]

[249]:
```
from scipy.special import exp10
from sklearn.metrics import mean_absolute_error as mae
```

[250]:
```
# Define the mape matric
def mape(y_true, y_pred):
    y_true = np.array(y_true).astype(np.float64)
    y_pred = np.array(y_pred).astype(np.float64)
    if y_true.shape != y_pred.shape:
        raise ValueError(
            f"y_true and y_pred have different shape for "
            f"{y_true.shape} != {y_pred.shape}")
    return np.nanmean(np.abs((y_true - y_pred) / np.abs(y_true)))
```

[251]:
```
def plot_forecast(df, other_info=''):
    fig, ax = plt.subplots(figsize=(25, 7))
    x = df.index.tolist()
    y_true = df['y_true'].tolist()
    y_pred = df['y_pred'].tolist()
    ax.plot(x, y_true, color='blue', label='Original')
    ax.plot(x, y_pred, color='red', label=other_info)

    ax.set_xlabel('Date (monthly)', fontsize=16)
    ax.set_ylabel('Volume (trips)', fontsize=16)
    ax.set_title(f'Frecasts using {other_info}', fontsize=20)

    ax.xaxis.set_tick_params(labelsize=16, rotation=45)
    ax.yaxis.set_tick_params(labelsize=16)
    ax.grid(axis='y', color='grey', linestyle='--', linewidth=0.5)

#     ax.xaxis.set_rotation('90')
    plt.legend(loc='upper left')
    plt.tight_layout()
    plt.show()
```

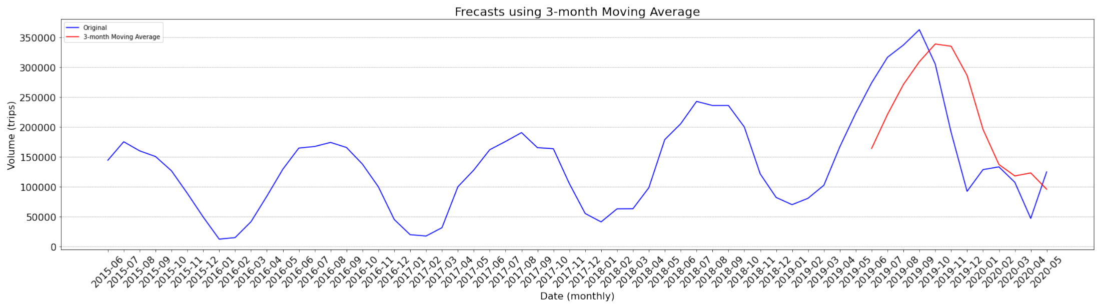
[252]:
```
def moving_average_forecast(timeseries, sliding_window, start_forecast_date,␣
↪end_forecast_date):
    # CHECK THE DATA PREPARATION
    if month_trip.index[0] > str(pd.to_datetime(FORCAST_START_DATE) - pd.
↪offsets.MonthBegin(sliding_window)):
        raise Exception('In order to forecast month {}, the previous {} months␣
↪data needed'.format(
            start_forecast_date, sliding_window))
```

```
    # The value of each time t is replaced by the mean of the previous N␣
↪months(not including itself)
    forecast_result = timeseries.rolling(window=3).mean().shift(1)
    forecast_result = forecast_result.loc[forecast_result.index >=␣
↪FORCAST_START_DATE]

    result_df = pd.DataFrame({'y_true': timeseries, 'y_pred': forecast_result})

    return result_df
```

[353]:
```
def model_eval(y_ture, y_pred, start_date, end_date):
    y_ture = y_ture.loc[(y_ture.index >= start_date) &
                        (y_ture.index <= end_date)]
    y_pred = y_pred.loc[(y_pred.index >= start_date) &
                        (y_pred.index <= end_date)]
    print('MAPE: {}'.format(mape(y_ture, y_pred)))
    print('MAD: {}'.format(mae(y_ture, y_pred)))
```

[320]:
```
FORCAST_START_DATE = '2019-06'
FORCAST_END_DATE = '2020-05'
SLIDING_WINDOW = 3
```

[255]:
```
result_df = moving_average_forecast(timeseries=month_trip,
                                    sliding_window=SLIDING_WINDOW,
                                    start_forecast_date=FORCAST_START_DATE,
                                    end_forecast_date=FORCAST_END_DATE)
plot_forecast(result_df, other_info=f'{SLIDING_WINDOW}-month Moving Average')
model_eval(result_df['y_true'],␣
↪result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.5449525413832923
MAD: 73796.66666666667
```

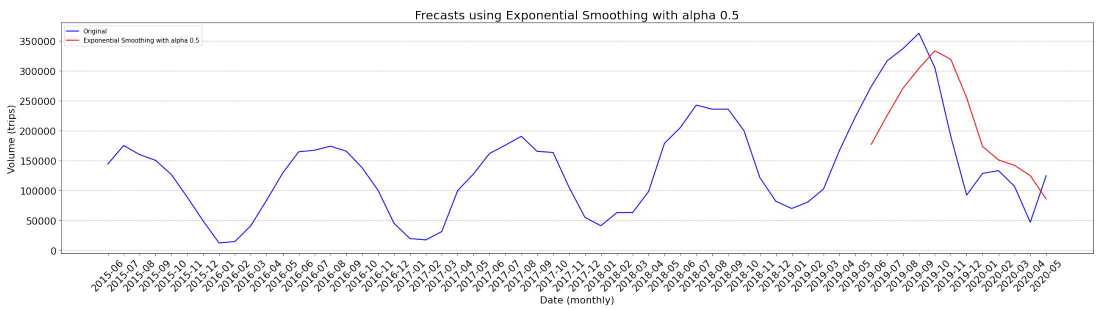
b. Provide your forecasts using exponential smoothing with a smoothing constant =0.5. [1 pts]

[256]:
```python
from statsmodels.tsa.api import SimpleExpSmoothing
```

[257]:
```python
def exponential_smoothing(timeseries, alpha, start_forecast_date, end_forecast_date):
    """Provide forecasts using exponential smoothing with a smoothing constant"""
    forecast_lst = pd.Series(pd.date_range(start_forecast_date, end_forecast_date, freq='MS').strftime("%Y-%m"))
    forecast_value = []
    for forcast_month in forecast_lst:
        timeseries_train = timeseries.loc[timeseries.index < forcast_month].tolist()
        SES_model = SimpleExpSmoothing(timeseries_train).fit(smoothing_level=alpha, optimized=False)
        forecast_value.append(SES_model.forecast(1)[0])

    SES_result = pd.Series(forecast_value, index=forecast_lst)
    result_df = pd.DataFrame({'y_true': timeseries, 'y_pred': SES_result})
    return result_df
```

[258]:
```python
SES_ALPHA = 0.5
```

[259]:
```python
result_df = exponential_smoothing(timeseries=month_trip,
                                  alpha=SES_ALPHA,
                                  start_forecast_date=FORCAST_START_DATE,
                                  end_forecast_date=FORCAST_END_DATE)
plot_forecast(result_df, other_info=f'Exponential Smoothing with alpha {SES_ALPHA}')
model_eval(result_df['y_true'], result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.5270872736829372
MAD: 70695.29033772778
```

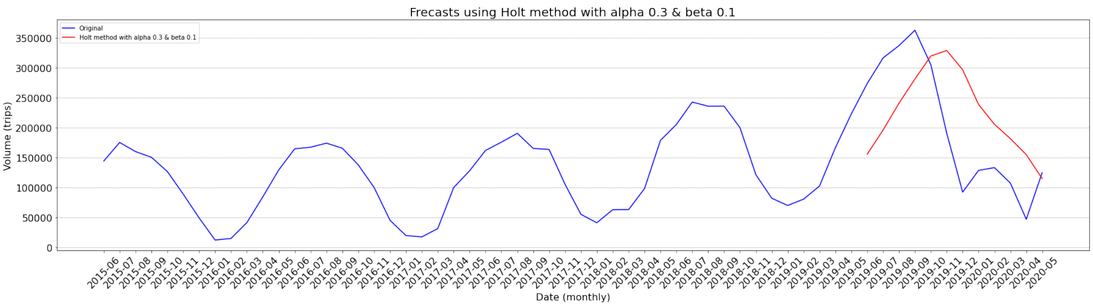
c. Provide your forecasts using Holt's method with =0.3 and =0.1. [1 pts]

[260]:
```python
from statsmodels.tsa.api import Holt
```

[261]:
```python
def holt_method(timeseries, alpha, beta, start_forecast_date, end_forecast_date):
    """Provide forecasts using Holt's method with alpha and beta"""
    forecast_lst = pd.Series(pd.date_range(
        start_forecast_date, end_forecast_date, freq='MS').strftime("%Y-%m"))
    forecast_value = []
    for forcast_month in forecast_lst:
        timeseries_train = timeseries.loc[timeseries.index < forcast_month].tolist()
        Holter_model = Holt(timeseries_train).fit(
        smoothing_level=alpha, smoothing_slope=beta, optimized=False)
        forecast_value.append(Holter_model.forecast(1)[0])

    Holter_result = pd.Series(forecast_value, index=forecast_lst)
    result_df = pd.DataFrame({'y_true': timeseries, 'y_pred': Holter_result})
    return result_df
```

[262]:
```python
HOLT_ALPHA = 0.3
HOLT_BETA = 0.1
```

[263]:
```python
result_df = holt_method(timeseries=month_trip,
                        alpha=HOLT_ALPHA,
                        beta=HOLT_BETA,
                        start_forecast_date=FORCAST_START_DATE,
                        end_forecast_date=FORCAST_END_DATE)
plot_forecast(result_df,other_info=f'Holt method with alpha {HOLT_ALPHA} & beta {HOLT_BETA}')
model_eval(result_df['y_true'], result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```



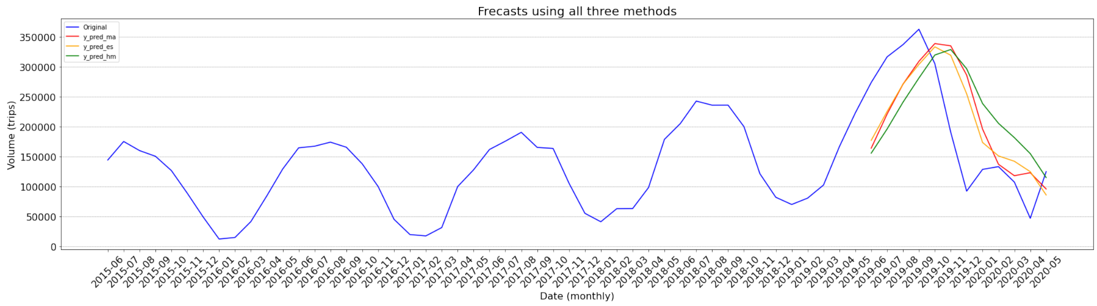

```
MAPE: 0.7338497610269354
MAD: 95866.41657870775
```

d. Plot the forecasts from all three methods above in the line chart, together with the actual trips for the periods 2019-06 to 2020-05. [1 pts]

[269]:
```python
def plot_all_method(full_results):
    fig, ax = plt.subplots(figsize=(25, 7))
    x = full_results.index.tolist()

    ax.plot(x, full_results['y_true'].tolist(), color='blue',label='Original')
    ax.plot(x, full_results['y_pred_ma'].tolist(),␣
↪color='red',label='y_pred_ma')
    ax.plot(x, full_results['y_pred_es'].tolist(),␣
↪color='orange',label='y_pred_es')
    ax.plot(x, full_results['y_pred_hm'].tolist(),␣
↪color='green',label='y_pred_hm')

    ax.set_xlabel('Date (monthly)', fontsize=16)
    ax.set_ylabel('Volume (trips)', fontsize=16)
    ax.set_title(f'Frecasts using all three methods', fontsize=20)

    ax.xaxis.set_tick_params(labelsize=16, rotation=45)
    ax.yaxis.set_tick_params(labelsize=16)
    ax.grid(axis='y', color='grey', linestyle='--', linewidth=0.5)

    #     ax.xaxis.set_rotation('45')
    plt.legend(loc='upper left')
    plt.tight_layout()
    plt.show()
```

[271]:
```python
ma_result = moving_average_forecast(
    timeseries=month_trip, sliding_window=SLIDING_WINDOW,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
ma_result.rename(columns={'y_pred': 'y_pred_ma'}, inplace=True)

es_result = exponential_smoothing(
    timeseries=month_trip, alpha=SES_ALPHA,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
es_result.rename(columns={'y_pred': 'y_pred_es'}, inplace=True)

hm_result = holt_method(
    timeseries=month_trip, alpha=HOLT_ALPHA, beta=HOLT_BETA,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
hm_result.rename(columns={'y_pred': 'y_pred_hm'}, inplace=True)

full_results = pd.merge(ma_result, es_result['y_pred_es'],
                        left_index=True, right_index=True)
```

```
full_results = pd.merge(full_results, hm_result['y_pred_hm'],
                        left_index=True, right_index=True)

plot_all_method(full_results)
```



e. Evaluate the above forecasting methods using MAD (Mean Absolute Deviation) and MAPE, respectively. [1 pts]

[266]:
```
print('******** MOVING AVERAGE ********')
model_eval(full_results['y_true'], full_results['y_pred_ma'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)

print('\n******** EXPONENTIAL SMOOTHING ********')
model_eval(full_results['y_true'], full_results['y_pred_es'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)

print('\n******** HOLT METHOD ********')
model_eval(full_results['y_true'], full_results['y_pred_hm'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```

```
******** MOVING AVERAGE ********
MAPE: 0.5449525413832923
MAD: 73796.66666666667

******** EXPONENTIAL SMOOTHING ********
MAPE: 0.5270872736829372
MAD: 70695.29033772778

******** HOLT METHOD ********
MAPE: 0.7338497610269354
MAD: 95866.41657870775
```

f. Discuss the performance of the forecasting methods, e.g., any suggestions for improvement. [1 pts]

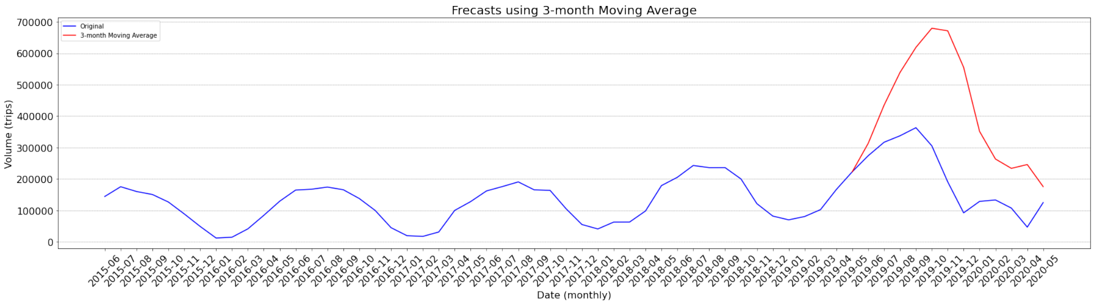
- We can observe that the three methods have the same delay relative to the real situation.

This delay is most likely due to seasonality.

- Suggestions for improvement: transform the original data, using the difference and log method. Carry out stationarity test to verify the stationarity of the time series.
- In this case(using stationary data), we need to covert the forecast on differenced data to non-differenced data forecast.

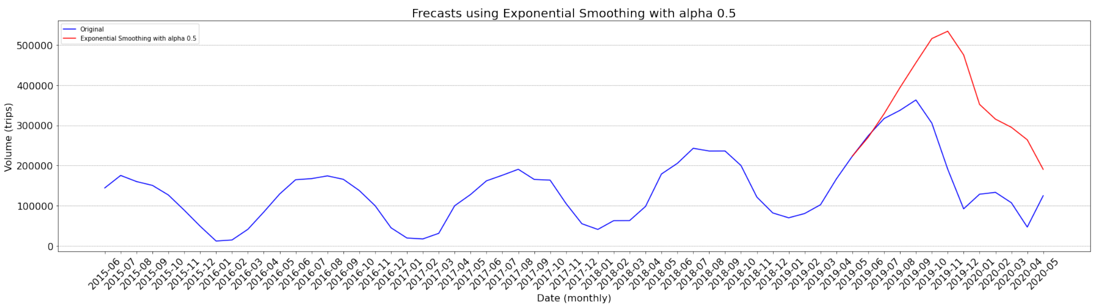
[221]:
```
def recover_origin(ts, ts_log, ts_stationary_pred, forcast_start_date,␣
↪pred_type):
    """Predicted values need to be restored by the relevant inverse␣
↪transformation."""
    ts_stationary_pred = ts_stationary_pred.dropna()
    if pred_type == "daily":
        origin_index = (pd.to_datetime(forcast_start_date) - pd.offsets.
↪DateOffset(1)).strftime("%Y-%m-%d")
        origin_num = ts_log[origin_index]
    elif pred_type == 'monthly':
        origin_index = (pd.to_datetime(forcast_start_date) - pd.offsets.
↪MonthBegin(1)).strftime("%Y-%m")
        origin_num = ts_log[origin_index]
    else:
        raise Exception
    # Recover the first-order difference
    diff_restored = pd.Series(origin_num, index=[origin_index]).
↪append(ts_stationary_pred).cumsum()

    # recover the log transformation
    log_recover = 10 ** diff_restored
    log_recover = log_recover.astype(int)

    # concatenate the result
    result = pd.concat([ts, log_recover], axis=1)
    result.columns = ['y_true', 'y_pred']
    return result
```

[163]:
```
station_result_df = moving_average_forecast(timeseries=month_trip_stationary,
                                    sliding_window=SLIDING_WINDOW,
                                    start_forecast_date=FORCAST_START_DATE,
                                    end_forecast_date=FORCAST_END_DATE)

result_df = recover_origin(month_trip, month_trip_log,␣
↪station_result_df['y_pred'], FORCAST_START_DATE, pred_type='monthly')
plot_forecast(result_df, other_info=f'{SLIDING_WINDOW}-month Moving Average')
model_eval(result_df['y_true'],␣
↪result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 1.5944921516090218
MAD: 221843.16666666666
```

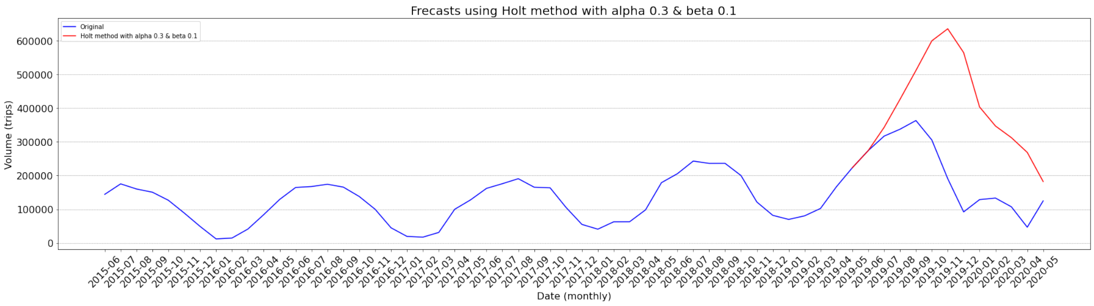
[267]:
```
station_result_df = exponential_smoothing(timeseries=month_trip_stationary,
                                          alpha=ALPHA,
                                          ␣
 ↪start_forecast_date=FORCAST_START_DATE,
                                          end_forecast_date=FORCAST_END_DATE)
result_df = recover_origin(month_trip, month_trip_log,␣
 ↪station_result_df['y_pred'],
                           FORCAST_START_DATE, pred_type='monthly')
plot_forecast(result_df,
              other_info=f'Exponential Smoothing with alpha {SES_ALPHA}')
model_eval(result_df['y_true'],␣
 ↪result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 1.4285772827330065
MAD: 164884.41666666666
```

[268]:
```
station_result_df = holt_method(timeseries=month_trip_stationary,
                                alpha=ALPHA,
                                beta=BETA,
                                start_forecast_date=FORCAST_START_DATE,
                                end_forecast_date=FORCAST_END_DATE)
```

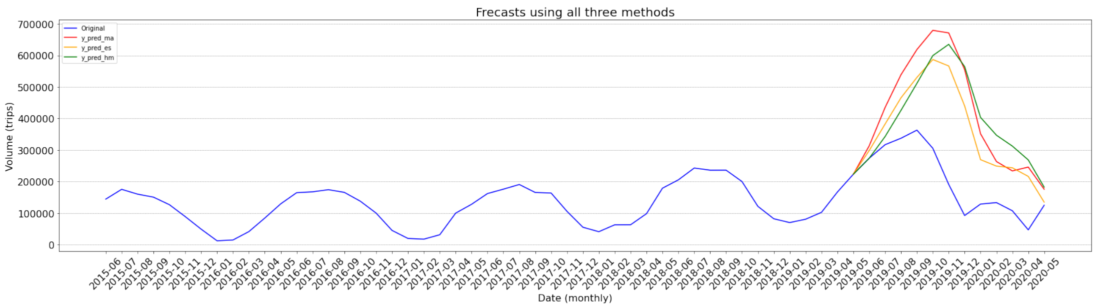
```
result_df = recover_origin(month_trip, month_trip_log,␣
↪station_result_df['y_pred'], FORCAST_START_DATE, pred_type='monthly')
plot_forecast(result_df,other_info=f'Holt method with alpha {HOLT_ALPHA} & beta␣
↪{HOLT_BETA}')
model_eval(result_df['y_true'],␣
↪result_df['y_pred'],start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 1.6684936030127824
MAD: 203917.75
```

[272]:
```
ma_station_result = moving_average_forecast(
    timeseries=month_trip_stationary, sliding_window=SLIDING_WINDOW,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
ma_result = recover_origin(month_trip, month_trip_log,␣
↪ma_station_result['y_pred'], FORCAST_START_DATE, pred_type='monthly')
ma_result.rename(columns={'y_pred': 'y_pred_ma'}, inplace=True)

es_station_result = exponential_smoothing(
    timeseries=month_trip_stationary, alpha=SES_ALPHA,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
es_result = recover_origin(month_trip, month_trip_log,␣
↪es_station_result['y_pred'], FORCAST_START_DATE, pred_type='monthly')
es_result.rename(columns={'y_pred': 'y_pred_es'}, inplace=True)

hm_station_result = holt_method(
    timeseries=month_trip_stationary, alpha=HOLT_ALPHA, beta=HOLT_BETA,
    start_forecast_date=FORCAST_START_DATE,
    end_forecast_date=FORCAST_END_DATE)
hm_result = recover_origin(month_trip, month_trip_log,␣
↪hm_station_result['y_pred'], FORCAST_START_DATE, pred_type='monthly')
hm_result.rename(columns={'y_pred': 'y_pred_hm'}, inplace=True)

full_results = pd.merge(ma_result, es_result['y_pred_es'],
```

```
                        left_index=True, right_index=True)
full_results = pd.merge(full_results, hm_result['y_pred_hm'],
                        left_index=True, right_index=True)

plot_all_method(full_results)
```



[273]:
```
print('******** MOVING AVERAGE ********')
model_eval(full_results['y_true'], full_results['y_pred_ma'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)

print('\n******** EXPONENTIAL SMOOTHING ********')
model_eval(full_results['y_true'], full_results['y_pred_es'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)

print('\n******** HOLT METHOD ********')
model_eval(full_results['y_true'], full_results['y_pred_hm'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```

```
******** MOVING AVERAGE ********
MAPE: 1.5944921516090218
MAD: 221843.16666666666

******** EXPONENTIAL SMOOTHING ********
MAPE: 1.2278635356494478
MAD: 163576.33333333334

******** HOLT METHOD ********
MAPE: 1.6684936030127824
MAD: 203917.75
```

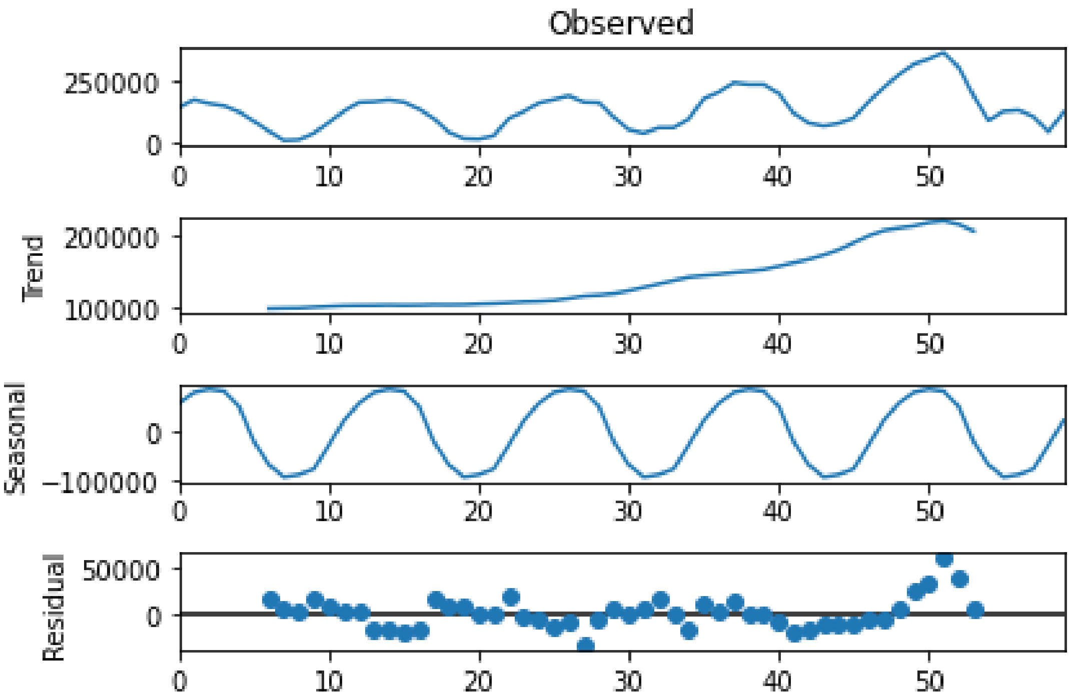
- Through the analysis of the results, the result of using the stationary sequence to predict is worse than that of the original sequence.
- But it does eliminate the delay that appeared before.
- Part of the reason why the result became worse is that none of the three methods can completely eliminate the upward trend of the sequence, and the use of exponents when restoring the original sequence may amplify this defect.

4. Use the histories from 2015-06 to 2019-05 to forecast the monthly trips from 2019-06 to 2020-05 using Holt-Winters' method and ARIMA.

a. Show the time series decomposition for periods 2015-06 to 2019-05 to identify trend and seasonality, if any. [1 pt]

[38]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

[39]:
```
result = seasonal_decompose(month_trip.tolist(), model='additive', period=12)
result.plot()
plt.show()
```



The results here are consistent with the previous analysis: - The use of vehicles has a clear upward trend (until the beginning of 2020) - There is yearly seasonality (the peak is from July to September, and the trough is from November to next year February)

b. Provide your forecasts using Holt-Winters' method. [2 pts]

[40]:
```
from statsmodels.tsa.api import ExponentialSmoothing
```

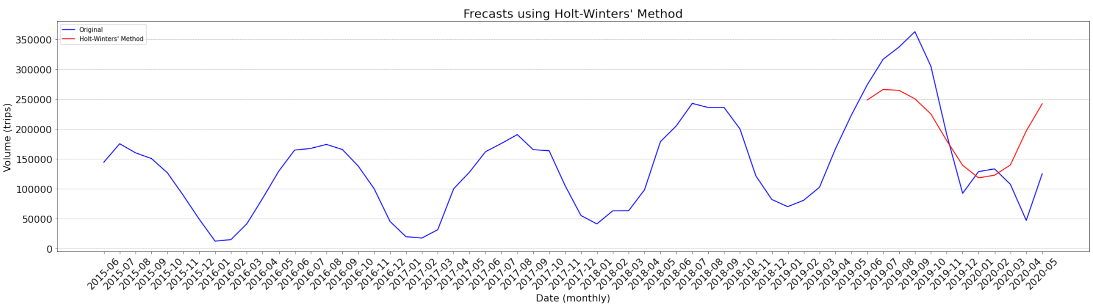
[321]:
```
def holt_winters_method(timeseries, start_forecast_date, end_forecast_date):
    timeseries_train = timeseries.loc[timeseries.index < start_forecast_date]
    timeseries_forecast = timeseries.loc[timeseries.index >=
                                         start_forecast_date]
    step_num = len(timeseries_forecast)
```

```
    # to silence the ValueWarning: No frequency information was provided, so␣
↪inferred frequency MS will be used.
    timeseries_train.index = pd.DatetimeIndex(
        timeseries_train.index.values, freq='MS')

    ES_model = ExponentialSmoothing(
        timeseries_train, trend='add', seasonal='add', seasonal_periods=12).
↪fit()
    print(ES_model.summary())

    ES_model = ES_model.forecast(step_num)
    ES_model.index = ES_model.index.strftime("%Y-%m")

    result_df = pd.DataFrame({'y_true': timeseries, 'y_pred': ES_model})

    return result_df
```

[322]:
```
result_df = holt_winters_method(timeseries=month_trip,
                                start_forecast_date=FORCAST_START_DATE,
                                end_forecast_date=FORCAST_END_DATE)
plot_forecast(result_df, other_info="Holt-Winters' Method")
model_eval(result_df['y_true'], result_df['y_pred'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```

```
                       ExponentialSmoothing Model Results
================================================================================
Dep. Variable:                    endog   No. Observations:                   48
Model:             ExponentialSmoothing   SSE                     6994258936.595
Optimized:                         True   AIC                            934.263
Trend:                         Additive   BIC                            964.203
Seasonal:                      Additive   AICC                           957.850
Seasonal Periods:                    12   Date:                 Tue, 15 Sep 2020
Box-Cox:                          False   Time:                         01:15:01
Box-Cox Coeff.:                    None
================================================================================
=
                          coeff                 code              optimized
--------------------------------------------------------------------------------
-
smoothing_level               0.5525095                alpha
True
smoothing_slope              2.3737e-08                 beta
True
smoothing_seasonal             0.000000                gamma
True
initial_level                1.5116e+05                  1.0
```

```
True
initial_slope                  2181.9353                  b.0
True
initial_seasons.0             -11469.657                  s.0
True
initial_seasons.1              3958.7294                  s.1
True
initial_seasons.2              220.38007                  s.2
True
initial_seasons.3             -16040.221                  s.3
True
initial_seasons.4             -43629.340                  s.4
True
initial_seasons.5             -90502.400                  s.5
True
initial_seasons.6            -1.3405e+05                  s.6
True
initial_seasons.7            -1.5724e+05                  s.7
True
initial_seasons.8            -1.5514e+05                  s.8
True
initial_seasons.9            -1.4012e+05                  s.9
True
initial_seasons.10            -85277.338                 s.10
True
initial_seasons.11            -41937.125                 s.11
True
--------------------------------------------------------------------------------
-
```




```
MAPE: 0.5174405163453567
MAD: 59948.10268166926
```

c. Identification of best fit ARIMA model. Explain the resulting model, e.g., any (seasonal) differencing. [2 pts]

[323]:
```python
import pmdarima as pm
```

[324]:
```python
model = pm.auto_arima(month_trip, seasonal = True, suppress_warnings=True)
print(model.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   60
Model:               SARIMAX(2, 0, 0)   Log Likelihood                -705.009
Date:                Tue, 15 Sep 2020   AIC                           1418.019
Time:                        01:15:21   BIC                           1426.396
Sample:                             0   HQIC                          1421.296
                                 - 60
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept   3.113e+04   9008.530      3.455      0.001    1.35e+04    4.88e+04
ar.L1          1.4408      0.080     18.018      0.000       1.284       1.598
ar.L2         -0.6638      0.091     -7.285      0.000      -0.842      -0.485
sigma2      9.224e+08      0.145   6.35e+09      0.000    9.22e+08    9.22e+08
================================================================================
===
Ljung-Box (Q):                       46.69   Jarque-Bera (JB):
13.92
Prob(Q):                              0.22   Prob(JB):
0.00
Heteroskedasticity (H):               5.36   Skew:
0.97
Prob(H) (two-sided):                  0.00   Kurtosis:
4.36
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
3.09e+25. Standard errors may be unstable.
```

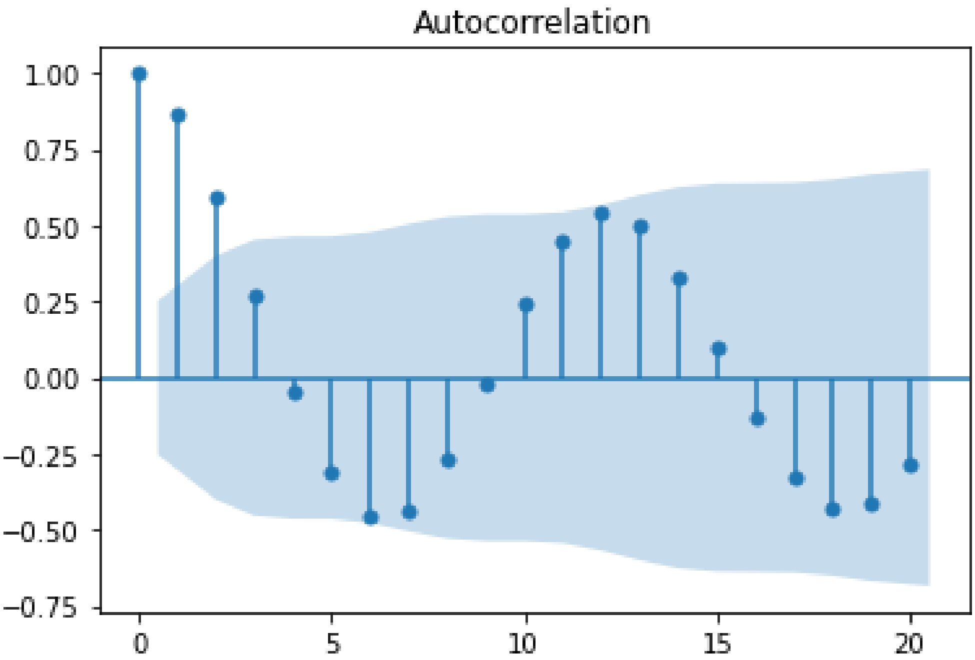
- A model with (only) two AR terms would be specified as an ARIMA of order (2,0,0).
- The SARIMA extension of ARIMA that explicitly models the seasonal element in univariate data. And there is no seasonal order taken into the model.

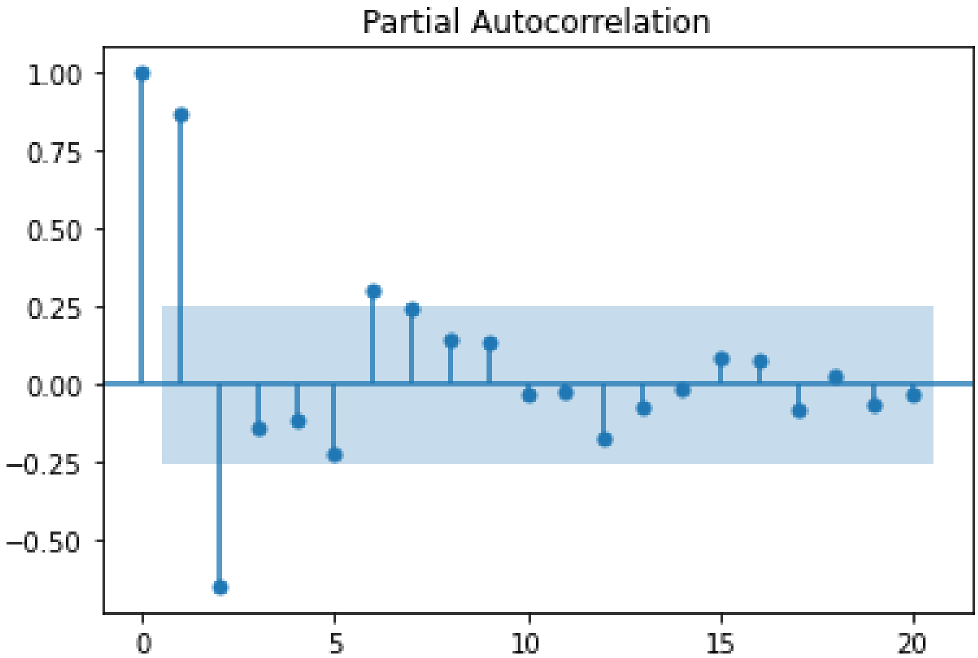
d. Plot ACF and PACF of fitted residuals to verify whether there is MA/AR effect left. [1 pt]

[45]:
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

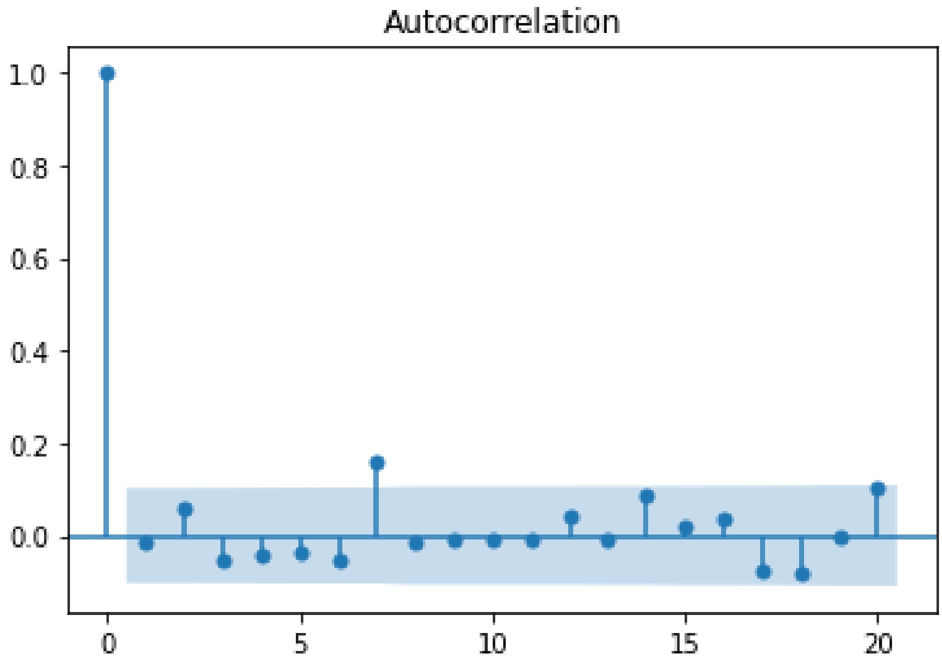
[276]:

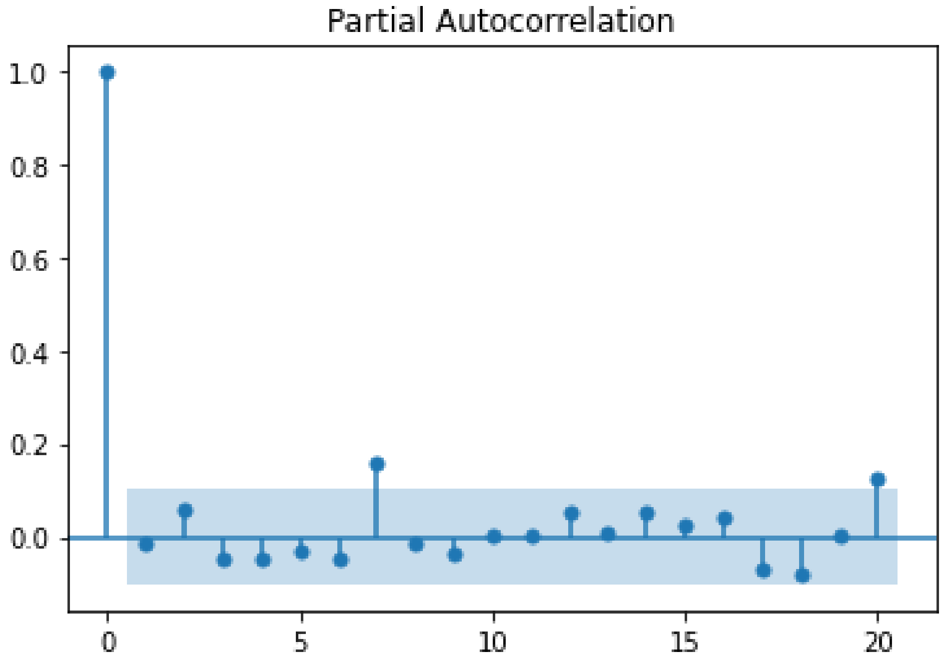
```
# plot original time series
plot_acf(month_trip.tolist(), lags=20)
plt.show()
# set method to silence RuntimeWarning
plot_pacf(month_trip.tolist(), lags=20, method='ywm')
plt.show()
```





[274]:
```
# plot residual
plot_acf(model.resid(), lags=20)
plt.show()
plot_pacf(model.resid(), lags=20, method='ywm')
plt.show()
```





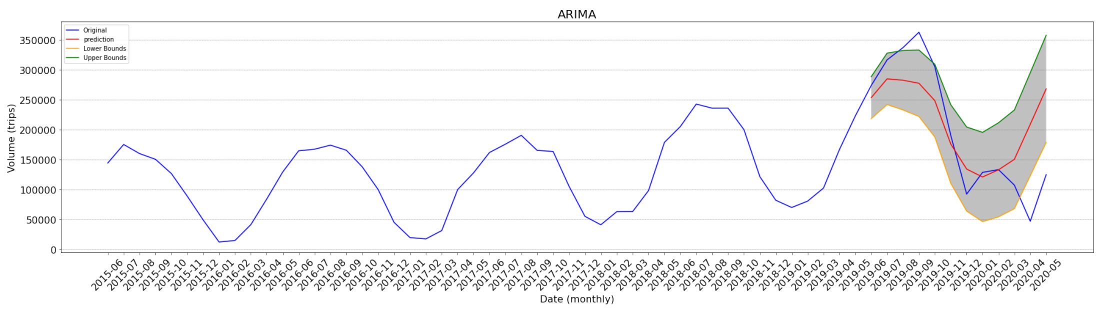
e.Forecast the trips for 2019-06 to 2020-05 using the best fit ARIMA model and plot the predictions with 95% confidence intervals. [**2 pts**]

[47]:
```python
def arima_forecast(timeseries, start_forecast_date, end_forecast_date):

    # Load/split data
    timeseries_train = timeseries.loc[timeseries.index < start_forecast_date]
    timeseries_forecast = timeseries.loc[(timeseries.index >=␣
↪start_forecast_date) &
                                         (timeseries.index <=␣
↪end_forecast_date)]
    step_num = len(timeseries_forecast)

    # Fit model
    model = pm.auto_arima(timeseries_train, seasonal=True,
                          m=12, suppress_warnings=True)  # m=seasonal length

    # make forecasts
    # predict N steps into the future
    pred, conf = model.predict(step_num, return_conf_int=True, alpha=0.05)

    model_df = pd.DataFrame()
    model_df['lower_bounds'] = [i[0] for i in conf]
    model_df['upper_bounds'] = [i[1] for i in conf]
    model_df['y_pred'] = list(pred)
    model_df.index = pd.Series(pd.date_range(
        start_forecast_date, end_forecast_date, freq='MS').strftime("%Y-%m"))

    result_df = pd.merge(left=pd.DataFrame(month_trip).rename(columns={'month':␣
↪'y_true'}),
                         right=model_df, how='left', right_index=True,␣
↪left_index=True)

    return result_df, model
```

[280]:
```python
def arima_plot(arima_result, title):
    fig, ax = plt.subplots(figsize=(25, 7))
    x = arima_result.index.tolist()
    ax.plot(x, arima_result['y_true'].tolist(), color='blue',
            label='Original')
    ax.plot(x, arima_result['y_pred'].tolist(), color='red',
            label='prediction')
    ax.plot(x, arima_result['lower_bounds'].tolist(), color='orange',
            label='Lower Bounds')
    ax.plot(x, arima_result['upper_bounds'].tolist(), color='green',
            label='Upper Bounds')

    ax.
↪fill_between(x,arima_result['lower_bounds'],arima_result['upper_bounds'],facecolor='silver'
```

```
    ax.set_xlabel('Date (monthly)', fontsize=16)
    ax.set_ylabel('Volume (trips)', fontsize=16)
    ax.set_title(title, fontsize=20)

    ax.xaxis.set_tick_params(labelsize=16, rotation=45)
    ax.yaxis.set_tick_params(labelsize=16)
    ax.grid(axis='y', color='grey', linestyle='--', linewidth=0.5)

    #     ax.xaxis.set_rotation('45')
    plt.legend(loc='upper left')
    plt.tight_layout()
    plt.show()
```

[281]:
```
result_df, model = arima_forecast(timeseries=month_trip,
                                  start_forecast_date=FORCAST_START_DATE,
                                  end_forecast_date=FORCAST_END_DATE)
arima_plot(result_df, title='ARIMA')
model_eval(result_df['y_true'], result_df['y_pred'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.5310480887395453
MAD : 55215.56640086445
```

5. Focus on the trip data from 2019-01 to 2019-12 only. Now the client of MSBA &Company wants to understand the key factors that affects the total daily ridership in the studied periods. Please explore auxiliary data sets and discuss your findings. [3 pts] [Hint: Weather data: https://www.meteoblue.com/en/weather/archive/era5/boston_united-states-of-america_4930956 . Students are also encouraged to explore other auxiliary data source]

Features: - Weather Dataset - Temperature: basic indicator - Precipitation: an indicator of whether rain or not - Wind speed: an indicator of whether suitable for taking scooter - Date-related Dataset - holiday - etc.

[332]:
```
# Set hyper parameter
TRAIN_START_DATE = '2019-01-01'
FORCAST_START_DATE = '2019-10-01'
FORCAST_END_DATE = '2019-12-31'
```

[333]:
```
tripdata_df['datetime'] = tripdata_df['starttime'].dt.strftime("%Y-%m-%d")
tripdata_used = tripdata_df.loc[(tripdata_df['datetime'] >= TRAIN_START_DATE) &
                                (tripdata_df['datetime'] <= FORCAST_END_DATE)]
```

[334]:
```
daily_trip = tripdata_used['datetime'].value_counts().sort_index()
```

[335]:
```
daily_trip_df = pd.DataFrame(daily_trip).rename(columns={'datetime': 'y_true'})
daily_trip_df['datetime'] = pd.to_datetime(daily_trip_df.index)
daily_trip_df = daily_trip_df.reset_index(drop=True)
```

[336]:
```
weather_data = read_from_csv('weather_data.csv', PROCESSED_DATA_DIR,
                             parse_dates=['datetime'])
weather_data['datetime'] = weather_data['datetime']
```

[337]:
```
dataset = pd.merge(left=daily_trip_df, right=weather_data,
                   on='datetime', how='inner')
```

[338]:
```
# Add Date-related Features
dataset['day'] = dataset['datetime'].dt.strftime("%d").astype(int)
dataset['dayofweek'] = dataset['datetime'].dt.dayofweek
dataset['is_workday'] = dataset['dayofweek'].apply(
    lambda x: 1 if x <= 4 else 0)
```

[339]:
```
import holidays
from datetime import date
```

[340]:
```
us_holidays = holidays.UnitedStates()
dataset['is_holiday'] = dataset['datetime'].apply(
    lambda x: 1 if x in us_holidays else 0)
```

[341]:
```
dataset.head()
```

[341]:
```
   y_true   datetime  Temperature_Minimum  Temperature_Maximum  \
0    1305 2019-01-01             2.348312            13.128311
1    2632 2019-01-02            -2.821688             1.618311
2    3005 2019-01-03            -1.311689             6.968312
3    3397 2019-01-04            -0.161688             7.998312
4     786 2019-01-05             1.728312             5.048312

   Temperature_Mean  RelativeHumidity_Minimum  RelativeHumidity_Maximum  \
0          7.768727                 49.318592                 95.652000
1         -0.883772                 31.418629                 67.223060
```

```
2         2.654561                   57.154278                  88.330734
3         3.625811                   48.568703                  73.006860
4         3.663312                   70.087240                  93.792020

   RelativeHumidity_Mean  MeanSeaLevelPressure_Minimum  \
0              71.862465                         997.7
1              48.663450                        1018.7
2              71.750340                        1009.3
3              63.310513                        1009.5
4              88.568260                         998.5

   MeanSeaLevelPressure_Maximum  …  WindSpeed_Maximum  WindSpeed_Mean  \
0                        1018.1  …          31.780067       23.699722
1                        1027.7  …          14.512064       10.105483
2                        1022.3  …          16.793140       11.653485
3                        1015.1  …          18.075441       12.926744
4                        1008.7  …          17.727943       10.884510

   WindDirection Dominant_None  GeopotentialHeight_Minimum  \
0                    261.37690                         -18
1                    339.22775                         149
2                    245.04233                          75
3                    225.24014                          77
4                    352.37183                         -12

   GeopotentialHeight_Maximum  GeopotentialHeight_Mean  day  dayofweek  \
0                         144                55.916668    1          1
1                         216               193.750000    2          2
2                         176               109.000000    3          3
3                         120                98.916664    4          4
4                          70                24.541666    5          5

   is_workday  is_holiday
0           1           1
1           1           0
2           1           0
3           1           0
4           0           0

[5 rows x 33 columns]
```

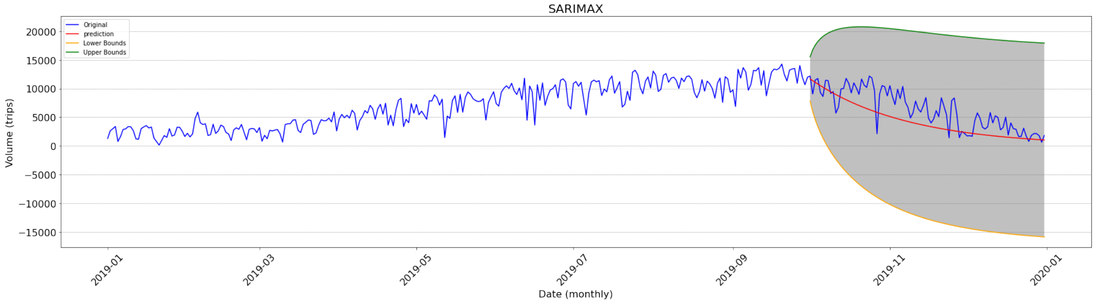
SARIMAX is like a complicated version of ARIMA. Optimal values of p, d, and q can be searched via a loop and grid search, as well as the seasonal values for p, d, and q. And also there could add more parameters in the SARIMAX function.

[342]:
```
import statsmodels.api as sm
```

[371]:
```python
def sarimax_forecast(df, exog_lst, start_forecast_date, end_forecast_date):

    # Load/split data
    df_train = df.loc[df['datetime'] < start_forecast_date]
    df_forecast = df.loc[(df['datetime'] >= start_forecast_date) &
                         (df['datetime'] <= end_forecast_date)]

    step_num = len(df_forecast)

    # Split the observed time-series and exogenous regressors
    endog_train = df_train['y_true']
    endog_forecast = df_forecast['y_true']
    exog_train = df_train[exog_lst]
    exog_forecast = df_forecast[exog_lst]

    # Fit model
    # Make forecasts
    if len(exog_lst):
        model = sm.tsa.statespace.SARIMAX(endog=endog_train, exog=exog_train,
                                          enforce_stationarity=False,
                                          enforce_invertibility=False)
        model = model.fit(maxiter=1000, warn_convergence=False)
        forecast = model.get_forecast(steps=step_num, exog=exog_forecast)
    else:
        model = sm.tsa.statespace.SARIMAX(endog=endog_train,
                                          enforce_stationarity=False,
                                          enforce_invertibility=False)
        model = model.fit(maxiter=1000, warn_convergence=False)
        forecast = model.get_forecast(steps=step_num)

    forecast_interval = forecast.conf_int()
    y_pred = forecast.predicted_mean
    pred_all = pd.concat([y_pred, forecast_interval], axis=1)
    pred_all.columns = ['y_pred', 'lower_bounds', 'upper_bounds']
    pred_all['datetime'] = pd.date_range(
        start_forecast_date, end_forecast_date, freq='D')

    result_df = pd.merge(left=df[['y_true', 'datetime']],
                         right=pred_all, how='left', on='datetime')
    result_df.index = result_df['datetime']

    return result_df, model
```

[372]:
```python
result_df, model = sarimax_forecast(df=dataset, exog_lst=[],
                                    start_forecast_date=FORCAST_START_DATE,
                                    end_forecast_date=FORCAST_END_DATE)
arima_plot(result_df, title='SARIMAX')
```

```
model_eval(result_df['y_true'], result_df['y_pred'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.40792774715829755
MAD: 2389.541413092803
```

[355]:
```
print(model.summary())
```

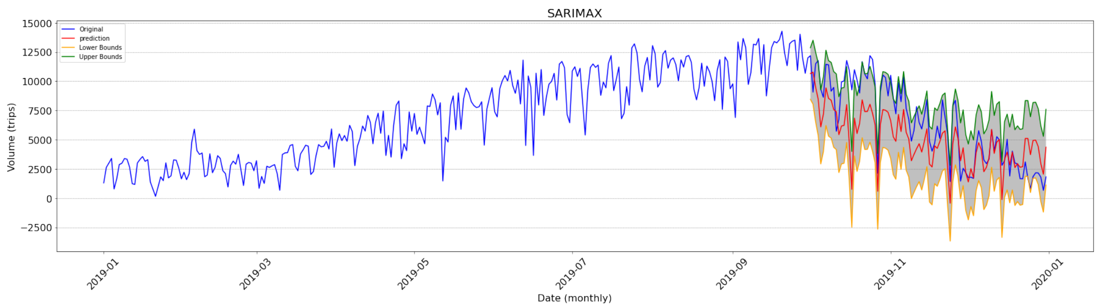
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                 y_true   No. Observations:                  272
Model:               SARIMAX(1, 0, 0)   Log Likelihood               -2440.175
Date:                Tue, 15 Sep 2020   AIC                           4884.350
Time:                        01:25:59   BIC                           4891.554
Sample:                             0   HQIC                          4887.243
                                - 272
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9738      0.014     67.324      0.000       0.945       1.002
sigma2      3.878e+06   2.51e+05     15.424      0.000    3.39e+06    4.37e+06
================================================================================
===
Ljung-Box (Q):                      190.84   Jarque-Bera (JB):
31.08
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               3.10   Skew:
-0.10
Prob(H) (two-sided):                  0.00   Kurtosis:
4.65
================================================================================
===

Warnings:
```

```
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

- From this result, although the MAPE is not very high, the prediction effect of the model is not ideal, especially the interval prediction effect.
- Next, try to add the exogenous variables to improve the model effect.

[373]:

```
exog_lst_full = ['Temperature_Minimum', 'Temperature_Maximum',␣
↪'Temperature_Mean',
                 'RelativeHumidity_Minimum', 'RelativeHumidity_Maximum',␣
↪'RelativeHumidity_Mean',
                 'MeanSeaLevelPressure_Minimum',␣
↪'MeanSeaLevelPressure_Maximum', 'MeanSeaLevelPressure_Mean',
                 'PrecipitationTotal_Summation', 'SnowfallAmount_Summation',␣
↪'CloudCoverTotal_Mean',
                 'SunshineDuration_Summation', 'Evapotranspiration_Summation',
                 'PBLHeight_Minimum', 'PBLHeight_Maximum', 'PBLHeight_Mean',
                 'WindGust_Minimum', 'WindGust_Maximum', 'WindGust_Mean',
                 'WindSpeed_Minimum', 'WindSpeed_Maximum', 'WindSpeed_Mean',
                 'WindDirection Dominant_None',
                 'GeopotentialHeight_Minimum', 'GeopotentialHeight_Maximum',␣
↪'GeopotentialHeight_Mean',
                 'day', 'dayofweek', 'is_workday', 'is_holiday']

result_df, model = sarimax_forecast(df=dataset, exog_lst=exog_lst_full,
                                    start_forecast_date=FORCAST_START_DATE,
                                    end_forecast_date=FORCAST_END_DATE)
arima_plot(result_df, title='SARIMAX')
model_eval(result_df['y_true'], result_df['y_pred'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.4362222118346819
MAD: 2065.216801665083
```

- After introducing exogenous variables to the model, the MAPE increases, the MAD decreases, and the model's predictions become more realistic.
- The increase of MAPE is partialy because the low MAPE of the previous model is caused by

the generally predicted value being lower than the true value. So the higher MAPE here is relatively acceptable.

- In other words, adding exogenous variables does improve the model effect.

[358]:
```
print(model.mle_retvals)
```

```
{'fopt': 8.373486516255104, 'gopt': array([ 2.44869014e-05,  1.27897692e-08,
4.23225900e-05, -6.89389879e-05,
        1.20093979e-04, -1.16954979e-04, -3.89289135e-04, -4.59752593e-04,
       -4.10761559e-04,  4.60799398e-05, -3.85281140e-05,  1.51807633e-04,
       -7.76026354e-04, -7.05451697e-05, -1.64280500e-04,  4.03786160e-04,
       -7.48590523e-05, -1.44950718e-05, -7.66455344e-05, -7.12274684e-05,
       -4.53752591e-05, -5.00328667e-05, -9.46016598e-06, -1.02211217e-04,
        3.30533645e-04, -8.31789748e-05,  1.60351554e-04, -2.93479019e-05,
        2.07300843e-07,  3.51732866e-05, -2.29828601e-05, -9.84173809e-04,
        7.32594431e-05]), 'fcalls': 15028, 'warnflag': 1, 'converged': False,
'iterations': 393}
```

- Lots of irrelevant exogenous variables cause the model fail to converge.
- Next, only useful variables are retained to make the model converge while maintaining a good model performance.

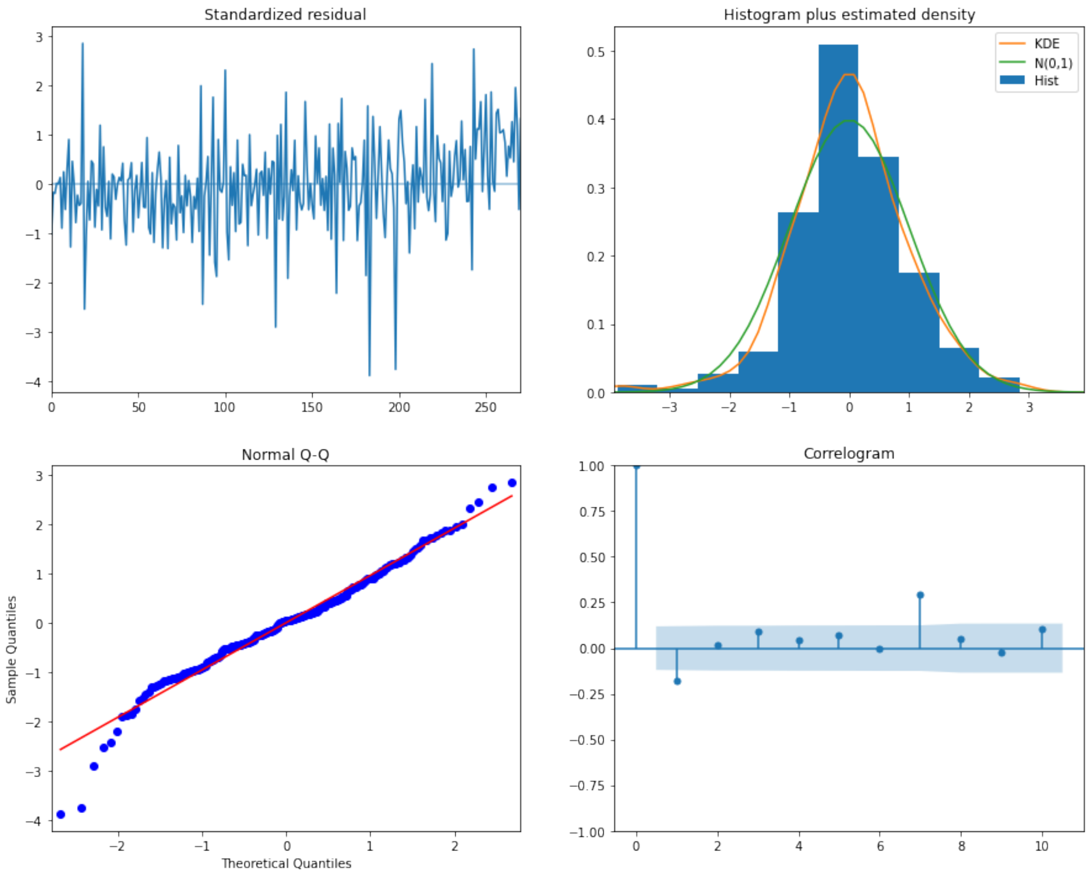
[359]:
```
print(model.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                 y_true   No. Observations:                  272
Model:               SARIMAX(1, 0, 0)   Log Likelihood               -2277.588
Date:                Tue, 15 Sep 2020   AIC                           4621.177
Time:                        01:26:14   BIC                           4740.047
Sample:                             0   HQIC                          4668.904
                                - 272
Covariance Type:                  opg
================================================================================
================
                                 coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------
Temperature_Minimum         -181.8214     82.227     -2.211      0.027
-342.984     -20.659
Temperature_Maximum         -162.4794     95.886     -1.694      0.090
-350.413      25.455
Temperature_Mean             576.1300    163.945      3.514      0.000
254.803     897.457
RelativeHumidity_Minimum      -0.5622     15.748     -0.036      0.972
-31.427      30.303
RelativeHumidity_Maximum      11.9421     13.344      0.895      0.371
-14.211      38.096
```

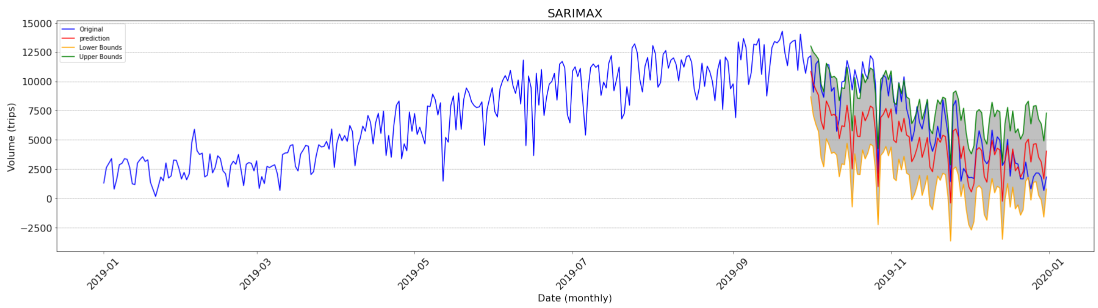
RelativeHumidity_Mean	4.6847	24.426	0.192	0.848	-43.189	52.558
MeanSeaLevelPressure_Minimum	-1106.9113	630.640	-1.755	0.079	-2342.943	129.120
MeanSeaLevelPressure_Maximum	-883.0381	474.349	-1.862	0.063	-1812.745	46.669
MeanSeaLevelPressure_Mean	1991.2926	1013.414	1.965	0.049	5.038	3977.547
PrecipitationTotal_Summation	-98.6419	21.428	-4.603	0.000	-140.640	-56.643
SnowfallAmount_Summation	27.0382	116.199	0.233	0.816	-200.708	254.784
CloudCoverTotal_Mean	4.6729	10.424	0.448	0.654	-15.758	25.104
SunshineDuration_Summation	1.9099	1.043	1.832	0.067	-0.134	3.954
Evapotranspiration_Summation	150.6438	122.095	1.234	0.217	-88.657	389.945
PBLHeight_Minimum	0.0997	0.891	0.112	0.911	-1.647	1.847
PBLHeight_Maximum	0.0847	0.328	0.258	0.796	-0.558	0.727
PBLHeight_Mean	0.8520	0.936	0.910	0.363	-0.983	2.687
WindGust_Minimum	-1.5305	28.008	-0.055	0.956	-56.425	53.364
WindGust_Maximum	-30.1916	22.140	-1.364	0.173	-73.586	13.203
WindGust_Mean	16.5477	67.712	0.244	0.807	-116.165	149.260
WindSpeed_Minimum	-66.8677	52.367	-1.277	0.202	-169.505	35.769
WindSpeed_Maximum	-85.6664	54.653	-1.567	0.117	-192.784	21.451
WindSpeed_Mean	115.7167	163.257	0.709	0.478	-204.260	435.694
WindDirection Dominant_None	-1.9003	0.994	-1.911	0.056	-3.849	0.049
GeopotentialHeight_Minimum	139.3753	77.181	1.806	0.071	-11.896	290.647
GeopotentialHeight_Maximum	109.2087	58.610	1.863	0.062	-5.665	224.083
GeopotentialHeight_Mean	-246.6524	124.262	-1.985	0.047	-490.202	-3.103
day	-11.4208	20.442	-0.559	0.576	-51.486	28.644
dayofweek	35.0937	64.963	0.540	0.589	-92.231	162.419

```
is_workday                    2015.2252    276.078      7.299      0.000
1474.122    2556.329
is_holiday                   -1709.3151    325.055     -5.259      0.000
-2346.411   -1072.219
ar.L1                            0.7322      0.058     12.655      0.000
0.619       0.846
sigma2                        1.269e+06   1.12e+05     11.329      0.000
1.05e+06    1.49e+06
================================================================================
===
Ljung-Box (Q):                      118.39   Jarque-Bera (JB):
37.77
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               1.92   Skew:
-0.30
Prob(H) (two-sided):                  0.00   Kurtosis:
4.72
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[360]:
```
model.plot_diagnostics(figsize=(15, 12))
plt.show()
```



[376]:
```
exog_lst_select = ['Temperature_Mean', 'MeanSeaLevelPressure_Mean',␣
↪'PrecipitationTotal_Summation',
                   'Evapotranspiration_Summation', 'WindSpeed_Mean',
                   'is_workday', 'is_holiday']

result_df, model = sarimax_forecast(df=dataset, exog_lst=exog_lst_select,
                                    start_forecast_date=FORCAST_START_DATE,
                                    end_forecast_date=FORCAST_END_DATE)
arima_plot(result_df, title='SARIMAX')
model_eval(result_df['y_true'], result_df['y_pred'],
           start_date=FORCAST_START_DATE, end_date=FORCAST_END_DATE)
```




```
MAPE: 0.4276895150879794
MAD: 2127.852603554388
```

[377]:
```
print(model.mle_retvals)
```

```
{'fopt': 8.415744474999084, 'gopt': array([-7.47313322e-07,  9.78577219e-06,
4.16910950e-07,  2.93631786e-07,
       -2.29682939e-07,  2.24197550e-05, -1.96093808e-05,  1.32500055e-04,
       -3.19579031e-05]), 'fcalls': 1190, 'warnflag': 0, 'converged': True,
'iterations': 101}
```

[379]:
```
print(model.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                 y_true   No. Observations:                  272
Model:               SARIMAX(1, 0, 0)   Log Likelihood               -2289.082
Date:                Tue, 15 Sep 2020   AIC                           4596.165
Time:                        01:47:02   BIC                           4628.584
Sample:                             0   HQIC                          4609.182
                                - 272
Covariance Type:                  opg
================================================================================
================
                                   coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
----------------
Temperature_Mean               207.1777     17.158     12.074      0.000
173.548     240.807
MeanSeaLevelPressure_Mean        2.9217      0.430      6.788      0.000
2.078       3.765
PrecipitationTotal_Summation  -104.3540     13.271     -7.863      0.000
-130.365     -78.343
Evapotranspiration_Summation   617.4280     75.349      8.194      0.000
469.747     765.109
```

```
WindSpeed_Mean                 -90.0968     18.621     -4.838      0.000
-126.593     -53.601
is_workday                    1850.6880    145.090     12.755      0.000
1566.316    2135.060
is_holiday                   -1550.3419    217.792     -7.118      0.000
-1977.207   -1123.477
ar.L1                            0.7447      0.039     19.285      0.000
0.669       0.820
sigma2                        1.227e+06   7.91e+04     15.520      0.000
1.07e+06    1.38e+06
================================================================================
===
Ljung-Box (Q):                      101.39   Jarque-Bera (JB):
29.43
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               3.74   Skew:
-0.14
Prob(H) (two-sided):                  0.00   Kurtosis:
4.59
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

- The model successfully converged and got better prediction results
- Useful exogenous variables are:
  - is today workday
  - is today holiday
  - Mean Temperature
  - Mean MeanSeaLevel Pressure
  - Precipitation Total Summation
  - Evapotranspiration Summation
  - Mean WindSpeed

6. [Optional] Focus on the trip data during 2019-01 and 2019-12 only. Now, the client of MSBA & Company wants to understand the key factors that explains the difference in the (average daily) ridership between different pairs of origin and destination. Please explore auxiliary data sets and discuss your findings. [3pts]

Last-Question

September 15, 2020

1 Optional Question

Focus on the trip data during 2019-01 and 2019-12 only. Now, the client of MSBA & Company wants to understand the key factors that explains the difference in the (average daily) ridership between different pairs of origin and destination. Please explore auxiliary data sets and discuss your findings. [3pts]

As for this problem, there are several categories of factors that will affect the daily average number of riders for a specific routine(Origin-destination pair). - Information only related to start/end location - Geographic information - Latitude - Longitude - District - Infrastructure information - Total docks - Traffic information - Rider gender distribution - Direction distribution(Identify most riderships are ride in or ride out?) - Peak hour(Identify the busiest time of the place) - Standard deviation of daily number(Identify the location's service is rigid demand or elastic demand.) - Features related to both locations - Geographic distance - Distance between two stations - Whether the two sites are cross-regional - Positioning distance - Gender distribution distance - Direction distribution distance - Peak hour distance - Standard deviation distance - Dock number gap

[1]:
```
import sys
import matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
sys.path.append(
    r'D:\OneDrive\Programming\documents_python\NUS␣
 ↪Courses\DBA5106\Course-DBA5106\assignment\IndividualAssignment2')
```

[3]:
```
from utils.logger import logger
from utils.config import PROCESSED_DATA_DIR
from utils.data_porter import read_from_csv
```

1.1 Data Cleaning

[4]:
```
# Set hyper parameter
START_DATE = '2019-01-01'
END_DATE = '2019-12-31'
```

[5]:
```
# Prepare the trip data
tripdata_df = read_from_csv('tripdata.csv', PROCESSED_DATA_DIR,
                            parse_dates=['starttime', 'stoptime'])
tripdata_df['datetime'] = tripdata_df['starttime'].dt.strftime("%Y-%m-%d")
tripdata_used = tripdata_df.loc[(tripdata_df['datetime'] >= START_DATE) &
                                (tripdata_df['datetime'] <= END_DATE)]
```

[6]:
```
# Prepare the station info
station_info = read_from_csv('Stations.csv', PROCESSED_DATA_DIR)
station_info['District'].value_counts()

# create usertype map(remain usertype id in the main file)
district_dict = {'Boston': 1, 'Cambridge': 2,'Somerville': 3,
                 'Brookline': 4, 'Everett': 5}
station_info['district_id'] = station_info['District'].map(district_dict)

# Drop unrelated columns
drop_lst = ['Name', 'District', 'Public']
station_info.drop(drop_lst, axis=1, inplace=True)

print(station_info.head())
```

```
   Station Id   Latitude  Longitude  Total docks  district_id
0         149  42.363796 -71.129164           18            1
1         378  42.380323 -71.108786           19            3
2         330  42.381001 -71.104025           15            3
3         116  42.370803 -71.104412           23            2
4         333  42.375002 -71.148716           25            2
```

[7]:
```
# Ignore the trips that station id is not in the station information file
station_lst = station_info['Station Id'].tolist()
tripdata_cleaned = tripdata_used.loc[(tripdata_used['start station id'].
 ↪isin(station_lst)) &
                                     (tripdata_used['end station id'].
 ↪isin(station_lst))]
tripdata_cleaned.dtypes
```

[7]:
```
tripduration                  int64
starttime            datetime64[ns]
stoptime             datetime64[ns]
start station id              int64
end station id                int64
bikeid                        int64
birth year                    int64
gender                      float64
usertype_id                   int64
datetime                     object
```

```
dtype: object
```

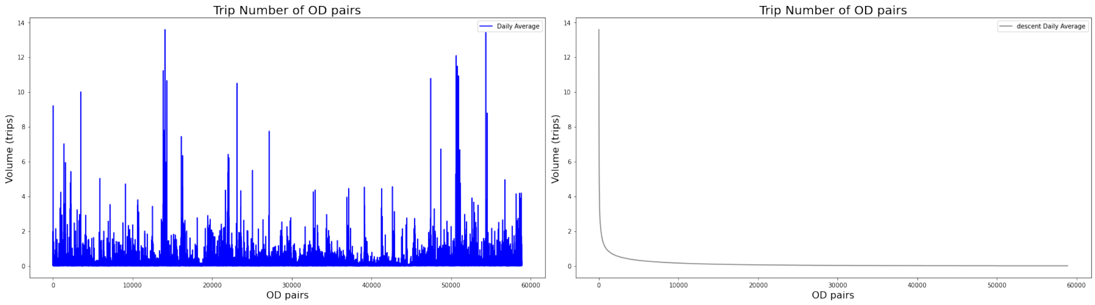
[8]:
```python
# To silence the Warning
pd.set_option('mode.chained_assignment', None)

# Creat unique id for a origin-destiney pair
tripdata_cleaned['od_pair'] = tripdata_cleaned.apply(
    lambda x: str(x['start station id']) + '_' + str(x['end station id']),␣
 ↪axis=1)
```

[9]:
```python
tripdata_cleaned.head(2)
```

[9]:
```
         tripduration               starttime                stoptime  \
5212224           371 2019-01-01 00:09:13.798 2019-01-01 00:15:25.336
5212225           264 2019-01-01 00:33:56.182 2019-01-01 00:38:20.880

         start station id  end station id  bikeid  birth year  gender  \
5212224                80             179    3689        1987     1.0
5212225               117             189    4142        1990     1.0

         usertype_id    datetime  od_pair
5212224            1  2019-01-01   80_179
5212225            1  2019-01-01  117_189
```

[10]:
```python
od_pair = tripdata_cleaned['od_pair'].value_counts().sort_index()/365
```

[11]:
```python
fig = plt.figure(figsize=(25, 7))
ax1 = plt.subplot(121)
ax1.plot(od_pair.tolist(), color='blue', label='Daily Average')
ax1.set_xlabel('OD pairs', fontsize=16)
ax1.set_ylabel('Volume (trips)', fontsize=16)
ax1.set_title(f'Trip Number of OD pairs', fontsize=20)
ax1.legend(loc='upper right')

ax2 = plt.subplot(122)
ax2.plot(od_pair.sort_values(ascending=False).tolist(),color='Grey',␣
 ↪label='descent Daily Average')
ax2.set_xlabel('OD pairs', fontsize=16)
ax2.set_ylabel('Volume (trips)', fontsize=16)
ax2.set_title(f'Trip Number of OD pairs', fontsize=20)
ax2.legend(loc='upper right')

plt.tight_layout()
plt.show()
```



1.2 Feature Engineering

1.2.1 Feature Engineering – Traffic information

- Information only related to start/end location
  - Traffic information
    * Daily Average Trips
    * Daily Average Ride In Trips
    * Daily Average Ride Out Trips
    * Rider gender distribution
    * Direction distribution(Identify most riderships are ride in or ride out?)
    * Peak hour(Identify the busiest time of the place)
    * Standard deviation of daily number(Identify the location's service is rigid demand or elastic demand.)

[12]:
```
def calcu_stat(station_id, stat):
    """calculate the station statistic information"""
    data_selected = tripdata_cleaned.loc[(tripdata_cleaned['start station id'] == station_id) |
                                         (tripdata_cleaned['end station id'] == station_id)]
    if stat == 'trip_num':
        return(len(data_selected))
    elif stat == 'ride_in_num':
        return(len(data_selected.loc[(tripdata_cleaned['end station id'] == station_id)]))
    elif stat == 'ride_out_num':
        return(len(data_selected.loc[(tripdata_cleaned['start station id'] == station_id)]))
    elif stat == 'ride_in_ratio':
        trip_num = len(data_selected)
        ride_in_num = len(
            data_selected.loc[(tripdata_cleaned['end station id'] == station_id)])
        return(ride_in_num/trip_num)
    elif stat == 'gender_ratio':
```

```python
        gender_ratio = len(
            data_selected.loc[(tripdata_cleaned['gender'] == 1)])/len(
            data_selected.loc[(tripdata_cleaned['gender'] == 0)])
        return(gender_ratio)
    elif stat == 'sd':
        return(data_selected['datetime'].value_counts().std())
    elif stat == 'ring_route_ratio':
        trip_num = len(data_selected)
        ring_route_num = len(
            tripdata_cleaned.loc[(tripdata_cleaned['start station id'] ==␣
↪station_id) &
                                 (tripdata_cleaned['end station id'] ==␣
↪station_id)])
        return(ring_route_num/trip_num)
    else:
        raise Exception
```

[13]:
```python
station_info.head(2)
```

[13]:
```
   Station Id   Latitude  Longitude  Total docks  district_id
0         149  42.363796 -71.129164           18            1
1         378  42.380323 -71.108786           19            3
```

[14]:
```python
station_info['trip_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='trip_num'))
station_info['ride_in_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_in_num'))
station_info['ride_out_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_out_num'))
station_info['ride_in_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_in_ratio'))
station_info['gender_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='gender_ratio'))
station_info['sd'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='sd'))
station_info['ring_route_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ring_route_ratio'))
station_info['ring_route_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ring_route_ratio'))
print('The statistical characteristics of the station are processed')
```

```
The statistical characteristics of the station are processed
```

[15]:
```python
station_info.head(2)
```

[15]:
```
   Station Id   Latitude  Longitude  Total docks  district_id  trip_num  \
0         149  42.363796 -71.129164           18            1     22081
```

```
1         378  42.380323 -71.108786          19             3     10880

   ride_in_num  ride_out_num  ride_in_ratio  gender_ratio         sd  \
0        11429         11144       0.517594      4.736295  36.722545
1         5364          5605       0.493015      7.928894  14.747012

   ring_route_ratio
0          0.022282
1          0.008180
```

1.2.2 Feature Engineering – Others related to start/end location

[16]:
```
dataset = pd.DataFrame(od_pair)
dataset.reset_index(inplace=True)
dataset.columns = ['od_pair', 'y_true']
```

[17]:
```
dataset['original_id'] = dataset['od_pair'].apply(lambda x: int(x.
 ↪split("_")[0]))
dataset['destination_id'] = dataset['od_pair'].apply(lambda x: int(x.
 ↪split("_")[1]))
dataset.head(2)
```

[17]:
```
   od_pair    y_true  original_id  destination_id
0   100_10  0.112329          100              10
1  100_100  1.986301          100             100
```

[18]:
```
dataset = pd.merge(left=dataset, right=station_info,
                   how='left', left_on='original_id', right_on='Station Id')
dataset = pd.merge(left=dataset, right=station_info,
                   how='left', left_on='destination_id', right_on='Station Id',␣
 ↪suffixes=['_o', '_d'])
```

1.2.3 Feature Engineering – Others related to both

- Features related to both locations
  - Geographic distance
    * Distance between two stations
    * Whether the two sites are cross-regional
  - Positioning distance
    * Gender distribution distance
    * Direction distribution distance
    * Peak hour distance
    * Standard deviation distance
    * Dock number gap

[19]:
```
dataset.head(2)
```

[19]:
```
    od_pair    y_true  original_id  destination_id  Station Id_o  Latitude_o  \
0    100_10  0.112329          100              10           100   42.396969
1   100_100  1.986301          100             100           100   42.396969

   Longitude_o  Total docks_o  district_id_o  trip_num_o  …  Longitude_d  \
0   -71.123024             25              3       30597  …   -71.108279
1   -71.123024             25              3       30597  …   -71.123024

   Total docks_d  district_id_d  trip_num_d  ride_in_num_d  ride_out_num_d  \
0             11              1       33897          17316           17181
1             25              3       30597          16707           14615

   ride_in_ratio_d  gender_ratio_d       sd_d  ring_route_ratio_d
0         0.510842        6.754360  55.949996            0.017701
1         0.546034        5.358989  40.135713            0.023695

[2 rows x 28 columns]
```

[20]:
```python
from math import radians, cos, sin, asin, sqrt

def haversine(lon1, lat1, lon2, lat2): # Longitude 1, Latitude 1, Longitude 2,␣
↪Latitude 2 (decimal number)
    """
    Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)
    """
    # Convert the decimal number into radians
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])

    # haversine
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat/2)**2 + cos(lat1) * cos(lat2) * sin(dlon/2)**2
    c = 2 * asin(sqrt(a))
    r = 6371 # The average radius of the earth (kilometers)
    return c * r * 1000
```

[21]:
```python
dataset['geographic_distance'] = dataset.apply(
    lambda x: haversine(x['Longitude_o'], x['Latitude_o'],
                        x['Longitude_d'], x['Latitude_d']), axis=1)
```

[22]:
```python
# Whether the two sites are cross-regional
dataset['cross_regional'] = dataset.apply(
    lambda x: 0 if x['district_id_o'] == x['district_id_d'] else 1, axis=1)
```

[23]:
```python
# Direction distribution distance
dataset['direction_distribution_distance'] = dataset.apply(
```

```
    lambda x: abs(x['ride_in_ratio_o'] - x['ride_in_ratio_d']), axis=1)
```

[24]:
```
# Standard deviation distance
dataset['sd_distance'] = dataset.apply(
    lambda x: abs(x['sd_o'] - x['sd_d']), axis=1)

# Mean value of the Standard deviation of two stations
dataset['sd_mean'] = dataset.apply(
    lambda x: (x['sd_o'] + x['sd_d'])/2, axis=1)
```

[25]:
```
# Dock number gap
dataset['dock_num_gap'] = dataset.apply(
    lambda x: abs(x['Total docks_o'] - x['Total docks_d']), axis=1)

# Mean value of the number of Dock number at two stations
dataset['dock_num_mean'] = dataset.apply(
    lambda x: (x['Total docks_o'] + x['Total docks_d'])/2, axis=1)
```

[26]:
```
# Mean value of the daily average trip number of two stations
dataset['trip_num_mean'] = dataset.apply(
    lambda x: (x['trip_num_o'] + x['trip_num_d'])/2, axis=1)
```

[27]:
```
dataset.head(2)
```

[27]:
```
    od_pair    y_true  original_id  destination_id  Station Id_o  Latitude_o  \
0    100_10  0.112329          100              10           100   42.396969
1   100_100  1.986301          100             100           100   42.396969

   Longitude_o  Total docks_o  district_id_o  trip_num_o  …       sd_d  \
0   -71.123024             25              3       30597  …  55.949996
1   -71.123024             25              3       30597  …  40.135713

   ring_route_ratio_d  geographic_distance  cross_regional  \
0            0.017701          5317.364565               1
1            0.023695             0.000000               0

   direction_distribution_distance  sd_distance    sd_mean  dock_num_gap  \
0                         0.035192    15.814283  48.042854            14
1                         0.000000     0.000000  40.135713             0

   dock_num_mean  trip_num_mean
0           18.0        32247.0
1           25.0        30597.0

[2 rows x 36 columns]
```

1.3 Multiple Linear Regression

[28]:
```
# Delete irrelevant items
drop_lst = ['od_pair', 'original_id', 'destination_id', 'Station Id_o',␣
↪'Station Id_d']
dataset = dataset.drop(drop_lst, axis=1)

# Data description
dataset.describe().head(2)
```

[28]:
```
            y_true    Latitude_o    Longitude_o  Total docks_o  district_id_o  \
count  58895.000000  58895.000000  58895.000000   58895.000000   58895.000000
mean       0.114028     42.354334    -71.089136      18.192139       1.571594

         trip_num_o  ride_in_num_o  ride_out_num_o  ride_in_ratio_o  \
count  58895.000000   58895.000000    58895.000000     58895.000000
mean   19647.679073    9995.761474     9980.825011         0.510624

       gender_ratio_o  …          sd_d  ring_route_ratio_d  \
count    58895.000000  …  58895.000000         58895.00000
mean         6.789064  …     31.791055             0.02626

       geographic_distance  cross_regional  direction_distribution_distance  \
count         58895.000000    58895.000000                     58895.000000
mean           3814.449189        0.487614                         0.032378

        sd_distance       sd_mean   dock_num_gap  dock_num_mean  trip_num_mean
count  58895.000000  58895.000000  58895.000000   58895.000000   58895.000000
mean      27.219594     32.035115      4.231921      18.182197   19494.550276

[2 rows x 31 columns]
```

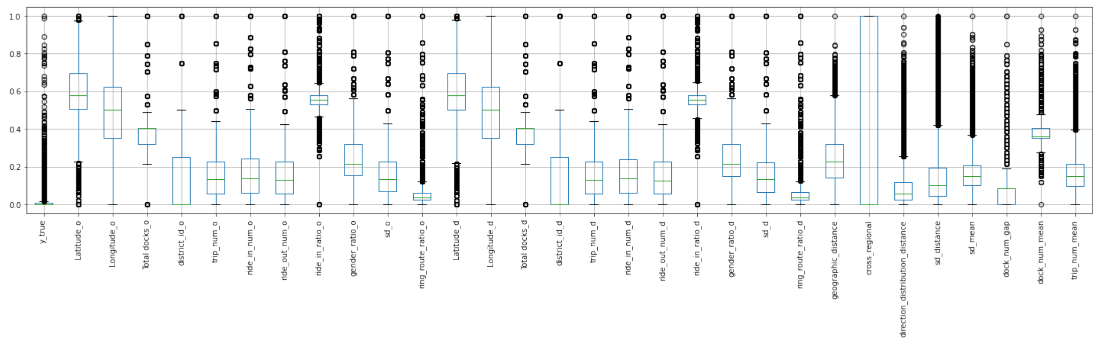
[29]:
```
# Missing value test
dataset[dataset.isnull()==True].count()
```

[29]:
```
y_true                             0
Latitude_o                         0
Longitude_o                        0
Total docks_o                      0
district_id_o                      0
trip_num_o                         0
ride_in_num_o                      0
ride_out_num_o                     0
ride_in_ratio_o                    0
gender_ratio_o                     0
sd_o                               0
ring_route_ratio_o                 0
```

```
Latitude_d                       0
Longitude_d                      0
Total docks_d                    0
district_id_d                    0
trip_num_d                       0
ride_in_num_d                    0
ride_out_num_d                   0
ride_in_ratio_d                  0
gender_ratio_d                   0
sd_d                             0
ring_route_ratio_d               0
geographic_distance              0
cross_regional                   0
direction_distribution_distance  0
sd_distance                      0
sd_mean                          0
dock_num_gap                     0
dock_num_mean                    0
trip_num_mean                    0
dtype: int64
```

[30]:
```
# Normalized
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
dataset_scale = scaler.fit_transform(dataset)
dataset_scale = pd.DataFrame(dataset_scale)
dataset_scale.columns = dataset.columns
```

[31]:
```
dataset_scale.boxplot(figsize=(25, 5))
plt.xticks(rotation=90)
plt.show()
```

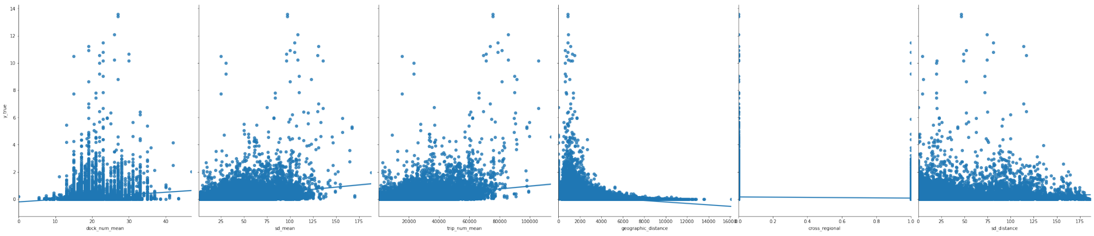


[32]:
```
# Correlation coefficient r(correlation coefficient) = cov(x,y) / x * y
# 0 ~ 0.3 weak correlation
```

```
# 0.3 ~ 0.6 moderate correlation
# 0.6 ~ 1 strong correlation
dataset_scale.corr()['y_true']
```

[32]:
```
y_true                              1.000000
Latitude_o                          0.042615
Longitude_o                         0.016018
Total docks_o                       0.118151
district_id_o                      -0.014742
trip_num_o                          0.258691
ride_in_num_o                       0.256800
ride_out_num_o                      0.259586
ride_in_ratio_o                    -0.021724
gender_ratio_o                      0.098052
sd_o                                0.243486
ring_route_ratio_o                 -0.069837
Latitude_d                          0.044523
Longitude_d                         0.020615
Total docks_d                       0.119359
district_id_d                      -0.019031
trip_num_d                          0.265761
ride_in_num_d                       0.266196
ride_out_num_d                      0.264367
ride_in_ratio_d                    -0.011715
gender_ratio_d                      0.096069
sd_d                                0.255302
ring_route_ratio_d                 -0.073733
geographic_distance                -0.306196
cross_regional                     -0.125794
direction_distribution_distance    -0.075724
sd_distance                         0.106085
sd_mean                             0.359147
dock_num_gap                        0.076230
dock_num_mean                       0.168310
trip_num_mean                       0.378669
Name: y_true, dtype: float64
```

[33]:
```
# By adding a parameter kind='reg', seaborn can add a best-fitting line and a␣
↪95% confidence band.
import seaborn as sns

sns.pairplot(dataset, x_vars=['dock_num_mean', 'sd_mean', 'trip_num_mean',␣
↪'geographic_distance', 'cross_regional', 'sd_distance'],
             y_vars='y_true', height=7, aspect=0.8, kind='reg')
plt.savefig("pairplot.jpg")
plt.show()
```



[34]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

variable_list = dataset_scale.columns
variable_list = variable_list.drop('y_true')

X_train,X_test,Y_train,Y_test =␣
↪train_test_split(dataset_scale[variable_list],dataset['y_true'],train_size=.
↪80)

LR_model = LinearRegression()

LR_model.fit(X_train,Y_train)

a  = LR_model.intercept_ # intercept

b = LR_model.coef_ # Regression coefficients

print('Intercept: ', a)
print('Regression coefficients: ', b)
```

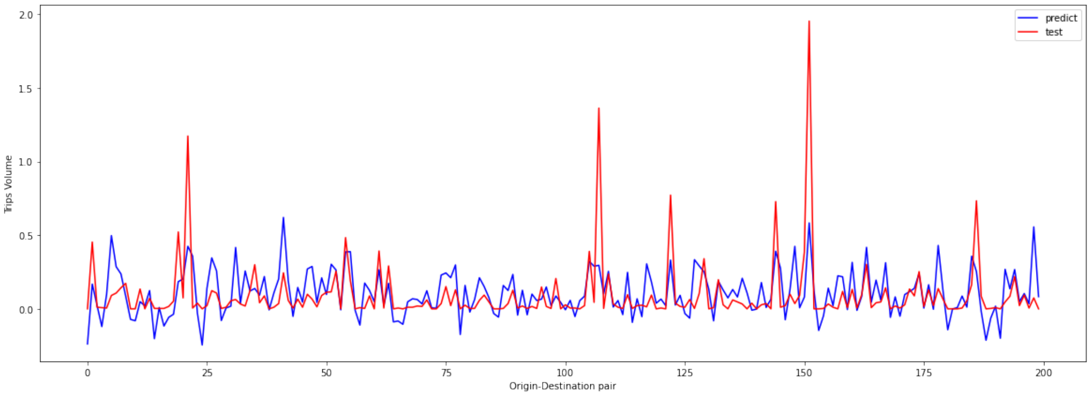
```
Intercept:  0.11918771603885987
Regression coefficients:  [-0.00612002 -0.079795    0.05314028  0.12323747
4.09131361 -2.74717387
 -2.74046716 -0.09322651 -0.02084284  0.31001354  0.26779192 -0.02077072
 -0.07973744  0.04479086  0.12594168  3.67567938 -2.02063789 -3.07531934
 -0.05118046 -0.01967976  0.30604996  0.26008544 -0.50784653 -0.13626559
  0.03787919 -0.67083899  0.30803175 -0.05096877  0.04896557  3.88349649]
```

[35]:
```
score = LR_model.score(X_train, Y_train)
print(score)
```

```
0.25955021485518937
```

[36]:
```
Y_pred = LR_model.predict(X_test)
plt.figure(figsize=(20,7))
plt.plot(range(len(Y_pred[:200])),Y_pred[:200],'b',label="predict")
plt.plot(range(len(Y_pred[:200])),Y_test[:200],'r',label="test")
```

```python
plt.legend(loc="upper right")
plt.xlabel("Origin-Destination pair")
plt.ylabel('Trips Volume')
plt.show()
```



- The final R-square of the model is 0.26.
- In real life, this model can only explain a part of the trip number of a Origin-Destiny pair.
- It also means that there are many variables that we have not taked into consideration.
- Varibles that contribute to the model:
  - 'dock_num_mean': Mean value of the dock number of the od pair
  - 'sd_mean': Mean value of the Demand Elasticity(Standard Deviation) of the od pair
  - 'trip_num_mean': Mean value of the daily average trip number of the od pair
  - 'geographic_distance': Geographical distance between two stations
  - 'cross_regional': Whether the two stations are cross-regional
  - 'sd_distance': The difference in demand elasticity between the two stations
- For improvement(neglected features):
  - Date information of sports games held in Boston(such as Boston Celtics Basketball Team)
  - Calendar of Boston Schools(Stanford/MIT)

data_process

September 15, 2020

1 Data Aggregation

[1]:
```
import sys
import pandas as pd
```

[2]:
```
sys.path.append(r'D:\OneDrive\Programming\documents_python\NUS␣
↪Courses\DBA5106\Course-DBA5106\assignment\IndividualAssignment2')
from utils.logger import logger
from utils.config import RAW_DATA_DIR, PROCESSED_DATA_DIR
from utils.data_porter import save_to_csv, read_from_csv
```

[3]:
```
# set hyperparameters
FIRST_DATA_YM = '2015-06'
LAST_DATA_YM = '2020-05'
```

[4]:
```
# generate date list(from FIRST_DATA_YM to LAST_DATA_YM)
date_lst = pd.date_range(FIRST_DATA_YM, LAST_DATA_YM, freq='MS').astype(str).
↪tolist()
date_lst = [''.join(date.split('-'))[:-2] for date in date_lst]
```

[5]:
```
# concat all the monthly data to one dataFrame
tripdata = None
for date in date_lst:
#     logger.debug(f'Processing {date} file.')
    suffix = '-hubway-tripdata.csv' if date <= '201804' else␣
↪'-bluebikes-tripdata.csv'
    monthly_file = date + suffix
    month_df = read_from_csv(monthly_file, RAW_DATA_DIR)
    # default join method is outer join.
    # set sort parameter to silence warning
    tripdata = month_df if tripdata is None else pd.concat([tripdata,␣
↪month_df], ignore_index=True, sort=False)
logger.info('Finish load all monthly file.')
```

```
LOG: 2020-09-15 22:42:53 [INFO] Finish load all monthly file.
```

2 Data Cleaning

[6]:
```
# Check NaN values in every columns
tripdata.isnull().sum()
```

[6]:
```
tripduration                     0
starttime                        0
stoptime                         0
start station id                 0
start station name               0
start station latitude           0
start station longitude          0
end station id                   0
end station name                 0
end station latitude             0
end station longitude            0
bikeid                           0
usertype                         0
birth year                  134471
gender                      124879
postal code                8165118
dtype: int64
```

2.1 Drop Features

[7]:
```
# drop postal code column because of massive missing values
tripdata.drop(columns = ['postal code'], inplace = True)
```

2.2 Replace Missing Values

[8]:
```
# Replace all NaN elements with 0s.
tripdata.fillna(0, inplace=True)
# Replace all \N elements with 0s.
tripdata.replace(r'\N', 0, inplace=True)
```

2.3 Specify Feature Type

[9]:
```
# Cast column 'birth year' to a specified dtype(int64).
tripdata['birth year'] = tripdata['birth year'].astype('int64')
# Cast column 'starttime' & 'stoptime' to a specified dtype(datetime64).
tripdata['starttime'] = tripdata['starttime'].astype('datetime64')
tripdata['stoptime'] = tripdata['stoptime'].astype('datetime64')
```

[10]:
```
tripdata.dtypes
```

[10]:
```
tripduration                         int64
starttime                   datetime64[ns]
stoptime                    datetime64[ns]
start station id                     int64
start station name                  object
start station latitude             float64
start station longitude            float64
end station id                       int64
end station name                    object
end station latitude               float64
end station longitude              float64
bikeid                               int64
usertype                            object
birth year                           int64
gender                             float64
dtype: object
```

3 Data Transformation

3.1 Process Station Info

[11]:
```
# extract station information(station id & station name)
start_station_info = tripdata[['start station id', 'start station name',
                               'start station latitude', 'start station␣
↪longitude']]
end_station_info = tripdata[['end station id', 'end station name',
                             'end station latitude', 'end station longitude']]
# rename the columns for later concat
station_info_lst = ['station_id','station_name', 'station_latitude',␣
↪'station_longitude']
start_station_info.columns = station_info_lst
end_station_info.columns = station_info_lst

# concat and drop duplicates
station_info = pd.concat([start_station_info, end_station_info], join='inner',␣
↪ignore_index=True)
station_info.drop_duplicates(subset=None, keep='first', inplace=True)
```

[12]:
```
# If errors = 'coerce', then invalid parsing will be set as NaN.
station_info['station_id'] = pd.to_numeric(station_info['station_id'],␣
↪errors='coerce').fillna(0)
station_info.sort_values('station_id', inplace=True)
```

[13]:
```
# drop duplicate id situation(one station have two name, multiple latitude/
↪longitude)
station_info_unique_id = station_info.copy()
```

```
station_info_unique_id.drop_duplicates(subset=['station_id'], keep='last',␣
 ↪inplace = True)
station_info_unique_id.sort_values('station_id', inplace=True)
```

[14]:
```
# drop station name columns from tripdata to reduce file size
tripdata.drop(columns=['start station name', 'end station name',
                       'start station latitude', 'start station longitude',
                       'end station latitude', 'end station longitude'],␣
 ↪inplace=True)
```

3.2 Process Usertype Info

[15]:
```
# find all unique usertype values
tripdata['usertype'].value_counts()
```

[15]:
```
Subscriber    6540965
Customer      1734651
Name: usertype, dtype: int64
```

[16]:
```
# create usertype map(remain usertype id in the main file)
usertype_dict = {'Subscriber':1,'Customer':2}
tripdata['usertype_id'] = tripdata['usertype'].map(usertype_dict)
```

[17]:
```
# save usertype id map to
usertype_info = pd.DataFrame(list(usertype_dict.items()),columns =␣
 ↪['usertype','usertype_id'])
```

[18]:
```
# drop usertype columns from tripdata to reduce file size
tripdata.drop(columns = ['usertype'], inplace = True)
```

3.3 Save to File

[19]:
```
# Save station info
save_to_csv(station_info, 'station_info.csv', PROCESSED_DATA_DIR)
save_to_csv(station_info_unique_id, 'station_info_unique_id.csv',␣
 ↪PROCESSED_DATA_DIR)
logger.info('Save station info to csv file.')

# Save usertype info
save_to_csv(usertype_info, 'usertype_info.csv', PROCESSED_DATA_DIR)
logger.info('Save usertype info to csv file.')

# Save trip data
save_to_csv(tripdata, 'tripdata.csv', PROCESSED_DATA_DIR)
logger.info('Save trip data to csv file.')
```

```
LOG: 2020-09-15 22:43:27 [INFO] Save station info to csv file.
LOG: 2020-09-15 22:43:27 [INFO] Save usertype info to csv file.
LOG: 2020-09-15 22:44:41 [INFO] Save trip data to csv file.
```

[20]:
```
tripdata.dtypes
```

[20]:
```
tripduration                   int64
starttime             datetime64[ns]
stoptime              datetime64[ns]
start station id               int64
end station id                 int64
bikeid                         int64
birth year                     int64
gender                       float64
usertype_id                    int64
dtype: object
```

[21]:
```
station_info.dtypes
```

[21]:
```
station_id             int64
station_name          object
station_latitude     float64
station_longitude    float64
dtype: object
```

[22]:
```
usertype_info.dtypes
```

[22]:
```
usertype       object
usertype_id     int64
dtype: object
```