STAT685-005-ForecastTrainingV2

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STAT 685: Dr. Suojin Wang's Group

Modeling Seoul Bike Sharing Demand - 004 Forecasting Training

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1 5 Forecasting

1.1 5.1 Business Scenaros

The purpose to predict bike demand is to make bikes available and accessible to the public at the right time. Noramlly, the data will be updated on a daily base for analysis. Forecasting to next 24 hours' demand can be conducted for high-level planning of the next day. To test the performance in this business scenario, we assume the data is updated at 0:00 AM of the day and all available data at the moment is used for model training to predict the next 24 hour demands.

If the infrastructure could support, data can be updated in real-time. Thus, an hourly model training could be conducted to predict the next hour demand. Any changes in the past hours could be considered in the next hour demand prediction. To test the perforamnce, the models will be trained hourly with all the data available at the moment (include demand data from last hour) and used to predict the demand in the next coming hour.

[2]:
```
import os
import sys
project_path = os.path.abspath(os.path.join(os.path.dirname(os.getcwd()), '.'))
sys.path.append(project_path)
from models.utilities_py import *
from models.xgb_estimator_py import *
import json
```

1.2 5.2 Daily Forecasting

1.2.1 5.2.1 Autocorrelation Features

When data is updated every day, the latest observation available for autocorrelation is lag 24 for all prediction timestamp. Therefore, autocorrelation features are added for demand from same hour 1 day ago, 2 days ago and 1 week ago. The model training is repeated daily for November 2018.

[4]:
```
# load data
dat = load_data()
# add past demand information, last day, 2 days ago, 1 week ago
dat_daily = dat.copy()
dat_daily = add_past_hour_demand(dat_daily, [24,48,7*24])
dat_daily.head(2).transpose()
```

[4]:

	168	169
Date	2017-12-08 00:00:00	2017-12-08 00:00:00
RentedBikeCount	233	230
Hour	0	1
Temp	-3.5	-3.7
Humidity	49	50
WindSpeed	2.6	2.5
Visibility	1893	1902
DewPointTemp	-12.6	-12.6
SolarRadiation	0	0
Rainfall	0	0
Snowfall	0	0
Seasons_Autumn	0	0
Seasons_Spring	0	0
Seasons_Summer	0	0
Holiday_No Holiday	1	1
FunctionalDay_No	0	0
lag24	198	218
lag48	145	144
lag168	254	204

1.2.2 5.2.2 Repeated Daily Training and Forecasting

- The model is repeatedly trained daily.
- Only next 24 hour demands are forecasted each time.

[6]:
```
date_list = get_default_date_list(dat)
print(f"Models are trained each day for {len(date_list)} days.")
```

```
Models are trained each day for 30 days.
```

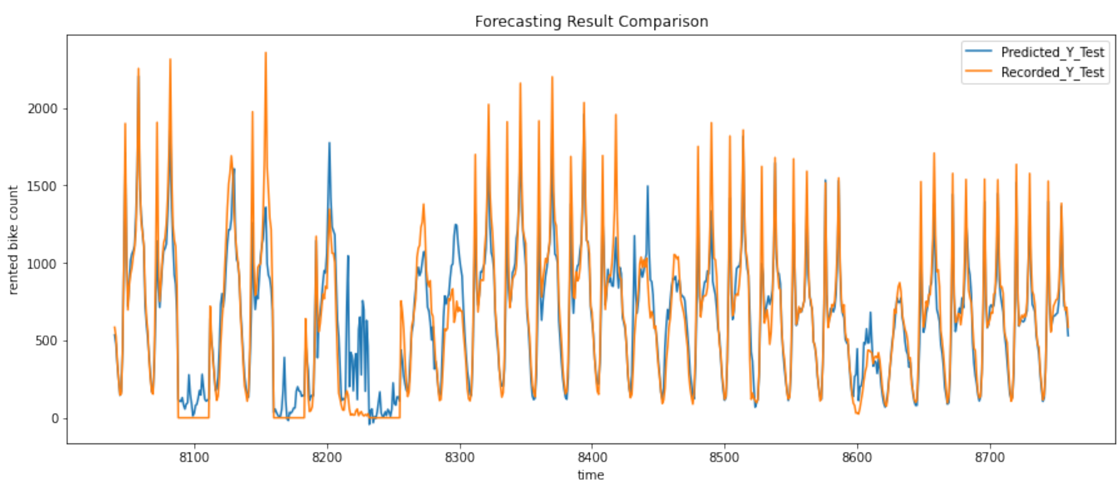
[ ]:
```
%%capture
# repeat model training and save result
sum_daily_cor, pred_daily_cor= run_repeat_forecast(dat_daily, date_list, None)
with open(os.path.join(project_path, "data/output_daily_cor.json"), 'w') as fp:
    json.dump(sum_daily_cor, fp)
pred_daily_cor.to_csv(os.path.join(project_path, "data/output_pred_daily_cor.
 ↪csv"), index=True)
```

[3]:
```
# read results
with open(os.path.join(project_path, "data/output_daily_cor.json"), 'r') as fp:
    sum_daily_cor = json.load(fp)
pred_daily_cor = pd.read_csv(os.path.join(project_path, "data/
↪output_pred_daily_cor.csv"), index_col=0)
```

[37]:
```
# printout result
printout_result(sum_daily_cor)
```

```
train_score: avg  0.9769; std  0.0006
mean_cv_score: avg  0.7990; std  0.0031
test_score: avg -0.1558; std  4.5441
run_time:  3414.4916
test_r2:  0.8601
```

[38]:
```
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(15,6))
_=pred_daily_cor.plot(xlabel="time", ylabel="rented bike count",
                      title="Forecasting Result Comparison", ax=ax)
```



1.3 5.3 Hourly Forecasting

1.3.1 5.3.1 Autocorrelation Features

When the data is updated every hour, the last hour demand can be used directly as an autocorrelation feature (lag 1). Therefore, we add demand for 1 hour ago, 2 hours ago, 1 day ago and 1 week ago as autocorrelation features to the data. The modeling training is conducted every hour and used to predict demand only for the coming hour.

[18]:
```
# load data
dat = load_data()
```

```
# add past demand information, last hour, 2 hours ago, 1 day ago
dat_hourly = dat.copy()
dat_hourly = add_past_hour_demand(dat_hourly, [1,2,24, 24*7])
dat_hourly.head(2).transpose()
```

[18]:

```
                                 168                  169
Date                 2017-12-08 00:00:00  2017-12-08 00:00:00
RentedBikeCount                      233                  230
Hour                                   0                    1
Temp                                -3.5                 -3.7
Humidity                              49                   50
WindSpeed                            2.6                  2.5
Visibility                          1893                 1902
DewPointTemp                       -12.6                -12.6
SolarRadiation                         0                    0
Rainfall                               0                    0
Snowfall                               0                    0
Seasons_Autumn                         0                    0
Seasons_Spring                         0                    0
Seasons_Summer                         0                    0
Holiday_No Holiday                     1                    1
FunctionalDay_No                       0                    0
lag1                                 259                  233
lag2                                 389                  259
lag24                                198                  218
lag168                               254                  204
```

1.3.2 5.3.2 Repeated Hourly Training and Forecasting

- The model is repeatedly trained hourly.
- Only next 1 hour demands are forecasted each time.

[ ]:

```
%%capture
# repeat model training and save result
hour_list = list(range(24))
sum_hourly_cor, pred_hourly_cor= run_repeat_forecast(dat_daily, date_list,␣
 ↪hour_list)
with open(os.path.join(project_path, "data/output_hourly_cor.json"), 'w') as fp:
    json.dump(sum_hourly_cor, fp)
pred_hourly_cor.to_csv(os.path.join(project_path, "data/output_pred_hourly_cor.
 ↪csv"), index=True)
```

[4]:

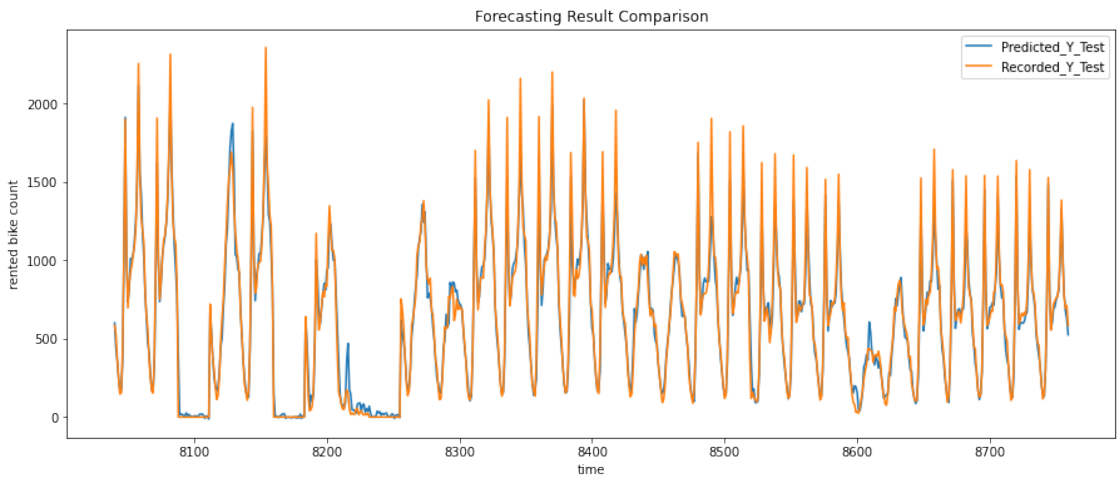
```
# read results
with open(os.path.join(project_path, "data/output_hourly_cor.json"), 'r') as fp:
    sum_hourly_cor = json.load(fp)
```

```
pred_hourly_cor = pd.read_csv(os.path.join(project_path, "data/
 ↪output_pred_hourly_cor.csv"), index_col=0)
```

[20]:
```
# printout result
printout_result(sum_hourly_cor)
```

```
train_score: avg  0.9946; std  0.0001
mean_cv_score: avg  0.9288; std  0.0011
test_score: avg  nan; std  nan
run_time:  91298.7513
test_r2:  0.9636
```

[39]:
```
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(15,6))
_=pred_hourly_cor.plot(xlabel="time", ylabel="rented bike count",
                       title="Forecasting Result Comparison", ax=ax)
```



[40]:
```
round(compare_table({"Daily": sum_daily_cor, "Hourly": sum_hourly_cor}), 3)
```

[40]:

	Daily	Hourly
train_score	0.977	0.995
mean_cv_score	0.799	0.929
test_score	-0.156	NaN
run_time	3414.492	91298.751
test_r2	0.860	0.964

[41]:
```
# plot prediction accuracy
compare_df = pred_daily_cor[['Recorded_Y_Test']]
compare_df['Daily_Forecast_w_corr'] = pred_daily_cor['Predicted_Y_Test']
compare_df['Hourly_Forecast_w_corr'] = pred_hourly_cor['Predicted_Y_Test']
fig, ax = plt.subplots(nrows=2, ncols=1, figsize=(15,12))
_=compare_df.plot(xlabel="time", ylabel="rented bike count",
```

```
                        title="Forecasting Result Comparison", ax=ax[0])
compare_df['Daily_w_corr_res'] = compare_df['Daily_Forecast_w_corr'] -␣
 ↪compare_df['Recorded_Y_Test']
compare_df['Hourly_w_corr_res'] = compare_df['Hourly_Forecast_w_corr'] -␣
 ↪compare_df['Recorded_Y_Test']
_=compare_df[['Daily_w_corr_res', 'Hourly_w_corr_res']].plot(xlabel="time",␣
 ↪ylabel="rented bike count",
                        title="Forecasting Residuals", ax=ax[1])
```

1.4 5.5 Improvement with Autocorrelations

[33]:
```
# load forecasting results without autocorrelation
with open(os.path.join(project_path, "data/output_daily_no_cor.json"), 'r') as␣
 ↪fp:
    sum_daily_no_cor = json.load(fp)
pred_daily_no_cor = pd.read_csv(os.path.join(project_path, "data/
 ↪output_pred_daily_no_cor.csv"), index_col=0)
```

```python
with open(os.path.join(project_path, "data/output_hourly_no_cor.json"), 'r') as␣
↪fp:
    sum_hourly_no_cor = json.load(fp)
pred_hourly_no_cor = pd.read_csv(os.path.join(project_path, "data/
↪output_pred_hourly_no_cor.csv"), index_col=0)
```

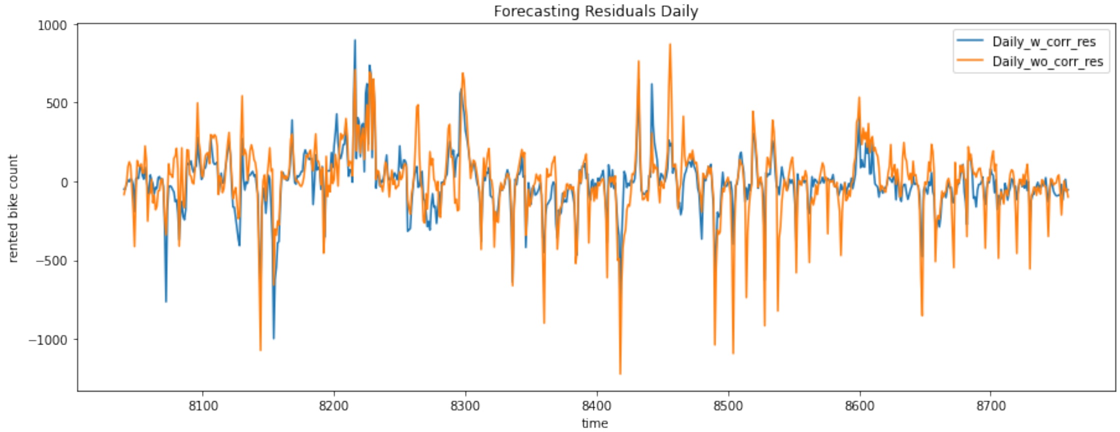
[34]:
```python
round(compare_table({"Daily_with_Autocorrelation": sum_daily_cor,
                     "Daily_without_Autocorrelation": sum_daily_no_cor,
                     "Hourly_with_Autocorrelation": sum_hourly_cor,
                     "Hourly_without_Autocorrelation": sum_hourly_no_cor
                    }), 3)
```

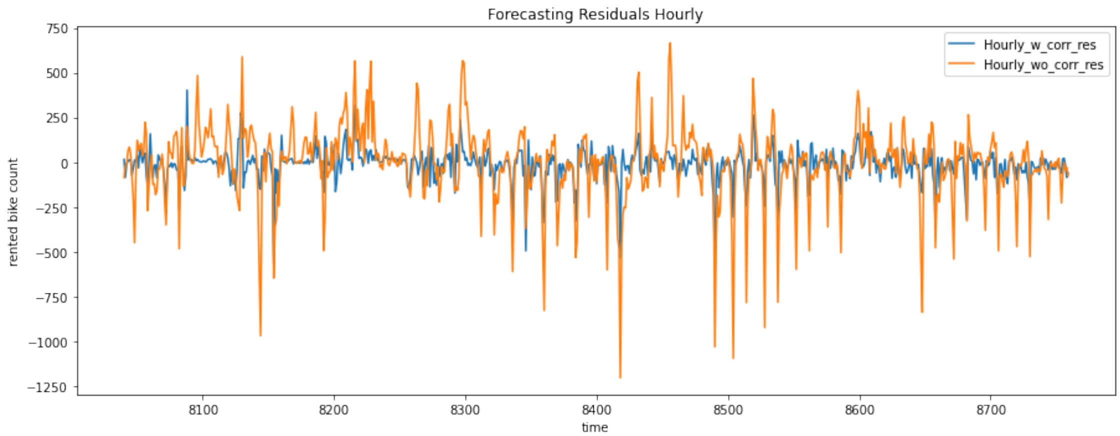
[34]:
```
               Daily_with_Autocorrelation  Daily_without_Autocorrelation  \
train_score                         0.977                          0.960
mean_cv_score                       0.799                          0.686
test_score                         -0.156                         -0.219
run_time                         3414.492                       1988.500
test_r2                             0.860                          0.775

               Hourly_with_Autocorrelation  Hourly_without_Autocorrelation
train_score                          0.995                           0.960
mean_cv_score                        0.929                           0.686
test_score                             NaN                             NaN
run_time                         91298.751                       54192.148
test_r2                              0.964                           0.817
```

[42]:
```python
compare_df['Daily_wo_corr_res'] = pred_daily_no_cor['Predicted_Y_Test'] -␣
↪pred_daily_no_cor['Recorded_Y_Test']
compare_df['Hourly_wo_corr_res'] = pred_hourly_no_cor['Predicted_Y_Test'] -␣
↪pred_hourly_no_cor['Recorded_Y_Test']
```

[43]:
```python
fig, ax = plt.subplots(nrows=2, ncols=1, figsize=(15,12))
_=compare_df[['Daily_w_corr_res', 'Daily_wo_corr_res']].plot(xlabel="time",␣
↪ylabel="rented bike count",
                   title="Forecasting Residuals Daily", ax=ax[0])
_=compare_df[['Hourly_w_corr_res', 'Hourly_wo_corr_res']].plot(xlabel="time",␣
↪ylabel="rented bike count",
                   title="Forecasting Residuals Hourly", ax=ax[1])
```


Forecasting Residuals Daily
Daily_w_corr_res
Daily_wo_corr_res
rented bike count
time
1000
500
0
−500
−1000
8100
8200
8300
8400
8500
8600
8700


Forecasting Residuals Hourly
Hourly_w_corr_res
Hourly_wo_corr_res
rented bike count
time
750
500
250
0
−250
−500
−750
−1000
−1250
8100
8200
8300
8400
8500
8600
8700

[ ]: