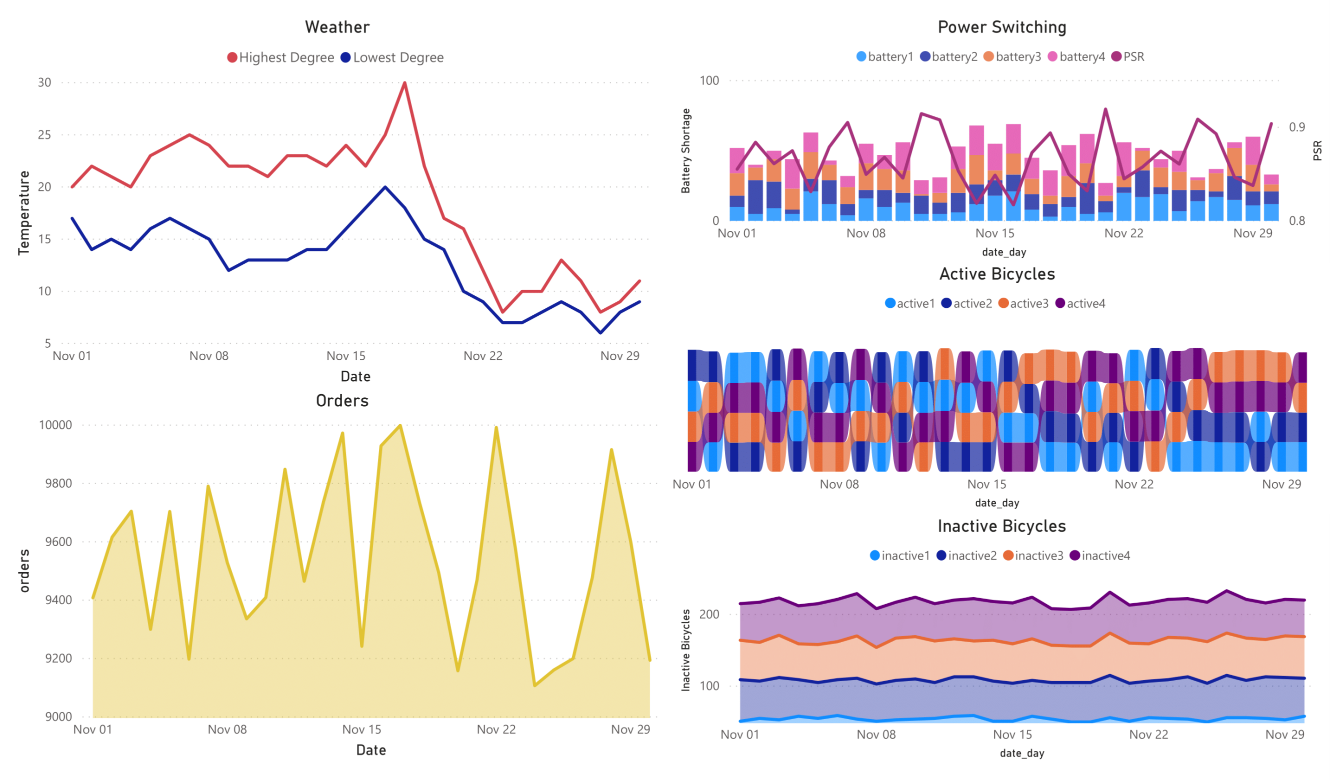
DiDi Internship

2020.09.29 - 2021.01.05

As a data operation intern in DiDi, it is my honor to get to know every extraordinary colleague and friend, leaving me this long lasting memory hard to forget. The main responsibility is to support all kinds of data, especially key indexes for our team, by utilizing Excel and Power BI, an example of the dashboard is shown below. (note: the data is made up and shows no exact perforance of the true business)



To fetch data from Hive, SQL is written to adapt to our needs, sample codes are listed below. (note: all the codes have nothing to do with the real scenario in business or database of the company, just to demonstrate several frequently-used snippets)

In [ ]:
```
-- Fetch orders data of city_1, city_2, city_3 in November
SELECT city, date_day, orders
FROM bicycles_indexes
WHERE city in ('city_1', 'city_2', 'city_3') AND MONTH(date_day) = 11;

-- Fetch batteries shortages data of city_1 in November
SELECT date_day, batteries_needs_1-batteries_finishs_1 as b1, batteries_needs_2-batteries_finishs_2 as b2, batteries_n
eeds_3 - batteries_finishs_3 as b3, batteries_needs_4 - batteries_finishs_4 as b4
FROM bicycles_indexes
WHERE city = 'city_1' AND MONTH(date_day) = 11;

-- Fetch Power Switching Rate data of city_1 in November and deliver in descending order
SELECT date_day, batteries_finishs/batteries_needs as b, batteries_finishs_1/batteries_needs_1 as b1, batteries_finish
s_2/batteries_needs_2 as b2, batteries_finishs_3/batteries_needs_3 as b3, batteries_finishs_4/batteries_needs_4 as b4
FROM bicycles_indexes
WHERE city = 'city_1' AND MONTH(date_day) = 11
ORDER BY b DESC;

-- Fetch each city's total active bicycles in November
SELECT city, SUM(active_bikes_1) as a1, SUM(active_bikes_2) as a2, SUM(active_bikes_3) as a3, SUM(active_bikes_4) as a
4
FROM bicycles_indexes
WHERE MONTH(date_day) = 11
GROUP BY city;

-- Join table 'special_days' and table 'bicycles_indexes' for city_1
SELECT * FROM special_days LEFT JOIN
(SELECT * FROM bicycles_indexes WHERE city = 'city_1') as city_1
ON special_days.date_day = city_1.date_day
ORDER BY special_days.date_day
```

The city our team is based on is one of the most popular cities for shared-bicycles and DiDi owns rich amount of business-related data, which makes it meaningful and feasible to predict the demands so that stuff could put more effort in specific time and location, the model was primitively built in course ELEN E6889 in Columbia University and incorporated way more features. The crucial difference of bicycle business from others is that it is significantly influenced by the weather condition, hence by dispatching bikes and allocating resources according to each day's temperature the team efficiency would be greatly improved. Although the data is business secret and could never be released, the model is illustrated below by using a public citibike database and NASA weather data.

In [296]:
```
# Environment Setup
from pyspark import SparkContext, SQLContext
from pyspark.sql import functions
from pyspark.sql.types import StructType, StructField, StringType, IntegerType, DoubleType, TimestampType
from pyspark.ml import Pipeline
from pyspark.ml.regression import DecisionTreeRegressor, GBTRegressor, RandomForestRegressor
from pyspark.ml.feature import VectorAssembler, VectorIndexer
from pyspark.ml.evaluation import RegressionEvaluator
import pandas as pd
import datetime
import folium
from folium.plugins import HeatMapWithTime
import calendar
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation
from IPython.display import HTML
```

In [111]:
```
SC = SparkContext('local', 'citibike')
sqlContext = SQLContext(SC)

# Stream citibike data
df = sqlContext.read.format('com.databricks.spark.csv').options(header='true', inferschema='true').load('201904-citibi
ke-tripdata.csv')
df_May = sqlContext.read.format('com.databricks.spark.csv').options(header='true', inferschema='true').load('201905-ci
tibike-tripdata.csv')
df_Jun = sqlContext.read.format('com.databricks.spark.csv').options(header='true', inferschema='true').load('201906-ci
tibike-tripdata.csv')
df_Jul = sqlContext.read.format('com.databricks.spark.csv').options(header='true', inferschema='true').load('201907-ci
tibike-tripdata.csv')
df = df.union(df_May)
df = df.union(df_Jun)
df = df.union(df_Jul)

df_519 = df.filter(df['start station id'] == 519)

hour_window = functions.window(functions.col('starttime'), '1 hour', '1 hour').start.alias('starttime')
hour_number = df_519.groupBy(hour_window).count()
hour_sort = hour_number.sort('starttime')

# Stream weather data and concatenate with citibike data
schema_weather = StructType([
    StructField('starttime', StringType(), True),
    StructField('SPD', DoubleType(), True),
    StructField('GUS', DoubleType(), True),
    StructField('SKC', DoubleType(), True),
    StructField('VSB', DoubleType(), True),
    StructField('TEMP', DoubleType(), True),
    StructField('DEWP', DoubleType(), True),
    StructField('SLP', DoubleType(), True),
    StructField('ALT', DoubleType(), True),
    StructField('STP', DoubleType(), True),
    StructField('PCP01', DoubleType(), True)
])

df_weather = sqlContext.read.format('com.databricks.spark.csv').options(header='true').schema(schema_weather).load('pr
ocessed_weather.csv')
df_join = df_weather.join(hour_sort, ['starttime'], 'left')
df_sort = df_join.sort('starttime')
df_sort = df_sort.withColumn('starttime', df_sort['starttime'].cast(TimestampType()))
df_filled = df_sort.fillna(0, subset='count')

# Add features 'hour' and 'is_weekend'
df_hour = df_filled.withColumn('hour', functions.hour('starttime'))
df_final = df_hour.withColumn('is_weekend', functions.dayofweek('starttime').isin([1, 7]).cast('int'))
df_final.show()
```

```
+-------------------+----+----+---+----+----+----+------+-----+------+-----+-----+----+----------+
|          starttime| SPD| GUS|SKC| VSB|TEMP|DEWP|   SLP|  ALT|   STP|PCP01|count|hour|is_weekend|
+-------------------+----+----+---+----+----+----+------+-----+------+-----+-----+----+----------+
|2019-04-01 00:00:00| 5.0|21.0|0.0|10.0|40.0|20.0|1014.4|29.98|1009.5|  0.0|    5|   0|         0|
|2019-04-01 01:00:00|13.0|22.0|1.0|10.0|38.0|18.0|1015.1| 30.0|1010.1|  0.0|    0|   1|         0|
|2019-04-01 02:00:00|10.0|18.0|0.0|10.0|36.0|17.0|1015.5|30.01|1010.5|  0.0|    0|   2|         0|
|2019-04-01 03:00:00|10.0|18.0|0.0|10.0|35.0|17.0|1016.1|30.03|1011.2|  0.0|    0|   3|         0|
|2019-04-01 04:00:00| 9.0| 0.0|0.0|10.0|35.0|16.0|1017.2|30.06|1012.2|  0.0|    0|   4|         0|
|2019-04-01 05:00:00| 8.0|20.0|0.0|10.0|34.0|16.0|1018.2|30.09|1013.2|  0.0|    3|   5|         0|
|2019-04-01 06:00:00| 8.0|24.0|0.0|10.0|33.0|15.0|1019.1|30.12|1014.2|  0.0|   16|   6|         0|
|2019-04-01 07:00:00|10.0|22.0|0.0|10.0|33.0|15.0|1020.4|30.16|1015.5|  0.0|   39|   7|         0|
|2019-04-01 08:00:00| 8.0|17.0|0.0|10.0|35.0|16.0|1020.9|30.17|1015.9|  0.0|   63|   8|         0|
|2019-04-01 09:00:00| 8.0| 0.0|0.0|10.0|37.0|16.0|1021.7|30.19|1016.6|  0.0|   38|   9|         0|
|2019-04-01 10:00:00| 7.0|24.0|0.0|10.0|39.0|16.0|1022.5|30.22|1017.6|  0.0|   18|  10|         0|
|2019-04-01 11:00:00| 8.0|24.0|0.0|10.0|40.0|16.0|1022.9|30.23|1017.9|  0.0|    7|  11|         0|
|2019-04-01 12:00:00|11.0|21.0|0.0|10.0|42.0|14.0|1023.2|30.24|1018.2|  0.0|   10|  12|         0|
|2019-04-01 13:00:00| 3.0| 0.0|0.0|10.0|44.0|13.0|1023.2|30.24|1018.2|  0.0|   16|  13|         0|
|2019-04-01 14:00:00| 0.0| 0.0|0.0|10.0|45.0|12.0|1023.3|30.24|1018.2|  0.0|   17|  14|         0|
|2019-04-01 15:00:00|10.0|20.0|0.0|10.0|45.0|10.0|1023.4|30.25|1018.6|  0.0|   22|  15|         0|
|2019-04-01 16:00:00|10.0|18.0|0.0|10.0|45.0| 9.0|1023.7|30.26|1018.9|  0.0|   32|  16|         0|
|2019-04-01 17:00:00|11.0|21.0|0.0|10.0|45.0| 8.0|1024.7|30.28|1019.6|  0.0|   86|  17|         0|
|2019-04-01 18:00:00| 5.0| 0.0|0.0|10.0|44.0| 9.0|1025.5|30.31|1020.6|  0.0|  133|  18|         0|
|2019-04-01 19:00:00| 6.0| 0.0|0.0|10.0|43.0| 8.0|1026.3|30.33|1021.3|  0.0|   40|  19|         0|
+-------------------+----+----+---+----+----+----+------+-----+------+-----+-----+----+----------+
only showing top 20 rows
```

In [250]:
```
# Split the dataset into training set, test set and realtime renewing set
df_model = df_final.drop('starttime')
list_model = df_model.collect()
training_list = list_model[0: 1464]
test_list = list_model[1464: 2184]
realtime_list = list_model[2184: 2924]
```

In [251]:
```
spark = SparkSession.builder.appName('citibike').getOrCreate()
training_df = spark.createDataFrame(training_list)
test_df = spark.createDataFrame(test_list)
realtime_df = spark.createDataFrame(realtime_list)

training_df.cache()
test_df.cache()
realtime_df.cache()
```

Out[251]:
```
DataFrame[SPD: double, GUS: double, SKC: double, VSB: double, TEMP: double, DEWP: double, SLP: double, ALT: double, S
TP: double, PCP01: double, count: bigint, hour: bigint, is_weekend: bigint]
```

In [218]:
```
# Build the pipeline of decision tree and train the model
features_columns = training_df.columns
features_columns.remove('count')
features_assembling = VectorAssembler(inputCols = features_columns, outputCol = 'features_assembled')
features_indexing = VectorIndexer(inputCol = 'features_assembled', outputCol = 'features', maxCategories = 25, handleI
nvalid = 'skip')
dt = DecisionTreeRegressor(featuresCol = 'features', labelCol = 'count', seed = 2021)

dt_pipeline = Pipeline(stages = [features_assembling, features_indexing, dt])
dt_model = dt_pipeline.fit(training_df)
dt_prediction = dt_model.transform(test_df)
evaluator = RegressionEvaluator(labelCol = 'count', predictionCol = 'prediction', metricName = 'rmse')
dt_rmse = evaluator.evaluate(dt_prediction)
print('Decision Tree Regressor:', dt_rmse)
```

```
Decision Tree Regressor: 11.890417633989733
```

In [216]:
```
# Build the pipeline of gradient boost tree and train the model
gbt = GBTRegressor(featuresCol = 'features', labelCol = 'count')
gbt_pipeline = Pipeline(stages = [features_assembling, features_indexing, gbt])
gbt_model = gbt_pipeline.fit(training_df)
gbt_prediction = gbt_model.transform(test_df)
gbt_rmse = evaluator.evaluate(gbt_prediction)
print('Gradient Boost Tree Regression:', gbt_rmse)
```

```
Gradient Boost Tree Regression: 13.682482439199084
```

In [217]:
```
# Build the pipeline of randomforest regressor
rf = RandomForestRegressor(numTrees=10, maxDepth=5, seed=2021, featuresCol='features', labelCol='count')
rf_pipeline = Pipeline(stages = [features_assembling, features_indexing, rf])
rf_model = rf_pipeline.fit(training_df)
rf_prediction = rf_model.transform(test_df)
rf_rmse = evaluator.evaluate(rf_prediction)
print('Random Forest Regressor:', rf_rmse)
```

```
Random Forest Regressor: 13.276845143846367
```

In [265]:
```
# Realtime streaming for Decision Tree Regressor
realtime_list = realtime_df.collect()
newtrain_list = training_df.collect()
july_prediction_list = []
for i in range(int(realtime_df.count()/12)):
    realtime_point = realtime_list[i*12:i*12+12]
    realtime_dataframe = spark.createDataFrame(realtime_point)
    prediction = dt_model.transform(realtime_dataframe)
    july_prediction_list = july_prediction_list + prediction.collect()
    newtrain_list = newtrain_list + realtime_point
    newtrain_df = spark.createDataFrame(newtrain_list)
    dt_model = dt_pipeline.fit(newtrain_df)

july_prediction_df = spark.createDataFrame(july_prediction_list)
df_reg = july_prediction_df.select('*').toPandas()
df_reg.to_csv('df_regression.csv')
```

In [266]:
```
# Realtime streaming for GBTR
realtime_list = realtime_df.collect()
newtrain_list = training_df.collect()
july_prediction_list = []
for i in range(int(realtime_df.count()/12)):
    realtime_point = realtime_list[i*12:i*12+12]
    realtime_dataframe = spark.createDataFrame(realtime_point)
    prediction = gbt_model.transform(realtime_dataframe)
    july_prediction_list = july_prediction_list + prediction.collect()
    newtrain_list = newtrain_list + realtime_point
    newtrain_df = spark.createDataFrame(newtrain_list)
    gbt_model = gbt_pipeline.fit(newtrain_df)

july_prediction_df = spark.createDataFrame(july_prediction_list)
df_gbtr = july_prediction_df.select('*').toPandas()
df_gbtr.to_csv('df_gbtr.csv')
```

In [267]:
```
# Realtime streaming for Random Forest
realtime_list = realtime_df.collect()
newtrain_list = training_df.collect()
july_prediction_list = []
for i in range(int(realtime_df.count()/12)):
    realtime_point = realtime_list[i*12:i*12+12]
    realtime_dataframe = spark.createDataFrame(realtime_point)
    prediction = rf_model.transform(realtime_dataframe)
    july_prediction_list = july_prediction_list + prediction.collect()
    newtrain_list = newtrain_list + realtime_point
    newtrain_df = spark.createDataFrame(newtrain_list)
    rf_model = rf_pipeline.fit(newtrain_df)

july_prediction_df = spark.createDataFrame(july_prediction_list)
df_rf = july_prediction_df.select('*').toPandas()
df_rf.to_csv('df_rf.csv')
```

In [271]:
```
# Load data and preprocess datetime
citibike = pd.read_csv('201907-citibike-tripdata.csv')
citibike['starttime'] = citibike['starttime'].str[:-5]
citibike['stoptime'] = citibike['stoptime'].str[:-5]
citibike['starttime'] = pd.to_datetime(citibike['starttime'])
citibike['stoptime'] = pd.to_datetime(citibike['stoptime'])
citibike = citibike.set_index('starttime')
```

In [280]:
```
# Create list to store lists of locations day by day, hour by hour
df_hour_list = []
day_list = list(set(citibike.index.date))
day_list.sort()
time_index = []
for day in day_list:
    for hour in range(0, 24):
        time_index.append(datetime.datetime.combine(day, datetime.time(hour)))
for day in day_list:
    for hour in range(0, 24):
        citibike_day = citibike.loc[citibike.index.date == day, ['start station latitude', 'start station longitude']]
        citibike_hour = citibike_day.loc[citibike_day.index.hour == hour, ['start station latitude', 'start station lo
ngitude']].groupby(['start station latitude', 'start station longitude']).sum().reset_index().values.tolist()
        citibike_demand = citibike_day.loc[citibike_day.index.hour == hour, ['start station latitude', 'start station
longitude']].groupby(['start station latitude', 'start station longitude']).size()
        demand_max = citibike_demand.values.max()
        demand_scaled = citibike_demand.values/demand_max
        for k in range(len(citibike_hour)):
            citibike_hour[k].append(demand_scaled[k])
        df_hour_list.append(citibike_hour)
```

In [ ]:
```
# Add trip events to the map
time_index = [str(x) for x in time_index]
map_time = folium.Map(location = [40.7470, -73.9955], tiles = 'CartoDB Positron', zoom_start = 13)

HeatMapWithTime(df_hour_list, index=time_index, auto_play = True, max_opacity = 0.5, gradient={0.2: 'cornflowerblue',
0.4: 'royalblue', 0.75: 'mediumblue', 1: 'blue'}).add_to(map_time)
map_time
```

https://youtu.be/BZXAwv2N72s

In [291]:
```
# load citibike data and preprocess datetime
citibike_07_519 = pd.read_csv('citibike_07_519.csv')
citibike_07_519 = citibike_07_519.drop(columns=['Unnamed: 0'], axis=1)

citibike_07_519['starttime'] = citibike_07_519['starttime'].str[:-5]
citibike_07_519['stoptime'] = citibike_07_519['stoptime'].str[:-5]
citibike_07_519['starttime'] = pd.to_datetime(citibike_07_519['starttime'])
citibike_07_519['stoptime'] = pd.to_datetime(citibike_07_519['stoptime'])

citibike_07_519 = citibike_07_519.set_index('starttime', drop=True)

# extract date from starttime
day_list = list(set(citibike_07_519.index.date))
day_list.sort()

# combine date and time
time_index = []
for day in day_list:
    for hour in range(0,24):
        time_index.append(datetime.datetime.combine(day, datetime.time(hour)))

# extract weekday from time_index
time_text = [x.date() for x in time_index]
weekday_text = [calendar.day_name[y.weekday()] for y in time_text]

# create list to store demand hour by hour
df_hour = []
for day in day_list:
    for hour in range(0,24):
        citibike_07_519_day = citibike_07_519.loc[citibike_07_519.index.date == day, ['start station latitude', 'start
station longitude']]
        citibike_07_519_demand = citibike_07_519_day.loc[citibike_07_519_day.index.hour == hour]
        df_hour.append(citibike_07_519_demand.shape[0])

# load regression, gbtr, rf result
df_reg = pd.read_csv('df_regression.csv')
reg_pre = df_reg['prediction']
df_gbtr = pd.read_csv('df_gbtr.csv')
gbtr_pre = df_gbtr['prediction']
df_rf = pd.read_csv('df_rf.csv')
rf_pre = df_rf['prediction']
```

In [292]:
```
# load weather data
weather_data = pd.read_csv('original_weather.csv')

# extract weather data hour by hour
weather_data['starttime'] = pd.to_datetime(weather_data['starttime'])
weather_data.set_index('starttime', inplace=True)
weather_data_5 = weather_data[weather_data.index.month == 5]

# extract temperature and wind speed data
temp_data = weather_data_5['TEMP']
speed_data = weather_data_5['SPD']
```

In [293]:
```
# create animation of original demands and predicted ones
fig, ax = plt.subplots()
ax.set_xlim(0, 24)
ax.set_ylim(0, 200)
ax.set_xticks(range(0, 24))
ax.set_xlabel('time(h)')
ax.set_ylabel('demands')
line, = ax.plot([], [])

plotlays, plotcols, labels = [4], ["cornflowerblue", "turquoise", "sienna", "moccasin"], ["original", "tree_reg", "gbt
r", "random forest"]
lines = []
for index in range(4):
    lobj = ax.plot([], [], color=plotcols[index], label=labels[index], linewidth=2)[0]
    ax.legend(loc='upper right')
    lines.append(lobj)

def init():
    for line in lines:
        line.set_data([], [])
    return lines

x_data = [0] * 24
y_data = [0] * 24
x_data2 = [0] * 24
y_data2 = [0] * 24
x_data3 = [0] * 24
y_data3 = [0] * 24
x_data4 = [0] * 24
y_data4 = [0] * 24

def animate(i):
    x_data[i%24] = i%24
    y_data[i%24] = df_hour[i]
    x_data2[i%24] = i%24
    y_data2[i%24] = reg_pre[i]
    x_data3[i%24] = i%24
    y_data3[i%24] = gbtr_pre[i]
    x_data4[i%24] = i%24
    y_data4[i%24] = rf_pre[i]
    xlist = [x_data, x_data2, x_data3, x_data4]
    ylist = [y_data, y_data2, y_data3, y_data4]
    ax.set_title("{}, Temperature: {}, Wind speed: {}".format(weekday_text[i], temp_data[i], speed_data[i]))

    for lnum, line in enumerate(lines):
        line.set_data(xlist[lnum], ylist[lnum])
    return lines

animation = FuncAnimation(fig, animate, init_func=init, frames=np.arange(0, 732, 1), interval=150)
HTML(animation.to_html5_video())
```

https://youtu.be/xgYG8Dk7ZCo