API Import

In [1]:

```
import requests
import json
import pandas as pd
from datetime import datetime
from time import sleep
import os

# Convert to datetime iso
def toIso(dt):
    return datetime.fromisoformat(dt)


def carparkApiCall(year, month, day, hour, minute, second, error_count):
    fDir = f'./data/{year}{month}{day}T{hour.zfill(2)}{minute.zfill(2)}{second.zfill(2)}.json'
    try:
        open(fDir, 'r')
    except:
        os.makedirs(os.path.dirname('./data/'), exist_ok=True)
        # If file doesn't exist, api call
        site = f'https://api.data.gov.sg/v1/transport/carpark-availability?date_time={year}-{month.zfill(2)}-{day.zfill(
        # print(site)
        response_API = requests.get(site)
        data = response_API.text
        data = json.loads(data)
        try:
            timestamp = data["items"][0]["timestamp"]
            data = data["items"][0]["carpark_data"]
        except:
            print(data)
            print(year,'/', month, '/', day, 'T', hour, minute, second)
            error_count+=1
            print("error count:", error_count)
            if error_count<=5:
                return carparkApiCall(year, month, day, hour, minute, second, error_count)
            else:
                "Api call failed more than 5 times :("
        # print(timestamp)
        with open(fDir, 'w') as fp:
            json.dump(data, fp)
    df = pd.read_json(fDir)
    for heading in ("total_lots","lot_type","lots_available"):
```

```
        df[heading] = df["carpark_info"].apply(lambda x: x[0][heading])
    # Transform data
    df = df.drop(["carpark_info"], axis=1)
    df['update_datetime'] = df['update_datetime'].apply(toIso)
    df["lots_available"] = df["lots_available"].astype(int)
    df["total_lots"] = df["total_lots"].astype(int)
    return df
```

Question 1.1 LTA Datamall API documentation Type of lots:

- C (for Cars)
- H (for Heavy Vehicles)
- Y (for Motorcycles)

image.png
[https://datamall.lta.gov.sg/content/dam/datamall/datasets/LTA_DataMall_API_User_Guide.pdf (https://datamall.lta.gov.sg/content/dam/datamall/datasets/LTA_DataMall_API_User_Guide.pdf)](https://datamall.lta.gov.sg/content/dam/datamall/datasets/LTA_DataMall_API_User_Guide.pdf)

Question 1.2

In [2]:
```
year = "2022"
month = "1"
day = "17"
hour = "4"
minute = "30"
second = "0"
curr_df = carparkApiCall(year, month, day, hour, minute, second,0)
curr_df.loc[0,'update_datetime']
# print(curr_df.head())
```

Out[2]:
```
Timestamp('2022-01-17 04:20:12')
```

1 second later

In [3]:
```
second = str(int(second) + 1)
next_df = carparkApiCall(year, month, day, hour, minute, second,0)
next_df.loc[0,'update_datetime']
```

Out[3]:
```
Timestamp('2022-01-17 04:20:12')
```

Iterate through intervals of 5 mins for 5 random hours and average the time difference of update_datetime.

In [4]:
```
from datetime import timedelta
from random import randint
from random import seed

total_time_interval = timedelta()
seed(10)
for _ in range (5):
    # samples for 5 different hours
    hour = str(randint(0,23))
    minute = "0"
    prev_df = carparkApiCall(year, month, day, hour, minute, second, 0)
    for i in range(5,59,5):
        # Iterate through interval of 5 mins
        next_min = str(int(minute) + i)
        next_df = carparkApiCall(year, month, day, hour, next_min, second, 0)
        # When different update_datetime is found
        if(prev_df.loc[0,'update_datetime'] != next_df.loc[0,'update_datetime']):
            prev_datetime = prev_df.loc[0,'update_datetime']
            next_datetime = next_df.loc[0,'update_datetime']
            total_time_interval += next_datetime - prev_datetime
            break
# Average time interval
print(total_time_interval/5)
```

```
0 days 00:30:30.200000
```

ANSWER

Approximate frequency at which the data values are updated is 30 mins 30 seconds

Question 1.3

Part I

How many carparks are included in the data.gov.sg car park database? There are 1966 carparks as of 1st October 2022

In [5]:
```
year = 2022
month = 10
day = 14
hour = 0
minute = 1
second = 0

dt = datetime(year, month, day, hour, minute, second)
# generate data
df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
carpark_count = pd.DataFrame(df).drop_duplicates(subset='carpark_number', keep="last")["carpark_number"].count()
print(f'There are {carpark_count} carparks as of {day}/{month}/{year}')
```

```
There are 1968 carparks as of 14/10/2022
```

Part II

Does this number vary based on the time? You should notice that it does vary with time.

In [6]:
```
year = 2022
month = 2
day = 2
hour = 0
minute = 1
second = 0

while month<=10:
    dt = datetime(year, month, day, hour, minute, second)
    # generate data

    df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
    carpark_count = pd.DataFrame(df).drop_duplicates(subset='carpark_number', keep="last")["carpark_number"].count()
    print(f'There are {carpark_count} carparks as of {day}/{month}/{year}')
    month += 1
```

```
There are 1958 carparks as of 2/2/2022
There are 1959 carparks as of 2/3/2022
There are 1960 carparks as of 2/4/2022
There are 1962 carparks as of 2/5/2022
There are 1962 carparks as of 2/6/2022
There are 1962 carparks as of 2/7/2022
There are 1962 carparks as of 2/8/2022
There are 1965 carparks as of 2/9/2022
There are 1966 carparks as of 2/10/2022
```

Answer

There are more carparks added every month.

Part III

A carpark may have malfunctioning sensors and nor report its data. Identify one of these carparks with anomalous sensors and a time period where that carpark's sensors were malfunctioning.

In [7]:

```
year = 2022
month = 9
day = 1
hour = 0
minute = 1
second = 0

malfunctioning = set()
dt = datetime(year, month, day, hour, minute, second)
# generate data
df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
df.sort_values(by=['total_lots'], inplace=True)
bad_carparks = df.loc[(df['lots_available'].astype(int) > df['total_lots'].astype(int))]
print(bad_carparks)
print(f'These carparks have malfunctioning sensors at {day}/{month}/{year} {str(hour).zfill(2)}:{str(minute).zfill(2)} :
```

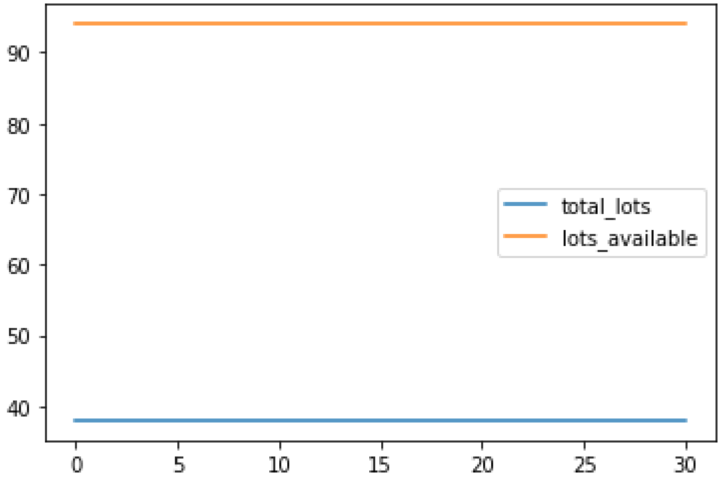
```
    carpark_number     update_datetime  total_lots lot_type  lots_available
648          P40L1 2016-02-15 21:52:35           2        C               6
549          Y49HV 2016-02-15 21:52:35           3        C              28
649          P40L2 2016-02-15 21:52:35           3        C               6
599          MR567 2016-02-15 21:52:35          38        C              94
926           SK24 2016-02-19 11:19:28         181        Y             200
927           SK24 2016-02-19 11:19:29         181        H             200
These carparks have malfunctioning sensors at 1/9/2022 00:01 : ['P40L1', 'Y49HV', 'P40L2', 'MR567', 'SK24', 'SK24']
```

In [8]:
```
#looking at MR567
# start date 1 Jul 2022 0000

import matplotlib.pyplot as plt

year = 2022
month = 7
day = 1
hour = 0
minute = 1
second = 0

dt = datetime(year, month, day, hour, minute, second)
dt_interval = timedelta(hours = 1)
total_hrs = 24*30
lots_available = []
total_lots = []
# generate data
for hr in range(total_hrs):
    dt = dt + dt_interval
    df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
    specific_data = df.loc[df["carpark_number"] == "MR567"].head(1)
    lots_available.append(specific_data["lots_available"].iloc[0])
    total_lots.append(specific_data["total_lots"].iloc[0])
plt.plot([x/24 for x in range(len(total_lots))], total_lots, label = "total_lots")
plt.plot([x/24 for x in range(len(lots_available))], lots_available, label = "lots_available")
plt.legend()
plt.show()
```



Answer

Since MR567 constantly has more available lots than total lots which is impossible, we can deduce that it is one of the carparks with faulty sensors.

Question 1.4

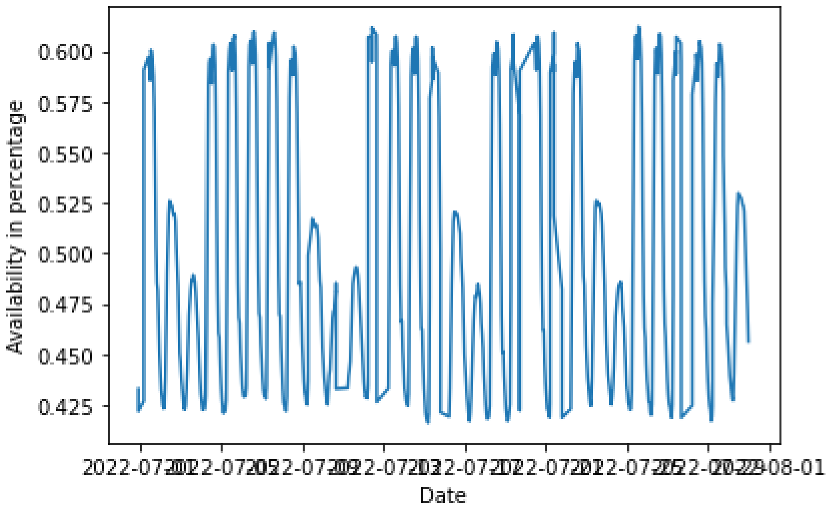
Generate hourly readings from the raw data. Select a one month interval and plot the hourly data (time-series) for that interval (aggregate results instead of plotting for each location individually). Identify any patterns in the visualization. Note: You will have to decide what to do if there are no carpark readings for a certain hour, for example, should you impute the missing data or ignore it.

In [9]:
```
# Calculate average availability in percentage
def avrAvail(df):
    df["availability_percentage"] = df["lots_available"]/df["total_lots"]
    return df["availability_percentage"].sum()/len(df.index)
```

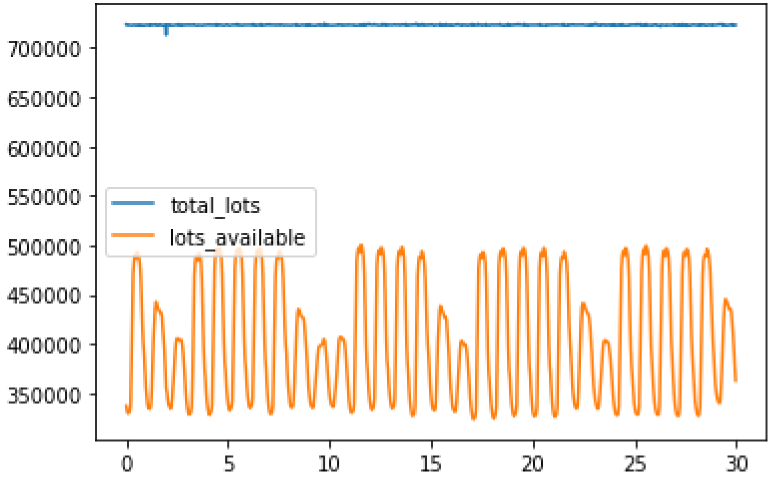
In [10]:
```
# start date 1 Jul 2022 0000
year = 2022
month = 7
day = 1
hour = 0
minute = 1
second = 0

dt = datetime(year, month, day, hour, minute, second)
dt_interval = timedelta(hours = 1)
total_hrs = 24*30
timeseries_data = {
    'dt':[],
    'avail': []
}
total_lots = []
lots_available = []
error_count = 0
# generate data
for hr in range(total_hrs):
    dt = dt + dt_interval
    df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
    lots_available.append(df["lots_available"].sum())
    total_lots.append(df["total_lots"].sum())
    timeseries_data['avail'].append(avrAvail(df))
    timeseries_data['dt'].append(df.loc[0,'update_datetime'])
```

In [11]:
```
plt.plot(timeseries_data['dt'], timeseries_data["avail"])
plt.xlabel("Date")
plt.ylabel("Availability in percentage")
plt.show()
```



In [12]:
```
plt.plot([x/24 for x in range(len(total_lots))], total_lots, label = "total_lots")
plt.plot([x/24 for x in range(len(lots_available))], lots_available, label = "lots_available")
plt.legend()
plt.show()
```



Question 1.5

Intuitively, we expect that carpark availability across certain carparks to be correlated. For example, many housing carparks would experience higher carpark availability during working hours. Using the same interval chosen in 1.4, write a function to find the top five carparks with which it shows the highest correlation. Demonstrate an example of this function call using a randomly selected carpark.

In [13]:
```
import numpy as np
def correlation(arr1,arr2):
    ret = np.corrcoef(arr1,arr2)
    return ret[0][1]
```

In [14]:

```
# start date 1 Jul 2022 0000
year = 2022
month = 7
day = 1
hour = 0
minute = 1
second = 0

dt = datetime(year, month, day, hour, minute, second)
dt_interval = timedelta(hours = 1)
total_hrs = 24*30
total_lots = []
lots_available = []
error_count = 0
d = {}
# generate data
for hr in range(total_hrs):
    dt = dt + dt_interval
    df = carparkApiCall(str(dt.year), str(dt.month), str(dt.day), str(dt.hour), str(dt.minute), str(dt.second), 0)
    for index, row in df.iterrows():
        if row["carpark_number"] in d:
            d[row["carpark_number"]].append((row["lots_available"],row["total_lots"]))
        else:
            d[row["carpark_number"]] = [(row["lots_available"],row["total_lots"])]
```

In [15]:

```
def get_top_correlated(carpark_number,d,top):
    ls = []
    for key in d:
        if key != carpark_number:
            ls.append((correlation(d[key],d[carpark_number]),key))
    ls.sort()
    return ls[:top]
```

In [16]:
```
result = get_top_correlated("HLM",d,5)
```

```
C:\Users\Ethan Wong\anaconda3\lib\site-packages\numpy\lib\function_base.py:2691: RuntimeWarning: invalid value encounte
red in true_divide
  c /= stddev[:, None]
C:\Users\Ethan Wong\anaconda3\lib\site-packages\numpy\lib\function_base.py:2692: RuntimeWarning: invalid value encounte
red in true_divide
  c /= stddev[None, :]
```

In [17]:
```
print(result)
resultDf = pd.DataFrame(result, columns = ['correlation','carpark'])
resultDf
```

```
[(0.9999999999999998, 'BJ65'), (0.9999999999999998, 'BL19'), (0.9999999999999998, 'C7'), (0.9999999999999998, 'CR30'),
(0.9999999999999998, 'HE12')]
```

Out[17]:

	correlation	carpark
0	1.0	BJ65
1	1.0	BL19
2	1.0	C7
3	1.0	CR30
4	1.0	HE12

Question 1.6
Group Project Proposal for Question 3: Please include a short proposal (around 500 words) of what your team intends to do for the Group Proposed Project in Question 3. For the group project proposal, you may use additional datasets to supplement your analysis or look at unaggregated data, etc. See Question 3 below for more information about this. Please use markdown in the iPython notebook to present your proposal.

Introduction / Problem statement

Often when travelling to an area, users might not know of the availability of car parks in that region. While estimates such as the popularity of the area might be helpful, it is still only a metric that is based on guessing. Having a tool that forecasts availability of car parks in an area based on historical data would thus be of good use to users who might be travelling to new places that they are unfamiliar with.

Data collection

For data collection, we plan to use the carpark availability data from data.gov.sg, together with onemap.gov.sg rest API to obtain the physical coordinates (https://www.onemap.gov.sg/docs/#coordinates-converters) of the carpark, and LTA's datamall for carpark prices (https://www.ura.gov.sg/maps/api/#car-park-list-and-rates).

Train-Test split and Validation

Data for training and validation will be collected over 20 weeks and merged with the location and price data for every carpark, ending with 2 weeks before the last Sunday passed as of when the data was collected.

Data for testing would then be collected for the 2 weeks after the training and validation data was tested. As we are doing time series regression, the test data would allow us to check for the performance of the model on a future dataset that the model was trained on.

Data Cleaning

The collected data has to be processed so that it becomes more meaningful and informative. We have identified some possible outliers in the data that have to be cleaned up before training our model. Possible methods to clean data include replacing the data with those of similar features or omitting them

Data on public holidays not coinciding with weekends

These are possible outliers that can skew the parking data as people might travel to places of special significance such as religious spots.

Data on new carparks

New carparks may not have sufficient data. Any carparks with less than 6 months of data will be considered a new carpark, and will not be included in the dataset.

Data on faulty carparks

We will identify a carpark as faulty if the number of available parking lots is more than the total parking lots, or if the number of available parking lots does not change for more than 24 hours.

Carpark type

We will only be considering carparks with car parking lots (lot_type C) for our initial dataset.

New features

Inserting day of week and time of day as new features to help in prediction.

Model usage

Models with linear classifiers such as Naive Bayes are not considered as due to the high dimensionality of the data, it might be difficult to linearly separate the data for our use case.

Thus, we are considering 2 options, Convolutional Neural Networks(CNN) and pre-existing models.

- Convolutional Neural Networks
  - Convolutional neural networks would be helpful as they are faster to train compared to other neural networks like Recurrent Neural Networks(RNN) due to their feature extracting characteristics.
  - They are also able to utilise local spatial coherence, which in this case is our spatial coordinates for the carpark.
- Pre-trained deep learning models for time series forecasting
  - Models like N-BEATS and DeepAR are pre-trained to handle multiple time series problems, which in our case is the data as it is handled on a weekly basis.
  - Training our models on top of these bases might improve the overall performance when forecasting.
  - Training time is drastically reduced as we are not training the entire neural network from scratch.