

# Week 3 Tasks Sub-list 3

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In [1]:

```
1 # packages
2 import pandas as pd
3 import numpy as np
4 import datetime
5 import copy
6 from itertools import combinations
```

In [2]:

```
1 # Read dataset
2 df = pd.read_csv('./Datasets/rawpvr_2018-02-01_28d_1083 TueFri.csv')
```

**Explanation:**

Read the original csv file 'rawpvr\_2018-02-01\_28d\_1083 TueFri.csv' into a dataframe.

In [3]:

```
1 # slice to acquire the 'Date' column
2 date = df.loc[:, 'Date']
3 # type conversion: string > timestamp
4 date = pd.to_datetime(date)
5 # calculate days of the week
6 days_of_week = [item.dayofweek for item in date]
7 # type conversion: list > series
8 days_of_week = pd.Series(np.array(days_of_week).T)
9 # update the column 'Flags' in the original dataframe
10 df.loc[:, 'Flags'] = days_of_week.map(lambda x: x+1, na_action='ignore')
11 # update the column 'Flag Text' in the original dataframe
12 df.loc[:, 'Flag Text'] = days_of_week.map(lambda x: 'Tuesday' if x == 1 else ('Friday' if x
    == 4 else ''), na_action='ignore')
13 # add a new column 'Time' to store the time of the date
14 df = df.assign(Time = pd.to_datetime(df['Date']).dt.time)
15 # add a new column 'DateWOTime' to store the date without the time
16 df = df.assign(DateWOTime = pd.to_datetime(df['Date']).dt.date)
17 # transform the type of data in the 'Date' column of the dataset: string > timestamp
18 df = df.assign(Date = pd.to_datetime(df['Date']))
19 # add a new column 'DateHour' to store the date in the format of '%year%-%month%-%day%
    %hour%:00:00'
20 df['DateHour'] = df['Date'].apply(lambda x: datetime.datetime(x.year, x.month, x.day,
    x.hour, 0, 0))
21 # add a new column 'Hour' to store the hour in the format of '%hour%:00:00'
22 df['Hour'] = df['Date'].apply(lambda x: datetime.time(x.hour, 0, 0))
```

**Explanation:**

This code block is the data preparation operations for the input dataset.

- Update the column `Flag` and `Flag Text` with the day of the week id and the day of the week, respectively.
  - Create a series of the days of week.

```
# slice to acquire the 'Date' column
date = df.loc[:, 'Date']
# type conversion: string > timestamp
date = pd.to_datetime(date)
# calculate days of the week
days_of_week = [item.dayofweek for item in date]
# type conversion: list > series
days_of_week = pd.Series(np.array(days_of_week).T)
```

Firstly, the column `Date` is sliced from the original dataframe and converted to the type `timestamp`. Then the days of week is calculated and its type is converted from `list` to `series` for adding columns in the dataframe.

- Update the columns `Flag` and `Flag Text`.

```
# update the column 'Flags' in the original dataframe
df.loc[:, 'Flags'] = days_of_week.map(lambda x: x+1, na_action='ignore')
# update the column 'Flag Text' in the original dataframe
df.loc[:, 'Flag Text'] = days_of_week.map(lambda x: 'Tuesday' if x == 1 else ('Friday' if x == 4 else ''), na_action='ignore')
```

Use `map` functions to map the series to the new columns in the dataframe with specified requirements.

- Add a new column `Time` in the dataframe to store the time in dates

```
# add a new column `time` in the dataframe to store the time of the date
df = df.assign(Time = pd.to_datetime(df['Date']).dt.time)
```

- Add a new 'DateWOTime' to store the date without the time

```
# add a new column `DateWOTime` in the dataframe to store the date without the time
df = df.assign(DateWOTime = pd.to_datetime(df['Date']).dt.date)
```

- Change the datatype of `Date` from `string` to `timestamp`

```
# transform the type of data in the 'Date' column of the dataset: string > timestamp
df = df.assign(Date = pd.to_datetime(df['Date']))
```

This operation is used for filtering the dataframe according to dates in the future and is a necessary step for continuing the very next data preparation operation.

- Add a new column `DateHour` to store the date in the format of `'%year%-%month%-%day% %hour%:00:00'`

```
# add a new column 'DateHour' to store the date in the format of '%year%-%month%-%day% %hour%:00:00'
df['DateHour'] = df['Date'].apply(lambda x: datetime.datetime(x.year, x.month, x.day, x.hour, 0, 0))
```

This operation is useful for filtering the dataframe according to one-hour time intervals.

The data preparation operations mainly focus on altering and adding variety of the time attribute for the convenience of filtering the dataframe according to time. In the future, for each sub-task, more data preparation operations are executed and they mainly focus on filtering to a new dataframe which is to meet the constraints for achieving the final goals.

# Task5

## Task5.1

---

### Solution:

In [4]:

```
1 # filter the dataset with regard to 'Flag Text'
2 df1 = df.loc[df['Flag Text'] == 'Tuesday']
3 # filter the dataset with regard to 'Time'
4 start_time = datetime.time(7, 0, 0)
5 end_time = datetime.time(19, 0, 0)
6 df1 = df1.loc[(df1['Time'] > start_time) & (df1['Time'] < end_time)]
```

### Explanation:

This code block is the data preparation operations for Task5.1 that filters the dataframe to a new dataframe `df1` according to constraints of the dataset in Task5.1.

- Filter the dataset with regard to `Flag Text` that the day of the week is Tuesday.

```
# filter the dataset with regard to 'Flag Text'
df1 = df.loc[df['Flag Text'] == 'Tuesday']
```

- Filter the dataframe with regard to `Time` that the time is between 7:00 and 19:00.

```
# filter the dataset with regard to 'Time'
start_time = datetime.time(7, 0, 0)
end_time = datetime.time(19, 0, 0)
df1 = df.loc[(df['Time'] > start_time) & (df['Time'] < end_time)]
```

In [5]:

```
1 num_cells = len(df1) # number of cells
2
3 # number of non-empty cells of the column 'Gap (s)'
4 num_non_e_cells_gap = len(df1['Gap (s)'].notna()[df1['Gap (s)'].notna() == True])
5 # column completeness of the column 'Gap (s)'
6 column_completeness_gap = 100 * num_non_e_cells_gap / num_cells
7
8 # number of non-empty cells of the column 'Headway (s)'
9 num_non_e_cells_headway = len(df1['Headway (s)'].notna()[df1['Headway (s)'].notna() == True])
10 # column completeness of the column 'Headway (s)'
11 column_completeness_headway = 100 * num_non_e_cells_headway / num_cells
12
13 print('column completeness gap: ' + str(column_completeness_gap))
14 print('column completeness headway: ' + str(column_completeness_headway))
```

column completeness gap: 98.03654443753885

column completeness headway: 98.96532007458049

### Explanation:

This code block is calculation of column completeness for the columns `Gap (s)` and `Headway (s)`. Firstly, the length of the columns in `df1` are calculated by `num_cells = len(df1)`. Then, the number of non-empty cells of each column are calculated like

```
# number of non-empty cells of the column 'Gap (s)'
num_non_e_cells_gap = len(df1['Gap (s)'].notna()[df1['Gap (s)'].notna() == True])
```

. Finally, the the values of column completeness are calculated like

```
# column completeness of the column 'Gap (s)'
column_completeness_gap = 100 * num_non_e_cells_gap / num_cells
```

### Result:

- column completeness gap: 98.03654443753885
- column completeness headway: 98.96532007458049

### Interpretation of the result:

The completeness values of the columns 'Gap (s)' and 'Headway (s)' are both over 98.0, which means that over 98 percent of the values are not empty. So for both the two columns, most of the records are filled with data. But there still exists a small proportion of missing values.

## Task5.2

---

### Solution:

In [6]:

```
1 # initialize dataframe for storing interpolated dataframe
2 df2 = df1.copy(deep=True)
3 # filter with regard to 'Lane Name'
4 df2 = df2.loc[df2['Lane Name'] == 'NB_MID']
```

### Explanation:

This code block is the data preparation operations for Task5.2. Because the dataset to be used in this task also requires the same constraints as in Task5.1, a new dataframe `df2` is created from the dataframe used in Task5.1 as initialization.

```
df2 = df1.copy(deep=True)
```

- Filter the dataframe with regard to `Lane Name` that the lane name is 'NB\_MID'

```
# filter with regard to 'Lane Name'
df2 = df2.loc[df2['Lane Name'] == 'NB_MID']
```

In conclusion, now the dataframe has additional restrictions that the `Flag Text` is 'Tuesday', the `Time` is ranged from 7:00 to 19:00, and the `Lane Name` is 'NB\_MID'. In the next code block, data manipulation on `df2` can be done with the preparation.

In [7]:

```
1 medians = dict() # key: column name, value: medians of the column
2 for column_name in ['Gap (s)', 'Headway (s)']:
3     # record unique hour
4     unique_hours = df2['Hour'].unique()
5
6     # calculate median values for all the time intervals
7     medians_col = dict() # key: hour, value: median value
8     for unique_hour in unique_hours:
9         # filter the dataframe with regard to date hour
10        filtered_df2 = df2.loc[df2['Hour'] == unique_hour]
11
12        # get the values of the column
13        values = filtered_df2[column_name]
14
15        # record the median
16        medians_col.update({unique_hour: values.median()})
17
18    # record the medians of the column
19    medians.update({column_name: medians_col})
20
21    # find the series of 'Date' of dataframe if the column_name is null
22    ss_date_missing = df2.loc[df2[column_name].isna()]['Date']
23
24    # update the cell of the dataframe with the median value
25    for item in ss_date_missing:
26        # get the row of the dataframe where the value is missing
27        tempdf = df2.loc[df2['Date'] == item]
28
29        # get the corresponding median value
30        median_value = medians[column_name].get(tempdf['Hour'].iloc[0])
31
32        # interpolate value to the dataframe
33        df2.loc[df2['Date'] == item, column_name] = median_value
34
35    # print results
36    # print(medians)
37
38    # clear memory
39    # del df1
40    # del df2
```

#### Explanation:

This code block is the data manipulation on `df2`. Overall, there are two processes explained below.

- Find median values of the columns `Gap (s)` and `Headway (s)` for all one-hour intervals.
  - Firstly we initialize the object to store all the median values. It is a dictionary storing names of the columns `Gap (s)` and `Headway (s)` as two keys. And their values are dictionaries that stores median values of corresponding columns with regard to one-hour time intervals in the day.

```
medians = dict() # key: column name, value: medians of the column
```

- Then we iterate over the two columns `Gap (s)` and `Headway (s)` to execute the same operations to them. Following mentioned operations are executed in this iteration.

```
for column_name in ['Gap (s)', 'Headway (s)']:
```

- To achieve the goal, we may want to iteratively filter `df2` according to each one-hour time interval between 7:00 and 19:00 and calculate median values. So to begin with we find all unique one-hour time intervals in `df2`.

```
# record unique hour
unique_hours = df2['Hour'].unique()
```

- Then we execute operations mentioned in the previous bullet point and the median values for the column are calculated and updated to `medians`.

```
# calculate median values for all the time intervals
medians_col = dict() # key: date hour, value: median value
for unique_hour in unique_hours:
    # filter the dataframe with regard to hour
    filtered_df2 = df2.loc[df2['Hour'] == unique_hour]

    # get the values of the column
    values = filtered_df2[column_name]

    # record the median
    medians_col.update({unique_hour: values.median()})

# record the medians of the column
medians.update({column_name: medians_col})
```

- Update the cells with missing values with the corresponding median values.
  - To achieve this goal, we need to find and record all the rows that have missing values. We can only take the column `Date` for future comparison as the dates are unique.

```
# find the series of 'Date' of dataframe if the column_name is null
ss_date_missing = df2.loc[df2[column_name].isna()]['Date']
```

- Now we can update the values by iteratively find a missing row in `df2` and update it with the corresponding value.

```
# update the cell of the dataframe with the median value
for item in ss_date_missing:
    # get the row of the dataframe where the value is missing
    tempdf = df2.loc[df2['Date'] == item]

    # get the corresponding median value
    median_value = medians[column_name].get(tempdf['Hour'].iloc[0])

    # interpolate value to the dataframe
    df2.loc[df2['Date'] == item, column_name] = median_value
```

In the iteration, the first step is to get the row that the date (unique key) in `df2` is matched with the one in `ss_date_missing`. The second step is to find the corresponding median value in `medians` according to the time of the row. The final step is updating the row.

**Result of median values:**

```
{'Gap (s)':
 {datetime.time(7, 0): 1.834,
 datetime.time(8, 0): 2.1020000000000003,
 datetime.time(9, 0): 2.08,
 datetime.time(10, 0): 2.5835,
 datetime.time(11, 0): 2.7785,
 datetime.time(12, 0): 2.795,
 datetime.time(13, 0): 2.7560000000000002,
 datetime.time(14, 0): 2.8049999999999997,
 datetime.time(15, 0): 2.577,
 datetime.time(16, 0): 2.3225,
 datetime.time(17, 0): 2.187,
 datetime.time(18, 0): 2.228},
 'Headway (s)':
 {datetime.time(7, 0): 2.722,
 datetime.time(8, 0): 3.1910000000000003,
 datetime.time(9, 0): 2.72,
 datetime.time(10, 0): 3.0,
 datetime.time(11, 0): 3.21,
 datetime.time(12, 0): 3.16,
 datetime.time(13, 0): 3.102,
 datetime.time(14, 0): 3.133,
 datetime.time(15, 0): 2.92,
 datetime.time(16, 0): 2.853,
 datetime.time(17, 0): 2.9065,
 datetime.time(18, 0): 2.79}}}
```

## Result of screenshot of the updated dataframe:

	Date	Lane	Lane Name	Direction	Direction Name	Speed (mph)	Headway (s)	Gap (s)	Flags	Flag Text	Time	DateWOTime	DateHour	Hour
68517	2018-02-06 07:00:01.160	2	NB_MID	1	North	27.962	1.720	1.834	2	Tuesday	07:00:01.160000	2018-02-06	2018-02-06 07:00:00	07:00:00
68518	2018-02-06 07:00:03.000	2	NB_MID	1	North	27.962	2.480	1.992	2	Tuesday	07:00:03	2018-02-06	2018-02-06 07:00:00	07:00:00
68521	2018-02-06 07:00:04.020	2	NB_MID	1	North	27.962	1.520	0.856	2	Tuesday	07:00:04.020000	2018-02-06	2018-02-06 07:00:00	07:00:00
68524	2018-02-06 07:00:05.020	2	NB_MID	1	North	29.205	1.226	0.680	2	Tuesday	07:00:05.020000	2018-02-06	2018-02-06 07:00:00	07:00:00
68529	2018-02-06 07:00:07.020	2	NB_MID	1	North	29.825	2.137	1.694	2	Tuesday	07:00:07.020000	2018-02-06	2018-02-06 07:00:00	07:00:00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
496010	2018-02-27 18:58:51.060	2	NB_MID	1	North	35.417	1.200	0.725	2	Tuesday	18:58:51.060000	2018-02-27	2018-02-27 18:00:00	18:00:00
496029	2018-02-27 18:59:26.080	2	NB_MID	1	North	41.010	35.200	34.941	2	Tuesday	18:59:26.080000	2018-02-27	2018-02-27 18:00:00	18:00:00
496050	2018-02-27 18:59:48.040	2	NB_MID	1	North	34.798	22.600	22.382	2	Tuesday	18:59:48.040000	2018-02-27	2018-02-27 18:00:00	18:00:00
496051	2018-02-27 18:59:50.000	2	NB_MID	1	North	33.554	1.800	1.343	2	Tuesday	18:59:50	2018-02-27	2018-02-27 18:00:00	18:00:00
496061	2018-02-27 18:59:58.060	2	NB_MID	1	North	43.495	7.600	7.307	2	Tuesday	18:59:58.060000	2018-02-27	2018-02-27 18:00:00	18:00:00

## Task6

## Solution:

In [8]:

```
1 # read the dataset of the site 1415
2 dfb = pd.read_csv('./Datasets/rawpvr_2018-02-01_28d_1415 TueFri.csv')
```

In [9]:

```
1 # apply the same data preparation executions to dataframe b
2
3 # slice to acquire the 'Date' column
4 date = dfb.loc[:, 'Date']
5 # type conversion: string > timestamp
6 date = pd.to_datetime(date)
7 # calculate days of the week
8 days_of_week = [item.dayofweek for item in date]
9 # type conversion: list > series
10 days_of_week = pd.Series(np.array(days_of_week).T)
11 # update the column 'Flags' in the original dataframe
12 dfb.loc[:, 'Flags'] = days_of_week.map(lambda x: x+1, na_action='ignore')
13 # update the column 'Flag Text' in the original dataframe
14 dfb.loc[:, 'Flag Text'] = days_of_week.map(lambda x: 'Tuesday' if x == 1 else ('Friday' if
x == 4 else ''), na_action='ignore')
15 # add a new column 'Time' to store the time of the date
16 dfb = dfb.assign(Time = pd.to_datetime(dfb['Date']).dt.time)
17 # add a new column 'DateWOTime' to store the date without the time
18 dfb = dfb.assign(DateWOTime = pd.to_datetime(dfb['Date']).dt.date)
19 # transform the type of data in the 'Date' column of the dataset: string > timestamp
20 dfb = dfb.assign(Date = pd.to_datetime(dfb['Date']))
21 # add a new column 'DateHour' to store the date in the format of '%year%-%month%-%day%
%hour%:00:00'
22 dfb['DateHour'] = dfb['Date'].apply(lambda x: datetime.datetime(x.year, x.month, x.day,
x.hour, 0, 0))
```

### Explanation:

In this code block, we simply execute the same data preparation operations for `dfb` as the ones we did for `df` for consistency and future usage.

In [10]:

```
1 # create a alias for the dataframe of the site 1083 for this task
2 dfa = df
3 # use a variable to reference the two dataframes
4 dfs = {'1083': dfa,
5        '1415': dfb}
```

### Explanation:

Firstly an alias of the dataframe for the site 1083 is created ( `dfa` ), this is for standardize the names for the dataframes in avoidance of generating potential inconsistency in the future. Then the dataframes are referenced together in one variable ( `dfs` ) for the convenience of coding.



In [11]:

```
1 # filter the two dataframes
2
3 # create a copy of the old dataframes
4 dfs1 = copy.deepcopy(dfs)
5 for key, df in dfs1.items():
6     # filter the dataframe with regard to 'Time'
7     start_time = datetime.time(17, 0, 0)
8     end_time = datetime.time(18, 0, 0)
9     df = df.loc[(df['Time'] > start_time) & (df['Time'] < end_time)]
10
11     # filter the dataframe with regard to 'Direction'
12     df = df.loc[df['Direction'] == 1]
13
14     # filter the dataframe with regard to 'Flag Text'
15     df = df.loc[df['Flag Text'] == 'Friday']
16
17     # record
18     dfs1[key] = df
```

#### *Explanation:*

This code block is the data preparation operations for Task6. Because the operations are specifically focused on Task6, we created a new version `dfs1` of the dataframe `dfs` similar to the things we did before `dfs1 = copy.deepcopy(dfs)` .\

Then we iterate on `dfs1` for each dataframe and perform the following operations.

- Filter the dataframe with regard to 'Time' that the time is between 17:00 and 18:00.

```
# filter the dataframe with regard to 'Time'
start_time = datetime.time(17, 0, 0)
end_time = datetime.time(18, 0, 0)
df = df.loc[(df['Time'] > start_time) & (df['Time'] < end_time)]
```

- Filter the dataframe with regard to 'Direction' that the direction is heading north.

```
# filter the dataframe with regard to 'Direction'
df = df.loc[df['Direction'] == 1]
```

- Filter the dataframe with regard to 'Flag Text' that the day of the week is Friday.

```
# filter the dataframe with regard to 'Flag Text'
df = df.loc[df['Flag Text'] == 'Friday']
```

In [12]:

```
1 # record unique lane names
2 unique_lane_names = dict()
3 for key, df in dfs1.items():
4     # find unique lane names for the dataframe
5     unique_lane_name = df['Lane Name'].unique()
6
7     # record
8     unique_lane_names.update({key: unique_lane_name})
```

**Explanation:** This code block is an intermediate process to record unique lane names `unique_lane_names` of the two dataframes for the usage in the next code block.

**Result of** `unique_lane_names` :

```
{'1083': array(['NB_OS', 'NB_MID', 'NB_NS'], dtype=object),
 '1415': array(['NE_NS', 'NE_OS'], dtype=object)}
```

In [13]:

```
1 # find average travel time of the lanes
2 avg_times_lanes = dict() # the average travel times of the two dataframes
3 for key, df in dfs1.items():
4     avg_times_lanes_df = list() # the average speeds of the dataframe
5     for lane_name in unique_lane_names[key]:
6         # filter the dataframe with regard to 'Lane Name'
7         filtered_df = df.loc[df['Lane Name'] == lane_name]
8
9         # calculate the average speed
10        avg_speed = filtered_df['Speed (mph)'].mean()
11
12        # calculate the average travel time in minute by the equation 'time =
distance/speed'
13        # 4.86km = 3.019864miles
14        avg_time_lane = 3.019864 / avg_speed * 60
15
16        # record
17        avg_times_lanes_df.append(avg_time_lane)
18    avg_times_lanes.update({key: avg_times_lanes_df})
19
20 # print result of average speeds in different lanes
21 print(avg_times_lanes)
22
23 # calculate the average value of the result
24 templ = list(map(lambda l: (len(l), sum(l)), avg_times_lanes.values()))
25 sum_templ = tuple(map(sum, zip(*templ))) # * is for unpacking the list cool
26 avg_time = sum_templ[1]/sum_templ[0]
27
28 # print result of average time
29 print(avg_time)
```

```
{'1083': [6.009038525021391, 6.295469340374707, 7.279743256362566], '1415': [7.51940
2241603255, 6.6714418953907915]}
6.7550190517505415
```

**Explanation:**

This code block is about finding the average travel times in different lanes and calculating their average value. The two processes are introduced below.

- Find the average travel times in different lanes.
  - To begin with, a dictionary `avg_times_lanes` is created `avg_times_lanes = dict()` to store the name of the sites as the keys and their corresponding average values with regard to different lanes.
  - Then the dataframes are iterated. In each iteration, we iteratively filter the dataframe with regard to the lane names.

```
for lane_name in unique_lane_names[key]:
    # filter the dataframe with regard to 'Lane Name'
    filtered_df = df.loc[df['Lane Name'] == lane_name]
```

- Next, the average speed of the `filtered_df` is calculated `avg_speed = filtered_df['Speed (mph)'].mean()` .
- Next, the average time was calculated by the average speed and the given distance, we firstly changed the unit of the distance from 'km' to 'miles' `avg_time_lane = 3.019864 / avg_speed * 60` .
- Finally we record the results, following is the integral process.

```
avg_times_lanes_df = list() # the average speeds of the dataframe
for lane_name in unique_lane_names[key]:
    # filter the dataframe with regard to 'Lane Name'
    filtered_df = df.loc[df['Lane Name'] == lane_name]

    # calculate the average speed
    avg_speed = filtered_df['Speed (mph)'].mean()

    # calculate the average travel time in minute by the equation 'time = distance/speed'
    # 4.86km = 3.019864miles
    avg_time_lane = 3.019864 / avg_speed * 60

    # record
    avg_times_lanes_df.append(avg_time_lane)
avg_times_lanes.update({key: avg_times_lanes_df})
```

- Calculate the average value of the average travel times.
  - For calculating the average value of the result, firstly the number of elements and the sum of the values of the elements are calculated and stored in `templ` .

```
templ = list(map(lambda l: (len(l), sum(l)), avg_times_lanes.values()))

[(3, 19.584251121758662), (2, 14.190844136994047)]
```

- Then, a map function is used to calculate the sum of values in the tuples in the list and finally calculate the average travel time by dividing the sum of speeds to the number of elements.

```
sum_templ = tuple(map(sum, zip(*templ))) # * is for unpacking the list cool
avg_time = sum_templ[1]/sum_templ[0]
```

### Results of average travel time in different lanes:

```
{'1083': [6.009038525021391, 6.295469340374707, 7.279743256362566],
 '1415': [7.519402241603255, 6.6714418953907915]}
```

### Result of overall average travel time:

- 6.7550190517505415 minutes

### Interpretation of the result:

The result shows that according to this dataset, the average travel time of north lanes between the two sites in the time from 17:00 to 18:00 in Friday is around 6.755 minutes.

## Task7.1

---

### Solution (i):

I can describe the *Row Completeness* as a set of fractions with regard to combinations of columns that can possibly have missing values, where the numerators are the numbers of rows that are with missing values in certain columns and the denominators are the total number of rows.

$$RowCompleteness_1 = \{RowCompleteness_C : C \text{ is the set of all possible combinations of columns}\}$$
$$RowCompleteness_C = NumberOfMissingRows_C \times 100 \div NumberOfRows$$

The row completeness value indicate the proportion of the number of not-missing values to the total number of values.

Besides we can calculate the row completeness of the proportion of the rows that have any missing values to the total number of rows.

$$RowCompleteness_2 = NumberOfRowsWithMissingValues \times 100 \div NumberOfRows$$

### Solution (ii):

In [14]:

```
1 # filter the dataframe as we did before
2 df3 = df1.copy(deep=True)
```

#### Explanation:

This code block is the data preparation operations for Task7.1. Since the filtering requirements in this task are the same as in Task5.1, we can reference to the codes in the Task5.1 section.

In [15]:

```
1 # find the columns that contain missing values
2 ifna_cols = df3.isna().any()
3 missing_cols = list(ifna_cols[ifna_cols == True].keys())
4
5 # find all possible combinations in the missing columns
6 # reference: https://stackoverflow.com/questions/464864/how-to-get-all-possible-combinations-
  of-a-list-s-elements?rq=1
7 combs = sum([list(map(list, combinations(missing_cols, i))) for i in range(len(missing_cols)
  + 1)], [])
8 combs.remove([])
```

#### Explanation:

Before we start the manipulations, we should know which columns contain missing values and find all possible combinations of them. As we do not need the empty set as a combination, we simply remove it from our combinations.

In [16]:

```
1 # initialize row completeness object
2 RC_count = dict() # key: combination of columns, value: count
3
4 for comb in combs:
5     # filter the dataframe with regard to combination of columns
6     filtered_df3 = df3[comb]
7
8     # calculate the number of rows that all cells are of missing values
9     count = len(filtered_df3.loc[filtered_df3.isnull().all(axis=1)].index)
10
11     # record
12     RC_count.update({str(comb): count})
13
14 # calculate the row completeness
15 total_count = len(df3.index)
16 RC1 = dict(zip(RC_count.keys(), map(lambda x: 100 * int(x) / total_count,
17                                     RC_count.values()))))
18
19 # calculate the the row completeness for the entire dataframe
20 count = len(df3.loc[df3.isnull().any(axis=1)].index)
21 RC2 = 100 * count / total_count
```

#### Explanation:

This code block is about calculating the row completeness.

- First, we initialize a row completeness count dictionary that stores the combinations of columns as key and the count of the rows that cells in the combination of columns are missing.

```
RC_count = dict() # key: combination of columns, value: count
```

- Then we iteratively filter `df3` with regard to the combination of columns `filtered_df3 = df3[comb]`, calculate the counts, and record them to `RC_count`.

```
for comb in combs:
    # filter the dataframe with regard to combination of columns
    filtered_df3 = df3[comb]

    # calculate the number of rows that all cells are of missing values
    count = len(filtered_df3.loc[filtered_df3.isnull().all(axis=1)].index)

    # record
    RC_count.update({str(comb): count})
RC_count
```

- Finally, we need to map `RC_count` according to the previously defined row completeness equation.

```
# calculate the row completeness
total_count = len(df3.index)
RC = dict(zip(RC_count.keys(), map(lambda x: 100 * int(x) / total_count, RC_count.values()))))
```

#### Result of Row Completeness Calculation 1:

```
{ "[ 'Speed (mph)' ]": 0.004474829086389061,
  "[ 'Headway (s)' ]": 1.0346799254195151,
  "[ 'Gap (s)' ]": 1.963455562461156,
  "[ 'Speed (mph)', 'Headway (s)' ]": 0.0,
  "[ 'Speed (mph)', 'Gap (s)' ]": 0.0,
  "[ 'Headway (s)', 'Gap (s)' ]": 1.0346799254195151,
  "[ 'Speed (mph)', 'Headway (s)', 'Gap (s)' ]": 0.0 }
```

### Result of Row Completeness Calculation 2:

1.967930391547545

## Discussion

### Interpretation of the Results

The result shows the values of row completeness considering all combinations of columns. Overall, the total rate of rows that have missing values is about 1.96793. For individual columns, the 'Speed (mph)' column has the minimum percentage of missing values, which is around 0.00447. And the column 'Gap (s)' has the highest proportion 1.96345. And we can infer from the result that for all the combinations that have the column 'Speed (mph)' and other columns, all the 'Speed (mph)' columns are filled with values. And in the combination ('Headway (s)', 'Gap (s)'), at least all the values in the column 'Headway (s)' are missing.

### Understanding of Completeness

The completeness is an important aspect in data quality. Data completeness can be defined that "the degree to which a data collection has values or all attributes of entities that are supposed to have values" [1]. In my interpretation, to see from the perspective of application, the completeness of data is that within the scale of the potential utilization of the data, values of objective attributes should be there for utilization. Hence completeness is inextricably linked with data quality. For implementation, in a dataset, the completeness can be demonstrated as the proportion of values that are stored to the number of possible records of the dataset. Or by Pipino, Lee, and Wang's definition [2], it is "a function of the missing values in a column of a table".

### Comparison of the two Completeness Formulas

I can compare the two formulas in terms of the difference between the representations of the completeness values. The row completeness demonstrates the completeness of values across multiple columns, while the column completeness demonstrate the completeness of values in columns. Hence the row completeness formula can show the degree of completeness over the entire dataset, while the column completeness formula shows the degree of completeness in specific columns. For this dataset, because only three columns may have missing values, calculating the row completeness formula regarding combinations of columns are easy to implement, and the values calculated can provide a more thorough overview of the completeness than the ones calculated column completeness formula. We can obtain the overview of the rate of any values in these columns are missing as well as the inspect of a specific combination of columns that all the values inside them are missing. In the column completeness calculation, we can only inspect the value for an individual column.

[1] Li, C.: Computing complete answers to queries in the presence of limited access patterns. VLDB J. 12, 211–277 (2003)

[2] Pipino, L.L., Lee, Y.W., Wang, R.Y.: Data quality assessment. Commun. ACM 45, 211–218 (2002)

## Task7.2

---

## Solution:

I use **Microsoft Excel** as the tool for this task.

### 1. Open the original dataset in Excel.

Date	Lane	Lane Nam	Direction	Direction	Speed (m)	Headway	Gap (s)	Flags	Flag Text
00:03.0	6	SB_NS	2	South	38.525			0	
00:22.0	5	SB_MID	2	South	32.31			0	
00:22.0	4	SB_OS	2	South	44.739			0	
00:36.0	6	SB_NS	2	South	33.554			0	
00:49.1	6	SB_NS	2	South	39.768	12.3	11.847	0	
00:52.1	2	NB_MID	1	North	64.623			0	
00:55.1	1	NB_NS	1	North	29.205	6.319		0	
00:58.0	2	NB_MID	1	North	37.283	6.2	6.089	0	
01:03.0	6	SB_NS	2	South	44.739	14.8	14.575	0	
01:04.1	2	NB_MID	1	North	41.01	5.155	5.242	0	
01:05.1	2	NB_MID	1	North	37.283	1.47	0.949	0	
01:09.0	5	SB_MID	2	South	36.039	47.1	47.017	0	
01:16.1	6	SB_NS	2	South	36.661	12.3	12.24	0	
01:40.0	3	NB_OS	1	North	45.361			0	
01:46.0	2	NB_MID	1	North	38.525	41.3	41.06	0	
01:48.0	5	SB_MID	2	South	47.224	38.9	38.639	0	
01:51.0	6	SB_NS	2	South	57.787	35.7	35.438	0	
#####	6	SB_NS	2	South	47.846	4.301	3.334	0	
#####	1	NB_NS	1	North	44.117	61.4	61.086	0	
01:57.1	6	SB_NS	2	South	49.709	1.957	1.599	0	
01:58.1	3	NB_OS	1	North	39.146	17.7	17.488	0	
02:04.0	2	NB_MID	1	North	29.825	18.4	17.744	0	
#####	6	SB_NS	2	South	41.01	37.2	36.997	0	
02:34.0	4	SB_OS	2	South	45.982	131.9	131.79	0	
02:36.1	6	SB_NS	2	South	42.253	1.721	1.482	0	
#####	6	SB_NS	2	South	36.661	3.997	3.067	0	
02:45.0	5	SB_MID	2	South	31.691	57.1	56.906	0	
02:54.1	6	SB_NS	2	South	33.554	14.9	14.644	0	
02:58.1	2	NB_MID	1	North	28.584	53.2	52.885	0	

### 2. For the entire column of "Flag Text", apply the function

`=IF(ISBLANK(A2), "", TEXT(A2, "ddd"))`

, which calculates days of the week regarding the "Date" column.

Date	Lane	Lane Nam	Direction	Direction	Speed (m)	Headway	Gap (s)	Flags	Flag Text
00:03.0	6	SB_NS	2	South	38.525			0	Friday
00:22.0	5	SB_MID	2	South	32.31			0	Friday
00:22.0	4	SB_OS	2	South	44.739			0	Friday
00:36.0	6	SB_NS	2	South	33.554			0	Friday
00:49.1	6	SB_NS	2	South	39.768	12.3	11.847	0	Friday
00:52.1	2	NB_MID	1	North	64.623			0	Friday
00:55.1	1	NB_NS	1	North	29.205	6.319		0	Friday
00:58.0	2	NB_MID	1	North	37.283	6.2	6.089	0	Friday
01:03.0	6	SB_NS	2	South	44.739	14.8	14.575	0	Friday
01:04.1	2	NB_MID	1	North	41.01	5.155	5.242	0	Friday
01:05.1	2	NB_MID	1	North	37.283	1.47	0.949	0	Friday
01:09.0	5	SB_MID	2	South	36.039	47.1	47.017	0	Friday
01:16.1	6	SB_NS	2	South	36.661	12.3	12.24	0	Friday
01:40.0	3	NB_OS	1	North	45.361			0	Friday
01:46.0	2	NB_MID	1	North	38.525	41.3	41.06	0	Friday
01:48.0	5	SB_MID	2	South	47.224	38.9	38.639	0	Friday
01:51.0	6	SB_NS	2	South	57.787	35.7	35.438	0	Friday
#####	6	SB_NS	2	South	47.846	4.301	3.334	0	Friday
#####	1	NB_NS	1	North	44.117	61.4	61.086	0	Friday
01:57.1	6	SB_NS	2	South	49.709	1.957	1.599	0	Friday
01:58.1	3	NB_OS	1	North	39.146	17.7	17.488	0	Friday
02:04.0	2	NB_MID	1	North	29.825	18.4	17.744	0	Friday
#####	6	SB_NS	2	South	41.01	37.2	36.997	0	Friday
02:34.0	4	SB_OS	2	South	45.982	131.9	131.79	0	Friday
02:36.1	6	SB_NS	2	South	42.253	1.721	1.482	0	Friday
#####	6	SB_NS	2	South	36.661	3.997	3.067	0	Friday
02:45.0	5	SB_MID	2	South	31.691	57.1	56.906	0	Friday
02:54.1	6	SB_NS	2	South	33.554	14.9	14.644	0	Friday
02:58.1	2	NB_MID	1	North	28.584	53.2	52.885	0	Friday

3. Then we want to add a new column "Time" that stores the corresponding time in the "Date" column, apply this function

=IF(ISBLANK(A2), "", TIME(HOUR(A2), MINUTE(A2), SECOND(A2)))

to the column to extract hour, minute, and second from the corresponding date. Then, update the type of the column from default "General" to "Time".

The screenshot shows the Excel interface with the formula bar displaying the function: `=IF(ISBLANK(A2), "", TIME(HOUR(A2), MINUTE(A2), SECOND(A2)))`. The worksheet contains a table with the following columns: Date, Lane, Lane Nam, Direction, Direction, Speed (m), Headway, Gap (s), Flags, Flag Text, and Time. The 'Time' column is highlighted in green, indicating it is the active column. The data in the 'Time' column is derived from the 'Date' column using the specified formula.

Date	Lane	Lane Nam	Direction	Direction	Speed (m)	Headway	Gap (s)	Flags	Flag Text	Time
00:03.0	6 SB_NS	2	South	38.525				0	Friday	0:00:03
00:22.0	5 SB_MID	2	South	32.31				0	Friday	0:00:22
00:22.0	4 SB_OS	2	South	44.739				0	Friday	0:00:22
00:36.0	6 SB_NS	2	South	33.554				0	Friday	0:00:36
00:49.1	6 SB_NS	2	South	39.768	12.3	11.847		0	Friday	0:00:49
00:52.1	2 NB_MID	1	North	64.623				0	Friday	0:00:52
00:55.1	1 NB_NS	1	North	29.205	6.319			0	Friday	0:00:55
00:58.0	2 NB_MID	1	North	37.283	6.2	6.089		0	Friday	0:00:58
01:03.0	6 SB_NS	2	South	44.739	14.8	14.575		0	Friday	0:01:03
01:04.1	2 NB_MID	1	North	41.01	5.155	5.242		0	Friday	0:01:04
01:05.1	2 NB_MID	1	North	37.283	1.47	0.949		0	Friday	0:01:05
01:09.0	5 SB_MID	2	South	36.039	47.1	47.017		0	Friday	0:01:09
01:16.1	6 SB_NS	2	South	36.661	12.3	12.24		0	Friday	0:01:16
01:40.0	3 NB_OS	1	North	45.361				0	Friday	0:01:40
01:46.0	2 NB_MID	1	North	38.525	41.3	41.06		0	Friday	0:01:46
01:48.0	5 SB_MID	2	South	47.224	38.9	38.639		0	Friday	0:01:48
01:51.0	6 SB_NS	2	South	57.787	35.7	35.438		0	Friday	0:01:51
01:51.0	6 SB_NS	2	South	47.846	4.301	3.334		0	Friday	0:01:55
01:57.1	1 NB_NS	1	North	44.117	61.4	61.086		0	Friday	0:01:56
01:57.1	6 SB_NS	2	South	49.709	1.957	1.599		0	Friday	0:01:57
01:58.1	3 NB_OS	1	North	39.146	17.7	17.488		0	Friday	0:01:58
02:04.0	2 NB_MID	1	North	29.825	18.4	17.744		0	Friday	0:02:04
02:34.0	6 SB_NS	2	South	41.01	37.2	36.997		0	Friday	0:02:34
02:34.0	4 SB_OS	2	South	45.982	131.9	131.79		0	Friday	0:02:34
02:36.1	6 SB_NS	2	South	42.253	1.721	1.482		0	Friday	0:02:36
02:36.1	6 SB_NS	2	South	36.661	3.997	3.067		0	Friday	0:02:39
02:45.0	5 SB_MID	2	South	31.691	57.1	56.906		0	Friday	0:02:45
02:54.1	6 SB_NS	2	South	33.554	14.9	14.644		0	Friday	0:02:54
02:58.1	2 NB_MID	1	North	28.584	53.2	52.885		0	Friday	0:02:58

4. Select the entire table, press **Ctrl** + **Shift** + **L** to initialize the filters. Then we can apply filtering to the table.

The screenshot shows the Excel interface with the 'Data' tab selected. The 'Time' column is highlighted in green, indicating it is the active column. The data in the 'Time' column is derived from the 'Date' column using the specified formula.

Date	Lane	Lane Nam	Direction	Direction	Speed (m)	Headway	Gap (s)	Flags	Flag Text	Time
00:03.0	6 SB_NS	2	South	38.525				0	Friday	0:00:03
00:22.0	5 SB_MID	2	South	32.31				0	Friday	0:00:22
00:22.0	4 SB_OS	2	South	44.739				0	Friday	0:00:22
00:36.0	6 SB_NS	2	South	33.554				0	Friday	0:00:36
00:49.1	6 SB_NS	2	South	39.768	12.3	11.847		0	Friday	0:00:49
00:52.1	2 NB_MID	1	North	64.623				0	Friday	0:00:52
00:55.1	1 NB_NS	1	North	29.205	6.319			0	Friday	0:00:55
00:58.0	2 NB_MID	1	North	37.283	6.2	6.089		0	Friday	0:00:58
01:03.0	6 SB_NS	2	South	44.739	14.8	14.575		0	Friday	0:01:03
01:04.1	2 NB_MID	1	North	41.01	5.155	5.242		0	Friday	0:01:04
01:05.1	2 NB_MID	1	North	37.283	1.47	0.949		0	Friday	0:01:05
01:09.0	5 SB_MID	2	South	36.039	47.1	47.017		0	Friday	0:01:09
01:16.1	6 SB_NS	2	South	36.661	12.3	12.24		0	Friday	0:01:16
01:40.0	3 NB_OS	1	North	45.361				0	Friday	0:01:40
01:46.0	2 NB_MID	1	North	38.525	41.3	41.06		0	Friday	0:01:46
01:48.0	5 SB_MID	2	South	47.224	38.9	38.639		0	Friday	0:01:48
01:51.0	6 SB_NS	2	South	57.787	35.7	35.438		0	Friday	0:01:51
01:51.0	6 SB_NS	2	South	47.846	4.301	3.334		0	Friday	0:01:55
01:57.1	1 NB_NS	1	North	44.117	61.4	61.086		0	Friday	0:01:56
01:57.1	6 SB_NS	2	South	49.709	1.957	1.599		0	Friday	0:01:57
01:58.1	3 NB_OS	1	North	39.146	17.7	17.488		0	Friday	0:01:58
02:04.0	2 NB_MID	1	North	29.825	18.4	17.744		0	Friday	0:02:04
02:34.0	6 SB_NS	2	South	41.01	37.2	36.997		0	Friday	0:02:34
02:34.0	4 SB_OS	2	South	45.982	131.9	131.79		0	Friday	0:02:34
02:36.1	6 SB_NS	2	South	42.253	1.721	1.482		0	Friday	0:02:36
02:36.1	6 SB_NS	2	South	36.661	3.997	3.067		0	Friday	0:02:39
02:45.0	5 SB_MID	2	South	31.691	57.1	56.906		0	Friday	0:02:45
02:54.1	6 SB_NS	2	South	33.554	14.9	14.644		0	Friday	0:02:54
02:58.1	2 NB_MID	1	North	28.584	53.2	52.885		0	Friday	0:02:58



5. Filter the sheet that the time is between 17:00 and 18:00, the direction is 1, and the day of the week is Friday.

Customly filter the 'Time' to be between 17:00 and 18:00.

The screenshot shows the Excel interface with a Custom AutoFilter dialog box open. The dialog box is titled "Custom AutoFilter" and has a "Show rows where:" section. Under this section, there are two criteria for the "Time" column: "is greater than" 17:00:00 and "is less than" 18:00:00. The "And" radio button is selected. The background spreadsheet shows columns A through W, with rows 1 through 30. The "Time" column (K) contains values ranging from 00:00 to 02:58. The "Direction" column (D) contains values like "South", "North", and "Mid".

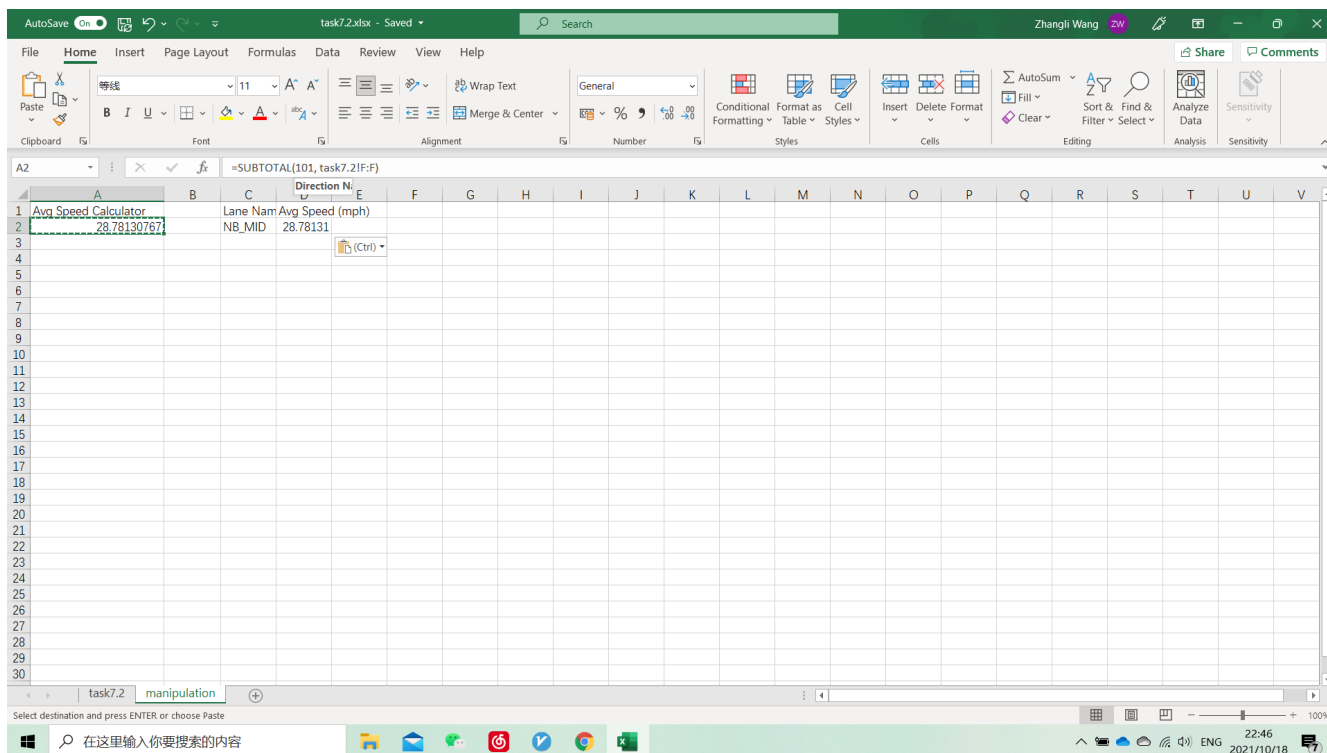
Filter the 'Direction Name' as 'North'.

The screenshot shows the Excel interface with the "Filter by Color" dialog box open. The dialog box is titled "Filter by Color" and has a "Text Filters" section. Under this section, there is a "Search" field with the text "North" entered. The "Filter by Color" section is also visible, showing a list of colors and their corresponding cell counts. The background spreadsheet shows columns A through W, with rows 1 through 30. The "Time" column (K) contains values ranging from 00:00 to 02:58. The "Direction" column (D) contains values like "South", "North", and "Mid".

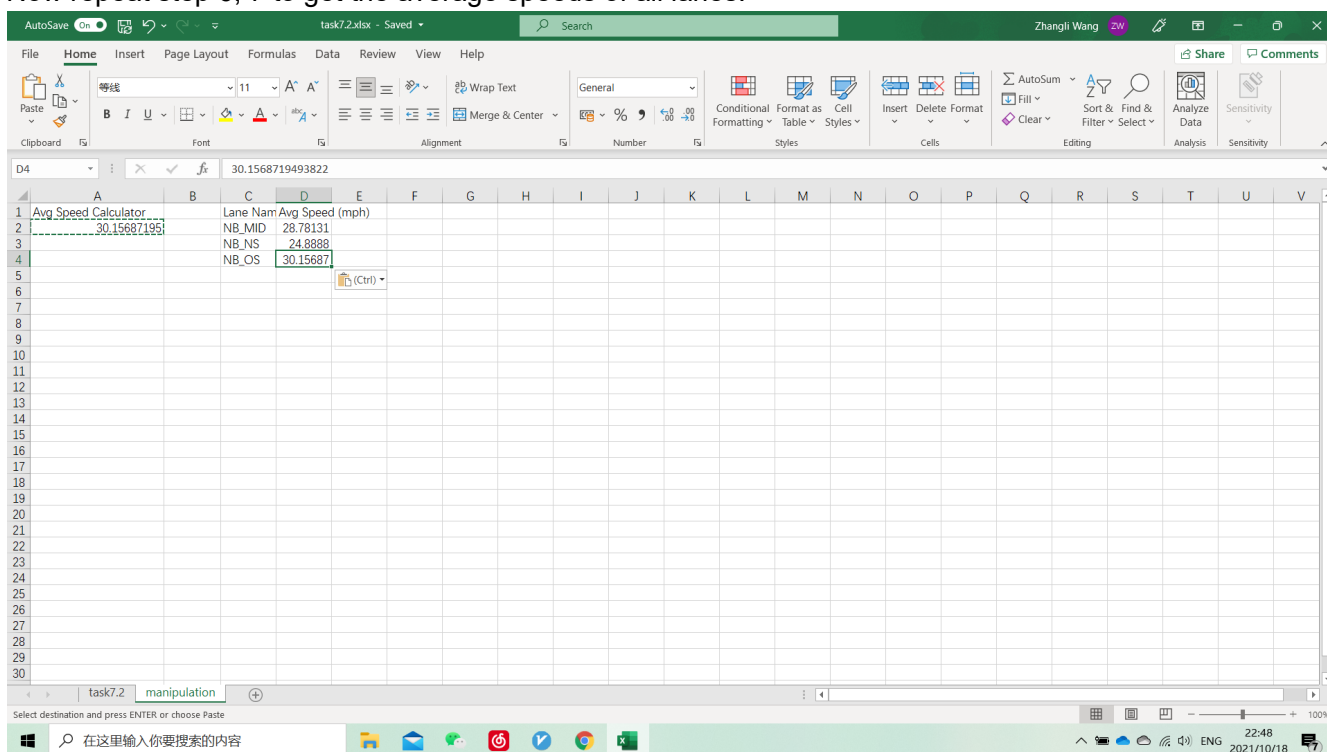
Filter the 'Flag Text' as Friday.



the corresponding place in the column 'Avg Speed (mph)'. We do this because the result of this function changes according to filtering.



8. Now repeat step 6, 7 to get the average speeds of all lanes.



9. Load the dataset of site 1415 in a newly created sheet named task7.2 1415 and repeat steps 1 to 8 for this sheet. After all steps are finished, we can acquire the average values of the five north lanes.

task7.2.xlsx - Saved

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task7.2 1083 task7.2 1415 manipulation

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22:57 2021/10/18

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Avg Speed Calculator		Lane Name	Avg Speed (mph)																	
2	30.15687195		NB_MID	28.78130767																	
3	27.1593222		NB_NS	24.88879913																	
4			NB_OS	30.15687195																	
5			NE_NS	24.09657499																	
6			NE_OS	27.1593222																	
7																					
8																					
9																					
10																					
11																					
12																					
13																					
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10. Now we can calculate the average time with the given distance and the speed with the function

$$=3.019864/D2*60$$

task7.2.xlsx - Saved

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AutoSum Fill Sort & Find & Filter Select Analyze Data Sensitivity

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task7.2 1083 task7.2 1415 manipulation

Ready

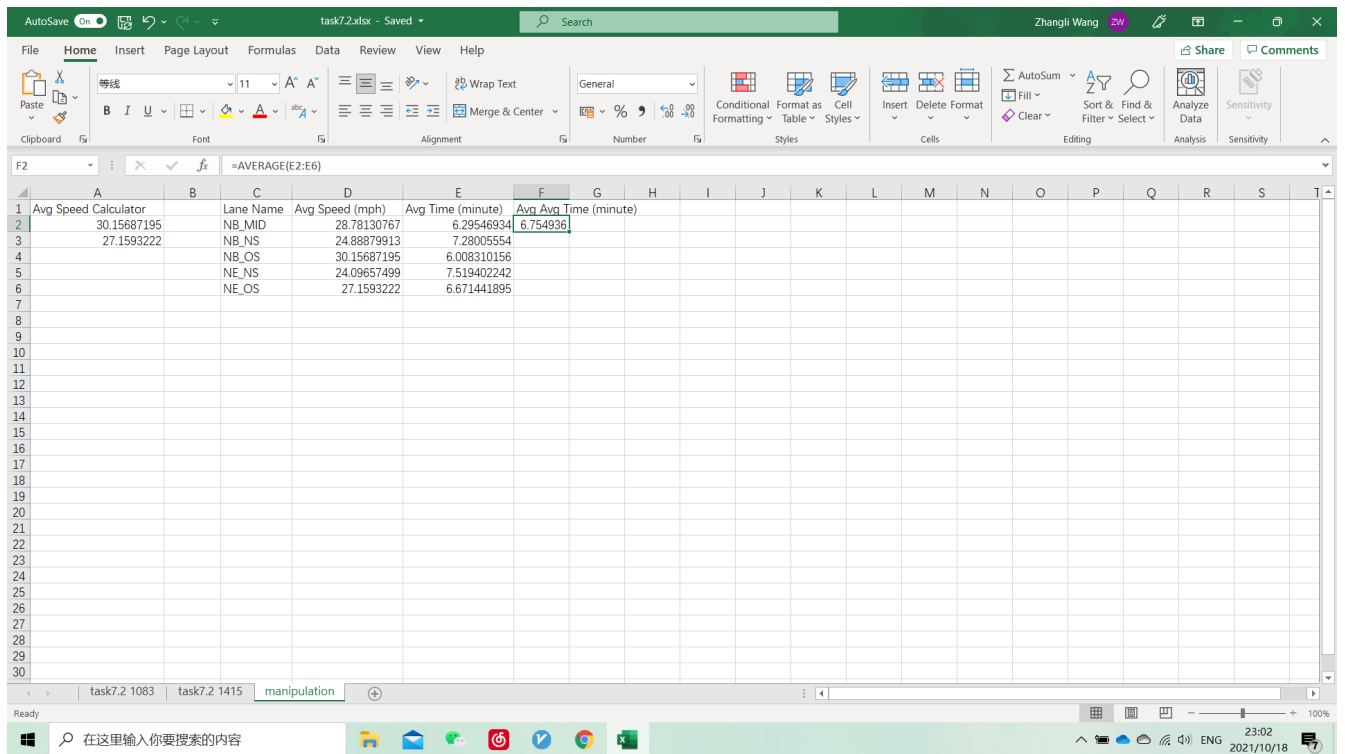
在这里输入你要搜索的内容

23:00 2021/10/18

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Avg Speed Calculator		Lane Name	Avg Speed (mph)	Avg Time (minute)																
2	30.15687195		NB_MID	28.78130767	6.29546934																
3	27.1593222		NB_NS	24.88879913	7.28005554																
4			NB_OS	30.15687195	6.008310156																
5			NE_NS	24.09657499	7.519402242																
6			NE_OS	27.1593222	6.671441895																
7																					
8																					
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Finally, we can compute the average over the average time by the function

$$=AVERAGE(E2:E6)$$



## Comparison of the Two Technologies

Both of the two technologies have the ability to solve the tasks, they both have built-in functions for the same purposes in terms of data manipulation. And they can both manipulate the tabular dataset by filtering according to columns and aggregating according to rows.

To discuss about the differences, the manipulation logics are different. For python, the manipulation is realized by codes. For Excel, the manipulation is realized by the combination of tools in the interface, such as the tool for applying filters to the 'Lane Name' column, and the built-in functions. Python codes can be compiled statically while every operation in Excel is executed instantaneously.

For python, one advantage is that the process of manipulation is more interpretable and reviewable for a programmer. And using Jupyter Notebook to program this coursework can help me to divide operations into stages and add explanation everywhere I want. For example, for every task, I can split my manipulation operations in different code blocks by mini goals. Another advantage can be that the library pandas imported in python has efficient built-in functions such as `loc` that can automatically optimize the data manipulation operations. But the disadvantage is that bugs can possibly occur everywhere in my codes and the intermediate dataset cannot be entirely displayed during the manipulation.

For Excel, the advantage is that the interface is intuitive and can display the data in a proper tabular structure and the drawing of charts is also very convenient. And for manipulating an entire column, Excel can help me with it with its tools conveniently rather than coding for loops manually. But the disadvantages are also significant. Because most of my manipulations are functions, their dependencies result in everytime I change a part of the Excel file, all the functions are re-calculated, which is time consuming. Another disadvantage can be that using tools in the interface and built-in functions in combination can bring incompatibility in some cases. For example, for calculating the average speed for different lanes, I have to manually filter the table for several times and then record the values manually. When the dataset become larger and more complex, each operation executed in Excel can take much longer time due to the deep function dependencies and large quantity of calculations. And manually manipulate some variables can be cumbersome.

