# **Transport Mode Detection - Nimish Agarwal (170440)**

## Setup

user

timestamp object

object

float64

```
In [1]:
# Mounting Drive
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive
Mounted at /content/drive
/content/drive
In [2]:
# Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta
import time
import io
In [3]:
MAIN DIR = 'My Drive/4th year Stuff/CE784A/TMD Dataset/'
DATASET DIR = MAIN DIR + 'cleaned.csv'
Part 1 - Reading and Exploring Dataset
In [4]:
df = pd.read csv(DATASET DIR)
df.head()
Out[4]:
                                  user
                                                 timestamp
                                                            X
                                                                 У
                                                                      z class
0 a2d80ed662f34d32951eb1c6ed076c313e358b73 2018-06-04 16:26:55.053 0.78 -9.13 -3.74
                                                                          bus
1 a2d80ed662f34d32951eb1c6ed076c313e358b73 2018-06-04 16:26:55.111 0.79 -9.11 -3.75
2 a2d80ed662f34d32951eb1c6ed076c313e358b73 2018-06-04 16:26:55.169 0.80 -9.12 -3.75
                                                                         bus
3 a2d80ed662f34d32951eb1c6ed076c313e358b73 2018-06-04 16:26:55.228 0.78 -9.14 -3.76
                                                                          bus
4 a2d80ed662f34d32951eb1c6ed076c313e358b73 2018-06-04 16:26:55.286 0.83 -9.12 -3.80
                                                                          bus
In [5]:
print(df.info())
print('classes: ', df['class'].unique())
# Unique users
print('Unique users: ', len(df['user'].unique()))
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5653053 entries, 0 to 5653052
Data columns (total 6 columns):
 # Column Dtype
--- ----
```

```
3
                float64
     У
 4
                float64
     Z
 5
    class
                object
dtypes: float64(3), object(3)
memory usage: 258.8+ MB
None
classes: ['bus' 'walk' 'car' 'bike' 'train' 'e-bike']
Unique users: 32
In [6]:
df.describe()
Out[6]:
```

```
        x
        y
        z

        count
        5.653053e+06
        5.653053e+06
        5.653053e+06

        mean
        1.499442e+00
        1.483885e+00
        2.484874e+00

        std
        4.657316e+00
        6.262899e+00
        5.800348e+00

        min
        -7.321000e+01
        -7.840000e+01
        -7.844000e+01

        25%
        -1.300000e+00
        -1.790000e+00
        -9.600000e+01

        50%
        7.100000e+01
        2.130000e+00
        3.500000e+00

        75%
        4.650000e+00
        6.260000e+00
        7.320000e+00

        max
        7.840000e+01
        7.834000e+01
        7.840000e+01
```

## Part 2 - Number of Unique Sequences

```
In [7]:

df['timestamp'] = pd.to_datetime(df["timestamp"])

df_temp = df[['user','class','timestamp']]

In [8]:
```

```
In [8]:

start=time.time()
  # get time difference by Row[i] - Row[i-1]
temp = (abs(df_temp['timestamp'][1:].reset_index(drop=True) - df_temp['timestamp'][:-1])
> timedelta(seconds = 10))
  # Changing mode
temp = temp | (df_temp['class'][1:].reset_index(drop=True) != df_temp['class'][:-1])
df_temp['gap'] = pd.concat([pd.DataFrame(data = [True]), temp ] ).reset_index(drop=True)
)

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g uide/indexing.html#returning-a-view-versus-a-copy
```

#### Per user per trasportation mode, No. of Unique Sequences

```
In [9]:
```

```
# Grouping dataset based on
df_temp2 = (df_temp.groupby(['user','class','gap']).count()).reset_index()
# Findng no. of unique sequences
df_temp2 = df_temp2[df_temp2.gap != False]
# taking 3 columns for simplicity
df_temp2 = df_temp2[['user','class','timestamp']]
df_temp2 = df_temp2.rename(columns={"timestamp":"Sequences"})
df_temp2 = df_temp2.reset_index(drop=True).groupby(["user","class","Sequences"]).count()
```

```
#dropping index
pd.set_option('display.max_rows', len(df_temp2))
display(df_temp2)
pd.reset_option('display.max_rows')
end=time.time()
print("Time to run the code :" ,end-start)
```

a2d80ed662f34d32951eb1c6ed076c313e358b73 bus 13 a526f3566e9c9024dfa7378eb4291d787a09fd37 car 15 walk 19 a59868c6eb3645eedbb343ce8c336ec6f2ef2324 bike 39 bus 27 car 68 walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 33 cace4ec0999436917986b4fa6e9317262c997bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115 car 32	user	class	Sequences
a59968c6eb3645eedbb343ce8c336ec6f2ef2324 bike 39 bus 27 car 68 walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 33 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	a2d80ed662f34d32951eb1c6ed076c313e358b73	bus	13
a59868c6eb3645eedbb343ce8c336ec6f2ef2324 bike 39 bus 27 car 68 walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 car950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 155	a526f3566e9c9024dfa7378eb4291d787a09fd37	car	15
bus 27 car 68 walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 155		walk	19
car 68 walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 155	a59868c6eb3645eedbb343ce8c336ec6f2ef2324	bike	39
walk 12 a92dee88f61123f923dccec01eeecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		bus	27
a92dee88f61123f923dccec01eecf1a81953b36 bus 4 ac4c17afeb69b39169eb301ab592696a8f353976 car 20 walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		car	68
ac4c17afeb69b39169eb301ab592696a8f353976 car walk 58 adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 cdr 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		walk	12
adaaae1a67ea9e43abd60ba945eccda0cb8821e0 bus 22 car 17 walk 10 b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	a92dee88f61123f923dccec01eeecf1a81953b36	bus	4
adaaae1a67ea9e43abd60ba945eccda0cb8821e0	ac4c17afeb69b39169eb301ab592696a8f353976	car	20
car		walk	58
b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 1552 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	adaaae1a67ea9e43abd60ba945eccda0cb8821e0	bus	22
b138d165100ef60bc793cac143742eb5aea4d6ba car 9 b45157069942d01310c3e7b74034166717bb25f9 car 3 walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		car	17
b45157069942d01310c3e7b74034166717bb25f9 car walk 2 b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		walk	10
b7b165e5637b5a0226068d907748f4bbfc61a320 car 194 walk 10 c453226e3616ae821cdcb38f38481c2a20f2482f bike 169 bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	b138d165100ef60bc793cac143742eb5aea4d6ba	car	9
b7b165e5637b5a0226068d907748f4bbfc61a320 car 194	b45157069942d01310c3e7b74034166717bb25f9	car	3
walk 10  c453226e3616ae821cdcb38f38481c2a20f2482f bike 169  bus 291  c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15  bus 14  walk 129  ca7950f223a8037b897d0547075dc138f9e43b20 walk 3  cace4ec0999436917986b4fa6e9317262c897bc2 car 72  cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4  ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22  car 80  d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6  car 132  walk 2  d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152  train 13  walk 6  d7dd12d83c81574137f858034b99f4cc83ab0718 car 147  d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12  walk 24  dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		walk	2
c453226e3616ae821cdcb38f38481c2a20f2482f         bike         169           bus         291           c5702d34b238fe68683f818e82cd3a3cd8a16366         bike         15           bus         14           walk         129           ca7950f223a8037b897d0547075dc138f9e43b20         walk         3           cace4ec0999436917986b4fa6e9317262c897bc2         car         72           cbde60baea002b694ecf2a3ff2d95be16b00efe1         bus         4           ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c         bus         22           car         80           d429974540bfd38c3367fe9f0c8682775ff4fa18         bus         6           car         132           walk         2           d7a1230d94f91a32cc079809748e52e8a4a6a22f         bike         152           train         13           walk         6           d7dd12d83c81574137f858034b99f4cc83ab0718         car         147           d8c047eaaee204b7b5cd71e2d67308b87b038ed3         car         12           walk         24           dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120         bike         115	b7b165e5637b5a0226068d907748f4bbfc61a320	car	194
bus 291 c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		walk	10
c5702d34b238fe68683f818e82cd3a3cd8a16366 bike 15 bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	c453226e3616ae821cdcb38f38481c2a20f2482f	bike	169
bus 14 walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		bus	291
walk 129 ca7950f223a8037b897d0547075dc138f9e43b20 walk 3 cace4ec0999436917986b4fa6e9317262c897bc2 car 72 cbde60baea002b694ecf2a3ff2d95be16b00efe1 bus 4 ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c bus 22 car 80 d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6 car 132 walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	c5702d34b238fe68683f818e82cd3a3cd8a16366	bike	15
ca7950f223a8037b897d0547075dc138f9e43b20       walk       3         cace4ec0999436917986b4fa6e9317262c897bc2       car       72         cbde60baea002b694ecf2a3ff2d95be16b00efe1       bus       4         ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c       bus       22         car       80         d429974540bfd38c3367fe9f0c8682775ff4fa18       bus       6         car       132         walk       2         d7a1230d94f91a32cc079809748e52e8a4a6a22f       bike       152         train       13         walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115		bus	14
cace4ec0999436917986b4fa6e9317262c897bc2         car         72           cbde60baea002b694ecf2a3ff2d95be16b00efe1         bus         4           ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c         bus         22           car         80           d429974540bfd38c3367fe9f0c8682775ff4fa18         bus         6           car         132           walk         2           d7a1230d94f91a32cc079809748e52e8a4a6a22f         bike         152           train         13           walk         6           d7dd12d83c81574137f858034b99f4cc83ab0718         car         147           d8c047eaaee204b7b5cd71e2d67308b87b038ed3         car         12           walk         24           dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120         bike         115		walk	129
cbde60baea002b694ecf2a3ff2d95be16b00efe1       bus       4         ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c       bus       22         car       80         d429974540bfd38c3367fe9f0c8682775ff4fa18       bus       6         car       132         walk       2         d7a1230d94f91a32cc079809748e52e8a4a6a22f       bike       152         train       13         walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115	ca7950f223a8037b897d0547075dc138f9e43b20	walk	3
ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c       bus       22         car       80         d429974540bfd38c3367fe9f0c8682775ff4fa18       bus       6         car       132         walk       2         d7a1230d94f91a32cc079809748e52e8a4a6a22f       bike       152         train       13         walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115	cace4ec0999436917986b4fa6e9317262c897bc2	car	72
d429974540bfd38c3367fe9f0c8682775ff4fa18       bus       6         car       132         walk       2         d7a1230d94f91a32cc079809748e52e8a4a6a22f       bike       152         train       13         walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115	cbde60baea002b694ecf2a3ff2d95be16b00efe1	bus	4
d429974540bfd38c3367fe9f0c8682775ff4fa18 bus 6	ce39f5d0705695fcd70a04ba6d84ac6beecd6f9c	bus	22
car       132         walk       2         d7a1230d94f91a32cc079809748e52e8a4a6a22f       bike       152         train       13         walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115		car	80
walk 2 d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	d429974540bfd38c3367fe9f0c8682775ff4fa18	bus	6
d7a1230d94f91a32cc079809748e52e8a4a6a22f bike 152 train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		car	132
train 13 walk 6 d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		walk	2
walk       6         d7dd12d83c81574137f858034b99f4cc83ab0718       car       147         d8c047eaaee204b7b5cd71e2d67308b87b038ed3       car       12         walk       24         dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120       bike       115	d7a1230d94f91a32cc079809748e52e8a4a6a22f	bike	152
d7dd12d83c81574137f858034b99f4cc83ab0718 car 147 d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12 walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115		train	13
d8c047eaaee204b7b5cd71e2d67308b87b038ed3 car 12		walk	6
walk 24 dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	d7dd12d83c81574137f858034b99f4cc83ab0718	car	147
dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120 bike 115	d8c047eaaee204b7b5cd71e2d67308b87b038ed3	car	12
		walk	24
car 32	dc0bdce306ec3b624fe0e6ecd1ffbd82cb970120	bike	115
		car	32

	walk	. 5
user dd82e3df4bebc74ed6b67877be79e29f401c16a3	class	Sequences 68
uu02690140600746000070776673623140767000	walk	2
dde95e125d89843f7032baa734ee4d34ec775aaf	bus	5
duesse izsusseron sozzalno recruo reci i sulli	car	2
	walk	8
de9892b879c83ea3d24fb4560873107cc4e86d48	car	114
uesos20075005e25024104500075107004600440	walk	36
dfnfn0404604b72b60004072450f00042f2nn25b	_	50
dfcfc0404691b73b69884073159f90843f2ac35b	bus	108
	car	155
- 400-0F-F0064447400-44-4-40070-40 <i>46-48</i>	-	199
e429a95c532f1117130c11e4a18379d84fa4ffa9	bus	
- LO-70540006400-L-6440L0406-4644L-L-070	car	39
eb9e7854290fd6ea9ebaf448b640fc1f1dbeb076	bus	2
	train 	1
	walk	2
ecfb0929250fb6dda66a4065441230ab27f094e5	car	158
	e-bike	16
	train	1
ed623d28c1e0071632a6110b8f8ed93f8af78b99	bus	10
	car	117
	walk	4
f1b7331b66e404c11eebb22933e733117bbb12c9	bike	172
	car	139
	walk	73
f5edd999397145a2ec1b244226fc83f99631760c	bus	16
	walk	13
f7ae1ce141c26db40ea8b090fb568a0c965310aa	car	2
faae5be800be2dfa897eea0bd2e5988cd53c4ec0	bike	136
	car	10
	walk	35

Time to run the code : 1.8916699886322021

#### **Part 3 - Time Window Partition**

```
In [10]:

df = pd.read_csv(DATASET_DIR)
    df['timestamp'] = df['timestamp'].astype('datetime64[s]')

In [11]:
```

```
start=time.time()
def helper_func(temp):
    temp = temp["timestamp"]
    temp = pd.DataFrame(data = temp).set_index("timestamp")
    temp["val"] = np.ones(len(temp))
    temp = temp.groupby(temp.index).count()
    temp = temp.resample('5s', origin='start').count()
    return len(temp[temp.val != 0])
```

```
# preprocessing data
df temp = df[['user','class','timestamp']]
temp = (abs(df temp['timestamp'][1:].reset index(drop=True) - df temp['timestamp'][:-1])
> timedelta(seconds = 10))
df temp['gap'] = pd.concat([pd.DataFrame(data = [True]), temp ] ).reset index(drop=True
df_temp2 = df_temp[df_temp["gap"] == True]
df temp2 = (df temp2.groupby(['user','class','gap']).apply(lambda x : x)).reset index().
drop(['gap'], axis=1)
df temp2["end timestamp"] = df temp.reset index()["timestamp"].iloc[(df temp2["index"]-1
).to numpy()[1:]].reset index(drop=True)
df temp2["end timestamp"].iloc[-1] = df["timestamp"].iloc[-1]
df_temp2[">than5sec"] = ((df_temp2["end_timestamp"] - df_temp2["timestamp"]) >= timedel
ta(seconds = 5))
df temp2["start index"] = (df temp2["index"].to numpy())
df temp2["end index"] = np.concatenate((((df temp2["index"]-1).to numpy()[1:]),[len(df)-
1]),axis = 0)
# starting and ending of each sequence
df temp3 = df temp2[df temp2[">than5sec"] == True]
a = list(range(df temp3["start index"].iloc[0] , df temp3["end index"].iloc[0]-df temp3[
"start index"].iloc[0]+1 ))
for i in range(1,len(df temp3)):
   a.extend(list(range(df temp3["start index"].iloc[i] , df temp3["end index"].iloc[i]
+1)))
df6 = df.iloc[a]
df temp3 = pd.DataFrame(df6.groupby(["user","class"]).apply(helper func))
df temp3 = df temp3.reset index().rename(columns={0:"#5 SecWindowSequences"}).groupby(["
user","class","#5 SecWindowSequences"]).count()
df temp3 = df temp3.reset index().groupby(["class"]).sum().reset index()
display(df temp3)
end=time.time()
print("Time to run the code :" ,end-start)
/usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row indexer,col indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:670: SettingWithCopyWarnin
g:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user g
uide/indexing.html#returning-a-view-versus-a-copy
  iloc. setitem with indexer(indexer, value)
```

#### class #5\_SecWindowSequences

0	bike	2958
1	bus	10543
2	car	20419
3	e-bike	78
4	train	594
5	walk	5825

Time to run the code: 38.75357675552368

### Part 4 - Feature Engineering

```
def feature_extraction(temp):
    return temp.set_index("timestamp").resample('5s', origin='start').agg({'x':['mean','max','min','std'],'y':['mean','max','min','std'],'z':['mean','max','min','std']})
In [16]:

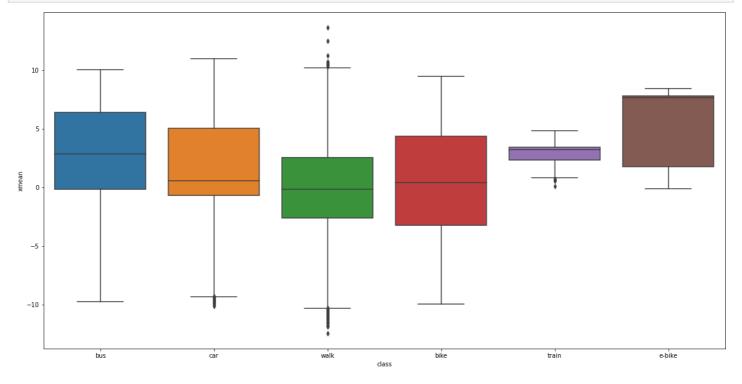
df_temp3 = pd.DataFrame(df6.groupby(["user","class"]).apply(feature_extraction)).reset_index().dropna()
df_temp3.columns = [''.join(col).strip() for col in df_temp3.columns.values]
df_temp3.head()
print(df temp3.shape)
```

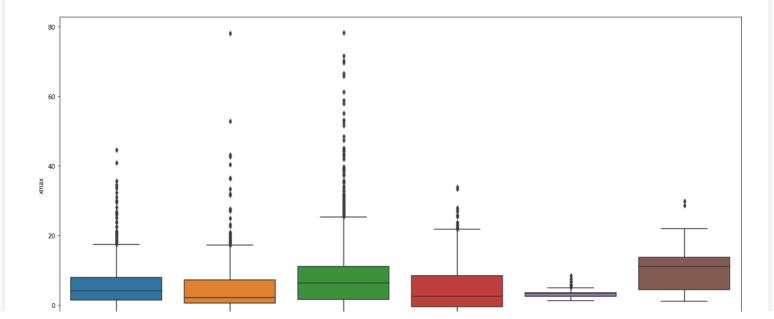
# Box Plots

(40366, 15)

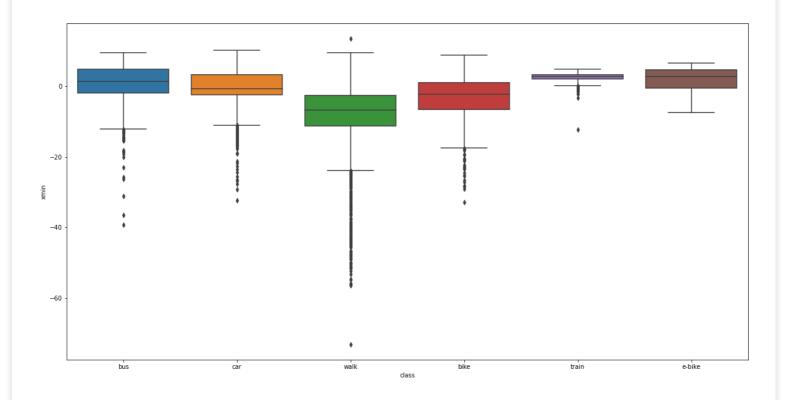
#### In [34]:

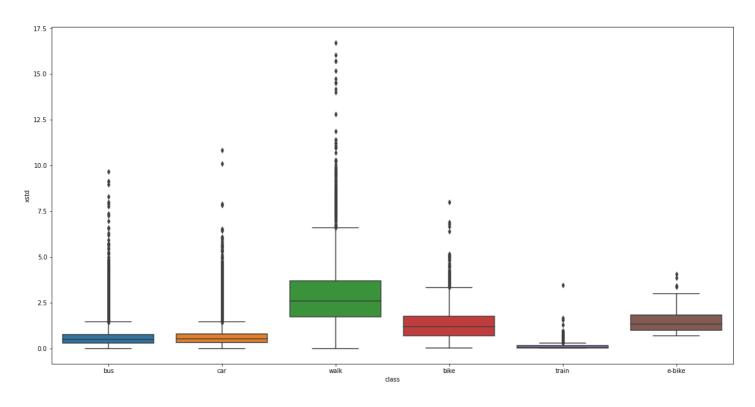
```
# Box Plots
fig, axes = plt.subplots(nrows=12, ncols=1, figsize=(20,12*12))
for i in range(3,15):
    sns.boxplot(x=df_temp3["class"], y=df_temp3.iloc[:,i], data=df_temp3, ax=axes[i-3])
```

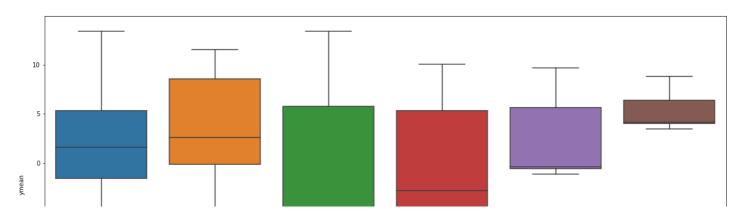


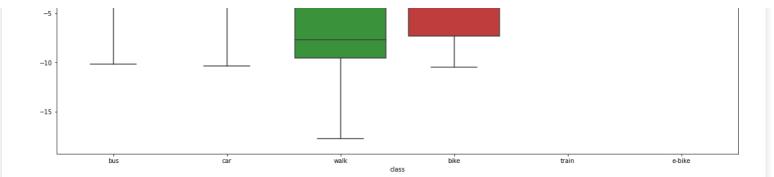


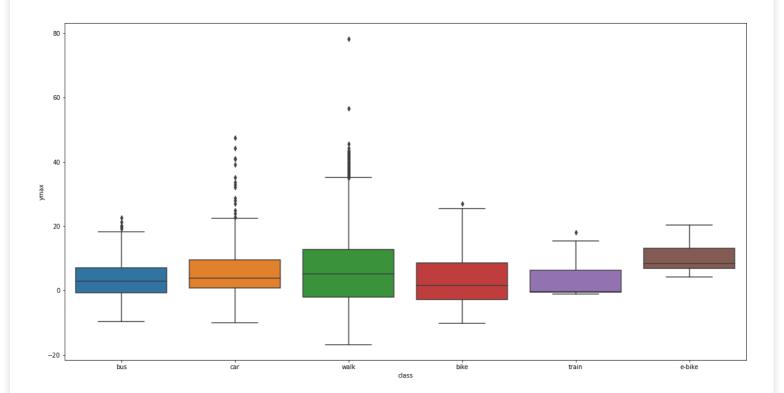


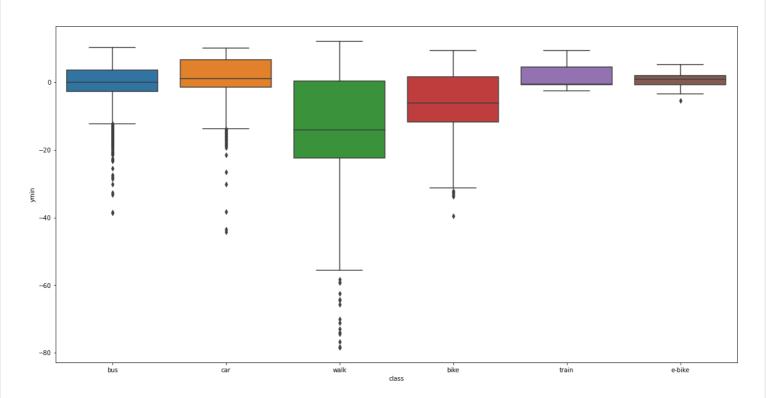


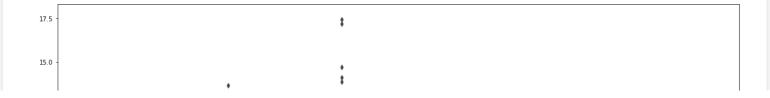


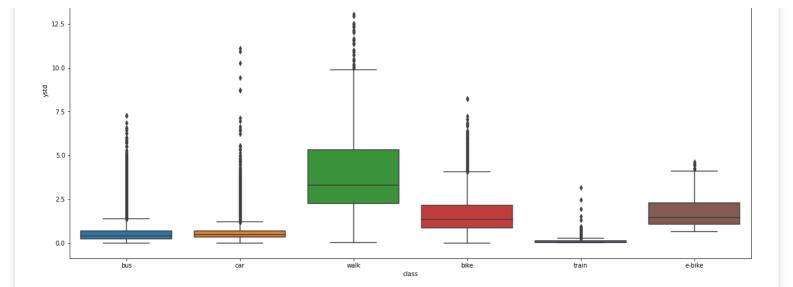


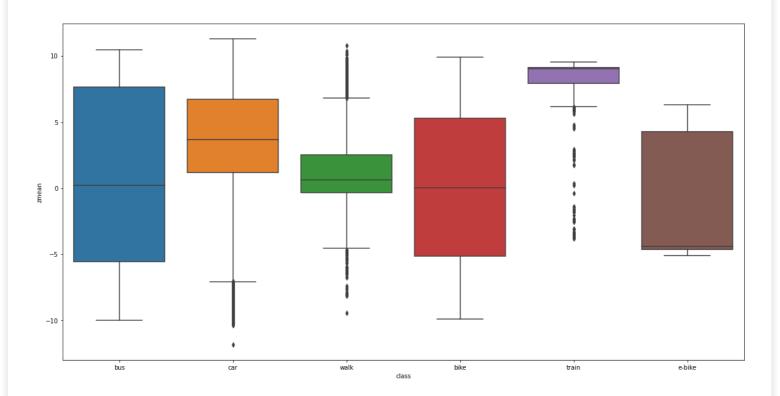


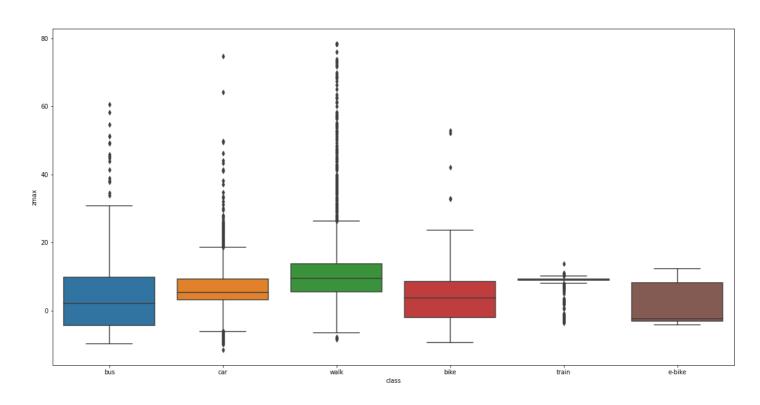


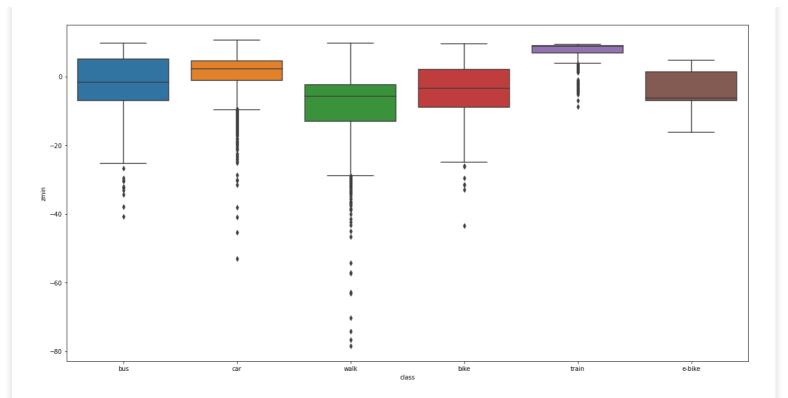


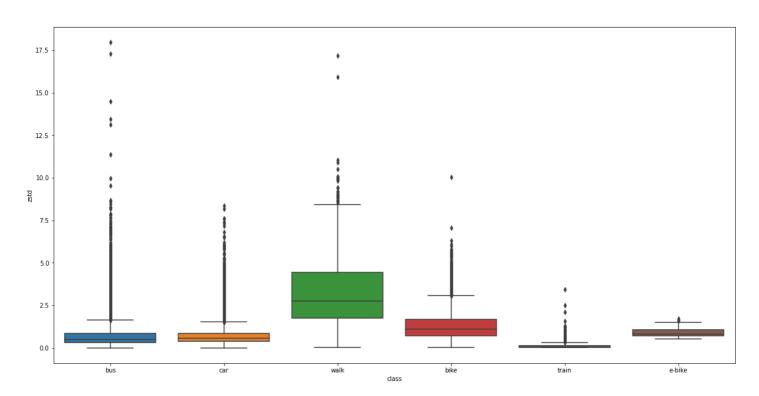












# Part 5 - Creating Balanced Dataset

```
In [18]:
```

```
# Choosing 78 rows from each mode randomly
MinDataPoints = min(df_temp3.groupby(['class']).apply(lambda x: len(x)))
print("Minimum Data Points in any Transportatation Mode => ", MinDataPoints)

def fun2(temp):
    return temp.sample(n = 78)
df_new = df_temp3.groupby(["class"]).apply(fun2)
df_new = df_new.reset_index(drop=True).iloc[:,1:].drop('timestamp',axis = 1).rename(col umns={'class':'target'})
pd.DataFrame(df_new.groupby(["target"]).apply(lambda x:len(x))).rename(columns={0:"#DataPoints"}).reset_index()
```

Minimum Data Points in any Transportatation Mode => 78

#### Out[18]:

```
target #DataPoints
    bike
                78
               78
1
    bus
               78
     car
               78
3 e-bike
                78
    train
   walk
               78
In [19]:
df new.shape
Out[19]:
(468, 13)
part 6 - Splitting dataset
Splitting
In [20]:
X = df new.drop('target', axis=1)
Y = df new['target']
In [21]:
from sklearn.model selection import train test split
x, x_test, y, y_test = train_test_split (X, Y, test_size=0.2, train size=0.8)
x_train, x_cv, y_train, y_cv = train_test_split(x,y, test_size = 0.25, train size =0.75)
In [22]:
print('No. of Datapoints:')
print('Training = ', len(x_train))
print('Cross Validation = ', len(x cv))
print('Testing = ', len(x_test))
```

No. of Datapoints: Training = 280Cross Validation = 94 Testing = 94

#### Part 7 - ML Model

#### LogRegr., SVM, decision tree and random forest classifier

```
In [23]:
```

```
# Turn the values into an array for feeding the classification algorithms.
x = x.values
x train = x train.values
x_{test} = x_{test.values}
x cv = x cv.values
y = y.values
y_train = y_train.values
y_test = y_test.values
y_cv = y_cv.values
```

#### In [24]:

```
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import precision score, recall score, f1 score, roc auc score, accur
acy score, classification report, confusion matrix
from sklearn.model selection import cross val score, KFold
from collections import Counter
from sklearn.pipeline import make_pipeline
import collections
import warnings
warnings.filterwarnings("ignore")
In [25]:
```

```
classifiers = {
   "LogisticRegression": LogisticRegression(),
   "Support Vector Classifier": SVC(kernel='linear', C=1),
   "Decision Tree Classifier": DecisionTreeClassifier(),
   "Random Forest Classifier": RandomForestClassifier()
classrep = []
confusionmatrices = {}
predicts = {}
kfold = KFold(n splits=4, random state=42)
for key, classifier in classifiers.items():
   classifier.fit(x train, y train)
   results = cross val score(classifier, x, y, cv = kfold)
   print("Classifier: "+classifier.__class__.__name__+" has a cross val score Accuracy:
%.3f%% (%.3f%%)" % (results.mean()*100.0, results.std()*100.0))
   predictions = classifier.predict(x test)
   s))
   predicts[key] = predictions
   classrep.append(classification report(y test, predictions));
   confusionmatrices[key] = confusion matrix(y test,predictions);
```

Classifier: LogisticRegression has a cross val score Accuracy: 65.763% (2.441%) Classification Report of LogisiticRegression:

precision recall f1-score support 0.39 0.42 18 bike 0.47 bus 0.35 0.32 0.33 19 car 0.67 0.50 0.57 20 e-bike 0.71 0.94 0.81 18 train 0.67 1.00 0.80 8 walk 0.45 0.45 0.45 11 0.56 94 accuracy 0.55 0.60 0.57 94 macro avg 0.56 0.55 94

0.55

weighted avg

Classifier: SVC has a cross val score Accuracy: 68.706% (2.451%) Classification Report of Support Vector Classifier:

	precision	recall	f1-score	support	
bike	0.42	0.44	0.43	18	
bus	0.47	0.47	0.47	19	
car	0.62	0.50	0.56	20	
e-bike	0.77	0.94	0.85	18	
train	0.89	1.00	0.94	8	
walk	0.33	0.27	0.30	11	
accuracy			0.59	94	
macro avg	0.59	0.61	0.59	94	
weighted avg	0.57	0.59	0.57	94	

Classifier: DecisionTreeClassifier has a cross val score Accuracy: 59.326% (6.660%) Classification Report of Decision Tree Classifier: precision recall f1-score support

```
bus
                0.47
                        0.42
                                 0.44
                                            19
                0.57
                        0.60
                                 0.59
                                            2.0
       car
                        0.94
     e-bike
               0.85
                                 0.89
                                            18
                        0.62
                                 0.71
      train
                0.83
                                            8
      walk
                0.58
                         0.64
                                 0.61
                                            11
                                  0.62
                                            94
   accuracy
                0.63
                         0.62
                                  0.62
                                            94
  macro avg
                         0.62
                                  0.61
                                            94
weighted avg
                0.61
Classifier: RandomForestClassifier has a cross val score Accuracy: 76.733% (2.917%)
Classification Report of Random Forest Classifier :
            precision recall f1-score support
                0.56 0.56
                                0.56
      bike
                                            18
       bus
               0.71
                        0.53
                                0.61
                                            19
               0.71
                        0.75
                                0.73
                                            20
       car
               0.85
                        0.94
                                0.89
     e-bike
                                            18
      train
               0.89
                       1.00
                                0.94
                                            8
               0.67
      walk
                        0.73
                                0.70
                                            11
```

0.72

0.74

0.72

0.50

18

94

94

94

#### **Artificial Neural Network**

accuracy

macro avg

weighted avg

bike

0.50

0.73 0.75 0.72 0.72

0.72

0.50

#### In [26]:

```
# Implementing ANN
# multi-class classification with Keras
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit learn import KerasClassifier
from keras.utils import np_utils
from sklearn.model selection import cross val score
from sklearn.model selection import KFold
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
```

#### In [27]:

```
X = df new.drop('target', axis=1)
Y = df new['target']
```

#### In [28]:

```
encoder = LabelEncoder()
encoder.fit(Y)
encoded Y = encoder.transform(Y)
# convert integers to dummy variables (i.e. one hot encoded)
dummy y = np utils.to categorical(encoded Y)
```

#### In [29]:

```
from sklearn.model selection import train test split
x, x_test, y, y_test = train_test_split (X, dummy_y, test_size=0.2, train_size=0.8)
```

#### In [30]:

```
print(x.shape)
print (y.shape)
```

(374, 12)

(374, 6)

```
In [31]:

n_inputs = x.shape[1]
y_out = y.shape[1]

# Defining Model

def baseline_model():
    model = Sequential()
    model.add(Dense(n_inputs, input_shape=(n_inputs, ), activation='relu'))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(y_out, activation='softmax'))
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

In [33]:
```

```
# Fitting and cross-validating ANN
estimator = KerasClassifier(build_fn=baseline_model, epochs=100, batch_size=5, verbose=0)
kfold = KFold(n_splits=5, shuffle=True)
results = cross_val_score(estimator, x, y, cv=kfold)
print("Neural Network Accuracy: %.2f%% (std. dev - %.2f%%)" % (results.mean()*100, results.std()*100))
```

Neural Network Accuracy: 74.86% (std. dev - 4.26%)