Engineering Analytics and Machine Learning Lab 3

for Specialist Diploma in Internet of Things

Author’s Name: Teo Kok Keong

1 Data Cleaning

1.1 Missing Data

Missing Data in Pandas was handled in two ways, the None and NaN.

In [1]:
```
import numpy as np
import pandas as pd

#Let's look at None as a python object
x = np.array([1, None, 3, 2])
x
```

Out[1]:
```
array([1, None, 3, 2], dtype=object)
```

In [2]:
```
#NaN is recognized by all systems that use standard IEEE floating-point repres
entation
y=np.array([1,np.nan,3,4])
print(y.dtype)
```

```
float64
```

In [3]:
```
#anything that have arithmetic operation with nan the result is nan

result=2+np.nan
print(result)
result2=np.nan/2
print(result2)
```

```
nan
nan
```

Pandas treat None and NaN essentially interchangeable for indicating missing or null values. To faciliate this convention, there are several useful methods to due with null values in Pandas data structure.

In [4]:
```
data=pd.Series([1,np.nan,'hello',None])
print(data)
```

```
0        1
1      NaN
2    hello
3     None
dtype: object
```

In [5]:
```
#we can detect null values using the isnull() method
print("isnull result")
print(data.isnull())

#we can do the opposite using the notnull() method
print("notnull  result")
print(data.notnull())
```

```
isnull result
0    False
1     True
2    False
3     True
dtype: bool
notnull  result
0     True
1    False
2     True
3    False
dtype: bool
```

1.2 Data Selection in Series

A Series object acts in many ways like a one-dimensional NumPy array, and in many ways like a standard Python dictionary. If we keep these two overlapping analogies in mind, it will help us to understand the patterns of data indexing and selection in these arrays

In [6]:
```
import pandas as pd
data = pd.Series([0.25, 0.5, 0.75, 1.0],index=['a', 'b', 'c', 'd'])
data
```

Out[6]:
```
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

In [7]:
```
# we can select any value by

data['b']
```

Out[7]:
```
0.5
```

In [8]:
```
#dictionary like expression

print('a' in data)   #check key 'a' exist

print('w' in data)    #check key 'w' exist

print(data.keys())

print(list(data.items()))

data['e']=1.25      #modify value to 1.25 with key='e'
print(data)
```

```
True
False
Index(['a', 'b', 'c', 'd'], dtype='object')
[('a', 0.25), ('b', 0.5), ('c', 0.75), ('d', 1.0)]
a    0.25
b    0.50
c    0.75
d    1.00
e    1.25
dtype: float64
```

In [9]:
```
#also can be slice and select by Numpy array

print(data['a':'c'])  #select data from key='a' to 'c'
print(data[0:2])      #select data by implicit integer index
print(data[(data>0.3)&(data<0.8)] )  #by masking only select value between 0.3
 and 0.8
print(data[['a','e']])   #select only value with key='a' and 'e'
```

```
a    0.25
b    0.50
c    0.75
dtype: float64
a    0.25
b    0.50
dtype: float64
b    0.50
c    0.75
dtype: float64
a    0.25
e    1.25
dtype: float64
```

In [10]:
```
#these selection can be use to mask out missing value
#lets redefine the data we have previously
data=pd.Series([1,np.nan,'hello',None])
print(data)
```

```
0        1
1      NaN
2    hello
3     None
dtype: object
```

In [11]:
```
print(data[data.notnull()])   #remove all the missing data
```

```
0        1
2    hello
dtype: object
```

In [12]:
```
#or there is convenience methods such as dropna() which mean removes NA value
print(data.dropna())
```

```
0        1
2    hello
dtype: object
```

Pandas DataFrame which is usually multidimensional is a little more complicated than Pandas Series. Simply because we cannot drop single values from a DataFrame, we can only drop full rows or full columns. However, that would affected a lot of other unrelated data points which essentially greatly reduce the number of data points. How to drop is very application dependent and there is no a simple all correct answer to all situations.

By default dropna() will drop all rows which any null value is present. We can dropna() of all column which any null is present by using the setting the axis='columns'

In [13]:
```
 df = pd.DataFrame([[1,      np.nan, 2],
                    [2,      3,      5],
                    [np.nan, 4,      6]])
print(df.dropna())     #drop all rolls with null value
print(df.dropna(axis='columns'))  #drop all columns with null value
```

```
     0    1  2
1  2.0  3.0  5
   2
0  2
1  5
2  6
```

```
In [14]: #lets see how we can clean data with finerr grain of control
         df[3] = np.nan   #add a third column that is all null values
         print(df)
         #The default of how='any', such that any row or column (depending on the axis
          keyword) containing a null value will be dropped.
         #we can set how='all' that mean only drop if cany row or column is all null va
         lue
         print(df.dropna(axis='columns',how='all'))
         #thresh let you specify what ist he minimum number of non-null values for the
          row/columns to be kept
         print(df.dropna(axis='rows', thresh=3))
```

```
     0    1  2   3
0  1.0  NaN  2 NaN
1  2.0  3.0  5 NaN
2  NaN  4.0  6 NaN
     0    1  2
0  1.0  NaN  2
1  2.0  3.0  5
2  NaN  4.0  6
     0    1  2   3
1  2.0  3.0  5 NaN
```

Sometime in certain application missing data can be replace by a certain number. In this section we are going to fill null values.

In [15]:
```
data1 = pd.Series([1, np.nan, 2, None, 3], index=list('abcde'))
print(data1)
#we can fill all null with any value such as 0 in  this example
print(data1.fillna(0))
#forward-fill to propagate the previous value value forward, mean to fill null
 value with value of the previous non-null value
print(data1.fillna(method='ffill'))
#the opposite would be back fill
print(data1.fillna(method='bfill'))
```

```
a    1.0
b    NaN
c    2.0
d    NaN
e    3.0
dtype: float64
a    1.0
b    0.0
c    2.0
d    0.0
e    3.0
dtype: float64
a    1.0
b    1.0
c    2.0
d    2.0
e    3.0
dtype: float64
a    1.0
b    2.0
c    2.0
d    3.0
e    3.0
dtype: float64
```

In [16]:
```
#we can do similar thing with dataframe
print(df)
print(df.fillna(method='ffill',axis=1)) #in row
print(df.fillna(method='ffill',axis=0)) #in column
#if previous value not available nan would remain
```

```
     0    1  2   3
0  1.0  NaN  2 NaN
1  2.0  3.0  5 NaN
2  NaN  4.0  6 NaN
     0    1    2    3
0  1.0  1.0  2.0  2.0
1  2.0  3.0  5.0  5.0
2  NaN  4.0  6.0  6.0
     0    1  2   3
0  1.0  NaN  2 NaN
1  2.0  3.0  5 NaN
2  2.0  4.0  6 NaN
```

Exercise 1

Load the data file april-2017.csv and use the head() and info() methods to understand more about the data. We want to drop the null values.

1. We cannot tolerate any null value, we would remove any rows/columns with any null values. Rows or Column is feasible in this case?
2. Perform operation so that we can keep the rows/columns it does not contain all null values and forward fill the null value.

In [17]:
```
import numpy as np
import pandas as pd

ddf=pd.read_csv('april-2017.csv')
ddf.head()
```

Out[17]:

	UTC time	3_temperature	3_humidity	3_pressure	3_pm1	3_pm25	3_pm10	140_te
0	2017-04-01T00:00:00	NaN	NaN	NaN	NaN	NaN	NaN	6
1	2017-04-01T01:00:00	NaN	NaN	NaN	NaN	NaN	NaN	6
2	2017-04-01T02:00:00	NaN	NaN	NaN	NaN	NaN	NaN	5
3	2017-04-01T03:00:00	NaN	NaN	NaN	NaN	NaN	NaN	5
4	2017-04-01T04:00:00	NaN	NaN	NaN	NaN	NaN	NaN	4

5 rows × 337 columns

In [18]:
```
ddf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 720 entries, 0 to 719
Columns: 337 entries, UTC time to 895_pm10
dtypes: float64(193), int64(143), object(1)
memory usage: 1.9+ MB
```

In [19]:
```
ddf.dropna(axis='columns').head()
```

Out[19]:

	UTC time	140_temperature	140_humidity	140_pressure	147_pressure	147_pm1	1
0	2017-04-01T00:00:00	6	92	101906	101829	69	6
1	2017-04-01T01:00:00	6	92	101869	101793	73	6
2	2017-04-01T02:00:00	5	94	101837	101760	76	7
3	2017-04-01T03:00:00	5	92	101834	101757	73	7
4	2017-04-01T04:00:00	4	94	101832	101755	74	7

5 rows × 144 columns

1.3 Date Time

Most Engineering data are time series, handling date time is one of the commonly data type. However date time come in all kind of format and many time when read from file it is read in as text/string. We would learn how to convert to proper python date time so that we could easily perform further processing.

Please refer to the below link for more on date time of Pandas:

https://pandas.pydata.org/pandas-docs/stable/generated/pandas.to_datetime.html (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.to_datetime.html)

Exercise 2

Read in the lab3_date1.csv file into Pandas dataframe and preview the data.

Clean the data to remove all null value.

```
In [20]: import numpy as np
         import pandas as pd

         dd=pd.read_csv('lab3_dateT.csv')
         dd.head()
         #the Datetime is read in as string/text we need to convert them to proper date
         time format
```

Out[20]:

	Datetime	this	Values
0	2017-04-01T00:00:00	NaN	1
1	2017-04-01T01:00:00	NaN	2
2	2017-04-01T02:00:00	NaN	3
3	2017-04-01T03:00:00	NaN	4
4	2017-04-01T04:00:00	NaN	5

```
In [21]: dd=dd.dropna(axis='columns')
         dd.head()
```

Out[21]:

	Datetime	Values
0	2017-04-01T00:00:00	1
1	2017-04-01T01:00:00	2
2	2017-04-01T02:00:00	3
3	2017-04-01T03:00:00	4
4	2017-04-01T04:00:00	5

Lets proceed to convert the Datetime read in (still a string) to proper Python date time.

```
In [22]: dd['Datetime']=pd.to_datetime(dd['Datetime'],format='%Y-%m-%dT%H:%M:%S',utc=Tr
         ue) #convert string to datetime
         #Note: the format string is provided as the date and time are seperated by 'T'
          rather than space
         dd.head()
```

Out[22]:

	Datetime	Values
0	2017-04-01 00:00:00+00:00	1
1	2017-04-01 01:00:00+00:00	2
2	2017-04-01 02:00:00+00:00	3
3	2017-04-01 03:00:00+00:00	4
4	2017-04-01 04:00:00+00:00	5

In [23]:
```
#convert the date time back to epoch notice that the epeoch is in us 1/1,000,0
00 second)
print(dd['Datetime'].astype(np.int64).head())
```

```
0    1491004800000000000
1    1491008400000000000
2    1491012000000000000
3    1491015600000000000
4    1491019200000000000
Name: Datetime, dtype: int64
```

In [24]:
```
dd.set_index('Datetime', inplace=True)  # set the date time as index
dd.head()
```

Out[24]:

	Values
Datetime	
2017-04-01 00:00:00+00:00	1
2017-04-01 01:00:00+00:00	2
2017-04-01 02:00:00+00:00	3
2017-04-01 03:00:00+00:00	4
2017-04-01 04:00:00+00:00	5

In [25]:
```
#lets plot our first graph just for fun
import matplotlib.pyplot as plt
plt.plot(dd)
plt.show()
```

```
<Figure size 640x480 with 1 Axes>
```

In [26]:
```
#lets see how we convert from unix timestamp to python datetime then back to u
nix timestamp
from datetime import timezone
t=pd.to_datetime(1539259685,unit='s')   #Thursday, 11 October 2018 12:08:05
print(t)
print(t.timestamp())  #back to unix timestamp
```

```
2018-10-11 12:08:05
1539259685.0
```

Exercise 3

Load remote_v3.csv and set the datetime to index (firstly convert to python datetime) then plot the scatter plot. Then select only data from 2017-08-11 09:00:00 to 2017-08-11 23:00:00 and plot the scatter plot

In [27]:
```
import numpy as np
import pandas as pd
from datetime import timezone
dd=pd.read_csv('remote_v3.csv')
dd.head()
```

Out[27]:

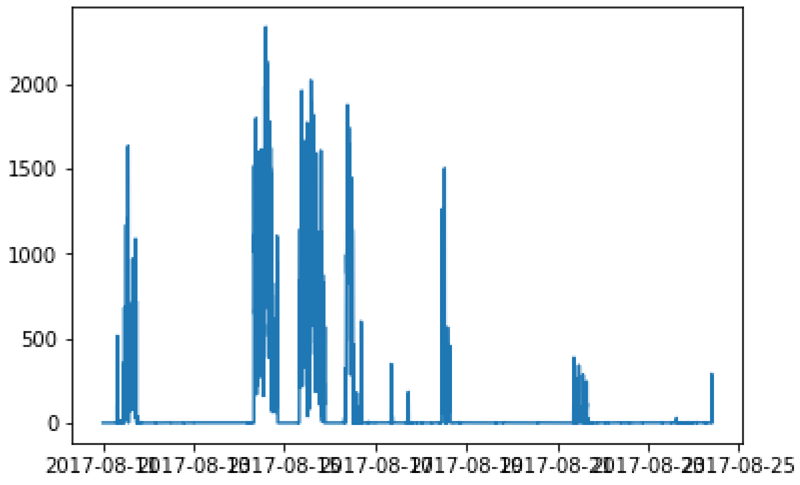
	time	value
0	2017-08-11 00:00:00+08:00	0.0
1	2017-08-11 00:03:00+08:00	0.0
2	2017-08-11 00:06:00+08:00	0.0
3	2017-08-11 00:09:00+08:00	0.0
4	2017-08-11 00:12:00+08:00	0.0

In [28]:
```
dd['time']=pd.to_datetime(dd['time'],format='%Y-%m-%d %H:%M:%S+08:00',utc=True
) #convert string to datetime
#tt=pd.to_datetime(dd['time'],format='%Y-%m-%d %H:%M:%S',utc=True) #convert st
ring to datetime
#dd['time']=(dd['time'].astype(np.int64)) /100000000   #convert to second
dd.set_index('time', inplace=True)
dd.head()
```

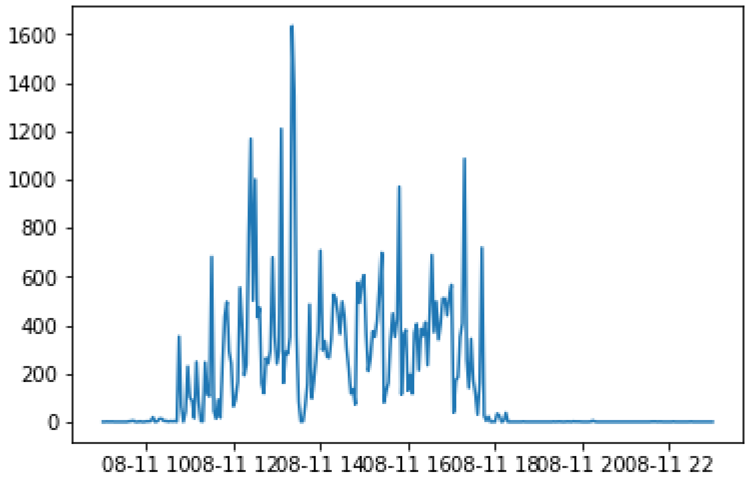
Out[28]:

	value
time	
2017-08-11 00:00:00+00:00	0.0
2017-08-11 00:03:00+00:00	0.0
2017-08-11 00:06:00+00:00	0.0
2017-08-11 00:09:00+00:00	0.0
2017-08-11 00:12:00+00:00	0.0

In [29]:
```
import matplotlib.pyplot as plt
plt.plot(dd)
plt.show()
```



In [30]:
```
aa= dd['2017-08-11 09:00:00':'2017-08-11 23:00:00']
plt.plot(aa)
plt.show()
```


1600
1400
1200
1000
800
600
400
200
0
08-11 10
08-11 12
08-11 14
08-11 16
08-11 18
08-11 20
08-11 22