Session 12: Tidy Data and Data Types

1. Converting Data Types

[1]:
```
import pandas as pd
df=pd.DataFrame([['3','NA'],['5','2'],['2','D']],columns=['A','B'])
df
```

	A	B
0	3	NA
1	5	2
2	2	D

[2]:
```
df.dtypes
```

```
A    object
B    object
dtype: object
```

[3]:
```
pd.to_numeric(df['A'])
```

```
0    3
1    5
2    2
Name: A, dtype: int64
```

[4]:
```
pd.to_numeric(df['B'],errors='ignore')
```

```
0    NA
1     2
2     D
Name: B, dtype: object
```

[5]:
```
pd.to_numeric(df['B'],errors='coeerce')
```

```
0    NaN
1    2.0
2    NaN
Name: B, dtype: float64
```

[6]:
```
df['A']=pd.to_numeric(df['A'],errors='cooerce')
df['B']=pd.to_numeric(df['B'],errors='cooerce')
df.dtypes
```

```
A      int64
B    float64
dtype: object
```

[7]:
```
df['B'].astype(str)
```

```
0    nan
1    2.0
2    nan
Name: B, dtype: object
```

```
[8]: df['B'].astype(str)[0]
```

```
'nan'
```

Q1: Create a `Series` object using the data from the following list, then convert it appropriately to numerical data and compute the sum.

```
l=['Not Available','3.2','5','']
```

Q2: Load in the "Marshall_Course_Enrollment_1516_1617.xlsx" file from the classroom schedulling dataset (available on Blackboard and used in session 10), and convert the "Course Suffix" column to numerical format. Then compute the proportion of course suffixes that are 500 or above.

2. Melting Data

```
[13]: raw=pd.DataFrame([['A',0,1],['B',3,2]],columns=['Person','X','Y'])
      raw
```

```
  Person  X  Y
0      A  0  1
1      B  3  2
```

```
[14]: raw.melt()
```

```
  variable value
0   Person     A
1   Person     B
2        X     0
3        X     3
4        Y     1
5        Y     2
```

```
[15]: raw.melt(id_vars='Person')
```

```
  Person variable  value
0      A        X      0
1      B        X      3
2      A        Y      1
3      B        Y      2
```

```
[16]: raw.melt(id_vars='Person',var_name='Item',value_name='Count')
```

```
  Person Item  Count
0      A    X      0
1      B    X      3
2      A    Y      1
3      B    Y      2
```

```
[17]: import pandas as pd
      base='https://raw.githubusercontent.com/chendaniely/pandas_for_everyone/master/data/'
      pew=pd.read_csv(base+'pew.csv')
      pew.iloc[:4,:5]
```

```
   religion  <$10k  $10-20k  $20-30k  $30-40k
0  Agnostic     27       34       60       81
1   Atheist     12       27       37       52
2  Buddhist     27       21       30       34
3  Catholic    418      617      732      670
```

Q3: Run the above code to download the Pew Research Center data on income and religion in the US, and create a DataFrame called "melted" which aggregates the income data into one variable, as shown below.

```
[19]: melted.head()
```

```
                religion income  count
0               Agnostic  <$10k     27
1                Atheist  <$10k     12
2               Buddhist  <$10k     27
3               Catholic  <$10k    418
4  Don't know/refused  <$10k     15
```

Melting the data as above allows you to more easily analyze the income data. For example, the following line plots a histogram of income for Hindus in the US.

```
[20]: melted.query('religion=="Hindu"').plot(x='income',y='count',kind='bar',legend=False)
```

3. Pivoting (Un-Melting) Data

```
[21]: raw2=raw.melt(id_vars='Person',var_name='Item',value_name='Count')
      raw2
```

```
  Person Item  Count
0      A    X      0
1      B    X      3
2      A    Y      1
3      B    Y      2
```

```
[22]: raw2.pivot(index='Person',columns='Item',values='Count')
```

```
Item    X  Y
Person
A       0  1
B       3  2
```

```
[23]: raw2.pivot(index='Person',columns='Item',values='Count').reset_index()
```

```
Item Person  X  Y
0         A  0  1
1         B  3  2
```

```
[24]: df=raw2.pivot(index='Person',columns='Item',values='Count').reset_index()
      df.columns.name=''
      df
```

```
  Person  X  Y
0      A  0  1
1      B  3  2
```

```
[25]: raw3=raw2.append({'Person':'A','Item':'X','Count':4},ignore_index=True)
      raw3
```

```
  Person Item  Count
0      A    X      0
1      B    X      3
2      A    Y      1
3      B    Y      2
4      A    X      4
```

```
[26]: raw3.pivot_table(index='Person',columns='Item',values='Count').reset_index()
```

```
Item Person  X  Y
0         A  2  1
1         B  3  2
```

```
[27]: raw3.pivot_table(index='Person',columns='Item',values='Count',aggfunc='sum')\
          .reset_index()
```

```
Item Person  X  Y
0         A  4  1
1         B  3  2
```

```
[28]: raw3.pivot_table(index='Person',columns='Item',values='Count',aggfunc='count')\
          .reset_index()
```

```
Item Person  X  Y
0         A  2  1
1         B  1  1
```

Q4: Apply the `pivot` function on the DataFrame named "melted" you created from Q3, and reset the index so as to get back the original DataFrame.

4. Illustrations of Tidying Data

4.1 Tidying Tabular Data

```
[30]: weather=pd.read_csv(base+'weather.csv').drop('id',axis=1)
      weather.iloc[:5,:7]
```

```
   year  month element  d1    d2    d3  d4
0  2010      1    tmax NaN   NaN   NaN NaN
1  2010      1    tmin NaN   NaN   NaN NaN
2  2010      2    tmax NaN  27.3  24.1 NaN
3  2010      2    tmin NaN  14.4  14.4 NaN
4  2010      3    tmax NaN   NaN   NaN NaN
```

```
[31]: melted=weather.melt(id_vars=['year','month','element']\
                              ,var_name='day',value_name='temperature')
      melted.head()
```

```
   year  month element day  temperature
0  2010      1    tmax  d1          NaN
1  2010      1    tmin  d1          NaN
2  2010      2    tmax  d1          NaN
3  2010      2    tmin  d1          NaN
4  2010      3    tmax  d1          NaN
```

```
[32]: pivoted=melted.pivot_table(index=['year','month','day'],columns='element'\
                                        ,values='temperature').reset_index()
      pivoted.head()
```

```
element  year  month  day  tmax  tmin
0        2010      1  d30  27.8  14.5
1        2010      2  d11  29.7  13.4
2        2010      2   d2  27.3  14.4
3        2010      2  d23  29.9  10.7
4        2010      2   d3  24.1  14.4
```

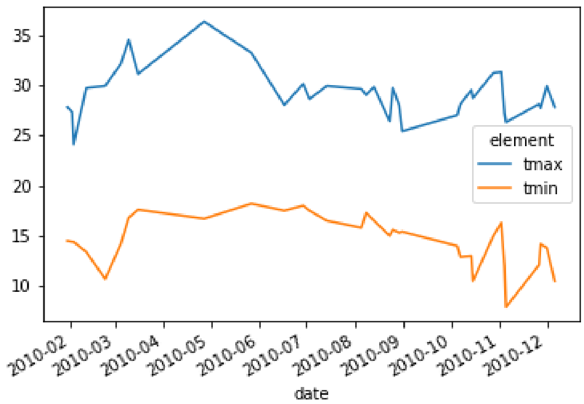
```
[33]: pivoted['day']=pivoted['day'].str.slice(1).astype(int)
      pivoted.head()
```

```
element  year  month  day  tmax  tmin
0        2010      1   30  27.8  14.5
1        2010      2   11  29.7  13.4
2        2010      2    2  27.3  14.4
3        2010      2   23  29.9  10.7
4        2010      2    3  24.1  14.4
```

```
[34]: pivoted['date']=pd.to_datetime(pivoted[['year','month','day']])
      pivoted=pivoted.set_index('date')
      pivoted.head()
```

```
element     year  month  day  tmax  tmin
date
2010-01-30  2010      1   30  27.8  14.5
2010-02-11  2010      2   11  29.7  13.4
2010-02-02  2010      2    2  27.3  14.4
2010-02-23  2010      2   23  29.9  10.7
2010-02-03  2010      2    3  24.1  14.4
```

```
[35]: pivoted[['tmax','tmin']].plot()
```



4.2 Tidying the Ebola Dataset

```
[36]: import pandas as pd
      base='https://raw.githubusercontent.com/chendaniely/pandas_for_everyone/master/data/'
      filename='country_timeseries.csv'
```

```
ebola=pd.read_csv(base+filename)
ebola['Date']=pd.to_datetime(ebola['Date'])
ebola.iloc[:5,:4]
```

```
        Date  Day  Cases_Guinea  Cases_Liberia
0 2015-01-05  289        2776.0            NaN
1 2015-01-04  288        2775.0            NaN
2 2015-01-03  287        2769.0         8166.0
3 2015-01-02  286           NaN         8157.0
4 2014-12-31  284        2730.0         8115.0
```

```
[37]: melted=ebola.melt(id_vars=['Day','Date'])
      melted.head()
```

```
   Day       Date      variable   value
0  289 2015-01-05  Cases_Guinea  2776.0
1  288 2015-01-04  Cases_Guinea  2775.0
2  287 2015-01-03  Cases_Guinea  2769.0
3  286 2015-01-02  Cases_Guinea     NaN
4  284 2014-12-31  Cases_Guinea  2730.0
```

```
[38]: splitted=melted['variable'].str.split('_',expand=True)
      splitted.head()
```

```
       0       1
0  Cases  Guinea
1  Cases  Guinea
2  Cases  Guinea
3  Cases  Guinea
4  Cases  Guinea
```

```
[39]: splitted.columns=['kind','country']
      melted2=pd.concat([melted,splitted],axis=1)
      melted2.head()
```

```
   Day       Date      variable   value   kind country
0  289 2015-01-05  Cases_Guinea  2776.0  Cases  Guinea
1  288 2015-01-04  Cases_Guinea  2775.0  Cases  Guinea
2  287 2015-01-03  Cases_Guinea  2769.0  Cases  Guinea
3  286 2015-01-02  Cases_Guinea     NaN  Cases  Guinea
4  284 2014-12-31  Cases_Guinea  2730.0  Cases  Guinea
```

```
[40]: ebola2=melted2.pivot_table(index=['Day','Date','country']\
                                  ,columns='kind',values='value').reset_index()
      ebola2.columns.name=''
      ebola2.head()
```

```
   Day       Date country  Cases  Deaths
0    0 2014-03-22  Guinea   49.0    29.0
1    2 2014-03-24  Guinea   86.0    59.0
2    3 2014-03-25  Guinea   86.0    60.0
3    4 2014-03-26  Guinea   86.0    62.0
4    5 2014-03-27  Guinea  103.0    66.0
```

```
[41]: ebola2.groupby('country')[['Cases','Deaths']].sum()\
          .sort_values(by='Cases',ascending=False)
```

```
                 Cases   Deaths
country
SierraLeone   211181.0  60352.0
Liberia       193833.0  89198.0
Guinea         84729.0  51818.0
Nigeria          636.0    233.0
UnitedStates      59.0     15.0
Mali              42.0     38.0
Senegal           27.0      0.0
Spain             16.0      3.0
```

```
[42]: ebola2.groupby('country')[['Cases','Deaths']].sum()\
          .sort_values(by='Cases',ascending=False)\
          .plot(kind='bar',subplots=True)
```