# PythonExercise 2 - Data Preprocessing in Python

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This document contains Python examples for data preprocessing. Data preprocessing consists of a broad set of techniques for cleaning, selecting, and transforming data to improve data mining analysis.

### 1. Data Quality Issues

#### 1.1. Loading the Wisconsin's breast cancer dataset

```
In [1]: import pandas as pd
         data = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/breast-cancer-wisconsin.data', header=None)
         data.columns = ['Sample code', 'Clump Thickness', 'Uniformity of Cell Size', 'Uniformity of Cell Shape',
                          'Marginal Adhesion', 'Single Epithelial Cell Size', 'Bare Nuclei', 'Bland Chromatin',
                          'Normal Nucleoli', 'Mitoses', 'Class']
         data = data.drop(['Sample code'],axis=1)
         print('Number of instances = %d' % (data.shape[0]))
         print('Number of attributes = %d' % (data.shape[1]))
         data.head()
         Number of instances = 699
        Number of attributes = 10
           Clump Thickness Uniformity of Cell Size Uniformity of Cell Shape Marginal Adhesion Single Epithelial Cell Size Bare Nuclei Bland Chromatin Normal Nucleoli Mitoses Class
                                                                                                         2
                                                                                                         2
                                                                 1
                                                                                                                    2
                                                                                                         3
                                                                                   3
                                                                                                         2
                                                                                                                                   3
```

#### 1.2. Missing Values

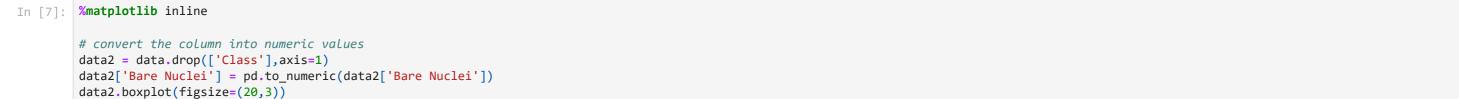
```
import numpy as np

# convert the missing values to NaNs
data = data.replace('?',np.NaN)

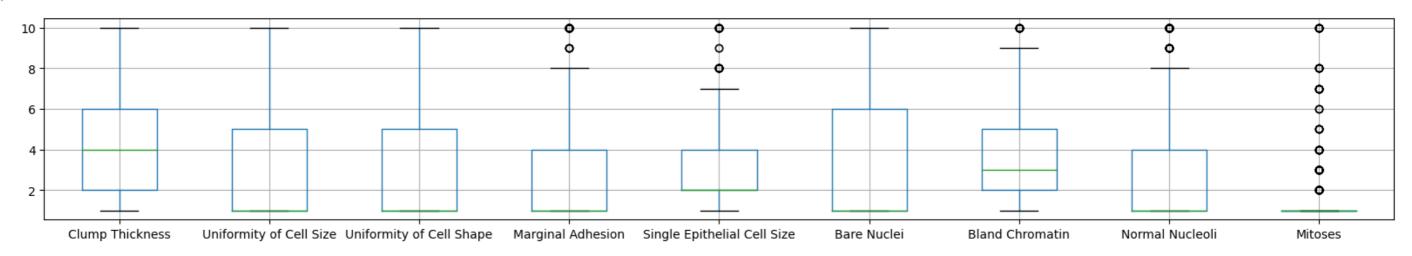
print('Number of instances = %d' % (data.shape[0]))
print('Number of attributes = %d' % (data.shape[1]))

# count the number of missing values in each column of the data
print('Number of missing values:')
for col in data.columns:
    print('\t%s: %d' % (col,data[col].isna().sum()))
```

```
Number of instances = 699
        Number of attributes = 10
        Number of missing values:
                Clump Thickness: 0
                Uniformity of Cell Size: 0
                Uniformity of Cell Shape: 0
                Marginal Adhesion: 0
                Single Epithelial Cell Size: 0
                Bare Nuclei: 16
                Bland Chromatin: 0
                Normal Nucleoli: 0
                Mitoses: 0
                Class: 0
In [5]: print('Number of rows in original data = %d' % (data.shape[0]))
        # discarding rows with missing values
        data2 = data.dropna()
        print('Number of rows after discarding missing values = %d' % (data2.shape[0]))
        Number of rows in original data = 699
        Number of rows after discarding missing values = 683
        1.3. Outliers
        # convert the column into numeric values
```



<Axes: > Out[7]:



```
In [8]: # standardizing the columns of the data
        Z = (data2-data2.mean())/data2.std()
        Z[20:25]
```

```
Clump Thickness Uniformity of Cell Size Uniformity of Cell Shape Marginal Adhesion Single Epithelial Cell Size Bare Nuclei Bland Chromatin Normal Nucleoli Mitoses
 Out[8]:
          20
                     0.917080
                                          -0.044070
                                                                 -0.406284
                                                                                    2.519152
                                                                                                           0.805662
                                                                                                                       1.771569
                                                                                                                                       0.640688
                                                                                                                                                       0.371049 1.405526
          21
                     1.982519
                                          0.611354
                                                                 0.603167
                                                                                   0.067638
                                                                                                           1.257272
                                                                                                                       0.948266
                                                                                                                                       1.460910
                                                                                                                                                       2.335921 -0.343666
          22
                     -0.503505
                                          -0.699494
                                                                 -0.742767
                                                                                   -0.632794
                                                                                                           -0.549168
                                                                                                                      -0.698341
                                                                                                                                       -0.589645
                                                                                                                                                       -0.611387 -0.343666
          23
                     1.272227
                                          0.283642
                                                                 0.603167
                                                                                   -0.632794
                                                                                                           -0.549168
                                                                                                                          NaN
                                                                                                                                       1.460910
                                                                                                                                                       0.043570 -0.343666
          24
                    -1.213798
                                          -0.699494
                                                                 -0.742767
                                                                                   -0.632794
                                                                                                           -0.549168
                                                                                                                      -0.698341
                                                                                                                                       -0.179534
                                                                                                                                                       -0.611387 -0.343666
 In [9]: print('Number of rows before discarding outliers = %d' % (Z.shape[0]))
          # discarding columns with Z > 3 or Z <= -3
          Z2 = Z.loc[((Z > -3).sum(axis=1)==9) & ((Z <= 3).sum(axis=1)==9),:]
          print('Number of rows after discarding missing values = %d' % (Z2.shape[0]))
          Number of rows before discarding outliers = 699
          Number of rows after discarding missing values = 632
          1.4. Duplicate Data
In [11]: # check for duplicate instances in the breast cancer dataset
```

```
In [11]: # check for duplicate instances in the breast cancer dataset
dups = data.duplicated()
print('Number of duplicate rows = %d' % (dups.sum()))
data.loc[[11,28]]
```

Number of duplicate rows = 236

Out[11]:

]:		Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
	11	2	1	1	1	2	1	2	1	1	2
	28	2	1	1	1	2	1	2	1	1	2

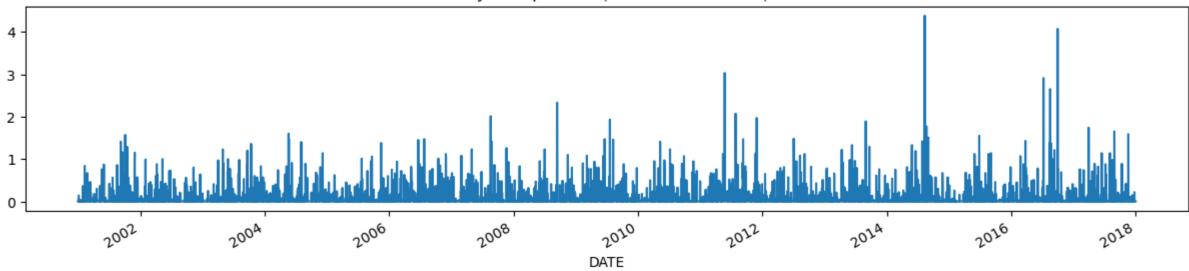
```
In [12]: print('Number of rows before discarding duplicates = %d' % (data.shape[0]))
# discarding duplicates
data2 = data.drop_duplicates()
print('Number of rows after discarding duplicates = %d' % (data2.shape[0]))
```

Number of rows before discarding duplicates = 699 Number of rows after discarding duplicates = 463

## 2. Aggregation

#### 2.1. Loading the precipitation time series data

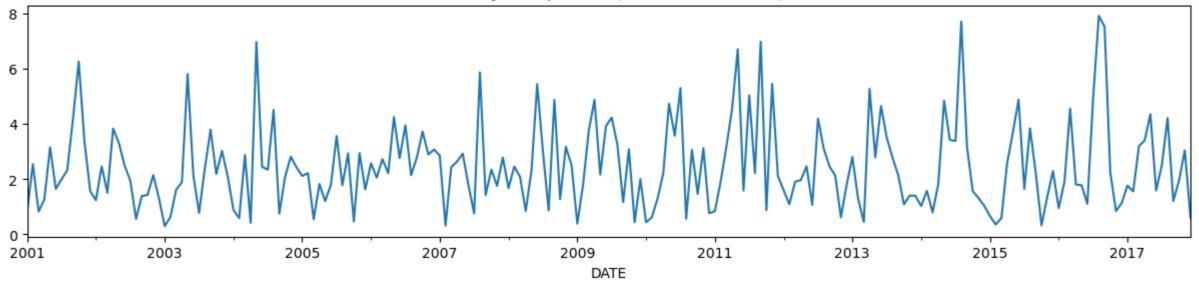
#### Daily Precipitation (variance = 0.0530)



```
In [14]: # The time series can be grouped and aggregated by month to obtain the total monthly precipitation values.
monthly = daily.groupby(pd.Grouper(freq='M')).sum()
ax = monthly.plot(kind='line',figsize=(15,3))
ax.set_title('Monthly Precipitation (variance = %.4f)' % (monthly.var()))
```

Out[14]: Text(0.5, 1.0, 'Monthly Precipitation (variance = 2.4241)')

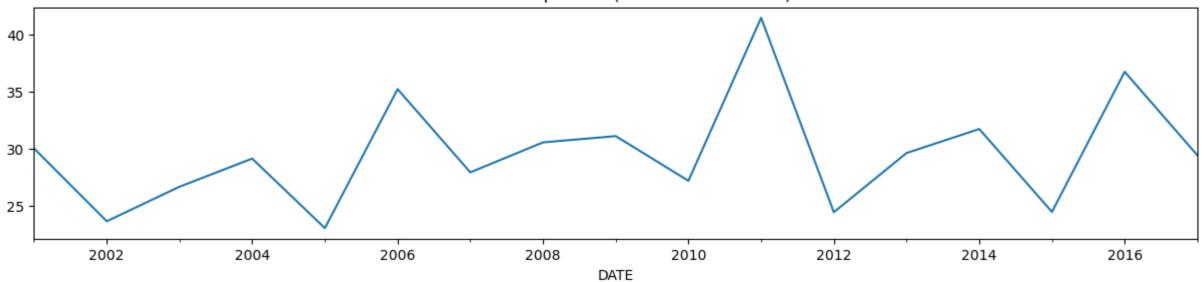
#### Monthly Precipitation (variance = 2.4241)



```
In [15]: # The daily precipitation time series are grouped and aggregated by year to obtain the annual precipitation values
annual = daily.groupby(pd.Grouper(freq='Y')).sum()
ax = annual.plot(kind='line',figsize=(15,3))
ax.set_title('Annual Precipitation (variance = %.4f)' % (annual.var()))
```

Out[15]: Text(0.5, 1.0, 'Annual Precipitation (variance = 23.6997)')

#### Annual Precipitation (variance = 23.6997)



## 3. Sampling

### 3.1. Loading the Wisconsin's breast cancer data

Out[20]:	!	Sample code	Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	<b>Bland Chromatin</b>	Normal Nucleoli	Mitoses	Class
	0	1000025	5	1	1	1	2	1	3	1	1	2
	1	1002945	5	4	4	5	7	10	3	2	1	2
	2	1015425	3	1	1	1	2	2	3	1	1	2
	3	1016277	6	8	8	1	3	4	3	7	1	2
	4	1017023	4	1	1	3	2	1	3	1	1	2

In [21]: # sample of size 3 is randomly selected (without replacement) from the original data
 sample = data.sample(n=3)
 sample

Out[21]:		Sample code	Clump Thickness	Uniformity of Cell Size	<b>Uniformity of Cell Shape</b>	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
	200	1214966	9	7	7	5	5	10	7	8	3	4
	651	1323477	1	2	1	3	2	1	2	1	1	2
	498	1204558	4	1	1	1	2	1	2	1	1	2

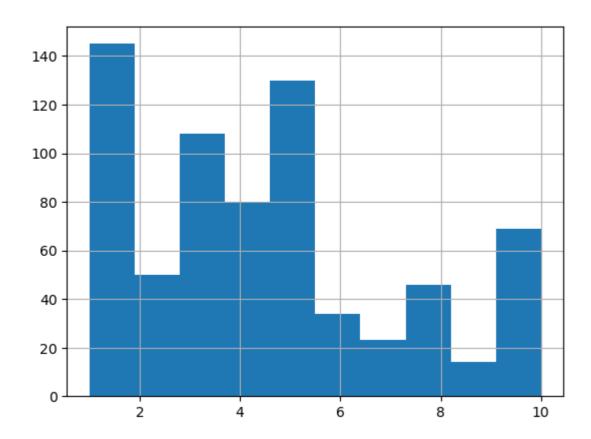
In [1]: # randomly select 1% of the data (without replacement) and display the selected samples
 sample = data.sample(frac=0.01, random\_state=1)
 sample

```
______
         NameError
                                                Traceback (most recent call last)
         Cell In[1], line 2
              1 # randomly select 1% of the data (without replacement) and display the selected samples
         ----> 2 sample = data.sample(frac=0.01, random_state=1)
              3 sample
         NameError: name 'data' is not defined
In [23]: # Perform a sampling with replacement to create a sample whose size is equal to 1% of the entire data
         sample = data.sample(frac=0.01, replace=True, random_state=1)
         sample
             Sample code Clump Thickness Uniformity of Cell Size Uniformity of Cell Shape Marginal Adhesion Single Epithelial Cell Size Bare Nuclei Bland Chromatin Normal Nucleoli Mitoses Class
Out[23]:
          37
                                   6
                                                     2
                 1081791
         235
                 1241232
          72
                                                     3
                                                                         3
                                                                                         2
                                                                                                             2
                1124651
                                   1
                 1303489
         645
                                   2
                                                                                                                                     2
         144
                1184241
                                                                                                             2
                                                                                                                                                              2
         129
                1177512
         583
                1115762
                                   3
                                                                                                             2
                                                                                                                                                             2
```

### 4. Discretization

```
In [24]: # we plot a histogram that shows the distribution of the attribute values
data['Clump Thickness'].hist(bins=10)
data['Clump Thickness'].value_counts(sort=False)
```

Name: Clump Thickness, dtype: int64



```
In [25]: # For the equal width method, we can apply the cut() function to discretize the attribute into 4 bins of similar interval widths
         bins = pd.cut(data['Clump Thickness'],4)
         bins.value_counts(sort=False)
         (0.991, 3.25] 303
Out[25]:
         (3.25, 5.5]
                          210
         (5.5, 7.75]
                           57
         (7.75, 10.0]
                         129
         Name: Clump Thickness, dtype: int64
In [26]: # For the equal frequency method, the qcut() function can be used to partition the values into 4 bins such that each bin has nearly the same number of instances
         bins = pd.qcut(data['Clump Thickness'],4)
         bins.value_counts(sort=False)
         (0.999, 2.0]
                        195
Out[26]:
                         188
         (2.0, 4.0]
```

## 5. Principal Component Analysis

164 152

Name: Clump Thickness, dtype: int64

(4.0, 6.0]

(6.0, 10.0]

```
In [27]: %matplotlib inline
    import matplotlib.pyplot as plt
    import matplotlib.image as mpimg
    import numpy as np

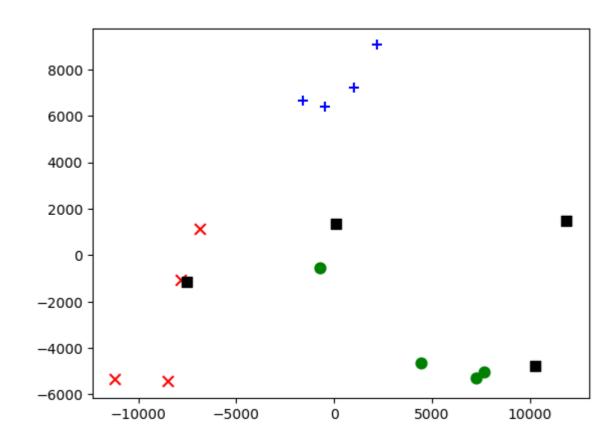
numImages = 16
    fig = plt.figure(figsize=(7,7))
    imgData = np.zeros(shape=(numImages,36963))

# application of PCA to an image dataset
    for i in range(1,numImages+1):
        filename = 'C:/Users/sanja/OneDrive/Desktop/University of Arizona Classes/INFO 523 - Data Mining/HW/r-python-exercise2-SanjaySiddi/data/pics/Picture'+str(i)+'.jpg'
        img = mpimg.imread(filename)
        ax = fig.add_subplot(4,4,i)
        plt.imshow(img)
```

```
plt.axis('off')
ax.set_title(str(i))
imgData[i-1] = np.array(img.flatten()).reshape(1,img.shape[0]*img.shape[1]*img.shape[2])
```



```
Out[28]:
                     pc1
                                  pc2
                                        food
           1 -1576.713362 6641.426119 burger
           2 -493.812166 6399.711927 burger
                990.090469 7235.264063 burger
           4 2189.876479 9049.733363 burger
           5 -7843.054234 -1063.209474
           6 -8498.431574 -5439.004991
                                        drink
           7 -11181.797285 -5318.605854
                                        drink
           8 -6851.914533 1126.243025
                                        drink
           9 7635.133058 -5044.118082
                                        pasta
          10
              -708.062499 -528.409960
                                        pasta
              7236.227159 -5301.416407
          11
                                        pasta
          12 4417.314542 -4658.923839
                                       pasta
          13 11864.519704 1473.193927 chicken
                 76.468728 1364.682872 chicken
          14
          15 -7505.665974 -1164.724404 chicken
          16 10249.821488 -4771.842285 chicken
In [29]: import matplotlib.pyplot as plt
          colors = {'burger':'b', 'drink':'r', 'pasta':'g', 'chicken':'k'}
          markerTypes = {'burger':'+', 'drink':'x', 'pasta':'o', 'chicken':'s'}
          # scatter plot to display the projected values
          for foodType in markerTypes:
              d = projected[projected['food']==foodType]
              plt.scatter(d['pc1'],d['pc2'],c=colors[foodType],s=60,marker=markerTypes[foodType])
```



In [ ]: