# 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

Number of instances = 699 Number of attributes = 10

Out[1]:		Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
	0	5	1	1	1	2	1	3	1	1	2
	1	5	4	4	5	7	10	3	2	1	2
	2	3	1	1	1	2	2	3	1	1	2
	3	6	8	8	1	3	4	3	7	1	2
	4	4	1	1	3	2	1	3	1	1	2

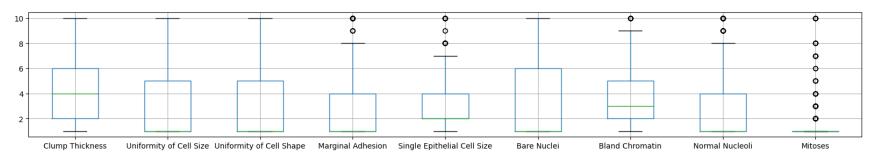
#### 1.2. Missing Values

# convert the column into numeric values
data2 = data.drop(['Class'],axis=1)

```
import numpy as np
In [2]:
        # 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 [3]: 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
In [4]: %matplotlib inline
```

```
data2['Bare Nuclei'] = pd.to_numeric(data2['Bare Nuclei'])
data2.boxplot(figsize=(20,3))
```

### Out[4]: <Axes: >



```
In [5]: # standardizing the columns of the data
Z = (data2-data2.mean())/data2.std()
Z[20:25]
```

Out[5]:		Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses
	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 [6]: 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]))</pre>
```

Number of rows before discarding outliers = 699 Number of rows after discarding missing values = 632

#### 1.4. Duplicate Data

```
In [7]: # 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[7]: Clump **Uniformity of Uniformity of** Marginal Single Epithelial **Bare Bland** Normal Mitoses Class **Thickness Cell Size Cell Shape** Adhesion **Cell Size** Nuclei Chromatin Nucleoli 2 11 2 1 1 2 2 28 2 2 1 1

```
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

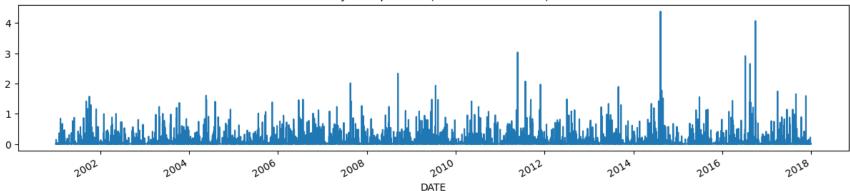
# 2. Aggregation

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

```
daily = pd.read csv('C:/Users/sanja/OneDrive/Desktop/University of Arizona Classes/INFO 523 - Data Mining/HW/r-python-e
In [9]:
        daily.index = pd.to datetime(daily['DATE'])
        daily = daily['PRCP']
        ax = daily.plot(kind='line',figsize=(15,3))
        ax.set title('Daily Precipitation (variance = %.4f)' % (daily.var()))
```

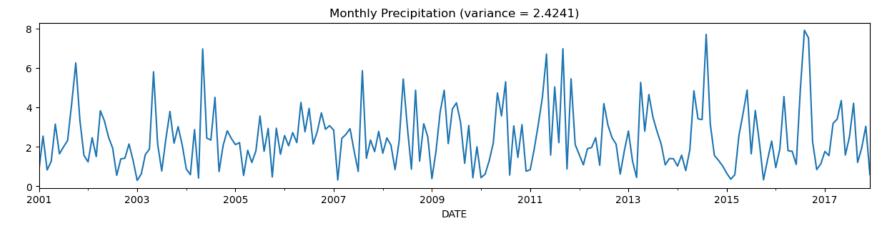
Text(0.5, 1.0, 'Daily Precipitation (variance = 0.0530)') Out[9]:

#### Daily Precipitation (variance = 0.0530)



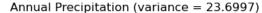
```
In [10]: # The time series can be grouped and aggregated by month to obtain the total monthly precipitation values.
monthly = daily.groupby(pd.Grouper(freq='M')).sum()
ax = monthly.plot(kind='line',figsize=(15,3))
ax.set_title('Monthly Precipitation (variance = %.4f)' % (monthly.var()))
```

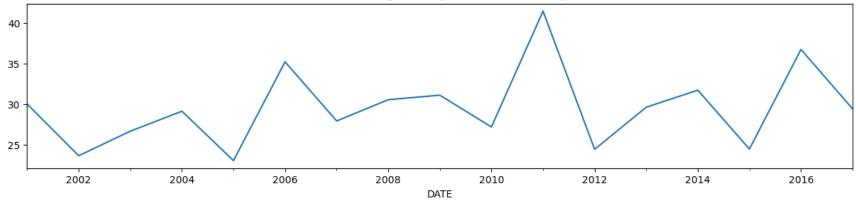
Out[10]: Text(0.5, 1.0, 'Monthly Precipitation (variance = 2.4241)')



```
In [11]: # 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[11]: Text(0.5, 1.0, 'Annual Precipitation (variance = 23.6997)')





# 3. Sampling

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

```
import pandas as pd
In [12]:
         data = pd.read csv('https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/breast-cancer-wis
         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.head()
```

Out[12]:		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
	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

```
# sample of size 3 is randomly selected (without replacement) from the original data
sample = data.sample(n=3)
sample
```

Out[13]:		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
	491	1119189	5	8	9	4	3	10	7	1	1	4
	589	1272166	5	1	1	1	2	1	1	1	1	2
	687	566346	3	1	1	1	2	1	2	3	1	2

In [14]: # randomly select 1% of the data (without replacement) and display the selected samples
 sample = data.sample(frac=0.01, random\_state=1)
 sample

ıt[14]:		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
	584	1217717	5	1	1	6	3	1	1	1	1	2
	417	1239967	1	1	1	1	2	1	2	1	1	2
	606	353098	4	1	1	2	2	1	1	1	1	2
	349	832567	4	2	3	5	3	8	7	6	1	4
	134	1180831	3	1	1	1	3	1	2	1	1	2
	502	1253917	4	1	1	2	2	1	2	1	1	2
	117	1173509	4	5	5	10	4	10	7	5	8	4

In [15]: # 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

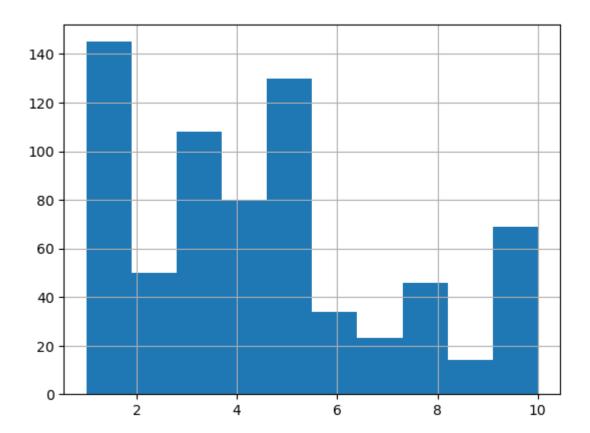
	Sample code	Clump Thickness	Uniformity of Cell Size	Uniformity of Cell Shape	Marginal Adhesion	Single Epithelial Cell Size	Bare Nuclei	Bland Chromatin	Normal Nucleoli	Mitoses	Class
37	1081791	6	2	1	1	1	1	7	1	1	2
235	1241232	3	1	4	1	2	?	3	1	1	2
72	1124651	1	3	3	2	2	1	7	2	1	2
645	1303489	3	1	1	1	2	1	2	1	1	2
144	1184241	2	1	1	1	2	1	2	1	1	2
129	1177512	1	1	1	1	10	1	1	1	1	2
	235 72 645 144	<ul> <li>code</li> <li>37 1081791</li> <li>235 1241232</li> <li>72 1124651</li> <li>645 1303489</li> <li>144 1184241</li> </ul>	code     Thickness       37     1081791     6       235     1241232     3       72     1124651     1       645     1303489     3       144     1184241     2	code         Thickness         Cell Size           37         1081791         6         2           235         1241232         3         1           72         1124651         1         3           645         1303489         3         1           144         1184241         2         1	code         Thickness         Cell Size         Cell Shape           37         1081791         6         2         1           235         1241232         3         1         4           72         1124651         1         3         3           645         1303489         3         1         1           144         1184241         2         1         1	code         Thickness         Cell Size         Cell Shape         Adhesion           37         1081791         6         2         1         1           235         1241232         3         1         4         1           72         1124651         1         3         3         2           645         1303489         3         1         1         1           144         1184241         2         1         1         1         1	Sample code         Clump Thickness         Uniformity of Cell Size         Uniformity of Cell Shape         Marginal Adhesion         Epithelial Cell Size           37         1081791         6         2         1         1         1           235         1241232         3         1         4         1         2           72         1124651         1         3         3         2         2           645         1303489         3         1         1         1         2           144         1184241         2         1         1         1         2	Sample code         Clump Thickness         Uniformity of Cell Size         Cell Shape         Marginal Adhesion         Epithelial Cell Size         Bare Nuclei           37         1081791         6         2         1         1         1         1           235         1241232         3         1         4         1         2         ?           72         1124651         1         3         3         2         2         1           645         1303489         3         1         1         1         2         1           144         1184241         2         1         1         1         2         1	Sample code         Clump Thickness         Cell Size         Uniformity of Cell Shape         Marginal Adhesion         Epithelial Cell Size         Bare Nuclei         Bland Chromatin           37         1081791         6         2         1         1         1         1         7           235         1241232         3         1         4         1         2         ?         3           72         1124651         1         3         3         2         2         1         7           645         1303489         3         1         1         1         2         1         2           144         1184241         2         1         1         1         2         1         2	Sample code         Clump Thickness         Uniformity of Cell Size         Marginal Adhesion         Epithelial Cell Size         Bare Nuclei         Bland Chromatin         Normal Nucleoli           37         1081791         6         2         1         1         1         1         7         1           235         1241232         3         1         4         1         2         ?         3         1           72         1124651         1         3         3         2         2         1         7         2           645         1303489         3         1         1         1         2         1         2         1           144         1184241         2         1         1         1         2         1         2         1	Sample code         Clump Thickness         Uniformity of Cell Size         Marginal Adhesion         Epithelial Cell Size         Bare Nuclei         Bland Chromatin         Normal Nucleoli           37         1081791         6         2         1         1         1         1         7         1         1           235         1241232         3         1         4         1         2         ?         3         1         1           72         1124651         1         3         3         2         2         1         7         2         1           645         1303489         3         1         1         1         2         1         2         1         2         1         1           144         1184241         2         1         1         1         2         1         2         1         1         1

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#### 4. Discretization

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```
In [16]: # 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)
               130
Out[16]:
               108
                34
                80
                46
         1
               145
                50
                23
         10
                69
                14
         Name: Clump Thickness, dtype: int64
```



```
In [17]: # For the equal width method, we can apply the cut() function to discretize the attribute into 4 bins of similar interv
bins = pd.cut(data['Clump Thickness'],4)
bins.value_counts(sort=False)
```

Out[17]: (0.991, 3.25] 303 (3.25, 5.5] 210 (5.5, 7.75] 57 (7.75, 10.0] 129

Name: Clump Thickness, dtype: int64

In [18]: # For the equal frequency method, the qcut() function can be used to partition the values into 4 bins such that each bi
bins = pd.qcut(data['Clump Thickness'],4)
bins.value\_counts(sort=False)

Out[18]: (0.999, 2.0] 195 (2.0, 4.0] 188 (4.0, 6.0] 164 (6.0, 10.0] 152 Name: Clump Thickness, dtype: int64

# 5. Principal Component Analysis

```
In [19]:
         %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-exerci
             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])
```



In [20]: import pandas as pd
from sklearn.decomposition import PCA

numComponents = 2
pca = PCA(n\_components=numComponents)
pca.fit(imgData)

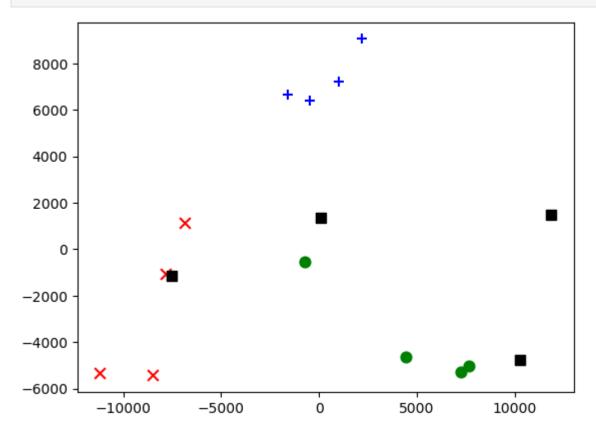
# Using PCA, the data matrix is projected to its first two principal components

#### Out[20]:

	pc1	pc2	food
1	-1576.637320	6641.099187	burger
2	-493.869833	6397.494042	burger
3	990.147898	7236.095006	burger
4	2189.875303	9051.220651	burger
5	-7842.906733	-1059.453103	drink
6	-8498.327622	-5437.391925	drink
7	-11181.806255	-5319.789127	drink
8	-6852.147014	1122.388582	drink
9	7635.242947	-5042.729453	pasta
10	-708.109660	-529.242327	pasta
11	7236.120687	-5302.947611	pasta
12	4417.242886	-4660.768445	pasta
13	11864.528182	1472.857851	chicken
14	76.508169	1366.710336	chicken
15	-7505.703721	-1164.681234	chicken
16	10249.842086	-4770.862430	chicken

# In [21]: 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 [ ]: