Data Cleaning

Missing Data

In [1]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import scipy as sp
import scipy.stats as stats
import math

import matplotlib.pyplot as plt # Required for plotting
np.random.seed(33)
```

In [2]:
```
incomplete_df = pd.DataFrame({'id': [1,2,3,2,2,3,1,1,1,2,4],
                              'type': ['one', 'one', 'two', np.nan, 'two', 'th
ree', 'one', 'two', 'one', 'three','one'],
                              'amount':
[345,928,np.NAN,645,113,942,np.NAN,539,np.NAN,814,np.NAN]
                             }, columns=['id','type','amount'])


incomplete_df
```

Out[2]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	NaN
3	2	NaN	645
4	2	two	113
5	3	three	942
6	1	one	NaN
7	1	two	539
8	1	one	NaN
9	2	three	814
10	4	one	NaN

Pandas Provides two functions to check if a cell is null -- is_null() / notnull()

Note they are inverses of each other

In [3]:
```
pd.isnull(incomplete_df)
```

Out[3]:

	id	type	amount
0	False	False	False
1	False	False	False
2	False	False	True
3	False	True	False
4	False	False	False
5	False	False	False
6	False	False	True
7	False	False	False
8	False	False	True
9	False	False	False
10	False	False	True

In [4]:
```
incomplete_df.notnull()
```

Out[4]:

	id	type	amount
0	True	True	True
1	True	True	True
2	True	True	False
3	True	False	True
4	True	True	True
5	True	True	True
6	True	True	False
7	True	True	True
8	True	True	False
9	True	True	True
10	True	True	False

They work on all pandas objects DataFrames and Series

In [5]:
```
pd.isnull(incomplete_df['amount'])
```

Out[5]:
```
0     False
1     False
2      True
3     False
4     False
5     False
6      True
7     False
8      True
9     False
10     True
Name: amount, dtype: bool
```

In [6]:
```
incomplete_df['amount'].notnull()
```

Out[6]:
```
0      True
1      True
2     False
3      True
4      True
5      True
6     False
7      True
8     False
9      True
10    False
Name: amount, dtype: bool
```

Operations with missing data

From the Pandas Documentation

-When summing data, NA (missing) values will be treated as zero
-If the data are all NA, the result will be NA
-Methods like cumsum and cumprod ignore NA values, but preserve them in the resulting arrays

In [7]:
```
print(incomplete_df['id'].mean())
print(incomplete_df['amount'].mean())
```

```
2.0
618.0
```

In [8]:
```
incomplete_df['amount'].cumsum()
```

Out[8]:
```
0      345
1     1273
2      NaN
3     1918
4     2031
5     2973
6      NaN
7     3512
8      NaN
9     4326
10     NaN
Name: amount, dtype: float64
```

Dealing with Missing Data

Drop it

In [9]:
```
incomplete_df
```

Out[9]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	NaN
3	2	NaN	645
4	2	two	113
5	3	three	942
6	1	one	NaN
7	1	two	539
8	1	one	NaN
9	2	three	814
10	4	one	NaN

Rows with any missing data

In [10]:
```
incomplete_df.dropna(axis=0)
```

Out[10]:

	id	type	amount
0	1	one	345
1	2	one	928
4	2	two	113
5	3	three	942
7	1	two	539
9	2	three	814

Columns with any missing data

In [11]:
```
incomplete_df.dropna(axis=1)
```

Out[11]:

	id
0	1
1	2
2	3
3	2
4	2
5	3
6	1
7	1
8	1
9	2
10	4

You can set a threshold for how many missing values is okay, however the sytax is odd, it's how many non-missing values you have. We can fix it with a little trick on the dataframe size

In [12]:
```
incomplete_df.dropna(axis=1,thresh=incomplete_df.shape[0]-1)
```

Out[12]:

	id	type
0	1	one
1	2	one
2	3	two
3	2	NaN
4	2	two
5	3	three
6	1	one
7	1	two
8	1	one
9	2	three
10	4	one

Pandas checks all columns, if we want to check only a single column we need to use our own function

In [13]:
```
incomplete_df[incomplete_df['amount'].notnull()==True]
```

Out[13]:

	id	type	amount
0	1	one	345
1	2	one	928
3	2	NaN	645
4	2	two	113
5	3	three	942
7	1	two	539
9	2	three	814

Filling Missing Data

Filling with Global Constant

In [14]:
```
incomplete_df.fillna(0)
```

Out[14]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	0
3	2	0	645
4	2	two	113
5	3	three	942
6	1	one	0
7	1	two	539
8	1	one	0
9	2	three	814
10	4	one	0

Filling with Column Statistics

In [15]:
```
incomplete_df.fillna(incomplete_df.mean())
```

Out[15]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	618
3	2	NaN	645
4	2	two	113
5	3	three	942
6	1	one	618
7	1	two	539
8	1	one	618
9	2	three	814
10	4	one	618

Any guesses why the Type column didn't fill?

In [16]:
```
#Be careful the fill can be with anything!
incomplete_df.fillna('MISSING')
```

Out[16]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	MISSING
3	2	MISSING	645
4	2	two	113
5	3	three	942
6	1	one	MISSING
7	1	two	539
8	1	one	MISSING
9	2	three	814
10	4	one	MISSING

You can also fill for specific columns

In [17]:
```
incomplete_df[['amount']].fillna(0)
```

Out[17]:

	amount
0	345
1	928
2	0
3	645
4	113
5	942
6	0
7	539
8	0
9	814
10	0

A little smarter, lets use the ID of the instance to fill it

NOTE! There is still a Missing Value as ID 4 only has 1 amount, which is missing, but it's a start

In [18]:
```
incomplete_df
```

Out[18]:

	id	type	amount
0	1	one	345
1	2	one	928
2	3	two	NaN
3	2	NaN	645
4	2	two	113
5	3	three	942
6	1	one	NaN
7	1	two	539
8	1	one	NaN
9	2	three	814
10	4	one	NaN

In [19]:
```
incomplete_df["amount"].fillna(incomplete_df.groupby("id")["amount"].mean())
```

Out[19]:
```
0     345
1     928
2     625
3     645
4     113
5     942
6     NaN
7     539
8     NaN
9     814
10    NaN
Name: amount, dtype: float64
```

In [20]:
```
incomplete_df.groupby("id")["amount"].mean()
```

Out[20]:
```
id
1    442
2    625
3    942
4    NaN
Name: amount, dtype: float64
```

Lets try some interpolation

Not quite regression filling (as it focuses on fitting the specific column, not the relation between columns, but along those lines

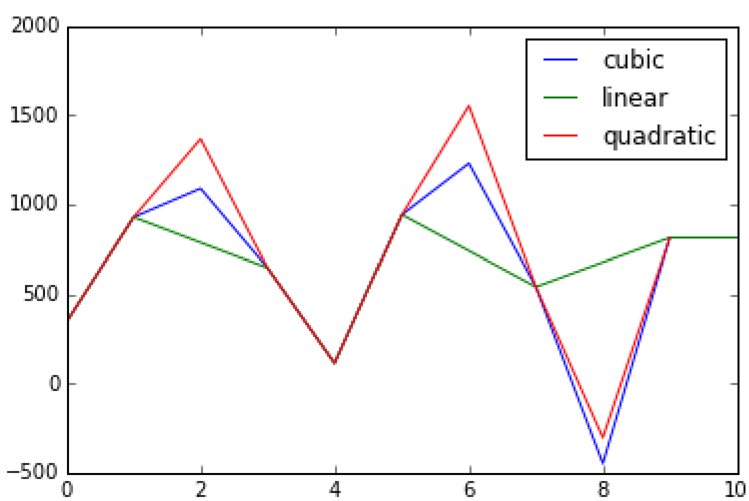
In [21]:
```
incomplete_df.interpolate()
```

Out[21]:

	id	type	amount
0	1	one	345.0
1	2	one	928.0
2	3	two	786.5
3	2	NaN	645.0
4	2	two	113.0
5	3	three	942.0
6	1	one	740.5
7	1	two	539.0
8	1	one	676.5
9	2	three	814.0
10	4	one	814.0

In [22]:
```
methods = ['linear', 'quadratic', 'cubic']
df = pd.DataFrame({m: incomplete_df['amount'].interpolate(method=m) for m in m
ethods})
df.plot()
```

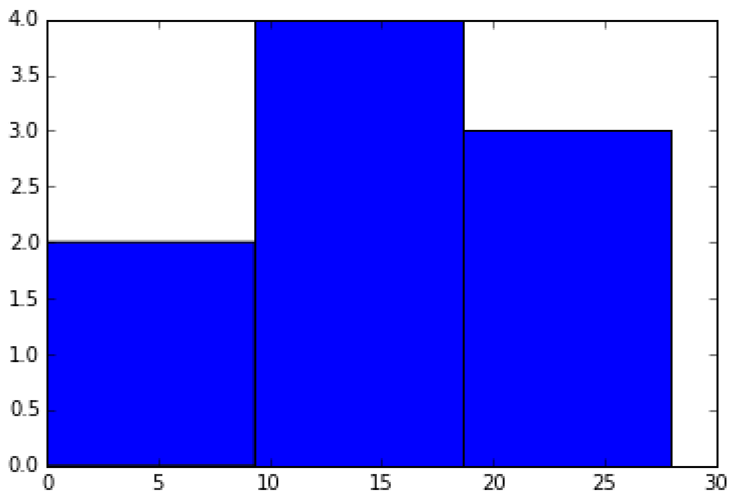
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe8b2043c90>



Binning

In [23]:
```
data = [0,4,12,16,16,18,24,26,28]
data = pd.DataFrame(data)
plt.hist(data[0],3)
```

Out[23]:
```
(array([ 2.,  4.,  3.]),
 array([  0.        ,   9.33333333,  18.66666667,  28.        ]),
 <a list of 3 Patch objects>)
```



In [24]:
```
data = [0,4,12,16,16,18,24,26,28]
num_bins = 3.0
w = (28-0)/num_bins

bin_ranges = []
current_val = np.min(data)
for i in xrange(0,int(num_bins)):
    bin_ranges.append((current_val,np.ceil(current_val+w)))
    current_val= np.ceil(current_val+w)

data = pd.DataFrame(data)
bin_ranges
```

Out[24]:
```
[(0, 10.0), (10.0, 20.0), (20.0, 30.0)]
```

In [25]:
```
for index,bin_range in enumerate(bin_ranges):
    data[(data[0]>=bin_range[0]) & (data[0]<bin_range[1])]=index

data
```

Out[25]:

	0
0	0
1	0
2	1
3	1
4	1
5	1
6	2
7	2
8	2

In [26]:
```
data = [0,4,12,16,16,18,24,26,28]

w = np.ceil(len(data)/3.0)

data = pd.DataFrame(data)
bin_ranges = []
current_val = 0
bin_val = 0
for i in data.iterrows():
    i[1][0]=bin_val
    current_val+=1
    if(current_val==w):
        bin_val+=1
        current_val=0

pd.concat([data,pd.DataFrame([0,4,12,16,16,18,24,26,28])],axis=1)
```

Out[26]:

	0	0
0	0	0
1	0	4
2	0	12
3	1	16
4	1	16
5	1	18
6	2	24
7	2	26
8	2	28

Outlier Detection

Statistical Methods

In [27]:
```
df=pd.DataFrame(np.random.normal(size=2000))
df.head()
```

Out[27]:

	0
0	-0.318854
1	-1.602981
2	-1.535218
3	-0.570401
4	-0.216728

In [28]:
```
df[np.abs(df[0]-df[0].mean())<=(3*df[0].std())] #keep only the ones that are w
ithin +3 to -3 standard deviations
```

Out[28]:

	0
0	-0.318854
1	-1.602981
2	-1.535218
3	-0.570401
4	-0.216728
5	0.254874
6	-0.149450
7	2.010783
8	-0.096784
9	0.422202
10	-0.225462
11	-0.637943
12	-0.016286
13	1.044217
14	-1.084880
15	-2.205925
16	-0.951219
17	0.832973
18	-1.000208
19	0.343463
20	1.546030
21	0.690081
22	-2.045853
23	0.334467
24	-0.641459
25	-0.222497
26	-1.230374
27	0.205848
28	0.821371
29	-0.493780
...	...
1970	0.232214

	0
1971	0.481052
1972	1.664419
1973	0.183759
1974	-1.483533
1975	-0.693506
1976	1.084030
1977	-2.452230
1978	-2.363002
1979	-0.562729
1980	1.003262
1981	0.931674
1982	1.482026
1983	-0.939460
1984	0.678064
1985	0.402213
1986	1.212572
1987	0.443469
1988	1.006570
1989	1.388796
1990	1.086052
1991	-1.209619
1992	-0.271168
1993	-0.653474
1994	-0.162643
1995	-0.144757
1996	1.403689
1997	0.528832
1998	-1.144815
1999	0.878984

1996 rows × 1 columns

In [29]:
```
q75, q25 = np.percentile(df[0], [75 ,25])
iqr = q75 - q25
1.5*iqr
```

Out[29]: 1.9751158056331399

Merging Data

Merging multiple data sources can easily cause missing data!

The Full tutorial on merging data can be found here [https://pandas.pydata.org/pandas-docs/stable/merging.html (https://pandas.pydata.org/pandas-docs/stable/merging.html)](https://pandas.pydata.org/pandas-docs/stable/merging.html)

In [30]:
```
 df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                        'B': ['B0', 'B1', 'B2', 'B3'],
                        'C': ['C0', 'C1', 'C2', 'C3'],
                        'D': ['D0', 'D1', 'D2', 'D3']},
                        index=[0, 1, 2, 3])

df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
                        'B': ['B4', 'B5', 'B6', 'B7'],
                        'C': ['C4', 'C5', 'C6', 'C7'],
                        'D': ['D4', 'D5', 'D6', 'D7']},
                         index=[4, 5, 6, 7])

df3 = pd.DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
                     'D': ['D2', 'D3', 'D6', 'D7'],
                     'F': ['F2', 'F3', 'F6', 'F7']},
                    index=[2, 3, 6, 7])
```

In [31]:
```
pd.concat([df1,df2],axis=1)
```

Out[31]:

	A	B	C	D	A	B	C	D
0	A0	B0	C0	D0	NaN	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN	NaN
2	A2	B2	C2	D2	NaN	NaN	NaN	NaN
3	A3	B3	C3	D3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	A4	B4	C4	D4
5	NaN	NaN	NaN	NaN	A5	B5	C5	D5
6	NaN	NaN	NaN	NaN	A6	B6	C6	D6
7	NaN	NaN	NaN	NaN	A7	B7	C7	D7

In [32]:
```
pd.concat([df1, df3], axis=1, join='inner')
```

Out[32]:

	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

In [33]:
```
pd.concat([df1, df3], axis=1, join_axes=[df1.index])
```

Out[33]:

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

In [34]:
```
data = (pd.DataFrame([(6, 20, 3), (5, 10, 3), (4, 5, 2), (3, 5, 2), (2, 5,
4)]))
data
```

Out[34]:

	0	1	2
0	6	20	3
1	5	10	3
2	4	5	2
3	3	5	2
4	2	5	4

In [35]:
```
data[~data.duplicated()]
```

Out[35]:

	0	1	2
0	6	20	3
1	5	10	3
2	4	5	2
3	3	5	2
4	2	5	4

In [36]:
```
data[~data.duplicated([2])]
```

Out[36]:

	0	1	2
0	6	20	3
2	4	5	2
4	2	5	4

In [37]:
```
data[~data.duplicated([1,2])]
```

Out[37]:

	0	1	2
0	6	20	3
1	5	10	3
2	4	5	2
4	2	5	4

Chi-Squared Analysis

In [38]:
```
from scipy.stats import chi2_contingency
obs = np.array([[250, 200], [50,1000]])
chi2,p,df,expected = chi2_contingency(obs)
expected
```

Out[38]:
```
array([[  90.,  360.],
       [ 210.,  840.]])
```

Covariance

In [39]:
```
data = (pd.DataFrame([(6, 20), (5, 10), (4, 14), (3, 5), (2, 5)]))
data
```

Out[39]:

	0	1
0	6	20
1	5	10
2	4	14
3	3	5
4	2	5

In [40]:
```
np.cov(data,rowvar=False,bias=True)[0][1]
```

Out[40]:
```
7.0
```