3030&7130ICT
Data Analytics

# Lab 01 – Data Processing with Python

## Table of Contents



# I. General information

All of your workshops and assignment need to be submitted to GitHub. Create a Github repository and fill the form https://forms.office.com/r/kE4f1eVasn


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## II. Data Input and Output

This notebook is the reference code for getting input and output, pandas can read a variety of file types using its pd.read_csv methods. Let's take a look at the most common data types:

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

### 1. CSV

#### CSV Input

```
In [25]: df = pd.read_csv('example.csv')
         df
```

Out[25]:

| | a | b | c | d |
|---|---|---|---|---|
| 0 | 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 | 7 |
| 2 | 8 | 9 | 10 | 11 |
| 3 | 12 | 13 | 14 | 15 |

#### CSV Output

```
In [24]: df.to_csv('example.csv',index=False)
```

## 2. Excel

Pandas can read and write excel files, keep in mind, this only imports data. Not formulas or images, having images or macros may cause this read_excel method to crash.

### Excel Input

In [35]:
```
pd.read_excel('Excel_Sample.xlsx',sheetname='Sheet1')
```

Out[35]:

| | a | b | c | d |
|---|---|---|---|---|
| 0 | 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 | 7 |
| 2 | 8 | 9 | 10 | 11 |
| 3 | 12 | 13 | 14 | 15 |

### Excel Output

In [33]:
```
df.to_excel('Excel_Sample.xlsx',sheet_name='Sheet1')
```

In [36]:
```
from sqlalchemy import create_engine
```

In [37]:
```
engine = create_engine('sqlite:///:memory:')
```

In [40]:
```
df.to_sql('data', engine)
```

In [42]:
```
sql_df = pd.read_sql('data',con=engine)
```

In [43]:
```
sql_df
```

Out[43]:

| | index | a | b | c | d |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 1 | 2 | 3 |
| 1 | 1 | 4 | 5 | 6 | 7 |
| 2 | 2 | 8 | 9 | 10 | 11 |
| 3 | 3 | 12 | 13 | 14 | 15 |

# III. Data Storage with Python

## 1. Pandas Introduction

Pandas is a Python library that makes handling tabular data easier. Since we're doing data science - this is something we'll use from time to time!

It's one of three libraries you'll encounter repeatedly in the field of data science:

### Pandas

Introduces "Data Frames" and "Series" that allow you to slice and dice rows and columns of information.

### NumPy

Usually you'll encounter "NumPy arrays", which are multi-dimensional array objects. It is easy to create a Pandas DataFrame from a NumPy array, and Pandas DataFrames can be cast as NumPy arrays. NumPy arrays are mainly important because of...

### Scikit_Learn

The machine learning library we'll use throughout this course is scikit_learn, or sklearn, and it generally takes NumPy arrays as its input.

So, a typical thing to do is to load, clean, and manipulate your input data using Pandas. Then convert your Pandas DataFrame into a NumPy array as it's being passed into some Scikit_Learn function. That conversion can often happen automatically.

Let's start by loading some comma-separated value data using Pandas into a DataFrame:

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

df = pd.read_csv("PastHires.csv")
df.head()
```

Out[1]:

| | Years Experience | Employed? | Previous employers | Level of Education | Top-tier school | Interned | Hired |
|---|---|---|---|---|---|---|---|
| **0** | 10 | Y | 4 | BS | N | N | Y |
| **1** | 0 | N | 0 | BS | Y | Y | Y |
| **2** | 7 | N | 6 | BS | N | N | N |
| **3** | 2 | Y | 1 | MS | Y | N | Y |
| **4** | 20 | N | 2 | PhD | Y | N | N |

head() is a handy way to visualize what you've loaded. You can pass it an integer to see some specific number of rows at the beginning of your DataFrame:

In [2]:
```
df.head(10)
```

Out[2]:

| | Years Experience | Employed? | Previous employers | Level of Education | Top-tier school | Interned | Hired |
|---|---|---|---|---|---|---|---|
| **0** | 10 | Y | 4 | BS | N | N | Y |
| **1** | 0 | N | 0 | BS | Y | Y | Y |
| **2** | 7 | N | 6 | BS | N | N | N |
| **3** | 2 | Y | 1 | MS | Y | N | Y |
| **4** | 20 | N | 2 | PhD | Y | N | N |
| **5** | 0 | N | 0 | PhD | Y | Y | Y |
| **6** | 5 | Y | 2 | MS | N | Y | Y |
| **7** | 3 | N | 1 | BS | N | Y | Y |
| **8** | 15 | Y | 5 | BS | N | N | Y |
| **9** | 0 | N | 0 | BS | N | N | N |

You can also view the end of your data with tail():

In [3]:
```
df.tail(4)
```

Out[3]:

| | Years Experience | Employed? | Previous employers | Level of Education | Top-tier school | Interned | Hired |
|---|---|---|---|---|---|---|---|
| **9** | 0 | N | 0 | BS | N | N | N |
| **10** | 1 | N | 1 | PhD | Y | N | N |
| **11** | 4 | Y | 1 | BS | N | Y | Y |
| **12** | 0 | N | 0 | PhD | Y | N | Y |

We often talk about the "shape" of your DataFrame. This is just its dimensions. This particular CSV file has 13 rows with 7 columns per row:

In [4]:
```
df.shape
```

Out[4]: (13, 7)

The total size of the data frame is the rows * columns:

In [5]:
```
df.size
```

Out[5]: 91

The len() function gives you the number of rows in a DataFrame:

In [6]:
```
len(df)
```

Out[6]: 13

If your DataFrame has named columns (in our case, extracted automatically from the first row of a .csv file,) you can get an array of them back:

In [7]:
```
df.columns
```

Out[7]:
```
Index(['Years Experience', 'Employed?', 'Previous employers',
       'Level of Education', 'Top-tier school', 'Interned', 'Hired'],
      dtype='object')
```

Extracting a single column from your DataFrame looks like this - this gives you back a "Series" in Pandas:

In [8]:
```
df['Hired']
```

Out[8]:
```
0     Y
1     Y
2     N
3     Y
4     N
5     Y
6     Y
7     Y
8     Y
9     N
10    N
11    Y
12    Y
Name: Hired, dtype: object
```

You can also extract a given range of rows from a named column, like so:

In [9]:
```
df['Hired'][:5]
```

Out[9]:
```
0    Y
1    Y
2    N
3    Y
4    N
Name: Hired, dtype: object
```

Or even extract a single value from a specified column / row combination:

In [10]:
```
df['Hired'][5]
```

Out[10]:
```
'Y'
```

To extract more than one column, you pass in a list of column names instead of a single one:

In [11]:
```
df[['Years Experience', 'Hired']]
```

Out[11]:

| | Years Experience | Hired |
|---|---|---|
| **0** | 10 | Y |
| **1** | 0 | Y |
| **2** | 7 | N |
| **3** | 2 | Y |
| **4** | 20 | N |
| **5** | 0 | Y |
| **6** | 5 | Y |
| **7** | 3 | Y |
| **8** | 15 | Y |
| **9** | 0 | N |
| **10** | 1 | N |
| **11** | 4 | Y |
| **12** | 0 | Y |

You can also extract specific ranges of rows from more than one column, in the way you'd expect:

In [12]:
```
df[['Years Experience', 'Hired']][:5]
```

Out[12]:

| | Years Experience | Hired |
|---|---|---|
| **0** | 10 | Y |
| **1** | 0 | Y |
| **2** | 7 | N |
| **3** | 2 | Y |
| **4** | 20 | N |

Sorting your DataFrame by a specific column looks like this:

In [13]:
```
df.sort_values(['Years Experience'])
```
Out[13]:

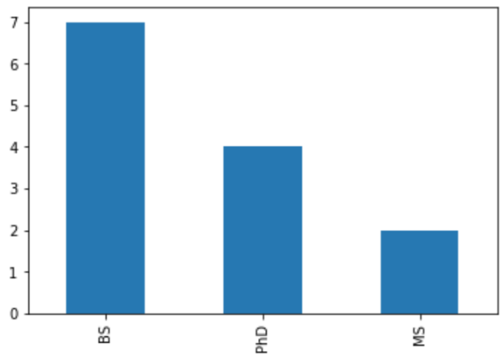
| | Years Experience | Employed? | Previous employers | Level of Education | Top-tier school | Interned | Hired |
|---|---|---|---|---|---|---|---|
| **1** | 0 | N | 0 | BS | Y | Y | Y |
| **5** | 0 | N | 0 | PhD | Y | Y | Y |
| **9** | 0 | N | 0 | BS | N | N | N |
| **12** | 0 | N | 0 | PhD | Y | N | Y |
| **10** | 1 | N | 1 | PhD | Y | N | N |
| **3** | 2 | Y | 1 | MS | Y | N | Y |
| **7** | 3 | N | 1 | BS | N | Y | Y |
| **11** | 4 | Y | 1 | BS | N | Y | Y |
| **6** | 5 | Y | 2 | MS | N | Y | Y |
| **2** | 7 | N | 6 | BS | N | N | N |
| **0** | 10 | Y | 4 | BS | N | N | Y |
| **8** | 15 | Y | 5 | BS | N | N | Y |
| **4** | 20 | N | 2 | PhD | Y | N | N |

You can break down the number of unique values in a given column into a Series using value_counts() - this is a good way to understand the distribution of your data:

In [14]:
```
degree_counts = df['Level of Education'].value_counts()
degree_counts
```
Out[14]:
```
BS      7
PhD     4
MS      2
Name: Level of Education, dtype: int64
```

Pandas even makes it easy to plot a Series or DataFrame - just call plot():

In [15]:
```
degree_counts.plot(kind='bar')
```
Out[15]: `<matplotlib.axes._subplots.AxesSubplot at 0x28f6d2b0240>`




## 2. Series

The first main data type we will learn about for pandas is the Series data type. Let's import Pandas and explore the Series object.

A Series is very similar to a NumPy array (in fact it is built on top of the NumPy array object). What differentiates the NumPy array from a Series, is that a Series can have axis labels, meaning it can be indexed by a label, instead of just a number location. It also doesn't need to hold numeric data, it can hold any arbitrary Python Object.

Let's explore this concept through some examples:

In [2]:
```
import numpy as np
import pandas as pd
```

**a. Creating a Series**

You can convert a list,numpy array, or dictionary to a Series:

```
In [3]: labels = ['a','b','c']
        my_list = [10,20,30]
        arr = np.array([10,20,30])
        d = {'a':10,'b':20,'c':30}
```

Using Lists

```
In [4]: pd.Series(data=my_list)

Out[4]: 0    10
        1    20
        2    30
        dtype: int64

In [5]: pd.Series(data=my_list,index=labels)

Out[5]: a    10
        b    20
        c    30
        dtype: int64

In [6]: pd.Series(my_list,labels)

Out[6]: a    10
        b    20
        c    30
        dtype: int64
```

NumPy Arrays

```
In [7]: pd.Series(arr)

Out[7]: 0    10
        1    20
        2    30
        dtype: int64

In [8]: pd.Series(arr,labels)

Out[8]: a    10
        b    20
        c    30
        dtype: int64
```

Dictionary

```
In [9]: pd.Series(d)

Out[9]: a    10
        b    20
        c    30
        dtype: int64
```

**b. Data in Series**

A pandas Series can hold a variety of object types:

```
In [10]: pd.Series(data=labels)

Out[10]: 0    a
         1    b
         2    c
         dtype: object

In [11]: # Even functions (although unlikely that you will use this)
         pd.Series([sum,print,len])

Out[11]: 0      <built-in function sum>
         1    <built-in function print>
         2      <built-in function len>
         dtype: object
```

**c. Using an index**

The key to using a Series is understanding its index. Pandas makes use of these index names or numbers by allowing for fast look ups of information (works like a hash table or dictionary). Let's see some examples of how to grab information from a Series. Let us create two sereis, ser1 and ser2:

```
In [12]: ser1 = pd.Series([1,2,3,4],index = ['USA', 'Germany','USSR', 'Japan'])

In [13]: ser1

Out[13]: USA        1
         Germany    2
         USSR       3
         Japan      4
         dtype: int64

In [14]: ser2 = pd.Series([1,2,5,4],index = ['USA', 'Germany','Italy', 'Japan'])

In [15]: ser2

Out[15]: USA        1
         Germany    2
         Italy      5
         Japan      4
         dtype: int64

In [16]: ser1['USA']

Out[16]: 1
```

Operations are then also done based off of index:

```
In [17]: ser1 + ser2

Out[17]: Germany    4.0
         Italy      NaN
         Japan      8.0
         USA        2.0
         USSR       NaN
         dtype: float64
```

Let's stop here for now and move on to DataFrames, which will expand on the concept of Series!

## 3. DataFrames

DataFrames are the workhorse of pandas and are directly inspired by the R programming language. We can think of a DataFrame as a bunch of Series objects put together to share the same index. Let's use pandas to explore this topic!

```
In [183]: import pandas as pd
          import numpy as np

In [184]: from numpy.random import randn
          np.random.seed(101)

In [185]: df = pd.DataFrame(randn(5,4),index='A B C D E'.split(),columns='W X Y Z'.split())

In [186]: df

Out[186]:
```

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

**a. Selection and Indexing**

Let's learn the various methods to grab data from a DataFrame

In [187]:
```
df['W']
```

Out[187]:
```
A    2.706850
B    0.651118
C   -2.018168
D    0.188695
E    0.190794
Name: W, dtype: float64
```

In [188]:
```
# Pass a list of column names
df[['W','Z']]
```

Out[188]:

| | W | Z |
|---|---|---|
| A | 2.706850 | 0.503826 |
| B | 0.651118 | 0.605965 |
| C | -2.018168 | -0.589001 |
| D | 0.188695 | 0.955057 |
| E | 0.190794 | 0.683509 |

In [189]:
```
# SQL Syntax (NOT RECOMMENDED!)
df.W
```

Out[189]:
```
A    2.706850
B    0.651118
C   -2.018168
D    0.188695
E    0.190794
Name: W, dtype: float64
```

## DataFrame Columns are just Series

In [190]:
```
type(df['W'])
```

Out[190]:
```
pandas.core.series.Series
```

## Creating a new column:

In [191]:
```
df['new'] = df['W'] + df['Y']
```

In [192]:
```
df
```

Out[192]:

| | W | X | Y | Z | new |
|---|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 | 3.614819 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 | -0.196959 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 | -1.489355 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 | -0.744542 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 | 2.796762 |

## Removing Columns

In [193]:
```
# Return a new DataFrame with the 'new'
# column dropped
df.drop('new',axis=1)
```

Out[193]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [194]:
```
# Not inplace unless specified!
df
```

Out[194]:

| | W | X | Y | Z | new |
|---|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 | 3.614819 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 | -0.196959 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 | -1.489355 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 | -0.744542 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 | 2.796762 |

In [195]:
```
# Drop the 'new' column of DataFrame itself
df.drop('new',axis=1,inplace=True)
```

In [196]:
```
df
```

Out[196]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

Can also drop rows this way:

In [197]:
```
df.drop('E',axis=0)
```

Out[197]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |


Can also drop rows this way:

In [197]:
```
df.drop('E',axis=0)
```

Out[197]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |


Selecting Rows

In [198]:
```
df.loc['A']
```

Out[198]:
```
W    2.706850
X    0.628133
Y    0.907969
Z    0.503826
Name: A, dtype: float64
```

Or select based off of position instead of label

In [199]:
```
df.iloc[2]
```

Out[199]:
```
W   -2.018168
X    0.740122
Y    0.528813
Z   -0.589001
Name: C, dtype: float64
```

Selecting subset of rows and columns

In [200]:
```
df.loc['B','Y']
```

Out[200]:
```
-0.84807698340363147
```

In [201]:
```
df.loc[['A','B'],['W','Y']]
```

Out[201]:

| | W | Y |
|---|---|---|
| A | 2.706850 | 0.907969 |
| B | 0.651118 | -0.848077 |

**b. Conditional Selection**

An important feature of pandas is conditional selection using bracket notation, very similar to numpy:

In [202]:
```
df
```

Out[202]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [203]:
```
df>0
```

Out[203]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | True | True | True | True |
| B | True | False | False | True |
| C | False | True | True | False |
| D | True | False | False | True |
| E | True | True | True | True |

In [204]:
```
df[df>0]
```

Out[204]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | NaN | NaN | 0.605965 |
| C | NaN | 0.740122 | 0.528813 | NaN |
| D | 0.188695 | NaN | NaN | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [205]:
```
df[df['W']>0]
```

Out[205]:

| | W | X | Y | Z |
|---|---|---|---|---|
| A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [206]:
```
df[df['W']>0]['Y']
```

Out[206]:
```
A    0.907969
B   -0.848077
D   -0.933237
E    2.605967
Name: Y, dtype: float64
```

In [207]:
```
df[df['W']>0][['Y','X']]
```

Out[207]:

| | Y | X |
|---|---|---|
| A | 0.907969 | 0.628133 |
| B | -0.848077 | -0.319318 |
| D | -0.933237 | -0.758872 |
| E | 2.605967 | 1.978757 |

For two conditions you can use | and & with parenthesis:

In [208]:
```
df[(df['W']>0) & (df['Y'] > 1)]
```

Out[208]:

| | W | X | Y | Z |
|---|---|---|---|---|
| E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

**c. More Index Details**

Let's discuss some more features of indexing, including resetting the index or setting it something else. We'll also talk about index hierarchy!

In [209]:
```
df
```

Out[209]:

| | W | X | Y | Z |
|---|---|---|---|---|
| **A** | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| **B** | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| **C** | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| **D** | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| **E** | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [210]:
```
# Reset to default 0,1...n index
df.reset_index()
```

Out[210]:

| | index | W | X | Y | Z |
|---|---|---|---|---|---|
| **0** | A | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| **1** | B | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| **2** | C | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| **3** | D | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| **4** | E | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [211]:
```
newind = 'CA NY WY OR CO'.split()
```

In [212]:
```
df['States'] = newind
```

In [213]:
```
df
```

Out[213]:

| | W | X | Y | Z | States |
|---|---|---|---|---|---|
| **A** | 2.706850 | 0.628133 | 0.907969 | 0.503826 | CA |
| **B** | 0.651118 | -0.319318 | -0.848077 | 0.605965 | NY |
| **C** | -2.018168 | 0.740122 | 0.528813 | -0.589001 | WY |
| **D** | 0.188695 | -0.758872 | -0.933237 | 0.955057 | OR |
| **E** | 0.190794 | 1.978757 | 2.605967 | 0.683509 | CO |

In [214]:
```
df.set_index('States')
```

Out[214]:

| | W | X | Y | Z |
|---|---|---|---|---|
| **States** | | | | |
| **CA** | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| **NY** | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| **WY** | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| **OR** | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| **CO** | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

In [215]:
```
df
```

Out[215]:

| | W | X | Y | Z | States |
|---|---|---|---|---|---|
| **A** | 2.706850 | 0.628133 | 0.907969 | 0.503826 | CA |
| **B** | 0.651118 | -0.319318 | -0.848077 | 0.605965 | NY |
| **C** | -2.018168 | 0.740122 | 0.528813 | -0.589001 | WY |
| **D** | 0.188695 | -0.758872 | -0.933237 | 0.955057 | OR |
| **E** | 0.190794 | 1.978757 | 2.605967 | 0.683509 | CO |

In [216]:
```
df.set_index('States',inplace=True)
```

In [218]:
```
df
```

Out[218]:

| | W | X | Y | Z |
|---|---|---|---|---|
| **States** | | | | |
| **CA** | 2.706850 | 0.628133 | 0.907969 | 0.503826 |
| **NY** | 0.651118 | -0.319318 | -0.848077 | 0.605965 |
| **WY** | -2.018168 | 0.740122 | 0.528813 | -0.589001 |
| **OR** | 0.188695 | -0.758872 | -0.933237 | 0.955057 |
| **CO** | 0.190794 | 1.978757 | 2.605967 | 0.683509 |

**d. Multi-Index and Index Hierarchy**

Let us go over how to work with Multi-Index, first we'll create a quick example of what a Multi-Indexed DataFrame would look like:

In [253]:
```
# Index Levels
outside = ['G1','G1','G1','G2','G2','G2']
inside = [1,2,3,1,2,3]
hier_index = list(zip(outside,inside))
hier_index = pd.MultiIndex.from_tuples(hier_index)
```

In [254]:
```
hier_index
```

Out[254]:
```
MultiIndex(levels=[['G1', 'G2'], [1, 2, 3]],
           labels=[[0, 0, 0, 1, 1, 1], [0, 1, 2, 0, 1, 2]])
```


Out[254]:
```
MultiIndex(levels=[['G1', 'G2'], [1, 2, 3]],
           labels=[[0, 0, 0, 1, 1, 1], [0, 1, 2, 0, 1, 2]])
```


In [257]:
```
df = pd.DataFrame(np.random.randn(6,2),index=hier_index,columns=['A','B'])
df
```

Out[257]:

| | | A | B |
|---|---|---|---|
| G1 | 1 | 0.153661 | 0.167638 |
| | 2 | -0.765930 | 0.962299 |
| | 3 | 0.902826 | -0.537909 |
| G2 | 1 | -1.549671 | 0.435253 |
| | 2 | 1.259904 | -0.447898 |
| | 3 | 0.266207 | 0.412580 |

Now let's show how to index this! For index hierarchy we use df.loc[], if this was on the columns axis, you would just use normal bracket notation df[]. Calling one level of the index returns the sub-dataframe:

In [260]:
```
df.loc['G1']
```

Out[260]:

| | A | B |
|---|---|---|
| 1 | 0.153661 | 0.167638 |
| 2 | -0.765930 | 0.962299 |
| 3 | 0.902826 | -0.537909 |

In [263]:
```
df.loc['G1'].loc[1]
```

Out[263]:
```
A    0.153661
B    0.167638
Name: 1, dtype: float64
```

In [265]:
```
df.index.names
```

Out[265]:
```
FrozenList([None, None])
```

In [266]:
```
df.index.names = ['Group','Num']
```

In [267]:
```
df
```

Out[267]:

| Group | Num | A | B |
|---|---|---|---|
| G1 | 1 | 0.153661 | 0.167638 |
| | 2 | -0.765930 | 0.962299 |
| | 3 | 0.902826 | -0.537909 |
| G2 | 1 | -1.549671 | 0.435253 |
| | 2 | 1.259904 | -0.447898 |
| | 3 | 0.266207 | 0.412580 |

In [270]:
```
df.xs('G1')
```

Out[270]:

| Num | A | B |
|---|---|---|
| 1 | 0.153661 | 0.167638 |
| 2 | -0.765930 | 0.962299 |
| 3 | 0.902826 | -0.537909 |

In [271]:
```
df.xs(['G1',1])
```
Out[271]:
```
A    0.153661
B    0.167638
Name: (G1, 1), dtype: float64
```

In [273]:
```
df.xs(1,level='Num')
```
Out[273]:

| Group | A | B |
|---|---|---|
| G1 | 0.153661 | 0.167638 |
| G2 | -1.549671 | 0.435253 |

# IV. Data Cleaning with Python

## 1. Missing Data

Let's show a few convenient methods to deal with Missing Data in pandas:

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

In [9]:
```
df = pd.DataFrame({'A':[1,2,np.nan],
                   'B':[5,np.nan,np.nan],
                   'C':[1,2,3]})
```

In [10]:
```
df
```
Out[10]:

| | A | B | C |
|---|---|---|---|
| 0 | 1.0 | 5.0 | 1 |
| 1 | 2.0 | NaN | 2 |
| 2 | NaN | NaN | 3 |

In [12]:
```
df.dropna()
```
Out[12]:

| | A | B | C |
|---|---|---|---|
| 0 | 1.0 | 5.0 | 1 |

In [13]:
```
df.dropna(axis=1)
```
Out[13]:

| | C |
|---|---|
| 0 | 1 |
| 1 | 2 |
| 2 | 3 |

In [14]:
```
df.dropna(thresh=2)
```
Out[14]:

| | A | B | C |
|---|---|---|---|
| 0 | 1.0 | 5.0 | 1 |
| 1 | 2.0 | NaN | 2 |

In [15]:
```
df.fillna(value='FILL VALUE')
```
Out[15]:

| | A | B | C |
|---|---|---|---|
| 0 | 1 | 5 | 1 |
| 1 | 2 | FILL VALUE | 2 |
| 2 | FILL VALUE | FILL VALUE | 3 |

In [17]:
```
df['A'].fillna(value=df['A'].mean())
```
Out[17]:
```
0    1.0
1    2.0
2    1.5
Name: A, dtype: float64
```

## 2. GroupBy

The groupby method allows you to group rows of data together and call aggregate functions

In [31]:
```
import pandas as pd
# Create dataframe
data = {'Company':['GOOG','GOOG','MSFT','MSFT','FB','FB'],
       'Person':['Sam','Charlie','Amy','Vanessa','Carl','Sarah'],
       'Sales':[200,120,340,124,243,350]}
```

In [32]:
```
df = pd.DataFrame(data)
```

In [33]:
```
df
```

Out[33]:

| | Company | Person | Sales |
|---|---|---|---|
| 0 | GOOG | Sam | 200 |
| 1 | GOOG | Charlie | 120 |
| 2 | MSFT | Amy | 340 |
| 3 | MSFT | Vanessa | 124 |
| 4 | FB | Carl | 243 |
| 5 | FB | Sarah | 350 |

Now you can use the .groupby() method to group rows together based off of a column name. For instance let's group based off of Company. This will create a DataFrameGroupBy object:

In [34]:
```
df.groupby('Company')
```

Out[34]: <pandas.core.groupby.DataFrameGroupBy object at 0x113014128>

You can save this object as a new variable:

In [35]:
```
by_comp = df.groupby("Company")
```

And then call aggregate methods off the object:

In [36]:
```
by_comp.mean()
```

Out[36]:

| | Sales |
|---|---|
| Company | |
| FB | 296.5 |
| GOOG | 160.0 |
| MSFT | 232.0 |

In [37]:
```
df.groupby('Company').mean()
```

Out[37]:

| | Sales |
|---|---|
| Company | |
| FB | 296.5 |
| GOOG | 160.0 |
| MSFT | 232.0 |

More examples of aggregate methods:

In [38]:
```
by_comp.std()
```

Out[38]:

| | Sales |
|---|---|
| Company | |
| FB | 75.660426 |
| GOOG | 56.568542 |
| MSFT | 152.735065 |

In [39]:
```
by_comp.min()
```

Out[39]:

| | Person | Sales |
|---|---|---|
| Company | | |
| FB | Carl | 243 |
| GOOG | Charlie | 120 |
| MSFT | Amy | 124 |

In [40]:
```
by_comp.max()
```
Out[40]:

| Company | Person | Sales |
|---|---|---|
| FB | Sarah | 350 |
| GOOG | Sam | 200 |
| MSFT | Vanessa | 340 |

In [41]:
```
by_comp.count()
```
Out[41]:

| Company | Person | Sales |
|---|---|---|
| FB | 2 | 2 |
| GOOG | 2 | 2 |
| MSFT | 2 | 2 |

In [42]:
```
by_comp.describe()
```
Out[42]:

| Company | | Sales |
|---|---|---|
| FB | count | 2.000000 |
| | mean | 296.500000 |
| | std | 75.660426 |
| | min | 243.000000 |
| | 25% | 269.750000 |
| | 50% | 296.500000 |
| | 75% | 323.250000 |
| | max | 350.000000 |
| GOOG | count | 2.000000 |
| | mean | 160.000000 |
| | std | 56.568542 |
| | min | 120.000000 |
| | 25% | 140.000000 |
| | 50% | 160.000000 |
| | 75% | 180.000000 |
| | max | 200.000000 |
| | count | 2.000000 |
| | mean | 232.000000 |
| | std | 152.735065 |

In [43]:
```
by_comp.describe().transpose()
```
Out[43]:

| Company | FB | | | | | | | | GOO | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max | count | mean | ... | 75% | ma |
| Sales | 2.0 | 296.5 | 75.660426 | 243.0 | 269.75 | 296.5 | 323.25 | 350.0 | 2.0 | 160.0 | ... | 180.0 | 200. |

1 rows × 24 columns

In [44]:
```
by_comp.describe().transpose()['GOOG']
```
Out[44]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Sales | 2.0 | 160.0 | 56.568542 | 120.0 | 140.0 | 160.0 | 180.0 | 200.0 |

## 3. Merging, Joining and Concatenating

There are 3 main ways of combining DataFrames together: Merging, Joining and Concatenating. In this lecture we will discuss these 3 methods with examples.

**a. Concatenation**

Example DataFrame

In [3]:
```
import pandas as pd
```

In [4]:
```
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])
```

In [5]:
```
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])
```

In [6]:
```
df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
                    'B': ['B8', 'B9', 'B10', 'B11'],
                    'C': ['C8', 'C9', 'C10', 'C11'],
                    'D': ['D8', 'D9', 'D10', 'D11']},
                    index=[8, 9, 10, 11])
```

In [7]:
```
df1
```

Out[7]:

| | A | B | C | D |
|---|---|---|---|---|
| **0** | A0 | B0 | C0 | D0 |
| **1** | A1 | B1 | C1 | D1 |
| **2** | A2 | B2 | C2 | D2 |
| **3** | A3 | B3 | C3 | D3 |

In [8]:
```
df2
```

Out[8]:

| | A | B | C | D |
|---|---|---|---|---|
| **4** | A4 | B4 | C4 | D4 |
| **5** | A5 | B5 | C5 | D5 |
| **6** | A6 | B6 | C6 | D6 |
| **7** | A7 | B7 | C7 | D7 |

In [12]:
```
df3
```

Out[12]:

| | A | B | C | D |
|---|---|---|---|---|
| **8** | A8 | B8 | C8 | D8 |
| **9** | A9 | B9 | C9 | D9 |
| **10** | A10 | B10 | C10 | D10 |
| **11** | A11 | B11 | C11 | D11 |

Concatenation basically glues together DataFrames. Keep in mind that dimensions should match along the axis you are concatenating on. You can use **pd.concat** and pass in a list of DataFrames to concatenate together:

In [10]:
```
pd.concat([df1,df2,df3])
```

Out[10]:

| | A | B | C | D |
|---|---|---|---|---|
| **0** | A0 | B0 | C0 | D0 |
| **1** | A1 | B1 | C1 | D1 |
| **2** | A2 | B2 | C2 | D2 |
| **3** | A3 | B3 | C3 | D3 |
| **4** | A4 | B4 | C4 | D4 |
| **5** | A5 | B5 | C5 | D5 |
| **6** | A6 | B6 | C6 | D6 |
| **7** | A7 | B7 | C7 | D7 |
| **8** | A8 | B8 | C8 | D8 |
| **9** | A9 | B9 | C9 | D9 |
| **10** | A10 | B10 | C10 | D10 |
| **11** | A11 | B11 | C11 | D11 |

In [18]:
```
pd.concat([df1,df2,df3],axis=1)
```

Out[18]:

| | A | B | C | D | A | B | C | D | A | B | C | D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | A0 | B0 | C0 | D0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **1** | A1 | B1 | C1 | D1 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2** | A2 | B2 | C2 | D2 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **3** | A3 | B3 | C3 | D3 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **4** | NaN | NaN | NaN | NaN | A4 | B4 | C4 | D4 | NaN | NaN | NaN | NaN |
| **5** | NaN | NaN | NaN | NaN | A5 | B5 | C5 | D5 | NaN | NaN | NaN | NaN |
| **6** | NaN | NaN | NaN | NaN | A6 | B6 | C6 | D6 | NaN | NaN | NaN | NaN |
| **7** | NaN | NaN | NaN | NaN | A7 | B7 | C7 | D7 | NaN | NaN | NaN | NaN |
| **8** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | A8 | B8 | C8 | D8 |
| **9** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | A9 | B9 | C9 | D9 |
| **10** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | A10 | B10 | C10 | D10 |
| **11** | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | A11 | B11 | C11 | D11 |

**b. Merging**

Example DataFrame

In [28]:
```
left = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
                     'A': ['A0', 'A1', 'A2', 'A3'],
                     'B': ['B0', 'B1', 'B2', 'B3']})

right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
                      'C': ['C0', 'C1', 'C2', 'C3'],
                      'D': ['D0', 'D1', 'D2', 'D3']})
```

In [29]:
```
left
```

Out[29]:

| | A | B | key |
|---|---|---|---|
| **0** | A0 | B0 | K0 |
| **1** | A1 | B1 | K1 |
| **2** | A2 | B2 | K2 |
| **3** | A3 | B3 | K3 |

In [30]:
```
right
```

Out[30]:

| | C | D | key |
|---|---|---|---|
| **0** | C0 | D0 | K0 |
| **1** | C1 | D1 | K1 |
| **2** | C2 | D2 | K2 |
| **3** | C3 | D3 | K3 |

The **merge** function allows you to merge DataFrames together using a similar logic as merging SQL Tables together. For example:

In [35]:
```
pd.merge(left,right,how='inner',on='key')
```

Out[35]:

| | A | B | key | C | D |
|---|---|---|---|---|---|
| **0** | A0 | B0 | K0 | C0 | D0 |
| **1** | A1 | B1 | K1 | C1 | D1 |
| **2** | A2 | B2 | K2 | C2 | D2 |
| **3** | A3 | B3 | K3 | C3 | D3 |

Or to show a more complicated example:

In [37]:
```
left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
                     'key2': ['K0', 'K1', 'K0', 'K1'],
                        'A': ['A0', 'A1', 'A2', 'A3'],
                        'B': ['B0', 'B1', 'B2', 'B3']})

right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
                               'key2': ['K0', 'K0', 'K0', 'K0'],
                                  'C': ['C0', 'C1', 'C2', 'C3'],
                                  'D': ['D0', 'D1', 'D2', 'D3']})
```

In [39]:
```
pd.merge(left, right, on=['key1', 'key2'])
```
Out[39]:

| | A | B | key1 | key2 | C | D |
|---|---|---|---|---|---|---|
| 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | C2 | D2 |

In [40]:
```
pd.merge(left, right, how='outer', on=['key1', 'key2'])
```
Out[40]:

| | A | B | key1 | key2 | C | D |
|---|---|---|---|---|---|---|
| 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | NaN | NaN |
| 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 3 | A2 | B2 | K1 | K0 | C2 | D2 |
| 4 | A3 | B3 | K2 | K1 | NaN | NaN |
| 5 | NaN | NaN | K2 | K0 | C3 | D3 |

In [41]:
```
pd.merge(left, right, how='right', on=['key1', 'key2'])
```
Out[41]:

| | A | B | key1 | key2 | C | D |
|---|---|---|---|---|---|---|
| 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | C2 | D2 |
| 3 | NaN | NaN | K2 | K0 | C3 | D3 |

In [42]:
```
pd.merge(left, right, how='left', on=['key1', 'key2'])
```
Out[42]:

| | A | B | key1 | key2 | C | D |
|---|---|---|---|---|---|---|
| 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | NaN | NaN |
| 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 3 | A2 | B2 | K1 | K0 | C2 | D2 |
| 4 | A3 | B3 | K2 | K1 | NaN | NaN |

**c. Joining**

Joining is a convenient method for combining the columns of two potentially differently-indexed DataFrames into a single result DataFrame.

In [46]:
```
left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                     'B': ['B0', 'B1', 'B2']},
                      index=['K0', 'K1', 'K2'])

right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
                     'D': ['D0', 'D2', 'D3']},
                      index=['K0', 'K2', 'K3'])
```
In [47]:
```
left.join(right)
```
Out[47]:

| | A | B | C | D |
|---|---|---|---|---|
| K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | NaN | NaN |
| K2 | A2 | B2 | C2 | D2 |

In [48]:
```
left.join(right, how='outer')
```
Out[48]:

| | A | B | C | D |
|---|---|---|---|---|
| K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | NaN | NaN |
| K2 | A2 | B2 | C2 | D2 |
| K3 | NaN | NaN | C3 | D3 |

## 4. Operations

There are lots of operations with pandas that will be really useful to you, but don't fall into any distinct category. Let's show them here in this lecture:

In [5]:
```
import pandas as pd
df = pd.DataFrame({'col1':[1,2,3,4],'col2':[444,555,666,444],'col3':['abc',
df.head()
```

Out[5]:

| | col1 | col2 | col3 |
|---|---|---|---|
| 0 | 1 | 444 | abc |
| 1 | 2 | 555 | def |
| 2 | 3 | 666 | ghi |
| 3 | 4 | 444 | xyz |

### a. Info on Unique Values

In [53]:
```
df['col2'].unique()
```

Out[53]:
```
array([444, 555, 666])
```

In [54]:
```
df['col2'].nunique()
```

Out[54]:
```
3
```

In [55]:
```
df['col2'].value_counts()
```

Out[55]:
```
444    2
555    1
666    1
Name: col2, dtype: int64
```

### b. Selecting Data

In [56]:
```
#Select from DataFrame using criteria from multiple columns
newdf = df[(df['col1']>2) & (df['col2']==444)]
```

In [57]:
```
newdf
```

Out[57]:

| | col1 | col2 | col3 |
|---|---|---|---|
| 3 | 4 | 444 | xyz |

### c. Applying Functions

In [58]:
```
def times2(x):
    return x*2
```

In [59]:
```
df['col1'].apply(times2)
```

Out[59]:
```
0    2
1    4
2    6
3    8
Name: col1, dtype: int64
```

In [60]:
```
df['col3'].apply(len)
```

Out[60]:
```
0    3
1    3
2    3
3    3
Name: col3, dtype: int64
```

In [61]:
```
df['col1'].sum()
```

Out[61]:
```
10
```

### d. Permanently Removing a Column

In [62]:
```
del df['col1']
```

In [63]:
```
df
```

Out[63]:

| | col2 | col3 |
|---|---|---|
| 0 | 444 | abc |
| 1 | 555 | def |
| 2 | 666 | ghi |
| 3 | 444 | xyz |

### e. Get column and index names:

In [64]:
```
df.columns
```

Out[64]: `Index(['col2', 'col3'], dtype='object')`

In [65]:
```
df.index
```

Out[65]: `RangeIndex(start=0, stop=4, step=1)`

### f. Sorting and Ordering a DataFrame:

In [66]:
```
df
```

Out[66]:

| | col2 | col3 |
|---|---|---|
| 0 | 444 | abc |
| 1 | 555 | def |
| 2 | 666 | ghi |
| 3 | 444 | xyz |

In [67]:
```
df.sort_values(by='col2') #inplace=False by default
```

Out[67]:

| | col2 | col3 |
|---|---|---|
| 0 | 444 | abc |
| 3 | 444 | xyz |
| 1 | 555 | def |
| 2 | 666 | ghi |

### g. Find Null Values or Check for Null Values

In [68]:
```
df.isnull()
```

Out[68]:

| | col2 | col3 |
|---|---|---|
| 0 | False | False |
| 1 | False | False |
| 2 | False | False |
| 3 | False | False |

In [69]:
```
# Drop rows with NaN Values
df.dropna()
```

Out[69]:

| | col2 | col3 |
|---|---|---|
| 0 | 444 | abc |
| 1 | 555 | def |
| 2 | 666 | ghi |
| 3 | 444 | xyz |

### h. Filling in NaN values with something else:

In [3]:
```
import numpy as np
```

In [6]:
```
df = pd.DataFrame({'col1':[1,2,3,np.nan],
                   'col2':[np.nan,555,666,444],
                   'col3':['abc','def','ghi','xyz']})
df.head()
```

Out[6]:

| | col1 | col2 | col3 |
|---|---|---|---|
| **0** | 1.0 | NaN | abc |
| **1** | 2.0 | 555.0 | def |
| **2** | 3.0 | 666.0 | ghi |
| **3** | NaN | 444.0 | xyz |

In [7]:
```
df.isnull()
```

Out[7]:

| | col1 | col2 | col3 |
|---|---|---|---|
| **0** | False | True | False |
| **1** | False | False | False |
| **2** | False | False | False |
| **3** | True | False | False |

In [8]:
```
df.dropna()
```

Out[8]:

| | col1 | col2 | col3 |
|---|---|---|---|
| **1** | 2.0 | 555.0 | def |
| **2** | 3.0 | 666.0 | ghi |

In [9]:
```
df.fillna('FILL')
```

Out[9]:

| | col1 | col2 | col3 |
|---|---|---|---|
| **0** | 1 | FILL | abc |
| **1** | 2 | 555 | def |
| **2** | 3 | 666 | ghi |
| **3** | FILL | 444 | xyz |

In [89]:
```
data = {'A':['foo','foo','foo','bar','bar','bar'],
      'B':['one','one','two','two','one','one'],
        'C':['x','y','x','y','x','y'],
        'D':[1,3,2,5,4,1]}

df = pd.DataFrame(data)
```

In [90]:
```
df
```

Out[90]:

| | A | B | C | D |
|---|---|---|---|---|
| **0** | foo | one | x | 1 |
| **1** | foo | one | y | 3 |
| **2** | foo | two | x | 2 |
| **3** | bar | two | y | 5 |
| **4** | bar | one | x | 4 |
| **5** | bar | one | y | 1 |

In [91]:
```
df.pivot_table(values='D',index=['A', 'B'],columns=['C'])
```

Out[91]:

| | C | x | y |
|---|---|---|---|
| **A** | **B** | | |
| **bar** | **one** | 4.0 | 1.0 |
| | **two** | NaN | 5.0 |
| **foo** | **one** | 1.0 | 3.0 |
| | **two** | 2.0 | NaN |

# V. Exercises

## 1. Sales

Fill in the TODO cells in sales.ipynb notebook.

- Fix column datatypes.
- Drop if duplicated or null.
- Sanity check for value ranges and to check assumptions
- Use regular expression and lambda function to parse data.

## 2. Job Market

Given the job market data in csv file. Create your own jupyter notebook and explore the data by:

- Load the data using Pandas.
- Visualize top 10 first rows
- Fix column datatypes.
- Aggregate existing columns into new column.

## 3. Web Scraping with BeautifulSoup – IMDB (OPTIONAL)

Write a Python script to download IMDB 250 Top Rated Movies. For each movie, you'll need to retrieve the movie title, the ranking, the initial release year, the casting and the rating. Your data must be stored in a proper imdb_top_250.csv file.
(You can implement your own code to get the same result)

```python
# Write a Python script to download IMDB 250 Top Rated Movies.
# For each movie, you'll need to retrieve the movie title, the ranking, the initial release year, the casting and
# the rating.
# Your data must be stored in a proper imdb_top_250.csv file.

import requests, csv
from bs4 import BeautifulSoup

def get_movies(url):
    response = requests.get(url)
    soup_imdb = BeautifulSoup(response.text)

    all_movies = soup_imdb.find_all("td", {"class":"titleColumn"})

    # get movie title :
    titles =

    # get ranking :
    rankings =

    # get release year :
    list_year =
    years = [element.text.strip("()") for element in list_year]

    # get casting :
    castings =

    #get rating :
    list_ratings =
    ugly_list = [element.text.strip("\n") for element in list_ratings]
    ratings = [element for element in ugly_list if ugly_list.index(element) % 2 == 0]

    mega_list = list(zip(titles, rankings, years, castings, ratings))
    mega_list = [list(elt) for elt in mega_list]

    # Write csv
    str_lst = [f"{mega_list[i][1]} / {mega_list[i][0]} ({mega_list[i][2]}) / Starring: {mega_list[i][3]}" \
    for i, val in enumerate(mega_list)]

    res = [elt.split("/") for elt in str_lst]

    with open("imdb_top_250.csv", "w") as f:
        writer = csv.writer(f, delimiter="-")
        writer.writerows(res)
```

```python
def main():
    url = "https://www.imdb.com/chart/top"
    get_movies(url)


if __name__ == "__main__":
    main()
```

```python
import pandas as pd

#Read CSV and show the first 5 rows
```

| | 0 | 1 | 2 |
|---|---|---|---|
| 0 | 1 | The Shawshank Redemption (1994) | Starring: Frank Darabont (dir.), Tim Robbins,... |
| 1 | 2 | The Godfather (1972) | Starring: Francis Ford Coppola (dir.), Marlon... |
| 2 | 3 | The Godfather: Part II (1974) | Starring: Francis Ford Coppola (dir.), Al Pac... |
| 3 | 4 | The Dark Knight (2008) | Starring: Christopher Nolan (dir.), Christian... |
| 4 | 5 | 12 Angry Men (1957) | Starring: Sidney Lumet (dir.), Henry Fonda, L... |