Data Preparation: <u>**Cleaning**</u> and Wrangling

Bloque III

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Data preparation: Cleaning and Wrangling

- The context of data analytics
  - One of the most common mistakes of data analytic projects is thinking that they start with “analysis”
  - In their natural form, the “Raw Data” usually have registry errors that make an exact analysis impossible
  - All the data records have to be pre-processed:
    - **In other words, the data must be cleaned, unified, consolidated and normalized, so that it can be used and extract valuable information.**

```
rs743534  10 135349226 GG
rs7435347 4  156654735 AG
rs743535  10 135349367 CC
rs743537  9  130634944 AA
rs743539  9  130633904 TG
rs7435399 4  24765819  TC
rs7435410 4  89456219  AG
rs7435411 4  169426096 GA
rs7435420 4  62150059  GA
rs743554  17 73754248  CC
rs7435595 4  179402198 AG
rs7435615 4  20399168  AG
rs743562  5  131872383 CT
rs7435646 4  100237492 TA
rs743567  14 23890982  AA
rs7435692 4  88489929  AC
rs743572  10 104597152 AG
rs7435768 4  116426581 TC
rs743577  1  11119135  GA
```

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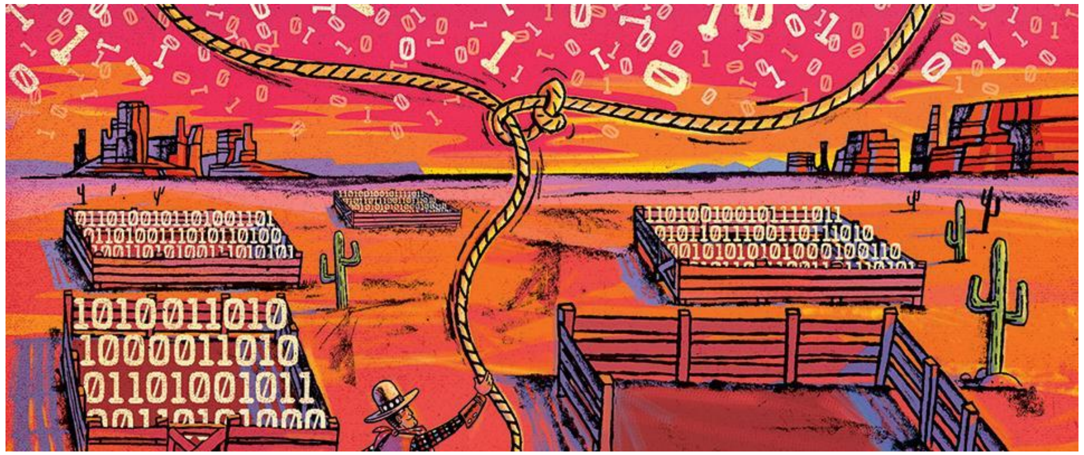
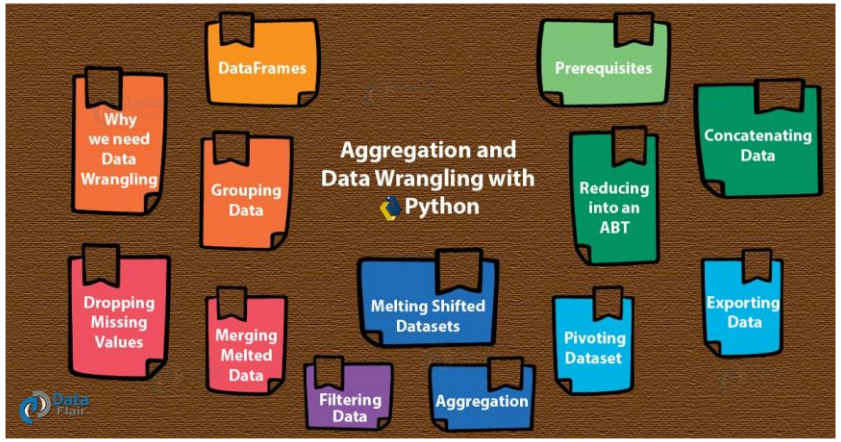
Data preparation: Cleaning and Wrangling

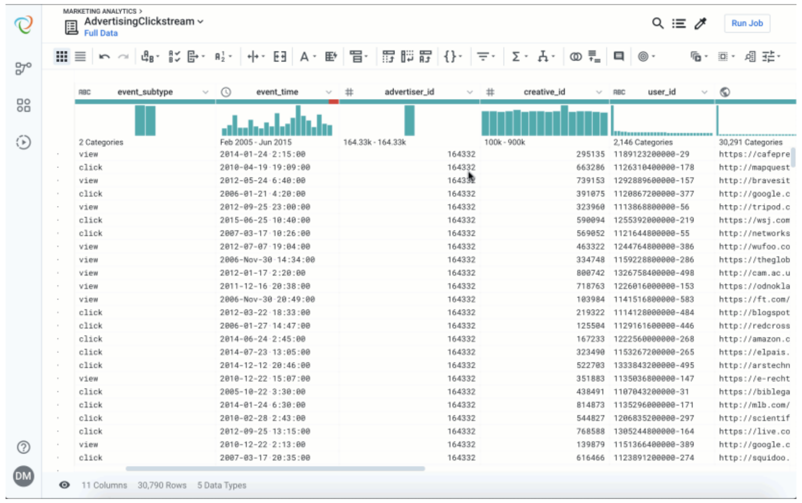
- The context of data analytics
  - Any data project needs a previous step to be successful, which comprises two main tasks:
    - Data Cleaning
    - Data Wrangling
  - In fact, they are usually the most time consuming for data analysts
    - According to a survey conducted in 2017, a data analyst can spend, on average, 80% of their time on Data Wrangling.



Data preparation: Cleaning and Wrangling

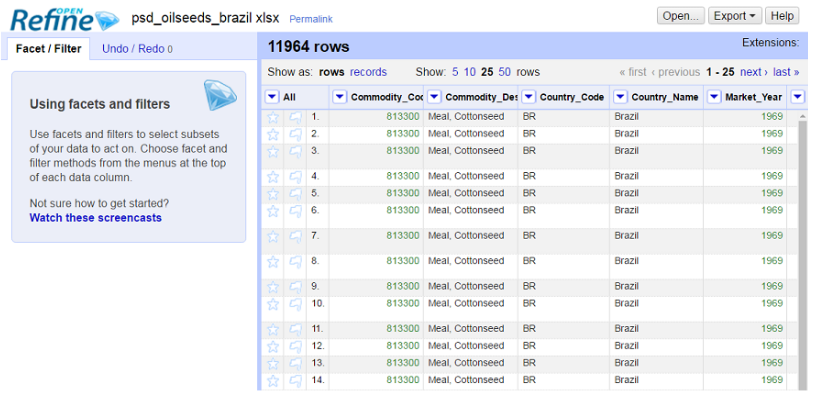
- Tools and methods for data preparation
  - Commercial: Trifacta https://www.trifacta.com/
  - Open source: Open Refine https://openrefine.org/
  - Do it by yourself!





event_subtype	event_time	advertiser_id	creative_id	user_id	
2 Categories	Feb 2005 - Jun 2015	164.33k - 164.33k	100k - 900k	2,146 Categories	30,291 Categories
view	2014-01-24 2:15:00	164332	295135	1189123200000-29	https://cafepre
click	2010-04-19 19:09:00	164332	663286	1126310400000-178	http://mapquest
view	2012-05-24 6:40:00	164332	739153	1292889600000-157	http://bravesit
click	2006-01-21 4:20:00	164332	391075	1120867200000-377	http://google.c
view	2012-09-25 23:00:00	164332	323960	1113868800000-56	http://tripod.c
click	2015-06-25 10:40:00	164332	590094	1255392000000-219	https://wsj.com
click	2007-03-17 10:26:00	164332	569052	1121644800000-55	http://networks
view	2012-07-07 19:04:00	164332	463322	1244764800000-386	http://wufoo.co
view	2006-Nov-30 14:34:00	164332	334748	1159228800000-286	https://theglob
view	2012-01-17 2:20:00	164332	800742	1326758400000-498	http://cam.ac.u
view	2011-12-16 20:38:00	164332	718763	1226016000000-153	https://odnokla
view	2006-Nov-30 20:49:00	164332	103984	1141516800000-583	https://ft.com/
click	2012-03-22 18:33:00	164332	219322	1114128000000-484	http://blogspot
click	2006-01-27 14:47:00	164332	125504	1129161600000-446	http://redcross
click	2014-06-24 2:45:00	164332	167233	1222560000000-268	http://amazon.c
click	2014-07-23 13:05:00	164332	323490	1153267200000-265	https://elpais.
click	2014-12-12 20:46:00	164332	522703	1333843200000-495	http://arstechn
view	2010-12-22 15:07:00	164332	351883	1135036800000-147	https://e-recht
click	2005-10-22 3:30:00	164332	438491	1107043200000-31	https://biblega
click	2014-01-24 6:30:00	164332	814873	1135296000000-171	http://mlb.com/
click	2010-02-28 2:43:00	164332	544827	1206835200000-297	http://scientif
click	2012-09-25 13:15:00	164332	768588	1305244800000-164	https://live.co
view	2010-12-22 2:13:00	164332	139879	1151366400000-389	http://google.c
click	2007-03-17 20:35:00	164332	616466	1123891200000-274	http://squidoo.

11 Columns 30,790 Rows 5 Data Types



psd_oilseeds_brazil xlsx Permalink

Using facets and filters

Use facets and filters to select subsets of your data to act on. Choose facet and filter methods from the menus at the top of each data column.

Not sure how to get started?
Watch these screencasts

11964 rows

Show as: **rows** records Show: 5 10 **25** 50 rows « first ‹ previous **1 - 25** next › last »

All	Commodity_Coc	Commodity_Des	Country_Code	Country_Name	Market_Year
1.	813300	Meal, Cottonseed	BR	Brazil	1969
2.	813300	Meal, Cottonseed	BR	Brazil	1969
3.	813300	Meal, Cottonseed	BR	Brazil	1969
4.	813300	Meal, Cottonseed	BR	Brazil	1969
5.	813300	Meal, Cottonseed	BR	Brazil	1969
6.	813300	Meal, Cottonseed	BR	Brazil	1969
7.	813300	Meal, Cottonseed	BR	Brazil	1969
8.	813300	Meal, Cottonseed	BR	Brazil	1969
9.	813300	Meal, Cottonseed	BR	Brazil	1969
10.	813300	Meal, Cottonseed	BR	Brazil	1969
11.	813300	Meal, Cottonseed	BR	Brazil	1969
12.	813300	Meal, Cottonseed	BR	Brazil	1969
13.	813300	Meal, Cottonseed	BR	Brazil	1969
14.	813300	Meal, Cottonseed	BR	Brazil	1969

Data preparation: Cleaning and Wrangling

- Data Cleaning and Preparation
  - Handling Missing Data
    - Filtering Out Missing Data
    - Filling In Missing Data
  - Data Transformation
    - Removing Duplicates
    - Transforming Data Using a Function or Mapping
    - Replacing Values
    - Renaming Axis Indexes
    - Discretization and Binning
    - Detecting and Filtering Outliers
    - Permutation and Random Sampling
  - String Manipulation
    - String Object Methods
    - Regular Expressions

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    - String Object Methods
    - Regular Expressions

Data preparation: Cleaning and Wrangling

- Handling Missing Data
  - For numeric data, pandas uses the floating-point value **NaN (Not a Number)** to represent missing data

```
In [10]: string_data = pd.Series(['aardvark', 'artichoke', np.nan, 'avocado’])

In [11]: string_data
Out[11]:
0 aardvark
1 artichoke
2 NaN
3 avocado
dtype: object
```

```
In [12]: string_data.isnull()

Out[12]:
0 False
1 False
2 True
3 False
dtype: bool
```

Data preparation: Cleaning and Wrangling

- Handling Missing Data
  - The built-in Python **None** value is also treated as NA in object arrays

```
In [13]: string_data[0] = None

In [14]: string_data.isnull()
Out[14]:
0 True
1 False
2 True
3 False
dtype: bool
```

  - NA Handling methods
    - **dropna** : Filter axis labels based on whether values for each label have missing data, with varying thresholds for how much missing data to tolerate
    - **fillna** : Fill in missing data with some value or using an interpolation method such as 'ffill' or 'bfill’
    - **isnull** : Return boolean values indicating which values are missing/NA
    - **notnull** : Negation of isnull

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Data preparation: Cleaning and Wrangling

- Handling Missing Data: Filtering Out Missing Data
  - **dropna** on a Series, it returns the Series with only the non-null data and index values

```
In [15]: from numpy import nan as NA

In [16]: data = pd.Series([1, NA, 3.5, NA, 7])

In [17]: data.dropna()

Out[17]:
0 1.0
2 3.5
4 7.0
dtype: float64
```

This is equivalent to:

```
In [18]: data[data.notnull()]

Out[18]:
0 1.0
2 3.5
4 7.0
dtype: float64
```

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Data preparation: Cleaning and Wrangling

- Handling Missing Data: Filtering Out Missing Data
    - **dropna** on Dataframe, it drops rows or columns that are all NA or only those containing any NAs. dropna by default drops any row containing a missing value:
    - Passing how='all' will only drop rows that are all NA:

```
In [23]: data.dropna(how='all’)
Out[23]:
            0          1          2
0           1.0        6.5        3.0
1           1.0        NaN        NaN
3           NaN        6.5        3.0
```

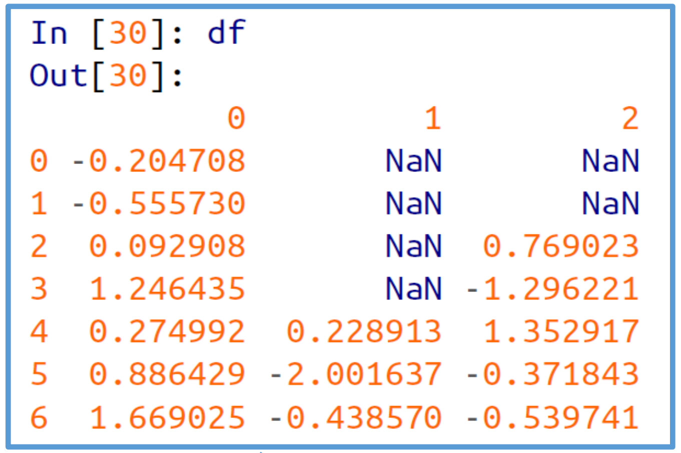
    - To drop columns, pass axis=1:

```
In [24]: data.dropna(axis=1, how='all')
```

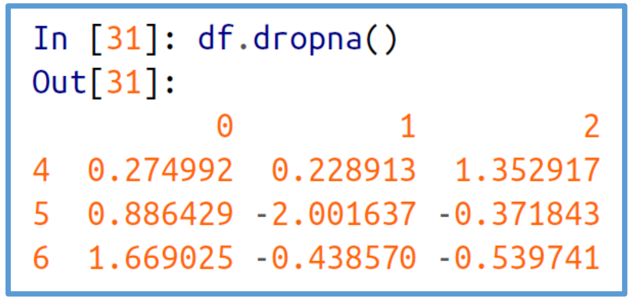
```
In [19]: data = pd.DataFrame([[1., 6.5, 3.], [1., NA, NA],
....:                                [NA, NA, NA], [NA, 6.5, 3.]])

In [20]: cleaned = data.dropna()

In [21]: data

Out[21]:
            0          1          2
0           1.0        6.5        3.0
1           1.0        NaN        NaN
2           NaN        NaN        NaN
3           NaN        6.5        3.0

In [22]: cleaned

Out[22]:
            0          1          2
0           1.0        6.5        3.0
```

Data preparation: Cleaning and Wrangling

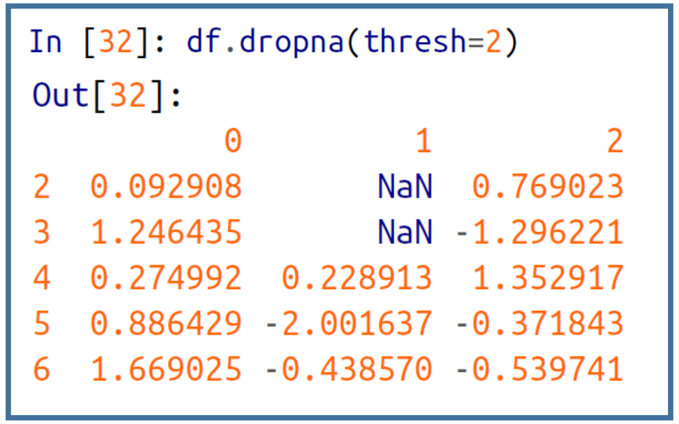
- Handling Missing Data: Filtering Out Missing Data
  - Filter out DataFrame rows tends to concern time series data
  - Suppose you want to keep only rows containing a certain number of observations. You can indicate this with the thresh argument:



```
In [30]: df
Out[30]:
          0         1         2
0 -0.204708       NaN       NaN
1 -0.555730       NaN       NaN
2  0.092908       NaN  0.769023
3  1.246435       NaN -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```



```
In [31]: df.dropna()
Out[31]:
          0         1         2
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```



```
In [32]: df.dropna(thresh=2)
Out[32]:
          0         1         2
2  0.092908       NaN  0.769023
3  1.246435       NaN -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

Data preparation: Cleaning and Wrangling

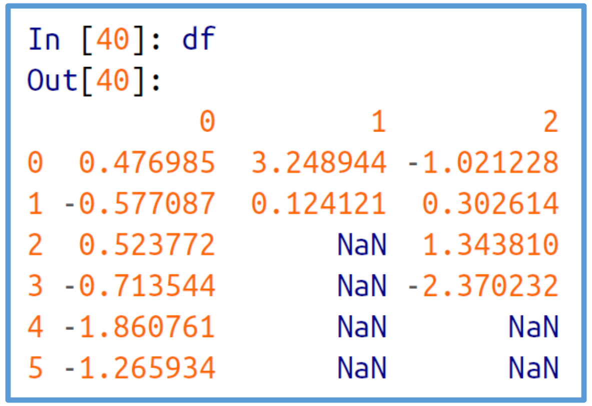
- Handling Missing Data: Filling In Missing Data
  - Rather than filtering out missing data (and potentially discarding other data along with it), you may want to fill in the "holes" in any number of ways
  - **fillna** method with a constant replaces missing values with that value
  - **fillna** with a dict, can use a different fill value for each column
  - **fillna** returns a new object, but it is possible to modify the existing object in-place

```
In [35]: _ = df.fillna(0, inplace=True)
```

```
In [33]: df.fillna(0)
Out[33]:
          0         1         2
0 -0.204708  0.000000  0.000000
1 -0.555730  0.000000  0.000000
2  0.092908  0.000000  0.769023
3  1.246435  0.000000 -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

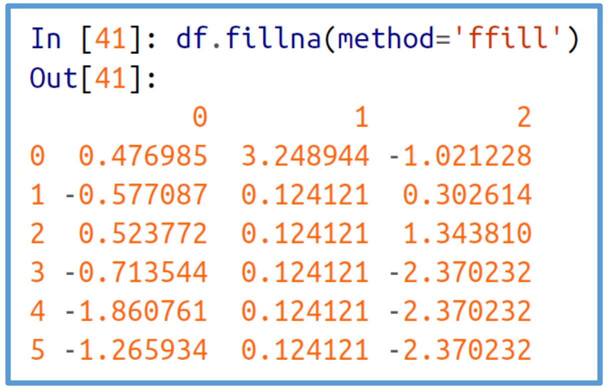
```
In [34]: df.fillna({1: 0.5, 2: 0})
Out[34]:
          0         1         2
0 -0.204708  0.500000  0.000000
1 -0.555730  0.500000  0.000000
2  0.092908  0.500000  0.769023
3  1.246435  0.500000 -1.296221
4  0.274992  0.228913  1.352917
5  0.886429 -2.001637 -0.371843
6  1.669025 -0.438570 -0.539741
```

Data preparation: Cleaning and Wrangling

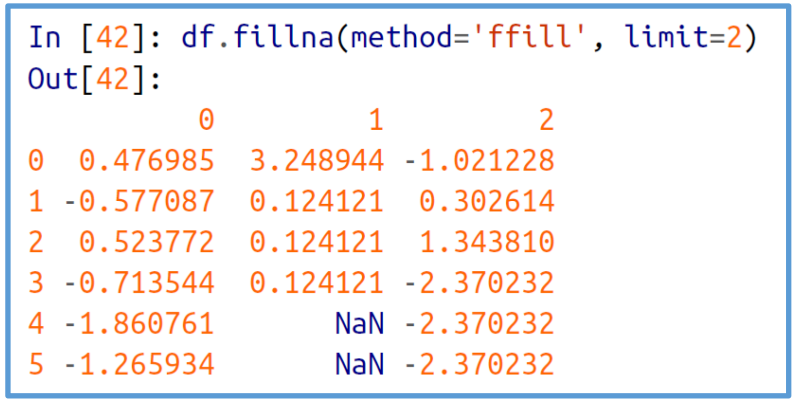


```
In [40]: df
Out[40]:
          0         1         2
0  0.476985  3.248944 -1.021228
1 -0.577087  0.124121  0.302614
2  0.523772       NaN  1.343810
3 -0.713544       NaN -2.370232
4 -1.860761       NaN       NaN
5 -1.265934       NaN       NaN
```

- Handling Missing Data: Filling In Missing Data
  - A set of interpolation methods can be also used with **fillna:**
    - **ffill:** to fill from front values
    - **ffill:** to backward fill the missing values

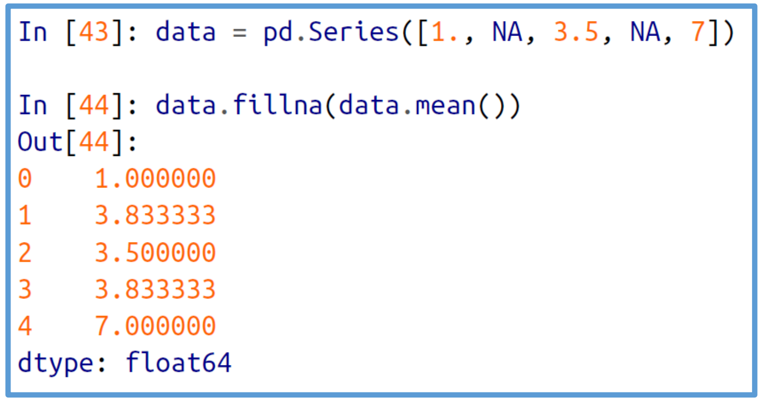


```
In [41]: df.fillna(method='ffill')
Out[41]:
          0         1         2
0  0.476985  3.248944 -1.021228
1 -0.577087  0.124121  0.302614
2  0.523772  0.124121  1.343810
3 -0.713544  0.124121 -2.370232
4 -1.860761  0.124121 -2.370232
5 -1.265934  0.124121 -2.370232
```

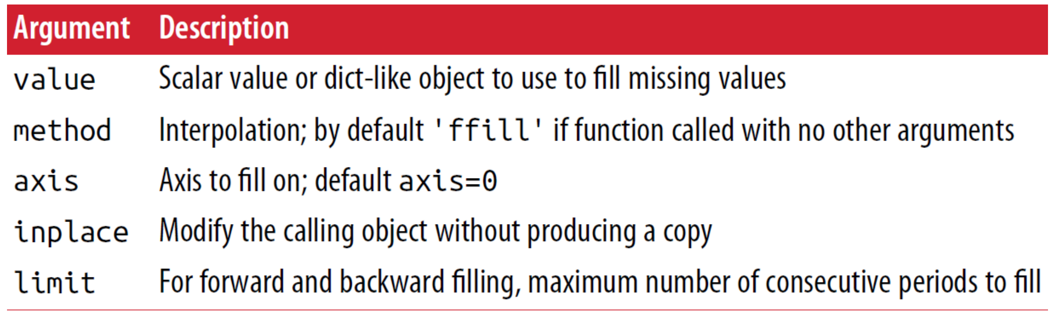


```
In [42]: df.fillna(method='ffill', limit=2)
Out[42]:
          0         1         2
0  0.476985  3.248944 -1.021228
1 -0.577087  0.124121  0.302614
2  0.523772  0.124121  1.343810
3 -0.713544  0.124121 -2.370232
4 -1.860761       NaN -2.370232
5 -1.265934       NaN -2.370232
```

  - pass the mean or median value of a Series



```
In [43]: data = pd.Series([1., NA, 3.5, NA, 7])

In [44]: data.fillna(data.mean())
Out[44]:
0    1.000000
1    3.833333
2    3.500000
3    3.833333
4    7.000000
dtype: float64
```



Argument	Description
`value`	Scalar value or dict-like object to use to fill missing values
`method`	Interpolation; by default `'ffill'` if function called with no other arguments
`axis`	Axis to fill on; default `axis=0`
`inplace`	Modify the calling object without producing a copy
`limit`	For forward and backward filling, maximum number of consecutive periods to fill

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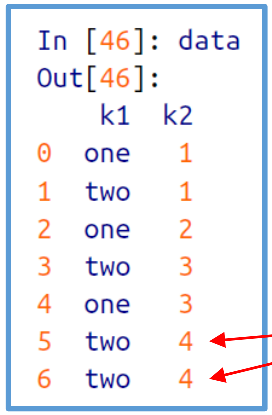
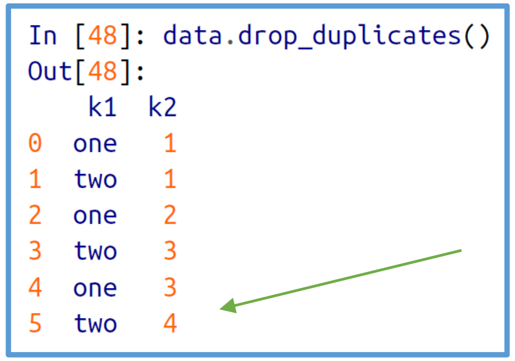
Data preparation: Cleaning and Wrangling

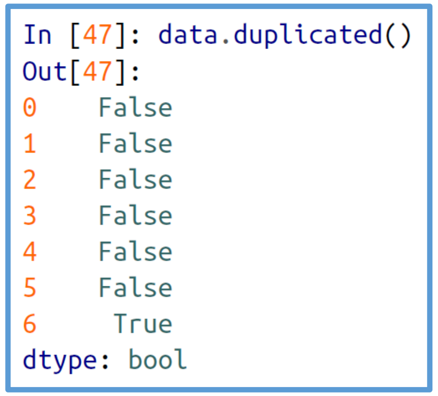
- Data Transformation: Removing Duplicates
  - DataFrame method **duplicated** returns a boolean Series indicating whether each row is a duplicate
  - **drop_duplicates** solves this issue
  - Specify any subset of columns to detect duplicates



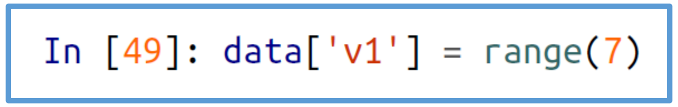
```
In [46]: data
Out[46]:
    k1  k2
0  one   1
1  two   1
2  one   2
3  two   3
4  one   3
5  two   4
6  two   4
```



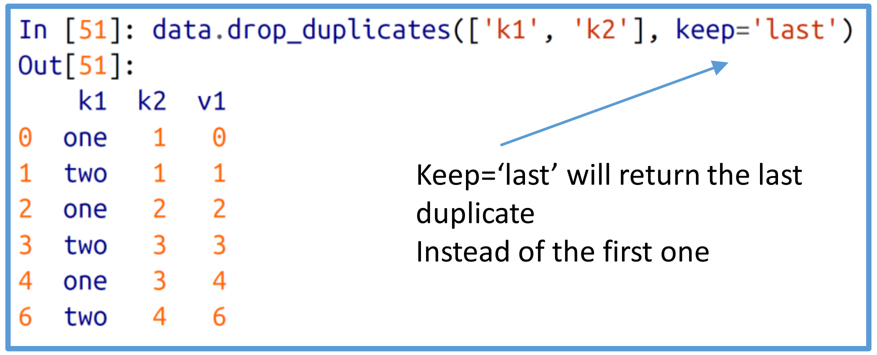
```
In [48]: data.drop_duplicates()
Out[48]:
    k1  k2
0  one   1
1  two   1
2  one   2
3  two   3
4  one   3
5  two   4
```



```
In [47]: data.duplicated()
Out[47]:
0    False
1    False
2    False
3    False
4    False
5    False
6     True
dtype: bool
```



```
In [49]: data['v1'] = range(7)
```



```
In [51]: data.drop_duplicates(['k1', 'k2'], keep='last')
Out[51]:
    k1  k2  v1
0  one   1   0
1  two   1   1
2  one   2   2
3  two   3   3
4  one   3   4
6  two   4   6
```

Keep='last' will return the last duplicate
Instead of the first one

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Data preparation: Cleaning and Wrangling

- Data Transformation: Transforming Data Using a Function or Mapping
  - For many datasets, you may wish to perform some transformation based on the values in an array, Series, or column in a DataFrame
    - Consider the following data collected about various kinds of meat

```
In [52]: data = pd.DataFrame({'food': ['bacon', 'pulled pork', 'bacon',
   ....:                               'Pastrami', 'corned beef', 'Bacon',
   ....:                               'pastrami', 'honey ham', 'nova lox'],
   ....:                      'ounces': [4, 3, 12, 6, 7.5, 8, 3, 5, 6]})
```

```
In [53]: data
Out[53]:
          food  ounces
0        bacon     4.0
1  pulled pork     3.0
2        bacon    12.0
3     Pastrami     6.0
4  corned beef     7.5
5        Bacon     8.0
6     pastrami     3.0
7    honey ham     5.0
8     nova lox     6.0
```

We want to add a column indicating the type of animal that each food came from. Let's write down a mapping of each distinct meat type to the kind of animal:

```
meat_to_animal = {
  'bacon': 'pig',
  'pulled pork': 'pig',
  'pastrami': 'cow',
  'corned beef': 'cow',
  'honey ham': 'pig',
  'nova lox': 'salmon'
}
```

```
In [55]: lowercased = data['food'].str.lower()
```

```
In [56]: lowercased
Out[56]:
0          bacon
1    pulled pork
2          bacon
3       pastrami
4    corned beef
5          bacon
6       pastrami
7      honey ham
8       nova lox
Name: food, dtype: object
```

Then we map

```
In [57]: data['animal'] = lowercased.map(meat_to_animal)

In [58]: data
Out[58]:
          food  ounces  animal
0        bacon     4.0     pig
1  pulled pork     3.0     pig
2        bacon    12.0     pig
3     Pastrami     6.0     cow
4  corned beef     7.5     cow
5        Bacon     8.0     pig
6     pastrami     3.0     cow
7    honey ham     5.0     pig
8     nova lox     6.0  salmon
```

Alternatively, we may use a lambda function to do the same

```
In [59]: data['food'].map(lambda x: meat_to_animal[x.lower()])
```

Data preparation: Cleaning and Wrangling

- Data Transformation: Replacing Values
  - **replace** provides a simpler and more flexible way to substitute values

    Let's consider this Series

```
In [61]: data
Out[61]:
0        1.0
1     -999.0
2        2.0
3     -999.0
4    -1000.0
5        3.0
dtype: float64
```

    - We can use replace, producing a new Series (unless you pass inplace=True)

```
In [62]: data.replace(-999, np.nan)
```

    - **replace** multiple values at once, you instead pass a list and then the substitute value

```
In [63]: data.replace([-999, -1000], np.nan)
```

    - To use a different replacement for each value, pass a list of substitutes

```
In [64]: data.replace([-999, -1000], [np.nan, 0])
```

    - The argument passed can also be a dict

```
In [65]: data.replace({-999: np.nan, -1000: 0})
```

```
Out[65]:
0    1.0
1    NaN
2    2.0
3    NaN
4    0.0
5    3.0
dtype: float64
```

Data preparation: Cleaning and Wrangling

- Data Transformation: Renaming Axis Indexes
  - Axis labels can be similarly transformed by a function or mapping of some form to produce new differently labelled objects

```
In [66]: data = pd.DataFrame(np.arange(12).reshape((3, 4)),
   ....:                     index=['Ohio', 'Colorado', 'New York'],
   ....:                     columns=['one', 'two', 'three', 'four'])
```

  - Axis indexes have a map method

```
In [67]: transform = lambda x: x[:4].upper()
```

```
In [69]: data.index = data.index.map(transform)

In [70]: data
Out[70]:
      one  two  three  four
OHIO    0    1      2     3
COLO    4    5      6     7
NEW     8    9     10    11
```

Data preparation: Cleaning and Wrangling

- Data Transformation: Renaming Axis Indexes
  - **rename** method: to create a transformed version of a dataset without modifying the original

```
In [71]: data.rename(index=str.title, columns=str.upper)
Out[71]:
      ONE  TWO  THREE  FOUR
Ohio    0    1      2     3
Colo    4    5      6     7
New     8    9     10    11
```

  - **rename** can be used in conjunction with a dict-like object providing new values for a subset of the axis labels

```
In [72]: data.rename(index={'OHIO': 'INDIANA'},
   ....:             columns={'three': 'peekaboo'})
Out[72]:
         one  two  peekaboo  four
INDIANA    0    1         2     3
COLO       4    5         6     7
NEW        8    9        10    11
```

To modify a dataset in-place, pass **inplace=True**

```
In [73]: data.rename(index={'OHIO': 'INDIANA'}, inplace=True)
```

Data preparation: Cleaning and Wrangling

- Data Transformation: Discretization and Binning
  - Continuous data is often discretized or otherwise separated into “bins” for analysis

```
In [75]: ages = [20, 22, 25, 27, 21, 23, 37, 31, 61, 45, 41, 32]
```

  - Let’s divide these into bins of 18 to 25, 26 to 35, 36 to 60, and finally 61 and older: use **cut** function in pandas

```
In [76]: bins = [18, 25, 35, 60, 100]

In [77]: cats = pd.cut(ages, bins)

In [78]: cats
Out[78]:
[(18, 25], (18, 25], (18, 25], (25, 35], (18, 25], ..., (25, 35], (60, 100], (35,
 60], (35, 60], (25, 35]]
Length: 12
Categories (4, interval[int64]): [(18, 25] < (25, 35] < (35, 60] < (60, 100]]
```

special Categorical object

Notación	Intervalo
$[a,b]$	$a \le x \le b$
$[a,b)$	$a \le x < b$
$(a,b]$	$a < x \le b$
(a,b)	$a < x < b$

Data preparation: Cleaning and Wrangling

Notación	Intervalo
$[a,b]$	$a \le x \le b$
$[a,b)$	$a \le x < b$
$(a,b]$	$a < x \le b$
(a,b)	$a < x < b$

- Data Transformation: Discretization and Binning
  - **pandas.cut**:
    - like an array of strings indicating the bin name
    - internally it contains a **categories** array specifying the distinct category names along with a labeling for the ages data in the **codes** attribute

```
In [79]: cats.codes
Out[79]: array([0, 0, 0, 1, 0, 0, 2, 1, 3, 2, 2, 1], dtype=int8)

In [80]: cats.categories
Out[80]:
IntervalIndex([(18, 25], (25, 35], (35, 60], (60, 100]]
              closed='right',
              dtype='interval[int64]')

In [81]: pd.value_counts(cats)
Out[81]:
(18, 25]     5
(35, 60]     3
(25, 35]     3
(60, 100]    1
dtype: int64
```

Histograming

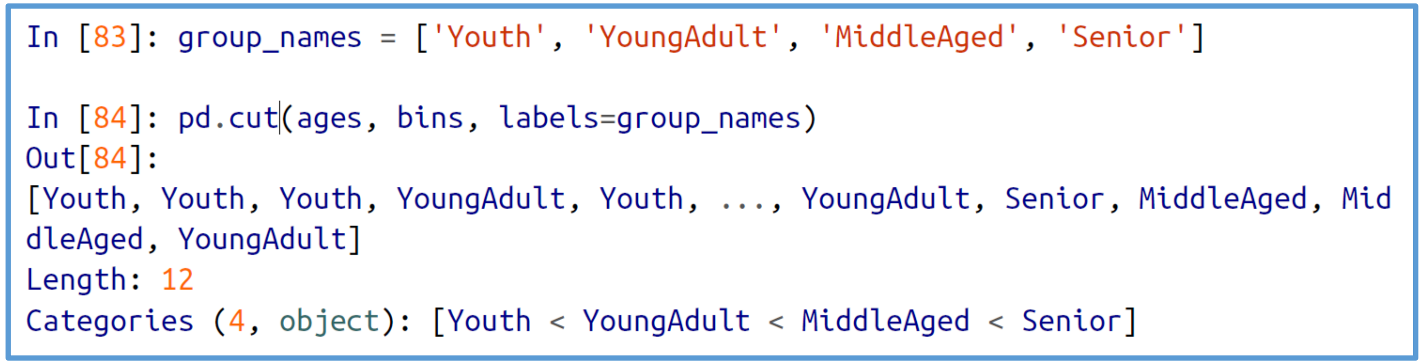
a parenthesis means that the side is *open*, while the square bracket means it is *closed* (inclusive);

It can be changed by passing right=False

```
In [82]: pd.cut(ages, [18, 26, 36, 61, 100], right=False)
```

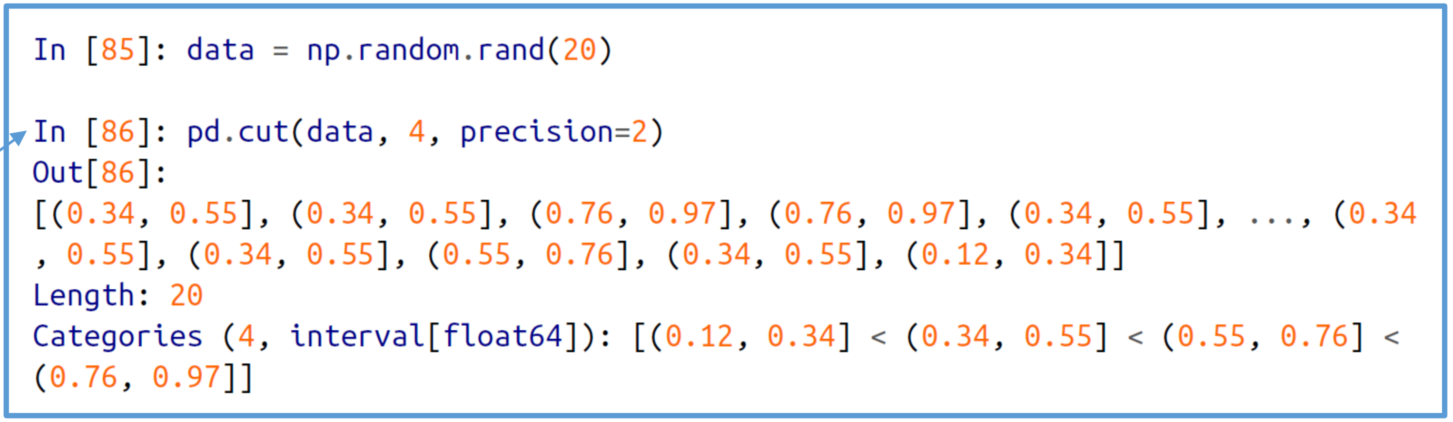
Data preparation: Cleaning and Wrangling

- Data Transformation: Discretization and Binning
  - **pandas.cut**:
    - It allows to pass own bin names by passing a list or array to the labels option



```
In [83]: group_names = ['Youth', 'YoungAdult', 'MiddleAged', 'Senior']

In [84]: pd.cut(ages, bins, labels=group_names)
Out[84]:
[Youth, Youth, Youth, YoungAdult, Youth, ..., YoungAdult, Senior, MiddleAged, Mid
dleAged, YoungAdult]
Length: 12
Categories (4, object): [Youth < YoungAdult < MiddleAged < Senior]
```

    - Compute equal-length bins based on the minimum and maximum values in the data



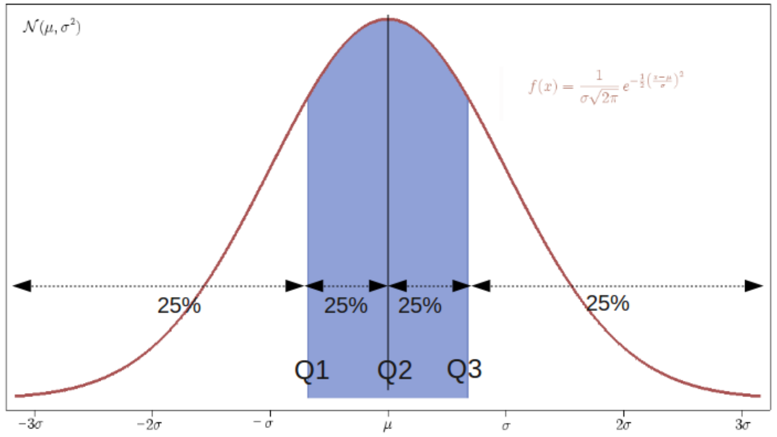
```
In [85]: data = np.random.rand(20)

In [86]: pd.cut(data, 4, precision=2)
Out[86]:
[(0.34, 0.55], (0.34, 0.55], (0.76, 0.97], (0.76, 0.97], (0.34, 0.55], ..., (0.34
, 0.55], (0.34, 0.55], (0.55, 0.76], (0.34, 0.55], (0.12, 0.34]]
Length: 20
Categories (4, interval[float64]): [(0.12, 0.34] < (0.34, 0.55] < (0.55, 0.76] <
(0.76, 0.97]]
```

precision=2 option limits the decimal precision to two digits

Data preparation: Cleaning and Wrangling

- Data Transformation: Discretization and Binning
  - **pandas.qcut**: bins the data based on sample **quantiles**
    - by definition roughly equal-size bins are obtained

```
In [87]: data = np.random.randn(1000)  # Normally distributed

In [88]: cats = pd.qcut(data, 4)  # Cut into quartiles

In [89]: cats
Out[89]:
[(-0.0265, 0.62], (0.62, 3.928], (-0.68, -0.0265], (0.62, 3.928], (-0.0265, 0.62]
, ..., (-0.68, -0.0265], (-0.68, -0.0265], (-2.95, -0.68], (0.62, 3.928], (-0.68,
 -0.0265]]
Length: 1000
Categories (4, interval[float64]): [(-2.95, -0.68] < (-0.68, -0.0265] < (-0.0265,
 0.62] <
                                    (0.62, 3.928]]
```



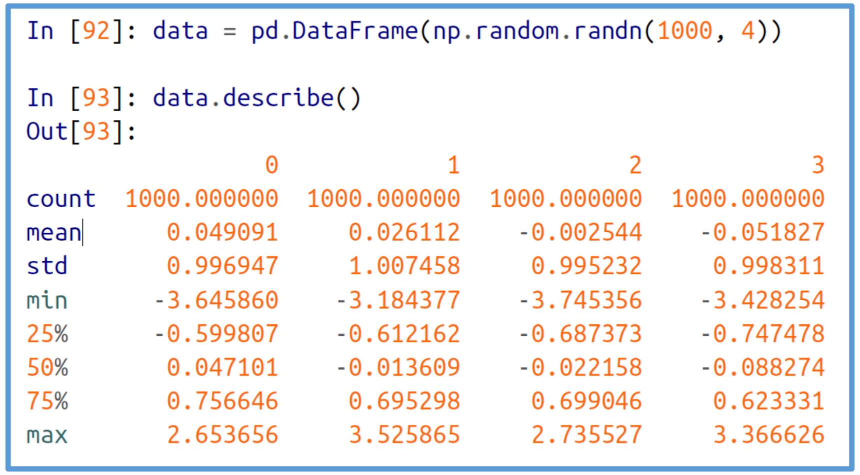
```
In [90]: pd.value_counts(cats)
Out[90]:
(0.62, 3.928]       250
(-0.0265, 0.62]     250
(-0.68, -0.0265]    250
(-2.95, -0.68]      250
dtype: int64
```

- Similar to cut you can pass your own quantiles (numbers between 0 and 1, inclusive)

```
In [91]: pd.qcut(data, [0, 0.1, 0.5, 0.9, 1.])
```

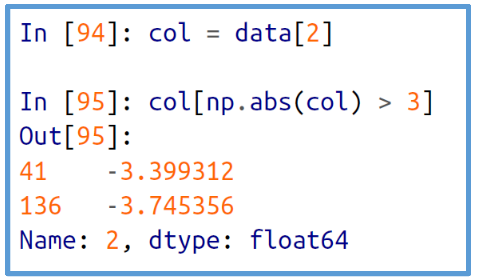
Data preparation: Cleaning and Wrangling

- Data Transformation: Detecting and Filtering Outliers
  - It’s a matter of array indexing
  - Having this DataFrame:



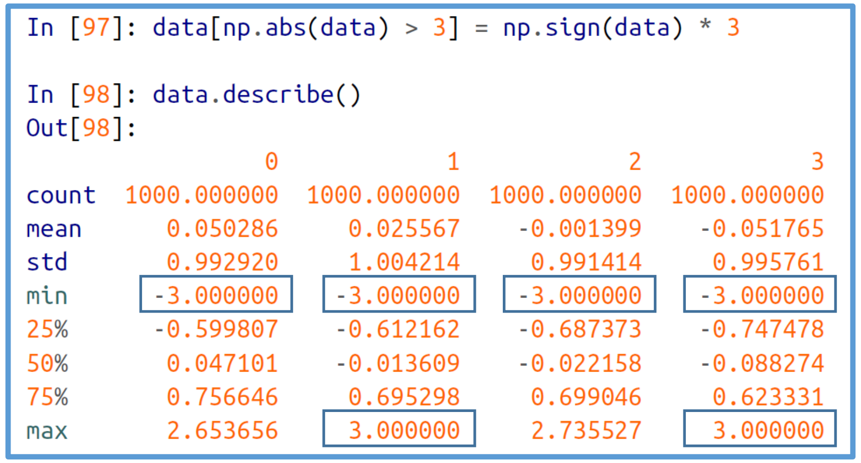
```
In [92]: data = pd.DataFrame(np.random.randn(1000, 4))

In [93]: data.describe()
Out[93]:
                 0            1            2            3
count  1000.000000  1000.000000  1000.000000  1000.000000
mean      0.049091     0.026112    -0.002544    -0.051827
std       0.996947     1.007458     0.995232     0.998311
min      -3.645860    -3.184377    -3.745356    -3.428254
25%      -0.599807    -0.612162    -0.687373    -0.747478
50%       0.047101    -0.013609    -0.022158    -0.088274
75%       0.756646     0.695298     0.699046     0.623331
max       2.653656     3.525865     2.735527     3.366626
```

    - Let’s find values in one of the columns exceeding 3 in absolute value:



```
In [94]: col = data[2]

In [95]: col[np.abs(col) > 3]
Out[95]:
41    -3.399312
136   -3.745356
Name: 2, dtype: float64
```

    - cap values outside the interval –3 to 3:



```
In [97]: data[np.abs(data) > 3] = np.sign(data) * 3

In [98]: data.describe()
Out[98]:
                 0            1            2            3
count  1000.000000  1000.000000  1000.000000  1000.000000
mean      0.050286     0.025567    -0.001399    -0.051765
std       0.992920     1.004214     0.991414     0.995761
min      -3.000000    -3.000000    -3.000000    -3.000000
25%      -0.599807    -0.612162    -0.687373    -0.747478
50%       0.047101    -0.013609    -0.022158    -0.088274
75%       0.756646     0.695298     0.699046     0.623331
max       2.653656     3.000000     2.735527     3.000000
```

np.sign(data) produces 1 and –1 values based on whether the values in data are positive or negative

Data preparation: Cleaning and Wrangling

- Data Transformation: Detecting and Filtering Outliers
  - Remove all the random numbers that lie in the lowest **quantile** and the highest quantile

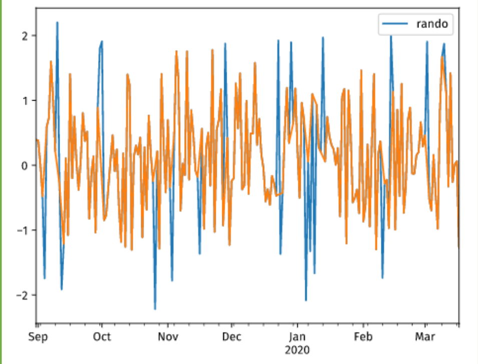
```
size=200

x = pd.Series(np.random.normal(size=size)) # 200 values
x = x[x.between(x.quantile(.15), x.quantile(.85))] # without outliers

print(x) # Now only 140 values
```

```
0       0.691716
1       0.519569
3      -0.145321
4      -0.490216
5      -0.357589
          ...
191    -0.254481
192     0.808355
194    -0.755343
196    -0.132525
199    -0.494869
Length: 140, dtype: float64
```

  - With two axes

```
import datetime

todays_date = datetime.datetime.now().date()
dates = pd.date_range(todays_date-datetime.timedelta(10), periods=size, freq='D’)

rando_nums = np.random.normal(size=size)
columns = ['rando’]

df = pd.DataFrame(rando_nums, index=dates, columns=columns)
df                # 200 random numbers indexed by days in a week
df.plot().get_figure()
```

```
y = df['rando’]
removed_outliers = y.between(y.quantile(.05), y.quantile(.95))

print(str(y[removed_outliers].size) + "/" + str(size) + " data points remain.")

y[removed_outliers].plot().get_figure()
```



  - **np.percentile**

Data preparation: Cleaning and Wrangling

- Data Transformation: Permutation and Random Sampling
  - **permutation** with the length of the axis you want to permute produces an array of integers indicating the new ordering

```
In [100]: df = pd.DataFrame(np.arange(5 * 4).reshape((5, 4)))

In [101]: sampler = np.random.permutation(5)

In [102]: sampler
Out[102]: array([3, 1, 4, 2, 0])
```

```
In [103]: df
Out[103]:
    0   1   2   3
0   0   1   2   3
1   4   5   6   7
2   8   9  10  11
3  12  13  14  15
4  16  17  18  19
```

```
In [104]: df.take(sampler)
Out[104]:
    0   1   2   3
3  12  13  14  15
1   4   5   6   7
4  16  17  18  19
2   8   9  10  11
0   0   1   2   3
```

  - To select a random subset without replacement, you can use the **sample** method on Series and DataFrame

```
In [105]: df.sample(n=3)
Out[105]:
    0   1   2   3
3  12  13  14  15
4  16  17  18  19
2   8   9  10  11
```

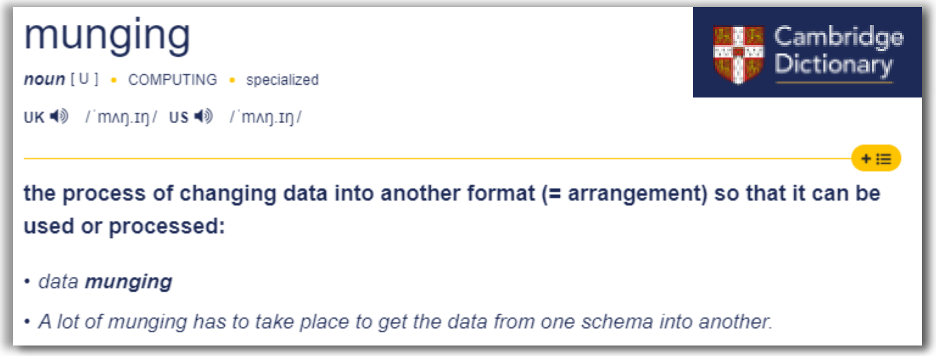
Data preparation: Cleaning and Wrangling

- Data Cleaning and Preparation
  - Handling Missing Data
    - Filtering Out Missing Data
    - Filling In Missing Data
  - Data Transformation
    - Removing Duplicates
    - Transforming Data Using a Function or Mapping
    - Replacing Values
    - Renaming Axis Indexes
    - Discretization and Binning
    - Detecting and Filtering Outliers
    - Permutation and Random Sampling
  - String Manipulation
    - String Object Methods
    - Regular Expressions

Data preparation: Cleaning and Wrangling

- String Manipulation: String Object Methods
  - In many **string munging** and scripting applications, built-in string methods are sufficient. Example
    - a comma-separated string can be broken into pieces with split

```
In [134]: val = 'a,b,  guido'

In [135]: val.split(',')
Out[135]: ['a', 'b', '  guido']
```



munging

noun [U] • COMPUTING • specialized

UK /ˈmʌŋ.ɪŋ/ US /ˈmʌŋ.ɪŋ/

the process of changing data into another format (= arrangement) so that it can be used or processed:

- *data **munging***
- *A lot of munging has to take place to get the data from one schema into another.*

    - split is often combined with strip to trim whitespace (including line breaks)

```
In [136]: pieces = [x.strip() for x in val.split(',')]

In [137]: pieces
Out[137]: ['a', 'b', 'guido']
```

    - These substrings could be concatenated together with a two-colon delimiter by passing a list or tuple to the **join** method on the string '::'

```
In [140]: '::'.join(pieces)
Out[140]: 'a::b::guido'
```

Data preparation: Cleaning and Wrangling

- String Manipulation: String Object Methods
  - Other methods are concerned with locating substrings
    - **index** and **find** methods to detect substrings

```
In [134]: val = 'a,b,  guido'
```

```
In [141]: 'guido' in val
Out[141]: True

In [142]: val.index(',')
Out[142]: 1

In [143]: val.find(':')
Out[143]: -1
```

index raises an exception if the string isn't found (versus returning –1)

val.index(':')

    - **count** returns the number of occurrences of a particular substring

```
In [145]: val.count(',')
Out[145]: 2
```

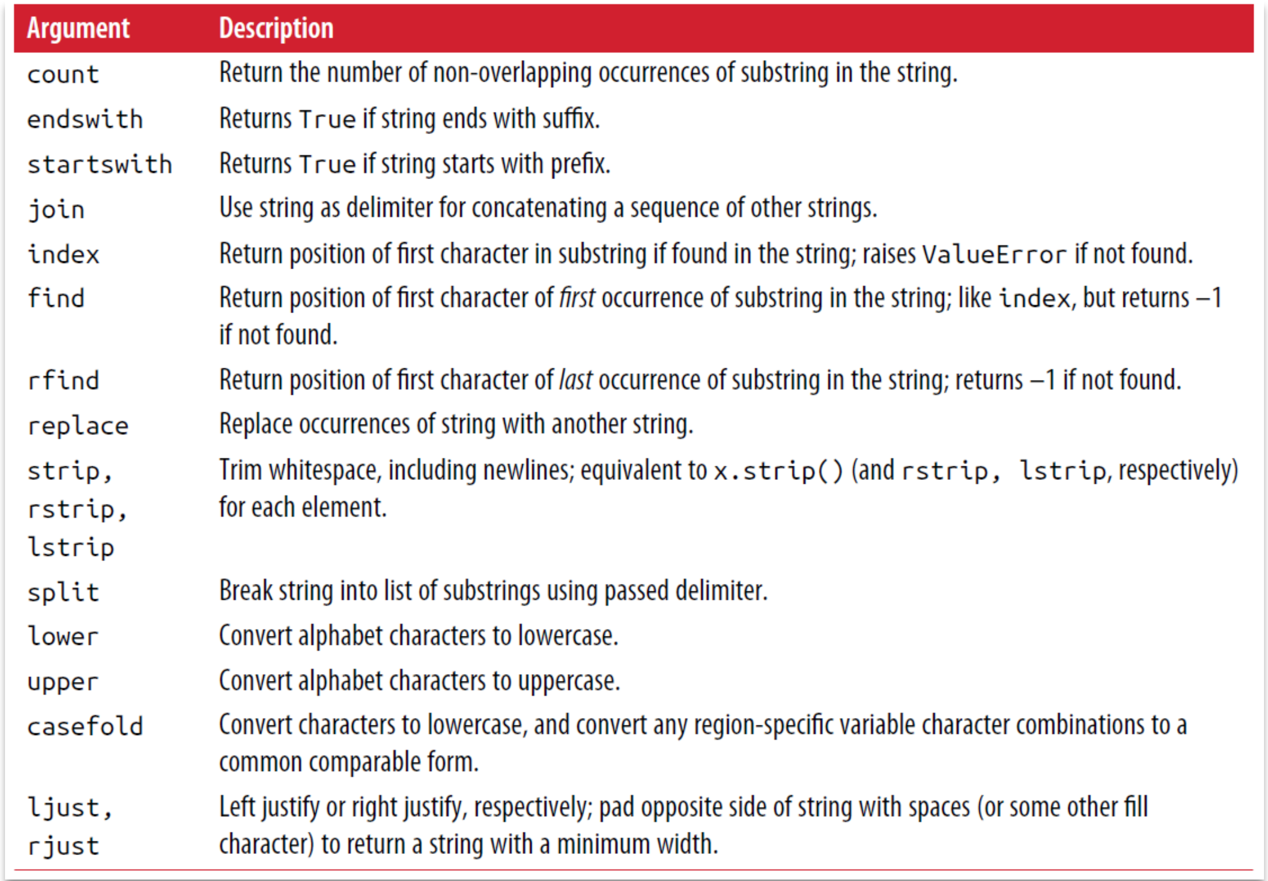
    - **replace** will substitute occurrences of one pattern for another.

```
In [146]: val.replace(',', '::')
Out[146]: 'a::b::  guido'

In [147]: val.replace(',', '')
Out[147]: 'ab  guido'
```

It is commonly used to delete patterns, too, by passing an empty string

Data preparation: Cleaning and Wrangling

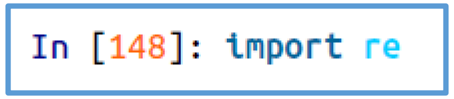
- String Manipulation: String Object Methods
  - Python built-in string methods



Argument	Description
`count`	Return the number of non-overlapping occurrences of substring in the string.
`endswith`	Returns `True` if string ends with suffix.
`startswith`	Returns `True` if string starts with prefix.
`join`	Use string as delimiter for concatenating a sequence of other strings.
`index`	Return position of first character in substring if found in the string; raises `ValueError` if not found.
`find`	Return position of first character of *first* occurrence of substring in the string; like `index`, but returns –1 if not found.
`rfind`	Return position of first character of *last* occurrence of substring in the string; returns –1 if not found.
`replace`	Replace occurrences of string with another string.
`strip`, `rstrip`, `lstrip`	Trim whitespace, including newlines; equivalent to `x.strip()` (and `rstrip, lstrip`, respectively) for each element.
`split`	Break string into list of substrings using passed delimiter.
`lower`	Convert alphabet characters to lowercase.
`upper`	Convert alphabet characters to uppercase.
`casefold`	Convert characters to lowercase, and convert any region-specific variable character combinations to a common comparable form.
`ljust`, `rjust`	Left justify or right justify, respectively; pad opposite side of string with spaces (or some other fill character) to return a string with a minimum width.

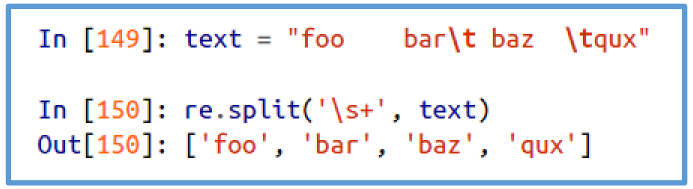
Data preparation: Cleaning and Wrangling

- String Manipulation: Regular Expressions
  - A single expression, commonly called a regex, is a string formed according to the regular expression language



```
In [148]: import re
```

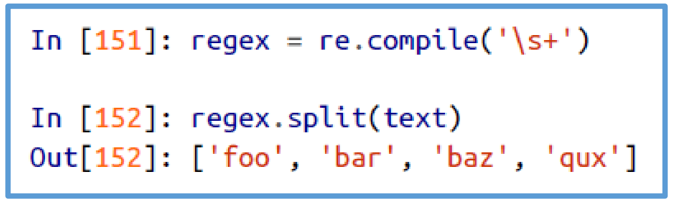
  - Python's built-in **re** module is responsible for applying regular expressions to strings



```
In [149]: text = "foo    bar\t baz  \tqux"

In [150]: re.split('\s+', text)
Out[150]: ['foo', 'bar', 'baz', 'qux']
```

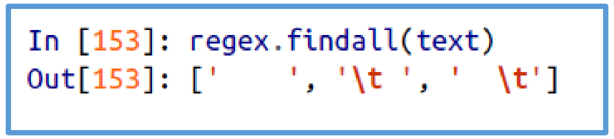
  - **re** functions fall into three categories
    - Pattern matching
    - Substitution
    - Splitting

Describing one or more whitespace characters is \s+



```
In [151]: regex = re.compile('\s+')

In [152]: regex.split(text)
Out[152]: ['foo', 'bar', 'baz', 'qux']
```

Compiling by yourself

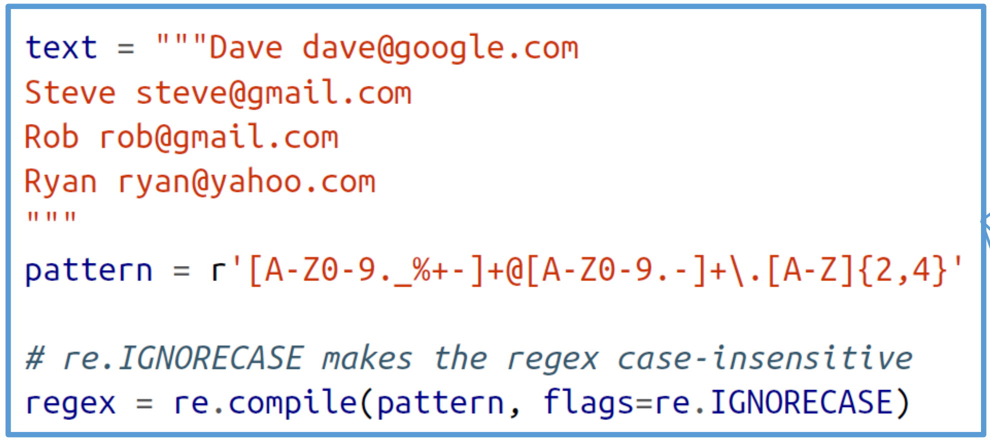


```
In [153]: regex.findall(text)
Out[153]: ['    ', '\t ', '  \t']
```

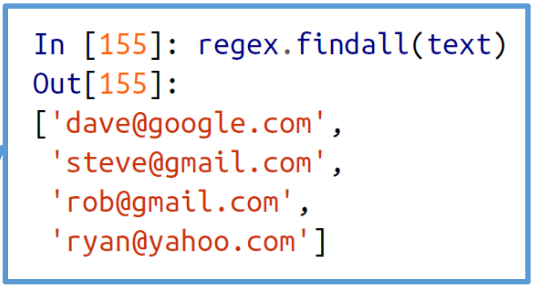
To avoid unwanted escaping with \ in a regular expression, use *raw* string literals like **r'C:\x'** instead of the equivalent 'C:\\x'.

Data preparation: Cleaning and Wrangling

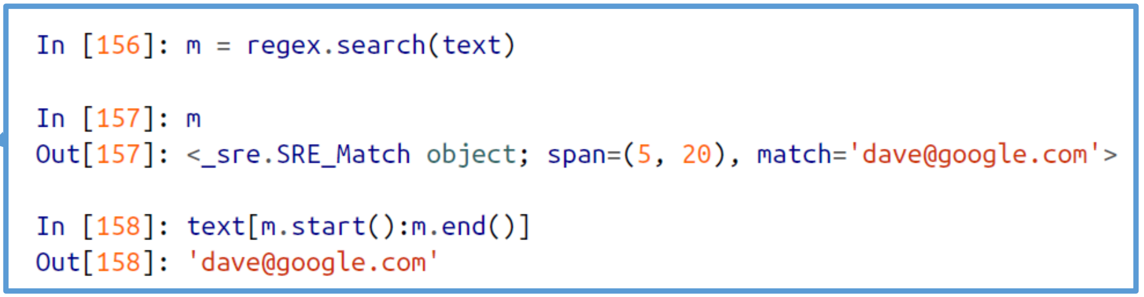
- String Manipulation: Regular Expressions
  - **findall** returns all matches in a string
  - **search** returns only the first match
  - **match** only matches at the beginning of the string



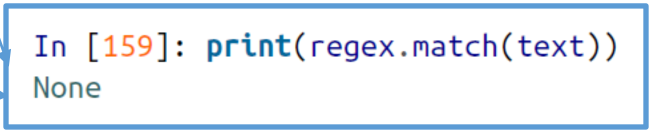
```python
text = """Dave dave@google.com
Steve steve@gmail.com
Rob rob@gmail.com
Ryan ryan@yahoo.com
"""
pattern = r'[A-Z0-9._%+-]+@[A-Z0-9.-]+\.[A-Z]{2,4}'

# re.IGNORECASE makes the regex case-insensitive
regex = re.compile(pattern, flags=re.IGNORECASE)
```



```
In [155]: regex.findall(text)
Out[155]:
['dave@google.com',
 'steve@gmail.com',
 'rob@gmail.com',
 'ryan@yahoo.com']
```



```
In [156]: m = regex.search(text)

In [157]: m
Out[157]: <_sre.SRE_Match object; span=(5, 20), match='dave@google.com'>

In [158]: text[m.start():m.end()]
Out[158]: 'dave@google.com'
```



```
In [159]: print(regex.match(text))
None
```

None, because it only will match if the pattern occurs at the start of the string

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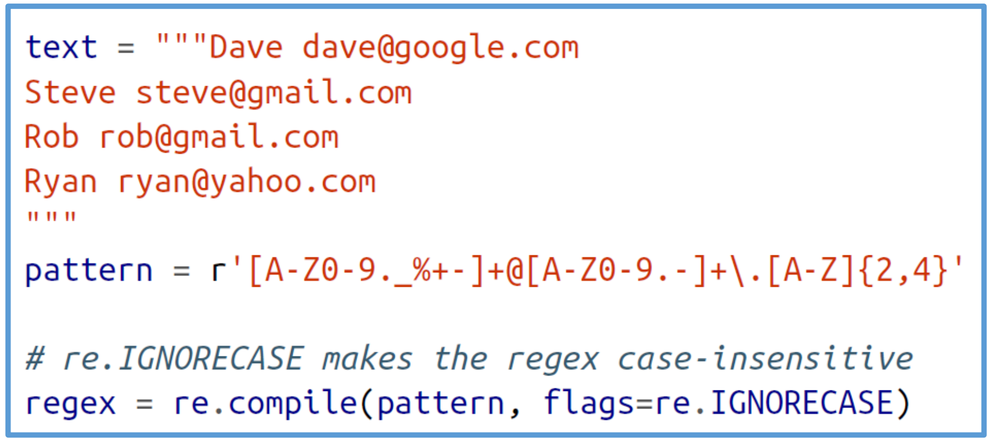
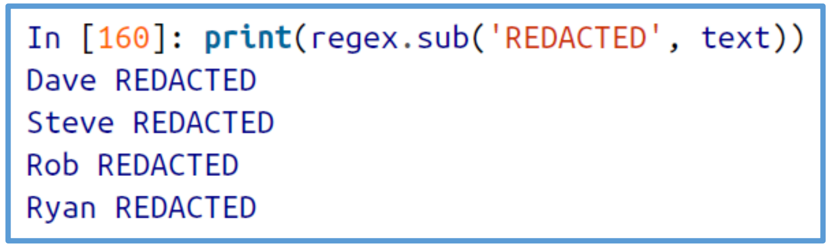
Data preparation: Cleaning and Wrangling

- String Manipulation: Regular Expressions
  - **sub** will return a new string with occurrences of the pattern replaced by the a new string



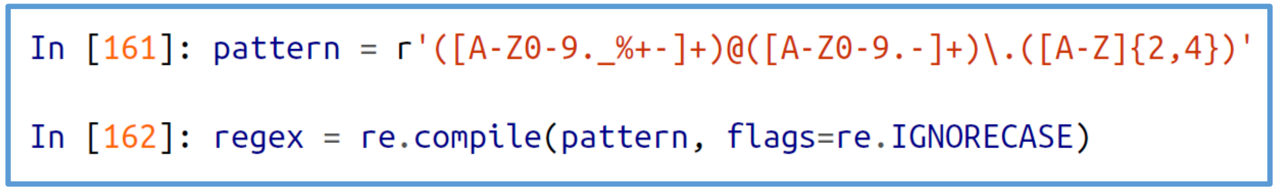
```
text = """Dave dave@google.com
Steve steve@gmail.com
Rob rob@gmail.com
Ryan ryan@yahoo.com
"""
pattern = r'[A-Z0-9._%+-]+@[A-Z0-9.-]+\.[A-Z]{2,4}'

# re.IGNORECASE makes the regex case-insensitive
regex = re.compile(pattern, flags=re.IGNORECASE)
```



```
In [160]: print(regex.sub('REDACTED', text))
Dave REDACTED
Steve REDACTED
Rob REDACTED
Ryan REDACTED
```

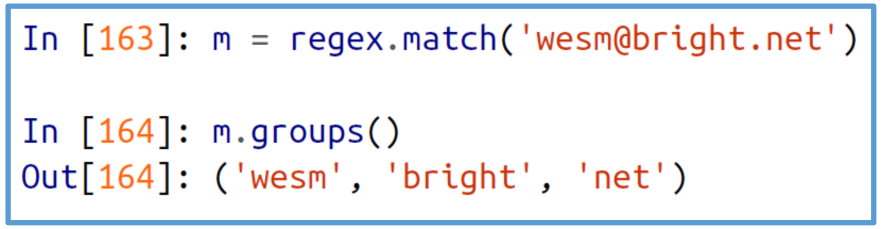
  - To segment components (username, domain name, and domain suffix) put parentheses around the parts of the pattern



```
In [161]: pattern = r'([A-Z0-9._%+-]+)@([A-Z0-9.-]+)\.([A-Z]{2,4})'

In [162]: regex = re.compile(pattern, flags=re.IGNORECASE)
```

  - A match object produced by this modified regex returns a tuple of the pattern components with its **groups** method

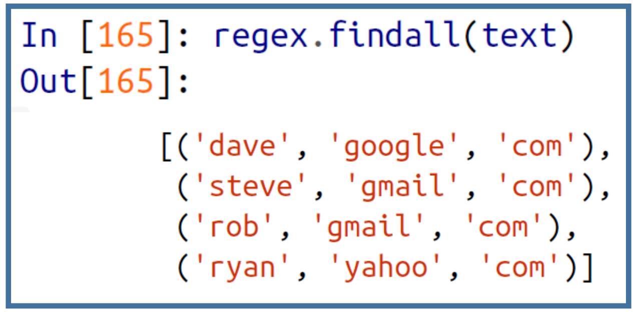


```
In [163]: m = regex.match('wesm@bright.net')

In [164]: m.groups()
Out[164]: ('wesm', 'bright', 'net')
```

Data preparation: Cleaning and Wrangling

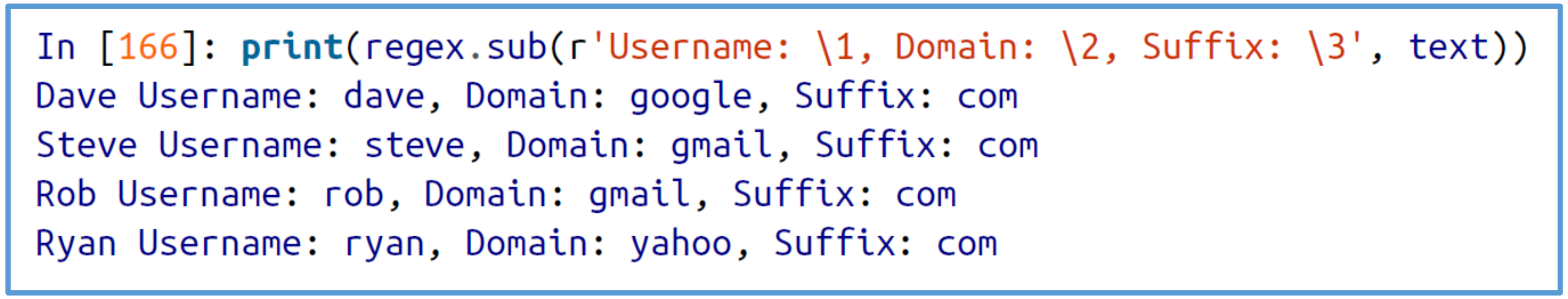
- String Manipulation: Regular Expressions
  - **findall** returns a list of tuples when the pattern has groups



```
In [165]: regex.findall(text)
Out[165]:

        [('dave', 'google', 'com'),
         ('steve', 'gmail', 'com'),
         ('rob', 'gmail', 'com'),
         ('ryan', 'yahoo', 'com')]
```

  - **sub** also has access to groups in each match using special symbols like \1 and \2
    - The symbol \1 corresponds to the first matched group, \2 corresponds to the second, and so forth



```
In [166]: print(regex.sub(r'Username: \1, Domain: \2, Suffix: \3', text))
Dave Username: dave, Domain: google, Suffix: com
Steve Username: steve, Domain: gmail, Suffix: com
Rob Username: rob, Domain: gmail, Suffix: com
Ryan Username: ryan, Domain: yahoo, Suffix: com
```