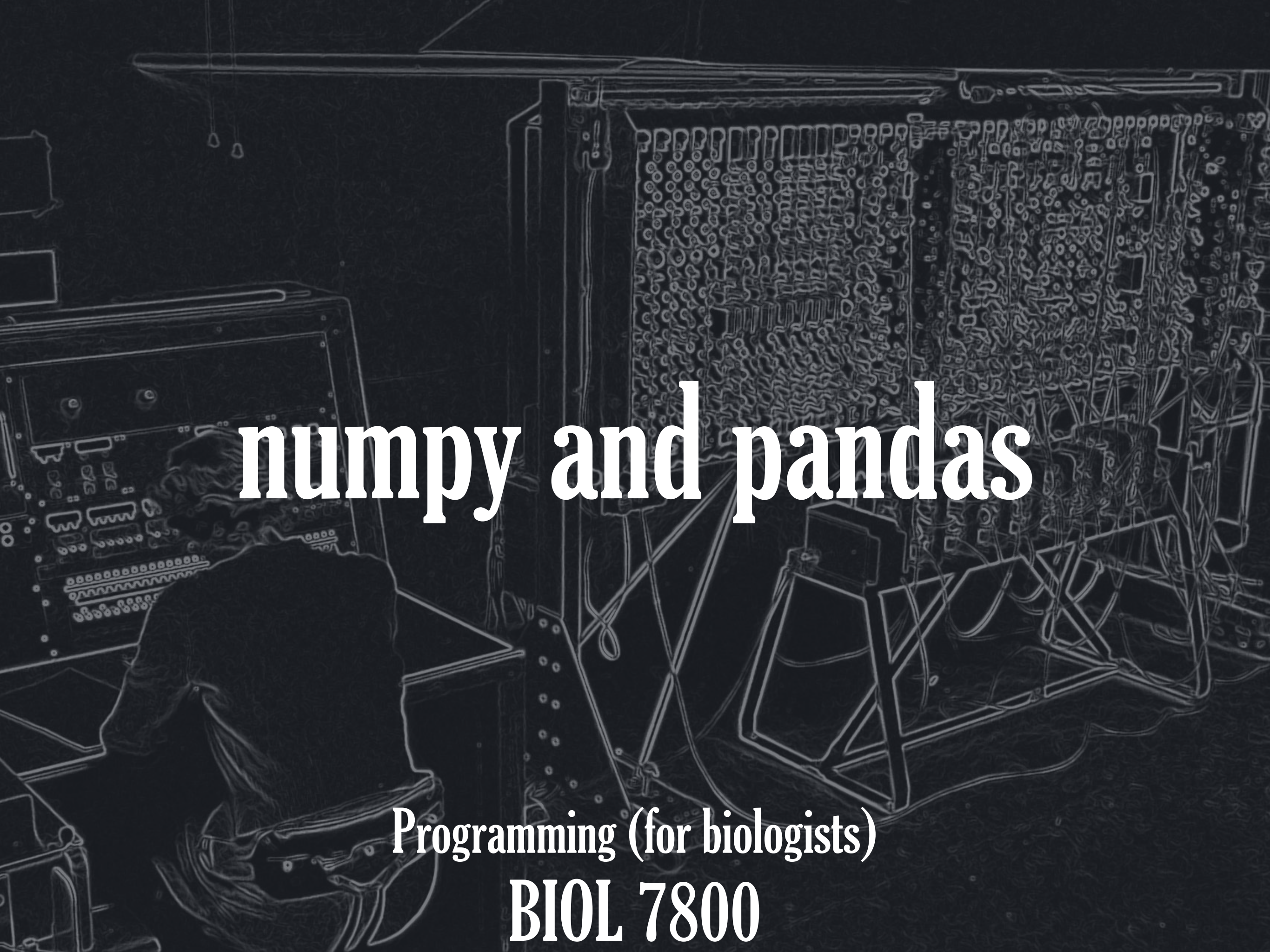




numpy and pandas

Programming (for biologists)
BIOL 7800

Python List

Enclosed in **square** brackets



You can **access** an **element**

```
my_list[3] = 'cool'
```

Python List

Enclosed in **square** brackets



You can **slice** a list

`my_list[2:4] = ['pretty', 'cool']`

Note: this returns **another list**

Python List

matrix

$$\begin{bmatrix} 1, & 2, & 3, & 4 \\ 5, & 6, & 7, & 8 \\ 9, & 10, & 11, & 12 \end{bmatrix}$$

But how do you represent a structure like this
with Python **lists**?

Python List

But how do you represent a structure like this
with Python `lists`?

```
my_matrix = [  
    [1, 2, 3, 4],  
    [5, 6, 7, 8],  
    [9, 10, 11, 12]  
]
```

```
print(my_matrix)
```

```
[[1, 2, 3, 4], [5, 6, 7, 8], [9, 10, 11, 12]]
```

Python List

This kind of does what we want...

```
print(my_matrix)
```

```
[[1, 2, 3, 4], [5, 6, 7, 8], [9, 10, 11, 12]]
```

```
print(my_matrix[0])
```

```
[1, 2, 3, 4]
```

← We can access "rows"

```
print(my_matrix[1][1])
```

← We can access "items"

Python List

But, there's a problem here... what if we want to perform operations on the matrix?

```
print(my_matrix * 2)
```

What do you expect this to produce?

Python List

But, there's a problem here... what if we want to perform operations on the matrix?

```
print(my_matrix * 2)
```

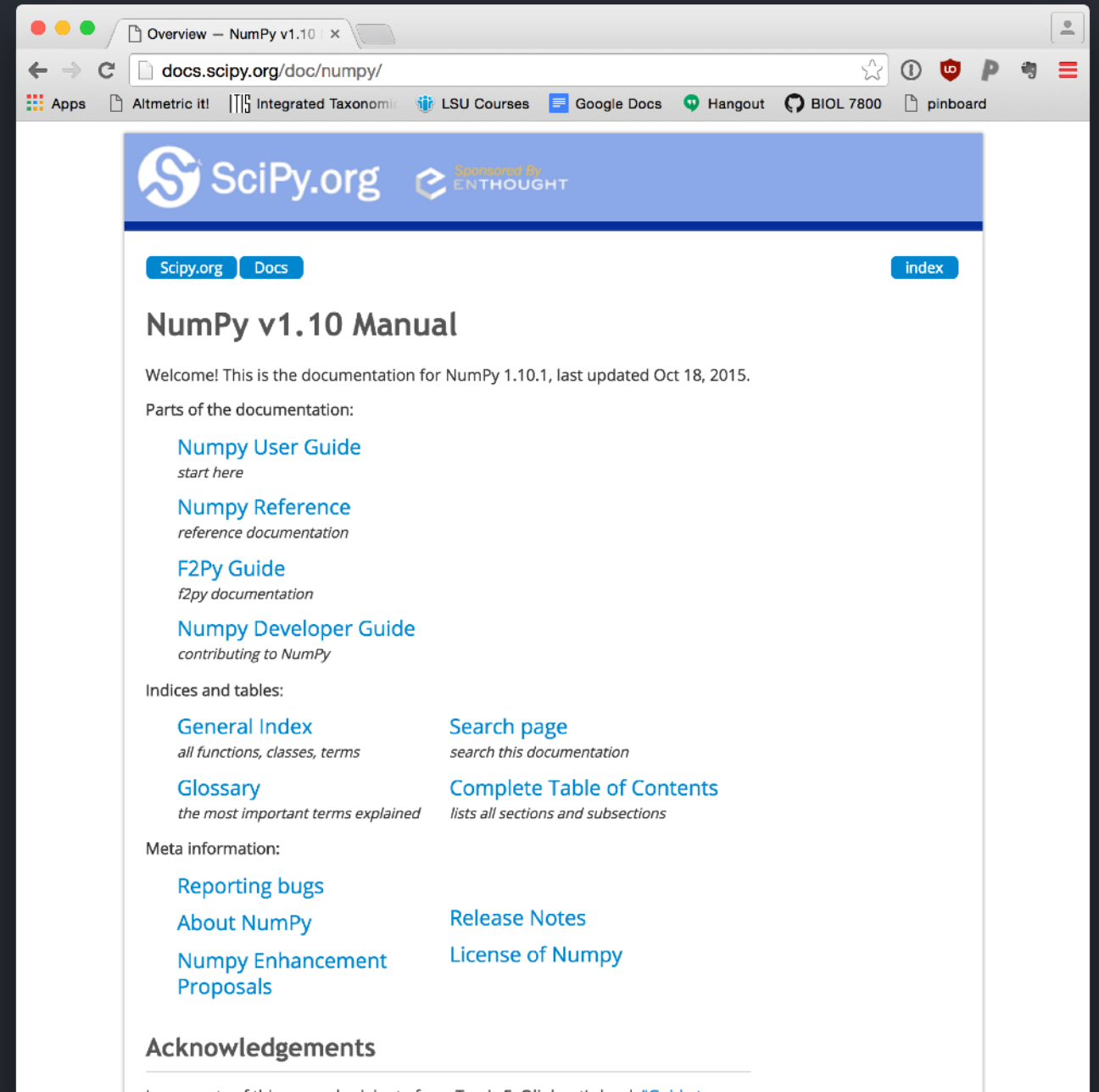
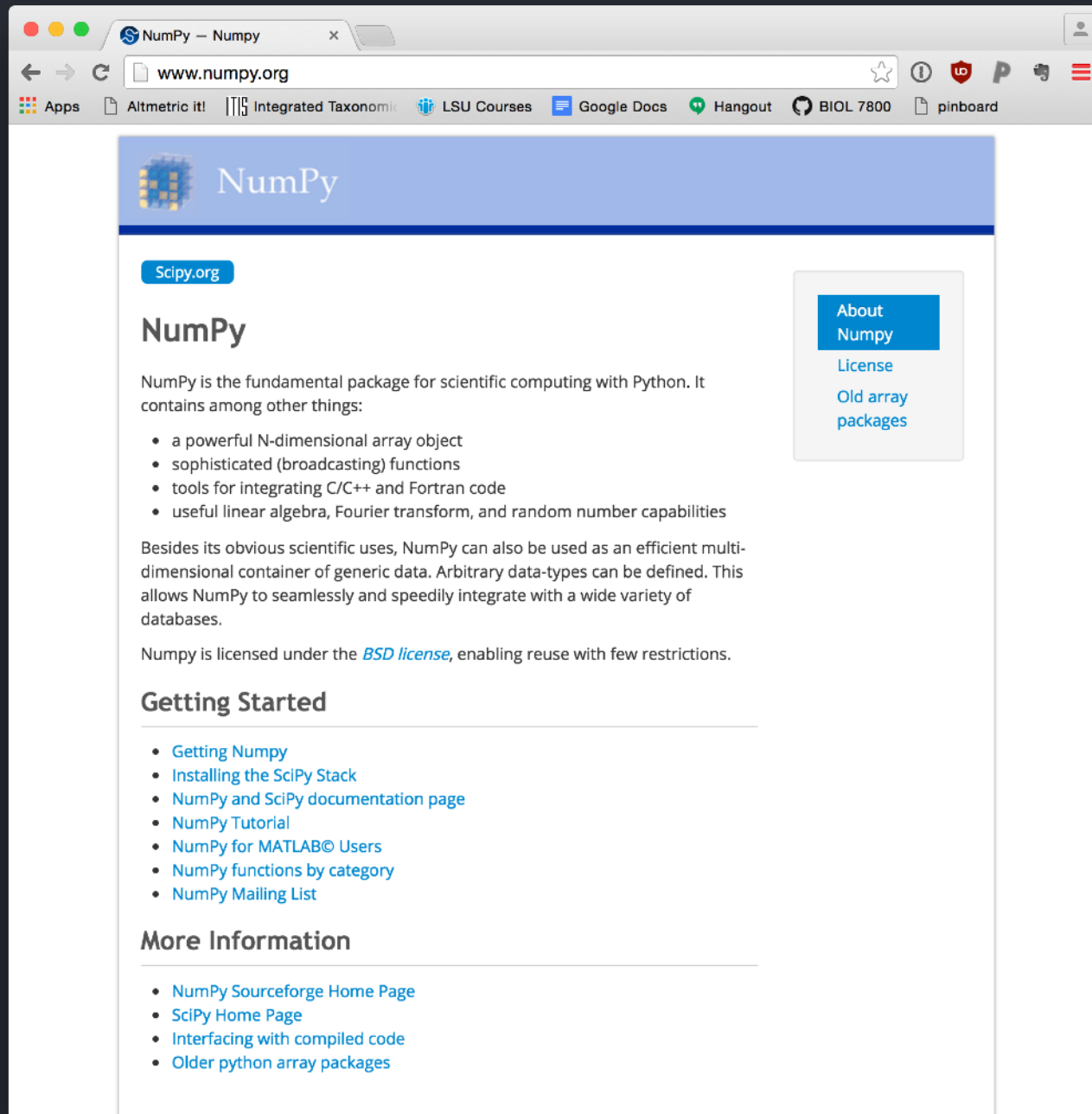
```
[[1, 2, 3, 4],  
 [5, 6, 7, 8],  
 [9, 10, 11, 12],  
 [1, 2, 3, 4],  
 [5, 6, 7, 8],  
 [9, 10, 11, 12]]
```

← Is this what you wanted?

and that's where

numpy (numerical python)

becomes useful



What is numpy?

(Very) Fast N-dimensional array objects

you can create matrices/arrays of any dimension
arrays can have many types (integer, float, string, etc)

(Very) Fast methods for operating on N-dim arrays

you can transform, reshape, slice, alter, multiple, add, etc., etc.

(Very) Fast random number and linear algebra capabilities

you can generate hundreds, thousands, millions of random numbers, etc.

Anatomy of a **numpy** array

(it's a lot like a list... sort of...)

```
In: import numpy
```

← Import **numpy**

```
In: my_array = numpy.array([1,2,3,4])
```

← Create array

```
In: my_array
```

```
Out: array([1, 2, 3, 4])
```

↖ Wrap a list in **numpy.array()**

```
In: my_array[0]
```

← Access element

```
Out: 1
```

```
In: my_array[1:3]
```

← Slice

```
Out: array([2, 3])
```

Anatomy of a **numpy** array

(but, it's also **not** like a list at all...)

In: `my_array = numpy.array([1,2,3,4])` ← Create array

In: `my_array*2` ← This operation multiplies every element by 2
Out: `array([2, 4, 6, 8])`

In: `my_array_2 = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `my_array_2`

Out: `array([[1, 2, 3, 4],
 [5, 6, 7, 8],
 [9, 10, 11, 12]])`

↖ We can have 2d arrays

In: `my_array_2[0]`

Out: `array([1, 2, 3, 4])`

← We can get a row slice

Anatomy of a **numpy** array

(but, it's also **not** like a list at all...)

In: `my_array_2 = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `my_array_2`

Out: `array([[1, 2, 3, 4],
 [5, 6, 7, 8],
 [9, 10, 11, 12]])`

← We can have 2d arrays

we can do "fancy" slicing

In: `my_array_2[:, 0]`

Out: `array([1, 5, 9])`

← We can get a column slice

In: `my_array_2[1:3, 1]`

Out: `array([6, 10])`

← We can get row + column slice

Anatomy of a **numpy** array

(but, it's also **not** like a list at all...)

we can do "fancy" indexing

In: `my_array = numpy.array([1,2,3,4])`

In: `keep = numpy.array([True,False,True,False])` ← We can slice/index an array
with another array!
(a boolean)

In: `my_array[keep]`

Out: `array([1, 3])`

In: `keep = numpy.array([0,2,3])`

← We can slice/index an array
with another array!
(index integers)

In: `my_array[keep]`

Out: `array([1, 3, 4])`

Anatomy of a **numpy** array

(array attributes)

In: `my_array = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `my_array`

Out: `array([[1, 2, 3, 4],
 [5, 6, 7, 8],
 [9, 10, 11, 12]])`

←↑ Create array
(notice double `[[ ]]`)

In: `my_array.ndim`

Out: `2`

← Get array
dimensions

In: `my_array.shape`

Out: `(3, 4)`

← Get array
shape (rows,cols)

In: `my_array.size`

Out: `12`

← Get array size
(total elements)

In: `my_array.dtype`

Out: `dtype('int64')`

← Get array data type

Anatomy of a **numpy** array

(array methods - remember, these are all very fast)

In: `my_array = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `my_array.sum()`

Out: 78



Get array
sum

In: `my_array.min()`

Out: 1



Get array minimum

In: `my_array.max()`

Out: 12



Get array maximum

In: `my_array.mean()`

Out: 6.5



Get array mean

In: `my_array.std()`

Out: 3.4520525295346629



Get array
standard deviation

Anatomy of a **numpy** array

(array methods - remember, these are all very fast)

In: `my_array = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `my_array.reshape(2,6)`

Out: `array([[1, 2, 3, 4, 5, 6],
 [7, 8, 9, 10, 11, 12]])`

← reshape the array
to (2 rows, 6 cols)

In: `my_array.reshape(6,2)`

Out: `array([[1, 2],
 [3, 4],
 [5, 6],
 [7, 8],
 [9, 10],
 [11, 12]])`

← reshape the array
to (6 rows, 2 cols)

Anatomy of a **numpy** array

(array methods - remember, these are all very fast)

In: `my_array = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])`

In: `new = my_array.reshape(3,2,2)`  reshape the array
to (3 dimensions, 2 rows, 2 cols)

Out: `array([[[1, 2],
 [3, 4]],

 [[5, 6],
 [7, 8]],

 [[9, 10],
 [11, 12]]])`

In: `new[0]`

Out: `array([[1, 2],
 [3, 4]])`

 `new[0]` is now
the first dimension

Anatomy of a **numpy** array

(array methods - remember, these are all very fast)

```
In: my_array = numpy.array([[1,2,3,4],[5,6,7,8],[9,10,11,12]])
```

```
In: my_array
```

```
array([[ 1,  2,  3,  4],  
       [ 5,  6,  7,  8],  
       [ 9, 10, 11, 12]])
```

```
In: my_array.sum(axis=0)
```

```
Out: array([15, 18, 21, 24])
```



You can perform operations by column

```
In: my_array.sum(axis=1)
```

```
Out: array([10, 26, 42])
```



You can perform operations by row

Anatomy of a **numpy** array

(array methods - remember, these are all very fast)

```
In: my_array
array([[ 1,  2,  3,  4],
       [ 5,  6,  7,  8],
       [ 9, 10, 11, 12]])
```

```
In: for row in my_array:
      print(row)
```

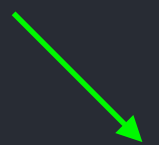
Out:

```
[1 2 3 4]
[5 6 7 8]
[ 9 10 11 12]
```



You can iterate
over rows

transpose



```
In: for col in my_array.T:
      print(col)
```

Out:

```
[1 5 9]
[ 2 6 10]
[ 3 7 11]
[ 4 8 12]
```



You can iterate over columns
(by *transposing the array*)

Anatomy of a **numpy** **array**

You can quickly create arrays of different types

```
In: my_array = numpy.zeros([3,3])
```

```
In: my_array
```

```
Out: array([[ 0.,  0.,  0.],  
           [ 0.,  0.,  0.],  
           [ 0.,  0.,  0.]])
```

```
In: my_array = numpy.ones([3,3])
```

```
In: my_array
```

```
Out: array([[ 1.,  1.,  1.],  
           [ 1.,  1.,  1.],  
           [ 1.,  1.,  1.]])
```

```
In: my_array = numpy.identity(3)
```

```
In: my_array
```

```
Out: array([[ 1.,  0.,  0.],  
           [ 0.,  1.,  0.],  
           [ 0.,  0.,  1.]])
```

Anatomy of a **numpy** **array**

You can quickly create arrays of different types

```
In: my_array_1 = numpy.ones([3,3])
```

```
In: my_array_1
```

```
Out: array([[ 1.,  1.,  1.],  
           [ 1.,  1.,  1.],  
           [ 1.,  1.,  1.]])
```

```
In: my_array_2 = numpy.identity(3)
```

```
In: my_array_2
```

```
Out: array([[ 1.,  0.,  0.],  
           [ 0.,  1.,  0.],  
           [ 0.,  0.,  1.]])
```

```
In: my_array_1 + my_array_2
```

```
Out: array([[ 2.,  1.,  1.],  
           [ 1.,  2.,  1.],  
           [ 1.,  1.,  2.]])
```



You can add arrays
(it's elementwise)

Anatomy of a **numpy** **array**

You can quickly create arrays of different types

```
In: my_array_1 = numpy.array(list('dog'))
```

```
In: my_array_1
```

```
Out: array(['d', 'o', 'g'],  
          dtype='<U1')
```

```
In: my_array_2 = numpy.array(list('cat'))
```

```
In: my_array_2
```

```
Out: array(['c', 'a', 't'],  
          dtype='<U1')
```

```
In: numpy.vstack([my_array_1, my_array_2]) ←—— You can stack arrays
```

```
Out: array([[ 'd', 'o', 'g'],  
          [ 'c', 'a', 't']],  
          dtype='<U1')
```

numpy

many, many, many, many other methods & functions

Now, one thing you may be thinking is that
numpy seems ideal for tabular data

So this



height	width
1	2
3	4
5	6
7	8
9	10
11	12

Can be represented
as this



In: my_array

Out: array([[1, 2],
[3, 4],
[5, 6],
[7, 8],
[9, 10],
[11, 12]])

numpy

Now, one thing you may be thinking is that **numpy** seems ideal for tabular data

So this



height	width
1	2
3	4
5	6
7	8
9	10
11	12

Can be represented
as this



```
In: my_array
Out: array([[ 1,  2],
           [ 3,  4],
           [ 5,  6],
           [ 7,  8],
           [ 9, 10],
           [11, 12]])
```

But, what's **one** problem here?

numpy

So this



height	width
1	2
3	4
5	6
7	8
9	10
11	12

Can be represented
as this



```
In: my_array  
Out: array([[ 1,  2],  
            [ 3,  4],  
            [ 5,  6],  
            [ 7,  8],  
            [ 9, 10],  
            [11, 12]])
```

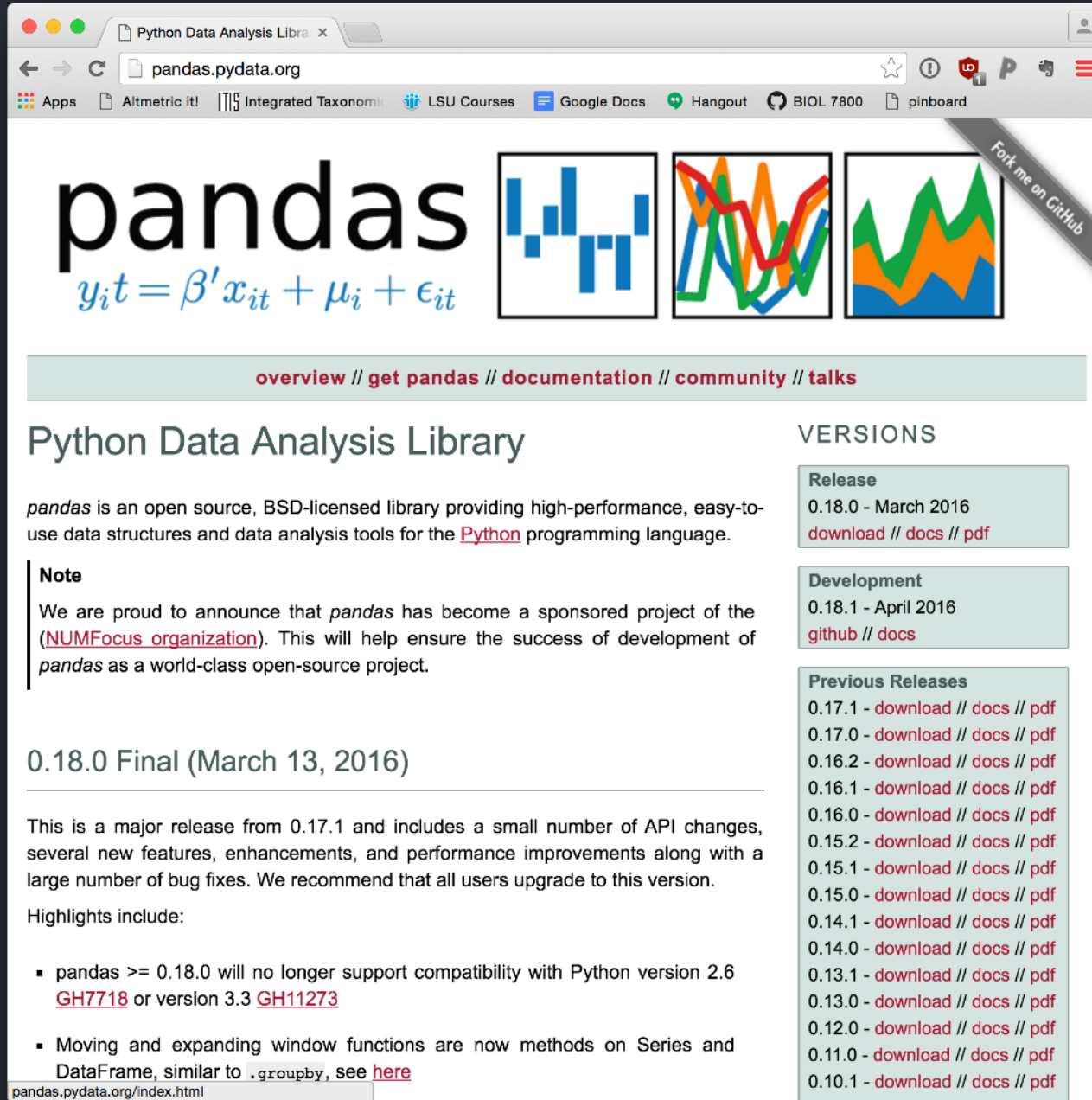
But, what's **one** problem here?

*It's **hard** to keep track of columns and rows*

`my_array[:, 0]`

`my_array[:, 1]`

and that's where **pandas** comes into play



The screenshot shows the pandas website with the following content:

- Header:** pandas logo with the equation $y_i t = \beta' x_{it} + \mu_i + \epsilon_{it}$ and three charts (bar, line, area).
- Navigation:** overview // get pandas // documentation // community // talks
- Python Data Analysis Library:**
 - Overview:** pandas is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.
 - Note:** We are proud to announce that pandas has become a sponsored project of the (NUMFocus organization). This will help ensure the success of development of pandas as a world-class open-source project.
- 0.18.0 Final (March 13, 2016):**
 - This is a major release from 0.17.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.
 - Highlights include:**
 - pandas >= 0.18.0 will no longer support compatibility with Python version 2.6 [GH7718](#) or version 3.3 [GH11273](#)
 - Moving and expanding window functions are now methods on Series and DataFrame, similar to `.groupby`, see [here](#)
- VERSIONS:**
 - Release:** 0.18.0 - March 2016 (download // docs // pdf)
 - Development:** 0.18.1 - April 2016 (github // docs)
 - Previous Releases:** 0.17.1 - download // docs // pdf, 0.17.0 - download // docs // pdf, 0.16.2 - download // docs // pdf, 0.16.1 - download // docs // pdf, 0.16.0 - download // docs // pdf, 0.15.2 - download // docs // pdf, 0.15.1 - download // docs // pdf, 0.15.0 - download // docs // pdf, 0.14.1 - download // docs // pdf, 0.14.0 - download // docs // pdf, 0.13.1 - download // docs // pdf, 0.13.0 - download // docs // pdf, 0.12.0 - download // docs // pdf, 0.11.0 - download // docs // pdf, 0.10.1 - download // docs // pdf

pandas is a data structure built on the **numpy** framework that gives us access to data as *"frames"* (also includes **many more** functions)

pandas

has two major types of data objects

Series

one dimensional labelled array

Data Frame

two-dimensional labelled array

pandas

Series - one dimensional, labelled array

```
In: import pandas as pd
```

```
In: my_series = pd.Series([1,2,3,4], index=['a','b','c','d']) ← Create series
```

```
In: my_series
```

```
Out:
```

```
a    1
```

```
b    2
```

```
c    3
```

```
d    4
```

```
dtype: int64
```

index holds data labels



```
In: my_series['a']
```

```
Out: 1
```

← We can slice by label

```
In: my_series['b':'c']
```

```
Out:
```

```
b    2
```

```
c    3
```

```
dtype: int64
```

← We can slice by labels

pandas

Series - one dimensional, labelled array

```
In: my_dict = {'a':1, 'b':2, 'c':3, 'd':4}
```

```
In: my_series = pd.Series(my_dict)
```

```
In: my_series
```

```
Out:
```

```
a    1
```

```
b    2
```

```
c    3
```

```
d    4
```

```
dtype: int64
```

← We can also create a series
from a **dict**

```
In: my_series[my_series > my_series.median()]
```

```
Out:
```

```
c    3
```

```
d    4
```

```
dtype: int64
```

← We can filter
with fancy indexing

```
In: my_series + my_series
```

```
Out:
```

```
a    2
```

```
b    4
```

```
c    6
```

```
d    8
```

```
dtype: int64
```

← We can perform
elementwise operations

pandas

Series - one dimensional, labelled array

```
In: my_dict = {'a':1, 'b':2, 'c':3, 'd':4}
```

```
In: my_series = pd.Series(my_dict)
```

```
In: my_series[1:]
```

← Slice rows b, c, d

```
Out:
```

```
b    2
```

```
c    3
```

```
d    4
```

```
dtype: int64
```

```
In: my_series[:-1]
```

← Slice rows a, b, c

```
Out:
```

```
a    1
```

```
b    2
```

```
c    3
```

```
dtype: int64
```

```
In: my_series[1:] + my_series[:-1]
```

← Add two slices together

```
Out:
```

```
a  NaN
```

```
b    4
```

```
c    6
```

```
d  NaN
```

```
dtype: float64
```

pandas operates on data based on the label (index). So, if there are not corresponding labels in a series, **you get no result**

pandas

Series - one dimensional, labelled array

```
In: my_series_1 = pd.Series({'a':1, 'b':2, 'c':3, 'd':4})
```

```
In: my_series_2 = pd.Series({'c':10, 'd':20, 'e':30, 'f':40})
```

```
In: my_series_1 + my_series_2
```

← Add two slices together

Out:

a NaN

b NaN

c 13

d 24

e NaN

f NaN

dtype: float64

pandas operates on data based on the label (index). So, if there are not corresponding labels in a series, you get no result

```
In: import numpy
```

```
In: numpy.exp(my_series_1 + my_series_2)
```

← most numpy functions also work with series

Out:

a NaN

b NaN

c 4.424134e+05

d 2.648912e+10

e NaN

f NaN

dtype: float64

(here, get exponential of **all** elements)

pandas

Data Frame - two-dimensional, labelled array

Lots of ways to create a **DataFrame**

```
In: my_series_1 = pd.Series({'a':1, 'b':2, 'c':3, 'd':4})
```

```
In: my_series_2 = pd.Series({'c':10, 'd':20, 'e':30, 'f':40})
```

```
In: my_df = pd.DataFrame({'col1': my_series_1, 'col2': my_series_2})
```

```
In: my_df
```

Out:

	col1	col2
a	1	NaN
b	2	NaN
c	3	10
d	4	20
e	NaN	30
f	NaN	40

pandas

Data Frame - two-dimensional, labelled array

Lots of ways to create a **DataFrame**

```
In: my_dict = {'one': [1., 2., 3., 4.], 'two': [4., 3., 2., 1.]}
```

```
In: my_df = pd.DataFrame(my_dict, index=['a','b','c','d'])
```

```
In: my_df
```

```
Out:
```

	one	two
a	1	4
b	2	3
c	3	2
d	4	1

```
In: my_df['one']['a':'c']
```

```
Out:
```

```
a    1  
b    2  
c    3
```

```
Name: one, dtype: float64
```

```
In: my_df['one']['a':'c'].sum()
```

```
Out: 6.0
```

pandas

Lots of ways to create a **DataFrame**

Read from a **CSV** file

```
In: print(open('table.csv').read())
```

Out:

height,width

1,2

3,4

5,6

7,8

9,10

11,12

```
In: my_df = pd.read_csv('table.csv')
```

```
In: my_df
```

Out:

	height	width
0	1	2
1	3	4
2	5	6
3	7	8
4	9	10
5	11	12

As 'table.csv'
in filesystem

height	width
1	2
3	4
5	6
7	8
9	10
11	12

pandas

Lots of ways to manipulate a **DataFrame**

```
In: my_df = pd.read_csv('table.csv')
```

```
In: my_df.T
```

Out:

```
      0  1  2  3  4  5
height 1  3  5  7  9 11
width  2  4  6  8 10 12
```

```
In: my_df_2 = pd.read_csv('table2.csv')
```

```
In: pd.concat([my_df, my_df_2])
```

Out:

```
   girth  height  length  width
0   NaN      1     NaN     2
1   NaN      3     NaN     4
2   NaN      5     NaN     6
3   NaN      7     NaN     8
4   NaN      9     NaN    10
5   NaN     11     NaN    12
0  100     NaN     10    NaN
1  200     NaN     20    NaN
2  300     NaN     30    NaN
3  400     NaN     40    NaN
4  500     NaN     50    NaN
5  600     NaN     60    NaN
```

As 'table.csv'

height	width
1	2
3	4
5	6
7	8
9	10
11	12

As 'table2.csv'

length	girth
10	100
20	200
30	300
40	400
50	500
60	600

How would we merge side-by-side (based on index)?

pandas

Lots of ways to manipulate a **DataFrame**

How would we merge side-by-side (based on index)?

As 'table.csv'

height	width
1	2
3	4
5	6
7	8
9	10
11	12

As 'table2.csv'

length	girth
10	100
20	200
30	300
40	400
50	500
60	600

```
In: my_df_2 = pd.read_csv('table2.csv')
```

```
In: new_df = pd.concat([my_df, my_df_2], axis = 1)
```

```
In: new_df
```

Out:

```
   height  width  length  girth
0        1      2      10    100
1         3      4      20    200
2         5      6      30    300
3         7      8      40    400
4         9     10      50    500
5        11     12      60    600
```

```
In: new_df['height'] > 5
```

```
0    False
```

```
1    False
```

```
2    False
```

```
3     True
```

```
4     True
```

```
5     True
```

```
Name: height, dtype: bool
```

pandas

Lots of ways to manipulate a DataFrame

How would we merge side-by-side (based on index)?

```
In: new_df['height'] > 5
```

```
Out:
```

```
0    False
1    False
2    False
3     True
4     True
5     True
Name: height, dtype: bool
```

```
In: new_df[new_df['height'] > 5]
```

```
Out:
```

```
   height  width  length  girth
3        7      8       40   400
4        9     10       50   500
5       11     12       60   600
```

```
In: new_df[new_df[(new_df['height'] > 5) & (new_df['width'] >= 10)]]
```

```
Out:
```

```
   height  width  length  girth
4        9     10       50   500
5       11     12       60   600
```

As 'table.csv'

height	width
1	2
3	4
5	6
7	8
9	10
11	12

As 'table2.csv'

length	girth
10	100
20	200
30	300
40	400
50	500
60	600

pandas

Lots of ways to manipulate a DataFrame

Lots of ways to do many things

many, many, many, many things

Too many things, in fact, to *show you all of them...*

(so, one small example)

pandas

Lots of ways to create a **DataFrame**

In: `amniote = pd.read_csv('Amniote_Database_Aug_2015.csv')`

In: `amniote.info()`

← Get info on data

Out:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21322 entries, 0 to 21321
Data columns (total 36 columns):
class                21322 non-null object
order                21322 non-null object
family               21322 non-null object
genus                21322 non-null object
species              21322 non-null object
subspecies           21322 non-null int64
common_name          21322 non-null object
female_maturity_d    21322 non-null float64
(...truncated...)
egg_width_mm         21322 non-null float64
egg_length_mm        21322 non-null float64
fledging_mass_g      21322 non-null float64
adult_svl_cm         21322 non-null float64
male_svl_cm          21322 non-null float64
female_svl_cm        21322 non-null float64
birth_or_hatching_svl_cm  21322 non-null float64
female_svl_at_maturity_cm  21322 non-null float64
female_body_mass_at_maturity_g  21322 non-null int64
no_sex_svl_cm        21322 non-null float64
no_sex_maturity_d    21322 non-null float64
dtypes: float64(28), int64(2), object(6)
memory usage: 6.0+ MB
```

pandas

Lots of ways to create a DataFrame

In: `amniote.head()`

Look at top rows of data

Out:

	class	order	family	genus	species	subspecies	\
0	Aves	Accipitriformes	Accipitridae	Accipiter	albogularis	-999	
1	Aves	Accipitriformes	Accipitridae	Accipiter	badius	-999	
2	Aves	Accipitriformes	Accipitridae	Accipiter	bicolor	-999	
3	Aves	Accipitriformes	Accipitridae	Accipiter	brachyurus	-999	
4	Aves	Accipitriformes	Accipitridae	Accipiter	brevipes	-999	

Missing entries seem to be coded -999

	common_name	female_maturity_d	litter_or_clutch_size_n	\
0	Pied Goshawk	-999.000	-999.00	
1	Shikra	363.468	3.25	
2	Bicolored Hawk	-999.000	2.70	
3	New Britain Sparrowhawk	-999.000	-999.00	
4	Levant Sparrowhawk	363.468	4.00	

(...truncated...)

In: `amniote.tail(4)`

Look at bottom (4) rows of data

Out:

	class	order	family	genus	species	\
21318	Reptilia	Testudines	Trionychidae	Palea	steindachneri	
21319	Reptilia	Testudines	Trionychidae	Pelochelys	bibroni	
21320	Reptilia	Testudines	Trionychidae	Pelodiscus	sinensis	
21321	Reptilia	Testudines	Trionychidae	Trionyx	triunguis	

	subspecies	common_name	\
21318	-999	Wattle-necked Soft-shelled Turtle	
21319	-999	Asian or Bibron's Giant soft-shelled Turtle	
21320	-999	Chinese Soft-shelled Turtle	
21321	-999	Nile Soft-shelled Turtle	

pandas

DataFrame methods

In: `amniote = amniote.replace(-999, numpy.nan)`

In: `amniote.head(2)`

Out:

	class	order	family	genus	species	subspecies	\
0	Aves	Accipitriformes	Accipitridae	Accipiter	albobularis	NaN	
1	Aves	Accipitriformes	Accipitridae	Accipiter	badius	NaN	

	common_name	female_maturity_d	litter_or_clutch_size_n	\
0	Pied Goshawk	NaN	NaN	
1	Shikra	363.468	3.25	

(...truncated...)

← Replace all -999 with numpy.nan

← Missing entries now coded NaN

subset data by reptiles

get litter/clutch size

use describe method on col

In: `amniote[amniote['class']=='Reptilia']['litter_or_clutch_size_n'].describe()`

Out:

count	2675.000000
mean	7.233857
std	10.129951
min	1.000000
25%	2.100000
50%	4.600000
75%	8.800000
max	156.000000

↑
Get descriptive statistics for all reptilian clutch sizes

pandas

DataFrame methods

get litter/clutch
size

Get max value

```
In: amniote[amniote['class']=='Aves']['litter_or_clutch_size_n'].max()
```

```
Out: 35.649999999999999
```

chained conditionals

subset data by birds

&

filter on litter/clutch size

```
In: amniote[(amniote['class'] == 'Aves') & (amniote['litter_or_clutch_size_n'] > 35)]
```

```
Out:
```

	class	order	family	genus	species	subspecies	\
3757	Aves	Passeriformes	Estrildidae	Neochmia	phaeton		NaN

	common_name	female_maturity_d	litter_or_clutch_size_n	\
3757	Crimson Finch	NaN	35.65	