Foreword

We have seen the use of jupyter notebooks.
As a matter of fact these slides are a notebook converted to (HTML) slides via the `jupyter-nbconvert` utility.
Get the code from gitlab here: https://gitlab.com/andreadotti/pyalghero2019 (https://gitlab.com/andreadotti/pyalghero2019) with, in an new terminal:

```
git clone https://gitlab.com/andreadotti/pyalghero2019
cd pyalghero2019
conda env create -f environment.yml
conda activate pycourse
. post-install.sh #Configure some extra stuff
```

The pre-installed environment `course` is enough to read/edit these slides.
Read the `README.md` file for additional instructions.

Python Introduction Course: Data Science tools

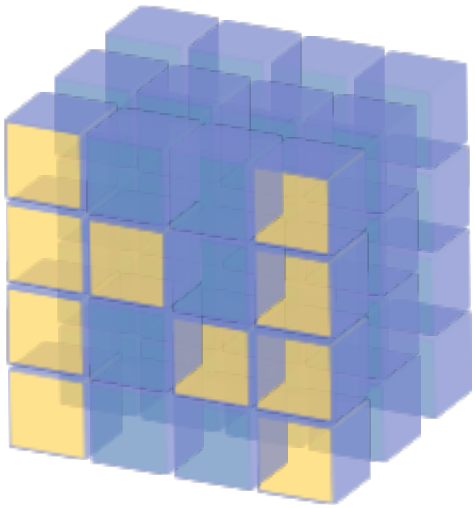
With emphasis on data-science problems
Geant4 Course at the 16th Seminar on Software for Nuclear, Sub-nuclear and Applied Physics, Porto Conte, Alghero (Italy), 26-31 May 2019. (https://agenda.infn.it/event/17240/)
This course is available on gitlab (https://gitlab.com/andreadotti/pyalghero2019)
Contact me: (mailto:andrea.dotti@gmail.com)

Scientific python stack

Get full documentation here (https://docs.scipy.org/doc/#).
Get a tutorial here (http://scipy-lectures.org/index.html)

The SciPy library contains several packages to perform specialized scientific calculations:

- Special functions (`scipy.special` (https://docs.scipy.org/doc/scipy/reference/tutorial/special.html))
- Integration (`scipy.integrate` (https://docs.scipy.org/doc/scipy/reference/tutorial/integrate.html))
- Optimization (`scipy.optimize` (https://docs.scipy.org/doc/scipy/reference/tutorial/optimize.html))
- Interpolation (`scipy.interpolate` (https://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html))
- Fourier Transforms (`scipy.fftpack` (https://docs.scipy.org/doc/scipy/reference/tutorial/fftpack.html))
- Signal Processing (`scipy.signal` (https://docs.scipy.org/doc/scipy/reference/tutorial/signal.html))
- Linear Algebra (`scipy.linalg` (https://docs.scipy.org/doc/scipy/reference/tutorial/linalg.html))
- Sparse Eigenvalue Problems with ARPACK (https://docs.scipy.org/doc/scipy/reference/tutorial/arpack.html)
- Compressed Sparse Graph Routines (`scipy.sparse.csgraph` (https://docs.scipy.org/doc/scipy/reference/tutorial/csgraph.html))
- Spatial data structures and algorithms (`scipy.spatial` (https://docs.scipy.org/doc/scipy/reference/tutorial/spatial.html))
- Statistics (`scipy.stats` (https://docs.scipy.org/doc/scipy/reference/tutorial/stats.html))



NumPy

Numpy

It is the foundation of python scientific stack.
The basic building block is the `numpy.array` data structure. It can be used as a python list of numbers, but it is a specialized efficient way of manipulating numbers in python.

In [4]:
```
import numpy as np
a = np.array([1, 2, 3, 4], dtype=float)
a
```

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

In [7]:
```
a = range(1000)
%timeit [ i**2 for i in a]
```

```
222 µs ± 3.93 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

In [8]:
```
b = np.arange(1000)
%timeit b**2
```

```
1.61 µs ± 10.6 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

In [10]:
```
c = np.array([[1,2],[3,4]])
c
```

Out[10]:
```
array([[1, 2],
       [3, 4]])
```

In [11]:
```
c.ndim
```

Out[11]:
```
2
```

In [12]:
```
c.shape
```

Out[12]:
```
(2, 2)
```

In [13]:
```
c = np.arange(27)
c.reshape((3,3,3))
```

Out[13]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [14]:
```
np.zeros((2,2))
```

Out[14]:
```
array([[0., 0.],
       [0., 0.]])
```

In [15]:
```
np.ones((2,1))
```

Out[15]:
```
array([[1.],
       [1.]])
```

In [18]:
```
a = np.arange(27).reshape((3,3,3))
np.ones_like(a)
```

Out[18]:
```
array([[[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]],

       [[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]],

       [[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]]])
```

In [19]:
```
np.eye(3)
```

Out[19]:
```
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

In [23]:
```
a = np.arange(10)
a
```

Out[23]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [24]:
```
a[0]
```

Out[24]:
```
0
```

In [25]:
```
a[-1]
```

Out[25]:
```
9
```

In [26]:
```
a[0:3]
```

Out[26]:
```
array([0, 1, 2])
```

In [27]:
```
a[::2]
```

Out[27]:
```
array([0, 2, 4, 6, 8])
```

In [35]:
```
a = a.reshape(5,2)
a
```

Out[35]:
```
array([[0, 1],
       [2, 3],
       [4, 5],
       [6, 7],
       [8, 9]])
```

In [33]:
```
a[3,1]
```

Out[33]:
```
7
```

In [34]:
```
a[2,:]
```

Out[34]:
```
array([4, 5])
```

Important: Views or copy

A slice or reshape is a view, simply a re-organization of the same data in memory, thus changing one element changes the same element in all views

In [41]:
```
a = np.arange(9)
```

In [42]:
```
b = a.reshape((3,3))
```

In [43]:
```
np.may_share_memory(a,b)
```

Out[43]:
```
True
```

In [44]:
```
a[3] = -1
```

In [45]:
```
b
```

Out[45]:
```
array([[ 0,  1,  2],
       [-1,  4,  5],
       [ 6,  7,  8]])
```

In [46]:
```
b = a.copy()
np.may_share_memory(a,b)
```

Out[46]:
```
False
```

Boolean masks for extracting values

A typical operation done in your daily physics data analysis is to extract from an array the values that match a condition. Consider an array of the energies of particles, and assume you want to use only the energies above a given threshold. Boolean masking comes at a rescue

In [52]:
```
ene = np.random.exponential(size=10, scale=10.) # 1/scale e^(-ene/scale)
ene
```

Out[52]:
```
array([ 4.85456007,  0.51860863,  3.69385318,  5.40459025,  3.83217684,
        5.31482774,  0.20313695,  7.66005641,  2.52100998, 12.84343854])
```

In [54]:
```
mask = ene > 2
mask
```

Out[54]:
```
array([ True, False,  True,  True,  True,  True, False,  True,  True,
        True])
```

In [55]:
```
ene[mask]
```

Out[55]:
```
array([ 4.85456007,  3.69385318,  5.40459025,  3.83217684,  5.31482774,
        7.66005641,  2.52100998, 12.84343854])
```

In [56]:
```
ene[ene<2]
```

Out[56]:
```
array([0.51860863, 0.20313695])
```

In [57]:
```
ene[ene<2] = 0
ene
```

Out[57]:
```
array([ 4.85456007,  0.        ,  3.69385318,  5.40459025,  3.83217684,
        5.31482774,  0.        ,  7.66005641,  2.52100998, 12.84343854])
```

Values with list of indexes

Similarly to boolean masks it is possible to access and modify values directly to an array using a list of indexes

In [60]:
```
status = np.random.randint(low=0,high=10,size=10)
status
```

Out[60]:
```
array([2, 7, 7, 7, 8, 6, 0, 7, 4, 4])
```

In [61]:
```
status[[0, 3, 5]]
```

Out[61]:
```
array([2, 7, 6])
```

In [63]:
```
status[[0, 3, 5]] = -1
status
```

Out[63]:
```
array([-1,  7,  7, -1,  8, -1,  0,  7,  4,  4])
```

Simple Operations

In [64]:
```
a = np.arange(4)
a
```

Out[64]:
```
array([0, 1, 2, 3])
```

In [65]:
```
a+1
```

Out[65]:
```
array([1, 2, 3, 4])
```

In [67]:
```
10**a
```

Out[67]:
```
array([   1,   10,  100, 1000])
```

In [68]:
```
np.sin(a)
```

Out[68]:
```
array([0.        , 0.84147098, 0.90929743, 0.14112001])
```

Reductions

In [78]:
```
a = np.random.randint(low=0,high=10,size=4)
a
```

Out[78]:
```
array([1, 8, 0, 9])
```

In [90]:
```
np.sum(a)
```

Out[90]:
```
18
```

In [91]:
```
np.max(a), np.min(a)
```

Out[91]:
```
(9, 0)
```

In [92]:
```
np.argmax(a), np.argmin(a)
```

Out[92]:
```
(3, 2)
```

In [93]:
```
np.mean(a), np.median(a), np.std(a)
```

Out[93]:
```
(4.5, 4.5, 4.031128874149275)
```

In [94]:
```
a = a.reshape(2,2)
a
```

Out[94]:
```
array([[1, 8],
       [0, 9]])
```

In [95]:
```
np.sum(a,axis=0)
```

Out[95]:
```
array([ 1, 17])
```

In [84]:
```
m1 = a>0
m1
```

Out[84]:
```
array([[ True,  True],
       [False,  True]])
```

In [96]:
```
np.all(m1)
```

Out[96]:
```
False
```

In [97]:
```
np.any(m1)
```

Out[97]:
```
True
```

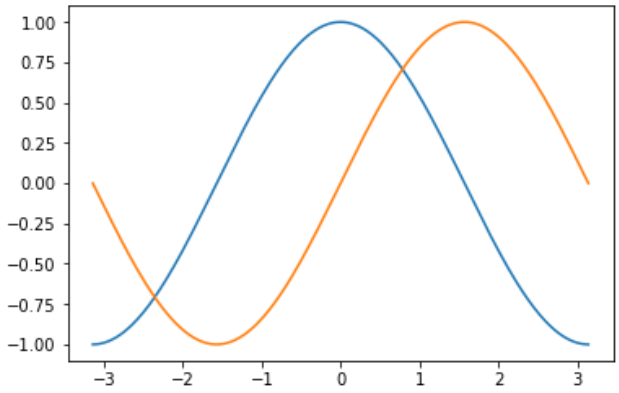
matplotlib

Matplotlib

Matplotlib is probably the most used Python package for 2D-graphics. It provides both a quick way to visualize data from Python and publication-quality figures in many formats. Other visualization packages exists, often these are built on top of `matplotlib`. The package is well integrated into IPython and Jupyter.

In [114]:
```
%matplotlib inline
from matplotlib import pyplot as plt
import numpy as np
X = np.linspace(-np.pi, np.pi, 256, endpoint=True)
C, S = np.cos(X), np.sin(X)
plt.plot(X,C)
plt.plot(X,S)
```

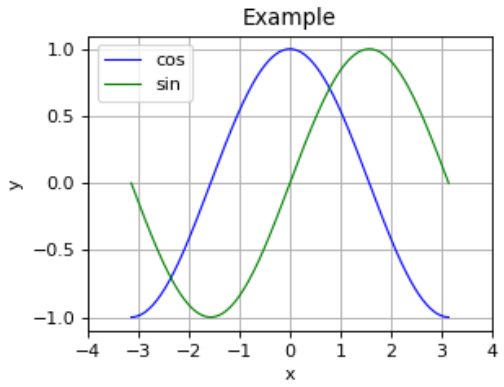
Out[114]:
```
[<matplotlib.lines.Line2D at 0x7f6c7a21c4e0>]
```



Customization

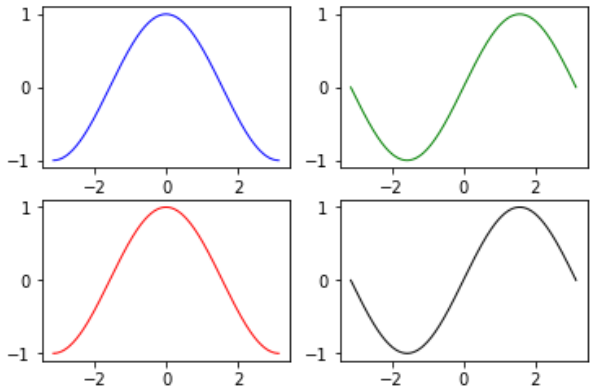
In [125]:
```
plt.figure(figsize=(4, 3), dpi=80)
plt.plot(X, C, color="blue", linewidth=1.0, linestyle="-", label="cos")
plt.plot(X, S, color="green", linewidth=1.0, linestyle="-", label="sin")
plt.xlim(-4.0, 4.0)
plt.xticks(np.linspace(-4, 4, 9, endpoint=True))
plt.savefig("example.png", dpi=72)
plt.grid()
plt.xlabel("x")
plt.ylabel("y")
plt.title("Example")
plt.legend(loc="best")
```

Out[125]:
```
<matplotlib.legend.Legend at 0x7f6c79c0bc18>
```



Multiple plots

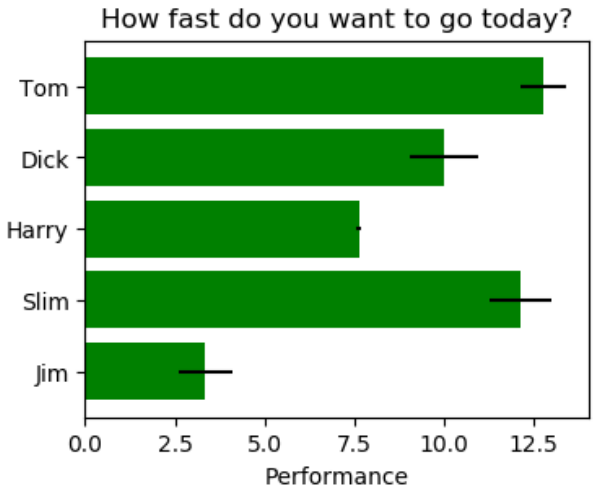
In [124]:
```
plt.figure(figsize=(6, 4))
plt.subplot(2, 2, 1)
plt.plot(X, C, color="blue", linewidth=1.0, linestyle="-", label="cos")
plt.subplot(2, 2, 2)
plt.plot(X, S, color="green", linewidth=1.0, linestyle="-", label="sin")
plt.subplot(2, 2, 3)
plt.plot(X, C, color="red", linewidth=1.0, linestyle="-", label="cos")
plt.subplot(2, 2, 4)
plt.plot(X, S, color="black", linewidth=1.0, linestyle="-", label="sin")
plt.show()
```



Examples

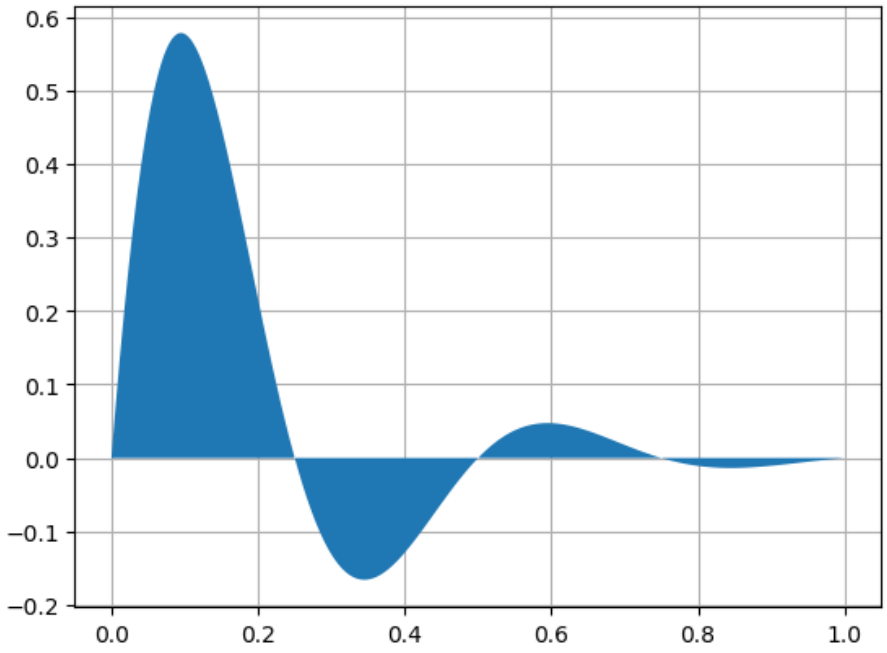
In [131]:

```
plt.rcdefaults()
fig, ax = plt.subplots(figsize=(4,3))
# Example data
people = ('Tom', 'Dick', 'Harry', 'Slim', 'Jim')
y_pos = np.arange(len(people))
performance = 3 + 10 * np.random.rand(len(people))
error = np.random.rand(len(people))
ax.barh(y_pos, performance, xerr=error, align='center',
        color='green', ecolor='black')
ax.set_yticks(y_pos)
ax.set_yticklabels(people)
ax.invert_yaxis()  # labels read top-to-bottom
ax.set_xlabel('Performance')
ax.set_title('How fast do you want to go today?')

plt.show()
```



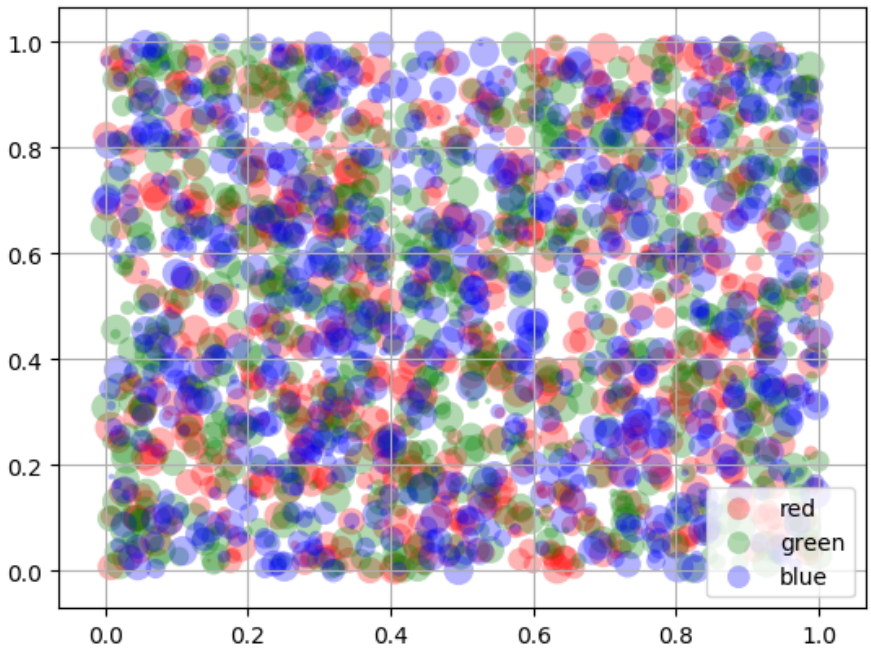
In [132]:

```
x = np.linspace(0, 1, 500)
y = np.sin(4 * np.pi * x) * np.exp(-5 * x)
fig, ax = plt.subplots()
ax.fill(x, y, zorder=10)
ax.grid(True, zorder=5)
plt.show()
```



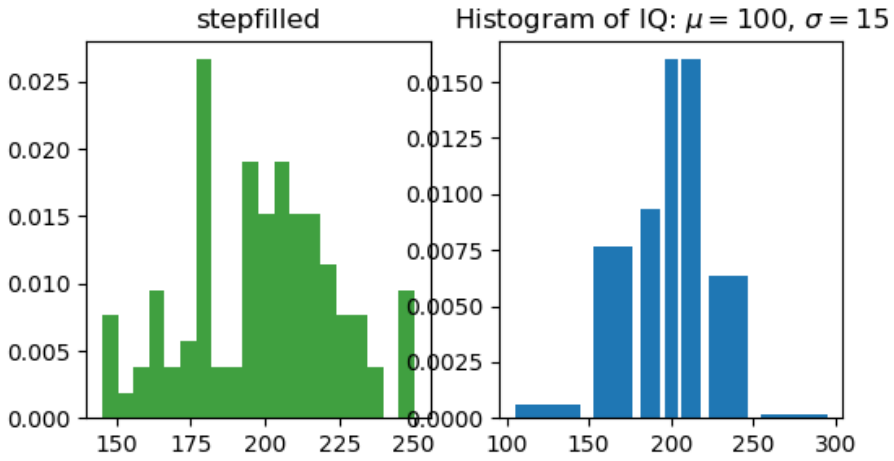
In [136]:

```
fig, ax = plt.subplots()
for color in ['red', 'green', 'blue']:
    n = 750
    x, y = np.random.rand(2, n)
    scale = 200.0 * np.random.rand(n)
    ax.scatter(x, y, c=color, s=scale, label=color,
               alpha=0.3, edgecolors='none')

ax.legend()
ax.grid(True)

plt.show()
```



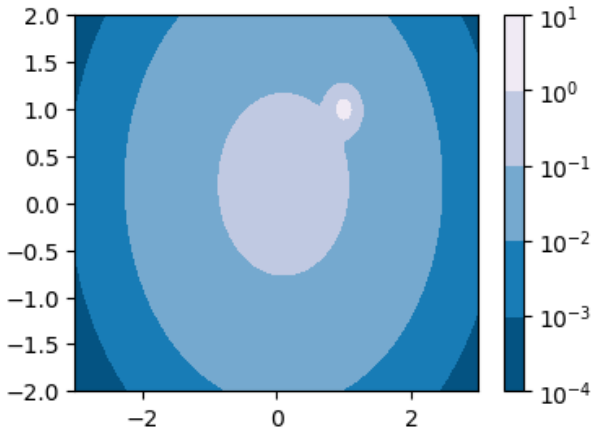
In [161]:

```
mu = 200
sigma = 25
x = np.random.normal(mu, sigma, size=100)
fig, (ax0, ax1) = plt.subplots(ncols=2, figsize=(6, 3))
ax0.hist(x, 20, density=1, histtype='stepfilled', facecolor='g', alpha=0.75)
ax0.set_title('stepfilled')
# Create a histogram by providing the bin edges (unequally spaced).
bins = [100, 150, 180, 195, 205, 220, 250, 300]
ax1.hist(x, bins, density=1, histtype='bar', rwidth=0.8)
ax1.set_title('unequal bins')
plt.title(r'Histogram of IQ: $\mu=100$, $\sigma=15$');
```

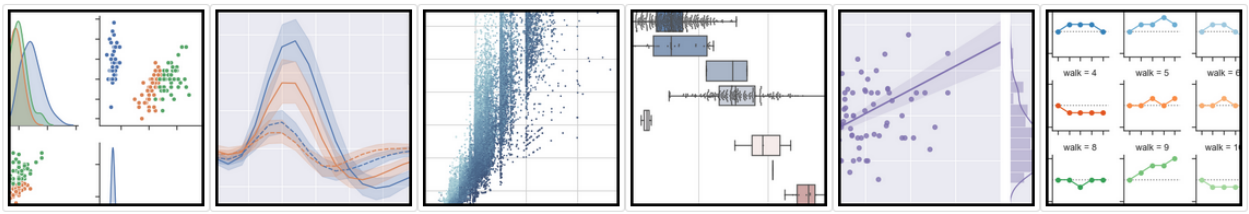


In [170]:

```
from matplotlib import colors, ticker, cm
from scipy.stats import multivariate_normal

N = 100
x = np.linspace(-3.0, 3.0, N)
y = np.linspace(-2.0, 2.0, N)

X, Y = np.meshgrid(x, y)
pos = np.empty(X.shape+(2,))
pos[:,:,0] = X; pos[:,:,1] = Y
# A low hump with a spike coming out of the top right.
# Needs to have z/colour axis on a log scale so we see both hump and spike.
# linear scale only shows the spike.
z = (multivariate_normal([0.1, 0.2], [[1.0, 0.],[0, 1.0]]).pdf(pos)
     + 0.1 * (multivariate_normal([1.0, 1.0],[[0.01, 0.],[0., 0.01]])).pdf(pos))
# Automatic selection of levels works; setting the
# log locator tells contourf to use a log scale:
fig, ax = plt.subplots(figsize=(4,3))
cs = ax.contourf(X, Y, z, locator=ticker.LogLocator(), cmap=cm.PuBu_r)
cbar = fig.colorbar(cs)
```



seaborn: statistical data visualization



Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

For a brief introduction to the ideas behind the library, you can read the introductory notes. Visit the installation page to see how you can download the package. You can browse the example gallery to see what you can do with seaborn, and then check out the tutorial and API reference to find out how.

To see the code or report a bug, please visit the github repository. General support issues are most at home on stackoverflow, where there is a seaborn tag.

Contents

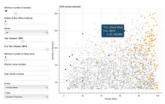
Features

- Relational: API | Tutorial
- Categorical: API | Tutorial
- Distributions: API | Tutorial
- Regressions: API | Tutorial
- Multiples: API | Tutorial
- Style: API | Tutorial
- Color: API | Tutorial

Gallery ¶

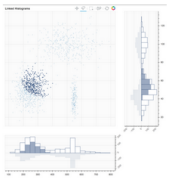
Server App Examples ¶

The examples linked below all show off usage of the Bokeh server. The Bokeh server provides a place where interesting things can happen—data can be updated to in turn update the plot, and UI and selection events can be processed to trigger more visual updates.



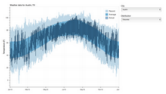
An interactive query tool for a set of IMDB data

Source code: movies



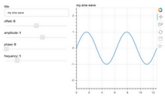
Shows axis histograms for selected *and* non-selected points in a scatter plot

Source code: selection_histogram



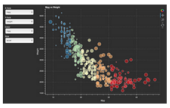
Interactive weather statistics for three cities.

Source code: weather



A basic demo that has sliders for controlling a plotted trigonometric function

Source code: sliders.py



Explore the "autompg" data set by selecting and highlighting different dimensions

Source code: crossfilter

A reproduction of the famous Gapminder demo, with embedded video added using a custom page template

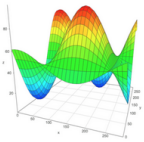
Source code: gapminder

Linked plots, summary statistics, and correlations for market data

Source code: stocks

Explore the "autompg" data set by selecting and highlighting different dimensions

Source code: export_csv



An updating 3d plot that demonstrates using using Bokeh custom extensions to wrap third-party JavaScript libraries

Source code: surface3d

Notebook Examples ¶

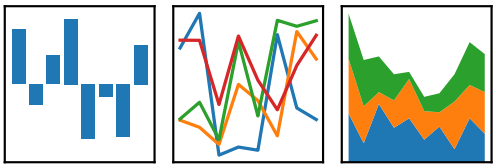
A large number of static examples may be viewed directly online (or downloaded and executed locally) at the Bokeh NBViewer Gallery.

Standalone Examples ¶

All of the examples below are located in the examples subdirectory of your Bokeh checkout. By "standalone" we mean that these examples make no use of the Bokeh server. These plots still have many interactive tools and features, including linked panning and brushing, and hover inspectors.

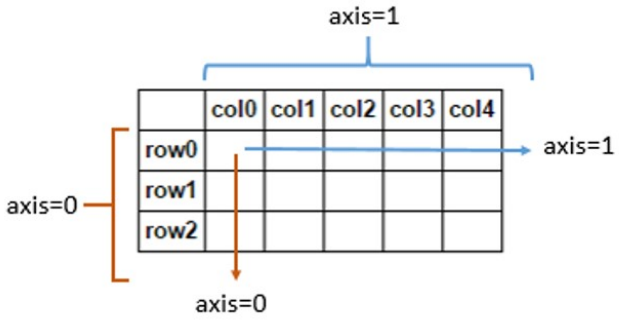
pandas

$$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$$



Pandas

Pandas is a high-performance, high-level library that provides tools for data analysis.
It relies on the concept of DataFrame: a structured collection of data organized in records.
This is the same concept of ROOT's `NTuple` that you are familiar with.
I think the name comes from R.



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

s = pd.Series( [1., 2., 3., np.nan, 5. ], index=["a","b","c","d","e"])
s
```

Out[2]:
```
a    1.0
b    2.0
c    3.0
d    NaN
e    5.0
dtype: float64
```

In [11]:
```
df = pd.DataFrame(
    {
        'Col1': [1.,2.,3.,4.],
        'Col2': ["a","b","c","d"],
        'Col3': [True, False, True, True]
    }
)
df
```

Out[11]:

	Col1	Col2	Col3
0	1.0	a	True
1	2.0	b	False
2	3.0	c	True
3	4.0	d	True

Reading/Saving dataframes

Pandas support reading writing to several data formats, via specialized routines, many other formats, because dataframe (with other names) are a common concept:

Format Type	Data Description	Reader	Writer
text	CSV	`read_csv`	`to_csv`
text	JSON	`read_json`	`to_json`
text	HTML	`read_html`	`to_html`
text	Local clipboard	`read_clipboard`	`to_clipboard`
binary	MS Excel	`read_excel`	`to_excel`
binary	HDF5 Format	`read_hdf`	`to_hdf`
binary	Feather Format	`read_feather`	`to_feather`
binary	Parquet Format	`read_parquet`	`to_parquet`
binary	Msgpack	`read_msgpack`	`to_msgpack`
binary	Stata	`read_stata`	`to_stata`
binary	SAS	`read_sas`	
binary	Pickle Format	`read_pickle`	`to_pickle`
SQL	SQL	`read_sql`	`to_sql`
SQL	Google Big Query	`read_gbq`	`to_gbq`

As you can see the physicists *ROOT* format is not natively supported. However some external software to read `TTree` s are available. For example `root_numpy` (http://scikit-hep.org/root_numpy/), `root_pandas` (https://github.com/scikit-hep/root_pandas), or `uproot` (https://github.com/scikit-hep/uproot). ROOT usually comes with pre-installed `pyROOT` library (the one on the provided VM works only for python2), that offers basic functionalities.

In [12]:
```
df.dtypes
```

Out[12]:
```
Col1    float64
Col2     object
Col3       bool
dtype: object
```

In [13]:
```
df.columns
```

Out[13]:
```
Index(['Col1', 'Col2', 'Col3'], dtype='object')
```

In [14]:
```
df.index
```

Out[14]:
```
RangeIndex(start=0, stop=4, step=1)
```

View data

In [25]:
```
df = pd.DataFrame( {'A':np.random.randint(0,10,100), 'B': [2**x for x in np.arange
(100)], 'C':"a"})
df.head()
```

Out[25]:

	A	B	C
0	4	1	a
1	2	2	a
2	0	4	a
3	9	8	a
4	3	16	a

In [26]:
```
df.tail(2)
```

Out[26]:

	A	B	C
98	5	0	a
99	9	0	a

In [27]:
```
df.describe()
```

Out[27]:

	A	B
count	100.000000	1.000000e+02
mean	4.420000	-2.560000e+00
std	2.985419	1.070389e+18
min	0.000000	-9.223372e+18
25%	2.000000	0.000000e+00
50%	5.000000	6.144000e+03
75%	7.000000	1.717987e+11
max	9.000000	4.611686e+18

Select data

In [86]:
```
dates = pd.date_range('20190527',periods=7)
df = pd.DataFrame( np.random.rand(7,4), index=dates, columns=['A','B','C','D'])
df
```

Out[86]:

	A	B	C	D
2019-05-27	0.944420	0.075201	0.167932	0.017186
2019-05-28	0.245307	0.577804	0.132167	0.372844
2019-05-29	0.459021	0.087459	0.647909	0.963480
2019-05-30	0.244232	0.261606	0.109693	0.494399
2019-05-31	0.575183	0.584652	0.113913	0.117457
2019-06-01	0.190005	0.692712	0.404453	0.995082
2019-06-02	0.931300	0.489561	0.193387	0.327648

In [43]:
```
df['A'] # or df.A
```

Out[43]:
```
2019-05-27    0.632271
2019-05-28    0.691208
2019-05-29    0.603331
2019-05-30    0.043723
2019-05-31    0.552101
2019-06-01    0.330455
2019-06-02    0.841736
Freq: D, Name: A, dtype: float64
```

In [44]:
```
df[0:2]
```

Out[44]:

	A	B	C	D
2019-05-27	0.632271	0.218192	0.139538	0.082094
2019-05-28	0.691208	0.700231	0.730246	0.328330

In [45]:
```
df['20190529':'20190531']
```

Out[45]:

	A	B	C	D
2019-05-29	0.603331	0.165942	0.199283	0.119786
2019-05-30	0.043723	0.162669	0.291625	0.120803
2019-05-31	0.552101	0.102359	0.702799	0.455912

In [46]:
```
dates
```

Out[46]:
```
DatetimeIndex(['2019-05-27', '2019-05-28', '2019-05-29', '2019-05-30',
               '2019-05-31', '2019-06-01', '2019-06-02'],
              dtype='datetime64[ns]', freq='D')
```

In [47]:
```
df.loc[dates[2]]
```

Out[47]:
```
A    0.603331
B    0.165942
C    0.199283
D    0.119786
Name: 2019-05-29 00:00:00, dtype: float64
```

In [48]:
```
df.loc[dates[2],['B','C']]
```

Out[48]:
```
B    0.165942
C    0.199283
Name: 2019-05-29 00:00:00, dtype: float64
```

In [53]:
```
df.iloc[2,2:4]
```

Out[53]:
```
C    0.199283
D    0.119786
Name: 2019-05-29 00:00:00, dtype: float64
```

In [55]:
```
df[ df>0.5 ]
```

Out[55]:

	A	B	C	D
2019-05-27	0.632271	NaN	NaN	NaN
2019-05-28	0.691208	0.700231	0.730246	NaN
2019-05-29	0.603331	NaN	NaN	NaN
2019-05-30	NaN	NaN	NaN	NaN
2019-05-31	0.552101	NaN	0.702799	NaN
2019-06-01	NaN	NaN	0.868320	0.510706
2019-06-02	0.841736	NaN	0.931434	NaN

Setting values

In [61]:
```
s = pd.Series( np.random.rand(7), index=dates )
s
```

Out[61]:
```
2019-05-27    0.547899
2019-05-28    0.465972
2019-05-29    0.127552
2019-05-30    0.996297
2019-05-31    0.691513
2019-06-01    0.029567
2019-06-02    0.376882
Freq: D, dtype: float64
```

In [63]:
```
df['E'] = s
df
```

Out[63]:

	A	B	C	D	E
2019-05-27	0.632271	0.218192	0.139538	0.082094	0.547899
2019-05-28	0.691208	0.700231	0.730246	0.328330	0.465972
2019-05-29	0.603331	0.165942	0.199283	0.119786	0.127552
2019-05-30	0.043723	0.162669	0.291625	0.120803	0.996297
2019-05-31	0.552101	0.102359	0.702799	0.455912	0.691513
2019-06-01	0.330455	0.227942	0.868320	0.510706	0.029567
2019-06-02	0.841736	0.088304	0.931434	0.300959	0.376882

In [64]:
```
df.loc[:,['C']] = 0
df
```

Out[64]:

	A	B	C	D	E
2019-05-27	0.632271	0.218192	0.0	0.082094	0.547899
2019-05-28	0.691208	0.700231	0.0	0.328330	0.465972
2019-05-29	0.603331	0.165942	0.0	0.119786	0.127552
2019-05-30	0.043723	0.162669	0.0	0.120803	0.996297
2019-05-31	0.552101	0.102359	0.0	0.455912	0.691513
2019-06-01	0.330455	0.227942	0.0	0.510706	0.029567
2019-06-02	0.841736	0.088304	0.0	0.300959	0.376882

Operations

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

Out[68]:
```
A    0.527832
B    0.237948
C    0.000000
D    0.274084
E    0.462240
dtype: float64
```

In [69]:
```
df.mean(axis=1)
```

Out[69]:
```
2019-05-27    0.296091
2019-05-28    0.437148
2019-05-29    0.203322
2019-05-30    0.264698
2019-05-31    0.360377
2019-06-01    0.219734
2019-06-02    0.321576
Freq: D, dtype: float64
```

Merging dataframes

In [76]:
```
df1 = pd.DataFrame( np.random.rand(7,2), index=dates, columns=['A','B'])
df2 = pd.DataFrame( np.random.rand(7,3), index=dates, columns=['C','D','E'])
pd.concat([df1,df2],sort=False)
```

Out[76]:

	A	B	C	D	E
2019-05-27	0.012169	0.252402	NaN	NaN	NaN
2019-05-28	0.420066	0.163832	NaN	NaN	NaN
2019-05-29	0.709032	0.134392	NaN	NaN	NaN
2019-05-30	0.245606	0.952309	NaN	NaN	NaN
2019-05-31	0.750060	0.851338	NaN	NaN	NaN
2019-06-01	0.334091	0.825410	NaN	NaN	NaN
2019-06-02	0.222300	0.897779	NaN	NaN	NaN
2019-05-27	NaN	NaN	0.781323	0.624619	0.382809
2019-05-28	NaN	NaN	0.932316	0.051429	0.823951
2019-05-29	NaN	NaN	0.246817	0.021852	0.699723
2019-05-30	NaN	NaN	0.700137	0.231148	0.373396
2019-05-31	NaN	NaN	0.340692	0.371376	0.751349
2019-06-01	NaN	NaN	0.567121	0.771248	0.712765
2019-06-02	NaN	NaN	0.970691	0.146501	0.218353

In [78]:
```
pd.concat([df1,df2],axis=1,join='inner')
```

Out[78]:

	A	B	C	D	E
2019-05-27	0.012169	0.252402	0.781323	0.624619	0.382809
2019-05-28	0.420066	0.163832	0.932316	0.051429	0.823951
2019-05-29	0.709032	0.134392	0.246817	0.021852	0.699723
2019-05-30	0.245606	0.952309	0.700137	0.231148	0.373396
2019-05-31	0.750060	0.851338	0.340692	0.371376	0.751349
2019-06-01	0.334091	0.825410	0.567121	0.771248	0.712765
2019-06-02	0.222300	0.897779	0.970691	0.146501	0.218353

Grouping

In [81]:
```
s = pd.Series( ["a","b","a","c","a","c","b"], index=dates)
df['E']=s
df
```

Out[81]:

	A	B	C	D	E
2019-05-27	0.632271	0.218192	0.0	0.082094	a
2019-05-28	0.691208	0.700231	0.0	0.328330	b
2019-05-29	0.603331	0.165942	0.0	0.119786	a
2019-05-30	0.043723	0.162669	0.0	0.120803	c
2019-05-31	0.552101	0.102359	0.0	0.455912	a
2019-06-01	0.330455	0.227942	0.0	0.510706	c
2019-06-02	0.841736	0.088304	0.0	0.300959	b

In [82]:
```
df.groupby('E').sum()
```

Out[82]:

	A	B	C	D
E				
a	1.787704	0.486493	0.0	0.657791
b	1.532944	0.788535	0.0	0.629290
c	0.374178	0.390611	0.0	0.631508

Pivot table

In [105]:
```
dates = pd.date_range('20190527',periods=6, name='date')
df = pd.DataFrame( np.random.rand(6,3), index=dates, columns=['A','B','C'])
df['D'] = pd.Series(["a","a","b","b","c","c"],index=dates)
df['E'] = pd.Series(["one","two","one","two","one","two"],index=dates)
df
```

Out[105]:

	A	B	C	D	E
date					
2019-05-27	0.474915	0.196110	0.301641	a	one
2019-05-28	0.057920	0.349846	0.670458	a	two
2019-05-29	0.878578	0.884794	0.904183	b	one
2019-05-30	0.456244	0.917951	0.879430	b	two
2019-05-31	0.592064	0.925768	0.601040	c	one
2019-06-01	0.403849	0.445142	0.004900	c	two

In [106]:
```
pd.pivot_table(df, values=['A','B','C'], index=['D','E'])
```

Out[106]:

		A	B	C
D	E			
a	one	0.474915	0.196110	0.301641
	two	0.057920	0.349846	0.670458
b	one	0.878578	0.884794	0.904183
	two	0.456244	0.917951	0.879430
c	one	0.592064	0.925768	0.601040
	two	0.403849	0.445142	0.004900

Plotting data

In [107]:
```
%matplotlib inline
df.plot()
```

Out[107]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f08ba132a20>
```