Widely used	Task oriented
- Numpy	- SymPy
- Matplotlib	- Blaze
- Scikit Learn	- Statsmodels
- Seaborn	- Bokeh
- Pandas	- Scrapy
- SciPy	- Requests

> **NumPy** stands for Numerical Python. The most powerful feature of NumPy is n-dimensional array. This library also contains basic linear algebra functions, Fourier transforms, advanced random number capabilities and tools for integration with other low level languages like Fortran, C and C++

In [5]:
```
import numpy as np
np.random.seed(0)  # seed for reproducibility

x1 = np.random.randint(10, size=6)  # One-dimensional array
x2 = np.random.randint(10, size=(3, 4))  # Two-dimensional array
x3 = np.random.randint(10, size=(3, 4, 5))  # Three-dimensional array
print("x3 ndim: ", x3.ndim)
print("x3 shape:", x3.shape)
print("x3 size: ", x3.size)
```

```
x3 ndim:  3
x3 shape: (3, 4, 5)
x3 size:  60
```

In [6]:
```
x1
```

Out[6]:
```
array([5, 0, 3, 3, 7, 9])
```

In [7]:
```
x2
```

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

In [8]:
```
x2[:2, :3]  # two rows, three columns
```

Out[8]:
```
array([[3, 5, 2],
       [7, 6, 8]])
```

In [9]:
```
x2[:3, ::2]  # all rows, every other column
```
Out[9]:
```
array([[3, 2],
       [7, 8],
       [1, 7]])
```
In [10]:
```
x2[::-1, ::-1] #Finally, subarray dimensions can even be reversed together:
```
Out[10]:
```
array([[7, 7, 6, 1],
       [8, 8, 6, 7],
       [4, 2, 5, 3]])
```
In [11]:
```
grid = np.arange(1, 10).reshape((3, 3))
print(grid) #Reshaping array
```
```
[[1 2 3]
 [4 5 6]
 [7 8 9]]
```
In [13]:
```
####Array Concatenation and Splitting
#Concatenations of arrays
x = np.array([1, 2, 3])
y = np.array([3, 2, 1])
np.concatenate([x, y])
```
Out[13]:
```
array([1, 2, 3, 3, 2, 1])
```
In [19]:
```
#splitting of arrays
x = [1, 2, 3, 99, 99, 3, 2, 1]
x1, x2, x3 = np.split(x, [3, 5])
print(x1, x2, x3)
grid = np.arange(16).reshape((4, 4))
grid
```
```
[1 2 3] [99 99] [3 2 1]
```
Out[19]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15]])
```
In [20]:
```
upper, lower = np.vsplit(grid, [2])
print(upper)
print(lower)
```
```
[[0 1 2 3]
 [4 5 6 7]]
[[ 8  9 10 11]
 [12 13 14 15]]
```

In [21]:
```python
left, right = np.hsplit(grid, [2])
print(left)
print(right)
```

```
[[ 0  1]
 [ 4  5]
 [ 8  9]
 [12 13]]
[[ 2  3]
 [ 6  7]
 [10 11]
 [14 15]]
```

In [26]:
```python
#Array Arithmetics
x = np.arange(4)
print("x     =", x)
print("x + 5 =", x + 5)
print("x - 5 =", x - 5)
print("x * 2 =", x * 2)
print("x / 2 =", x / 2)
print("x // 2 =", x // 2)  # floor division
print("-x     = ", -x)
print("x ** 2 = ", x ** 2)
print("x % 2  = ", x % 2)
print(-(0.5*x + 1) ** 2)
np.add(x, 2)
```

```
x     = [0 1 2 3]
x + 5 = [5 6 7 8]
x - 5 = [-5 -4 -3 -2]
x * 2 = [0 2 4 6]
x / 2 = [0.  0.5 1.  1.5]
x // 2 = [0 0 1 1]
-x     =  [ 0 -1 -2 -3]
x ** 2 =  [0 1 4 9]
x % 2  =  [0 1 0 1]
[-1.   -2.25 -4.   -6.25]
```

Out[26]:
```
array([2, 3, 4, 5])
```

In [29]:

```
#trignometry
theta = np.linspace(0, np.pi, 3)
print("theta      = ", theta)
print("sin(theta) = ", np.sin(theta))
print("cos(theta) = ", np.cos(theta))
print("tan(theta) = ", np.tan(theta))
x = [-1, 0, 1]
print("x         = ", x)
print("arcsin(x) = ", np.arcsin(x))
print("arccos(x) = ", np.arccos(x))
print("arctan(x) = ", np.arctan(x))

#Exponents and logarithms
x = [1, 2, 3]
print("x     =", x)
print("e^x   =", np.exp(x))
print("2^x   =", np.exp2(x))
print("3^x   =", np.power(3, x))
x =  [1,  2,  4,  10]
print("x     =", x)
print("ln(x)    =", np.log(x))
print("log2(x)  =", np.log2(x))
print("log10(x) =", np.log10(x))
```

```
theta      =  [0.         1.57079633 3.14159265]
sin(theta) =  [0.0000000e+00 1.0000000e+00 1.2246468e-16]
cos(theta) =  [ 1.000000e+00  6.123234e-17 -1.000000e+00]
tan(theta) =  [ 0.00000000e+00  1.63312394e+16 -1.22464680e-16]
x         =  [-1, 0, 1]
arcsin(x) =  [-1.57079633  0.          1.57079633]
arccos(x) =  [3.14159265 1.57079633 0.        ]
arctan(x) =  [-0.78539816  0.          0.78539816]
x     = [1, 2, 3]
e^x   = [ 2.71828183  7.3890561  20.08553692]
2^x   = [2. 4. 8.]
3^x   = [ 3  9 27]
x     = [1, 2, 4, 10]
ln(x)    = [0.         0.69314718 1.38629436 2.30258509]
log2(x)  = [0.         1.         2.         3.32192809]
log10(x) = [0.         0.30103    0.60205999 1.        ]
```

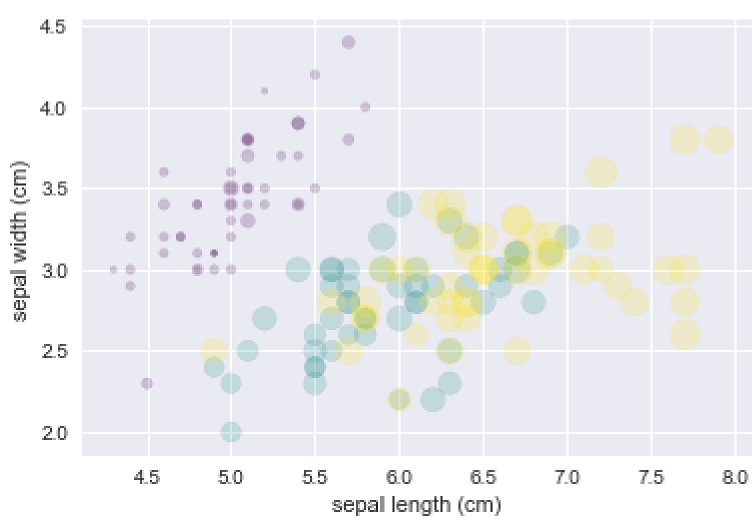
> **SciPy** stands for Scientific Python. SciPy is built on NumPy. It is one of the most useful library for variety of high level science and engineering modules like discrete Fourier transform, Linear Algebra, Optimization and Sparse matrices.

In [30]:
```
from scipy import special
# Gamma functions (generalized factorials) and related functions
x = [1, 5, 10]
print("gamma(x)      =", special.gamma(x))
print("ln|gamma(x)| =", special.gammaln(x))
print("beta(x, 2)    =", special.beta(x, 2))
# Error function (integral of Gaussian)
# its complement, and its inverse
x = np.array([0, 0.3, 0.7, 1.0])
print("erf(x)  =", special.erf(x))
print("erfc(x) =", special.erfc(x))
print("erfinv(x) =", special.erfinv(x))
```

```
gamma(x)      = [1.0000e+00 2.4000e+01 3.6288e+05]
ln|gamma(x)| = [ 0.          3.17805383 12.80182748]
beta(x, 2)    = [0.5        0.03333333 0.00909091]
erf(x)  = [0.         0.32862676 0.67780119 0.84270079]
erfc(x) = [1.         0.67137324 0.32219881 0.15729921]
erfinv(x) = [0.         0.27246271 0.73286908        inf]
```

Scikit Learn for machine learning. Built on NumPy, SciPy and matplotlib, this library contains a lot of effiecient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction.

In [134]:
```
#Iris data from Scikit-Learn, where each sample is one of three types of flowers
#has had the size of its petals and sepals carefully measured
from sklearn.datasets import load_iris
iris = load_iris()
features = iris.data.T

plt.scatter(features[0], features[1], alpha=0.2,
            s=100*features[3], c=iris.target, cmap='viridis')
plt.xlabel(iris.feature_names[0])
plt.ylabel(iris.feature_names[1]);
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

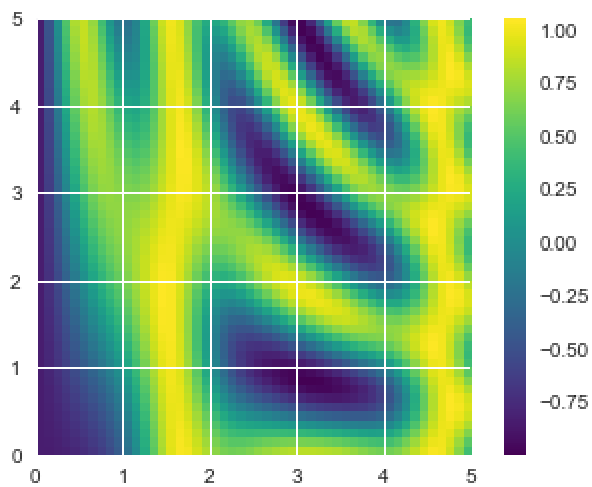
In [ ]:

In [ ]:

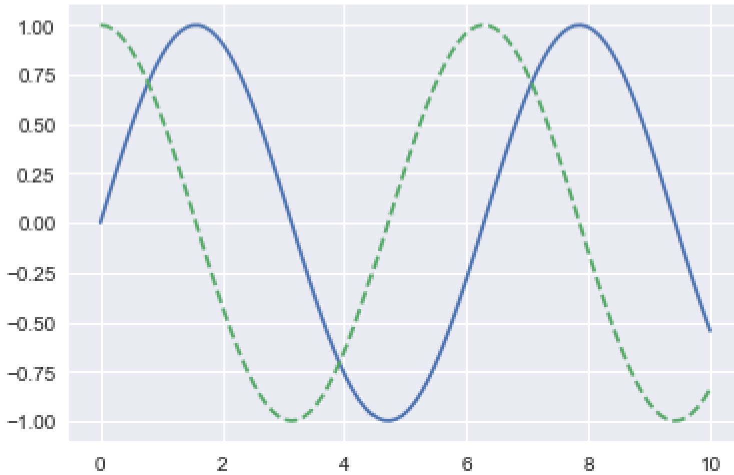
Matplotlib for plotting vast variety of graphs, starting from histograms to line plots to heat plots.. You can use Pylab feature in ipython notebook (ipython notebook –pylab = inline) to use these plotting features inline. If you ignore the inline option, then pylab converts ipython environment to an environment, very similar to Matlab. You can also use Latex commands to add math to your plot.

In [35]:

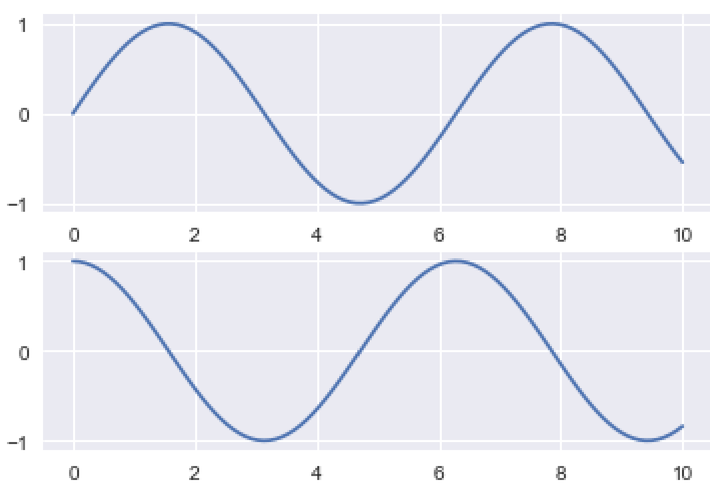
```
#Plotting a two-dimensional function
# x and y have 50 steps from 0 to 5
x = np.linspace(0, 5, 50)
y = np.linspace(0, 5, 50)[:, np.newaxis]

z = np.sin(x) ** 10 + np.cos(10 + y * x) * np.cos(x)

%matplotlib inline
import matplotlib.pyplot as plt

plt.imshow(z, origin='lower', extent=[0, 5, 0, 5],
           cmap='viridis')
plt.colorbar();
```



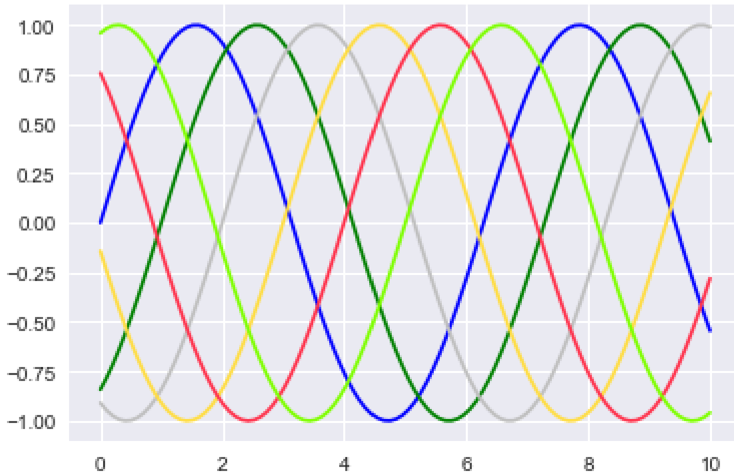
In [123]:
```
import numpy as np
x = np.linspace(0, 10, 100)

fig = plt.figure()
plt.plot(x, np.sin(x), '-')
plt.plot(x, np.cos(x), '--');
```



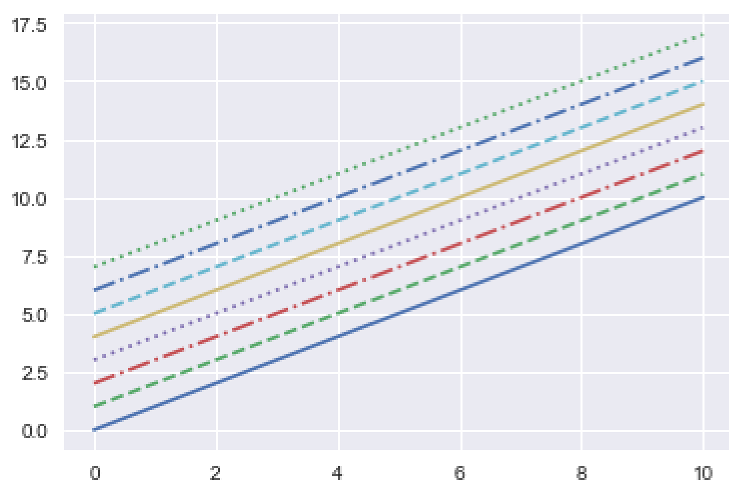
In [127]:
```
plt.figure()  # create a plot figure

# create the first of two panels and set current axis
plt.subplot(2, 1, 1) # (rows, columns, panel number)
plt.plot(x, np.sin(x))

# create the second panel and set current axis
plt.subplot(2, 1, 2)
plt.plot(x, np.cos(x));
```



In [128]:
```
plt.plot(x, np.sin(x - 0), color='blue')        # specify color by name
plt.plot(x, np.sin(x - 1), color='g')           # short color code (rgbcmyk)
plt.plot(x, np.sin(x - 2), color='0.75')        # Grayscale between 0 and 1
plt.plot(x, np.sin(x - 3), color='#FFDD44')     # Hex code (RRGGBB from 00 to FF)
plt.plot(x, np.sin(x - 4), color=(1.0,0.2,0.3)) # RGB tuple, values 0 to 1
plt.plot(x, np.sin(x - 5), color='chartreuse'); # all HTML color names supported
```

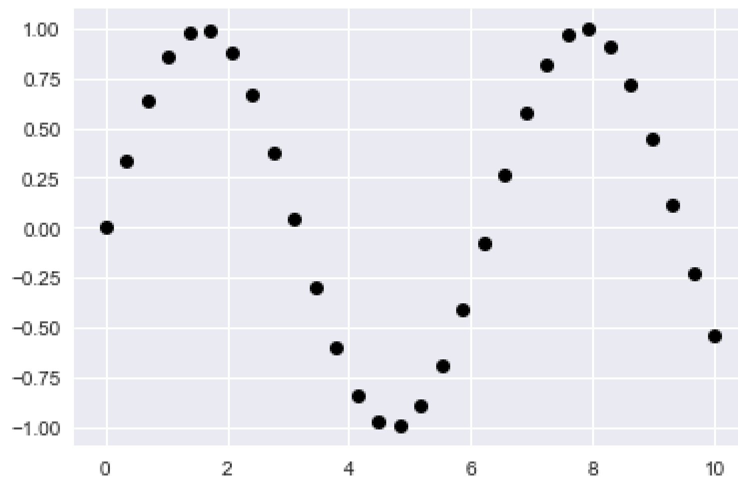


In [129]:
```
plt.plot(x, x + 0, linestyle='solid')
plt.plot(x, x + 1, linestyle='dashed')
plt.plot(x, x + 2, linestyle='dashdot')
plt.plot(x, x + 3, linestyle='dotted');

# For short, you can use the following codes:
plt.plot(x, x + 4, linestyle='-')  # solid
plt.plot(x, x + 5, linestyle='--') # dashed
plt.plot(x, x + 6, linestyle='-.') # dashdot
plt.plot(x, x + 7, linestyle=':');  # dotted
```



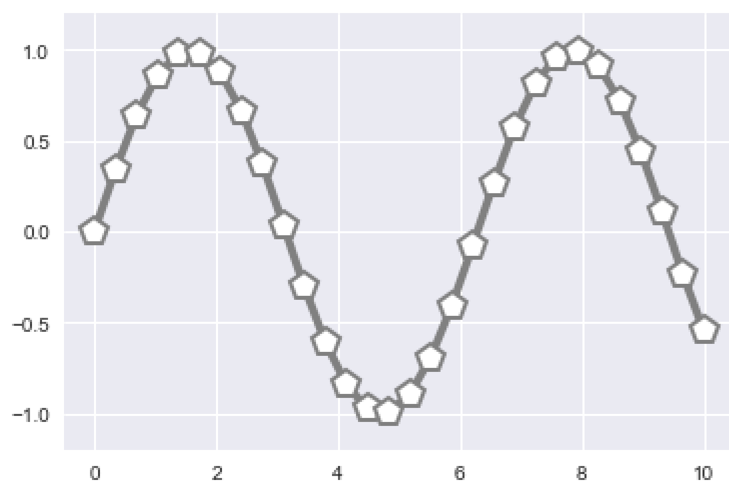
In [130]:

```
x = np.linspace(0, 10, 30)
y = np.sin(x)

plt.plot(x, y, 'o', color='black');
```



In [131]:

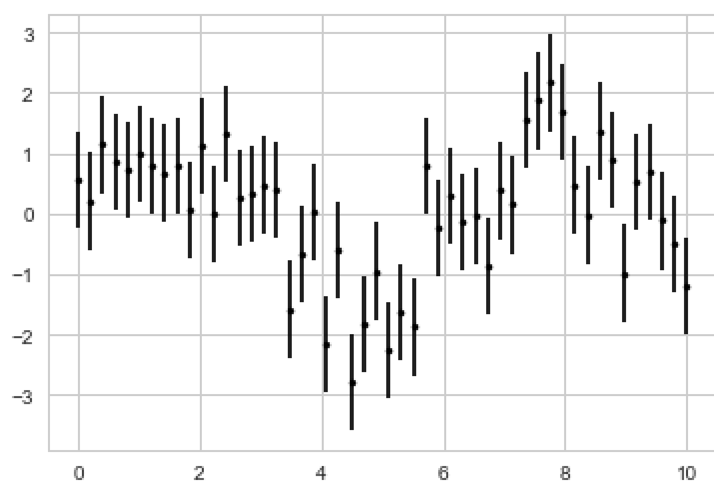
```
plt.plot(x, y, '-p', color='gray',
         markersize=15, linewidth=4,
         markerfacecolor='white',
         markeredgecolor='gray',
         markeredgewidth=2)
plt.ylim(-1.2, 1.2);
```



In [132]:
```
#Scatter Plots with plt.scatter
rng = np.random.RandomState(0)
x = rng.randn(100)
y = rng.randn(100)
colors = rng.rand(100)
sizes = 1000 * rng.rand(100)

plt.scatter(x, y, c=colors, s=sizes, alpha=0.3,
            cmap='viridis')
plt.colorbar();  # show color scale
```

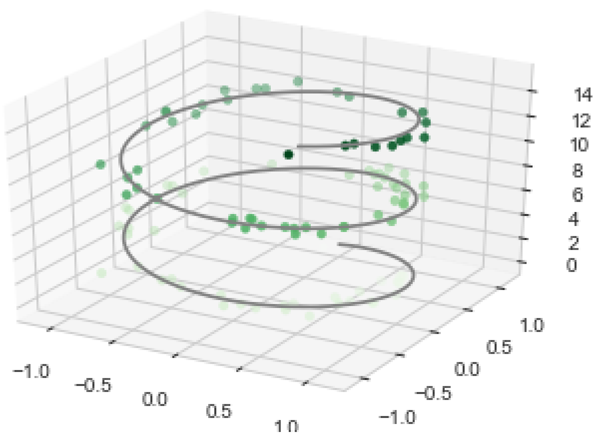
Visualizing Errors

In [139]:
```
#Basic Errorbars
x = np.linspace(0, 10, 50)
dy = 0.8
y = np.sin(x) + dy * np.random.randn(50)

plt.errorbar(x, y, yerr=dy, fmt='.k');
```

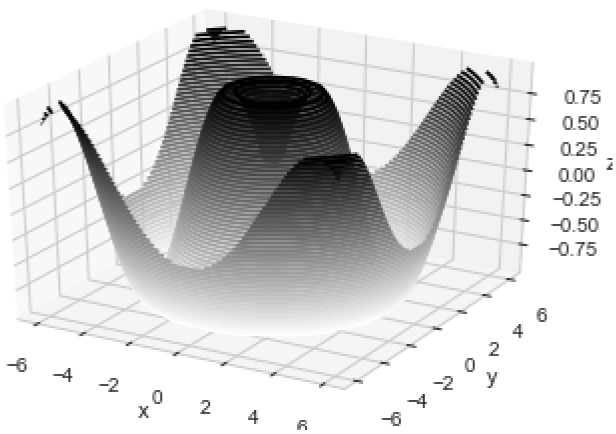


3D plotting

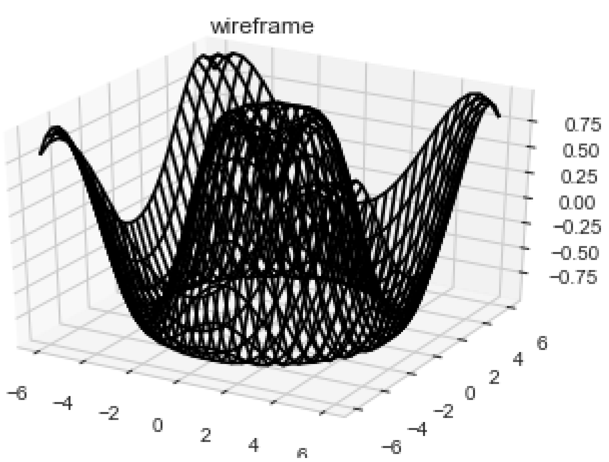
In [149]:
```
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = plt.axes(projection='3d')

# Data for a three-dimensional line
zline = np.linspace(0, 15, 1000)
xline = np.sin(zline)                 #sin
yline = np.cos(zline)                 #cos
ax.plot3D(xline, yline, zline, 'gray')

# Data for three-dimensional scattered points
zdata = 15 * np.random.random(100)
xdata = np.sin(zdata) + 0.1 * np.random.randn(100)
ydata = np.cos(zdata) + 0.1 * np.random.randn(100)
ax.scatter3D(xdata, ydata, zdata, c=zdata, cmap='Greens');
```



In [150]:
```
#Three-dimensional Contour Plots

def f(x, y):
    return np.sin(np.sqrt(x ** 2 + y ** 2))

x = np.linspace(-6, 6, 30)
y = np.linspace(-6, 6, 30)

X, Y = np.meshgrid(x, y)
Z = f(X, Y)
fig = plt.figure()
ax = plt.axes(projection='3d')
ax.contour3D(X, Y, Z, 50, cmap='binary')
ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z');
```

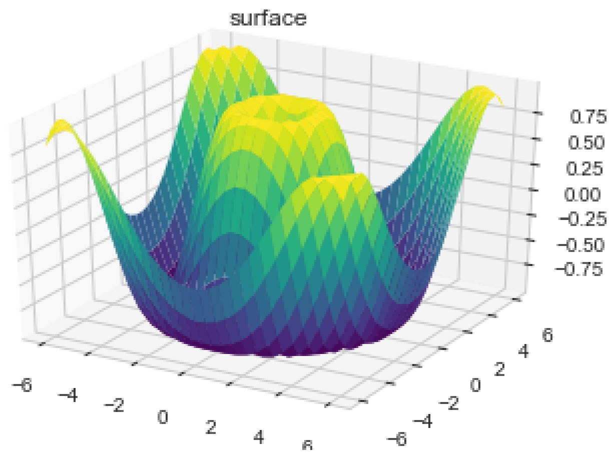


In [153]:
```
#Wireframes and Surface Plots
fig = plt.figure()
ax = plt.axes(projection='3d')
ax.plot_wireframe(X, Y, Z, color='black')
ax.set_title('wireframe');
```



In [154]:

```
ax = plt.axes(projection='3d')
ax.plot_surface(X, Y, Z, rstride=1, cstride=1,
                cmap='viridis', edgecolor='none')
ax.set_title('surface');
```



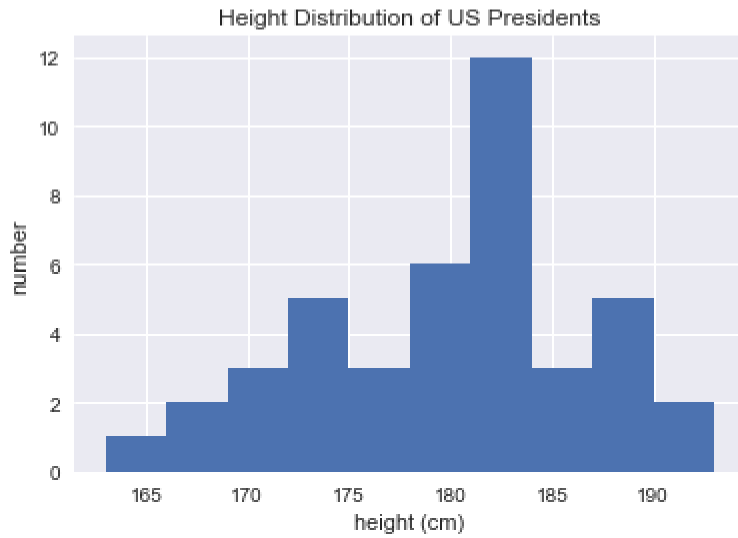
Pandas for structured data operations and manipulations. It is extensively used for data munging and preparation. Pandas were added relatively recently to Python and have been instrumental in boosting Python's usage in data scientist community.

In [32]:

```
import pandas as pd
data = pd.read_csv('data/president_heights.csv')
heights = np.array(data['height(cm)'])
print(heights)
print("Mean height:       ", heights.mean())
print("Standard deviation:", heights.std())
print("Minimum height:    ", heights.min())
print("Maximum height:    ", heights.max())
print("25th percentile:   ", np.percentile(heights, 25))
print("Median:            ", np.median(heights))
print("75th percentile:   ", np.percentile(heights, 75))
```

```
[189 170 189 163 183 171 185 168 173 183 173 173 175 178 183 193 178 173
 174 183 183 168 170 178 182 180 183 178 182 188 175 179 183 193 182 183
 177 185 188 188 182 185]
Mean height:        179.73809523809524
Standard deviation: 6.931843442745892
Minimum height:     163
Maximum height:     193
25th percentile:    174.25
Median:             182.0
75th percentile:    183.0
```

In [33]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn; seaborn.set()  # set plot style
plt.hist(heights)
plt.title('Height Distribution of US Presidents')
plt.xlabel('height (cm)')
plt.ylabel('number');
```



In [82]:
```
#The Series-as-dictionary analogy can be made even more clear by constructing a Se
population_dict = {'California': 38332521,
                   'Texas': 26448193,
                   'New York': 19651127,
                   'Florida': 19552860,
                   'Illinois': 12882135}
population = pd.Series(population_dict)
population
```

Out[82]:
```
California    38332521
Texas         26448193
New York      19651127
Florida       19552860
Illinois      12882135
dtype: int64
```

In [83]:
```
#DataFrame as a generalized NumPy array

area_dict = {'California': 423967, 'Texas': 695662, 'New York': 141297,
             'Florida': 170312, 'Illinois': 149995}
area = pd.Series(area_dict)
area
```

Out[83]:
```
California    423967
Texas         695662
New York      141297
Florida       170312
Illinois      149995
dtype: int64
```

In [86]:
```
states = pd.DataFrame({'population': population,
                       'area': area})
states
```
Out[86]:

	population	area
California	38332521	423967
Texas	26448193	695662
New York	19651127	141297
Florida	19552860	170312
Illinois	12882135	149995

In [87]:
```
#Data Selection in DataFrame
area = pd.Series({'California': 423967, 'Texas': 695662,
                  'New York': 141297, 'Florida': 170312,
                  'Illinois': 149995})
pop = pd.Series({'California': 38332521, 'Texas': 26448193,
                 'New York': 19651127, 'Florida': 19552860,
                 'Illinois': 12882135})
data = pd.DataFrame({'area':area, 'pop':pop})
data
```
Out[87]:

	area	pop
California	423967	38332521
Texas	695662	26448193
New York	141297	19651127
Florida	170312	19552860
Illinois	149995	12882135

In [88]:
```
data['density'] = data['pop'] / data['area']
data
```
Out[88]:

	area	pop	density
California	423967	38332521	90.413926
Texas	695662	26448193	38.018740
New York	141297	19651127	139.076746
Florida	170312	19552860	114.806121
Illinois	149995	12882135	85.883763

In [91]:
```
#transpose
data.T
```

Out[91]:

	California	Texas	New York	Florida	Illinois
area	4.239670e+05	6.956620e+05	1.412970e+05	1.703120e+05	1.499950e+05
pop	3.833252e+07	2.644819e+07	1.965113e+07	1.955286e+07	1.288214e+07
density	9.041393e+01	3.801874e+01	1.390767e+02	1.148061e+02	8.588376e+01

In [93]:
```
# Dropping null values

df = pd.DataFrame([[1,      np.nan, 2],
                   [2,      3,      5],
                   [np.nan, 4,      6]])
df
```

Out[93]:

	0	1	2
0	1.0	NaN	2
1	2.0	3.0	5
2	NaN	4.0	6

In [94]:
```
df.dropna()
```

Out[94]:

	0	1	2
1	2.0	3.0	5

In [95]:
```
df.dropna(axis='columns')
```

Out[95]:

	2
0	2
1	5
2	6

In [96]:
```python
#Hierarchical Indexing
index = [('California', 2000), ('California', 2010),
         ('New York', 2000), ('New York', 2010),
         ('Texas', 2000), ('Texas', 2010)]
populations = [33871648, 37253956,
               18976457, 19378102,
               20851820, 25145561]
pop = pd.Series(populations, index=index)
pop
```

Out[96]:
```
(California, 2000)    33871648
(California, 2010)    37253956
(New York, 2000)      18976457
(New York, 2010)      19378102
(Texas, 2000)         20851820
(Texas, 2010)         25145561
dtype: int64
```

In [97]:
```python
pop[('California', 2010):('Texas', 2000)]
```

Out[97]:
```
(California, 2010)    37253956
(New York, 2000)      18976457
(New York, 2010)      19378102
(Texas, 2000)         20851820
dtype: int64
```

In [98]:
```python
pop[[i for i in pop.index if i[1] == 2010]]
```

Out[98]:
```
(California, 2010)    37253956
(New York, 2010)      19378102
(Texas, 2010)         25145561
dtype: int64
```

In [100]:
```python
#The Better Way: Pandas MultiIndex
index = pd.MultiIndex.from_tuples(index)
index
```

Out[100]:
```
MultiIndex(levels=[['California', 'New York', 'Texas'], [2000, 2010]],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])
```

In [108]:
```python
class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier, monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a, eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

In [112]:
```python
#Relational Algebra:
# Joins
# One to one join
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering', 'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})
display('df1', 'df2','pd.merge(df1, df2)')
```

Out[112]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df2

	employee	hire_date
0	Lisa	2004
1	Bob	2008
2	Jake	2012
3	Sue	2014

pd.merge(df1, df2)

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

In [113]:
```python
#Many to one join
df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                    'supervisor': ['Carly', 'Guido', 'Steve']})
display('df3', 'df4', 'pd.merge(df3, df4)')
```

Out[113]:

df3

	employee	group	hire_date
0	Bob	Accounting	2008
1	Jake	Engineering	2012
2	Lisa	Engineering	2004
3	Sue	HR	2014

df4

	group	supervisor
0	Accounting	Carly
1	Engineering	Guido
2	HR	Steve

pd.merge(df3, df4)

	employee	group	hire_date	supervisor
0	Bob	Accounting	2008	Carly
1	Jake	Engineering	2012	Guido
2	Lisa	Engineering	2004	Guido
3	Sue	HR	2014	Steve

In [115]:
```
#Many to Many join
df5 = pd.DataFrame({'group': ['Accounting', 'Accounting',
                              'Engineering', 'Engineering', 'HR', 'HR'],
                    'skills': ['math', 'spreadsheets', 'coding', 'linux',
                               'spreadsheets', 'organization']})
display('df1', 'df5', "pd.merge(df1, df5)")
```

Out[115]:

df1

	employee	group
0	Bob	Accounting
1	Jake	Engineering
2	Lisa	Engineering
3	Sue	HR

df5

	group	skills
0	Accounting	math
1	Accounting	spreadsheets
2	Engineering	coding
3	Engineering	linux
4	HR	spreadsheets
5	HR	organization

pd.merge(df1, df5)

	employee	group	skills
0	Bob	Accounting	math
1	Bob	Accounting	spreadsheets
2	Jake	Engineering	coding
3	Jake	Engineering	linux
4	Lisa	Engineering	coding
5	Lisa	Engineering	linux
6	Sue	HR	spreadsheets
7	Sue	HR	organization

In [116]:
```
## US STATE DATA
pop = pd.read_csv('data/state-population.csv')
areas = pd.read_csv('data/state-areas.csv')
abbrevs = pd.read_csv('data/state-abbrevs.csv')

display('pop.head()', 'areas.head()', 'abbrevs.head()')
```

Out[116]:

pop.head()

	state/region	ages	year	population
0	AL	under18	2012	1117489.0
1	AL	total	2012	4817528.0
2	AL	under18	2010	1130966.0
3	AL	total	2010	4785570.0
4	AL	under18	2011	1125763.0

areas.head()

	state	area (sq. mi)
0	Alabama	52423
1	Alaska	656425
2	Arizona	114006
3	Arkansas	53182
4	California	163707

abbrevs.head()

	state	abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA

In [117]:
```
#JOIN
merged = pd.merge(pop, abbrevs, how='outer',
                  left_on='state/region', right_on='abbreviation')
merged = merged.drop('abbreviation', 1) # drop duplicate info
merged.head()
```

Out[117]:

	state/region	ages	year	population	state
0	AL	under18	2012	1117489.0	Alabama
1	AL	total	2012	4817528.0	Alabama
2	AL	under18	2010	1130966.0	Alabama
3	AL	total	2010	4785570.0	Alabama
4	AL	under18	2011	1125763.0	Alabama

In [118]:
```
merged.isnull().any()
```

Out[118]:
```
state/region    False
ages            False
year            False
population       True
state            True
dtype: bool
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

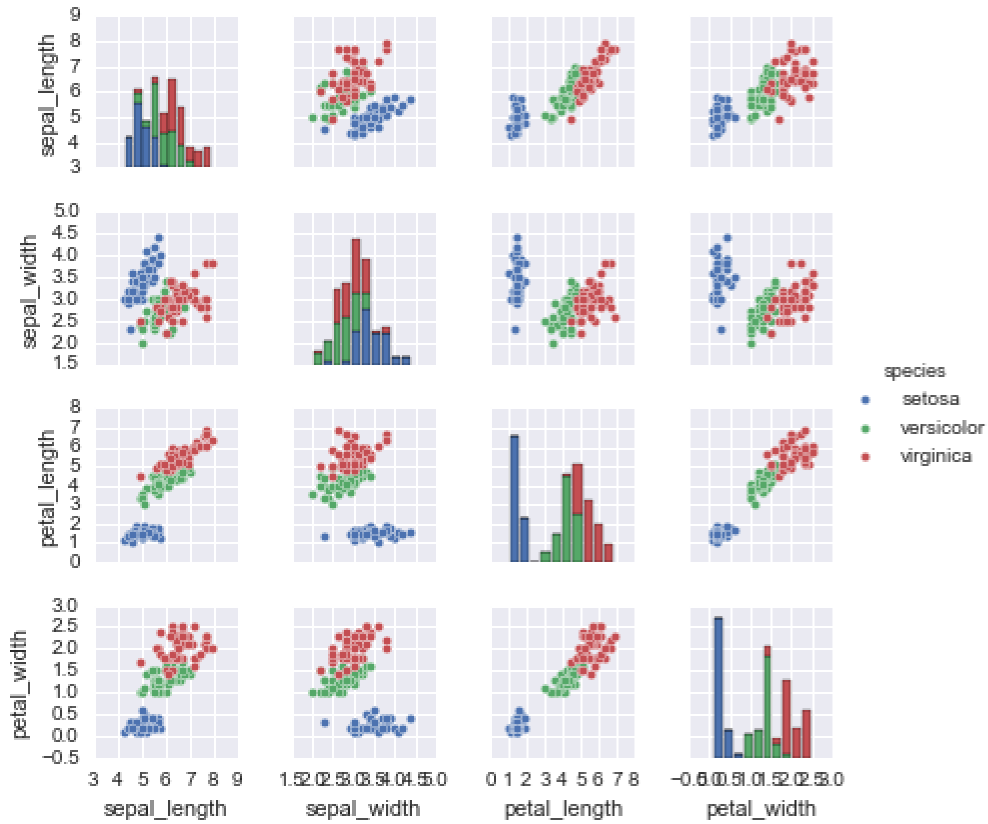
> **Scikit** Learn for machine learning. Built on NumPy, SciPy and matplotlib, this library contains a lot of effiecient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction.

In [170]:
```
import seaborn as sns
iris = sns.load_dataset('iris')
iris.head()
```

Out[170]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [169]:
```python
%matplotlib inline
import seaborn as sns; sns.set()
sns.pairplot(iris, hue='species', size=1.5);
```



In [183]:
```python
X_iris = iris.drop('species', axis=1)
X_iris.shape
```

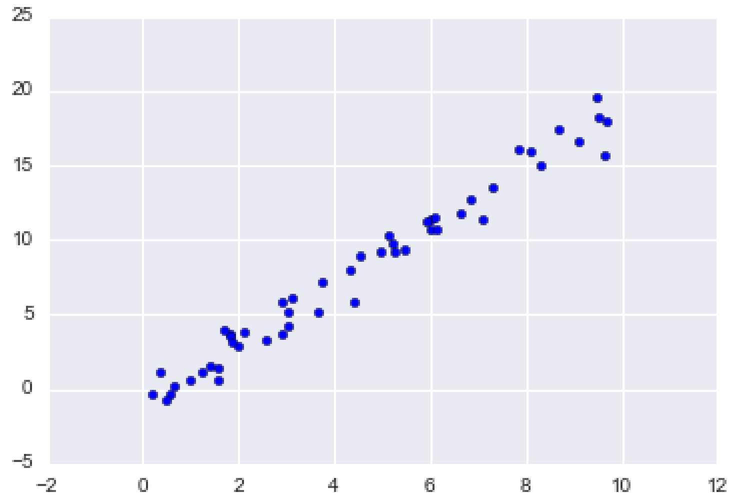
Out[183]: (150, 4)

In [184]:
```python
y_iris = iris['species']
y_iris.shape
```

Out[184]: (150,)

Supervised learning example: Simple linear regression

In [171]:
```
import matplotlib.pyplot as plt
import numpy as np

rng = np.random.RandomState(42)
x = 10 * rng.rand(50)
y = 2 * x - 1 + rng.randn(50)
plt.scatter(x, y);
```



In [173]:
```
#choose a model
from sklearn.linear_model import LinearRegression
model = LinearRegression(fit_intercept=True)
## Arrange the data into a features matrix
X = x[:, np.newaxis]
X.shape
```

Out[173]:
```
(50, 1)
```

In [174]:
```
#fit the model to the data
model.fit(X,y)
```

Out[174]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [177]:
```
model.coef_, model.intercept_
```

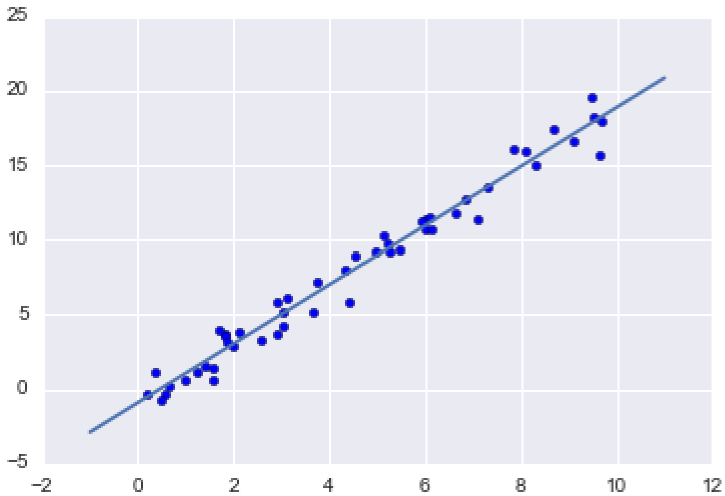
Out[177]:
```
(array([1.9776566]), -0.9033107255311164)
```

In [178]:
```
# predict the unknown data
xfit = np.linspace(-1, 11)
```

In [179]:
```
Xfit = xfit[:, np.newaxis]
yfit = model.predict(Xfit)
```

In [180]:

```
#plot the regressio nline
plt.scatter(x, y)
plt.plot(xfit, yfit);
```



Supervised learning example: Iris classification

In [185]:

```
from sklearn.cross_validation import train_test_split
Xtrain, Xtest, ytrain, ytest = train_test_split(X_iris, y_iris,
                                                random_state=1)
```

In [186]:

```
from sklearn.naive_bayes import GaussianNB # 1. choose model class
model = GaussianNB()                       # 2. instantiate model
model.fit(Xtrain, ytrain)                  # 3. fit model to data
y_model = model.predict(Xtest)             # 4. predict on new data
```

In [187]:

```
from sklearn.metrics import accuracy_score
accuracy_score(ytest, y_model)
```

Out[187]:

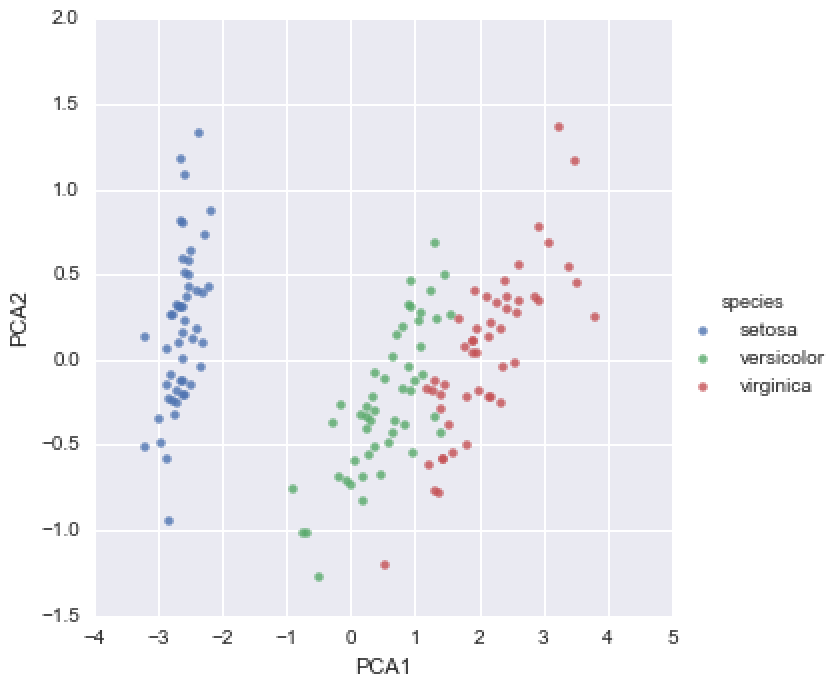
```
0.9736842105263158
```

Unsupervised learning example: Iris dimensionality

In [188]:

```
from sklearn.decomposition import PCA  # 1. Choose the model class
model = PCA(n_components=2)            # 2. Instantiate the model with hyperparam
model.fit(X_iris)                      # 3. Fit to data. Notice y is not specifie
X_2D = model.transform(X_iris)         # 4. Transform the data to two dimensions
```

In [189]:
```python
iris['PCA1'] = X_2D[:, 0]
iris['PCA2'] = X_2D[:, 1]
sns.lmplot("PCA1", "PCA2", hue='species', data=iris, fit_reg=False);
```

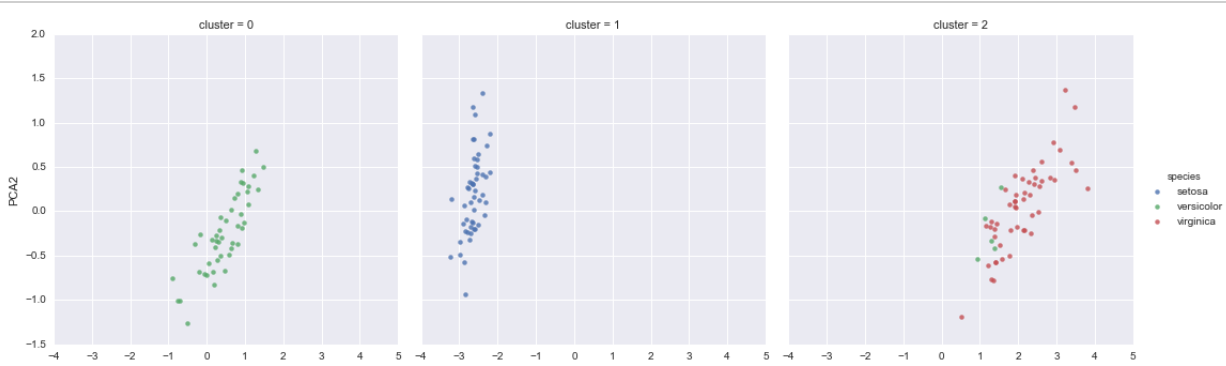


Unsupervised learning: Iris clustering

In [190]:
```python
from sklearn.mixture import GMM      # 1. Choose the model class
model = GMM(n_components=3,
            covariance_type='full')  # 2. Instantiate the model with hyperparamet
model.fit(X_iris)                    # 3. Fit to data. Notice y is not specified!
y_gmm = model.predict(X_iris)        # 4. Determine cluster labels
```

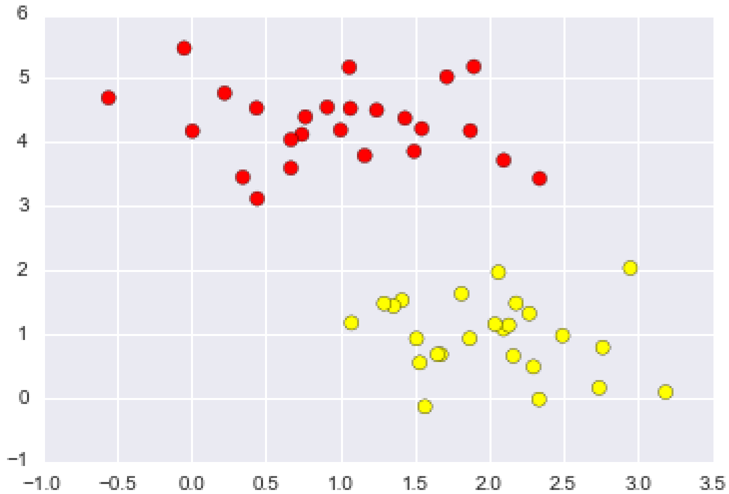
...

In [191]:
```python
iris['cluster'] = y_gmm
sns.lmplot("PCA1", "PCA2", data=iris, hue='species',
           col='cluster', fit_reg=False);
```

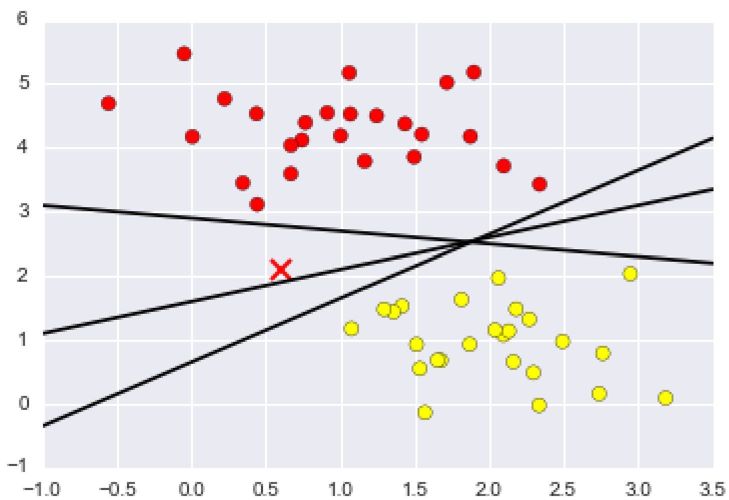


Support Vector Machines

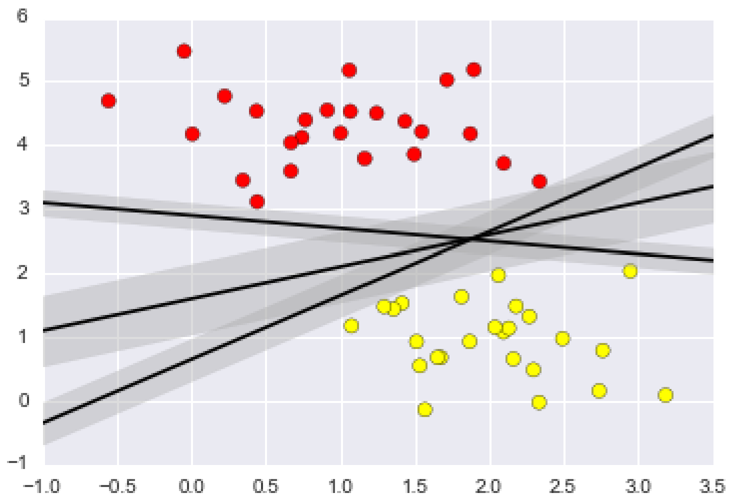
In [200]:
```
from sklearn.datasets.samples_generator import make_blobs
X, y = make_blobs(n_samples=50, centers=2,
                  random_state=0, cluster_std=0.60)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn');
```



In [201]:
```
xfit = np.linspace(-1, 3.5)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')
plt.plot([0.6], [2.1], 'x', color='red', markeredgewidth=2, markersize=10)

for m, b in [(1, 0.65), (0.5, 1.6), (-0.2, 2.9)]:
    plt.plot(xfit, m * xfit + b, '-k')

plt.xlim(-1, 3.5);
```

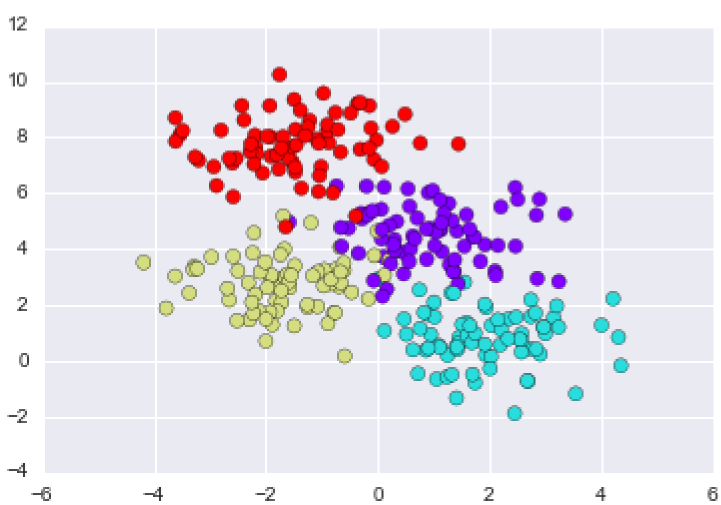


In [202]:
```
#Support Vector Machines: Maximizing the Margin
xfit = np.linspace(-1, 3.5)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='autumn')

for m, b, d in [(1, 0.65, 0.33), (0.5, 1.6, 0.55), (-0.2, 2.9, 0.2)]:
    yfit = m * xfit + b
    plt.plot(xfit, yfit, '-k')
    plt.fill_between(xfit, yfit - d, yfit + d, edgecolor='none',
                     color='#AAAAAA', alpha=0.4)

plt.xlim(-1, 3.5);
```



Decision Tree

In [203]:
```
from sklearn.datasets import make_blobs

X, y = make_blobs(n_samples=300, centers=4,
                  random_state=0, cluster_std=1.0)
plt.scatter(X[:, 0], X[:, 1], c=y, s=50, cmap='rainbow');
```

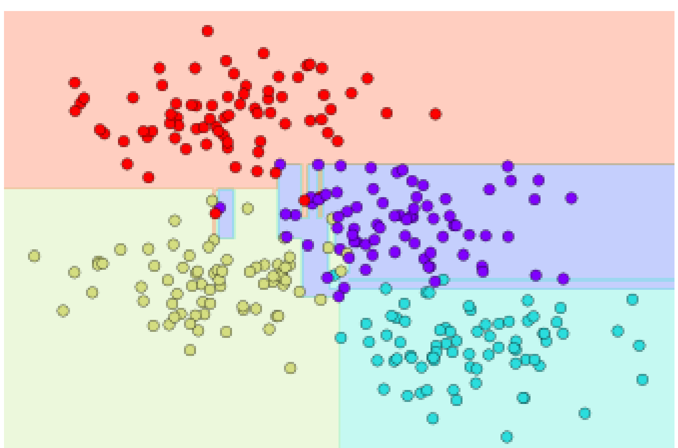


In [204]:
```
from sklearn.tree import DecisionTreeClassifier
tree = DecisionTreeClassifier().fit(X, y)
```

In [205]:
```
def visualize_classifier(model, X, y, ax=None, cmap='rainbow'):
    ax = ax or plt.gca()

    # Plot the training points
    ax.scatter(X[:, 0], X[:, 1], c=y, s=30, cmap=cmap,
               clim=(y.min(), y.max()), zorder=3)
    ax.axis('tight')
    ax.axis('off')
    xlim = ax.get_xlim()
    ylim = ax.get_ylim()

    # fit the estimator
    model.fit(X, y)
    xx, yy = np.meshgrid(np.linspace(*xlim, num=200),
                         np.linspace(*ylim, num=200))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)

    # Create a color plot with the results
    n_classes = len(np.unique(y))
    contours = ax.contourf(xx, yy, Z, alpha=0.3,
                           levels=np.arange(n_classes + 1) - 0.5,
                           cmap=cmap, clim=(y.min(), y.max()),
                           zorder=1)

    ax.set(xlim=xlim, ylim=ylim)
```

In [206]:
```
visualize_classifier(DecisionTreeClassifier(), X, y)
```

```
C:\Anaconda3\lib\site-packages\matplotlib\contour.py:960: UserWarning: The foll
owing kwargs were not used by contour: 'clim'
  s)
```



In [ ]:

In [ ]:

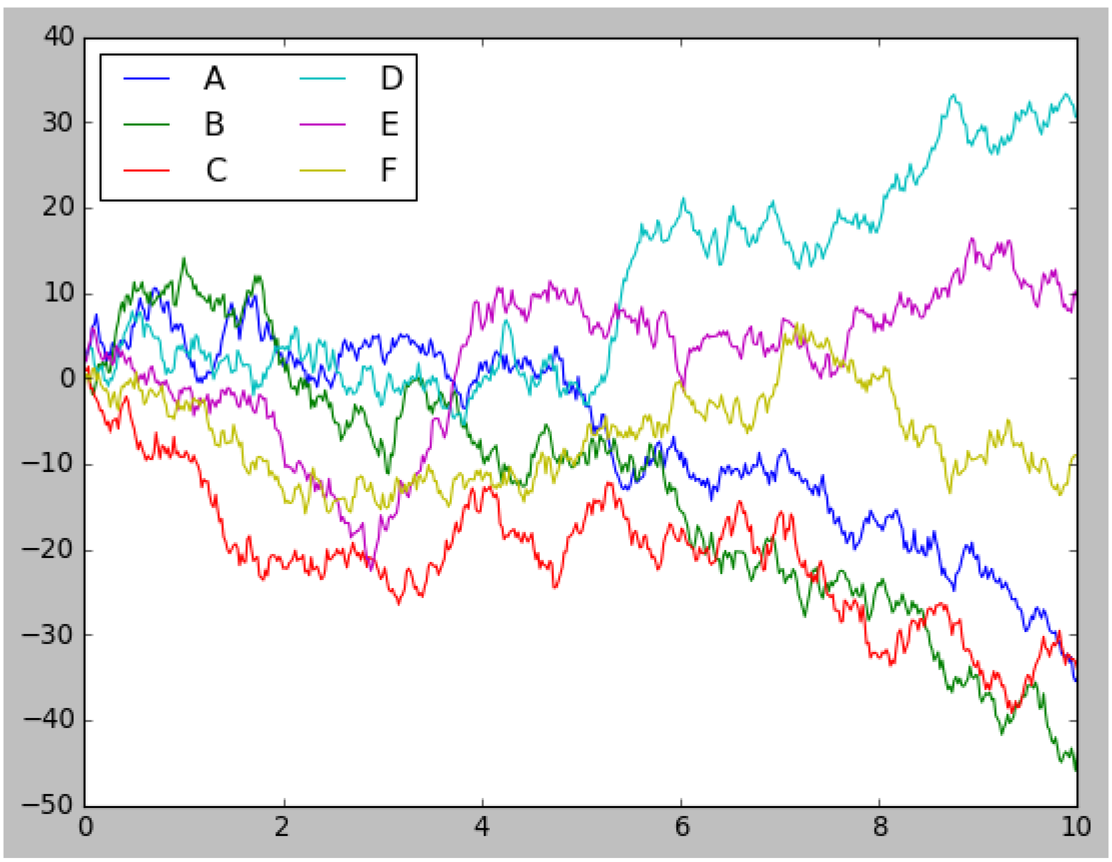
Statsmodels for statistical modeling. Statsmodels is a Python module that allows users to explore data, estimate statistical models, and perform statistical tests. An extensive list of descriptive statistics, statistical tests, plotting functions, and result statistics are available for different types of data and each estimator.

In [ ]:

Seaborn for statistical data visualization. Seaborn is a library for making attractive and informative statistical graphics in Python. It is based on matplotlib. Seaborn aims to make visualization a central part of exploring and understanding data.

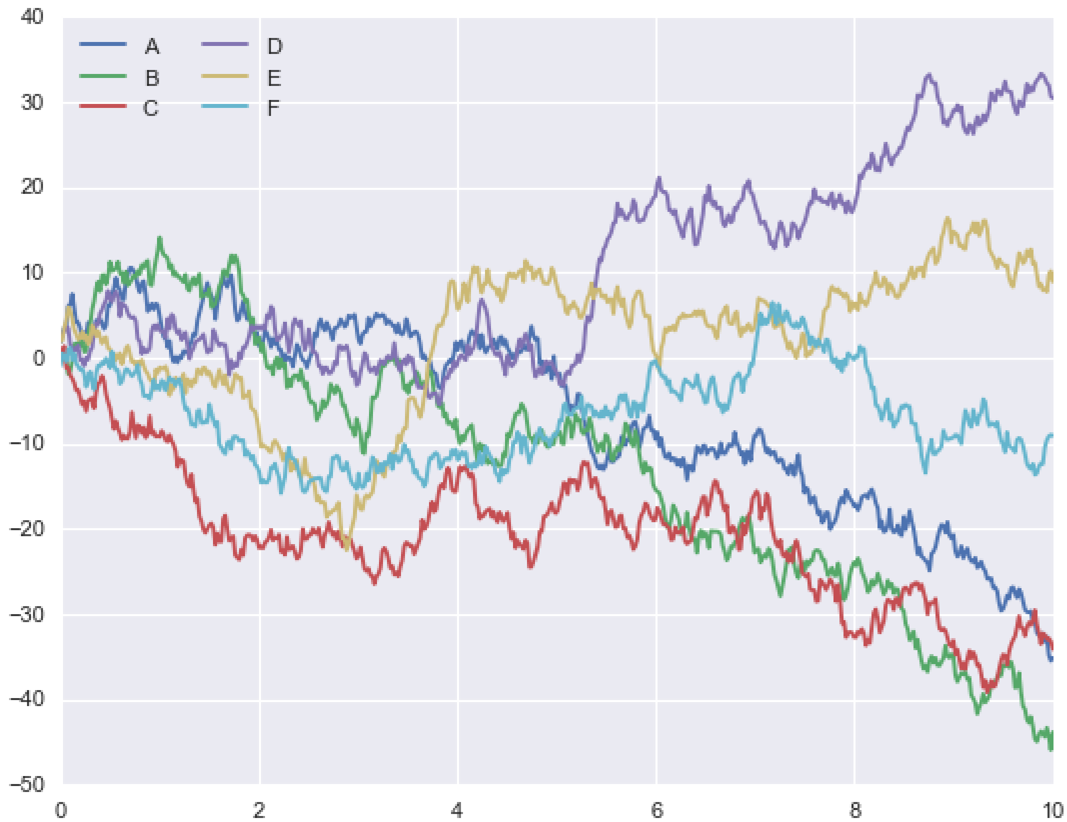
In [156]:

```
plt.style.use('classic')
# Create some data
rng = np.random.RandomState(0)
x = np.linspace(0, 10, 500)
y = np.cumsum(rng.randn(500, 6), 0)
# Plot the data with Matplotlib defaults
plt.plot(x, y)
plt.legend('ABCDEF', ncol=2, loc='upper left');
```



In [158]:

```
import seaborn as sns
sns.set()
# same plotting code as above!
plt.plot(x, y)
plt.legend('ABCDEF', ncol=2, loc='upper left');
```

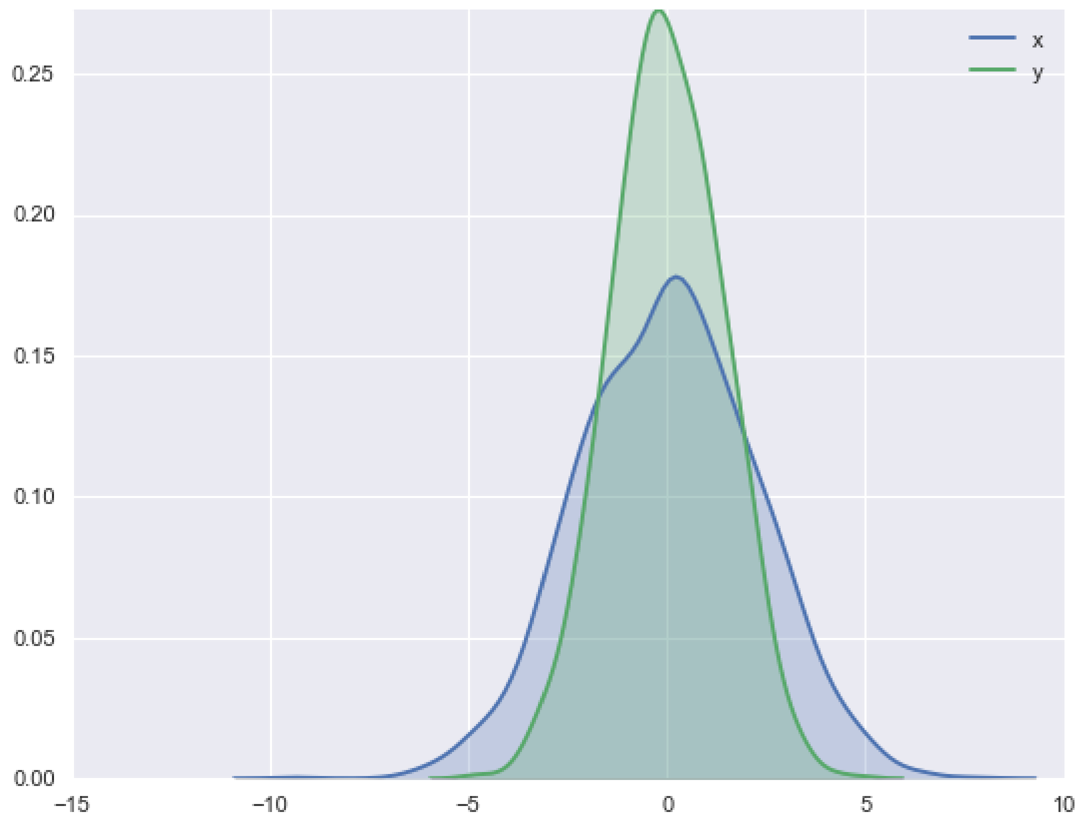


In [159]:

```
##Histograms, KDE, and densities


data = np.random.multivariate_normal([0, 0], [[5, 2], [2, 2]], size=2000)
data = pd.DataFrame(data, columns=['x', 'y'])

for col in 'xy':
    plt.hist(data[col], normed=True, alpha=0.5)
```

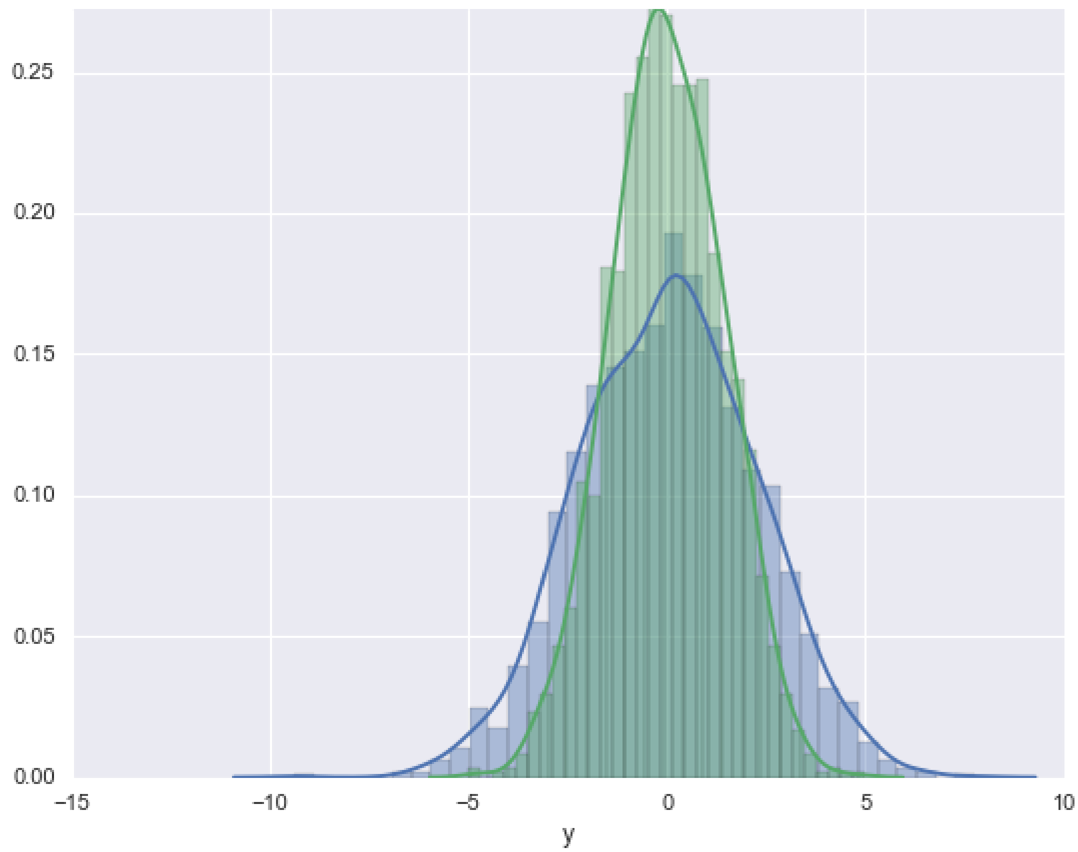
```
C:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
C:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
In [160]: for col in 'xy':
              sns.kdeplot(data[col], shade=True)
```



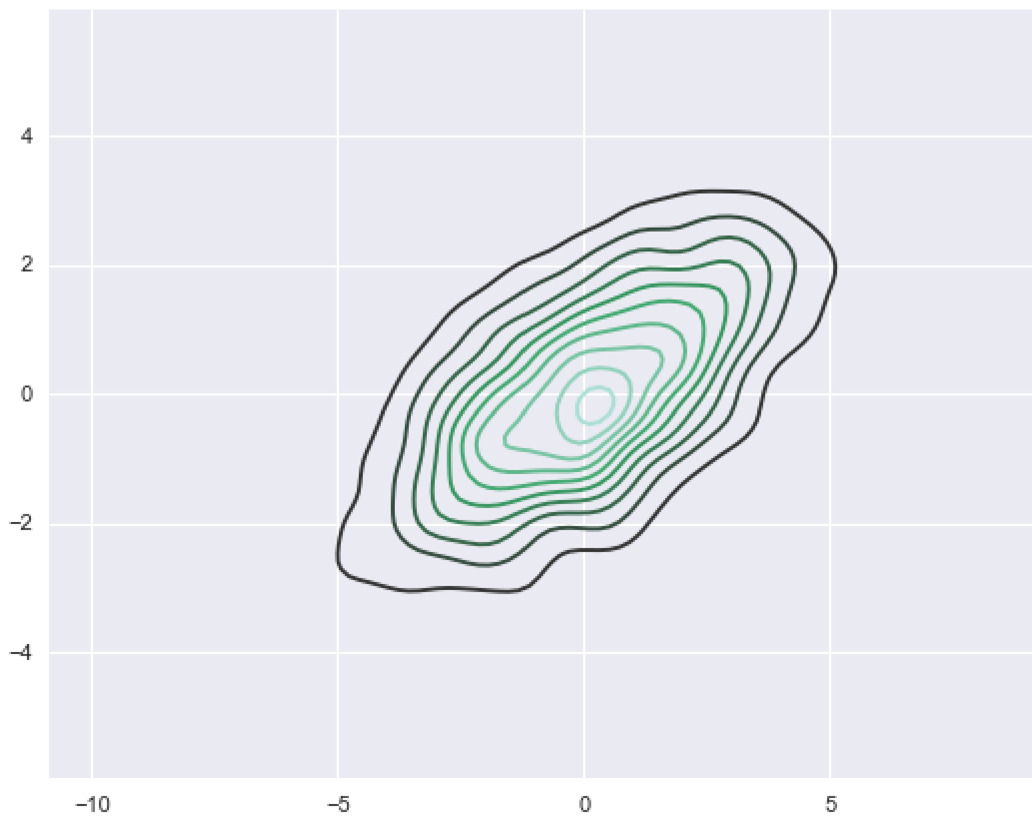
In [161]:
```
#Histograms and KDE can be combined using distplot:
sns.distplot(data['x'])
sns.distplot(data['y']);
```

```
C:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
C:\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

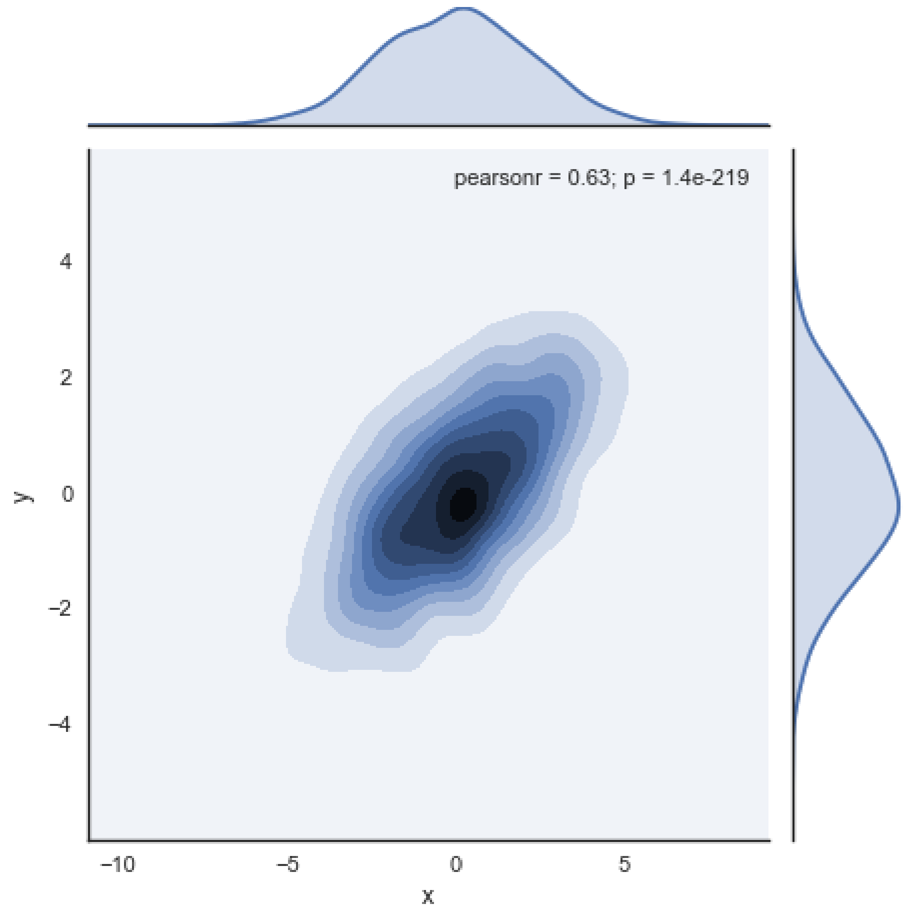


In [162]:
```
sns.kdeplot(data);
```

```
C:\Anaconda3\lib\site-packages\seaborn\distributions.py:645: UserWarning: Passi
ng a 2D dataset for a bivariate plot is deprecated in favor of kdeplot(x, y), a
nd it will cause an error in future versions. Please update your code.
  warnings.warn(warn_msg, UserWarning)
```



In [165]:
```
# Understand the distribution
with  sns.axes_style('white'):
    sns.jointplot("x", "y", data, kind='kde');
```



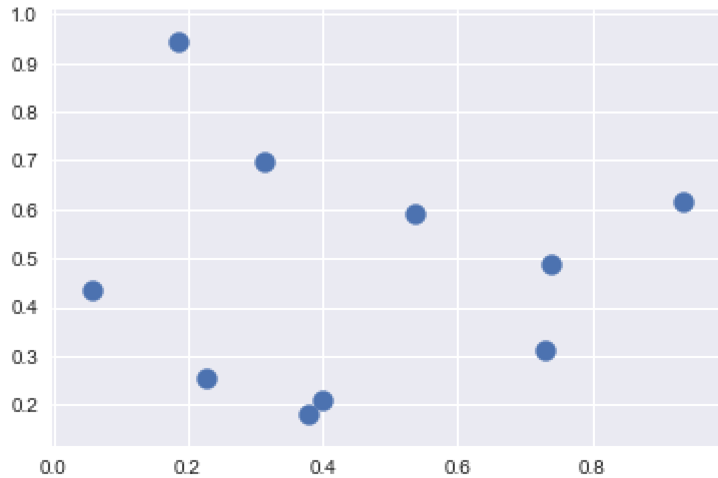
In [ ]:

In [ ]:

Running below two code snippets to generate random point and plots

In [80]:

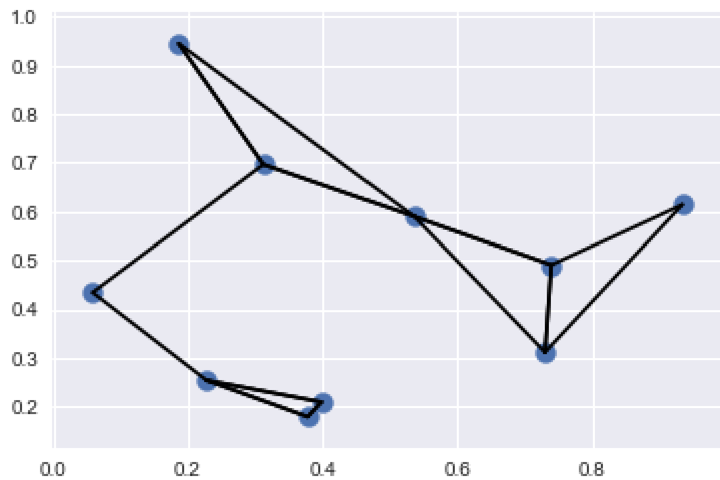
```
## k-Nearest Neighbors Clustering

X  = np.random.rand(10, 2)
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn; seaborn.set() # Plot styling
plt.scatter(X[:, 0], X[:, 1], s=100);
```



the distance between each pair of points. Recall that the squared-distance between two points is the sum of the squared differences in each dimension; using the efficient broadcasting (Computation on Arrays: Broadcasting) and aggregation (Aggregations: Min, Max, and Everything In Between) routines provided by NumPy we can compute the matrix of square distances

In [81]:
```python
dist_sq = np.sum((X[:, np.newaxis, :] - X[np.newaxis, :, :]) ** 2, axis=-1)
# for each pair of points, compute differences in their coordinates
differences = X[:, np.newaxis, :] - X[np.newaxis, :, :]
print("differences in shape ",differences.shape)
# square the coordinate differences
sq_differences = differences ** 2
print("square the coordinate difference ",sq_differences.shape)
# sum the coordinate differences to get the squared distance
dist_sq = sq_differences.sum(-1)
print('sum the coordinate differences ',dist_sq.shape)
###
print("diagonal",dist_sq.diagonal())
nearest = np.argsort(dist_sq, axis=1)
print("Nearest:\n",nearest)

K = 2
nearest_partition = np.argpartition(dist_sq, K + 1, axis=1)
plt.scatter(X[:, 0], X[:, 1], s=100)

# draw lines from each point to its two nearest neighbors
K = 2

for i in range(X.shape[0]):
    for j in nearest_partition[i, :K+1]:
        # plot a line from X[i] to X[j]
        # use some zip magic to make it happen:
        plt.plot(*zip(X[j], X[i]), color='black')
#Each point in the plot has lines drawn to its two nearest neighbors.
```

```
differences in shape  (10, 10, 2)
square the coordinate difference  (10, 10, 2)
sum the coordinate differences  (10, 10)
diagonal [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
Nearest:
 [[0 5 2 1 8 3 9 6 4 7]
 [1 5 8 2 0 3 9 6 4 7]
 [2 5 1 3 0 9 6 8 7 4]
 [3 9 6 2 1 7 5 8 0 4]
 [4 8 1 7 6 5 3 9 0 2]
 [5 2 1 0 3 8 9 6 7 4]
 [6 9 3 7 8 1 2 5 4 0]
 [7 6 8 3 9 1 4 2 5 0]
 [8 1 4 7 6 5 3 9 2 0]
 [9 3 6 2 7 1 5 8 0 4]]
```



Bokeh for creating interactive plots, dashboards and data applications on modern web-browsers. It empowers the user to generate elegant and concise graphics in the style of D3.js. Moreover, it has the capability of high-performance interactivity over very large or streaming datasets.

```
In [ ]:
```

Blaze for extending the capability of Numpy and Pandas to distributed and streaming datasets. It can be used to access data from a multitude of sources including Bcolz, MongoDB, SQLAlchemy, Apache Spark, PyTables, etc. Together with Bokeh, Blaze can act as a very powerful tool for creating effective visualizations and dashboards on huge chunks of data.

```
In [ ]:
```

Scrapy for web crawling. It is a very useful framework for getting specific patterns of data. It has the capability to start at a website home url and then dig through web-pages within the website to gather information.

```
In [ ]:
```

SymPy for symbolic computation. It has wide-ranging capabilities from basic symbolic arithmetic to calculus, algebra, discrete mathematics and quantum physics. Another useful feature is the capability of formatting the result of the computations as LaTeX code.

In [ ]:

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```

Requests for accessing the web. It works similar to the the standard python library urllib2 but is much easier to code. You will find subtle differences with urllib2 but for beginners, Requests might be more convenient.

In [ ]:

```

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