In [52]:
```
ctemps = [5, 10, 12, 14, 10, 23, 41, 30, 12, 24, 12, 18, 29]

ftemps1 = [(t * 9/5) + 32 for t in ctemps]
ftemps2 = {(t * 9/5) + 32 for t in ctemps}
print("\n", ftemps1, type(ftemps1))
print("\n", ftemps2, type(ftemps2))


evens = [2, 4, 6, 8, 10, 12, 14, 16, 18, 20]

list_evenSquared = [e ** 2 for e in evens]
print("\nList comprehension", list_evenSquared)

set_evenSquared = {e ** 2 for e in evens}
print("\nSet comprehension", set_evenSquared)
```

```
 [41.0, 50.0, 53.6, 57.2, 50.0, 73.4, 105.8, 86.0, 53.6, 75.2, 53.6, 64.4, 8
4.2] <class 'list'>

 {64.4, 73.4, 41.0, 105.8, 75.2, 50.0, 84.2, 53.6, 86.0, 57.2} <class 'set'>

List comprehension [4, 16, 36, 64, 100, 144, 196, 256, 324, 400]

Set comprehension {64, 256, 100, 4, 36, 196, 324, 16, 144, 400}
```

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

a = np.array([[1, 2],
              [3, 4]])

b = np.array([[5, 6],
              [7, 8]])

print("Vertical stacking:", np.vstack((a, b)))

# horizontal stacking
print("Horizontal stacking:", np.hstack((a, b)))


c = [5, 6]
# stacking columns
print("Column stacking:", np.column_stack((a, c)))
```

```
Vertical stacking: [[1 2]
 [3 4]
 [5 6]
 [7 8]]
Horizontal stacking: [[1 2 5 6]
 [3 4 7 8]]
Column stacking: [[1 2 5]
 [3 4 6]]
```

In [38]:
```
import pandas as pd
import numpy as np
s = pd.Series([0, 1, 4, 9, 16, 25], name='squares')

print(s.index)
print(s.values, s.index)
print(s[2:4])
```

```
RangeIndex(start=0, stop=6, step=1)
[ 0  1  4  9 16 25] RangeIndex(start=0, stop=6, step=1)
2    4
3    9
Name: squares, dtype: int64
```

In [39]:
```
pop2014 = pd.Series([100, 99.3, 95.5, 93.5, 92.4, 84.8, 84.5, 78.9, 74.3, 72.8
],
                    index=['Java', 'C', 'C++', 'Python', 'C#', 'PHP', 'JavaScr
ipt', 'Ruby', 'R', 'Matlab'])

pop2015 = pd.Series({'Java': 100, 'C': 99.9, 'C++': 99.4, 'Python': 96.5, 'C#'
: 91.3,
                     'R': 84.8, 'PHP': 84.5, 'JavaScript': 83.0, 'Ruby': 76.2,
'Matlab': 72.4})

print(pop2014)

print(pop2015) # index sort
```

```
Java          100.0
C              99.3
C++            95.5
Python         93.5
C#             92.4
PHP            84.8
JavaScript     84.5
Ruby           78.9
R              74.3
Matlab         72.8
dtype: float64
C              99.9
C#             91.3
C++            99.4
Java          100.0
JavaScript     83.0
Matlab         72.4
PHP            84.5
Python         96.5
R              84.8
Ruby           76.2
dtype: float64
```

In [40]:
```
print(pop2014.index)
print(pop2014.iloc[0:2])
print(pop2014.loc[:'Ruby'])
```

```
Index(['Java', 'C', 'C++', 'Python', 'C#', 'PHP', 'JavaScript', 'Ruby', 'R',
       'Matlab'],
      dtype='object')
Java    100.0
C        99.3
dtype: float64
Java          100.0
C              99.3
C++            95.5
Python         93.5
C#             92.4
PHP            84.8
JavaScript     84.5
Ruby           78.9
dtype: float64
```

loc gets rows (or columns) with particular labels from the index.

iloc gets rows (or columns) at particular positions in the index (so it only takes integers).

ix usually tries to behave like loc but falls back to behaving like iloc if a label is not present in the index

In [41]:
```
twoyears = pd.DataFrame({'2014': pop2014, '2015': pop2015})
print(twoyears)
```

```
             2014   2015
C            99.3   99.9
C#           92.4   91.3
C++          95.5   99.4
Java        100.0  100.0
JavaScript   84.5   83.0
Matlab       72.8   72.4
PHP          84.8   84.5
Python       93.5   96.5
R            74.3   84.8
Ruby         78.9   76.2
```

In [42]:
```
twoyears['Average'] = 0.5*(twoyears['2014'] + twoyears['2015'])
print(twoyears)
```

```
             2014   2015  Average
C            99.3   99.9    99.60
C#           92.4   91.3    91.85
C++          95.5   99.4    97.45
Java        100.0  100.0   100.00
JavaScript   84.5   83.0    83.75
Matlab       72.8   72.4    72.60
PHP          84.8   84.5    84.65
Python       93.5   96.5    95.00
R            74.3   84.8    79.55
Ruby         78.9   76.2    77.55
```

In [45]:
```
test_data = pd.DataFrame(np.random.choice(['a', 'b', 'c', 'd'], (3, 3)), index
=[1, 2, 3], columns=['AA', 'BB', 'CC'])
print(test_data)
```

```
  AA BB CC
1  d  b  a
2  d  c  a
3  b  c  c
```

# pandas aggregation

In [53]:
```
open('tips.csv','r').readlines()[:10]
```

Out[53]:
```
['total_bill,tip,gender,smoker,day,time,size\n',
 '16.99,1.01,Female,No,Sun,Dinner,2\n',
 '10.34,1.66,Male,No,Sun,Dinner,3\n',
 '21.01,3.5,Male,No,Sun,Dinner,3\n',
 '23.68,3.31,Male,No,Sun,Dinner,2\n',
 '24.59,3.61,Female,No,Sun,Dinner,4\n',
 '25.29,4.71,Male,No,Sun,Dinner,4\n',
 '8.77,2,Male,No,Sun,Dinner,2\n',
 '26.88,3.12,Male,No,Sun,Dinner,4\n',
 '15.04,1.96,Male,No,Sun,Dinner,2\n']
```

In [54]:
```
tips = pd.read_csv('tips.csv')
```

In [55]:
```
tips.head()
```

Out[55]:

| | total_bill | tip | gender | smoker | day | time | size |
|---|---|---|---|---|---|---|---|
| **0** | 16.99 | 1.01 | Female | No | Sun | Dinner | 2 |
| **1** | 10.34 | 1.66 | Male | No | Sun | Dinner | 3 |
| **2** | 21.01 | 3.50 | Male | No | Sun | Dinner | 3 |
| **3** | 23.68 | 3.31 | Male | No | Sun | Dinner | 2 |
| **4** | 24.59 | 3.61 | Female | No | Sun | Dinner | 4 |

In [56]:
```
tips.mean()
```

Out[56]:
```
total_bill    19.785943
tip            2.998279
size           2.569672
dtype: float64
```

In [85]:
```
tips.dtypes
```

Out[85]:
```
total_bill    float64
tip           float64
gender         object
smoker         object
day            object
time           object
size            int64
dtype: object
```

In [57]:
```
tips.describe()
```

Out[57]:

| | total_bill | tip | size |
|---|---|---|---|
| **count** | 244.000000 | 244.000000 | 244.000000 |
| **mean** | 19.785943 | 2.998279 | 2.569672 |
| **std** | 8.902412 | 1.383638 | 0.951100 |
| **min** | 3.070000 | 1.000000 | 1.000000 |
| **25%** | 13.347500 | 2.000000 | 2.000000 |
| **50%** | 17.795000 | 2.900000 | 2.000000 |
| **75%** | 24.127500 | 3.562500 | 3.000000 |
| **max** | 50.810000 | 10.000000 | 6.000000 |

In [62]:
```
tips.shape # row count
```

Out[62]:
```
(244, 7)
```

In [63]:
```
tips.groupby('gender').mean()
```

Out[63]:

| | total_bill | tip | size |
|---|---|---|---|
| **gender** | | | |
| **Female** | 18.056897 | 2.833448 | 2.459770 |
| **Male** | 20.744076 | 3.089618 | 2.630573 |

In [64]:
```
tips.groupby(['gender','smoker']).mean()
```

Out[64]:

| | | total_bill | tip | size |
|---|---|---|---|---|
| **gender** | **smoker** | | | |
| **Female** | **No** | 18.105185 | 2.773519 | 2.592593 |
| | **Yes** | 17.977879 | 2.931515 | 2.242424 |
| **Male** | **No** | 19.791237 | 3.113402 | 2.711340 |
| | **Yes** | 22.284500 | 3.051167 | 2.500000 |

In [66]:
```
pd.pivot_table(tips,'total_bill','gender','smoker')

# pandas.pivot_table(data, values=None, index=None, columns=None, aggfunc='mea
n',
#         fill_value=None, margins=False, dropna=True, margins_name='All')

# Create a spreadsheet-style pivot table as a DataFrame.
```

Out[66]:

| smoker | No | Yes |
|---|---|---|
| **gender** | | |
| **Female** | 18.105185 | 17.977879 |
| **Male** | 19.791237 | 22.284500 |

In [70]:
```
pd.pivot_table(tips,'total_bill',['gender','smoker'],['day','time'])
# pandas.pivot_table(data, values=None, index=None, columns=None, aggfunc='mea
n')
```

Out[70]:

| | day | Fri | | Sat | Sun | Thur | |
|---|---|---|---|---|---|---|---|
| | **time** | **Dinner** | **Lunch** | **Dinner** | **Dinner** | **Dinner** | **Lunch** |
| **gender** | **smoker** | | | | | | |
| **Female** | **No** | 22.750 | 15.980000 | 19.003846 | 20.824286 | 18.78 | 15.899167 |
| | **Yes** | 12.200 | 13.260000 | 20.266667 | 16.540000 | NaN | 19.218571 |
| **Male** | **No** | 17.475 | NaN | 19.929063 | 20.403256 | NaN | 18.486500 |
| | **Yes** | 25.892 | 11.386667 | 21.837778 | 26.141333 | NaN | 19.171000 |

# Data Frame Creation and visualization

In [3]:
```
import pandas as pd
from matplotlib import pyplot as plt
url='http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data'
df = pd.read_csv(url)

df.head()
```

Out[3]:

| | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
|---|---|---|---|---|---|
| 0 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 1 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 2 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 3 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| 4 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |

In [4]:
```
df.columns = ['sepal_length','sepal_width','petal_length','petal_width','flowe
r_type']
df['flower_type'] = df['flower_type'].astype('category')
df.flower_type = df.flower_type.cat.rename_categories([0,1,2])

df.head()
```

Out[4]:

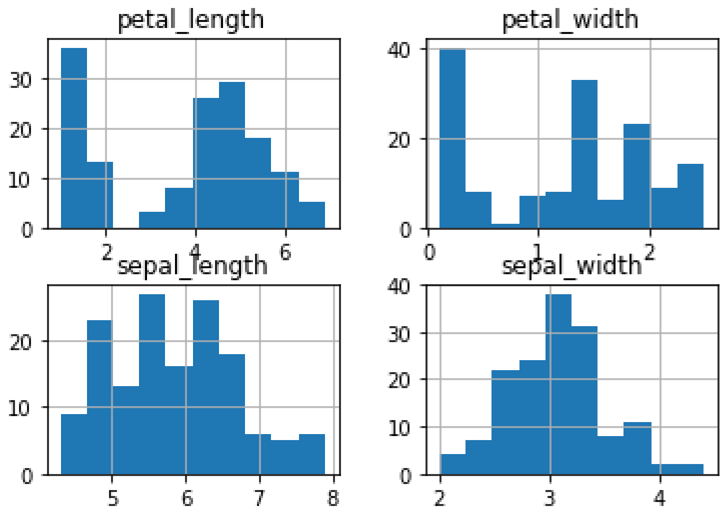
| | sepal_length | sepal_width | petal_length | petal_width | flower_type |
|---|---|---|---|---|---|
| 0 | 4.9 | 3.0 | 1.4 | 0.2 | 0 |
| 1 | 4.7 | 3.2 | 1.3 | 0.2 | 0 |
| 2 | 4.6 | 3.1 | 1.5 | 0.2 | 0 |
| 3 | 5.0 | 3.6 | 1.4 | 0.2 | 0 |
| 4 | 5.4 | 3.9 | 1.7 | 0.4 | 0 |

In [5]:
```
df['flower_type'].describe()
```

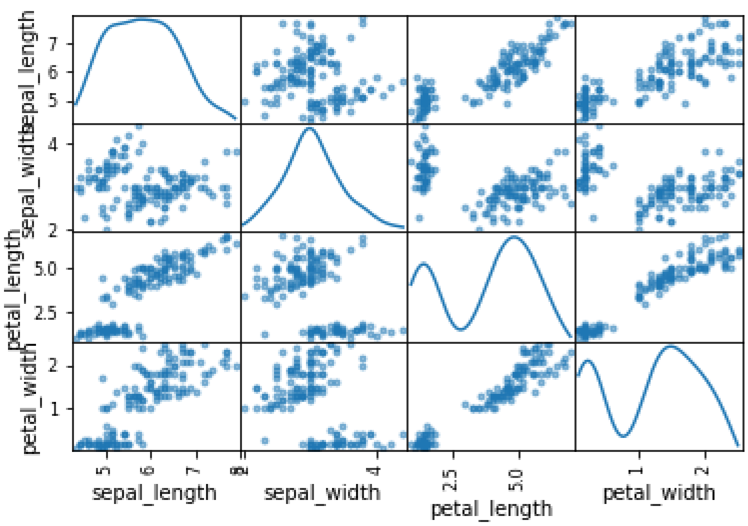
Out[5]:
```
count     149
unique      3
top         2
freq       50
Name: flower_type, dtype: int64
```

s = pd.Series(['a', 'a', 'b', 'c']) s.describe() count 4 unique 3 top a freq 2 dtype: object https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.describe.html

In [6]:
```
df.hist()
plt.show()
```




In [11]:
```
pd.scatter_matrix(df, diagonal='kde')
plt.show()
```




‘bar’ or ‘barh’ for bar plots ‘hist’ for histogram ‘box’ for boxplot ‘kde’ or ‘density’ for density plots ‘area’ for area plots ‘scatter’ for scatter plots ‘hexbin’ for hexagonal bin plots ‘pie’ for pie plots [https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html#visualization-kde (https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html#visualization-kde)](https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html#visualization-kde)

More general: [http://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html (http://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html)](http://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html)

In [ ]:

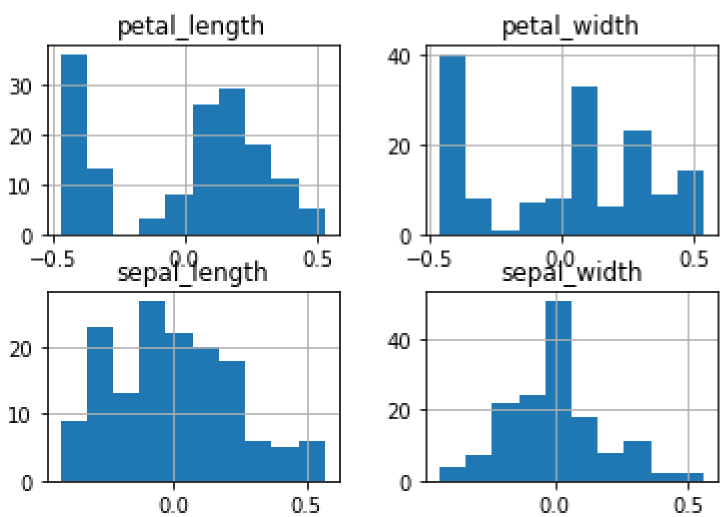
# More Operations on the Data Frame

In [25]:
```
df = df.sort_values(by='sepal_width')
df.head()
```

Out[25]:

| | sepal_length | sepal_width | petal_length | petal_width | flower_type |
|---|---|---|---|---|---|
| **59** | 5.0 | 2.0 | 3.5 | 1.0 | 1 |
| **61** | 6.0 | 2.2 | 4.0 | 1.0 | 1 |
| **118** | 6.0 | 2.2 | 5.0 | 1.5 | 2 |
| **67** | 6.2 | 2.2 | 4.5 | 1.5 | 1 |
| **92** | 5.0 | 2.3 | 3.3 | 1.0 | 1 |

In [9]:
```
# Normalizing your data set
df=df.ix[:,0:4].apply( lambda f: ( f - f.mean() )/( f.max() - f.min() ) )
df.hist()
plt.show()
```




In [26]:
```
# Get a random sample from the data set
df=df.sample(frac=1.0)
df.head()
```

Out[26]:

| | sepal_length | sepal_width | petal_length | petal_width | flower_type |
|---|---|---|---|---|---|
| **113** | 5.8 | 2.8 | 5.1 | 2.4 | 2 |
| **36** | 4.9 | 3.1 | 1.5 | 0.1 | 0 |
| **62** | 6.1 | 2.9 | 4.7 | 1.4 | 1 |
| **98** | 5.7 | 2.8 | 4.1 | 1.3 | 1 |
| **15** | 5.4 | 3.9 | 1.3 | 0.4 | 0 |

In [27]:
```
# Split the data set into test and train set
train=df.sample(frac=0.8,random_state=123)
test=df.drop(train.index)
```

# Read/Write

In [28]:
```
df.to_csv('iris_normalized.csv')
new_df = pd.read_csv('iris_normalized.csv')
new_df.head()
```

Out[28]:

| | Unnamed: 0 | sepal_length | sepal_width | petal_length | petal_width | flower_type |
|---|---|---|---|---|---|---|
| **0** | 113 | 5.8 | 2.8 | 5.1 | 2.4 | 2 |
| **1** | 36 | 4.9 | 3.1 | 1.5 | 0.1 | 0 |
| **2** | 62 | 6.1 | 2.9 | 4.7 | 1.4 | 1 |
| **3** | 98 | 5.7 | 2.8 | 4.1 | 1.3 | 1 |
| **4** | 15 | 5.4 | 3.9 | 1.3 | 0.4 | 0 |

# Deal with missing data

In [15]:
```
import numpy as np
df = pd.DataFrame([[np.nan, 2, np.nan, 0],
                   [3, 4, np.nan, 1],
                   [np.nan, np.nan, np.nan, 5],
                   [np.nan, 3, np.nan, 4]],
                   columns=list('ABCD'))
df
```

Out[15]:

| | A | B | C | D |
|---|---|---|---|---|
| **0** | NaN | 2.0 | NaN | 0 |
| **1** | 3.0 | 4.0 | NaN | 1 |
| **2** | NaN | NaN | NaN | 5 |
| **3** | NaN | 3.0 | NaN | 4 |

In [16]:
```
df.fillna(0)
```

Out[16]:

| | A | B | C | D |
|---|---|---|---|---|
| **0** | 0.0 | 2.0 | 0.0 | 0 |
| **1** | 3.0 | 4.0 | 0.0 | 1 |
| **2** | 0.0 | 0.0 | 0.0 | 5 |
| **3** | 0.0 | 3.0 | 0.0 | 4 |

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.fillna.html#pandas.DataFrame.fillna (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.fillna.html#pandas.DataFrame.fillna)

In [17]:
```
 df = pd.DataFrame({"name": ['Alfred', 'Batman', 'Catwoman'],
                    "toy": [np.nan, 'Batmobile', 'Bullwhip'],
                    "born": [pd.NaT, pd.Timestamp("1940-04-25"),
                             pd.NaT]})
df
```

Out[17]:

| | born | name | toy |
|---|---|---|---|
| **0** | NaT | Alfred | NaN |
| **1** | 1940-04-25 | Batman | Batmobile |
| **2** | NaT | Catwoman | Bullwhip |

In computer programming, a sentinel value (also referred to as a flag value, trip value, rogue value, signal value, or dummy data) is a special value in the context of an algorithm which uses its presence as a condition of termination, typically in a loop or recursive algorithm.

floating-point NaN

In [18]:
```
df.dropna()
```

Out[18]:

| | born | name | toy |
|---|---|---|---|
| **1** | 1940-04-25 | Batman | Batmobile |

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.dropna.html#pandas.DataFrame.dropna (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.dropna.html#pandas.DataFrame.dropna)

# Features extraction

# Text Features

In [71]:
```
from sklearn.feature_extraction.text import CountVectorizer

sample = ['sample of evil', 'evil queen', 'horizon problem']
vec = CountVectorizer()
X = vec.fit_transform(sample)
# print(X.toarray())
feature_extraction = pd.DataFrame(X.toarray(), columns=vec.get_feature_names
())
print(feature_extraction)
```

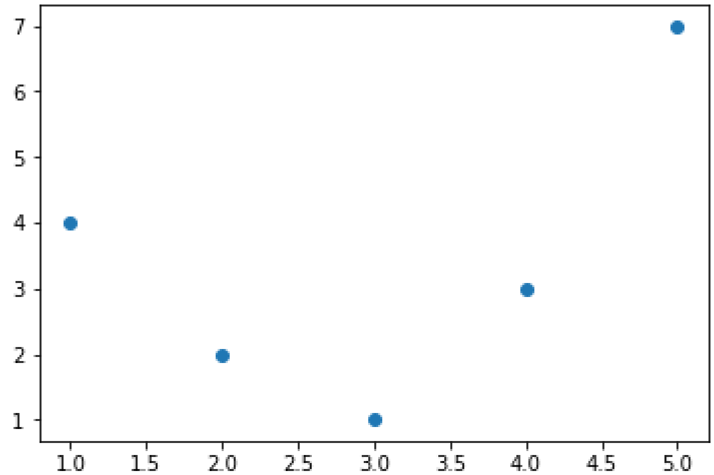
```
   evil  horizon  of  problem  queen  sample
0     1        0   1        0      0       1
1     1        0   0        0      1       0
2     0        1   0        1      0       0
```

In [73]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

vec = TfidfVectorizer()
X = vec.fit_transform(sample)
feature_extraction = pd.DataFrame(X.toarray(), columns=vec.get_feature_names
())
print(feature_extraction)
```

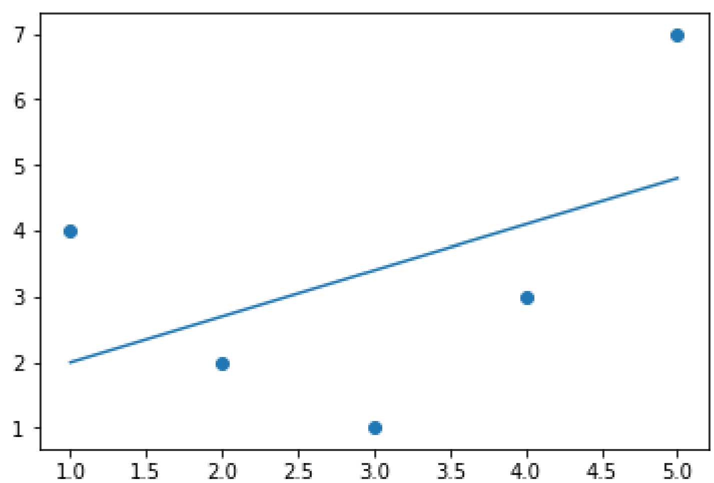
```
       evil   horizon        of   problem     queen    sample
0  0.473630  0.000000  0.622766  0.000000  0.000000  0.622766
1  0.605349  0.000000  0.000000  0.000000  0.795961  0.000000
2  0.000000  0.707107  0.000000  0.707107  0.000000  0.000000
```

# Derived Features

In [76]:
```
%matplotlib inline
# For jupyter notebook only
import numpy as np
import matplotlib.pyplot as plt

x = np.array([1, 2, 3, 4, 5])
y = np.array([4, 2, 1, 3, 7])
plt.scatter(x, y)
plt.show()
```

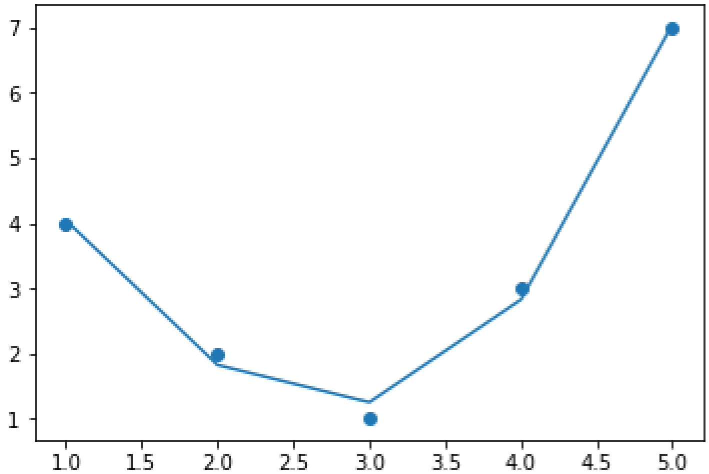



In [77]:
```
from sklearn.linear_model import LinearRegression
x = np.array([1, 2, 3, 4, 5])
y = np.array([4, 2, 1, 3, 7])
X = x[:, np.newaxis]
model = LinearRegression().fit(X, y)
yfit = model.predict(X)
plt.scatter(x,y)
plt.plot(x, yfit)
plt.show()
```



In [83]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
x = np.array([1, 2, 3, 4, 5])
y = np.array([4, 2, 1, 3, 7])
X = x[:, np.newaxis]
print("X\n", X)
poly = PolynomialFeatures(degree=3, include_bias=False)
X2 = poly.fit_transform(X)
# https://datascience.stackexchange.com/questions/12321/difference-between-fit
-and-fit-transform-in-scikit-learn-models
print("\nX2\n", X2)


model = LinearRegression().fit(X2, y)
yfit = model.predict(X2)
plt.scatter(x,y)
plt.plot(x, yfit)
plt.show()


#     degree : integer
#     The degree of the polynomial features

#     include_bias : boolean
#     If True (default), then include a bias column,
#     the feature in which all polynomial powers are zero
#     (i.e. a column of ones - acts as an intercept term in a linear model).


#     rows = np.array([0, 3], dtype=np.intp)
#     columns = np.array([0, 2], dtype=np.intp)
#     rows[:, np.newaxis]
#     array([[0],
#        [3]])

#     # intp    Integer used for indexing (same as C ssize_t; normally either
 int32 or int64
```

```
X
 [[1]
 [2]
 [3]
 [4]
 [5]]

X2
 [[   1.    1.    1.]
 [   2.    4.    8.]
 [   3.    9.   27.]
 [   4.   16.   64.]
 [   5.   25.  125.]]
```




# Scipy

- A collection of mathematical algorithms
- Gives Python similar capabilities as Matlab
- Many submodules are used for different domains
- We will see examples from linalg and optimize submodules
- For details: http://docs.scipy.org/doc/scipy/reference/tutorial/index.html (http://docs.scipy.org/doc/scipy/reference/tutorial/index.html)

linalg: Linear Algebra submodule

Linear algebra submodule provides several routines for matrix computations. For example to find the inverse of matrix A

In [33]:
```
from scipy import linalg as la
import numpy as np
A = np.array([[5,3,5],[2,2,0], [1,3,1]])
iA = la.inv(A)
print(iA)
```

```
[[  8.33333333e-02   5.00000000e-01  -4.16666667e-01]
 [ -8.33333333e-02  -1.15648232e-17   4.16666667e-01]
 [  1.66666667e-01  -5.00000000e-01   1.66666667e-01]]
```

# Solving linear systems of equations

Ax=b

In [35]:
```
A = np.array([[5,3,5], [2,2,0], [1,3,1]])
b = np.array([ 2, 5, 1])
x = la.solve(A,b)
print('Solution:', x)
# x = la.inv(A).dot(b) # same result
```

```
Solution: [ 2.25  0.25 -2.  ]
```

# More Will Come...

# http://book.pythontips.com/en/latest/map_filter.html (http://book.pythontips.com/en/latest/map_filter.html)

map filter reduce

In [ ]:
```

```