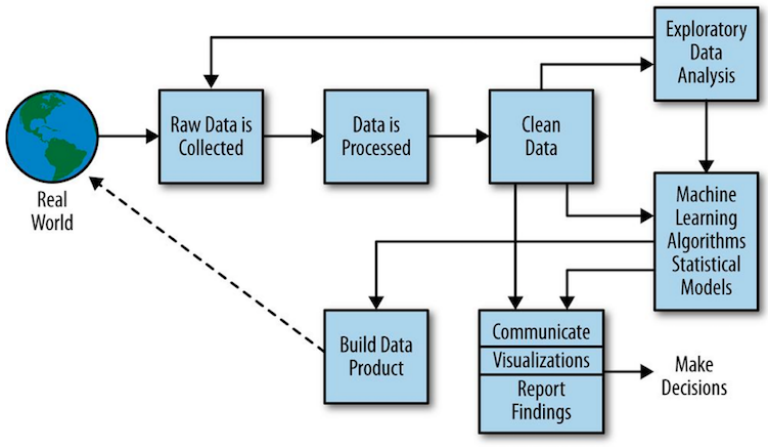
Applied Machine Learning : Day 1

Agenda - Day 1

- Introduction
- Python Numerics
- Pandas
- Data-Driven
- SciKit-Learn

Introduction

Data Science Pipeline



"Doing Data Science"

Big Concepts

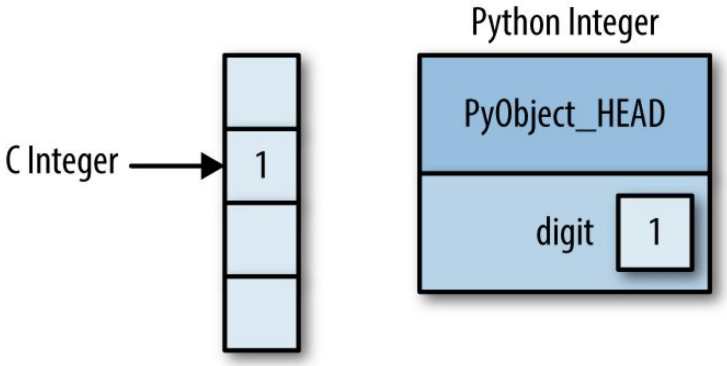
- Data as an Asset
- Role of Context
- Bad Data + ML = No Good
- Data Familiarity

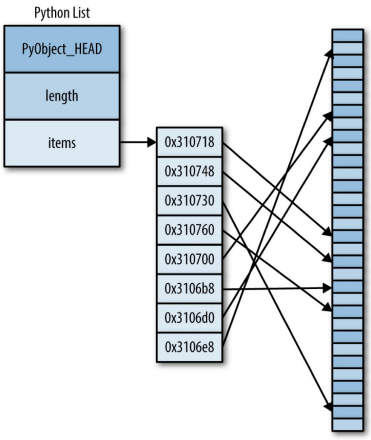
Big Concepts

- Data as an Asset
- Role of Context
- Bad Data + ML = No Good
- Data Familiarity
- Curse of Dimensionality

Exercise

Python Numerics


Python Integer
C Integer
1
PyObject_HEAD
digit
1


Python List
PyObject_HEAD
length
items
0x310718
0x310748
0x310730
0x310760
0x310700
0x3106b8
0x3106d0
0x3106e8

```
import numpy as np
np.random.seed(0)

def compute_reciprocals(values):
  output = np.empty(len(values))
  for i in range(len(values)):
    output[i] = 1.0 / values[i]

  return output

values = np.random.randint(1, 10, size = 5)
compute_reciprocals(values)
```

```
Out[1]: array([ 0.16666667, 1. , 0.25 , 0.25 , 0.125 ])
```

```
In[2]: big_array = np.random.randint(1, 100, size = 1000000)
       %timeit compute_reciprocals(big_array)

1 loop, best of 3: 2.91 s per loop
```


http://www.numpy.org

```
import numpy as np
```

```
>>> x = 2.345
```

```
>>> x - 2.345
0.0
```

```
>>> x - 2.345 == 0.0
True
```

```
>>> 1.0 == 1 * 0.1
False
```



```
import numpy as np
```

```
>>> x = 2.345
```

```
>>> x - 2.345
0.0
```

```
>>> x - 2.345 == 0.0
True
```

```
>>> 1.0 == 1 * 0.1
False
```

```
>>> 1.0 == (1 * 0.1)
False
```

np.trunc()

- nearest integer i which is closer to zero than x is

np.trunc()

- nearest integer i which is closer to zero than x is

```
>>> np.trunc(x)
2.0
```

np.floor()

- the largest integer i, such that i <= x

```
>>> np.floor(x)
2.0
```

```
>>> np.floor(2.01)
2.0
```


np.floor()

- the largest integer i, such that i <= x

```
>>> np.floor(x)
2.0
```

```
>>> np.floor(2.01)
2.0
```

```
>>> np.floor(2.00)
2.0
```

np.ceil()

- the smallest integer i, such that i >= x

```
>>> np.ceil(x)
3.0
```

```
>>> np.ceil(2.01)
3.0
```

```
>>> np.ceil(2.0)
2.0
```

```
>>> np.ceil(x) - 1
2.0
```


np.ceil()

- the smallest integer i, such that i >= x

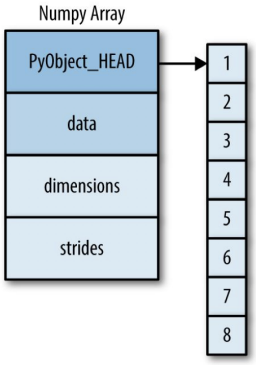
```
>>> np.ceil(x)
3.0
```

```
>>> np.ceil(2.01)
3.0
```

```
>>> np.ceil(2.0)
2.0
```

```
>>> np.ceil(x) - 1
2.0
```

```
>>> np.ceil(2.01) - 1
2.0
```



"Python Data Science Handbook"


```
>>> import numpy as np
>>> np.array([1, 4, 2, 5, 3])
array([1, 4, 2, 5, 3])
```

```
>>> import numpy as np
>>> np.array([1, 4, 2, 5, 3])
array([1, 4, 2, 5, 3])
```

```
>>> np.array([3.14, 4, 2, 3])
array([ 3.14,  4.  ,  2.  ,  3.  ])
```

```
>>> np.array([1, 2, 3, 4], dtype='float32')
array([ 1.,  2.,  3.,  4.], dtype=float32)
```

```
>>> np.array([range(i, i + 3) for i in [2, 4, 6]])
array([[2, 3, 4],
       [4, 5, 6],
       [6, 7, 8]])
```

```
>>> np.zeros(10, dtype=int)
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

```
>>> np.ones((3, 5), dtype=float)
array([[ 1.,  1.,  1.,  1.,  1.],
       [ 1.,  1.,  1.,  1.,  1.],
       [ 1.,  1.,  1.,  1.,  1.]])
```



```
>>> import numpy as np
>>> np.array([1, 4, 2, 5, 3])
array([1, 4, 2, 5, 3])
```

```
>>> np.array([3.14, 4, 2, 3])
array([ 3.14,  4.  ,  2.  ,  3.  ])
```

```
>>> np.array([1, 2, 3, 4], dtype='float32')
array([ 1.,  2.,  3.,  4.], dtype=float32)
```

```
>>> np.array([range(i, i + 3) for i in [2, 4, 6]])
array([[2, 3, 4],
       [4, 5, 6],
       [6, 7, 8]])
```

```
>>> np.zeros(10, dtype=int)
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

```
>>> np.ones((3, 5), dtype=float)
array([[ 1.,  1.,  1.,  1.,  1.],
       [ 1.,  1.,  1.,  1.,  1.],
       [ 1.,  1.,  1.,  1.,  1.]])
```


```
>>> np.full((3, 5), 3.14)
array([[ 3.14,  3.14,  3.14,  3.14,  3.14],
       [ 3.14,  3.14,  3.14,  3.14,  3.14],
       [ 3.14,  3.14,  3.14,  3.14,  3.14]])
```

```
>>> np.arange(0, 20, 2)
array([ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18])
```

```
>>> np.linspace(0, 1, 5)
array([ 0.  ,  0.25,  0.5 ,  0.75,  1.  ])
```

```
>>> np.random.random((3, 3))
array([[ 0.33687321,  0.57661167,  0.77955889],
       [ 0.7441428 ,  0.53766224,  0.62966105],
       [ 0.27348138,  0.27234265,  0.71558399]])
```

```
>>> np.random.normal(0, 1, (3, 3))
array([[-2.02151788, -0.04433702, -0.16415692],
       [ 0.28498092,  0.4638266 ,  0.64989753],
       [-0.93943869, -1.90040282, -0.94711293]])
```

```
>>> np.random.randint(0, 10, (3, 3))
array([[7, 3, 0],
       [3, 3, 4],
       [9, 2, 6]])
```

```
>>> np.eye(3)
array([[ 1.,  0.,  0.],
       [ 0.,  1.,  0.],
       [ 0.,  0.,  1.]])
```


Converting array types

Converting array types

```
>>> x = np.linspace(0,10,50)
>>> x
array([  0.        ,   0.20408163,   0.40816327,   0.6122449 ,
         0.81632653,   1.02040816,   1.2244898 ,   1.42857143,
         1.63265306,   1.83673469,   2.04081633,   2.24489796,
         2.44897959,   2.65306122,   2.85714286,   3.06122449,
         3.26530612,   3.46938776,   3.67346939,   3.87755102,
         4.08163265,   4.28571429,   4.48979592,   4.69387755,
         4.89795918,   5.10204082,   5.30612245,   5.51020408,
         5.71428571,   5.91836735,   6.12244898,   6.32653061,
         6.53061224,   6.73469388,   6.93877551,   7.14285714,
         7.34693878,   7.55102041,   7.75510204,   7.95918367,
         8.16326531,   8.36734694,   8.57142857,   8.7755102 ,
         8.97959184,   9.18367347,   9.3877551 ,   9.59183673,
         9.79591837,  10.        ])
```


Converting array types

```
>>> x = np.linspace(0,10,50)
>>> x
array([  0.        ,   0.20408163,   0.40816327,   0.6122449 ,
         0.81632653,   1.02040816,   1.2244898 ,   1.42857143,
         1.63265306,   1.83673469,   2.04081633,   2.24489796,
         2.44897959,   2.65306122,   2.85714286,   3.06122449,
         3.26530612,   3.46938776,   3.67346939,   3.87755102,
         4.08163265,   4.28571429,   4.48979592,   4.69387755,
         4.89795918,   5.10204082,   5.30612245,   5.51020408,
         5.71428571,   5.91836735,   6.12244898,   6.32653061,
         6.53061224,   6.73469388,   6.93877551,   7.14285714,
         7.34693878,   7.55102041,   7.75510204,   7.95918367,
         8.16326531,   8.36734694,   8.57142857,   8.7755102 ,
         8.97959184,   9.18367347,   9.3877551 ,   9.59183673,
         9.79591837,  10.        ])
```

```
>>> x.astype(int)
array([ 0,  0,  0,  0,  0,  1,  1,  1,  1,  1,  2,  2,  2,  2,  2,  3,  3,
        3,  3,  3,  4,  4,  4,  4,  4,  5,  5,  5,  5,  5,  6,  6,  6,  6,
        6,  7,  7,  7,  7,  7,  8,  8,  8,  8,  8,  9,  9,  9,  9, 10])
```

Multi-dimensional Arrays

```
>>> x2 = np.random.randint(10, size=(3, 4))
array([[3, 3, 0, 9],
       [0, 9, 7, 0],
       [5, 6, 2, 5]])
```

```
>>> x2[0, 0]
3
>>> x2[2, 0]
5
>>> x2[2, -1]
5
```

```
>>> x2[0, 0] = 12
>>> x2
array([[12,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```


Multi-dimensional Arrays


```
>>> x2 = np.random.randint(10, size=(3, 4))
array([[3, 3, 0, 9],
       [0, 9, 7, 0],
       [5, 6, 2, 5]])
```

```
>>> x2[0, 0]
3
>>> x2[2, 0]
5
>>> x2[2, -1]
5
```

```
>>> x2[0, 0] = 12
>>> x2
array([[12,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```


```
>>> np.arange(0,9).reshape(3,3)
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

Numpy Array Slicing

```
>>> x = np.arange(10)
>>> x[:5]
array([0, 1, 2, 3, 4])
>>> x[5:]
array([5, 6, 7, 8, 9])
```

```
>>> x[4:7]
array([4, 5, 6])
```

```
>>> x[::2]
array([0, 2, 4, 6, 8])
```

```
>>> x[1::2]
array([1, 3, 5, 7, 9])
```

```
>>> x[::-1]
array([9, 8, 7, 6, 5, 4, 3, 2, 1, 0])
```

```
>>> x[5::-2]
array([5, 3, 1])
```


Filtering 1 dimensonial data

```
>>> x = np.array([ 1, 1, 2, 1, 0, 3, 0, 0 ])
```

Filtering 1 dimensonial data

```
>>> x = np.array([ 1, 1, 2, 1, 0, 3, 0, 0 ])
```

```
>>> np.nonzero(x)
(array([0, 1, 2, 3, 5]),)
```

```
>>> x[np.nonzero(x)]
array([1, 1, 2, 1, 3])
```

```
>>> x[np.nonzero(x < 3)]
array([1, 1, 2, 1, 0, 0, 0])
```


Filtering 2 dimensional data

```
>>> x = np.array([[1,0,0], [0,2,0], [1,1,0]])
>>> x
array([[1, 0, 0],
       [0, 2, 0],
       [1, 1, 0]])
```

Filtering 2 dimensional data

```
>>> x = np.array([[1,0,0], [0,2,0], [1,1,0]])
>>> x
array([[1, 0, 0],
       [0, 2, 0],
       [1, 1, 0]])
```

```
>>> np.nonzero(x)
(array([0, 1, 2, 2]), array([0, 1, 0, 1]))
```

```
>>> x[ np.nonzero(x) ]
array([1, 2, 1, 1])
```

```
>>> np.transpose(np.nonzero(x))
array([[0, 0],
       [1, 1],
       [2, 0],
       [2, 1]])
```


Multi-dimensional Subarrays

Multi-dimensional Subarrays

```
>>> x2
array([[12,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```

```
>>> x2[:2, :3]
array([[12,  3,  0],
       [ 0,  9,  7]])
```

```
>>> x2[:3, ::2]
array([[12,  0],
       [ 0,  7],
       [ 5,  2]])
```


Multi-dimensional Subarrays

```
>>> x2
array([[12,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```

```
>>> x2[:2, :3]
array([[12,  3,  0],
       [ 0,  9,  7]])
```

```
>>> x2[:3, ::2]
array([[12,  0],
       [ 0,  7],
       [ 5,  2]])
```

```
>>> x2[::-1, ::-1]
array([[ 5,  2,  6,  5],
       [ 0,  7,  9,  0],
       [ 9,  0,  3, 12]])
```

Subarray Views

```
>>> x2
array([[12,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```

```
>>> x2_sub = x2[:2, :2]
>>> x2_sub
array([[12,  3],
       [ 0,  9]])
```

```
>>> x2_sub[0, 0] = 99
>>> x2_sub
array([[99,  3],
       [ 0,  9]])
```

```
>>> x2
array([[99,  3,  0,  9],
       [ 0,  9,  7,  0],
       [ 5,  6,  2,  5]])
```


Vectorized Operations

Vectorized Operations

```
big_array = np.random.randint(1, 100, size=1000000)
```

```
In [2]: big_array = np.random.randint(1, 100, size=1000000)
   ...: %timeit (1.0 / big_array)
   ...:
100 loops, best of 3: 3.51 ms per loop
```

```
In [4]: big_array = np.random.rand(1000000)
   ...: %timeit sum(big_array)
   ...: %timeit np.sum(big_array)
10 loops, best of 3: 85.2 ms per loop
1000 loops, best of 3: 400 µs per loop
```

```
>>> x = np.arange(9).reshape((3, 3))
>>> 2 ** x
array([[  1,   2,   4],
       [  8,  16,  32],
       [ 64, 128, 256]])
```

```
>>> x = np.arange(4)
>>> -(0.5*x + 1) ** 2
array([-1.  , -2.25, -4.  , -6.25])
```


Operator	ufunc	Description
+	np.add	Addition (e.g., 1 + 1 = 2)
-	np.subtract	Subtraction (e.g., 3 - 2 = 1)
-	np.negative	Unary negation (e.g., -2)
*	np.multiply	Multiplication (e.g., 2 * 3 = 6)
/	np.divide	Division (e.g., 3 / 2 = 1.5)
//	np.floor_divide	Floor division (e.g., 3 // 2 = 1)
**	np.power	Exponentiation (e.g., 2 ** 3 = 8)
%	np.mod	Modulus/remainder (e.g., 9 % 4 = 1)

Trigonometric ufuncs

```
>>> theta = np.linspace(0, np.pi, 3)
>>> theta
array([ 0.        ,  1.57079633,  3.14159265])
>>> np.sin(theta)
array([  0.00000000e+00,   1.00000000e+00,   1.22464680e-16])
>>> np.cos(theta)
array([  1.00000000e+00,   6.12323400e-17,  -1.00000000e+00])
>>> np.tan(theta)
array([  0.00000000e+00,   1.63312394e+16,  -1.22464680e-16])
>>> x         =  [-1, 0, 1]
>>> np.arcsin(x)
array([-1.57079633,  0.        ,  1.57079633])
>>> np.arccos(x)
array([ 3.14159265,  1.57079633,  0.        ])
>>> np.arctan(x)
array([-0.78539816,  0.        ,  0.78539816])
```


Exponent and Logarithm ufuncs

```
>>> x = [1, 2, 3]
>>> np.exp(x)
array([  2.71828183,   7.3890561 ,  20.08553692])
>>> np.exp2(x)
array([ 2.,  4.,  8.])
>>> np.power(3, x)
array([ 3,  9, 27])
>>> x = [1, 2, 4, 10]
>>> np.log(x)
array([ 0.        ,  0.69314718,  1.38629436,  2.30258509])
>>> np.log2(x)
array([ 0.        ,  1.        ,  2.        ,  3.32192809])
>>> np.log10(x)
array([ 0.        ,  0.30103   ,  0.60205999,  1.        ])
```

Aggregate ufuncs

```
>>> x = np.arange(1, 6)
>>> np.add.reduce(x)
15
>>> np.multiply.reduce(x)
120
>>> np.add.accumulate(x)
array([ 1,  3,  6, 10, 15])
>>> np.multiply.accumulate(x)
array([  1,   2,   6,  24, 120])
```


Exercise

Pandas

https://pandas.pydata.org/

Pandas Series

```
>>> import pandas as pd
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0])
>>> data
0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64
```


Pandas Series

```
>>> import pandas as pd
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0])
>>> data
0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64
```

```
>>> data.values
array([ 0.25,  0.5 ,  0.75,  1.  ])
>>> data.index
RangeIndex(start=0, stop=4, step=1)
```

Pandas Series

```
>>> import pandas as pd
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0])
>>> data
0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64
```

```
>>> data.values
array([ 0.25,  0.5 ,  0.75,  1.  ])
>>> data.index
RangeIndex(start=0, stop=4, step=1)
```

```
>>> data[1]
0.5
```


Pandas Series

```
>>> import pandas as pd
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0])
>>> data
0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64
```

```
>>> data.values
array([ 0.25,  0.5 ,  0.75,  1.  ])
>>> data.index
RangeIndex(start=0, stop=4, step=1)
```

```
>>> data[1]
0.5
```

```
>>> data[1:3]
1    0.50
2    0.75
dtype: float64
```

```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```



```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```

```
>>> data
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```

```
>>> data
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
>>> data['c']
0.75
```



```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```

```
>>> data
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
>>> data['c']
0.75
```


```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=[2, 5, 3, 7])
```

```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```

```
>>> data
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
>>> data['c']
0.75
```

```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=[2, 5, 3, 7])
```

```
>>> data
2    0.25
5    0.50
3    0.75
7    1.00
dtype: float64
```



```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=['a', 'b', 'c', 'd'])
```

```
>>> data
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
>>> data['c']
0.75
```

```
>>> data = pd.Series([0.25, 0.5, 0.75, 1.0], index=[2, 5, 3, 7])
```

```
>>> data
2    0.25
5    0.50
3    0.75
7    1.00
dtype: float64
```

```
>>> data[5]
0.5
```

Implicit and Explicit Indexing

Implicit and Explicit Indexing

```
>>> data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
>>> data
1    a
3    b
5    c
dtype: object
```

Implicit and Explicit Indexing

```
>>> data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
>>> data
1    a
3    b
5    c
dtype: object
```

```
>>> data[1]
'a'
```


Implicit and Explicit Indexing

```
>>> data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
>>> data
1    a
3    b
5    c
dtype: object
```

```
>>> data[1]
'a'
```

```
>>> data[1:3]
3    b
5    c
dtype: object
```

loc and iloc

loc and iloc

```
>>> data
1    a
3    b
5    c
dtype: object
```

loc and iloc

```
>>> data
1    a
3    b
5    c
dtype: object
```

```
>>> data.loc[1]
'a'
>>> data.loc[1:3]
1    a
3    b
dtype: object
```


loc and iloc

```
>>> data
1    a
3    b
5    c
dtype: object
```

```
>>> data.loc[1]
'a'
>>> data.loc[1:3]
1    a
3    b
dtype: object
```

```
>>> data.iloc[1]
'b'
>>> data.iloc[1:3]
3    b
5    c
dtype: object
```

Python dicts as Series

```
>>> population_dict = {'California': 38332521,
                       'Texas': 26448193,
                       'New York': 19651127,
                       'Florida': 19552860,
                       'Illinois': 12882135}
>>> population = pd.Series(population_dict)
```


Python dicts as Series

```
>>> population_dict = {'California': 38332521,
                       'Texas': 26448193,
                       'New York': 19651127,
                       'Florida': 19552860,
                       'Illinois': 12882135}
>>> population = pd.Series(population_dict)
```

```
>>> population
California    38332521
Florida       19552860
Illinois      12882135
New York      19651127
Texas         26448193
dtype: int64
```

Python dicts as Series

```
>>> population_dict = {'California': 38332521,
                       'Texas': 26448193,
                       'New York': 19651127,
                       'Florida': 19552860,
                       'Illinois': 12882135}
>>> population = pd.Series(population_dict)
```

```
>>> population
California    38332521
Florida       19552860
Illinois      12882135
New York      19651127
Texas         26448193
dtype: int64
```

```
>>> population['California']
38332521
```


Python dicts as Series

```
>>> population_dict = {'California': 38332521,
                       'Texas': 26448193,
                       'New York': 19651127,
                       'Florida': 19552860,
                       'Illinois': 12882135}
>>> population = pd.Series(population_dict)
```

```
>>> population
California    38332521
Florida       19552860
Illinois      12882135
New York      19651127
Texas         26448193
dtype: int64
```

```
>>> population['California']
38332521
```

```
>>> population['California':'Illinois']
California    38332521
Florida       19552860
Illinois      12882135
dtype: int64
```

Pandas DataFrame

Pandas DataFrame

```
>>> area_dict = {'California': 423967, 'Texas': 695662, 'New York': 141297,
                 'Florida': 170312, 'Illinois': 149995}
>>> area = pd.Series(area_dict)
>>> area
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
dtype: int64
```

Pandas DataFrame

```
>>> area_dict = {'California': 423967, 'Texas': 695662, 'New York': 141297,
                 'Florida': 170312, 'Illinois': 149995}
>>> area = pd.Series(area_dict)
>>> area
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
dtype: int64
```

```
>>> states = pd.DataFrame({'population': population,
                           'area': area})
>>> states
              area  population
California  423967    38332521
Florida     170312    19552860
Illinois    149995    12882135
New York    141297    19651127
Texas       695662    26448193
```

```
>>> states.index
Index([u'California', u'Florida', u'Illinois', u'New York', u'Texas'],
  dtype='object')
```



```
>>> states.index
Index([u'California', u'Florida', u'Illinois', u'New York', u'Texas'],
  dtype='object')
```


```
>>> states.columns
Index([u'area', u'population'], dtype='object')
```

```
>>> states.index
Index([u'California', u'Florida', u'Illinois', u'New York', u'Texas'],
  dtype='object')
```

```
>>> states.columns
Index([u'area', u'population'], dtype='object')
```

```
>>> states['area']
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
Name: area, dtype: int64
```



```
>>> states.index
Index([u'California', u'Florida', u'Illinois', u'New York', u'Texas'],
  dtype='object')
```

```
>>> states.columns
Index([u'area', u'population'], dtype='object')
```

```
>>> states['area']
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
Name: area, dtype: int64
```


```
>>> states.values
array([[  423967, 38332521],
       [  170312, 19552860],
       [  149995, 12882135],
       [  141297, 19651127],
       [  695662, 26448193]])
```

Sales Data

```
>>> dat = pd.read_csv("data/WA_Fn-UseC_-Sales-Win-Loss.csv")
>>> dat.columns
Index(['Opportunity Number', 'Supplies Subgroup', 'Supplies Group', 'Region',
       'Route To Market', 'Elapsed Days In Sales Stage', 'Opportunity Result',
       'Sales Stage Change Count', 'Total Days Identified Through Closing',
       'Total Days Identified Through Qualified', 'Opportunity Amount USD',
       'Client Size By Revenue', 'Client Size By Employee Count',
       'Revenue From Client Past Two Years', 'Competitor Type',
       'Ratio Days Identified To Total Days',
       'Ratio Days Validated To Total Days',
       'Ratio Days Qualified To Total Days', 'Deal Size Category'],
      dtype='object')
```


Sales Data

```
>>> dat = pd.read_csv("data/WA_Fn-UseC_-Sales-Win-Loss.csv")
>>> dat.columns
Index(['Opportunity Number', 'Supplies Subgroup', 'Supplies Group', 'Region',
       'Route To Market', 'Elapsed Days In Sales Stage', 'Opportunity Result',
       'Sales Stage Change Count', 'Total Days Identified Through Closing',
       'Total Days Identified Through Qualified', 'Opportunity Amount USD',
       'Client Size By Revenue', 'Client Size By Employee Count',
       'Revenue From Client Past Two Years', 'Competitor Type',
       'Ratio Days Identified To Total Days',
       'Ratio Days Validated To Total Days',
       'Ratio Days Qualified To Total Days', 'Deal Size Category'],
      dtype='object')
```

```
>>> dat['Opportunity Result']
0         Won
1        Loss
2         Won
3        Loss
4        Loss
5        Loss
6         Won
7        Loss
...
```

Counting Values

```
>>> dat['Opportunity Result'].value_counts()
Loss    60398
Won     17627
Name: Opportunity Result, dtype: int64
```


Counting Values

```
>>> dat['Opportunity Result'].value_counts()
Loss    60398
Won     17627
Name: Opportunity Result, dtype: int64
```

```
>>> dat['Supplies Group'].value_counts()
Car Accessories           49810
Performance & Non-auto    27325
Tires & Wheels              609
Car Electronics             281
Name: Supplies Group, dtype: int64
```

Counting Values

```
>>> dat['Opportunity Result'].value_counts()
Loss    60398
Won     17627
Name: Opportunity Result, dtype: int64
```

```
>>> dat['Supplies Group'].value_counts()
Car Accessories           49810
Performance & Non-auto    27325
Tires & Wheels              609
Car Electronics             281
Name: Supplies Group, dtype: int64
```

```
>>> dat['Elapsed Days In Sales Stage'].value_counts()
16     5010
44     2388
62     1738
7      1629
23     1455
37     1412
45     1238
24     1233
35     1226
...
```


Top Five values

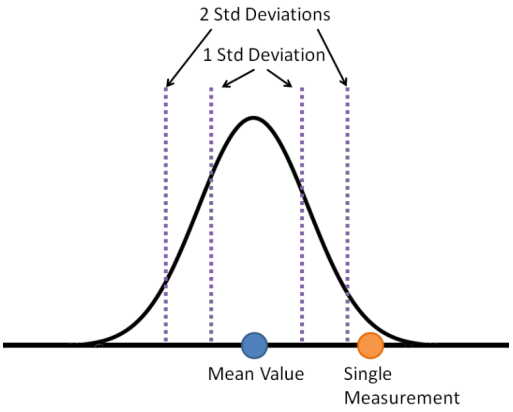
```
>>> dat['Supplies Subgroup'].value_counts()[:5]
Motorcycle Parts           15174
Exterior Accessories       13876
Garage & Car Care           9733
Shelters & RV               9606
Batteries & Accessories     9192
Name: Supplies Subgroup, dtype: int64
```

Extracting Columns

```
>>> region_results = dat[["Region", "Opportunity Result"]]
>>> region_results.shape
(78025, 2)
>>> region_results.head
0          Northwest               Won
1            Pacific              Loss
2            Pacific               Won
3                NaN              Loss
4            Pacific              Loss
5            Pacific              Loss
6            Pacific               Won
7            Pacific              Loss
8          Northwest              Loss
9            Pacific              Loss
10         Northwest              Loss
11           Midwest              Loss
12           Midwest              Loss
13           Pacific              Loss
14           Midwest              Loss
15         Northwest               Won
...
```

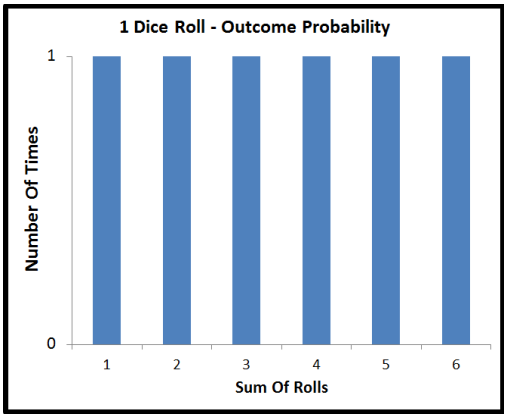

Exercise

Data-Driven



http://www.fairlynerdy.com/intuitive-guide-statistical-significance/

CC BY-SA 2.0, https://www.flickr.com/photos/glennf/8365840281



http://www.fairlynerdy.com/intuitive-guide-statistical-significance/

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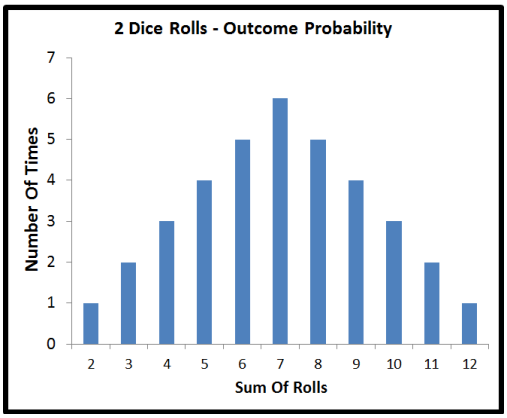
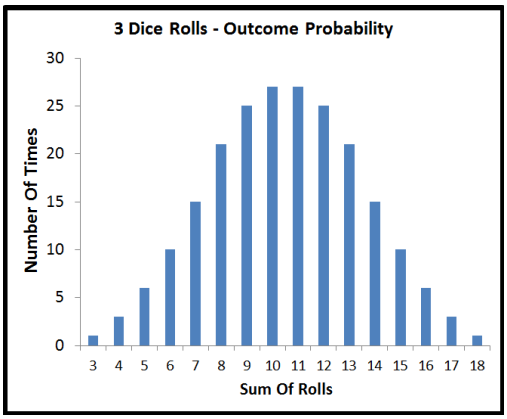
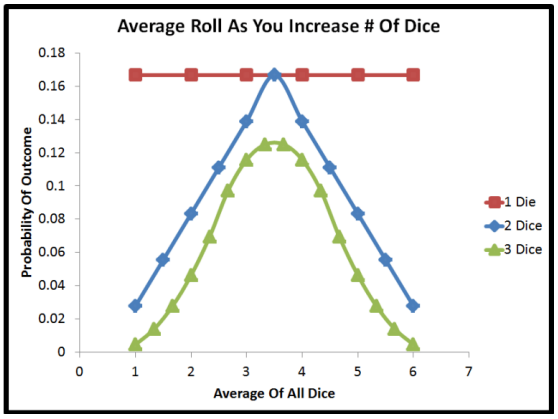
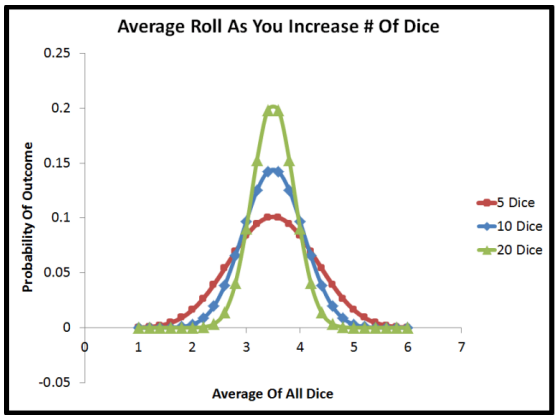
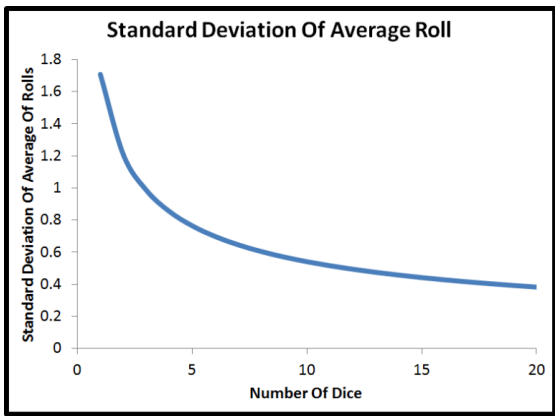


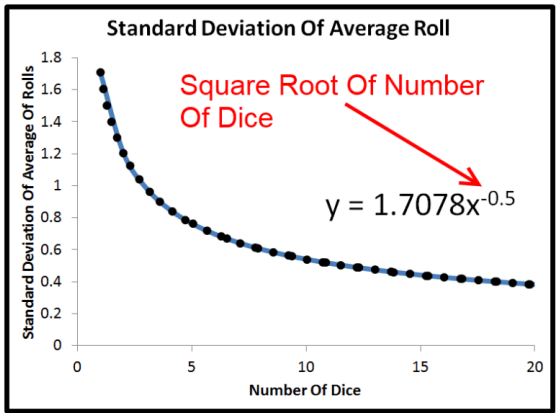
http://www.fairlynerdy.com/intuitive-guide-statistical-significance/


3 Dice Rolls - Outcome Probability
Number Of Times
30
25
20
15
10
5
0
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Sum Of Rolls


Average Roll As You Increase # Of Dice
Probability Of Outcome
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
0 1 2 3 4 5 6 7
Average Of All Dice
1 Die
2 Dice
3 Dice


Average Roll As You Increase # Of Dice
Probability Of Outcome
0.25
0.2
0.15
0.1
0.05
0
-0.05
0
1
2
3
4
5
6
7
Average Of All Dice
5 Dice
10 Dice
20 Dice


Standard Deviation Of Average Roll
Standard Deviation Of Average Of Rolls
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
5
10
15
20
Number Of Dice



http://www.fairlynerdy.com/intuitive-guide-statistical-significance/

$$y = 1.7078x^{-0.5}$$

$$y = 1.7078x^{-0.5}$$

$$y = \frac{1.7078}{\sqrt{x}}$$

$$y = 1.7078x^{-0.5}$$

$$y = \frac{1.7078}{\sqrt{x}}$$

$$y = \frac{\sigma}{\sqrt{n}}$$

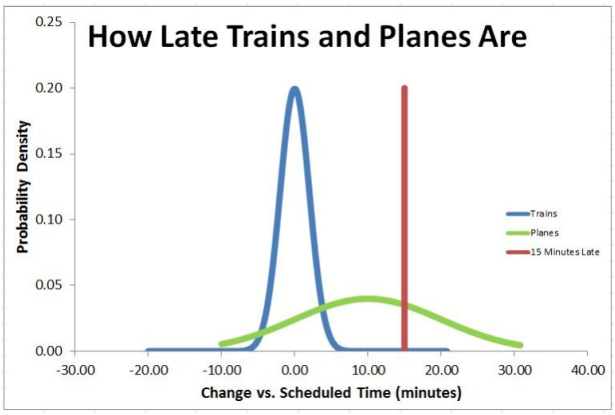
Z Test

$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

Z Test

$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

Variable	Meaning
$\bar{x}$	sample mean
μ_0	population mean
σ	population standard deviation
n	test sample size



http://www.fairlynerdy.com/understanding-statistical-significance

$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

```
>>> import numpy
>>> import math
>>> mu = 500
>>> sigma = 100
>>> alpha = 0.05
```

$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

```
>>> import numpy
>>> import math
>>> mu = 500
>>> sigma = 100
>>> alpha = 0.05
```

```
>>> samples = [434,694,457,534,720,400,484,478,610,641,425,636,
               454,514,563,370,499,640,501,625,612,471,598,509,531]
>>> len(samples)
25
>>> numpy.mean(samples)
536.0
>>> xbar = numpy.mean(samples)
```


$$Z = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

```
>>> import numpy
>>> import math
>>> mu = 500
>>> sigma = 100
>>> alpha = 0.05
```

```
>>> samples = [434,694,457,534,720,400,484,478,610,641,425,636,
               454,514,563,370,499,640,501,625,612,471,598,509,531]
>>> len(samples)
25
>>> numpy.mean(samples)
536.0
>>> xbar = numpy.mean(samples)
```

```
>>> (xbar - mu) / (sigma / math.sqrt(len(samples)))
1.8
```

http://www.stat.ufl.edu/~athienit/Tables/Ztable.pdf

Standard Normal Probabilities

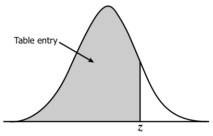
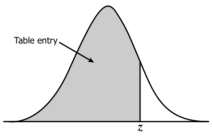


Table entry for z is the area under the standard normal curve to the left of z.

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767

Standard Normal Probabilities



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0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767

Standard Normal Probabilities

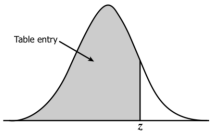

Table entry for z is the area under the standard normal curve to the left of z.

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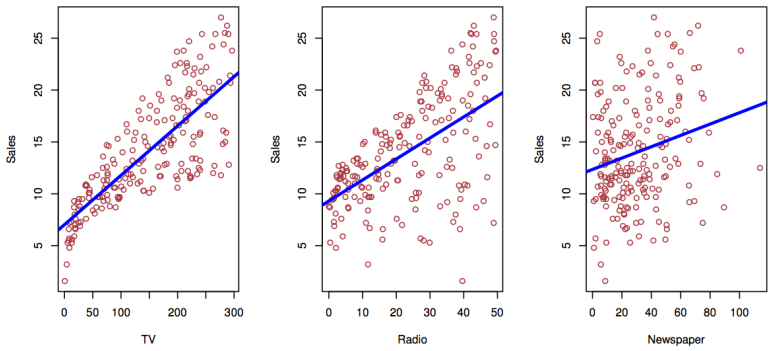
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767

Exercise

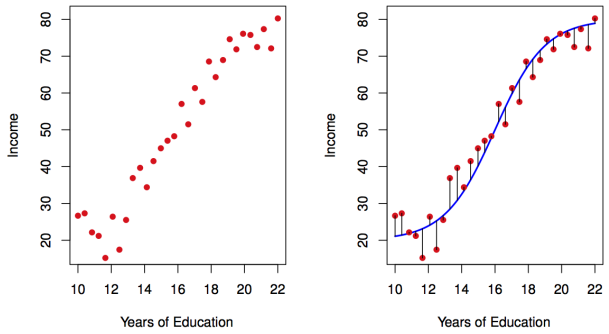
"In the past century, data collection often was carried out by statistical sampling since data was manually collected and therefore expensive. The prudent researcher would design the process to maximize the information that could be extracted from the data. In this century, data are arriving by firehose and without design."

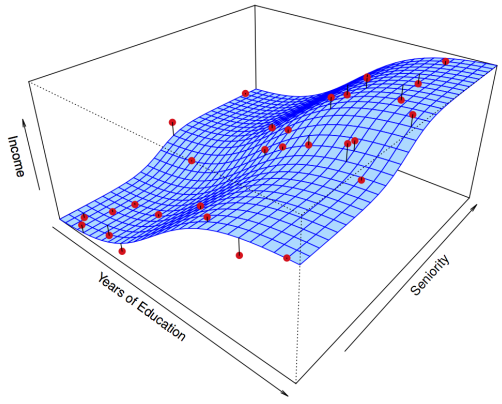
"Algorithms for Data Science", Steele et al



"An Introduction to Statistical Learning", James et al

$$Y = f(X) + \epsilon$$


Income
Years of Education
Income
Years of Education


Income
Years of Education
Seniority

$$\hat{Y} = \hat{f}(X)$$

Types of Errors

Types of Errors

- Reducible

Types of Errors

- Reducible
- Irreducible

$$E(Y - \hat{Y})^2 = E[f(X) + \epsilon - \hat{f}(X)]^2$$

$$E(Y - \hat{Y})^2 = E[f(X) + \epsilon - \hat{f}(X)]^2$$

$$= \underbrace{[f(X) - \hat{f}(X)]^2}_{Reducible} + \underbrace{Var(\epsilon)}_{Irreducible}$$

Estimating f()

Estimating f()

- Parametric methods

Estimating f()

- Parametric methods
- Non-parametric methods

$$f(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

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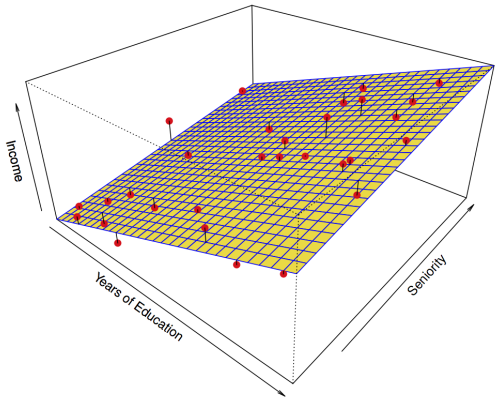
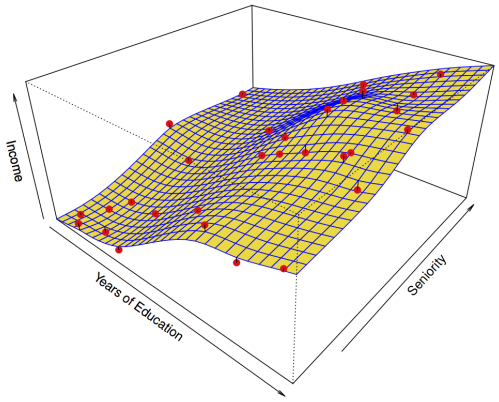
$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

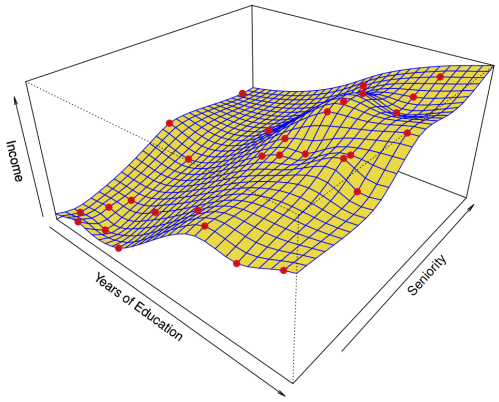
$$f(X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

$$Y \approx \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

$$income \approx \beta_0 + \beta_1 \times education + \beta_2 \times seniority$$


Income
Years of Education
Seniority


Income
Years of Education
Seniority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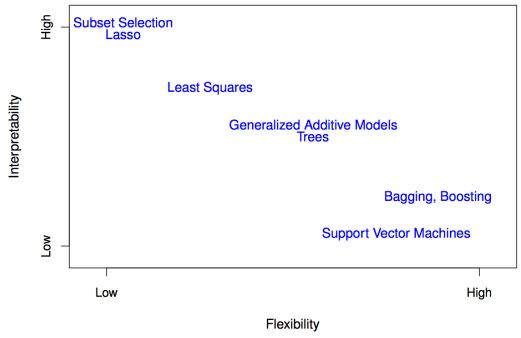
High
Low
Interpretability
Subset Selection
Lasso
Least Squares
Generalized Additive Models
Trees
Bagging, Boosting
Support Vector Machines
Low
High
Flexibility

Measuring Fitness

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{f}(x_i))^2$$

Training MSE

Given training data $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$

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Given training data $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$

Compute $\hat{f}(x_1), \hat{f}(x_2), \ldots, \hat{f}(x_n)$

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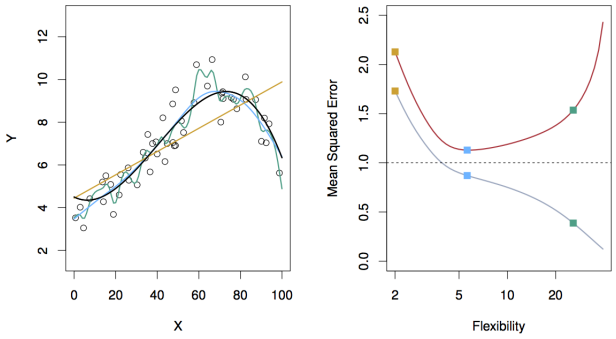
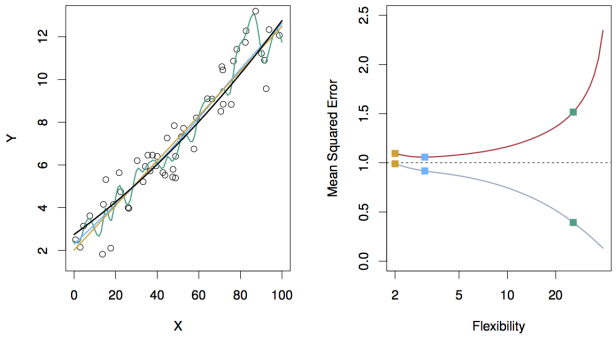
$\hat{f}(x_0) \approx y_0$ is more important!

$$Ave(\hat{f}(x_0) - y_0)^2$$


Y
X
Mean Squared Error
Flexibility


Y
X
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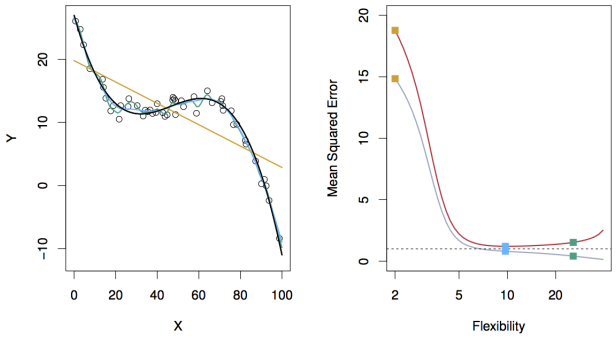

"An Introduction to Statistical Learning", James et al

Bias-Variance Trade-Off

$$E(y_0 - \hat{f}(x_0))^2 = Var(\hat{f}(x_0)) + [Bias(\hat{f}(x_0))]^2 + Var(\epsilon)$$

Bias-Variance Trade-Off

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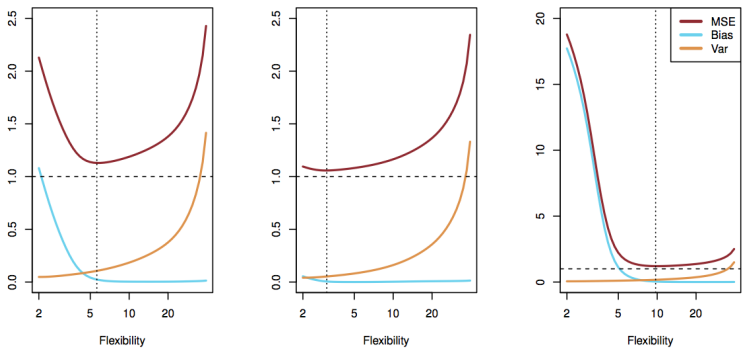
Term	Meaning
$E(y_0 - \hat{f}(x_0))^2$	expected test MSE
$Var(\hat{f}(x_0))$	amount estimate would change with different training data
$[Bias(\hat{f}(x_0))]^2$	error introduced in approximation
$Var(\epsilon)$	irreducible error



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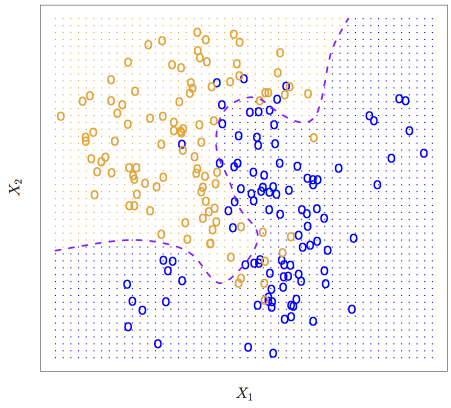
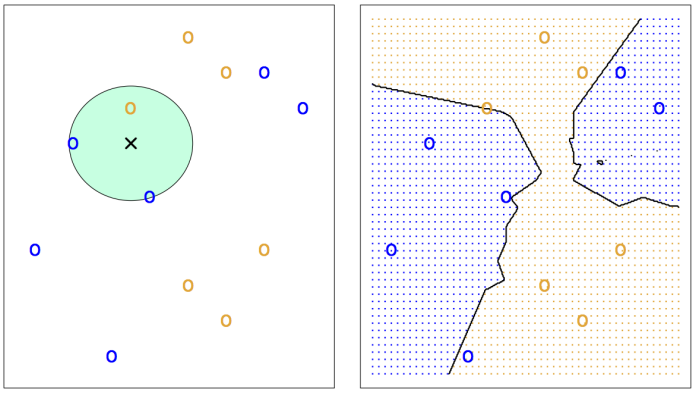
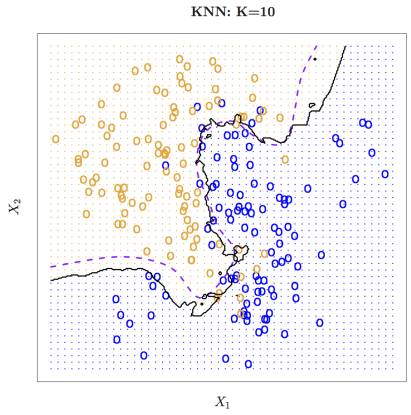

X_2
X_1





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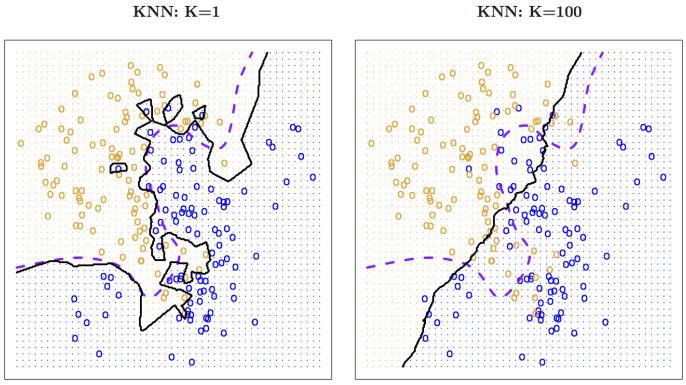

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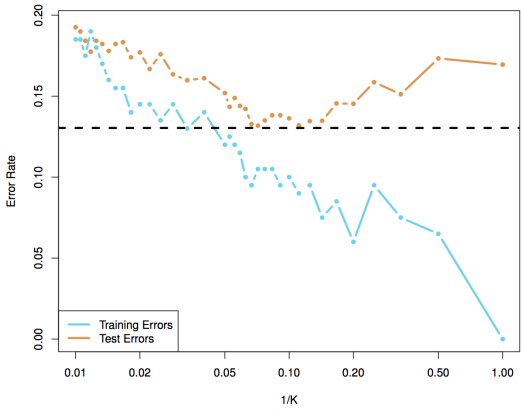

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SciKit-Learn

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- Popular python library providing efficient implementation of a large number of machine learning algorithms
- Purposely designed to be clean and uniform across tools

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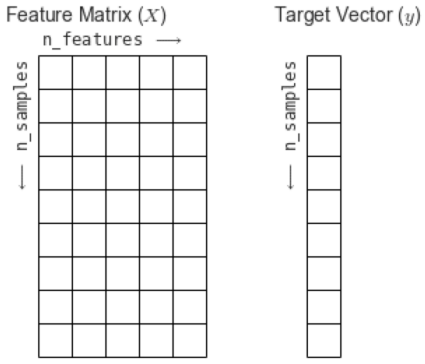
- Popular python library providing efficient implementation of a large number of machine learning algorithms
- Purposely designed to be clean and uniform across tools
- Consistent data representation and common interface

SciKit-Learn Data Representation



"Python Data Science Handbook"


```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets

np.random.seed(5)

iris = datasets.load_iris()
dat = pd.DataFrame(data= np.c_[iris['data'], iris['target']],
                   columns= iris['feature_names'] + ['target'])
```

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```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0.0
1	4.9	3.0	1.4	0.2	0.0
2	4.7	3.2	1.3	0.2	0.0
3	4.6	3.1	1.5	0.2	0.0
4	5.0	3.6	1.4	0.2	0.0
5	5.4	3.9	1.7	0.4	0.0
6	4.6	3.4	1.4	0.3	0.0
7	5.0	3.4	1.5	0.2	0.0
8	4.4	2.9	1.4	0.2	0.0
9	4.9	3.1	1.5	0.1	0.0
10	5.4	3.7	1.5	0.2	0.0
11	4.8	3.4	1.6	0.2	0.0


```
# Set up the feature matrix

>>> X_iris = dat.drop('target', axis=1)
>>> X_iris.shape
(150, 4)
```

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>>> X_iris = dat.drop('target', axis=1)
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(150, 4)
```

```
# Set up the target vector

>>> y_iris = iris['target']
>>> y_iris.shape
(150,)
```


Estimator API

- Driven by a set of principles documented in a paper: https://arxiv.org/pdf/1309.0238.pdf

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  - Consistency
  - Allow Inspection
  - Limited object hiearchies
  - Composition
  - Sensible defaults

General Flow

General Flow

- Choose a model

General Flow

- Choose a model
- Choose model hyperparameters

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- Arrange data into a features matrix and target vector

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General Flow

- Choose a model
- Choose model hyperparameters
- Arrange data into a features matrix and target vector
- Fit the model to the data with the fit() method
- Apply the model to test data (predict() or transform())

Examples

Examples

```
from sklearn.linear_model import LinearRegression
model = LinearRegression(fit_intercept=True)
model.fit(x[:, np.newaxis], y)
xfit = np.linspace(0,10,1000)
yfit = model.predict(xfit[:,np.newaxis])
```


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```

```
from sklearn.tree import DecisionTreeClassifier
tree_clf = DecisionTreeClassifier(max_depth=2)
tree_clf.fit(X_iris, y_iris)
tree_clf.predict([[5, 1.5, 2, 2.0]])
```

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```

```
from sklearn.cluster import KMeans
X, y = make_blobs(random_state=1)
kmeans = KMeans(n_clusters=3)
kmeans.fit(X)
kmeans.labels_
```


Exercise