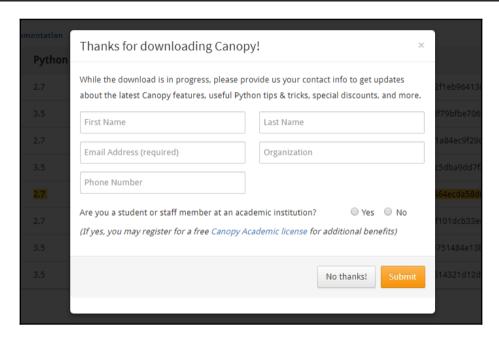
Graphic Bundle

Chapter 1 : Getting Started





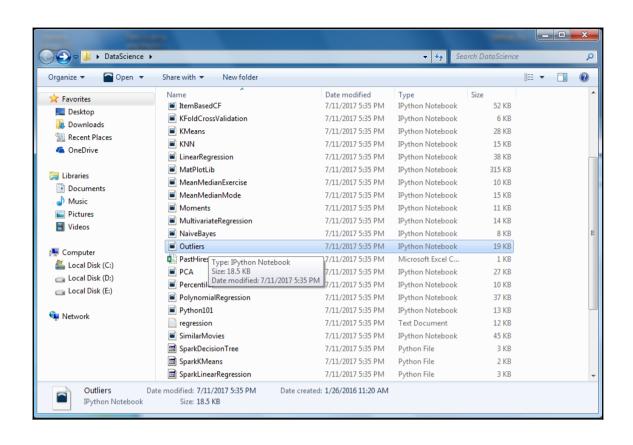
Standard Installers					
v2.1.3 v1.7.4 Documentation					
Platform	Python		Released	Size	MD5
Linux [64-bit]	2.7	🕹 download	2017-06-16	697.8 MB	57b828e913e15a6ec12f1eb964138c82
Linux [64-bit]	3.5	≛ download	2017-06-16	574.8 MB	7412235d9f72acc603df79bfbe706bee
macOS [64-bit]	2.7	å download	2017-06-16	572.1 MB	d0ee780d2e7541e0c11a84ec9f29cbb2
macOS [64-bit]	3.5	å download	2017-06-16	464.0 MB	d8c15b4763d8c55202c5dba9dd7f3157
Windows [64-bit]	2.7	å download	2017-06-16	513.8 MB	3821c0a63abfe8d13d464ecda58d627c
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Windows [64-bit]	3.5	å download	2017-06-16	431.3 MB	82c62c8549a9b02a4fe751484e13bb48
Windows [32-bit]	3.5	≛ download	2017-06-16	350.2 MB	f378349261eeb9d8bc614321d12d0264

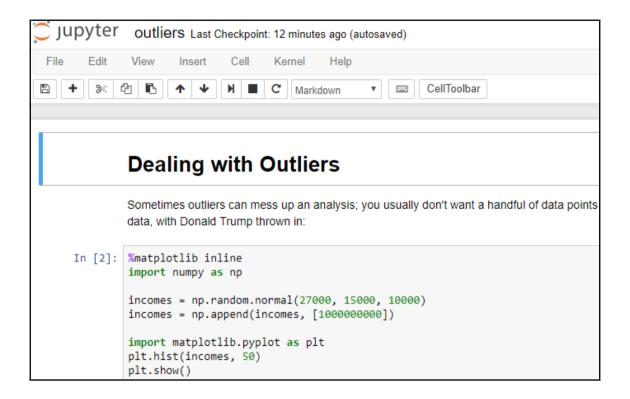


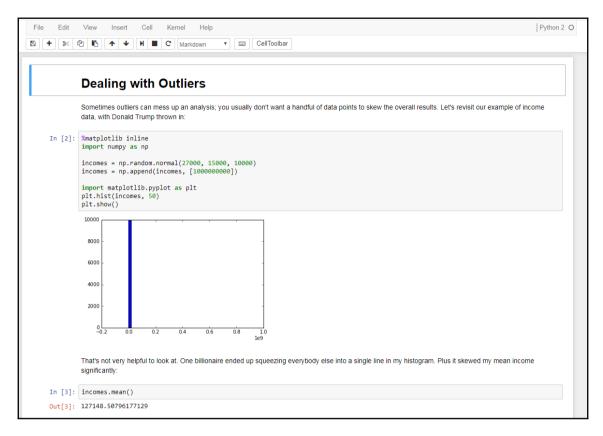


```
%quickref -> Quick reference.
help -> Python's own help system.
object? -> Details about 'object', use 'objec

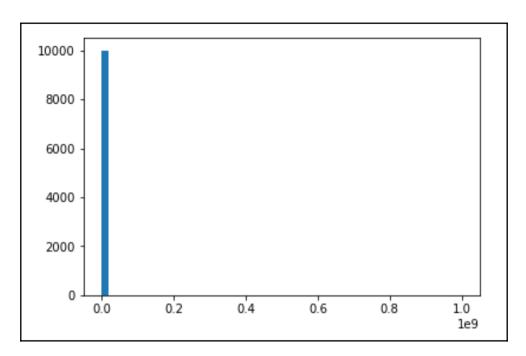
In [1]: !pip install pydotplus
```

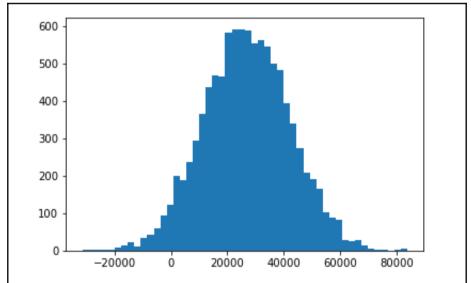


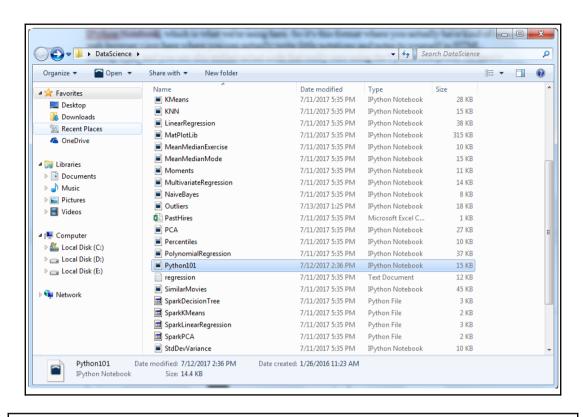












Python Basics Whitespace is Important In [1]: listOfNumbers = [1, 2, 3, 4, 5, 6] for number in listOfNumbers: print (number), if (number & 2 == 0): print ("is even") else: print ("is odd") print ("All done.") 1 is odd 2 is even 3 is odd 4 is even 5 is odd 6 is even All done.

Python Basics

Whitespace Is Important

```
In [1]: listOfNumbers = [1, 2, 3, 4, 5, 6]
for number in listOfNumbers:
    print (number),
    if (number & 2 == 0):
        print ("is even")
    else:
        print ("is odd")

print ("All done.")

1
    is odd
    2
    is even
    3
    is odd
    4
    is even
    5
    is odd
    6
    is even
    All done.
```

Whitespace Is Important

```
In [4]: listOfNumbers = [1, 2, 3, 4, 5, 6]
```

```
1 is odd
2 is even
3 is odd
4 is even
5 is odd
6 is even
All done.
```

Python Basics

Whitespace Is Important

```
In [9]: listOfNumbers = [1, 2, 3, 4, 5, 6]
for number in listOfNumbers:
    print (number),
    if (number % 2 == 0):
        print ("is even")
    else:
        print ("sodd")

print ("Hooray! We're all done. Let's party!")

1
    is odd
2
    is even
3
    is odd
4
    is even
5
    is odd
6
    is even
Hooray! We're all done. Let's party!
```

```
[ 23.50119237 28.3470395 27.68512972 27.43957344 22.66626262 25.98055199 27.87395644 25.99525487 20.36318406 22.77226693]
```

```
    [ 48.79441876
    63.77818473
    61.24157056
    47.38182128
    52.5623337

    55.80574543
    55.16594437
    53.59688042
    50.57639509
    60.44058303]
```

```
In [8]: # Like a map or hash table in other languages
         captains = {}
         captains["Enterprise"] = "Kirk"
         captains["Enterprise D"] = "Picard"
         captains["Deep Space Nine"] = "Sisko"
         captains["Voyager"] = "Janeway"
         print (captains['Voyager'])
         Janeway
In [9]: print (captains.get("Enterprise"))
         Kirk
In [10]: print (captains.get("NX-01"))
         None
In [11]: for ship in captains:
             print (ship + ":" + captains[ship])
         Deep Space Nine:Sisko
         Enterprise:Kirk
         Voyager: Janeway
         Enterprise D:Picard
```

```
Enterprise D: Picard
Deep Space Nine: Sisko
Enterprise: Kirk
Voyager: Janeway
```

```
In [ ]:
```

```
Canopy 64bit) E:\DataScience>python test.py

1 is odd

2 is even

3 is odd

4 is even

5 is odd

6 is even
Hooray! We're all done. Let's party!

(Canopy 64bit) E:\DataScience>
```

```
File Edit View Search Run Tools Window Help
File Browser
                         × test.py
ilter: All Files (*)
                                 1 listOfNumbers = [1, 2, 3, 4, 5, 6]
> hhagyashree
                                  2
3 for number in listOfNumbers:
4 print (number),
5 if (number % 2 == 0):
6 print ("is even")
7 else:
8 print ("is odd")
     test.py
                                 10 print ("Hooray! We're all done. Let's party!")
                              **Xquickref -> Quick reference.
help -> Python's own help system.
object? -> Details about 'object', use 'object??' for extra details.
                              In [9]: %run "C:\Users\bhagyashree\Desktop\DataScience\DataScience\test.py"
                              2
is even
                              is odd
                             is even
                             6
is even
Hooray! We're all done. Let's party!
Cursor pos 10: 47 Python 2
                                                                                                                                                                              ~\Desktop\DataScience\DataScience\test.p
```

```
Python

C:\Users\joeld ▼ X

In [1]: %run "C:/Users/joeld/Desktop/Data Science/DataScience/test.py" ↑

1 is odd
2 is even
3 is odd
4 is even
5 is odd
6 is even
Hooray! We're all done. Let's party!

In [2]: |
```

```
Python C:\Users\joeld ▼ X

In [9]: stuff= [1, 2, 3, 4]

In [10]: len(stuff)
Out[10]: 4
```

```
Python

C:\Users\joeld ▼ X

Welcome to Canopy's interactive data-analysis environment!

Type '?' for more information.

In [1]: |
```

```
Python

C:\Users\joeld ▼ X

Welcome to Canopy's interactive data-analysis environment!

Type '?' for more information.

In [1]: stuff

NameErrorTraceback (most recent call last)

<ipython-input-1-9eb84090956c> in <module>()
----> 1 stuff

NameError: name 'stuff' is not defined

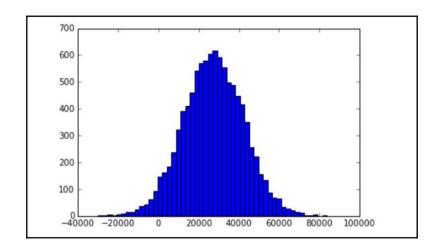
In [2]: stuff = [4, 5, 6]

In [3]: |

▼
```

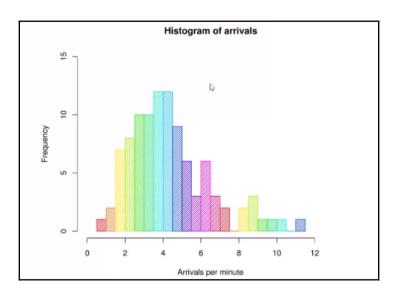
Chapter 2: Statistics and Probability Refresher, and Python Practice



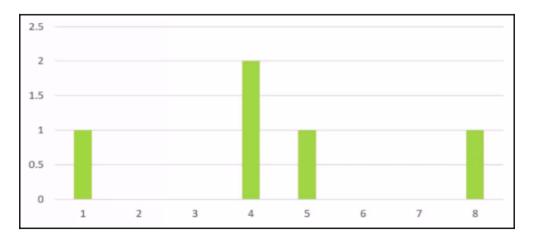


```
Out[7]:
        array([69, 87, 31, 22, 78, 37, 77, 32, 18, 59, 29, 43, 34, 33, 56, 83, 66,
               30, 77, 74, 31, 21, 85, 50, 47, 26, 72, 62, 33, 45, 86, 50, 86, 56,
               31, 84, 78, 27, 76, 42, 83, 64, 48, 54, 70, 56, 24, 50, 50, 71, 49,
               20, 85, 61, 33, 83, 55, 21, 60, 80, 56, 89, 61, 56, 52, 55, 20, 31,
               69, 50, 21, 52, 31, 83, 43, 77, 27, 67, 39, 39, 26, 38, 40, 73, 50,
               31, 87, 23, 50, 34, 69, 45, 83, 51, 88, 41, 64, 59, 40, 89, 57, 62,
               55, 75, 38, 51, 24, 21, 18, 75, 58, 62, 81, 65, 89, 64, 43, 33, 53,
               72, 20, 56, 19, 26, 81, 68, 70, 70, 41, 59, 50, 77, 62, 31, 87, 58,
               63, 83, 35, 55, 38, 85, 53, 66, 28, 74, 42, 28, 80, 69, 54, 25, 74,
               58, 27, 42, 87, 46, 43, 44, 33, 40, 21, 21, 73, 48, 87, 63, 84, 55,
               61, 66, 48, 73, 27, 60, 34, 77, 59, 58, 50, 70, 30, 76, 72, 33, 80,
               43, 63, 49, 60, 61, 53, 55, 79, 38, 46, 38, 81, 66, 29, 81, 46, 19,
               49, 57, 31, 18, 25, 47, 20, 88, 33, 88, 50, 22, 57, 39, 20, 59, 63,
               38, 35, 59, 28, 23, 56, 50, 46, 65, 46, 88, 87, 34, 73, 75, 32, 49,
               67, 77, 86, 38, 80, 36, 64, 79, 65, 51, 46, 54, 23, 82, 56, 41, 78,
               19, 45, 38, 70, 74, 56, 87, 49, 69, 30, 25, 22, 71, 39, 41, 46, 72,
               33, 72, 88, 37, 75, 39, 37, 21, 67, 86, 77, 20, 46, 53, 22, 85, 73,
               89, 67, 24, 24, 25, 62, 56, 58, 44, 63, 30, 36, 73, 49, 45, 26, 33,
               20, 62, 75, 34, 81, 59, 64, 27, 43, 23, 62, 75, 81, 40, 65, 29, 61,
               55, 81, 35, 68, 79, 86, 43, 35, 74, 59, 80, 75, 60, 82, 66, 54, 37,
               54, 71, 88, 46, 55, 63, 79, 89, 48, 61, 68, 78, 51, 32, 26, 48, 78,
               76, 62, 19, 19, 63, 20, 44, 28, 34, 58, 44, 36, 70, 34, 67, 50, 33,
               31, 18, 72, 55, 49, 63, 81, 65, 51, 46, 22, 55, 77, 76, 53, 79, 47,
               57, 46, 27, 29, 49, 71, 19, 85, 86, 77, 89, 59, 67, 26, 50, 79, 85,
               68, 51, 30, 18, 73, 52, 22, 53, 56, 26, 45, 60, 83, 50, 34, 68, 65,
               27, 72, 24, 34, 37, 52, 67, 79, 79, 24, 65, 71, 28, 29, 61, 34, 77,
               35, 59, 50, 83, 27, 32, 18, 81, 36, 46, 48, 39, 52, 23, 37, 62, 54,
               53, 50, 34, 36, 88, 83, 39, 89, 65, 83, 73, 66, 28, 36, 56, 86, 65,
               28, 46, 18, 61, 69, 80, 85, 29, 85, 44, 18, 61, 68, 83, 89, 53, 65,
               55, 66, 87, 55, 43, 32, 84])
```

```
array([41, 74, 26, 31, 31, 31, 20, 64, 59, 76, 80, 59, 53, 50, 29, 67, 55,
Out[12]:
                82, 41, 40, 77, 41, 73, 52, 38, 87, 28, 87, 60, 47, 87, 66, 71, 77,
                85, 40, 22, 40, 74, 69, 44, 46, 72, 60, 69, 56, 19, 84, 80, 83, 22,
                63, 74, 31, 32, 20, 58, 71, 56, 43, 32, 67, 32, 51, 79, 54, 25, 81,
                50, 55, 86, 75, 30, 37, 37, 37, 56, 22, 85, 82, 58, 78, 32, 50, 52,
                70, 85, 37, 34, 83, 41, 52, 46, 55, 84, 64, 19, 86, 46, 65, 77, 80,
                82, 86, 65, 41, 35, 44, 45, 34, 46, 51, 83, 82, 53, 50, 84, 83, 29,
                47, 80, 75, 72, 81, 40, 75, 74, 57, 27, 71, 76, 65, 27, 75, 32, 26,
                34, 20, 58, 19, 18, 26, 73, 60, 31, 34, 46, 80, 76, 30, 70, 68, 71,
                45, 44, 47, 30, 39, 35, 60, 44, 45, 83, 64, 21, 35, 25, 70, 86, 53,
                65, 87, 66, 88, 48, 18, 29, 60, 50, 29, 67, 45, 83, 76, 62, 25, 41,
                56, 23, 60, 56, 59, 77, 64, 74, 39, 43, 24, 55, 88, 60, 19, 32, 49,
                59, 88, 69, 82, 56, 70, 34, 52, 85, 70, 79, 26, 37, 60, 40, 32, 20,
                81, 43, 47, 83, 67, 27, 30, 21, 24, 40, 43, 83, 79, 47, 36, 66, 37,
                76, 20, 48, 81, 58, 62, 27, 21, 88, 31, 62, 38, 83, 33, 41, 68, 38,
                43, 44, 49, 51, 82, 48, 53, 75, 56, 48, 38, 76, 37, 41, 62, 26, 32,
                53, 40, 89, 40, 19, 29, 73, 71, 81, 63, 36, 56, 30, 60, 67, 47, 20,
                62, 86, 84, 88, 37, 47, 35, 37, 26, 48, 36, 53, 19, 77, 46, 63, 87,
                60, 40, 72, 86, 41, 58, 29, 43, 36, 69, 75, 56, 55, 33, 66, 22, 46,
                73, 45, 30, 42, 51, 24, 18, 54, 45, 73, 37, 54, 84, 29, 73, 82, 47,
                55, 68, 42, 60, 25, 46, 89, 37, 20, 34, 24, 40, 61, 66, 72, 71, 30,
                50, 29, 24, 60, 30, 76, 67, 66, 19, 75, 33, 21, 21, 45, 38, 47, 69,
                71, 83, 50, 40, 24, 38, 47, 72, 25, 26, 77, 44, 39, 35, 36, 42, 73,
                78, 77, 62, 43, 84, 66, 41, 48, 69, 65, 52, 45, 85, 43, 77, 31, 50,
                61, 69, 71, 77, 89, 65, 41, 35, 88, 37, 87, 75, 21, 38, 73, 31, 66,
                25, 25, 69, 71, 46, 86, 66, 82, 24, 77, 44, 81, 72, 25, 50, 58, 22,
                85, 42, 44, 62, 71, 89, 77, 29, 65, 62, 62, 26, 65, 21, 49, 37, 82,
                26, 72, 26, 35, 45, 51, 63, 87, 25, 29, 72, 53, 33, 76, 65, 22, 22,
                87, 40, 46, 46, 89, 52, 55, 44, 66, 71, 78, 44, 70, 51, 73, 74, 44,
                71, 53, 84, 76, 61, 76, 33])
```

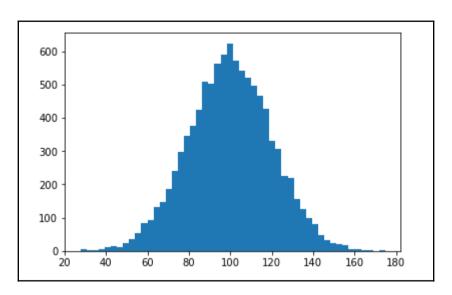


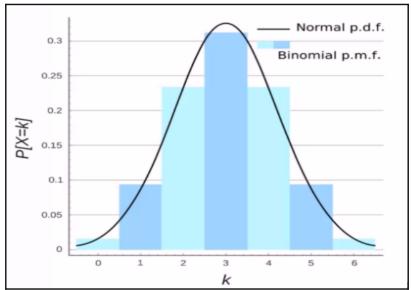
 σ^2 = (11.56 + 0.16 + 0.36 + 0.16 + 12.96) / 5 = 5.04

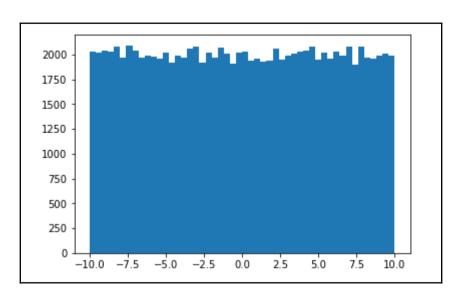


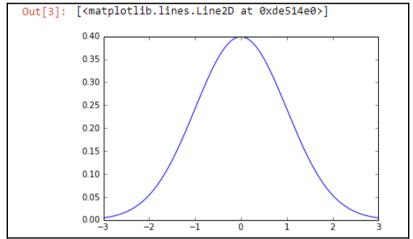
$$\sigma^2 = \frac{\sum (X-\mu)^2}{N}$$

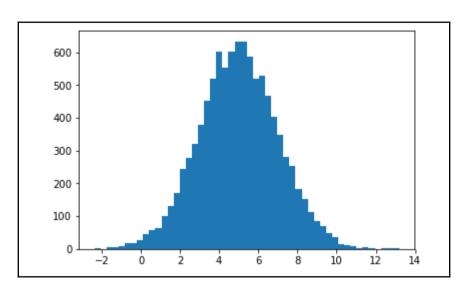
$$s^2 = \frac{\sum (X - M)^2}{N - 1}$$

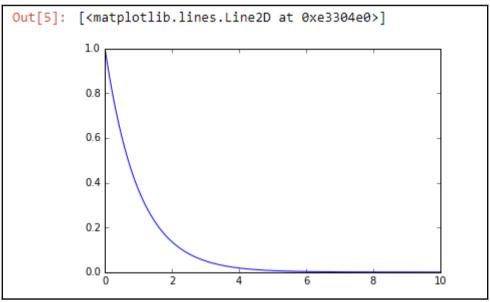


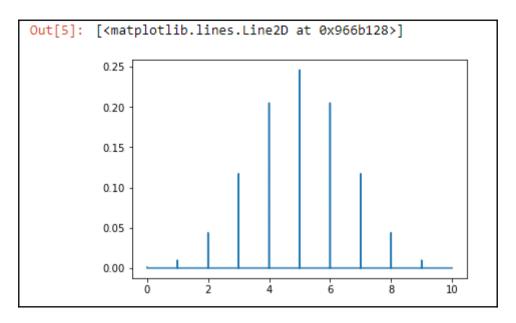


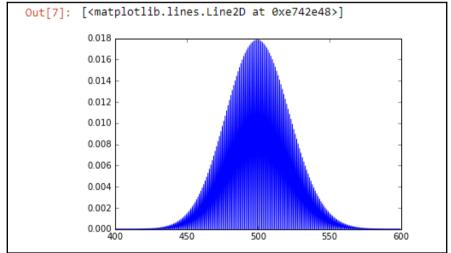


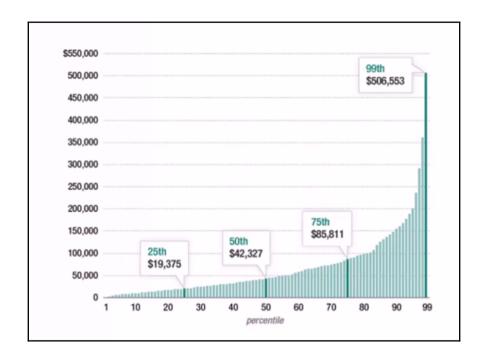


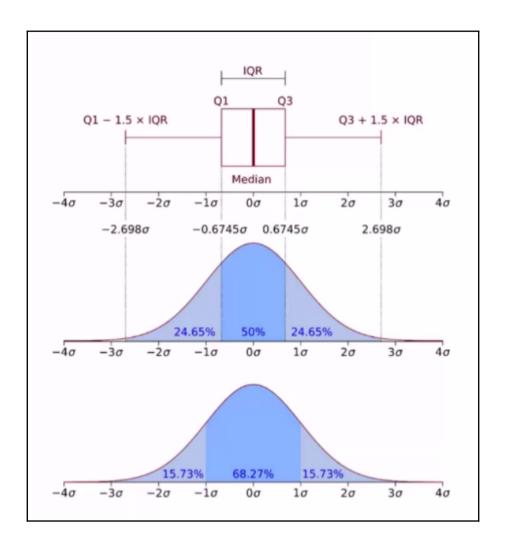


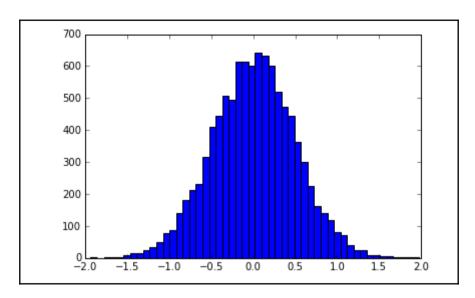




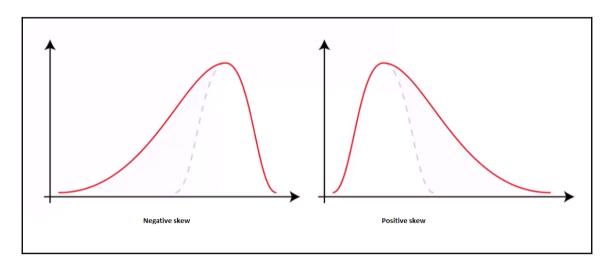


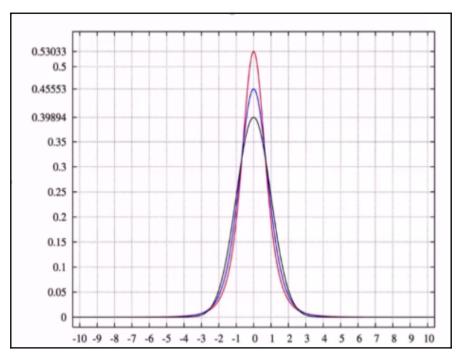


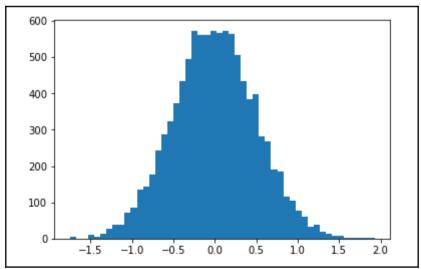




 $\mu_n = \int_{-\infty}^{\infty} (x-c)^n f(x) dx$ (for moment n around value c)

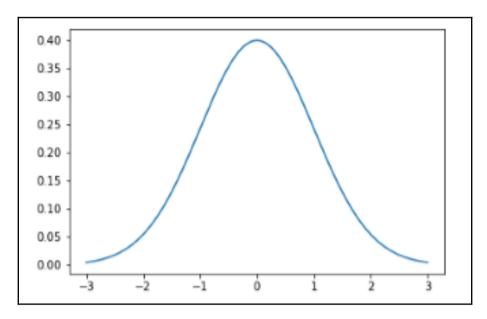


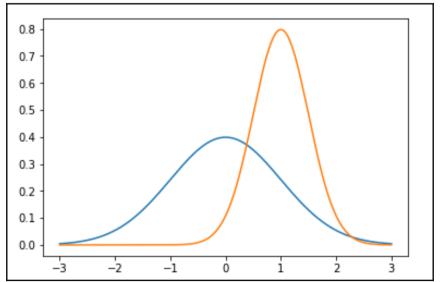


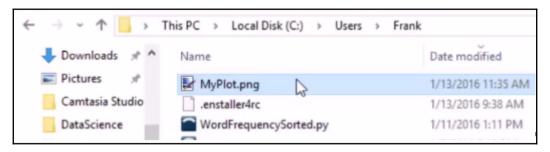


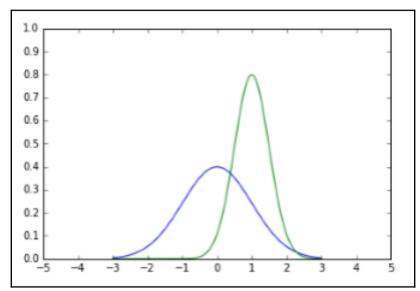
Chapter 3: Matplotlib and Advanced

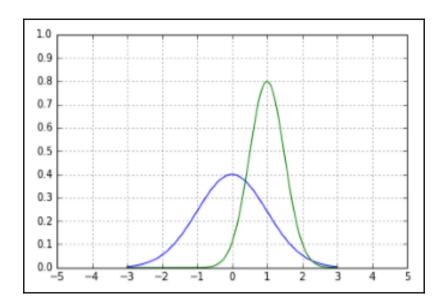
Probability Concepts

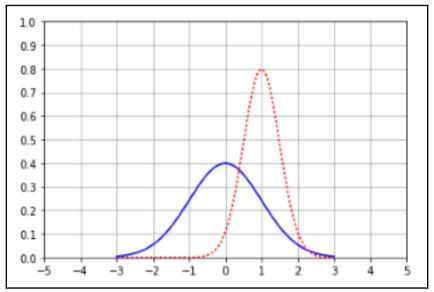


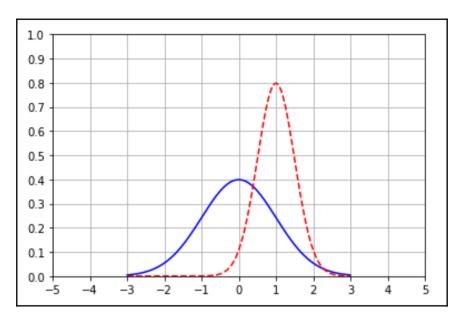


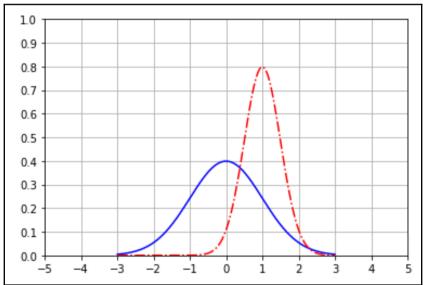


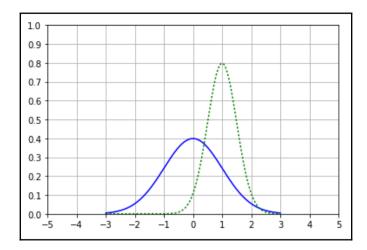


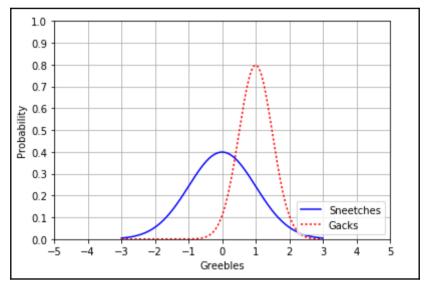




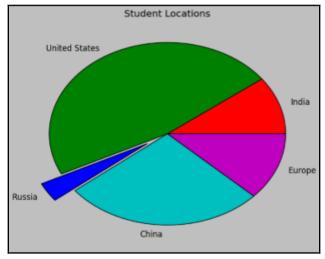


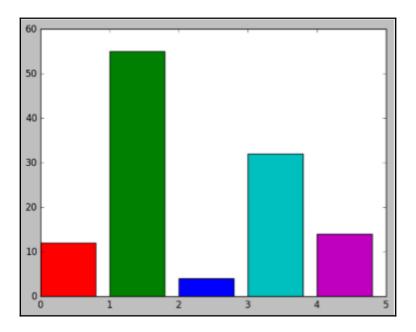


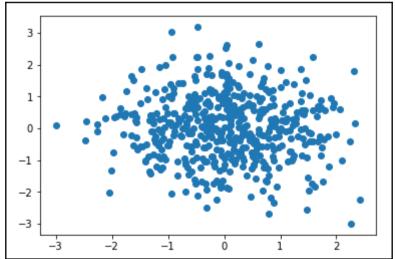


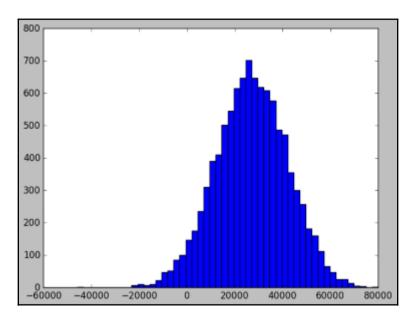


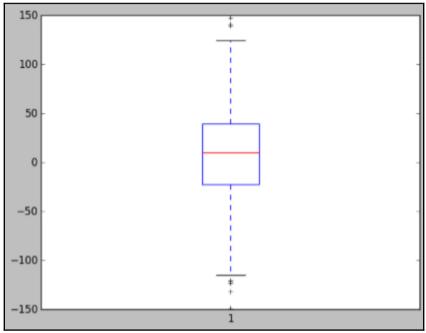


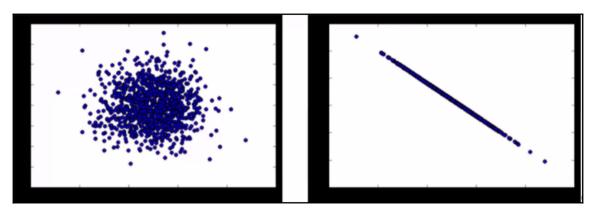


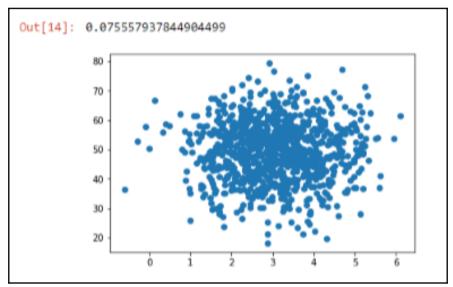


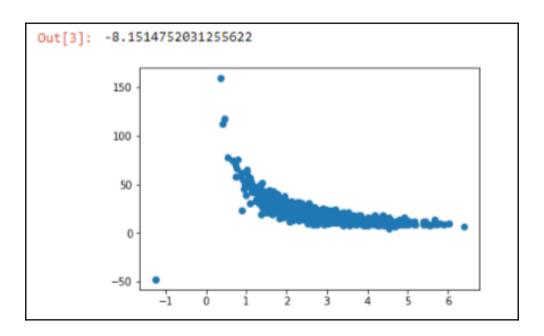




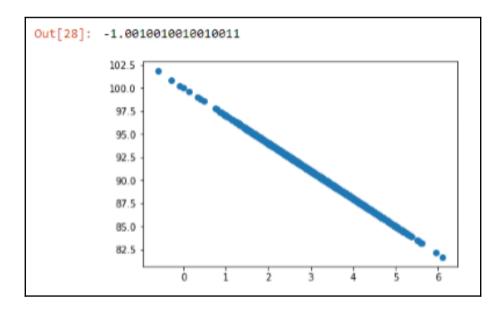








Out[3]: -0.46775563114087165



$$P(B \mid A) = \frac{P(A,B)}{P(A)}$$

$$P(B|A) = \frac{P(A,B)}{P(A)} = \frac{0.6}{0.8} = 0.75$$

```
In [2]: totals
Out[2]: {20: 16576, 30: 16619, 40: 16632, 50: 16805, 60: 16664, 70: 16704}

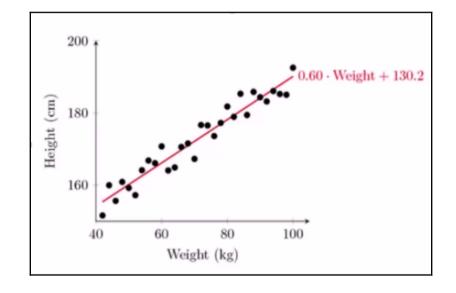
In [3]: purchases
Out[3]: {20: 3392, 30: 4974, 40: 6670, 50: 8319, 60: 9944, 70: 11713}

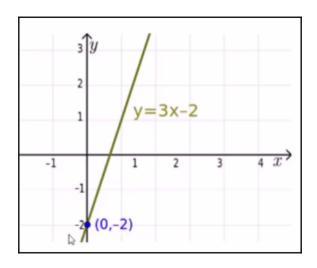
In [4]: totalPurchases
Out[4]: 45012
```

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$

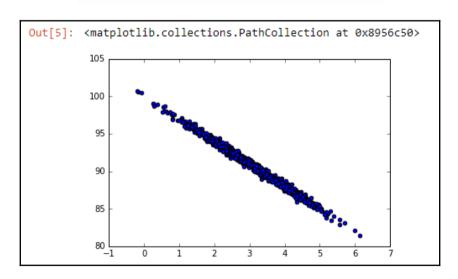
$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} = \frac{0.003*0.99}{0.013} = 22.8\%$$

Chapter 4: Predictive Models

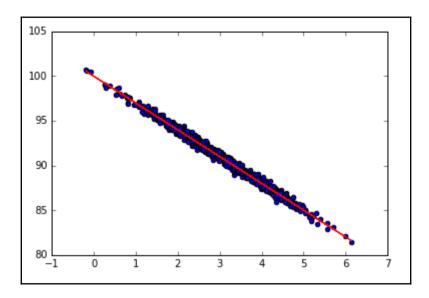


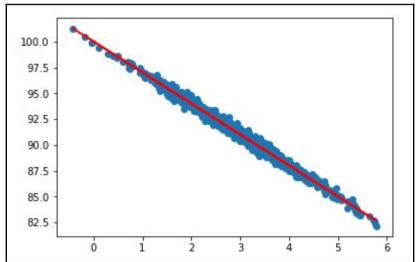


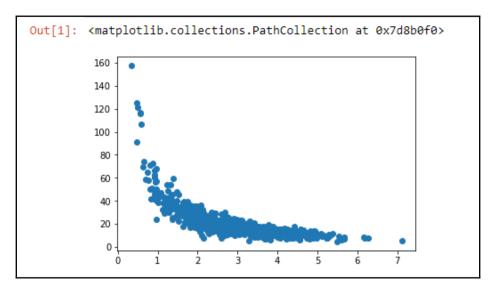
 $1.0 - \frac{\textit{sum of squared errors}}{\textit{sum of squared variation from mean}}$

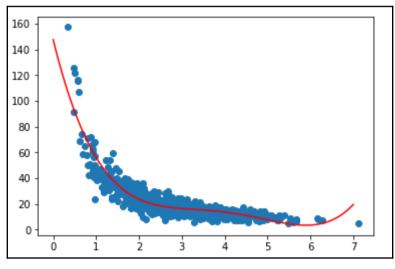


Out[4]: 0.98984146047689425

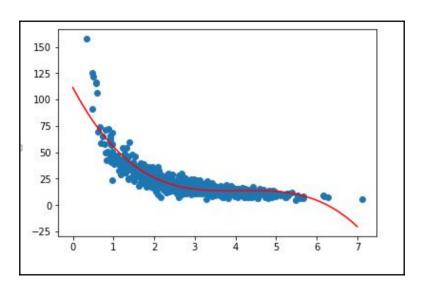








0.82937663963



For example, $price = \alpha + \beta_1 \text{mileage} + \beta_2 \text{age} + \beta_2 \text{doors}$

Out[2]:		Price	Mileage	Make	Model	Trim	Туре	Cylinder	Liter	Doors	Cruise	Sound	Leather
	0	17314.103129	8221	Buick	Century	Sedan 4D	Sedan	6	3.1	4	1	1	1
	1	17542.036083	9135	Buick	Century	Sedan 4D	Sedan	6	3.1	4	1	1	0
	2	16218.847862	13196	Buick	Century	Sedan 4D	Sedan	6	3.1	4	1	1	0
	3	16336.913140	16342	Buick	Century	Sedan 4D	Sedan	6	3.1	4	1	0	0
	4	16339.170324	19832	Buick	Century	Sedan 4D	Sedan	6	3.1	4	1	0	1

Out[3]: OLS Regression Results

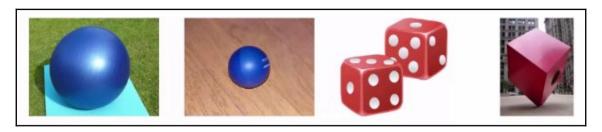
Dep. Variable:	Price	R-squared:	0.042
Model:	OLS	Adj. R-squared:	0.038
Method:	Least Squares	F-statistic:	11.57
Date:	Tue, 26 Jan 2016	Prob (F-statistic):	1.98e-07
Time:	12:18:05	Log-Likelihood:	-8519.1
No. Observations:	804	AIC:	1.705e+04
Df Residuals:	800	BIC:	1.706e+04
Df Model:	3		
Covariance Type:	nonrobust		

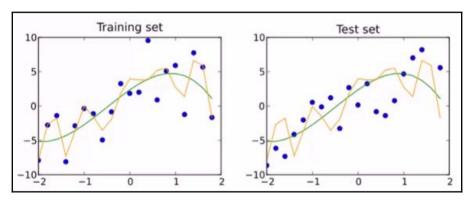
	coef	std err	t	P> t	[95.0% Conf. Int.]
const	3.125e+04	1809.549	17.272	0.000	2.77e+04 3.48e+04
Mileage	-0.1765	0.042	-4.227	0.000	-0.259 -0.095
Model_ord	-39.0387	39.326	-0.993	0.321	-116.234 38.157
Doors	-1652.9303	402.649	-4.105	0.000	-2443.303 -862.558

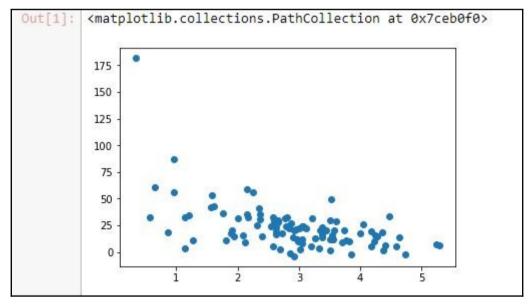
Omnibus:	206.410	Durbin-Watson:	0.080
Prob(Omnibus):	0.000	Jarque-Bera (JB):	470.872
Skew:	1.379	Prob(JB):	5.64e-103
Kurtosis:	5.541	Cond. No.	1.15e+05

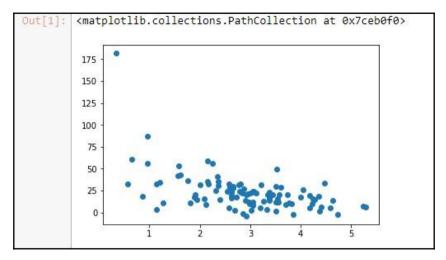
Out[5]:		Price
	Doors	s
	2	23807.135520
	4	20580.670749

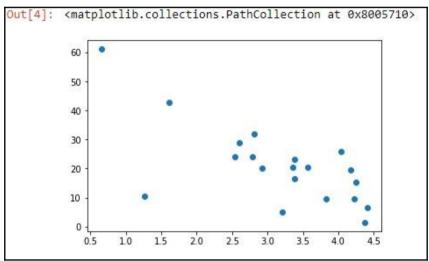
Chapter 5: Machine Learning with Python

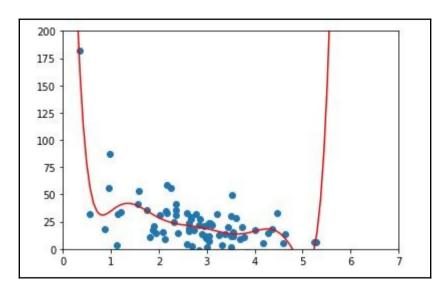


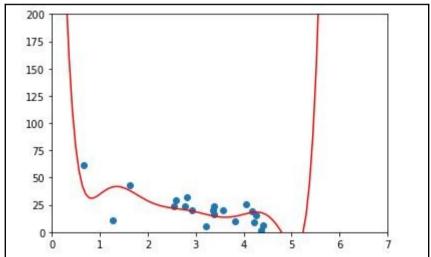












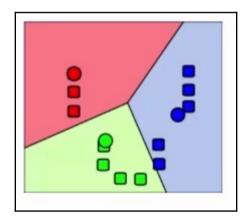
$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$

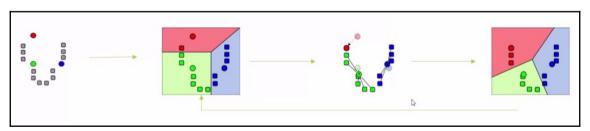
$$P(Spam \mid Free) = \frac{P(Spam)P(Free \mid Spam)}{P(Free)}$$

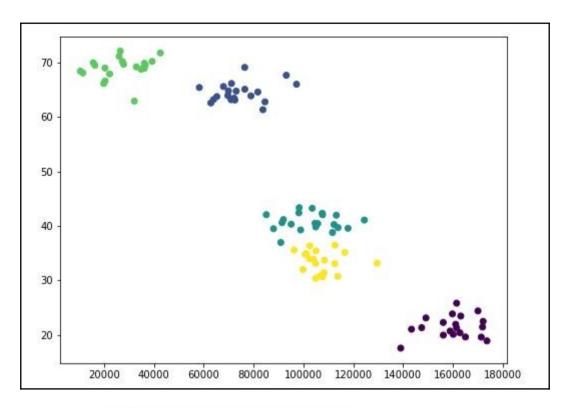
P(Free|Spam)P(Spam) + P(Free|Not Spam)P(Not Spam))

		Class	message
C	C:\Users\deveshc\Desktop\DataScience\emails\spam\00001.7848dde101aa985090474a91ec93fcf0	spam	HTML PUBLIC "-//W3C//DTD H</td
С	C:\Users\deveshc\Desktop\DataScience\emails\spam\00002.d94f1b97e48ed3b553b3508d116e6a09	spam	1) Fight The Risk of Cancer!\n\nhttp://www.ad
C	C:\Users\deveshc\Desktop\DataScience\emails\spam\00003.2ee33bc6eacdb11f38d052c44819ba6c	spam	1) Fight The Risk of Cancer!\n\nhttp://www.ac
С	C:\Users\deveshc\Desktop\DataScience\emails\spam\00004.eac8de8d759b7e74154f142194282724	spam	***************************************
C	C:\Users\deveshc\Desktop\DataScience\emails\spam\00005.57696a39d7d84318ce497886896bf90d	spam	I thought you might like these:\n\n1) Slim Dov

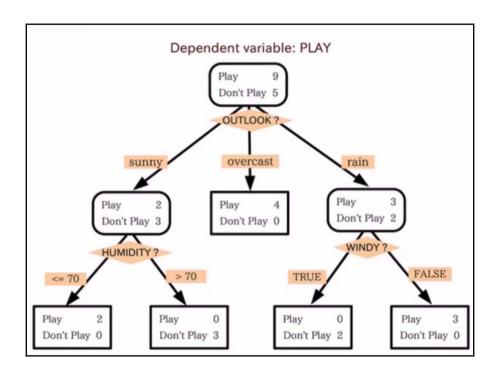
Out[13]: MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)



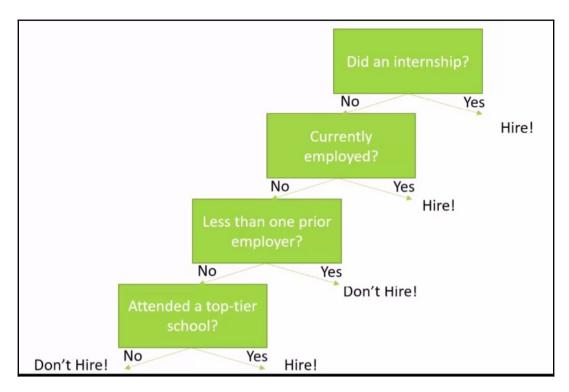




 $H(S)=-p_1\ln p_1-\cdots-p_n\ln p_n$ $p_i \text{ represents the proportion of the data labeled for each class}$

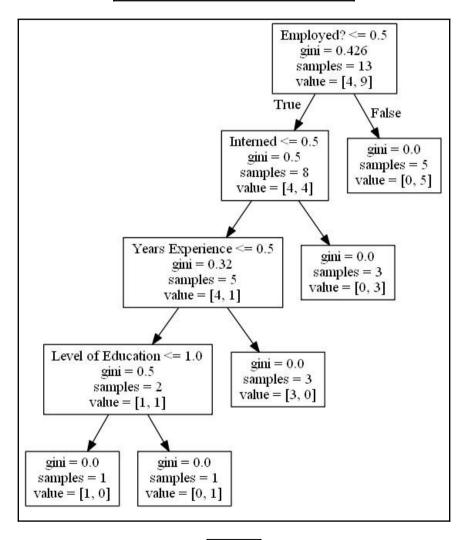


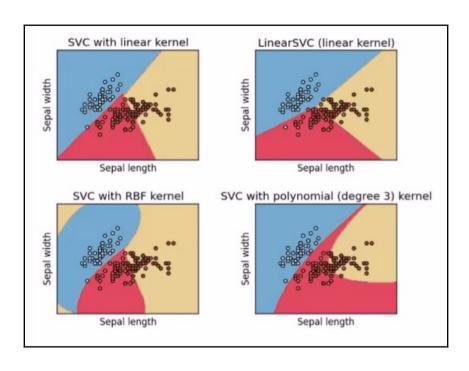
Candidate ID	Years Experience	Employed?	Previous employers	Level of Education	Top-tier school	Interned	Hired	
0	10	1	4	0	0	0	1	
1	0	0	0	0	1	1	1	
2	7	0	6	0	0	0	0	
3	2	1	1	1	1	0	1	
4	20	0	2	2	1	0	0	

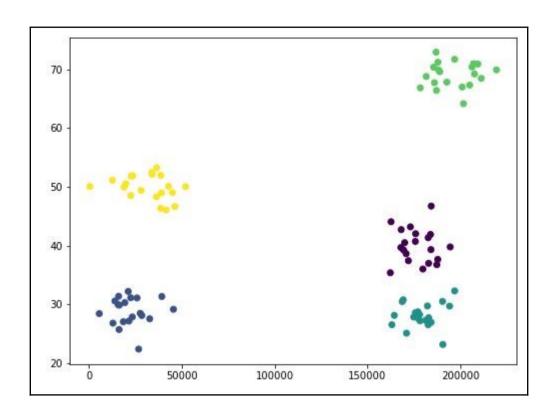


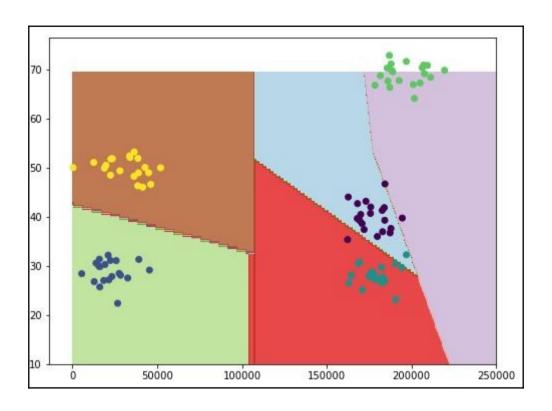
ut[2]:		Years Experience	Employed?	Previous employers	Level of Education	Top-tier school	Interned	Hired
	0	10	Y	4	BS	N	N	Y
	1	0	N	0	BS	Y	Y	Υ
	2	7	N	6	BS	N	N	N
	3	2	Y	1	MS	Y	N	Y
	4	20	N	2	PhD	Y	N	N

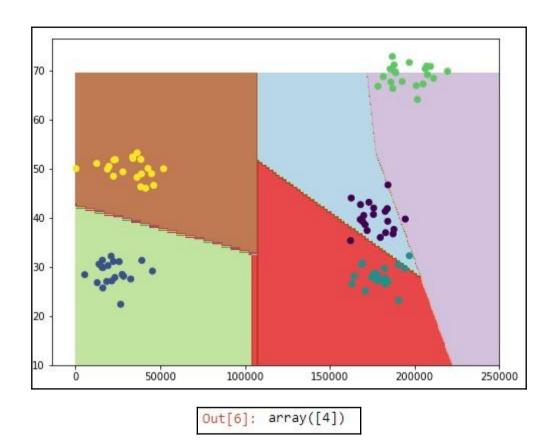
Out[3]:		Years Experience	Employed?	Previous employers	Level of Education	Top-tier school	Interned	Hired
	0	10	1	4	0	0	0	1
	1	0	0	0	0	1	1	1
	2	7	0	6	0	0	0	0
	3	2	1	1	1	1	0	1
	4	20	0	2	2	1	0	0



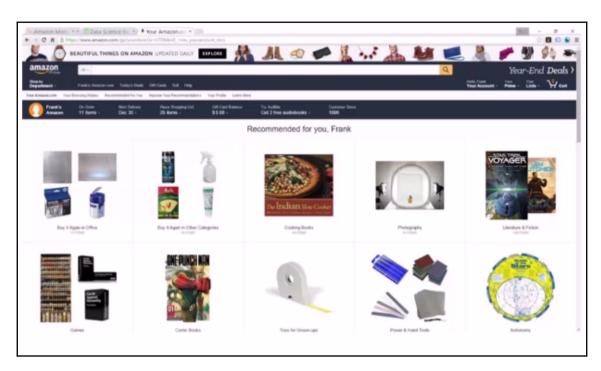




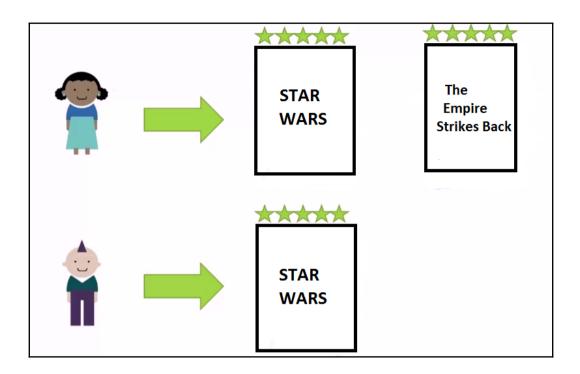


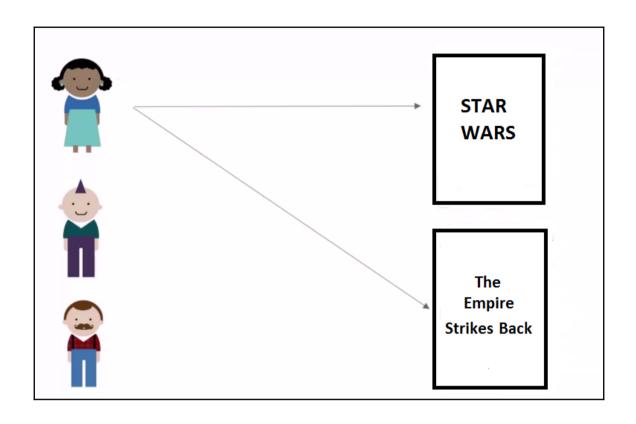


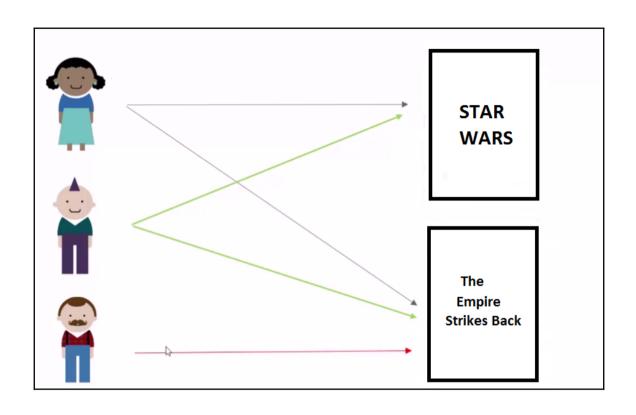
Chapter 6: Recommender Systems

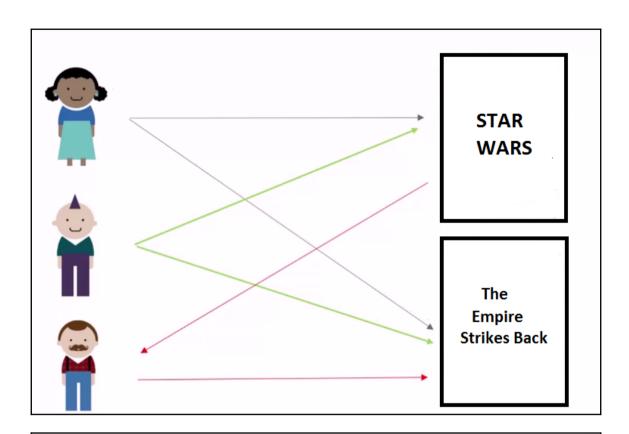












Finding Similar Movies

We'll start by loading up the MovieLens dataset. Using Pandas, we can very quickly load the rows of the u.data and u.item files that we care about, and merge them together so we can work with movie names instead of ID's. (In a real production job, you'd stick with ID's and worry about the names at the display layer to make things more efficient. But this lets us understand what's going on better for now.)

```
In [1]: import pandas as pd

r_cols = ['user_id', 'movie_id', 'rating']
 ratings = pd.read_csv('e:/sundog-consult/udemy/datascience/ml-100k/u.data', sep='\t', names=r_cols, usecols=range(3))

m_cols = ['movie_id', 'title']
 movies = pd.read_csv('e:/sundog-consult/udemy/datascience/ml-100k/u.item', sep='|', names=m_cols, usecols=range(2))

ratings = pd.merge(movies, ratings)
```

In [2]: ratings.head()

Out[2]:

	movie_id	title	user_id	rating
0	1	Toy Story (1995)	308	4
1	1	Toy Story (1995)	287	5
2	1	Toy Story (1995)	148	4
3	1	Toy Story (1995)	280	4
4	1	Toy Story (1995)	66	3

In [2]: ratings.head() Out[2]: movie_id title user_id rating 0 1 Toy Story (1995) 308 1 1 Toy Story (1995) 287 5 2 1 Toy Story (1995) 148 4 3 1 Toy Story (1995) 280 4 4 1 Toy Story (1995) 66 3

title	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)		20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	 Yankee Zulu (1994)	Year of the Horse (1997)	,	Young Frankenstein (1974)	Young Guns (1988)
user_id															
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	2	5	NaN	NaN	3	4	NaN	NaN	 NaN	NaN	NaN	5	3
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1	NaN	 NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	2	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN

Out[5]:		0
	title	
	'Til There Was You (1997)	0.872872
	1-900 (1994)	-0.645497
	101 Dalmatians (1996)	0.211132
	12 Angry Men (1957)	0.184289
	187 (1997)	0.027398
	2 Days in the Valley (1996)	0.066654
	20,000 Leagues Under the Sea (1954)	0.289768
	2001: A Space Odyssey (1968)	0.230884
	39 Steps, The (1935)	0.106453
	8 1/2 (1963)	-0.142977

```
Out[6]: title
       Full Speed (1996)
                                                                                              1.000000
       Star Wars (1977)
                                                                                              1.000000
                                                                                              1.000000
       Mondo (1996)
                                                                                              1.000000
       Man of the Year (1995)
                                                                                              1.000000
       Line King: Al Hirschfeld, The (1996)
       Outlaw, The (1943)
                                                                                              1.000000
       Hurricane Streets (1998)
                                                                                              1.000000
                                                                                              1.000000
       Hollow Reed (1996)
       Scarlet Letter, The (1926)
                                                                                              1.000000
       Safe Passage (1994)
                                                                                              1.000000
       Good Man in Africa, A (1994)
                                                                                              1.000000
       Golden Earrings (1947)
                                                                                              1.000000
       Old Lady Who Walked in the Sea, The (Vieille qui marchait dans la mer, La) (1991)
                                                                                              1.000000
       No Escape (1994)
                                                                                              1.000000
       Ed's Next Move (1996)
                                                                                              1.000000
       Stripes (1981)
                                                                                              1.000000
       Cosi (1996)
                                                                                              1.000000
       Commandments (1997)
                                                                                              1.000000
       Twisted (1996)
                                                                                              1.000000
                                                                                              1.000000
       Beans of Egypt, Maine, The (1994)
       Last Time I Saw Paris, The (1954)
                                                                                              1.000000
       Maya Lin: A Strong Clear Vision (1994)
                                                                                              1.000000
       Designated Mourner, The (1997)
                                                                                              0.970725
       Albino Alligator (1996)
                                                                                              0.968496
       Angel Baby (1995)
                                                                                              0.962250
       Prisoner of the Mountains (Kavkazsky Plennik) (1996)
                                                                                              0.927173
       Love in the Afternoon (1957)
                                                                                              0.923381
       'Til There Was You (1997)
                                                                                              0.872872
       A Chef in Love (1996)
                                                                                              0.868599
```

Out[8]:

	ratin	g
6	size	mean
title		
'Til There Was You (1997)	9	2.333333
1-900 (1994)	5	2.600000
101 Dalmatians (1996)	109	2.908257
12 Angry Men (1957)	125	4.344000
187 (1997)	41	3.024390

Out[9]:

	ratin	g
20 20 20 20 20 20 20 20 20 20 20 20 20 2	size	mean
title		
Close Shave, A (1995)	112	4.491071
Schindler's List (1993)	298	4.466443
Wrong Trousers, The (1993)	118	4.466102
Casablanca (1942)	243	4.456790
Shawshank Redemption, The (1994)	283	4.445230
Rear Window (1954)	209	4.387560
Usual Suspects, The (1995)	267	4.385768
Star Wars (1977)	584	4.359589
12 Angry Men (1957)	125	4.344000
Citizen Kane (1941)	198	4.292929
To Kill a Mockingbird (1962)	219	4.292237
One Flew Over the Cuckoo's Nest (1975)	264	4.291667
Silence of the Lambs, The (1991)	390	4.289744
North by Northwest (1959)	179	4.284916
Godfather, The (1972)	413	4.283293

Out[11]:		(rating, size)	(rating, mean)	similarity
	title			
	101 Dalmatians (1996)	109	2.908257	0.211132
	12 Angry Men (1957)	125	4.344000	0.184289
	2001: A Space Odyssey (1968)	259	3.969112	0.230884
	Absolute Power (1997)	127	3.370079	0.085440
	Abyss, The (1989)	151	3.589404	0.203709

Out[12]:		(rating, size)	(rating, mean)	similarity
	title). 30	
	Star Wars (1977)	584	4.359589	1.000000
	Empire Strikes Back, The (1980)	368	4.206522	0.748353
	Return of the Jedi (1983)	507	4.007890	0.672556
	Raiders of the Lost Ark (1981)	420	4.252381	0.536117
	Austin Powers: International Man of Mystery (1997)	130	3.246154	0.377433
	Sting, The (1973)	241	4.058091	0.367538
	Indiana Jones and the Last Crusade (1989)	331	3.930514	0.350107
	Pinocchio (1940)	101	3.673267	0.347868
	Frighteners, The (1996)	115	3.234783	0.332729
	L.A. Confidential (1997)	297	4.161616	0.319065
	Wag the Dog (1997)	137	3.510949	0.318645
	Dumbo (1941)	123	3.495935	0.317656
	Bridge on the River Kwai, The (1957)	165	4.175758	0.316580
	Philadelphia Story, The (1940)	104	4.115385	0.314272
	Miracle on 34th Street (1994)	101	3.722772	0.310921

Out[1]:		movie_id	title	user_id	rating
	0	1	Toy Story (1995)	308	4
	1	1	Toy Story (1995)	287	5
	2	1	Toy Story (1995)	148	4
	3	1	Toy Story (1995)	280	4
	4	1	Toy Story (1995)	66	3

Out[2]:	title	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)		20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	 Yankee Zulu (1994)	Year of the Horse (1997)		Young Frankenstein (1974)	Young Guns (1988)
	user_id														9	
	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN
	1	NaN	NaN	2	5	NaN	NaN	3	4	NaN	NaN	 NaN	NaN	NaN	5	3
	2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1	NaN	 NaN	NaN	NaN	NaN	NaN
	3	NaN	NaN	NaN	NaN	2	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN
	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN
	5 rows ×			NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN	NaN

title	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)	2 Days in the Valley (1996)	20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	 Yankee Zulu (1994)	Year of the Horse (1997)	You So Crazy (1994
title													
'Til There Was You (1997)	1.0	NaN	-1.000000	-0.500000	-0.500000	0.522233	NaN	-0.426401	NaN	NaN	 NaN	NaN	NaN
1-900 (1994)	NaN	1	NaN	NaN	NaN	NaN	NaN	-0.981981	NaN	NaN	 NaN	NaN	NaN
101 Dalmatian (1996)	s -1.0	NaN	1.000000	-0.049890	0.269191	0.048973	0.266928	-0.043407	NaN	0.111111	 NaN	-1.000000	NaN
12 Angry Men (1957) -0.5	NaN	-0.049890	1.000000	0.666667	0.256625	0.274772	0.178848	NaN	0.457176	NaN	NaN	NaN
187 (1997)	-0.5	NaN	0.269191	0.666667	1.000000	0.596644	NaN	-0.554700	NaN	1.000000	 NaN	0.866025	NaN

1:	title	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)		20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	 Yankee Zulu (1994)	Year of the Horse (1997)	Crazy	Young Frankenstein (1974)
	title				6.5										
	'Til There Was You (1997)	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN
	1-900 (1994)	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN
	101 Dalmatians (1996)	NaN	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN
- 1	12 Angry Men (1957)	NaN	NaN	NaN	1	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN
	187 (1997)	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	 NaN	NaN	NaN	NaN

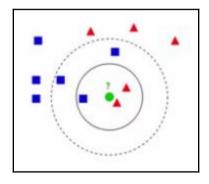
```
Out[5]: title
    Empire Strikes Back, The (1980) 5
    Gone with the Wind (1939) 1
    Star Wars (1977) 5
    Name: 0, dtype: float64
```

```
Adding sims for Empire Strikes Back, The (1980)...
Adding sims for Gone with the Wind (1939) ...
Adding sims for Star Wars (1977)...
sorting...
title
Empire Strikes Back, The (1980)
                                                       5.000000
Star Wars (1977)
                                                       5.000000
Empire Strikes Back, The (1980)
                                                       3.741763
Star Wars (1977)
                                                       3.741763
Return of the Jedi (1983)
                                                       3.606146
Return of the Jedi (1983)
                                                       3.362779
Raiders of the Lost Ark (1981)
                                                       2.693297
Raiders of the Lost Ark (1981)
                                                       2.680586
Austin Powers: International Man of Mystery (1997)
                                                       1.887164
Sting, The (1973)
                                                       1.837692
dtype: float64
```

```
Out[8]: title
       Empire Strikes Back, The (1980)
                                                     8.877450
       Star Wars (1977)
                                                    8.870971
       Return of the Jedi (1983)
                                                    7.178172
       Raiders of the Lost Ark (1981)
                                                   5.519700
       Indiana Jones and the Last Crusade (1989) 3.488028
                                                   3.366616
       Bridge on the River Kwai, The (1957)
       Back to the Future (1985)
                                                    3.357941
       Sting, The (1973)
                                                    3.329843
       Cinderella (1950)
                                                    3.245412
       Field of Dreams (1989)
                                                    3.222311
       dtype: float64
```

```
Out[9]: title
        Return of the Jedi (1983)
                                                     7.178172
        Raiders of the Lost Ark (1981)
                                                     5.519700
        Indiana Jones and the Last Crusade (1989)
                                                     3.488028
        Bridge on the River Kwai, The (1957)
                                                     3.366616
        Back to the Future (1985)
                                                     3.357941
        Sting, The (1973)
                                                     3.329843
        Cinderella (1950)
                                                     3.245412
        Field of Dreams (1989)
                                                     3.222311
        Wizard of Oz, The (1939)
                                                     3.200268
        Dumbo (1941)
                                                     2.981645
        dtype: float64
```

Chapter 7 : More Data Mining and Machine Learning Techniques



Customers Who Watched This Item Also Watched

















Out[1]:		user_id	movie_id	rating
	0	0	50	5
	1	0	172	5
	2	0	133	1
	3	196	242	3
	4	186	302	3

Out[4]:		size
	movie_id	
	1	0.773585
	2	0.222985
	3	0.152659
	4	0.356775
	5	0.145798

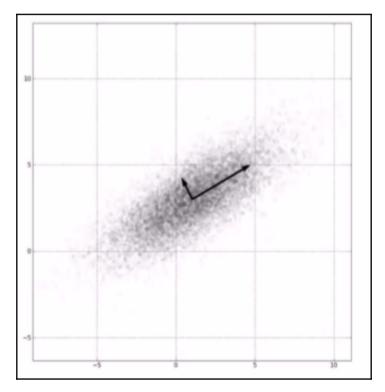
```
('Toy Story (1995)',
[0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
0.77358490566037741,
3.8783185840707963)
```

0.8004574042309891

Liar Liar (1997) 3.15670103093
Aladdin (1992) 3.81278538813
Willy Wonka and the Chocolate Factory (1971) 3.63190184049
Monty Python and the Holy Grail (1974) 4.0664556962
Full Monty, The (1997) 3.92698412698
George of the Jungle (1997) 2.68518518519
Beavis and Butt-head Do America (1996) 2.78846153846
Birdcage, The (1996) 3.44368600683
Home Alone (1990) 3.08759124088
Aladdin and the King of Thieves (1996) 2.84615384615

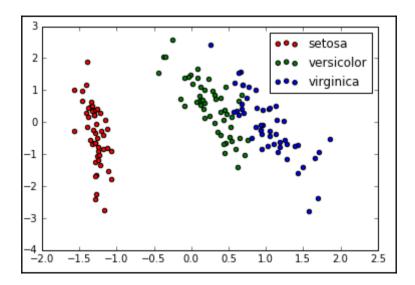
3.3445905900235564

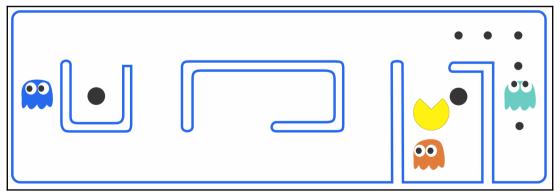




```
150
4
['setosa', 'versicolor', 'virginica']
```

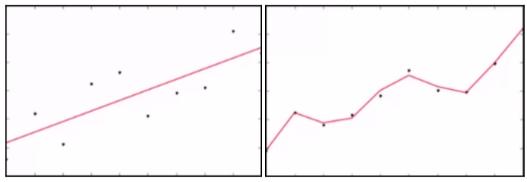
[0.92461621 0.05301557] 0.977631775025





Chapter 8: Dealing with Real-World Data





 $Error = Bias^2 + Variance$

Out[2]: 0.96666666666666667

[1.	1.	0.9	0.93333333	1.]
0.9666666	66667				

[1.	1.	0.9	0.93333333	1.]
0.9666666666	7				

```
IOErrorTraceback (most recent call last)
<ipython-input-3-281d53278f3c> in <module>()
        1 URLCounts = {}
        2
----> 3 with open(logPath, "r") as f:
        4 for line in (l.rstrip() for l in f):
        5 match= format_pat.match(line)

IOError: [Errno 2] No such file or directory: 'E:\\sundog-consult\\Udemy\\DataScience\\access_log.txt'
```

```
/xmlrpc.php: 68494
/wp-login.php: 1923
/: 440
/blog/: 138
/robots.txt: 123
/sitemap index.xml: 118
/post-sitemap.xml: 118
/category-sitemap.xml: 117
/page-sitemap.xml: 117
/orlando-headlines/: 95
/san-jose-headlines/: 85
http://51.254.206.142/httptest.php: 81
/comics-2/: 76
/travel/: 74
/entertainment/: 72
/world/: 70
/business/: 70
/weather/: 70
/national/: 70
/national-headlines/: 70
```

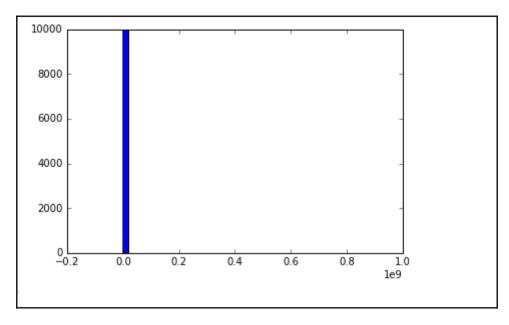
```
/: 434
/blog/: 138
/robots.txt: 123
/sitemap index.xml: 118
/post-sitemap.xml: 118
/category-sitemap.xml: 117
/page-sitemap.xml: 117
/orlando-headlines/: 95
/san-jose-headlines/: 85
http://51.254.206.142/httptest.php: 81
/comics-2/: 76
/travel/: 74
/entertainment/: 72
/world/: 70
/business/: 70
/weather/: 70
/national/: 70
/national-headlines/: 70
/defense-sticking-head-sand/: 69
/about./: 69
```

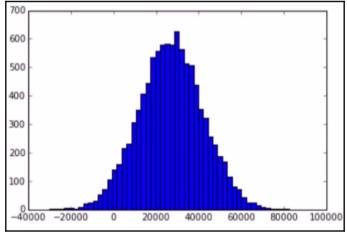
54.165.199.171 - - [05/Dec/2015:09:32:05 +0000] "GET /blog/ HTTP/1.0" 200 31670 "-" "-"

```
Mozilla/4.0 (compatible: MSIE 7.0; Windows NT 6.0): 68484
Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0): 1724
W3 Total Cache/0.9.4.1: 468
Mozilla/5.0 (compatible; Baiduspider/2.0; +http://www.baidu.com/search/spider.html): 278
Mozilla/5.0 (compatible; Googlebot/2.1; +http://www.google.com/bot.html): 248
Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/46.0.249
0.86 Safari/537.36: 158
Mozilla/5.0 (Windows NT 6.1; WOW64; rv:40.0) Gecko/20100101 Firefox/40.0: 144
Mozilla/5.0 (iPad; CPU OS 8 4 like Mac OS X) AppleWebKit/600.1.4 (KHTML, like Gecko) Versio
n/8.0 Mobile/12H143 Safari/600.1.4: 120
Mozilla/5.0 (Linux; Android 5.1.1; SM-G900T Build/LMY47X) AppleWebKit/537.36 (KHTML, like G
ecko) Chrome/46.0.2490.76 Mobile Safari/537.36: 47
Mozilla/5.0 (compatible; bingbot/2.0; +http://www.bing.com/bingbot.htm): 43
Mozilla/5.0 (compatible; MJ12bot/v1.4.5; http://www.majestic12.co.uk/bot.php?+): 41
Opera/9.80 (Windows NT 6.0) Presto/2.12.388 Version/12.14: 40
Mozilla/5.0 (compatible; YandexBot/3.0; +http://yandex.com/bots): 27
Mozilla/5.0 (Linux; Android 5.1.1; SM-G900T Build/LMY47X) AppleWebKit/537.36 (KHTML, like G
```

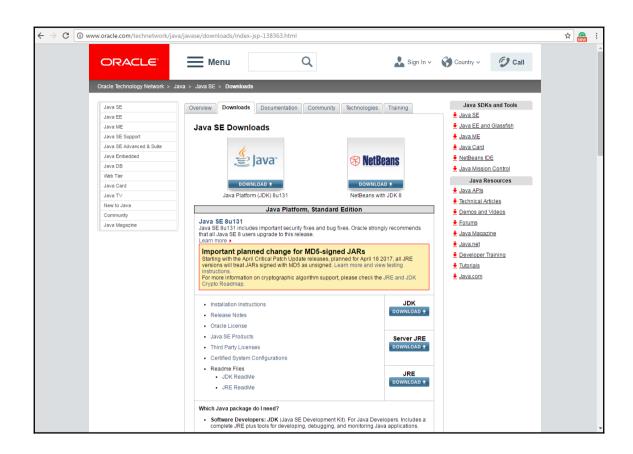
```
/: 77
/orlando-headlines/: 36
/?page id=34248: 28
/wp-content/cache/minify/000000/M9bPKixNLarUy00szs8D0Z15AA.js: 27
/wp-content/cache/minify/000000/1Y7dDoIwDIVfiG0KxkfxfnbdK04HuxICTy-it8Zwl5PzfSftzPCckJem-x4qUWArqBPl5myqZLEqyhdOaoxTo
GyGaiALiOfUnIzOqDLOdSZGE-nOlpc3kopDzrSyavVVt_veb5qSDVhjsQ6dHh_B_eE_z2pYIGJ7iBWKeEio_eT9UQe4xHhDl127mGRryVu_pRc.js: 27
/wp-content/cache/minify/000000/M9AvyUjVzUstLy7PLErVz8lMKkosqtTPKtTvTi7KLCgpBgA.js: 27
/wp-content/cache/minify/000000/fY45DoAwDAQ FMvkRQgFA5ZyWLajiN9zNHR0083MRkyt-pIctqYFJPedKyYzfHg2Pz0FiENAzaD07AxcpKmTo
loRvDjZt8KEfhBUGjZYCf8Fb0fvAlTXCw.css: 25
/?author=1: 21
/wp-content/cache/minify/000000/hcrRCYAwDAXAhXyEjiQ1YKAh4SVSx3cE7 uG7ASr4M9qq3kGWykladklK84LHtRj My6Y0Pfqcz-AA.js: 20
/wp-content/uploads/2014/11/nhn1.png: 19
/wp-includes/js/wp-emoji-release.min.js?ver=4.3.1: 17
/wp-content/cache/minify/000000/BcGBCQAgCATAiUSaKYSERPk3avzuht4SkBJnt4tHJdqqnPBqKldesTcN1R8.js: 17
/wp-login.php: 16
/comics-2/: 12
/world/: 12
/favicon.ico: 10
/wp-content/uploads/2014/11/babyblues.jpg: 6
/wp-content/uploads/2014/11/garfield.ipg: 6
/wp-content/uploads/2014/11/violentcrime.jpg: 6
/robots.txt: 6
```

```
/: 77
/orlando-headlines/: 36
/world/: 12
/comics-2/: 12
/weather/: 4
/about/: 4
/australia/: 4
/national-headlines/: 3
/sample-page/feed/: 2
/feed/: 2
/technology/: 2
/science/: 2
/entertainment/: 1
/san-jose-headlines/: 1
/business/: 1
/travel/feed/: 1
```





Chapter 9: Apache Spark - Machine Learning on Big Data



Java Platform, Standard Edition

Java SE 8u131

Java SE 8u131 includes important security fixes and bug fixes. Oracle strongly recommends that all Java SE 8 users upgrade to this release.

Learn more >

Important planned change for MD5-signed JARs

Starting with the April Critical Patch Update releases, planned for April 18 2017, all JRE versions will treat JARs signed with MD5 as unsigned. Learn more and view testing instructions.

For more information on cryptographic algorithm support, please check the JRE and JDK Crypto Roadmap.

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JDK

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JRE

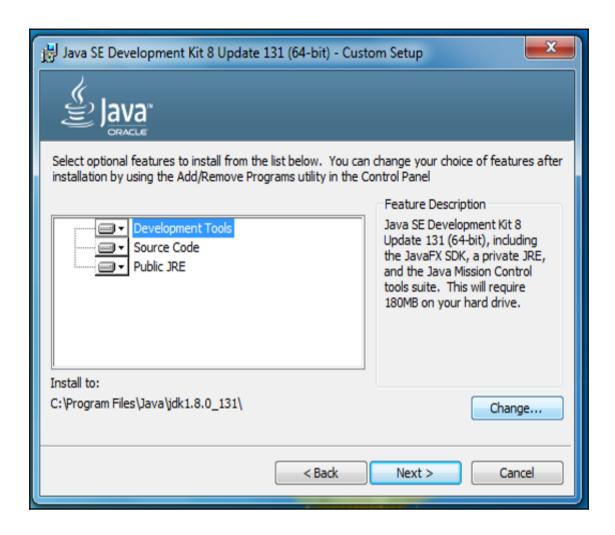
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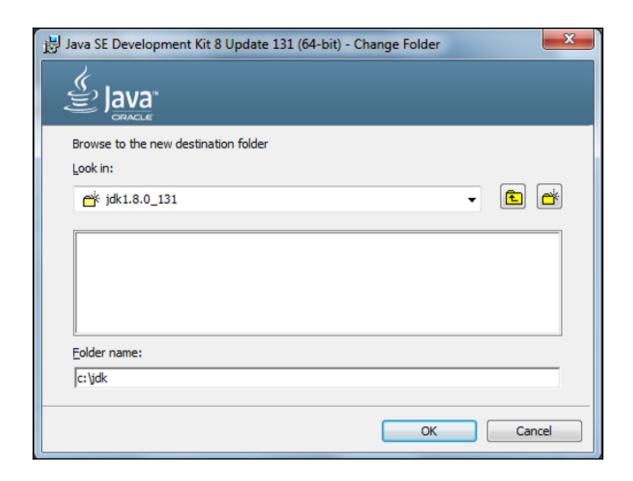
Java SE Development Kit 8u131

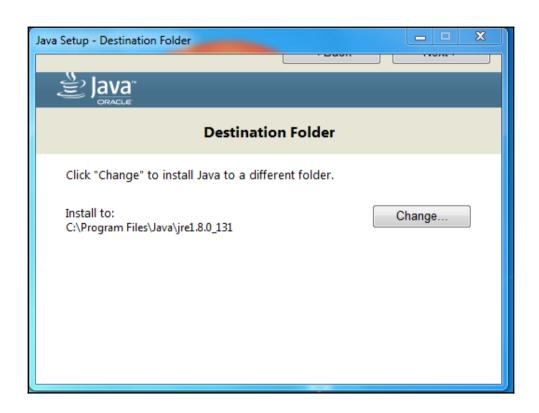
You must accept the Oracle Binary Code License Agreement for Java SE to download this software.

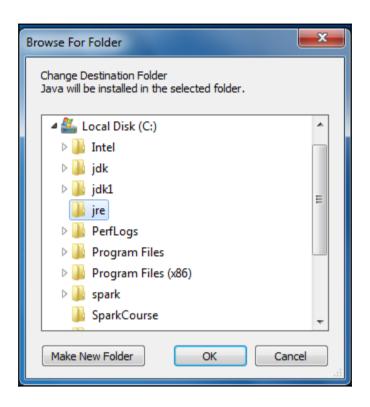
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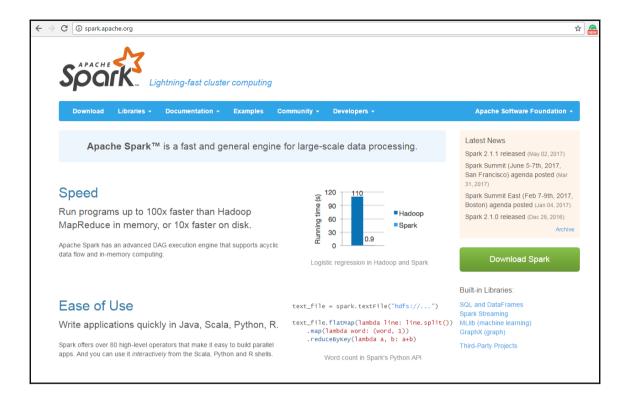
Product / File Description	File Size	Download
Linux ARM 32 Hard Float ABI	77.87 MB	₱jdk-8u131-linux-arm32-vfp-hflt.tar.gz
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Solaris SPARC 64-bit	99.13 MB	₱jdk-8u131-solaris-sparcv9.tar.gz
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Solaris x64	96.96 MB	₹jdk-8u131-solaris-x64.tar.gz
Windows x86	191.22 MB	₹jdk-8u131-windows-i586.exe
Windows x64		₹jdk-8u131-windows-x64.exe









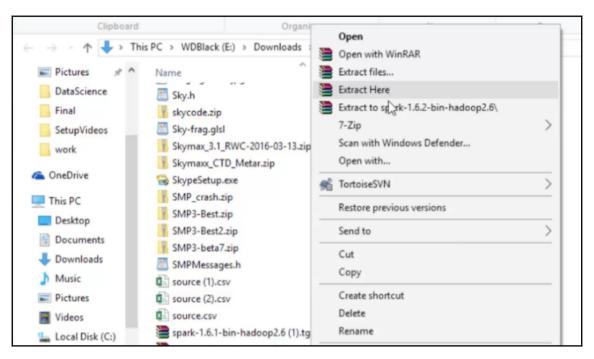


Download Apache Spark™

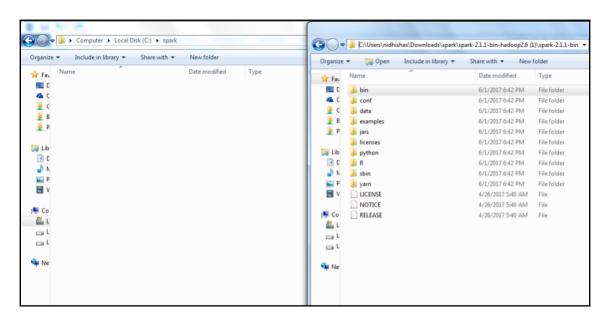
- 1. Choose a Spark release: 2.1.1 (May 02 2017) ▼
- 2. Choose a package type: Pre-built for Apache Hadoop 2.7 and later
- 3. Choose a download type: Direct Download
- 4. Download Spark: spark-2.1.1-bin-hadoop2.7.tgz
- 5. Verify this release using the 2.1.1 signatures and checksums and project release KEYS.

Note: Starting version 2.0, Spark is built with Scala 2.11 by default. Scala 2.10 users should download the Spark source package and build with Scala 2.10 support.

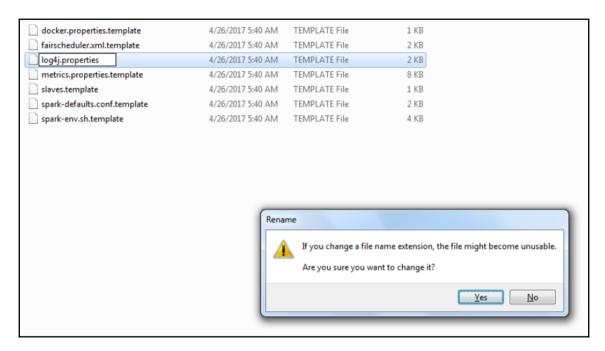
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RARLAB	WinRAR and RAR archiver downloads			
Home				
RAR	Latest English WinRAR and RAR beta versions			
	Software name	User interface	License	Size
News	WinRAR x86 (32 bit) 5.50 beta 3	Graphical and command line	Trial	1947 F
Themes	WinRAR x64 (64 bit) 5.50 beta 3	Graphical and command line	Trial	2162 F
Extras	RAR 5.50 beta 3 for Linux	Command line only	Trial	531 K
Downloads	RAR 5.50 beta 3 for Linux x64	Command line only	Trial	521 k
	RAR 5.50 beta 3 for FreeBSD	Command line only	Trial	920 K
Dealers	RAR 5.50 beta 3 for Mac OS X	Command line only	Trial	499 K
eedback				
Partnership	Latest localized WinRAR beta versions			
mprint	Language		Version	Size
Other	Arabic (32 bit)		5.50 beta 3	1993 K
uner	Arabic (64 bit)		5.50 beta 3	2209 K
	Armenian (32 bit)		5.50 beta 3	1989 F
	Armenian (64 bit)		5.50 beta 3	2204 k
	Chinese Traditional (32 bit)		5.50 beta 3	2192 K
	Chinese Traditional (64 bit)		5.50 beta 3	2413 K
	English (32 bit)		5.50 beta 3	1947 K
	English (64 bit)		5.50 beta 3	2162 K
	Finnish (32 bit)		5.50 beta 3	1989 K
	Finnish (64 bit)		5.50 beta 3 5.50 beta 3	2206 K
	French (32 bit) French (64 bit)		5.50 beta 3	2044 K
	German (32 bit)		5.50 beta 3	
	German (64 bit)		5.50 beta 3	2293 k
	Hungarian (32 bit)		5.50 beta 3	1987 K
	Hungarian (64 bit)		5.50 beta 3	
	Lithuanian (32 bit)		5.50 beta 3	2014 K
	Lithuanian (64 bit)		5.50 beta 3	2232 K
	Mongolian (32 bit)		5.50 beta 2	
	Mongolian (64 bit)		5.50 beta 2	
	Portuguese (32 bit)		5.50 beta 3	1988 K
	Portuguese (64 bit)		5.50 beta 3	
	Portuguese Brazilian (32 bit)		5.50 beta 3	3444 K
	Portuguese Brazilian (64 bit)		5.50 beta 3	3669 K
	Romanian (32 bit)		5.50 beta 2	
	Romanian (64 bit)		5.50 beta 2	2240 K
	Russian (32 bit)		5.50 beta 3	2094 K
	Russian (64 bit)		5.50 beta 3	
	Serbian Cyrillic (32 bit)		5.50 beta 3	2027 K
	Serbian Cyrillic (64 bit)		5.50 beta 3	2243 k
	Swedish (32 bit)		5.50 beta 3	1988 K
	Swedish (64 bit)		5.50 beta 3	2204 K
	Ukrainian (32 bit)		5.50 beta 3	1990 k
	Ukrainian (64 bit)		5.50 beta 3	2209 K



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	6/1/2017 6:42 PM	File folder	
📗 data	6/1/2017 6:42 PM	File folder	
examples	6/1/2017 6:42 PM	File folder	
📗 jars	6/1/2017 6:42 PM	File folder	
licenses	6/1/2017 6:42 PM	File folder	
\mu python	6/1/2017 6:42 PM	File folder	
〗 R	6/1/2017 6:42 PM	File folder	
📗 sbin	6/1/2017 6:42 PM	File folder	
퉱 yarn	6/1/2017 6:42 PM	File folder	
LICENSE	4/26/2017 5:40 AM	File	18 KB
NOTICE	4/26/2017 5:40 AM	File	25 KB
RELEASE	4/26/2017 5:40 AM	File	1 KB



log4j.properties.template 4/26/20 metrics.properties.template 4/26/20	017 5:40 AM TEMPLATE File 017 5:40 AM TEMPLATE File 017 5:40 AM TEMPLATE File	2 KB 2 KB 8 KB
metrics.properties.template 4/26/20	017 5:40 AM TEMPLATE File	
		8 KB
slaves.template 4/26/20	AT E-40 ANA TENADI ATE EIL-	
	017 5:40 AM TEMPLATE File	1 KB
spark-defaults.conf.template 4/26/20	017 5:40 AM TEMPLATE File	2 KB
spark-env.sh.template 4/26/20	017 5:40 AM TEMPLATE File	4 KB

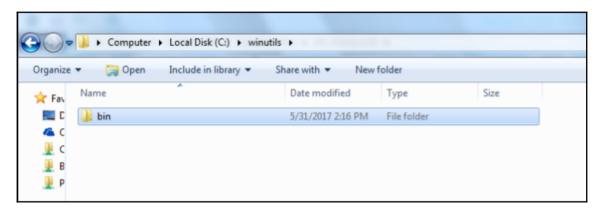


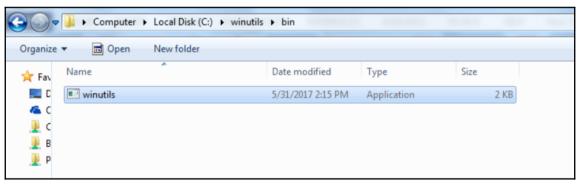
18	# Set everything to be logged to the console
19	log4j.rootCategory=INFO, console
20	log4j.appender.console=org.apache.log4j.ConsoleAppender
21	log4j.appender.console.target=System.err
22	log4j.appender.console.layout=org.apache.log4j.PatternLayout
23	log4j.appender.console.layout.ConversionPattern=%d{yy/MM/dd HH:mm:ss} %p %c{1}: %m%n

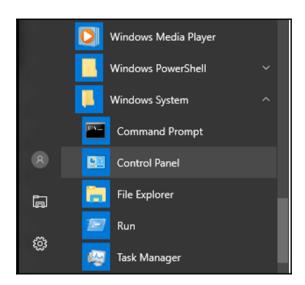
http://media.sundog-soft.com/winutils.exe
http://media.sundog-soft.com/winutils.exe
http://media.sundog-soft.com/winutils.exe - Google Search

Z ZA_Connect	5/31/2017 1:14 PM	Application	477 KB
Z ZA_Connect (2)	5/31/2017 4:44 PM	Application	477 KB
ZA_Connect (1)	5/31/2017 4:34 PM	Application	477 KB
winzip21	3/29/2017 6:36 PM	Application	2 KB
winutils	5/31/2017 2:15 PM	Application	2 KB
winrar-x64-55b3	5/31/2017 1:05 PM	Application	2 KB

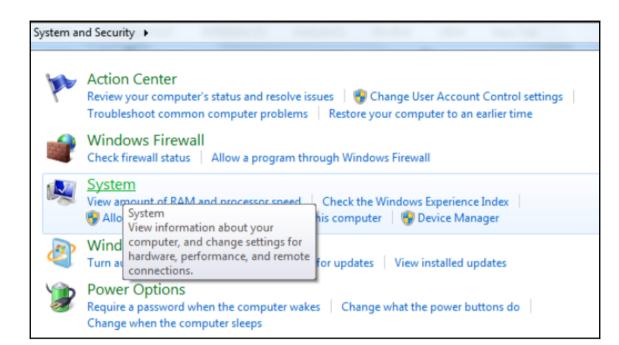




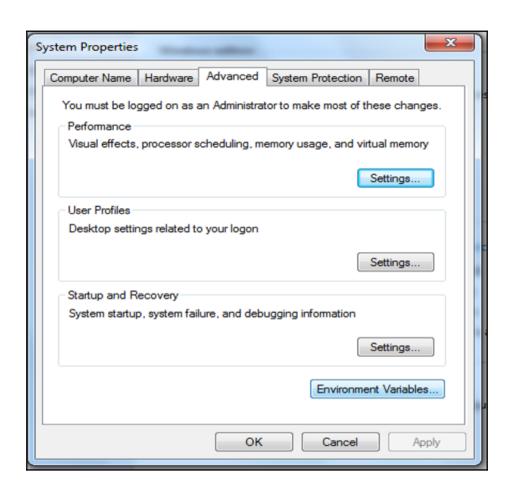


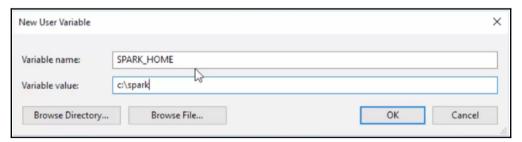




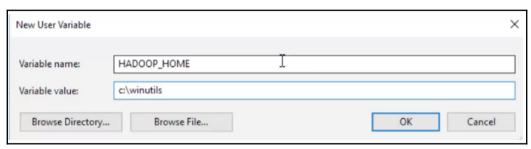


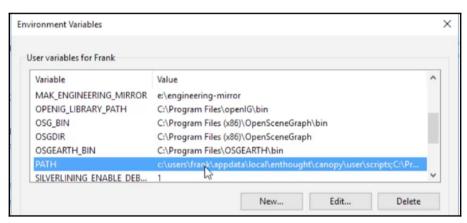


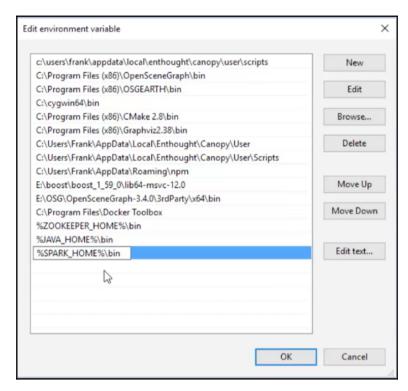


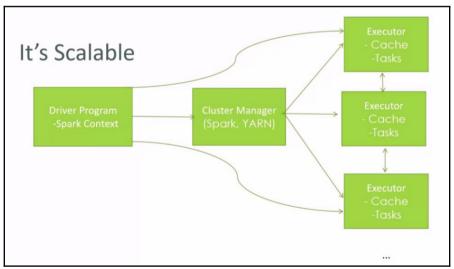


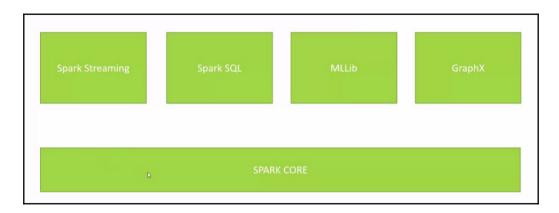












Python code to square numbers in a data set:

nums = sc.parallelize([1, 2, 3, 4]) squared = nums.map(lambda x: x * x).collect()

Scala code to square numbers in a data set:

val nums = sc.parallelize(List(1, 2, 3, 4)) val squared = nums.map(x => x * x).collect()

```
parkDecisionTree.py
  1 from pyspark.mllib.regression import LabeledPoint
 2 from pyspark.mllib.tree import DecisionTree
  3 from pyspark import SparkConf, SparkContext
 4 from numpy import array
 6 # Boilerplate Spark stuff:
 7 conf = SparkConf().setMaster("local").setAppName("SparkDecisionTree")
 8 sc = SparkContext(conf = conf)
 9
10 # Some functions that convert our CSV input data into numerical
11 # features for each job candidate
12 def binary(YN):
       if (YN == 'Y'):
13
14
           return 1
15
       else:
                                                   Ι
16
           return 0
17
18 def mapEducation(degree):
19
       if (degree == 'BS'):
20
           return 1
21
       elif (degree =='MS'):
22
           return 2
23
       elif (degree == 'PhD'):
24
           return 3
25
       else:
26
           return 0
27
```

```
parkDecisionTree.py
  1 from pyspark.mllib.regression import LabeledPoint
 2 from pyspark.mllib.tree import DecisionTree
 3 from pyspark import SparkConf, SparkContext
 4 from numpy import array
 6 # Boilerplate Spark stuff:
 7 conf = SparkConf().setMaster("local").setAppName("SparkDecisionTree")
 8 sc = SparkContext(conf = conf)
10 # Some functions that convert our CSV input data into numerical
11 # features for each job candidate
12 def binary(YN):
13
       if (YN == 'Y'):
14
           return 1
15
       else:
16
           return 0
17
18 def mapEducation(degree):
19
       if (degree == 'BS'):
20
           return 1
21
       elif (degree =='MS'):
22
           return 2
23
       elif (degree == 'PhD'):
24
           return 3
25
       else:
26
           return 0
27
```

```
43 rawData = sc.textFile("e:/sundog-consult/udemy/datascience/PastHires.csv")
44 header = rawData.first()
45 rawData = rawData.filter(lambda x:x != header)
46
47 # Split each line into a list based on the comma delimiters
48 csvData = rawData.map(lambda x: x.split(","))
49
50 # Convert these lists to LabeledPoints
51 trainingData = csvData.map(createLabeledPoints)
52
53 # Create a test candidate, with 10 years of experience, currently employed,
54 # 3 previous employers, a BS degree, but from a non-top-tier school where
55 # he or she did not do an internship. You could of course load up a whole
56 # huge RDD of test candidates from disk, too.
57 testCandidates = [ array([10, 1, 3, 1, 0, 0])]
58 testData = sc.parallelize(testCandidates)
```

	Α	В	C	D	E	F	G
1	Years Exp	Employed	Previous 6	Level of E	Top-tier s	Interned	Hired
2	10	Υ	4	BS	N	N	Υ
3	0	N	0	BS	Υ	Υ	Υ
4	7	N	6	BS	N	N	N
5	2	Υ	1	MS	Υ	N	Υ
6	20	N	2	PhD	Υ	N	N
7	0	N	0	PhD	Υ	Υ	Υ
8	5	Υ	2	MS	N C	Υ	Υ
9	3	N	1	BS	N	Υ	Υ
10	15	Υ	5	BS	N	N	Υ
11	0	N	0	BS	N	N	N
12	1	N	1	PhD	Υ	N	N
13	4	Υ	1	BS	N	Υ	Υ
14	0	N	0	PhD	Υ	N	Υ

	A	В	C	D	E	F	G
1	Years Exp	Employed	Previous e	Level of E	Top-tier s	Interned	Hired
2	10	Υ	4	BS	N	N	Υ
3	0	N	0	BS	Υ	Υ	Υ

```
Hire prediction:

1.0

Learned classification tree model:

DecisionTreeModel classifier of depth 4 with 9 nodes

If (feature 1 in {0.0})

If (feature 5 in {0.0})

If (feature 3 in {1.0})

Predict: 0.0

Else (feature 3 not in {1.0})

Predict: 1.0

Else (feature 0 > 0.0)

Predict: 0.0

Else (feature 1 not in {0.0})

Predict: 1.0

Else (feature 5 not in {0.0})

Predict: 1.0

Else (feature 1 not in {0.0})
```

```
Hire prediction:
                                                                                 1 Years Exp Employed Previous Level of E Top-tier s Interned Hired
Learned classification tree model:
DecisionTreeModel classifier of depth 4 with 9 nodes
If (feature 1 in {0.0})
                                                                                          10 Y
                                                                                                             4 RS
                                                                                                                        N
                                                                                                             0 BS
                                                                                           0 N
    If (feature 5 in {0.0})

If (feature 0 <= 0.0)

If (feature 3 in {1.0})
                                                                                           7 N
                                                                                                             6 BS
                                                                                                                                           N
                                                                                                             1 MS
                                                                                           2 Y
                                                                                                                                 N
                                                                                          20 N
                                                                                                             2 PhD
                                                                                                                                 N
                                                                                                                                          N
                                                                                           0 N
                                                                                                             0 PhD
        Predict: 0.0
       Else (feature 3 not in {1.0})
Predict: 1.0
                                                                                                             2 MS
                                                                                           5 Y
                                                                                                                        N
                                                                                                                           ¢
                                                                                           3 N
                                                                                                             1 BS
                                                                                                                        N
      Else (feature 0 > 0.0)
                                                                                 10
                                                                                          15 Y
                                                                                                             5 BS
                                                                                                                        N
       Predict: 0.0
                                                                                           0 N
                                                                                                             0 BS
                                                                                                                        N
                                                                                                                                 N
                                                                                                                                          N
    Else (feature 5 not in {0.0})
                                                                                                             1 PhD
                                                                                           1 N
                                                                                                                                          Ν
      Predict: 1.0
                                                                                 13
                                                                                           4 Y
                                                                                                             1 BS
                                                                                                                        Ν
   Else (feature 1 not in {0.0})
Predict: 1.0
                                                                                 14
                                                                                                             0 PhD
                                                                                           0 N
```

```
7K = 5
 8
9 # Boilerplate Spark stuff:
10 conf = SparkConf().setMaster("local").setAppName("SparkKMeans")
11 sc = SparkContext(conf = conf)
12
13 #Create fake income/age clusters for N people in k clusters
14 def createClusteredData(N, k):
15
      random.seed(10)
16
      pointsPerCluster = float(N)/k
                                            0
17
      X = []
18
      for i in range (k):
19
          incomeCentroid = random.uniform(20000.0, 200000.0)
20
          ageCentroid = random.uniform(20.0, 70.0)
21
          for j in range(int(pointsPerCluster)):
              X.append([random.normal(incomeCentroid, 10000.0), random.normal(ageCentroid, 2.0)])
22
23
      X = array(X)
```

```
ile Edit View Search Run Tools Window Help
TF-IDF.py 🔯
  1 from pyspark import SparkConf, SparkContext
  2 from pyspark.mllib.feature import HashingTF
  3 from pyspark.mllib.feature import IDF
  5 # Boilerplate Spark stuff:
  6 conf = SparkConf().setMaster("local").setAppName("SparkTFIDF")
  7 sc = SparkContext(conf = conf)
  9 # Load documents (one per line).
 10 rawData = sc.textFile("e:/sundog-consult/Udemy/DataScience/subset-small.tsv")
 11 fields = rawData.map(lambda x: x.split("\t"))
 12 documents = fields.map(lambda x: x[3].split(" "))
13
 14 # Store the document names for later:
 15 documentNames = fields.map(lambda x: x[1])
 17 # Now hash the words in each document to their term frequencies:
 18 hashingTF = HashingTF(100000) #100K hash buckets just to save some memory
 19 tf = hashingTF.transform(documents)
 20
 21 # At this point we have an RDD of sparse vectors representing each document,
 22 # where each value maps to the term frequency of each unique hash value.
 24 # Let's compute the TF*IDF of each term in each document:
 25 tf.cache()
 26 idf = IDF(minDocFreq=2).fit(tf)
 27 tfidf = idf.transform(tf)
```

Best document for Gettysburg is: (29.777067781559442, u'Abraham Lincoln')

```
1 from __future__ import print_function
   3 from pyspark.ml.regression import LinearRegression
   5 from pyspark.sql import SparkSession
  6 from pyspark.ml.linalg import Vectors
        # Create a SparkSession (Note, the config section is only for Windows!)
spark = SparkSession.builder.config("spark.sql.warehouse.dir", "file://C:/temp").appName("LinearRegression").getOrCreate()
  11
  12
  13
         # Load up our data and convert it to the format MLLib expects.
        inputLines = spark.sparkContext.textFile("regression.txt")
        data = inputLines.map(lambda x: x.split(",")).map(lambda x: (float(x[0]), Vectors.dense(float(x[1]))))
        # Convert this RDD to a DataFrame
colNames = ["label", "features"]
  18
  19
        df = data.toDF(colNames)
  20
  21
         # Note, there are lots of cases where you can avoid going from an RDD to a DataFrame.
         # Perhaps you're importing data from a real database. Or you are using structured streaming
                                                                                                                                             C/Jan Pr
```

```
(0.8643234408131227,
(0.9571202568137612,
(0.9428438235828938, 1.34)
(1.0499170728143994, 1.36)
(0.9571202568137612, 1.38)
(1.057055289429833, 1.41)
(0.9142909571211588, 1.44)
(0.9285673903520263, 1.47)
1.1212992389687366,
(0.8928763072748577,
(1.2569253546619772, 1.53)
(1.135575672199604, 1.53)
(1.1070228057378693, 1.53)
(1.2355107048156762, 1.54)
(1.1498521054304716, 1.55)
  164128538661339, 1.56)
  135575672199604, 1.59)
   1784049718922063, 1.61)
   392551470355218, 1.78)
1.214096054969375, 1.8)
(1.264063571277411, 1.82)
(1.342583954047182, 1.86)
1.4924865029712902, 2.09)
```

Chapter 10: Testing and Experimental Design

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- . 3 months of technical support and maintenance
- . A personalized ficense code to untock our trial SDK's for your project.

Out[1]: Ttest indResult(statistic=-14.075196812141339, pvalue=8.8277957363196977e-45)

Out[2]: Ttest indResult(statistic=0.088886198511817435, pvalue=0.92917324220169051)

Out[6]: Ttest indResult(statistic=0.20964627681745385, pvalue=0.83394397202032966)

Out[9]: Ttest indResult(statistic=-0.075342911693641518, pvalue=0.93994188742749496)

Out[10]: Ttest indResult(statistic=0.0, pvalue=1.0)