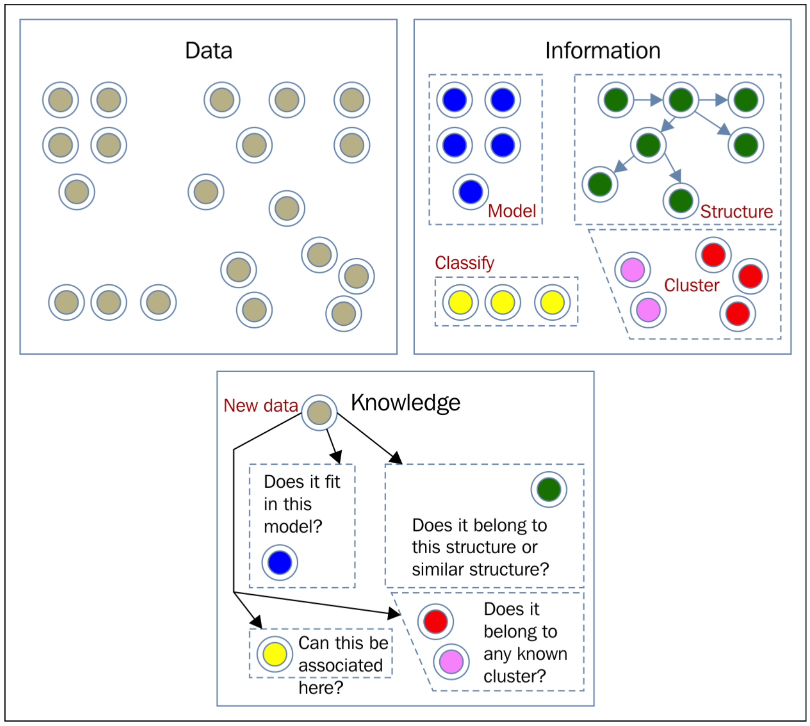
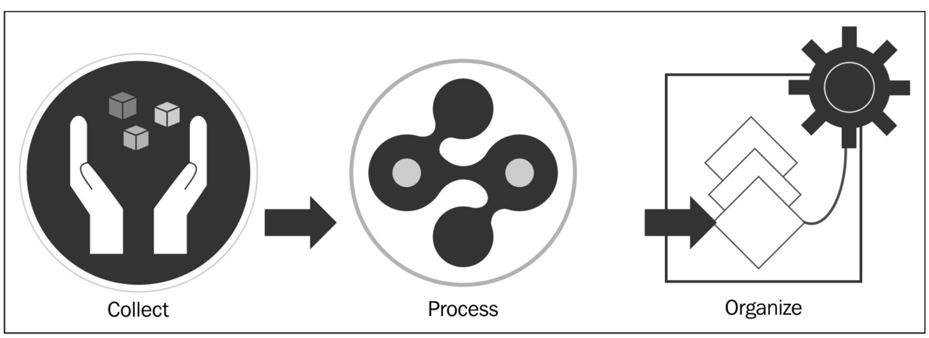
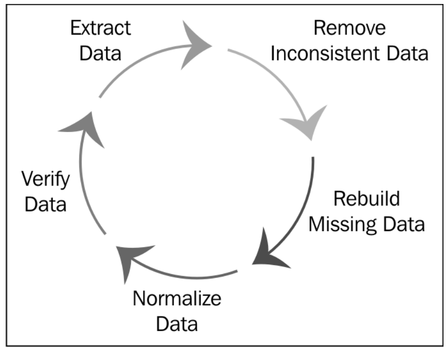
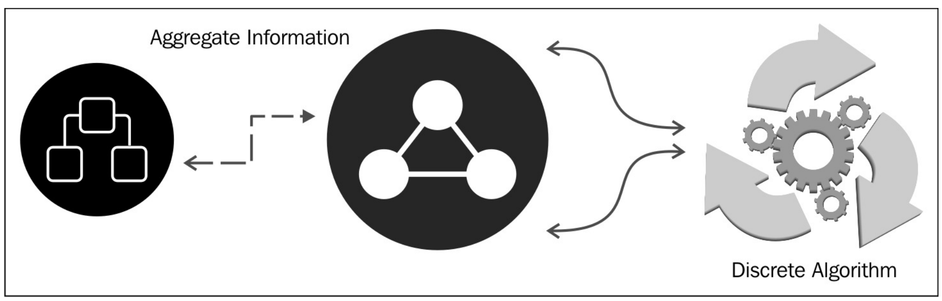
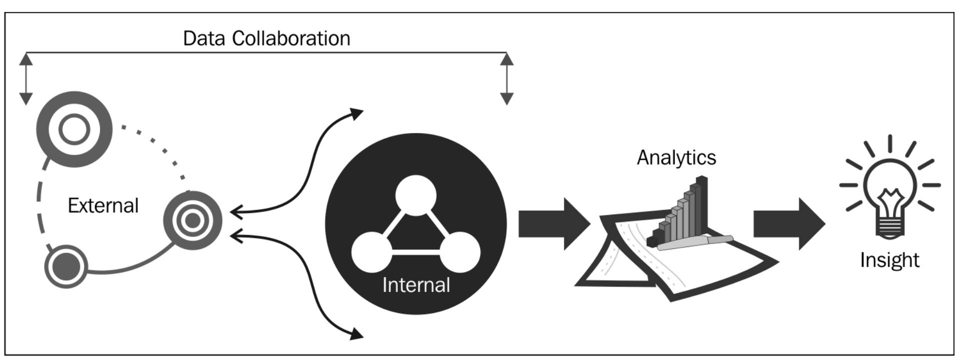
Chapter 1: A Conceptual Framework for Data Visualization

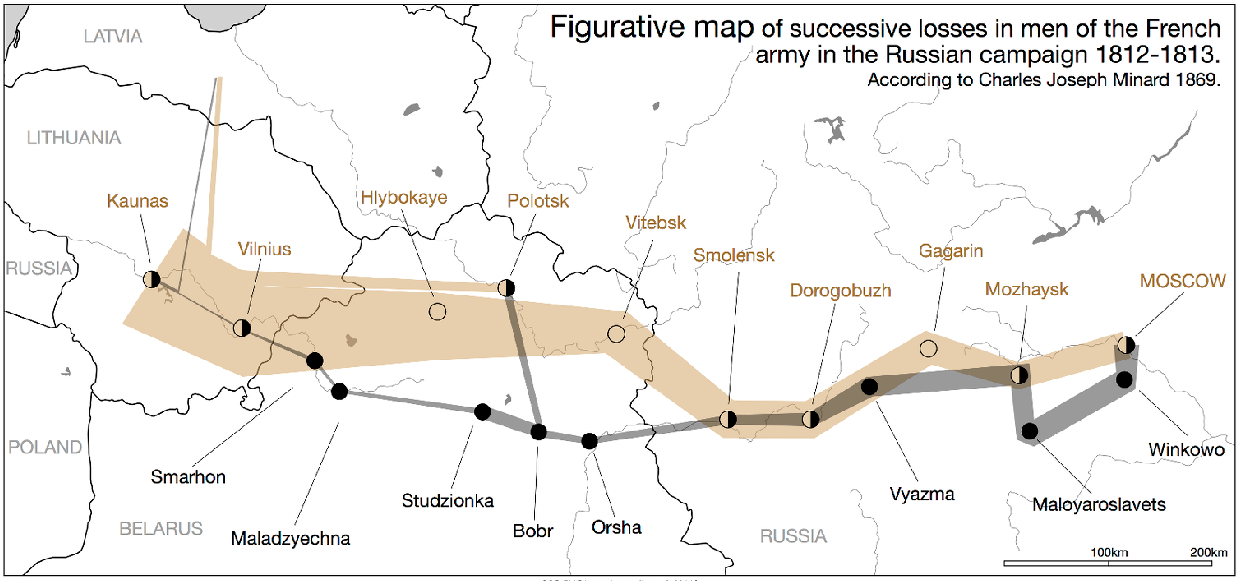


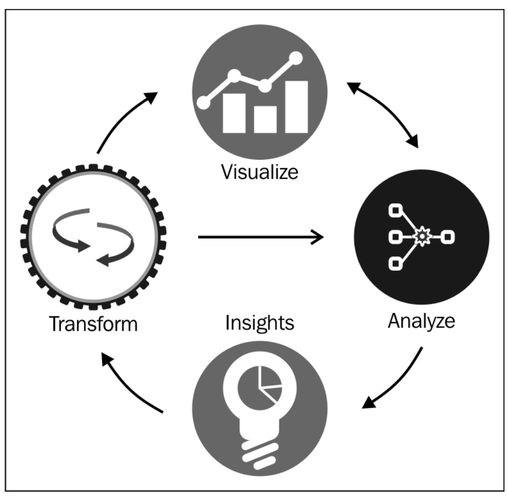


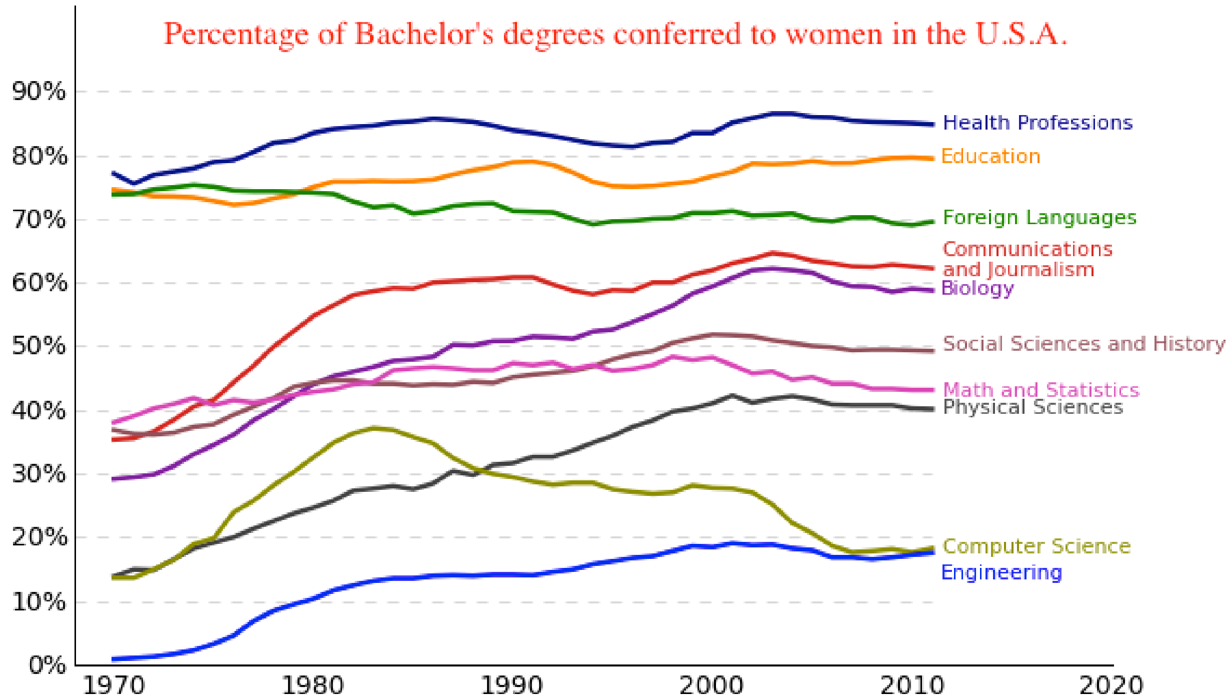

Extract
Data
Remove
Inconsistent Data
Rebuild
Missing Data
Normalize
Data
Verify
Data

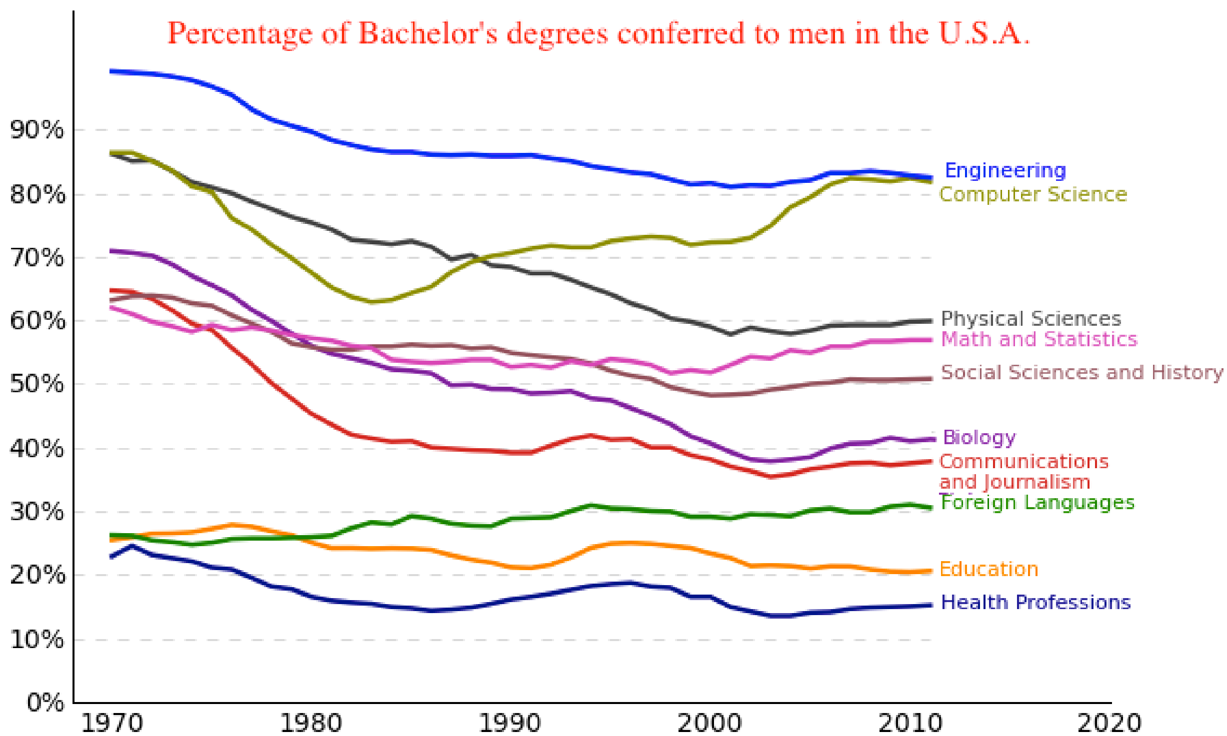

Aggregate Information
Discrete Algorithm

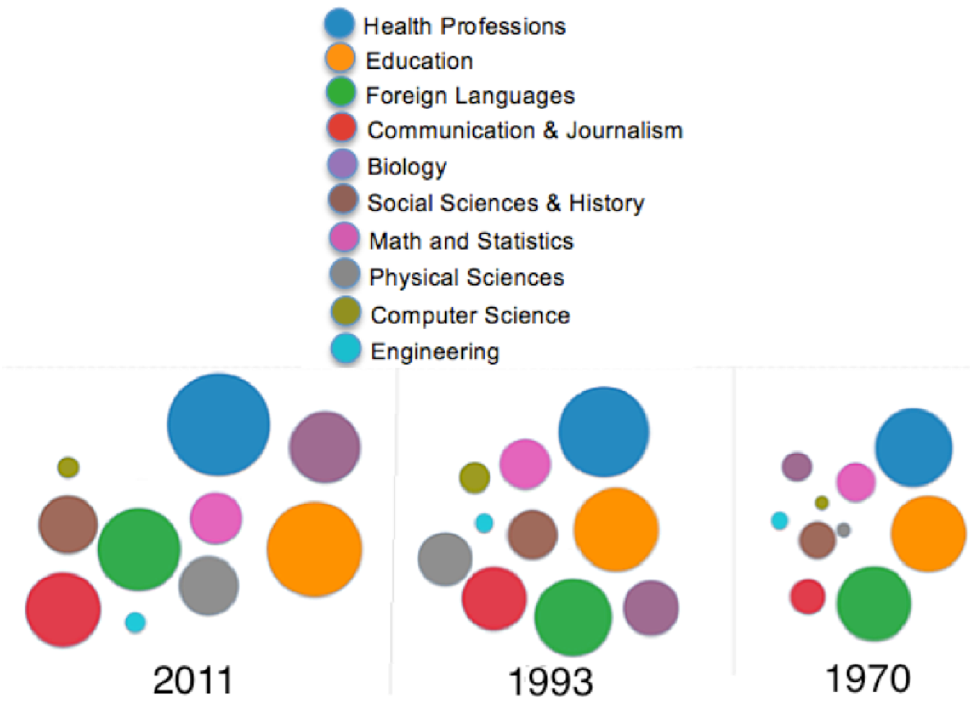

Data Collaboration
External
Internal
Analytics
Insight


Figurative map of successive losses in men of the French army in the Russian campaign 1812-1813.
According to Charles Joseph Minard 1869.
LATVIA
LITHUANIA
RUSSIA
POLAND
BELARUS
RUSSIA
Kaunas
Vilnius
Hlybokaye
Polotsk
Vitebsk
Smolensk
Dorogobuzh
Gagarin
Mozhaysk
MOSCOW
Winkowo
Maloyaroslavets
Vyazma
Orsha
Bobr
Studzionka
Maladzyechna
Smarhon
100km
200km

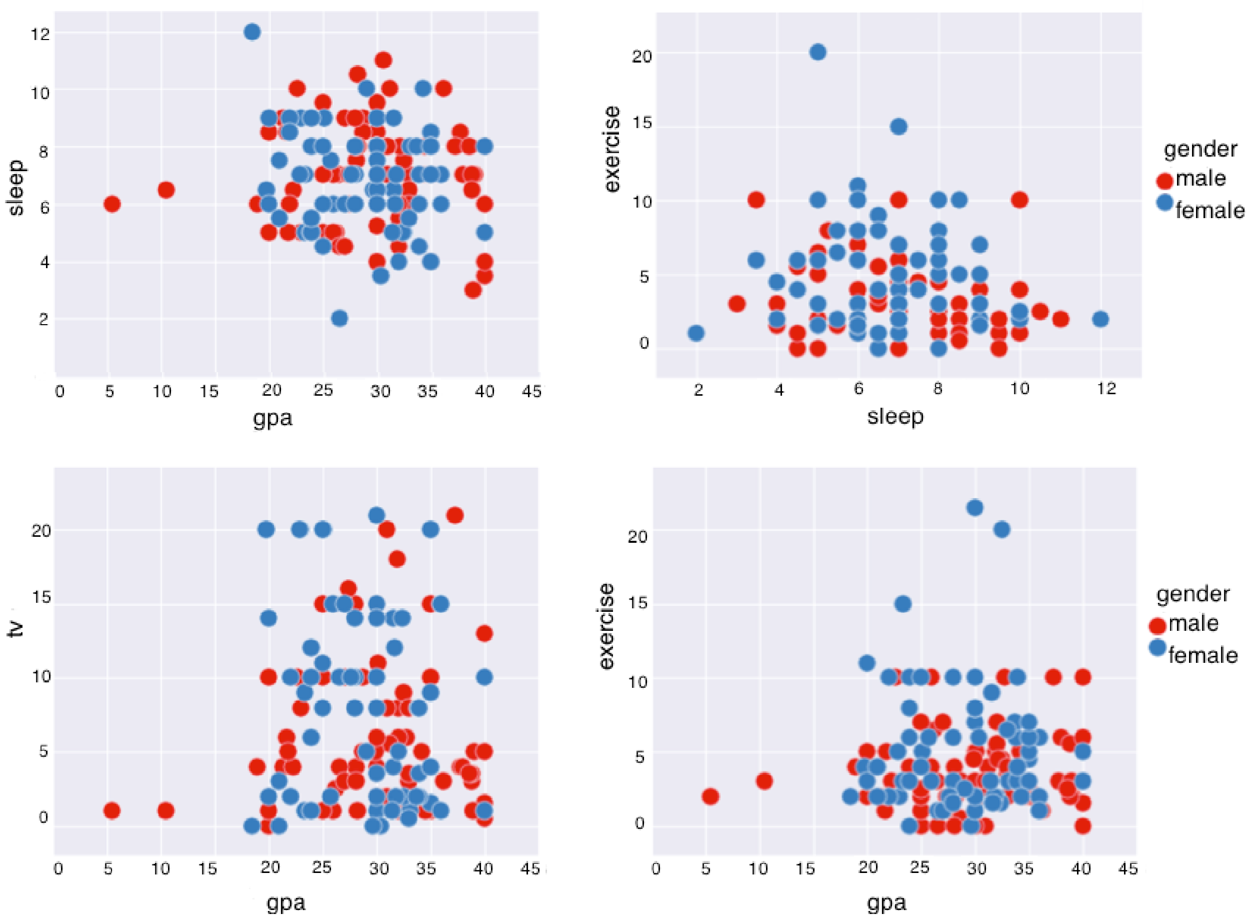

Visualize
Transform
Insights
Analyze


Percentage of Bachelor's degrees conferred to women in the U.S.A.
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1970
1980
1990
2000
2010
2020
Health Professions
Education
Foreign Languages
Communications and Journalism
Biology
Social Sciences and History
Math and Statistics
Physical Sciences
Computer Science
Engineering

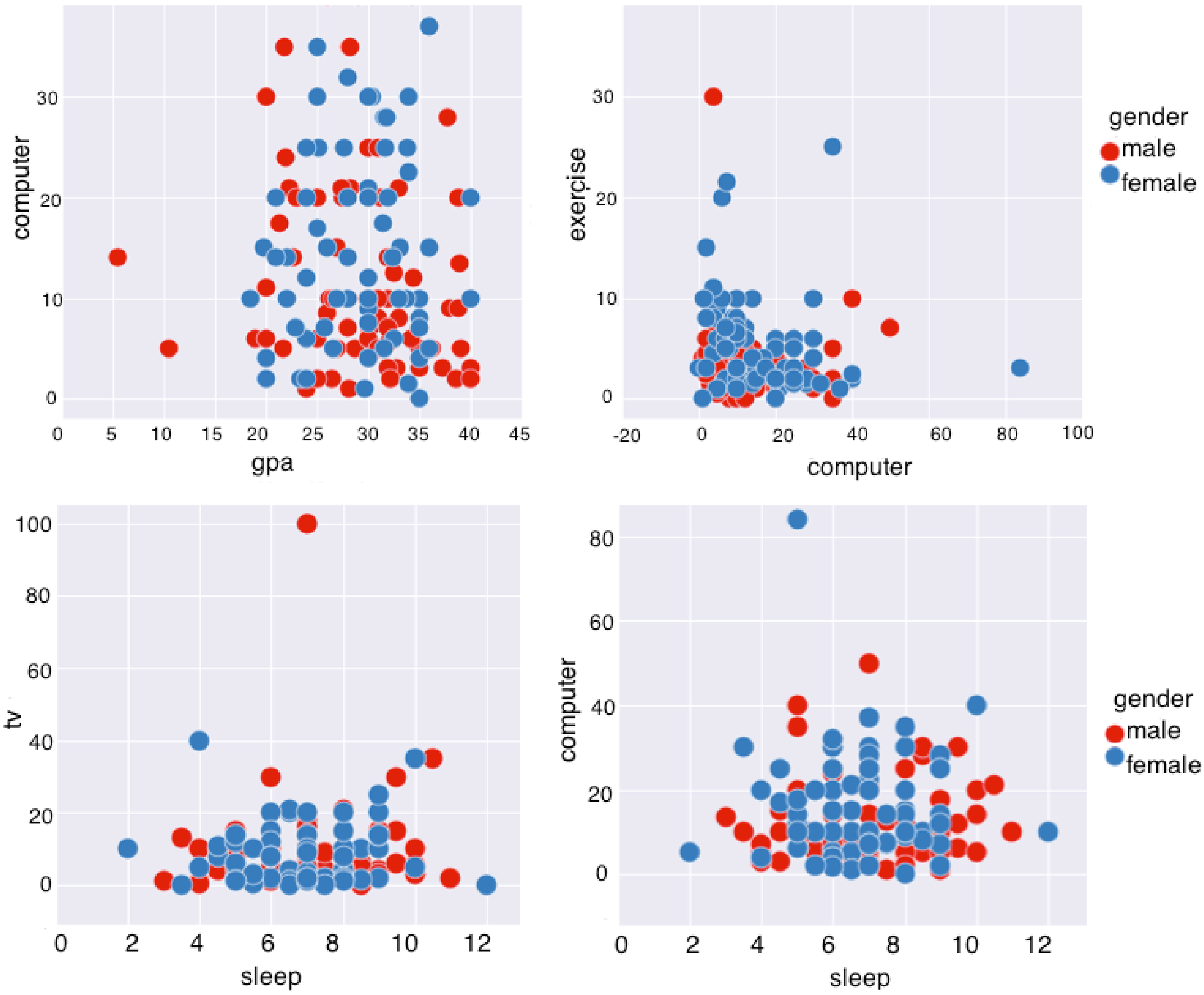

Percentage of Bachelor's degrees conferred to men in the U.S.A.
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1970
1980
1990
2000
2010
2020
Engineering
Computer Science
Physical Sciences
Math and Statistics
Social Sciences and History
Biology
Communications and Journalism
Foreign Languages
Education
Health Professions



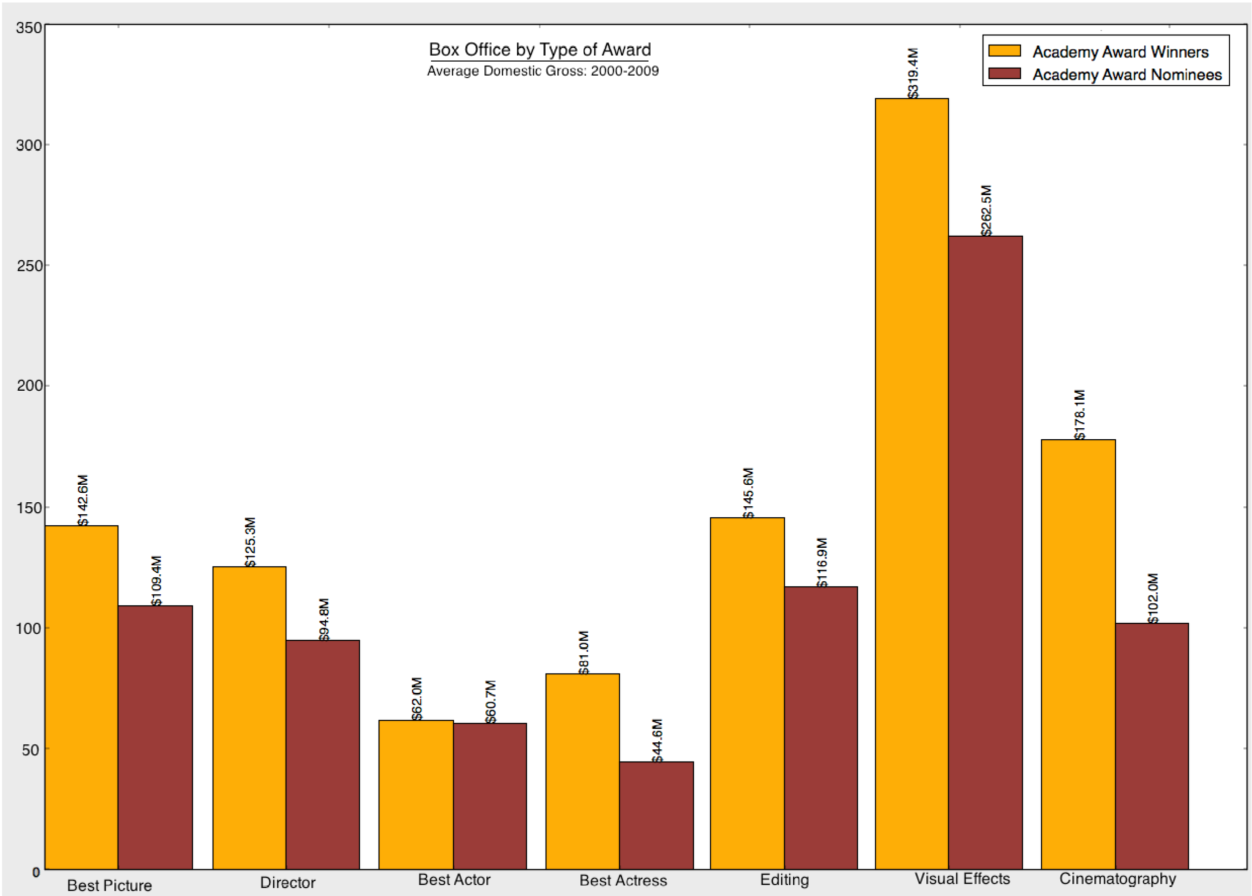
gender	tv	computer	sleep	height	momheight	dadheight	exercise	gpa
Female	13.0	10.0	3.50	66.0	66.0	71.0	10.0	4.000
Male	20.0	7.0	9.00	72.0	64.0	65.0	2.0	2.300
Male	15.0	15.0	6.00	68.0	62.0	74.0	3.0	2.600
Male	8.0	20.0	6.00	68.0	59.0	70.0	6.0	2.800
Female	2.5	10.0	5.00	64.0	65.0	70.0	6.5	2.620
Male	2.0	14.0	9.00	68.5	60.0	68.0	2.0	2.200
Female	4.0	28.0	8.50	69.0	66.0	76.0	3.0	3.780
Female	8.0	10.0	7.00	66.0	63.0	70.0	4.5	3.200
Male	1.0	15.0	8.00	70.0	68.0	71.0	3.0	3.310
Male	8.0	25.0	4.50	67.0	63.0	66.0	6.0	3.390
Male	3.5	9.0	8.00	68.0	62.0	64.0	8.0	3.000
Female	11.0	20.0	5.00	68.0	64.0	69.0	0.0	2.500
Male	10.0	14.0	8.00	68.0	61.0	72.0	10.0	2.800
Male	1.0	84.0	5.00	61.0	62.0	62.0	3.0	2.340
Female	10.0	11.0	9.00	65.0	62.0	66.0	5.0	2.000

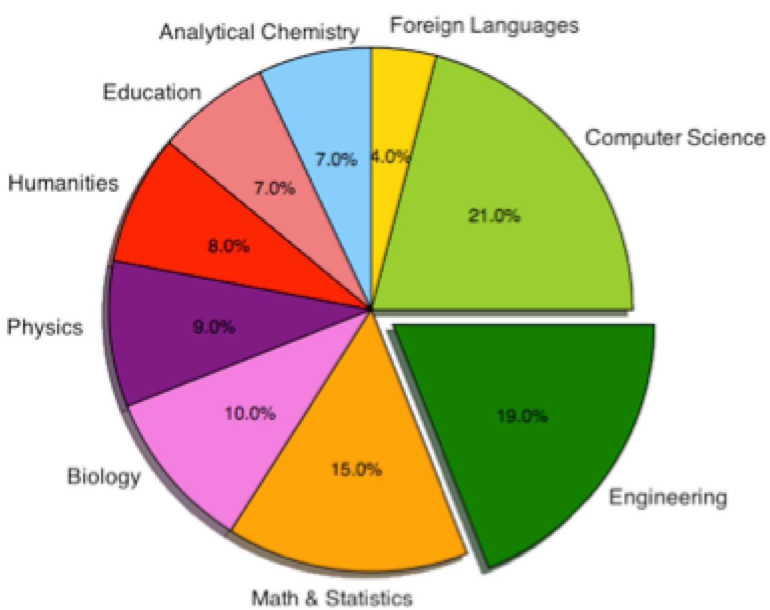


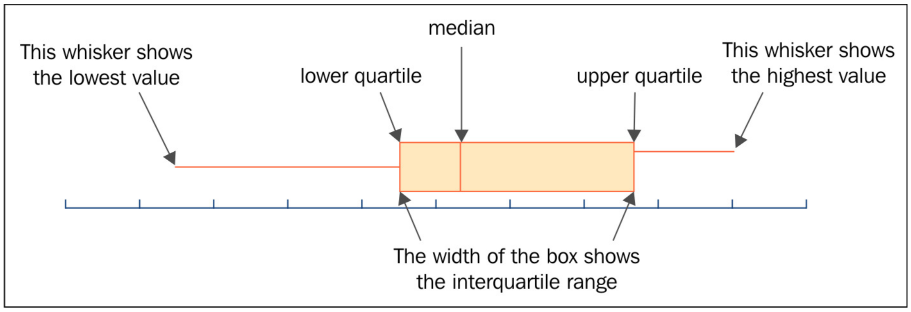
sleep
gpa
exercise
sleep
gender
male
female
tv
gpa
exercise
gpa
gender
male
female

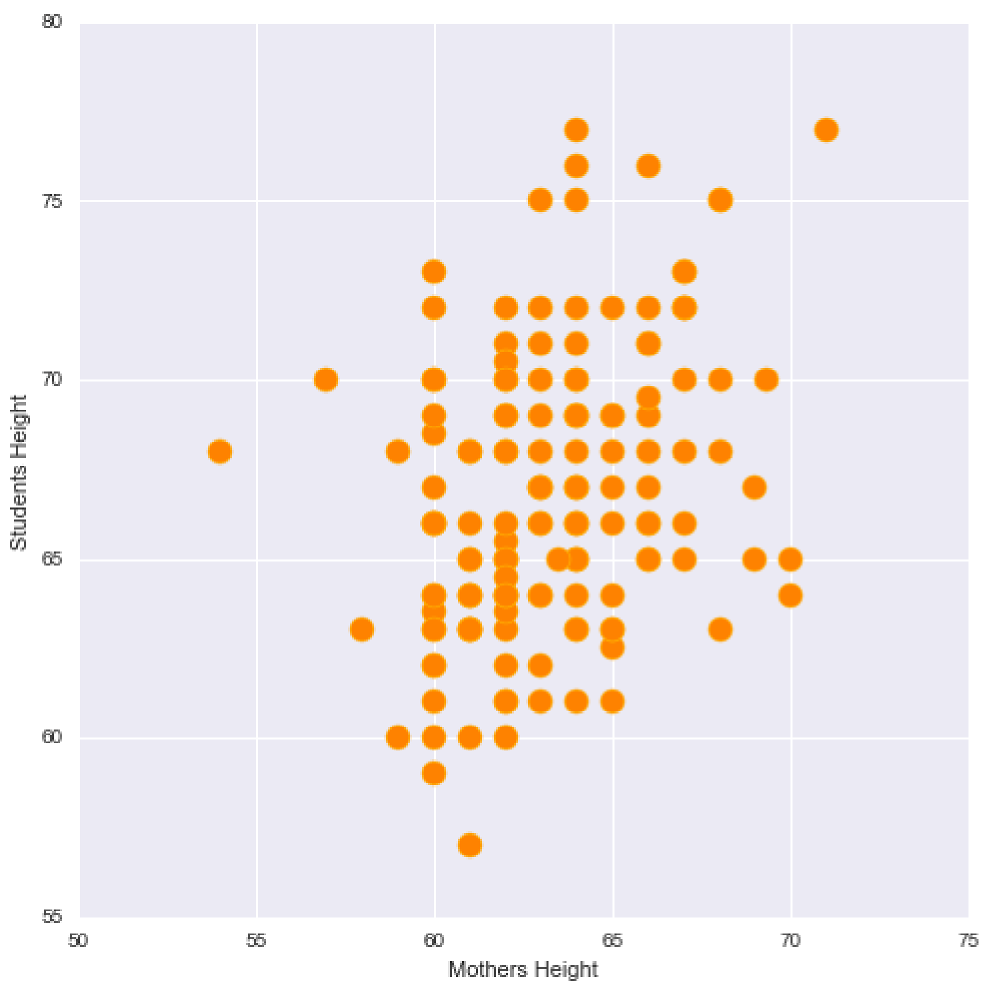


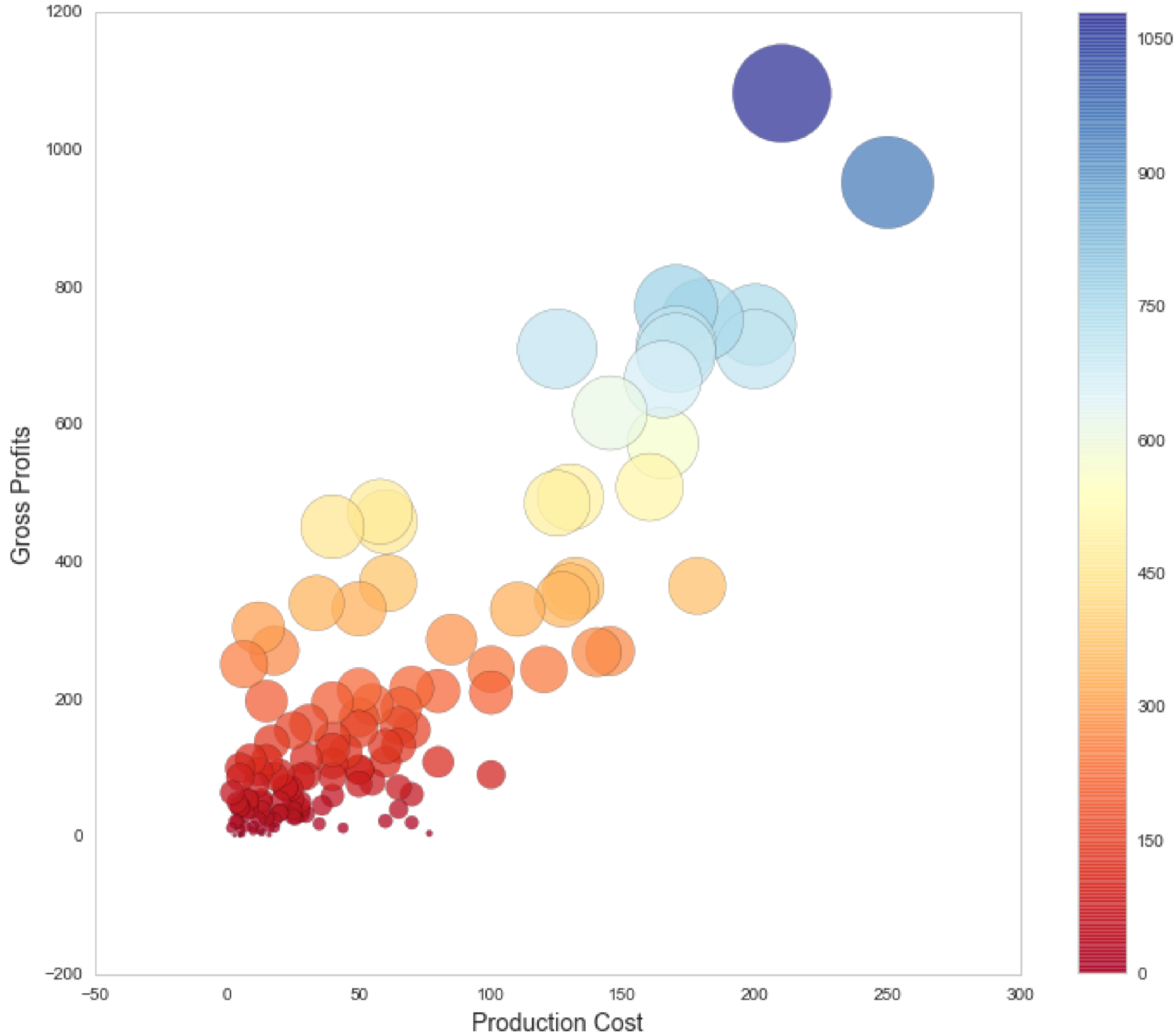
computer
gpa
0
5
10
15
20
25
30
35
40
45
30
20
10
exercise
computer
-20
60
80
100
gender
male
female
tv
sleep
2
4
6
8
12
60
80
100
computer
sleep
40


Box Office by Type of Award
Average Domestic Gross: 2000-2009
Academy Award Winners
Academy Award Nominees
350
300
250
200
150
100
50
0
$142.6M
$109.4M
$125.3M
$94.8M
$62.0M
$60.7M
$81.0M
$44.6M
$145.6M
$116.9M
$319.4M
$262.5M
$178.1M
$102.0M
Best Picture
Director
Best Actor
Best Actress
Editing
Visual Effects
Cinematography

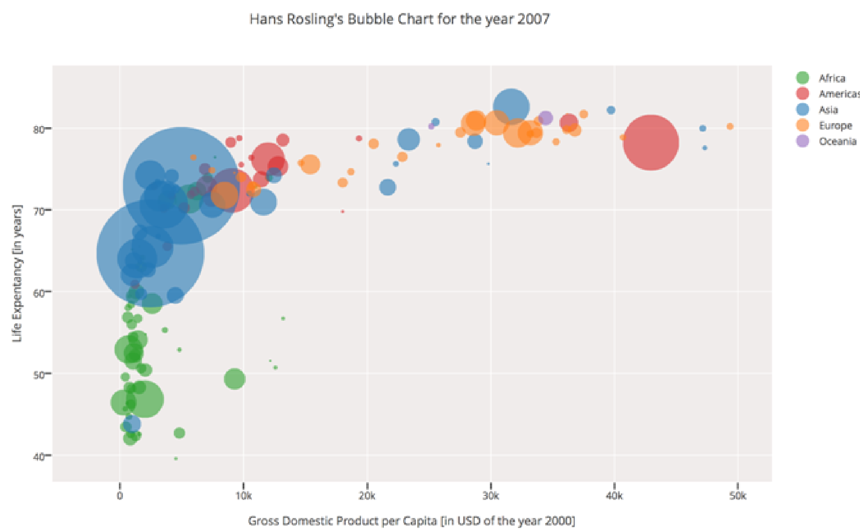

Analytical Chemistry
Foreign Languages
Education
Computer Science
Humanities
Physics
Biology
Engineering
Math & Statistics
7.0%
4.0%
7.0%
21.0%
8.0%
9.0%
10.0%
15.0%
19.0%

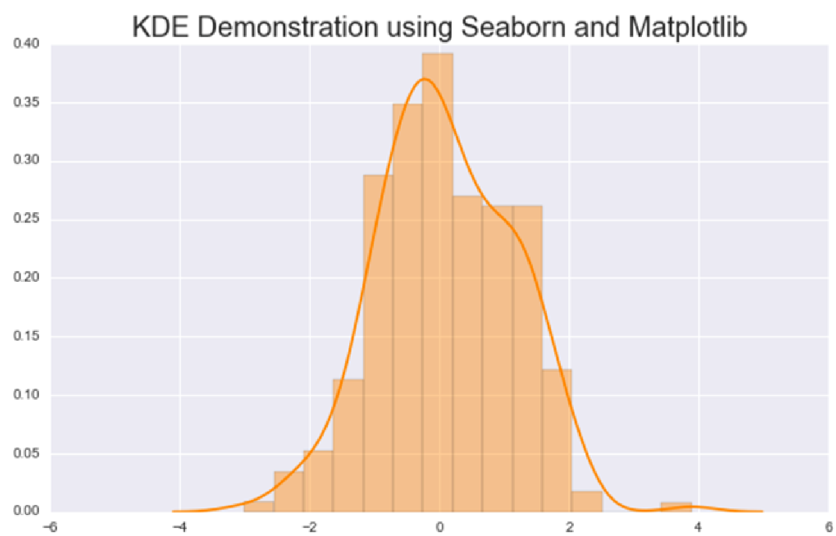

median
This whisker shows
the lowest value
lower quartile
upper quartile
This whisker shows
the highest value
The width of the box shows
the interquartile range

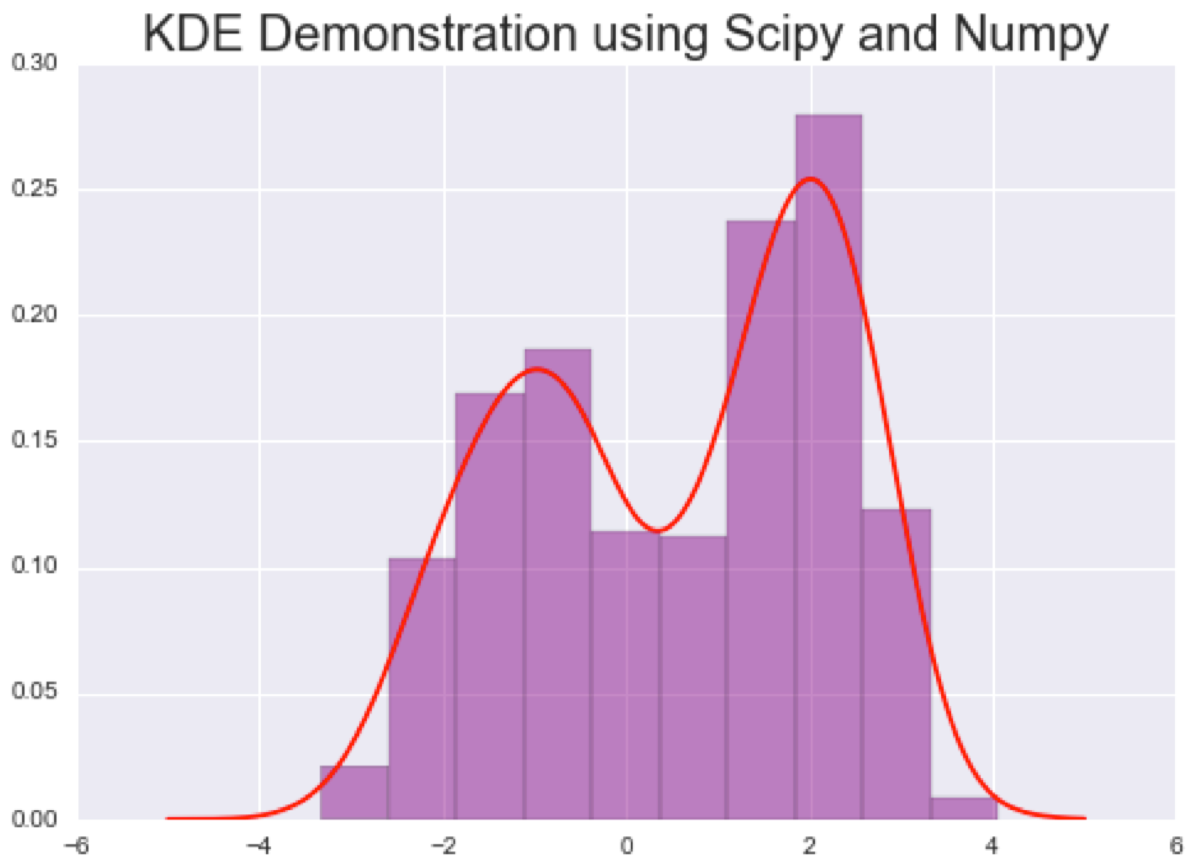

Students Height
Mothers Height
80
75
70
65
60
55
50
55
60
65
70
75



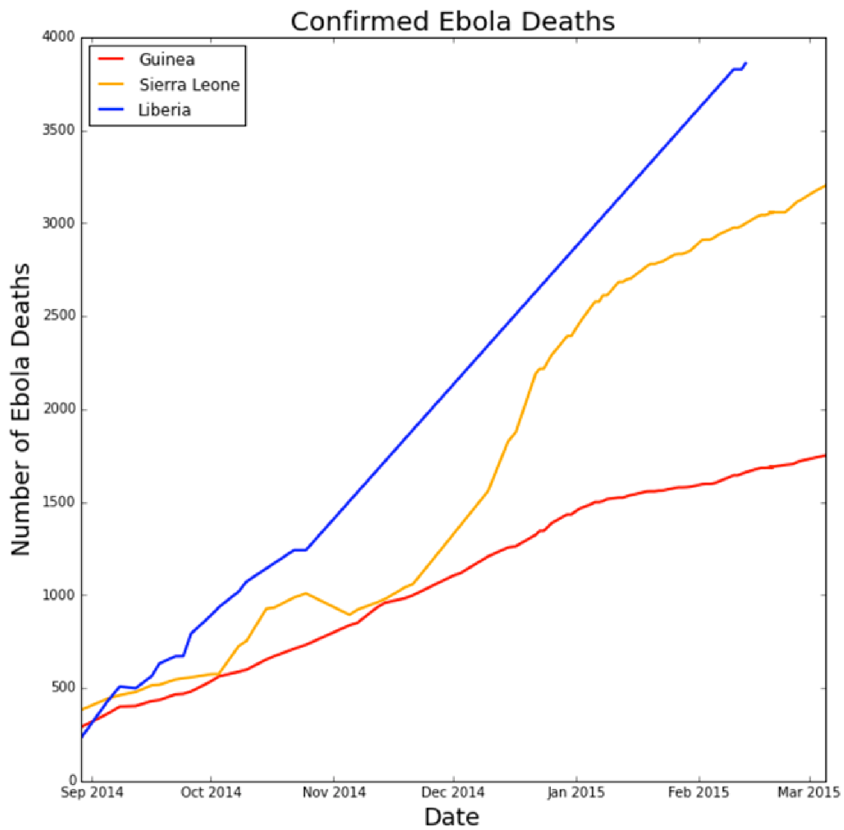
1200
1000
800
600
400
200
0
−200
Gross Profits
−50
0
50
100
150
200
250
300
Production Cost
1050
900
750
600
450
300
150
0


Hans Rosling's Bubble Chart for the year 2007
Africa
Americas
Asia
Europe
Oceania
Life Expectancy [in years]
80
70
60
50
40
0
10k
20k
30k
40k
50k
Gross Domestic Product per Capita [in USD of the year 2000]

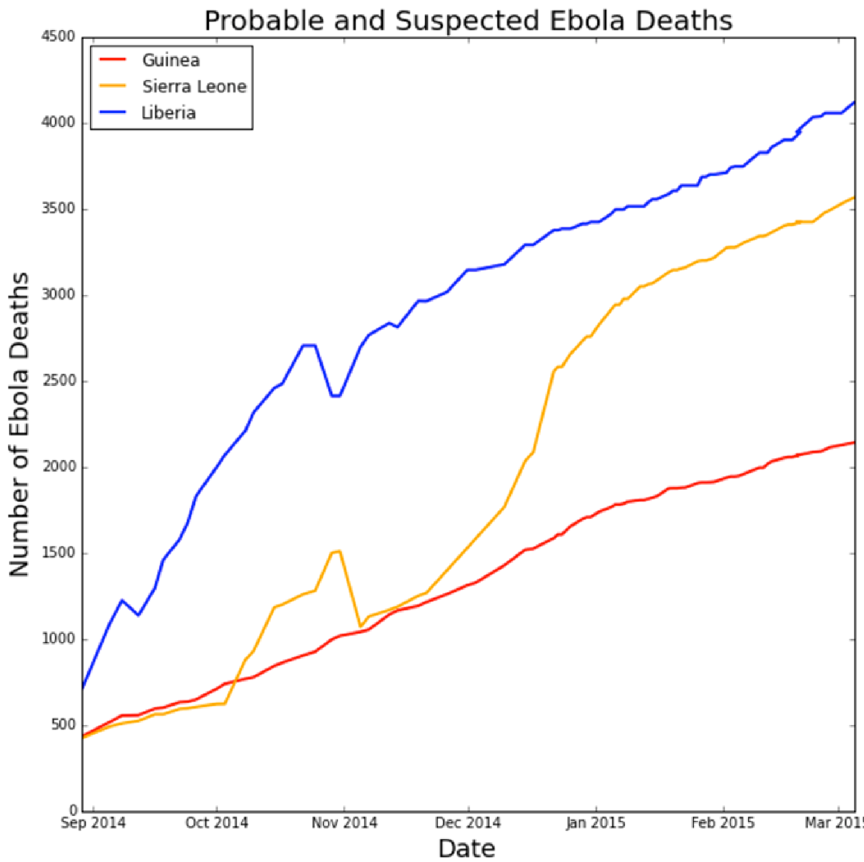

KDE Demonstration using Seaborn and Matplotlib
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−6
−4
−2
0
2
4
6



Chapter 2: Data Analysis and Visualization

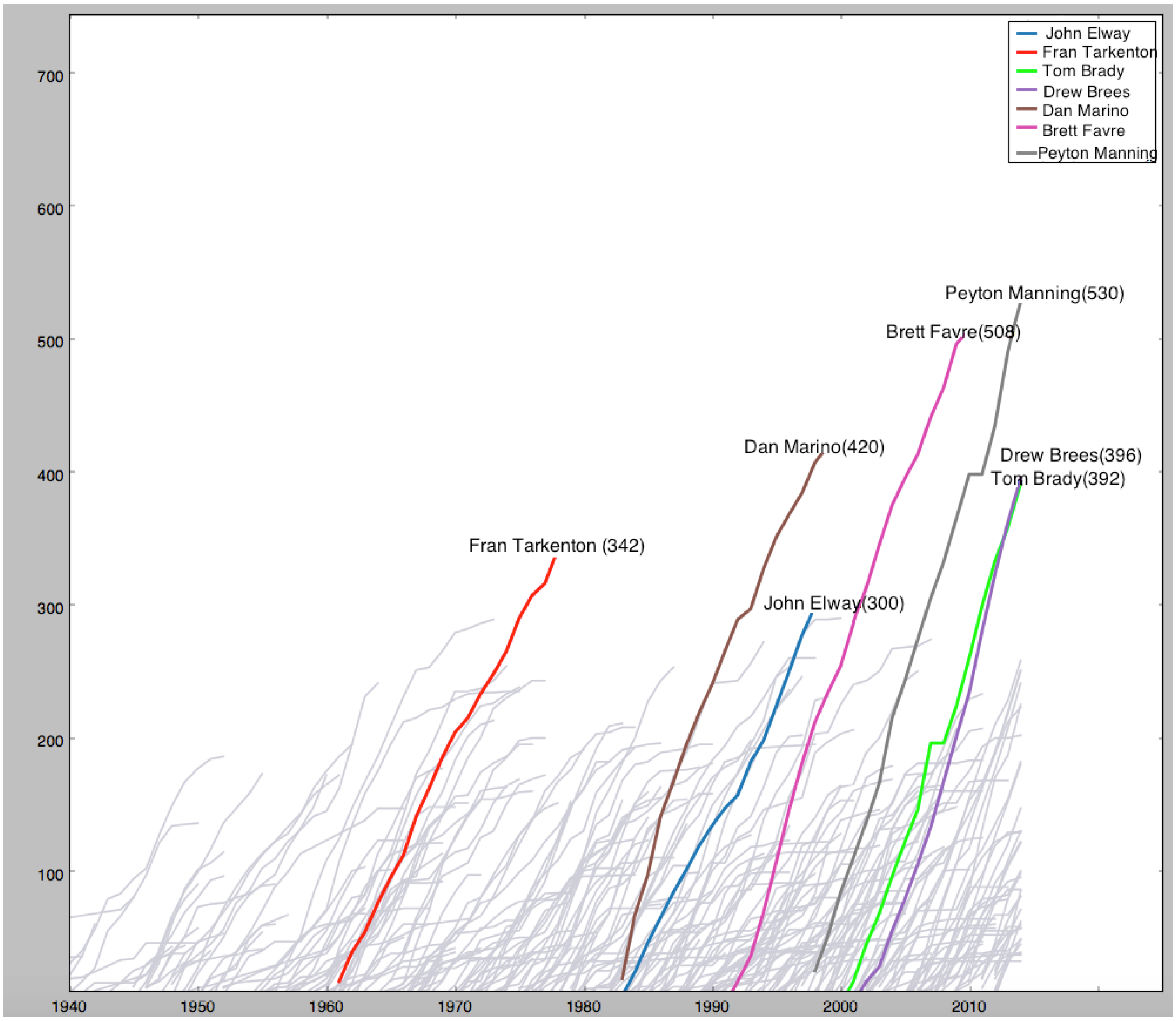


Confirmed Ebola Deaths
Guinea
Sierra Leone
Liberia
Number of Ebola Deaths
4000
3500
3000
2500
2000
1500
1000
500
0
Sep 2014
Oct 2014
Nov 2014
Dec 2014
Jan 2015
Feb 2015
Mar 2015
Date

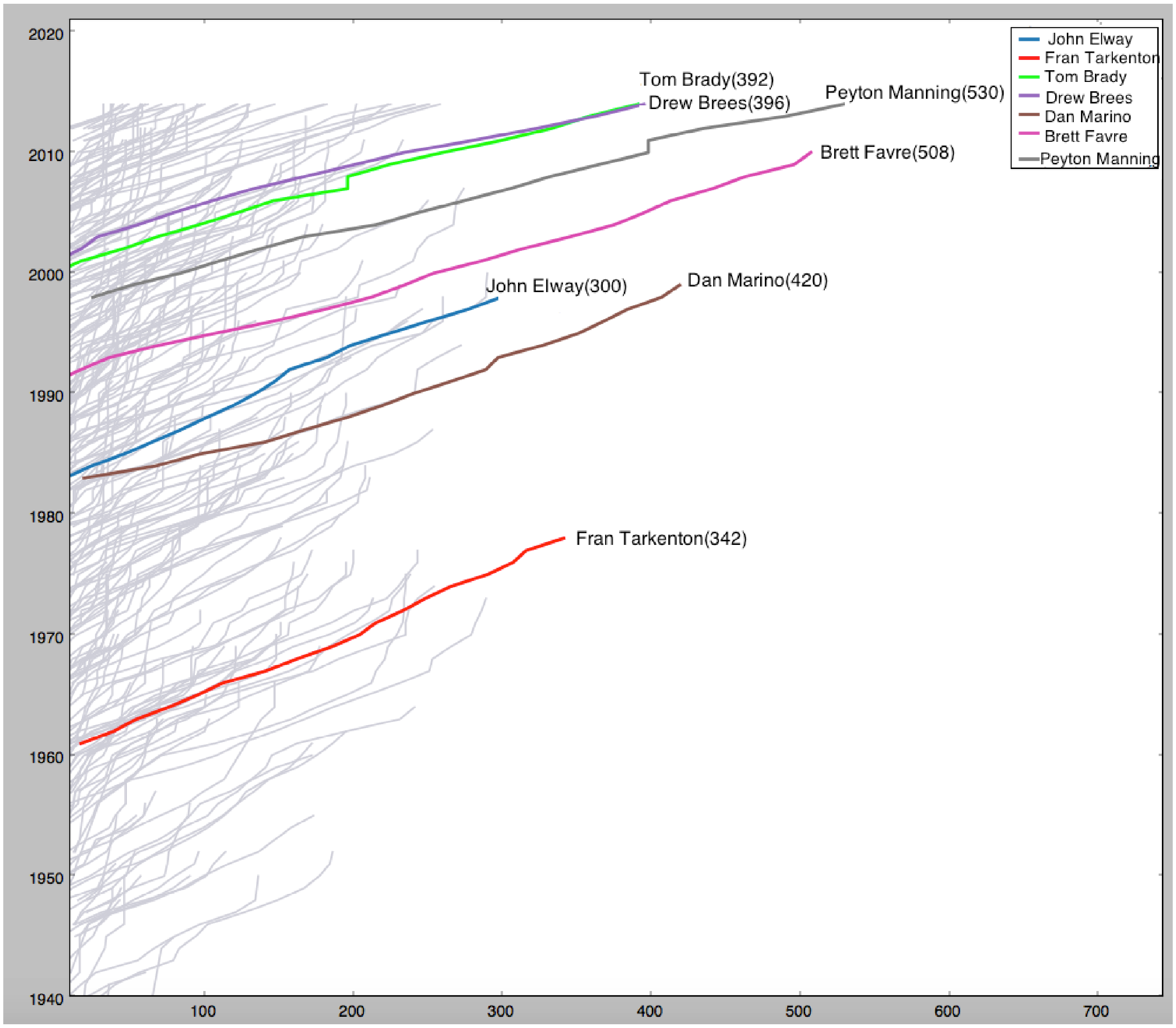


Probable and Suspected Ebola Deaths
Guinea
Sierra Leone
Liberia
Number of Ebola Deaths
Date
0
500
1000
1500
2000
2500
3000
3500
4000
4500
Sep 2014
Oct 2014
Nov 2014
Dec 2014
Jan 2015
Feb 2015
Mar 2015

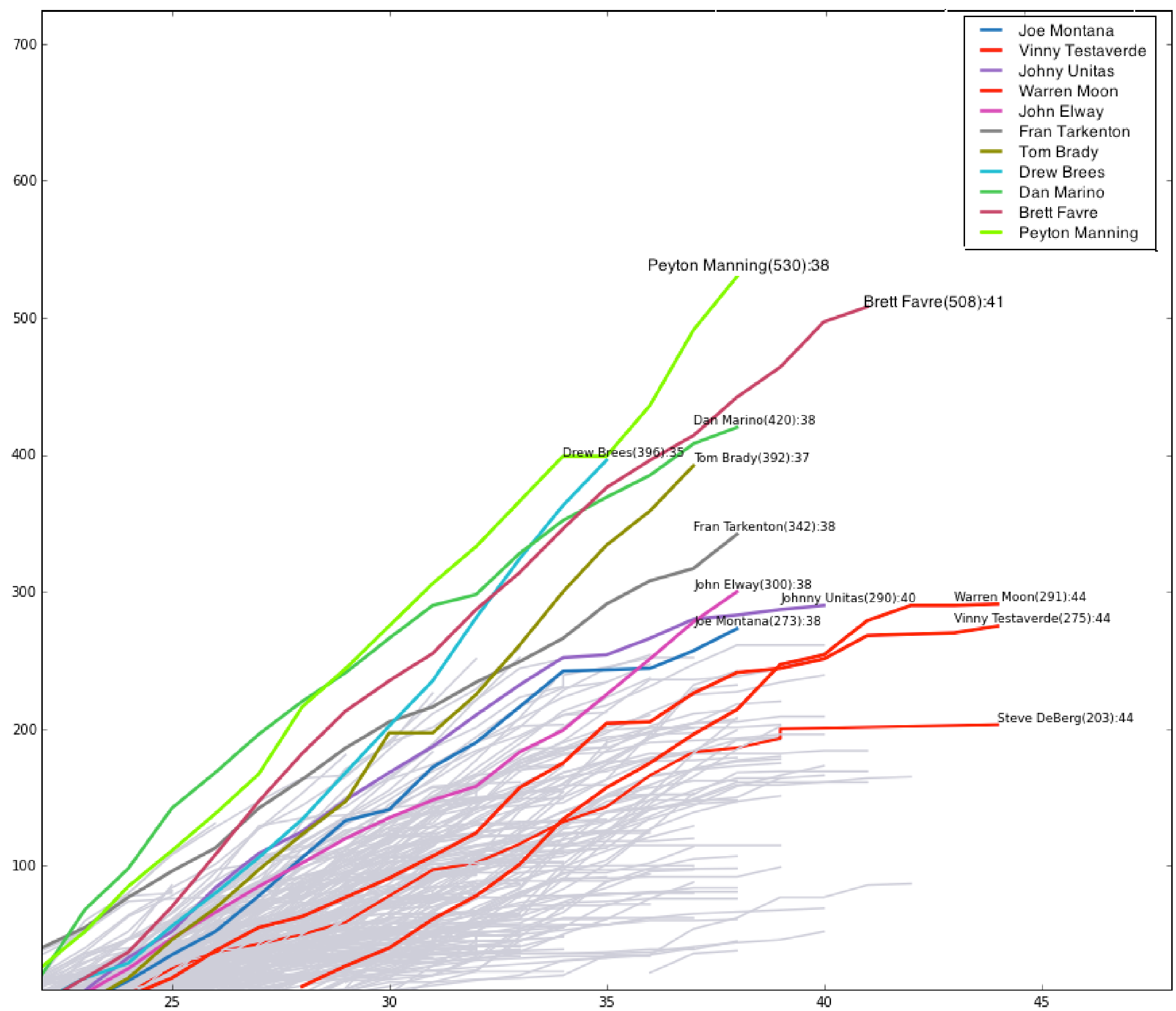
Name	Year	Age	Cmp	Att	Yds	TD	Teams
Peyton Manning	1998	22	326	575	3739	26	Multi
Peyton Manning	1999	23	331	533	4135	26	Multi
Peyton Manning	2000	24	357	571	4413	33	Multi
Peyton Manning	2001	25	343	547	4131	26	Multi
Peyton Manning	2002	26	392	591	4200	27	Multi
Peyton Manning	2003	27	379	566	4267	29	Multi
Peyton Manning	2004	28	336	497	4557	49	Multi
Peyton Manning	2005	29	305	453	3747	28	Multi
Peyton Manning	2006	30	362	557	4397	31	Multi
Peyton Manning	2007	31	337	515	4040	31	Multi
Peyton Manning	2008	32	371	555	4002	27	Multi
Peyton Manning	2009	33	393	571	4500	33	Multi
Peyton Manning	2010	34	450	679	4700	33	Multi
Peyton Manning	2011	35	0	0	0	0	Multi
Peyton Manning	2012	36	400	583	4659	37	Multi
Peyton Manning	2013	37	450	659	5477	55	Multi



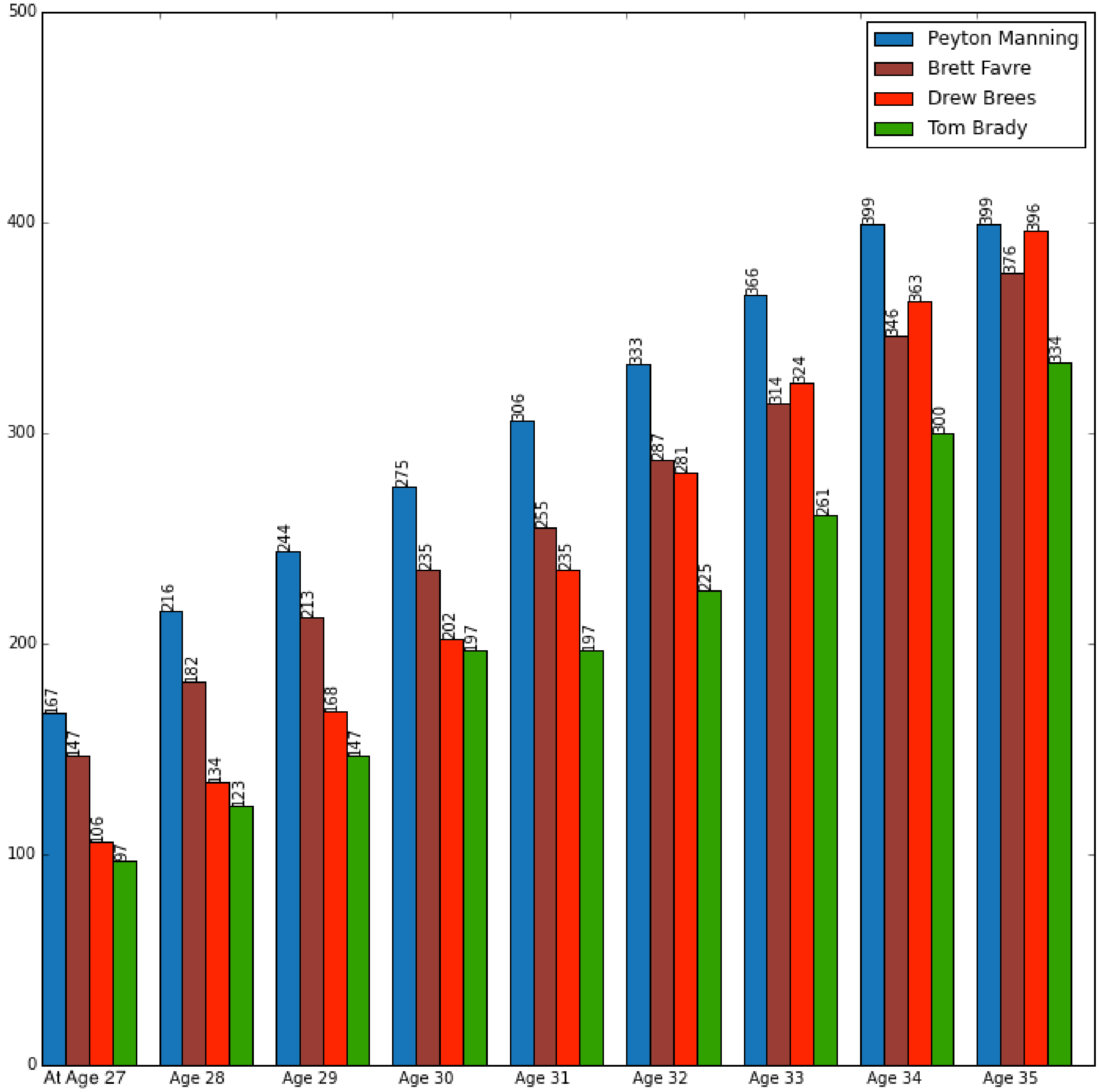
John Elway
Fran Tarkenton
Tom Brady
Drew Brees
Dan Marino
Brett Favre
Peyton Manning
Peyton Manning(530)
Brett Favre(508)
Dan Marino(420)
Drew Brees(396)
Tom Brady(392)
Fran Tarkenton (342)
John Elway(300)
700
600
500
400
300
200
100
1940
1950
1960
1970
1980
1990
2000
2010



John Elway
Fran Tarkenton
Tom Brady
Drew Brees
Dan Marino
Brett Favre
Peyton Manning
Tom Brady(392)
Drew Brees(396)
Peyton Manning(530)
Brett Favre(508)
John Elway(300)
Dan Marino(420)
Fran Tarkenton(342)
2020
2010
2000
1990
1980
1970
1960
1950
1940
100
200
300
400
500
600
700



Joe Montana
Vinny Testaverde
Johny Unitas
Warren Moon
John Elway
Fran Tarkenton
Tom Brady
Drew Brees
Dan Marino
Brett Favre
Peyton Manning
Peyton Manning(530):38
Brett Favre(508):41
Dan Marino(420):38
Drew Brees(396):35
Tom Brady(392):37
Fran Tarkenton(342):38
John Elway(300):38
Johnny Unitas(290):40
Warren Moon(291):44
Vinny Testaverde(275):44
Joe Montana(273):38
Steve DeBerg(203):44
700
600
500
400
300
200
100
25
30
35
40
45



Peyton Manning
Brett Favre
Drew Brees
Tom Brady
500
400
300
200
100
0
At Age 27
Age 28
Age 29
Age 30
Age 31
Age 32
Age 33
Age 34
Age 35
167
147
106
97
216
182
134
123
244
213
168
147
275
235
202
197
306
255
235
197
333
287
281
225
366
314
324
261
399
346
363
300
399
376
396
334

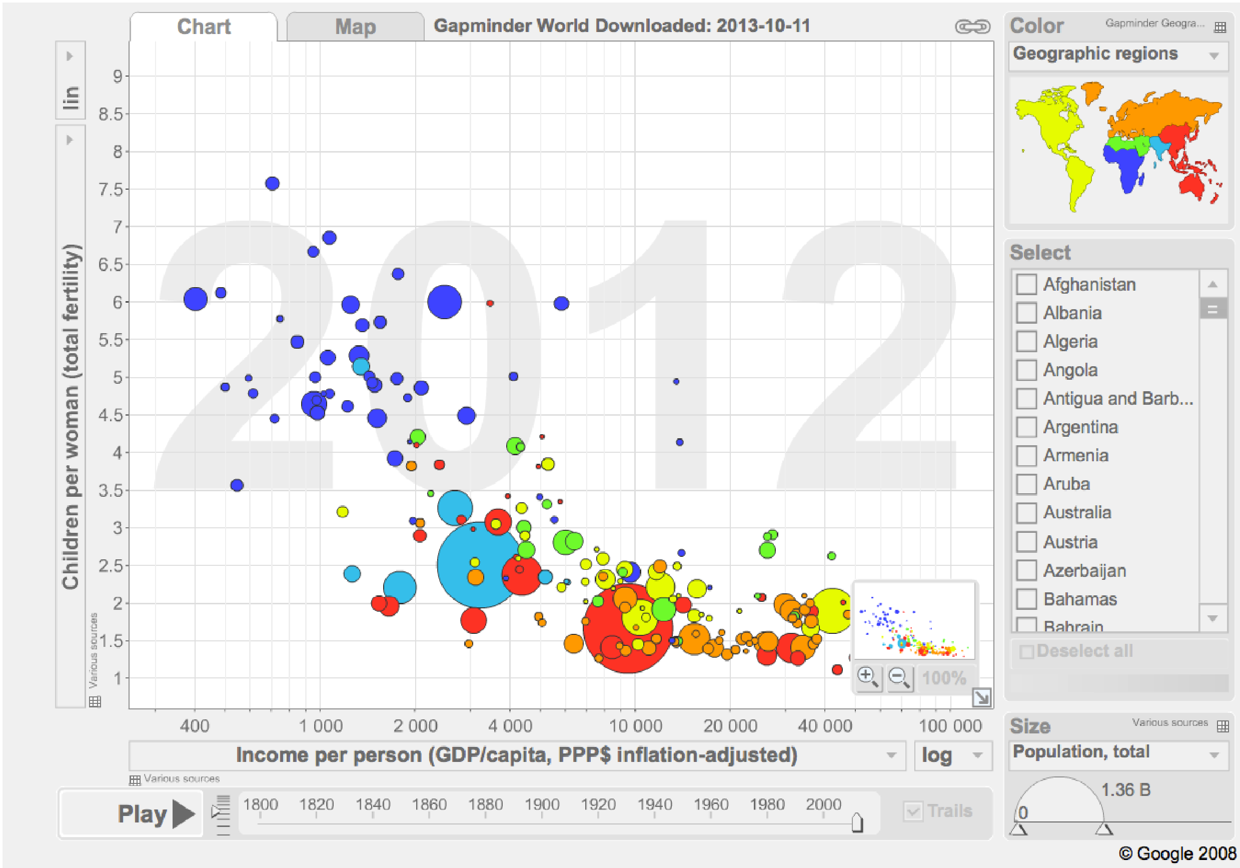
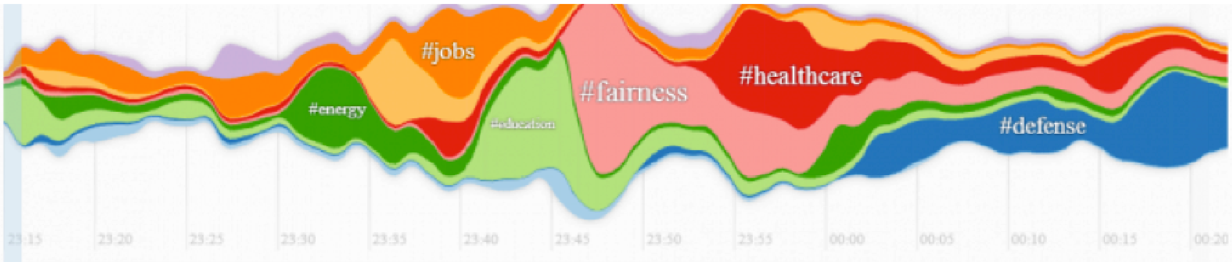


Chart
Map
Gapminder World Downloaded: 2013-10-11
2012
Children per woman (total fertility)
lin
9
8.5
8
7.5
7
6.5
6
5.5
5
4.5
4
3.5
3
2.5
2
1.5
1
400
1 000
2 000
4 000
10 000
20 000
40 000
100 000
Income per person (GDP/capita, PPP$ inflation-adjusted)
log
Various sources
100%
Play
1800
1820
1840
1860
1880
1900
1920
1940
1960
1980
2000
Trails
Color
Geographic regions
Select
Afghanistan
Albania
Algeria
Angola
Antigua and Barb...
Argentina
Armenia
Aruba
Australia
Austria
Azerbaijan
Bahamas
Bahrain
Deselect all
Size
Various sources
Population, total
1.36 B
0
© Google 2008



#SOTU2014: See the State of The Union address minute by minute on Twitter   Tweet   Embed

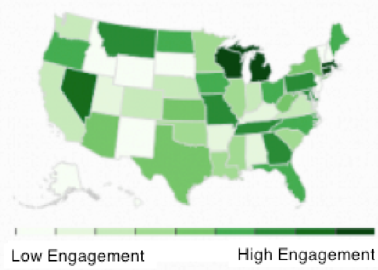
Explore the speech and see the realtime reaction on Twitter. Scroll to a paragraph to see the volume of Tweets, the subjects debated on Twitter and where people are talking about them across the U.S. Click the spikes on the chart and see which paragraphs are being talked about most. Share your key paragraphs: each one has a unique url for you to Tweet.

Mr. Speaker, Mr. Vice President, Members of Congress, my fellow Americans:

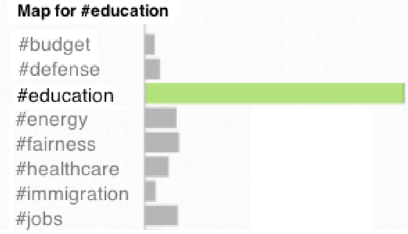
Today in America, a teacher spent extra time with a student who needed it, and did her part to lift America's graduation rate to its highest level in more than three decades.

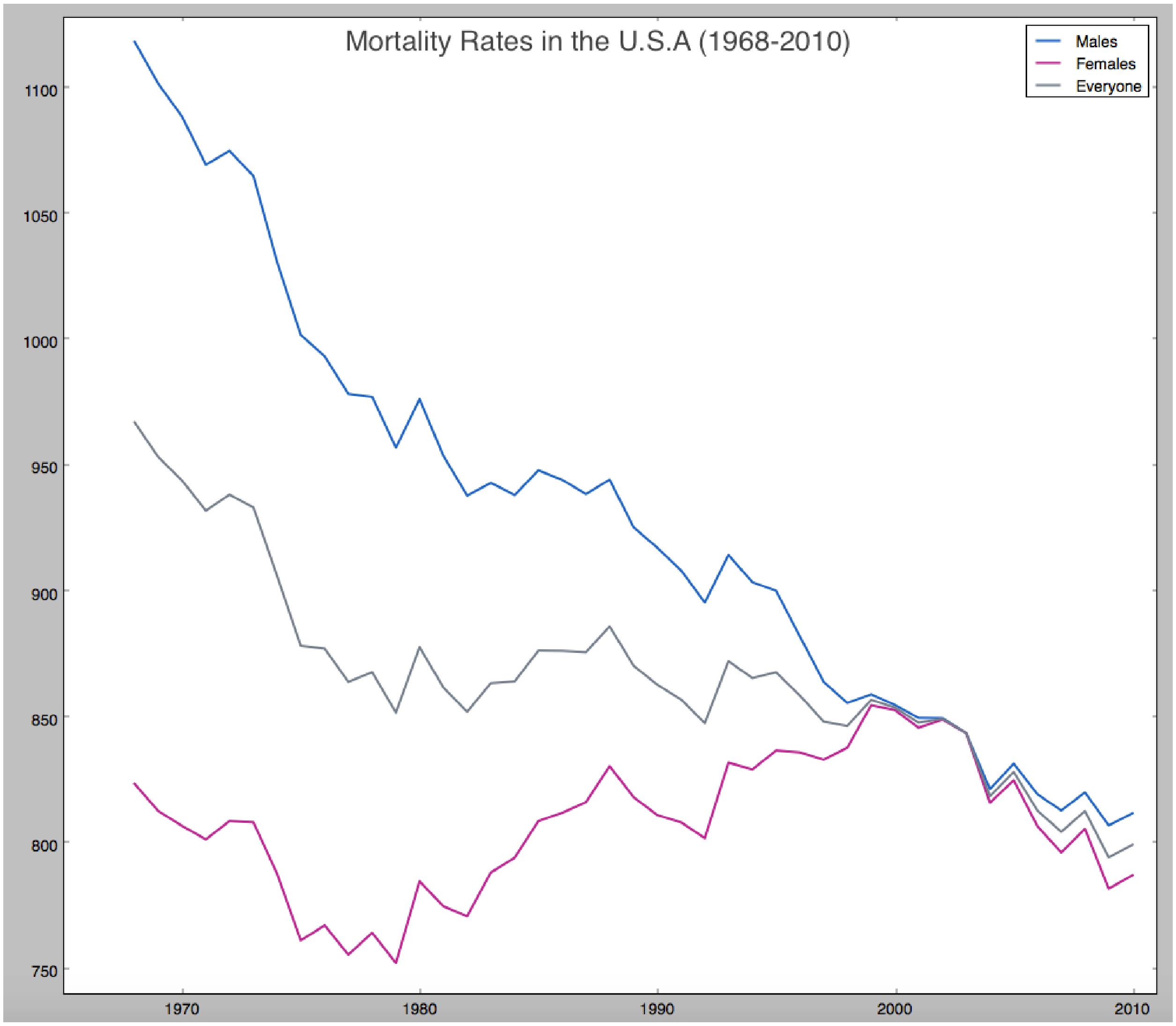
An entrepreneur flipped on the lights in her tech startup, and did her part to add to the more than eight million new jobs our businesses have

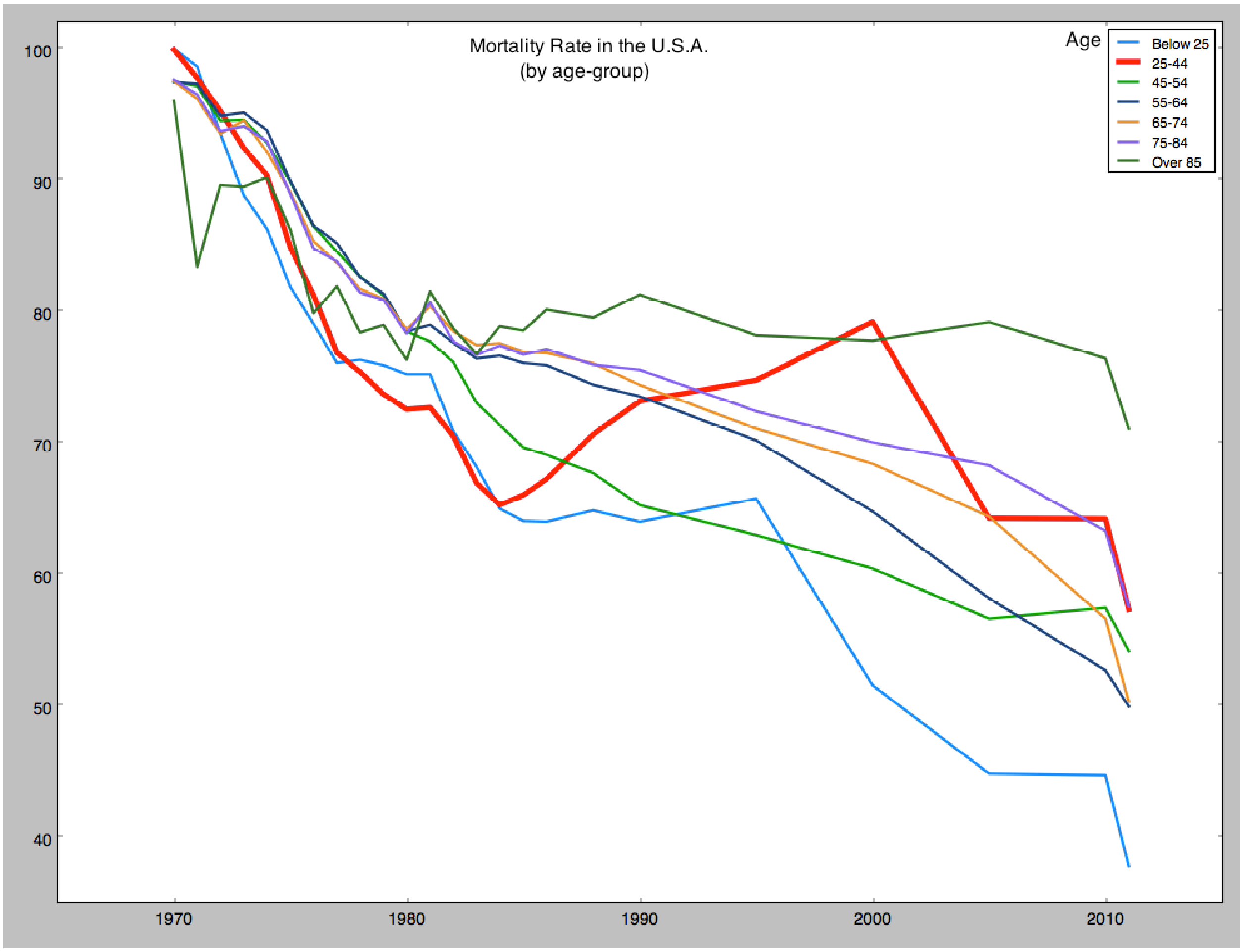
Real-time engagement distribution on Twitter for this paragraph

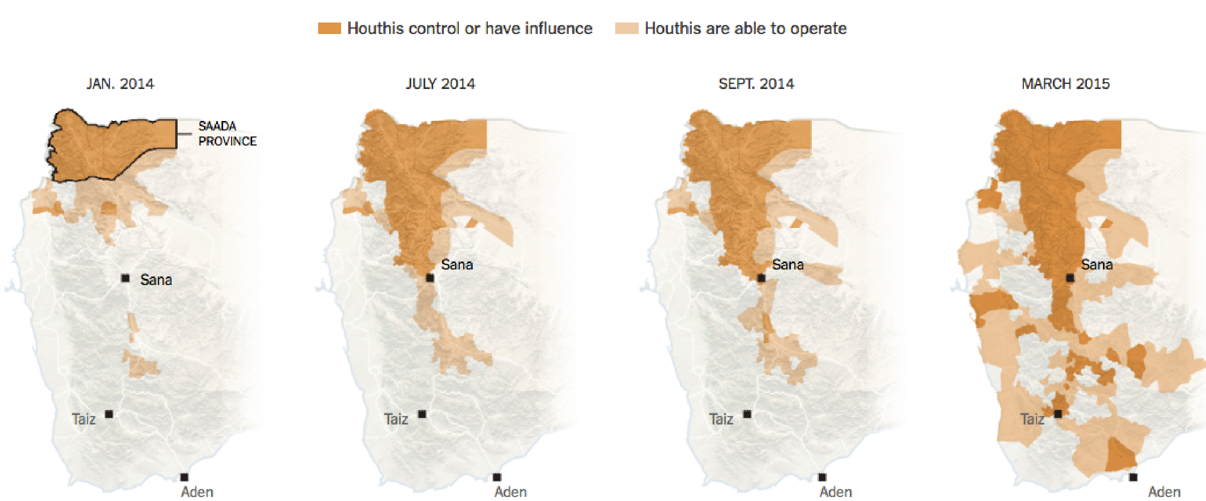


Map for #education

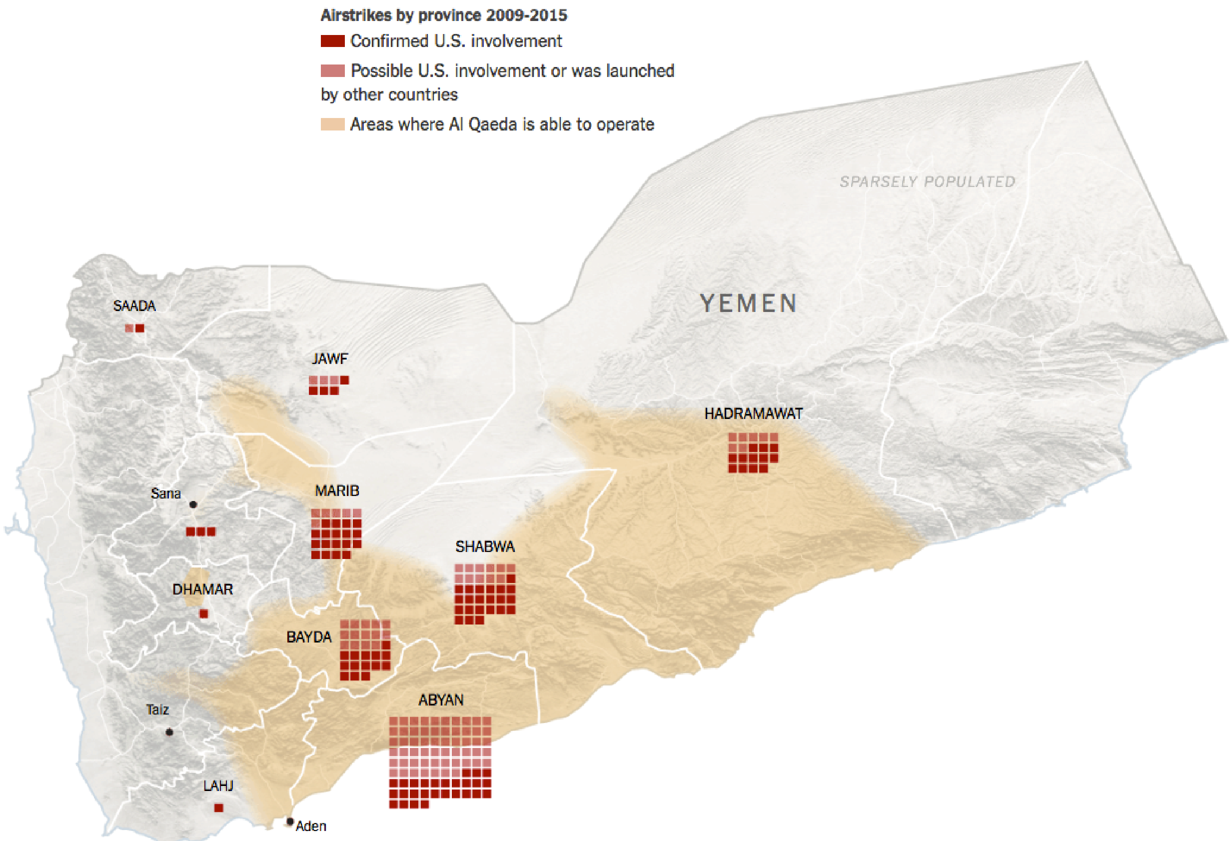


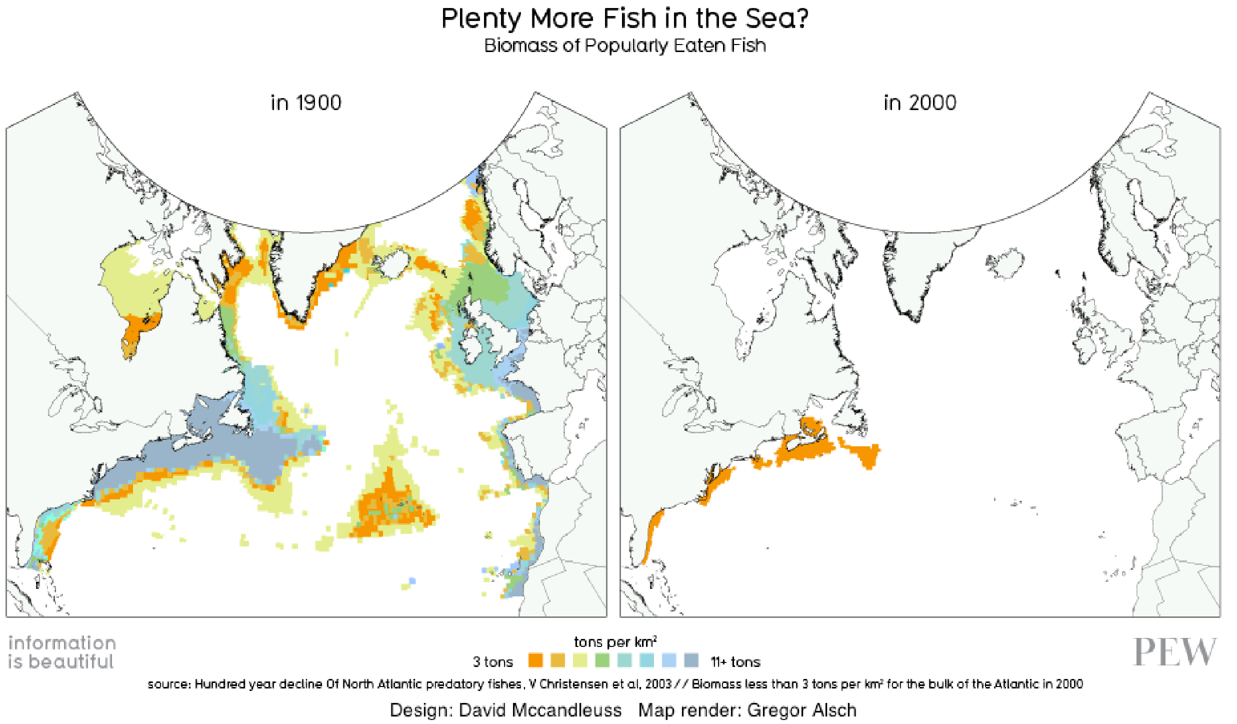

Mortality Rates in the U.S.A (1968-2010)
Males
Females
Everyone
1100
1050
1000
950
900
850
800
750
1970
1980
1990
2000
2010

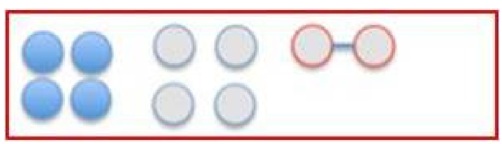


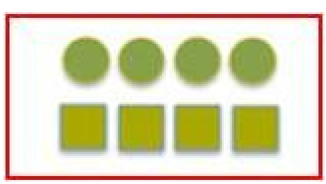


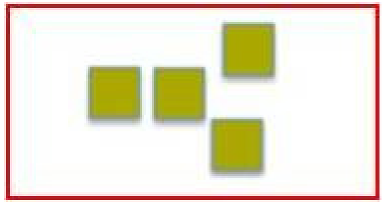
Source: American Enterprise Institute's Critical Threats Project

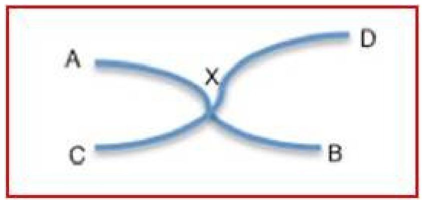

Airstrikes by province 2009-2015
Confirmed U.S. involvement
Possible U.S. involvement or was launched by other countries
Areas where Al Qaeda is able to operate
SPARSELY POPULATED
YEMEN
SAADA
JAWF
HADRAMAWAT
Sana
MARIB
SHABWA
DHAMAR
BAYDA
ABYAN
Taiz
LAHJ
Aden

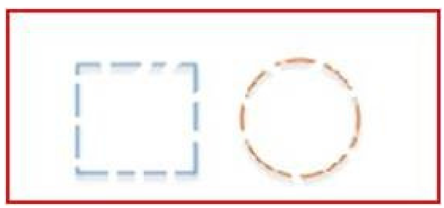

Plenty More Fish in the Sea?
Biomass of Popularly Eaten Fish
in 1900
in 2000
information is beautiful
tons per km²
3 tons
11+ tons
PEW
source: Hundred year decline Of North Atlantic predatory fishes, V Christensen et al, 2003 // Biomass less than 3 tons per km² for the bulk of the Atlantic in 2000
Design: David Mccandleuss   Map render: Gregor Alsch

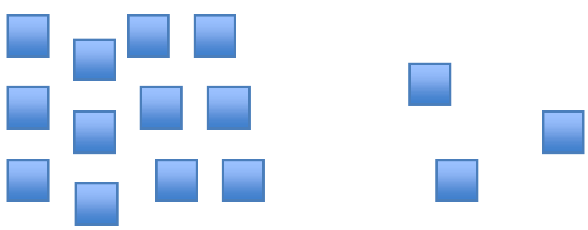






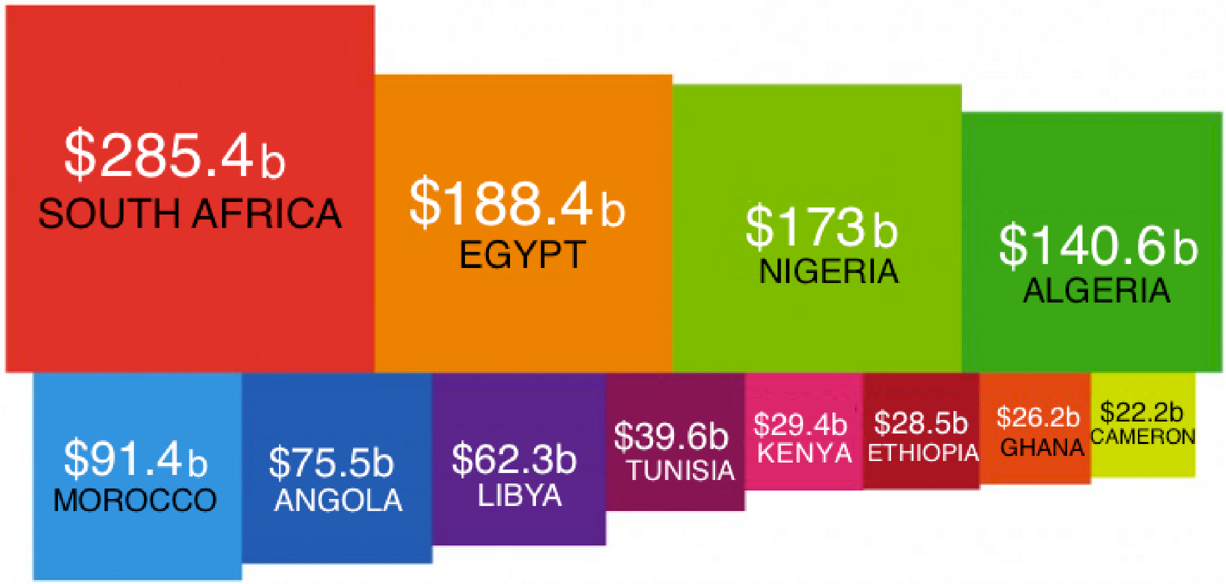


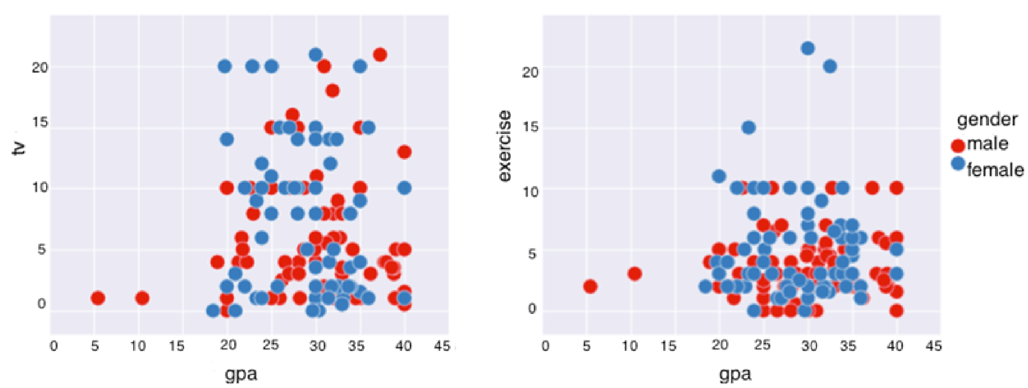


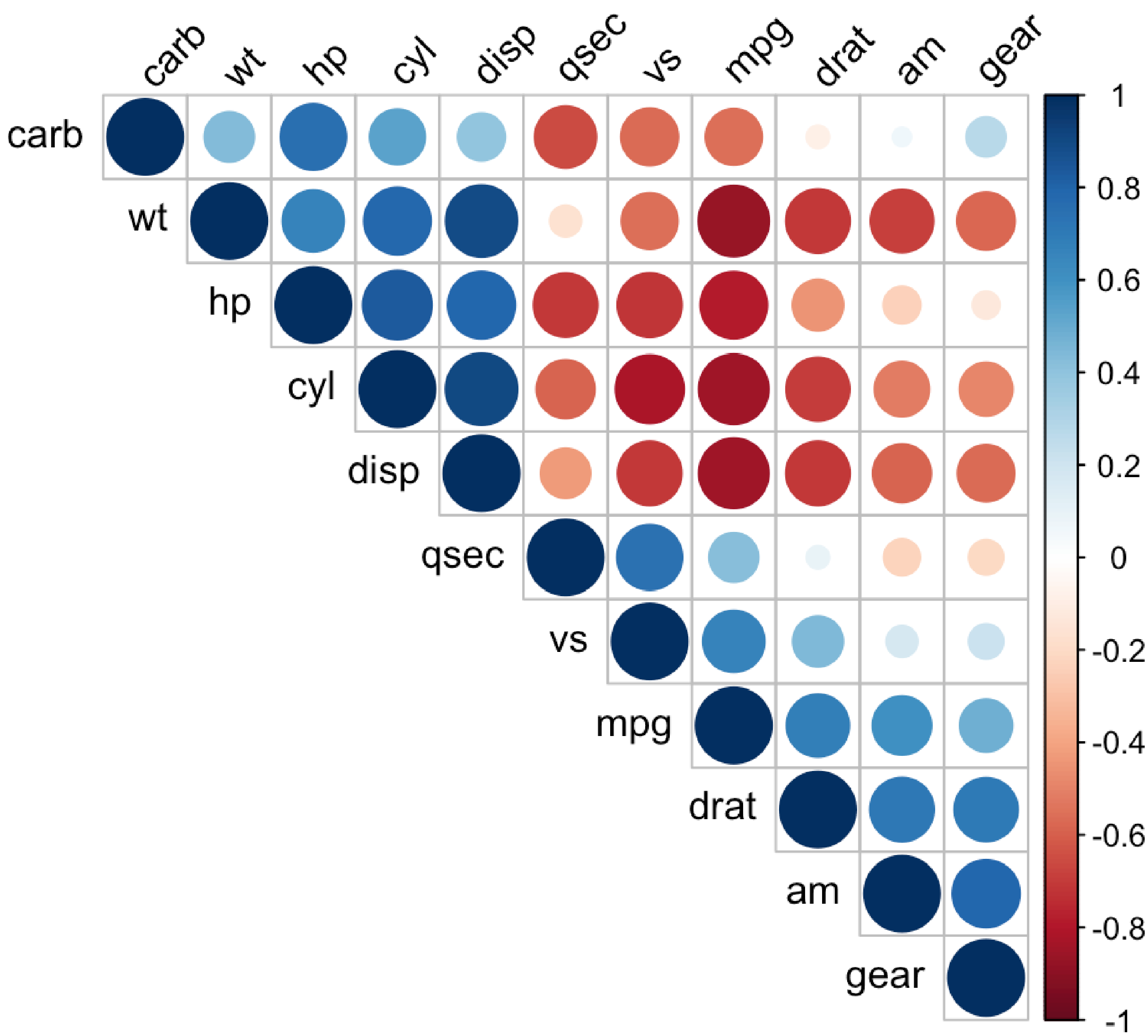


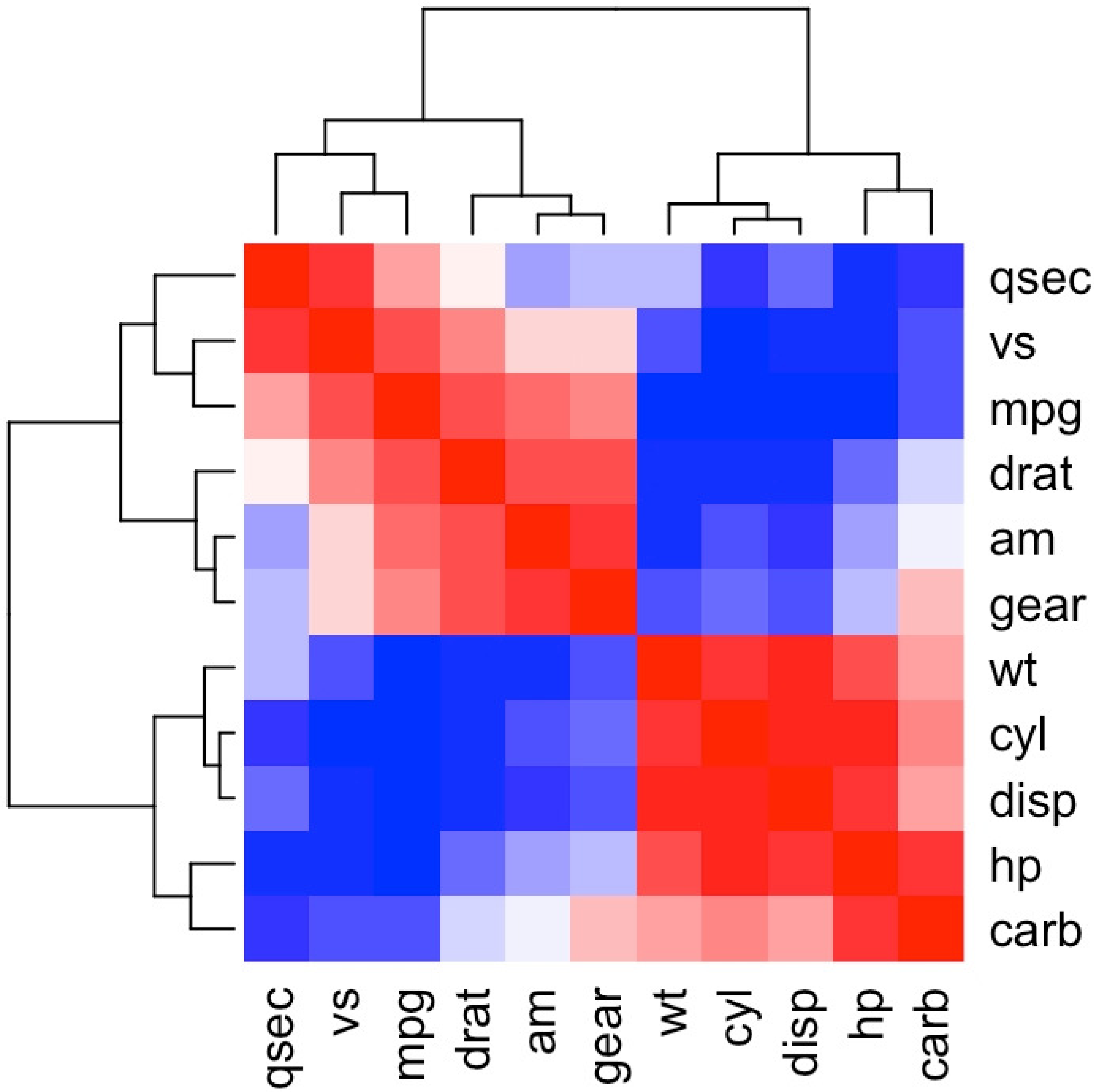
Proximity

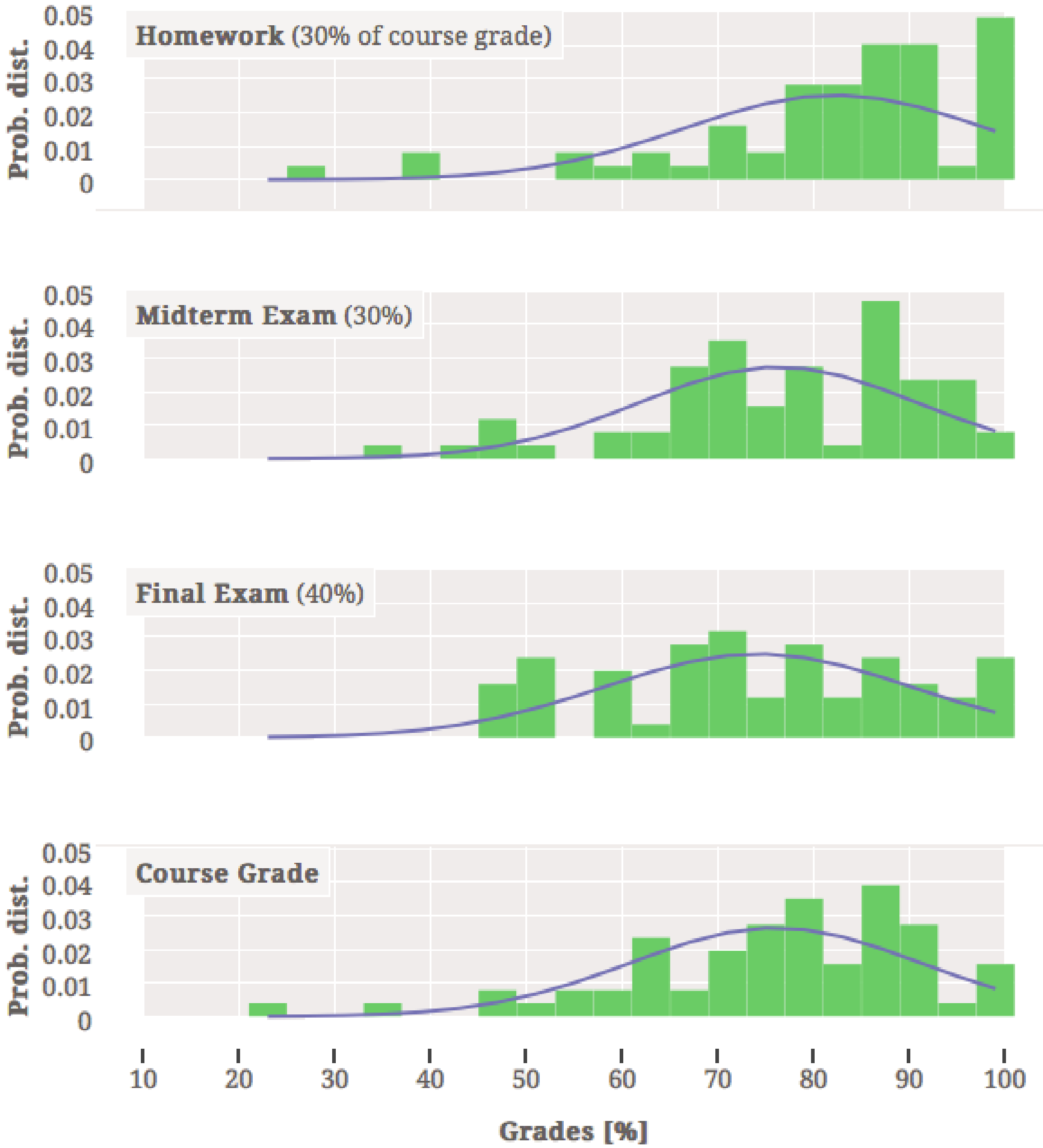
No Proximity

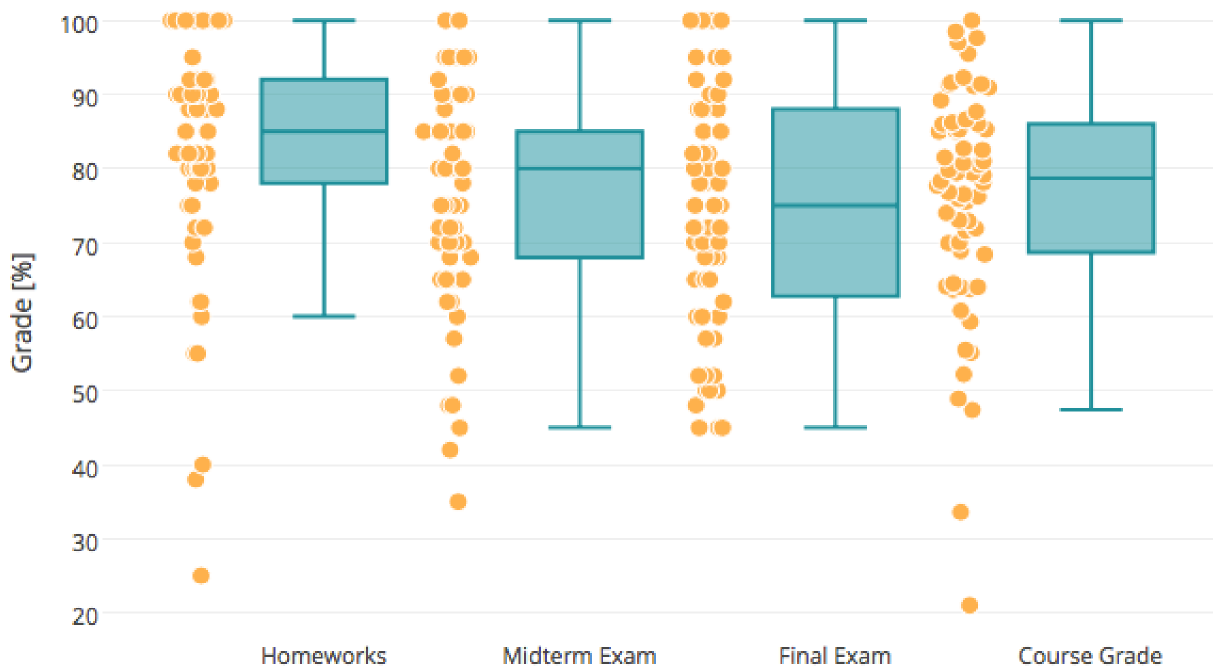

$285.4b
SOUTH AFRICA
$188.4b
EGYPT
$173b
NIGERIA
$140.6b
ALGERIA
$91.4b
MOROCCO
$75.5b
ANGOLA
$62.3b
LIBYA
$39.6b
TUNISIA
$29.4b
KENYA
$28.5b
ETHIOPIA
$26.2b
GHANA
$22.2b
CAMERON


tv
gpa
exercise
gpa
gender
male
female

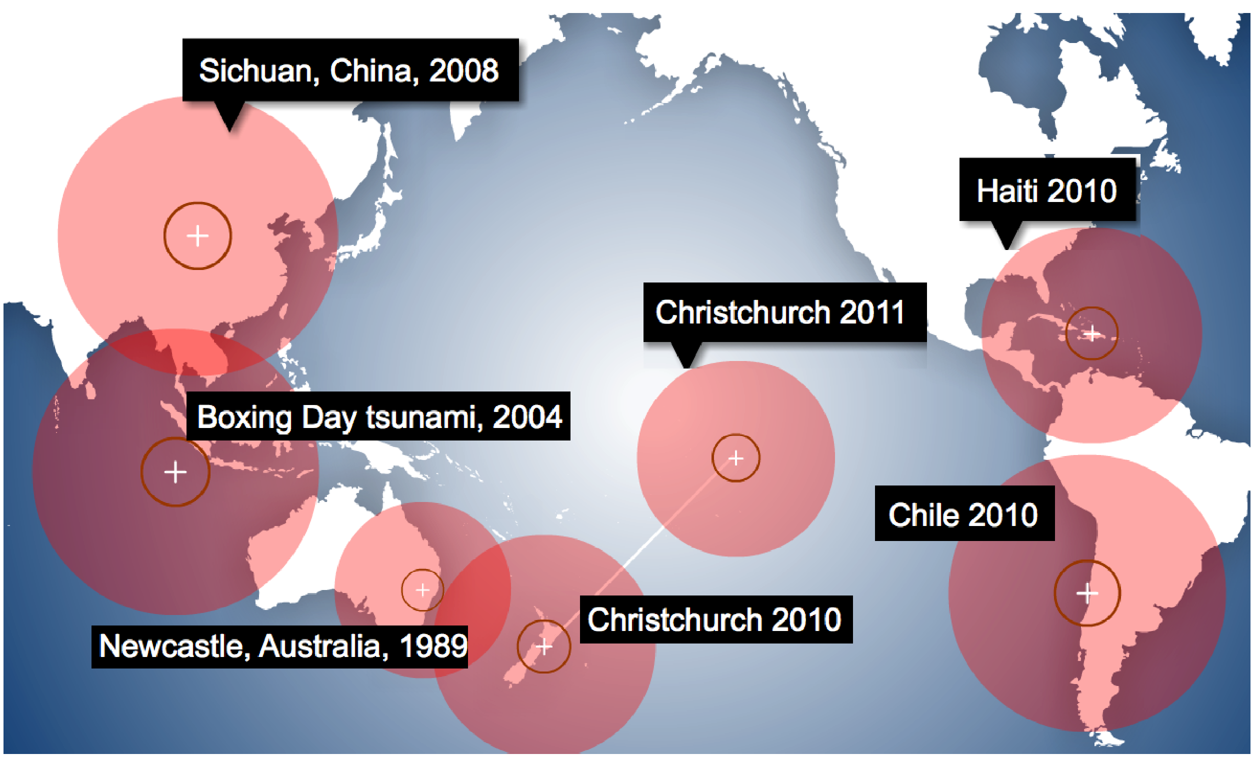

carb
wt
hp
cyl
disp
qsec
vs
mpg
drat
am
gear
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1


qsec
vs
mpg
drat
am
gear
wt
cyl
disp
hp
carb

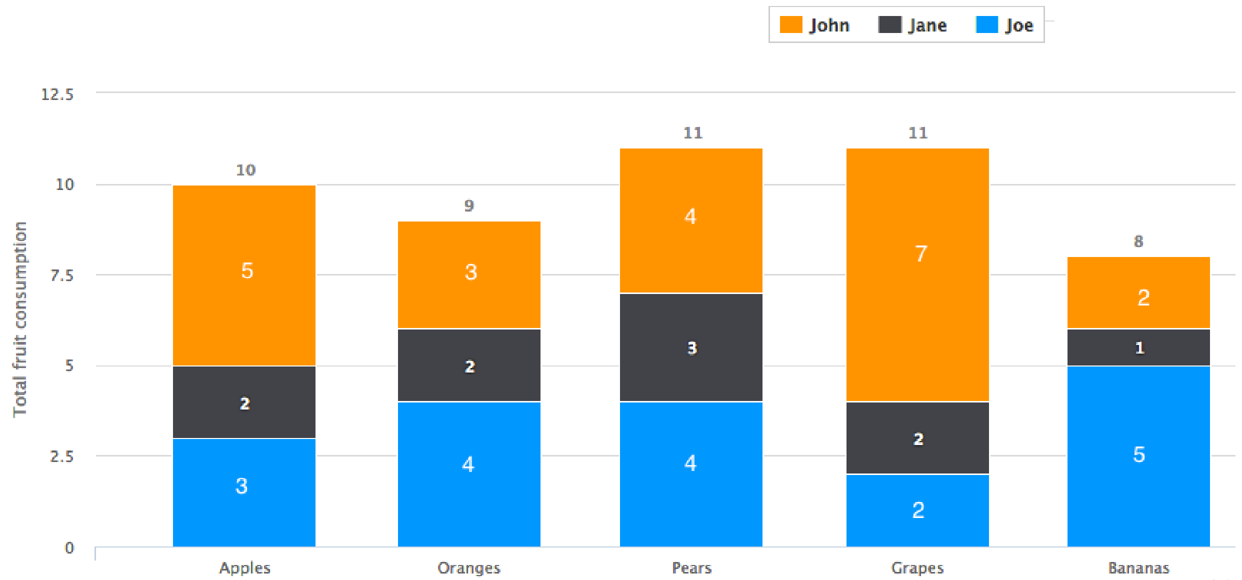

Homework (30% of course grade)
Midterm Exam (30%)
Final Exam (40%)
Course Grade
Prob. dist.
0.05
0.04
0.03
0.02
0.01
0
10
20
30
40
50
60
70
80
90
100
Grades [%]



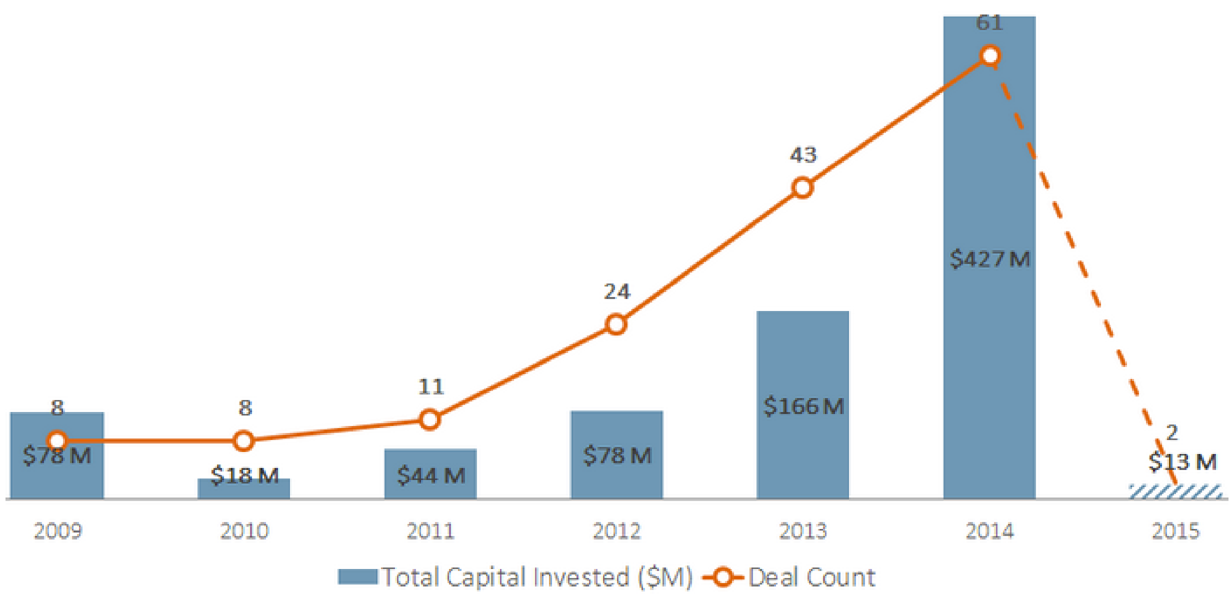
Grade [%]
100
90
80
70
60
50
40
30
20
Homeworks
Midterm Exam
Final Exam
Course Grade

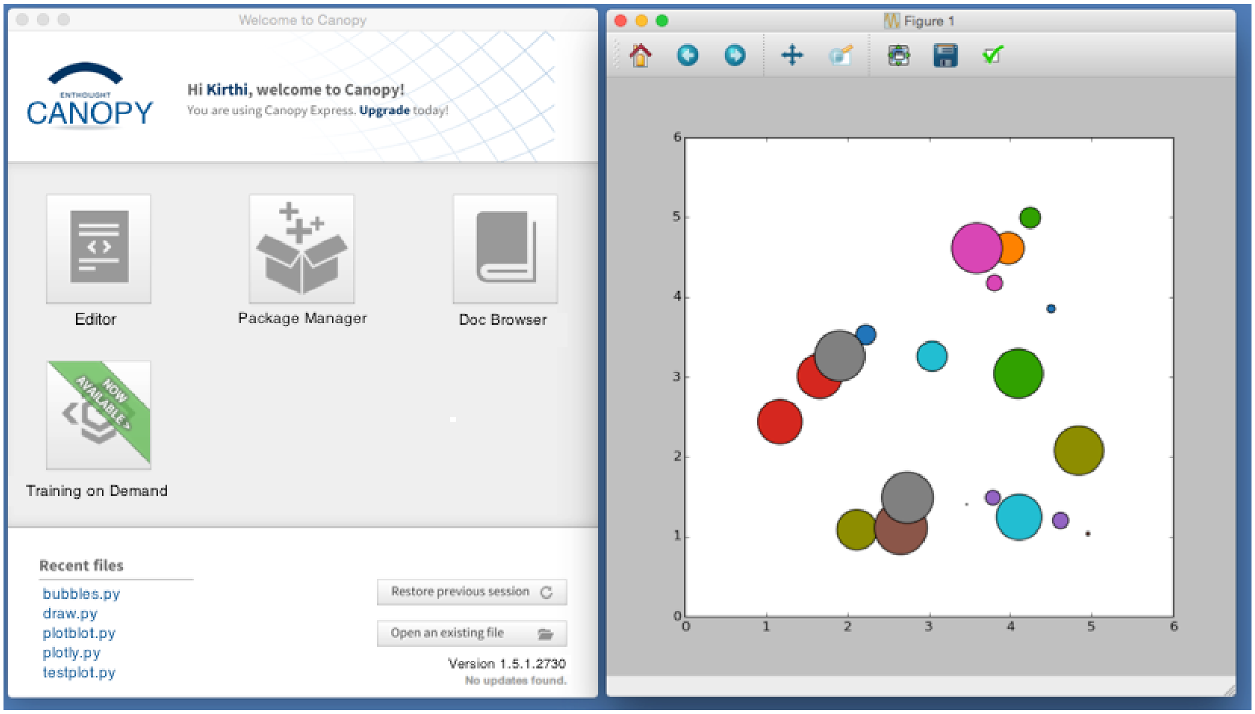


Sichuan, China, 2008
Haiti 2010
Christchurch 2011
Boxing Day tsunami, 2004
Chile 2010
Christchurch 2010
Newcastle, Australia, 1989



VC Investment in Wearables Startups





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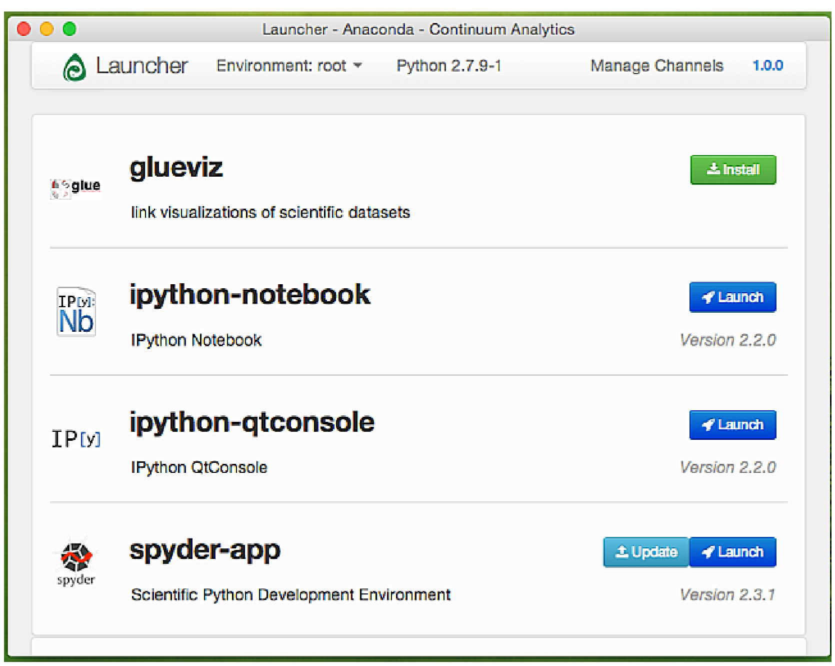
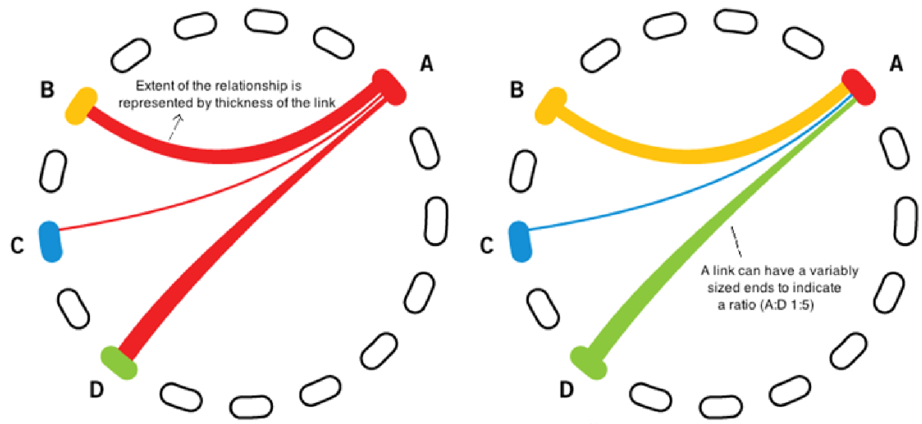
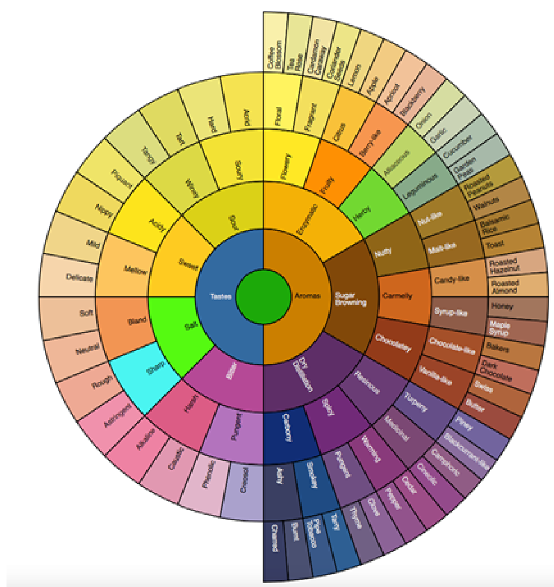
plotly.py
testplot.py
Restore previous session
Open an existing file
Version 1.5.1.2730
No updates found.
Figure 1



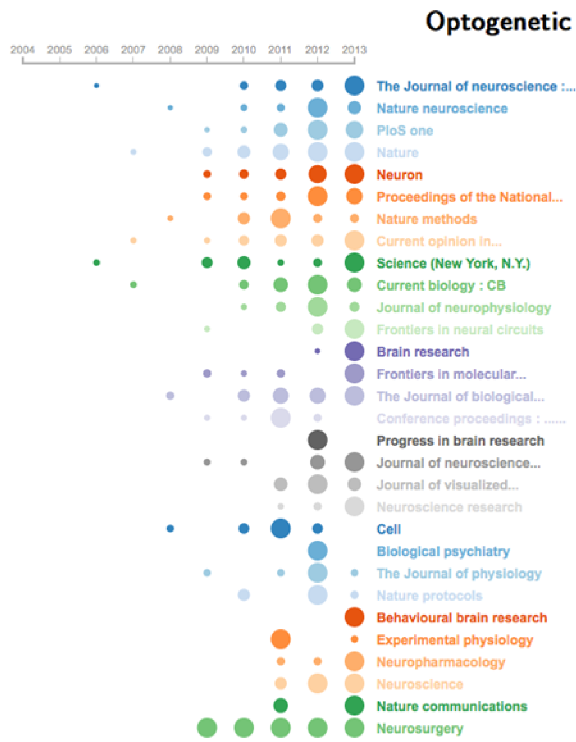
Launcher - Anaconda - Continuum Analytics
Launcher
Environment: root
Python 2.7.9-1
Manage Channels
1.0.0
glueviz
Install
link visualizations of scientific datasets
ipython-notebook
Launch
IPython Notebook
Version 2.2.0
ipython-qtconsole
Launch
IPython QtConsole
Version 2.2.0
spyder-app
Update
Launch
Scientific Python Development Environment
Version 2.3.1



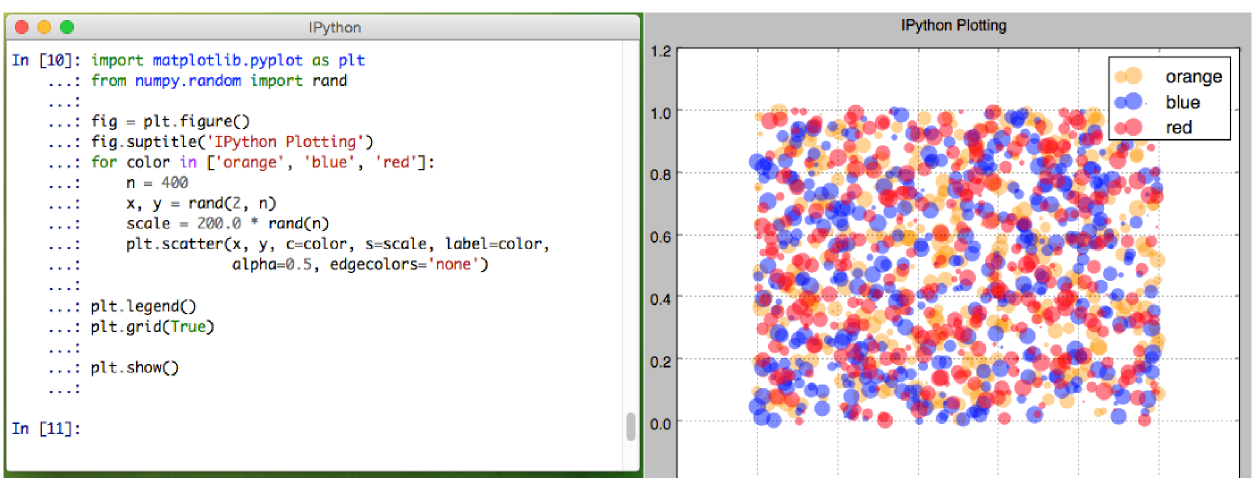
A
B
C
D
Extent of the relationship is
represented by thickness of the link
A
B
C
D
A link can have a variably
sized ends to indicate
a ratio (A:D 1:5)



Tastes
Aromas
Sugar Browning
Dry Distillation
Enzymatic
Sweet
Sour
Salt
Bitter
Flowery
Fruity
Herby
Nutty
Carmelly
Chocolatey
Resinous
Spicy
Carbony
Acidy
Winey
Mellow
Bland
Sharp
Harsh
Pungent



Chapter 3: Getting Started with the Python IDE



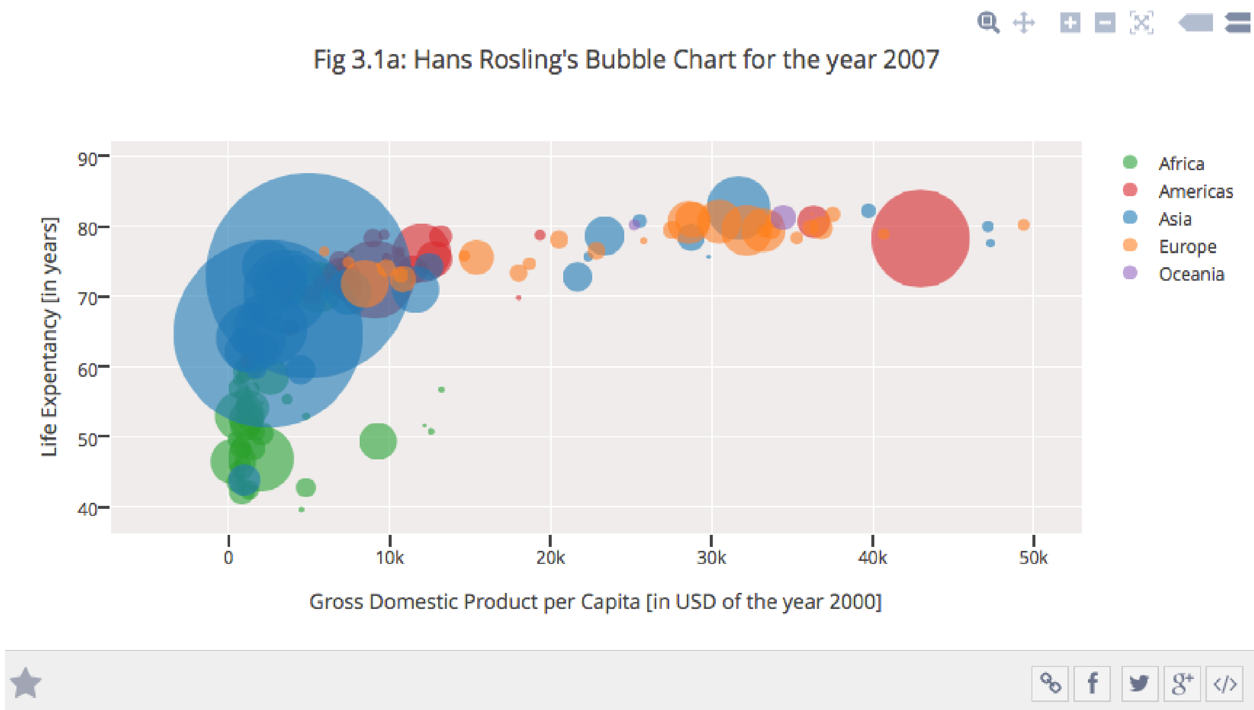
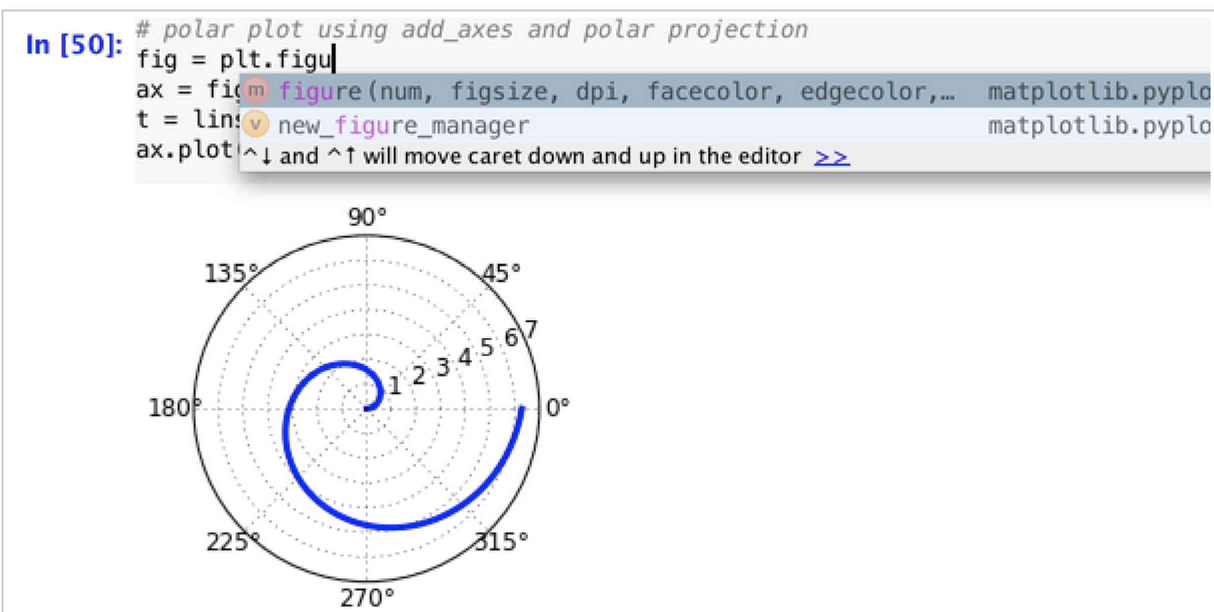
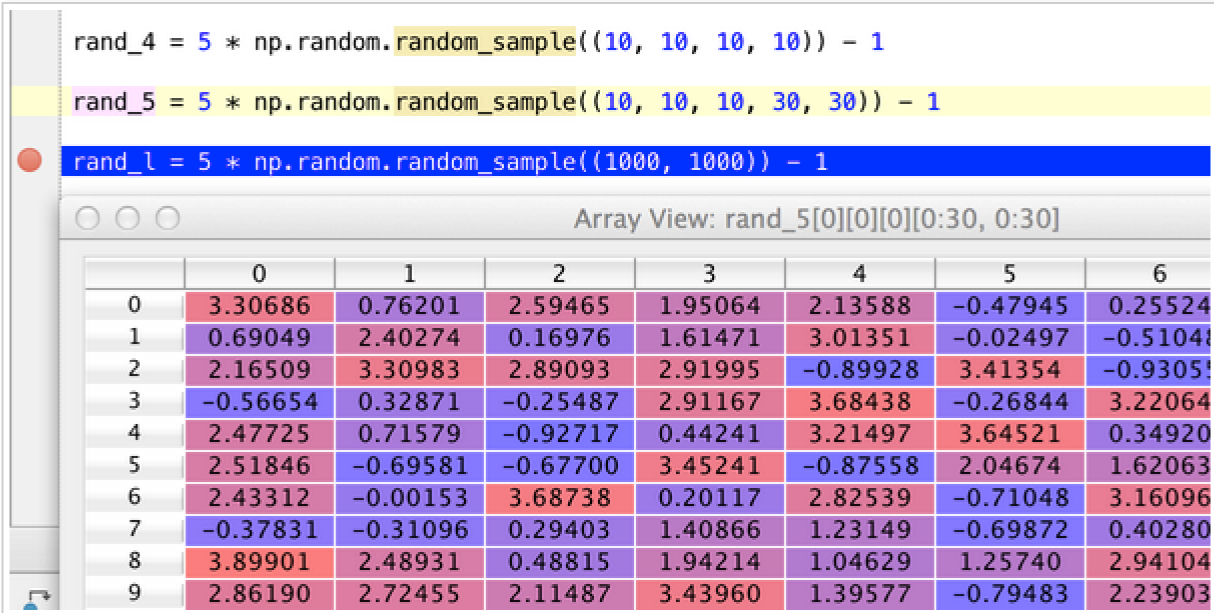
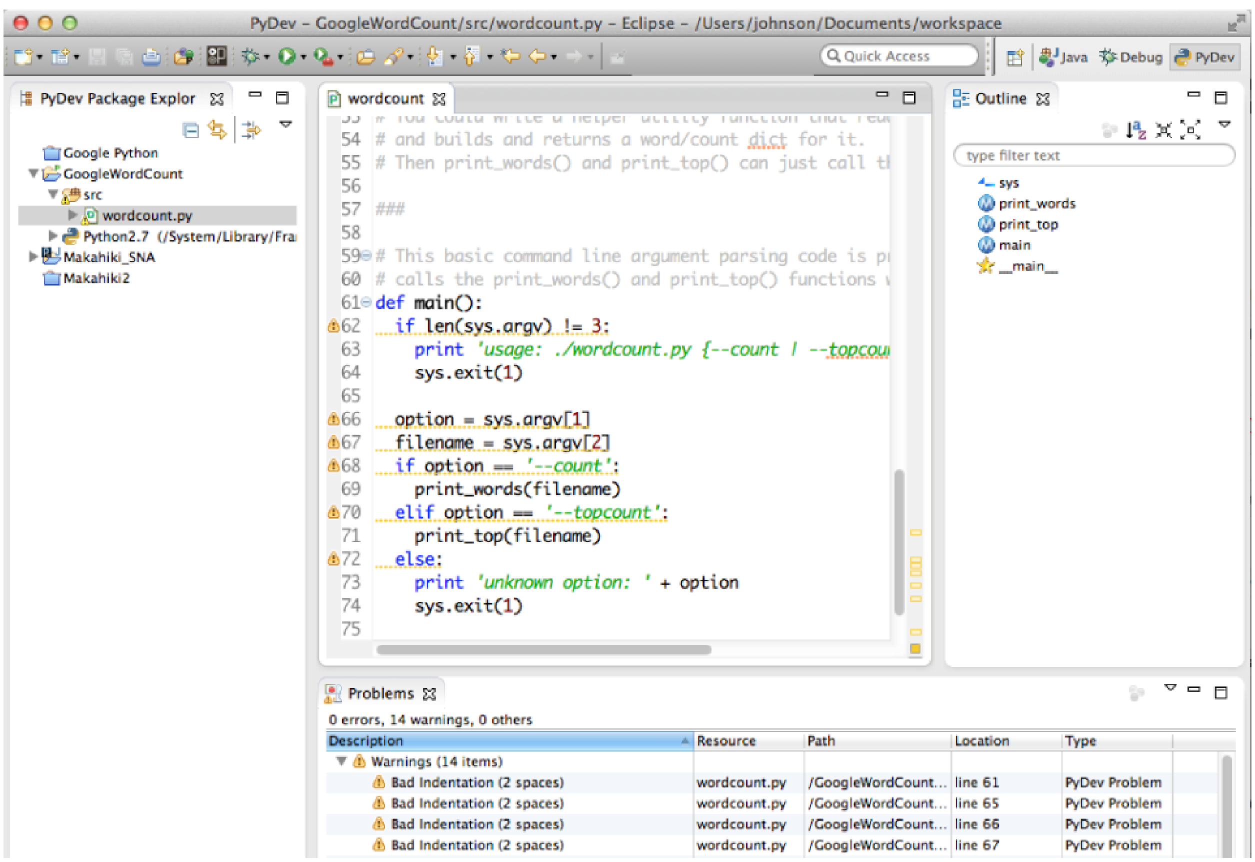


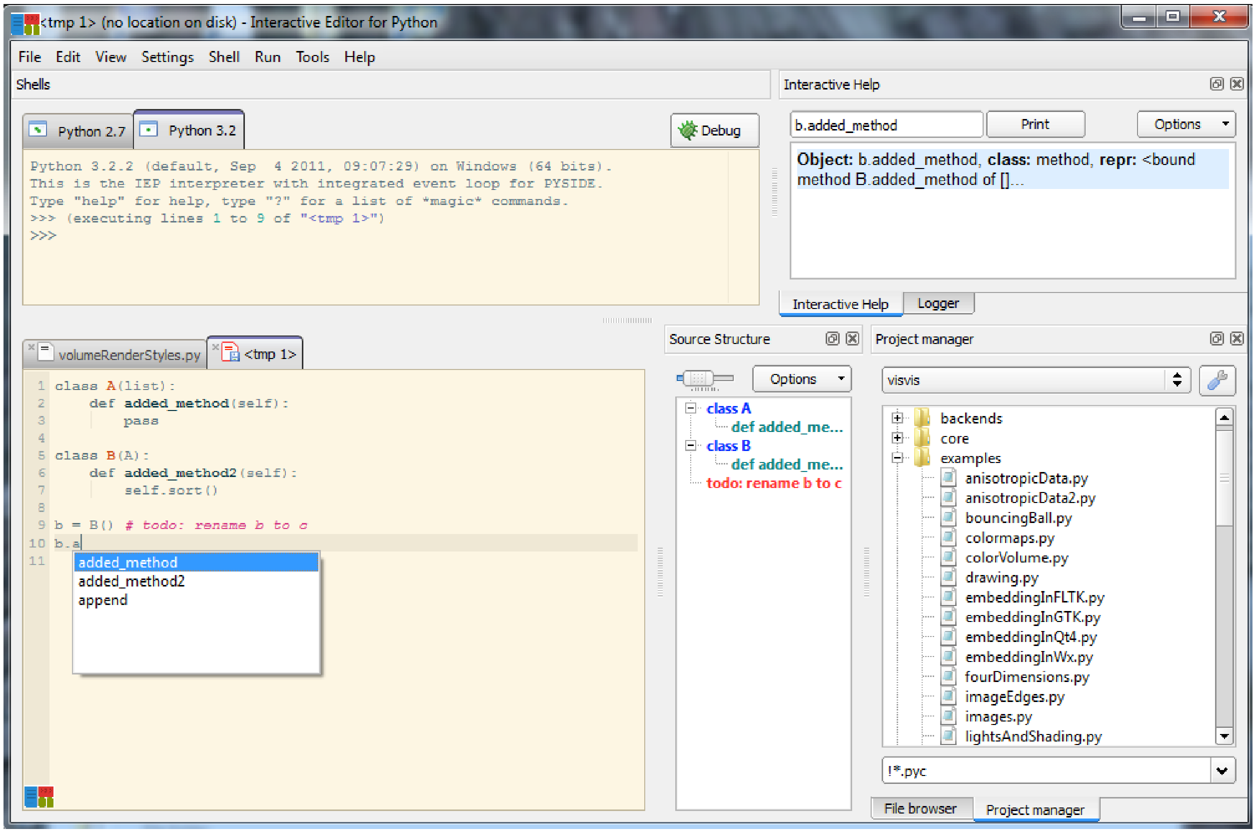
Fig 3.1a: Hans Rosling's Bubble Chart for the year 2007
Life Expectancy [in years]
90
80
70
60
50
40
0
10k
20k
30k
40k
50k
Gross Domestic Product per Capita [in USD of the year 2000]
Africa
Americas
Asia
Europe
Oceania

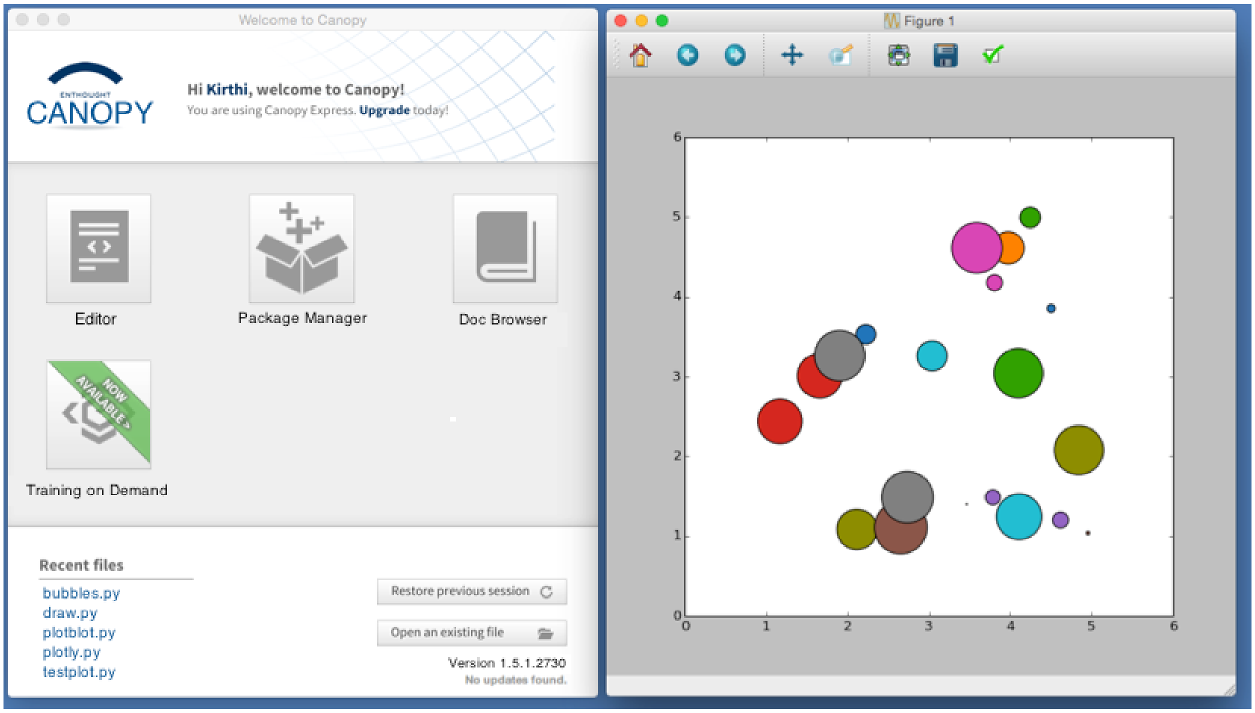


In [50]:
# polar plot using add_axes and polar projection
fig = plt.figu
ax = fig
t = lins
ax.plot
figure(num, figsize, dpi, facecolor, edgecolor,… matplotlib.pyplo
new_figure_manager matplotlib.pyplo
^↓ and ^↑ will move caret down and up in the editor >>
90°
135°
45°
180°
0°
225°
315°
270°
1 2 3 4 5 6 7


rand_4 = 5 * np.random.random_sample((10, 10, 10, 10)) - 1
rand_5 = 5 * np.random.random_sample((10, 10, 10, 30, 30)) - 1
rand_l = 5 * np.random.random_sample((1000, 1000)) - 1
Array View: rand_5[0][0][0][0:30, 0:30]
0 1 2 3 4 5 6
0 3.30686 0.76201 2.59465 1.95064 2.13588 -0.47945 0.25524
1 0.69049 2.40274 0.16976 1.61471 3.01351 -0.02497 -0.5104
2 2.16509 3.30983 2.89093 2.91995 -0.89928 3.41354 -0.9305
3 -0.56654 0.32871 -0.25487 2.91167 3.68438 -0.26844 3.22064
4 2.47725 0.71579 -0.92717 0.44241 3.21497 3.64521 0.34920
5 2.51846 -0.69581 -0.67700 3.45241 -0.87558 2.04674 1.62063
6 2.43312 -0.00153 3.68738 0.20117 2.82539 -0.71048 3.16096
7 -0.37831 -0.31096 0.29403 1.40866 1.23149 -0.69872 0.40280
8 3.89901 2.48931 0.48815 1.94214 1.04629 1.25740 2.94104
9 2.86190 2.72455 2.11487 3.43960 1.39577 -0.79483 2.23903


PyDev - GoogleWordCount/src/wordcount.py - Eclipse - /Users/johnson/Documents/workspace
Quick Access
Java
Debug
PyDev
PyDev Package Explor
Google Python
GoogleWordCount
src
wordcount.py
Python2.7 (/System/Library/Fra
Makahiki_SNA
Makahiki2
wordcount
and builds and returns a word/count dict for it.
Then print_words() and print_top() can just call t
###
# This basic command line argument parsing code is p
# calls the print_words() and print_top() functions
def main():
if len(sys.argv) != 3:
print 'usage: ./wordcount.py {--count | --topcou
sys.exit(1)
option = sys.argv[1]
filename = sys.argv[2]
if option == '--count':
print_words(filename)
elif option == '--topcount':
print_top(filename)
else:
print 'unknown option: ' + option
sys.exit(1)
Outline
type filter text
sys
print_words
print_top
main
__main__
Problems
0 errors, 14 warnings, 0 others
Description
Resource
Path
Location
Type
Warnings (14 items)
Bad Indentation (2 spaces) wordcount.py /GoogleWordCount... line 61 PyDev Problem
Bad Indentation (2 spaces) wordcount.py /GoogleWordCount... line 65 PyDev Problem
Bad Indentation (2 spaces) wordcount.py /GoogleWordCount... line 66 PyDev Problem
Bad Indentation (2 spaces) wordcount.py /GoogleWordCount... line 67 PyDev Problem


<tmp 1> (no location on disk) - Interactive Editor for Python
File Edit View Settings Shell Run Tools Help
Shells
Python 2.7
Python 3.2
Debug
Python 3.2.2 (default, Sep 4 2011, 09:07:29) on Windows (64 bits).
This is the IEP interpreter with integrated event loop for PYSIDE.
Type "help" for help, type "?" for a list of *magic* commands.
>>> (executing lines 1 to 9 of "<tmp 1>")
>>>
Interactive Help
b.added_method
Print
Options
Object: b.added_method, class: method, repr: <bound method B.added_method of []...
Interactive Help
Logger
volumeRenderStyles.py
<tmp 1>
class A(list):
def added_method(self):
pass
class B(A):
def added_method2(self):
self.sort()
b = B() # todo: rename b to c
b.a
added_method
added_method2
append
Source Structure
Options
class A
def added_me...
class B
def added_me...
todo: rename b to c
Project manager
visvis
backends
core
examples
anisotropicData.py
anisotropicData2.py
bouncingBall.py
colormaps.py
colorVolume.py
drawing.py
embeddingInFLTK.py
embeddingInGTK.py
embeddingInQt4.py
embeddingInWx.py
fourDimensions.py
imageEdges.py
images.py
lightsAndShading.py
!*.pyc
File browser
Project manager



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ENTHOUGHT
CANOPY
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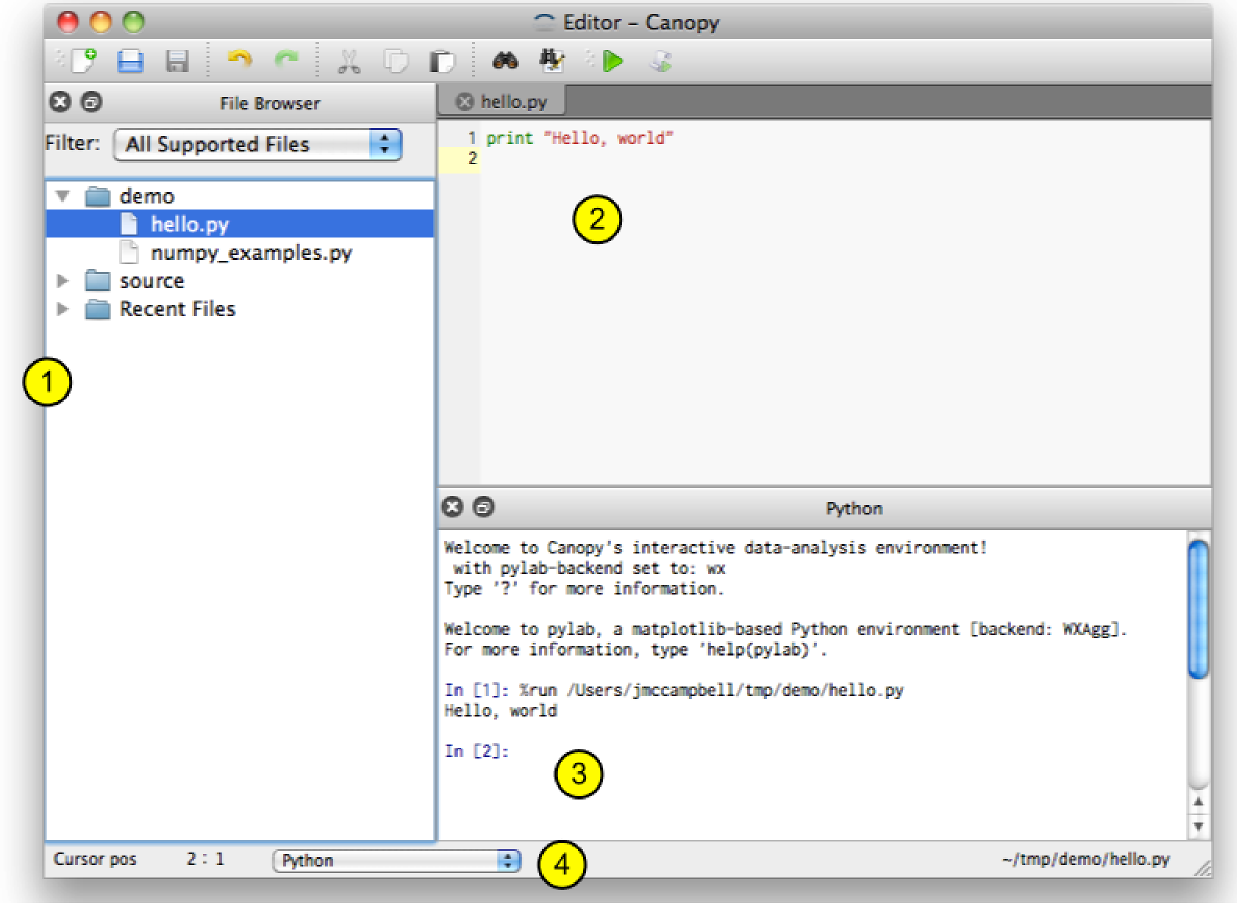
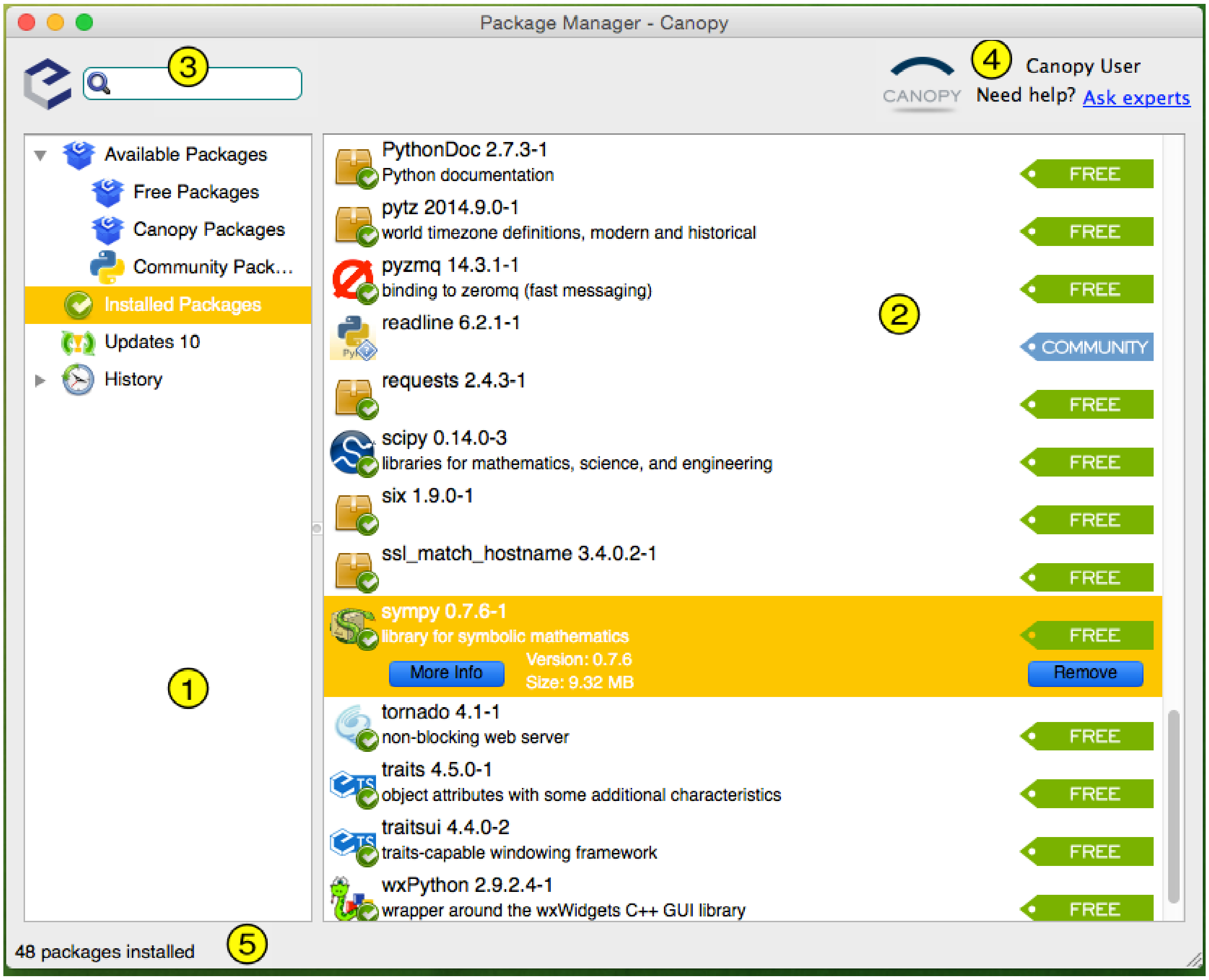
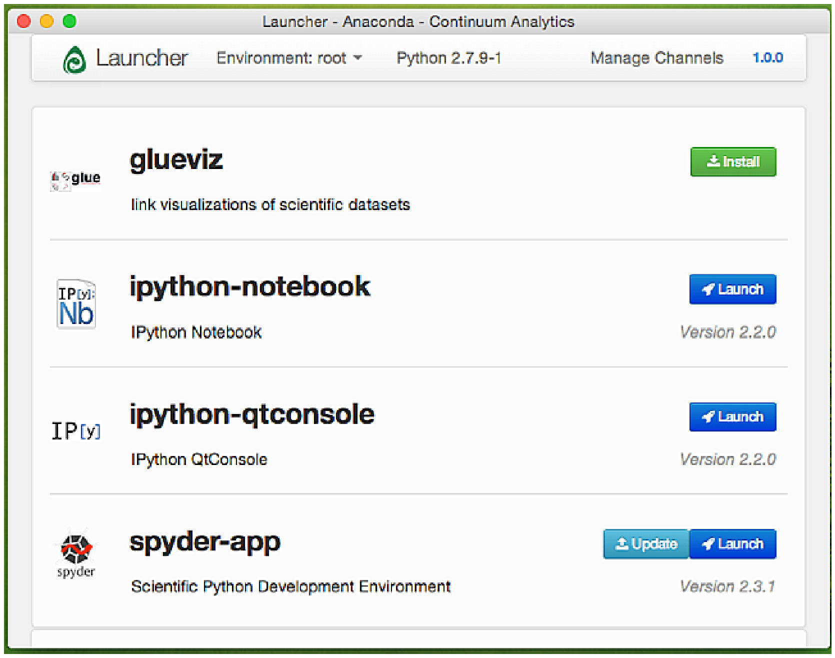
Editor
Package Manager
Doc Browser
Training on Demand
Recent files
bubbles.py
draw.py
plotblot.py
plotly.py
testplot.py
Restore previous session
Open an existing file
Version 1.5.1.2730
No updates found.
Figure 1

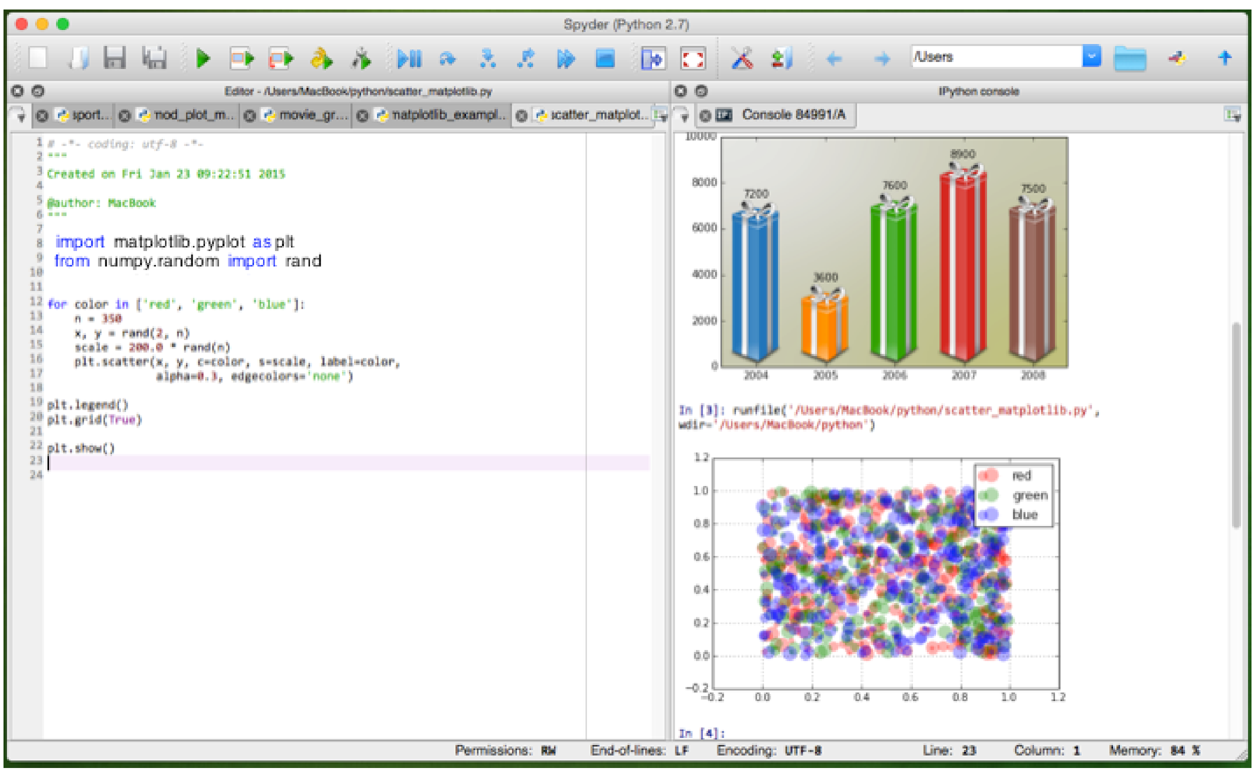

Editor – Canopy
File Browser
Filter: All Supported Files
demo
hello.py
numpy_examples.py
source
Recent Files
1
hello.py
1 print "Hello, world"
2
2
Python
Welcome to Canopy's interactive data-analysis environment!
with pylab-backend set to: wx
Type '?' for more information.
Welcome to pylab, a matplotlib-based Python environment [backend: WXAgg].
For more information, type 'help(pylab)'.
In [1]: %run /Users/jmccampbell/tmp/demo/hello.py
Hello, world
In [2]:
3
Cursor pos 2 : 1
Python
4
~/tmp/demo/hello.py

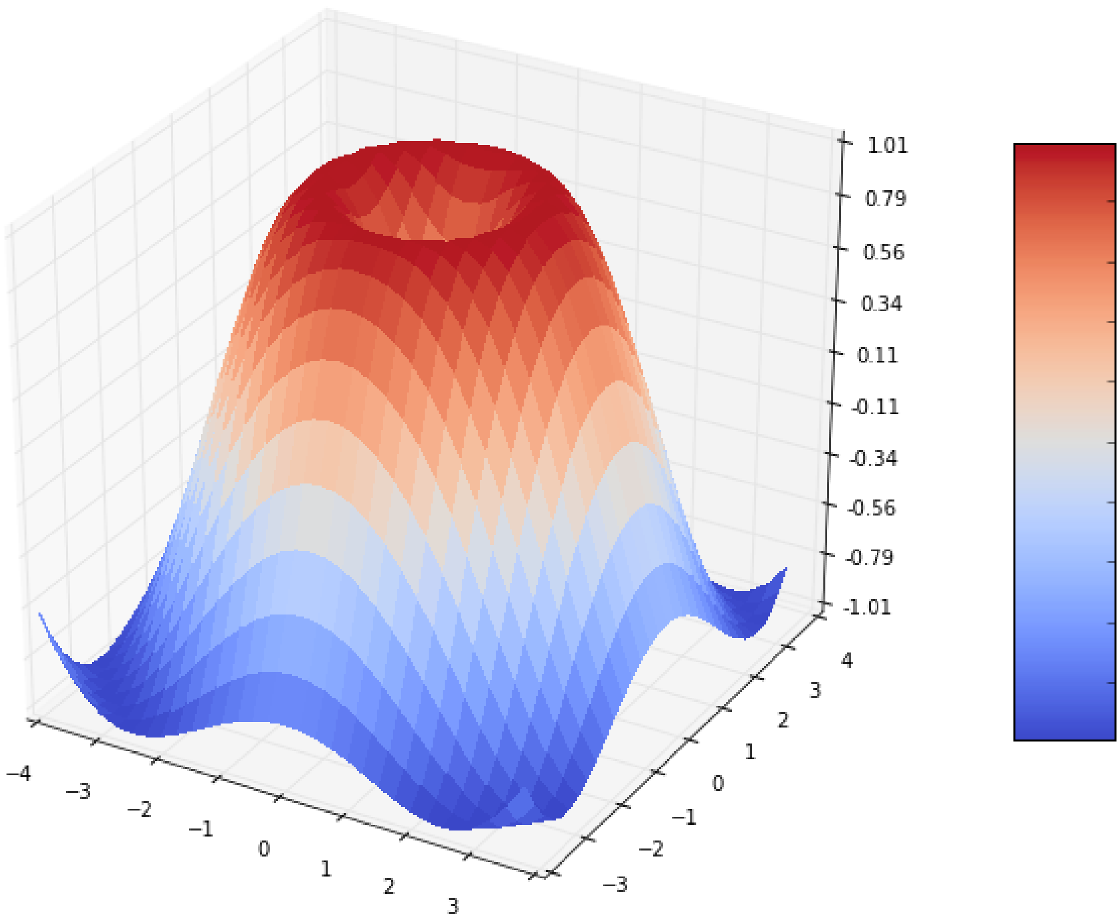

Documentation Browser – Canopy
http://help.canopy/toplevel-docs.html
DOCUMENTATION
User guide and online help
ENTHOUGHT
CANOPY
Canopy User Guide
Click here to view the Canopy User Guide
Online Help
Click on the links below to view documentation on the Python language itself or any of these popular Python extensions.
Python Tutorial
Python Documentation
IPython
NumPy
SciPy
Chaco
Enaml
Envisage
Mayavi
Pandas
scikit-image
scikit-learn
Sympy
Tips
The documentation browser lets you navigate to any page with code and run the code blocks within Canopy. The code can either be run at the Python prompt or copied to the clipboard by right-clicking on the code block and selecting the appropriate menu item.
If the page is Sphinx generated and has a sidebar, it can be hidden/shown by clicking on the button added at the extreme left.

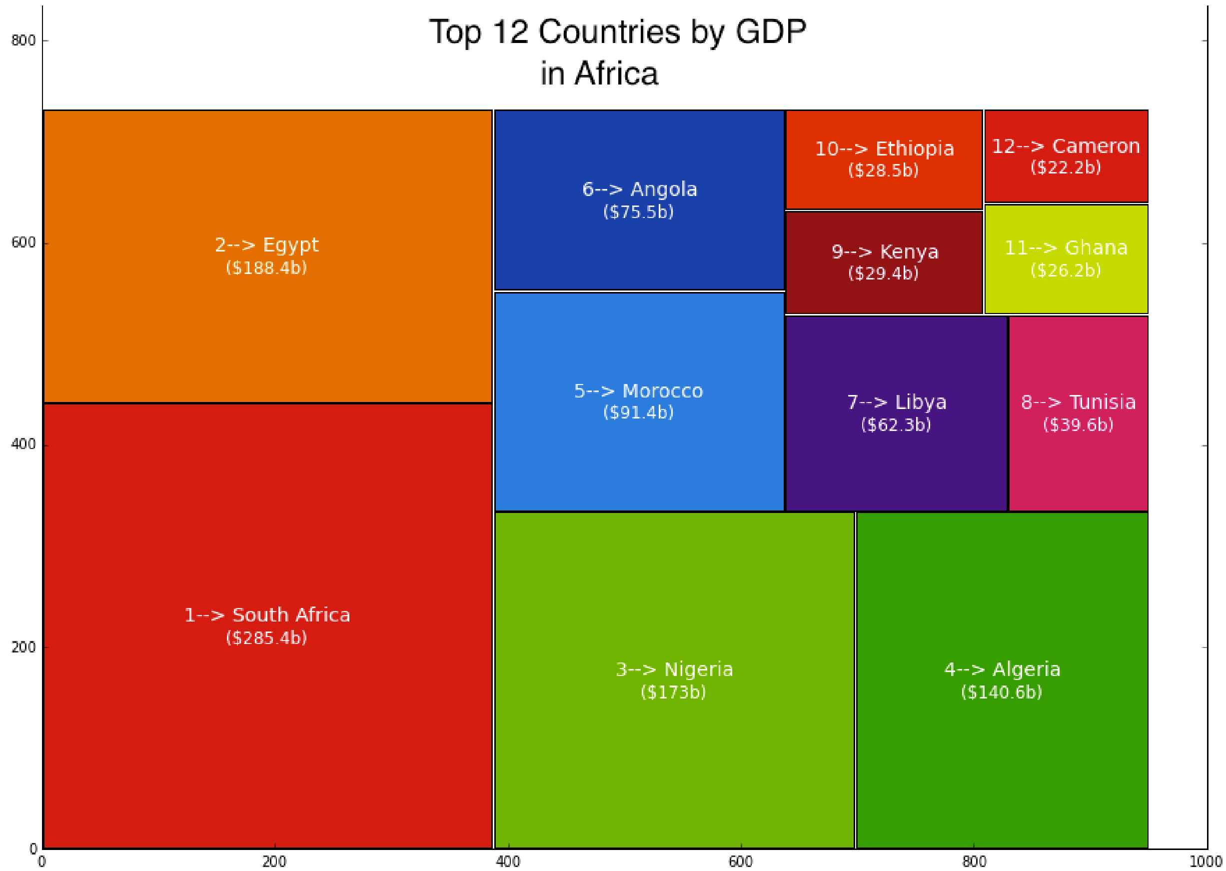


Package Manager - Canopy
3
4
Canopy User
Need help? Ask experts
CANOPY
Available Packages
Free Packages
Canopy Packages
Community Pack...
Installed Packages
Updates 10
History
1
PythonDoc 2.7.3-1
Python documentation
FREE
pytz 2014.9.0-1
world timezone definitions, modern and historical
FREE
pyzmq 14.3.1-1
binding to zeromq (fast messaging)
FREE
2
readline 6.2.1-1
COMMUNITY
requests 2.4.3-1
FREE
scipy 0.14.0-3
libraries for mathematics, science, and engineering
FREE
six 1.9.0-1
FREE
ssl_match_hostname 3.4.0.2-1
FREE
sympy 0.7.6-1
library for symbolic mathematics
FREE
More Info
Version: 0.7.6
Size: 9.32 MB
Remove
tornado 4.1-1
non-blocking web server
FREE
traits 4.5.0-1
object attributes with some additional characteristics
FREE
traitsui 4.4.0-2
traits-capable windowing framework
FREE
wxPython 2.9.2.4-1
wrapper around the wxWidgets C++ GUI library
FREE
48 packages installed
5

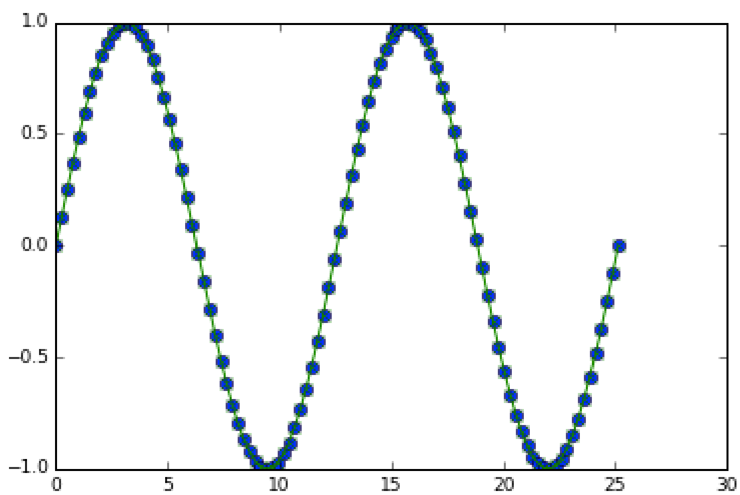

Launcher - Anaconda - Continuum Analytics
Launcher
Environment: root
Python 2.7.9-1
Manage Channels
1.0.0
glueviz
Install
link visualizations of scientific datasets
ipython-notebook
Launch
IPython Notebook
Version 2.2.0
ipython-qtconsole
Launch
IPython QtConsole
Version 2.2.0
spyder-app
Update
Launch
Scientific Python Development Environment
Version 2.3.1


Spyder (Python 2.7)
/Users
IPython console
Console 84991/A
import matplotlib.pyplot as plt
from numpy.random import rand
In [4]:
Permissions: RW
End-of-lines: LF
Encoding: UTF-8
Line: 23
Column: 1

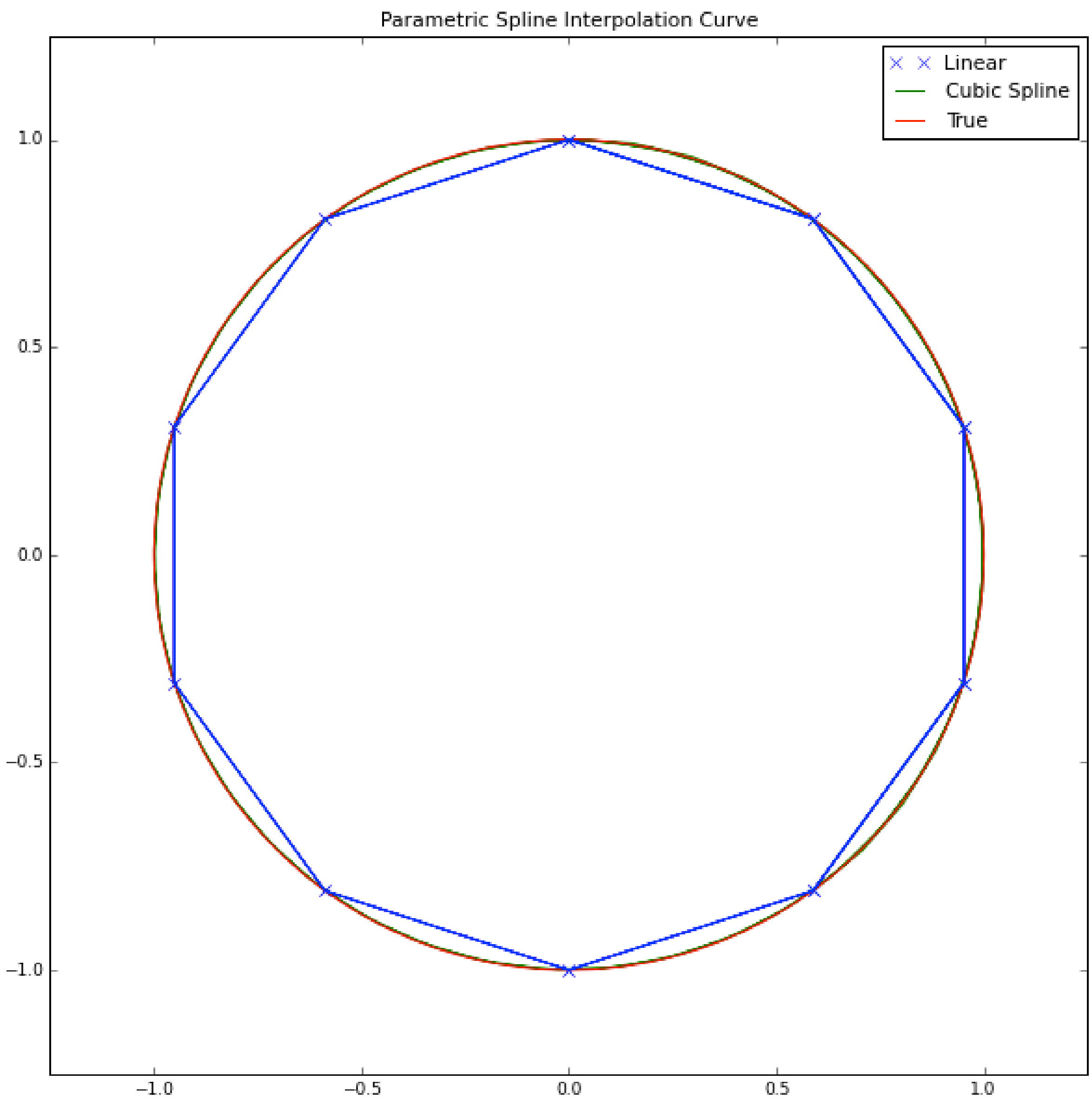

1.01
0.79
0.56
0.34
0.11
-0.11
-0.34
-0.56
-0.79
-1.01
−4
−3
−2
−1
0
1
2
3
4
3
2
1
0
−1
−2
−3
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8



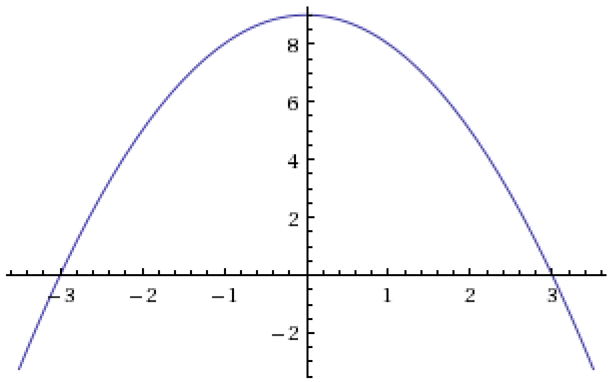
Chapter 4: Numerical Computing and Interactive Plotting



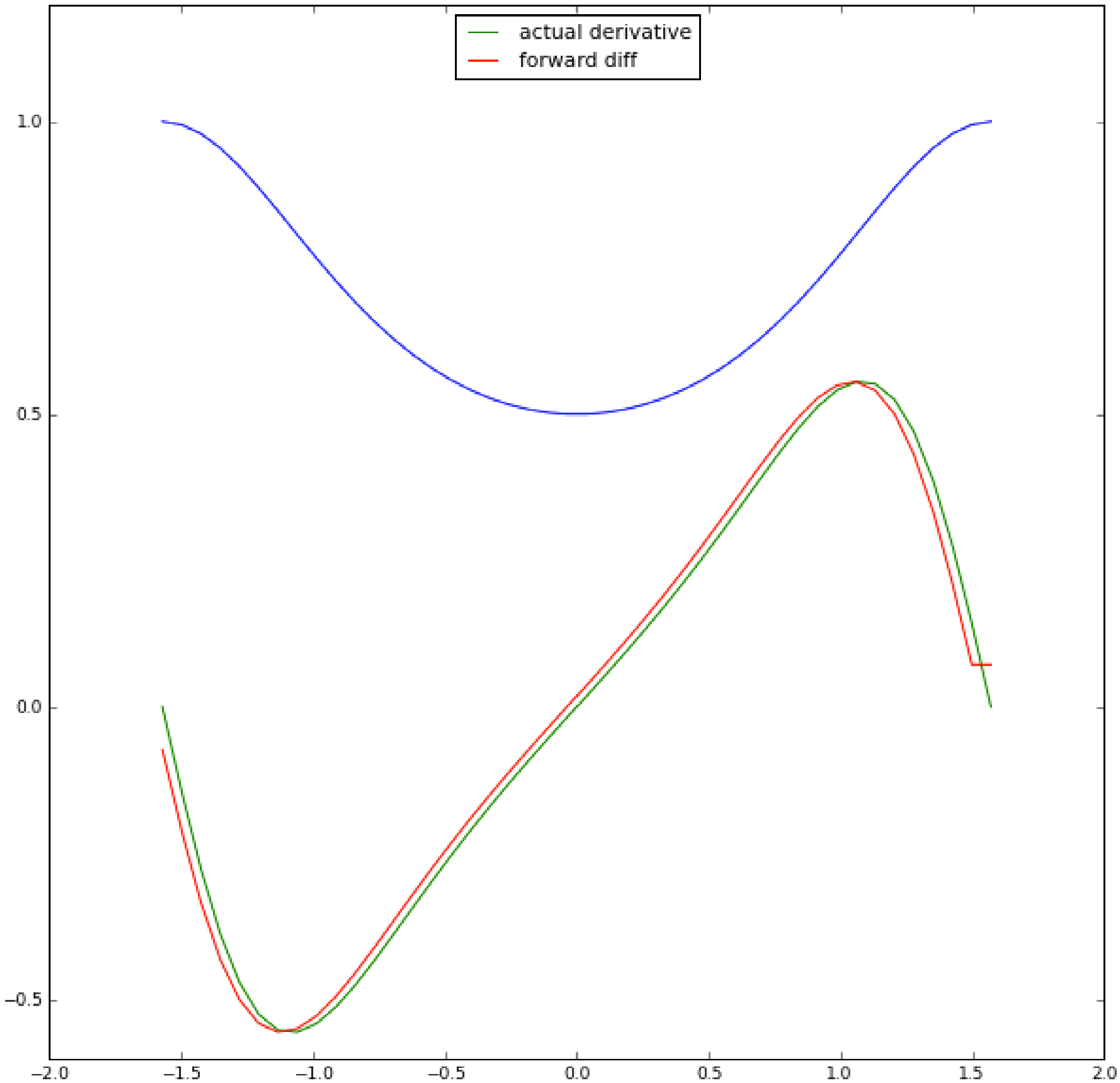
$$(3x^3 + 4x^2 + 5x + 5)(4x^3 + x^2 - 3x + 3)$$
$$= (12x^6 + 9x^5 + 15x^4 + 22x^3 + 2x^2 + 15)$$

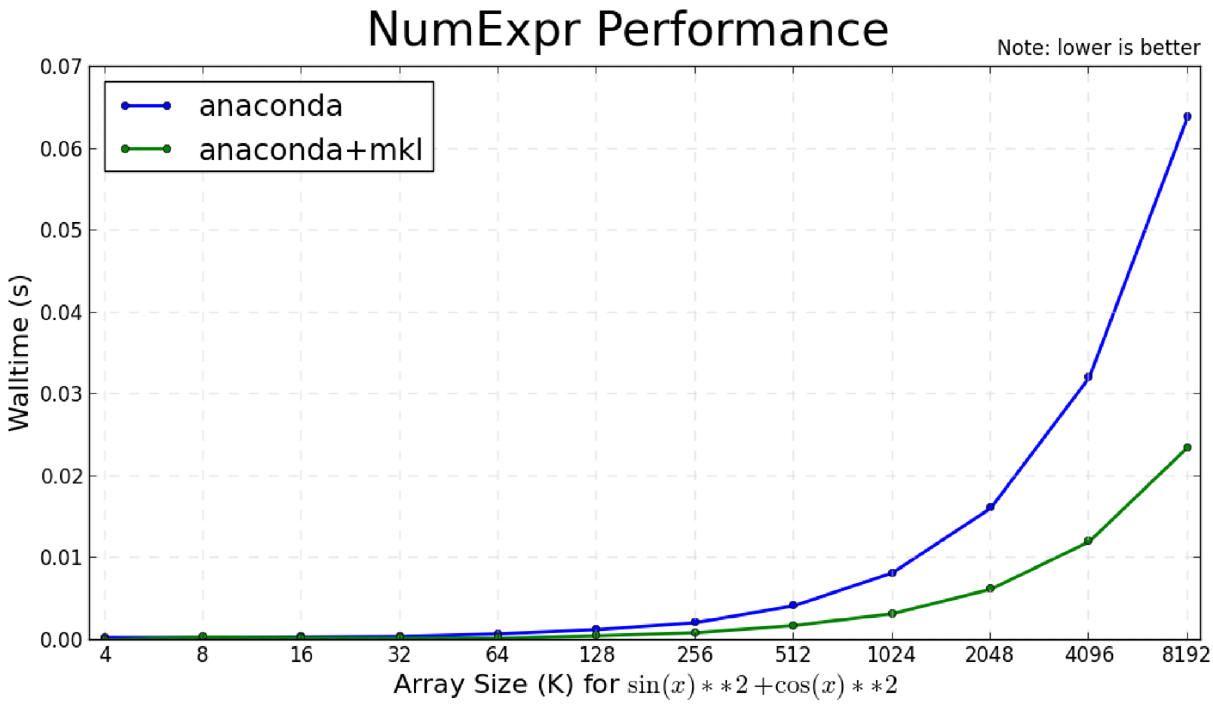


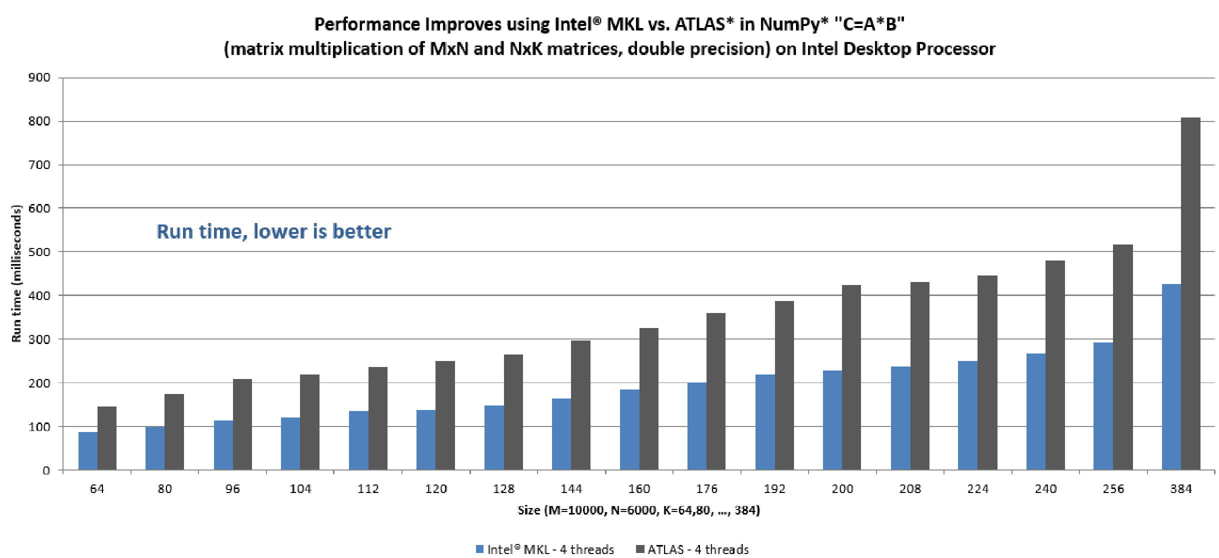
$$\int_{-3}^{3} 9 - x^2 \; dx = 9(3+3) - \frac{1}{3}(3^3 + 3^3) = 54 - 18 = 36$$



$$\frac{d}{dx}\left(\frac{1}{1+cos^2(x)}\right) = \frac{sin2x}{(1+cos^2x)^2}$$


actual derivative
forward diff
1.0
0.5
0.0
−0.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

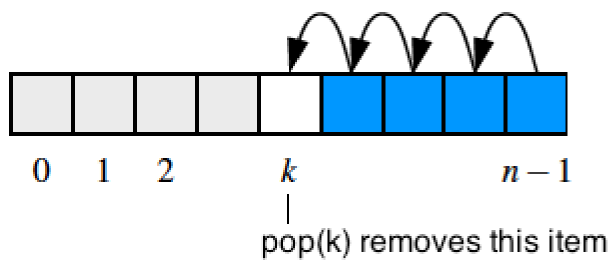




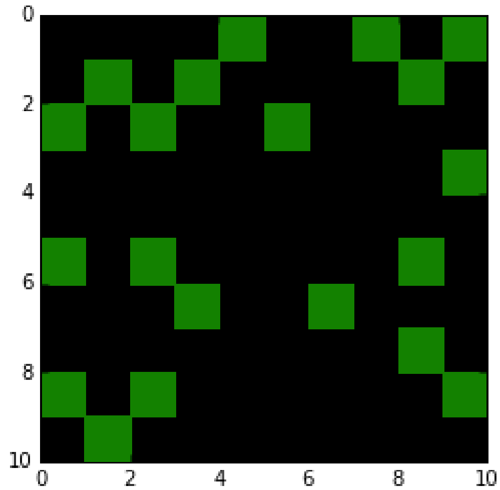
Configuration Info - Versions: Intel® Math Kernel Library (Intel® MKL) 11.1 update 1, ATLAS* 3.10.1 with LAPACK 3.4.2, NumPy* 1.8.0, SciPy* 0.13.2, Python 3.3; Hardware: Intel® Core® i5-4670T Processor (6 MB LLC, 2.30Ghz), 4 GB of RAM; Operating System: Fedora 16 x86_64; Benchmark Source: Intel Corporation.

Performance tests and ratings are measured using specific computer systems and/or components and reflect the approximate performance of Intel products as measured by those tests. Any difference in system hardware or software design or configuration may affect actual performance. Buyers should consult other sources of information to evaluate the performance of systems or components they are considering purchasing. For more information on performance tests and on the performance of Intel products, refer to www.intel.com/performance/resources/benchmark_limitations.htm.

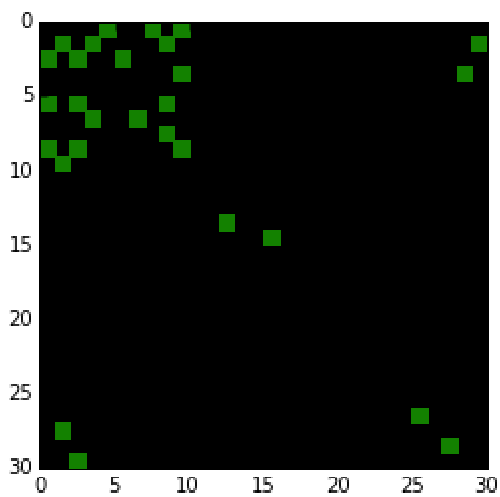
$$A = \begin{bmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \\ 1 & 2 & 3 \end{bmatrix}$$



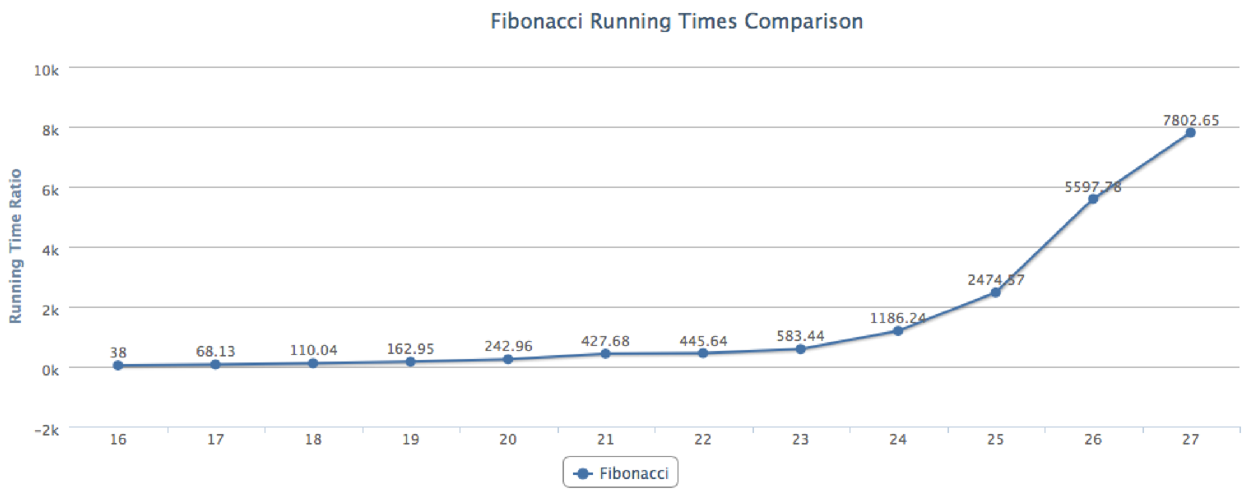
$$A = \begin{bmatrix} 0 & 0 & 0 & 0 & 2 & 0 & 0 & 1 & 0 & 2 \\ 0 & 4 & 0 & 3 & 0 & 0 & 0 & 0 & 1 & 0 \\ 6 & 0 & 1 & 0 & 0 & 7 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 3 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

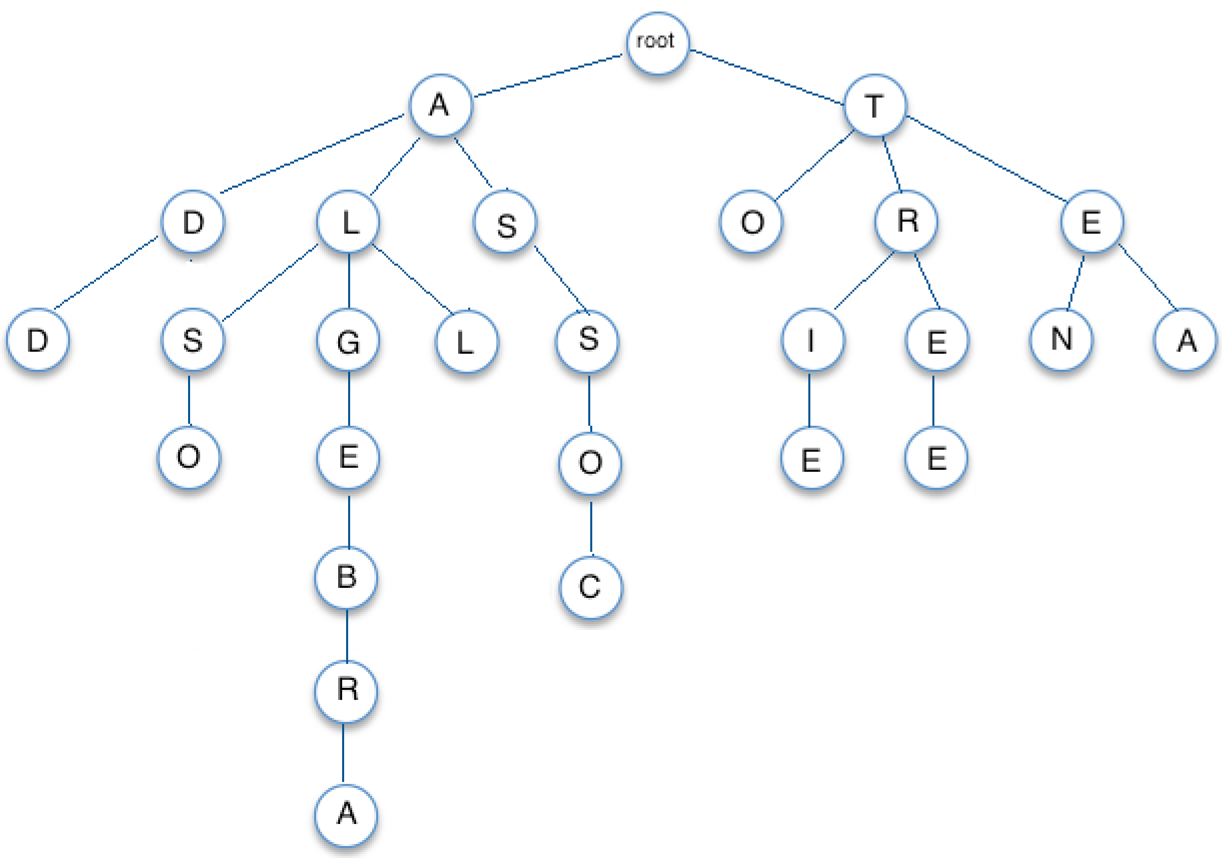


0
2
4
6
8
10
0
2
4
6
8
10

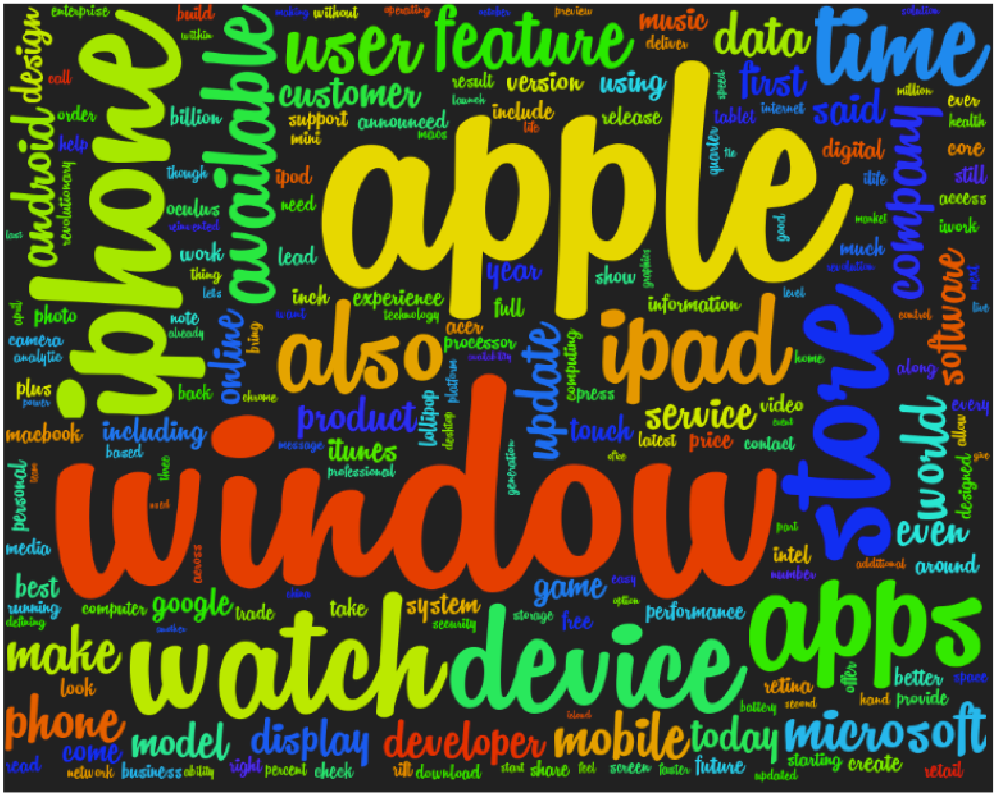


0
5
10
15
20
25
30
0
5
10
15
20
25
30


Fibonacci Running Times Comparison
Running Time Ratio
10k
8k
6k
4k
2k
0k
-2k
16
17
18
19
20
21
22
23
24
25
26
27
38
68.13
110.04
162.95
242.96
427.68
445.64
583.44
1186.24
2474.57
5597.78
7802.65
Fibonacci

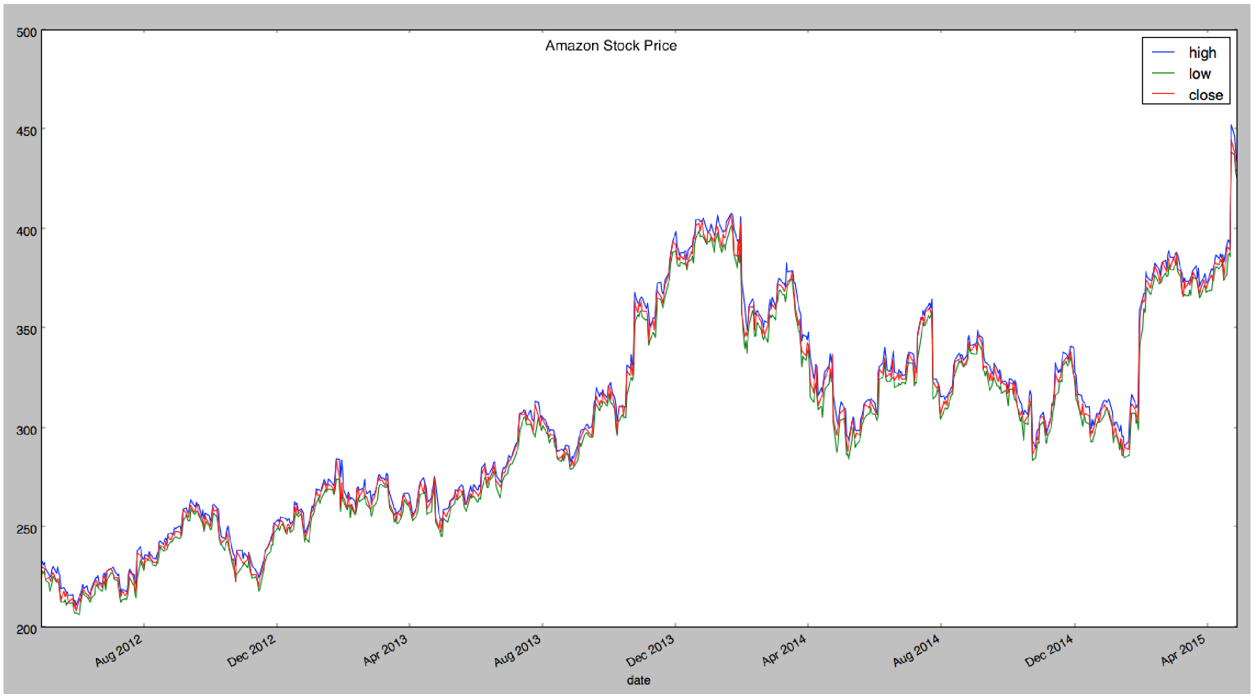

root
A
T
D
L
S
O
R
E
D
S
G
L
S
I
E
N
A
O
E
O
E
E
B
C
R
A

season
Future
Analytics
Perspectives
Amazon
Current
statistic
baseball
Sports
Media
fighting
justice
Data Science
Radar
O
Reilly
Social
Internet
finance
video
Making
stats
Hazard
Visualization
knowledge
analyzes
based
Premier
Conference
Science
Things
criminal
Twitter
crime
Shore
smart
problem
world
Experts
Facts
Big
Data
wanted
Computers
Business
Changing
Machine
League
Learning
cloud
minutes
moneyball
Infographics
Coutinho

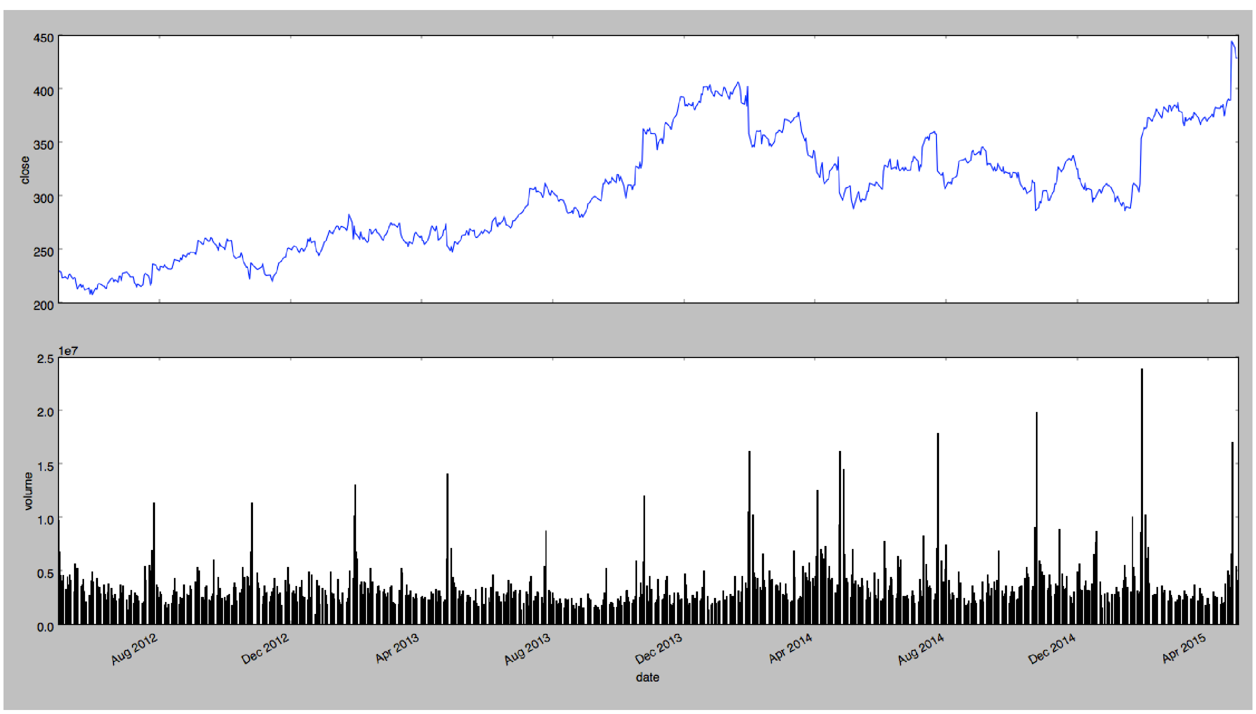


$$p(+) = e^{\frac{1}{w_p - w_n + 1}}$$

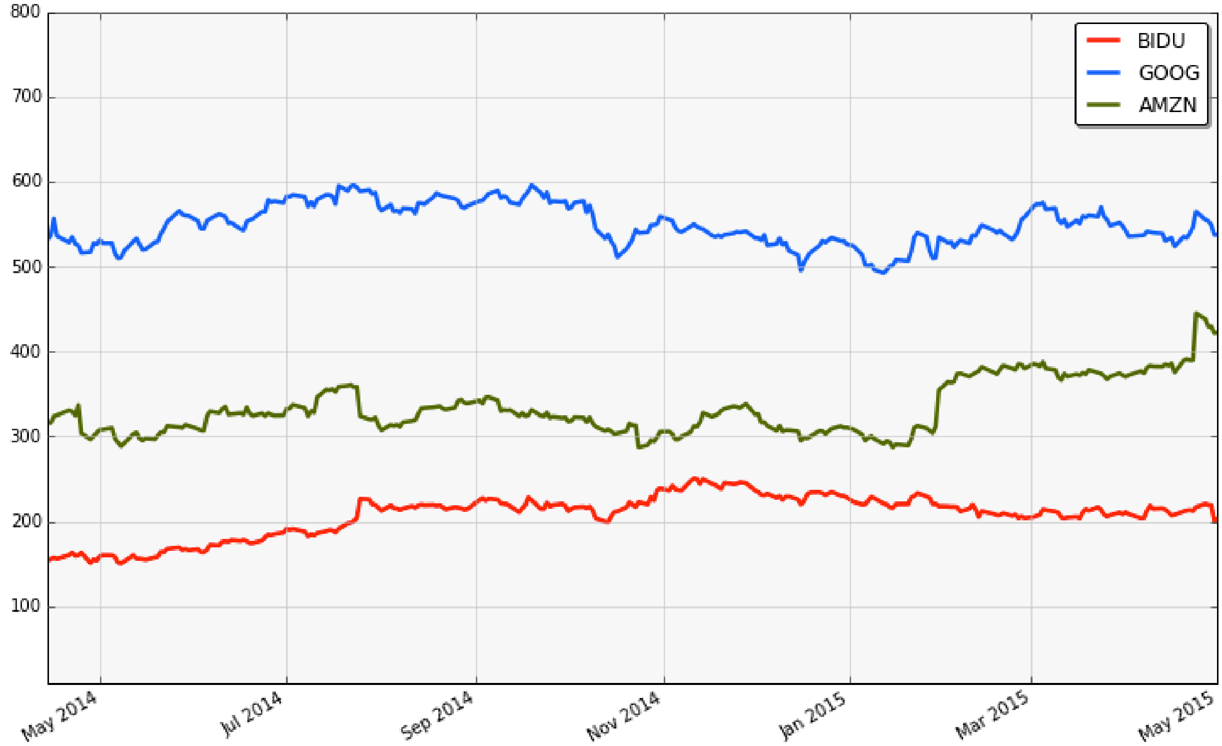
$$p(-) = 1 - p(+)$$



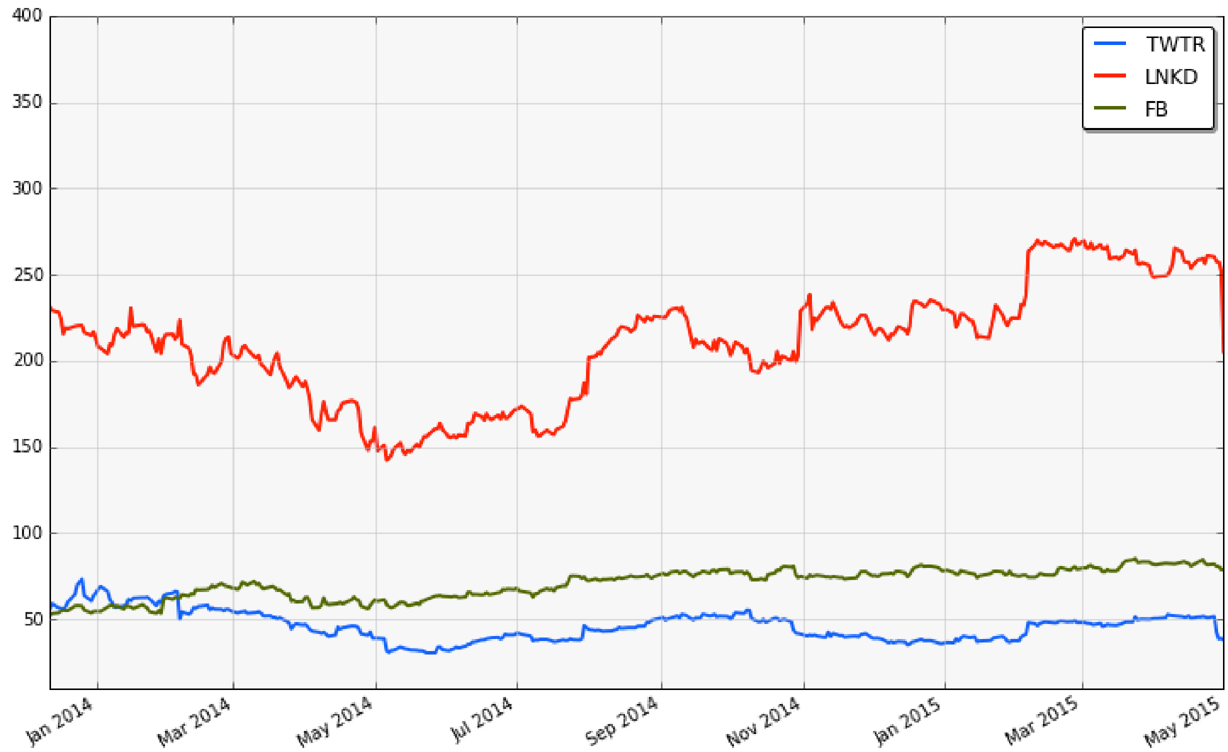
Amazon Stock Price
high
low
close
500
450
400
350
300
250
200
Aug 2012
Dec 2012
Apr 2013
Aug 2013
Dec 2013
Apr 2014
Aug 2014
Dec 2014
Apr 2015
date



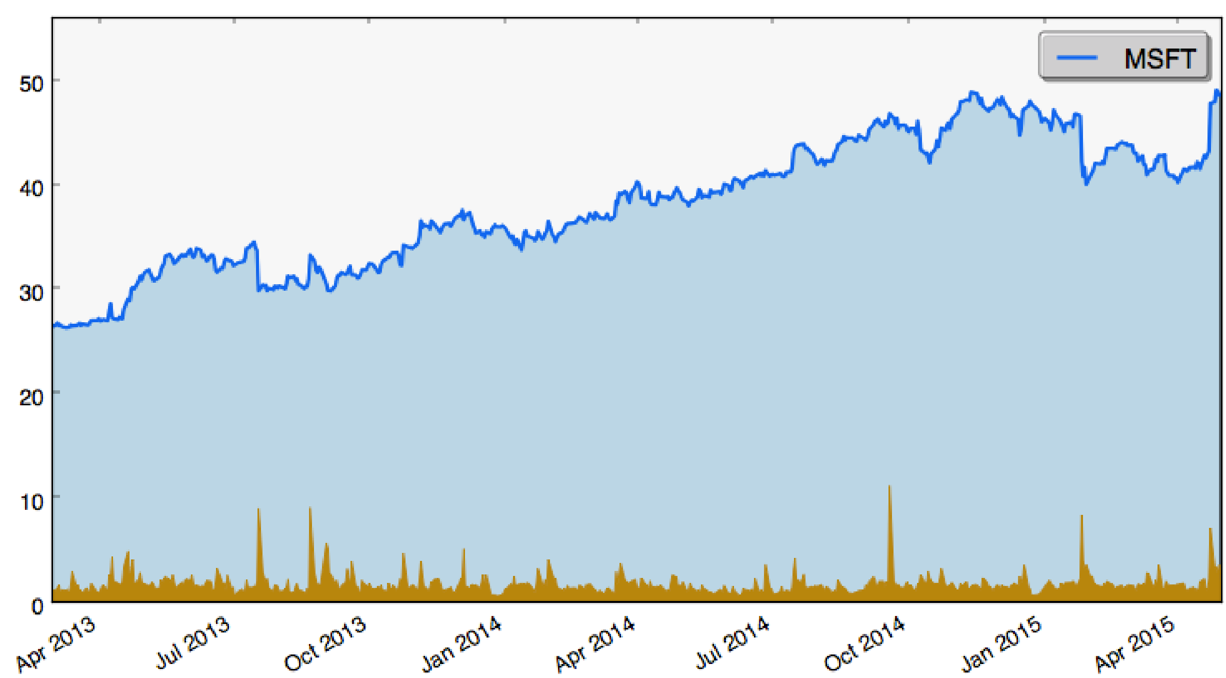
close
450
400
350
300
250
200
volume
1e7
2.5
2.0
1.5
1.0
0.5
0.0
Aug 2012
Dec 2012
Apr 2013
Aug 2013
Dec 2013
Apr 2014
Aug 2014
Dec 2014
Apr 2015
date



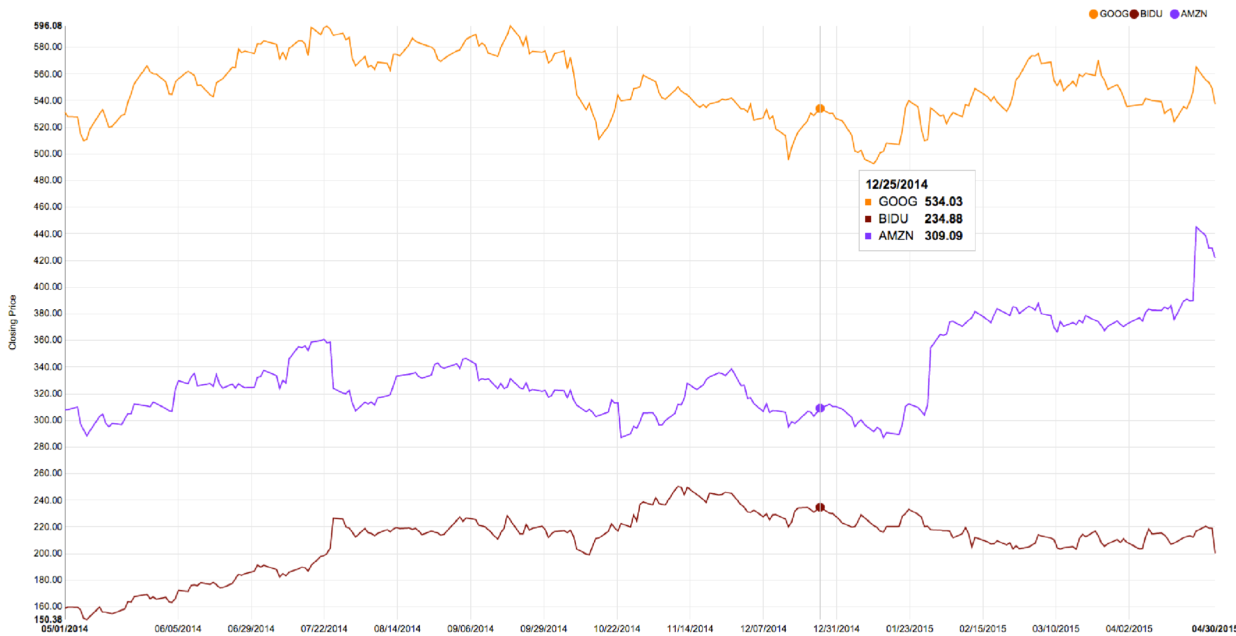
800
700
600
500
400
300
200
100
BIDU
GOOG
AMZN
May 2014
Jul 2014
Sep 2014
Nov 2014
Jan 2015
Mar 2015
May 2015



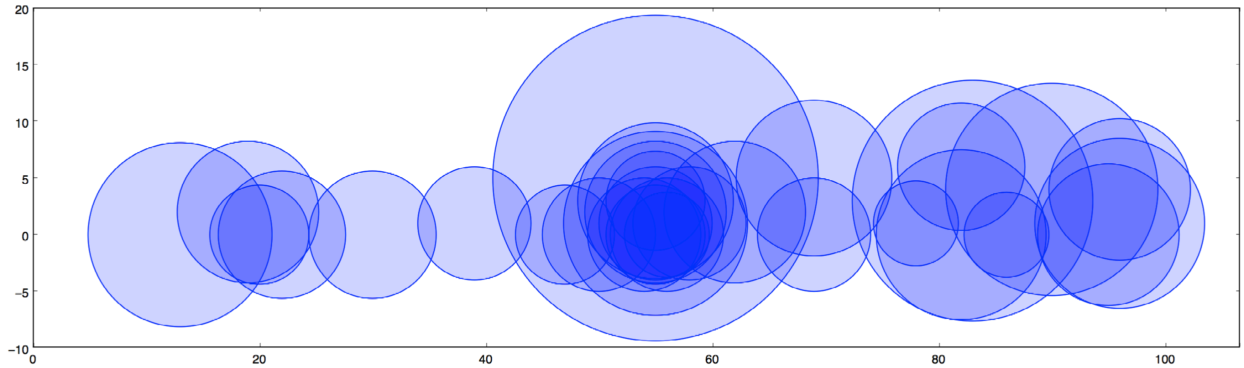
400
350
300
250
200
150
100
50
TWTR
LNKD
FB
Jan 2014
Mar 2014
May 2014
Jul 2014
Sep 2014
Nov 2014
Jan 2015
Mar 2015
May 2015

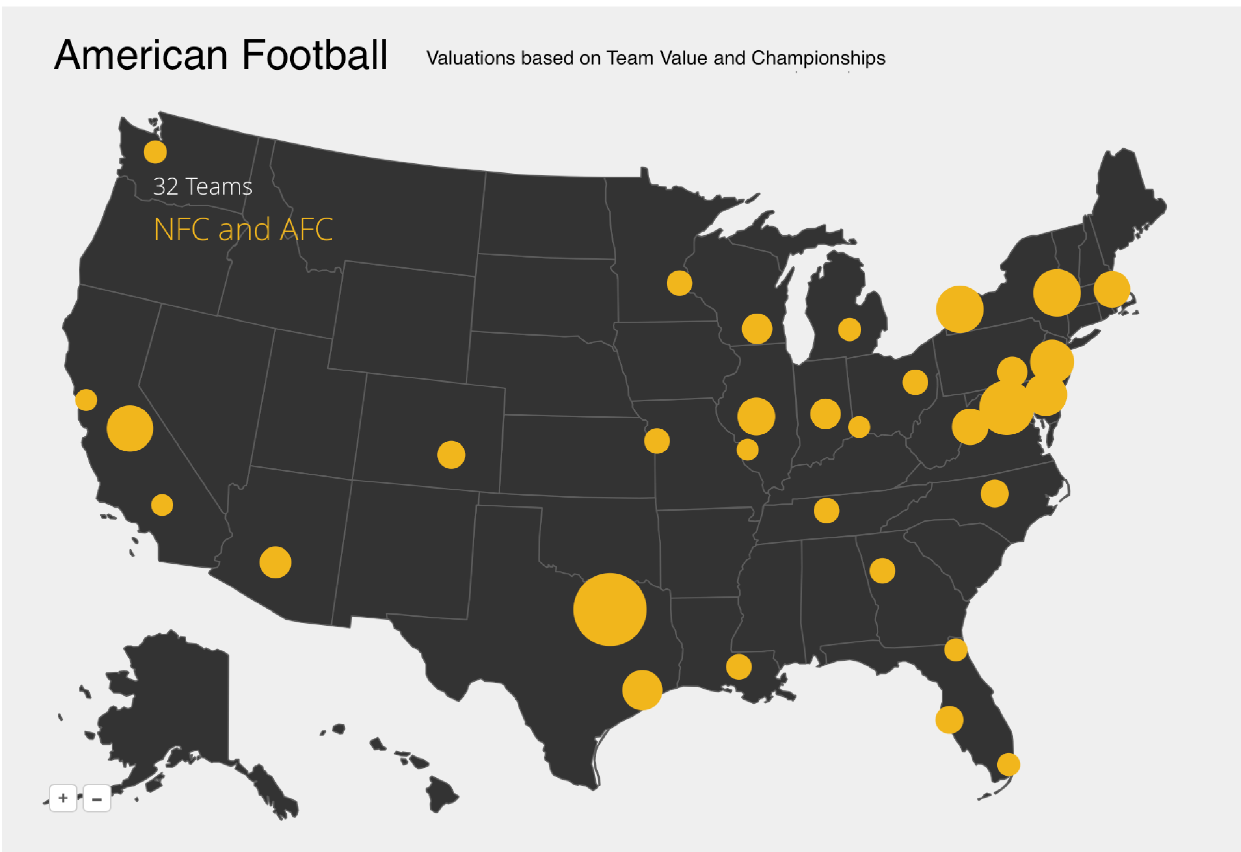


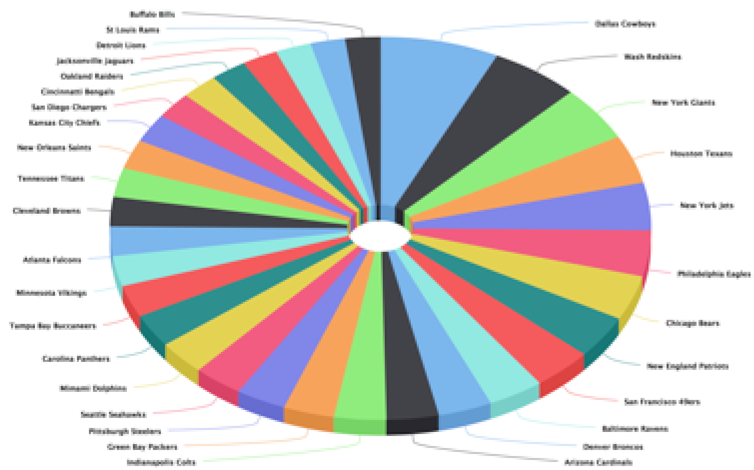
MSFT
50
40
30
20
10
0
Apr 2013
Jul 2013
Oct 2013
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015

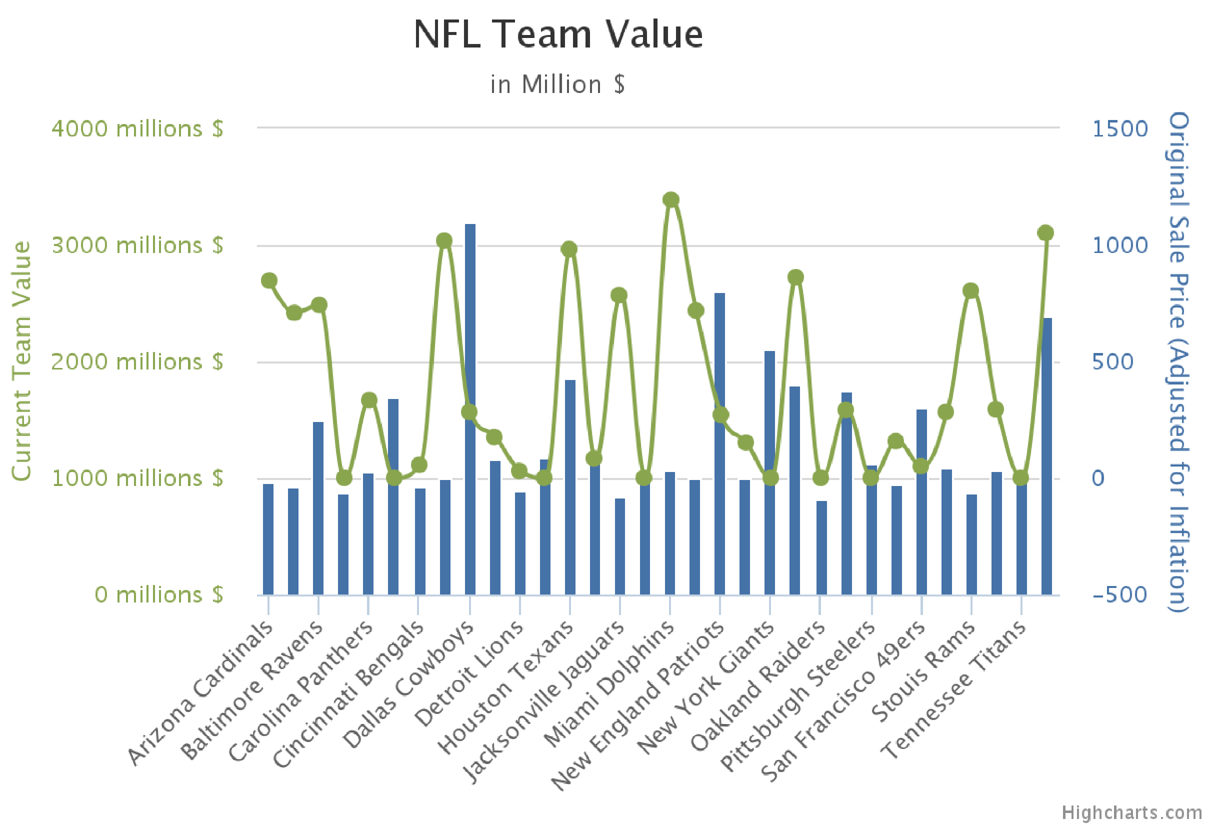


	Team.name	Team.value	Years.Completed	Num.Championships	Championships.yr.average
1	Dallas Cowboys	3210	55	5	23.18
2	Washington Redskins	2400	83	3	12.22
3	New York Giants	2100	90	4	13.88
4	Houston Texans	1850	13	0	5.00
5	New York Jets	1810	55	1	8.63
6	Philadelphia Eagles	1750	82	0	5.00
7	Chicago Bears	1700	96	1	7.08
8	New England Patriots	1635	55	4	15.90
9	San Francisco 49ers	1600	69	5	19.49
10	Baltimore Ravens	1500	19	2	26.05


20
15
10
5
0
−5
−10
0
20
40
60
80
100


American Football
Valuations based on Team Value and Championships
32 Teams
NFC and AFC
+
−


Buffalo Bills
St Louis Rams
Detroit Lions
Jacksonville Jaguars
Oakland Raiders
Cincinnati Bengals
San Diego Chargers
Kansas City Chiefs
New Orleans Saints
Tennessee Titans
Cleveland Browns
Atlanta Falcons
Minnesota Vikings
Tampa Bay Buccaneers
Carolina Panthers
Mimami Dolphins
Seattle Seahawks
Pittsburgh Steelers
Green Bay Packers
Indianapolis Colts
Dallas Cowboys
Wash Redskins
New York Giants
Houston Texans
New York Jets
Philadelphia Eagles
Chicago Bears
New England Patriots
San Francisco 49ers
Baltimore Ravens
Denver Broncos
Arizona Cardinals

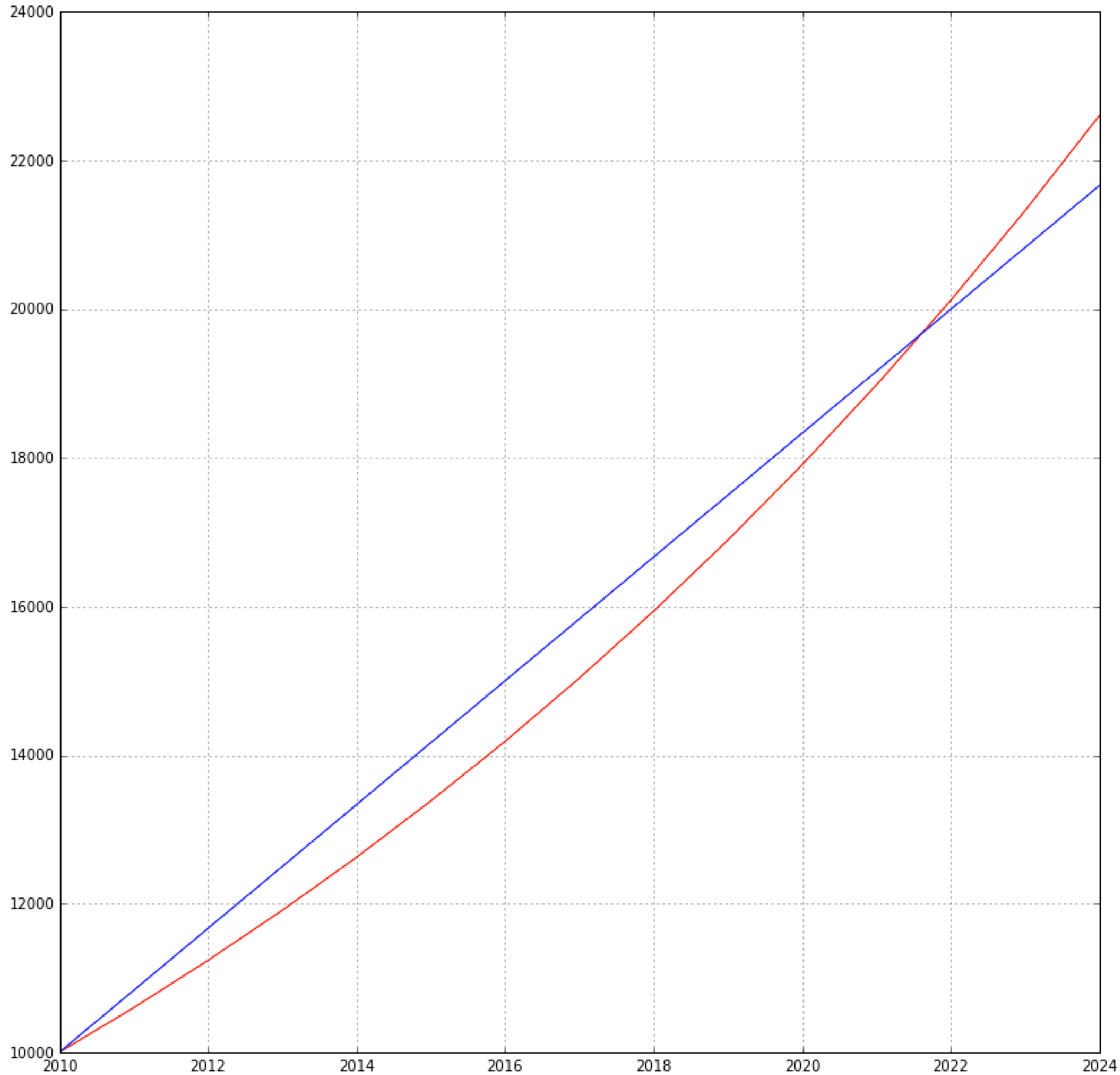

NFL Team Value
in Million $
Current Team Value
4000 millions $
3000 millions $
2000 millions $
1000 millions $
0 millions $
Original Sale Price (Adjusted for Inflation)
1500
1000
500
0
-500
Arizona Cardinals
Baltimore Ravens
Carolina Panthers
Cincinnati Bengals
Dallas Cowboys
Detroit Lions
Houston Texans
Jacksonville Jaguars
Miami Dolphins
New England Patriots
New York Giants
Oakland Raiders
Pittsburgh Steelers
San Francisco 49ers
Stouis Rams
Tennessee Titans
Highcharts.com

Chapter 5: Financial and Statistical Models

$$\frac{P_{t+1}}{P_t} = 1 + R_{t+1}$$

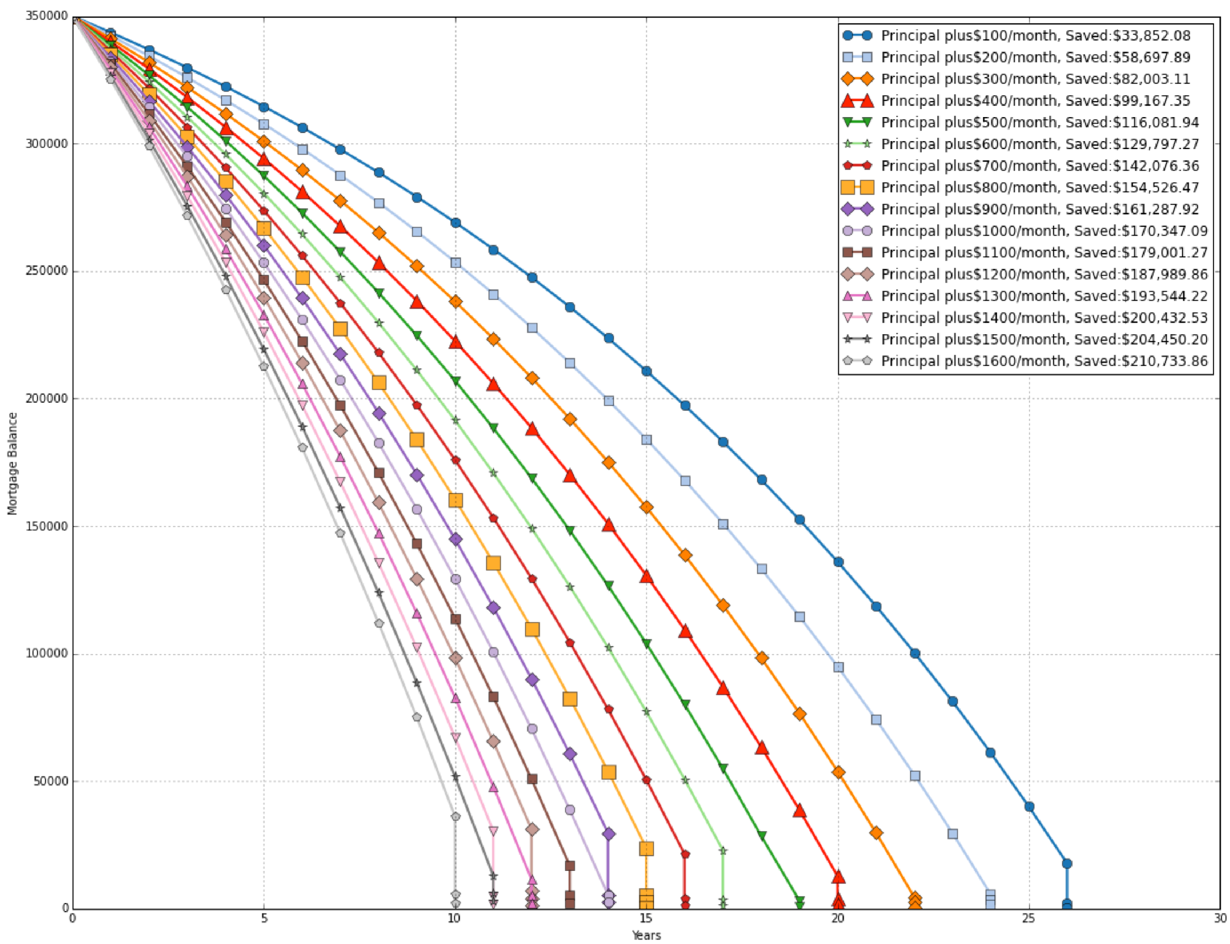
$$\begin{aligned} 1 + R_t(k) &= \frac{P_t}{P_{t-k}} \\ &= \left(\frac{P_t}{P_{t-1}}\right)\left(\frac{P_{t-1}}{P_{t-2}}\right)\cdots\left(\frac{P_{t-k+1}}{P_{t-k}}\right) \\ &= \left(1 + R_t\right)\left(1 + R_{t-1}\right)\ldots\left(1 + R_{t-k+1}\right) \end{aligned}$$

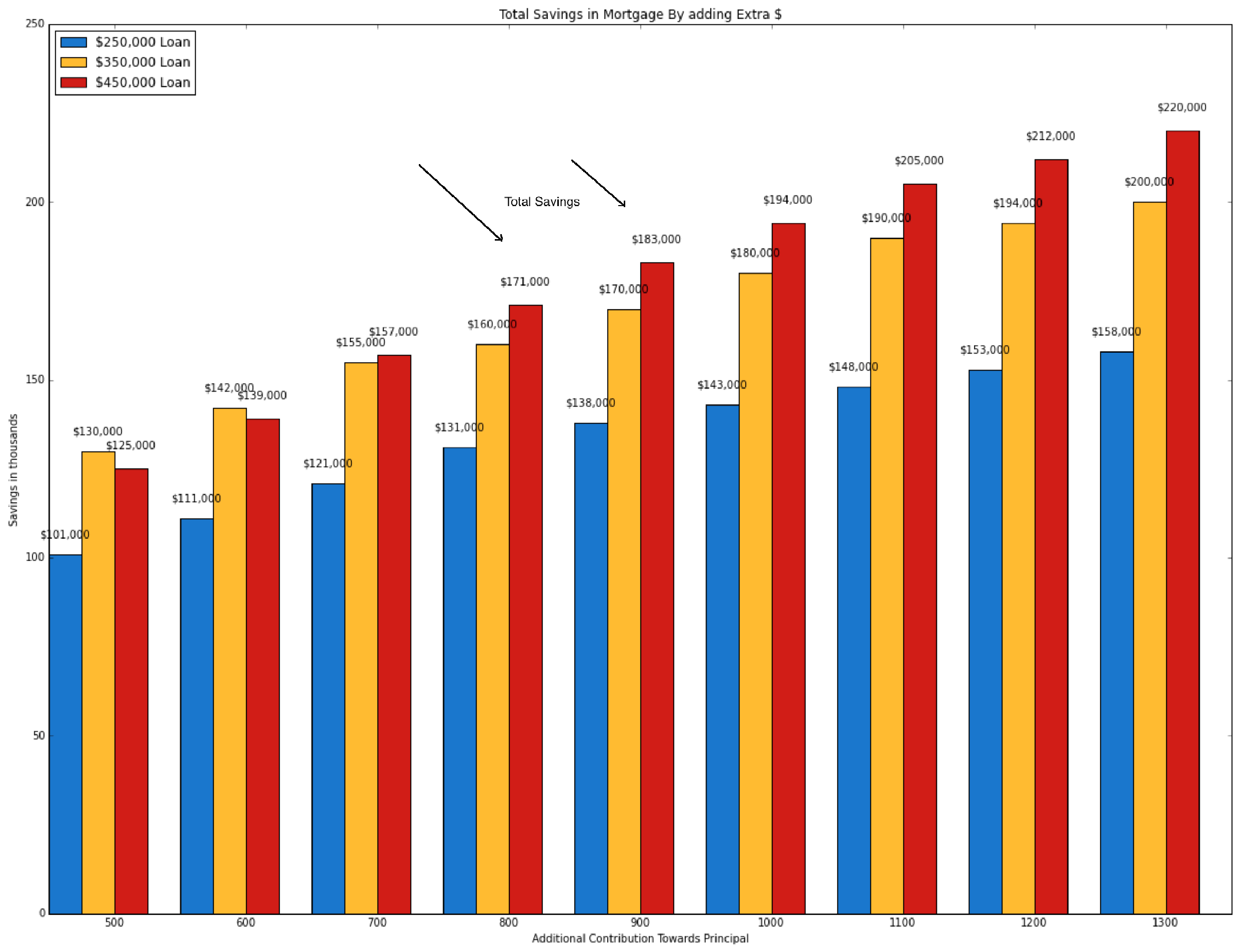
$$1 + R_t(k) = \frac{\left(1 + R_t\right)}{\left(1 + F_t\right)}\frac{\left(1 + R_{t-1}\right)}{\left(1 + F_{t-1}\right)}\cdots\frac{\left(1 + R_{t-k+1}\right)}{\left(1 + F_{t-k+1}\right)}$$



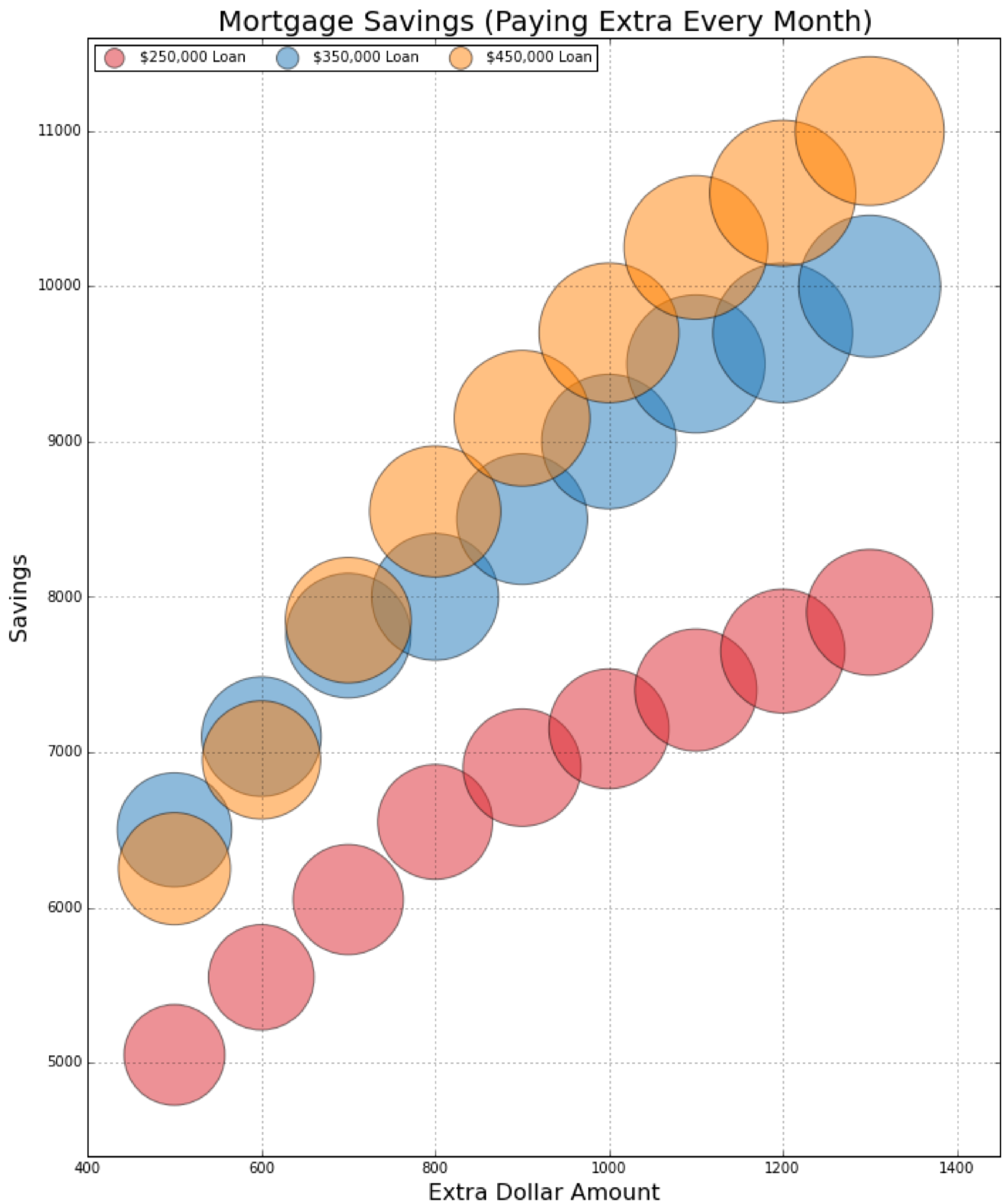
$$1 + R_t = \frac{P_t + D_t}{P_{t-1}}$$

$$350,000\times\left(1+\frac{5}{100}\times 30\right)=350,000\times\frac{5}{2}=875,000$$

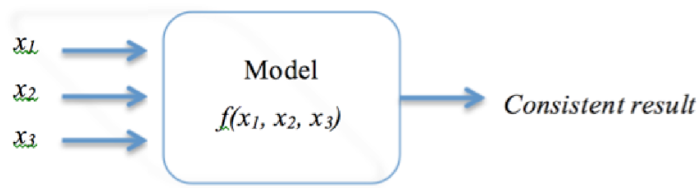


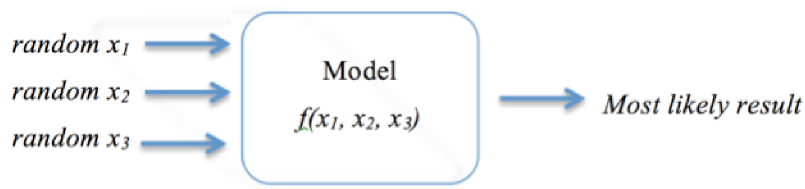


Total Savings in Mortgage By adding Extra $
$250,000 Loan
$350,000 Loan
$450,000 Loan
Savings in thousands
Additional Contribution Towards Principal
Total Savings
0
50
100
150
200
250
500
600
700
800
900
1000
1100
1200
1300
$101,000
$130,000
$125,000
$111,000
$142,000
$139,000
$121,000
$155,000
$157,000
$131,000
$160,000
$171,000
$138,000
$170,000
$183,000
$143,000
$180,000
$194,000
$148,000
$190,000
$205,000
$153,000
$194,000
$212,000
$158,000
$200,000
$220,000

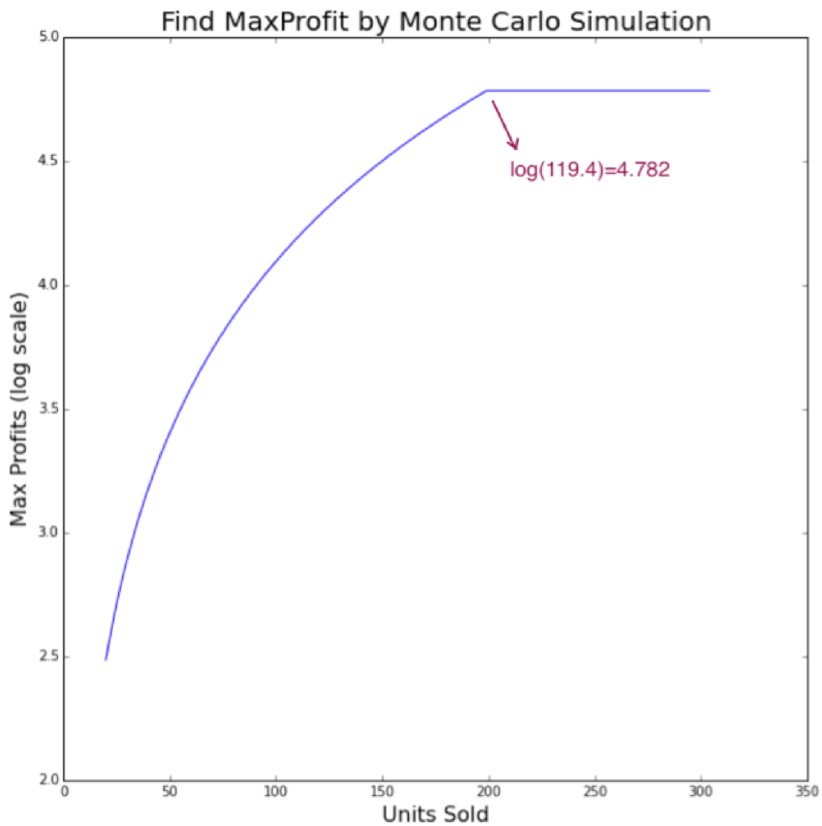


Mortgage Savings (Paying Extra Every Month)
$250,000 Loan
$350,000 Loan
$450,000 Loan
Savings
Extra Dollar Amount
11000
10000
9000
8000
7000
6000
5000
400
600
800
1000
1200
1400





$$P = \begin{cases} 0.6s & \text{if } d \geq s \\ 0.6d - 0.4(s-d) & \text{if } s > d \end{cases}$$



$$Profit = \int_{s}^{140} \frac{0.6s}{60} dx + \int_{80}^{s} \frac{0.6x - 0.4(s-x)}{60} dx$$

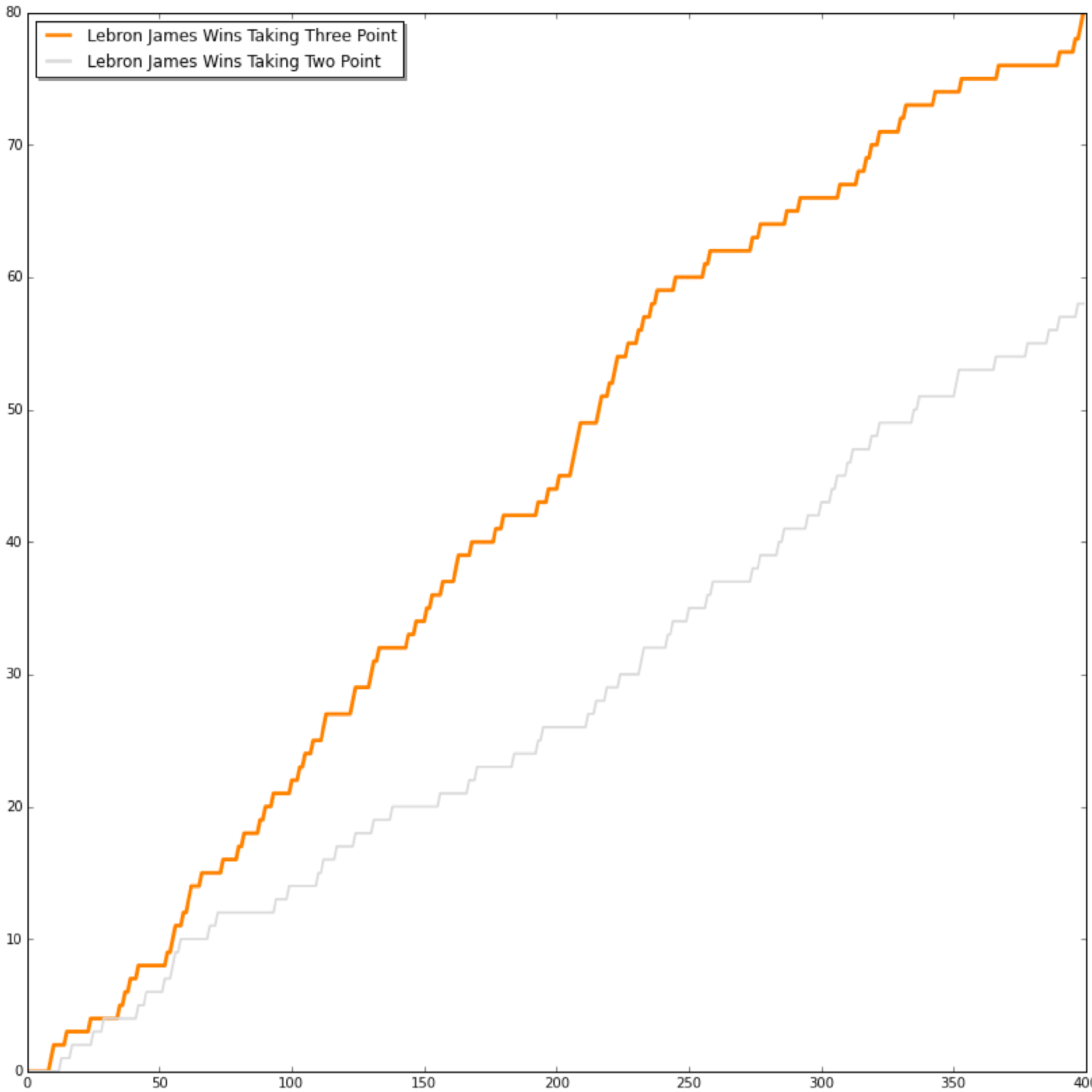
$$= \int_{s}^{140} \frac{0.6s}{60} dx + \int_{80}^{s} \frac{(x - 0.4s)}{60} dx$$

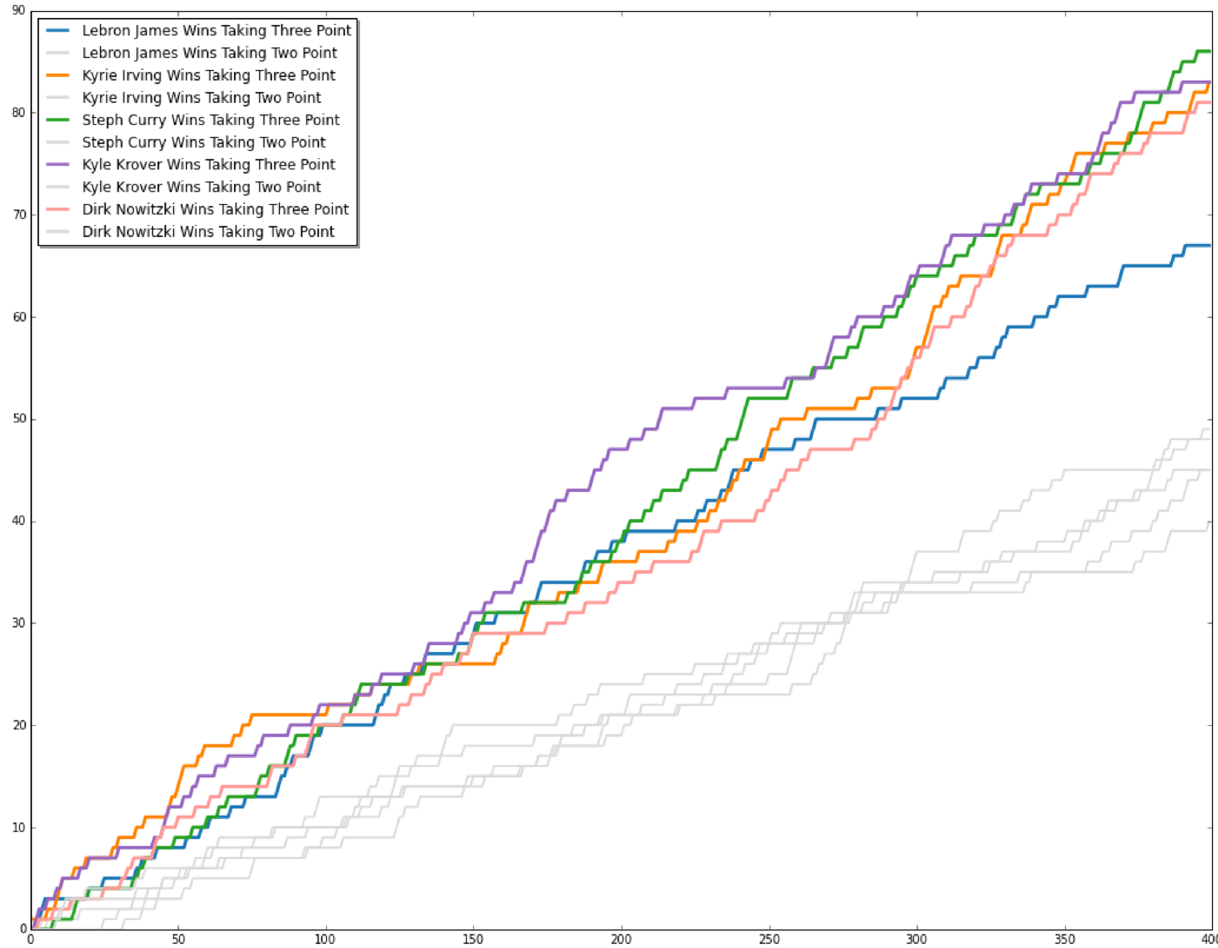
$$= \frac{s}{100}(140 - s) + \frac{s^2}{600} + \frac{8}{15}s - \frac{160}{3}$$

$$= \frac{7}{5}s - \frac{s^2}{100} + \frac{s^2}{600} + \frac{8}{15}s - \frac{160}{3}$$

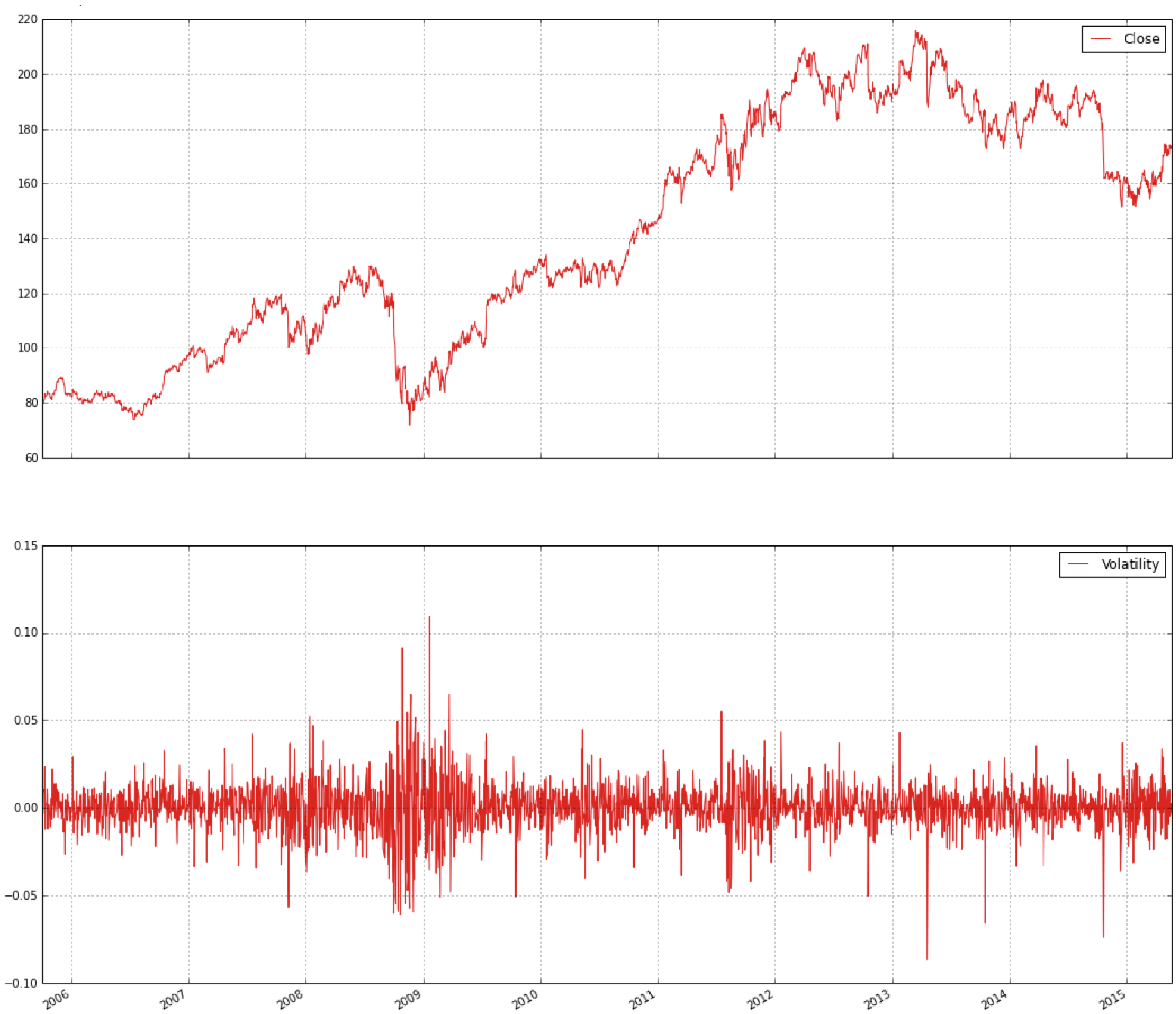
$$= -\frac{5}{600}s^2 + \frac{29}{15}s - \frac{160}{3}$$

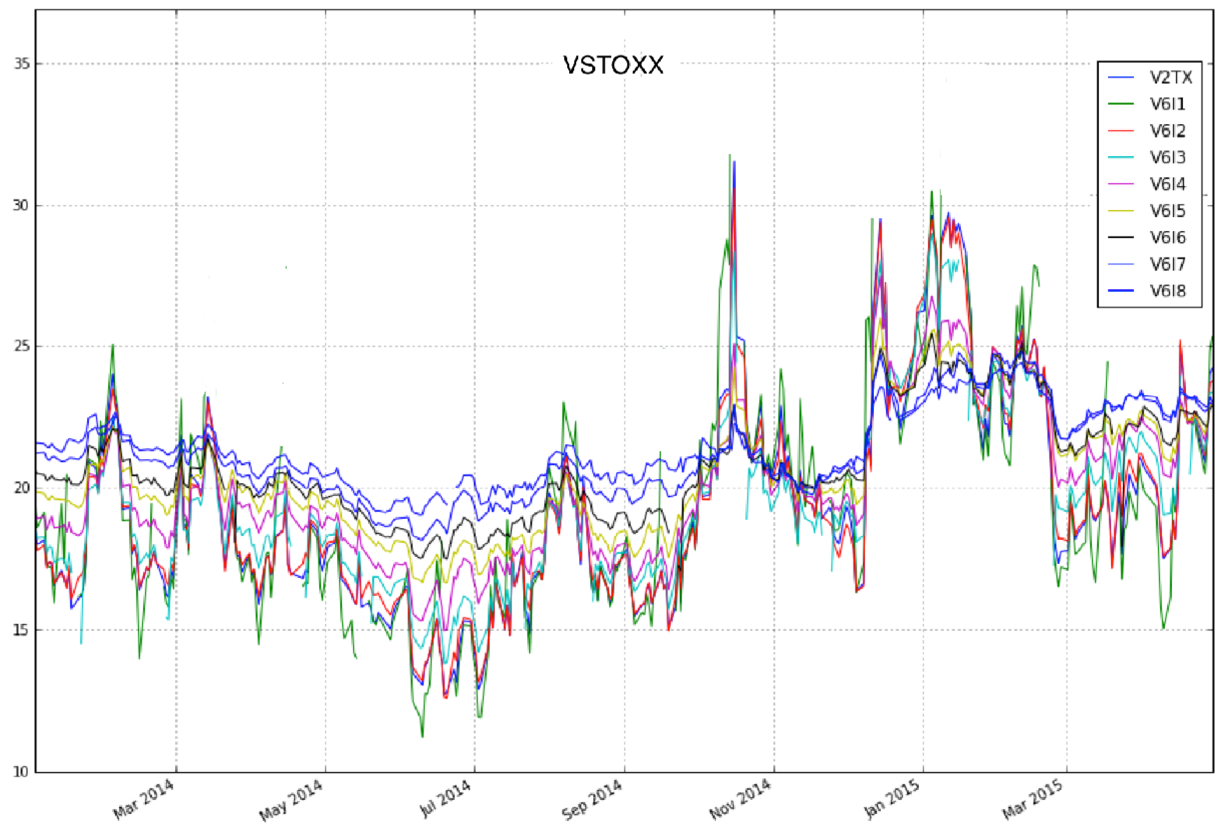
$$-\frac{s}{60} + \frac{29}{15} = 0 \;\Rightarrow s = \frac{29 \times 60}{15} = 116$$


Lebron James Wins Taking Three Point
Lebron James Wins Taking Two Point
0
10
20
30
40
50
60
70
80
0
50
100
150
200
250
300
350
400

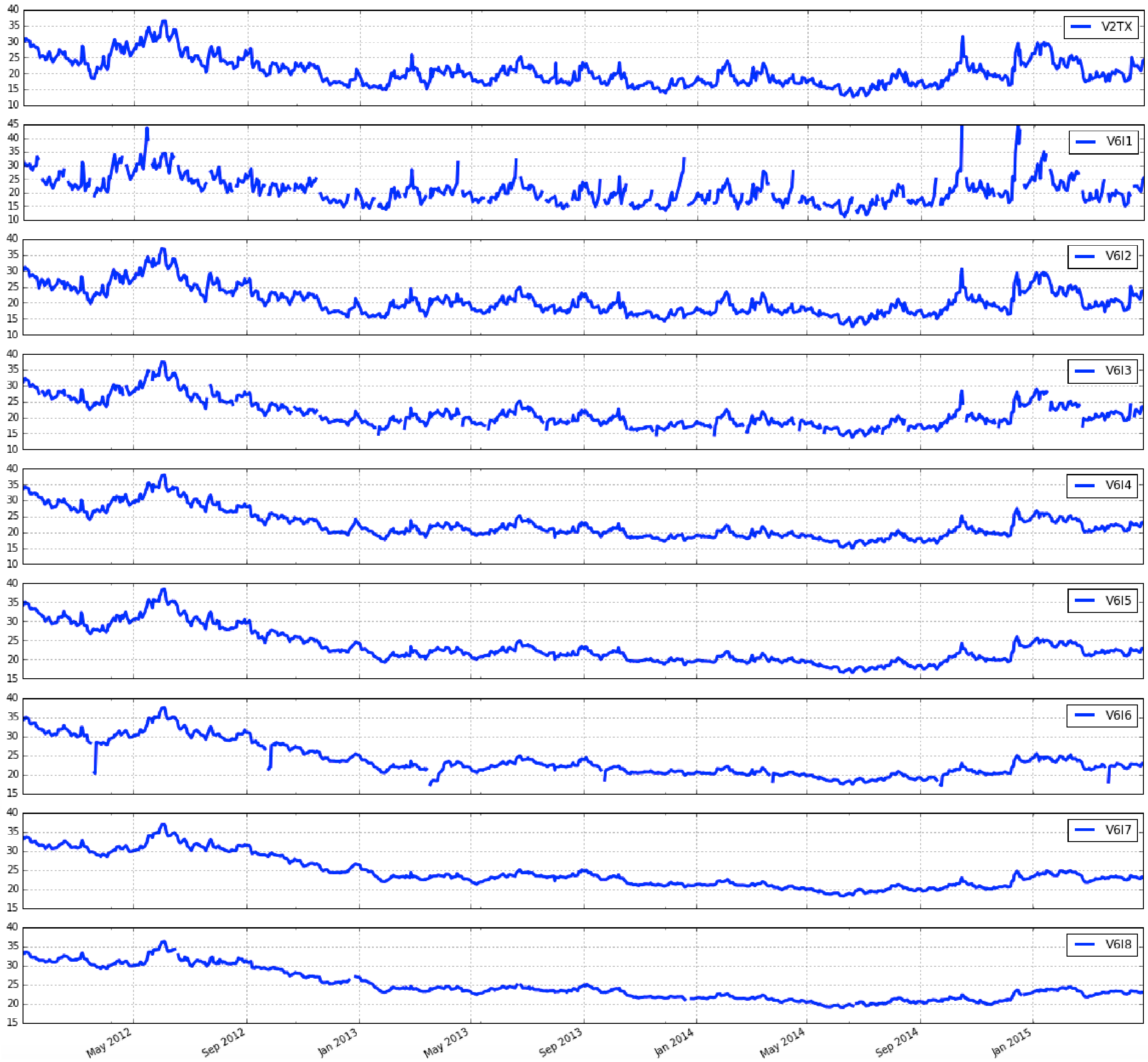


Lebron James Wins Taking Three Point
Lebron James Wins Taking Two Point
Kyrie Irving Wins Taking Three Point
Kyrie Irving Wins Taking Two Point
Steph Curry Wins Taking Three Point
Steph Curry Wins Taking Two Point
Kyle Krover Wins Taking Three Point
Kyle Krover Wins Taking Two Point
Dirk Nowitzki Wins Taking Three Point
Dirk Nowitzki Wins Taking Two Point
0
10
20
30
40
50
60
70
80
90
0
50
100
150
200
250
300
350
400


Close
220
200
180
160
140
120
100
80
60
Volatility
0.15
0.10
0.05
0.00
−0.05
−0.10
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015



VSTOXX
V2TX
V6I1
V6I2
V6I3
V6I4
V6I5
V6I6
V6I7
V6I8
35
30
25
20
15
10
Mar 2014
May 2014
Jul 2014
Sep 2014
Nov 2014
Jan 2015
Mar 2015



V2TX
V6I1
V6I2
V6I3
V6I4
V6I5
V6I6
V6I7
V6I8
May 2012
Sep 2012
Jan 2013
May 2013
Sep 2013
Jan 2014
May 2014
Sep 2014
Jan 2015

$$C_o = S_o N(d_1) - Xe^{-rT} N(d_2)$$

$$d_1 = \frac{ln\left(\frac{S_o}{X}\right) + \left(r + \frac{\sigma^2}{T}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{ln\left(\frac{S_o}{X}\right) + \left(r - \frac{\sigma^2}{T}\right)T}{\sigma\sqrt{T}}$$

$N(d)$ *is standard Normal Distribution*

where

S_o = *the stock price* T = *time to expiration*

X = *exercise price or strike price* r = *risk free interest rate*

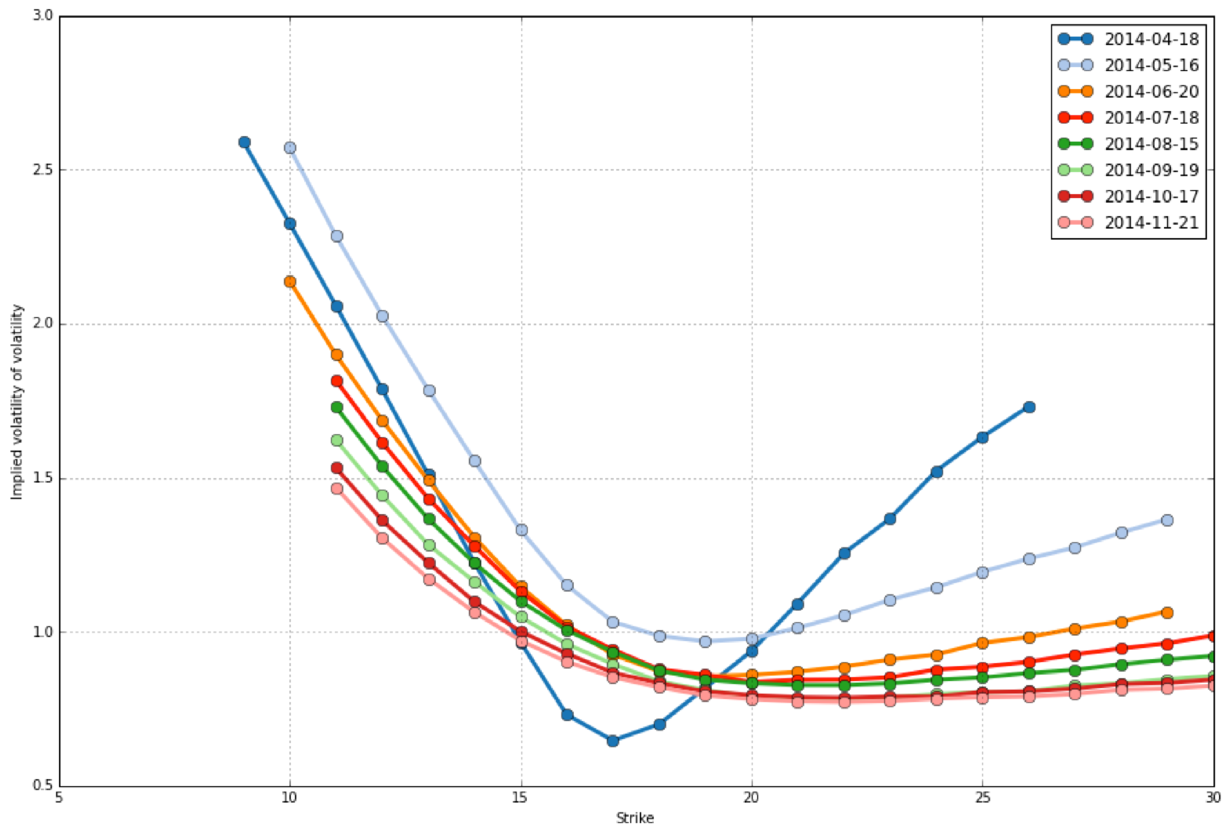
σ = *standard deviation of log returns (volatility)*

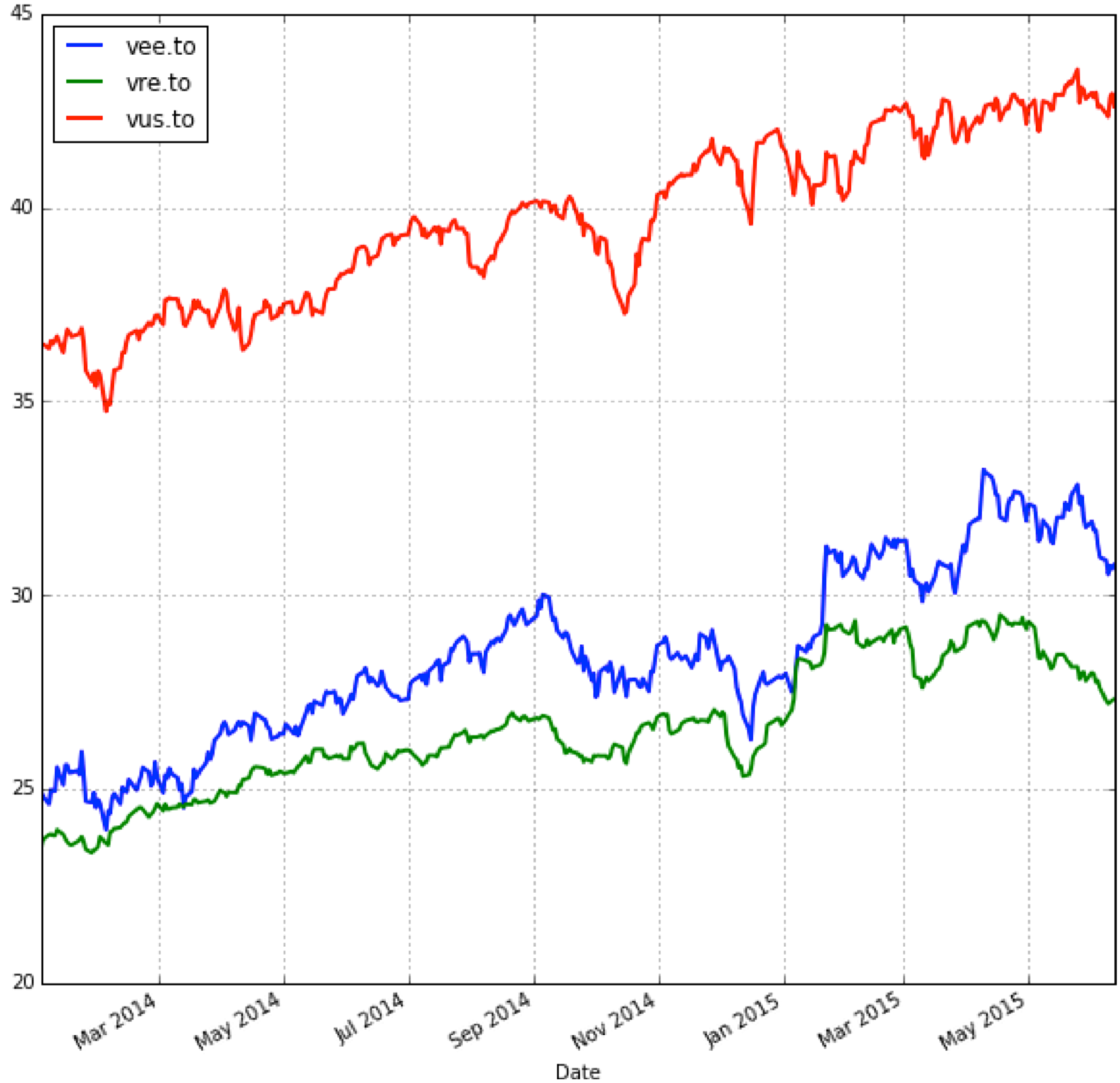
$$Vega = \frac{\partial C_o}{\partial \sigma} = S_o N'(d_1)\sqrt{T}$$

$$\frac{\partial C(\sigma_n)}{\partial \sigma_n} = -\left(\frac{C_{n+1} - C^*}{\sigma_{n+1} - \sigma_n}\right)$$

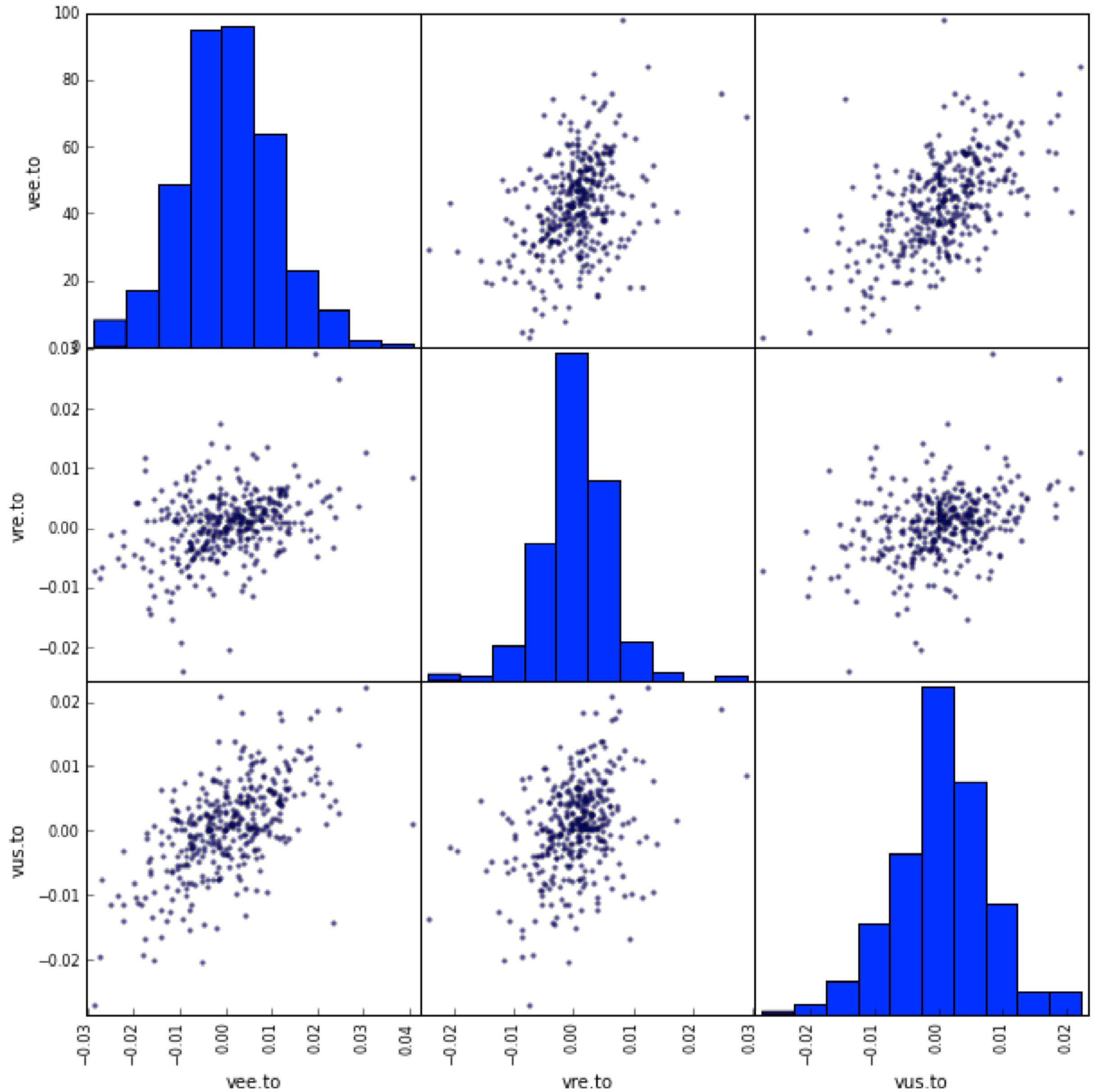
$$\Rightarrow \sigma_{n+1} - \sigma_n = -\left(\frac{C_{n+1} - C^*}{\frac{\partial C(\sigma_n)}{\partial \sigma_n}}\right)$$

$$\Rightarrow \sigma_{n+1} = \sigma_n - \left(\frac{C_{n+1} - C^*}{vega}\right)$$


3.0
2.5
2.0
1.5
1.0
0.5
5
10
15
20
25
30
Strike
Implied volatility of volatility
2014-04-18
2014-05-16
2014-06-20
2014-07-18
2014-08-15
2014-09-19
2014-10-17
2014-11-21



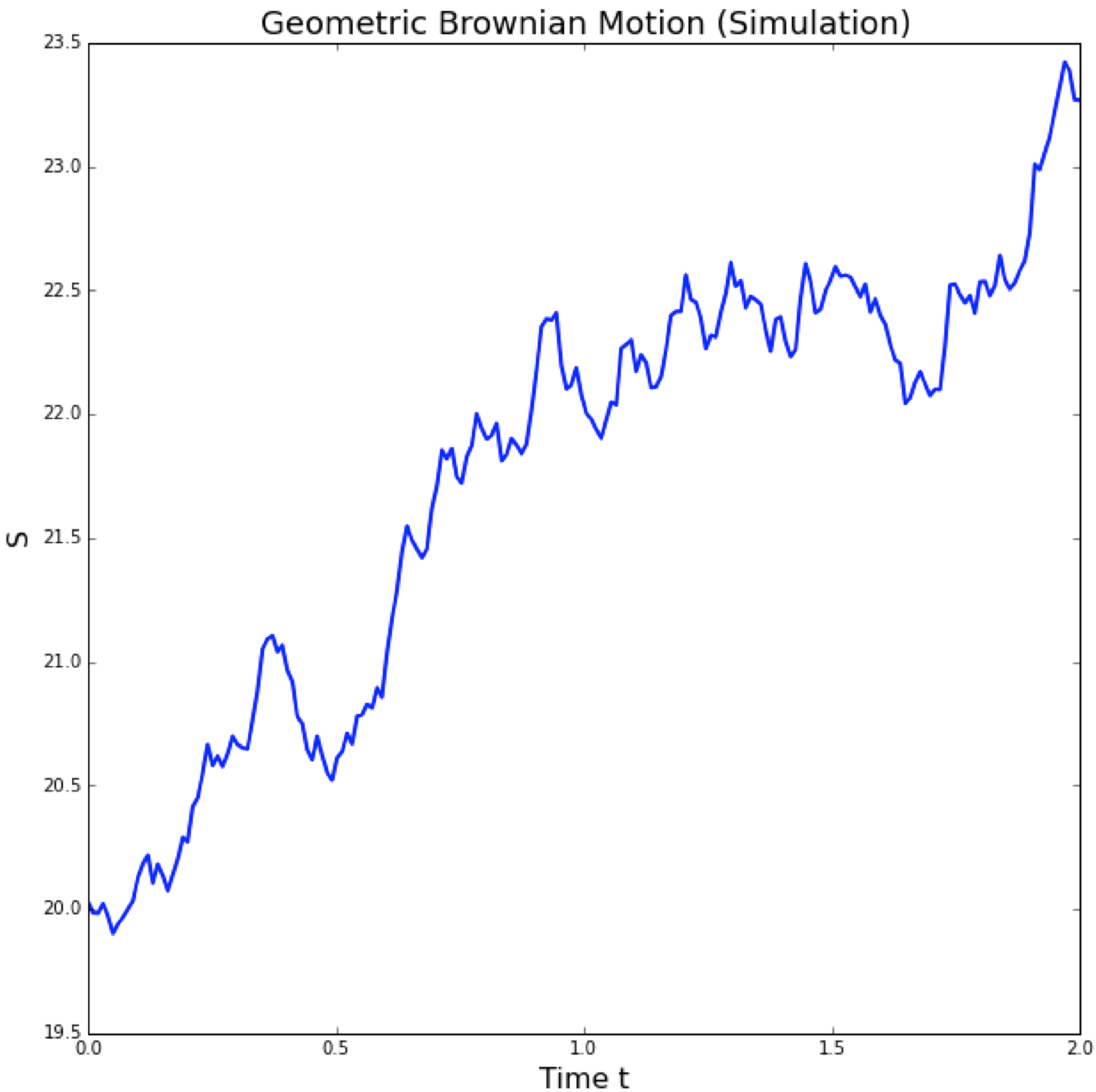
45
40
35
30
25
20
vee.to
vre.to
vus.to
Mar 2014
May 2014
Jul 2014
Sep 2014
Nov 2014
Jan 2015
Mar 2015
May 2015
Date

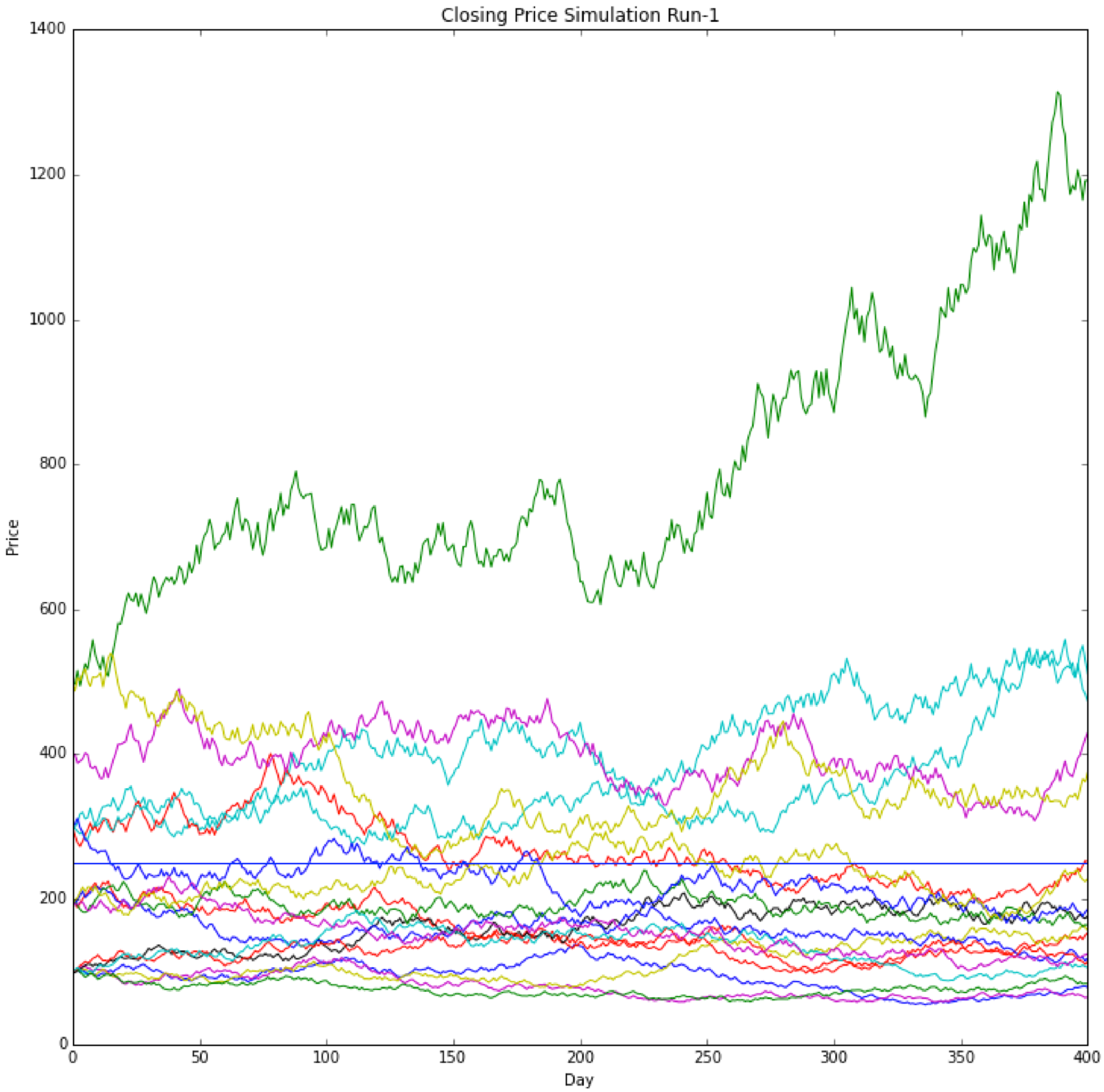


$$dS_t = uS_t dt + \sigma S_t dW_t$$

$$\frac{dS_t}{S_t} = udt + \sigma dW_t$$

$$S_t = S_o exp^{\left(\left(u-\frac{\sigma^2}{2}\right)t+\sigma W_t\right)}$$



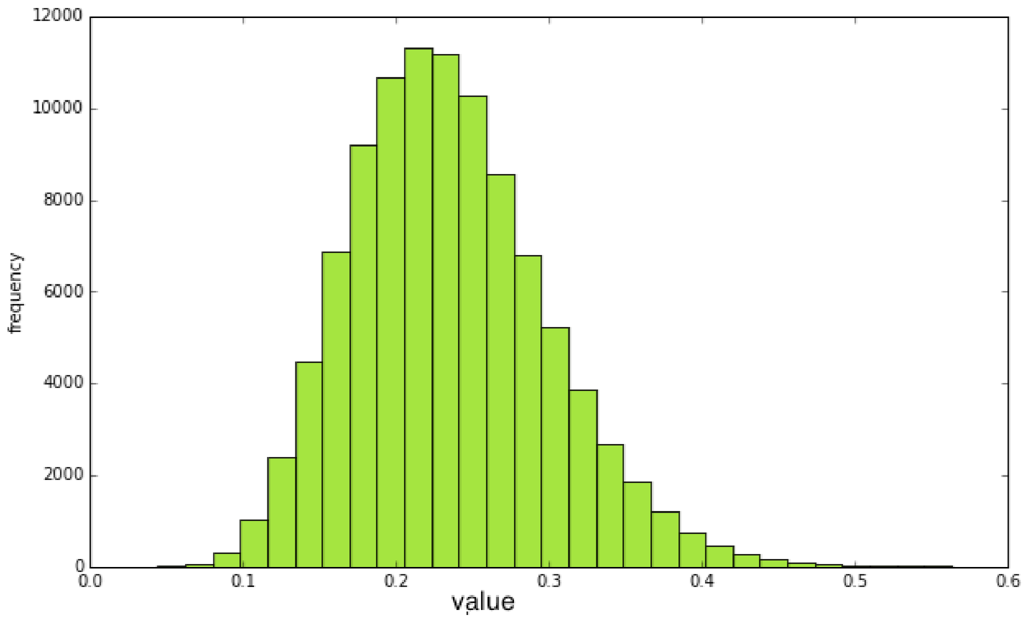


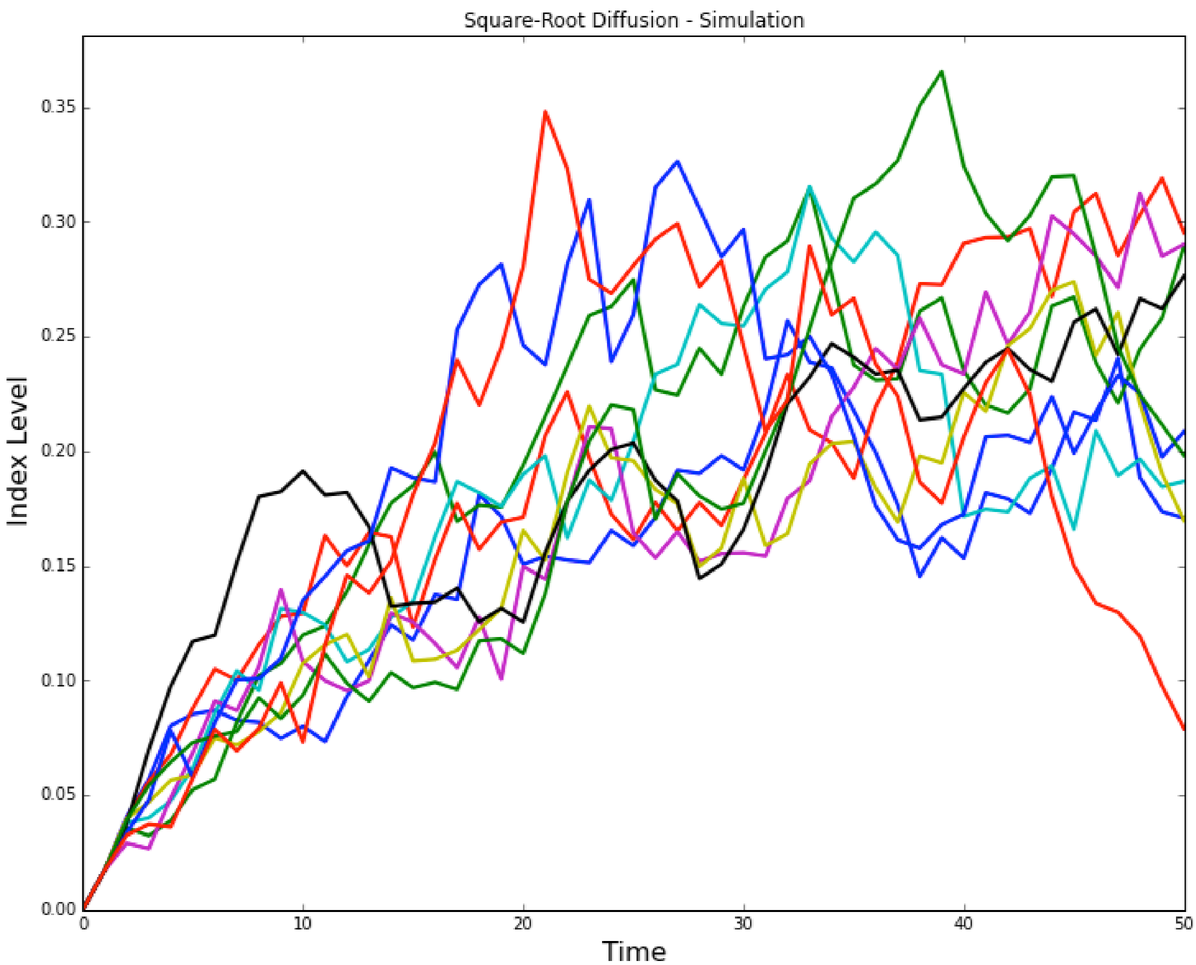
$$dx_t = \underbrace{k\left(\theta - x_t\right)dt}_{\text{Drift part}} + \sigma \underbrace{\sqrt{x_t}}_{\text{Diffusion}} dW_t$$

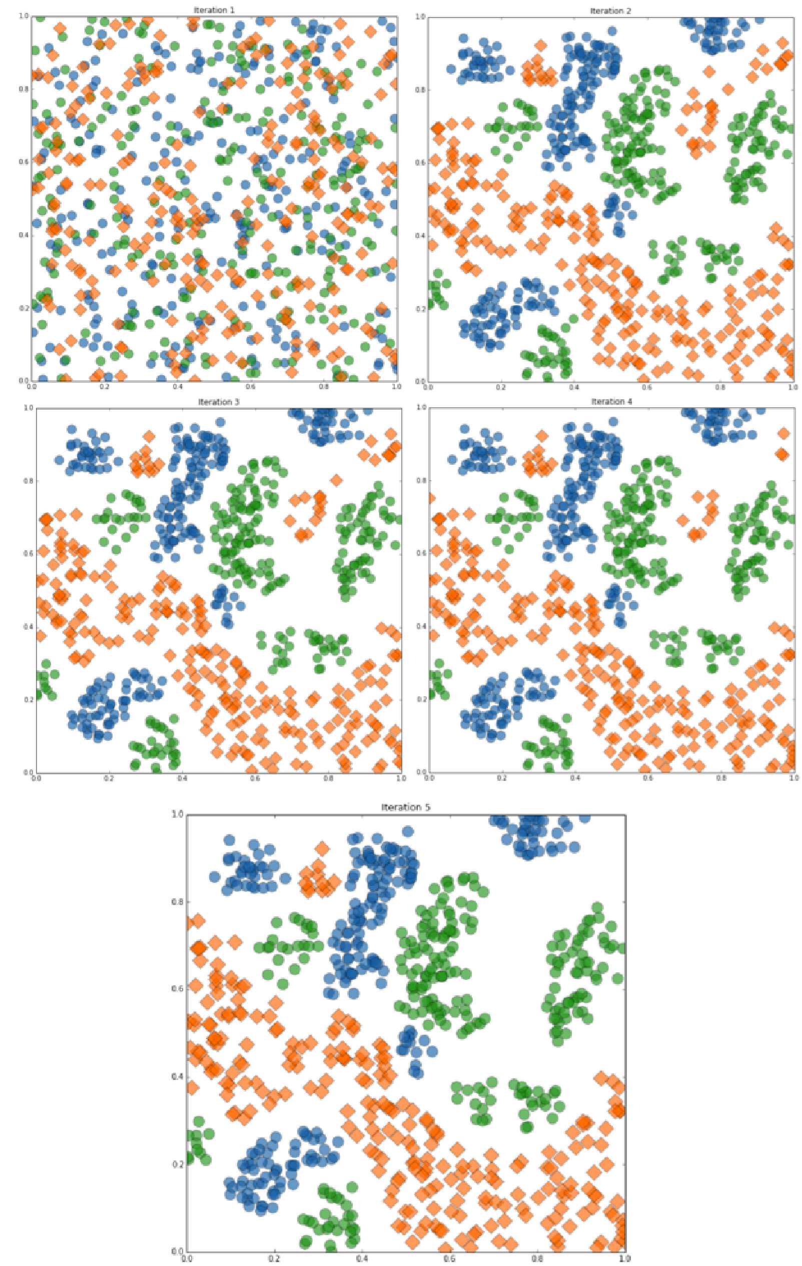
$$x_t^{new} = x_s^{new} + k\left(\theta - x_s^+\right)\Delta t + \sigma\sqrt{x_s^+ \Delta t}\, w_t$$

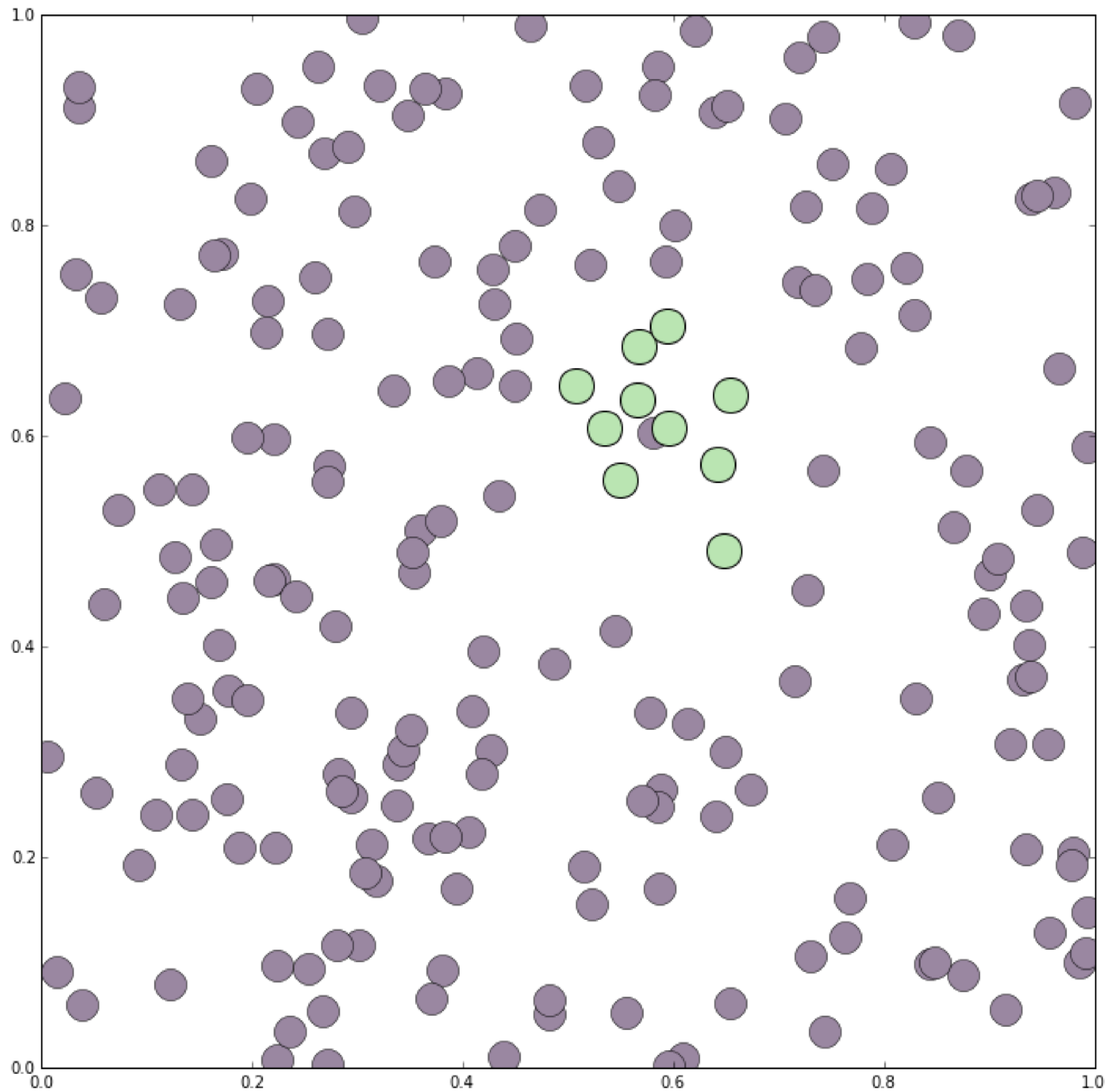
$$x_t = x_t^+$$

$$where\; x_s^+ = \max\left(x_s, 0\right) and\; x_t^+ = \max\left(x_t, 0\right)$$


12000
10000
8000
6000
4000
2000
0
frequency
0.0
0.1
0.2
0.3
0.4
0.5
0.6
value


Square-Root Diffusion - Simulation
Index Level
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
Time

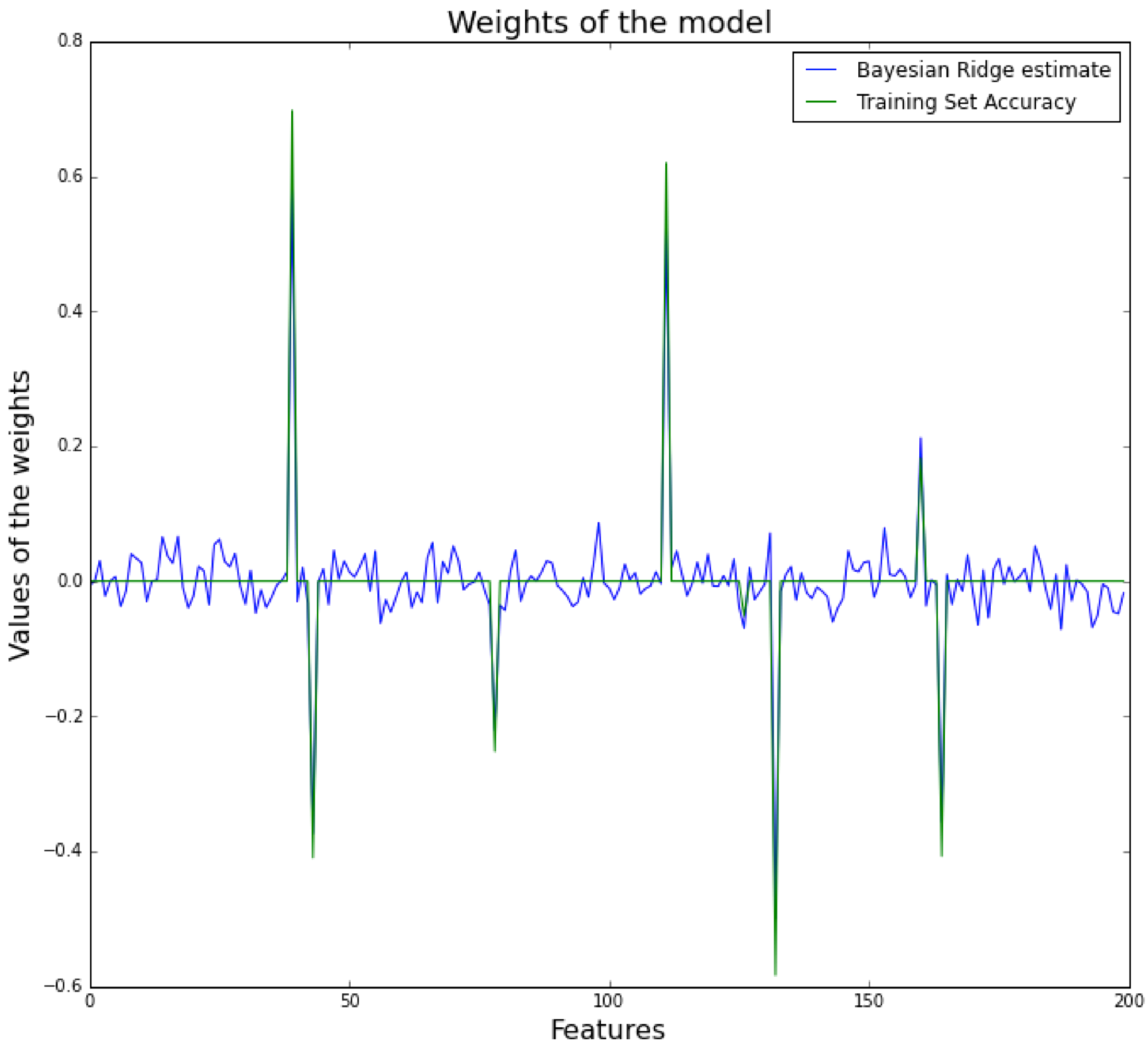

Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5

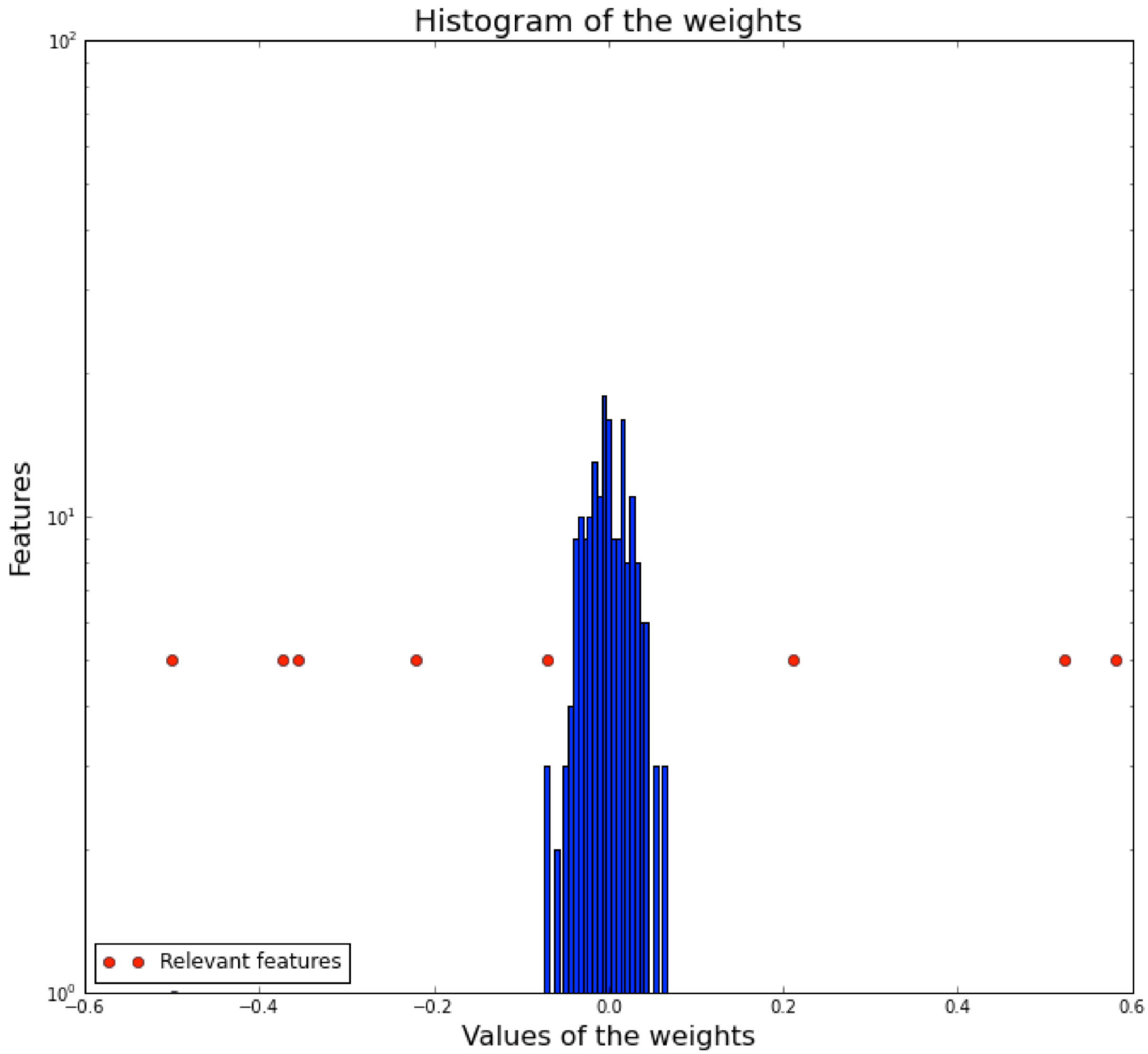


Predicted value $\hat{y}$ *is given by*

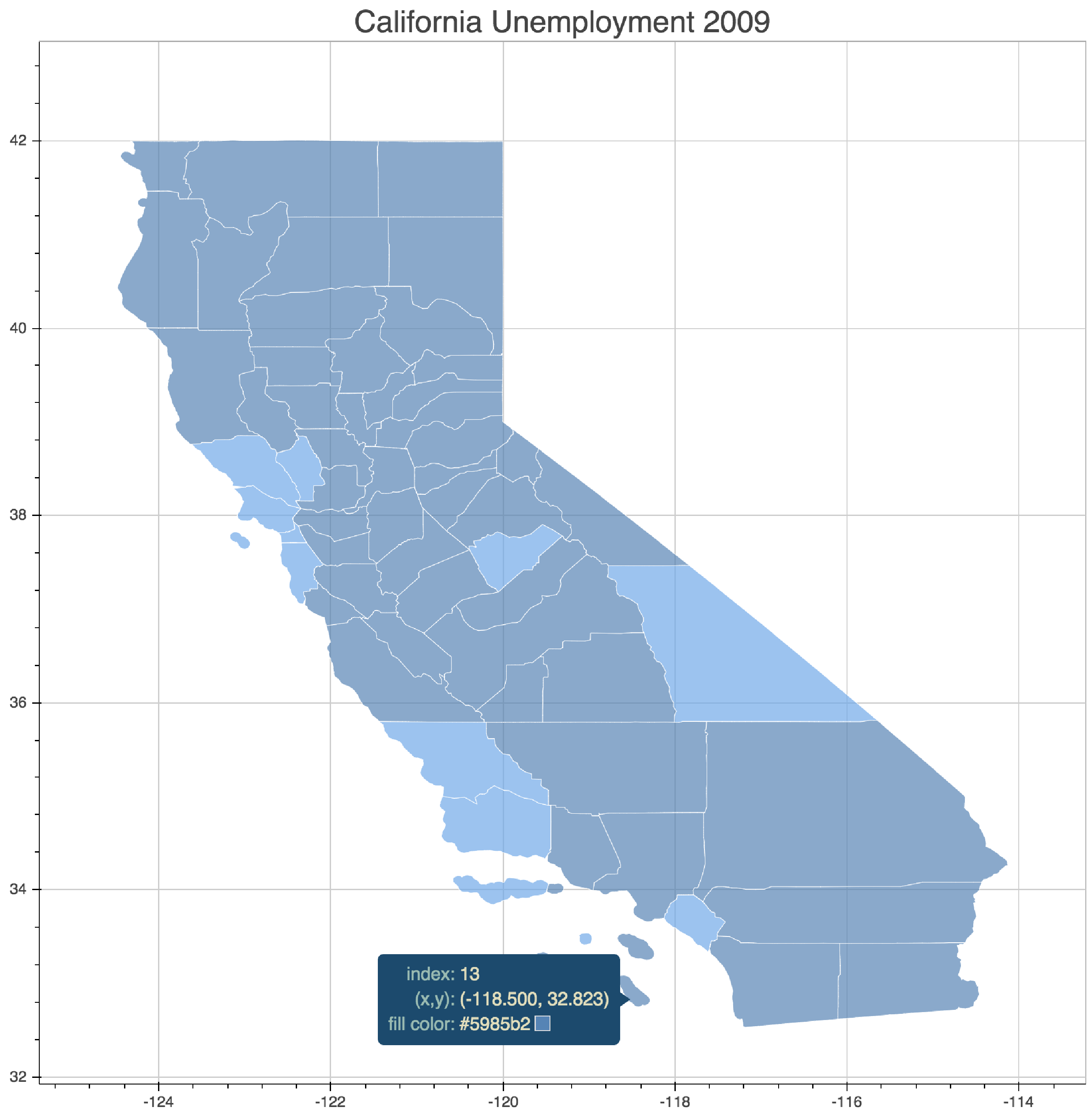
$$\hat{y}\left(w, x\right) = w_o + w_1 x_1 + w_2 x_2 + \ldots + w_n x_n = w_o + \sum_{i=0}^{n} w_i x_i$$

$$f(x) = w^T \phi(x)$$
$$w \sim N(0, \sigma_0^2 I)$$
$$Y_i \sim N(w^T \phi(x_i), \sigma^2)$$

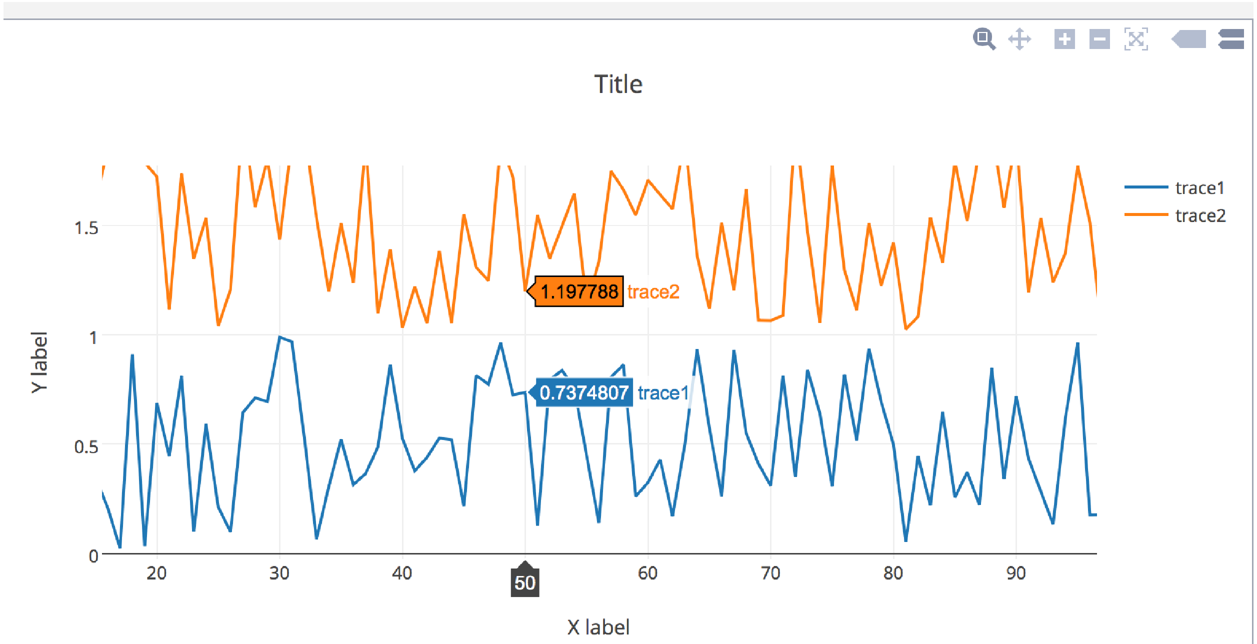




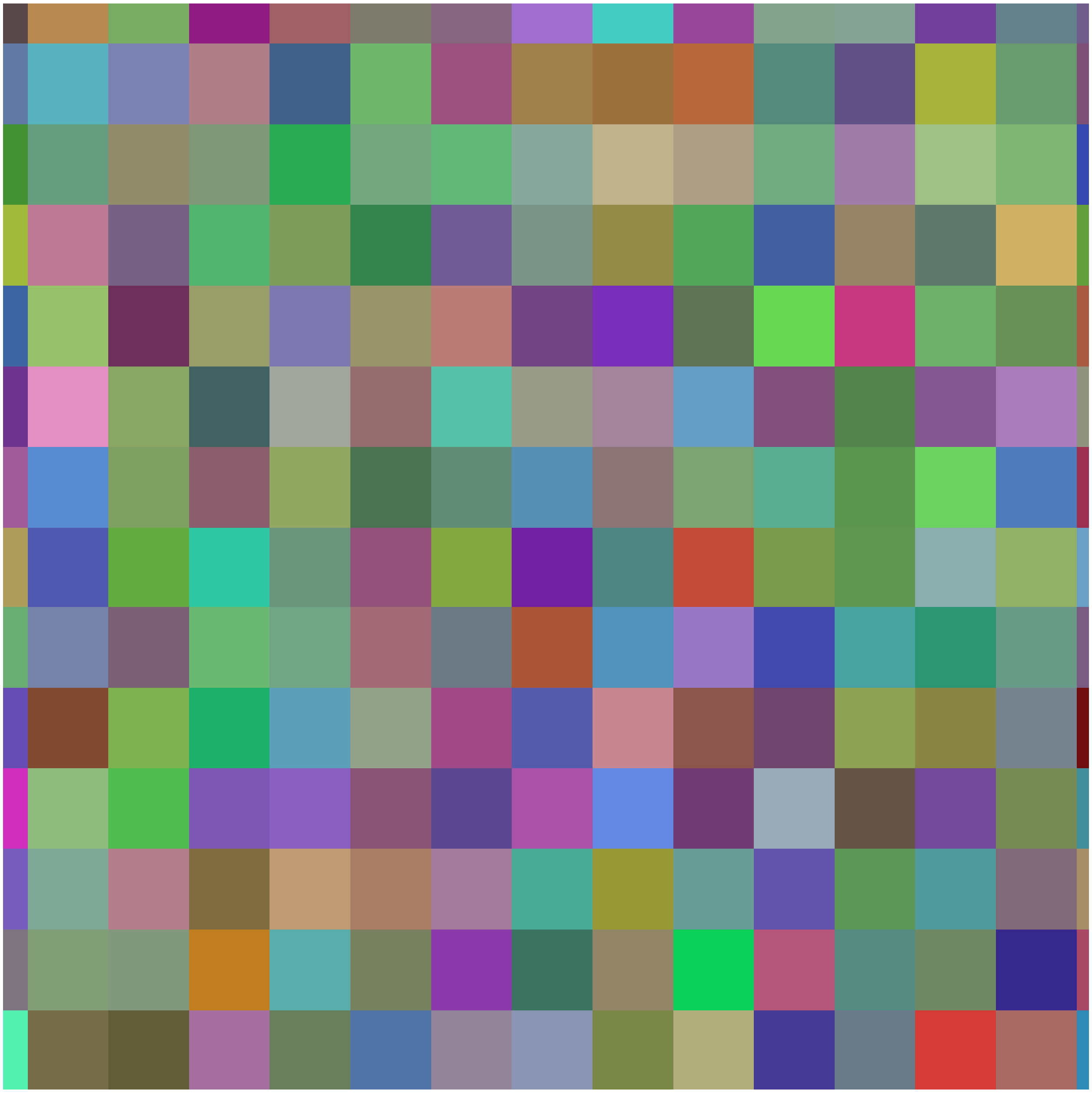
Histogram of the weights
Features
Values of the weights
Relevant features
10^2
10^1
10^0
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.6



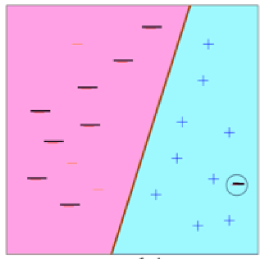
California Unemployment 2009
42
40
38
36
34
32
-124
-122
-120
-118
-116
-114
index: 13
(x,y): (-118.500, 32.823)
fill color: #5985b2



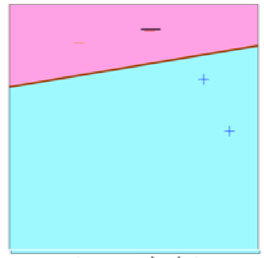
Title
trace1
trace2
1.197788 trace2
0.7374807 trace1
Y label
1.5
1
0.5
0
20
30
40
50
60
70
80
90
X label



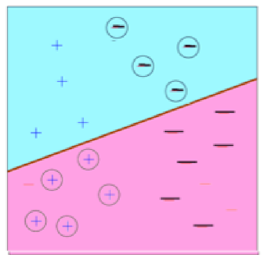
Chapter 6: Statistical and Machine Learning



useful

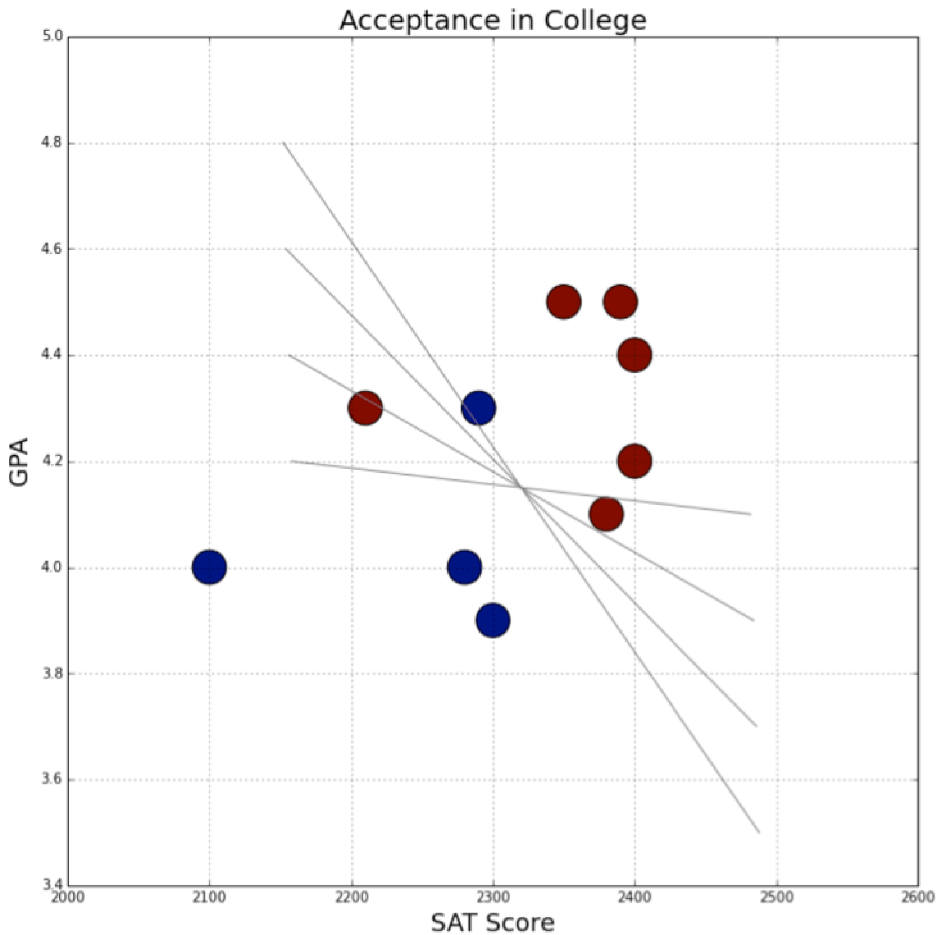


not enough data



training error

	SAT.Score	GPA	Accepted
1	2400	4.4	Y
2	2350	4.5	Y
3	2400	4.2	Y
4	2290	4.3	N
5	2100	4.0	N
6	2380	4.1	Y
7	2300	3.9	N
8	2280	4.0	N
9	2210	4.3	Y
10	2390	4.5	Y



$$y = \beta_0 + \beta_1 x$$

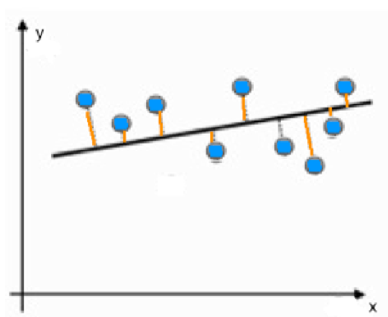
where y is the response

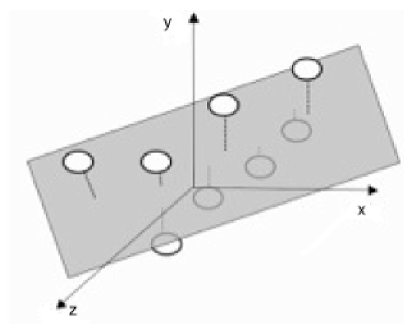
$x =$ feature

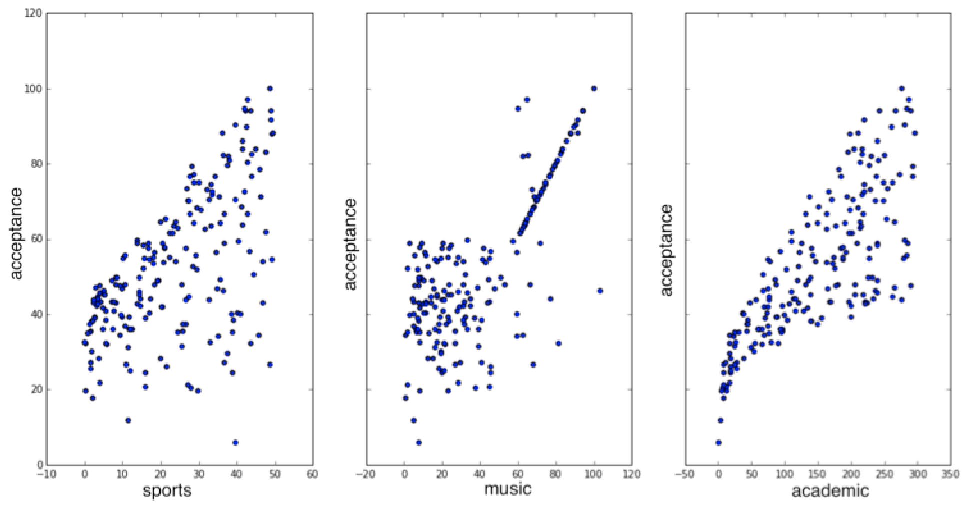
$\beta_0 =$ intercept

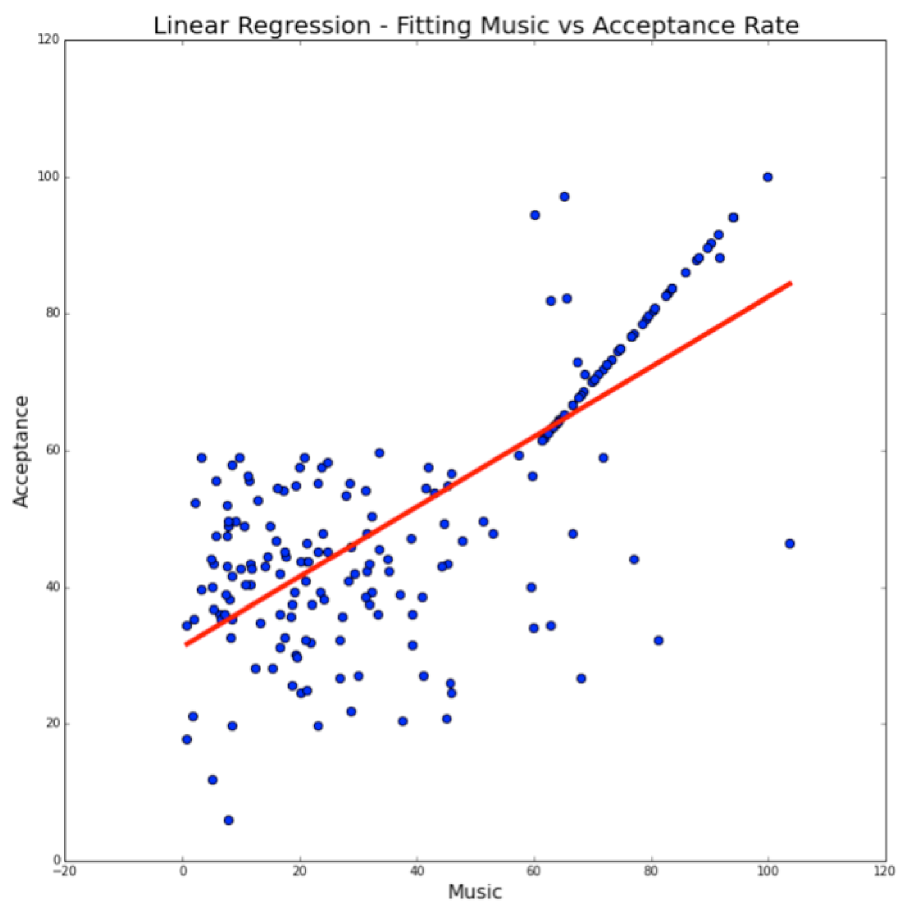
$\beta_1 =$ is the coefficient for x

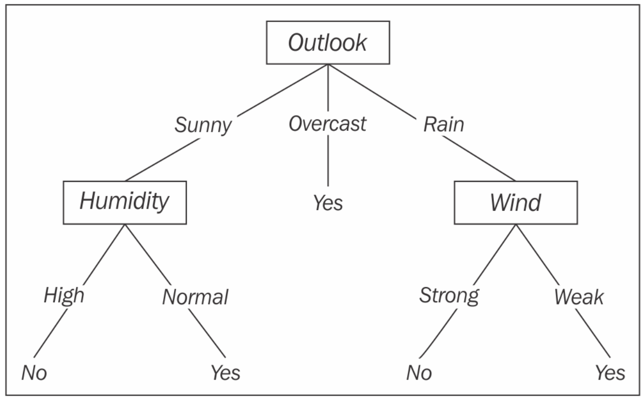
	X	academic	sports	music	acceptance
1	1	230.1	37.8	62.9090909	81.851852
2	2	44.5	39.3	41.0000000	38.518519
3	3	17.2	45.9	63.0000000	34.444444
4	4	151.5	41.3	68.5185185	68.518519
5	5	180.8	10.8	53.0909091	47.777778
6	6	8.7	48.9	68.1818182	26.666667
7	7	57.5	32.8	21.3636364	43.703704
8	8	120.2	19.6	10.5454545	48.888889
9	9	8.6	2.1	0.9090909	17.777778
10	10	199.8	2.6	19.2727273	39.259259
11	11	66.1	5.8	22.0000000	31.851852
12	12	214.7	24.0	64.4444444	64.444444
13	13	23.8	35.1	59.9090909	34.074074
14	14	97.5	7.6	6.5454545	35.925926
15	15	204.1	32.9	70.3703704	70.370370
16	16	195.4	47.7	82.9629630	82.962963
17	17	67.8	36.6	103.6363636	46.296296
18	18	281.4	39.6	90.3703704	90.370370
19	19	69.2	20.5	16.6363636	41.851852
20	20	147.3	23.9	17.3636364	54.074074

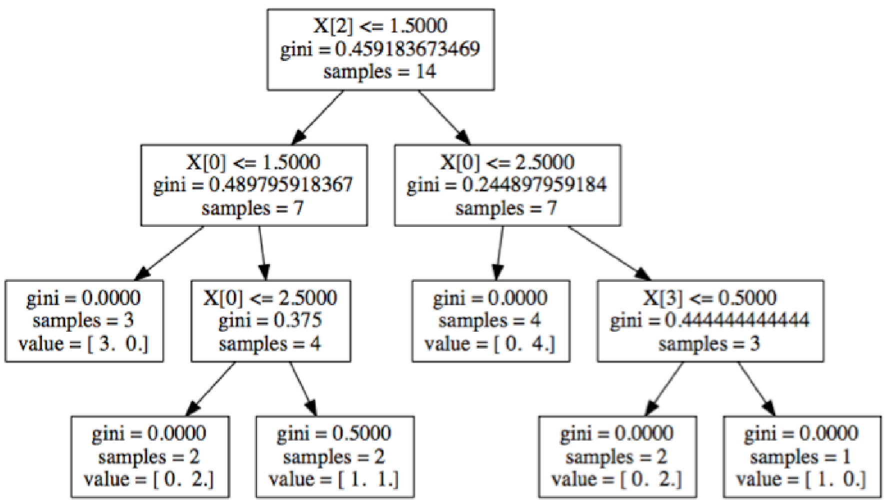


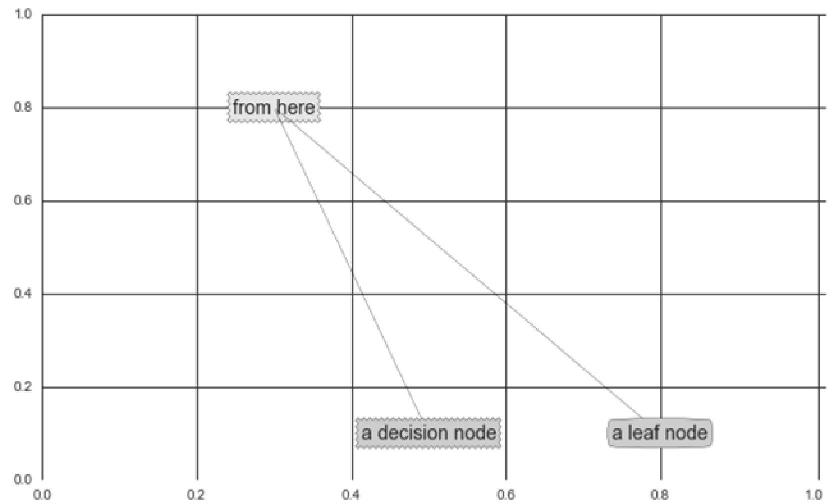


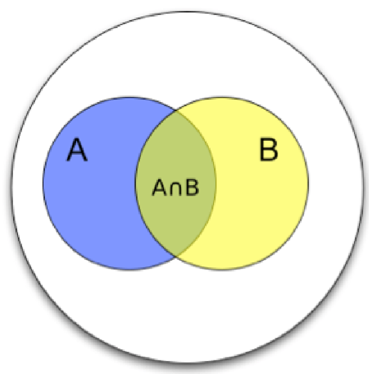

acceptance
sports
music
academic


Linear Regression - Fitting Music vs Acceptance Rate
Acceptance
Music


Outlook
Sunny
Overcast
Rain
Humidity
Yes
Wind
High
Normal
Strong
Weak
No
Yes
No
Yes


X[2] <= 1.5000
gini = 0.459183673469
samples = 14
X[0] <= 1.5000
gini = 0.489795918367
samples = 7
X[0] <= 2.5000
gini = 0.244897959184
samples = 7
gini = 0.0000
samples = 3
value = [3. 0.]
X[0] <= 2.5000
gini = 0.375
samples = 4
gini = 0.0000
samples = 4
value = [0. 4.]
X[3] <= 0.5000
gini = 0.444444444444
samples = 3
gini = 0.0000
samples = 2
value = [0. 2.]
gini = 0.5000
samples = 2
value = [1. 1.]
gini = 0.0000
samples = 2
value = [0. 2.]
gini = 0.0000
samples = 1
value = [1. 0.]





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

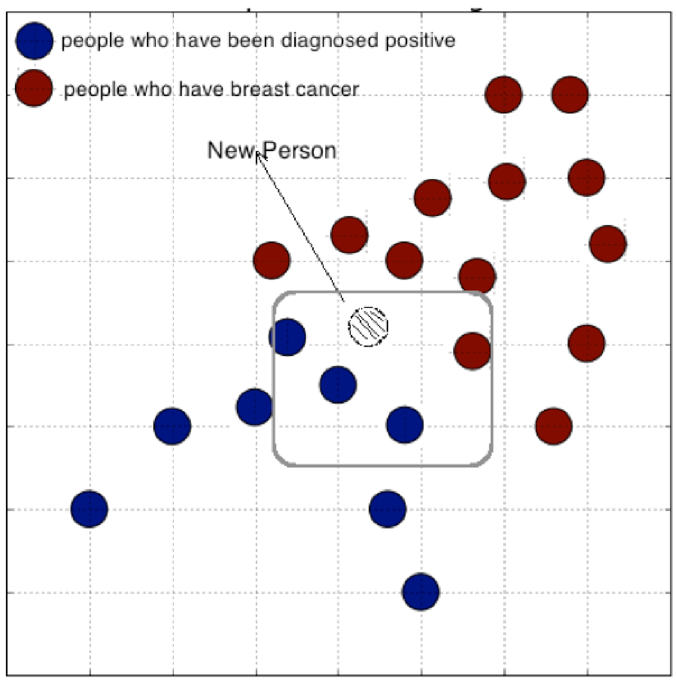
$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

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

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

$$\Rightarrow P(A \cap B) = P(B \mid A)P(A) = P(A \mid B)P(B)$$

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



$$prior\ probability\ of\ red = \frac{13}{21}$$

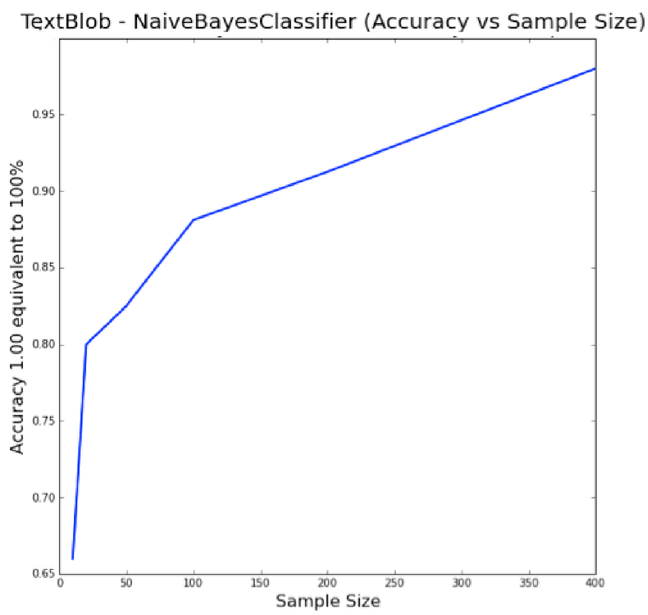
$$prior\ probability\ of\ blue = \frac{8}{21}$$

$$likelihood\ of\ x\ given\ red = \frac{Number\ of\ red\ \text{in the vicinity}}{Total\ number\ of\ reds} = \frac{1}{13}$$

$$likelihood\ of\ x\ given\ blue = \frac{Number\ of\ blue\ \text{in the vicinity}}{Total\ number\ of\ blue} = \frac{3}{8}$$

$$posterior\ probability\ of\ x\ being\ red = \frac{1}{13} \times \frac{13}{21} = \frac{1}{21}$$

$$posterior\ probability\ of\ x\ being\ blue = \frac{3}{8} \times \frac{8}{21} = \frac{3}{21} = \frac{1}{7}$$

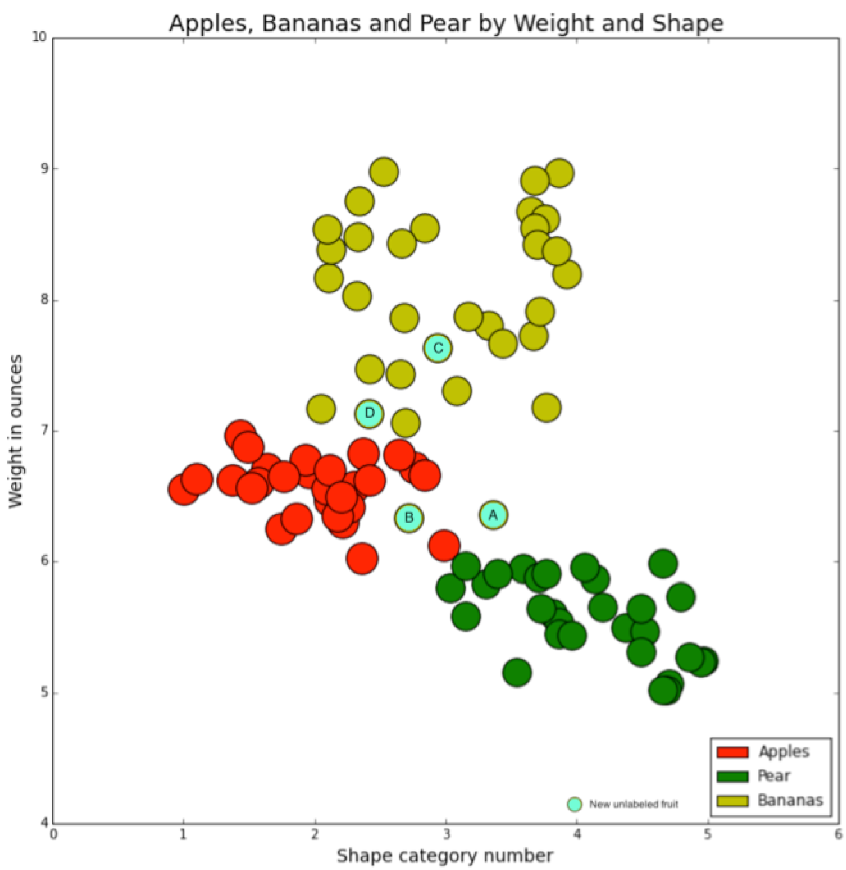


$$\text{Euclidean Distance} \quad \sqrt{\sum_{i=1}^{k}\left(x_i - y_i\right)^2}$$

$$\text{Manhattan Distance} \quad \sum_{i=1}^{k}\left|x_i - y_i\right|$$

$$\text{Minkowski Distance} \quad \left(\sum_{i=1}^{k}\left(\left|x_i - y_i\right|\right)^q\right)^{\frac{1}{q}}$$

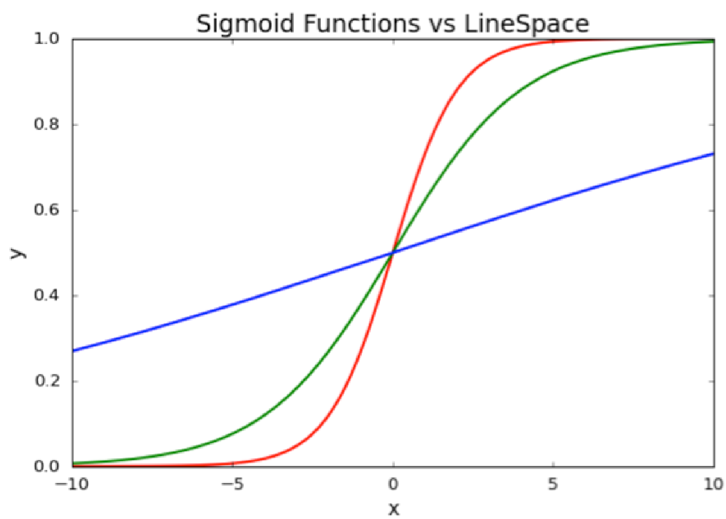
	Shape	Weight	Fruit
1	1.747993	6.244728	Apple
2	2.160436	6.548997	Apple
3	2.308360	6.568994	Apple
4	2.989498	6.116004	Apple
5	2.217408	6.298844	Apple
6	3.550124	5.148646	Banana
7	4.795393	5.729825	Banana
8	4.380994	5.491813	Banana
9	4.975395	5.243866	Banana
10	4.714245	5.061763	Banana
11	1.644232	6.710433	Apple
12	2.101244	8.531404	Pear
13	2.847359	8.541824	Pear
14	3.759746	8.609348	Pear
15	3.436196	7.667397	Pear
16	2.420651	7.471596	Pear
17	1.960733	6.678455	Apple
18	1.861635	6.320602	Apple



$$\log \frac{P(x)}{1-P(x)} = \sum_{j=0}^{n} b_j x_j = z$$

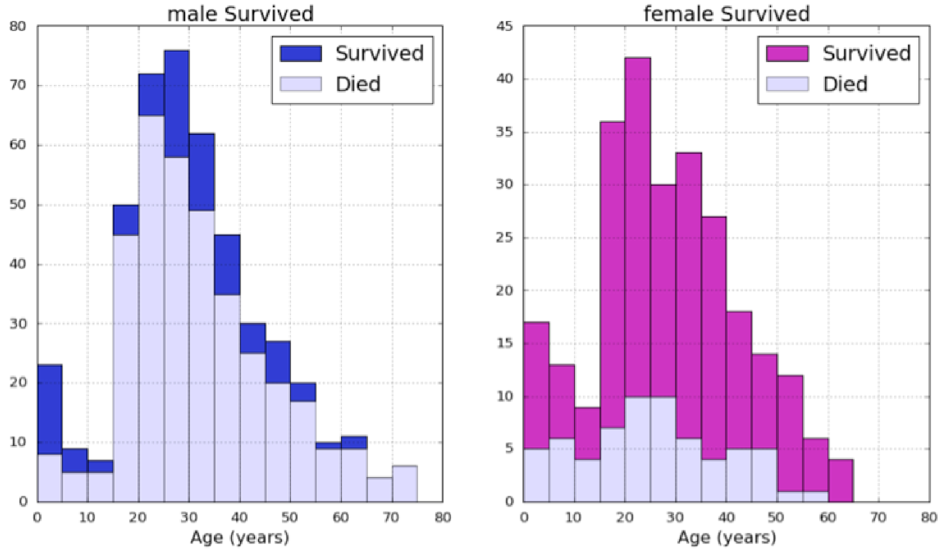
$$\frac{P(x)}{1-P(x)} = e^z$$

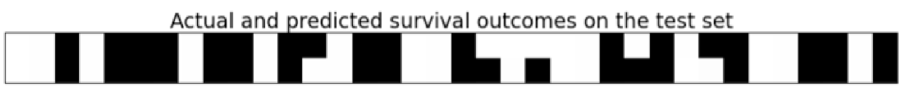
$$\Rightarrow \; P(x) = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}}$$

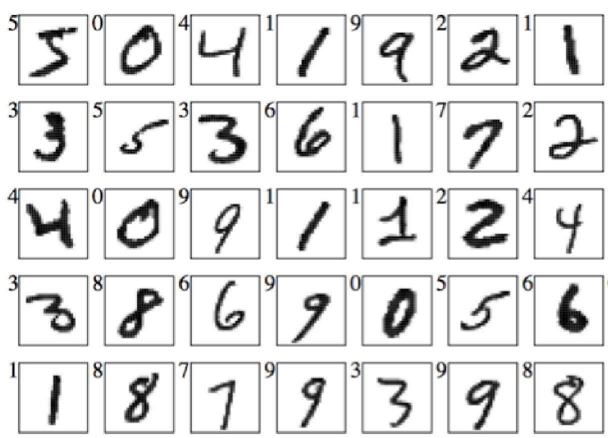


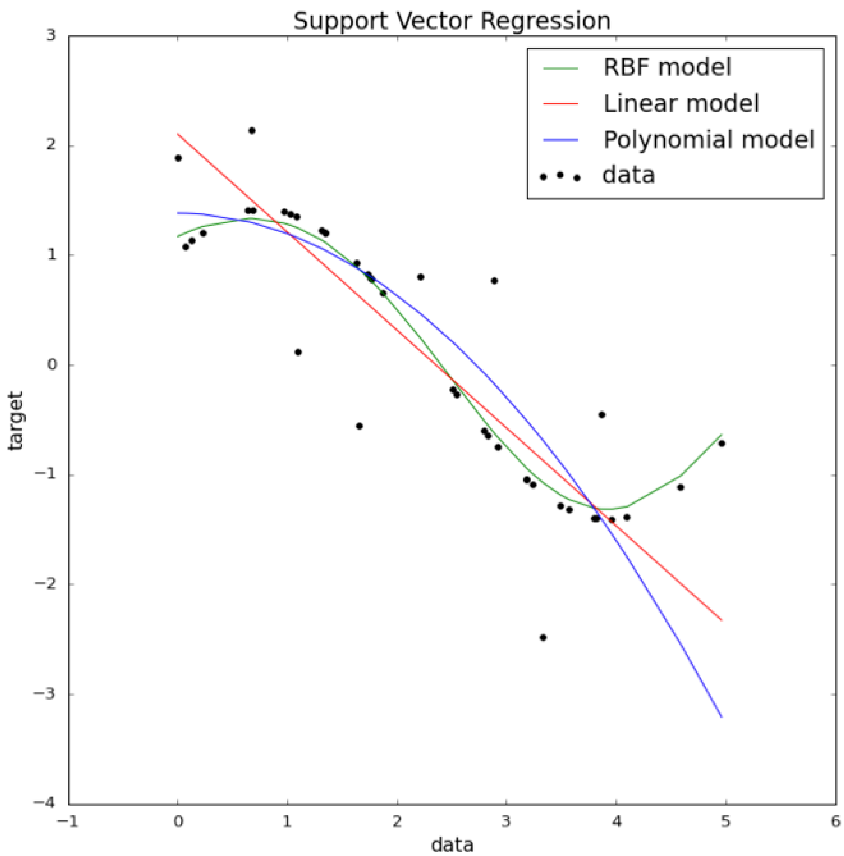
$$P(happy) = \frac{e^z}{1+e^z}$$

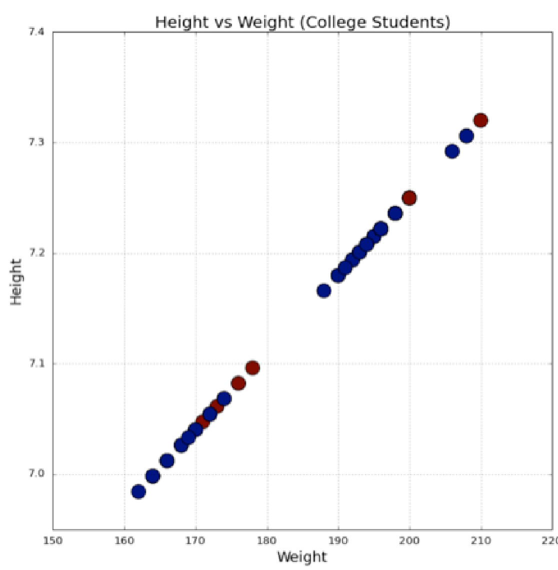
$$P(sad) = 1 - P(happy) = \frac{1}{1+e^z}$$


male Survived
Survived
Died
Age (years)
female Survived
Survived
Died
Age (years)

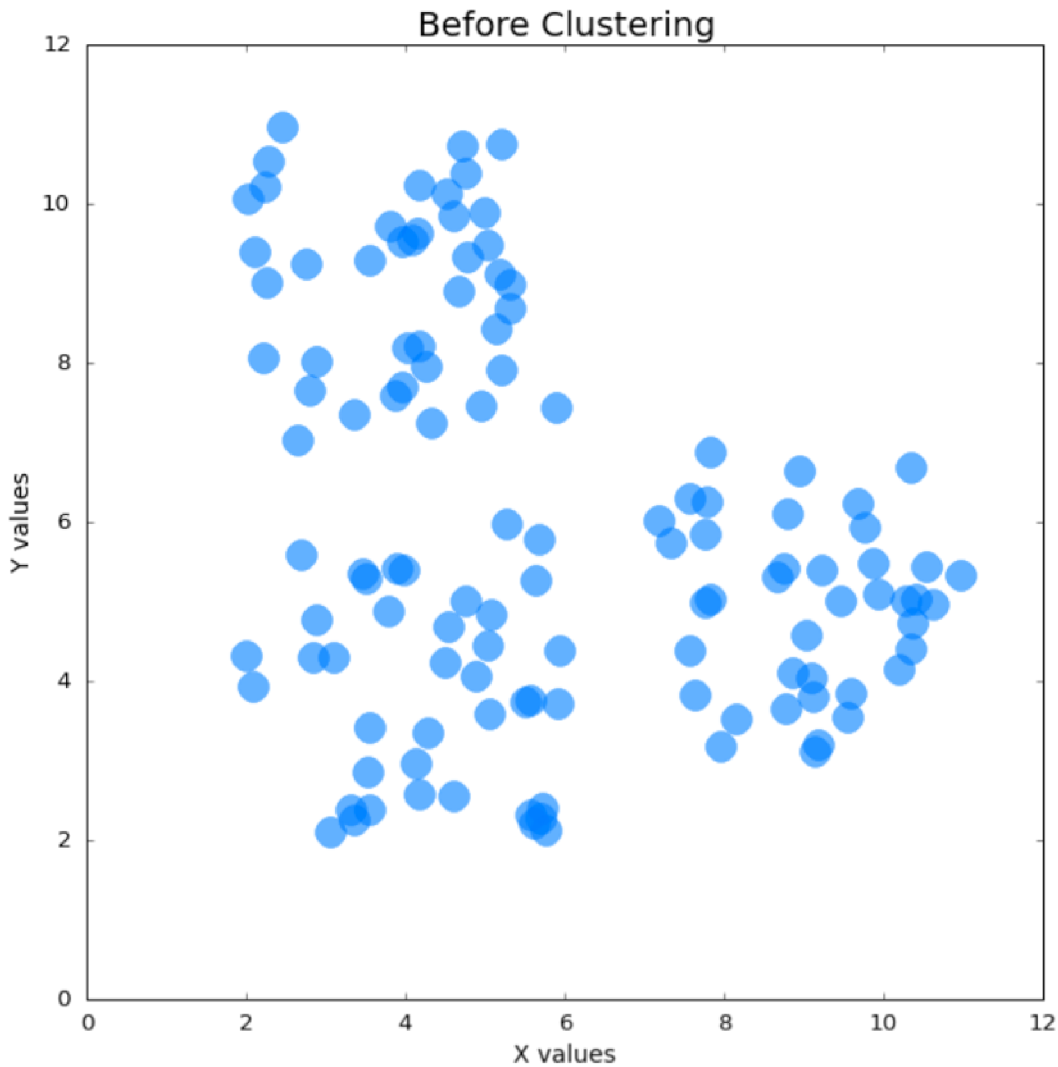

Actual and predicted survival outcomes on the test set


5 0 4 1 9 2 1
3 5 3 6 1 7 2
4 0 9 1 1 2 4
3 8 6 9 0 5 6
1 8 7 9 3 9 8

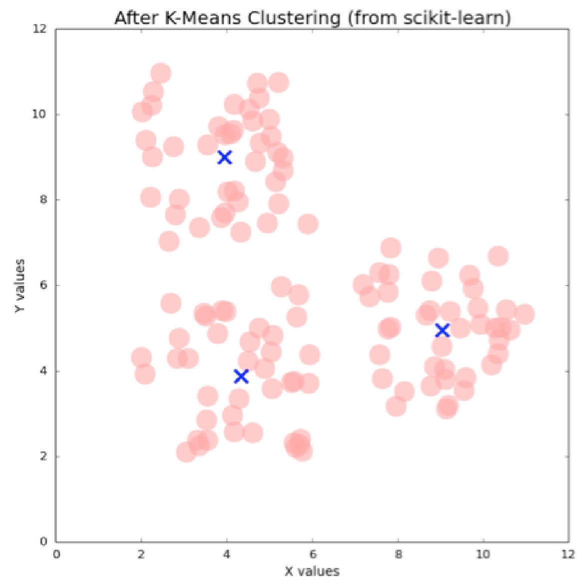

Support Vector Regression
RBF model
Linear model
Polynomial model
data
target
data
3
2
1
0
−1
−2
−3
−4
−1
0
1
2
3
4
5
6

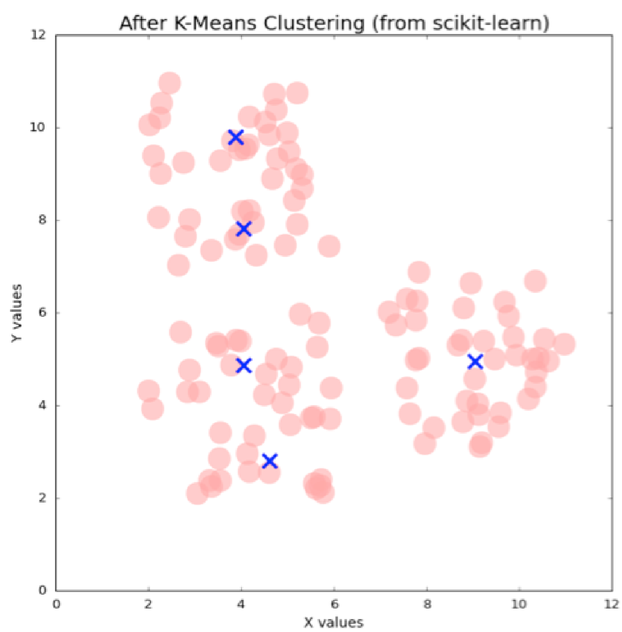

Height vs Weight (College Students)
Height
Weight
7.4
7.3
7.2
7.1
7.0
150
160
170
180
190
200
210
220


PCA via scikit-learn (using SVD)
Sepal Length
Petal Width
3
2
1
0
−1
−2
−3
−4
−4
−3
−2
−1
0
1
2
3
4

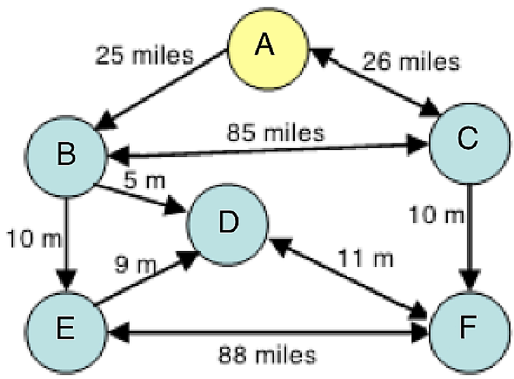


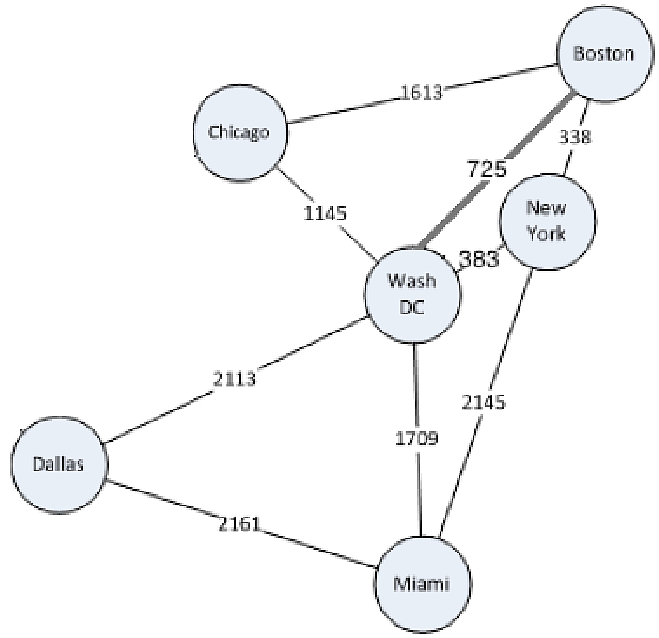
Before Clustering
Y values
X values
0
2
4
6
8
10
12

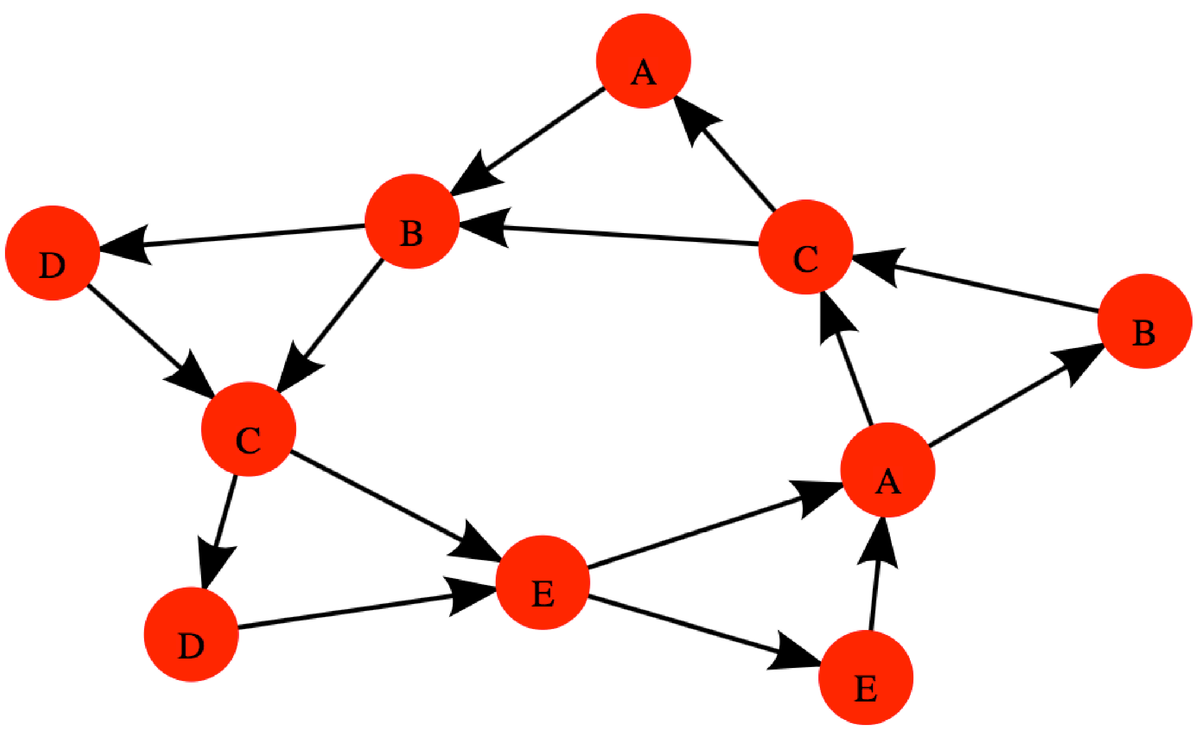


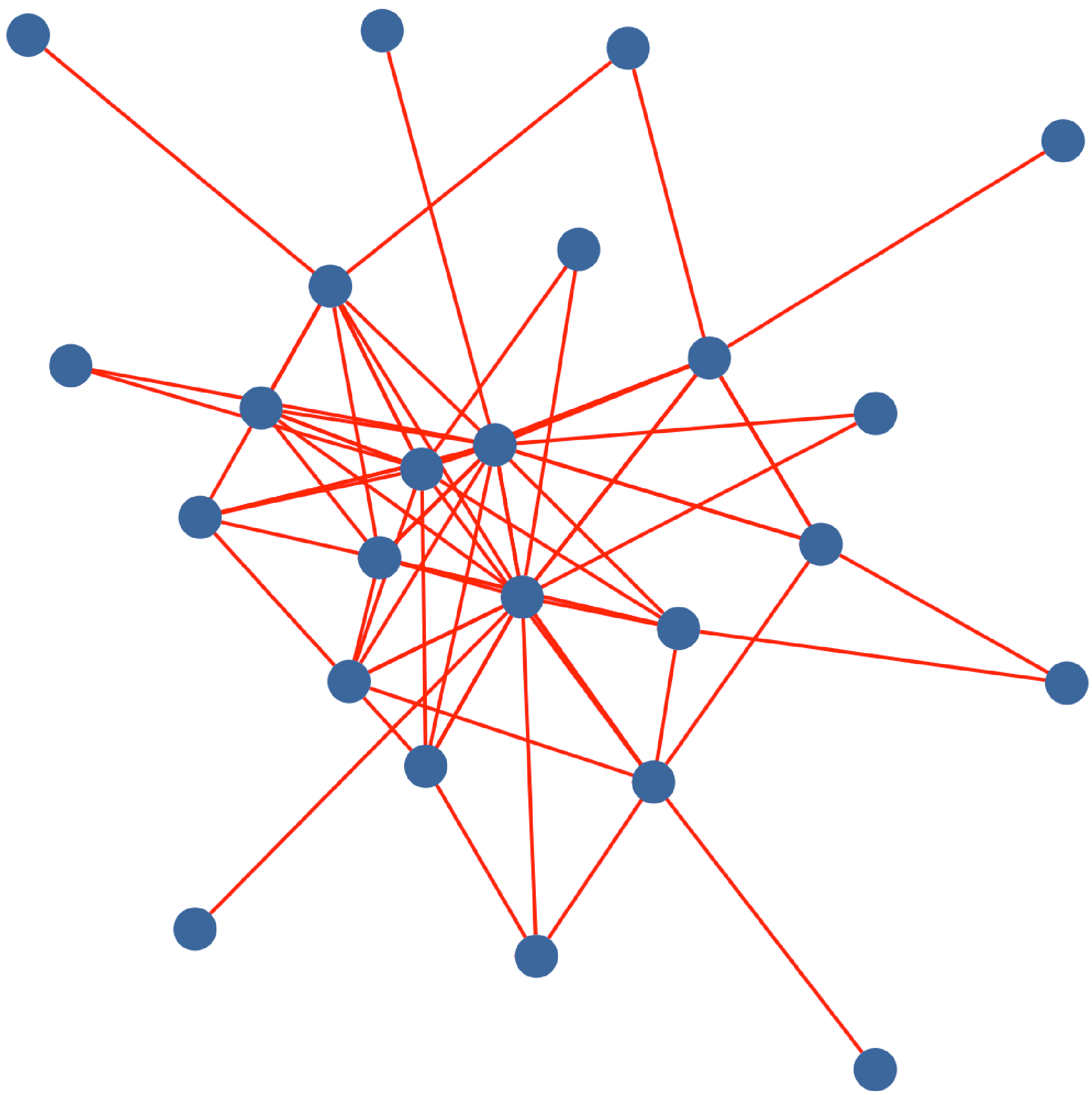


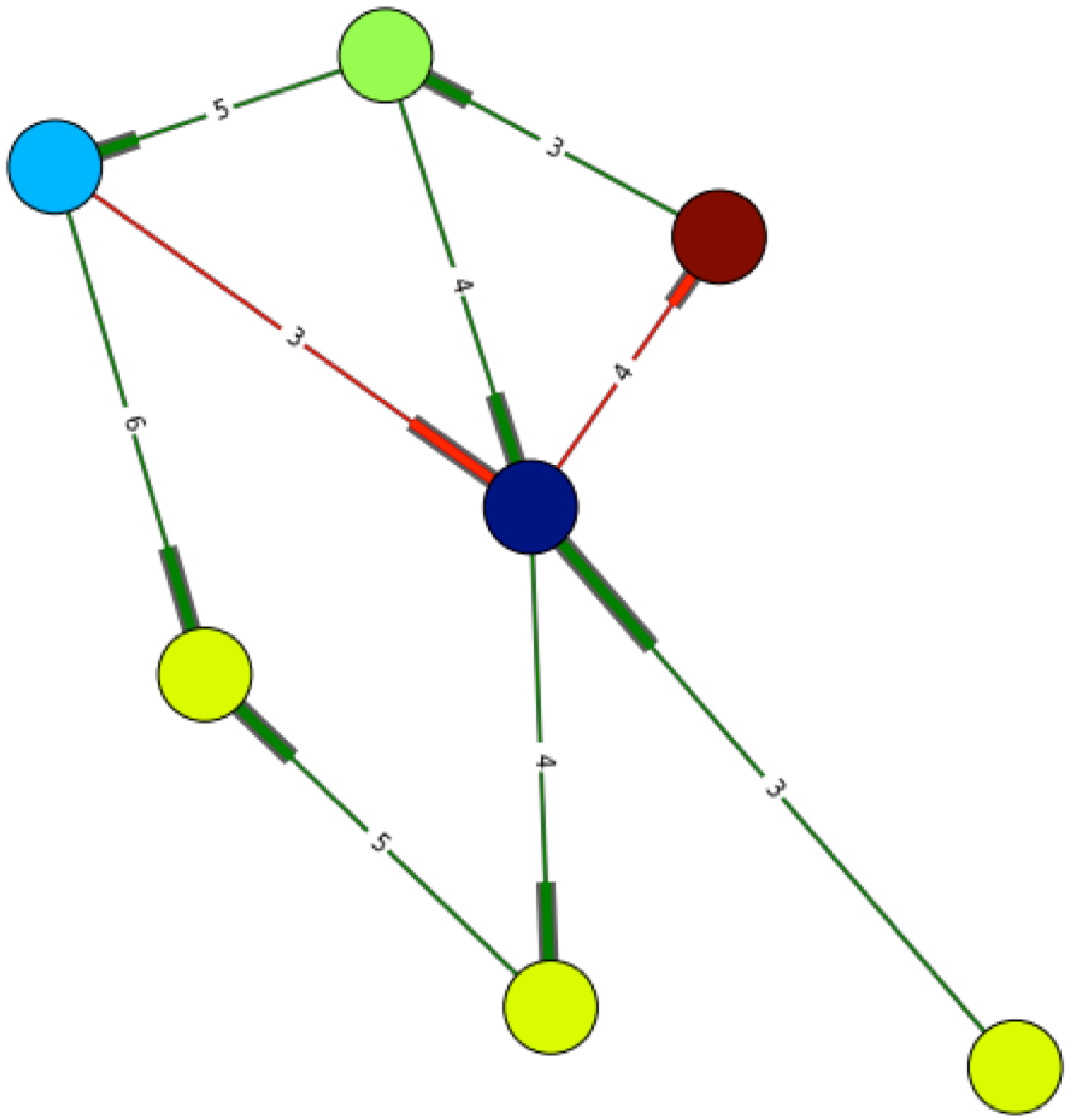
Chapter 7: Bioinformatics, Genetics, and Network Models

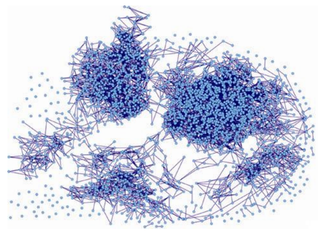

A
25 miles
26 miles
B
85 miles
C
5 m
D
10 m
10 m
9 m
11 m
E
F
88 miles

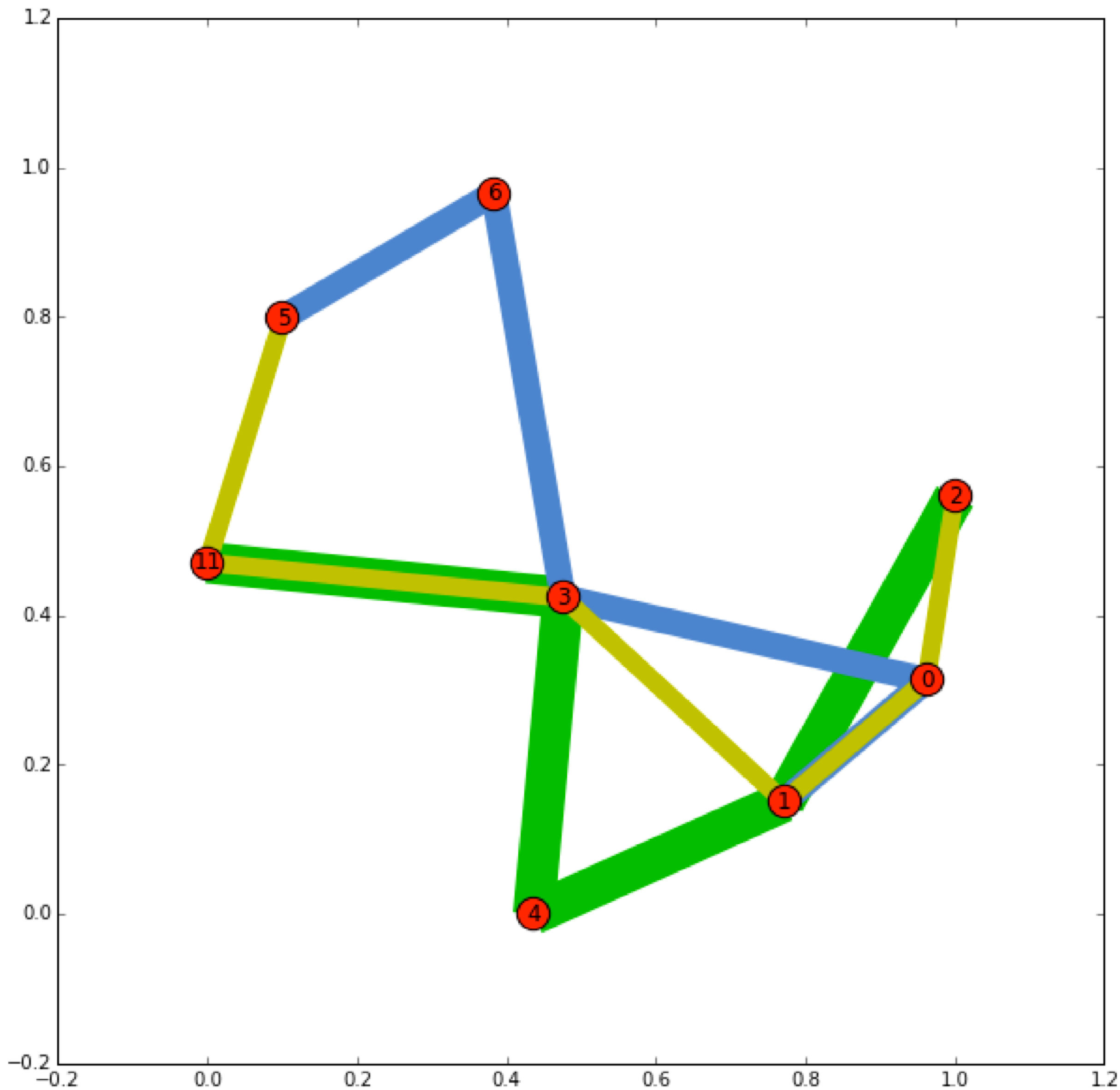

Boston
Chicago
1613
338
725
New York
1145
383
Wash DC
2113
2145
1709
Dallas
2161
Miami


A
B
D
C
B
C
A
D
E
E

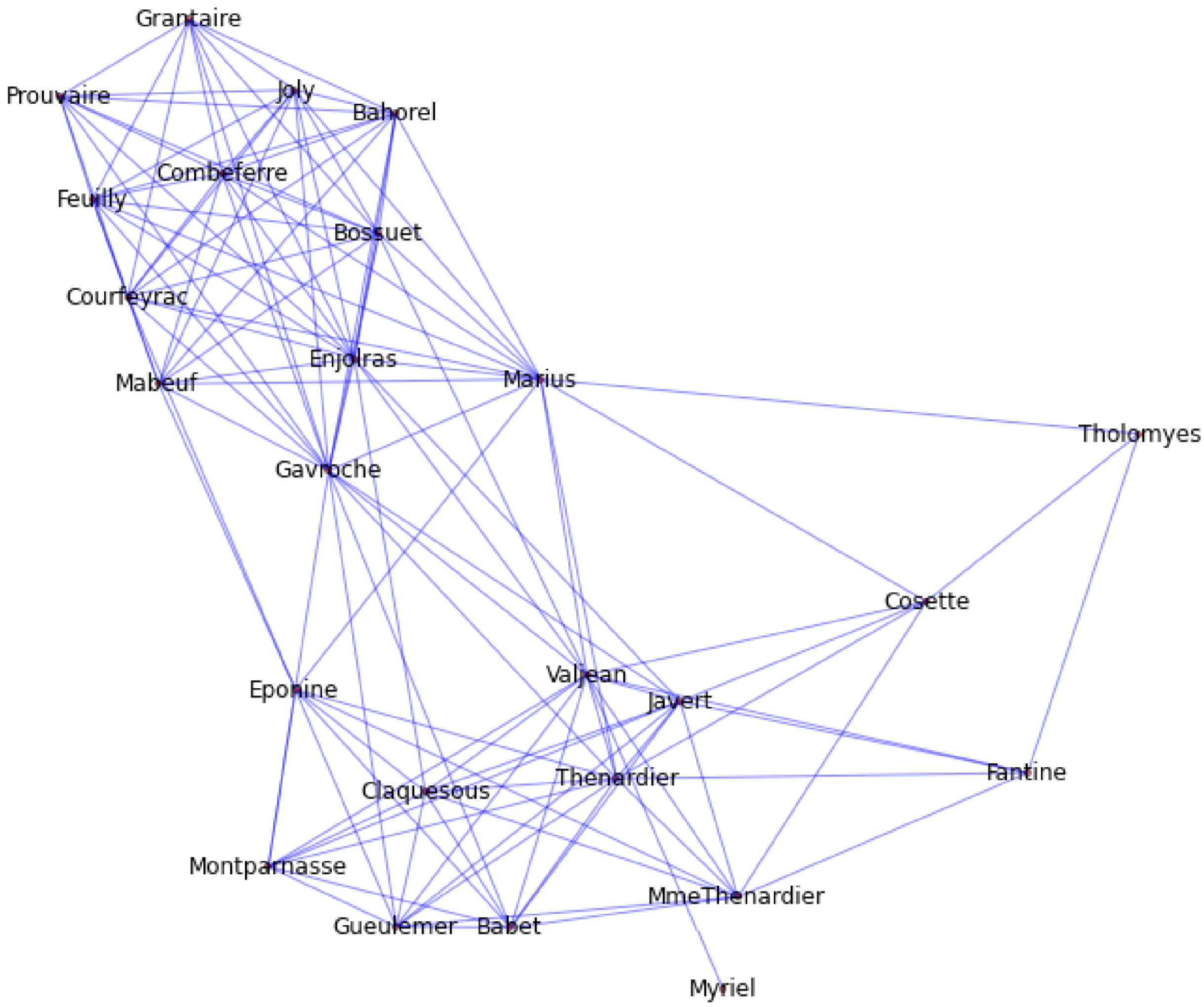


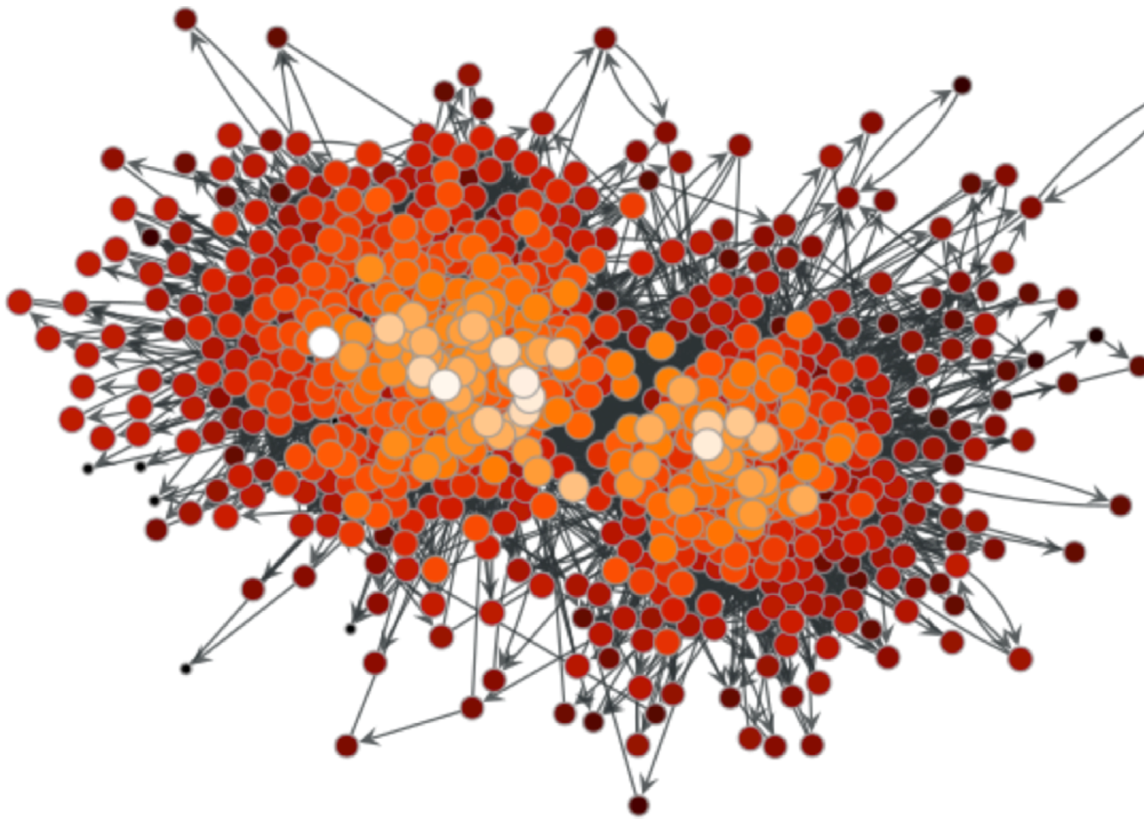

5
3
4
3
4
6
4
3
5

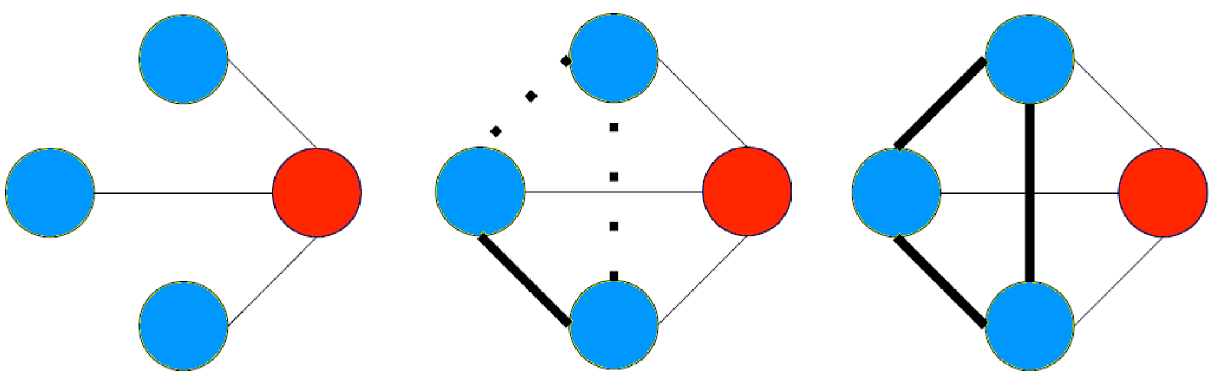




1.2
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
6
5
11
3
2
0
1
4


Grantaire
Prouvaire
Joly
Bahorel
Combeferre
Feuilly
Bossuet
Courfeyrac
Enjolras
Mabeuf
Marius
Tholomyes
Gavroche
Cosette
Valjean
Eponine
Javert
Fantine
Claquesous
Thenardier
Montparnasse
MmeThenardier
Gueulemer
Babet
Myriel





There are no pairs formed among neighbours

There is only one pair formed among neighbours

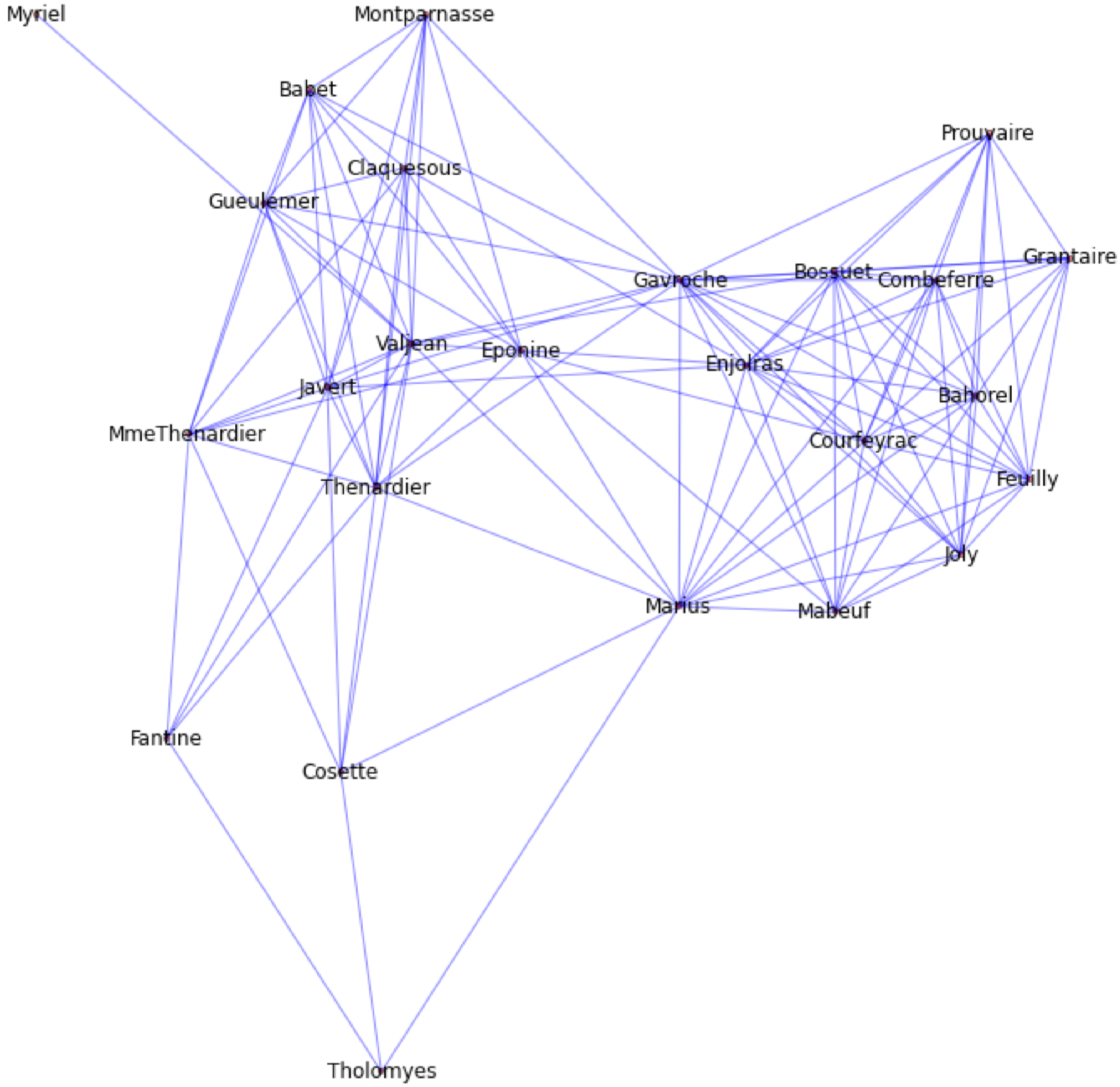
There are three pairs formed among neighbours

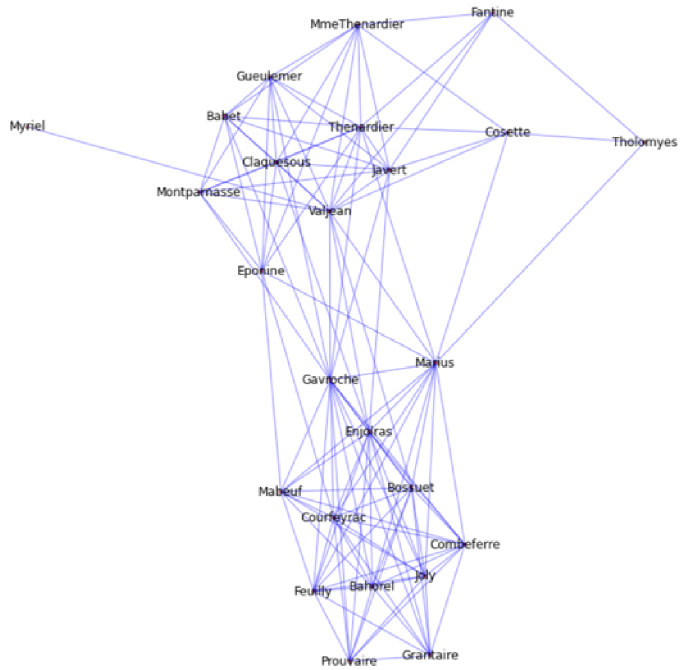
$$C_i = \frac{2 \times (links\ to\ the\ node\ i)}{n_b (n_b - 1)}$$

where n _ b is the number of neighbors to node i

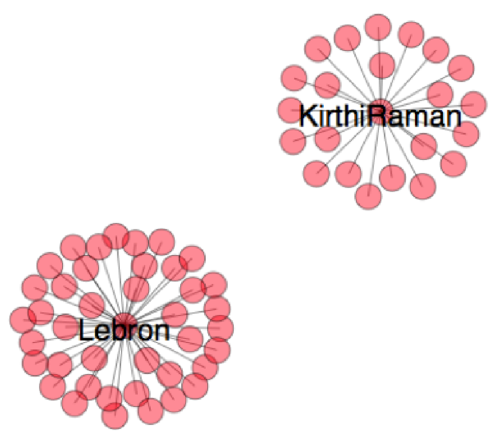
$$C_i = \frac{2 \times (links\ to\ the\ node\ i)}{n_b (n_b - 1)}$$

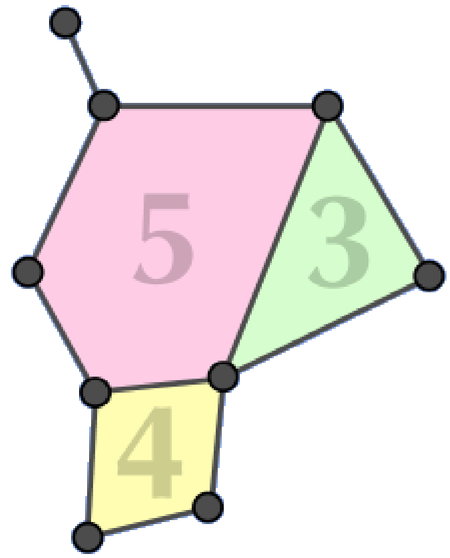
where n _ b is the number of neighbors to node i

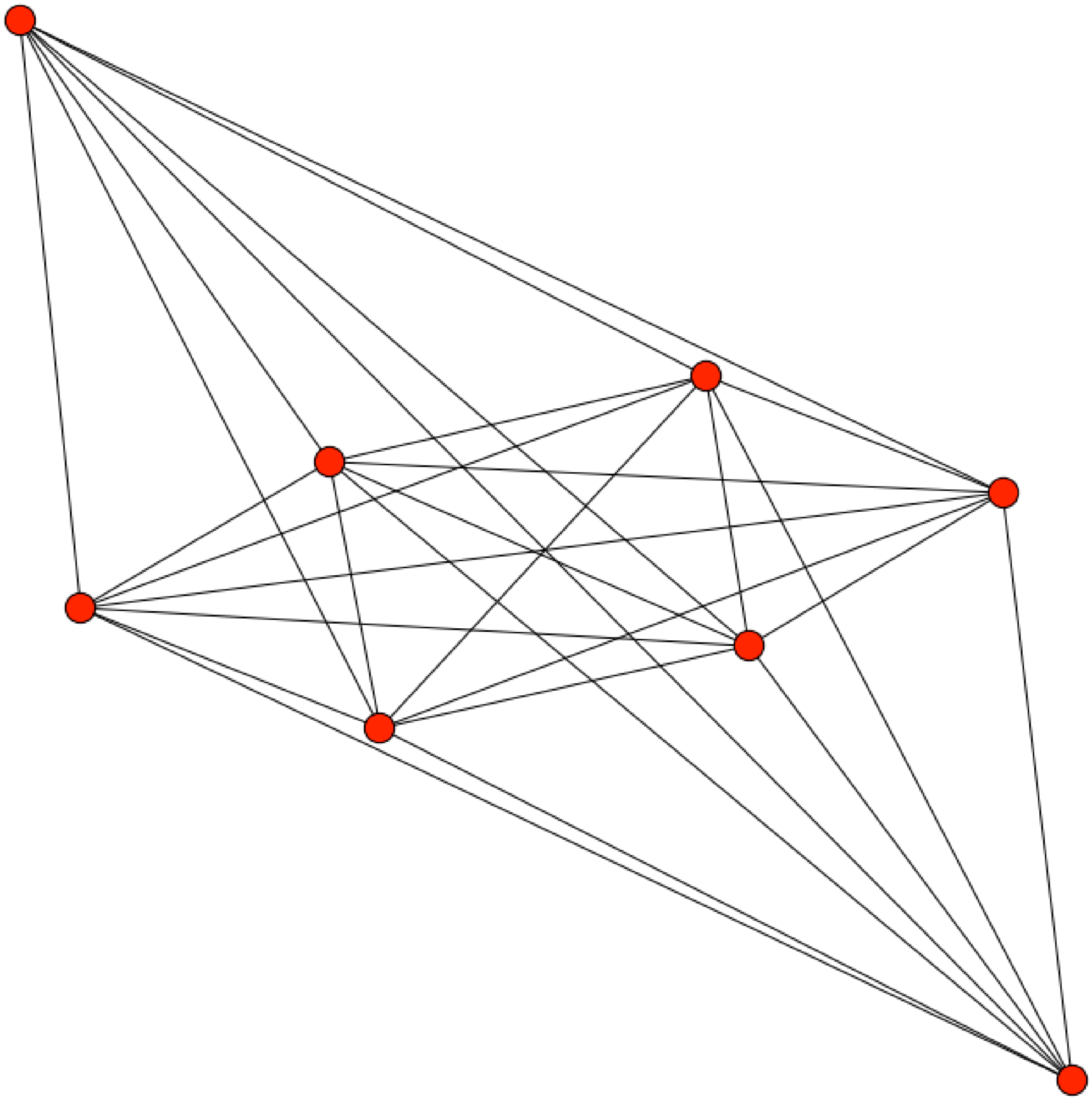

Myriel
Montparnasse
Babet
Prouvaire
Claquesous
Gueulemer
Grantaire
Gavroche
Bossuet
Combeferre
Valjean
Eponine
Enjolras
Javert
Bahorel
MmeThenardier
Courfeyrac
Thenardier
Feuilly
Joly
Marius
Mabeuf
Fantine
Cosette
Tholomyes

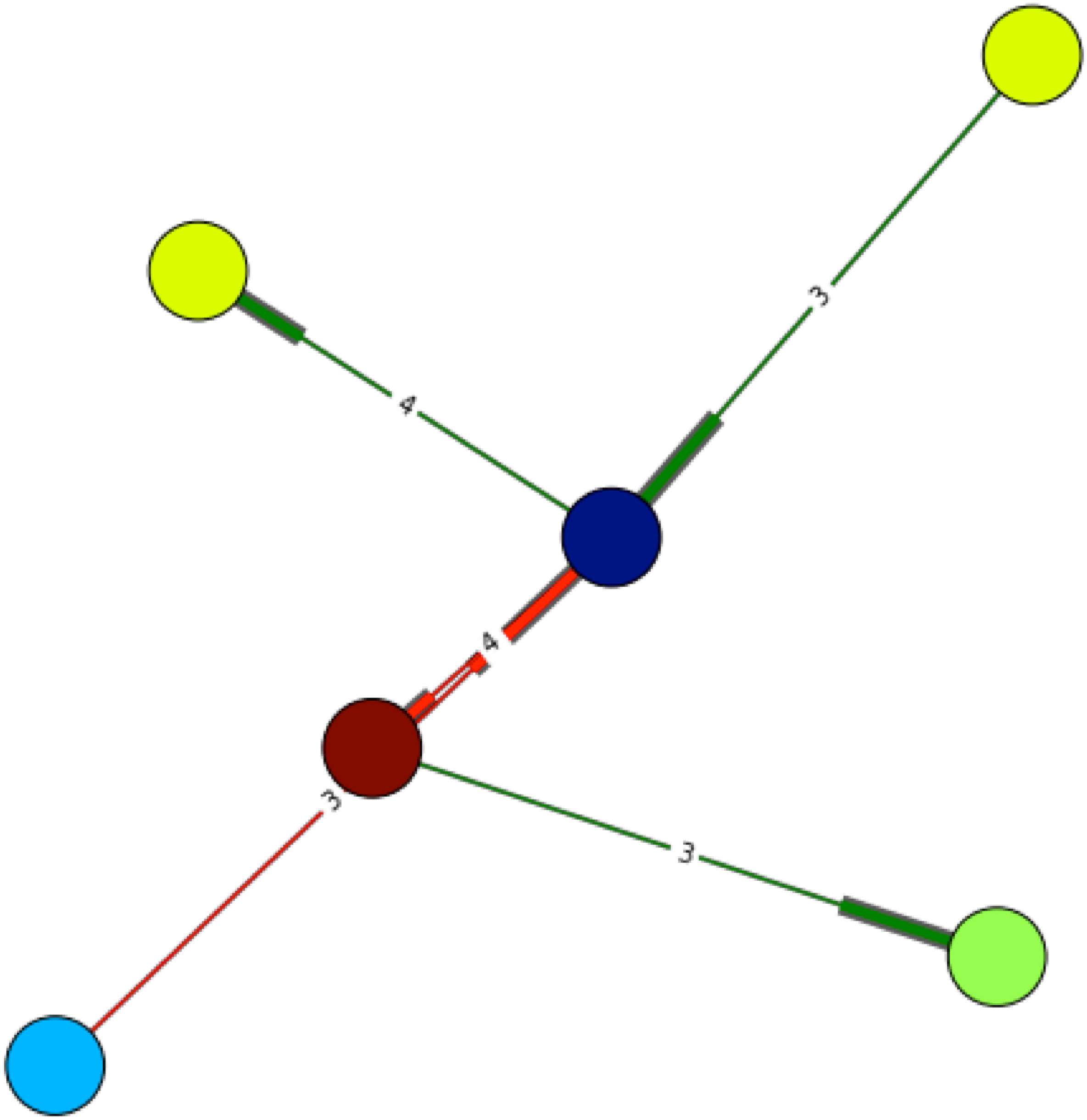


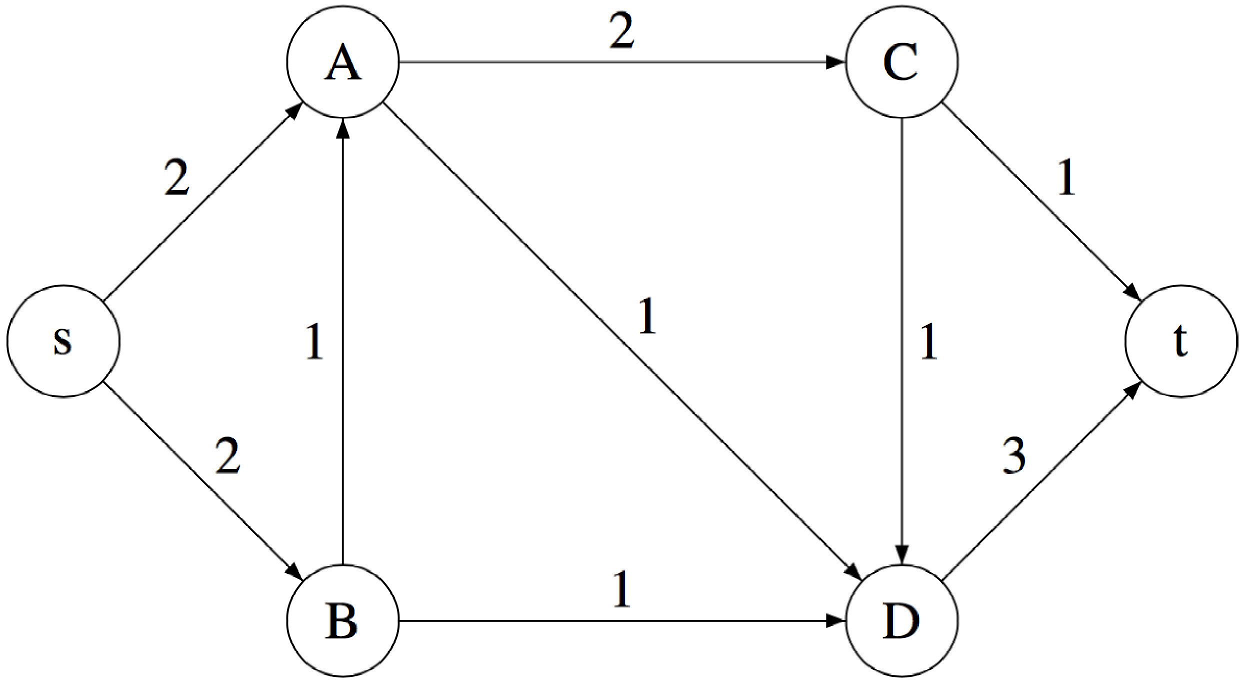
Followers in small Twitter network



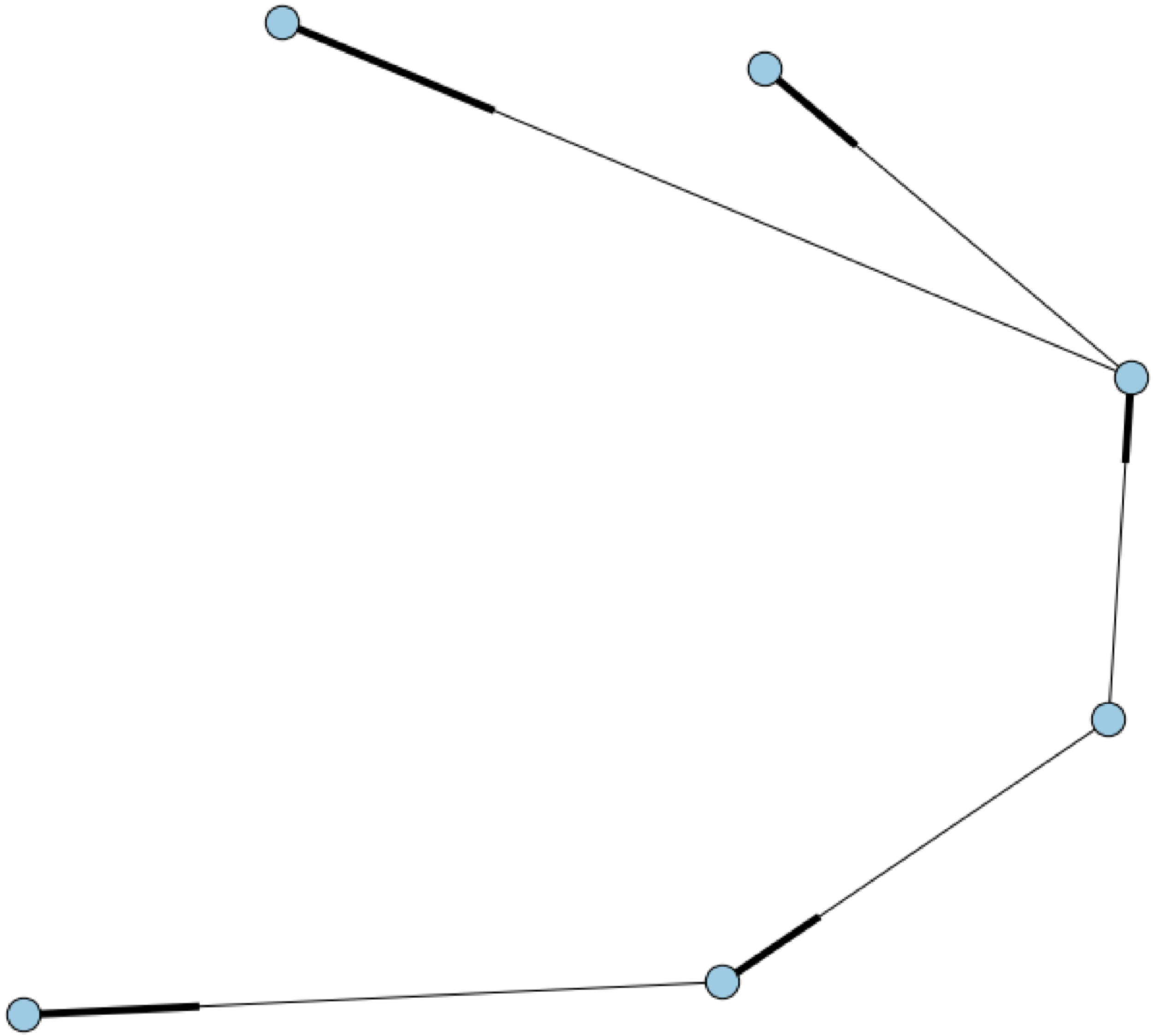

5
3
4

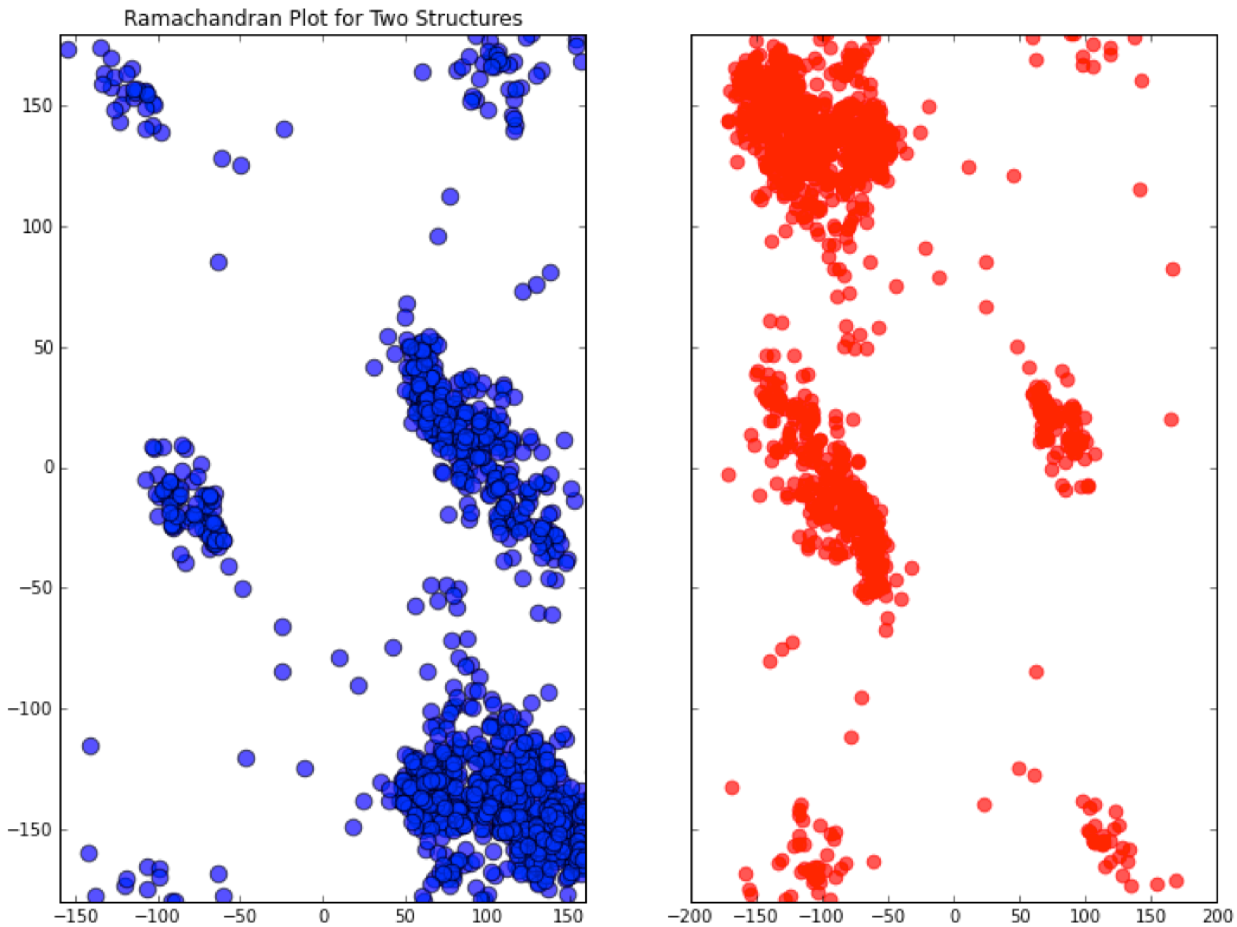



3
4
4
3
3

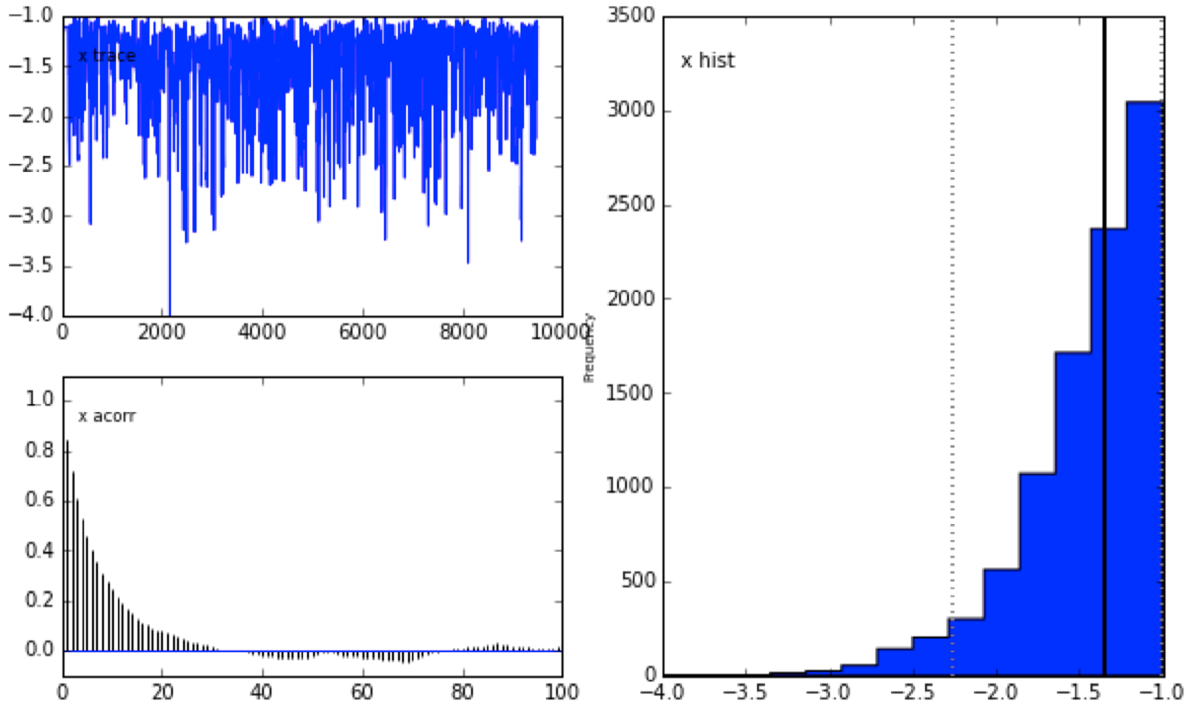


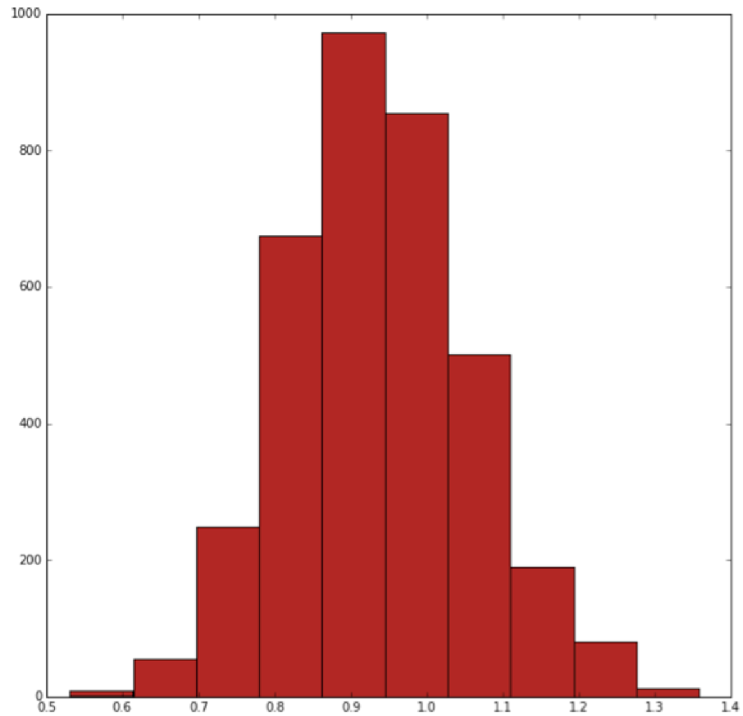
s
A
B
C
D
t
2
2
1
2
1
1
1
1
3




Ramachandran Plot for Two Structures
150
100
50
0
−50
−100
−150
−150 −100 −50 0 50 100 150
−200 −150 −100 −50 0 50 100 150 200

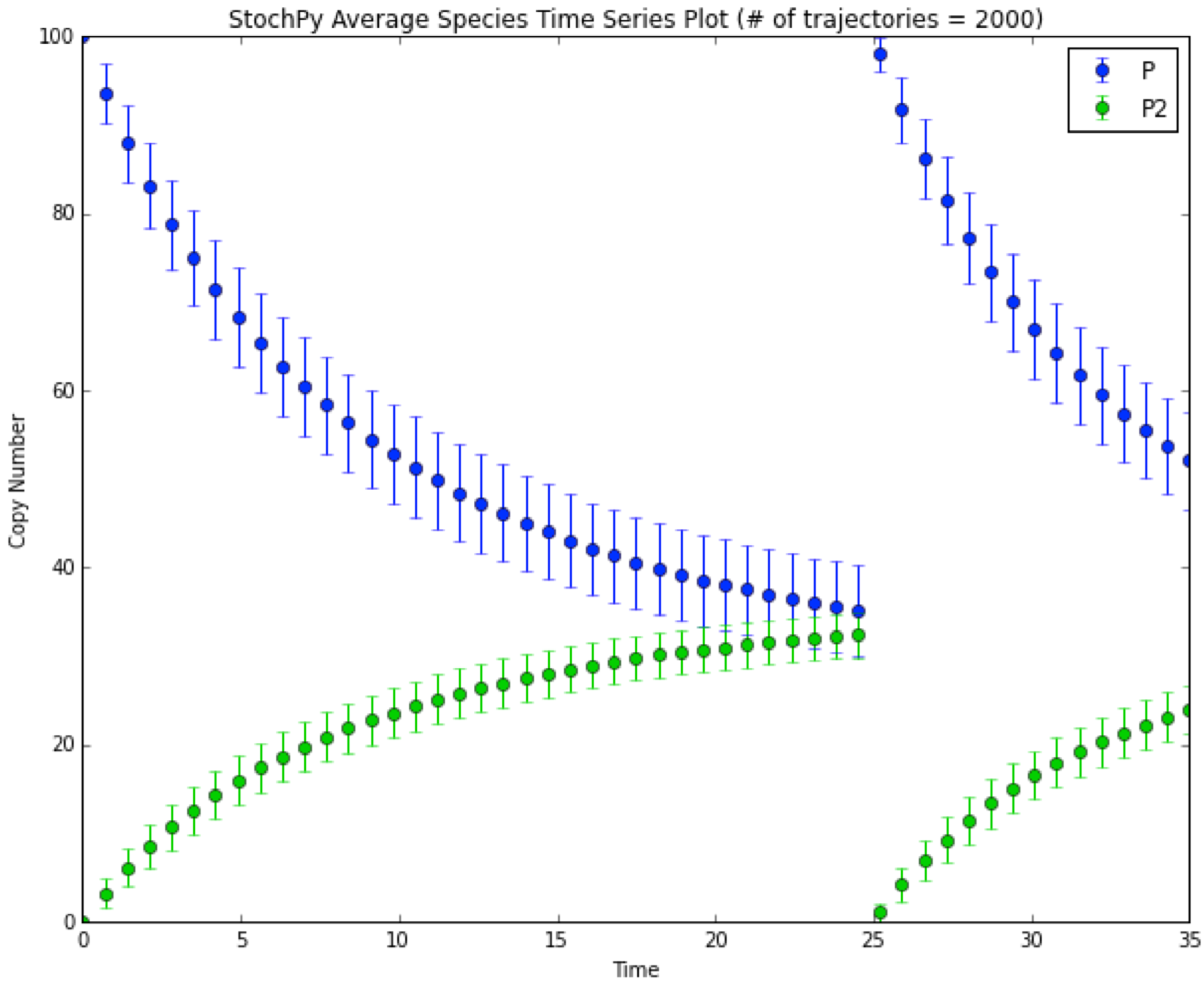
[----------------100%----------------] 10000 of 10000 complete in 0.4 secPlotting x





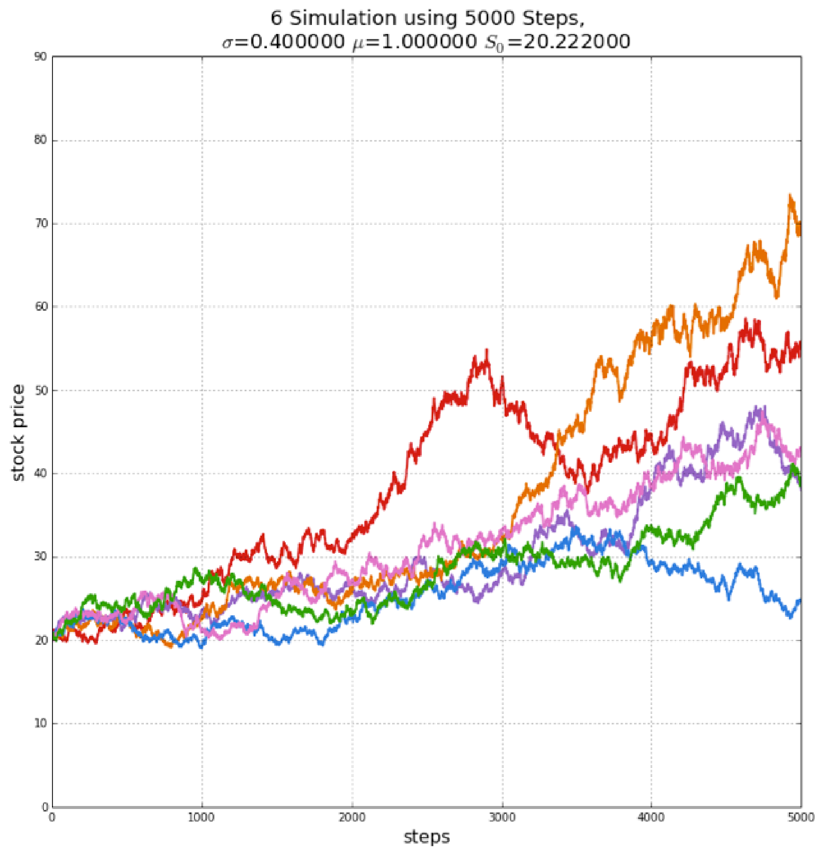
1000
800
600
400
200
0
0.5
0.6
0.7
0.8
0.9
1.0
1.1
1.2
1.3
1.4

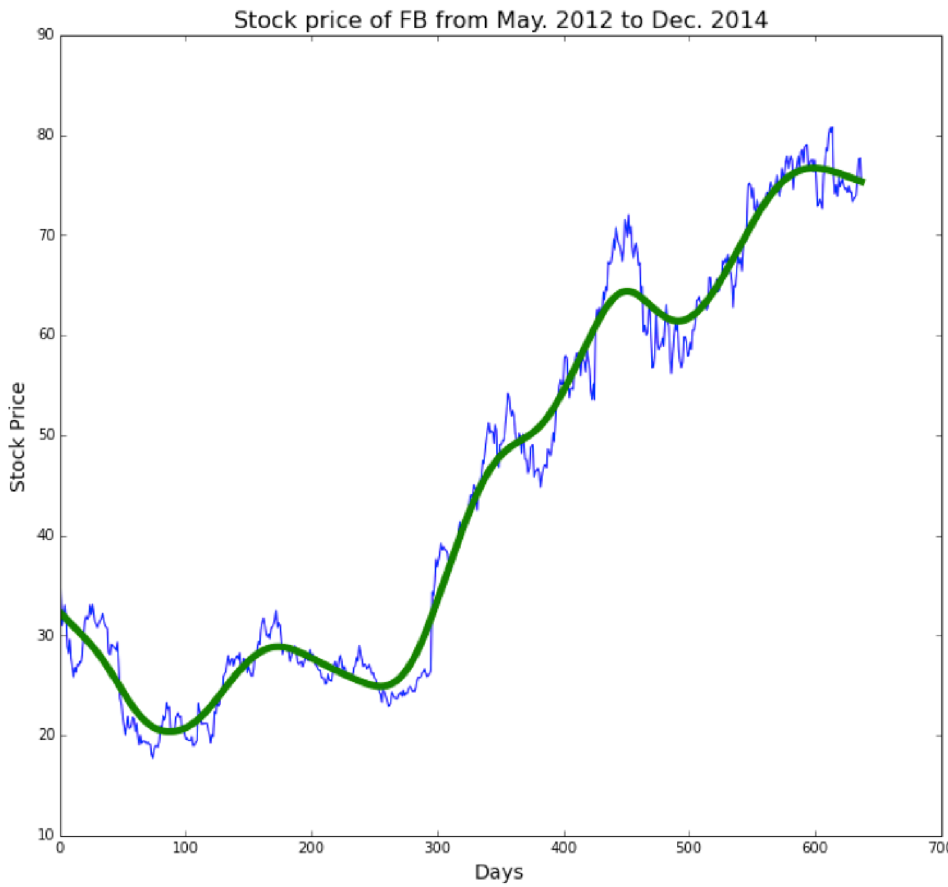
```
Info: Direct method is selected to perform stochastic simulations.
Parsing file: /Users/kvenkatr/Stochpy/pscmodels/ImmigrationDeath.psc
Info: No reagents have been fixed
Parsing file: /Users/kvenkatr/Stochpy/pscmodels/dsmts-003-04.xml.psc
Info: No reagents have been fixed
Event(s) detected.
Info: 2000 trajectories are generated
Info: Simulation time: 8.24345302582
```

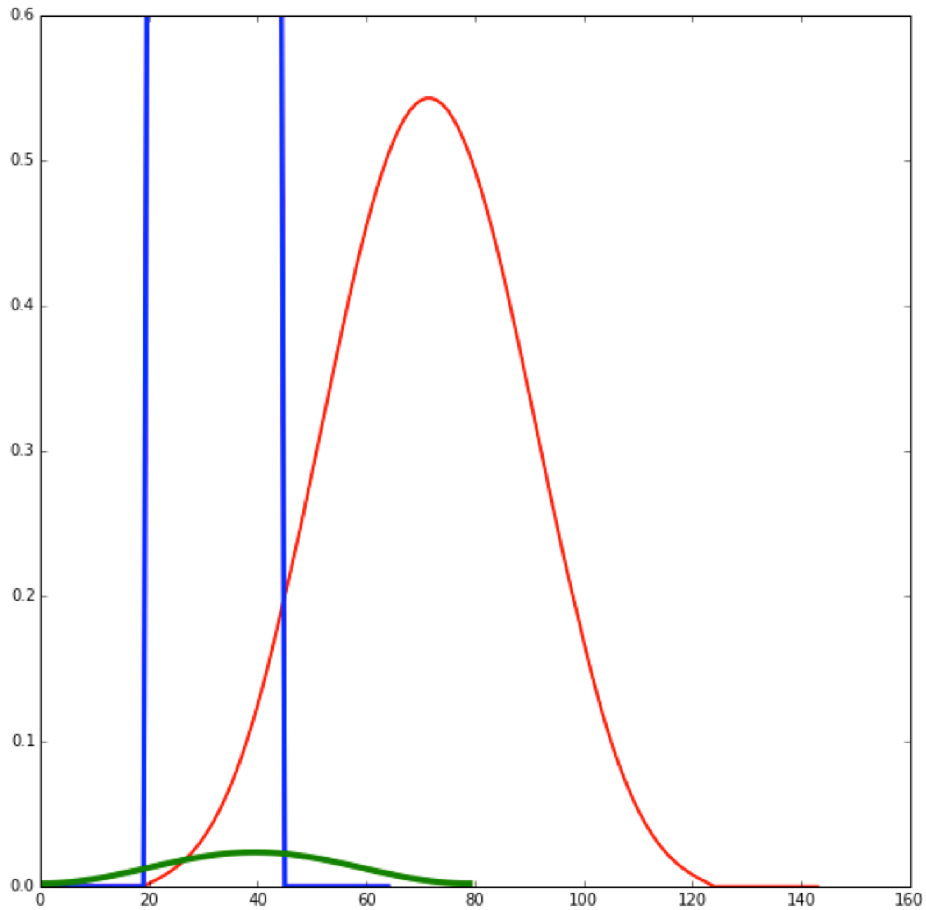


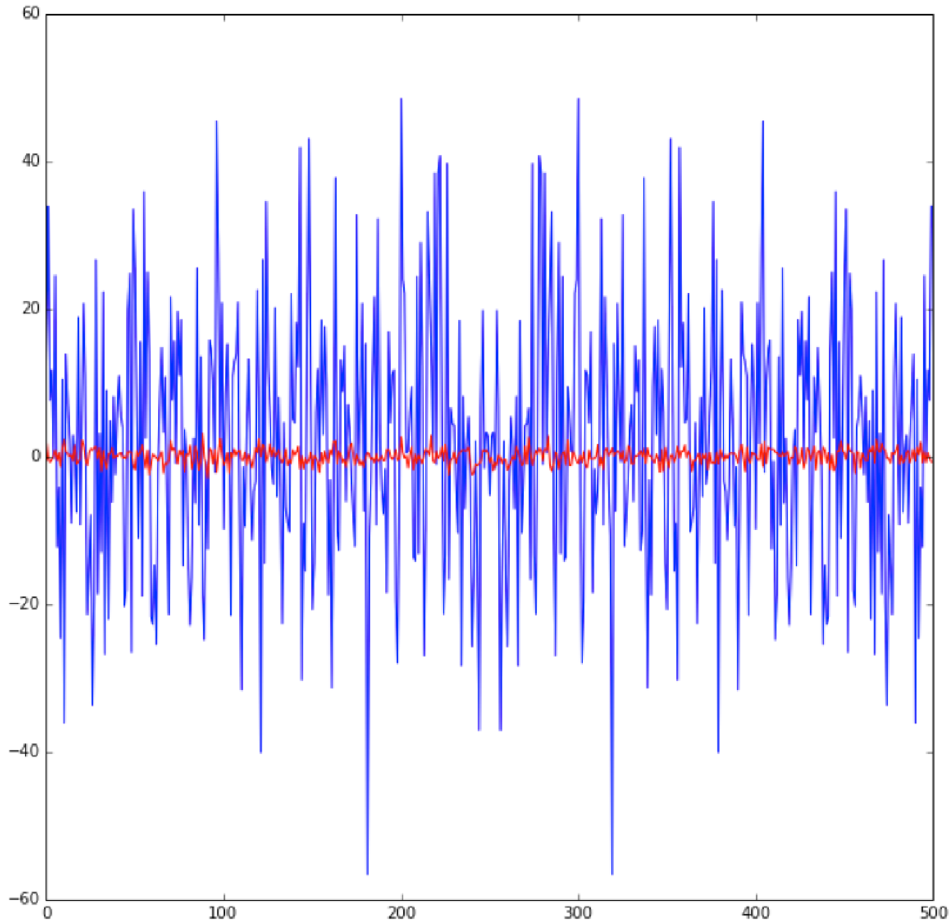
Chapter 8: Advanced Visualization

$$dS_t = \mu \; S_t \; dt + \sigma \; S_t \; dW_t$$


6 Simulation using 5000 Steps,
σ=0.400000 μ=1.000000 S_0=20.222000
stock price
steps
0
10
20
30
40
50
60
70
80
90
0
1000
2000
3000
4000
5000

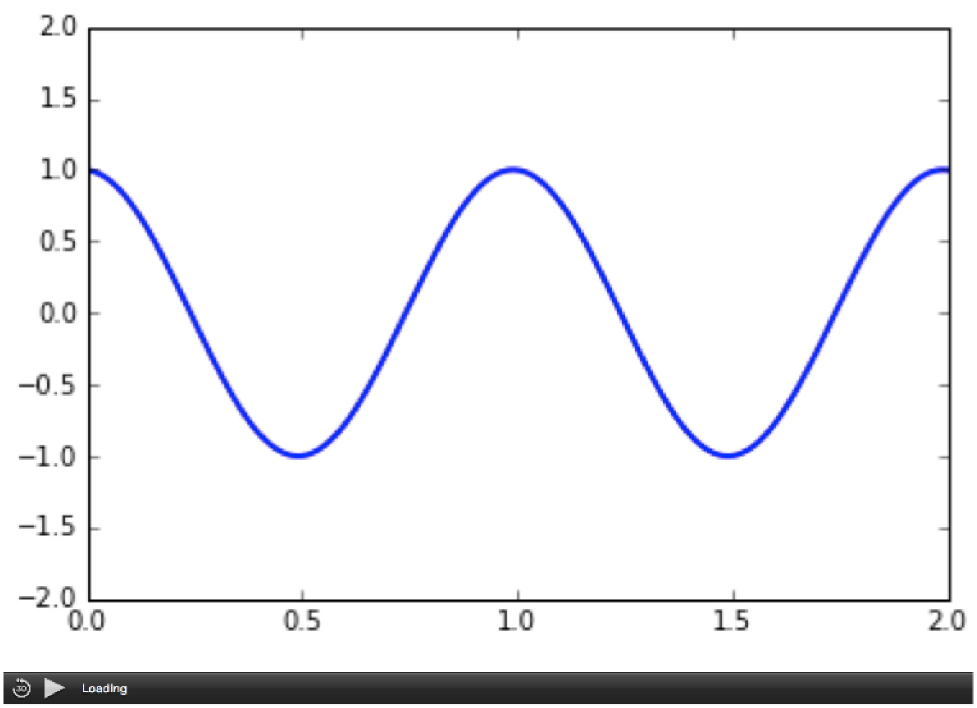

Stock price of FB from May. 2012 to Dec. 2014
Stock Price
Days
90
80
70
60
50
40
30
20
10
0
100
200
300
400
500
600
700

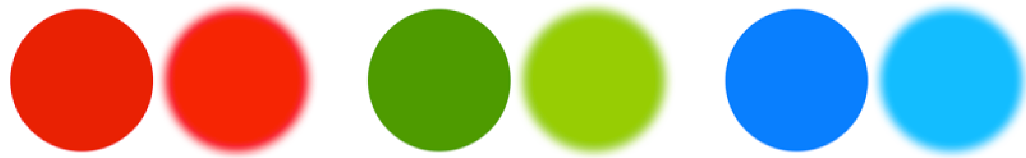

0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
20
40
60
80
100
120
140
160

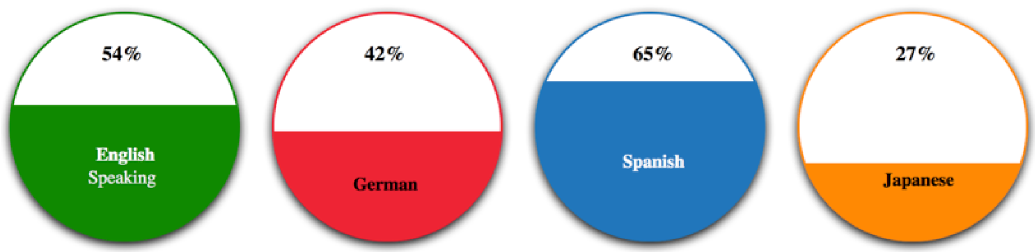


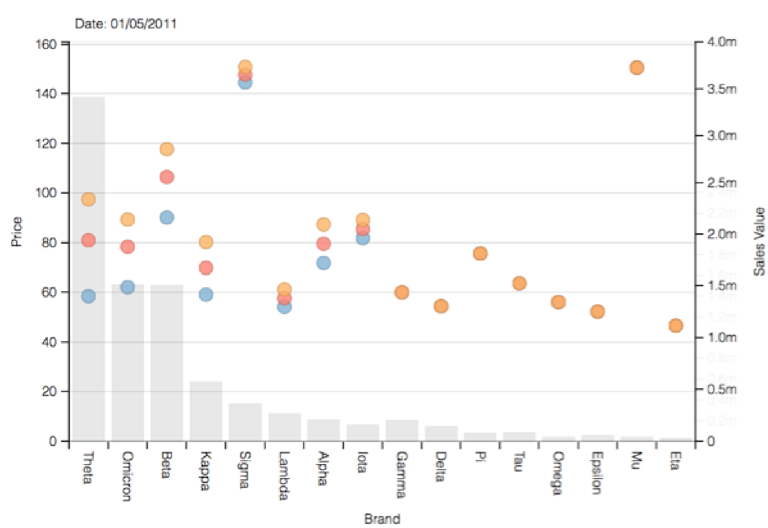
60
40
20
0
−20
−40
−60
0
100
200
300
400
500

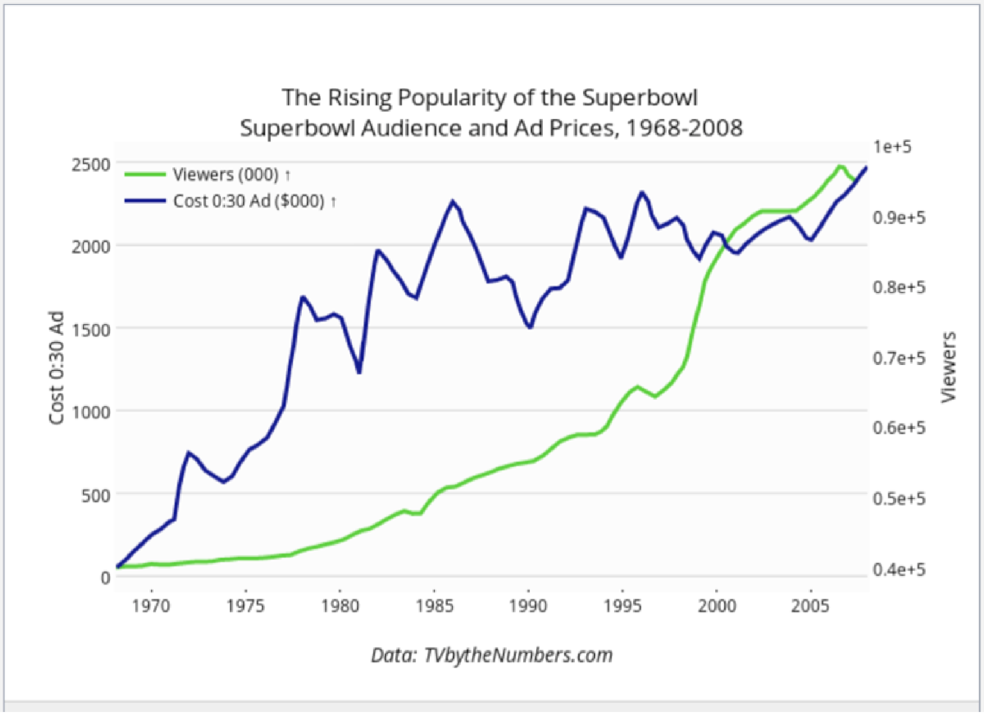

OpenCV
OpenCV


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
0.0
0.5
1.0
1.5
2.0
Loading




54%
English
Speaking
42%
German
65%
Spanish
27%
Japanese


Date: 01/05/2011
Price
160
140
120
100
80
60
40
20
0
4.0m
3.5m
3.0m
2.5m
2.0m
1.5m
1.0m
0.5m
0
Sales Value
Theta
Omicron
Beta
Kappa
Sigma
Lambda
Alpha
Iota
Gamma
Delta
Pi
Tau
Omega
Epsilon
Mu
Eta
Brand



The Rising Popularity of the Superbowl
Superbowl Audience and Ad Prices, 1968-2008
Viewers (000) ↑
Cost 0:30 Ad ($000) ↑
Cost 0:30 Ad
2500
2000
1500
1000
500
0
1e+5
0.9e+5
0.8e+5
0.7e+5
0.6e+5
0.5e+5
0.4e+5
Viewers
1970
1975
1980
1985
1990
1995
2000
2005
Data: TVbytheNumbers.com