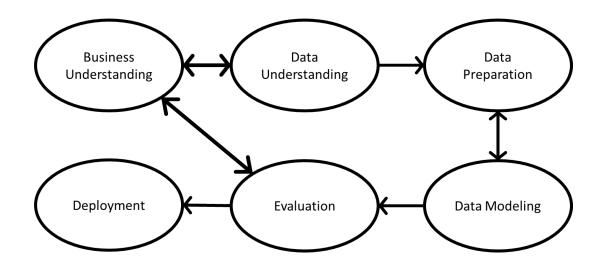
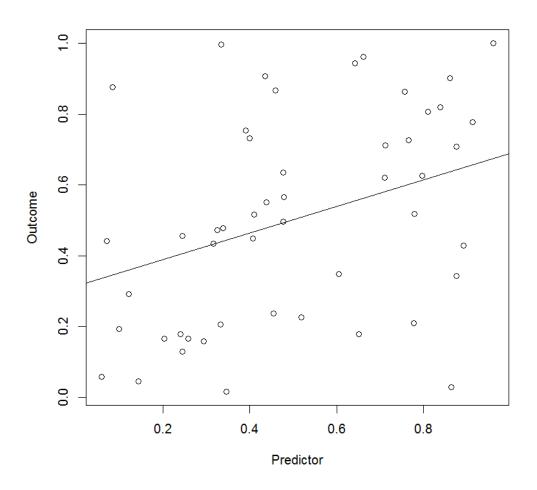
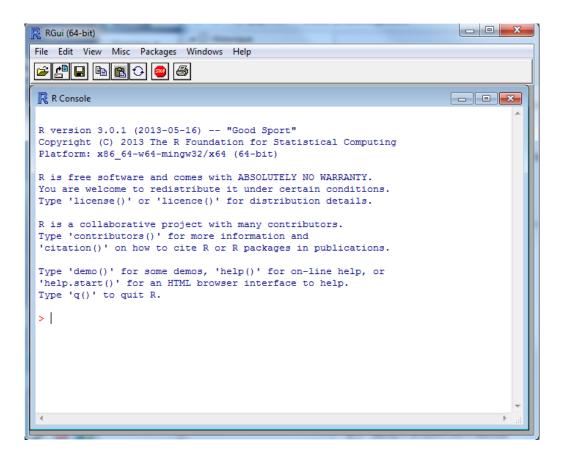
# Learning Predictive Analytics with R

## **Preface:**

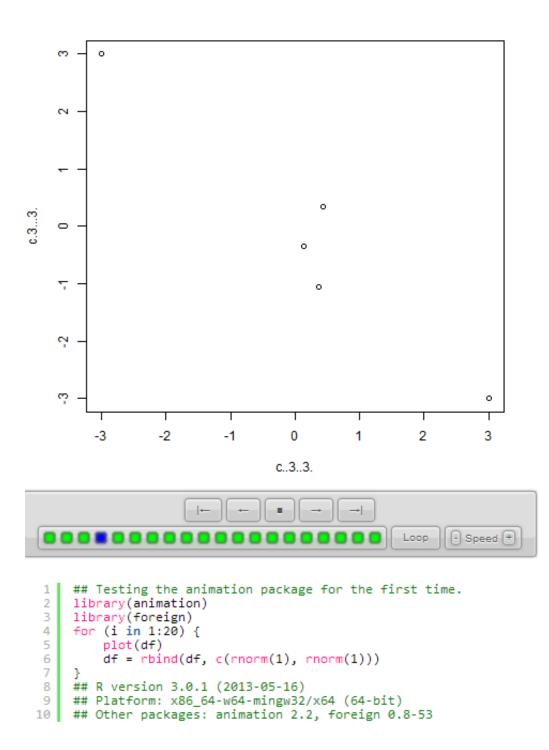




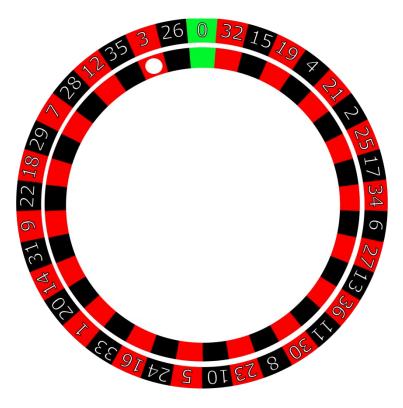
Chapter 1: Setting GNU R for Predictive Analytics



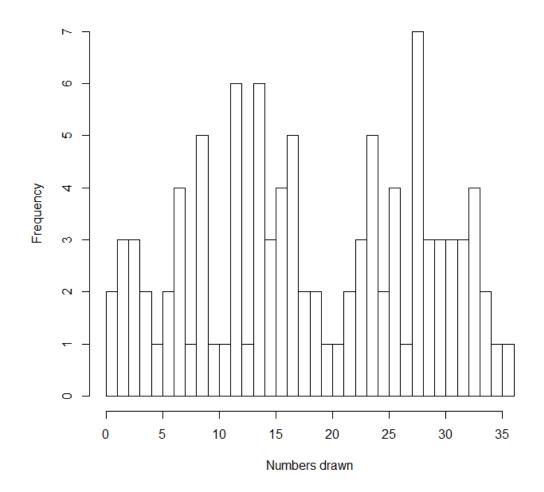
R R packages available		• ×
Packages in library	<pre>`C:/PROGRA~1/R/RFORPA~1.1/library':</pre>	<u>^</u>
base	The R Base Package	
boot	Bootstrap Functions (originally by Angelo Canty for S)	
class	Functions for Classification	
cluster	Cluster Analysis Extended Rousseeuw et al.	
codetools	Code Analysis Tools for R	-
compiler	The R Compiler Package	=
datasets	The R Datasets Package	
foreign	Read Data Stored by Minitab, S, SAS, SPSS,	
	Stata, Systat, dBase,	
graphics	The R Graphics Package	
grDevices	The R Graphics Devices and Support for Colours	
	and Fonts	
grid	The Grid Graphics Package	
KernSmooth	Functions for kernel smoothing for Wand & Jones (1995)	
lattice	Lattice Graphics	
MASS	Support Functions and Datasets for Venables and	
	Ripley's MASS	
Matrix	Sparse and Dense Matrix Classes and Methods	
methods	Formal Methods and Classes	
mgcv	Mixed GAM Computation Vehicle with GCV/AIC/REML	
	smoothness estimation	-
•		►

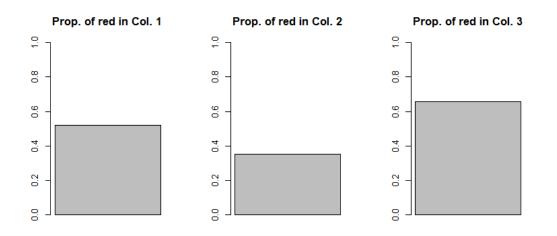


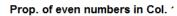
Chapter 2: Visualizing and Manipulating Data Using R



## Frequency of numbers drawn

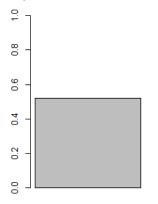


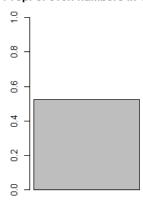


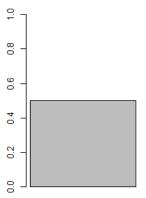


Prop. of even numbers in Col. 2

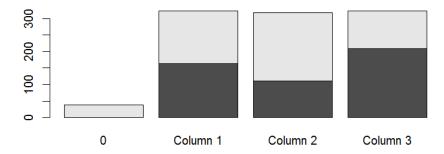




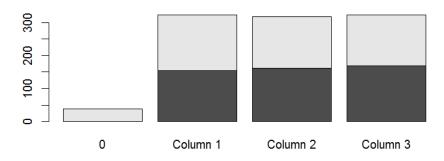


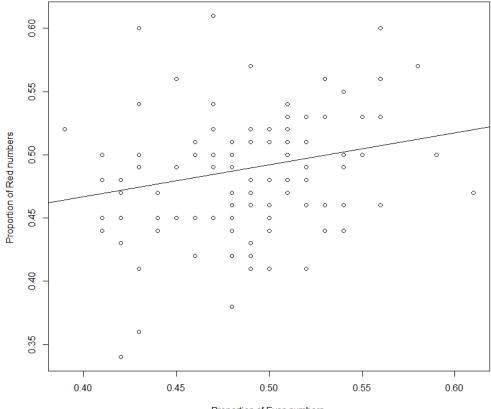


#### Red numbers in Columns 1, 2 and 3



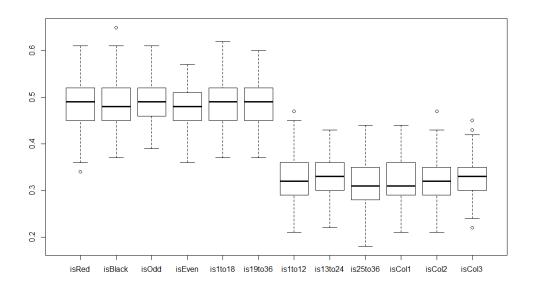
Even numbers in Columns 1, 2 and 3

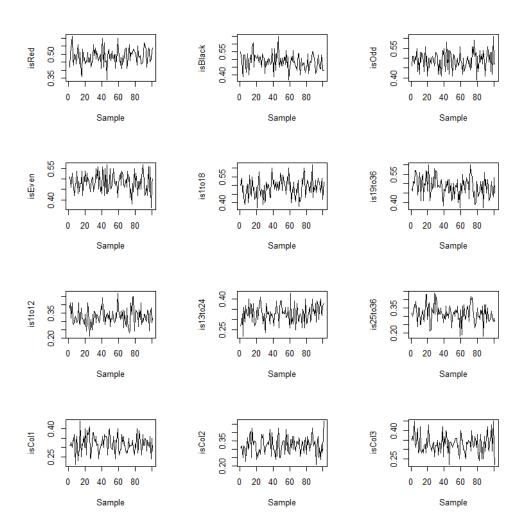




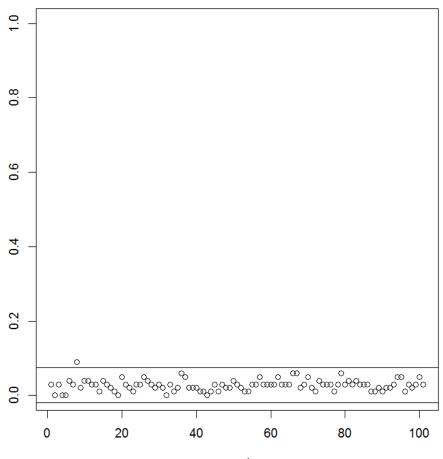
Relationship between attributes Red and Even

Proportion of Even numbers

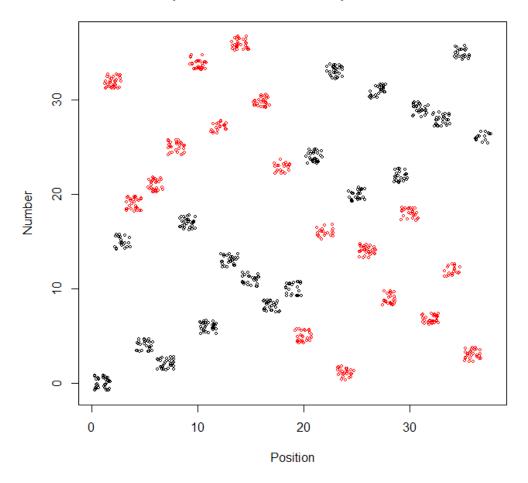




## Proportion of zeros



sample

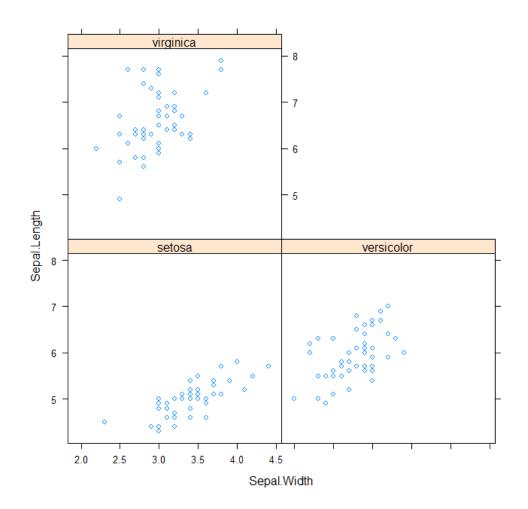


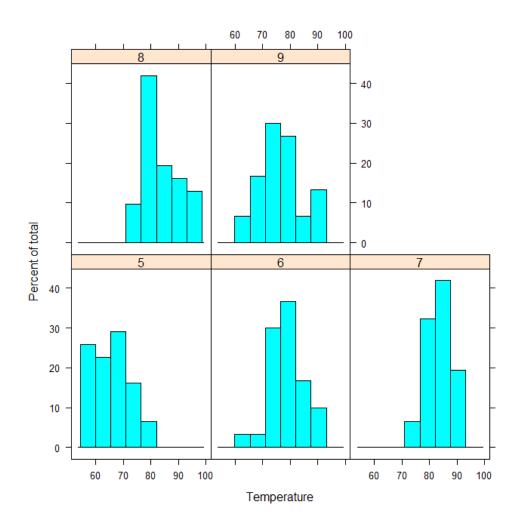
Relationship between number and position on the wheel

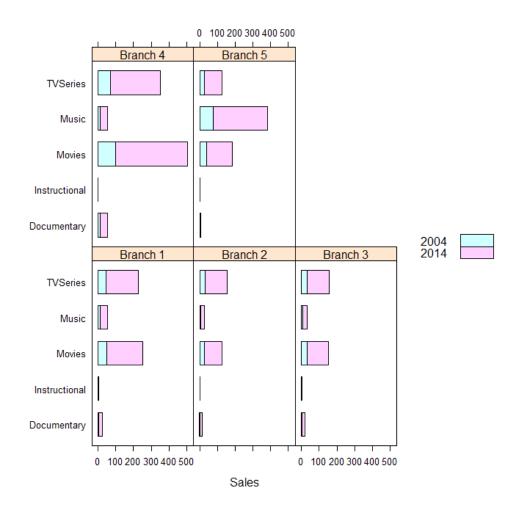
			0	
1-18		1	2	3
1-10	1.+17	4	5	6
EVEN	1st 12	7	8	9
EVEN		10	11	12
	2nd 12	13	14	15
RED		16	17	18
DIACK	ELACK	19	20	21
BLACK		22	23	24
		25	26	27
ODD	3rd 12	28	29	30
10.26	3ra 12	31	32	33
19-36		34	35	36
		2-1	2-1	2-1

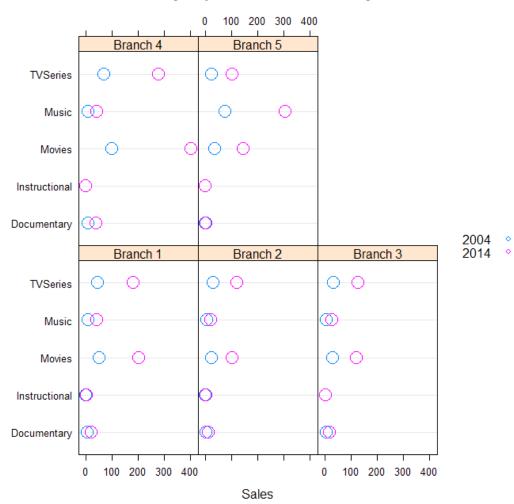
# Chapter 3: Data Visualization with Lattice

R Console			
<pre>&gt; library(lattice) &gt; search() [1] ".GlobalEnv" [4] "package:graphics" [7] "package:datasets" [10] "package:base" &gt;  </pre>	"package:lattice" "package:grDevices" "package:methods"	"package:stats" "package:utils" "Autoloads"	
			►

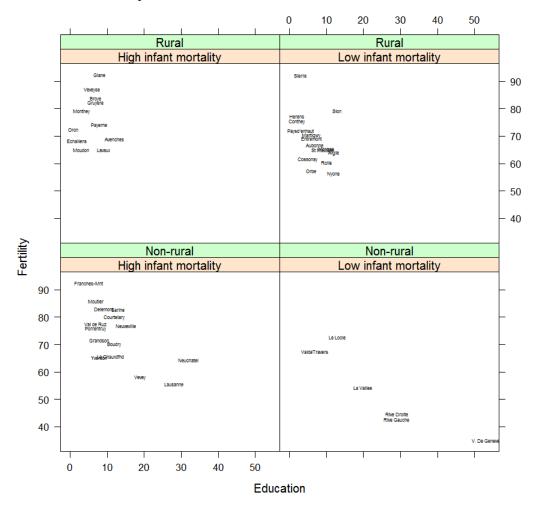




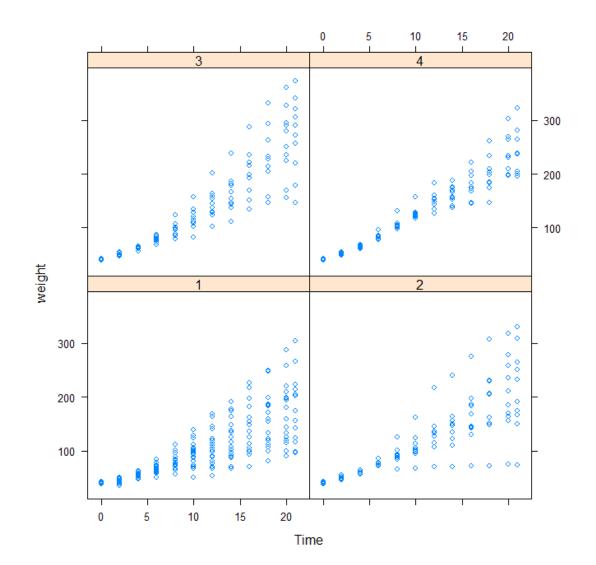


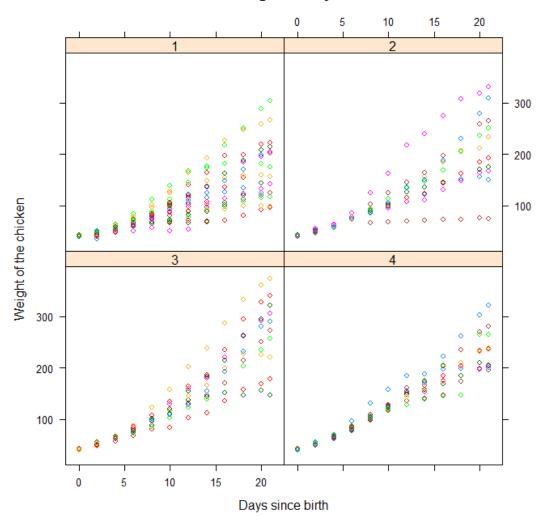


#### Sales by department, branch and year



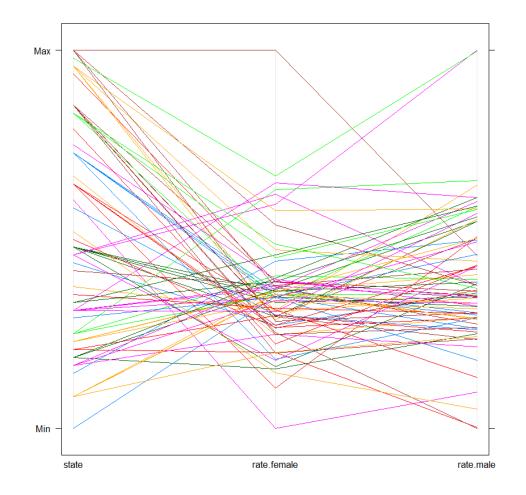
#### Fertility and education in 1888 Occidental Switzerland





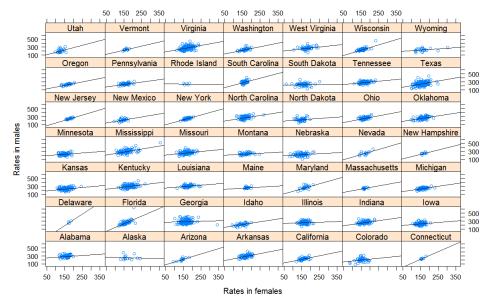
Chicken growth by diet

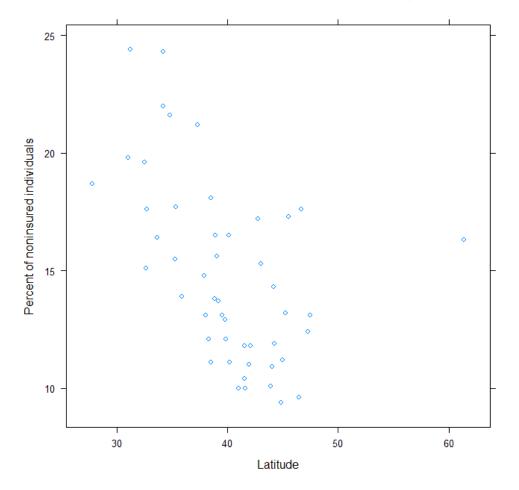
R Console				
> head(USCancerF	Rates, 3)			<b>^</b>
	rate.male LCL95	.male UCL95.male	rate.female LCL95.	female
alabama,pickens	363.7	423.2	151.0	123.6
alabama, bullock	345.7	274.2 431.4	140.5	102.8
alabama,russell	340.7	304.5 380.9	182.3	161.3
	UCL95.female	state cou	unty	
alabama,pickens	183.6 Ala	abama Pickens Cou	unty	
alabama, bullock	189.7 Ala	abama Bullock Cou	unty	
alabama,russell	205.5 Ala	abama Russell Cou	unty	
> summary(USCand	erRates)			
rate.male	LCL95.male	UCL95.male	rate.female	
Min. : 76.5	Min. : 34.6	Min. :160.9	Min. : 63.5	
1st Qu.:228.8	1st Qu.:189.3	1st Qu.:269.6	1st Qu.:150.5	
Median :254.8	Median :217.8	Median :301.3	Median :165.4	
Mean :257.4	Mean :215.2	Mean :311.0	Mean :165.0	
3rd Qu.:283.8	3rd Qu.:244.4	3rd Qu.:342.0	3rd Qu.:177.8	
		Max. :774.3		
		NA's :10	NA's :63	
	UCL95.female			
		Texas : 235	-	
		Georgia : 157		
		-	Mode :character	
	Mean :202.7	-		
	3rd Qu.:217.5			
	Max. :786.8			
	NA's :63	(Other) :2179		
>				
4				
				E. 1



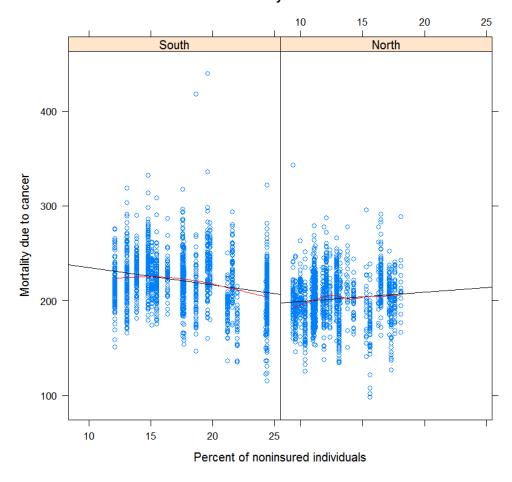
Max - Utah	Vermont	Virginia	Washington	West Virginia	Wisconsin	Wyoming
Min		WARDEN ST. SHORE				
Oregon	Pennsylvania	Rhode Island	South Carolina	South Dakota	Tennessee	Texas – Max
						Min
Max - New Jersey	New Mexico	New York	North Carolina	North Dakota	Ohio	Oklahoma
Min -						
Minnesota	Mississippi	Missouri	Montana	Nebraska	Nevada	New Hampshire - Max
						Min
Max - Kansas	Kentucky	Louisiana	Maine	Maryland	Massachusetts	Michigan
Min						
Delaware	Florida	Georgia	Idaho	Illinois	Indiana	lowa – Max
						Min
Max - Alabama	Alaska	Arizona	Arkansas	California	Colorado	Connecticut
Min -						
F M	F M	F M	F M	F M	F M	F M

#### Death due to cancer



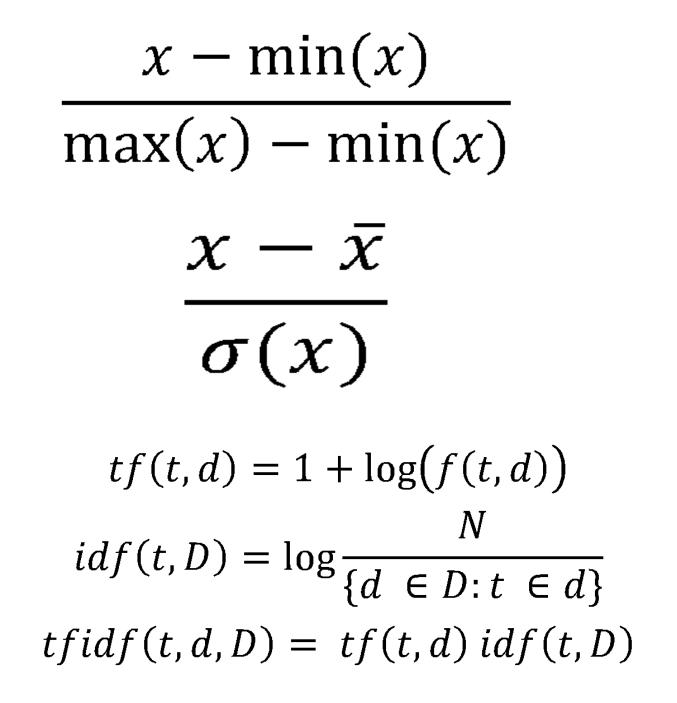


#### State latitude and health insurance coverage



Health insurance coverage and Mortality due to cancer by latitude

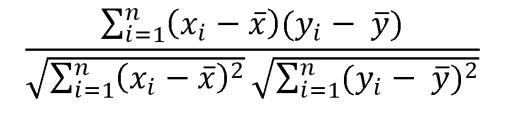
Chapter 4: Cluster Analysis



$$\sum_{i=1}^{n} |p_i - q_i|$$

$$\sqrt{(\sum_{i=1}^n p_i - q_i)^2}$$

$$\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$



# $\frac{|A \cap B|}{|A \cup B|}$

1. Initiate centroids randomly



4.

- 2. Compute distance from each case to each centroid
- 3. Assign case to the closest cluster (smaller distance between case and centroid)
  - Update centroids using mean value of observations pertaining to given cluster

(repeat until convergence)

#### 2-cluster solution

	murder	10 30 50		50 200 350		
10 30 50		rape	, , , , , , , , , , , , , , , , , , ,	<b>\$</b>		
			robbery			200 B
60 200 350			,°°°,	assault		ి శ్రీ జ్యా
_	°°°°° °°°°°	*** ***	°°°°° °°°°°° &		burglary	500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500 - 500
400 800 1200	5 10 15		° ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° ° °		500 1500	car.theft

4-cluster solution
--------------------

murder	10 30 50		50 200 350		
2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	rape	, ,	<b>,</b>		
	, 	robbery			**************************************
	<b>*</b> ***		assault	, ,	*** ***
°°°° °°°°		***** \$***	<b>,</b> , , , , , , , , , , , , , , , , , ,	burglary	500 1500
		9°°°° 9°°°° 100 400		500 1500	car.theft

3-cluste	r s	olut	tion	
	50	200	350	

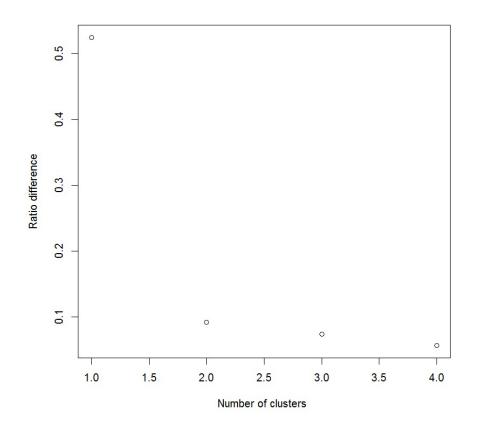
murder	8°°°	<b>``</b> ``` &	, 		
200 - 10 200	rape	, ,	<b>,</b>		
		robbery	, .* . .*		**************************************
8 20 30	**** ****		assault		*** ***
		°°°°° %		burglary	
40 40 100 100 100 100 100 100 100 100 10		*****			car.theft
5 10 15		100 400		500 1500	

5-cluster	solutior
-----------	----------

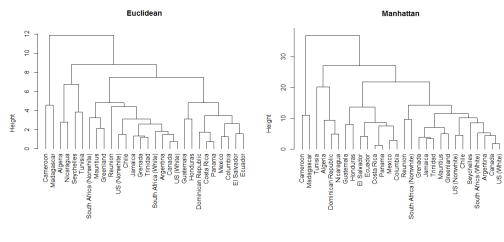
₽

400 800

	10 30 50		50 200 350		400 800 120	30
murder				• • • • • • • •		5 10 15
	rape	<b>,</b> ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,		,		
		robbery	, , <b>,</b>		Å.,	100 400
• • • • • • • • • • • • • • • • • • •	<u>```</u>	••••• ••••	assault	*** ****	ູ່ ຜູ້ ຜູ້	
°°°°°		***** ***		burglary		100
		<b>**</b> ****			car.theft	
5 10 15		100 400		500 1500		

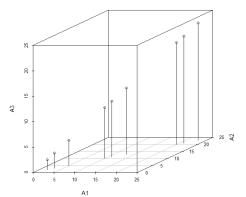


Chapter 5: Agglomerative Clustering Using hclust()

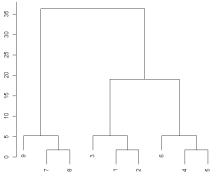




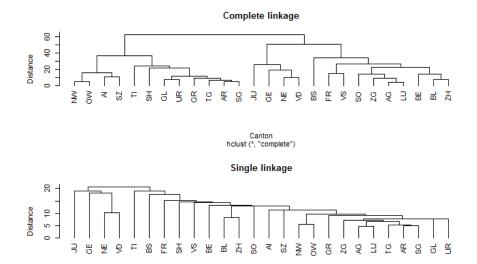




Cluster Dendrogram

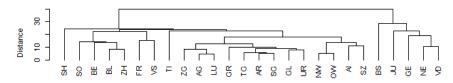


dist(cbind(A1, A2, A3)) hclust (\*, "complete")

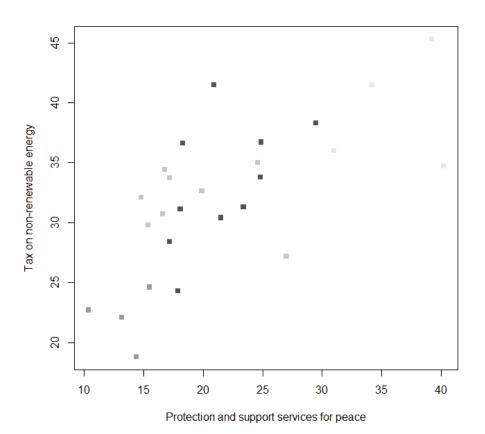


Canton hclust (\*, "single")

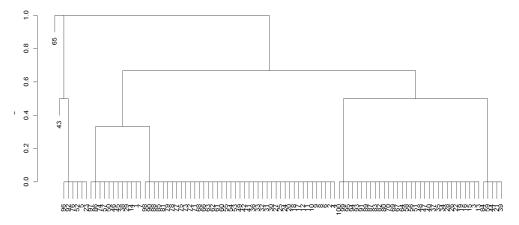
Average linkage



Canton hclust (\*, "average")



#### Cluster Dendrogram



dist(Trucks.onoff, method = "binary") hclust (\*, "complete")

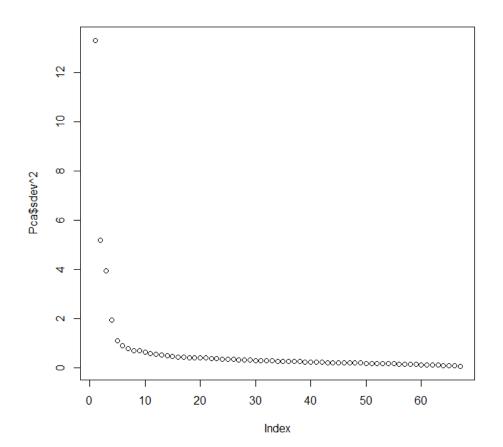
Canton	Europe	Medicine	Speed	Military1	Military2	Bishopric	Taxes1	Military3	Protection	Taxes2
AG	17	34	17	50.9	51.1	64.5	18.8	17.1	17.2	28.4
AI	6.8	24.9	10.6	37.3	37.8	67.2	14.3	11.5	10.4	22.7
AR	13.5	28.4	18.5	45.6	46.1	65.9	20.9	17.6	17.2	33.7
BE	23.4	31.4	22.1	57.7	57.4	60.2	24.2	19.6	20.9	41.5
BL	22.6	30.6	23.1	54.5	53.2	67.3	23.6	22.9	23.4	31.3

R	R Console											23
>	round (ag	gregate	e(swiss_vo	otes[2:	11], list	(clusters),	mean),1)					^
	Group.1	Europe	Medicine	Speed	Military1	Military2	Bishopric	Taxes1	Military3	Protection	Taxes2	
1	1	21.6	30.8	20.4	52.9	52.7	66.9	21.9	20.9	21.6	33.2	
2	2	9.9	27.8	13.0	43.0	42.6	66.8	15.2	13.6	13.4	22.1	
3	3	14.0	32.6	19.7	44.2	44.2	63.8	21.8	17.6	19.0	31.9	
4 >	4	42.2	23.2	18.5	48.0	49.0	60.8	23.8	34.3	36.2	39.4	0
۰												

# Chapter 6: Dimensionality Reduction with Principal Component Analysis

R Console	
<pre>&gt; myPCA(iris[1:4]) [[1]] [1] 4.22824171 0.24267075 0.07820950 0.02383509</pre>	
[[2]] [,1] [,2] [,3] [,4] [1,] 0.36138659 -0.55658877 -0.58202985 0.3154872 [2,] -0.08452251 -0.73016143 0.59791083 -0.3197231 [3,] 0.58667061 0.17337266 0.07623608 -0.4798390 [4,] 0.35828920 0.07548102 0.54583143 0.7536574	
[[3]] [,1] [,2] [,3] [,4] [1,] -2.02428352 -0.482693188 0.31226649 -0.95505451 [2,] -2.01460877 0.51348442 -0.23304573 -0.66448564 [3,] -2.18920532 0.327211755 0.17756654 -0.86020941 [4,] -2.11639295 0.593665486 0.11931399 -0.87931870 [5,] -2.08731760 -0.570920955 0.51973192 -1.06650727 [6,] -1.73132921 -1.341378475 0.80628723 -1.01796720 [7,] -2.17609795 0.091188104 0.59813723 -0.97332307 [8,] -2.00000554 -0.226060611 0.29496353 -0.94698205 [9,] -2.21342812 1.077467178 -0.01878407 -0.78162853 [10,] -2.03247716 0.345887445 -0.1631864 -0.86389521 [11,] -1.88362122 -1.04576708 0.38007671 -1.01464540 [12,] -2.03876163 -0.057655800 0.39458964 -1.05036235	E
<	4

	motiv),2,sum	)							
active	afraid	alert	angry	anxious	aroused	ashamed	astonished	at.ease	
6	5	11	9	1849	6	11	13	17	
at.rest	attentive	blue	bored	calm	cheerful	clutched.up	confident	content	
17	6	5	4	82	1850	23	7	22	
delighted	depressed	determined	distressed	drowsy	dull	elated	energetic	enthusiastic	
6	17	7	8	12	9	15	6	6	
excited	fearful	frustrated	full.of.pep	gloomy	grouchy	guilty	happy	hostile	
6	20	11	12	12	5	5	16	11	
idle	inactive	inspired	intense	interested	irritable	jittery	lively	lonely	
1848	1846	6	7	12	16	6	10	6	
nervous	placid	pleased	proud	quiescent	quiet	relaxed	sad	satisfied	
17	19	13	7	136	5	7	10	7	
scared	serene	sleepy	sluggish	sociable	sorry	still	strong	surprised	
10	12	16	8	6	15	12	7	6	
tense	tired	tranquil	unhappy	upset	vigorous	wakeful	warmhearted	wide.awake	
10	10	1843	5	8	10	10	7	12	



> print.psych		
Principal Com		
	<pre>= motiv[, -ToSuppress], nfactors = 5, rotate = "varimax",</pre>	
	issing = T)	
	ings (pattern matrix) based upon correlation matrix	4 BC5 h2 112
lively		
excited		
enthusiastic		
full.of.pep		1 -0.01 0.47 0.53
energetic		
active		
elated		
vigorous		
happy	0172 0130 0124 0105 0106 0132	/ 0.24 0.41 0.59 1 -0.21 0.29 0.71
pleased		$0.21 \ 0.29 \ 0.71$
aroused		
inspired		5 -0.03 0.55 0.45 1 -0.15 0.63 0.37
proud		5 -0.11 0.56 0.44
determined		9 -0.03 0.47 0.53
strong		
delighted		7 -0.08 0.49 0.51 8 -0.01 0.38 0.62
sociable		
confident		
alert		
warmhearted		
satisfied		
interested		
attentive		
wakeful		
content		
intense		
surprised		
astonished		
unhappy	-0.16 0.74 0.00 0.03 0.25 0.64 0.36 scared 51 0.08 0.27 -0.12 0.09	
irritable	-0.09 0.70 -0.22 0.22 -0.03 0.60 0.40 ashamed 6 -0.03 0.33 0.01 -0.03	
grouchy	-0.13 0.70 -0.11 0.28 -0.03 0.60 0.40 guilty 32 0.02 0.31 0.02 0.00	
upset	-0.08 0.70 -0.06 0.02 0.36 0.62 0.38 sorry 56 -0.02 0.45 0.06 0.02	
gloomy	-0.18 0.69 0.04 0.16 0.22 0.59 0.41 nervous 42 0.18 0.30 -0.26 0.03	3 0.55 0.50 0.50
blue	-0.14 0.69 0.08 0.04 0.28 0.58 0.42	

	RC1	RC2	RC3	RC4	RC5	
SS loadings	14.25	8.56	5.09	4.86	4.57	
Proportion Var	0.21	0.13	0.08	0.07	0.07	
Cumulative Var	0.21	0.34	0.42	0.49	0.56	
Proportion Explained	0.38	0.23	0.14	0.13	0.12	
Cumulative Proportion	0.38	0.61	0.75	0.88	1.00	

Test of the hypothesis that 5 components are sufficient.

The degrees of freedom for the null model are 2211 and the objective function was 45.86 The degrees of freedom for the model are 1886 and the objective function was 6.28 The total number of observations was 3896 with MLE Chi Square = 24294.41 with prob < 0

Fit based upon off diagonal values = 0.99>

 $(A - \lambda I)^k \mathbf{v} = \mathbf{0}$ 

$$partVar_i = \frac{eigen_i}{\sum_{i=i}^{n} eigen_i}$$

# Chapter 7: Exploring Association Rules with Apriori

```
> rules = apriori(Groceries)
```

parameter specific confidence minval 0.8 0.1					-	
algorithmic contro filter tree heap 0.1 TRUE TRUE						
apriori - find ass version 4.21 (2004 set item appearanc set transactions . sorting and recodi creating transacti checking subsets o writing [0 rul creating S4 object	.05.09) es[0 item(s) [169 item(s), ng items [8 on tree done f size 1 2 done e(s)] done [0.00	<pre>(c) 1996-2004 Cl ] done [0.00s]. 9835 transaction item(s)] done [0 e [0.00s]. [0.00s]. os].</pre>	hristian (s)] dong	Borgelt		

```
> rules = apriori(Groceries, parameter = list(support = 0.05, confidence = .1))
parameter specification:
 confidence minval smax arem aval originalSupport support minlen maxlen target ext
          0.1
                  0.1 1 none FALSE TRUE 0.05 1 10 rules FALSE
algorithmic control:
 filter tree heap memopt load sort verbose
     0.1 TRUE TRUE FALSE TRUE 2
                                                   TRUE
apriori - find association rules with the apriori algorithm
version 4.21 (2004.05.09) (c) 1996-2004 Christian Borgelt
set item appearances ... [0 item(s)] done [0.00s].
set transactions ... [169 item(s), 9835 transaction(s)] done [0.00s].
sorting and recoding items ... [28 item(s)] done [0.00s].
creating transaction tree ... done [0.00s].
checking subsets of size 1 2 done [0.00s].
writing ... [14 rule(s)] done [0.00s].
creating S4 object ... done [0.00s].
> inspect(rules)
  lhs
                                 rhs
                                                                support confidence
                                                                                             lift
1 {}
                              => {bottled water}
                                                            0.11052364 0.1105236 1.000000
                              => {tropical fruit} 0.10493137 0.1049314 1.000000
2 {}
                              => {root vegetables} 0.10899847 0.1089985 1.000000
3 {}
4 {}
                              => {soda}
                                                            0.17437722 0.1743772 1.000000
5
                              => {yogurt}
                                                            0.13950178 0.1395018 1.000000
   {}
                                                            0.18393493 0.1839349 1.000000
6 {}
                              => {rolls/buns}
7 {}
                              => {other vegetables} 0.19349263 0.1934926 1.000000
8 {}
                             => {whole milk} 0.25551601 0.2555160 1.000000
                                                            0.05602440 0.4016035 1.571735
9 {yogurt}
                             => {whole milk}
                                                            0.05602440 0.2192598 1.571735
10 {whole milk}
                            => {yogurt}
11 {rolls/buns}
                            => {whole milk}
                                                         0.05663447 0.3079049 1.205032
12 {whole milk}
                             => {rolls/buns}
                                                            0.05663447 0.2216474 1.205032
13 {other vegetables} => {whole milk}
                                                           0.07483477 0.3867578 1.513634
14 {whole milk}
                             => {other vegetables} 0.07483477 0.2928770 1.513634
 > summary(ICU)

        age
        sex
        race
        service
        cancer
        renal
        infect

        Min.
        :16.00
        Female:
        76
        Black:
        15
        Medical:
        93
        No
        :180
        No
        :181
        No
        :116

        1st Qu.:
        :46.75
        Male
        :124
        Other:
        10
        Surgical:
        107
        Yes:
        20
        Yes:
        19
        Yes:
        84

    died
   No :160
  Yes: 40
              Median :63.00
                                               White:175
              Mean :57.55
              3rd Qu.:72.00
              Max. :92.00

        hrtrate
        previcu
        admit
        fracture
        po2

        Min.
        : 39.00
        No :170
        Elective : 53
        No :185
        >60 :184

        1st Qu.:
        : 80.00
        Yes: 30
        Emergency:147
        Yes: 15
        <=60: 16</td>

                 systolic
    cpr
   No :187
              Min. : 36.0
              1st Qu.:110.0
   Yes: 13
              Median :130.0
                                Median : 96.00
              Mean :132.3
                                Mean : 98.92
              3rd Ou.:150.0
                                3rd Ou.:118.25
              Max. :256.0 Max. :192.00

        ph
        pco
        bic
        creatin

        >=7.25:187
        <=45:180</td>
        >=18:185
        <=2:190</td>

        <7.25:13</td>
        >45:20
        <18:15</td>
        >2:10

                                                        coma
                                                                           white
                                                                                       uncons
                                                      None :185
                                                                     White : 25
                                                                                       No :185
                                                      Stupor: 5 Non-white:175 Yes: 15
                                                      Coma : 10
```

```
> inspect(rules)
                                 support confidence lift
   lhs
                        rhs
                    => {creatin=<=2} 0.950 0.9500000 1.000000
1 {}
2 {cancer=No} => {creatin=<=2} 0.855 0.9500000 1.000000

      2
      {concerned}
      >
      {concerned}
      >
      0.860
      0.9555556
      1.038647

      3
      {pco=<=45}</td>
      =>
      {ph=>=7.25}
      0.875
      0.9722222
      1.039810

      4
      {pco=<=45}</td>
      =>
      {ph=>=7.25}
      0.860
      0.9502762
      1.016338

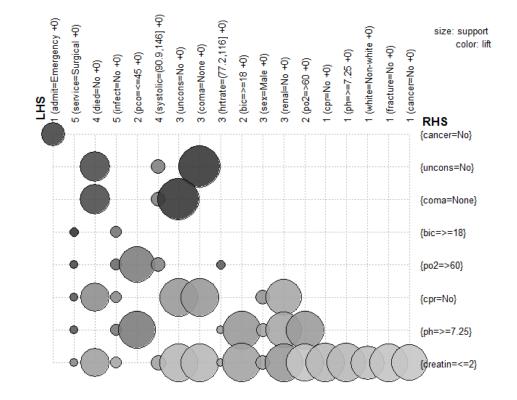
      5
      {renal=No}
      =>
      {ph=>=7.25}
      0.860
      0.9502762
      1.016338

      6
      {renal=No}
      =>
      {ph=>=7.25}
      0.860
      0.9502762
      1.016338

7 {renal=No} => {creatin=<=2} 0.880 0.9723757 1.023553
                   => {ph=>=7.25} 0.880 0.9565217 1.023018
8 {po2=>60}
9 {po2=>60}
                   => {creatin=<=2} 0.875 0.9510870 1.001144
10 {uncons=No} => {coma=None} 0.925 1.0000000 1.081081
> inspect(rulesDeath)
   lhs
                             rhs support confidence
                                                                        lift
1 {infect=Yes,
    admit=Emergency} => {died=Yes} 0.120 0.3478261 1.739130
2 {service=Medical,
    white=Non-white} => {died=Yes} 0.120 0.3037975 1.518987
3 {infect=Yes,
    admit=Emergency,
     white=Non-white} => {died=Yes} 0.115 0.3650794 1.825397
 4 {infect=Yes,
    admit=Emergency,
                      => {died=Yes} 0.100 0.3448276 1.724138
    pco=<=45}
5 {cancer=No,
     infect=Yes,
     admit=Emergency} => {died=Yes} 0.115 0.3432836 1.716418
6 {infect=Yes,
    admit=Emergency,
    po2=>60}
                          => {died=Yes} 0.105 0.3620690 1.810345
7 {infect=Yes,
    admit=Emergency,
                      => {died=Yes} 0.110 0.3437500 1.718750
     fracture=No}
8 {infect=Yes,
     admit=Emergency,
                         => {died=Yes} 0.100 0.3333333 1.666667
     ph=>=7.25}
 9 {cancer=No,
     infect=Yes,
     white=Non-white} => {died=Yes} 0.110 0.3098592 1.549296
10 {infect=Yes,
     po2=>60,
     white=Non-white} => {died=Yes} 0.100 0.3076923 1.538462
```

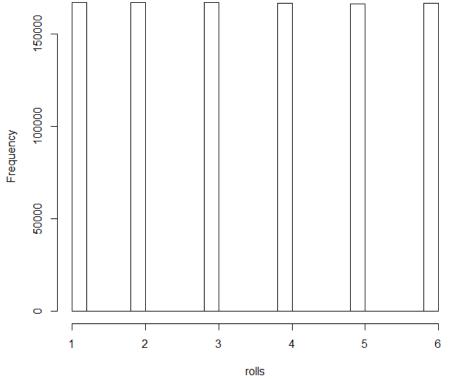
45 {cancer=No,infect=Yes,admit=Emergency,po2=>60,white=Non-white} => {died=Yes} 0.100 0.3921569 1.960784	> 1	nead(rulesDeath.df.sorted)						
				rules	support	confidence	lift	
	45	{cancer=No, infect=Yes, admit=Emergency, po2=>60, white=Non-white}	=>	{died=Yes}	0.100	0.3921569	1.960784	
19 {infect=Yes,admit=Emergency,po2=>60,white=Non-white} => {died=Yes} 0.100 0.3846154 1.923077	19	{infect=Yes,admit=Emergency,po2=>60,white=Non-white}	=>	{died=Yes}	0.100	0.3846154	1.923077	
47 {cancer=No,infect=Yes,admit=Emergency,fracture=No,po2=>60} => {died=Yes} 0.100 0.3773585 1.886792	47	{cancer=No,infect=Yes,admit=Emergency,fracture=No,po2=>60}	=>	{died=Yes}	0.100	0.3773585	1.886792	
23 {infect=Yes,admit=Emergency,fracture=No,po2=>60} => {died=Yes} 0.100 0.3703704 1.851852	23	<pre>{infect=Yes,admit=Emergency,fracture=No,po2=&gt;60}</pre>	=>	{died=Yes}	0.100	0.3703704	1.851852	
21 {cancer=No,infect=Yes,admit=Emergency,po2=>60} => {died=Yes} 0.105 0.3684211 1.842105	21	{cancer=No,infect=Yes,admit=Emergency,po2=>60}	=>	{died=Yes}	0.105	0.3684211	1.842105	
<pre>3 {infect=Yes,admit=Emergency,white=Non-white} =&gt; {died=Yes} 0.115 0.3650794 1.825397</pre>	3	{infect=Yes,admit=Emergency,white=Non-white}	=>	{died=Yes}	0.115	0.3650794	1.825397	

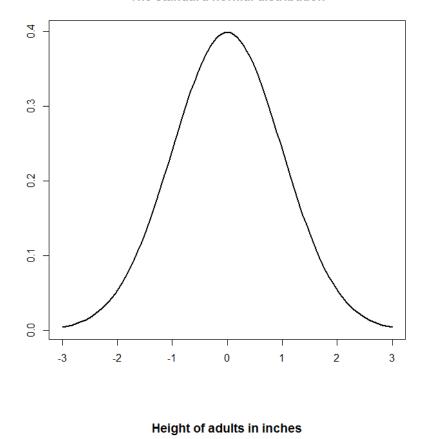
Grouped matrix for 45 rules



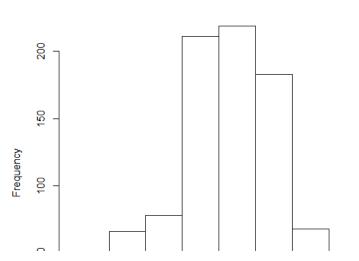
# Chapter 8: Probability Distributions, Covariance, and Correlation

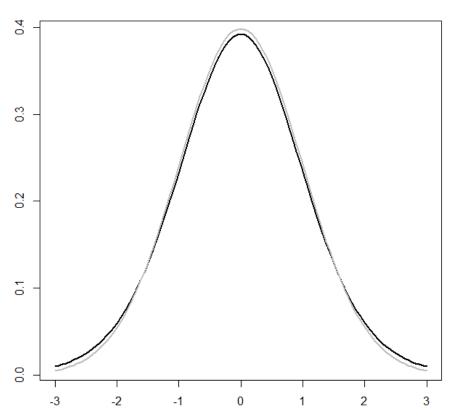
#### Histogram of rolls



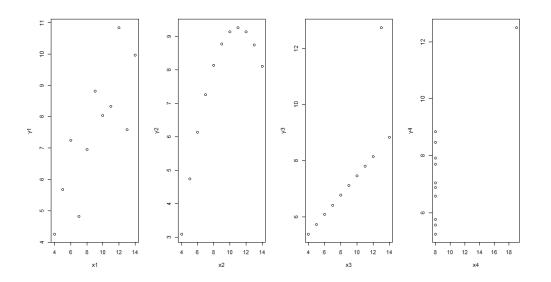


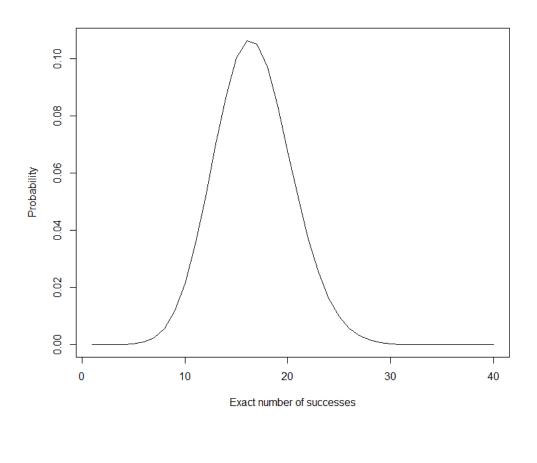
The standard normal distribution

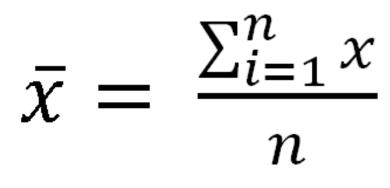




The t distribution



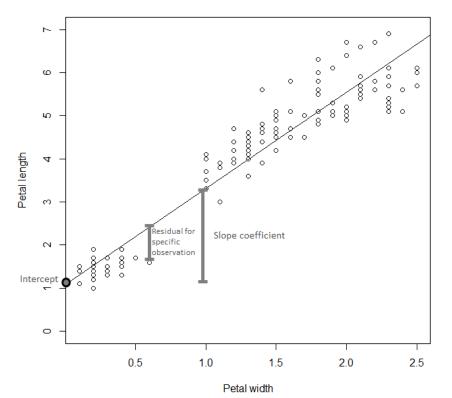




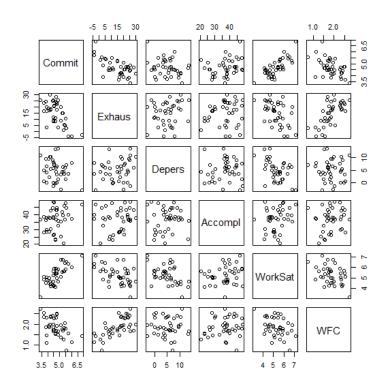
$$s^{2} = \frac{\sum_{i=1}^{n} (x - \bar{x})^{2}}{n - 1}$$
$$s = \sqrt{\frac{\sum_{i=1}^{n} (x - \bar{x})^{2}}{n - 1}}$$
$$\sum_{i=1}^{n} (x - \bar{x})^{2} (y - \bar{y})^{2}}$$

$$cov(x,y) = \frac{\sum_{i=1}^{n} (x-x)^2 (y-y)^2}{n-1}$$

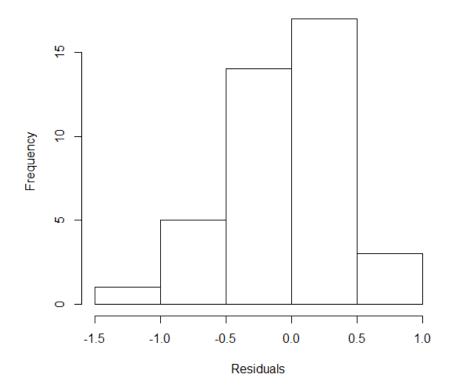
Chapter 9: Linear Regression

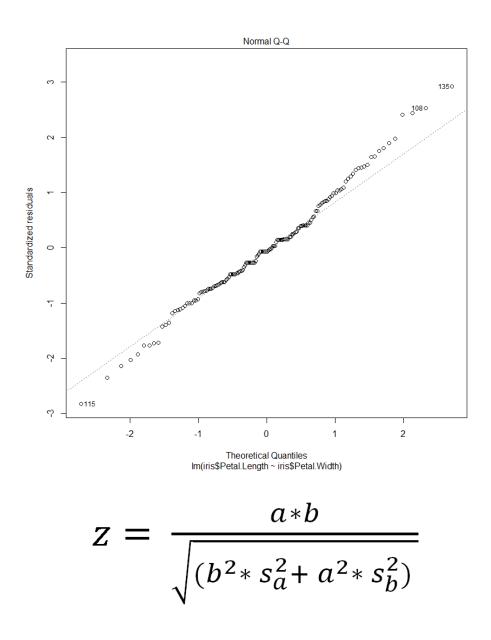


#### Relationship between petal length and petal width



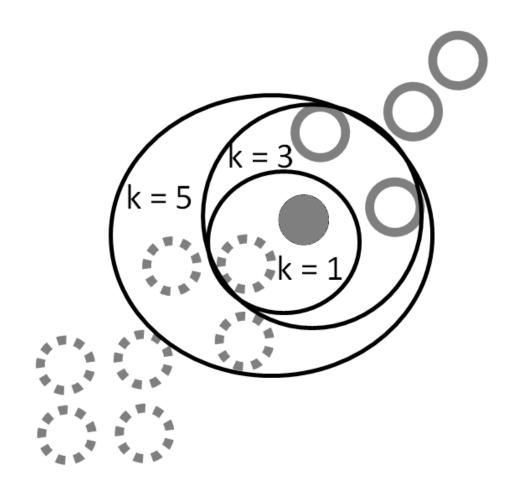
## Histogram of residuals





$$\bar{x} \pm z * \frac{s}{\sqrt{n}}$$

Chapter 10: Classification with k-Nearest Neighbors and Naïve Bayes

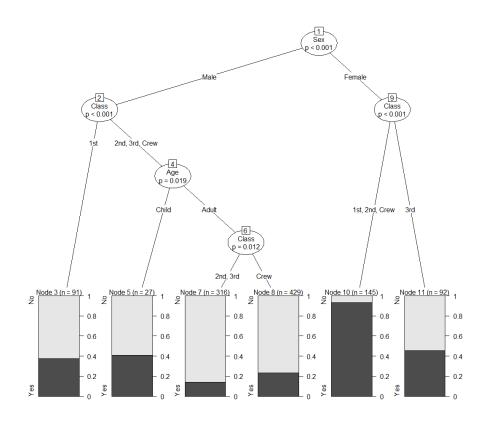


```
Naive Bayes Classifier for Discrete Predictors
Call:
naiveBayes.default(x = as.matrix(DiseaseZ[1:10, 1:6]), y = as.matrix(DiseaseZ[1:10,
   7]))
A-priori probabilities:
as.matrix(DiseaseZ[1:10, 7])
NO YES
0.4 0.6
Conditional probabilities:
Smoking
as.matrix(DiseaseZ[1:10, 7]) NO
                                             YES
                          NO 0.7500000 0.2500000
                          YES 0.3333333 0.6666667
                            Drinking
as.matrix(DiseaseZ[1:10, 7]) NO YES
NO 0.7500000 0.2500000
                          YES 0.1666667 0.8333333
                             PhysicalActivity
as.matrix(DiseaseZ[1:10, 7]) NO YES
NO 0.25 0.75
                          YES 0.50 0.50
Movies
as.matrix(DiseaseZ[1:10, 7]) NO YES
NO 0.5000000 0.5000000
                          YES 0.6666667 0.3333333
                            Music
as.matrix(Disease2[1:10, 7]) NO YES
NO 0.75 0.25
                          YES 0.50 0.50
                            Sunbathing
as.matrix(DiseaseZ[1:10, 7]) NO YES
NO 0.7500000 0.2500000
                          YES 0.3333333 0.6666667
```

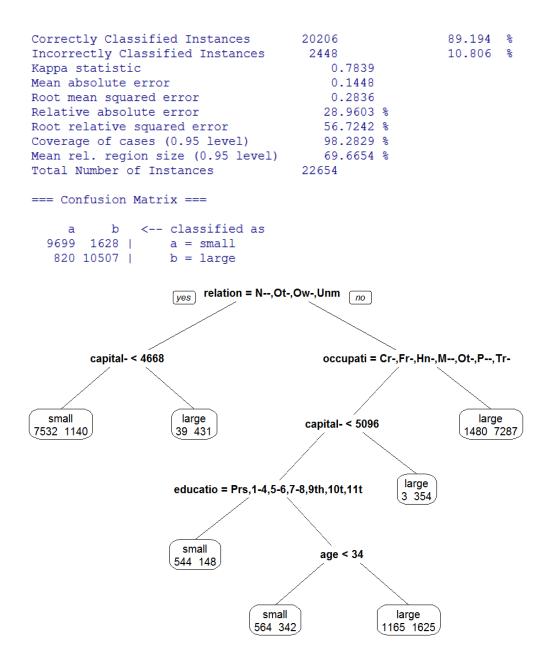
```
Naive Bayes Classifier for Discrete Predictors
Call:
naiveBayes.default(x = TRAIN[1:3], y = TRAIN[[4]])
A-priori probabilities:
TRAIN[[4]]
     No
          Yes
0.6873905 0.3126095
Conditional probabilities:
       Class
TRAIN[[4]] 1st 2nd 3rd Crew
      No 0.08535032 0.11719745 0.33503185 0.46242038
      Yes 0.30812325 0.15406162 0.23529412 0.30252101
       Sex
TRAIN[[4]]
             Male Female
     No 0.91592357 0.08407643
      Yes 0.50140056 0.49859944
       Age
TRAIN[[4]] Child Adult
      No 0.03057325 0.96942675
      Yes 0.07002801 0.92997199
```

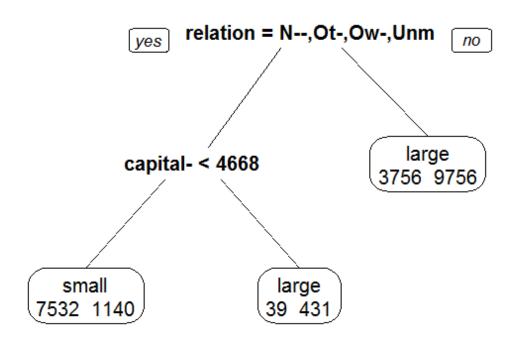
$$\sum_{i=1}^{n} |p_i - q_i|$$
$$\sqrt{(\sum_{i=1}^{n} p_i - q_i)^2}$$

**Chapter 11: Classification Trees** 



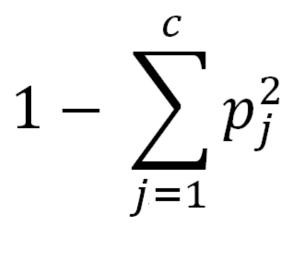
age	workclass fn	lwgt	education	education-num	mar	ital-status	occupation
Min. :17.00 Private	:33906 Min.	: 12285 HS-0	grad :15784	Min. : 1.00	Divorced	: 6633 Prof-s	pecialty : 6172
1st Qu.:28.00 Self-emp-no	t-inc: 3862 1st Qu	.: 117551 Some	e-college:10878	1st Qu.: 9.00	Married-AF-spouse	: 37 Craft-	repair : 6112
Median :37.00 Local-gov	: 3136 Median	: 178145 Back	nelors : 8025	Median :10.00	Married-civ-spous	e :22379 Exec-m	anagerial: 6086
Mean :38.64 State-gov	: 1981 Mean	: 189664 Mast	ters : 2657	Mean :10.08	Married-spouse-ab	sent: 628 Adm-cl	erical : 5611
3rd Qu.:48.00 Self-emp-in	c : 1695 3rd Qu	.: 237642 Asso	oc-voc : 2061	3rd Qu.:12.00	Never-married	:16117 Sales	: 5504
Max. :90.00 (Other)	: 1463 Max.	:1490400 11th	n : 1812	Max. :16.00	Separated	: 1530 (Other	:16548
NA's	: 2799	(Ot)	ner) : 7625		Widowed	: 1518 NA's	: 2809
relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-count	ry income
Husband :19716 Amer	-Indian-Eskimo: 470	Female:16192	Min. : 0	Min. : 0.0	Min. : 1.00	United-States:4383	2 small:24720
Not-in-family :12583 Asia:	n-Pac-Islander: 1519	Male :32650	1st Qu.: 0	1st Qu.: 0.0	1st Qu.:40.00	Mexico : 95	l large: 7841
Other-relative: 1506 Blac	k : 4685		Median : 0	Median : 0.0	Median :40.00	Philippines : 29	5 NA's :16281
Own-child : 7581 Othe	r : 406		Mean : 1079	Mean : 87.5	Mean :40.42	Germany : 20	5
Unmarried : 5125 White	e :41762		3rd Qu.: 0	3rd Qu.: 0.0	3rd Qu.:45.00	Puerto-Rico : 18	1
Wife : 2331			Max. :99999	Max. :4356.0	Max. :99.00	(Other) : 251	7
						NA's : 85	7



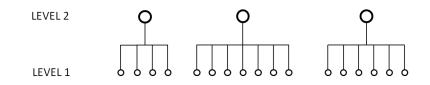


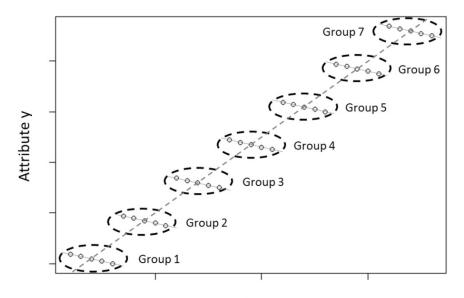
 $-\sum_{i=1}^{c} p_i (log_2 p_i)$ 

$$-\sum_{i=1}^{c} \frac{|Ti|}{|T|} \log_2 \frac{|Ti|}{|T|}$$

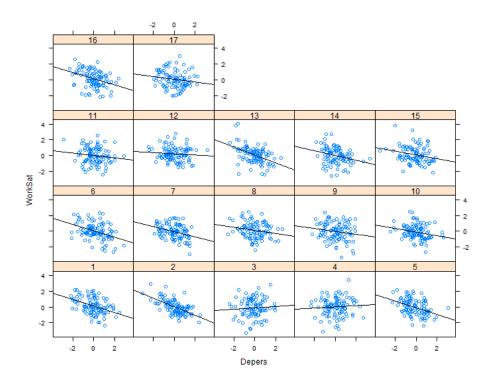


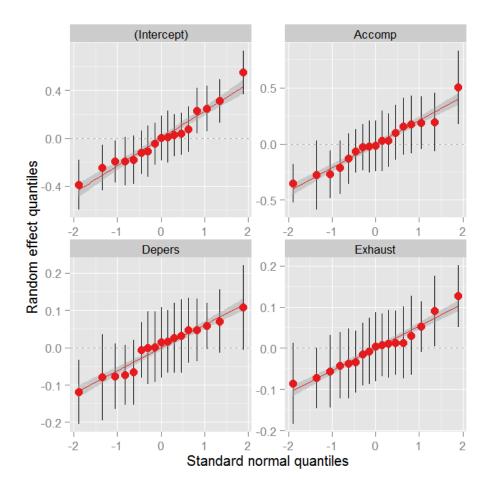
# Chapter 12: Multilevel Analyses

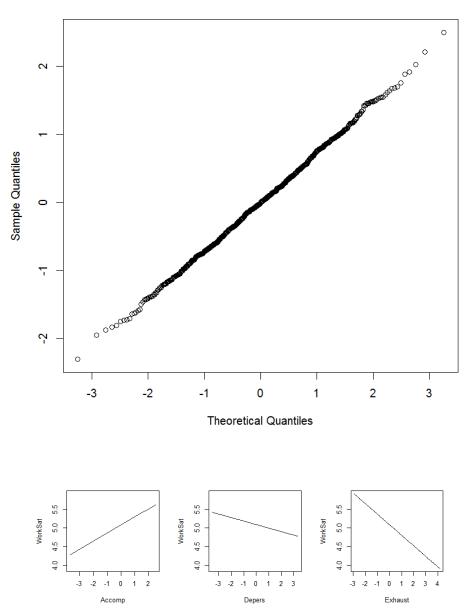












Normal Q-Q Plot

```
Linear mixed model fit by REML ['lmerMoc
 Formula: WorkSat ~ 1 + (1 | hosp)
    Data: NursesML
 REML criterion at convergence: 4321.9
 Scaled residuals:
     Min
                1Q Median
                                    3Q
                                            Max
 -3.8527 -0.6556 -0.0038 0.6823 4.0239
 Random effects:
  Groups Name
                          Variance Std.Dev.
         (Intercept) 0.06988 0.2643
  hosp
  Residual
                           0.72564 0.8518
 Number of obs: 1700, groups: hosp, 17
 Fixed effects:
               Estimate Std. Error t value
 (Intercept) 5.10679 0.06736 75.81
Data: NursesMLtrain
Models:
null: WorkSat ~ 1 + (1 | hosp)
model: WorkSat ~ Accomp + Depers + Exhaust + (1 | hosp)
Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
null 3 2156.3 2170.5 -1075.15 2150.3
model 6 1984.2 2012.6 -986.08 1972.2 178.15 3 < 2.2e-16 ***
____
Signif. codes: 0 `***' 0.001 `**' 0.01 `*' 0.05 `.' 0.1 ` ' 1
```

Linear mixed model fit by maximum likelihood ['lmerMod'] Formula: WorkSat ~ Accomp + Depers + Exhaust + (1 | hosp) Data: NursesMLtrain BIC logLik deviance df.resid AIC 1984.2 2012.6 -986.1 1972.2 844 Scaled residuals: Min 1Q Median 3Q Max -3.0252 -0.6756 0.0225 0.6616 3.4649 Random effects: Groups Name Variance Std.Dev. hosp (Intercept) 0.06674 0.2583 Residual 0.57345 0.7573 Number of obs: 850, groups: hosp, 17 Fixed effects: Estimate Std. Error t value (Intercept) 5.11854 0.06783 75.46 Accomp 0.17611 0.03749 4.70 Depers -0.07335 0.03135 -2.34 Exhaust -0.29215 0.02935 -9.95 Correlation of Fixed Effects: (Intr) Accomp Depers Accomp 0.000 Depers 0.000 0.041 Exhaust 0.000 0.044 -0.490

```
Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: WorkSat ~ Accomp + Depers + Exhaust + (1 + Accomp + Depers +
       Exhaust | hosp)
       Data: NursesMLtrain
         AIC BIC logLik deviance df.resid
   1970.5 2041.7 -970.2 1940.5
                                                                                     835
Scaled residuals:
Min 1Q Median 3Q Max
-3.1422 -0.6826 0.0028 0.6510 3.4045
Random effects:
                                             Variance Std.Dev. Corr
 Groups Name

        Name
        Variance
        Statuce
        Corr

        (Intercept)
        0.060492
        0.24595

        Accomp
        0.058726
        0.24233
        -0.56

        Depers
        0.005805
        0.07619
        -0.17
        0.83

        Exhaust
        0.004594
        0.06778
        0.74
        -0.24
        0.34

        1
        0.536849
        0.73270
        0.74
        0.34
        0.34

 hosp
 Residual
Number of obs: 850, groups: hosp, 17
Fixed effects:
                        Estimate Std. Error t value

        Intercept
        5.06994
        0.06531
        77.63

        Accomp
        0.21722
        0.07044
        3.08

        Depers
        -0.09408
        0.03628
        -2.59

        Exhaust
        -0.28444
        0.03371
        -8.44

Correlation of Fixed Effects:
(Intr) Accomp Depers
Accomp -0.448
Depers -0.074 0.384
Exhaust 0.336 -0.073 -0.251
```

#### **Chapter 13: Text Analytics with R**

> Terr	ns.seasonal	
	Topic 1	Topic 2
[1,]	"vaccin"	"year"
[2,]	"state"	"peopl"
[3,]	"get"	"influenza"
[4,]	"com"	"center"
[5,]	"dai"	"time"
[6,]	"month"	"diseas"
[7,]	"million"	"strain"
[8,]	"viru"	"doctor"
[9,]	"yesterdai"	"case"
[10,]	"report"	"nytim"
[11,]	"week"	"winter"
[12,]	"shot"	"week"
[13,]	"feder"	"protect"
[14,]	"drug"	"url"
[15,]	"nytim"	"control"
[16,]	"death"	"sai"
[17,]	"problem"	"nation"
[18,]	"countri"	"recommend"
[19,]	"season"	"ag"
[20,]	"expect"	"risk"

> Terms.non.seasonal Topic 1 Topic 2 [1,] "nytim" "infect" [2,] "offici" "diseas" [3,] "viru" "year" [4,] "world" "week" [5,] "million" "peopl" [6,] "prevent" "outbreak" [7,] "nation" "pandem" [8,] "work" "influenza" [9,] "come" "sai" [10,] "confirm" "countri" [11,] "unit" "case" [12,] "peopl" "com" [13,] "found" "human" [14,] "strain" "url" [15,] "month" "di" [16,] "case" "test" [17,] "start" "spread" [18,] "get" "govern" [19,] "report" "includ" [20,] "effect" "viru"

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#### Welcome

You already know that NYTimes.com is an unparalleled source of news and information. But now it's a premier source of data, too — why just read the news when you can hack it?

#### **Getting Started**

Gallery API Console

Overview

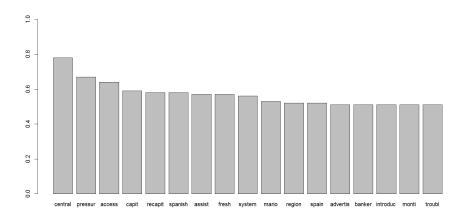
Available APIs Keys Forum

- The Times Developer Network is our API clearinghouse and community. Here's how to get started:

- Request an <u>API key</u>
   Read the API <u>documentation</u>, <u>FAQ</u> and <u>Terms of Use</u>
   Use the <u>API Tool</u> to experiment without writing code
- 4. Browse the application gallery
- 5. Connect with other developers in the  $\underline{forum}$

To see your API keys and rate limits, visit the Keys page.

Copyright 2014 The New Y	ork Times	API Terms of Use	NYTimes.com	Privacy Policy	Careers	
[	zister Your Appli Name of your app Web Site	cation plication (you can change it	later)			
ľ	low did you hear a	bout this API?				
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	Issue a new key	y for Article Search API				
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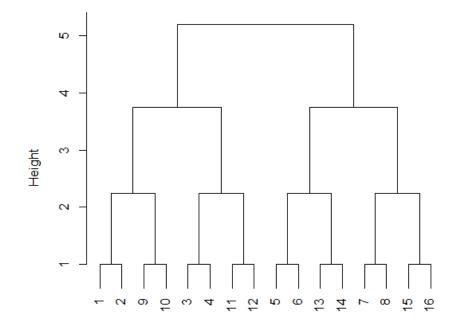


#### Chapter 14: Cross-validation and Bootstrapping using Caret and Exporting Predictive Models Using PMML

Fold	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Iteration 6	Iteration 7	Iteration 8	Iteration 9	Iteration 10
Fold 1	Train	Test								
Fold 2	Train	Test	Train							
Fold 3	Train	Test	Train	Train						
Fold 4	Train	Train	Train	Train	Train	Train	Test	Train	Train	Train
Fold 5	Train	Train	Train	Train	Train	Test	Train	Train	Train	Train
Fold 6	Train	Train	Train	Train	Test	Train	Train	Train	Train	Train
Fold 7	Train	Train	Train	Test	Train	Train	Train	Train	Train	Train
Fold 8	Train	Train	Test	Train						
Fold 9	Train	Test	Train							
Fold 10	Test	Train								

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### Cluster Dendrogram



dist(DF) hclust (\*, "complete")