

Nonparametric Statistical Methods

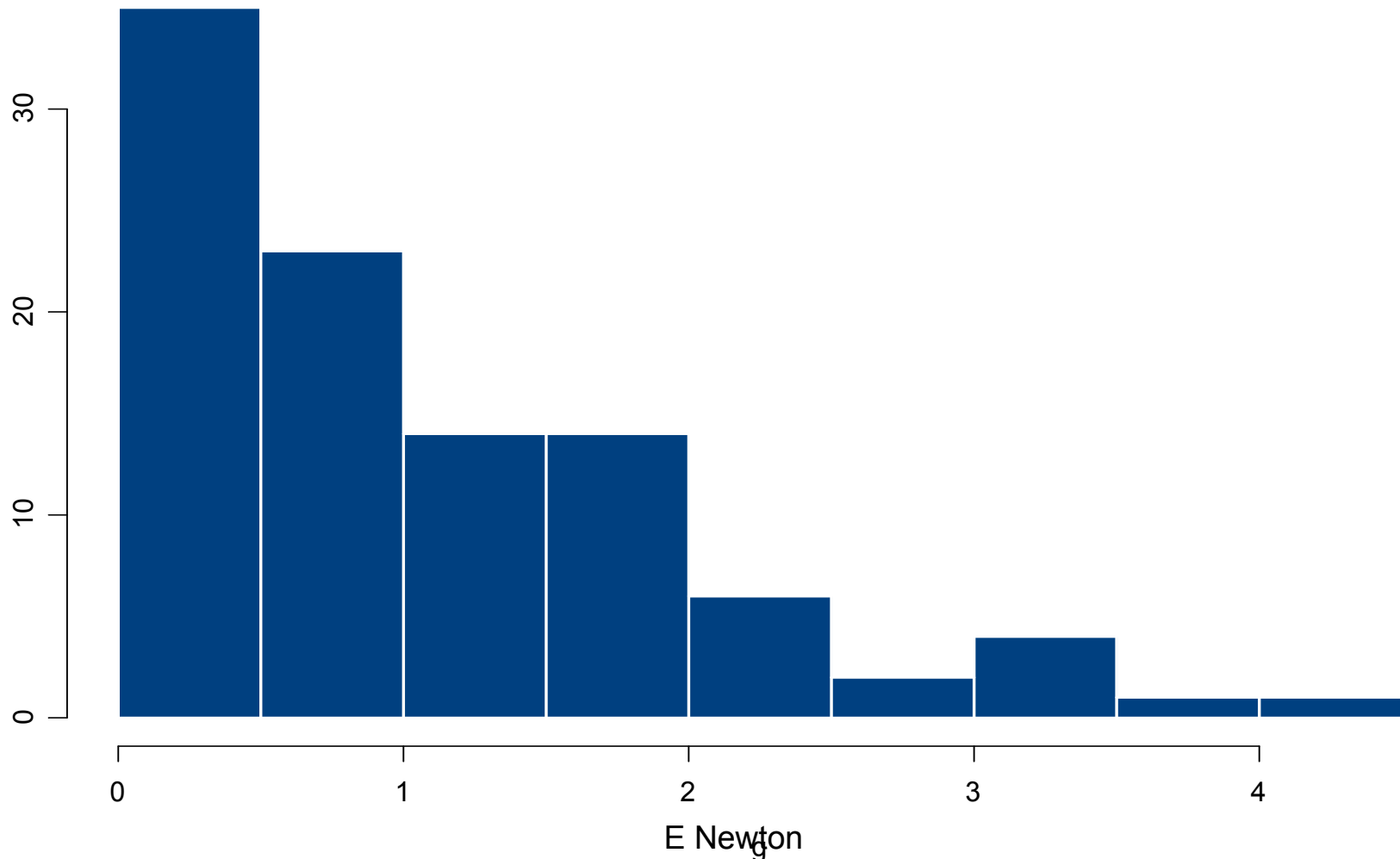
Corresponds to Chapter 14 of
Tamhane and Dunlop

Slides prepared by Elizabeth Newton (MIT)

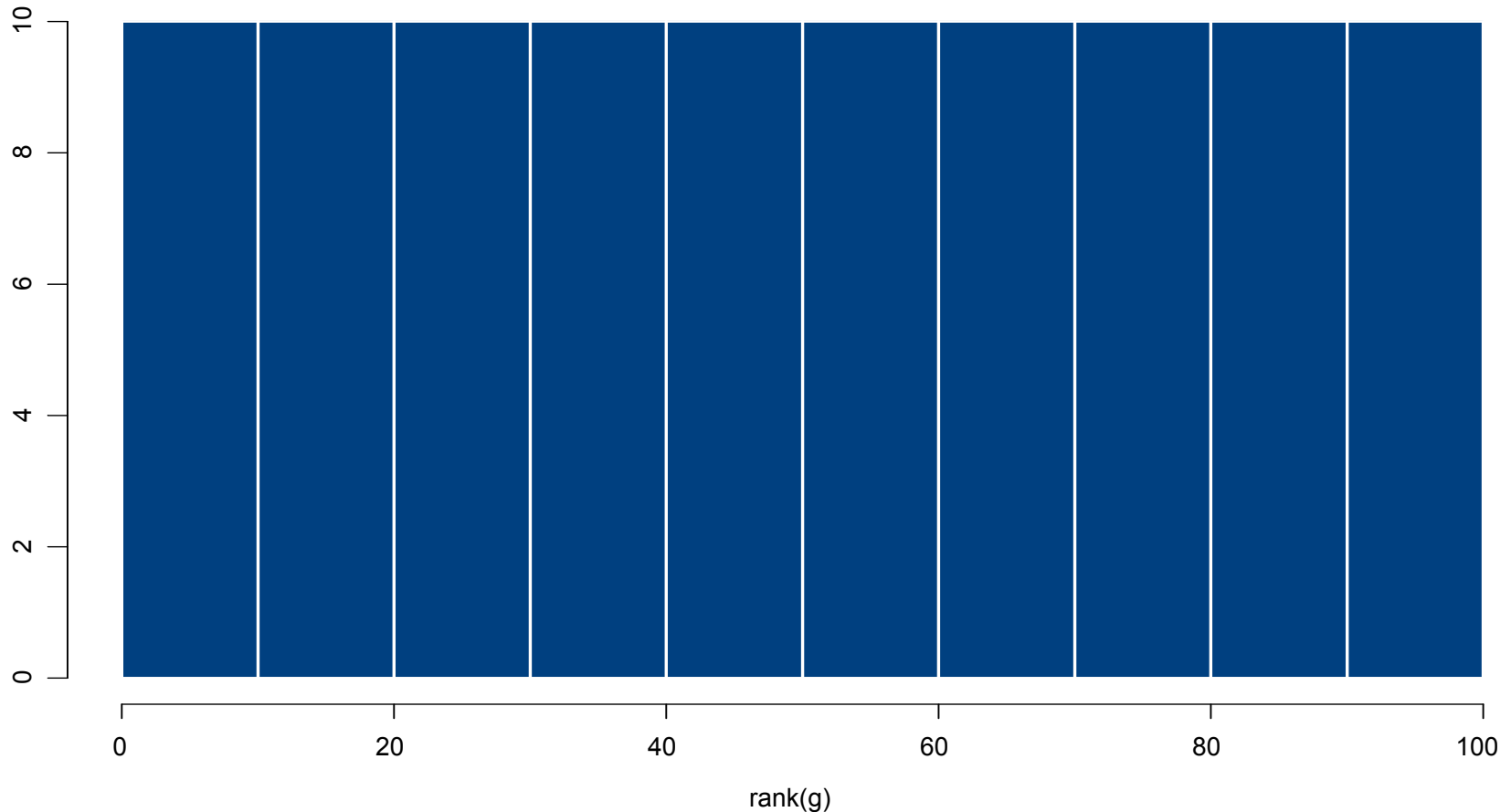
Nonparametric Methods

- Most NP methods are based on ranks instead of original data
- Reference: Hollander & Wolfe, Nonparametric Statistical Methods

Histogram of 100 gamma(1,1) r.v.'s



Histogram of ranks of 100 r.v.'s



E Newton

Parametric and Nonparametric Tests

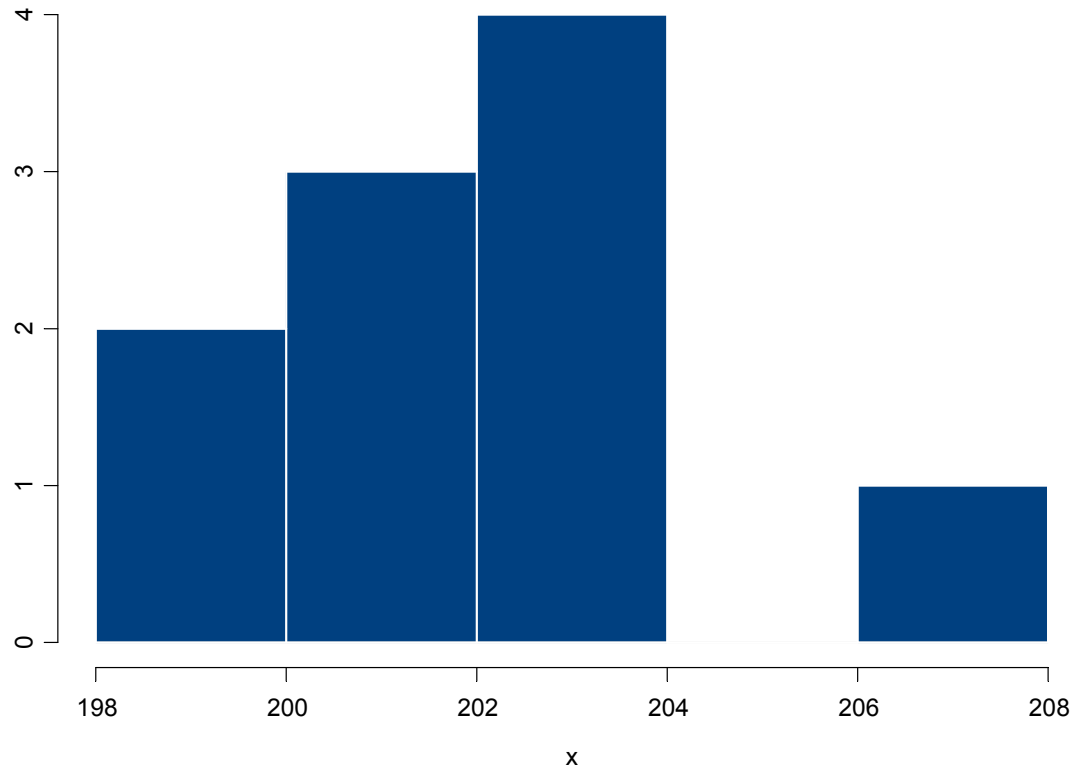
Type of test	Parametric	Nonparametric
Single Sample	z and t tests	Sign test
		Wilcoxon Signed Rank Test
Two independent samples	z and t tests	Wilcoxon Rank Sum Test
		Mann Whitney U Test

Type of test	Parametric	Nonparametric
Several Independent Samples	ANOVA CRD	Kruskal-Wallace Test
Several Matched Samples	ANOVA RBD	Friedman Test
Correlation	Pearson	Spearman Rank Correlation
	E Newton	Kendall's Rank Correlation

Sign Test

- Inference on median (u) for a single sample, size n
- $H_0: u=u_0$ vs. $H_1: u \neq u_0$
- Count the number of x_i 's that are greater than u_0 and denote this s^+
- The number of x_i 's less than u are $s^- = n - s^+$
- Reject H_0 if s^+ is large or if s^- is small.
- Under H_0 , s^+ (and s^-) has binomial($n, 1/2$) distribution
- Large sample z test

Histogram of thermostat data



E Newton

Sign Test in S-Plus

```
> thermostat
```

```
[1] 202.2 203.4 200.5 202.5 206.3 198.0 203.7 200.8  
    201.3 199.0
```

```
> thermostat<200
```

```
[1] F F F F F T F F F T
```

```
> sum(thermostat<200)
```

```
[1] 2
```

```
> 2*pbinom(sum(thermostat<200),10,0.5)
```

```
[1] 0.109375
```

Wilcoxon Signed Rank Test

- Inference on median (u), single sample, size n
- Assumes population distribution is symmetric
- $H_0: u = u_0$ vs. $H_1: u \neq u_0$
- $d_i = x_i - u_0$
- Rank order $|d_i|$
- W_+ = sum of ranks of positive differences
- W_- = sum of ranks of negative differences
- $W_{\max} = \max(W_+, W_-)$
- Reject H_0 if W_{\max} is large.
- Null Distribution – see text
- Large sample z test

S-Plus wilcox.test for thermostat data

```
> thermostat
[1] 202.2 203.4 200.5 202.5 206.3 198.0 203.7 200.8
    201.3 199.0

> sum(rank(abs(thermostat-200))[-c(6,10)])
[1] 47

> wilcox.test(thermostat,mu=200)
```

Exact Wilcoxon signed-rank test

```
data: thermostat
signed-rank statistic V = 47, n = 10, p-value =
0.0488
alternative hypothesis: true mu is not equal to 200
E Newton
```

S-Plus parametric t-test for thermostat data

```
> t.test(thermostat, mu=200)
```

One-sample t-Test

data: thermostat

t = 2.3223, df = 9, p-value = 0.0453

alternative hypothesis: true mean is not equal to 200

95 percent confidence interval:

200.0459 203.4941

sample estimates:

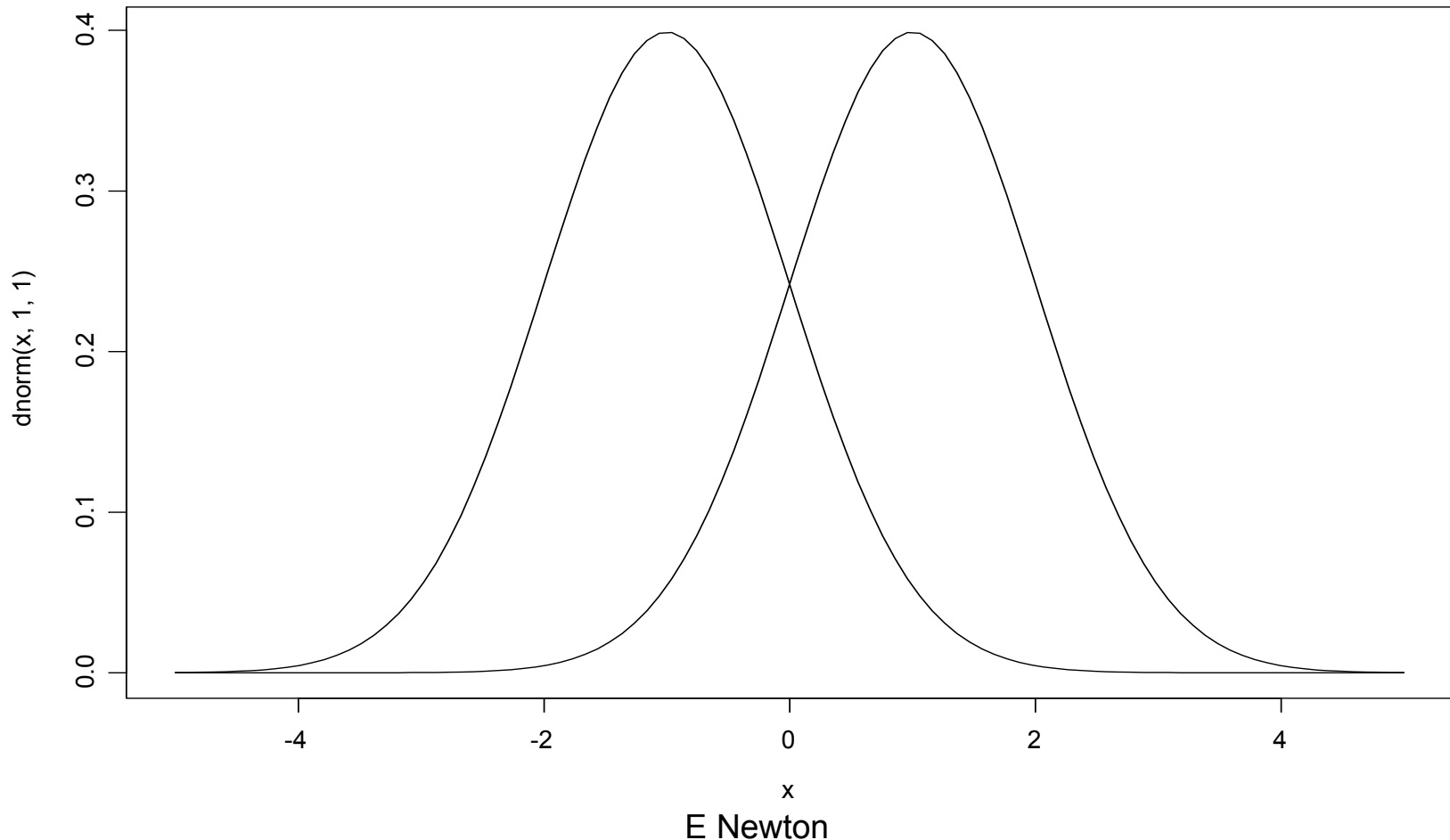
mean of x

201.77

Location-Scale Families

- See course textbook, page 575.

2 normal pdf's with location parameters = -1 and 1, scale parameter = 1



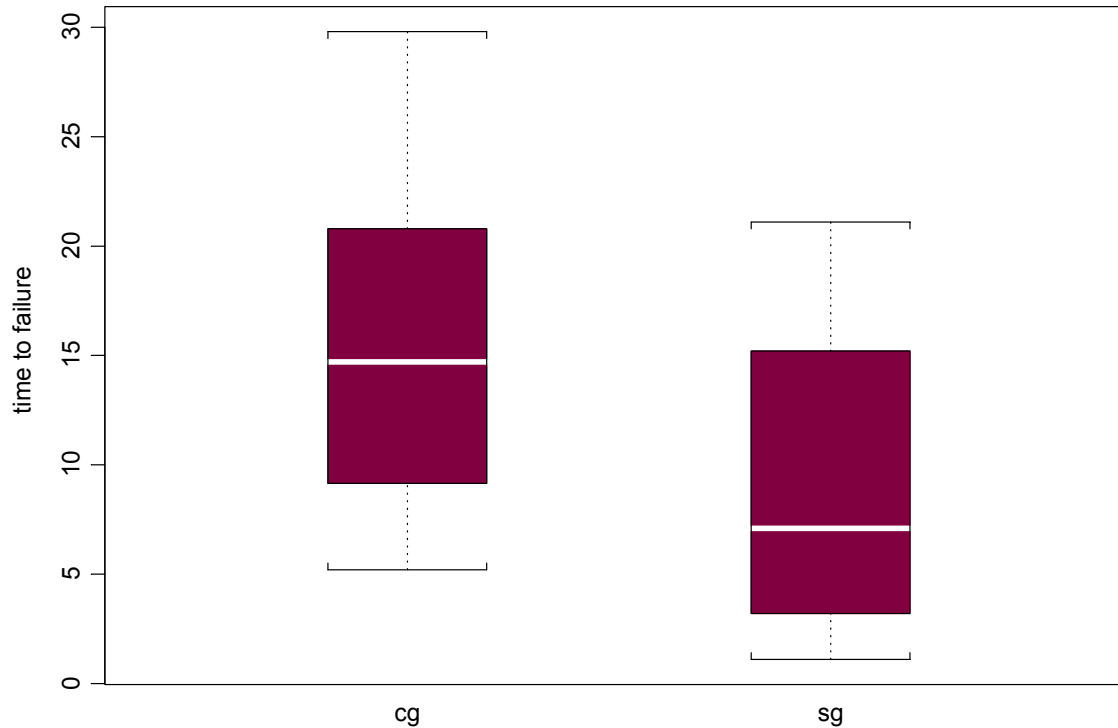
Wilcoxon Rank Sum Test

- Inference on location of distribution of 2 independent random samples X and Y (e.g. from control and treatment population).
- Assume $X \sim Y + \Delta$
- $H_0: \Delta = 0$ vs. $H_1: \Delta \neq 0$
- Rank all $N = n_1 + n_2$ observations
- $W =$ sum of ranks assigned to the Y 's (or X 's, whichever has smaller sample size)
- Reject H_0 if W is extreme

Mann-Whitney U test

- Equivalent to Wilcoxon rank sum test
- Compare each x_i with each y_i .
- There are $n_x * n_y$ such comparisons
- U = number of pairs in which $x_i < y_i$.
- U = number of pairs in which $x_i < y_i$.
- $U = U + (n_x(n_x + 1) + n_y(n_y + 1))/2$ (when no ties)
- Reject H_0 if U is extreme.

Boxplots of times to failure for control and stressed capacitors



S-Plus wilcox.test

```
> wilcox.test(cg, sg)
```

Exact Wilcoxon rank-sum test

data: cg and sg

rank-sum statistic $W = 95$, $n = 8$, $m = 10$, p-value =
0.1011

alternative hypothesis: true mu is not equal to 0

S-Plus parametric t-test

```
> t.test(cg,sg)
```

Standard Two-Sample t-Test

data: cg and sg

t = 1.8105, df = 16, p-value = 0.089

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-1.103506 14.018506

sample estimates:

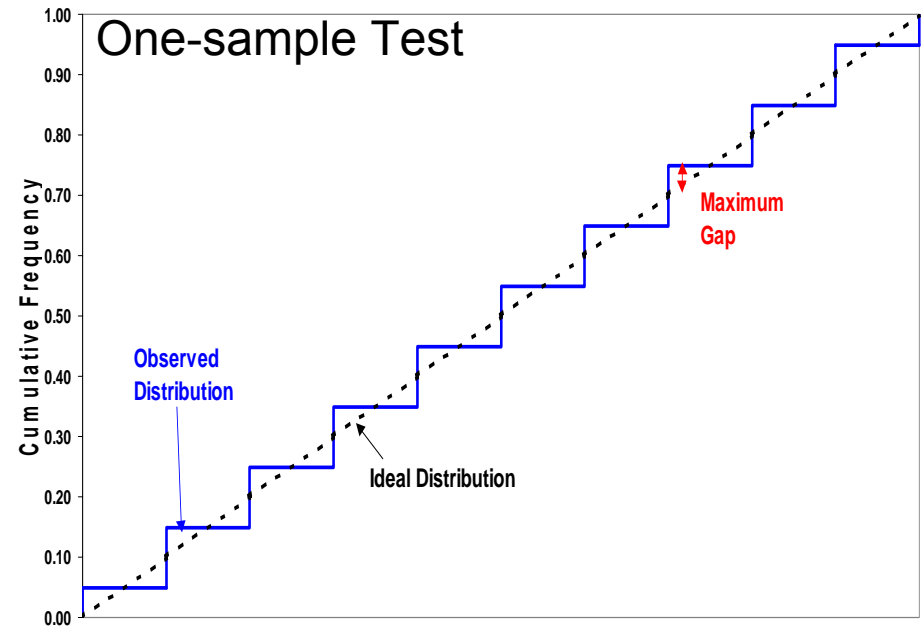
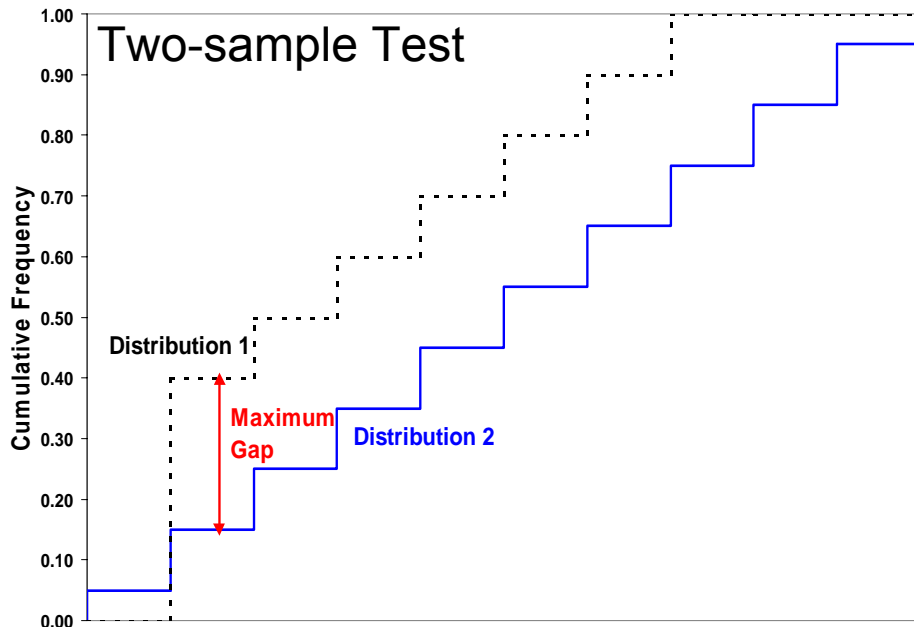
mean of x mean of y

15.5375 9.08

Kolmogorov-Smirnov Tests

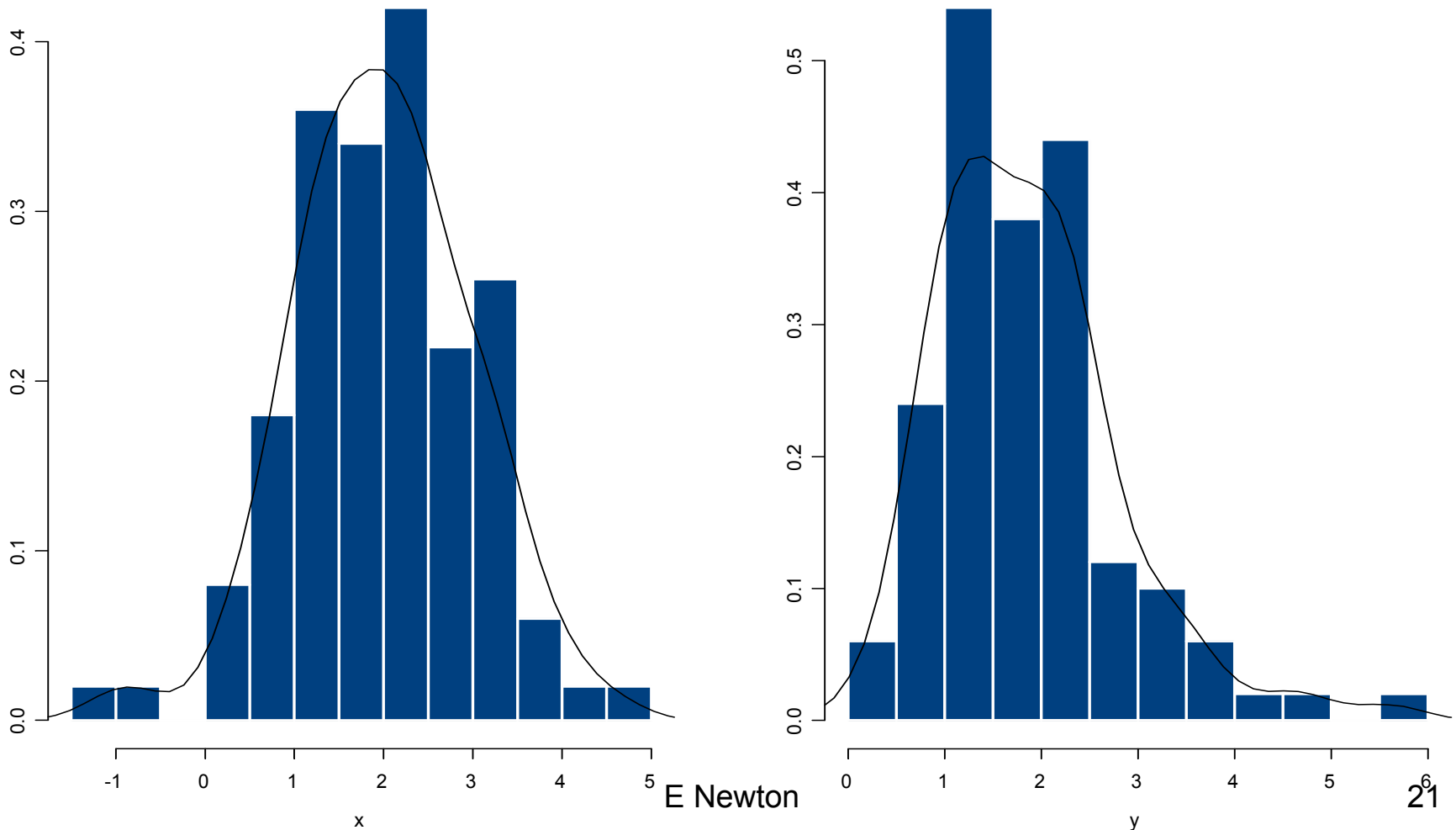
The Kolmogorov-Smirnov test detects differences in location, scale, skewness, or whatever (any differences between two distributions), uses two empirical cumulative distribution functions (step functions).

There is also a one-sample version for testing the distance between some observed data and a specified (ideal) distribution.



Tests the maximum gap between the observed distribution and the hypothesized distribution as a function of sample size (tables or p-values).

Histograms of 100 random normal (2,1) deviates and 100 random gamma(4,2) deviates



Kolmogorov-Smirnov Tests

```
> ks.gof(x,y)
```

Two-Sample Kolmogorov-Smirnov Test

```
data:  x and y
```

```
ks = 0.15, p-value = 0.2112
```

```
alternative hypothesis: cdf of x does not equal the  
                        cdf of y for at least one sample point.
```

```
> ks.gof(y)
```

One sample Kolmogorov-Smirnov Test of Composite Normality

```
data:  y
```

```
ks = 0.0969, p-value = 0.0216
```

```
alternative hypothesis: True cdf is not the normal distn. with  
                        estimated parameters
```

```
sample estimates:
```

```
mean of x standard deviation of x
```

```
1.865857                0.9421928
```

Kruskal-Wallis Test

- Inference for several independent samples
- Assume distributions of each of the samples differ only possibly in location.
- $X_{ij} = \theta + \tau_j + e_{ij}$.
- $H_0: \tau_1 = \tau_2 = \dots = \tau_k$, vs. $H_1: \tau_i \neq \tau_j$ for some $i \neq j$
- Rank all $N = n_1 + n_2 + \dots + n_a$ observations.
- Calculate rank sums and averages in each group
- Calculate KW test statistic = kw (see text)
- Reject H_0 for large values of kw
- For large n_i 's, null dist'n of kw χ^2_{a-1}

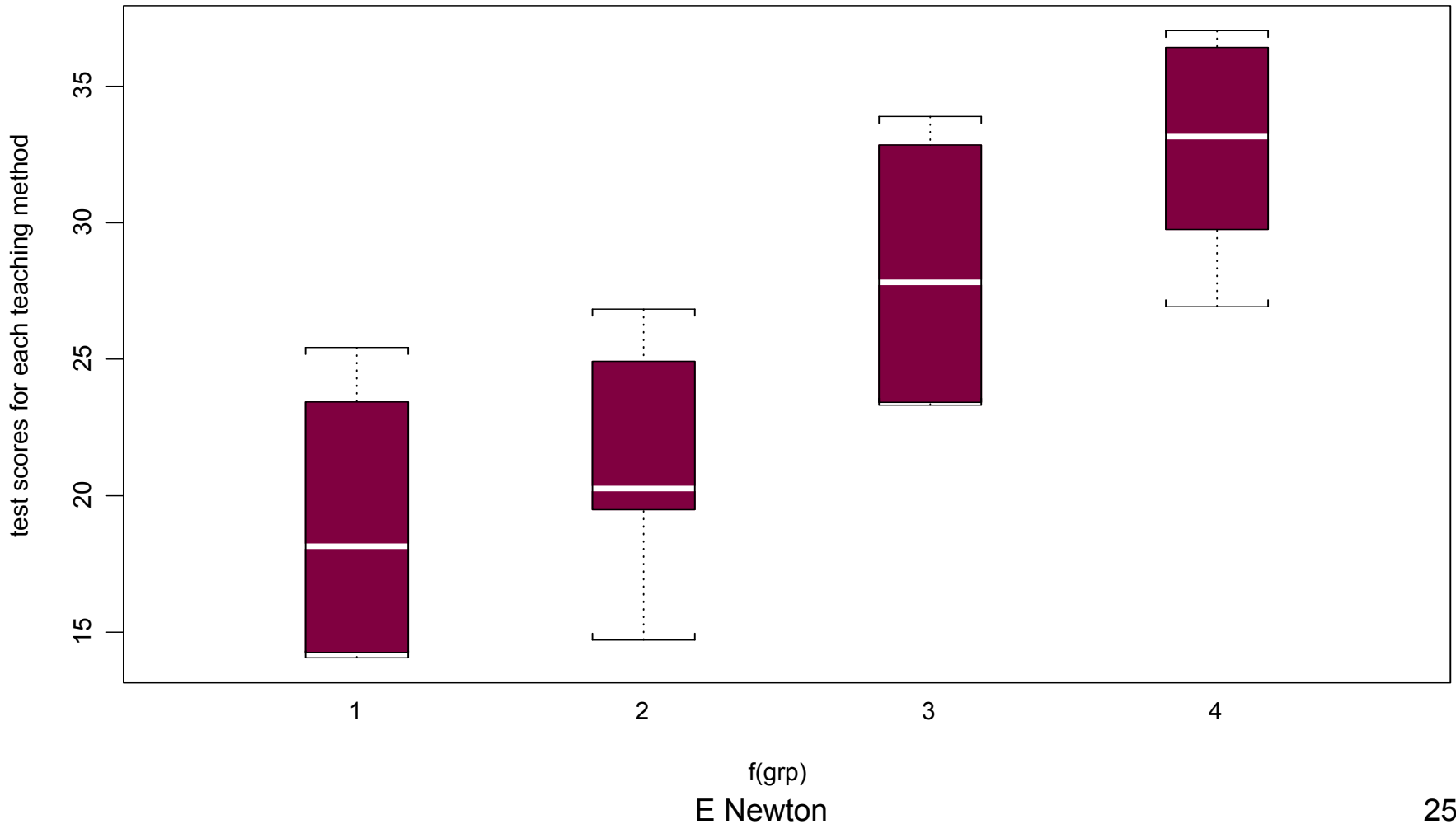
Test scores for four different teaching methods (page 582)

```
scm<-matrix(score,7,4)
```

```
> scm
```

```
      [,1]  [,2]  [,3]  [,4]  
[1, ] 14.06 14.71 23.32 26.93  
[2, ] 14.26 19.49 23.42 29.76  
[3, ] 14.59 20.20 24.92 30.43  
[4, ] 18.15 20.27 27.82 33.16  
[5, ] 20.82 22.34 28.68 33.88  
[6, ] 23.44 24.92 32.85 36.43  
[7, ] 25.43 26.84 33.90 37.04
```


Plot.factor(f(grp),score)



Ranks of Test Scores

```
> scmr<-matrix(rank(score),7,4)
> scmr
      [,1] [,2] [,3] [,4]
[1,]    1  4.0 11.0   18
[2,]    2  6.0 12.0   21
[3,]    3  7.0 14.5   22
[4,]    5  8.0 19.0   24
[5,]    9 10.0 20.0   25
[6,]   13 14.5 23.0   27
[7,]   16 17.0 26.0   28

> tmp<-apply(scmr,2,sum)
> tmp
[1]  49.0  66.5 125.5 165.0

> (12/(28*29))*sum((tmp^2)/7)-3*29
[1] 18.13406
```

Kruskal-Wallis test in S-Plus

```
> kruskal.test(scm, col(scm))
```

Kruskal-Wallis rank sum test

data: scm and col(scm)

Kruskal-Wallis chi-square = 18.139, df = 3,
p-value = 0.0004

alternative hypothesis: two.sided

ANOVA for test scores

```
summary(aov(score~f(grp)))
```

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
f(grp)	3	830.1914	276.7305	15.93607	6.509182e-006
Residuals	24	416.7609	17.3650		

Friedman Test

- Inference for several matched samples
- a treatments, b blocks
- $H_0: \tau_1 = \tau_2 = \dots = \tau_k$, vs. $H_1: \tau_i \neq \tau_j$ for some $i \neq j$
- Rank observations separately within each block
- Calculate rank sums
- Calculate the Friedman statistic, fr (see text)
- Reject H_0 for large values of fr
- For b large, $fr \sim \chi^2_{a-1}$

Ranks within Blocks (rows)

```
> scmr<-t(apply(scm,1,rank))
> scmr
      [,1] [,2] [,3] [,4]
[1,]    1    2    3    4
[2,]    1    2    3    4
[3,]    1    2    3    4
[4,]    1    2    3    4
[5,]    1    2    3    4
[6,]    1    2    3    4
[7,]    1    2    3    4

> tmp<-apply(scmrb,2,sum)
[1]  7 14 21 28

> (12/(4*7*5))*sum(tmp^2)-3*7*5
[1] 21
```

Friedman test in S-Plus

- `> friedman.test(scm, col(scm), row(scm))`
- Friedman rank sum test
- data: `scm` and `col(scm)` and `row(scm)`
- Friedman chi-square = 21, df = 3, p-value = 0.0001
- alternative hypothesis: `two.sided`

ANOVA test score data with blocks

```
> summary(aov(score~f(grp)+f(blk)))
```

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
f(grp)	3	830.1914	276.7305	260.4768	5.220000e-015
f(blk)	6	397.6377	66.2729	62.3804	4.558276e-011
Residuals	18	19.1232	1.0624		

Correlation Methods

- Pearson Correlation: measures only linear association.
- Spearman Correlation: correlation of the ranks
- Kendall's Tau: based on number of concordant and discordant pairs.

Kendall's Tau

- Assume: the n bivariate observations $(X_1, Y_1), \dots, (X_n, Y_n)$ are a random sample from a continuous bivariate population.
- H_0 : X_i, Y_i are independent
- H_0 : $F(x, y) = F(x)F(y)$
- Measure dependence by finding the number of concordant and discordant pairs.
- Population correlation coefficient:
$$\tau = 2 * P \{ (X_2 - X_1)(Y_2 - Y_1) > 0 \} - 1$$

Kendall's Tau

For $1 \leq i < j \leq n$:

$$Q((X_i, Y_i), (X_j, Y_j)) = \begin{cases} 1, & \text{if } (X_i - X_j)(Y_i - Y_j) > 0 \\ 0, & \text{if } (X_i - X_j)(Y_i - Y_j) = 0 \\ -1, & \text{if } (X_i - X_j)(Y_i - Y_j) < 0 \end{cases}$$

$$K = \sum_{i=1}^{n-1} \sum_{j=i+1}^n Q((X_i, Y_i), (X_j, Y_j))$$

$$\hat{\tau} = \frac{2K}{n(n-1)}$$

Kendall's Tau example

```
> m
  1  3  2  4
1 NA  1  1  1
2 NA NA -1  1
3 NA NA NA  1
4 NA NA NA NA

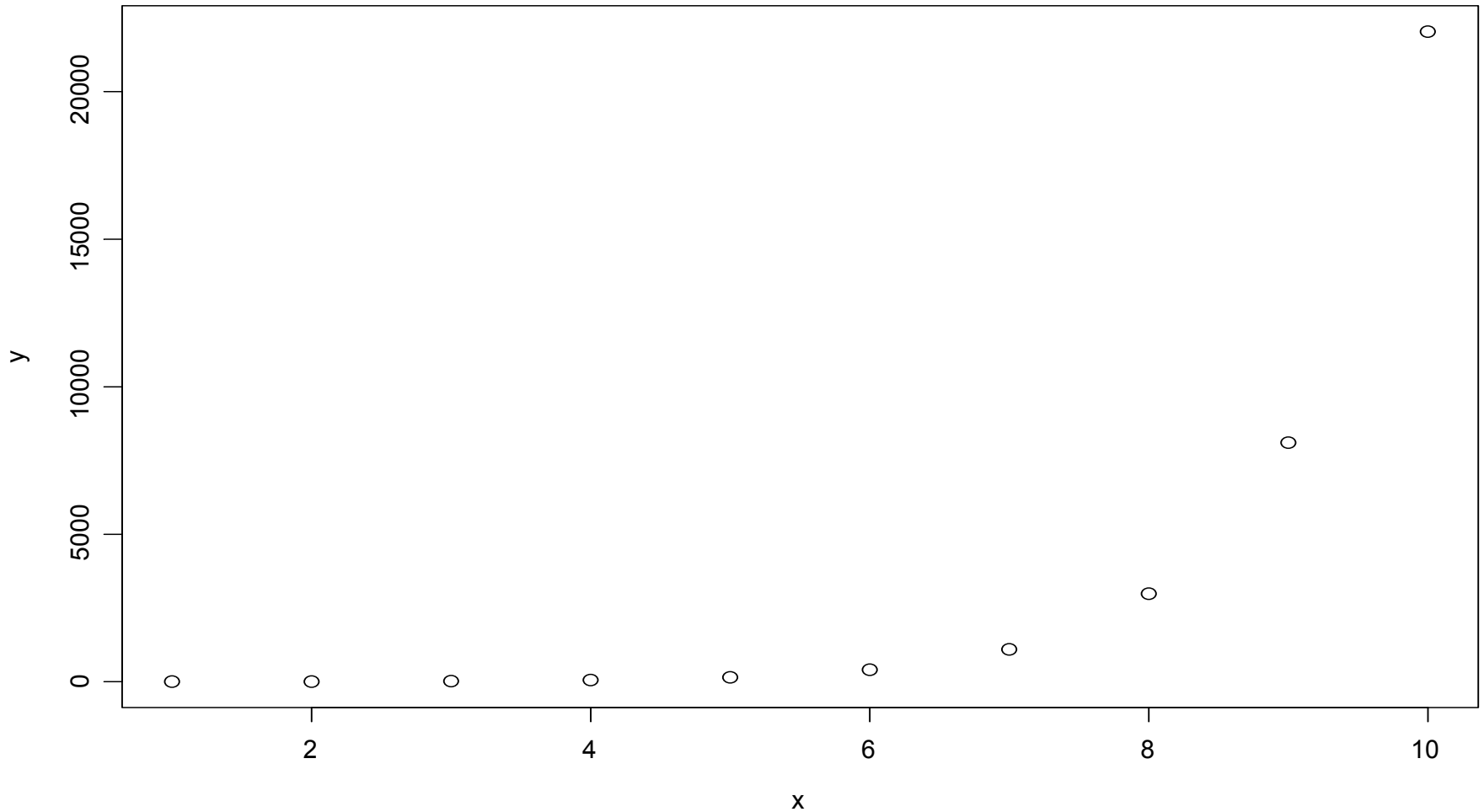
> 2*sum(m,na.rm=T)/12
[1] 0.6666667

> cor.test(c(1,2,3,4),c(1,3,2,4),method="k")
```

Kendall's rank correlation tau

```
data:  c(1, 2, 3, 4) and c(1, 3, 2, 4)
normal-z = 1.3587, p-value = 0.1742
alternative hypothesis: true tau is not equal to 0
sample estimates:
      tau
0.6666667
```

$$x=1:10$$
$$y=\exp(x)$$



Pearson Correlation

```
> cor.test(x,y,method="p")
```

Pearson's product-moment correlation

```
data: x and y
```

```
t = 2.9082, df = 8, p-value = 0.0196
```

```
alternative hypothesis: true coef is not  
equal to 0
```

```
sample estimates:
```

```
cor
```

```
0.7168704
```

Spearman Correlation

```
> cor.test(x,y,method="s")
```

```
Spearman's rank correlation
```

```
data: x and y
```

```
normal-z = 2.9818, p-value = 0.0029
```

```
alternative hypothesis: true rho is not  
equal to 0
```

```
sample estimates:
```

```
rho
```

```
1
```

Kendall Correlaton

```
> cor.test(x,y,method="k")
```

```
Kendall's rank correlation tau
```

```
data: x and y
```

```
normal-z = 4.0249, p-value = 0.0001
```

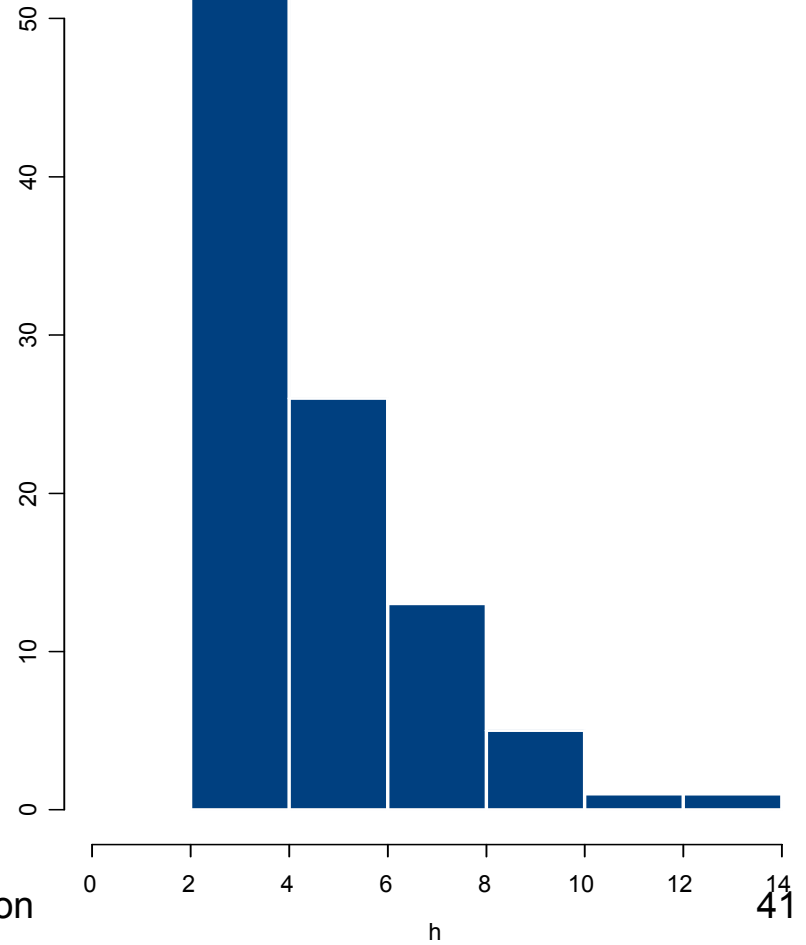
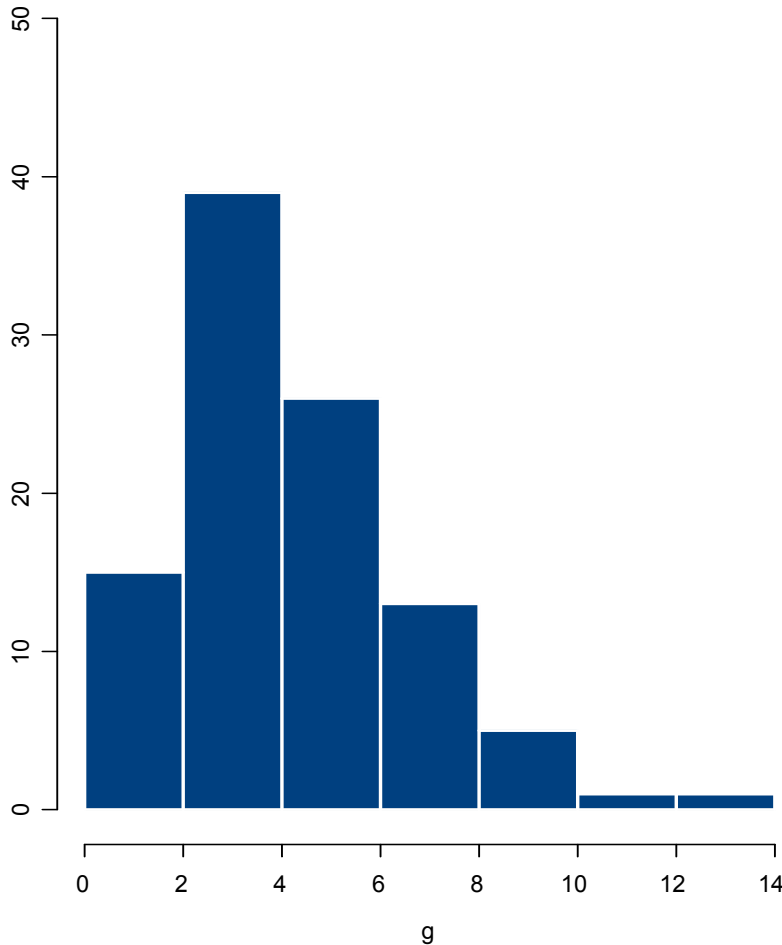
```
alternative hypothesis: true tau is not  
equal to 0
```

```
sample estimates:
```

```
tau
```

```
1
```


Example - Environmental Data – Censored below LOD



Resampling Methods

- Parametric methods – Inference based on assumed population distribution
- Resampling methods – No assumption about functional form of population distribution.
- Permutation Tests – 2 sample problem
- Jackknife – Delete one observation at a time
- Bootstrap – resample with replacement

Permutation Tests

- Goal: estimate difference in means (2 sample problem)
- $(x_1, x_2, \dots, x_{n_1})$ and $(y_1, y_2, \dots, y_{n_2})$ are independent samples drawn from F_1 and F_2 .
- $H_0: F_1 = F_2 \Rightarrow$ all assignments of labels x and y equally likely.
- Choose SRS of size n_1 from $n_1 + n_2$ observations and label as x , label rest as y .
- Calculate value of test statistic (e.g. difference in means) for each assignment \rightarrow permutation distribution.
- There are $\binom{n_1 + n_2}{n_1}$ possible distinct assignments (capacitor data set Ex14.7, $n_1 = 8$, $n_2 = 10$, number of assignments = 43,758)

Jackknife

- Goal: estimate distribution and standard error of statistic (e.g. median or mean)
- Draw n samples of size $n-1$ from original sample, by deleting one observation at a time.
- Calculate m_j^* =mean (median) from each sample

$$JSE(m) = \sqrt{\frac{n-1}{n} \sum_{j=1}^n (m_j^* - \bar{m}^*)^2}$$

- JSE is exact for mean, not necessarily very good for median

Bootstrap

- Goal: estimate distribution, standard error, confidence interval of statistic (e.g. mean, median, correlation)
- Draw B samples of size n , with replacement, from original sample
- Calculate test statistics from each sample

$$BSE(m) = \sqrt{\frac{\sum_{j=1}^B (m_j^* - \bar{m}^*)^2}{B-1}}$$

Swiss Data Set in S-Plus

Fertility Data for Switzerland in 1888

SUMMARY:

The `swiss.fertility` and `swiss.x` data sets contain fertility data for Switzerland in 1888.

ARGUMENTS:

swiss.fertility

standardized fertility measure $I[g]$ for each of 47 French-speaking provinces of Switzerland in approximately 1888.

swiss.x

matrix with 5 columns that contain socioeconomic indicators for the provinces:
1) percent of population involved in agriculture as an occupation; 2) percent of "draftees" receiving highest mark on army examination; 3) percent of population whose education is beyond primary school; 4) percent of population who are Catholic; and, 5) percent of live births who live less than 1 year (infant mortality).

SOURCE:

Mosteller and Tukey (1977). *Data Analysis and Regression*. Addison-Wesley.

Unpublished data used by permission of Francine van de Walle. Population Study Center, University of Pennsylvania, Philadelphia, PA.

Bootstrap estimates and CI for variance of education

```
> educ<-swiss.x[,3]
> var(educ)
[1] 92.45606
```

```
> educ.boot<-bootstrap(educ,var,trace=F)
> summary(educ.boot)
```

Call:

```
bootstrap(data = educ, statistic = var, trace = F)
```

Number of Replications: 1000

Summary Statistics:

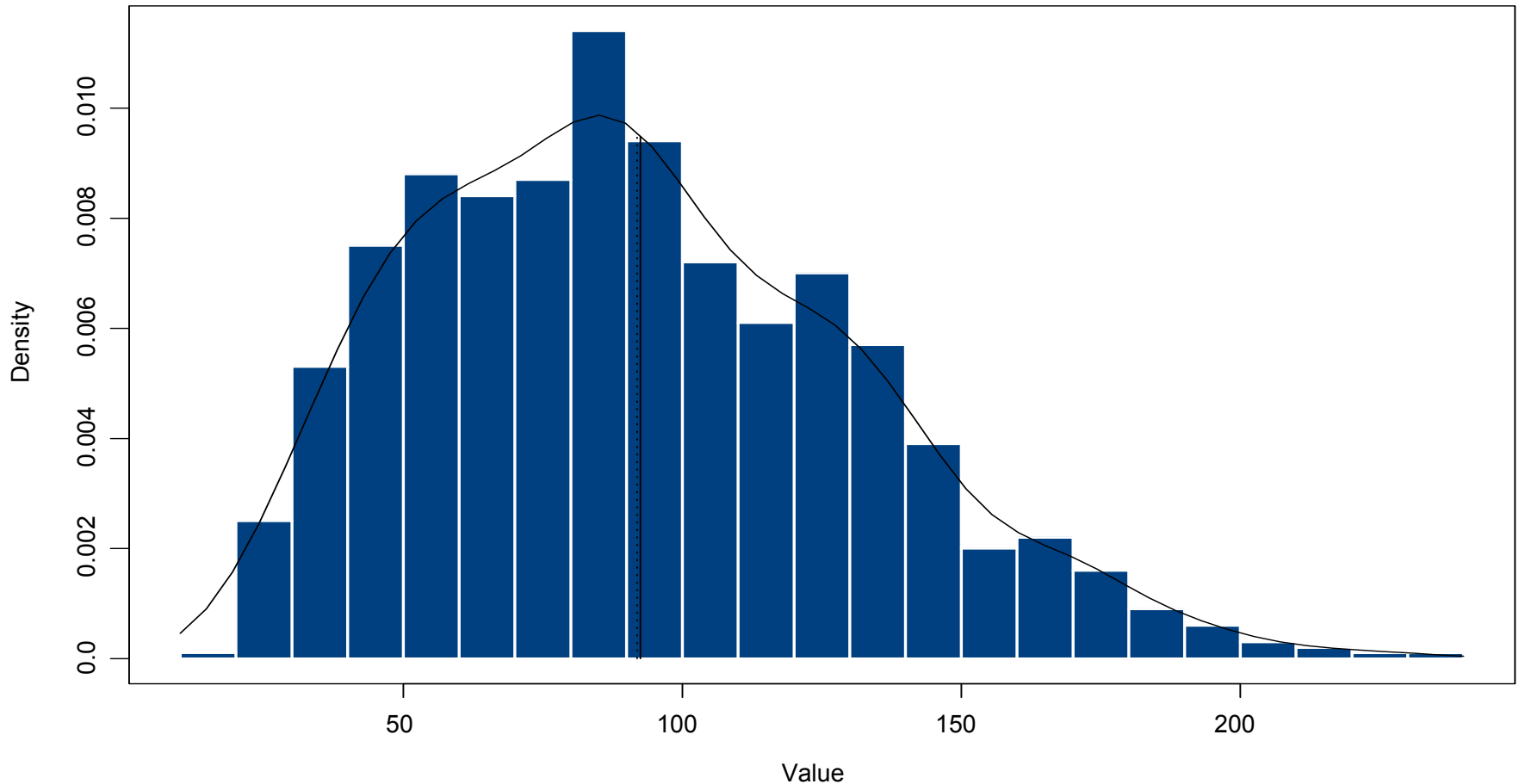
	Observed	Bias	Mean	SE
var	92.46	-0.5972	91.86	39.14

Empirical Percentiles:

	2.5%	5%	95%	97.5%
var	29.98	36.26	165.3	175

Histogram of variance estimates obtained from 1000 bootstrap samples

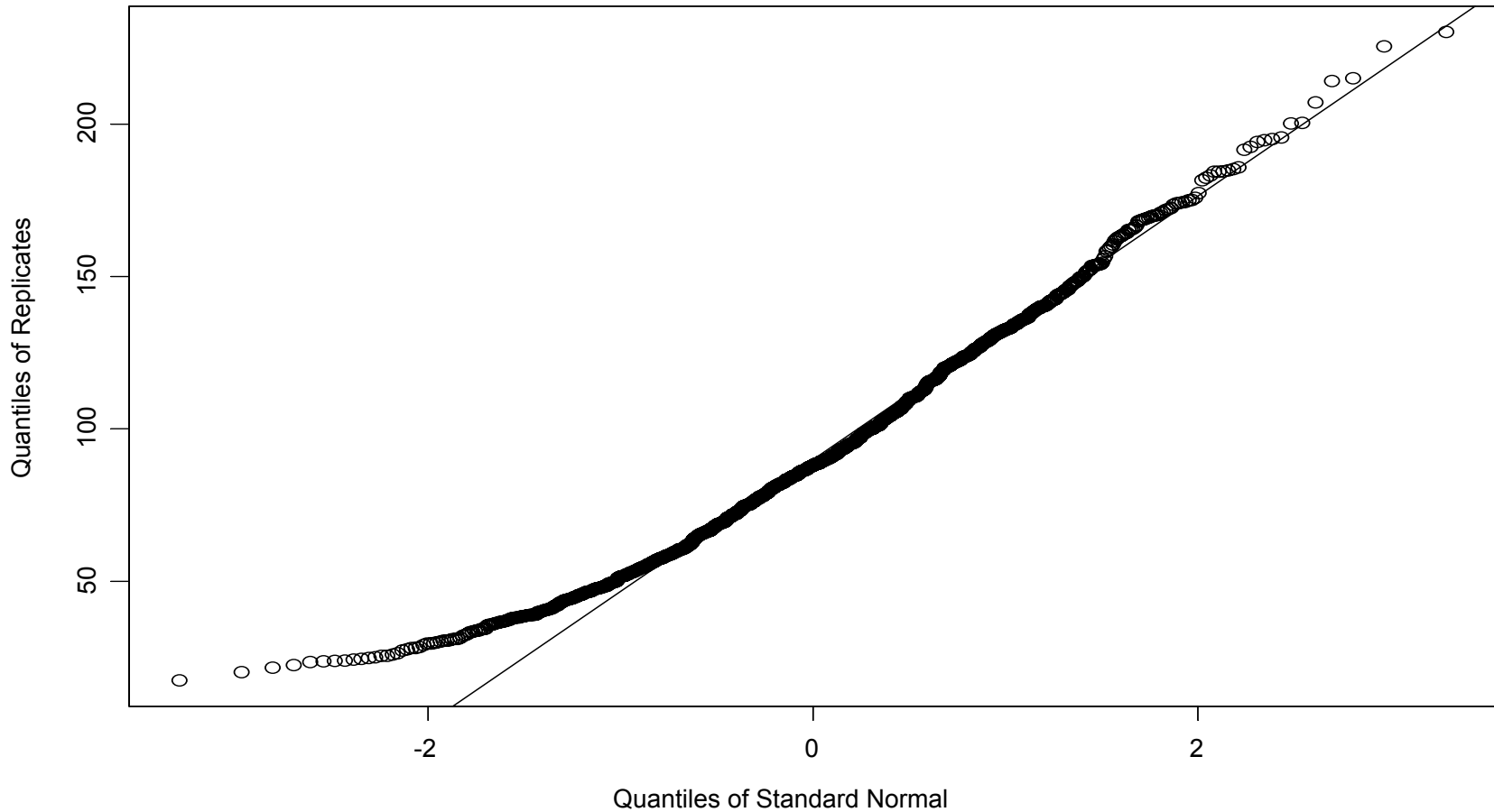
var



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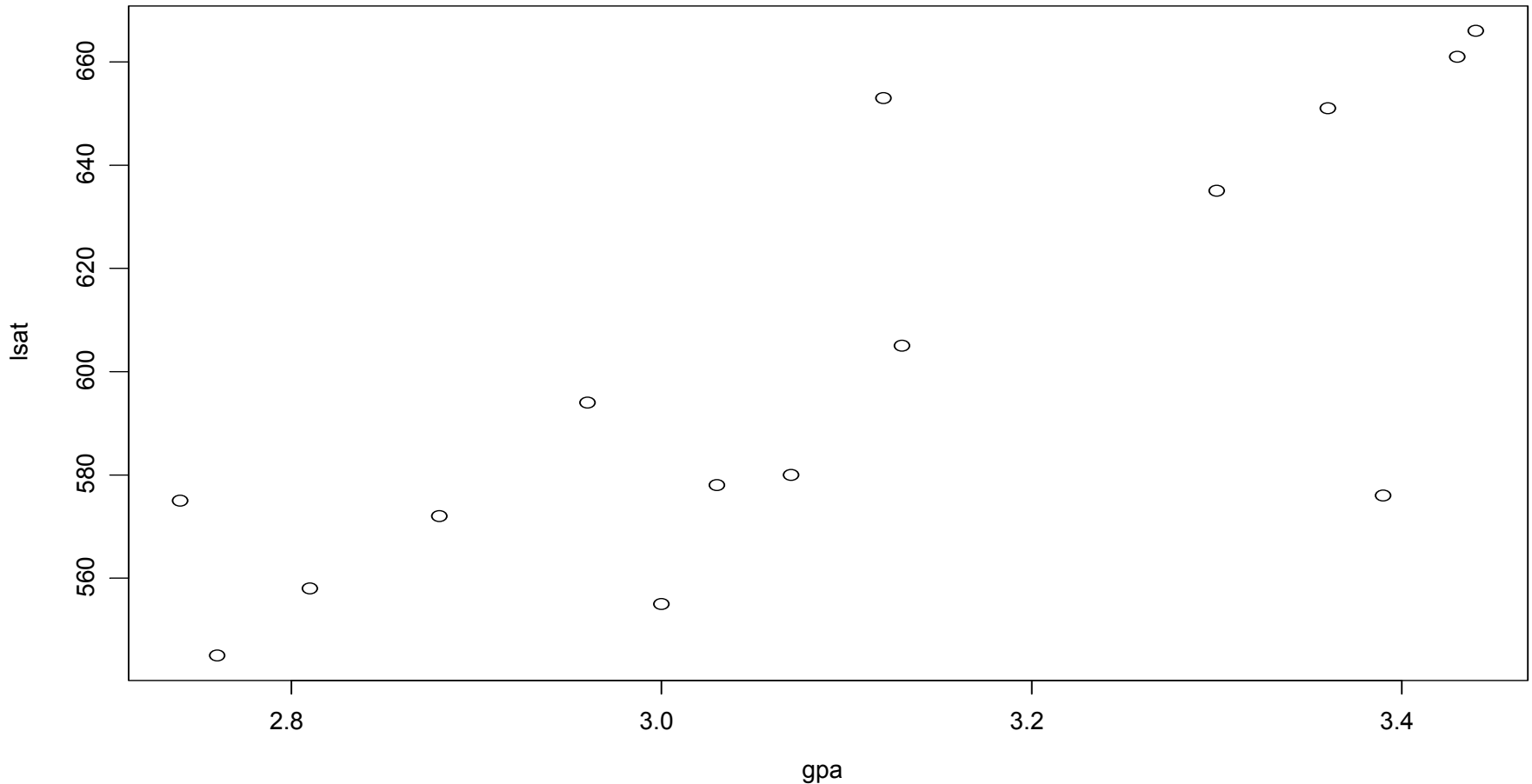
QQ plot of variance estimates

var



E Newton

Plot of LSAT scores by GPA for a sample of 15 schools



Bootstrap estimates and CI for correlation between LSAT and GPA

```
> law.boot<-bootstrap(law.data, cor(lsat,gpa), trace=F)
> summary(law.boot)
Call:
bootstrap(data = law.data, statistic = cor(lsat, gpa), trace = F)
```

Number of Replications: 1000

Summary Statistics:

	Observed	Bias	Mean	SE
Param	0.7764	-0.00506	0.7713	0.1368

Empirical Percentiles:

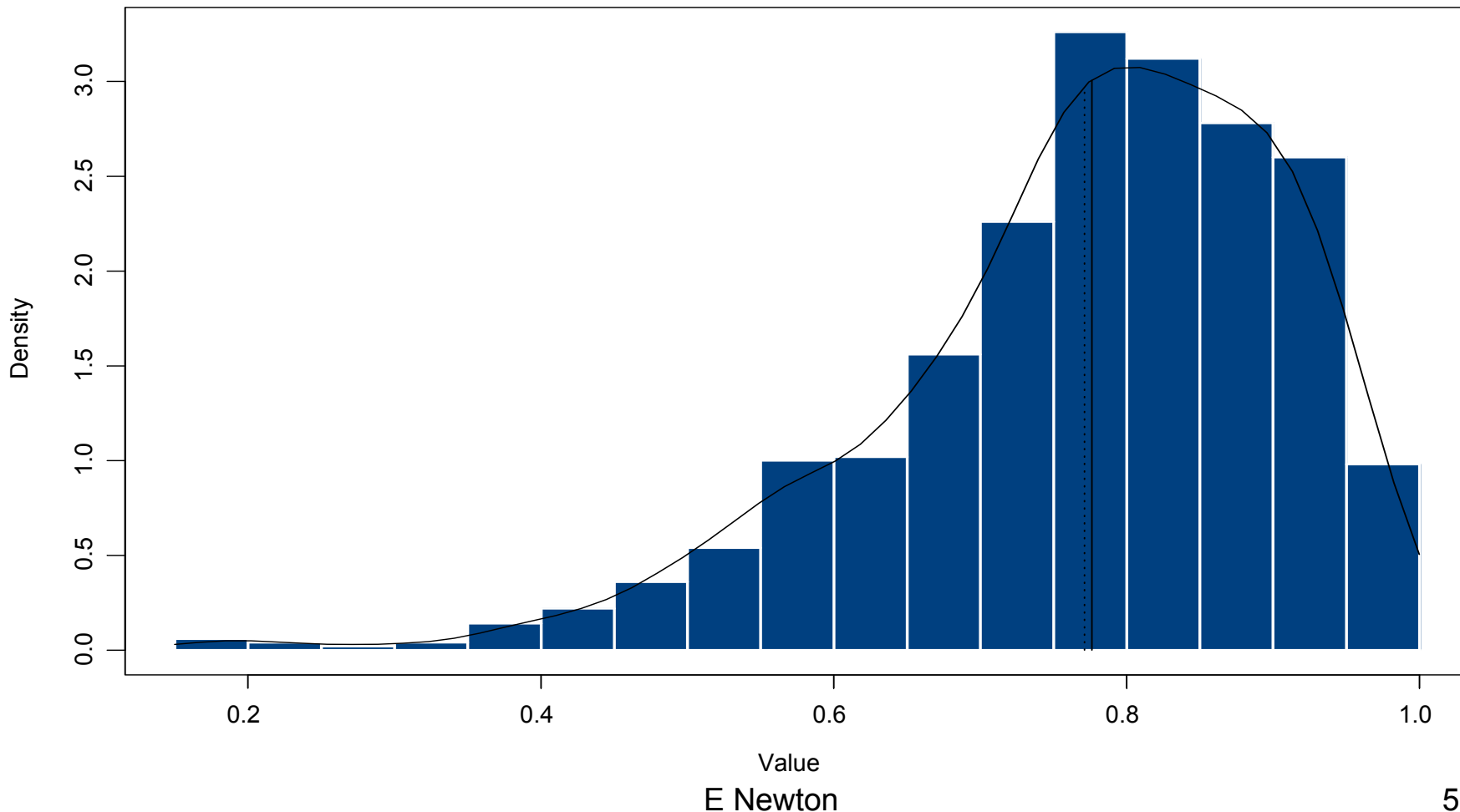
	2.5%	5%	95%	97.5%
Param	0.449	0.5133	0.947	0.9623

BCa Confidence Limits:

	2.5%	5%	95%	97.5%
Param	0.2623	0.4138	0.9232	0.9413

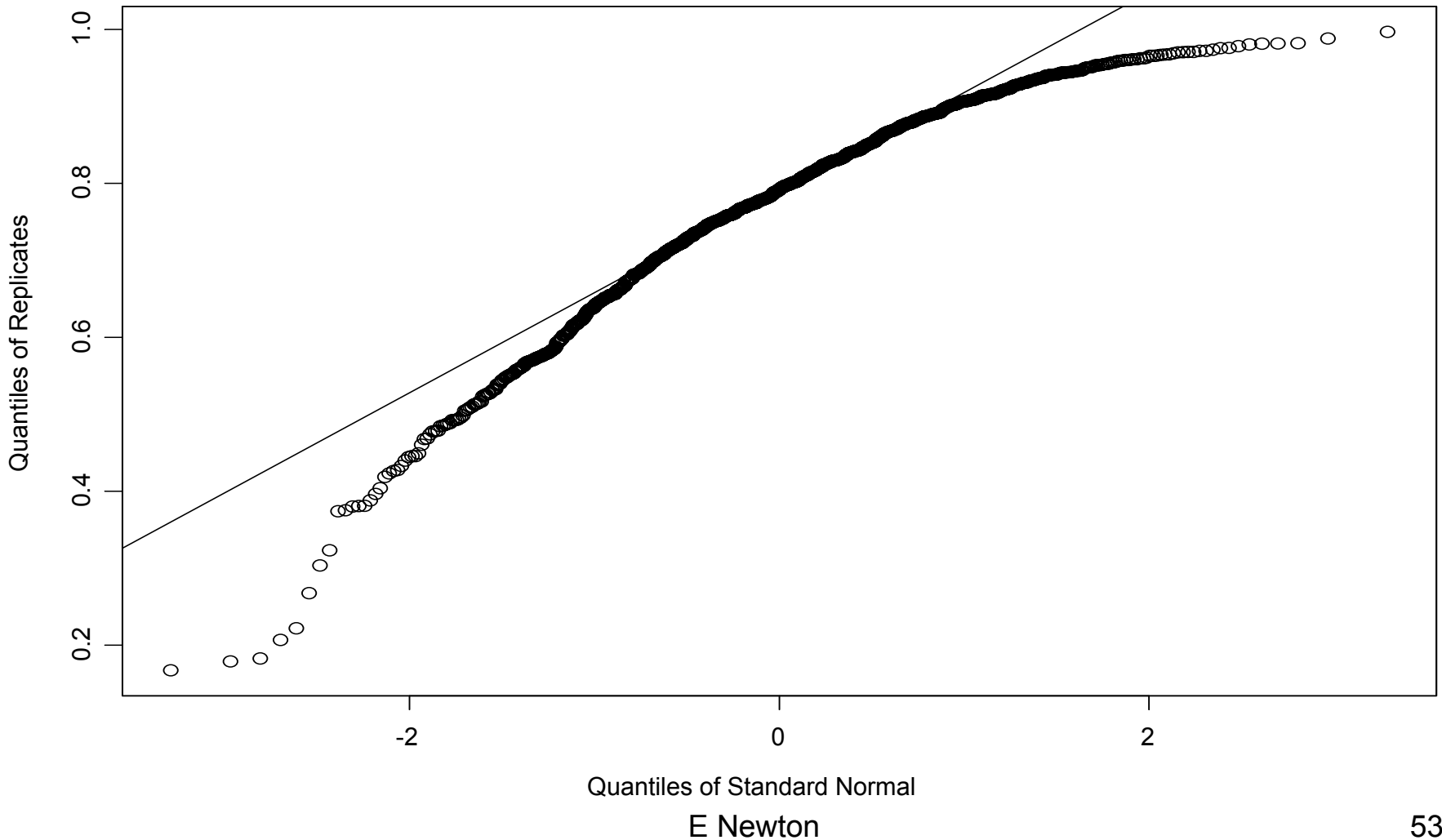
Histogram of correlation estimates obtained from 1000 bootstrap samples

Param



QQ Plot of correlation estimates

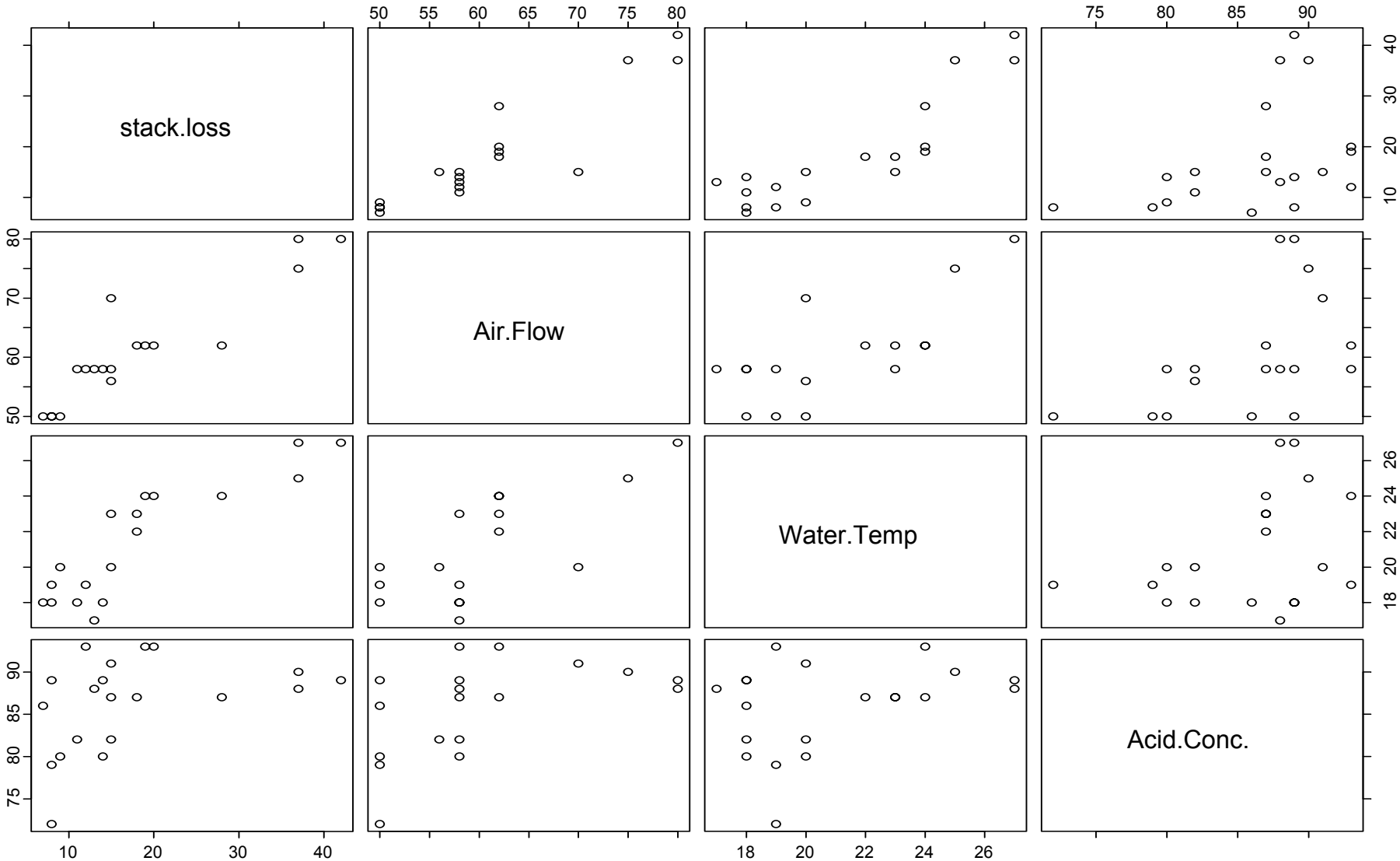
Param



S-Plus Stack-loss data set

- **Stack-loss Data**
- **SUMMARY:**
- The `stack.loss` and `stack.x` data sets are from the operation of a plant for the oxidation of ammonia to nitric acid, measured on 21 consecutive days.
- **ARGUMENTS:**
- **`stack.loss`**
 - percent of ammonia lost (times 10).
- **`stack.x`**
 - matrix with 21 rows and 3 columns representing air flow to the plant, cooling water inlet temperature, and acid concentration as a percentage (coded by subtracting 50 and then multiplying by 10).
- **SOURCE:**
- Brownlee, K.A. (1965). *Statistical Theory and Methodology in Science and Engineering*. New York: John Wiley & Sons, Inc.
- Draper and Smith (1966). *Applied Regression Analysis*. New York: John Wiley & Sons, Inc.
- Daniel and Wood (1971). *Fitting Equations to Data*. New York: John Wiley & Sons, Inc.

S-Plus stack loss data set



Summary of stack loss regression

```
> summary(tmp)
```

```
Call: lm(formula = stack.loss ~ Air.Flow + Water.Temp + Acid.Conc., data =  
stack)
```

```
Residuals:
```

Min	1Q	Median	3Q	Max
-7.238	-1.712	-0.4551	2.361	5.698

```
Coefficients:
```

	Value	Std. Error	t value	Pr(> t)
(Intercept)	-39.9197	11.8960	-3.3557	0.0038
Air.Flow	0.7156	0.1349	5.3066	0.0001
Water.Temp	1.2953	0.3680	3.5196	0.0026
Acid.Conc.	-0.1521	0.1563	-0.9733	0.3440

```
Residual standard error: 3.243 on 17 degrees of freedom
```

```
Multiple R-Squared: 0.9136
```

```
F-statistic: 59.9 on 3 and 17 degrees of freedom, the p-value is 3.016e-009
```

```
Correlation of Coefficients:
```

	(Intercept)	Air.Flow	Water.Temp
Air.Flow	0.1793		
Water.Temp	-0.1489	-0.7356	
Acid.Conc.	-0.9016	-0.3389	0.0002

Summary of stack loss bootstrap output

```
summary(stack.boot)
```

```
Call:
```

```
bootstrap(data = stack, statistic = coef(lm(stack.loss ~ Air.Flow  
+ Water.Temp + Acid.Conc., stack)), trace = F)
```

```
Number of Replications: 1000
```

```
Summary Statistics:
```

	Observed	Bias	Mean	SE
(Intercept)	-39.9197	0.5691396	-39.3505	9.3731
Air.Flow	0.7156	0.0016734	0.7173	0.1777
Water.Temp	1.2953	-0.0264873	1.2688	0.4798
Acid.Conc.	-0.1521	-0.0006978	-0.1528	0.1261

```
Empirical Percentiles:
```

	2.5%	5%	95%	97.5%
(Intercept)	-56.0109	-53.4216	-21.92994	-18.75262
Air.Flow	0.3903	0.4366	1.00261	1.04605
Water.Temp	0.4004	0.5131	2.07381	2.23633
Acid.Conc.	-0.4285	-0.3740	0.03282	0.05912

Summary of stack loss bootstrap output

```
summary(stack.boot)
```

BCa Confidence Limits:

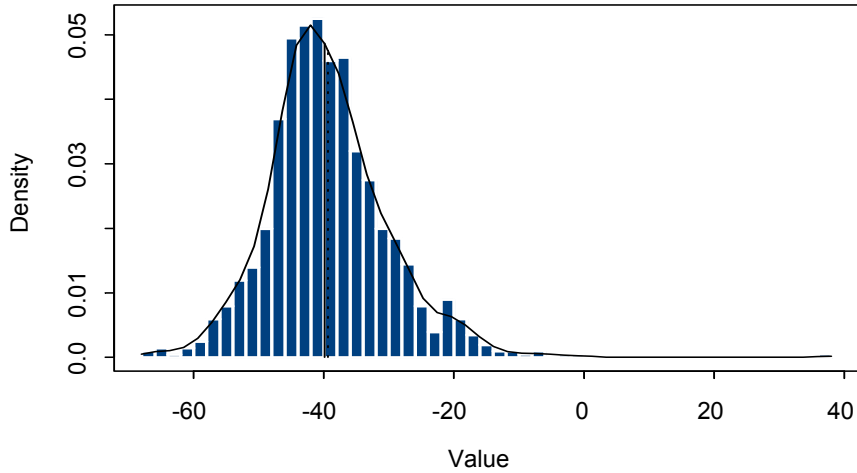
	2.5%	5%	95%	97.5%
(Intercept)	-55.6465	-52.6606	-21.451125	-18.55810
Air.Flow	0.3266	0.4120	0.992007	1.01855
Water.Temp	0.5244	0.6193	2.264165	2.40956
Acid.Conc.	-0.4629	-0.4101	-0.007724	0.04459

Correlation of Replicates:

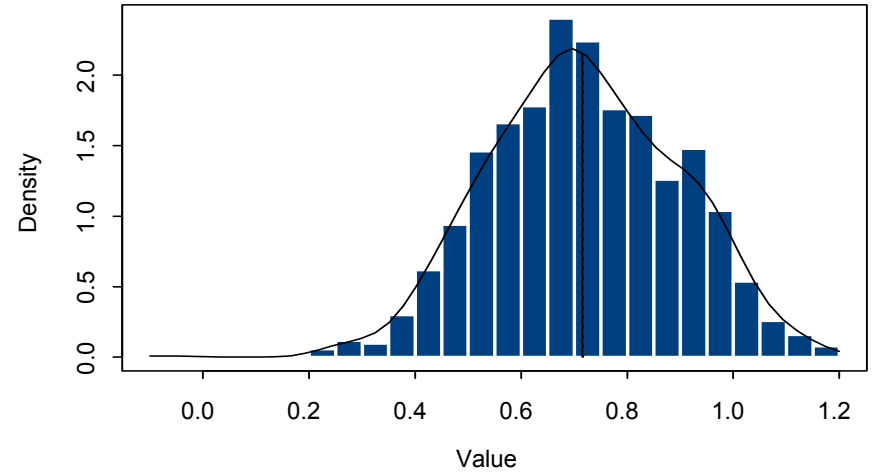
	(Intercept)	Air.Flow	Water.Temp	Acid.Conc.
(Intercept)	1.00000	-0.17636	0.09902	-0.80236
Air.Flow	-0.17636	1.00000	-0.78822	-0.07635
Water.Temp	0.09902	-0.78822	1.00000	-0.24463
Acid.Conc.	-0.80236	-0.07635	-0.24463	1.00000

Histograms of regression coefficients

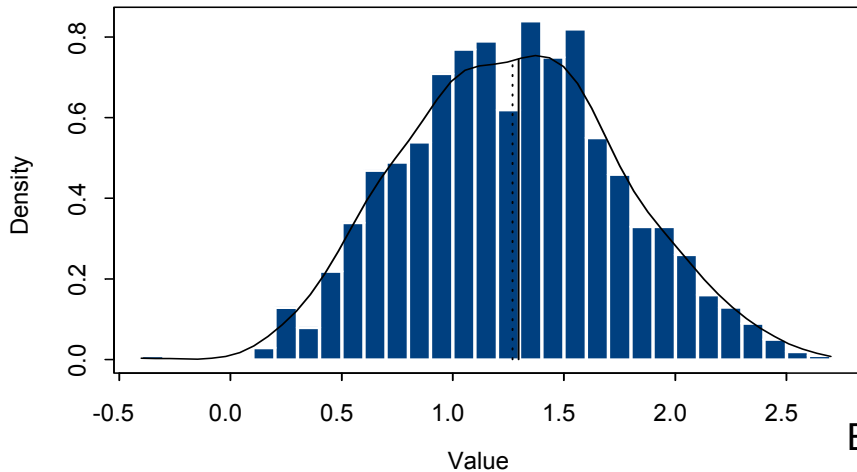
(Intercept)



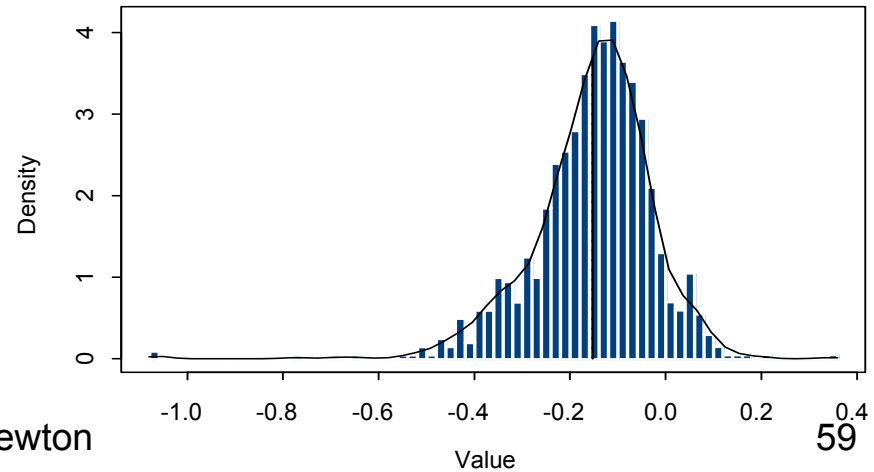
Air.Flow



Water.Temp



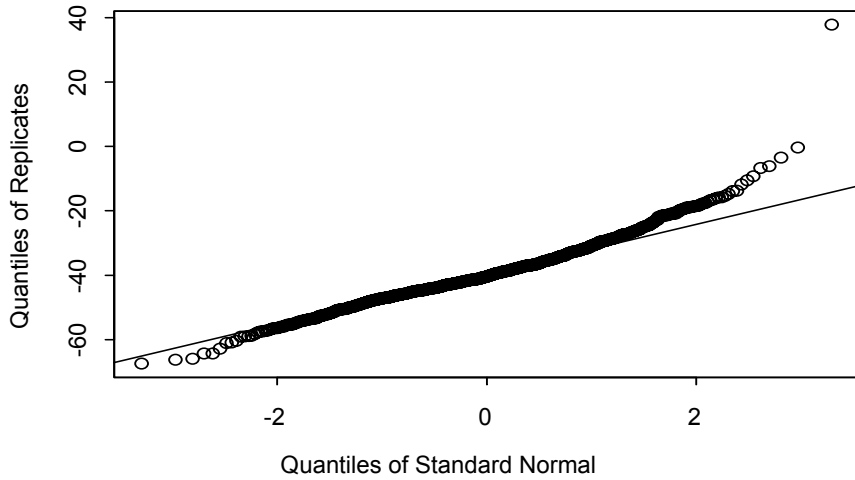
Acid.Conc.



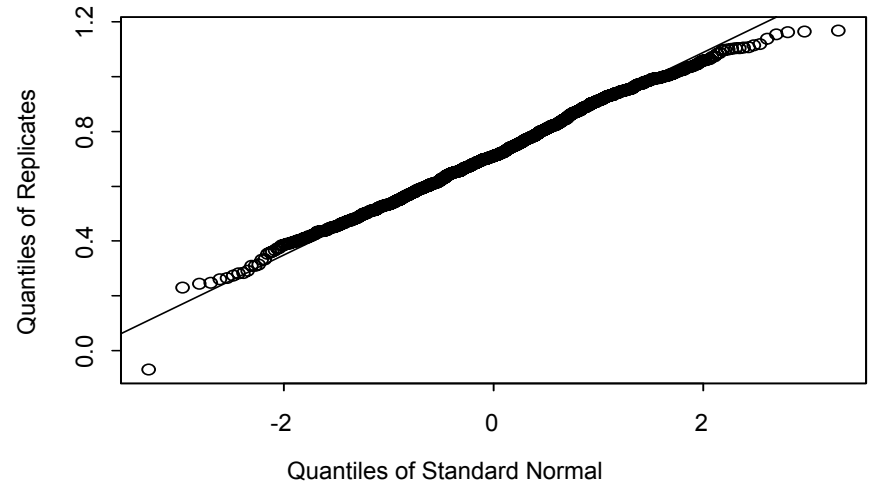
E Newton

QQ Plots of regression coefficients

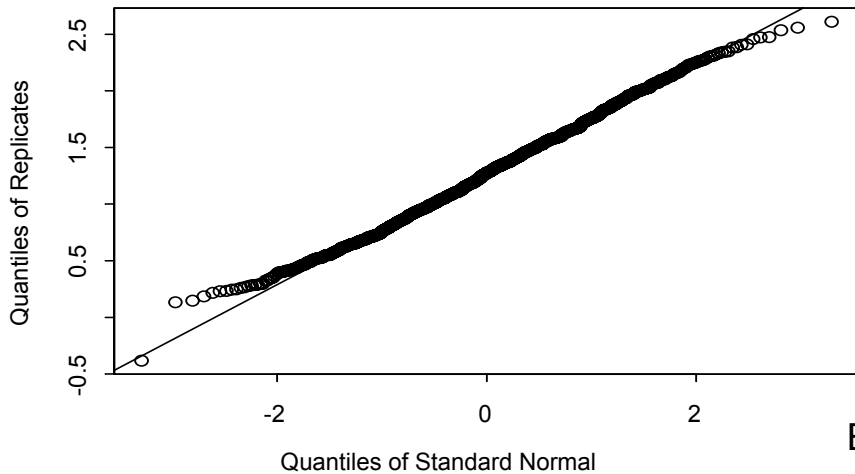
(Intercept)



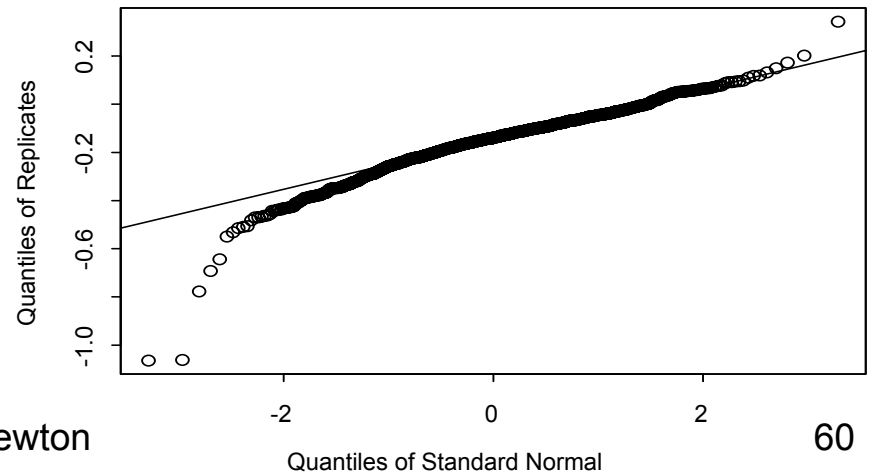
Air.Flow



Water.Temp



Acid.Conc.



E Newton

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