Identifying Key Statistical Papers From 1985 to 2002 Using Citation Data for Applied Biostatisticians

Michael J. Schell (2010)

The American Statistician, 64:4, 310-317

- This article uses the citation count history of articles to identify key papers from 1985 to 2002 from 12 statistics journals for applied biostatisticians.
- Articles with the highest expected applied uses 20 years post publication were identified using joinpoint regression.

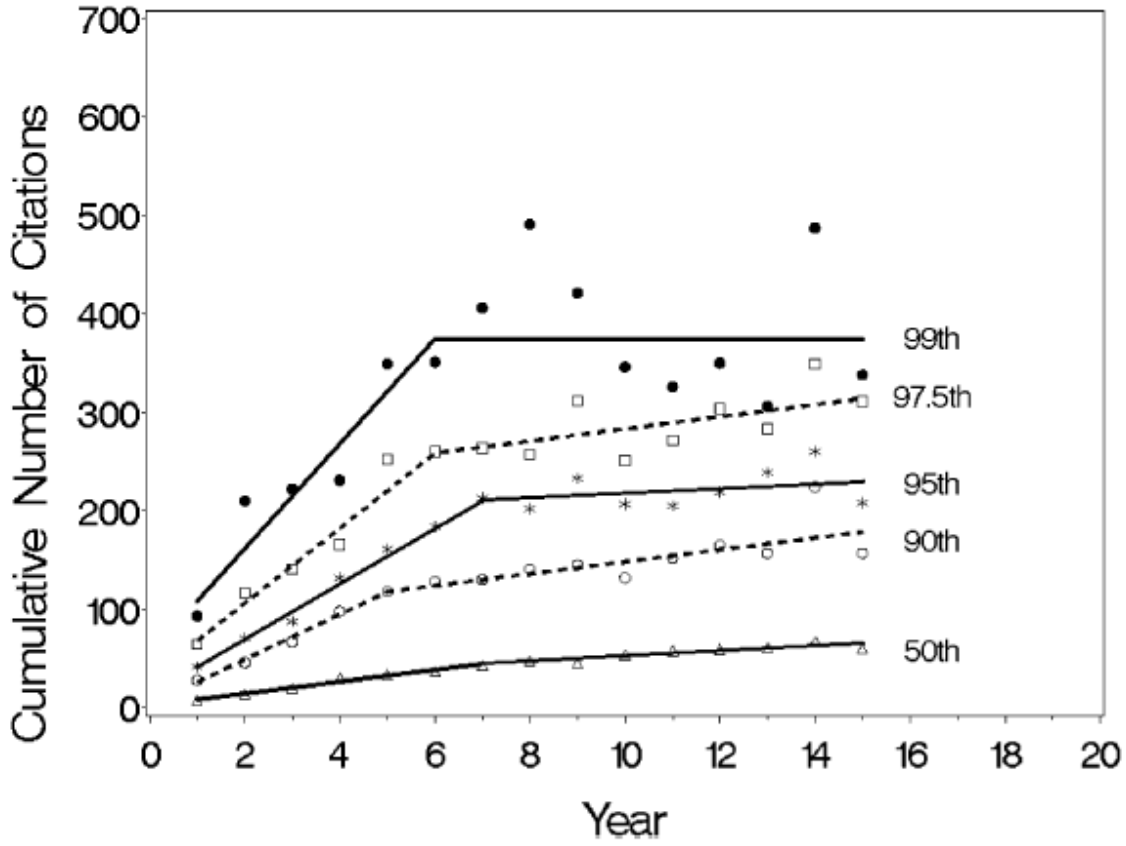


Figure 2. Plot of the cumulative number of citations by year since publication for selected percentiles (50th through 99th) for the *Journal of Clinical Oncology*. Trends across years were fitted using join-

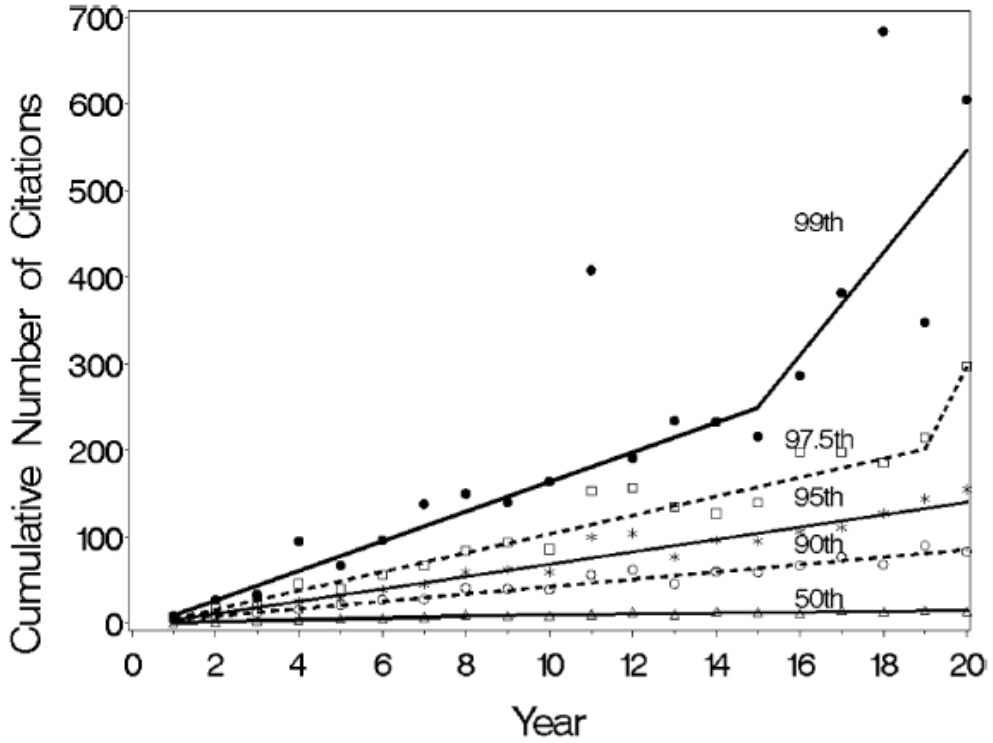


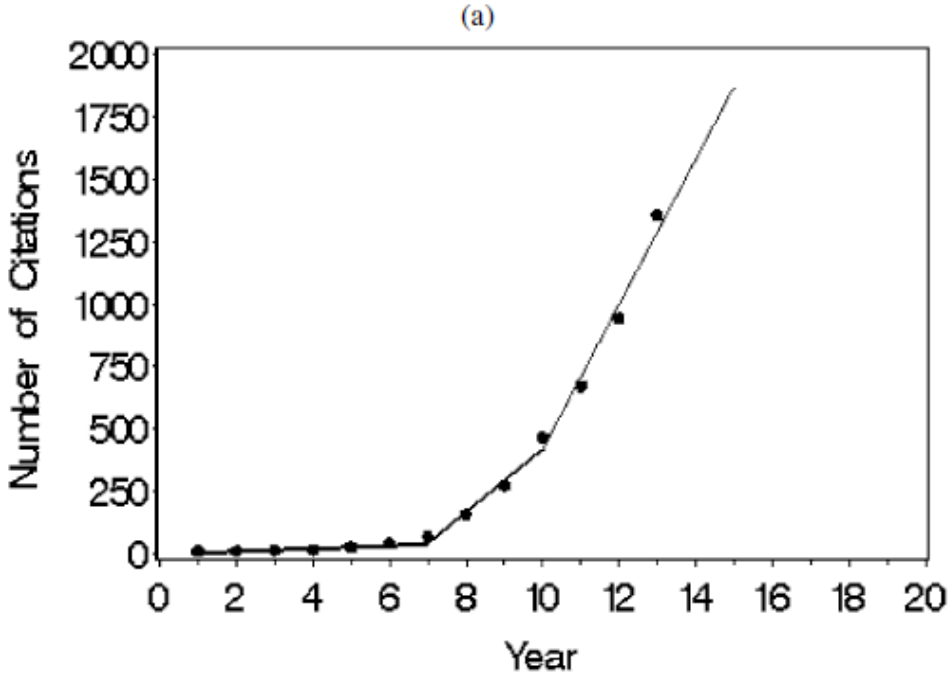
Figure 1. Plot of the cumulative number of citations by year since publication for selected percentiles (50th through 99th) for five influential statistical journals. Trends across years were fitted using joinpoint

Table 2. Average applied and semi-applied fraction percentages for early, intermediate, and recent citations by journal for highly cited articles.*

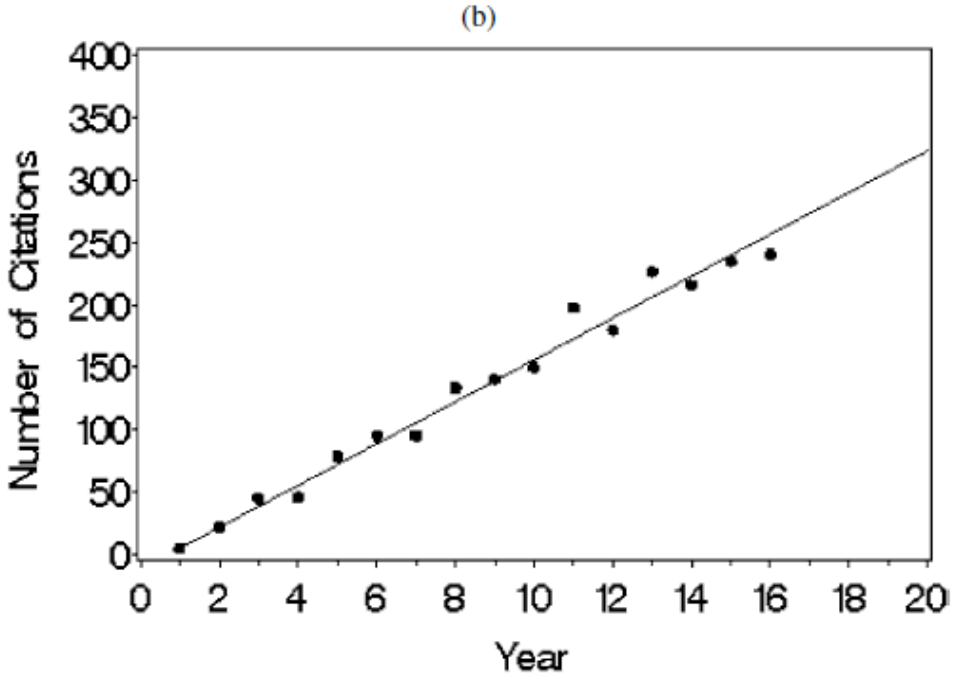
		Applied fraction %			Semi-applied fraction %		
Journal	*N*	Early	Inter.	Recent	Early	Inter.	Recent
Stat Med	27	81	85	90	4	4	3
Bmcs	27	62	71	72	13	9	8
Bmka	13	58	63	72	8	6	7
JASA	46	33	40	47	12	12	12
JRSS-B	23	32	37	40	13	14	15
Overall	136	51	57	62	11	9	9

*136 articles from 1985 to 2002 with ≥15 citations/year as assessed on 3/15/07. Inter. = Intermediate.

Nr. 1 (enimtsiteeritud)



Nr. 6


(b)
Number of Citations
400
350
300
250
200
150
100
50
0
0
2
4
6
8
10
12
14
16
18
20
Year

Nr. 33

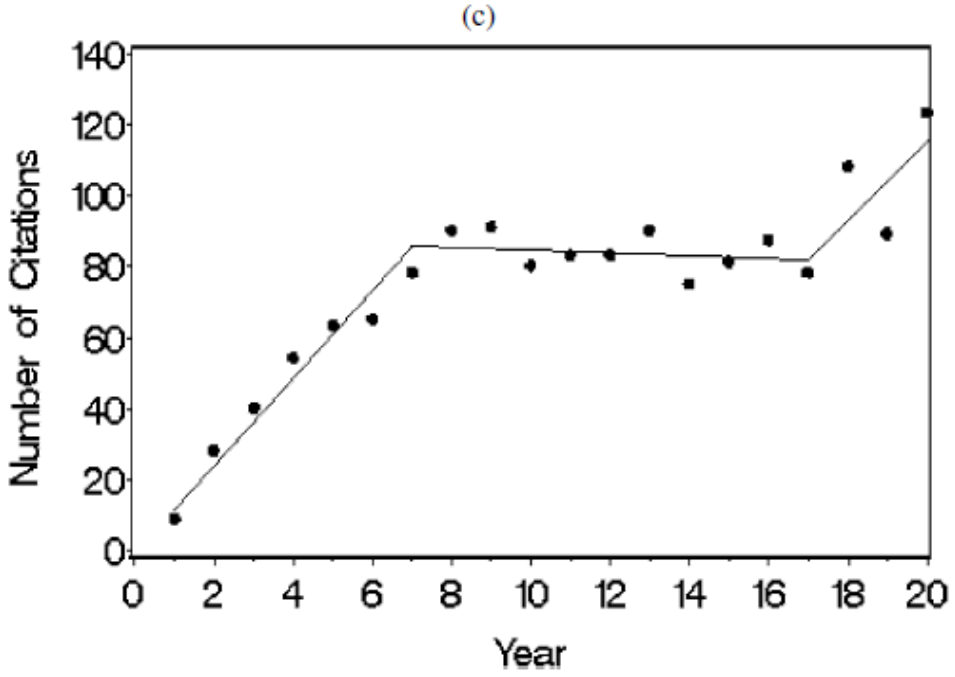

(c)
Number of Citations
0
20
40
60
80
100
120
140
0
2
4
6
8
10
12
14
16
18
20
Year

Table 3. Ranking of the top articles for applied biostatisticians, 1985–2002.

Rank #	First author	Journal, Year	Joinpoint fit[a]	Yrs	RAF[b]	Estimated citations[c]		
						2008	Year 20 Total	AC20
1	Benjamini	*JRSS-B*, 1995	6.2; 7, 122.4; 10, 280.9	13	84	1249	2232	1875
2	Higgins	*Stat Med*, 2002	48.6	6	100	244	584	584
3	Liang	*Bmka*, 1986	7.3; 5, 29.9	22	72	538	508	366
4	D'Agostino	*Stat Med*, 1998	10.2; 6, 28.4	10	100	167	309	309
5	Kass	*JASA*, 1995	14.0; 11, 59.8	13	60	282	492	295
6	Guo	*Bmcs*, 1992	16.7	16	96	256	289	278
7	Spiegelhalter	*JRSS-B*, 2002	38.6	6	56	213	482	270
8	Storey	*JRSS-B*, 2002	31.2	6	72	174	393	267
9	Zeger	*Bmcs*, 1986	3.8; 4, 13.5	22	100	256	242	242
10	Harrell	*Stat Med*, 1996	13.0	12	100	162	214	214
11	Begg	*Bmcs*, 1994	3.6; 8, 20.6	14	96	149	210	202
12	Benjamini	*AnnS*, 2001	14.4; 3, 27.2	7	60	144	320	192
13	Fine	*JASA*, 1999	4.2; 4, 9.8; 7, 23.2	9	88	90	217	191
...	...	...	...	...	...	...	...	...

Nr 1

J. R. Statist. Soc. B (1995)
57, *No.* 1, *pp.* 289–300

Controlling the False Discovery Rate: a Practical and Powerful Approach to Multiple Testing

By YOAV BENJAMINI† and YOSEF HOCHBERG

Tel Aviv University, Israel

[Received January 1993. Revised March 1994]

	Declared non-significant	*Declared significant*	*Total*
True null hypotheses	**U**	**V**	m_0
Non-true null hypotheses	**T**	**S**	$m - m_0$
	$m - \mathbf{R}$	**R**	m

Bonferroni garanteerib (FWER): $P(V \geq 1) < \alpha$

Valeavastusmäär (FDR): $P(R>0)E(V/R|R>0) < \alpha$

3. FALSE DISCOVERY RATE CONTROLLING PROCEDURE

3.1. *The Procedure*

Consider testing $H_1, H_2, \ldots, H_m$ based on the corresponding p-values $P_1, P_2, \ldots, P_m$. Let $P_{(1)} \leqslant P_{(2)} \leqslant \ldots \leqslant P_{(m)}$ be the ordered p-values, and denote by $H_{(i)}$ the null hypothesis corresponding to $P_{(i)}$. Define the following Bonferroni-type multiple-testing procedure:

$$\text{let } k \text{ be the largest } i \text{ for which } P_{(i)} \leqslant \frac{i}{m} q^*;$$

$$\text{then reject all } H_{(i)}\ i = 1, 2, \ldots, k. \qquad (1)$$

P-väärtused:	0.001	0.028	0.029	0.041	0.342
(järjestatult)					
	0.05/testide arv				
Võrdlus:	0.01	0.02	0.03	0.04	0.05
FDR otsus:	H1	H1	H1	H0	H0
Bonferroni:	H1	H0	H0	H0	H0

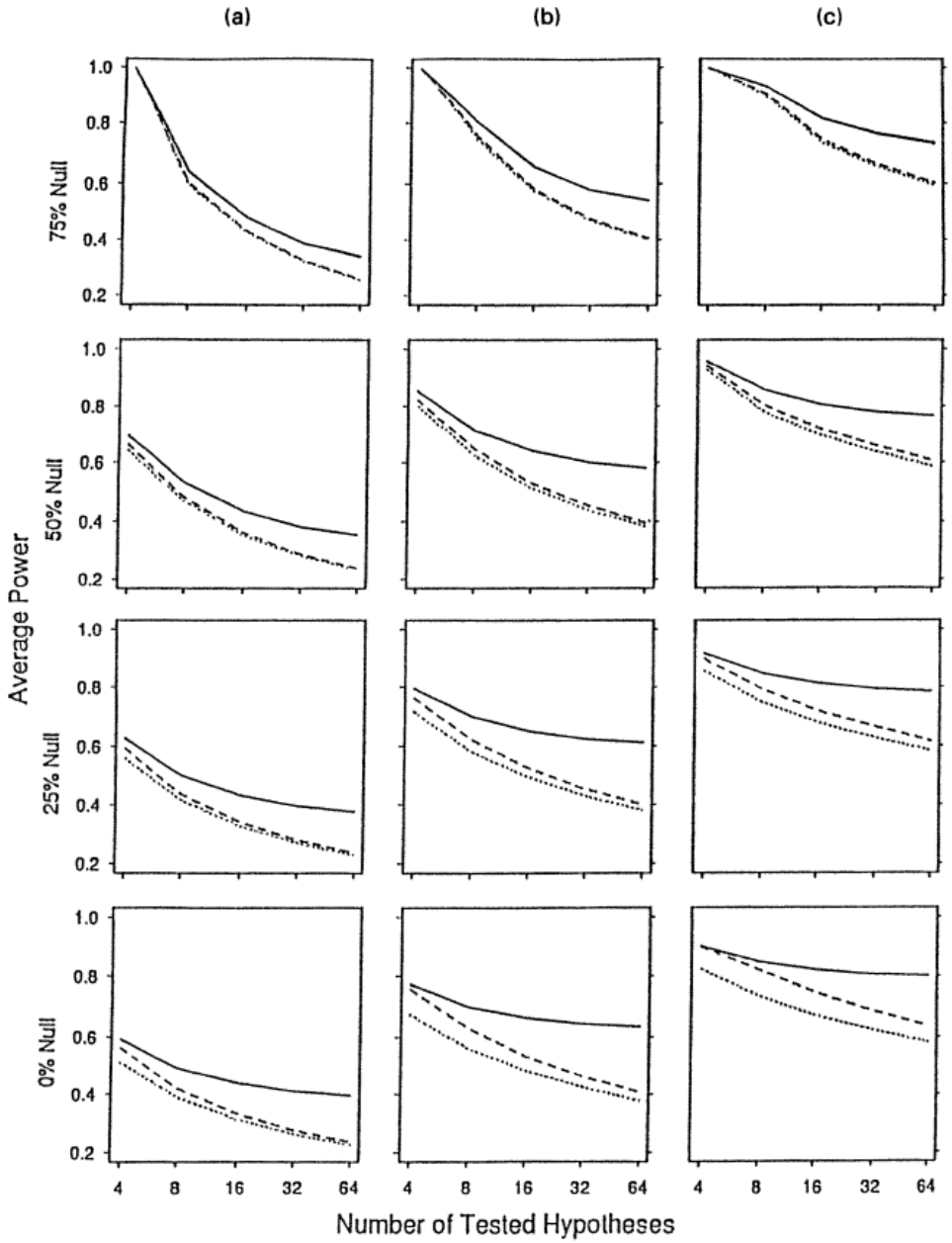


Fig. 1. Simulation-based estimates of the average power (the proportion of the false null hypotheses which are correctly rejected) for two FWER controlling methods, the Bonferroni (·····) and Hochberg's (1988) (-----) methods, and the FDR controlling procedure (———): (a) decreasing; (b) equally spread; (c) increasing

Nr. 12

The Annals of Statistics
2001, Vol. 29, No. 4, 1165–1188

THE CONTROL OF THE FALSE DISCOVERY RATE IN MULTIPLE TESTING UNDER DEPENDENCY

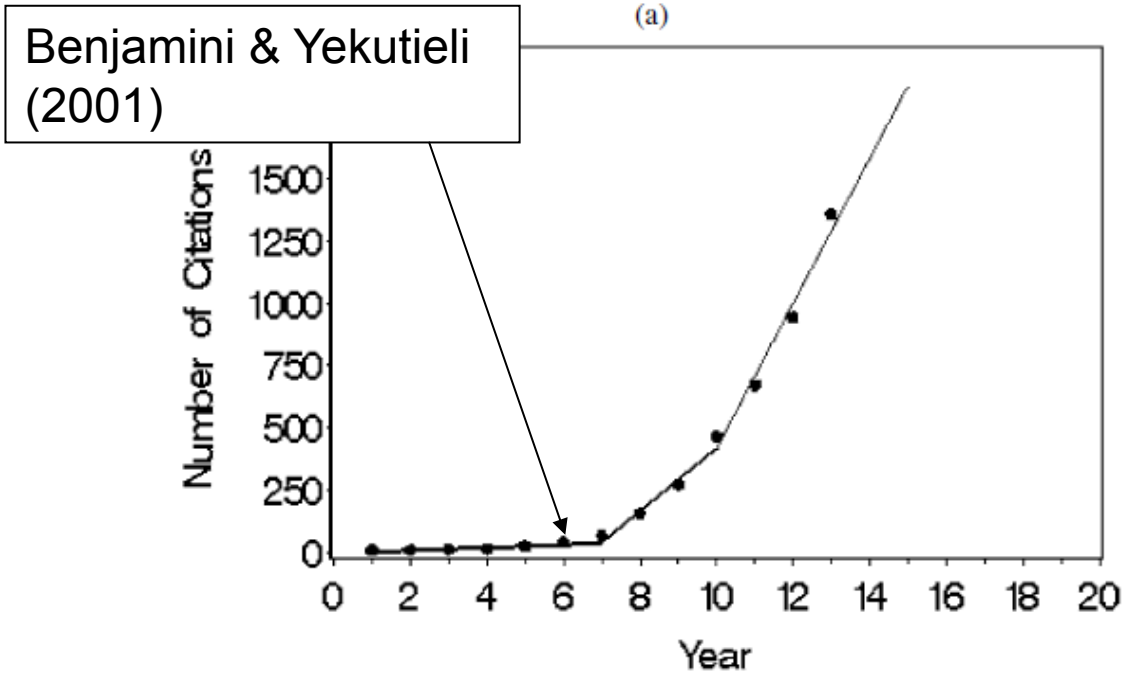
BY YOAV BENJAMINI[1] AND DANIEL YEKUTIELI[2]

Tel Aviv University

Benjamini and Hochberg suggest that the false discovery rate may be the appropriate error rate to control in many applied multiple testing problems. A simple procedure was given there as an FDR controlling procedure for independent test statistics and was shown to be much more powerful than comparable procedures which control the traditional familywise error rate. We prove that this same procedure also controls the false discovery rate when the test statistics have positive regression dependency on each of the test statistics corresponding to the true null hypotheses. This condition for positive dependency is general enough to cover many problems of practical interest, including the comparisons of many treatments with a single control, multivariate normal test statistics with positive correlation matrix and multivariate t. Furthermore, the test statistics may be discrete, and the tested hypotheses composite without posing special difficulties. For all other forms of dependency, a simple conservative modification of the procedure controls the false discovery rate. Thus the range of problems for which a procedure with proven FDR control can be offered is greatly increased.

Sõltuvad testid – ikka FDR sobib

Benjamini & Hochberg (1995) tsiteeringud



Nr 8, 31,8 tsiteeringut/aastas

J. R. Statist. Soc. B (2002)
64, *Part* 3, *pp.* 479–498

A direct approach to false discovery rates

John D. Storey

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[Received June 2001. Revised December 2001]

Storey põhipunktid

$$\mathrm{pFDR} = E\left(\frac{V}{R}\middle| R > 0\right).$$

Defineerib

q-väärtuse

Defineerib

q-väärtuse

Peab hindama kehtivate nullhüpoteeside osakaalu kõigi kontrollitavate hüpoteeside seas: töötab paremini siis, kui p-väärtuseid on palju ja kui nullhüpoteesi korral on p-väärtuste jaotuseks ikkagi ühtlane jaotus (ei sobi mitteparameetrilised testid? Väikesed kõrvalekalded eeldustest võivad meetodi untsu keerata?)

Näited R'is

```
> library(qvalue)
> p=c(0.001, 0.028, 0.029, 0.041, 0.8)
> qvalue(p=p)
$pi0
[1] 0.3923321
$qvalues
[1] 0.00196166 0.01896272 0.01896272
```

Storey pFDR

```
> library(mult
> mt.rawp2adjp(p
   "SidakSD", "B
```

Bonferron-Holm

(FDER alati)

4*0.028=0,112

B-H FDR

Positiivselt sõltuvatele testidele

```
      rawp Bonferroni  Holm Hochberg SidakSS SidakSD    BH    BY   ABH TSBH_0.05
[1,] 0.001      0.005 0.005    0.005   0.005   0.005 0.005 0.011 0.003     0.004
[2,] 0.028      0.140 0.112    0.082   0.132   0.107 0.048 0.110 0.029     0.039
[3,] 0.029      0.145 0.112    0.082   0.137   0.107 0.048 0.110 0.029     0.039
[4,] 0.041      0.205 0.112    0.082   0.189   0.107 0.051 0.117 0.031     0.041
[5,] 0.800      1.000 0.800    0.800   1.000   0.800 0.800 1.000 0.480     0.640
```

FWER erijuhtudel

B-H FDR

Suvaliselt sõltuvatele testidele

Nr. 2

STATISTICS IN MEDICINE
Statist. Med. 2002; **21**:1539–1558 (DOI: 10.1002/sim.1186)

Quantifying heterogeneity in a meta-analysis

Julian P. T. Higgins*,† and Simon G. Thompson

MRC Biostatistics Unit, Institute of Public Health, Robinson Way, Cambridge CB2 2SR, U.K.

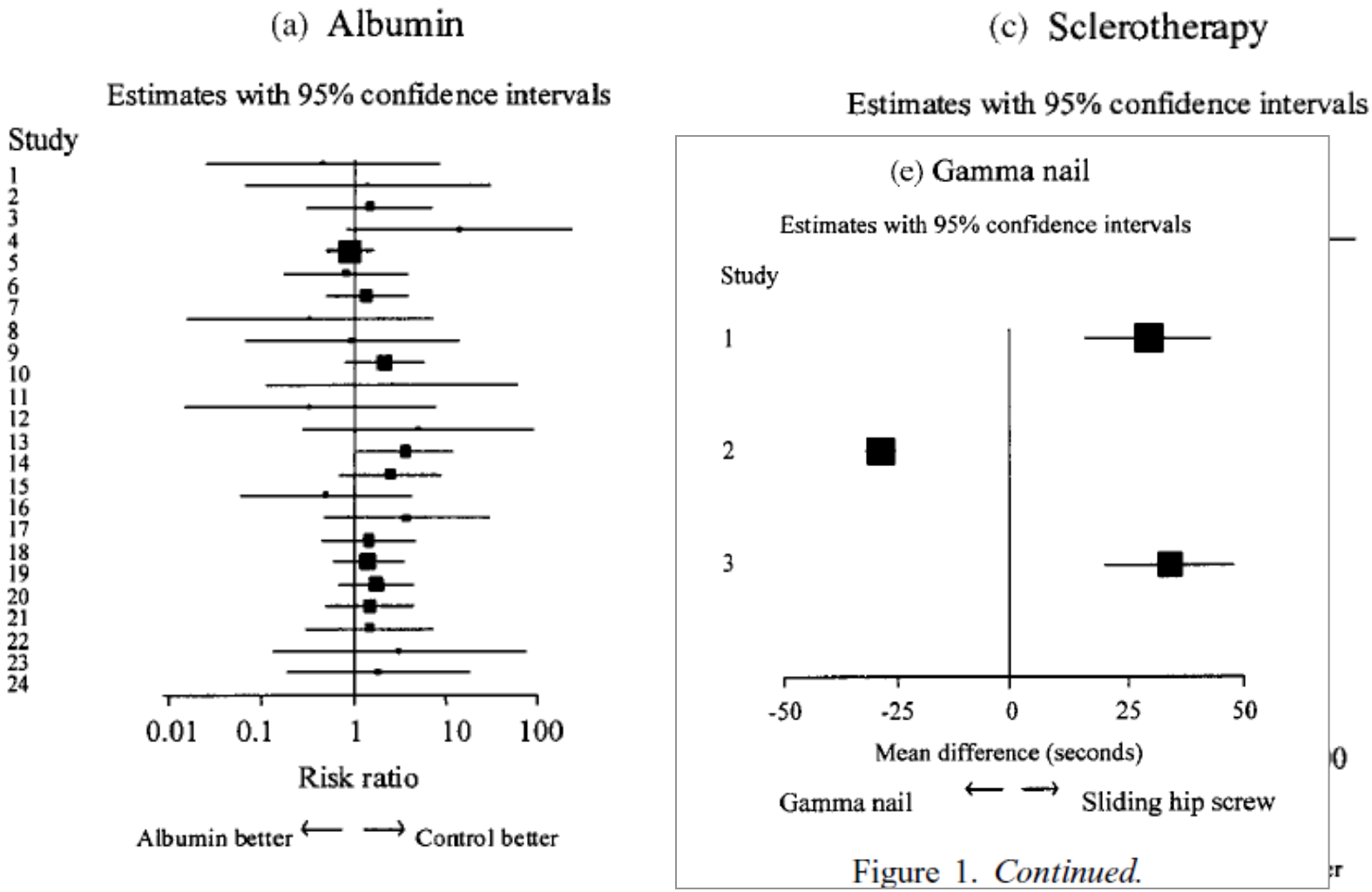


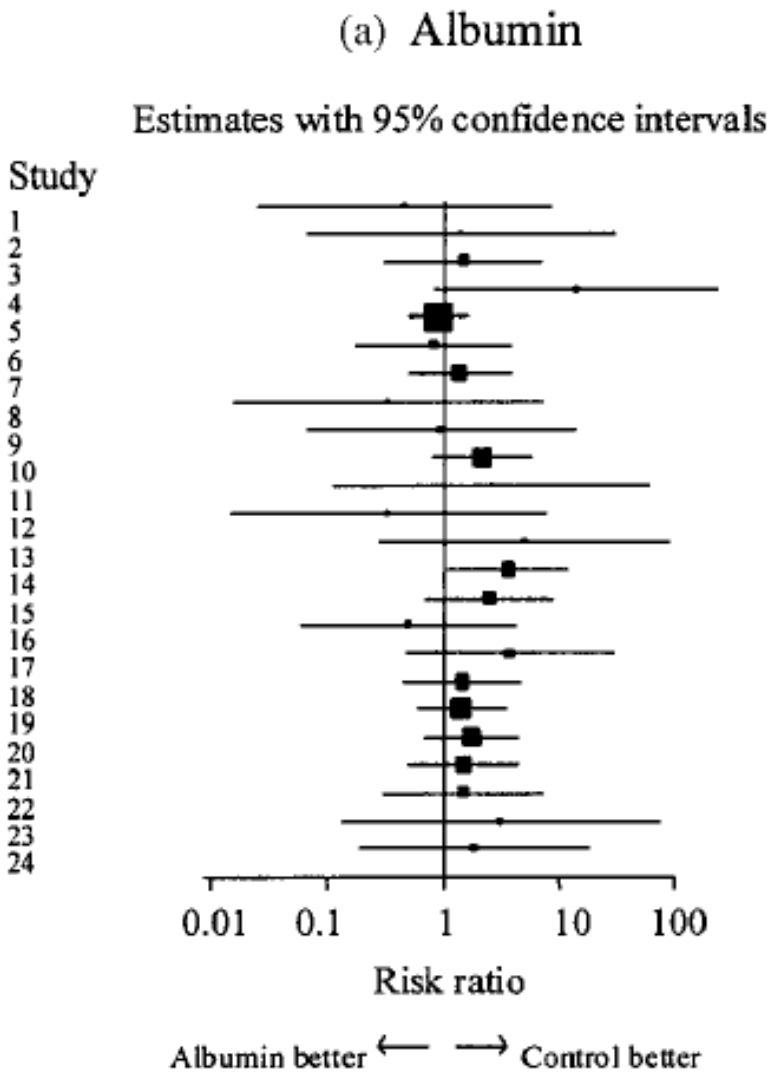
Figure 1. *Continued.*

Autorite soovitus

(Tegeliku) efektisuuruse dispersioon üle erinevate uuringupopulatsioonide

$$I^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \hat{\sigma}^2}$$

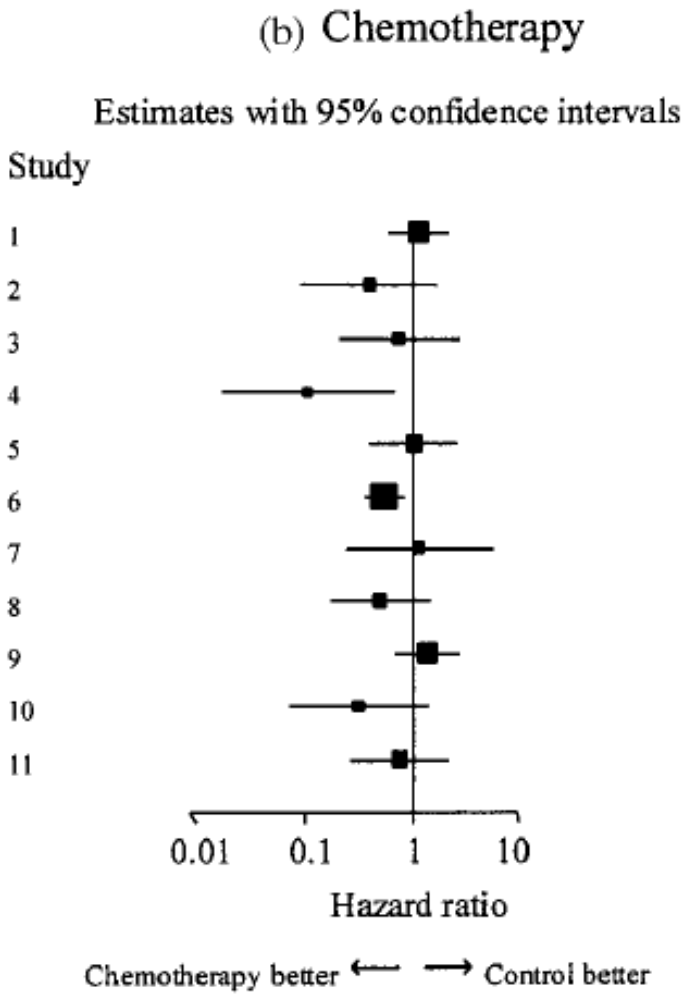
Üksikindiviidi (ravi)efekti dispersioon üle erinevate populatsioonide



$I^2 = 0$

Populatsioonides raviefekt ei erine

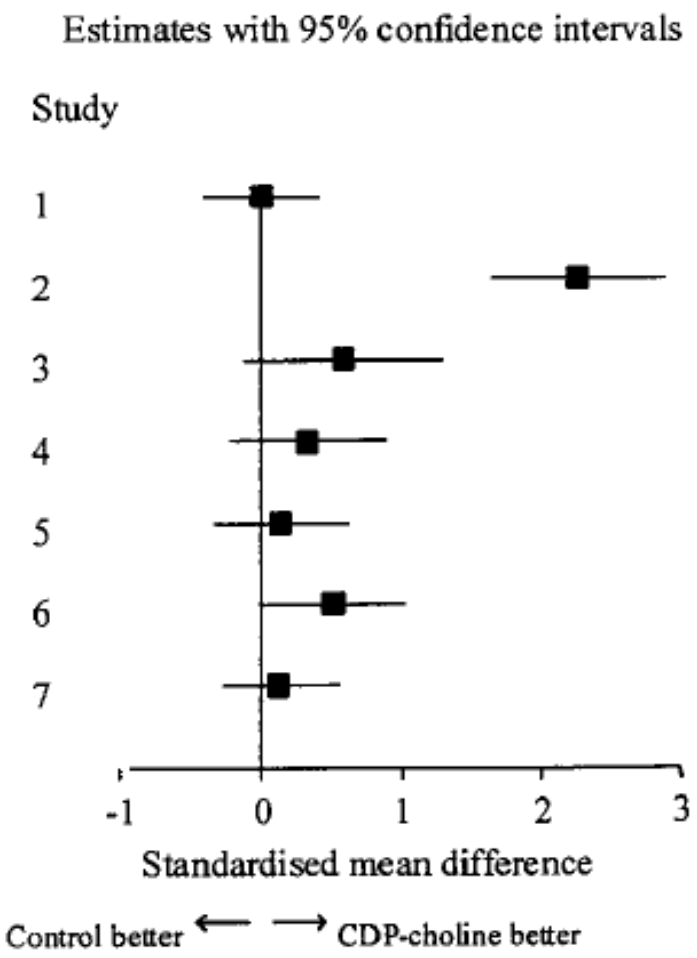
p=0,91



I^2 = 0,2

P-value: 0,17

(d) CDP-choline



I^2 = 0,86

Nr. 3

Biometrika (1986), **73**, 1, *pp.* 13–22
Printed in Great Britain

Longitudinal data analysis using generalized linear models

BY KUNG-YEE LIANG AND SCOTT L. ZEGER
Department of Biostatistics, Johns Hopkins University, Baltimore, Maryland 21205, U.S.A.

GEE

Nr. 9

BIOMETRICS 42, 121–130
March 1986

Longitudinal Data Analysis for Discrete and Continuous Outcomes

Scott L. Zeger and Kung-Yee Liang

Department of Biostatistics, Johns Hopkins University,
School of Hygiene and Public Health,
615 N. Wolfe Street, Baltimore, Maryland 21205, U.S.A.

Sõltuvad vaatlused

Y	X	
12,3	3	Inimene 1
12,7	3	
8,6	12,4	Inimene 2
8,9	12,3	
20,4	1,8	
…	….	…

Andmestik 2

Y
6,6
6,8
22,9
23,1
11,5
….

Andmestik 3

Y
17,7
17,9
9,7
9,1
14,7
….

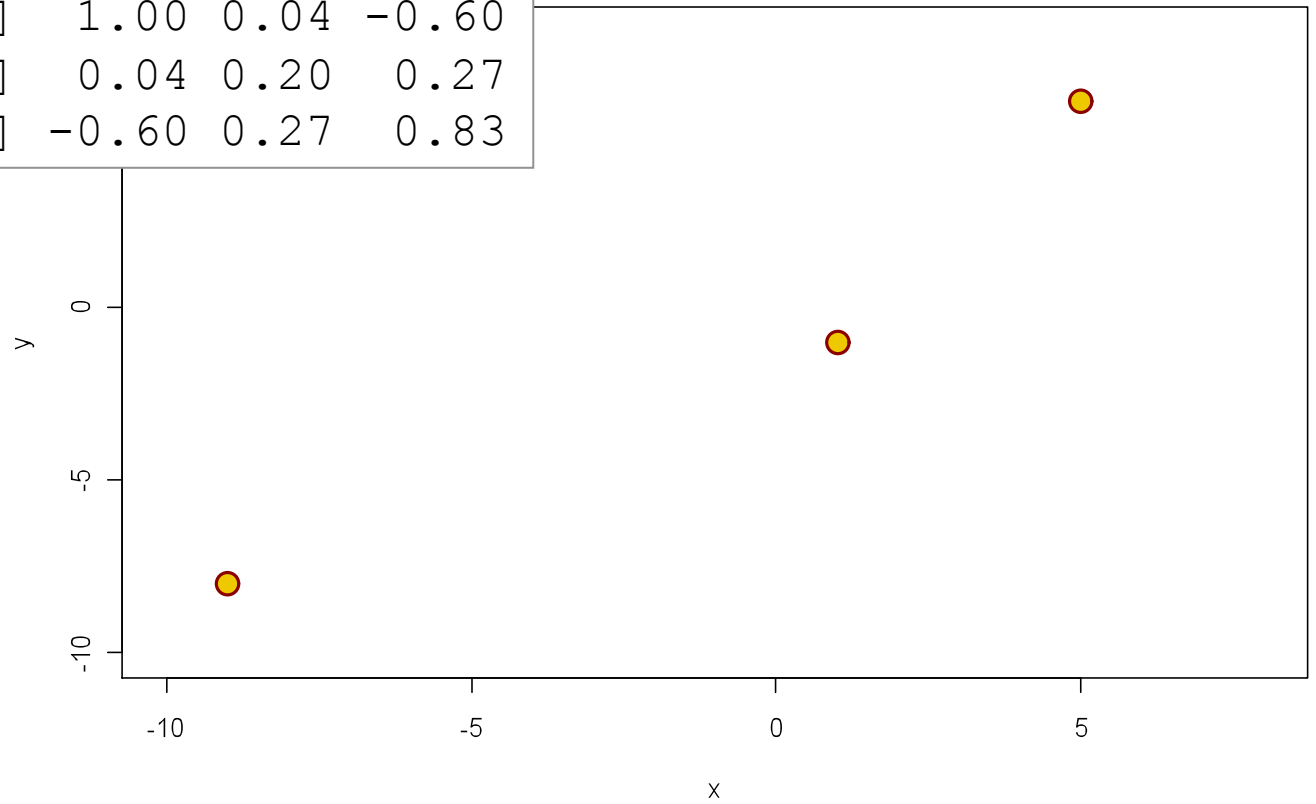
Hüpoteetiline olukord

	Obs 1	Obs 2
Andmestik 1	12,3	12,7
Andmestik 2	6,6	6,8
Andmestik 3	17,7	17,9
Andmestik 4	23,1	23,6
.....	....	....

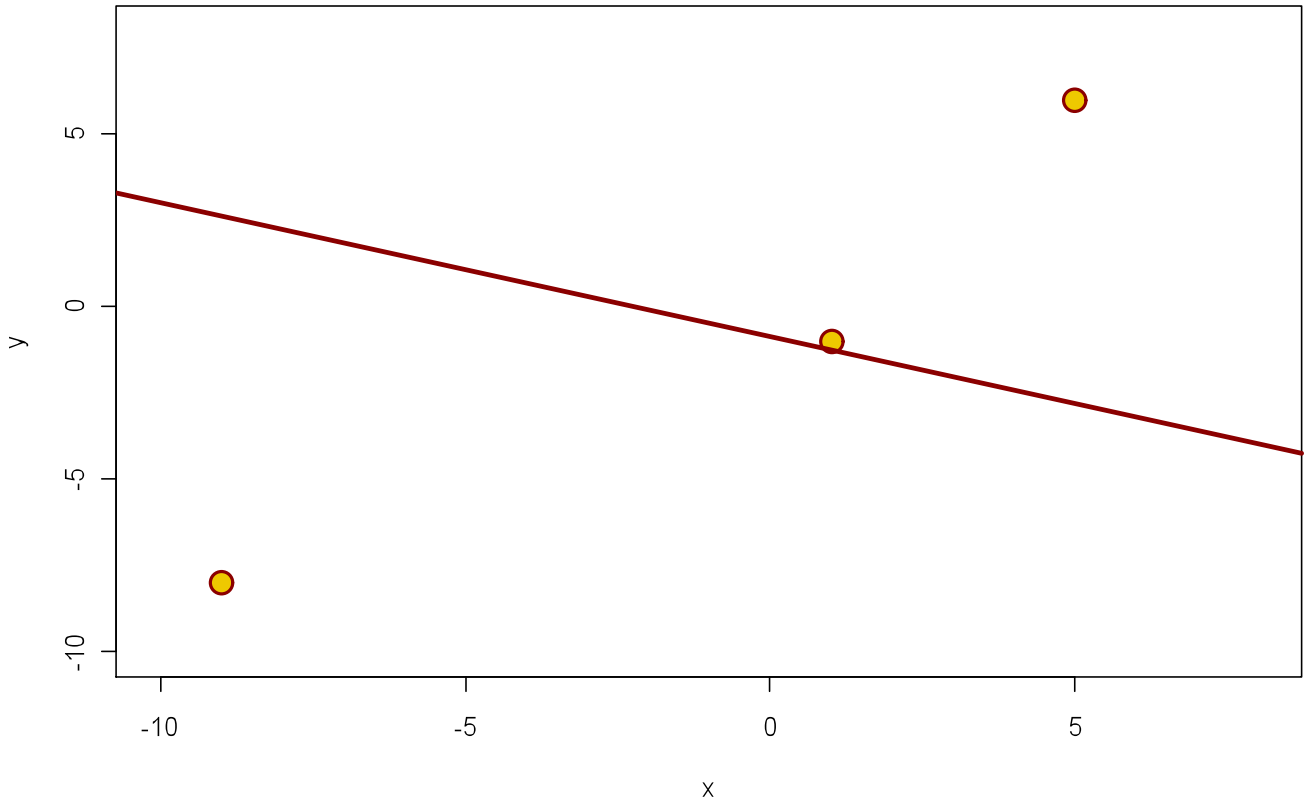
Kui cor(Obs1, Obs2)<>0, siis sõltuvad vaatlused.

Näide: lihtne regressioonanalüüs

```
> V
       [,1] [,2]  [,3]
[1,]   1.00 0.04 -0.60
[2,]   0.04 0.20  0.27
[3,] -0.60 0.27  0.83
```



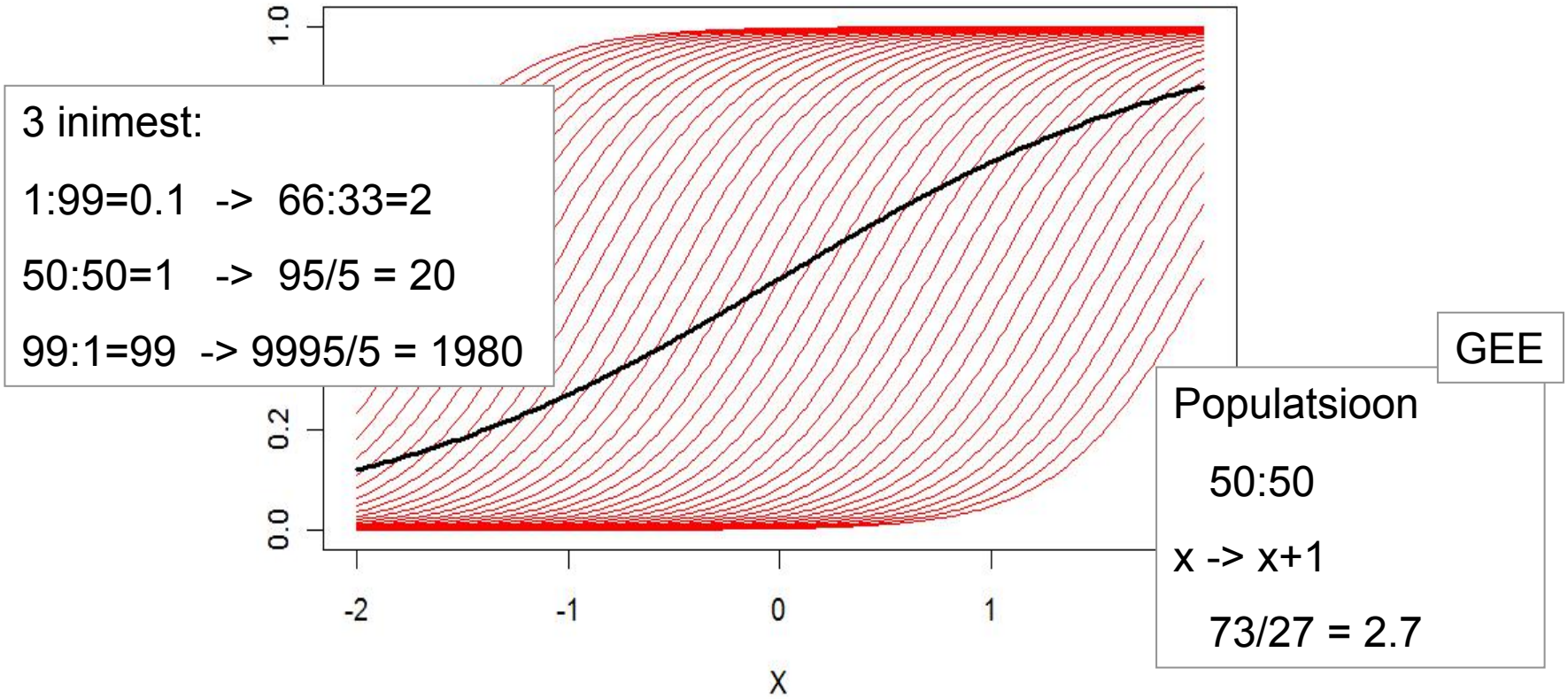
Näide: lihtne regressioonanalüüs



Seos geneetikaga

- Vaatlused on sõltuvad, kui tegemist on sugulastega (kaks venda on väga tugevalt sõltuvad, kaks eestlast üsna tugevalt sõltuvad, eestlane ja soomlane sõltuvad, eestlane ja maoori ehk pole sõltuvad...). Kui uuritav tunnus pole normaaljaotusega (binaarne, poissoni jaotusega vms), siis vajame antud artikli abi...

Marginaalne või tinglik mudel



Subject specific effects of X on Pr(Death), OR = 20 per 1 unit increase in X

Population average effect of X on Pr(Death), OR = 2.7 per 1 unit increase in X

	GLMM	GEE
Parameter	Estimate (s.e.)	Estimate (s.e.)
Intercept group A	−1.6308 (0.4356)	−0.7219 (0.1656)
Intercept group B	−1.7454 (0.4478)	−0.6493 (0.1671)
Slope group A	−0.4043 (0.0460)	−0.1409 (0.0277)
Slope group B	−0.5657 (0.0601)	−0.2548 (0.0380)

Nr. 4

STATISTICS IN MEDICINE
Statist. Med. **17**, 2265–2281 (1998)

TUTORIAL IN BIOSTATISTICS

PROPENSITY SCORE METHODS FOR BIAS REDUCTION IN THE COMPARISON OF A TREATMENT TO A NON-RANDOMIZED CONTROL GROUP

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Table IV. Comparison of covariates for subjects with and without epidural before and after propensity score stratification

	No epidural ($N = 775$) mean (sd)	Epidural ($N = 1003$) mean (sd)	F-statistics before stratification[†]	F-statistics after stratification[‡]
Pregnancy and labour characteristics				
Treated with active management of labour protocol	0·337 (0·47)	0·279 (0·45)	6·87**	0·20
Centimetres dilated at admission	3·95 (1·96)	2·79 (1·42)	208·01***	0·65
Artificially ruptured membranes (yes/no)	0·556 (0·50)	0·594 (0·49)	2·60	0·03
Gestational age (weeks)	39·9 (1·24)	40·2 (1·24)	22·28***	0·17
Infant birthweight (grams)	3374 (401)	3463 (416)	20·65***	0·20
Infant's gender (male = 1)	0·529 (0·50)	0·510 (0·50)	0·60	0·28
Initial rate of cervical dilation	58·3 (28·3)	42·9 (27·1)	135·20***	0·70
Maternal chronic hypertension	0·026 (0·16)	0·021 (0·14)	0·46	0·03
Maternal pregnancy induced hypertension (yes/no)	0·023 (0·15)	0·028 (0·16)	0·38	0·17
Maternal demographic/physical characteristics				
Maternal height (inches)	64·9 (2·8)	64·5 (2·6)	11·14**	0·10
Maternal pre-pregnant weight (pounds)	131·3 (21·6)	133·9 (22·9)	5·58*	0·07
Mother's age (years)	29·3 (5·1)	29·4 (5·3)	0·19	0·43
Insurance: private	0·857 (0·35)	0·882 (0·32)	2·55	2·75
public	0·101 (0·30)	0·084 (0·28)	1·51	0·54
Maternal race: white	0·677 (0·47)	0·735 (0·44)	7·01**	0·07
black	0·134 (0·34)	0·127 (0·33)	0·17	0·12
Hispanic	0·080 (0·27)	0·071 (0·26)	0·54	0·03

*$0{\cdot}05 > p > 0{\cdot}01$ **$0{\cdot}01 > p > 0{\cdot}001$ ***$0{\cdot}001 > p$

[†] F-statistic = square of two-sample t-statistic

[‡] F-statistic for main effect of epidural use after adjusting for propensity score quintile

Regressiooni kontekstis

$$\hat{\tau} = (\bar{Y}_t - \bar{Y}_c) - \beta(\bar{X}_t - \bar{X}_c)$$

Keisrilõike tõenäosus märkimisväärselt suurem epiduraalanalgeesiat saanud sünnitajate seas isegi siis, kui võtame arvesse sellesse gruppi kuuluvate sünnitajate kehvemat seisundit.

Näide 2: Perevägivald. Kas vägivallatseja arreteerimine aitab vältida järgmisi vägivallatsemisi?

Nr. 6.

BIOMETRICS 48, 361–372
June 1992

Performing the Exact Test of Hardy–Weinberg Proportion for Multiple Alleles

Sun Wei Guo[1,*] and Elizabeth A. Thompson[1,2]

[1] Department of Biostatistics, SC-32,
[2] Department of Statistics, GN-22,
University of Washington, Seattle, Washington 98195, U.S.A.

Nr. 7

J. R. Statist. Soc. B (2002)
64, *Part* 4, *pp.* 583–639

Bayesian measures of model complexity and fit

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Nicola G. Best,

Imperial College School of Medicine, London, UK

Bradley P. Carlin

University of Minnesota, Minneapolis, USA

and Angelika van der Linde

University of Bremen, Germany

Nr. 10

STATISTICS IN MEDICINE, VOL. 15, 361–387 (1996)

TUTORIAL IN BIOSTATISTICS

MULTIVARIABLE PROGNOSTIC MODELS: ISSUES IN DEVELOPING MODELS, EVALUATING ASSUMPTIONS AND ADEQUACY, AND MEASURING AND REDUCING ERRORS

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