Stat-JR Workflow & eBook Workshop 3rd September 2015 Bristol

1. Introduce eBook project

- 1. Introduce eBook project
- 2. Overview of Stat-JR software package:
 - past & current developments

- 1. Introduce eBook project
- 2. Overview of Stat-JR software package:
 - past & current developments
- 3. Bringing the two together: developing Stat-JR tools & content via the eBook project







Research objectives include:

 Developing tools to support interactive eBooks / workflows for statistical analyses



- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:



- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies



- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes



- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant

Project uses Stat-JR package...



- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant





• "Stat-juh"

- "Stat-juh"
- Jon Rasbash

- "Stat-juh"
- Jon Rasbash

- "Stat-juh"
- Jon Rasbash
- ESRC-funded



- "Stat-juh"
- Jon Rasbash
- ESRC-funded
- Developed by CMM members & other colleagues at...
 University of BRISTOL
 Southampto

E·S·R·C ECONOMIC * SOCIAL RESEARCH RESE

- "Stat-juh"
- Jon Rasbash
- ESRC-funded



- Developed by CMM members & other colleagues at...
 University of BRISTOL
 University of Southampton
- Current release version distributed with Bristol's MLwiN software package...

- "Stat-juh"
- Jon Rasbash
- ESRC-funded



- Developed by CMM members & other colleagues at...
 University of BRISTOL
 University of Southampton
- Current release version distributed with Bristol's MLwiN software package...
- ...which is free to UK academics, but other users need to pay.











Choice of interface

Three different ways to interact with Stat-JR:

1. Point-and-click menu-driven interface (TREE)

2. eBook interface (DEEP)

3. Command line interface (runStatJR)

Choice of interface

Three different ways to interact with Stat-JR:

Point-and-click menu-driven interface (TREE)

2. eBook interface (DEEP)

3. Command line interface (runStatJR)

• Response:

			l	
L			Ŀ	

• Explanatory variables:

school	
student	
normexam	
cons	
standirt	
girl	
schgend	
avsirt	
chav	
rband	



Ourrent input string: {}	
	Set

Command: RunStatJR(template='Regression1', dataset='tutorial', invars = {}, estoptions = {})

Ready (1s)

• Response:

	1
•	

Section 2018 Explanatory variables:

ashaal	
school	
student	
normexam	
cons	
standIrt	
girl	
schgend	
avsirt	
schav	
vrband	
Vibaliu	-
	-



Current input string: {}	
	Set

Command: RunStatJR(template='Regression1', dataset='tutorial', invars = {}, estoptions = {})

Change template

1-Level 2-Level 3-Level Alternative MCMC methods aML Averages Binomial CAR Categorical predictors Causal Censored Changepoint Cluster analysis Complementary log-log Complex level 1 ConvergingC Correlated classifications Correlation CustomC Data manipulation Diagnostics eStat Factor analysis GenStat_model gretl_model Informative priors Interactions JAGS Logit MATLAB_script MDS Measurement error Minitab_model Missing data MIXREGLS Mixture MLwiN:point & click MLwiN IGLS MLwiN MCMC MLwiN script Model Multiple imputation Multiple membership Multivariate response Negative binomial N-Level

Normal Octave_script OpenBUGS Ordered multinomial Orthogonal parameterisation PCA Plots Poisson Population ecology Predictions Probit PyScript Python PyMC Python script Quiz R:comments R_CARBayes R_glm R_INLA R_Ime4 R_MASS R_MCMCgImm R_MCMCpack R_mgcv R_RStan R_script R_scriptMCMC Random slopes Recapture Record linkage Reference category ROC SABRE SAS_model Saving and Loading Selection Simulation Spatial SPSS_model SPSS_script Standard deviation Stata_model Stata_script Summary stats SuperMix Survey T Unordered multinomial VPC WinBUGS [reset]

×

Current input string: {}

Ocmmand: RunStatJR(template='Regreence

1&2LevelMod 1LevelBlock	-	Name:
1LevelBlock 1LevelCatRef 1LevelComplex 1LevelFactorAnalysis 1LevelInteractions 1LevelMod 1LevelModAML 1LevelModCo	Ŧ	Description:
		Close Us

igs Debu

Change template

1-Level 2-Level 3-Level Alternative MCMC methods aML Averages Binomial CAR Categorical predictors Causal Censored Changepoint Cluster analysis Complementary log-log Complex level 1 ConvergingC Correlated classifications Correlation CustomC Data manipulation Diagnostics eStat Factor analysis GenStat_model gretl_model Informative priors Interactions JAGS Logit MATLAB_script MDS Measurement error Minitab_model Missing data MIXREGLS Mixture MLwiN:point & click MLwiN IGLS MLwiN MCMC MLwiN script Model Multiple imputation Multiple membership Multivariate response Negative binomial N-Level Normal Otave script OpenBUGS Ordered multinomial Orthogonal parameterisation PCA Plots Poisson Population ecology Predictions Probit PyScript Python PyMC Python script Quiz R:comments R_CARBages R_glm R INLA R_Ime4 R_MASS R_MCMCglmm R_MCMCpack R_mgcv R_RStan R_script R_scriptMCMC Random slopes Recapture Record linkage Reference category ROC SABRE SAS model Saving and Loading Selection Simulation Spatial SPSS model SPSS script Standard deviation Stata model Stata script Summary stats SuperMix Survey T Unordered multinomial VPC WinBUGS [reset]

Ocmmand: RunStatJR(template='Regre

Current input string: {}





×

Set

×

Change template

1-Level 2-Level 3-Level Alternative MCMC methods aML Averages Binomial CAR Categorical predictors Causal Censored Changepoint Cluster analysis Complementary log-log Complex level 1 ConvergingC Correlated classifications Correlation CustomC Data manipulation Diagnostics eStat Factor analysis GenStat_model gretl_model Informative priors Interactions JAGS Logit MATLAB_script MDS Measurement error Minitab_model Missing data MIXREGLS Mixture MLwiN:point & click MLwiN IGLS MLwiN MCMC MLwiN script Model Multiple imputation Multiple membership Multivariate response Negative binomial N-Level Normal Otave script OpenBUGS Ordered multinomial Orthogonal parameterisation PCA Plots Poisson Population ecology Predictions Probit PyScript Python PyMC Python script Quiz R:comments R_CARBages R_glm R INLA R_Ime4 R_MASS R_MCMCglmm R_MCMCpack R_mgcv R_RStan R_script R_scriptMCMC Random slopes Recapture Record linkage Reference category ROC SABRE SAS model Saving and Loading Selection Simulation Spatial SPSS model SPSS script Standard deviation Stata model Stata script Summary stats SuperMix v T Unordered multinomial VPC WinBUGS [reset]

Ocmmand: RunStatJR(template='Regre

Current input string: {}



Set

× Change template 1-Level 2-Level 3-Level Alternative MCMC methods aML Averages Binomial CAR Categorical predictors Causal Censored Changepoint Cluster analysis Complementary log-log Complex level 1 ConvergingC Correlated classifications Correlation CustomC Data manipulation Diagnostics eStat Factor analysis GenStat_model gretl_model Informative priors Interactions JAGS Logit MATLAB_script MDS Measurement error Minitab_model Missing data MIXREGLS Mixture MLwiN:point & click MLwiN IGLS MLwiN MCMC MLwiN script Model Multiple imputation Multiple membership Multivariate response Negative binomial N-Level Normal Otave script OpenBUGS Ordered multinomial Orthogonal parameterisation PCA Plots Poisson Population ecology Predictions Probit PyScript Python PyMC Python script Quiz R:comments R_CARBases R_gim PINLA R_Ime4 R_MASS R_MCMCgImm R_MCMCpack R_mgcv R_RStan R_script R_scriptMCMC Random slopes Recapture Record linkage Reference category ROC SABRE SAS model Current input string: {} Saving and Loading Selection Simulation Spatial SPSS model SPSS script Standard deviation Stata_model Stata_script Summary stats SuperMix Y T Unordered multinomial VPC WinBUCS [reset] Regression2 Name: Regression2 Ocmmand: RunStatJR(template='Regre Description: Fits 1 level Normal multiple regression models in several packages. Close

-

× Change template 1-Level 2-Level 3-Level Alternative MCMC methods aML Averages Binomial CAR Categorical predictors Causal Censored Changepoint Cluster analysis Complementary log-log Complex level 1 ConvergingC Correlated classifications Correlation CustomC Data manipulation Diagnostics eStat Factor analysis GenStat_model gretl_model Informative priors Interactions JAGS Logit MATLAB_script MDS Measurement error Minitab_model Missing data MIXREGLS Mixture MLwiN:point & click MLwiN IGLS MLwiN MCMC MLwiN script Model Multiple imputation Multiple membership Multivariate response Negative binomial N-Level Normal Otave script OpenBUGS Ordered multinomial Orthogonal parameterisation PCA Plots Poisson Population ecology Predictions Probit PyScript Python PyMC Python script Quiz R:comments R_CARBases R_gim PINLA R_Ime4 R_MASS R_MCMCgImm R_MCMCpack R_mgcv R_RStan R_script R_scriptMCMC Random slopes Recapture Record linkage Reference category ROC SABRE SAS model Current input string: {} Saving and Loading Selection Simulation Spatial SPSS model SPSS script Standard deviation Stata_model Stata_script Summary stats SuperMix v T Unordered multinomial VPC WinBUCS [reset] Regression2 Name: Regression2 Ocmmand: RunStatJR(template='Regre Description: Fits 1 level Normal multiple regression models in several packages. Close

Set


*Untitled1 [DataSet0] - PASW Statistics Data Editor



sform	<u>A</u> nalyze <u>G</u> raphs	Utilities Add-g	ons <u>Wi</u> ndow	Help							
	Reports	•	#	5				ABC			
	D <u>e</u> scriptive Stati:	stics 🕨 🕨									
	Ta <u>b</u> les	•	1	1	1		1	1	Visible	e:4 of4 Variak	bles
Subje	Compare Means	•	var	var	var	var	var	var	var	var	
	<u>G</u> eneral Linear N	1odel 🕨 🕨									
	Generali <u>z</u> ed Line	ar Models 🛛 🕨									
	Mi <u>x</u> ed Models	•	🗽 Linear								
	<u>C</u> orrelate	•									
	<u>R</u> egression	•									
	Loglinear	•									
	Classi <u>f</u> y	•									
	Dimension Reduc	ction 🕨									
	Sc <u>a</u> le	•									
	<u>N</u> onparametric T	ests 🕨									
	Forecasting	•									
	<u>S</u> urvival	•									
	Multiple Respons										
	🚮 Missing Value Ai										
	Multiple Imputatio	n 🕨									
	Complex Sample	s 🕨									
	Quality Control	•									
	🛜 ROC Cur <u>v</u> e										
	7.00 2.00	23.30									
, 	.00 2.00	23.30								•	▼

							PASW Statistic	s Processor is	ready		
	Terrer		T		1						

Data View

Linear...

1

Variable View





🔢 *Untitled1 [DataSet0] - PASW Statistics Data Editor



Data View

🛃 start

Linear...

⊻i	jew <u>D</u> ata	<u>T</u> ra	insform	<u>A</u> nalyz	ze <u>G</u> ra	aphs	<u>U</u> tilities	Add- <u>o</u> r	ıs <u>W</u> in	dow	<u>H</u> elp											
ľ		ÚQ,			Reports			•	tt.	* ,					<u>А</u>	Ø		ABG				
				C	Descriptiv	∕e Statis	stics	•		,			• •	,			_			ailala: d	of 4 Variat	
					[ables			•											VI	SIDIE: 4	or 4 variar	Jies
_	Measure_		Subje	c	Co <u>m</u> pare l	Means			var		var		var	va	r	var		var	var		var	
	26.			9	<u>3</u> eneral L	inear M	lodel	•														
	25.			G	Generali <u>z</u>	ed Line	ar Models	•														
	34.			N	/li <u>x</u> ed Mo	dels		•	🛄 Line	ar												
	69.	00		S	<u>C</u> orrelate			•														
	62.	00		Ē	Regressio	n		•														
	45.	00		L	.oglinear			•														
	36.	00		c	Classi <u>f</u> y			•														
	51.	00		Ū	Dimensior	n Reduc	ction	•														
	53.	00		s	Sc <u>a</u> le			•														
	54.	00		N	Jonparam	netric To	ests	•														
	2.	00		F	orecastir	ng		•														
	34.	00			Survival			•														
	36.	00			- Aultiple Re	espons	e	•														
	4.	00					nal <u>y</u> sis															
	24.	00			/ultiple Im			•														
	86.	00			Complex S																	
	12.	00			Quality Co		-															
	24.	00			ROC Cur <u>v</u>																	
	23.	00		1.00	(00 04) <u>v</u>	1.00		0.40														
	12.	00		7.00		2.00	2	3.30														
=	4																					
	Variable View	,																				
J																				- [[-		
					1				T e				I. co		I	_		ocessor is				
t	Pr-	actica	al 1.docx ·	- Mic		E-book	.mk2		0	Micro	soft Offic	9 P	🛛 🎯 In	box - Mozil	la Thund		*Untit	led1 [Data:	5et0	EN	16:	52

*Untitled1 [DataSet0] - PASW Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Add-ons Window Help





• Response:

l	•	

Section 2017 Explanatory variables:

school	
student	
normexam	
ons	
tandirt	
jirl	
chgend	
vslrt	
chav	
rband	
	_





Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {}, estoptions = {})

Debug-





Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {}, estoptions = {})

•

• Response:

normexam

• Explanatory variables:

A.k.a. X, Predictor variables, Independent variables, etc.	^
Note: if you wish to include an intercept then you need to add it (e.g. a constant of ones) as one of the explanatory variables.	
Once you've selected a variable, you have the opportunity to indicate whether it's categorical or not, if categorical, dummy variables will be added to the model on your behalf.	Ŧ
	*
	Ŧ





Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {}, estoptions = {})

Ready (1s)

• Response:

normexam remove

Sexplanatory variables:

cons,standIrt remove

Choose estimation engine:

eStat	
WinBUGS	
OpenBUGS	
MLwiN_MCMC	
MLwin_IGLS	
R_MCMCgImm	
R_glm	
Stata_model	
Python_PyMC	

Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {})

Ŧ

B Response:

normexam remove

Sexplanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm

Next

Ourrent input string: {'y': 'normexam', 'x': 'cons,standlrt'}	
	Set

Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {})

• Response:

normexam remove

B Explanatory variables:

cons,standlrt remove

Choose estimation engine:

R_glm





Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {})

@ Response:

normexam remove

Second Explanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm remove

Run

Ourrent input string: {'y': 'normexam', 'x': 'cons,standIrt', 'Engine': 'R_glm'}	
	Set

• Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {'Engine': 'R_glm'})

Edit

datafile.dta 🔽 Popout

datafil	le.dta		0
	normexam	cons	standIrt
1	0.261324	1	0.619059 🔺
2	0.134067	1	0.205802
3	-1.72388	1	-1.36458



O Response:

normexam remove

Second Explanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm remove

Run





@ Response:

normexam remove

Second Explanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm remove

Run

Ourrent input string: {'y': 'normexam', 'x': 'cons,standIrt', 'Engine': 'R_glm'}	
	Set

Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {'Engine': 'R_gIm'})

Edit datafile.dta Popout

datafil	e.dta		0
	normexam	CO.	standIrt
1	0.261324	1	0.619059 🔺
2	0.134067	1	0.205802
3	-1.72388	1	-1.36458

Debug 🗸

Edit



	normexam	cons	standIrt
1	0.261324	1	0.619059
2	0.134067	1	0.205802
3	-1.72388	1	-1.36458
4	0.967586	1	0.205802
5	0.544341	1	0.371105
б	1.7349	1	2.18944
7	1.03961	1	-1.11662
8	-0.129085	1	-1.03397
9	-0.939378	1	-0.538061
10	-1.21949	1	-1.44723
11	2.40869	1	2.43739
12	0.610729	1	2.10679
13	-1.83669	1	0.040499
14	-0.129085	1	1.19762
15	2.20312	1	2.52004
16	1.24053	1	1.11497
17	1.7349	1	1.03232
18	1.31014	1	0.784362
19	-0.623051	1	-1.11662
20	1.03961	1	-1.19927
21	-1.02907	1	-0.372758
22	-1.21949	1	-1.36458
23	0.328072	1	-0.951318
24	-0.492781	1	-2.35639
25	1.90034	1	-0.0421524

	Edit	datafile.dta 💌	Popout			
ſ		datafile.dta				
	datafi	equation.tex script.R			•	
		normexa	m	cons	standIrt	
	1		0.261324	1	0.619059 🔺	
	2		0.134067	1	0.205802	
	3		-1.72388	1	-1.36458	
	4		0.967586	1	0.205802	
	5		0.544341	1	0.371105	
	б		1.7349	1	2.18944	
	7		1.03961	1	-1.11662	
	8		-0.129085	1	-1.03397	
	9		-0.939378	1	-0.538061	
	10		-1.21949	1	-1.44723	
	11		2.40869	1	2.43739	
	12		0.610729	1	2.10679	
	13		-1.83669	1	0.040499	
	14		-0.129085	1	1.19762	
	15		2.20312	1	2.52004	
	16		1.24053	1	1.11497	
	17		1.7349	1	1.03232	
	18		1.31014	1	0.784362	
	19		-0.623051	1	-1.11662	
	20		1.03961	1	-1.19927	
	21		-1.02907	1	-0.372758	
	22		-1.21949	1	-1.36458	
	23		0.328072	1	-0.951318	
	24		-0.492781	1	-2.35639	
	25		1.90034	1	-0.0421524	

Ready (1s)

	Edit	datafile.dta 💌	Popout			
\bigcap	_	datafile.dta equation.tex				_
	datafi	script.R			•	
		normexa	im	cons	standIrt	
	1		0.261324	1	0.619059 🔺	
	2		0.134067	1	0.205802	
	3		-1.72388	1	-1.36458	
	4		0.967586	1	0.205802	
	5		0.544341	1	0.371105	
	б		1.7349	1	2.18944	
	7		1.03961	1	-1.11662	
	8		-0.129085	1	-1.03397	
	9		-0.939378	1	-0.538061	
	10		-1.21949	1	-1.44723	
	11		2.40869	1	2.43739	
	12		0.610729	1	2.10679	
	13		-1.83669	1	0.040499	
	14		-0.129085	1	1.19762	
	15		2.20312	1	2.52004	
	16		1.24053	1	1.11497	
	17		1.7349	1	1.03232	
	18		1.31014	1	0.784362	
	19		-0.623051	1	-1.11662	
	20		1.03961	1	-1.19927	
	21		-1.02907	1	-0.372758	
	22		-1.21949	1	-1.36458	
	23		0.328072	1	-0.951318	
	24		-0.492781	1	-2.35639	
	25		1.90034	1	-0.0421524	









#fit the model using
 myModel <- glm(formula,
#print summary of the</pre>

Scripts Macros



Scripts Macros Equations









• Response:

normexam remove

Sexplanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm remove

Run

Current input string: {'y': 'normexam', 'x': 'cons,standlrt', 'Engine': 'R_glm'}
 Set
 Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standlrt'},

estoptions = {'Engine': 'R_glm'})





• Response:

normexam remove

Sexplanatory variables:

cons,standIrt remove

Choose estimation engine:

R_glm remove



Ourrent input string: {'y': 'normexam', 'x': 'cons,standlrt', 'Engine': 'R_glm'}

Set

• Command: RunStatJR(template='Regression2', dataset='tutorial', invars = {'y': 'normexam', 'x': 'cons,standIrt'}, estoptions = {'Engine': 'R_glm'})







datafi	le.dta			
	normexam	cons	standIrt	
1	0.261324	1	0.619059	
2	0.134067	1	0.205802 -	
3	-1.72388	1	-1.36458	

datafile dta

Popout









datafi	le.dta			
	normexam	cons	standIrt	
1	0.261324	1	0.619059	
2	0.134067	1	0.205802 -	
3	-1.72388	1	-1.36458	

datafile dta

Popout



datafile.dta				
	normexam	cons	standlrt	
1	0.261324	1	0.619059	
2	0.134067	1	0.205802 -	
3	-1.72388	1	-1.36458	

-

datafile.dta

Popout



datafil	e.dta		C
	normexam	60	standlrt
1	0.261324	1	0.619059
2	0.134067	1	0.205802
3	-1.72388	1	-1.36458



Ready (3s)

Debug 🗸

datafile.dta

• Popout

	normexam	cons	standIrt
1	0.261324	1	0.619059
2	0.134067	1	0.205802
3	-1.72388	1	-1.36458
4	0.967586	1	0.205802
5	0.544341	1	0.371105
б	1.7349	1	2.18944
7	1.03961	1	-1.11662
8	-0.129085	1	-1.03397
9	-0.939378	1	-0.538061
10	-1.21949	1	-1.44723
11	2.40869	1	2.43739
12	0.610729	1	2.10679
13	-1.83669	1	0.040499
14	-0.129085	1	1.19762
15	2.20312	1	2.52004
16	1.24053	1	1.11497
17	1.7349	1	1.03232
18	1.31014	1	0.784362
19	-0.623051	1	-1.11662
20	1.03961	1	-1.19927
21	-1.02907	1	-0.372758
22	-1.21949	1	-1.36458
23	0.328072	1	-0.951318
24	-0.492781	1	-2.35639
25	1.90034	1	-0.0421524

Start again Dataset - tutorial Template -



Ready (3s)

Debug-

datafile.dta Ŧ Popout datafile.dta equation.tex 6 script.R output.log standIrt exam cons estimates.dta 0.261324 0.619059 1 ggNorm.svg residuals.dta 0.134067 1 0.205802 ResivsFitted.svg -1.723881 -1.36458stats.dta 0.967586 1 0.205802 ModelResults 1 0.371105 0.544341 ModelParameters ModelFit 2.18944 1.7349 1 7 1.03961 1 -1.116628 -0.1290851 -1.033979 -0.939378 1 -0.538061 -1.219491 -1.4472310 2.40869 1 2.43739 11 12 0.610729 1 2.10679 -1.836691 0.040499 13 14 -0.1290851 1.19762 15 2.20312 1 2.52004 1 16 1.24053 1.11497 17 1.7349 1 1.03232 18 1.31014 1 0.784362 -1.11662 1 19 -0.623051 1.03961 1 -1.1992720 1 21 -1.02907-0.37275822 -1.219491 -1.36458 1 23 0.328072 -0.951318-0.492781 -2.35639 24 1 1 25 1.90034 -0.0421524

tutorial



Ready (3s)

Settings

Debug 🗸

datafile.dta	Popout		
datafile.dta equation.tex			
script.R			
output.log	exam	cons	standIrt
estimates.dta	0.261324	1	0.619059
qqNorm.svg residuals.dta	0.134067	1	0.205802
ResivsFitted.svg	-1.72388	1	-1.36458
stats.dta ModelResults	0.967586	1	0.205802
ModelParameters	0.544341	1	0.371105
ModelFit	1.7349	1	2.18944
7	1.03961	1	-1.11662
8	-0.129085	1	-1.03397
9	-0.939378	1	-0.538061
10	-1.21949	1	-1.44723
11	2.40869	1	2.43739
12	0.610729	1	2.10679
13	-1.83669	1	0.040499
14	-0.129085	1	1.19762
15	2.20312	1	2.52004
16	1.24053	1	1.11497
17	1.7349	1	1.03232
18	1.31014	1	0.784362
19	-0.623051	1	-1.11662
20	1.03961	1	-1.19927
21	-1.02907	1	-0.372758
22	-1.21949	1	-1.36458
23	0.328072	1	-0.951318
24	-0.492781	1	-2.35639
25	1.90034	1	-0.0421524


















Stat-JR:TREE

tutorial



Ready (3s)

Settings Debug 🗸

datafile.dta	Popout				
datafile.dta					
equation.tex					
script.R					
output.log	exam	cons	standIrt		
estimates.dta gqNorm.svg	0.2613	24 1	0.619059		
esiduals.dta	0.1340	57 1	0.205802		
ResivsFitted.sv	g -1.723	38 1	-1.36458		
stats.dta	0.9675	36 1	0.205802		
/lodelResults					
/lodelParamet/ /lodelFit	ers 0.3443				
7	1.039				
8	-0.1290				
9	-0.9393	78 1	1 -0.5380		
10	-1.219	19 1	-1.44723		
11	2.408	59 1	2.43739		
12	0.6107	29 1	2.10679		
13	-1.836	59 1	0.040499		
14	-0.1290	35 1	1.19762		
15	2.203	12 1	2.52004		
16	1.240	53 1	1.11497		
17	1.73	19 1	1.03232		
18	1.310	4 1	0.784362		
19	-0.6230	51 1	-1.11662		
20	1.039	51 1	-1.19927		
21	-1.029	07 1	-0.372758		
22	-1.219	1 0	-1.36458		
23	0.3280	72 1	-0.951318		
24	-0.4927				
25	1.900				

Stat-JR:TREE

Ŧ

tutorial Template -

Ready (3s)

Debug 🗸

```
output.log
```

Popout

```
R version 3.0.1 (2013-05-16) -- "Good Sport"
Copyright (C) 2013 The R Foundation for Statistical Computing
Platform: x86 64-w64-mingw32/x64 (64-bit)
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.
 Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
>
> local({r <- getOption("repos"); r["CRAN"] <- "http://cran.r-project.org"; options(repos = r)})</pre>
> # Note that when Stat-JR interoperates with R, it sets the working
> # directory to wherever the user's temporary files are stored, i.e.
> # workdir = tempdir(). The data to be modelled, this script, and the
> # files exported from R, are all saved there.
>
> # test to see if foreign package is already installed, if not, then install it
> if (!require(foreign)) {
+ install.packages("foreign")
```

Stat-JR:TREE

Ŧ

tutorial Template -



Settings

output.log

Popout

```
R version 3.0.1 (2013-05-16) -- "Good Sport"
Copyright (C) 2013 The R Foundation for Statistical Computing
Platform: x86 64-w64-mingw32/x64 (64-bit)
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.
 Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
>
> local({r <- getOption("repos"); r["CRAN"] <- "http://cran.r-project.org"; options(repos = r)})</pre>
> # Note that when Stat-JR interoperates with R, it sets the working
> # directory to wherever the user's temporary files are stored, i.e.
> # workdir = tempdir(). The data to be modelled,
                                                     ipt, and the
> # files exported from R, are all saved there
                                                      # # # # # # #
>
> # test to see if foreign package is already installed, if not, then install it
> if (!require(foreign)) {
+ install.packages("foreign")
```



Ready (3s)

```
>
> # Below we specify the model formula, formatted as y \sim x1 + x2 + ...
> # Since Stat-JR assumes users have included the intercept in their list
> # of explanatory variables, -1 removes the intercept which the glm
> # function otherwise adds by default.
>
> formula <- normexam ~ cons + standlrt - 1
> # fit the model using the glm function, specifying the formula, data, and distribution (with iden
tity link) in its arguments
> myModel <- glm(formula, data = mydata, family = gaussian(identity))</pre>
> # print summary of the model fit
> summary(myModel)
Call:
glm(formula = formula, family = gaussian(identity), data = mydata)
Deviance Residuals:
    Min
              10 Median
                               3Q
                                       Max
-2.65615 -0.51848 0.01264 0.54399 2.97399
Coefficients:
        Estimate Std. Error t value Pr(>|t|)
        -0.001191 0.012642 -0.094
                                  0.925
cons
standlrt 0.595057 0.012730 46.744 <2e-16 ***
_ _ _
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for gaussian family taken to be 0.6487385)
   Null deviance: 4049.4 on 4059 degrees of freedom
Residual deviance: 2631.9 on 4057 degrees of freedom
AIC: 9766.5
Number of Fisher Scoring iterations: 2
```



Ready (3s)

```
>
> # Below we specify the model formula, formatted as y \sim x1 + x2 + ...
> # Since Stat-JR assumes users have included the intercept in their list
> # of explanatory variables, -1 removes the intercept which the glm
> # function otherwise adds by default.
>
> formula <- normexam ~ cons + standlrt - 1
> # fit the model using the glm function, specifying the formula, data, and distribution (with iden
tity link) in its arguments
> myModel <- glm(formula, data = mydata, family = gaussian(identity))</pre>
> # print summary of the model fit
> summary(myModel)
Call:
glm(formula = formula, family = gaussian(identity), data = mydata)
Deviance Residuals:
    Min
              10
                  Median
                               ЗQ
                                       Max
-2.65615 -0.51848 0.01264 0.54399 2.97399
Coefficients:
        Estimate Std. Error t value Pr(>|t|)
        -0.001191 0.012642 -0.094
                                  0.925
cons
standlrt 0.595057 0.012730 46.744 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for gaussian family taken to
                                                 6487385)
   Null deviance: 4049.4 on 4059 degrees of fr
Residual deviance: 2631.9 on 4057 degrees of freedom
AIC: 9766.5
Number of Fisher Scoring iterations: 2
```

Stat-JR:TR	EE Start again	Dataset - tutorial	Template -	Regression2	Ready (3s)	Settings	Debug
						Set	
	Command: RunSta estoptions = {'Engine ModelResults		ion2', dataset='tuto	orial', invars = {'y': 'nor	mexam', 'x': 'cons,star	ndirť'},	
	Results Parameters:						
	parame	ter	est		se		
	co	cons -0.0011911191497		0.0126422981796			
	stand	lirt 0.59	5056780156		0.0127300927553		
	Model:						
		Statistic		Value			
		deviance	•	2631.93206193			
		nulldeviance	•	4049.43302581			
		aid	•	9766.50937651			
		convergeo	1	1			
		ite	r	2			



Choice of interface

Three different ways to interact with Stat-JR:



2. eBook interface (DEEP)

3. Command line interface (runStatJR)

Choice of interface

Three different ways to interact with Stat-JR:

1. Point-and-click menu-driven interface (TREE)



3. Command line interface (runStatJR)

Stat-JR's eBook interface: **DEEP**

Documents with

Embedded

Execution and

Provenance



Multilevel modelling with the 'tutorial' dataset

Finished

- Previous **1** 2 3 4 5 Next → Go to page

[₽]Overview

Exploring the tutorial dataset

Summary table of tutorial dataset

Plotting variables

Densityplot

-XY plot

^LYour choice of plot

Cross-tabulation

PModelling the dataset

Hodelling one or two

Comparing a 1-level
 and 2-level model

Partitioning variance in a 2-level model References

Exploring explanatory variables

> -Summary table of tutorial dataset

中Choosing your

This eBook provides a brief introduction to multilevel modelling using the tutorial dataset.

We are developing eBooks as a means of exploring data and learning about statistics. They're an interactive environment, and dynamic content will appear tailored to choices you make as you read through.

You progress through the pages either by navigating via the page number blocks at the top and bottom of the page, or via the hierarchical table of contents on the left (this automatically updates as new content becomes available as a result of your choices).

EBook functionality is still being developed, so you may notice the odd thing here or there yet to be finessed (such as the large number of decimal places sometimes returned!), but we nevertheless wanted to introduce you to what we hope you find to be an interesting means of exploring statistics, and we would very much appreciate any comments you have.

Note that there may be a short delay until all available contents on a particular page are uploaded - you can keep an eye on progress either via the gauge in the top-left corner of the browser window, or by looking at the command window running in the background.

NB: if your eBook crashes, then you can reload the eBook by choosing Debug > Reload eBook from the black bar towards the top of this window. That will wipe you're previous choices, I'm afraid, but it will (hopefully) breathe life back into the software!

The tutorial dataset

Overview

The tutorial dataset is one of the example datasets provided with the Stat-JR package (as well as with the software package MLwiN) and is summarised below. This dataset was selected from a much larger dataset of examination results from six inner London Education Authorities (school boards). A key aim of the original analysis was to establish whether some secondary schools were more 'effective' than others in promoting students' learning and development, taking account of variations in the characteristics of students when they started secondary school. The analysis then looked for factors associated with any school differences found. Thus the focus was on an analysis of examination performance after adjusting for student intake achievements.

Exploring the tutorial dataset

We'll be modelling **normexam** as the response (or y) variable: as the summary below indicates, this represents the students' exam score at age 16, normalised to have an approximately standard Normal distribution.

In fact you can view the full dataset via the Resources button, which you can find in the black har at the top of this window. In the resulting

0:5-

14:47

13/06/2012










































Finished

–	
∲-Overviev	N
E-Thot	utorial dataset
	utonai uataset

Exploring the tutorial dataset

> -Summary table of tutorial dataset

Plotting variables

Densityplot

-XY plot

└Your choice of plot

Cross-tabulation

Modelling the dataset

 Modelling one or two levels?

> E-Comparing a 1-level and 2-level model

> > Choosing your explanatory variables

> > > 1-level model

-2-level model

-Partitioning variance in a 2-level model

← Previous	1	2	3	4	5	Next →	Go to page
------------	---	---	---	---	---	--------	------------

Modelling the dataset

Modelling one or two levels?

If a dataset has a hierarchical or clustered structure, such as students nested within schools, and an analysis neglects to model that structure appropriately, it can compromise the conclusions drawn from it in very important ways. Whilst there are a variety of ways to analyse such a structure, multilevel modelling is an efficient and informative way to do so (e.g. see: Goldstein, 2011; Steele, 2008).

In some situations, however, a given hierarchy may be irrelevant; in a hypothetical example, if we had 4059 dogs nested within 65 towns of habitation, then (for argument's sake) it is perhaps unlikely that the inferences we draw from a model exploring the association between 'speed' and 'breed' would change if we took account of the town in which the dog lived.

In other situations such a structure may matter much more, though: e.g. the exam performance of a pupil may, on average, be more likely to be similar to the exam performance of another pupil in the same school than the exam performance of another pupil in a different school, conceivably due to differences between schools in their pupil selection procedures, socioeconomic status of the catchment area, teaching methods and personnel, and so on. So here we may be missing a very important piece of information, violating the model's assumptions, if we simply ignore the fact that some of the pupils in our sample go to the same school, whereas others do not.

Comparing a 1-level and 2-level model

So, if we want to investigate, for instance, the association between exam scores at age 16 (normexam, in this example) and those gained earlier at age 11 (standirt), how can we tell whether it's important for an analysis to take into account a multilevel structure of students nested within schools?

Well, one way we can investigate that is by fitting a single-level (or 1-level) model, ignoring the fact that pupils went to certain schools, and then compare the results of that analysis to a 2-level model which allows for random effects for both students and schools.

We'll use Stat-JR's in-house estimation engine, eSTAT, to fit both models, eSTAT uses MCMC estimation, and so, for each, we'll run 1 chain for a burn-in of 1,000 and then 2,000 main iterations (otherwise, we'll choose 1 as the value of the random seed, and of the thinning factor too).

Below you can choose the explanatory variables you'd like to include in the two models (normexam has been pre-selected as the response variable); to vary only the random effects structure between the two models, choose the same explanatory variables for each. For example, if you chose cons and standIrt for each model, this would fit the model(s) we referred to just above.

> 15:05 13/06/2012



Finished

<u>н</u> .	
[†] Overview	
	t

Exploring the tutorial dataset

> -Summary table of tutorial dataset

Plotting variables

Densityplot

-XY plot

└Your choice of plot

Cross-tabulation

Modelling the dataset

 Modelling one or two levels?

> E-Comparing a 1-level and 2-level model

> > Choosing your explanatory variables

> > > 1-level model

-2-level model

-Partitioning variance in a 2-level model

Previous 5 Next ---Go to page 2 3

Modelling the dataset

Modelling one or two levels?

If a dataset has a hierarchical or clustered structure, such as students nested within schools, and an analysis neglects to model that structure appropriately, it can compromise the conclusions drawn from it in very important ways. Whilst there are a variety of ways to analyse such a structure, multilevel modelling is an efficient and informative way to do so (e.g. see: Goldstein, 2011; Steele, 2008).

In some situations, however, a given hierarchy may be irrelevant; in a hypothetical example, if we had 4059 dogs nested within 65 towns of habitation, then (for argument's sake) it is perhaps unlikely that the inferences we draw from a model exploring the association between 'speed' and 'breed' would change if we took account of the town in which the dog lived.

In other situations such a structure may matter much more, though: e.g. the exam performance of a pupil may, on average, be more likely to be similar to the exam performance of another pupil in the same school than the exam performance of another pupil in a different school, conceivably due to differences between schools in their pupil selection procedures, socioeconomic status of the catchment area, teaching methods and personnel, and so on. So here we may be missing a very important piece of information, violating the model's assumptions, if we simply ignore the fact that some of the pupils in our sample go to the same school, whereas others do not.

Comparing a 1-level and 2-level model

So, if we want to investigate, for instance, the association between exam scores at age 16 (normexam, in this example) and those gained earlier at age 11 (standirt), how can we tell whether it's important for an analysis to take into account a multilevel structure of students nested within schools?

Well, one way we can investigate that is by fitting a single-level (or 1-level) model, ignoring the fact that pupils went to certain schools, and then compare the results of that analysis to a 2-level model which allows for random effects for both students and schools.

We'll use Stat-JR's in-house estimation engine, eSTAT, to fit both models, eSTAT uses MCMC estimation, and so, for each, we'll run 1 chain for a burn-in of 1,000 and then 2,000 mai otherwise, we'll choose 1 as the value of the random seed, and of the thinning factor too).

Below you can choose the explanatory variable include in the two models (normexam has been pre-selected as the response variable); to vary only the random effects structure between the two models, choose the same explanatory variables for each. For example, if you chose cons and standirt for each model, this would fit the model(s) we referred to just above.

> 15:05 13/06/2012















```
\begin{split} \operatorname{normexam}_{i} &\sim \operatorname{N}(\mu_{i}, \sigma^{2}) \\ \mu_{i} &= \beta_{0} \operatorname{cons}_{i} + \beta_{1} \operatorname{standlrt}_{i} + u_{\operatorname{school}[i]} \\ u_{\operatorname{school}[i]} &\sim \operatorname{N}(0, \sigma_{u}^{2}) \\ \beta_{0} &\propto 1 \\ \beta_{1} &\propto 1 \\ \tau &\sim \Gamma(0.001, 0.001) \\ \sigma^{2} &= 1/\tau \\ \tau_{u} &\sim \Gamma(0.001, 0.001) \\ \sigma_{u}^{2} &= 1/\tau_{u} \end{split}
```

about

Û

. 🖬 🍈

17:47

15/06/2012

Deviance statistic and DIC diagnostic

Results

Summary table of tutorial dataset

E-Comparing a 1-level and

explanatory variables

-1-level model

2-level model

2-level Model

中Modelling the dataset

levels?

中Modelling one or two

2-level model

₱Equations

₽Results

中Choosing your





- 0

13:31 07/01/2013

23

Multilevel modelling with the 'tutorial' dataset

Finished

eBookDemo

		Res
中Overview	Â	Dev
de-The tutorial dataset		Belo
		deci
Summary table of		S0, a
tutorial dataset	Ξ	Sta
∲-Plotting variables		50
Densityplot		\bar{D}
-XY plot		D
^L Your choice of plot		D(
Cross-tabulation		pL
↓ ₽ Modelling the dataset		
Hodelling one or two		DI
中Comparing a 1-level and 2-level model		
-Choosing your		
explanatory		Sun
variables		Thes
-1-level model		
		(NB)

2-level model

₽-Results

Deviance statistic and DIC diagnostic

₽-Summary of

\leftarrow Previous	1	2	3	4	5	Next \rightarrow		Go to page	
-----------------------	---	---	---	---	---	--------------------	--	------------	--

Results

Deviance statistic and DIC diagnostic

+

Below you'll see the DIC diagnostic, along with the parameters from which it is derived, for both models (with apologies for the number of decimal places!)

So, according to the DIC, which model appears to be better?

	deviance across all (post-burnin) iterations. e at the expected value of the unknown parameters ($ heta$).	9763.49 9760.51	9209.21
$D(ar{ heta})$ Deviand	e at the expected value of the unknown parameters ($ heta$).	9760.51	
			9148.95
pD The effe	tive number of parameters, computed as $ar{D}$ - $D(ar{ heta})$.	2.98	60.25
DIC i.e. it is a	e Information Criterion (Spiegelhalter et al, 2002); this is computed as $D(\bar{\theta}) + 2pD$: measure of goodness of model fit which adjusts for model complexity, allowing o be compared: a smaller DIC suggests a better model .	9766.47	9269.46

Summary of parameter estimates: tables

These tables contain the parameter estimates, providing, for each, values for the following:

(NB: for this, and all other models fitted in this eBook, you can view other outputs, such as MCMC diagnostic plots, via the **Resources** button in the black bar at the top).

- Mean: posterior mean estimate;
- SD: posterior standard deviation;
- ESS: effective sample size.

1-LEVEL MODEL



A

Finished				<u> </u>					
	← Previou	us 1 2	3 4	5 Next →		Go to page			
	Results								
∲-Overview	Deviance s	statistic and DI	C diagnostic						
	Below you'll	see the DIC diag	gnostic, along v	with the parame	eters from	which it is deri	ived, for both models (with	apologies for th	ne number of
È Exploring the tutorial dataset	decimal plac	ces!)							
Summary table of	So, accordin	ng to the DIC, whi	ich model appe	ears to be bette	r?				
tutorial dataset	Statistic	Description						1-level model	2-level model
Protting variables	_								
Densityplot	Đ	Average devian	ice across all (post-burnin) ite	rations.			9763.49	9209.21
Your choice of plot	$D(\bar{\theta})$	Deviance at the	e expected valu	e of the unknow	vn parame	eters ($ heta$).		9760.51	9148.95
Cross-tabulation	pD	The effective nu	umber of paran	neters, compute	ed as $ar{D}$ -	$D(\bar{\theta}).$		2.98	60.25
₽ Modelling the dataset		Deviance Inforr	mation Criterio	n (Spiegelhalte	r et al, 200)2); this is com	puted as $D(ar{ heta})+2pD$:		
中Modelling one or two levels?	DIC	i.e. it is a meas models to be c	sure of goodne: compared: a sn	ss of model fit v naller DIC sugg	vhich adju ests a be	sts for model (tter model.	complexity, allowing	9766.47	9269.46
Comparing a 1-level									
∲-Choosing your									
explanatory	Summary	of parameter e	estimates: tal	oles					
variables	These table	es contain the par	rameter estima	tes, providing, f	for each, v	alues for the fo	llowing:		
2-level model		s, and all other m e black bar at the		this eBook, you	u can viev	v other outputs	, such as M CMC diagnos	tic plots, via the	Resources
Results		osterior mean es							
Deviance statistic	 SD: post 	terior standard d	eviation;						
diagnostic	 ESS: effective 	fective sample siz	ze.						
₽ Summary of +	1-LEVEL MO	ODEL							
	N. P.			۷ 🚺		C:\		- Pr (13:31 07/01/2013



- 0

X



[⊕]Overview

EStat E-Book reader Save Upload Export - 22

Multilevel modelling with the 'tutorial' dataset

Finished

dataset

DExploring the tutorial

Summary table of

tutorial dataset

P-Plotting variables

-Densityplot

Cross-tabulation

-Your choice of plot

-XY plot

Modelling the dataset

levels?

Modelling one or two

Comparing a 1-level and 2-level model

> Choosing your explanatory

> > 1-level model 2-level model

and DIC diagnostic

variables

₽-Results

eBookDemo

← Previous 3 5 Next → Go to page

Partitioning variance in a 2-level model

+

For some multilevel models, such as the 2-level random intercept model you fitted here, it is guite straightforward to calculate how much of the unexplained variance is attributable to each level, a parameter which may be of interest to the researcher.

So, let's pluck a few statistics out of the results tables which appear above, and see how we would do this.

In the 2-level model, the parameter σ^2 (i.e. 'sigma2', as it appears in the results table of parameter estimates) is the variance attributable to differences between pupils within a school, whereas σ_u^2 ('sigma2_u') is the variance attributable to differences between schools.

Therefore, to calculate what proportion of residual variance is attributed to level 2 (known as the Variance Partition Coefficient: in this instance, the residual variance attributable to differences between schools), we simply divide σ_u^2 by the total variance, i.e.:

 $\sigma_u^2/(\sigma_u^2 + \sigma^2) =$ Variance Partition Coefficient (VPC)

Here, then, for our 2-level model we have (with rounding):

0.097 / (0.097 + 0.567) = 0.146

So, the proportion of the unexplained variance attributable to differences between schools in the 2-level model you specified is 0.146.

You may find it interesting to see how these parameter estimates change if you run the 2-level model with different explanatory variables.

For example, if you keep only cons in, and therefore fit what some call a variance components model what does the total variance add up to? (Approximately!) Why might that be?

If you add a range of different explanatory variables (in addition to cons), how does the proportion of variance attributable to level 2 change? Does the addition of school-level, or pupil-level, explanatory variables have any bearing on this?

References

Goldstein, H. (2011) Multilevel Statistical Models. 4th Edition. Chichester, UK: Wiley.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A. (2002) Bayesian measures of model complexity and fit. Journal of the Royal Statistical Society, Series B, 64, 583-639.

Steele, F. (2008) Module 5: Introduction to Multilevel Modelling Concepts. LEMMA VLE, University of Bristol, Centre for Multilevel Modelling. Accessed at www.bristol.ac.uk/cmm/learning/course.html.

Go to page

Previous 5 Next →



13:31 07/01/2013 EStat E-Book reader Upload Save Export

← Previous

13:31 07/01/2013

x

Multilevel modelling with the 'tutorial' dataset

Next →

Finished

eBookDemo



Partitioning variance in a 2-level model

+

For some multilevel models, such as the 2-level random intercept model you fitted here, it is quite straightforward to valculate how much of the unexplained variance is attributable to each level, a parameter which may be of interest to the researcher.

Go to page

So, let's pluck a few statistics out of the results tables which appear above, and see how we would do this.

In the 2-level model, the parameter σ^2 (i.e. 'sigma2', as it appears in the results table of parameter estimates) is the variance attributable to **differences between pupils** within a school, whereas σ^2_u ('sigma2_u') is the variance attributable to **differences** between schools

Therefore, to calculate what proportion of residual variance is attributed to level 2 (known as the Variance Partition Coefficient: in this instance, the residual variance attributable to differences between schools), we simply divide σ_u^2 by the total variance, i.e.:

 $\sigma_u^2/(\sigma_u^2 + \sigma^2) =$ Variance Partition Coefficient (VPC)

Here, then, for our 2-level model we have (with rounding):

0.097 / (0.097 + 0.567) = 0.146.

So, the proportion of the unexplained variance attributable to differences between schools in the 2-level model you specified is 0.146.

You may find it interesting to see how these parameter estimates change if you run the 2-level model with different explanatory variables.

For example, if you keep only cons in, and therefore fit what some call a variance components model what does the total variance and up to? (Approximately!) Why might that be?

If you add a range of different explanatory variables (in addition to **cons**), how does the proportion of variance attributable to revel 2 change? Does the addition of school-level, or pupil-level, explanatory variables have any bearing on this?

References

Goldstein, H. (2011) Multilevel Statistical Models. 4th Edition. Chichester, UK: Wiley.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A. (2002) Bayesian measures of model complexity and fit. Journal of the Royal Statistical Society, Series B, 64, 583-639.

Steele, F. (2008) Module 5: Introduction to Multilevel Modelling Concepts. LEMMA VLE, University of Bristol, Centre for Multilevel Modelling. Accessed at www.bristol.ac.uk/cmm/learning/course.html.

Go to page

← Previous 1 2 3 4 5 Next →













-2

0

normexam

And now looking at the R script, you can see that groups is now listed as an argument in the densityplot function to indicate that we're

grouping the data by a particular variable (the one you chose!) - you can see that the title (and the position) of the legend has also been

-4

2

0:**%**____

4

template PlotsViaR

∲-Overview

Purpose of the template -Authors of template

-Authors of documentation

Date of documentation

Examples

library(foreign)
<pre>mydata<-read.dta("datafile.dta") summary(mydata)</pre>
PACKages<-as.character(data.frame(installed.packages())\$Package) test<-("lattice" %in% PACKages)
<pre>if (!test) { install.packages("lattice",repos="http://cran.r-project.org")</pre>
} library(lattice)
<pre>png("Plot1.png",width=733,height=550) densityplot(~normexam,groups=gir1,auto.key=list(space='right',title="girl"),data=mydata) dev.off()</pre>

specified via auto.key (which you could naturally change by directly editing the script and re-running in R).

R script

13:51 31/08/2012

about





Further developments to Stat-JR as part of current grant

1. Point-and-click menu-driven interface (TREE)

2. eBook interface (DEEP)

3. Command line interface (runStatJR)

Further developments to Stat-JR as part of current grant

- 1. Point-and-click menu-driven interface (TREE)
- 2. eBook interface (DEEP)
- **3. Command line** interface (runStatJR)

4. Workflow system



Blockly

- About
- Installation
- Custom Blocks
- Hacking

Support 🗹

View On GitHub

Blockly is a library for building visual programming editors. Try it:





Blockly

- About
- Installation
- Custom Blocks
- Hacking
 - Support 🛽

Our workflow system is written using **Blockly**... ...a visual block programming editor developed by Google (similar to Scratch)

View On GitHub

Blockly is a library for building visual programming editors. Try it:

Logic Loops Math Text if 256 Count 🔹 > • Lists set Count T to 0 do Colour Game Over >> print Variables Functions

Upload Dataset -

Run





Dump









Selected

block: 186












Selected Control block: 290 Logic Math Lists Text Hypothesis Data Preparation times repeat 🕻 Data Exploration do Models Post-process Input Output Variables Procedures Other Dummy







Selected Control block: 290 Logic Math Lists Text Hypothesis Data Preparation times repeat Data Exploration Models Post-process 5 " Input do Output Variables Procedures Other Dummy



Selected Control block: 290 Logic Math Lists Text Hypothesis Data Preparation times repeat Data Exploration Models Post-process 5 Input do Output Variables Procedures Other Dummy



Selected Control block: 290 Logic Math Lists Text Hypothesis Data Preparation repeat 📘 5 times Data Exploration Models Post-process Input do Output Variables Procedures Other Dummy

Stat-JR:WF Clear Examples Upload Dataset -Debug Dump Save Run Selected Control set run_predictor_summaryYN 🔻 to Ask yes/no Do you want to examine plots & surr block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 ftrue 🔻 Math Lists do if continuous_predictorsYN 🔹 💷 ftrue 🔻 Text for each item 🚺 in list 🔋 continuous predictors list 🔻 do Hypothesis Data Preparation do #1 univariate - continuous - summary with: Data Exploration í 🔻 var Models Post-process if categorical predictorsYN 🔹 💷 (true 🔻 Input Output do for each item 🚺 in list 🔋 categorical_predictors_list 🔻 Variables do #2 univariate - categorical - summary with: Procedures ÎΤ var Other Dummy Ask yes/no (Do you want to examine plots & set run_y_conditional_summaryYN 🔹 to 🔯 if

run_y_conditional_summaryYN 🕤 😑 🔹

continuous_predictorsYN *

for each item 🚺 in list 🔋

do

۵ if

do

do

🛛 true 🔻

true 🔻

var1

var2

response

= 7

#3 bivariate - continuous by continuous - summary with:

continuous_predictors_list 🔻







Stat-JR:WF Examples Upload Dataset -Debug Clear Dump Save Run Selected Control set run_predictor_summaryYN v to Ask yes/no Do you want to examine plots & sur block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 true 🔻 Math Lists Can ask the do ۲ if ______continuous_predictorsYN •____ = • ftrue 🔻 Text user questions sentinuous predictors list for each item do Hypothesis Data Preparation do #1 univariate - continuous - summar Can use conditional Data Exploration î T var statements... Models Post-process ...and loops if categorical_predictorsYN 🔹 💷 Input Output for each item (i v) in lice categorical predictors list v do Can call procedures Variables do #2 univariate - categorical - summary with: defined elsewhere in Procedures var workflow Other Dummy environment Ask yes/no (Do you want to exan e plots & set run_y_conditional_summaryYN v to 🗯 if run_y_conditional_summaryYN 🕤 😑 🔹 🛛 true 🔻 do ۵ if continuous_predictorsYN 🔹 true 🔻 = 7 continuous predictors list for each item 🚺 in list 🔋 do do #3 bivariate - continuous by continuous - summary with.

response

var1

var2















Ocmmand: RunStatJR(template='Histogram', dataset='tutorial', invars = {'vals': 'normexam', 'bins': '15'}, estoptions = {})











```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
'Produces a histogram from a column of data, with the number of bins chosen by the user.'
 version = '1.0.0'
tags = [ 'Plots' ]
engines = ['Python script']
inputs = '''
vals = DataVector('Values: ')
bins = Integer('Number of bins: ')
...
pythonscript = '''
from io import BytesIO
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure(figsize=(8,8))
ax = fig.add subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print figure(buf, dpi=80, format='svg')
buf.seek(0)
outputs['histogram.svg'] = ImageOutput(buf.getvalue())
buf.close()
...
```

```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
'Produces a histogram from a column of data, with the number of bins chosen by the user.'
 version = '1.0.0'
tags = [ 'Plots' ]
                                                         ... can also find this
engines = ['Python script']
                                                            information by
inputs = '''
vals = DataVector('Values: ')
                                                               looking in
bins = Integer('Number of bins: ')
...
                                                            template code
pythonscript = '''
                                                                  itself...
from io import BytesIO
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure(figsize=(8,8))
ax = fig.add subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print figure(buf, dpi=80, format='svg')
buf.seek(0)
outputs['histogram.svg'] = ImageOutput(buf.getvalue())
buf.close()
...
```

```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
'Produces a histogram from a column of data, with the number of bins chosen by the user.'
 version = '1.0.0'
tags = [ 'Plots' ]
                                                         ... can also find this
engines = ['Python script']
                                                            information by
inputs = '''
vals = DataVector('Values: ')
                                                                looking in
bins = Integer('Number of bins: ')
. . .
                                                             template code
pythonscript = '''
                                                                  itself...
from io import BytesIO
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure (figsize=(8, 8))
ax = fig.add subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print figure(buf, dpi=80, format='svg')
buf.seek(0)
outputs['histogram.svg'] = ImageOutput(buf.getvalue())
buf.close()
...
```

```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
  'Produces a histogram from a column of data, with the number of bins chosen by the user.'
  _version_ = '1.0.0'
```

```
inputs = '''
vals = DataVector('Values: ')
bins = Integer('Number of bins: ')
'''
```

```
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend_agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure(figsize=(8,8))
ax = fig.add_subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print_figure(buf, dpi=80, format='svg')
buf.seek(0)
outputs['histogram.svg'] = ImageOutput(buf.getvalue())
buf.close()
'''
```

```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
'Produces a histogram from a column of data, with the number of bins chosen by the user.'
__version__ = '1.0.0'
```

```
inputs = '''
vals = DataVector('Values: ')
bins = Integer('Number of bins: ')
'''
```

```
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend_agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure(figsize=(8,8))
ax = fig.add_subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print_figure(buf, dpi=80, format='svg')
buf.seek(0)
outputs['histogram.svg'] = ImageOutput(buf.getvalue())
buf.Close()
'''
```

```
# Copyright (c) 2013, University of Bristol and University of Southampton.
from EStat.Templating import Template
class TemplateHistogram(Template):
'Produces a histogram from a column of data, with the number of bins chosen by the user.'
__version__ = '1.0.0'
```

```
inputs = '''
vals = DataVector('Values: ')
bins = Integer('Number of bins: ')
'''
```

```
from matplotlib.figure import Figure
import matplotlib.lines as lines
from matplotlib.backends.backend_agg import FigureCanvasAgg
import EStat
from EStat.Templating import *
fig = Figure(figsize=(8,8))
ax = fig.add_subplot(100 + 10 + 1, xlabel = vals)
ax.hist(datafile.variables[vals]['data'], bins)
canvas = FigureCanvasAgg(fig)
buf = BytesIO()
canvas.print_figure(buf, dpi=80, format='svg')
outputs['histogram.svg'] = ImageOutput...
```

Stat-JR:WF Clear Examples Upload Dataset -Debug Dump Save Run Selected Control set run_predictor_summaryYN 🔻 to Ask yes/no Do you want to examine plots & surr block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 ftrue 🔻 Math Lists do if continuous_predictorsYN 🔹 💷 ftrue 🔻 Text for each item 🚺 in list 🔋 continuous predictors list 🔻 do Hypothesis Data Preparation do #1 univariate - continuous - summary with: Data Exploration í 🔻 var Models Post-process if categorical predictorsYN 🔹 💷 (true 🔻 Input Output do for each item 🚺 in list 🔋 categorical_predictors_list 🔻 Variables do #2 univariate - categorical - summary with: Procedures ÎΤ var Other Dummy Ask yes/no (Do you want to examine plots & set run_y_conditional_summaryYN 🔹 to 🔯 if

run_y_conditional_summaryYN 🕤 😑 🔹

continuous_predictorsYN *

for each item 🚺 in list 🔋

do

۵ if

do

do

🛛 true 🔻

true 🔻

var1

var2

response

= 7

#3 bivariate - continuous by continuous - summary with:

continuous_predictors_list 🔻



Practical 1...

Accessories > Command Prompt

cd /d c:\Users\your_username

mkdir .statjr

Open E:\tree

(Best in Chrome, so open Chrome & copy address across from Internet Explorer)

Open Settings (in black bar at top of browser)

Find "Location of G++ compiler (Windows only)"

Change this to:

E:\MinGW\bin

Press Set

eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant

eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes

statistical analysis assistant

8 Chapter 3

A key to assist in your choice of statistical test

Starting at step 1 in the list above move through the key following the path that best describes your data. If you are unsure about any of the terms used then consult the glossary or the relevant sections of the next two chapters. This is not a true dichotomous key and at several points there are more than two routes or end points.

There may be several end points appropriate to your data that result from this key. For example you may wish to know the correct display method for the data and then the correct measure of dispersion to use. If this is the case, go through the key twice.

All the tests and techniques mentioned in the key are described in later chapters.

Italics indicate instructions about what you should do.

Numbers in brackets indicate that the point in the key is something of a compromise destination.

There are several points where rather arbitrary numbers are used to determine which path you should take. For example, I use 30 different observations as the arbitrary level at which to split continuous and discontinuous data. If your data set falls close to this level you should not feel constrained to take one path if you feel more comfortable with the other.

Not testing any hypothesis but simply want to present, summarize

Dytham, C (2010) Choosing & Using Statistics: A Biologist's Guide. Hoboken, NJ: Wiley-Blackwell

¹ Testing a clear hypothesis and associated null hypothesis (e.g. $H_1 = 25$ blood glucose level is related to age and $H_0 =$ blood glucose is not related to age).

K	•	8	🚖 / 298		И
---	---	---	---------	--	---

1 Testing a clear hypothesis and associated null hypothesis (e.g. $H_1 = blood$ glucose level is related to age and $H_0 = blood$ glucose is not related to age). Not testing any hypothesis but simply want to present, summarize or explore data.	25 2	
2 Methods to summarize and display the data required.	3	
Data exploration for the purpose of understanding and getting a feel for the data or perhaps to help with formulation of hypotheses. For example, you may wish to find possible groups within the data (e.g. 10 morphological variables have been taken from a large number of carabid beetles; the multivariate test may establish whether they can be divided into separate taxa).	60	
3 There is only one collected variable under consideration (e.g. the only variable measured is brain volume although it may have been measured from several different populations). There is more than one measured variable (e.g. you have measured the number of algae per millilitre <i>and</i> the water pH in the same sample).	4 24	
4 The data are discrete; there are fewer than 30 different values (e.g. number of species in a sample).	5	
		Dytham
		Choosir
		Statistic
		Biologis
		Hoboke
		Wiley-B

Oytham, C (2010) Choosing & Using tatistics: A Biologist's Guide. Hoboken, NJ: Viley-Blackwell

.

	The data are continuous; there are more than 29 different values (e.g. bee wing length measured to the nearest 0.01 mm). (<i>Note</i> : the distinction between the above is rather arbitrary.)	16		
5	There is only one group or sample (e.g. all measurements taken from the same river on the same day).	6		
	There is more than one group or sample (e.g. you have measured the number of antenna segments in a species of beetle and have divided the sample according to sex to give two groups).	15		
6	A graphical representation of the data is required.			
	A numerical summary or description of the data required.	11		
7	A display of the whole distribution is required. Crude display of position and spread of data is required: <i>use a box</i> <i>and whisker display to show medians, range and inter-quartile range,</i> <i>page 49 (also known as a box plot).</i>	8		
8	Values have real meaning (e.g. number of mammals caught per night). Values are arbitrary labels that have no real sequence (e.g. different vegetation-type classifications in an area of forest).	10 9		
	There are fewer than 10 different values or classifications: <i>draw a pie chart, page 52. Ensure that each segment is labelled clearly and that adjacent shading patterns are as distinct as possible. Avoid using three-dimensional or shadow effects, dark shading or colour. Do not</i>			
			Dytham, C (2010)	
	add the proportion in figures to the 'piece' of the pie as this information is redundant.		Choosing & Using Statistics: A	
	There are 10 or more different values or classifications: <i>amalgamate</i>			
	values until there are fewer than 10 or divide the sample to produce			
	two sets each with fewer than 10 values. Ten is a level above which it is difficult to distinguish different sections of the pie or to have sufficiently distinct shading patterns.		Biologist's Guide. Hoboken, NJ: Wiley-Blackwell	
10				
Building a Statistical Analysis Assistant



0 < Daryl Pregibon: "Incorporating statistical expertise into computer software Why put statistical expertise into software? environments for statisticians

0 < Daryl Pregibon: "Incorporating statistical expertise into computer software Why put statistical expertise Daryl Pregibon: "Inco 0 < carrying out the plan sequence of analysis steps, with checks, exploration of alternation for a particular type of analysis ¢ ::

Pregibon, D. (1987) "Incorporating Statistical Expertise into Computer Software". 2nd International Tampere Conference in Stats.

Daryl Pregibon: "Incorporating statistical expertise into computer software"

We're not going to be successful in implementing expertise [which depends on understanding] the context of the problem... this is what humans are so good at, and computers are so bad at: common sense reasoning, knowing how to interact with the subject matter – we can't teach a computer that much.

Pregibon, D. (1987) "Incorporating Statistical Expertise into

for a particular two

Computer Software". 2nd International Tampere Conference in Stats.

0 < Daryl Pregibon: "Incorporating statistical expertise into computer software" Why put statistical expertise 0 < Daryl Pregibon: "Incorporating statistical expertise into computer softwar carrying out the plan sequence of analysis steps, with checks, exploration of alternation for a particular type of analysis ø ::

Pregibon, D. (1987) "Incorporating Statistical Expertise into Computer Software". 2nd International Tampere Conference in Stats.

As stated in the open letter, the intelligence part of "AI", as it is currently to make good decisions, plans, or inferences" And, according to Superintelligence author Nick Bostrom, in this context "the ideal is that of the perfect Bayesian agent, one that makes probabilistically optimal use of available information".

The Bayesian ideal "constitutes a kind of optimality notion," Bostrom said." It specifies what an ideally rational agent would do. Such a thing might be computationally intractable to achieve, but it creates an ideal against which one could measure practicable systems; one can see how far they deviate from this ideal, and one can consider for some possible change to any actual system whether it would take it closer to the Bayesian ideal or further away."

Now, consider again the AI tasked with creating a million paperclips. One might think that it would stop manufacturing the objects once its goal had been reached. But there is a problem, according to Bostrom: "IF the AI is a sensible Bayesian agent, it would never assign exactly zero probability to the hypothesis that it has not yet achieved its goal - this, after all, being an empirical hypothesis against which the AI can have only uncertain perceptual evidence. The AI should therefore continue

to make paperclips in order to reduce the (perhaps astronomically small) probability that it has somehow failed to make at least a million of them, all appearances notwithstanding. There is nothing to be lost by continuing paperclip production and there is always at least some microscopic probability increment of achieving its final goal to be attained."

This might be frustrating more than frightening, at least to begin with. Worry only sets in when the AI starts devoting more and more of Earth's dwindling resources to the creation of ever more paperclips. Are such concerns overblown? Perhaps.

But Google's Peter Norvig (another signatory to the open letter) thinks Bostrom is right to be worried about unintended consequences. "If we build systems that are game-theoretic or utility maximisers, we won't get what we're hoping to get. It's the three wishes from the genie problem. The genie technically delivers, but it isn't what we really want."

14 significance february2015

As stated in the open letter, the intelligence part of 'A1', as it is currently practiced, relates to 'statistical and economic notions of rationality – colloquially, the ability **Statistician**

A Q&A with Zoubin Ghahramani discussing his Google-backed project to create an artificial intelligence for data science

ast year, Zoubin Ghahramani won \$750 000 in research funding from Google. The money came as a no-stringsattached donation to support a project being led by Ghahramani, professor of information engineering in the University of Cambridge Machine Learning Group

The project is called the Automatic Statistician. It aims to broduce an artificial intelligence for statistics and data science, one that can automate the process of statistical model selection, data analysis and reporting.

What inspired the Automatic Statistician project, and how has the idea evolved since its initial conception?

I've had a long-standing interest in probabilistic modelling, and in particular in Bayesian model selection. One of the hardest things when confronted with new data is to know what kinds of models to apply. Each individual researcher may have a small set of modelling tools at his or her disposal and limited patience to implement and test different models. For almost a decade, I had this idea that it would be really interesting and useful to develop an online tool where one could upload data and a computer could try to develop and test models for the data, reporting back what it had discovered. A nice thing about probabilistic

nodels is that they are compositional, in the sense that you can build more complex models out of simpler ones, like building complex objects out of Lego bricks. Statistics provides excellent methods to determine the

appropriate complexity of a model given the data available; I'm thinking of tools from Bayesian nonparametrics, and ideas such as the marginal likelihood (Bayesian model evidence), and cross-validation. Putting these ideas together, along with the explosion of interest in so-called "big data" and the "data sciences", and the demand for expertise in data analysis, created the perfect storm for the Automatic Statistician. What really got it going was working with three brilliant PhD students: James Lloyd, David Duvenaud, and Roger Grosse.

The project started by looking at automatically determining the kernel (or covariance function) for Gaussian process nonlinear regression by composing together simpler kernels. We then moved on to looking



Zoubin Ghahramani (right), with research associat James Lloyd: "We'd really like to provide a tool that is useful to many people. It should help data scientists and statisticians become more productive

© 2015 The Royal Statistical Society

Ghahramani, Z (2015) The Automatic Statistician. Significance, 12(1), 14-15.

Stat-JR:WF Clear Examples Upload Dataset -Debug Dump Save Run Selected Control set run_predictor_summaryYN 🔻 to Ask yes/no Do you want to examine plots & surr block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 ftrue 🔻 Math Lists do if continuous_predictorsYN 🔹 💷 ftrue 🔻 Text for each item 🚺 in list 🔋 continuous predictors list 🔻 do Hypothesis Data Preparation do #1 univariate - continuous - summary with: Data Exploration í 🔻 var Models Post-process if categorical predictorsYN 🔹 💷 (true 🔻 Input Output do for each item 🚺 in list 🔋 categorical_predictors_list 🔻 Variables do #2 univariate - categorical - summary with: Procedures ÎΤ var Other Dummy Ask yes/no (Do you want to examine plots & set run_y_conditional_summaryYN 🔹 to 🔯 if

run_y_conditional_summaryYN 🕤 😑 🔹

continuous_predictorsYN *

for each item 🚺 in list 🔋

do

۵ if

do

do

🛛 true 🔻

(true 🔻

var1

var2

response

= 7

#3 bivariate - continuous by continuous - summary with:

continuous_predictors_list 🔻











Block 34 None







Block 58 ProcedureCall(#2 univariate - categorical - summary, Variable(i))



Block 61 None



Block 62 None

4

Correlation coefficient: 0.59



Block 62 None

Correlation coefficient: 0.59



Block 63 ProcedureCall(#3 bivariate - continuous by continuous - summary, Variable(response), Variable(i))

Block 64 None

•

-

•

Block 65 None

Block 66 None

•

Block 67 None

Correlation coefficient: 0.29





Block 91 None







•



Block 96 None



Block 97 None

Variable summarised: normexam	vrband == 1	vrband == 2	vrban d == 3
Ν	1176	2344	539
Number of missing values	0	0	0
Mean	0.735631883144	-0.141659572721	-0.989824473858
Median	0.747227728387	-0.129084676504	-1.02908880107
Min	-2.29173	-2.75288	-3.66607
Мах	3.66609	2.7018	1.66181
SD	0.856097	0.827098	0.831329
IQR	1.115993	1.102174	1.106852

Block 98 ProcedureCall(#4 bivariate - continuous by categorical - summary, Variable(response), Variable(i))

Variable transformation explanatory text

Performing the transformations

Here's how the transformations you asked for were calculated.

Log transformation

Since **standIrt**_l has values equal to or less than zero, a constant was first added prior to the log-transformation (it's not possible to get log values for negative numbers nor for zero). Here a constant was added to bring the minimum value up to 1 (and thus the log-transformed minimum value is 0), although we could have chosen other constants. In the outputted dataset, the transformed variable appears as **loge_standIrt_plus_cons**.

$$\begin{split} &\log _ standlrt_plus_cons_i = \ln(standlrt_i + 1 + |standlrt_{min}|) \\ &\log _ standlrt_plus_cons_i = \ln(standlrt_i + 1 + 2.935) \\ &\log _ standlrt_plus_cons_i = \ln(standlrt_i + 3.935) \end{split}$$

Square root transformation

Since **standIrt**, has negative values, a constant was first added prior to the square-root-transformation (there's no square-root for negative values). Here we've just added the absolute value of the minimum value of **standIrt**, so that the mimimum value prior to square-root-transformation is now zero (but we could have used a different constant). In the outputted dataset, the transformed variable appears as **sqrt_standIrt_plus_cons**.

$$\begin{split} \text{sqrt_standlrt_plus_cons}_i &= \sqrt{\text{standlrt}_i + |\text{standlrt}_{min}|} \\ \text{sqrt_standlrt_plus_cons}_i &= \sqrt{\text{standlrt}_i + 2.935} \end{split}$$

Variable transformation explanatory text

Performing the transformations

Here's how the transformations you asked for were calculated.

Log transformation

Since standIrt, has values equal to or less than zero, a constant was first added prior to the log-transformation (it's not possible to get log values for negative numbers nor for zero). Here a constant was added to bring the minimum value up to 1 (and thus the log-transformed minimum value is 0), although we could have chosen other constants. In the outputted dataset, the transformed variable appears as loge_standIrt_plus_cons.

$$\begin{split} &\log e_standlrt_plus_cons_i = \ln(standlrt_i + 1 + |standlrt_{min}|) \\ &\log e_standlrt_plus_cons_i = \ln(standlrt_i + 1 + 2.935) \\ &\log e_standlrt_plus_cons_i = \ln(standlrt_i + 3.935) \end{split}$$

E.g. talking user through some transformations they may consider...

Square root transformation

Since **standIrt**, has negative values, a constant was first added prior to the square-root-transformation (there's no square-root for negative values). Here we've just added the absolute value of the minimum value of **standIrt**, so that the mimimum value prior to square-root-transformation is now zero (but we could have used a different constant). In the outputted dataset, the transformed variable appears as **sqrt_standIrt_plus_cons**.

```
\begin{split} \text{sqrt\_standlrt\_plus\_cons}_i &= \sqrt{\text{standlrt}_i + |\text{standlrt}_{min}|} \\ \text{sqrt\_standlrt\_plus\_cons}_i &= \sqrt{\text{standlrt}_i + 2.935} \end{split}
```

Percentile	standirt	standIrt with cons (for sqrt)	sqrt_standlrt_plus_cons	standIrt with cons (for log)	loge_star	dirt_plus_cons	
0%	-2.935	0	0	1.0	0		
2.5%	-2.108	0.909	0.909	0.602	0.602		
25%	-0.621	1.521	1.521	1.198	1.198		
50%	0.0405	1.725	1.725	1.38	1.38		
75%	0.619	1.885	1.885	1.516	1.516		
97.5%	1.941	2.208	2.208	1.771	1.771		
100%	3.016	5.951	2.439	6.951	1.939	E.g. talking user through some transformations they may consider	



Block 16 OutputObject(mcmctext)

MCMC estimation methods are simulation based which means that rather than a point estimate (and accompanying standard error) for each parameter they instead produce a (dependent) chain of values from the posterior distribution of the parameter. In fact in Stat-JR several chains are run from differing starting values/ random number seeds and so for each parameter we have several chains of values that can be combined to summarise the parameter. For parameter beta_1 we can first look at the posterior mean which has value 0.563 and standard deviation of the chain which has value 0.0125 and plays the role of standard error for the parameter. We might also consider the posterior median which has value 0.563 as an alternative if the distribution is not symmetric. Here the median is close to the mean as the posterior is reasonably symmetric. We can use the quantiles of the distribution and so we see a 95% credible interval for beta_1 is 0.539 to 0.588. We can look at the 3 chains for the parameter beta_1 and we can also look at kernel density plots (which are like smoothed histograms) of the 3 chains on a single plot:



Due to the nature of MCMC algorithms updating parameters in separate steps there is some dependence in the parameter chains produced. One way of investigating this is to look at auto-correlation functions (acf) for the chains. Essentially an acf examines how correlated a chain of values is with a similar chain shifted by a number of iterations (the lag). We can plot such a function for a series of lags as shown below.







Stat-JR:WF Clear Examples Upload Dataset -Debug Dump Save Run Selected Control set run_predictor_summaryYN 🔻 to Ask yes/no Do you want to examine plots & surr block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 ftrue 🔻 Math Lists do if continuous_predictorsYN 🔹 💷 ftrue 🔻 Text for each item 🚺 in list 🔋 continuous predictors list 🔻 do Hypothesis Data Preparation do #1 univariate - continuous - summary with: Data Exploration í 🔻 var Models Post-process if categorical predictorsYN 🔹 💷 (true 🔻 Input Output do for each item 🚺 in list 🔋 categorical_predictors_list 🔻 Variables do #2 univariate - categorical - summary with: Procedures ÎΤ var Other Dummy Ask yes/no (Do you want to examine plots & set run_y_conditional_summaryYN 🔹 to 🔯 if

run_y_conditional_summaryYN 🕤 😑 🔹

continuous_predictorsYN *

for each item 🚺 in list 🔋

do

۵ if

do

do

🛛 true 🔻

(true 🔻

var1

var2

response

= 7

#3 bivariate - continuous by continuous - summary with:

continuous_predictors_list 🔻





Practical 2...

Achieving many of the key operations via workflow blocks...



Achieving many of the key operations via workflow blocks...







Achieving key operations via XPath queries in eBook html documents...

Achieving key operations via XPath queries in eBook html documents...

```
class="deep dynamic hidden" data-deep-showon="template2-out-
summary" data-deep-
expression="//row[@row='beta 0']/element[@col='Mean'] ">The mean for
<strong>\(\beta 0\)</strong> is<strong>
<span class="deep dynamic output" data-deep-id="template2-out-</pre>
summary" data-deep-
expression="round(1000*(//row[@row='beta 0']/element[@col='Mean']))
div 1000"></span>
(<span class="deep dynamic output" data-deep-id="template2-out-
summary" data-deep-
expression="round(1000*(//row[@row='beta 0']/element[@col='Std']))
div 1000"></span>)</strong>:
summary" data-deep-
expression="//row[@row='beta 0']/element[@col='Mean'] >
//row[@row='beta 0']/element[@col='Std']*1.96 or
//row[@row='beta 0']/element[@col='Mean'] <</pre>
//row[@row='beta 0']/element[@col='Std']*(-1.96) ">
this value <strong><font color="green">is
significant</font></strong>.
<q/>
summary" data-deep-
expression="not(//row[@row='beta 0']/element[@col='Mean'] >
//row[@row='beta 0']/element[@col='Std']*1.96 or
//row[@row='beta 0']/element[@col='Mean'] <</pre>
//row[@row='beta 0']/element[@col='Std']*(-1.96)) ">
this value is <strong><font color="red">not
significant</font></strong>.
```

Achieving key operations via XPath queries in eBook html documents...



eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant

eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant

Working with a range of social scientists...

Working with a range of social scientists...

• ...we ask them to choose a quantitative research question they have investigated...

Working with a range of social scientists...

- ...we ask them to choose a quantitative research question they have investigated...
- ...and then work with them to develop it into an interactive case study using Stat-JR.
Working with a range of social scientists...

- ...we ask them to choose a quantitative research question they have investigated...
- ...and then work with them to develop it into an interactive case study using Stat-JR.
- User will be able to interact with this resource: e.g. investigating alternative avenues the analyst may have taken.

Working with a range of social scientists...

- ...we ask them to choose a quantitative research question they have investigated...
- ...and then work with them to develop it into an interactive case study using Stat-JR.
- User will be able to interact with this resource: e.g. investigating alternative avenues the analyst may have taken.
- Aim is to help demystify the process of quantitative research, and shed light on the day-to-day decisions working analysts make.



Report

 ...as even this simple analysis shows, the path taken when investigating a quantitative research question can be a convoluted one!

- ...as even this simple analysis shows, the path taken when investigating a quantitative research question can be a convoluted one!
- Workflow interface may help abstract main elements, and illustrate how its components fit thematically together.

- ...as even this simple analysis shows, the path taken when investigating a quantitative research question can be a convoluted one!
- Workflow interface may help abstract main elements, and illustrate how its components fit thematically together.
- Workflow environment will eventually be integrated into our eBook interface.

Number of scholarly articles found in the most recent complete year (2014) for each software package.



Muenchen, RA. **The Popularity of Data Analysis Software** http://r4stats.com/articl es/popularity/ Change in the number of scholarly articles using each software in the most recent two complete years (2013 to 2014). Packages shown in red are "hot" and growing, while those shown in blue are "cooling down" or declining.



Muenchen, RA. **The Popularity of Data Analysis Software** http://r4stats.com/articl es/popularity/ The number of scholarly articles found in each year by Google Scholar. Only the top six "classic" statistics packages are shown



KDnuggets poll on programming tools used for an analytics / data mining / data science work in 2013



eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant

eBook project funded by ESRC



Research objectives include:

- Developing tools to support interactive eBooks / workflows for statistical analyses
- Using these tools to produce:
 - library of case studies
 - library of methodological advice / notes
 - statistical analysis assistant



Module 3: Multiple Regression MLwiN Practicals

Ξ

Fiona Steele¹ Centre for Multilevel Modelling

Contents

Introdu	ction to the Scottish Youth Cohort Trends Dataset	4
P3.1	Regression with a Single Continuous Explanatory Variable	5
P3.1 P3.1		
P3.2	Comparing Groups: Regression with a Single Categorical Explanatory Variable 2	5
P3.2 P3.2 P3.2	2 Attainment by parental social class	26
P3.3	Regression with More than One Explanatory Variable (Multiple Regression) 3	3
P3.4	Interaction Effects	7
P3.4 P3.4 P3.4 P3.4	 Fitting separate models for boys and girls	13 15
P3.5	Checking Model Assumptions in Multiple Regression	8
P3.5 P3.5		

ſ	Library Search Bristol Uni 🗴 Read: Choosing and Using Sta 🗴 🕂 Stat-JR 1.0.3:WF 🛛 🗙	5 Stat-JR 1.0.3:WF	×	Exploring Joint Frailty Models	× 57 Stat-JR 1.0.3:WF	× Microsoft Word - Module3 m ×	+				x
•	https://www.cmm.bris.ac.uk/lemma/pluginfile.php/296/mod_resource/content/2/Module3Practice.pdf			⊽ Cł	Q lemma online course	→ ☆ 自 🛡 🖡	Â	ø	Ċ.	1 -	≡
	★ Page: 3 of 30		+ 140%					0	۵		»

Module 3 (Practice): Multiple Regression

P3.1 Regression with a Single Continuous Explanatory Variable

P3.1 Regression with a Single Continuous Explanatory Variable

We will begin by looking at the relationship between attainment (SCORE) and cohort (COHORT90). Has attainment changed over time and, if so, is the trend linear?

P3.1.1 Examining the data

To access the data files associated with this tutorial, you must have an account with LEMMA. To open the first data file,

From within the LEMMA Learning Environment

- Go to Module 3: Multiple regression, and scroll down to MLwiN Datafiles
- If you do not already have MLwiN to open the datafile with, click (get MLwiN).
- Click " ^{III} 3.1.wsz"

When the worksheet is opened, the filename will appear in the title bar of the main window. The **Names** window will also appear, giving a summary of the data in the worksheet:

a Names						
O Edit name	Toggl	e Categor	cal Categorie	Description	Copy Paste	Delete Data Help
Name	Cn		missing	min	max	categorical description
CASEID SCORE	1	33988	0	1	38192	False
SCORE	2	33988	0	0	75	Falso
COHOR190	3	33988	0	-6	8	False
FEMALE	4	33988	0	0	1	false
SCLASS	5	33988	0	1	4	Fabo
C6	6	0	0	0	0	False
C7	7	0	0	0	0	False

The MLwiN worksheet holds the data and other information in a series of columns, as on a spreadsheet. There are initially named c1, c2, etc. but we recommend that they be given meaningful names to show what their content relates to. This has already been done in the worksheet that you have loaded.

Each line in the body of the **Names** window summarises a column of data. In the present case only the first five of the 400 columns of the worksheet contain data. Each column contains 33988 values, one for each student represented in the data set. There are no missing values, and the minimum and maximum value in each column are shown. It is possible to define a variable as categorical (we shall do this later) and to add variable descriptions.

Module 3 (Practice): Multiple Regression P3.1.1 Examining the data

The following window appears:

goto lii	ne 1	view <u>H</u> elp F	ont 🔽 Show val	ue labels		
	CASEID(33988)	SCORE(33988)	COHORT90(339:	FEMALE(33988)	SCLASS(33988)	1
1	339.000	49.000	-6.000	0.000	2.000	F
2	340.000	18.000	-6.000	0.000	3.000	
3	345.000	46.000	-6.000	0.000	4.000	
4	346.000	43.000	-6.000	0.000	3.000	
5	352.000	17.000	-6.000	0.000	3.000	
6	353.000	29.000	-6.000	0.000	2.000	
7	354.000	15.000	-6.000	0.000	3.000	
8	361.000	19.000	-6.000	0.000	2.000	
9	362.000	45.000	-6.000	0.000	3.000	
10	363.000	12.000	-6.000	0.000	1.000	
11	6824.000	0.000	-4.000	0.000	1.000	
12	6826.000	0.000	-4.000	0.000	3.000	
13	6827.000	20.000	-4.000	0.000	2.000	
14	6828.000	32.000	-4.000	0.000	1.000	
15	6829.000	0.000	-4.000	0.000	2.000	
16	6834.000	24.000	-4.000	0.000	3.000	1

Because there are only five variables in the data file, all columns can be seen. When there are more variables, you can view any selection of columns, spreadsheet fashion, as follows:

- Click the View button
- Select columns to view
- Click OK

You can select a block of adjacent columns either by pointing and dragging or by selecting the column at one end of the block and holding down 'Shift' while you select the column at the other end. You can add to an existing selection by holding down 'Ctrl' while you select new columns or blocks. Use the scroll bars of the **Data** window to move horizontally and vertically through the data, and move or resize the window if you wish. You can go straight to line 1000, for example, by typing 1000 in the **goto line** box, and you can highlight a particular cell by pointing and clicking. This provides a means to edit data.

Having viewed the data we will examine SCORE and COHORT90, the variables to be considered in our first regression analysis.

block: 1306

Control Logic Math Lists Text Start Hypothesis Comment Workflow for module 3 of LEMMA training material... >>> **Data Preparation** Data Exploration "Workflow written by Chris Charlton and William B... " Comment Models set nopause T to false 🔻 Post-process Mod3.1 with: Input to Pause with: nopause nopause 🔻 Output nopause 🚺 if nopause • Variables Mod3.2 with: Procedures do nopause 🔻 Set Input " cols " Ask yes/no do you want to continue? nopause Other Mod3.3 with: Dummy nopause nopause 🔻 Mod3.4 with: to Mod3.1 with: nopause Sel. nopause 🔻 nopause Mod3.5 with: to Mod3.2 with: nopause Sel. nopause 🔻 nopause to Mod3.3 with: nopause Sel. to Mod3.4 with: nopause Sel. to Mod3.5 with: nopause Sel..

Stat-JR:WF Exa	nples Clear Dump Save Upload Dataset <i></i>	Ru	n Debug-
Control Logic Math Lists Text Hypothesis Data Preparation Data Exploration Models Post-process Input Output Variables Procedures Other Dummy	Statt Comment (* Workflow for module 3 of LEMMA training material		Selected block: 25

Stat-JR:WF Clear Examples Upload Dataset -Debug Dump Save Run Selected Control set run_predictor_summaryYN 🔻 to Ask yes/no Do you want to examine plots & surr block: Logic 🔯 if run_predictor_summaryYN 🔹 💷 ftrue 🔻 Math Lists do if continuous_predictorsYN 🔹 💷 ftrue 🔻 Text for each item 🚺 in list 🔋 continuous predictors list 🔻 do Hypothesis Data Preparation do #1 univariate - continuous - summary with: Data Exploration í 🔻 var Models Post-process if categorical predictorsYN 🔹 💷 (true 🔻 Input Output do for each item 🚺 in list 🔋 categorical_predictors_list 🔻 Variables do #2 univariate - categorical - summary with: Procedures ÎΤ var Other Dummy Ask yes/no (Do you want to examine plots & set run_y_conditional_summaryYN 🔹 to





Practical 3...