Conducting a Binary/Binomial Logistic Regression in jamovi

A class of 60 undergraduate law students took part in mock trials in which they were assessed on their ability to defend a fictitious client against a criminal charge. Fellow students acted as jury members for the mock trials and in each case handed down a verdict. Students were assessed on the quality of their presentation and confidence in defending their fake clients, while it was a badge of honour to also receive a not guilty verdict. Students were randomly allocated to use one of two television lawyer mentors to model their approach. Thirty students were instructed to model their style on the character of Annalise Keating from the television series *How to Get Away with Murder*¹ while the other thirty were told to emulate Harvey Specter from the television series *Suits*². The Unit Coordinator decided to run some analysis to see the extent to which a student lawyer's success in getting a not guilty verdict from the student jury could be predicted from the television lawyer model and their grade in the first year criminal law subject. Knowing that many of her students came from families where at least one parent was also a lawyer she decided to also see if having lawyer parents could also play a predictive role in her model. As the dependent variable or outcome variable here is dichotomous or binary (guilty or not guilty) and the predictors are a mixture of categorical and continuous variables a binary/binomial logistic regression is in order.

Step 1 – Taking a look at the data.

DATA VARIABLE	
Verdict	
Description	
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Data type (integer +) not guilty	. Has been
Missing values specified as a nominal variable i	n Measure
type and is the first column of o	data. This
	anu gunty.
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37 not guilty Annalise Ke 7 Mother	
38 guilty Harvey Spec 4 Neither	
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& Verdict 🚯 Televisio 💩 Crim La 🚽 Parent L	
36 not guilty Annalise Ke 7 Mother Harvey Specter.	
37 not guilty Annalise Ke 7 Mother	
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 ¹ Further information about the television series How to Get Away with Murder can be found at <u>https://en.wikipedia.org/wiki/How to Get Away with Murder</u>.
 ² Further information about the television series Suits can be found at <u>https://en.wikipedia.org/wiki/Suits (American TV series)</u>.

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		DATA VARIAN	BLE 101 Grade			
		Measure type	e ៅ Ordinal	\$		Levels
	/	Data type 🔲	Integer 🗘	(auto)	4	
	<	Missing value	es		5	
					6	
					7	
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🐣 Verdict	🐣 Televisio	d Crim La	Parent L			
35 not guilty	Annalise Ke	6	Both			
36 not guilty	Annalise Ke	7	Mother			

		DATA VARIA	BLE				
		Parent L	awyers				
		Description					
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					Father	3	
					Retain	unused levels (
🐣 Verdict	合 Televisio	💼 Crim La	🔒 Parent L				
34 not guilty	Harvey Spec	4	Father				
35 not guilty	Annalise Ke	6	Both				
36 not guilty	Annalise Ke	7	Mother				

In the third column of our data spreadsheet we have the variable "Crim Law 101 Grade", which as the name suggests is the grade each student achieved for the first year criminal law subject. The measure type has been set as ordinal as technically grades are not equal interval. However for our analysis we will treat this variable as a continuous predictor.

Our final variable is "Parent Lawyers" specifying how many of each student's parents are lawyers. There are four levels: neither, mother, father and both. This variable is somewhat ordinal in nature however as we are also denoting which parent is the lawyer when only one is a lawyer this variable is more appropriately labelled as nominal.

Step 2 – Navigating to the binary/binomial logistic regression menu.

Ex	ploration T-Tes	ts ANOVA	Regression	Frequencies	Factor
	🐣 Verdict	🐣 Televisio	Correlation	n Matrix	nt L
34	not guilty	Harvey Spec	Partial Cor	relation	
35	not guilty	Annalise Ke	Linear Reg	ression	
36	not guilty	Annalise Ke			
37	not guilty	Annalise Ke	Logistic Regre	ssion	
38	guilty	Harvey Spec	2.2.1		
39	not guilty	Annalise Ke	2 Outcome	es Binomial	
40	not guilty	Annalise Ke	N Outcome	26	
41	not guilty	Annalise Ke	N Outcome	Bultinomial	
42	guilty	Harvey Spec	Ordinal Ou	tcomes	
43	not guilty	Harvey Spec			

On the Analyses tab select the Regression menu. Then under "Logistic Regression" select 2 Outcomes, Binomial.

Step 3 – Selecting analysis options

First let's specify out dependent variable and move our predictors to the appropriate spots



Before looking at our output we'll specify all the options we would like from the options drop down menus.



We'll need to head into four of these drop down lists for our needs and we'll step through them one at a time.

✓ Reference Levels	
Variable	Reference Level
🐣 Verdict	guilty
🐣 Television Lawyer Model	Annalise Keating
🐣 Parent Lawyers	Neither

The Reference Levels tab is very important. It allows us to choose what will be considered our reference category for our dependent variable and any categorical predictors we have. Some will be chosen as a default. We can either leave them as they are or choose to change them.

For our dependent variable the desirable or target outcome is to obtain a not guilty verdict. A not guilty verdict reflects greater "lawyering" skill in our mock trial. This means that guilty needs to be our reference category. *jamovi* will consider which ever category has the lowest code value in as the reference category. As we had coded not guilty as 1 and guilty as 2 in our data file, *jamovi* defaulted to having not guilty as the reference category. We can (and have in the above screen shot) change this to our desired reference category.

For the Television Lawyer Model it doesn't make that much difference which we pick as the reference category so we can leave it at what jamovi has picked.

The Parent Lawyers variable also has an intuitive reference category so we'll leave that as is too.

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✓ Model Fit		
Fit Measures	Pseudo R ²	The Model Fit drop down list has a collecting fit and pseudo <i>R</i> ² s for us to select from. default Deviance (or -2 <i>LL</i>) and the AIC wing selected and we'll also ask for overall mode test. Under Pseudo <i>R</i> ² the McFadden's is default but we'll also ask for Cox and Snell Nagelkerke as they are more common reported.
Model Coefficients Omnibus Tests Likelihood ratio tests Estimate (Log Odds Ratio) Confidence interval Interval 95 %	Odds Ratio Confidence interval Interval 95 %	Under the Model Coefficients drop down we'll ask for Odds ratio, also known as Ex and their associated confidence intervals these are what we use to interpret the imp our individual predictors.
Y Prediction		
Cut-Off Predictive Cut-off plot Image: Class Cut-off value 0.5 Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Class Cut-off value 0.5 Image: Cut-off value 0.5 Image: Cut-off value 0.5	Measures ROC sification table ROC curve uracy AUC cificity sitivity	And finally under the Prediction drop dow in the "Predictive Measures" section we'l for accuracy, specificity, and sensitivity a classification table to help see how these derived.

With all our selections made here is our output in all its glory.

Juer Fit	Measure	es								_		
								Overall Mo	odel Test	_		
Model	Devia	ance /	AIC R ²	/lcF	² CS	R² _N	χ²	d	f p	_		
	55.04	628 67.0	04628 0.32	959 0.	36303	0.48695	27.061	53 5	5 0.00006	_		
odel Coe	efficient	ts - Verdic	t									
										95% Confide	nce Interval	-
	Pr	redictor		Estima	e SI		Z	р	Odds ratio	Lower	Upper	-
ntercept	t			-5.561	7 2.03	277 -	2.73596	0.00622	0.00384	7.15063e-5	0.20651	
elevisio Harve Parent La	n Lawye y Specte awyers:	er Model: :er – Annal	ise Keating	1.484	7 0.80	211	1.85033	0.06427	4.41129	0.91581	21.24828	
Mothe	er – Neit	ther		1.6123	1 0.88	589	1.81794	0.06907	5.01438	0.88165	28.51924	
E				2.1778	3 1.38	584	1.56809	0.11686	8.82717	0.58028	134.27814	
Father	r – Neith - Neithe	er er		2,1905	1 0.99	362	2.19354	0.02827	8.93978	1.26270	63.29243	
Father Both - Crim Law Vote. Est	r – Neith - Neithe v 101 Gr timates	represent	the log odd	2.1905 0.7058 s of "Ver	1 0.999 1 0.359 lict = not	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y"	1.26270 1.00237	63.29243 4.09294	
Father Both - Crim Law Vote. Est redictio	r – Neithe - Neithe v 101 Gr timates on fication	represent Table – V Pred	the log odd erdict icted	2.1905 0.7058 s of "Ver	1 0.994 1 0.354	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y"	1.26270 1.00237	63.29243 4.09294	-
Father Both - Crim Law Vote. Est redictio	r – Neithe - Neithe v 101 Gr. timates on fication erved	represent Table – V Pred guilty	the log odd erdict icted not guilty	2.1905 0.7058 s of "Vere % Corre	1 0.999 1 0.359 lict = not ct	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y"	1.26270 1.00237	63.29243 4.09294	-
Father Both - Crim Law Vote. Est redictio	r – Neithe - Neithe v 101 Gr. timates on fication erved guilty guilty	represent Table – V Pred guilty 19 3	the log odd erdict icted not guilty 7 31	2.1905 0.7058 s of "Vern % Corre 73.0768 91.176	1 0.99i 1 0.35i lict = not	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y"	1.26270 1.00237	63.29243 4.09294	
Father Both - Crim Law Vote. Est redictio Classi Obse not Note	r – Neithe - Neithe v 101 Gr. timates on fication erved guilty guilty . The cu	represent Table – V Pred guilty 19 3 ut-off valu	the log odd erdict icted not guilty 7 31 e is set to 0	2.1905 0.7058 s of "Vere % Corre 73.0768 91.1764 5	1 0.994 1 0.354 lict = not ct 2 7	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y*	ve all v	we ne	ed to interpret and write u
Father Both - Crim Law Vote. Est redictio Classi Obse not Note	r – Neith - Neithe v 101 Gr. timates on fication erved guilty guilty . The cu	represent a Table – V Pred guilty 19 3 ut-off valu	the log odd erdict icted not guilty 7 31 e is set to 0	2.190 0.7058 s of "Vere % Corre 73.076 91.1764 5	1 0.99i 1 0.35i lict = not	362 391 guilty"	2.19354 1.96655 vs. "Verd	0.02827 0.04923 ict = guilt	8.93978 2.02549 y*	ve all v	we ne	ed to interpret and write u now so let's push on.
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Step 4a – Finding the components for reporting the omnibus results / overall model statistics

We've run all we need to write up our χ^2 analysis.

The components we'll report are:

- 1. The χ^2 statistic, *df* and *p* value our significance test for the overall model.
- 2. Effect size in the form of a range from Cox and Snell to Nagelkerke.
- 3. Prediction accuracy to help describe how well we can predict our outcome.

						Overall Model Test			
Model	Deviance	AIC	R ² McF	R ² CS	R² _N	χ²	df	р	
1	55.04628	67.04628	0.32959	0.36303	0.48695	27.06153	5	0.00006	

Prediction



N.B., As the R²s provided in logistic regression are viewed as "pseudo" and less precise than an R² in a standard or ordinary least squares regression, it is common to report several and provide a range. Alternatively the most conservative McFadden estimate could be reported if a more cautionary approach is preferred.

Deviance (also referred to as -2LL) is sometimes reported but mostly not. An AIC is not commonly reported for a binary logistic regression model.

The Write Up (Part 1):

A binary logistic regression was conducted to determine whether a student jury returning a not guilty verdict in student mock trials could be predicted by the television lawyer emulated, prior criminal law subject grade or familial lawyer lineage of the student acting for the defence. The overall model was significant, χ^2 (5) = 27.06, p < .001, with between 36.3% and 48.7% of the variance in the odds of a not guilty verdict explained by the predictor set. Across both outcome categories, 83.3% of cases were accurately classified, with sensitivity somewhat higher than specificity. Guilty verdicts were correctly predicted in 91.2% of cases compared to 73.1% of guilty verdicts.

Step 4b – Finding the components for reporting results for individual predictors

We'll create a table to contain the results about the individual predictors and then put together some summary text.

The elements needed for the regression table are:

- 1. *p* values for each predictor to determine the significance of each predictor's contribution to the model
- 2. Effect sizes in the form of *Bs* and Exp(*B*)s
- 3. Confidence intervals around the Exp(*B*)s.

						95% Confide	nce Interva
Predictor	Estimate	SE	Z	р	Odds ratio	Lower	Upper
ntercept	-5.56157	2.03277	-2.73596	0.00622	0.00384	7.15063e-5	0.20651
Television Lawyer Model: Harvey Specter – Annalise Keating	1.48417	0.80211	1.85033	0.06427	4.41129	0.91581	21.24828
Parent Lawyers: Mother – Neither	1.61231	0.88689	1.81794	0.06907	5.01438	0.88165	28.51924
Father – Neither	2.17783	1.38884	1.56809	0.11686	8.82717	0.58028	134.27814
Both – Neither	2.19051	0.99862	2.19354	0.02827	8.93978	1.26270	63.29243
Crim Law 101 Grade	0.70581	0.35891	1.96655	0.04923	2.02549	1.00237	4.09294

Table 1

Logistic regression results for the prediction of a student jury not guilty verdict from student contested mock trials

	Exp(B)	95% CI for Exp(<i>B</i>)		В	р
		LL	UL		
Television Lawyer Model					
Harvey Specter	4.41	0.92	21.25	1.48	.064
Parent Lawyers					
Mother	5.01	0.88	28.52	1.61	.069
Father	8.83	0.58	134.28	2.18	.117
Both Parents	8.94	1.26	63.29	2.19	.028
Criminal Law 101 Grade	2.03	1.00	4.09	0.71	.049

Note. The reference category for Television Lawyer Model was Annalise Keating. The reference category for Parent Lawyers was neither.

Write Up (Part 2):

A student acting for the defence having both two parent lawyers significantly increased the odds of not guilty verdict by 783% compared to having neither parent being a lawyer. The odds of a not guilty verdict were also significantly increased by 103% with each unit increase in Criminal Law 101 grade. No other predictors significantly related to the odds of a not guilty verdict.

Created by Janine Lurie in consultation with the Statistics Working Group within the School of Psychology, University of Queensland $^{\rm 3}$

Based on *jamovi* v.1.8.4⁴

³ The Statistics Working Group was formed in November 2020 to review the use of statistical packages in teaching across the core undergraduate statistics units. The working group is led by Winnifred Louis and Philip Grove, with contributions from Timothy Ballard, Stefanie Becker, Jo Brown, Jenny Burt, Nathan Evans, Mark Horswill, David Sewell, Eric Vanman, Bill von Hippel, Courtney von Hippel, Zoe Walter, and Brendan Zietsch.

⁴ The jamovi project (2021). jamovi (Version 1.8.4) [Computer Software]. Retrieved from <u>https://www.jamovi.org</u>