Data, method, and knowledge
Evidence-based institutional research

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真實數據, 正確方法, 合理判斷, 具體建議
Evidence-based institutional research

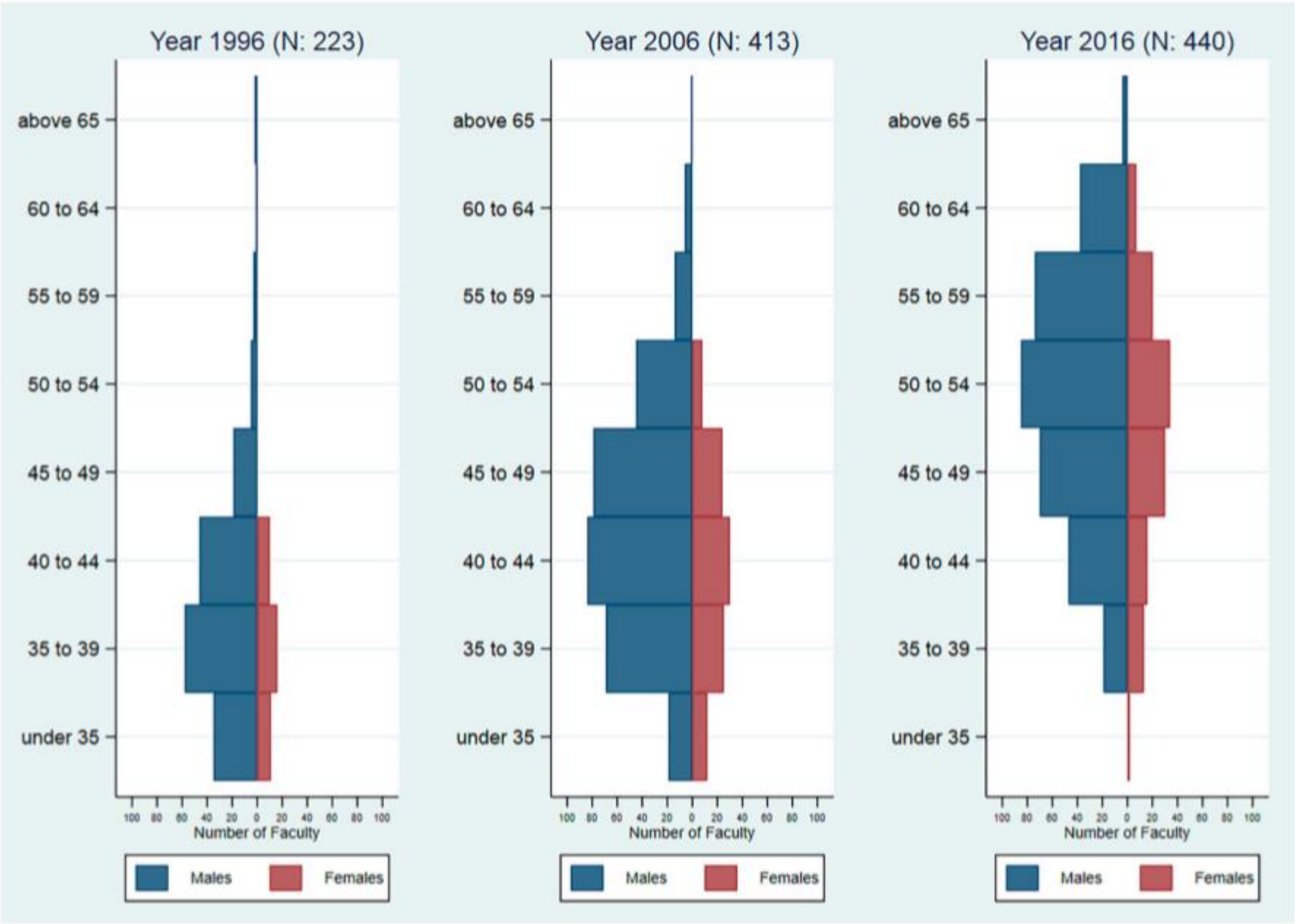

Figure 1. Pyramid of faculty population.

Table 3. Conditional growth curve model.

	(1)		(2)		(3)	
IV: Granted Research Project	Model 1		Model 2		Model 3	
age	−0.020	(0.012)	0.152**	(0.047)	0.114	(0.385)
age^2			−0.001***	(0.000)	−0.001	(0.009)
age^3					−0.000	(0.000)
Gender						
Male	0.204*	(0.086)	0.209*	(0.087)	0.209*	(0.087)
Faculty Rank						
Associate Prof	0.125*	(0.054)	0.114*	(0.054)	0.114*	(0.054)
Professor	0.362***	(0.072)	0.359***	(0.072)	0.358***	(0.073)
Fields						
STEM	0.363***	(0.079)	0.383***	(0.079)	0.383***	(0.079)
Administration	0.111*	(0.050)	0.103*	(0.050)	0.103*	(0.050)
Teaching hours						
Grad Level	0.002	(0.005)	0.002	(0.005)	0.002	(0.005)
College Level	−0.002	(0.004)	−0.002	(0.004)	−0.002	(0.004)
Master Advisees	0.061***	(0.007)	0.057***	(0.007)	0.057***	(0.007)
PhD Advisees	0.077***	(0.013)	0.070***	(0.013)	0.070***	(0.013)
Constant	1.266*	(0.510)	−2.382*	(1.091)	−1.869	(5.356)
Random intercept model						
	Estimates	Std. Err.	Estimates	Std. Err.	Estimates	Std. Err.
Id: identity						
var(_cons)	0.264***	(0.032)	0.268***	(0.032)	0.268***	(0.032)
Residual: AR(1)						
rho	0.343***	(0.017)	0.343***	(0.017)	0.343***	(0.017)
var(e)	0.729***	(0.020)	0.726***	(0.020)	0.726***	(0.020)
Centered Year	Year		Year		Year	
N of observation	4039		4039		4039	
N of faculty	288		288		288	
Wald χ^2	298.80		311.04		310.99	
Prob > χ^2	0.000***		0.000***		0.000***	

Note: Standard errors in parentheses.
*$p < .05$.
**$p < .01$.
***$p < .001$.

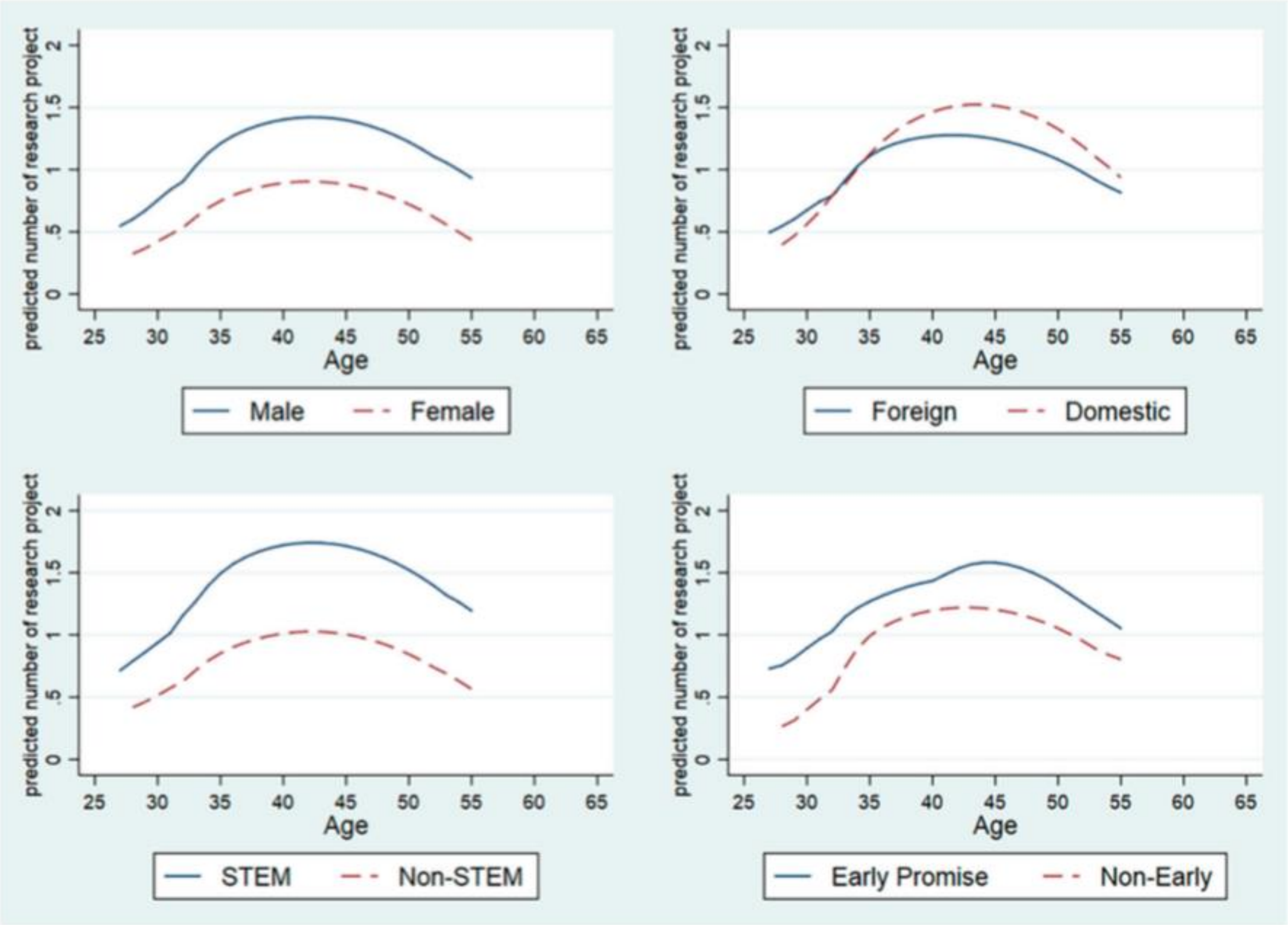

Figure 2. Heterogeneity effect unconditional.

Note: double–exponential smoothing is applied.

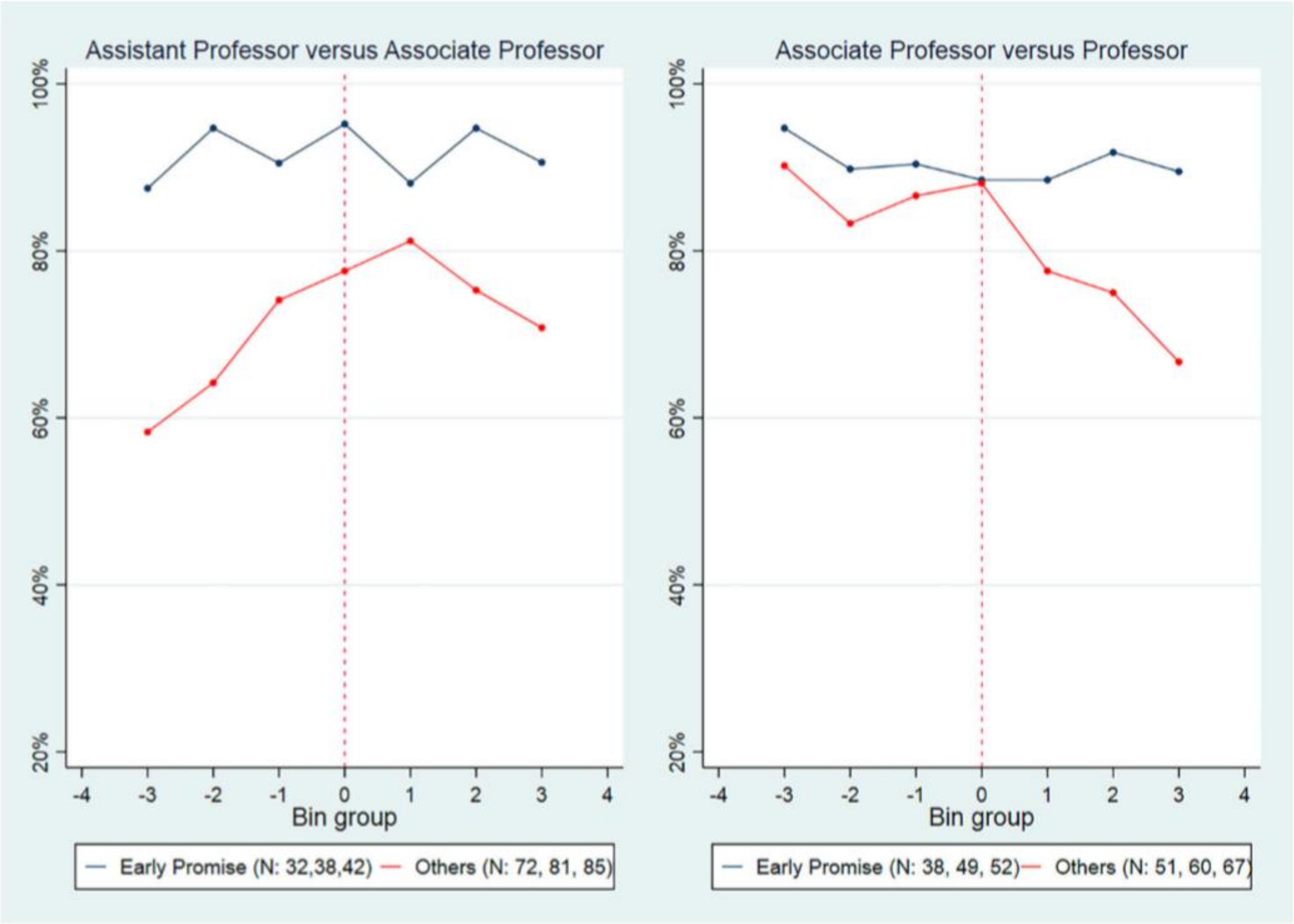

Figure 3. Schedule of reinforcement.

表 3

是否完成雙主修或輔系的多項式邏輯迴歸分析結果

	人文及藝術類							
	模式 1				模式 2			
	(1) 雙主修		(2) 輔系		(3) 雙主修		(4) 輔系	
	係數	標準誤	係數	標準誤	係數	標準誤	係數	標準誤
女性	0.79	0.68	0.85	0.62	0.80	0.68	0.89	0.61
第一代大學生	1.48	1.01	-1.51	0.94	1.47	1.00	-1.58	0.87
綜合能力	0.04	1.08	-0.78	1.06	-.00	0.21	0.72***	0.20
一般能力	-0.16	0.30	-0.20	0.30				
數學邏輯	0.14	0.85	1.71	1.01				
家庭收入	0.29	0.27	-0.52	0.30	0.29	0.27	-0.49	0.28
家長最高職業聲望	0.02	0.15	0.44*	0.19	0.20	0.15	0.44*	0.19
父親教育程度	0.85*	0.37	-0.05	0.31	0.85*	0.37	-0.17	0.36
母親教育程度	-0.16	0.29	-0.53	0.37	-0.16	0.29	-0.46	0.32
常數項	-7.76	2.23	-2.53	1.52	-7.78	2.19	-2.66	1.50
樣本數	613				613			
Pseudo R^2	.129				.109			
Prob > x^2	.001**				.003**			

註：以TEPS-B所附樣本權重調整。

* $p < .05$　** $p < .01$　*** $p < .001$

圖 1　控制組與實驗組的傾向分數分布

表 4

預測變項的平衡檢定

	人文及藝術類			
	雙主修		輔系	
	標準化誤差	方差比	標準化誤差	方差比
女性	-0.03	1.06	-0.25	1.53
第一代大學生	0.00	1.00	0.11	0.82
綜合能力	-0.06	0.86	0.17	0.27
一般能力	-0.05	0.64	0.14	0.32
數學邏輯	-0.06	0.80	0.03	0.40
家庭收入	-0.04	1.01	0.04	0.39
家長最高職業聲望	0.00	0.78	-0.02	1.10
父親教育程度	-0.04	0.98	0.07	0.84
母親教育程度	-0.01	1.07	-0.14	1.02

註：以傾向分數倒數加權迴歸調整法（雙重強韌估計法）（inverse-probability-weighted regression adjustment）調整權重。

表 5

雙主修與輔系平均處理效果

		人文及藝術類			
		畢業 3 年內最高月薪（取自然對數值）		工作與專長相關程度	
		（1）雙主修	（2）輔系	（3）雙主修	（4）輔系
普通最小平方法	係數	0.011	-0.002	0.277	0.018
	標準誤	（0.105）	（0.108）	（0.278）	（0.274）
雙重強韌估計法	係數	0.008	-0.057	0.269	0.048
	標準誤	（0.107）	（0.095）	（0.277）	（0.399）

* $p < .05$ ** $p < .01$ *** $p < .001$

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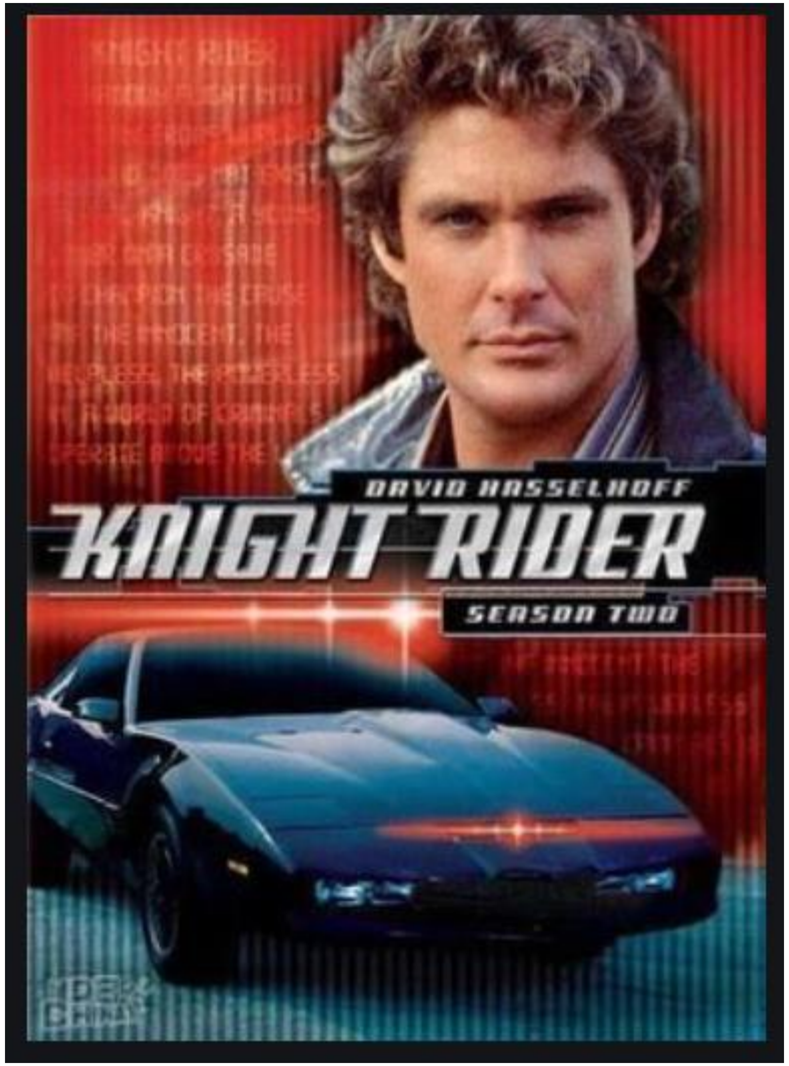
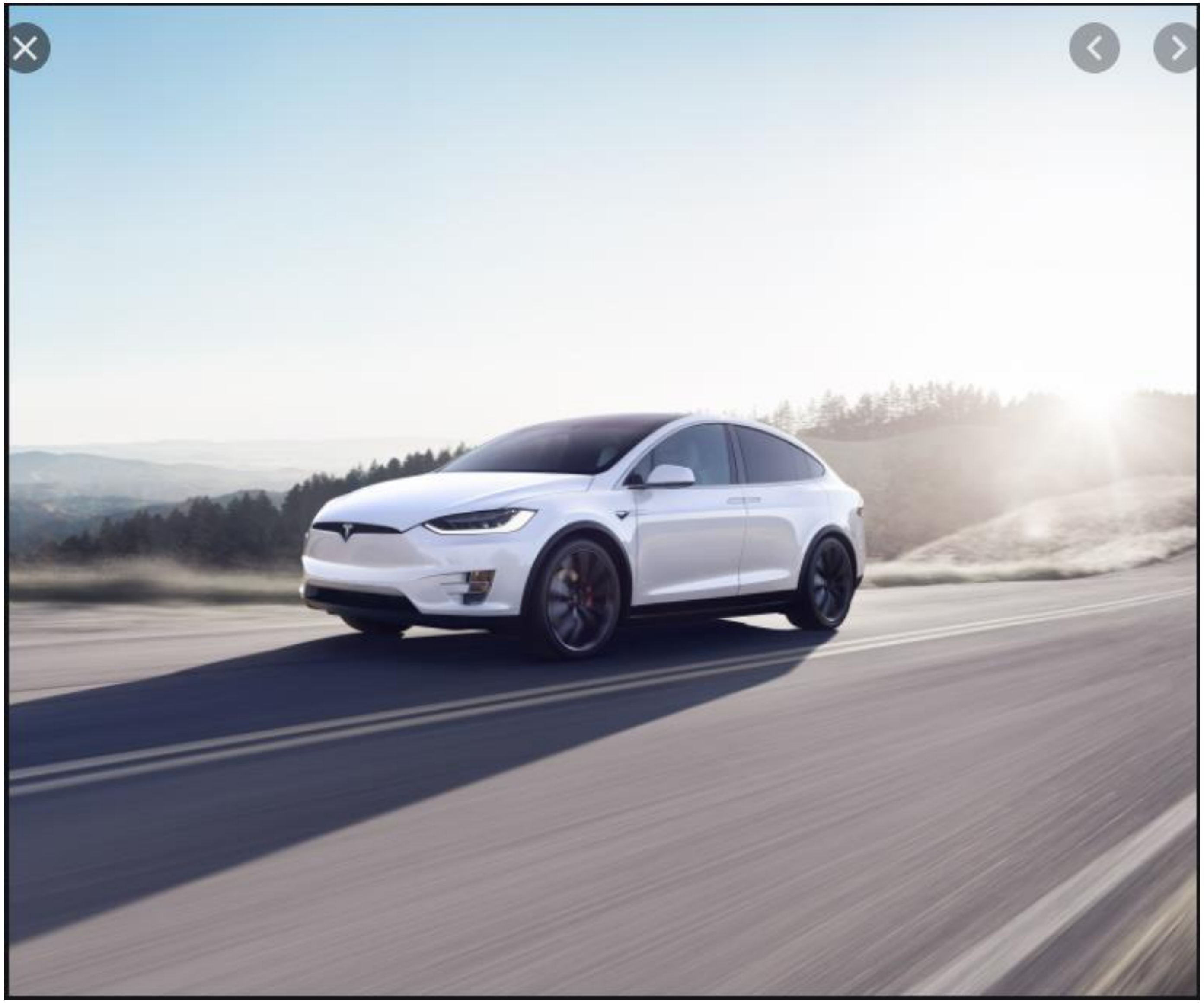

DAVID HASSELHOFF
KNIGHT RIDER
SEASON TWO



Context-aware Nonlinear and Neural Attentive Knowledge-based Models for Grade Prediction

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Grade prediction can help students and their advisers select courses and design personalized degree programs based on predicted future course performance. One of the successful approaches for accurately predicting a student's grades in future courses is Cumulative Knowledge-based Regression Models (CKRM). CKRM learns shallow linear models that predict a student's grades as the similarity between his/her knowledge state and the target course. However, there can be more complex interactions among prior courses taken by a student, which cannot be captured by the current linear CKRM model. Moreover, CKRM and other grade prediction methods ignore the effect of concurrently-taken courses on a student's performance in a target course. In this paper, we propose context-aware nonlinear and neural attentive models that can potentially better estimate a student's knowledge state from his/her prior course information, as well as model the interactions between a target course and concurrent courses. Compared to the competing methods, our experiments on a large real-world dataset consisting of more than 1.5 million grades show the effectiveness of the proposed models in accurately predicting students' grades. Moreover, the attention weights learned by the neural attentive model can be helpful in better designing their degree plans.

The UK used a formula to predict students' scores for canceled exams. Guess who did well.

The formula predicted rich kids would do better than poor kids who'd earned the same grades in class.

By Kelsey Piper | Aug 22, 2020, 7:30am EDT