Modeling data with more than two levels

03.30.22



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Announcements

- Mini-project 02
 - o Team evaluation & feedback due on Fri, April 1 at 11:59pm.
- HW 04 due **Fri, Apr 1** at 11:59pm
- Final project optional draft due Fri, Apr 15, final report due Wed, Apr 27

<u>Click here</u> for Google slides for exercises.



Learning goals

- Write form of model for models with more than two levels.
- Interpret fixed and random effects at each level
- See how three-level models are used in data analysis example



Data: Housing prices in Southampton

The data includes the price and characteristics for 918 houses sold between 1986 and 1991 in Southampton, England. The data were originally collected from a local real estate agency and were analyzed in the 1991 article "Specifying and Estimating Multi-Level Models for Geographical Research" by Kelvyn Jones. The primary variables of interest are

- price: Sales price in thousands of £
- Age: Age of the house
- **Bedrooms**: Number of bedrooms
- House Type: (semi-detached, detached, bungalow, terrace, flat)
- **Central heating**: Whether house has central heating (0: yes, 1: no)
- **Garage**: Number of garages (none, single, double)
- **Districts**: one of 34 districts (baseline:)
- STA 310
- Half-years: Half-year periods beginning the second half of 1986

Data structure

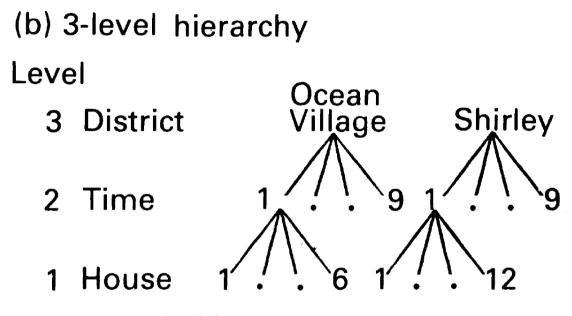


FIGURE 2. Hierarchical data structures

Adapted from Figure 2b from Jones (1991)



Note: The paper uses different symbols to represent parameters than what is in the textbook. The slides will follow the textbook.

Unconditional means model

$$Y_{ijk} = lpha_0 + ilde{u}_i + u_{ij} + \epsilon_{ijk}$$

Level One (house)

$$Y_{ijk} = a_{ij} + \epsilon_{ijk}, \quad \epsilon_{ijk} \sim N(0,\sigma^2)$$

Level Two (time)

$$a_{ij} = a_i + u_{ij}, ~~ u_{ij} \sim N(0, \sigma_u^2)$$

Level Three (district)

$$a_i = lpha_0 + ilde{u}_i, ~~ ilde{u}_i \sim N(0, \sigma_{ ilde{u}}^2)$$



Label the terms of the composite model

- ullet Y_{ijk} : Price of house k^{th} sold in the j^{th} time period in district i
- α_0 :
- ϵ_{ijk} :
- \bullet u_{ij}
- \tilde{u}_i :
- ullet σ : House-to-house variability within a given time period
- σ_u : Variability over time within a district

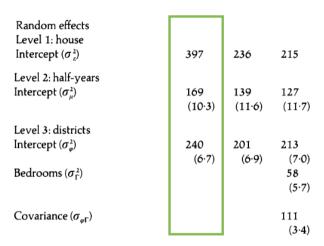


• $\sigma_{\tilde{u}}$: District-to-district variability

Model A

TABLE I. ML estimates for house price variation

	Α	Model B	С	
Fixed effects				
Level 1: house				
Intercept (β_0)	58-1	57.0	56.7	
Age (β_1)		0.0	0.0	
0 · 1 /		(0.1)	(0.1)	
House type		` ′	, ,	
detached (β_i)		22.3	21.1	
7 2		(11-2)	(11.0)	
bungalow(β_3)		17.9	15.7	
0 1,5		(5.6)	(5.2)	
terrace (β_4)		2.7	3.0	
•		(1.8)	(2.0)	
flat (β_s)		1.1	-0.9	
		(0.5)	(0.4)	
Bedrooms $(\beta_{\mathfrak{o}})$		9.5	8.0	
· ·		(9.5)	(4.7)	
Central heating (β_7)		−3 ·1	-3.1	
0.,		(2.6)	(2.6)	
Garage				
single (β_s)		6.7	6.6	
		(4.6)	(4.8)	
double (β ₉)		26-1	24.1	
-		(6·1)	(5.8)	



Interpret $\hat{\beta}_0$ (this is α_0 in our model notation)



Table 1 from Jones (1991)

Model A: Random effects

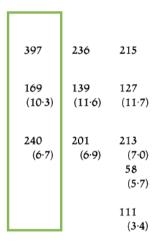
Random effects Level 1: house Intercept (σ_{ϵ}^2)

Level 2: half-years Intercept (σ_n^2)

Level 3: districts Intercept (σ_{φ}^2)

Bedrooms (σ_{Γ}^2)

Covariance $(\sigma_{\alpha\Gamma})$



- 1. Calculate the intraclass correlation for time.
- 2. Calculate the intraclass correlation coefficient for districts.
- 3. Is there evidence the multilevel model structure is useful for this data?

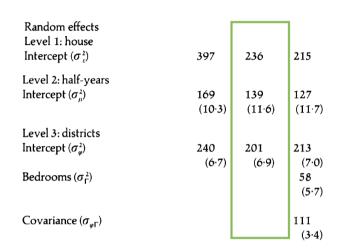


Model B: Add covariates + random intercepts

TABLE I. ML estimates for house price variation

	Α	Model B	С
Fixed effects			
Level 1: house			
Intercept (β_0)	58.1	57.0	56.7
Age (β_1)		0.0	0.0
3 4 12		(0.1)	(0.1)
House type		` ′	` ′
$detached(\beta_2)$		22.3	21.1
.		(11-2)	(11.0)
bungalow(β_3)		17.9	15.7
0 17		(5.6)	(5·2)
terrace $(\beta_{\scriptscriptstyle A})$		2.7	3.0
		(1.8)	(2.0)
flat (β_s)		1.1	-0.9
		(0.5)	(0.4)
Bedrooms (β_{c})		9.5	8.0
		(9.5)	(4.7)
Central heating (β_7)		−3 ·1	−3·1
2 . ,		(2-6)	(2.6)
Garage			
single (β_s)		6.7	6.6
		(4.6)	(4.8)
double ($oldsymbol{eta}_{9}$)		26-1	24.1
		(6·1)	(5·8)





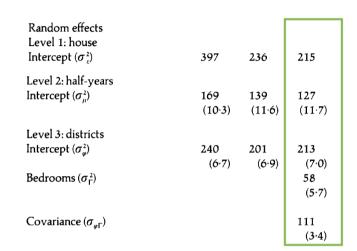
- 1. Write the composite model.
- 2. Which variables appear to have a statistically significant effect on price?
- 3. Use this model to interpret the covariate assigned to your group.

Model C: Additional random effect

TABLE I. ML estimates for house price variation

	Α	Model B	С	
Fixed effects				
Level 1: house				
Intercept (β_0)	58.1	57·0	56.7	
Age (β_1)		0.0	0.0	
		(0.1)	(0.1)	
House type				
$detached(\beta_2)$		22.3	21.1	
		(11-2)	(11.0)	
bungalow(β_3)		17.9	15.7	
		(5.6)	(5·2)	
terrace ($oldsymbol{eta}_{\scriptscriptstyle 4}$)		2.7	3.0	
		(1.8)	(2.0)	
flat ($oldsymbol{eta}_{\scriptscriptstyle 5}$)		1.1	-0.9	
		(0.5)	(0.4)	
Bedrooms (β_s)		9.5	8.0	
		(9.5)	(4.7)	
Central heating (β_7)		-3.1	−3 ·1	
		(2.6)	(2.6)	
Garage				
single $(oldsymbol{eta}_s)$		6.7	6.6	
		(4.6)	(4.8)	
double ($oldsymbol{eta}_{\scriptscriptstyle{9}}$)		26.1	24.1	
		(6.1)	(5·8)	





- 1. How does this model differ from Model B?
- 2. Write the composite model.
- 3. Write the Level One, Level Two, and Level Three models.



Visualizing price by district over time

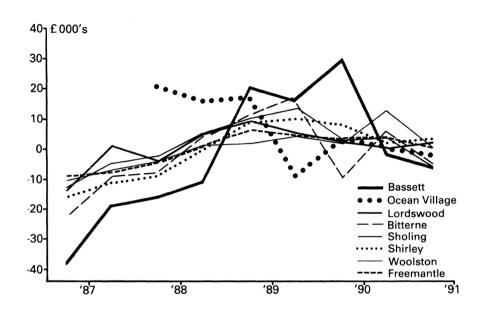


Figure 3 from Jones (1991)

- 1. What do you observe from the plot?
- 2. What terms in the model can be understood from the plot?
- 3. How might you use this type of plot to support decisions you make in the analysis?



Price by district and bedrooms

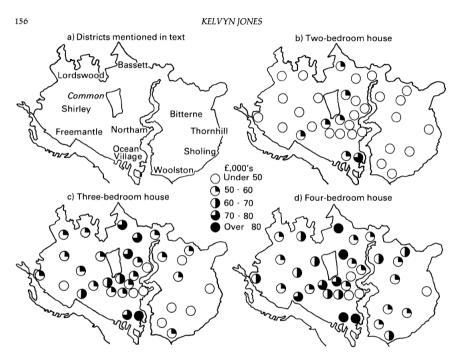


FIGURE 4. District house price variations, 1986–1990, based on level-3 random effects for model C

Figure 4 from Jones (1991)

- 1. What do you observe from the plot?
- 2. What terms in the model can be understood from the plot?
- 3. How might you use this type of plot to support decisions you make in the analysis?

How does our understanding of the effect of bedrooms differ in this model compared to Model B?



Acknowledgements

- Jones, K. (1991). <u>Specifying and estimating multi-level models for geographical</u> <u>research</u>. Transactions of the institute of British geographers, 148-159.
- Beyond Multiple linear regression
 - Chapter 10: Multilevel data with more than two levels

