

Chapter 4

Hierarchical Models

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Chapter 4. Hierarchical Models

Bayesian Model (non-hierarchical)

$$p(\tilde{y} | \theta)$$
$$\pi(\theta)$$

Hierarchical Bayesian Model

$$p(\tilde{y} | \theta) \quad \longleftarrow \quad 1^{\text{st}} \text{ Level}$$
$$\pi(\theta | \gamma) \quad \longleftarrow \quad 2^{\text{nd}} \text{ Level}$$
$$\pi(\gamma) \quad \longleftarrow \quad 3^{\text{rd}} \text{ Level}$$

The hierarchical Bayesian Model treats the parameters of the prior distribution as random variables. This fact adds a new level to the model.

Bayesian Analysis

Chapter 4. Hierarchical Models

If we take a random sample of size n , y_1, \dots, y_n , then we can write the hierarchical bayesian model as:

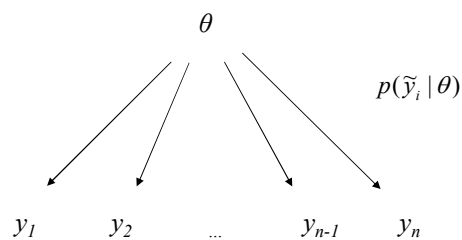
$$\begin{aligned}\tilde{y}_i | \theta_i &\sim p(\tilde{y}_i | \theta_i) && \text{for } i=1, \dots, n \\ \theta_i | \gamma &\sim \pi(\theta_i | \gamma) \\ \gamma &\sim \psi(\gamma)\end{aligned}$$

\tilde{y}_i	observable variable	$p(\tilde{y}_i \theta_i)$	probability distribution
θ_i	parameter	$\pi(\theta_i \gamma)$	prior distribution
γ	hyperparameter	$\psi(\gamma)$	hyperprior distribution

Chapter 4. Hierarchical Models

Bayesian Model (non-hierarchical)

$$\begin{aligned}\tilde{y}_i | \theta &\sim p(\tilde{y}_i | \theta) \\ \theta &\sim \pi(\theta)\end{aligned}$$



The y 's are generated by the probability model $p(\tilde{y}_i | \theta)$

Bayesian Analysis

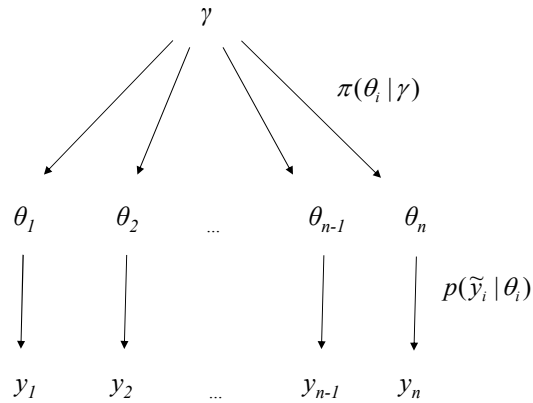
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Hierarchical Bayesian Model

$$\tilde{y}_i | \theta_i \sim p(\tilde{y}_i | \theta_i)$$

$$\theta_i | \gamma \sim \pi(\theta_i | \gamma)$$

$$\gamma \sim \psi(\gamma)$$



The y 's are generated by the probability model $p(\tilde{y}_i | \theta_i)$, and the θ 's are generated by $\pi(\theta_i | \gamma)$

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Example: Hospitals

Exercise 6.2 Surgical: Institutional ranking. This exercise considers mortality rates in 12 hospitals performing cardiac surgery in babies. The data are shown below:

Hospital	No of ops	No of deaths
A	47	0
B	148	18
C	119	8
D	810	46
E	211	8
F	196	13
G	148	9
H	215	31
I	207	14
J	97	8
K	256	29
L	360	24

The objective of this study is to know the probability of death around all the hospitals in the country, not only in the hospitals that are in the sample.

Chapter 4. Hierarchical Models

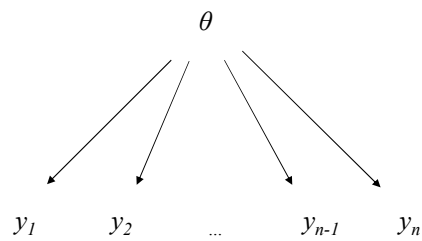
Example: Hospitals

y_i := number of deaths in the i -th hospital for $i=1, \dots, 12$
 n_i := number of surgeries in the i -th hospital

Model A

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta)$$

$$\theta \sim \text{Beta}(a=1, b=1)$$



Where θ is the probability of dying, and it is the same for all hospitals

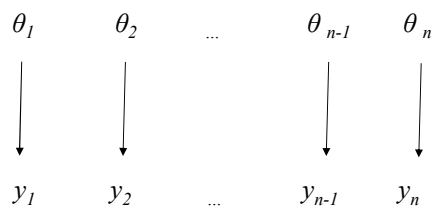
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Example: Hospitals

Model B

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i \sim \text{Beta}(1, 1)$$



Where θ_i is the probability of dying for the i -th hospital for $i=1, \dots, 12$, but we don't know anything about the death probability from other hospitals.

Chapter 4. Hierarchical Models

Example: Hospitals

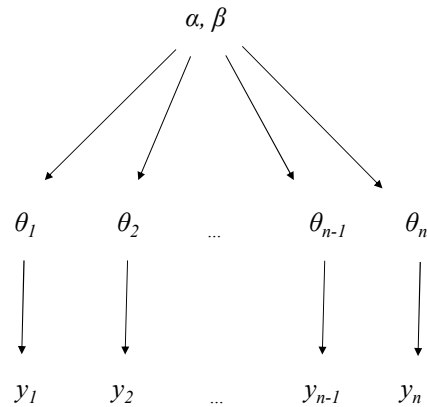
Model C

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i | \alpha, \beta \sim \text{Beta}(\alpha, \beta)$$

$$\alpha \sim \text{Gamma}(0.01, 0.001)$$

$$\beta \sim \text{Gamma}(0.01, 0.001)$$



We can make inference and prediction at different levels

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Example: Hospitals

Model C (hierarchical):

All we know about the probability of dying in the i -th hospital is in :

$$\pi(\theta_i | y)$$

And we can make inference of the probability of dying in a hospital that is not in the sample using the posterior predictive distribution of the second level:

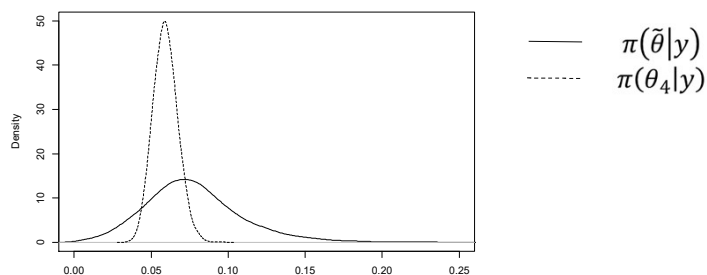
$$\pi(\tilde{\theta} | y) = \iint \pi(\tilde{\theta} | \alpha, \beta) \pi(\alpha, \beta | y) d\alpha d\beta$$

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Example: Hospitals

Posterior probability distribution of the probability of dying for hospital n° 4

Posterior probability distribution of the probability of dying for a new hospital



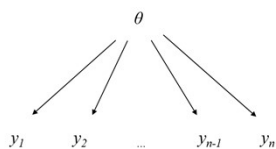
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Example: Hospitals

Model A

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta)$$

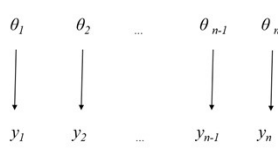
$$\theta \sim \text{Beta}(1, 1)$$



Model B

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i \sim \text{Beta}(1, 1)$$



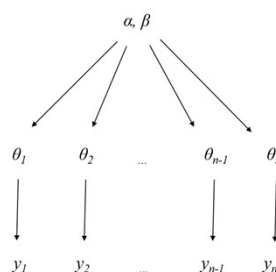
Model C

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

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Chapter 4. Hierarchical Models

Example: Hospitals

Model A

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta)$$

$$\theta \sim \text{Beta}(1, 1)$$

parameters

θ
$\theta^{(1)}$
$\theta^{(2)}$
\vdots
$\theta^{(M)}$

simulations

Model B

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i \sim \text{Beta}(1, 1)$$

parameters

θ_1	θ_2	...	θ_{12}
$\theta_1^{(1)}$	$\theta_2^{(1)}$...	$\theta_{12}^{(1)}$
$\theta_1^{(2)}$	$\theta_2^{(2)}$...	$\theta_{12}^{(2)}$
\vdots			
$\theta_1^{(M)}$	$\theta_2^{(M)}$...	$\theta_{12}^{(M)}$

simulations

Model C

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i | \alpha, \beta \sim \text{Beta}(\alpha, \beta)$$

$$\alpha \sim \text{Gamma}(0.01, 0.001)$$

$$\beta \sim \text{Gamma}(0.01, 0.001)$$

parameters

θ_1	θ_2	...	θ_{12}	α	β
$\theta_1^{(1)}$	$\theta_2^{(1)}$...	$\theta_{12}^{(1)}$	$\alpha^{(1)}$	$\beta^{(1)}$
$\theta_1^{(2)}$	$\theta_2^{(2)}$...	$\theta_{12}^{(2)}$	$\alpha^{(2)}$	$\beta^{(2)}$
\vdots					
$\theta_1^{(M)}$	$\theta_2^{(M)}$...	$\theta_{12}^{(M)}$	$\alpha^{(M)}$	$\beta^{(M)}$

simulations

Chapter 4. Hierarchical Models

Example: Hospitals

$$\tilde{y}_i | \theta_i \sim \text{Binomial}(n_i, \theta_i)$$

$$\theta_i | \alpha, \beta \sim \text{Beta}(\alpha, \beta)$$

$$\alpha \sim \text{Gamma}(0.01, 0.001)$$

$$\beta \sim \text{Gamma}(0.01, 0.001)$$

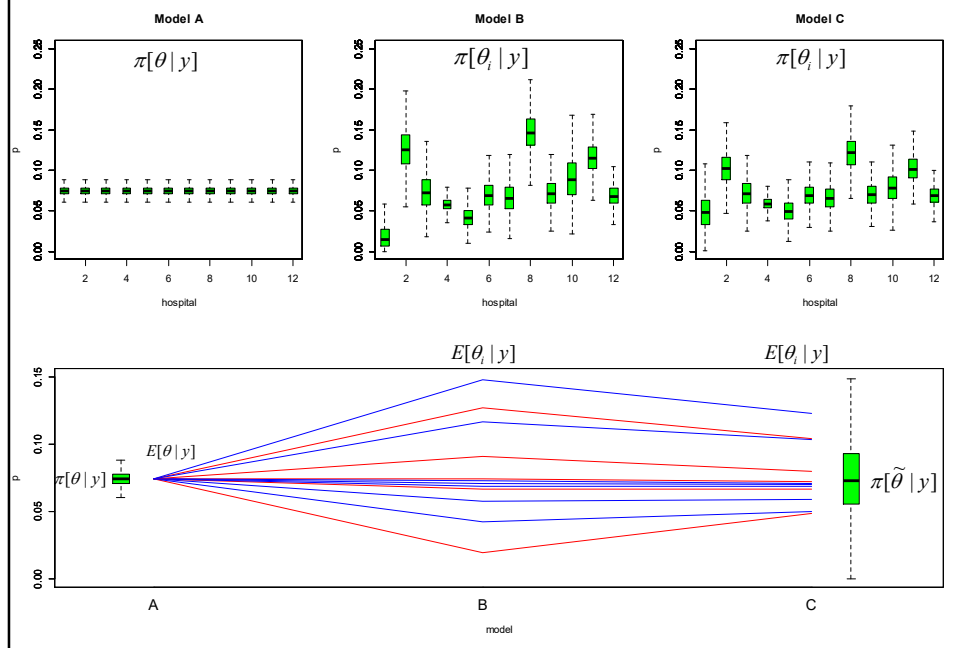
parameters

θ_1	θ_2	...	θ_{12}	α	β
$\theta_1^{(1)}$	$\theta_2^{(1)}$...	$\theta_{12}^{(1)}$	$\alpha^{(1)}$	$\beta^{(1)}$
$\theta_1^{(2)}$	$\theta_2^{(2)}$...	$\theta_{12}^{(2)}$	$\alpha^{(2)}$	$\beta^{(2)}$
\vdots					
$\theta_1^{(M)}$	$\theta_2^{(M)}$...	$\theta_{12}^{(M)}$	$\alpha^{(M)}$	$\beta^{(M)}$

simulations

Bayesian Analysis

Chapter 4. Hierarchical Models



Chapter 4. Hierarchical Models

Example: Hospitals

Can we do a ranking for the sample hospitals?

Chapter 4. Hierarchical Models

Example: Hospitals

	parameter				Ranking			
	θ_1	θ_2	...	θ_{12}	R_1	R_2	...	R_{12}
simulations	$\theta_1^{(1)}$	$\theta_2^{(1)}$...	$\theta_{12}^{(1)}$	$R_1^{(1)}$	$R_2^{(1)}$...	$R_{12}^{(1)}$
	$\theta_1^{(2)}$	$\theta_2^{(2)}$...	$\theta_{12}^{(2)}$	$R_1^{(2)}$	$R_2^{(2)}$...	$R_{12}^{(2)}$
	\vdots				\vdots			
	$\theta_1^{(M)}$	$\theta_2^{(M)}$...	$\theta_{12}^{(M)}$	$R_1^{(M)}$	$R_2^{(M)}$...	$R_{12}^{(M)}$

In each simulation we create a new *Ranking* variable for each hospital

For example, if in the first simulation after sorting the values of θ 's we get:

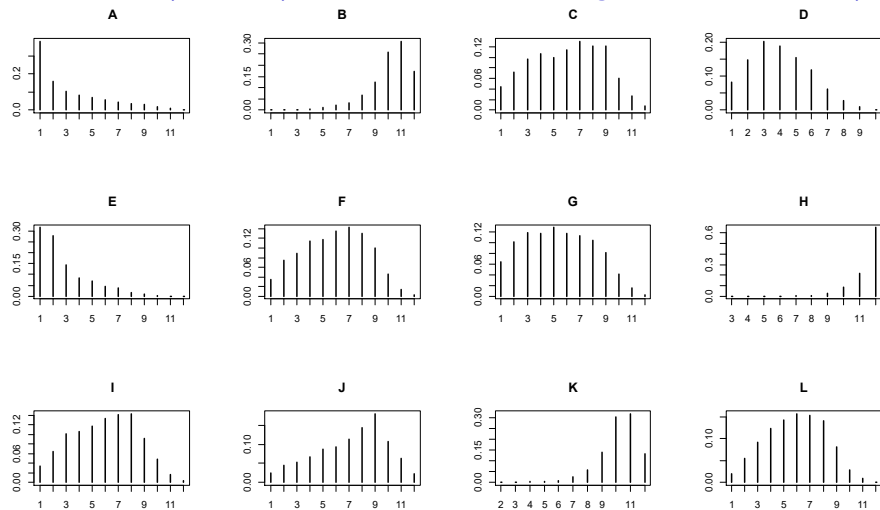
$$\theta_2^{(1)} < \theta_3^{(1)} < \theta_5^{(1)} < \theta_{12}^{(1)} < \theta_4^{(1)} < \theta_{11}^{(1)} < \theta_9^{(1)} < \dots < \theta_1^{(1)}$$

Then the ranking variable will be:

$$R_1^{(1)} = 12, R_2^{(1)} = 1, R_3^{(1)} = 2, R_4^{(1)} = 5, \dots, R_{12}^{(1)} = 4$$

Chapter 4. Hierarchical Models

The Posterior probability Distribution for the *ranking* variable for each hospital



		A	B	C	D	E	F	G	H	I	J	K	L
80% CI	10%	1	8	2	2	1	2	2	10	3	3	9	3
	90%	7	12	9	7	6	9	9	12	9	10	12	9

Bayesian Analysis

Chapter 4. Hierarchical Models

I encourage you to read chapter 5 (Hierarchical models) and chapter 15 (*Hierarchical Linear Models*) from the book:

Gelman A, Carlin J, Stern H, Dunson D, Vehtari A, and Rubin D (2014). *Bayesian Data Analysis* (3rd ed). London: Chapman & Hall.