Chapter 5

- 5.1 Lead-in to hierarchical models
- 5.2 Exchangeability (important concept)
- 5.3 Bayesian analysis of hierarchical models (we can do computation with Stan)
- 5.4 Hierarchical normal model (we can do computation with Stan)
- 5.5 Example: parallel experiments in eight schools (uses hierarchical normal model, part of exercises)
- 5.6 Meta-analysis (can be skipped)
- 5.7 Weakly informative priors for hierarchical variance parameters

Hierarchical model

- Example: CVD treatment effectiveness
  - in hospital j the survival probability is θ_j
  - observations y_{ij} tell whether patient i survived in hospital j

$$\begin{array}{cccc} \theta_1 & \theta_2 & \cdots & \theta_n \\ \downarrow & \downarrow & & \downarrow \\ y_{i1} & y_{i2} & & y_{in} \end{array}$$

Hierarchical model

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$$\begin{tikzcd}
\theta_1 \arrow[d] & \theta_2 \arrow[d] & \cdots & \theta_n \arrow[d] \\
y_{i1} & y_{i2} & & y_{in}
\end{tikzcd}$$

  - sensible to assume that θ_j are similar

$$\begin{tikzcd}
& \tau \arrow[dl] \arrow[d] \arrow[drr] & & \\
\theta_1 \arrow[d] & \theta_2 \arrow[d] & \cdots & \theta_n \arrow[d] \\
y_{i1} & y_{i2} & & y_{in}
\end{tikzcd}$$

  - natural to think that θ_j have common population distribution
  - θ_j is not directly observed and the population distribution is unknown

Hierarchical model: terms

Level 1: observations given parameters $p(y_{ij}|\theta_j)$

$$
\begin{array}{cccccc}
p(\theta_j|\tau) & \theta_1 & \theta_2 & \cdots & \theta_n & \text{parameters} \\
 & \downarrow & \downarrow & & \downarrow & \\
p(y_{ij}|\theta_j) & y_{i1} & y_{i2} & & y_{in} & \text{observations}
\end{array}
$$

Joint posterior

$$
\begin{aligned}
p(\theta, \tau|y) &\propto p(y|\theta, \tau)p(\theta, \tau) \\
&\propto p(y|\theta)p(\theta|\tau)p(\tau)
\end{aligned}
$$

Hierarchical model: terms

Level 1: observations given parameters $p(y_{ij}|\theta_j)$

Level 2: parameters given hyperparameters $p(\theta_j|\tau)$

$$
\begin{tikzcd}
p(\tau) & & \tau \arrow[dl] \arrow[d] \arrow[drr] & & & \text{hyperparameter} \\
p(\theta_j|\tau) & \theta_1 \arrow[d] & \theta_2 \arrow[d] & \cdots & \theta_n \arrow[d] & \text{parameters} \\
p(y_{ij}|\theta_j) & y_{i1} & y_{i2} & & y_{in} & \text{observations}
\end{tikzcd}
$$

Joint posterior

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\begin{aligned}
p(\theta,\tau|y) &\propto p(y|\theta,\tau)p(\theta,\tau) \\
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Compare

- "Separate model" (model with separate/independent effects)

$$\begin{array}{ccccc} \theta_1 & \theta_2 & \cdots & \theta_n \\ \downarrow & \downarrow & & \downarrow \\ y_1 & y_2 & & y_n \end{array}$$

Compare

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- "Joint model" (model with a common effect / pooled model)

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- Hierarchical model

$$\begin{tikzcd} & \tau \arrow[dl] \arrow[d] \arrow[drr] & & \\ \theta_1 \arrow[d] & \theta_2 \arrow[d] & \cdots & \theta_n \arrow[d] \\ y_1 & y_2 & & y_n \end{tikzcd}$$

Hierarchical binomial model: rats

- Medicine testing
- Type F344 female rats in control group given placebo
  - count how many get endometrial stromal polyps
  - familiar binomial model example

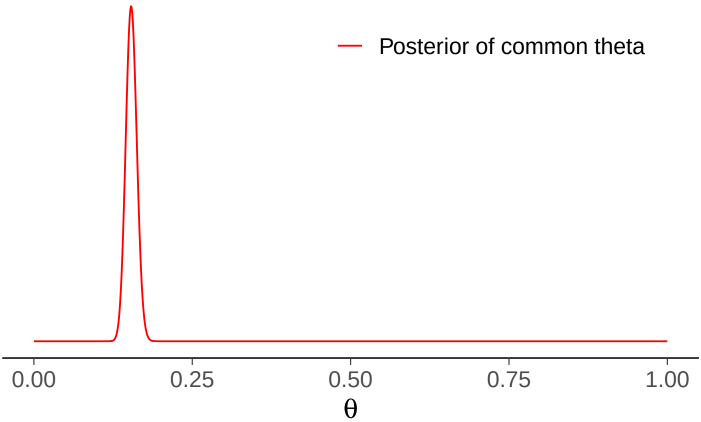
Hierarchical binomial model: rats

- Medicine testing
- Type F344 female rats in control group given placebo
  - count how many get endometrial stromal polyps
  - familiar binomial model example
- Experiment has been repeated 71 times

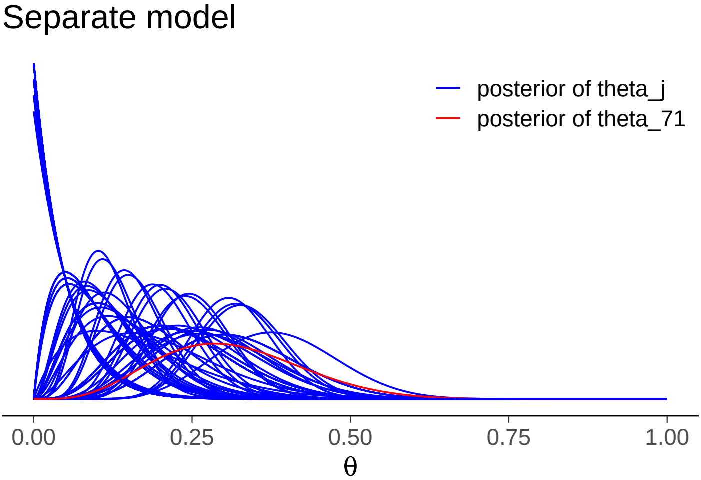
0/20	0/20	0/20	0/20	0/20	0/20	0/20	0/19	0/19	0/19
0/19	0/18	0/18	0/17	1/20	1/20	1/20	1/20	1/19	1/19
1/18	1/18	2/25	2/24	2/23	2/20	2/20	2/20	2/20	2/20
2/20	1/10	5/49	2/19	5/46	3/27	2/17	7/49	7/47	3/20
3/20	2/13	9/48	10/50	4/20	4/20	4/20	4/20	4/20	4/20
4/20	10/48	4/19	4/19	4/19	5/22	11/46	12/49	5/20	5/20
6/23	5/19	6/22	6/20	6/20	6/20	16/52	15/46	15/47	9/24
4/14									

Hierarchical binomial model: rats

Pooled model

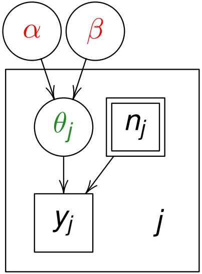


Hierarchical binomial model: rats



Hierarchical binomial model: rats

- Hierarchical binomial model for rats
  prior parameters α and β are unknown



$$\theta_j|\alpha,\beta \sim \mathrm{Beta}(\theta_j|\alpha,\beta)$$

$$y_j|n_j,\theta_j \sim \mathrm{Bin}(y_j|n_j,\theta_j)$$

- Joint posterior $p(\theta_1,\ldots,\theta_J,\alpha,\beta|y)$
  - multiple parameters

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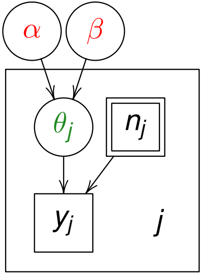
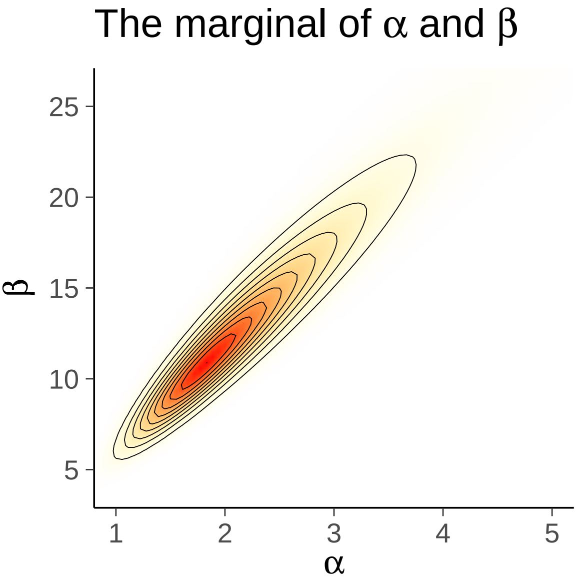


- Joint posterior $p(\theta_1,\ldots,\theta_J,\alpha,\beta|y)$
  - multiple parameters
  - factorize $\prod_{j=1}^{J} p(\theta_j|\alpha,\beta,y)p(\alpha,\beta|y)$

Hierarchical binomial model: rats

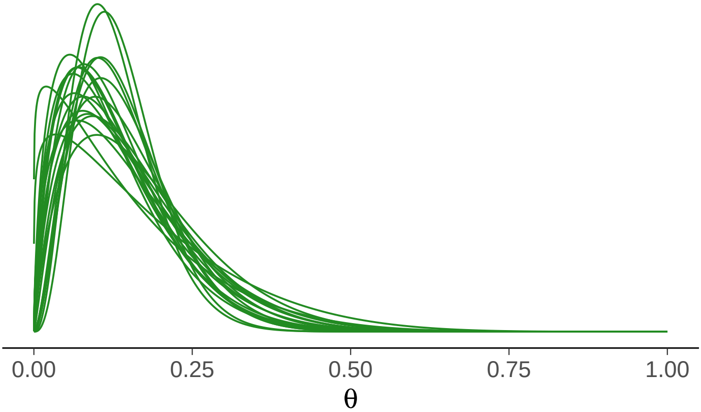
- Population prior Beta($\theta_j|\alpha, \beta$)
- Hyperprior $p(\alpha, \beta)$?
  - α, β both affect the location and scale
  - BDA3 has $p(\alpha, \beta) \propto (\alpha + \beta)^{-5/2}$
    - diffuse prior for location and scale (BDA3 p. 110)
- demo5_1

Hierarchical binomial model: rats



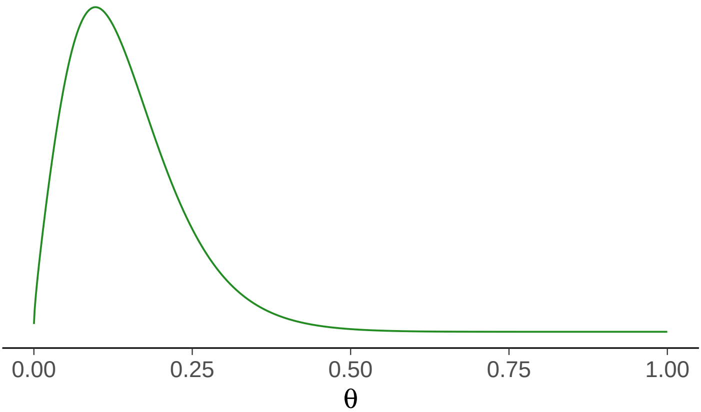
Hierarchical binomial model: rats

Beta(α,β) given posterior drwas of α and β



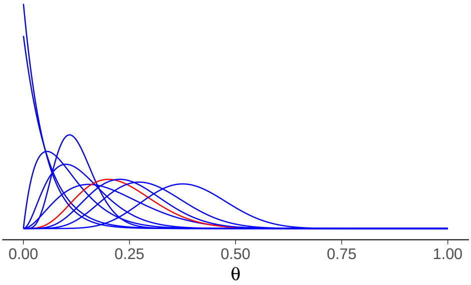
Hierarchical binomial model: rats

Population distribution (prior) for θ_j



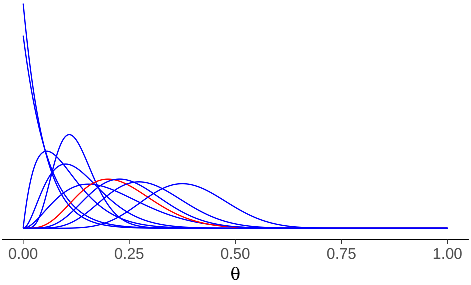
Hierarchical binomial model: rats

Separate model

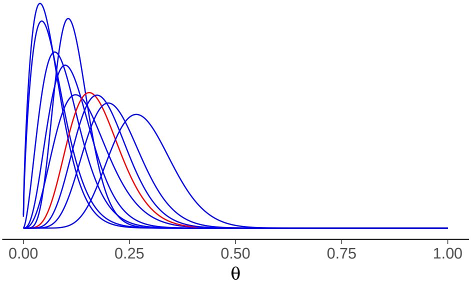


Hierarchical binomial model: rats

Separate model

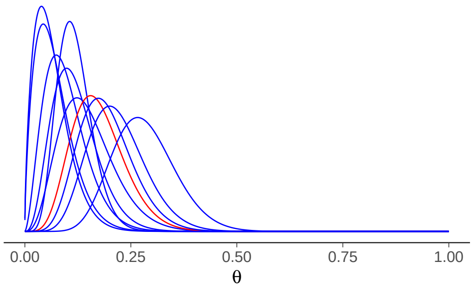


Hierarchical model



Hierarchical binomial model: rats

Hierarchical model



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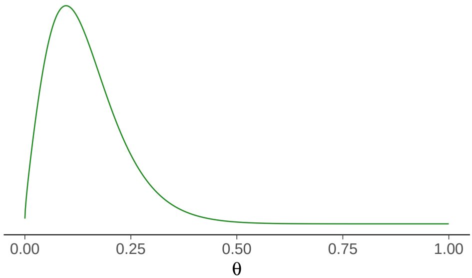
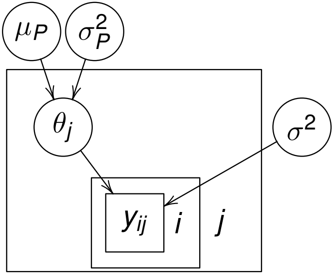


Hierarchical normal model: factory

- Factory has 6 machines which quality is evaluated
- Assume hierarchical model
  - each machine has its own (average) quality θ_j and common variance σ^2

$$\theta_j | \mu_P, \sigma_P^2 \sim \mathrm{N}(\mu_P, \sigma_P^2)$$

$$y_{ij} | \theta_j \sim \mathrm{N}(\theta_j, \sigma_j^2)$$



- Can be used to predict the future quality produced by each machine and quality produced by a new similar machine

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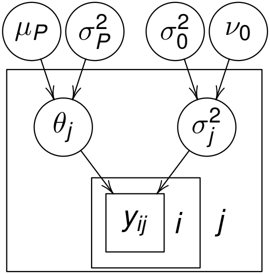

$$\sigma_j^2|\sigma_0^2,\nu_0 \sim \text{Inv-}\chi^2(\sigma_0^2,\nu_0)$$

$$y_{ij}|\theta_j \sim \mathrm{N}(\theta_j,\sigma_j^2)$$

- Can be used to predict the future quality produced by each machine and quality produced by a new similar machine

Hierarchical normal model: 8 schools

- Example: SAT coaching effectiveness
    - in USA commonly used Scholastic Aptitude Test (SAT) is designed so that short term practice should not improve the results significantly
    - schools have anyway coaching courses
    - test the effectiveness of the coaching courses

Hierarchical normal model: 8 schools

- Example: SAT coaching effectiveness
  - in USA commonly used Scholastic Aptitude Test (SAT) is designed so that short term practice should not improve the results significantly
  - schools have anyway coaching courses
  - test the effectiveness of the coaching courses
- SAT
  - standardised multiple choice test
  - mean about 500 and standard deviation about 100
  - most scores between 200 and 800
  - different topics, e.g., V=Verbal, M=Mathematics
  - pre-test PSAT

Hierarchical normal model: 8 schools

- Effectiveness of the SAT coaching
  - students had made pre-tests PSAT-M and PSAT-V
  - part of students were coached
  - linear regression was used to estimate the coaching effect y_j for the shool j (could be denoted with $\bar{y}_{.j}$, too) and variances σ_j^2
  - y_j approximately normally distributed, with variances assumed to be known based on about 30 students per school
  - data is group means and variances (not personal results)

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- Data:

School	A	B	C	D	E	F	G	H
y_j	28	8	-3	7	-1	1	18	12
σ_j	15	10	16	11	9	22	20	28

Hierarchical normal model for group means

- J experiments, unknown θ_j and known σ^2

$$y_{ij}|\theta_j \sim \mathrm{N}(\theta_j, \sigma^2), \quad i = 1, \ldots, n_j; \quad j = 1, \ldots, J$$

- Group j sample mean and sample variance

$$\begin{aligned}
\bar{y}_{.j} &= \frac{1}{n_j}\sum_{i=1}^{n_j} y_{ij} \\
\sigma_j^2 &= \frac{\sigma^2}{n_j}
\end{aligned}$$

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- Use model

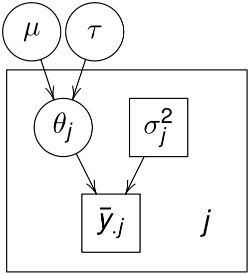
$$\bar{y}_{.j}|\theta_j \sim \mathrm{N}(\theta_j, \sigma_j^2)$$

this model can be generalized so that, σ_j^2 can be different from each other for other reasons than n_j

Hierarchical normal model for group means

$\theta_j|\mu,\tau \sim \mathrm{N}(\mu,\tau)$

$\bar{y}_{.j}|\theta_j \sim \mathrm{N}(\theta_j,\sigma_j^2)$



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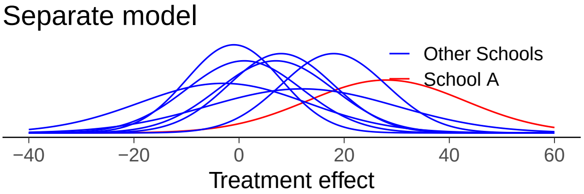

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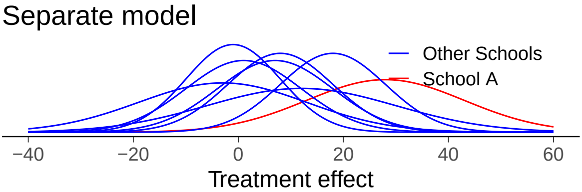
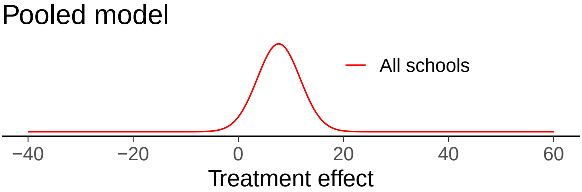
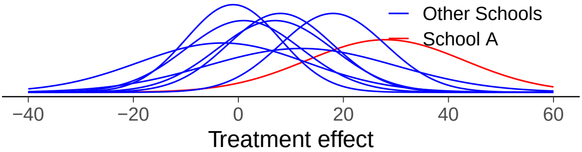


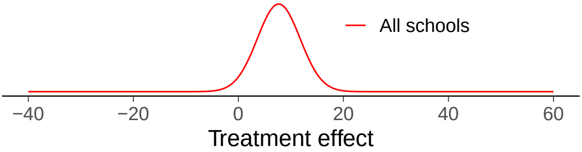


Hierarchical normal model: 8 schools

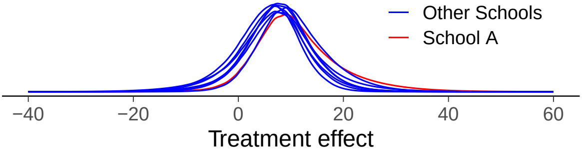
Separate model



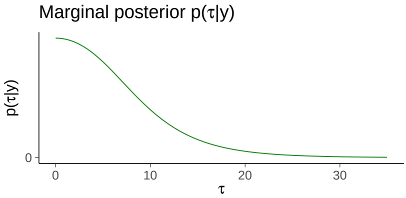
Pooled model



Hierarchical model



Hierarchical normal model: 8 schools



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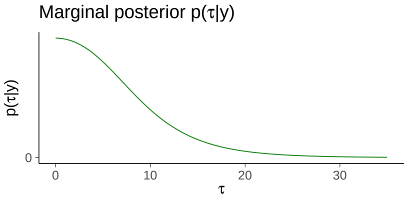

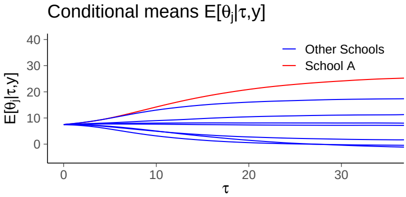

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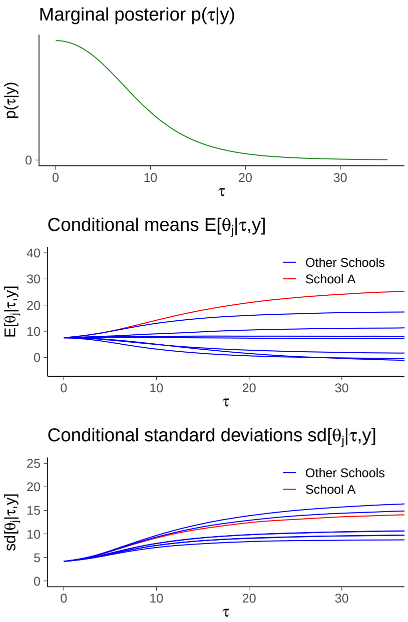

Exchangeability

- Justifies why we can use
  - a joint model for data
  - a joint prior for a set of parameters
- Less strict than independence

Exchangeability

- *Exchangeability*: Parameters $\theta_1, \ldots, \theta_J$ (or observations $y_1, \ldots, y_J$) are exchangeable if the joint distribution p is invariant to the permutation of indices $(1, \ldots, J)$
- e.g.
$$p(\theta_1, \theta_2, \theta_3) = p(\theta_2, \theta_3, \theta_1)$$
- Exchangeability implies symmetry: If there is no information which can be used *a priori* to separate θ_j form each other, we can assume exchangeability. ("Ignorance implies exchangeability")

Exchangeability

- Exchangeability does not mean that the results of the experiments could not be different
  - e.g. if we know that the experiments have been in two different laboratories, and we know that the other laboratory has better conditions for the rats, but we do not know which experiments have been made in which laboratory
  - a priori experiments are exchangeable
  - model could have unknown parameter for the laboratory with a conditional prior for rats assumed to come form the same place (clustering model)

Exchangeability

- The simplest form of the exchangeability (but not the only one) for the parameters θ conditional independence

$$p(x_1, \ldots, x_J|\theta) = \prod_{j=1}^{J} p(x_j|\theta)$$

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$$p(x_1, \ldots, x_J|\theta) = \prod_{j=1}^{J} p(x_j|\theta)$$

- Let $(x_n)_{n=1}^{\infty}$ to be an infinite sequence of exchangeable random variables. De Finetti's theorem then says that there is some random variable θ so that x_j are conditionally independent given θ, and joint density for $x_1, \ldots, x_J$ can be written in the *iid mixture* form

$$p(x_1, \ldots, x_J) = \int \left[\prod_{j=1}^{J} p(x_j|\theta) \right] p(\theta) d\theta$$

Exchangeability

- Counter example: A six sided die with probabilities (a finite sequence!) $\theta_1, \ldots, \theta_6$
  - without additional knowledge $\theta_1, \ldots, \theta_6$ exchangeable
  - due to the constraint $\sum_{j=1}^{6} \theta_j$, parameters are not independent and thus joint distribution can not be presented as iid mixture

Exchangeability

- See examples in the BDA_notes_ch5.pdf

Exchangeability and additional information

- Example: bioassay
  - y_i number of dead animals are not exchangeable alone

Exchangeability and additional information

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  - x_i dose is additional information

Exchangeability and additional information

- Example: bioassay
  - y_i number of dead animals are not exchangeable alone
  - x_i dose is additional information
  - (x_i, y_i) exchangeable and logistic regression was used

$$p(\alpha, \beta | y, n, x) \propto \prod_{i=1}^{n} p(y_i | \alpha, \beta, n_i, x_i) p(\alpha, \beta)$$

Hierarchical exchangeability

- Example: hierarchical rats example
  - all rats not exchangeable

Hierarchical exchangeability

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  - all rats not exchangeable
  - in a single laboratory rats exchangeable

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Hierarchical exchangeability

- Example: hierarchical rats example
  - all rats not exchangeable
  - in a single laboratory rats exchangeable
  - laboratories exchangeable
  - $\rightarrow$ hierarchical model

Partial or conditional exchangeability

- Conditional exchangeability
  - if y_i is connected to an additional information x_i, so that y_i are not exchangeable, but (y_i, x_i) exchangeable use joint model or conditional model $(y_i | x_i)$.

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- Partial exchangeability
  - if the observations can be grouped (a priori), then use hierarchical model