## STATISTICS 536B, Lecture #7

March 19, 2015



How much better is Drug C than Drug A?

As before represent *i*-th trial data via sample log-OR and SE:  $(y_i, \sigma_i)$ 

(But keep track of which pair of treatments are being compared in each trial.)

Generically, think of  $\delta_{i,RS}$  as being the log-odds-ratio for treatment S compared to treatment R, in the i-th study population.

In fact, with three treatments (A,B,C) we assume the following random effects structure

$$\delta_{i} = \begin{pmatrix} \delta_{i,AB} \\ \delta_{i,AC} \end{pmatrix} \sim \mathcal{N}\left( \begin{pmatrix} d_{AB} \\ d_{AC} \end{pmatrix}, \tau^{2} \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix} \right)$$

with the implicit **consistency assumption** that  $\delta_{i,BC} = \delta_{i,AC} - \delta_{i,AB}$ , and similarly  $d_{BC} = d_{AC} - d_{AB}$ . Why correlation 0.5???

So can think about  $(Y_{i,RS}|\delta_i) \sim N(\delta_{i,RS}, \sigma_i^2)$ 

## So marginally (with random effects integrated away...)

$$Y \sim N(Xd, D),$$

## And we know how to handle linear models

$$Y \sim N(Xd, D),$$

leads to

$$\hat{d} = (X^T D^{-1} X)^{-1} X^T D^{-1} Y$$

and

$$Var(\hat{d}) = (X^T D^{-1} X)^{-1}$$

```
> y
[1] 1.21 0.81 0.64 1.23 0.54 0.23
> sqrt(sig2)
[1] 0.43 0.34 0.30 0.37 0.29 0.26
> dsgn
     [,1] [,2]
[1,] 1
             0
[2,] 1 0
[3,] 1 0
[4,] -1 1
[5,] -1 1
[6,] -1 1
> tau2 <- .15^2
```

```
vr <- solve(t(dsgn) %*% solve(diag(sig2+tau2)) %*% dsgn)</pre>
```

```
est <- vr%*%t(dsgn)%*%solve(diag(sig2+tau2))%*%y</pre>
```

```
### drug B versus drug A
> c(est[1],sqrt(vr[1,1]))
[1] 0.83 0.22
```

### drug C versus drug A
> c(est[2], sqrt(vr[2,2]))
[1] 1.41 0.29

```
### drug C versus drug B
> cntrst <- c(-1,1)
> c( sum(cntrst*est), sqrt(t(cntrst)%*%vr%*%cntrst)) )
[1] 0.58 0.19
```

Success counts for (A,B) trial:  

$$Z_{i,A} \sim \text{Binomial}(n_i, \text{expit}(\mu_i))$$
  
 $Z_{i,B} \sim \text{Binomial}(n_i, \text{expit}(\mu_i + \delta_{i,AB}))$   
Or for (B,C) trial:  
 $Z_{i,B} \sim \text{Binomial}(n_i, \text{expit}(\mu_i + \delta_{i,AB}))$   
 $Z_{i,C} \sim \text{Binomial}(n_i, \text{expit}(\mu_i + \delta_{i,AC}))$   
Then  $\mu_i \sim N(0, \kappa^2)$  and, as before,

$$\delta_{i} = \begin{pmatrix} \delta_{i,AB} \\ \delta_{i,AC} \end{pmatrix} \sim \mathcal{N}\left( \begin{pmatrix} d_{AB} \\ d_{AC} \end{pmatrix}, \tau^{2} \begin{pmatrix} 1 & 0.5 \\ 0.5 & 1 \end{pmatrix} \right)$$

## In fact, typically interpreted/fit as a Bayesian hierarchical model, say using WinBUGS

	network meta-analysis	all other biostat. apps.
Bayesian	rule	exception
non-Bayesian	exception	rule