

Meta-analysis: Choosing the right tool for the job

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 - Network meta-analysis
 - Model-based meta-analysis
- Analysis of Alzheimer's disease data
- Summary



Setting

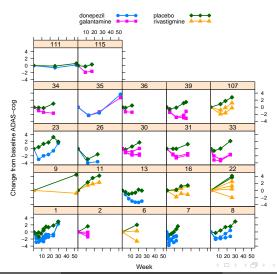
- Suppose we are developing a new compound for the symptomatic treatment of Alzheimer's disease
- We are interested in understanding the efficacy of the currently marketed treatments
- We perform a systematic review of the literature and come up with 22 controlled clinical trials

Drug	# Studies		
Donepezil	8		
Galantamine	9		
Rivastigmine	6		

The data are available at www.opendiseasemodels.org.



Longitudinal ADAS-cog data (ignoring dose)



There are a number of potential objectives of interest

- What are the relative effects of marketed doses at Month 6?
 - Donepezil 10 mg vs. placebo
 - Donepezil 10 mg vs. Galantamine 24 mg
 - Donepezil 10 mg. vs. Rivastigmine
- What are the effects at other time points (e.g., Months 1, 3, 12)?
- What are the effects at other doses?
- What is the rate of change (disease progression) in this patient population?
- What is the effect and/or rate of change in different populations?



Uses of the meta-analysis results

Ultimately we want to be able to use these analyses to inform decisions

- Trial design (e.g., parallel vs. cross-over; sample size; adaptive vs. fixed designs)
- Threshold for Go/No-Go decisions
- Comparative effectiveness



The objectives we have and how we want to use them should dictate the type of models we fit

- Traditional pairwise comparison meta-analysis
- Network meta-analysis

Models

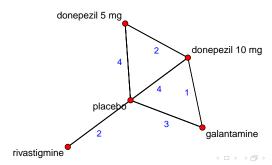
Model-based meta-analysis

One approach will not necessarily be the best for all situations

Pairwise meta-analysis

Pairwise Meta-analysis

- Pairwise meta-analysis is the classic method for combining summary level information across multiple studies (see Whitehead, 2002, for a good reference).
- It enables pooling of direct evidence across studies of two treatments



Pairwise random-effects meta-analysis model

Models

For a set of studies comparing treatments i = 1 and i = 2, the basic pairwise random-effects meta-analysis model is

$$egin{aligned} Y_{ij} &= \mu_i + \delta_i I_{[j=2]} + \epsilon_{ij} \ \delta_i &\sim \mathcal{N}(\Delta, au^2) \ \epsilon_{ij} &\sim \mathcal{N}(0, s_{ij}^2) \end{aligned}$$

where

- Y_{ii} and s_{ii} are data
- the μ_i are fixed study-level effects in the reference group,
- $-i = 1, \dots, \#$ of studies
- -i = 1 for the reference group and i = 2 for the experimental group.

The primary focus of inference is usually on Δ and τ^2 .



- In the context of the AD dataset, Y_{ij} is the change from baseline ADAS-cog score in group j of study i.
- We will estimate effects for Donepezil 5 mg, Donepezil 10 mg, Galantamine 24 mg, and Rivastigmine (≥ 6 mg),
- Thus, we would fit 4 separate models (one for each possible comparison to placebo).
- Then we have eight parameters of interest

Drug group	Mean	Variance
Donepezil 5 mg	Δ_{D5}	$ au_{D5}^2$
Donepezil 10 mg	Δ_{D10}	$ au_{D10}^2$
Galantamine 24 mg	Δ_G	$ au_G^2$
Rivastigmine	Δ_R	$ au_R^2$

Pairwise meta-analysis

Key assumptions of the pairwise meta-analysis model

Assumptions

- No model assumed for μ_i
- Study-specific treatment effects (δ_i) are exchangeable across studies
- Exchangeability is across the set of studies relevant for the comparison of interest, not across all studies

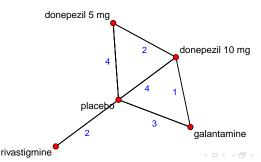
Exchangeability \approx the study-specific effects come from a common distribution, e.g., $\delta_i \sim N(\Delta, \tau^2)$.



Network meta-analysis

Network Meta-analysis

- Network meta-analysis (aka mixed treatment comparison) is an extension to traditional pairwise meta-analysis (Lumley 2002; Lu and Ades. 2004).
- It enables pooling of direct and indirect evidence in one model (12 studies).



• A network meta-analysis model for the mean change from baseline ADAS-cog data $(Y_{i,j})$ can be expressed as

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eq P \end{aligned} \ &\epsilon_{i,j} &\sim oldsymbol{N}(0, oldsymbol{s}_{i,j}^2) \end{aligned}$$

and i indexes study and $j \in \{P, D5, D10, R, G\}$ indexes the treatment group

• Usually assume that $\tau_j^2 = \tau^2$

Models

Network meta-analysis

Key assumptions of network meta-analysis model

Dias et al. (2011) highlight the key assumptions of the network meta-analysis model:

Assumptions

- No model assumed for μ_{i,P}
- Study-specific treatment effects, $\delta_{i,j}$ are exchangable across *all* studies (i.e., even studies without treatment j).
- If we assume $\tau_j^2 = \tau^2$, then $Corr(\delta_{1j}, \delta_{1j'}) = 0.5$ (Lu and Ades, 2009)



Network meta-analysis

Models

The exchangeability assumption is crucial

- Enables coherent indirect comparisons of two treatments with no direct evidence
- Enables a coherent synthesis of direct and indirect evidence
 - E.g., Trials comparing drug A vs. drug B with trials comparing drug A vs. placebo and drug B vs. placebo
- The consistency equations (e.g., $\Delta_{D10,D5} = \Delta_{D10} \Delta_{D5}$) follow directly from this assumption
 - The consistency equations are what allow us to make statistically coherent indirect comparisons

If consistency in the network doesn't hold true, this may be due to a violation of the exchangeability assumption.

See Dias et al (2011) for more details.



Model-based meta-analysis

- There is no single method for performing a model-based meta-analysis
- Models will depend on data and objectives.
- Models can be landmark (single time-point) or longitudinal; dose-response or not.
- This approach has been much less rigorously defined and developed than traditional and Network MA.
- Many examples in the literature



For the ADAS-cog data, we will use a model very similar to the longitudinal dose-response model published by Ito et al. (2009):

$$Y_{ijk} = \eta_{1i} + \alpha_i \cdot t_{ijk}$$

 $+\epsilon_{iik}$

where

$$\alpha_i = \alpha + \eta_{2i}$$

i indexes study, i indexes treatment arm, k indexes visit

Emax_i, ET50_i, and θ_i are drug-specific parameters.

$$\eta_i = (\eta_{1i}, \eta_{2i}, \eta_{3i})^T \sim MVN(\mathbf{0}, \Omega)$$

 $\epsilon_{ijk} \sim N(\mathbf{0}, \sigma^2/N_{ijk})$



For the ADAS-cog data, we will use a model very similar to the longitudinal dose-response model published by Ito et al. (2009):

$$Y_{ijk} = \eta_{1i} + \alpha_i \cdot t_{ijk} + \beta \cdot \left(e^{-Keq \cdot t_{ijk}} - e^{-Kel \cdot t_{ijk}} \right) + \epsilon_{ijk}$$

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$$Y_{ijk} = \eta_{1i} + \alpha_i \cdot t_{ijk} + \beta \cdot \left(e^{-Keq \cdot t_{ijk}} - e^{-Kel \cdot t_{ijk}}\right) + \frac{\mathsf{Emax}_j \cdot \left(\frac{d_{ijk}}{RD_j}\right)^{\theta_j} \cdot t_{ijk}}{\mathsf{ET50}_j \cdot e^{\eta_{3j}} + t_{ijk}} + \epsilon_{ijk}$$

where

$$\alpha_i = \alpha + \eta_{2i}$$

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Estimating differences with the MBMA model

Models

The traditional and network meta-analysis models, model the difference between groups directly.

With the MBMA model, we derive these from the model. For example, at Month 6

$$\delta_{i,D10} = \frac{\mathsf{Emax}_D \cdot \left(\frac{10}{5}\right)^{\theta_D} \cdot 6}{\mathsf{ET50}_D \cdot e^{\eta_{3i}} + 6}$$

and

$$\Delta_{D10} = median[\delta_{i,D10}] = \frac{\mathsf{Emax}_D \cdot \left(\frac{10}{5}\right)^{\theta_D} \cdot 6}{\mathsf{ET50}_D + 6}$$



Assumptions of MBMA

Assumptions

- Structural form of model
- Placement of random effects
- Study-level vs. treatment arm-level random effects
- Exchangeable random effects (across the set of studies and/or arms)
- Other implicit assumptions depending on the model
 - E.g., for the ADAS-cog model, the correlation of difference from placebo for two arms in the same study is 1.0 (as compared to 0.5 for the network meta-analysis model).



Assumptions can bring benefits

- Incorporate regimens with changing doses
- Pool across diseases
- Pool across times/doses that don't match.
- Pool across study design differences
- Pool across different endpoints
- etc.



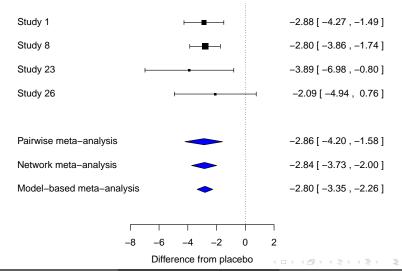
Analysis of ADAS-cog data

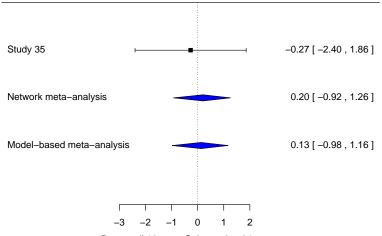
Compare estimates and uncertainty from various models and approaches

- Donepezil 10 mg vs. placebo at Month 6
 - Direct and indirect evidence of effect
- Donepezil 10 mg vs Galantamine 24 mg at Month 6
 - Limited direct evidence + indirect evidence
- Donepezil 10 mg vs. Rivastigmine at Month 6
 - Indirect evidence only
- Effects of donepezil at doses other than 5 and 10 mg
 - Indirect evidence via the model

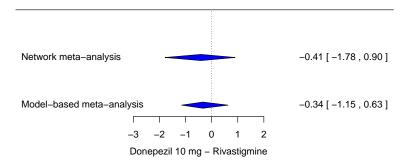


Donepezil 10 mg vs. Placebo at Month 6



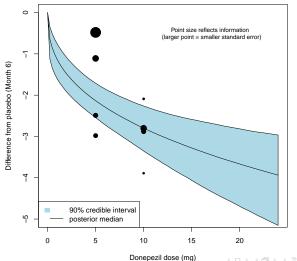


Donepezil 10 mg – Galantamine 24 mg up a la para la pa





Donepezil dose response at Month 6





Conclusions

- We should not take a 'one-model-fits-all' approach to meta-analysis
- There are times when a simpler model (with well understood assumptions) may be preferred to a model-based meta-analysis
 - Even simple meta-analysis models make assumptions

	Pairwise MA	Network MA	МВМА
Estimating difference between groups - Inference based on direct evidence - Inference based on indirect evidence Extrapolation/interpolation in dose, time, etc.	√	√ √	√ √ √



Conclusions

- We should not take a 'one-model-fits-all' approach to meta-analysis
- There are times when a simpler model (with well understood) assumptions) may be preferred to a model-based meta-analysis
 - Even simple meta-analysis models make assumptions

	Pairwise MA	Network MA	MBMA
Donepezil 10 mg vs. Placebo	✓	✓	✓
Donepezil 10 mg vs. Galantamine 24 mg		\checkmark	\checkmark
Disease progression			\checkmark
Dose response			\checkmark



- When other aspects other than simple treatment group differences are of interest, a MBMA may provide more insight and utility
 - E.g., estimating disease progression rate or duration of placebo effect
 - Simulation to evaluate clinical trial designs or decision rules
 - Comes with more (and less transparant) assumptions



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- Mike Dodds
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References

- Dias, S., Welton, N.J., Sutton, A.J. & Ades, A.E. NICE DSU Technical Support Document 2: A Generalised Linear Modelling Framework for Pairwise and Network Meta-Analysis of Randomised Controlled Trials. 2011; last updated August 2011. Available from http://www.nicedsu.org.uk
- Ito, K., Ahadieh, S., Corrigan, B., French, J., Fullerton, T., Tensfeldt, T. Disease progression meta-analysis model in Alzheimer's disease. Alzheimer's and Dementia 2010; 6(1): 39-53.
- Lu G, Ades A. Combination of direct and indirect evidence in mixed treatment comparisons. Statistics in Medicine 2004; 23: 3105-3124.
- Lu, G., Ades, A. Modeling between-trial variance structure in mixed treatment comparisons. Biostatistics 2009; 10(4):792-805.
- Lumley T. Network meta-analysis for indirect treatment comparisons. Statistics in Medicine 2002; 21: 2313-2324.
- Whitehead, A. (2002). Meta-analysis of Controlled Clinical Trials. Wiley: Chichester.





'Typical' doses: 5 & 10 mg donepezil, 24 mg Galantamine, \geq 6 mg Rivastigmine

If other time points and doses tell us something about the effects at Month 6 for the doses of interest, we are limiting ourselves if we restrict to the smaller set of data . . .

 A random effects network meta-analysis model for the mean change from baseline ADAS-cog data $(Y_{i,j})$ can be expressed as

$$egin{aligned} Y_{i,j} &= \mu_{i,P} + \delta_{i,j} + \epsilon_{i,j} \ \end{aligned}$$
 where $\delta_{i,j} \sim extstyle extstyle N(\Delta_i, au_i^2) \quad j
eq P$

and i indexes study and $j \in \{P, D5, D10, R, G\}$ indexes the treatment group

- Usually assume that $\tau_i^2 = \tau^2$
- The parameters Δ_i , $j \neq P$ are the *basic* parameters of the model; from these, the other differences can be derived.
 - E.g., the difference between the effect of donepezil 10 mg and 5 mg is $\Delta_{D10} - \Delta_{D5}$

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- For studies with more than 2 treatment groups, we need to account for the correlation between $\delta_{i,j}$ and $\delta_{i,j'}$.
- Under the assumption that $Var(\delta_{i,j}) = \tau^2$ for all i and j, it can be shown that the correlation is 0.5.
- For example, for a trial with placebo, donepezil 5 and 10 mg:

$$egin{aligned} \delta_i &= \left(\delta_{i,D5}, \delta_{i,D10}
ight) \sim \mathcal{N}\left(\Delta_i, \Omega_i
ight) \ ext{where} \ \Delta_i &= \left(\Delta_{D5}, \Delta_{D10}
ight) \ \Omega_i &= au^2 \left(egin{array}{cc} 1 & 0.5 \ 0.5 & 1 \end{array}
ight) \end{aligned}$$

