

Automated generation of node-split models for the assessment of inconsistency in mixed treatment comparisons

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SRSM 2012, Aix-en-Provence, France, June 2012



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Mixed treatment comparisons [2]

- Extension of pair-wise meta-analysis
- Enables *consistent* estimation on a network of trials
- Assumption: trials are exchangeable
- Assumption needs to be verified
 - Primarily: epidemiological judgment – trial characteristics
 - **Secondarily: statistical models to detect**
 - heterogeneity
 - inconsistency

Consistency models (random effects) [2, 3, 5]

- Likelihood for study i in terms of random effects δ_i :

$$\mathbf{data}_i \sim f_i(\delta_i, \dots) .$$

- Random effects assumed normal:

$$\delta_{i,b,x} \sim \mathcal{N}(d_{b,x}, \sigma^2) ; \quad \begin{pmatrix} \delta_{i,b,x} \\ \vdots \\ \delta_{i,b,z} \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} d_{b,x} \\ \vdots \\ d_{b,z} \end{pmatrix}, \Sigma \right)$$

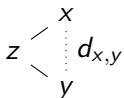
- And the relative effects $d_{x,y}$ are assumed consistent:

$$d_{x,y} = d_{x,z} + d_{z,y}$$

(follows from exchangeability assumption)

Consistency / inconsistency

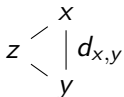
- Use consistency assumption to fill in missing comparisons:



Could be problematic/inconsistent

Can NOT be detected

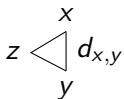
- Consistent synthesis of existing comparisons:



Could be inconsistent

Can be detected

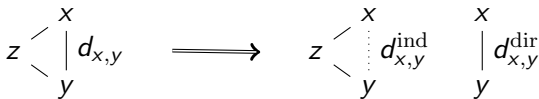
- Synthesis with only three-arm trials:



Can NOT be inconsistent

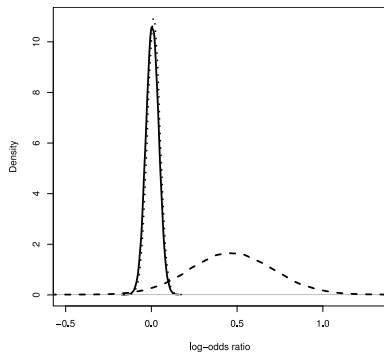
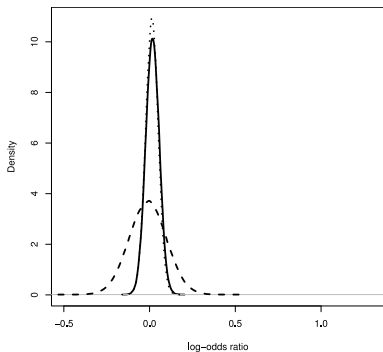
Node-splitting models [1]

- Node-split models: split comparison $d_{x,y}$
 - Pair-wise meta-analysis of direct evidence $\rightarrow d_{x,y}^{\text{dir}}$
 - Consistency model of all other evidence $\rightarrow d_{x,y}^{\text{ind}}$
 - Under exchangeability, expect $d_{x,y}^{\text{ind}} = d_{x,y}^{\text{dir}}$

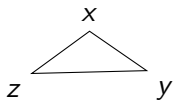


- Requires one model *per split node*

Node-splitting: example results

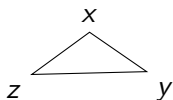


Node-splitting models: multi-arm trials

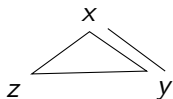


NOT inconsistent

Node-splitting models: multi-arm trials

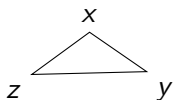


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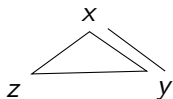


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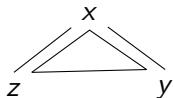
Node-splitting models: multi-arm trials



NOT inconsistent

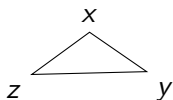


NOT inconsistent

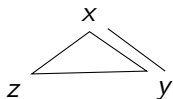


Potentially inconsistent?

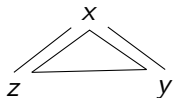
Node-splitting models: multi-arm trials



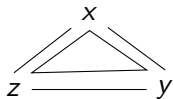
NOT inconsistent



NOT inconsistent



Potentially inconsistent?



Potentially inconsistent!

Node-splitting: open problems

- What nodes should be split?
 - Easy for simple cases
 - But has to work for *any* network
- How to generate model structure?
 - Already solved for consistency models [6]
 - Strategy: choose split nodes carefully
 - apply method for consistency models

Choosing split nodes

- Ideally: split 'minimal set' of comparisons
 - But: that is very difficult to determine [4, 7]
- Practical compromise: simple (local) decision rule:
 - efficiently computable
 - splits all potential inconsistencies
 - splits only potential inconsistencies

Choosing split nodes: basic rule (\leq 3-arm trials)

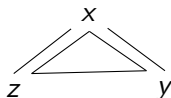
Given an evidence network, split $d_{a,b}$ iff:

- a and b are connected in the reduced network,
- consisting of the studies that *do not* include both a and b .

Choosing split nodes: basic rule (≤ 3 -arm trials)

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Split $d_{x,y}$?

Choosing split nodes: basic rule (≤ 3 -arm trials)

Given an evidence network, split $d_{a,b}$ iff:

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Split $d_{x,y}$?

y Remove studies with x and y . \rightarrow NO.

Choosing split nodes: basic rule (≤ 3 -arm trials)

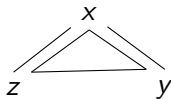
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Split $d_{y,z}$?

Choosing split nodes: basic rule (≤ 3 -arm trials)

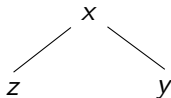
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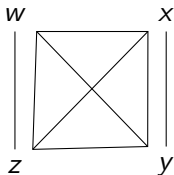
y Remove studies with x and y . \rightarrow NO.



Split $d_{y,z}$?

Remove studies with y and z . \rightarrow YES.

Choosing split nodes: basic rule (fails for 4-arm trials)



Split $d_{y,z}$?

Choosing split nodes: basic rule (fails for 4-arm trials)

w
|
z

x
|
y

Split $d_{y,z}$?

Remove studies with y and z . → ???

Choosing split nodes: full rule (n -arm trials)

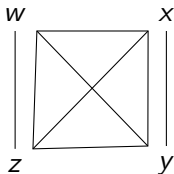
Given an evidence network, split $d_{a,b}$ iff:

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- by removing the a and b arms from studies including both.

Choosing split nodes: full rule (n -arm trials)

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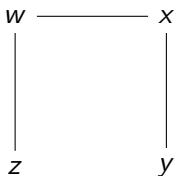


Split $d_{y,z}$?

Choosing split nodes: full rule (n -arm trials)

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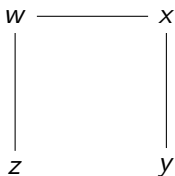
Split $d_{y,z}$?

Apply rule \rightarrow YES.

Choosing split nodes: full rule (n -arm trials)

Given an evidence network, split $d_{a,b}$ iff:

- a and b are connected in the reduced network,
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Split $d_{y,z}$?

Apply rule → YES.

The full rule:

- Works in general (for n -arm trials)
 - Because trials are fully connected graphs

Results: rule is appropriate

- Only splits nodes that are potentially inconsistent
 - Network of evidence independent of direct is connected
 - Equivalent to '3 independent sources'
- Splits a node for all independent potential inconsistencies
 - And probably more (redundancies)
- Will not bore you with the proofs!

Model generation is trivial

- Model generation for consistency models is trivial [6]
- The indirect evidence are just a consistency model
 - Assured by careful formulation of decision rule
- The direct evidence are just a pair-wise model
- More arbitrariness than for consistency models
 - $d_{x,y}$ is split, and occurs in a multi-arm trial
 - Which arm do we include in the $d_{x,y}^{\text{ind}}$ model?
 - Arm x ?
 - Arm y ?
 - Neither?

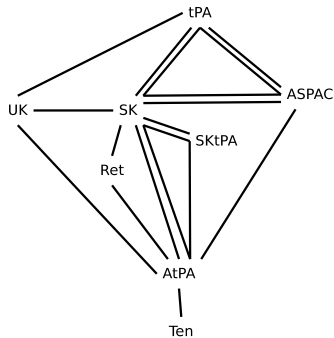
Implementation: GeMTC Software

- Methods implemented in free / open source software
- Available from <http://drugis.org/>

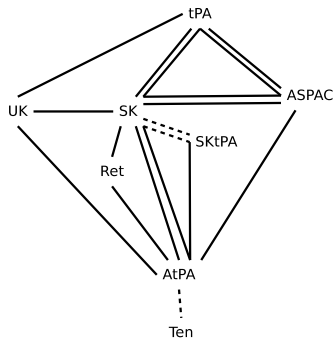
The screenshot displays the GeMTC 0.12.4 software interface. The main window shows a dataset titled "luades-thrombolytic.gemtc" with a table of data. The table has columns for "A", "RATE", "dataset", and "about". The data is organized into groups (01, 02, 03, 04, 05, 06, 07, 08) and includes treatments like ASPAC, AtPA, Ret, SK, SKRPA, Ten, UK, and TPA. A dialog box titled "Generate BUGS/JAGS code for luades-thrombolytic" is open, showing options for "Syntax" (BUGS or JAGS), "Model type" (Consistency, Inconsistency, or NodeSplit), and a "Split node" dropdown menu. The "Number of chains" is set to 4, and the "Initial values scaling" is set to "d.ATPA.ASPAC". The "Tuning iterations" and "Simulation iterations" are also visible.

A	RATE	dataset	about
01			
		Responders	Sample size
SK	1472		20163
AtPA	652		10344
SKRPA	723		10328
02			
SK	1455		13780
tPA	1418		13746
ASPAC	1448		13773
03			
SK	9		130
tPA	6		123
04			
SK	5		63
tPA	2		59
05			
SK			
tPA			
06			
SK			
tPA			
07			
SK			
tPA			
08			
SK			
tPA			

Example network







Example network






Discussion

- Proposed a decision rule for which nodes to split
- Model generation identical to consistency models
 - NOT true in general (depends on decision rule)
- Automated method + free / open source software
 - Choosing nodes to split by hand can be difficult
 - Remove tedium: specify many models for complex networks
 - Less opportunity to make small mistakes
 - Heuristically generated defaults preferable to static ones

References I

-  S. Dias, N. J. Welton, D. M. Caldwell, and A. E. Ades. Checking consistency in mixed treatment comparison meta-analysis. *Stat Med*, 29(7-8, Sp. Iss. SI):932–944, 2010.
-  S. Dias, N. J. Welton, A. J. Sutton, and A. E. Ades. NICE DSU technical support document 2: A generalised linear modelling framework for pairwise and network meta-analysis of randomised controlled trials. *Technical report*, 2011. updated August 2011.
-  Guobing Lu and A. E. Ades. Combination of direct and indirect evidence in mixed treatment comparisons. *Stat Med*, 23(20):3105–3124, 2004.
-  Guobing Lu and A. E. Ades. Assessing evidence inconsistency in mixed treatment comparisons. *J Am Stat Assoc*, 101(474):447–459, 2006.

References II

-  Georgia Salanti, Julian P. T. Higgins, A. E. Ades, and John P. A. Ioannidis. Evaluation of networks of randomized trials. *Stat Methods Med Res*, 17(3):279–301, 2008.
-  G. van Valkenhoef, G. Lu, B. de Brock, H. Hillege, A. E. Ades, and N. J. Welton. Automating network meta-analysis. *Research Synthesis Methods*, 2012. (in press).
-  G. van Valkenhoef, T. Tervonen, B. de Brock, and H. Hillege. Algorithmic parametrization of mixed treatment comparisons. *Stat Comput*, 2011. (in press).

Thank you!

Questions?

Slides available at <http://drugis.org>



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