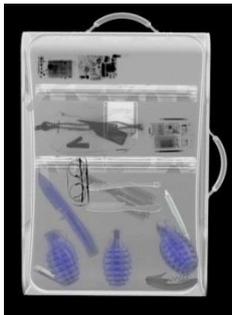


**The Sequential Refined Conditioning method: addressing under- and overspecification of EJ in dependence modelling**  
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3rd – 5th July 2017



# Motivation(s) of our modelling/elicitation method

## Why use the sequential refined conditioning method?

- Address the *underspecification* issue of assessed dependence models\*:
- Underspecification means that we have not elicited enough information for modelling a unique distribution as various alternatives are compatible with the given (partial) information

*It is desirable that the resulting joint distribution is unique and is only based on experts' judgements, i.e. no unspecified assumptions*

- Proposed solution: modelling non-assessed parts of distribution as minimally informative

- Address the *overspecification* issue of assessed dependence models\*:

- For overspecification, an expert's assessments about related parts of a distribution are contradictory and infeasible; potentially occurring due to an increased cognitive complexity for experts when assessing a variety of detailed, related distribution features

*It is desirable that the assessments exhibit a low cognitive complexity for experts despite allowing for flexibility of the assessed parts and level of detail of the distribution*

- Proposed solution: only ever eliciting single conditioning sets, explicit guidance on feasible ranges

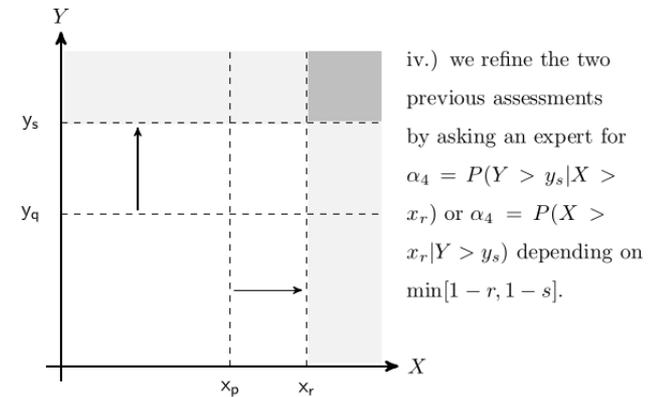
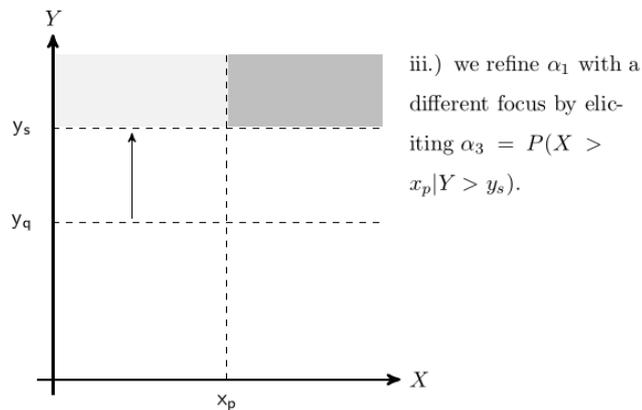
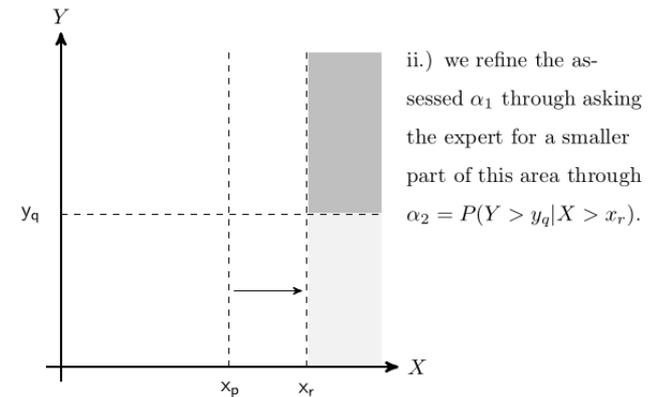
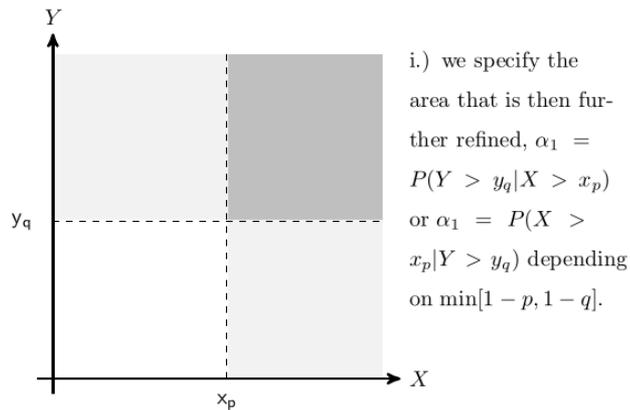
*\*note: we consider non-parametric dependence models, under- and overspecification might also occur in parametric settings*



## Addressing overspecification:

- Proposing a sequential elicitation procedure that gives explicit guidance on feasible assessments (in any part and level of detail of the joint distribution) and only ever elicits single conditioning sets:
  1. initial four step procedure (only marginals are specified at this point)
  2. further assessing *within given area*
  3. further assessing *newly given area*

# SRC: initial elicitation sequence (1/4)



# SRC: initial elicitation sequence (2/4)

➤ Feasible ranges are given by:

$$0 \leq \alpha_1 \leq 1$$

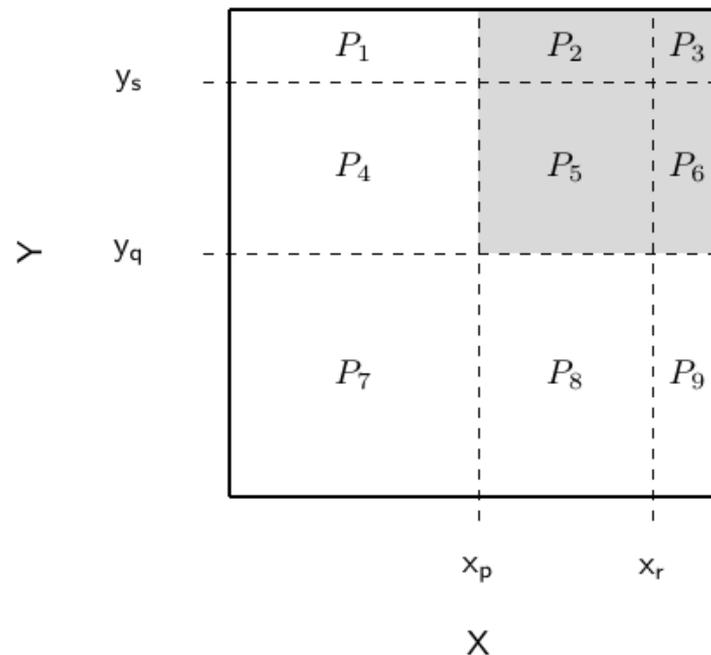
$$0 \leq \alpha_2 \leq \begin{cases} \min \left[ 1, \frac{(1-p)\alpha_1}{1-r} \right] & \text{if } p \geq q \\ \min \left[ 1, \frac{(1-q)\alpha_1}{1-r} \right] & \text{if } q \geq p \end{cases}$$

$$0 \leq \alpha_3 \leq \begin{cases} \min \left[ 1, \frac{(1-p)\alpha_1}{1-s} \right] & \text{if } p \geq q \\ \min \left[ 1, \frac{(1-q)\alpha_1}{1-s} \right] & \text{if } q \geq p \end{cases}$$

$$0 \leq \alpha_4 \leq \begin{cases} \min \left[ \frac{-\min[1-p, 1-q]\alpha_1 + (1-r)\alpha_2 + (1-s)\alpha_3}{\min[1-r, 1-s]}, \frac{(1-s)\alpha_3}{1-r} \right] & \text{if } r \geq s \\ \min \left[ \frac{-\min[1-p, 1-q]\alpha_1 + (1-r)\alpha_2 + (1-s)\alpha_3}{\min[1-r, 1-s]}, \frac{(1-r)\alpha_2}{1-s} \right] & \text{if } s \geq r \end{cases}$$

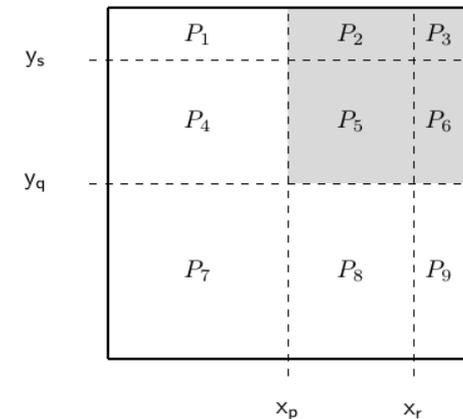
# SRC: initial elicitation sequence (3/4)

- After the initial elicitation sequence (all four steps; we can always stop before), the joint distribution is given as below:



# SRC: initial elicitation sequence (4/4)

➤ Resulting probability masses are given by:



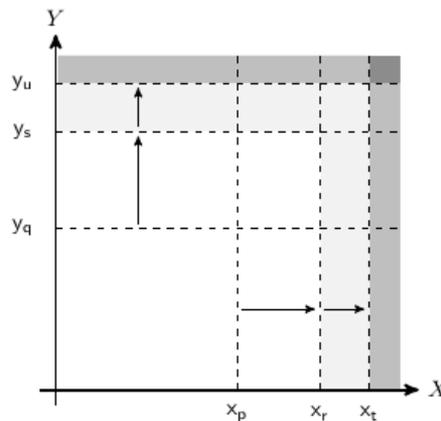
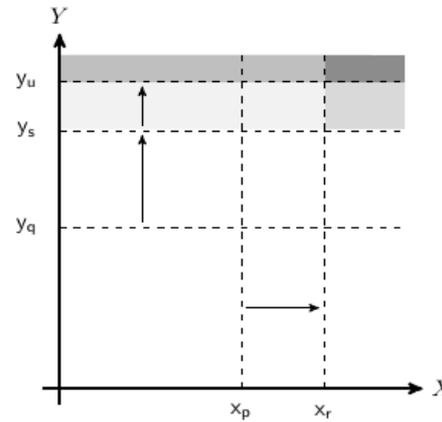
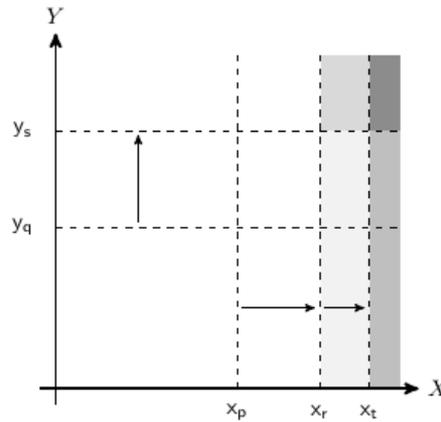
$$P_3 = \min[1 - r, 1 - s]\alpha_4$$

$$P_6 = (1 - r)\alpha_2 - \min[1 - r, 1 - s]\alpha_4$$

$$P_2 = (1 - s)\alpha_3 - \min[1 - r, 1 - s]\alpha_4$$

$$P_5 = \min[1 - p, 1 - q]\alpha_1 - (1 - r)\alpha_2 - (1 - s)\alpha_3 + \min[1 - r, 1 - s]\alpha_4$$

# SRC: further assessing *within given area* (1/4)



- v.)  $\alpha_5 = P(Y > y_s | X > x_t)$ ,
  - vi.)  $\alpha_6 = P(X > x_r | Y > y_u)$
  - and vii.)  $\alpha_7 = P(Y > y_u | X > x_t)$  or  $\alpha_7 = P(Y > y_u | X > x_t)$
- (clockwise): refining further the previously assessed area of  $P_4$ .

# SRC: further assessing *within given area* (2/4)

➤ Feasible ranges are given by:

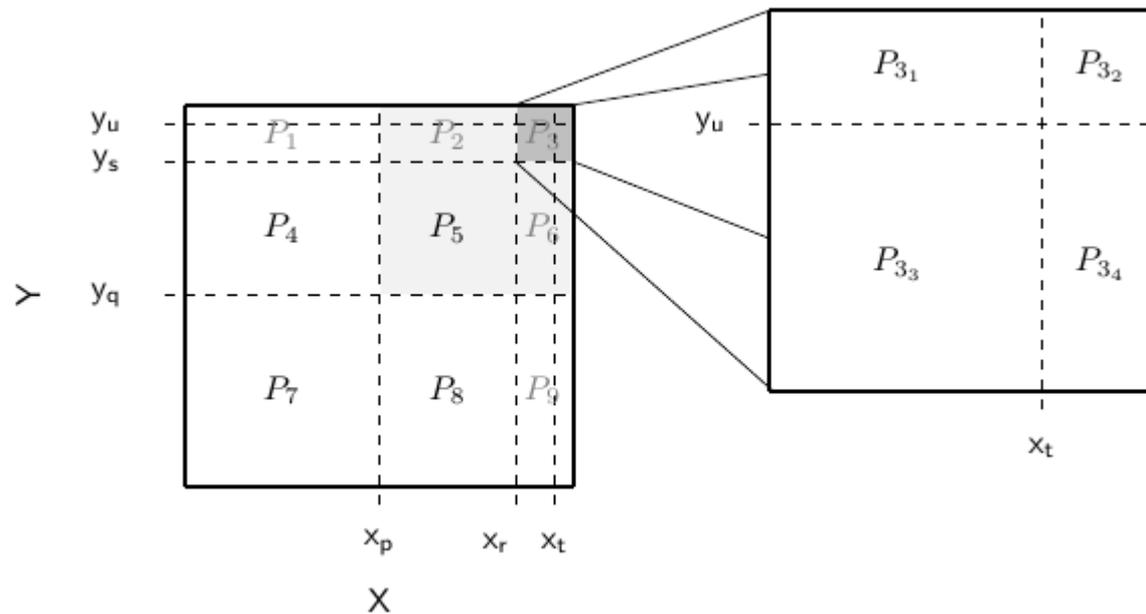
$$0 \leq \alpha_5 \leq \frac{\min[1-r, 1-s]\alpha_4}{1-t}$$

$$0 \leq \alpha_6 \leq \frac{\min[1-r, 1-s]\alpha_4}{1-u}$$

$$\max\left[0, \frac{-\min[1-r, 1-s]\alpha_4 + (1-t)\alpha_5 + (1-u)\alpha_6}{\min[1-t, 1-u]}\right] \leq \alpha_7 \leq \begin{cases} \min\left[\alpha_5, \frac{(1-u)\alpha_6}{1-t}\right] & \text{if } t \geq u \\ \min\left[\alpha_6, \frac{(1-t)\alpha_5}{1-u}\right] & \text{if } u \geq t \end{cases}$$

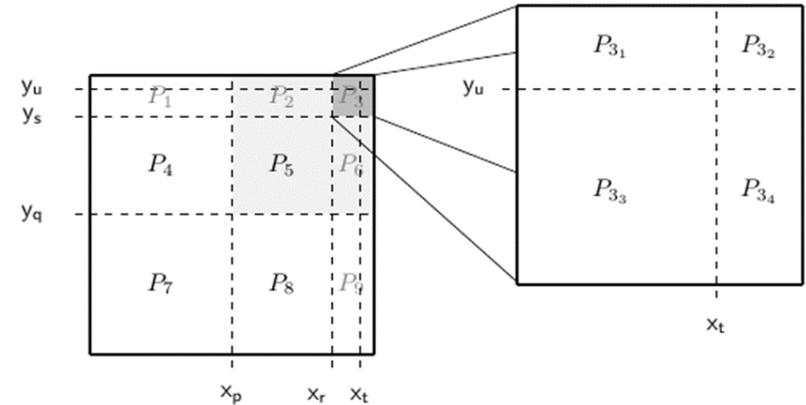
# SRC: further assessing *within given area* (3/4)

➤ After further within a given area, the joint distribution is given as below:



# SRC: further assessing *within given area* (4/4)

➤ Resulting probability masses are given by:



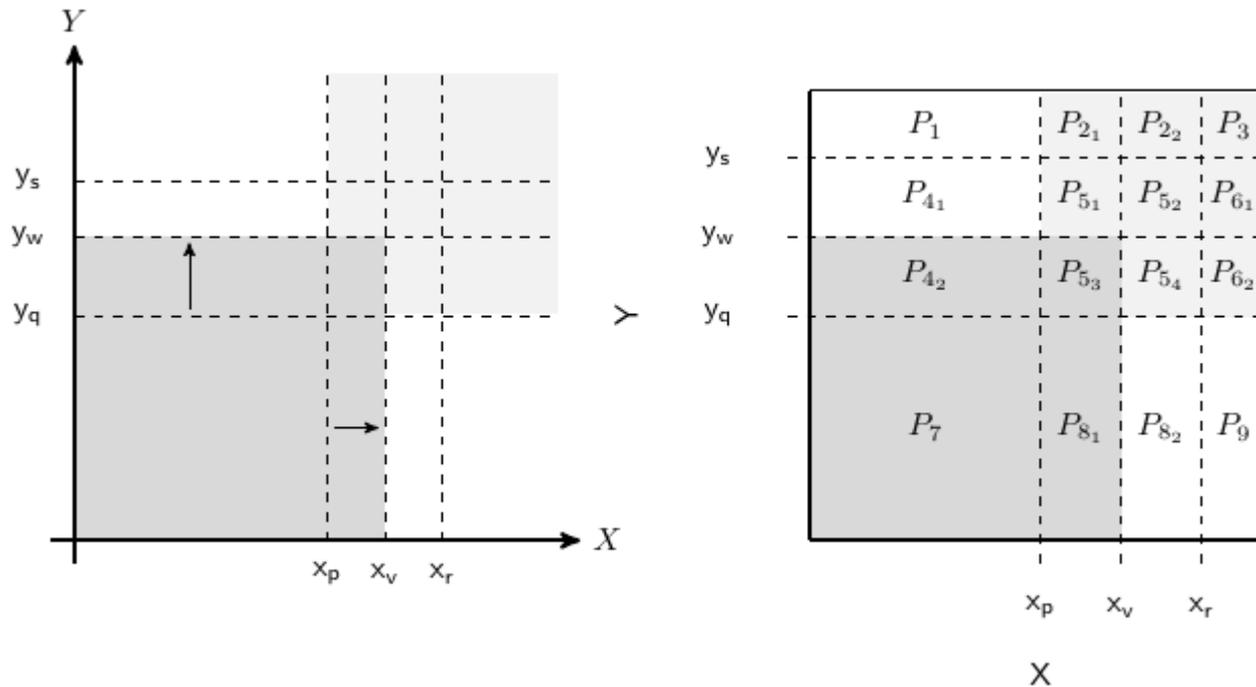
$$P_{3_2} = \min[1 - t, 1 - u]\alpha_7$$

$$P_{3_1} = (1 - t)\alpha_5 - \min[1 - t, 1 - u]\alpha_7$$

$$P_{3_4} = (1 - u)\alpha_6 - \min[1 - t, 1 - u]\alpha_7$$

$$P_{3_3} = \min[1 - r, 1 - s]\alpha_4 - (1 - t)\alpha_5 - (1 - u)\alpha_6 + \min[1 - t, 1 - u]\alpha_7$$

# SRC: further assessing *newly given area*



## Addressing underspecification:

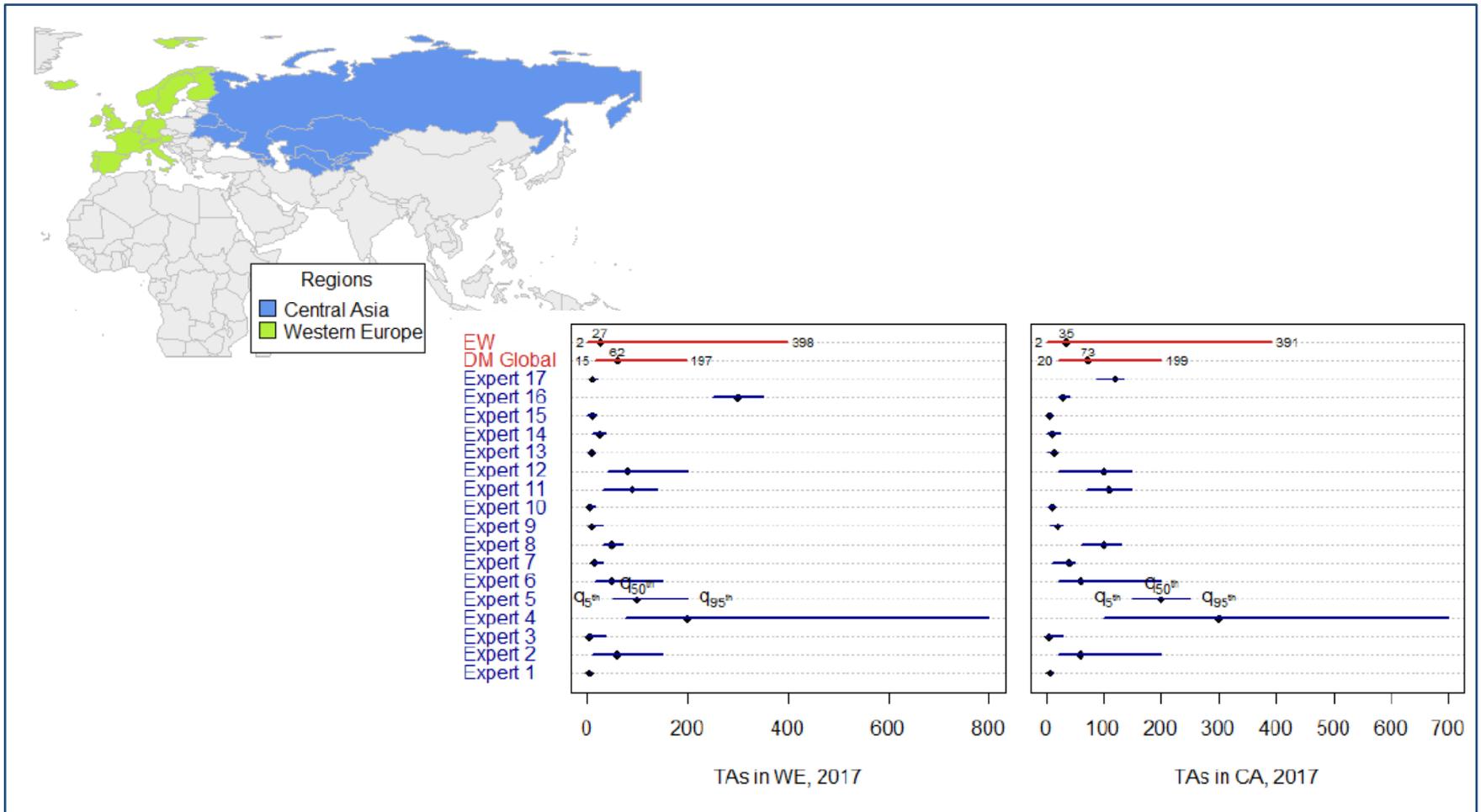
- Proposing a minimum information solution:
- Formally, we aim for modelling dependence through distribution which is chosen to have minimum information (Kullback-Leibler divergence (Kullback and Leibler, 1951)) with respect to the independent uniform distribution with the same marginals given a finite number of constraints

# Illustrative example (1/3):

## *Assessing spatial dependence of terrorism risk*

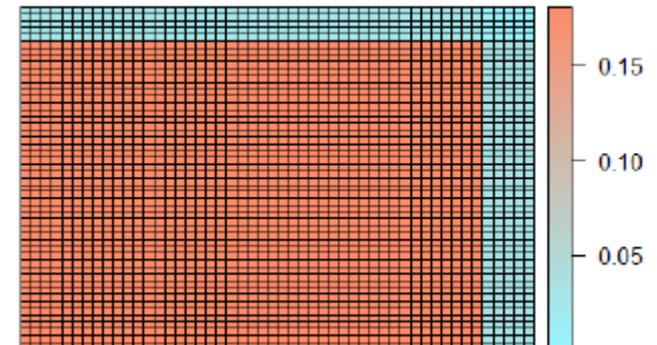
- Experts were insurance underwriters and professionals of related service providers
- Elicitation of marginal distribution through the Classical model (Cooke, 1991)
- Terrorism risk came to the attention of insurers after 9/11
  - Before, often covered as an unnamed peril under an all-risk commercial and home owners coverage for property and contents (e.g. in US)
  - More generally, the worst 15 terrorist attacks in terms of number of casualties have occurred since 1982
  - Mathematically, problem of terrorism in terms of frequency-severity relationships can be described by a power law, i.e. attack severities order of magnitude larger than the mean might not be unusual
- Terrorism risk poses particular challenges due to intelligent adversaries
  - Spatial dependence evoked from attackers through globally and locally active terrorist groups; such foci are often due to motivations, followed ideologies, and structure of groups
    - E.g. some groups are hierarchically structured, others work as satellite cells which has an effect on counter-terrorism measures applicable
  - Spatial dependence also determined by defender's vulnerabilities

# Illustrative example (2/3): *Assessing spatial dependence of terrorism risk*



# Illustrative example (3/3): *Assessing spatial dependence of terrorism risk*

$\alpha_i$	Framing	"Given that we observe [...]"	Conditional Probability	Assessment
$\alpha_1$	"[...] more than 73 terrorist attacks in CA, what is your probability that we observe more than 62 terrorist attacks in WE?"		$P(Y > \vartheta_{0.5}   X > \varpi_{0.5})$	0.5
$\alpha_2$	"[...] more than 199 terrorist attacks in CA, what is your probability that we observe more than 62 terrorist attacks in WE?"		$P(Y > \vartheta_{0.5}   X > \varpi_{0.95})$	0.75
$\alpha_3$	"[...] more than 197 terrorist attacks in WE, what is your probability that we observe more than 73 terrorist attacks in CA?"		$P(X > \varpi_{0.5}   Y > \vartheta_{0.95})$	0.9
$\alpha_4$	"[...] more than 199 terrorist attacks in CA, what is your probability that we observe more than 197 terrorist attacks in WE?"		$P(Y > \vartheta_{0.95}   X > \varpi_{0.95})$	0.25
$\alpha_5$	"[...] more than 199 terrorist attacks in CA, what is your probability that we observe more than 225 terrorist attacks in WE?"		$P(Y > \vartheta_{0.99}   X > \varpi_{0.95})$	0.1
$\alpha_6$	"[...] more than 225 terrorist attacks in WE, what is your probability that we observe more than 199 terrorist attacks in CA?"		$P(X > \varpi_{0.95}   Y > \vartheta_{0.99})$	0.15



Thank you for your attention.