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Investigating behaviour change using a Bayesian network approach

Crossing the boundaries of disciplines

14-3-2023

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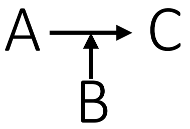
CASE STUDY DESCRIPTION

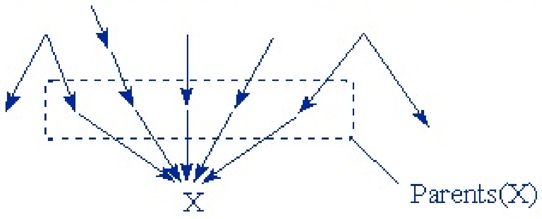
- Interventions to promote Physical Activity (PA)
  - Affecting determinants (for example awareness)
    - Mediator: A ⟶ B ⟶ C
    - Moderator:

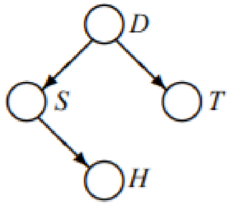


- Aim: insight into behavioural change mechanism
- Previous research: complex structures not investigated
- Technique: Bayesian network
- Note: integrated dataset of 5 studies
  - Data at concept level

BAYESIAN NETWORK (BN)

- Unlabeled probabilistic model
    - Represented as Directed Acyclic Graph G=(V,E)
- Parameters: $\mathbb{P}(X_i \mid \Pi_i)$
- Local Markov property: $X_v \perp\!\!\!\perp X_{V \setminus \mathrm{de}(v)} \mid X_{\mathrm{pa}(v)} \quad \text{for all } v \in V$
- Equivalent models
    - A -> B -> C   A <- B -> C   A <- B <- C
    - A -> B <- C
- Temporal BN: restrictions time dimension
- Bayesian statistics (applying Bayes theorem $P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$)





OUR CASE STUDY : DECISION-MAKING AND DATA PREPARATION PHASES

- Getting started
    - Disciplines get to know each other (jargon, etc.)
    - Specification of research aim
    - Overview of available data
    - Decisions wrt integrated dataset
- Data preparation
    - Coding derived variables
        - Measurement errors
    - **Integration**
        -> **Note**: missing data created

OUR CASE STUDY : MODELLING AND VISUALISATION

LEARNING A BAYESIAN NETWORK

- Structure (and parameter) learning
- Approaches: knowledge-based, **data-driven**, information fusion
- Classes of structure learning algorithms:
    - **Scored-based**
    - Constraint-based
    - Hybrid

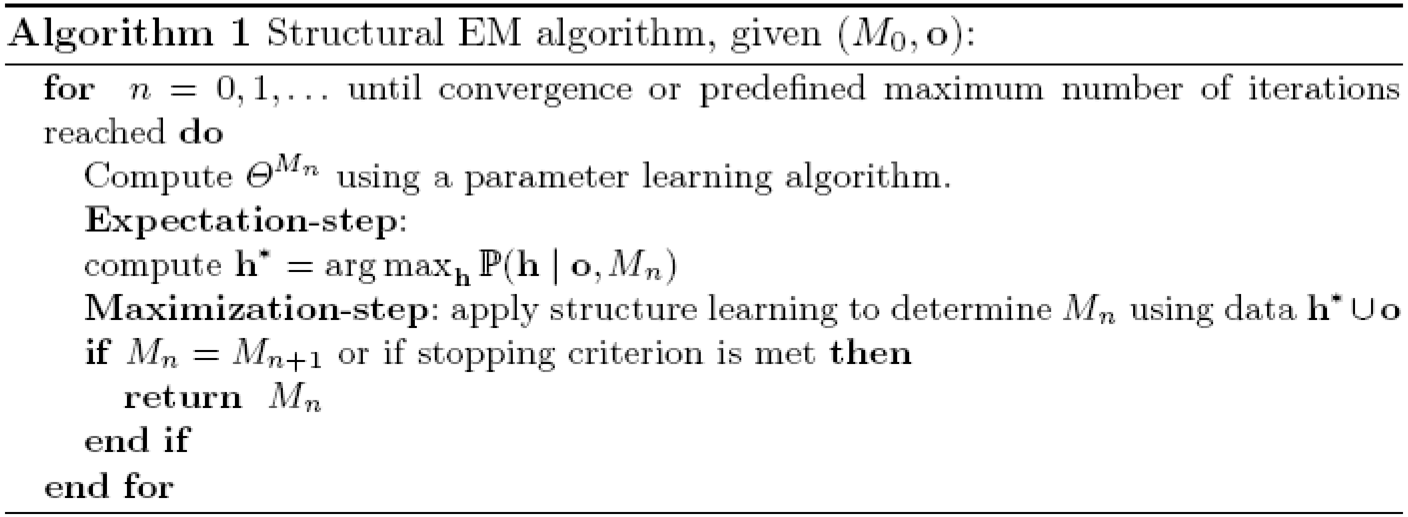
-> In our case study: tabu search, maximising BIC score

OUR CASE STUDY : MODELLING AND VISUALISATION CONT.

MISSING DATA

Compared performance of

Mean imputation, multiple imputation, **structural EM**



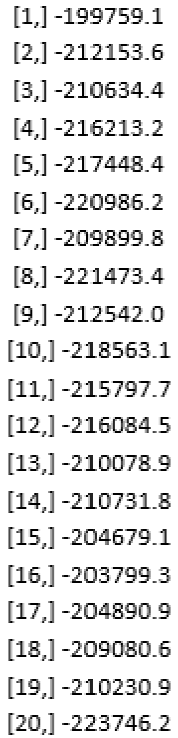
Algorithm 1 Structural EM algorithm, given $(M_0, \mathbf{o})$:

```
for $n = 0, 1, \ldots$ until convergence or predefined maximum number of iterations reached do
    Compute $\Theta^{M_n}$ using a parameter learning algorithm.
    Expectation-step:
    compute $\mathbf{h}^* = \arg\max_{\mathbf{h}} \mathbb{P}(\mathbf{h} \mid \mathbf{o}, M_n)$
    Maximization-step: apply structure learning to determine $M_n$ using data $\mathbf{h}^* \cup \mathbf{o}$
    if $M_n = M_{n+1}$ or if stopping criterion is met then
        return $M_n$
    end if
end for
```

OUR CASE STUDY : MODELLING AND VISUALISATION CONT.

MODEL INSTABILITY

- Bootstrap analysis to evaluate significance of arcs
    - Common: edges classified into FPs, FNs, **TPs**
    - Resulting models from different runs differed --------->
        - Cause: emphasis on instable “original” model
    - **Change in approach**
        - Look at % of bootstrap samples in which edges occur



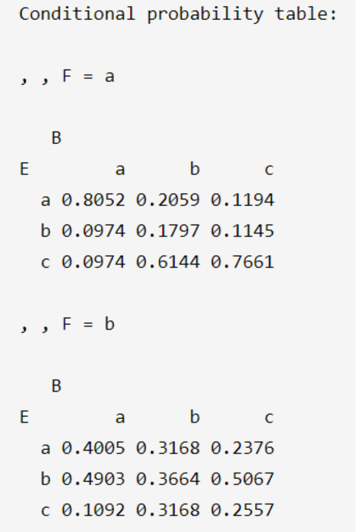
```
 [1,] -199759.1
 [2,] -212153.6
 [3,] -210634.4
 [4,] -216213.2
 [5,] -217448.4
 [6,] -220986.2
 [7,] -209899.8
 [8,] -221473.4
 [9,] -212542.0
[10,] -218563.1
[11,] -215797.7
[12,] -216084.5
[13,] -210078.9
[14,] -210731.8
[15,] -204679.1
[16,] -203799.3
[17,] -204890.9
[18,] -209080.6
[19,] -210230.9
[20,] -223746.2
```

OUR CASE STUDY : MODELLING AND VISUALISATION CONT.

INTERPRETABLE RESULTS

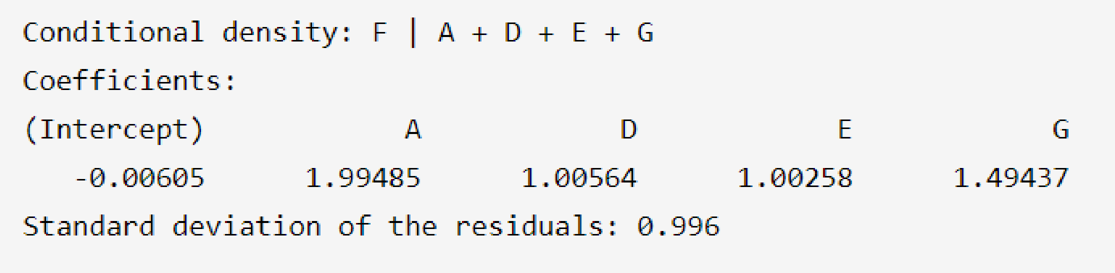
- Distill relevant pathways -> from intervention to outcomes
- Strenght of relations in the model -> mutual information

CPT



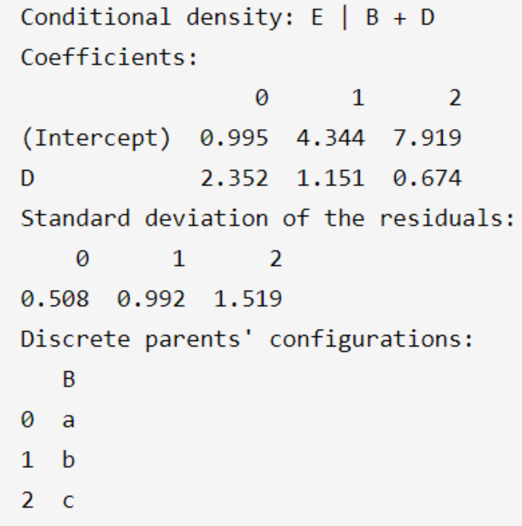
```
Conditional probability table:

, , F = a

   B
E         a      b      c
  a 0.8052 0.2059 0.1194
  b 0.0974 0.1797 0.1145
  c 0.0974 0.6144 0.7661

, , F = b

   B
E         a      b      c
  a 0.4005 0.3168 0.2376
  b 0.4903 0.3664 0.5067
  c 0.1092 0.3168 0.2557
```

CDF



```
Conditional density: F | A + D + E + G
Coefficients:
(Intercept)            A            D            E            G
   -0.00605      1.99485      1.00564      1.00258      1.49437
Standard deviation of the residuals: 0.996
```

Hybrid

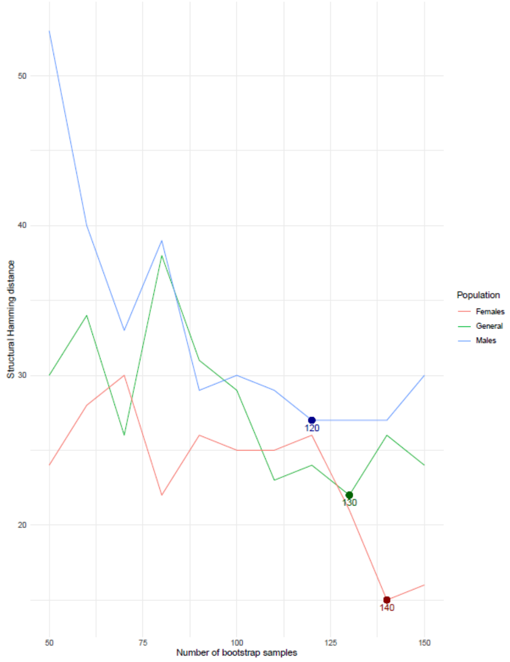


```
Conditional density: E | B + D
Coefficients:
                  0      1      2
(Intercept)   0.995  4.344  7.919
D             2.352  1.151  0.674
Standard deviation of the residuals:
    0      1      2
0.508  0.992  1.519
Discrete parents' configurations:
    B
0   a
1   b
2   c
```

- Visualisation of graphs -> easy to interpret

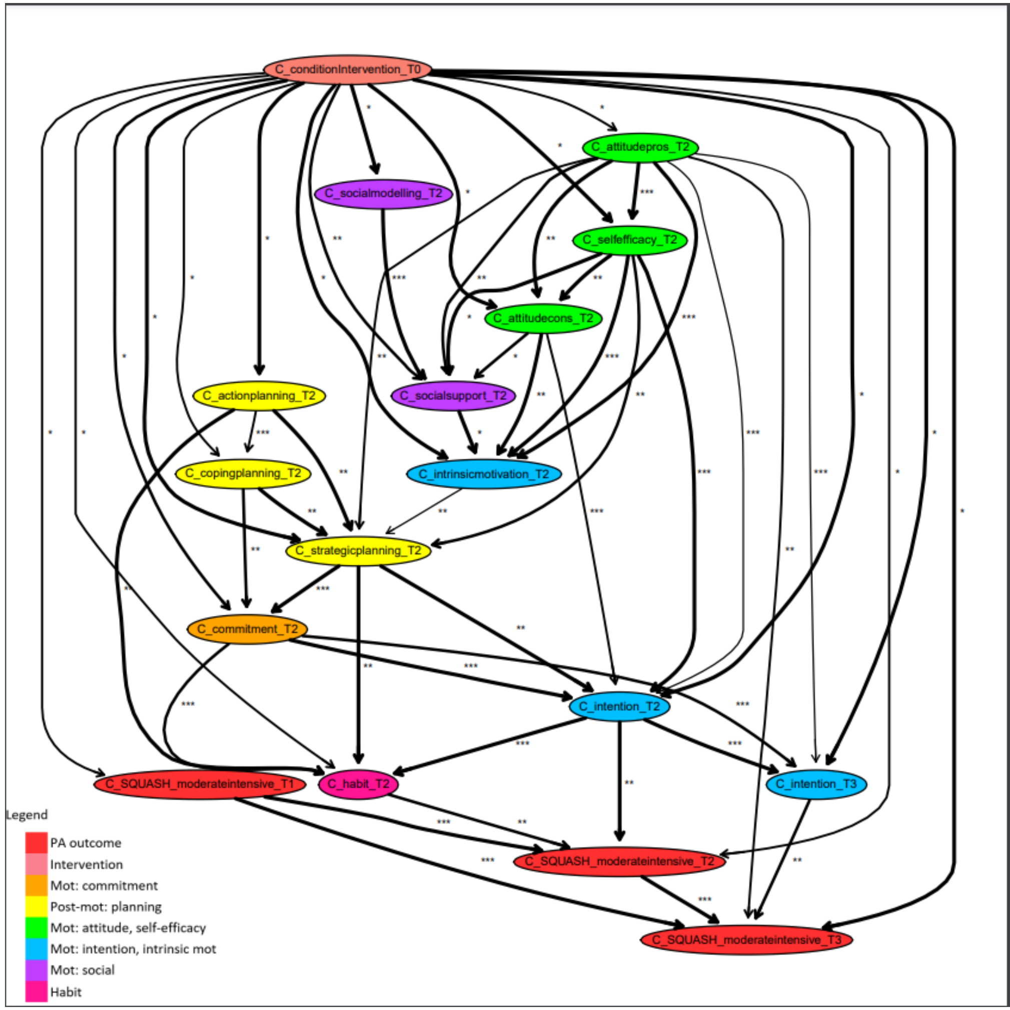
OUR METHODOLOGY

- (Selection of) integrated dataset
- For each bootstrap sample:
    - Structural EM with tabu search (optimising BIC)
    - Temporal restrictions
- Decision #bootstrap samples: Structural Hamming Distance --->
- Sub-model from averaged BN
    - Stability at least 0.6
    - Relevant paths
- Visualisation
    - Arc thickness: (grouping of) arc stability
    - Parameter asterisks: (relative grouping) MI strength
    - Colouring of nodes



INTERPRETATION OF RESULTING BAYESIAN NETWORK MODELS

- Aim: improve intervention effects
- Models:
    - **For all participants (>= 50)**
    - Sub-populations
      Gender, age, education, disability
- Discussion:
  Emphasize determinants of important or of minor role?



Questions or suggestions?