Network Structures for Psychological Constructs

The Case of Empathy

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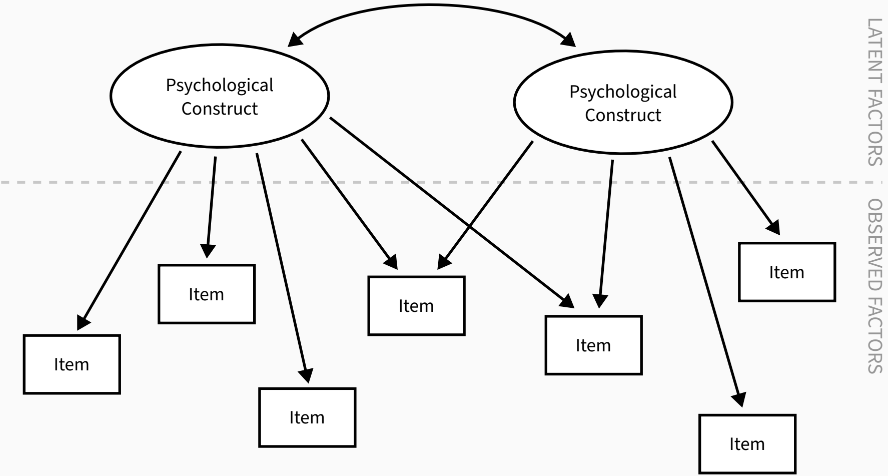
Psychological constructs facilitate the understanding and explanation of human behaviour by enabling prediction, with a certain probability, of how an individual is likely to act in a certain situation.

From a statistical point of view, they can be modelled as:

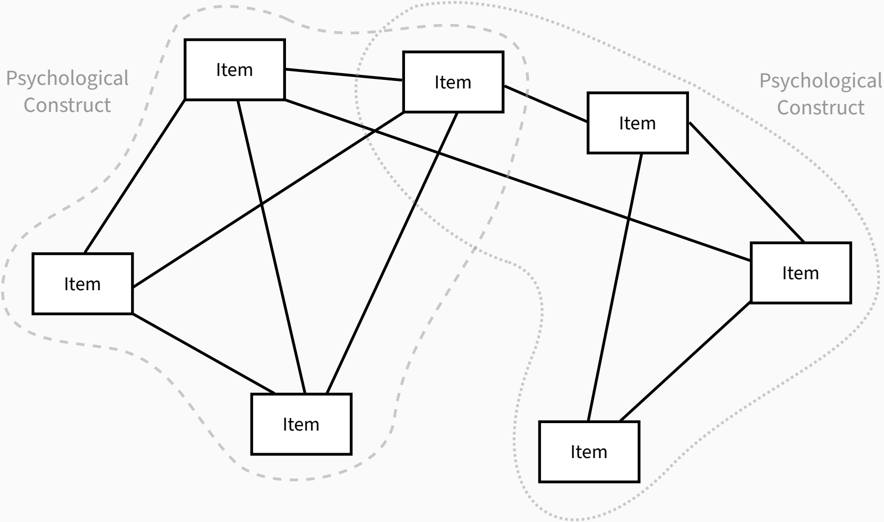
- Latent Factors [27, 29]: constructs are unobservable entities that determine the values of the measurable items.
- Network Analysis [2, 18]: constructs are complex systems represented as networks composed of nodes (the items constituting the construct) and edges (the connections among items).

Here we will concentrate on the latter to study empathy [3], following up from a previous study [4].

Latent Factor Models



Network Models



Why Network Models?

- Latent factor models require many assumptions [29] whose impact is difficult to verify, leading to subjective results that are driven by pragmatic considerations rather than research hypotheses [29, 30, 23].
- Network models have fewer unverifiable assumptions. They are more exploratory: they disaggregate constructs into their components and model their relationships. They also require smaller sample sizes [1].
  - Among network models, there is a long tradition of using structural equation models. They are expressly causal and they can include latent variables, which is good! But they require us to specify the complete causal structure and they also have many unverifiable assumptions [15].

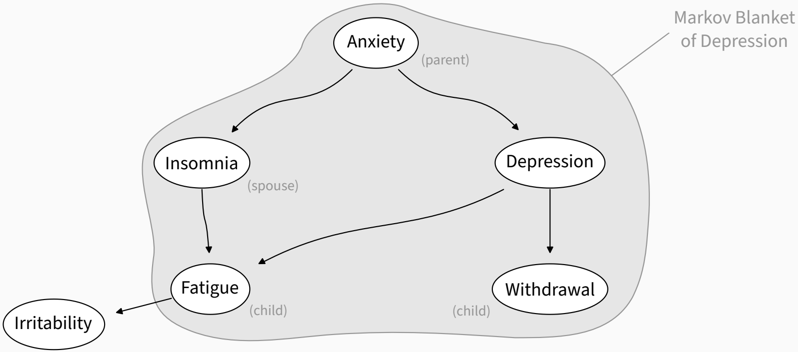
NOTE: latent variables and psychological constructs are distinct entities, and we should only equate them when all requisite causal assumptions have been explicitly delineated [13].

Bayesian Networks as Causal Models

Bayesian networks (BNs) [26] are an ideal compromise because:

- they encode the direction of edges and are the foundation upon which causal reasoning is built [22];
- they can be learned from data, unlike structural equation models, and there is plenty of R software to do it (*bnlearn* [25], *pcalg* [17], etc.);
- they can easily accommodate different types of variables, including ordinal variables from Likert scales [21];
- they can be used for hypothesis generation and more in general to answer any causal or probabilistic query;
- they have been applied to psychosis [20], obsessive-compulsive disorder [19], depression [5] and dissociation [7];
- best practices in psychology and psychiatry are documented [6].

How Does a Bayesian Network Look Like



$$
\begin{aligned}
&\mathrm{P}(\text{Anxiety}, \text{Insomnia}, \text{Fatigue}, \text{Depression}, \text{Withdrawal}, \text{Irritability}) = \\
&\quad \mathrm{P}(\text{Anxiety})\,\mathrm{P}(\text{Insomnia} \mid \text{Anxiety})\,\mathrm{P}(\text{Depression} \mid \text{Anxiety}) \\
&\quad \mathrm{P}(\text{Fatigue} \mid \text{Insomnia}, \text{Depression})\,\mathrm{P}(\text{Withdrawal} \mid \text{Depression}) \\
&\quad \mathrm{P}(\text{Irritability} \mid \text{Fatigue})
\end{aligned}
$$

Bayesian networks are defined by:

- a network structure, a directed acyclic graph (DAG) $\mathcal{G}$, in which each node corresponds to a random variable X_i;
- a global probability distribution $\mathbf{X}$ with parameters Θ, which factorises into smaller local probability distributions according to the arcs in $\mathcal{G}$:

$$\mathrm{P}(\mathbf{X}, \Theta) = \prod_{i=1}^{p} \mathrm{P}(X_i \mid \Pi_{X_i}; \Theta_{X_i}) \quad \text{where} \quad \Pi_{X_i} = \{\text{parents of } X_i\}.$$

The main role of the network structure is to express the conditional independence relationships among the variables in the model through graphical separation.

Learning a BN $(\mathcal{G}, \Theta)$ from a data set $\mathcal{D}$ is performed in two steps:

$$\underbrace{\mathrm{P}(\mathcal{G}, \Theta \mid \mathcal{D})}_{\text{learning}} = \underbrace{\mathrm{P}(\mathcal{G} \mid \mathcal{D})}_{\text{structure learning}} \cdot \underbrace{\mathrm{P}(\Theta \mid \mathcal{G}, \mathcal{D})}_{\text{parameter learning}}.$$

Structure learning consists in finding the DAG that first the data the best:

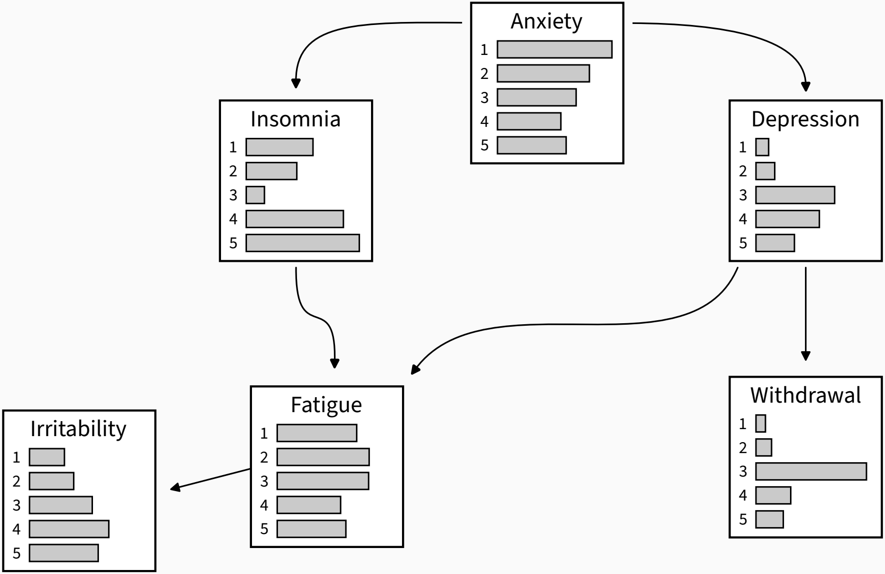
$$\mathrm{P}(\mathcal{G} \mid \mathcal{D}) \propto \mathrm{P}(\mathcal{G})\,\mathrm{P}(\mathcal{D} \mid \mathcal{G}) = \mathrm{P}(\mathcal{G}) \int \mathrm{P}(\mathcal{D} \mid \mathcal{G}, \Theta)\,\mathrm{P}(\Theta \mid \mathcal{G})\,d\Theta,$$

where $\mathrm{P}(\mathcal{G})$ represents our prior knowledge of the DAG.

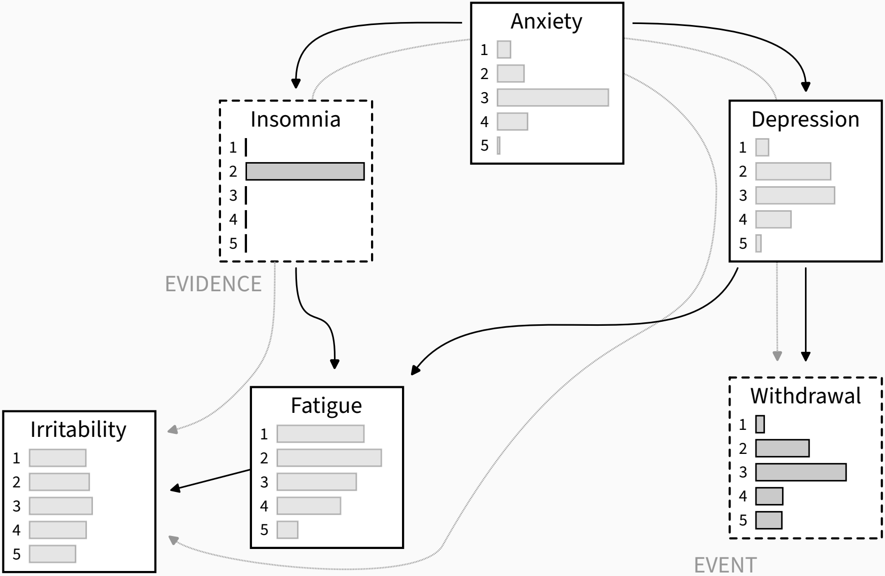
Parameter learning consists in estimating the parameters for the local distributions:

$$\mathrm{P}(\mathcal{D} \mid \mathcal{G}) = \prod_{i=1}^{N} \left[\int \mathrm{P}\left(X_i \mid \Pi_{X_i}, \Theta_{X_i}\right) \mathrm{P}\left(\Theta_{X_i} \mid \Pi_{X_i}\right)\, d\Theta_{X_i} \right].$$

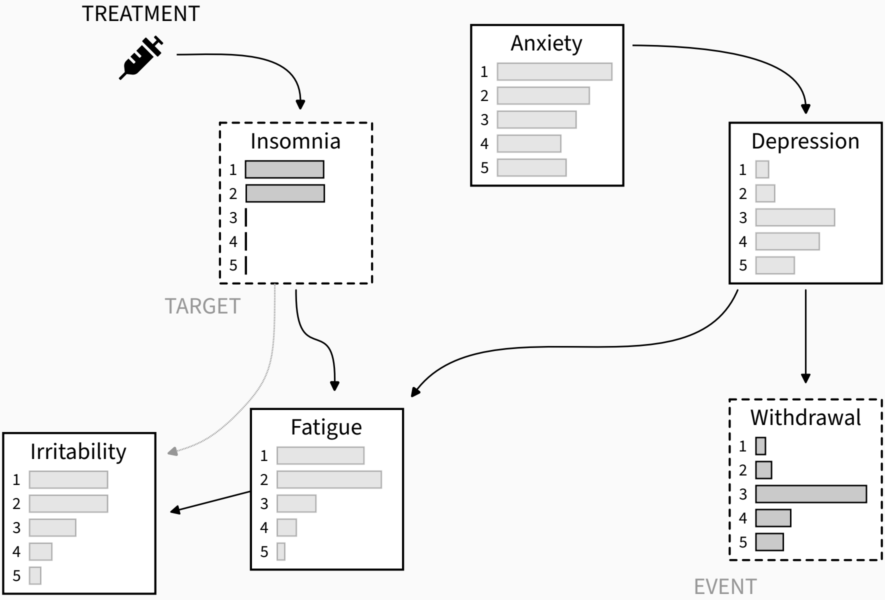
Bayesian Networks: Inference



Bayesian Networks: Conditional Probability Queries



Bayesian Networks: Interventions



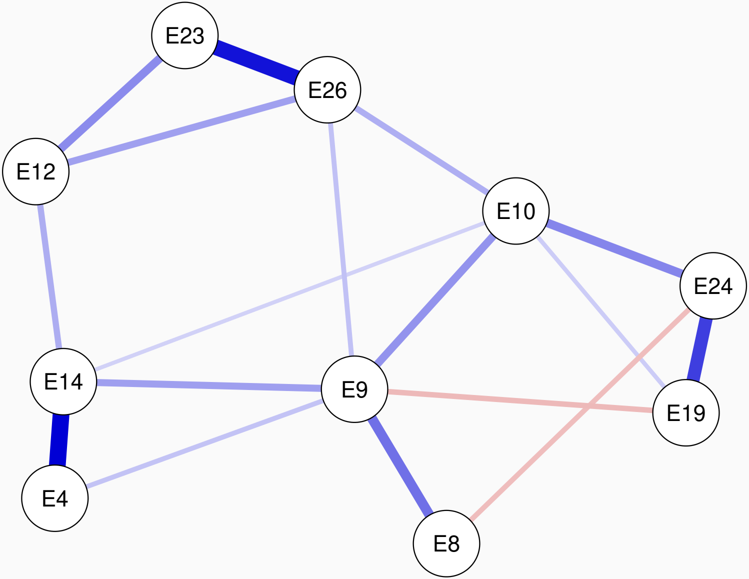
The Data and the Reanalysis

- Questionnaire with 28 items.
- 1973 French-speaking university students in Belgium:
  - aged between 17 and 25;
  - 57% were women;
  - 1270 answered the full questionnaire.
- We selected the 10 items that were most interconnected in the previous analysis [4].
- We learned a causal network on those 10 items, assuming a Gaussian Bayesian network (variables are normally distributed, dependencies are linear correlations).
- We validated the main causal pathways with the literature.

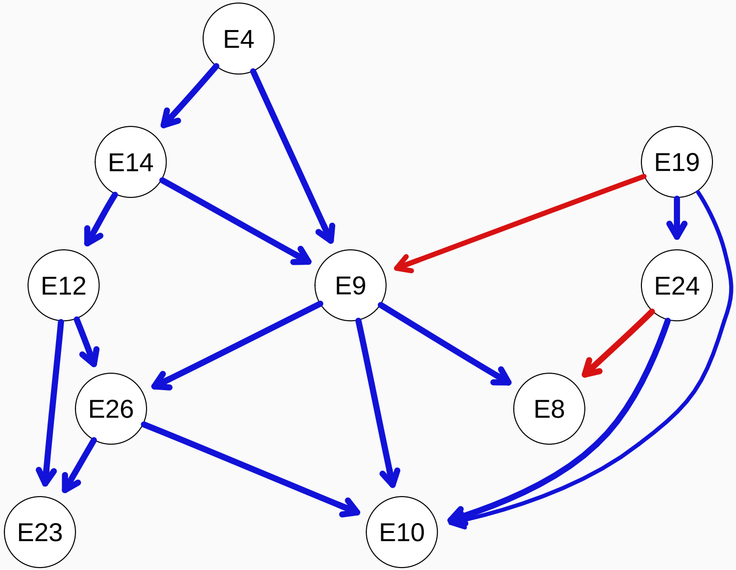
The Variables

E4	Empathic Concern	"Sometimes I don't feel very sorry for other people when they have problems."
E8	Perspective Taking	"I try to look at everybody's side of a disagreement before I make a decision."
E9	Empathic Concern	"When I see someone being taken advantage of, I feel kind of protective towards them."
E10	Personal Distress	"I sometimes feel helpless when I am in the middle of a very emotional situation."
E12	Fantasy	"Becoming extremely involved in a good book or movie is somewhat rare for me."
E14	Empathic Concern	"Other people's misfortunes do not usually disturb me a great deal."
E19	Personal Distress	"I am usually pretty effective in dealing with emergencies."
E23	Fantasy	"When I watch a good movie, I can very easily put myself in the place of a leading character."
E24	Distress	"I tend to lose control during emergencies."
E26	Fantasy	"When I am reading an interesting story or novel, I imagine how I would feel if the events in the story were happening to me."

An Undirected Network Model



A Causal Network Model



Validation of the Causal Network Model

- Two main plausible causal chains: E4 $\rightarrow$ E14 $\rightarrow$ E12 $\rightarrow$ E26 and E19 $\rightarrow$ E24 $\rightarrow$ E10, with E9 connecting their roots. Emotional components as more likely to be potential causes, intellectual components as more likely to be potential effects in the empathy construct.
- Empathic concern is causally important in the construct [4, 8].
- Personal distress is an emotional component of empathy associated with psychological problems linked to difficult situations, such as burnout [9, 10, 11, 12, 14, 16, 28].
- BEWARE: causal sufficiency may be violated if there are sociological, environmental, economic, and even genetic latent variables that cause the items interacting in the network [24].
- BEWARE: the sample comprised university students, which may limit the generalisability of the results.

Conclusions

- Causal networks represent psychological constructs as causal pathways, which allows for an intuitive graphical interpretation and for formal causal inference.
- Learning them requires fewer data and fewer assumptions on the side of the researcher.
- They can validate existing theoretical hypothesis and generate new ones to guide new research.

- ✓ Modelling Psychological Constructs
- ✓ Bayesian Networks in Psychology
- ✓ Empathy
- ✓ Conclusions
- → **Acknowledgements**

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That's all!

Happy to discuss in more detail.

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