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Modelling UK home energy use using Bayesian Networks

David Shipworth

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Same House + different occupants = different energy use.

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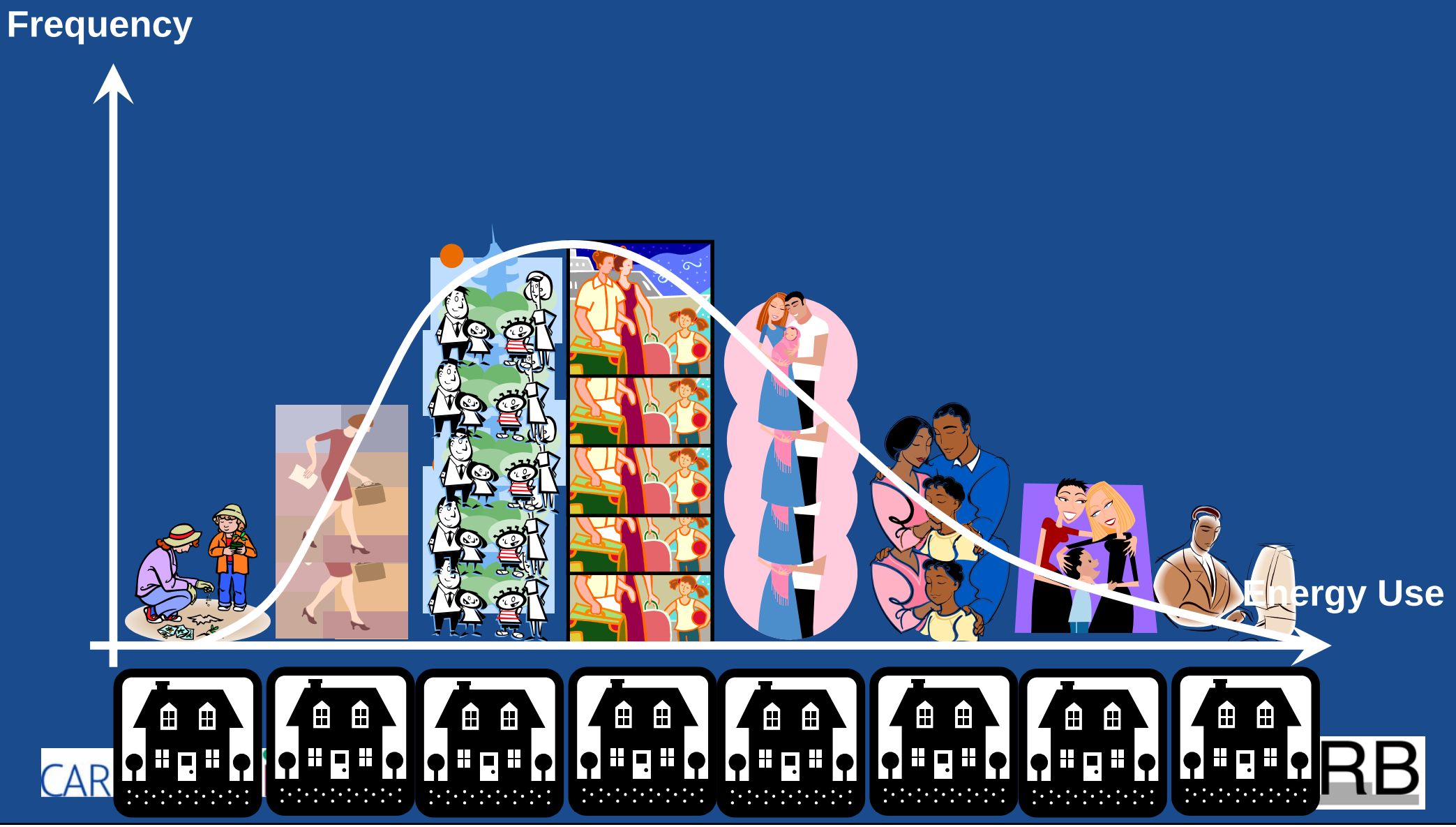
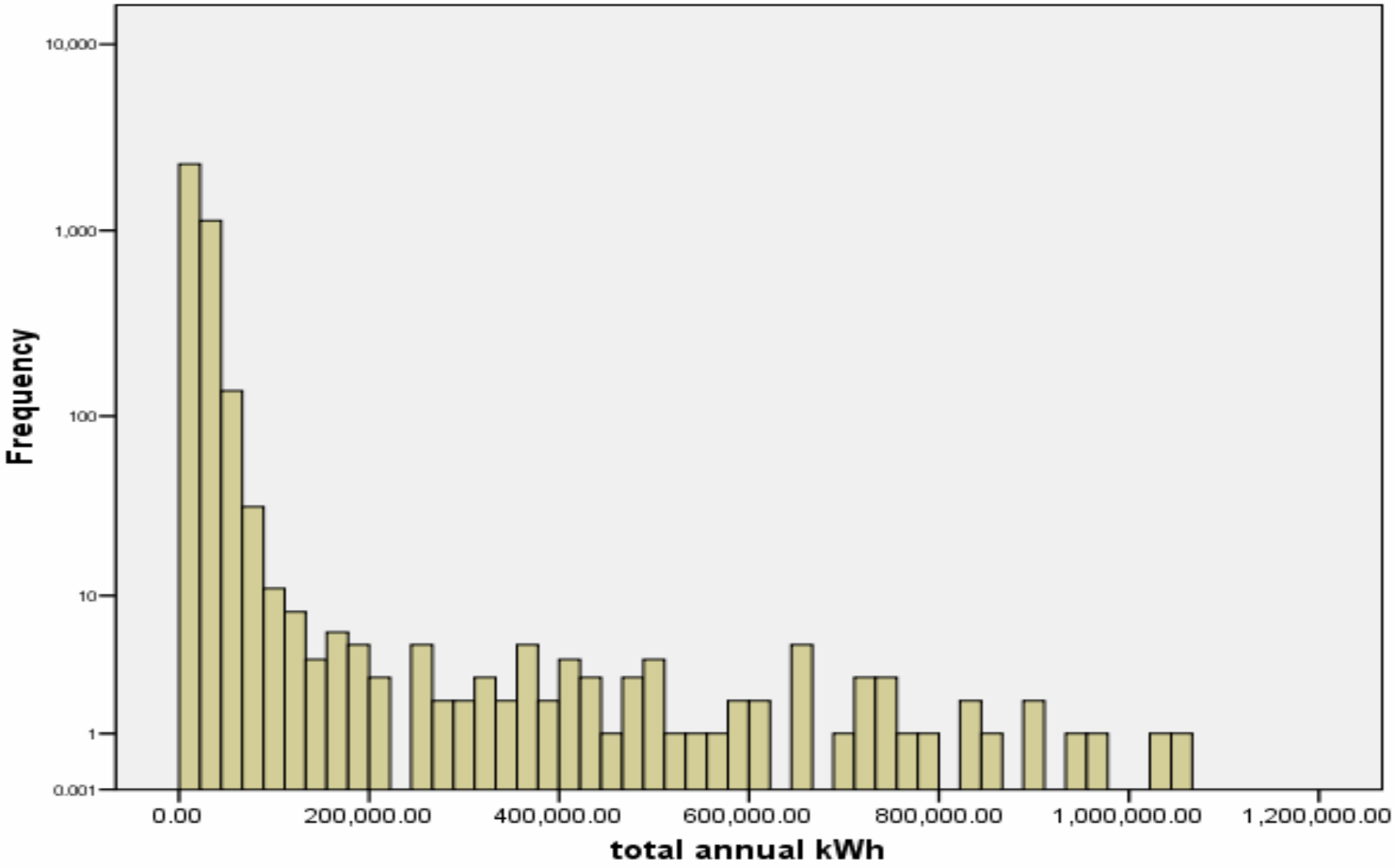


Same occupants + different houses = different energy use.

Different occupants + different houses = radically different energy use

(EHCS '96, n = 3,676, Mean ~30,000 kWh)



One solution: model home energy use as joint distribution over a domain of variables

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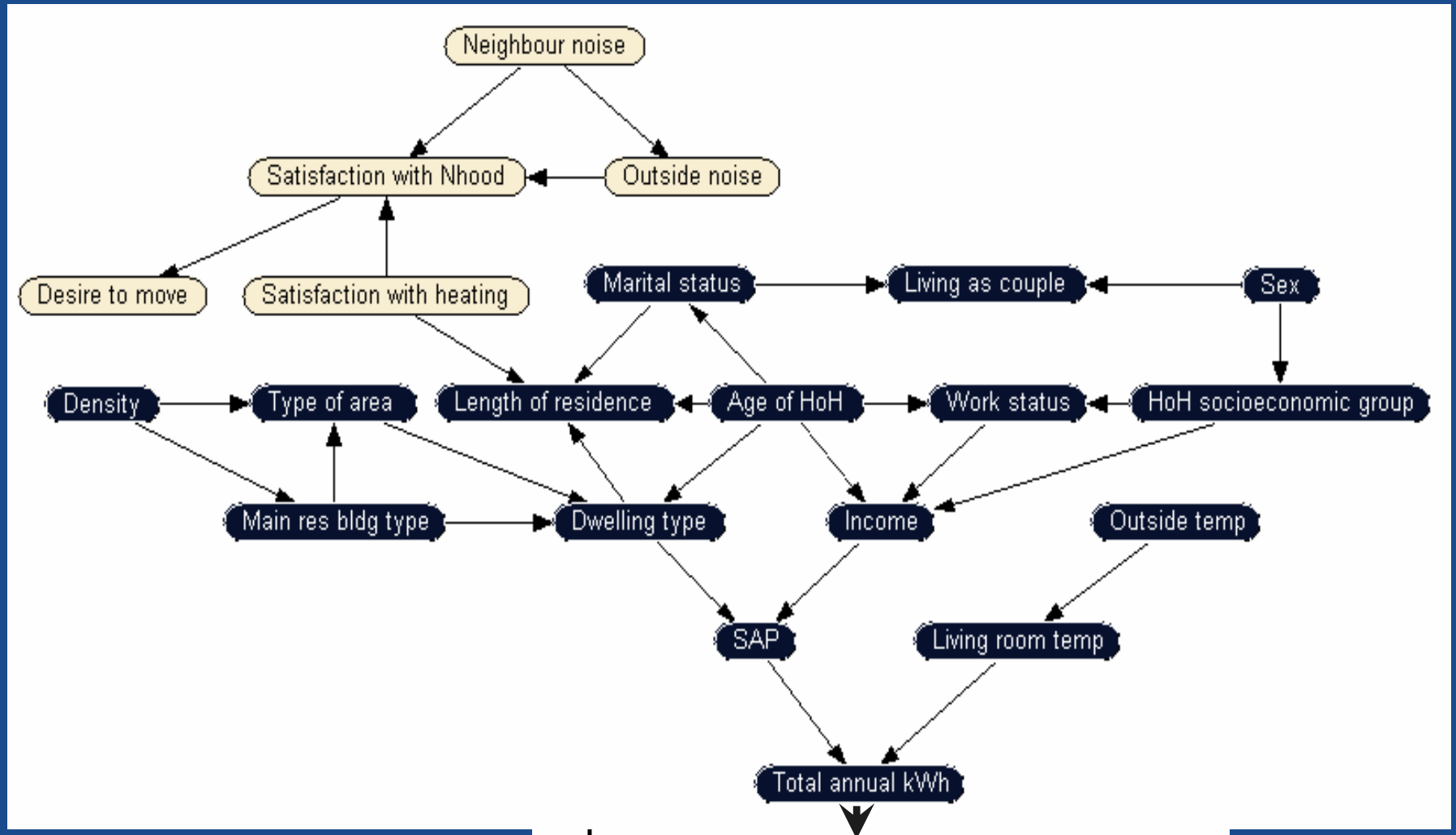

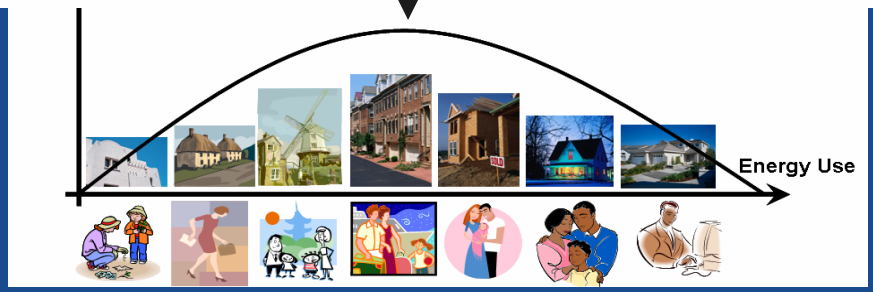

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Questions are then:

1. What knowledge domains are relevant?
2. What variables within these domains should we measure and model?
3. What are the relationships between these variables?
4. What probabilities describe these relationships?

Bayesian Belief Networks

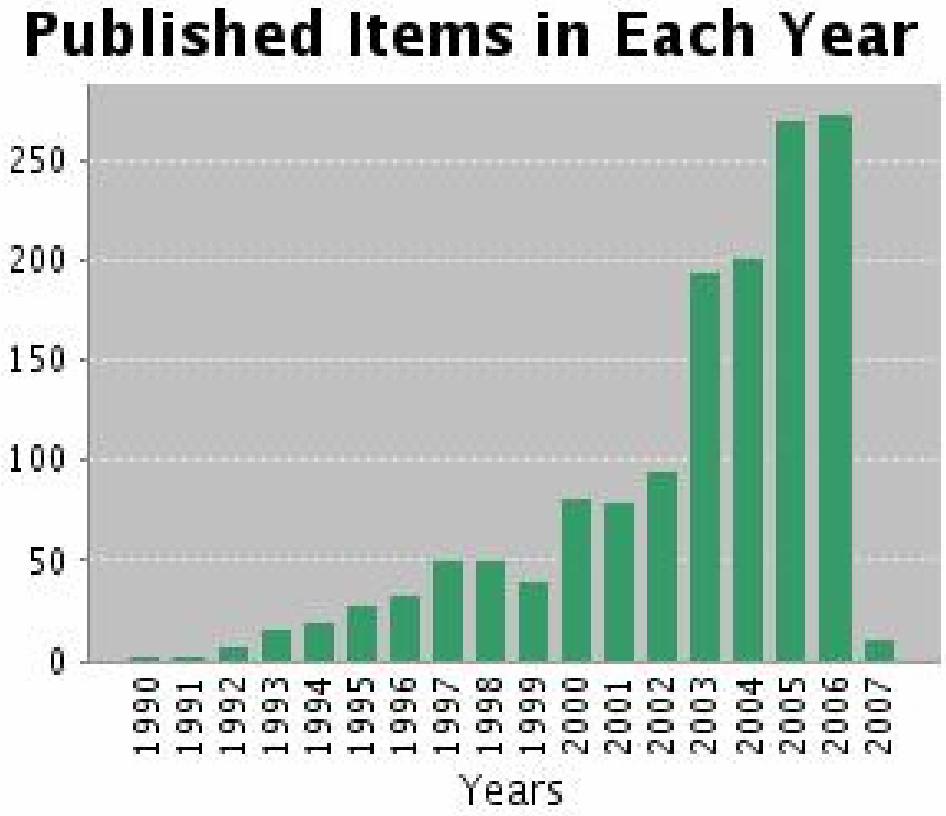
- *'Graphical models are a marriage between probability theory and graph theory. ... Probability theory provides the glue whereby the parts are combined, ensuring that the system as a whole is consistent, and providing ways to interface models to data. The graph theoretic side of graphical models provides both an intuitively appealing interface by which humans can model highly-interacting sets of variables as well as a data structure that lends itself naturally to the design of efficient general-purpose algorithms.'*
  (Jordon 1999 p.1)

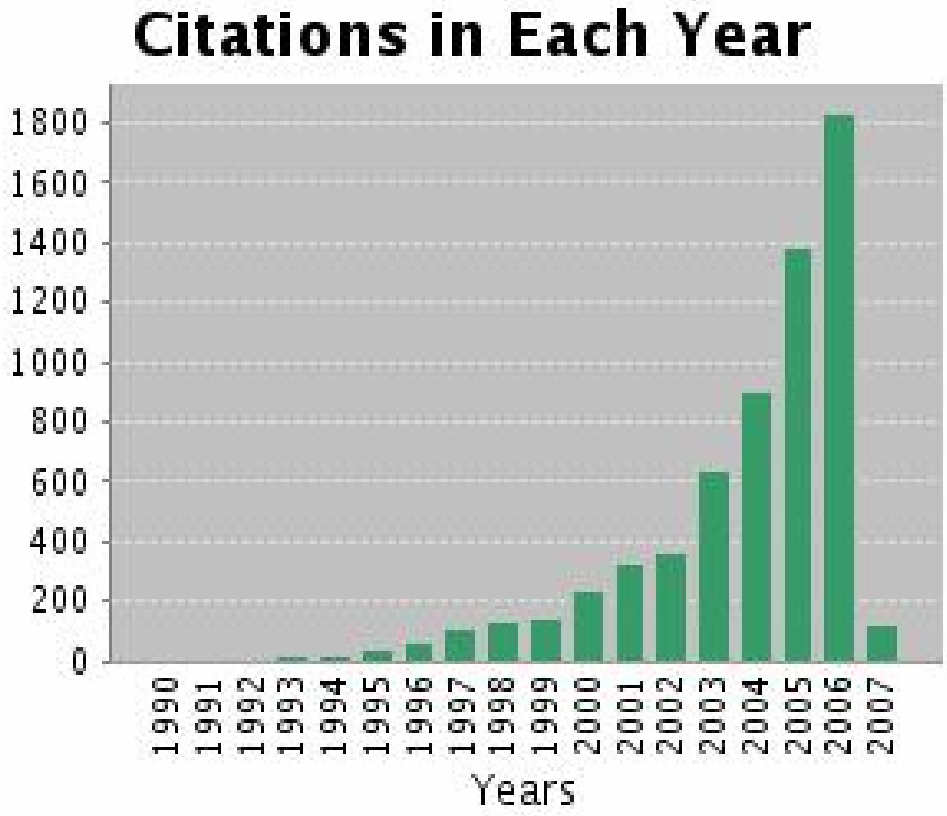
Methodological advantages

- Integration of qualitative and quantitative data from experts, case studies, data-sets and models;
- Integrate of new data as it becomes available;
- Highlight conflicts or synergies between variables.
- Intuitive display of relationships between variables;
- Straightforward sensitivity testing.
- 'Subjective probability' provides common epistemological 'common ground' between social and engineering approaches
- Create consensus based decision support systems;

Growth of literature
TS="Bayesian Network*" ISI

TS="Bayesian Network*"
DocType=All document types; Language=All languages; Databases=SCI-EXPANDED, SSCI, A&HCI; Timespan





Environmental applications

- Management of fisheries (Halls & Burn 2002);
- Management of wildlife (Cohen 1988);
- Management of forests (Crome et al 1996);
- Environmental management (Marcot et al (2002)
- Ecological decision making (Dixon and Ellison 1996);
- Decision support for land use change (Bacon et al 2002);
- Participatory resource management (Cain et al 1999);
- Integrated water resource management (Bromley et al 2004)
- Participatory agricultural land management (Cain et al 2003)

Graph theoretic definition of BBN

- Let $D = (V,E)$ be a Directed Acyclic Graph (DAG), where V is a finite set of nodes and E is a finite set of directed edges between the nodes. The DAG defines the structure of the Bayesian network.
- Each node $v \in V$ in the graph corresponds to a variable X_v. The set of variables associated with the graph D is then $X = (X_v)_{v \in V}$.
  - Bottcher & Dethlefsen (2003 p.2)

Graph theoretic definition of BBN

- To each node v with parents pa(v) a local probability distribution, p($x_v|x_{pa(v)}$), is attached. The set of local probability distributions for all variables in the network is P.
- A Bayesian network for a set of random variables X is the pair (D,P). The possible lack of directed edges in D encodes conditional independencies between the random variables X through the decomposition (factorization) of the joint probability distribution.

$$p(X_1, X_2, \ldots, X_V) = \prod_{v \in V} p\left(x_v \middle| x_{pa(v)}\right)\P$$

The medical 'Alarm' network

(Monitored variables of intensive-care patients)

- 37 2-state variables gives unstructured state-space of 2^{37} parameters
- Structuring this reduces it to 509 parameters
- The structure permits 'factorization' of the states-pace and makes the problem tractable

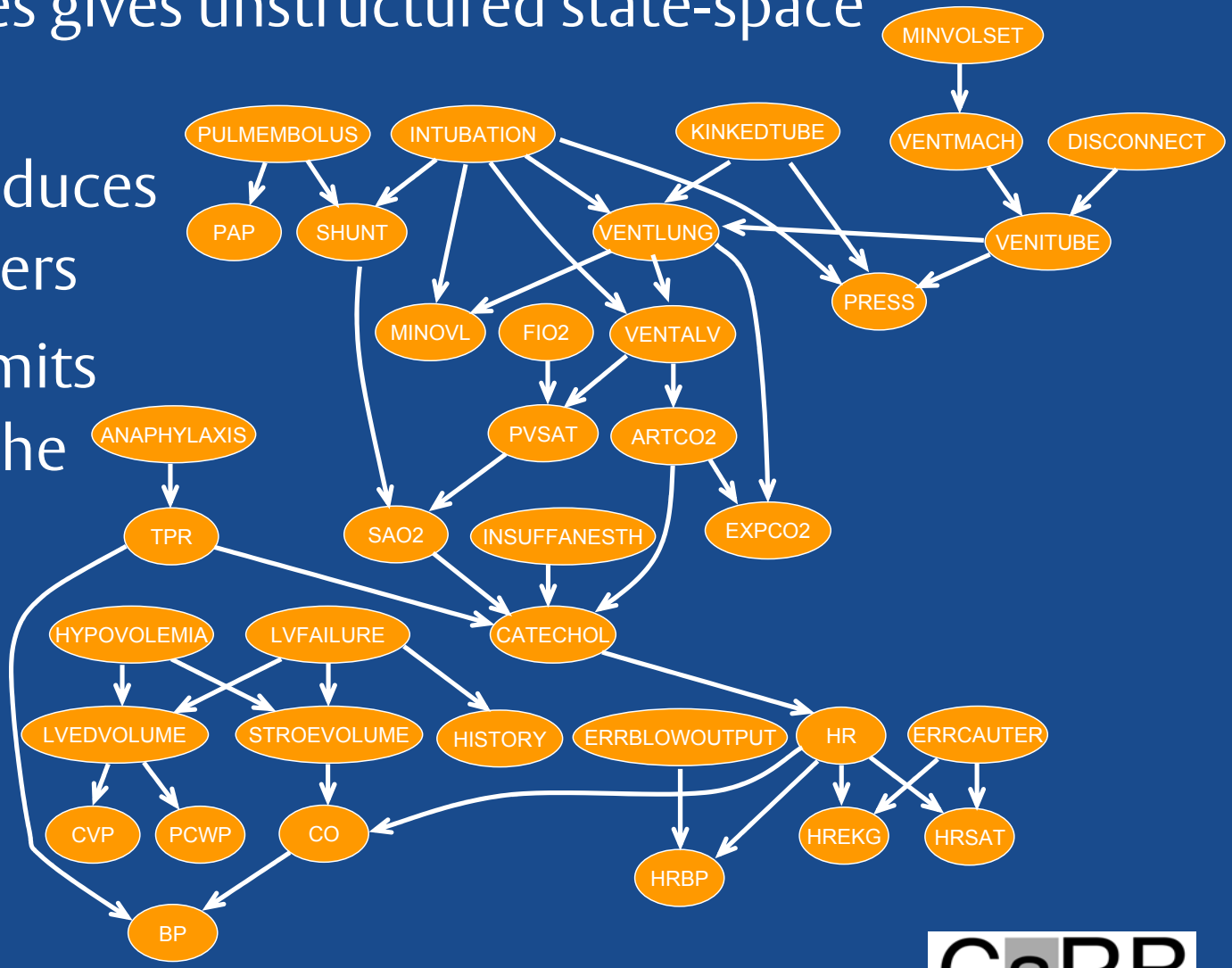


Figure from N. Friedman via K. Murphy

BBN construction

- Identification of the domain variables;
- Identification of the relationships between these variables and;
- Identification of the probabilities describing these relationships
    - (Druzdzel & van der Gaag 2000).

1. What knowledge domains are relevant?

- Sociological theories
  - Socio-technical systems theory; Actor network theory
- Psychological theories
  - Attitude-behaviour models
- Economic theories
  - Rational action models
- Physical theories
  - Building thermal simulation
- Different sets of variables
- Different relationships between variables

Psychological theories:
Bagozzi's Comprehensive Model of Consumer Action
(Ref: Jackson 2005, Figure 17)

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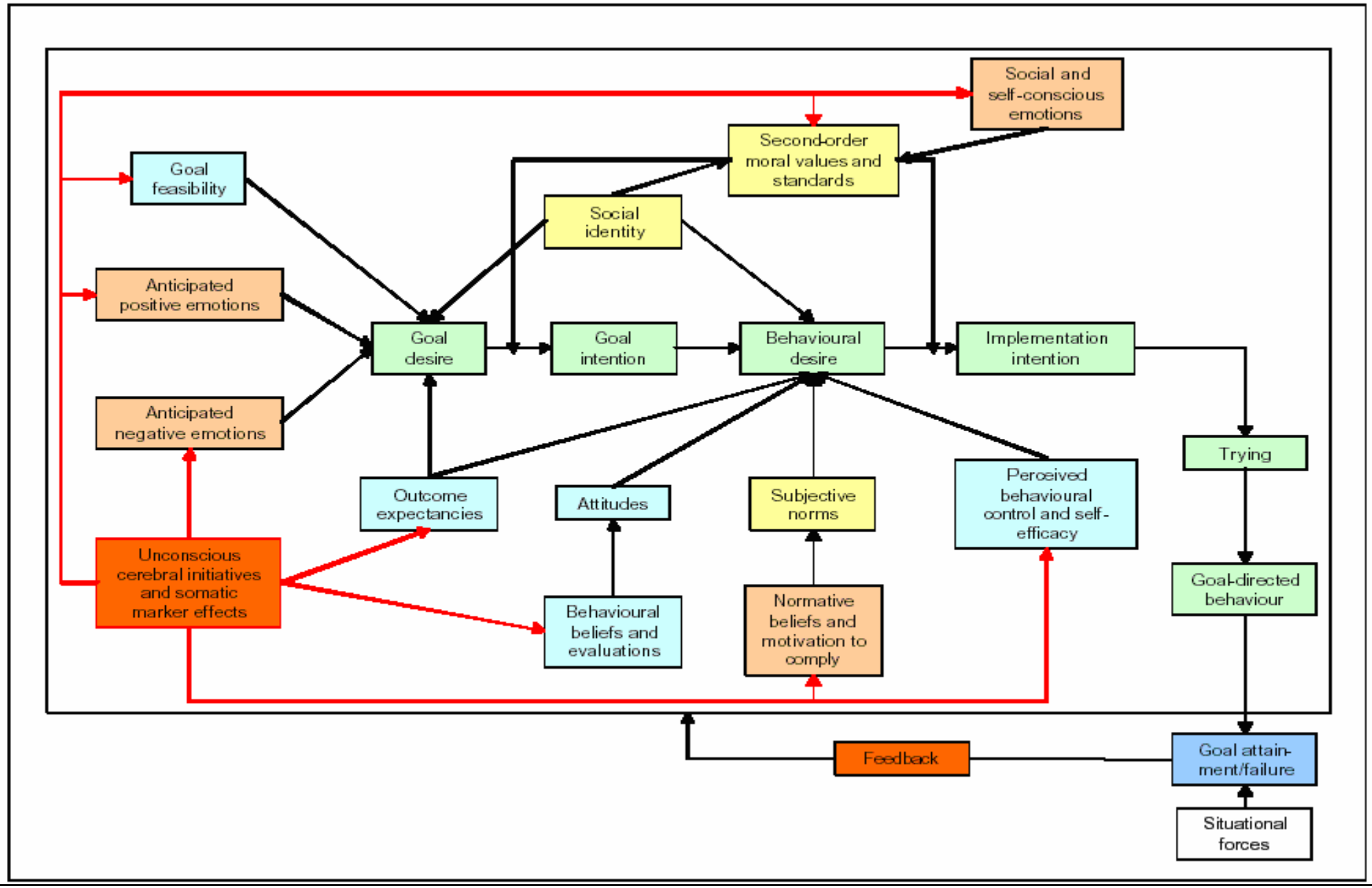
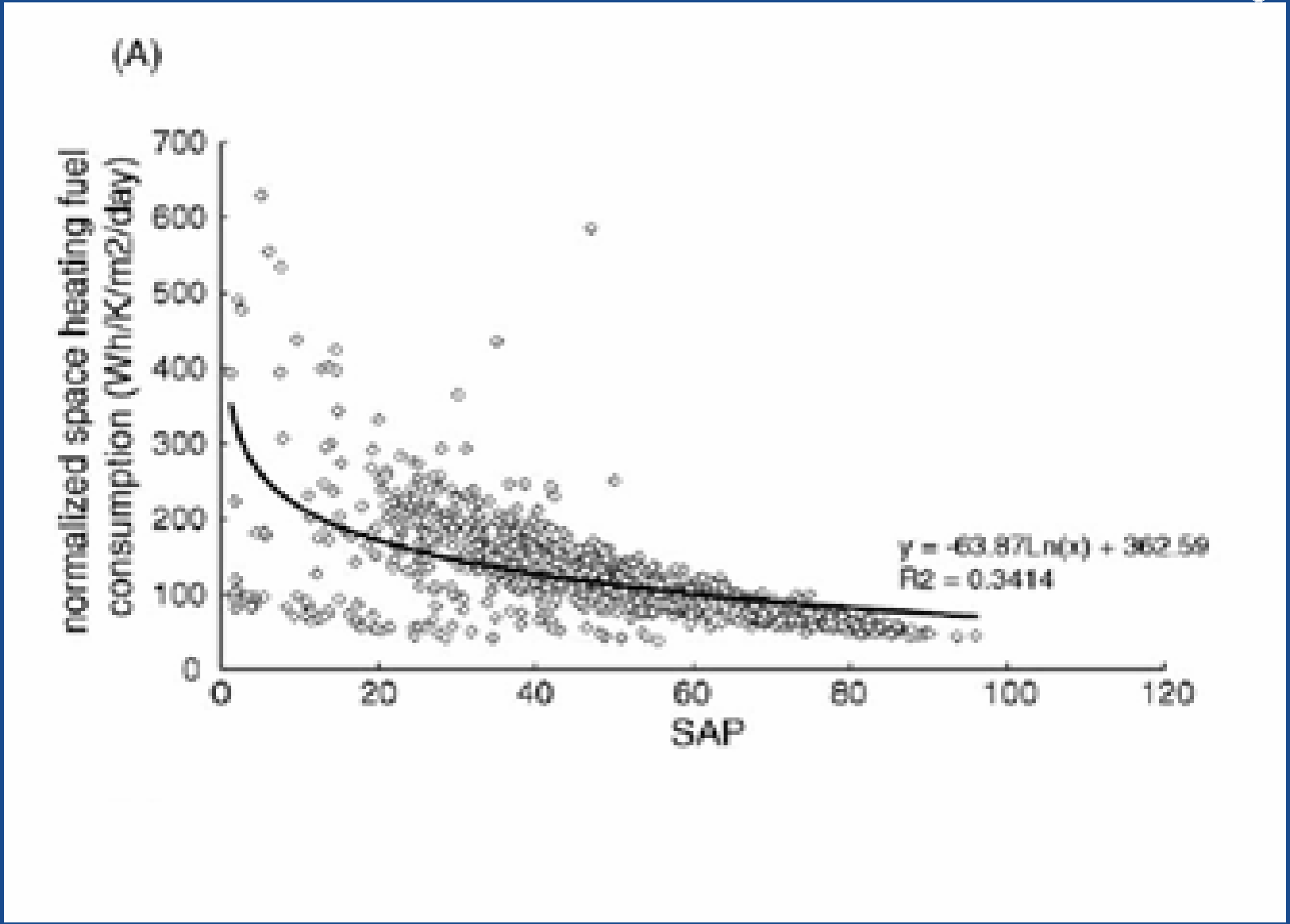


Physical theories: The SAP (theory)



Hong, S. H., T. Oreszczyn and I. Ridley (2006). "The impact of energy efficient refurbishment on the space heating fuel consumption in English dwellings." Energy and Buildings 38(10): 1171-1181

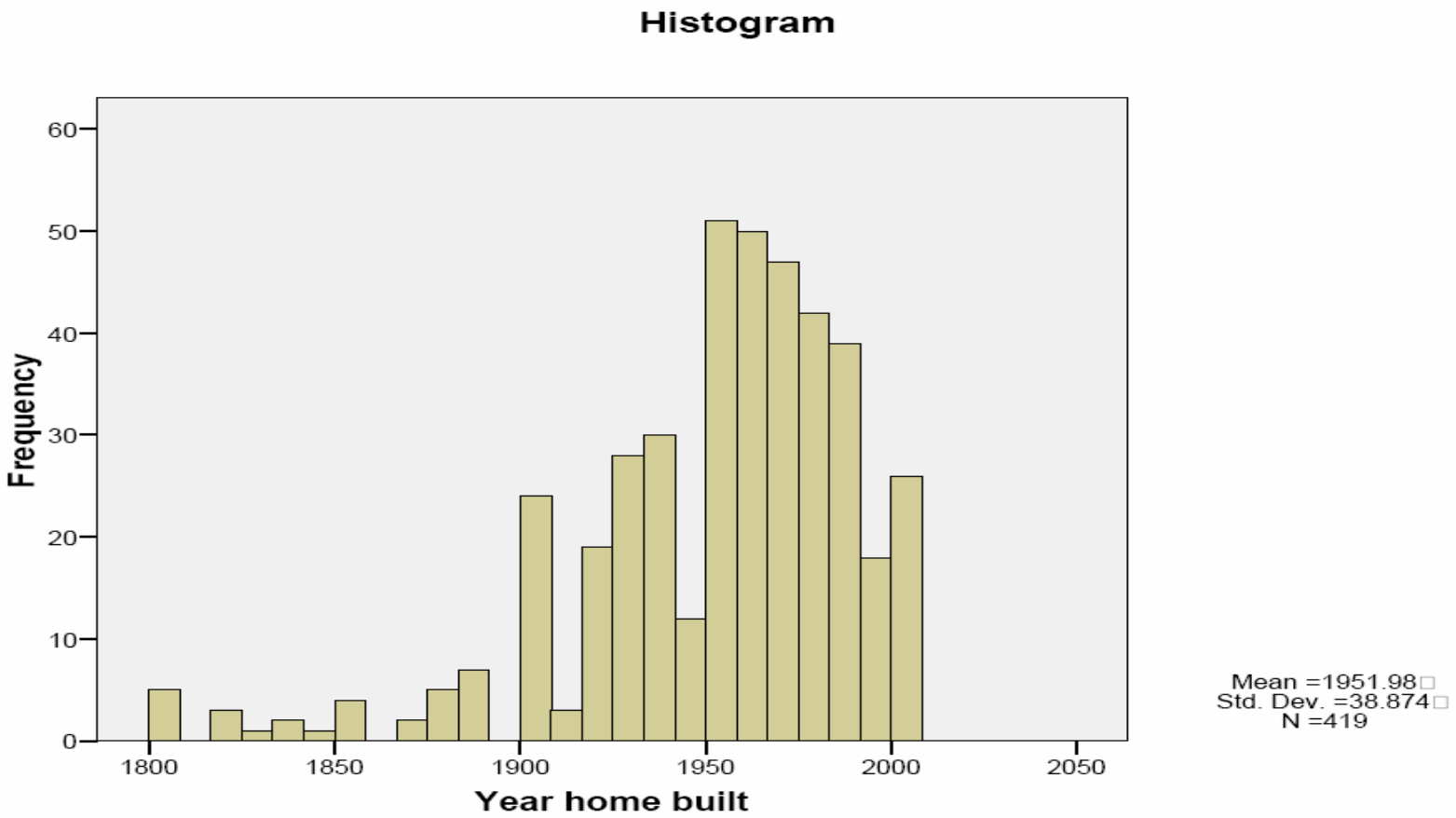
What variables within these domains should we measure and model?

- Reviews of:
  - Technical literature
  - Psychological literature
  - Sociological literature
  - Economic literature
- Look for variables which are:
  - Supported by empirical evidence
  - Supported by multiple authors
  - Supported by established theories
  - Likely to explain a significant means of energy use
  - Policy actionable or have good explanatory power
  - Allow replication of previous studies for longitudinal analysis

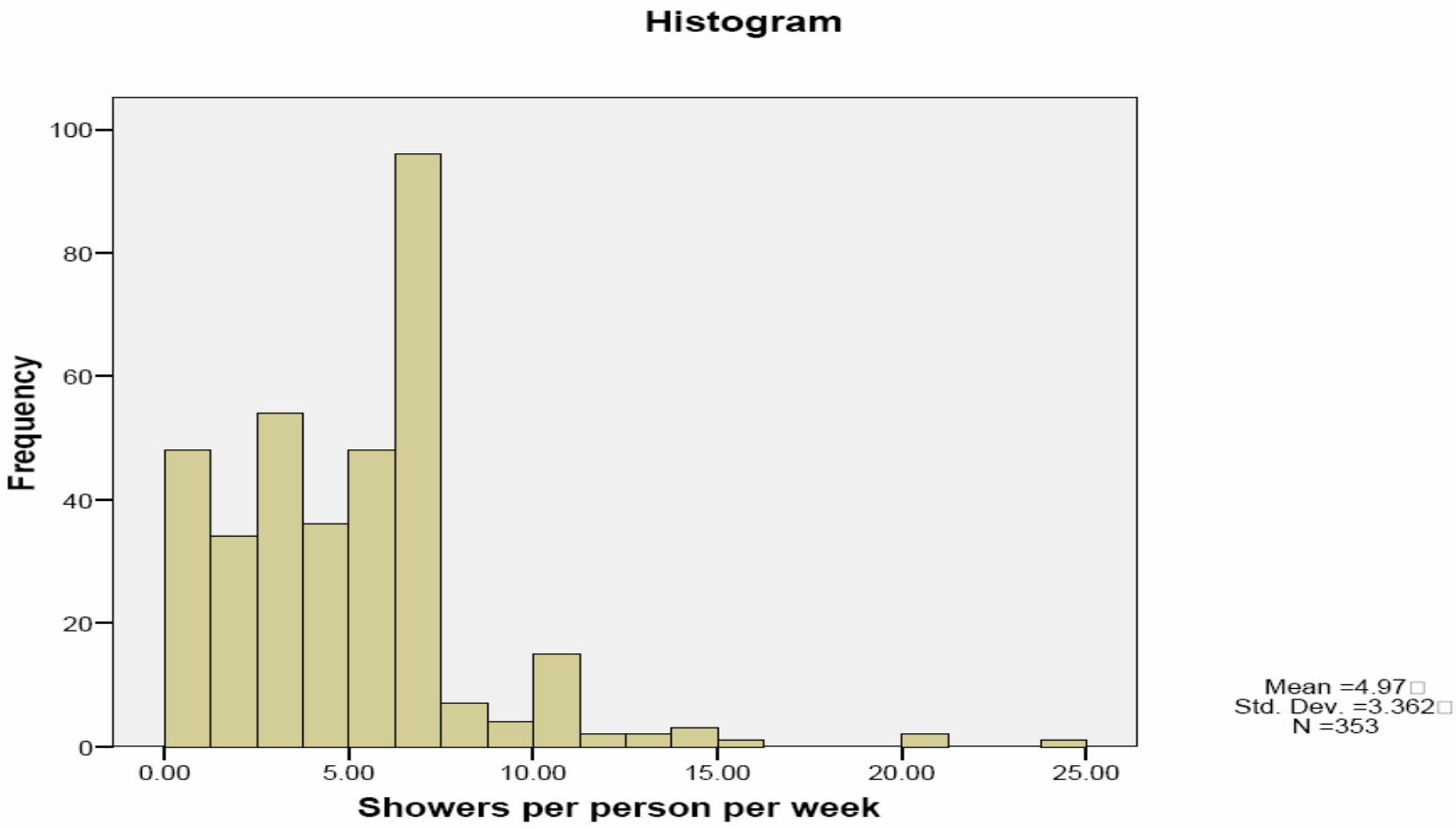
Some variables measured in CaRB DomNat survey

- Other Heating Controls & Usage
  - Additional Heating (Frequency of use)
  - Heating on if at home
  - Curtains use
- Ventilation
  - Windows & Doors Open
  - Extractor Fans / Cooker Hoods
- Occupancy Patterns
  - Weekly Occupancy Patterns
- Bathing Technology & Practices
  - Shower Technology
  - Bathing / Showering Practices
  - Pools, Sauna's and Hot Tubs
- Built Form
  - Accommodation Type
  - Number of Storeys
  - Age of Building
  - Loft & Insulation
  - Walls & Insulation
  - Double-Glazing
  - Curtains – not in any so far
  - Draught-proofing
  - Number & Types of Rooms (in types of heating section)
  - Conservatory & Glazing
  - Internal Doors

Age of dwelling



Showers per person per week



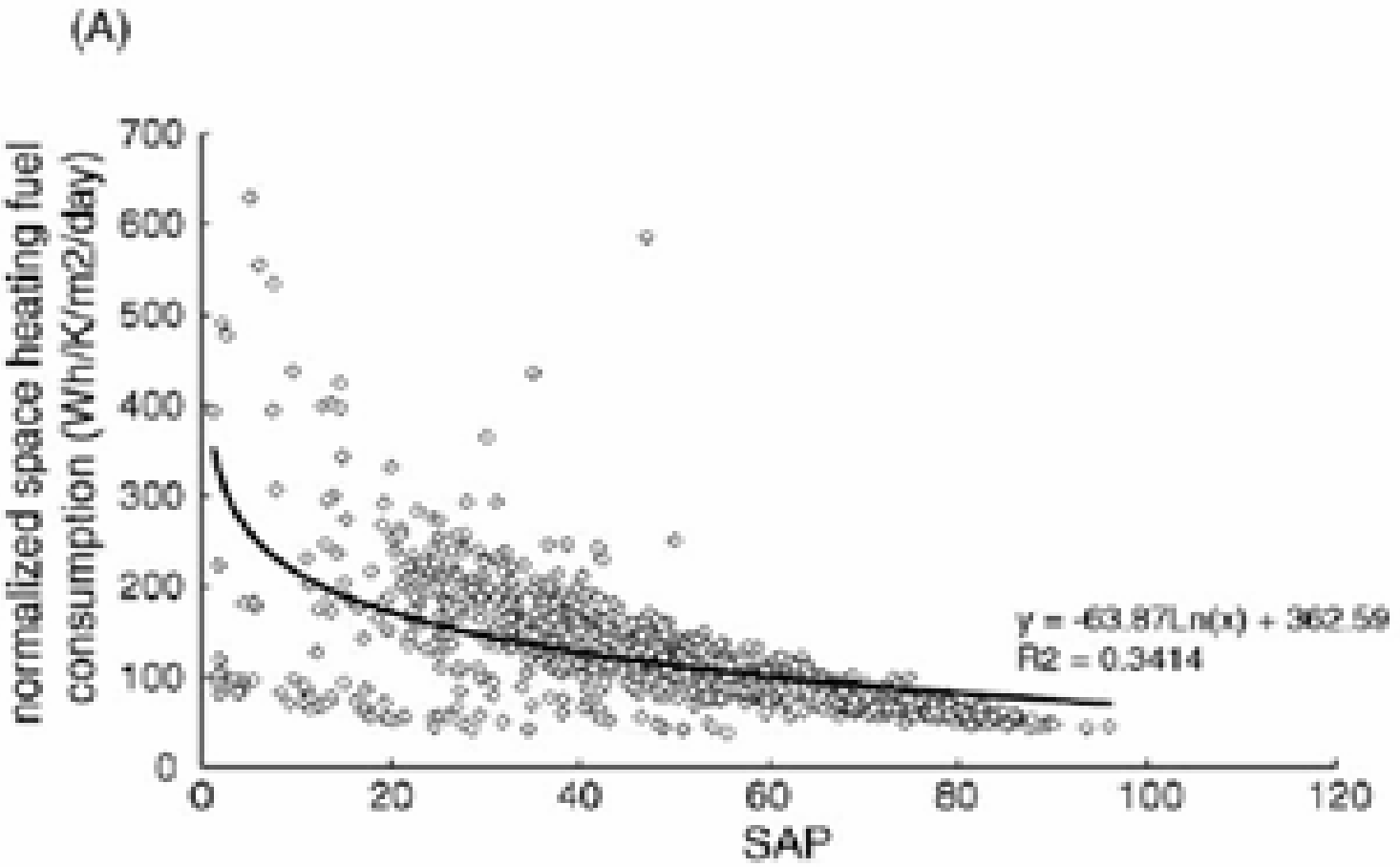
2. What are the relationships between these variables?

- In Bayesian Networks, the relationship between variables is called the ‘architecture’ or ‘structure’.
- Two main ways of determining structure:
  - Elicitation from domain experts
  - Learning from data

Elicitation from domain experts

- Excellent if:
  - The domain of knowledge are well defined
  - There is a consensus on main variables within that domain
  - There is separation between domains
  - There is a history of sound empirical statistical study in the domain
  - There is a consensus on relationship between variables within that domain.
  - There is a consensus on research approach
    - Theory vs Empirical
    - Qualitative vs Quantitative
    - Statistical vs Deterministic

Physical theories: The SAP (theory)



Hong, S. H., T. Oreszczyn and I. Ridley (2006). "The impact of energy efficient refurbishment on the space heating fuel consumption in English dwellings." Energy and Buildings 38(10): 1171-1181

Physical Theories: The SAP (empirical)

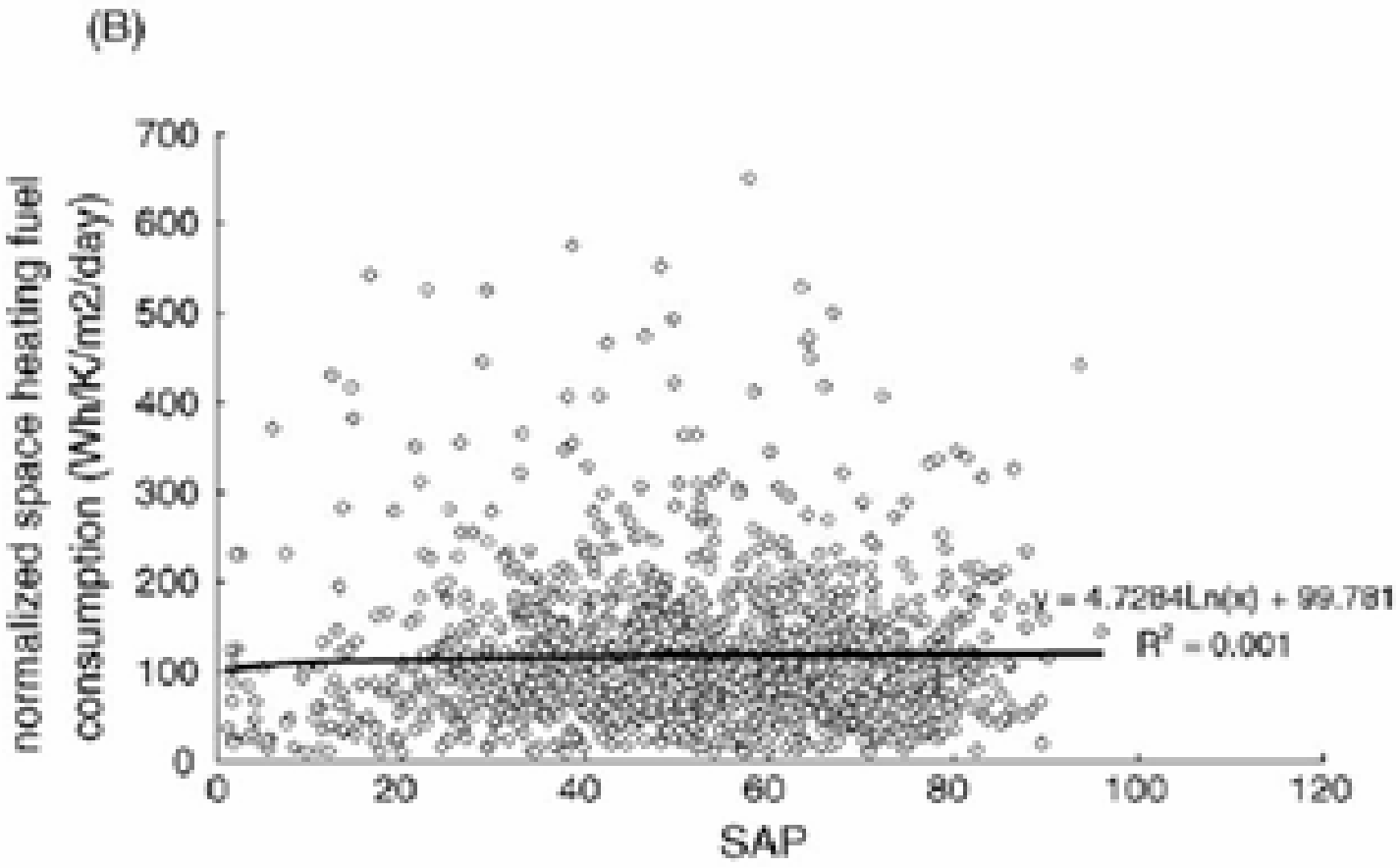


Fig. 5. Comparison of normalized space heating fuel consumption and SAP. (A) Modeled and (B) monitored.

Hong, S. H., T. Oreszczyn and I. Ridley (2006). "The impact of energy efficient refurbishment on the space heating fuel consumption in English dwellings." Energy and Buildings 38(10): 1171-1181

2. Structure learning from data

- The 'model space'
  - Robinson (1977) showed that the size of the model space (number of different DAGs) grows super-exponentially with the number of nodes.
  - Thus: r(2) = 3; r(3) = 25; r(5) = 29,281; r(10) ≈ 4.2 x 10^{18}

(Leray & Francois, 2004)

$$r(n) = \sum_{i=1}^{n} (-1)^{i+1} \binom{n}{i} 2^{i(n-i)} r(n-i) = n^{2^{\mathcal{O}(n)}}$$

Searching model space for models which fit the data

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- Model space is huge
- ∴ need a heuristic search strategy
- ∴ need a scoring system for DAGs
  - Need a *decomposible* and *equivalent* score
    - *Decomposible* if score is sum or product a function of a node and its parents
    - *Equivalent* if score is same for equivalent DAGs
- BIC (Schwartz 1978) is widely used

$$BIC(\mathcal{B}, D) = \log \mathbb{P}(D|\mathcal{B}, \theta^{ML}) - \frac{1}{2} Dim(\mathcal{B}) \log N$$

Markov Equivalence

- If two DAGs have the same joint probability distribution P(X) (i.e. the structure creates the same set of conditional dependencies between variables) they are said to be 'Markov equivalent' and belong to the same 'Markov equivalent class'.
- DAGs are Markov equivalent IFF they have the same edge support and the same set of 'V' structures. (Verma & Pearl, 1990)

Bayes' rule and Markov Equivalent DAGs

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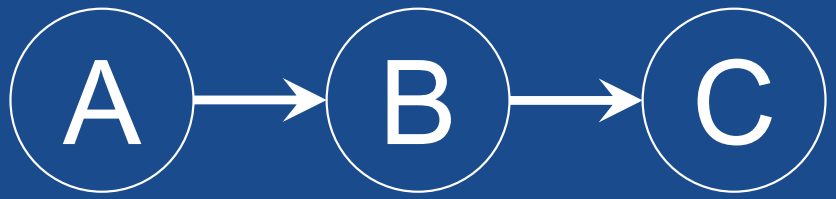
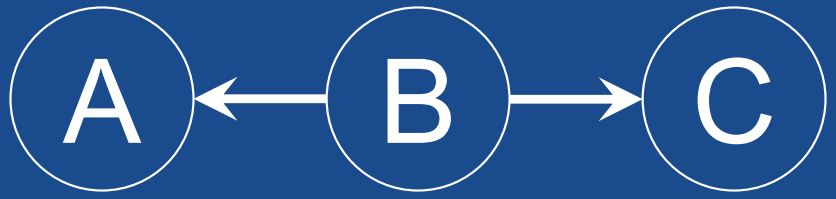
- $P(A,B,C) =$

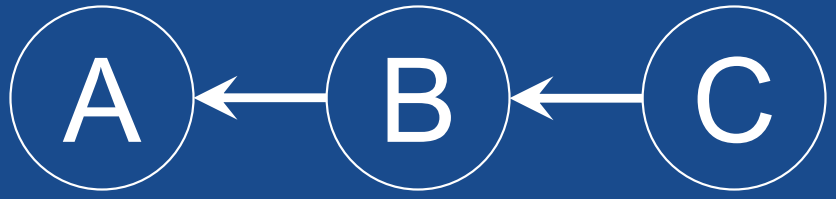
$P(A)P(B|A)P(C|B) =$



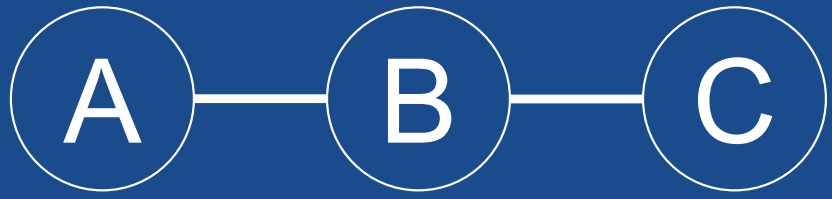
$P(A|B)P(B)P(C|B) =$



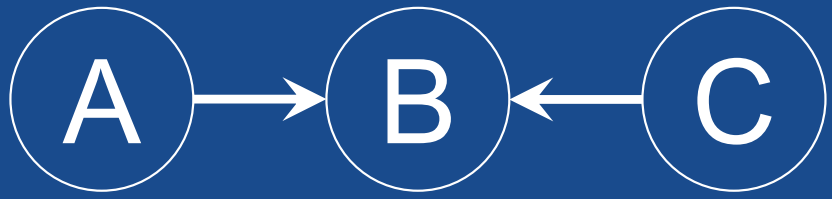
$P(A|B)P(B|C)P(C) =$



CPDAG =



$\neq P(A)P(B|A,C)P(C) =$



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Searching model space for models which fit the data

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- BIC measures fit of joint probability distribution (JPD) to data
- But JPD is unique only to Markov equivalence class level
- CPDAGs are unique to Markov equivalence classes
- Multiple DAGs per CPDAG
- Structure searches can't distinguish DAGs within CPDAGs

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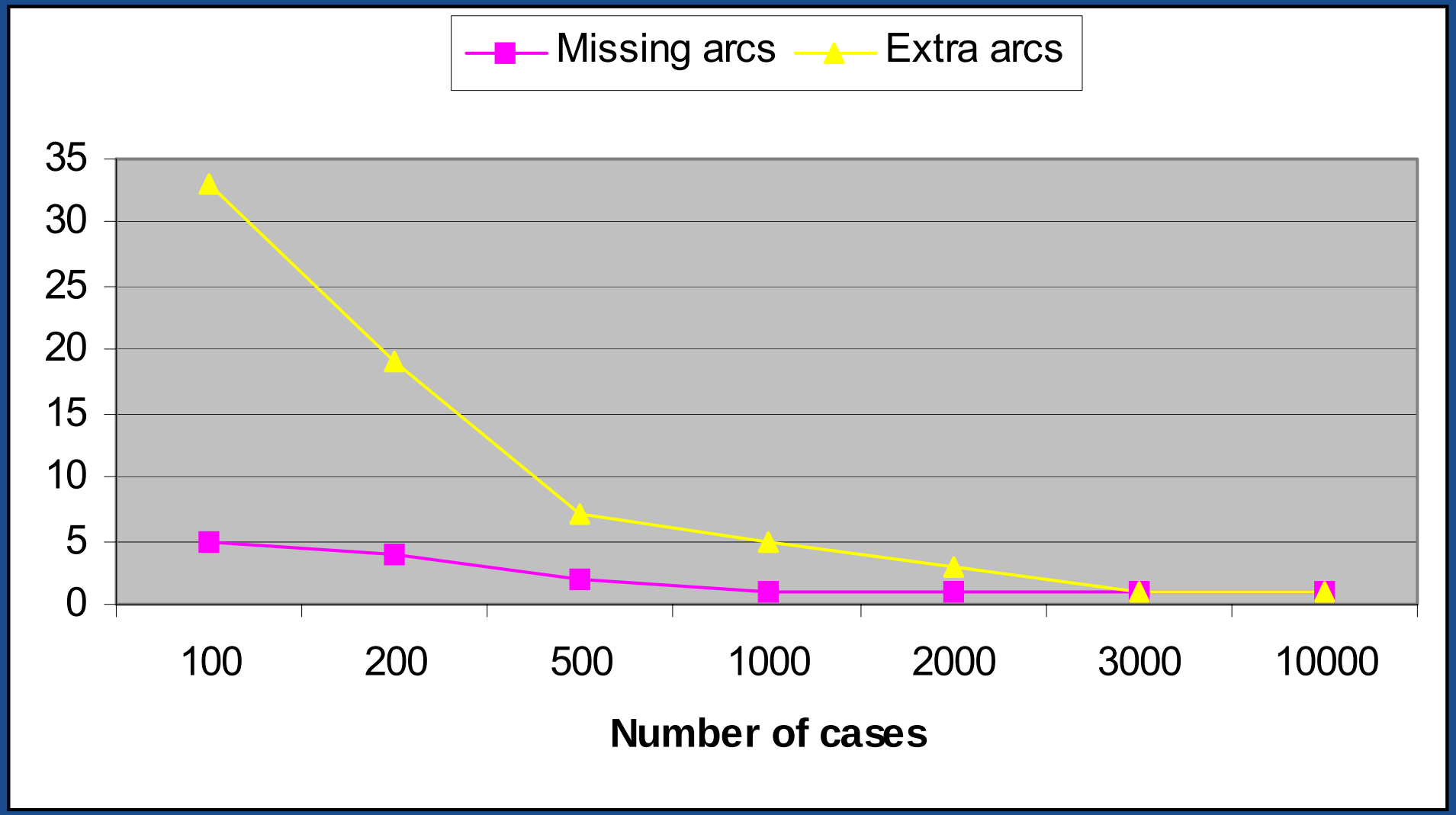
Structure learning errors by number of cases for 'K2' algorithm on 37 node 'ALARM' network



Data from Cooper & Herskovits 1993

Search algorithm performance

(Leray & Francois, 2004)

- Test algorithms by dataset length, editing distance and BIC score (n≈30).

INSURANCE	250	500	1000	2000	5000	10000	15000
MWST	37;-3373	34;-3369	36;-3371	35;-3369	34;-3369	34;-3369	34;-3369
K2	56,-3258	62;-3143	60;-3079	64;-3095	78;-3092	82;-3080	85;-3085
K2(2)	26;-3113	22;-2887	20;-2841	21;-2873	21;-2916	18;-2904	22;-2910
K2+T	42;-3207	40;-3009	42;-3089	44;-2980	47;-2987	51;-2986	54;-2996
K2-T	55;-3298	57;-3075	57;-3066	65;-3007	70;-2975	72;-2968	73;-2967
MCMC*	50;-3188	44;-2967	46;-2929	40;-2882	50;-2905	51;-2898	54;2892
GS	37;-3228	39;-3108	30;-2944	33;-2888	29;-2859	25;-2837	28;-2825
GS+T	43;-3255	35;-3074	28;-2960	26;-2906	33;-2878	19;-2828	21;-2820
GES	43;-2910	41;-2891	39;-2955	41;-2898	38;-2761	38;-2761	38;-2752
SEM	50;-4431	57;-4262	61;-4396	61;-4092	69;-4173	63;-4105	63;-3978

Figure 3: Editing measures and BIC scores divided by 100 and rounded obtained with different methods (in row) for several dataset lengths (in column) (* As the method MCMC is not determinimistic the results are a mean over five runs).

Table from Leray & Francois 2004

MATLAB: BNT: SLP: GES

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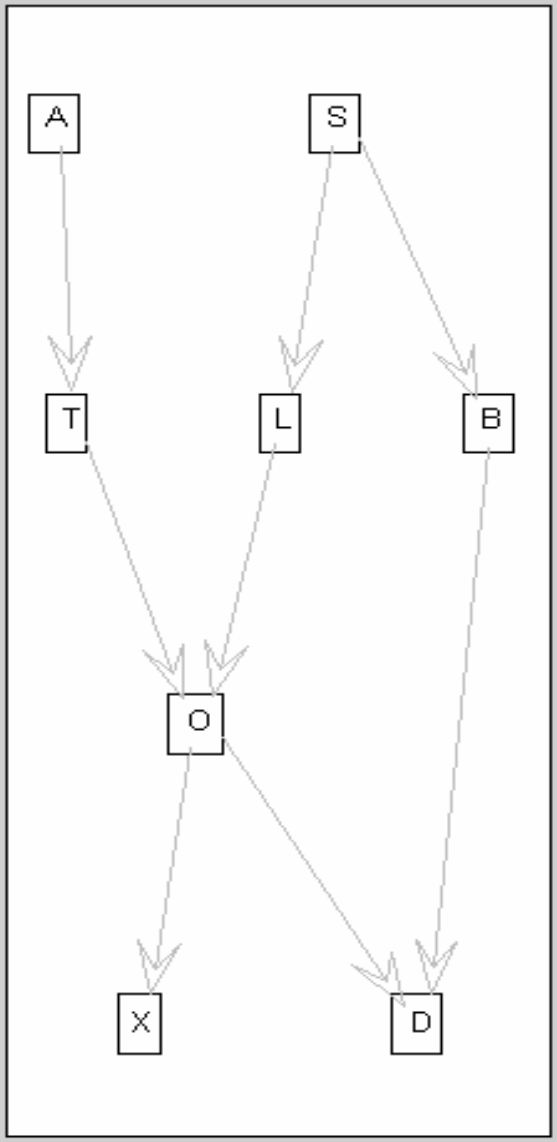
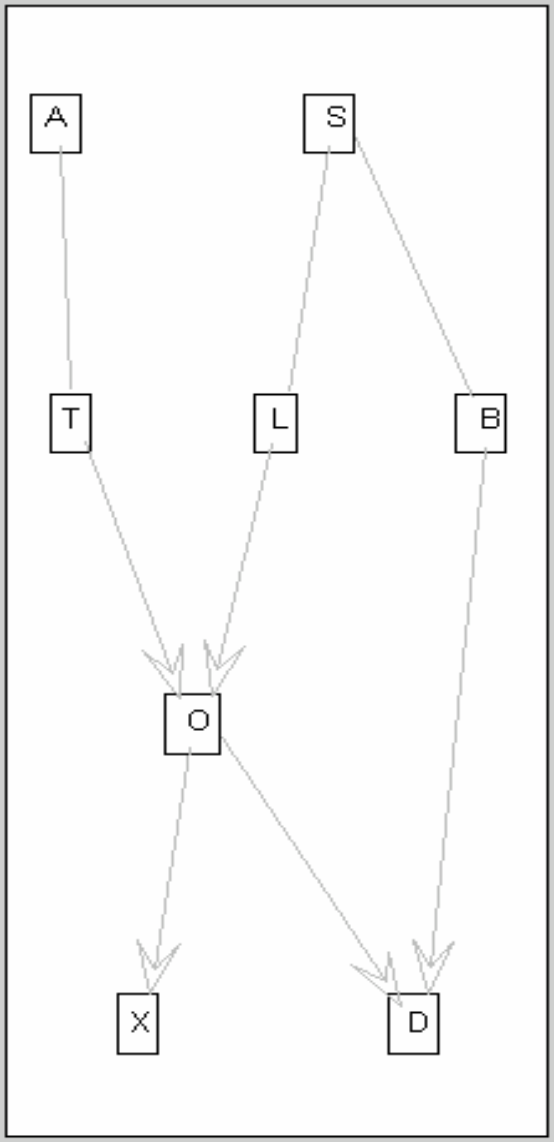
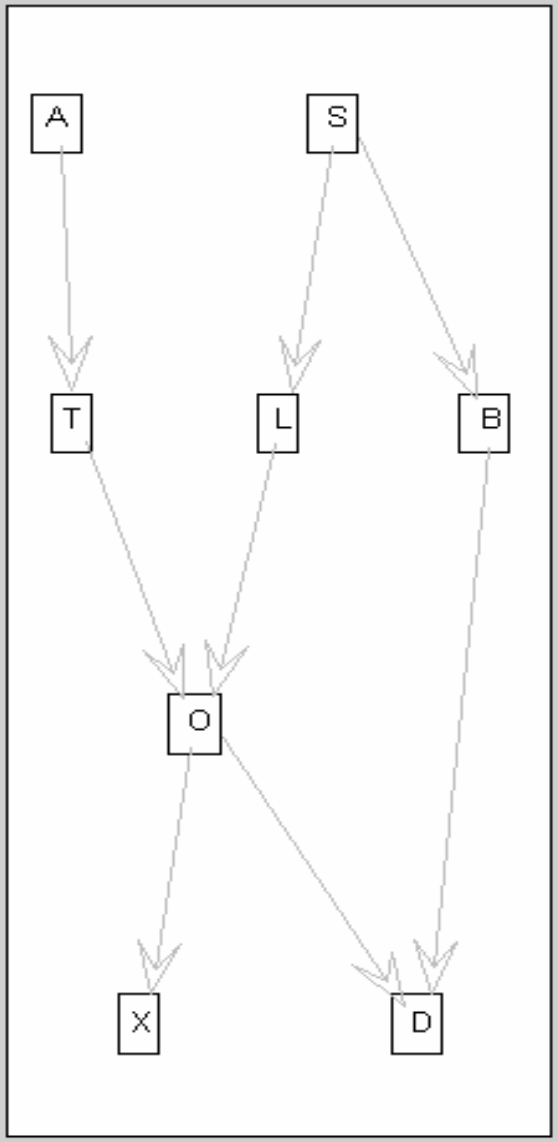
ASIA original graph



GES CPDAG (cache)



GES DAG (cache)



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MATLAB: BNT: SLP: PC

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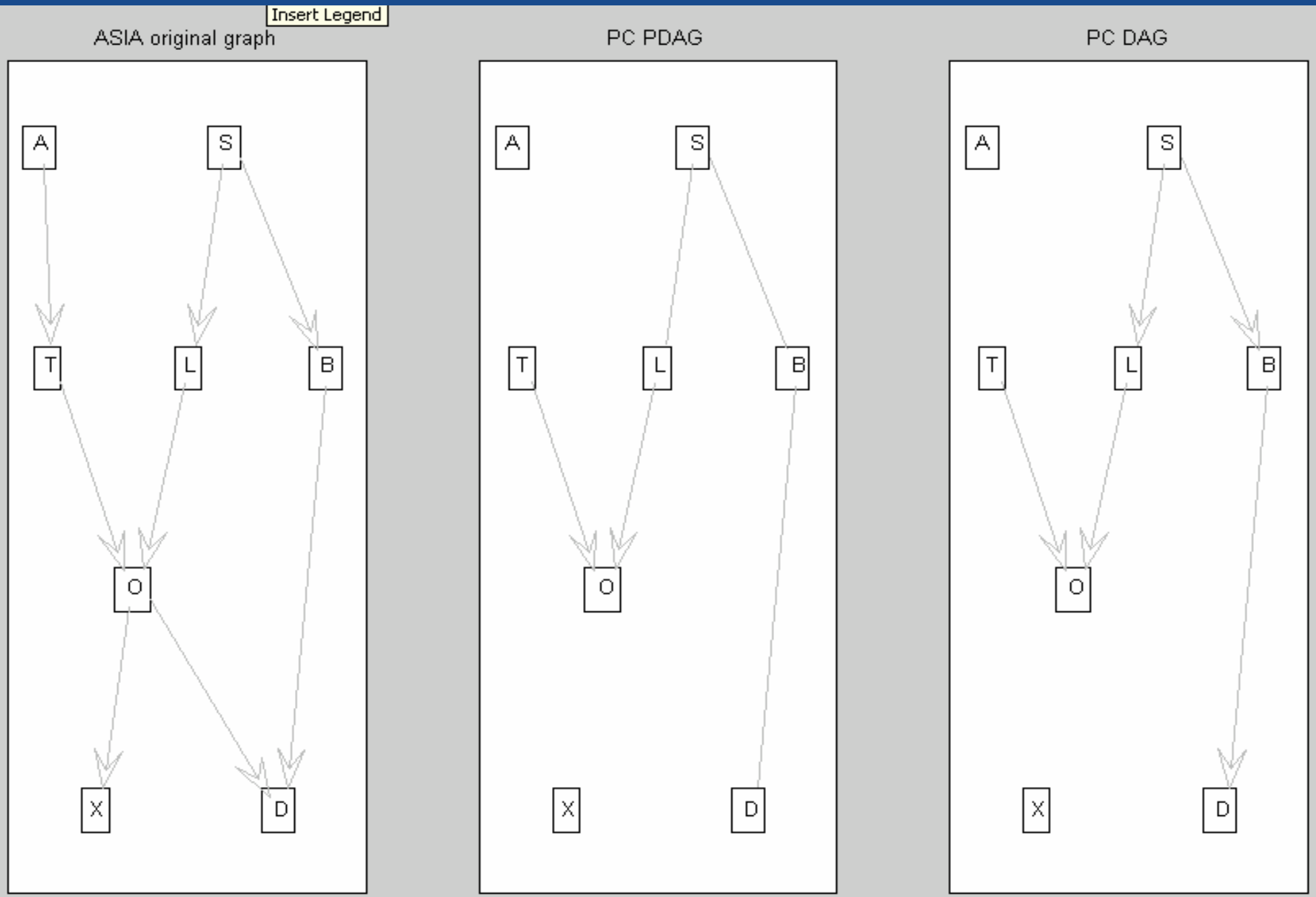

MATLAB: BNT: SLP: MWSP

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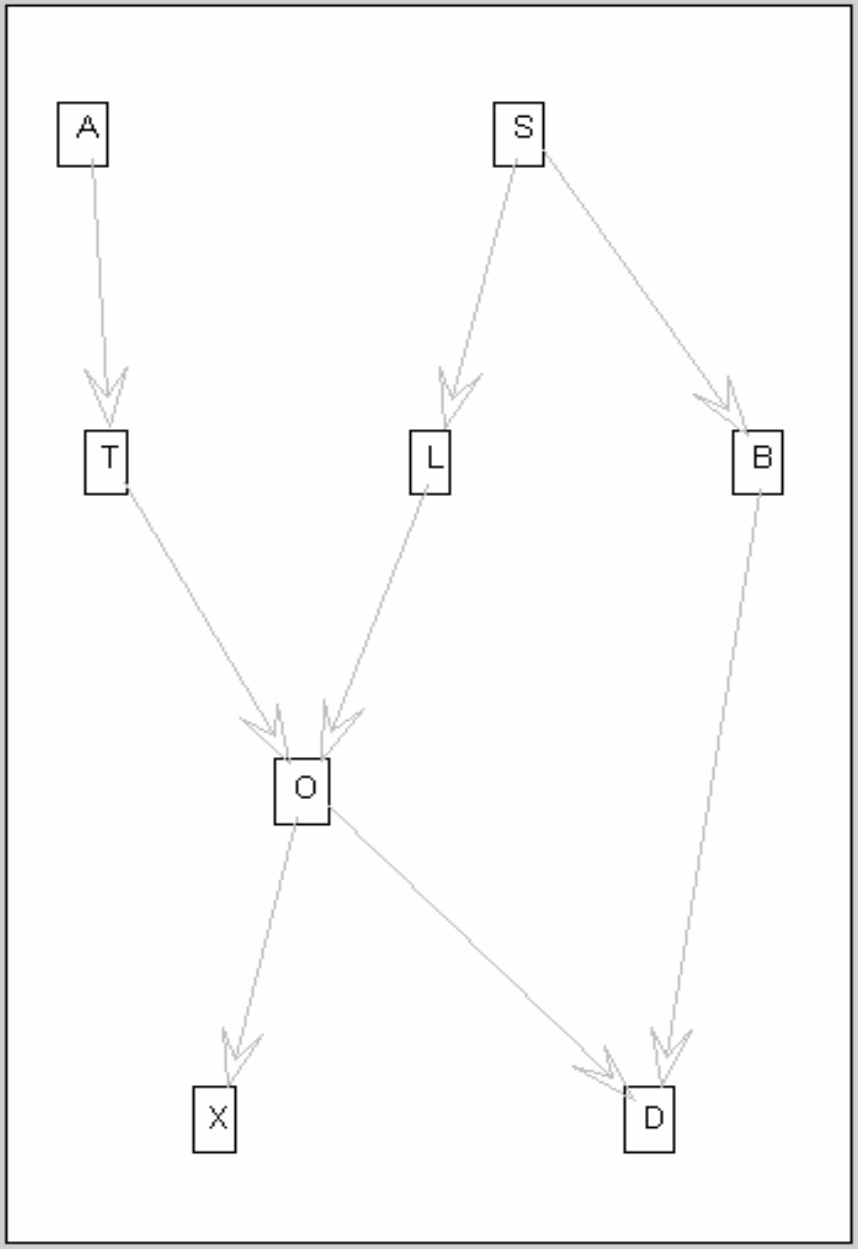
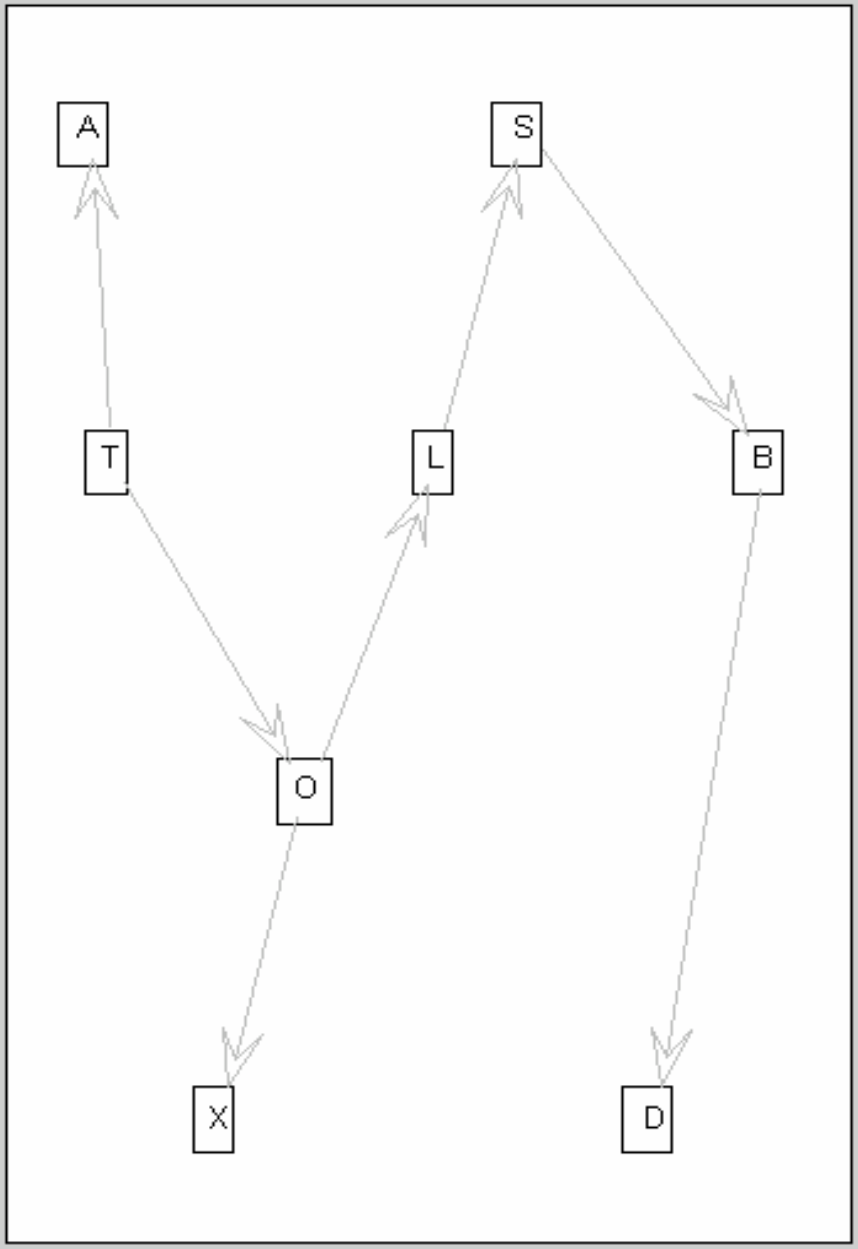
ASIA original graph



MWST DAG



3. What probabilities describe these relationships ?

- **Parameter learning**
  - Quantitative data about each variable is gathered from the surveys for each household
  - This data is read into the BBN model in the form of a ‘case file’

Parameter learning

- Debate in literature on importance of sample size (N) vs. 'subject to item' ratio.
- Consensus that for other multivariate methods like BBNs (Principal Components Analysis; Exploratory Factor Analysis; etc) that 'Subject to item' ratio is more important.
- 'Subject to Item' ratio is the number of respondents (subjects) per line of the Conditional Probability Table in each node of the BBN

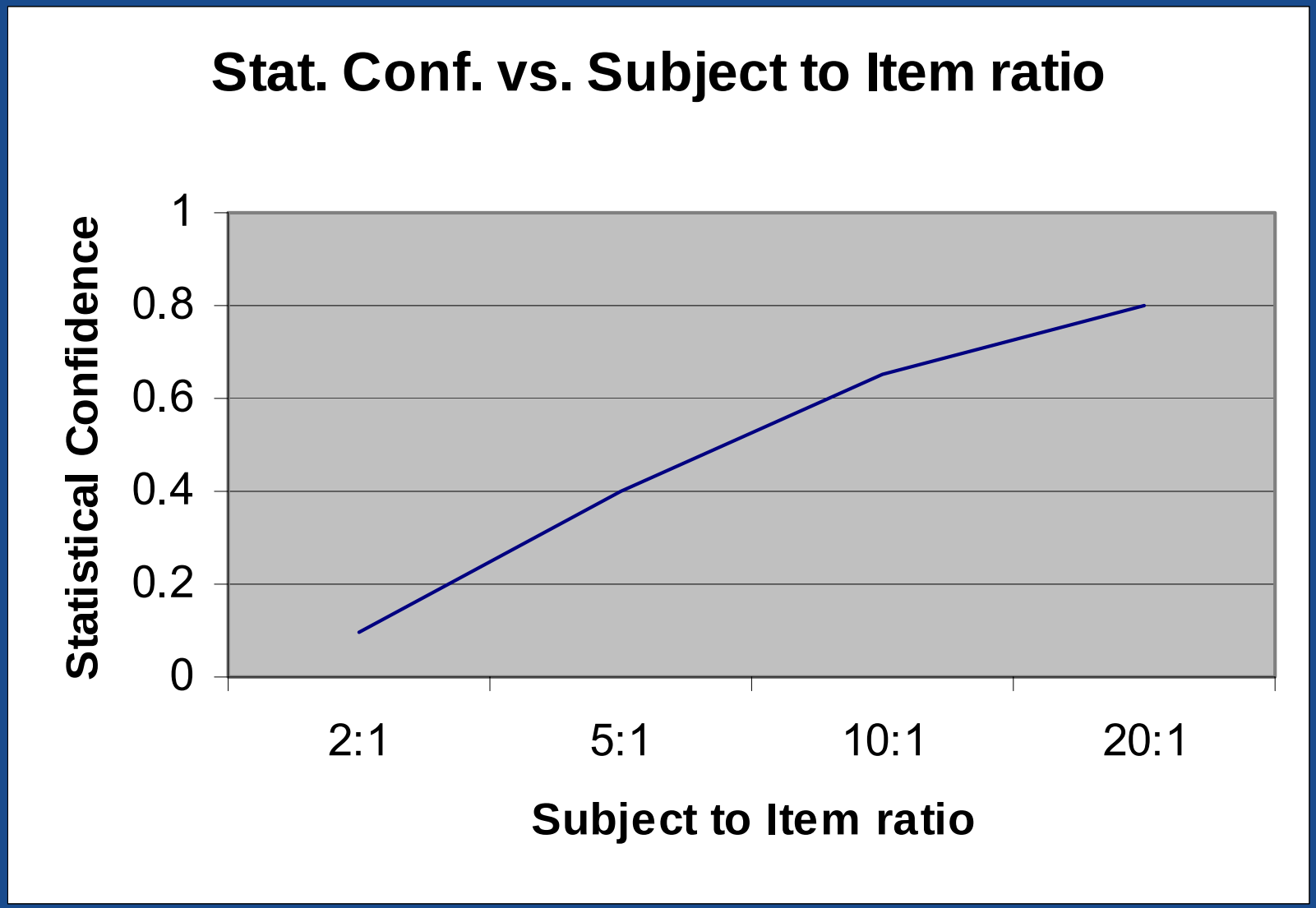
Node: Env_aware

Chance

Apply | Okay | Load | Close

Education	Energy Market Segment	Low	Medium	High
Primary	Pleasure seekers	60.000	30.000	10.000
Primary	Apperance Conscious	70.000	20.000	10.000
Primary	Lifestyle Simplifiers	30.000	40.000	30.000
Primary	Resource Conservers	25.000	40.000	35.000
Primary	Hassle Avoiders	70.000	20.000	10.000
Primary	Value Seekers	50.000	30.000	20.000
Secondary	Pleasure seekers	60.000	30.000	10.000
Secondary	Apperance Conscious	70.000	20.000	10.000
Secondary	Lifestyle Simplifiers	30.000	40.000	30.000
Secondary	Resource Conservers	25.000	40.000	35.000
Secondary	Hassle Avoiders	70.000	20.000	10.000
Secondary	Value Seekers	50.000	30.000	20.000
Graduate	Pleasure seekers	50.000	35.000	15.000
Graduate	Apperance Conscious	60.000	25.000	15.000
Graduate	Lifestyle Simplifiers	20.000	45.000	35.000
Graduate	Resource Conservers	15.000	45.000	40.000
Graduate	Hassle Avoiders	60.000	25.000	15.000
Graduate	Value Seekers	40.000	35.000	25.000
Post Graduate	Pleasure seekers	40.000	35.000	25.000
Post Graduate	Apperance Conscious	50.000	25.000	25.000
Post Graduate	Lifestyle Simplifiers	10.000	45.000	45.000
Post Graduate	Resource Conservers	5.000	45.000	50.000
Post Graduate	Hassle Avoiders	50.000	25.000	25.000
Post Graduate	Value Seekers	30.000	35.000	35.000

Subject to Item ratios for parameter learning from literature



Data from various papers

Interaction between network structure, variable states and case data

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- In BNs, subject to item ratios depend on:
  - The number of states of each variable
  - The number of parents of each variable
- Limit BN variables to 3-states
- Limit number of parent variables per child variable to 3
  - 3*3*3*10 = 270 *respondents* for ~ 70% confidence
  - 3*3*3*20 = 540 *respondents* for ~ 85% confidence

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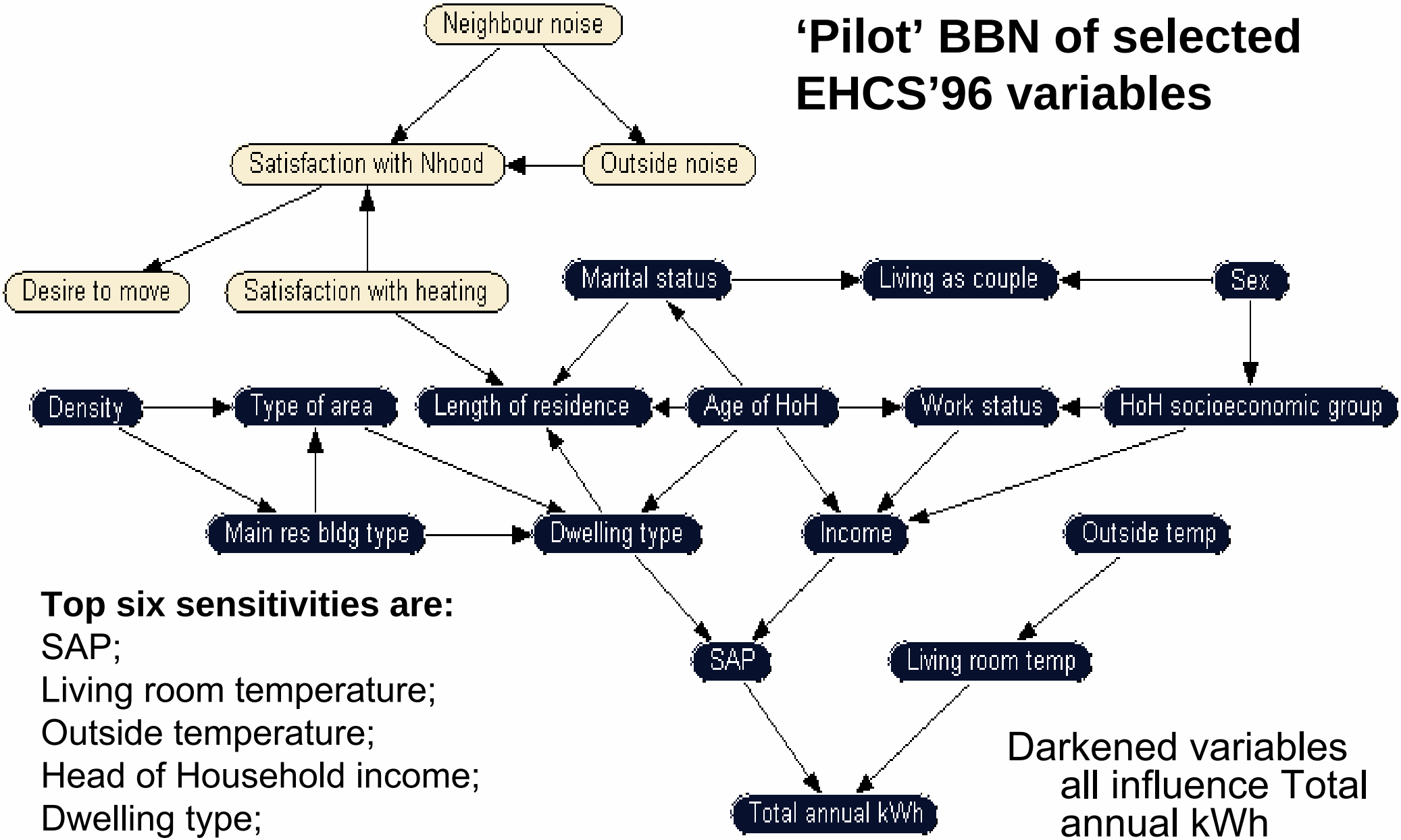
Network development

1. *Sensitivity analysis*: Which variables are key?
2. *Uncertainty analysis*: Does the network as a whole remain within expected bounds.
3. *Pruning*: Delete insensitive variables and links.
4. *Refining*: Additional quantitative analysis to reassess key probabilities.
5. *Extending*:
   - Primary qualitative research to extend the network and refine contingencies
   - Primary quantitative research is conducted to populate new nodes with probability data.
6. Go to step 1(repeat 'till money or time runs out!)

Conclusions

- Provides policy focused decision support
- Supports evidence based policy making
- Transdisciplinary research epistemology
- Knowledge synthesis consistent with Realist Review method
- Models 'learn' through continual integration of data
- Provides 'cross-fertilisation' between fields
- Models specific 'take-back' effects
- Allows for identification of very specific 'barriers' and programme interventions to rectify them.

‘Pilot’ BBN of selected EHCS’96 variables



Top six sensitivities are:

SAP;
Living room temperature;
Outside temperature;
Head of Household income;
Dwelling type;
Employment status;
Head of Household SEC

Darkened variables all influence Total annual kWh

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Further information:

- **website: http://www.carb.org.uk**
- **email: info@carb.org.uk**

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