OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

INF FAKULTÄT FÜR INFORMATIK

Probabilistic Graphical Models: On Reasoning, Learning, and Revision

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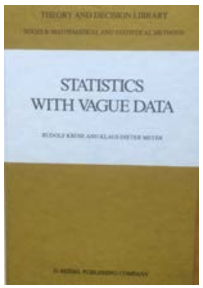
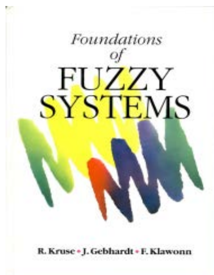
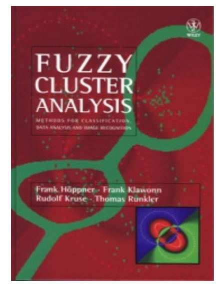
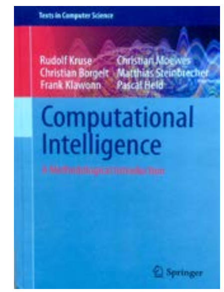
Computational Intelligence Group Magdeburg

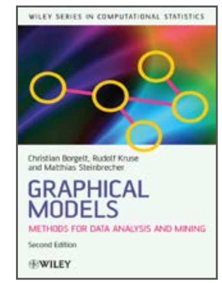
Research: Data Sciences, Intelligent Systems   www.computational-intelligence.eu



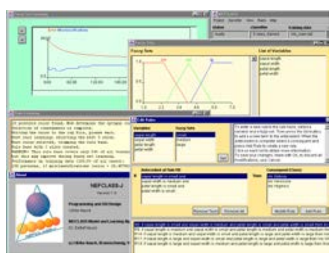








Software Tools: NEFCLASS, Information Miner



Transfers: Industrial Projects (BT, SAP, Siemens, Volkswagen,…), Spin Offs

Property planning - Volkswagen

Property family	Car body	Motor	Radio	Doors	Seat cover	Makeup mirror	…
Property	Hatch-back	2.8 L 150 kW Otto	Type alpha	4	Leather, Type L3	yes	…

Complexity

- About 200 variables
- Typically 4 to 8, but up to 150 possible instances per variable
- More than 2^{200} possible combinations available

Knowledge about the Planning

Rules

- 10000 Technical Rules for Item Combinations, e.g.

$$\text{IF} \;\; \text{Motor} = m_4 \;\; \text{AND} \;\; \text{Heating} = h_1$$
$$\text{THEN} \;\; \text{Generator} \in \{g_3, g_4, g_5\}$$

- Often 6-dimensional, sometimes more than 10 dimensions

- 500000 marketing oriented rules (with uncertainty)

- The rules are often changing

Data

- Specification of millions of built cars

Planning Tasks

Calculation of part demands

Compute the installation rate of a given item combination

Simulation

Analyze customers‘ preferences with respect to those persons who use a navigation system in a VW Polo

Marketing and Sales stipulation

Installation rate of Navigation system increase from 20% to 30%

Capacity Restrictions

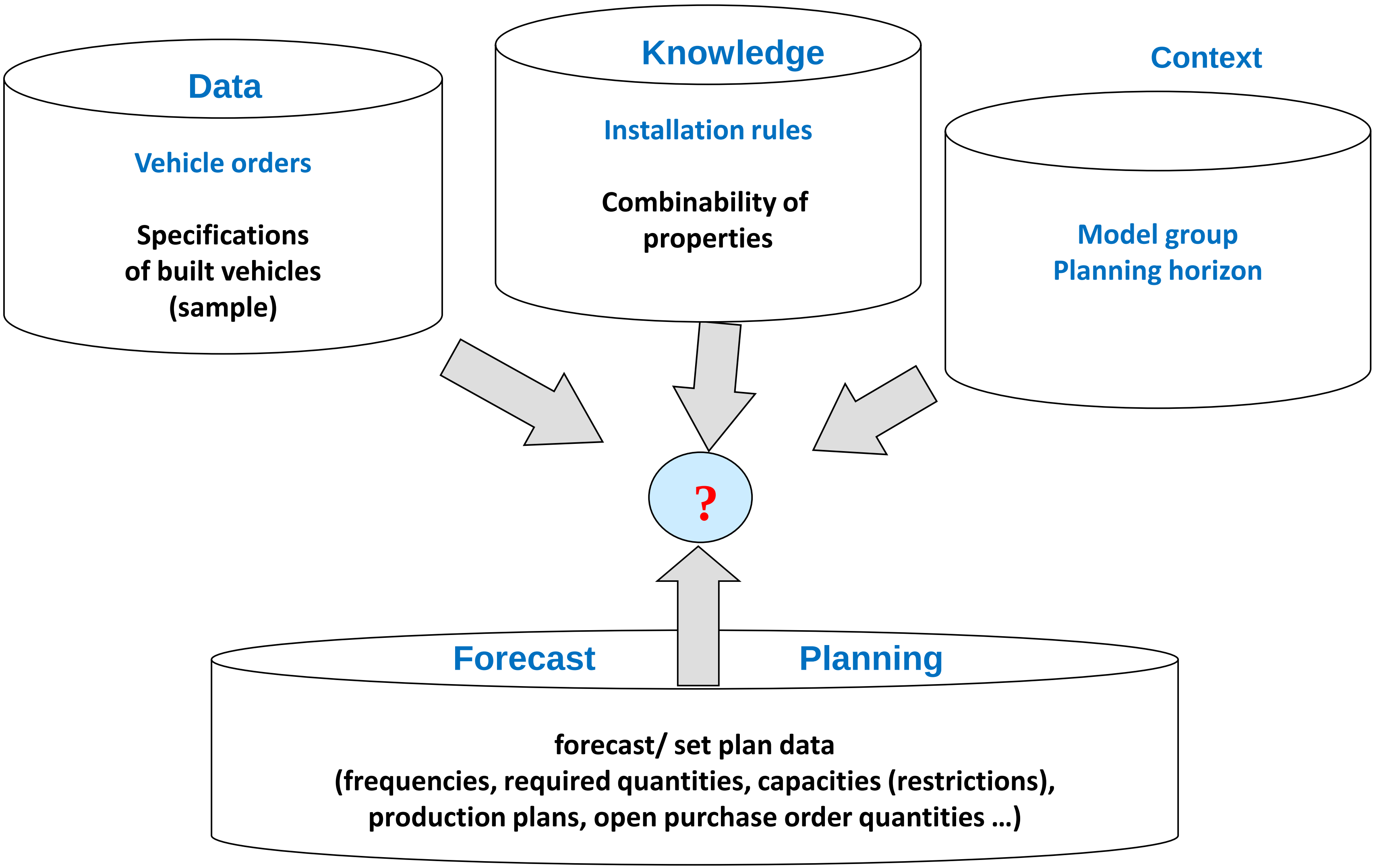
Maximum availability of seat coverings in leather is 5000

Belief Change (EC Project Defeasible Reasoning)

Gärdenfors: An agent (planner) is in a Belief State,

he is using the operations Focussing and Revision

How to manage the uncertain information about planning?



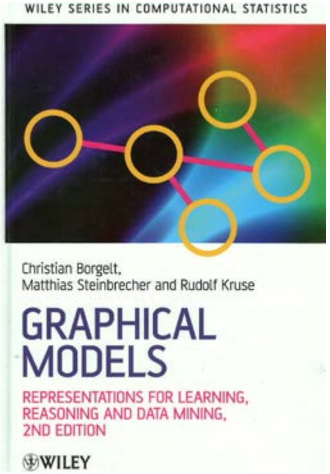
Requirements for the Planning System

- Assistant System for Handling Estimates for Installation Rates
- **The planners should enjoy comfort without loosing competence**

- **Explanation of the Results (Explainable AI)**
- Explicit, Sound, Transparent Model

- Answers to the planners questions in real time (seconds)
- Different Model Groups and Different Planning Intervals:
  5000 planning scenarios handled by 350 planners worldwide
- Implementation by a CI Group spin off (lead by Jörg Gebhardt)

Our Modelling Approach: Decomposable Models

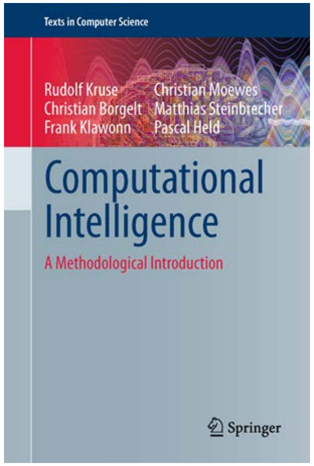


Configuration Management: Relations

Installation Rate Management: Subjective Probabilities

Problem

High dimensionality (here typically 200 dim)



Solution: Decomposition

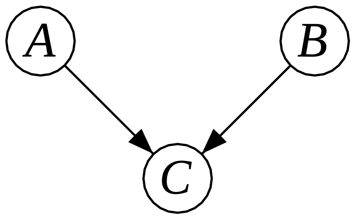
Instead of one high dimensional global model use

several connected local low dimensional models

Graphical Models

Relational, Possibilistic, Bayes- and Markov-Networks

How to find a suitable decomposition of a probability space?



A,B,C (Random) Variables

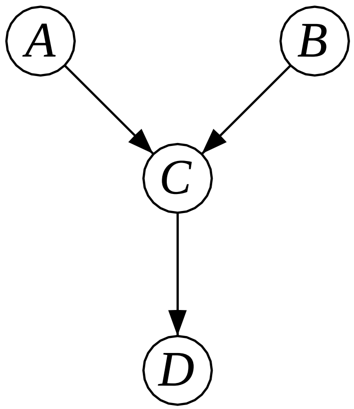
A quality of ingredients

B cook‘s skill

C meal quality

If C is not known, A and B are independent.

If C is known, then A and B become (conditionally) dependent given C.



A,B,C,D (Random) Variables

A quality of ingredients

B cook‘s skill

C meal quality

D restaurant success

If nothing is known about the restaurant success or meal quality or both, the cook’s skills and quality of the ingredients are unrelated, that is, independent.

However, if we observe that the restaurant has no success, we can infer that the meal quality might be bad.

If we further learn that the ingredients quality is high, we will conclude that the cook’s skills must be low, thus rendering both variables dependent.

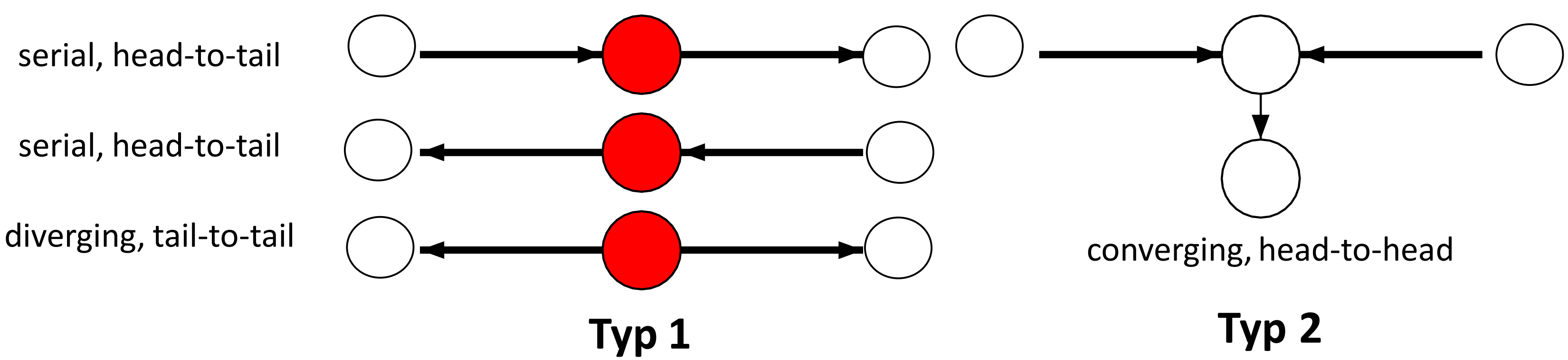
Decomposition: $P(A,B,C,D) = P(A)P(B)P(C|A,B)P(D|C)$

Separation in directed Graphs (d-separation)

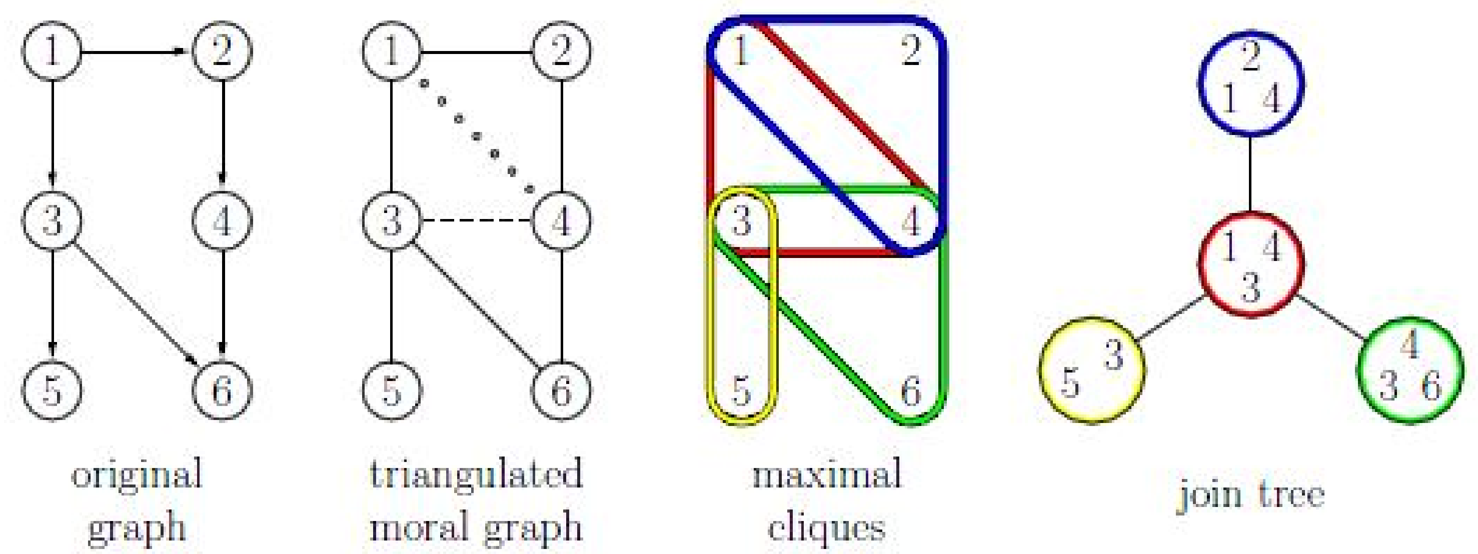
Z d -separates **X** from **Y** if all paths (pathes in reverse to arrows are allowed) from **X** to **Y** are blocked by a node in **Z.**

A node *A* is blocking a path, if its edge directions along the path

- are of type 1 and $A \in Z$, or
- are of type 2 und neither A nor one of its descendants is in **Z**.



Decomposition:
Automatic Join Tree Generation using d-separation



Efficient Reasoning in Markov-Networks

Consistent Decomposition

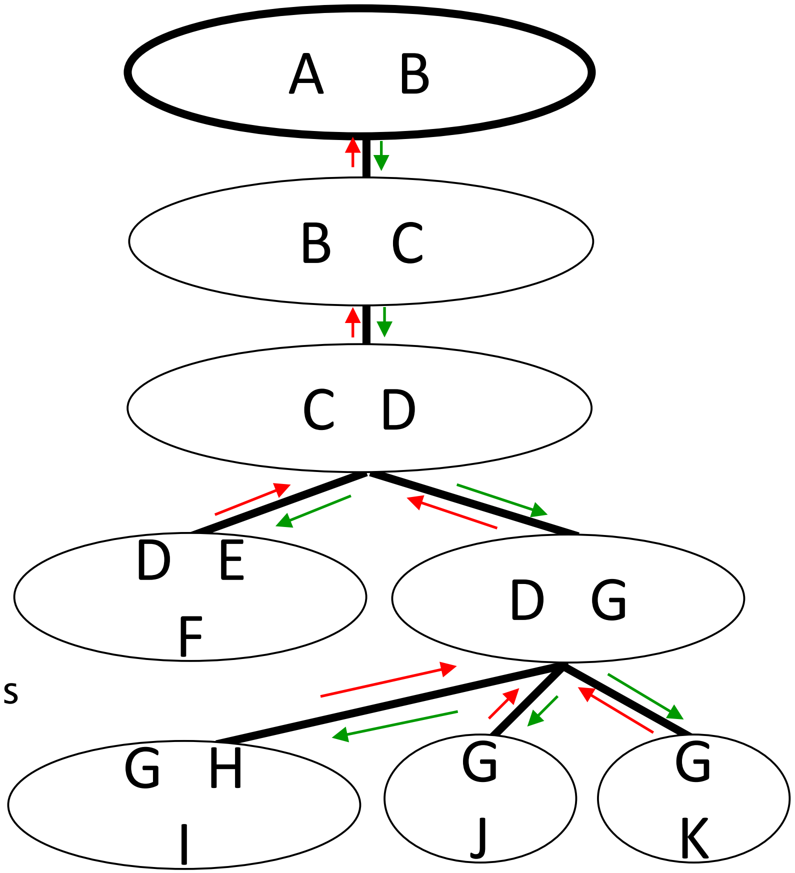
- Distributions only over the cliques (conditional independencies)
- Validity of all combinations registered and available

Fast Conditioning in Hyper Tree

- Propagation by traversing the net twice (collect & distribute)

Efficient planning

- Planning requirements as conditional distributions
- Calculation of frequencies for arbitrary property combinations (focusing analyses, simulations) in real time



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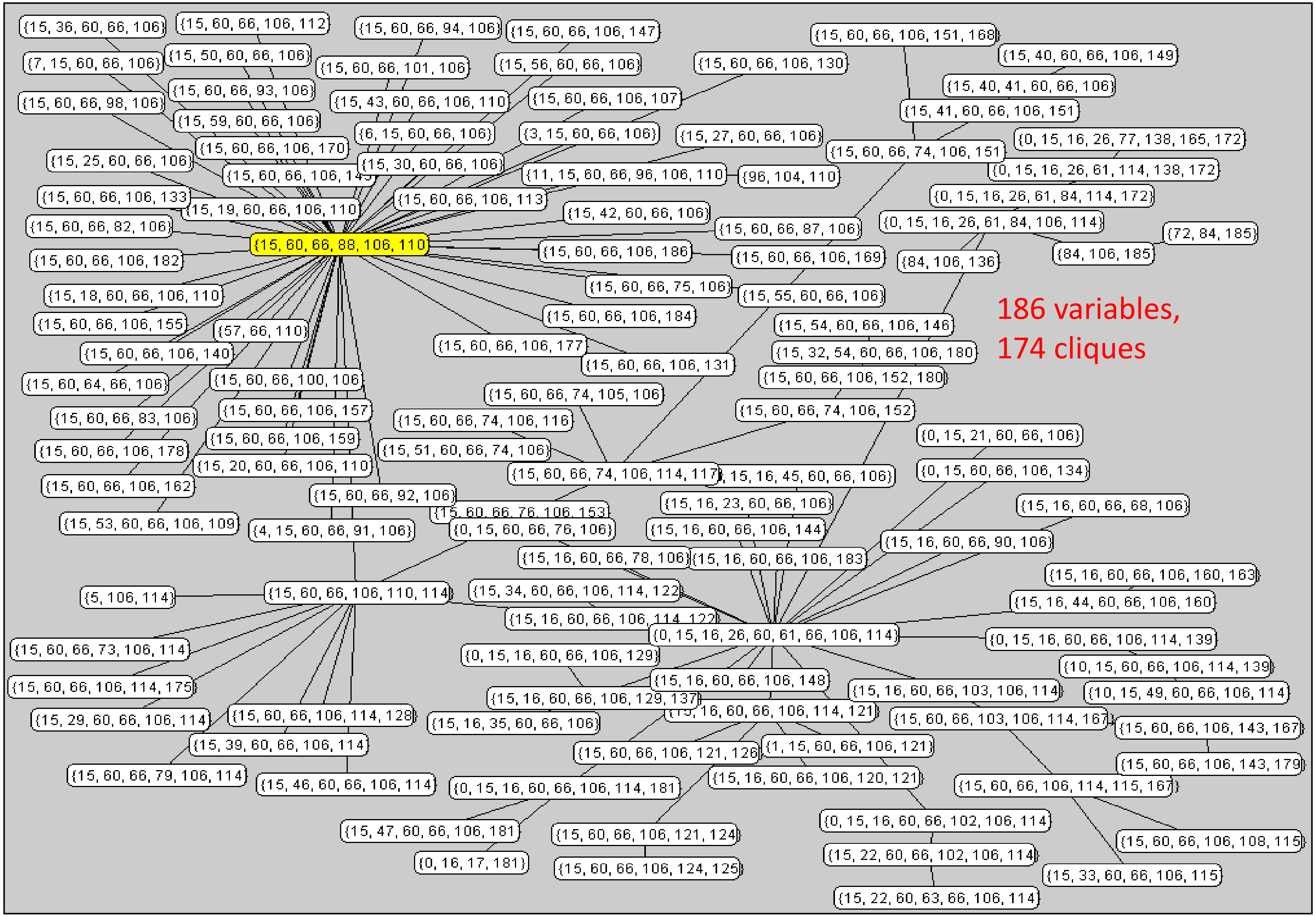
Example: Markov Network for VW Bora



Example: System EPL (EigenschaftsPLanung) at VW

In worldwide use : 15 developers, 350 planners

Different planning responsibilities with individual workflow

- Structure Induction
- Base distribution
- Assessment of demand for approx. 40 planning intervals (weeks, months)
- 5000 different Markov networks in use daily
- Focusing: Fast calculation of conditional and marginal probabilities

Example for one planning week

Data volume (cumulative per week)	Across all 166 Model groups	Single Model group
Number of Markov Nets	75.787	1.054
Total size (compressed)	79,9 GB	3,8 GB
… for one planning interval	**Model group 1**	**Model group 2**
Planning requirement	4.424	1.299
Number of variables	203	204
Number of cliques	174	156
Network size (compressed, RAM: ~Factor 10)	8,5 MB	17,9 MB
Largest clique (only positive probabilities)	130.806 tupels 9 variables	1.489.515 tupels 14 variables

Relevant research topics

Fusion of Qualitative and Quantitative Knowledge
Data, Rule Systems, Conditional Independence Statements, Contexts

Learning the Model from Data
Local and Global Structure

Revision of Big Decomposable Models
Relational, Probabilistic Graphical Models

User Interaction
Handling Inconsistencies, Explanation of Solutions, Level of Assistency

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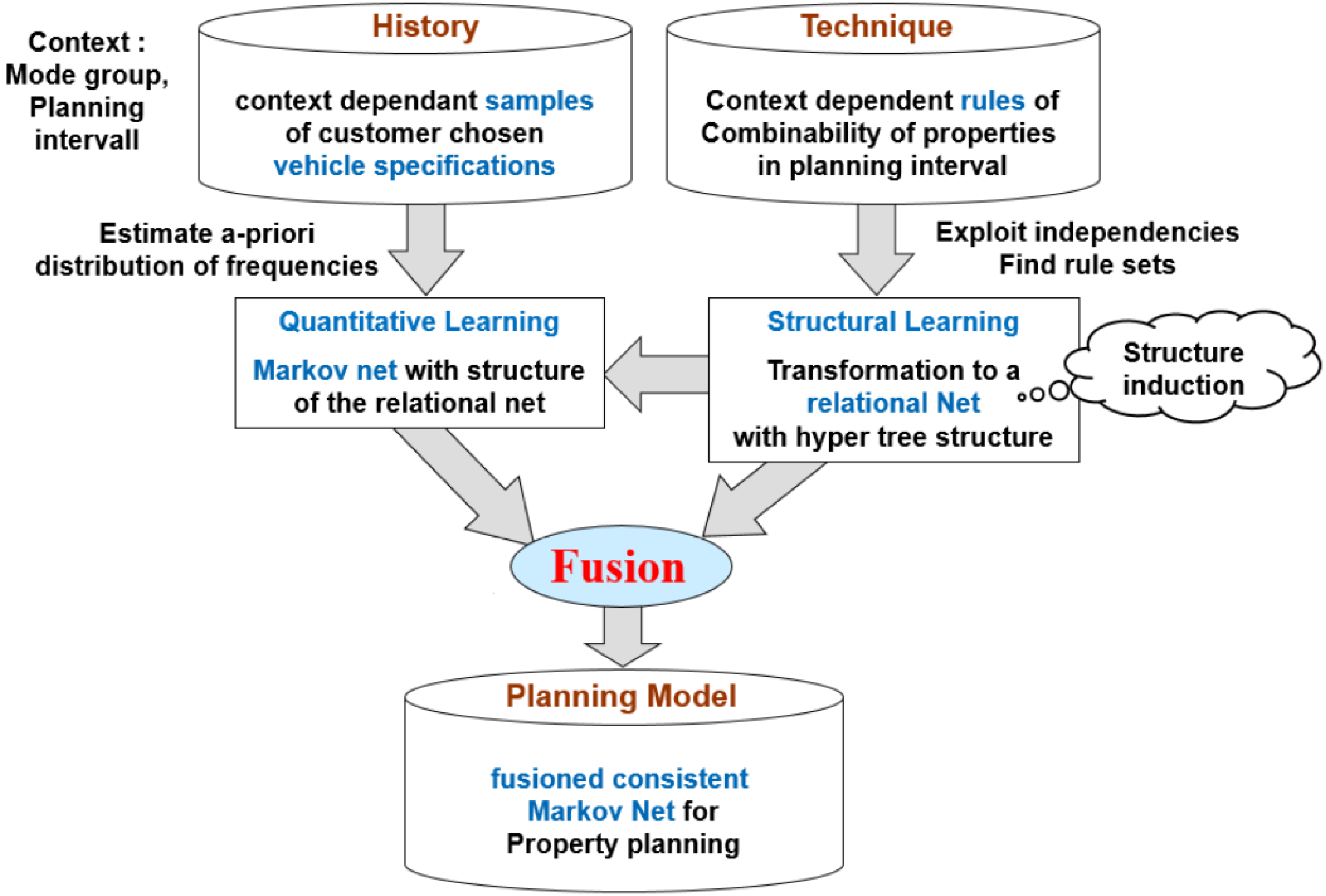
How to learn new Planning Models?



Revision

Prior Probability Distribution

New Conditional Probabilities:
Marketing Stipulations, Capacity Restrictions

REVISON

Principle of minimal Change

Posterior Probability Distribution including *specified* **and** *inferred* changes.

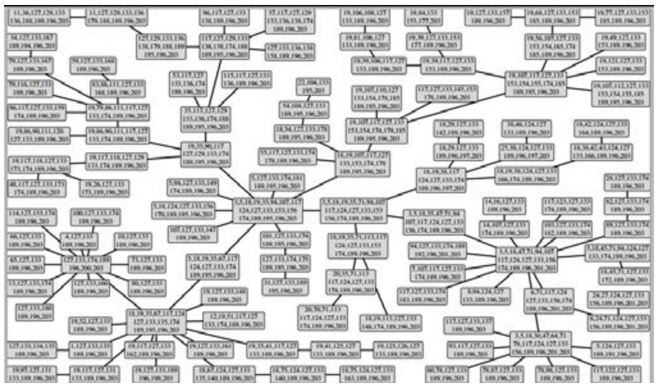
Information-theoretically closest to the prior distribution

Revision Operator

- Iterative Proportional Fitting (Biproportional Fitting, RAS Algorithm, Matrix Scaling)
- Algorithms for Adapting the Marginal Distributions
- Stepwise Modification of the Probability Distribution
- Process converge for Non-Contradicting Revision Statements
- Approx. 7000 Revision Assignments per Week and Model

Inconsistencies

Complex Structure



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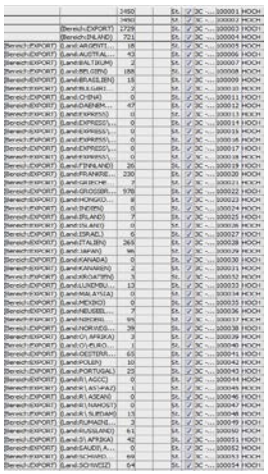
Many Changes



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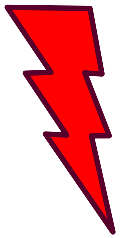
Inconsistencies



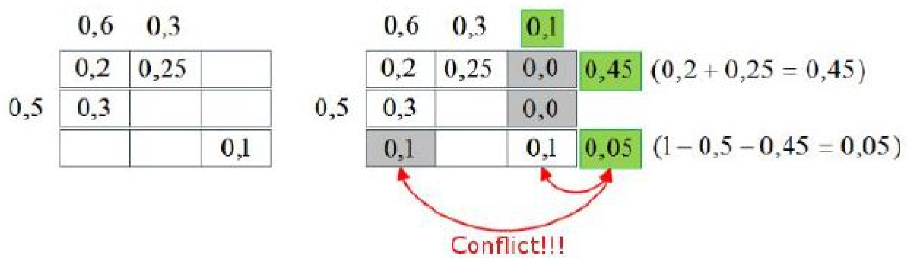
Outer Inconsistencies

Revision assigments inconsistent with zero-values in prior distribution

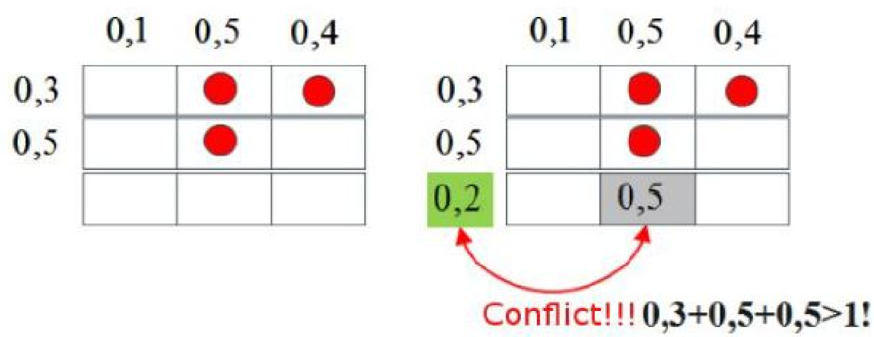
Inner Inconsistencies

Revision assignments are inconsistent, independent of prior distribution

Inconsistencies: Examples



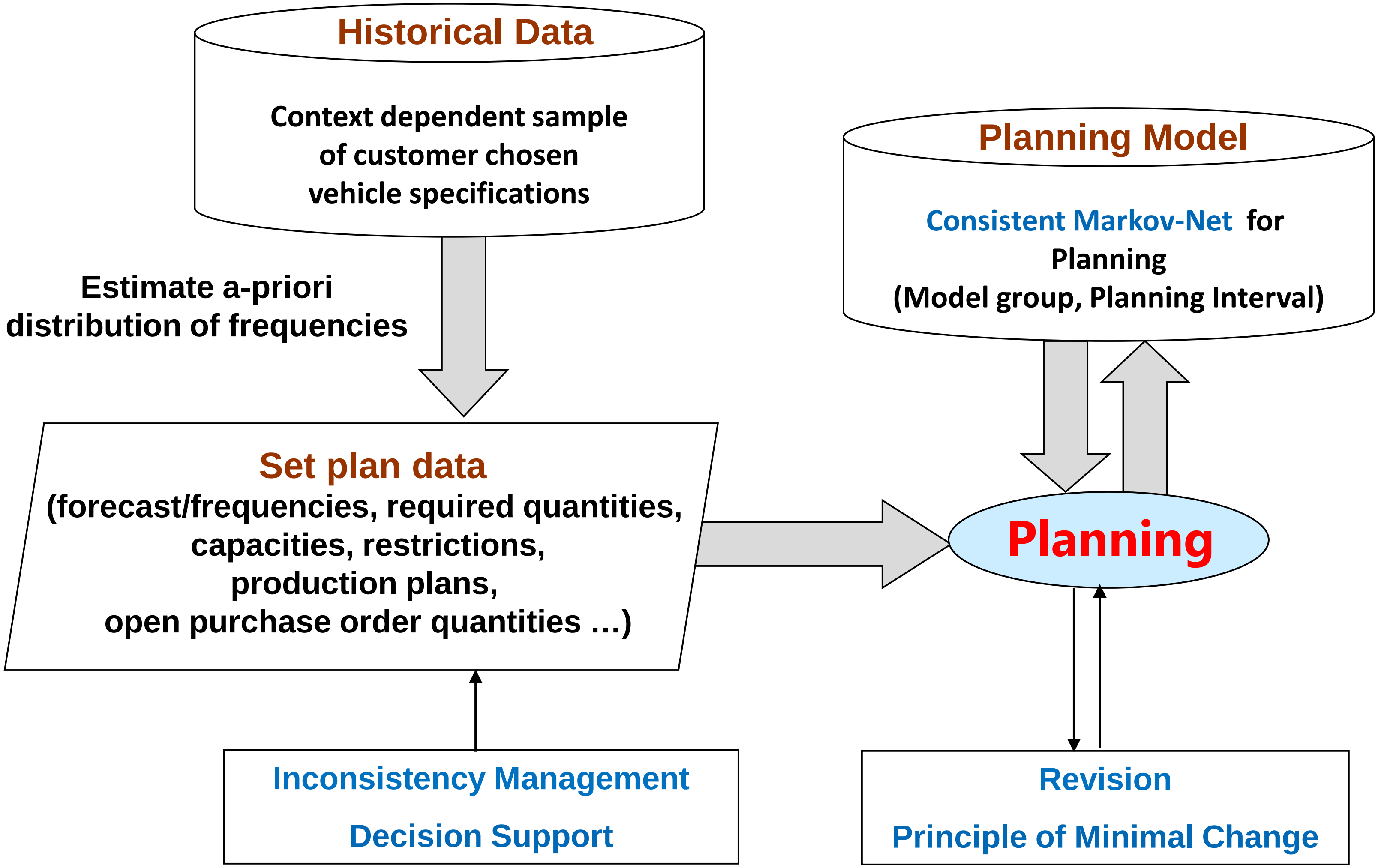
Inner Inconsistency



Outer Inconsistency

It is not easy to configure revision statements without creating inconsistencies!
How to explain the user how to change his desired revision statements?

Planning Operation: Revision



Conclusion

For assistant systems in industry pure data driven approaches are often not sufficient due to deficits in explainability.

The combination of quantitative (data, learning) and qualitative (knowledge about independence, causalities, rules, contexts) methods often gives more powerful frameworks for solving high-dimensional problems.

Current methods of computational intelligence can handle hundreds of variables, high-dimensional dependencies, and context information, while the human expert steers the process and validates the results.

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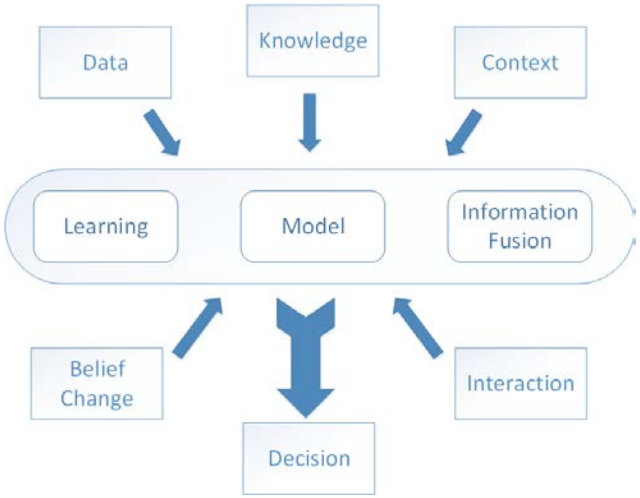
Conclusion

The methodology in this application can be transferred to other areas



Lots of interesting technical problems:

How to ensure reliability in autonomous system (e.g. cars):?

How to explain the results to the user?

Don't forget:

The human should be in the centre of AI solutions – social and legal aspects are often more important for success than technical aspects

What comes next in AI?

BBVA Foundation

Frontiers of Knowledge Awards 2022

Category: Information and Communication

Winner:

Judea Pearl

What comes next in AI?

Associations ("observing") Bayes, belief, conditional probability,…
What does a symptom say about a disease? How would observing X change my belief in Y?

Intervention ("doing") Do-Operator, model revision,…
If I take aspirin, will my headache be cured? What would Y be if I did X?

Causality („understanding") Counterfactuals,…
Was it X that caused Y? What if X hadn't occurred? What if I had acted differently? Did Aspirin Stop My Headache? What if I hadn't smoked in the last 2 years?

Judea Pearl and Dana Mackenzie, The Book of Why: The New Science of Cause and Effect, 2018