Probabilistic Graphical Models: On Reasoning, Learning, and Revision

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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

<table>
<thead>
<tr>
<th>Property family</th>
<th>Car body</th>
<th>Motor</th>
<th>Radio</th>
<th>Doors</th>
<th>Seat cover</th>
<th>Makeup mirror</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Property</td>
<td>Hatchback</td>
<td>2.8 L 150 kW Otto</td>
<td>Type alpha</td>
<td>4</td>
<td>Leather, Type L3</td>
<td>yes</td>
<td>...</td>
</tr>
</tbody>
</table>

### 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.
  \[
  \text{IF Motor} = m_4 \quad \text{AND Heating} = h_1 \\
  \text{THEN Generator} \in \{g_3, g_4, g_5\}
  \]
- 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?

**Data**
- Vehicle orders
- Specifications of built vehicles (sample)

**Knowledge**
- Installation rules
- Combinability of properties

**Context**
- Model group
- Planning horizon

**Forecast**
- forecast/ set plan data
  - (frequencies, required quantities, capacities (restrictions), production plans, open purchase order quantities ...)

**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.
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-separated \( X \) 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 \( Z \).

Typ 1

Typ 2

serial, head-to-tail
serial, head-to-tail
converging, head-to-head

diverging, tail-to-tail
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
Example: Markov Network for VW Bora

186 variables, 174 cliques
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

<table>
<thead>
<tr>
<th>Data volume (cumulative per week)</th>
<th>Across all 166 Model groups</th>
<th>Single Model group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Markov Nets</td>
<td>75,787</td>
<td>1,054</td>
</tr>
<tr>
<td>Total size (compressed)</td>
<td>79,9 GB</td>
<td>3,8 GB</td>
</tr>
</tbody>
</table>

... for one planning interval

<table>
<thead>
<tr>
<th>Planning requirement</th>
<th>Model group 1</th>
<th>Model group 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of variables</td>
<td>203</td>
<td>204</td>
</tr>
<tr>
<td>Number of cliques</td>
<td>174</td>
<td>156</td>
</tr>
<tr>
<td>Network size (compressed, RAM: ~Factor 10)</td>
<td>8,5 MB</td>
<td>17,9 MB</td>
</tr>
<tr>
<td>Largest clique (only positive probabilities)</td>
<td>130,806 tupels 9 variables</td>
<td>1,489,515 tupels 14 variables</td>
</tr>
</tbody>
</table>
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 Assisstency
How to learn new Planning Models?

Context: Mode group, Planning intervall

History
- context dependant samples of customer chosen vehicle specifications

Technique
- Context dependent rules of Combinability of properties in planning interval
- Exploit independencies, Find rule sets

Quantitative Learning
- Markov net with structure of the relational net

Structural Learning
- Transformation to a relational Net with hyper tree structure

Fusion

Planning Model
- fusioned consistent Markov Net for Property planning
Revision

Prior Probability Distribution

New Conditional Probabilities:
Marketing Stipulations, Capacity Restrictions

REVISION

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

Many Changes

Inconsistencies

Outer Inconsistencies
Revision assignments inconsistent with zero-values in prior distribution

Inner Inconsistencies
Revision assignments are inconsistent, independent of prior distribution
Inconsistencies: Examples

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

Historical Data

Context dependent sample of customer chosen vehicle specifications

Estimate a-priori distribution of frequencies

Set plan data
(forecast/frequencies, required quantities, capacities, restrictions, production plans, open purchase order quantities …)

Planning Model

Consistent Markov-Net for Planning
(Model group, Planning Interval)

Planning

Inconsistency Management
Decision Support

Revision

Principle of Minimal Change
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.
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