

Using Bayesian Networks To Infer Product Rankings From User Needs

UMAP 2010 Workshop on Intelligent Techniques for
Web Personalisation and Recommender Systems

Sven Radde and Burkhard Freitag

Institute for Information Systems and Software Technology
University of Passau, Germany

20-Jun-2010



Overview

- 1 Use Case
- 2 Domain (Meta-)Modeling
- 3 Product Ranking

Use Case

- Conversational recommender system
 - Closely follow 'natural' recommendation practices
- Mobile communications domain
 - Industry partner
 - Reference implementation
 - Recommendations
 - Dialogue management
 - Product presentation / sales process
 - Knowledge maintenance



Challenge

Preferences about technical attributes...

- ...are necessary to produce recommendations
- ...cannot be elicited from customers

Example

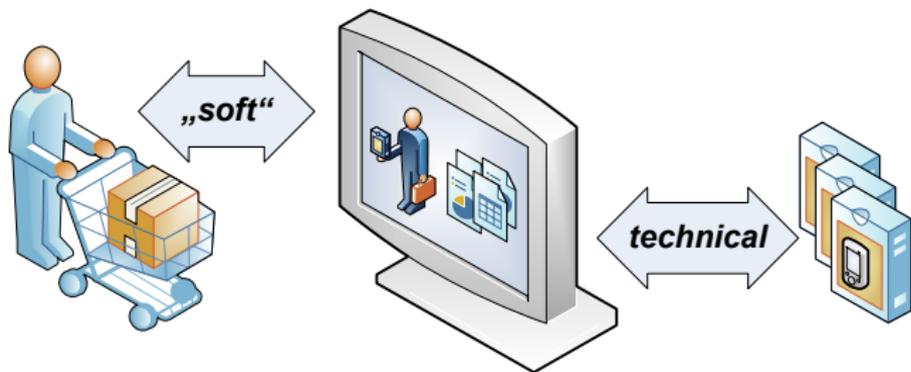
Consider these technical properties:

- Bluetooth
- Wi-Fi
- UMTS (with/without HSDPA?)

Which of these are needed for mobile access to e-mail? And what else?

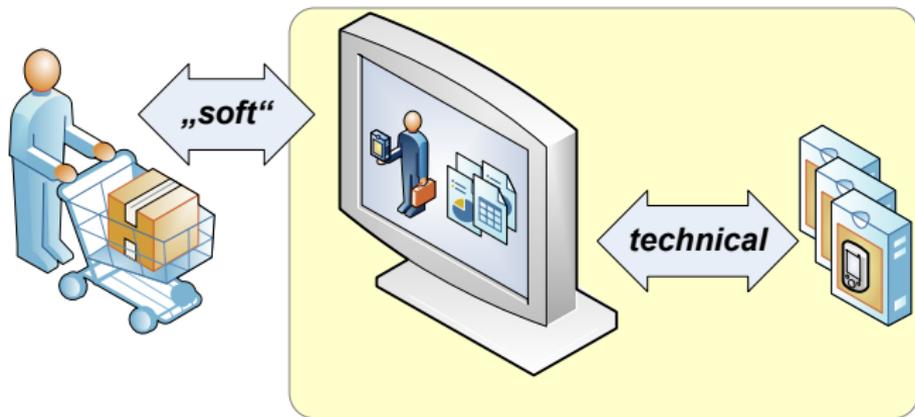
Solution

- 1 Elicit “soft” preferences, i.e. ask questions about customer needs, expectations or desires
- 2 *Infer preferences* about technical properties
 - Domain modelling to capture necessary knowledge
- 3 *Recommend items* based on the inferred preferences



Solution

- 1 Elicit “soft” preferences, i.e. ask questions about customer needs, expectations or desires
- 2 *Infer preferences* about technical properties
 - Domain modelling to capture necessary knowledge
- 3 *Recommend items* based on the inferred preferences

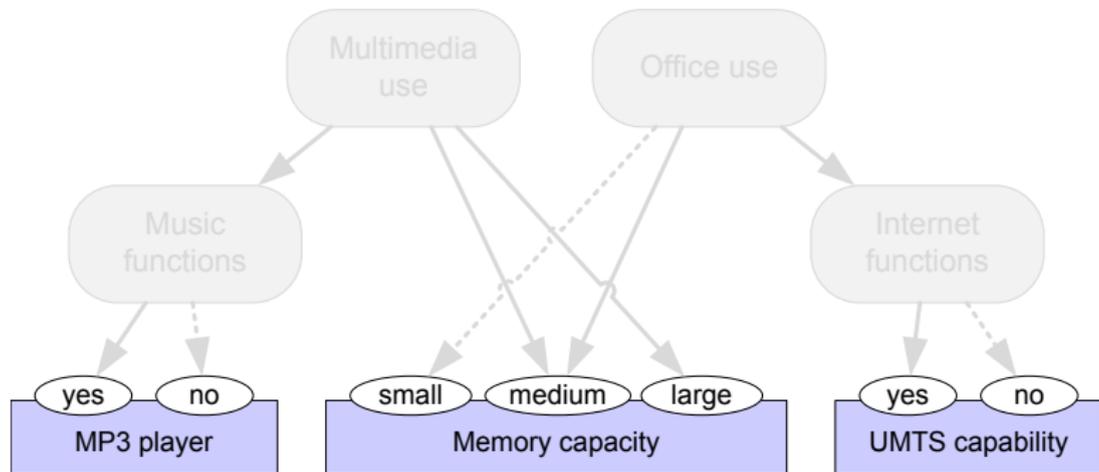


Overview

- 1 Use Case
- 2 Domain (Meta-)Modeling**
- 3 Product Ranking

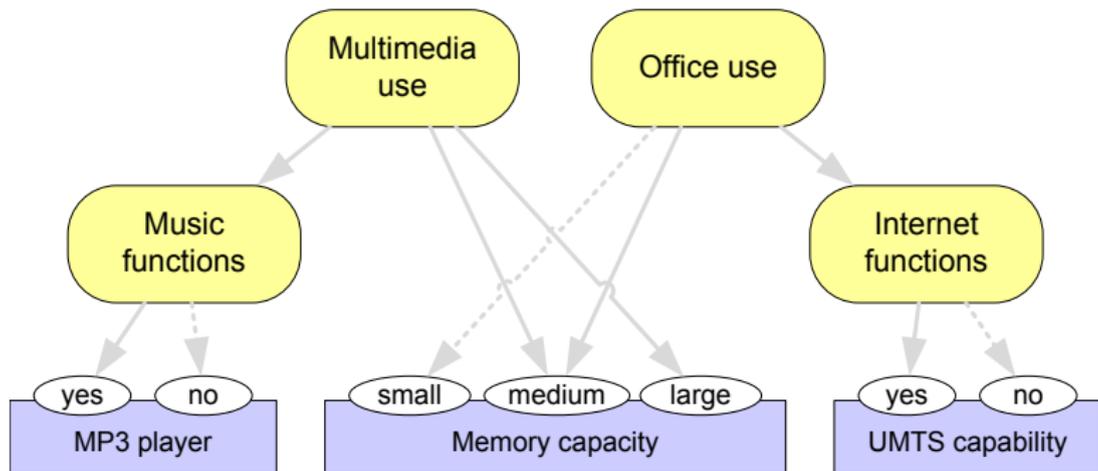
Modeling Principles

- Describe technical properties of the articles in the domain
- Define customer traits that are relevant for marketing
- Define causal influences between customer traits and technical properties



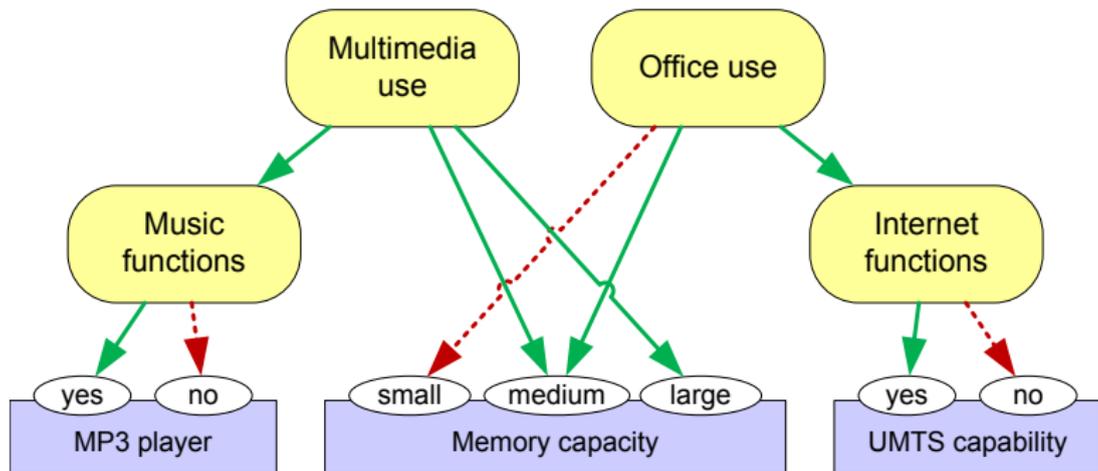
Modeling Principles

- Describe technical properties of the articles in the domain
- Define customer traits that are relevant for marketing
- Define causal influences between customer traits and technical properties



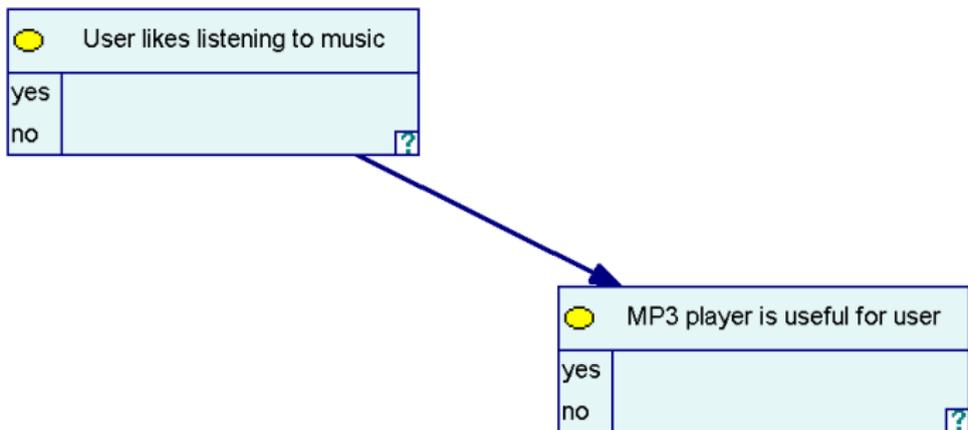
Modeling Principles

- Describe technical properties of the articles in the domain
- Define customer traits that are relevant for marketing
- Define causal influences between customer traits and technical properties



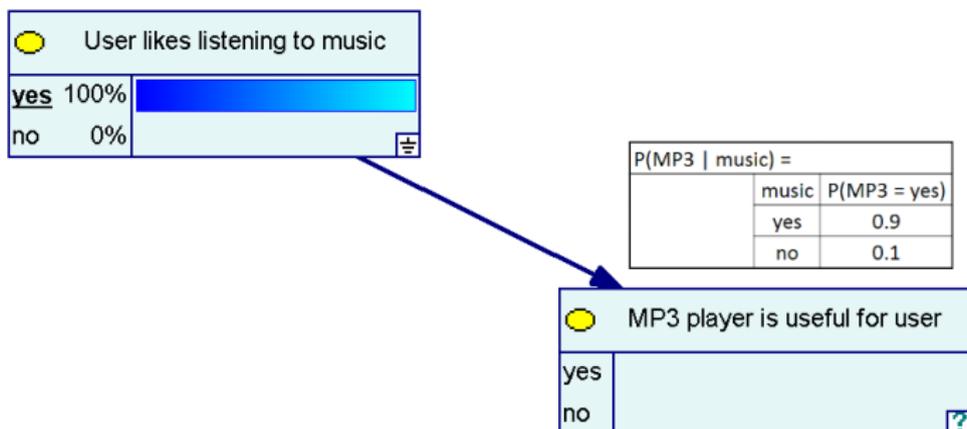
Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables



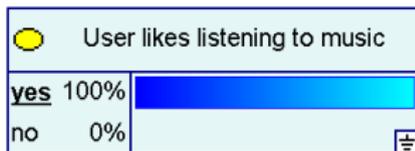
Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables

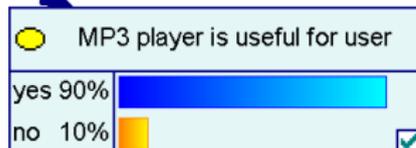


Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables



| P(MP3 music) = | | |
|------------------|-------|--------------|
| | music | P(MP3 = yes) |
| | yes | 0.9 |
| | no | 0.1 |



Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables

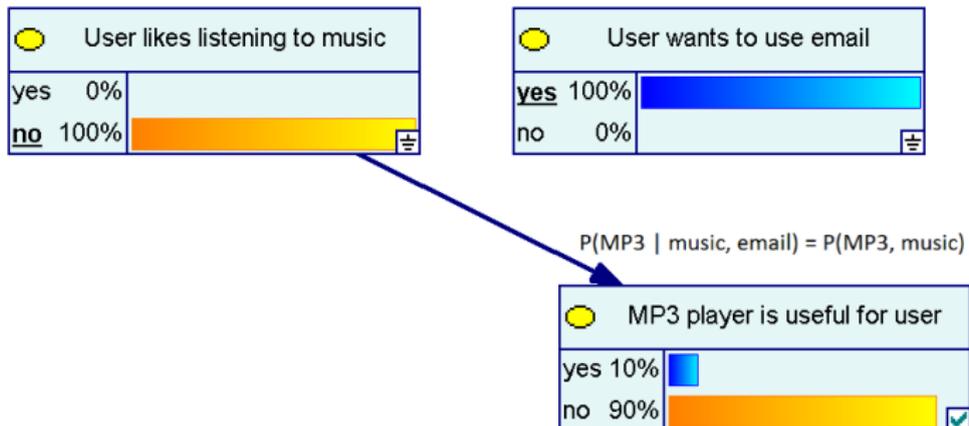


| | | |
|------------------|-------|--------------|
| P(MP3 music) = | | |
| | music | P(MP3 = yes) |
| | yes | 0.9 |
| | no | 0.1 |



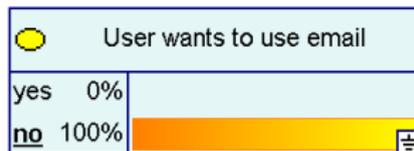
Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables

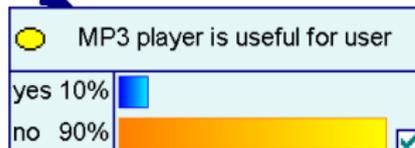


Bayesian Networks

- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables



$$P(\text{MP3} \mid \text{music, email}) = P(\text{MP3, music})$$

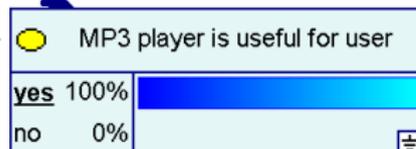


Bayesian Networks

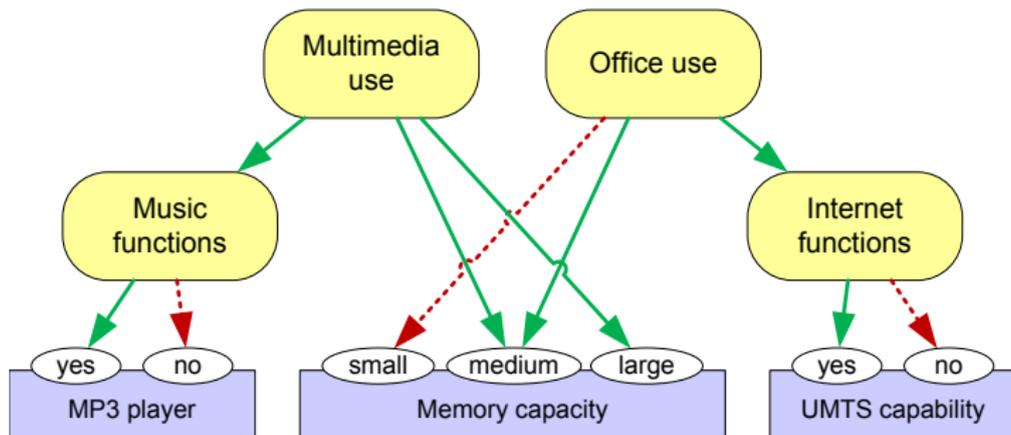
- Directed Acyclical Graph
 - Nodes: Random variables
 - Edges: Conditional (in)dependencies between variables



$$P(MP3|music) = \frac{P(music|MP3)P(MP3)}{P(music)}$$

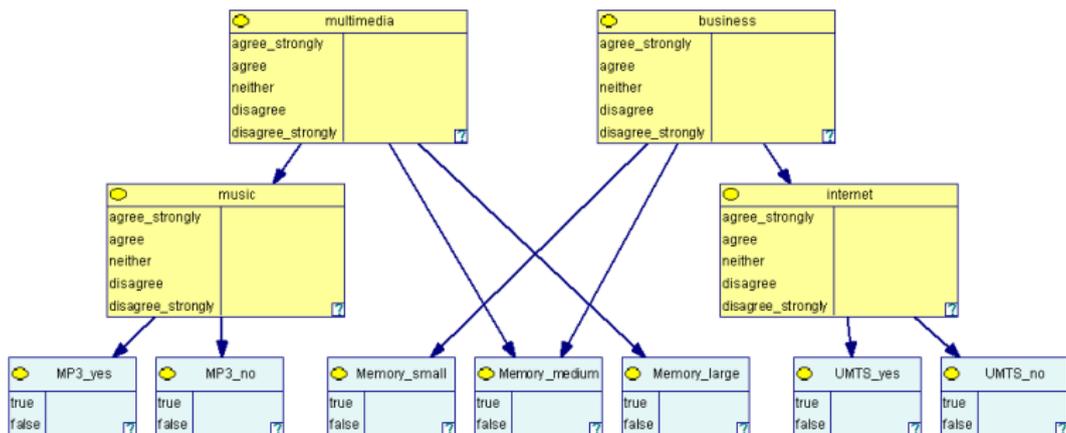


Bayesian Inference Engine



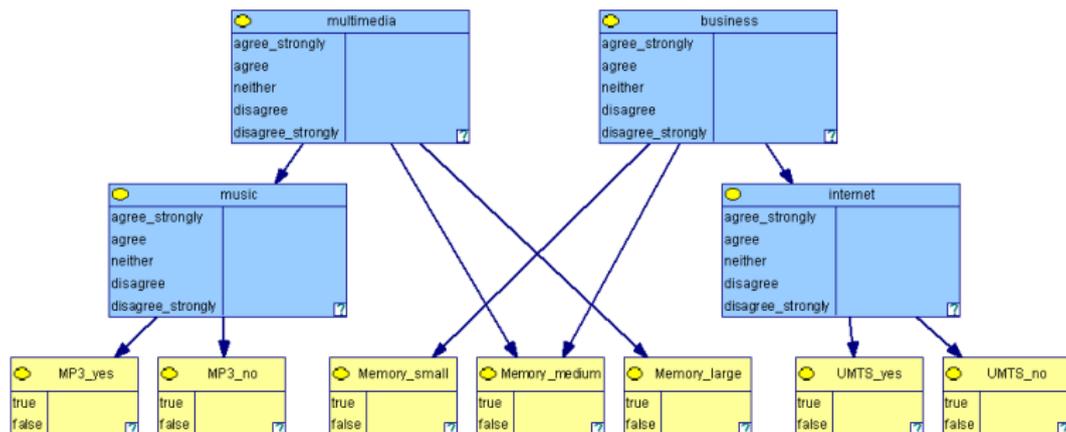
- How do we use a Bayes net to capture the causal relationships in our domain?

Bayesian Inference Engine



- **Needs** \Rightarrow random variables with “Likert” scale
 - Flexible number of states possible
 - Accommodate answer granularity
 - Commonly five states

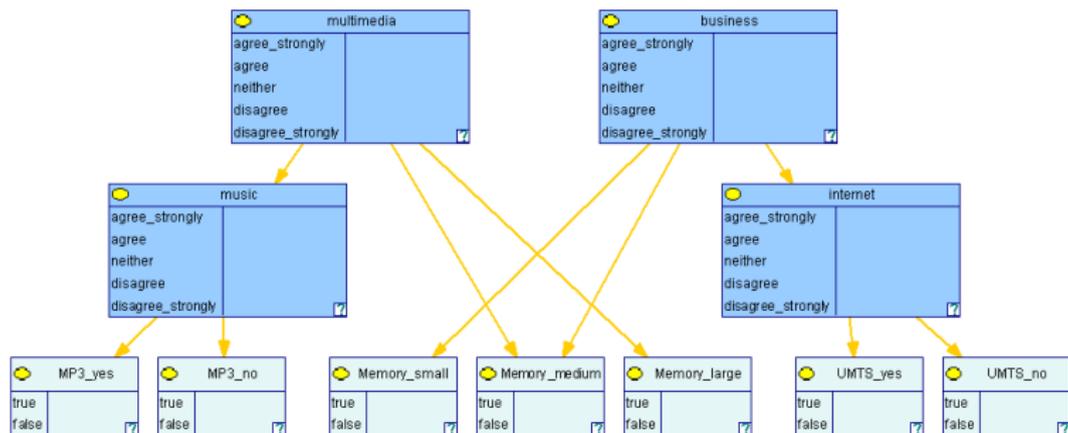
Bayesian Inference Engine



- **Attribute values** \Rightarrow boolean variables

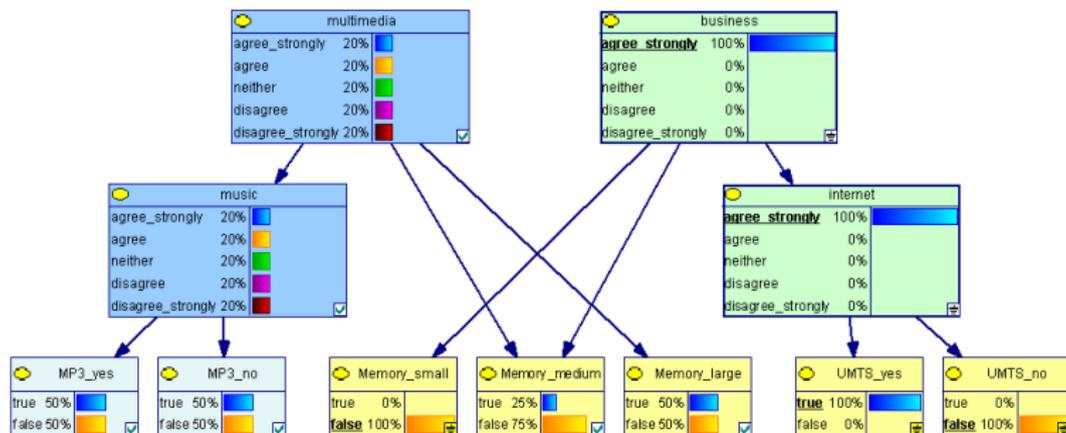
- Model likelihood that a value is useful for the customer
- Likelihoods of values of the same attribute are independent

Bayesian Inference Engine



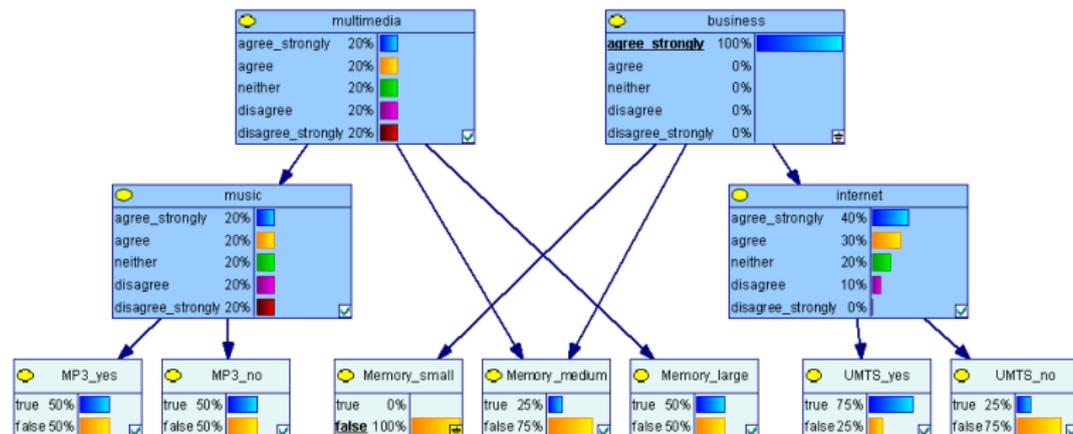
- **Influences** \Rightarrow probability tables
 - Generated in an offline step

Bayesian Inference Engine



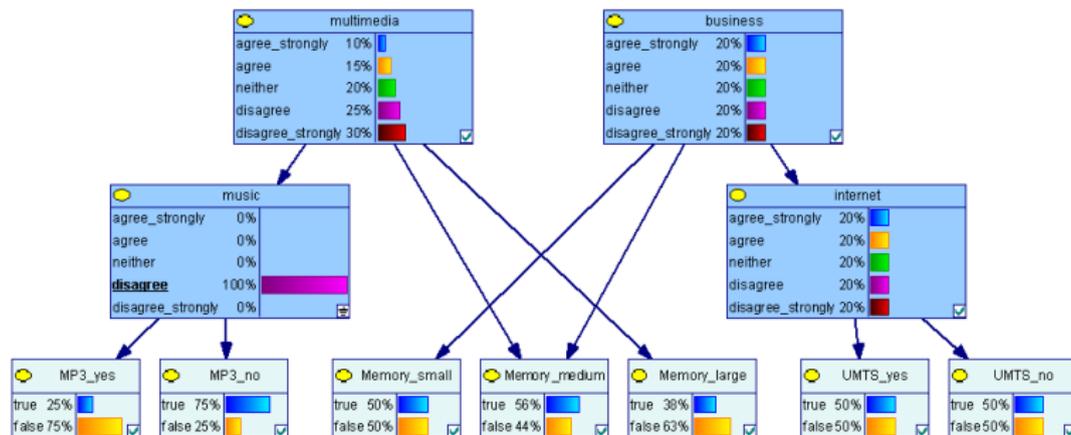
- Insert answers as **evidence** for the needs
- Read the **posteriori** probability distributions from the attribute values

Flexibility of the Inference Engine



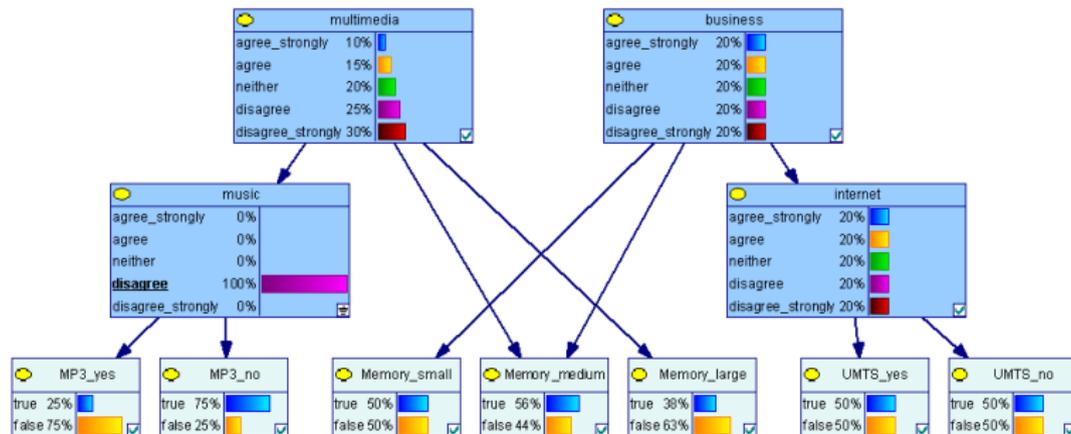
- No fixed ordering of questions
- Transparent belief revision
- Recommendations from the start
 - More evidence/answers $\hat{=}$ less uncertainty

Flexibility of the Inference Engine



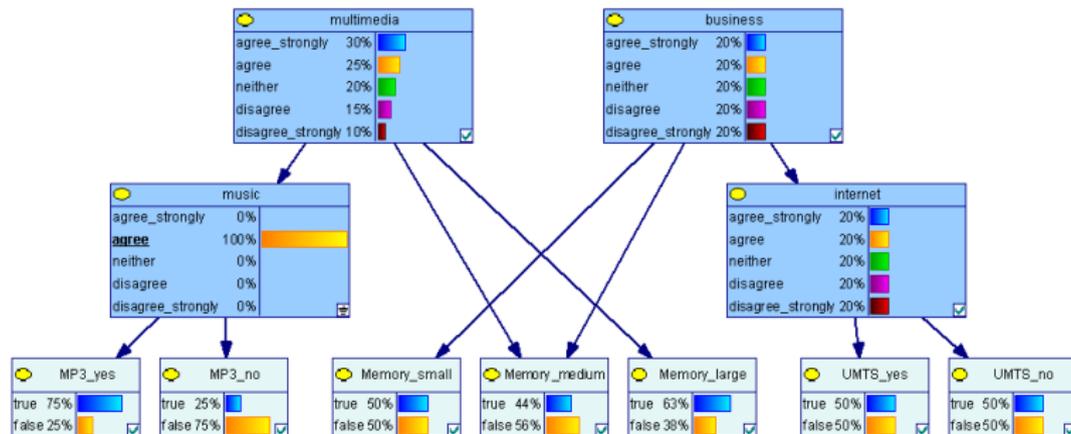
- No fixed ordering of questions
- Transparent belief revision
- Recommendations from the start
 - More evidence/answers $\hat{=}$ less uncertainty

Flexibility of the Inference Engine



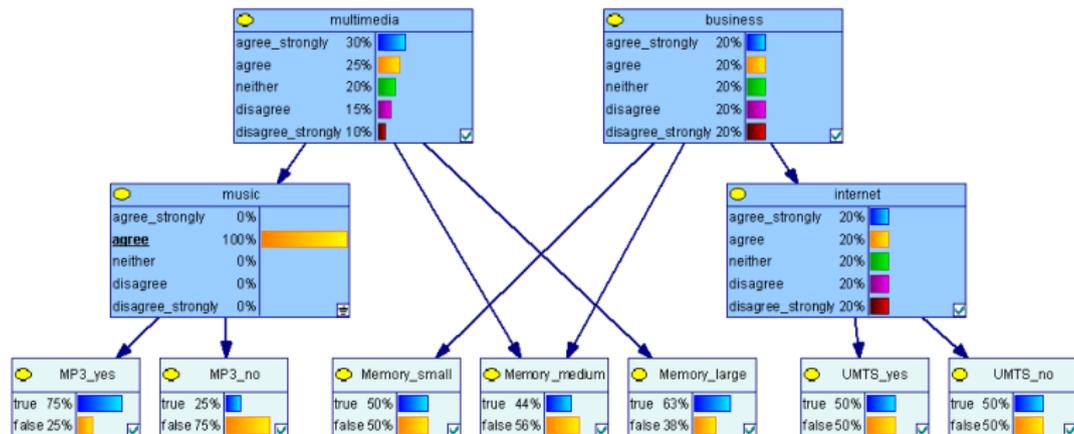
- No fixed ordering of questions
- Transparent belief revision
- Recommendations from the start
 - More evidence/answers $\hat{=}$ less uncertainty

Flexibility of the Inference Engine



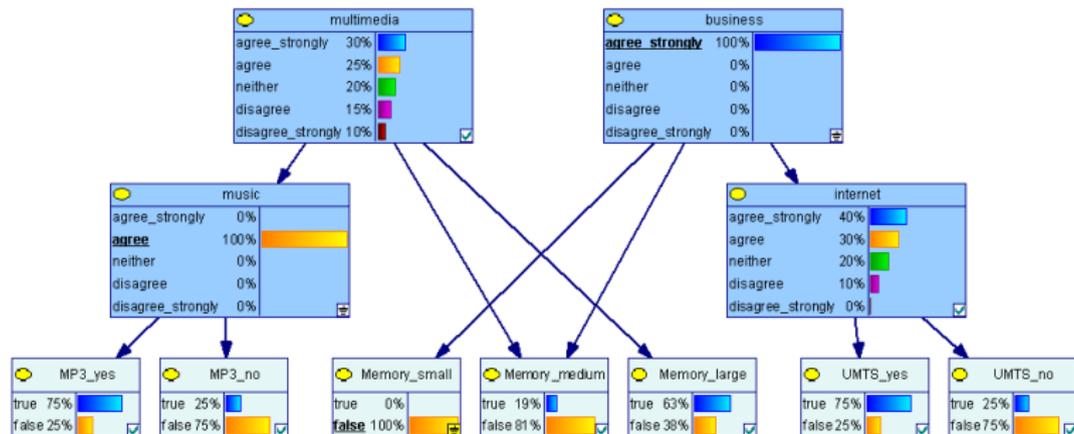
- No fixed ordering of questions
- Transparent belief revision
- Recommendations from the start
 - More evidence/answers $\hat{=}$ less uncertainty

Flexibility of the Inference Engine



- No fixed ordering of questions
- Transparent belief revision
- **Recommendations from the start**
 - More evidence/answers $\hat{=}$ less uncertainty

Flexibility of the Inference Engine



- No fixed ordering of questions
- Transparent belief revision
- **Recommendations from the start**
 - More evidence/answers $\hat{=}$ less uncertainty

Overview

- 1 Use Case
- 2 Domain (Meta-)Modeling
- 3 Product Ranking**

Ranking by MAUT

General idea: Construct a multi-attribute utility-function based on the current dialogue state

- Determine utility value for each possible value of an attribute
- Determine relative importance/weight of attribute
- Calculate a product's overall utility by using a weighted sum
 - Common in multi-attribute utility theory
 - Implementation in SQL

SQL Ranking Query

- Use a standard “ORDER BY” clause to implement the ordering
 - Compatible to all SQL databases

Example

```
SELECT  *, ($utilityfunction) as UTILITY
FROM    Cellphones
ORDER BY UTILITY DESC;
```

The result set may be restricted:

- By a top-k operator (e.g., return the 10 most highly ranked products)
- By hard constraints (e.g., exclude certain product properties from the result set)

Utility Function

Example

```
$utilityfunction =  
  $utility(att_1)$ * weight(att_1) + ... +  
  $utility(att_n)$ * weight(att_n)
```

- **Weighted sum:** Sum up each value's utility, weighted by the attribute's importance

Utility Function

Example

```
$utilityfunction =  
  $utility(att_1)$ * weight(att_1) + ... +  
  $utility(att_n)$ * weight(att_n)
```

Example

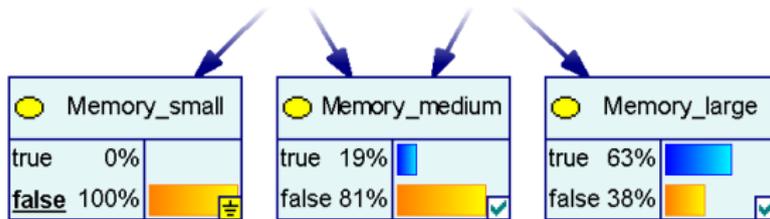
```
$utility(att_x) =  
  CASE WHEN att_x = val_x1 THEN u(val_x1) ELSE 0.0 END + ... +  
  CASE WHEN att_x = val_xn THEN u(val_xn) ELSE 0.0 END
```

- Realize \$utility as a large set of CASE-WHEN statements
- May be implemented as a stored procedure for increased efficiency
- Use database-specific optimizations (e.g., ENUM-datypes)

Utility of an Attribute Value

- Based on posteriori-probability in the Bayes net:

$$u_{av} := p(r_{av} = true \mid \dots)$$
- All utilities are 'independent'



Example

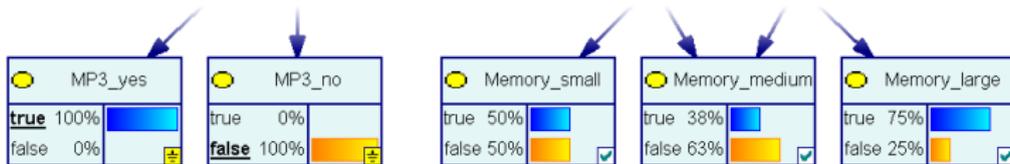
$$u_{small} = 0.0$$

$$u_{medium} = 0.19$$

$$u_{large} = 0.63$$

Distinctiveness of an Attribute

- Clearer customer opinion $\hat{=}$ more important for recommendations
- Clearer customer opinion $\hat{=}$ more *distinctive* predictions



Example

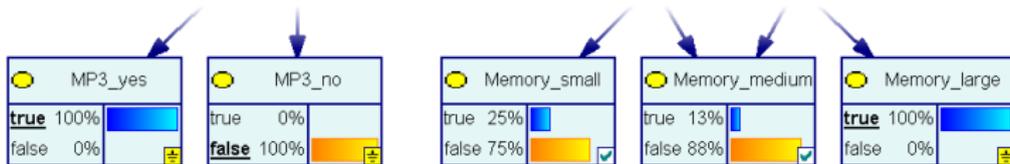
$$d_{MP3} = 1.0$$

$$d_{Memory} = 0.247$$

(normalized to [0..1])

Distinctiveness of an Attribute

- Clearer customer opinion $\hat{=}$ more important for recommendations
- Clearer customer opinion $\hat{=}$ more *distinctive* predictions



Example

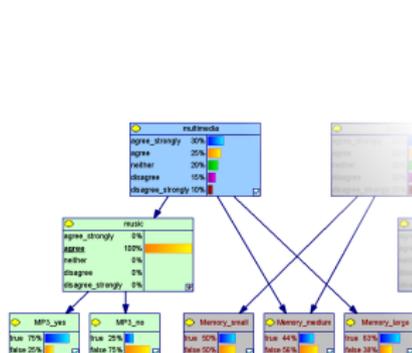
$$d_{MP3} = 1.0$$

$$d_{Memory} = 0.747$$

(normalized to [0..1])

Further Components of the Weight of an Attribute

- Situation factor
 - Attributes with no connection to already-answered questions are ignored (i.e., are assigned a weight of 0.0)
 - Makes recommendations more intuitive
- Static weight
 - Assigned by domain experts
 - Some attributes are inherently more important than others (e.g., digital camera resolution vs. ability to send EMS)



Evaluation

- Expert evaluations
 - System is in active use with our industry partner
 - ⇒ Validity of the implemented business process
 - Market study to analyze recommendations
 - ⇒ Recommendation quality
- Public presentations
 - University events
 - ⇒ Applicability to different domains
 - Exhibition at Cebit fair 2010

Summary & Outlook

- Approach to derive “hard” product rankings from “soft” customer preferences
 - Utility function for use with MAUT
 - Alternative: Pareto-optimality techniques (*not shown today*)

- In the (near) future:
 - Extend evaluations
 - Explanations
 - Recommendations
 - Dialogue behaviour
 - Sell it ;-)

Thank you!

Your
questions and comments
are welcome!

Bayes nets modeled with GeNIe (<http://dsl.sis.pitt.edu/>)

