Two applications of Bayesian networks

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Contents:

- Bayesian networks as a model for reasoning with uncertainty
- Building probabilistic models
- Building "good" strategies using the models
- Application 1: Adaptive testing
- Application 2: Decision-theoretic troubleshooting

An example of a Bayesian network:



Building Bayesian network models

three basic approaches

- Discussions with domain experts: expert knowledge is used to get the structure and parameters of the model
- A dataset of records is collected and a machine learning method is used to to construct a model and estimate its parameters.
- A combination of previous two: e.g. experts helps with the stucture, data are used to estimate parameters.

An example of a strategy:



 X_3 is more difficult question than X_2 which is more difficult than X_1 .

Building strategies using the models

For all terminal nodes $\ell \in \mathcal{L}(s)$ of a strategy s we define:

- steps that were performed to get to that node (e.g. questions answered in a certain way). It is called collected evidence e_{ℓ} .
- Using the probabilistic model of the domain we can compute probability of getting to a terminal node $P(\mathbf{e}_{\ell})$.
- Also during the process, when we have collected certain evidence e we can update the probability of getting to a terminal node, which now corresponds to conditional probability P(e_l)

Building strategies using the models

For all terminal nodes $\ell \in \mathcal{L}(\mathbf{s})$ of a strategy \mathbf{s} we have also defined:

• an evaluation function $f : \bigcup_{s \in S} \mathcal{L}(s) \mapsto \mathbb{R}$.

For each strategy we can compute:

• expected value of the strategy:

$$E_f(\mathbf{s}) = \sum_{\ell \in \mathcal{L}(\mathbf{s})} P(\mathbf{e}_\ell) \cdot f(\mathbf{e}_\ell)$$

The goal:

• find a strategy that maximizes (minimizes) its expected value

Using entropy as an information measure

"The lower the entropy of a probability distribution the more we know."

$$H(P(\mathbf{S})) = -\sum_{\mathbf{s}} P(\mathbf{S} = \mathbf{s}) \cdot \log P(\mathbf{S} = \mathbf{s})$$



Entropy in node *n*

 $H(\mathbf{e}_n) = H(P(\mathbf{S} \mid \mathbf{e}_n))$

Expected entropy at the end of test \mathbf{t}

$$E_H(\mathbf{t}) = \sum_{\ell \in \mathcal{L}(\mathbf{t})} P(\mathbf{e}_{\ell}) \cdot H(\mathbf{e}_{\ell})$$

 \mathcal{T} ... the set of all possible tests (e.g. of a given length)

A test t^{\star} is **optimal** iff

 $\mathbf{t}^{\star} = \arg\min_{\mathbf{t}\in\mathcal{T}} E_H(\mathbf{t})$.

Application 1: Adaptive test of basic operations with fractions

Examples of tasks:

T_1 :	$\left(\frac{3}{4}\cdot\frac{5}{6}\right)-\frac{1}{8}$	=	$\frac{15}{24} - \frac{1}{8} = \frac{5}{8} - \frac{1}{8} = \frac{4}{8} =$	$\frac{1}{2}$
T_2 :	$\frac{1}{6} + \frac{1}{12}$	=	$\frac{2}{12} + \frac{1}{12} = \frac{3}{12} = \frac{1}{4}$	
T_3 :	$\frac{1}{4} \cdot 1\frac{1}{2}$	=	$\frac{1}{4} \cdot \frac{3}{2} = \frac{3}{8}$	
T_4 :	$\left(\frac{1}{2}\cdot\frac{1}{2}\right)\cdot\left(\frac{1}{3}+\frac{1}{3}\right)$	=	$\frac{1}{4} \cdot \frac{2}{3} = \frac{2}{12} = \frac{1}{6}$.	

Elementary and operational skills

СР	Comparison (common nu- merator or denominator)	$\frac{1}{2} > \frac{1}{3}, \frac{2}{3} > \frac{1}{3}$
AD	Addition (comm. denom.)	$\frac{1}{7} + \frac{2}{7} = \frac{1+2}{7} = \frac{3}{7}$
SB	Subtract. (comm. denom.)	$\frac{2}{5} - \frac{1}{5} = \frac{2-1}{5} = \frac{1}{5}$
MT	Multiplication	$\frac{1}{2} \cdot \frac{3}{5} = \frac{3}{10}$
CD	Common denominator	$\left(\frac{1}{2},\frac{2}{3}\right) = \left(\frac{3}{6},\frac{4}{6}\right)$
CL	Cancelling out	$\frac{4}{6} = \frac{2 \cdot 2}{2 \cdot 3} = \frac{2}{3}$
СІМ	Conv. to mixed numbers	$\frac{7}{2} = \frac{3 \cdot 2 + 1}{2} = 3\frac{1}{2}$
СМІ	Conv. to improp. fractions	$3\frac{1}{2} = \frac{3 \cdot 2 + 1}{2} = \frac{7}{2}$

Misconceptions

Label	Description	Occurrence
MAD	$\frac{a}{b} + \frac{c}{d} = \frac{a+c}{b+d}$	14.8%
MSB	$\frac{a}{b} - \frac{c}{d} = \frac{a-c}{b-d}$	9.4%
MMT1	$\frac{a}{b} \cdot \frac{c}{b} = \frac{a \cdot c}{b}$	14.1%
MMT2	$\frac{a}{b} \cdot \frac{c}{b} = \frac{a+c}{b \cdot b}$	8.1%
ММТ3	$\frac{a}{b} \cdot \frac{c}{d} = \frac{a \cdot d}{b \cdot c}$	15.4%
MMT4	$\frac{a}{b} \cdot \frac{c}{d} = \frac{a \cdot c}{b+d}$	8.1%
MC	$a\frac{b}{c} = \frac{a \cdot b}{c}$	4.0%

Student model



Evidence model for task T1 $\left(\frac{3}{4} \cdot \frac{5}{6}\right) - \frac{1}{8} = \frac{15}{24} - \frac{1}{8} = \frac{5}{8} - \frac{1}{8} = \frac{4}{8} = \frac{1}{2}$

 $T1 \hspace{0.1in} \Leftrightarrow \hspace{0.1in} MT \And CL \And ACL \And SB \And \neg MMT3 \And \neg MMT4 \And \neg MSB$



Skill Prediction Quality



Application 2: Troubleshooting - Light print problem



- Problems: F_1 Distribution problem, F_2 Defective toner, F_3 Corrupted dataflow, and F_4 Wrong driver setting.
- Actions: *A*₁ Remove, shake and reseat toner, *A*₂ Try another toner, and *A*₃ Cycle power.
- Questions: Q_1 Is the configuration page printed light?

Troubleshooting strategy



The task is to find a strategy $\mathbf{s} \in \mathcal{S}$ minimising expected cost of repair

$$E_{CR}(\mathbf{s}) = \sum_{\ell \in \mathcal{L}(\mathbf{s})} P(\mathbf{e}_{\ell}) \cdot (t(\mathbf{e}_{\ell}) + c(\mathbf{e}_{\ell}))$$

Going commercial...

• Hugin Expert A/S.

software product: Hugin - a Bayesian network tool.
http://www.hugin.com/

• Educational Testing Service (ETS)

the world's largest private educational testing organization In 2000/2001 more than 3 millions students took the ETS's largest exam SAT. Research unit doing research on adaptive test using Bayesian networks: http://www.ets.org/research/

SACSO Project

Systems for Automatic Customer Support Operations

- research project of Hewlett Packard and Aalborg University. The troubleshooter offered as DezisionWorks by Dezide Ltd. http://www.dezide.com/