Informatics 2D: Reasoning and Agents

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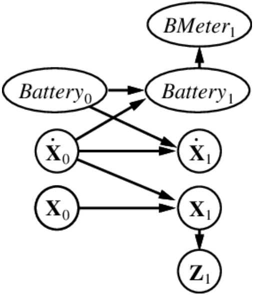
Lecture 28b: Dynamic Bayesian Networks II

Where are we?

Last time...

- Dynamic Bayesian Networks:
  - Which random variables and dependencies (the graphical component)?
  - What kind of probability distributions?
- Saw an example where the model is deficient in a scenario that's likely to occur.
- **Today:** What can you do about that?

Reminder: Transient failure model



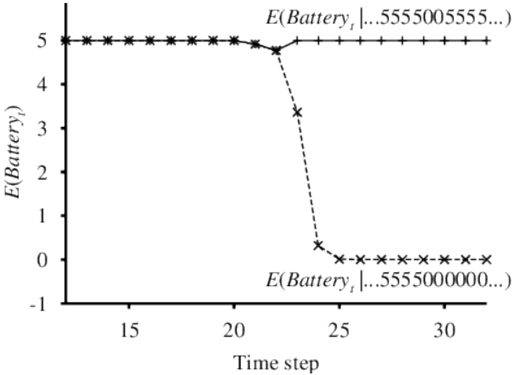
- *BMeter* and *Z* are observed; all others are latent
- Gaussian Error model for $\mathbf{P}(BMeter_t|Battery_t)$
- We saw last time that a sudden drop from 5 to 0 for *BMeter* leads to poor quality inference.

How to fix inferences about errors: first attempt

- To handle failure properly, sensor model must include possibility of (radical) meter failure
- Simplest failure model: assign larger probability to 0 reading than a Gaussian error model would; e.g. $P(BMeter_t = 0 | Battery_t = 5) = 0.03$
- When faced with 0 reading, provided that predicted probability of empty battery is much less than 0.03, best explanation is meter failure
- This model is much less susceptible to poor inference, because an explanation is available
- However, it cannot cope with **persistent** failure either

Transient failure model

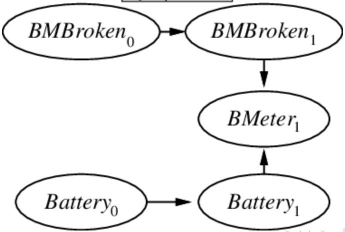
- Handling transient failure with explicit error models
- In case of permanent failure the robot will (wrongly) believe the battery is empty



How to fix inferences about errors: second attempt

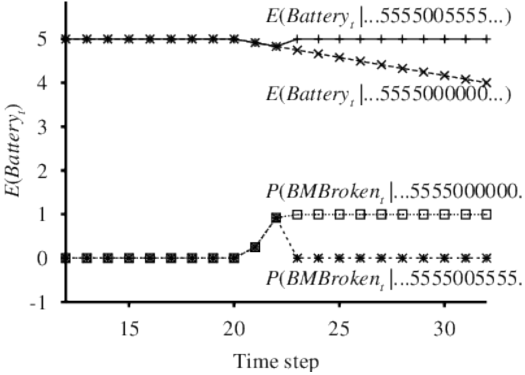
- **Persistent failure models** describe how sensor behaves under normal conditions and after failure
- Add additional variable *BMBroken*, and CPT to next *BMBroken* state has a very small probability if not broken, but 1.0 if broken before (**persistence arc**)
- When *BMBroken* is true, *BMeter* will be 0 regardless of *Battery*:

B_0	$P(B_1)$
t	1.000
f	0.001



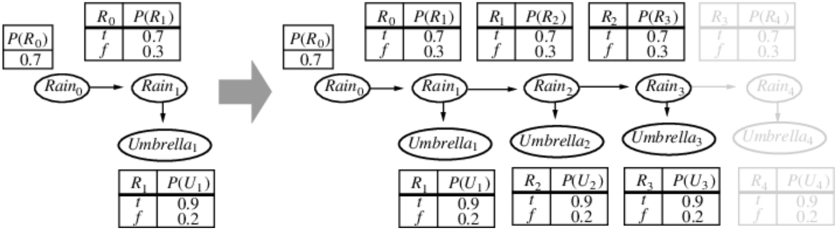
Persistent failure

- In case of temporary blip probability of broken sensor rises quickly but goes back if 5 is observed
- In case of persistent failure, robot assumes discharge of battery at "normal" rate



Exact inference in DBNs

- Since DBNs are BNs, we already have inference algorithms like variable elimination
- Essentially DBN equivalent to infinite "unfolded" BN, but slices beyond required inference period are irrelevant
- **Unrolling**: reproducing basic time slice to accommodate observation sequence



Exact inference in DBNs

- Exact inference in DBNs is intractable, and this is a major problem.
- There are approximate inference methods that work well in practice.
- This issue is currently a hot topic in AI...

Summary

- Account of time and uncertainty complete
- Looked at general Markovian models
- HMMs
- DBNs as general case
- Quite intractable, but powerful
- Next time: **Decision Making under Uncertainty**

QUESTION:
Write down the equation for the query $\mathbf{P}(BMBroken_{\mathbf{2}}|Battery_{\mathbf{1}} = 5, BMeter_{\mathbf{2}} = 0, BMBroken_{\mathbf{1}} = 0)$ in terms of the sum and product of conditional probabilities that are specified in the probabilities tables of the DBN given in the lecture.

$$
\begin{aligned}
&\mathbf{P}(BMB_{\mathbf{2}}|B_{\mathbf{1}} = 5, BM_{\mathbf{2}} = 0, BMB_{\mathbf{1}} = 0) = \\
&\quad \alpha \mathbf{P}(BMB_{\mathbf{2}}, B_{\mathbf{1}} = 5, BM_{\mathbf{2}} = 0, BMB_{\mathbf{1}} = 0) && \text{Bayes} \\
&\quad = \alpha \sum_{b_{\mathbf{2}}} \mathbf{P}(BMB_{\mathbf{2}}, b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BM_{\mathbf{2}} = 0, BMB_{\mathbf{1}} = 0) && \text{marginalisation} \\
&\quad = \alpha \sum_{b_{\mathbf{2}}} \mathbf{P}(BM_{\mathbf{2}} = 0|BMB_{\mathbf{2}}, B_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0)\mathbf{P}(BMB_{\mathbf{2}}, b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0) && \text{Bayes} \\
&\quad = \alpha \sum_{b_{\mathbf{2}}} \mathbf{P}(BM_{\mathbf{2}} = 0|BMB_{\mathbf{2}}, B_{\mathbf{2}})\mathbf{P}(BMB_{\mathbf{2}}, b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0) && \text{Markov} \\
&\quad = \alpha \sum_{b_{\mathbf{2}}} \mathbf{P}(BM_{\mathbf{2}} = 0|BMB_{\mathbf{2}}, b_{\mathbf{2}})\mathbf{P}(BMB_{\mathbf{2}}|b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0)\mathbf{P}(b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0) && \text{Bayes} \\
&\quad = \alpha' \sum_{b_{\mathbf{2}}} \mathbf{P}(BM_{\mathbf{2}} = 0|BMB_{\mathbf{2}}, b_{\mathbf{2}})\mathbf{P}(BMB_{\mathbf{2}}|b_{\mathbf{2}}, B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0)\mathbf{P}(b_{\mathbf{2}}|B_{\mathbf{1}} = 5, BMB_{\mathbf{1}} = 0) && \text{Bayes} \\
&\quad = \alpha' \sum_{b_{\mathbf{2}}} \mathbf{P}(BM_{\mathbf{2}} = 0|BMB_{\mathbf{2}}, b_{\mathbf{2}})\mathbf{P}(BMB_{\mathbf{2}}|BMB_{\mathbf{1}} = 0)\mathbf{P}(b_{\mathbf{2}}|B_{\mathbf{1}} = 5) && \text{Markov}
\end{aligned}
$$