Informatics 2D: Reasoning and Agents

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Lecture 28a: Dynamic Bayesian Networks I

Where are we?

So far. . .

- Inference in temporal models
- Filtering, hindsight, Viterbi etc.
- Specific instances: HMMs

Today. . .

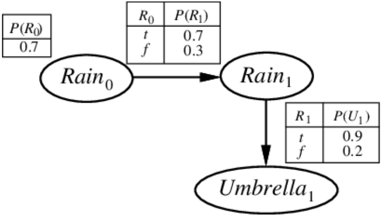
- **Dynamic Bayesian Networks**

Dynamic Bayesian Networks

- We've already seen an example of a DBN—Umbrella World
- A DBN is a BN describing a temporal probability model that can have *any number* of state variables $\mathbf{X}_t$ and evidence variables $\mathbf{E}_t$
- HMMs are DBNs with a single state and a single evidence variable
- But recall that one can *combine* a set of discrete (evidence or state) variables into a single variable (whose values are tuples).
- So every discrete-variable DBN can be described as a HMM.
- So why bother with DBNs?
- Because decomposing a complex system into constituent variables, as a DBN does, ameliorates sparseness in the temporal probability model

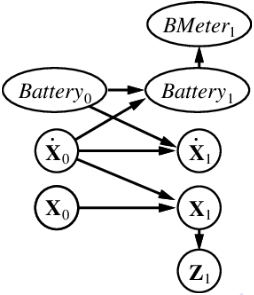
Constructing DBNs

- We have to specify prior distribution of state variables $\mathbf{P}(\mathbf{X}_0)$, transition model $\mathbf{P}(\mathbf{X}_{t+1}|\mathbf{X}_t)$, and sensor model $\mathbf{P}(\mathbf{E}_t|\mathbf{X}_t)$
- Also, we have to fix topology of nodes
- Stationarity assumption
  most convenient to specify topology for first slice
- Umbrella world example:



An example

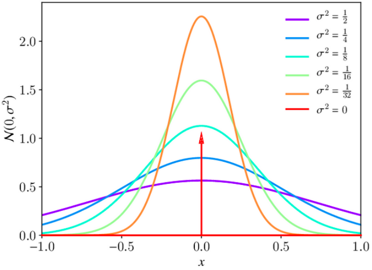
- Consider a battery-driven robot moving in the $X \times Y$ plane
- Let $\mathbf{X}_t = (X_t, Y_t)$ and $\dot{\mathbf{X}}_t = (\dot{X}_t, \dot{Y}_t)$ state variables for position and velocity, and $\mathbf{Z}_t$ measurements of position (e.g. GPS)
- Add $Battery_t$ for battery charge level and $BMeter_t$ for the measurement of it
- We obtain the following basic model:



Modelling failure

- Assume $Battery_t$ and $BMeter_t$ take on discrete values (e.g. integer between 0 and 5)
- These variables should be identically distributed (CPT=identity matrix) unless error creeps in
- One way to model error is through **Gaussian error model**, i.e. a small Gaussian error is added to the meter reading

Gaussian Error model



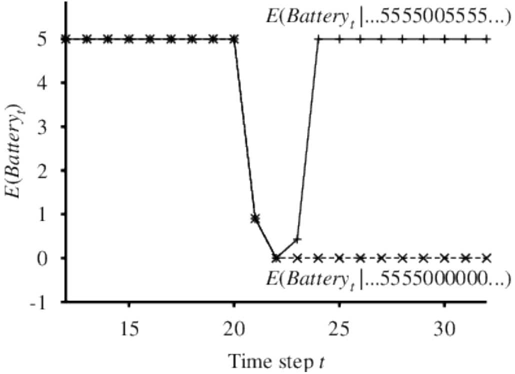
- The bigger the σ, the more expected errors there are.
- We can approximate this also for the discrete case through an appropriate distribution.
- Error 'on one side' when meter reading is 5 or 0.
- But problem can be much worse:
  sensor failure rather than inaccurate measurements.

Transient failure

- **Transient failure**: sensor occasionally sends inaccurate data
- Robot example: after 20 consecutive readings of 5 suddenly $BMeter_{21} = 0$
- In Gaussian error model belief about $Battery_{21}$ depends on:
  - Sensor model: $\mathbf{P}(BMeter_{21} = 0 | Battery_{21})$ and
  - Prediction model: $\mathbf{P}(Battery_{21} | BMeter_{1:20})$
- If probability of large sensor error is smaller than sudden transition to 0, then with high probability battery is considered empty
- A measurement of zero at $t = 22$ will make this (almost) certain
- After a reading of 5 at $t = 23$ the probability of full battery will go back to high level
- But robot made completely wrong judgement ...

Transient failure

- Curves for prediction depending on whether $BMeter_t$ is only 0 for $t = 22/23$ or whether it stays 0 indefinitely



Summary

Dynamic Bayesian Networks:

- In constructing a model, you must decide:
  - The set of random variables (observable and latent)
  - Their dependencies
  - The kind of probability distributions for each CPT
- We've seen an example where the choice is suboptimal
- Next time: **How do we improve the model?**