CS 112: Computer System Modeling Fundamentals

> Prof. Jenn Wortman Vaughan May 26, 2011 Lecture 17

Reminders & Announcements

- Homework 5 has been posted on the website
- Catch up on your reading now!

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 - The sequence of words in an "English-looking" document

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The key independence assumption is the Markov property, which we can represent using a Bayesian network:

$$X_0 \longrightarrow X_1 \longrightarrow X_2 \longrightarrow X_3 \longrightarrow \cdots$$

A Simple Example

- What are the states?
- What are the transition probabilities?

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- The best representation depends on the problem you are trying to solve

The Markov Property

My faulty router can be either online or offline. If it is online one day, it will be online the next day with probability 0.8. If it is offline one day, it will remain offline the next day with probability 0.4.

If it remains offline for four straight days, I get it (temporarily) repaired, resetting it to the online state.

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Exercise: Derive this recursion yourself using the total probably rule and the probability of a sequence of states!

$$P(X_0 = 1 | X_0 = 1) = 1$$
 $P(X_0 = 2 | X_0 = 1) = 0$

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$$P(X_2 = 2 | X_0 = 1) = 0.24$$

$$P(X_3 = 1 | X_0 = 1) = 0.752$$

$$P(X_3 = 2 | X_0 = 1) = 0.248$$

$$\begin{split} P(X_0 = 1 \mid X_0 = 1) &= 1 & P(X_0 = 2 \mid X_0 = 1) = 0 \\ P(X_1 = 1 \mid X_0 = 1) &= 0.8 & P(X_1 = 2 \mid X_0 = 1) = 0.2 \\ P(X_2 = 1 \mid X_0 = 1) &= 0.76 & P(X_2 = 2 \mid X_0 = 1) = 0.24 \\ P(X_3 = 1 \mid X_0 = 1) &= 0.752 & P(X_3 = 2 \mid X_0 = 1) = 0.248 \\ P(X_4 = 1 \mid X_0 = 1) &= 0.7504 & P(X_4 = 2 \mid X_0 = 1) = 0.2496 \end{split}$$

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$$P(X_0 = 1 | X_0 = 2) = 0$$
 $P(X_0 = 2 | X_0 = 2) = 1$

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Classification of States

Accessibility: State *j* is accessible from state *i* if for some *n*, the *n*-step transition probability from *i* to *j* is positive.

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The set of all states accessible from a recurrent state form a recurrent class. Note that all of the states in a recurrent class are accessible from each other.

Periodicity

- A recurrent class is periodic if it can be broken into d > 1 disjoint subsets $S_1, S_2, ..., S_d$ in such a way that
 - All transitions from states in S_i lead to states in S_{i+1} for $i \in \{1, ..., d-1\}$
 - All transitions from states in S_d lead to states in S_1
- The period of the class is the number *d* of subsets