

You are trying to diagnose whether your computer is broken or not. On a given day, your computer's hidden state is either *broken* or *working*. Each day you make one of the following observations: *blue-screen*, *slow*, or *snappy*, depending on the state of your computer. You decide to use the following HMM to model your daily observations:

Initial Distribution		Transition Distribution			Emission Distribution		
State	$P(X_{\bullet})$	State	Next State	$P(X_{t+1} X_t)$	State	Observation	$P(O_t X_t)$
<i>working</i>	0.9	<i>working</i>	<i>working</i>	0.9	<i>working</i>	<i>snappy</i>	0.7
<i>broken</i>	0.1	<i>working</i>	<i>broken</i>	0.1	<i>working</i>	<i>slow</i>	0.2
		<i>broken</i>	<i>broken</i>	1.0	<i>working</i>	<i>blue-screen</i>	0.1
		<i>broken</i>	<i>working</i>	0.0	<i>broken</i>	<i>snappy</i>	0.1
					<i>broken</i>	<i>slow</i>	0.4
					<i>broken</i>	<i>blue-screen</i>	0.5

What is the most likely sequence of hidden states X_1, X_2, X_3 given the observation sequence (*snappy*, *slow*, *blue-screen*)?

The Viterbi algorithm from the course notes has the recursive relationship:

$$m_1[x_1] = P(e_1|x_1)P(x_1)$$

$$m_t[x_t] = P(e_t|x_t) \max_{x_{t-1}} P(x_t|x_{t-1})m_{t-1}[x_{t-1}]$$

Day 1:

$$m_1[\textit{working}] = P(\textit{snappy}|\textit{working})P(\textit{working}) = 0.7 * 0.9 = 0.63$$

$$m_1[\textit{broken}] = P(\textit{snappy}|\textit{broken})P(\textit{broken}) = 0.1 * 0.1 = 0.01$$

Day 2:

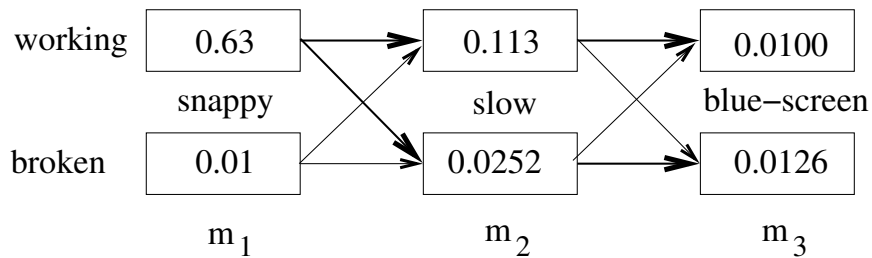
$$\begin{aligned} m_2[\textit{working}] &= P(\textit{slow}|\textit{working}) \max \begin{cases} P(\textit{working}|\textit{working})m_1[\textit{working}] \\ P(\textit{working}|\textit{broken})m_1[\textit{broken}] \end{cases} \\ &= 0.2 \max\{0.9 * 0.63, 0.0 * 0.01\} = 0.113 \end{aligned}$$

$$\begin{aligned} m_2[\textit{broken}] &= P(\textit{slow}|\textit{broken}) \max \begin{cases} P(\textit{broken}|\textit{working})m_1[\textit{working}] \\ P(\textit{broken}|\textit{broken})m_1[\textit{broken}] \end{cases} \\ &= 0.4 \max\{0.1 * 0.63, 1.0 * 0.01\} = 0.0252 \end{aligned}$$

Day 3:

$$\begin{aligned}
 m_3[working] &= P(\text{blue-screen}|\text{working}) \max \left\{ \begin{array}{l} P(\text{working}|\text{working})m_2[\text{working}] \\ P(\text{working}|\text{broken})m_2[\text{broken}] \end{array} \right\} \\
 &= 0.1 * \max\{0.9 * 0.113, 0.0 * 0.0252\} = 0.0100 \\
 m_3[\text{broken}] &= P(\text{blue-screen}|\text{broken}) \max \left\{ \begin{array}{l} P(\text{broken}|\text{working})m_2[\text{working}] \\ P(\text{broken}|\text{broken})m_2[\text{broken}] \end{array} \right\} \\
 &= 0.5 * \max\{0.1 * 0.113, 1.0 * 0.0252\} = 0.0126
 \end{aligned}$$

Fill in the appropriate m_i values in the trellis below. Emphasize the back pointers by thickening the edges in the trellis from the final m_3 values for both states *working* and *broken*.



working, broken, broken is the optimal sequence.