## Lecture 19: Examples with Message-passing Algorithms

Location: Rowe 1011 Instructor: Vlado Keselj
Time: 16:05-17:25

## Previous Lecture

- Message-passing

1. Isolated factor node to variable node
2. Isolated variable node to factor node
3. General factor node to variable node
4. General variable node to factor node

- Inference tasks using message passing

1. Marginalization with one variable
2. Marginalization with multiple variables
3. Conditioning with one variable
4. Conditioning with multiple variables
5. Completion in general

### 16.4 Message-Passing Inference Algorithm: Burglar-Earthquake Example

In this example we use the previously given Burglar-Earthquake Bayesian Network:


The given tables are:


| $B$ | $E$ | $A$ | $\mathrm{P}(A \mid B, E)$ |
| :---: | :---: | :---: | :---: |
| $T$ | $T$ | $T$ | 0.95 |
| $T$ | $T$ | $F$ | 0.05 |
| $T$ | $F$ | $T$ | 0.94 |
| $T$ | $F$ | $F$ | 0.06 |
| $F$ | $T$ | $T$ | 0.29 |
| $F$ | $T$ | $F$ | 0.71 |
| $F$ | $F$ | $T$ | 0.001 |
| $F$ | $F$ | $F$ | 0.999 |


| $A$ | $J$ | $\mathrm{P}(J \mid A)$ |
| :---: | :---: | :---: |
| $T$ | $T$ | 0.90 |
| $T$ | $F$ | 0.10 |
| $F$ | $T$ | 0.05 |
| $F$ | $F$ | 0.95 |


| $A$ | $M$ | $\mathrm{P}(M \mid A)$ |
| :---: | :---: | :---: |
| $T$ | $T$ | 0.70 |
| $T$ | $F$ | 0.30 |
| $F$ | $T$ | 0.01 |
| $F$ | $F$ | 0.99 |

Our first step is to translate this network into a factor graph:


The function nodes correspond to conditional probabilities in the following way: $f_{1} \sim \mathrm{P}(B), f_{2} \sim \mathrm{P}(E)$, $f_{3} \sim \mathrm{P}(A \mid B, E), f_{4} \sim \mathrm{P}(J \mid A)$, and $f_{5} \sim \mathrm{P}(M \mid A)$.

## Burglar-Earthquake Example Problem

- John called, probability that Burglar is in the house
$-P(B=T \mid J=T)=$ ?
- Conditioning with one variable

Problem: Calculate the probability that a burglar is in the house, if we know that John has called. We "hard-wire" the variable $J$ to the value $T$, and analyze which messages we need to compute:


The messages are calculated in the following way:


Calculation of the remaining messages requires a bit more calculations:

| $f_{4} \rightarrow A$ |  |  |  |  |
| :--- | :--- | ---: | :--- | :--- |
|  |  |  |  |  |
| $A$ | $J$ | $J \rightarrow f_{4}$ | $f_{4}$ |  |
| $A=T$ | $T$ | 1 | $\cdot 0.90$ | $=0.9$ |
|  | $F$ | 0 | $\cdot 0.10$ | $=0$ |
|  |  |  | $\Sigma$ | $=0.9$ |
| $A=F$ | $T$ | 1 | $\cdot 0.05$ | $=0.05$ |
|  | $F$ | 0 | $\cdot 0.95$ | $=0$ |
|  |  |  | $\Sigma$ | $=0.05$ |


| $f_{5} \rightarrow A$ |  |  |  |  |
| :--- | :--- | ---: | :--- | :--- |
| $A$ | $M$ | $M \rightarrow f_{5}$ | $f_{5}$ |  |
| $A=T$ | $T$ | 1 | $\cdot 0.70$ | $=0.7$ |
|  | $F$ | 1 | $\cdot 0.30$ | $=0.3$ |
|  |  |  | $\Sigma$ | $=1$ |
| $A=F$ | $T$ | 1 | $\cdot 0.01$ | $=0.01$ |
|  | $F$ | 1 | $\cdot 0.99$ | $=0.99$ |
|  |  |  | $\Sigma$ | $=1$ |

Hence the messages are: \begin{tabular}{c|c}
$A$ \& $f_{4} \rightarrow A$ <br>
\hline$T$ \& 0.9 <br>
$F$ \& 0.05

 and 

and <br>
\hline

 

$A$ <br>
\hline
\end{tabular}

multiplication of messages coming into $A:$|  |  |
| :---: | :---: |
| $A$ | $A \rightarrow f_{3}$ |
| $T$ | 0.9 |
|  | $F$ |

Finally, we compute the message $f_{3} \rightarrow B$ :

| $f_{3} \rightarrow B$ |  |  |  |  |  |  |
| :--- | :--- | :--- | ---: | :--- | :--- | :--- |
| $B$ | $E$ | $A$ | $E \rightarrow f_{3}$ | $A \rightarrow f_{3}$ | $f_{3}$ |  |
| $B=T$ | $T$ | $T$ | 0.002 | $\cdot 0.9$ | $\cdot 0.95$ | $=0.00171$ |
|  | $T$ | $F$ | 0.002 | $\cdot 0.05$ | $\cdot 0.05$ | $=0.000005$ |
|  | $F$ | $T$ | 0.998 | $\cdot 0.9$ | $\cdot 0.94$ | $=0.844308$ |
|  | $F$ | $F$ | 0.998 | $\cdot 0.05$ | $\cdot 0.06$ | $=0.002994$ |
|  |  |  |  |  | $\Sigma$ | $=0.849017$ |


| $f_{3} \rightarrow B$ |  |  |  |  |  |  |
| :--- | :--- | :--- | ---: | :--- | :--- | :--- |
| $B$ | $E$ | $A$ | $E \rightarrow f_{3}$ | $A \rightarrow f_{3}$ | $f_{3}$ |  |
| $B=F$ | $T$ | $T$ | 0.002 | $\cdot 0.9$ | $\cdot 0.29$ | $=0.000522$ |
|  | $T$ | $F$ | 0.002 | $\cdot 0.05$ | $\cdot 0.71$ | $=0.000071$ |
|  | $F$ | $T$ | 0.998 | $\cdot 0.9$ | $\cdot 0.001$ | $=0.0008982$ |
|  | $F$ | $F$ | 0.998 | $\cdot 0.05$ | $\cdot 0.999$ | $=0.0498501$ |
|  |  |  |  |  | $\Sigma$ | $=0.0513413$ |

Hence, the message $f_{3} \rightarrow B$ is: | $B$ | $f_{3} \rightarrow B$ |
| :---: | :---: |
| $T$ | 0.849017 |
| $F$ | 0.0513413 |

Final Calculation $P(B=T \mid J=T)$
Now, we can compute $\mathrm{P}(B=T \mid J=T)$ by multiplying component-wise the messages arriving at $B$, and by normalizing the result:

$$
\begin{aligned}
P(B=T \mid J=T) & =\frac{f_{1} \rightarrow B(T) \cdot f_{3} \rightarrow B(T)}{f_{1} \rightarrow B(T) \cdot f_{3} \rightarrow B(T)+f_{1} \rightarrow B(F) \cdot f_{3} \rightarrow B(F)} \\
& =\frac{0.001 \cdot 0.849017}{0.001 \cdot 0.849017+0.999 \cdot 0.513413}=0.01628373
\end{aligned}
$$

### 16.5 Message Passing Algorithm: POS Tagging Example

The HMM tagging using message passing would work as follows:


Training data:

```
swat V flies N like P ants N
time N flies V like P an D arrow N
```

Trained HMM Model:

| $T_{1}$ | $\mathrm{P}\left(T_{1}\right)$ |
| :---: | :---: |
| N | 0.5 |
| V | 0.5 |


| $T_{i-1}$ | $T_{i}$ | $\mathrm{P}\left(T_{i} \mid T_{i-1}\right)$ |
| :---: | :---: | :---: |
| D | N | 1 |
| N | P | 0.5 |
| N | V | 0.5 |
| P | D | 0.5 |
| P | N | 0.5 |
| V | N | 0.5 |
| V | P | 0.5 | and


| $T_{i}$ | $W_{i}$ | $\mathrm{P}\left(W_{i} \mid T_{i}\right)$ |
| :---: | :---: | :--- |
| D | an | $2 / 3 \approx 0.666666667$ |
| D | * | $1 / 3 \approx 0.333333333$ |
| N | ants | $2 / 9 \approx 0.222222222$ |
| N | arrow | $2 / 9 \approx 0.222222222$ |
| N | flies | $2 / 9 \approx 0.222222222$ |
| N | time | $2 / 9 \approx 0.222222222$ |
| N | * | $1 / 9 \approx 0.111111111$ |
| P | like | 0.8 |
| P | $*$ | 0.2 |
| V | flies | 0.4 |
| V | swat | 0.4 |
| V | $*$ | 0.2 |

## Tagging Example

Slide notes:

## Tagging Example

- Example: "flies are like flies"
- Represent HMM as the following Bayesian Network:


Let us again use the example sentence "flies are like flies", which we used in a previous example with HMM. First, we will represent HMM configuration as a Bayesian Network with observable variables "hard-wired" to their values, as follows:


Slide notes:
POS Tagging as Message Passing

- Solving a completion problem
- Algorithm steps:
- Create a factor graph
- Hard-wire output variables
- Use message passing with maximization
- Find maximum-likely completion
- We will calculate only necessary messages

The corresponding factor graph is:


The messages are calculated as follows:

| $T_{1}$ | $m_{1}$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $D$ | 0 |  | $W_{1}$ | $m_{2}$ |
| $N$ | 0.5, flies | 1 |  |  |
| $P$ | 0 |  | an | 0 |
| $V$ | 0.5 |  | $\vdots$ | 0 |.

Calculation of $m_{3}$ is done as follows:


The other messages are:

| $T_{1}$ | $m_{4}\left(=m_{1} \cdot m_{3}\right)$ |  | $T_{2}$ | $m_{5}$ |
| :---: | :---: | :--- | :--- | :---: |
| $D$ | $0 \cdot 0=0$ |  |  |  |
| $D$ | $D$ | 0 |  |  |
| $N$ | $0.5 \cdot 2 / 9=1 / 9$ |  | $N$ | 0.1 |$m_{5}$ is calculated as follows:


| $m_{5}$ |  |  |
| :--- | :--- | :--- |
| $T_{2}=D$ | $T_{1}=D: 0 \cdot f_{3}$ |  |
|  | $T_{1}=N: \frac{1}{9} \cdot 0$ | $=0$ |
|  | $T_{1}=P: 0 \cdot 0.5$ | $=0$ |
|  | $T_{1}=V: 0.2 \cdot 0$ | $=0$ |
|  |  | $\max : 0$ |

$$
\begin{array}{rll} 
& =0 \\
& T_{1}=N: \frac{1}{9} \cdot 0 & =0 \\
& T_{1}=P: 0 \cdot 0.5 & =0 \\
& T_{1}=V: 0.2 \cdot 0.5 & =0.1 \\
& & \text { max:0.1 }
\end{array}
$$

$$
\begin{aligned}
& \begin{array}{rll|}
\end{array} \\
&
\end{aligned}
$$

To calculate $m_{9}$, we have the following intermediate calculations:

| $m_{9}$ |  | $m_{9}$ | $$ |  |
| :---: | :---: | :---: | :---: | :---: |
| $T_{3}=D$ | $T_{2}=D: 0 \cdot 0 \quad=0$ | $T_{3}=N$ |  |  |
|  | $T_{2}=N: \frac{1}{90} \cdot 0 \quad=0$ |  |  |  |
|  | $T_{2}=P: \frac{1}{50} \cdot 0.5=0.01$ |  |  |  |
|  | $T_{2}=V: \frac{1}{90} \cdot 0 \quad=0$ |  |  |  |
|  | max:0.01 |  |  |  |
| $m_{9}$ | $m_{8} \cdot f_{3}$ |  |  |  |
| $T_{3}=P$ | $T_{2}=D: 0 \cdot 0 \quad=0$ |  |  |  |
|  | $T_{2}=N: \frac{1}{90} \cdot 0.5=1 / 180$ |  |  |  |
|  | $T_{2}=P: \frac{1}{50} \cdot 0 \quad=0$ |  |  |  |
|  | $T_{2}=V: \frac{1}{90} \cdot 0.5=1 / 180$ |  |  |  |
|  | max:1/180 |  |  |  |



To calculate $m_{13}$, we have the following intermediate calculations:


| $m_{13}$ |  | $m_{12} \cdot f_{3}$ |
| :--- | :--- | :--- |
| $T_{4}=V$ | $T_{3}=D: 0 \cdot 0$ | $=0$ |
|  | $T_{3}=N: 0 \cdot 0.5$ | $=0$ |
|  | $T_{3}=P: \frac{1}{225} \cdot 0$ | $=0$ |
|  | $T_{3}=V: 0 \cdot 0$ | $=0$ |
|  |  | max:0 |



To maximize the product of probabilities of $T_{4}$ we calculate:

| $T_{4}$ | $m_{13} \cdot m^{2}$ |
| :---: | :---: |
| $D$ | $\frac{1}{450}$. |
| $N$ | $\frac{1}{450} \cdot$ |
| $P$ | $0 \cdot 0$ |
| $V$ | $0 \cdot 0$. |
|  |  |
| value. We ca |  |
|  |  |
|  |  |
| $T_{3}$ |  |
| $D$ | $m_{17}$ |
| $N$ | $2 / 9$ |
| $P$ | $1 / 9$ |
| $V$ | $1 / 9$ |

To find optimal $T_{3}$ we calculate:

| $T_{3}$ | $m_{9} \cdot m_{11} \cdot m_{17}$ |  |  |
| :---: | :---: | :--- | :--- | :--- |
| $D$ | $0.01 \cdot 0 \cdot \frac{2}{9}$ | $=0$ |  |
| $N$ | $0.01 \cdot 0 \cdot 0$ | $=0$ |  |
| $P$ | $\frac{1}{180} \cdot 0.8 \cdot \frac{1}{9}$ | $=1 / 2025$ |  |
| $V$ | $\frac{1}{180} \cdot 0 \cdot \frac{1}{9}$ | $=0$ |  |$\quad$ and we obtain: $T_{3}^{*}=P$


| $T_{3}$ | $m_{18}=m_{17} \cdot m_{11}$ |  | $T_{2}$ | $m_{19}=m_{18} \cdot f_{3}$ for $T_{3}=P$ |
| :---: | :---: | :---: | :---: | :---: |
|  | Then, | 0 |  | $\frac{4}{45} \cdot 0=0$ |
| $N$ | 0 | $N$ | $\frac{4}{45} \cdot \frac{1}{2}=2 / 45$ |  |
| $P$ | $\frac{1}{9} \cdot 0.8=4 / 45$ | $P$ | $\frac{4}{45} \cdot 0=0$ |  |
| $V$ | 0 |  | $V$ | $\frac{4}{45} \cdot \frac{1}{2}=2 / 45$ |

To find optimal $T_{2}$ we calculate:

| $T_{2}$ | $m_{19} \cdot m_{5} \cdot m_{7}$ |  |
| :---: | :---: | :--- |
| $D$ | $0 \cdot 0 \cdot \frac{1}{3}$ | $=0$ |
| $N$ | $\frac{2}{45} \cdot 0.1 \cdot \frac{1}{9}$ | $=1 / 2025$ | and we can choose either $N$ or $V$. Let us choose $T_{2}^{*}=V$.

To find optimal $T_{1}$ we calculate:

| $T_{1}$ | $m_{1} \cdot m_{3} \cdot m_{21}$ |  |
| :---: | :---: | :--- |
| $D$ | $0 \cdot 0 \cdot 0$ | $=0$ |

$\begin{array}{lcl}N & 0.5 \cdot \frac{2}{9} \cdot \frac{1}{225} & =1 / 2025 \\ P & 0 \cdot 0 \cdot 0 & =0\end{array}$ and we obtain $T_{1}^{*}=N$.
$\begin{array}{ll}P & 0 \cdot 0 \cdot 0\end{array}=0$
V $0.5 \cdot 0.4 \cdot 0=0$

To summarize, the most probable values of unknown variables $T_{1}, T_{2}, T_{3}$, and $T_{4}$ are:

$$
T_{1}^{*}=N \quad T_{2}^{*}=V \quad T_{3}^{*}=P \quad T_{4}^{*}=N
$$

