

# The iHMMpredict algorithm

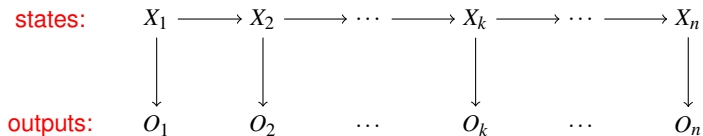
State sequence prediction in imprecise hidden Markov models

Jasper De Bock and Gert de Cooman

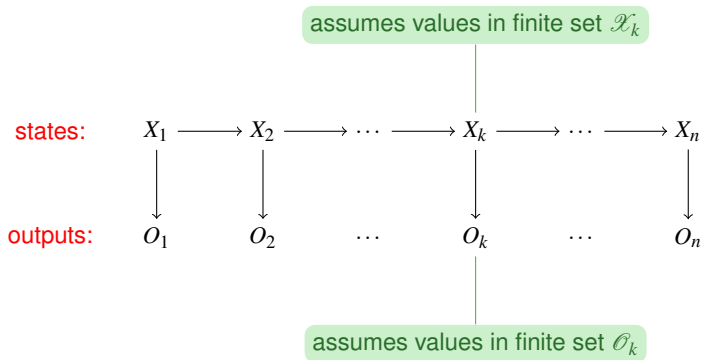
Ghent University, SYSTeMS  
{Jasper.DeBock,Gert.deCooman}@UGent.be

IDSIA, 30 November 2010

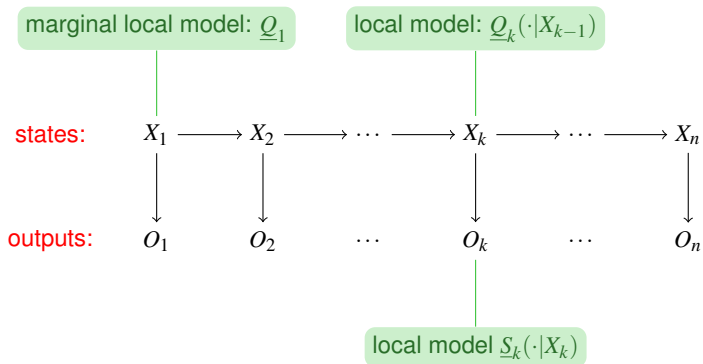
# Imprecise Hidden Markov Model (iHMM)



# Imprecise Hidden Markov Model (iHMM)



# Imprecise Hidden Markov Model (iHMM)



# Recursive construction of the joint

First step

local model:  $\underline{Q}_n(\cdot|X_{n-1})$

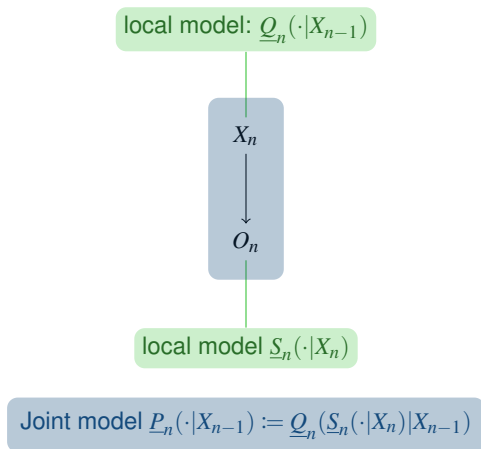
$X_n$

$O_n$

local model  $\underline{S}_n(\cdot|X_n)$

# Recursive construction of the joint

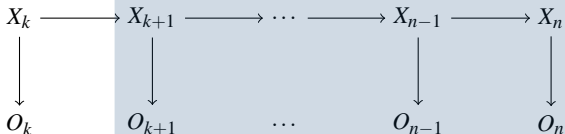
First step



# Recursive construction of the joint

## Recursive step

local model:  $\underline{Q}_k(\cdot|X_{k-1})$



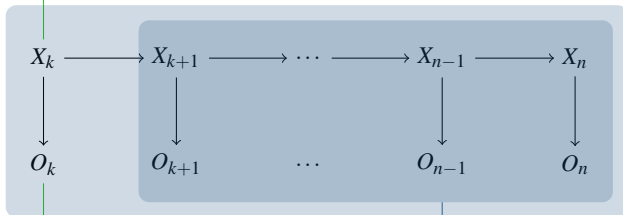
local model  $\underline{S}_k(\cdot|X_k)$

joint model  $\underline{P}_{k+1}(\cdot|X_k)$

# Recursive construction of the joint

## Recursive step

local model:  $\underline{Q}_k(\cdot|X_{k-1})$



local model  $\underline{S}_k(\cdot|X_k)$

joint model  $\underline{P}_{k+1}(\cdot|X_k)$

Independent natural extension  $\underline{E}_k(\cdot|X_k) := \underline{S}_k(\cdot|X_k) \otimes \underline{P}_{k+1}(\cdot|X_k)$

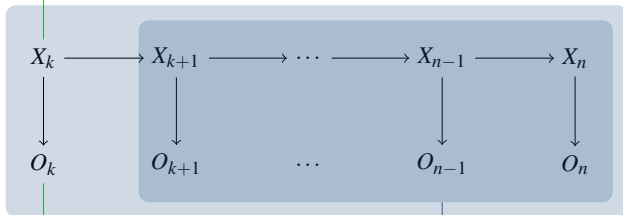
Joint model  $\underline{P}_k(\cdot|X_{k-1}) := \underline{Q}_k(\underline{E}_k(\cdot|X_k)|X_{k-1})$



# Recursive construction of the joint

## Recursive step

local model:  $\underline{Q}_k(\cdot|X_{k-1})$



local model  $\underline{S}_k(\cdot|X_k)$

joint model  $\underline{P}_{k+1}(\cdot|X_k)$

Independent natural extension  $\underline{E}_k(\cdot|X_k) := \underline{S}_k(\cdot|X_k) \otimes \underline{P}_{k+1}(\cdot|X_k)$

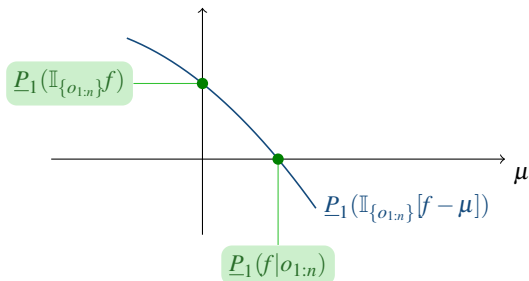
Joint model  $\underline{P}_k(\cdot|X_{k-1}) := \underline{Q}_k(\underline{E}_k(\cdot|X_k)|X_{k-1})$

$\underline{E}_k(\cdot|X_k)$  is factorising  $\Rightarrow$  very handy recursive expressions!

## Updating the joint with the observations $o_{1:n}$

Since all local models are strictly positive:  $\underline{P}_1(\{o_{1:n}\}) > 0$ .

Generalised Bayes Rule yields uniquely coherent value of  $\underline{P}_1(f|o_{1:n})$ .



$$\underline{P}_1(f|o_{1:n}) \leq 0 \Leftrightarrow \underline{P}_1(\mathbb{I}_{\{o_{1:n}\}}(f)) \leq 0.$$

# The notion of optimality we use: maximality

We define a partial order  $\succ$  on state sequences:

$$\hat{x}_{1:n} \succ x_{1:n} \Leftrightarrow \underline{P}_1(\mathbb{I}_{\{\hat{x}_{1:n}\}} - \mathbb{I}_{\{x_{1:n}\}} | o_{1:n}) > 0$$

# The notion of optimality we use: maximality

We define a partial order  $\succ$  on state sequences:

$$\hat{x}_{1:n} \succ x_{1:n} \Leftrightarrow \underline{P}_1(\mathbb{I}_{\{\hat{x}_{1:n}\}} - \mathbb{I}_{\{x_{1:n}\}} | o_{1:n}) > 0$$

A state sequence is optimal if it is undominated, or maximal:

$$\begin{aligned} \hat{x}_{1:n} \in \text{opt}(\mathcal{X}_{1:n} | o_{1:n}) &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) x_{1:n} \not\succeq \hat{x}_{1:n} \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}} | o_{1:n}) \leq 0 \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{o_{1:n}\}} [\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}}]) \leq 0, \end{aligned}$$

# The notion of optimality we use: maximality

We define a partial order  $\succ$  on state sequences:

$$\hat{x}_{1:n} \succ x_{1:n} \Leftrightarrow \underline{P}_1(\mathbb{I}_{\{\hat{x}_{1:n}\}} - \mathbb{I}_{\{x_{1:n}\}} | o_{1:n}) > 0$$

A state sequence is optimal if it is undominated, or maximal:

$$\begin{aligned} \hat{x}_{1:n} \in \text{opt}(\mathcal{X}_{1:n} | o_{1:n}) &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) x_{1:n} \not\succeq \hat{x}_{1:n} \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}} | o_{1:n}) \leq 0 \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{o_{1:n}\}} [\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}}]) \leq 0, \end{aligned}$$

$\underline{P}_1(\mathbb{I}_{\{o_{1:n}\}} [\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}}])$  can be easily determined recursively!

# The notion of optimality we use: maximality

We define a partial order  $\succ$  on state sequences:

$$\hat{x}_{1:n} \succ x_{1:n} \Leftrightarrow \underline{P}_1(\mathbb{I}_{\{\hat{x}_{1:n}\}} - \mathbb{I}_{\{x_{1:n}\}} | o_{1:n}) > 0$$

A state sequence is optimal if it is undominated, or maximal:

$$\begin{aligned} \hat{x}_{1:n} \in \text{opt}(\mathcal{X}_{1:n} | o_{1:n}) &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) x_{1:n} \not\succeq \hat{x}_{1:n} \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}} | o_{1:n}) \leq 0 \\ &\Leftrightarrow (\forall x_{1:n} \in \mathcal{X}_{1:n}) \underline{P}_1(\mathbb{I}_{\{o_{1:n}\}} [\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}}]) \leq 0, \end{aligned}$$

$\underline{P}_1(\mathbb{I}_{\{o_{1:n}\}} [\mathbb{I}_{\{x_{1:n}\}} - \mathbb{I}_{\{\hat{x}_{1:n}\}}])$  can be easily determined recursively!

Aim of the algorithm:

Determine  $\text{opt}(\mathcal{X}_{1:n} | o_{1:n})$  efficiently.

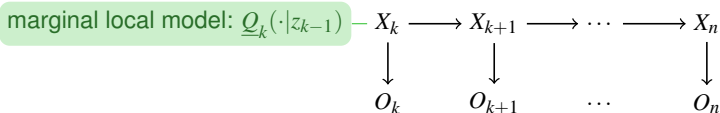
# More general optimality operators

$$\text{opt}(\mathcal{X}_{k-1} | z_{k-1}, o_{k:n})$$

$$\hat{x}_{k:n} \in \text{opt}(\mathcal{X}_{k-1} | z_{k-1}, o_{k:n})$$

$$\Leftrightarrow (\forall x_{k:n} \in \mathcal{X}_{k:n}) \underline{P}_k(\mathbb{I}_{\{o_{k:n}\}}[\mathbb{I}_{\{x_{k:n}\}} - \mathbb{I}_{\{\hat{x}_{k:n}\}}] | z_{k-1}) \leq 0.$$

These are the optimal sequences for part of the original iHMM:



The corresponding joint lower prevision is precisely  $\underline{P}_k(\cdot | z_{k-1})$ .

# The Principle of Optimality

$$\hat{x}_{k:n} \in \text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n}) \Rightarrow \hat{x}_{k+1:n} \in \text{opt}(\mathcal{X}_{k+1:n} | \hat{x}_k, o_{k+1:n}).$$

And so we can say that:

$$\text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n}) \subseteq S_k := \bigcup_{z_k \in \mathcal{X}_k} z_k \oplus \text{opt}(\mathcal{X}_{k+1:n} | z_k, o_{k+1:n}).$$

And therefore:

$$\text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n}) = \text{opt}(S_k | z_{k-1}, o_{k:n}).$$



# Checking if a final state $\hat{x}_n$ is optimal

$$\hat{x}_n \in \text{opt}(\mathcal{X}_n | z_{k-1}, o_k) \Leftrightarrow (\forall x_n \in \mathcal{X}_n) \underline{P}_n(\mathbb{I}_{\{o_n\}} [\mathbb{I}_{\{x_n\}} - \mathbb{I}_{\{\hat{x}_n\}}] | z_{n-1}) \leq 0.$$

This is OK if  $x_n = \hat{x}_n$ , so we can use the equivalent condition:

$$(\forall x_n \in \mathcal{X}_n \setminus \{\hat{x}_n\}) \underline{Q}_n(\mathbb{I}_{\{x_n\}} \underline{S}_n(\{o_n\} | x_n) - \mathbb{I}_{\{\hat{x}_n\}} \bar{S}_n(\{o_n\} | \hat{x}_n) | z_{n-1}) \leq 0.$$

So for every  $z_{n-1}$  we can easily find  $\text{opt}(\mathcal{X}_n | z_{n-1}, o_n)$ .

# Checking if a state sequence $\hat{x}_{k:n}$ is optimal

$$\hat{x}_{k:n} \in \text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n}) \\ \Leftrightarrow (\forall x_{k:n} \in \mathcal{X}_{k:n}) \underline{P}_k(\mathbb{I}_{\{o_{k:n}\}} [\mathbb{I}_{\{x_{k:n}\}} - \mathbb{I}_{\{\hat{x}_{k:n}\}}] | z_{k-1}) \leq 0.$$

Since  $\hat{x}_{k:n} \in \mathcal{S}_k$ , the inequality holds when  $x_k = \hat{x}_k$ .

This leads to the equivalent condition:

$$(\forall x_k \neq \hat{x}_k) (\forall x_{k+1:n} \in \mathcal{X}_{k+1:n}) \underline{Q}_k(\mathbb{I}_{\{x_k\}} \beta(x_{k:n}) - \mathbb{I}_{\{\hat{x}_k\}} \alpha(\hat{x}_{k:n}) | z_{k-1}) \leq 0.$$

where

$$\beta(z_{k:n}) := \underline{S}_k(\{o_k\} | z_k) \prod_{i=k+1}^n \underline{S}_i(\{o_i\} | z_i) \underline{Q}_i(\{z_i\} | z_{i-1}) \\ \alpha(z_{k:n}) := \bar{S}_k(\{o_k\} | z_k) \prod_{i=k+1}^n \bar{S}_i(\{o_i\} | z_i) \bar{Q}_i(\{z_i\} | z_{i-1}).$$

# Checking if a state sequence $\hat{x}_{k:n}$ is optimal

Equivalent formulations for  $\hat{x}_{k:n} \in \text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n})$

$$(\forall x_k \neq \hat{x}_k)(\forall x_{k+1:n} \in \mathcal{X}_{k+1:n}) \underline{Q}_k(\mathbb{I}_{\{x_k\}} \beta(x_{k:n}) - \mathbb{I}_{\{\hat{x}_k\}} \alpha(\hat{x}_{k:n}) | z_{k-1}) \leq 0$$

is equivalent to

$$(\forall x_k \neq \hat{x}_k) \underline{Q}_k(\mathbb{I}_{\{x_k\}} \beta_k^{\max}(x_k) - \mathbb{I}_{\{\hat{x}_k\}} \alpha(\hat{x}_{k:n}) | z_{k-1}) \leq 0,$$

where

$$\beta_k^{\max}(x_k) := \max_{\substack{z_{k:n} \in \mathcal{X}_{k:n} \\ z_k = x_k}} \beta(z_{k:n}).$$

# Checking if a state sequence $\hat{x}_{k:n}$ is optimal

Equivalent formulations for  $\hat{x}_{k:n} \in \text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n})$

$$(\forall x_k \neq \hat{x}_k) \underline{Q}_k(\mathbb{I}_{\{x_k\}} \beta_k^{\max}(x_k) - \mathbb{I}_{\{\hat{x}_k\}} \alpha(\hat{x}_{k:n}) | z_{k-1}) \leq 0$$

is equivalent to

$$(\forall x_k \neq \hat{x}_k) \alpha(\hat{x}_{k:n}) \geq \alpha_{\text{threshold}}(\hat{x}_k, x_k | z_{k-1}),$$

where

$$\begin{aligned} \alpha_{\text{threshold}}(\hat{x}_k, x_k | z_{k-1}) \\ := \min \left\{ \alpha \in \mathbb{R} : \underline{Q}_k(\mathbb{I}_{\{x_k\}} \beta_k^{\max}(x_k) - \alpha \mathbb{I}_{\{\hat{x}_k\}} | z_{k-1}) \leq 0 \right\} \end{aligned}$$

and finally, this is in turn equivalent to:

$$\alpha(\hat{x}_{k:n}) \geq \alpha^{\text{opt}}(\hat{x}_k | z_{k-1}) := \max_{x_k \neq \hat{x}_k} \alpha_{\text{threshold}}(\hat{x}_k, x_k | z_{k-1}).$$

# Determining the set of optimal $\hat{x}_{k:n}$

by backward-forward recursion

For  $k = n \rightarrow 1$ :

$$\text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n}) = \{\hat{x}_{k:n} \in S_k : \alpha(\hat{x}_{k:n}) \geq \alpha^{\text{opt}}(\hat{x}_k | z_{k-1})\}$$

Now recurse forward:

**First step:** Fix any  $\hat{x}_k \in \mathcal{X}_k$ .

Then there is some optimal state sequence  $z_{k:n} \in \text{opt}(\mathcal{X}_{k:n} | z_{k-1}, o_{k:n})$  such that  $z_k = \hat{x}_k$  if and only if

$$\max_{\substack{z_{k:n} \in \mathcal{X}_{k:n} \\ z_k = \hat{x}_k}} \alpha(z_{k:n}) =: \alpha_k^{\text{max}}(\hat{x}_k) \geq \alpha^{\text{opt}}(\hat{x}_k | z_{k-1}).$$

# Determining the set of optimal $\hat{x}_{k:n}$

by backward-forward recursion

**Second step:** Fix any  $\hat{x}_k$  for which  $\alpha_k^{\max}(\hat{x}_k) \geq \alpha^{\text{opt}}(\hat{x}_k|z_{k-1})$ .

Consider any first state  $\hat{x}_{k+1}$  of some element  $\hat{x}_{k+1:n}$  of  $\text{opt}(\mathcal{X}_{k+1:n}|\hat{x}_k, o_{k+1:n})$  then:

$$\begin{aligned}\alpha(\hat{x}_{k:n}) &\geq \alpha^{\text{opt}}(\hat{x}_k|z_{k-1}) \\ &\Leftrightarrow \alpha(\hat{x}_{k+1:n})\bar{S}_{k+1}(\{o_{k+1}\}|\hat{x}_{k+1})\bar{Q}_{k+2}(\{\hat{x}_{k+2}\}|\hat{x}_{k+1}) \geq \alpha^{\text{opt}}(\hat{x}_k|z_{k-1}) \\ &\Leftrightarrow \alpha(\hat{x}_{k+1:n}) \geq \alpha^{\text{opt}}(\hat{x}_{k:k+1}|z_{k-1}) := \frac{\alpha^{\text{opt}}(\hat{x}_k|z_{k-1})}{\bar{S}_k(\{o_k\}|\hat{x}_k)\bar{Q}_{k+1}(\{\hat{x}_{k+1}\}|\hat{x}_k)}\end{aligned}$$

So we see that there is some  $z_{k:n} \in \text{opt}(\mathcal{X}_{k:n}|z_{k-1}, o_{k:n})$  such that  $z_k = \hat{x}_k$  and  $z_{k+1} = \hat{x}_{k+1}$  if and only if

$$\alpha_{k+1}^{\max}(\hat{x}_{k+1}) \geq \alpha^{\text{opt}}(\hat{x}_{k:k+1}|z_{k-1}).$$

Go on until you reach the end of the chain ...