

Application: predicting the earthquake rate

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5th Sipta School

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What do we want to do?

Predicting future earthquake rates

We want to predict **number of earthquakes** and **seismic states** in future years, based on number of earthquakes in previous years, from 1900 to 2006.

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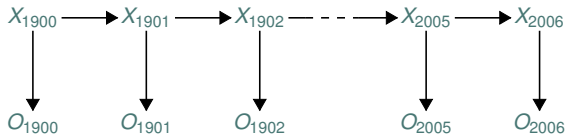
Assumptions:

- ▶ Earth can be in 3 possible seismic states $\lambda_1 = 13.15$, $\lambda_2 = 19.72$ and $\lambda_3 = 29.71$,
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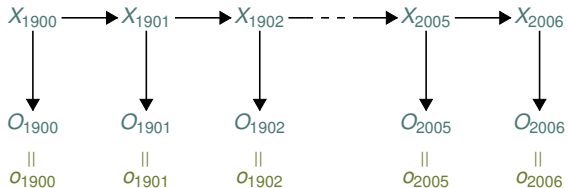
Our application: inference and learning

graphical representation: stationary imprecise hidden Markov model



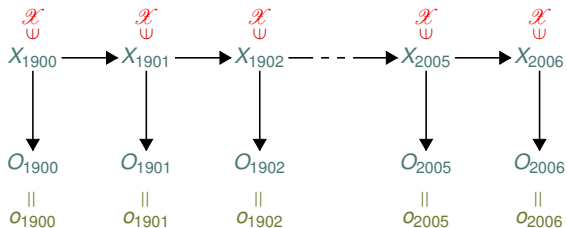
Our application: inference and learning

observations



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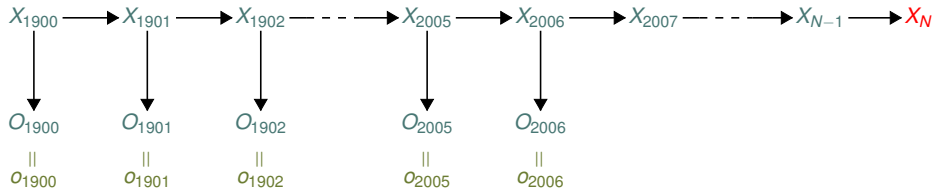
state variables



A state variable represents the seismic state: $\mathcal{X} = \{\lambda_1, \lambda_2, \lambda_3\}$

Our application: inference and learning

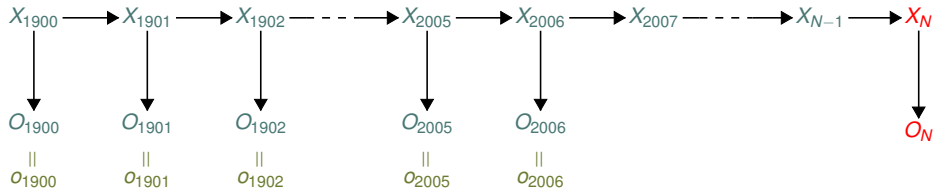
no observations for future years: Markov chain



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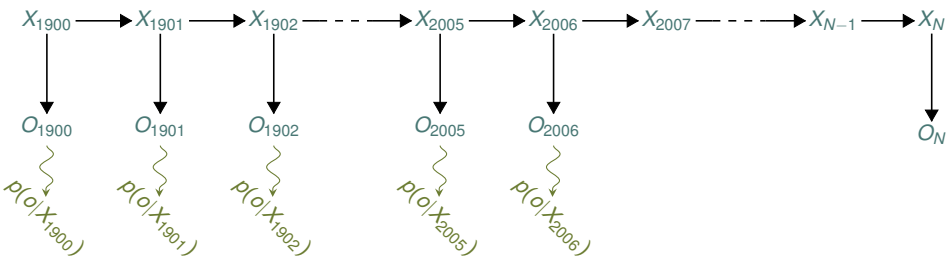
INFERENCE: predicting future earthquakes



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Our application: inference and learning

known emission model

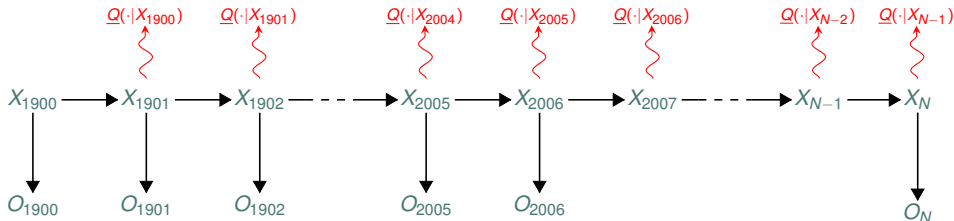


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Our application: inference and learning

LEARNING: unknown transition model



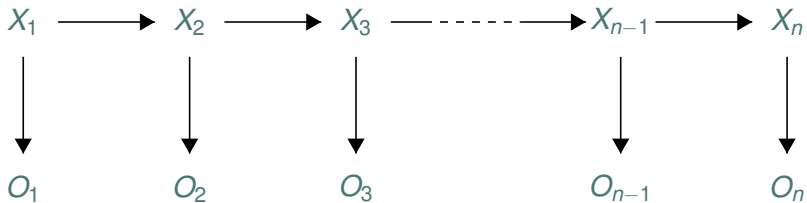
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The transition model is unknown: $Q(\cdot|X) = ?$

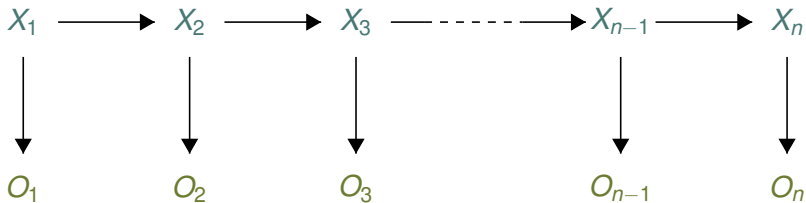
Our problem: estimating the
local models

Setting of our problem



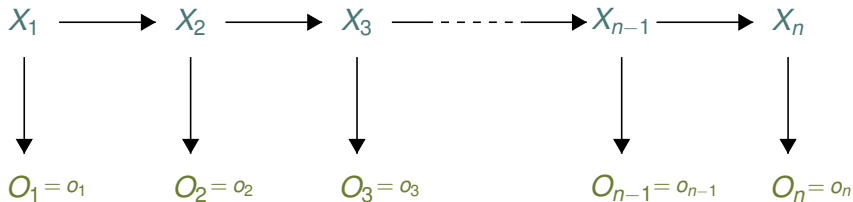
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Suppose we know the output sequence



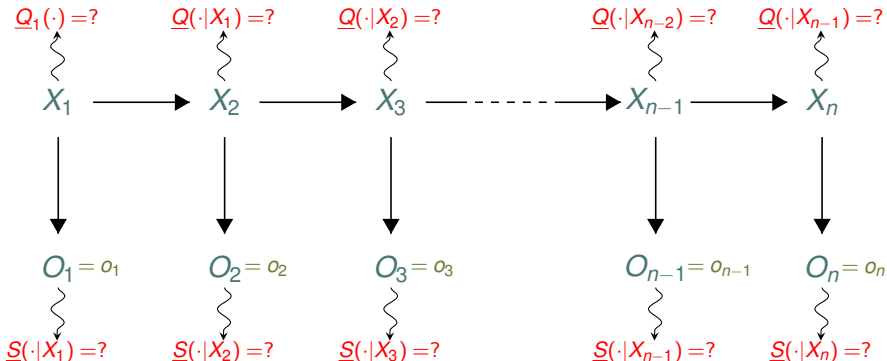
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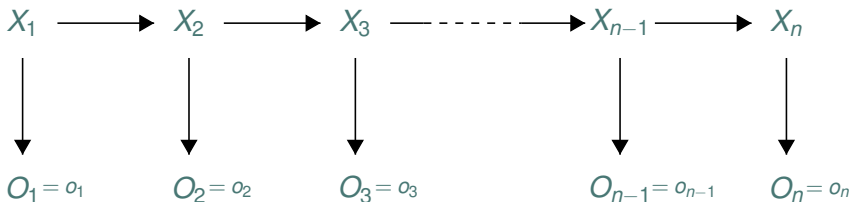
Suppose we know the output sequence: $O_{1:n} = o_{1:n} \in \mathcal{O}^n$,
we want to estimate the unknown **local uncertainty models**.



An easier problem

What if the state sequence were known?

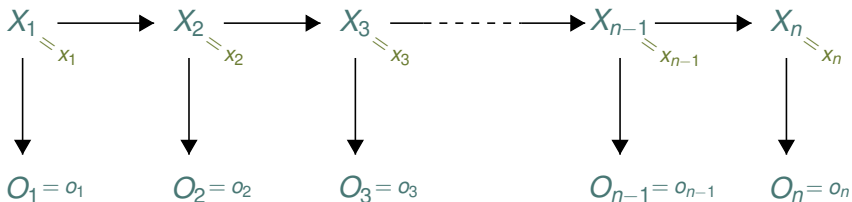
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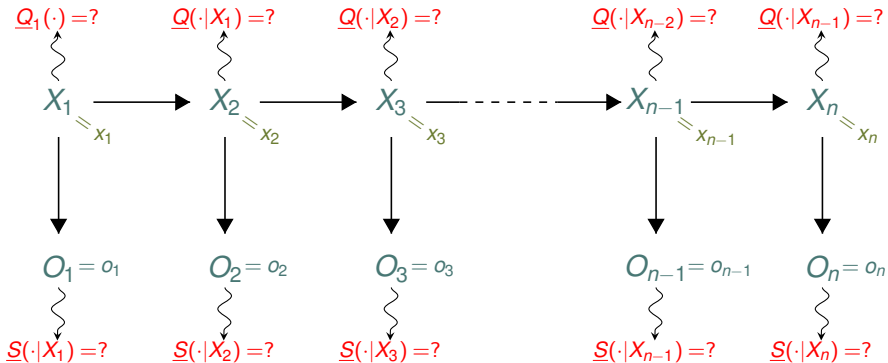
Suppose we know in addition also the state sequence: $X_{1:n} = x_{1:n} \in \mathcal{X}^n$



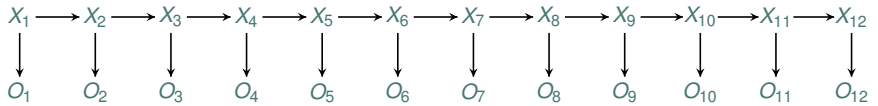
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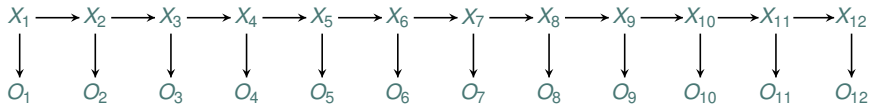
Suppose we know in addition also the state sequence: $X_{1:n} = x_{1:n} \in \mathcal{X}^n$,
how can we learn local models now?



Solution

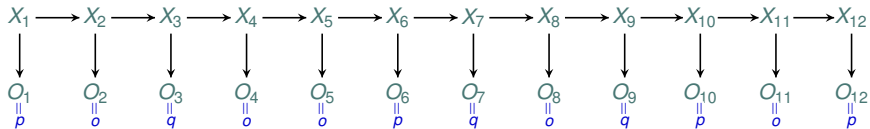


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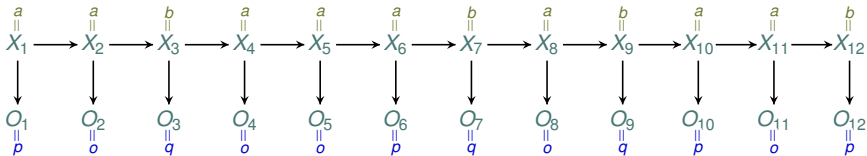
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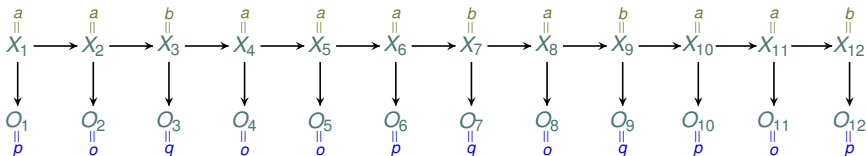
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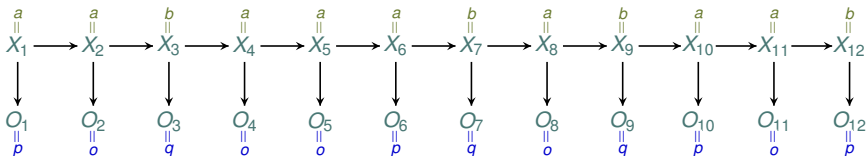
With (known) hidden state sequence $x_{1:n}$ and output sequence $o_{1:n}$ ($x, y \in \mathcal{X}$ and $z \in \mathcal{O}$):

n_x : number of times a state x is reached,

$n_{x,y}$: number of times a state transition from x to y takes place,

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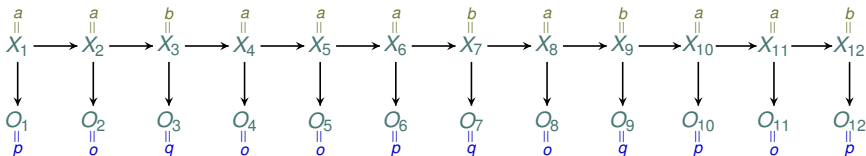
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Here:

$$\left. \begin{aligned} n_a &= 8, n_b = 4, \\ n_{a,a} &= 4, n_{a,b} = 4, n_{b,a} = 3, n_{b,b} = 0, \\ n_{a,o} &= 5, n_{a,p} = 3, n_{a,q} = 0, \\ n_{b,o} &= 0, n_{b,p} = 1, n_{b,q} = 3. \end{aligned} \right\}$$

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With these counts, how can we estimate local models?

Imprecise Dirichlet model

We use the **imprecise Dirichlet model (IDM)** to compute estimates for the local models. If $n(A)$ is the number of occurrences of an event A in N experiments, then the lower and upper probability of A according to an IDM are defined as

$$\underline{P}(A) = \frac{n(A)}{s + N} \quad \text{and} \quad \overline{P}(A) = \frac{s + n(A)}{s + N}.$$

$s > 0$ is the **number of pseudo-counts**, which is an inverse measure of the speed of convergence to a precise model.

Now, we use the quantities n_x , $n_{x,y}$ and $n_{x,z}$ (with $x, y \in \mathcal{X}$ and $z \in \mathcal{O}$) to estimate the imprecise transition and emission models:

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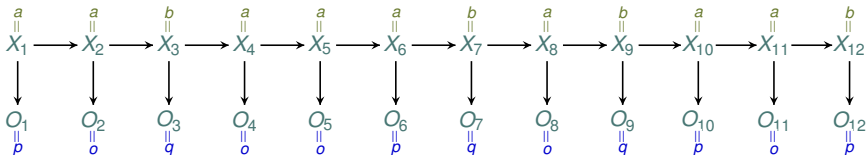
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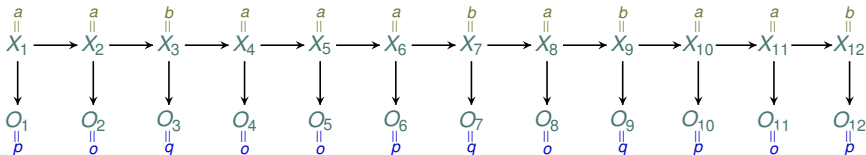
Example



(with $x, y \in \mathcal{X}$ and $z \in \mathcal{O}$):

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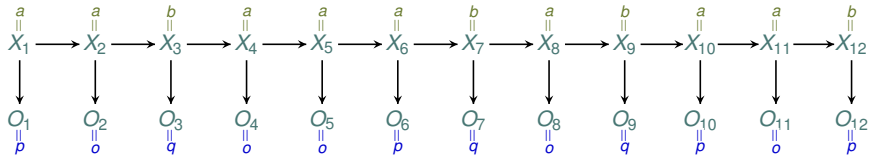
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Here, with $s = 2$:

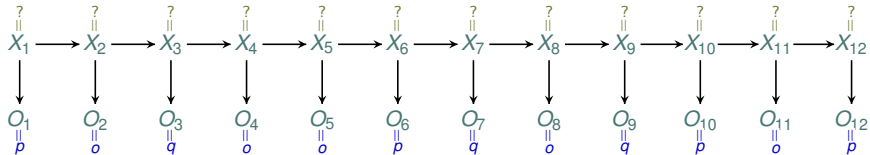
$$\begin{array}{llll} \underline{Q}(\{a\}|a) = 2/5, & \overline{Q}(\{a\}|a) = 3/5, & \underline{Q}(\{b\}|a) = 2/5, & \overline{Q}(\{b\}|a) = 3/5, \\ \underline{Q}(\{a\}|b) = 3/5, & \overline{Q}(\{a\}|b) = 1, & \underline{Q}(\{b\}|b) = 0, & \overline{Q}(\{b\}|b) = 2/5, \\ \underline{S}(\{o\}|a) = 1/2, & \overline{S}(\{o\}|a) = 7/10, & \underline{S}(\{o\}|b) = 0, & \overline{S}(\{o\}|b) = 1/3, \\ \underline{S}(\{p\}|a) = 3/10, & \overline{S}(\{p\}|a) = 1/2, & \underline{S}(\{p\}|b) = 1/6, & \overline{S}(\{p\}|b) = 1/2, \\ \underline{S}(\{q\}|a) = 0, & \overline{S}(\{q\}|a) = 1/5, & \underline{S}(\{q\}|b) = 1/5, & \overline{S}(\{q\}|b) = 3/5. \end{array}$$

But the state sequence is
hidden...

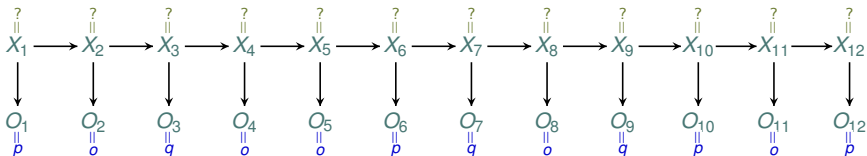
We are almost there



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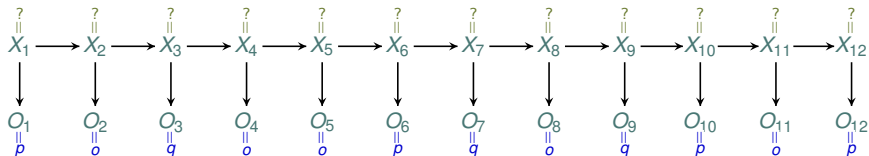


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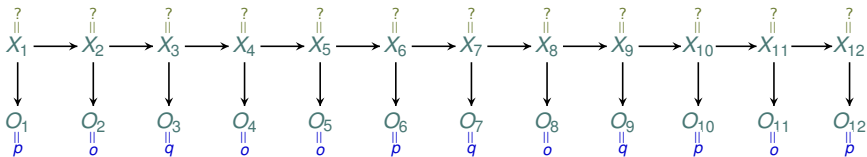
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(with $x, y \in \mathcal{X}$ and $z \in \mathcal{O}$) n_x , $n_{x,y}$ and $n_{x,z}$ are random variables N_x , $N_{x,y}$
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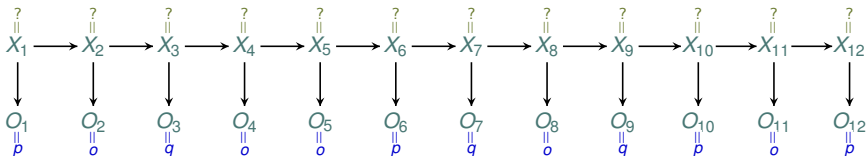


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Idea: instead of using real counts, use estimates:

$$\begin{aligned} &\hat{n}_x, \\ &\hat{n}_{x,y}, \\ &\hat{n}_{x,z}. \end{aligned}$$

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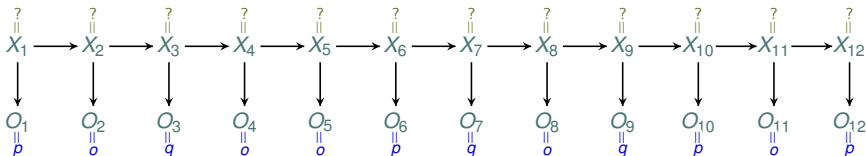


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Idea: instead of using **real counts**, use **expected counts**:

$$\begin{aligned}\hat{n}_x &= E(N_x | o_{1:n}, \theta^*), \\ \hat{n}_{x,y} &= E(N_{x,y} | o_{1:n}, \theta^*), \\ \hat{n}_{x,z} &= E(N_{x,z} | o_{1:n}, \theta^*).\end{aligned}$$

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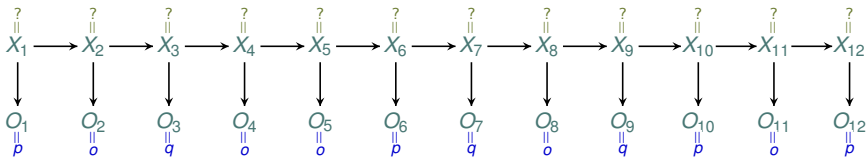
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$o_{1:n}$ is the known output sequence, and θ^* represents the model parameter.

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$o_{1:n}$ is the known output sequence, and θ^* represents the model parameter. We can calculate θ^* with the Baum–Welch algorithm, so the idea makes sense.

Estimated local models

With known state sequence $x_{1:n}$ ($x, y \in \mathcal{X}$ and $z \in \mathcal{O}$) :

$$\underline{Q}(\{y\}|x) = \frac{n_{x,y}}{s + \sum_{y^* \in \mathcal{X}} n_{x,y^*}} \text{ and } \bar{Q}(\{y\}|x) = \frac{s + n_{x,y}}{s + \sum_{y^* \in \mathcal{X}} n_{x,y^*}},$$

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Estimated local models

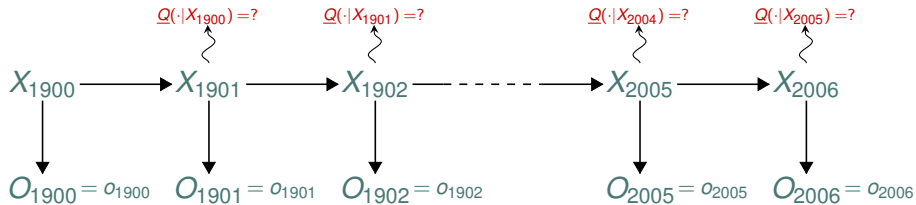
With **unknown** state sequence $X_{1:n}$ ($x, y \in \mathcal{X}$ and $z \in \mathcal{O}$):

$$\underline{Q}(\{y\}|x) = \frac{\hat{n}_{x,y}}{s + \sum_{y^* \in \mathcal{X}} \hat{n}_{x,y^*}} \text{ and } \bar{Q}(\{y\}|x) = \frac{s + \hat{n}_{x,y}}{s + \sum_{y^* \in \mathcal{X}} \hat{n}_{x,y^*}},$$

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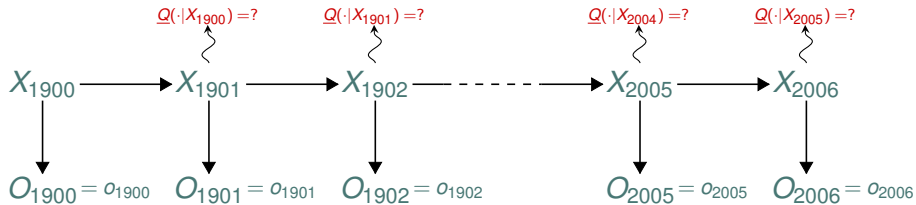
Predicting future earthquake rates

Learned model

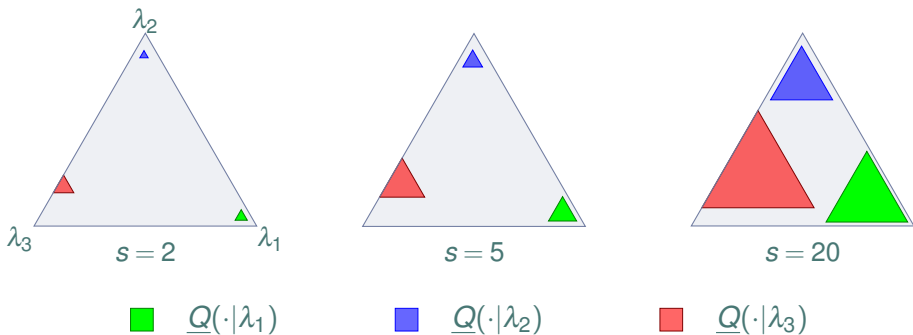


Based on the data, we learn the (imprecise) transition model.

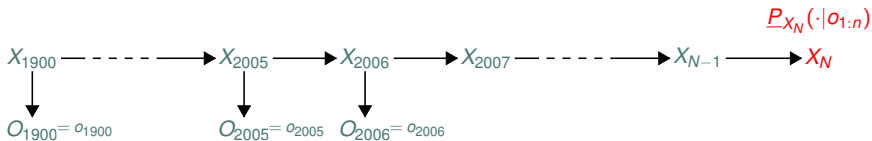
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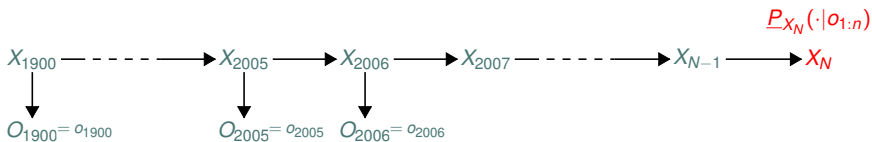


Predicting future earthquake rates

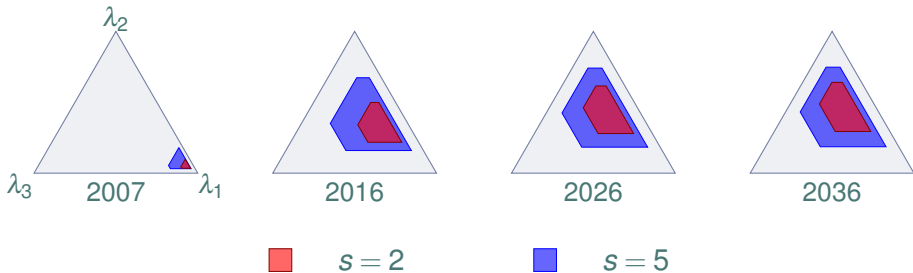


With the learned imprecise hidden Markov model, we predict future earthquake rates. We use the MePiCTIr algorithm (De Cooman et al., 2010).

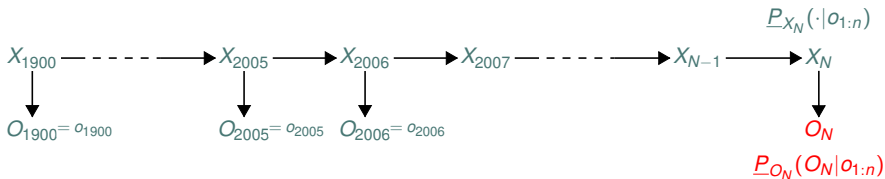
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