

# Hidden Markov models

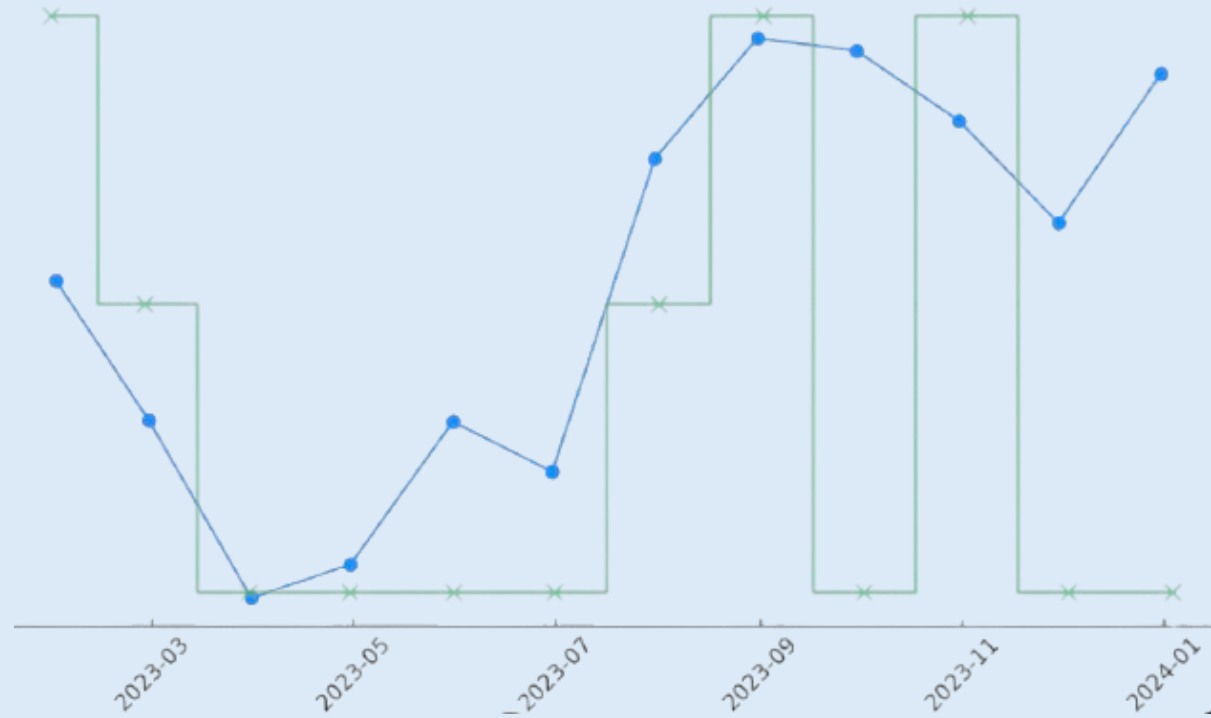
## Training session

*February 21st 2025*

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Sofia Ruiz Suarez, Eric St Marie.

# Hidden Markov models:

- Time-series models

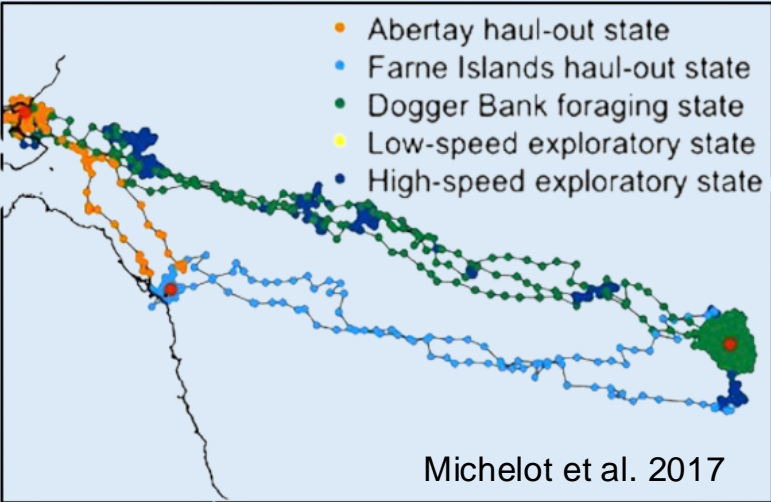


- observation arise from a hidden Markov process
- Markov process = the future depends only on the present

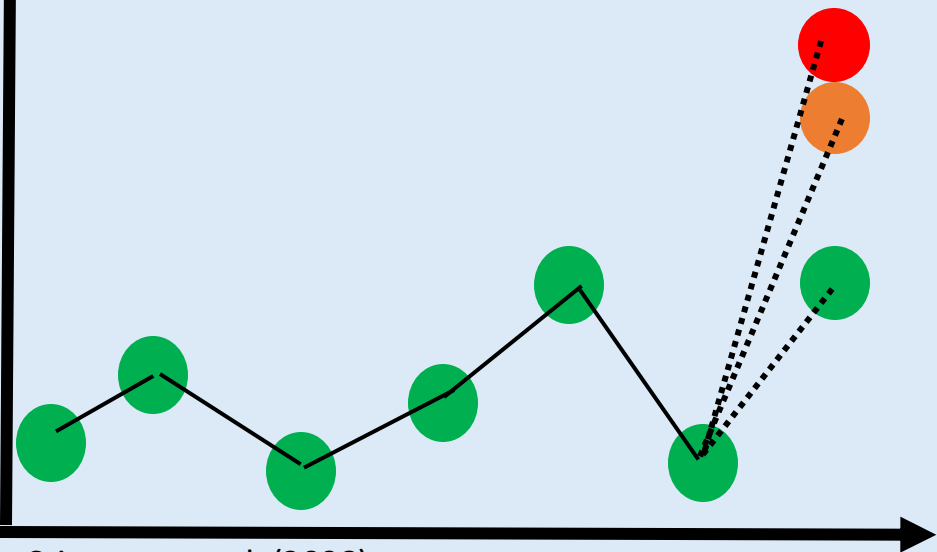
# Speech Recognition



# Behaviour segmentation



# Credit card fraud detection



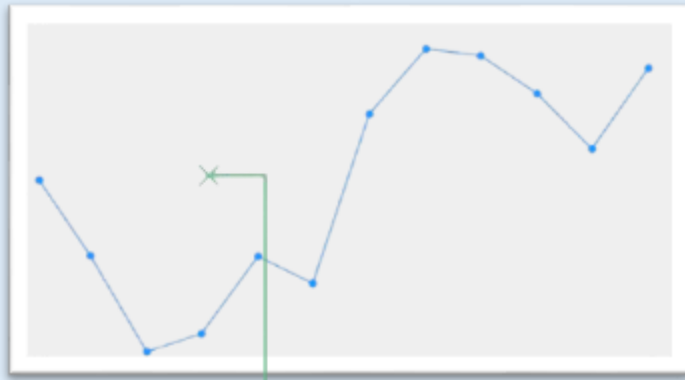
Srivastava et al. (2008)

# Alzheimer's disease progression stage identification:

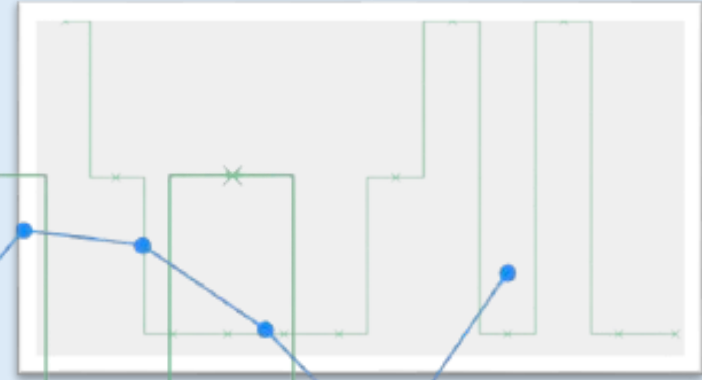


Lin and Song (2021)

# Two processes:



Observation process



Hidden states process

- Signal

- Distributed depending on the states at the same time

- Markovian

- Number of states is finite.

- Each transition from one state to the other is assigned a probability

2023-03

2023-05

2023-07

2023-09

2023-11

2024-01

# Markovian process:

*Example: weather in Vancouver*

Only two types of weather:



# Markovian process:

*Example: weather in Vancouver on **day t** is  $S_t$*

$$P(s_t = \text{cloud} \mid s_{t-1} = \text{cloud with rain}, s_{t-2} = \text{cloud with rain}, \dots, s_0 = \text{cloud})$$

# Markovian process:

*Example: weather in Vancouver on **day t** is  $S_t$*

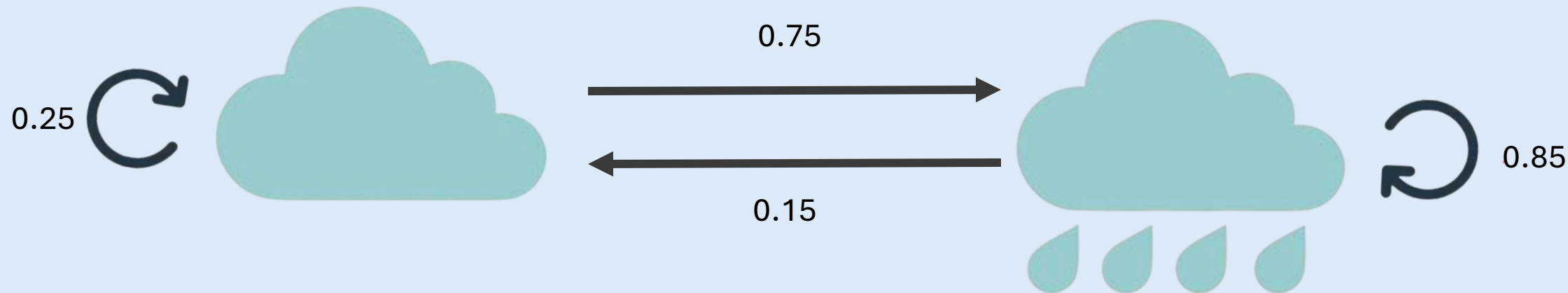
$$P(s_t = \text{cloud} \mid s_{t-1} = \text{cloud with rain}, s_{t-2} = \text{cloud with rain}, \dots, s_0 = \text{cloud}) = P(s_t = \text{cloud} \mid s_{t-1} = \text{cloud with rain})$$

**Markov property:** weather from tomorrow only depends on the weather from today

- The probability that it is not rainy on day  $t$  only depends on the weather at day  $t-1$

# Markovian process:

*Example: weather in Vancouver*





# Hidden Markov model:

*Example: weather in Vancouver*

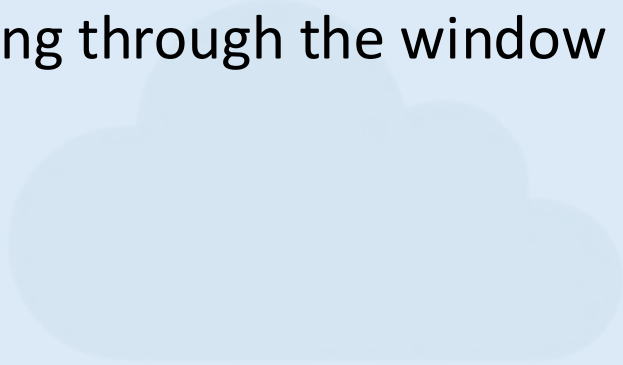


- Imagine you are in an appartement with a window very high up for several days
- You can't see outside, but you can see the light filtering through
- You're trying to figure out what the weather is like outside (rainy, cloudy).

# Hidden Markov model:

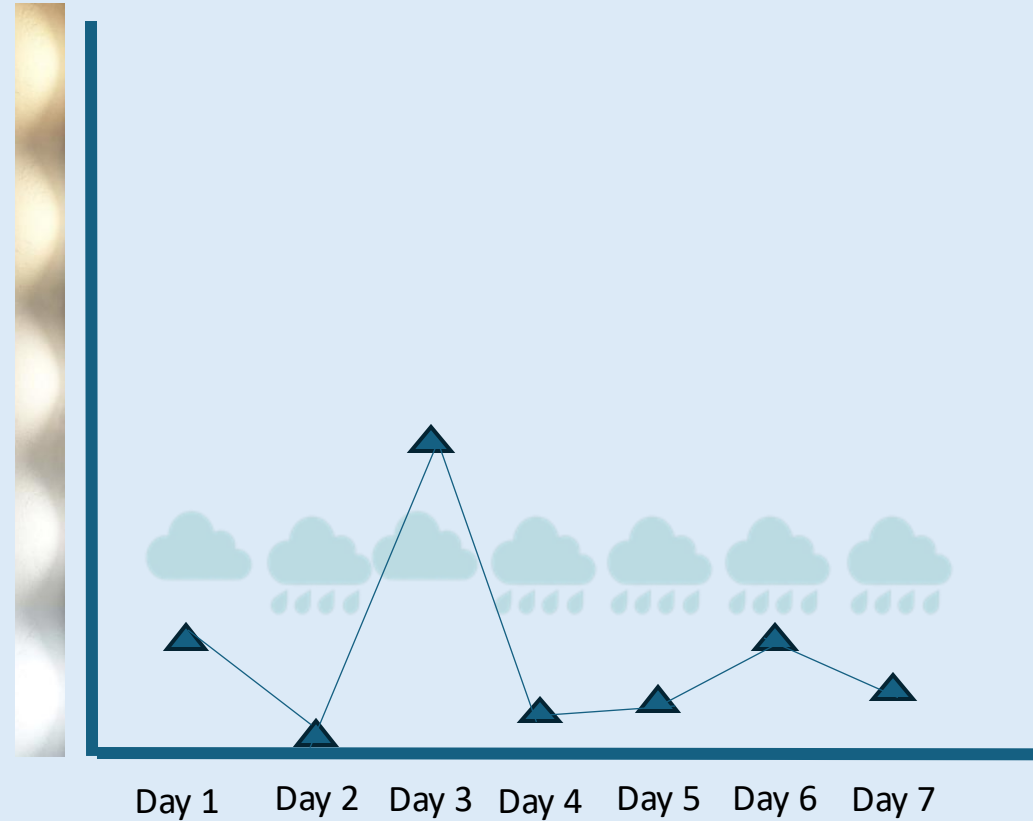
*Example: weather in Vancouver*

**Observation:** brightness of the light coming through the window



**Hidden state:** weather outside

brightness



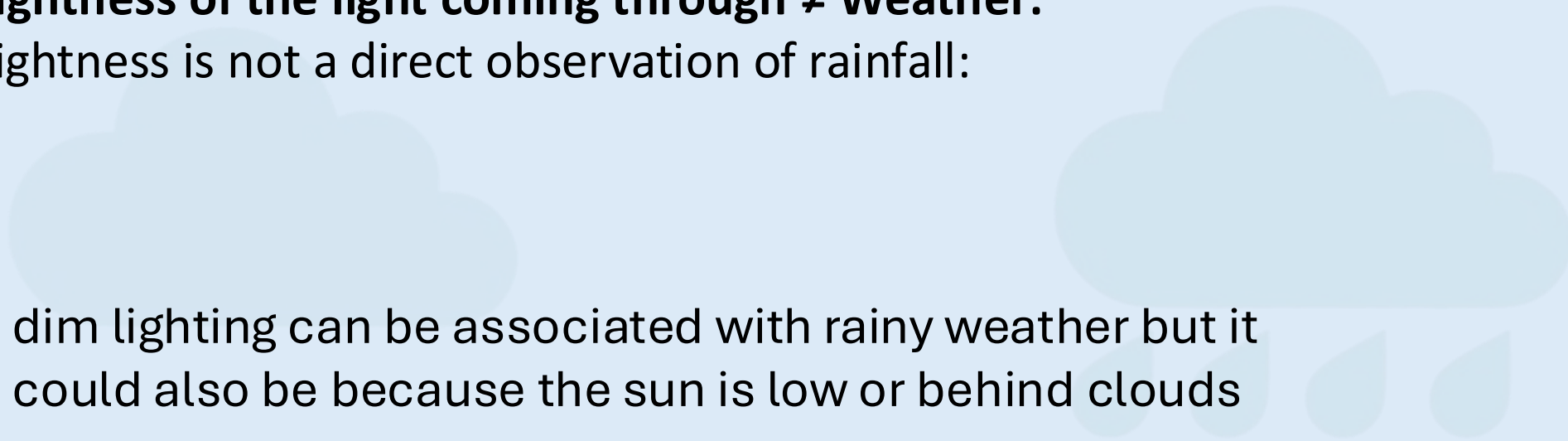
# Hidden Markov model:

*Example: weather in Vancouver*

**Brightness of the light coming through  $\neq$  Weather:**



Brightness is not a direct observation of rainfall:

- dim lighting can be associated with rainy weather but it could also be because the sun is low or behind clouds



# Hidden Markov model:

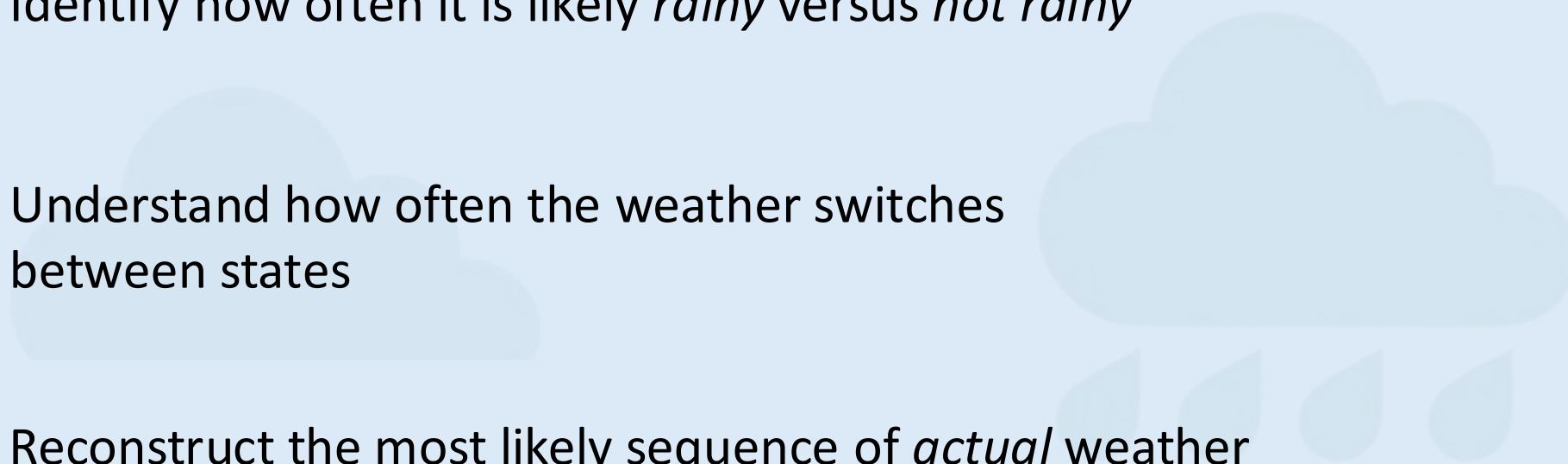
*Example: weather in Vancouver*

- The weather follows its own dynamic
- The distribution of the brightness depends on the weather:
  - When  , the brightness might follow a normal distribution with mean=50.
  - When  , the brightness could be much lower, around mean =30.

# Hidden Markov model:

*Example: weather in Vancouver*

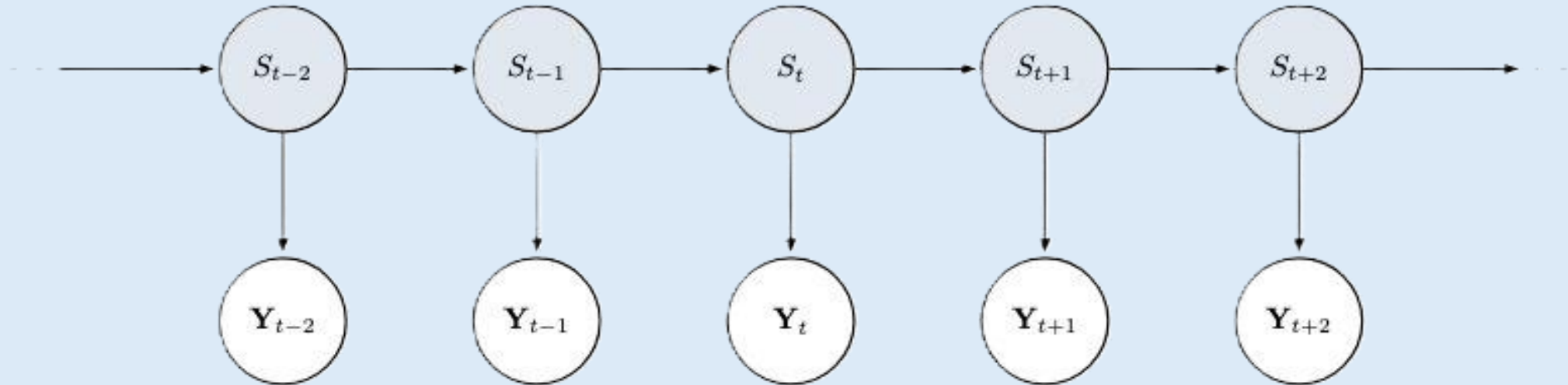
- Identify how often it is likely *rainy* versus *not rainy*
- Understand how often the weather switches between states
- Reconstruct the most likely sequence of *actual* weather states (rainy/not rainy) from the observed brightness: *state decoding*



# Hidden Markov model:

*Basic structure*

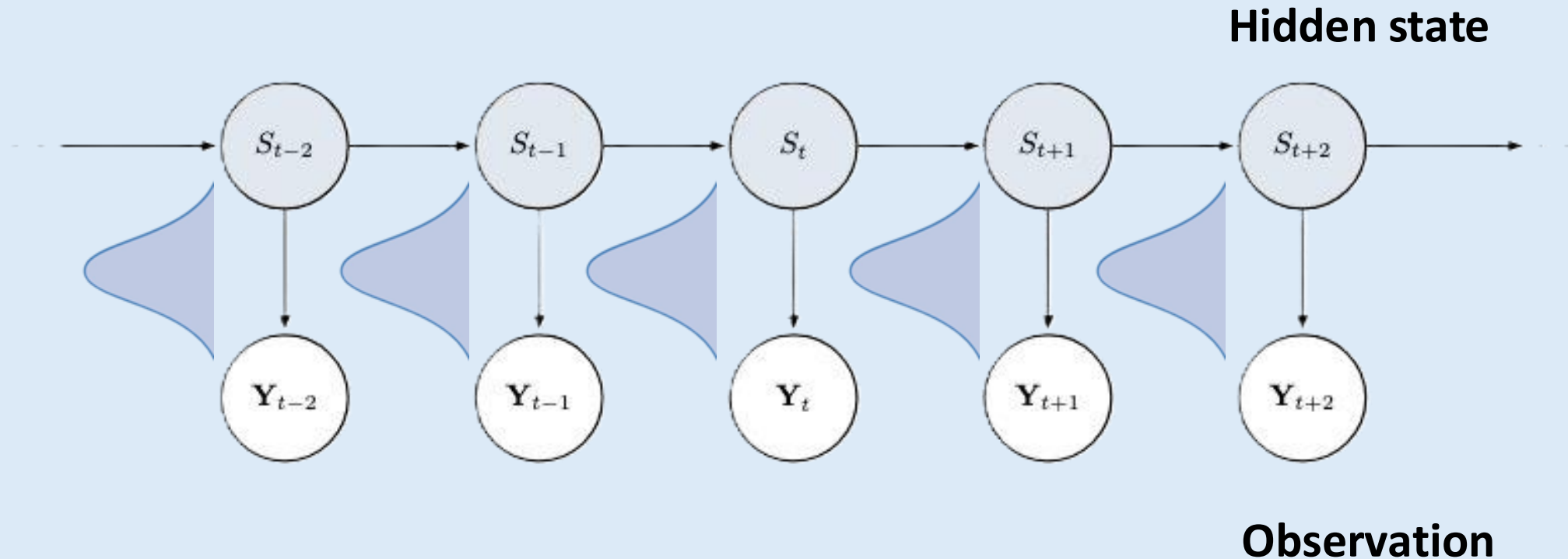
**Hidden state:** weather outside



**Observation:** brightness of  
the light coming through the  
window

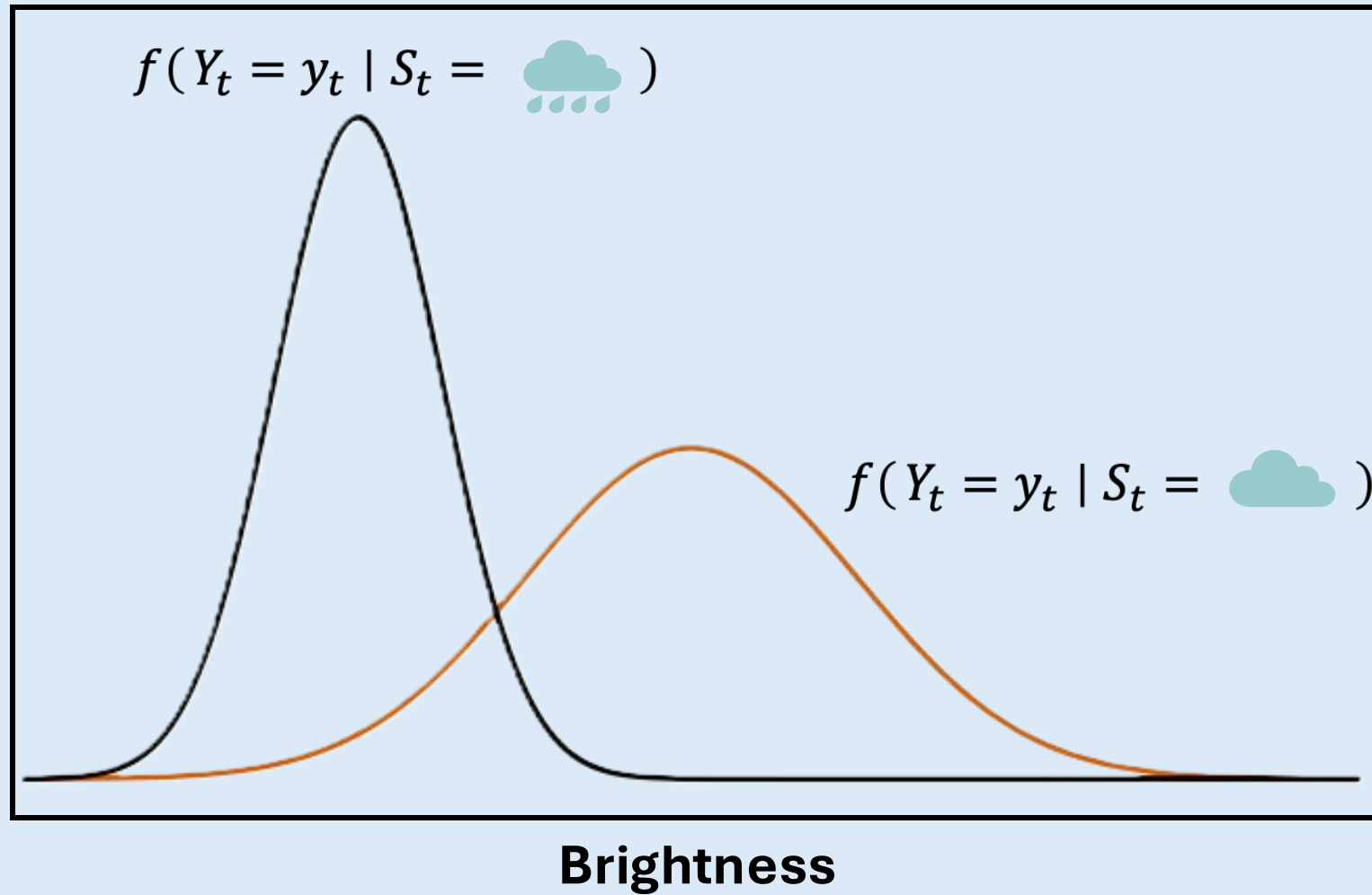
# Hidden Markov model:

The aim is to learn the hidden through the observed process



we establish a probabilistic relationship between both processes

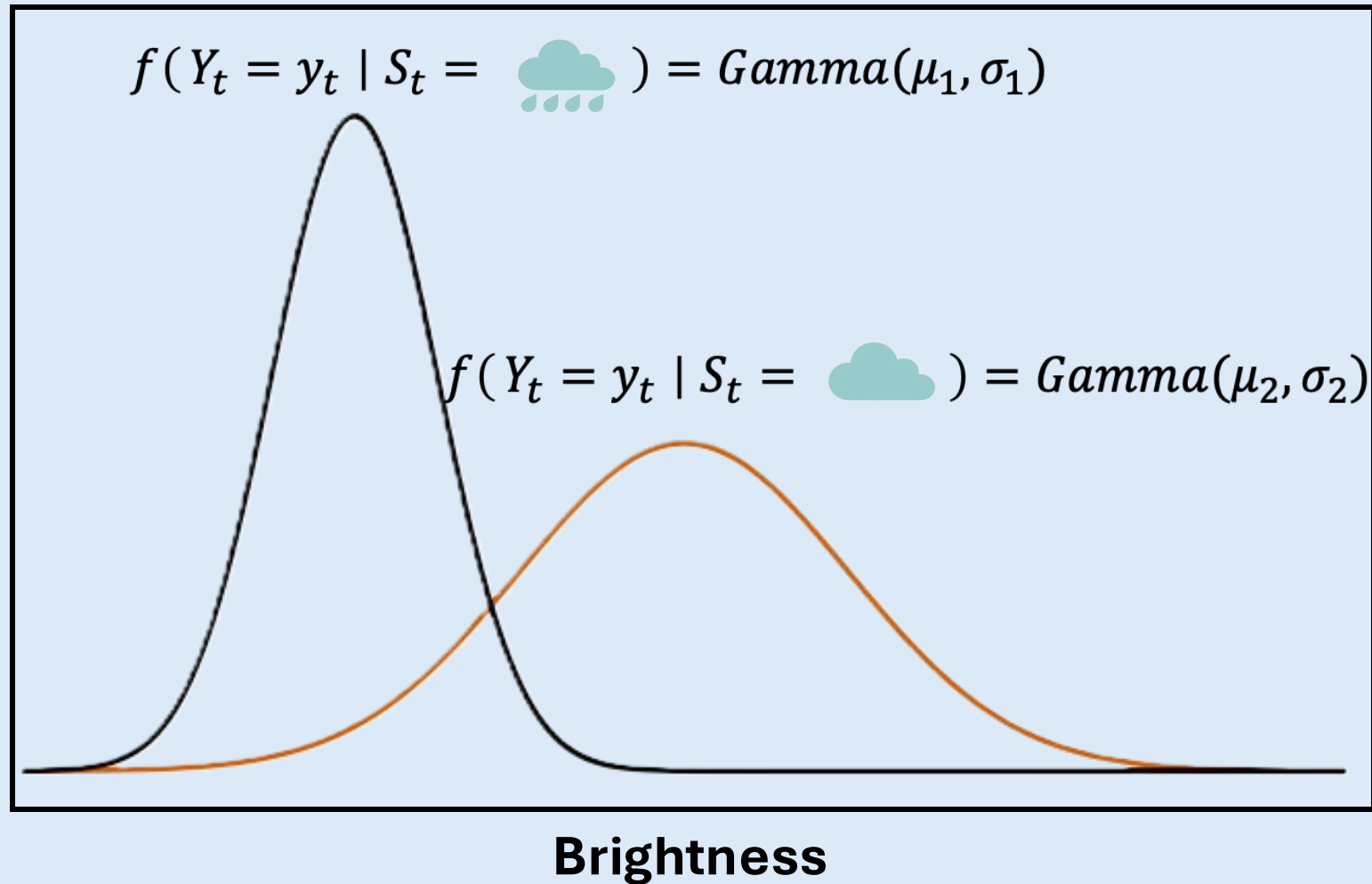
## State-dependent distributions:





# State-dependent distributions:

Specified with different parameter values



# Hidden Markov model:

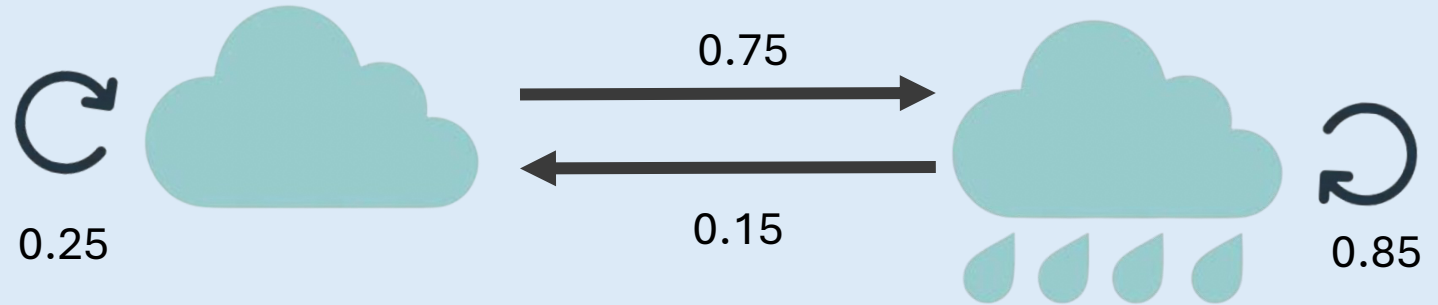
Can be fully characterized by:

- The number of states



- The initial distribution of the Markov process

- The transition probabilities



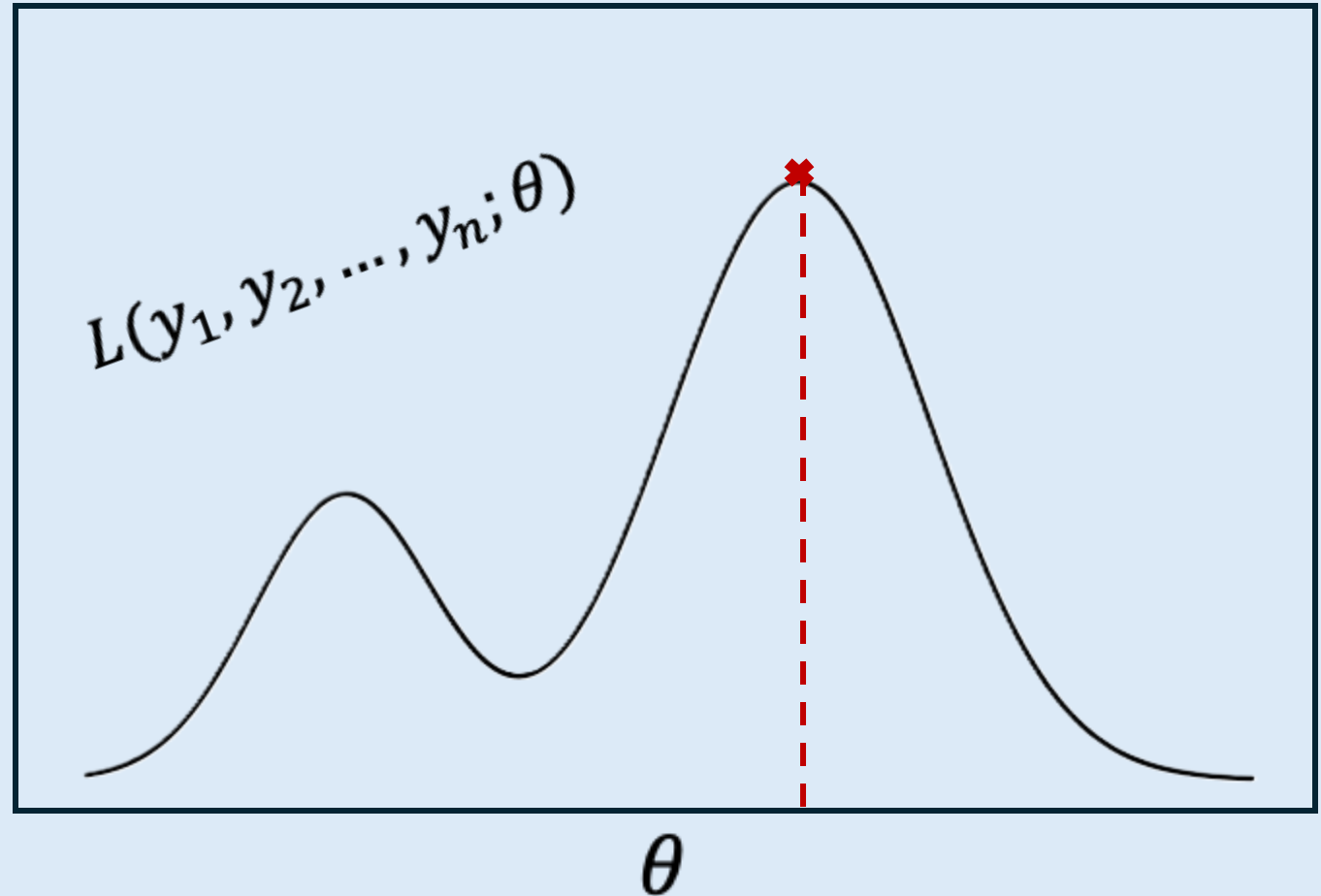
- The state-dependent distributions

$$f(Y_t = y_t \mid S_t = \text{cloud}) / f(Y_t = y_t \mid S_t = \text{rain})$$

# Maximum Likelihood:

*Specifying the model*

- We look for the parameter values ( $\theta$ ) that best explain our data
- The "most likely to have produced the data observed"
- The likelihood is maximized using numerical algorithms (multiple starting values)

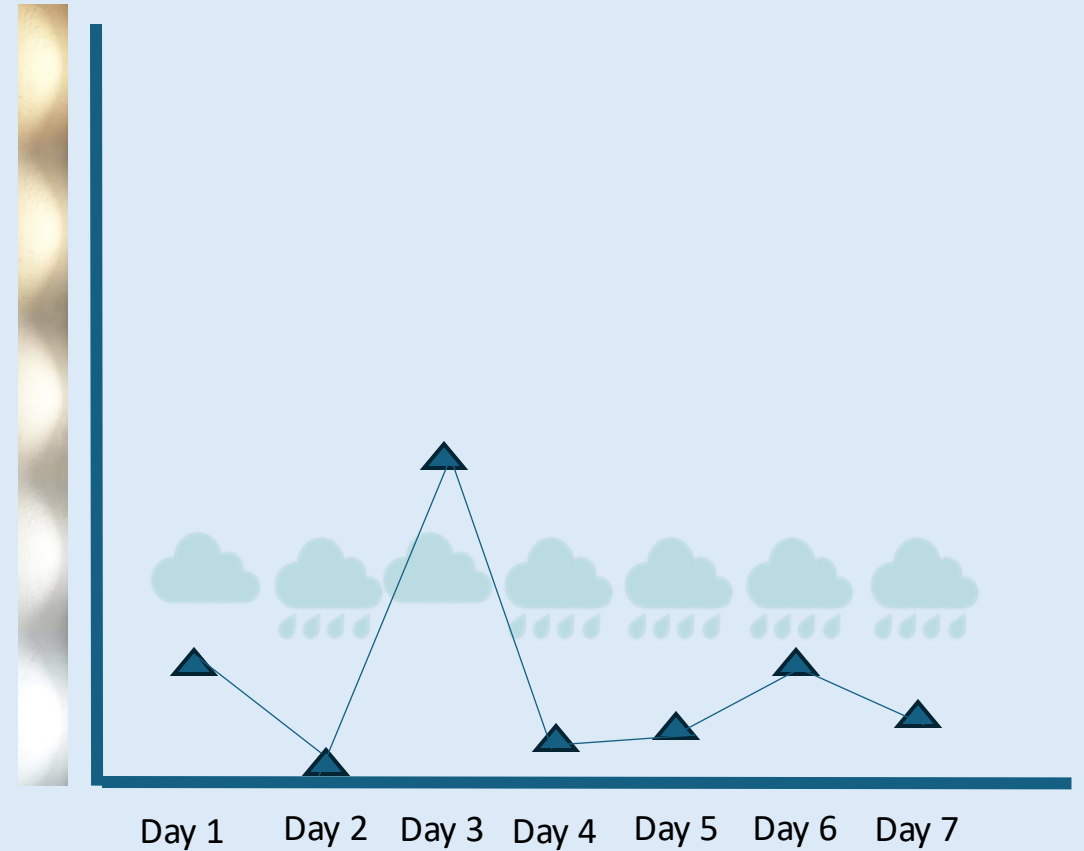


# State decoding:

*Making sense of the HMM*

- Often the goal is to identify (classify) the state process
- Probabilistic algorithms identify the state sequence best explaining the data observed
- Expert "interpretation" of the states

brightness



# Covariates:

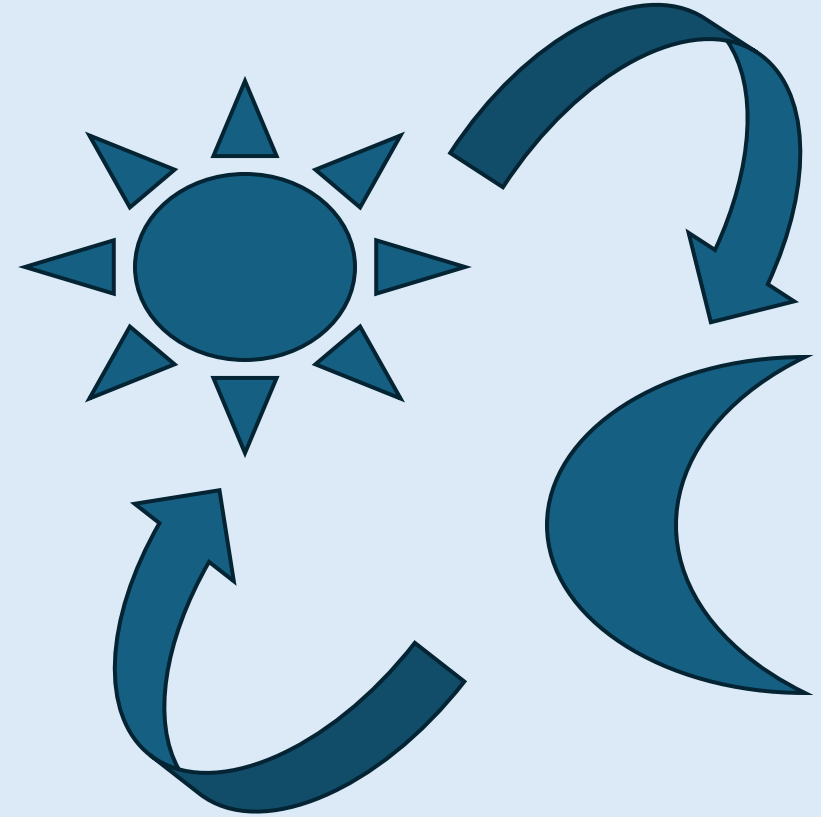
*Incorporating additional information*

- e.g., time of the day ( $x$ )
- In state-dependent distributions:

$$\mu_1 = h(x)$$

- In transition probabilities:

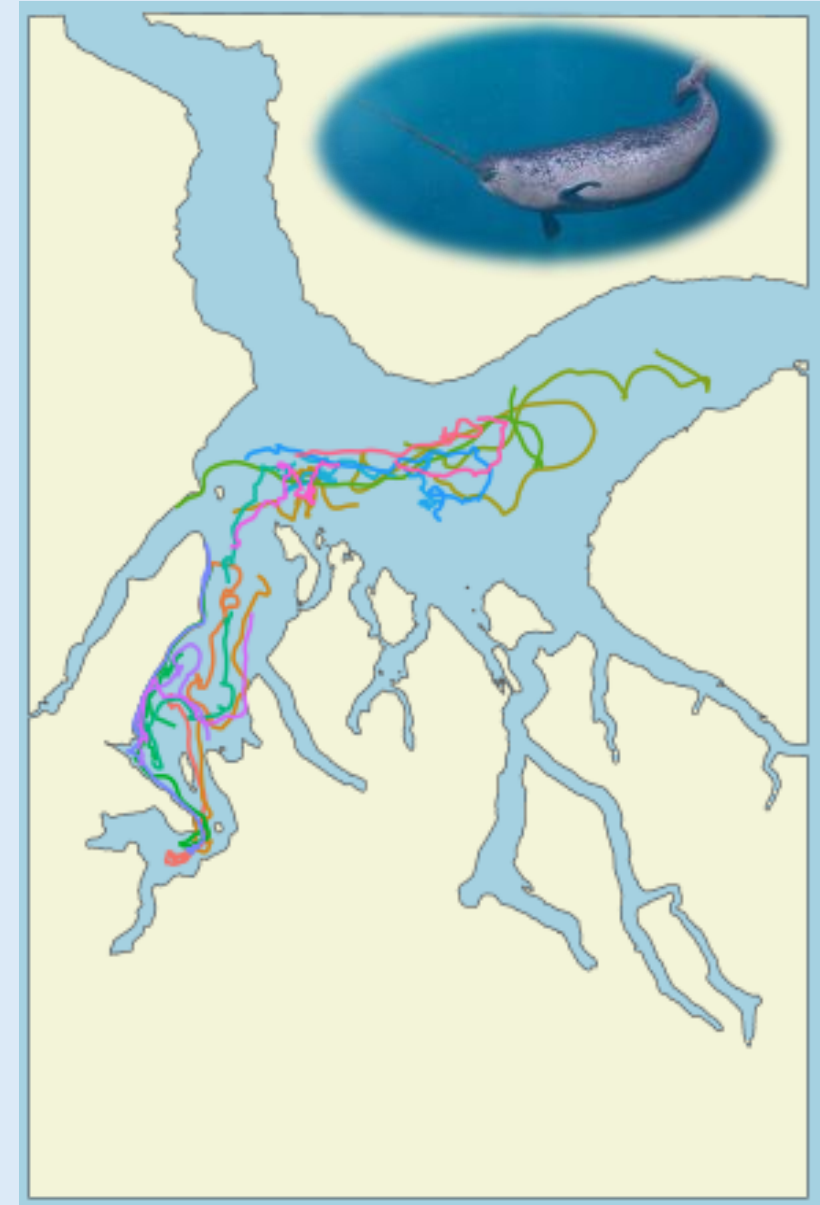
$$P(S_t = \text{☁} \mid S_{t-1} = \text{☁}) = g(x)$$



# Hidden Markov models R tutorial:

## *Narwhal data*

- Dr. Marianne Marcoux (Fisheries and Oceans, Canada)
- GPS coordinates over time (observed)
- Used to infer behaviours (hidden), e.g., travelling or foraging



# Hidden Markov models R tutorial:

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# Hidden Markov models R tutorial:

## *Blacktip reef shark*

- Accelerometer data, activity measurements (observed)
- Used to infer behaviours (hidden), e.g., travelling
- Incorporate covariates for transitions between states





# Thank you!

