





# IDALAB

EFFICIENT DATA ANALYTICS SOLUTIONS



PARIS  
LODRON  
UNIVERSITÄT  
SALZBURG

Simon's Hilarious

FOR AIRPLANE

# World state



# True dynamics

**Problem design - capture the right thing**

- Rarely the observation  $o$  is the state  $s$ , the world state is, but often we assume it is certainty equivalence!



• PRO MDP  $\Rightarrow$  MDPs!



# MDP



- Solve an SDM problem: Information  $\rightarrow$  Decision  $\rightarrow$  Information  $\rightarrow$  Decision  $\rightarrow$  ...

• Generally stochastic!

• Consequently we build a feedback system not planning too far in the future:

- Define a state  $s_t = h_t(o_t, a_{t-1}, o_{t-1}, a_{t-2}, o_{t-2} . . . )$ , as a function holding sufficient statistics until time step  $t$  for a decision - (example pong)

- Decision based on  $s_t$  via:  $a_t = \pi_t(s_t)$  - the policy - optimise an expected aggregate of future rewards







$$O_{t-1}$$

$$O_{t-2}$$



$O_t$

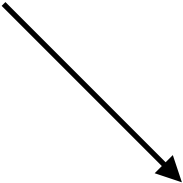


# Internal representation











$$\pi_t(s_t) = a_t$$

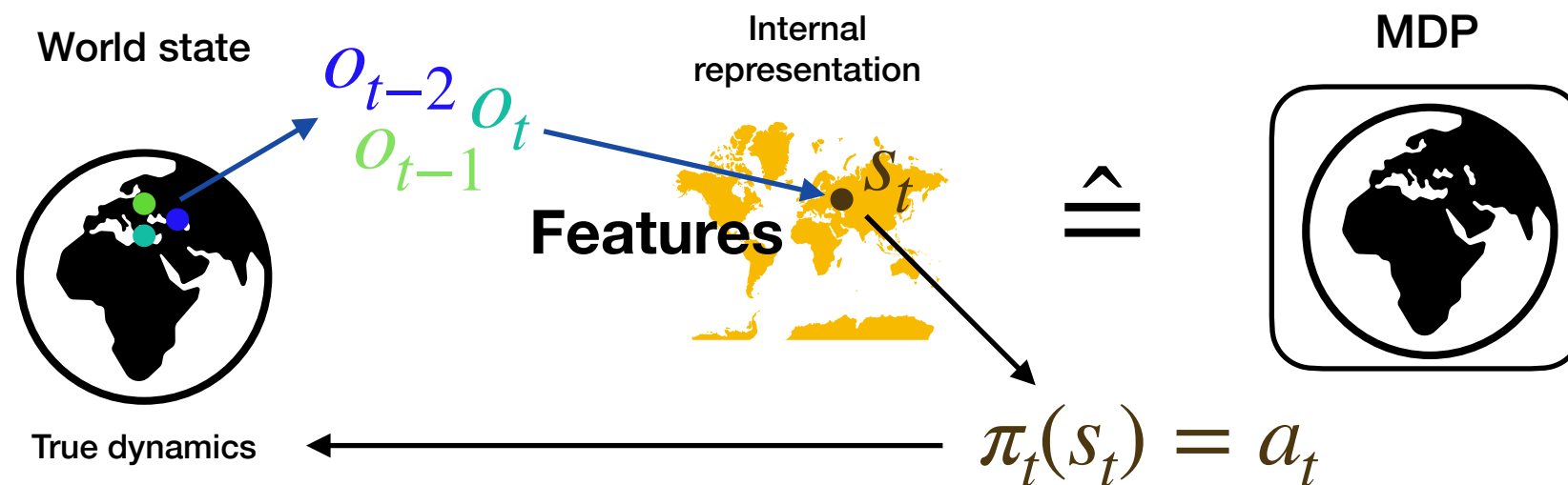


Featuring



# Problem design - capture the right thing

- Solve an SDM problem: Information  $\rightarrow$  Decision  $\rightarrow$  Information  $\rightarrow$  Decision  $\rightarrow \dots$
- Generally stochastic!
- Consequently we build a feedback system not planing too far in the future:
  - Define a **state**  $s_t = h_t(o_t, a_{t-1}, o_{t-1}, a_{t-2}, o_{t-2} \dots)$ , as a function holding **sufficient statistics** until time step  $t$  for a decision - (example pong)
  - Decision based on  $s_t$  via:  $a_t = \pi_t(s_t)$  - the policy - optimise an expected aggregate of future rewards



- Rarely the observation  $o$  is the state  $s$ , the world state is, but often we assume it is certainty equivalence!
- POMDP  $\Rightarrow$  MDPs!

# How bad is it?

- Linear POMDP: believe state -  $O_t = h_t(S_t, A_t, W_t)$ 
  - ➔ Static output feedback is NP hard (linear in  $O_t$  and dynamics)
  - ➔ General POMDPs are PSPACE hard
- There are ways out - separation principle:
  - ➔ Filtering  $\hat{s}_t = f(\{o_t\})$  - prediction problem
  - ➔ Action based on certainty equivalence
  - ➔ Optimal filtering - if dynamics are linear and noise is Gaussian - Kalman filtering - general belief propagation - LQG
  - ➔ Kalman filtered state - optimal in estimation and control
  - ➔ Estimate state with prediction  $S_t = h(\tau_t)$ ,  $\tau_t$  are time lags