Active Inference

An Introduction

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Introduction

What Is Active Inference?

Active Inference is a framework derived from the **Free Energy Principle (FEP)** developed by **Karl Friston**.

It explains *how agents perceive, learn, and act* by **minimizing** a quantity called **variational free energy**.

At its core, Active Inference is about:

- **Belief updating** (*perception/inference*)
- **Policy selection** (*action*)
- **Learning** (*model updating*)

All of this hinges on **Bayesian probability theory**.

What Are Bayesian Probabilities?

Bayesian probability is a **degree of belief**.

You start with a prior belief and then update it based on new evidence using **Bayes' Theorem**:

$$P(h \mid d) = \frac{P(d \mid h) \cdot P(h)}{P(d)}$$

Where:

- $P(h \mid d)$: **Posterior** (updated belief after seeing data d)
- $P(h)$: **Prior** (initial belief)
- $P(d \mid h)$: **Likelihood** (how probable the data is, assuming the hypothesis)
- $P(d)$: **Marginal likelihood** (normalization constant)

How Does Bayesian probability theory Fit into Active Inference?

Inference (Perception)

The agent uses **Bayesian inference** to infer hidden states of the world from observations.

Corresponding terms between Bayesian inference and active inference

- **Prior:** What the agent believes about the state of the world.
- **Likelihood:** The model of how observations are generated from hidden states.
- **Posterior:** Updated belief after observing something.

Action (Policy Selection)

Rather than just reacting, the agent **actively selects actions (policies)** that are expected to **minimize future surprise**.

Instead of computing surprise directly, it minimizes the **expected free energy**:

$$\mathbb{E}[G(\pi)] = \underbrace{\text{Expected divergence from preferred outcomes}}_{\text{Risk}} + \underbrace{\text{Expected information gain}}_{\text{Ambiguity reduction}}$$

Here again, **Bayesian reasoning** plays a central role:

- Beliefs about outcomes given actions are updated using Bayesian inference.
- Policies are selected to reduce uncertainty and fulfill prior preferences.

Learning (Model Updating)

Agents refine their internal **generative model** using **Bayesian updates**.

- The generative model

$$P(o, s) = P(o \mid s) \cdot P(s)$$

  is adjusted to better explain the sensory input.
- Parameters (e.g., transition probabilities, observation models) are updated based on observed data.

Variational Bayes in Active Inference

In practice, exact Bayesian inference is hard. So Active Inference uses **Variational Bayes**:

- It approximates the true posterior $P(s \mid o)$ with a simpler distribution $Q(s)$.
- Minimizes **variational free energy**:

$$F = \mathbb{E}_Q \left[\ln Q(s) - \ln P(o, s) \right]$$

Minimizing F makes $Q(s)$ closer to the true posterior and aligns beliefs with observations.

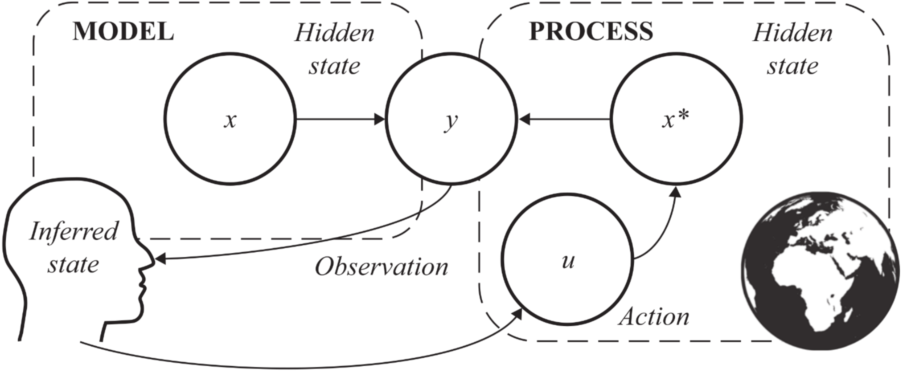

Figure: **Visual Summary of Active Inference**. Active Inference emerges as an integrative framework, synthesizing ideas from Bayesian inference, predictive processing, and the Free Energy Principle. It bridges concepts such as Bayes' theorem and generative models with processes like self-organization, niche construction, and planning as inference.

pymdp

The library includes tools to:

1. Define generative models that encode beliefs about how hidden states produce observations.
2. Implement belief updating, policy evaluation, and policy selection based on expected free energy.
3. Simulate agents that perceive, act, and plan in synthetic or task-specific environ- ments.

Simulation

Initial Setup pymdp Simulation

- **Goal:** Simulate an agent regulating temperature using Active Inference.
- **Environment:**
  - **A matrix** encodes noisy perception: $P(o \mid s)$
  - **B matrix** defines state transitions: $P(s' \mid s, a)$
  - **C vector** encodes preferences over outcomes (e.g., avoid cold/hot)
- **Agent setup:**
  - 3 hidden states (cold, optimal, hot)
  - 3 possible observations and 3 actions (left, stay, right)
  - Uses ‘pymdp.Agent‘ with A, B, C specified

Perception–Action Cycle in the Simulation

Each time step:

1. **Observation:** Agent observes the environment (e.g., sees 'cold')
2. **Inference:** `agent.infer_states(o)` updates beliefs $Q(s)$
3. **Policy Selection:** `agent.infer_policies()` evaluates actions
4. **Action Sampling:** `agent.sample_action()` chooses next move
5. **Environment Update:** State transitions using B and observation via A
6. **Logging:** Observations, beliefs, actions, and true states saved to DataFrame

The agent performs Active Inference by minimizing expected free energy and tracking internal state transitions.

	obs_temperature_observation	belief_temperature_state	action	state
0	0	[0.8, 0.10000000000000006, 0.10000000000000006]	0	0
1	0	[0.8595041322314049, 0.10743801652892568, 0.03...	0	0
2	0	[0.863115306810519, 0.107889413351315, 0.02899...	0	0
3	0	[0.863331500824629, 0.10791643760307869, 0.028...	0	1
4	1	[0.10791805416743239, 0.8633444333394585, 0.02...	1	1
5	0	[0.49181466313994227, 0.4918146631399421, 0.01...	1	1
6	1	[0.1107016838112753, 0.8856134704902014, 0.003...	1	1
7	1	[0.015376741010890337, 0.9841114246969785, 0.0...	1	1
8	2	[0.015321845290023266, 0.98059809856148, 0.004...	1	1
9	2	[0.014896398299711011, 0.95336949118149, 0.031...	1	1

Figure: **Simulation Table: Observations, Beliefs, Actions, and States** A step-by-step record of the microorganism's interaction with its environment. Each row shows what the agent observed, its belief distribution across temperature states, the action it chose, and the true environmental state. The agent gradually converges to and maintains itself in the optimal zone.

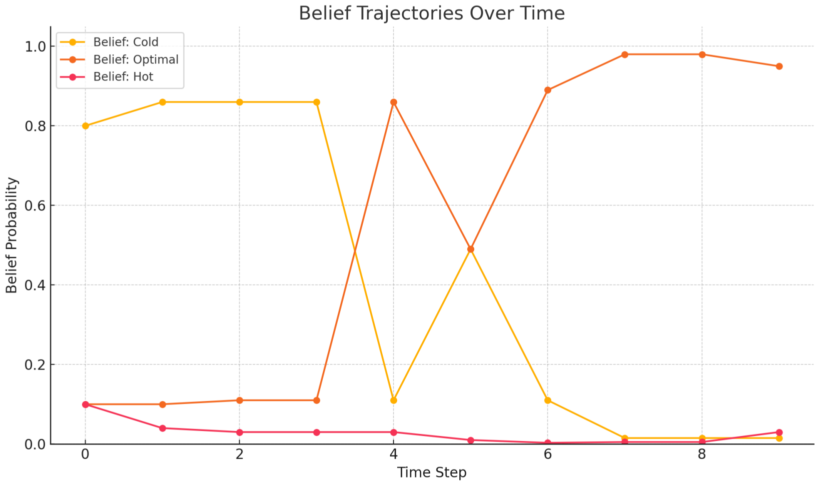

Figure: **Belief Trajectories Over Time** This plot shows how the microorganism's belief over its environmental temperature evolves during simulation. Initially, it strongly believes it is in a cold state, but over time, its beliefs shift toward the optimal state, guided by observations and prior preferences encoded through Active Inference.

Conclusion

Conclusion

- **Active Inference** provides a powerful framework to unify **perception**, **action**, and **learning** as **inferential processes**.
- It builds on the **Free Energy Principle**, offering a biologically plausible account of adaptive behavior.
- The framework supports both **theoretical understanding** and **practical modeling** of cognitive systems.
- Through **pymdp**, we can explore real-world applications in AI, neuroscience, and psychology.
- Ultimately, Active Inference provides a solid applicable concept on **how living systems make sense of the world**.

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Thank you for your attention!