

Adaptive WM

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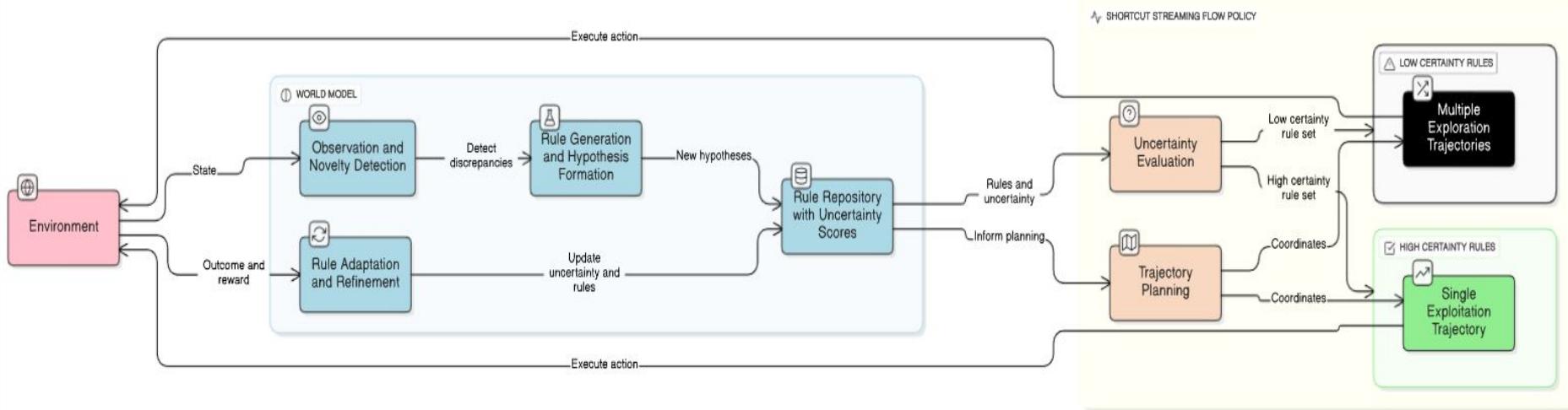
Overall Architecture

RQ- Can we have adaptive world model that can observe , reason and adapt its understanding of the world as the agent explores by modifying its own rules?

Proposed architecture -

World Model (WM) = The scientist (generates hypotheses, maintains rules)

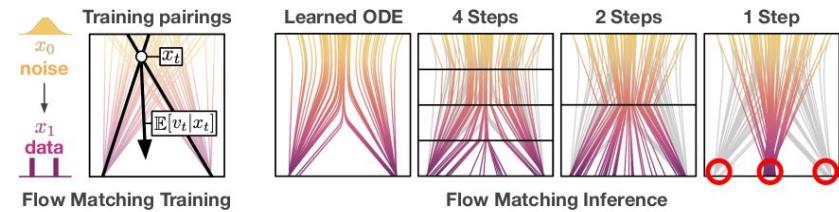
Shortcut Streaming Flow Policy = The experimenter (efficiently tests hypotheses by jumping through state-action space/state space)



What are shortcuts

RQ- How can we make diffusion models generate in ONE step instead of 128 steps, without sacrificing quality?

$$x_t = (1 - t)x_0 + tx_1 \quad \text{and} \quad v_t = x_1 - x_0.$$



$$\bar{v}_\theta(x_t, t) \approx \mathbb{E}_{x_0, x_1 \sim D} [v_t \mid x_t] \quad \mathcal{L}^F(\theta) = \mathbb{E}_{x_0, x_1 \sim D} [||\bar{v}_\theta(x_t, t) - (x_1 - x_0)||^2]$$

Shortcuts

Condition the network on BOTH:

1. **Current noise level (t):** Where am I in the denoising process?
2. **Desired step size (d):** How big of a jump am I taking?

Self Consistency property of shortcuts

$$x'_{t+d} = x_t + s(x_t, t, d) d.$$

$$s(x_t, t, 2d) = s(x_t, t, d)/2 + s(x'_{t+d}, t+d, d)/2$$

$$\mathcal{L}^S(\theta) = E_{x_0 \sim \mathcal{N}, x_1 \sim D, (t, d) \sim p(t, d)} \left[\underbrace{\|s_\theta(x_t, t, 0) - (x_1 - x_0)\|^2}_{\text{Flow-Matching}} + \underbrace{\|s_\theta(x_t, t, 2d) - s_{\text{target}}\|^2}_{\text{Self-Consistency}} \right],$$

where $s_{\text{target}} = s_\theta(x_t, t, d)/2 + s_\theta(x'_{t+d}, t+d, d)/2$ and $x'_{t+d} = x_t + s_\theta(x_t, t, d)d$.

Example and Implications of shortcut models

1. Ask model: "From $x=2$, take step $d=0.25$ " → model says "go +3" → land at $x=2.75$
2. Ask model: "From $x=2.75$, take step $d=0.25$ " → model says "go +3.2" → land at $x=5.95$
3. Target for $d=0.5$: average = $(3 + 3.2)/2 = 3.1$
4. Train: $s(x=2, d=0.5)$ should output 3.1

By conditioning on d , one model learns to handle ANY inference budget (1 step, 10 steps, 100 steps) at test time. You choose speed vs quality AFTER training, not before.

For future state prediction: Same model can predict 1-step ahead (fast, less accurate) or 50-steps ahead (slow, more accurate) depending on the WM needs .

Shortcuts for future state prediction

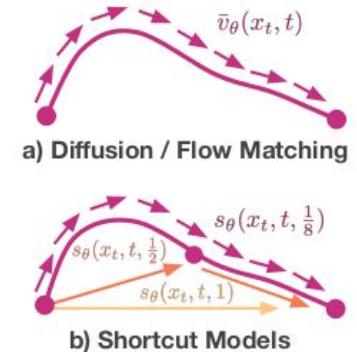
Velocity field for state space -

$$v_\theta : S \times A^k \times \mathbb{R}_+ \rightarrow T_S$$

Rate change of state -

$$\frac{ds}{dt} = v_\theta(s(t), \mathbf{a}, t)$$

- A state s (where you are now)
- An action sequence \mathbf{a} (what you plan to do)
- Time t (when you're doing it)



The exact solution - (but we need to know $s(\tau)$ at every intermediate time τ)

$$s_{t+d} = s_t + \int_t^{t+d} v_\theta(s(\tau), \mathbf{a}, \tau) d\tau$$

Shortcut approximation

Approximation -

$$s_\theta(s_t, \mathbf{a}, t, d) \approx s_t + v_\theta(s_t, \mathbf{a}, t) \cdot d$$

Self consistency in state space -

$$s_\theta(s_t, \mathbf{a}, t, 2d) = s_\theta(s_t, \mathbf{a}, t, d) + s_\theta(s_{t+d}, \mathbf{a}', t+d, d)$$

Velocity matching -

$$\mathcal{L}_v = \|v_\theta(s_t, \mathbf{a}, t) - \dot{s}_{\text{true}}(s_t, \mathbf{a}, t)\|^2$$

Self consistency loss -

$$\mathcal{L}_{\text{flow}} = \|s_\theta(s_t, \mathbf{a}, t, 2d) - [s_\theta(s_t, \mathbf{a}, t, d) + s_\theta(s_{t+d}, \mathbf{a}', t+d, d)]\|^2$$

Inputs needed

- Any obvious oversight in this approach (in terms of math or concepts)
- Suggestions for simulators/worlds that can validate this approach quickly?
- Any particular evals to run ?
- Where do you think more mathematical rigour is needed?
- Baselines to compare against?