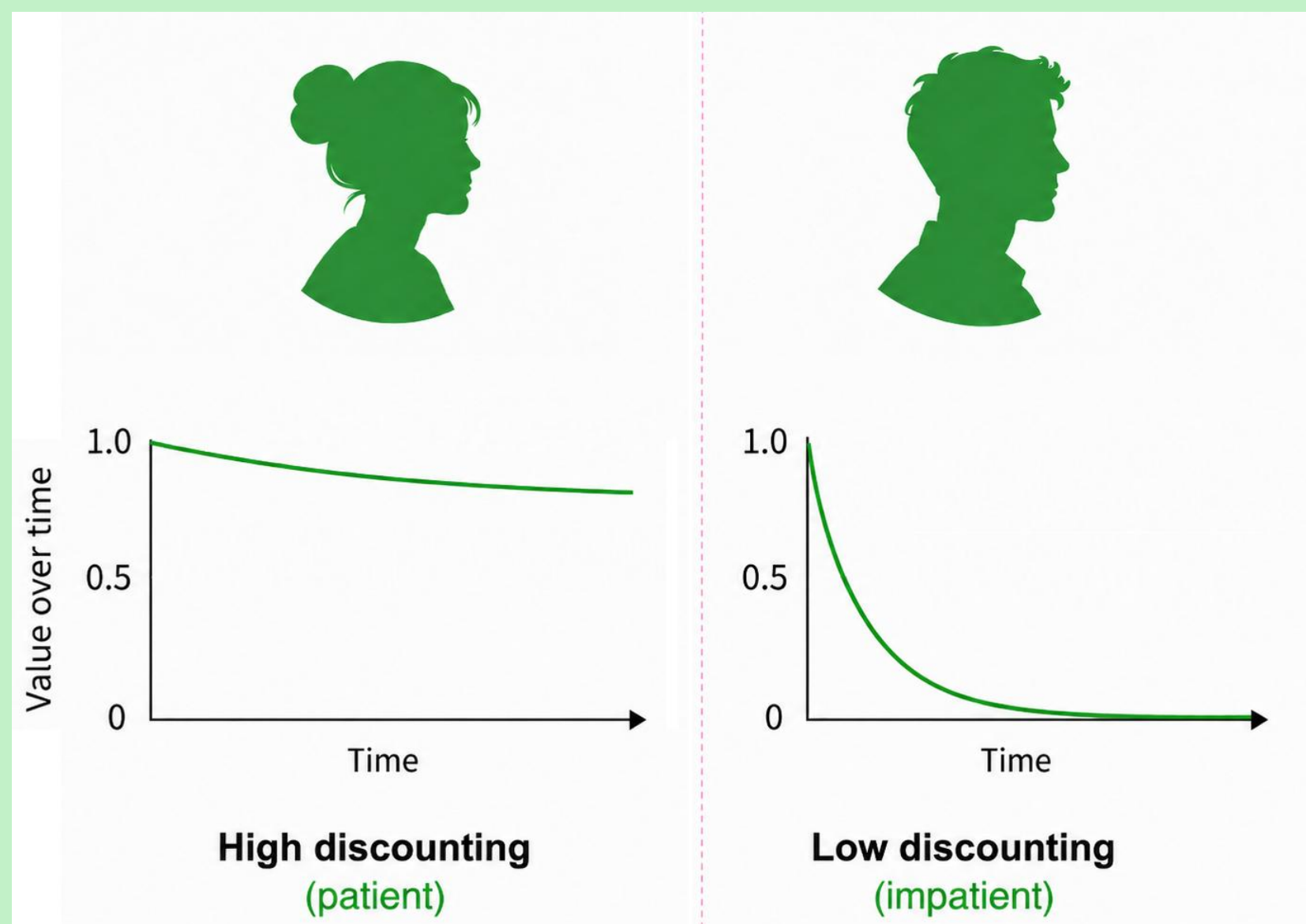


Social Welfare under Heterogeneous Time Preferences

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Heterogeneous Time Preferences



Principal_i payoff under policy π :

$$V_i^\pi = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \lambda_i^t R_i^t \right]$$

Social Welfare: $SW(\pi) = \sum_i V_i^\pi$

Optimisation Objective: $\max_{\pi} SW(\pi)$

After a finite horizon, deviations cannot help

for every deviation, there exists a finite horizon k such that, for all $t \geq k$:

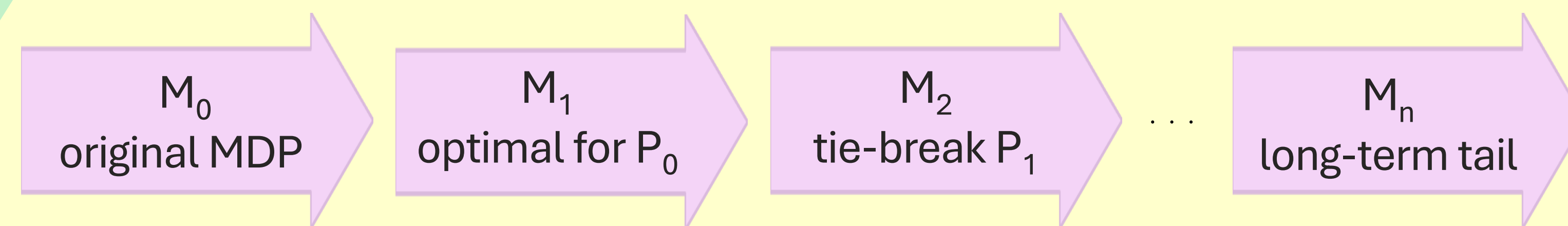
$$\sum_i \Delta_t(s, a, i) \geq 0$$

Why k is small under spacing?

- A typical bound has shape $k = \mathcal{O} \left(\frac{\log(\text{value ratio})}{\log(\lambda_i/\lambda_{i+1})} \right)$
- Only the prefix before k needs time-dependent optimisation; after that, follow the long-term tail.

Deviation rewards: $R_k^\Delta(s, a) = \sum_i \lambda_i^k \Delta_0(s, a, i)$

Long-term Behavior: Lexicographic Tail



Order principals by patience:

$$\lambda_0 > \lambda_1 > \lambda_2 > \lambda_3 > \dots > \lambda_n$$

1. Optimise MDP for most patient principal. Restrict to optimal actions.
2. Break ties using the next most patient principal.
3. Continue until last principal.

Initial Deviation

for Principal_i:

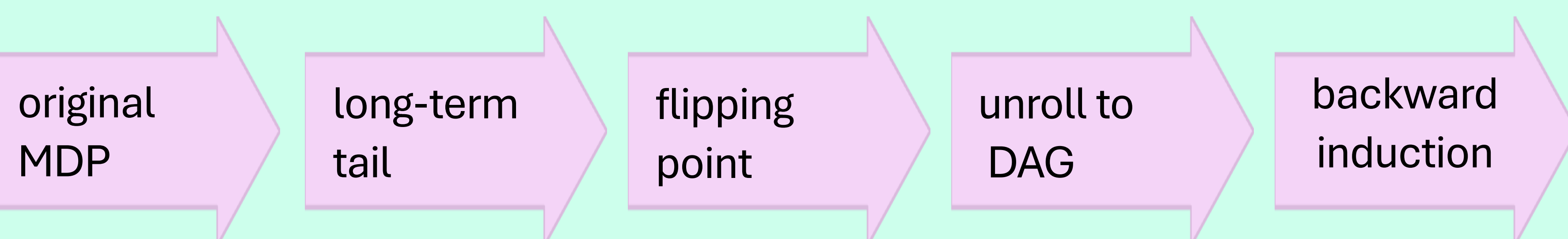
$$\Delta_0(s, a, i) = R(s, a, i) + \lambda_i \sum_{s'} p(s' | s, a) V_i(s') - V_i(s)$$

after t steps

$$\Delta_t(s, a, i) = \lambda_i^t \Delta_0(s, a, i)$$

social effect

$$\sum_i \Delta_t(s, a, i) = \sum_i \lambda_i^t \Delta_0(s, a, i)$$



$$\pi^* = \underbrace{[\text{finite prefix}]}_{\text{counting memory}} \cdot \underbrace{[\pi]_{\text{long}}^\omega}_{\text{stationary tail}}$$

Complexity Contrast

Insist on stationary simplicity

- Loses social welfare
- Positional threshold is NP-hard
- Randomisation help but not optimum

Allow structured finite memory

- ✓ Attains optimal social welfare.
- ✓ Welfare computable in PTIME.
- ✓ Pure counting strategies are sufficient.

Scalability

