

Asymptotic Optimality in Restless Bandit

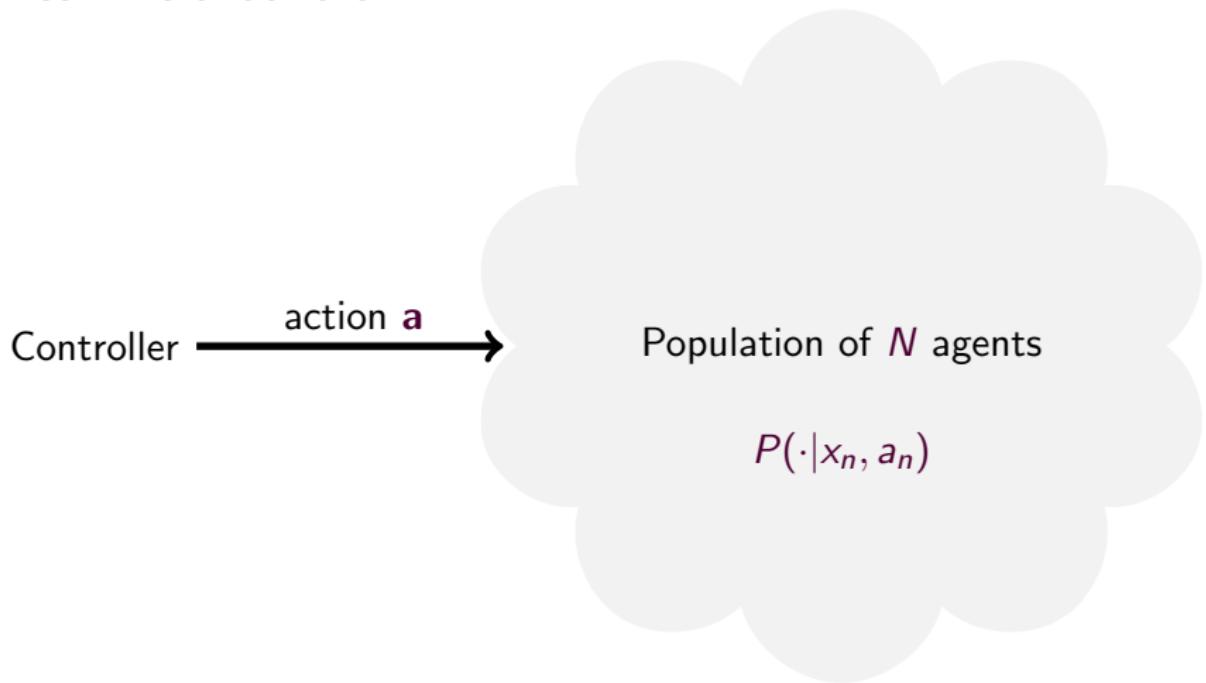
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joint work with Bruno Gaujal, Dheeraj Narasimha and Chen Yan

Inria

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Mean field control



Mean field control



$$P(\cdot | x_n, a_n)$$

The computational difficulty increases with N but " $N = \infty$ " is easy.

- How to use the $N = +\infty$ solution for finite N ?
- How efficient is this? (i.e., how fast does it become optimal?)

This talk will focus on *Markovian bandits*

N statistically identical **arms** (=agents)

- Discrete time, finite state space.
- $P(\cdot|s_n, a_n)$ and $r(s_n, a_n)$.

Maximize expected reward

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \sum_{n=1}^N r(s_n(t), a_n(t)).$$

This talk will focus on *Markovian bandits*

N statistically identical **arms** (=agents)

- Discrete time, finite state space.
- $P(\cdot|s_n, a_n)$ and $r(s_n, a_n)$.

Maximize expected reward

$$\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \sum_{n=1}^N r(s_n(t), a_n(t)).$$

Hard constraint: $\forall t : \sum_{n=1}^N a_n(t) \leq \alpha N$.

- If $a_n(t) \in \{0, 1\}$: Markovian bandit (**this talk**)
- If $a_n(t) \in \{0, 1\}^d$: Weakly coupled MDP.

Example: Resource allocation



Arm/agent can be:

- Tasks (e.g., scheduling)
- Workers (e.g., maintenance problems)
- Electric vehicles (e.g., charging)

Outline

1 The (relaxed) mean-field control problem

2 Three types of policies

- Index policies
- FTVA
- Model predictive control

3 Performance guarantee

4 Conclusion

The mean-field control problem (Whittle's relaxation)

Replace “For all t , $\sum_{n=1}^N a_n(t) \leq \alpha N$ ” by **in steady-state**: $\sum_{n=1}^N \mathbb{E}[a_n] \leq \alpha N$ ”

⇒ This is a constrained MDP and can be solved by an LP (Altman 99).

The mean-field control problem (Whittle's relaxation)

Replace “For all t , $\sum_{n=1}^N a_n(t) \leq \alpha N$ ” by **in steady-state**: $\sum_{n=1}^N \mathbb{E}[a_n] \leq \alpha N$ ”

⇒ This is a constrained MDP and can be solved by an LP (Altman 99).

$$V_{rel} := \max_{x \in \Delta, y \geq 0} \sum_{s,a} r_{s,a} y_{s,a}$$

$$\text{s.t. } x_{s'} = \sum_s y_{s,a} P(s'|s, a) \quad \text{Markov transitions}$$

$$x_s = \sum_a y_{s,a} \quad \text{action taken}$$

$$\sum_s y_{s,1} = \alpha \quad \text{relaxed budget constraint}$$

where $x_s = \mathbf{P}[s_n = s]$ and $y_{s,a} = \mathbf{P}[s_n = s, a_n = a]$.

How does a solution look like?

```
bandit_lp.BanditRandom(4, seed=1).relaxed_lp_average_reward(alpha=0.4)
```

Action 0 Action 1

$$y^* = \begin{bmatrix} & 0.232 \\ 0.028 & 0.168 \\ 0.210 & \\ 0.171 & \\ 0.191 & \end{bmatrix}$$

Note: $0.232 + 0.168 = \alpha = 0.4$.

How does a solution look like?

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bandit_lp.BanditRandom(4, seed=1).relaxed_lp_average_reward(alpha=0.4)
```

Action 0 Action 1

$$y^* = \begin{bmatrix} & 0.232 \\ 0.028 & 0.168 \\ 0.210 & \\ 0.171 & \\ 0.191 & \end{bmatrix} \Rightarrow \pi^* = \begin{bmatrix} 1 \\ 0.857 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Note: $0.232 + 0.168 = \alpha = 0.4$.

Can I apply this to the original (non-relaxed) problem?

π^* is optimal for the constrained MDP $\sum_n \mathbb{E}[A_n] = \alpha N$.

Tentative solution:

$$S(t) = [2, 0, 1, 3, 0, 0, 0, 3, 2, 3, 1, 1, 2, 0, 4]$$

\Downarrow Sample $A_n(t) \sim \pi^*(S_n(t))$ (indep.)

$$\tilde{A}_{\pi^*}(t) = [0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0]$$

Problem: here $8 = \sum_{n=1}^N \tilde{A}_n(t) \neq \alpha N = 6$.

Historical perspective

and possible solutions

- ➊ Whittle index (88) (Nino-Mora, 90s-2000s) / LP-index (Verloop 15)
 - ▶ Works extremely well in practice
 - ▶ Often asymptotically optimal (UGAP, Weber and Weiss 91).
 - ▶ When they are: exponentially fast. (G, Gaujal, Yan 2023).
- ➋ FTVA – Follow the virtual advice (Hong et al, 2023, 2024)
 - ▶ Whittle index can fail (when UGAP fails)
 - ▶ Asymptotically optimal in theory, not in practice.
- ➌ Model predictive control (G., Narasimha 2024, G, Gaujal, Yan 2023)
 - ▶ Best of both worlds

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Index policy: LP-index and Whittle index

Action 0 Action 1

$$y^* = \begin{bmatrix} & 0.232 \\ 0.028 & 0.168 \\ 0.210 & \\ 0.171 & \\ 0.191 & \end{bmatrix} \xrightarrow{\text{LPindex}} I = \begin{bmatrix} 1.216 \\ 0 \\ -0.418 \\ -0.878 \\ -0.237 \end{bmatrix}$$

Index policy: priority to largest index: $0 > 1 > 4 > 2 > 3$.

Index policy: LP-index and Whittle index

Action 0 Action 1

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Index policy: priority to largest index: $0 > 1 > 4 > 2 > 3$.

$$S(t) = [0, 0, 0, 0, 0, 1, 1, 1, 2, 2, 2, 3, 3, 3, 4]$$

$$A_{Idx}(t) = [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]$$

Index policy: LP-index and Whittle index

Action 0 Action 1

$$y^* = \begin{bmatrix} & 0.232 \\ 0.028 & 0.168 \\ 0.210 & \\ 0.171 & \\ 0.191 & \end{bmatrix} \xrightarrow{\text{LPindex}} I = \begin{bmatrix} 1.216 \\ 0 \\ -0.418 \\ -0.878 \\ -0.237 \end{bmatrix}$$

Index policy: priority to largest index: $0 > 1 > 4 > 2 > 3$.

$$S(t) = [0, 0, 0, 0, 0, 1, 1, 1, 2, 2, 2, 3, 3, 3, 4]$$

$$A_{Idx}(t) = [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]$$

$$\left(\tilde{A}_{\pi^*}(t) = [1, 1, 1, 1, 1, 1, \textcolor{red}{1}, \textcolor{red}{1}, 0, 0, 0, 0, 0, 0, 0] \right) \quad \text{from } \pi^*$$

Where does the LP-index comes from?

The $N = \infty$ is a constraint MDP:

- $P(\cdot|s_n, a_n)$ and $r(s_n, a_n)$ s.t. in steady-state, $\mathbf{P}[a_n] = \alpha$.

Where does the LP-index comes from?

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- $P(\cdot|s_n, a_n)$ and $r(s_n, a_n)$ s.t. in steady-state, $\mathbf{P}[a_n] = \alpha$.

Idea: use a Lagrangian relaxation:

- $P(\cdot|s_n, a_n)$ and $r(s_n, a_n) - \lambda a_n$.



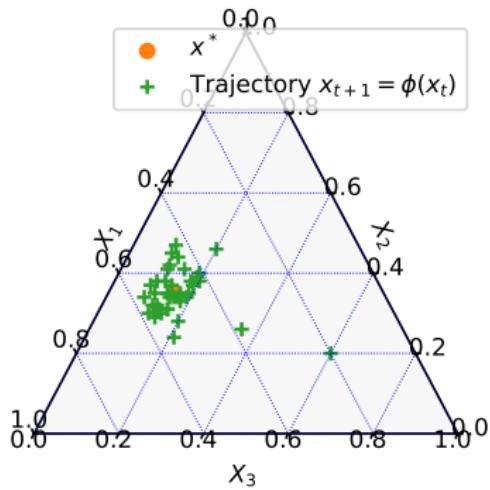
Penalty for activation

Index of state s : $I_s = Q_\lambda(s, 1) - Q_\lambda(s, 0)$.

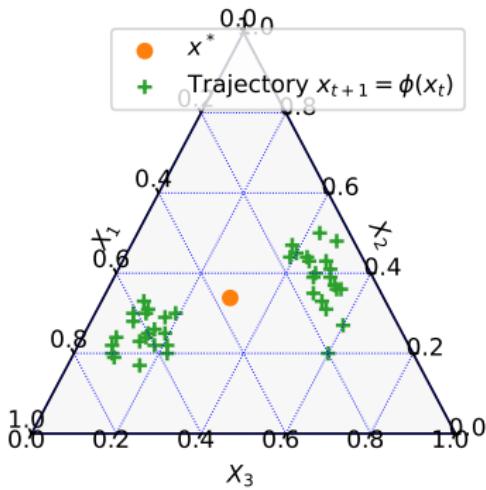
Whittle index / LP-index can fail

Theorem (Weber-Weiss 90)

Whittle is asymptotically optimal under UGAP (=stability) but can fail.



(a) UGAP is satisfied



(b) UGAP is not satisfied

FTVA (Follow the virtual advice, Hong et al. 2023)

Sample $\tilde{A}_n \sim \pi(\tilde{S}_n)$ and $A \leftarrow \text{cap}(\tilde{A})$

If $S_n = \tilde{S}_n$ and $A_n = \tilde{A}$: **then**: couple $S_n(t+1)$ and $\tilde{S}_n(t+1)$
else: wait for them to synchronize.

	Real	Virtual (uses π^*)
S	0 0 0 0 1 1 1 2 2 2 3 3 3 4	[0 0 0 0 0 1 1 1 2 2 2 3 3 3 4]
A		[1 1 1 1 1 1 1 1 0 0 0 0 0 0 0]
S		
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S	0 0 0 0 0 1 1 1 2 2 2 3 3 3 4	[0 0 0 0 0 1 1 1 2 2 2 3 3 3 4]
A	0 0 1 1 1 1 1 0 0 0 0 0 0 0	[1 1 1 1 1 1 1 1 0 0 0 0 0 0 0]
S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A		[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S		
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A	0 0 1 1 1 1 1 0 0 0 0 0 0 0	[1 1 1 1 1 1 1 1 0 0 0 0 0 0 0]
S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
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A	0 0 1 1 1 1 1 0 0 0 0 0 0 0	[1 1 1 1 1 1 1 1 0 0 0 0 0 0 0]
S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A		[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S		
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S		
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A		[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A	1 1 0 0 0 0 1 1 1 1 0 0 0 0 0	[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A	1 1 0 0 0 0 1 1 1 1 0 0 0 0 0	[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
S	4 3 3 3 2 1 1 0 4 3 3 2 0 1 4	[2 0 3 3 2 1 1 0 4 3 3 2 0 1 4]
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A	1 1 0 0 0 0 1 1 1 1 0 0 0 0 0	[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
S	4 3 3 3 2 1 1 0 4 3 3 2 0 1 4	[2 0 3 3 2 1 1 0 4 3 3 2 0 1 4]
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S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A	1 1 0 0 0 0 1 1 1 1 0 0 0 0 0	[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
S	4 3 3 3 2 1 1 0 4 3 3 2 0 1 4	[2 0 3 3 2 1 1 0 4 3 3 2 0 1 4]
A	0 1 0 0 0 1 1 1 0 0 0 0 1 1 0	[0 1 0 0 0 1 1 1 0 0 0 0 1 1 0]
S	0 4 2 2 1 2 4 4 0 2 4 4 1 0 3	[4 4 2 2 1 2 4 4 0 2 4 4 1 0 3]
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A	0 1 1 1 1 1 1 0 0 0 0 0 0 0	[1 1 1 1 1 1 1 1 0 0 0 0 0 0]
S	3 0 4 4 4 3 2 0 0 3 1 2 2 2 0	[2 3 4 4 4 3 2 0 0 3 1 2 2 2 0]
A	1 1 0 0 0 0 0 1 1 0 1 0 0 0 1	[0 0 0 0 0 0 0 1 1 0 1 0 0 0 1]
S	4 4 1 0 1 2 1 1 2 4 0 3 3 3 3	[3 2 1 0 1 2 1 1 2 4 0 3 3 3 3]
A	0 0 1 1 1 0 1 1 0 0 1 0 0 0 0	[0 0 1 1 1 0 1 1 0 0 1 0 0 0 0]
S	3 0 2 4 3 3 0 1 1 0 4 3 4 4 2	[3 4 2 4 3 3 0 1 1 0 4 3 4 4 2]
A	1 1 0 0 0 0 1 1 1 1 0 0 0 0 0	[0 0 0 0 0 0 1 1 1 1 0 0 0 0 0]
S	4 3 3 3 2 1 1 0 4 3 3 2 0 1 4	[2 0 3 3 2 1 1 0 4 3 3 2 0 1 4]
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S	0 4 2 2 1 2 4 4 0 2 4 4 1 0 3	[4 4 2 2 1 2 4 4 0 2 4 4 1 0 3]
A	1 1 0 0 1 0 0 0 1 0 0 0 1 1 0	[0 0 0 0 1 0 0 0 1 0 0 0 1 1 0]

Model predictive control

The “LP-update policy”

We define a finite-horizon deterministic problem:

$$V_\tau(\mathbf{S}) := \max_{y \geq 0} \sum_{t=0}^{\tau} \sum_{s,a} r_{s,a} y_{s,a}(t)$$

$$\text{s.t. } \sum_a y_{s,a}(t+1) = \sum_s y_{s,a}(t) P(s'|s, a) \quad \text{Markov transitions}$$

$$\sum_s y_{s,1}(t) = \alpha \quad \text{relaxed budget constraint}$$

$$\sum_a y_{s,a}(0) = \frac{1}{N} \sum_{n=1}^N \mathbf{1}_{\{S_n(t)=s\}} \quad \text{initial state}$$

We then apply $y_{s,a}(0)$ to all states.

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Assumptions

We consider the following deterministic dynamical system:

$$\phi(\mathbf{x}) = \mathbb{E} [\mathbf{X}(t+1) \mid \mathbf{X}(t) = \mathbf{x} \wedge A \sim \text{index}],$$

and we call y^* the solution of V_{rel} , with $x_s^* = \sum_a y_{sd,a}^*$.

We define the following conditions:

UGAP $\lim_{t \rightarrow \infty} x_{t+1} = \phi(x_t)$ converges to x^* uniformly for all x .

Local stability ϕ is locally stable around x^* .

Degenerate $y_{s,1} = 0$ or $y_{s,0} = 0$ for all s .

Theoretical guarantees

Theorem (Weber-Weiss, G,G,Y23)

Under UGAP and non-degenerate: $V_{index} \geq V_{rel} - e^{-\Omega(N)}$.

Theorem (Hong et al. 23)

If P is ergodic, then: $V_{FTVA} \geq V_{rel} - O(1/\sqrt{N})$.

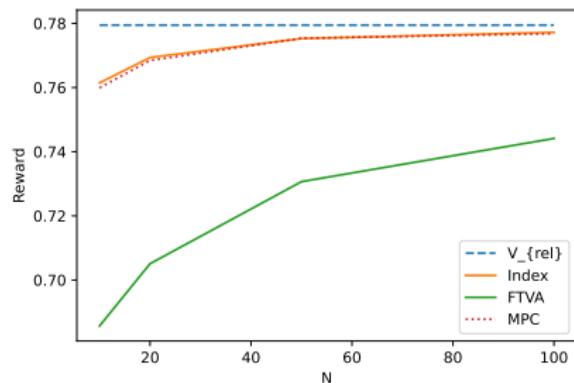
Theorem (G,N 24)

① If P is ergodic: $V_{MPC} \geq V_{rel} - O(1/\sqrt{N})$.

② Under non-degenerate and local stability: $V_{MPC} \geq V_{rel} - e^{-\Omega(N)}$.

Illustration

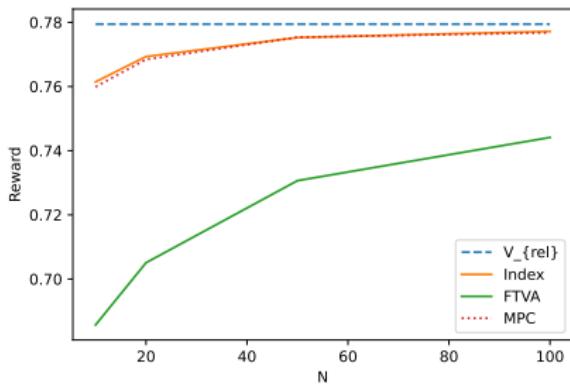
The random example.



UGAP + non-degenerate.

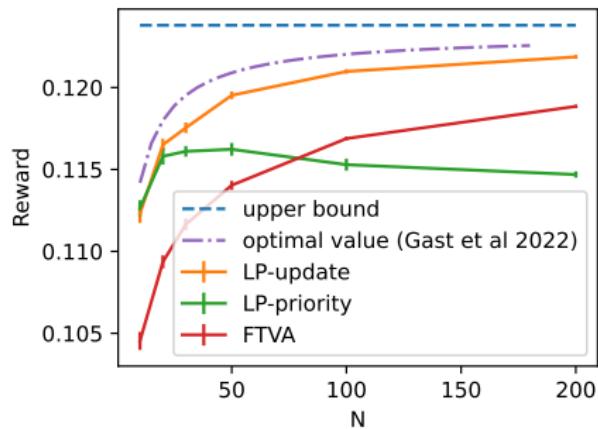
Illustration

The random example.



UGAP + non-degenerate.

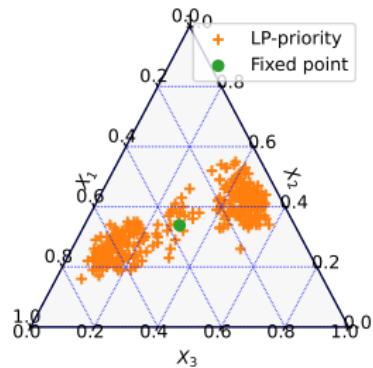
Example from Yan 2023.



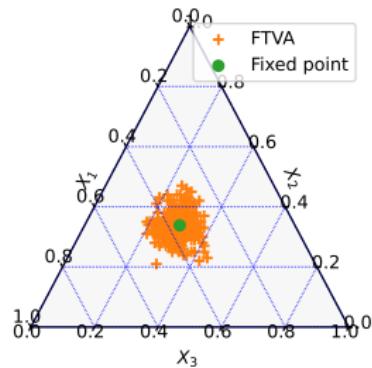
No UGAP nor local stability.

Illustration of non-UGAP

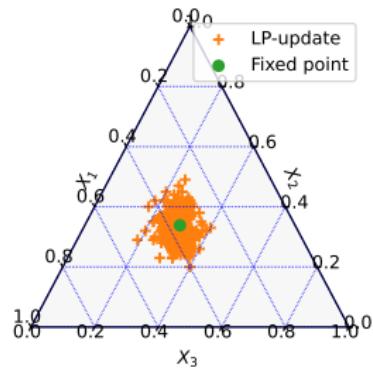
Example from Yan 2023 (3D example)



(a) Index



(b) FTVA



(c) MPC

Outline

1 The (relaxed) mean-field control problem

2 Three types of policies

- Index policies
- FTVA
- Model predictive control

3 Performance guarantee

4 Conclusion

Conclusion

For Markovian bandits, mean-field control can be solved by an LP.

- Can be generalized to weakly coupled MDPs.

Simple policies (priority rule) are not always optimal.

- When they are, they become optimal exponentially fast.
- This talk: comparison of various approaches.

Conclusion

For Markovian bandits, mean-field control can be solved by an LP.

- Can be generalized to weakly coupled MDPs.

Simple policies (priority rule) are not always optimal.

- When they are, they become optimal exponentially fast.
- This talk: comparison of various approaches.
- Open questions: learning, continuous state-spaces.

<http://polaris.imag.fr/nicolas.gast/>

- *LP-based policies for restless bandits: necessary and sufficient conditions for (exponentially fast) asymptotic optimality.* G. Gaujal Yan. MMOR 2023. <https://arxiv.org/abs/2106.10067>
- *Restless Bandits with Average Reward: Breaking the Uniform Global Attractor Assumption.* Hong, Xie, Chen, and Wang. NeurIPS 2023.
- *Model Predictive Control is Almost Optimal for Restless Bandit.* G. Narasimha. 2024. Under review.