

On the interplay between average and discount optimality in robust MDPs

Julien Grand-Clément (HEC Paris)

Marek Petrik (University of New Hampshire)

Nicolas Vieille (HEC Paris)

ICCOPT 2025

This talk in one slide

Main objective:

Solve (robust) MDPs with average return

Why it's interesting?

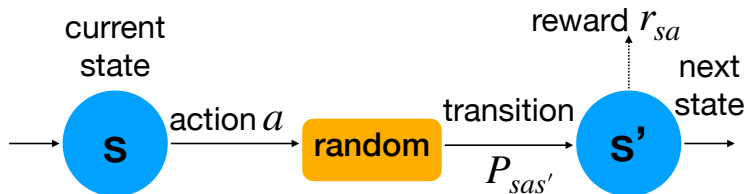
Well-studied for MDPs and stochastic games...

... largely understudied for robust MDPs

Main results:

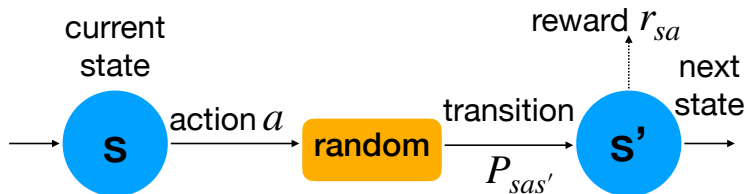
1. Properties of average optimal policies for robust MDPs
2. Computing average opt. policies by solving discounted problems

Setup for robust Markov decision process



- Finite set of states and actions
- History-dependent policy $\pi \in \Pi_H$: maps finite histories to actions
- Transition probabilities $\mathbf{P} = (P_{sas'})$, **unknown**: $\mathbf{P} \in \mathcal{U}$

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This talk: \mathcal{U} convex compact, sa-rectangular:

$$\mathcal{U} = \times_{(s,a) \in \mathcal{S} \times \mathcal{A}} \mathcal{U}_{sa}, \quad \mathcal{U}_{sa} \subset \Delta(\mathcal{S})$$

Discounted and average returns

Given a policy $\pi \in \Pi_S$ and some transitions $\mathbf{P} \in \mathcal{U}$:

Discounted return: for a *discount factor* $\gamma \in [0, 1)$,

$$R_\gamma(\pi, \mathbf{P}) = (1 - \gamma) \sum_{t=0}^{\infty} \gamma^t \cdot \mathbb{E}^{\pi, \mathbf{P}} [r_{s_t a_t}]$$

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Average return:

$$R_{\text{AVG}}(\pi, \mathbf{P}) = \lim_{T \rightarrow +\infty} \frac{1}{T+1} \sum_{t=0}^T \mathbb{E}^{\pi, \mathbf{P}} [r_{s_t a_t}]$$

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Hardy-Littlewood: $\lim_{\gamma \rightarrow 1} R_\gamma(\pi, \mathbf{P}) = R_{\text{AVG}}(\pi, \mathbf{P})$

Blackwell [Bla62]: for $\gamma \rightarrow 1$, discount opt. policies are average opt.

Main objective in this talk: Find a policy π solving

$$\sup_{\pi \in \Pi_H} \inf_{\mathbf{P} \in \mathcal{U}} R_{\text{AVG}}(\pi, \mathbf{P}) \quad (1)$$

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Sketch of our approach:

- “Optimal discounted policies are average optimal for γ large enough”
- \Rightarrow “let’s just solve discounted models for γ large enough”

Definition: The Blackwell discount factor

The *Blackwell discount factor* $\gamma_{bw} \in [0, 1)$ is the smallest discount factor such that the set of stationary discount optimal policies does not change for all γ in $(\gamma_{bw}, 1)$.

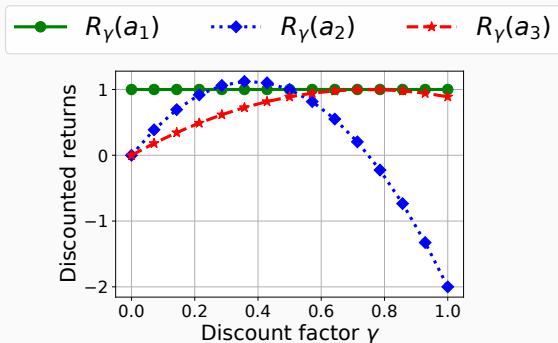


Figure 1: Example with three policies a_1, a_2, a_3

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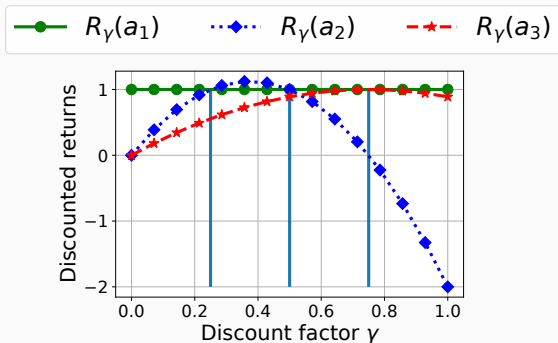


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Theorem 5 in [Bla62] ¹:

The Blackwell discount factor exists for finite MDPs.

Extension by [Sma66] for finite MDPs:

The interval $[0, 1)$ can be partitioned into finitely many subintervals, inside which the set of stationary discount optimal policies is constant.

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1. Upper bound on γ_{bw} for MDPs?
2. Existence and upper bounds for robust MDPs?

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Bound on the Blackwell discount factor γ_{bw} for MDPs

$\gamma \mapsto R_\gamma(\pi)$ is a *rational function* of $\gamma \in [0, 1]$:

$$R_\gamma(\pi) = \frac{\text{poly}_1(\gamma)}{\text{poly}_2(\gamma)}$$

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Root separation: [Lag69],[Had93],[Mah62],[Rum79]...

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Let $Q = \sum_{i=0}^n a_i X^i$ with $a_i \in \mathbb{Z}$, $\max_i |a_i| \leq H$ and $Q(1) = 0$.

$\exists \text{SEP}(n, H) > 0$ such that $Q(x) \neq 0$ for $1 - \text{SEP}(n, H) < x < 1$.

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For $\gamma > 1 - \text{SEP}(n, H)$, “discounted returns can’t intersect!”

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$\Rightarrow \gamma_{\text{bw}} \leq 1 - \text{SEP}(n, H)$

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Remains to bound degree/height of $Q \rightarrow$ use “closed-form” for $R_\gamma(\pi)$

Main bound on the Blackwell discount factor γ_{bw} for MDPs

Theorem [GCP24]

Consider a finite MDP instance with:

- M = maximum rewards and common denominator for transitions
- S = number of states

Then

$$1 - \gamma_{\text{bw}} \geq \Omega\left(\frac{1}{(2M)^{S^2}}\right).$$

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Note 2: MDPs can be solved in $\tilde{O}(|\log(1 - \gamma)|)$ [Ye05]

\Rightarrow weakly-polytime algorithms for computing average optimal policies.

The case of robust MDPs

What about robust MDPs?

The Blackwell discount factor exists γ_{bw} for \mathcal{U} sa-rec. AND:

- [TB07]: based on ℓ_∞ -ball
- [GGC22]: \mathcal{U} polytope
- [WVA⁺23]: unichain assumption + average optimal policy unique.

Q: Existence of γ_{bw} for general sa-rectangular, compact convex \mathcal{U} ?

Counterexample to existence the Blackwell discount factor γ_{bw}

Theorem

The Blackwell discount factor **may not exist**, even for sa-rectangular convex compact uncertainty set \mathcal{U} .

Long story short: worst-case discounted returns oscillate as $\gamma \rightarrow 1$

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Jérôme Bolte, ICCOPT, Monday July 2021 2025:

"Oscillations are always hidden behind monsters"

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We construct an instance with one state s and two actions a_1, a_2 s.t.:

- Action a_1 is optimal for $\gamma = 1 - \frac{1}{2k}$
- Action a_2 is optimal for $\gamma = 1 - \frac{1}{2k+1}$

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Intuition: the next two functions oscillate and intersect as $\gamma \rightarrow 1$:

$$\gamma \mapsto \min_{P \in \mathcal{U}_{sa_1}} R_\gamma(a_1, P)$$

$$\gamma \mapsto \min_{P \in \mathcal{U}_{sa_2}} R_\gamma(a_2, P)$$

Preventing oscillations with definability

Definable functions [Cos00] (definition and o-minimality: see (2)):

- “Building blocks”: multinomials and \exp
- Stable under several operations:
If f, g are definable, then so are $f + g, f \circ g, f \times g, f/g, -f, f^{-1}$
- Stable by max and min:
Pointwise max and min of definable functions are definable
- Definable sets = graph of definable functions

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Example: $\mathcal{U}_{sa} = \{\mathbf{p} \in \Delta(\mathcal{S}) \mid f(\mathbf{p}, \hat{\mathbf{p}}) \leq \alpha\}$ is definable if f is definable

Why do we care?

Existence the Blackwell discount factor γ_{bw}

Definability prevents oscillations:

Monotonicity Lemma

If $f : (a, b) \rightarrow \mathbb{R}$ is definable, we can partition (a, b) into *finitely* many subintervals, in which f is either constant or strictly monotone.

Discounted returns can not oscillate when \mathcal{U} is definable:

Lemma

If \mathcal{U} is definable, then $\gamma \mapsto \min_{P \in \mathcal{U}} R_\gamma(\pi, P)$ is definable.

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Putting everything together:

Theorem

Let \mathcal{U} be an sa-rectangular convex compact uncertainty set.

If \mathcal{U} is definable, then the Blackwell discount factor γ_{bw} exists.

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Putting everything together:

Theorem

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If \mathcal{U} is definable, then the Blackwell discount factor γ_{bw} exists.

Next question: how to bound γ_{bw} away from 1?

Bound on the Blackwell discount factor γ_{bw} for robust MDPs

Theorem [GCP24]

Consider a finite MDP instance with \mathcal{U} sa-rectangular and:

- M = maximum rewards and common denominator for transitions
- S = number of states
- $\mathcal{U}_{sa} = \ell_1$ or ℓ_∞ balls around nominal transition probabilities.

Then

$$1 - \gamma_{\text{bw}} \geq \Omega\left(\frac{1}{(4M)S^2}\right).$$

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RMDPs can be solved in $\tilde{O}((1 - \gamma)^{-1})\dots$

... So we *don't* obtain a polytime algorithm!

Open Questions and Future Work

More in the papers:

Bounding γ_{bw} for robust MDPs [GCP24]

A complete treatment of average optimality for sa-rec. RMDPs [GCPV23]

The case of s-rec. RMDPs [GCPV23, GCV25]

A more refined analysis of γ_{bw} for stochastic games [GGCK25]

Next steps:

sa-rec. RMDPS: computing average optimal policies?

The case of ϵ -optimal policies?

Unichain/irreducible, weakly-communicating, absorbing, etc.

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Thank you!



David Blackwell.

Discrete dynamic programming.

The Annals of Mathematical Statistics, pages 719–726, 1962.



Michel Coste.

An introduction to o-minimal geometry.

Istituti editoriali e poligrafici internazionali Pisa, 2000.



Julien Grand-Clément and Marek Petrik.

Reducing blackwell and average optimality to discounted mdps via the blackwell discount factor.

Advances in Neural Information Processing Systems, 36, 2024.



Julien Grand-Clement, Marek Petrik, and Nicolas Vieille.

Beyond discounted returns: Robust markov decision processes with average and blackwell optimality.

arXiv preprint arXiv:2312.03618, 2023.



Julien Grand-Clément and Nicolas Vieille.
Playing against a stationary opponent.
arXiv preprint arXiv:2503.15346, 2025.



Vineet Goyal and Julien Grand-Clément.
Robust Markov decision processes: Beyond rectangularity.
Mathematics of Operations Research, 2022.



Stéphane Gaubert, Julien Grand-Clément, and Ricardo D Katz.
Thresholds for sensitive optimality and blackwell optimality in stochastic games.
arXiv preprint arXiv:2506.18545, 2025.



J. Hadamard.
Étude sur les propriétés des fonctions entières et en particulier d'une fonction considéré par Riemann.
Journal de Mathématiques Pures et Appliquées, 58:171–215, 1893.



G. Iyengar.

Robust dynamic programming.

Mathematics of Operations Research, 30(2):257–280, 2005.



J. L. Lagrange.

Sur la résolution des équations numériques.

Mémoires de l'Académie royale des Sciences et Belles-Lettres de Berlin, XXIII, 1769.



K. Mahler.

On some inequalities for polynomials in several variables.

J. London Math. Soc, 37(1):341–344, 1962.



M. Mignotte and M. Waldschmidt.

On algebraic numbers of small height: linear forms in one logarithm.

Journal of Number Theory, 47(1):43–62, 1994.



A. Nilim and L. El Ghaoui.

Robust control of Markov decision processes with uncertain transition probabilities.

Operations Research, 53(5):780–798, 2005.



Siegfried M Rump.

Polynomial minimum root separation.

Mathematics of Computation, 33(145):327–336, 1979.



Richard D Smallwood.

Optimum policy regions for markov processes with discounting.

Operations Research, 14(4):658–669, 1966.



Ambuj Tewari and Peter L Bartlett.

Bounded parameter Markov decision processes with average reward criterion.

In *International Conference on Computational Learning Theory*, pages 263–277. Springer, 2007.



Yue Wang, Alvaro Velasquez, George Atia, Ashley Prater-Bennette, and Shaofeng Zou.

Robust average-reward markov decision processes.

In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, pages 15215–15223, 2023.



C. K. Yap.

Fundamental problems of algorithmic algebra, volume 49.

Oxford University Press Oxford, 2000.



Y. Ye.

A new complexity result on solving the Markov decision problem.

Mathematics of Operations Research, 30(3):733–749, 2005.

Definition: definable set and definable function [Cos00]

A subset of \mathbb{R}^n is *definable* if it is the image, under a canonical projection $\mathbb{R}^{n+k} \rightarrow \mathbb{R}^n$ that eliminates any set of k variables, of a set of the form

$$\{\mathbf{x} \in \mathbb{R}^{n+k} \mid \text{Poly}(x_1, \dots, x_{n+k}, \exp(x_1), \dots, \exp(x_{n+k})) = 0\} \quad (2)$$

A function is definable if its graph is definable.

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Main results in [GCPV23]

Uncertainty set \mathcal{U}	Discount optimality	Average optimality	Blackwell optimality
Singleton (MDPs)	stationary, deterministic	stationary, deterministic	stationary, deterministic
sa-rectangular, compact	stationary, deterministic	stationary, deterministic	<ul style="list-style-type: none"> • may not exist • $\exists \pi$ stationary deterministic, π ϵ-Blackwell optimal, $\forall \epsilon > 0$ • π also average optimal
sa-rectangular, compact, definable	stationary, deterministic	stationary, deterministic	<ul style="list-style-type: none"> • stationary, deterministic • π also average optimal
s-rectangular, compact convex	stationary, randomized	<ul style="list-style-type: none"> • may not exist • may be history-dependent, randomized 	may not exist

Main results in [GCPV23]

Our main results for the *average return*:

$$\sup_{\pi \in \Pi_H} \inf_{P \in \mathcal{U}} \mathbb{E}^{\pi, P} \left[\limsup_{T \rightarrow +\infty} \frac{1}{T+1} \sum_{t=0}^T r_{s_t a_t s_{t+1}} \right].$$

1. For sa-rectangular RMDPs:

- Optimality of stationary deterministic policies
- Strong duality (existence of a value)
- “All” optimality criteria (\liminf , \limsup) are equivalent
- Optimal average value = $\lim_{\gamma \rightarrow 1} \text{VAL}_{\gamma}$

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2. For s-rectangular RMDPs:

- Non-existence of optimal policies in general
- The Big Match: Markovian policies are optimal
- Optimality criteria are not equivalent

Our main results for *Blackwell optimality*:

For sa-rectangular RMDPs:

- Blackwell optimal policies may not exist in general
- ϵ -Blackwell optimal stationary policies always exist
- Non-Lipschitzness of the discounted value functions as $\gamma \rightarrow 1$
- *Definable* uncertainty sets \Rightarrow existence of stationary Blackwell optimal policies

For s-rectangular RMDPs:

- Blackwell optimal policies may not exist in general