

Stochastic billiards on generalized parabolic domains: recurrence versus transience.

Conrado da Costa

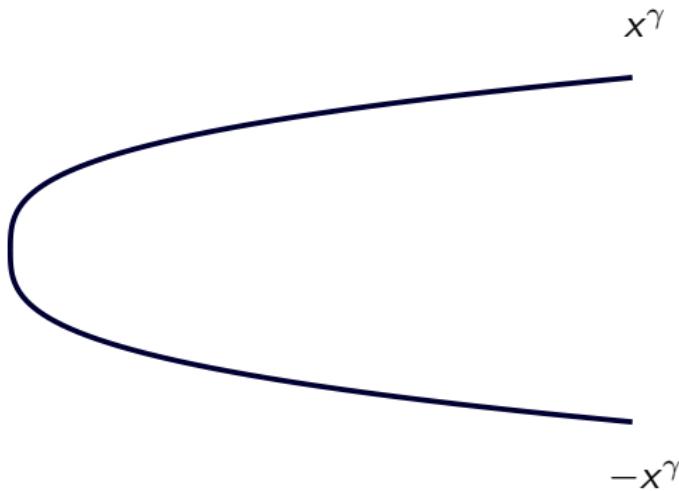
Department of Mathematical Sciences (Durham University)

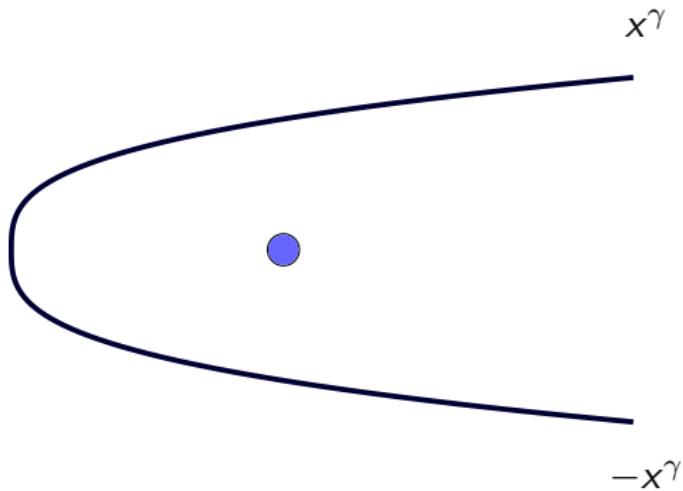


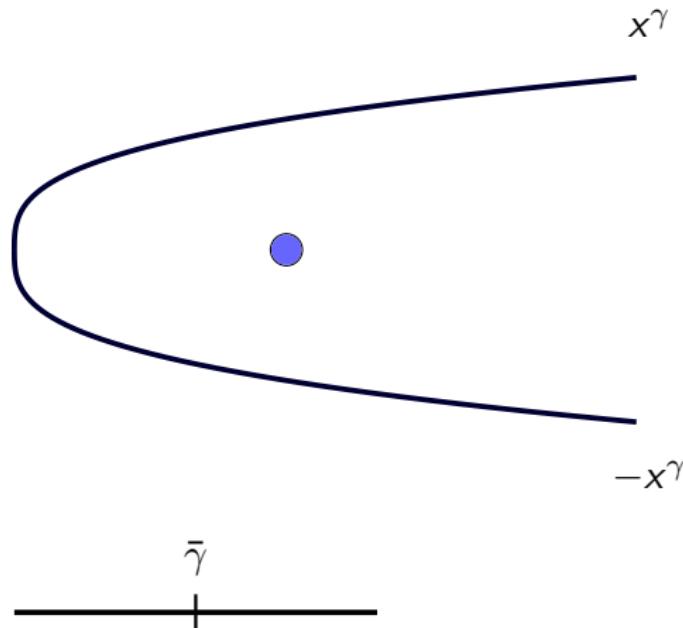
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Probability Seminar @ UFRJ

16 Mai, 2022







Outline

Introduction

Context

Main idea

Model and result

Classification

From Stochastic billiards to Half-strip models

Lamperti regime

Lyapunov functions

The project

The project



Mikhail Menshikov



Andrew Wade

The project



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08 M. Vachkovskaia, MM, AW Reflecting billiards

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Non-homogeneous random walks

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Non-homogeneous random walks

14 N. Georgiou & AW Half-strip model.

The project



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| 17 | C. Lo & AW | with generalized Lamperti drift. |

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this work | with generalized Lamperti drift.
with compact (uncountable) many states. |

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Interesting: $d \leq 2$ recurrent, $d \geq 3$ transient

Classification heuristics

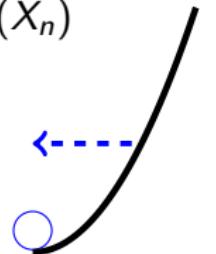
Supermartingale: $\mathbb{E}[f(X_{n+1})|\mathcal{F}_n] \leq f(X_n)$

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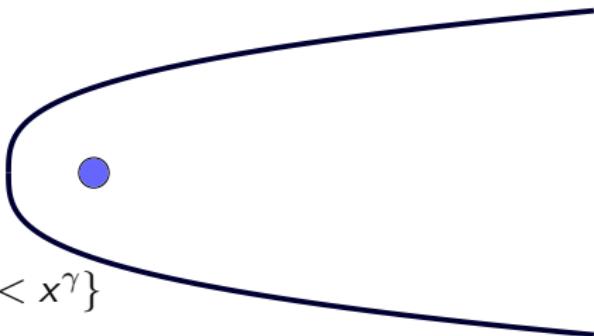


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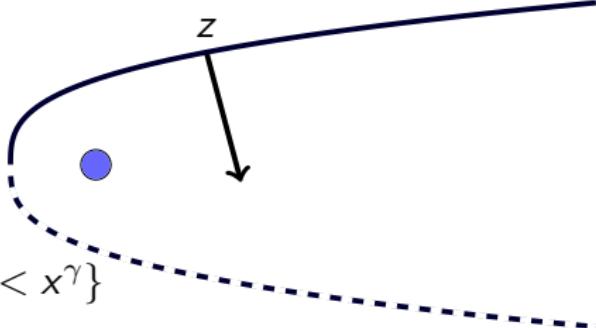
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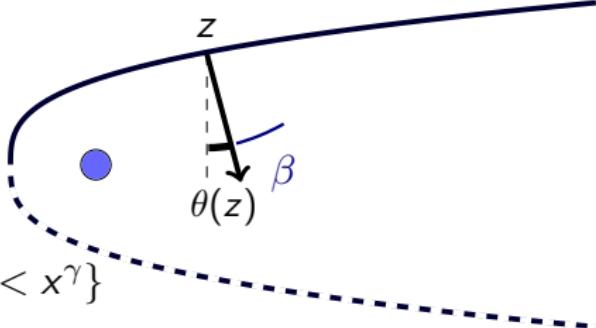


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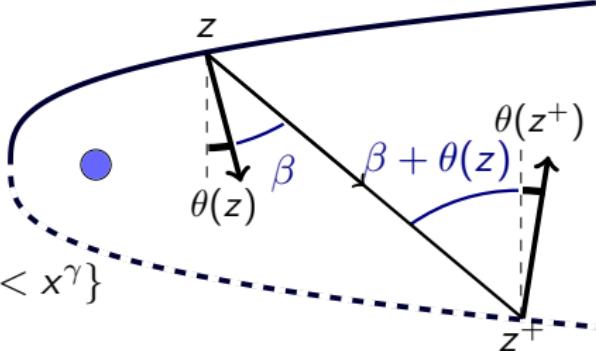
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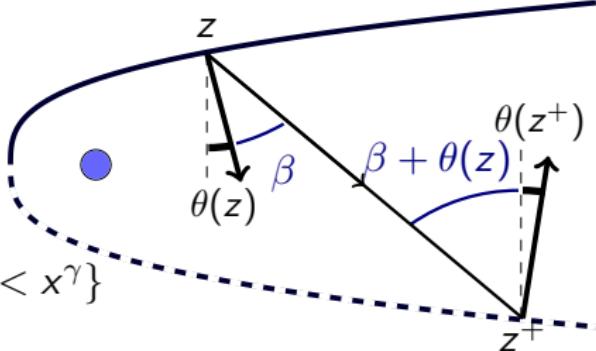
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The construction of the (Markov) process (Z_n, α_n) is complete.

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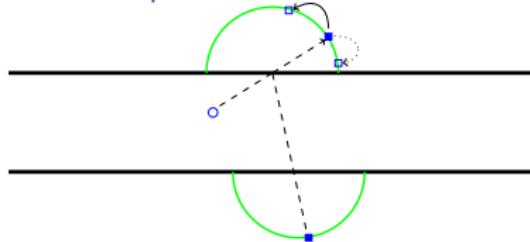
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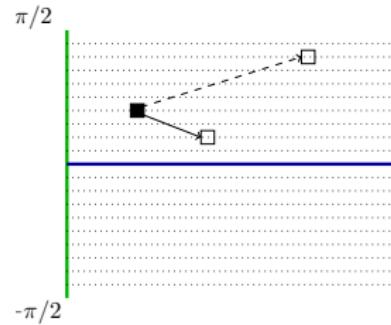
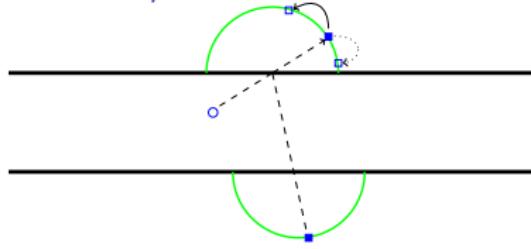
recurrent if $\gamma < \gamma_c$, transient if $\gamma > \gamma_c$.

SB and HS, translation heuristics

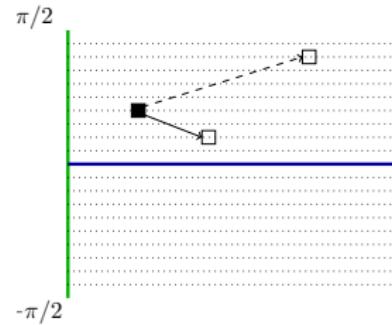
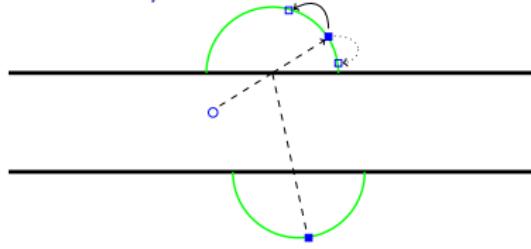
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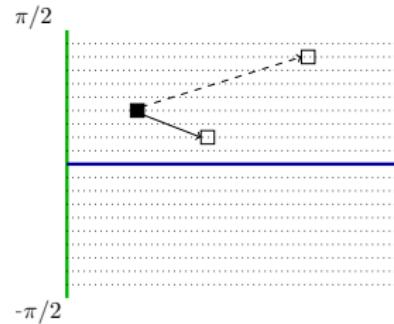
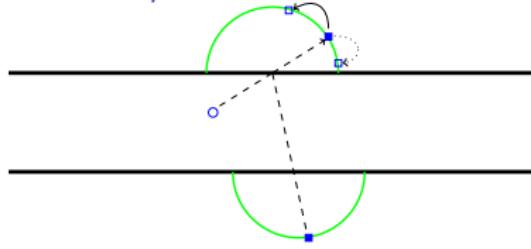


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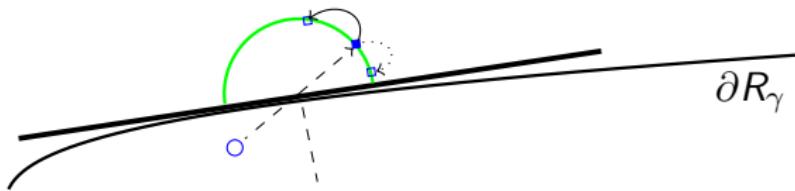


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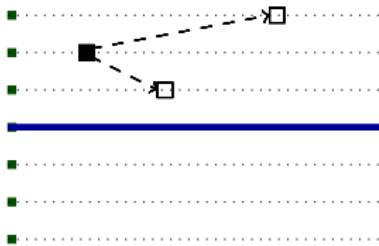


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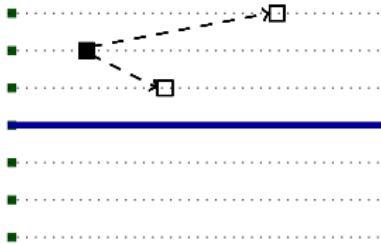


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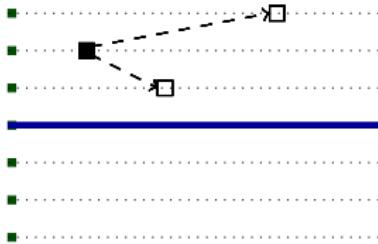
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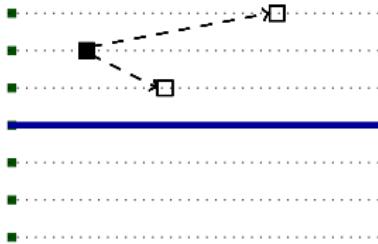
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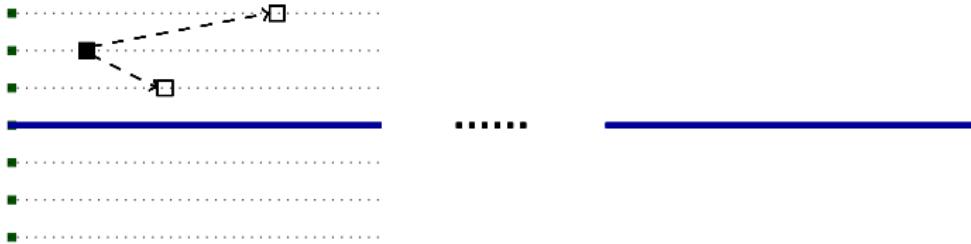
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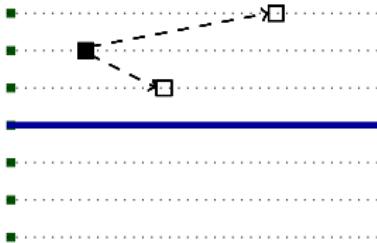
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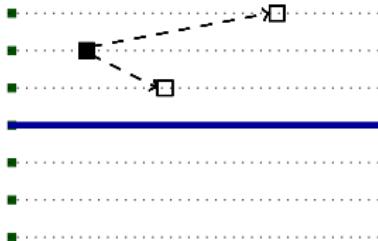
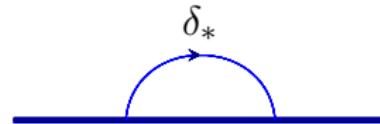
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Non-confinement: $\mathbb{P}(\limsup_n X_n = \infty) = 1$

Lamperti regime

First and second moment conditions

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Strict Lamperti regime $\mathbf{d} \equiv 0$.

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with $o_{x, \alpha}$ an error term such that

$$\lim_{x \rightarrow \infty} \sup_{\alpha \in S} |o_{x, \alpha}| = 0.$$

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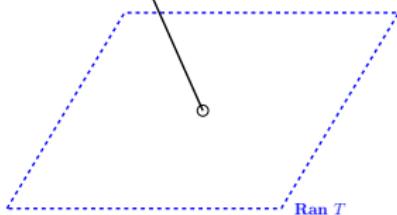
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$$-\psi_\alpha = \int (\varphi_\beta - \varphi_\alpha) K_b(\alpha, d\beta)$$

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$$\mathbb{E}_{x,\alpha} [F_{\nu,\varphi}(X_1, \alpha_1) - F_{\nu,\varphi}(x, \alpha)] = \frac{\nu}{2} x^{\nu-2} (\delta_r + \nu s_\alpha^2 + o_{x,\alpha}).$$

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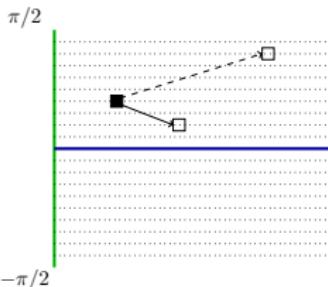
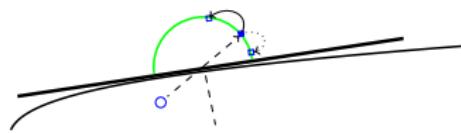
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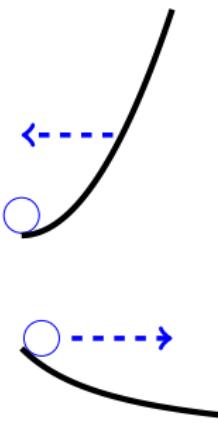
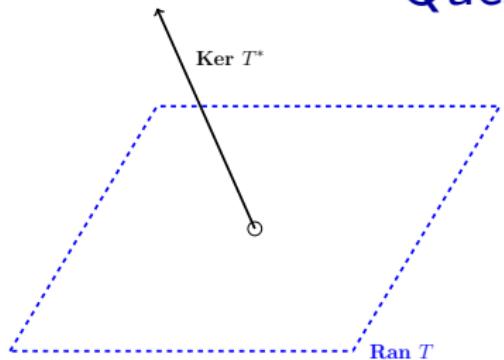
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ν small, if $\delta_r < 0$, $\nu > 0$: recurrent,

 if $\delta_r > 0$, $\nu < 0$: transient.



Questions?



The general Result

Generalized Lamperti drift

$$\int d\alpha \pi(d\alpha) = 0$$

there exists $\psi_0 \in C_b(S)$ (unique up to translation) with

$$A_1 := \int_S \psi_0(\beta) \varpi(\beta) \tan(\beta) d\beta \quad A_2 := \int_S \psi_0(\beta) \varpi'(\beta) d\beta$$

$$c(\gamma) := \gamma(1 + A_1 - A_2 + 2\bar{\rho}_2) - A_1 - \bar{\rho}_2$$

$c(\gamma) > 0$ recurrent, $c(\gamma) < 0$ transient.

$$\psi_0(\alpha) = 2 \sum_{n=1}^{\infty} \int_S \mathcal{K}_b(\alpha, d\beta) \tan \beta.$$

An example

- $\int_S \mathcal{K}_b(\alpha, d\beta) \tan \beta = \lambda \tan \alpha.$ $\pi(A) = \pi(-A)$
 $\gamma < \gamma_c :$ recurrent $\gamma > \gamma_c :$ transient

In general : $c(\gamma) = \gamma(1 + A_1 - A_2 + 2\bar{\rho}_2) - A_1 - \bar{\rho}_2$

if $1 + A_1 - A_2 + 2\bar{\rho}_2 > 0 :$ $\gamma_g = \frac{A_1 + \bar{\rho}_2}{1 + A_1 - A_2 + 2\bar{\rho}_2}$

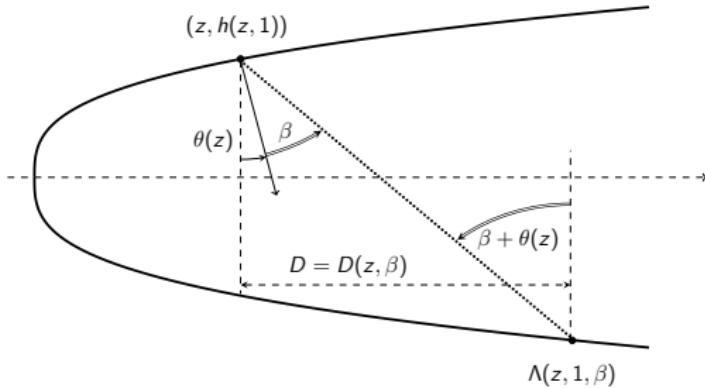
Two challenges:

- ▶ Construct the example
- ▶ Show that $\gamma_c = \gamma_g$

Open questions:

- ▶ Could $\gamma_c \neq \gamma_g?$
- ▶ Is $1 + A_1 - A_2 + 2\bar{\rho}_2 > 0?$
- ▶ Is $\gamma_g < 1?$

The displacement



$$\begin{aligned} D &= (z^\gamma + (z + D)^\gamma) \tan(\theta(z) + \beta) \\ &= z^\gamma [2 + \gamma z^{-1} D + O(z^{2\gamma-2})] \frac{\tan \beta + \tan \theta(z)}{1 - \tan \beta \tan \theta(z)} \\ &= (2z^\gamma \tan \beta + 2\gamma z^{2\gamma-1}(1 + \tan^2 \beta) + O(z^{3\gamma-2})) \\ &\quad \times (1 + \gamma z^{\gamma-1} \tan \beta + O(z^{2\gamma-2})) \end{aligned}$$

$$\sup_{\beta \in S_1} |D(z, \beta) - [2z^\gamma \tan \beta + 2\gamma z^{2\gamma-1} + 4\gamma z^{2\gamma-1} \tan^2 \beta]| = O(z^{3\gamma-2})$$