

# NUMERICAL METHOD FOR OPTIMAL STRATEGIES FOR IMPULSE CONTROL OF PIECEWISE DETERMINISTIC MARKOV PROCESS

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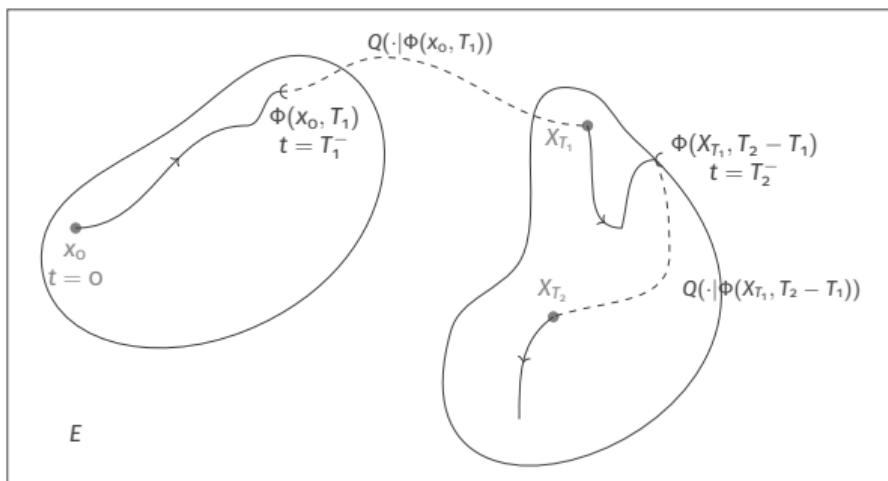


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# PIECEWISE DETERMINISTIC MARKOV PROCESS (PDMP)

## DEFINITION

Move randomly from one deterministic regime to another.



The process  $X = (X_t)_{t \geq 0}$  is defined on the state space  $E$  by 3 local characteristics.

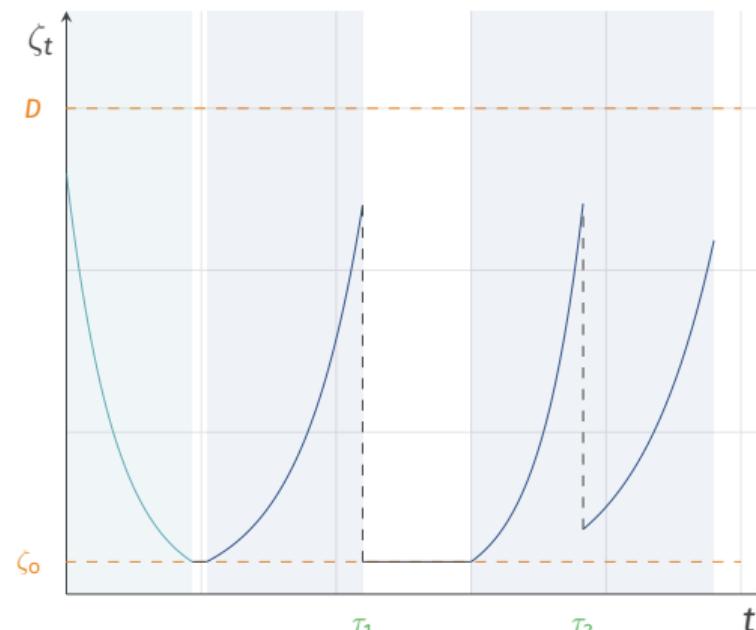
### LOCAL CHARACTERISTICS

- Flow  $\Phi$  (deterministic motion of the process)
- Jump Intensity  $\lambda$  (occurrence of random jumps)
- Markov Kernel  $Q$  (post-jump localisation)

# IMPULSE CONTROL FOR PDMP

## EXAMPLE

Select new starting point for the process at interventions to minimize a cost function.



# IMPULSE CONTROL FOR PDMP

## DEFINITION

### STRATEGY

$$\mathcal{S} = (\tau_n, R_n)_{n \geq 1}$$

- $\tau_n$  intervention dates
- $R_n$  new positions after intervention

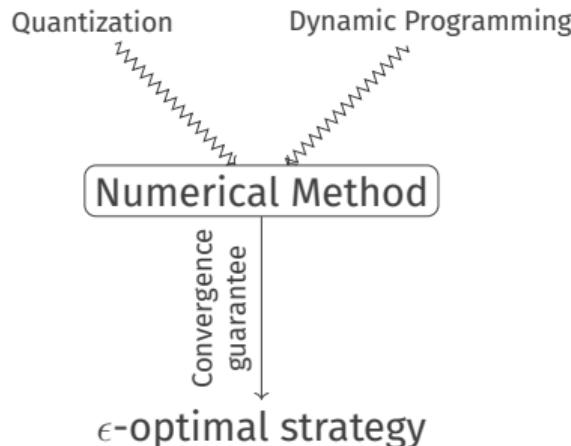
$$J^{\mathcal{S}}(x) = E_x^{\mathcal{S}} \left[ \int_0^\infty e^{-\alpha s} \underbrace{f(X_s)}_{\text{running cost}} ds + \sum e^{-\alpha \tau_i} \underbrace{c(X_{\tau_i}, X_{\tau_i+})}_{\text{intervention cost}} \right]$$

$$V(x) = \underbrace{\inf_{\mathcal{S} \in \mathbb{S}} J^{\mathcal{S}}(x)}_{\text{Value function}}$$

# RESOLUTION

$\epsilon$ -OPTIMAL STRATEGY

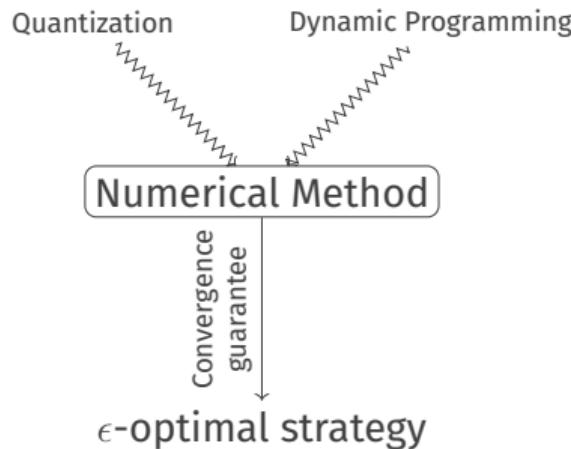
$$V(\mathcal{S}_\epsilon, x) \leq V(x) + \epsilon$$



Challenges :

- Numerical
- Mathematical

# CONCLUSION



Numerical method :

- Get  $\epsilon$ -optimal strategy
- Convergence guarantee

Limits :

- Process fully observed (including jump dates)
- Process fully known

# PERSPECTIVES

## ONGOING WORK

Solve **partially observed** PDMP with a **partially known model** using **Deep Reinforcement Learning Algorithm**.

## LIMITS

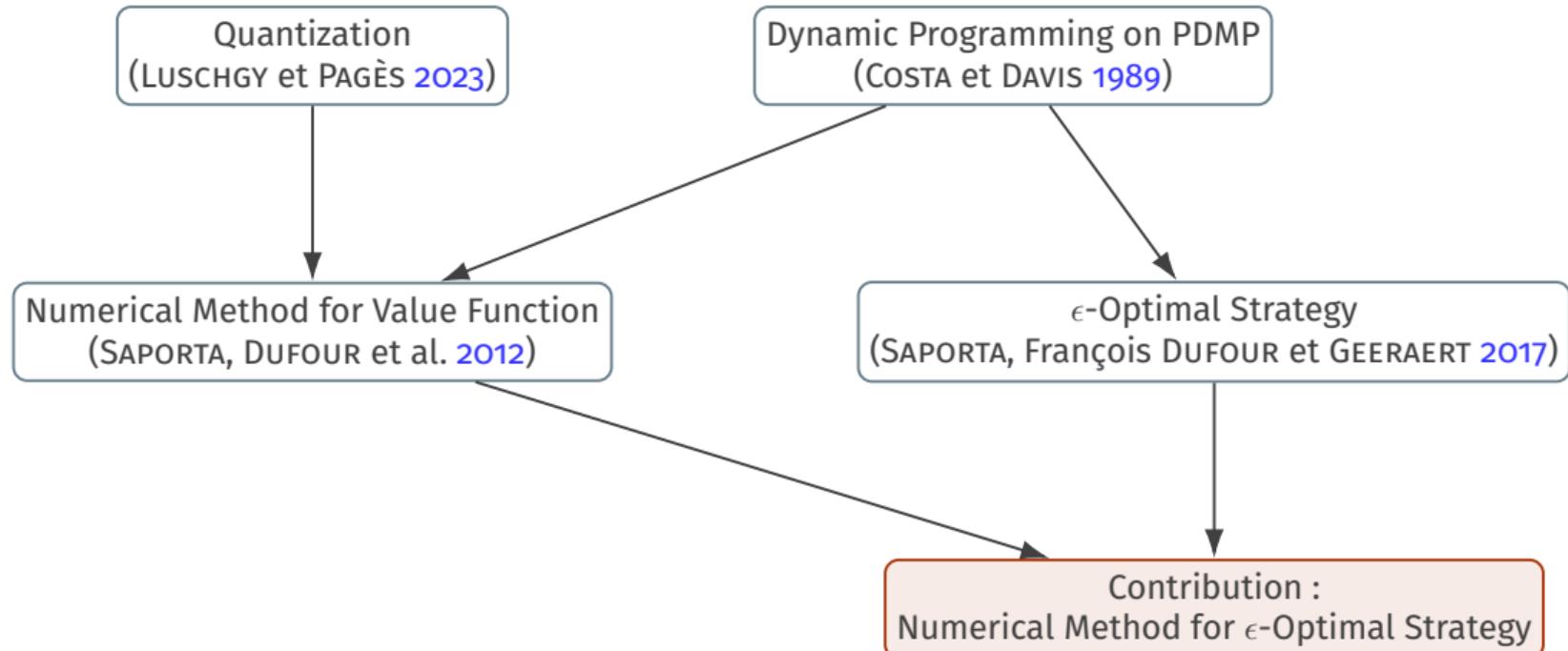
Neural network resolution methods are difficult to interpret and the cost function is complicated to calibrate.

## CURRENT WORK

With this method, we aim to :

- **Easily test multiple cost functions.**
- **Compare the resulting strategies** and choose the best one based on various objectives.

# SUMMARY



## REFERENCES

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