

# Stochastic Perron's Method in Linear and Nonlinear Problems

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# Happy Birthday Yannis!

*Γιάννη, Χρόνια σου πολλά!*

# Outline

Quick overview of DP and HJB's

Objective

Main Idea of Stochastic Perron's Method

Linear case

Obstacle problems and Dynkin games

Back to general control problems

Conclusions

# Summary

New look at an old (set of) problem(s).

## **Disclaimer:**

- ▶ not trying to "reinvent the wheel" but provide a different view (and a new tool)

## **Questions:**

- ▶ why a new look?
- ▶ how/ the tool we propose

# Stochastic Control Problems

State equation

$$\begin{cases} dX_t = b(t, X_t, \alpha_t)dt + \sigma(t, X_t, \alpha_t)dW_t \\ X_s = x. \end{cases}$$

$$X \in \mathbb{R}^n, W \in \mathbb{R}^d$$

$$\text{Cost functional } J(s, x, \alpha) = \mathbb{E}[\int_s^T R(t, X_t, \alpha_t)dt + g(X_T)]$$

Value function

$$v(s, x) = \sup_{\alpha} J(s, x, \alpha).$$

Comments: all formal, no filtration, admissibility, etc. Also, we have in mind other classes of control problems as well.

# (My understanding of) Continuous-time DP and HJB's

Two possible approaches

1. analytic (direct)
2. probabilistic (study the properties of the value function)

# The Analytic approach

1. write down the DPE/HJB

$$\begin{cases} u_t + \sup_{\alpha} \{ L_t^{\alpha} u + R(t, x, \alpha) \} = 0 \\ u(T, x) = g(x) \end{cases}$$

2. solve it i.e.

- ▶ prove existence of a smooth solution  $u$
- ▶ (if lucky) find a closed form solution  $u$

3. go over verification arguments

- ▶ proving existence of a solution to the closed-loop SDE
- ▶ use Itô's lemma and uniform integrability, to conclude  $u = v$  and the solution of the closed-loop eq. is optimal

## Analytic approach cont'd

Conclusions: the existence of a smooth solution of the HJB (with some properties) implies

1.  $u = v$  (uniqueness of the smooth solution)
2. (DPP)

$$v(s, x) = \sup_{\alpha} \mathbb{E} \left[ \int_s^{\tau} R(t, X_t, \alpha_t) dt + v(\tau, X_{\tau}) \right]$$

3.  $\alpha(t, x) = \arg \max$  is the optimal feedback

Complete description: Fleming and Rishel

smooth sol of (DPE)  $\rightarrow$  (DPP)+value fct is the unique sol



## Probabilistic/Viscosity Approach

1. prove the (DPP)
2. show that (DPP)  $\longrightarrow v$  is a viscosity solution
3. IF viscosity comparison holds, then  $v$  is the unique viscosity solution

(DPP)+visc. comparison  $\rightarrow v$  is the unique visc sol(DPE)

**Meta-Theorem** If the value function is the unique viscosity solution, then finite difference schemes approximate the value function and the optimal feedback control (approximate backward induction works).

## Comments on probabilistic approach

1. quite hard (actually very hard compared to deterministic case)
  - 1.1 by approx with discrete-time or smooth problems (Krylov)
  - 1.2 work directly on the value function (El Karoui, Borkar, Hausmann, Bouchard-Touzi for a weak version)
2. non-trivial, but easier than 1: Fleming-Soner, Bouchard-Touzi
3. has to be proved separately (analytically) anyway

## Probabilistic/Viscosity Approach pushed further

Sometimes we are lucky:

- ▶ using the specific structure of the HJB can prove that a viscosity solution of the DPE is actually smooth!
- ▶ if that works we can just come back to the Analytic approach and go over step 3, i.e. we can perform verification using the smooth solution  $v$  (the value function) to obtain
  1. the (DPP)
  2. Optimal feedback control  $\alpha(t, x)$

(DPP)  $\rightarrow$   $v$  is visc. sol  $\rightarrow$   $v$  is smooth sol  $\rightarrow$  (DPP) + opt. controls

Examples: Shreve and Soner, Pham

## Viscosity solution is smooth, cont'd

- ▶ the first step is hardest to prove
- ▶ the program seems circular

**Question:** can we just avoid the first step, proving the (DPP)?

**Answer:** yes, we can use (Ishii's version of) Perron's method to construct (quite easily) a viscosity solution.

Lucky case, revisited

Perron  $\rightarrow$  visc. sol  $\rightarrow$  smooth sol  $\rightarrow$  unique+(DPP) +opt. controls

Example: Janeček, S.

**Comments:**

- ▶ old news for PDE
- ▶ the new approach is analytic/direct

## Perron's method

**General Statement:** sup over sub-solutions and inf over super-solutions are solutions.

$$v^- = \sup_{w \in \mathcal{U}^-} w, v^+ = \inf_{w \in \mathcal{U}^+} w \text{ are solutions}$$

**Ishii's version of Perron (1984):** sup over viscosity sub-solutions and inf over viscosity super-solutions are viscosity solutions.

$$v^- = \sup_{w \in \mathcal{U}^-, \text{visc}} w, v^+ = \inf_{w \in \mathcal{U}^+, \text{visc}} w \text{ are viscosity solutions}$$

**Question:** why not inf/sup over classical super/sub-solutions?

**Answer:** Because one cannot prove (in general/directly) the result is a viscosity solution. The classical solutions are not enough (the set of classical solutions is not stable under max or min).

## Objective

Provide a method/tool to replace the first two steps in the program

Perron  $\rightarrow$  visc. sol  $\rightarrow$  smooth sol  $\rightarrow$  unique+(DPP) +opt. controls

in case one cannot prove viscosity solutions are smooth ("the unlucky case")

New method/tool  $\rightarrow$  **construct** a visc. sol  $u \rightarrow u = v +(\text{DPP})$

Why not try a version of Perron's method?

## Perron's method, recall

(Ishii's version) Provides viscosity solutions of the HJB

$$v^- = \sup_{w \in \mathcal{U}^-, \text{visc}} w, v^+ = \inf_{w \in \mathcal{U}^+, \text{visc}} w$$

### Problem:

- ▶  $w$  does NOT compare to the value function  $v$  UNLESS one proves  $v$  is a viscosity solutions already AND the viscosity comparison
- ▶ if we ask  $w$  to be classical semi-solutions, we cannot prove that the inf/sup are viscosity solutions

# Main Idea

Perform Perron's Method over a class of semi-solutions which are

- ▶ weak enough to conclude (in general/directly) that  $v^-$ ,  $v^+$  are viscosity solutions
- ▶ strong enough to compare with the value function **without studying the properties of the value function**

We know that

classical sol  $\rightarrow$  (DPP)  $\rightarrow$  viscosity sol

Actually, we have

classical semi-sol  $\rightarrow$  half-(DPP)  $\rightarrow$  viscosity semi-sol

Translation

"half (DPP) = stochastic semi-solution"

**Main property:** stochastic sub and super-solutions DO compare with the value function  $v$ !



# Stochastic Perron Method, quick summary

## General Statement:

- ▶ supremum over stochastic sub-solutions is a viscosity (super)-solution

$$v_* = \sup_{w \in \mathcal{U}^-, \text{stoch}} w \leq v$$

- ▶ infimum over stochastic super-solutions is a viscosity (sub)-solution

$$v^* = \inf_{w \in \mathcal{U}^+, \text{stoch}} w \geq v$$

Conclusion:

$$v_* \leq v \leq v^*$$

IF we have a viscosity comparison result, then  $v$  is the unique viscosity solution!

(SP)+visc comp  $\rightarrow$  (DPP)+  $v$  is the unique visc sol of (DPE)

## Some comments

- ▶ the Stochastic Perron Method plus viscosity comparison substitute for (large part of) verification (in the analytic approach)
- ▶ this method represents a "probabilistic version of the analytic approach"
- ▶ loosely speaking, stochastic sub and super-solutions amount to sub and super-martingales
- ▶ stochastic sub and super-solution have to be carefully defined (depending on the control problem) as to obtain viscosity solutions as sup/inf (and to retain the comparison build in)

## Linear case

Want to compute  $v(s, x) = \mathbb{E}[g(X_T^{s,x})]$ , for

$$\begin{cases} dX_t = b(t, X_t)dt + \sigma(t, X_t)dW_t \\ X_s = x. \end{cases}$$

Assumption: continuous coefficients with linear growth

There exist (possibly non-unique) weak solutions of the SDE.

$$\left( (X_t^{s,x})_{s \leq t \leq T}, (W_t^{s,x})_{s \leq t \leq T}, \Omega^{s,x}, \mathcal{F}^{s,x}, \mathbb{P}^{s,x}, (\mathcal{F}_t^{s,x})_{s \leq t \leq T} \right),$$

where the  $W^{s,x}$  is a  $d$ -dimensional Brownian motion on the stochastic basis

$$(\Omega^{s,x}, \mathcal{F}^{s,x}, \mathbb{P}^{s,x}, (\mathcal{F}_t^{s,x})_{s \leq t \leq T})$$

and the filtration  $(\mathcal{F}_t^{s,x})_{s \leq t \leq T}$  satisfies the usual conditions. We denote by  $\mathcal{X}^{s,x}$  the non-empty set of such weak solutions.

## Which selection of weak solutions to consider?

Just take sup/inf over all solutions.

$$v_*(s, x) := \inf_{X^{s,x} \in \mathcal{X}^{s,x}} \mathbb{E}^{s,x}[g(X_T^{s,x})]$$

and

$$v^*(s, x) := \sup_{X^{s,x} \in \mathcal{X}^{s,x}} \mathbb{E}^{s,x}[g(X_T^{s,x})].$$

The (linear) PDE associated

$$\begin{cases} -v_t - L_t v = 0 \\ v(T, x) = g(x), \end{cases} \quad (1)$$

Assumption:  $g$  is bounded (and measurable).

# Stochastic sub and super-solutions

## Definition

A stochastic sub-solution of (1)  $u : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$

1. lower semicontinuous (LSC) and bounded on  $[0, T] \times \mathbb{R}^d$ . In addition  $u(T, x) \leq g(x)$  for all  $x \in \mathbb{R}^d$ .
2. for each  $(s, x) \in [0, T] \times \mathbb{R}^d$ , and each weak solution  $X^{s,x} \in \mathcal{X}^{s,x}$ , the process  $(u(t, X_t^{s,x}))_{s \leq t \leq T}$  is a submartingale on  $(\Omega^{s,x}, \mathbb{P}^{s,x})$  with respect to the filtration  $(\mathcal{F}_t^{s,x})_{s \leq t \leq T}$ .

Denote by  $\mathcal{U}^-$  the set of all stochastic sub-solutions.

## Semi-solutions cont'd

Symmetric definition for stochastic super-solutions  $\mathcal{U}^+$ .

### Definition

A stochastic super-solution  $u : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$

1. upper semicontinuous (USC) and bounded on  $[0, T] \times \mathbb{R}^d$ . In addition  $u(T, x) \geq g(x)$  for all  $x \in \mathbb{R}^d$ .
2. for each  $(s, x) \in [0, T] \times \mathbb{R}^d$ , and each weak solution  $X^{s,x} \in \mathcal{X}^{s,x}$ , the process  $(u(t, X_t^{s,x}))_{s \leq t \leq T}$  is a supermartingale on  $(\Omega^{s,x}, \mathbb{P}^{s,x})$  with respect to the filtration  $(\mathcal{F}_t^{s,x})_{s \leq t \leq T}$ .

## About the semi-solutions

- ▶ if one chooses a Markov selection of weak solutions of the SDE (and the canonical filtration), super and sub solutions are the time-space super/sub-harmonic functions with respect to the Markov process  $X$
- ▶ we use the name associated to Stroock–Varadhan. In Markov framework, sub+ super-solution is a stochastic solution in the definition of Stroock-Varadhan.

The definition of semi-solutions are strong enough to provide comparison to the expectation(s).

For each  $u \in \mathcal{U}^-$  and each  $w \in \mathcal{U}^+$  we have

$$u \leq v_* \leq v^* \leq w.$$

Define

$$v^- := \sup_{u \in \mathcal{U}^-} u \leq v_* \leq v^* \leq v^+ := \inf_{w \in \mathcal{U}^+} w.$$

We have (need to be careful about point-wise inf)

$$v^- \in \mathcal{U}^-, \quad v^+ \in \mathcal{U}^+.$$

# Linear Stochastic Perron

## Theorem

(Stochastic Perron's Method) *If  $g$  is bounded and LSC then  $v^-$  is a bounded and LSC viscosity supersolution of*

$$\begin{cases} -v_t - L_t v \geq 0, \\ v(T, x) \geq g(x). \end{cases} \quad (2)$$

*If  $g$  is bounded and USC then  $v^+$  is a bounded and USC viscosity subsolution of*

$$\begin{cases} -v_t - L_t v \leq 0, \\ v(T, x) \leq g(x). \end{cases} \quad (3)$$

**Comment:** new method to construct viscosity solutions (recall  $v^-$  and  $v^+$  are anyway stochastic sub and super-solutions).



# Verification by viscosity comparison

## Definition

Condition  $CP(T, g)$  is satisfied if, whenever we have a bounded (USC) viscosity sub-solution  $u$  and a bounded LSC viscosity super-solution  $w$  we have  $u \leq w$ .

## Theorem

*Let  $g$  be bounded and continuous. Assume  $CP(T, g)$ . Then there exists a unique bounded and continuous viscosity solution  $v$  to (1), and*

$$v_* = v = v^*.$$

*In addition, for each  $(s, x) \in [0, T] \times \mathbb{R}^d$ , and each weak solution  $X^{s,x} \in \mathcal{X}^{s,x}$ , the process  $(v(t, X^{s,x}))_{s \leq t \leq T}$  is a martingale on  $(\Omega^{s,x}, \mathbb{P}^{s,x})$  with respect to the filtration  $(\mathcal{F}_t^{s,x})_{s \leq t \leq T}$ .*

Comments:

- ▶  $v$  is a stochastic solution (in the Markov case)
- ▶ if comparison holds for all  $T$  and  $g$ , then the diffusion is actually Markov (but we never use that explicitly)

## Idea of proof

Similar to Ishii.

To show that  $v^-$  is a super-solution

- ▶ touch  $v^-$  from below with a smooth test function  $\varphi$
- ▶ if the viscosity super-solution property is violated, then  $\varphi$  is locally a smooth sub-solution
- ▶ push it to  $\varphi_\varepsilon = \varphi + \varepsilon$  slightly above, to still keep it still a smooth sub-solution (locally)
- ▶ Itô implies that  $\varphi_\varepsilon$  is also (locally wrt stopping times) a submartingale along  $X$
- ▶ take  $\max\{v^-, \varphi_\varepsilon\}$ , still a stochastic-subsolution (need to "patch" sub-martingales along a sequence of stopping times)

Comments: why don't we need Markov property? Because we only use Itô, which does not require the diffusion to be Markov.

## Obstacle problems and Dynkin games

First example of non-linear problem.

Same diffusion framework as for the linear case. Choose a selection of weak solutions  $X^{s,x}$  to save on notation.

$g : \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $l, u : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$  *bounded* and measurable,  
 $l \leq u$ ,  $l(T, \cdot) \leq g \leq u(T, \cdot)$ .

Denote by  $\mathcal{T}^{s,x}$  the set of stopping times  $\tau$  (with respect to the filtration  $(\mathcal{F}_t^{s,x})_{s \leq t \leq T}$ ) which satisfy  $s \leq \tau \leq T$ .

The first player ( $\rho$ ) *pays* to the second player ( $\tau$ ) the amount

$$J(s, x, \tau, \rho) := \\ = \mathbb{E}^{s,x} \left[ \mathbb{I}_{\{\tau < \rho\}} l(\tau, X_\tau^{s,x}) + \mathbb{I}_{\{\rho \leq \tau, \rho < T\}} u(\rho, X_\rho^{s,x}) + \mathbb{I}_{\{\tau = \rho = T\}} g(X_T^{s,x}) \right].$$

## Dynkin games, cont'd

*Lower value of the Dynkin game*

$$v_*(s, x) := \sup_{\tau \in \mathcal{T}^{s,x}} \inf_{\rho \in \mathcal{T}^{s,x}} J(s, x, \tau, \rho)$$

and the *upper value of the game*

$$v^*(s, x) := \inf_{\rho \in \mathcal{T}^{s,x}} \sup_{\tau \in \mathcal{T}^{s,x}} J(s, x, \tau, \rho).$$

$$v_* \leq v^*$$

Remark: we could appeal directly to what is known about Dynkin games to conclude  $v_* \leq v^*$ , but this is exactly what we wish to avoid.

## DPE equation for Dynkin games

$$\begin{cases} F(t, x, v, v_t, v_x, v_{xx}) = 0, & \text{on } [0, T) \times \mathbb{R}^d, \\ u(T, \cdot) = g, \end{cases} \quad (4)$$

where

$$\begin{aligned} F(t, x, v, v_t, v_x, v_{xx}) &:= \\ &\max\{v - u, \min\{-v_t - L_t v, v - l\}\} \\ &= \min\{v - l, \max\{-v_t - L_t v, v - u\}\}. \end{aligned} \quad (5)$$

# Super and Subolutions

## Definition

$\mathcal{U}^+$ , is the set of functions  $w : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}$

1. are continuous (C) and bounded on  $[0, T] \times \mathbb{R}^d$ .  $w \geq l$  and  $w(T, \cdot) \geq g$ .
2. for each  $(s, x) \in [0, T] \times \mathbb{R}^d$ , and any stopping time  $\tau_1 \in \mathcal{T}^{s,x}$ , the function  $w$  along the solution of the SDE is a super-martingale in between  $\tau_1$  and the first (after  $\tau_1$ ) hitting time of the upper stopping region  $\mathcal{S}^+(w) := \{w \geq u\}$ . More precisely, for any  $\tau_1 \leq \tau_2 \in \mathcal{T}^{s,x}$ , we have

$$w(\tau_1, X_{\tau_1}^{s,x}) \geq \mathbb{E}^{s,x} \left[ w(\tau_2 \wedge \rho^+, X_{\tau_2 \wedge \rho^+}^{s,x}) \mid \mathcal{F}_{\tau_1}^{s,x} \right] - \mathbb{P}^{s,x} \text{ a.s.}$$

where the stopping time  $\rho^+$  is defined as

$$\rho^+(v, s, x, \tau_1) = \inf \{ t \in [\tau_1, T] : X_t^{s,x} \in \mathcal{S}^+(w) \}.$$

**Question:** why the starting stopping time? No Markov property.

# Stochastic Perron for obstacle problems

Define symmetrically sub-solutions  $\mathcal{U}^-$ . Now define, again

$$v^- := \sup_{w \in \mathcal{U}^-} w \leq v_* \leq v^* \leq v^+ := \inf_{w \in \mathcal{U}^+} w.$$

Cannot show  $v^- \in \mathcal{U}^-$  or  $v^+ \in \mathcal{U}^+$ , but it is not really needed. All is needed is stability with respect to max/min, not sup/inf (and this is the reason why we can assume continuity).

## Theorem

- ▶  $v^-$  is viscosity super-solution of the (DPE)
- ▶  $v^+$  is viscosity sub-solution of the (DPE)

# Verification by comparison for obstacle problems

## Theorem

- ▶ *if comparison holds, then there exists a unique and continuous viscosity solution  $v$ , equal to  $v^- = v_* = v^* = v^+$*
- ▶ *the first hitting times are optimal for both players*

In the Markov case, Peskir showed (with different definitions for sub, super-solutions, which actually involve the value function) that

$$v^- = v^+$$

by showing that  $v^- = \text{"value function"} = v^+$ . Peskir generalizes the characterization of value function in optimal stopping problems.



## What about optimal stopping $u = \infty$ ?

Classic work of El Karoui, Shiryaev: in the Markov case, the value function is the least excessive function. In our notation

$$v^+ := \inf_{w \in \mathcal{U}^+} w = v.$$

**Comment:** the proof requires to actually show that  $v \in \mathcal{U}^+$ . We avoid that, showing that

$$v^- \leq v \leq v^+,$$

and then using comparison.

We provide a short cut to conclude the value function is the continuous viscosity solution of the free-boundary problem (study of continuity in Bassan and Ceci)

# Back to the original control problem

work in progress

- ▶ can define the classes of stochastic super and sub-solutions such that
- ▶ the Stochastic Perron's method (existence part) works well (at least away from  $T$ )

Left to do:

- ▶ study the possible boundary layer at  $T$
- ▶ go over verification by comparison (easy once the first step is done)

# Conclusions

- ▶ new method to construct viscosity solutions as sup/inf of stochastic sub/super-solutions
- ▶ compare directly with the value function
- ▶ if we have viscosity comparison, then the value fct is the unique continuous solution of the (DPE) and the (DPP) holds

## Conjecture

Any PDE that is associated to a stochastic optimization problem can be approached by Stochastic Perron's Method.

Games are a longer shot, but should work out.