# Continuous time Principal Agent and optimal planning

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Nicole  $3\times25$ , May 23, 2019





 Principal delegates management of output process X, only observes X

• Agent devotes effort  $a \Longrightarrow X^a$ , chooses optimal effort by

$$V_A := \max_{\mathbf{a}} \mathbb{E} U_A ( -c(\mathbf{a}))$$





- Principal delegates management of output process X, only observes X pays salary defined by contract  $\xi(X)$
- Agent devotes effort  $a \Longrightarrow X^a$ , chooses optimal effort by

$$V_A(\xi) := \max_{\mathbf{a}} \mathbb{E} \ U_A(\xi(X^{\mathbf{a}}) - c(\mathbf{a})) \implies \hat{a}(\xi)$$

Principal chooses optimal contract by solving

$$\max_{\xi} \mathbb{E} U_P \left( X^{\hat{a}(\xi)} - \xi(X^{\hat{a}(\xi)}) \right)$$
 under constraint  $V_A(\xi) \geq \rho$ 

→ Non-zero sum Stackelberg game





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### (Static) Principal-Agent Problem ==> Continuous time

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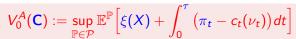


### Principal-Agent problem formulation

#### Contract $C = (\tau, \pi, \xi)$

au  $\mathbb{F}-$ stopping time,  $\pi$   $\mathbb{F}-$ adapted, and  $\xi$   $\mathcal{F}_{ au}-$ mble

#### Agent problem



 $\mathbb{P} \in \mathcal{P}$  : weak solution of Output process :

$$dX_t = b_t(X, \nu_t)dt + \sigma_t(X, \nu_t)dW_t^{\mathbb{P}} \quad \mathbb{P} - \text{a.s.}$$

for some  $\nu$  valued in U

Principal problem choose among acceptable contracts  $= \{C : V^A(C) > 0\}$ 

$$\Xi_{
ho} := \left\{ \mathbf{C} : V_0^A(\mathbf{C}) \geq \rho \right\}$$

best contract, given Agent's optimal response  $\mathbb{P}^*(\mathbb{C})$ 

$$V_0^P := \sup_{\mathbf{C} \in \Xi_{
ho}} \mathbb{E}^{\,\mathbb{P}^*(\mathbf{C})} \Big[ U \Big( \ell(X) - \xi(X) - \int_0^ au \pi_t(X) dt \Big) \Big]$$

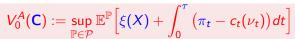


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## Mean field games and optimal planning

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 $\tau$   $\mathbb{F}$ -stopping time,  $\pi$   $\mathbb{F}$ -adapted, and  $\xi$   $\mathcal{F}_{\tau}$ -mble

Agent problem

$$V_0^A( extsf{C}) := \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \Big[ \xi(X) + \int_0^ au ig(\pi_t - c_t(
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### A general solution approach

• Path-dependent Hamiltonian for the Agent problem :

$$H_t^{\pi}(\omega, \mathbf{z}, \gamma) := \sup_{\mathbf{u} \in \mathbf{U}} \left\{ b_t(\omega, \mathbf{u}) \cdot \mathbf{z} + \frac{1}{2} \sigma_t \sigma_t^{\top}(\omega, \mathbf{u}) : \gamma + \pi_t(\omega) - c_t(\omega, \mathbf{u}) \right\}$$

• For  $Y_0 \in \mathbb{R}$ ,  $Z, \Gamma \mathbb{F}^X$  — prog meas, define  $\mathbb{P}$ —a.s. for all  $\mathbb{P} \in \mathcal{P}$ 

$$Y_t^{Z,\Gamma} = Y_0 + \int_0^t Z_s \cdot dX_s + \frac{1}{2}\Gamma_s : d\langle X \rangle_s - H_s^{\pi}(X,Z_s,\Gamma_s)ds$$

#### Proposition

$$V_Aig( au,\pi,Y^{Z,\Gamma}_ auig)=Y_0.$$
 Moreover  $\mathbb{P}^*$  is optimal iff

$$\nu_t^* = \operatorname{Arg\max}_{u \in U} H_t^{\pi}(Z_t, \Gamma_t) = \hat{\nu}(Z_t, \Gamma_t)$$

**Proof** classical verification argument in stochastic control



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Proof classical verification argument in stochastic control



#### Principal problem restricted to revealing contracts

#### Dynamics of the pair (X, Y) under "optimal response"

$$dX_{t} = b_{t}(X, \hat{\nu}(Z_{t}, \Gamma_{t}))dt + \sigma_{t}(X, \hat{\nu}(Z_{t}, \Gamma_{t}))dW_{t}$$
  
$$dY_{t}^{Z,\Gamma} = Z_{t} \cdot dX_{t} + \frac{1}{2}\Gamma_{t} : d\langle X \rangle_{t} - H_{t}^{\pi}(X, Z_{t}, \Gamma_{t})dt$$

is a (1 state augmented) controlled SDE with controls  $(\pi, \mathbb{Z}, \Gamma)$ 

#### ⇒ Principal's value function under revealing contracts :

$$V_{P} \geq V_{0}(X_{0}, Y_{0}) := \sup_{\substack{(\tau, \pi) \\ (Z, \Gamma) \in \mathcal{V}}} \mathbb{E}\Big[U\Big(\ell(X) - Y_{\tau}^{Z, \Gamma} - \int_{0}^{\tau} \pi_{t} dt\Big)\Big], \ \forall \ Y_{0} \geq \rho$$

$$\text{where } \mathcal{V} := \Big\{(Z, \Gamma) : \ Z \in \mathbb{H}^{2}(\mathcal{P}) \ \text{and} \ \mathcal{P}^{*}\big(Y_{T}^{Z, \Gamma}\big) \neq \emptyset\Big\}$$

### Reduction to standard control problem

#### Theorem

Assume  $V \neq \emptyset$ . Then

$$V_0^P = \sup_{Y_0 \ge \rho} V_0(X_0, Y_0)$$

Given maximizer  $Y_0^*$ , the corresponding optimal controls  $(\tau^*, \pi^*, \mathbf{Z}^*, \mathbf{\Gamma}^*)$  induce an optimal contract  $\mathbf{C}^* = (\tau^*, \pi^*, \xi^*)$  with

$$\xi^* = Y_0^* + \int_0^T Z_t^* \cdot dX_t + \frac{1}{2} \Gamma_t^* : d\langle X \rangle_t - H_t^{\pi^*} (X, Z_t^*, \Gamma_t^*) dt$$

Sannikov '08 Cvitanić, Possamaï & NT '15 Lin, Ren, NT & Yang '19



#### Comments on the theorem

#### **Examples of volatility control problems**

Portfolio optimization

$$dV_t = \theta_t \cdot dS_t$$

Demand-Response programs in electricity retail market

$$dX_t = \frac{\alpha_t}{dt} + \frac{\beta_t}{dt} \cdot dW_t$$

#### Open to many extensions

- agent may also choose optimally to quit (Sannikov)
- many agents, many principals under competition (Possamaï &...)
- Limited liability (Possamaï & Villeneuve)



#### Recall the subclass of contracts

$$Y_t^{Z,\Gamma} = Y_0 + \int_0^t Z_s \cdot dX_s + \frac{1}{2} \Gamma_s : d\langle X \rangle_s - H_s(X, Y_s^{Z,\Gamma}, Z_s, \Gamma_s) ds$$

$$\mathbb{P} - \text{a.s. for all } \mathbb{P} \in \mathcal{P}$$

To prove the main result, it suffices to prove the representation

$$\text{for all } \xi \in ??? \quad \exists \; \big(Y_0,Z,\Gamma\big) \quad \text{s.t.} \quad \xi = Y_T^{Z,\Gamma}, \; \mathbb{P}-\text{a.s. for all } \mathbb{P} \in \mathcal{P}$$

OR, weaker sufficient condition

for all 
$$\xi \in ??$$
  $\exists (Y_0^n, Z^n, \Gamma^n)$  s.t. " $Y_T^{Z^n, \Gamma^n} \longrightarrow \xi$ "



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• Path-dependent Hamiltonian for the Agent problem :

$$H_t^{\pi}(\omega, z, \gamma) := \sup_{\mathbf{u} \in \mathbf{U}} \left\{ b_t(\omega, \mathbf{u}) \cdot z + \frac{1}{2} \sigma_t \sigma_t^{\top}(\omega) : \gamma + \pi_t(\omega) - c_t(\omega, \mathbf{u}) \right\}$$

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-a.s. for some  $\mathbb{P}_0 \in \mathcal{P}$ 

( $\mathcal{P}$  dominated set of measures by Girsanov)

Representation problem reduces to

$$Y_{\tau}^{Z,0} = \xi, \quad \mathbb{P}_0 - \text{a.s.} \quad \text{Backward SDE...} \quad \Box$$



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Pardoux & Peng '90, El Karoui, Peng & Quenez '96



•  $H_t(\omega, y, z, \gamma)$  non-decreasing and convex in  $\gamma$ , the

$$H_t(\omega, y, z, \gamma) = \sup_{\sigma} \left\{ \frac{1}{2} \sigma^2 : \gamma - H_t^*(\omega, y, z, \sigma) \right\}$$

• Let 
$$\hat{\sigma}_t^2 := \frac{d\langle X \rangle}{dt}$$
, and introduce

$$k_t := H_t(Y_t, Z_t, \Gamma_t) - \frac{1}{2}\hat{\sigma}_t^2 : \Gamma_t + H_t^*(Y_t, Z_t, \hat{\sigma}_t) : \ge 0$$
 and " $\inf_{\mathbb{P} \in \mathcal{P}} k_t = 0$ "

Then, required representation  $\xi = Y_{\tau}^{Z,\Gamma}$ ,  $\mathcal{P}-q.s.$  is **equivalent to** 

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 $\Longrightarrow$  2BSDE up to approximation of nondecreasing process  $K=\int_0^{\cdot}k_tdt$ 



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 $\Rightarrow$  2BSDE up to approximation of nondecreasing process  $K = \int_0^\infty k_t dt...$ 

### Wellposedness of random horizon 2<sup>nd</sup>order backward SDE

$$\begin{split} Y_{t \wedge \tau} &= \xi + \int_{t \wedge \tau}^{\tau} F_s(Y_s, Z_s, \hat{\sigma}_s) ds - \int_{t \wedge \tau}^{\tau} Z_s \cdot dX_s + \int_{t \wedge \tau}^{\tau} dK_s, \quad \mathcal{P} - \text{q.s.} \\ K \text{ non-decreasing, and } \inf_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[ \int_{s \wedge \tau}^{t \wedge \tau} dK_r \right] = 0, \ s \leq t \end{split}$$

#### Theorem (Y. Lin, Z. Ren, NT & J. Yang '18)

Assume 
$$\exists \rho > -\mu, \ \mathbf{q} > 1 : \mathcal{E}^{L}[|e^{\rho \tau}\xi|^{\mathbf{q}}] + \mathcal{E}^{L}[(\int_{0}^{\tau}|e^{\rho t}f_{t}^{0}|^{2}ds)^{\frac{\mathbf{q}}{2}}] < \infty$$

Then, Random horizon 2BSDE has a unique solution (Y, Z) with

$$Y \in \mathcal{D}_{\eta,\tau}^{p}, \ \ Z \in \mathcal{H}_{\eta,\tau}^{p} \quad \text{for all} \quad \eta \in [-\mu,\rho), \ \ p \in [1,q)$$

$$\|Y\|_{\mathcal{D}^{\boldsymbol{\rho}}_{\eta,\tau}}^{\boldsymbol{\rho}}:=\mathcal{E}^{\boldsymbol{L}}\Big[\sup_{t<\tau}\big|e^{\eta t}Y_{t}\big|^{\boldsymbol{\rho}}\Big],\ \|Z\|_{\mathcal{H}^{\boldsymbol{\rho}}_{\eta,\tau}}^{\boldsymbol{\rho}}:=\mathcal{E}^{\boldsymbol{L}}\Big[\Big(\int_{0}^{\tau}\!\!\big|e^{\eta t}\,\widehat{\sigma}_{t}^{\mathrm{T}}Z_{t}\big|^{2}dt\Big)^{\frac{\boldsymbol{\rho}}{2}}\Big]$$

Extends Soner, NT & Zhang '12 and Possamaï, Tan & Zhou '18 Closely connected to G-BSDE, Hu, Ji, Peng & Song '14



### Mean field games

Consider a croud of agents in MFG equilibrium:

$$V_0^{\mathcal{A}}(\underline{\mu},\xi) := \sup_{\mathbb{P} \in \mathcal{P}} J(\underline{\mu},\xi,\mathbb{P}) = J(\underline{\mu},\xi,\hat{\mathbb{P}}_{\xi}^{\underline{\mu}})$$

where 
$$J(\mathbb{P},\mu,\xi) := \mathbb{E}^{\mathbb{P}} \Big[ \xi(X) - \int_0^{\mathcal{T}} c_t(\mu_t,lpha_t,eta_t) dt \Big]$$

and  $\mathbb{P} \in \mathcal{P}$  is weak solution of controlled process :

$$\mathbb{P} \circ (X_0)^{-1} = \mu_0$$
, and  $dX_t = \sigma_t(X, \beta_t) [\lambda_t(X, \alpha_t) dt + dW_t^{\mathbb{P}}], \mathbb{P} - a.s.$ 

#### **Definition** (Mean field game equilibrium)

$$\hat{m{\mu}}$$
 is an MFG equilibrium if  $\hat{\mathbb{P}}_{m{\xi}}^{\hat{m{\mu}}} \circ (X_t)^{-1} = \hat{m{\mu}}_{m{t}}$ , for all  $t \leq T$ 



### P.L. Lions' Planning Problem

- uncontrolled diffusion  $\sigma_t(\beta) = I_d$
- Markov setting :  $\lambda_t(\omega) = \lambda_t(\omega_t)$ , c..., and  $\xi(\omega) = g(\omega_T)$

#### Planning Problem

- Let  $\mu_0, \nu$  be given probability measures on  $\mathbb{R}^d$
- Find  $g: \mathbb{R}^d \longmapsto \mathbb{R}$  so that

MFG equilibrium  $\hat{\mu}$  exists and  $\hat{\mu}_0 = \mu_0$ ,  $\hat{\mu}_T = \nu$ 

#### Interpretation: optimal transport, regulation

Start from croud distributed as  $\mu_0$ . Choose an appropriate incentive cost  $g: \mathbb{R}^d \longmapsto \mathbb{R}$  so as to force the MFG equilibrium to the target distribution  $\nu$  at time T.

 $\implies$  Unique solution exists for any pair  $(\mu,\nu)...$ Lions '10, Achdou Y, Camilli F & Capuzzo Dolcetta '12, Porretta



### Path-dependent formulation of the Planning Problem

#### Allow the incentive cost $\xi$ to be path-dependent

#### Path-dependent Planning Problem

- Let  $\mu_0, \nu$  be given probability measures on  $\mathbb{R}^d$
- Find  $\xi: \Omega \longrightarrow \mathbb{R}$ ,  $\mathcal{F}_T$ —measurable, so that

MFG equilibrium 
$$\hat{\mu}$$
 exists and  $\hat{\mu}_0 = \mu_0$ ,  $\hat{\mu}_T = \nu$ 

- More freedom for the choice of incentive regulation
- Multiple solutions, in general





### MFG equilibria with varying path-dependent cost $\xi$

#### Forward description of MFG equilibria

For all controls  $(Z,\Gamma)$ , let  $\xi^{Z,\Gamma}:=Y^{Z,\Gamma}_T$ , where  $Y^{Z,\Gamma}$  is defined by the McKean-Vlasov controlled process

$$dY_t^{Z,\Gamma} = Z_t \cdot dX_t + \frac{1}{2}\Gamma_t : d\langle X \rangle_t - H_t(Y_t^{Z,\Gamma}, Z_t, \Gamma_t, \mu_t)$$

 $\mu_t = \mathbb{P} \circ X_t^{-1}$  distribution of  $X_t$  with controls defined as maximizers of H

$$dX_t = \nabla_z H_t(\cdots) dt + \left[2\nabla_\gamma H_t(\cdots)\right]^{1/2} dW_t$$

- Multiple solutions, in general
- Skorohod embedding problem is a particular case :
  - planning exists iff  $\mu_0 \leq \nu$  in convex order
  - Many solutions exist... sometimes corresponding to various X COLECTION OF THE PROPERTY OF T optimization criteria!



### Optimal Planning Problem

#### MFG transport plans from $\mu_0$ to $\nu$ in $Prob(\mathbb{R}^d)$

- $\Xi(\mu_0, \nu)$  :  $\xi \in \Lambda^0(\Omega, \mathcal{F}_T)$  s.t. there exists an MFG equilibrium  $\mu$  satisfying  $\hat{\mathbb{P}}^{\mu}_{\varepsilon} \circ (X_T)^{-1} = \nu$
- Given the planner criterion  $\phi: \Omega \times \Lambda^0(\Omega, \mathcal{F}_T) \longrightarrow \mathbb{R}$ , solve

$$V^{\mathrm{P}} := \sup_{\xi \in \Xi(\mu_{\mathbf{0}}, \nu)} \mathbb{E}^{\hat{\mathbb{P}}^{\mu}_{\xi}} \Big[ \phi(X, \xi(X)) \Big]$$

#### Theorem (Z. Ren, X. Tan & NT)

Planner problem can be restricted to forward MV transport plans

$$V^{\mathrm{P}} = \sup_{Z,\Gamma:\; \hat{\mathbb{P}}^{Z,\Gamma} \circ (X_T)^{-1} = \nu} \mathbb{E}^{\hat{\mathbb{P}}^{Z,\Gamma}} \left[ \phi \left( X, Y_T^{Z,\Gamma} \right) \right]$$



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#### Nonlinear expectation operators

 $\mathcal{P}^0$ : subset of local martingale measures, i.e.

$$dX_t = \sigma_t dW_t$$
,  $\mathbb{P} - \text{a.s. for all}$   $\mathbb{P} \in \mathcal{P}^0$ 

⇒ Nonlinear expectation

$$\mathcal{E}:=\sup_{\mathbb{P}\in\mathcal{P}^{\mathbf{0}}}\mathbb{E}^{\mathbb{P}}$$

Similarly,  $\mathcal{P}^{\mathcal{L}}$ : subset of measures  $\mathbb{Q}^{\lambda}$  such that

$$dX_t = \sigma_t(\lambda_t dt + dW_t), \quad \mathbb{Q} - \text{a.s. for some} \quad \lambda, \ \mathbb{F} - \text{adapted}, \ |\lambda| \leq L$$

⇒ Another nonlinear expectation

$$\mathcal{E}^{\mathcal{L}} := \sup_{\mathbb{P} \in \mathcal{P}^{\mathcal{L}}} \mathbb{E}^{\mathbb{Q}}$$



 $\mathcal{E}$  and  $\mathcal{E}^L$  will play the role of Sobolev norms...

#### Nonlinearity

#### Assumptions on $F: \mathbb{R}_+ \times \omega \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{S}^d_+ \longrightarrow \mathbb{R}$

(C1<sub>L</sub>) Lipschitz in  $(y, \sigma z)$ :

$$|F(.,y,z,\sigma)-F(.,y',z',\sigma)| \leq L(|y-y'|+|\sigma(z-z')|)$$

(C2 $_{\mu}$ ) Monotone in y:

$$(y-y') \cdot [F(.,y,.) - F(.,y',.)] \le -\mu |y-y'|^2$$

**Denote**  $f_t^0 := F_t(0, 0, \widehat{\sigma}_t)$ 

**Remark** Deterministic finite horizon  $\tau = T: (C2)_{\mu}$  not needed Soner, NT & Zhang '14 and Possamaï, Tan & Zhou '16



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