

# Addressing hierarchical jointly-convex generalized Nash equilibrium problems with nonsmooth payoffs

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# Outline

motivating application: hierarchical multi-portfolio selection

generalized variational inequality formulations

projected gradient-like algorithms

numerical results

# multi-portfolio selection

$\nu = 1, \dots, N$ :

$$\text{minimize}_{y^\nu} \theta_\nu^l(y^\nu, y^{-\nu}) + \varphi_\nu^l(y^\nu) \quad \text{s.t.} \quad y^\nu \in Y_\nu$$

$$\theta_\nu^l(y^\nu, y^{-\nu}) = -l_\nu(y^\nu) + \rho_\nu R_\nu(y^\nu) + TC_\nu(y^\nu, y^{-\nu})$$

$$\varphi_\nu^l(y^\nu) = \tau_\nu \|y^\nu\|_1$$

$$Y_\nu = \left\{ y^\nu \in [l_\nu, u_\nu]^K : \sum_{i=1}^K y_i^\nu \leq 1 \right\}$$

Yang, Y., Rubio, F., Scutari, G., Palomar, D. P. (2013). Multi-portfolio optimization: A potential game approach. IEEE Tran Sign Proc, 61

Lampariello, L., Neumann, C., Ricci, J. M., Sagratella, S., Stein, O. (2021). Equilibrium selection for multi-portfolio optimization. Europ J Oper Res, 295

# Nash equilibrium problem (lower-level NEP)

find  $y \in Y \triangleq Y_1 \times \cdots \times Y_N$  such that

$\nu = 1, \dots, N$ :

$$\theta_\nu^l(y^\nu, y^{-\nu}) + \varphi_\nu^l(y^\nu) \leq \theta_\nu^l(v^\nu, y^{-\nu}) + \varphi_\nu^l(v^\nu), \quad \forall v^\nu \in Y_\nu$$

assumptions A

**A1**  $Y_\nu$  is nonempty, convex and compact,  $\nu = 1, \dots, N$

**A2**  $\theta_\nu^l \in C^1$  is convex with respect to  $y^\nu$ ,  $\nu = 1, \dots, N$

**A3**  $[\nabla_{y^\nu} \theta_\nu^l]_{\nu=1}^N$  is monotone on  $Y$

**A4**  $\varphi_\nu^l$  is convex and locally Lipschitz,  $\nu = 1, \dots, N$

# hierarchical multi-portfolio selection

$\mu = 1, \dots, M :$

$$\text{minimize}_{x^\mu} \theta_\mu^u(x^\mu, x^{-\mu}) + \varphi_\mu^u(x^\mu) \quad \text{s.t.} \quad (x^\mu, x^{-\mu}) \in E$$

$$x^\mu = [y^\nu]_{\nu \in \mathcal{S}_\mu}$$

$$\theta_\mu^u(x^\mu, x^{-\mu}) = - \sum_{\nu \in \mathcal{S}_\mu} l_\nu(y^\nu) + \rho_\mu \sum_{\nu \in \mathcal{S}_\mu} R_\nu(y^\nu) + TC_\mu(x^\mu, x^{-\mu}),$$

$$\varphi_\mu^u(x^\mu) = \tau_\mu \sum_{\nu \in \mathcal{S}_\mu} \|y^\nu\|_1$$

$E \triangleq$  solutions of the lower-level NEP

Lampariello, L., Priori, G., Sagratella, S. (2022). On the solution of monotone nested variational inequalities. Math Meth Oper Res, 96

# hierarchical generalized Nash equilibrium problem

find  $x \in E$  such that

$\mu = 1, \dots, M$ :

$$\theta_{\mu}^u(x^{\mu}, x^{-\mu}) + \varphi_{\mu}^u(x^{\mu}) \leq \theta_{\mu}^u(w^{\mu}, x^{-\mu}) + \varphi_{\mu}^u(w^{\mu}), \quad \forall w^{\mu} : (w^{\mu}, x^{-\mu}) \in E$$

assumptions B

**B1**  $\theta_{\mu}^u \in C^1$  is convex with respect to  $x^{\mu}$ ,  $\mu = 1, \dots, M$

**B2**  $[\nabla_{x^{\mu}} \theta_{\mu}^u]_{\mu=1}^M$  is monotone on  $Y$

**B3**  $\varphi_{\mu}^u$  is convex and locally Lipschitz,  $\mu = 1, \dots, M$

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## lower-level GVI formulation

find  $y \in Y$  such that

$$\exists f_y \in F(y) : f_y^T (v - y) \geq 0, \quad \forall v \in Y$$

where

$$F(y) = \left[ \nabla_{y^\nu} \theta'_\nu(y) \right]_{\nu=1}^N + \left[ \partial_{y^\nu} \varphi'_\nu(y^\nu) \right]_{\nu=1}^N$$

properties under assumptions A and B

- ▶  $E = \text{SOL}(F, Y)$
  - ▶  $\text{SOL}(F, Y)$ , and then  $E$ , are nonempty and compact
  - ▶  $F$  is maximal monotone and outer semi-continuous
- $\implies \text{SOL}(F, Y)$ , and then  $E$ , are convex sets
- $\implies$  the hierarchical GNEP is jointly-convex



## on maximal monotonicity

- ▶  $T : \mathbb{R}^p \rightrightarrows \mathbb{R}^p$  is monotone if

$$(\hat{t} - \tilde{t})^T (\hat{u} - \tilde{u}) \geq 0, \quad \forall (\hat{u}, \hat{t}), (\tilde{u}, \tilde{t}) \in \text{gph}(T)$$

- ▶  $T : \mathbb{R}^p \rightrightarrows \mathbb{R}^p$  is maximal monotone if it is monotone and  $\forall (\hat{u}, \hat{t}) \notin \text{gph}(T), \exists (\tilde{u}, \tilde{t}) \in \text{gph}(T) : (\hat{t} - \tilde{t})^T (\hat{u} - \tilde{u}) < 0$
- ▶ every continuous monotone single-valued mapping is maximal monotone (not true for multi-valued mappings)

### Lemma

consider the following conditions on  $T : \mathbb{R}^p \rightrightarrows \mathbb{R}^p$ :

$$(\hat{u}, \hat{t}) \in \text{gph}(T) \tag{L1}$$

$$(\hat{t} - t)^T (\hat{u} - u) \geq 0, \quad \forall (u, t) \in \text{gph}(T) \tag{L2}$$

if  $T$  is monotone, then (L1) implies (L2)

if  $T$  is maximal monotone, then (L2) implies (L1)

## hierarchical GVI formulation

find  $x \in \text{SOL}(F, Y)$  such that

$$\exists g_x \in G(x) : g_x^T(w - x) \geq 0, \quad \forall w \in \text{SOL}(F, Y)$$

where

$$G(x) = [\nabla_{x^\mu} \theta_\mu^u(x)]_{\mu=1}^M + [\partial_{x^\mu} \varphi_\mu^u(x^\mu)]_{\mu=1}^M$$

properties under assumptions A and B

- ▶ every  $x \in \text{SOL}(G, \text{SOL}(F, Y))$  is a (variational) solution of the hierarchical GNEP
- ▶  $\text{SOL}(G, \text{SOL}(F, Y))$  is nonempty and compact  
 $\implies$  the solution set of the hierarchical GNEP is nonempty
- ▶  $G$  is maximal monotone and outer semi-continuous  
 $\implies \text{SOL}(G, \text{SOL}(F, Y))$  is convex

## Tikhonov GVI subproblem

given  $\eta \geq 0$ , find  $y \in Y$  such that

$$\exists h_y^\eta \in H_\eta(y) : h_y^{\eta T}(v - y) \geq 0, \quad \forall v \in Y$$

where

$$H_\eta(y) = F(y) + \eta G(y)$$

### Theorem

given  $\delta \geq 0$ , let  $y \in Y$  such that

$$\exists h_y^\eta \in H_\eta(y) : h_y^{\eta T}(v - y) \geq -\delta, \quad \forall v \in Y$$

then

$$\exists f_y \in F(y) : f_y^T(v - y) \geq -\delta - \eta\Lambda, \quad \forall v \in Y$$

$$\exists g_y \in G(y) : g_y^T(v - y) \geq -\delta/\eta, \quad \forall v \in \text{SOL}(F, Y)$$

where  $\Lambda = \max_{y \in Y} \max_{g_y \in G(y)} \|g_y\| \max_{x, v \in Y} \|x - v\|$

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# projected gradient-like scheme

given  $\{\gamma_k\}, \{\eta_k\}, y_1 \in Y$

for every  $k = 1, \dots$  compute:

$$f_{y_k} \in F(y_k), \quad g_{y_k} \in G(y_k), \quad h_{y_k}^{\eta_k} \leftarrow f_{y_k} + \eta_k g_{y_k},$$
$$y_{k+1} \leftarrow P_Y(y_k - \gamma_k h_{y_k}^{\eta_k})$$

for every  $k = \bar{k}, \dots$  compute:

$$z_k \leftarrow \frac{\sum_{j=\bar{k}}^k \gamma_j y_j}{\sum_{j=\bar{k}}^k \gamma_j}$$

# convergence properties 1

assumptions C

**C1**  $\{\gamma_k\}$  is non-increasing,  $0 < \gamma_k \rightarrow 0$ , and  $\{\gamma_k\} \notin \ell_1$

**C2**  $\{\eta_k\}$  is non-increasing,  $0 < \eta_k \rightarrow \eta \geq 0$

Theorem

**a)** if  $\{\gamma_k\} \in \ell^2$ , and  $\{\gamma_k(\eta_j - \eta)\} \in \ell^1$ , then

$$\forall u \in \text{SOL}(H_\eta, Y), \exists l_u \geq 0 : \lim_{k \rightarrow \infty} \|y_k - u\|^2 = l_u$$

**b)** if  $y_k \rightarrow \bar{y}$ , then  $\bar{y} \in \text{SOL}(H_\eta, Y)$

**c)**  $\|y_{k+1} - y_k\| \rightarrow 0$

**d)**  $z_k \rightarrow \bar{z} \in \text{SOL}(H_\eta, Y)$

## convergence properties 2

additional assumptions D

**D1**  $\eta = 0$

**D2**  $\frac{\gamma_k}{\eta_k} \rightarrow 0$

**D3**  $\eta_k \sum_{j=1}^k \gamma_j \rightarrow \infty$

Theorem

**a)** if  $y_k \rightarrow \bar{y}$ , then  $\bar{y} \in \text{SOL}(G, \text{SOL}(F, Y))$

**b)**  $z_k \rightarrow \bar{z} \in \text{SOL}(G, \text{SOL}(F, Y))$

# complexity bounds

consider harmonic sequences:

$$\gamma_k = \frac{\bar{\gamma}}{k^\alpha}, \quad \eta_k = \frac{\bar{\eta}}{k^\beta} + \eta, \quad k \geq 1$$

$\alpha$	$\beta$	convergence properties	complexity
$1 - \epsilon$	$1 - \epsilon$	$\limsup_{\Delta \rightarrow \infty} \ y_{k+\Delta} - u\ ^2 - \ y_k - u\ ^2 \leq \delta,$ $u \in \text{SOL}(H_\eta, Y)$	$\mathcal{O}(\delta^{-1/(1-2\epsilon)})$
0.5	0.5	$h_v^\eta{}^T(v - z_k) \geq -\delta, \quad \forall v \in Y, h_v^\eta \in H_\eta(v)$	$\mathcal{O}(\delta^{-2})$
0.5	0.25	$f_v^T(v - z_k) \geq -\delta, \quad \forall v \in Y, f_v \in F(v)$ $g_v^T(v - z_k) \geq -\delta, \quad \forall v \in \text{SOL}(F, Y), g_v \in G(v)$	$\mathcal{O}(\delta^{-4})$



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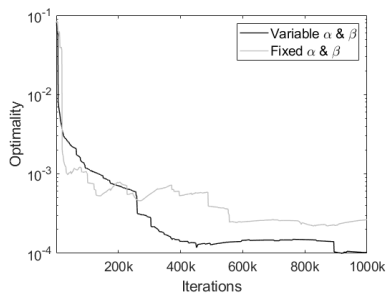
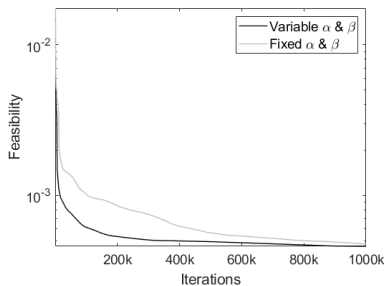
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**numerical results**

# hierarchical multi-portfolio selection models

- ▶  $N = 25$ ,  $M = 5$ ,  $\mathcal{S}_\mu = \{1 + 5(\mu - 1), \dots, 5 + 5(\mu - 1)\}$
- ▶ data sets:  $K = 10$  assets from Euro Stoxx 50 (SX5E);  
 $K = 29$  assets from Dow Jones Industrial Average (DJIA)
- ▶ accounts 1-15 are regularized at the lower-level;  
accounts 16-25 are regularized at the upper-level
- ▶  $\text{feas}(y, f_y) \triangleq \max_{v \in Y} -f_y^T(v - y)$   
 $\geq -\min_{v \in Y} \min_{f_v \in F(v)} f_v^T(v - y)$
- ▶  $\text{opt}(y, f_y, g_y) \triangleq \max_{v \in Y} -(1/\eta)(f_y + \eta g_y)^T(v - y)$   
 $\geq -\min_{v \in \text{SOL}(F, Y)} \min_{g_v \in G(v)} g_v^T(v - y)$

## SX5E full regularization 1



## results 2

		feas( $z_{\bar{I}}, f_{z_{\bar{I}}}$ )			feas( $y_{\bar{I}}, f_{y_{\bar{I}}}$ )		opt( $y_{\bar{I}}, f_{y_{\bar{I}}}, g_{y_{\bar{I}}}$ )
		$\bar{k} = 0$	$\bar{k} = 0.4\bar{I}$	$\bar{k} = 0.8\bar{I}$			
SX5E	No reg	2.2225e-04	9.8603e-05	9.6364e-05	9.5698e-05	9.1130e-05	
	Low. reg. 1	1.0859e-03	2.3361e-04	2.2854e-04	2.2719e-04	8.6980e-05	
	Low. reg. 2	2.4301e-03	3.1726e-04	3.0886e-04	3.0703e-04	6.1042e-05	
	Full reg. 1	1.5472e-03	4.7882e-04	4.6261e-04	4.5935e-04	1.0150e-04	
	Full reg. 2	2.8817e-03	5.5899e-04	5.4486e-04	5.4262e-04	6.9896e-05	
DIJA	No reg.	9.2238e-04	3.2620e-04	3.1930e-04	3.1754e-04	1.9082e-04	
	Low. reg. 1	3.4512e-03	6.7104e-04	6.7104e-04	6.5528e-04	1.7030e-04	
	Low. reg. 2	8.2720e-04	8.2720e-04	8.3136e-04	8.2720e-04	2.0577e-04	
	Full reg. 1	3.8326e-03	8.8701e-04	8.6774e-04	8.6284e-04	2.6538e-04	
	Full reg. 2	7.6527e-03	1.0600e-03	1.0416e-03	1.0365e-03	2.7482e-04	

#Accounts	SX5E		DIJA	
	1–15	16–25	1–15	16–25
<i>No regularization</i>	0.00%	0.00%	0.00%	0.00%
<i>Lower regularization 1</i>	28.00%	0.00%	38.62%	0.00%
<i>Lower regularization 2</i>	44.67%	0.00%	56.78%	0.00%
<i>Full regularization 1</i>	28.00%	25.00%	38.62%	12.07%
<i>Full regularization 2</i>	44.67%	24.00%	56.55%	11.72%