Game Theory Motivating Examples

By Hamed Kebriaei

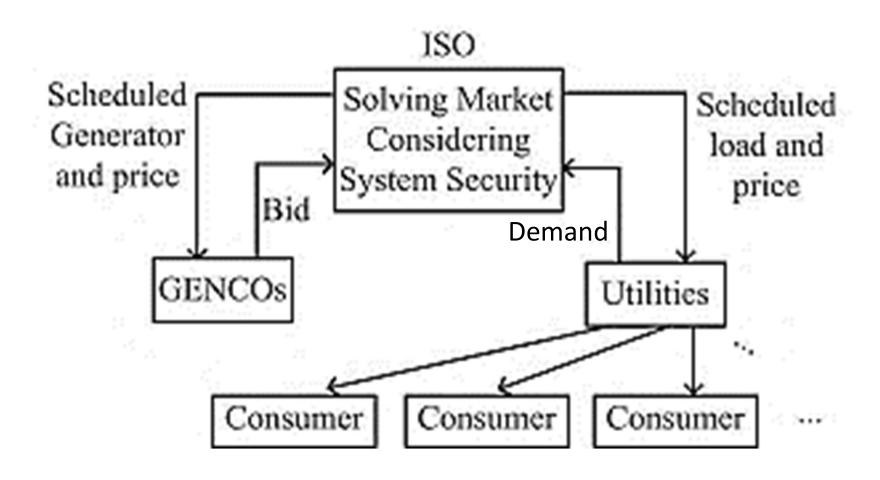
Outline: Application of the game theory in:

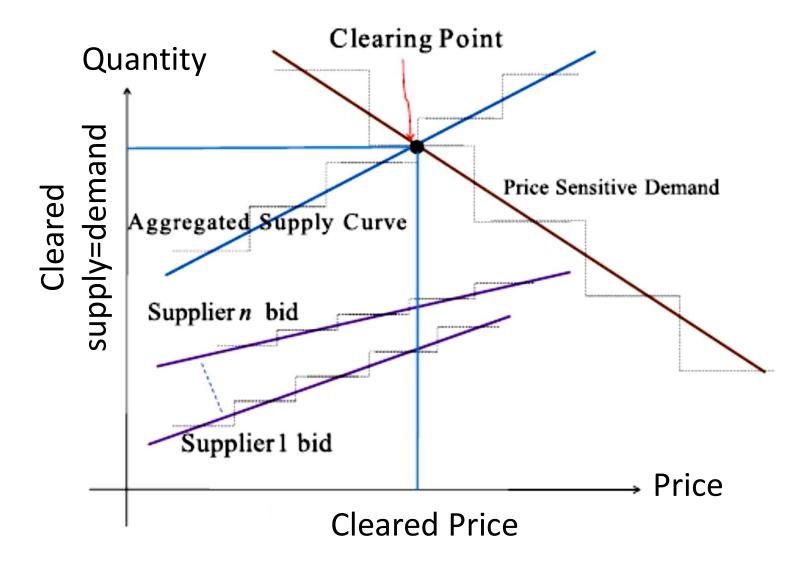
- Market (Electricity Market)
- Blockchain Network
- Wireless Networks: CDMA-OFDMA
- Smart Grids
- Intelligent Transportation systems
- Social Networks
- Biology: Cancer tumor—stroma interactions
- Deep Learning
- Cognitive Neuroscience

• Game Model:

- Players (decision makers)
- Objectives
- Actions (Strategies)
- Coupling term

Electricity Market





Electricity Market

Decision variables of generator i:

$$Q_i = \eta_i(\lambda_i - eta_i), \qquad i = 1, 2, \dots, n$$

Demand =
$$\sum_{i=1}^{n} Q_i$$

$$D_0 - \vartheta \lambda = \sum_{i=1}^n \eta_i (\lambda - \beta_i) = \lambda \sum_{i=1}^n \eta_i - \sum_{i=1}^n \eta_i \beta_i.$$

$$\lambda = \frac{D_0 + \sum_i \eta_i \beta_i}{\vartheta + \sum_i \eta_i}.$$

How to bid?

$$\pi_i = Q_i^c \lambda - C_i(Q_i^c)$$
 $i = 1, 2, ..., n$

Where

$$\lambda = \frac{D_0 + \sum_i \eta_i \beta_i}{\vartheta + \sum_i \eta_i}. \qquad Q_i^c = \eta_i (\lambda - \beta_i)$$

$$C_i(Q_i) = a_i Q_i^2 + b_i Q_i + c_i$$

- Baldick, Ross, Ryan Grant, and Edward Kahn.
 "Theory and application of linear supply function equilibrium in electricity markets." *Journal of regulatory economics* 25.2 (2004): 143-167.
- Kebriaei, Hamed, and Luigi Glielmo. "Estimation, learning, and stability analysis of supply function equilibrium game for generation companies." *IEEE Systems Journal* 12.3 (2016): 2577-2588.

Blockchain (Bitcoin) Network

Chance of winning the mining game for a player

$$P_i^{win} = \frac{x_i}{\sum_{j \in \mathcal{N}} x_j},$$
 Computational effort

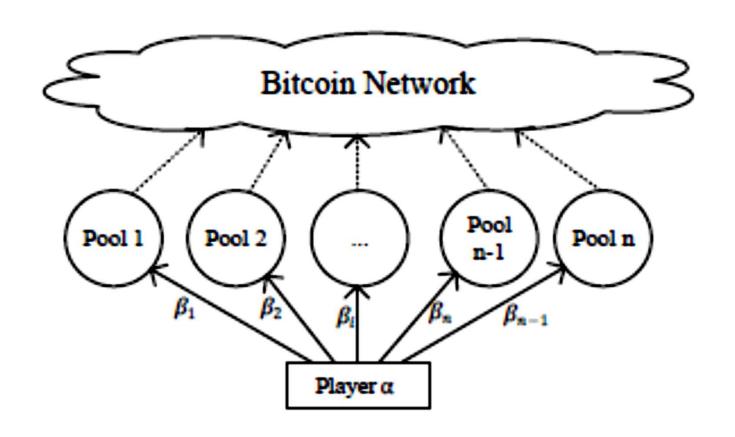
Expected utility of player *i* in a pool:

$$A_i \frac{x_i}{\sum_{k \in \mathcal{N}_i} x_k} \times \frac{\sum_{k \in \mathcal{N}_i} x_k}{\sum_{j \in \mathcal{N}} x_j},$$

Payoff function of player i

$$J_{i}(x) = \begin{cases} A_{i} \frac{x_{i}}{\sum_{j \in \mathcal{N}} x_{j}} - p_{i}x_{i}, & \sum_{j \in \mathcal{N}} x_{j} > 0, \\ 0 & \sum_{j \in \mathcal{N}} x_{j} = 0, \end{cases}$$

 Taghizadeh, Amirheckmat, Hamed Kebriaei, and Dusit Niyato. "Mean field game for equilibrium analysis of mining computational power in blockchains." *IEEE Internet of Things Journal* 7.8 (2020): 7625-7635.



Game in BWH (block withholding) Attack in Blockchain

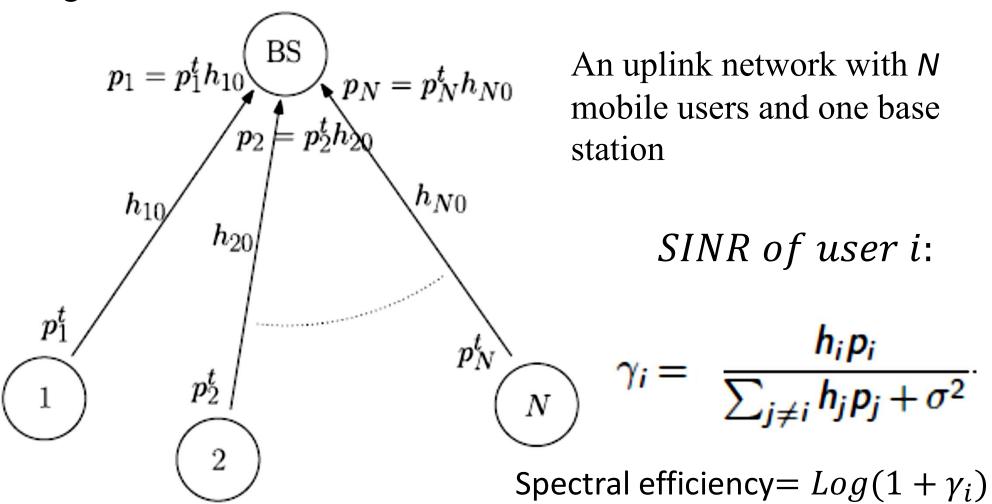
A Summary of Game Theoretical Applications for Security in Blockchains

	REF.	GAME MODEL	PLAYER	ACTION	STRATEGY	PAYOFF	SOLUTION
Selfish Mining Attack	[35]	Non-cooperative game	Mining pools	Infiltrate other pools to launch BWH attack	Determination of the infiltration rate	Mining rewards minus cost	Nash equilibrium
	[55]	Splitting game	One miner and pools	Distribute mining power for selfish mining	Determination of the power distribution	Mining rewards minus cost	Mixed strategy Nash equilibrium
	[56]	Mean-payoff game	Mining pools	Migrate to other pools to launch PBWH attack	Determination of the migration rate	Mean-payoff	Mean-payoff objective
	[50]	Stochastic game	Miners	Block withholding (BWH) attack	Selection between honest mining and selfish mining	Social welfare	Zero- Determinant strategy
	[57]	Non-cooperative game	Miners	Selfish propagation attack	Selection of identity duplication and transactions relaying	Mining rewards	Nash equilibrium
	[33]	Non-cooperative game	Miners	Fork chain	Selection of fork to mine	Transaction fees	Nash equilibrium
	[58]	Non-cooperative game	Miners	Delay submitting shares	Decision of the proper time to submit shares	Mining rewards	Nash equilibrium
	[28]	Non-cooperative game	Miners	Select or create a chain to mine	Selection of the chain to mine	Mining rewards	Nash equilibrium
	[28]	Stochastic game	Miners	BWH attack	Decision of the proper time to release the block	Mining rewards	Nash equilibrium
13				Post smart contract	2 2		

• Liu, Ziyao, et al. "A survey on applications of game theory in blockchain." *arXiv preprint arXiv:1902.10865* (2019).

Single-cell CDMA networks

Several transmitters can send information simultaneously over a single communication channel



Cost of User i

$$c_i(p_i, \mathbf{p}_{-i}) = \lambda_i p_i - \alpha_i \log(1 + \gamma_i), \ p_i \ge 0, \forall i,$$

$$\min_{p} \sum_{i} c_i(p_i, p_{-i})$$

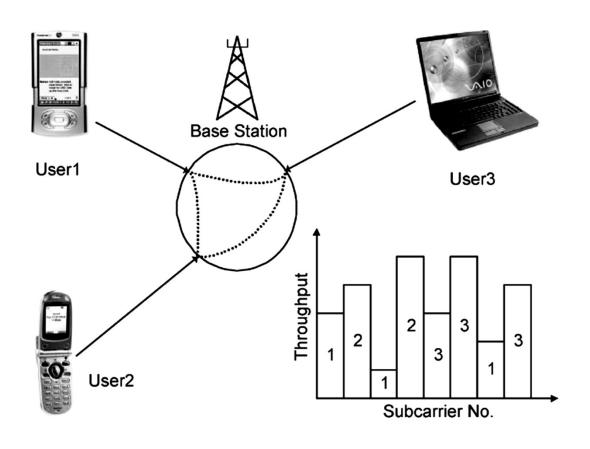
Cooperation

$$\min_{p_i} c_i(p_i, p_{-i}), i = 1, 2, ... N$$

Competition

 Han, Zhu, et al. Game theory in wireless and communication networks: theory, models, and applications. Cambridge university press, 2012.

OFDMA resource-allocation model



- An uplink scenario of a singlecell multiuser system.
- There are, in total, *N* users randomly located within the cell.
- The users want to share their transmissions among K
 different subcarriers/channels.

subcarrier assignment matrix A with $[A]_{ij} = a_{ij}$

$$a_{ij} = \begin{cases} 1, & \text{if } r_{ij} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

$$P = [p_{ij}]$$
 power-allocation matrix

user i's transmission rate R_i is allocated to different subcarriers j

$$r_{ij} = W \log_2 \left(1 + \frac{p_{ij} h_{ij} c_3}{\sigma^2} \right)$$

$$R_i = \sum_{j=1}^K r_{ij}$$

$$\max_{A,P} U = \prod_{i=1}^{N} (R_i - R_{\min}^i)$$

s.t.
$$\begin{cases} \sum_{i=1}^{N} a_{ij} = 1, \forall j \in \mathcal{K}, \\ R_i \geq R_{\min}^i, \forall i, \\ \sum_{j=1}^{K} p_{ij} \leq p_{\max}, \forall i \in \mathcal{N}. \end{cases}$$

 Han, Zhu, Zhu Ji, and KJ Ray Liu. "Fair multiuser channel allocation for OFDMA networks using Nash bargaining solutions and coalitions." *IEEE Transactions on Communications* 53.8 (2005): 1366-1376.

Demand Response in Smart Grids

Price of energy at each hour (n) as a function of total demand

$$p(n) = f(\sum_{i=1}^{N} x_i(n))$$
 Total demand of user i at hour n

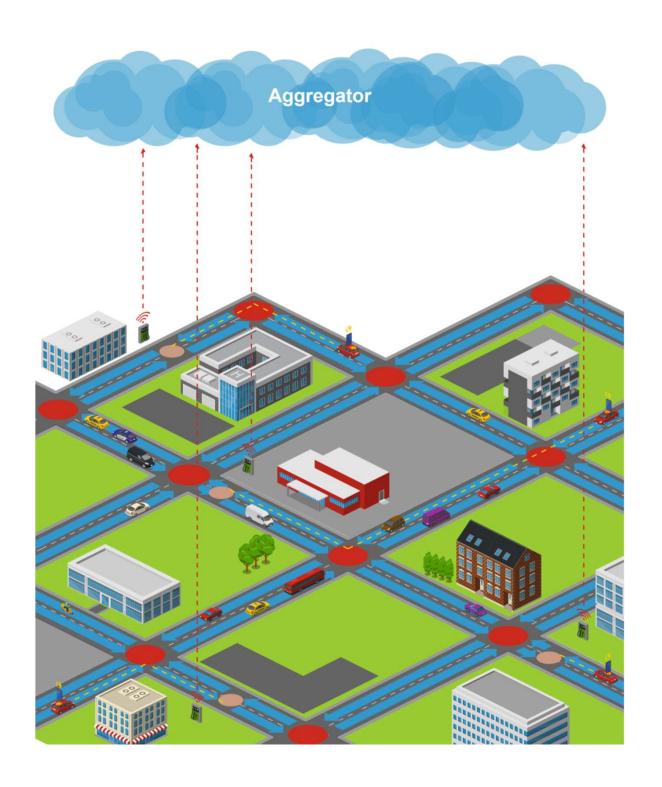
Example: $p(n) = a(n) + b \sum_{i=1}^{N} x_i(n)$

 $u_i(x_i)$ Utility function of user i

Payoff function of user i

$$g_i(x_i, x_{-i}) = \sum_n (u_i(x_i(n)) - x_i(n)p(n))$$

• Samadi, Pedram, et al. "Advanced demand side management for the future smart grid using mechanism design." *IEEE Transactions on Smart Grid* 3.3 (2012): 1170-1180.



Joint
Routing and
Destination
Planning of
Electric
Vehicles

Players

A transportation network with N EV driving users and D charging stations

Transportation network

modeled as a strongly connected directed graph

$$\mathcal{V} = \{1, \dots, V\} \qquad \qquad \mathcal{E} = \{1, \dots, E\}$$

Strategies

$$t_i = \begin{bmatrix} t_i^d \end{bmatrix}_{d=1}^D \qquad r_i = \begin{bmatrix} r_i^e \end{bmatrix}_{e=1}^E$$
The destination $d \in D$ by

probability of choosing destination $d \in \mathcal{D}$ by user i.

probability of choosing road $e \in \mathcal{E}$ by user i

$$x_i = \operatorname{col}(r_i, t_i) \in \mathbb{R}_{>0}^{E+D}$$

Payoffs

$$J_i(r_i, t_i, \sigma(r), \varphi(t)) = U_i(r_i, t_i) + \omega_i C_i^{travel} + C_i^{service}$$

traffic congestion

$$C_i^{travel}\left(r_i,\sigma(r)\right) = \sum_{e=1}^{E} l_e \left(\sigma_e\left(r^e\right)\right) r_i^e$$

$$l_e(\sigma_e(r^e)) = a_e \left(1 + \theta \left(\frac{\sigma_e(r^e)}{b_e} \right)^{\xi} \right) \qquad \sigma_e(r^e) = s_e + \sum_{i=1}^{N} r_i^{e^i}$$

Energy demand

$$C_i^{service}(t_i, \varphi_d(t)) = \sum_{d=1}^{D} \left[\overline{q_i p_d(\varphi_d(t^d))} + \underline{\rho_d} \right] t_i^{d'}$$

per-unit cost of charging

once paid fixed cost of parking

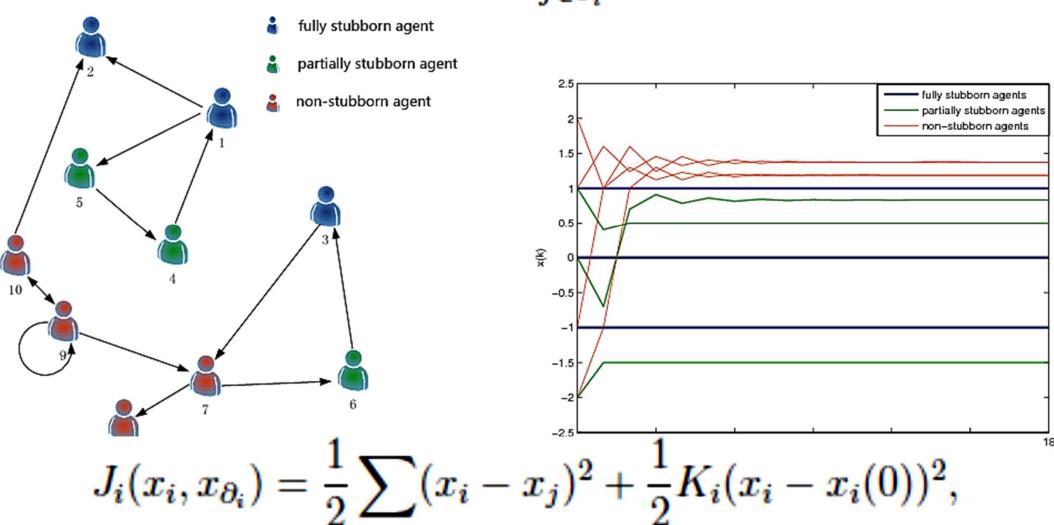
$$p_{d}(\varphi_{d}(t^{d})) = \delta_{d}\left(\frac{\varphi_{d}(t^{d})}{\kappa_{d}}\right) \qquad \varphi_{d}(t^{d}) = \sum_{i=1}^{N} \tilde{q}_{i}^{d} \qquad \tilde{q}_{i}^{d} = q_{i}t_{i}^{d}$$

expected total demand

 Bakhshayesh, Babak Ghaffarzadeh, and Hamed Kebriaei. "Decentralized Equilibrium Seeking of Joint Routing and Destination Planning of Electric Vehicles: A Constrained Aggregative Game Approach." IEEE Transactions on Intelligent Transportation Systems (2021).

Opinion Dynamics in Social Networks

$$x_i(t+1) = \frac{1}{d_i + K_i} \sum_{j \in \partial_i} x_j(t) + \frac{K_i}{d_i + K_i} x_i(0)$$



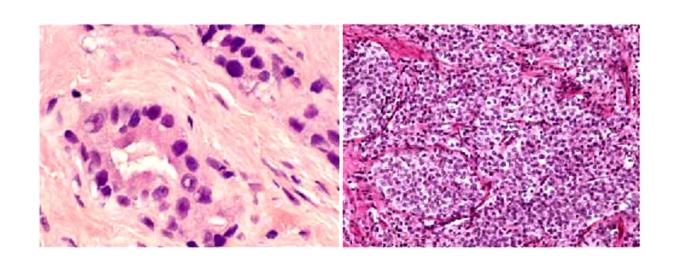
 Ghaderi, Javad, and Rayadurgam Srikant. "Opinion dynamics in social networks: A local interaction game with stubborn agents." 2013 American Control Conference. IEEE, 2013.

 Pagan, Nicolò, and Florian Dörfler. "Game theoretical inference of human behavior in social networks." *Nature Communications* 10.1 (2019): 1-12.

prostate cancer tumor—stroma interactions: insights from an evolutionary game tumor phenotypes

Table I Payoff table that represents the interactions between the three cell types considered in the model

	S	D -	
S	0	α	0
D	$1+\alpha-\beta$ $1-\gamma$	$1-2\beta$ $1-\gamma$	$1-\beta+\rho$ $1-\gamma$
1	$1-\gamma$	$1-\gamma$	$1-\gamma$

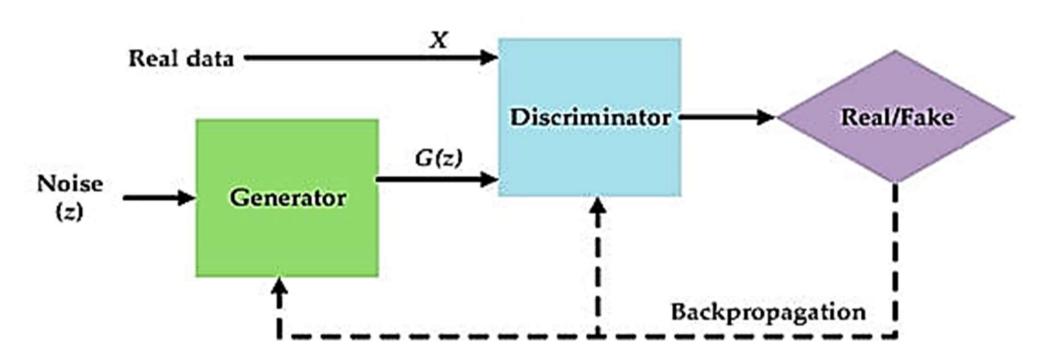


$$p_{t+1}^{\mathrm{I}} = p_t^{\mathrm{I}} \frac{W(\mathrm{I})}{\bar{W}},$$

$$p_{t+1}^{\mathrm{D}} = p_t^{\mathrm{D}} \frac{W(\mathrm{D})}{\bar{W}}.$$

• Basanta, David, et al. "Investigating prostate cancer tumour—stroma interactions: clinical and biological insights from an evolutionary game." *British journal of cancer* 106.1 (2012): 174-181.

GAN: Deep Learning and Game Theory



GANGs: Generative Adversarial Network Games

- GANs view the learning problem as a zero-sum game between the following two players:
- 1) generator G aiming to generate real-like samples from a random noise input
- 2) discriminator D trying to distinguish G's generated samples from real training data.

 This game is commonly formulated through a minimax game problem as follows

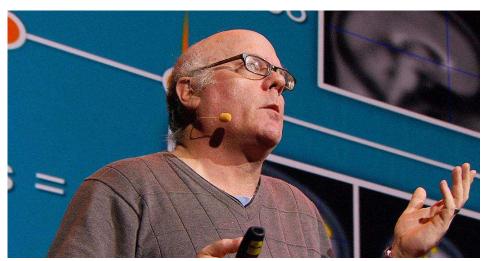
$$\min_{G \in \mathcal{G}} \max_{D \in \mathcal{D}} V(G, D)$$

• *V* (*G*, *D*) denotes the minimax objective for generator G and discriminator D capturing how dissimilar G's produced samples and real training data are.

Farnia, Farzan, and Asuman Ozdaglar. "Do GANs always have Nash equilibria?
"International Conference on Machine Learning. PMLR, 2020.

Game Theory and Cognitive Neuroscience Colin Camerer TED Talk





Link to the Video



https://www.ted.com/talks/colin camerer when you remaking a deal what segoing on in your brain?language=en

