#### Algorithmic Game Theory

#### Computing Stackelberg Equilibrium

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March 18, 2019



the leader – publicly commits to a strategy

- the leader publicly commits to a strategy
- the follower(s) play a Nash equilibrium with respect to the commitment of the leader

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$$\underset{\sigma \in \Sigma; \forall i \in \mathcal{N} \setminus \{1\} \sigma_i \in BR_i(\sigma_{-i})}{\operatorname{arg\,max}} u_1(\sigma)$$

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The followers need to break ties in case there are multiple NE:

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arbitrary but fixed tie breaking rule

The followers need to break ties in case there are multiple NE:

- arbitrary but fixed tie breaking rule
- Strong SE the followers select such NE that maximizes the outcome of the leader (when the tie-braking is not specified we mean SSE),

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Exact Weak Stackelberg equilibrium does not have to exist.

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$1 \setminus 2$	a	b	c	d	e
U	(2,4)	(6, 4)	(9, 0)	(1, 2)	(7, 4)
D	(8,4)	(0, 4)	(3, 6)	(1, 5)	(0, 0)

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<sup>1</sup>Figure from [9].

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The problem is polynomial for two-players normal-form games; 1 is the leader, 2 is the follower.

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Baseline polynomial algorithm requires solving  $|S_2|$  linear programs:

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Baseline polynomial algorithm requires solving  $|S_2|$  linear programs:

$$\max_{\sigma_1 \in \Sigma_1} \sum_{s_1 \in \mathcal{S}_1} \sigma_1(s_1) u_1(s_1, s_2)$$
$$\sum_{s_1 \in \mathcal{S}_1} \sigma_1(s_1) u_2(s_1, s_2) \ge \sum_{s_1 \in \mathcal{S}_1} \sigma_1(s_1) u_2(s_1, s_2') \quad \forall s_2' \in \mathcal{S}_2$$
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one for each  $s_2 \in \mathcal{S}_2$  assuming  $s_2$  is the best response of the follower.

We can reformulate the program as a mixed-integer linear program (MILP) that is a basis for the hard cases (e.g., computing a SE in Bayesian games):

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$$\begin{aligned} \max_{\sigma \in \Sigma, y \in \{0,1\}^{|S_2|}} \sum_{s \in \mathcal{S}} \sigma(s_1, s_2) u_1(s_1, s_2) \\ 0 \leq \sigma(s_1, s_2) \leq y(s_2) \quad \forall s_1, s_2 \in \mathcal{S}_{1,2} \\ \sum_{s_1, s_2 \in \mathcal{S}_{1,2}} \sigma(s_1, s_2) u_2(s_1, s_2) \geq \sum_{s_1, s_2 \in \mathcal{S}_{1,2}} \sigma(s_1, s_2) u_2(s_1, s_2') \quad \forall s_2' \in \mathcal{S}_2 \\ \sum_{s_1, s_2 \in \mathcal{S}_{1,2}} \sigma(s_1, s_2) = 1 \\ \sum_{s_2 \in \mathcal{S}_2} y(s_2) = 1 \end{aligned}$$

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two-player EFGs with chance (there exists a FPTAS for this case [2]),

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Main algorithms are based on the sequence-form LCP for computing NE:

$$\begin{split} v_{\inf_{i}(\sigma_{i})} &= s_{\sigma_{i}} + \sum_{I'_{i} \in \mathcal{I}_{i}: \operatorname{seq}_{i}(I'_{i}) = \sigma_{i}} v_{I'_{i}} + \sum_{\sigma_{-i} \in \Sigma_{-i}} g_{i}(\sigma_{i}, \sigma_{-i}) \cdot r_{-i}(\sigma_{-i}) \quad \forall i, \sigma_{i} \\ r_{i}(\sigma_{i}) &= \sum_{a \in A(I_{i})} r_{i}(\sigma_{i}a) \quad \forall i \in \mathcal{N} \forall I_{i} \in \mathcal{I}_{i}, \ \sigma_{i} = \operatorname{seq}_{i}(I_{i}) \\ r_{i}(\emptyset) &= 1 \quad 0 = r_{i}(\sigma_{i}) \cdot s_{\sigma_{i}} \quad \forall i \in \mathcal{N} \forall \sigma_{i} \in \Sigma_{i} \\ 0 \leq r_{i}(\sigma_{i}) ; \quad 0 \leq s_{\sigma_{i}} \quad \forall i \in \mathcal{N} \forall \sigma_{i} \in \Sigma_{i} \\ &= \sum_{\sigma \in \mathcal{I}} r_{i}(\sigma_{i}) \in \mathbb{R} \end{split}$$

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MILP for computing SE for two-player extensive-form game with perfect recall:

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$$\begin{split} \max_{p,r,v,s} \sum_{z \in \mathcal{Z}} p(z) u_1(z) \mathcal{C}(z) \\ v_{\inf_{2}(\sigma_2)} &= s_{\sigma_2} + \sum_{I' \in \mathcal{I}_2: \operatorname{seq}_2(I') = \sigma_2} v_{I'} + \sum_{\sigma_1 \in \Sigma_1} r_1(\sigma_1) g_2(\sigma_1, \sigma_2) \quad \forall \sigma_2 \in \Sigma_2 \\ r_i(\emptyset) &= 1 \quad r_i(\sigma_i) = \sum_{a \in A_i(I_i)} r_i(\sigma_i a) \quad \forall i \in \mathcal{N} \; \forall I_i \in \mathcal{I}_i, \sigma_i = \operatorname{seq}_i(I_i) \\ 0 &\leq s_{\sigma_2} \leq (1 - r_2(\sigma_2)) \cdot M \quad \forall \sigma_2 \in \Sigma_2 \\ 0 &\leq p(z) \leq r_2(\operatorname{seq}_2(z)) \quad \forall z \in \mathcal{Z} \\ 0 &\leq p(z) \leq r_1(\operatorname{seq}_1(z)) \quad \forall z \in \mathcal{Z} \\ 1 &= \sum_{z \in \mathcal{Z}} p(z) \mathcal{C}(z) \\ r_2(\sigma_2) \in \{0, 1\} \quad \forall \sigma_1 \in \Sigma_1 \\ 0 &\leq r_1(\sigma_1) \leq 1 \quad \forall \sigma_2 \in \Sigma_2 \end{split}$$

## Stackelberg and Correlated Equilibrium

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We can compute a Stackelberg equilibrium if we modify an algorithm for computing an optimal correlated equilibrium.

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Properties:

 the objective is the same as in the MILP case (or multiple LPs) case,

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Properties:

- the objective is the same as in the MILP case (or multiple LPs) case,
- strategy σ does not necessarily corresponds to Stackelberg equilibrium (the follower can receive multiple recommendations that are best responses).

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How does it work in EFGs?

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How does it work in EFGs?



We can define a Stackelberg extension of EFCE [2] – the leader (1) controls the correlation device, (2) sends signals to the follower, (3) maximizes her expected utility.

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We can follow the same steps [3]:

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consider an algorithm for computing an optimal EFCE in an EFGs

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incremental strategy generation [4]

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incremental strategy generation [4]

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Instance $\backslash \epsilon$	0.01	0.05	0.1	0.15	0.2	0.25	0.3
4a All-Points	0%	0%	0%	0.9%	2.42%	3.01%	3.23%
4a No-Info	0%	0.35%	0.72%	1.29%	1.77%	2.5%	2.55%
4b All-Points	0%	0%	0%	0.56%	0.8%	2.39%	2.48%
4b No-Info	0%	0.16%	0.67%	1.27%	2.15%	2.42%	2.86%
4c All-Points	0%	0%	0.033%	0.79%	3.47%	4.8%	6.38%
4c No-Info	0%	0.24%	0.89%	1.75%	1.75%	1.75%	1.75%

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 Using Finite State Machines for Computing SE (under review for EC '19)

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  - in an EFG, these restrictions can be described using (for example) Finite State Machines



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#### References I

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