

---

# **Socially Optimal Non-Discriminatory Restrictions for Continuous-Action Games**

Michael Oesterle, Guni Sharon

---

# Socially Optimal Non-Discriminatory Restrictions for Continuous-Action Games

Michael Oesterle, Guni Sharon

---

**In multi-player games,**

**allowing fewer actions**

**uniformly for all players**

**can increase social welfare**

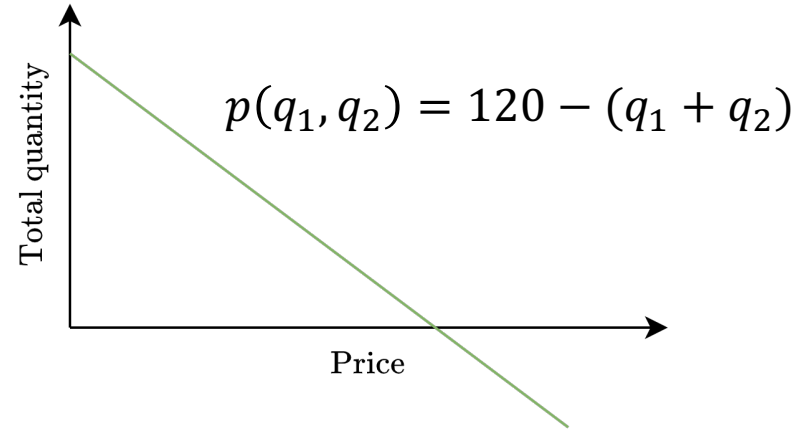
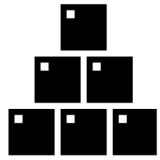
Socially Optimal Non-Discriminatory Restrictions  
for Continuous-Action Games

Michael Oesterle, Guo'sha

---

**In multi-player games,  
allowing fewer actions  
uniformly for all players  
can increase social welfare  
...and we can show how!**

# Multi-Player Games Need Governance For Optimal Social Welfare

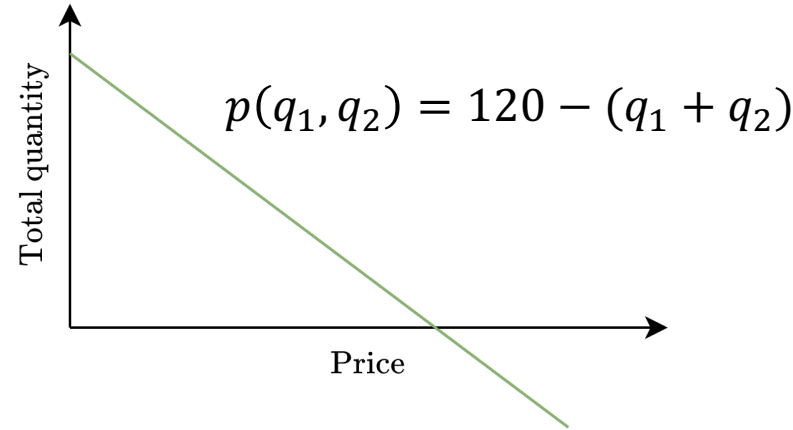
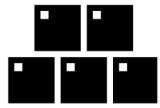
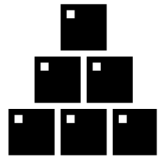


Each player's profit is quantity times price:

$$u_i(q_1, q_2) = (p(q_1, q_2) - 12) \cdot q_i$$

*What is the best strategy for a player to make maximum profit?*

# Multi-Player Games Need Governance For Optimal Social Welfare



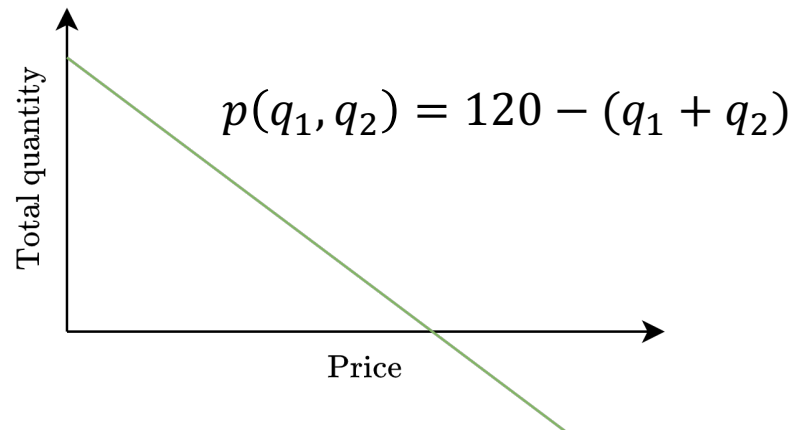
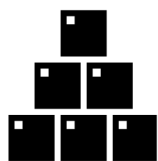
Each player's profit is quantity times price:

$$u_i(q_1, q_2) = (p(q_1, q_2) - 12) \cdot q_i$$

*What is the best strategy for a player to make maximum profit?*

- If the players can choose their quantities freely, they each produce 36
- However, the social welfare (sum of profits) is maximized when both produce 27

# Multi-Player Games Need Governance For Optimal Social Welfare



Each player's profit is quantity times price:

$$u_i(q_1, q_2) = (p(q_1, q_2) - 12) \cdot q_i$$

*What is the best strategy for a player to make maximum profit?*

- If the players can choose their quantities freely, they each produce 36
- However, the social welfare (sum of profits) is maximized when both produce 27
- **Restricting the quantities by introducing an upper bound increases social welfare**

# What Can A Governance Do?

---

- Reward shaping: Change which actions players prefer  
*Example: Marginal Cost Tolling (Sharon et al. 2017) for traffic networks*



# What Can A Governance Do?

---

- Reward shaping: Change which actions players prefer  
*Example: Marginal Cost Tolling (Sharon et al. 2017) for traffic networks*
- Action space shaping: Change which actions players can take  
*Example: Road closures for traffic networks*

# What Can A Governance Do?

---

- Reward shaping: Change which actions players prefer  
*Example: Marginal Cost Tolling (Sharon et al. 2017) for traffic networks*
- **Action space shaping: Change which actions players can take**  
*Example: Road closures for traffic networks*

Specifically: Compute  
socially optimal  
action space restrictions

# What Is Restriction-Based Governance?

---

- Making the action space smaller can be an effective means to increase social welfare



Discrete action space



Continuous action space

# What Is Restriction-Based Governance?

---

- Making the action space smaller can be an effective means to increase social welfare



Restricted discrete action space



Continuous action space

# What Is Restriction-Based Governance?

---

- Making the action space smaller can be an effective means to increase social welfare



Restricted discrete action space



Restricted continuous action space

# What Is Restriction-Based Governance?

---

- Making the action space smaller can be an effective means to increase social welfare



Restricted discrete action space



Restricted continuous action space

- By allowing the same actions for all players, we create a “fair”, non-discriminatory governance (a reward-shaping mechanism like Vickrey-Clarke-Groves (VCG) would not usually do this)

# What Is The Goal Of Our Paper?

---

In a **Normal-Form Game** with a **social utility** function,  
find a **subset of the action space**  
which results in the **maximum social welfare**,  
when all **players act selfishly**

# How Do We Find Optimal Restrictions?

---

- Start from the full action space



# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)

# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)
- Tentatively remove such an action and repeat, while keeping track of loose ends

# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)
- Tentatively remove such an action and repeat, while keeping track of loose ends
- Output the restriction with the highest social welfare

# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)
  - Use an equilibrium oracle function to find “safely removable actions”
- Tentatively remove such an action and repeat, while keeping track of loose ends
- Output the restriction with the highest social welfare

# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)
  - Use an equilibrium oracle function to find “safely removable actions”
- Tentatively remove such an action and repeat, while keeping track of loose ends
  - Always remove half-open intervals, based on a resolution parameter
- Output the restriction with the highest social welfare

# How Do We Find Optimal Restrictions?

---

- Start from the full action space
- Identify actions which should be removed (how?)
  - Use an equilibrium oracle function to find “safely removable actions”
- Tentatively remove such an action and repeat, while keeping track of loose ends
  - Always remove half-open intervals, based on a resolution parameter
- Output the restriction with the highest social welfare
  - Apply a depth-first search over possible restrictions

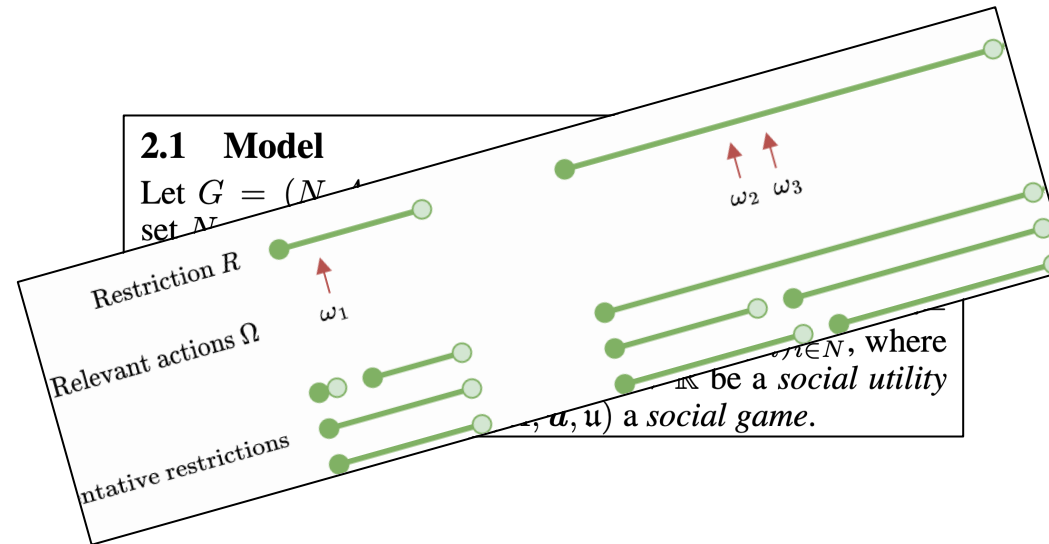
# What Are The Technical Details?

---

## 2.1 Model

Let  $G = (N, A, \mathbf{u})$  be a Normal-Form Game with player set  $N = \{1, \dots, n\}$  and action space  $A$  which applies to all players (“uniform” NFG). Writing product sets and vectors of variables in bold face, a joint action is given by  $\mathbf{a} \in \mathbf{A} := A^N$ . The players’ utility functions are  $\mathbf{u} = (u_i)_{i \in N}$ , where  $u_i : \mathbf{A} \rightarrow \mathbb{R}$ . Moreover, let  $u : \mathbf{A} \rightarrow \mathbb{R}$  be a *social utility function*. We call  $G = (N, A, \mathbf{u}, u)$  a *social game*.

# What Are The Technical Details?





# What Are The Technical Details?

## Algorithm 1: Socially Optimal Action-Space Restrictor (SOAR)

**Data:** Social Game  $G = (N, A, \mathbf{u}, \mathbf{u})$ , equilibrium oracle  $\mu$ , resolution  $\epsilon$

**Result:** Socially optimal restriction  $\hat{R}^* \subseteq A$

```
1  $(\hat{R}^*, \hat{u}^*) \leftarrow (A, \mathbf{u}(\mu(A)))$ 
2  $Q \leftarrow$  Queue with content  $A$ 
3 while  $Q$  is not empty do
4    $R \leftarrow Q.dequeue()$ 
   // Loop through relevant actions
5   for  $\omega \in \Omega(\mu(R))$  do
6      $R' \leftarrow R.remove(\mathcal{U}_\epsilon(\omega))$  // Tentative restriction
7     if  $R'$  is not empty and has not been explored before then
8        $Q.enqueue(R')$ 
9       if  $\mathbf{u}(\mu(R')) > \hat{u}^*$  then
10         $(\hat{R}^*, \hat{u}^*) \leftarrow (R', \mathbf{u}(\mu(R')))$ 
11      end
12    end
13  end
14 end
15 return  $\hat{R}^*$ 
```

# What Are The Technical Details?

**Proposition 1.** Given some  $x \in \mathbb{R}$ , let  $\mathcal{U}_\epsilon(x) := [x-\epsilon, x+\epsilon)$  denote the half-open  $\epsilon$ -neighborhood of  $x$ , and for a vector  $\mathbf{x} \in \mathbb{R}^N$ , let  $\mathcal{U}_\epsilon(\mathbf{x}) := \cup_{i \in N} \mathcal{U}_\epsilon(x_i) \subseteq \mathbb{R}$  (note that this neighborhood is still one-dimensional!). Assume that  $\mathbf{a} \in A$  is a joint action such that  $\mathcal{N} \subseteq \mathbf{R}$  with  $R := A \setminus \mathcal{U}_\epsilon(\mathbf{a})$ . Then

$$\mathcal{N} \subseteq \mathcal{N}|_R,$$

which means that invalidating actions within the  $\epsilon$ -neighborhood of  $\mathbf{a}$  removes none of the Nash Equilibria from  $G$ .

*Proof.* Let  $\mathbf{x} \in \mathcal{N}$  be an NE over the action space  $A$ , and let  $R$  be defined as in the statement of the proposition. Then

$$x_i \in \mathcal{B}_i(x_{-i}) \quad \forall i \in N$$

$$\implies u_i(\mathbf{x}) \geq u_i(a', x_{-i}) \quad \forall a' \in A \quad \forall i \in N$$

$$\xRightarrow{R \subseteq A} u_i(\mathbf{x}) \geq u_i(a', x_{-i}) \quad \forall a' \in R \quad \forall i \in N$$

$$\xRightarrow{\mathbf{x} \in R} x_i \in \mathcal{B}_i|_R(x_{-i}) \quad \forall i \in N$$

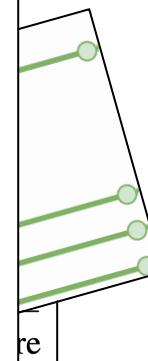
ion-Space Re-

), equilibrium

$$\hat{R}^* \subseteq A$$

nt actions

Tentative



**Theorem 1.** Let  $G = (N, A, \mathbf{u}, \mathbf{u})$  be a social game. If Assumption 2 holds, and for a sufficiently small  $\epsilon > 0$ , Algorithm 1 finds an optimal restriction  $R^*$ .

*Proof.* SOAR terminates after finitely many steps: Any tentative restriction  $R'$  produced by a reduction of some  $R \in Q$  continues a chain of increasingly constrained restrictions, as in Proposition 2, and the length of such a chain is bounded by  $\lceil \frac{b-a}{\epsilon} \rceil$ .

At the point of termination,  $Q$  is empty. Condition (i) in Proposition 4 does not hold anymore, which means that  $\hat{R}^*$  is indeed an optimal restriction.  $\square$

8  
9  
10  
11  
12  
13  
14  
15

if  
end  
end  
end  
return  $\hat{R}^*$

# What Are The Technical Details?

**Proposition 1.** Given some  $x \in \mathbb{R}$ , let  $\mathcal{U}_\epsilon(x) := [x-\epsilon, x+\epsilon)$  denote the half-open  $\epsilon$ -neighborhood of  $x$  and for a vector

## Experiments

### Parameterized Cournot Game (CG)

```
In [ ]: results = []
epsilon, decimals = 0.1, 3
solver = IntervalUnionRestrictionSolver(epsilon=epsilon)
progress_bar = display(progress(0, 100), display_id=True)
lambda_min, lambda_max = 10.0, 200.0
lambdas = list(np.round(np.arange(lambda_min, lambda_max, 1.0), decimals=decimals))

print(f'Solving {len(lambdas)} Cournot games...')
for i, lambda_ in enumerate(lambdas):
    progress_bar.update(progress(i, len(lambdas)))

    u_1 = QuadraticTwoPlayerUtility(0, [-1.0, 0.0, -1.0, lambda_, 0.0, 0.0])
    u_2 = QuadraticTwoPlayerUtility(1, [0.0, -1.0, -1.0, 0.0, lambda_, 0.0])

    a = IntervalUnion([(0.0, lambda_)])
    g = GovernedNormalFormGame(a, [u_1, u_2], u_1 + u_2)

    results.append(solver.solve(g, nash_equilibrium_oracle=worst_hill_climbing_nash_equilibrium))

progress_bar.update(progress(len(lambdas), len(lambdas)))

print('Done!')
```

15 return  $\hat{R}^*$

Proposition 4 does not hold anymore, which means that  $\hat{R}^*$  is indeed an optimal restriction. ☐

# How Do We Measure If This Works?

---



**By how much does it get better?**

- (Absolute and relative) improvement of social welfare

# How Do We Measure If This Works?

---



**By how much does it get better?**

- (Absolute and relative) improvement of social welfare



**How restrictive do we have to be?**

- Degree of restriction (proportion of allowed and forbidden actions)

# How Do We Measure If This Works?

---



## By how much does it get better?

- (Absolute and relative) improvement of social welfare



## How restrictive do we have to be?

- Degree of restriction (proportion of allowed and forbidden actions)

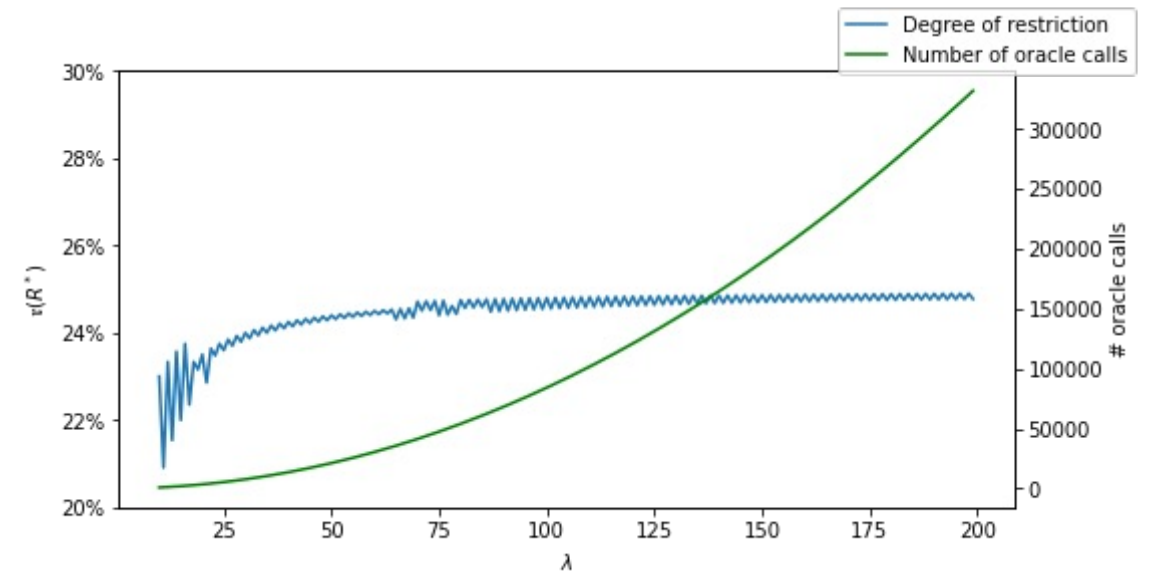
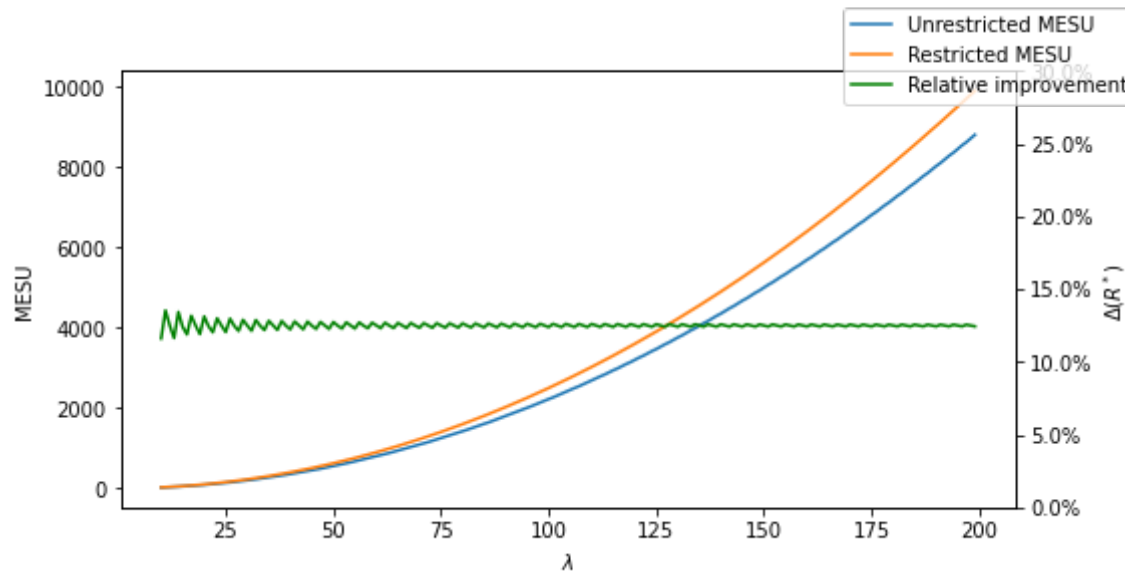


## How long does it take to find the optimal restriction?

- Number of tentative restrictions / oracle calls

# Does It Work?

Yes!



MESU = Minimum Equilibrium Social Utility

Degree of restriction = Proportion of forbidden actions

# Does It Work?

---

Yes, but...



# Does It Work?

---

**Yes, but...**

... we need an oracle to tell us the equilibrium for a given restriction

# Does It Work?

---

**Yes, but...**

... we need an oracle to tell us the equilibrium for a given restriction

... we can (currently) only handle one-dimensional action spaces

# Does It Work?

---

**Yes, but...**

... we need an oracle to tell us the equilibrium for a given restriction

... we can (currently) only handle one-dimensional action spaces

... non-discriminatory restrictions only make sense in so-called coordination games

# Key Message and Contact

---

What: Non-discriminatory action space restrictions in multi-player games

Why: Optimizing and standardizing regulatory restrictions

How: Informed depth-first search on the action space



<https://github.com/michoest/aaai-2023>  
(Repository with paper and code)

**Michael Oesterle**, University of Mannheim

*michael.oesterle@uni-mannheim.de*

**Guni Sharon**, Texas A&M University

*guni@tamu.edu*



Right now!



Tonight!



Anytime!