

Game Theory

Daniel Mao

Contents

1	First Chapter	1
1.1	First Section	1
1.2	Groups of Games	1
2	Strategic Games	7
2.1	Pure Strategies	7
2.2	Nash Equilibrium of Pure Strategies	8
2.3	Domination for Pure Strategies	10
2.4	Mixed Strategies	11
2.5	Nash Equilibrium of Mixed Strategies	12
2.6	Domination for Mixed Strategies	13
3	Lemke-Homson Algorithm	17
4	Market Models	19
4.1	Cournot Oligopoly Model	19
4.2	Bertrand Oligopoly Model	20
5	Routing Games	23
5.1	Atomic Selfish Routing Game	23
5.2	Non-atomic Selfish Routing	24
5.3	Potential Function of Atomic Selfish Routing Game	28

Chapter 1

First Chapter

1.1 First Section

DEFINITION 1.1 (Winning Position). Consider a two-player game. We say that a player has a **winning position** if and only if optimal play by that player guarantees a win.

DEFINITION 1.2 (Losing Position). Consider a two-player game. We say that a player has a **losing position** if and only if an optimal move by their opponent guarantees a loss.

PROPOSITION 1.3.

- From a winning position (player to move), there exists a move that leads to a losing position for the other player.
- From a losing position (player to move), every move leads to a winning position for the other player.

1.2 Groups of Games

DEFINITION 1.4 (Equivalent Games). Let G and H be two impartial games. We say that G and H are **equivalent** if and only if for all impartial games J , $G + J$ is a losing position if and only if $H + J$ is a losing position.

- for all impartial games J , $G + J$ is a losing position if and only if $H + J$ is a losing position.
- for all impartial games J , $G + J$ is a winning position if and only if $H + J$ is a winning position.

PROPOSITION 1.5. Game equivalence is an equivalence relation. That is, “ \equiv ” is:

- Reflexive: $\forall G$, we have $G \equiv G$.
- Symmetric: $\forall G, H$, we have $G \equiv H \iff H \equiv G$.
- Transitive: $\forall G, H, K$, we have $((G \equiv H) \wedge (H \equiv K)) \implies G \equiv K$.

PROPOSITION 1.6. $\forall G, H, J$, we have $G \equiv H \implies G + J \equiv H + J$.

PROPOSITION 1.7. $G \equiv H$ implies that G and H are both winning or both losing.

LEMMA 1.8. G is a losing position if and only if $G \equiv *0$.

Proof. Backward Direction: Suppose that $G \equiv *0$. Then $\forall J$, $G + J$ is a losing position if and only if $*0 + J$ is a losing position. In particular, take $J := *0$, then $G + *0$ is a losing position if and only if $*0 + *0$ is a losing position. Notice $G + *0 = *0$ and $*0 + *0 = *0$. So G is a losing position if and only if $*0$ is a losing position. We know that $*0$ is indeed a losing position. So G is a losing position.

Forward Direction: Suppose that G is a losing position. I will show that $G \equiv *0$. Let J be an arbitrary impartial game. Notice $*0 + J = J$. So there remains to show that $G + J$ is losing if and only if J is losing.

Suppose that $G + J$ is a losing position. I will show that J is a losing position. Assume for the sake of contradiction that J is not losing. Then J is winning. Let $J \rightarrow J'$ be a move such that J' is losing. Since G is losing and J' is losing, we get $G + J'$ is losing. So $G + J$ is winning. However, this contradicts to the assumption that $G + J$ is losing. So J is losing.

Suppose that J is a losing position. I will show that $G + J$ is a losing position. Double strong well-founded induction.

□

G is winning and J is losing, then $G + J$ is winning???

DEFINITION 1.9 (Group of Game). Let \mathcal{G} be a set of games. Let $*$: $\mathcal{G} \times \mathcal{G} \rightarrow \mathcal{G}$ be a binary operation on \mathcal{G} . We say that $(\mathcal{G}, *)$ is a **group** if and only if the following conditions hold:

1. Associativity: $\forall G_1, G_2, G_3 \in \mathcal{G}, (G_1 * G_2) * G_3 \equiv G_1 * (G_2 * G_3)$.
2. Identity: $\exists I \in \mathcal{G}$ such that $\forall G \in \mathcal{G}, G * I \equiv I * G \equiv G$.
3. Inverse: $\forall G \in \mathcal{G}, \exists H \in \mathcal{G}$ such that $G * H \equiv H * G \equiv I$.

LEMMA 1.10. $G \equiv H$ if and only if $G + H \equiv *0$.

Proof. Forward Direction: Suppose that $G \equiv H$. I will show that $G + H \equiv *0$. Since $G \equiv H$, we get

$$G + H \equiv H + H, \text{ by the}$$

□

LEMMA 1.11. Let G and H be impartial combinatorial games. Suppose that

- For each option G' of G , there exists an option of H which is equivalent to G' .
- For each option H' of H , there exists an option of G which is equivalent to H' .

Then $G \equiv H$.

Proof. Since $G' + H' \equiv *0$, we get $G + H \equiv *0$.

□

THEOREM 1.12 (Sum of NIM Heaps). Suppose $n_1, \dots, n_k \in \mathbb{Z}_{++}$ are distinct powers of 2. Then we have

$$*(n_1 + \dots + n_k) \equiv (*n_1 + \dots + *n_k).$$

Proof. **Base Case:** $n = 0$.

Inductive Step: Suppose the theorem holds for all positive integers less than n . Write n as $n = 2^{a_1} + \dots + 2^{a_k}$ where $a_1 > \dots > a_k$. Define

$$q := n - 2^{a_1} = 2^{a_2} + \dots + 2^{a_k}.$$

Note that $q < 2^{a_1} < n$. Apply the induction hypothesis on q , we get

$$*q \equiv *2^{a_2} + \dots + *2^{a_k}$$

Now there remains to show that $*n \equiv *2^{a_1} + *q$. Consider the options of $*n$: $\{*(n-1), *(n-2), \dots, *0\}$ and the options of $*2^{a_1} + *q$: $\{G + *q, *2^{a_1} + H\}$ where G is some option of $*2^{a_1}$ and H is some option of $*q$.

Consider the set $\{*i + *q : 0 \leq i < 2^{a_1}\}$ of options of $*2^{a_1} + *q$.

Consider the set $\{*2^{a_1} + *i : 0 \leq i < q\}$ of options of $*2^{a_1} + *q$. Write i as $i = 2^{b_1} + 2^{b_2} + \dots$. Notice $2^{a_1} + i < 2^{a_1} + q < n$. So by the inductive hypothesis, we get

$$*(2^{a_1} + i) = *(2^{a_1} + 2^{b_1} + 2^{b_2} + \dots) = *2^{a_1} + *2^{b_1} + *2^{b_2} + \dots$$

So the set of options of $*n$ is equivalent to the set of options for $*2^{a_1} + *q$. So $*n \equiv *2^{a_1} + *2^{a_2} + \dots$ □

EXAMPLE 1.13.

$$\begin{aligned} (5, 9, 8) &= *5 + *9 + *8 = *(4 + 1) + *(8 + 1) + *8 \\ &= *4 + *1 + *8 + *1 + *8 = *4. \end{aligned}$$

So the optimal move is to take away the $*4$: $(5, 9, 8) \rightarrow (1, 9, 8)$.

DEFINITION 1.14 (Balance, Unbalanced). We say that a NIM position (a_1, \dots, a_q) is **balanced** if and only if $a_1 \oplus \dots \oplus a_q = 0$. We say that it is **unbalanced** otherwise.

THEOREM 1.15. A NIM position (a_1, \dots, a_q) is a losing (winning) position if and only if it is balanced (unbalanced).

DEFINITION 1.16 (Minimum Excludant). Given a subset $S \subsetneq \mathbb{N}$, we define $\text{mex}(S)$ to be the smallest element of $\mathbb{N} \setminus S$.

THEOREM 1.17 (MEX Rule). Let $S \subsetneq \mathbb{N}$. Let G be an impartial game whose options are equivalent to $\{ *s : s \in S \}$. Then $G \equiv *(\text{mex}(S))$.

Proof. Let $m := \text{mex}(S)$. By the Generalized Copycat principle, it suffices to show that $G + *m \equiv *0$.

Consider an option of the form $G + *m'$ for some $m' < m$. Since $m = \text{mex}(S)$ and $m' < m$, we have $m' \in S$. Then there exists an option G' of G such that $G' \equiv *m'$. The other player can move to $G' + *m'$. Since $G' \equiv *m'$, the game $G' + *m'$ is a losing position (copycat principle). So $G + *m'$ is winning.

Consider an option of the form $G' + *m$ of $G + *m$. Recall that the options of G are $\{ *n : n \in S \}$. Let $k \in S$ be a natural number such that $G' \equiv *k$. Then $G' + *m \equiv *k + *m$. Since $m \notin S$ and $k \in S$, $*k + *m$ is winning. So $G' + *m$ is winning.

Hence all options of $G + *m$ are winning. So $G + *m$ is losing. So $G \equiv *m$. \square

COROLLARY 1.18. For every impartial game G , there exists a natural number $n \in \mathbb{N}$ such that $G \equiv *n$.

Proof. We use (well-founded) induction on G .

Base case: If G has no options, then $G \equiv *0$.

Inductive step: Suppose the set of options for G is finite and are G^1, \dots, G^q . By the induction hypothesis, $\forall i \in \{1, \dots, q\}$, we have $G^i \equiv *n_i$ for some $n_i \in \mathbb{N}$. So the set of options of G are equivalent to $\{ *n_1, \dots, *n_q \}$. Apply the MEX rule with $S := \{n_1, \dots, n_q\}$, we have

$$G \equiv *(\text{mex}(S)) = *(\text{mex}(\{n_1, \dots, n_q\})).$$

\square

Chapter 2

Strategic Games

2.1 Pure Strategies

DEFINITION 2.1 (Extensive Games). Games with game trees are called **extensive games with perfect information**.

DEFINITION 2.2 (Strategy). A **strategy** (for a player) specifies a move for every decision node for that player. i.e., a function that maps each decision node to a move.

DEFINITION 2.3 (Strategy Profile). A **strategy profile** specifies a strategy for every player. We represent a strategy (profile) by concatenating moves.

DEFINITION 2.4 (Strategic Form). The **strategic form** of a game consists of:

- A set $N = \{1, \dots, n\}$ of players;
- A set S_i of strategies for $i \in N$;
- A utility function $u_i : S_1 \times \dots \times S_n \rightarrow \mathbb{R}$, for each $i \in N$.

A strategic form is a $|S_1| \times \dots \times |S_n| \times N$ dimensional tensor.

2.2 Nash Equilibrium of Pure Strategies

DEFINITION 2.5 (Nash Equilibrium). Let $N := \{1, \dots, n\}$ denote the set of players. Let \mathcal{S}_i denote the set of strategies for player i , for $i \in N$. Let $\mathcal{S} := \mathcal{S}_1 \times \dots \times \mathcal{S}_n$. We say that a strategy profile $s^* = (s_1, \dots, s_n) \in \mathcal{S}$ is a **Nash equilibrium** if and only if $\forall i \in N, \forall s'_i \in \mathcal{S}_i$, we have

$$u_i(s_1, \dots, s'_i, \dots, s_n) \leq u_i(s^*).$$

That is, no one player can improve over their utility in s^* by unilaterally deviating in their strategy.

EXAMPLE 2.6 (Prisoner's Dilemma). The Prisoner's dilemma consists of two players, each with strategies Q and C , with payoffs:

	Q	C
Q	(2, 2)	(0, 3)
C	(3, 0)	(1, 1)

- (C, C) is the only Nash equilibrium.
- (C, C) is suboptimal overall.

EXAMPLE 2.7 (Bach-Stravinsky).

	Bach	Stravinsky
Bach	(2, 1)	(0, 0)
Stravinsky	(0, 0)	(1, 2)

- (B, B) and (S, S) are both Nash equilibria.

EXAMPLE 2.8 (Matching Pennies).

	Heads	Tails
Heads	$(+1, -1)$	$(-1, +1)$
Tails	$(-1, +1)$	$(+1, -1)$

- Player 1 bets on match; player 2 bets on a mismatch.

- Example of a zero-sum game.
- This game has no Nash equilibrium.
- Later in the course we will see that has a mixed Nash equilibrium.

EXAMPLE 2.9. numbers to be fixed

	L	R
T	(2, 1)	(0, 0)
M	(0, 0)	(1, 2)
B	(0, 0)	(1, 2)

Would player 1 ever choose T ?

- No, because M is always better than T .
- In this case, T is strictly dominated by M .

2.3 Domination for Pure Strategies

DEFINITION 2.10 (Strictly Dominate). Let $i \in N$. Let $s_i, s'_i \in \mathcal{S}_i$ be two strategies. Let $\mathcal{S}_{-i} := \bigoplus_{j \neq i} \mathcal{S}_j$. We say that s_i **strictly dominates** s'_i if and only if

$$\forall s_{-i} \in \mathcal{S}_{-i}, \quad u_i(s_i, s_{-i}) > u_i(s'_i, s_{-i}).$$

DEFINITION 2.11 (Weakly Dominate). Let $i \in N$. Let $s_i, s'_i \in \mathcal{S}_i$ be two strategies. Let $\mathcal{S}_{-i} := \bigoplus_{j \neq i} \mathcal{S}_j$. We say that s_i **weakly dominates** s'_i if and only if

$$\forall s_{-i} \in \mathcal{S}_{-i}, \quad u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i}),$$

and $\exists s_{-i}^* \in \mathcal{S}_{-i}$ for which the inequality holds strictly.

DEFINITION 2.12 (Best Response Function). We define the **best response func-**

tion for Player i to be a function $B_i : \bigoplus_{j \neq i} \mathcal{S}_j \rightarrow \mathcal{P}(\mathcal{S}_i)$ given by

$$\begin{aligned} B_i(s_{-i}) &:= \{s_i \in \mathcal{S}_i : \forall s'_i \in \mathcal{S}_i, u_i(s'_i, s_{-i}) \leq u_i(s_i, s_{-i})\} \\ &= \operatorname{argmax}_{s'_i \in \mathcal{S}_i} \{u_i(s'_i, s_{-i})\}. \end{aligned}$$

In other words, $B_i(s_{-i})$ is the set consisting of all strategies of Player i that yield the maximum payoff against (s_{-i}) .

PROPOSITION 2.13. A strategy profile $s^* = (s_1, \dots, s_n) \in \mathcal{S}$ is a Nash equilibrium if and only if

$$\forall i \in N, \quad s_i \in B_i(s_{-i}).$$

2.4 Mixed Strategies

DEFINITION 2.14 (Mixed Strategy). Let \mathcal{S}_i denote the set of strategies for player i . We define a **mixed strategy** $x^{(i)}$ over \mathcal{S}_i to be a probability distribution over \mathcal{S}_i . That is, $x^{(i)} \in \mathbb{R}^{\mathcal{S}_i}$ is such that $x^{(i)} \geq \mathbf{0}$ and $\mathbf{1}^\top x^{(i)} = 1$.

DEFINITION 2.15 (Mixed Strategy Profile). We define a **mixed strategy profile** to be a vector $\vec{x} = (x^{(1)}, \dots, x^{(n)}) \in \mathbb{R}^{\mathcal{S}_1} \times \dots \times \mathbb{R}^{\mathcal{S}_n}$ specifying a mixed strategy $x^{(i)} \in \mathbb{R}^{\mathcal{S}_i}$ for each player $i \in N$.

DEFINITION 2.16 (Expected Utility). Let $\vec{x} = (x^{(1)}, \dots, x^{(n)})$ denote a mixed strategy profile. We define the **expected utility** of player i in \vec{x} , denoted by $u_i(\vec{x})$, to be a number given by

$$u_i(\vec{x}) := \sum_{\vec{s} \in \mathcal{S}} \left[u_i(\vec{s}) \prod_{j \in \{1, \dots, n\}} x_{s_j}^{(j)} \right] = \sum_{s_i \in \mathcal{S}_i} x_{s_i}^{(i)} \sum_{\vec{s} \in \mathcal{S}, \vec{s}_i = s_i} \left[u_i(\vec{s}) \prod_{j \neq i} x_{s_j}^{(j)} \right].$$

We define the **expected utility of strategy** s_i in \vec{x} to be

$$u_i(s_i, \vec{x}) := \sum_{\vec{s} \in \mathcal{S}, \vec{s}_i = s_i} \left[u_i(\vec{s}) \prod_{j \neq i} x_{s_j}^{(j)} \right].$$

2.5 Nash Equilibrium of Mixed Strategies

DEFINITION 2.17 (Mixed Nash Equilibrium). Let $\bar{x} = (\bar{x}^{(1)}, \dots, \bar{x}^{(n)})$ be a mixed strategy. We say that \bar{x} is a **mixed Nash equilibrium** if and only if $\forall i \in \{1, \dots, n\}$, for any mixed strategy $x^{(i)}$ over \mathcal{S}_i , we have

$$u_i(\bar{x}) \geq u_i(\bar{x}^1, \dots, x^i, \dots, \bar{x}^n).$$

DEFINITION 2.18 (Best Response). Given a profile $\bar{x}^{-i} = (\bar{x}^1, \dots, \bar{x}^{i-1}, \bar{x}^{i+1}, \dots, \bar{x}^n)$ of mixed strategies of players in $N \setminus \{i\}$, the best response for \bar{x}^{-i} is the set $B_i(\bar{x}^{-i})$ of all mixed strategies x^i of player i that maximize the expected utility

$$u.$$

PROPOSITION 2.19. Best response functions are continuous.

THEOREM 2.20. A strategy profile is a mixed Nash equilibrium if and only if it lies on both player's best-response graphs.

Optimization problems:

$$\begin{aligned} \text{(P)} \quad & \max \quad \sum_{s \in \mathcal{S}_i} \bar{x}_s^i \cdot u_i(s, \bar{x}^{-i}) \\ & \text{subject to:} \quad \sum_{s \in \mathcal{S}_i} \bar{x}_s^i = 1, \\ & \quad \quad \quad \bar{x}^i \geq 0. \end{aligned}$$

$$\begin{aligned} \text{(D)} \quad & \min \quad y \\ & \text{subject to:} \quad y \geq u_i(s, \bar{x}^{-i}), \forall s \in \mathcal{S}_i. \end{aligned}$$

Conversely, we prove that every mixed strategy that chooses from among locally optimal strategies is an optimal strategy...

THEOREM 2.21 (Support Characterization). Given mixed strategies \bar{x}^{-i} of player in $N \setminus \{i\}$, a mixed strategy \bar{x}^i is in $B_i(\bar{x}^{-i})$ if and only if $\bar{x}_s^i > 0$ implies that $s \in \mathcal{S}_i$ is a strategy of maximum expected payoff (against \bar{x}^{-i}).

COROLLARY 2.22. The set $B_i(\bar{x}^{-i})$ is a polyhedron.

Proof. Let $S' \subseteq S$ be the subset consisting of pure strategies s that maximize $u_i(s, \bar{x}^{-1})$. Then

$$B_i(\bar{x}^{-i}) = \{x^i : \text{supp}(x^i) \subseteq S' \text{ and } \sum_{s \in S'} x_s^i = 1\}.$$

□

2.6 Domination for Mixed Strategies

DEFINITION 2.23 (Strictly Dominate). A strategy $s_i \in \mathcal{S}_i$ **strictly dominates** strategy $s'_i \in \mathcal{S}_i$ if and only if

$$\forall j \neq i, \forall s_j \in \mathcal{S}_j, \quad u_i(s_1, \dots, s_i, \dots, s_n) > u_i(s_1, \dots, s'_i, \dots, s_n).$$

DEFINITION 2.24. Let x^i be a mixed strategy over \mathcal{S}_i . Let $s_i \in \mathcal{S}_i$ be a pure strategy. We say that x^i **strictly dominates** s_i if and only if

$$\forall s_{-i} \in \mathcal{S}_{-i}, \quad u_i(x^i, s_{-i}) > u_i(s_i, s_{-i}).$$

THEOREM 2.25. Let $\bar{x} \in \bigoplus_{i=1}^n \mathbb{R}_+^{S_i}$ be a mixed Nash equilibrium. Let $s \in \mathcal{S}_i$ be a pure strategy. Suppose that there exists a mixed strategy $x^i \in \mathbb{R}_+^{S_i}$ over \mathcal{S}_i that strictly dominates s , then $\bar{x}_s^i = 0$.

Proof. Assume for the sake of contradiction that $\bar{x}_s^i > 0$.

□

DEFINITION 2.26 (Zero-Sum Game). We say that a game is a **zero-sum game** if and only if

$$\forall s \in \mathcal{S}, \quad \sum_{i=1}^n u_i(s) = 0.$$

Player 1's linear program:

$$\begin{aligned} (P_1) \quad & \max \quad \nu_r \\ \text{subject to:} \quad & x^{(1)\top} A_{\cdot,j} \geq \nu_r, \quad \forall j \in S_2, \\ & 1^\top x^{(1)} = 1, x^{(1)} \geq 0. \end{aligned}$$

Player 2's linear program:

$$\begin{aligned} (P_2) \quad & \min \quad \nu_c \\ \text{subject to:} \quad & A_{i,\cdot} x^{(2)} \leq \nu_c, \quad \forall i \in S_1, \\ & 1^\top x^{(2)} = 1, x^{(2)} \geq 0. \end{aligned}$$

They are duals of each other, both feasible and bounded.

These are equivalent to the following programs:

$$\begin{aligned} (P'_1) \quad & \max \quad (0_{|S_1|}^\top, 1) \begin{pmatrix} x^{(1)} \\ \nu_r \end{pmatrix} \\ \text{subject to} \quad & \begin{pmatrix} A^\top & -1_{|S_2|} \\ 1_{|S_1|}^\top & 0 \\ -1_{|S_1|}^\top & 0 \end{pmatrix} \begin{pmatrix} x^{(1)} \\ \nu_r \end{pmatrix} \geq \begin{pmatrix} 0_{|S_2|} \\ 1 \\ -1 \end{pmatrix}, \\ & x^{(1)} \geq 0_{|S_1|}. \\ (P'_2) \quad & \min \quad (0_{|S_2|}^\top, 1) \begin{pmatrix} x^{(2)} \\ \nu_c \end{pmatrix} \\ \text{subject to:} \quad & \begin{pmatrix} A & 1_{|S_1|} \\ -1_{|S_2|}^\top & 0 \\ 1_{|S_2|}^\top & 0 \end{pmatrix} \begin{pmatrix} x^{(2)} \\ \nu_c \end{pmatrix} \geq \begin{pmatrix} 0_{|S_1|} \\ 1 \\ -1 \end{pmatrix} \\ & x^{(2)} \leq 0_{|S_2|}. \end{aligned}$$

THEOREM 2.27. Every finite strategic game has a mixed Nash equilibrium.

Proof. Let $x \in \prod_{i \in N} \Delta_{|S_i|}$ be a mixed strategy profile. Define for each $i \in \{1, \dots, N\}$ and each $s_i \in S_i$ a function $\Phi_{s_i}^{(i)} : \prod_{i \in N} \Delta_{|S_i|} \rightarrow \mathbb{R}_+$ by

$$\Phi_{s_i}^{(i)}(x) := \max(0, u_i(s_i, x^{-1}) - u_i(x)).$$

Then

- $\Phi_{s_i}^{(i)}(x)$ is positive only if the pure strategy $s_i \in \mathcal{S}_i$ yields higher expected payoff than the mixed strategy $x^{(i)}$;
- By the Support Characterization theorem, $\Phi_{s_i}^{(i)}(x) = 0$ for all $s_i \in \mathcal{S}_i$ if and only if $x^{(i)}$ is a best response to x^{-i} ;
- $\Phi_{s_i}^{(i)}$ is not necessarily differentiable, but it is continuous.

Define a function $f : \prod_{i \in N} \Delta_{|\mathcal{S}_i|} \rightarrow \prod_{i \in N} \Delta_{|\mathcal{S}_i|}$ by $f(x) := \bar{x}$ where \bar{x} is given by:

$$\bar{x}_{s_i}^{(i)} := .$$

Then

•

Let $i \in \{1, \dots, n\}$ be arbitrary. Let $s_i \in \mathcal{S}_i$ such that $\hat{x}_{s_i}^{(i)} > 0$ and $u_i(s_i, \hat{x}^{-i}) \leq u_i(\hat{x})$. Then $\Phi_{s_i}^{(i)}(\hat{x}) = 0$ and

$$\hat{x}_{s_i}^{(i)} = (f(\hat{x}))_{s_i}^{(i)} = \frac{\hat{x}_{s_i}^{(i)} + 0}{1 + \sum_{s \in \mathcal{S}_i} \Phi_s^{(i)}(\hat{x})}.$$

So $\forall s \in \mathcal{S}_i$, we have $\Phi_s^{(i)}(\hat{x}) = 0$. So $\forall i \in \{1, \dots, n\}$, $\hat{x}^{(i)}$ is a best response to \hat{x}^{-i} . So \hat{x} is a Nash equilibrium. \square

THEOREM 2.28 (Daskalakis, Goldberg, Papadimitriou (2008)). NASH is polynomial parity argument for directed graphs (PPAD)-complete.

REMARK 2.29. NASH, BROUWER, and BORSUK-ULAM are PPAD-complete.

REMARK 2.30. The following problems are NP-complete:

- Find a Nash equilibrium maximizing total utility.
- Find two Nash equilibria (or determine that only one exists).

...

Chapter 3

Lemke-Homson Algorithm

Let \mathcal{S}_1 and \mathcal{S}_2 denote the strategies for player 1 and player 2, respectively. Let $A, B \in \mathbb{R}^{\mathcal{S}_1 \times \mathcal{S}_2}$ denote the payoff matrices for player 1 and player 2, respectively. Consider the following system

$$\begin{aligned}
 (P) \quad & \min \quad 0 \\
 \text{subject to:} \quad & \mathbb{1}^\top x^{(i)} = 1, \quad \forall i \in \{1, 2\}, \\
 & Ax^{(2)} \leq \mathbb{1}v_1, \\
 & B^\top x^{(1)} \leq \mathbb{1}v_2, \\
 & \sum_{i \in \mathcal{S}_i} x_i^{(1)}(v_1 - A_{i \cdot} x^{(2)}) = 0, \\
 & \sum_{j \in \mathcal{S}_j} x_j^{(2)}(v_2 - B_{\cdot j}^\top x^{(1)}) = 0, \\
 & x^{(1)} \in \mathbb{R}^{\mathcal{S}_1}, x^{(2)} \in \mathbb{R}^{\mathcal{S}_2}, v_1, v_2 \in \mathbb{R}.
 \end{aligned}$$

Note that this is a feasibility problem.

CLAIM 3.1. A non-negative solution to this system is a mixed Nash equilibrium.

Proof. By the Support Characterization theorem, $x^{(1)}$ and $x^{(2)}$ are best responses to each other. \square

DEFINITION 3.2 (Lemke-Homson Algorithm). Define $\bar{x}^{(1)} := x^{(1)}/v_2 \in \mathbb{R}^{\mathcal{S}_1}$ and $\bar{x}^{(2)} := x^{(2)}/v_1 \in \mathbb{R}^{\mathcal{S}_2}$. Add slack variables $\gamma^{(1)} \in \mathbb{R}^{\mathcal{S}_1}$ and $\gamma^{(2)} \in \mathbb{R}^{\mathcal{S}_2}$. Then we get the **Lemke-Homson system**:

$$\begin{aligned}
(P) \quad & \min \quad 0 \\
& \text{subject to: } A\bar{x}^{(2)} + \gamma^{(1)} = \mathbb{1}, \\
& \quad B^\top \bar{x}^{(1)} + \gamma^{(2)} = \mathbb{1}, \\
& \quad \sum_{i \in \mathcal{S}_1} \bar{x}_i^{(1)} \gamma_i^{(1)} = 0, \\
& \quad \sum_{j \in \mathcal{S}_2} \bar{x}_j^{(2)} \gamma_j^{(2)} = 0, \\
& \quad \bar{x}^{(1)}, \gamma^{(1)} \in \mathbb{R}_+^{\mathcal{S}_1}, \\
& \quad \bar{x}^{(2)}, \gamma^{(2)} \in \mathbb{R}_+^{\mathcal{S}_2}.
\end{aligned}$$

REMARK 3.3. The first two constraints yield

$$\begin{bmatrix} 0 & A & I & 0 \\ B^\top & 0 & 0 & I \end{bmatrix} \begin{pmatrix} \bar{x}^{(1)} \\ \bar{x}^{(2)} \\ \gamma^{(1)} \\ \gamma^{(2)} \end{pmatrix} = \mathbb{1}.$$

Note that there is a trivial (basic) solution to the above system: $\gamma^{(i)} = \mathbb{1}$ and $\bar{x}^{(i)} = 0$, for $i \in \{1, 2\}$. However, there is no mixed strategy with all entries zero.

REMARK 3.4. Set $v_1 := (\mathbb{1}^\top \bar{x}^{(2)})^{-1}$, $v_2 := (\mathbb{1}^\top \bar{x}^{(1)})^{-1}$, and $x^{(1)} := v_2 \bar{x}^{(1)}$, $x^{(2)} := v_1 \bar{x}^{(2)}$ to get a feasible solution to the original problem.

THEOREM 3.5. For a non-degenerate game, the Lemke-Howson algorithm terminates in a finite number of steps.

Proof Idea. It suffices to show that no basis repeats. □

Chapter 4

Market Models

4.1 Cournot Oligopoly Model

DEFINITION 4.1 (Cournot Oligopoly Model). Let $c \in \mathbb{R}_{++}$ denote the cost of production. Let $\alpha \in \mathbb{R}_{++}$ denote the maximum cost that the buyers are willing to pay. Suppose that $c < \alpha$ and

$$C_i(q_i) := cq_i, \forall i \in N, \text{ and}$$
$$P(\vec{q}) := \max(\alpha - \sum_{i \in N} q_i, 0).$$

PROPOSITION 4.2 (Utility Function). The utility for player i , under the Cournot Oligopoly Model, is

$$u_i(\vec{q}) = \begin{cases} q_i(\alpha - c - \sum_{j \in N} q_j), & \text{if } \alpha - \sum_{j \in N} q_j \geq 0 \\ -cq_i, & \text{otherwise.} \end{cases}$$

PROPOSITION 4.3 (Best Response Function). The best response function for

player i , under the Cournot Oligopoly Model, is

$$B_i(\vec{q}_{-i}) = \begin{cases} \frac{1}{2}(\alpha - c - \sum_{j \neq i} q_j), & \text{if } \alpha - c - \sum_{j \neq i} q_j \geq 0 \\ 0, & \text{otherwise.} \end{cases}$$

PROPOSITION 4.4 (Nash Equilibrium). The Nash equilibrium is \vec{q}^* where $\forall i \in N$,

$$\vec{q}_i^* = \frac{\alpha - c}{n + 1}.$$

4.2 Bertrand Oligopoly Model

PROPOSITION 4.5. Let $A := \operatorname{argmin}_{j \in [n]} \{p_j\}$. Let $m := |A|$. Then the utility function

$$u_i(\vec{p}) = \begin{cases} p_i \frac{D(p_i)}{m} - C_i\left(\frac{D(p_i)}{m}\right), & \text{if } i \in A \\ -C_i(0), & \text{otherwise.} \end{cases}$$

4.2.1 Two Player, Linear Cost, Inverse Linear Demand

PROPOSITION 4.6 (Utility Function). Let c denote the cost of production. Let α denote the maximum price that the consumers are willing to pay. Suppose that $n = 2$, $C_i(q_i) = cq_i$, and $D(p) = \max(\alpha - p, 0)$. Then firm i makes a profit of

$$u_i(p_1, p_2) = \begin{cases} (\alpha - p_i)(p_i - c), & \text{if } p_i < p_j \\ \frac{1}{2}(\alpha - p_i)(p_i - c), & \text{if } p_i = p_j \\ 0, & \text{if } p_i > p_j \end{cases}$$

for $i \in \{1, 2\}$ and $j := 3 - i$.

PROPOSITION 4.7 (Best Reponse Function). Let p^* denote the profit-maximizing price in a monopoly. That is, $p^* := \frac{c + \alpha}{2}$ is the value of p that maximizes $(\alpha - p)(p - c)$.

Then the best response function B_i for player i is

$$B_i(p_j) = \begin{cases} \{p_i : p_i > p_j\}, & \text{if } p_j < c \\ \{p_i : p_i \geq c\}, & \text{if } p_j = c \\ \emptyset, & \text{if } c < p_j \leq p^* \\ \{p^*\}, & \text{if } p^* < p_j \end{cases}$$

for $i \in \{1, 2\}$ and $j := 3 - i$.

PROPOSITION 4.8 (Nash Equilibrium). The only point that the graphs of B_1 and B_2 intersect is (c, c) .

REMARK 4.9.

- Payoff functions can be discontinuous;
- Best responses can be non-existent;
- Graphs of best response functions can be disconnected.

EXAMPLE 4.10 (Infinite Games with no Nash Equilibrium).

- Non-compact strategy space: $S_1 = S_2 := [0, 1)$, $u_i(s_1, s_2) := s_i$.
- Discontinuous payoff functions: $S_1 = S_2 := [0, 1]$, $u_i(s_1, s_2) := \begin{cases} s_i, & \text{if } s_i < 1 \\ 0, & \text{if } s_i = 1 \end{cases}$.
- Discontinuous pay off functions:

Chapter 5

Routing Games

5.1 Atomic Selfish Routing Game

DEFINITION 5.1 (Atomic Selfish Routing Game). An **atomic selfish routing game** consists of

- A directed graph $G = (V, E)$;
- A set of players $N = \{1, \dots, n\}$;
- A source-target pair $(s_i, t_i) \in V \times V$ for each $i \in N$;
- A traffic $r_i \in \mathbb{R}_{++}$ for each $i \in N$;
- A cost function $c_e : \mathbb{R}_{++} \rightarrow \mathbb{R}_{++}$ that is continuous and non-decreasing.

REMARK 5.2. Atomic selfish routing game is a special case of finite strategic game. The strategy set \mathcal{P}_i for player i is the set of all $s_i t_i$ -paths in G . We assume that $\forall i \in N$, $\mathcal{P}_i \neq \emptyset$. A strategy profile is a vector $\vec{p} = (p_1, \dots, p_n)$ of paths. Let $f_e^{\vec{p}}$ denote the total number of units of traffic in \vec{p} on edge e . If $r_i = 1$ for all $i \in N$, then $f_e^{\vec{p}}$ equals the number of occurrences of e in \vec{p} . The utility of player i is

$$u_i(\vec{p}) = - \sum_{e \in E(p_i)} c_e(f_e^{\vec{p}}).$$

DEFINITION 5.3 (Flow for Atomic). Let $\mathcal{P} := \bigcup_{i \in N} \mathcal{P}_i$. We define a **flow** to be a function $f : N \times \mathcal{P} \rightarrow \mathbb{R}_+$. We say that f is **feasible** if and only if $\forall i \in N, \exists p_i \in \mathcal{P}_i$ such that $\forall p \in \mathcal{P}$, we have

$$f(i, p) = \begin{cases} r_i, & \text{if } p = p_i \\ 0, & \text{otherwise.} \end{cases}$$

i.e., each player sets all of its traffic to exactly one path that is available for that player.

DEFINITION 5.4 (Cost for Atomic). We define the **cost of a path** p w.r.t. a flow f , denoted by $c_p(f)$, to be a number given by

$$c_p(f) := \sum_{e \in E(p)} c_e(f_e) \text{ where } f_e := \sum_{q \in \{q \in \mathcal{P} : e \in q\}} \sum_{i \in N} f(i, q).$$

We define the **cost of a flow** f to be an element of \mathbb{R} given by

$$C(f) := \sum_{e \in E(G)} c_e(f_e) f_e.$$

DEFINITION 5.5 (Equilibrium Flow). We say that a feasible flow f is a **equilibrium flow** if and only if $\forall i \in N, \forall p, \tilde{p} \in \mathcal{P}_i$, we have

$$f(i, p) > 0 \implies c_p(f) \leq c_{\tilde{p}}(\tilde{f})$$

where \tilde{f} is the flow identical to f except that $\tilde{f}(i, p) = 0$ and $\tilde{f}(i, \tilde{p}) = r_i$.

5.2 Non-atomic Selfish Routing

DEFINITION 5.6 (Non-atomic Selfish Routing). A **non-atomic selfish routing game** consists of

- A directed graph $G = (V, E)$ (multiple edges are allowed).
- A set of players $N = \{1, \dots, n\}$.

- For each player $i \in N$, a source-target pair $(s_i, t_i) \in V \times V$. We assume that $\forall i, j \in N, (s_i, t_i) = (s_j, t_j) \implies i = j$.
-

DEFINITION 5.7 (Flow for Non-atomic). Let \mathcal{P}_i denote the set of all $s_i t_i$ -paths in G . Let $\mathcal{P} := \bigcup_{i \in N} \mathcal{P}_i$. We define a **flow** to be a function $f : \mathcal{P} \rightarrow \mathbb{R}_+$. We say that a flow f is **feasible** if and only if

$$\forall i \in N, \quad \sum_{p \in \mathcal{P}_i} f(p) = r_i.$$

DEFINITION 5.8 (Cost for Non-atomic). Let $f : \mathcal{P} \rightarrow \mathbb{R}_+$ be a flow. We define the **cost of a path** p w.r.t. a flow f to be

$$c_p(f) := \sum_{e \in E(p)} c_e(f_e) \text{ where } f_e := \sum_{q \in \mathcal{P} : e \in E(q)} f(q).$$

We define the **cost of a flow** f to be

$$C(f) := \sum_{p \in \mathcal{P}} c_p(f) f(p) = \sum_{e \in E} c_e(f_e) f_e.$$

DEFINITION 5.9 (Equilibrium Flow). We say that a feasible flow is **equilibrium** if and only if

$$\forall i \in N, \forall p, \tilde{p} \in \mathcal{P}_i, \quad f_p > 0 \implies c_p \dots$$

THEOREM 5.10. Let (G, \vec{r}, c) be a non-atomic selfish routing instance. Then

1. The instance (G, \vec{r}, c) admits at least one equilibrium flow.
2. If f and \tilde{f} are equilibrium flows for (G, \vec{r}, c) , then $c_e(f_e) = c_e(\tilde{f}_e)$ for every edge e .

DEFINITION 5.11 (Marginal Cost Functions). Let $e \in E$ and $p \in \mathcal{P}$. We define the **marginal cost functions** to be

$$c_e^*(x) := \frac{d(x \cdot c_e(x))}{dx} = c_e(x) + x \cdot c_e'(x) = \frac{\partial}{\partial f_e} C(f),$$

$$c_p^*(f) := \sum_{e \in E(p)} c_e^*(f_e) = \sum_{e \in E(p)} \frac{\partial}{\partial f_e} C(f).$$

LEMMA 5.12. Let $C : \mathbb{R}^n \rightarrow \mathbb{R}$ be a convex differentiable function. Let $S \subseteq \mathbb{R}^n$ be a nonempty convex set. Then a feasible point $x^* \in S$ is optimal for the convex problem

$$\min C(x) \quad \text{s.t.} \quad x \in S$$

if and only if

$$\forall x \in S, \quad \nabla C(x^*) \cdot (x - x^*) \geq 0.$$

THEOREM 5.13. Let (G, \vec{r}, c) be a non-atomic selfish routing instance such that for every edge e , the function $x \mapsto x \cdot c_e(x)$ is convex and differentiable. Let c_e^* denote the marginal cost function of the edge e . Then f^* is an optimal flow for (G, \vec{r}, c) if and only if $\forall i \in N, \forall p_1, p_2 \in \mathcal{P}_i$ such that $f^*(p_1) > 0$, we have $c_{p_1}^*(f^*) \leq c_{p_2}^*(f^*)$.

Proof. (\Rightarrow) Suppose that f^* is optimal. Assume for the sake of contradiction that $\exists i \in N, \exists p_1, p_2 \in \mathcal{P}_i$ such that $f^*(p_1) > 0$ and $c_{p_1}^*(f^*) > c_{p_2}^*(f^*)$. Define for each $\varepsilon > 0$ a flow $f : \mathcal{P} \rightarrow \mathbb{R}_+$ by

$$f(p) := \begin{cases} f^*(p_1) - \varepsilon, & \text{if } p = p_1 \\ f^*(p_2) + \varepsilon, & \text{if } p = p_2 \\ f^*(p), & \text{otherwise.} \end{cases} \implies (f - f^*)_e = \begin{cases} -\varepsilon, & \text{if } e \in E(p_1) \setminus E(p_2) \\ +\varepsilon, & \text{if } e \in E(p_2) \setminus E(p_1) \\ 0, & \text{otherwise.} \end{cases}$$

Then

$$\begin{aligned} \langle \nabla C(f^*), f - f^* \rangle &= \varepsilon \sum_{e \in E(p_2) \setminus E(p_1)} c_e^*(f_e^*) - \varepsilon \sum_{e \in E(p_1) \setminus E(p_2)} c_e^*(f_e^*) \\ &= \varepsilon \left[\sum_{e \in E(p_2)} c_e^*(f_e^*) - \sum_{e \in E(p_1)} c_e^*(f_e^*) \right] \end{aligned}$$

$$= \varepsilon(c_{p_2}^*(f^*) - c_{p_1}(f^*)) < 0.$$

(\Leftarrow) Suppose that... I will show that f^* is an optimal flow for (G, \vec{r}, e) . Now for any feasible flow $f : \mathcal{P} \rightarrow \mathbb{R}_+$ obtained from f^* by shifting ε units...

$$\langle \nabla C(f^*), f - f^* \rangle = \varepsilon(c_{p_2}^*(f^*) - c_{p_1}^*(f^*)) \geq 0.$$

□

Define

$$\Phi(f) := \sum_{e \in E} h_e(f_e) \text{ where } h_e(f_e) := \int_0^{f_e} c_e(x) dx.$$

Then

$$c_p^*(f) = \sum_{e \in E(p)} h'_e(f_e) = \sum_{e \in E(p)} c_e(f_e) = c_p(f).$$

...

THEOREM 5.14. Every non-atomic selfish routing game admits a Nash flow.

Proof. Define

$$h_e(f_e) := \int_0^{f_e} c_e(x) dx.$$

Then h_e is convex and differentiable. Notice that a differentiable function is convex on an interval if and only if its derivative is non-decreasing. So c_e are continuous, non-decreasing, and non-negative. □

Proof. If f and \tilde{f} are equilibrium flows for (G, \vec{r}, c) , then $c_e(f_e) = c_e(\tilde{f}_e)$ for every edge e . Suppose that f and \tilde{f} are both Nash flows. Then f and \tilde{f} are both minimizers of Φ . So $\Phi(f) = \Phi(\tilde{f})$. Since the feasible set is convex, $\forall \lambda \in [0, 1]$, $\lambda f + (1 - \lambda)\tilde{f}$ is also feasible. Note that $\Phi(f) := \sum_{e \in E} h_e(f_e)$ is a sum of convex function and hence convex. So

$$\Phi(\lambda f + (1 - \lambda)\tilde{f}) \leq \lambda \Phi(f) + (1 - \lambda)\Phi(\tilde{f}) = \Phi(f) = \Phi(\tilde{f}).$$

So $\lambda \mapsto \Phi(\lambda f + (1 - \lambda)\tilde{f})$ is a constant function. For a sum of convex functions to be constant, each summand must be linear. So $h_e(f_e) = \int_0^{f_e} c_e(x) dx$ is linear. So $c_e(x)$ is constant from f to \tilde{f} . □

THEOREM 5.15. Suppose $\gamma \geq 1$ satisfies $\forall e \in E, \forall x \geq 0$, we have

$$x \cdot c_e(x) \leq \gamma \int_0^x c_e(y) dy.$$

Then the price of anarchy is at most γ .

REMARK 5.16. Note that $\gamma < 1$ is impossible since $\forall e \in E, \forall x \geq 0$,

$$\begin{aligned} \frac{d}{dy}(y \cdot c_e(y)) &= c_e(y) + y \cdot c'_e(y) \geq c_e(y) \\ \implies x \cdot c_e(x) &= \int_0^x \frac{d}{dy}(y \cdot c_e(y)) dy \geq \int_0^x c_e(y) dy. \end{aligned}$$

Proof. By the previous calculation, $\forall f : \mathcal{P} \rightarrow \mathbb{R}$, we have

$$C(f) = \sum_{e \in E} f_e \cdot c_e(f_e) \geq \sum_{e \in E} \int_0^{f_e} c_e(x) dx = \Phi(f).$$

So for all feasible flows f and \tilde{f} where f is a Nash flow, we then have

$$C(f) \leq \gamma \Phi(f) \leq \gamma \Phi(\tilde{f}) \leq \gamma C(\tilde{f}).$$

□

EXAMPLE 5.17. Let $c_e(x)$ be given by $c_e(x) = \sum_{i=0}^d a_i x^i$ for some $d \in \mathbb{Z}_{++}$ and $a_0, \dots, a_d \in \mathbb{R}_{++}$. Then we have

$$\begin{aligned} x \cdot c_e(x) &= \sum_{i=0}^d a_i x^{i+1} \text{ and} \\ (d+1) \int_0^x c_e(y) dy &= (d+1) \sum_{i=0}^d \frac{a_i}{i+1} x^{i+1} = \sum_{i=0}^d \frac{d+1}{i+1} a_i x^{i+1} \geq x \cdot c_e(x). \end{aligned}$$

Hence we can take $\gamma = d+1$ in the theorem. So the price of anarchy is at most $d+1$.

5.3 Potential Function of Atomic Selfish Routing Game

DEFINITION 5.18 (Potential Function). Suppose $r_1 = \dots = r_n = r$ for some $r \in \mathbb{R}$. Then there exists a Nash equilibrium. Define $\mathcal{P} := \bigcup_{i=1}^n \mathcal{P}_i$. Define for each $e \in E$ a number $f_e^{\vec{p}} \in \mathbb{Z}_+$ by $f_e^{\vec{p}} := |\{i \in N : e \in E(\vec{p}_i)\}|$. We define the **potential function** of an atomic selfish routing game, denoted by Φ , to be a function from $\mathcal{P}_1 \times \dots \times \mathcal{P}_n$ to \mathbb{R} given by

$$\Phi(\vec{p}) := \sum_{e \in E} \sum_{i=1}^{f_e^{\vec{p}}} c_e(i).$$

DEFINITION 5.19 (Exact Potential Game). We say that a finite strategic game is an **exact potential game** if and only if there exists a potential function $\Phi : \mathcal{S}_1 \times \dots \times \mathcal{S}_n \rightarrow \mathbb{R}$ such that $\forall i \in N, \forall s_i, s'_i \in \mathcal{S}_i$,

$$\Phi(s_i, s_{-i}) - \Phi(s'_i, s_{-i}) = u_i(s'_i, s_{-i}) - u_i(s_i, s_{-i}).$$

Notice that utilities are negatives of the cost. So if Φ increases, u_i would decrease, and vice versa.

THEOREM 5.20. An atomic selfish routing game is an exact potential game with potential function $\Phi : \mathcal{P}_1 \times \dots \times \mathcal{P}_n \rightarrow \mathbb{R}$ given by

$$\Phi(\vec{p}) = \sum_{e \in E} \sum_{i=1}^{f_e^{\vec{p}}} c_e(i).$$

Proof. Let $i \in N$, $s_i, s'_i \in \mathcal{S}_i$ be arbitrary. Let $p_i := (s_i, s_{-i})$ and $p'_i := (s'_i, s_{-i})$. Then

$$\begin{aligned} \Phi(\vec{p}) - \Phi(\vec{p}') &= \sum_{e \in E} \sum_{i=1}^{f_e^{\vec{p}}} c_e(i) - \sum_{e \in E} \sum_{i=1}^{f_e^{\vec{p}'}} c_e(i) \\ &= \sum_{e \in E(p_i) \setminus E(p'_i)} c_e(f_e^{\vec{p}}) - \sum_{e \in E(p'_i) \setminus E(p_i)} c_e(f_e^{\vec{p}'}) \\ &= \sum_{e \in E(p_i)} c_e(f_e^{\vec{p}}) - \sum_{e \in E(p'_i)} c_e(f_e^{\vec{p}'}) \\ &= (-u_i(\vec{p})) - (-u_i(\vec{p}')) = u_i(\vec{p}') - u_i(\vec{p}). \end{aligned}$$

□

THEOREM 5.21. Every exact potential game has a Nash equilibrium.

Proof. Notice that the set of strategy profiles $\mathcal{S} = \mathcal{S}_1 \times \dots \times \mathcal{S}_n$ is a finite set. Let $\vec{s} \in \mathcal{S}$ be a minimizer of Φ . Assume for the sake of contradiction that \vec{s} is not a Nash equilibrium, then $\exists i \in N, \exists s'_i \in \mathcal{S}_i$ such that $u_i(\vec{s}') - u_i(\vec{s}) > 0$. By the preceding theorem we get $\Phi(\vec{s}) - \Phi(\vec{s}') > 0$, which contradicts to the assumption that \vec{s} is a minimizer of Φ . \square

DEFINITION 5.22 $((\lambda, \mu)$ -smooth). Let $\lambda \geq 0$ and $\mu < 1$. Let $f : \mathbb{R}_{++} \rightarrow \mathbb{R}_{++}$. We say that f is **(λ, μ) -smooth** if and only if

$$\forall x, y \in \mathbb{R}_{++}, \quad yf(x) \leq \lambda yf(y) + \mu xf(x).$$

EXAMPLE 5.23. Let $f(x) := ax + b$ for some $a, b \in \mathbb{R}_{++}$. Then f is $(1, 1/4)$ -smooth.

Proof. Let $x, y \in \mathbb{R}_{++}$ be arbitrary. Then

$$0 \leq a\left(\frac{1}{2}x - y\right)^2 = \frac{1}{4}x^2 - axy + ay^2 \iff axy - ay^2 \leq \frac{1}{4}ax^2$$

...

\square

THEOREM 5.24 (Variational Inequality Characterization). Let f be a feasible flow. Then f is a Nash flow if and only if

$$\forall \text{ feasible flow } f^*, \quad \sum_{e \in E} c_e(f_e)f_e \leq \sum_{e \in E} c_e(f_e)f_e^*.$$

Proof. Define for any feasible flow f^*

$$H(f^*) = \sum_{e \in E} c_e(f_e)f_e^*$$

Then

$$H(f^*) = \sum_{e \in E} c_e(f_e)f_e^* = \sum_{e \in E} c_e(f_e) \sum_{p \in \mathcal{P}: e \in E(p)} f_p^* = \sum_{e \in E} \sum_{p \in \mathcal{P}: e \in E(p)} c_e(f_e)f_p^*$$

$$= \sum_{p \in \mathcal{P}} \sum_{e \in E: e \in E(p)} c_e(f_e) f_p^* = \sum_{p \in \mathcal{P}} c_p(f) f_p^* = \sum_{i=1}^N \sum_{p \in \mathcal{P}_i} c_p(f) f_p^*.$$

(\Rightarrow) Suppose that f is a Nash flow. Then $\forall p \in \mathcal{P}_i, f_p > 0 \implies \forall \hat{p} \in \mathcal{P}_i, c_p(f) \leq c_{\hat{p}}(f)$. So the summation in $H(f)$ is a weighted average of minimal possible terms, whereas the summation in $H(f^*)$ is a weighted average of possibly larger terms. So $H(f) \leq H(f^*)$.

(\Leftarrow) Suppose that f is a minimizer of H . Then the summation in $H(f)$ must only assign positive weights to the smallest possible values of $c_p(f)$. So $\forall p \in \mathcal{P}_i, f_p > 0 \implies \forall \hat{p} \in \mathcal{P}_i, c_p(f) \leq c_{\hat{p}}(f)$. \square

THEOREM 5.25. Consider a non-atomic selfish routing game. Suppose that c_e is (λ, μ) -smooth for all $e \in E$. Then

$$C(f) \leq \frac{\lambda}{1 - \mu} C(\hat{f})$$

whenever f is a Nash flow and \hat{f} is an optimal flow.

Proof.

$$\begin{aligned} C(f) &= \sum_{e \in E} c_e(f_e) f_e \leq \sum_{e \in E} c_e(f_e) \hat{f}_e, \text{ by the above theorem} \\ &\leq \lambda \sum_{e \in E} c_e(\hat{f}_e) \hat{f}_e + \mu \sum_{e \in E} c_e(f_e) f_e, \text{ by smoothness of } c_e \\ &= \lambda C(\hat{f}) + \mu C(f). \end{aligned}$$

\square