

## CSE 6319 Notes 3: Mechanism Design (Part 3)

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### 3.I. VCG AND SCORING RULES (KP 16; N 9; R 7)

Social Surplus Maximization and the General VCG Mechanism (KP 16.2)

Example 16.2.4 - Roads for three cities

Example 16.2.5 - Employee housing

Example 16.2.8 - Spectrum auctions

Scoring Rules (KP 16.3 - SKIP)

### 3.J. COMBINATORIAL AUCTIONS (N 11; R 8)

Introduction (N 11.1)

$m$  indivisible items,  $n$  bidders

**Definition 11.1** A valuation  $v$  is a real-valued function that for each subset  $S$  of items,  $v(S)$  is the value that bidder  $i$  obtains if he receives this bundle of items. A valuation must have “free disposal,” i.e., be monotone: for  $S \subseteq T$  we have that  $v(S) \leq v(T)$ , and it should be “normalized”:  $v(\emptyset) = 0$ .

Sets  $S$  and  $T$  with  $S \cap T = \emptyset$ :

Complements:  $v(S \cup T) > v(S) + v(T)$

Substitutes:  $v(S \cup T) < v(S) + v(T)$

**Definition 11.2** An *allocation* of the items among the bidders is  $S_1, \dots, S_n$  where  $S_i \cap S_j = \emptyset$  for every  $i \neq j$ . The *social welfare* obtained by an allocation is  $\sum_i v_i(S_i)$ . A socially efficient allocation (among bidders with valuations  $v_1, \dots, v_n$ ) is an allocation with maximum social welfare among all allocations.

Issues

Computational complexity

Representation and communication

Strategic behavior

Applications: [bichler.pdf](#) [newman.pdf](#) [parkes\\_iBundle.pdf](#)

## Single-Minded Case (N 11.2)

**Definition 11.3** A valuation  $v$  is called *single minded* if there exists a bundle of items  $S^*$  and a value  $v^* \in \mathbb{R}^+$  such that  $v(S) = v^*$  for all  $S \supseteq S^*$ , and  $v(S) = 0$  for all other  $S$ . A single-minded bid is the pair  $(S^*, v^*)$ .

**Definition 11.4** The allocation problem among single-minded bidders is the following:

**INPUT:**  $(S_i^*, v_i^*)$  for each bidder  $i = 1, \dots, n$ .

**OUTPUT:** A subset of winning bids  $W \subseteq \{1, \dots, n\}$  such that for every  $i \neq j \in W$ ,  $S_i^* \cap S_j^* = \emptyset$  (i.e., the winners are compatible with each other) with maximum social welfare  $\sum_{i \in W} v_i^*$ .

### Intractability

**Proposition 11.5** The allocation problem among single-minded bidders is NP-hard. More precisely, the decision problem of whether the optimal allocation has social welfare of at least  $k$  (where  $k$  is an additional part of the input) is NP-complete.

(Proof is by reduction from Independent-Set)

**Proposition 11.6** Approximating the optimal allocation among single-minded bidders to within a factor better than  $m^{1/2-\epsilon}$  is NP-hard.

### Incentive-Compatible Approximation

**Definition 11.7** Let  $V_{sm}$  denote the set of all single-minded bids on  $m$  items, and let  $A$  be the set of all allocations of the  $m$  items between  $n$  players. A mechanism for single-minded bidders is composed of an allocation mechanism  $f : (V_{sm})^n \rightarrow A$  and payment functions  $p_i : (V_{sm})^n \rightarrow \mathbb{R}$  for  $i = 1, \dots, n$ . The mechanism is computationally efficient if  $f$  and all  $p_i$  can be computed in polynomial time. The mechanism is incentive compatible (in dominant strategies) if for every  $i$ , and every  $v_1, \dots, v_n, v'_i \in V_{sm}$ , we have that  $v_i(a) - p_i(v_i, v_{-i}) \geq v_i(a') - p_i(v'_i, v_{-i})$ , where  $a = f(v_i, v_{-i})$ ,  $a' = f(v'_i, v_{-i})$  and  $v_i(a) = v_i$  if  $i$  wins in  $a$  and zero otherwise.

Issue with VCG - loses incentive compatibility

**Theorem 11.8** The greedy mechanism is efficiently computable, incentive compatible, and produces a  $\sqrt{m}$  approximation of the optimal social welfare.

### The Greedy Mechanism for Single-Minded Bidders:

#### Initialization:

- Reorder the bids such that  $v_1^*/\sqrt{|S_1^*|} \geq v_2^*/\sqrt{|S_2^*|} \geq \dots \geq v_n^*/\sqrt{|S_n^*|}$ .
- $W \leftarrow \emptyset$ .

**For  $i = 1 \dots n$  do:** if  $S_i^* \cap \left( \bigcup_{j \in W} S_j^* \right) = \emptyset$  then  $W \leftarrow W \cup \{i\}$ .

#### Output:

Allocation: The set of winners is  $W$ .

Payments: For each  $i \in W$ ,  $p_i = v_j^*/\sqrt{|S_j^*|/|S_i^*|}$ , where  $j$  is the smallest index such that  $S_i^* \cap S_j^* \neq \emptyset$ , and for all  $k < j, k \neq i$ ,  $S_k^* \cap S_j^* = \emptyset$  (if no such  $j$  exists then  $p_i = 0$ ).

**Figure 11.1.** The mechanism achieves a  $\sqrt{m}$  approximation for combinatorial auctions with single-minded bidders.

(For Payments,  $S_j$  is the first bundle after  $S_i$  with an element in common with  $S_i$ . Thus,  $S_j$  is the first bundle “disqualified” from  $W$  by  $S_i$ .)

**Lemma 11.9** A mechanism for single-minded bidders in which losers pay 0 is incentive compatible if and only if it satisfies the following two conditions:

- Monotonicity:** A bidder who wins with bid  $(S_i^*, v_i^*)$  keeps winning for any  $v'_i > v_i^*$  and for any  $S'_i \subset S_i^*$  (for any fixed settings of the other bids).
- Critical Payment:** A bidder who wins pays the minimum value needed for winning: the infimum of all values  $v'_i$  such that  $(S_i^*, v'_i)$  still wins.

**Lemma 11.10** Let  $OPT$  be an allocation (i.e., set of winners) with maximum value of  $\sum_{i \in OPT} v_i^*$ , and let  $W$  be the output of the algorithm, then  $\sum_{i \in OPT} v_i^* \leq \sqrt{m} \sum_{i \in W} v_i^*$ .

Walrasian Equilibrium and the LP Relaxation (N 11.3)

Winner Determination Problem = Determine the Allocation

May be stated as a (integer/fractional) linear program (N p. 276)

Dual LP Relaxation also includes prices and utilities

**Definition 11.11** For a given bidder valuation  $v_i$  and given item prices  $p_1, \dots, p_m$ , a bundle  $T$  is called a *demand* of bidder  $i$  if for every other bundle  $S \subseteq M$  we have that  $v_i(S) - \sum_{j \in S} p_j \leq v_i(T) - \sum_{j \in T} p_j$ .

**Definition 11.12** A set of nonnegative prices  $p_1^*, \dots, p_m^*$  and an allocation  $S_1^*, \dots, S_m^*$  of the items is a *Walrasian equilibrium* if for every player  $i$ ,  $S_i^*$  is a demand of bidder  $i$  at prices  $p_1^*, \dots, p_m^*$  and for any item  $j$  that is not allocated (i.e.,  $j \notin \bigcup_{i=1}^n S_i^*$ ) we have  $p_j^* = 0$ .

**Theorem 11.13 (The First Welfare Theorem)** Let  $p_1^*, \dots, p_m^*$  and  $S_1^*, \dots, S_n^*$  be a Walrasian equilibrium, then the allocation  $S_1^*, \dots, S_n^*$  maximizes social welfare. Moreover, it even maximizes social welfare over all fractional allocations, i.e., let  $\{X_{i,S}^*\}_{i,S}$  be a feasible solution to the linear programming relaxation. Then,  $\sum_{i=1}^n v_i(S_i^*) \geq \sum_{i \in N, S \subseteq M} X_{i,S}^* v_i(S)$ .

**Theorem 11.15 (The Second Welfare Theorem)** If an integral optimal solution exists for LPR, then a Walrasian equilibrium whose allocation is the given solution also exists.

**Corollary 11.16** A Walrasian equilibrium exists in a combinatorial-auction environment if and only if the corresponding linear programming relaxation admits an integral optimal solution.

Bidding Languages (N 11.4)

Atom:  $(S, p)$  - price  $p$  for a bundle  $S$  of items

$(\{\text{TV}, \text{DVD player}\}, \$100)$

OR: any subset of the atoms may be satisfied, but an item may be matched only once

$(\{\text{TV}\}, \$200) \text{ OR } (\{\text{PC}\}, \$700)$

XOR: only one of the atoms may be satisfied

$(\{\text{TV}\}, \$200) \text{ XOR } (\{\text{PC}\}, \$700)$

Maximization:

More formally, both OR and XOR bids are composed of a collection of pairs  $(S_i, p_i)$ , where each  $S_i$  is a subset of the items, and  $p_i$  is the maximum price that he is willing to pay for that subset. For the valuation  $v = (S_1, p_1) \text{ XOR }, \dots, \text{ XOR } (S_k, p_k)$ , the value of  $v(S)$  is defined to be  $\max_{i|S_i \subseteq S} p_i$ . For the valuation  $v = (S_1, p_1) \text{ OR }, \dots, \text{ OR } (S_k, p_k)$ , one must be a little careful and the value of  $v(S)$  is defined to be the maximum over all possible “valid collections”  $W$ , of the value of  $\sum_{i \in W} p_i$ , where  $W$  is a valid collection of pairs if for all  $i \neq j \in W$ ,  $S_i \cap S_j = \emptyset$ .

Combinations of OR and XOR

**Definition 11.18** Let  $v$  and  $u$  be valuations, then  $(v \text{ XOR } u)$  and  $(v \text{ OR } u)$  are valuations and are defined as follows:

- $(v \text{ XOR } u)(S) = \max(v(S), u(S))$ .
- $(v \text{ OR } u)(S) = \max_{R, T \subseteq S, R \cap T = \emptyset} v(R) + u(T)$

Negative results on “compactly representing” downward sloping valuations . . .

## Dummy Items

Representing XORs as ORs using dummy items:

$$(S_1, p_1) \text{ XOR } (S_2, p_2) \text{ becomes } (S_1 \cup \{d\}, p_1) \text{ OR } (S_2 \cup \{d\}, p_2)$$

OR\* - Implicitly augments each set of items with the same dummy item

Formally, we let each bidder  $i$  have its own set of dummy items  $D_i$ , which only he can bid on. An OR\* bid by bidder  $i$  is an OR bid on the augmented set of items  $M \cup D_i$ . The value that an OR\* bid gives to a bundle  $S \subseteq M$  is the value given by the OR bid to  $S \cup D_i$ . Thus, for example, for the set of items  $M = \{a, b, c\}$ , the OR\* bid  $(\{a, d\}, 1) \text{ OR } (\{b, d\}, 1) \text{ OR } (\{c\}, 1)$ , where  $d$  is a dummy item, is equivalent to  $((\{a\}, 1) \text{ XOR } (\{b\}, 1)) \text{ OR } (\{c\}, 1)$ .

An equivalent but more appealing “user interface” is to let bidders report a set of atomic bids together with “constraints” that signify which bids are mutually exclusive. Each constraint can then be converted into a dummy item that is added to the conflicting atomic bids. Despite its apparent simplicity, this language can simulate general OR/XOR formulae.

**Theorem 11.21** *Any valuation that can be represented by OR/XOR formula of size  $s$  can be represented by OR\* bids of size  $s$ , using at most  $s^2$  dummy items.*

## Iterative Auctions: The Query Model

Concept: Develop valuation over time rather than expecting complete elicitation upfront.

**Value query:** *The auctioneer presents a bundle  $S$ , the bidder reports his value  $v(S)$  for this bundle.*

**Demand query (with item prices<sup>2</sup>):** *The auctioneer presents a vector of item prices  $p_1, \dots, p_m$ ; the bidder reports a demand bundle under these prices, i.e., some set  $S$  that maximizes  $v(S) - \sum_{i \in S} p_i$ .*

Relationship:

**Lemma 11.22** *A value query may be simulated by  $mt$  demand queries, where  $t$  is the number of bits of precision in the representation of a bundle's value.*

**Lemma 11.23** *An exponential number of value queries may be required for simulating a single demand query.*

Linear programming for demand queries . . .

N p. 286 (classes of CA solvers and quality of approximation) and 287 (classes of valuations)

## Communication Complexity (N 11.6)

[https://amturing.acm.org/award\\_winners/yao\\_1611524.cfm](https://amturing.acm.org/award_winners/yao_1611524.cfm)

**Theorem 11.27** *For every  $\epsilon > 0$ , approximating the social welfare in a combinatorial auction to within a factor strictly smaller than  $\min\{n, m^{1/2-\epsilon}\}$  requires exponential communication.*

## Ascending Auctions (N 11.7)

### Ascending Item-Price Auctions

**Definition 11.28** A valuation  $v_i$  satisfies the *substitutes* (or *gross-substitutes*) property if for every pair of item-price vectors  $\vec{q} \geq \vec{p}$  (coordinate-wise comparison), we have that the demand at prices  $q$  contains all items in the demand at prices  $p$  whose price remained constant. Formally, for every  $A \in \text{argmax}_S\{v(S) - \sum_{j \in S} p_j\}$ , there exists  $D \in \text{argmax}_S\{v(S) - \sum_{j \in S} q_j\}$ , such that  $D \supseteq \{j \in A \mid p_j = q_j\}$ .

(Goods may be substitutes or independent, but not complements.)

Also implies submodularity, for every two bundles  $S$  and  $T$ ,

$$v(S) + v(T) \geq v(S \cup T) + v(S \cap T)$$

### An item-price ascending auction for substitutes valuations:

#### Initialization:

For every item  $j \in M$ , set  $p_j \leftarrow 0$ .  
For every bidder  $i$  let  $S_i \leftarrow \emptyset$ .

#### Repeat

For each  $i$ , let  $D_i$  be the demand of  $i$  at the following prices:  
 $p_j$  for  $j \in S_i$  and  $p_j + \epsilon$  for  $j \notin S_i$ .

If for all  $i$   $S_i = D_i$ , exit the loop;

Find a bidder  $i$  with  $S_i \neq D_i$  and update:

- For every item  $j \in D_i \setminus S_i$ , set  $p_j \leftarrow p_j + \epsilon$
- $S_i \leftarrow D_i$
- For every bidder  $k \neq i$ ,  $S_k \leftarrow S_k \setminus D_i$

**Finally:** Output the allocation  $S_1, \dots, S_n$ .

**Figure 11.3.** An item-price ascending auction that ends up with a nearly optimal allocation when bidders' valuations have the (gross) substitutes property.

**Definition 11.29** An allocation  $S_1, \dots, S_n$  and a prices  $p_1, \dots, p_m$  are an  $\epsilon$ -Walrasian equilibrium if  $\bigcup_i S_i \supseteq \{j \mid p_j > 0\}$  and for each  $i$ ,  $S_i$  is a demand of  $i$  at prices  $p_j$  for  $j \in S_i$  and  $p_j + \epsilon$  for  $j \notin S_i$ .

**Theorem 11.30** *For bidders with substitutes valuations, the auction described in Figure 11.3 ends with an  $\epsilon$ -Walrasian equilibrium. In particular, the allocation achieves welfare that is within  $n\epsilon$  from the optimal social welfare.*

**Claim 11.31** At every stage of the auction, for every bidder  $i$ ,  $S_i \subseteq D_i$ .

$m \cdot v_{max}/\epsilon$  stages (iterations of **Repeat**)

Similar to the Uniform-Price Multi-Unit Auction for Budgeted Bidders, demand reduction to improve utility (payoff) is possible (N Example 11.32)

Ascending Bundle-Price Auction

$p_i(S)$  - personalized bundle price on bundle  $S$  for bidder  $i$

Demand for bidder  $i$  are the bundles that maximize  $v_i(S) - p_i(S)$

**A bundle price auction:**

**Initialization:** For every player  $i$  and bundle  $S$ , let  $p_i(S) \leftarrow 0$ .

**Repeat**

- Find an allocation  $T_1, \dots, T_n$  that maximizes revenue at current prices, i.e.,  $\sum_{i=1}^n p_i(T_i) \geq \sum_{i=1}^n p_i(Y_i)$  for any other allocation  $Y_1, \dots, Y_n$ . (Bundles with zero prices will not be allocated, i.e.,  $p_i(T_i) > 0$  for every  $i$ .)
- Let  $L$  be the set of losing bidders, i.e.,  $L = \{i | T_i = \emptyset\}$ .
- For every  $i \in L$  let  $D_i$  be a demand bundle of  $i$  under the prices  $\vec{p}$ .
- If for all  $i \in L$ ,  $D_i = \emptyset$  then terminate.
- For all  $i \in L$  with  $D_i \neq \emptyset$ , let  $p_i(D_i) \leftarrow p_i(D_i) + \epsilon$ .

**Figure 11.4.** A bundle price auction which terminates with the socially efficient allocation for any profile of bidders.

**Definition 11.33** Personalized bundle prices  $\vec{p} = \{p_i(S)\}$  and an allocation  $S = (S_1, \dots, S_n)$  are called a *competitive equilibrium* if:

- For every bidder  $i$ ,  $S_i$  is a demand bundle, i.e., for any other bundle  $T_i \subseteq M$ ,  $v_i(S_i) - p_i(S_i) \geq v_i(T_i) - p_i(T_i)$ .
- The allocation  $S$  maximizes *seller's revenue* under the current prices, i.e., for any other allocation  $(T_1, \dots, T_n)$ ,  $\sum_{i=1}^n p_i(S_i) \geq \sum_{i=1}^n p_i(T_i)$ .

**Definition 11.35** A bundle  $S$  is an  $\epsilon$ -*demand* for a player  $i$  under the bundle prices  $\vec{p}_i$  if for any other bundle  $T$ ,  $v_i(S) - p_i(S) \geq v_i(T) - p_i(T) - \epsilon$ . An  $\epsilon$ -*competitive equilibrium* is similar to a competitive equilibrium (Definition 11.33), except each bidder receives an  $\epsilon$ -demand under the equilibrium prices.

**Theorem 11.36** For any profile of valuations, the bundle-price auction described in Figure 11.4 terminates with an  $\epsilon$ -competitive equilibrium. In particular, the welfare obtained is within  $n\epsilon$  from the optimal social welfare.

Finding each allocation is NP-hard.

## (2016 FCC) SPECTRUM AUCTIONS

R 8 and appendix to first chapter of Milgrom book <https://www.amazon.com/dp/023117599X>

<https://www.fcc.gov/auctions>

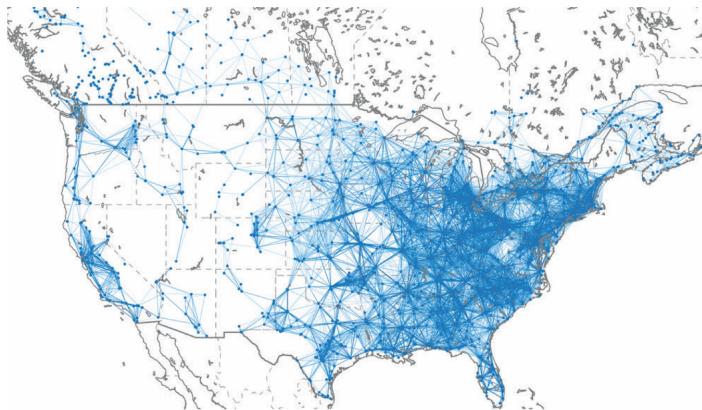
Goal: Reallocate 500 MHz from TV to wireless internet (and reduce US national debt)

Concepts:

Forward auction to allocate bandwidth (upload, download, interference)

Vendors need channels per “partial economic area”

**Figure 1. Interference graph visualizing the FCC's constraint data<sup>9</sup> (2 990 stations; 2 575 466 channel-specific interference constraints).**



( newman.pdf )

Reverse auction to acquire bandwidth

UHF stations get money and possibly VHF channel assignment

VHF stations get money and go out of business

Value index =  $(\text{population served} \cdot \text{degree of interference})^{0.5}$

Opening bid total \$120B with goal of decreasing to \$86B

Use of SAT solver to check feasibility of “repacking”

( [potassco.org](http://potassco.org) Knuth: [www.amazon.com/dp/0134397606](https://www.amazon.com/dp/0134397606) )

Forward Auction Features:

Multiple Round Simultaneous Clock Auctions

Rule: If the price isn't increasing, can't decrease demand

Rule: May not increase overall activity from round to round

Rule: Up-front cash deposit to cover activity

Mandatory bid increments to avoid “signaling”

Bidders must avoid “exposure problem”

### 3.K. MATCHING MARKETS

Maximum Weighted Matching (Assignment Problem) (KP 17.1)

Notes 1, p. 5 (KP 3.2) introduced:

Maximum matching (bipartite)

Minimum vertex cover

Hall’s marriage theorem

Konig’s Lemma:  $|\text{maximum matching}| = |\text{minimum vertex cover}|$

Hide and Seek game

Matching market problem:

Input: valuations for  $n$  buyers on  $n$  items (one seller)

Find price vector  $p^*$  and maximum matching  $M$  to maximize the social surplus

$$\sum_i (v_{iM(i)} - p_{M(i)}^*) + \sum_j p_j^* = \sum_i v_{iM(i)}$$

Map this need to generalized König’s Lemma:

**THEOREM 17.1.1.** *Given a nonnegative matrix  $V = (v_{ij})_{n \times n}$ , let*

$$K := \{(\mathbf{u}, \mathbf{p}) \in \mathbb{R}^n \times \mathbb{R}^n : u_i, p_j \geq 0 \text{ and } u_i + p_j \geq v_{ij} \forall i, j\}.$$

*Then*

$$\min_{(\mathbf{u}, \mathbf{p}) \in K} \left\{ \sum_i u_i + \sum_j p_j \right\} = \max_{\text{matchings } M} \left\{ \sum_i v_{i,M(i)} \right\}.$$

$(\mathbf{u}, \mathbf{p})$  is a minimum (fractional) cover.  $M$  is a maximum weight matching.

Observation:  $u_i$  and  $p_j$  cannot exceed the largest value in  $V$ .

Classic Algorithms for Matching:

Minimization instead of maximization . . .

Integers instead of floating-point . . .

Trivial:  $O(n^4)$

Start with trivial matching

Iteratively find negative cycles to improve (Floyd-Warshall)

Hungarian method:  $O(n^3)$

Papadimitriou & Steiglitz <https://www.amazon.com/dp/0486402584/>

Knuth <https://www-cs-faculty.stanford.edu/~knuth/sgb.html>

## Envy-Free Prices (KP 17.2)

Preferred item(s) - Based on price vector  $\mathbf{p}$  and buyer  $i$ , item  $j$  such that

$$\forall k \quad v_{ij} - p_j \geq v_{ik} - p_k \text{ and } v_{ij} \geq p_j$$

### Demand graph $D(\mathbf{p})$

Bipartite graph connecting buyers to their preferred items

$\mathbf{p}$  is *envy-free* if  $D(\mathbf{p})$  is a perfect matching

LEMMA 17.2.2. Let  $V = (v_{ij})_{n \times n}$ ,  $\mathbf{u}, \mathbf{p} \in \mathbb{R}^n$ , all nonnegative, and let  $M$  be a perfect matching from  $[n]$  to  $[n]$ . The following are equivalent:

- (i)  $(\mathbf{u}, \mathbf{p})$  is a minimum cover of  $V$  and  $M$  is a maximum weight matching for  $V$ .
- (ii) The prices  $\mathbf{p}$  are envy-free prices,  $M$  is contained in the demand graph  $D(\mathbf{p})$ , and  $u_i = v_{iM(i)} - p_{M(i)}$ .

COROLLARY 17.2.3. Let  $\mathbf{p}$  be an envy-free pricing for  $V$  and let  $M$  be a perfect matching of buyers to items. Then  $M$  is a maximum weight matching for  $V$  if and only if it is contained in  $D(\mathbf{p})$ .

LEMMA 17.2.4. The envy-free price vectors for  $V = (v_{ij})_{n \times n}$  form a **lattice**: Let  $\mathbf{p}$  and  $\mathbf{q}$  be two vectors of envy-free prices. Then, defining

$$a \wedge b := \min(a, b) \quad \text{and} \quad a \vee b := \max(a, b),$$

the two price vectors

$$\mathbf{p} \wedge \mathbf{q} = (p_1 \wedge q_1, \dots, p_n \wedge q_n) \quad \text{and} \quad \mathbf{p} \vee \mathbf{q} = (p_1 \vee q_1, \dots, p_n \vee q_n)$$

are also envy-free.

COROLLARY 17.2.5. Let  $\mathbf{p}$  minimize  $\sum_j p_j$  among all envy-free price vectors for  $V$ . Then:

- (i) Every envy-free price vector  $\mathbf{q}$  satisfies  $p_i \leq q_i$  for all  $i$ .
- (ii)  $\min_j p_j = 0$ .

THEOREM 17.2.6. Given an  $n \times n$  nonnegative valuation matrix  $V$ , let  $M^V$  be a maximum weight matching and let  $\|M^V\|$  be its weight; that is,  $\|M^V\| = \sum_i v_{iM^V(i)}$ . Write  $V_{-i}$  for the matrix obtained by replacing row  $i$  of  $V$  by  $\mathbf{0}$ . Then the lowest envy-free price vector  $\mathbf{p}$  for  $V$  and the corresponding utility vector  $\mathbf{u}$  are given by

$$M^V(i) = j \implies p_j = \|M^{V_{-i}}\| - (\|M^V\| - v_{ij}), \quad (17.5)$$

$$u_i = \|M^V\| - \|M^{V_{-i}}\| \quad \forall i. \quad (17.6)$$

COROLLARY 17.2.9 gives symmetric details for the highest envy-free price vector

Introducing seller value  $s_j$  (i.e. reserve price) (LP 17.2.2)

Replace each  $v_{ij}$  by  $\max(v_{ij} - s_j, 0)$

Envy-Free Division of Rent (KP 17.3; `cake.sun.pdf` `cake.su.pdf`)

Previous use of Sperner's lemma for cake division may be adapted to rent problem (indivisible rooms). P. 940 of `cake.su.pdf` alludes to this.

<https://www.nytimes.com/interactive/2014/science/rent-division-calculator.html>

Assuming that at least one matching has weights whose sum is no less than the sum for the lowest envy-free rent vector (THEOREM 17.2.6) and no more than the sum for the highest envy-free rent vector (COROLLARY 17.2.9), envy-free rent division may be achieved. (KP p. 305).

<https://ranger.uta.edu/~weems/NOTES6319/AUCTION/fairRent.c>

Maximum Matching by Ascending Auctions (KP 17.4)

$V$  is a non-negative integer matrix

Much like “item-price ascending auction for substitutes valuations”

- Fix the minimum bid increment  $\delta = 1/(n + 1)$ .
- Initialize the prices  $\mathbf{p}$  of all items to 0 and set the matching  $M$  of bidders to items to be empty.
- As long as  $M$  is not perfect:
  - one unmatched bidder  $i$  selects an item  $j$  in his demand set

$$D_i(\mathbf{p}) := \{j \mid v_{ij} - p_j \geq v_{ik} - p_k \quad \forall k \quad \text{and } v_{ij} \geq p_j\}$$

and bids  $p_j + \delta$  on it.

(We will see that the demand set  $D_i(\mathbf{p})$  is nonempty.)

- If  $j$  is unmatched, then  $M(i) := j$ ; otherwise, say  $M(\ell) = j$ , remove  $(\ell, j)$  from the matching and add  $(i, j)$ , so that  $M(i) := j$ .
- Increase  $p_j$  by  $\delta$ .

**THEOREM 17.4.1.** Suppose that the elements of the valuation matrix  $V = (v_{ij})$  are integers. Then the above auction terminates with a maximum weight matching  $M$ , and the final prices  $\mathbf{p}$  satisfy

$$M(i) = j \implies v_{ij} - p_j \geq v_{ik} - p_k - \delta \quad \forall k. \quad (17.11)$$

### Matching Buyers and Sellers (Assignment Games) (KP 17.5)

$n$  buyers,  $n$  sellers,  $v_{ij}$  is the value  $i$  assigns to house  $j$  (value to owner is 0)

$j$  selling to  $i$  at price  $p_j$  gives utility of  $u_i = v_{ij} - p_j$

**DEFINITION 17.5.1.** An **outcome**  $(M, \mathbf{u}, \mathbf{p})$  of the assignment game is a matching  $M$  between buyers and sellers and a partition  $(u_i, p_j)$  of the value  $v_{ij}$  on every matched edge; i.e.,  $u_i + p_j = v_{ij}$ , where  $u_i, p_j \geq 0$  for all  $i, j$ . If buyer  $i$  is unmatched, we set  $u_i = 0$ . Similarly,  $p_j = 0$  if seller  $j$  is unmatched.

We say the outcome is **stable**<sup>2</sup> if  $u_i + p_j \geq v_{ij}$  for all  $i, j$ .

**PROPOSITION 17.5.2.** An outcome  $(M, \mathbf{u}, \mathbf{p})$  is stable if and only if  $M$  is a maximum weight matching for  $V$  and  $(\mathbf{u}, \mathbf{p})$  is a minimum cover for  $V$ . In particular, every maximum weight matching supports a stable outcome.

**DEFINITION 17.5.3.** Let  $(M, \mathbf{u}, \mathbf{p})$  be an outcome of the assignment game. Define the **excess**  $\beta_i$  of buyer  $i$  to be the difference between his utility and his **best outside option**<sup>3</sup>; i.e., (denoting  $x_+ := \max(x, 0)$ ),

$$\beta_i := u_i - \max_k \{(v_{ik} - p_k)_+ : (i, k) \notin M\}.$$

Similarly, the **excess**  $s_j$  of seller  $j$  is

$$s_j := p_j - \max_\ell \{(v_{\ell,j} - u_\ell)_+ : (\ell, j) \notin M\}.$$

The outcome is **balanced** if it is stable and, for every matched edge  $(i, j)$ , we have  $\beta_i = s_j$ .

**THEOREM 17.5.5.** Every assignment game has a balanced outcome. Moreover, the following process converges to a balanced outcome: Start with the minimum cover  $(\mathbf{u}, \mathbf{p})$  where  $\mathbf{p}$  is the vector of lowest envy-free prices and a maximum weight matching  $M$ . Repeatedly pick an edge in  $M$  to balance, ensuring that every edge in  $M$  is picked infinitely often.

**LEMMA 17.5.6.** Let  $(M, \mathbf{u}, \mathbf{p})$  be a stable outcome with  $\beta_i \geq s_j \geq 0$  for every  $(i, j) \in M$ . Pick a pair  $(i, j) \in M$  with  $\beta_i > s_j$  and balance the pair by performing the update

$$u'_i := u_i - \frac{\beta_i - s_j}{2} \quad \text{and} \quad p'_j := p_j + \frac{\beta_i - s_j}{2},$$

leaving all other utilities and profits unchanged. Then the new outcome is stable and has excesses  $\beta'_i = s'_j$  and  $\beta'_k \geq s'_\ell \geq 0$  for all  $(k, \ell) \in M$ .

### (LP 17.5.1 Positive seller values)

## Application to Weighted Hide-and-Seek Games (KP 17.6)

Instead of 0/1 weights (section 3.2), general payoffs  $h_{ij}$  are used.

Theorem 17.1.1 is applied to obtain minimax result for zero-sum game.

Example 17.6.2