Fair Division of Goods, Bads, and Mixed

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(Based on joint work with S. Boodaghians, B. R. Chaudhary, J. Garg, and P. McGlaughlin)

Divisible items



Goal: Find *fair* and *efficient* allocation



Model



- A: set of n agents
- *M*: set of *m* divisible items (manna)
 - \Box Supply of every item is one





Each agent *i* has

 \square Concave valuation function $V_i: \mathbb{R}^m_+ \to \mathbb{R}$ over bundles of items

Goal: Find *fair* and *efficient* allocation

Example: Half moon cookie















Agreeable (Fair)

Envy-free: No agent *envies* other's allocation over her own.

Proportional: Each agent *i* gets value at least $\frac{v_i(M)}{n}$

Non-wasteful (Efficient)

Pareto-optimal: No other allocation is better for all.

(Nash) Welfare Maximizing



Agreeable (Fair)

Envy-free

Proportional

Non-wasteful (Efficient)

Pareto-optimal

(Nash) Welfare Maximizing

Competitive Equilibrium (with equal income)

Competitive Equilibrium (CE)

traditional setting...



Competitive Equilibrium: Demand = Supply

Demand

w/ equal income (CEEI): Each agent has one dollar to spend

CEEI: Properties



Demand optimal bundle

Competitive Equilibrium: Demand = Supply An agent can afford anyone's bundle, but demands hers ⇒ Envy-free

Envy-free, everything allocated ⇒ Proportional

 1^{st} welfare theorem \Rightarrow Pareto-optimal

CE History



Adam Smith (1776)



Leon Walras (1880s)



Irving Fisher (1891)



Arrow-Debreu (1954) (Nobel prize)

(Existence of CE in the exchange model w/ firms)

. . .

Computation of CE (w/ goods)

Algorithms

- Convex programming formulations
 - □ Eisenberg-Gale (1959): CEEI w/ 1-homogeneous valuations
 - □ Shmyrev (2009), DGV (2013), CDGJMVY (2017) ...
- (Strongly) Poly-time algorithms (linear valuations)
 DPSV (2002), Orlin (2010), DM (2015), GV (2019) ...
- Simplex-like algorithms: Eaves (1976), GM.SV (2011), GM.V (2014),
 ...

Complexity

- PPAD: Papadimitrou'92, CDDT'09, VY'11, CPY'17, Rubinstein'18, ...
- FIXP: EY'09, GM.VY'17, F-RHHH'21 ...

*Chen, Cole, Deng, Devanur, Duan, Dai, Etessami, Filos-Ratsikas, Garg, Gkatzelis, Hansen, Hogh, Hollender, Jain, Mai, Mehlhorn, Papadimitriou, Paparas, Saberi, Sohoni, Vazirani, Vegh, Yazdanbod, Yannakakis, ...

CE with Bads/Chores



w/ equal income (CEEI): Each agent *has to earn* one dollar

CE with Mixed Items



Demand optimal bundle

Competitive Equilibrium: Demand = Supply



Bad/Mixed Manna: Known Results

Bogomolnaia-Moulin-Sandomirskiy-Yanovskaia (2017)

 $\Box V_i s$ are 1-homogeneous



Bad/Mixed Manna: Known Results

Bogomolnaia-Moulin-Sandomirskiy-Yanovskaia (2017) *V_is* are 1-homogeneous



Bad/Mixed Manna: Known Results

- Bogomolnaia-Moulin-Sandomirskiy-Yanovskaia (Econometrica'17)
 - \Box *V_is* are 1-homogeneous: CEEI characterization
 - □ CEEI set is non-convex even with linear vals, bads only.
 - In contrast, for goods: convex CE set, (strongly) poly-time algos.
 - "expect computational difficulties"
- Linear V_i s, #agents or #items is a constant:
 - □ Branzei-Sandomiskiy'19 (to appear in OR): poly-time for bad manna
 - □ Garg-McGlaughlin (AAMAS'20): poly-time for mixed manna

Questions: Complexity w/ linear valuations? Is even efficient approximation possible?

Our Results

Bads manna, linear valuations

CEEI

- Boodaghians-Chaudhury-M. (SODA 2022):
 - An *exterior-point method* to find an approximate CEEI (FPTAS)
 - □ Extends to 1-homogeneous valuations.
 - \Box Extends to mixed manna and to CE.

General method: coordinate-wise monotone functions.

Linear Bads: Exterior-point Method

Bads w/ Linear Valuations

- A: set of n agents
 - □ Each agent needs to earn \$1
- *M*: set of *m* divisible bads/chores
 - □ Supply of every chore is one



Each agent *i* has

 \Box Valuations: $V_i(x_i) = \sum_j V_{ij} x_{ij}$

 \Box Disutility: $V_{ij} \leq 0$. $D_{ij} = |V_{ij}|, D_i(x_i) = \sum_j D_{ij} x_{ij}$

CEEI: KKT Points of

$$x \text{ feasible} \equiv \sum_{i \in A} x_{ij} = 1, \forall j \in M; x \ge 0$$

Goods ($V_{ij} \ge 0$) [EG'59]

Bads [BMSY'17]

 $\max_{x \text{ feasible}} \Pi_{i \in N} V_i(x_i)$

 $\min_{\substack{x \text{ feasible}}} \prod_{i \in N} D_i(x_i)$ s.t. $D_i(x_i) > 0, \forall i$

CEEI: KKT Points of



KKT Points: Geometric view



Why gives CEEI?

Bads CEEI

Given prices $p = (p_1, ..., p_m)$ of items

• Optimal bundle: agent *i* demands $x'_i \in \underset{x: p \cdot x \ge 1}{argmin} \sum_j D_{ij} x_j$

□ Pain-per-buck-earned:
$$\frac{D_{ij}}{p_j}$$
 from chore *j*

□ Demand *j* only if it gives minimum pain-per-buck $(MPB_i) = \min_k \frac{D_{ik}}{p_k}$ $\forall j \in M, \ x'_{ij} > 0 \Rightarrow \frac{D_{ij}}{p_i} = MPB_i \Rightarrow D_i(x'_i) = MPB_i * 1(=\text{earning})$

Demand = Supply

$$\forall j, \quad \sum_i x'_{ij} = 1$$

KKT Points → CEEI [BMSY'17]

$$\operatorname{local}_{\substack{d \text{ feasible} \\ d > 0}} \sum_{i} \log(d_i) \quad \operatorname{Gradient} \propto \frac{1}{d_i}$$

Proof idea: let $p_j = \min_i a_i D_{ij}$ $\Rightarrow p_j \le a_i D_{ij}, \ \forall (i,j)$ $\Rightarrow \frac{1}{a_i} \le \frac{D_{ij}}{p_j}, \ \forall (i,j)$

 \Rightarrow for each agent $i, \frac{1}{a_i} \le \min_j \frac{D_{ij}}{p_j} = MPB_i$

⇒ using supp. hyp. property, show that
$$\frac{1}{a_i} = \min_j \frac{D_{ij}}{p_j} = MPB_i$$

⇒ (∵ *KKT*) $d_i^* = \frac{1}{a_i} = MPB_i$ ⇒ CEEI!





Extension [BCM.'21]: ϵ -KKT gives ϵ -CEEI (where all agents earns $(1 \pm \epsilon)$)

Easy, apply gradient-decent!

Pitfalls of Local Search (GD)

Tricky to ensure, open constraint $d_i > 0$

- to $min \sum_i log(d_i)$ move in $(-1/d_i)$ direction.
 - \Box Smaller d_i s reduce fast.
- Experimentally, even with log-barriers $\min_{x} \sum_{i} \log(D_{i}(x_{i})) + 0.01 \sum_{i} \log(\sum_{j} x_{ij})$
- Intuitively: unstable local min



An exterior approach

Observation: Local max from the exterior

• Move in $\frac{1}{d_i}$ direction increases smaller $d_i s!$

Idea: Approach from exterior. How? Nonconvex region! Any potential function? How to show fast convergence? The exterior

Approach from the exterior

How? Nonconvex region! Any potential function?



Potential function!



Exterior Points Method

Goal: Hyperplane normal ≈ Gradient

- e^t is t^{th} exterior infeasible point.
- d^t is t^{th} point on boundary
- a^t is t^{th} supp. hyperplane normal

1. Set $d^t \leftarrow$ nearest feasible point to e^t

2.
$$a^t \leftarrow (e^t - d^t)$$
 supp. hyperplane normal

3. Stop if $a^t \approx \left(\frac{1}{d_1^t}, \dots, \frac{1}{d_n^t}\right)$

4. Set
$$e^{t+1} \leftarrow \operatorname{argmax} \sum_i \log(d_i)$$
 along the supp. hyperplane



Iterative ⇒ Approximate KKT. Sufficient.

Correctness & Convergence

Lemma: Approximate KKT gives approximate CEEI

Lemma: Objective $\sum_i \log(d_i(x_i))$ always increasing \Rightarrow *Potential Function*

Lemma: Either

- 1. Increase potential by $\geq \Omega(\epsilon^2/n^2)$ - OR -
- 2. Terminate with $(1 + \varepsilon)$ -approximate KKT

Convergence Rate

Lemma: Either

- 1. Increase potential by $\geq \Omega(\epsilon^2/n^2)$ - OR -
- 2. Terminate with $(1 + \varepsilon)$ -approximate KKT

Poly-time: FPTAS

Lemma: Approximate KKT gives approximate CEEI

Lemma: Objective $\sum_i \log(d_i(x_i))$ always increasing \Rightarrow *Potential Function*

Lemma: Either

1. Increase potential by
$$\geq \Omega(\epsilon^2/n^2)$$

- OR -

2. Terminate with $(1 + \varepsilon)$ -approximate KKT

Theorem: If $\log(d_i) \leq L \quad \forall i$, search terminates in $O(\binom{n^3L}{\epsilon^2})$ steps.

Extensions

- 1-Homogeneous (Obstacles)
- Function access: value oracle
- D space need not be convex. $D + R_+^n$
- *"Set d^t* ← nearest feasible point to e^t"
 If exact, will get exactly supp. hyp.
 If approximate, (GD), error gives δ-approx. supp. hyp.
 - Algorithm needs pre-images and feasibility $d: \mapsto x$. Fully explicit, efficient,
 - □ If *linear*, everything is LP
 - □ In general w/ only oracle access, introduces errors.



algo in linear setting

Extensions

CE (unequal weights): w_i for agent i

$$L(d) = \sum_{i} w_i \log d_i$$

Mixed manna: [BMSY'17]

- 1. +ve instance \sim goods manna
- 2. Null instance ~ feasibility problem
- 3. -ve instance \sim bads manna
 - Infeasible starting point is tricky.



Exchange Model (Barter system, re-allocation)

Exchange Model

- A: set of n agents
- *M*: set of *m* divisible chores
 - □ Supply of every item is one



- Each agent *i* has
 - \Box Linear disutility $D_i: \mathbb{R}^m_+ \to \mathbb{R}. D_i(x_i) = \sum_j D_{ij} x_{ij}$

Exchange: *W*_{*ij*} units of chore *j*

• Need to earn enough to pay for her chores.

Motivation/Examples



Living for help



Timebank



Students teaching each other

Exchange Model (w/∞)

A: set of n agents
M: set of m divisible bads
Supply of every item is one



Each agent *i* has

- \Box Linear disutility $D_i: \mathbb{R}^m_+ \to \mathbb{R}. D_i(x_i) = \sum_j D_{ij} x_{ij}$
- \Box Exchange: W_{ij} units of item j

What if agent *i* does not have skills to do chore *j*? Set D_{ij} to ∞

Existence of CE? [BGMM. ITCS'22]

Need not exist



- Assumption 1: Strongly connected economy graph
 Suffices for goods manna, but not for bads manna
- Still checking existence is strongly NP-hard.

 \Box Even for CEEI. And $\frac{11+\epsilon}{12}$ -approximation.

Assumption 2: A pair of agents can either do the same set of chores or a disjoint sets of chores.

Unavoidable: If the sets differ by one chore, CE may not exist.

Existence of CE? [BGMM. ITCS'22]

- Assumption 1: Strongly connected economy graph (standard)
- Assumption 2: A pair of agents can either do the same set of chores or a disjoint sets of chores. (Unavoidable)

Theorem: CE always exists under the two assumptions.

Difficulty: Undefined optimal bundles at zero prices.Solution: Modify price domain s.t. o.b. are always defined.Proof uses both Kakutani and Brouwer fixed-point theorems.The latter nested inside the former.

Computation in Exchange?

Difficulty: Not easy! With linear valuations, no hardness results known.

Combinatorial Algorithms? (faster, flowbased, intuitive price-update dynamics, ...) Difficulty: The *surplus-decrease approach*, central for the goods case, fails.

Recent Work [BGMM.'21]

Exchange: PPAD-hard, even $\frac{1}{poly(n)}$ approximation.

CEEI (CE): Combinatorial algorithm

- FPTAS (faster).
- Exact CEEI if $D_{ij} = (1 + \alpha)^{k_{ij}}$ (quadratic time)
- Puts the problem in PLS \Rightarrow in CLS [BGMM.'21, FGHS'21]

Under linear valuations First separation: CEEI vs Exchange

(solution set is non-convex in both)

Open Questions

Exact CEEI: Hard or easy?

Strategic analysis: Price-of-Anarchy

Dynamics: Proportional response?



THANK YOU