Research at the Interface of Computer Science and Economics



Swaprava Nath IIT Kanpur

DCS2019 Discussion Meeting, ICTS Bangalore

July 10, 2019

• **Voting** – choosing an alternative collectively

- Voting choosing an alternative collectively
- Collective choice with monetary transfers utility is transferable via money

- Voting choosing an alternative collectively
- Collective choice with monetary transfers utility is transferable via money
- Participatory democracy polar opposite of representative democracy

- Voting choosing an alternative collectively
- Collective choice with monetary transfers utility is transferable via money
- Participatory democracy polar opposite of representative democracy
- Peer grading for larger reach and uniform measurement in education

- Voting choosing an alternative collectively
- Collective choice with monetary transfers utility is transferable via money
- Participatory democracy polar opposite of representative democracy
- Peer grading for larger reach and uniform measurement in education
- Self-enforcing environment protection incentivizing carpooling with price design

- Voting choosing an alternative collectively
- Collective choice with monetary transfers utility is transferable via money
- Participatory democracy polar opposite of representative democracy
- Peer grading for larger reach and uniform measurement in education
- Self-enforcing environment protection incentivizing carpooling with price design

Analytical Toolbox

- Game Theory
- Non-linear optimization
- Mechanism design
- Real analysis
- Approximation algorithms
- Probabilistic concentration bounds

- Voting choosing an alternative collectively this talk!
- Collective choice with monetary transfers utility is transferable via money – this talk!
- Participatory democracy polar opposite of representative democracy
- Peer grading for larger reach and uniform measurement in education
- Self-enforcing environment protection incentivizing carpooling with price design

Analytical Toolbox

- Game Theory
- Non-linear optimization
- Mechanism design
- Real analysis
- Approximation algorithms
- Probabilistic concentration bounds

Mechanism Design with Incomplete Information

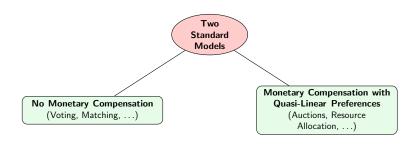
- ullet Set of alternatives $A=\{a_1,\ldots,a_m\}$
- Set of agents $N = \{1, \dots, n\}$

Mechanism Design with Incomplete Information

- Set of alternatives $A = \{a_1, \dots, a_m\}$
- Set of agents $N = \{1, \dots, n\}$
- Agents have private information about the "preferences / valuations" over the alternatives

Mechanism Design with Incomplete Information

- Set of alternatives $A = \{a_1, \dots, a_m\}$
- Set of agents $N = \{1, \dots, n\}$
- Agents have private information about the "preferences / valuations" over the alternatives



Voting Model

- Suppose $|A| \ge 3$
- Suppose all preferences (strict) are admissible

Voting Model

- Suppose $|A| \ge 3$
- Suppose all preferences (strict) are admissible

Question: What social choice functions (SCF) are strategyproof, i.e., truth-telling is a dominant strategy?

Voting Model

- Suppose $|A| \ge 3$
- Suppose all preferences (strict) are admissible

Question: What social choice functions (SCF) are strategyproof, i.e., truth-telling is a dominant strategy?

Answer: Only the dictatorial ones (Gibbard (1973), Satterthwaite (1975))

Voting Model

- $\bullet \ \, \mathsf{Suppose} \, \, |A| \geq 3$
- Suppose all preferences (strict) are admissible

Question: What social choice functions (SCF) are strategyproof, i.e., truth-telling is a dominant strategy?

Answer: Only the dictatorial ones (Gibbard (1973), Satterthwaite (1975))

Quasi-Linear Model

Question: What is the counterpart of the Gibbard-Satterthwaite theorem?

Voting Model

- $\bullet \ \, \mathsf{Suppose} \, \, |A| \geq 3$
- Suppose all preferences (strict) are admissible

Question: What social choice functions (SCF) are strategyproof, i.e., truth-telling is a dominant strategy?

Answer: Only the dictatorial ones (Gibbard (1973), Satterthwaite (1975))

Quasi-Linear Model

Question: What is the counterpart of the Gibbard-Satterthwaite theorem?

Answered by Roberts (1979)

Voting Model

- $\bullet \ \, \mathsf{Suppose} \, \, |A| \geq 3$
- Suppose all preferences (strict) are admissible

Question: What social choice functions (SCF) are strategyproof, i.e., truth-telling is a dominant strategy?

Answer: Only the dictatorial ones (Gibbard (1973), Satterthwaite (1975))

Quasi-Linear Model

Question: What is the counterpart of the Gibbard-Satterthwaite theorem?

Answered by Roberts (1979)

- Dictatorial SCFs are strategyproof transfers are not required
- Efficient SCFs are strategyproof with VCG payments
- Roberts' answer: affine maximizers

Affine Maximizers

Definition (Affine Maximizer)

An SCF $F: V^n \to A$ is an affine maximizer if there exists $w_i \geq 0, i \in N$, not all zero, and a function $\kappa: A \to \mathbb{R}$ such that,

$$F(v) \in \arg\max_{a \in A} \left(\sum_{i \in N} w_i v_i(a) + \kappa(a) \right).$$

Affine Maximizers

Definition (Affine Maximizer)

An SCF $F: V^n \to A$ is an affine maximizer if there exists $w_i \geq 0, i \in N$, not all zero, and a function $\kappa: A \to \mathbb{R}$ such that,

$$F(v) \in \arg\max_{a \in A} \left(\sum_{i \in N} w_i v_i(a) + \kappa(a) \right).$$

Special cases:

• $w_i = 1, \forall i \text{ and } \kappa \equiv 0$: allocatively efficient SCF

Affine Maximizers

Definition (Affine Maximizer)

An SCF $F: V^n \to A$ is an affine maximizer if there exists $w_i \geq 0, i \in N$, not all zero, and a function $\kappa: A \to \mathbb{R}$ such that,

$$F(v) \in \arg\max_{a \in A} \left(\sum_{i \in N} w_i v_i(a) + \kappa(a) \right).$$

Special cases:

- $w_i = 1, \forall i \text{ and } \kappa \equiv 0$: allocatively efficient SCF
- $w_d=1$, for some d, $w_i=0, \forall i\neq d$ and $\kappa\equiv 0$: dictatorial SCF

Roberts' Theorem

Theorem (Roberts 1979)

Let the allocation space A be arbitrary and finite with $|A| \geq 3$. If the space of valuations V is unrestricted, then an onto and strategyproof SCF $F: V^n \to A$ is an affine maximizer.

$$F(v) \in \arg\max_{a \in A} \left(\sum_{i \in N} w_i v_i(a) + \kappa(a) \right).$$

Roberts' Theorem

Theorem (Roberts 1979)

Let the allocation space A be arbitrary and finite with $|A| \geq 3$. If the space of valuations V is unrestricted, then an onto and strategyproof SCF $F: V^n \to A$ is an affine maximizer.

$$F(v) \in \arg\max_{a \in A} \left(\sum_{i \in N} w_i v_i(a) + \kappa(a) \right).$$

Payments are of the following form: for all $i \in N$

$$p_i(v_i, v_{-i}) = \begin{cases} \frac{1}{w_i} \left(\sum_{j \neq i} w_j v_j(F(v)) + \kappa(F(v)) + h_i(v_{-i}) \right), & w_i > 0 \\ 0 & w_i = 0 \end{cases}$$

	IBMSmartCloud	(I) Cloud	cisco
Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5 x	0.1	0.3

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	y		

• Value differences cannot be arbitrary - if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) - u_i(y) = 0$ for all $u \in U^n$

	IBMSmartCloud	(I) Cloud	cisco
Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5	0.1	0.3
	x		

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	y		

- Value differences cannot be arbitrary if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) u_i(y) = 0$ for all $u \in U^n$
- Clearly, the proof of Roberts (1979) does not go through

	IBMSmartCloud	(I) Cloud	dinin
Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5	0.1	0.3
	x		

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	y		

- Value differences cannot be arbitrary if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) u_i(y) = 0$ for all $u \in U^n$
- Clearly, the proof of Roberts (1979) does not go through
- However,

	IBMSmartCloud	(I) Cloud	dinin
Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5 x	0.1	0.3
	ı.		

	BMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	y		

- Value differences cannot be arbitrary if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) u_i(y) = 0$ for all $u \in U^n$
- Clearly, the proof of Roberts (1979) does not go through
- However,
 - affine maximizer result holds!

Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5 x	0.1	0.3

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	y		

- Value differences cannot be arbitrary if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) u_i(y) = 0$ for all $u \in U^n$
- Clearly, the proof of Roberts (1979) does not go through
- However,
 - affine maximizer result holds!
 - with an additional assumption

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.2	0.8	0.5
Bob	0.3	0.1	0.2
Carol	0.5 x	0.1	0.3

	IBMSmartCloud	(n) Cloud	cisco
Alice	0.4	0.5	0.2
Bob	0.3	0.1	0.2
Carol	0.3	0.4	0.6
	$\underline{\hspace{1cm}}$		

- Value differences cannot be arbitrary if two distinct alternatives x and y have identical i-th row, i.e., $x_i = y_i$, then $u_i(x) u_i(y) = 0$ for all $u \in U^n$
- Clearly, the proof of Roberts (1979) does not go through
- However,
 - ► affine maximizer result holds!
 - with an additional assumption
 - ► and a different proof technique

Theorem

If $n \geq 3$, every onto, allocation non-bossy and strategyproof SCF $F: U^n \to A$ is an affine maximizer. If n=2, the result holds without the allocation non-bossiness assumption.

¹Nath and Sen, "Affine Maximizers in Domains with Selfish Valuations", in **ACM** Transactions on Economics and Computation (TEAC), 2015.

Theorem

If $n \geq 3$, every onto, allocation non-bossy and strategyproof SCF $F: U^n \to A$ is an affine maximizer. If n=2, the result holds without the allocation non-bossiness assumption.

¹Nath and Sen, "Affine Maximizers in Domains with Selfish Valuations", in **ACM** Transactions on Economics and Computation (TEAC), 2015.

Theorem

If $n \geq 3$, every onto, allocation non-bossy and strategyproof SCF $F: U^n \to A$ is an affine maximizer. If n=2, the result holds without the allocation non-bossiness assumption.

The proof technique uses the fact that the allocation domain is continuous

¹Nath and Sen, "Affine Maximizers in Domains with Selfish Valuations", in ACM Transactions on Economics and Computation (TEAC), 2015.

Theorem

If $n \geq 3$, every onto, allocation non-bossy and strategyproof SCF $F: U^n \to A$ is an affine maximizer. If n=2, the result holds without the allocation non-bossiness assumption.

- The proof technique uses the fact that the allocation domain is continuous
- Roberts' kind of argument works everywhere except the points where at least one component of the allocations are identical

7 / 12 Computational Economics Swaprava Na

¹Nath and Sen, "Affine Maximizers in Domains with Selfish Valuations", in **ACM** Transactions on Economics and Computation (TEAC), 2015.

Theorem

If $n \geq 3$, every onto, allocation non-bossy and strategyproof SCF $F: U^n \to A$ is an affine maximizer. If n=2, the result holds without the allocation non-bossiness assumption.

- The proof technique uses the fact that the allocation domain is continuous
- Roberts' kind of argument works everywhere except the points where at least one component of the allocations are identical
- It uses the continuity argument to claim the result to hold even at those points (the points form a measure zero space)

¹Nath and Sen, "Affine Maximizers in Domains with Selfish Valuations", in ACM Transactions on Economics and Computation (TEAC), 2015.

Preferences and Domains

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

Preferences and Domains

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

Single peaked preferential domain

Preferences and Domains

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

Single peaked preferential domain

• Introduced by Black (1948)

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:
 - either always strictly increasing, or

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

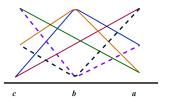
- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:
 - either always strictly increasing, or
 - always strictly decreasing, or

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:
 - either always strictly increasing, or
 - always strictly decreasing, or
 - first strictly increasing and then strictly decreasing

• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

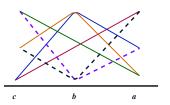
- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:
 - either always strictly increasing, or
 - always strictly decreasing, or
 - first strictly increasing and then strictly decreasing



• Consider strict preferences, which are linear orders (no ties) over a set of alternatives. Preference profile, $\mathcal{P} = \{P_1, P_2, \cdots, P_n\}$

Single peaked preferential domain

- Introduced by Black (1948)
- Definition: A preference profile is single-peaked if there exists an intrinsic ordering of the alternatives such that every voter's preference along this order is:
 - either always strictly increasing, or
 - always strictly decreasing, or
 - first strictly increasing and then strictly decreasing



Single-peakedness provides a number of nice properties, including non-manipulability.

• A much *refined plan or protocol* can be designed for such domains which satisfy several desirable axioms

 A much refined plan or protocol can be designed for such domains which satisfy several desirable axioms

Example

The *median voting rule* in the single peaked domain ensures that no voter can gain by misreporting her preference

 A much refined plan or protocol can be designed for such domains which satisfy several desirable axioms

Example

The *median voting rule* in the single peaked domain ensures that no voter can gain by misreporting her preference

• Computing winners for many important voting rules such as *Kemeny* is computationally intractable

• A much refined plan or protocol can be designed for such domains which satisfy several desirable axioms

Example

The *median voting rule* in the single peaked domain ensures that no voter can gain by misreporting her preference

• Computing winners for many important voting rules such as *Kemeny* is computationally intractable

Example

Most of these problems become *efficiently solvable* in a single peaked domain (Cornaz and Spanjaard (2013))

 \bullet Recognition algorithms: a profile ${\cal P}$ and a domain ${\cal D}$

- \bullet Recognition algorithms: a profile ${\cal P}$ and a domain ${\cal D}$
- \bullet Does there exist a polynomial time algorithm to decide whether ${\cal P}$ belongs to the domain ${\cal D}?$

- ullet Recognition algorithms: a profile ${\mathcal P}$ and a domain ${\mathcal D}$
- ullet Does there exist a polynomial time algorithm to decide whether ${\cal P}$ belongs to the domain ${\cal D}$?
- There are some efficient recognition algorithms, e.g., Trick (1989) for single peaked domain $(\mathcal{O}(|N|.|A|^2))$, Doignon and Falmagne (1994) for single crossing etc.

- ullet Recognition algorithms: a profile ${\mathcal P}$ and a domain ${\mathcal D}$
- ullet Does there exist a polynomial time algorithm to decide whether ${\cal P}$ belongs to the domain ${\cal D}$?
- There are some efficient recognition algorithms, e.g., Trick (1989) for single peaked domain $(\mathcal{O}(|N|.|A|^2))$, Doignon and Falmagne (1994) for single crossing etc.

Limitations

 Require the whole preference profile – pre-election polls, surveys etc., sample only a partial population

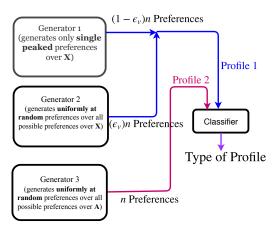
- ullet Recognition algorithms: a profile ${\mathcal P}$ and a domain ${\mathcal D}$
- Does there exist a polynomial time algorithm to decide whether $\mathcal P$ belongs to the domain $\mathcal D$?
- There are some efficient recognition algorithms, e.g., Trick (1989) for single peaked domain $(\mathcal{O}(|N|.|A|^2))$, Doignon and Falmagne (1994) for single crossing etc.

Limitations

- Require the whole preference profile pre-election polls, surveys etc., sample only a partial population
- Real world profiles do not occur perfectly from a domain can be nearly single peaked

Sampling and Near Single Peakedness²

Problem 1: $(\epsilon_v, \epsilon_a, \delta, D)$ - Random Outliers vs Random Profile Test

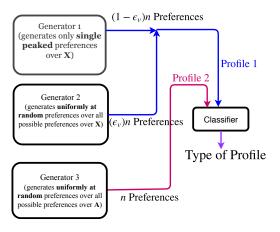


11 / 12 Computational Economics Swaprava Na

²Dey, Nath, and Shakya, "Testing Preferential Domains Using Sampling", in Autonomous Agents and Multiagent Systems (AAMAS), 2019.

Sampling and Near Single Peakedness²

Problem 1: $(\epsilon_v, \epsilon_a, \delta, D)$ - Random Outliers vs Random Profile Test



 $X\subseteq A,\ |X|=(1-\epsilon_a)|A|.\ D$ is the domain (e.g. single peaked). Classification is correct with error probability at most $\delta.$

11 / 12 Computational Economics Swaprava Na

²Dey, Nath, and Shakya, "Testing Preferential Domains Using Sampling", in Autonomous Agents and Multiagent Systems (AAMAS), 2019.

Results Summary

Input profile		Sample complexity
Possibility 1	Possibility 2	Sample Complexity
$\epsilon_v n$ random		$\mathcal{O}(\frac{1}{(1-\epsilon_n)^2}\log\frac{1}{\delta})$
preferences away		$(1-\epsilon_v)^2 \log \delta$
$\epsilon_v n$ arbitrary		$\mathcal{O}(\frac{1}{(1-3\epsilon_v)^2}\ln\frac{1}{\delta})$
preferences away	random	for $\epsilon_v < 1/3$
$\epsilon_a m$ alternatives	random	$\mathcal{O}(\log \frac{\log_{1/\epsilon_a} 1/\delta}{\delta} \times$
away		$\log_{1/\epsilon_a} \frac{1}{\delta} \log \log_{1/\epsilon_a} 1/\delta)$
	$\epsilon'_v n$ arbitrary	
$\epsilon_v n$ arbitrary preferences away	preferences	$\mathcal{O}(\frac{1}{(\epsilon'_v - \epsilon_v)^2} (2^m m^2 \log^2 m))$
preferences away	away	$+\log 1/\delta))$
	$\epsilon_a'm$	$\Omega(n\log 1/\delta)$ even for $\epsilon_a=0$
$\epsilon_a m$ alternatives	alternatives	and for every $0<\epsilon_a'\leq 1$
away	away	and $0 < \delta < \frac{1}{2}$

Results Summary

Input profile		Sample complexity
Possibility 1	Possibility 2	Sample complexity
$\epsilon_v n$ random		$\mathcal{O}(\frac{1}{(1-\epsilon_n)^2}\log\frac{1}{\delta})$
preferences away		$O((1-\epsilon_v)^2\log \delta)$
$\epsilon_v n$ arbitrary		$\mathcal{O}(\frac{1}{(1-3\epsilon_v)^2}\ln\frac{1}{\delta})$
preferences away	random	for $\epsilon_v < 1/3$
$\epsilon_a m$ alternatives		$\mathcal{O}(\log \frac{\log_{1/\epsilon_a} 1/\delta}{\delta} \times$
away		$\log_{1/\epsilon_a} \frac{1}{\delta} \log \log_{1/\epsilon_a} 1/\delta)$
	$\epsilon'_v n$ arbitrary	
$\epsilon_v n$ arbitrary preferences away	preferences	$\mathcal{O}(\frac{1}{(\epsilon_n' - \epsilon_n)^2} (2^m m^2 \log^2 m))$
preferences away	away	$+\log 1/\delta))$
	$\epsilon_a'm$	$\Omega(n\log 1/\delta)$ even for $\epsilon_a=0$
$\epsilon_a m$ alternatives	alternatives	and for every $0 < \epsilon'_a \le 1$
away	away	and $0 < \delta < \frac{1}{2}$

The results use concentration bounds asymptotic in \boldsymbol{n} to find the sample complexity bounds

