Chiticismo of VCG

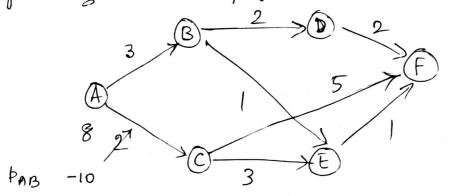
- (1) Privacy: neveal valuations truthfully
 - if the interaction had to happen beyond one bround, it may be preferable to use a mechanism that uses the minimal information needed for the current nound and not have spillover effect.
 - This also has a concern about the introduction of take agents to increase the payment of the winner.

 Once it is known that the value war high enough,
 this take agents may be the second losing bid too introduced by a melicions of anctioneer.

2) Susceptib	rility to (Collusion	/	
Player	» A	В	Paymen	± ,
 	200(2	50) 0	150	(100)
2	100/1	(o) O	50	(0)
2		250	O	(0)
<i>⊘</i>		20		- /

3) Not 7 mgal: doesn't charge an amount close to the seller's valuation / cost. VCG is guaranteed to bring neverne / no deficit, but the payment could be very large.

Example of shortest path (houting a packet / an delivery item) e.g. Amazon delivering your item



This is a west

Setup - Rasy way

to consider this
is by negating all

Values and payments

Effect of payment to AB due to AE'S cost $P_{AB} = 0 - (-1) + (-2) - 0 + (-3) - 0 = -4$

(4) Revenue Monotonicity Violated

trevenue monotonicity: revenue weakly increases

with number of agents.

() 0				
	×	Y	fayment	
(0	90	0 -> 0	
2	100	0	90-0	
3	100	0	D	

split on merging of agents is now problematic.

Not July Budget Balanced.

almost always some surplus will be left.

Cannot be me allo me distributed as that will change their purjoffs. Cannot be invested to things that can affect The payoffs - e.g. to charity if someone cares for it etc. It has to be destroyed - known as money burning.

Caution: this does not mean VCG is useless. Rather it is the most-used mechanism with money - but needs to be carefully applied and good to know its limitations.

Generalization of VCG

Need to expand the class of mechanism to take care of multiple limitations

- · Budget Balance issue
- · Equal weightage for every agent may not be hequired

Affine Maximizer allocation rule

- · Superclass of VCG mechanisms / efficient allocations - therefore lope to satisfy more Properties.
- · Can ask to a Gibbard Sattenthwaite kind of question in the quasi-linear setting with public goods

$$f^{AM}(\theta) \in \underset{a \in A}{\operatorname{argmax}} \left(\sum_{i \in N} w_i \theta_i(a) + \mathcal{K}(a) \right)$$

Where Wi > 0 + i EN and not all zero K: A -> IR is any arbitrary function.

Special cases:

(1) Efficients:

(2) Dictatorial

Wis are different =) not anonymous

K's are y for different a => gives emphasis on certain allocations than others.

Définition: An AM rule fam with weights wi, ien and k satisfier independente of non-influential agents (INA) if for all its with wi= 0 we have that $f(\theta_i, \theta_i) = f(\theta_i', \theta_i), \forall \theta_i, \theta_i' \forall \theta_i$.

Tie-breaking requirement. If a dictatorial rule has same value for two different alternatives and The tie is broken by the valuation of a non-dictatorial agent - it violates INA.

Theorem: An INA affine maximizer tule is implementable.

Note: Without HO INA, an affine max may not be truthful/implementable. E.g., pick the worst alternative of the Wi=0 agent.

Proof: Consider the payment
$$\frac{AM}{P_i}(\theta_i, \theta_i) = \begin{cases}
\frac{1}{W_i} \left[h_i(\theta_i) - \left(\sum_{j \neq i} W_j \theta_j(f^{AM}(\theta)) + K(f^{AM}(\theta)) \right) \\
+ i : W_i > 0
\end{cases}$$

$$\forall i : W_i = 0$$

Payoff of agat i it wi>0
$$\theta_{i}(f^{AM}(\theta)) - \beta_{i}^{AM}(\theta_{i}, \theta_{i})$$

$$= \frac{1}{W_{i}} \left[\sum_{j \in N} w_{j} \theta_{j}(f^{AM}(\theta)) + K(f^{AM}(\theta)) \right] + K(f^{AM}(\theta_{i}, \theta_{i}))$$

$$= \frac{1}{W_{i}} \left[\sum_{j \in N} w_{j} \theta_{j}(f^{AM}(\theta_{i}, \theta_{i}, \theta_{i})) + K(f^{AM}(\theta_{i}, \theta_{i}, \theta_{i})) \right]$$

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$$= \frac{1}{W_{i}} \left[\int_{i} w_{j} \theta_{i}(f^{AM}(\theta_{i}, \theta_{i}, \theta_{i$$

for $i: W_i = 0$ $f^{AM}(\theta_i, \theta_i) = f^{AM}(\theta_i', \theta_i) \quad \forall \quad \theta_i', \theta_i, \forall \theta_i'$ and payment in zero, a so the agent is weakly trultiful.

Similar to GS theorem, we ask what if the valuations are unnestricted.

 $\theta_i:A\to\mathbb{R}$ G_i contains all such valuation functions, no restriction imposed.

· A little rangement difficult assumption for neal scenarios, but this givet a benchmark of what is possible to be DSIC in the QL domain.

With this unnestricted space of valuations, we can characterize the class of DSIC mechanisms

Theonem [Roberts' Freomem]

Let A be finite with |A| > 3. If the type space is unnestricted, then every onto and implementable allocation rule must be an affine maximizer.

Proof skipped.

As before, nestricting the space of valuations/types gives no more mechanisms that are DSIC.

For example, there are more than VCG/gr Groves mechanisms that are truthful in auction settings.