# Mechanism Design Powered by Social Interactions

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A tutorial @ AAMAS, IJCAI 2019

# 2009 DARPA Red Balloon Challenge

 The \$40,000 challenge award would be granted to the first team to submit the locations of 10 moored, 8-foot, red weather balloons at 10 previously undisclosed fixed locations in the continental United States.



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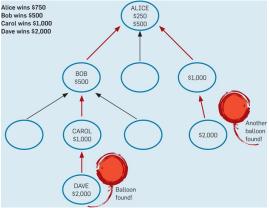
## 2009 DARPA Red Balloon Challenge

MIT Crowdsourced Solution (The Winner):

- "We're giving \$2000 per balloon to the first person to send us the correct coordinates, but that's not all – we're also giving \$1000 to the person who invited them. Then we're giving \$500 whoever invited the inviter, and \$250 to whoever invited them, and so on ..."
- got over 5,000 of participants, won the competition in under 9 hours.

# 2009 DARPA Red Balloon Challenge

#### MIT Crowdsourced Solution (The Winner):



• Pickard, G., et al., Time-Critical Social Mobilization. Science, 2011. 334(6055): p. 509-12.

# PinDuoDuo (like Groupon)



# What are the incentives?

# More participants, higher chance to win!!!

- 2009 DARPA Red Balloon Challenge
  - Inviting more friends has higher chance to win (higher utility)
- PinDuoDuo
  - Inviting more friends has higher chance to get cheap items (higher utility)

# What if it is a competition?

- Resource allocation (auctions)
- Task allocation (crowdsourcing)
- Information propagation with budget
- Social choice (voting)

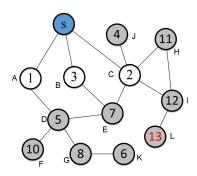
More participants means lower chance to win!!!

# **Diffusion Mechanism Design**

#### Mechanism Design on Social Networks

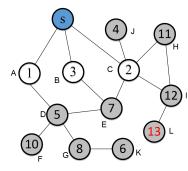
Design mechanisms/markets under competitive environment such that participants are incentivized to invite more participants/competitors to join the mechanisms.

### Starter: Promote a Sale via Social Networks



- The seller (blue node) sells one item and has only three connections/neighbours in the network (A,B,C).
- Each node is a potential buyer and the value is her highest willing payment to buy the item (valuation).
- The seller's revenue of applying second price auction (VCG) without promotion is 2.
- but the highest willing payment in the network is 13.

### Starter: Promote a Sale via Social Networks



#### Question

How the seller could do to increase her profit?

## **Traditional Sale Promotions**

Traditional sale promotions:

- Promotions via agents
- Keywords based ads via search engines such as Google
- Ads via social media such as WeChat, Facebook, Twitter

# **Traditional Sale Promotions**

Traditional sale promotions:

- Promotions via agents
- Keywords based ads via search engines such as Google
- Ads via social media such as WeChat, Facebook, Twitter

#### Challenge

- The return of these promotions are unpredictable.
- The seller may LOSE from the promotions.

# Tackle the Challenge

Build promotion inside the market mechanism such that

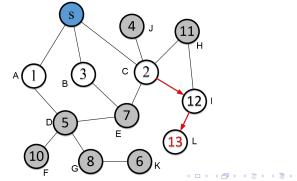
- the promotion will never bring negative utility/revenue to the seller.
- all buyers who are aware of the sale are incentivized to diffuse the sale information to all her neighbours.

"Diffusion Mechanism Design"

# **New Challenges**

Why a buyer would bring more buyers to compete with her?

- only if their diffusion are rewarded, but the seller doesn't want to lose!
- we cannot just pay each node a fixed amount to incentivise them to diffuse the information.



# Outline



Mechanism Design Review

- The History
- Second Price Auction (VCG)

2 Diffusion Mechanism Design

The History

# Outline



### Mechanism Design Review

- The History
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### 2 Diffusion Mechanism Design

- Resource Allocation
- Task Allocation
- Information Propagation

The History

# What is Mechanism Design

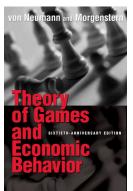
# What is Mechanism/Market Design?

• it is known as Reverse Game Theory

The History

# What is Game Theory

 Game theory is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers (wiki) [von Neumann and Morgenstern 1944].



- Non-cooperative games: Go, poker, rock-paper-scissors
- Cooperative games: coordination games

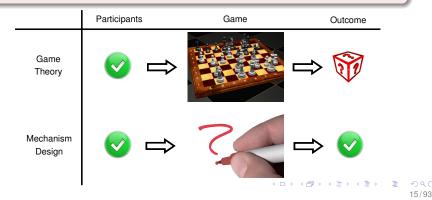
The History

# Mechanism Design (Reverse Game Theory)

Mechanism Design is to answer...

#### Question

How to design a mechanism/game, toward desired objectives, in strategic settings?



How to design a mechanism/game, toward desired objectives,

The History

# Mechanism Design (Reverse Game Theory)

Mechanism Design is to answer...



Question

in strategic settings?

**Roger B. Myerson** (born March 29, 1951, University of Chicago, US)

- Nobel Prize for economics (2007), for "having laid the foundations of mechanism design theory."
- Eleven game-theorists have won the economics Nobel Prize.

The History

# Algorithmic Game Theory (AGT)

 Algorithmic game theory is an area in the intersection of game theory and algorithm design, whose objective is to design algorithms in strategic environments (wiki) [Nisan et al. 2007].



Algorithmic Game Theory Edited by Noam Nisan, Tim Boughgarden, Éva Tardos, and Vijay V. Vazirani Foreword by Christos H. Papadimitriou

- Computing in Games: algorithms for computing equilibria
- Algorithmic Mechanism Design: design games that have both good game-theoretical and algorithmic properties

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#### The History

# Algorithmic Game Theory in Artificial Intelligence

- Algorithmic game theory research in AI:
  - Game Playing: computation challenges, AlphaGo, poker
  - Social Choice: preferences aggregation, voting, prediction
  - Mechanism Design: the allocation of scarce resources, ad auctions
- Many IJCAI Computers and Thought Award (outstanding young scientists in artificial intelligence) winners had worked on AGT:
  - Sarit Kraus (1995), Nicholas Jennings (1999), Tuomas Sandholm (2003), Peter Stone (2007), Vincent Conitzer (2011), and Ariel Procaccia (2015)

Second Price Auction (VCG)

# Outline



### Mechanism Design Review

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- Second Price Auction (VCG)

### 2 Diffusion Mechanism Design

- Resource Allocation
- Task Allocation
- Information Propagation

Second Price Auction (VCG)

# A Mechanism Design Example

### **Design Goal**

# How can a house-seller sell her house with the "highest" revenue?



• Challenge: the seller doesn't know how much the buyers are willing to pay (their valuations).

Second Price Auction (VCG)

# A Mechanism Design Example

### **Design Goal**

# How can a house-seller sell her house with the "highest" revenue?



Solution: Second Price Auction (Vickrey Auction/VCG)

- Input: each buyer reports a price/bid to the seller
- Output: the seller decides
  - allocation: the agent with the highest price wins.
  - payment: the winner pays the second highest price.

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Second Price Auction (VCG)

# A Mechanism Design Example

### **Design Goal**

# How can a house-seller sell her house with the "highest" revenue?



Solution: Second Price Auction (Vickrey Auction/VCG)

#### Properties:

- Efficient: maximising social welfare
- Truthful: buyers report their valuations truthfully

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Second Price Auction (VCG)

### Is this the BEST the seller can do?

#### Question

What can the seller do to FURTHER increase her profit?

- estimate a good reserve price [Myerson 1981]
  - requires a good estimation of buyers' valuations
- promotions: let more people know/participate in the auction

Second Price Auction (VCG)

### Is this the BEST the seller can do?

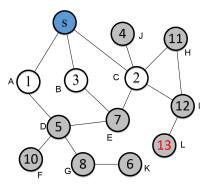
#### Question

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Second Price Auction (VCG)

# Recap: Promote a Sale via Social Networks



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# Outline



- 2 Diffusion Mechanism Design
  - Resource Allocation
  - Task Allocation
  - Information Propagation

Mechanism Design Review

**Resource Allocation** 





- The History
- Second Price Auction (VCG)

### 2 Diffusion Mechanism Design

- Resource Allocation
- Task Allocation
- Information Propagation

Resource Allocation

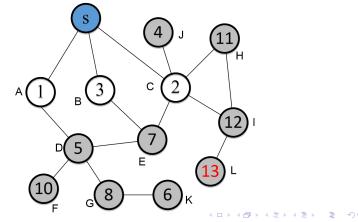
# Our Solutions: Information Diffusion Mechanisms

- Bin Li, Dong Hao, Dengji Zhao, Tao Zhou: Mechanism Design in Social Networks. AAAI'17.
- Dengji Zhao, Bin Li, Junping Xu, Dong Hao, Nick Jennings: Selling Multiple Items via Social Networks. AAMAS'18.
- Bin Li, Dong Hao, Dengji Zhao, Tao Zhou: *Customer Sharing in Economic Networks with Costs*. IJCAI-ECAI'18.
- Bin Li, Dong Hao, Dengji Zhao, Makoto Yokoo: Diffusion and Auction on Graphs. IJCAI'19.
- Wen Zhang, Dengji Zhao, Hanyu Chen: *Redistribution Mechanism on Networks*. AAMAS'20.
- Wen Zhang, Dengji Zhao, Yao Zhang: *Incentivize Diffusion with Fair Rewards*. ECAI'20.
- Bin Li, Dong Hao, Dengji Zhao: Incentive-Compatible Diffusion Auctions. IJCAI'20.

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# The First Diffusion Mechanism

 Bin Li, Dong Hao, Dengji Zhao, Tao Zhou: Mechanism Design in Social Networks. AAAI'17.

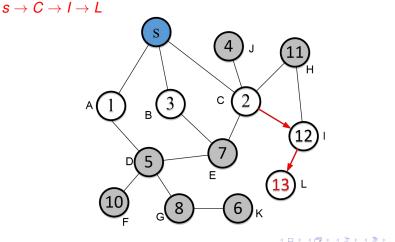


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Resource Allocation

# Information Diffusion Paths

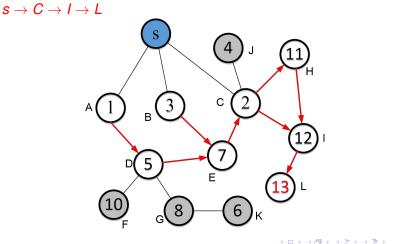
An information diffusion path from the seller to node L:



Resource Allocation

# Information Diffusion Paths

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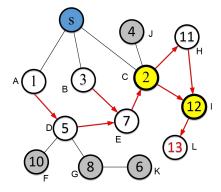


Mechanism Design Review

Diffusion Mechanism Design

**Resource Allocation** 

# **Diffusion Critical Nodes**



#### Definition

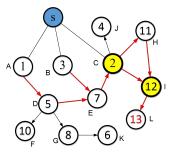
*i* is *j*'s diffusion critical node if all the information diffusion paths started from the seller *s* to *j* have to pass *i*.

 nodes C and I are L's only diffusion critical nodes.

# Information Diffusion Mechanism [Li et al. AAAI'17]

The payment definition (second-price-like):

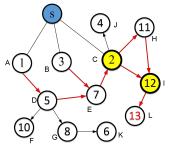
- If a buyer or one of her "*diffusion critical children*" gets the item, then the buyer pays the highest bid of the others (without the buyer's participation);
- otherwise, her payment is zero.



# Information Diffusion Mechanism [Li et al. AAAI'17]

The payment definition (second-price-like):

- If a buyer or one of her "diffusion critical children" gets the item, then the buyer pays the highest bid of the others (without the buyer's participation);
- otherwise, her payment is zero.



If the item is allocated to *L*, the payments of C, I and L are 10, 11, 12 respectively .

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# Information Diffusion Mechanism

#### The allocation definition:

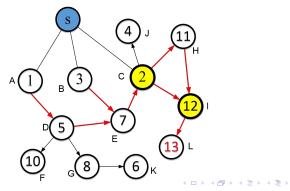
- Identify the node *i* with the highest bid and the node's diffusion critical node path  $P_{c_i} = (c_i^1, c_i^2, ..., i)$ .
- Give the item to the first node of P<sub>ci</sub>, the node pays to the seller and then decides to whether keep the item or pass it to the next node in P<sub>ci</sub>:
  - If the payment of the next node is greater than the bid of the current node, passes it to the next node and receives the payment from the next node; the next node makes a similar decision;
  - otherwise, keep the item.

**Resource Allocation** 

## The Information Diffusion Mechanism

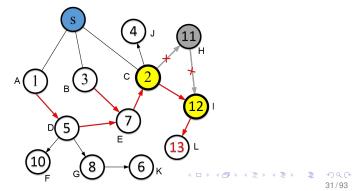
The outcome of the Information Diffusion Mechanism:

- the item is allocated to node I.
- node I pays 11 to C, C pays 10 to the seller.
- the utilities of I, C, the seller are 1, 1, 10.



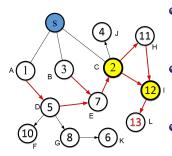
# Why Buyers are Happy to Diffuse the Information?

- buyers receive the information earlier have higher priority to win the item (*C* chooses before *I* and *I* chooses before *L*).
- diffuse the information to more buyers will potentially increase their reward (if C does not invite H, her utility is 0).



**Resource Allocation** 

## Properties of the Information Diffusion Mechanism



- Truthful: report true valuation and diffuse the sale information to all her neighbours is a dominate strategy.
- Individually Rational: no buyer will receive a negative utility to join the mechanism.
- Seller's Revenue Improved: the seller's revenue is non-negative and is ≥ that of the VCG without diffusion.

Resource Allocation



- Diffusion mechanisms for combinatorial exchanges
- Diffusion with costs and delays
- Network structure based revenue analysis
- Applications/implementations in the existing social networks
- Other mechanisms to further improve the revenue and/or the efficiency

**Resource Allocation** 

## Diffusion Mechanisms for Combinatorial Exchanges

#### Challenge

How to generalise the mechanism to combinatorial settings?

## Diffusion Mechanisms for Combinatorial Exchanges

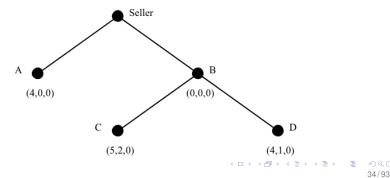
Consider the following simple setting:

- A seller sells three units of one commodity, e.g. MacBook computers.
- Each buyer has a diminishing marginal utility for consuming the goods.

# Diffusion Mechanisms for Combinatorial Exchanges

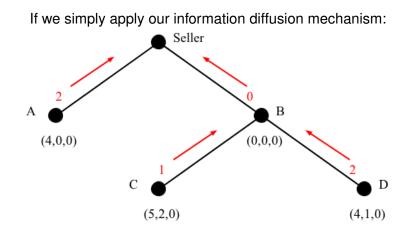
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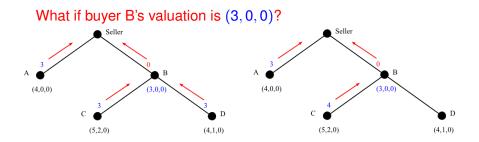
Resource Allocation

## Diffusion Mechanisms for Combinatorial Exchanges



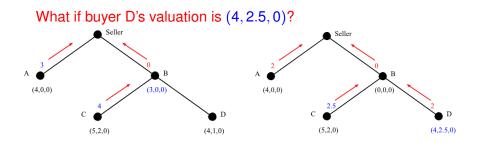
**Resource Allocation** 

### Diffusion Mechanisms for Combinatorial Exchanges



**Resource Allocation** 

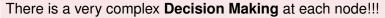
#### Diffusion Mechanisms for Combinatorial Exchanges

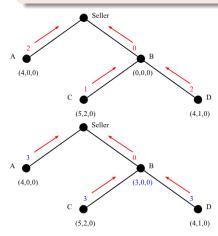


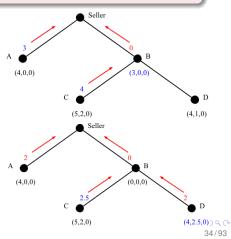
**Resource Allocation** 

## Diffusion Mechanisms for Combinatorial Exchanges

#### Challenge







## Why is it so complex when there are multiple items?

To achieve truthfulness:

- The mechanism has to maximise each node's utility under truthful reporting.
- Each node's payment should not depend on her valuation.

The complexity we had:

- A node can influence her payments by controlling the items passed to her children.
- A node can influence the payments of her peers, without changing her own allocation and payments.
- This leads to a decision loop (very complex optimization) and may not able to maximise everyone's utility.

Resource Allocation

## Reduce the Complexity

#### The Main Idea

A node CANNOT influence the payments she receives by controlling the items passed to her children.

Simplify the decision complexity we had:

- A node can influence her received payments by controlling the items passed to her children.
- A node can influence the payments of her peers, without changing her own allocation and payments.
- This leads to a decision loop and may not able to maximise everyone's utility.

# One Solution: Sell Multiple Homogeneous Items

*Selling Multiple Items via Social Networks* [Zhao et al. AAMAS'18]

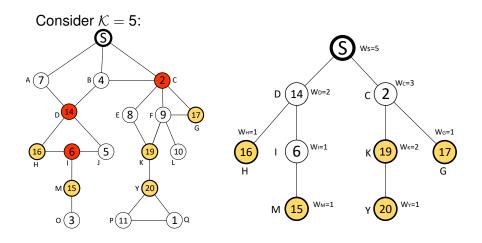
- generalises the result from [Li et al. 2017];
- agent i's reward/payment doesn't depends on how many of i's children received items;
- agent pays to the seller directly rather than to their parent;

The setting:

- A seller sells  $\mathcal{K} \ge 1$  homogeneous items;
- each buyer requires at most one item (single-unit demand);
- the rest is the same as [Li et al. 2017].

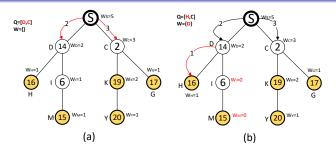
Resource Allocation

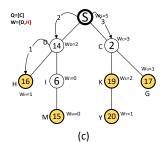
## The Generalised Diffusion Mechanism

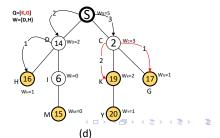


#### Resource Allocation

## The Generalised Diffusion Mechanism



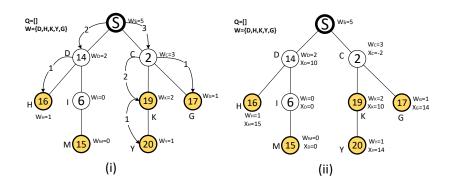




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**Resource Allocation** 

#### The Generalised Diffusion Mechanism



# The Allocation Policy of the Generalisation

Node/buyer i receives one item if and only if

- the top  $\mathcal{K}$ -highest valued children of *i* (and their parents, who are also *i*'s children) do not participate
- and *i* wins under the efficient allocation with their absence given that all *i*'s (critical) parents' allocation is determined and fixed.

# The Payment Policy of the Generalisation

Node *i*'s utility is the social welfare difference of the efficient allocation between

the top *K*-highest valued children of *i* (and their parents, who are also *i*'s children) do not participate (guarantees that *i*'s payment does not depend on how many items *i*'s children get)

and *i* (and all her children) does not participate
 Formally, *i*'s payment is:

$$\begin{cases} \mathcal{SW}_{-D_i} - (\mathcal{SW}_{-\mathcal{C}_i^{\mathcal{K}}} - v'_i) & \text{if } i \in W, \\ \mathcal{SW}_{-D_i} - \mathcal{SW}_{-\mathcal{C}_i^{\mathcal{K}}} & \text{if } i \in \bigcup_{j \in W} \mathcal{P}_j(\theta') \setminus W, \\ 0 & \text{otherwise.} \end{cases}$$

where W is the set of nodes each of whom received one item.

Resource Allocation

## Properties of the Generalisation

- Truthful: report true valuation and diffuse the sale information to all her neighbours is a dominate strategy for each node.
- Individually Rational: no node will receive a negative utility to join the mechanism.
- Seller's Revenue Improved: the seller's revenue is non-negative and is ≥ that of the VCG without diffusion.

Resource Allocation

## Truthfulness and IR

Given i's payment:

$$\begin{cases} \mathcal{SW}_{-D_i} - (\mathcal{SW}_{-\mathcal{C}_i^{\mathcal{K}}} - \mathbf{v}_i') & \text{if } i \in W, \\ \mathcal{SW}_{-D_i} - \mathcal{SW}_{-\mathcal{C}_i^{\mathcal{K}}} & \text{if } i \in \bigcup_{j \in W} \mathcal{P}_j(\theta') \setminus W, \\ 0 & \text{otherwise.} \end{cases}$$

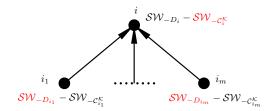
if *i* reports truthfully, *i*'s utility is:

 $\mathcal{SW}_{-\mathcal{C}_{i}^{\mathcal{K}}} - \mathcal{SW}_{-\mathcal{D}_{i}}$ 

- $SW_{-D_i}$  is the optimal social welfare without *i*'s participation
- SW<sub>-C<sup>K</sup><sub>i</sub></sub> is the optimal social welfare when the top K-highest valued children of *i* (and their parents, who are also *i*'s children) do not participate

**Resource Allocation** 

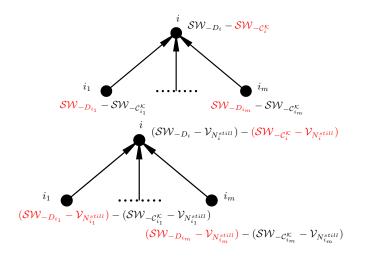
#### Guaranteed Revenue Improvement for the Seller



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**Resource Allocation** 

#### Guaranteed Revenue Improvement for the Seller



**Resource Allocation** 

#### Guaranteed Revenue Improvement for the Seller

$$i_{1} (SW_{-D_{i}} - \mathcal{V}_{N_{i}^{still}}) - (SW_{-\mathcal{C}_{i}^{\kappa}} - \mathcal{V}_{N_{i}^{still}})$$

$$i_{m}$$

$$(SW_{-D_{i_{1}}} - \mathcal{V}_{N_{i_{1}}^{still}}) - (SW_{-\mathcal{C}_{i_{1}}^{\kappa}} - \mathcal{V}_{N_{i_{1}}^{still}})$$

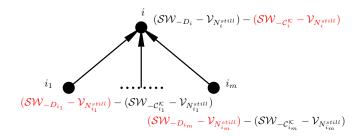
$$(SW_{-D_{i_{m}}} - \mathcal{V}_{N_{i_{m}}^{still}}) - (SW_{-\mathcal{C}_{i_{m}}^{\kappa}} - \mathcal{V}_{N_{i_{m}}^{still}})$$

$$\mathcal{SW}_{-\mathcal{C}_{i}^{\mathcal{K}}} - \mathcal{V}_{\mathcal{N}_{i}^{ ext{still}}} \leq \sum_{i_{l}} (\mathcal{SW}_{-\mathcal{D}_{i_{l}}} - \mathcal{V}_{\mathcal{N}_{i_{l}}^{ ext{still}}})$$

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Resource Allocation

## Guaranteed Revenue Improvement for the Seller

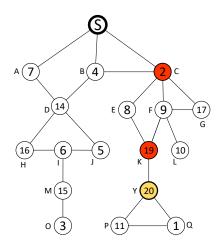


#### Theorem (Zhao et al. 2018)

The revenue of the generalised information diffusion mechanism is greater than or equal to  $\mathcal{K} \times v_{\mathcal{K}+1}$ , where  $v_{\mathcal{K}+1}$  is the  $(\mathcal{K} + 1)$ -th largest valuation report among  $r_s$ , assume that  $|r_s| > \mathcal{K}$ .

**Resource Allocation** 

## What happens when $\mathcal{K} = 1$ ?



Resource Allocation

## Are the mechanisms fair?

- According to the theorem of small-world networks, the chance for a node to be a cut-point in a well-connected network is very low.
- We hope to give rewards to all the related buyers not only the cut-points on the paths to the winner.

Resource Allocation

## Solution: Redistribute Rewards among Agents

#### Incentivize Diffusion with Fair Rewards [Zhang et al. ECAI'20]

- redistribute rewards among critical ancestors based on IDM
- all critical ancestors have positive expected utilities
- seller's revenue is not reduced

**Resource Allocation** 

# What if for non-profit purpose?

Redistribution mechanism is:

- to do the efficient resource allocation
- not for profit

Challenges:

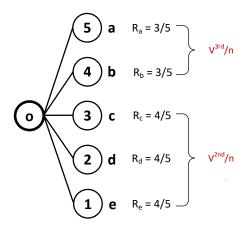
- how to achieve a more efficient allocation?
- how to maintain wealth among agents?

Mechanism Design Review

Diffusion Mechanism Design

**Resource Allocation** 

## **Cavallo Mechanism**

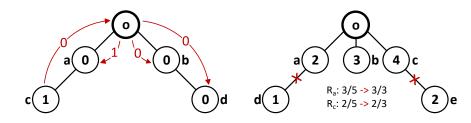


- Allocation: agent with the highest valuation wins the item
- **Payment**: winner pays the second price
- Redistribution: each agent receives the owner's revenue without her participation divided by the total number of agents

**Resource Allocation** 

## Why not Cavallo Mechanism on Networks?

- Run a deficit
- Disincentivize the diffusion

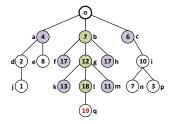


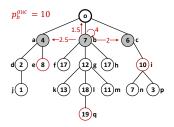
Mechanism Design Review

Diffusion Mechanism Design

**Resource Allocation** 

#### Redistribution Mechanism in Trees [Zhang et al. AAMAS'20]





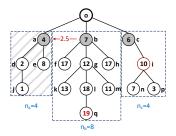
For each ancestor:

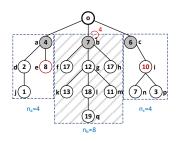
- Allocation: keep the item if her valuation is greater than or equal to her payment
- Payment: the highest valuation without her participation
- Redistribution: a monotone increasing function to the number of descendants

Diffusion Mechanism Design

**Resource Allocation** 

## Details for Redistribution





#### For agent a:

• Without her participation, b's payment becomes  $v_i = 10$ 

• 
$$R_a = 10 * \frac{4}{4+8+4} = 2.5$$

For agent *b*:

Without her participation, c
 will be the new ancestor
 and her payment is v<sub>e</sub> = 8

• 
$$R_b = 8 * \frac{8}{4+8+4} = 4$$

Resource Allocation

# Properties of the Mechanism

The mechanism works for all graphs only by updating the definition of critical ancestors.

- Individually Rational: each agent will not have a negative utility as long as she reports her true valuation.
- Truthful: reporting true valuation and inviting all her neighbours is a dominate strategy.
- Asymptotically Budget-balanced: when the number of participants goes to infinity, almost all the money will be redistributed back to the participants.
- No Deficit: the resource owner will never pay some extra money for the allocation.

**Resource Allocation** 

# A General Characterization of Diffusion Auction Mechanisms

Incentive-Compatible Diffusion Auctions [Li et al. IJCAI'20]

- characterize a sufficient and necessary condition for all incentive-compatible and individually rational diffusion auctions.
- propose a class of natural monotonic allocation policies with optimal payment policy that maximizes the seller's revenue.

Resource Allocation

#### The sufficient and necessary condition

Theorem:

- A diffusion auction (π, x) is incentive-compatible and individually rational if and only if for all type profile t and all *i*, P1 – P5 are satisfied, where
  - $P1: \pi$  is value-monotonic,
  - $P2: \tilde{x}_i$  and  $\bar{x}_i$  are bid-independent,

• P3: 
$$\tilde{x}_i(r_i) - \bar{x}_i(r_i) = v_i^*(r_i)$$
,

•  $P4: \tilde{x}_i$  and  $\bar{x}_i$  are diffusion-monotonic,

• 
$$P5: \bar{x}_i(\emptyset) \leq 0.$$

Resource Allocation

### **Open Questions**

- More general settings
  - characterize truthful diffusion mechanisms, revenue monotonicity is the key?
- When there is a diffusion cost
  - how to guarantee the seller will not lose?
- Privacy concern and the seller's strategies
  - the seller discovery the whole network and she may cheat as well!
- False-name manipulations
  - a node may create multiple ids as her neighbours to gain more payment?
- many more...

#### Task Allocation





- The History
- Second Price Auction (VCG)

#### 2 Diffusion Mechanism Design

- Resource Allocation
- Task Allocation
- Information Propagation

### Diffusion Mechanism Design for Task Allocation

- Wen Zhang, Yao Zhang, Dengji Zhao: *Collaborative Data Acquisition*. AAMAS'20.
- Yao Zhang, Xiuzhen Zhang, Dengji Zhao: Sybil-proof Answer Querying Mechanism. IJCAI'20.

# Diffusion Mechanism Design for Task Allocation

Resource allocation vs task allocation:

- task requires more participants' contribution (collaboration)
- but participants' contribution may conflict with each other (competition)

#### Crowdsourcing Data Acquisition [Zhang et al. AAMAS'20]

- a requester is collecting data from the crowd
- more participants gives richer dataset
- participants' contribution depends on the quality of their provided data
- if two participants offer the same data, how to calculate their contribution?

#### Crowdsourcing Data Acquisition [Zhang et al. AAMAS'20]

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# Shapley Value?

Task Allocation

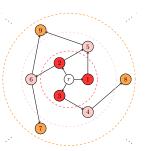


The problem of the Shapley value:

- two participants offer the same data will share the same Shapley value
  - the Shapley value is doubled if one of them didn't participate

# Solution: Layered Shapley Value

- participants are layered
- the Shapley value is calculated for each lower layer first
- the calculation for higher layer assumes that lower layers' participants are always in the coalition





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Task Allocation

### Solution: Layered Shapley Value

$$\hat{\phi}_{i} = \sum_{S \subseteq L_{l_{i}} - \{i\}} \frac{|S|!(|L_{l_{i}}| - |S| - 1)!}{|L_{l_{i}}|!} \cdot \left( v\left(D'_{L^{*}_{l_{i}-1} \cup S \cup \{i\}}\right) - v\left(D'_{L^{*}_{l_{i}-1} \cup S}\right) \right)$$

Properties:

- participants are incentivized to invite more participants (new participants do not compete with them)
- the requester does not need to pay for redundant data

# Sybil-proof Answer Querying [Zhang et al. IJCAI'20]

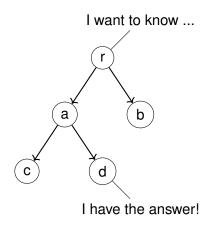


Figure: Query via Network

- Online networks has offered many opportunities for people to collaborate remotely in real time, e.g.
   P2P file sharing and Q&A platforms.
- Utilizing the social connections, we can enhance the power of answer querying via networks, e.g. DARPA Red Balloon Challenge.

# Sybil-proof Answer Querying

- Fact: An SIR path mechanism cannot be both SP and CP.
- What if relax SIR to IR?
- **Theorem**: A path mechanism is IR, SP and CP if and only if it is a two-headed mechanism.

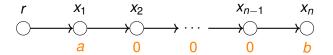


Figure: The rewards distributed by a two-headed mechanism

# Sybil-proof Answer Querying

- What if relax CP to λ-CP?
- New Idea: Double Geometric Mechanism

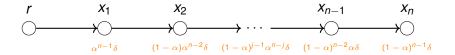


Figure: The rewards distributed by a double geometric mechanism

 Characterization: Under mild condition, the properties of IC, SIR, BC, SP, 2-CP and ρ-SS determines a DGM.

#### Information Propagation

### Outline



- The History
- Second Price Auction (VCG)

#### 2 Diffusion Mechanism Design

- Resource Allocation
- Task Allocation
- Information Propagation

Information Propagation

#### Mechanism Design for Information Propagation

 Haomin Shi, Yao Zhang, Zilin Si, Letong Wang, Dengji Zhao: Maximal Information Propagation with Budgets. ECAI'20. Information Propagation

# Maximal Information Propagation with Budgets

- The sponsor *s* wants to propagate some information to the social network modelled as a directed acyclic graph G = (N, E).
- The sponsor holds a fixed budget *B*, which is prepared as agents' rewards.

#### Challenge

How to find a reward scheme that is propagation incentive compatible and budget balanced?

Information Propagation

# Maximal Information Propagation with Budgets

#### Budget Distribution Scheme

#### Budget Distribution Scheme

INPUT: the graph G and the budget B.

- 1. Using breadth first search to compute the layer sets  $L_1, L_2, \ldots, L_{l_{max}}$  and  $L_{l_{max+1}}$ .
- For each i ∈ L<sub>1</sub>, set b'<sub>i</sub> = B/|L<sub>1</sub>|.
- For each *l* in {1,..., *l*<sub>max</sub>}
- (a) For each i ∈ L<sub>l</sub> compute A<sub>i</sub> according to its propagation.
- (b) Let  $B_l = (1 \beta) \sum_{i \in L_l} b'_i + \beta \sum_{i \in L_l} A_i b'_i$  and  $B'_{l+1} = \sum_{i \in L_l} b'_i B_l$ .
- (c) Distribute B<sub>l</sub> to agents in L<sub>l</sub>, i.e., for agent i in L<sub>l</sub>, she gets r<sub>i</sub> as reward.
- (d) Distribute B'<sub>l+1</sub> to agents in L<sub>l+1</sub>, i.e., for agent j in L<sub>l+1</sub>, she gets b'<sub>j</sub> as current reward.

OUTPUT: the reward vector r.

- Parameterize the distribution between 2 layers;
- Split the origin amount in the upper layer into 2 parts;
- The budget distribution scheme is IR and WBB.

Information Propagation

# Maximal Information Propagation with Budgets

#### Budget Distribution Scheme Instance

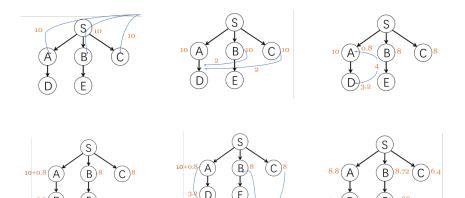
Distribution Algorithm between Two Adjacent Layers INPUT: the graph G and $b'_i$ for each $i \in L_l$ .	
<ol> <li>For each agent i ∈ L<sub>l</sub>, set r<sub>i</sub> = i.V<sub>b</sub> + i.V<sub>h</sub>, initialize i.V<sub>b</sub></li> <li>b'<sub>i</sub> and i.V<sub>b</sub> = 0.</li> </ol>	_
<ol> <li>For each agent j ∈ L<sub>l+1</sub>, initialize b'<sub>j</sub> = 0.</li> <li>For each agent j ∈ L<sub>l+1</sub></li> </ol>	
(a) Let P be the set of agents in L <sub>l</sub> who propagate inform tion to j.	1a-
(b) For each agent i' ∈ P:	
<ul> <li>For each agent i ∈ L<sub>l</sub> \ {i'}, set</li> </ul>	
$\begin{split} i'.V_h \leftarrow i'.V_h + \alpha\beta \cdot i.V_b \\ b'_j \leftarrow b'_j + \alpha(1-\beta) \cdot i.V_b \\ i.V_b \leftarrow i.V_b - \alpha \cdot i.V_b \end{split}$	
OUTPUT: $r_i$ for each agent $i \in L_l$ and $b'_j$ for each agent $j$ $L_{l+1}$ .	€

- Incentivize propagation based on competition in the same level;
- Agents will get extra reward for their invitation from their competitors;
- This instance is IR, BB, and PIC.

Information Propagation

# Maximal Information Propagation Example

#### • Example: Incentivies from Peer Pressure



Summary

### What we have covered

Mechanism Design Powered by Social Interactions

- Diffusion Mechanism for Resource Allocation (competitive environment)
  - for selling single and multiple items
- Diffusion Mechanism for Task Allocation (both competitive and collaborative)
  - crowdsourcing, sybil-proof, execution uncertainty
- Diffusion Mechanism for Information Propagation
  - information propagation with budgets

http://dengji-zhao.net/ijcai19.html