

Maximal Matching for Double Auction

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Stock Exchanges



How to Choose Stock Exchanges

Question

Which stock market will you choose?

How to Choose Stock Exchanges

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Which stock market will you choose?

The one...

- you can earn more money
- has higher chance to get traded
- most other people go

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How do you know?

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How do you know?

- **Market Liquidity**

What is Market Liquidity?

- ① number of transactions
- ② trade volume (buy/sell-volume)
 - the sum of the price of transacted orders

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Double Auction

Outline

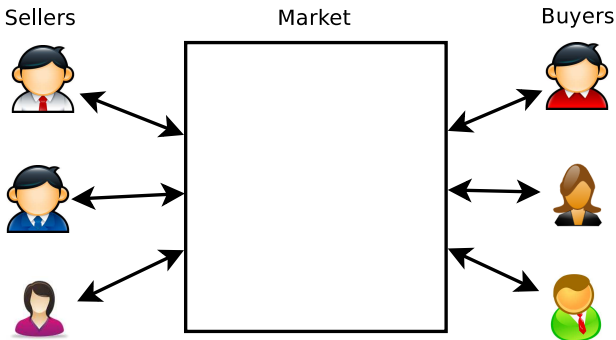
- 1 Background
 - Double Auction
- 2 Existing Matching
 - Equilibrium Matching
- 3 Maximal Matching
 - The Algorithm
 - Properties of Maximal Matching
- 4 Experiments
 - Settings
 - Results
- 5 Conclusion

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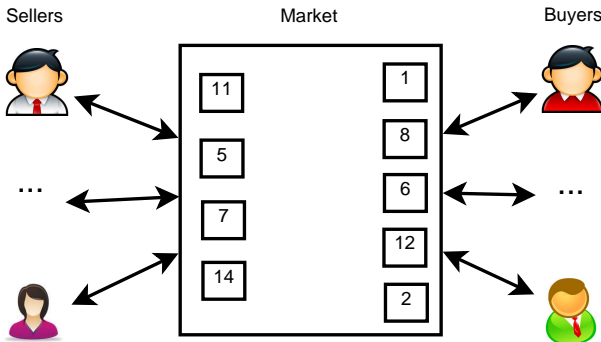
Model

- Three roles: **seller**, **buyer**, and **market maker**.
- One commodity, e.g. google's stocks.



Model

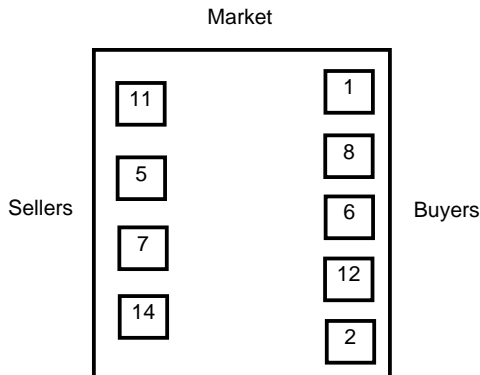
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Exchanging Rules

For market maker:

- which sell offer to be matched with which buy offer?
- what is the price for each match?

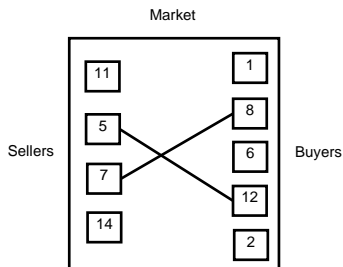


Definitions

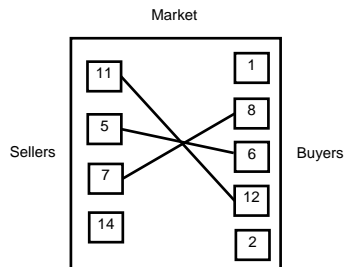
- **Ask:** offer (price) submitted by a seller, the **minimum** price willing to sell
- **Bid:** offer (price) submitted by a buyer, the **maximum** price willing to buy
- **Matching:** a set of pairs of ask and bid, where in each pair
 - **bid's price \geq ask's price**
 - **no bid or ask belongs to more than one pair**
- **Market Liquidity:**
 - number of transactions (matching size)
 - trade volume (buy/sell-volume)
 - buy-volume: the sum of the price of transacted bids
 - sell-volume: the sum of the price of transacted asks
- **Auctioner's Profit:** The **price difference** between matched bids and asks

Matching Examples

- bid's price \geq ask's price
- no bid or ask belongs to more than one pair



$$\text{Profit} = (12+8)-(5+7) = 8$$



$$\text{Profit} = (12+8+6)-(5+7+11) = 3$$

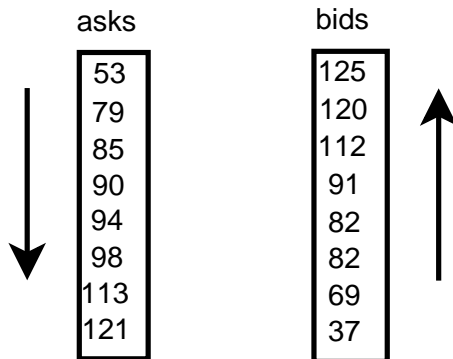
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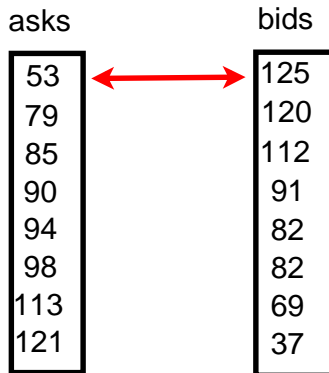
Main Idea

- 1 **Sort** all asks (bids) in ascending (descending) order w.r.t. their price.
- 2 Based on this sort order, starting at the **top**, add each ask-bid pair to the result matching, if ask's price \leq bid's price.

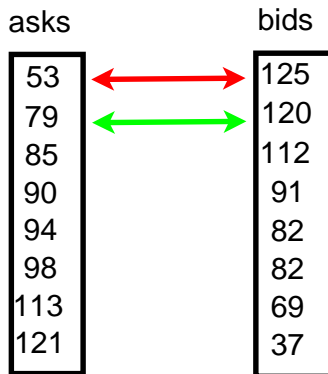
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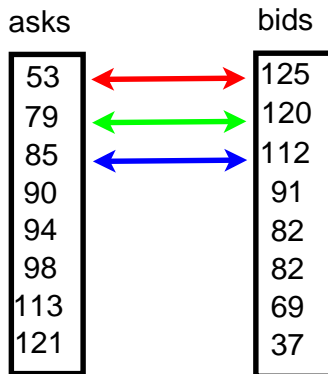
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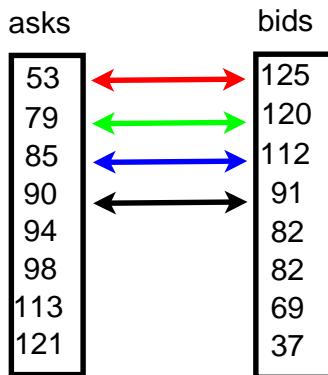
Main Idea



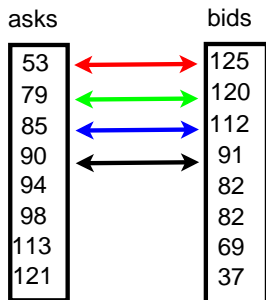
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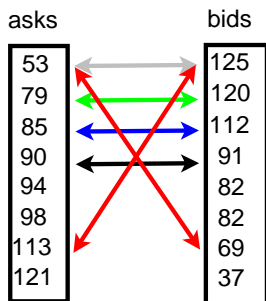


Properties of Equilibrium Matching



- ① profit maximizing (141)
- ② market liquidity can be improved
 - ① transactions: 4
 - ② buy/sell-volume: 448/307

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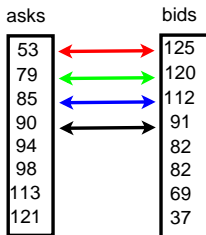
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What We Want?

- 1 Maximizing market liquidity
- 2 Keeping as much profit as we can

General Idea



Equilibrium Matching

- 1 Starting from equilibrium matching
- 2 Matching unmatched shouts (asks and bids) as **many** as we can
- 3 Decreasing profit as **less** as we can

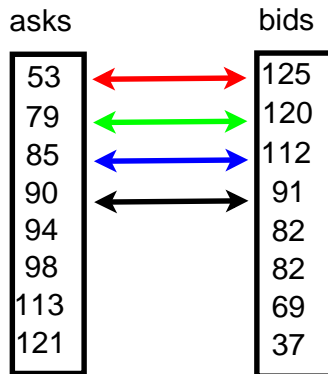
Looking Extra Matchable Shouts

Question

How to find extra matchable shouts?

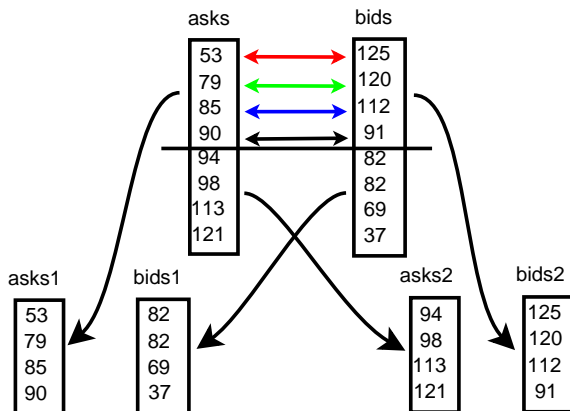
Looking Extra Matchable Shouts

Equilibrium Matching



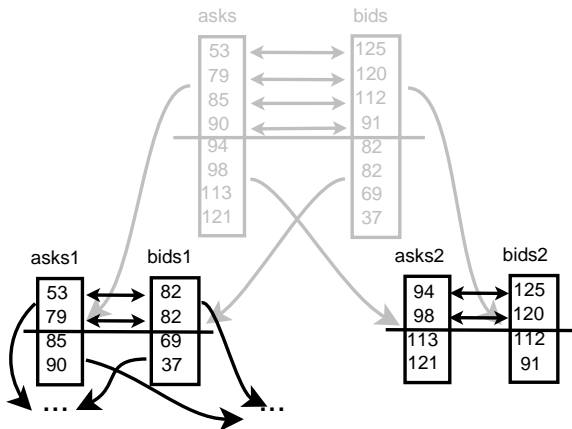
Looking Extra Matchable Shouts

Decompose Matching



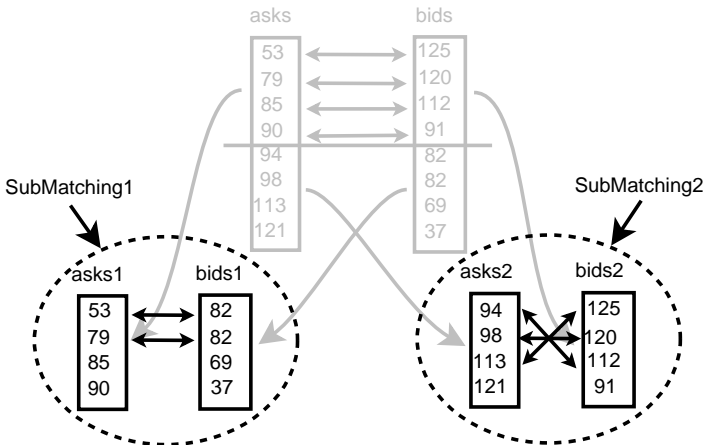
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Maximal Matching in Sub-matchings



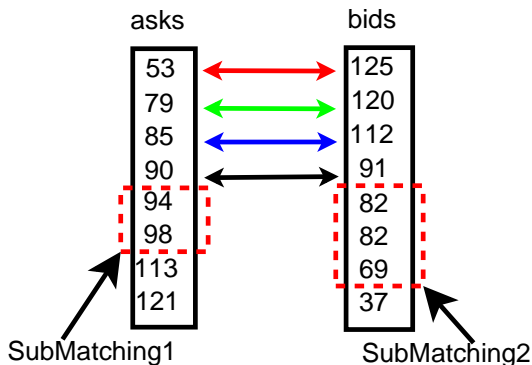
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Maximal Matching in Sub-matchings



Looking Extra Matchable Shouts

Extra Matchable Shouts



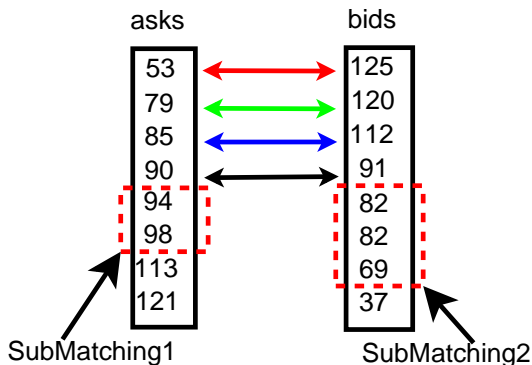
Decreasing Profit as Less as We Can

Question

How to keep profit as much as we can?

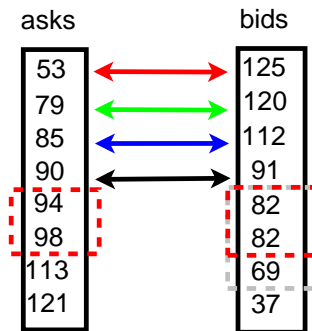
Decreasing Profit as Less as We Can

Extra Matchable Shouts



Decreasing Profit as Less as We Can

Removing Bad Ones (Balancing)



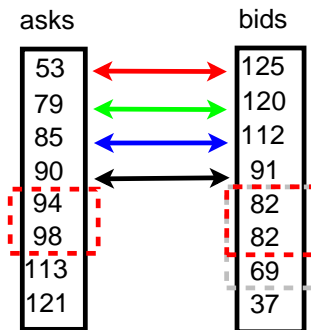
Cross-Match Matchable Shouts

Question

How to match extra matchable ones?

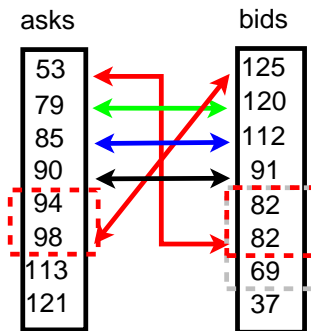
Cross-Match Matchable Shouts

Final Extra Matchable Shouts



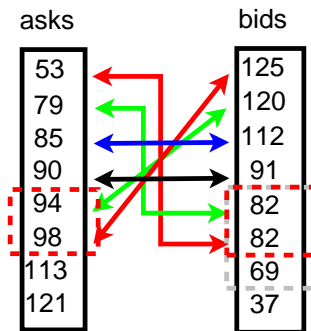
Cross-Match Matchable Shouts

Cross-Matching



Cross-Match Matchable Shouts

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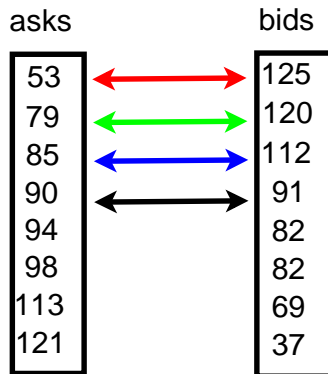
The Algorithm

Algorithm 3.1: MaximalMatching

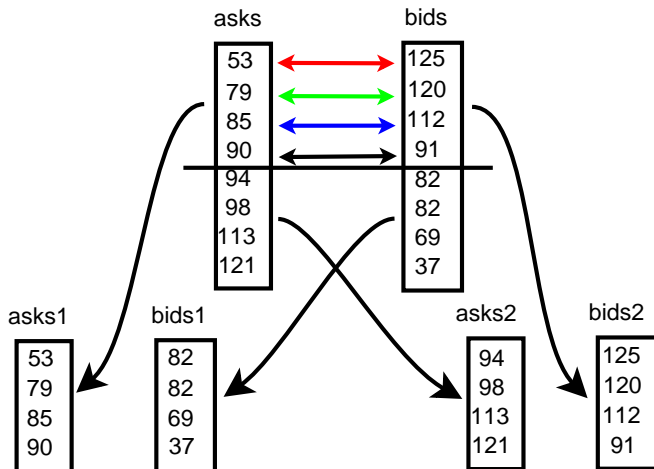
- 1 $Matching \leftarrow \text{EquilibriumMatching}(Asks, Bids);$
 - 2 $MatchedAsks \leftarrow$ all asks from $Matching$ in ascending order;
 - 3 $MatchedBids \leftarrow$ all bids from $Matching$ in descending order;
 - 4 $MM1 \leftarrow \text{MaximalMatching}(MatchedAsks, (Bids \setminus MatchedBids));$
 - 5 $MM2 \leftarrow \text{MaximalMatching}((Asks \setminus MatchedAsks), MatchedBids);$
 - 6 $NumberOfExtraMatchableMatches \leftarrow \text{Min}(|MM1|, |MM2|);$
 - 7 **Cross-match extra matchable asks and bids;**
-

The Algorithm

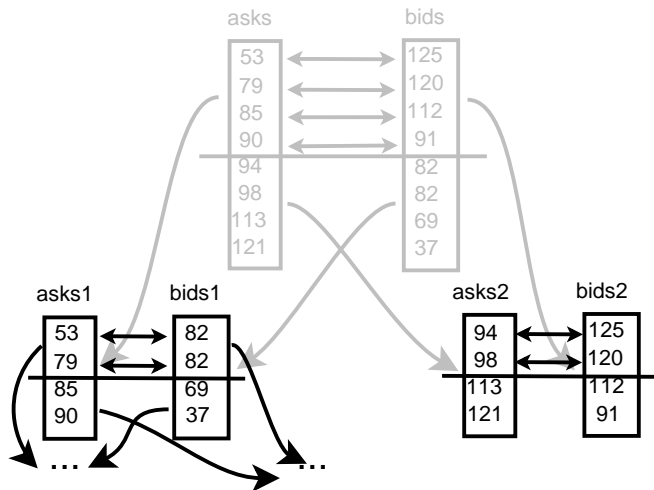
Equilibrium Matching



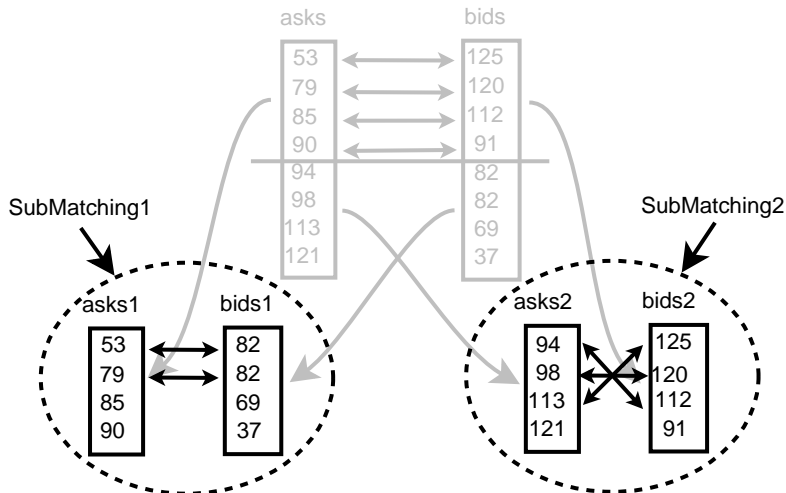
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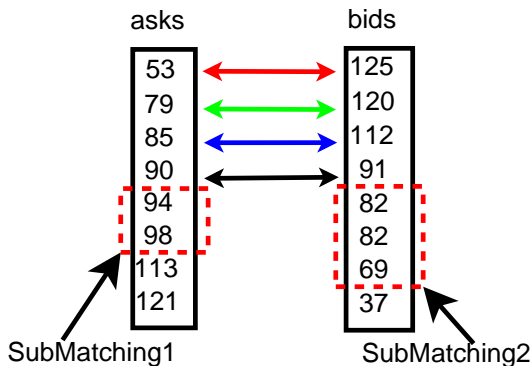
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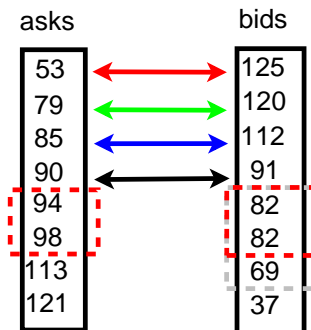
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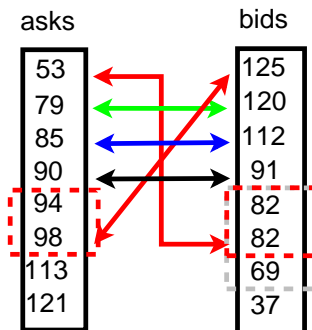
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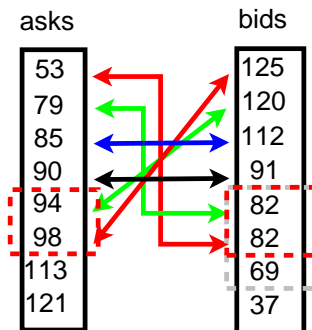
The Algorithm



The Algorithm



The Algorithm



Complexity of Maximal Matching

Worst case performance:

- $O(\max(n_a, n_b) \log \max(n_a, n_b) + \min(n_a, n_b)^2)$, where n_a (n_b) is the number of asks (bids).

The Main Result

Theorem

Maximizing Transactions: Given a set of shouts, the *size* of maximal matching is *maximal*.

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Maximizing Transactions: Given a set of shouts, the *size* of maximal matching is *maximal*.

Sketch proof.

- 1 Induction:
 - assume the two sub-matchings are maximal
 - then the parent matching is also maximal
- 2 Base:
 - no bid's price \geq any ask's price



The Main Result

Theorem

Maximizing Transactions: Given a set of shouts, the *size* of maximal matching is *maximal*.

Theorem

Maximizing Sell-Volume/Profit: Given a set of shouts, maximal matching *maximizes buy-volume* and *minimizes sell-volume*. Auctioneer's *profit is maximal* among all matchings with the same size.

The Main Result

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Maximizing Transactions: Given a set of shouts, the **size** of maximal matching is **maximal**.

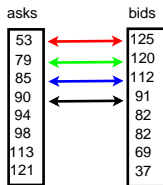
Theorem

Maximizing Sell-Volume/Profit: Given a set of shouts, maximal matching **maximizes buy-volume** and **minimizes sell-volume**. Auctioneer's **profit is maximal** among all matchings with the same size.

Proof.

Because of the descending (ascending) order of bids (asks), and maximal matching always matches the **first** n biggest (smallest) bids (asks), where n is the size of the matching. □

Equilibrium Matching vs Maximal Matching

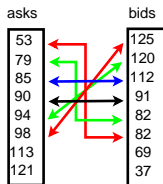


Equilibrium Matching

- profit maximizing (141)
- market liquidity can be improved
 - 1 transactions: 4
 - 2 buy/sell-volume: 448/307

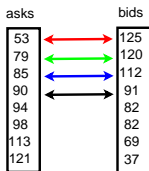
Maximal Matching

- profit maximizing (conditional) (113)
- market liquidity maximizing
 - 1 transactions: 6
 - 2 buy/sell-volume: 612/499



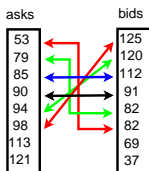
Maximal Matching is Really Nice?

From **economic** point of view:



Equilibrium Matching

- 1 either *incentive compatible*
- 2 or *efficient*
- 3 profit maximizing



Maximal Matching

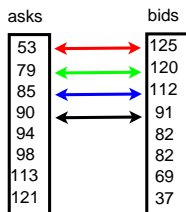
- 1 not *incentive compatible*
- 2 not *efficient*
- 3 less profit

Empirical Findings in the Long Term

Question

Can a stock market owner **improve market liquidity** to get **more traders** and **more profit**?

Empirical Findings in the Long Term

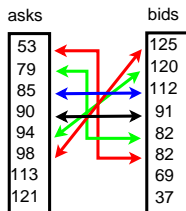


Equilibrium Matching

- 1 less traders
- 2 less profit

Maximal Matching

- 1 more traders
- 2 more profit

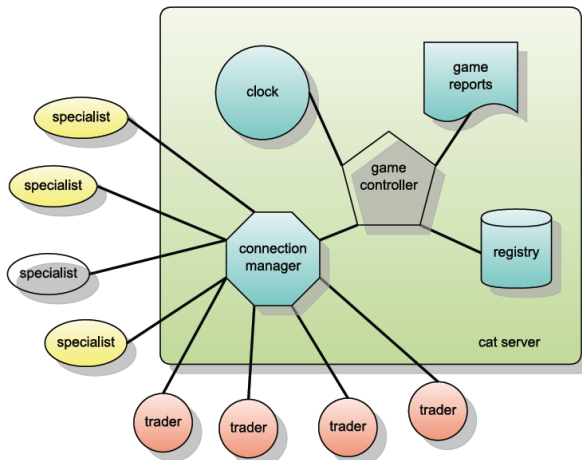


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Test Platform

Trading-Agent Competition Market Design (CAT)



Test Settings

Markets:

- 1 *EM*: with equilibrium matching
- 2 *MM*: with maximal matching

Traders:

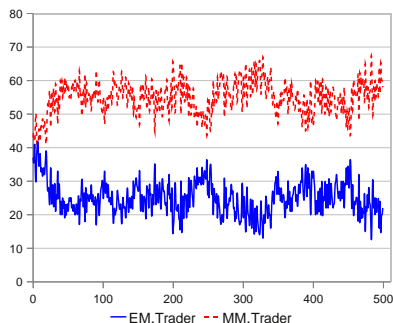
- 80 (40 sellers and 40 buyers) with **profit seeking** strategies
- they can only submit offers to sell or buy **one** goods
- **not** allowed to have **more than one** offer at the same time

Others:

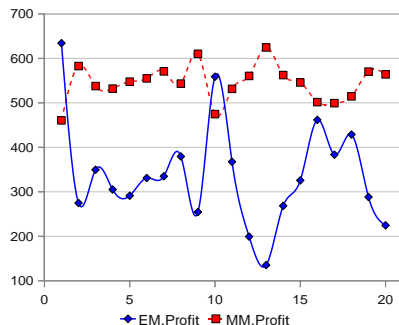
- **500** virtual days, **10 rounds** in each day
- each trader only chooses **one** market to trade in each day
- each trader has a **fixed number of goods**, say 3, to trade in each day

Results

Experimental Results



Trader Distribution



Auctioneer's Profit (avg/25ds)

Our CAT Specialist: *jackaroo*

jackaroo achievements (leader: Dongmo Zhang, UWS):

- CAT 2007: 4th
- CAT 2008: 3rd
- CAT 2009: Champion
- CAT 2010: 2nd

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Summary

Matching for Double Auction

- Equilibrium Matching
- **Maximal Matching**
 - maximizes market liquidity
 - maximizes profit (conditional)
 - empirical findings
 - attracting traders
 - increasing profit

Further research directions:

- Online Double Auction, i.e. adding **temporal information**,
 - e.g. a sell offer would look like...
“I want to sell a house only between **Jan 2011** and **March 2011**.”

Acknowledgments

- **People:** Dongmo Zhang, Laurent Perrussel, Md Khan, *jackaroo* team, and anonymous reviewers.
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Thank you for your attention!

Outline

- 6 Complexities
- 7 Online Mechanism Design

Complexities

Worst case performance:

- Maximal Matching:
 - $O(\max(n_a, n_b) \log \max(n_a, n_b) + \min(n_a, n_b)^2)$, where n_a (n_b) is the number of asks (bids).
- the Hopcroft-Karp algorithm:
 - $O(|E| \sqrt{n_a + n_b})$, where $|E| \geq (n_{em})^2$, n_{em} is the size of equilibrium matching in our model.

Outline

6 Complexities

7 Online Mechanism Design

- Motivation
- Online Mechanism Design Examples

Why Online?

Mechanism Design has focused on static settings where

- no uncertainty,
- the participants are **known** and **independent**,
- (mostly) only **one decision** to make.

But many real environments are **dynamic** in the sense of that

- the **number** of participants is changing,
- the **private information** of participants is changing.

Examples

- stock exchanges.
- peer-to-peer file sharing (e.g. BitTorrent).
- allocating computational resources (e.g. CPU time) to jobs arriving over time.

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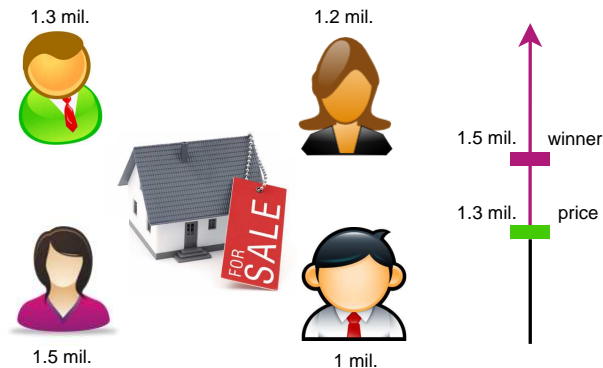
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Example I (Dynamic Buyers)

Online Vickrey Auction

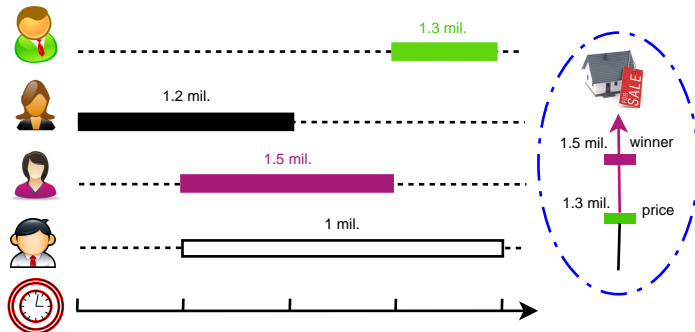
Example I (Dynamic Buyers)

Vickrey Auction (second-price sealed-bid)



Example I (Dynamic Buyers)

Online Vickrey Auction

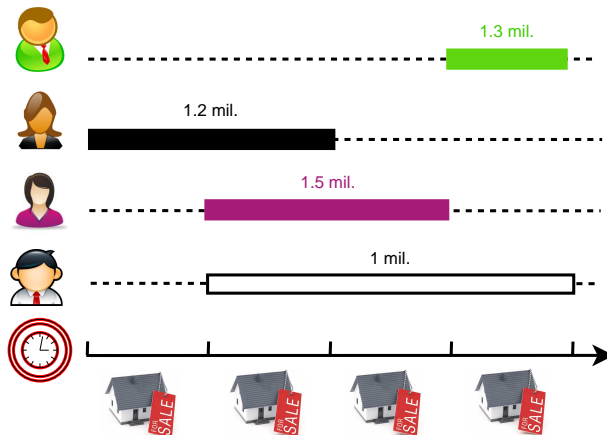


Example II (Dynamic Buyers)

Selling **many identical** houses (goods) in different time

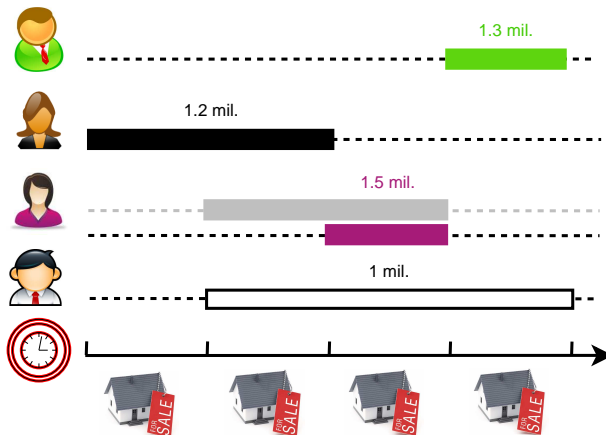
Example II (Dynamic Buyers)

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Example III (Dynamic Seller)

Ad Auction



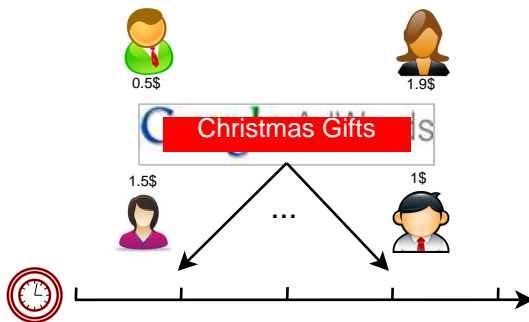
Example III (Dynamic Seller)

Ad Auction: buyers bid for “Keyword”



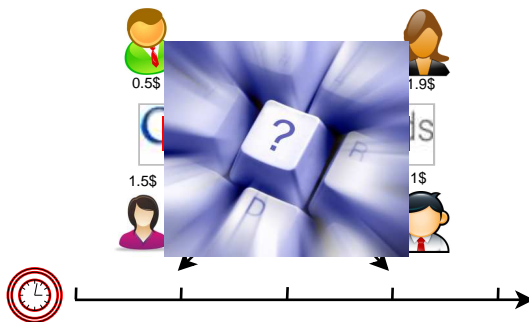
Example III (Dynamic Seller)

Ad Auction: dynamic arrival of “Keyword”



Example III (Dynamic Seller)

Ad Auction: how many “Keyword” will arrive?



Example IV (Dynamic Sellers and Buyers)

Exchanges: stock, currency, futures...

Example IV (Dynamic Sellers and Buyers)

Exchanges: stock, currency, futures...

Double Auction

Example IV (Dynamic Sellers and Buyers)

Exchanges: stock, currency, futures...

Online Double Auction

Summary

- Dynamics from buyers
 - online Vickrey auction (one goods to sell)
 - many goods to sell in a fixed schedule
- Dynamics from sellers
 - Ad auctions
- Dynamics from both
 - online double auction (exchanges)

Challenges

- dynamics provide **new strategies** for participants
- solutions of static mechanism design are **insufficient**

Static vs Online Mechanism Design

- (Static) Mechanism Design
 - well studied since 60s
 - got many nice results (e.g. Vickery auctions)
- **Online** Mechanism Design
 - just addressed (since 2000)
 - many real environments are dynamic, e.g. exchanges
 - new challenges (uncertainties of future)

What We Bring?

Economists:

- incentive constraint

Computer Scientists:

- computational constraint