Manipulation of Stable Matchings using Minimal Blacklists

Yannai A. Gonczarowski

The Hebrew University of Jerusalem Microsoft Research

July 29, 2014

Proc. of the 15th ACM Conference on Economics & Computation (EC 2014)

The Stable Matching Problem (Gale&Shapley 1962)

Results Overview

the Depths

Summary

The Stable Matching Problem (Gale&Shapley 1962)

- Two disjoint finite sets: women W and men M.
 - One-to-one.
 - Assume |W| = |M| for now.

The Stable Matching Problem (Gale&Shapley 1962)

- Two disjoint finite sets: women W and men M.
 - One-to-one
 - Assume |W| = |M| for now.
- A preferences list for each woman and for each man.
 - Strictly ordered.
 - The blacklist is the set of those not on the preference list.

A Po

Overview

the Depths

Summa

The Stable Matching Problem (Gale&Shapley 1962)

- Two disjoint finite sets: women W and men M.
 - One-to-one.
 - Assume |W| = |M| for now.
- A preferences list for each woman and for each man.
 - Strictly ordered.
 - The *blacklist* is the set of those not on the preference list.
- The goal: a stable matching.
 - *M-rational*: No man is matched with a woman from his blacklist.
 - W-rational: No woman is matched with a man from her blacklist.
 - If w and m are not matched, then at least one of them prefers their spouse (or lack thereof) over the other.

The Stable Matching Problem (Gale&Shapley 1962)

- Two disjoint finite sets: women W and men M.
 - One-to-one
 - Assume |W| = |M| for now.
- A preferences list for each woman and for each man.
 - Strictly ordered.
 - The blacklist is the set of those not on the preference list.
- The goal: a stable matching.
 - M-rational: No man is matched with a woman from his blacklist.
 - W-rational: No woman is matched with a man from her blacklist.
 - If w and m are not matched, then at least one of them prefers their spouse (or lack thereof) over the other.

Roth (2002)

"Successful matching mechanisms produce stable outcomes."

Gale-Shapley and *M*-Optimality

Δ Pol

Results Overview

A Peek Into

Summar

Gale-Shapley and *M*-Optimality

Gale and Shapley (1962)

A stable matching exists for every profile of preference lists.

A Po

Overview

A Peek Into

Summar

Gale-Shapley and M-Optimality

Gale and Shapley (1962)

A stable matching exists for every profile of preference lists. An efficient algorithm for finding the (unique) M-optimal one.

A Po

Overview

A Peek Into

ummar

Gale-Shapley and M-Optimality

Gale and Shapley (1962)

A stable matching exists for every profile of preference lists. An efficient algorithm for finding the (unique) M-optimal one.

McVitie and Wilson (1971)

The M-optimal stable matching = the W-worst stable matching.

A Po

Overview

A Peek Into

Summar

Gale-Shapley and M-Optimality

Gale and Shapley (1962)

A stable matching exists for every profile of preference lists. An efficient algorithm for finding the (unique) M-optimal one.

McVitie and Wilson (1971)

The M-optimal stable matching = the W-worst stable matching.

Dubins and Freedman (1981)

No man can gain from unilaterally manipulating the M-optimal stable matching.

A Po

Results Overview

A Peek Into

Summar

Gale-Shapley and M-Optimality

Gale and Shapley (1962)

A stable matching exists for every profile of preference lists. An efficient algorithm for finding the (unique) M-optimal one.

McVitie and Wilson (1971)

The M-optimal stable matching = the W-worst stable matching.

Dubins and Freedman (1981)

No man can gain from unilaterally manipulating the M-optimal stable matching.

Gale and Sotomayor (1985)

Generally, there is a woman who would be better off lying when the M-optimal stable matching is used.

Full-Side Manipulation

Δ Poll

Results Overview

A Peek Into

Summar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one.

A Poll

Results Overview

A Peek Into

Summar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

A Pol

Results Overvie

A Peek Into

ummar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

A Pol

Results Overvie

A Peek Into

ummar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

The coalition of all women can force the W-optimal stable matching as the M-optimal one by truncating preference lists.

Requires blacklists.

A Pol

Results Overvie

A Peek Into

oummar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

- Requires blacklists.
- · Possibly long blacklists.

A Pol

Results Overview

A Peek Into

oummar

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

- Requires blacklists.
- Possibly long blacklists.
- Possibly each of size |M| 1.

A Pol

Results Overview

A Peek Into

summai

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

- Requires blacklists.
- Possibly long blacklists.
- Possibly each of size |M| 1.
- Conspiracy is painfully obvious.

A Po

Results

A Peek Into

Full-Side Manipulation

The coalition of all men can force any W-rational perfect matching as the M-optimal stable one. (Distinct top choices.)

Gale and Sotomayor (1985)

The coalition of all women can force the W-optimal stable matching as the M-optimal one by truncating preference lists.

- Requires blacklists.
- Possibly long blacklists.
- Possibly each of size |M| 1.
- Conspiracy is painfully obvious.

Gusfield and Irving (1989)

No results are known regarding achieving this by any means other than such preference-list truncation, i.e. by also permuting preference lists.

A Poll

Results Overview

A Peek Int

Summa

A Short Poll



Define $n \triangleq |W| = |M|$. The women may force the W-optimal stable matching as the M-optimal one, using a profile of preference lists with average blacklist size no more than . . .

A Poll

Overview

Summar

A Short Poll



Define $n \triangleq |W| = |M|$. The women may force the W-optimal stable matching as the M-optimal one, using a profile of preference lists with average blacklist size no more than . . .

3
$$O(n^{1/c})$$

$$O(\frac{n}{\log n})$$

$$6n-c$$



By truncation

A Poll

A Peek Into

Summa





stal stall preference of the Markets & Auctions on may force the W-optimal one, using a profile of preference Markets average blacklist size no more than . . .

1 c

 $O(\log n)$

3 $O(n^{1/c})$

 $O(\frac{n}{\log n})$

 \uparrow

By truncation

Summa





Stall Seminar (Nov 123):

Stall optimal one, using a profile of prefe Dagstunic Markets average blacklist size no more than ...

1 c ←

2 O(log n)

3 $O(n^{1/c})$

 $O(\frac{n}{\log n})$

 \uparrow

By truncation

Results Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

• The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1.

Results

Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

• The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1. (Compare to each woman having a blacklist size of |M|-1.)

Results Overview

A Peek Into

Summar

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1.
 (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.

Results Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1. (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.
- This profile of preference lists may be computed efficiently.

Results Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1. (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.
- This profile of preference lists may be computed efficiently.
- Generally, many such profiles of preference lists exist.

Results Overview

A Peek Into

Summa

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1.
 (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.
- This profile of preference lists may be computed efficiently.
- Generally, many such profiles of preference lists exist.

A far more "inconspicuous" manipulation.

Results Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1. (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.
- This profile of preference lists may be computed efficiently.
- Generally, many such profiles of preference lists exist.

A far more "inconspicuous" manipulation, esp. if preference-list lengths are bounded (e.g. New York High School Match).

Results Overview

Answering Gusfield and Irving's Open Question

Summary of Main Result (Weak Version)

- The women may force any M-rational perfect matching as the unique stable matching, using a profile of preference lists in which at most half of the women have blacklists, and in which the average blacklist size is less than 1. (Compare to each woman having a blacklist size of |M|-1.)
- Each of these bounds is tight: it cannot be improved upon.
- This profile of preference lists may be computed efficiently.
- Generally, many such profiles of preference lists exist.

A far more "inconspicuous" manipulation, esp. if preference-list lengths are bounded (e.g. New York High School Match).

If women pay a price for every man they blacklist, then order-of-magnitude improvement.

ckground

A D. I

Unbalanced Markets and Partial Matchings

Results Overview

A Peek Into

Results Overview

Unbalanced Markets and Partial Matchings

A Phase Change

ckground

Results Overview

Overview

A Peek Into

_

ummar

Unbalanced Markets and Partial Matchings

A Phase Change

 When there are less women than men (and all women are to be matched), no blacklists are required whatsoever.

Results Overview

A Peek Into

Summa

Unbalanced Markets and Partial Matchings

- When there are less women than men (and all women are to be matched), no blacklists are required whatsoever.
- When there are more women than men (or if not all women are to be matched), each to-be-unmatched woman may have to blacklist as many as all men.

Results Overview

A Peek Into the Depths

Summa

Unbalanced Markets and Partial Matchings

- When there are less women than men (and all women are to be matched), no blacklists are required whatsoever.
- When there are more women than men (or if not all women are to be matched), each to-be-unmatched woman may have to blacklist as many as all men.
- Ashlagi *et al.* (2013) show a similar phase change w.r.t. the expected ranking of the stable partners of each participant on this participant's preference list in a random market. ($\log n \text{ vs. } n/\log n$)

Results Overview

A Peek Into the Depths

Summa

Unbalanced Markets and Partial Matchings

- When there are less women than men (and all women are to be matched), no blacklists are required whatsoever.
- When there are more women than men (or if not all women are to be matched), each to-be-unmatched woman may have to blacklist as many as all men.
- Ashlagi *et al.* (2013) show a similar phase change w.r.t. the expected ranking of the stable partners of each participant on this participant's preference list in a random market. ($\log n \text{ vs. } n/\log n$)
- (cf. the shoe market.)

Results Overview

A Peek Into

Summa

Unbalanced Markets and Partial Matchings

- When there are less women than men (and all women are to be matched), no blacklists are required whatsoever.
- When there are more women than men (or if not all women are to be matched), each to-be-unmatched woman may have to blacklist as many as all men.
- Ashlagi et al. (2013) show a similar phase change w.r.t. the expected ranking of the stable partners of each participant on this participant's preference list in a random market. ($\log n \text{ vs. } n/\log n$)
- (cf. the shoe market.)
- Completely different proofs.

Results Overview

Summar

Improved Insight into Matching Markets

Both phase-change results lead to a similar conclusion in different senses:

The preferences of the smaller side of the market (even if only slightly smaller) play a far more significant role than may be expected in determining the stable matchings, and those of the larger side — a considerably insignificant one.

Results Overview

Summar

Improved Insight into Matching Markets

Both phase-change results lead to a similar conclusion in different senses:

The preferences of the smaller side of the market (even if only slightly smaller) play a far more significant role than may be expected in determining the stable matchings, and those of the larger side — a considerably insignificant one.

In a sense, our results extend this qualitative statement from a random matching market to any matching market.

Results Overview

A Peek Into

Summar

Improved Insight into Matching Markets

Both phase-change results lead to a similar conclusion in different senses:

The preferences of the smaller side of the market (even if only slightly smaller) play a far more significant role than may be expected in determining the stable matchings, and those of the larger side — a considerably insignificant one.

In a sense, our results extend this qualitative statement from a random matching market to any matching market.

More generally: our results shed light on the question of how much, if at all, do given preferences for one side *a priori* impose limitations on the set of stable matchings under various conditions.

Δ Pol

Results Overview

A Peek Into

Summar

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the *buyers*) has preferences.

Results Overview

the Depths

Summa

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the *buyers*) has preferences.

 AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.

Results Overview

A Peek Into the Depths

oumma

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the *buyers*) has preferences.

- AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.
- School priorities are very coarse (and sometimes nonexistent, e.g. NYC High School Match), so a tie-breaking rule is required.

Results Overview

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the buyers) has preferences.

- AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.
- School priorities are very coarse (and sometimes) nonexistent, e.g. NYC High School Match), so a tie-breaking rule is required.
- Both papers: a single lottery for all schools (intuitively less "fair") results in higher social welfare than a different lottery for each school.

Background A Poll

Results Overview A Peek Into

Summa

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the *buyers*) has preferences.

- AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.
- School priorities are very coarse (and sometimes nonexistent, e.g. NYC High School Match), so a tie-breaking rule is required.
- Both papers: a single lottery for all schools (intuitively less "fair") results in higher social welfare than a different lottery for each school.
- A concrete supporting argument from our result: if goods have no preferences, then

Background
A Poll

Results Overview A Peek Into

6

Summa

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the *buyers*) has preferences.

- AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.
- School priorities are very coarse (and sometimes nonexistent, e.g. NYC High School Match), so a tie-breaking rule is required.
- Both papers: a single lottery for all schools (intuitively less "fair") results in higher social welfare than a different lottery for each school.
- A concrete supporting argument from our result: if goods have no preferences, then many lotteries = all buyer-rational matchings are possible*;

Results

Overview

"Example Insight": Goods Allocation Problems

In goods allocation problems, only one of the sides (the buyers) has preferences.

- AS03 and A+09 consider using a version of the (student-optimal) Gale-Shapley algorithm for assigning school seats to children.
- School priorities are very coarse (and sometimes) nonexistent, e.g. NYC High School Match), so a tie-breaking rule is required.
- Both papers: a single lottery for all schools (intuitively less "fair") results in higher social welfare than a different lottery for each school.
- A concrete supporting argument from our result: if goods have no preferences, then many lotteries = all buyer-rational matchings are possible*; single lottery = random serial (buyer) dictatorship

A Dal

Overview

A Peek Into the Depths

Summary

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Overview

A Peek Into the Depths

Summar

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- lacktriangledown I he unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ .
- **2** The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- ⚠ The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$, i.e. at most the number of women who have empty

Results Overview

A Peek Into the Depths

Summar

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- lacksquare The unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ
 - 2 The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
 - **3** n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- The combined size of all blacklists in \mathcal{P}_W is at most $n-n_t$ i.e. at most the number of women who have empty

Overview

A Peek Into the Depths

Summa

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- **1** The unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ .
- ② The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- ⚠ The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$ i.e. at most the number of women who have empty blacklists.

Overview

A Peek Into

the Depths
Summary

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- **1** The unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ .
- 2 The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
- ③ n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- ⚠ The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$ i.e. at most the number of women who have empty blacklists.

Overview

A Peek Into

the Depths
Summary

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- **1** The unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ .
- 2 The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
- **3** n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 1 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$ i.e. at most the number of women who have empty blacklists.

Overview

A Peek Into

the Depths
Summary

Full Result for Balanced Markets

Theorem (Manipulation with Minimal Blacklists)

Define $n \triangleq |W| = |M|$. Let \mathcal{P}_M be a profile of preference lists for M. For every M-rational perfect matching μ , there exists a profile \mathcal{P}_W of preference lists for W, s.t. all the following hold.

- **1** The unique stable matching, given \mathcal{P}_W and \mathcal{P}_M , is μ .
- 2 The blacklists in \mathcal{P}_W are pairwise disjoint, i.e. no man appears in more than one blacklist.
- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- **4** The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$, i.e. at most the number of women who have empty blacklists.

A Po

Overview

A Peek Into

the Depths

Summar

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- **4** The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

A Peek Into

the Depths

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_h , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

$$70000000 (n_b = 1)$$

A Po

Overview

A Peek Into

the Depths

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

A Poll

Overview

A Peek Into

the Depths

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

$$42000000 (n_b = 2)$$

Results

A Peek Into the Depths

Summar

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

$$7\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$$
 $(n_b=1)$
 $1\ 1\ 1\ 1\ 0\ 0\ 0\ 0$
 $(n_b=4)$
 $4\ 2\ 0\ 0\ 0\ 0\ 0\ 0$
 $(n_b=2)$
 $4\ 1\ 0\ 0\ 0\ 0\ 0$
 $(n_b=2)$

Results Overview

A Peek Into the Depths

Summar

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

```
egin{array}{llll} 7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & (n_b = 1) \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & (n_b = 4) \\ 4 & 2 & 0 & 0 & 0 & 0 & 0 & (n_b = 2) \\ 4 & 1 & 0 & 0 & 0 & 0 & 0 & (n_b = 2) \\ 3 & 1 & 1 & 0 & 0 & 0 & 0 & (n_b = 3) \\ & \vdots & & & & & & & & & & & & \\ \end{array}
```

Overview

A Peek Into the Depths

Summar

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_b , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- **4** The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

Examples of blacklist sizes for n = 8:

```
7\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ (n_b=1)
1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\ (n_b=4)
4\ 2\ 0\ 0\ 0\ 0\ 0\ 0\ (n_b=2)
4\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ (n_b=3)
\vdots
```

Tightness

Each of these is the optimal solution for some \mathcal{P}_M and μ .

Tradeoff: #Blacklists vs. Combined Blacklist Size

- 3 n_h , the number of women who have nonempty blacklists in \mathcal{P}_W , is at most $\frac{n}{2}$.
- 4 The combined size of all blacklists in \mathcal{P}_W is at most $n-n_b$.

Examples of blacklist sizes for n = 8:

```
70000000
               (n_b = 1)
1\ 1\ 1\ 1\ 0\ 0\ 0\ 0 (n_b=4)
42000000 (n_b = 2)
4\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ (n_b=2)
31100000 (n_b = 3)
```

Tightness

Each of these is the optimal solution for some \mathcal{P}_M and μ .

A Po

Results Overview

A Peek Into the Depths

Summary

The Gale-Shapley Deferred-Acceptance Algorithm

A version modelled after Dubins and Freedman's (1981)

The following algorithm yields the M-optimal stable matching.

Results

A Peek Into

Summar

The Gale-Shapley Deferred-Acceptance Algorithm

A version modelled after Dubins and Freedman's (1981)

The following algorithm yields the M-optimal stable matching.

Setup: Every man serenades under the window of the woman he prefers most.

Overview

A Peek Into

the Depths
Summary

The Gale-Shapley Deferred-Acceptance Algorithm

A version modelled after Dubins and Freedman's (1981)

The following algorithm yields the M-optimal stable matching.

- 1 Setup: Every man serenades under the window of the woman he prefers most.
- ② A man is scheduled for rejection if he is blacklisted by the woman to whom he serenades, or if she prefers another man currently serenading under her window.

Results Overview A Peek Into

the Depths

The Gale-Shapley Deferred-Acceptance Algorithm

A version modelled after Dubins and Freedman's (1981)

The following algorithm yields the M-optimal stable matching.

- 1 Setup: Every man serenades under the window of the woman he prefers most.
- ② A man is scheduled for rejection if he is blacklisted by the woman to whom he serenades, or if she prefers another man currently serenading under her window.
- 3 On each night, choose an arbitrary man scheduled for rejection. He moves to serenade under the window of the woman next on his preference list, if such woman exists.

The (unique) M-optimal matching is always reached, regardless of the arbitrary choices made during the run.

A Peek Into

the Depths

The Gale-Shapley Deferred-Acceptance Algorithm

A version modelled after Dubins and Freedman's (1981)

The following algorithm yields the M-optimal stable matching.

- Setup: Every man serenades under the window of the woman he prefers most.
- 2 A man is scheduled for rejection if he is blacklisted by the woman to whom he serenades, or if she prefers another man currently serenading under her window.
- 3 On each *night*, choose an arbitrary man scheduled for rejection. He moves to serenade under the window of the woman next on his preference list, if such woman exists.
- 4 When no men are scheduled for rejection, the algorithm terminates. Each woman is matched with the man serenading under her window; everyone else is unmatched.

The (unique) M-optimal matching is always reached, regardless of the arbitrary choices made during the run.

A Pol

Results Overview

A Peek Into the Depths

Summar

Tightness Overview

A Poll

Results Overview

A Peek Into the Depths

ummary

Tightness Overview

ckground

A Pol

Results Overview

A Peek Into the Depths

Summary

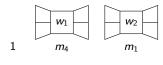
```
w_1 \mid m_1 \text{ (Blacklist: } m_4, m_3, m_2)

w_2 \mid m_2 > m_1 > m_4 > m_3

w_3 \mid m_3 > m_2 > m_1 > m_4

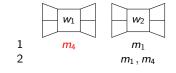
w_4 \mid m_4 > m_3 > m_2 > m_1
```

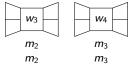




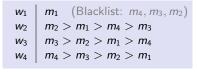


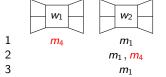


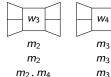










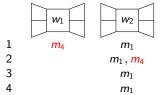


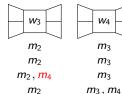
A Peek Into

the Depths

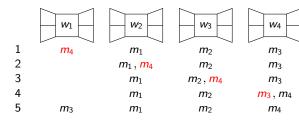
 m_1 $w_2 > w_3 > w_4 > w_1$ $w_3 > w_4 > w_1 > w_2$ m_2 $w_4 > w_1 > w_2 > w_3$ m_3 m_4 $w_1 > w_2 > w_3 > w_4$

W_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W 2	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W_4	$m_4 > m_3 > m_2 > m_1$





w_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W 2	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W_4	$m_4 > m_3 > m_2 > m_1$

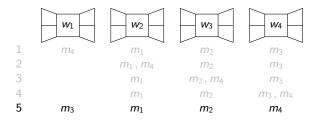


A Peek Into

the Depths

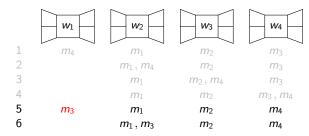


w_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W 2	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W4	$m_4 > m_3 > m_2 > m_1$

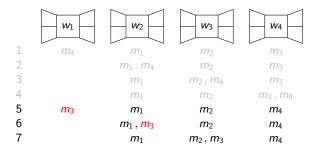


Summai

w_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W 2	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W_4	$m_4 > m_3 > m_2 > m_1$
	14 >5 >2 >1



$w_2 \mid m_2 > m_1 > m_4 > m_3$	
$w_3 \mid m_3 > m_2 > m_1 > m_4$	
$w_1 \mid m_1 \text{ (Blacklist: } m_4, m_3, m_1 \ w_2 \mid m_2 > m_1 > m_4 > m_3 \ w_3 \mid m_3 > m_2 > m_1 > m_4 \ w_4 \mid m_4 > m_3 > m_2 > m_1$	



$$m_1$$
 | $w_2 > w_3 > w_4 > w_1$
 m_2 | $w_3 > w_4 > w_1 > w_2$
 m_3 | $w_4 > w_1 > w_2 > w_3$
 m_4 | $w_1 > w_2 > w_3 > w_4$

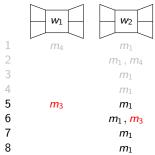
 m_4

$$w_2 > w_3 > w_4 > w_1$$

 $w_3 > w_4 > w_1 > w_2$

$$w_4 > w_1 > w_2 > w_3$$

$$w_1$$
 m_1 (Blacklist: m_4 , m_3 , m_2)
 w_2 $m_2 > m_1 > m_4 > m_3$
 w_3 $m_3 > m_2 > m_1 > m_4$
 w_4 $m_4 > m_3 > m_2 > m_1$









W3



W4

$$m_4, m_2$$

 m_4

A Peek Into

the Depths

 $w_2 > w_3 > w_4 > w_1$ m_1 m_2 m_3

 $w_3 > w_4 > w_1 > w_2$ $W_4 > W_1 > W_2 > W_3$

 $w_1 > w_2 > w_3 > w_4$

W₁ W_2 W_3

 W_4

 m_1

 $m_2 > m_1 > m_4 > m_3$

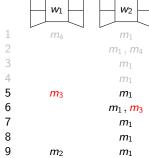
W3

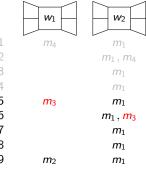
 $m_3 > m_2 > m_1 > m_4$

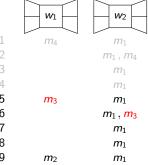
 $m_4 > m_3 > m_2 > m_1$

W4

(Blacklist: m_4, m_3, m_2)

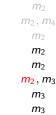
















 m_4

A Peek Into

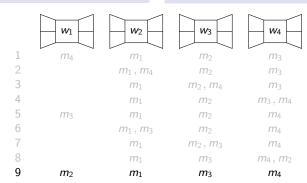
the Depths

 $w_2 > w_3 > w_4 > w_1$ m_1 m_2 m_3

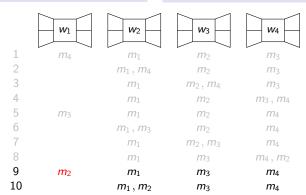
 $w_3 > w_4 > w_1 > w_2$ $W_4 > W_1 > W_2 > W_3$

 $w_1 > w_2 > w_3 > w_4$ m_4

(Blacklist: m_4, m_3, m_2) W₁ m_1 $m_2 > m_1 > m_4 > m_3$ W_2 W_3 $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$ W_4



w_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W ₂	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W_4	$m_4 > m_3 > m_2 > m_1$



 m_1 m_2 m_3 m_4 $w_2 > w_3 > w_4 > w_1$ $w_3 > w_4 > w_1 > w_2$

 $w_1 > w_2 > w_3 > w_4$

 $W_4 > W_1 > W_2 > W_3$

W₁ W_2 W_3

 W_4

 m_1

 $m_2 > m_1 > m_4 > m_3$

W3

 $m_3 > m_2 > m_1 > m_4$

 $m_4 > m_3 > m_2 > m_1$

W4

(Blacklist: m_4, m_3, m_2)

2

 W_1

4

9 10

11

 W_2

 m_2 m_1

mз

 m_3

 m_4 m_4

 m_1 m_2 m_3 m_4

11

12

 $w_2 > w_3 > w_4 > w_1$ $W_3 > W_4 > W_1 > W_2$ $W_4 > W_1 > W_2 > W_3$

 $w_1 > w_2 > w_3 > w_4$

W₁ W_2

 W_3

 W_4

 m_1

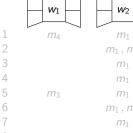
 $m_2 > m_1 > m_4 > m_3$

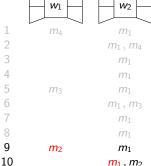
 $m_3 > m_2 > m_1 > m_4$

 $m_4 > m_3 > m_2 > m_1$

W4

(Blacklist: m_4, m_3, m_2)





 m_1, m_2 m_2

 m_2

mз

 m_3

 m_3, m_1

 m_3

W3

 m_4 m_4

 m_4 m_4, m_1

 m_1 m_2 m_3 m_4

 $W_4 > W_1 > W_2 > W_3$

 $w_2 > w_3 > w_4 > w_1$

 W_1

 $W_3 > W_4 > W_1 > W_2$

 $w_1 > w_2 > w_3 > w_4$

W₁ W_2

 W_3

 W_4

 m_1

W3

 $m_2 > m_1 > m_4 > m_3$

 $m_3 > m_2 > m_1 > m_4$

 $m_4 > m_3 > m_2 > m_1$

W4

(Blacklist: m_4 , m_3 , m_2)

2 4

9 m_2

10 11

12 13

 m_1

 m_2 m_2

 W_2

 m_2

 m_1, m_2

 m_1

mз m_3 m_3, m_1

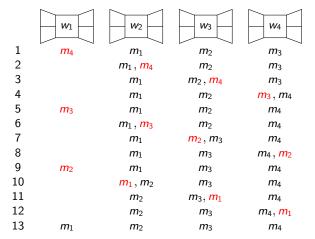
 m_3 m_3

 m_4 m_4 m_4

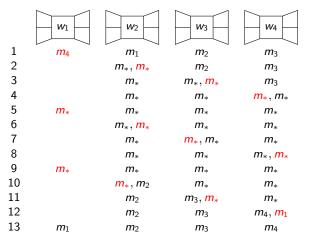
 m_4, m_1 m_4

m_1	$w_2 > w_3 > w_4 > w_1$
m_2	$w_3 > w_4 > w_1 > \frac{w_2}{}$
m_3	$w_4 > w_1 > w_2 > w_3$
m_4	$w_2 > w_3 > w_4 > w_1$ $w_3 > w_4 > w_1 > w_2$ $w_4 > w_1 > w_2 > w_3$ $w_1 > w_2 > w_3 > w_4$

w_1	m_1 (Blacklist: m_4 , m_3 , m_2) $m_2 > m_1 > m_4 > m_3$ $m_3 > m_2 > m_1 > m_4$ $m_4 > m_3 > m_2 > m_1$
W 2	$m_2 > m_1 > m_4 > m_3$
<i>W</i> ₃	$m_3 > m_2 > m_1 > m_4$
W_4	$m_4 > m_3 > m_2 > m_1$

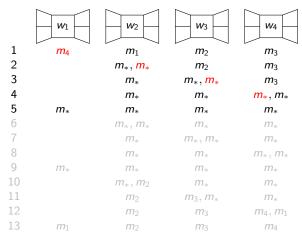


 $w_2 > w_3 > w_4 > w_1$ m_1 m_2 $W_3 > W_4 > W_1 > W_2$ $W_4 > W_1 > W_2 > W_3$ m_3 $w_1 > w_2 > w_3 > w_4$ m_4

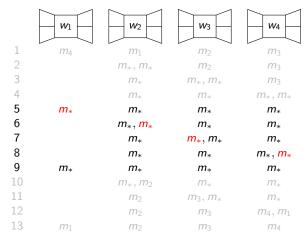


the Depths

W_1	m_1 (Blacklist: m_4, m_3, m_2)
W2	
W3	
W4	

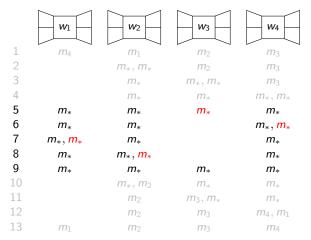


$$w_1$$
 m_1 (Blacklist: m_4, m_3, m_2)
 w_2 $m_2 > m_1 > m_4 > m_3$
 w_3 $m_3 > m_2 > m_1 > m_4$
 w_4 $m_4 > m_3 > m_2 > m_1$



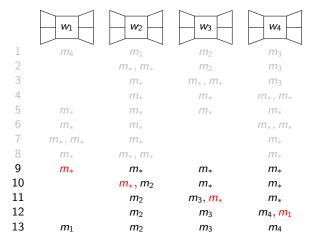
Summar

$$w_1$$
 m_1 (Blacklist: m_4, m_3, m_2)
 w_2 $m_2 > m_1 > m_4 > m_3$
 w_3 $m_3 > m_2 > m_1 > m_4$
 w_4 $m_4 > m_3 > m_2 > m_1$



ummar

$$egin{array}{lll} w_1 & m_1 & (\mbox{Blacklist: } m_4, m_3, m_2) \ w_2 & m_2 > m_1 > m_4 > m_3 \ w_3 & m_3 > m_2 > m_1 > m_4 \ w_4 & m_4 > m_3 > m_2 > m_1 \ \end{array}$$

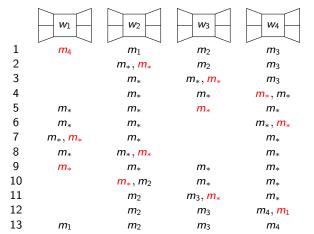


Results Overview

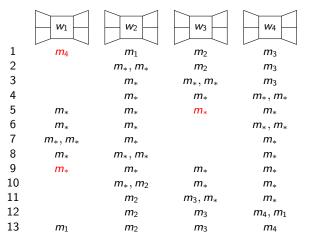
A Peek Into the Depths

m_1	$w_2 > w_3 > w_4 > w_1$
m_2	$w_3 > w_4 > w_1 > \frac{w_2}{}$
m_3	$w_4 > w_1 > w_2 > w_3$
m_4	$ w_2 > w_3 > w_4 > w_1 w_3 > w_4 > w_1 > w_2 w_4 > w_1 > w_2 > w_3 w_1 > w_2 > w_3 > w_4 $
1114	101 / 102 / 103 / 104

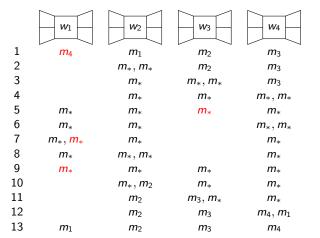
```
egin{array}{lll} w_1 & m_1 & (\mbox{Blacklist: } m_4, m_3, m_2) \\ w_2 & m_2 > m_1 > m_4 > m_3 \\ w_3 & m_3 > m_2 > m_1 > m_4 \\ w_4 & m_4 > m_3 > m_2 > m_1 \end{array}
```



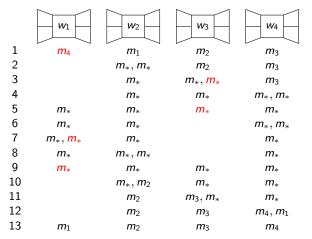
```
egin{array}{lll} w_1 & m_1 & (\mbox{Blacklist: } m_4, m_3, m_2) \\ w_2 & m_2 > m_1 > m_4 > m_3 \\ w_3 & m_3 > m_2 > m_1 > m_4 \\ w_4 & m_4 > m_3 > m_2 > m_1 \\ \end{array}
```



 $w_2 > w_3 > w_4 > w_1$ m_1 m_2 $W_3 > W_4 > W_1 > W_2$ $W_4 > W_1 > W_2 > W_3$ m_3 $w_1 > w_2 > w_3 > w_4$ m_4



m_1	$w_2 > w_3 > w_4 > w_1$
m_2	$w_3 > w_4 > w_1 > w_2$
m_3	$w_4 > w_1 > w_2 > w_3$
m_4	$ w_2 > w_3 > w_4 > w_1 w_3 > w_4 > w_1 > w_2 w_4 > w_1 > w_2 > w_3 w_1 > w_2 > w_3 > w_4 $



ckaround

A Pol

Results Overview

A Peek Into the Depths

ummary

Construction Overview for an Easier Special Case

 Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.

A Poll

Overview

A Peek Into

the Depths

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.

Results Overview

A Peek Into the Depths

ummar

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.

Results
Overview

A Peek Into

the Depths

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.

Results Overview A Peek Into

the Depths

ummar

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.
- Let m' be repeatedly rejected until serenading to $\mu(m')$, who then rejects her suitor . . .

Results Overview A Peek Into

the Depths

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.
- Let m' be repeatedly rejected until serenading to $\mu(m')$, who then rejects her suitor . . .
- Let $\mu(\tilde{w})$ be repeatedly rejected until serenading to \tilde{w} .

Results Overview A Peek Into

the Depths

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.
- Let m' be repeatedly rejected until serenading to $\mu(m')$, who then rejects her suitor . . .
- Let $\mu(\tilde{w})$ be repeatedly rejected until serenading to \tilde{w} .
- Only \tilde{w} blacklists anyone. More men have reached their intended partner than have been blacklisted.

Results Overview

A Peek Into the Depths

Summai

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.
- Let m' be repeatedly rejected until serenading to $\mu(m')$, who then rejects her suitor . . .
- Let $\mu(\tilde{w})$ be repeatedly rejected until serenading to \tilde{w} .
- Only \tilde{w} blacklists anyone. More men have reached their intended partner than have been blacklisted.
- Naïve next step: choose some \tilde{w}' and trigger another rejection cycle.

- Assume that the top choices of men are distinct, i.e. each man serenades under a unique window on the first night.
- We build a profile of preference lists for the women s.t. each woman prefers $\mu(w)$ most. $\Rightarrow \mu$ is W-optimal.
- Choose a woman \tilde{w} not serenaded-to by $\mu(\tilde{w})$, and have her blacklist her suitor m.
- Let m be repeatedly rejected until serenading to $\mu(m)$, who then rejects her suitor m'.
- Let m' be repeatedly rejected until serenading to $\mu(m')$, who then rejects her suitor . . .
- Let $\mu(\tilde{w})$ be repeatedly rejected until serenading to \tilde{w} .
- Only \tilde{w} blacklists anyone. More men have reached their intended partner than have been blacklisted.
- Naïve next step: choose some \tilde{w}' and trigger another rejection cycle.
- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.

ckground

Δ Poll

Results Overview

A Peek Into the Depths

Summary

Construction Overview for an Easier Case (2)

ullet Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.

A Poll

Overview

A Peek Into

the Depths

ummar

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.

Results
Overview
A Peek Into

the Depths

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.
- Iteratively merge more and more cycles.

Results Overview A Peek Into

the Depths
Summary

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.
- Iteratively merge more and more cycles.
- When no more merging is possibly, every woman w not serenaded-to by $\mu(w)$ has not rejected anyone yet.

Results Overview A Peek Into

the Depths
Summary

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.
- Iteratively merge more and more cycles.
- When no more merging is possibly, every woman w not serenaded-to by $\mu(w)$ has not rejected anyone yet.
- Such merging can be done without resimulating in every stage.

Results Overview A Peek Into

the Depths
Summary

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.
- Iteratively merge more and more cycles.
- When no more merging is possibly, every woman w not serenaded-to by $\mu(w)$ has not rejected anyone yet.
- Such merging can be done without resimulating in every stage.
- Surprising: decisions can be implemented online ("unintuitive algorithm"), if women control the scheduling. Overall time complexity: $\Theta(n^2)$ (optimal).

Results Overview

A Peek Into the Depths

- Problem: all candidates for the role of \tilde{w}' may have already rejected many men, whom we'd have to blacklist.
- Solution: show that it is possible to carefully "merge" the cycles, i.e. alter the preferences, "without blacklisting excessively-many men", s.t. the "chain reaction" triggered by \tilde{w} causes all rejections from both rejection cycles.
- Iteratively merge more and more cycles.
- When no more merging is possibly, every woman w not serenaded-to by $\mu(w)$ has not rejected anyone yet.
- Such merging can be done without resimulating in every stage.
- Surprising: decisions can be implemented online ("unintuitive algorithm"), if women control the scheduling. Overall time complexity: $\Theta(n^2)$ (optimal).
- General case harder to analyse and slower to compute (and not online). "Conclusion": the men inadvertently help the women in a sense by trying to force some matching.

ckground

A Poll

Overview

A Peek Into the Depths

Summary

Construction Overview: General Case

• No assumption regarding distinctness of top choices.

Results

A Peek Into the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.

Results
Overview

A Peek Into

the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.

Results Overview

A Peek Into the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.
- More involved analysis. Requires resimulations to compute. No (known) online method.

Overview

A Peek Into

the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.
- More involved analysis. Requires resimulations to compute. No (known) online method.
- Overall time complexity: $O(n^3)$. Avg. case $O(n^2 \log n)$ (due to properties of random permutations).

Overview

A Peek Into

the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.
- More involved analysis. Requires resimulations to compute. No (known) online method.
- Overall time complexity: $O(n^3)$. Avg. case $O(n^2 \log n)$ (due to properties of random permutations).
- Extends to unbalanced markets / partial matchings.

Results Overview

A Peek Into the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.
- More involved analysis. Requires resimulations to compute. No (known) online method.
- Overall time complexity: $O(n^3)$. Avg. case $O(n^2 \log n)$ (due to properties of random permutations).
- Extends to unbalanced markets / partial matchings.
- When unmatched men exist, we're back to $\Theta(n^2)$.*

Results Overview

A Peek Into the Depths

Summar

- No assumption regarding distinctness of top choices.
- If we let the algorithm run with arbitrary preferences (s.t. each woman w prefers $\mu(w)$ most) until it converges, then by the time it stops, all "candidates for the role of \tilde{w} " may have already rejected many men.
- Solution: show that there exists a candidate whose rejection cycle can be merged into the above run.
- More involved analysis. Requires resimulations to compute. No (known) online method.
- Overall time complexity: $O(n^3)$. Avg. case $O(n^2 \log n)$ (due to properties of random permutations).
- Extends to unbalanced markets / partial matchings.
- When unmatched men exist, we're back to Θ(n²).*
 General idea: follow the naïve construction; use these men as "placeholders" to initiate cycles without blacklisting.

A Poll

Results Overview

A Peek Into

Summary

Summary

 Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.

Results

A Peek Into

Summary

- Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.
- In balanced markets, what can we deduce regarding the M-optimal stable matching given only the men's preferences?

Results

A Peek Into

Summary

- Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.
- In balanced markets, what can we deduce regarding the M-optimal stable matching given only the men's preferences? Not much, really.

Results Overview

A Peek Into

Summary

- Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.
- In balanced markets, what can we deduce regarding the M-optimal stable matching given only the men's preferences? Not much, really.
- Phase change revisited: the preferences of the smaller side have significantly more impact on the stable matchings.

Results

A Peek Into

Summary

- Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.
- In balanced markets, what can we deduce regarding the M-optimal stable matching given only the men's preferences? Not much, really.
- Phase change revisited: the preferences of the smaller side have significantly more impact on the stable matchings.
- Intuition can be misleading; interesting and surprising results regarding marriage markets still exist.

Results Overview

A Peek Into

Summary

- Answered Gusfield and Irving's 1989 open question, fully characterizing possible optimal blacklist sizes.
- In balanced markets, what can we deduce regarding the M-optimal stable matching given only the men's preferences? Not much, really.
- Phase change revisited: the preferences of the smaller side have significantly more impact on the stable matchings.
- Intuition can be misleading; interesting and surprising results regarding marriage markets still exist.
- See the full paper (on arXiv) for the full results.

Results

Overview

A Peek Into

Summary

Questions?

Thank you!

