University of Glasgow

Profile-based optimal matchings in Stable Marriage

Frances Cooper

Joint work with: Prof David Manlove

Outline

Outline

- Matching problems

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- Fairness

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- Finding fair stable matchings

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- Experiments

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- Matching problems
- Fairness
- Finding fair stable matchings
- Experiments
- Future work

Matching Problems

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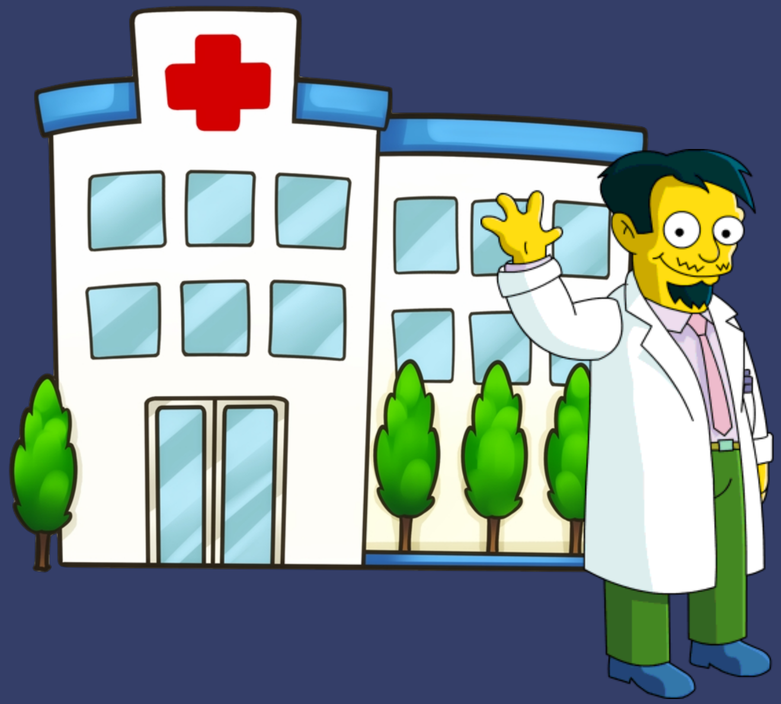
- Assign one set of entities to another set of entities

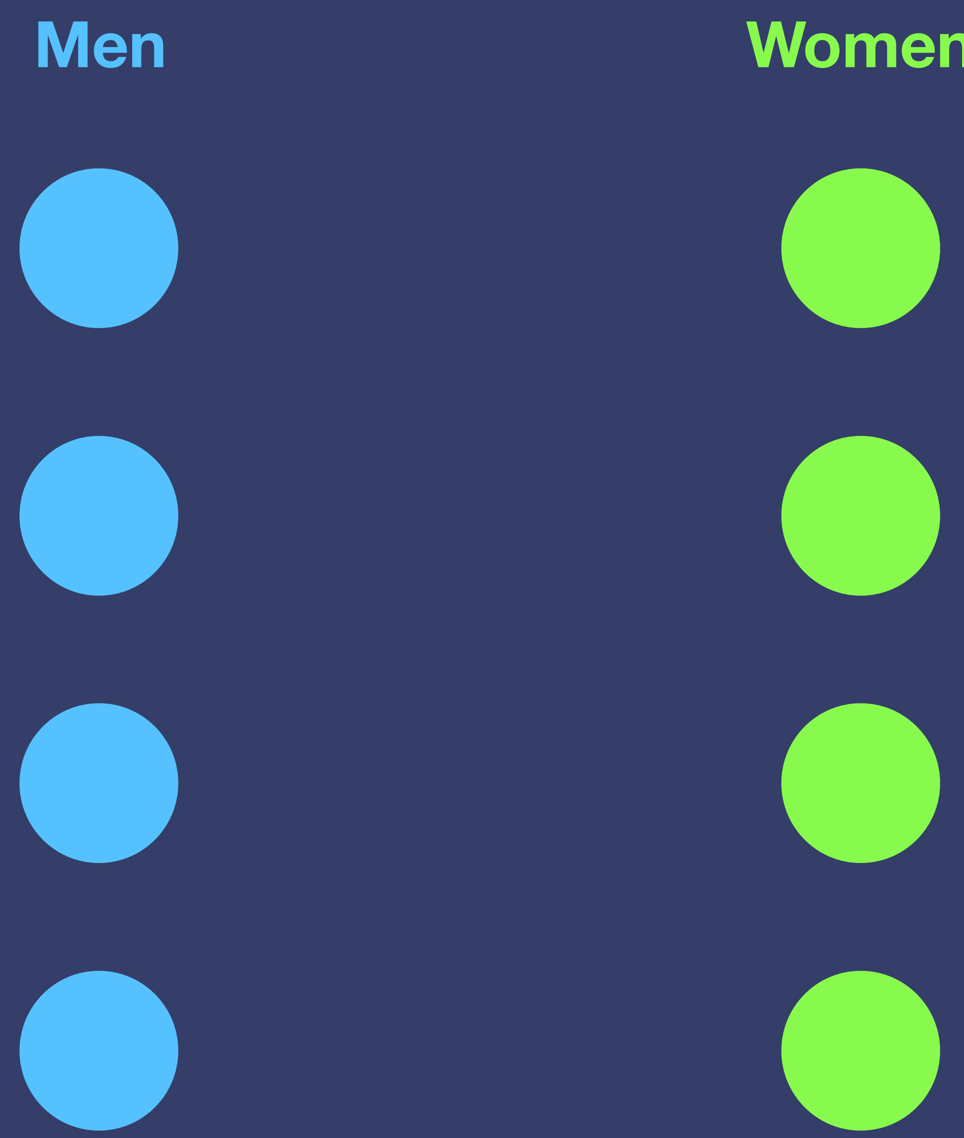
Matching Problems



- Assign one set of entities to another set of entities
- Based on preferences and capacities

Stable Marriage

Stable Marriage



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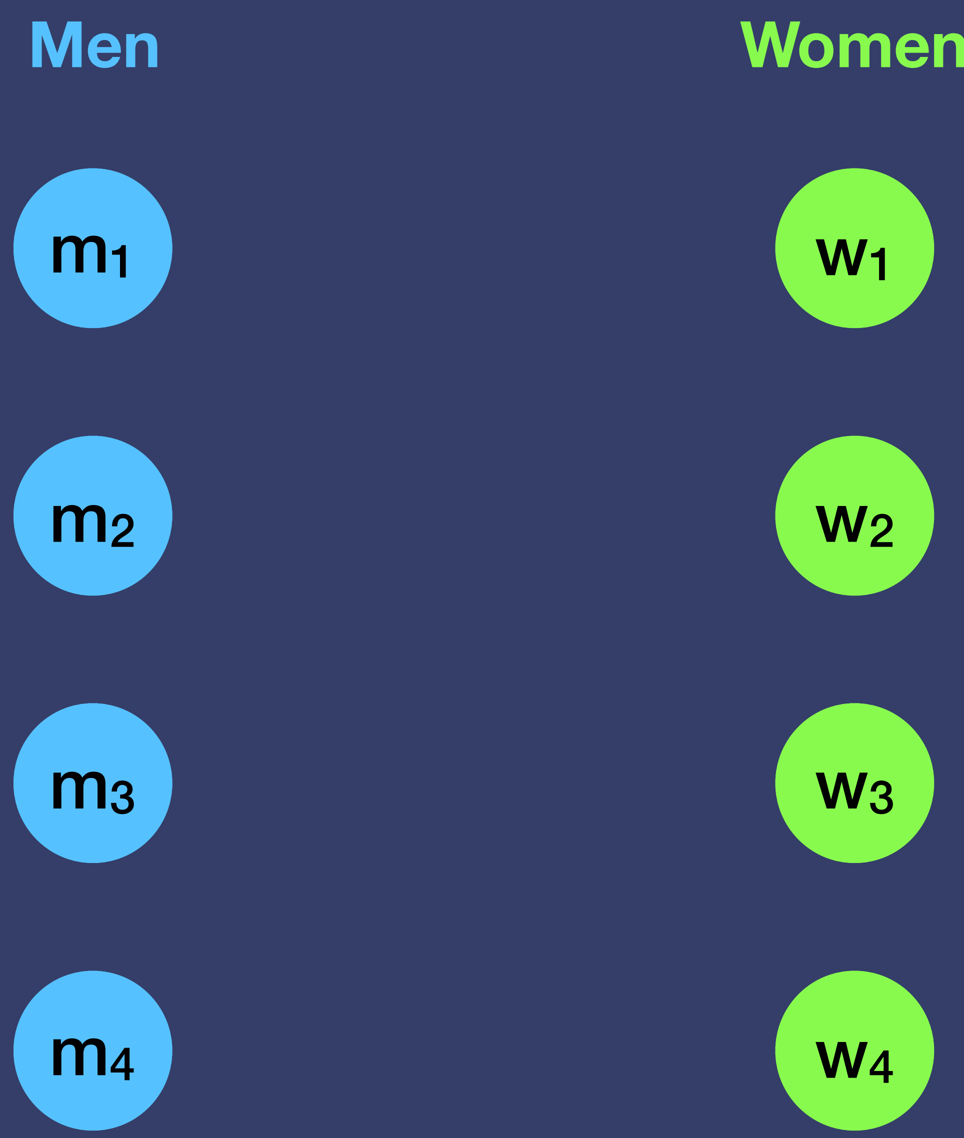

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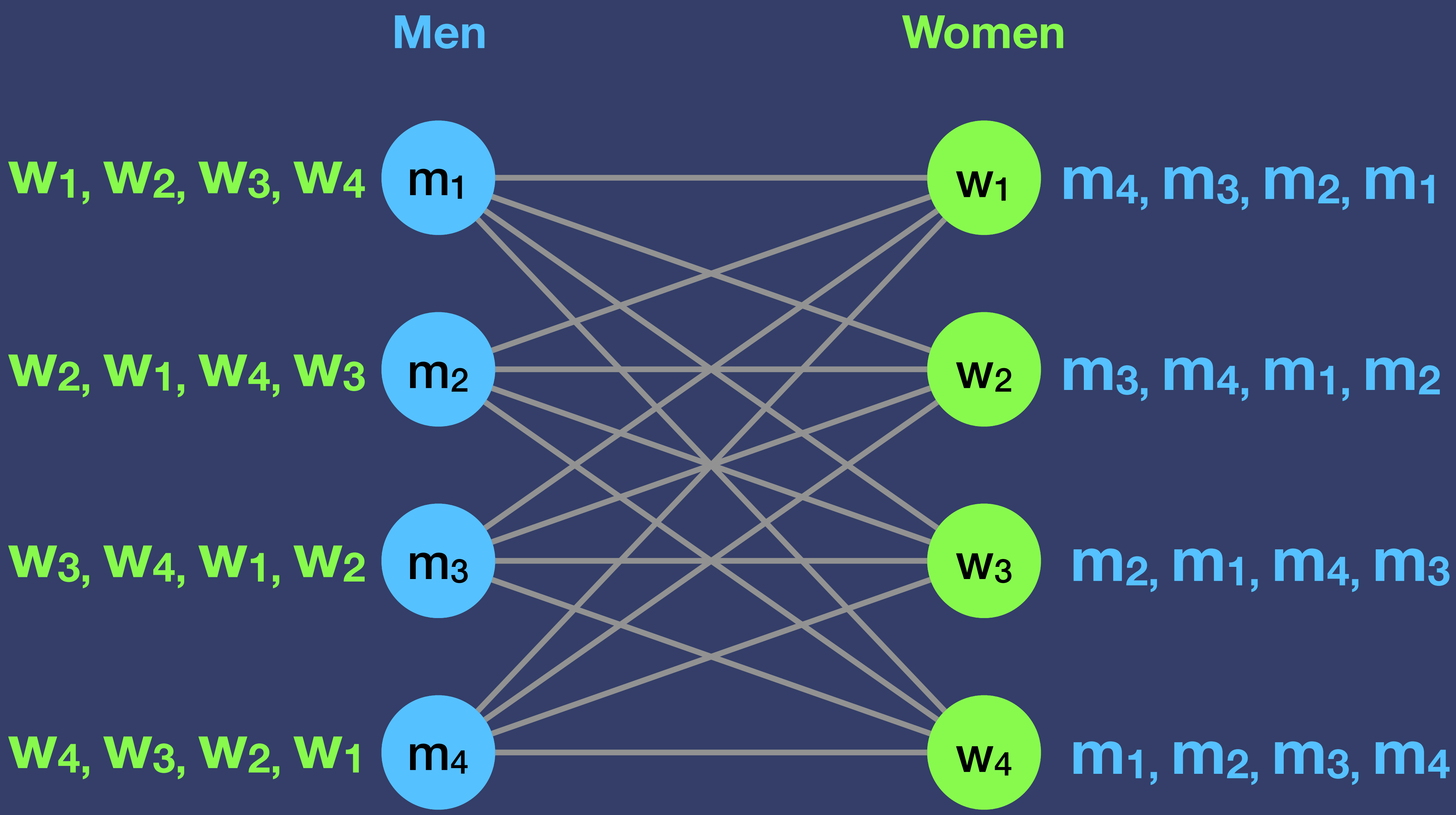

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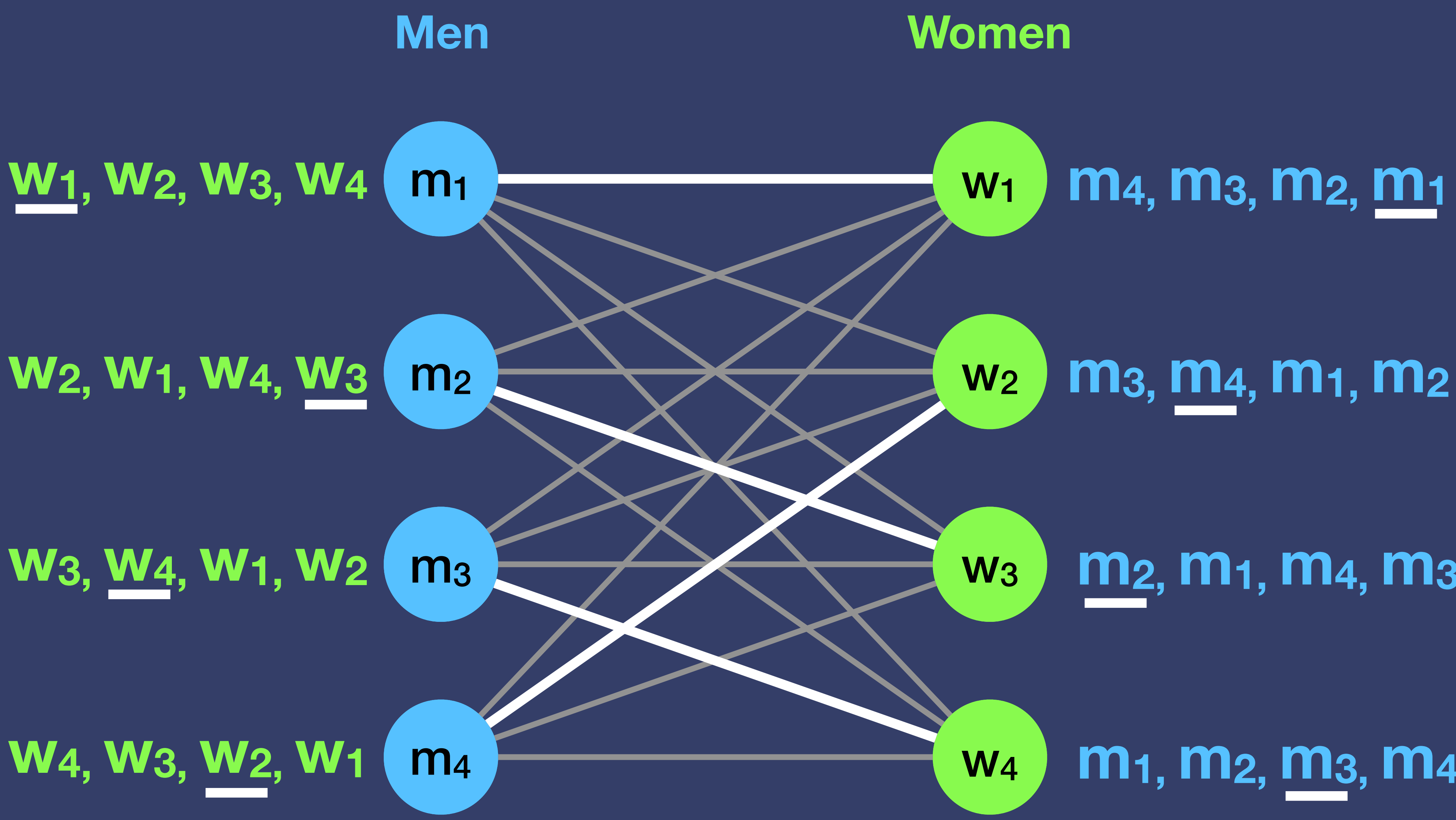
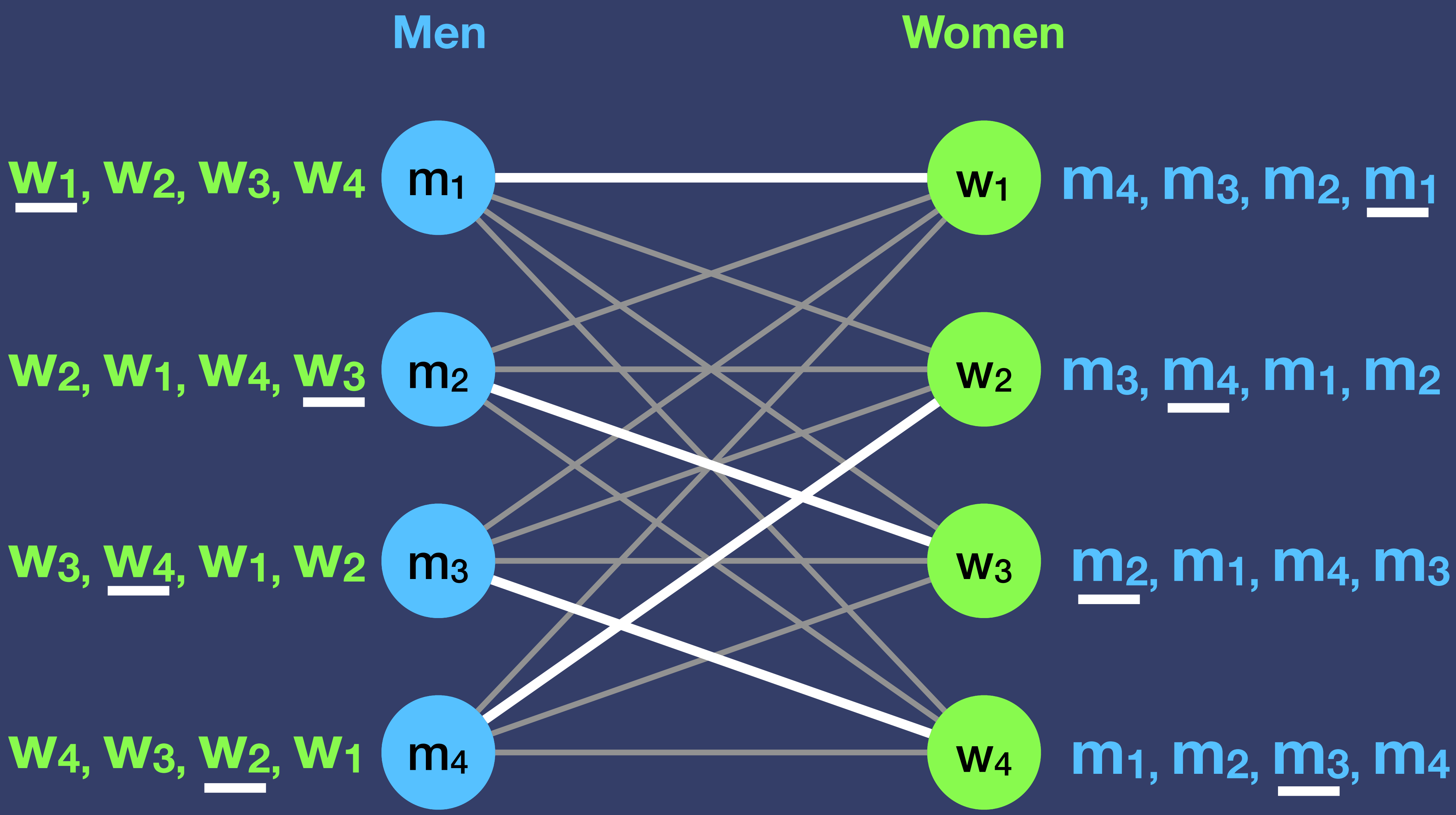


Rank

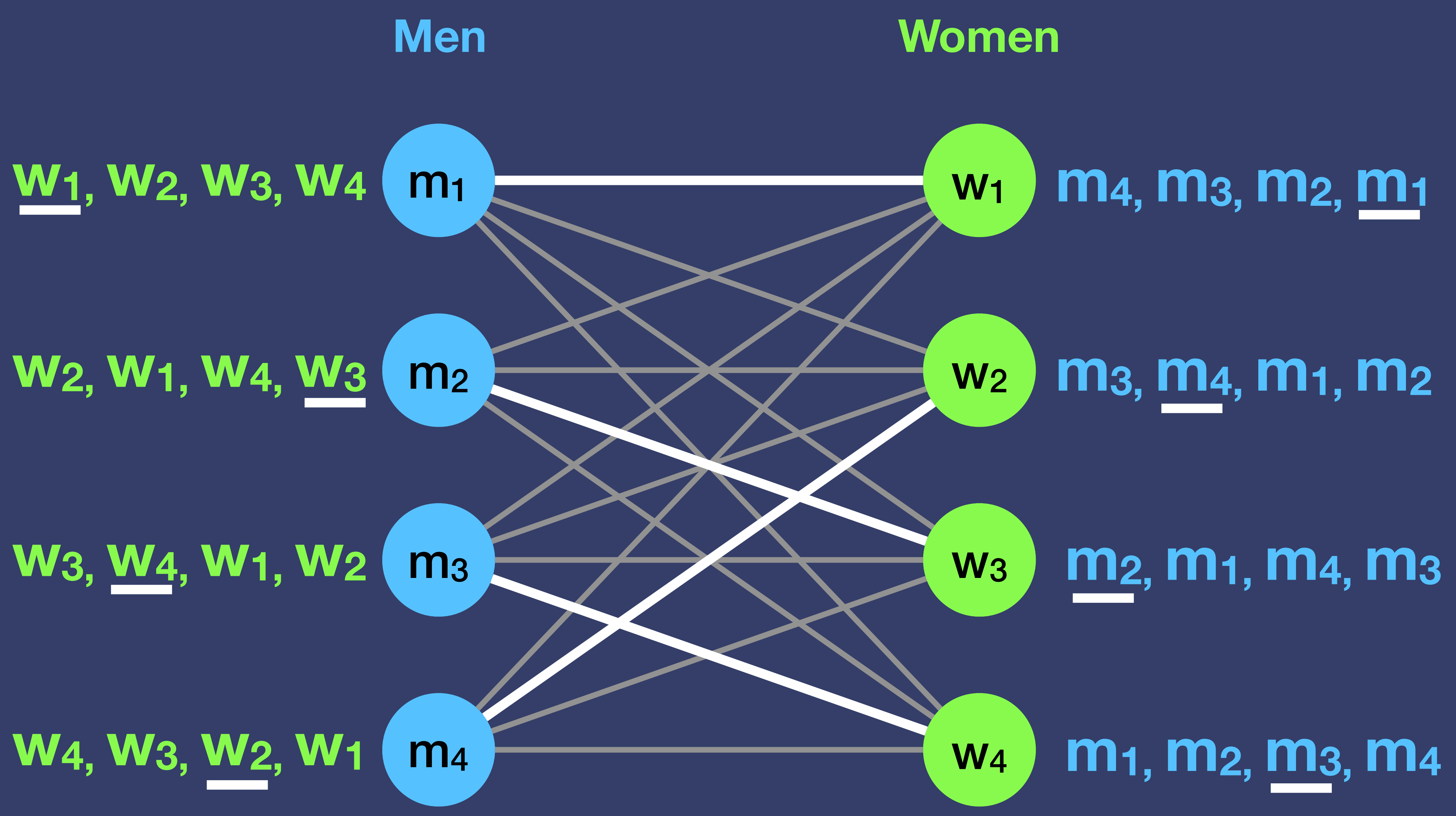
Stable Marriage



Rank

Degree

Stable Marriage

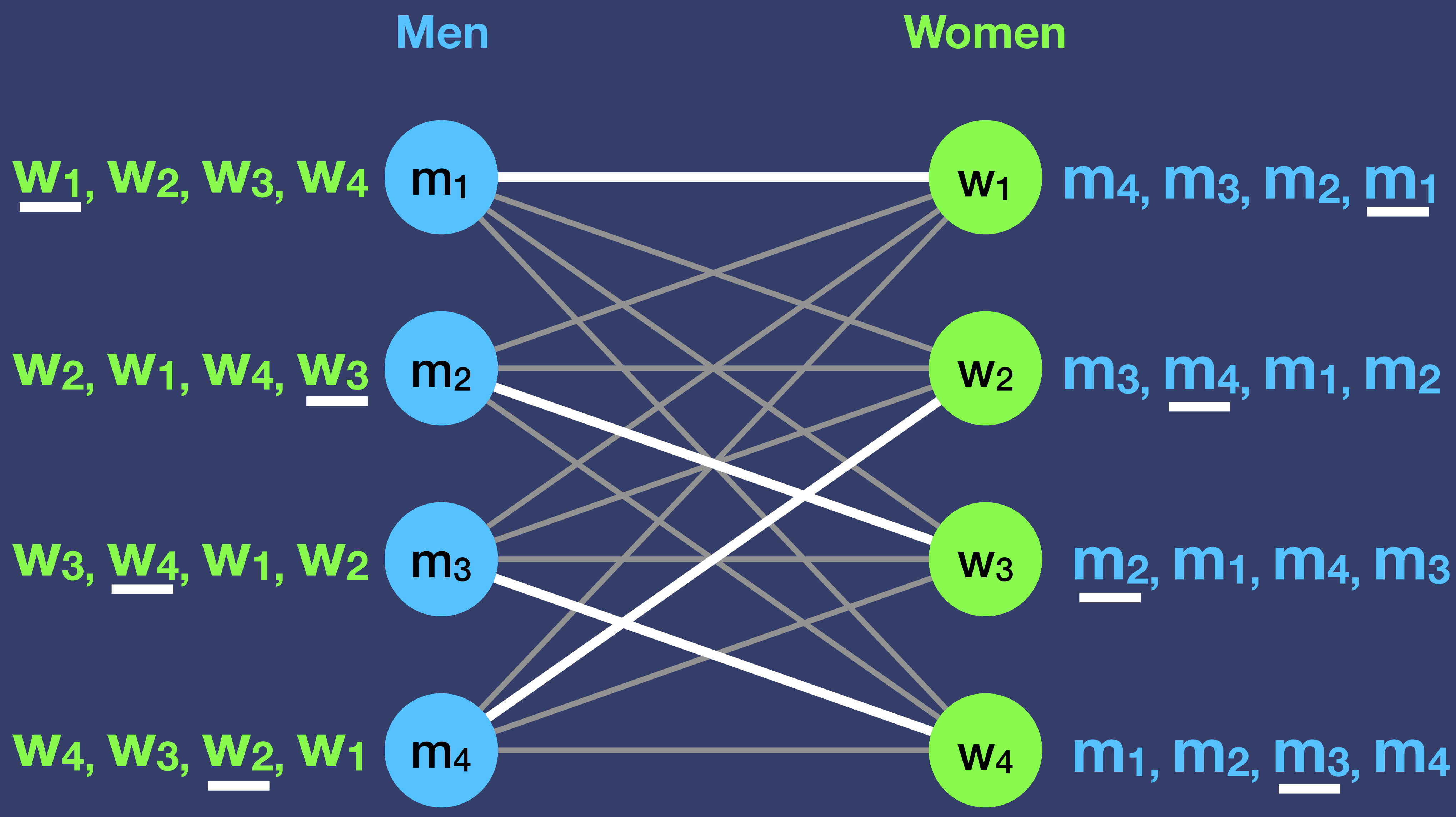


Rank

Degree

Profile <_, _, _, _>

Stable Marriage



Stable Marriage

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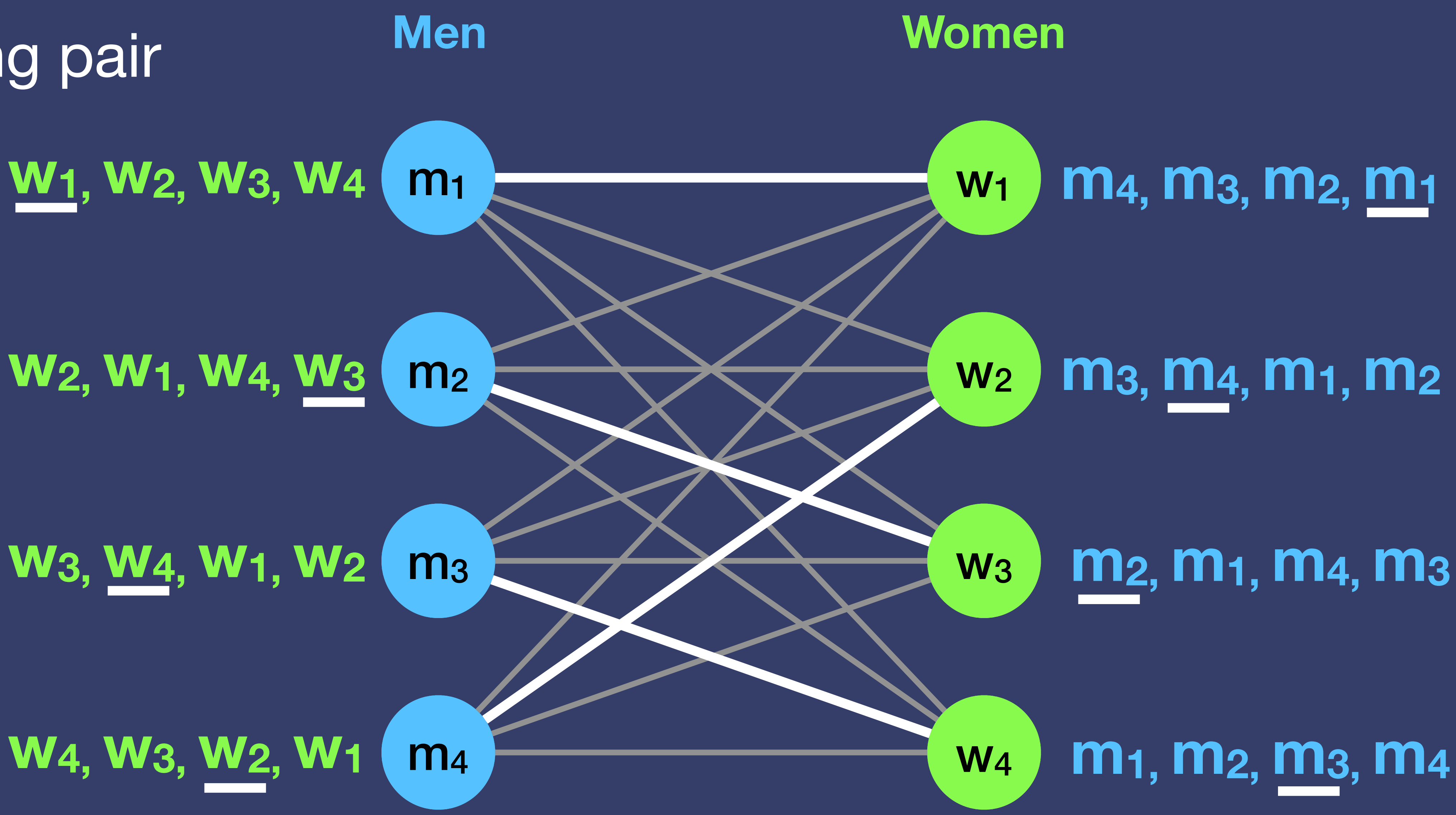
Profile <_, _, _, _>

Blocking pair



Stable Marriage

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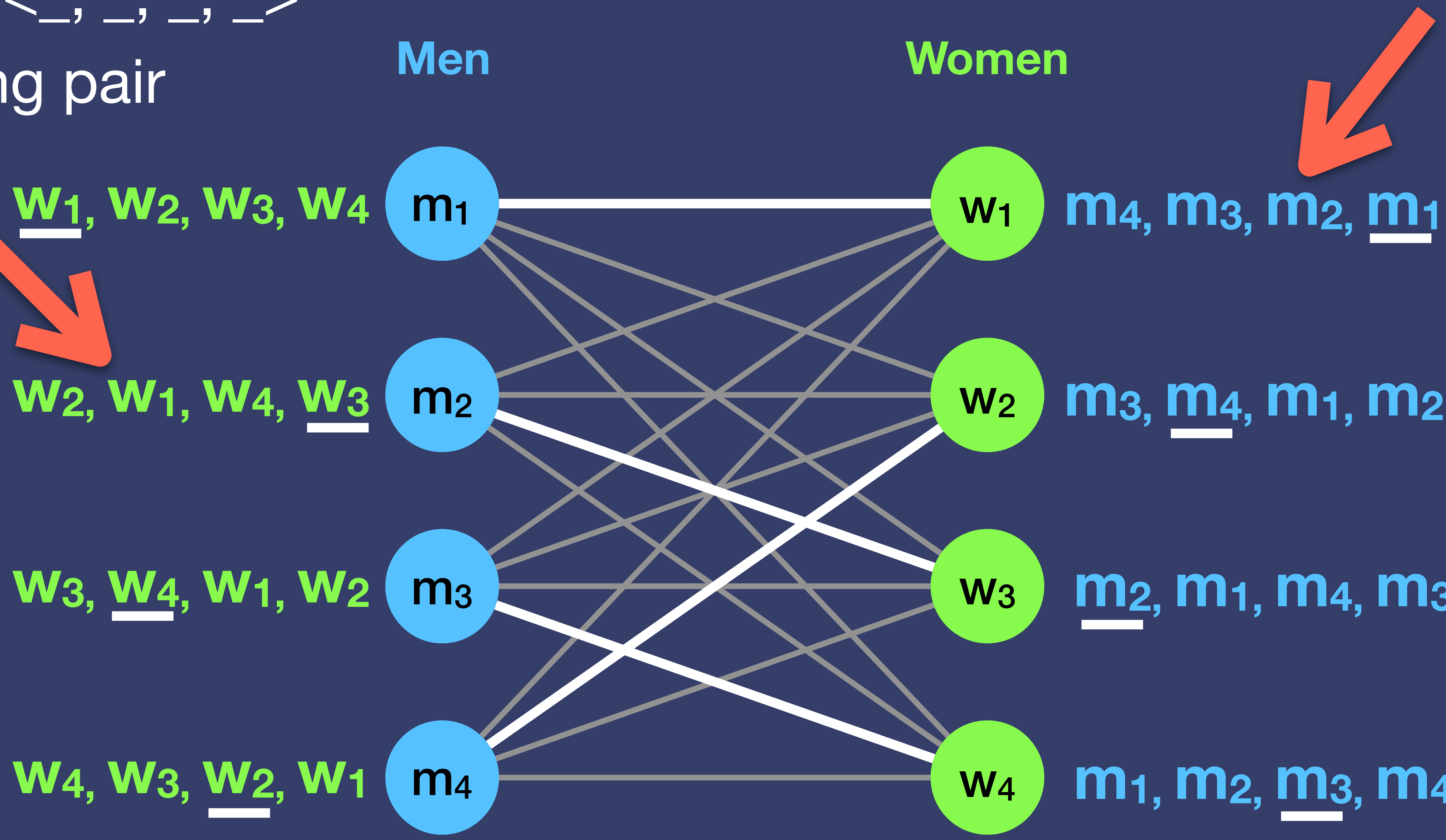

Stable Marriage

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Profile <_, _, _, _>

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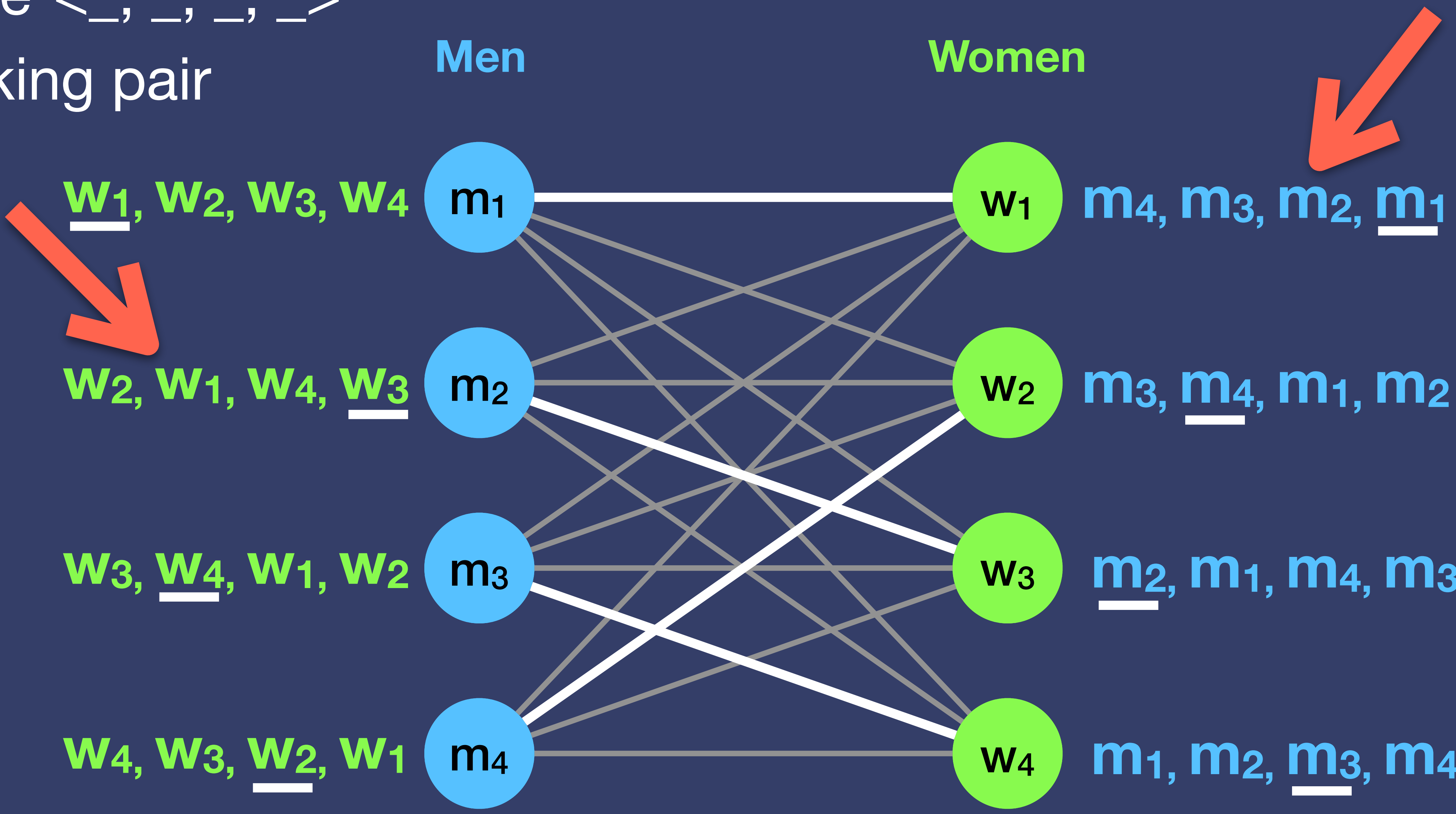

A **stable matching** is a matching with no blocking pairs

Fairness


CORN DOGS
CORN DOGS
SUPER DOG
SUPER DOG
LONG DOG ON A STICK
COLD DRINKS
DOG ON A STICK
CORN DOGS

Fairness

- Many stable matchings per instance

Fairness

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- Want to find a stable matching that provides some kind of equality between men and women

Fairness

- Many stable matchings per instance
- Want to find a stable matching that provides some kind of equality between men and women
- Several different fairness measures

Fairness measures

Fairness measures

Sex-equal - minimise the differences between the sum of ranks for men and the sum of ranks for women - NP-hard

Complexity of the Sex-Equal Stable Marriage Problem; Japan Journal of Industrial and Applied Mathematics; 1993; Kato

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Rank-maximal - maximises the number assigned to their first choice, and subject to that, their second, and so on (maximises profile lexicographically) - Polynomial

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Generous - minimises the number assigned to their last choice, and subject to that, their second to last, and so on (minimises reverse profile lexicographically) - Polynomial

Fairness measures

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Fairness measures

Fairness measures

Sex-equal

Sum men ranks: 10

Sum women ranks: 10

Sex-equal difference: 0

Profile: <0, 4, 4, 0>

m_1: w_1, w_2, $\underline{w_3}$, w_4

m_2: w_2, $\underline{w_1}$, w_4, w_3

m_3: w_3, $\underline{w_4}$, w_1, w_2

m_4: w_4, w_3, $\underline{w_2}$, w_1

w_1: m_4, m_3, $\underline{m_2}$, m_1

w_2: m_3, $\underline{m_4}$, m_1, m_2

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m_4: $w_4, w_3, \underline{w_2}, w_1$

w_1: $m_4, m_3, \underline{m_2}, m_1$
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w_3: $m_2, \underline{m_1}, m_4, m_3$
w_4: $m_1, m_2, \underline{m_3}, m_4$

Rank-maximal

Sum men ranks: 4

Sum women ranks: 16

Sex-equal difference: 12

Profile: <4, 0, 0, 4>

m_1: $\underline{w_1}, w_2, w_3, w_4$
m_2: $\underline{w_2}, w_1, w_4, w_3$
m_3: $\underline{w_3}, w_4, w_1, w_2$
m_4: $\underline{w_4}, w_3, w_2, w_1$

w_1: $m_4, m_3, m_2, \underline{m_1}$
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Generous

Sum men ranks: 8

Sum women ranks: 12

Sex-equal difference: 4

Profile: <0, 4, 4, 0>

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Fairness measures

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also generous

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Finding a Rank-maximal stable matching

Using $O(n^5 \log n)$ Irving, Gusfield and Leather Approach

An efficient algorithm for the "optimal" stable marriage; Journal of the ACM; 1987; Irving, Gusfield, Leather

Rotations

Rotations

- Rotation - series of man-woman pairs that take us from one stable matching to another when permuted

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R_1 $\begin{matrix} m_1 & m_4 \\ w_2 & w_3 \end{matrix}$

Rotations

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R_1	m_1	m_4
	w_2	w_3

M_1	m_1	m_2	m_3	m_4
	w_2	w_1	w_4	w_3

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R_1: m_1 m_4 / w_2 w_3

M_1: m_1 m_2 m_3 m_4 / w_2 w_1 w_4 w_3

↓ R_1

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R_1

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w_2	w_3

M_1

m_1	m_2	m_3	m_4
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↓ R_1

M_2

m_1	m_2	m_3	m_4
w_3	w_1	w_4	w_2

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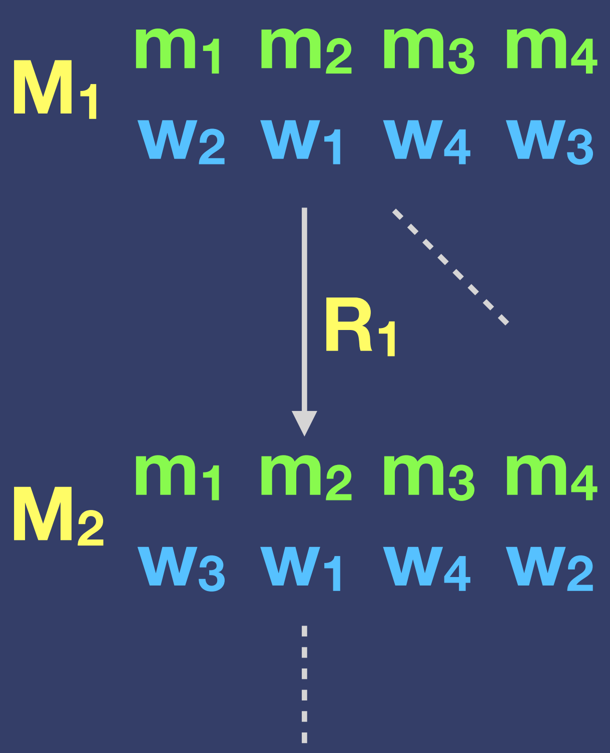

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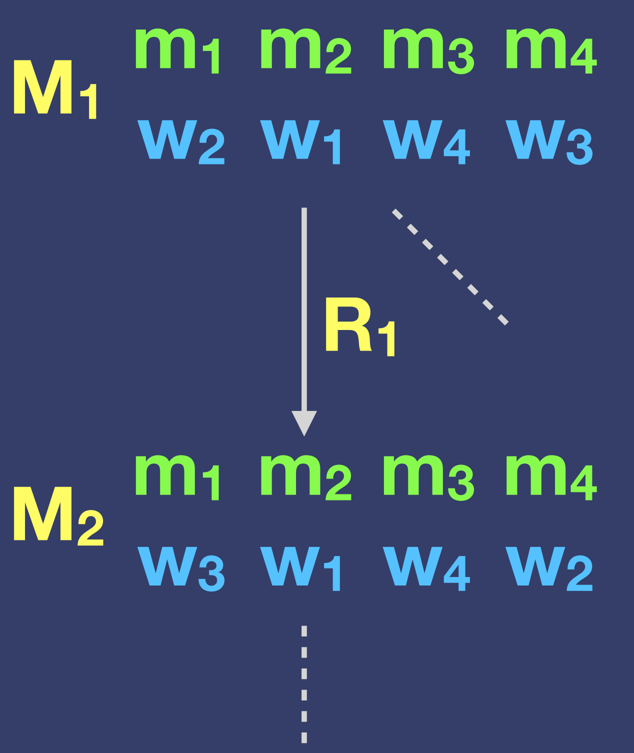
- Can only eliminate *exposed* rotations



Rotations

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w_2	w_3

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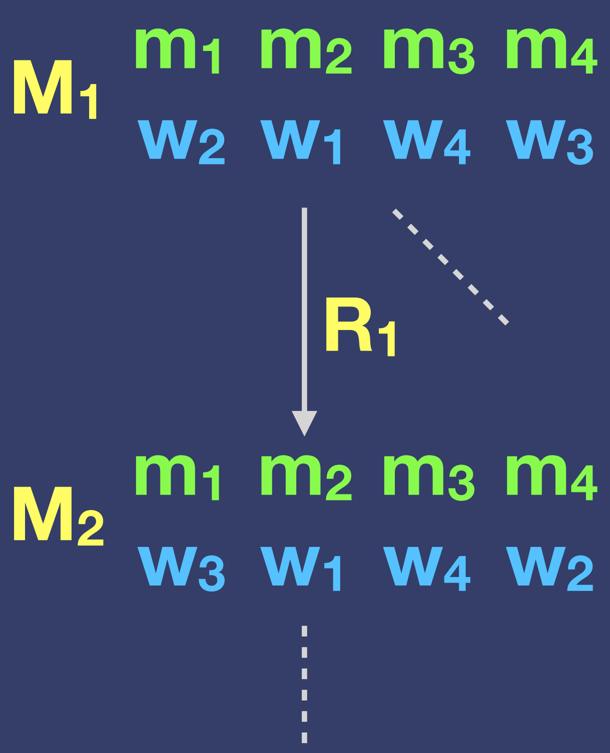
R_2

m_1	m_2
w_1	w_2



Rotations

- Rotation - series of man-woman pairs that take us from one stable matching to another when permuted

R_1: m_1 m_4 / w_2 w_3

- Can only eliminate *exposed* rotations

R_2: m_1 m_2 / w_1 w_2

- $O(n^2)$ algorithm to find all rotations

Rotation weights

Rotation weights

Rotation profile

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- Profile of a rotation is the change in profile of the matching if it is eliminated.

Rotation weights

Rotation profile

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- $p = \langle p_1, p_2, \ldots p_n \rangle$

E.g. $p = \langle 2, -1, 0, -1 \rangle$

Rotation weights

Rotation profile

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- convert rotation profiles to a single exponential number

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Rotation weight

- convert rotation profiles to a single exponential number
- $w(p) = p_1 * n^{n-1} + p_2 * n^{n-2} + \ldots + p_n$ E.g. $w(p) = 111$

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Rotation weights

Rotation profile

- Profile of a rotation is the change in profile of the matching if it is eliminated.
- $p = \langle p_1, p_2, \ldots p_n \rangle$ E.g. $p = \langle 2, -1, 0, -1 \rangle$

Rotation weight

- convert rotation profiles to a single exponential number
- $w(p) = p_1 * n^{n-1} + p_2 * n^{n-2} + \ldots + p_n$ E.g. $w(p) = 111$

If a rotation has a positive weight then we want to eliminate it if possible as it helps us find a rank-maximal matching.

Rotation poset

Rotation poset

- Displays order in which rotations can be eliminated

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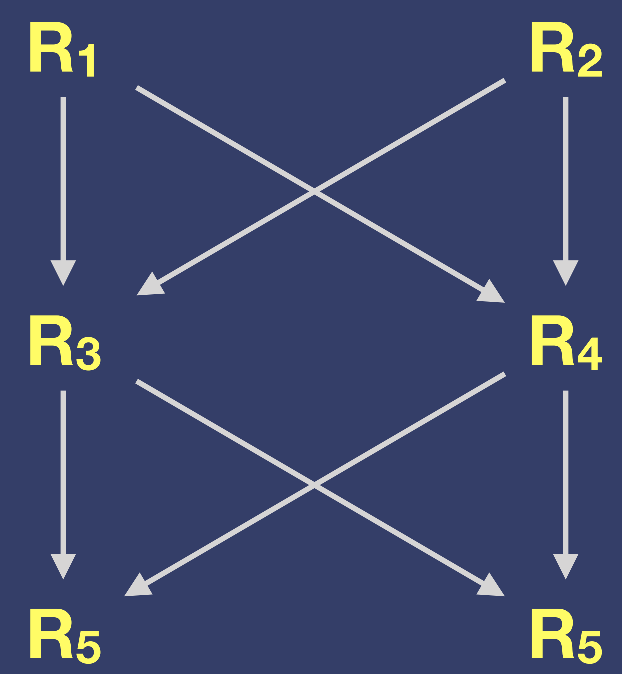

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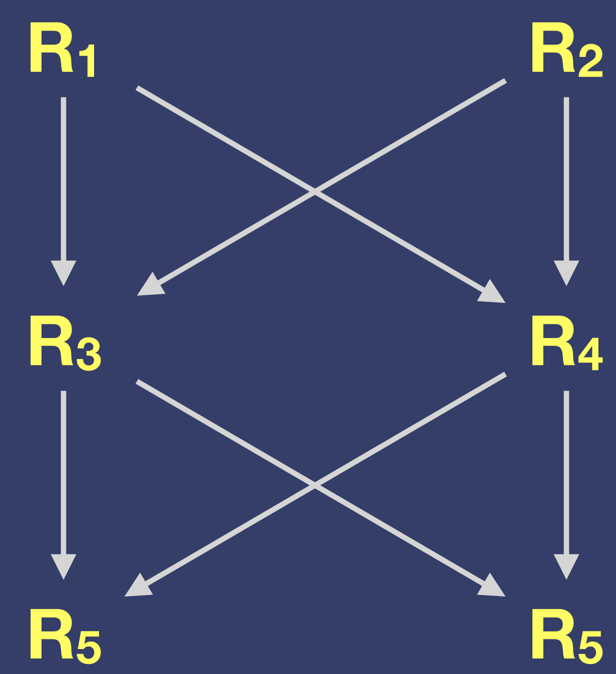

- The set of stable matchings are in 1-1 correspondence with the closed subsets of the poset

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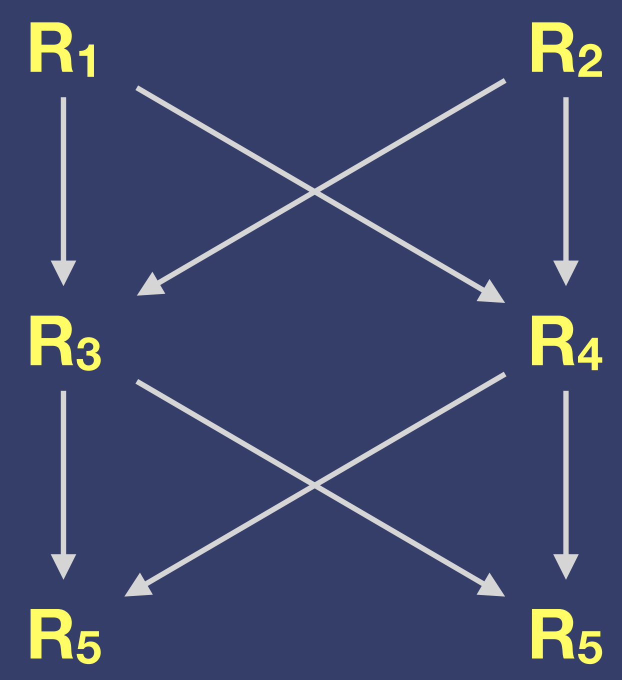

- The set of stable matchings are in 1-1 correspondence with the closed subsets of the poset

- Want: Max weight closed subset of the rotation poset

Flow Network

Flow Network

- Build a flow network based on the rotation poset

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- The max flow relates to the max closed subset

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Flow Network

- Build a flow network based on the rotation poset
- The max flow relates to the max closed subset
- Use a min-cut max-flow algorithm to find max flow
    - Sleator-Tarjan max-flow algorithm O(n^5 logn)

can be improved -
we'll look at this later

Steps

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1. List rotations

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2. Build rotation poset

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$O(n^5 \log n)$ using Irving, Gusfield and Leather approach

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Weights are exponentially large:

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- Calculations may cause overflow / inaccuracies for primitive types

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- Calculations may cause overflow / inaccuracies for primitive types
- Memory issues for types that can store arbitrarily large numbers

Rank-maximal stable matching using a vector-based approach

Combinatorial approach

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- We present a vector-based combinatorial approach - no need to use exponential weights

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  <1, 4, 0, 0, -2, 0, 0, 0, 0, 0, 0, -3, 0, 0, 0, 0 >

Combinatorial approach

- We present a vector-based combinatorial approach - no need to use exponential weights
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  - distribution of rotation profiles are non uniform
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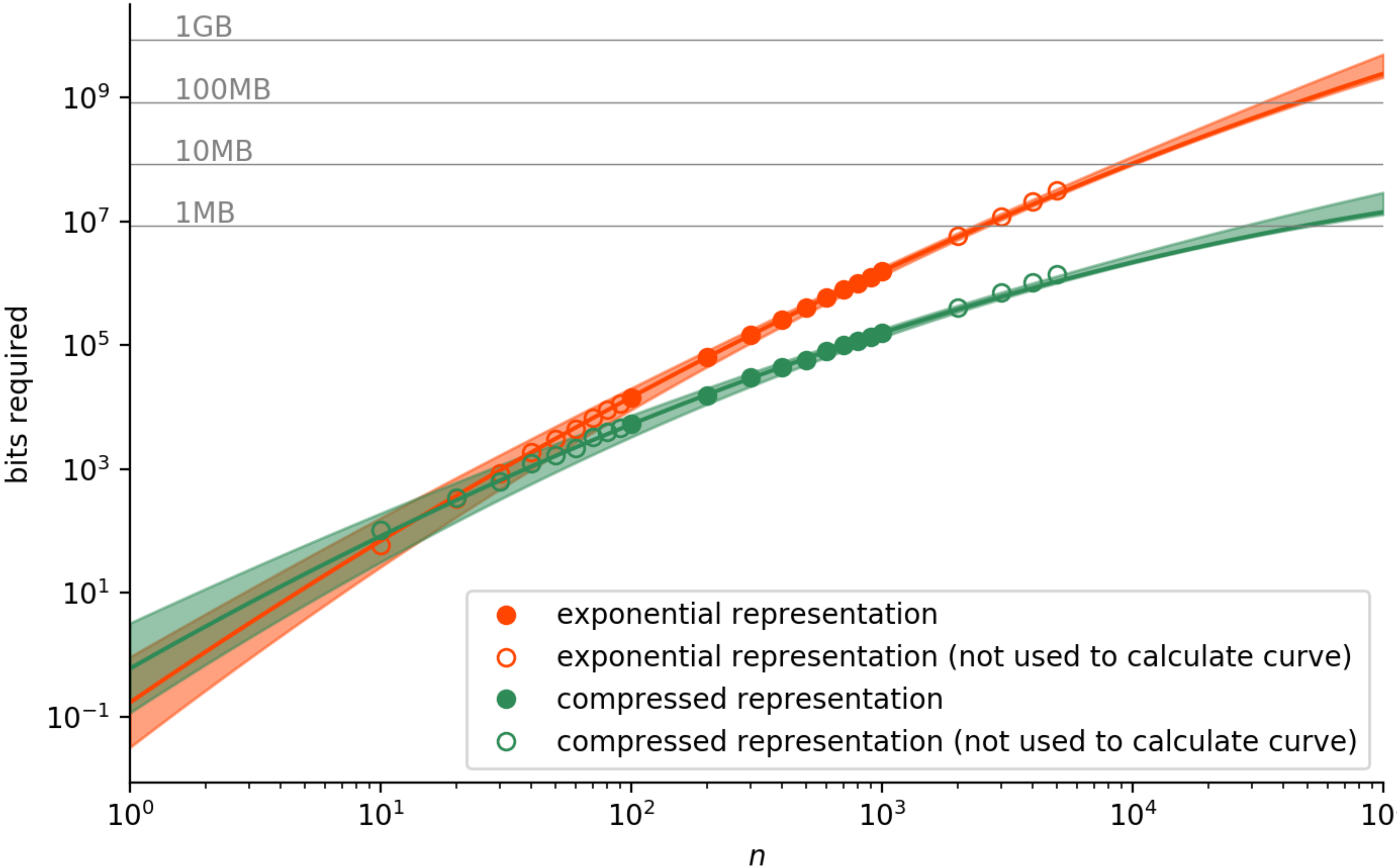
<1, 4, 0, 0, -2, 0, 0, 0, 0, 0, 0, -3, 0, 0, 0, 0 >

save the index and value of non zero elements (lossless)

<(0,1), (1,4), (4,-2), (11,-3)>

Combinatorial approach



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- adds complications
- Had to define our own arithmetic over these vectors

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3. Proved Max Flow-Min Cut Theorem extends to vector-based setting
4. Proved could adapt the Sleator-Tarjan Max-Flow algorithm to use vector capacities and flows

★ Can find a rank-maximal stable matching in $O(n^5 \log n)$ using vectors - matches the exponential approach (but with added bonus of vector compression) ★

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★ Generous stable matching can be found in $O(n^2d^3 \log n)$ time - competitive when d is small ★

d is degree of the minimum-regret stable matching

Experimental results

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    - CPLEX up to size n = 60 for the number of stable matchings

Average number of first choices

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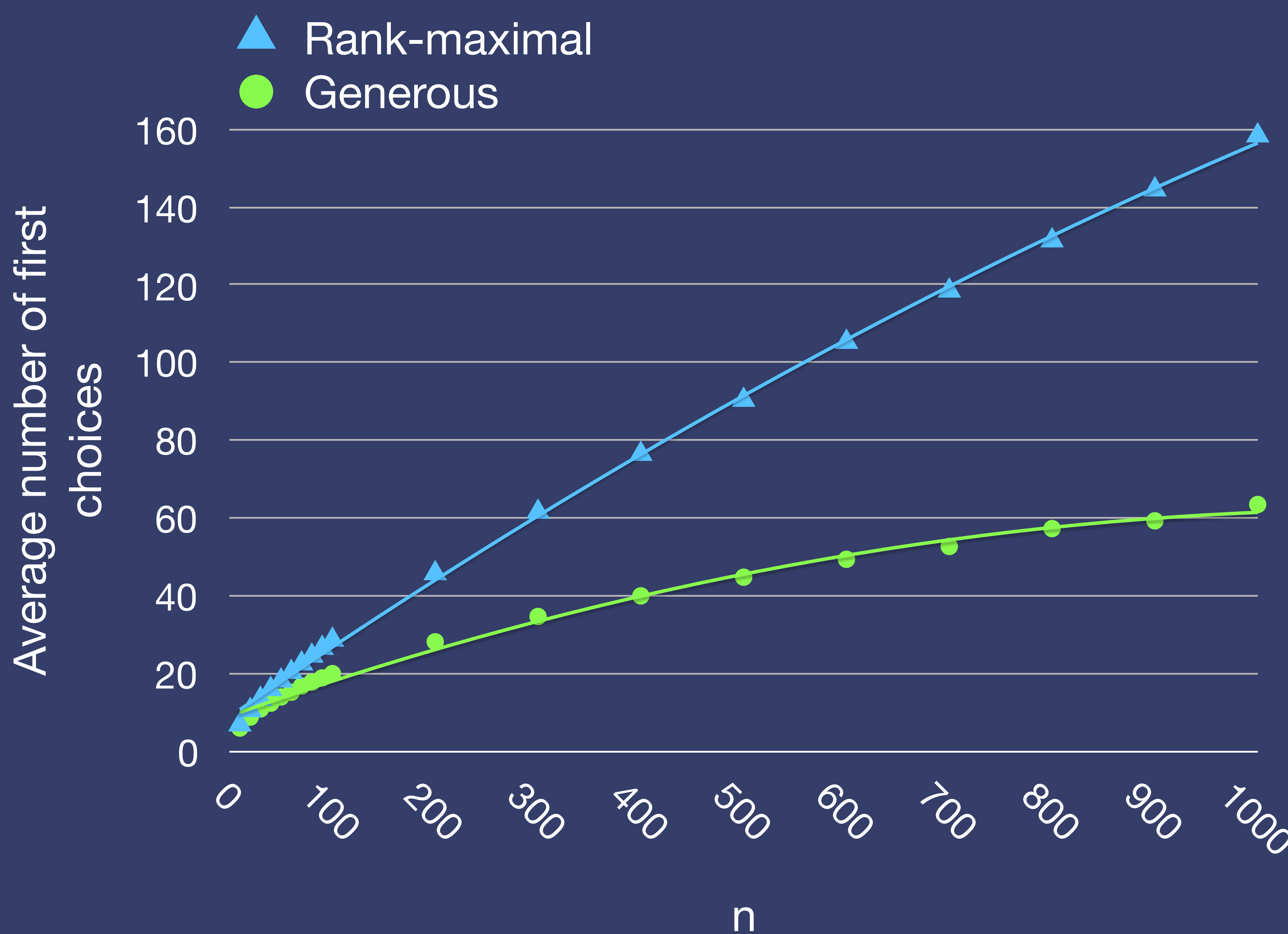

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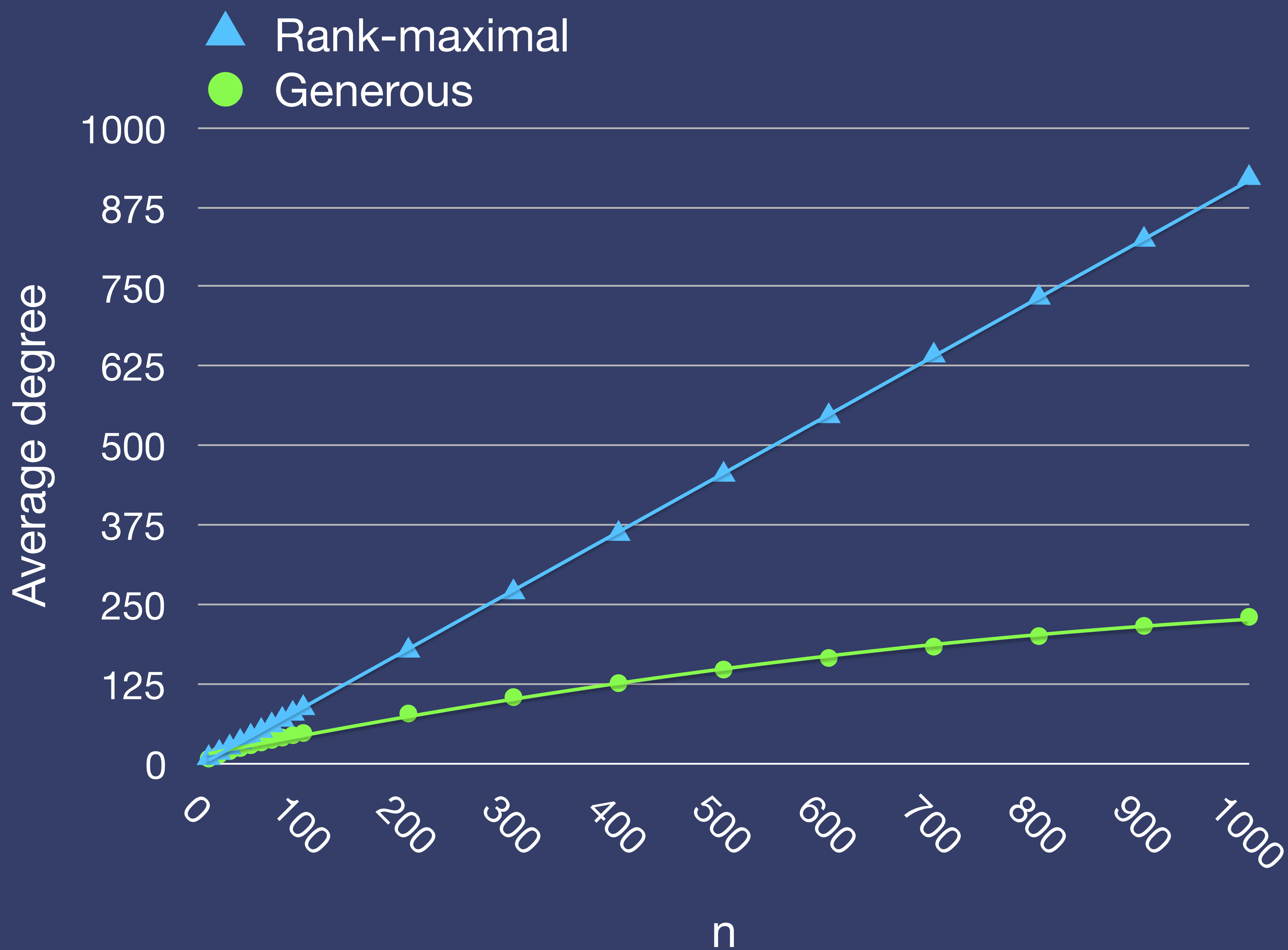
Average degree

Average degree



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Sex-equal score

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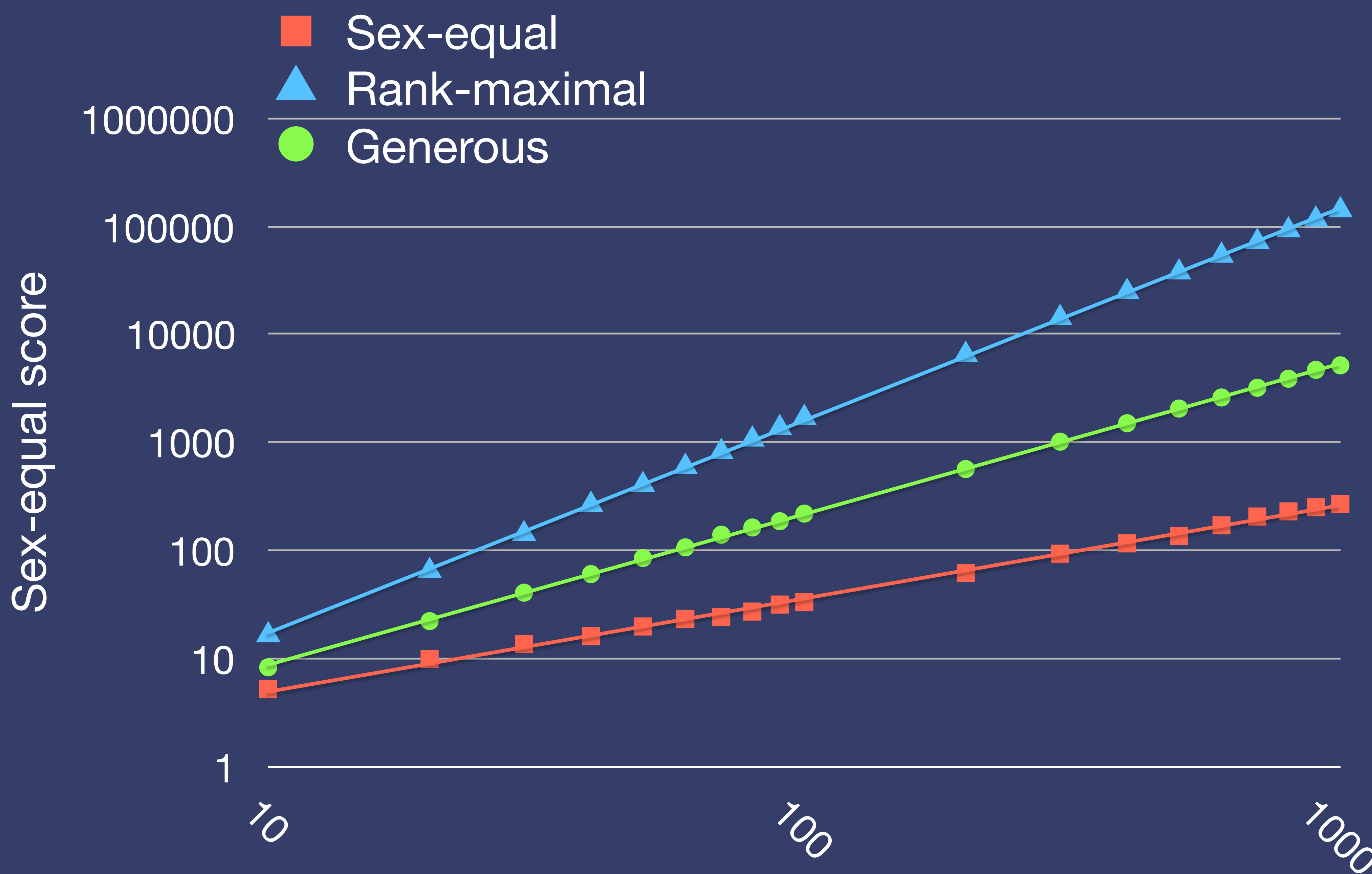

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Future Work

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Thank you

Summary

- Matching problems
- Fairness
- Finding fair stable matchings
- Experiments
- Future work: adapting algorithms to vector-based setting for improved time complexity

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