### Optimizing over Serial Dictatorships

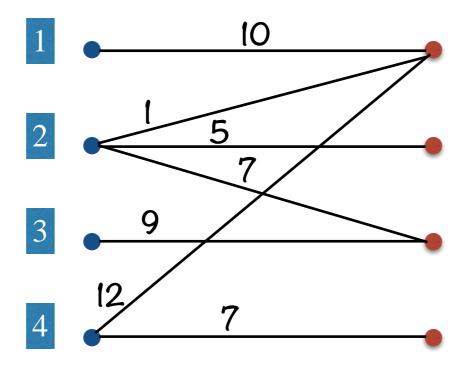


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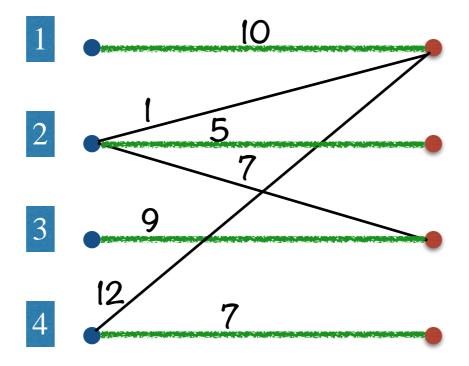




remaining edge weights = 0

Complete weighted bipartite graph

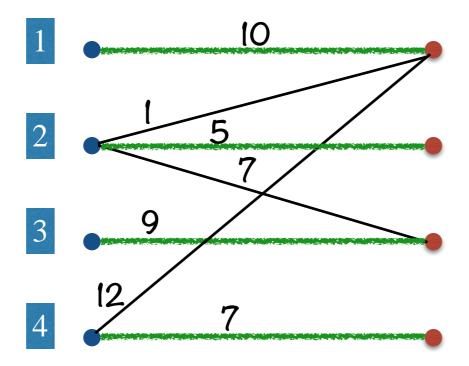
Goal: Maximum-weight matching



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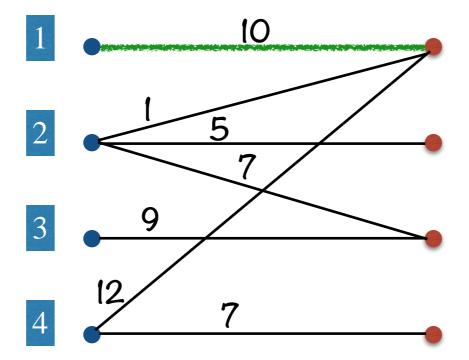
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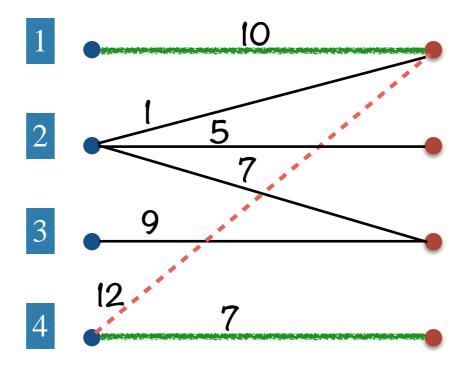
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Action sequence: 1 4 3 2 produces the maximum-weight matching



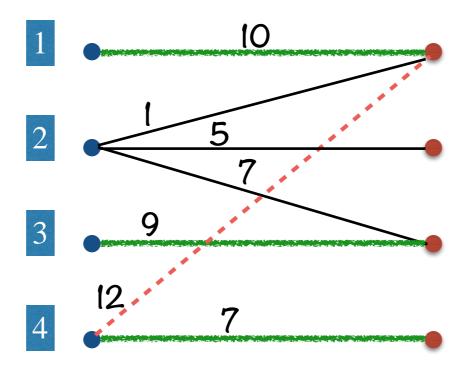
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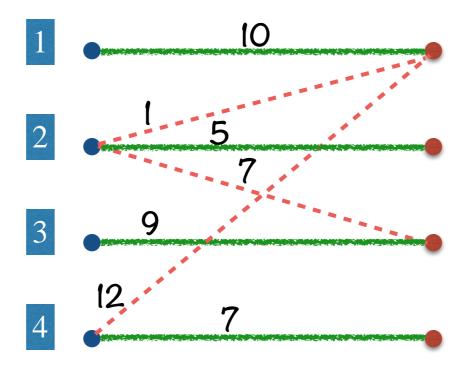
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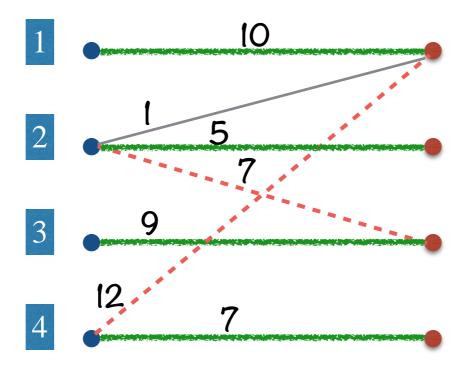
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**Theorem:** Any max-weight matching in a complete weighted bipartite graph, can always be induced by an action sequence of n agents.

- A set  $\{1, 2, \dots, n\}$  of n entities
- *Monotone* valuation functions,  $v_i : S \to \mathbb{R}_+$  for all  $i \in [n]$  (S is the set of all *ordered* subsets of  $[n] \setminus \{i\}$ )



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**Goal:** Understand the query complexity (# value queries required) of finding an action sequence  $\sigma$  that optimizes  $\sum_{i \in [n]} v_i(\sigma^i)$ , where  $\sigma^i$ : prefix of i in  $\sigma$ 

For  $\sigma = (1432)$ , the sum is  $v_1(\phi) + v_4(1) + v_3(14) + v_2(143)$ 

- Monotone valuation functions,  $v_i : \mathcal{S} \to \mathbb{R}_+$  for all  $i \in [n]$
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For instances with binary valuations and a given parameter  $\varepsilon > 0$ 

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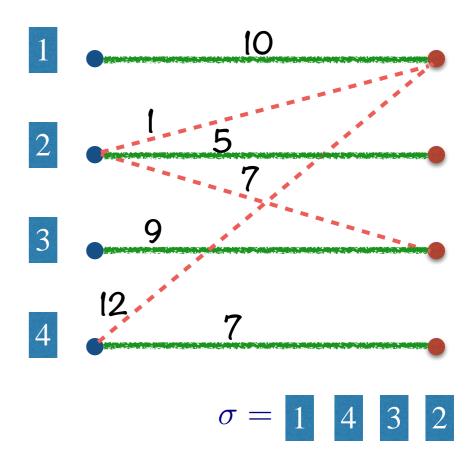
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- any *deterministic* algorithm that makes at most  $n^{1/\varepsilon}$  value queries has an *approximation ratio* of at least  $n\varepsilon$ .
- any *randomized* algorithm that makes at most  $\mathcal{O}(poly(n))$  value queries has an *approximation ratio* of at least  $n\left(\frac{\log\log n}{\log n}\right)$ .

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### Maximum weight matching:

 $v_i(S)$  = value of maximum-valued item available for i, after agents in S have picked their items.



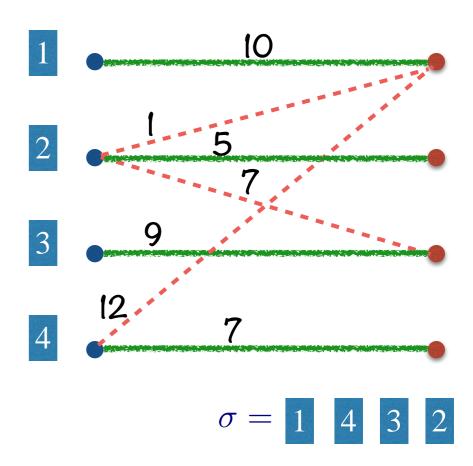
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#### Our results:

• Any max-weight matching **has** a corresponding *action sequence* of *n* agents that induces it.



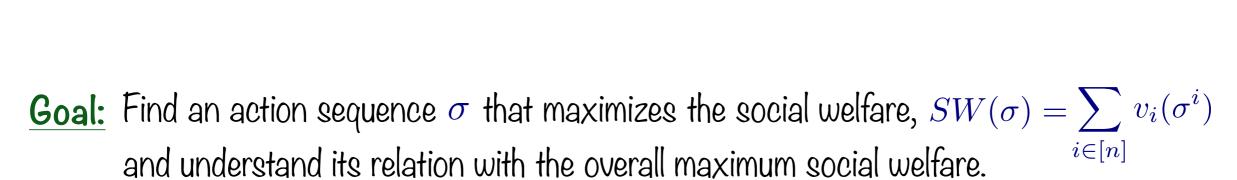
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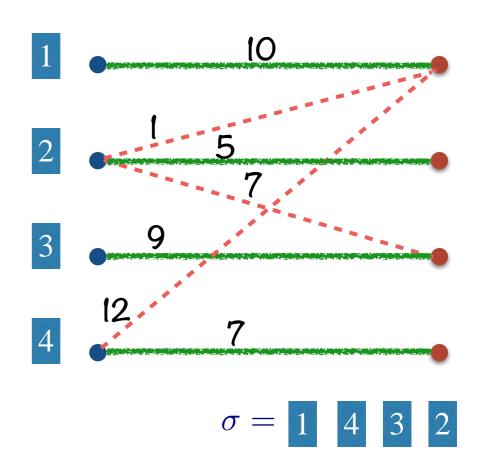
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- Any max-weight matching **has** a corresponding *action sequence* of *n* agents that induces it.
- 2-approximation polynomial-time algorithm. Can we do better?





### Maximum Satisfiability (weighted version):

 $v_i(S)$  = Maximum weight of **new** clauses satisfied by variable  $x_i$  after the variables in ordered set S have been set as T or F.

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#### Our results:

- An optimal assignment for MAX-SAT may *not* be produced from *any* action sequence of *n* variables!
- Given an instance of MAX-SAT, does there exist an action sequence for all 1's assignment?

NP-complete

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  - Maximum-weight Matching in bipartite graph
  - X Maximum-weight Matching in non-bipartite graph
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  - X Longest path with maximum-weight
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### Longest path with maximum weight:

 $v_i(S)$  = Maximum weight that node i can achieve such that the underlying structure is a union of paths

#### Our results:

- An optimal assignment for Longest-Path may not be produced from any action sequence of *n* nodes.
- For any instance of Longest-Path, there always exists an action sequence that recovers 1/2 of the optimal value.

*Conjecture:* The above factor is 2/3.

**Goal:** Find an action sequence  $\sigma$  that maximizes the social welfare,  $SW(\sigma) = \sum_{i \in [n]} v_i(\sigma^i)$  and understand its relation with the overall maximum social welfare.