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Don't Roll the Dice, Ask Twice: The Two-Query Distortion of Matching Problems and Beyond

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Abstract

1 In most social choice settings, the participating agents express their preferences
2 over the different alternatives in the form of linear orderings. While this clearly
3 simplifies preference elicitation, it inevitably leads to poor performance with respect
4 to optimizing a cardinal objective, such as the social welfare, since the values of
5 the agents remain virtually unknown. This loss in performance because of lack of
6 information is measured by the notion of *distortion*. A recent array of works put
7 forward the agenda of designing mechanisms that learn the values of the agents for
8 a small number of alternatives via *queries*, and use this limited extra information
9 to make better-informed decisions, thus improving distortion. Following this
10 agenda, in this work we focus on a class of combinatorial problems that includes
11 most well-known matching problems and several of their generalizations, such
12 as One-Sided Matching, Two-Sided Matching, General Graph Matching, and k -
13 Constrained Resource Allocation. We design *two-query* mechanisms that achieve
14 the best-possible worst-case distortion in terms of social welfare, and outperform
15 the best-possible expected distortion achieved by randomized ordinal mechanisms.

16 1 Introduction

17 The notion of *distortion* in social choice settings was defined to capture the loss in aggregate
18 objectives due to the lack of precise information about the preferences of the participants [Procaccia
19 and Rosenschein, 2006]. More concretely, the distortion was originally defined as a measure of the
20 deterioration of the total happiness of the agents when access is given only to the (ordinal) preference
21 rankings of the agents, rather than to the complete numerical (cardinal) information about their
22 preferences. This research agenda has successfully been applied to a plethora of different settings,
23 giving rise to a rich and vibrant line of work in major venues at the intersection of computer science
24 and economics. For a comprehensive overview, see the survey of Anshelevich et al. [2021].

25 Out of all of these scenarios, some of the most fundamental are *matching* problems, in which agents
26 are matched to items or other agents, aiming to maximize the *social welfare* of the matching (the total
27 value of the agents). An example is the classic *One-Sided Matching* setting [Hylland and Zeckhauser,
28 1979], where the goal is to match n items to n agents based on the preferences of the agents over
29 the items. For this setting, Filos-Ratsikas et al. [2014] showed that the best achievable distortion is

30 $\Theta(\sqrt{n})$. Importantly, this guarantee is only possible if one is allowed to use *randomization* and the
31 values of the agents are *normalized*.¹

32 Moving on from merely preference rankings, Amanatidis et al. [2021b] recently put forward the
33 agenda of studying the tradeoffs between information and efficiency, when the employed mechanisms
34 are equipped with the capability of learning the values of the agents via *queries*. The rationale is
35 that asking the agents for more detailed information about only *a few* options is still cognitively
36 not too burdensome, and could result in notable improvements on the distortion. This was indeed
37 confirmed in that work for general social choice, and in a follow-up work for several matching
38 problems [Amanatidis et al., 2021a]. Specifically, the latter work shows that it is possible to obtain
39 distortion $O(n^{1/k})$ with $O(\log n)$ queries per agent for any constant integer k , and distortion $O(1)$
40 with $O(\log^2 n)$ queries per agent. Crucially, the mechanisms achieving these bounds do not use
41 randomization nor demand the values to be normalized.

42 While these works make a significant first step, they leave some important questions unanswered.
43 The mechanisms they propose require a logarithmic number of queries to achieve *any* significant
44 improvement. Answering that many queries might still be cognitively too demanding for the agents,
45 especially when there is a large number of possible options. The main high-level motivation of this
46 research agenda, from our perspective, is that a small amount of information can be more valuable
47 than randomization. But what does really constitute a “small amount”? Ideally, we would like to
48 design mechanisms that make only a few queries per agent, independently of the size of the input
49 parameters. Since with a single query, sub-linear distortion bounds are not possible [Amanatidis
50 et al., 2021a,b], the first fundamental question that we would like to answer is the following:

51 *What is the best achievable distortion when we can only ask two queries per agent?*

52 1.1 Results and Technical Overview

53 We settle the aforementioned question for several matching problems, including *One-Sided Matching*,
54 *Two-Sided Matching*, *General Graph Matching*, and other more general graph-theoretic problems.
55 For all matching problems considered, we show that there is a deterministic mechanism that makes
56 two queries per agent, runs in polynomial time, and achieves a distortion of $O(\sqrt{n})$. This upper
57 bound is based on a novel mechanism, which we call `MATCH-TWOQUERIES` in the case of One-
58 Sided Matching (see Mechanism 1). The mechanism asks two queries per agent and computes a
59 maximum-weight matching based of the revealed values due to these queries. It starts by querying the
60 agents at the first position of their preference rankings. For the second query, it computes a certain
61 type of assignment A of agents to items (or agents to agents in more general matching problems), to
62 which we refer as a *sufficiently representative assignment*, and queries the agents about the items they
63 are assigned to in A . The existence of such an assignment for all instances is far from trivial, and one
64 of our main technical contributions is to show its existence and efficient computation for the wide
65 range of problems we consider.

66 We also show that no deterministic mechanism for these settings that makes two queries per agent
67 can achieve a distortion better than $\Omega(\sqrt{n})$. This lower bound follows by a more general construction
68 yielding a lower bound of $\Omega(n^{1/\lambda})$ on the distortion of any mechanism that makes a constant number
69 λ of queries for any of these mechanisms. This mirrors the corresponding lower bounds of Amanatidis
70 et al. [2021a] for One-Sided Matching.

71 While our results apply to general matching settings, their most impressive implications are for One-
72 Sided Matching: We show that by using only *two* cardinal queries per agent, we can match the bound
73 of $\Theta(\sqrt{n})$ for purely ordinal mechanisms, *without requiring randomization or any normalization*.
74 `MATCH-TWOQUERIES` clearly also outperforms another mechanism of Amanatidis et al. [2021a],
75 which uses two queries and achieves a distortion of $O(n^{2/3}\sqrt{\log n})$ assuming that the values of each
76 agent sum up to 1. In contrast, our mechanism works for unrestricted values, and achieves the best
77 possible distortion of $O(\sqrt{n})$ based on conceptually much simpler ideas.

78 **Results for general social choice.** Given that our approach works for a wide variety of matching
79 problems, one might be curious as to whether similar arguments could be used to show bounds for

¹Note that if any of these assumptions is relaxed, it is impossible to achieve sub-linear distortion using only ordinal information.

80 the general social choice setting, where n agents have preferences over m alternatives, and the goal is
81 to select an alternative with high social welfare; this was after all the original setting that Amanatidis
82 et al. [2021b] studied in the introduction of the information-distortion tradeoff research agenda. In
83 this setting, the situation is quite similar: the upper bounds follow by mechanisms that ask $O(\log m)$
84 queries, and nothing positive is known for smaller numbers of queries.

85 We show that a mechanism with structure similar to that of MATCH-TWOQUERIES can indeed
86 achieve a distortion of $O(\sqrt{m})$ using only two queries, subject to being able to compute a sufficiently
87 representative set of alternatives, which is analogous of the sufficiently representative assignment
88 in matching problems. It turns out that this property is very closely connected to the notion of an
89 (*approximately*) *stable committee* [Jiang et al., 2020, Cheng et al., 2020], and it follows that it exists
90 when $m = \Omega(n)$, thus allowing us to obtain the desired bound of $O(\sqrt{m})$ when this is true. This case
91 is quite natural, as it captures instances where a group of people need to decide over a large set of
92 possible options (e.g., shortlisting candidates for a job, deciding the best paper for a conference, etc.).
93 Interestingly, in contrast to the matching setting for which we show that sufficiently representative
94 assignments can be found via a simple greedy algorithm, computing sufficiently representative sets
95 of alternatives in general social choice requires rather involved techniques [Jiang et al., 2020, Cheng
96 et al., 2020]. An obvious open question here is whether the $O(\sqrt{m})$ bound can also be achieved by
97 asking only two queries when $m = o(n)$. This seems to be a more challenging task to prove; we
98 discuss it further in Section 6.

99 We also show that the bound of $O(\sqrt{m})$ is the best possible, as part of a more general distortion
100 lower bound of $\Omega(m^{1/\lambda})$ for mechanisms that make a constant number λ of queries per agent; the
101 latter result significantly improves the previously known lower bound of $\Omega(m^{1/2(\lambda+1)})$ [Amanatidis
102 et al., 2021b].

103 **Roadmap.** For the sake of presentation, we fully demonstrate how our methodology works for the
104 *One-Sided Matching* problem in Section 3. Before doing so, we start with some necessary notation
105 and terminology in Section 2. In Section 4, we briefly discuss other graph-theoretic problems for
106 which our methodology can be applied; all missing details are presented in the full version. Our
107 results for general social choice are presented in Section 5; again, the detailed proofs are deferred to
108 the full version. We conclude with some interesting open problems in Section 6.

109 1.2 Additional Related Work

110 The literature on the distortion of ordinal mechanisms in social choice is long and extensive, focusing
111 primarily on settings with normalized utilities (e.g., [Boutilier et al., 2015, Caragiannis et al., 2017,
112 Filos-Ratsikas et al., 2020]), or with metric preferences (e.g., [Anshelevich et al., 2018, Anshelevich
113 and Postl, 2017, Gkatzelis et al., 2020]); see the survey of Anshelevich et al. [2021] for a detailed
114 exposition. The distortion of mechanisms for One-Sided Matching and more general graph-theoretic
115 problems has been studied in a series of works for a variety of preference models, but solely with
116 ordinal information [Anshelevich and Zhu, 2018, Abramowitz and Anshelevich, 2018, Anshelevich
117 and Zhu, 2017, Anshelevich and Sekar, 2016, Filos-Ratsikas et al., 2014, Caragiannis et al., 2016].

118 Besides the papers of Amanatidis et al. [2021b,a], the effect of limited cardinal information on the
119 distortion has also been studied in other works [Abramowitz et al., 2019, Mandal et al., 2019, 2020,
120 Benadè et al., 2021]. Mostly related to us is the paper of Ma et al. [2021] which considered the
121 One-Sided Matching problem with a different type of cardinal queries, and showed qualitatively
122 similar results to Amanatidis et al. [2021a] for Pareto optimality (rather than social welfare).

123 Our upper bound for the general social choice setting makes use of the results of Cheng et al. [2020]
124 and Jiang et al. [2020] for (approximately) stable committees (see also Aziz et al. [2017]); a stable
125 committee is very similar to a representative set of alternatives in our terminology. Cheng et al.
126 [2020] showed that, while *exactly* stable committees do not always exist [Jiang et al., 2020], finding
127 a random version of such committees, coined *stable lotteries*, is always possible and can be done
128 in polynomial time. Later on, Jiang et al. [2020] showed that, via an intricate derandomization
129 process, stable lotteries can yield approximately stable committees, where the approximation is a
130 small multiplicative constant; for our purposes, this is sufficient. Interestingly, very recently, Ebadian
131 et al. [2022] used stable lotteries to construct a purely ordinal randomized social choice mechanism
132 that achieves the best possible distortion under unit-sum normalized values.

133 2 Preliminaries on One-Sided Matching, Mechanisms, and Distortion

134 In One-Sided Matching, there is a set \mathcal{N} of n agents and a set \mathcal{A} of n items. Each agent $i \in \mathcal{N}$ has
 135 a value $v_{i,j}$ for each item $j \in \mathcal{A}$; we refer to the matrix $\mathbf{v} = (v_{i,j})_{i \in \mathcal{N}, j \in \mathcal{A}}$ as the *valuation profile*.
 136 A (one-sided) matching $X : \mathcal{N} \rightarrow \mathcal{A}$ is a bijection from the set of agents to the set of items, i.e.,
 137 each agent is *matched* to a different single item. Our goal is to choose a matching X to maximize
 138 the *social welfare*, defined as the total value of the agents for the items they have been matched to
 139 according to X : $\text{SW}(X|\mathbf{v}) = \sum_{i \in \mathcal{N}} v_{i,X(i)}$. Usually \mathbf{v} is clear from the context, so we then simplify
 140 our notation to $\text{SW}(X)$ for the social welfare of matching X .

141 As in most of the related literature, we assume that we do not have access to the valuation profile of
 142 the agents. Instead, we have access to the *ordinal preference* \succ_i of each agent i , which is derived
 143 from the values of the agent for the items, such that $a \succ_i b$ if $v_{i,a} \geq v_{i,b}$; we refer to the vector
 144 $\succ_{\mathbf{v}} = (\succ_i)_{i \in \mathcal{N}}$ as the *ordinal profile* of the agents.

145 A *mechanism* \mathcal{M} in our setting operates as follows: It takes as input the ordinal profile $\succ_{\mathbf{v}}$ of the
 146 agents. It then makes a number $\lambda \geq 1$ of *queries* per agent to learn part of the valuation profile. In
 147 particular, each agent is asked her value for at most λ items. Given the answers to the queries, and
 148 also using the ordinal profile, \mathcal{M} computes a feasible solution (here a matching) $\mathcal{M}(\succ_{\mathbf{v}})$.

149 In this paper we focus on mechanisms that make two queries per agent, i.e., $\lambda = 2$, and compute a
 150 solution of high social welfare. However, pinpointing an (approximately) optimal solution without
 151 having full access to the valuation profile of the agents can be quite challenging; the ordinal profile may
 152 be consistent with a huge number of different valuation profiles, even after the queries. Nevertheless,
 153 we aim to achieve the best asymptotic performance possible, as quantified by the notion of *distortion*.

Definition 1. The *distortion* of a mechanism \mathcal{M} is the worst-case ratio (over the set \mathcal{V} of all valuation profiles in instances with n agents and n items) between the optimal social welfare and the social welfare of the solution chosen by \mathcal{M} :

$$\text{dist}(\mathcal{M}) = \sup_{\mathbf{v} \in \mathcal{V}, |\mathcal{N}|=n, |\mathcal{A}|=n} \frac{\max_{X \in \mathcal{X}} \text{SW}(X|\mathbf{v})}{\text{SW}(\mathcal{M}(\succ_{\mathbf{v}})|\mathbf{v})},$$

154 where \mathcal{X} is the set of all matchings between \mathcal{N} and \mathcal{A} .

155 3 An Optimal Two-Query Mechanism

156 In this section, we present a mechanism for One-Sided Matching that makes two queries per agent
 157 and achieves a distortion of $O(\sqrt{n})$. Due to the lower bound of $\Omega(n^{1/\lambda})$ on the distortion of
 158 any mechanism that can make up to λ queries per agent shown by Amanatidis et al. [2021a], our
 159 mechanism is asymptotically best possible when $\lambda = 2$.

160 Without any normalization assumptions about the valuation functions, it is easy to see that a mecha-
 161 nism cannot have *any* guarantee unless it queries every agent about her favorite item. However, there
 162 are no obvious criteria suggesting how to use the *second* query. Before we present the details of
 163 our mechanism, we define a particular type of assignment of agents to items that will be critical for
 164 deciding where to make the second queries.

165 **Definition 2.** A many-to-one assignment A of agents to items (i.e., each agent is assigned to one
 166 item, but multiple agents may be assigned to the same item) is a *sufficiently representative assignment*
 167 if (a) For every item $j \in \mathcal{A}$, there are at most \sqrt{n} agents assigned to j ; (b) For any matching X , there
 168 are at most \sqrt{n} agents that prefer the item they are matched to in X to the item they are assigned to
 169 in A .

170 A natural question at this point is whether a sufficiently representative assignment exists for any
 171 instance, and if so, whether it can be efficiently computed. In Section 3.2, we present a simple
 172 polynomial-time algorithm for this task.

173 3.1 The Mechanism

174 Our mechanism MATCH-TWOQUERIES (Mechanism 1) first queries every agent about her favorite
 175 item. Next, it computes a sufficiently representative assignment A (see Section 3.2) and queries each

176 agent about the item she is assigned to in A . Finally, it outputs a matching that maximizes the social
 177 welfare based *only* on the revealed values (all other values are set to 0). Although computational
 178 efficiency is not our primary focus here, if we use a polynomial-time algorithm for computing a
 179 maximum weight matching (e.g., the Hungarian method [Kuhn, 1956]), MATCH-TWOQUERIES runs
 180 in polynomial time as well.

Mechanism 1 MATCH-TWOQUERIES($\mathcal{N}, \mathcal{A}, \succ_{\mathbf{v}}$)

- 1: Query each $i \in \mathcal{N}$ about her favorite item w.r.t. \succ_i
 - 2: Compute a *sufficiently representative assignment* A
 - 3: Query each agent about the item she is assigned to in A
 - 4: Set all non-revealed values to 0
 - 5: **return** a maximum-weight perfect matching Y
-

181 Of course, if we compare the mechanism’s behaviour to an actual optimal matching X , we expect to
 182 see that we asked agents about the “wrong” items most of the time: for many agents the second query
 183 is about better items than what they are matched to in X , and for many agents it is about worse items.
 184 The desired bound of $O(\sqrt{n})$ on the distortion of MATCH-TWOQUERIES is established by balancing
 185 the loss due to each of these two cases.

186 **Theorem 1.** MATCH-TWOQUERIES has distortion $O(\sqrt{n})$.

187 *Proof.* Consider any instance with valuation profile \mathbf{v} . Let Y be the matching computed by the
 188 MATCH-TWOQUERIES mechanism when given as input the ordinal profile $\succ_{\mathbf{v}}$, and let X be an
 189 optimal matching. Let $\text{SW}_R(Y)$ be the *revealed* social welfare of Y , i.e., the total value of the agents
 190 for the items they are matched to in Y and for which they *were queried* about. We will show that
 191 $\text{SW}(X) \leq (1 + 2\sqrt{n}) \cdot \text{SW}_R(Y)$, and then use the fact that $\text{SW}(Y) \geq \text{SW}_R(Y)$ to directly get the
 192 desired bound on the distortion.

We can write the optimal social welfare as

$$\text{SW}(X) = \text{SW}_R(X) + \text{SW}_C(X),$$

where $\text{SW}_R(X)$ is the revealed social welfare of X that takes into consideration only the values revealed by the queries, whereas $\text{SW}_C(X)$ is the *concealed* social welfare of X that takes into consideration only the values not revealed by any queries. Since Y is the matching that maximizes the social welfare based only on the revealed values, we have that

$$\text{SW}_R(X) \leq \text{SW}_R(Y). \quad (1)$$

To bound the quantity $\text{SW}_C(X)$, let S be the set of agents who are not queried about the items they are matched to in X . We partition S into the following two subsets consisting of agents for whom the second query of the mechanism is used to ask about items that the agents consider *better* or *worse* than the items they are matched to in X . Recall that an agent i is queried about the item $A(i)$ she is assigned to according to the sufficiently representative assignment A . So, S is partitioned into

$$S^{\geq} = \{i \in S : v_{i,A(i)} \geq v_{i,X(i)}\}, \quad \text{and} \quad S^{<} = \{i \in S : v_{i,A(i)} < v_{i,X(i)}\}.$$

Given these sets, we can now write

$$\text{SW}_C(X) = \text{SW}_C^{\geq}(X) + \text{SW}_C^{<}(X),$$

where

$$\text{SW}_C^{\geq}(X) = \sum_{i \in S^{\geq}} v_{i,X(i)}$$

and

$$\text{SW}_C^{<}(X) = \sum_{i \in S^{<}} v_{i,X(i)}.$$

For every item j , let $S_j^{\geq} = \{i \in S^{\geq} : A(i) = j\}$ be the set of all agents in S^{\geq} that are queried about j by the mechanism using the second query. Thus, $S^{\geq} = \bigcup_{j \in \mathcal{A}} S_j^{\geq}$. Since A is a sufficiently

representative assignment, $|S_j^{\geq}| \leq \sqrt{n}$ for every item j . Therefore,

$$\begin{aligned}
\text{SW}_C^{\geq}(X) &= \sum_{j \in \mathcal{A}} \sum_{i \in S_j^{\geq}} v_{i,X(i)} \leq \sum_{j \in \mathcal{A}} \sum_{i \in S_j^{\geq}} v_{i,j} \\
&\leq \sum_{j \in \mathcal{A}} |S_j^{\geq}| \cdot \max_{i \in S_j^{\geq}} v_{i,j} \leq \sqrt{n} \sum_{j \in \mathcal{A}} \max_{i \in S_j^{\geq}} v_{i,j} \\
&\leq \sqrt{n} \cdot \text{SW}_R(Y).
\end{aligned} \tag{2}$$

193 For the last inequality, recall that A assigns every agent to a single item, and thus the sets S_j^{\geq} are
194 disjoint. In addition, the values of all the agents for the items they are matched to according to A
195 are revealed by the second query of the mechanism. Since we can match the agent in S_j^{\geq} that has
196 the maximum value for j to j , and Y maximizes the social welfare based on the revealed values, we
197 obtain that $\text{SW}_R(Y) \geq \sum_{j \in \mathcal{A}} \max_{i \in S_j^{\geq}} v_{i,j}$.

Next consider the quantity $\text{SW}_C^{\leq}(X)$. By the fact that A is a sufficiently representative assignment, it follows that $|S^{\leq}| \leq \sqrt{n}$; otherwise X would constitute a matching for which there are strictly more than \sqrt{n} agents that prefer the item they are matched to in X to the item they are assigned to by A . Combined with the fact that all agents are queried at the first position of their ordinal preferences, we obtain

$$\begin{aligned}
\text{SW}_C^{\leq}(X) &= \sum_{i \in S^{\leq}} v_{i,X(i)} \leq \sum_{i \in S^{\leq}} \max_{j \in \mathcal{A}} v_{i,j} \\
&\leq |S^{\leq}| \cdot \max_{i \in S^{\leq}} \max_{j \in \mathcal{A}} v_{i,j} \\
&\leq \sqrt{n} \cdot \text{SW}_R(Y).
\end{aligned} \tag{3}$$

198 The bound follows directly by (1), (2) and (3). \square

199 3.2 Computing Sufficiently Representative Assignments

200 To establish the correctness of MATCH-TWOQUERIES, we need to ensure that a sufficiently rep-
201 resentative assignment exists for any ordinal profile and that it can be computed efficiently. For
202 this we present a simple polynomial time algorithm, which we call \sqrt{n} -SERIAL DICTATORSHIP
203 (Mechanism 2). This algorithm creates \sqrt{n} copies of each item and then runs a serial dictatorship
204 algorithm, which first fixes an ordering of the agents and then assigns each agent to her most pre-
205 ferred available item according to her ordinal preference. It is easy to see that the running time of
206 \sqrt{n} -SERIAL DICTATORSHIP is polynomial (in particular, it is $O(n^{1.5})$).

Mechanism 2 \sqrt{n} -SERIAL DICTATORSHIP($\mathcal{N}, \mathcal{A}, \succ_v$)

- 1: Let \mathcal{B} be a multiset containing \sqrt{n} copies of each $j \in \mathcal{A}$
 - 2: **for** every agent $i \in \mathcal{N}$ **do**
 - 3: Let α_i be a most preferred item of agent i in \mathcal{B}
 - 4: Remove α_i from \mathcal{B}
 - 5: **end for**
 - 6: **return** $A = (\alpha_i)_{i \in \mathcal{N}}$
-

207 **Theorem 2.** *For any instance, the output of \sqrt{n} -SERIAL DICTATORSHIP is a sufficiently representa-*
208 *tive assignment.*

209 *Proof.* Let A be the output of the algorithm. During the execution of the algorithm, whenever every
210 copy of an item has been assigned, we say that such an item is *exhausted*. Assume, towards a
211 contradiction, that A is not a sufficiently representative assignment. By construction, every item
212 is assigned to at most \sqrt{n} agents, so there must be a matching violating the second condition of
213 Definition 2. That is, there is a subset of items \mathcal{A}' and a subset of agents \mathcal{N}' , such that $|\mathcal{A}'| = |\mathcal{N}'| >$
214 \sqrt{n} , and each agent $i \in \mathcal{N}'$ prefers to be assigned to a distinct item $\beta_i \in \mathcal{A}'$ (i.e., $\beta_i \neq \beta_j$ for $i \neq j$)
215 instead of the item she is assigned to in A .

216 Consider any agent $i \in \mathcal{N}'$. The fact that this agent was not assigned to β_i by the algorithm implies
 217 that when the agent was picked, item β_i was exhausted. Since this is true for all agents in \mathcal{N}' , at
 218 the end of the algorithm all items of \mathcal{A}' must be exhausted. However, an item is exhausted when all
 219 its \sqrt{n} copies have been assigned and there are n agents in total, so we can only have as many as
 220 $n/\sqrt{n} = \sqrt{n}$ exhausted items. This means that $|\mathcal{A}'| \leq \sqrt{n}$, a contradiction. \square

221 4 Further Combinatorial Optimization Problems

222 The approach of Section 3 can be extended to a much broader class of graph-theoretic problems.
 223 Informally, it works when the objective is to maximize an additive function over subgraphs of a given
 224 graph which contain all “small” matchings and have constant maximum degree. To make things more
 225 concrete, given a constant $k \in \mathbb{N}$ and a weighted graph G on n nodes, we say that a family \mathcal{F} of
 226 subgraphs of G is a *matching extending k -family* if:

- 227 • Graphs in \mathcal{F} have maximum degree at most k ;
- 228 • For any matching M of G of size at most $\lfloor n/3k \rfloor$, there is a graph in \mathcal{F} containing M .

229 Clearly, the set of matchings of a graph is a matching extending 1-family, but it is not hard to see that
 230 different constraints are also captured, e.g., the set of subgraphs that are unions of disjoint paths and
 231 even cycles is a matching extending 2-family.

232 We are ready to introduce the general problem that we tackle here. As this is a special case of the
 233 class of problems captured by Ordinal-Max-on-Graphs (introduced by Amanatidis et al. [2021a]), we
 234 use a similar formulation and name.

235 **Ordinal- k -Max-on-Graphs:** Fix a constant $k \in \mathbb{N}$ and let \mathcal{N} be a set of n agents. Every agent
 236 $i \in \mathcal{N}$ has a (private) valuation function $v_i : \mathcal{N} \rightarrow \mathbb{R}_{\geq 0}$. We are given a graph $G = (\mathcal{N}, E)$, an
 237 ordinal profile $\succ_{\mathbf{v}} = (\succ_i)_{i \in \mathcal{N}}$ consistent with $\mathbf{v} = (v_i)_{i \in \mathcal{N}}$, and a concise description of a matching
 238 extending k -family \mathcal{F} . The goal is to find some $H \in \mathcal{F}$ that maximizes $\sum_{\{i,j\} \in E(H)} v_i(j)$.

239 Besides One-Sided Matching, a large number of problems that are relevant to computational social
 240 choice are captured by Ordinal- k -Max-on-Graphs. We give a few examples:

241 **General Graph k -Matching:** Given a graph G , find a k -matching of maximum value, i.e., \mathcal{F} contains
 242 the subgraphs of G of maximum degree at most k and is a matching extending k -family. The problem
 243 becomes the **General Graph Matching** problem when $k = 1$; by also assuming that G is bipartite,
 244 we have the celebrated **Two-Sided Matching** problem [Gale and Shapley, 1962, Roth and Sotomayor,
 245 1992].

246 **k -Constrained Resource Allocation:** Given a bipartite graph $G = (\mathcal{N}_1 \cup \mathcal{N}_2, E)$, assign at most k
 247 nodes of \mathcal{N}_2 to each node in \mathcal{N}_1 so that the total value of the corresponding edges is maximized. That
 248 is, \mathcal{F} contains all 1-to- k matchings of G and is again a matching extending k -family. The problem
 249 for $k = 1$ becomes One-Sided Matching. Here \mathcal{N} is partitioned into the set \mathcal{N}_1 of “actual agents”
 250 and the set \mathcal{N}_2 of “items”, and $v_i(j)$ can be strictly positive only for $i \in \mathcal{N}_1, j \in \mathcal{N}_2$.

251 **Short Cycle Packing:** Given an integer ℓ and a weighted complete graph G , find a collection of
 252 node-disjoint cycles of length at most ℓ so that their total weight is maximized. Here, \mathcal{F} is a matching
 253 extending 3-family (note that $k = 2$ for any ℓ). It is worth mentioning that Short Cycle Packing is *not*
 254 a generalization of any of the matching problems above. It is also closely related to Clearing Kidney
 255 ℓ -Exchanges [Abraham et al., 2007].

256 It is straightforward to extend the notion of distortion (Definition 1) for Ordinal- k -Max-on-Graphs
 257 by taking the supremum over all instances of a certain size n and letting \mathcal{X} be the set of feasible
 258 solutions of each instance.

259 As already discussed, for One-Sided Matching there is a lower bound of $\Omega(n^{1/\lambda})$ on the distortion of
 260 deterministic mechanisms that make up to $\lambda \geq 1$ queries per agent [Amanatidis et al., 2021a]. We can
 261 get the analogous result for *any* problem captured by Ordinal- k -Max-on-Graphs using a reduction
 262 that preserves distortion up to a constant factor. Further, by appropriately using the ideas of Section 3,
 263 we show that this lower bound is asymptotically tight for the case of two queries. For the statements
 264 of the theorems below, we assume that $k \in \mathbb{N}$ is a constant and that for every (general / bipartite)
 265 graph G , a matching extending k -family $\mathcal{F}(G)$ is specified.

266 **Theorem 3.** *No deterministic mechanism using at most $\lambda \geq 1$ queries per agent can achieve a*
 267 *distortion better than $\Omega(n^{1/\lambda})$ for Ordinal- k -Max-on-Graphs.*

268 For the positive result below, we rely on the existence of a *generalization* of sufficiently representative
 269 assignments. While the construction is very similar, the counting argument here is less intuitive
 270 compared to the case of One-Sided Matching.

271 **Theorem 4.** *There is a deterministic mechanism for Ordinal- k -Max-on-Graphs which uses at most*
 272 *two queries per agent and has distortion $O(\sqrt{n})$.*

273 Our mechanisms run in polynomial time whenever there is a polynomial-time algorithm for the full
 274 information version of the corresponding optimization problem. Luckily, all variants of matching
 275 problems we presented above can be solved efficiently by Edmond’s algorithm [Edmonds, 1965] or
 276 its extensions [Marsh III, 1979].

277 **Corollary 5.** *There are deterministic polynomial-time mechanisms for General Graph Matching,*
 278 *Two-Sided Matching, General Graph k -Matching, and k -Constrained Resource Allocation which all*
 279 *use at most two queries per agent and have distortion $O(\sqrt{n})$.*

280 5 Towards Tight Bounds for General Social Choice

281 Here we consider the general social choice setting where a set \mathcal{N} of n agents have preferences
 282 over a set \mathcal{A} of m alternatives. As in the One-Sided Matching problem, there is a valuation profile
 283 $\mathbf{v} = (v_{i,j})_{i \in \mathcal{N}, j \in \mathcal{A}}$ specifying the non-negative value that each agent i has for every alternative j .
 284 The goal is to choose a single alternative $x \in \mathcal{A}$ to maximize the social welfare, that is, the total value
 285 of the agents for x : $\text{SW}(x|\mathbf{v}) = \sum_{i \in \mathcal{N}} v_{i,x}$. Again, when \mathbf{v} is clear from context, we will drop it
 286 from notation. Similarly to One-Sided Matching and the problems discussed in the previous section,
 287 \mathbf{v} is unknown, and we are only given access to the ordinal profile $\succ_{\mathbf{v}}$ that is induced by \mathbf{v} . Social
 288 choice mechanisms must decide a single alternative based only on $\succ_{\mathbf{v}}$ and the values they can learn
 289 by making a small number of queries. The notion of distortion (Definition 1) can be extended for
 290 this setting as well, by taking the supremum over all instances with n agents and m alternatives, and
 291 letting \mathcal{X} be the set \mathcal{A} of alternatives.

292 For this general social choice setting, Amanatidis et al. [2021b] showed a lower bound of
 293 $\Omega(m^{1/(2(\lambda+1))})$ on the distortion of mechanisms that make at most $\lambda \geq 1$ queries per agent.
 294 We improve this result by showing a lower bound of $\Omega(m^{1/\lambda})$ for any constant λ . The full proof of
 295 the following theorem can be found in the full version.

296 **Theorem 6.** *In the social choice setting, the distortion of any deterministic mechanism that makes at*
 297 *most a constant number $\lambda \geq 1$ of queries per agent is $\Omega(m^{1/\lambda})$.*

298 *Proof sketch.* Let \mathcal{M} be an arbitrary mechanism that makes at most $\lambda \geq 1$ queries per agent. Consider
 299 the following instance with n agents and $m = n$ alternatives. We assume that m satisfies the condition
 300 $m \geq \frac{1}{2} \sum_{\ell=1}^{\lambda} m^{(\lambda-\ell+1)/\lambda} + 2$, and also that it is superconstant; otherwise the theorem holds trivially.
 301 We partition the set of alternatives \mathcal{A} into $\lambda + 2$ sets $A_1, A_2, \dots, A_{\lambda+1}, A_{\lambda+2}$, such that

- 302 • $|A_\ell| = \frac{1}{2} m^{(\lambda-\ell+1)/\lambda}$ for $\ell \in [\lambda]$;
- 303 • $|A_{\lambda+1}| = 2$;
- 304 • $|A_{\lambda+2}| = m - \frac{1}{2} \sum_{\ell=1}^{\lambda} m^{(\lambda-\ell+1)/\lambda} - 2$.

305 The ordinal profile has the following properties:

- 306 • For every $\ell \in [\lambda + 1]$, each alternative $j \in A_\ell$ is ranked at position ℓ by a set $T_{j,\ell}$ of
 307 $\frac{m}{|A_\ell|} = \Theta(m^{(\ell-1)/\lambda})$ agents.
- 308 • For every $\ell \in [\lambda]$, every pair of agents that rank the same alternative in A_ℓ at position ℓ , rank
 309 the same alternative in $A_{\ell+1}$ at position $\ell + 1$.

310 • For every agent, the alternatives that she does not rank in the first $\lambda + 1$ positions are ranked
 311 arbitrarily from position $\lambda + 2$ to m .

312 For every agent i , a query of \mathcal{M} for alternative j reveals a value of $m^{-\ell/\lambda}$ if i ranks j at position
 313 $\ell \in [\lambda + 1]$, and a value of 0 if i ranks j at any other position.

314 Let y be the alternative that \mathcal{M} chooses as the winner for this instance. No matter the choice of y , we
 315 will define the cardinal profile so that it is consistent to the information revealed by the queries of \mathcal{M} ,
 316 and the values of the agents for alternative y are also consistent to the information that would have
 317 been revealed, irrespective of whether those values have actually been revealed. That is, any agent
 318 has a value of $m^{-\ell/\lambda}$ for y if she ranks y at position $\ell \in [\lambda + 1]$, and a value of 0 if she ranks y at any
 319 other position. Hence, the social welfare of y is $\Theta(m^{(\ell-1)/\lambda}) \cdot m^{-\ell/\lambda} = \Theta(m^{-1/\lambda})$ if $y \in A_\ell$ for
 320 $\ell \in [\lambda + 1]$, or 0 if $y \in A_{\lambda+2}$. Consequently, to show the desired bound of $\Omega(m^{1/\lambda})$ on the distortion
 321 of \mathcal{M} , it suffices to assume that $y \in A_\ell$ for some $\ell \in [\lambda + 1]$, and prove that the values of the agents
 322 that have not been revealed and do not correspond to alternative y can always be defined such that
 323 there exists an alternative $x \neq y$ with social welfare $\Omega(1)$. The remaining details showing that such
 324 an x always exists can be found in the full version. \square

325 Our approach for all the problems discussed in the previous sections can also be applied to the much
 326 more general social choice setting, *subject to* being able to compute a particular set of alternatives.

327 **Definition 3.** Let $c \geq 1$ be any constant. A subset of alternatives $B \subseteq \mathcal{A}$ with $|B| \leq c \cdot \sqrt{m}$ is a
 328 *sufficiently representative set* if, for every alternative $j \in \mathcal{A}$, at most \sqrt{m} agents prefer j over their
 329 favorite alternative in B .

330 We now present a mechanism that works *under the assumption* that sufficiently representative sets of
 331 alternatives can be (efficiently) computed; we discuss this assumption right after the statement of
 332 Theorem 7.

Mechanism 3 SC-TWOQUERIES($\mathcal{N}, \mathcal{A}, \succ_v$)

- 1: Query each agent about her favorite alternative
 - 2: Compute a sufficiently representative set B
 - 3: Query each agent for her favorite alternative in B
 - 4: For every $j \in \mathcal{A}$, compute the revealed welfare $\text{SW}_R(j)$
 - 5: **return** $y \in \arg \max_{j \in \mathcal{A}} \text{SW}_R(j)$
-

333 In particular, SC-TWOQUERIES (Mechanism 3) first queries each agent about her overall favorite
 334 alternative (the one ranked first). Then, given a sufficiently representative set of alternatives B , it
 335 queries each agent for her favorite alternative in B . Given the answers to these two queries per agent,
 336 the mechanism outputs an alternative that maximizes the *revealed* social welfare which is based only
 337 on the values learned from the queries.

338 **Theorem 7.** *The mechanism SC-TWOQUERIES has distortion $O(\sqrt{m})$, when restricted to the social
 339 choice instances for which a sufficiently representative set of alternatives exists.*

340 A sufficiently representative set of alternatives trivially exists when m is much larger than n (namely,
 341 when $m = \Omega(n^2)$). In contrast, when m is much smaller than n , sufficiently representative sets of
 342 alternatives do not always exist.² Jiang et al. [2020] showed the following useful result:

343 **Theorem 8** ([Jiang et al., 2020]). *For any $\xi \in [n]$, there exists a set S of alternatives with $|S| \leq$
 344 $16 \cdot n/\xi$ such that for every $j \in \mathcal{A}$, there are at most ξ agents that prefer j over their favorite
 345 alternative in S .*

346 A set S as in the theorem above is called an *approximately stable committee* Cheng et al. [2020],
 347 Jiang et al. [2020]. Clearly, when $m = \Omega(n)$ and $\xi = \sqrt{n}$, an approximately stable committee is also

²For example, for any $k > \sqrt{m}$, consider an instance with $n = k \cdot m!$ agents, such that for each possible ordering of the m alternatives there are exactly k agents that have it as their preference. Then, for any subset B of at most \sqrt{m} alternatives and any alternative $j \in \mathcal{A} \setminus B$, there are at least $k > \sqrt{m}$ agents that prefer j over any alternative in B .

348 a sufficiently representative set with $c = 16$. Therefore, combining Theorems 7 and 8, we obtain the
349 following.

350 **Corollary 9.** *When $m = \Omega(n)$, SC-TWOQUERIES has distortion $O(\sqrt{m})$.*

351 **6 Conclusion and Open Problems**

352 In this paper, we showed that for a large class of problems, which includes One-Sided Matching and
353 many other well-studied graph-theoretic problems, it is possible to achieve a distortion of $O(\sqrt{n})$
354 using a deterministic mechanism that makes at most two queries per agent, and that this is best
355 possible asymptotically. Our whole methodology is based on computing assignments of agents
356 to items or other agents that exhibit a very particular structure. In addition, in the social choice
357 setting, when $m = \Omega(n)$, sets of alternatives with analogous properties can be computed, and our
358 methodology yields a two-query mechanism with best possible distortion for this setting as well.

359 It is an interesting open problem to design a mechanism that makes two queries and achieves the
360 best possible distortion of $O(\sqrt{m})$ when $m = o(n)$, or show that this is impossible. We suspect that
361 to obtain a positive result one would need to come up with an adaptive mechanism, which decides
362 where to ask each query based on the answers to all previous ones. Another question, about any of
363 the problems we considered, is whether one can design mechanisms that make at most a constant
364 $\lambda \geq 3$ queries per agent and their distortion matches the lower bound of $\Omega(n^{1/\lambda})$ (or, in the case of
365 social choice, $\Omega(m^{1/\lambda})$).

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