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# Supplementary Material

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## 1 Upper Bounds

### 1.1 Deterministic Elicitation, Deterministic Aggregation

**Theorem 1.** For  $t \in [m] \setminus \{1\}$  and  $\ell \in \mathbb{N}$ , we have

$$C(\text{PREFTHRESHOLD}_{t,\ell}) = \log \left[ \binom{m}{t} \cdot (\ell + 1)^t \right] = \Theta \left( t \log \frac{m(\ell + 1)}{t} \right),$$

$$\text{dist}(\text{PREFTHRESHOLD}_{t,\ell}) = O \left( m^{1+2/\ell} / t \right).$$

For  $t = 1$  and  $\ell \in \mathbb{N}$ , we have

$$C(\text{PREFTHRESHOLD}_{1,\ell}) = \log(m\ell), \quad \text{dist}(\text{PREFTHRESHOLD}_{1,\ell}) = O \left( m^{1+1/\ell} \right).$$

*Proof.* It is evident that the number of possible responses that a voter can provide under  $\text{PREFTHRESHOLD}_{t,\ell}$  is  $\binom{m}{t} \cdot (\ell + 1)^t$  if  $t > 1$ , and  $m\ell$  if  $t = 1$ . Taking the logarithm of this gives us the desired communication complexity.

We now establish the distortion of  $\text{PREFTHRESHOLD}_{t,\ell}$ . Let  $\vec{v} = (v_1, \dots, v_n)$  be the underlying valuations of voters. For alternative  $a \in A$ , recall that  $\text{sw}(a, \vec{v}) = \sum_{i \in N} v_i(a)$ , and

$$\widehat{\text{sw}}(a) = \sum_{i \in N} \widehat{v}_i(a) = \sum_{i \in N: a \in S_i^t} \widehat{v}_i(a) = \sum_{i \in N: a \in S_i^t} U_{p_i, a}.$$

Let  $\widehat{a} \in \arg \max_{a \in A} \widehat{\text{sw}}(a)$  be the alternative chosen by the rule, and let  $a^* \in \arg \max_{a \in A} \text{sw}(a, \vec{v})$  be an alternative maximizing social welfare.

We begin by finding an upper bound on  $\text{sw}(a^*, \vec{v})$  in terms of  $\widehat{\text{sw}}(\widehat{a})$ .

$$\begin{aligned} \text{sw}(a^*, \vec{v}) &= \sum_{i \in N} v_i(a^*) = \sum_{i \in N: a^* \in S_i^t} v_i(a^*) + \sum_{i \in N: a^* \notin S_i^t} v_i(a^*) \\ &\leq \sum_{i \in N: a^* \in S_i^t} v_i(a^*) + \sum_{i \in N: a^* \notin S_i^t} \left( \frac{\sum_{a \in S_i^t} v_i(a)}{t} \right) \\ &\leq \sum_{i \in N: a^* \in S_i^t} \widehat{v}_i(a^*) + \frac{\sum_{a \in A \setminus \{a^*\}} \sum_{i \in N: a^* \notin S_i^t \wedge a \in S_i^t} \widehat{v}_i(a)}{t} \\ &\leq \widehat{\text{sw}}(a^*) + \frac{\sum_{a \in A \setminus \{a^*\}} \widehat{\text{sw}}(a)}{t} \leq \widehat{\text{sw}}(\widehat{a}) + \frac{(m-1) \cdot \widehat{\text{sw}}(\widehat{a})}{t} = \frac{m+t-1}{t} \cdot \widehat{\text{sw}}(\widehat{a}), \end{aligned} \tag{1}$$

where the third transition holds because for every  $i \in N$  with  $a^* \notin S_i^t$  and every  $a \in S_i^t$ , we have  $v_i(a^*) \leq v_i(a)$ ; the fourth transition holds because for every  $i \in N$  and  $a \in S_i^t$ ,  $v_i(a) \leq \widehat{v}_i(a)$ ; the fifth transition follows from the definition of  $\widehat{\text{sw}}$ ; and the sixth transition holds because  $\widehat{a}$  is a maximizer of  $\widehat{\text{sw}}$ .

We now establish the distortion for  $t > 1$ . The first step is to derive an upper bound on  $\widehat{\text{sw}}(\widehat{a})$  in terms of  $\text{sw}(\widehat{a}, \vec{v})$ . Our bucketing implies that for all  $i \in N$  and  $a \in S_i^t$ , we have  $v_i(a) \leq \widehat{v}_i(a) \leq m^{2/\ell} v_i(a) + \frac{1}{m^2}$ . Using this, we can derive the following.

$$\widehat{\text{sw}}(\widehat{a}) = \sum_{i \in N: \widehat{a} \in S_i^t} \widehat{v}_i(\widehat{a}) \leq \sum_{i \in N: \widehat{a} \in S_i^t} \left( m^{2/\ell} v_i(\widehat{a}) + \frac{1}{m^2} \right) \leq m^{2/\ell} \text{sw}(\widehat{a}, \vec{v}) + \frac{n}{m^2}. \quad (2)$$

Next, we derive a lower bound on  $\widehat{\text{sw}}(\widehat{a})$ , which helps establish a lower bound on  $\text{sw}(\widehat{a}, \vec{v})$ . Note that for each voter  $i \in N$ ,  $\sum_{a \in S_i^t} v_i(a) \geq t/m$ . Hence,

$$\sum_{a \in A} \widehat{\text{sw}}(a) = \sum_{i \in N} \sum_{a \in S_i^t} \widehat{v}_i(a) \geq \sum_{i \in N} \sum_{a \in S_i^t} v_i(a) \geq \frac{n \cdot t}{m}.$$

Because  $\widehat{a}$  is a maximizer of  $\widehat{\text{sw}}$ , this yields  $\widehat{\text{sw}}(\widehat{a}) \geq n \cdot t/m^2$ . Substituting this into Equation (2), we get

$$\frac{n}{m^2} + \text{sw}(\widehat{a}, \vec{v}) \cdot m^{2/\ell} \geq \widehat{\text{sw}}(\widehat{a}) \geq \frac{n \cdot t}{m^2} \Rightarrow \text{sw}(\widehat{a}, \vec{v}) \geq \frac{n \cdot (t-1)}{m^2} \cdot m^{-2/\ell} \geq \frac{n}{m^2} \cdot m^{-2/\ell}. \quad (3)$$

Applying Equations (1), (2), and (3) in this order, we have

$$\begin{aligned} \frac{\text{sw}(a^*, \vec{v})}{\text{sw}(\widehat{a}, \vec{v})} &\leq \frac{m+t-1}{t} \cdot \frac{\widehat{\text{sw}}(\widehat{a})}{\text{sw}(\widehat{a}, \vec{v})} \leq \frac{m+t-1}{t} \cdot \left( m^{2/\ell} + \frac{n}{m^2 \cdot \text{sw}(\widehat{a}, \vec{v})} \right) \\ &\leq \frac{m+t-1}{t} \cdot \left( m^{2/\ell} + m^{2/\ell} \right) \in O(m^{1+2/\ell}/t). \end{aligned}$$

For  $t = 1$ , we have that for every  $i \in N$  and  $a \in S_i^t$ ,  $v_i(a) \leq \widehat{v}_i(a) \leq m^{1/\ell} v_i(a)$ . Hence, in Equation (2), the additive factor of  $n/m^2$  disappears and the multiplicative factor of  $m^{2/\ell}$  becomes  $m^{1/\ell}$ , yielding  $\widehat{\text{sw}}(\widehat{a}) \leq \text{sw}(\widehat{a}, \vec{v}) \cdot m^{1/\ell}$ . Similarly, Equation (3) becomes  $\text{sw}(\widehat{a}, \vec{v}) \geq \frac{n}{m^2} \cdot m^{-1/\ell}$ . Following the same line of proof as for the case of  $t > 1$ , we obtain

$$\frac{\text{sw}(a^*, \vec{v})}{\text{sw}(\widehat{a}, \vec{v})} \leq m \cdot \frac{\widehat{\text{sw}}(\widehat{a})}{\text{sw}(\widehat{a}, \vec{v})} \leq m \cdot m^{1/\ell},$$

which is the desired bound on distortion.  $\square$

## 1.2 Randomized Elicitation, Randomized Aggregation

**Theorem 2.** *For every voting rule  $f$  and  $s \in [m]$ , we have  $C^m(\text{RANDSUBSET}(f, s)) = C^s(f) + \log \lceil \log(4m) \rceil$  and  $\text{dist}^m(\text{RANDSUBSET}(f, s)) \leq \frac{4m}{s} \cdot \text{dist}^s(f)$ .*

*Proof.* Let  $\vec{v} = (v_1, \dots, v_n)$  denote the underlying valuations of voters. First, let us consider a fixed choice of  $S \subseteq A$  with  $|S| = s$ . Due to our bucketing, we have that for every  $i \in N$ ,

$$\frac{v_i(S)}{2} - \frac{1}{4m} \leq L_{p_i} \leq v_i(S). \quad (4)$$

Recall that in the input to the aggregation rule of  $f$ , we have  $4m \cdot L_{p_i}$  copies of the response  $\rho_i$  of voter  $i$ . Hence, the social welfare function approximated by the aggregation rule of  $f$  is given by

$$\forall a \in S, \widehat{\text{sw}}(a, \vec{v}) = \sum_{i \in N} 4m \cdot L_{p_i} \cdot \frac{v_i(a)}{v_i(S)} = 4m \sum_{i \in N} v_i(a) \cdot \frac{L_{p_i}}{v_i(S)}.$$

Combining this with Equation (4), we have that for each  $a \in S$ ,

$$\widehat{\text{sw}}(a, \vec{v}) \geq 4m \sum_{i \in N} v_i(a) \cdot \left( \frac{1}{2} - \frac{1}{4m \cdot v_i(S)} \right) = 2m \cdot \text{sw}(a, \vec{v}) - \sum_{i \in N} \frac{v_i(a)}{v_i(S)} \geq 2m \cdot \text{sw}(a, \vec{v}) - n, \quad (5)$$

as well as

$$\widehat{\text{sw}}(a, \vec{v}) \leq 4m \sum_{i \in N} v_i(a) \cdot 1 = 4m \cdot \text{sw}(a, \vec{v}). \quad (6)$$

Let  $\hat{a}$  denote the alternative chosen by our rule. Because the distortion of  $f$  for choosing an alternative from  $S$  is  $\text{dist}^s(f)$ , we have that  $\mathbb{E}[\widehat{\text{sw}}(\hat{a}, \vec{v})] \geq \max_{a \in S} \widehat{\text{sw}}(a, \vec{v}) / \text{dist}^s(f)$ . Note that so far, we have fixed  $S$ . The expectation on the left hand side is due to the fact that even for fixed  $S$ ,  $\hat{a}$  can be randomized if  $f$  is randomized.

Next, we take expectation over the choice of  $S$ , and use the fact that the optimal alternative  $a^* \in \arg \max_{a \in A} \text{sw}(a, \vec{v})$  belongs to  $S$  with probability  $s/m$ . We obtain

$$\mathbb{E}[\widehat{\text{sw}}(\hat{a}, \vec{v})] \geq \frac{\mathbb{E}[\max_{a \in S} \widehat{\text{sw}}(a, \vec{v})]}{\text{dist}^s(f)} \geq \frac{\frac{s}{m} \cdot \widehat{\text{sw}}(a^*, \vec{v})}{\text{dist}^s(f)} \geq \frac{\frac{s}{m} (2m \cdot \text{sw}(a^*, \vec{v}) - n)}{\text{dist}^s(f)}, \quad (7)$$

where the final transition follows from Equation (5). On the other hand, from Equation (6), we have

$$\mathbb{E}[\widehat{\text{sw}}(\hat{a}, \vec{v})] \leq 4m \mathbb{E}[\text{sw}(\hat{a}, \vec{v})]. \quad (8)$$

Combining Equations (7) and (8), we have that

$$\text{dist}^m(\text{RANDSUBSET}(f, s)) = \frac{\text{sw}(a^*, \vec{v})}{\mathbb{E}[\widehat{\text{sw}}(\hat{a}, \vec{v})]} \leq \frac{\text{sw}(a^*, \vec{v})}{\frac{\text{sw}(a^*, \vec{v})}{2} - \frac{n}{4m}} \cdot \frac{m}{s} \cdot \text{dist}^s(f) \leq \frac{4m}{s} \cdot \text{dist}^s(f),$$

where the final transition uses the fact that  $\text{sw}(a^*, \vec{v}) \geq (1/m) \cdot \sum_{a \in A} \text{sw}(a, \vec{v}) = n/m$ . This establishes the desired distortion bound. Since each voter answers the query of  $f$  for  $s$  alternatives and chooses one of  $\lceil \log(4m) \rceil$  buckets, we get  $C^m(\text{RANDSUBSET}(f, s)) = C^s(f) + \log \lceil \log(4m) \rceil$ , as desired.  $\square$

## 2 Lower Bounds

### 2.1 Direct Lower Bounds for Deterministic Elicitation

We start by establishing a straightforward lemma. Recall that for a valuation  $v \in \Delta^m$ ,  $\text{supp}(v)$  denotes the support of  $v$ .

**Lemma 1.** *Let  $f$  be a voting rule which uses deterministic elicitation and deterministic aggregation. Let  $q^*$  be the query used by  $f$ . If some compartment of  $q^*$  contains two valuations  $v^1$  and  $v^2$  such that  $\text{supp}(v^1) \cap \text{supp}(v^2) = \emptyset$ , then the distortion of  $f$  is unbounded.*

*Proof.* Suppose compartment  $P$  contains valuations  $v^1$  and  $v^2$  such that  $\text{supp}(v^1) \cap \text{supp}(v^2) = \emptyset$ . Let  $\hat{a}$  be the alternative returned by  $f$  when all voters pick compartment  $P$ . Pick  $t \in \{1, 2\}$  such that  $\hat{a} \notin \text{supp}(v^t)$ . Note that  $v^t(\hat{a}) = 0$ , but there exists  $a^* \in \text{supp}(v^t)$  such that  $v^t(a^*) > 0$ .

Define voter valuations  $\vec{v} = (v_1, \dots, v_n)$  such that  $v_i = v^t$  for each  $i \in N$ . This yields  $\text{sw}(\hat{a}, \vec{v}) = 0$  and  $\text{sw}(a^*, \vec{v}) > 0$ , which implies that  $f$  must have infinite distortion.  $\square$

**Theorem 3.** *Every voting rule that has deterministic elicitation, deterministic aggregation, and communication complexity strictly less than  $\log m$  has unbounded distortion.*

*Proof.* We need the following definition. For  $a \in A$ , we say that the *unit valuation* corresponding to  $a$  is the valuation  $v^a \in \Delta^m$  for which  $v^a(a) = 1$ . Let  $f$  be a voting rule that has deterministic elicitation and deterministic aggregation, and let  $C(f) < \log m$ . Hence, the query used by  $f$  must partition  $\Delta^m$  into less than  $m$  compartments.

Because there are  $m$  unit valuations, by the pigeonhole principle there must exist distinct  $a, b \in A$  such that  $v^a$  and  $v^b$  belong to the same compartment. Because  $\text{supp}(v^a) \cap \text{supp}(v^b) = \emptyset$ , Lemma 1 implies that the distortion of  $f$  must be infinite.  $\square$

**Theorem 4.** *Let  $f$  be a voting rule which uses deterministic elicitation and has  $C(f) \leq \log m$ . If  $f$  uses deterministic aggregation, then  $\text{dist}(f) = \Omega(m^2)$ . If  $f$  uses randomized aggregation, then  $\text{dist}(f) = \Omega(m)$ .*

*Proof.* Let  $f$  be a voting rule which has deterministic elicitation and  $C(f) \leq \log m$ . As argued above, we can assume  $C(f) = \log m$  without loss of generality. Hence, the query  $q^*$  used by  $f$  partitions  $\Delta^m$  into  $m$  compartments. Let  $\mathcal{P} = (P_1, \dots, P_m)$  denote the set of compartments. If  $f$  has unbounded distortion, we are done. Suppose  $f$  has bounded distortion.

Due to Lemma 1, each of  $m$  unit vectors must belong to a different compartment. Since there are  $m$  compartments, we identify each compartment by the unit valuation it contains. For  $a \in A$ , let  $P^a$  denote the compartment containing unit valuation  $v^a$ . Before we construct adversarial valuations, we need to define *low valuations* and *high valuations*.

*Low valuations:* We say that a valuation  $v \in \Delta^m$  is a *low valuation* if  $|\text{supp}(v)| = m/5$  and  $v(a) = 5/m$  for every  $a \in \text{supp}(v)$ . Let  $\Delta^{m,\text{low}}$  denote the set of all low valuations. Due to Lemma 1, we have

$$v \in \Delta^{m,\text{low}} \cap P^a \Rightarrow a \in \text{supp}(v) \wedge v(a) = \frac{5}{m}. \quad (9)$$

Let  $\mathcal{L} = \{P \in \mathcal{P} : P \cap \Delta^{m,\text{low}} \neq \emptyset\}$  be the set of compartments containing at least one low valuation, and  $A^\mathcal{L} = \{a \in A : P^a \in \mathcal{L}\}$  be the set of alternatives corresponding to these compartments.

We claim that  $|A^\mathcal{L}| = |\mathcal{L}| \geq 4m/5 + 1$ . Suppose for contradiction that  $|A^\mathcal{L}| \leq 4m/5$ . Then,  $|A \setminus A^\mathcal{L}| \geq m/5$ . Hence, there exists a low valuation  $v \in \Delta^{m,\text{low}}$  such that  $\text{supp}(v) \subseteq A \setminus A^\mathcal{L}$ . Let  $a \in A$  be the alternative for which  $v \in P^a$ . Because  $P^a$  contains a low valuation,  $a \in A^\mathcal{L}$  by definition. Thus, the construction of  $v$  ensures  $v(a) = 0$ . We have  $v \in \Delta^{m,\text{low}} \cap P^a$  with  $v(a) = 0$ , which contradicts Equation (9). Hence,  $|A^\mathcal{L}| \geq 4m/5 + 1$ .

*High valuations:* We say that a valuation  $v \in \Delta^m$  is a *high valuation* if  $|\text{supp}(v)| = 2$  and  $v(a) = 1/2$  for each  $a \in \text{supp}(v)$ . Let  $\Delta^{m,\text{high}}$  denote the set of high valuations. Note that  $|\Delta^{m,\text{high}}| = \binom{m}{2}$ . Similarly to the case of low valuations, we can apply Lemma 1, and obtain that

$$v \in \Delta^{m,\text{high}} \cap P^a \Rightarrow a \in \text{supp}(v) \wedge v(a) = \frac{1}{2}. \quad (10)$$

For  $a \in A$ , let  $\mathcal{H}^a = \{P \in \mathcal{L} : \exists v \in \Delta^{m,\text{high}} \cap P \text{ s.t. } a \in \text{supp}(v)\}$ . In words,  $\mathcal{H}^a$  is the set of compartments from  $\mathcal{L}$  which contain at least one high valuation  $v$  for which  $v(a) = 1/2$ . Let  $A^{\text{high}} = \{a \in A : |\mathcal{H}^a| \geq m/5\}$ . We claim that  $|A^{\text{high}}| \geq m/6$ .

Suppose this is not true. Let  $B = |A \setminus A^{\text{high}}|$ . Then,  $|B| \geq 5m/6$ . Consider  $a \in B$ . Each of the  $m-1$  high valuations which contain  $a$  in their support must belong to some compartments in  $\mathcal{H}^a \cup (\mathcal{P} \setminus \mathcal{L})$ . Since  $|\mathcal{H}^a| \leq m/5 - 1$  for  $a \in B$  and  $|\mathcal{P} \setminus \mathcal{L}| \leq m/5 - 1$ , the  $m-1$  high valuations containing  $a$  in their support are distributed across at most  $2m/5 - 2$  compartments. However, due to Lemma 1, a compartment other than  $P^a$  can contain at most one high valuation with  $a$  in its support. Hence,  $P^a$  must contain at least  $m-1 - (2m/5 - 3) = 3m/5 + 2$  high valuations. Thus, we have established that  $|B| \geq 5m/6$  and for each  $a \in B$ ,  $P^a$  contains at least  $3m/5 + 2$  high valuations. Thus, the number of high valuations is at least  $(5m/6) \cdot (3m/5 + 2) > m^2/2 > \binom{m}{2}$ , which is a contradiction. Thus, we have  $|A^{\text{high}}| \geq m/6$ .

We are now ready to prove the desired result for both deterministic and randomized aggregation.

*Voter responses:* When responding to the query  $q^*$ , suppose each compartment  $P \in \mathcal{L}$  is picked by a set  $N_P$  of  $n/|\mathcal{L}|$  voters.

*Deterministic aggregation:* Let  $\hat{a}$  denote the alternative picked by  $f$ . We claim that  $\hat{a} \in A^\mathcal{L}$ . If  $\hat{a} \notin A^\mathcal{L}$ , consider voter valuations  $\vec{v}$  such that every voter  $i$  picking compartment  $P^a \in \mathcal{L}$  has valuation  $v_i = v^a$ . Since  $\hat{a} \notin A^\mathcal{L}$ , we have  $v_i(\hat{a}) = 0$  for each  $i \in N$ , i.e.,  $\text{sw}(\hat{a}, \vec{v}) = 0$ . Since  $\text{sw}(a, \vec{v}) > 0$  for some  $a \in A$ ,  $f$  has infinite distortion, which is a contradiction. Thus, we must have  $\hat{a} \in A^\mathcal{L}$ .

Now, let us construct the voter valuations as follows. Pick a low valuation  $\hat{v} \in P^{\hat{a}} \cap \Delta^{m,\text{low}}$ , which exists because we have established  $\hat{a} \in A^\mathcal{L}$ . Note that  $\hat{v}(\hat{a}) = 5/m$ . For each  $i \in N_{P^{\hat{a}}}$ , let  $v_i = \hat{v}$ .

Pick  $a^* \in A^{\text{high}} \setminus \{\hat{a}\}$ . Let  $\bar{P}$  be the compartment containing the high valuation under which both  $\hat{a}$  and  $a^*$  have utility  $1/2$ . For each  $P \in \mathcal{H}^{a^*} \setminus \{P^{\hat{a}}, \bar{P}\}$ , and for each  $i \in N_P$ , let  $v_i$  be the high valuation in  $P$  such that  $v_i(a^*) = 1/2$  and  $v_i(\hat{a}) = 0$ . For every other  $P^a \in \mathcal{L}$  and every  $i \in N_{P^a}$ , let  $v_i = v^a$ .

Observe that under these valuations,  $\text{sw}(\hat{a}, \vec{v}) = \Theta(n/m^2)$ , whereas, since  $|\mathcal{H}^{a^*}| \geq m/5$  and  $|\mathcal{L}| \leq |\mathcal{P}| = m$ ,  $\text{sw}(a^*, \vec{v}) = \Theta(n)$ . We conclude that  $\text{dist}(f) = \Omega(m^2)$ .

*Randomized aggregation:* Note that  $f$  must select at least one alternative  $a^* \in A^{\text{high}}$  with probability at most  $1/|A^{\text{high}}| \leq 6/m$ . Construct voter valuations such that for every  $P \in \mathcal{H}^{a^*}$  and every  $i \in N_P$ ,  $v_i$  is the high valuation under which  $v_i(a^*) = 1/2$ . For every  $P^a \in \mathcal{L} \setminus \mathcal{H}^{a^*}$ , and for every  $i \in N_{P^a}$ , let  $v_i = v^a$ . It holds that  $\text{sw}(a^*, \vec{v}) = \Theta(n)$  (as before), whereas  $\text{sw}(a, \vec{v}) = O(n/m)$  for every  $a \in A \setminus \{a^*\}$ . Because  $f$  selects  $a^*$  with probability at most  $6/m$ , we have  $\mathbb{E}_{\hat{a} \sim f(\vec{v})}[\text{sw}(\hat{a}, \vec{v})] = O(n/m)$ , implying  $\text{dist}(f) = \Omega(m)$ , as required.  $\square$

## 2.2 Lower Bound for Plurality Votes

In this section, we show that eliciting plurality votes (whereby each voter picks her most favorite alternative) results in  $\Omega(m)$  distortion, even with randomized aggregation. This is implied by Theorem 4, which proves this for any elicitation that has at most  $\log m$  communication complexity. However, for the special case of plurality votes, we can provide a much simpler proof.

**Theorem 5.** *Every voting rule which elicits plurality votes incurs  $\Omega(m)$  distortion.*

*Proof.* For simplicity, let the number of voters  $n$  be divisible by the number of alternatives  $m$ . Consider an input profile in which the set of voters  $N$  is partitioned into equal-size sets  $\{N_a\}_{a \in A}$  such that for each  $a \in A$ ,  $a$  is the most favorite alternative of every voter in  $N_a$ .

Take any voting rule  $f$ . It must return some alternative  $a^* \in A$  with probability at most  $1/m$ . Now, construct adversarial valuations of voters  $\vec{v}$  as follows.

- For all  $i \in N_{a^*}$ ,  $v_i(a^*) = 1$  and  $v_i(a) = 0$  for all  $a \in A \setminus \{a^*\}$ .
- For all  $\hat{a} \in A \setminus \{a^*\}$  and  $i \in N_{\hat{a}}$ ,  $v_i(\hat{a}) = v_i(a^*) = 1/2$  and  $v_i(a) = 0$  for all  $a \in A \setminus \{a^*, \hat{a}\}$ .

Under these valuations, we have  $\text{sw}(a^*, \vec{v}) \geq n/2$ , while  $\text{sw}(a, \vec{v}) = (n/m) \cdot (1/2)$  for every  $a \in A \setminus \{a^*\}$ . Hence, the distortion of  $f$  is

$$\text{dist}(f) \geq \frac{\text{sw}(a^*, \vec{v})}{\frac{1}{m} \text{sw}(a^*, \vec{v}) + \frac{m-1}{m} \frac{n}{2m}} = \Omega(m),$$

where the final transition holds when substituting  $\text{sw}(a^*, \vec{v}) \geq n/2$ .  $\square$

## 3 Lower Bounds Through Multi-Party Communication Complexity

### 3.1 Lower Bound on the Communication Complexity of $\text{FDISJ}_{m,s,t}$

In this section, we prove a lower bound on the communication complexity of multi-party fixed-size set-disjointness. Let us recall Theorem 6.

**Theorem 6.** *For a sufficiently small constant  $\delta > 0$  and  $m \geq (3/2)st$ ,  $R_\delta(\text{FDISJ}_{m,s,t}) = \Omega(s)$ .*

*Proof.* Suppose there is a  $\delta$ -error protocol  $\Pi$  for  $\text{FDISJ}_{m,s,t}$ . We use it to construct a  $2\delta$ -error protocol  $\Pi'$  for  $\text{DISJ}_{m',t'}$ , where  $m' = st/2$  and  $t' = 2t$ .

Consider an instance  $(S'_1, \dots, S'_{t'})$  of  $\text{DISJ}_{m',t'}$ . Due to the promise that the sets are either pairwise disjoint or pairwise uniquely intersecting, we have that at most one of the  $m'$  elements can appear in multiple sets. Hence,  $\sum_{i=1}^{t'} |S'_i| \leq m' - 1 + t'$ . Due to the pigeonhole principle, there must exist at least  $t'/2 = t$  sets of size at most  $2(m' + t' - 1)/t'$ . Note that

$$\frac{2(m' + t' - 1)}{t'} = \frac{st/2 + 2t - 1}{t} = \frac{s}{2} + 2 - \frac{1}{t} \leq s.$$

The final transition holds when  $s \geq 4$ . When  $s < 4$ , the lower bound of  $\Omega(s)$  is trivial.

Consider a set of  $t$  players  $\{i_1, \dots, i_t\}$  such that  $|S'_{i_k}| \leq s$  for each  $k \in [t]$ . Suppose that each such player  $i_k$  adds  $s - |S'_{i_k}|$  unique elements to  $S'_{i_k}$  and creates a set  $S_{i_k}$  with  $|S_{i_k}| = s$ . The number of unique elements required is at most  $st$ . Hence, the total number of elements used in sets  $S_{i_1}, \dots, S_{i_t}$  is at most  $m' + st = (3/2)st \leq m$ . In other words, these sets can be created using the  $m$ -element universe of  $\text{FDISJ}_{m,s,t}$ . Further, it is easy to check that sets  $S_{i_1}, \dots, S_{i_t}$  are pairwise disjoint (resp. pairwise uniquely intersecting) if and only if sets  $S'_{i_1}, \dots, S'_{i_t}$  are pairwise disjoint (resp. pairwise uniquely intersecting). Thus,  $(S_{i_1}, \dots, S_{i_t})$  is a valid instance of  $\text{FDISJ}_{m,s,t}$  and has the same solution as the instance  $(S'_{i_1}, \dots, S'_{i_t})$  of  $\text{DISJ}_{m',t'}$ .

Our goal is to construct a  $2\delta$ -error protocol  $\Pi'$  for  $\text{DISJ}_{m',t'}$  that solves  $(S'_{i_1}, \dots, S'_{i_t})$  by effectively running the given  $\delta$ -error protocol  $\Pi$  for  $\text{FDISJ}_{m,s,t}$  on  $(S_{i_1}, \dots, S_{i_t})$ . We could ask each player  $i$  to report a single bit indicating whether  $|S'_i| \leq s$ , determine  $t$  players for which this holds, and then run  $\Pi$  on them. However, this would add a  $t'$ -bit overhead. Instead, we would like to bound the overhead in terms of the communication cost of  $\Pi$ , denoted  $|\Pi|$ , which could be significantly smaller.

This is achieved as follows. We first order the players according to a uniformly random permutation  $\sigma$ . Then, we simulate  $\Pi$ . Every time  $\Pi$  wants to interact with a new player, we ask players that we have not interacted with so far, in the order in which they appear in  $\sigma$ , whether their sets have size at most  $s$ , until we find one such player. Then, we let  $\Pi$  interact with this player. Protocol  $\Pi'$  terminates naturally when protocol  $\Pi$  terminates (and returns the same answer), but terminates abruptly if, at any point, it has interacted with more than  $2|\Pi|/\delta$  players (and returns an arbitrary answer).

Note that  $|\Pi|$  is also an upper bound with the number of players that  $\Pi$  needs to interact with. Let  $X$  be the smallest index such that there are at least  $|\Pi|$  players having sets of size at most  $s$  among the first  $X$  players in  $\sigma$ . Then, because at least half of the players have sets of size at most  $s$ , we have  $\mathbb{E}[X] \leq 2 \cdot |\Pi|$ . Due to Markov's inequality, we have that  $\Pr[X > 2|\Pi|/\delta] \leq \delta$ . Hence, the probability that  $\Pi'$  terminates abruptly is at most  $\delta$ . When it does not terminate abruptly, it returns the wrong answer with probability at most  $\delta$  (as  $\Pi$  is a  $\delta$ -error protocol). Hence, due to the union bound, we conclude that  $\Pi'$  is a  $2\delta$ -error protocol for  $\text{DISJ}_{m',t'}$ .

Finally, we have that  $|\Pi'| \leq 2|\Pi|/\delta + |\Pi| = |\Pi|(1 + 2/\delta)$ . When  $\delta$  is sufficiently small, [Gronmeier \[1\]](#) showed that  $|\Pi'| \geq R_{2\delta}(\text{DISJ}_{m',t'}) = \Omega(m'/t') = \Omega(s)$ . Hence, we have that  $|\Pi| = \Omega(s)$ . Since this holds for every  $\delta$ -error protocol  $\Pi$  for  $\text{FDISJ}_{m,s,t}$ , we have  $R_\delta(\text{FDISJ}_{m,s,t}) = \Omega(s)$ .  $\square$

### 3.2 Lower Bounds on the Communication Complexity of Voting Rules

**Theorem 7.** *For a voting rule  $f$  with elicitation rule  $\Pi_f$  and  $\text{dist}(f) = d$ , the following hold.*

- If  $\Pi_f$  is deterministic, then  $C(f) \geq \Omega(m/d^2)$ .
- If  $\Pi_f$  is randomized, then  $C(f) \geq \Omega(m/d^3)$ .

*Proof.* Let  $t = 2 \cdot \text{dist}(f)$  and  $s = 2m/(3t)$ . Note that for these parameters, we have  $R_\delta(\text{FDISJ}_{m,s,t}) = \Omega(s)$  from Theorem 6.

Consider an input  $(S_1, \dots, S_t)$  to  $\text{FDISJ}_{m,s,t}$  with a universe  $U$  of size  $m$ . Let us create an instance of the voting problem with a set of  $n$  voters  $N$  and a set of  $m$  alternatives  $A$ . Each alternative in  $A$  corresponds to a unique element of  $U$ . Partition the set of voters  $N$  into  $t$  equal-size buckets  $\{N_1, \dots, N_t\}$ . Here, bucket  $N_i$  corresponds to player  $i$ , and consists of  $n/t$  voters that each have valuation  $v^{S_i}$  given by  $v^{S_i}(a) = 1/s$  for each  $a \in S_i$  and  $v^{S_i}(a) = 0$  for each  $a \notin S_i$ . Let  $\vec{v}$  denote the resulting profile of voter valuations. Note that under these valuations,  $\text{sw}(a, \vec{v}) = \frac{n}{ts} \sum_{i=1}^t \mathbb{1}[a \in S_i]$ , where  $\mathbb{1}$  is the indicator variable. Due to the promise that an element either belongs to at most one set or belongs to every set, we have  $\text{sw}(a, \vec{v}) \in \{0, n/(ts), n/s\}$ . We say that  $a$  is a “good” alternative if  $\text{sw}(a, \vec{v}) = n/s$  and a “bad” alternative otherwise.

We define two processes that will help covert our voting rule  $f$  into a protocol for  $\text{FDISJ}_{m,s,t}$ .

*Process E:* In this process, we ask each player  $i$  to respond to the query posed by voting rule  $f$  (possibly selected in a randomized manner) according to valuation  $v^{S_i}$ . We note that this requires a total of  $t \cdot C(f)$  bits of communication from the players.

*Process A:* We take players' responses from process E, create  $n/t$  copies of the response of each player, and pass the resulting profile as input to the aggregation rule  $\Gamma_f$  to obtain the returned alternative  $\hat{a}$  (possibly selected in a randomized manner). We end the process by determining if  $\hat{a}$  is a good alternative or a bad alternative. This requires eliciting 2 extra bits of information: we can ask any two players  $i$  and  $j$  whether their sets contain  $\hat{a}$ , and due to the promise of  $\text{FDISJ}_{m,s,t}$ , we know that  $\hat{a}$  is good if and only if it belongs to both  $S_i$  and  $S_j$ .

Knowing whether  $\hat{a}$  is good or bad is useful for solving the given instance of  $\text{FDISJ}_{m,s,t}$  due to the following reason.

1. If  $(S_1, \dots, S_t)$  is a "NO input", then we know that every alternative is a bad alternative. Hence,  $\text{sw}(a, \vec{v}) \leq (n/t) \cdot (1/s) = n/(ts)$  for each  $a \in A$ . In particular, this implies  $\text{sw}(\hat{a}, \vec{v}) \leq n/(ts)$  with probability 1.
2. If  $(S_1, \dots, S_t)$  is a "YES input", then there exists a unique good alternative  $a^* \in A$  with  $\text{sw}(a^*, \vec{v}) = n/s$ , and every other alternative  $a$  is a bad alternative with  $\text{sw}(a, \vec{v}) \leq n/(ts)$ . Because  $\text{dist}(f) = t/2$ , we have that  $\mathbb{E}[\text{sw}(\hat{a}, \vec{v})] \geq \frac{n/s}{t/2} = \frac{2n}{ts}$ . This implies that  $\Pr[\text{sw}(\hat{a}, \vec{v}) = n/s] = \Pr[\hat{a} = a^*] \geq 1/t$  because if  $\Pr[\hat{a} = a^*] < 1/t$ , then  $\mathbb{E}[\text{sw}(\hat{a}, \vec{v})] < (1/t) \cdot (n/s) + 1 \cdot n/(ts) = 2n/(ts)$ , which is a contradiction.

We are now ready to use  $f$  to construct a protocol for  $\text{FDISJ}_{m,s,t}$ , and use Theorem 6 to derive a lower bound on  $C(f)$ . We consider two cases depending on whether the elicitation rule  $\Pi_f$  is deterministic or randomized.

1. *Deterministic elicitation:* In this case, we run process E once and then run process A  $t \ln(1/\delta)$  times. In a NO input, we always get a bad alternative. In a YES input, each run of process A returns a good alternative with probability at least  $1/t$ . Hence, the probability that we get a good alternative at least once is at least  $1 - (1 - 1/t)^{t \ln(1/\delta)} \geq 1 - \delta$ . Hence, this is a  $\delta$ -error protocol for  $\text{FDISJ}_{m,s,t}$  which requires  $t \cdot C(f) + t \ln(1/\delta) \cdot 2$  bits of total communication from the players. Using Theorem 6, we have that  $t \cdot (C(f) + 2 \ln(1/\delta)) = \Omega(s)$ . Using  $s = 2m/(3t)$  and  $t = 2d$ , we have  $C(f) = \Omega(m/d^2)$ .
2. *Randomized elicitation:* In this case, we run E once followed by running A once. And we repeat this entire process  $t \ln(1/\delta)$  times. Note that we need to repeat process E because the elicitation is also randomized. Like in the previous case, we always get a bad alternative in a NO input, and get a good alternative with probability at least  $1/t$  in each run in a YES input. Hence, in a YES input, we get a good alternative in at least one run with probability at least  $1 - (1 - 1/t)^{t \ln(1/\delta)} \geq 1 - \delta$ . This results in a  $\delta$ -error protocol for  $\text{FDISJ}_{m,s,t}$  which requires  $t \ln(1/\delta) \cdot (t \cdot C(f) + 2)$  bits of total communication from the players. Using Theorem 6, we have  $t \ln(1/\delta) \cdot (t \cdot C(f) + 2) = \Omega(s)$ . Using  $s = 2m/(3t)$  and  $t = 2d$ , we have  $C(f) = \Omega(m/d^3)$ .

These are the desired lower bounds on  $C(f)$ . □

## References

- [1] A. Gronemeier. Asymptotically optimal lower bounds on the NIH-multi-party information complexity of the AND-function and disjointness. In *Proceedings of the 26th International Symposium on Theoretical Aspects of Computer Science (STACS)*, pages 505–516, 2009.