

## A Proofs from Section 4

### A.1 Proof of Theorem 4.1

We reuse notations  $e^{(j)}$ ,  $i^{(j)}$ , and  $\mathbf{s}^{(j)}$  from Section 3. We iteratively define  $\mathbf{o}^{(0)} = \mathbf{o}, \mathbf{o}^{(1)}, \dots, \mathbf{o}^{(B)}$  as follows. For each  $j \in [B]$ , we define  $S_i^{(j)} = \text{supp}_i(\mathbf{o}^{(j-1)}) \setminus \text{supp}_i(\mathbf{s}^{(j-1)})$ . We have two cases to consider:

- Suppose that  $e^{(j)} \in S_{i'}^{(j)}$  for some  $i' \neq i^{(j)}$ . In this case, let  $o^{(j)}$  be an arbitrary element in  $S_{i^{(j)}}^{(j)}$ . Then, we define  $\mathbf{o}^{(j-1/2)}$  as the resulting vector obtained from  $\mathbf{o}^{(j-1)}$  by assigning 0 to the  $e^{(j)}$ -th element and the  $o^{(j)}$ -th element, and then define  $\mathbf{o}^{(j)}$  as the resulting vector obtained from  $\mathbf{o}^{(j-1/2)}$  by assigning  $i^{(j)}$  to the  $e^{(j)}$ -th element and  $i'$  to the  $o^{(j)}$ -th element.
- Suppose that  $e^{(j)} \notin S_{i'}^{(j)}$  for any  $i' \neq i^{(j)}$ . In this case, we set  $o^{(j)} = e^{(j)}$  if  $e^{(j)} \in S_{i^{(j)}}^{(j)}$ , and we set  $o^{(j)}$  to be an arbitrary element in  $S_{i^{(j)}}^{(j)}$  otherwise. Then, we define  $\mathbf{o}^{(j-1/2)}$  as the resulting vector obtained from  $\mathbf{o}^{(j-1)}$  by assigning 0 to the  $o^{(j)}$ -th element, and then define  $\mathbf{o}^{(j)}$  as the resulting vector obtained from  $\mathbf{o}^{(j-1/2)}$  by assigning  $i^{(j)}$  to the  $e^{(j)}$ -th element.

Note that  $|\text{supp}_i(\mathbf{o}^{(j)})| = B_i$  holds for every  $i \in [k]$  and  $j \in \{0, 1, \dots, B\}$ , and  $\mathbf{o}^{(B)} = \mathbf{s}^{(B)} = \mathbf{s}$ . Moreover, we have  $\mathbf{s}^{(j-1)} \preceq \mathbf{o}^{(j-1/2)}$  for every  $j \in [B]$ .

*Proof of Theorem 4.1.* We first show that, for each  $j \in [B]$ ,

$$2(f(\mathbf{s}^{(j)}) - f(\mathbf{s}^{(j-1)})) \geq f(\mathbf{o}^{(j-1/2)}) - f(\mathbf{o}^{(j)}). \quad (2)$$

For each  $j \in [B]$ , let  $y^{(j)} = \Delta_{e^{(j)}, i^{(j)}} f(\mathbf{s}^{(j-1)})$ . We first note that  $f(\mathbf{s}^{(j)}) - f(\mathbf{s}^{(j-1)}) = y^{(j)}$ .

We consider the following two cases:

- Suppose that  $e^{(j)} \in S_{i'}^{(j)}$  for some  $i' \neq i^{(j)}$ . Let  $a^{(j-1/2)} = \Delta_{o^{(j)}, i^{(j)}} f(\mathbf{o}^{(j-1/2)})$ ,  $a^{(j)} = \Delta_{e^{(j)}, i^{(j)}} f(\mathbf{o}^{(j-1/2)})$ ,  $b^{(j-1/2)} = \Delta_{e^{(j)}, i'} f(\mathbf{o}^{(j-1/2)})$ , and  $b^{(j)} = \Delta_{o^{(j)}, i'} f(\mathbf{o}^{(j-1/2)})$ . Note that  $f(\mathbf{o}^{(j-1/2)}) - f(\mathbf{o}^{(j)}) = a^{(j-1/2)} - a^{(j)} + b^{(j-1/2)} - b^{(j)}$ . From the monotonicity of  $f$ , it suffices to show that  $2y^{(j)} \geq a^{(j-1/2)} + b^{(j-1/2)}$ . Since  $e^{(j)}$  and  $i^{(j)}$  are chosen greedily, we have  $y^{(j)} \geq \Delta_{o^{(j)}, i^{(j)}} f(\mathbf{s}^{(j-1)})$  and  $y^{(j)} \geq \Delta_{e^{(j)}, i'} f(\mathbf{s}^{(j-1)})$ . Also, since  $\mathbf{s}^{(j-1)} \preceq \mathbf{o}^{(j-1/2)}$ , we have  $\Delta_{o^{(j)}, i^{(j)}} f(\mathbf{s}^{(j-1)}) \geq a^{(j-1/2)}$  and  $\Delta_{e^{(j)}, i'} f(\mathbf{s}^{(j-1)}) \geq b^{(j-1/2)}$  from the orthant submodularity. Combining these inequalities, we get (2).
- Suppose that  $e^{(j)} \notin S_{i'}^{(j)}$  for any  $i' \neq i^{(j)}$ . Let  $a^{(j-1/2)} = \Delta_{o^{(j)}, i^{(j)}} f(\mathbf{o}^{(j-1/2)})$ , and  $a^{(j)} = \Delta_{e^{(j)}, i^{(j)}} f(\mathbf{o}^{(j-1/2)})$ . Note that  $f(\mathbf{o}^{(j-1/2)}) - f(\mathbf{o}^{(j)}) = a^{(j-1/2)} - a^{(j)}$ . From the monotonicity of  $f$ , it suffices to show that  $2y^{(j)} \geq a^{(j-1/2)}$ . Since  $e^{(j)}$  and  $i^{(j)}$  are chosen greedily, we have  $y^{(j)} \geq \Delta_{o^{(j)}, i^{(j)}} f(\mathbf{s}^{(j-1)})$ . Also, since  $\mathbf{s}^{(j-1)} \preceq \mathbf{o}^{(j-1/2)}$ , we have  $\Delta_{o^{(j)}, i^{(j)}} f(\mathbf{s}^{(j-1)}) \geq a^{(j-1/2)}$  from the orthant submodularity. Combining these inequalities, we get (2).

Then, we have

$$f(\mathbf{o}) - f(\mathbf{s}) = \sum_{j=1}^B (f(\mathbf{o}^{(j-1/2)}) - f(\mathbf{o}^{(j)})) \leq \sum_{j=1}^B 2(f(\mathbf{s}^{(j)}) - f(\mathbf{s}^{(j-1)})) = 2(f(\mathbf{s}) - f(\mathbf{0})) \leq 2f(\mathbf{s}).$$

Hence, we have  $f(\mathbf{s}) \geq f(\mathbf{o})/3$ .  $\square$

### A.2 Proof of Theorem 4.2

We reuse notations  $e^{(j)}$ ,  $i^{(j)}$ ,  $S_i^{(j)}$ , and  $\mathbf{s}^{(j)}$ . Let  $R^{(j)}$  be the set of elements sampled in the  $j$ -th iteration. We iteratively define  $\mathbf{o}^{(0)} = \mathbf{o}, \mathbf{o}^{(1)}, \dots, \mathbf{o}^{(B)}$  as follows. If  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$  is empty, we regard that the algorithm failed. Otherwise, we have two cases to consider:

- Suppose that  $e^{(j)} \in S_{i'}^{(j)}$  for some  $i' \neq i^{(j)}$ . In this case, let  $o^{(j)}$  be an arbitrary element in  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$ . Then, we define  $\mathbf{o}^{(j-1/2)}$  and  $\mathbf{o}^{(j)}$  as in Section 4.1.
- Suppose that  $e^{(j)} \notin S_{i'}^{(j)}$  for any  $i' \neq i^{(j)}$ . In this case, we set  $o^{(j)} = e^{(j)}$  if  $e^{(j)} \in S_{i^{(j)}}^{(j)}$  (and hence in  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$ ), and we set  $o^{(j)}$  to be an arbitrary element in  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$  otherwise. Then, we define  $\mathbf{o}^{(j-1/2)}$  and  $\mathbf{o}^{(j)}$  as in Section 4.1.

If  $\mathbf{o}^{(1)}, \dots, \mathbf{o}^{(B)}$  are well defined, or in other words, if  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$  is not empty for each  $j \in [B]$ , then the rest of the analysis is completely the same as in Section 4.1, and we achieve an approximation ratio of  $1/3$ . Hence, it suffices to show that  $\mathbf{o}^{(1)}, \dots, \mathbf{o}^{(B)}$  are well defined with a high probability.

**Lemma A.1.** *With probability at least  $1 - \delta$ , we have  $R^{(j)} \cap S_{i^{(j)}}^{(j)}$  is not empty for every  $j \in [B]$ .*

*Proof.* Fix  $j \in [B]$ . If  $|R^{(j)}| = n$ , then we clearly have  $\Pr[R^{(j)} \cap S_{i^{(j)}}^{(j)} \neq \emptyset] = 0$ . Otherwise we have

$$\begin{aligned} \Pr[R^{(j)} \cap S_{i^{(j)}}^{(j)} \neq \emptyset] &= \left(1 - \frac{|S_{i^{(j)}}^{(j)}|}{|V \setminus \text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}\right)^{|R^{(j)}|} = \left(1 - \frac{B_{i^{(j)}} - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}{n - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}\right)^{|R^{(j)}|} \\ &\leq \exp\left(\frac{B_{i^{(j)}} - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}{n - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|} \frac{n - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}{B_{i^{(j)}} - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|} \log \frac{B}{\delta}\right) = \frac{\delta}{B}. \end{aligned}$$

By the union bound over  $j \in [B]$ , the lemma follows.  $\square$

*Proof of Theorem 4.2.* By Lemma A.1 and the previous analysis in Section 4.1, we have that Algorithm 4 outputs a  $1/3$ -approximate solution with probability at least  $1 - \delta$ .

The number of evaluations of  $f$  is at most

$$\begin{aligned} &k \sum_{j \in [B]} \frac{n - |\text{supp}_{i^{(j)}}(\mathbf{s}^{(j-1)})|}{B_{i^{(j)}} - |\text{supp}_{i^{(j-1)}}(\mathbf{s}^{(j)})|} \log \frac{B}{\delta} \leq k \sum_{i \in [k]} \sum_{j \in [B_i]} \frac{n - j + 1}{B_i - j + 1} \log \frac{B}{\delta} \\ &= k \sum_{i \in [k]} \sum_{j \in [B_i]} \frac{n - B_i + j}{j} \log \frac{B}{\delta} = O\left(k \sum_{i \in [k]} (B_i + (n - B_i) \log B_i) \log \frac{B}{\delta}\right) \\ &= O\left(kn \log \frac{B}{\delta} \cdot \sum_{i \in [k]} \log B_i\right) = O\left(kn \log \frac{B}{\delta} \cdot k \log \frac{\sum_{i \in [k]} B_i}{k}\right) = O\left(k^2 n \log \frac{B}{k} \log \frac{B}{\delta}\right), \end{aligned}$$

where we used the AM-GM inequality in the last line.  $\square$

## B Proofs from Section 5

### B.1 $k$ -submodularity of the influence maximization problem

In this section, we show that the function  $\sigma : (k+1)^V \rightarrow \mathbb{R}_+$  used in the influence maximization problem is monotone  $k$ -submodular. In order to show the  $k$ -submodularity of  $\sigma$ , it suffices to show that  $\sigma$  is orthant submodular by Theorem 2.1. Pairwise monotonicity is obvious since  $\sigma$  is monotone.

To show the orthant submodularity of  $f$ , we first describe a convenient way of handling the diffusion process. Fix topic  $i$ . Then for each edge  $(u, v) \in E$ , we preserve it with probability  $p_{u,v}^i$  and discard it with the remaining probability. Let  $G^i$  be the directed graph consisting of the preserved edges. Given a seed  $\mathbf{s} \in (k+1)^V$ , the set of vertices reachable from  $\text{supp}_i(\mathbf{s})$  in  $G^i$  corresponds to the set  $A_i(\text{supp}_i(\mathbf{s}))$ . Recall that  $A_i(\text{supp}_i(\mathbf{s}))$  is a random variable. Kempe *et al.* [11] showed that the function  $\mathbb{E}[|A_i(\cdot)|]$  is submodular.

Fix  $\mathbf{x} = (X_1, \dots, X_k)$  and  $\mathbf{y} = (Y_1, \dots, Y_k)$  with  $\mathbf{x} \preceq \mathbf{y}$ ,  $e \notin \bigcup_{\ell \in [k]} Y_\ell$  and  $i \in [k]$ . We want to show that  $\Delta_{e,i}f(\mathbf{x}) \geq \Delta_{e,i}f(\mathbf{y})$ . Note that

$$\begin{aligned} \Delta_{e,i}f(\mathbf{x}) - \Delta_{e,i}f(\mathbf{y}) &= \mathbf{E} \left[ \left| A_i(X_i \cup \{e\}) \cup \bigcup_{j \neq i} A_j(X_j) \right| - \left| A_i(X_i) \cup \bigcup_{j \neq i} A_j(X_j) \right| \right] \\ &\quad - \mathbf{E} \left[ \left| A_i(Y_i \cup \{e\}) \cup \bigcup_{j \neq i} A_j(Y_j) \right| - \left| A_i(Y_i) \cup \bigcup_{j \neq i} A_j(Y_j) \right| \right]. \end{aligned} \quad (3)$$

Let  $S = \bigcup_{j \neq i} A_j(X_j)$  and  $T = \bigcup_{j \neq i} A_j(Y_j)$ . Then,

$$(3) = \mathbf{E} \left[ \left| (A_i(X_i \cup \{e\}) \setminus A_i(X_i)) \setminus S \right| \right] - \mathbf{E} \left[ \left| (A_i(Y_i \cup \{e\}) \setminus A_i(Y_i)) \setminus T \right| \right]. \quad (4)$$

Since  $S \subseteq T$  for every fixed  $G^j$  for  $j \neq i$ , we have

$$(4) \geq \mathbf{E} \left[ \left| A_i(X_i \cup \{e\}) \setminus A_i(X_i) \right| \right] - \mathbf{E} \left[ \left| A_i(Y_i \cup \{e\}) \setminus A_i(Y_i) \right| \right] \geq 0.$$

The last inequality holds from the submodularity of  $A_i(\cdot)$ .

## B.2 $k$ -submodularity of the sensor placement problem

Recall that  $\Omega = \{X_e^i\}_{i \in [k], e \in V}$ , where  $X_e^i$  represents the observation collecting from a sensor of the  $i$ -th kind at the  $e$ -th location and  $f : (k+1)^V \rightarrow \mathbb{R}_+$  was defined as  $f(\mathbf{y}) = H(\bigcup_{e \in \text{supp}(\mathbf{x})} \{X_e^{\mathbf{x}(e)}\})$ , where  $H$  is the entropy function. It is well known that  $H$  is monotone submodular. In order to show that  $f : (k+1)^V \rightarrow \mathbb{R}_+$  is a  $k$ -submodular function, it suffices to show its pairwise monotonicity and orthant submodularity by Theorem 2.1.

We first show that  $f$  is monotone, which particularly implies that  $f$  is pairwise monotone. Let  $\mathbf{y} = (Y_1, \dots, Y_k) \in (k+1)^V$ . Then, we can associate  $\mathbf{y}$  with a set  $\mathcal{S}_{\mathbf{y}} = \{X_e^i \mid i \in [k], e \in Y_i\}$ . Then for any  $i \in [k]$ , and  $e \in V \setminus \bigcup_{j \in \ell} Y_j$ , we have  $\Delta_{i,e}f(\mathbf{y}) = H(\{X_e^i\} \mid \mathcal{S}_{\mathbf{y}})$ . Since  $H(\cdot)$  is monotone, we have  $\Delta_{i,e}f(\mathbf{y}) \geq 0$ .

To see the orthant submodularity, let  $\mathbf{y} = (Y_1, \dots, Y_k)$  and  $\mathbf{y}' = (Y'_1, \dots, Y'_k)$  with  $\mathbf{y} \preceq \mathbf{y}'$ . Also, let  $i \in [k]$  and  $e \in V \setminus \bigcup_{j \in [k]} Y'_j$ . Then,  $\Delta_{e,i}f(\mathbf{y}) = H(\{X_e^i\} \mid \mathcal{S}_{\mathbf{y}})$  and  $\Delta_{e,i}f(\mathbf{y}') = H(\{X_e^i\} \mid \mathcal{S}_{\mathbf{y}'})$ . Since  $\mathcal{S}_{\mathbf{y}'} \subseteq \mathcal{S}_{\mathbf{y}}$ , we have  $\Delta_{e,i}f(\mathbf{y}) \geq \Delta_{e,i}f(\mathbf{y}')$  from the submodularity of  $H$ .