

## A. Missing Proofs from Section 4

### A.1. Proof of Lemma 1

*Proof.* The proof is constructive and is inspired by (Calinescu et al., 2011; Han et al., 2020). For clarity, we provide a procedure to construct  $\sigma_i(\cdot)$ , as shown by Algorithm 3. Suppose that the elements in  $S_i$  are  $\{z_1, \dots, z_q\}$  (listed according to the order that they are added into  $S_i$ ). Algorithm 3 finds a series of sets  $J_0 \subseteq J_1 \subseteq \dots \subseteq J_q = Q_i$  such that all the elements in  $M_t = J_t \setminus J_{t-1}$  is mapped to  $z_t$  by  $\sigma_i(\cdot)$  for any  $t \in \{1, 2, \dots, q\}$ . From Algorithm 3, it can be easily seen that  $\sigma_i(\cdot)$  satisfies the conditions required by the lemma. The only problem left is to prove that all the elements in  $Q_i$  is mapped by  $\sigma_i(\cdot)$ , i.e., to prove  $J_0 = \emptyset$ . Indeed, we can prove a stronger result  $\forall t \in \{0, 1, \dots, q\} : |J_t| \leq kt$  by induction:

- When  $t = q$ , we will prove  $|J_q| \leq kq$  by showing that  $S_i$  is a base of  $Q_i \cup S_i$ . It is obvious that each element  $u \in O_i^-$  satisfies  $S_i \cup \{u\} \notin \mathcal{I}$  according to the definition of  $O_i^-$ . Moreover, for any element  $u \in \cup_{j \in [q] \setminus \{i\}} (O_j^{i-} \cup \widehat{O}_j^{i-})$ , we must have  $S_i \cup \{u\} \notin \mathcal{I}$ , because otherwise we have  $S_i^<(u) \cup \{u\} \in \mathcal{I}$  due to  $S_i^<(u) \subseteq S_i$  and the down-closed property of independence systems, contradicting the definition of  $O_j^{i-}$  and  $\widehat{O}_j^{i-}$ . These reasoning implies that  $S_i$  is a base of  $Q_i \cup S_i$ . Note that  $Q_i \subseteq O$ . So we can get  $|J_q| = |Q_i| \leq k|S_i| = kq$  according to the definition of  $k$ -systems.
- Suppose that  $|J_t| \leq kt$  holds, we will prove  $|J_{t-1}| \leq k(t-1)$ . If the set  $C_t$  determined in Line 3 of Algorithm 3 has a cardinality larger than  $k$ , then we have  $|M_t| = k$  according to Algorithm 3 and hence  $|J_{t-1}| = |J_t| - k \leq k(t-1)$ . If  $|C_t| \leq k$ , then  $\{z_1, \dots, z_{t-1}\}$  must be a base of  $\{z_1, \dots, z_{t-1}\} \cup J_{t-1}$ , because there does not exist  $u \in J_{t-1} \setminus \{z_1, \dots, z_{t-1}\}$  such that  $\{z_1, \dots, z_{t-1}\} \cup \{u\} \in \mathcal{I}$  according to Algorithm 3. So we also have  $|J_{t-1}| \leq k(t-1)$  according to  $J_{t-1} \in \mathcal{I}$  and the definition of  $k$ -systems.

From the above reasoning we know  $J_0 = \emptyset$ . So the lemma follows.  $\square$

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#### Algorithm 3 CONSTRUCTING THE MAPPING $\sigma_i(\cdot)$

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**Initialize:** Denote the elements in  $S_i$  as  $\{z_1, \dots, z_q\}$ , where elements are listed according to the order that they are added into  $S_i$ ;  $J_q \leftarrow Q_i$

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1: for  $t = q$  to 0 do
2:    $C_t \leftarrow \{e \in J_t \setminus \{z_1, \dots, z_{t-1}\} : \{z_1, \dots, z_{t-1}, e\} \in \mathcal{I}\}$ 
3:   if  $|C_t| \leq k$  then
4:      $M_t \leftarrow C_t$ 
5:   end if
6:   if  $|C_t| > k$  then
7:     if  $z_t \in C_t$  then
8:       Find a subset  $M_t \subseteq C_t$  satisfying  $|M_t| = k$  and  $z_t \in M_t$ 
9:     else
10:      Find a subset  $M_t \subseteq C_t$  satisfying  $|M_t| = k$ 
11:    end if
12:  end if
13:  Let  $\sigma_i(z) = z_t$  for all  $z \in M_t$ ;  $J_{t-1} \leftarrow J_t \setminus M_t$ 
14: end for

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### A.2. Proof of Lemma 2

*Proof.* We first prove Eqn. (3). According to the definitions of  $O_j^{i+}$  and  $\widehat{O}_j^{i+}$ , any element  $u \in O_j^{i+} \cup \widehat{O}_j^{i+}$  can also be added into  $S_i$  without violating the feasibility of  $\mathcal{I}$  when  $u$  is inserted into  $\widehat{S}_j$ . Therefore, according to the greedy rule of RANDOMMULTIGREEDY and the submodularity of  $f(\cdot)$ , we must have

$$\forall u \in O_j^{i+} \cup \widehat{O}_j^{i+} : f(u | S_i) \leq f(u | S_i^<(u)) \leq f(u | S_j^<(u)) = \delta(u) \quad (11)$$

Now we prove Eqn. (4). Recall that  $Q_i = \cup_{j \in [q] \setminus \{i\}} (O_j^{i-} \cup \widehat{O}_j^{i-}) \cup (O \cap S_i) \cup O_i^-$ . According to Lemma 1, any element  $u \in O_j^{i-} \cup \widehat{O}_j^{i-}$  ( $j \neq i$ ) can be added into  $S_i^<(\pi_i(u))$  without violating the feasibility of  $\mathcal{I}$ . Moreover,  $u$  must have not been

considered by the algorithm at the moment that  $\pi_i(u)$  is added into  $S_i$ , because otherwise we have  $S_i^<(u) \subseteq S_i^<(\pi_i(u))$  and hence  $S_i^<(u) \cup \{u\} \in \mathcal{I}$  due to the definition of independence systems, which contradicts the definitions of  $O_j^{i-}$  and  $\widehat{O}_j^{i-}$ . Therefore, according to the greedy rule of RANDOMMULTIGREEDY and submodularity, we can get

$$\forall u \in O_j^{i-} \cup \widehat{O}_j^{i-} : f(u | S_i) \leq f(u | S_i^<(u)) \leq f(u | S_i^<(\pi_i(u))) \leq f(\pi_i(u) | S_i^<(\pi_i(u))) = \delta(\pi_i(u)) \quad (12)$$

By similar reasoning, we can also prove  $\forall u \in O_i^- : f(u | S_i) \leq f(u | S_i^<(\pi_i(u))) \leq \delta(\pi_i(u))$ . Finally,  $f(u | S_i) \leq \delta(\pi_i(u))$  trivially holds for all  $u \in O \cap S_i$  as  $\pi_i(u) = u$  due to Lemma 1. So the lemma follows.  $\square$

### A.3. Proof of Lemma 3

As the proof of Lemma 3 is a bit involved, we first introduce Lemma 9, and then use Lemma 9 to prove Lemma 3.

**Lemma 9.** *We have*

$$\sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \left( \sum_{u \in O_j^{i+}} \delta(u) + \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) \right) + \sum_{u \in O_i^-} \delta(\pi_i(u)) \right) \leq \ell(k + \ell - 2)f(S^*) \quad (13)$$

*Proof.* For any  $i \in [\ell]$ , let  $\lambda(i) = (i \bmod \ell) + 1$ . So we have

$$\sum_{i \in [\ell]} \sum_{u \in O_{\lambda(i)}^{i+}} \delta(u) = \sum_{j \in [\ell]} \sum_{u \in O_j^{\lambda^{-1}(j)+}} \delta(u) \leq \sum_{j \in [\ell]} \sum_{u \in O \cap S_j} \delta(u) = \sum_{i \in [\ell]} \sum_{u \in O \cap S_i} \delta(u), \quad (14)$$

where the inequality is due to  $O_j^{\lambda^{-1}(j)+} \subseteq O \cap S_j$  and  $\forall u \in S_j : \delta(u) > 0$ . So we can get

$$\begin{aligned} \sum_{i \in [\ell]} \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in O_j^{i+}} \delta(u) &= \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i, \lambda(i)\}} \sum_{u \in O_j^{i+}} \delta(u) + \sum_{u \in O_{\lambda(i)}^{i+}} \delta(u) \right) \\ &\leq \sum_{i \in [\ell]} \sum_{j \in [\ell] \setminus \{i, \lambda(i)\}} \sum_{u \in O \cap S_j} \delta(u) + \sum_{i \in [\ell]} \sum_{u \in O \cap S_i} \delta(u) \end{aligned} \quad (15)$$

$$\leq \ell(\ell - 2)f(S^*) + \sum_{i \in [\ell]} \sum_{u \in O \cap S_i} \delta(u) \quad (16)$$

where we leverage Eqn. (14) to derive Eqn. (15), and Eqn. (16) is due to  $\sum_{u \in O \cap S_j} \delta(u) \leq \sum_{u \in S_j} \delta(u) \leq f(S_j) \leq f(S^*)$ . Moreover, we can get

$$\begin{aligned} &\sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \left( \sum_{u \in O_j^{i+}} \delta(u) + \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) \right) + \sum_{u \in O_i^-} \delta(\pi_i(u)) \right) \\ &= \sum_{i \in [\ell]} \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in O_j^{i+}} \delta(u) + \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) + \sum_{u \in O_i^-} \delta(\pi_i(u)) \right) \\ &\leq \ell(\ell - 2)f(S^*) + \sum_{i \in [\ell]} \left( \sum_{u \in O \cap S_i} \delta(u) + \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) + \sum_{u \in O_i^-} \delta(\pi_i(u)) \right) \end{aligned} \quad (17)$$

$$\begin{aligned} &= \ell(\ell - 2)f(S^*) + \sum_{i \in [\ell]} \sum_{u \in Q_i} \delta(\pi_i(u)) \\ &\leq \ell(\ell - 2)f(S^*) + k \sum_{i \in [\ell]} \sum_{u \in S_i} \delta(u) \end{aligned} \quad (18)$$

$$\leq \ell(\ell - 2)f(S^*) + k \sum_{i \in [\ell]} f(S_i) \leq \ell(k + \ell - 2)f(S^*) \quad (19)$$

where  $Q_i = \cup_{j \in [\ell] \setminus \{i\}} (O_j^{i-} \cup \widehat{O}_j^{i-}) \cup (O \cap S_i) \cup O_i^-$  is defined in Lemma 1; Eqn. (17) is due to Eqn. (16); and Eqn. (18) is due to Lemma 1. So the lemma follows.  $\square$

Now we provide the proof of Lemma 3:

*Proof.* Let  $G_i = [\cup_{j \in [\ell] \setminus \{i\}} (O_j^{i+} \cup O_j^{i-} \cup \widehat{O}_j^{i+} \cup \widehat{O}_j^{i-})] \cup O_i^- \cup [O \cap D_i]$  for all  $i \in [\ell]$ . It is not hard to see that  $G_i \subseteq O \setminus S_i$  and  $\forall u \in O \setminus (S_i \cup G_i) : f(u | S_i) \leq 0$ . Therefore, we can get

$$\begin{aligned}
 & \sum_{i \in [\ell]} \left( f(O \cup S_i) - f(S_i) \right) \\
 \leq & \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \left( \sum_{u \in O_j^{i+} \cup \widehat{O}_j^{i+}} f(u | S_i) + \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} f(u | S_i) \right) + \sum_{u \in O_i^-} f(u | S_i) + \sum_{u \in O \cap D_i} f(u | S_i) \right) \quad (20) \\
 \leq & \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \left( \sum_{u \in O_j^{i+} \cup \widehat{O}_j^{i+}} \delta(u) + \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) \right) + \sum_{u \in O_i^-} \delta(\pi_i(u)) + \sum_{u \in O \cap D_i} \delta(u) \right) \quad (21) \\
 = & \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \left( \sum_{u \in O_j^{i+}} \delta(u) + \sum_{u \in O_j^{i-} \cup \widehat{O}_j^{i-}} \delta(\pi_i(u)) \right) + \sum_{u \in O_i^-} \delta(\pi_i(u)) \right) \\
 & + \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in \widehat{O}_j^{i+}} \delta(u) + \sum_{u \in O \cap D_i} \delta(u) \right) \\
 \leq & \ell(k + \ell - 2)f(S^*) + \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in \widehat{O}_j^{i+}} \delta(u) + \sum_{u \in O \cap D_i} \delta(u) \right) \quad (22)
 \end{aligned}$$

where Eqn. (20) is due to submodularity of  $f(\cdot)$ ; Eqn. (21) is due to Lemma 2 and submodularity; and Eqn. (22) is due to Lemma 9. Moreover, we can get

$$\begin{aligned}
 & \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in \widehat{O}_j^{i+}} \delta(u) + \sum_{u \in O \cap D_i} \delta(u) \right) \leq \sum_{i \in [\ell]} \left( \sum_{j \in [\ell] \setminus \{i\}} \sum_{u \in O \cap D_j} \delta(u) + \sum_{u \in O \cap D_i} \delta(u) \right) \quad (23) \\
 = & \sum_{i \in [\ell]} \sum_{j \in [\ell]} \sum_{u \in O \cap D_j} \delta(u) = \ell \sum_{u \in \mathcal{N}} X_u \cdot \delta(u) \quad (24)
 \end{aligned}$$

where Eqn. (23) is due to  $\widehat{O}_j^{i+} \subseteq O \cap D_j$  and  $\forall u \in D_j : \delta(u) > 0$ . Combining Eqn. (22) and Eqn. (24) finishes the proof of Lemma 3.  $\square$

#### A.4. Proof of Lemma 4

We first quote the following lemma presented in (Buchbinder et al., 2014):

**Lemma 10.** (Buchbinder et al., 2014) *Given a ground set  $\mathcal{N}$  and any non-negative submodular function  $g(\cdot)$  defined on  $2^{\mathcal{N}}$ , we have  $\mathbb{E}[g(Y)] \geq (1-p)g(\emptyset)$  if  $Y$  is a random subset of  $\mathcal{N}$  such that each element in  $\mathcal{N}$  appears in  $Y$  with probability of at most  $p$  (not necessarily independently).*

With the above lemma, Lemma 4 can be proved as follows:

*Proof.* We first prove Eqn. (6). Note that  $S_1, S_2, \dots, S_\ell$  are disjoint sets. Using submodularity, we have

$$\begin{aligned}
 & \sum_{i=1}^{\ell} f(S_i \cup O) \geq f(O) + f(S_1 \cup S_2 \cup O) + \sum_{i=3}^{\ell} f(S_i \cup O) \\
 \geq & 2f(O) + f(S_1 \cup S_2 \cup S_3 \cup O) + \sum_{i=4}^{\ell} f(S_i \cup O) \geq \dots \geq (\ell-1)f(O) + f(\cup_{i=1}^{\ell} S_i \cup O) \quad (25)
 \end{aligned}$$

Let  $g : 2^{\mathcal{N}} \mapsto \mathbb{R}_{\geq 0}$  be a non-negative submodular function defined as:  $\forall S \subseteq \mathcal{N} : g(S) = f(S \cup O)$ . As each element in  $\mathcal{N}$  appears in  $\cup_{i=1}^{\ell} S_i$  with probability of no more than  $p$ , We can use Lemma 10 to get

$$\mathbb{E}[f(\cup_{i=1}^{\ell} S_i \cup O)] = \mathbb{E}[g(\cup_{i=1}^{\ell} S_i)] \geq (1-p)g(\emptyset) = (1-p)f(O) \quad (26)$$

Combining Eqn. (25) and Eqn. (26) finishes the proof of Eqn. (6).

Next, we prove Eqn. (7). For any  $u \in \mathcal{N}$ , let  $Y_u = 1$  if  $u \in \cup_{i=1}^{\ell} S_i$  and  $Y_u = 0$  otherwise; let  $\mathcal{E}_u$  be an arbitrary event denoting all the random choices of RANDOMMULTIGREEDY up until the time that  $u$  is considered to be added into a candidate solution, or denoting all the randomness of RANDOMMULTIGREEDY if  $u$  is never considered. Note that we have  $\sum_{u \in \mathcal{N}} Y_u \cdot \delta(u) \leq \sum_{i=1}^{\ell} f(S_i)$ . Therefore, by the law of total probability, we only need to prove

$$\forall u \in \mathcal{N} : \frac{1-p}{p} \mathbb{E}[Y_u \cdot \delta(u) \mid \mathcal{E}_u] \geq \mathbb{E}[X_u \cdot \delta(u) \mid \mathcal{E}_u] \quad (27)$$

for any event  $\mathcal{E}_u$  defined above. Note that we have  $X_u = 0$  and hence Eqn. (27) clearly holds if  $u \notin O$  or  $u$  is never considered by the algorithm. Otherwise we have  $\mathbb{E}[Y_u \cdot \delta(u) \mid \mathcal{E}_u] = p \cdot \delta(u)$  and  $\mathbb{E}[X_u \cdot \delta(u) \mid \mathcal{E}_u] = (1-p) \cdot \delta(u)$  due to the reason that  $u$  is accepted with probability of  $p$  and discarded with probability of  $1-p$ . Combining all these results completes the proof of Eqn. (7).  $\square$

### A.5. Proof of Theorem 2

For clarity, we first provide the detailed design of the accelerated version of RANDOMMULTIGREEDY, as shown by Algorithm 5. In the  $t$ -th iteration, Algorithm 5 calls a procedure CHOOSE to greedily find an candidate element  $v_i$  for  $S_i$  satisfying  $f(v_i \mid S_i) > 0$  and  $S_i \cup \{v_i\} \in \mathcal{I}$  for each  $i \in [\ell]$ . The CHOOSE procedure also returns an index  $i_t$  same to that in Algorithm 1. After that, Algorithm 5 runs similarly as Algorithm 1, i.e., it inserts  $v_{i_t}$  into  $S_{i_t}$  with probability  $p$ , and then enters the  $(t+1)$ -th iteration. Note that the elements  $v_1, \dots, v_{\ell}$  and  $v_{i_t}$  found in the  $t$ -th iteration are also used to call CHOOSE in the  $(t+1)$ -th iteration, so that CHOOSE need not to identify a new  $v_i$  for all  $i \in [\ell] : v_i \neq v_{i_t}$  (as  $S_i$  does not change for these  $i$ 's) and hence time efficiency can be improved. Finally, Algorithm 5 returns the optimal set among  $S_1, \dots, S_{\ell}$  and  $S_0$ , where  $S_0$  is the singleton set with the maximum utility.

Next, we provide a brief description on the CHOOSE procedure. As explained in Sec. 4.1, CHOOSE maintains  $\ell$  sets  $A_1, A_2, \dots, A_{\ell}$  such that  $v_i$  can be selected from  $A_i$ . At the first time that CHOOSE is called, CHOOSE assigns each element  $u \in A_i$  a weight  $w_i(u) = f(u \mid \emptyset)$  and an integer  $\tau_i(u)$  indicating how many times  $w_i(u)$  has been updated (Lines 3–7). Afterwards, CHOOSE runs as that described in Sec. 4.1 and finds  $v_i$  for each  $i \in [\ell]$ . Finally, CHOOSE identifies  $v_{i^*}$  from  $\{v_i : i \in [\ell]\}$  which has the maximum marginal gain, and it also removes  $v_{i^*}$  from all  $A_i : i \in [\ell]$  because  $v_{i^*}$  will be used as  $v_{i^*}$  by Algorithm 5.

Note that Algorithm 5 differs from Algorithm 1 in two points: (1) the element  $u_t$  found in the  $t$ -th iteration is only an  $(\frac{1}{1+\epsilon})$ -approximate solution; (2) there are elements removed from  $A_i$  due to ‘‘too many updates’’. Based on this observation, we can slightly modify the proofs for Algorithm 1 to prove Theorem 2, as presented below:

*Proof.* Let  $L_i$  denote the set of all elements removed from  $A_i$  due to Line 25 of Algorithm 4. We can slightly modify Definition 5 to re-define the sets  $O_j^{i+}, O_j^{i-}, \widehat{O}_j^{i+}, \widehat{O}_j^{i-}, O_i^-$  as follows:

$$\begin{aligned} O_j^{i+} &= \{u \in O \cap S_j : S_i^<(u) \cup \{u\} \in \mathcal{I}\} \setminus L_i; \\ O_j^{i-} &= \{u \in O \cap S_j : S_i^<(u) \cup \{u\} \notin \mathcal{I}\} \setminus L_i; \\ \widehat{O}_j^{i+} &= \{u \in O \cap D_j : S_i^<(u) \cup \{u\} \in \mathcal{I}\} \setminus L_i; \\ \widehat{O}_j^{i-} &= \{u \in O \cap D_j : S_i^<(u) \cup \{u\} \notin \mathcal{I}\} \setminus L_i; \\ O_i^- &= \{u \in O \setminus U : S_i \cup \{u\} \notin \mathcal{I} \wedge f(u \mid S_i) > 0\} \setminus L_i; \end{aligned}$$

With this new definition, it can be easily verified that each element  $u$  in  $O_j^{i+} \cup O_j^{i-} \cup \widehat{O}_j^{i+} \cup \widehat{O}_j^{i-}$  is still a candidate considered for  $S_i$  in the CHOOSE procedure when the algorithm tries to insert  $u$  into  $S_j$ . Therefore, according to the greedy rule of RANDOMMULTIGREEDY and the  $(1+\epsilon)^{-1}$ -approximation ratio of CHOOSE, we can use similar reasoning as that

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**Algorithm 4** CHOOSE( $S_1, S_2, \dots, S_\ell, v_1, \dots, v_\ell, v^*$ )
 

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1: if  $\cup_{i=1}^\ell S_i = \emptyset$  then
2:   Let  $A_i \leftarrow \{u \in \mathcal{N} : \{u\} \in \mathcal{I} \wedge f(u | \emptyset) > 0\}$  for all  $i \in [\ell]$ ;
3:   for all  $i \in [\ell]$  do
4:     Let  $w_i(u) \leftarrow f(u | \emptyset)$  and  $\tau_i(u) \leftarrow 0$  for all  $u \in A_i$ ;
5:     Store  $A_i$  as a priority list according to the non-increasing order of  $w_i(u) : u \in A_i$  for all  $i \in [\ell]$ ;
6:     Let  $v_i \leftarrow \arg \max_{u \in A_i} w_i(u)$ ;
7:   end for
8: else
9:    $C \leftarrow [\ell] \setminus \{j \in [\ell] : (v_j \neq v^*) \vee (v_j = \text{NULL})\}$ 
10:  for all  $i \in C$  do
11:    Let  $v_i \leftarrow \text{NULL}$  and remove all elements in  $A_i$  with non-positive weights;
12:    while  $A_i \neq \emptyset$  do
13:      pop out the top element  $u$  from  $A_i$ ;
14:      if  $f(u | S_i)$  has been computed then
15:         $v_i \leftarrow u$ ; exit while;
16:      end if
17:      if  $S_i \cup \{u\} \notin \mathcal{I}$  then
18:        continue;
19:      end if
20:       $old \leftarrow w_i(u)$ ;  $\tau_i(u) \leftarrow \tau_i(u) + 1$ ;
21:      Compute  $f(u | S_i)$  and let  $w_i(u) \leftarrow f(u | S_i)$ ;
22:      if  $w_i(u) \geq \frac{old}{1+\epsilon}$  then
23:         $v_i \leftarrow u$ ; exit while;
24:      else
25:        if  $\tau_i(u) \leq \lceil \log_{1+\epsilon} \frac{\ell r}{\epsilon} \rceil$  then
26:          re-insert  $u$  into  $A_i$  and resort the elements in  $A_i$ ;
27:        end if
28:      end if
29:    end while
30:  end for
31: end if
32: Let  $i^* \leftarrow \arg \max_{i \in [\ell]: v_i \neq \text{NULL}} f(v_i | S_i)$  and remove  $v_{i^*}$  from  $A_i$  for all  $i \in [\ell]$ 
33: Output:  $v_1, v_2, \dots, v_\ell, i^*$ 

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for Lemma 2 to prove

$$\forall u \in O_j^{i+} \cup \widehat{O}_j^{i+} : f(u | S_i) \leq (1 + \epsilon)\delta(u); \quad (28)$$

$$\forall u \in \cup_{j \in [\ell] \setminus \{i\}} (O_j^{i-} \cup \widehat{O}_j^{i-}) \cup (O \cap S_i) \cup O_i^- : f(u | S_i) \leq (1 + \epsilon)\delta(\pi_i(u)); \quad (29)$$

With the above results, we can use similar reasoning as that in Lemma 3 to prove:

$$\frac{1}{1 + \epsilon} \sum_{i \in [\ell]} f(O | S_i) \leq \ell(k + \ell - 2)f(S^*) + \ell \sum_{u \in \mathcal{N}} X_u \cdot \delta(u) + \sum_{i \in [\ell]} \sum_{u \in L_i \cap O} f(u | S_i) \quad (30)$$

Moreover, we have

$$\sum_{u \in L_i \cap O} f(u | S_i) \leq \sum_{u \in L_i \cap O} f(u | \emptyset)(1 + \epsilon)^{-\lceil \log_{1+\epsilon} \frac{\ell r}{\epsilon} \rceil} \leq \sum_{u \in L_i \cap O} \frac{\epsilon}{\ell r} f(u) \leq \epsilon f(S^*) / \ell \quad (31)$$

where the first inequality is due the reason that the weight of each element  $u \in L_i$  have been updated in CHOOSE procedure for more than  $\lceil \log_{1+\epsilon} \frac{\ell r}{\epsilon} \rceil$  times and it diminishes by a factor of  $\frac{1}{1+\epsilon}$  for each update. Combining Eqn. (30), Eqn. (31) and Lemma 4, we can prove

$$f(O) \leq \left[ (1 + \epsilon) \frac{\ell(k + \frac{\ell}{p} - 1)}{\ell - p} - \frac{(\ell - 1)\epsilon - \epsilon^2}{\ell - p} \right] \mathbb{E}[f(S^*)] \quad (32)$$

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**Algorithm 5** RANDOMMULTIGREEDY( $\ell, p$ ) /\*with acceleration\*/
 

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**Initialize:**  $\forall i \in [\ell] : S_i \leftarrow \emptyset; v_i \leftarrow \text{NULL}; t \leftarrow 1; u_0 \leftarrow \text{NULL};$   
 1: **repeat**  
 2:    $(v_1, v_2, \dots, v_\ell, i_t) \leftarrow \text{CHOOSE}(S_1, \dots, S_\ell, v_1, \dots, v_\ell, u_{t-1})$   
 3:   **if**  $\exists j \in [\ell] : v_j \neq \text{NULL}$  **then**  
 4:      $u_t \leftarrow v_{i_t};$   
 5:     **With probability**  $p$  **do**  $S_{i_t} \leftarrow S_{i_t} \cup \{u_t\}$   
 6:      $t \leftarrow t + 1$   
 7:   **end if**  
 8: **until**  $(\forall i \in [\ell] : v_i = \text{NULL})$   
 9:  $u^* \leftarrow \arg \max_{u \in \mathcal{N} \wedge \{u\} \in \mathcal{I}} f(u); S_0 \leftarrow \{u^*\}$   
 10:  $S^* \leftarrow \arg \max_{S \in \{S_0, S_1, S_2, \dots, S_\ell\}} f(S); T \leftarrow t - 1$   
 11: **Output:**  $S^*, T$

---

Therefore, the approximation ratio of the accelerated RANDOMMULTIGREEDY algorithm is at most  $(1 + \epsilon)(1 + \sqrt{k})^2$  when  $\ell = 2, p = \frac{2}{1 + \sqrt{k}}$  (for a randomized algorithm), or at most  $(1 + \epsilon)(k + \sqrt{k} + \lceil \sqrt{k} \rceil + 1)$  when  $\ell = \lceil \sqrt{k} \rceil + 1, p = 1$  (for a deterministic algorithm). Finally, it can be seen that the CHOOSE procedure incurs at most  $\mathcal{O}(\log_{1+\epsilon} \frac{\ell r}{\epsilon})$  value and independence oracle queries for each element in each  $A_i : i \in [\ell]$ . So the total time complexity of the accelerated RANDOMMULTIGREEDY algorithm is at most  $\mathcal{O}(\ell n \log_{1+\epsilon} \frac{\ell r}{\epsilon}) = \mathcal{O}(\frac{\ell n}{\epsilon} \log \frac{\ell r}{\epsilon})$ , which completes the proof.  $\square$

## B. Missing Proofs from Section 5

### B.1. Proof of Lemma 5

*Proof.* Given any element set  $Y \subseteq \mathcal{N}$  and any realization  $\phi$ , let  $g(Y, \phi) := f(Y \cup \mathcal{N}(\pi_{\text{opt}}, \phi), \phi)$ . It is easy to verify that the non-negative function  $g(\cdot, \phi)$  is submodular. Thus, given a fixed realization  $\phi$ , by Lemma 10, we know that

$$\mathbb{E}_{\pi_{\mathcal{A}}} [g(\mathcal{N}(\pi_{\mathcal{A}}, \phi), \phi)] \geq (1 - p)g(\emptyset, \phi) \quad (33)$$

Therefore, we have

$$f_{\text{avg}}(\pi_{\text{opt}} @ \pi_{\mathcal{A}}) = \mathbb{E}_{\Phi} [\mathbb{E}_{\pi_{\mathcal{A}}} [g(\mathcal{N}(\pi_{\mathcal{A}}, \Phi), \Phi)]] \geq \mathbb{E}_{\Phi} [(1 - p)g(\emptyset, \Phi)] = (1 - p)f_{\text{avg}}(\pi_{\text{opt}}), \quad (34)$$

which completes the proof.  $\square$

### B.2. Proof of Lemma 6

*Proof.* We first give an equivalent expression of the expected utility by a function of conditional expected marginal gains. Given a deterministic policy  $\pi$  and a realization  $\phi$ , for each  $u \in \mathcal{N}$ , let  $Y_u(\phi)$  be a boolean random variable such that  $Y_u(\phi) = 1$  if  $u \in \mathcal{N}(\pi, \phi)$  and  $Y_u(\phi) = 0$  otherwise. Further, denote by  $\psi_u^\pi(\phi)$  the partial realization observed by  $\pi$  right before considering  $u$  under realization  $\phi$ , and denote by  $\Psi_u^\pi$  a random partial realization right before considering  $u$  by  $\pi$ . We also use  $Y_u(\psi_u^\pi(\phi))$  to represent  $Y_u(\phi)$ , since the partial realization  $\psi_u^\pi(\phi)$  suffices to determine whether  $u$  is added to the solution under realization  $\phi$ . Thus,

$$\begin{aligned}
 & \mathbb{E}_{\Phi} [f(\mathcal{N}(\pi, \Phi), \Phi)] \\
 = & \mathbb{E}_{\Phi} \left[ \sum_{u \in \mathcal{N}} \left( Y_u(\Phi) \cdot (f(\text{dom}(\psi_u^\pi(\Phi)) \cup \{u\}, \Phi) - f(\text{dom}(\psi_u^\pi(\Phi)), \Phi)) \right) \right] \\
 = & \sum_{u \in \mathcal{N}} \mathbb{E}_{\Psi_u^\pi} \left[ \mathbb{E}_{\Phi} \left[ Y_u(\Phi) \cdot (f(\text{dom}(\Psi_u^\pi) \cup \{u\}, \Phi) - f(\text{dom}(\Psi_u^\pi), \Phi)) \mid \Phi \sim \Psi_u^\pi \right] \right] \\
 = & \sum_{u \in \mathcal{N}} \mathbb{E}_{\Psi_u^\pi} \left[ Y_u(\Psi_u^\pi) \cdot \Delta(u \mid \Psi_u^\pi) \right] = \sum_{u \in \mathcal{N}} \mathbb{E}_{\Phi} \left[ \mathbb{E}_{\Psi_u^\pi} \left[ Y_u(\Psi_u^\pi) \cdot \Delta(u \mid \Psi_u^\pi) \mid \Phi \sim \Psi_u^\pi \right] \right] \\
 = & \sum_{u \in \mathcal{N}} \mathbb{E}_{\Phi} \left[ Y_u(\Phi) \cdot \Delta(u \mid \psi_u^\pi(\Phi)) \right] = \mathbb{E}_{\Phi} \left[ \sum_{u \in \mathcal{N}(\pi, \Phi)} \Delta(u \mid \psi_u^\pi(\Phi)) \right]. \quad (35)
 \end{aligned}$$

Denote by  $\psi(\pi_{\mathcal{A}}, \phi)$  the observed partial realization at the end of  $\pi_{\mathcal{A}}$  under realization  $\phi$ . Then, similar to the above analysis, we have

$$\begin{aligned}
 f_{\text{avg}}(\pi_{\mathcal{A}} @ \pi_{\text{opt}}) &= \mathbb{E}_{\Phi, \pi_{\mathcal{A}} @ \pi_{\text{opt}}} [f(\mathcal{N}(\pi_{\mathcal{A}} @ \pi_{\text{opt}}, \Phi), \Phi)] \\
 &= \mathbb{E}_{\pi_{\mathcal{A}} @ \pi_{\text{opt}}} \left[ \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi_u(\Phi)) + \sum_{u \in \mathcal{N}(\pi_{\text{opt}}, \Phi) \setminus \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi(\pi_{\mathcal{A}}, \Phi) \cup \psi_u^{\pi_{\text{opt}}}(\Phi)) \right] \\
 &= f_{\text{avg}}(\pi_{\mathcal{A}}) + \mathbb{E}_{\pi_{\mathcal{A}} @ \pi_{\text{opt}}} \left[ \sum_{u \in \mathcal{N}(\pi_{\text{opt}}, \Phi) \setminus \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi(\pi_{\mathcal{A}}, \Phi) \cup \psi_u^{\pi_{\text{opt}}}(\Phi)) \right] \\
 &\leq f_{\text{avg}}(\pi_{\mathcal{A}}) + \mathbb{E}_{\pi_{\mathcal{A}}} \left[ \sum_{u \in \mathcal{N}(\pi_{\text{opt}}, \Phi) \setminus \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi_u(\Phi)) \right],
 \end{aligned}$$

where the inequality is due to adaptive submodularity and  $\psi_u(\Phi) \subseteq \psi(\pi_{\mathcal{A}}, \Phi) \subseteq \psi(\pi_{\mathcal{A}}, \Phi) \cup \psi_u^{\pi_{\text{opt}}}(\Phi)$ .  $\square$

### B.3. Proof of Lemma 7

*Proof.* Since  $f_{\text{avg}}(\pi_{\mathcal{A}}) = \mathbb{E}_{\pi_{\mathcal{A}}} \left[ \mathbb{E}_{\Phi} \left[ \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi_u(\Phi)) \right] \right]$ , it suffices to prove

$$\sum_{u \in O_1(\phi)} \Delta(u | \psi_u(\phi)) \leq k \cdot \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi)} \Delta(u | \psi_u(\phi)) \quad (36)$$

for any given realization  $\phi \in Z^{\mathcal{N}}$  and fixed randomness of  $\pi_{\mathcal{A}}$ . Given a realization  $\phi$ , let  $\hat{u}_i$  be the  $i$ -th element selected by  $\pi_{\mathcal{A}}$  and let  $\hat{S}_i$  be the first  $i$  elements picked, i.e.,  $\hat{S}_i = \{\hat{u}_1, \dots, \hat{u}_i\}$ , for  $i = 1, 2, \dots, h$  where  $h := |\mathcal{N}(\pi_{\mathcal{A}}, \phi)|$ . Suppose that there exists a partition  $O_{1,1}, O_{1,2}, \dots, O_{1,h}$  of  $O_1(\phi)$  such that for all  $i = 1, 2, \dots, h$ ,

$$\sum_{u \in O_{1,i}} \Delta(u | \psi_u(\phi)) \leq k \cdot \Delta(\hat{u}_i | \psi_{\hat{u}_i}(\phi)), \quad (37)$$

then Eqn. (36) must hold due to

$$\sum_{u \in O_1(\phi)} \Delta(u | \psi_u(\phi)) = \sum_{i=1}^h \sum_{u \in O_{1,i}} \Delta(u | \psi_u(\phi)) \leq k \cdot \sum_{i=1}^h \Delta(\hat{u}_i | \psi_{\hat{u}_i}(\phi)) = k \cdot \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi)} \Delta(u | \psi_u(\phi)). \quad (38)$$

Therefore, we just need to show the existence of such a desired partition of  $O_1$ , as proved below.

We use the following iterative algorithm to find the partition, which is inspired by (Calinescu et al., 2011). Define  $\mathcal{N}_h := O_1(\phi)$ . For  $i = h, h-1, \dots, 2$ , let  $B_i := \{u \in \mathcal{N}_i | \hat{S}_{i-1} \cup \{u\} \in \mathcal{I}\}$ . If  $|B_i| \leq k$ , set  $O_{1,i} = B_i$ . Otherwise, pick an arbitrary  $O_{1,i} \subseteq B_i$  with  $|O_{1,i}| = k$ . Then, set  $\mathcal{N}_{i-1} = \mathcal{N}_i \setminus O_{1,i}$ . Finally, set  $O_{1,1} = \mathcal{N}_1$ . Clearly,  $|O_{1,i}| \leq k$  for  $i = 2, \dots, h$ . We further show that  $|O_{1,1}| \leq k$ . We prove it by contradiction and assume  $|O_{1,1}| > k$ . If  $|B_2| \leq k$ , then we have  $\hat{S}_1 \cup \{u\} \notin \mathcal{I}$  for every  $u \in \mathcal{N}_1$  according to the above process. So  $\hat{S}_1$  is a base of  $\hat{S}_1 \cup \mathcal{N}_1$ , which implies that  $|\mathcal{N}_1| \leq k \cdot |\hat{S}_1|$ , contradicting the assumption that  $|\mathcal{N}_1| = |O_{1,1}| > k$ . Consequently, it must hold that  $|B_2| > k$  and hence  $|O_{1,2}| = k$  and  $|\mathcal{N}_2| > 2k$ . Using a similar argument, we can recursively get that  $|B_i| > k$  and hence  $|O_{1,i}| = k$  and  $|\mathcal{N}_i| > ik$  for any  $i = 3, \dots, h$ , e.g.,  $|\mathcal{N}_h| > hk$ . However, as  $\hat{S}_h$  is a base of  $\hat{S}_h \cup O_1(\phi)$ , we should have  $|\mathcal{N}_h| = |O_1(\phi)| \leq hk$ , which shows a contradiction. Therefore, we can conclude that  $|O_{1,i}| \leq k$  for all  $i = 1, 2, \dots, h$ .

According to the partition  $O_{1,i} : i \in [h]$  constructed above, it is obvious that for every  $u \in O_{1,i}$ ,  $\hat{S}_{i-1} \cup \{u\} \in \mathcal{I}$ . This implies that for every  $u \in O_{1,i}$ ,  $u$  cannot be considered before  $\hat{u}_i$  is added by  $\pi_{\mathcal{A}}$ , i.e.,  $\psi_{\hat{u}_i}(\phi) \subseteq \psi_u(\phi)$ . Meanwhile, due to the greedy rule of ADAPTRANDOMGREEDY, it follows that  $\Delta(\hat{u}_i | \psi_{\hat{u}_i}(\phi)) \geq \Delta(u | \psi_{\hat{u}_i}(\phi))$  for each  $u \in O_{1,i}$ . Hence,

$$\sum_{u \in O_{1,i}} \Delta(u | \psi_u(\phi)) \leq \sum_{u \in O_{1,i}} \Delta(u | \psi_{\hat{u}_i}(\phi)) \leq \sum_{u \in O_{1,i}} \Delta(\hat{u}_i | \psi_{\hat{u}_i}(\phi)) \leq k \cdot \Delta(\hat{u}_i | \psi_{\hat{u}_i}(\phi)) \quad (39)$$

holds for any  $i \in [h]$ . Combining the above results completes the proof.  $\square$

### B.4. Proof of Lemma 8

*Proof.* Again, since  $f_{\text{avg}}(\pi_{\mathcal{A}}) = \mathbb{E}_{\pi_{\mathcal{A}}} \left[ \mathbb{E}_{\Phi} \left[ \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi_u(\Phi)) \right] \right]$ , we only need to prove that, for any  $\phi \in Z^{\mathcal{N}}$ ,

$$\mathbb{E}_{\pi_{\mathcal{A}}} \left[ \sum_{u \in O_2(\phi)} \Delta(u | \psi_u(\phi)) \right] \leq \frac{1-p}{p} \cdot \mathbb{E}_{\pi_{\mathcal{A}}} \left[ \sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi)} \Delta(u | \psi_u(\phi)) \right]. \quad (40)$$

Given a realization  $\phi \in Z^{\mathcal{N}}$ , for each  $u \in \mathcal{N}$ , let  $X_u$  be a random variable such that  $X_u = 1$  if  $u \in O_2(\phi)$  and  $X_u = 0$  otherwise. So we have

$$\sum_{u \in O_2(\phi)} \Delta(u | \psi_u(\phi)) = \sum_{u \in \mathcal{N}} (X_u \cdot \Delta(u | \psi_u(\phi))). \quad (41)$$

Similarly, for each  $u \in \mathcal{N}$ , let  $Y_u$  be a random variable such that  $Y_u = 1$  if  $u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi)$  and  $Y_u = 0$  otherwise. Thus,

$$\sum_{u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi)} \Delta(u | \psi_u(\phi)) = \sum_{u \in \mathcal{N}} (Y_u \cdot \Delta(u | \psi_u(\phi))). \quad (42)$$

Therefore, it is sufficient to prove:

$$\forall u \in \mathcal{N} : \mathbb{E}_{\pi_{\mathcal{A}}} [X_u \cdot \Delta(u | \psi_u(\phi))] \leq \frac{1-p}{p} \cdot \mathbb{E}_{\pi_{\mathcal{A}}} [Y_u \cdot \Delta(u | \psi_u(\phi))] \quad (43)$$

Observe that, for any given  $u \in \mathcal{N}$ , if  $\Delta(u | \psi_u(\phi)) \leq 0$  or  $\text{dom}(\psi_u(\phi)) \cup \{u\} \notin \mathcal{I}$ , then we have  $u \notin \mathcal{N}(\pi_{\mathcal{A}}, \phi)$  and  $u \notin O_2(\phi)$  by definition, which indicates  $X_u = Y_u = 0$ . Consider the event that  $\Delta(u | \psi_u(\phi)) > 0$  and  $\text{dom}(\psi_u(\phi)) \cup \{u\} \in \mathcal{I}$ , and denote such an event as  $\mathcal{E}_u$ . Since  $\Pr[u \in \mathcal{N}(\pi_{\mathcal{A}}, \phi) | \mathcal{E}_u] = p$ , it is trivial to see that

$$\mathbb{E}_{\pi_{\mathcal{A}}} [Y_u \cdot \Delta(u | \psi_u(\phi))] = p \cdot \mathbb{E}_{\psi_u(\phi)} [\Delta(u | \psi_u(\phi)) | \mathcal{E}_u] \cdot \Pr[\mathcal{E}_u], \quad (44)$$

where the expectation is taken over the randomness of  $\psi_u(\phi)$  (i.e.,  $\psi_u(\phi) \sim \mathcal{E}_u$ ) due to the internal randomness of algorithm. On the other hand, if  $u \in O(\phi)$ , then we have  $\Pr[u \in O_2(\phi) | \mathcal{E}_u] = 1 - p$  as  $u$  is discarded with probability of  $1 - p$ , while we also have  $\Pr[u \in O_2(\phi) | \mathcal{E}_u] = 0$  if  $u \notin O(\phi)$ . Thus, we know  $\Pr[u \in O_2(\phi) | \mathcal{E}_u] \leq (1 - p)$  and hence we can immediately get

$$\mathbb{E}_{\pi_{\mathcal{A}}} [X_u \cdot \Delta(u | \psi_u)] \leq (1 - p) \cdot \mathbb{E}_{\psi_u(\phi)} [\Delta(u | \psi_u(\phi)) | \mathcal{E}_u] \cdot \Pr[\mathcal{E}_u]. \quad (45)$$

The lemma then follows by combining all the above reasoning.  $\square$

### B.5. Proof of Theorem 3

*Proof.* According to Lemmas 6–8, we have

$$\begin{aligned} f_{\text{avg}}(\pi_{\mathcal{A}} @ \pi_{\text{opt}}) - f_{\text{avg}}(\pi_{\mathcal{A}}) &\leq \mathbb{E}_{\pi_{\mathcal{A}}, \Phi} \left[ \sum_{u \in \mathcal{N}(\pi_{\text{opt}}, \Phi) \setminus \mathcal{N}(\pi_{\mathcal{A}}, \Phi)} \Delta(u | \psi_u(\Phi)) \right] \\ &\leq \mathbb{E}_{\pi_{\mathcal{A}}, \Phi} \left[ \sum_{u \in O_1(\Phi)} \Delta(u | \psi_u(\Phi)) + \sum_{u \in O_2(\Phi)} \Delta(u | \psi_u(\Phi)) \right] \\ &\leq \left( k + \frac{1-p}{p} \right) \cdot f_{\text{avg}}(\pi_{\mathcal{A}}) \end{aligned}$$

where the second inequality is due to the definition of  $O_3(\Phi)$ , i.e.,  $\Delta(u | \psi_u(\Phi)) \leq 0$  for every  $u \in O_3(\Phi)$ . Combining the above result with Lemma 5 gives

$$f(\pi_{\text{opt}}) \leq \frac{kp+1}{p(1-p)} \cdot f_{\text{avg}}(\pi_{\mathcal{A}}). \quad (46)$$

Moreover,  $\frac{kp+1}{p(1-p)}$  achieves its minimum value of  $(1 + \sqrt{k+1})^2$  at  $p = (1 + \sqrt{k+1})^{-1}$ . Finally, the  $\mathcal{O}(nr)$  time complexity is evident, as the algorithm incurs  $\mathcal{O}(n)$  oracle queries for each selected element.  $\square$