

Settling the open problems in Kleinberg-Oren time-inconsistent planning models

SHENKE XIAO, Tsinghua University
 YICHONG XU, Tsinghua University
 YIFENG TENG, Tsinghua University
 ZIHE WANG, Tsinghua University
 PINGZHONG TANG, Tsinghua University

This article shows an extended work of [Kleinberg and Oren 2014]. It gives more properties of the graph time-inconsistency model raised in [Kleinberg and Oren 2014] by solving three open problems proposed in [Kleinberg and Oren 2014]. Generally speaking, it gives a tight upper bound for the ratio of actual cost due to time-inconsistency to minimum theoretic cost, and shows the hardness of motivating agent. In the end of this article, it also shows some directions of further work based on this model or its extended version.

Categories and Subject Descriptors: J.4 [Social and Behavioral Sciences]: Economics

Additional Key Words and Phrases: behavior economics, time-inconsistency, NP-hardness

1. INTRODUCTION

This article is generally based on [Kleinberg and Oren 2014]. According to [Kleinberg and Oren 2014], there is a common fact in behavioral economics that people always prefer present profile to future profile, which is called time-inconsistency. [Kleinberg and Oren 2014] has formalized a graph-theoretic model to simulate this phenomenon. In this model, it regards the edges as steps to reach the final target, and each edge has a cost which represents the cost of this step. To keep the integrality of this article, we will restate the model in the next section. [Kleinberg and Oren 2014] has shown many interesting properties of this model, and proposes three open problems in the end. The main result of this article is to solve these problems.

Section 2 restates this basic graph model shown by Kleinberg and Oren formally. The next three sections solves the three problems respectively. Section 3 gives a tight bound of the cost ratio (i.e. the ratio between the ideal minimum cost and the actual cost due to time-inconsistency) for a graph with some constraints. Section 4 shows the hardness of motivating an agent by removing edges or nodes in the graph, while Section 5 shows the hardness of motivating an agent by dispersing the reward over nodes in the graph, by reducing them to well-known 3-SAT problem. At last in Section 6, we shows a conclusion and some further directions of relative works.

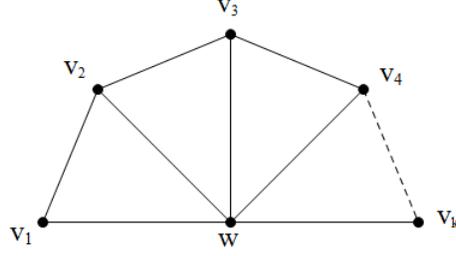
2. BASIC MODEL

In this section we restate the graph-theoretic model shown by [Kleinberg and Oren 2014] and fix some important definitions. As [Kleinberg and Oren 2014] defines, we have an acyclic direct graph G with a start node s and a target node t , where each edge (u, v) has a non-negative cost $c(u, v)$. For any node u, v , denote by $d(u, v)$ the minimum total cost from u to v , i.e.

$$d(u, v) = \min_{P \in \mathcal{P}(u, v)} \sum_{e \in P} c(e),$$

where $\mathcal{P}(u, v)$ is the set of all possible paths from u to v . For simplifying, denote $d(v) = d(v, t)$ for any node v . We also have a present-bias parameter $\beta \in [0, 1]$. An agent starts at s and goes along the edges towards t . In each step, the agent lying in node u chooses the out-neighbor v that minimizes $c(u, v) + \beta d(v)$ (if more than one node minimizes this value, the agent choose one arbitrarily).

We can see this model simulates the time-inconsistency phenomenon to some extent.

Fig. 1. a visible graph of \mathcal{F}_k

While making choices, the agent considers future cost by multiplying the cost with the coefficient β , which means that it cares more about present (the cost of edge it chooses presently). The smaller β is, the less the agent cares about future. Suppose P is the s - t path the agent chooses, then the *cost ratio* r is defined as $\sum_{e \in P} c(e)/d(s)$, i.e. the ratio of actual cost to theoretical minimum cost.

There are also some important concepts given in [Kleinberg and Oren 2014] and we would restate them as follows. “Given two undirected graph H and K , we say that H contains a K -minor if we can map each node κ of K to a connected subgraph S_κ in H , with the properties that (i) S_κ and $S_{\kappa'}$ are disjoint for every two nodes κ, κ' of K , and (ii) if (κ, κ') is an edge of K , then in H there is some edge connecting a node in S_κ with a node in $S_{\kappa'}$ ” ([Kleinberg and Oren 2014] 554). “Let $\sigma(G)$ denote the skeleton of G , the undirected graph obtained by removing the directions on the edges of G . Let \mathcal{F}_k denote the graph with nodes v_1, v_2, \dots, v_k , and w , and edges (v_i, v_{i+1}) for $i = 1, \dots, k-1$, and (v_i, w) for $i = 1, \dots, k$ ” ([Kleinberg and Oren 2014] 555). See Figure 1. \mathcal{F}_k is a very special structure in this setting. [Kleinberg and Oren 2014] has shown that a graph containing \mathcal{F}_k -minor may have exponential cost ratio, and a graph with asymptotic exponential cost ratio must contain an \mathcal{F}_k -minor. In fact, we will give a stronger result immediately in the next section.

3. MAXIMUM COST RATIO

The first open problem proposed by [Kleinberg and Oren 2014] is that what is the maximum cost ratio (or do not exist) if $\sigma(G)$ does not contain an \mathcal{F}_k -minor. Roughly speaking, the problem asks how much can the waste resulted by time-inconsistency reaches. Note an edge is exactly an \mathcal{F}_1 , we will assume $k > 1$ in the following article. Next we will prove the following theorem:

THEOREM 3.1. *For any $k > 1$, if $\sigma(G)$ does not contain an \mathcal{F}_k -minor, the cost ratio is at most β^{2-k} .*

We prove some lemmas firstly.

3.1. Some Lemmas

LEMMA 3.2. *Fix real numbers t_1, t_2, \dots, t_n such that $t_i \geq i + 1$ for $i = 1, 2, \dots, n$. Let $S_i = \{j | 1 \leq j < i, t_j \geq i\}$ for $i = 1, 2, \dots, n$. Then for any sequence $\{x_i, i = 1, 2, \dots\}$ and for $m = 2, 3, \dots, n$, we have*

$$x_{m-1} + \sum_{j \in S_{m-1}} x_j = \sum_{j: t_j = m-1} x_j + \sum_{j: m-1 < t_j < m} x_j + \sum_{j \in S_m} x_j,$$

and

$$\sum_{j \in S_m} x_j = x_{m-1} + \sum_{j \in S_{m-1}: t_j \geq m} x_j.$$

PROOF. For $m = 2, 3, \dots, n$, note $t_{m-1} \geq m$, i.e. $m-1 \in S_m$ and $m-1 \notin S_{m-1}$, we have

$$\begin{aligned} S_{m-1} \cup \{m-1\} &= \{m-1\} \cup \{j | 1 \leq j < m-1, t_j \geq m-1\} \\ &= \{m-1\} \cup \{j | 1 \leq j < m-1, t_j \geq m\} \cup \{j | m-1 \leq t_j < m-1\} \\ &= S_m \cup \{j | t_j = m-1\} \cup \{j | m-1 < t_j < m\}, \end{aligned}$$

where all sets in each side of the equality are disjoint. Thus

$$x_{m-1} + \sum_{j \in S_{m-1}} x_j = \sum_{j: t_j = m-1} x_j + \sum_{j: m-1 < t_j < m} x_j + \sum_{j \in S_m} x_j.$$

Also note

$$\sum_{j: t_j = m-1} x_j + \sum_{j: m-1 < t_j < m} x_j = \sum_{j: m-1 \leq t_j < m} x_j = \sum_{j \in S_{m-1}: m-1 \leq t_j < m} x_j,$$

we have

$$\sum_{j \in S_m} x_j = x_{m-1} + \sum_{j \in S_{m-1}} x_j - \sum_{j \in S_{m-1}: m-1 \leq t_j < m} x_j = x_{m-1} + \sum_{j \in S_{m-1}: t_j \geq m} x_j.$$

□

LEMMA 3.3. Fix real numbers t_1, t_2, \dots, t_n such that $t_i \geq i+1$ for $i = 1, 2, \dots, n$. Let $S_i = \{j | 1 \leq j < i, t_j \geq i\}$ for $i = 1, 2, \dots, n$. Sequence $\{a_i, i = 1, 2, \dots\}$ and $\{b_i, i = 1, 2, \dots\}$ are constructed as follows:

$$\begin{aligned} a_1 &= 1, a_i = \beta b_{i-1} + \sum_{j: i-1 < t_j < i} (1-\beta)b_j, \\ b_i &= a_i + \sum_{j: t_j = i} (1-\beta)b_j. \end{aligned}$$

Then for $i = 1, 2, \dots, n+1$, we have

$$a_i \geq \beta^{|S_i|}.$$

PROOF. Fix i . Firstly we prove that for $m = 1, 2, \dots, n$ we have

$$a_m + \sum_{j \in S_m} (1-\beta)b_j = 1.$$

This can be proved by induction on m : it holds for $m = 1$, and if it holds for $m-1$, then

$$\begin{aligned} &a_m + \sum_{j \in S_m} (1-\beta)b_j \\ &= b_{m-1} - (1-\beta)b_{m-1} + \sum_{j: m-1 < t_j < m} (1-\beta)b_j + \sum_{j \in S_m} (1-\beta)b_j \\ &= a_{m-1} + \sum_{j: t_j = m-1} (1-\beta)b_j - (1-\beta)b_{m-1} + \sum_{j: m-1 < t_j < m} (1-\beta)b_j + \sum_{j \in S_m} (1-\beta)b_j \\ &= a_{m-1} + \sum_{j \in S_{m-1}} (1-\beta)b_j \end{aligned} \tag{1}$$

$$= 1,$$

where equality (1) is held by Lemma 3.2. Let $S_i = \{j_1, j_2, \dots, j_{|S_i|}\}$ where $j_1 < j_2 < \dots < j_{|S_i|}$. Then for $l = 1, 2, \dots, |S_i|$ we have $t_{j_l} \geq i > j_l$, thus for all $1 \leq p \leq l \leq |S_i|$, we have $t_{j_p} \geq i \geq j_l + 1 > j_p$, i.e. $j_p \in S_{j_l+1}$. Now we can obtain for $l = 1, 2, \dots, |S_i|$,

$$b_{j_l} + \sum_{p=1}^{l-1} (1-\beta)b_{j_p} = \beta b_{j_l} + \sum_{p=1}^l (1-\beta)b_{j_p} \leq a_{j_l+1} + \sum_{j \in S_{j_l+1}} (1-\beta)b_j = 1.$$

Note $a_i + \sum_{p=1}^{|S_i|} (1-\beta)b_{j_p} = 1$, to prove $a_i \geq \beta^{|S_i|}$, we only need to prove $\sum_{p=1}^{|S_i|} (1-\beta)b_{j_p} \leq 1 - \beta^{|S_i|}$, or more strongly

$$\sum_{p=1}^l (1-\beta)b_{j_p} \leq 1 - \beta^l$$

for $l = 1, 2, \dots, |S_i|$. We prove it by induction on l : for $l = 1$ it holds trivially, and if it holds for $l - 1$, then

$$\begin{aligned} \sum_{p=1}^l (1-\beta)b_{j_p} &= \sum_{p=1}^{l-1} (1-\beta)b_{j_p} + (1-\beta)b_{j_l} \\ &\leq \sum_{p=1}^{l-1} (1-\beta)b_{j_p} + (1-\beta) \left(1 - \sum_{p=1}^{l-1} (1-\beta)b_{j_p} \right) \\ &= \beta \sum_{p=1}^{l-1} (1-\beta)b_{j_p} + 1 - \beta \\ &\leq \beta (1 - \beta^{l-1}) + 1 - \beta \\ &= 1 - \beta^l. \end{aligned}$$

□

LEMMA 3.4. *Let P be a path of G , and u_1, u_2, \dots, u_k are nodes in order in P . If for $i = 1, 2, \dots, k - 1$, there exists a path P_i such that (i) it starts at u_i , and (ii) the second crossing point in P_i with P (say u'_i) exists and lies behind u_k (not including u_k) in P , then $\sigma(G)$ contains an \mathcal{F}_k -minor.*

PROOF. Let v_1, v_2, \dots, v_k, w' name the nodes of an \mathcal{F}_k such that there are exactly edges (v_i, v_{i+1}) for $i = 1, 2, \dots, k - 1$ and edges (v_i, w') for $i = 1, 2, \dots, k$. Let U_1, U_2, \dots, U_k, W be subgraphs of $\sigma(G)$ which are constructed by their nodes completely: there is an edge between two nodes in one subgraph if and only if this edge exists in $\sigma(G)$. The nodes of these subgraph are collected as follows: for $i = 1, 2, \dots, k - 1$, nodes of U_i are nodes between u_i and u_{i+1} in P (including u_i and not including u_{i+1}); U_k is exactly u_k ; and nodes W are made up of k parts $V_1, V_2, \dots, V_{k-1}, W'$ where V_i are nodes between u_i and u'_i in P'_i (including u'_i and not including u_i) for $i = 1, 2, \dots, k - 1$ and W' are all nodes after u_k in P (not including u_k). See Figure 2.

For each $1 \leq i \leq k$, U_i is connected, as its nodes are connected by P . Then we show that W is also connected. Note that the nodes in V_i are connected through P_i for $i = 1, 2, \dots, k - 1$ while the nodes in W' are connected through P , and V_i and W' are also joint by u'_i for $i = 1, 2, \dots, k - 1$, we can conclude that W is connected.

Trivial to see that U_1, U_2, \dots, U_k, W are disjoint. For $i = 1, 2, \dots, k - 1$, U_i and U_{i+1} are connected by the edge lying before u_{i+1} in P , and U_i and W are connected by the edge

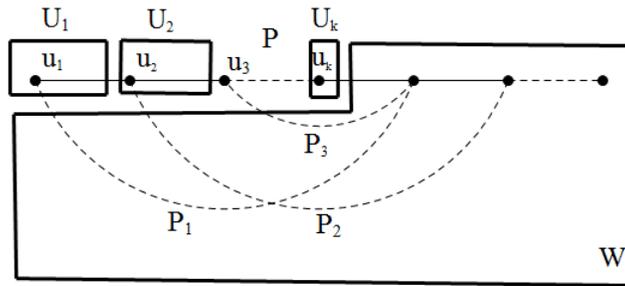


Fig. 2. the graph contains an \mathcal{F}_k -minor.

lying after u_i in P'_i . U_k and W are connected by the edge lying after u_k in P . Now we can establish a map f from $\{v_1, v_2, \dots, v_k, w'\}$ to $\{U_1, U_2, \dots, U_k, W\}$ where $f(v_i) = U_i$ for $i = 1, 2, \dots, k$ and $f(w') = W$. By definition, we can conclude that $\sigma(G)$ contains an \mathcal{F}_k -minor. \square

3.2. Main Proof

Now we would prove Theorem 3.1.

PROOF. We firstly fix some notations: Let P be the path that the agent actually travels. For any node u in P , denote by u' the first node after u in P . For any pair of nodes u, v in P , denote by $c(u, v)$ the total cost of edges between u and v in P . A node u in P is a *shortcut node* if the second point of the path from u to t with minimum total cost (note the first node is just u) is not u' , and suppose that there are n shortcut nodes: u_1, u_2, \dots, u_n in order. For $i = 1, 2, \dots, n$, denote by w_i the second crossing point of P and the u_i - t path P_i with the minimum total cost (note the first crossing point is u_i , and if more than one path has the minimum total cost, arbitrarily choose one), and denote by v_i the first node after u_i on P_i .

Note the agent at u_i does not choose P'_i , we have

$$d(u_i, w_i) + \beta d(w_i) \geq c(u_i, v_i) + \beta d(v_i, w_i) + \beta d(w_i) \geq c(u_i, u'_i) + \beta d(u'_i).$$

Adding both sides by $(1 - \beta)d(w_i)$ we have

$$d(u_i) \geq c(u_i, u'_i) + \beta d(u'_i) + (1 - \beta)d(w_i). \quad (2)$$

Now for $i = 1, 2, \dots, n$, define t_i as follows: if there exists j such that $w_i = u_j$, then $t_i = j$; otherwise if there exists j such that $w_i = u'_j$, then $t_i = j + 0.5$; otherwise t_i is the smallest index such that u_{t_i} lies after w_i in P (if no such index, $t_i = n + 1$). We have the following lemma.

LEMMA 3.5. For $i = 1, 2, \dots, n$, t_i has the following properties:

- (1) $t_i \geq i + 1$;
- (2) if $j < t_i < j + 1$ for some positive integer j , then $w_i = u'_j$;
- (3) if t_i is an integer, $d(w_i) \geq d(u_{t_i})$;
- (4) if $t_i \geq j$ for some positive integer $j > 1$, then w_i lies after u_{j-1} in P .

PROOF. (1) We know w_i must lie after u_i in P . If $w_i = u'_i$, note u_i is a shortcut node, we have

$$c(u_i, u'_i) + d(u'_i) > d(u_i) \geq c(u_i, u'_i) + \beta d(u'_i) + (1 - \beta)d(w_i) = c(u_i, u'_i) + d(u'_i),$$

which is a contradiction! Hence w_i must lie after u'_i in P . By the definition of t_i , if there exists j such that $w_i = u_j$, then u_j lies after u'_i in P , i.e. $t_i = j \geq i + 1$. Otherwise if

there exists j such that $w_i = u'_j$, then u'_j lies after u'_i in P , i.e. $t_i = j + 0.5 > j \geq i + 1$; if such j does not exist, u_{t_i} lies after w_i , or u'_i in P , i.e. $t_i \geq i + 1$.

(2) In this case $t_i = j + 0.5$, then $w_i = u'_j$ by the definition of t_i directly.

(3) If there exists j such that $w_i = u_j$, then $t_i = j$ so that $d(w_i) = d(u_j) = d(u_{t_i})$. Otherwise if there exists j such that $w_i = u'_j$, t_i is not an integer, and it makes a contradiction; if such j does not exist, u_{t_i} lies after w_i in P and there is no shortcut node between them (otherwise we will choose this node as u_{t_i}), hence $d(w_i) = d(u_{t_i}) + c(w_i, u_{t_i}) \geq d(u_{t_i})$.

(4) If there exists l such that $w_i = u_l$, then $l = t_i \geq j$, hence u_l , or w_i lies after u_{j-1} in P . Otherwise if there exists l such that $w_i = u'_l$, then $l + 0.5 = t_i \geq j$, or $l \geq j$, hence u'_l , or w_i lies after u_{j-1} in P ; if such l does not exist, t_i is the smallest index such that u_{t_i} lies after w_i in P , also note there does not exist l such that $w_i = u_l$, we have u_{t_i-1} , or u_{j-1} lies before w_i in P . \square

By Lemma 3.5 (1), we can use these t_i as the same parameters in Lemma 3.3 to construct S_1, S_2, \dots, S_n and sequences $\{a_i, i = 1, 2, \dots\}, \{b_i, i = 1, 2, \dots\}$. Generally speaking, S_i represents those shortcut nodes whose shortcut "comes back" after or at u_i . Next we are trying to use inequality (2) iteratively to get an inequality with the following form:

$$d(s) \geq \sum_{e \in P} \alpha(e)c(e),$$

for some coefficient α . If the inequality with this form is obtained, the bound with cost ratio can be obtained easily. In fact we have the following inequality that for $i = 1, 2, \dots, n + 1$,

$$d(s) \geq \sum_{j=1}^i (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_{i+1} d(u'_i) + \sum_{j \in S_{i+1}} (1 - \beta) b_j d(w_j),$$

where u'_0 and u_{n+1} are defined as s and t respectively. We prove the inequality above by induction on i : it holds for $i = 1$, and if it holds for $i - 1$, then

$$\begin{aligned} d(s) &\geq \sum_{j=1}^{i-1} (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_i d(u'_{i-1}) + \sum_{j \in S_i} (1 - \beta) b_j d(w_j) \\ &= \sum_{j=1}^{i-1} (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_i (c(u'_{i-1}, u_i) + d(u_i)) + \sum_{j: t_j = i} (1 - \beta) b_j d(w_j) \\ &\quad + \sum_{j: i < t_j < i+1} (1 - \beta) b_j d(w_j) + \sum_{j \in S_i: t_j \geq i+1} (1 - \beta) b_j d(w_j) \\ &\geq \sum_{j=1}^{i-1} (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_i c(u'_{i-1}, u_i) + \left(a_i + \sum_{j: t_j = i} (1 - \beta) b_j \right) d(u_i) \\ &\quad + \sum_{j: i < t_j < i+1} (1 - \beta) b_j d(u'_i) + \sum_{j \in S_i: t_j \geq i+1} (1 - \beta) b_j d(w_j) \tag{3} \\ &\geq \sum_{j=1}^{i-1} (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_i c(u'_{i-1}, u_i) \\ &\quad + b_i (c(u_i, u'_i) + \beta d(u'_i) + (1 - \beta) d(w_i)) \end{aligned}$$

$$\begin{aligned}
& + \sum_{j:i < t_j < i+1} (1-\beta)b_j d(u'_i) + \sum_{j \in S_i: t_j \geq i+1} (1-\beta)b_j d(w_j) \\
\geq & \sum_{j=1}^i (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + \left(\beta a_i + \sum_{j:i < t_j < i+1} (1-\beta)b_j \right) d(u'_i) \\
& + (1-\beta)b_i d(w_i) + \sum_{j \in S_i: t_j \geq i+1} (1-\beta)b_j d(w_j) \\
= & \sum_{j=1}^i (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_{i+1} d(u'_i) + \sum_{j \in S_{i+1}} (1-\beta)b_j d(w_j), \tag{4}
\end{aligned}$$

where inequality (3) is held by Lemma 3.5 (2) and (3), and the last step (4) is held by Lemma 3.2. Now choose i to be n , we can get

$$\begin{aligned}
d(s) & \geq \sum_{j=1}^n (a_j c(u'_{j-1}, u_j) + b_j c(u_j, u'_j)) + a_{n+1} d(u'_n) \\
& \geq \sum_{j=1}^n \left(\beta^{|S_j|} c(u'_{j-1}, u_j) + \beta^{|S_j|} c(u_j, u'_j) \right) + \beta^{|S_{n+1}|} c(u'_n, t). \tag{5}
\end{aligned}$$

where the last step (5) holds by Lemma 3.3.

At last, we are going to prove $|S_i| \leq k-2$ for $i = 1, 2, \dots, n+1$. If $|S_i| \geq k-1$ for some i , choose $k-1$ elements from S_i , say j_1, j_2, \dots, j_{k-1} where $j_1 < j_2 < \dots < j_{k-1} < i$. For $l = 1, 2, \dots, k-1$, note $t_{j_l} \geq i$, by Lemma 3.5 (4) w_{j_l} must lie after u_{i-1} , or $u'_{j_{k-1}}$ in P , and also $w_{j_l} \neq u'_{j_{k-1}}$ (otherwise $t_{j_l} = j_{k-1} + 0.5 < i$), w_{j_l} must lie after $u'_{j_{k-1}}$ in P . Now consider $u_{j_1}, u_{j_2}, \dots, u_{j_{k-1}}, u'_{j_{k-1}}$. They lie in P in order, and for $l = 1, 2, \dots, k-1$, P_{j_l} starts at u_{j_l} , and the next crossing point of P_{j_l} and P lies after $u'_{j_{k-1}}$ in P , thus by Lemma 3.4, $\sigma(G)$ contains an \mathcal{F}_k -minor, which forms a contradiction. Now we have proved $|S_i| \leq k-2$.

Hence

$$d(s) \geq \sum_{j=1}^n \left(\beta^{|S_j|} c(u'_{j-1}, u_j) + \beta^{|S_j|} c(u_j, u'_j) \right) + \beta^{|S_{n+1}|} c(u'_n, t) \geq \beta^{k-2} c(s, t),$$

or

$$\frac{c(s, t)}{d(s)} \leq \beta^{2-k}. \quad \square$$

3.3. Tightness of the Bound

So far we have achieved an upper bound for r , now we would like to provide an example to show that the bound is achievable. We would simply use the example mentioned in [Kleinberg and Oren 2014] to show a graph may have exponential cost ratio, i.e. the graph obtained from \mathcal{F}_{k-1} by adding directions (see Figure 3). In fact, this example is a real example of shipping packages that was proposed firstly in [Akerlof 1991]. According to the analysis in [Kleinberg and Oren 2014], the cost ratio of the graph is exactly β^{2-k} , which proves the tightness of our upper bound.

4. HARDNESS OF FINDING MOTIVATING SUBGRAPHS

[Kleinberg and Oren 2014] also extends the model to allow the agent to give up: it sets a reward r at the target node, and suppose the agent is in u now, if $\min_v c(u, v) + \beta d(v) >$

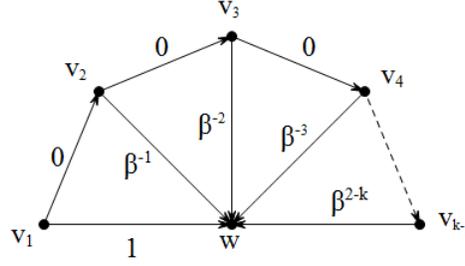


Fig. 3. Akerlof's example

βr , i.e. the weighted cost is less than the reward, the agent will stop and give up. [Kleinberg and Oren 2014] also gave the definition of *motivating graph*: a graph is motivating if the agent will arrive at the target node finally. [Kleinberg and Oren 2014] stated that for a non-motivating graph, we can delete some nodes or edges to make it motivating. The second problem is whether there is a polynomial-time algorithm that “takes an instance G (including a reward r) and determines whether G contains a motivating subgraph with reward r ?” ([Kleinberg and Oren 2014] 563), i.e. to find a motivating subgraph of the original graph. In this section, we are going to show the following theorem:

THEOREM 4.1. *Define problem **ms** as follows: for an acyclic graph G with n nodes, given reward r on target node and present bias β , find a motivating subgraph of G . Then **ms** is NP-hard.*

[Kleinberg and Oren 2014] introduced a concept named *minimal motivating subgraph* to denote a motivating subgraph of the original graph, such that every subgraph of it is not motivating. Before proving Theorem 4.1, we first consider a easier problem related to minimal motivating subgraphs.

4.1. Hardness of finding minimal motivating subgraph

In this section, we would show that finding a minimal motivating subgraph is hard. Define problem **mms** as follows: for an acyclic graph G with n nodes, given reward r on target node and present bias β , find a minimal motivating subgraph of G . Then we have

THEOREM 4.2. ***mms** is NP-hard.*

PROOF. We show that finding a valid assignment to a 3-CNF can be polynomial-time reduced to an instance of **mms**. Consider a 3-CNF with n variables x_1, x_2, \dots, x_n and m clauses C_1, C_2, \dots, C_m . Construct a weighted acyclic graph G with $4m + 3n + 7$ vertices as follows:

- (1) Each clause C_i corresponds to 4 nodes $u_i, u_{i,1}, u_{i,2}, u_{i,3}$, $1 \leq i \leq m$;
- (2) Each variable x_i corresponds to 3 nodes $v_i, v_{i,1}, v_{i,2}$, $1 \leq i \leq n$;
- (3) The other 7 nodes are start node s , target node t and interior points w_1, w_2, w_3, w_4 and w_5 ;
- (4) For any clause $C_i = y_{i,1} \vee y_{i,2} \vee y_{i,3}$: for $j = 1, 2, 3$, if $y_{i,j}$ is x_k , then there is a link $u_i \rightarrow u_{i,j}$ with weight 16, and a link $u_{i,j} \rightarrow v_k$ with weight 11. We call such two links an “expensive path” from u_i to v_k ; if $y_{i,j}$ is $\neg x_k$, then there is a link $u_i \rightarrow u_{i,j}$ with weight 9, and a link $u_{i,j} \rightarrow v_k$ with weight 11. We call such two links a “cheap path” from u_i to v_k .

evaluated cost from the former node of v_i to t would be at least $10 + (10 + 12)\beta = 12.2 > \beta r$. Thus exactly one path remains. \square

LEMMA 4.5. *Let G' be a minimal motivating subgraph of G , then for any $1 \leq i \leq m$, exactly one node among $u_{i,1}, u_{i,2}, u_{i,3}$ is included in G' .*

PROOF. Fix i . Theorem 5.1 in [Kleinberg and Oren 2014] stated that every node in a minimal motivating subgraph has no more than two outgoing edges, thus at most one of the three nodes can be included, as u_i has already got one out-degree in the bus from Lemma 4.3. If all three nodes are eliminated, the agent would not travel to u_i as its evaluated cost from the former node of v_i to t would be at least $8 + (8 + 39)\beta = 12.7 > \beta r$. Hence exactly one of the three nodes remains in G' . \square

Now we would show how to transform a valid assignment of a 3-CNF to a corresponding minimal motivating subgraph of G .

LEMMA 4.6. *Given a valid assignment to a 3-CNF, there exists a polynomial-time algorithm finding a minimal motivating subgraph of graph G constructed from the formula.*

PROOF. Construct a subgraph G' of the original graph G as follows. For $1 \leq i \leq m$, let $C_i = y_{i,1} \vee y_{i,2} \vee y_{i,3}$, assume $y_{i,j}$ is assigned true without loss of generality, then preserve only $u_{i,j}$ among $\{u_{i,1}, u_{i,2}, u_{i,3}\}$, eliminate the other two nodes from G ; for each $1 \leq i \leq n$, if x_i is assigned true, delete $v_{i,1}$ (the more expensive one), otherwise delete $v_{i,2}$. Observe that for any $1 \leq i \leq m$, there is no path from node u_i to t formed by two consecutive cheap paths or expensive paths. To show that the remaining graph is a motivating graph, it suffices to show that at any time the agent would travel through the bus and does not halt on his way.

- (1) The agent is at u_i , $0 \leq i \leq m - 1$ (let $u_0 = s$): Notice that the distance from u_{i+1} to t is $16 + 11 + 12 = 9 + 11 + 19 = 39$, thus the evaluated cost would be $8 + 3.9 = 11.9$ if the agent wants to go to u_{i+1} ; the cost to follow the expensive path would be greater than 16, while the cost to travel to follow the cheap path would be $9 + (11 + 19)\beta = 12 > \beta r$. Thus the agent would go straight to u_{i+1} .
- (2) The agent is at u_m, w_1, w_2, w_3 or w_4 : the only reasonable move for the agent should be following the bus. At u_m, w_1, w_2, w_3, w_4 , the respective evaluated cost would be 11.9, 11.8, 11.9, 11.9, 10 respectively, which are all no larger than βr .
- (3) The agent is at v_i , $1 \leq i \leq n$: the only reasonable move for the agent should be following the bus, and the largest possible evaluated cost would be 11.9, which is no larger than βr .

Finally, we remove w_5 if possible, and it can be verified that w_5 can be removed if and only if x_1 is assigned true. The minimality of the graph follows from Lemma 4.3, 4.4 and 4.5, and the entire procedure can be definitely done in polynomial time. \square

To see how Lemma 4.6 works, consider $(x_1 \vee \neg x_2 \vee x_3) \wedge (x_2 \vee \neg x_3 \vee x_4)$ as an example. A valid assignment would be $x_1 = \neg x_2 = \neg x_3 = x_4 = 1$, and the corresponding minimal motivating subgraph would be shown in Figure 5.

Finally, we would like to see how a minimal motivating subgraph of G can be transformed to a valid assignment to the 3-CNF.

LEMMA 4.7. *Let G' be a minimal motivating subgraph of G . For any $1 \leq i \leq n$, if the expensive path from v_i to t is remained, assign $x_i = 0$, otherwise assign $x_i = 1$, then the assignment is a valid assignment to the original 3-CNF.*

PROOF. To show that the assignment is valid, we only need to show that for any $1 \leq i \leq m$, in G' there is a path from u_i to t that is a cheap path from u_i to some v_k ,

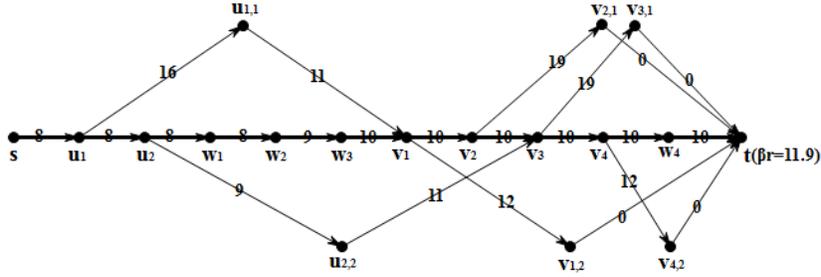


Fig. 5. Corresponding minimal motivating subgraph of $(x_1 \vee \neg x_2 \vee x_3) \wedge (x_2 \vee \neg x_3 \vee x_4)$.

then an expensive path from v_k to t , meaning that x_k is assigned false, C_i is satisfied as it includes $\neg x_k$; or there is a path from u_i to t that is an expensive path from u_i to some v_k , then a cheap path from v_k to t , meaning that x_k is assigned true, C_i is satisfied as it includes x_k . From Lemma 4.3, 4.4 and 4.5 we only need to show that there is no path from node u_i to t formed by two consecutive cheap paths or two consecutive expensive paths. Consider the following two cases.

- (1) Assume by way of contradiction there is a cheap path from u_i to some v_k , then a cheap path from v_k to t , here i is maximum. Then at u_i , choosing the cheap path leads to an evaluated cost $9 + (11 + 12)\beta = 11.3$, while choosing the bus leads to an evaluated cost at least 11.9 . Then the agent would go through the cheap path, while at the next vertex he would evaluate the cost to be at least $11 + 12\beta = 12.2 > \beta r$, then he would halt here, which contradicts the fact that G' is a motivating graph.
- (2) Assume by way of contradiction there is an expensive path from u_i to some v_k , then an expensive path from v_k to t . This is impossible since when the agent is at u_{i-1} , he would evaluate traveling through the bus with cost $8 + (16 + 11 + 19)\beta = 12.6 > \beta r$, which means that he would rather not go through $u_{i-1} \rightarrow u_i$.

Directly from the two cases above we show the correctness of the lemma. \square

From Lemma 4.6 and Lemma 4.7, we know that if we can find a minimal motivating subgraph for any graph in polynomial time, we may find a polynomial time algorithm finding a valid assignment for any 3-CNF, which finishes the proof of Theorem 4.2. \square

4.2. Main Proof

Now we are going to prove Theorem 4.1, which implies not only finding a minimal motivating subgraph is hard, it is also difficult to find a not minimal one.

PROOF. Assume by way of contradiction we have a poly-time algorithm \mathcal{A} to solve **ms**, consider the following algorithm solving **mms**.

The correctness of the algorithm is straightforward, while the running time of the algorithm is polynomial of the size of the graph. From Theorem 4.2 we know that **ms** is NP-hard. \square

5. HARDNESS OF MOTIVATING AGENTS TO REACH THE GOAL

[Kleinberg and Oren 2014] also considers the case where we can put rewards on all nodes in the graph, denoted by $r(v)$ for each node; the agent at node u will continue to

ALGORITHM 1: Solve **mms** by Applying Algorithm Solving **ms**.

Input: An acyclic graph G , reward r on target node and present bias β .

Output: Reject the input or output a minimal motivating subgraph.

Use \mathcal{A} to check whether G has an motivating subgraph;

if no then

 reject the input;

else

while G contains some edges **do**

for each edge e in G **do**

 Use \mathcal{A} to check whether G has a motivating subgraph after deleting e ;

if yes then

 record e ;

end

end

if G has no motivating subgraph after deleting e for each edge e **then**

 output G ;

else

 delete an edge recorded from G ;

end

end

end

move if and only if there exists a path P such that

$$c'(P) = c(u, v_0) + \beta \sum_{v \in P} (c(v, v') - r(v)) \leq 0,$$

where v_0 denotes the first node in P , and v' denotes the next node of v on P . Let $c(t, t') = 0$. And the agent chooses the path that minimize $c'(P)$. We aim to find the configuration that puts the smallest total sum of rewards that motivates the agent to finish at t .

5.1. Problem statement

We considers multiple versions of this problem, as suggested by [Kleinberg and Oren 2014]. In the first version, only positive rewards are allowed, and we can put rewards on every node of the graph. But due to the trivialness of this problem, in this we might put rewards that is never claimed - the agent simply use the reward as on its shortest path but then deviates from its original computation. In the third version, we consider the possible use of negative rewards; the negative reward might be used to get the agent rid of paths that appears to be costless but then becomes very costly (for example, a path start with 0 and then an edge with a very large cost). In this version, we define the sum of rewards to be the sum of absolute values of all rewards put on nodes; we do this because if we define the sum as the direct sum, we can put a rewards of $-\infty$ at some node that there still exists a path from s to t if deleted.

We formally restate this problem:

*Finding the Minimum Total Reward for an agent with present bias β (**fmtr** $_{\beta}$)*

- Input: a weighted acyclic graph G , node s, t , and a possible total possible reward R .
- Output: Whether there exists a reward setting $r(v), \forall v \in G$, such that the agent with a present bias β follows a path P from s to t using the strategy stated above, and that

$$\sum_{v \in G} |r(v)| \leq R.$$

The following three editions gives different constraints on the reward setting:

fmtr_β I: $r(v) \geq 0, \forall v$.

fmtr_β II: $r(v) \geq 0, \forall v \in P; r(v) = 0, \forall v \notin P$.

fmtr_β III: No constraints: $r(v) \in \mathbb{R}$.

5.2. Main Theorem

Unfortunately, we find that this problem, along with each form of it, are all NP-hard:

THEOREM 5.1. ***fmtr**_β I,II,III are NP-hard for all $\beta < 1$.*

Generally, we prove the NP-hardness by reducing 3-SAT to **fmtr**_β.

5.3. Graph construction

For any 3-SAT instance, suppose it has m clauses and n variables.

Let $x = \beta^{-1} - 1, y = \frac{1}{2}x$, and

$$\begin{aligned} g_k &= 6(2n - k), \\ h_k &= 6(2n - k) + 6 + y, \\ r_t &= 12n - 6 + 6\beta^{-1}, \\ l &= \left\lceil \frac{nx + 12n + 6\beta^{-1} - 6}{\beta x} \right\rceil + 1. \end{aligned}$$

We choose n large enough such that

$$nx = n(\beta^{-1} - 1) > 2\beta^{-1}.$$

We construct graph G in the following way: We construct l nodes for each clause i , namely $a_{i,1}, a_{i,2}, \dots, a_{i,l}, b_i$; and 4 nodes u_i, u'_i, v_i, v'_i for each variable i . We also have node c^* , and s, t . We construct edges with weights in the following configuration: (each triple is the start node, end node and the weight of an edge respectively)

- (1) $(s, a_{i,1}, 0); (a_{i,1}, b_i, 0); (a_{i,j}, a_{i,j+1}, \beta x); (a_{i,l}, a_{i+1,1}, 0); (1 \leq i \leq m - 1, 1 \leq j \leq l - 1)$
- (2) $(a_{m,l}, c_1, 0), (c_i, c_{i+1}, 6), (c_n, u_n, 6), (c_n, u'_n, 6); (1 \leq i \leq n - 1)$
- (3) $(u_i, v_i, x); (u'_i, v'_i, x); (1 \leq i \leq n)$
- (4) $(v_i, u_{i-1}, 6); (v_i, u'_{i-1}, 6); (v'_i, u_{i-1}, 6); (v'_i, u'_{i-1}, 6); (1 \leq i \leq n)$
- (5) $(u_0, t, 0); (u'_0, t, 0).$

For a clause i that contains variable k , we construct $(b_i, u_{k-1}, h_k), (b_i, u'_{k-1}, h_k)$. If it contains a positive subclause of k , we construct $(a_{i,j}, v_k, g_k), 2 \leq j \leq l$; otherwise if it contains “not variable k ”, we construct $(a_{i,j}, v'_k, g_k), 2 \leq j \leq l$. An illustration of the graph is depicted below. For simplicity, direct values of h_k and g_k are drawn. The graph shows an example of a clause with v_n and $\neg v_k$. The feasibility of this graph is easily seen from the fact that $\beta < 1$ (so $x > 0$). We now prove the following main proposition:

PROPOSITION 5.2. *The 3-CNF is satisfiable if and only if G has a minimum total reward of at most $nx + r_t$.*

5.4. Two Lemmas

To start with the proof, we first give two lemmas:

LEMMA 5.3. *We have*

$$h_k \beta^{-1} + 6(k - 1) > nx + r_t, \tag{6}$$

$$g_k \beta^{-1} + 6k > nx + r_t, \tag{7}$$

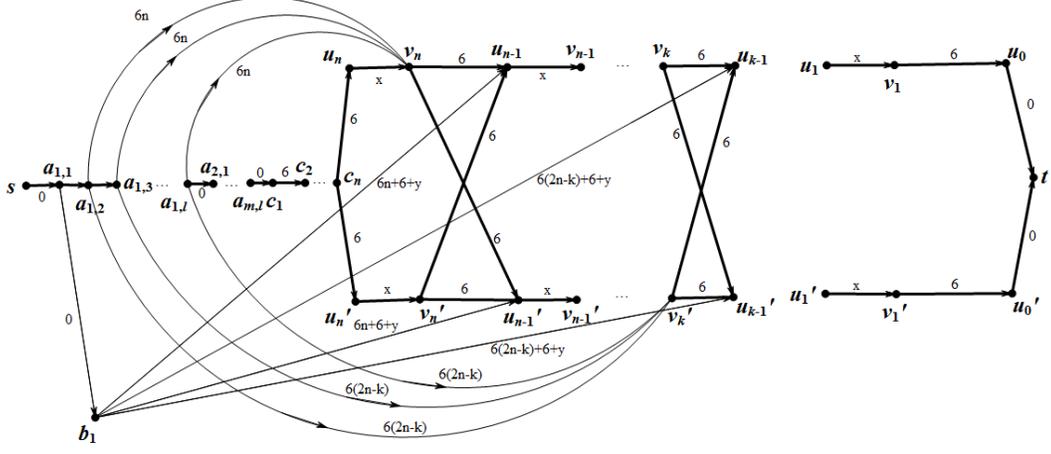


Fig. 6. Example figure for proving theorem 5.1, with a clause with v_n and $\neg v_k$. Edges that might be traveled by the agent are in bold lines.

$$(l-1)\beta x > r_t + nx, \quad (8)$$

$$h_k < x + g_k + 6, \quad (9)$$

$$x + g_k - x + 6k < r_t, \quad (10)$$

$$x + g_k - x + 6k < h_k + 6(k-1), \quad (11)$$

$$\beta x + g_k - x + 6k < r_t, \quad (12)$$

$$6\beta^{-1} + 6(n-1) + 6n = r_t, \quad (13)$$

$$x + g_k - x + 6k < g_k\beta^{-1} - x + 6k. \quad (14)$$

PROOF. We have

$$\begin{aligned} h_k\beta^{-1} + 6(k-1) &= \beta^{-1}(6(2n-k) + 6 + y) + 6(k-1) \\ &> \beta^{-1}6(2n-k) + 6k \\ &= g_k\beta^{-1} + 6k. \end{aligned}$$

On the other hand,

$$\begin{aligned} g_k\beta^{-1} + 6k &= \beta^{-1}6(2n-k) + 6k \\ &\geq 6n + 6n\beta^{-1} \\ &= 12n + 6n(\beta^{-1} - 1) \\ &= 12n + 6nx \\ &> nx + 12n + 6\beta^{-1} - 6 = nx + r_t. \end{aligned}$$

The last inequality is because the way we choose n : $nx > 2\beta^{-1}$. So we prove (6) and (7). We just choose an l large enough for (8) to stand: here we have

$$r_t + nx = 12n - 6 + 6\beta^{-1} + nx \leq \beta x(l-1).$$

(9) is obvious from definition; For (10) the left hand side is

$$g_k + 6k = 6(2n-k) + 6k = 12n < r_t.$$

For (11) the right hand side is

$$h_k + 6(k-1) = 12n + y > 12n,$$

which is the left hand side. (12) is a direct induction of (10). (13) is the definition of r_t . For (14), it is sufficient to prove that

$$x < g_k(\beta^{-1} - 1).$$

In fact we have

$$g_k(\beta^{-1} - 1) = g_k x = 6(2n - k)x > x.$$

So we prove all the inequalities and equalities. \square

LEMMA 5.4. *The agent continues to move if and only if there exists a path P such that*

$$\beta^{-1}c(P) = \beta^{-1}c(e_1) + \sum_{e \in P: e \neq e_1} c(e) \leq \sum_{v \in P} r(v),$$

where e_1 is the first edge of P .

PROOF. This lemma can be obtained simply by multiplying β^{-1} in the definition of motivating the agent. \square

By this lemma, we assume that the agent evaluates

$$\beta^{-1}c(e_1) + \sum_{e \in P: e \neq e_1} c(e)$$

instead of $c(P)$ for every path P at each node; this makes convenience for discussions follow.

5.5. Achievability

PROPOSITION 5.5. *If the 3-CNF is satisfiable, then G has a minimum total reward of at most $nx + r_t$.*

PROOF. If the 3-CNF is satisfiable, we construct a reward as follows: Let $r(v_i) = x$ if variable i is true, otherwise let $r(v'_i) = x$; and $r(t) = r_t$. All other nodes have reward 0. We now prove that this is a valid setting: We define the length value of a path P from v to v' , denoted $l(P)$, to be the sum of all weights on the path minus sum of all rewards on the path except v and v' :

$$l(P) = \sum_{e \in P} c(e) - \sum_{u \in P: u \neq v, v'} r(u).$$

The distance of a node v to t , denoted $d(v)$, is defined as the minimum length value of all paths getting from v to t . In fact, it's easy to see that in this setting all v_i, v'_i have $d(v_i) = d(v'_i) = 6 + (k - 1)(6 + x - x) = 6k$, and if variable i is true then $d(u_i) = 6k$, otherwise $d(u'_i) = 6k$.

- (1) node s will go $a_{1,1}$ because (12) ($d(a_{1,1}) \leq \beta x + g_k - x + d(v_k) = x + g_k - x + 6k \leq r_t$).
- (2) $a_{i,1}$ will go to $a_{i,2}$: The path that goes through $a_{i,2}$ and then v_k (not losing generality, suppose v_k is true) has length value $x + g_k - x + d(v_k) = x + g_k - x + 6k$, and the path that goes through b_i has length value $h_k + 6(k - 1)$. So we derive this from (10) and (11).
- (3) $a_{i,j}, j < l$ will go to $a_{i,j+1}$, because (10) and (14) (The path that uses $a_{i,j}$ to v_k has length value $g_k \beta^{-1} + 6k$).
- (4) $a_{i,l}, i < m$ will go to $a_{i+1,1}$, because the path from $a_{i+1,1} \rightarrow a_{i+1,2} \rightarrow v_k \rightarrow t$ has length value $\beta x + g_k - x + 6k$. So we derive this from (12) and (14).
- (5) $a_{m,l}$ will go to c_1 , because (13).
- (6) c_i will go to c_{i+1} for $1 \leq i \leq n - 1$, because (13).

- (7) c_n will go to u_n^* (here $u_n^* = u_n$ if variable n is true, otherwise $u_n^* = u'_n$) because (13).
 (8) The agent then travels from u_n^* to t , which is trivial by easy computation on the weight values.

□

5.6. Satisfiability

PROPOSITION 5.6. *If the 3-CNF is satisfiable, then G has a minimum total reward of at most $nx + r_t$.*

PROOF. First notice that in the minimum reward setting the agent cannot traverse through any b_i to u_k , since otherwise it requires at least $\beta^{-1}h_k + 6(k-1) > r_t + nx$ (by (6)) rewards.

On the other hand, in a minimum setting the edge $(a_{i,j}, v_k)$ also cannot be used, since otherwise it requires at least $\beta^{-1}g_k + 6k > r_t + nx$ (by (7)) rewards.

Combine the two facts above, we know that the agent will reach c_1 . Notice that all path from c_1 to t has the form $c_1c_2 \cdots c_n u_n^* v_n^* u_{n-1}^* \cdots v_1^* t$, where $u_i^* \in \{u_i, u'_i\}$, $v_i^* \in \{v_i, v'_i\}$. On c_1 , the agent evaluates the cost of any of these paths (excluding the rewards put) to be $6\beta^{-1} + 6(n-1) + 6n = r_t + nx$ (by (13)), so at least $r_t + nx$ rewards has to be put on nodes $\{c_1, c_2, \dots, c_n, u_n, \dots, u_1, u'_n, \dots, u'_1, v_n, \dots, v_1, v'_n, \dots, v'_1, t\}$, in all three versions of \mathbf{fmtr}_β . And so if G has a minimal reward of at most $r_t + nx$, no reward is put at nodes $a_{i,j}$ or b_i . Also in \mathbf{fmtr}_β III, no negative rewards can be given. consider the path that the agent chooses the shortest on c_1 , we know that there must be a path from c_1 to t that has a total reward (including reward on t) of $r_t + nx$. Then since there's no path from v_k to v'_k , u_k to u'_k (vice versa), we can't put rewards on both v_k and v'_k or u_k and u'_k .

Consider the following arrangement: if node v_k has rewards on it, let variable $v_k = \text{true}$; otherwise let variable $v_k = \text{false}$. In the following, we prove this arrangement gives a valid arrangement of the original 3-SAT clause.

Note that if v_k has rewards, then v'_k doesn't have; vice versa. So to prove this proposition we only need to prove that for every clause i , the 3 v kind nodes (call them $v_{k_1}^*, v_{k_2}^*, v_{k_3}^*, v_k^* \in \{v_k, v'_k\}$) that $a_{i,2}$ connects to has at least one of them has costs. To prove this, first notice that the shortest path from $a_{i,2}$ to t must be through some $v_{k_j}^*$: The path through $a_{i,j}$ ($j > 2$) and then to $v_{k_j}^*$ has same costs but an additional βx cost; and the path from $a_{i+1,1}$ has cost at least $\beta x(l-1) > nx + r_t$ (by (8) and that $a_{i,j}$ doesn't have reward), which is larger than the total sum reward.

If none of $v_{k_1}^*, v_{k_2}^*, v_{k_3}^*$ has reward on it, then we have

$$d(a_{i,2}) = \min_{1 \leq j \leq 3, v_{k_j}^*} g_{k_j} + d(v_{k_j}^*) = \min_{1 \leq j \leq 3} \min\{g_{k_j} + 6 + d(u_{k_j-1}), g_{k_j} + 6 + d(u'_{k_j-1})\} := S.$$

So at $a_{i,1}$ the edge to $a_{i,2}$ is evaluated as $\beta x \cdot \beta^{-1} + S = x + S$, since $a_{i,1}$ does not have reward. On the other hand, the path to b_i is evaluated as (also, b_i does not have reward)

$$\begin{aligned} 0 + d(b_i) &= \min_{1 \leq j \leq 3} \min\{h_{k_j} + d(u_{k_j-1}), h_{k_j} + d(u'_{k_j-1})\} \\ &< \min_{1 \leq j \leq 3} \min\{g_{k_j} + x + 6 + d(u_{k_j-1}), g_{k_j} + x + 6 + d(u'_{k_j-1})\} \text{ (by (9))} \\ &= x + S. \end{aligned}$$

So the agent will go to b_i , which makes contradiction with above. So $v_{k_1}, v_{k_2}, v_{k_3}$ will have at least one of them has rewards. Since it's impossible that both v_k and v'_k has rewards, we proved the proposition. □

Combine the two sides above, we prove the main theorem.

6. CONCLUSION AND FURTHER WORK

So far we have extended the work of [Kleinberg and Oren 2014]. Firstly, we have shown the close relationship between the special structure \mathcal{F}_k and exponential cost ratio, thus we should avoid this structure when we design the way of work if we do not want to waste due to time-inconsistency. Also, we have shown the hardness of deleting edges or distributing the reward to motivate the agent. This may be a bad properties of the motivation model.

As an extension of our work, we can consider other forms of the problem, for example, for \mathbf{fmtr}_β , we can give the following extensions:

fmtr_β IV: We can put rewards on every edge and node of the graph. In this situation, the agent gets the reward directly when he travels through it, instead of multiplying it by β ;

fmtr_β V: We can put any reward on any node, but only pays those reward that the agent actually claimed.

It's in fact easy to see that \mathbf{fmtr}_β IV is in \mathcal{P} : we can simply find the shortest path (without the agent) of the graph, and put on each edge the cost of this edge. This configuration have total cost the same as the shortest path, which is of course the smallest possible.

On the other hand, \mathbf{fmtr}_β V seems to be NPC. This problem is beyond the scope of our method; we can put rewards on both v and v' nodes. But maybe with slight changes of the model, we can still prove this hardness.

Besides extensions of the problem, it's also beneficial to explore approximation algorithms of this problem. Also, practical algorithms that works for reality problems are also a good exploration. We can also consider the case of multiple agents who cooperate to get the target node.

REFERENCES

- AKERLOF, G. A. 1991. Procrastination and obedience. *The American Economic Review*, 1–19.
- KLEINBERG, J. AND OREN, S. 2014. Time-inconsistent planning: a computational problem in behavioral economics. In *Proceedings of the fifteenth ACM conference on Economics and computation*. ACM, 547–564.