Optimizing Roadside Advertisement Dissemination in Vehicular Cyber-Physical Systems

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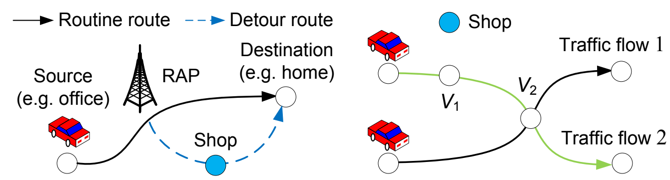
***Abstract*—In this paper, we address a promising application in the Vehicular Cyber-Physical Systems (VCPS) called roadside advertisement dissemination. Its scenario involves three elements: the drivers in the vehicles, Roadside Access Points (RAPs), and shops. The shop wants to attract as many customers as possible, through using RAPs to disseminate advertisements to the passing vehicles. Upon receiving an advertisement, the driver may detour to the shop, while the detour probability depends on the detour distance. Given a fixed number of RAPs and the traffic distribution, we want to optimize the RAP placement for the shop to maximally attract potential customers. This problem is a non-trivial extension of traditional coverage problems, where we use RAPs to cover the traffic flows. If we place RAPs at locations that can provide small detour distances to attract more customers, these locations may not be located in heavy traffic regions. On the other hand, heavy traffic regions cover more flows, but they can cause large detour distances to make shopping less attractive to customers. To balance the above tradeoff, RAP placement algorithms are proposed. Moreover, since the real-world traffic distributions have some patterns, we also propose near-optimal solutions for a special case, i.e., the Manhattan grid scenario. Real trace-driven experiments validate the competitive performance of the proposed algorithms.**

Keywords*—*Vehicular cyber-physical systems, advertisement dissemination, placement, coverage problem.

I. Introduction

Vehicular Cyber-Physical Systems (VCPS) refer to a new generation of vehicular systems with integrated computational and physical capabilities that can interact with humans through many new modalities [1]. While traditional vehicular systems were generally considered to be an imperceptible composition of the physical world, the VCPS actively interact with humans through communications, which yield a very tight coordination between cyber and physical resources [2]. Therefore, when building VCPS, it is critical to consider the perceptions and reactions of the human (i.e., the drivers in the vehicles). The effectiveness and efficiency of the VCPS will largely depend on how the human could benefit from such a system [3].

In this paper, we address a novel and promising application in the VCPS called roadside advertisement dissemination [4]. Its scenario involves three basic elements: the drivers in the vehicles (the human factor), Roadside Access Points (RAPs), and shops. The shop wants to attract as many customers as possible, by using RAPs to disseminate electronic advertisements to the passing vehicles. The drivers may decide to go shopping or not, upon receiving advertisements. An example is shown in Fig. 1(a), where a commuter drives back home after work. During his/her trip home, he/she receives an interesting advertisement from a RAP, and then decides to detour to the shop with the purchasing potential. We observe that the driver may give up going shopping if the extra detour distance to the shop is large. This is because the shopping interest cannot overcome a long and tiring journey. On the other hand, if the shop is on the way home, the drivers are more likely to stop by, since it takes only a little extra time. Here, we focus on the scenario with one shop, since our model can be easily extended to scenarios with multiple shops (as discussed later).



(a) The detour model. (b) The RAP placement.

Fig. 1. The scenario of the roadside advertisement dissemination.

As shown in Fig. 1(b), there are some traffic flows on the streets. Each traffic flow represents a certain number of people that drive back home from work. Given a fixed number of RAPs and the traffic distribution that can be obtained from the historical record, we focus on optimizing the RAP placement for the shop, as to maximally attract potential customers. Our problem is a non-trivial extension of traditional coverage problems, where we use RAPs to cover the traffic flows. Then, there exists a tradeoff between the traffic density and the detour probability for the RAP placement problem. Let us consider the placement of only one RAP in Fig. 1(b). If we place the RAP at V_1 (nearby the shop), then this RAP can only cover the traffic flow 2, while the traffic flow 1 is not covered. On the other hand, if we place the RAP at V_2, then the detour distance is large. Although both the traffic flows 1 and 2 are covered, the corresponding drivers are not likely to go shopping, due to a large detour distance. Our problem becomes more challenging when placing multiple RAPs. Let us consider the placement of two RAPs in Fig. 1(b). Suppose these two RAPs are placed at V_1 and V_2, respectively. Then, the RAP at V_2 becomes meaningless for the drivers in the traffic flow 2, since the RAP at V_1 provides a smaller detour distance for those drivers. Redundant advertisements do not provide extra shopping interest for the human. If a driver decides not to go shopping for a smaller detour distance, then he/she would not go shopping for a larger detour distance. Accordingly, the geographical density of RAPs should also be controlled.

Furthermore, the real-world traffic distributions have some patterns, which can be utilized for the RAP placement. For example, the streets in the Manhattan are mapped as a grid, meaning that all the vehicles have only four possible moving directions. This means that the overlaps among RAPs are more geometrically controllable. Another interesting observation is that multiple shortest paths exist, connecting a pair of locations in the Manhattan grid streets. These properties post unique challenges on optimizing the RAP placement.

Our main contributions are summarized as follows:

- We address a novel and promising application called roadside advertisement dissemination, which follows the design principle of the VCPS. The model is a non-trivial extension of traditional coverage problems.
- A threshold utility function and a decreasing utility function are used to model the driver's detour probability, respectively. For the general RAP placement problem, greedy solutions with ratios of $1-1/e$ and $1-1/\sqrt{e}$ to the optimal solutions are proposed for those two utility functions, respectively.
- Since the real-world traffic distributions have some patterns, we further study the RAP placement problem in the Manhattan grid street scenario, where we propose solutions with tightened bounds.
- Extensive experiments are conducted to evaluate the proposed solutions. The results are shown from different perspectives to provide insightful conclusions.

The remainder of this paper is organized as follows. In Section II, the related work is surveyed. In Section III, the general models are described with corresponding solutions. In Section IV, we discuss the RAP placement problem under the Manhattan grid scenario. Section V includes the experiments. Finally, we conclude the paper in Section VI.

II. Related Work

Cyber-physical systems are engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core [5]. The VCPS are special types of cyper-physical systems designed for vehicles. While traditional researches in Vehicular Ad-hoc Networks (VANETs) study data dissemination protocols that are imperceptible by humans, the VCPS take humans' perceptions into account [6]. For example, the data dissemination mechanism studied in [7] considers the data to be location-dependent, the paradigms of which humans are not aware of. By contrast, the data dissemination in the VCPS is humanized. Li et al. [3] considered a human-oriented service scheduling in the VCPS, where a driver is not able to receive multiple services in a short time. Wagh et al. [8] proposed that the data composition in the VCPS should be flexible enough for the drivers.

Currently, the advertisement dissemination is considered as a novel and promising application in the VCPS [9, 10], since advertisements belong to the practically useful data. While traditional studies focus on scenarios of online advertisements [11–13], Li et al. [4] first considered the advertisement dissemination in the VCPS as a bandwidth allocation problem, in which the locations of the RAPs are pre-fixed. We focus on optimizing the RAP placement for the advertisement dissemination. The advertisement dissemination has also been studied from different perspectives. Shen et al. [14] studied

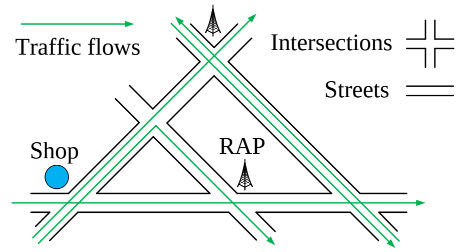


Fig. 2. The scenario for the RAP placement problem.

the message authentication problem for safety advertisements. Stojmenovic [15] focused on an auction problem.

Our RAP placement problem is also related to the existing set cover problems [16], since RAPs are used to cover the passing vehicles. However, our problem cannot be fully solved by existing techniques, since the detour distance is an important factor in the RAP placement problem. The location for a driver to receive the advertisement is critical for his/her detour decision, meaning that the impacts of the RAPs are not independent of each other. Although the set cover problem has been well-solved with some greedy approximation algorithms, our problem brings more unique challenges.

III. General Models and Solutions

In this section, we set up the model for the RAP placement problem. Bounded solutions are also proposed.

A. Model and Problem Formulation

As shown in Fig. 2, our advertisement dissemination scenario is based on a directed graph $G = (V, E)$, where V is a set of nodes (i.e., street intersections), and $E \subseteq V^2$ is a set of directed edges (i.e., one-way and two-way streets). Some traffic flows exist on the streets. We assume that all cars start from and stop at intersections. This assumption brings limited errors, since the distance between a parked car and its nearest intersection is never greater than the length of half a street. Let $T_{i,j}$ denote the traffic flow from intersections i to j. The traveling path for $T_{i,j}$ is unique and is known a priori (a shortest path in general). $T_{i,j}$ can be interpreted as a certain number of vehicles that travel daily from i to j (e.g., return home from the office). T denotes the set of traffic flows that can be targeted for the advertisement dissemination. Traffic flows that do not include sufficient potential customers, such as cars going from home to the office, are not counted in T.

We start with the scenario with only one shop. To attract customers, the shop places a fixed number, k, of RAPs at street intersections for the advertisement dissemination. A placed RAP would send electronic advertisements to all passing vehicles. Upon receiving advertisements, the drivers may decide to go shopping or not, depending on the detour distance to the shop. For each traffic flow, $T_{i,j} \in T$, its detour distance is denoted by $d_{i,j}$ and can be calculated as follows. (i) Suppose $T_{i,j}$ only goes through one RAP, as shown in Fig. 3. Upon receiving advertisements, the distance of the shortest path from the current location to the shop is d', that from the shop to the destination j is d'', and that from the current location to the destination j directly is d'''. Then, we have $d_{i,j} = d' + d'' - d'''$. (ii) If the traffic flow $T_{i,j}$ goes through multiple RAPs, then the

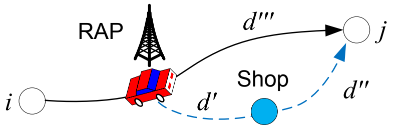


Fig. 3. The calculation of the detour distance.

corresponding detour distance should be the minimum detour distance among all these RAPs. This is because redundant advertisements do not provide extra shopping interest for the human. If the driver decides not to go shopping for a smaller detour distance, then he/she would not go shopping for a larger detour distance. Our model can also be easily extended to scenarios with multiple shops. For those cases, the result depends on the shop that provides the smallest detour distance among all the shops. For simplicity, we do not consider the commercial competition among different shops, in terms of attracting the drivers.

The roadside advertisement dissemination belongs to an application in the VCPS, where the perceptions of the humans should be considered upon designing the system. Therefore, we introduce a utility function, $f(d_{i,j})$, to describe the detour probability of the driver. We observe that the driver may give up going shopping if the shop is far way from his/her routine route. This is because the shopping interest cannot overcome a long and tiring journey. Hence, $f(d_{i,j})$ should be non-increasing with respect to $d_{i,j}$. In this paper, two kinds of utility functions are considered, namely threshold utility function and decreasing utility function. The former one means that the detour probability is a certain constant, if $d_{i,j}$ is no greater than a threshold, D. It is shown as:

$$f(d_{i,j}) = \begin{cases} \alpha(T_{i,j}) & \text{if } d_{i,j} \leq D \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

In Eq. 1, $\alpha(T_{i,j})$ shows the advertisement attractiveness for the drivers in the traffic flow $T_{i,j}$. This is known a priori through historical statistics. Then, the decreasing utility function means that $f(d_{i,j})$ is strictly decreasing from $\alpha(T_{i,j})$ to 0 with respect to $d_{i,j}$. An example of such a function could be:

$$f(d_{i,j}) = \begin{cases} \alpha(T_{i,j}) \cdot (1 - d/D) & \text{if } d_{i,j} \leq D \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

For each traffic flow $T_{i,j}$, an expectation of $f(d_{i,j}) \cdot T_{i,j}$ drivers would detour to the shop as potential customers.

In this paper, we study the RAP placement problem. Given a fixed number of RAPs and the traffic flows, we want to optimize the RAP placement for the shop, as to maximally attract potential customers. The challenge comes from the tradeoff between the traffic density and the detour probability. If we place RAPs at locations that can provide small detour distances to attract more customers, these locations may not be located in heavy traffic regions, i.e., $f(d_{i,j})$ is large but $T_{i,j}$ is small. On the other hand, heavy traffic regions cover more flows, but they can cause large detour distances to make shopping less attractive to customers, i.e., $T_{i,j}$ is large but $f(d_{i,j})$ is small. Another challenge lies on the geographical density of the placed RAPs. Placing multiple RAPs on a traffic flow does not bring extra shopping interest for the human. Hence, it is unnecessary to place too many RAPs within a small area. In the next two subsections, we will propose bounded solutions for the two kinds of utility functions, respectively.

Algorithm 1 A greedy solution

Input: The directed graph G; the set of traffic flows T; The number of RAPs to place (i.e., k);
Output: The RAP placement;

Mark all traffic flows as uncovered;
for $i = 1$ to k **do**
  Among all the intersections, find the one that can attract maximum drivers from the uncovered traffic flows;
  Place a RAP at that intersection, and then mark the corresponding traffic flows as covered;
return the RAP placement;

B. RAP Placement with Threshold Utility Function

In this subsection, we discuss the RAP placement problem, using the threshold utility function in Eq. 1. The detour probability is fixed, if the detour distance is no greater than a threshold. Then, we have the following two definitions:

Definition 1: An intersection *includes* a traffic flow, if (i) this traffic flow goes through this intersection, and (ii) the detour distance for this traffic flow at this intersection is no greater than the threshold D in Eq. 1.

Definition 2: A RAP *covers* a traffic flow, if this RAP is placed at an intersection that includes this traffic flow.

If a traffic flow is included by multiple intersections, then placing a RAP at any of these intersections can cover this traffic flow. If a traffic flow is covered by one RAP, then using more RAPs to cover this traffic flow does not attract more drivers to the shop as potential customers. This is because these RAPs bring identical detour probabilities for that traffic flow, under the threshold utility function (redundant advertisements do not bring extra shopping interest for the human).

It turns out that our RAP placement problem with the threshold utility function is essentially a weighted maximum coverage problem [17], which is an NP-hard problem, as follows. First, there are some sets defined over a domain of elements associated with weights. The goal of the weighted maximum coverage problem is to select k sets, such that the total weight of elements within the selected sets is maximized. In our problem, the elements correspond to the traffic flows, and the sets correspond to the intersections. The weight of a traffic flow is its number of expected drivers that detour to the shop ($f(d_{i,j}) \cdot T_{i,j}$), if this traffic flow is covered. The selection of a set corresponds to the placement of a RAP.

It is well-known that the weighted maximum coverage problem has a greedy algorithm that can achieve a ratio of $1 - 1/e$ to the optimal solution [18]. This greedy algorithm iteratively selects the set, the total weight of uncovered elements in which is maximum among all the unselected sets. We can use that greedy algorithm to solve the RAP placement problem, as shown in Algorithm 1. We iteratively place a RAP at an intersection that can attract maximum drivers from uncovered traffic flows. The geographical density of the RAPs can be controlled by Algorithm 1, since the covered traffic flows are no longer considered for the subsequent RAP placement. A RAP is not likely to be placed near an existing RAP, since the nearby traffic flows have been covered. The algorithm complexity is $O(|V|^3 + k|V||T|)$, where k is the number of

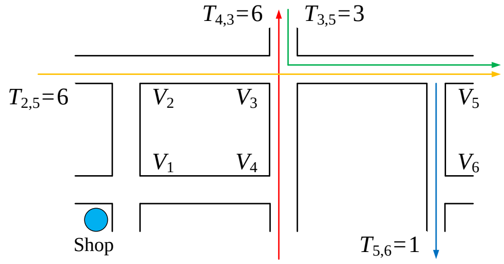


Fig. 4. An example of the RAP placement ($k = 2$ and $D = 6$).

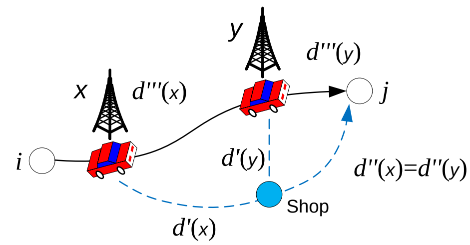


Fig. 5. An illustration for the proof of Theorem 1.

RAPs, $|V|$ is the total number of intersections, and $|T|$ is the total number of traffic flows. $O(|V|^3)$ results from the calculation of detour distances, since we need to calculate the shortest paths between all pairs of nodes. This aims to determine whether an intersection includes a traffic flow or not. $O(k|V||T|)$ comes from the greedy approach, which has k steps. Each greedy step takes $O(|V||T|)$, since we need to examine all the intersections. Examining each intersection takes $O(|T|)$, as we need to check all the traffic flows.

For a better explanation, an example is shown in Fig. 4, where we have two RAPs ($k = 2$) to place. The distances between neighboring intersections are 1. The threshold D is set to be 6. The shop is located at V_1. The $\alpha(T_{i,j})$ in Eq. 1 is set to be 1 for all the traffic flows. In this example, there are four traffic flows, which are initialized as uncovered in Algorithm 1. At the first step, V_3 is picked to place a RAP, since it can attract maximum drivers from uncovered traffic flows ($T_{2,5} + T_{3,5} + T_{4,3} = 15$). Then, these three traffic flows are marked as covered (no longer considered for the subsequent RAP placement). The remaining uncovered traffic is $T_{5,6}$. Therefore, the second RAP is placed at V_5 to cover $T_{5,6}$. The algorithm terminates for this example, since all the traffic flows are covered. Note that V_6 does not include $T_{5,6}$, since its detour distance is 8 (the path changes from V_5V_6 to $V_5V_6V_5V_3V_2V_1V_2V_3V_5V_6$). Since the detour distance is larger than the threshold D, the driver would not detour to the shop, upon receiving the advertisement at V_6.

It can be seen that the RAP placement problem with the threshold utility function is solvable. This is because the tradeoff between the traffic density and the detour probability is weakened by the threshold utility function, where the detour probability is discrete (either zero or a fixed constant). The idea is that we can eliminate the intersections with zero detour probabilities, and thus greatly simplify the RAP placement problem. In the next subsection, we will focus on the RAP placement problem with the decreasing utility function, which is a non-trivial extension of traditional coverage problems.

C. RAP Placement with Decreasing Utility Function

In this subsection, we discuss the RAP placement problem, using the decreasing utility function. For a better explanation, let us revisit the example in Fig. 4 with the decreasing utility function in Eq. 2. Suppose the two RAPs are still placed at V_3 and V_5, which is the optimal placement with the threshold utility function. For the decreasing utility function, the detour probability for $T_{2,5}$ and $T_{4,3}$ at V_3 is $1 \times (1 - \frac{4}{6}) = \frac{1}{3}$ with a detour distance of 4 (the path for $T_{2,5}$ changes from $V_2V_3V_5$ to $V_2V_3V_4V_1V_4V_3V_5$). $T_{3,5}$ is covered by two RAPs. However, the drivers in $T_{3,5}$ would detour at V_3 rather than V_5, since the detour distance at V_3 is smaller than that at V_5. Therefore, the detour probability for $T_{3,5}$ is also $1 \times (1 - \frac{4}{6}) = \frac{1}{3}$ with a detour distance of 4. Meanwhile, the detour probability for $T_{5,6}$ is 0 with a detour distance of 6. Therefore, the total number of detoured drivers is $(6 + 6 + 3) \times \frac{1}{3} = 5$. However, a better strategy for this example is to place these two RAPs at V_2 and V_4, respectively. Under this strategy, the detour probability for $T_{2,5}$ is $1 \times (1 - \frac{2}{6}) = \frac{2}{3}$ with a detour distance of 2 (the path changes from $V_2V_3V_5$ to $V_2V_1V_2V_3V_5$). The detour probability for $T_{4,3}$ is also $\frac{2}{3}$, and the total number of detoured drivers is $(6+6) \times \frac{2}{3} = 8$. This placement strategy attracts more drivers, since it takes the detour distance into consideration. Although V_3 and V_5 have more passing traffic flows, the corresponding detour distances are larger. Being different from the threshold utility function where we can simply use a RAP to cover traffic flows, here we should further consider the detour distance for optimizing the RAP placement.

At this time, a natural idea would still be a greedy approach. Instead of placing RAPs at the intersections that can cover maximum uncovered traffic, we can place RAPs at the intersections that can attract maximum drivers under the existing placement. If we go back to the example in Fig. 4, then the first RAP would be placed at V_3, since it would attract maximum drivers ($(6 + 6 + 3) \times (1 - \frac{4}{6}) = 5$) at the first step. Then, a RAP is placed at V_2 at the second step, since $[6 \times (1 - \frac{2}{6})] - [6 \times (1 - \frac{4}{6})] = 2$ more drivers can be attracted. This is because the drivers in $T_{2,5}$ can have a smaller detour distance at V_2 (a larger detour probability). However, this solution only attracts $2 + 5 = 7$ drivers to the shop, while placing these two RAPs at V_2 and V_4 is still a better strategy.

The key insight behind the above phenomenon involves the overlaps between RAPs. When the second RAP is placed at V_2, the first RAP at V_3 becomes useless for the traffic flow $T_{2,5}$. This is because the second RAP at V_2 provides a smaller detour distance than that at V_3. Let us consider a driver in $T_{2,5}$. As previously mentioned, if this driver decides not to go shopping at V_2, he/she would make the same decision at V_3 due to the larger detour distance. Although the two RAPs at V_2 and V_3 both cover $T_{2,5}$, the one at V_2 provides more powerful coverage due to the smaller detour distance. In terms of $T_{2,5}$, the coverages of the two RAPs have overlaps, which is the key challenge for the RAP placement. If a traffic flow goes through multiple RAPs, then the corresponding detour probability depends on the RAP that provides the minimum detour distance. Further analysis leads to the following theorem:

Theorem 1: For a specified traffic flow $T_{i,j}$ that goes from i to j, the first RAP on its path always provides a smaller detour distance than all the other RAPs on the path.

Algorithm 2 A composite greedy solution

Input: The directed graph G; the set of traffic flows T; The number of RAPs to place (i.e., k);
Output: The RAP placement;

```
Mark all traffic flows as uncovered;
for i = 1 to k do
    Candidate intersection i: Among all the intersections, find the one that can attract maximum drivers from the uncovered traffic flows;
    Candidate intersection ii: Among all the intersections, find the one that can attract maximum additional drivers from the covered traffic flows, through providing smaller detour distances;
    Compare intersections i and ii, place a RAP at the one that can attract more drivers to the shop;
    Mark the corresponding traffic flows as covered;
return the RAP placement;
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Proof: As shown in Fig. 5, let us select two arbitrary RAPs (say x and y) that cover the traffic flow $T_{i,j}$. Then, the difference between the detour distances of x and y is:

$$[d'(x)+d''(x)+d'''(x)] - [d'(y)+d''(y)+d'''(y)] \\ = d'(x) - \{d'(y)+[d'''(x)-d'''(y)]\} < 0 \quad (3)$$

In Eq. 3, $\{d'(y)+[d'''(x)-d'''(y)]\}$ is the distance from x to the shop via y. Since $d'(x)$ is the shortest path from x to the shop, it is smaller than $\{d'(y)+[d'''(x)-d'''(y)]\}$. Hence, the detour distance at x is smaller than that at y. Since x and y are arbitrarily selected, Theorem 1 is true. ■

Theorem 1 shows that the first RAP on the path of a traffic flow provides the smallest detour distance for this traffic flow. If a driver decides not to go shopping at the first RAP, he/she would make the same decision at later RAPs due to the larger detour distance. Therefore, for a specified traffic flow, the first RAP overlaps the subsequent RAPs for the decreasing utility function. The subsequent RAPs are useless for this traffic flow, since none of the drivers would detour at the subsequent RAPs. The key insight of this phenomenon is that the first RAP provides the highest traveling flexibility for the drivers.

To maximally attract potential customers for the shop, the RAP placement involves two critical factors. (i) The first factor is to find an intersection, the RAP placement at which a maximum amount of drivers can be attracted from the uncovered traffic flows. This factor is similar to that for the threshold utility function. (ii) The second factor is to find an intersection, the RAP placement at which maximum additional drivers can be attracted from the covered traffic flows. This factor represents the overlaps among RAPs, where we want to find intersections that can provide smaller detour distances for the covered traffic flows. If we consider only one of the above factor, then the resulting greedy algorithm cannot guarantee an approximation bound. Therefore, Algorithm 2 is proposed based on a composite greedy objective using two factors. At each greedy step, Algorithm 2 picks out the better one from two candidate intersections that are corresponding to the above two factors: (i) attract drivers from uncovered traffic flows, and (ii) attract additional drivers from covered traffic flows by providing smaller detour distances, i.e., overlaps among RAPs. The performance of Algorithm 2 is guaranteed as follows:

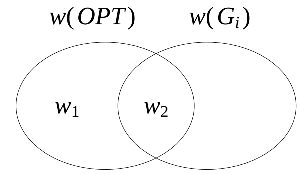


Fig. 6. An illustration for the proof of Theorem 2.

Theorem 2: Algorithm 2 achieves a ratio of $1 - 1/\sqrt{e}$ to the optimal solution, in terms of maximizing the number of attracted drivers who detour to the shop.

Proof: Let OPT denote the optimal RAP placement. G_i is the RAP placement obtained by Algorithm 2, after the first i steps. G_i should include i RAPs and G_k is the final RAP placement obtained by Algorithm 2. $G_{i+1}\backslash G_i$ is the placed RAP at the $(i+1)^{th}$ step. Let $w(\cdot)$ be a function that denotes the number of attracted drivers for the corresponding RAP placement. Then, let us focus on the difference between OPT and G_i. As shown in Fig. 6, OPT can attract more drivers than G_i, for the following two reasons. (i) OPT may cover some traffic flows that are uncovered by G_i. The number of attracted drivers for this part is denoted as w_1. (ii) OPT may provide smaller detour distances for some traffic flows in G_i. The number of additional attracted drivers for this part is denoted as w_2. Then, we have

$$w(OPT) - w(G_i) \leq w_1 + w_2 \quad (4)$$

The "$\leq$" in Eq. 4 result from the fact that G_i may cover some traffic flows that are uncovered by OPT, or G_i may also provide smaller detour distances for some traffic flows in OPT. Let us focus on the $(i+1)^{th}$ step in Algorithm 2. Since the candidate intersection i in Algorithm 2 attracts maximum drivers from the uncovered traffic flows, we have

$$\frac{w_1}{k} \leq w(G_{i+1}\backslash G_i) = w(G_{i+1}) - w(G_i) \quad (5)$$

The key is that OPT includes k RAPs, the average of which should cover no greater traffic flows than candidate intersection i in Algorithm 2 at the $(i+1)^{th}$ step, due to its greedy nature. Meanwhile, $w(G_{i+1}\backslash G_i)$ should be no less than the number of attracted drivers by the candidate intersection i, since Algorithm 2 picks the better one among the two candidate intersections. Similarly, for the overlaps, we have

$$\frac{w_2}{k} \leq w(G_{i+1}\backslash G_i) = w(G_{i+1}) - w(G_i) \quad (6)$$

This is because the candidate intersection ii in Algorithm 2 attracts maximum additional drivers from the covered traffic flows. The average number of additional attracted drivers for RAPs in OPT should be no greater than that for the candidate intersection ii. Combing Eqs. 4, 5, and 6, we have

$$\frac{w(OPT) - w(G_i)}{2k} \leq w(G_{i+1}) - w(G_i) \quad (7)$$

Since $w(OPT) \geq w(G_i)$ and $w(OPT) \geq w(G_{i+1})$ by the definition of the optimal solution, Eq. 7 can be rewritten as

$$w(OPT) - w(G_i) \geq \frac{2k}{2k-1}[w(OPT) - w(G_{i+1})] \quad (8)$$

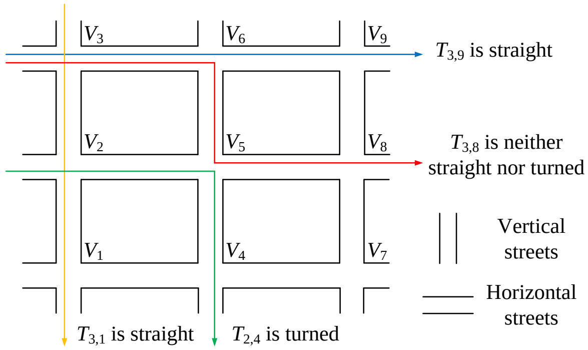


Fig. 7. An illustration of the Manhattan grid streets.

Considering $w(G_0) = 0$ means that no RAP has been placed at the beginning, the recursion in Eq. 8 leads to

$$w(OPT) \geq \left[\frac{2k}{2k-1}\right]^k [w(OPT) - w(G_k)] \\ \geq \sqrt{e} \cdot [w(OPT) - w(G_k)] \quad (9)$$

This is because $e = lim_{k\to\infty}(1+\frac{1}{k})^k$ by its definition. Then, Eq. 9 can be rewritten as

$$w(G_k) \geq (1 - \frac{1}{\sqrt{e}}) \cdot w(OPT) \quad (10)$$

Since G_k is the result obtained by Algorithm 2, Eq. 10 means that it achieves a ratio of $1 - 1/\sqrt{e}$ to the optimal solution, in terms of maximizing the number of attracted drivers. ■

Algorithm 2 guarantees the performance ratio through considering both covering uncovered traffic flows and providing covered traffic flows with smaller detour distances. It can be applied to scenarios with any kinds of non-decreasing utility functions. Algorithm 2 would reduce to Algorithm 1, if we use the threshold utility function. In terms of the time complexity, Algorithm 2 also takes $O(|V|^3 + k|V||T|)$. $O(|V|^3)$ results from the calculation of detour distances, through finding out the shortest paths between all pairs of nodes. $O(k|V||T|)$ comes from the greedy approach, which has k steps. At each greedy step, searching for the candidate intersection i takes a time complexity of $O(|V||T|)$, since we need to examine all the intersections for all the traffic flows. Searching for the candidate intersection ii also takes $O(|V||T|)$, since the first RAP on the path provides the smallest detour distance.

IV. RAP PLACEMENT FOR MANHATTAN GRID

In the previous section, we discuss the RAP placement for the general scenario. However, the real-world traffic distributions have some patterns, which can be utilized for the RAP placement. Therefore, in this section, we look into a special RAP placement under the Manhattan grid scenario.

A. Properties of Manhattan Grid

The Manhattan grid streets plan is a type of city plan in which streets run at right angles to each other. In this city plan, vehicles can only move in four given directions (north, south, east, and west), as shown in Fig. 7. For presentation simplicity, we classify the streets into vertical streets and horizontal streets, based on their orientations.

The key property of the Manhattan grid streets is the existences of multiple shortest paths between pairs of intersections. For example, in Fig. 7, the shortest path from V_1 to V_6 could be $V_1V_2V_3V_6$, $V_1V_2V_5V_6$, and $V_1V_4V_5V_6$. Therefore, we relax the constraint used in the previous section, where the traveling path for a traffic flow is unique and is known a priori. In this section, the traveling path for a traffic flow is not pre-fixed. Let us consider a driver with potential shopping interests in the daily traffic flow $T_{1,6}$, who wants to travel from V_1 to V_6 day by day (e.g, return home from the office). His/Her traveling path would be a random one of the three shortest paths. At this time, what could happen if a RAP is placed at V_3? This driver would definitely choose $V_1V_2V_3V_6$ as his/her traveling path, since it is one of the shortest paths with a free additional advertisement. Therefore, the traveling paths of traffic flows may partially depend on the RAP placement. In this section, we consider a traffic flow, $T_{i,j}$, to travel along one of the shortest paths from i to j; if a RAP is placed in one of the shortest path, then the traffic flows would choose that path to obtain a free additional advertisement. Locations of placed RAPs are assumed to be known by all the drivers through the internet (they are published as a part of the city plan).

Considering the above property, we reformulate the RAP placement problem under the Manhattan grid scenario, as follows. The shop is located in the center of a square region with area $D \times D$. All traffic flows would go through this square region via their shortest paths. For a specified traffic flow, if a RAP is placed in one of its shortest paths, this traffic flow would travel through that path to obtain a free advertisement. The new formulation in this section is much more specific than the previous formulation. However, it can represent some real-world traffic patterns, which can be utilized for the RAP placement as discussed in the following two subsections.

B. Manhattan RAP Placement with Threshold Utility Function

In this subsection, we discuss the Manhattan RAP placement problem, using the threshold utility function. Note that the problem keeps to be NP-hard, since an intersection can still include multiple traffic flows (a set can include multiple elements in the maximum coverage problem). We start with the following definition for the grid streets:

***Definition** 3:* A traffic flow is *straight*, if it travels straightforwardly along a vertical or horizontal street. A traffic flow is *turned*, if it enters and exits the grid through different orientations (vertical or horizontal).

For example, in Fig. 7, the traffic flows $T_{3,1}$ and $T_{3,9}$ are both straight. $T_{2,4}$ is turned, since it enters the grid through a horizontal street and exits the grid through a vertical street. Note that $T_{3,8}$ is neither straight nor turned, since it enters the grid through a horizontal street and exits the grid through another horizontal street. All traffic flows are assumed to go through this square region along their shortest paths, meaning that no traffic flow would start from or stop at V_5.

Now, we have the following two observations. (i) A turned traffic flow has multiple shortest traveling paths, therefore, the locations of RAPs may have some impacts on its actual traveling path. (ii) A straight traffic flow has only one shortest traveling path, and thus its traveling path would not be impacted by the RAP placement. Hence, a two-stage RAP

Algorithm 3 A two-stage solution

Input: The square region; the set of traffic flows T;
The number of RAPs to place (i.e., k);
Output: The RAP placement;

```
1: if k ≤ 4 then
2:     return the optimal solution by exhaustive search;
3: for each corner of the square region do
4:     Place a RAP at that corner;
5: Mark all straight traffic flows as uncovered;
6: for i = 1 to k − 4 do
7:     Among all the intersections, place a RAP at the one
       that can attract maximum drivers from the uncovered
       straight traffic flows;
8:     Mark the corresponding straight traffic flows as covered;
9: return the RAP placement;
```

placement algorithm is proposed as Algorithm 3. The RAPs are placed for turned and straight traffic flows, respectively. The intuition behind Algorithm 3 includes two parts. (i) Four RAPs at the corners of the grid can cover all the turned traffic flows. This is because each turned traffic flow has one shortest path going through a corner of the grid. Drivers in turned traffic flows would like to go to the corner for a free advertisement without extra traveling distances. (ii) The optimal placement for the straight traffic flows can be obtained through a simple greedy algorithm. This is because a RAP can cover at most one horizontal-straight traffic flow (similar for vertical-straight traffic flows). The performance of Algorithm 3 is guaranteed:

Theorem 3: For the turned and straight traffic flows, Algorithm 3 achieves a ratio of $1-\frac{4}{k}$ to the optimal solution, under Manhattan grid scenario with the threshold utility function.

Proof: Note that the shop is located in the center of the square region with area $D \times D$. Therefore, the detour distance at any intersection would be no greater than D. With the threshold utility function, it means that the drivers would go to the shop upon receiving an advertisement. Then, the following proof is composed of two parts. The first part is for the turned traffic flows and the second part is for the straight traffic flows.

In the first part, we prove that four RAPs at the corners of the grid are enough to cover all the turned traffic flows (lines 3 and 4 in Algorithm 3). Let us consider a traffic flow that enters the grid via the west boundary of the grid and exits the grid via the south boundary of the grid. An example would be the traffic flow $T_{2,4}$ in Fig. 7. The shortest paths for this traffic flow only include two kinds of orientations: going toward east or going southward at an intersection. If this traffic flow goes toward south to the end and then goes eastward, it would result in a shortest path that goes through the southwest corner of the grid. For example, such a shortest path for $T_{2,4}$ in Fig. 7 is $V_2V_1V_4$ that goes through the corner V_1. Since $V_2V_1V_4$ is a shortest path for $T_{2,4}$ with a free advertisement, drivers in $T_{2,4}$ would choose $V_2V_1V_4$ as their traveling paths. Through enumerating all the possible orientations, we can conclude that four RAPs at the corners can cover all the turned traffic flows.

In the second part, we focus on the straight traffic flows. By definition, an intersection can only cover, at most, one vertical-straight traffic flow and, at most, one horizontal-straight traffic flow. Algorithm 3 (lines 5 to 8) covers the maximum $k-4$ vertical-straight traffic flows and the maximum $k-4$ horizontal-straight traffic flows. Therefore, it obtains a optimal placement for straight traffic flows, using $k-4$ RAPs.

The overall optimal placement for both turned and straight traffic flows has k RAPs, which can at most cover all turned traffic flows, the maximum k vertical-straight traffic flows, and the maximum k horizontal-straight traffic flows. Therefore, for the straight and turned traffic flows, Algorithm 3 achieves a ratio of $\frac{k-4}{k} = 1-\frac{4}{k}$ to the optimal solution, under the Manhattan grid scenario with the threshold utility function. ■

Algorithm 4 A modified two-stage solution

Input: The square region; the set of traffic flows T;
The number of RAPs to place (i.e., k);
Output: The RAP placement;

```
1: Same as Algorithm 3, except the change of lines 3 and 4:
   For each corner of the square region, A RAP is placed in
   the middle of that corner and the shop;
```

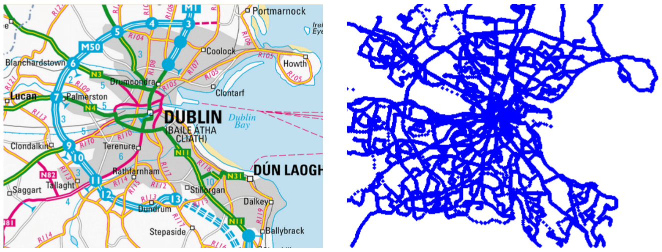
When k becomes larger, $1-\frac{4}{k}$ moves closer to 1, meaning that Algorithm 3 is a near-optimal solution for a large k. Algorithm 3 does not consider the traffic flows, which are neither straight nor turned (such as $T_{3,8}$ in Fig. 7). However, through real data-driven experiments (in the evaluation section), we show that this problem does not lead to a significant performance degradation. The intuition is that, if an intersection can cover maximum straight traffic flows, it is also likely to cover a large amount of traffic flows that are neither straight nor turned, due to the locality property of traffic flows. In the next subsection, we will study the Manhattan RAP placement problem with the decreasing utility function.

C. Manhattan RAP Placement with Decreasing Utility Function

In this subsection, we discuss the Manhattan RAP placement problem, using the decreasing utility function. The idea is similar to that in the previous subsection, where we place RAPs for turned and straight traffic flows, respectively. However, the overlaps among RAPs bring some performance degradations as previously analyzed. Then, Algorithm 4 is proposed as a modification of Algorithm 3. Algorithm 4 has two prerequisites: (i) the detour distances of turned traffic flows are uniformly distributed in the interval of $[0, D]$, (ii) the decreasing utility function is the one in Eq. 2. Under these assumptions, we have:

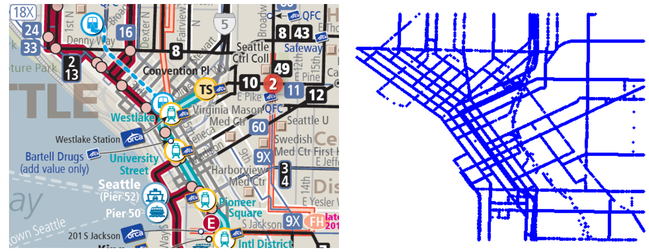
Theorem 4: For the turned and straight traffic flows, Algorithm 4 achieves a ratio of $\frac{1}{2}-\frac{2}{k}$ to the optimal solution, under Manhattan grid scenario with the decreasing utility function.

Proof: This proof is similar to that for Theorem 3. First, we prove that the four RAPs in the middle of the corner and the shop can attract half of the maximum drivers from turned traffics. This is because the turned traffic flows have an average detour distance of $\frac{D}{2}$, while the four RAPs cover half of the turned traffic flows with the detour distance $\frac{D}{2}$. Then, we show that the remaining $k-4$ RAPs can attract half of the maximum drivers from straight traffic flows. This is because Algorithm 4 can attract no fewer drivers than the maximum drivers from $k-4$ traffic straight flows (either vertical or horizontal). Through a similar argument, it can be seen that Algorithm 4 achieves a ratio of $\frac{1}{2}(1-\frac{4}{k}) = \frac{1}{2}-\frac{2}{k}$ to the optimal solution. ■



(a) The Dublin map. (b) The bus traces.

Fig. 8. The map and bus traces for Dublin's central area.



(a) The Seattle map. (b) The bus traces.

Fig. 9. The map and bus traces for Seattle's central area.

V. Evaluations

A. Real Trace-driven Datasets and Basic Settings

In this section, we conduct experiments based on two real traces, i.e., Dublin bus trace [19] and Seattle bus trace [20]. The city plan of Dublin is not grid-based, and thus the Dublin bus trace is used to test our Algorithms 1 and 2 for the general scenario in Section III. Meanwhile, The city plan of Seattle is partially grid-based, and thus the Seattle bus trace is used to test our algorithms for both the general scenario in Section III and the Manhattan grid scenario in Section IV.

For the Dublin bus trace, we focus on the part within Dublin's central area, which is a $80,000 \times 80,000$ square feet area as shown in Fig. 8. The Dublin bus trace includes bus ID, longitude, latitude, and vehicle journey ID. The vehicle journey is a given run on a journey pattern, which corresponds to our concept of the traffic flow. Buses with the same vehicle journey ID have similar routing paths in terms of longitude and latitude. To obtain the number of attracted customers, we assume that each bus in Dublin carries 100 passengers (who are potential customers for the shop) per day on average.

For the Seattle bus trace, we also focus on the part within Seattle's central area, which is a $10^4 \times 10^4$ square feet area as shown in Fig. 9. The Seattle bus trace includes bus ID, x-coordinate, y-coordinate, and route ID. Each route is regarded as a traffic flow. Buses with the same route ID have similar routing paths in terms of x and y coordinates. To obtain the number of attracted customers, we assume that each bus in Seattle carries 200 passengers per day in average.

According to the amount of passing traffic flows, all the street intersections in both traces are classified into city's center, city, or suburb. This is used to observe the impact of the shop location. Then, in our experiments, three utility functions are used. The first one is the threshold utility function in Eq. 1. The second one is the decreasing utility function i in Eq. 2, which decays linearly. The third one is the decreasing utility function ii, which is defined as the following:

$$f(d_{i,j}) = \begin{cases} \alpha(T_{i,j}) \cdot (1 - \sqrt{d/D}) & \text{if } d_{i,j} \leq D \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

Under the same detour distance, d, and the same threshold, D, the detour probability of the threshold utility function is the largest, that of the decreasing utility function i is in the middle, and that of the decreasing utility function ii is the smallest. In these three utility functions, $\alpha(T_{i,j})$ is set to be 0.001 for all the traffic flows. This means that a person receiving advertisements has a probability of 0.001 to go shopping [4], if the shop is on the way (i.e., no extra detour distance).

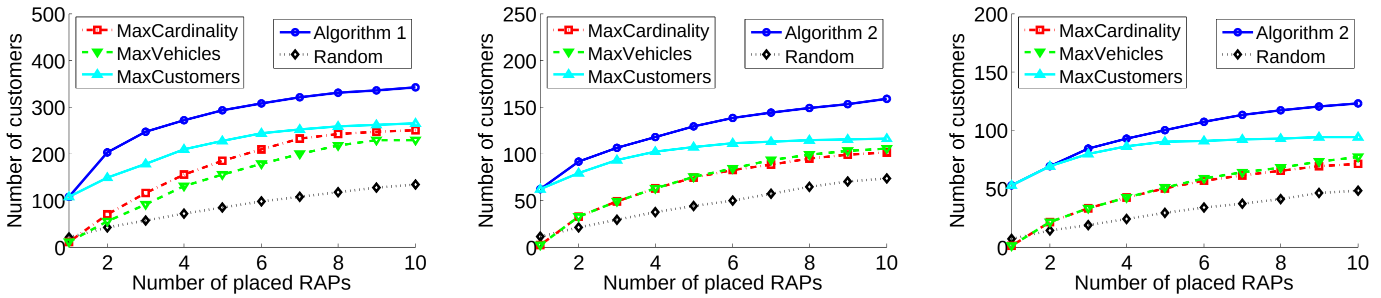
B. Comparison Algorithms and Metrics

In our experiments, four baseline algorithms (namely MaxCardinality, MaxVehicles, MaxCustomers, and Random) are used for comparisons as the following. (i) MaxCardinality ranks the intersections by the number of passing traffic flows, and then places the RAPs at the top-k intersections. (ii) MaxVehicles ranks the intersections by the number of passing buses, and then also place the RAPs at the top-k intersections. (iii) MaxCustomers ranks the intersections by the number of attracted customers if a RAP is placed. Then, MaxCustomers also places RAPs at the top-k intersections. This algorithm is equivalent to the optimal algorithm, when $k = 1$. (iv) Random places RAPs uniform-randomly at the intersections within the $D \times D$ square region centered at the shop.

Our experiments focus on the relationship between the number of placed RAPs and the number of attracted customers, under different settings (utility functions, threshold D, and shop locations). All the street intersections are classified into city's center, city, or suburb, depending on the amount of passing traffic flows. In the following experiments, if we say that the shop is located in the city, it means that intersections with tags of city are randomly selected as the shop locations. All the results are averaged over 1,000 times for smoothness.

C. Evaluation Results in the Dublin Bus Trace

The evaluation results in the Dublin bus trace under the general scenario are shown in Figs. 10 and 11. Fig. 10 focuses on the impact of the utility function, where the shop is located in the city with the threshold $D = 20,000$ feet. It can be seen that all algorithms attract more customers under the threshold utility function than the decreasing utility functions i and ii. This is because the detour probability of the threshold utility function is the largest among the three utility functions, under the same d and D. In Fig. 10(a) with the threshold utility function, the performance gap between the Algorithm 1 and the other algorithms is significant (around 30% performance gain for $k = 10$). This is because Algorithm 1 has considered that different RAPs may cover the same traffic flow, meaning that the geographical density of the RAPs is controlled. Meanwhile, in Fig. 10(b) with the decreasing utility function i, Algorithm 2 is also significantly better. This is because it has considered the overlaps among RAPs (some RAPs can provide smaller detour distances for a traffic flow). However, in Fig. 10(c) with the decreasing utility function ii, Algorithm 2 has a smaller performance gain. This is because the decreasing utility function ii decays very fast with respect to the detour distance, meaning that we have to place RAPs around the shop.

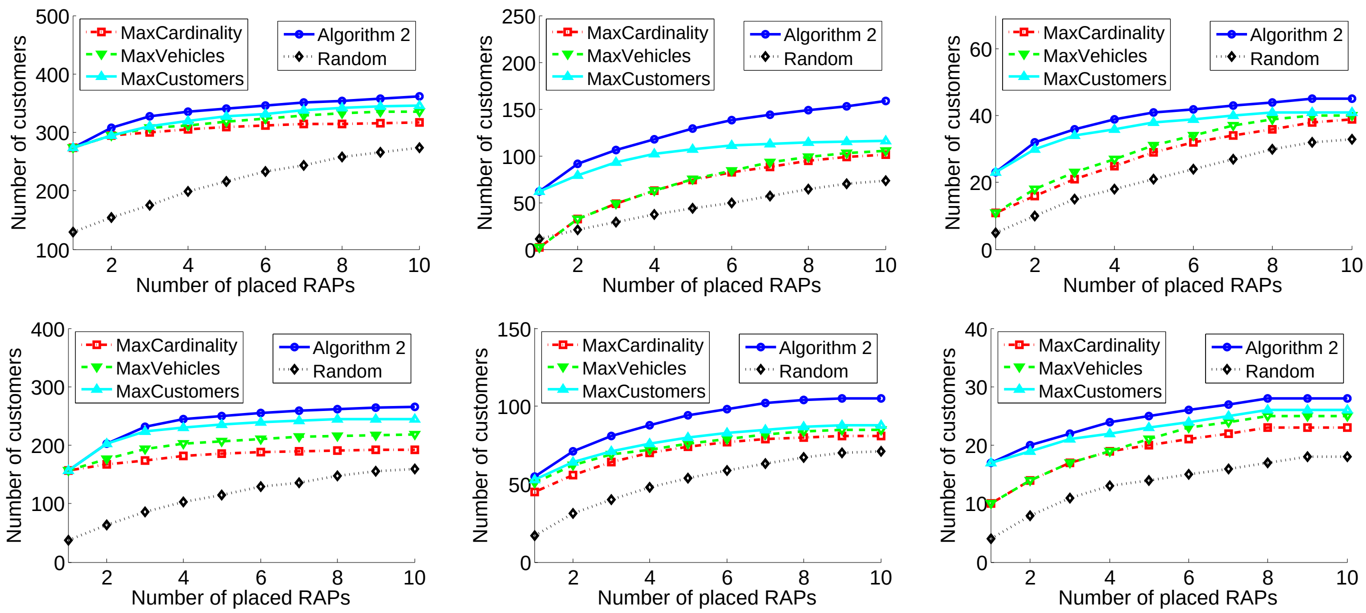


(a) Threshold utility function.

(b) Decreasing utility function i.

(c) Decreasing utility function ii.

Fig. 10. The experimental results for the Dublin bus traces with different utility functions. The shop is located in the city with $D = 20,000$ feet.



(a) The shop is located in the city's center.

(b) The shop is located in the city.

(c) The shop is located in the suburb.

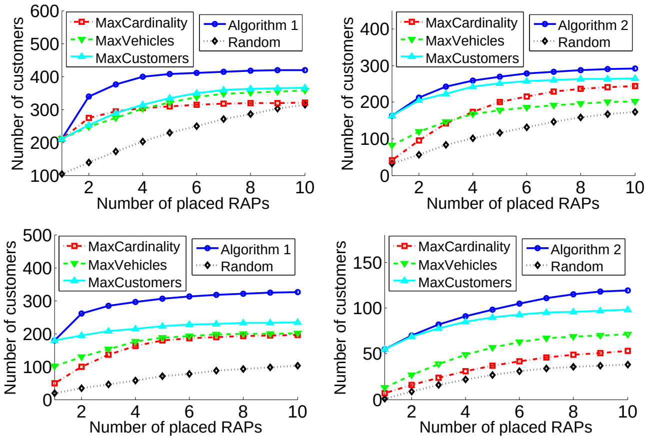
Fig. 11. The experimental results for the Dublin bus traces with different shop locations. The decreasing utility function i is used with different threshold D.

Fig. 11 shows the impact of the shop location and the threshold D, under the decreasing utility function i. Figs. 11(a), 11(b), and 11(c) show the results for different shop locations. For each subfigure, the top and bottom parts show the results with D=20, 000 and D=10, 000 feet, respectively. The performance gain of Algorithm 2 is relatively small, when the shop is located in the city's center or suburb. If the shop is located in the city's center, randomly placing RAPs around the shop can already cover most traffic flows with small detour distances, meaning that different placement strategies have a limited performance gap. On the other hand, if the shop is located in the suburb, none of the placement strategies can cover too many traffic flows. The threshold D is also critical. A larger D means that the drivers are more likely to detour to the shop, and thus, the shop can attract more customers. When the shop is located in the city's center, a large D does not bring too many additional customers, since most traffic flows are already nearby the shop. When the shop is located in the suburb, a large D still does not bring too many additional customers, since the detour distances are large. However, when the shop is located in the city, as shown in Fig. 11(b), a large D would bring many more customers, since more traffic flows are covered with relatively small detour distances.

D. Evaluation Results in the Seattle Bus Trace

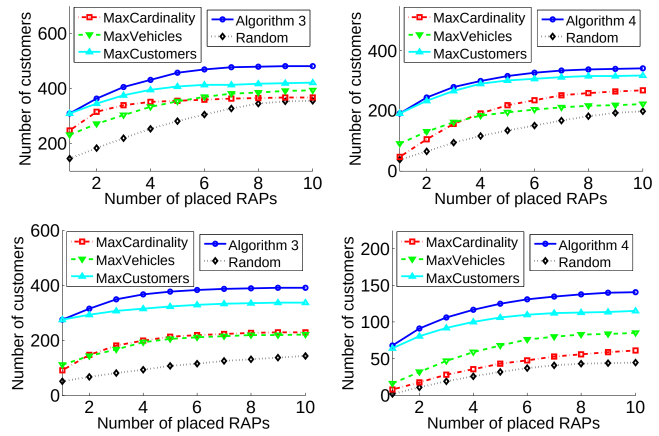
The evaluation results in the Seattle bus trace under the general scenario and the Manhattan grid scenario are shown in Figs. 12 and 13, respectively. The shop is located in the city. We focus on the impacts of different utility functions with different threshold D. The threshold utility function is used in Figs. 12(a) and 13(a), while the decreasing utility function is used in Figs. 12(b) and 13(b). For each subfigure, the top and bottom parts show the results with D=2, 500 and D=1, 000 feet, respectively. In Fig. 12, it can be seen that all algorithms attract more customers under the threshold utility function than the decreasing utility functions i, since the former one brings higher detour probabilities. The threshold D also has an important impact on the number of attracted customers, especially when the shop is located in the city. The number of attracted customers with D=2, 500 feet is 30% more than that with D=1, 000 feet. The results in Fig. 12 are consistent with our experiments in the Dublin bus trace.

Fig. 13 shows the results in the Seattle bus trace under the Manhattan grid scenario. Note that the city plan of Seattle is not fully grid-based, meaning that there should be some performance degradations for Algorithms 3 and 4. Compared



(a) Threshold utility function. (b) Decreasing utility function i.

Fig. 12. The experimental results for the Seattle bus traces under the general scenario in Section III. The shop is located in the city. Different utility functions with different threshold D are used for comparisons.



(a) Threshold utility function. (b) Decreasing utility function i.

Fig. 13. The experimental results for the Seattle bus traces under the Manhattan grid scenario in Section IV. The shop is located in the city. Different utility functions with different threshold D are used for comparisons.

with the results under the general scenario in Fig. 12, more customers are attracted under the Manhattan grid scenario. This is because the traveling paths of all the traffic flows are pre-fixed under the general scenario, the assumption of which is relaxed here. Under the Manhattan grid scenario, if a traffic flow has multiple shortest paths, it would choose the path with RAPs to obtain a free advertisement. Meanwhile, it can also be seen that the threshold utility function brings more customers than the decreasing utility function i. A larger threshold D also brings more customers to the shop.

VI. Conclusion and Future Work

In this paper, we address the roadside advertisement dissemination problem that involves elements: the drivers, RAPs, and shops. The shop uses RAPs to disseminate advertisements to the drivers, as to attract customers. Upon receiving an advertisement, the driver may detour to the shop, while a larger detour distance brings a no greater detour probability. We are interested in optimizing the RAP placement for the shop, as to maximally attract potential customers. The key challenge is to balance the tradeoff between the traffic density and the detour probability. Bounded RAP placement algorithms are proposed for the general scenario and the Manhattan grid scenario. Extensive real trace-driven experiments validate the competitive performance of the proposed algorithms. Our future work would consider a further scheduling with respect to multiple shops and multiple kinds of advertisements.

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