Learning the Relevance of Parking Information in VANETs[1]

Piotr Szczurek, Bo Xu, Ouri Wolfson
Department of Computer Science
University of Illinois at Chicago
Chicago, IL, U.S.A.
pszczu1@uic.edu,
{boxu,wolfson}@cs.uic.edu

Jie Lin
Department of Civil and
Materials Engineering
University of Illinois at Chicago
Chicago, IL, U.S.A.
janelin@uic.edu

Naphtali Rishe
School of Computing and
Information Sciences
Florida International University
Miami, FL, U.S.A.
rishen@cis.fiu.edu

ABSTRACT
The use of Vehicular Ad-Hoc Network (VANET) has been applied to many applications involving information dissemination. Many of such applications are limited by the communication limitations of a VANET, such as limited transmission range and bandwidth. This imposes a necessity for evaluating the relevance of information. This paper proposes the use of machine learning for finding relevance of information for a parking information dissemination system. The proposed method uses the learned relevance for aiding vehicles in decision making by finding the probability that a given parking location will be available at the time of arrival. The method was evaluated through simulations and the results show that the proposed method is successful at learning the relevance of parking reports, which resulted in lower parking discovery times for vehicles.

Categories and Subject Descriptors
H.4.3 [**Information Systems Applications**]: Communications Applications; C.2.4 **[Computer-Communication Networks]**: Distributed Systems

General Terms
Algorithms, Performance, Experimentation.

Keywords
data dissemination, machine learning, parking, ranking.

1. INTRODUCTION
Recently, the use of vehicular ad-hoc networks (VANETs) has gained attention for purposes of information dissemination in a variety of applications, such as parking [1, 2, 3, 4, 5] or traffic information dissemination [7]. A common problem in all of such applications is evaluating the relevance of a piece of information for specific vehicles. Finding relevance helps in ranking pieces of information and might also aid vehicles in making decisions. Ranking is a concern in VANETs, because multiple information dissemination applications may have to share a limited amount of bandwidth, possibly with high density of vehicles. Knowing relevance can also aid in making decisions. For example, in a parking application, the relevance information might determine which parking location to pursue. Existing methods for parking information systems either relied on heuristic approaches for relevance estimation [1, 2] or assumed vehicles know which information is irrelevant [3, 4]. In [5], relevance function is based on a formula for parking space availability probability, but parameters of this formula would not be known to vehicles. In this paper, a method is proposed to learn a model that can be used to calculate relevance of a piece of information. The relevance values can then be used for ranking, thereby dealing with issues of bandwidth in VANETs. The same learned model can also be used for aiding vehicles in decision making. The method was evaluated by simulation, with results showing that the method was able to match the performance of ranking by an equation, which can be considered optimal for relevance estimation in the simulated model. The advantage of the machine learning method is the ability to combine several attributes of reports without knowledge of the given problem, making it easy to apply the technique to parking availability dissemination.

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2. MODEL DEFINITIONS
The environment consists of a set of vehicles. A subset of these is equipped with GPS and devices capable of computation and short-range wireless communication. The vehicles that are equipped are called *participating vehicles*, otherwise they are called *non-participating vehicles*. Some of the vehicles, called *consumers*, actively look for available parking spaces. Participating vehicles which are not looking for parking are called *brokers*. Consumers traverse the road network around a predetermined *search path*. When a consumer encounters an available parking space while traversing the search path, it parks there and makes the parking space unavailable for some time. Participating consumers may leave off the search path to pursue a parking space that is referenced by parking information. When a participating consumer leaves its parking space, it generates a *parking availability report*, containing a *report identifier, location,* and *timestamp.* The report identifier provides a unique number for each report. The location is the coordinates of the parking space given by the GPS. The timestamp is the time at which the report is produced. Each vehicle stores all its reports in a reports database on the vehicle. Only the most recent report for a given location is kept.

Dissemination of reports is done by periodic broadcasts. Every *Bi* seconds, vehicles send *Bsize* reports to other vehicles within their transmission range. Participating consumers do not disseminate

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reports about parking spaces that they are pursuing. Reports are ranked by a *ranking function* that maps each report to a value between 0 (least relevance) to 1 (most relevant). The highest ranked reports are selected for each broadcast. When a participating consumer receives a parking availability report, it may choose to deviate from its search path and try to obtain the parking space referenced in the report. Such parking space then becomes the *target parking space* for that vehicle. When multiple reports exist, the target parking space is chosen according to the ranking function. Each time the vehicle receives new reports, the target parking space decision is reevaluated based on current values of the ranking function. A participating consumer always parks at the first available parking space it reaches, regardless whether or not the space is the target one. When the target space is reached, but it is unavailable at that time, the vehicle continues to search for parking along the predetermined search path.

3. METHOD DESCRIPTION

The general idea behind the method is to use the received reports as an input to a machine learning process. Over time, each vehicle learns a model that can estimate the probability that a report is relevant to an arbitrary recipient, and the model can then be used as a ranking function. The model used to estimate the probability that the report will be relevant consists of two parts: *duplication model* and *conditional relevance model*. The duplication model is used to find the *novelty factor*, which is the probability that a given report is not a duplicate to a neighboring node. The conditional relevance model estimates the probability that a given report is relevant to the recipient, assuming the report is new to the recipient. The rank value of a report R to vehicle v is the multiplication of the estimates from both models.

In order to learn the probability that a sent report would be a duplicate, a technique based on the MALENA algorithm is used. Details of this algorithm are given in [6]. To learn the conditional relevance model, the Naïve Bayes method is used. Training examples are formed by two attributes of the report (age and distance) as input and the relevance feedback as output. A parking availability report r received by vehicle v is labeled *relevant* if the parking space referred to in r is available when v reaches it. A positive example is created when v parks. Otherwise, if v reaches the space and it is unavailable, r is a negative example. Over time, the conditional relevance model learns the mapping from reports' attributes to the probability of the parking space being available.

4. EVALUATION

Evaluation was performed by simulating vehicles on a grid road network that is 1.2x1.2 mile^2 in area. Available parking spaces were mapped to intersections, for a total of 36 spaces. Vehicles were placed on the grid at random locations. Broker vehicles moved continuously to random waypoints, while consumers traversed a randomly selected search path (a square). Tests were performed across a range of broadcast sizes (1-36 reports), numbers of consumers (10-50), parking unavailability times (10-30 min), broker densities (50-200 veh. per sq. mile), and transmission ranges (50-300 meters). The time between broadcasts was fixed at 5 seconds, mean vehicle speed was 20 mph, and 50% of consumers were participating. Total simulated time was 20 hours for each of the 29 tests. Results were compared to ranking by age or distance alone, and to the parking availability formula (IGS) given in [5]. The IGS method represents the optimal combination of age and distance. Each ranking method was tested with and without the use of the novelty factor. The average parking discovery time was measured for each participating consumer. This metric measured the average time a vehicle was looking for parking since it was put on the grid. This was compared with the case of no report dissemination (i.e. blind search). The average improvement over blind search over all 29 tests is given in fig. 1. It shows that machine learning was able to nearly match the performance of the IGS equation, which was shown to exactly calculate the availability probability. This illustrates that the proposed method can successfully learn an optimal combination of relevant attributes for estimating relevance.

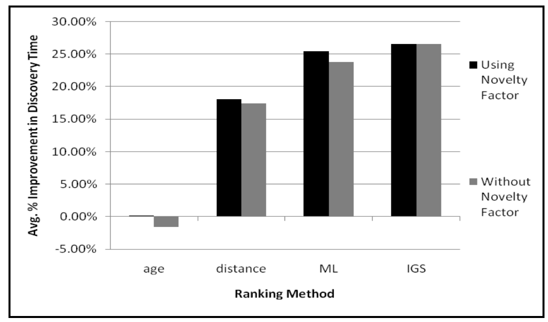

Figure 1. Average % of discovery time improvement.

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