Spatio-temporal Information Ranking in VANET Applications

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Vehicular ad-hoc networks (VANETs) is a promising approach to the dissemination of spatio-temporal information such as the current traffic condition of a road segment or the availability of a parking space. Due to the constraint of the communication bandwidth, only a limited number of information items may be transmitted upon a vehicle-to-vehicle communication opportunity. Ranking becomes critical in this situation, by enabling the most important information to be transmitted under the bandwidth constraint. In this paper we propose a method for online learning of spatio-temporal information ranking in VANETs. In this method, mobile nodes such as vehicles judge the relevance of incoming information items and use them as training examples for Naive Bayesian learning. Additionally, a separate machine learning algorithm is used to estimate the probability of a duplicate item being transmitted. The method is used in place of commonly used heuristics, and is evaluated for travel time and parking availability dissemination applications.

Keywords: Information dissemination, machine learning, parking information systems, travel time dissemination, VANET

1. INTRODUCTION

A vehicular ad-hoc network (VANET) is a set of vehicles that communicate with each other via unregulated, short-range wireless technologies such as WiFi or DSRC [DSRC 2003]. The use of VANETs has allowed the creation of systems for information dissemination, many of which related to dissemination of real-time traffic data. Examples include disseminating parking availability [Caliskan et al. 2004], travel speeds [Wischhof et al. 2003; Zhong et al. 2008], or traffic video clips [Guo et al. 2005; Lee et al. 2009]. Such systems enable drivers to lower their travel times and reduce parking search times, which results in savings of fuel cost, emissions, and time. These benefits are directly related to the quantity and quality of information that can be disseminated.

Due to limited transmission radius and bandwidth, the quantity of disseminated information that can be disseminated using a VANET is constrained. Although individual pieces of information may be small in size, in combination, they could easily exceed the bandwidth capacity of a VANET. For example, in a travel time dissemination application, each individual travel time report might be on order of tens of bytes, yet with thousands of road segments, exchange of such information among vehicles might be prohibitive. The problem is exacerbated when considering sharing bandwidth among multiple applications. This makes it important to focus

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on the quality of information that is being disseminated. This can be done by ranking information that needs to be sent by its relevance for the receiving vehicles. In VANET applications, the information is typically spatio-temporal in nature. It is hence intuitive that the relevance depends on attributes such the age (i.e., how long ago the information was generated) and distance (i.e., how far is the vehicle from a point to which the information pertains). These spatio-temporal attributes need to be combined to find the relevance. Although heuristics based on intuition may be used for this purpose, knowing how to combine the attribute in an optimal manner depends on knowledge of particular applications and may not be trivial.

Based on work in [Szczurek et al. 2009], this paper presents a method for ranking spatio-temporal information using relevance, which is found using a machine learning method. Using this approach allows for combining several, known to be relevant attributes, into a single relevance value. The relevance value can then be subsequently used for ranking information. Vehicles can use this ranking of information to decide which information should be transmitted. They can also use it as an aid in decision making. For example, ranking parking availability reports allows a vehicle to identify a parking location that is most likely to be available upon arrival. The advantage of this method is that it can be applied for different VANET applications and does not require extensive knowledge or analysis of the application in order to rank the information.

In our method, the VANET disseminates reports over time, where each report represents a piece of sensed spatio-temporal information such as the traffic condition of a road segment or the availability of a parking space. Vehicles which receive such reports can use them to possibly alter their behavior. For example, they can change their travel route or pursue a particular parking space. We postulate that finding which reports are most useful and hence relevant, depends on their spatio-temporal attributes. A useful report is one that impacts the decisions of the receiving vehicle, such as changing its travel route.

To find the relevance of reports, this work uses machine learning. The machine learning algorithm learns the probability that a report is relevant as a function of its attributes such as its age and distance. It does so by first identifying the attributes that indicate the relevance. Second, the Naïve Bayes learning method is used to find a mapping from the attribute values to the probability of a report being relevant.

This paper presents the implementation of the machine learning method for two VANET applications: parking availability dissemination and travel time dissemination. In the parking application, we assume vehicles are searching for a parking location with the highest chance of being available upon arrival to that location. The relevance is thus defined in terms of probability of availability. Using the parking application, we show that the machine learning algorithm successfully combined spatio-temporal attributes of information in order to calculate the relevance. We do so by evaluating using a simple simulation model for which an analytically derived function exists, which calculates the availability probability [Wolfson et al. 2005]. For travel time dissemination, no such analytical functions currently exist, so most methods typically rely on heuristics. Simulation results for travel time dissemination show that the machine learning technique achieved better performance than

the use of individual spatio-temporal attributes or a heuristic based on combination of the attributes. In the simulated environment the vehicles were able to choose better routes and lower their travel times as a result of the use of the proposed technique for ranking reports.

2. RELEVANT WORK

Techniques for ranking of information are related to those for cache management in mobile wireless networks. Work by Datta et al. [2004], Perich et al. [2004], and Zhang et al. [2007] used abstract utility functions which could be defined for given applications. These can be thought of as a more general form of the relevance function, which our machine learning method instantiates. Other work for ranking uses a weighted combination of popularity, reliability, and size [Sailhan and Issarny 2002], but authors of this work do not discuss how the weights should be determined. In [Zhang 2009] reports are ranked such that the number of replicas of each report is proportional to the square root of its access frequency. According to [Cohen and Shenker 2002], such a distribution of replicas has the optimal replication performance in minimizing the query cost. However, using access frequency is not always a suitable solution because access frequency of a newly produced report is always small but it is the newly produced report that is usually of most interest in VANET applications.

A number of approaches to parking information systems using VANETs currently exist. Leontiadis and Mascolo [2007] and Prinz et al. [2009] both propose a method based on a publish/subscribe paradigm which could be used for parking. Although such systems might filter out information which is irrelevant, they do not rank the information and they typically rely on the subscribers knowing which information is relevant. A number of heuristic methods exist for estimating relevancy of parking information. For example, Delot et al. [2009], used an encounter probability as a relevance function, which is estimated based on weighted average of spatio-temporal characteristics of the parking information. The authors did not state how the weights should be found. In [Caliskan et al. 2006], the relevance is based on an ad-hoc function which is the sum of report age and distance, where the distance is the time needed for a vehicle to arrive at the given location. The availability probability has been used for relevance by Lu et al. [2009] and Wolfson et al. [2005]. In both, the arrivals of vehicles are modeled by a Poisson process which is assumed to be known by the parking information system.

Information ranking in the context of travel time dissemination has typically relied on heuristics. In [Zhong et al. 2008], traffic reports are ranked using a heuristic computed based on the sum of the age and distance of a report. The use of machine learning for estimating relevance in travel time dissemination environments has been introduced in [Szczurek et al. 2009]. In this work, simulated scenarios of a travel time dissemination system are used to generate synthetic training examples, which are formed by input attributes of age and distance and a Boolean output, based on whether a report with the given attributes would change a vehicle's travel path. It is shown that using only the incoming reports, the learned model could accurately predict whether a vehicle's path would change. The learning was performed offline, after generating all of the synthetic training examples.

3. MODEL DEFINITIONS

The system consists of a set of *mobile nodes*. A node is a physical entity capable of data computation, storage, and short range wireless communication. A node can also observe its environment through a *sensing device*. The sensing device may be a camera installed in the car, an odometer, or GPS. Examples of nodes include vehicles equipped with on-board computers and Wi-Fi.

At any point in time, a node may create a *report*, which contains the data derived from the sensing device. The data is formed as a fixed set of *attributes* and their values. An attribute identifies the type of the data value. An example of a report is a speed report, whose attributes are time and current speed. Other examples of reports include reports about traffic accidents or available parking spaces.

Every node x carries a *reports database* of size *RRsize*. The reports database contains reports the node has received or created over time. All the reports have the same size, although the generalization to variable size is possible. The reports in the report database are sorted in order, according to a value given by the *ranking function*. The ranking function, *Rf*, maps every possible report into a *rank* i.e. number between 0 and 1. It is assumed that higher ranks are given to more important reports for an arbitrary recipient. When it is the case that the reports database is full, upon insertion and re-ranking, the lowest ranked reports will be discarded, until all reports can be stored within the given capacity.

Each node n can transmit to and receive from other nodes that are within transmission range, denoted *Tr*. These nodes are called neighbors of n. Every *Bi* seconds, each node broadcasts *Bsize* reports to its neighbors. The time between broadcasts is called the *inter-broadcast interval* and the number of reports that are broadcast is called the *broadcast size*. The value of *Bsize* depends on the report size and the available bandwidth and can be computed using a bandwidth optimization method such as the one introduced in [Wolfson et al. 2005]. The reports with the highest ranking values are sent in each broadcast.

Certain nodes, called *feedback nodes*, can judge the *relevance* of a report they receive. The relevance represents the expected utility of a report to an arbitrary neighbor of the feedback node. In other words, how useful would the report be to the recipient? This value is numeric and can be either Boolean or real valued. In cases where nodes assign numeric values, those will be assumed real valued in the range of 0 to 1. When nodes can only judge whether the report was good or bad, the report's value is Boolean (0 for bad, 1 for good). As an example, consider a report that represents the availability of a parking space. The node (vehicle) can judge the report as "good"if the parking space remains available when the node reaches it. The problem in this model is thus to find a ranking function that allows for the most relevant reports to be disseminated during every broadcast.

4. METHOD DESCRIPTION

In general, our relevance ranking method works using received reports as an input to a machine learning process. It is assumed that certain nodes have the ability to make relevance judgments when they receive a report. Given this, a supervised learning algorithm can be used with the judged relevance as the given output. Over time, each feedback node 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. Feedback nodes disseminate their learned models along with the reports so their learned models are shared with non-feedback nodes.

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 (i.e., has not been received by) 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 (i.e. it is not a duplicate). The rank value of a report R to neighboring node n is the multiplication of the estimates from both models:

$$\begin{aligned} rank(R) &= \text{Prob(R is new to a neighboring node n)} \\ &\times \text{Prob(R is relevant to a neighboring node n, provided it is new to n).} \end{aligned} \tag{1}$$

Note that the separation into duplication and conditional relevance models is not theoretically necessary, because a duplicate report is automatically not relevant. Therefore a single model could have been used, but experimental testing (not shown in this paper) revealed that using separate models allows for higher performance.

In the next subsection, we first describe the details of the duplication model and then the conditional relevance model is described in subsection 4.2. Subsection 4.3 explains the Naïve Bayes model used for the conditional relevance model and 4.4 describes how the conditional relevance models are shared among nodes.

4.1 Duplication Model

The duplication model learns the probability that a sent report would be a duplicate. In order to learn this probability, an existing technique called MALENA is used [Xu et al. 2009]. This technique works as follows. For each report r stored at a node n, n maintains a *duplication indicator vector* (DIV) for r. The DIV consists of two attributes of r: *fin* and *broadcast age*. Fin is the number of times r has been received by n. Intuitively, the higher the fin, the more likely that r is a duplicate, since this means that r has already been widely disseminated by other nodes. The broadcast age of report r for node n is the number of broadcasts that have been sent by n since r was last broadcast by n. Intuitively, the higher the broadcast age, the less likely that r is a duplicate, since this means that n has not broadcast r since a long time ago. When r is transmitted, its DIV is attached to r. A receiver node m of r checks whether or not r is a duplicate, and the respective DIV becomes a training example. Specifically, if r is a duplicate, then *neg*, the number of negatives for the respective DIV is increased by one. Otherwise, *pos*, number of positives is increased by one. Initially, both *neg* and *pos* start at zero for all DIVs. Given the DIV, the probability that report will not be a duplicate can be calculated simply by dividing the number of positives by the sum of positives and negatives.

To calculate the broadcast age of r, n remembers the time of the last broadcast that includes r. The broadcast age of r is then calculated by dividing the time passed since the last broadcast of r by the length of the inter-broadcast interval.

For newly created reports that have never been broadcast, the broadcast age is infinite. For reports that have been received but not yet broadcast, the broadcast age is defined as zero.

Training examples for the duplication model are created after a node receives a set of reports. In order to detect the duplicate reception, a node n remembers the id's of all the reports it has ever received. A positive or negative example will be created for the duplication model depending on whether the node has the id of the report in its list. All duplicate reports are immediately discarded.

4.2 Conditional Relevance Model

This model assumes that the report that is received has never previously been received. Then the model estimates the probability that the report is relevant to the recipient, which we call the *conditional relevance*. To provide the necessary training data for learning the relevance model, each report is augmented with additional attributes related to the sender of the report. Although dependent on the actual application, the attributes in spatio-temporal environments would generally depend on time and space. By knowing these attributes, the receiving node can learn the mapping from the sender's and report's characteristics to the relevance of a report. The receiving node, which would later resend the report, can then estimate the relevance to a future receiver.

For the purpose of learning the conditional relevance model, we use the Naïve Bayes online learning. In [Szczurek el al. 2009] the Naïve Bayesian algorithm was shown to be performing similarly to other machine learning algorithms for relevance probability estimation. Additionally, simple and efficient online versions of the Naïve Bayesian algorithm exist. This means the nodes would not have to incur a high computational cost for maintaining the relevance model, which is important in online learning environments.

4.3 Naïve Bayes Learning System

Let x_1,x_2,...,x_k be the values of the X_1,X_2,...,X_k attributes of a report r. According to the Bayes's theorem, the probability that r is relevant to the receiver is

$$P(relevant|x_1, x_2, ..., x_k) = \frac{P(relevant).P(x_1, x_2, ..., x_k|relevant)}{P(x_1, x_2, ..., x_k)} \tag{2}$$

where

$$\begin{aligned} P(x_1, x_2, ..., x_k) &= P(relevant).P(x_1, x_2, ..., x_k|relevant) \\ &+ P(not-relevant).P(x_1, x_2, ..., x_k|not-relevant) \end{aligned} \tag{3}$$

Assume that X_1,X_2,...,X_k are conditionally independent. We have

$$\begin{aligned} P(x_1, x_2, \cdots, x_k|relevant) &= P(x_1|relevant) \\ &\cdot P(x_2|relevant) \cdot ... \cdot P(x_k|relevant) \end{aligned} \tag{4}$$

$$P(x_1, x_2, ..., x_k|not-relevant) = P(x_1|not-relevant) \cdot P(x_2|not-relevant) \cdot ... \cdot P(x_k|not-relevant) \quad (5)$$

Thus, in order to calculate the probability that r is relevant to its receiver, we need to compute two values: *P(relevant)* and *P(x_i|relevant)*. *P(relevant)* is estimated to be the ratio between the number of positive examples and the total number of examples. *P(x_i|relevant)* is estimated as follows. For numeric attributes, we assume that values of x_i for positive examples follow a normal distribution. We collect the mean and variance of the normal distribution from the positive examples. *P(x_i|relevant)* is then estimated using the probability density function of normal distribution:

$$P(x_i|relevant) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i-u)^2}{2\sigma^2}} \quad (6)$$

For nominal attributes, *P(x_i|relevant)* is estimated as the ratio between the number of positive examples with $X_i = x_i$ and the total number of positive examples. *P(not-relevant)* and *P(x_i|not-relevant)* are estimated similarly to their "relevant"counterparts.

4.4 Model Sharing

Since conditional relevance training can only be done by feedback nodes, a model sharing procedure is used to disseminate the learned models. The procedure works as follows. When a feedback node n broadcasts its set of reports, it includes with it the learned model Naïve Bayes model, which is based on a set of k training examples. A receiving node then replaces its model with the received one if it is based on more than k training examples. Otherwise, it continues to use its own model. Since models based on more training examples are more likely to be accurate, the model sharing procedures allows non-feedback nodes to learn along with feedback nodes and for all nodes to improve their conditional relevance models over time.

5. APPLICATION TO DISSEMINATION OF PARKING AVAILABILITY

This section will discuss how the online machine learning method can be used in a parking availability dissemination application. The machine learning approach is applied in order to rank reports with the learned conditional relevance and duplication models. The model is also used to determine which parking spaces a vehicle should pursue when it receives a report. We show that the method successfully learns the relevance of reports by comparing it in simulations with a function that was proved to be optimal in the given simulated model.

5.1 The Application Environment

5.1.1 *Vehicles.* The environment consists of a set of vehicles. A subset of these vehicles is equipped with GPS and devices capable of computation and short-range wireless communication. The set of vehicles that are equipped we call *participating vehicles*, otherwise they are labeled *non-participating vehicles*. Some of the vehicles

actively look for available parking spaces. Vehicles that actively look for parking are called *consumers*. Participating vehicles which are not looking for parking are called *brokers*. The feedback nodes in this model are the participating consumers, while non-feedback nodes are the brokers. We assume that consumers traverse the road network around a *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.

5.1.2 *Parking Availability Reports.* When a participating vehicle leaves its parking space, it generated a *parking availability report*. This report stores the following fields: *report identifier, location, and timestamp*. The report identifier provides a unique number for each report and is used for duplicate detection. The location is the coordinates of the parking space given by the GPS. The timestamp is the time at which the report is produced. Dissemination of reports is done as described in Section 3, with the exception that participating consumers do disseminate reports about parking spaces they are pursuing.

All reports are stored in the reports database. Only the most recent reports for a given location are kept. Incoming reports for a location provided by an existing report are treated as duplicates if their timestamps are the same or older than the existing report.

5.1.3 *Target Parking Space Updates.* When a consumer vehicle 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 (i.e., never previously received) reports, the target parking space decision is reevaluated based on current values of the ranking function.

Consumer vehicles park in the first available parking space, regardless whether or not they are pursuing their target parking space. Therefore, the target parking space may never be reached. When it is reached, but it is unavailable at that time, the vehicle continues to search for parking along a search path.

5.2 The Conditional Relevance Model

In this subsection we instantiate the conditional relevance model for the parking availability dissemination application.

5.2.1 *Relevance Definition.* For parking availability dissemination applications, we define being relevant as follows: a parking availability report r received by vehicle v is relevant if the parking space referred to in the report is available when v reaches it. A positive example is hence created when the vehicle parks. Otherwise, if the vehicle reaches the space and it is unavailable, it is a negative example.

Since the relevance model will also be used to decide which parking spaces will be pursued, the learning of negative examples can be skewed. Additionally, a vehicle pursuing a far away parking space will reach its intended target infrequently, because another parking space might be available along the way. This will again skew the learning of negative examples. To deal with this issue, when it is the case that a vehicle pursuing a target parking space happens to find parking along the

way, it will generate a positive report with attribute values as if another vehicle has just left that space.

5.2.2 *Attribute Selection.* As in the travel time dissemination application, parking availability reports are spatio-temporal in nature. The age and distance are hence included in the conditional relevance model, where age is the time since report was created and distance is the time needed to reach the parking space. Formal justifications for using these attributes for parking applications can be found in [Wolfson et al. 2005], where the authors prove that under certain conditions, a function of age and distance is equivalent to the probability that the parking space would be available if the vehicle would decide to pursue it.

5.2.3 *Training Examples and Model Sharing.* Training examples for the duplication model are created by every participating vehicle when they receive a set of reports. The procedure is the same as for travel time dissemination. Conditional relevance training examples are created when a participating consumer reaches the target parking space. When a consumer initially chooses its target parking space, the values of age and distance are saved. Once the target space is reached, a positive or negative example is created depending whether the space is available or unavailable, respectively. The created example is created using the previously saved age and distance values and the appropriate relevancy label (i.e. positive or negative).

5.3 Evaluation

In this section we evaluated the machine learning method used in parking availability dissemination. The results will demonstrate that machine learning method is able to combine age and distance attributes in an optimal way, where optimal is given by the equation derived in [Wolfson et al. 2005].

5.3.1 *Simulation Method.* A custom simulator is used to evaluate the method. In the simulation, vehicles are randomly placed on a grid road network that is 1.2 miles by 1.2 miles in area. Distance between subsequent intersections in the grid is 0.1 miles. Available parking spaces are mapped to points at intersections in the grid. One parking space is assigned to every other intersection, for a total of 36 (see figure 1). There are u broker vehicles per square mile of the grid network and c consumer vehicles. Out of the c consumers, w is the fraction of participating vehicles.

Mobility Model. Vehicles are placed on the grid at random locations. Broker vehicles move about according to a random waypoint mobility model. They generate a random location to be their destination and they traverse to that location along the shortest path. Once the destination is reached, another one is chosen. Consumer vehicles move around a set of road segments defined by the *search square*. The squared is defined such that the side length is 0.4 miles, the vehicle is on one of the sides with equal probability, and the square is aligned with the grid network such that the vehicle is as close to the middle of the side as possible and has at least one parking space in its path. A participating consumer may leave its search square to pursue its target parking space. In that case, it traverses the shortest path to the target parking space. The speed, in miles per hour, of every vehicle

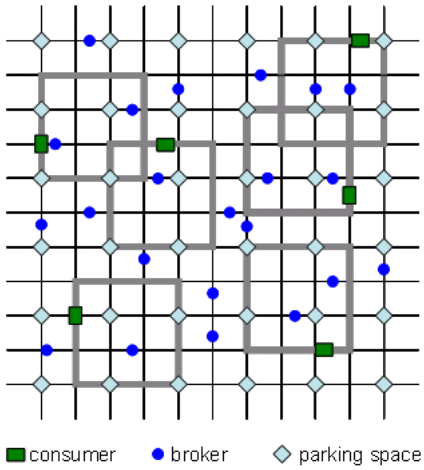

Figure. 1: The grid network, parking spaces, search squares, brokers and consumers.

is chosen randomly from the interval [v-5, v+5], where v is the average speed of vehicles.

When a consumer vehicle parks at an available parking space, it is removed and another consumer is placed at the same location with the same search square. If that consumer is participating, the conditional relevance model is inherited from the old consumer. The parking space where the old consumer parked becomes unavailable for a random length of time according to an exponential distribution with mean q.

Simulation Parameters. All the simulation parameters and their values are summarized in Table I.

Table I: DEFAULT SIMULATION PARAMETERS

Parameter	**Values**
Total number of parking spaces	36
Simulated area	1.2x1.2 sq. miles
Broker density (u)	100 per square mile
Number of consumers (c)	20
Percentage of participating consumers (w)	50%
Transmission range (Tr)	250 meters
Mean vehicle speed (v)	20 mph
Mean of parking unavailability time (q)	20 minutes
Broadcast size (Bsize)	1 report
Inter-Broadcast interval (Bi)	5 seconds
Report database size (RRsize)	36 reports
Total simulation time	20 hours

Learning Model Bootstrapping. Since initially the online learning models do not contain any examples, their performance will be much lower than it potentially could be over time. Therefore, we chose to bootstrap the models. This was done

by running the simulation with default parameters for a total simulation time of 72 hours. After this time, the learned duplication and conditional relevance models are saved and used as the initial models for all tests.

Ranking Methods. Five ranking methods are compared. For each one, the duplication model is used to calculate the novelty factor, which is used as a multiplier for a given ranking function. This is done to focus on the effects of the conditional relevance model. The following ranking functions are used (labels in parentheses):

(1) 1/age. (age)
(2) 1/distance. (distance)
(3) $e^{-\alpha.age-\beta.distance}$, where α=φ, β=φ/v, and φ=$2 \cdot c \cdot v/l$, and where c is the number of consumers, v is the mean speed of consumers and l is the length of all road segments in the network. This function is derived in [Wolfson et al. 2005] and is part of a method called Information Guided Search. (IGS)
(4) Conditional relevance probability output using the proposed machine learning method. (ML)

As in travel time dissemination, the first method (age) ranks solely based on age, while the second method (distance) ranks solely based on distance. The third method (IGS) is based on an equation derived by Wolfson et al. [2005]. It computes the probability that a given space is unoccupied given its age and distance under a certain limited model. The model used for deriving the IGS equation assumes arrivals at parking spaces follow a Poisson distribution. The issue with this equation is that it depends on the knowledge of several parameters, such as the number of consumers or their mean speed, which would be unknown in a real environment. It therefore can be said to represent an ideal benchmark case. The last method (ML) is our proposed machine learning method with age and distance as attributes.

Performance Metric. To compare the different ranking methods, we measured the average *discovery time* for participating consumer vehicles. The discovery time is the difference in time between when a consumer is created and when it finds an available parking space. We then compared this time with the average discovery time in a case in which every consumer uses a *blind search*. This means that no vehicle is participating and can only find parking spaces that are along its search path. The percentage decrease between the blind search time and the given ranking time is then shown in figures as the percentage improvement in discovery time.

5.3.2 *Results.* In this section we show the simulation results. 25 tests were performed using various parameter values. In each test, a single parameter was modified, while keeping the rest at default values. Each ranking method was tested with and without the use of the novelty factor, which is determined by the duplication model. The average of the percentage improvement in discovery time for each ranking method was calculated and is shown in the figure below.

The figure above shows that machine learning was able to nearly match the performance of the IGS equation, which was shown to exactly calculate the availability probability. In fact, as will be later shown, in almost every individual test, the discovery time performance closely matched that of IGS. Both methods were significantly better than both age and distance rankings. This illustrates that the

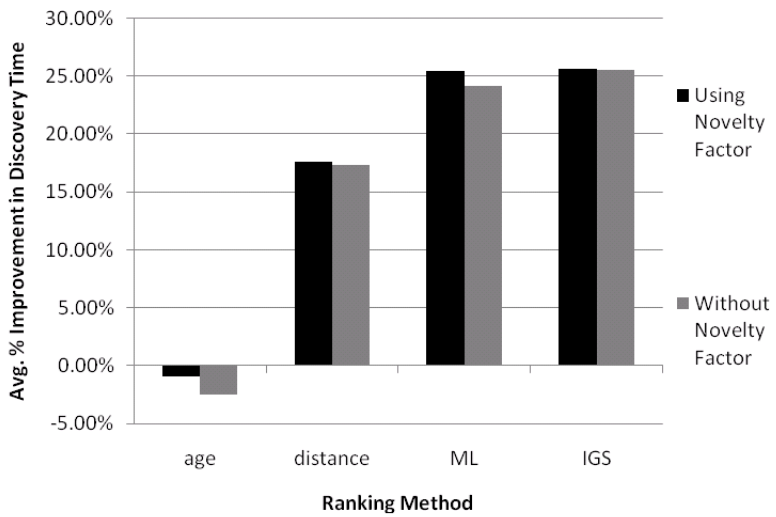

Figure. 2: Average ٪of discovery time improvement.

proposed method can successfully learn an optimal combination of relevant attributes.

Although using distance outperformed using age by a wide margin on average, individual test results showed that distance is not always the best attribute to use and as will be shown later, in 2 out of 25 tests, age is actually superior. The use of the novelty factor shows that the duplication model effectively eliminates duplicate reports from being disseminated. The performance of all ranking methods improves with the use of the novelty factor, although the margin is small. This is because of the small number of reports being disseminated. As will be shown later in the travel time dissemination application, the effects can be much larger when the number of reports in the system is higher.

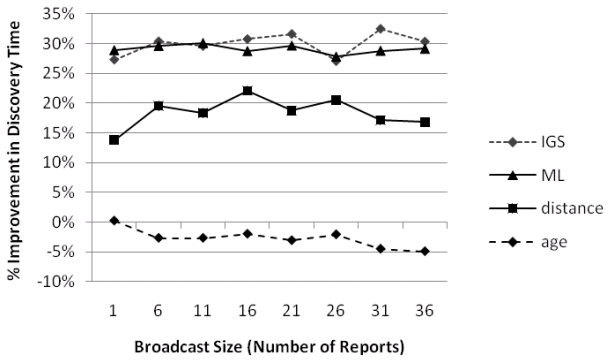

Figure. 3(a): Broadcast size

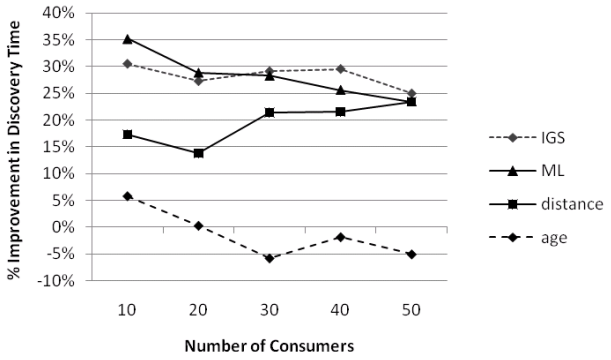

Figure. 3(b): Number of consumers

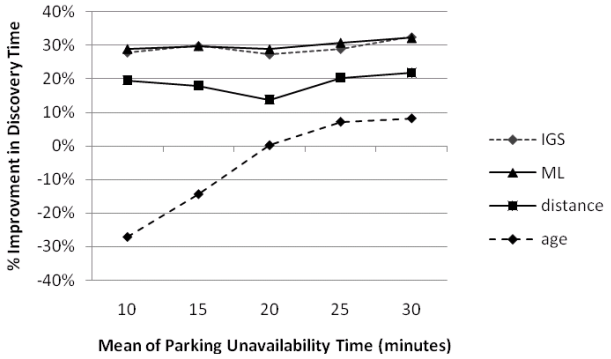

Figure. 3(c): Parking unavailability time

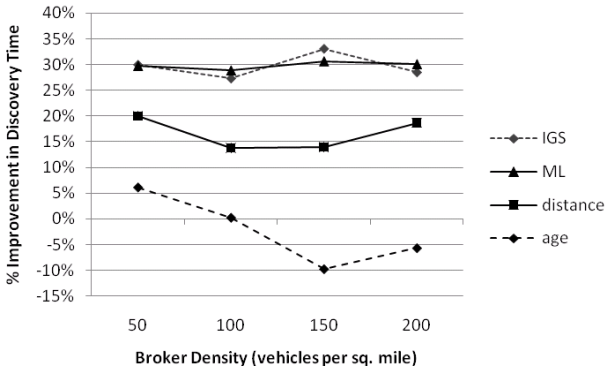

Figure. 3(d): Broker density

Effects of Broadcast Size. Figure 3(a) shows the performance of the different ranking methods when varying the broadcast size. The results show that broadcast

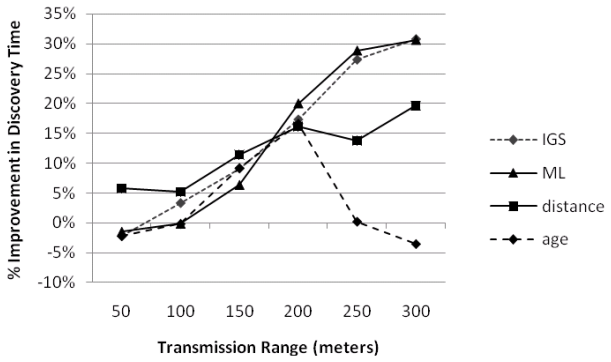

Figure. 3(e): Transmission range

Figure. 3. Percentage of discovery time improvement across varying simulation parameter values.

size generally has no effect on discovery time. This means there is little to gain from broadcasting more than one report at a time. Throughout the broadcast size range, using age and distance resulted in the lowest improvement on average, with 18.3%for distance and -2.7%for age. Machine learning averaged a 29.1%improvement, significantly higher than either age or distance, closely following the performance of IGS, which averaged 29.9%.

Effects of the Number of Consumers. Figure 3(b) shows the performance of the different ranking methods when varying the number of consumers. As the figure shows, the performance of age ranking generally decreases as number of consumers increases, while distance ranking performance is the opposite. The reason for this is that with a high number of consumers, the probability of parking availability is decreasing throughout and therefore it may not be worth it to pursue far away parking spaces. This effect was the reason for the general decrease in performance for all method, with the exception of distance, as the number of consumers increases.

Effects of Parking Unavailability Time. In fig. 3(c), the impact of varying the mean of parking unavailability time is shown. Similarly to previous results, ML came close to the performance of using IGS and outperformed age and distance by a significant margin. The results show that for distance based rankings (i..e, all but age), the unavailability time does not have much effect on percentage improvement in discovery time. Age ranking improves performance as the mean time increases, because there is less variability in the parking space availability. To see this, consider an extreme example, in which mean unavailability time is close to 0. In that case, age would no longer matter, since the parking is almost guaranteed to be available by the time the vehicle arrives. The age hence becomes an irrelevant attribute.

Effects of Broker Density. Broker density affects how quickly information is disseminated. As a result, it affects ranking performance in two ways. On one hand, as broker density increases, the speed of dissemination also increases and this improves performance because vehicles are able to rank based on a greater

amount of information. On the other hand, the increased information causes greater competition among participating consumers, which results in lower performance. This second effect is especially evident for age ranking, as can be seen in fig. 3(d). At high densities, most consumers will receive a generated report in a short amount of time, which will cause all such consumers to pursue the same parking space. When distance is used in the ranking method, the effect is mitigated because competition will be more localized. Ranking methods which use a combination of age and distance thus do not have much variance in their performance.

Effects of the Transmission Range. Figure 3(e) shows how performance varies across a range of transmission range values. Similar to broker density, this parameter impacts the speed of information dissemination and therefore the two effects that affected performance for broker density are present in transmission range tests. Unlike broker density, transmission range has a much bigger impact on dissemination, because of its major impact on the communication delay (i.e. difference between generated and received time). As a result, the graphs of IGS and ML show performance follows an "S"shape: very low performance at close transmission range (50m), high gains in performance in the 100m to 250m range, and marginal improvement at 300m. With distance ranking, the shape of the performance curve is flatter, but still generally increasing with increased range. Note the slightly erratic behavior of the curve can be attributed to the use of the novelty factor, which causes some randomness in the dissemination of the reports. Tests (not shown) without novelty factor, show a monotonically increasing curve for distance ranking. For age, the effect of increased competition causes a decrease in performance after 200m range.

6. APPLICATION TO TRAVEL TIME DISSEMINATION

This section will discuss how the online machine learning method for the estimation of relevance can be used to improve dissemination of vehicle travel times on a road network. We use the STRAW vehicle simulator and show that the use of machine learning approach for ranking allows vehicles to lower their average travel times when compared against ranking using heuristics.

6.1 The Application Environment

6.1.1 *Vehicles.* As in the previous application, the environment consists of a set of vehicles, a subset of which is equipped with GPS and devices capable of computation and short-range wireless communication. Every vehicle traverses a road network to a predetermined destination, which it reaches along the path with the shortest travel time, given the information it currently has in its local database. In the rest of this paper, when we say shortest path we refer to the shortest travel time path. In this model, every participating vehicle is a feedback node.

6.1.2 *Travel Time Reports.* As each participating vehicle fully traverses a particular road segment, it uses its GPS to record the travel time. This information is then saved in a *travel time report.* This report stores the following fields: *report and road segment identifiers, travel time,* and *timestamp.* The report identifier provides a unique number for each report and is used for duplicate detection. The road segment identifier is used to match the report to a particular road segment. The

travel time is the time measured by the given vehicle's GPS. The timestamp is the time at which the report is produced. Reports are disseminated as described in Section 3.

6.1.3 *Digital Map.* Each vehicle holds a digital map used for storing information about road segments and their travel times. The digital map of a vehicle v is a weighted graph G=<V,E >where V is the set of vertices (intersections) and E is the set of edges (road segments), with the weight of each edge e being the travel time estimate of e maintained by v. A number of properties are associated with each road segment. The properties of road segments that are of interest in this paper are: *road segment identifier, road type, travel time estimate, list of k most recent reports pertaining to the segment.* The road segment identifier uniquely determines the particular road segment in the digital map. Road type indicates the physical characteristics of the particular road segment. There are several types that are defined (e.g. highways, arterial roads) and each corresponds to a different free-flow travel time on that segment. We call any non-highway segment a *city street segment.* The travel time estimate is the estimated time required to traverse the road segment. This estimate is calculated as the average travel-time of the k reports the vehicle has received or generated with the most recent timestamps.

6.1.4 *Travel Time Updates.* The following travel time update policy was used for the purposes of this paper. For each road segment s, a vehicle keeps a sliding window of the k youngest reports (i.e., the reports with the greatest timestamps) it has received in the digital map. In the experiments of this paper k is set to 10. When a report z regarding s is received, z is applied to update the travel time of s as follows. If the timestamp of z is smaller than the least timestamp in the sliding window (i.e., z is older than the oldest report in the sliding window), then z is discarded. Otherwise, the report in the sliding window with the least timestamp is replaced by z; the travel time of s is updated to be the average of the reports in the new sliding window. After the travel time of s is updated, the shortest path is recalculated. Thus, the shortest path is recalculated for each received report.

6.2 The Conditional Relevance Model

In this subsection we instantiate the conditional relevance model introduced in Section 3.2 in the context of travel time dissemination.

6.2.1 *Relevance Definition.* In general, a report is relevant if it has an impact on the decisions of the recipient. For travel time dissemination applications, we define being relevant as follows: a report r received by vehicle v is relevant if it changes the shortest path from $v's$ current location to its destination. A report thus becomes a positive example if the report changes the shortest path of the recipient vehicle. Otherwise, it is a negative example. In the rest of this subsection we complete the instantiation by specifying and justifying the attributes used for learning the conditional relevance model.

6.2.2 *Attribute Selection.* Due to the spatio-temporal nature of the travel time reports, the most obvious attributes to include for the conditional relevance model relate to time and space. To capture the temporal aspect of the reports we will define the *age* of a report. The *age* of a report r is the difference, in seconds,

between the current time and the time at which r was created. To capture the spatial aspect, we introduce a distance measure that will be defined as follows: the *distance* of a report r contained by vehicle v with digital map DM about road segment rs is the shortest travel time, in seconds, from $v's$ current location to the mid-point of the rs when the weight is the free-flow travel time for every road segment in DM.

Now we justify the selection of these attributes. Our justification methodology is to show that if a report R_1 is better than a report R_2 on one attribute but is the same as R_2 on the other attributes, then the relevance of R_1 is not lower than that of R_2, i.e. the probability that R_1 changes a vehicle's shortest path is not lower than that R_2 does so. In order to isolate the effect of the duplication model and concentrate on the conditional relevance model, we assume that neither R_1 nor R_2 has been previously received by the vehicle. Denote by R.age the age attribute of a report R, and by R.travel-time the travel time estimate attribute of R.

In the following we justify the age attribute. Intuitively, when all attributes are fixed, a younger report is more relevant than an older one. This is because an older report is more likely to be older than the oldest report in the sliding window of the corresponding road segment and therefore is discarded by the travel time update policy. Thus the probability that the older report changes a vehicle's shortest path is lower than that the younger one does so. This intuition is formalized by the following theorem.

THEOREM 6.3.2. *Consider a vehicle v at a vertex s at time t, and two reports R_1 and R_2 that pertain to the same edge e of the road network. Assume that R_1.travel-time=R_2.travel-time, and R_1.age <R_2.age, and that if v receives the single report R_2 at time t then it changes v's shortest path. Then if at time t vehicle v receives the single report R_1 instead of R_2, it changes v's shortest path as well.*

PROOF. Since R_2 changes *v's* shortest path, R_2 must be younger than the oldest report in the sliding window of e (otherwise R_2 would have been discarded). Since R_1 is younger than R_2, R_1 must also be younger than the oldest report in the sliding window of e and changes *v's* shortest path.

Theorem 6.3.2 indicates that when the other conditions are fixed, a younger report is more relevant that an older one. In other words, if a vehicle has R_1 and R_2 and room to transmit only a single report, then it should transmit R_1 instead of R_2 because it will be at least as relevant to an arbitrary vehicle v. Due to theorem 1, the ages of reports can be used to rank reports according to their probability of being relevant.

Similarly, it can be shown that under certain conditions, a report with a smaller distance is more relevant that a report with a longer distance. Intuitively, under uniformity assumptions, if a road segment e is far from a vehicle v, then the probability that the destination of v is beyond e is small, and therefore the probability that *v's* shortest path passes e is small. Thus the probability that a report pertaining e changes *v's* shortest path is small. In summary, both attributes can be said to be useful, yet it is not obvious how to combine both attributes to achieve a better ranking. This is where the machine learning method comes into play.

6.2.3 *Training Examples and Model Sharing.* Training examples are created using the *RelevanceTrain* algorithm, given by the following pseudocode:

Algorithm - *RelevanceTrain (Travel Times)* Input - R: Set of received reports by vehicle v Outputs - E_d: Set of training examples for duplication model E_r: Set of training examples for conditional relevance model
1. Select and remove report r from R in any order. 2. IF r has been previously received by v, THEN discard r, create negative example and add to E_d, GOTO step 1 ELSE Create positive example and add to E_d, GOTO step 1 3. Save the current digital map state and use report r to update the digital map of v using the previously describe travel time update policy. 4. Recompute the shortest travel-time path from the current location of v to the destination. IF shortest path changes, THEN create positive example and add to E_r ELSE create negative example and add to E_r 5. Restore the digital map state to the previous state (before the travel time update). 6. IF R is not empty, GOTO step 1

The algorithm works by first checking for duplicates. At that point either a positive or negative example will be created for the duplication model. Then, if it is determined that the report is not a duplicate, relevance of the report is determined based on whether it would change the path of the vehicle. Based on this, a positive or negative report is created for the conditional relevance model.

After all the reports in R are processed, any reports that were identified as non-duplicate in step 1 are applied to update the digital map of the vehicle. Note that while the example creation procedure does temporarily update the digital map, the update is rolled back after the examples are created. This is done so that the order of examining reports does not affect whether the report will create a positive or negative example.

For travel time dissemination, it is assumed every vehicle is GPS equipped. Every vehicle can therefore act as a feedback node. It is hence unnecessary to use model sharing in this application.

6.3 Evaluation

The purpose of the evaluation is to establish the feasibility of the machine learning method. This was accomplished by determining whether the learned model allowed the vehicles to make better route decisions.

6.3.1 *Simulation Method.* In order to evaluate the usefulness of the learned model, the STreet RAndom Waypoint (STRAW) simulator [Choffnes and Bustamante 2005] was used to generate a scenario in which vehicles disseminate travel time reports periodically. The road network is a 6 km by 4 km region of downtown Chicago taken from the digital map published by the Geographic Data Technology Inc. (see figure 4). 100 vehicles were deployed in the road network.

Mobility Model. An open mobility model is assumed. In this model, vehicles are assumed to pass through the region, rather than travel within it. Thus each vehicle v is placed at a random location on the boundary of the road network, and another random boundary location on the road network is selected to be the

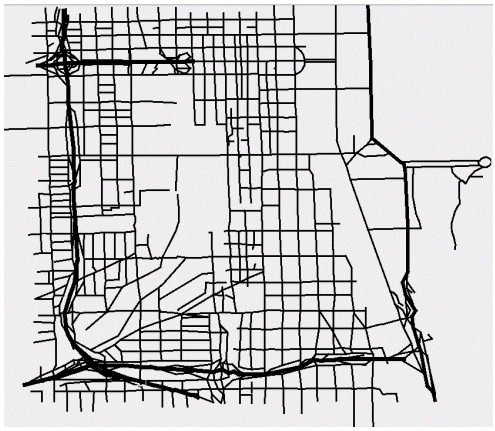

Figure. 4: Simulated road network: portion of downtown Chicago

destination. Vehicle v then moves from the origin to the destination, along the shortest travel time path given its current digital map state. When the destination is reached, the vehicle is assumed to have left the boundary. Another destination is randomly selected and the vehicle is assumed to be new [1]. Its digital map is thus reset to contain no travel time reports and its report database is emptied. The learned conditional relevance and duplication models are preserved. The justification for this is that a newly entering vehicle will also have a learned model that it has learned while moving outside of the region.

Out of the 100 vehicles, 10 are participating, meaning they broadcast and generate reports. The other 90 are non-participating and thus always follow the shortest free-flow travel time path. The simulation procedure is continued until 100 trips are made by each vehicle. A total of 1000 trips are thus made by the participating vehicles. At that time, the simulation ends.

Accident Model. We assume that during the time of simulation, non-recurring traffic conditions exist, such as in case of accidents on the road. To simulate these conditions, 40 slow-downs are initially introduced at randomly selected highway segments. For the slow-down segments, the maximum speed is set to be 3 km/h. Each slow-down lasts for a time period that follows an exponential distribution with the mean of 20 minutes. When a slow-down recovers, another slow-down is introduced at a randomly selected highway road segment. Thus at any point in time the number of slow-downs in the road network is fixed.

Simulation Parameters. All the simulation parameters and their values are summarized in Table II. These parameters are the default for all simulations.

Learning Model Bootstrapping. Bootstrapping of models was performed like in the parking application. The simulation with default parameters was run for a total simulation time of 72 hours. The learned duplication and conditional relevance models were then saved and used as the initial models for all tests.

[1]For purpose of calculating vehicle trips, each vehicle is labeled at the start of the simulation. This label is persistent throughout the simulation even though the vehicle is assumed to be a new vehicle once it reaches its destination.

Table II: DEFAULT SIMULATION PARAMETERS

Parameter	**Values**
Total number of road segments	1562
Simulated area	6x4 sq. km (see fig. 1)
Total number of vehicles	100
Number of participating vehicles	10%
Transmission range (Tr)	250 meters
Number of slow-downs	40 slow-downs randomly among highway segments
Maximum speed at slow-down segments	3km/hour
Mean of slow-down persistence time	20 minutes
Broadcast interval (Bi)	5 seconds
Report database size (RRsize)	100 reports
Broadcast size (Bsize)	10 reports
Total number of trips	1000

Ranking Methods. We compared four different ranking methods:

(1) Ranking by age. (age)
(2) Ranking by distance. (distance)
(3) Ranking by 1/(age+distance). This method was a heuristic used in the TrafficInfo method [Zhong et al. 2008]. (TrafficInfo)
(4) Conditional relevance probability output using the proposed machine learning method with age and distance as attributes. (online-ML-age-distance)

In addition to the above ranking methods, three baselines were also tested: *full-info*, *non-info*, and *unlimited-bandwidth*. The baselines reflect theoretical upper and lower bound performance. Full-info is an ideal case where vehicles receive all the reports as soon as they are created and thus have the full available information; no bandwidth, memory, or transmission range limitations are considered. Non-info is a case when vehicles do not exchange any information. Unlimited-bandwidth is a case when the report database size is unlimited and the vehicles broadcast every report they have ever received or generated. The unlimited-bandwidth baseline shows the best achievable performance that can be expected in the mobile peer-to-peer environment when transmission range and connectedness are the only limitations. The difference between the unlimited-bandwidth and the full-info baselines is that in unlimited-bandwidth, the reports are disseminated periodically instead of instantly and that the dissemination is done within the transmission range of the disseminating vehicle.

Performance Metrics. Two metrics were used for evaluation. The first is the *average trip time*, which measures the time it takes to reach a destination averaged across all vehicles and trips. This metric shows how the prioritization scheme affects the decision choices of vehicles. Note that because travel times change over time, having more accurate information will not always lead to better route decisions.

To measure the fidelity of the disseminate information that a given ranking method will provide, we introduce the *average travel-time fidelity* metric. This metric was collected as follows. Every 10 seconds, for each vehicle, the absolute value of the difference between the travel time along the shortest path according to

vehicle's current information and the path according to *full information digital map* was calculated. A full information digital map is defined as a digital map which is updated with every report ever created, as soon as it was created. The difference values are then averaged at the end of the simulation.

6.3.2 *Using Machine Learning for Combining Attributes.* In this section we show how the machine learning method can be used to combine two attributes which are known to be relevant, in order to improve performance.

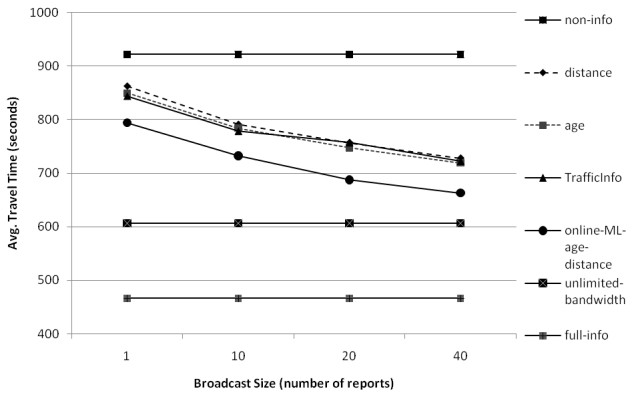

Figure. 5(a): Broadcast Size

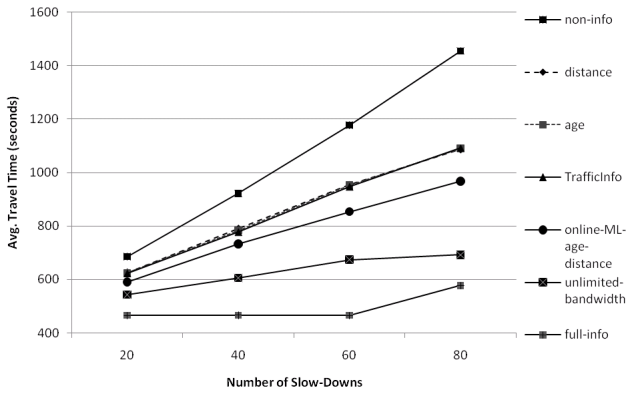

Figure. 5(b): Slow-Downs

Figure 5(a) shows the performance of the different ranking methods when varying the broadcast size. As would be expected, the performance of all ranking methods generally improves as broadcast size increases. The machine learning method maintains a lead in performance across all broadcast size values. In comparison, the TrafficInfo method of combining the two attributes does not significantly improve performance over individual attributes, although it does offer a marginal

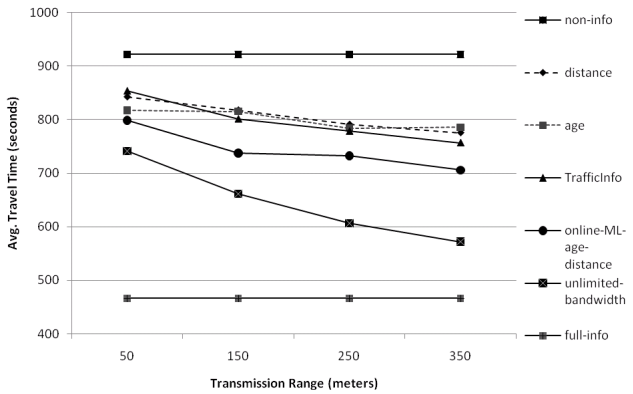

Figure. 5(c): Transmission Range

improvement at small values of broadcast size. A similar result was the case when the number of slow-downs and transmission range were varied (see Figures 5(b) and 5(c)). The average travel-time fidelity results were proportional to the average travel time results for all ranking methods. A figure showing these results was hence omitted from this paper.

6.3.3 *Using Additional Attributes to Improve Performance.* Aside from age and distance, there are also additional attributes that may be used to capture the relevance of a report. In this section, we used two additional attributes for the machine learning: *road type* and *percentage of shortest paths*. The *road type* can be either a highway or city-street segment, depending on its free-flow travel speed. Given a road network, RN, a vertex [2] s in RN and a road segment rs, *the percentage of shortest paths* (%SP(RN,s,rs)) is the number of shortest paths starting from s to all possible vertices in RN that pass through rs, divided by the total number of all possible vertices. Figure 4 shows the performance when all four attributes are used for the conditional relevance model. The result using all four attributes is labeled as online-ML-all attributes. As can be seen in fig. 6, the use of additional attributes provides a significant improvement for average travel time. Additionally, for broadcast size of 40, the performance comes close to the unlimited-bandwidth benchmark. This means that the online machine learning method provides near optimal ranking at that point. As with the previous tests, the average travel-time fidelity results were similar to average travel time results.

7. CONCLUSION

This paper proposed a machine learning approach to ranking of information in VANET applications. The method uses incoming reports in order to provide input to supervised machine learning algorithms. The learned model reflects the relevance of information for the receiving vehicles. Ranked information can be used to deal with bandwidth issues in VANETs and to aid vehicles in decision making.

[2]For this paper, we use the midpoints of road segments as possible vertices

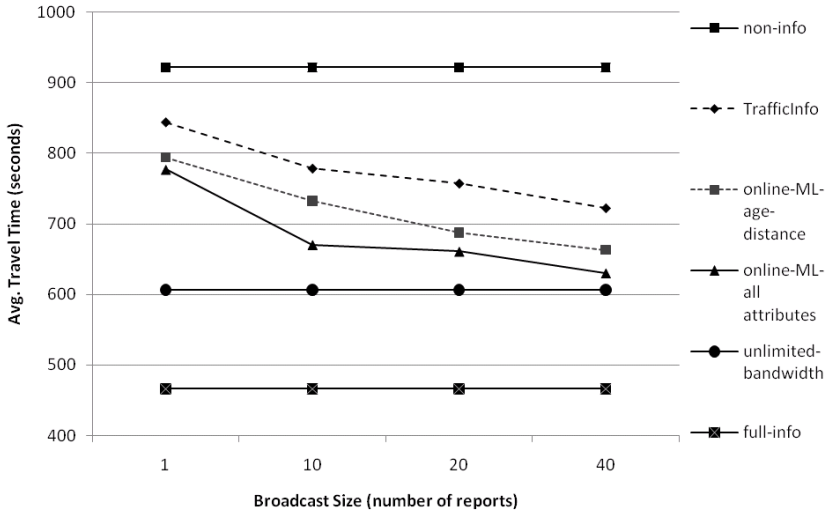

Figure. 6: Comparison between attributes - Broadcast size vs. average travel time.

The method was evaluated using two VANET applications. In the parking availability dissemination application, the method was able to match the performance of an optimal method in terms of the parking discovery time. For the travel time dissemination application, the results showed that vehicles utilizing the machine learning method had lower average travel times than when heuristic methods were used. For both applications, the main advantage of using the proposed technique is that several, known to be useful attributes can be easily combined in a way that improves the dissemination performance, without extensive knowledge or analysis of the application.

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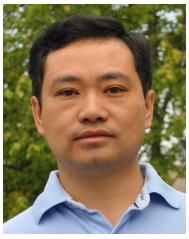

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