

Socially Optimal Personalized Routing with Preference Learning

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Abstract

Traffic congestion has become inescapable across the United States, especially in urban areas. Yet, support is lacking for taxes to fund expansion of the existing network. Thus, it is imperative to find novel ways to improve efficiency of the existing infrastructure. A major obstacle is the inability to enforce socially optimal routes among the commuters. We propose to improve routing efficiency by leveraging heterogeneity in commuter preferences. We learn individual driver preferences over the route characteristics and use these preferences to recommend socially optimal routes that they will likely follow. The combined effects of socially optimal routing and personalization help bridge the gap between utopic and user optimal solutions. We take the view of a recommendation system with a large user base but no ability to enforce routes in a highly congested network. We *(a)* develop a framework for learning individual driver preferences over time, and *(b)* devise a mathematical model for computing personalized socially optimal routes given (potentially partial) information on driver preferences. We evaluated our approach on data collected from Amazon Mechanical Turk and compared with Logistic Regression and our model improves prediction accuracy by over 12%.

Disclosure

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Contents

1	Introduction	1
1.1	Background and Motivation	1
1.2	Contributions	4
1.3	Structure of the Report	5
2	Literature Review	6
2.1	Routing	6
2.2	Utility Theory and Preference Learning	9
3	System Model & Problem Description	12
4	Methodology	14
4.1	Clustering Drivers and Learning their Preferences	14
4.2	Socially Optimal Personalized Routing	18
5	Experimental Results	21
5.1	Survey Design Procedure and AMT Data Gathering	21
5.2	Preference Learning Results	23
6	Implementation	35
7	Conclusion and Future Directions	36
	References	37
	Appendix: The Survey	49

List of Figures

1	Sample Question	22
2	Summary of the Demographic Information from AMT Survey	24
3	Routes Choices Are obviously Different	25
4	Route Choices Are not obviously Different	26
5	Route Choices Are Indifferent	26
6	Accuracy Comparison In Sample and Out of Sample: Proposed Approach <i>vs</i> Logistic Regression	28
7	Accuracy as a Function of the Weight w	33

List of Tables

1	Survey Responses for each Question	23
2	Accuracy on the Training and Testing Sets based on Different Clustering Methods .	27
3	Proposed Approach In Sample	29
4	Logistic Regression Approach In Sample	30
5	Proposed Approach Out of Sample	31
6	Logistic Regression Approach Out of Sample	31
7	Proposed Approach In Sample Results with Feature 6 Dropped	32
8	Proposed Approach Out of Sample with Feature 6 Dropped	32

1 Introduction

1.1 Background and Motivation

According to data from the Bureau of Transportation Statistics and the World Bank [85], from 1990 to 2018, the number of registered vehicles increased by 43% [85]. During that period, Vehicle-miles traveled (VMT) increased by over 63.4% [85] and the population size grew by 30.9% [85]. However, the total road mileage of public roads and lane miles increased by a mere 7.4%. The growth of the population and VMT combined with limited infrastructure expansion works have resulted in the swamping of the transportation capacity. In fact, rising traffic congestion is an inescapable condition in large and growing metropolitan areas across the world, causing huge economic losses and severely damaging quality of life. The report from INRIX [2], a company that specializes in car services and transportation analytics, showed that in 2017, the average U.S. commuter spent over 51 hours in traffic congestion and the congestion cost drivers \$305 billion in direct and indirect cost, an increase of \$10 billion from 2016. In large urban areas, these numbers were even grimmer. For example, the Los Angeles drivers spent an average of 102 hours sitting in traffic last year, which cost Los Angeles drivers over \$2,828 on average, equaling more than \$19.2 billion to the city as a whole. This cost includes the value of fuel, time wasted in congestion, and the increase in prices to households from freight trucks sitting in traffic.

Besides the huge economic losses and impedance to quality of life, traffic congestion can increase air pollution and negatively impact health. The Transportation Research Board, which is a division of the National Academies, a private, nonprofit institution that includes the National Academy of Sciences, National Academy of Engineering, Institute of Medicine, and National Research Council, mentioned that vehicle emissions have become the dominant source of air pollution [1]. The increasing severity and duration of traffic congestion have the potential to greatly increase pollutant emissions and to degrade air quality [41]. In 2013, Zhang and Batterman used data from the Michigan Department of Transportation (MDOT) and Southeast Michigan Council of Governments (SEMCOG) to analyze the impact of pollution: they used an incremental analysis and concluded that air pollution (specifically NO_2) increases exponentially with traffic congestion [100]. Hennessy and Wiesenthal found that when drivers experience traffic congestion, they more easily become aggressive and stressed. Using a Likert scale which is a type of rating scale, ranging from 0 (low stress level) to 4 (high stress level), they found that when congestion is high, stress levels on the scale double (from 0.8 to 1.73) [43].

Given the grim direct and indirect effects of congestion, there is an urgent need for a solution. Litman [57] mentioned that there are five congestion reduction strategies: (a) roadway expansion; (b) improvement of space-efficient modes (e.g., more bike lanes, more frequent public transportation, or more sidewalks and paths); (c) transport pricing reforms (e.g., road tolls that are increased under congested conditions, or increases in fuel price); (d) smart growth development policies (e.g., improve transport options, or parking management); (e) Transportation Demand Management (TDM) program (e.g., employee transport management, transportation management associations, or mobility management marketing). These strategies aim to provide an institutional framework for implementing strategies such as rideshare matching and pricing reforms, and in various ways encourage travelers to try efficient alternatives.

Cambridge Systematics, Inc, which is an independent, employee-owned transportation consultancy firm with corporate headquarters located in Medford, MA, also gave some strategies. In its report which was prepared for the Federal Highway Administration, it pointed out that there are three ways to deal with congestion: (a) adding more base capacity, (b) operating existing capacity more efficiently, and (c) encouraging travel and land use patterns that utilize the system in less congestion inducing ways [89].

In summary, congestion reduction strategies are of two types: they consist in either (a) expanding the network or (b) using the existing network more efficiently. Cervero mentioned that road expansion strategies require long planning horizons before they can mitigate congestion [19]. With population forecast to grow by 40 million by 2030 according to the U.S. Census Bureau [85] and public support to increase taxation to conduct the necessary infrastructure expansion works remaining low, there is an urgent need for innovation to improve operating efficiency of the existing road network with aim to minimize e.g., aggregate delay, congestion, or pollution. In order to reduce traffic congestion as soon as possible, we need to find a way to improve operating efficiency of the *existing* road network.

A popular way to improve efficiency of the network is to leverage the sharing economy, e.g., ad hoc ride sourcing services such as Uber¹ or Lyft². Malhotra and Van Alstyne mentioned that even though the sharing economy is a good thing and can help transportation, it takes time to balance conflicting needs [62]. In their research, they showed that the ride sourcing services do not always carry commercial insurance, which is harmful to the economy and makes the sharing economy become the skimming economy. A natural way to improve traffic network operating efficiency is by

¹<https://www.uber.com/>

²<https://www.lyft.com/>

ameliorating either commuter routing or mode choice.

A common method is to assign users to the paths of smallest individual latency under the current conditions, giving rise to a so-called user-optimal (or user equilibrium) solution. When the user equilibrium is achieved, the transportation cost of any traveler cannot be reduced by unilaterally changing routes. Dial presented a space- and time-efficient path-based solution algorithm for the classical static user-equilibrium traffic assignment problem [25]. It assumes that travelers choices are based on fixed, known situations, in contrast to real-world traffic situations. In order to create a more realistic model, researchers introduced a new framework named stochastic user equilibrium (SUE) model [23], which includes randomly-distributed elements in the drivers' perceptions. Even though it captures some of the uncertainties present in reality, it is hard to explain or observe all the factors that motivate path choice [96]. The stochastic user equilibrium model is hard to realize because characterizing one's own preferences is a difficult task. In addition, the user equilibrium model is a suboptimal solution [40]. Guo et al. [40] used a mathematical method to prove the difference between the socially optimal solution and the user equilibrium solution. The upper bound on this difference can reach up to 1.429. The reason behind this difference is due to the user equilibrium solution's ignoring the impact of each driver's route on the overall traffic.

A better way (at least in theory) to improve traffic network efficiency is by coordinating individual users in a centralized manner to achieve a *socially optimal* (also known as *system optimal*) solution. The system optimal solution optimizes overall network performance [61] through the use of a single central coordinator. Some researchers introduced a system that computes a system optimal traffic assignment [48]. However, this is an idealized model. It is unattainable in practice for several reasons. First, system optimal solutions assign some users to considerably longer routes for the benefit of others [80]. Since users are self-interested, they will choose routes that are best for them with little regard for the impact of their choice on the other users [9]. At the same time, empirical evidence shows that users are reluctant to follow advice generated from system optimal solutions [15]. Second, traditional metrics used in system optimal solutions are travel time [36], and travel cost (toll charge) [42]. Both are assumed to be identical for all users (homogeneous users) [97]. In fact, several studies have shown that users have highly heterogeneous preferences over routes and modes. Horton and Reynolds for example mentioned that commuters are influenced by a variety of factors such as distance bias, environment experience, and so on [46]. In a survey conducted in 1988 with responses of 2892 Seattle commuters, Spyridakis et al. investigated different metrics for routes (e.g., commute time, commute distance, commute safety, commute enjoyment) [84]. The

authors found that different commuters consider different characteristics when deciding which route to employ.

The gap between the efficiency of the socially optimal (utopic) solution and the equilibrium (de facto) solution is referred to as the *Price of Anarchy*. In this project, we aim to investigate and exploit the heterogeneity in driver preferences in terms of the various route characteristics (e.g., path length, mode choice, tolerance level for travel time uncertainty, frequency of accidents, road works, or traffic jams) to propose socially optimal routes that are personalized to each driver and thus likely to be adhered to, thereby reducing the Price of Anarchy and improving routing efficiency.

Specifically, we propose to bridge the gap between the socially optimal and user optimal solutions by learning individual user preferences over route characteristics to (a) better spread traffic in the network and (b) design personalized system optimal routes that are likely to be adhered to by even egocentric drivers. Our framework can be viewed as a system optimization solution integrating user preferences.

1.2 Contributions

The main contributions of our work in this project can be summarized as follows:

- **Curated Collection of Questions to Learn Driver Preferences.** We use 2012 highway data from Archived Data Management System (ADMS), which is funded by the Los Angeles County Metropolitan Transportation Authority (Metro), to create a carefully curated data-driven collection of questions which, with minimal number of questions, can be used to successfully elicit preferences of drivers over routes. Each question consists of an origin-destination (O-D) pair and two routes (drawn from the 6 fastest routes between this origin and this destination). The two routes are mapped out and several characteristics of the routes are displayed (e.g., average travel time, chance that the travel time will exceed a certain amount, etc.).
- **Data Collection for Preference Elicitation.** Using the carefully curated collection of questions, we created an online survey which asks users their personal characteristics (e.g., age, gender) and their answers to the questions. We posted this survey on Amazon Mechanical Turk (AMT)³ and gathered responses from over 400 individuals.
- **Learning User Route Choice and Modeling Uncertainty in User Preferences.** We

³<https://www.mturk.com/>

propose a method for learning user route choice that also enables us to explicitly capture uncertainty in the preferences of users over routes. Our proposed approach first clusters users based on their responses to the survey and builds, for each cluster, an *uncertainty set* of all utility functions that are compatible with the answers to the survey. We evaluate our approach on the data collected from AMT. Compared with Logistic Regression, the standard approach for modeling user preferences in the literature, our method improves prediction accuracy by over 12%.

- **Socially Optimal Routes.** We propose a mathematical optimization model for computing system optimal routes that account for user preferences. We build upon the multi-class socially optimal routing problem, mapping driver clusters constructed during the learning phase to classes. We augment the formulation with constraints that stipulate that users should only be offered routes that are close to their preferred route in the sense that the utility derived from the route offered should be close to the utility derived from their (personally) preferred route. This formulation yields solutions that bridge the gap between the socially optimal (utopic) solution and the user equilibrium (de facto) solution. A single design parameter can be used to control the trade-off between suboptimality (in the sense of social optimality) of the proposed solution and likelihood of adherence to the offered routes (from the user perspective).

1.3 Structure of the Report

The rest of the report is organized as follows. In Section 2, we review the literature related to our work. In Section 3, we describe the problem at hand. In Section 4, we introduce the mathematical models that are used to learn user preferences and to compute socially optimal routes. In Section 5, we present details about the survey (e.g., survey methodology and statistical analysis of the survey) and the model’s analysis. In Section 6, we describe how we implemented the proposed model and we conclude in Section 7.

2 Literature Review

In this section, we review the literature relevant to our research. We focus on previous work on routing and preference learning and position our paper in this literature.

2.1 Routing

The Traffic Assignment Problem is the key problem for the long term planning and evaluation of urban transportation networks [28]. The objective of this problem is to assign the traffic flow of each OD pair to links of urban transportation networks. There are many types of traffic models: all-or-nothing assignment, incremental assignment, capacity restraint assignment, user equilibrium assignment (UE), stochastic user equilibrium assignment (SUE), and system optimum assignment (SO) [12]. The frequently used models are all-or-nothing, UE and SO.

The all-or-nothing assignment consists in assigning all trips between a fixed origin and destination to the links constituting a single shortest connecting path [24]. However, this model is unrealistic. Indeed, as Dial [24] pointed out, there are three main problems in this model: first, instability (a slight, insignificant change in input can yield significantly different output); second, failure to reflect actual behavior (cannot consider the effect of capacity restraint and unable to allow for realistic random variation of route selection among individual travelers), and lastly, inaccuracy.

UE and SO were originally introduced by Wardrop [95] in 1952 as general principles for determining the assignment of traffic to alternative routes. In the first principle (UE assignment), journey times in all routes actually used are equal and less than those that would be experienced by a single vehicle on any unused route. In the second principle (SO assignment), the average journey time is a minimum at equilibrium.

System Optimal Assignment. The SO assignment was first considered in the static setting [86, 53], which is called the Static SO assignment. It tried to improve traffic flow with a given traffic network information. However, the assumption that all information known is unrealistic in real life. In order to make this method more realistic, researchers focused their attention into the system optimum assignment in a dynamic setting. The Dynamic SO traffic assignment aims to determine time-varying link flows in a congested road network, where drivers are assumed to be cooperative in minimizing the total transportation time [37]. There are two general formulations of this problem: one is formulated based on link flows and the other is based on path flows. The main differences between these two are whether the traffic flow dynamics are in the constraints

(link-based) or in the objective function (path-based).

In 1978, Merchant and Nemhauser [64] first considered, formulated and analyzed the dynamic system optimum assignment with link flows (the M-N model). This model only includes one destination and presents a non-convex feasible set, making it hard to solve [83]. Later, in 1987, Carey [17] modified the M-N model and developed a convex programming model for least-cost flow on a general congested network on which flows vary over time. Both models are formulated in discrete time. In 1989, Friesz et al. [33] improved upon the M-N model by allowing for flows to be continuous in time. However, the model made by Friesz et al. is static, being based only on the current information of the traffic condition. In real life, the decisions may continuously change through time as network conditions evolve. However, the dynamic system optimum assignment is hard to solve because it involves both spatial and temporal interaction among the traffic, making it difficult to be described using a convex constraint set [83]. Ziliaskopoulos [102] developed a linear programming formulation for this problem. Even though its formulation only involves a single destination (but multiple origins), compared with the aforementioned formulations, it is more realistic.

Another approach, which considers path flows, is introduced by Ghali and Smith [37]. In their work, they propose a procedure to evaluate the Path Marginal Cost (PMC, the change in network flow cost caused by an additional unit of flow on a certain path departed at a certain time) in a general time. This procedure overestimates the PMC [6]. Recently, Tajtehranifard et al. [90] combined the static and dynamic traffic assignment models, leveraging the computational efficiency of static traffic assignment models, and yet capturing the realism of the traffic flow, with less complexity and a lower computational burden.

No matter which approach is used, all models assume that drivers accept the recommendations made by the route system. Yet, Schneider et al. [79] introduced a concept of the “Homo Economicus,” which characterizes humans as selfish rational maximizers of personal utility. Based on this concept, in selecting their routes, individuals usually like to obtain the highest benefits of their choices regardless of the impact of their choices on the other individuals, making the system optimum assignment unattainable in the real world.

User Equilibrium Assignment and Route Choice. In the User Equilibrium assignment, no user can benefit by unilaterally changing his/her route/mode while others keep theirs unchanged [95, 32]. In the early deterministic user equilibrium model, individuals are assumed to have perfect knowledge about the path costs and choose the route that minimizes their own travel costs [10].

Thus, users are assumed to be homogeneous in their preferences and omniscient about travel times. In reality however, both these assumptions fail to hold. Consequently, several researchers have relaxed these assumptions, aiming to explicitly capture the variations in individual perceptions or preferences, and reflecting the imperfect knowledge that individuals have about the network [60]. This improved framework is referred to as Stochastic User Equilibrium. It was introduced by Daganzo and Sheffi [22] who modeled errors/differences in individuals' perceptions of costs (which can also be thought of as variations in preferences) by random variables. In 1982, Powell and Sheffi [69] proposed a mathematical programming model to address this problem.

Two commonly used models for the random distributions of the errors (differences) in the costs/preferences are Gumbel [24] and Normal [22] distributions, corresponding to multinomial logit (MNL) and multinomial probit (MNP) route choice models, respectively.

The MNL model was originally introduced by Daganzo and Sheffi [22]. The MNL model assumes that the random error terms are independently and identically distributed with the same fixed variances [81]. This assumption makes the MNL model unable to account for overlapping between routes and unable to account for perception of variance with respect to trips of different lengths [54]. In order to overcome these shortages, many researchers extended this model. These extensions can be classified into two groups according to their structure [71]. In the first group, either the deterministic or the random error term in the additive disutility function of the MNL model are modified while maintaining the Gumbel distributed random error term assumption. Zhou et al. [101] developed a model that captures the route similarity using different attributes in the commonality factors, representing a more realistic route choice behavior. To be able to relax the assumption of non-overlapping routes, the so-called path-sized logit model was introduced. In this model, a logarithmic correction term is used to account for different path sizes determined by the length of the links within a path and the relative lengths of paths that share a link [45]. In the second group, the assumption of a Gumbel distributed random error term is dropped. Models of this type are based on the generalized extreme value (GEV) theory [66], which uses a two-level structure to capture the similarity among routes through the random error component of the disutility function. Cross-nested logit (CNL) [70], the paired combinatorial logit (PCL) model [18], and the generalized nested logit (GNL) model [11] fall into this type. However, no closed-form MNL model has been provided to simultaneously address both route overlapping and route-specific perception variance problems in the literature [54].

The MNP model is an alternative to the MNL model [22]. It is based on the assumption

of a normal distribution for the random component [71]. Compared with the MNL model, the MNP model can handle route overlapping and identical perception variance problems which the MNL model faced [54]. However, the MNP model does not have a closed-form solution and it is computationally difficult when the choice set contains many routes. The common way to solve the MNP model is to use Monte Carlo simulation [82], Clark’s approximation method [39] or a numerical method [76].

Compared with the SO, the UE is able to capture the behavior of individuals as self-interested agents, resulting in a decrease in network performance [77]. The Price of Anarchy characterizes the gap between the UE and the SO. This notion was first introduced by Koutsoupias and Papadimitriou [56]. Youn et al. [98] analyzed the travel times in road networks of several major cities and found that in the worst case, PoA reaches 1.3, indicating that individuals waste 30% of their travel time by not being coordinated.

In this project, we aim to bring the PoA to a value closer to 1, thus bridging the gap between the UE and SO solutions. In order to achieve this goal, we will leverage the heterogeneity in user preferences. Our work is thus closely related to the literature on utility theory and preference learning, which we discuss next.

2.2 Utility Theory and Preference Learning

Utility Theory. Utility theory is concerned with the study of quantitative representations of people’s preferences and choices [31]. It was originally introduced in 1982 by Kahneman and Tversky [49]. Morgenstern and Von Neumann [65], Savage [78], and Pratt [72] pointed out that the attractiveness of different alternatives depends on a) the likelihoods of the possible consequences of each alternative, and b) the preferences of the decision makers for those consequences. They can be estimated using probabilities and utilities, respectively [51]. Morgenstern and Von Neumann [65] provided three basic axioms about utility theory. The first axiom requires completeness: For any product pair p and q , either product p is preferred to product q ($p \succ q$), product q is preferred to product p ($q \succ p$) or the individual is indifferent ($p = q$). The second axiom is transitivity: For any product triple p , q and r , if $p \succ q$ and $q \succ r$, then $p \succ r$. The last axiom is a mathematical assumption about continuity of preference: There exists some probability such that the decision-maker is indifferent between the “best” and the “worst” outcome. Almost all utility theory is based on these three axioms. Based on these three axioms, Ramsey [74] developed expected utility (Under uncertainty, individuals will choose the act that will result in the highest expected utility [73]);

Pareto [67] developed ordinal utility. Instead of obtaining an absolute quantity, it tells the consumers whether the commodity derives more or less or equal satisfaction when compared with another [55], and Fishburn [30] developed a skew-symmetric bilinear utility. Instead of having a single decision criteria, skew-symmetric bilinear utility is a useful general decision model that encompass many decision criteria [38].

Preference Learning. A core part of utility theory is concerned with preference learning (or preference elicitation). Preference learning refers to the problem of estimating the preferences of a single individual or a group of individuals [99, 47]. This notion is used in machine learning, knowledge discovery, information retrieval, statistics, social choice theory, multiple criteria decision-making, decision-making under risk and uncertainty, and operations research among others. [35].

A preference learning model usually uses limited data with aim to correctly rank items in a choice set by order of preference of an individual or group of individuals, or to classify these alternatives into some pre-defined and ordered classes [29]. A preference learning model involves a set of alternatives characterized by a vector or features, and aggregates the information about these alternatives to generate a satisfactory recommendation about the best choice, ranking, or classification. The model has the form of a utility function, binary relation, or a set of monotonic "if..., then..." decision rules [65].

Hüllermeier and Fürnkranz [47] leveraged supervised machine learning to establish the relationship between features describing individuals and preference models. Cohen et al. [21] learned a two-argument function $\text{PREF}(u,v)$, which returns a numerical measure of how certain it is that u should be ranked before v . Fürnkranz and Hüllermeier [34] used a collection of training examples which are associated with a finite set of decision alternatives to give a set of pairwise preferences between labels, expressing one label is better than another.

Recently, researchers from the fields of machine learning, artificial intelligence, marketing and operations research, motivated in part by applications, have devised preference models and ways in which to illicit preference. Bertsimas and O’Hair [13] used integer optimization to address human inconsistency, robust optimization and conditional value at risk (CVaR) to account for loss aversion, and adaptive conjoint analysis and linear optimization to frame the questions to learn preferences. Since preferences/utilities are often hard to elicit precisely and that only incomplete information is available, several authors have proposed to take a robust optimization approach when optimizing utility. Dubra et al. [26] studied the problem of obtaining an expected utility representation for a

potentially incomplete preference relation. Armbruster and Delage [7] considered the problem of optimal decision making under uncertainty but assume that the decision maker’s utility function is not completely known. In their research, they considered all the utilities that meet some criteria, such as preferring certain lotteries over other lotteries and being risk averse (behavior of humans, who, when exposed to uncertainty, attempt to lower that uncertainty). March [63] have noted that human beings have unstable, inconsistent, incompletely evoked, and imprecise goals at least in part because human abilities limit preference orderliness. They pointed out that preferences’ predictions are inconsistent with observations of decision-making. Thus, predicting a users’ preferences is a difficult task. MacDonald et al. showed that there exist two different types of preference inconsistency: random and non-random inconsistency [58]. Random inconsistency is due to changes in mood, weather, and any number of random factors that cannot be directly measured [87]. Non-random inconsistency is present when an entire group of users is similarly inconsistent in their choices (due to e.g., mores and traditions).

Preference Learning in TAP. In TAP, there typically exists more than one way to travel between two places, which means that a route choice decision is involved [16]. Generally, individual preferences over routes vary based on route characteristics which in turn will influence their route choices [14]. Tilahun et al. [91] evaluated individual preferences for five different cycling environments by trading off a better facility with a higher travel time against a less attractive facility at a lower travel time. They used an adaptive stated preference survey to extract the individuals’ preferences. Khattak et al. used a survey to study drivers’ diversion propensity [52]. They found that drivers expressed a higher willingness to divert if expected delays on their usual route increased, if delay information was received from radio traffic reports compared with observing congestion and if trip direction was home-to-work rather than work-to-home. Wardman et al. used the survey to detect the effect on drivers’ route choices of information provided by variable message sign (VMS) [94]. They used one question with different information to detect drivers’ preferences.

In this project, we aim to learn driver preferences and leverage preference heterogeneity to offer them route recommendations that they will likely accept, thus relieving congestion effectively.

3 System Model & Problem Description

In this section, we begin by introducing the road network model that underlies our approach. We then introduce our model of commuters and their preferences. Finally, we describe the problem at hand.

Road Network with Edge and Node Features. We consider a directed traffic network which we model by means of a graph $\mathcal{G} := (\mathcal{N}, \mathcal{A})$ with node set \mathcal{N} and edge set \mathcal{A} . Each node $n \in \mathcal{N}$ represents an intersection in the traffic network and each edge $e := (u, v) \in \mathcal{A}$ with $u, v \in \mathcal{N}$ represents the *directed* road segment between intersections u and v (with traffic traveling from u to v). Existence of edge $e = (u, v)$ in the set \mathcal{A} indicates that there is a direct way to travel from u to v without passing through an intersection. Each edge $e \in \mathcal{A}$ and each intersection $n \in \mathcal{N}$ have (potentially stochastic) characteristics, which we collect in vectors $\xi_e^e \in \mathbb{R}^{n_e}$ and $\xi_n^n \in \mathbb{R}^{n_n}$, respectively. These vectors may include, for example, the stochastic time needed to travel through the road segment and the stochastic wait-time at the intersection, respectively. They may also include deterministic characteristics, such as the number of lanes of the road and the presence or absence of a stop sign at the intersection, or simply the length of the road segment.

Path Features. A path is a sequence n_1, \dots, n_t of distinct nodes, together with an associated sequence e_1, \dots, e_{t-1} of edges such that $e_k = (n_k, n_{k+1})$, $k = 1, \dots, t-1$. Given a path p with nodes n_1, \dots, n_t , we can create a vector of features (or characteristics) of the path by taking nonlinear functions of the features of the nodes and edges involved in the path. Thus, the feature vector $\xi_p \in \mathbb{R}^{n_p}$ of path p is given by $\xi_p := \phi(\{\xi_{(n_k, n_{k+1})}^e, \xi_{n_k}^n\}_{k=1, \dots, t-1})$, where $\phi : \mathbb{R}^{(t-1)n_e} \times \mathbb{R}^{tn_n} \rightarrow \mathbb{R}^{n_p}$ maps the features of the nodes and edges traversed by the path into features of the path (e.g., maximum wait time at a given intersection, minimum number of lanes, and average travel time).

Heterogeneous Commuters. On this road network, there is a large number D of *heterogeneous* drivers indexed by $d \in \mathcal{D}$. Each driver d aims to commute from an origin $o_d \in \mathcal{N}$ to a given destination $d_d \in \mathcal{N}$. Departing from the literature on the Traffic Assignment Problem, we associate with each driver a (known) feature vector $f_d \in \mathbb{R}^{n_d}$ (including for example demographic information on the driver) and an *unknown* utility function $u_d : \mathbb{R}^{n_p} \rightarrow \mathbb{R}$ which maps the features of a path to a number quantifying the utility that the drivers receives from choosing path p when traveling from a given origin to a given destination. Given two paths p and p' with the same origin and same destination, we let $p \succ_d p'$ indicate that driver d *strictly prefers* p over p' , i.e., $p \succ_d p'$ if and only if

$u_d(\xi_p) > u_d(\xi_{p'})$. Accordingly, we let $p \prec_d p'$ if and only if $u_d(\xi_p) < u_d(\xi_{p'})$. Finally, we let $p =_d p'$ if and only if $u_d(\xi_p) = u_d(\xi_{p'})$, i.e., driver d is indifferent between the two options.

Utility Model. In the literature, several mathematical models of utility functions have been proposed, such as random utility model [93], expected utility model [50], stated utility model [4], etc. In our research, we make the common assumption that the utility functions u_d of each driver $d \in \mathcal{D}$ are linear, see e.g., [13]. Thus, $u_d(\xi_p) := u_d^\top \xi_p$ for some vector $u_d \in \mathbb{R}^{n_p}$. Drivers can choose from a set of paths $\mathcal{P} = \{p_1, p_2, p_3, \dots\}$ from o_d to d_d . Following classical utility theory, we assume:

1. For every pair p_1 and $p_2 \in \mathcal{P}$ and driver $d \in \mathcal{D}$, either $p_1 \succ_d p_2$, $p_2 \succ_d p_1$ or $p_1 =_d p_2$.
2. For every triple $p_1, p_2, p_3 \in \mathcal{P}$, if $p_1 \succ p_2$ and $p_2 \succ p_3$, then $p_1 \succ p_3$.

Problem Description. We consider the problem of routing the heterogeneous commuters in this network in a way that minimizes overall congestion while offering drivers routes that are “close” (in terms of their own perceived utility) to their preferred route so as to maximize adherence to the recommended routes. Our approach proceeds in two steps, which we detail below:

1. **Clustering Drivers and Learning their Preferences.** The first step of our approach consists in: (a) clustering drivers based on their personal characteristics and/or their answers to a small set of questions asking them to chose one of two alternative routes to travel from a given origin to a given destination, and (b) determining, for each cluster, a utility function that minimizes the prediction error for the drivers in that cluster. Our proposed approach allows for inconsistencies in the user responses.
2. **Socially Optimal Personalized Routing.** The second step of our approach consists in formulating a Socially Optimal Traffic Assignment wherein drivers are only assigned to routes that are “close” to their preferred assignment in terms of perceived utility. Our proposed approach is able to account for imperfect knowledge of the utilities of the drivers (due to e.g., inability to know all the features that enter the decision-making of users and/or inability to learn the utility functions after only few questions and/or inconsistency in responses for users in the same cluster).

4 Methodology

In this section, we detail our proposed approach to learn driver preferences to propose personalized socially optimal routes bridging the gap between the utopic socially optimal assignment and the de-facto user equilibrium solution.

4.1 Clustering Drivers and Learning their Preferences

Preliminary Pairwise Comparison Data. We assume that we have at our disposal survey data about preferences of drivers on a collection of O-D pairs (details about the data collection can be found in section 5.1). The data takes the following form: we have a question set $\mathcal{Q} = \{1, 2, \dots, Q\}$, where Q is the number of questions. Each question corresponds to a pairwise comparison of routes for the same O-D pair. Thus, associated with each question $i \in \mathcal{Q}$ are two paths, A_i and B_i , with path features ξ_A^i and ξ_B^i , respectively. Our data consists of a carefully curated set of questions \mathcal{Q} (The details is shown in Appendix). For each question i , each driver $d \in \mathcal{D}$ has indicated: *a*) if they prefer route A_i over route B_i , denoted by $A_i \succ_d B_i$; *b*) if they prefer route B over A , denoted $A_i \prec_d B_i$; *c*) or if they are indifferent, denoted by $A_i =_d B_i$.

Clustering Drivers. Due to the personalization, our socially optimal assignment formulation is a large scale routing problem. In order to mitigate the ensuing computational challenges of solving for a socially optimal personalized assignment (More details are shown in Section 4.2), we begin by clustering users (aka drivers) so that drivers that belong to the same cluster will be assumed to have the same utility function, enabling us to reduce the complexity of the assignment formulation. As will become clear later on, this clustering approach has also added benefits in that it enables us to learn the utilities of the drivers better (improved out of sample performance) (More details are shown in Section 4.1).

By definition, clustering is the assignment of a set of observations (in this case the drivers) into subsets (called clusters) so that observations in the same cluster are, in some sense, similar. There are three popular types of clustering algorithms: connectivity models [75], centroid models [20], and distribution models [88].

In our project, we employ the K -means algorithm, which belongs to the class of centroid models. K -means is a method used to automatically partition a data set into K groups [59], where K is a user-selected parameter. The algorithm initially selects K cluster centers and then iteratively refines them, as follows:

1. Each instance (in this case each driver) $d \in \mathcal{D}$ is assigned to its closest cluster center.
2. Each cluster center C_k , $k \in \mathcal{K}$ is updated to be the mean of its constituent instances (in this case drivers), where $\mathcal{K} := \{1, \dots, K\}$ is the set of cluster number.

The algorithm iterates between 1 and 2 above and ends when there are no further change in the assignment of instances to clusters. In particular, at termination, the algorithm returns a partition of the set of drivers \mathcal{D} into K subsets $\{\mathcal{S}_k\}_{k \in \mathcal{K}}$ such that $\cup_{k \in \mathcal{K}} \mathcal{S}_k = \mathcal{D}$ and $\mathcal{S}_l \cap \mathcal{S}_h = \emptyset$, $\forall l, h : l \neq h$. We use \mathcal{S}_k to represent the set of users (drivers) belonging to cluster k , $k \in \mathcal{K}$. There are a total of K clusters in our problem. The number of clusters can be chosen in the training phase. For convenience, we let $m_k := |\mathcal{S}_k|$ denote the number of users in cluster k .

For our approach in Section 4.1, drivers in the same cluster should have similar answers to the train questions. In our project, we tried clustering drivers based: a) on their personal characteristics (demographics) only; b) on their answers to a subset of the questions only; and c) based on both.

Learning Driver Preferences. We assume that all drivers within each cluster have the same utility function $u_k(\xi_p) := u_k^\top \xi_p$, $k \in \mathcal{K}$, for some $u_k \in \mathbb{R}^{n_p}$. In the next section, we propose an approach for learning the vector u_k . This assumption should hold if drivers who are similarly situated have similar preferences. Next, we propose an approach for learning driver preferences, i.e., values for the utility vector u_k associated with all drivers belonging to cluster k , $k \in \mathcal{K}$. Fix the cluster $k \in \mathcal{K}$. With a slight abuse of notation (ignoring the index of the cluster), we let $\mathcal{S}_i^{A \succ B}$, $\mathcal{S}_i^{B \succ A}$, and $\mathcal{S}_i^{A=B} \subseteq \mathcal{S}_k$, respectively denote the sets of users in cluster k which, for question i , prefer A to B , B to A , or are indifferent, respectively. Thus, $\mathcal{S}_i^{A \succ B} \cup \mathcal{S}_i^{B \succ A} \cup \mathcal{S}_i^{A=B} = \mathcal{S}_k$, $\mathcal{S}_i^{A \succ B} \cap \mathcal{S}_i^{B \succ A} = \emptyset$, $\mathcal{S}_i^{A \succ B} \cap \mathcal{S}_i^{A=B} = \emptyset$ and $\mathcal{S}_i^{B \succ A} \cap \mathcal{S}_i^{A=B} = \emptyset$. Accordingly, we define $c_i^{A \succ B} = |\mathcal{S}_i^{A \succ B}|$, $c_i^{B \succ A} = |\mathcal{S}_i^{B \succ A}|$, and $c_i^{A=B} = |\mathcal{S}_i^{A=B}|$, so that $c_i^{A \succ B}$, $c_i^{B \succ A}$, and $c_i^{A=B}$ represent the number of drivers in cluster k who, for the i th question, prefer A to B , B to A , or are indifferent, respectively.

For each cluster k and each question i , we introduce the corresponding binary variables $y_i^{A \succ B}$, $y_i^{B \succ A}$, and $y_i^{A=B}$ to indicate if, under the utility vector u_k , A should be preferred to B , B should be preferred to A or users are expected to be indifferent.

Consider the following mixed-integer linear optimization problem with equally weighted errors:

$$\begin{aligned}
& \text{maximize} && \sum_{i=1}^Q (c_i^{A>B} y_i^{A>B} + c_i^{B>A} y_i^{B>A} + c_i^{A=B} y_i^{A=B}) \\
& \text{subject to} && y_i^{A>B} + y_i^{B>A} + y_i^{A=B} = 1 && \forall i \in \mathcal{Q} \\
& && u_k^\top (\xi_A^i - \xi_B^i) \geq \epsilon - M(1 - y_i^{A>B}) && \forall i \in \mathcal{Q} \\
& && u_k^\top (\xi_B^i - \xi_A^i) \geq \epsilon - M(1 - y_i^{B>A}) && \forall i \in \mathcal{Q} \\
& && u_k^\top (\xi_A^i - \xi_B^i) = z_i^+ - z_i^- && \forall i \in \mathcal{Q} \\
& && z_i^+ \leq \epsilon + M(1 - y_i^{A=B}) && \forall i \in \mathcal{Q} \\
& && z_i^- \leq \epsilon + M(1 - y_i^{A=B}) && \forall i \in \mathcal{Q} \\
& && y_i^{A>B} \in \{0, 1\} && \forall i \in \mathcal{Q} \\
& && y_i^{B>A} \in \{0, 1\} && \forall i \in \mathcal{Q} \\
& && y_i^{A=B} \in \{0, 1\} && \forall i \in \mathcal{Q} \\
& && z_i^+ \geq 0 && \forall i \in \mathcal{Q} \\
& && z_i^- \geq 0 && \forall i \in \mathcal{Q}
\end{aligned} \tag{EW}$$

where M is a “big- M ” constant.

The decision variables are $u_k \in \mathbb{R}^{n_p}$, $y_i^{A>B}$, $y_i^{A<B}$, and $y_i^{A=B} \in \{0, 1\}$, and z_i^+ and $z_i^- \in \mathbb{R}$. The variables $y_i^{A>B}$, $y_i^{A<B}$, and $y_i^{A=B}$ indicate, for cluster k , question i , and under the utility vector u_k , if A should be preferred to B ($u_k^\top \xi_A^i - u_k^\top \xi_B^i \geq \epsilon$), B should be preferred to A ($u_k^\top \xi_B^i - u_k^\top \xi_A^i \geq \epsilon$), or users are expected to be indifferent ($|u_k^\top \xi_A^i - u_k^\top \xi_B^i| \leq \epsilon$). The variables z_i^+ and z_i^- are used, when we predict indifference ($|u_j^\top \xi_A - u_j^\top \xi_B| \leq \epsilon$), to force the corresponding $y_i^{A=B}$ to equal one. In order to avoid the strict inequality constraints, we introduce ϵ , which is small enough. If the utility difference is within ϵ , we predict they are indifferent.

An interpretation of the constraints is as follows. The first constraint ensures that we can only predict, for each question, one of the following options: A is preferred to B , B is preferred to A , or the two options are equally good. The second constraint ensures that if A is preferred to B then the utility derived from route A should be greater than the utility derived from route B . The third constraint admits a similar interpretation for the case when B is preferred to A . The fourth constraint is used to define z_i^+ and z_i^- as the positive and negative parts of the difference in the utilities of routes A and B . The fifth and sixth constraints ensure that if the two routes are equally good, then the difference in utility derived from the two options lies in the range $[-\epsilon, \epsilon]$.

The objective of this problem is to maximize the number of users in cluster k whose preferences we predict correctly (in the training data). Indeed, each term in the summation in the objective

function is the number of individuals for which the prediction was correct (equal to their actual choice).

The model provided by Bertsimas and O’Hair [13] and our model both considered preference inconsistency. Bertsimas and O’Hair set the percentage of preference inconsistency in advance. In our approach, instead of giving the constraint on the preference inconsistency, we minimize it.

Learning Driver Preferences with Weighted Objective. In the formulation above, all types of correct/incorrect predictions have the same cost. However, in practice, there are some errors that are more “costly” than others in terms of the traffic assignment problem we ultimately solve. For example, if the user states that he/she is indifferent, incorrectly predicting they will pick route A (or equivalently route B) is not a grave mistake since it will yield an acceptable recommendation. On the other hand, predicting that the user will choose route A when he really prefers route B is a more serious error and should be more costly. Based on this analysis, we revise our model as shown below. The formulation is almost identical to the one employed above. We only modify the objective function. In this formulation, we introduce a weight $w \in [0, 1]$, which represents the penalty when our predictions are either the exact opposite of the preferences entered by the users or when the users have a clear preferences (they either prefer A or B), but we predict that they will be indifferent. The corresponding weight $(1 - w)$ corresponds to the cost incurred when users have no preference and we incorrectly predict that they will prefer either A or B .

$$\begin{aligned}
& \text{minimize} && \sum_{i=1}^Q [wc_i^{B>A}(1 - y_i^{B>A}) + wc_i^{A>B}(1 - y_i^{A>B}) + (1 - w)c_i^{A=B}(1 - y_i^{A=B})] \\
& \text{subject to} && y_i^{A>B} + y_i^{B>A} + y_i^{A=B} = 1 && \forall i \in Q \\
& && u_k^\top(\xi_A^i - \xi_B^i) \geq \epsilon - M(1 - y_i^{A>B}) && \forall i \in Q \\
& && u_k^\top(\xi_B^i - \xi_A^i) \geq \epsilon - M(1 - y_i^{B>A}) && \forall i \in Q \\
& && u_k^\top(\xi_A^i - \xi_B^i) = z_i^+ - z_i^- && \forall i \in Q \\
& && z_i^+ \leq \epsilon + M(1 - y_i^{A=B}) && \forall i \in Q \\
& && z_i^- \leq \epsilon + M(1 - y_i^{A=B}) && \forall i \in Q \\
& && y_i^{A>B} \in \{0, 1\} && \forall i \in Q \\
& && y_i^{B>A} \in \{0, 1\} && \forall i \in Q \\
& && y_i^{A=B} \in \{0, 1\} && \forall i \in Q \\
& && z_i^+ \geq 0 && \forall i \in Q \\
& && z_i^- \geq 0 && \forall i \in Q \\
& && && (\mathcal{GW})
\end{aligned}$$

Evaluation of the Proposed Approaches. In both methods, the objectives are the same, predicting the users' preferences with as few errors as possible within each cluster. There are two types of accuracies that are worth investigating: accuracy in the prediction of preferences for new users and accuracy in predicting user preferences for new routes for existing users. In Section 5, we will investigate the performance of our approach for both settings.

4.2 Socially Optimal Personalized Routing

Having learned the user/driver preferences (in a cluster-wise fashion), we next propose to use heterogeneity in the driver preferences to improve efficiency of the overall transportation system. Specifically, we propose a model that accounts for user preferences to ensure adherence to the socially optimal solution.

Using the same notation as in Section 3, we introduce our personalized routing problem. We let $\mathcal{W} \subseteq \mathcal{N} \times \mathcal{N}$ denote a set of O-D pairs in the road network (these do not necessarily coincide with the O-D pairs that we used in the questions, see Section 4.1). For each specific O-D pair $w \in \mathcal{W}$, we use \mathcal{R}_w to represent all the possible route choices for that pair (In this project, we only consider the 10 fastest route choices in terms of expected travel time). For each route $r \in \mathcal{R}_w$, the set of links through which it passes is well defined and we let $\delta_{er}^w = 1$ if and only if route r passes

through link e ; $= 0$ else.

We assume that we have clustered users into K clusters indexed in the set \mathcal{K} using the approach from Section 4.1. We use d_w^k to represent the traffic demand for cluster $k \in \mathcal{K}$ and the specific O-D pair $w \in \mathcal{W}$, which we assume to be perfectly known. Using the model we generated in Section 4.1, for each cluster $k \in \mathcal{K}$, we have a corresponding utility vector $u_k \in \mathbb{R}^{n_p}$. Letting $\xi_r \in \mathbb{R}^{n_p}$ denote the feature vector of path $r \in \mathcal{R}_w$, the utility of route r for users in cluster k is given by $u_k(r) = u_k^\top \xi_r$. The maximum utility derived from a user in cluster k that need to travel through O-D pair $w \in \mathcal{W}$ is given by $u_k^*(w) := \max_{r \in \mathcal{R}_w} u_k^\top \xi_r$.

Using the information above, we formulate a mathematical optimization problem inspired from the multi-class traffic assignment formulation from the literature, see [68]. For each $k \in \mathcal{K}$ and $r \in \mathcal{R}_w$, we let $y_r^{(k,w)} \in \{0, 1\}$, so that $y_r^{(k,w)} = 1$ if at least some individuals in cluster k using O-D pair w employ route $r \in \mathcal{R}_w$. We let $f_r^{(k,w)}$ denote the traffic flow for route choice $r \in \mathcal{R}_w$ contributed by cluster k . The decision variable v_e represents the traffic flow passing through link e . We use $v_e^{(k,w)}$ to represent the traffic flow through link e that is contributed by cluster k and used to satisfy the traffic demand for O-D pair w . Given an instantaneous flow x , $t(x)$ represents the associated travel time.

We propose to only allow routes to be offered to users whose utility is within γ of the utility of their optimal route; here γ is a parameter selected by the network operator (e.g., the route recommendation system). This ensures that drivers are likely to adhere to the route choice recommended to them.

$$\begin{aligned}
& \text{minimize} && \sum_{e \in \mathcal{A}} \int_0^{v_e} t(x) dx \\
& \text{subject to} && \sum_{r \in \mathcal{R}_w} f_r^{(k,w)} = d_w^k && \forall w \in \mathcal{W}, k \in \mathcal{K} \\
& && f_r^{(k,w)} \geq 0 && \forall r \in \mathcal{R}_w, w \in \mathcal{W}, k \in \mathcal{K} \\
& && v_e = \sum_{w \in \mathcal{W}} \sum_{k \in \mathcal{K}} v_e^{(k,w)} && \forall e \in \mathcal{A} \\
& && v_e^{(k,w)} = \sum_{r \in \mathcal{R}_w} \delta_{er}^w f_r^{(k,w)} && \forall k \in \mathcal{K} \\
& && f_r^{(k,w)} \leq M y_r^{(k,w)} && \forall r \in \mathcal{R}_w, w \in \mathcal{W}, k \in \mathcal{K} \\
& && u_k^*(w) - u_k(r) \leq \gamma + M(1 - y_r^{(k,w)}) && \forall r \in \mathcal{R}_w, w \in \mathcal{W}, k \in \mathcal{K} \\
& && y_r^{(k,w)} \in \{0, 1\} && \forall r \in \mathcal{R}_w, w \in \mathcal{W}, k \in \mathcal{K}
\end{aligned} \tag{1}$$

An interpretation of the constraints is as follows. The first constraint ensures that the demand for each O-D pair $w \in \mathcal{W}$ and each cluster $k \in \mathcal{K}$ is satisfied. The second constraint ensures that

all traffic flows are non-negative. The third constraint defines the traffic flow through link e as the sum of the traffic flows through link e that are associated with each cluster k and each O-D pair w . The fourth constraint ensures that the traffic flow through link e contributed by cluster k is the summation of all the routes $r \in R_w$ traffic flow contributed by cluster k , if this route r consists of link e . The fifth constraint ensures the route that will be chosen having its utility value in an acceptable range ($u_k^*(w) - u_k(r) \leq \gamma$).

The objective of this formulation is to minimize the travel time over the entire network (socially optimal). This socially optimal objective is counterbalanced by the requirement to offer user routes that meet, to the extent possible, the user preferences (approximation to user optimal).

5 Experimental Results

In this section, we begin by presenting the survey design procedure and data gathering approach that we used in order to learn user preferences. Then, we describe the results of our preference learning model and compare it to the results of other commonly used preference learning models.

5.1 Survey Design Procedure and AMT Data Gathering

Historical Traffic Data. The historical traffic data we used to generate the survey is the 2012 highway data from the Archived Data Management System (ADMS). This system is funded by the Los Angeles County Metropolitan Transportation Authority (L.A. Metro). All data was captured by multiple sensors on Los Angeles’s highways. It includes distance between two arbitrary adjacent sensors and every 15 minutes the sensors collected the travel speed. We used the data to calculate the travel time for each link and combined them together to get the travel time for the routes. The travel time we considered is during the morning period of 9:00 AM-12:00 PM. The other information we considered is the minimum travel time during this period and the chance that the travel time will be longer than a constant time (more details are presented later). We also collected information on traffic accident incidences. Specifically, the percentage of total year traffic accidents was obtained from the Statewide Integrated Traffic Records System⁴, which is a database that serves as a means to collect and process data gathered from a collision scene.

Survey Design. Based on the previous research [91], in our survey, we collected two different types of features from the drivers: demographic characteristics and preference information from carefully curated route choices for given O-D pairs.

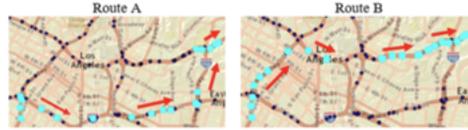
We collected the following demographic information which may play a role in individual preferences over route characteristics: gender, age, marital status, number of dependents in their families, education level, ethnicity, employment status, and driving years. Past research has shown that demographic differences can influence the drivers’ preferences [16].

With regards to route choice, we considered the following features for each route which are important determinants of route choice [44, 27, 92]: distance (miles), average travel time (minutes), minimum travel time (minutes), chance that the travel time will be longer than a constant, percentage of total yearly traffic accidents on this route and number of different freeway interchanges on this route. A sample question is shown in Figure 1. The full survey can be found in the Appendix.

⁴<http://iswitrs.chp.ca.gov/Reports/jsp/userLogin.jsp>

Q4: Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	10	8.7
Average Time (Minutes)	14.51	16.83
Minimum Time (Minutes)	9.75	8.28
Chance that the travel time will be longer than 20 minutes	2.38%	36.90%
Percentage of total yearly traffic accidents on this route	0.70%	0.87%
Number of different freeways on the route	4	3



- Route A
- Route B
- I have no preference

Figure 1: Sample Question

To identify suitable route choice questions, we proceeded as follows. First, we mined the traffic data and selected O-D pairs for which there existed several routes with different traffic distribution patterns (e.g., different expected travel time and different standard deviation or skewness characteristics). For these O-D pairs, we only selected routes that were among the 10 fastest routes in terms of expected travel time (the idea is that if the expected travel time is too long, the other characteristics of the route become unimportant). For the chosen O-D pairs and among all such routes, we manually selected route pairs that resulted in “interesting” comparisons: we only selected pairs of routes where one did not clearly *dominate* the other one. We identified 15 such route pairs (aka questions). To keep the survey length tractable in length to the respondents, we asked each participant 15 questions. For each question, based on the six features provided for each route and the map of the routes, the respondent provided their preference (i.e., indicate which route they prefer: Route A, Route B or that they are indifferent).

Data Gathering on Amazon Mechanical Turk. We posted our survey on Amazon Mechanical Turk (AMT)⁵, which operates a marketplace for work that requires human intelligence. We were able to collect 457 answers, 446 of which were valid. We identified invalid responses, which we discarded, as follows: we added to the survey one question (pairwise comparison) in which one of the answers strictly dominated the other one in all respects. If a respondent chose the dominated option and completed the survey within 2 minutes (the average completion time was 6 minutes and

⁵<https://www.mturk.com/>

the standard deviation was 2.87 minutes), we discarded the answers from this respondent.

Demographics of Respondents. The demographics of the survey population are summarized in Figure 2. There were 276 (resp. 170) males (resp. female) respondents). Most respondents’ ages fell into the range [25, 34]. Most respondents were single or, if married, had children. Out of the 446 respondents, 310 had less than or equal to 2 dependents. A total of 127 respondents had 3 to 5 dependents and only 9 individuals had more than 5 dependents. Among all the respondents, there were 117 who had a high school diploma, 204 people who had an undergraduate degree, and 125 people who had a graduate degree. Even though around 61.6% of the respondents had jobs unrelated to driving, the majority of people answering this survey had more than 5 years driving experience.

Question	Prefer Route A	Prefer Route B	No Preference
Q1	163	268	15
Q2	217	198	31
Q3	79	342	25
Q4	340	96	10
Q5	308	107	31
Q6	172	257	17
Q7	182	236	28
Q8	359	71	16
Q9	323	104	19
Q10	96	337	13
Q11	148	286	12
Q12	142	251	53
Q13	110	284	52
Q14	322	98	26
Q15	158	200	88

Table 1: Survey Responses for each Question

Route Choices of Survey Respondents. A summary of the survey questions’ responses is shown in Table 1.

5.2 Preference Learning Results

Having collected the preference data from AMT, we now evaluate our proposed preference learning schemes from Section 4.1 on this data; in particular, we study the in- and out-of-sample performance of our approach and evaluate the impact of the clustering method.

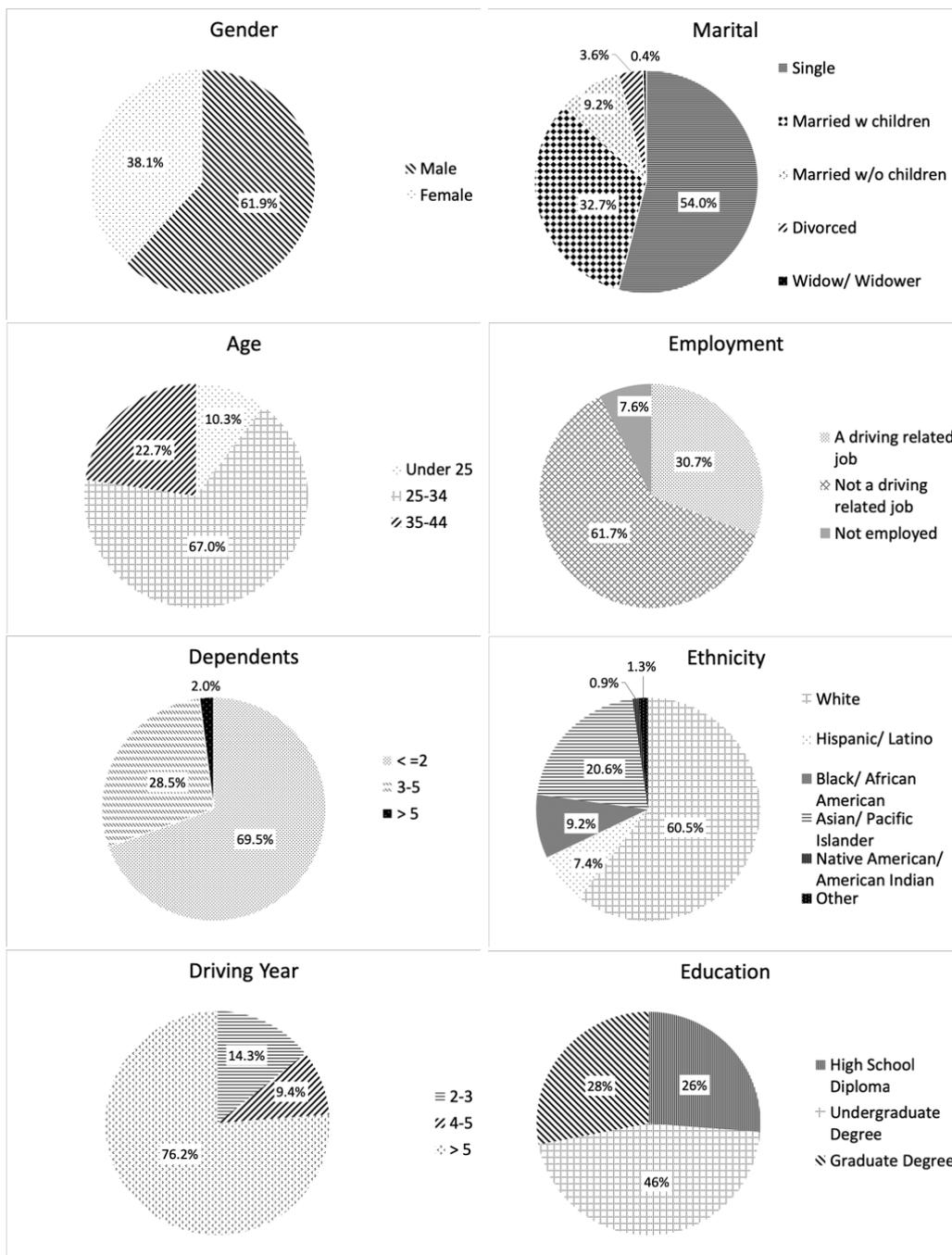


Figure 2: Summary of the Demographic Information from AMT Survey

Splitting the Data into Training and Testing. Based on Section 4.1, we investigate the performance of our approach in two contexts: *a)* prediction of route preferences for new users; and *b)* prediction of preferences over new routes for existing users. Depending on the prediction task we split the data in two different ways: in case *a)* we split the participants into train and test users

(80% train data, and 20% test data chosen at random); in case *b*) we split the questions into train and test questions (5 training and 10 testing). The 5 questions used for training were chosen as follows. We classified the questions into three types:

1. Route choices are obviously different. In our survey, Q3, Q4, Q5, Q8, Q9, Q10, Q13, and Q14 belong to this type. For example, Q5 in Figure 3 shows that Route A dominates Route B in regards to the first three features while Route B dominates route A in the last two features.

Q5: Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	26.32	31.83
Average Time (Minutes)	31.26	34.24
Minimum Time (Minutes)	24.85	29.69
Chance that the travel time will be longer than 40 minutes	15.00%	14.29%
Percentage of total yearly traffic accidents on this route	0.62%	0.37%
Number of different freeways on the route	4	3



Route A
 Route B
 I have no preference

Figure 3: Routes Choices Are obviously Different

2. Route choices are different but the difference is not trivially obvious. In our survey, Q1, Q2, Q6, Q7, Q11, and Q12 are of this type. An example is shown in Figure 4, which is Q6 in our survey. Figure 4 shows that the average travel time, percentage of total yearly traffic accidents and the number of freeway interchanges have no differences between the two routes. Only two features show any difference, which are travel distance and the chance that the travel time will be longer than a constant time.

3. Route choices are indifferent. In our survey, Q15 belongs to this type, which is shown in Figure 5. From Figure 5, we can find that the differences of the features are not significant except for a slight difference in the number of freeway interchanges.

Their ratio is 8:6:1. We randomly picked 5 questions out of the 15 questions followed by the

Q6: Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	20.94	24.20
Average Time (Minutes)	22.14	22.63
Minimum Time (Minutes)	19.21	21.94
Chance that the travel time will be longer than 25 minutes	20.24%	5.95%
Percentage of total yearly traffic accidents on this route	NA	NA
Number of different freeways on the route	2	2



- Route A
- Route B
- I have no preference

Figure 4: Route Choices Are not obviously Different

Q15: Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	59.66	59.86
Average Time (Minutes)	70.34	72.34
Minimum Time (Minutes)	55.54	56.01
Chance that the travel time will be longer than 85 minutes	11.74%	8.53%
Percentage of total yearly traffic accidents on this route	1.78%	1.52%
Number of different freeways on the route	2	4



- Route A
- Route B
- I have no preference

Figure 5: Route Choices Are Indifferent

above ratio. The 5 questions that ended up being selected were Q2, Q3, Q4, Q7, and Q15, see Appendix. We use these as the train questions during this whole section.

Cluster Strategy	Accuracy in sample	Accuracy out of sample
<i>C1</i> : Demographic information	60.86%	56.18%
<i>C2</i> : Answer to route choice questions	66.91%	63.27%
<i>C3</i> : <i>C1</i> and <i>C2</i> combined	63.73%	59.46%

Table 2: Accuracy on the Training and Testing Sets based on Different Clustering Methods

Choosing a Clustering Strategy. There are two types of information collected by the survey, and we propose to investigate the performance of the three different clustering strategies for the survey respondents:

C1 Clustering respondents based on drivers’ demographic information;

C2 Clustering respondents based on drivers’ answers to route choice questions in the survey; and

C3 Clustering respondents based on both drivers’ demographic information and drivers’ answers to route choice questions.

We tried all three clustering strategies, varying the number of clusters from 1 to the number of users (250 in this instance). Table 2 shows the best accuracy for each clustering strategy in sample (on the training set) and its corresponding result out of sample (on the testing set). From this table, it can be seen that *C2* has the highest accuracy. Therefore, for the remainder of our analysis, we use clustering strategy *C2*. It is interesting to note that clustering individuals based on their demographic information alone (strategy *C1*) yields the worst results among all clustering strategies. Having identified *C2* as the best clustering strategy, we now investigate the performance of the preference learning models \mathcal{EW} and \mathcal{GW} mentioned in Section 4.1.

5.2.1 Formulation \mathcal{EW} using all the features

First, we investigate the performance of Formulation \mathcal{EW} , which is shown in Section 4.1, to learn the utility function of the users in each cluster.

We investigate the performance of our approach as we vary the number of clusters; the aim being to make as many correct predictions as possible. We tried all possible cluster sizes, ranging from all users in one cluster to all individuals as a single cluster. If we only have one cluster, even though it can simplify the model, it assumes every driver has the same preference. In this situation, drivers may not follow the provided recommendations in real life. Another extreme situation is that each individual as a single cluster. In theory, it can capture the driver’s preference perfectly if we have enough information for this individual and all his/her choice is consistent with his/her

preference, which is unrealistic in real life. For each question, we compare our results with the conventional approach from the literature: Logistic Regression [3, 5, 8]. The results are shown in Figures 6

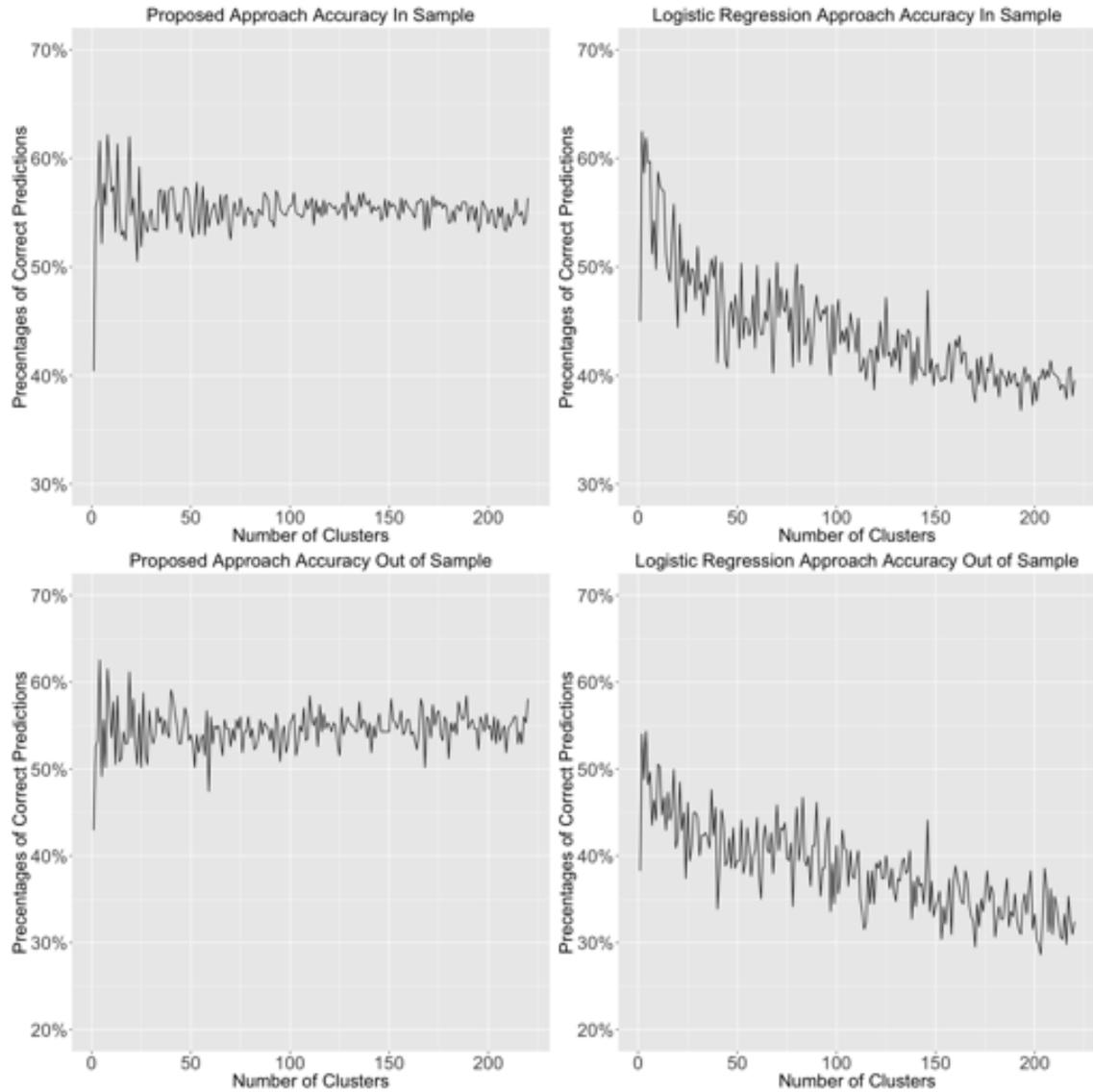


Figure 6: Accuracy Comparison In Sample and Out of Sample: Proposed Approach *vs* Logistic Regression

Figure 6 shows the average accuracy rate using our approach and the Logistic Regression Method among all training questions. We vary the number of clusters from 1 to 250. With our proposed approach in sample, the accuracy range is $[0.4, 0.65]$. If we remove the situation that we only have one cluster, the accuracy range becomes $[0.5, 0.65]$, which is smaller than the accuracy

Table 3: Proposed Approach In Sample

(a) Counts				
Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	5465	353	2443	8261
$A = B$	987	143	759	1889
$A < B$	1920	388	5382	7690
Sum	8372	884	8584	17840

(b) Percentage				
Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	65.3%	39.9%	28.5%	133.7%
$A = B$	11.8%	16.2%	8.8%	36.8%
$A < B$	22.9%	43.9%	62.7%	129.5%
Sum	100.0%	100.0%	100.0%	300.0%

range provided by Logistic Regression ($[0.35, 0.65]$). From the figure, we see that *a*) using our approach, the accuracy rate range is much smaller than using Logistic Regression, indicating that the result generated by our approach is stable. In addition, the accuracy of our approach remains approximately constant as the number of clusters is varied. On the contrary, the accuracy of the Logistic Regression has a far higher variability and decreases fast as the number of clusters is increased; *b*) comparing these two approaches, we can find that our approach’s performance is better than Logistic Regression’s performance. We can get the same conclusion for the test data. In addition, from this figure, we can find that using our approach, the accuracy difference between the train data and test data is not huge, which indicates that our approach can capture the users’ preference correctly.

Based on the above results, we set the number of clusters to four for both our approach and Logistic Regression. Table 3 and Table 4 show the prediction situation using our approach and Logistic Regression approach across all questions. For both tables, part (*a*) is the number of correct predictions and part (*b*) is the percentage correct. For both tables, the elements in the diagonal are the number when our prediction is the same as the users’ choices. Other elements are the incorrect prediction (which means that our predictions are different from their choices).

From Table 3 and Table 4, we can see the number of strict correct predictions (predicting the same answer as the users’ selected) is 10990, which is 61.6% and if we get rid of the no preference option, the percentage increases to 64.0%. Table 4 shows the results using Logistic Regression. From Table 4, we can find that the number of strict correct predictions is 10878, which is similar to

Table 4: Logistic Regression Approach In Sample

(a) Counts

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	5190	328	3709	8872
$A = B$	1085	226	1122	2433
$A < B$	2097	330	3421	6535
Sum	8372	884	8584	17840

(b) Percentage

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	62.0%	37.1%	23.3%	122.4%
$A = B$	13.0%	25.6%	13.1%	51.6%
$A < B$	25.0%	37.3%	63.6%	126.0%
Sum	100.0%	100.0%	100.0%	300.0%

our approach. The correct prediction percentage is 61.0%. Without the no preference option, the correct prediction percentage increases to 62.8%. It seems that our approach and logistic regression are similar if we only consider the train data. However, when we apply our approach and Logistic Regression Method into the test data, our approach shows a great advantage. The results are shown in Table 5 and Table 6.

From Table 5 and Table 6, we can find that our approach is better than Logistic Regression. When we consider the test data, we get the number of strict correct prediction is 2789 and its corresponding accuracy rate is 62.5%. While using Logistic Regression, the number of strict correct prediction is 2408 and its corresponding accuracy rate is only 55.0%. In addition, comparing Table 3 with Table 5, we can find that accuracy rate in the test data is a little higher than the accuracy rate generated using train data. This difference is not huge, which indicates that our approach is stable.

5.2.2 Formulation $\mathcal{E}\mathcal{W}$ using subset of features

When we obtained the utility function, we find that the last feature (*Number of different freeways on the route*) is not significant. In this section, we delete the last feature (*Number of different freeways on the route*) and only use the first five attributes to formulate each cluster's utility function.

The accuracy results are shown in Table 7 and Table 8. In order to be comparable with our previous results, here, we still cluster users into 4 groups.

We can compare Table 3 with Table 7; Table 5 with Table 8. First, from Table 3 and Table

Table 5: Proposed Approach Out of Sample

(a) Counts

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	1414	103	536	2051
$A = B$	213	52	203	467
$A < B$	516	102	1324	1942
Sum	2143	254	2063	4460

(b) Percentage

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	66.0%	39.8%	26.0%	131.7%
$A = B$	9.9%	20.1%	9.8%	39.9%
$A < B$	24.1%	40.2%	64.2%	128.4%
Sum	100.0%	100.0%	100.0%	300.0%

Table 6: Logistic Regression Approach Out of Sample

(a) Counts

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	1198	101	656	1955
$A = B$	213	51	203	467
$A < B$	732	102	1204	2038
Sum	2143	254	2063	4460

(b) Percentage

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	55.9%	39.8%	31.8%	127.5%
$A = B$	9.9%	20.1%	9.8%	39.9%
$A < B$	34.2%	40.2%	58.4%	132.7%
Sum	100.0%	100.0%	100.0%	300.0%

Table 7: Proposed Approach In Sample Results with Feature 6 Dropped

(a) Counts

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	6714	602	4510	11826
$A = B$	48	32	26	106
$A < B$	1610	250	4048	5908
Sum	8372	884	8584	17840

(b) Percentage

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	80.2%	68.1%	52.5%	200.8%
$A = B$	0.6%	3.6%	0.3%	4.5%
$A < B$	19.2%	28.3%	47.2%	94.7%
Sum	100.0%	100.0%	100.0%	300.0%

Table 8: Proposed Approach Out of Sample with Feature 6 Dropped

(a) Counts

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	1574	190	1021	2785
$A = B$	15	4	62	81
$A < B$	554	60	980	1594
Sum	2143	254	2063	4460

(b) Percentage

Prediction \ Response	$A > B$	$A = B$	$A < B$	Sum
$A > B$	73.4%	74.8%	49.5%	192.2%
$A = B$	0.7%	1.6%	3.0%	4.0%
$A < B$	25.9%	23.6%	47.5%	103.7%
Sum	100.0%	100.0%	100.0%	300.0%

7, we can find when the user predicts $A \succ B$, the accuracy using this new utility function is higher than the previous one (when we use all five attributes to formulate the utility function). The correct prediction when users prefer route A increases from 5465 to 6714, increasing 18.6%. However, the accuracy of predicting the users' preferences when users choose no preference or prefer route B decreases. We can get the same conclusion when we compare Table 5 and Table 8.

5.2.3 Formulation \mathcal{GW}

As we mentioned in Section 4.1, each type of violation should have different penalty values. Here we take this into consideration and generate the accuracy change as the penalty value changes. The results are shown in Figure 7. In order to be comparable with the previous results, we still cluster the users into 4 groups.

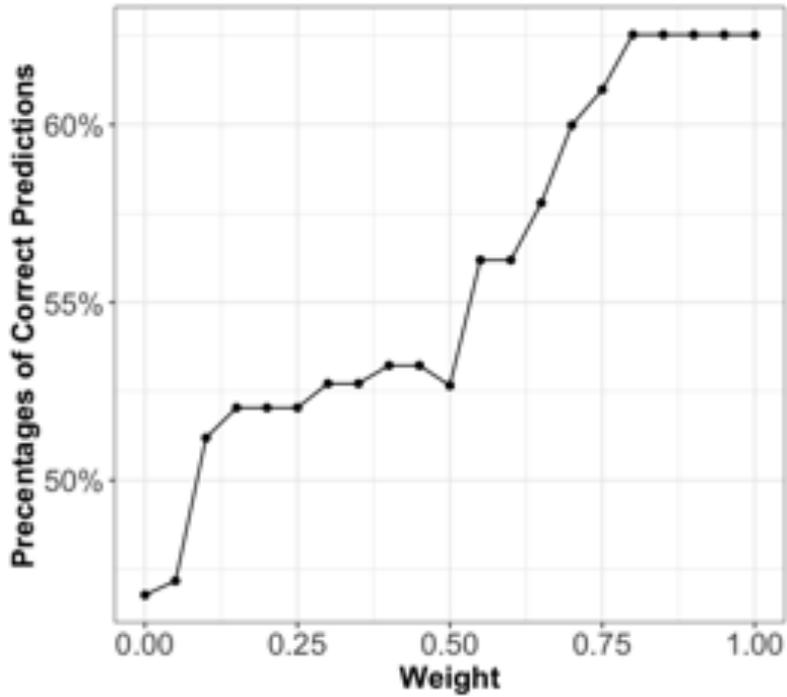


Figure 7: Accuracy as a Function of the Weight w

From this graph, we can find when we increase the penalty value w mentioned in Section 4.1, the percentage of correct predictions increases. When the penalty value is equal to zero, it means that we have no penalty for exact opposite prediction and no penalty for the prediction is no preference even though users have preferences, while it has a heavy penalty for the violation when users have no preference and we give them a specific preference. In this situation, in order to minimize the objective value, we will predict all users have no preference. As w increases, we can

predict some specific preferences. In the extreme situation, when w is equal to one, it means that we do not care about the users who have no preference. In this situation, just randomly give them a specific preference.

Figure 7 gives us a hint that we need to choose a smart penalty value so that we can obtain a good utility function for each cluster.

6 Implementation

A typical application of this project is the transportation system of major urban centers such as Los Angeles. This project uses mixed integer linear programming to learn the utility function and then based on these utilities develops route suggestions to users. The implementation of our proposed mechanism requires suitable programming software tools such as Python, R, etc. It also requires using the survey we generated to obtain information about users' preferences. The information in the survey is created using Python and the entire solution framework is implemented in R.

7 Conclusion and Future Directions

In this report, we study the problem of reducing the congestion while taking the users' preferences into consideration. In this problem, the routes' features are known in advance. Next, we use these routes' features to generate the survey and use this survey to collect the users' information about its preferences. We use this collected information and use integer linear programming to formulate the users' utility function.

In this problem, we use integer linear programming to formulate the utility function, considering the users' inconsistency. We compare the absolute number and percentage of correct predictions with the Logistic Regression method. The experimental results show that our proposed approach has better performance than the Logistic Regression method in both the train and test data and show that our prediction is stable no matter how many clusters we have. We also revised the formulation to reflect the fact that not all incorrect predictions are of the same magnitude and we added different weights to different incorrect predictions to the formulation.

More work can be done along the lines of improving the personalized options. For example, in our research, we only include highways. Side roads have more characteristic that may influence the users' choice. In addition, we can develop online algorithms for learning the preferences of the users.

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Appendix: The Survey

Please turn over.

Default Question Block

University of Southern California
Epstein Department of Industrial & Systems Engineering
Ethel Percy Andrus Gerontology Center
3715 McClintock Ave, Los Angeles, CA 90089

INFORMED CONSENT FOR NON-MEDICAL RESEARCH**Learning Driver Route Preferences to Reduce Traffic Network Congestion**

You are invited to participate in a research study conducted by Professor Phebe Vayanos, PhD, Professor Maged Dessouky, PhD, and Yung Peng, M.Sc. at the University of Southern California. To be eligible to participate in the study you must: a) be over 18 years old, b) be proficient in English, c) be proficient with controlling a computer using a mouse and keyboard, d) hold a driver's license for at least 2 years, e) reside in Los Angeles for at least 2 years, f) drive on a weekly basis. This study is funded by the U.S. Department of Transportation via the METRANS Transportation Center. Your participation is voluntary. You should read the information below, and ask questions about anything you do not understand, before deciding whether to participate. Please take as much time as you need to read the consent form. You may also decide to discuss participation with your family or friends. If you decide to participate, you will be asked to accept this form. You will be given a copy of this form.

PURPOSE OF THE STUDY

The purpose of the study is to learn driver route preferences in traffic (road) networks. More concretely, this study aims to identify/learn the key route characteristics/factors that influence how individual drivers choose which routes to employ to get to their intended destinations in a traffic network. Examples of route characteristics include, but are not limited to: distance, expected trip duration, best-case trip duration, traffic conditions, number of freeways, percentage of traffic accidents, etc. Knowing individual driver preferences will enable us to build a personalized route recommendation system. Such a system may not only be valuable for drivers who will be able to obtain route recommendations matching their preferences but also for society. Indeed, we anticipate that providing drivers with routes that they are likely to adhere to will make traffic conditions more predictable and enable us to provide socially optimal routes that reduce congestion.

STUDY PROCEDURES

If you volunteer to participate in this study, you will be asked to answer a computer based online questionnaire asking you basic demographic questions, and questions about your route preferences. The section of the questionnaire related to your route preferences consists of 10 questions. Each of the questions in this part of the questionnaire will put you in a (fictitious) context of daily life: it will show you a map displaying your (fictitious) current location and your (fictitious) destination. The system will then offer you 2 recommended routes taking you from your current location to your intended destination. You will also be shown the characteristics of each of the proposed routes. You will then be asked to choose your preferred route between the ones proposed. We anticipate that each question in this part should take no more than one minute to complete (the time it takes you to choose a particular route in your day-to-day life).

POTENTIAL RISKS AND DISCOMFORTS

We do not anticipate any risks from participating in this research. You may find answering the questionnaires annoying, boring, or repetitive. If this happens, please know that you can take a break or skip a question. You have the right to refuse to answer any question(s) you don't want to.

POTENTIAL BENEFITS TO PARTICIPANTS TO SOCIETY

We anticipate that this study will enable us to better predict and control traffic congestion in road networks, thus reducing congestion and benefitting society.

CONFIDENTIALITY

Your participation is confidential. Any identifiable information obtained in connection with this study will remain confidential and will not be linked to your responses.

We will keep your records for this study confidential as far as permitted by law. However, if we are required to do so by law, we will disclose confidential information about you. The members of the research team, the funding agency and the University of Southern California's Human Subjects Protection Program (HSPP) may access the data. The HSPP reviews and monitors research studies to protect the rights and welfare of research subjects.

All data will be kept in a locked drawer inside a locked office and/or on password protected computers. All identifiable information will be destroyed once the study is completed. The remaining data will be maintained indefinitely and may be used in future research studies or for educational purposes. If you do not want your data used in future research studies or for educational purposes, you should not participate in this study.

When the results of the research are published, or discussed in conferences, no identifiable information will be used.

PARTICIPATION AND WITHDRAWAL

Your participation is voluntary. You may withdraw your consent at any time and discontinue participation without penalty. You are not waiving any legal claims, rights or remedies because of your participation in this research study.

ALTERNATIVES TO PARTICIPATION

If you joined the student subject pool, your alternative may be to participate in another study or to write a paper, please contact the Subject Pool Coordinator for further information.

INVESTIGATOR'S CONTACT INFORMATION

If you have any questions or concerns about the research, please feel free to contact either the PI, Phebe Vayanos at phebe.vayanos@usc.edu, the co-PI, Maged Dessouky at maged@usc.edu, or Ying Peng at yingpeng@usc.edu.

RIGHTS OF RESEARCH PARTICIPANT – IRB CONTACT INFORMATION

If you have questions, concerns, or complaints about your rights as a research participant or the research in general and are unable to contact the research team, or if you want to talk to someone independent of the research team, please contact the University Park Institutional Review Board (UPIRB), 3720 South Flower Street #301, Los Angeles, CA 90089-0702, (213) 821-5272 or upirb@usc.edu

By clicking on “Next”, you confirm that you have read the information provided above, have been given a chance to have your questions answered, and agree to participate in this study.

Basic Information

Please specify your gender

- Male
- Female
- Other

Please specify your age

- Under 25 years old
- 25-34 years old
- 35-44 years old
- 45-59 years old
- 60 years old or older

Please specify your marital status

- Single
- Married with children
- Married without children

- Divorced
- Widow/Widower

Please specify the number of dependents in your family

- Less than or equal to 2
- 3-5
- more than 5

Please specify your highest degree or level of school you have completed. If currently enrolled, highest degree received.

- High School Diploma
- Undergraduate Degree
- Graduate Degree
- None

Please specify your ethnicity

- White
- Hispanic or Latino
- Black or African American
- Asian / Pacific Islander
- Native American or American Indian
- Other

Please specify your employment status

- Employed in a driving related job
- Employed in not a driving related job
- Not employed

Please specify your driving years

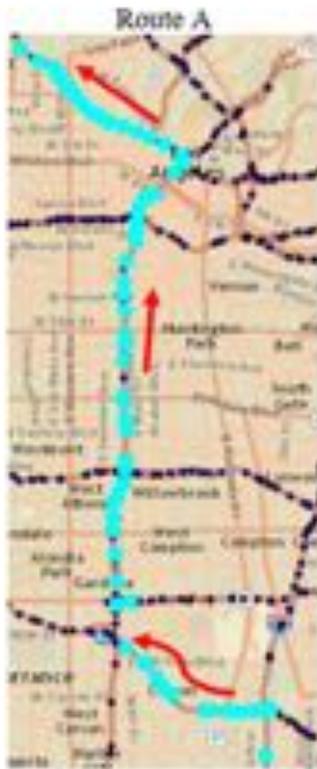
- 2-3
- 4-5
- more than 5

Block 2

In Los Angeles, there are a lot of route choices between two locations. In this part, we want to know your preference so that in the future, we can give you a better route recommendation.

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	28.3	30.5
Average Time (Minutes)	38.35	36.85
Minimum Time (Minutes)	26.37	28.42
Chance that the travel time will be longer than 45 minutes	25%	7.14%
Percentage of total yearly traffic accidents on this route	1.97%	2.26%
Number of different freeways on the route	4	4



-
- Route A
 Route B
 I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	26.0	28.7
Average Time (Minutes)	29.62	29.61
Minimum Time (Minutes)	24.96	26.65
Chance that the travel time will be longer than 32 minutes	32.14%	21.43%
Percentage of total yearly traffic accidents on this route	1.43%	1.71%
Number of different freeways on the route	3	5



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	29.7	26.0
Average Time (Minutes)	31.52	29.62
Minimum Time (Minutes)	28.31	24.96
Chance that the travel time will be longer than 35 minutes	4.76%	5.95%
Percentage of total yearly traffic accidents on this route	1.48%	1.43%
Number of different freeways on the route	4	3



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	10	8.7
Average Time (Minutes)	14.51	16.83
Minimum Time (Minutes)	9.75	8.28
Chance that the travel time will be longer than 20 minutes	2.38%	36.90%
Percentage of total yearly traffic accidents on this route	0.70%	0.87%
Number of different freeways on the route	4	3



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	26.32	31.83
Average Time (Minutes)	31.26	34.24
Minimum Time (Minutes)	24.85	29.69
Chance that the travel time will be longer than 40 minutes	15.00%	14.29%
Percentage of total yearly traffic accidents on this route	0.62%	0.37%
Number of different freeways on the route	4	3



-
- Route A
 - Route B
 - I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	20.94	24.20
Average Time (Minutes)	22.14	22.63
Minimum Time (Minutes)	19.21	21.94
Chance that the travel time will be longer than 25 minutes	20.24%	5.95%
Percentage of total yearly traffic accidents on this route	NA	NA
Number of different freeways on the route	2	2



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	24.67	20.37
Average Time (Minutes)	24.86	22.83
Minimum Time (Minutes)	24.10	18.68
Chance that the travel time will be longer than 26 minutes	3.56%	16.07%
Percentage of total yearly traffic accidents on this route	1.83%	1.2%
Number of different freeways on the route	3	2



- Route A
- Route B

I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	24.67	23.34
Average Time (Minutes)	27.73	33.07
Minimum Time (Minutes)	23.85	21.84
Chance that the travel time will be longer than 35 minutes	2.68%	41.07%
Percentage of total yearly traffic accidents on this route	1.83%	2.05%
Number of different freeways on the route	3	3



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	21.73	20.01
Average Time (Minutes)	21.75	22.56
Minimum Time (Minutes)	20.34	19.48
Chance that the travel time will be longer than 25 minutes	1.19%	19.05%
Percentage of total yearly traffic accidents on this route	1.52%	1.37%
Number of different freeways on the route	3	2



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

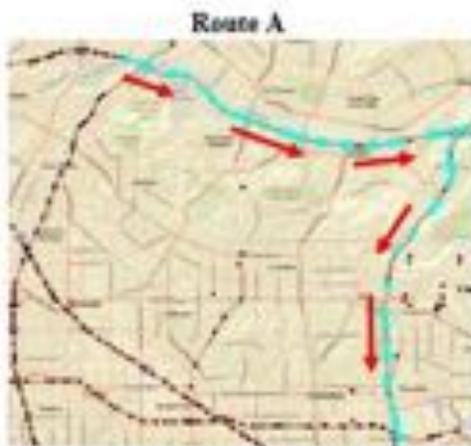
Description	Route A	Route B
Distance (Miles)	22.33	24.46
Average Time (Minutes)	35.39	29.55
Minimum Time (Minutes)	20.75	22.94
Chance that the travel time will be longer than 35 minutes	48.21%	8.04%
Percentage of total yearly traffic accidents on this route	1.06%	1.26%
Number of different freeways on the route	3	5



-
- Route A
 - Route B
 - I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	24.94	30.94
Average Time (Minutes)	30.22	31.68
Minimum Time (Minutes)	24.18	29.89
Chance that the travel time will be longer than 35 minutes	20.84%	3.13%
Percentage of total yearly traffic accidents on this route	1.97%	1.26%
Number of different freeways on the route	2	3



-
- Route A
 - Route B

- I have no preference

Based on the following information, which route do you prefer?

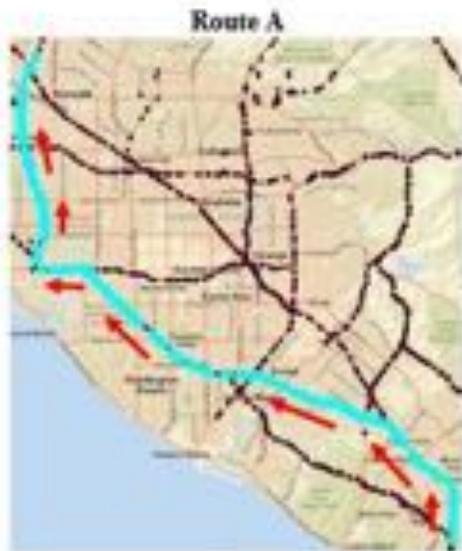
Description	Route A	Route B
Distance (Miles)	20.23	17.54
Average Time (Minutes)	21.10	20.36
Minimum Time (Minutes)	18.95	15.93
Chance that the travel time will be longer than 23 minutes	5.31%	8.85%
Percentage of total yearly traffic accidents on this route	0.57%	0.57%
Number of different freeways on the route	2	2



- Route A
- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	44.22	45.02
Average Time (Minutes)	44.09	44.19
Minimum Time (Minutes)	41.25	41.93
Chance that the travel time will be longer than 50 minutes	10.7%	3.57%
Percentage of total yearly traffic accidents on this route	1.08%	1.48%
Number of different freeways on the route	5	3

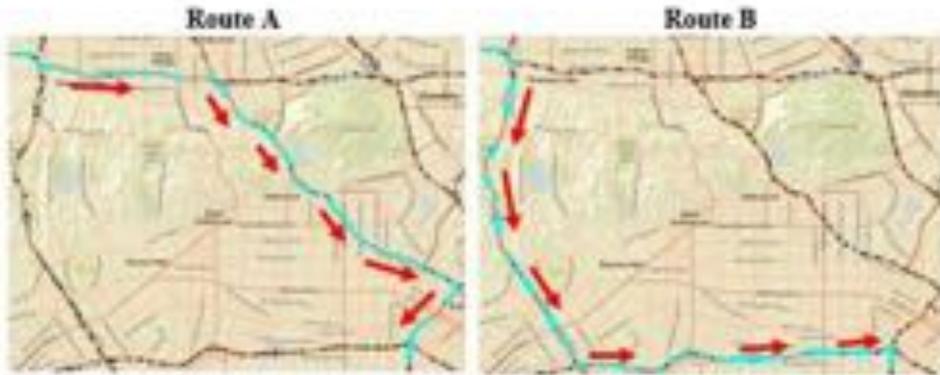


- Route A

- Route B
- I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	22.23	20.20
Average Time (Minutes)	29.59	31.22
Minimum Time (Minutes)	28.51	23.21
Chance that the travel time will be longer than 30 minutes	23.21%	58.93%
Percentage of total yearly traffic accidents on this route	NA	NA
Number of different freeways on the route	3	3



-
- Route A
 - Route B
 - I have no preference

Based on the following information, which route do you prefer?

Description	Route A	Route B
Distance (Miles)	59.66	59.86
Average Time (Minutes)	70.34	72.34
Minimum Time (Minutes)	55.54	56.01
Chance that the travel time will be longer than 85 minutes	11.74%	8.53%
Percentage of total yearly traffic accidents on this route	1.78%	1.52%
Number of different freeways on the route	2	4



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- Route A

- Route B
- I have no preference