Deep Inverse Reinforcement Learning for Route Choice Modeling

Zhan Zhao\textsuperscript{a,b,*}, Yuebing Liang\textsuperscript{a}

\textsuperscript{a} Department of Urban Planning and Design, The University of Hong Kong, Hong Kong
\textsuperscript{b} Musketeers Foundation Institute of Data Science, The University of Hong Kong, Hong Kong

Abstract

Route choice modeling, i.e., the process of estimating the likely path that individuals follow during their journeys, is a fundamental task in transportation planning and demand forecasting. Classical methods generally adopt the discrete choice model (DCM) framework with linear utility functions and high-level route characteristics. While several recent studies have started to explore the applicability of deep learning for travel choice modeling, they are all path-based with relatively simple model architectures and cannot take advantage of detailed link-level features. Existing link-based models, while theoretically promising, are generally not as scalable or flexible enough to account for the destination characteristics. To address these issues, this study proposes a general deep inverse reinforcement learning (IRL) framework for link-based route choice modeling, which is capable of incorporating high-dimensional features and capturing complex relationships. Specifically, we adapt an adversarial IRL model to the route choice problem for efficient estimation of destination-dependent reward and policy functions. Experiment results based on taxi GPS data from Shanghai, China validate the improved performance of the proposed model over conventional DCMs and other imitation learning baselines, even for destinations unseen in the training data. We also demonstrate the model interpretability using explainable AI techniques. The proposed methodology provides a new direction for future development of route choice models. It is general and should be adaptable to other route choice problems across different modes and networks.

Keywords: Route choice modeling, Inverse reinforcement learning, Deep neural networks, Travel behavior, Trajectory data mining

1. Introduction

With increasing urban populations and limited infrastructure capacity, traffic congestion has become a pressing issue. As congestion typically occurs in transportation networks, it is important to understand, and ultimately predict, how individuals move between places through a complex network and how various factors affect their decisions. The increasing popularity of devices equipped with location sensors offers unprecedented possibilities
for studying detailed human movements and better comprehending individual routing preferences. This requires specialized analytical methods to extract human routing behavior patterns from large-scale trajectory data.

Route choice modeling, a fundamental step in transportation planning and forecasting, is the process of estimating the likely path that individuals follow during their journeys (Prato, 2009). Empirical studies have repeatedly shown that chosen routes often deviate significantly from the shortest paths (Jan et al., 2000; Lima et al., 2016). Therefore, route choice models are needed to appraise perceptions of route attributes, forecast routing behavior under hypothetical scenarios, predict future traffic conditions on transportation networks, and potentially guide us to design better urban infrastructure.

Conventional route choice models adopt the discrete choice model (DCM) framework and can be generally categorized into two types. The most common type is path-based in the sense that the model describes a discrete choice among paths, where each path is a sequence of network links that connects an origin to a destination. Path-based models are simple but requires sampling potential paths to form a finite choice set, which is a nontrivial task in a large and complex network (e.g., urban road networks). The other type is link-based where the route choice problem is formulated as a sequence of link choices. Link-based models have several advantages. First, they do not require path sampling and tend to produce more consistent model estimates (Fosgerau et al., 2013). Second, they are generally more suited to incorporate detailed link-level features (e.g., bike lanes for cyclists), which is useful for evaluating transportation network design. Third, they can be easily extended for dynamic routing situations when travelers may change route choices en route in response to updated link features (e.g., traffic congestion for drivers). Despite of these theoretical advantages, existing link-level models are not well equipped to account for the information about the trip destination and its spatial relationship with the current location. In addition, like most DCMs, they assume linear utility functions and are generally unable to uncover complex human routing preferences. Therefore, we need a more flexible link-based model to incorporate destination information and capture complex routing preferences. One promising approach is to apply deep neural networks (DNNs).

In recent years, deep learning has emerged as a powerful alternative to classical DCMs based on microeconomic theories such as random utility maximization. Because of their multilayer structure and diverse architecture design, DNNs can capture nonlinear relationships and incorporate high-dimensional features, and have shown state-of-the-art performance in many problems, especially for mode choice modeling (Cantarella and de Luca, 2005; Wang et al., 2020). There are relatively few studies applying DNNs for route choice modeling, and all are path-based (Marra and Corman, 2021). Link-based models typically need to adopt a sequential structure to capture the behavioral patterns in a series of link choices. Although several recent works demonstrated the potential of sequential DNNs for trajectory prediction (Liang and Zhao, 2021) and trajectory generation (Choi et al., 2021), they still lack explicit consideration of the destination information that is essential for the route choice problem. As route choice models are commonly used to understand human routing preferences and make travel predictions for planning purposes, they require good interpretability and generalizability, which are often lacking in deep learning methods. This study aims to fill these
In this study, we propose a deep inverse reinforcement learning (IRL) framework for link-based route choice modeling. IRL is well suited because it is structurally similar to dynamic DCMs (Rust, 1987), behaviorally interpretable, and flexible enough to incorporate deep architectures and high-dimensional features. In this framework, the link-based route choice problem is formulated as a Markov Decision Process (MDP), and the goal is to recover the underlying reward function (similar to utility functions) from observed human trajectories. Unlike previous works, we assume that both the reward and policy functions are conditional on the trip destination and can be efficiently approximated using DNNs. Specifically, a conditional version of adversarial IRL, or AIRL (Fu et al., 2018) is introduced to learn these functions from the data in a model-free fashion. Several alternatives of the proposed model are also tested, including a simpler behavioral cloning (BC) method and Generative Adversarial Imitation Learning (GAIL) (Ho and Ermon, 2016). Extensive experiments are conducted using taxi GPS data on a selected road network from Shanghai, China, and the results validate the improved prediction performance of the proposed model over classical DCMs as well as other DNN baselines. The improvement holds even for destinations unseen in the training data, demonstrating the generalizability of the model. In addition, we examine the model interpretability from global and local perspectives using explainable AI techniques. While this study focuses on the route choice of drivers on a road network, the proposed methodology is general and should be adaptable to other route choice problems across different modes and networks.

2. Literature Review

2.1. Discrete Choice Models for Route Choice Modeling

Existing route choice models generally adopt the DCM framework and fall into two types—path-based and link-based. One main challenge for path-based models is the need to account for the correlation between overlapping alternative paths, and numerous methods have been developed to address this issue, including the widely used path size logit (PSL) (Ben-Akiva and Bierlaire, 1999). In a real-sized network, there can be a large number of possible paths connecting each origin-destination (OD) pair. To estimate path-based models, one has to make assumptions about which paths to consider and generate a finite choice set, typically using some sort of path-generation algorithms such as link elimination (Azevedo et al., 1993) and constrained enumeration (Prato and Bekhor, 2007). However, it has been shown that parameter estimates can vary significantly based on the definition of choice sets (Frejinger et al., 2009).

These issues with path-based models have motivated the development of link-based models in recent years. Fosgerau et al. (2013) proposed the recursive logit model, where a path choice is modeled as a sequence of link choices using a dynamic discrete choice framework. They found that the recursive logit is equivalent to a path-based multinomial logit model with an unrestricted choice set, but can produce more consistent parameter estimates without requiring path sampling. Later studies proposed several extensions, including the nested recursive logit (Mai et al., 2015) and discounted recursive logit (Oyama and Hato, 2017).
The applicability of such models have been demonstrated in various route choice scenarios across different modes (de Freitas et al., 2019; Nassir et al., 2019; Zimmermann et al., 2017). However, existing link-based models generally lack scalability and are not flexible enough to incorporate destination features. Attributes of the trip destination have important influence on the route choice, and should be considered in the model, but the large number of possible destinations are difficult to model directly in relatively simple DCM structures. We need more flexible model structures that are able to handle high-dimensional features such as the destination.

2.2. Inverse Reinforcement Learning for Route Choice Modeling

Parallel to the development of recursive logit models, IRL has emerged as a general yet powerful framework to model sequential decision processes (e.g. routing) over the past two decades. While the goal of reinforcement learning (RL) is to learn a decision process to produce behavior that maximizes some predefined reward function, IRL inverts the problem and aims to extract a reward function from demonstration data that explains observed human behavior (Abbeel and Ng, 2004; Ng and Russell, 2000). The reward function is usually specified by a number of features, and the learnt parameters describe human preferences, which is similar to the utility function in DCMs. IRL is closely connected to imitation learning (IL), only with different learning objectives. While IRL aims to recover the reward function, IL focuses on directly learning the optimal policy from the data.

As the original IRL is prone to noise and often ambiguous, Ziebart et al. (2008) proposed the maximum entropy IRL (MaxEntIRL), which employs the principle of maximum entropy to resolve the ambiguity in choosing a distribution over decisions. In fact, it has been shown to share many similarities with the recursive logit, as both can model route choices as a sequence of link choices and can estimate a probability distribution over all feasible paths (Zimmermann and Frejinger, 2020; Koch and Dugundji, 2020). A common weakness of both is that they rely on relatively simple linear utility or reward functions with no explicit consideration of destination features, which can limit model expressiveness and performance. Furthermore, the need to compute all path probabilities through dynamic programming may limit the model scalability in larger networks.

Recent years have seen growing interest in the use of deep architecture for reward function approximation in RL/IRL (Mnih et al., 2015). Wulfmeier et al. (2016) extended the MaxEntIRL approach with DNNs, and it has been adapted for delivery route planning (Liu et al., 2020). Ho and Ermon (2016) proposed Generative Adversarial Imitation Learning (GAIL), which combines the core idea of IRL with the generative adversarial framework. Although it has been applied to taxi driver strategy learning (Zhang et al., 2020) and synthetic trajectory generation (Choi et al., 2021), GAIL is still an IL approach, and cannot estimate specific reward functions or reveal routing preferences. More recently, a similar adversarial architecture was adopted in Adversarial Inverse Reinforcement Learning (AIRL), which is able to recover reward functions in large, high-dimensional problems (Fu et al., 2018). Specifically for route choice analysis, such DNN-based IRL/IL methods have yet to be explored.
2.3. Interpretable Deep Learning

While it has long been recognized that DNNs can outperform DCMs for choice prediction (Cantarella and de Luca, 2005), a central critique of deep learning is its lack of interpretability. Understanding why a model makes a certain prediction is essential for explaining the underlying human behavior and ensure the trustworthiness of the model. As a result, recent work has investigated theories and methods for interpretable deep learning (Doshi-Velez and Kim, 2017). For mode choice analysis, Wang et al. (2020) demonstrated that DNNs can provide economic information as complete as classical DCMs, including utilities, elasticities and values of time. One key idea is that the interpretation of DNNs has to be based on the full function of choice probabilities rather than on individual parameters, as in DCMs. Also focusing on mode choice modeling, Alwosheel et al. (2021) proposed the use of activation maximization and layer-wise relevance propagation techniques to assess the validity of relationships learned in neural networks. For mobility flow (or destination choice) analysis, Simini et al. (2021) showed that DNNs can not only significantly outperform the classical gravity model, but also be interpreted using SHapley Additive exPlanations (SHAP), which estimates the contribution of each feature based on how its absence changes the model prediction (Lundberg and Lee, 2017). This inspires us to consider a deep learning approach to route choice modeling, which can potentially improve performance while preserving most of the interpretability as in classical DCMs.

3. Methodology

3.1. Route Choice as a Markov Decision Process

The route choice problem can be regarded as a Markov decision process (MDP) (Ziebart et al., 2008), which provides a mathematical framework for modeling the sequential decision processes of an agent (or traveler). An MDP is generally defined as $M = \{S, A, T, R, \gamma\}$, where $S$ denotes the state space, $A$ the set of possible actions, $T(s, a, s')$ a transition model that determines the next state $s' \in S$ given the current state $s \in S$ and action $a \in A$, $R(s, a)$ the reward function that offers rewards to the agent based on its current state and action, and $\gamma$ the discount factor between future and present rewards. For the route choice problem, MDP is usually episodic, where the episode ends when the agent reaches the desired destination. In such cases, reward discounts are unnecessary, but we often set it slightly lower than 1 for computational efficiency. In this study, we set $\gamma$ as 0.99 following Zhang et al. (2020). In addition, a policy $\pi(a \mid s)$ is a specific state-to-action mapping. Assuming policies are stochastic, $\pi(a \mid s)$ gives the probability of choosing action $a$ at state $s$ under policy $\pi$. In the RL setting, the reward $R$ is given, and the objective is to find the optimal policy $\pi^*$ that maximizes the expected cumulative reward for the agent. In the IRL setting, however, $R$ is unknown, and the objective is to recover the reward function from the observed behavior trajectories $X = \{x_1, x_2, ..., x_N\}$ that are assumed to be sampled from the optimal policy $\pi^*$. Specifically for the route choice problem on a road network, we can define a basic MDP as follows:
• **State.** Each state \( s \in S \) is a link of the road network indicating the current location of the traveler. Depending on data availability, the dynamic traffic condition of each link can be incorporated, but is outside the scope of this study. We will focus on the spatial aspect and use the traveler’s location as the core determinant of a state, following most prior works (Ziebart et al., 2008; Fosgerau et al., 2013).

• **Action.** An action \( a \in A \) indicates the link-to-link movement choice, which can be either a road link ID (i.e. the link to pass through next) or a movement direction. Our previous work (Liang and Zhao, 2021) has shown that a directional representation can yield better route prediction performance, and 8 directions are adequate to uniquely map most link-to-link movements in large road networks. Therefore, we will define 8 actions, as shown in Figure 1. Note that only a subset of these 8 actions are valid for most states. Compared to prior works (Ziebart et al., 2008; Choi et al., 2021), our action definition is more precise and generalizable to diverse road network layouts.

• **Transition model.** For route choice analysis, \( T(s, a, s') \) is often considered to be deterministic (Ziebart et al., 2008), which means that given the current state an action will always lead to the same next state. A state-action mapping is used to track the valid actions at each state and the resulting next states.

• **Policy.** A policy \( \pi(a | s) \) determines how traveler acts in different routing situations. Essentially, it represents a certain routing behavior pattern. The “optimal” policy \( \pi^* \) is basically the most representative routing pattern underlying actual human route choices. This is unknown in route choice analysis, but we may be able to infer it from observed trajectories \( X \) sampled from \( \pi^* \).

• **Reward function.** While a policy \( \pi \) represents a certain **routing pattern**, a reward function \( R(s, a) \) represents a set of **routing preferences**. The latter is more fundamental, succinct, and arguably more generalizable, than the former. Similarly, the “optimal” reward function \( R^* \) indicates the most representative routing preferences that best explain human routing behavior. This is similar to estimating the best utility function in utility-based DCMs. Specifically, \( R(s, a) \) can be considered as determining the utility derived from taking action \( a \) at state \( s \).

In existing link-based route choice models, the destination information is usually not explicitly considered, even though it is a critical factor determining route choice behavior. To explicitly account for the destination effect, we denote the destination as \( c \), and let both the reward and policy to be conditional on \( c \). Therefore, we will have \( R(s, a \mid c) \) instead of \( R(s, a) \), and \( \pi(a \mid s, c) \) instead of \( \pi(a \mid s) \). This makes sense, as the utility of taking action \( a \) at state \( s \) can be very different based on where the destination is. In this way, we can capture the influence of the destination on routing behavior, and make the model generalizable to multiple destinations. Furthermore, other contextual information such as the time of day, weather, and travel purpose (if known) can be appended to \( c \) as an extended context vector. Because of the many destinations available and different possible contextual information that can be added, the context vector \( c \) is typically high-dimensional. Although such information can be merged into the state definition, we choose to separate \( s \) and \( c \) to highlight the difference. Unlike state \( s \), context \( c \) is assumed to be fixed during a trip and
Figure 1: Definition of action space. We take two steps to define action space: action mapping (a) and action relabeling (b). First, we calculate the heading difference between each connected link pair and discretize the heading difference to 8 action (i.e. direction) labels. If two links connecting with the same link share the same direction label, we then relabel one of them to the closest available action space.

not directly affected by traveler’s actions. This makes our model formulation different from prior works (Ziebart et al., 2008; Fosgerau et al., 2013). Without loss of generality, we will mostly use \( c \) to refer to the destination of a trip from now on.

3.2. Route Choice as an Inverse Reinforcement Learning Problem

Recall that IRL for route choice modeling seeks to infer the reward function \( R(s, a \mid c) \) given a set of observed trajectories \( X = \{x_1, x_2, ..., x_N\} \) that are assumed to be drawn from an optimal policy \( \pi^*(a \mid s, c) \). Note that each observed trajectory is a sequence of station-action pairs with a certain destination. Let us denote the \( i \)-th trajectory as \( x_i = \{(s_{t_i}^{(i)}, a_{t_i}^{(i)}), (s_2^{(i)}, a_2^{(i)}), ..., (s_{T_i}^{(i)}, a_{T_i}^{(i)}) \mid c^{(i)}\} \), where \( (s_{t_i}^{(i)}, a_{t_i}^{(i)}) \) is the \( t \)-th state-action pair of \( x_i \), \( c^{(i)} \) the destination, and \( T_i \) the length of the trajectory.

In large road networks, there are many possible combinations of \( (s, a, c) \), making it difficult to obtain a robust estimate of \( R(s, a \mid c) \). A common solution is to approximate it with a parameterized reward function \( R_{\theta}(s, a \mid c) \), where \( \theta \) is the function parameters to be learned. The specific function approximation can take many different forms, among which DNNs are generally more flexible and adept in dealing with high-dimensional features. As the total reward of a whole trajectory \( x_i \) is simply the sum of the discounted rewards for each state-action pair in the trajectory, with the parameterized reward function this can be expressed as

\[
R_{\theta}(x_i) = \sum_{t=1}^{T_i} \gamma^t R_{\theta}(s_{t_i}^{(i)}, a_{t_i}^{(i)} \mid c^{(i)}).
\] (1)

While the underlying policy that generates the observed trajectories is assumed to be “optimal”, actual routing behavior may be suboptimal and vary across individuals. Even for the same OD pair, different travelers may choose different routes. To address this issue, the principle of maximum entropy is adopted to handle behavioral suboptimality as well as
stochasticity by operating on the distribution over possible trajectories. Following the Max-EntIRL formulation (Ziebart et al., 2008), the probability of observing any given trajectory $x$ is proportional to the exponential of its cumulative reward:

$$P_\theta(x) = \frac{1}{Z} \exp \left( R_\theta(x) \right)$$

(2)

where the partition function $Z$ is the integral of $R_\theta(x)$ over all possible trajectories. Therefore, we can frame the IRL problem as solving the maximum likelihood problem based on the observed trajectories:

$$\max_\theta \sum_{i=1}^{N} \log (P_\theta(x_i))$$

(3)

One main challenge to solve the above optimization problem is the computation of $Z$ in Eq. (2). Traditional methods are model-based, in that they leverage the known dynamics of the routing environment to compute $Z$ exactly through dynamic programming (Ziebart et al., 2008). However, because of the large number of feasible paths in real-sized networks, this can be very computationally expensive. A more recent approach is based on model-free methods. Instead of computing $Z$ exactly, we can estimate it by learning a separate sampling distribution (or policy) that approximate the actual trajectory distribution (Finn et al., 2016b). Essentially, this requires us to learn both the reward and policy functions simultaneously, making it possible to recast Eq. (3) as a generative adversarial network (GAN) optimization problem (Finn et al., 2016a). For specific implementation, we will focus on one of the latest such methods called Adversarial IRL (AIRL) (Fu et al., 2018), and show how it can be adapted to solving the route choice problem efficiently.

3.3. Preliminaries: Adversarial Inverse Reinforcement Learning

In this study, we adapt an AIRL framework to inversely learn the reward and policy functions from observed trajectory data, which will allow us to recover the underlying routing preferences and predict route choice behaviors. In this section, we provide a brief introduction of AIRL, and highlight its limitations in its original form for route choice modeling, before introducing an adapted version of the model named RCM-AIRL in the next section.

AIRL is an inverse reinforcement learning algorithm based on an adversarial reward learning formulation. As in original GANs (Goodfellow et al., 2014), AIRL typically consists of two models that are trained simultaneously: a generator $G$ and a discriminator $D$. The AIRL discriminator is tasked with classifying its inputs as either the output of the generator, or actual samples from the underlying data distribution. The generator, on the other hand, aims to find a policy $\pi_G$ to produce outputs that are classified by the discriminator as coming from $\pi^*$. Essentially, the generator determines the policy, and the discriminator specifies the reward function.

Fu et al. (2018) showed that the trajectory-centric formulation as in Finn et al. (2016a) can complicate model training. Instead, it is easier to perform discrimination over state-action pairs. Therefore, the discriminator is defined as

$$D_{\theta,\phi}(s, a) = \frac{\exp \left( f_{\theta,\phi}(s, a) \right)}{\exp \left( f_{\theta,\phi}(s, a) \right) + \pi_G(a | s)}$$

(4)
where $f_{\theta, \phi}(s, a)$ is a function related to the reward to be learned. For a deterministic transition model as in our case, $f_{\theta, \phi}(s, a)$ is defined as

$$f_{\theta, \phi}(s, a) = g_{\theta}(s, a) + \gamma h_{\phi}(s') - h_{\phi}(s) \quad (5)$$

where $s'$ is the next state given the current state $s$ and action $a$, $g_{\theta}(s, a)$ is a reward approximator and $h_{\phi}(s)$ is a shaping term to mitigate the effects of unwanted reshaping on the reward approximator. At optimality $f^{*}(s, a)$ is the advantage function of the optimal policy (Fu et al., 2018).

The objective of the discriminator $D$ is to minimize the cross-entropy loss between generated data and actual ones:

$$\min_{\theta, \phi} -E_{D} \left[ \log \left( D_{\theta, \phi}(s, a) \right) \right] - E_{\pi_{G}} \left[ \log \left( 1 - D_{\theta, \phi}(s, a) \right) \right] \quad (6)$$

There are different ways to formulate the reward. In AIRL, given the discriminator $D$, Fu et al. (2018) defines a modified reward function as an entropy-regularized policy objective:

$$R_{\theta, \phi}(s, a) = \log \left( D_{\theta, \phi}(s, a) \right) - \log \left( 1 - D_{\theta, \phi}(s, a) \right) = f_{\theta, \phi}(s, a) - \log \pi_{G}(a \mid s) \quad (7)$$

where $f_{\theta, \phi}(s, a)$ is from Eq. (5), and $- \log \pi_{G}(a \mid s)$ is added to encourage higher entropy. To be consistent with AIRL, we will use this reward function formulation in the rest of the paper. Based on this formulation, the objective of the generator $G$ is simply to find the policy $\pi_{G}$ that can generate trajectories with maximum reward:

$$\max_{\pi_{G}} E_{\pi_{G}} \left[ R_{\theta, \phi}(s, a) \right] \quad (8)$$

The simultaneous training of $G$ and $D$ corresponds to a minmax two-player game, where the two models are pitted against each other (Goodfellow et al., 2014). Competition in this game drives both models to improve until a global optimum is reached.

The original AIRL model (Fu et al., 2018) is experimented with continuous control tasks and achieves state-of-the-art performance compared to several imitation learning baselines. However, it may not work well for route choice modeling. From preliminary experiments, we found that trajectories generated by the standard AIRL can easily get stuck in a loop and never reach the desired destination. The likely reason is that the reward function learned in AIRL only depends on state-action pairs (i.e., the traveler’s current link and movement direction), ignoring the fact that a traveler’s route choice preference is closely related to the desired destination. To consider the destination information, a possible approach is to train a separate model for each destination (Fosgerau et al., 2013), which however is quite inefficient in real-world applications. Instead, a more generalizable approach would be to develop a conditional modeling framework to include the destination as part of the contextual information $c$. For example, Mirza and Osindero (2014) introduced conditional GANs to generate MNIST digits conditioned on class labels. Zhang et al. (2020) developed conditional GAIL to imitate the cruising behavior of taxi drivers conditioned on driver information. Following the same idea, we introduce a conditional version of AIRL for route choice modeling (RCM-AIRL) in the next section.
3.4. RCM-AIRL: Adversarial IRL for Route Choice Modeling

The main idea behind RCM-AIRL is that the knowledge learned from trajectories with different destinations is transferable and thus we can use a single reward and policy model to capture the routing preferences towards different destinations. To transfer knowledge across trajectories towards different destinations, we introduce a conditional AIRL specifically for route choice modeling. The main idea is to have both the generator and discriminator depend on the context features related to the destination, in addition to the features about the state and action. Figure 2 shows the model framework of RCM-AIRL. As in AIRL, RCM-AIRL consists of a discriminator (reward estimator) and a generator (policy estimator). We also use a value estimator to calculate the expected return of a current state to a specific destination. Below we provide more details on each module and the training algorithm of RCM-AIRL.

3.4.1. Policy Estimator G (RCM-AIRL Generator)

The policy estimator \( G \) aims to generate realistic human trajectories given an OD pair. At each step, \( G \) takes two types of features as input: one is state features \( F_s \), indicating features of the current link (e.g., link length); the other is context features \( F_c \), indicating features related to the destination (e.g., the shortest distance from the current link to the destination). The output of \( G \) is the probability distribution for a traveler to choose different actions (i.e., directions) given the current state \( s \) and destination \( c \). Using the origin link as the start state and the destination link as condition, the policy estimator recursively generates the next state (i.e., link) until the destination is reached. However, through experiments, we find that using the features of current state-destination pairs, denoted as \( F = [F_s; F_c] \), can still fail to achieve satisfying results. This is because the action choice of a traveler is determined by not only features of the current state, but also possible next state features. We denote possible next states as \( S'(s) = \{ s'(a) | \forall a \in A \} \), where \( s'(a) \) represents the next state given the current state \( s \) and action \( a \). One challenge of incorporating features
of $S'(s)$ is that in an irregular road network, the size of $S'(s)$ may vary for different links. To make the policy estimator applicable to all links in the network, we develop a network structure as illustrated in Figure 3. It consists of four main steps: (1) Finding possible next states: given a state $s$, find the next state $s'(a)$ via each action (i.e. direction) $a \in A$. If no valid state exists for $a$, $s'(a)$ is assigned with a mask state denoted as $s_m$. (2) Creating a feature matrix: aggregate the state and context features of $s$ and $S'(s)$ in a $3 \times 3$ feature matrix. (3) Convolutional neural networks (CNNs) embedding: use two-layer CNNs with a kernel size of 2 to learn a latent space vector from the feature matrix. (4) Producing action probability: with the latent space learned from CNNs as input, generate outputs using a two-layer feed-forward network followed by a softmax function.

Figure 3: The network structure of the generator $G$

3.4.2. Reward Estimator $D$ (RCM-AIRL Discriminator)

The primary goal of the discriminator is to distinguishing real human trajectories from generated ones. In the conditional AIRL, the discriminator takes the following form:

$$D_{\theta, \phi}(s, a|c) = \frac{\exp \left( f_{\theta, \phi}(s, a|c) \right)}{\exp \left( f_{\theta, \phi}(s, a|c) \right) + \pi_G(a \mid s, c)}$$

where $f_{\theta, \phi}(s, a|c)$ is defined as

$$f_{\theta, \phi}(s, a|c) = g_{\theta}(s, a|c) + \gamma h_{\phi}(s'|c) - h_{\phi}(s|c).$$

To approximate $f_{\theta, \phi}(s, a|c)$, we use a network structure as displayed in Figure 4. The reward estimator consists of two sub-networks, one for the reward approximator $g_{\theta}(s, a|c)$ and the other for the reward shaping term $h_{\phi}(s|c)$. For $g_{\theta}(s, a|c)$, since it is quite intuitive that the reward of taking an action is also dependent on possible next state features, we use a two-layer CNN network to summarize features of current and surrounding states into a latent space vector similar to the policy network $G$. In addition, action features may also influence the reward. For example, travelers may prefer going straight to making right or left turns. We represent action features as a one-hot vector $F_a$, and concatenate it with the learned vector from the CNN embedding layer. $g_{\theta}(s, a|c)$ is then learned using a two-layer...
feed-forward network. The shaping term $h_\phi(s|c)$ is approximated using a two-layer feed-forward network, with features of current states $F = [F_s; F_c]$ as input. Although it is also possible to use a CNN network for $h_\phi(s|c)$ similar to $g_\theta(s, a|c)$, through experiments we find that the feed-forward network used in our current model can achieve similar performance with higher computation efficiency. This can be potentially explained that the shaping term $h_\phi(s|c)$ can be regarded as the expected future reward of state $s$ conditioned on destination $c$, and is thus in a sense mostly independent of features of next possible states. With the approximated $g_\theta(s, a|c)$, $h_\phi(s|c)$ and $h_\phi(s'|c)$ values, we can compute $f_{\theta, \phi}(s, a|c)$ using Eq. (10). Once we have $D_{\theta, \phi}(s, a|c)$, the reward can be estimated similar to Eq. (7):

$$R_{\theta, \phi}(s, a | c) = \log (D_{\theta, \phi}(s, a | c)) - \log (1 - D_{\theta, \phi}(s, a | c))$$ (11)

Figure 4: The network structure of the discriminator $D$

3.4.3. Value Estimator $V$

In model implementation, we also use a value estimator to calculate the expected return of the current state $s$ to a destination $c$, denoted as $V(s|c)$. The input of the value estimator is current state and destination features $F = [F_s; F_c]$ and we use a two-layer feed-forward network to estimate the value of each state-destination pair.

3.4.4. Training Algorithm

In this section, we introduce the training process of RCM-AIRL. Recall that Fu et al. (2018) showed that it would be easier to perform discrimination over state-action pairs than trajectories. Therefore, we split the training trajectories $X$ into multiple state-action-destination triplets, forming a training set denoted as $\tilde{X} = \{(s_t(i), a_t(i), c_t(i)) \mid \forall t \in \{1, 2, ..., T_i\}, i \in \{1, 2, ..., N\}\}$. During the training process, we randomly sample a batch of actual data $\tilde{X}_e$ from $\tilde{X}$ at each epoch $e$. In addition, we randomly initialize OD pairs and feed them to the policy estimator $G$ to recursively generate synthetic trajectories. Obviously, each generated trajectory ends when it reaches the destination. A generated sample data set is created by splitting the synthetic trajectories into state-action-destination triplets, denoted as $\tilde{X}_e$. With the actual and synthetic data $\tilde{X}_e$ and $\tilde{X}_e$, the parameters of models are then updated.
using batch gradient descent approach. Specifically, at each epoch \(e\), the reward estimator \(D\) is updated by minimizing the following function:

\[
L_D(\theta, \phi) = -E_{\tilde{X}_e} \left[ \log (D_{\theta,\phi}(s, a | c)) \right] - E_{\hat{X}_e} \left[ \log (1 - D_{\theta,\phi}(s, a | c)) \right]
\]  

(12)

The policy network is trained using a state-of-the-art policy gradient algorithm, namely Proximal Policy Optimization (PPO) (Schulman et al., 2017). It works by maximizing a clipped surrogate objective:

\[
L_G(\pi_G) = E_{\hat{X}_e} \left[ \min \left( r_G(a|s,c) \hat{A}(s,a | c), \text{clip} \left( r_G(a|s,c), 1 - \epsilon, 1 + \epsilon \right) \hat{A}(s,a | c) \right) \right]
\]  

(13)

where the term \(r_G(a|s,c) = \pi_G(a|s,c)/\pi_{G,\text{old}}(a|s,c)\) denotes the probability ratio between the new policy \(\pi_G(a|s,c)\) and the old one \(\pi_{G,\text{old}}(a|s,c)\). The clip function \(\text{clip}(\ast)\) truncates \(r_G(a|s,c)\) within the range of \([1 - \epsilon, 1 + \epsilon]\) and \(\epsilon\) is a pre-defined hyperparameter set as 0.2 in our case. \(\hat{A}(s,a | c)\) denotes the estimated advantage of state-action pair \((s,a)\) conditional on the destination \(c\) and is calculated by adapting the generalized advantage estimator (Schulman et al., 2015). Specifically, for a trajectory \(x\) with length \(T\), the estimated advantage is calculated as:

\[
\hat{A}(s_t, a_t | c) = \begin{cases} 
\delta_t + \gamma \lambda \hat{A}(s_{t+1}, a_{t+1} | c) & t = 1, 2, ..., T_i - 1, \\
\delta_t & t = T_i,
\end{cases}
\]  

(14)

\[
\delta_t = R_{\theta,\phi}(s_t, a_t | c) + \gamma V(s_{t+1} | c) - V(s_t | c)
\]  

(15)

where the parameter \(\lambda\) is used to balance bias and variance and set as 0.95, \(R_{\theta,\phi}(s_t, a_t | c)\) is the estimated reward of the \(t\)-th step of the \(i\)-th trajectory and calculated from Eq. (11), \(V(s_t | c)\) is the estimated value from the value estimator.

The value network is trained by minimizing the difference between the return calculated from \(\hat{A}(s,a | c)\) and the output from the value network:

\[
L_V(\theta_v) = E_{\hat{X}_e} \left[ (\hat{A}(s,a | c) + V_{\theta_v,\text{old}}(s | c) - V_{\theta_v}(s | c))^2 \right],
\]  

(16)

where \(\theta_v, \theta_{v,\text{old}}\) denotes the new and old parameters of the value estimator respectively.

### 3.5. Two Imitation Learning Alternatives to RCM-AIRL

Imitation learning (IL) is closely related to IRL. While IRL tries to recover the optimal reward function \(R^*\) from observed behavior, IL aims to directly learn the optimal policy \(\pi^*\). IL methods can be useful, and sometimes easier to implement, when we focus mostly on route choice predictions, and are less concerned about uncovering the underlying routing preferences. In this section, we introduce two IL methods that can be adapted for route choice modeling. They will later be used as a baseline models to benchmark RCM-AIRL.
3.5.1. RCM-BC: Behavioral Cloning for Route Choice Modeling

In sequential decision-making domains, behavioral cloning (BC) is commonly used as a simpler alternative to IRL. BC applies supervised learning to directly train a policy that matches states to actions based on observed behavior. It is simple and often effective for small problems or with abundant data. However, like most supervised learning methods, it assumes i.i.d data, and thus does not consider the sequential dependencies between state-action pairs within each trajectory. In this section, we introduce a conditional BC approach to route choice modeling, named RCM-BC.

Given the observed trajectories, we divide the trajectories into independent state-action-destination triplets. The objective of RCM-BC is to learn a policy $\pi_B$ that maximizes the likelihood of the observed data:

$$\max_{\pi_B} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \log (\pi_B(a^{(i)}_t \mid s^{(i)}_t, c^{(i)}))$$

(17)

Similar to the policy network $G$ of RCM-AIRL, we approximate $\pi_B$ with a CNN as illustrated in Figure 3. The output of the model is the probability distribution of actions given a state-destination pair and the model parameters are updated using the cross-entropy loss:

$$L(\theta_B) = -\sum_{i=1}^{N} \sum_{t=1}^{T_i} \hat{a}^{(i)}_t \log \hat{P}(a^{(i)}_t),$$

(18)

where $\theta_B$ denotes the set of parameters in RCM-BC, $\hat{a}^{(i)}_t$ is a one-hot vector indicating the true action at time step $t$ in the $i$-th trajectory and $\hat{P}(a^{(i)}_t)$ is the corresponding probability predicted by the model.

3.5.2. RCM-GAIL: Generative Adversarial Imitation Learning for Route Choice Modeling

Generative adversarial imitation learning (GAIL) is a state-of-the-art model-free imitation learning algorithm [Ho and Ermon, 2016]. The formulation of GAIL shares similarities with AIRL as they are both based on the adversarial learning framework. The main difference is that AIRL takes a specific form in its discriminator to recover an unshaped reward, while GAIL directly learns a policy from demonstration data and does not attempt to recover the reward function. Since GAIL has not yet been adapted to the route choice problem, in this section we introduce a conditional GAIL for route choice modeling, namely RCM-GAIL, which will also be used as a baseline for RCM-AIRL.

Similar to RCM-AIRL, RCM-GAIL consists of three main modules: a discriminator, a generator and a value estimator. The discriminator acts as a classifier to distinguish actual and generated data, while the generator aims to generate realistic trajectories that can confuse the discriminator. For fair comparison, we use the same network structure of the generator $G$ and value estimator $V$ for RCM-GAIL as those in RCM-AIRL. For the discriminator, we use the sub-network to approximate $g_\theta(s, a)$ in RCM-AIRL. Compared with the policy, the reward is more fundamental and thus more generalizable to unseen environments. As we will show later in experiment results (see section 5), RCM-AIRL
can achieve consistently better performance than RCM-GAIL for the route choice problem, albeit not by a large margin, and produce more interpretable behavioral insights.

4. Experiment Settings

4.1. Data

For route choice analysis, the most important data are the observed trajectories $X$. The specific dataset used in this study is retrieved from one of the major taxi companies in Shanghai, China. It contains the GPS traces of 10,609 taxis from 2015-04-16 to 2015-04-21. In our experiments, we only target a specific region of Shanghai with sufficient trajectory coverage (see Figure 5). The selected road network consists of 320 intersection nodes and 714 road links. There are over 35 million records in the selected region, with an average sampling rate of roughly 10 seconds. Each record consists of the information of taxi ID, date, time, longitude, latitude and occupied flag, which is a binary indicator flagging whether the taxi is occupied. For route choice analysis, we only include occupied taxi trips with a well-defined destination to better approximate general routing scenarios. The GPS data has been mapped onto road networks using an open-source map matching method called Fast Map Matching [Yang and Gidófalvi 2018], which is itself an implementation of the ST-Match approach [Lou et al. 2009]. We filter out trips that are too short (fewer than 15 road links) or too cyclic (visiting the same link more than once). This results in 24,470 trajectories for experiments covering 664 destinations.

Figure 5: The road network used in our experiments
4.2. Baseline Models

We compare RCM-AIRL, RCM-BC and RCM-GAIL against the following baseline models:

- **Path Size Logit (PSL)** ([Ben-Akiva and Bierlaire, 1999]) is arguably the most commonly used route choice model in the literature. To account for overlaps across routes, it extends the Multinomial Logit (MNL) model by including correction terms to penalize routes that share links with other routes. The probability of choosing a route $j$ from a set of candidate routes $J$ is given by

$$P(j) = \frac{\exp(v(j) + \beta \ln(\kappa_j))}{\sum_{j' \in J} \exp(v(j') + \beta \ln(\kappa_{j'}))} \quad (19)$$

where $P_j$ is the probability of choosing route $j$, $v(j)$ is a linear function to approximate the deterministic utility of route $j$, $\beta \geq 0$ is the path size scaling parameter, and $\kappa_j \in (0, 1]$ is the path size term for route $j$. More distinct routes with less shared links tend to have a larger path size term. In our implementation, we choose 5 shortest paths for each OD pair to form the candidate choice set based on Marra and Corman (2021). The following path-level features are included for the computation of utility scores: path length, number of link segments, number of turns (including left, right and u-turns) and traversing frequency of different link levels (which will be discussed later).

- **DNN-PSL** ([Marra and Corman, 2021; He et al., 2020]) is an extension of PSL by using deep neural networks to infer the utility function of path alternatives. Compared with PSL, DNN-PSL is more flexible to capture nonlinear relationships and advanced context features. In our implementation, we employ a two-layer feed-forward network to approximate the utility function following He et al. (2020). For fair comparison, we use the same candidate path sets and feature settings as PSL.

- **Recursive Logit** ([Fosgerau et al., 2013]) is a link-based route choice model, where the route choice is modeled as a sequence of link choices using a dynamic discrete choice framework. The Recursive Logit model gives probabilities of choosing the next state $s'$ at state $s$ according to the formula:

$$P(s' \mid s) = \frac{\exp(v(s' \mid s) + V(s'))}{\sum_{s'' \in S(s)} \exp(v(s'' \mid s) + V(s''))}, \quad (20)$$

where $v(s' \mid s)$ is a linear function to approximate the instantaneous utility of choosing the next link $s'$ at state $s$, $V(s')$ is a value function to represent the expected downstream utility of choosing $s'$. Compared with PSL, it skips path sampling and can achieve more consistent results. In our implementation, the following link-level features are considered for the computation of utility scores: link length, link level and moving direction.
4.3. Feature Extraction

As introduced earlier, we consider three types of features in the model. **State features** $F_s$ capture characteristics of each link. **Context features** $F_c$ are those features dependent on the final destination. Instead of directly characterizing the destination itself, we find that it is better to use features to describe the relationship between the current state and destination. **Action features** $F_a$ indicate the moving directions of the traveler. Table 1 provides a detailed description of each input feature.

| Feature         | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| **State features $F_s$** |                                                                             |
| Link length     | The length of a link.                                                        |
| Link level      | Whether a link belongs to primary, secondary, tertiary, living street,       |
|                 | residential or unclassified link level.                                      |
| **Context features $F_c$** |                                                                             |
| Shortest distance | The shortest travel distance from the current link to the destination.      |
| Number of links | The number of links in the shortest path from the current link to the        |
|                 | destination.                                                                |
| Number of turns | The number of left, right and u-turns along the shortest path from the       |
|                 | current link to the destination.                                            |
| Frequency of link levels | The number of primary, secondary, tertiary, living street, residential and |
|                 | unclassified links in the shortest path from the current link to the        |
|                 | destination.                                                                |
| **Action features $F_a$** |                                                                             |
| Direction       | Whether the traveler is moving front, right front, right, right back,       |
|                 | back, left back, left or left front.                                         |

4.4. Evaluation Metrics

For model evaluation, we measure the similarity of true and predicted trajectories using the following three metrics:

- **Edit Distance (ED)**. Edit distance is a common way of quantifying how dissimilar two sequences are to one another by counting the minimum number of operations required to transform one sequence into the other. It is computed as:

$$ED = \frac{1}{N} \sum_{i=1}^{N} \min \left( \frac{\text{Edit}(\hat{x}_i, x_{i,ref})}{T_{i,ref}}, 1 \right),$$

where $N$ is the number of trajectories in the test set, $\hat{x}_i$ is the $i$-th predicted trajectory, $x_{i,ref}$ is the reference trajectory in the test set with the same OD and $T_{i,ref}$ is the length of $x_{i,ref}$. It is worth to note that for an OD pair, there may exist multiple reference trajectories. In such cases, we compare the predicted trajectory with all reference trajectories in the test set and keep the best performance.
• **BiLingual Evaluation Understudy score (BLEU).** In machine translation, BLEU score measures how similar a candidate text is to the reference texts, with values closer to one representing more similar texts. Recent research has also used it to measure trajectory similarities (Choi et al., 2021). It works by comparing $n$-gram matches between each predicted trajectory to the reference trajectories with the same OD in the test set:

$$BLEU_n = \frac{1}{N} \sum_{i=1}^{N} \min(1, \frac{T_i}{T_{i,\text{ref}}})(\prod_{j=1}^{n} P_j)^{\frac{1}{n}},$$  \hspace{1cm} (22)

$$P_j = \frac{\sum_{m \in C_j} \min(w_m, w_{m,\text{max}})}{W},$$  \hspace{1cm} (23)

where $C_j$ is a set of unique $j$-gram chunks in the predicted trajectory, $w_m$ is the number of occurrences of chunk $m$ in the predicted trajectory; $w_{m,\text{max}}$ is the maximum number of occurrences of chunk $m$ in one reference trajectory, and $M$ is the total number of chunks in the predicted trajectory.

• **Jensen-Shannon Distance (JSD).** In probability theory, JSD measures the similarity between two probability distributions based on KL (Kullback–Leibler) divergence. In our case, we use the route frequencies (i.e., the occurrence of each unique route divided by the total number of trajectories) to represent the probability distribution of a trajectory dataset. Predicted trajectories that do not exist in the test set are labeled as “unseen” routes following Choi et al. (2021). Given the probability distribution of the observed and predicted trajectories $p$ and $q$, the JS distance is defined as follows:

$$d_{js} = \sqrt{\left( D_{KL}(p \parallel \frac{p + q}{2}) + D_{KL}(q \parallel \frac{p + q}{2}) \right) / 2}$$  \hspace{1cm} (24)

where $D_{KL}$ is the KL divergence, and $D_{KL}(p \parallel q)$ is also known as the relative entropy of $p$ with respect to $q$, which is defined as:

$$D_{KL}(p \parallel q) = \sum_i p_i \log \frac{p_i}{q_i}.$$  \hspace{1cm} (25)

5. Results

5.1. **Comparison of Model Performance**

In this section, we evaluate the performance of different models on two datasets: one is a single-destination dataset, including 749 trajectories to the same destination; the other is a multi-destination dataset, which includes 244,70 trajectories covering 664 destinations. For each dataset, we use 20% data for model training and 80% for testing.

Table 2 summarizes the prediction performance of different models on both datasets. It can be found that RCM-BC, RCM-GAIL and RCM-AIRL all perform significantly better than the existing baseline models, suggesting the effectiveness of IRL/IL methods for route
choice modeling. Compared to RCM-BC and RCM-GAIL, RCM-AIRL performs better regarding all evaluation metrics, confirming the advantage of the IRL framework over IL for the route choice problem. Unlike RCM-BC, RCM-AIRL can better estimate long-term reward and capture the probability distribution of route choices. Relative to RCM-GAIL, RCM-AIRL can better recover the underlying reward function, which makes it more robust for route choice modeling under different routing environments.

Among baseline models, DNN-PSL performs slightly better than PSL on the single-destination data while achieves similar performance on the multi-destination data. This suggests that the contribution of DNNs on PSL might not be significant on our dataset, though this might change when more sophisticated features are included. On the single-destination data, Recursive Logit performs better than PSL regarding ED and BLEU. This is potentially because Recursive Logit can be regarded as an extension of PSL with an infinite set of path choices. However, Recursive Logit performs relatively poor regarding JSD. While PSL considers a set of reasonably good paths, Recursive Logit considers all possible path choices and the probability distribution of route frequencies can be more spread out. On the multi-destination data, PSL performs notably better than Recursive Logit regarding all evaluation metrics. This is because Recursive Logit assigns a fixed utility score for each state-action pair regardless of the destination. Compared with these baseline models, our proposed RCM-AIRL framework can improve the prediction performance significantly, with ED improvement by 57.0% and 30.3% on single- and multi-destination data respectively.

| Models          | Single-destination | Multi-destination |
|-----------------|--------------------|-------------------|
|                 | ED     | BLEU  | JSD  | ED     | BLEU  | JSD  |
| Path-based      |         |       |      |         |       |      |
| PSL             | 0.211  | 0.746 | 0.325 | 0.287  | 0.643 | 0.406 |
| DNN-PSL         | 0.207  | 0.750 | 0.320 | 0.287  | 0.643 | 0.406 |
| Recursive Logit | 0.209  | 0.770 | 0.362 | 0.328  | 0.608 | 0.444 |
| Link-based      |         |       |      |         |       |      |
| RCM-BC          | 0.133  | 0.868 | 0.297 | 0.221  | 0.744 | 0.329 |
| RCM-GAIL        | 0.104  | 0.888 | 0.306 | 0.229  | 0.718 | 0.323 |
| RCM-AIRL        | 0.089  | 0.895 | 0.253 | 0.200  | 0.754 | 0.316 |

To intuitively compare different models, Figure 6 illustrates several predicted trajectories for two example OD pairs using models trained on the multi-destination dataset. As evidenced by the ED scores, RCM-AIRL can more accurately trace the real trajectories in the two selected cases. PSL and DNN-PSL tend to minimize the travel distance, and may not capture the deviation from shortest paths that are observed in actual route choices. There are some obvious detours in the predicted trajectories of Recursive Logit and GAIL (see Figure 6b). For Recursive Logit, this is because it does not consider destination-specific utilities. For GAIL, this is potentially because the learned model is not as generalizable to different routing environments. BC fails to provide satisfying results either, which might be due to the lack of consideration for long-term reward.
5.2. Model Generalizability to Unseen Destinations

DNNs may easily suffer from low generalizability when applied to testing data different from training data. For route choice analysis, this may occur when the model encounters new destinations that are unseen in during model training. To investigate the model generalizability, we design specific training and testing datasets so that destinations in the test set are never seen during the training phase. This setting allows us to properly evaluate how the model generalize to new routing scenarios.

Another disadvantage of applying DNNs for choice modeling is their need for large amounts of training data. When sufficient training data is provided, DNNs can usually outperform traditional models since they can capture more complex relationships. However, when only limited training data is available, DNNs may not work well. To investigate how the amount of training data influences the model performance, we use a fixed test set with 14450 trips but vary the training data size from 100, 1000 to 10000 trajectories.

Table 3: Performance comparison of different models to unseen destinations using different amounts of training data

| Models               | 100 training trips | 1000 training trips | 10000 training trips |
|----------------------|--------------------|----------------------|-----------------------|
|                      | ED    | BLEU   | JSD  | ED    | BLEU   | JSD  | ED    | BLEU   | JSD  |
| Path-based           |        |        |      |        |        |      |        |        |      |
| PSL                  | 0.264  | 0.674  | 0.387| 0.264  | 0.674  | 0.387| 0.264  | 0.674  | 0.387|
| DNN-PSL              | 0.264  | 0.674  | 0.387| 0.264  | 0.674  | 0.387| 0.264  | 0.674  | 0.387|
| Recursive Logit      | 0.358  | 0.604  | 0.489| 0.357  | 0.607  | 0.496| 0.351  | 0.613  | 0.486|
| Link-based           |        |        |      |        |        |      |        |        |      |
| RCM-BC               | 0.557  | 0.475  | 0.537| 0.399  | 0.600  | 0.454| 0.207  | 0.749  | 0.315|
| RCM-GAIL             | 0.303  | 0.655  | 0.400| 0.250  | 0.703  | 0.356| 0.225  | 0.725  | 0.344|
| RCM-AIRL             | 0.248  | 0.709  | 0.356| 0.205  | 0.753  | 0.316| 0.194  | 0.766  | 0.301|

Table 3 summarizes the prediction performance of different models on unseen destinations using different amounts of training data. It is found that RCM-AIRL still achieves
the best performance compared with the other models. With only 100 training trajectories, RCM-AIRL can already outperform traditional models. As the training data size increases to 1000 trajectories, the relatively improvement is enlarged. The results with 10,000 trajectories are slightly better than the results with 1000 trajectories. This suggests that RCM-AIRL is generalizable to unseen data and has relatively low requirement of training data. The performance of PSL and Recursive Logit does not change much as the training data increases. This is reasonable since these models assume linear relationships and have only a small number of parameters to estimate. Adding training data does not contribute much to the performance of DNN-PSL either. This is potentially because DNNs are restricted by the pre-defined choice set in path-based models and cannot fully uncover the complex relationships. Unlike conventional DCMs or path-based deep learning models, the performance of RCM-BC is significantly affected by the amount of training data. With 100 or 1000 training trips, RCM-BC performs much poorer than the other models, while with 10000 training trips, RCM-BC can achieve similar performance with RCM-AIRL. This is because behavior cloning assumes the data is i.i.d and thus has a high requirement of training data to uncover meaningful relationships. With 100 training trips, RCM-GAIL is unable to provide satisfactory results either. With more training data, the performance of RCM-GAIL can be improved greatly, but is still worse than RCM-AIRL. This suggests that the training of IL methods tend to require more data than comparative IRL methods, at least for route choice modeling.

5.3. Interpretability of Learned Route Choice Behavior

In addition to modeling realistic route choice behaviors, understanding the underlying human routing preferences is important for transportation network planning, policy design, and infrastructure investment. Interpretability of such models are also essential for ensuring the model trustworthiness. In this section, we explore why RCM-AIRL makes such predictions from both global and local perspectives.

From a global perspective, we use SHapley Additive exPlanations (SHAP) to understand how the input features influence the estimation results from the reward network of RCM-AIRL. SHAP is an explainable AI technique which uses a game theoretic approach to explain machine learning models (Lundberg and Lee, 2017). Specifically, it assigns each feature an optimal Shapley value, which indicates how the presence or absence of a feature changes the model prediction result (i.e., the estimated reward in our case). Recall that the input of the reward network consists of three types of features: state features of the current link, context features related to the destination, and action features denoting the movement direction. We show the distribution of SHAP values for different features in Figure 7. It can be found that the mean Shapley value of the distance to the destination is much larger than the other features. From the distribution of SHAP values, we can further find that shorter distances are associated with higher SHAP values. As expected, travelers prefer shorter routes to reduce their travel costs. In addition to travel distance, the link level also influences route choices: primary and secondary links are related with positive SHAP values, indicating that travelers prefer main roads which usually have better driving conditions and allow vehicles to travel faster. Another factor that influences driving behavior is the movement direction. It is
found that moving forward (e.g., front) is assigned with a positive SHAP value, while moving left, right and backward are assigned with negative SHAP values, suggesting that drivers prefer moving straight ahead to making turns. Moreover, left turns are associated with higher feature importance than right turns. In cities with right-hand traffic (e.g., Shanghai), making left turns usually requires waiting longer at intersections, and thus derives higher cost compared with right turns.

Figure 7: Distribution of Shapley values for all features in the discriminator of RCM-AIRL. (Fc denotes context features, Fs denotes state features and Fa denotes action features)

From a local perspective, we can use the model estimates to quantitatively compare the reward scores assigned to different states and actions. Specifically, the reward $R(s, a \mid c)$ learned from the reward estimator can be used to approximate the instantaneous utility derived from choosing an action $a$ at state $s$ conditioned on destination $c$, while the value $V(s \mid c)$ learned from the value estimator can be used to represent the expected downstream utility of choosing a state $s$ with destination $c$. In Figure 8a, we visualize the estimated value of different links to a selected destination. Generally, links that are closer to the destination would be assigned with a higher value score. In this way, the model is encouraged to choose next link associated with a shorter distance to the destination. In Figure 8b, we illustrate the estimated reward of taking different actions along a selected route. It can be found that drivers do not always choose the next link that can maximize the reward. For example, at state $s_1$, the traveler chooses $a_2$, while $R(s_1, a_2 \mid c) < R(s_1, a_1 \mid c)$. This indicates that travelers may consider not only short-term but also long-term utilities, demonstrating the advantage of IRL in considering the cumulative reward throughout the whole trip.
5.4. Effect of Latent Individual Features

Classical DCMs for choice modeling often include both attributes of the alternatives (i.e., paths or links) and characteristics of decision makers (i.e., individual travelers) such as age, gender, income, etc. In our proposed modeling framework, characteristics of each individual traveler can be treated as part of the context information $c$. Due to data limitations, we are not able to incorporate explicit individual characteristics in the experiments. Nevertheless, because each GPS trace is associated with a vehicle ID (assumed to be an individual identifier), it is still possible to extract latent individual features directly from data with DNNs. Specifically, we can learn an embedding vector for each individual traveler as part of the route choice model, which would enable personalized routing behavior prediction that is useful for some transportation applications. In this section, we conduct experiments to explore whether the latent individual features learned from DNNs can contribute to the model performance. To ensure that abundant training data for each driver is provided, we select 50 drivers with the most trips for the experiments, and for each driver, we split 80% of trajectories into training data and 20% into test data. The results with and without individual embedding features are summarized in Table 4. It is found that incorporating individual features can indeed contribute to model performance when sufficient training data is provided. This also validates the advantage of deep neural networks in incorporating complex and high-dimensional context features. When training data is sufficient, it is possible to include more context features, such as time of the day, network structure, etc, which we will leave for future work. When only a limited amount of training data is available, it is still possible to train a well-performing model with good generalizability and interpretability using handcrafted network features, as illustrated in our previous experiments.

6. Conclusion

In this paper, we propose a deep inverse reinforcement learning (IRL) framework for route choice modeling. In this framework, the route choice problem is formulated as a Markov
Decision Process, and the goal is to recover the underlying reward function (i.e., routing preferences) that can best explain, and ultimately predict, actual human route choice behavior. Unlike previous works, both the reward and policy functions are assumed to be conditional on the trip destination and other contextual information, making the framework generalizable to different routing scenarios. Specifically, a conditional version of the adversarial IRL (AIRL) approach is introduced to learn these functions efficiently from the data in a model-free fashion. To validate the proposed approach (RCM-AIRL), extensive experiments are conducted using taxi GPS data from Shanghai, and results confirm its improved performance over conventional discrete choice models as well as two imitation learning baselines—behavioral cloning (RCM-BC) and Generative Adversarial Imitation Learning (RCM-GAIL). The performance improvement holds even for unseen destinations and limited training data. We also demonstrate the model interpretability using shapely additive explanations, which reveal the reward distribution across the road network and the effects of different features. The proposed methodology is general and should be adaptable to other route choice problems across different modes and networks.

The proposed RCM-AIRL is distinct from other baseline models, and thus provides a new and promising direction for future development of route choice models. Unlike widely used path-based models such as Path Size Logit, RCM-AIRL is link-based and does not require path sampling. Therefore, it can leverage detailed network features and potentially deal with dynamic routing environments. Compared to existing link-based models like Recursive Logit, the inclusion of deep architectures in RCM-AIRL makes it flexible enough to incorporate high-dimensional features and capture complex relationships. In particular, the conditional model structure allows for explicit consideration of the destination information, which is essential for route choice modeling especially in multi-destination scenarios. The two imitation learning alternatives, RCM-BC and RCM-GAIL, share some similarities with RCM-AIRL but show relatively worse performances. Unlike IRL, imitation learning does not aim to recover the reward function and instead tries to directly estimate the policy. However, the reward function (i.e., routing preferences) is more fundamental, robust and generalizable than the policy (i.e., routing patterns). In addition, the ability to uncover underlying routing preferences is important to ensure model trustworthiness and design actionable policies. Between the RCM-BC and RCM-GAIL, the former assumes i.i.d data and essentially ignores the sequential dependencies across link choices within the same trip. Nevertheless, behavioral cloning is structurally simple, easier to train, and can achieve good performance with abundant training data, making it a useful alternative in certain situations.

This study is not without its limitations, and future research can extend this work in several directions. First, the proposed RCM-AIRL is trained based on adversarial learning,
but generative adversarial networks (GANs) in general can be difficult to train, which is itself an unresolved issue in artificial intelligence research. Training GANs usually depend on careful model tuning and feature engineering. More work needs to be done to investigate how model specification and hyperparameters influence the stability and convergence behavior of the model. Second, features tested in this study are mostly based on prior literature and can be further extended. One advantage of deep learning methods is their ability to incorporate high-dimensional features. Therefore, future studies may examine the effects of other complex features, such as traffic dynamics, road network design and land use patterns, on human routing behavior. Third, the experiments in this study are only based on taxi GPS data on a relatively small road network. Future studies should explore how to extend the proposed model to a larger network and compare performance across multiple travel modes. The former requires additional measures to tackle data sparsity problems and the latter needs inclusion of mode-specific features. Last, in this work we only consider model generalizability to unseen destinations in the same network. Future research may further investigate how such deep learning models can generalize to new networks and entirely new cities. Again, this will depend on the specific network representation and feature selection in the model.

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