Intention Recognition in Real-Time Interactive Navigation Maps

Demonstration Track

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ABSTRACT

In this demonstration, we develop IntentRec4Maps, a system to recognise users' intentions in real-time interactive navigation maps. IntentRec4Maps uses the Google Maps Platform as the real-world interactive map, and a well-known approach for recognising intentions in real-time. We showcase IntentRec4Maps using two different *Path-Planners* and a *Large Language Model* (LLM).

KEYWORDS

Intention Recognition, Goal Recognition, Path Planning

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1 INTRODUCTION

Real-time interactive navigation maps are integral tools in our daily lives. Interactive maps use *Global Positioning* (e.g., GPS, GLONASS, Galileo, BeiDou) to provide accurate and real-time location information. Mobile applications use such technologies to enable users to track their location and receive turn-by-turn directions for walking, driving, or public transportation. Existing interactive navigation maps include *markers* for various location points of interest, such as restaurants, gas stations, hotels, etc. This helps users to plan their routes based on their interests or needs during a journey. Interactive navigation maps, such as Google Maps, Apple Maps, Waze, MapBox, etc, require *Path-Planning* algorithms [3, 5, 7] (along with *heuristics*) to generate optimal routes for users. This functionality can be further enriched by integrating real-time traffic data, historical traffic patterns, and various other real-world factors that could ensure the generation of optimal routes. Nevertheless, as far as we are aware, existing interactive navigation maps platforms do not provide *Real-Time Intention Recognition* [8, 10, 11] for individuals.

Empowering centralised systems with the ability to recognise the intended locations of users (either driving, walking, etc) could be beneficial to monitor and track resources in a more effective way, such as vehicles or personnel, packages to be delivered, etc, and is of significant importance for logistics, fleet management, or any scenario in which asset movement needs to be closely monitored.

IntentRec4Maps is a system able to recognise users' intended locations in interactive maps for real-world navigation, and uses the Google Maps Platform for interactive navigation, as it provides useful *Application Programming Interfaces* (API), such as *Maps Embed* API, *Directions* API, *Geocoding* API, etc. IntentRec4Maps recognises users's intentions with a real-time recognition approach called *Mirroring* [19]. *Intention Recognition* has been applied to many distinct scenarios, such as digital games [14], recognition of culinary recipes in video streams [6], decision-making advisor [17], behaviour explanation [2], behavioural cues for recognising intentions [16], intention recognition in latent space images [1], and intent recognition of pedestrians/cyclists via 2D pose estimation [4]. To our knowledge, our system pioneers real-time intention recognition in interactive navigation maps. We test the efficiency [20] of IntentRec4Maps in complex recognition problems using two different symbolic *Path-Planners* and a *Large Language Model* (LLM). We showcase our system in a video on https://youtu.be/Nf8g9dxqvFw.

2 INTENTREC4MAPS

IntentRec4Maps comprises two main components (Figure 1): the *Interactive Map Platform* component (Section 2.1), which relies on the Google Maps Platform and its APIs to display the interactive map for real-time intention recognition; and the *Real-Time Intention Recognition* component (Section 2.2), which performs real-time recognition using an input information (possible intentions, observations, etc), and yields a probability distribution of the most and least likely intentions in response to received observations.

2.1 Interactive Map Platform

We use the Google Maps Platform as the interactive map, as it provides a very robust set of APIs for real-world navigation. The environment where IntentRec4Maps performs intention recognition

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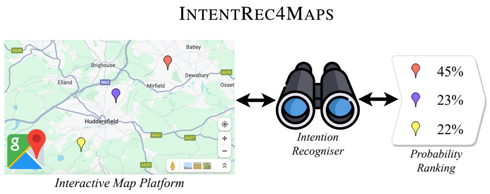

Figure 1: IntentRec4Maps Overview.

is represented by the road network with *location points of interest* (denoted as loc), and the *state-space* consists of the geographical locations on the map. A *location point* is represented using *latitude* and *longitude* coordinates, e.g., loc = ⟨53.483959, −2.244644⟩. Actions consist of moving from one location point to another, following a specific route (or path) according to a transportation mode (e.g., walking, driving, cycling, public transport). A route $\pi = \{\texttt{loc}_1, ...\texttt{loc}_n\}$ is a sequence of *latitude* and *longitude* coordinates that achieves a specific location point from an initial location point. Our system relies on the Earth's sphere space (defined in the previous paragraph) to define an *Intention Recognition* problem in real-world navigation maps. An *Intention Recognition* problem in real-world navigation maps is a tuple $\langle \mathcal{M}, init_{\texttt{loc}}, \mathcal{I}, Obs \rangle$, where: $\mathcal{M}$ is the *real-world map environment*, represented by a road network with location points as latitude and longitude; $init_{\texttt{loc}}$ represents the *initial location point* as latitude and longitude; $\mathcal{I} = \{\texttt{loc}_1, ...\texttt{loc}_n\}$ is a set of intended *location points* that an observed user may aim to achieve; and *Obs* is a sequence of *observations* (represented as latitude and longitude coordinates) that the system observes incrementally, representing a sequence of observed coordinates for achieving an *intended location point* $\texttt{loc}^* \in \mathcal{I}$. An "ideal solution" is recognising (as *top-1* intention in the probability ranking) the *intended location point* $\texttt{loc}^* \in \mathcal{I}$ (which is **unknown** from the system's perspective) that an observed user aims to achieve for an observation sequence *Obs*. We encode an *Intention Recognition* problem using JSON (JavaScript Object Notation).

2.2 Real-Time Intention Recognition

IntentRec4Maps uses the well-known *Mirroring* [9, 19] online recognition, a model-based recognition approach [13**?**]. Vered et al. [19] argues that we humans tend to infer other people's intentions by "*mirroring*" their *observed* behaviour with some "*optimal* (*ideal*)" expected behaviour. We adapt *Mirroring* for real-world navigation maps, and compute two types of routes for the observed user, as follows. We first compute an **ideal route** π from the initial location $init_{\texttt{loc}}$ for every location point loc in the set of possible intentions $\mathcal{I}$. Afterwards, we compute what we call **observation route** π_{Obs}, a route that complies with the observations in *Obs*, and is computed from the initial $init_{\texttt{loc}}$ complying with the observations *Obs* and then achieving each of the possible intentions $\mathcal{I}$. Thus, for every possible intended location in $\mathcal{I}$, we compare its ideal route π with its observation route π_{Obs} and compute a *score* (denoted as ϵ). The score ϵ ($0 \leq \epsilon \leq 1$) represents how "compliant" (assuming optimal routes [12]) the sequence of observations *Obs* from the agent's behaviour is to a route π for achieving a location point of interest. The closer ϵ is to zero for location point of interest, the .more likely such a location point interest is the intended one. We adopt the probabilistic framework of Ramírez and Geffner [15] to compute a posterior probability distribution for every location point loc in $\mathcal{I}$ using the score ϵ. We formalised it as $\mathbb{P}(loc \mid Obs) = \eta \cdot \mathbb{P}(loc) \cdot \mathbb{P}(Obs \mid loc)$, where η is normalisation factor, $\mathbb{P}(loc)$ is a prior probability for a location point, and $\mathbb{P}(Obs \mid loc)$ is the probability of the observations *Obs* for a location point. We compute $\mathbb{P}(Obs \mid loc)$ using the score ϵ, namely, $\mathbb{P}(Obs \mid loc) = [1 + (1 - \epsilon)]^{-1}$. The computation of $\mathbb{P}(Obs \mid loc)$ involves comparing the routes π and π_{Obs} to compute the score ϵ. Fundamentally, ϵ estimates the similarity between the routes π and π_{Obs}, point by point, using the *Haversine Formula* implemented in the $\epsilon(\pi, \pi_{Obs})$ function, ensuring a geographically accurate assessment of spatial separation of the points in π and π_{Obs} in the Earth's sphere space. We apply a threshold to determine when two location points similar enough according to their spherical distance, allowing for fine-tuning of the similarity comparison based on specific needs. The *similarity distance comparison* between the location points in π and π_{Obs}, is denoted as $(l_\pi, l_{\pi_{Obs}}) =$

$$2 \cdot R \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_{\pi_{Obs}}) \cdot \cos(lat_\pi) \cdot \sin^2\left(\frac{\Delta long}{2}\right)}\right)$$

where R is the spherical radius, $\langle lat_\pi, long_\pi \rangle$ and $\langle lat_{\pi_{Obs}}, long_{\pi_{Obs}} \rangle$ correspond to the latitude and longitude coordinates for the routes location points in π and π_{Obs}, respectively, and $\Delta lat = |lat_{\pi_{Obs}} - lat_\pi|$ and $\Delta long = |long_{\pi_{Obs}} - long_\pi|$.

We used three experimental setups and tested different ways of extracting routes (paths) for the recognition process: (1) we use the Google Maps *Route-Planner*, as a *Baseline*; (2) we use the MapBox *Route-Planner*[1]; and (3) we use a LLM (i.e., ChatGPT4 API[2]) as a route-planner, asking directions via prompt. The *Baseline* represents the IntentRec4Maps and an observed person using the same navigation system, specifically, the Google Maps API. We use MapBox as an alternative navigation system for the recognition process, making the recognition process more difficult. The rationale for using an LLM as a route-planner is to investigate how "reliable" an LLM is when used as a solver for a reasoning/planning process, drawing inspiration from the work of [18].

3 CONCLUSIONS

We developed IntentRec4Maps[3], a novel recognition system that is able to recognise users' intentions in real-time interactive navigation maps. Our system employees the *Haversine Formula* to compute distances between locations in the Earth's sphere space. We aim to extend IntentRec4Maps and implement other recognition functionalities, such as dealing with irrational [12] and possibly adversarial behaviour, and noisy and spurious observations.

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[1] https://docs.mapbox.com/help/getting-started/directions/
[2] https://openai.com/blog/gpt-4-api-general-availability
[3] https://github.com/PeijieZ/IntentRec4Maps

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