An Explainable Knowledge-based AI Framework for Mobility as a Service

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Abstract

Mobility as a Service (MaaS) is a relatively new domain where new types of knowledge systems have recently emerged. It combines various modes of transportation and different kinds of data to present personalized services to travellers based on transport needs. A knowledge-based framework based on Artificial Intelligence (AI) is proposed in this paper to integrate, analyze, and process different types of mobility data. The framework includes a knowledge acquisition process to extract and structure data from various sources, including mobility experts and add new information to a knowledge base. The role of AI in this framework is to aid in automatically discovering knowledge from various data sets and recommend efficient and personalized mobility services with explanations. A scenario is also presented to demonstrate the interaction of the proposed framework's modules.

1 Introduction

In recent years, with an increasing number of transport services offered in cities and the advancements in technology, an innovative Mobility as a Service (MaaS) concept was introduced [7]. MaaS combines different transportation modes to deliver users' various services based on transport needs, including trip planning, reservation, and payments, through a single interface [8]. The main goal of MaaS is to make commuting convenient for travellers and offer them flexible, priceworthy, reliable, and sustainable mobility services for goods shipping and delivery. Integrating various services and systems such as electronic ticketing, booking, route planning, and payment services across different modes of transportation can make this happen, as part of Smart Cities transformation [13].

Artificial Intelligence (AI) is also increasingly used these days in MaaS to develop advanced mobility services [5] leveraging both spatial (location-based) and temporal detail recorded frequently by devices such as smartphones, micro-mobility vehicles, on-board vehicle computers, or app-based navigation systems to improve traffic flow or transportation logistics. One of the prerequisites of using AI models in a multi-stakeholder domain such as transportation is to provide explainability and the possibility of tracing back the decisions made to their sources. It is crucial for building trust and adoption of AI systems in settings where transparency is required due to high-stakes scenarios [6].

The interpretation of huge amount of data collected from several sources can not be achieved without the presence of a knowledge-based AI system. For example, if a knowledge-based AI system can capture travellers' preferences, it can exclude travel plans or routes of no interest to those users. However, how to obtain this knowledge is one of the key open challenges. Broadly speaking, it can be acquired by extracting and structuring data or information from various sources, including human experts, and storing the data into a knowledge base. The system's knowledge acquisition process may consist of collecting facts, designing rules, concepts, procedures, heuristics formulas, relationships, ontologies, statistics, or other helpful information. Acquiring specific knowledge about travellers allows MaaS to recommend a ranked list of MaaS planes/routes to select the ones that better fit the user's preferences by inferring the similarity of available plans to the user's

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profile. Knowledge-based AI systems also enable the possibility of providing the right information to the right user with understandable explanations. In this study, we investigate how one can combine different information sources with an understanding of the traveller's context to present a personalized service to travellers based on the users' preferences. The article aims at proposing a knowledge-based AI framework to provide personalized and explainable mobility services to travellers, service providers, drivers, and other mobility users. This framework covers procedures for data collection, knowledge extraction, inference, recommendations and explanations.

2 Related Works

Understanding what makes MaaS particularly challenging is the first step toward identifying the essential features required of the proposed framework in this study. AI has been generally used successfully in many different settings in the field of transportation over the years; see, for example [14, 10, 2, 15].

A recent study [9] proposed an AI model to predict the traffic intensity before the vehicles reach the intersection. The vehicle trajectory data was collected from GPS sensors, longitudinal, lateral and yaw motion, heading and speed of automobile movements. The vehicles with similar conditions were clustered to provide a route planner to users. In terms of traffic flow prediction, Li and Xu [11] developed a short-term traffic flow prediction model based on Support Vector Regression (SVR) to improve the accuracy of traffic flow prediction systems on the California Highway Performance Evaluation System (PeMS) videos. AI-based models are also used to classify driving styles, ranging from aggressive to calm. The classification algorithms are widely used to customize driver assistance systems, assess mobility, crash risk, fuel consumption, or emissions, among others. For example, Mohammadnazar et. al [12] extracted volatility measures based on speed, lateral longitudinal acceleration, and temporal driving volatility (using a 3-second time-frame window) from a set of data and used them for cluster drivers (in aggressive, normal, and calm) using K-means and K-medoids methods. Although several studies applied various AI-based models in MaaS, relatively few of them considered leveraging knowledge-based systems in the models to provide personalized and explainable mobility services. Arnaoutaki et al. [1], as an example, proposed a hybrid knowledge-based system that uses constraint programming mechanisms to provide mobility plans to travellers based on their preferences and exclude the routes that do not match those preferences. Close to this study and in conjunction with the other AI-based models, we propose a knowledge-based AI mobility framework that utilizes context information and knowledge of mobility (acquired from travellers and vehicles) to provide personalized mobility services while being interpretable and explainable for both travellers and domain experts.

3 Proposed Framework for Mobility as a Service

There are different sources of mobility knowledge, including contextual data (weather, traffic, disruptions), operational (routes, schedules, business rules, and deliveries), personal (passengers, travellers, and drivers) and transactional (booking, tickets, and payments). We propose a knowledge-based framework (Figure 1) that provides customized, explainable, and enriched services based on various types of mobility data. The framework intends to integrate different mobility data types processes, analyze them, and recommend a real-time personalized service with customized explanations based on mobility users' needs. We will discuss the main modules of this framework briefly below.

3.1 Semantic enrichment

A semantic enrichment module matches concepts in a system with the most appropriate semantic entities available from various sources. It leverages mobility ontologies, vocabularies, and API services to fetch data and integrate similar entities using semantic similarities metrics from different resources. The outcome of this module is an enriched set of entities that are injected into the knowledge base.

3.2 Mobility ontology

Ontology can be seen as a formal representation of entities in a domain, their relations, properties or attributes, and constraints. Different mobility concepts can be defined as terminologies and vocabularies to describe real-world features or phenomena associated with a specific discipline, domain or application and their relationships. Developing mobility ontologies in a knowledge-based AI system facilitates knowledge acquisition and allows knowledge reasoning. The concepts of ambiguity and semantic heterogeneity in mobility systems can be resolved using ontologies in knowledge bases. Leveraging ontologies also solves semantic heterogeneity problems and enriches

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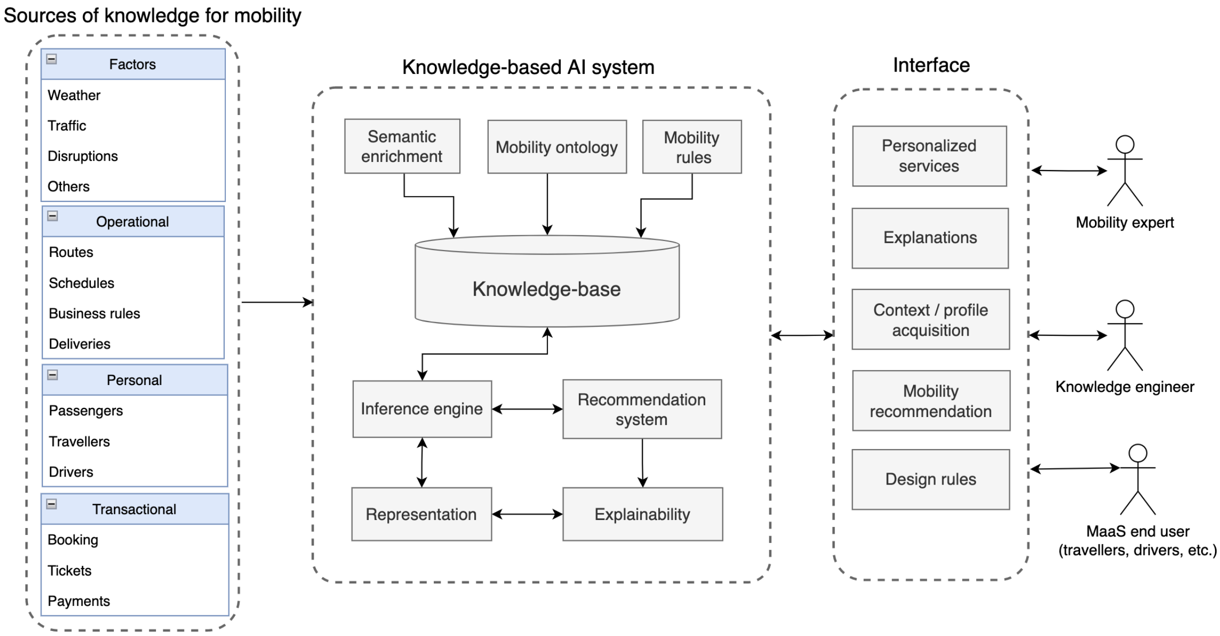

Figure 1. Knowledge-based AI framework for mobility as a service

services' descriptions to make their semantics machine-interpretable and provides efficient search results.

3.3 Rule engine

Ontologies assist in defining new entities, concepts and their relationships. However, information about the context and procedural knowledge are usually represented by logic rules in the form of condition–action pairs: *IF condition holds, THEN perform action.* Conditions usually contain patterns and variables that may be linked to facts. Each rule has a first, matching part, and a second, action one, which modifies the working memory or outputs something. A rule may have variables that are linked to values in the working memory using pattern matching [3]. For example, consider a rule stating that a traveller would not use an e-bike in rainy weather; the variables ?t (traveler), ?e (e-bike), and ?u (uses) are matched to all the available data that satisfies the condition.

3.4 Recommendation system

The recommender systems understand the preferences and needs of MaaS users, their context and their environment to assist them with a personalized mobility service. The recommendation system module of the proposed framework is connected to the inference engine, explainability, and representation modules to suggest a customized and personalized mobility service based on inductive reasoning.

3.5 Representation

The representation module is responsible for preparing the outputs of the recommender system and explainability modules and visualizing them understandably and convincingly for the users. Since different explanations and visualizations might be needed for various users, this module assigns proper explanations and delivers them to the interface layer to be visualized.

3.6 Explainability

Explainability makes an AI system more understandable, transparent and responsible while reducing risks. This module is responsible for justifying the personalized recommendation made by the recommendation system – to both travellers and domain experts. For example, the module explains the reasons for recommending a specific service (e.g., a taxi with an electric car) for a traveller or, in extreme cases, why no recommendations are available for a particular user. One approach toward explainability is using features suggested by experts to bridge the gap between knowledge-driven and data-driven approaches.

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4 Scenario

The following scenario shows how a knowledge-based AI system can provide a customized and personalized service to two different travellers. As Figure 2 illustrates, the knowledge-based AI system (forming the core of the proposed framework) is connected to contextual and non-contextual sources, such as public transport, taxi, rental car services, and weather data – to capture various information. It also provides a mobile application or wearable device for travellers to address their needs and schedules. With the help of mobility experts and knowledge engineers, a set of rules is created based on the different information and integrated into the knowledge base. These rules are updated regularly based on changing circumstances, trends in mobility patterns, etc.

In this scenario, two travellers, namely Alex and Mary, usually use e-bikes on Wednesdays. However, the system notices that next Wednesday will be rainy, based on weather forecast data. The system uses a rule engine and concludes that travellers cannot ride e-bikes in rainy weather, recommending an alternative transportation solution with an explanation to each traveller. According to the knowledge base, Mary is interested in sustainable mode of transportation and prefers using electric cars, while Alex likes gas automobiles. The system searches the taxi drivers in Mary's area and arranges a taxi service with an electric car for her. It also suggests a gas car for Alex according to his location. Both travellers are connected to the corresponding taxi drivers. If there are no taxi drivers available for these travellers, the AI system might not provide any recommendations and notifies the domain expert or knowledge engineer to add a new rule to the system to expand its functionality.

5 Discussion

Knowledge-based AI systems can make valuable contributions to generating flexible and intelligent solutions; however, there are several challenges due to the complexity of mobility services. Collecting the requirements of MaaS users and accessing real-time data (contextual and non-contextual) from several sources is challenging. Also, updating the proposed knowledge base with, e.g., contextual data such as weather or traffic information requires real-time services to respond to the travellers' up-to-date requirements and needs. Furthermore, connecting different types of data with various structures and identifying their semantic relationships adds another challenge while providing richer explainable services. In terms of semantic enrichment, a semi-automatic approach should be followed to enrich different types of data coming into the system and facilitate interoperability issues in MaaS. A mobility expert with extensive knowledge of mobility data should construct a mobility ontology or adjust existing ontologies in the system and define rules in the system. To answer questions like "what should happen if someone uses e-bikes in rainy weather?", the mobility expert should inject a rule in the knowledge base. The system should provide tools and interfaces to update and optimize the system's rules efficiently.

In terms of explainability, one type of explanation can not be sufficient for different mobility users such as domain experts, knowledge engineers, and Maas end-users. Although recently emerged explainability approaches [4] can address the knowledge engineers' needs, they have not been adapted to handle the requirements of mobility stakeholders and end-users. Recommendations augmented with reasoning and explanations can increase awareness of the framework's performance.

6 Conclusion

In the light of technological advancement in the mobility domain due to widespread AI adoption, individuals demand more personalized transportation solutions. Off the shelf, AI solutions provide pieces of the puzzle to solve transportation needs in MaaS. This paper proposed a knowledge-based AI framework considering all the necessary modules to enable new services in MaaS, including three important modules (knowledge base, recommendation system, and explainability) to provide personalized and explainable services to MaaS users. Although a scenario was presented to support the proposed framework, further investigation is needed concerning the development of its modules and their technical interactions.

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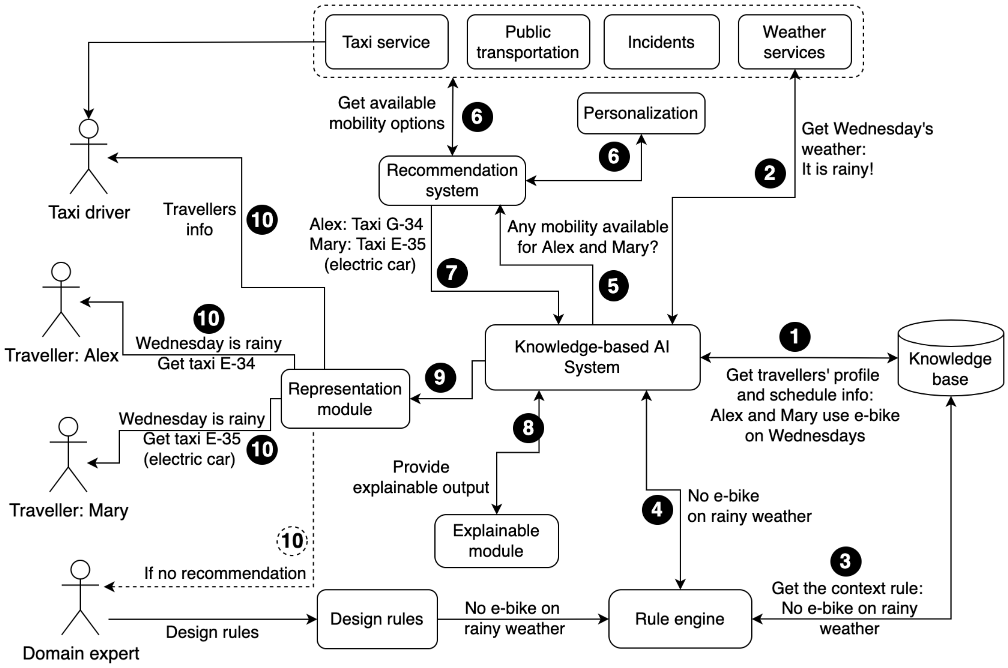

Figure 2. A scenario based on the proposed knowledge-based AI framework

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