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Multimodal Route Planner with Cycling Integration

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Abstract
This paper focuses on multimodal route planning with support for public transport, walking, and both private and shared bicycles. The aim is to design a routing approach that enables seamless combination of transport modes while addressing the limitations of real-world systems. This solution is based on an implemented routing engine that combines multiple transport modes into a unified model. As part of the proposed solution, a prediction model is incorporated to estimate the future number of available bicycles at rental stations, thereby increasing the reliability of the planning process. The proposed system is capable of generating feasible routes across combined transport modes constrained by user preferences. The work provides a practical framework for more reliable urban route planning and can be extended to other mobility systems.

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1. Introduction

Efficient urban mobility is an important problem. Users often need to combine different modes such as public transport, walking, and shared mobility services, which increases the complexity of routing. Here, existing solutions fail, requiring users to use multiple applications in separate steps.

The goal is to design a multimodal route planning system that combines different transport modes into a single feasible route while respecting user preferences and real-world constraints. The core problem is reliable route generation while handling dynamic factors such as bicycle availability.

Currently used applications, such as Google Maps[1] or Mapy.com[2], primarily support unimodal route planning. However, they lack effective support for combining multiple modes of transport within a single route, especially when integrating private or shared bicycles with other forms of transport.

The proposed approach introduces a multimodal routing system that integrates multiple transport networks into a unified model. It extends traditional routing by incorporating predicted bicycle availability, allowing the system to consider not only current but also expected future conditions when generating routes.

The main contribution is a practical multimodal routing application that combines multiple transport modes with predictive insights. The work demonstrates an improved reliability of route planning and provides a framework that can be extended to other mobility systems and dynamic environments.

[1]https://www.google.com/maps
[2]https://mapy.com

2. Design Proposal

The architecture Figure 1 consists of three key components: the data layer, frontend, and backend. Backend represents the core of the application and provides two main functionalities: route planning and prediction of bike availability. It also communicates with frontend via REST API and integrates multiple data sources.

Directly integrated data sources include **GTFS-RT** for real-time vehicle information, **GTFS** for static public transport data, and **GBFS** for shared bicycle data. Some data are not available in real-time and are therefore collected continuously and stored in a database, such as **historical bike availability** and **weather data**.

The application uses external services such as **OpenTripPlanner 2** for route planning using RAPTOR [1] and A^* [2] and **Lissy** [3] for route shapes and historical delays. The client also communicates directly with an external service to retrieve **Digital Elevation Model tiles**, which provide elevation data that are used to determine elevation gain and elevation profile of routes.

3. Solution

This section describes the proposed solution and its key components, along with the achieved results.

3.1 Routing Engine

The routing engine Figure 2 is the core component of the backend application. The planner can determine the most suitable options, allowing the user to fully rely on automatic decision-making. The user can also define leg preferences and partially specify the journey.

The engine processes all waypoint groups and divides them into multimodal and unimodal groups. Multimodal groups must be decomposed into smaller segments, while unimodal groups can be routed directly and attached to the remaining solution tree.

3.2 Multimodal Algorithms

As part of the proposed solution, two multimodal transport strategies are used. The first, **B2PT**, combines public transport followed by a bike segment, while the second, **PT2B**, starts with a bike segment followed by public transport. One of the six proposed variants is illustrated in Figure 3.

These approaches aim to maximize the use of bicycle segments while minimizing detours and backtracking during the journey.

3.3 Station/Rack Selection

The planner addresses the station selection problem, where the goal is to choose the most suitable bike station or rack for a given route. During routing, only one or two candidate stations are selected in order to reduce the number of similar routes that differ only slightly. The origin and destination stations are selected based on the following criteria:

- **Predicted bikes.** Number of bikes available for the origin station, and **capacity** for the destination station.
- **Route angle.** Angular deviation from the main route direction.
- **Distance to the station.** Length of the walking segment to the station.

The weights of individual criteria are determined using the analytic hierarchy process [4]. The final station selection is then based on a weighted evaluation function.

3.4 Prediction

Prediction is used as a supporting component in the station selection process. The pipeline for both training and application usage is shown in Figure 4. It combines historical bike availability data with temporal features such as time of the day, day of the week, and whether it is a working day.

The TCN model [5] is further enriched with partial information from nearby stations, proximity to public transport stops, and historical weather data, such as temperature and wind speed, which are commonly used in bike availability prediction tasks [6]. Among static features, factors such as population density and station location are also considered. A comparison of RMSE per station is presented on map in Figure 5.

3.5 Computation Optimization

The final part focuses on improving computational performance. Since the application integrates numerous data sources, it was necessary to ensure real-time usability. Therefore, key bottlenecks were identified and optimized, with the impact of individual optimizations shown in Figure 6.

The most significant improvements were achieved through the use of a planning cache, asynchronous processing, and caching of Lissy data.

4. Conclusions

The result of this work is a web application Figure 7 that enables route planning using public transport, walking, and private and shared bicycles. The routes are presented on a map and as an itinerary.

The system is enhanced with additional features such as bike sharing availability prediction, real-time and historical public transport delay information, and the ability to modify parts of the route, for example, by changing a connection or selecting a different bike station.

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