Demo Abstract: Indoor Place Prediction on Smart Phones

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ABSTRACT

High-accuracy and low-latency indoor place prediction for mobile users is crucial to enable applications for assisted living, emergency services, smart homes, and augmented reality. Previous studies on indoor place prediction use complex infrastructure with multiple visual/wireless anchors or multiple wireless access points. These localization techniques are difficult to deploy, may negatively impact user privacy through location tracking, and their data collection is not suitable for personalized place prediction. To solve these challenges, this paper proposes GoPlaces, a novel app that fuses inertial sensor data with WiFi-RTT estimated distances to predict the future indoor places visited by a user. GoPlaces does not require any infrastructure, except for one cheap off-the-shelf WiFi access point that supports ranging with RTT. In addition, it enables personalized place naming and prediction through its on-the-phone data collection and protects users' location privacy because user's data never leaves the phone. GoPlaces uses an attention-based bidirectional long short-term memory model to detect user's current trajectory, which is then used together with historical information stored in a prediction tree to infer user's future places. We implemented GoPlaces in Android and evaluated it in several indoor spaces. The experimental results demonstrate prediction accuracy as high as 92%, low latency, and low resource consumption on the phones.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**.

KEYWORDS

Indoor place prediction, Sensor fusion, WiFi-RTT, Time series analysis, Deep learning, Human mobility, Smart phones

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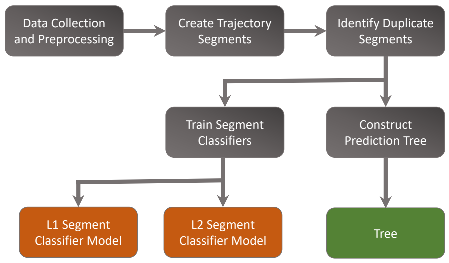
1 INTRODUCTION

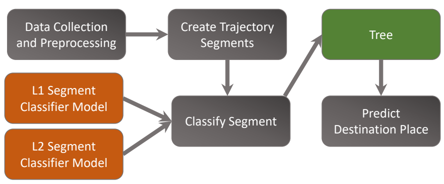
With the development of indoor positioning technology and the widespread availability of mobile and wearable devices, there has been an explosive growth in the amount of indoor mobile trajectory data. Location prediction can use this data to infer the location of a user at a given time in the future and enable new applications or services. Previous studies have shown that people typically follow habits in indoor spaces, and 93% of user behavior is predictable [4].

Knowing the places to be visited by a moving user has positive implications in many application scenarios such as assisted living, emergency services, smart homes, and augmented reality (AR). In a fire emergency, 911 calls can have special access to the caller's latest predicted location and share it with the firefighters to locate the right building entry point for rescue. In a smart home, the door can be unlocked automatically and the lights turned on when the user is predicted to go in that room, or a smart music system can adjust its volume when the user is predicted to move to another place. Other applications may warn the user that the WiFi signal strength is weak at the predicted place, or the phone can change the settings automatically for user privacy before reaching a common area in a shared living space (e.g., turn off sound notifications). Furthermore, AR applications can perform rendering before the user reaches its predicted place to improve the user experience.

Creating an indoor place prediction system is difficult, as it needs to detect the user's current position, and accurate data needed for localization is not readily available. Since the precision of GPS is very low inside buildings, many studies use complex infrastructure to get better accuracy in localization. For example, indoor localization based on visual anchors needs to attach pre-defined image tags at certain known locations in the environment. Other types of indoor localization use multiple ultra-wideband (UWB) anchor nodes with known coordinates, and the user needs to carry a UWB tag to communicate with the anchors to estimate location. In addition, different forms of wireless fingerprinting and multi-lateration have been explored for indoor localization, including WiFi, RFID, acoustic, light, and magnetism. The WiFi-based solutions dominate because WiFi access points (APs) are ubiquitous in indoor environments. These solutions are typically designed for localization or tracking, not for place prediction, and they suffer from one or more of the following problems: they are costly or difficult to deploy;



(a) The training Phase



(b) Inference Phase

Figure 1: Architecture of GoPlaces app

they have not been designed for personalized place naming and prediction; they may be dangerous from a privacy point of view.

2 GOPLACES OVERVIEW

We propose GoPlaces, a place prediction smart phone app that does not require any infrastructure, except for one cheap off-the-shelf WiFi AP that supports ranging with WiFi-RTT [3]. Due to this feature, such APs can become common in houses, shops, or workplaces in the near future. However, knowing the distance from a single AP is not enough to localize the user. GoPlaces' idea is to detect user's walking trajectories by augmenting the WiFi-RTT distance measurements with mobile sensor measurements, specifically accelerometer and magnetometer data. Although the data collected from sensors are usually noisy, GoPlaces finds similar patterns for the sequence of data collected along a trajectory, and it identifies a trajectory by analyzing the walking orientation and the series of distance measurements. To achieve this, we design novel algorithms and deep learning models to divide each trajectory into smaller segments, classify segments, and predict places to be visited. We also propose a data augmentation technique to generate synthetic data that reduces the manual effort to collect training data, increases robustness, and boosts prediction performance.

GoPlaces enables personalized place naming and place prediction through its on-the-phone data collection, training, and inference algorithms. By design, GoPlaces also leads to the better privacy protection of user's locations and trajectories because the user's data never leaves the phone. Furthermore, the single WiFi-RTT AP cannot localize the users accurately to detect their trajectories. To the best of our knowledge, GoPlaces is the first accurate place prediction system that uses a single WiFi AP as infrastructure. This makes GoPlaces a practical solution in real-life settings.

GoPlaces needs a list of places labeled with semantic names (e.g., office desk, dining table), and users should be able to collect data for training without significant manual effort. The system architecture of GoPlaces is shown in Figure 1. The figure illustrates both phases for training and inference in GoPlaces. Data collection and preprocessing are similar for both phases. To collect data for training, the user selects an origin and a destination place for the trajectory, and then walks between these places. If the places are not yet labeled, the user has to assign them semantic names. The data for a trajectory is stored on the phone as a sequence of data blocks. The collected data is preprocessed to remove noise, especially from the WiFi-RTT distance sequence. Next, the trajectories are divided into segments using a change point detection (CPD) algorithm that analyzes changes in the walking direction. Since the same segment can be identified in different overlapping trajectories, the next module identifies duplicate segments and assigns the same segment ID to all of them. These segments are used as input for the Attention-BiLSTM [2] segment classifier (Figure 2), which identifies the segment IDs by analyzing WiFi-RTT distance trends and walking direction trends of a segment. As two different segments may exhibit similar trends in some cases, GoPlaces also analyzes connected segments to distinguish different segments. We assign different IDs for individual segments (L1) and joint segments (L2), train two different classifiers, and store the sequence of segment IDs in the form of a prediction tree.

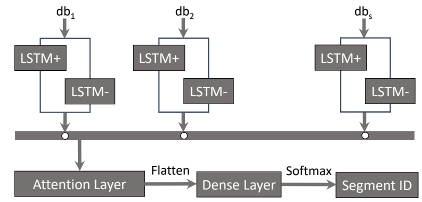


Figure 2: Framework for Attention-BiLSTM model

During inference, the user data is collected while walking and data blocks for the last t seconds are analyzed by the CPD algorithm to divide trajectories into segments. Then, the classifiers will get the ID of each segment, and the prediction tree will match trajectories consisting of a sequence of segments and predict places.

3 DEMONSTRATION

We implemented GoPlaces in Android using DL4J [1], which provides support for training and inference on the phones, and evaluated it in several indoor spaces using Google Nest WiFi AP and commodity phones. The place prediction accuracy depends on the percentage of the trajectory traveled by the user. The experimental results demonstrate prediction accuracy of the top two places as high as 92% when 90% of the trajectory is traveled, and as high as 77% when 75% of the trajectory is traveled. We also demonstrate that GoPlaces is feasible in real life because it has low latency and low resource consumption on the phones.

This demonstration will show how GoPlaces labels places, collects trajectory data, trains the place prediction model, and performs indoor place prediction. Specifically, we will perform a live demonstration to predict the next place for a moving user.

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