Towards Personalized Context-Aware Recommendation Agent in Mobile Social Networks

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***Abstract*—This paper proposes a personalized context-aware recommendation towards the development of an autonomous intelligent agent for an individual user on online social networks. The goal is to automatically provide personalized and context-dependent recommendations of a list of relevant items, including friends, points of interest, and advertisements, to a user in a current situation. The proposed agent is a mobile application that incorporates user contexts gathered by various mobile device sensors, including implicit and explicit data, to adapt suggestions to a user by understanding the semantic meaning of personal and location data. Web 3.0 technologies are also used to improve the production of intelligent recommendations through the power of AI techniques and decentralization. Users can communicate directly without relying on central authorities, which is beneficial for data protection and security.**

***Keywords*—friend recommendation; POI recommendation; intelligent personal agent; social network; Web 3.0.**

I. Introduction

With the advancement of the Web 2.0 era, almost all websites advance toward the growth of user-generated content while also improving interoperability and usability for end users [1]. It enables people to communicate, interact, and collaborate with each other through two-way communication in online virtual communities. Internet users can contribute information, such as text posts or comments, documents, videos, and photos, via various social media platforms using computer desktops, laptops, and mobile devices [2]. As a result, any user can be both a content producer and a content consumer. Meta (formerly Facebook), Twitter, and a variety of blogs are examples of Web 2.0 platforms that enable users to share personal information, locations, interests, and activities on the Internet at any time and from any location.

Currently, the massive growth of wireless and mobile technologies enables users to access various Internet services, mainly social media platforms, through their smart devices [3]. Smart devices, such as smartphones, tablets, and smartwatches, have become an essential part of modern life, allowing people to contribute content, share information, and interact more easily and interactively through the Internet. One of the most critical applications that takes advantage of the widespread adoption of smartphones is Location-Based Social Networks (LBSNs), which allow mobile users to record locations, geo-tagged photos, and geographical information [4]. Friend and Points-of-Interest (POIs) recommendations are the important components of individual services in LBSN applications [5], which have recently attracted much attention from researchers. These services aim to assist users by suggesting similar friends and exploring exciting places according to user information, such as profiles, preferences, interests, and historical locations. This keeps raw contextual data, such as weather conditions, traffic conditions, seasons, and locations on a daily basis. However, such services lack user privacy, identity, and the ability to detect and recognize contextual data in the current situation to deliver appropriate information to users. Therefore, there is a growing demand for a personalized and context-dependent intelligent assistant capable of interpreting user behavior and making relevant suggestions for users.

The emerging Web 3.0 aims to make the Web more context-aware and intelligent in decentralized infrastructures, also referred to as decentralized intelligent Web [6]. It has the ability to understand meaning through data analysis in order to automatically provide the user with highly personalized and appropriate suggestions of items by incorporating innovative technologies, such as semantic web, Artificial Intelligence (AI), Natural Language Processing (NLP), data mining, Machine Learning (ML), recommendation agents, Augmented Reality (AR), and Virtual Reality (VR) into ubiquitous networks [7]. This will be accomplished by empowering each user to become the owner of their data and providing a richer overall experience due to the numerous innovations implemented. In addition, Web 3.0 enables participants to interact freely, publicly, and privately with others without the need for central authorities or permission, avoiding scalability and single point of failure issues. In other words, each user regains full control over their data and privacy.

To fulfill the innovative functionalities, this paper proposes a personalized context-aware recommendation referred to as an autonomous intelligent agent for an individual user. The goal is to automatically provide personalized and context-dependent recommendations of a list of relevant items, including friends, POIs, and advertisements, to a user within a current situation by analyzing and understanding contextual data. The proposed agent is developed as a mobile application to assist users who want to meet new friends, discover interesting POIs, and receive helpful information within their surrounding area using swipe and tap gestures. It is also an autonomous assistant with Peer-to-Peer (P2P) communication, which means users can freely and anonymously login and logout into the application without authentication methods, making the application continuously and highly dynamic. A mobile device can automatically record historical data of a user as the timeline of events in the current environment, such as real-time weather conditions, locations, time of day, seasons, and temperatures, using a variety of sensor technologies, such as Bluetooth, Wi-Fi, and Global Positioning System (GPS). These raw historical data are stored in a local database on a mobile device to preserve personal data privacy. Moreover, it supports users to privately communicate and transfer data with each other within a local network, which provides a way for secure and robust wireless communications with protecting data.

The proposed agent is designed to quickly provide new friends, POIs, and advertisements to users by understanding the contextual meaning under the basic use of NLP and ML techniques without requiring high processing power on mobile devices. These techniques also assist in avoiding the problem of information overload by recommending the most relevant information to users while improving its suggestions, adaptability, and social media user experience. To explain the importance of the research work, the main contributions are divided into four aspects.

- A new conceptual framework for a personalized context-aware recommendation agent is proposed. The goal of this agent is to automatically interpret contextual data and provide users with recommendations for a variety of items, including friends, POIs, and advertisements, that better match their expectations.
- A novel method for personalized POI recommendation is introduced. The method utilizes user preferences and location histories to generate recommendations for a list of candidate POIs within a geospatial range around a user's current location, making it easier for users to find matches for POIs.
- A novel method for the semantic matchmaking engine of friend recommendation is introduced. The method determines how similar two pieces of user information are in terms of lexical and semantic similarity.
- The proposed agent also enables mobile users to receive excellent services, such as private messages, games or puzzles, local recommendations, and advertising campaigns, such as promotions or discounts from local venues via Wi-Fi networks. This task is intended to entertain and engage users through various services while also assisting businesses in maximizing profits.

The rest of the paper is structured as follows: Section 2 examines research on social networking sites, Web 3.0, friend recommendations, and POI recommendations. Section 3 illustrates the research methodology. The use cases of the proposed agent are explained in Section 4. Finally, Section 5 concludes and gives directions for further research.

II. Background and Related Work

In this section, the fundamental concepts for implementing the proposed agent are introduced in detail, including social networking sites, Web 3.0, friend recommendations, and POI recommendations. Then, the related research work is discussed.

A. Social Networking Sites

A social networking site, a subcategory of social media [19], is defined as a website that allows people to create or share content, ideas, activities, backgrounds, and interests through online virtual communities and networks [8]. These websites offer a highly interactive medium for creating and communicating digital content among individuals or groups, resulting in valuable knowledge sharing. On a more personal level, social networking sites enable users to communicate with friends and family and learn new things. At the business level, social networking sites enable users to have a conversation with audiences, gain customer feedback, and evaluate digital marketing campaigns.

B. Web 3.0

The first generation of the Web is Web 1.0, which provides only static information for users without the ability to create and interact with web pages. The lack of active interaction between users and the Web resulted in Web 2.0, the second generation of the Internet. Web 2.0 facilitates interaction between users and sites. Users can interact with one another and create profiles for themselves on social networking sites. However, Web 2.0 does not respect the privacy of its user's personal information. That is, users do not have ownership or control over their data. Personal information is stored on a server managed by technology companies and used for targeted advertisements and marketing campaigns. Web 3.0 is a concept for a new iteration of the World Wide Web. It is also referred to as the evolution of a semantically intelligent web by leveraging emerging technologies that heavily rely on blockchain technology, AI, semantic web, data mining, ML, NLP, VR/AR, Internet of Things (IoT), and edge computing [9]. Users retain control over their data and content. Algorithms will now use all that data to improve the user experience and make the Web more personalized and familiar.

C. Friend Recommendation

The number of new users on social networking sites has been rising rapidly. Friend recommendation plays a critical role in assisting users in finding potential friends, making new friends, and expanding their social circle. As a result, the function of recommending friends to users has appeared in various applications, which is becoming increasingly popular [10]. The goal of friend recommendation systems is to automatically suggest a list of similar friends with similar interests or relevant characteristics. Most friend recommendation applications utilize personal user profiles or behaviors to discover potential friends that a target user might be interested in. Zhang and Xu [11] designed a framework for friend recommendations that

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can characterize user interest in context and content as well as combine domain knowledge to improve recommendation quality. Lam and Riedl [20] used latent feature mining to calculate user similarity and proposed a random walking model for getting friend recommendations. Guo et al. [12] proposed a semantic-based friend recommendation method to find friends based on their lifestyles rather than their social activities. However, the lack of a description of semantic information about user activity preferences makes the recommendation quality unsatisfactory.

D. POI Recommendation

POI recommendations play an important role in LBSNs that aim to provide personalized recommendations of POIs, such as restaurants, tourist spots, cinemas, and stores. Recommending suitable POIs for mobile users by analyzing their historical check-in records and other multimodal data has become a research hotspot. Wang et al. [13] proposed a probabilistic trust-based recommendation model for social networks. Ye et al. [14] created a power-law distribution model to describe geographical influence on user check-in behaviors and improved the POI recommendation quality by incorporating geographical influence into the CF method. Lian et al. [15] proposed a combinative recommendation framework that incorporates the physical check-in characters and social influence of users into the recommendation model. In addition to check-in activities, context information can be used to improve recommendation quality [16]. Gao et al. [17] investigated the content information in the POI recommendation system, including user preferences, location characteristics, and emotion distinctions.

From previous research, most of the existing recommendations on social networking systems ignore user preferences and contextual data. Moreover, the current recommendation systems are designed to be the centralization of control, where all data is stored and controlled by central servers. These systems will regain full control of the data, resulting in security and privacy concerns regarding public and private personal information. This paper differs from traditional research in that the proposed agent incorporates both explicit and implicit feedback from a user, which provides excellent sources of feedback data that the proposed agent can understand and recognize about the current situation of the user and improve the quality of recommendations. The proposed agent is designed to protect the data privacy of all mobile users and make them more permissionless. This means that users can have equal access to data while maintaining their privacy and communicating privately with others. In addition, Web 3.0 technologies are used to improve the production of intelligent recommendation agents and decision-making processes by leveraging ML and NLP.

III. Methodology

This section describes a new conceptualized framework of the proposed agent to provide relevant recommendations considering privacy protection for an individual user depending on the situation. The main idea behind this framework is based on contextual data investigation and Web 3.0 technologies with a decentralized approach, which leads to significant improvements in autonomous intelligence, privacy, user control data, and interactive experience. The framework overview is explained and illustrated in Figure 1.

This framework is proposed in mobile situations to provide personalized and context-dependent adaptive recommendations to a user based on the environmental factors of a given user situation, consisting of three different sources: implicit data (e.g., locations, time of day, and weather conditions); explicit data (e.g., user profile, preference, expertise, and biography); and textual data, i.e., the ability to access information from a variety of online sources, such as documents, webpages, and publications. The environmental and physical data derived from mobile device sensors, such as Bluetooth, GPS, and Wi-Fi technologies, are considered as contextual data. The contextual data is locally stored in a secure database on a mobile device to preserve the privacy of the user. The proposed agent automatically interprets the contextual data and accurately adapts suggestions for a list of relevant items, such as friends, POIs, and advertisements. It operates continuously and autonomously within an environment that is aware of its environment through various mobile device sensors. The proposed agent consists of three main components: (1) friend recommendation; (2) POI recommendation; and (3) advertisement recommendation. Each of the components is explained below.

A. The Component of Friend Recommendation

The main goal of this component is to present a new friendship method based on their personal information through Bluetooth Low Energy (BLE) technology inspired by COVID-19 contact tracing apps [21] [22]. This component generates a list of potential friends with similar interests, ranked by a similarity score. The overview of the proposed component is explained and illustrated in Figure 2.

The component aims to provide a perfect match in the vicinity of people based on user profiles and preferences. Personal data will be stored locally on each device, preventing access and control over data by authorities or anyone else. Users have complete control over their data, which means they can change how their data is used or shared at any time in the application settings. The Bluetooth connection module uses BLE to regularly broadcast a message within a signal range in a decentralized manner to find active users and anonymously collect a user profile from the active user to measure user similarity. When paired with all currently active users, the module will return a list of potential friends with similar interests, ranked by a similarity score. If a user is close enough (within 2 meters) to people who have common interests, the user will get a notification with new friends. Users can use a mobile phone to make new friends and send direct messages to them without relying on a central server. The proposed component consists of three main modules: (1) personal information management; (2) semantic matchmaking

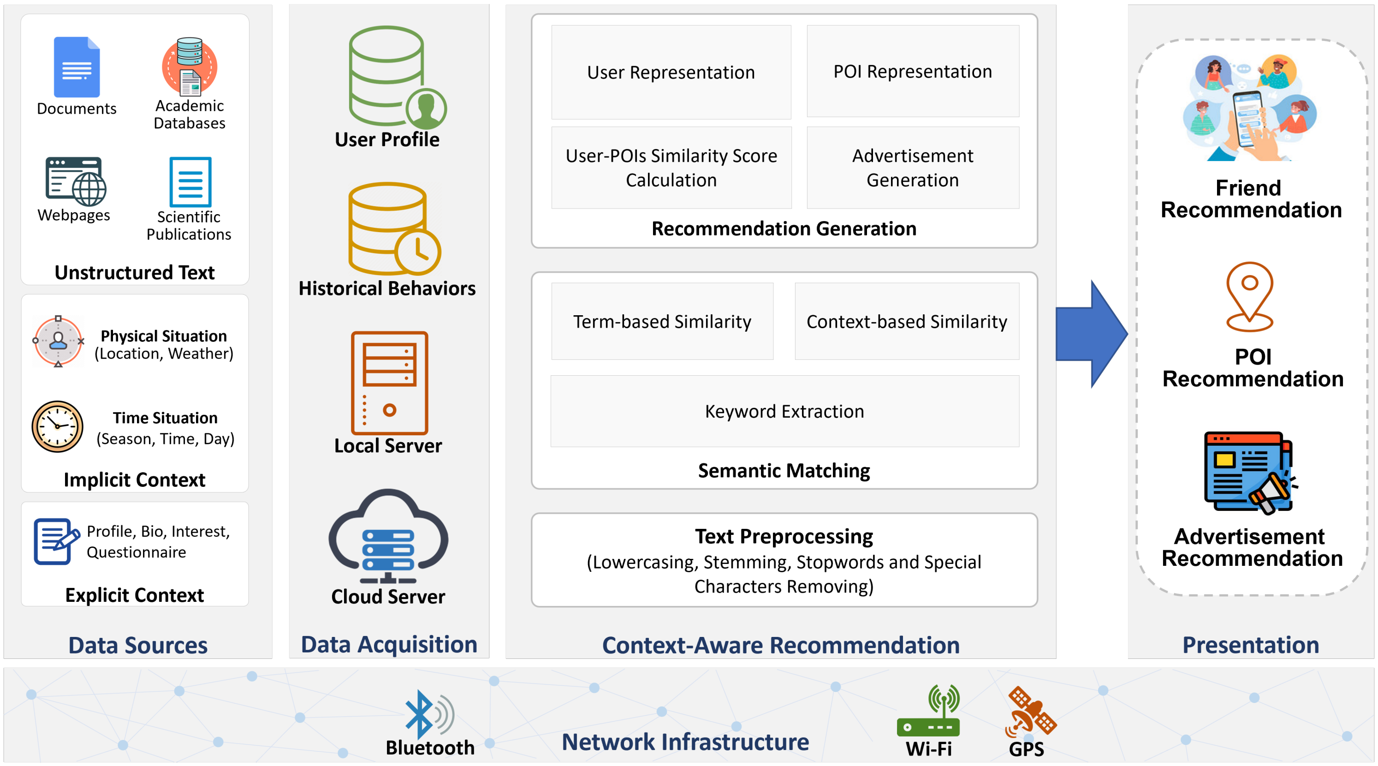

Figure 1. The framework of personalized context-aware recommendation agent

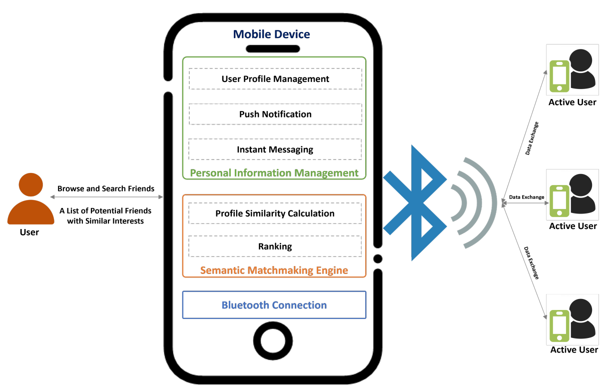

Figure 2. The overview of friend recommendation component

engine; and (3) Bluetooth connection, where each step is given in detail below.

1) *Personal information management:* This module is the management of information that allows users to control their personal data and manage their online identity by enabling individuals to gather, store, update, and share personal data. This module contains three basic operations. The first operation is a process of controlling which users can update their profile information. The second operation is the process of directly sending a notification to a user's mobile device. A push notification is a personalized notification asking to make a friend. It serves as a quick communication channel, enabling users to convey messages to interesting users. The third operation is a process that allows users to communicate privately with friends without Internet access or cellular data. A user profile consists of four factors, including user interests, personalities, areas of expertise, and short texts from the biography.
   a) *User interest:* This is manually entered by choosing interests from a list of controlled vocabularies, such as cooking, soccer, and shopping.
   b) *User personality:* Personalities, such as age, gender, weight, height, and education, are used for search filtering to narrow and customize search results that a user manually enters into text fields.
   c) *User expertise:* This automatically generates expertise areas and knowledge of an individual user from documents and academic databases using crawlers or APIs to harvest user bibliographies on the Internet and represent an expertise profile to the user. The construction of expertise areas utilizes a keyword extraction approach based on a statistical and linguistic features-based technique that automatically extracts the most important words from text profiles.
   d) *User bio:* This is manually filled out by a user in the form of free text.
2) *Semantic matchmaking engine:* This is an important module for estimating semantic similarity between the

source and target text pieces based on their meaning by focusing on text profiles. The semantic matching engine compares the user profile with other profiles using a text similarity technique and suggests a suitable list of similar users. User interests, expertise, and biographies are combined to improve the accuracy of recommending similar users. The text similarity technique measures the similarity score between two pieces of personal information based on lexical and semantic similarity, covering both word level and context level using NLP techniques, word embeddings, and cosine similarity. Each user profile is cleaned up and transformed from unstructured textual data into an appreciable format. A word embedding technique encodes and converts textual data into a numeric format as a vector representation. Two vectors are compared using cosine similarity to extract semantically similar text from user profiles and return a similarity score. This engine consists of three functions as follows: (1) text preprocessing; (2) matching; and (3) ranking.

a) *Text preprocessing:* The personal data is cleaned up to extract meaningful features using a preprocessing function, including removing non-ASCII values, special characters, HTML tags, stop words, and raw format conversion.

b) *Matching:* This is due to a text profile written in natural language formats by a user, which leads to the complexity of the text. This function aims to measure the semantic similarity of two user profiles at a word and context level using word embeddings, which can handle synonyms or words with similar meanings in the computation of similarity. Lastly, two similarity scores derived from term-based and context-based similarity are combined and calculated as the average score. This function can be divided into three tasks as follows: (1) term-based similarity; (2) context-based similarity; and (3) average similarity score calculation.

- *Term-based similarity:* This task aims to determine how similar two texts are at the word level. It measures the similarity score between two sets of words based on the Jaccard coefficient. The Jaccard coefficient is defined as the intersection and union of these two sets of words that refer to the number of common words over a total number of words, which provides a similarity score ranging from 0 to 1. The Jaccard similarity score is 1, indicating that the two-word sets are identical. The similarity score of a word can be defined by equation (1) as follows:

$$J\left(W_1, W_2\right) = \frac{|W_1 \cap W_2|}{|W_1 \cup W_2|} \qquad (1)$$

where W_1 and W_2 are the sets of words edited by a source user and a target user, respectively.

- *Context-based similarity:* This task aims to measure the semantic similarity of two texts at the context level. The average pairwise similarity (APS) is proposed to calculate the similarity score between two short bios of users based on word embeddings with the assumption that similar words should have similar vectors. The similarity score between a word in the source bio and every word in the target bio is calculated as the maximum similarity score from a pre-trained word embedding model. The similarity score can be defined by equation (2) as follows:

$$APS\left(S_1, S_2\right) = \frac{\sum_{w \in s_1} Max(sim_{v \in s_2}(w,v))}{|S_1|} \qquad (2)$$

where S_1 and S_2 are short bios of a source user and a target user, respectively. $Max(sim_{v \in s_2}(w,v))$ returns the maximum similarity score. The function $sim_{v \in s_2}(w,v)$ denotes the similarity score between w and v based on a word embedding model. $|S_1|$ is the number of words in S_1.

- *Average similarity score calculation:* This task calculates the average similarity score by adding all scores and dividing the total by the number of values. The semantic similarity score ranges from 0 to 1, indicating how similar two texts are semantic. A score close to 0 indicates a weak similarity, while a score of 1 indicates a perfect similarity. The average similarity score (AVG) is defined by equation (3) as follows:

$$AVG = \frac{J(I_1,I_2)+J(E_1,E_2)+APS(S_1,S_2)}{3} \qquad (3)$$

where I_1 and I_2 are user interests of a source user and a target user. E_1 and E_2 are expert profiles of a source user and a target user. S_1 and S_2 are user bios of a source user and a target user, respectively.

c) *Ranking:* The function can re-rank a list of candidate friends to consider probability, additional criteria, or constraints to filter some candidates and return the top-ranked friends according to the similarity score to the user.

3) *Bluetooth connection:* This module uses Bluetooth Low Energy technology, a form of wireless communication designed for short-range communication and low-energy consumption. Applications can run on a small battery for a longer time while maintaining signal strength. It allows mobile applications to communicate and exchange data with each other within the range of the Bluetooth signal, using radio waves to communicate wirelessly. The information exchanged between devices through a network is governed by rules and conventions that can be defined in communication protocol specifications. The proposed network topology supported in Bluetooth comes with point-to-point and broadcast connectivity. It allows users

to send or receive data between mobile devices or all neighboring active devices within a close range. Mobile devices must always be paired and connected, with each of the two devices trusting the other and securely exchanging data using encryption to ensure data confidentiality against attackers.

Generally, the component enables users to manually enter and update their profiles and preferences at any time in the application settings. The similarity score is calculated using user interests, expertise, and biographies. The search results are filtered by personal information. Finally, this component suggests matching friends with a similarity score to users whose profiles are highly similar.

B. The Component of POI Recommendation

This component aims to automatically recommend places of interest with detailed information based on matching a user's personal preferences and historical location records within a predefined range from the current location. The overview of the POI recommendation is illustrated in Figure 3.

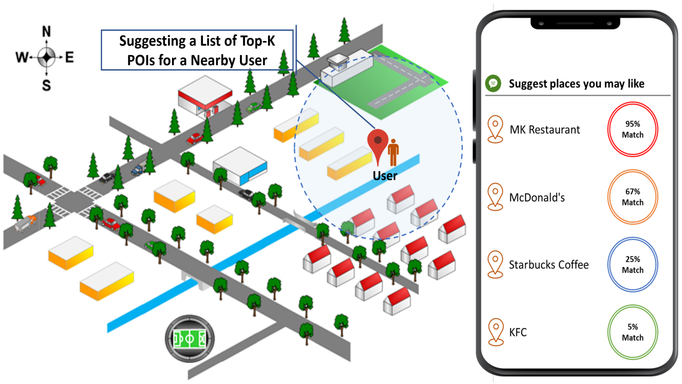

Figure 3. The overview of POI recommendation

A smartphone allows a mobile user to explore interesting POIs within a predefined range around the current location. When candidate POIs match the user preferences, the mobile user will receive an automatic push notification with a list of top-K POIs. The matching POIs are expressed as a percentage, with a higher number indicating how likely a user is to be interested in a given context. Consequently, the matches against user preferences are based on visited locations. The match percentage indicates how closely user preferences correspond to POIs. The process framework overview of the POI recommendation is explained and illustrated in Figure 4.

The main concept of this framework suggests interesting POIs by matching the personal preferences of a user against categories of POIs. A hierarchical taxonomy of venue categories from Foursquare [18] is leveraged to map a location context into categories. The user preferences are created by mining a large amount of historical check-in data to extract locations and converting these locations into categories represented as a user preference feature vector. Each of the candidate POIs around the current location of a user is also

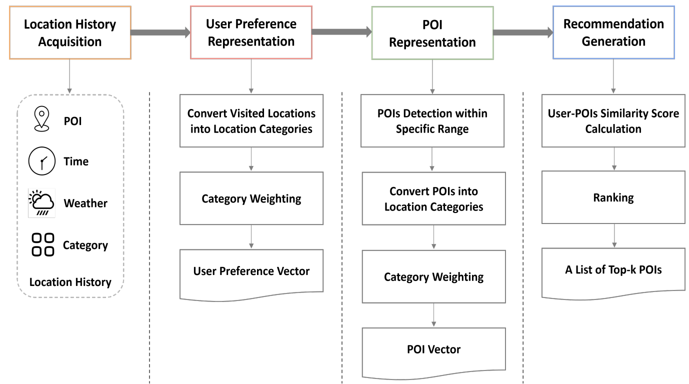

Figure 4. The framework overview of POI recommendation

mapped into categories represented as a feature vector of the POI. The category weighting model is presented to assign weights to important categories based on the level of location categories. The similarity score between a vector of user preferences and each POI vector is calculated using cosine similarity, while the decision tree algorithm with a given context, including weather conditions and time of day, is used to improve the ranking process and return effective results for POIs. This framework consists of four modules as follows: (1) location history acquisition; (2) user preference representation; (3) POI representation; and (4) recommendation generation.

1) *Location history acquisition:* Mobile users can provide rich contextual information to mobile devices equipped with GPS and communication sensors. These mobile devices use signals through the combination of GPS, Bluetooth, and Wi-Fi to determine location data. This module incorporates contextual data based on a user's current situation, such as location, weather, time, user activity, and geotagged location, which are extremely useful for making appropriate recommendations. The location history of a user is a record of previously visited places, including check-in data and trajectories. A mobile device automatically records the locations a user visits daily, as well as the time and duration. A large amount of location history data also provides an opportunity to understand better and model the user preferences.
2) *User preference representation:* The location histories of a user can be implied as interests. This module thus learns the user preferences from the history data to recommend appropriate POIs. All of the POIs in historical data are mapped into sequential groups of categories as a document to model the personal preferences of a user using the location category hierarchy method, describing the characteristics of a location by transforming a POI in a low-level location space into a high-level location space, carrying meaningful information better than the POI name. This module is divided into four tasks as follows: (1) word cleaning; (2) vocabulary building; (3) binary vector representation; and (4) category weighting,

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which is explained below.

a) *Word cleaning:* This is the most important step in removing noise from raw data and making raw data more valuable for building models. As a result, this task is usually preceded by significant preprocessing, including word cleaning, stop word removal, stemming, and lemmatization to reduce the dimensionality problem.

b) *Vocabulary building:* The historical data of a user is considered as a document, and all location categories in the history data are treated as words. It then builds a vocabulary in the sequential group of categories as a list of unique words. The list of unique words is represented as a numerical feature vector of the user preferences.

c) *Binary vector representation:* This is the process of converting the historical data to a numerical vector of numbers 0 and 1 without semantic information.

d) *Category weighting:* The task applies the fundamental concepts of Vector Space Model (VSM) and Term Frequency-Inverse Document Frequency (TF-IDF) for the vector representation of words. The category weighting (CW) model is a representation that describes the occurrence of categories within the location history data of a user. This model assigns a weight to the significance of a particular category on the basis of the raw frequency of the categories (CF) and the weighted category level (WCL) over a whole collection of categories. The category weighting is defined by equation (4) as follows:

$$CW(c) = cf(c) \cdot wcl(c) \tag{4}$$

where c is the name of the location category. cf is the number of times that a category occurs in a category collection with the assumption that a user frequently visiting the same place has more importance. wcl is the weighted category level, which ranges from 0.1 to 0.4. The top level of the Foursquare category hierarchy is defined as a score of 0.1. The bottom level has a score of 0.4, assuming that the bottom level can indicate the specific information of venues more informative than the top level.

3) *POI representation:* The candidate POIs around a current location of a user are represented as a numerical feature vector. The location category hierarchy method converts a POI into a category sequence. The process of converting a POI into a feature vector encoded in the numerical form is similar to the component of the user preference representation.

4) *Recommendation generation:* This module computes the similarity score of two vectors to generate a list of POIs for a target user. The vectors of the user preferences and each POI are used to determine the relevant POIs. This module is divided into two tasks as follows: (1) user-POI similarity score calculation; and (2) ranking, which is explained below.

a) *User-POI similarity score calculation:* Cosine similarity is used to measure the similarity score between the user preferences u and each POI p, which evaluates the angle between two normalized vectors. Therefore, the high cosine similarity score indicates that the two vectors are similar. The similarity score is defined by equation (5).

$$sim\left(\overrightarrow{u}, \overrightarrow{p}\right) = \frac{\overrightarrow{u} \cdot \overrightarrow{p}}{\|\overrightarrow{u}\| \|\overrightarrow{p}\|} = \frac{\sum_{i=1}^{n} u_i p_i}{\sqrt{\sum_{i=1}^{n} u_i^2}\sqrt{\sum_{i=1}^{n} p_i^2}} \tag{5}$$

where $\overrightarrow{u}$ and $\overrightarrow{p}$ are the n-dimensional vectors of a user preference and a POI, respectively.

b) *Ranking:* The decision tree algorithm is used to assign a priority ranking to existing results based on the specific interests of a user, which consists of two factors: weather conditions and time of day. The priority ranking categorizes existing results by assigning a priority of low, medium, or high.

C. The Component of Advertisement Recommendation

This component aims to deliver a personalized greeting or excellent services, allowing mobile users to connect to a local server via Wi-Fi networks. It automatically offers friendly services, such as private messages, games or puzzles, local recommendations, and advertising campaigns, such as promotions or discounts. Furthermore, it enables users to meet people who share their interests based on criteria and proximity. The process overview of the component is explained and illustrated in Figure 5.

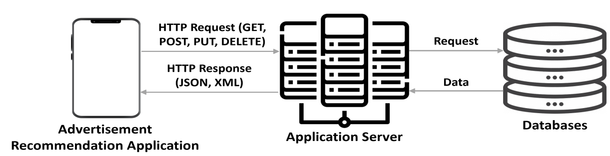

Figure 5. The process overview of advertisement recommendation

The proposed advertisement recommendation application deployed on a mobile device sends an HTTP request with the personal data of a user to a local application server to offer useful resources and services. The resources and services matched with the user are delivered to the application in several formats via HTTP, including JSON, HTML, or plain text. The user then receives push notifications on smartphones according to their locations while the user is active on the application. The wireless infrastructure of a venue allows mobile users to connect to a local server. Wi-Fi technology is used to create a virtual boundary around a specific area with IP addresses to detect and locate the position of a connected device based on the signal from a Wi-Fi router. The router assigns local IP addresses to connected devices, allowing them to communicate and share data on the local network behind the router. This component is intended to entertain and engage users by providing excellent services, such as games and related content. It can help businesses boost operational efficiencies and generate higher revenues. It has also become critical for improving audience experiences in large venues, such as airports, shopping malls, corporate campuses, and conferences, filled with visitors interacting with their locations.

IV. Use Cases

The proposed agent is a mobile application designed to assist users who want to meet new friends, find interesting POIs, and receive useful information via GPS, Wi-Fi, and Bluetooth technologies within a surrounding area. The proposed agent could be used in various use cases. For example, audiences who enter an academic conference and open an application connected to a local Wi-Fi network will receive push notifications about available scheduled programs during the academic conference. In another case, the proposed advertisement recommendation could benefit both customers and stores. Customers walk around a store and open an application connected to the free Internet access in a venue. The personalized advertisements can be delivered directly to the mobile devices of consumers with notifications about promotions and menu items related to that store.

V. Conclusion and Future Work

The paper introduces a personalized context-aware recommendation agent, a new concept in development on online social networks for assisting a user with context-dependent recommendations and personal data protection. The proposed agent consists of three challenging components: (1) friend recommendation; (2) POI recommendation; and (3) advertisement recommendation. These components analyze the behavior of a user depending on the current situation by using location history and contextual data to recommend friends, POIs, and advertisements based on machine learning, natural language processing, and decentralization. It also allows users to communicate with each other within a specified circle of their current geographical positions. In addition, this agent is expected to improve user experiences and make appropriate recommendations for users in different environments.

The future work will continue to assist people in various aspects of their lives and become more intelligent, similar to popular personal assistants, such as Alexa (Amazon), Siri (Apple), and Google Assistant (Google). The future agent should have the ability to recognize more contextual data, understand the behavior of an individual, and provide intelligent services to a user via voice commands using natural language. It should also assist in answering and responding to questions related to the current environment based on the combination of user input and context awareness captured via a smart device.

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