Chapter 1

Distributed Artificial Intelligence in Indoor Positioning

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Abstract

This chapter aims to provide state of the art algorithms, methods and application applied in the real world that have not applied before. Specifically, indoor positioning is of paramount importance nowadays because people spend most of their time indoors. That fact has already given researchers the opportunity to enhance the location accuracy into a sub-meter level so that new machine learning models can be created, designed and built o this sector. In addition, apart from the basic and the most well-known methods of finding the position of a user indoors, which are the trilateration, triangulation and fingerprinting, new upcoming methods also can be designed keeping usual error functions in mind. That, in conjunction with the fact that once the data are collected, new machine learning(ML)/recommender systems (RS) can be created, designed, implemented and applied considering the input features of the Bluetooth Low Energy(BLE) positioning given in combination with the user’s profile. A new case scenario would be a recommender system that allows staff and personnel to provide recommendations about BLE/or similar equipment to the personnel and the experts about which sensors and generally speaking kit should be bought considering the characteristics, specifications and application as input features. Once that is taken into consideration and keeping the user location, positioning in mind, the areas that the aforementioned techniques that the algorithms can be applied are common clothes stores, shopping malls, product sheds, warehouses, airports, airplanes/vessels, hospitals, public services guidance information. Database server plays an important role in the selection of it especially in terms of performance in IoT data gatethered such them [7] In this section, the examination of the creation, monitoring and implementation of further and better Application Programmming Interface (API)’s should be taken into consideration which examine the health of the equipment and subsequently and thoroughly suggest to the personnel for their best optimal performance.

Keywords: Artificial Intelligence, Distributed Systems, machine learning techniques, network clustering, short-range wireless communication, recommender systems, sensors, actuators

1. Introduction

Since the invention and exponential usage growth of the internet which started all but in the late of 90s, the messages to each user had already started becoming even much more personalized. Filtering information has already

Sensors	Battery	Range	Accuracy
Wi-Fi	moderate consump.	$\lessapprox$500 m (1640 ft.)	$\lessapprox$10 m (32 ft.)
BLE	Low consump.	$\lessapprox$70 m (230 ft.)	$\lessapprox$2-4m (10 ft.)
BLE 5.1	Low consump.	$\lessapprox$75 m (328 ft.)	$\lessapprox$0.5-1 m (2.4 ft.)
BLE 5.2	Low consump.	$\lessapprox$100 m (328 ft.)	$\lessapprox$0.5 m (1.6 ft.)
UWB	Low consump.	$\lessapprox$35cm (115 ft.)	$\lessapprox$0.1-0.5 m (0.98 ft.)

Table 1.
Differences on Positioning technologies in terms of Battery, Range and Accuracy.

become the number one priority in the Artificial Intelligence (AI) research field since the early 90s when up coming worth researching systems, named after recommender systems, are suitable for this task. Going back in the 90s, recommender systems were first introduced in a technical report as digital bookshelf [3, 16]. Since then, a huge breakthrough has been made once every day equations, similarity metrics, sorting tasks, novel algorithms including basics algebra, probabilities, graph theory, statistics and subsequently novel state-of-the-art machine learning techniques such that neural networks (NN). The application peak on recommender systems, nowadays, simply, is the conjunction of novel state-of-the-art matrix factorization techniques with neural networks. Simply, these techniques combine linear algebra with graph theory and probabilities. The goal of recommender system, in real world researching application is to provide a list which its context, no matter what this is, for example a movies list, is closely similar to the user's tastes. Apparently, the goal is not to recommend items that, in the movies example, the user has already seen. In research-wise scenarios, the goal, simply, is to analyze, cleanse, process, examine and therefore, experiment and extract the best optimal model which gives the best accuracy score in comparison with baseline and previous state-of-the-art algorithms.

Short-range wireless communication systems are very simply a technology that connects devices within space to execute various tasks such that, in real world scenarios, connecting to the Wi-Fi router from a smartphone. In this case, Wi-Fi router, simply, sends signals with an appropriate and small number of data in octares. Once the device's information transferring that the password and verification is matched, then the smartphone is connected to the internet. Short-range wireless communications are Wi-Fi, Bluetooth classic, smart or ready, BLE 5.1, 5.2 and Ultra Wide Band. The most important and quintessential specifications are given in table 1.

According to Table 1, in terms of power consumption, Wi-Fi is the only short range communication technology which consumes more than the rest of them and that is the main reason, Wi-Fi ranges up to 500 meters. In contrast, the rest of the technologies, such as BLE Smart or ready, BLE 5.1 and BLE 5.2 range in less tahn 100 meters. In addition, in terms of accuracy, the BLE 5.1, BLE 5.2 and UWB provide the best optimal localization and positioning indoors since they achieve an accuracy rate less than a meter. Wi-Fi and BLE provide an accuracy rate of less than 2 to 4 and 10 meters, respectively [5, 10, 14, 20, 22**?**].

Subsequently, after comprehensively and conceptually gain a clear image of the technologies and its architectures described above the goal is to connect the parts and create, design, implement and deploy as a last stage, a system based on indoor positioning technologies distributed on various smart case scenarios, which in our case, are algorithms and techniques.

So, after examining and testing recommender system algorithms, the real-world applications short-range communications technologies, the next step is the examination and implementation of algorithms mostly appropriately applied in order to find the position indoors. The most well-known ones are the trilateration, triangulation and fingerprinting techniques. Simply, each one of them uses a different approach in order to locate and position the user indoors. State-of-the-art methods can be discussed, created, designed, implementation and examined in order to locate user's position indoors in a much better accuracy performance.

After doing so, simply, an additional chapter is the creation, design and implementation of health performance systems in case a device such as a sensor/actuator is of poor performance such as low battery or battery leakage, a notification pop up can be displayed to the staff/personnel [18]. Thus, they can thoroughly examine the case and immediately/shortly/directly do the appropriate tasks.

2. Distributed Artificial Intelligence

Nowadays, artificial intelligence plays an important role into everyday people's lives. Specifically, creating, designing, implementing and thus, training the recommender system model requires computational cost. The records of robust, resilient, distributed dataset (based on Resilient, Distributed, Dataset (RDD) model as mentioned in [34]) that firstly introduced by Apache Spark. The goal is to train and run machine learning models on a computer cluster, simply on a numerous computers, so that the training part is distributed since the data belong to the big data category that consists of millions records/entries. Millions of such entries can be gathered and collected from Indoor Positioning devices, such that Wi-Fi, Bluetooth Low Energy and Ultra Wide Band. For example, a distinguishing example is gathering and collecting temperature data from BLE sensors built-in for a very few months. Taking this example into consideration, indeed, millions of records can be easily gathered and subsequently analyzed, cleansed, modeled and trained.

Additional functionalities can also be taken into consideration for every day, general purposes, such that the ones that have already been built int in BLE 5.2 new protocol that i currently available on the market. [17, 20, 21]. Such applications mostly are about the safety of people's lives and generally speaking in case of an emergency indoors, which is the same application scenario compared to large scale ones [8].

So, after placing the kit appropriately indoors and deploying the models, there is a variety of state-of-the-art algorithms that based on the nature of the data and the application are applied. Factorization machines are mostly used the data are categorical [25]. Neural Networks applied on image classification, whether that is binary or multi-class ones using state-of-the-art few line code API's, such as Tensorflow or Keras [11, 29]. They can also be applied in text analysis, time series and sound signal processing. The architercutre of the Neural Networks changed throughout time and Deep Neural Networks (DNN) came to the surface in which the architecture changes slightly, but the efficiency on computational cost, resources allocation and last but not least the accuracy of the model shed light on various application in todays real-world applications. Specifically, the particular data structure considering to belong to graph theory, is mostly applicable on grand scale data at a very low computational cost. The application of the Deep Neural Networks is mostly found on unstructured or unlabeled data such as computer vision, audio/speech recognition, machine translation, sentence classification and sentiment analysis. Two of the most popular neural network topologies are Convolutional Neural Networks and Recurrent Neural Networks. So, specifically, CNN's are for images that features are about to be extracted, machine translation, sentiment analysis and sentence classification, whereas RNN's are appropriate for time-series and data that are considered to be sequential of non specified length [4, 33]. Simply, the difference between neural networks and deep neural networks is the fact that deep neural networks insert the forward and back pass propagations which are able to automatically update through multiplicative and additive methods the weights and biases placed at the edges of the features considered as nodes [15].

One of the biggest neural network topology advancement in the world of neural networks is the Rescrticted Boltzmann Machines (RBM) [27]. The particular neural network intuitively consists of just two layers, the visible and the hidden ones. Well, the difference between the rest of the network topologies is the fact that the units between the layers are not connected. It is an exceptional topology because it deal with sparse data problem in the field of recommender systems. During training the network after feeding it with a train set, the weights and biases are learned only for the instances that actually exist in the training data set. The missing values or the values that the machine might put them as zero's whereas they are still past of the missing data set, are excluded [6].

3. Indoor Positioning Systems

Indoor Positioning Systems play an important role in terms of user localization and positioning users and items indoors. Their main application as firstly focused on positioning a users indoors with the least optimal accuracy error in terms of location indoors. Different methods have already been created, designed, implemented so that they are used in production line and for research-purposes [19]. The most important ones are trilateration, triangulation and fingerprinting. Each one of them can be applied on technologies such as Wi-Fi, BLE and Ultra Wide Band (UWB) [12, 24, 32]. New upcoming technologies, especially the ones that belong to BLE and UWB which include the direction finding attribute promise an accuracy error of sub-meter. In addition, the direction finding feature makes these technologies direct a user even more precisely indoors [1, 2, 30]. Simply, both of the technologies use nodes, gateways, receivers/senders, database server, API's as third-party infrastructure and mobile/native/web Applications.

The applications of indoor positioning systems vary based on the application in real-world problems. Some of them are used in health-care hospitalities, such that hospitals, open care centers for elderly, psychiatric institutions for personal health care and safety purposes. Others are used in airports, shopping malls, clothes stores, universities, galleries, museums, beauty shops. Each of these systems has its own capabilities [9, 10, 13, 23, 26].

There are system that support monitoring, notifying and taking cared of the equipment of the sensors and actuators. These systems are in particular are designed for that purpose [24].

Algorithms	RMSE	MAE	HR	cHR	ARHR	Coverage	Diversity	Novelty
RBM Grid Search CV	1.1830	0.9864	0.0036	0.0035	0.0027	0.0000	0.0512	999.356
RBM Simple	1.1872	0.9914	0.0030	0.0030	0.0020	0.0000	0.0337	959.6132
Random	1.4385	1.1478	0.0089	0.0089	0.0015	1.0000	0.0719	557.8365

Table 2.
RBM performance evaluation on RMSE, MAE, HR, cHR, ARHR, Coverage, Diversity and Novelty.

4. Research Methodology

So, the research methodology that is formed in this case is by formulating the space into the shape of a grid. After setting the appropriate items into the corresponding grid square, the goal is to apply apply a Grid Search CV RBM algorithm in the data gathered from user's mobility indoors. The reason that we apply RBM algorithm is the fact that while a user navigates indoors , they rate on item they have already visited. The application scenario is an indoor space, a smartphone application that is built into smart phones. The user whilst navigating indoors launched the application to gather and collect information for they personal purposes. After receiving and counting the information that is nearby based on they position a pop up notification is shared on the screen so that they are asked to provide rating for the particular information received. In a variety of spaces, the information items are updated regularly since as they evolve. The particular algorithm is also used because the missing values are not taken into consideration and subsequently they are discarded. Also, the cold-start problem is solved since the specific algorithm is a collaborative filtering algorithm so that items are recommended firstly based on their profile only up until data are gathered, collected, cleansed, processed, trained, tested, modeled, evaluated and deployed.

4.1 Research Results

For this particular experiment, we carried out experiments on a 100.000 million records-ratings which include 9000 items by 600 users. Experiments were run on a Windows 11 Operating System (OS) that carries 16 GB RAM at 2400MHz frequency, 256 SSD Hard drive and an AMD Ryzen 5 4-core processor with Integrated Graphics card Radeon Vega Mobile Gfx. Table 2 summarizes the results based on RMSE, MAE, HR, cHR, ARHR, Coverage, Diversity and Novelty metrics.

Apart from the most common machine learning metrics, the time throughput is examined in order to measure the time the particular models lasted in terms of 100.000 million records that were available. The metric performs better once the values that it gives are higher. Equation 1 describes best the fraction in million of records per seconds.

$$TimeThroughput(TT) = \frac{No.ofrecords}{processingtime}\frac{pts}{sec} \tag{1}$$

Table 3 summarizes the results of the Time Throughput in millions of records per time in seconds.

Algorithms	Time Throughput
RBM Grid Search CV	100.000/79200=1.2620
RBM Simple	100.000/600=36.0000
Random	100.000/300=333.3333

Table 3.
Time Throughput in terms of number of records examined per seconds.

According to Table 3 in terms of speed, random outperformed both, Tuned RBM and RBM with the time throughput to be equal to 333 no. of records per seconds. RBM performed better than the tuned RBM, but worse than the random model decreasing its performance by 108%. Tuned RBM was the worst in terms of time throughput in which the results by 350% and 3700% compared with RBM and the random one, respectively.

According to Table 2 , the best results are given by the RBM which the hyperparameters were tune on 10 hidden layers, learning rate equal to 0.01, epochs were equal to 20 and the batch size equal to 20. Tuned RBM outperformed plain RBM and a random algorithm which in this case is the Normal predictor considered as random found in the literature [28, 31]. In case of the Tuned RBM with 10 cross-validation tests, RMSE equals to 1.1830, MAE equals to 0.9864, HR equals to 0.0036, cHR equals to 0.0035, ARHR equals to 0.0027, Coverage equals to 0, Diversity equals to 0.0512 and Novelty equals to 999.356. In case of RBM without tuning, RMSE results equal to 1.1872, MAE equals to 0.9914, HR equals to 0.0030, cHR equals to 0.0030, ARHR equals to 0.0020, Coverage equals to 0, Diversity equals to 0.0337 and Novelty equals to 959.6132. The normal predictor model gave the worst results in all the metrics, but coverage. The RMSE score equals to 1.4385, MAE equals to 1.1478, HR equals to 0.0089, cHR equals to 0.0089, ARHR equals to 0.0015, Coverage equals to 1, Diversity equals to 0.0719 and Novelty 557.8365. Intuitively, an algorithm outperforms in terms of RMSE and MAE once the values are lower. In addition, an algorithm outperforms in terms of HR, cHR, ARHR, Coverage, Diversity and Novelty once the values are higher.

4.2 Acronyms and abbreviations

Feet (ft) Meters (m) Consumption (CONSUMP) Operating System (OS) Gigabytes (GB) MegaHertz (MHz) Root Mean Square Error (RMSE) Mean Average Error (MAE) Hit Rate (HR) cumulative Hit Rate (cHR) Average Reciprocal Hit Rate (ARHR) Time Throughput (TT) University of Ioannina (UOI)

5. Conclusions

Recommending items outdoors has already become an old field of study since GPS and the accuracy that it provides helped researchers get in-depth in the very early stage of its invention. Studying recommendations in smaller scale area and in particular, recommending items indoors has become vital and important research topic in today's researchers interests. Short-range wireless communications even enhanced positioning users indoors, which is something that makes recommender systems models much more accurate in providing personalized information to the end-user. This research work focused on the performance evaluation of the RBM model, its tuned version and a random one, which in this case is the normal prediction. Results have shown that the hyperparameter tuned RBM model outperformed the rest of the two algorithms in terms of RMSE, MAE, HR, cHR, ARHR, Coverage, Diversity and Novelty, but normal predictor outperformed the rest of the two models in terms of Coverage. In addition, a new metric is proposed, named after Time Throughput, which examined the number of records stored statically into the database in the units of seconds. Results have shown that the normal predictor algorithm outperformed the tuned RBM and the simplest form of its, RBM. To sum up, considering the metrics performance evaluation and time throughput results, the best model for this case is the simple form of RBM model.

Conflict of interest

The authors declare no conflict of interest

Abbreviations

AI	Artificial Intelligence
RS	Recommender Systems
ML	Machine Learning
TT	Time Throughput
BLE	Bluetooth Low Energy
UWB	Ultra Wide Band
RBM	Restricted Boltzmann Machine
NN	Neural Network
DNN	Deep Neural Network

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