Graph-Based Deep Learning for Multi-Floor Indoor Localization

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Abstract

This project aims to investigate indoor localization systems using a graph-based deep-learning approaches inspired by the research in the literature. The project focuses on graph construction and model development to accurately predict the location of users within complex indoor environments. We leverage a graph structure to model the connections between access points (APs) and waypoints, forming a heterogeneous graph. The graph construction considers the signal propagation between APs and devices, capturing the relationship between them. The constructed graph incorporates node features, such as AP identifiers and waypoint coordinates, as well as edge features, including RSSI values. Through supervised learning, the model is initially trained using labeled data from a source domain. Then, through semi-supervised adversarial domain adaptation, the model fine-tunes its parameters using both labeled source domain data and unlabeled target domain data, enabling effective transfer learning.

1. Introduction

Indoor localization is a critical task with applications in various domains, including navigation systems, asset tracking, and context-aware services. This project draws inspiration from the research paper on Graph Location Networks [1], which proposes a graph-based deep learning approach for indoor localization. We aim to build upon their work and develop a unique system that integrates graph-based models, deep learning techniques, and zero-shot learning to achieve accurate and robust multi-floor indoor localization.

2. Related Work

Authors in [1] presents Graph Location Networks (GLN), a method for image-based indoor localization using graph-based techniques and zero-shot learning. GLN employs graph neural networks (GNNs) to process graph data and extract location embeddings for classification. The method consists of feature extraction, message passing, and location prediction modules. It extends to zero-shot localization by training location embeddings and learning a compatibility function. The approach allows accurate localization even for unseen locations and achieves promising results in the experiments conducted.

In [2], authors describes the data preprocessing steps, including standardizing the RSSI values and transforming the AP bssids into integer indices. The construction of graphs is explained, with the aim of representing the connection relationships between APs and waypoints. Heterogeneous graphs are formed, and subgraphs are created for each waypoint, incorporating 1st-order and 2nd-order neighboring nodes. Two neural network models are presented: Deep Sets and WiDAGCN. The Deep Sets model utilizes a summation operation to maintain permutation invariance, while the WiDAGCN model combines graph convolutional networks (GCNs) with adversarial domain adaptation. The structure and components of both models are described, highlighting their architecture and key operations. The paper then discusses the training schemes. In the supervised learning approach, the models are fine-tuned using labeled data from the source domain and a limited amount of labeled data from the target domain. Different fine-

tuning methods are compared. In the semi-supervised adversarial domain adaptation approach, a feature extractor and regressor are trained to generate domain-invariant features, while a domain discriminator acts as an adversary to align the features to a common distribution. The training process and loss functions used are explained.

In [3], authors presents a method for localization using a graph neural network (GNN) and spatial information. The approach involves building a graph based on the positions of access points (APs) and their distances. If a complete map is not available, the distances between APs are estimated using the RSSI measurements from the training set. The GNN is then applied to the graph to classify the RSSI measurements into different zones. The GNN extends convolutional neural networks (CNNs) to graphs by using the graph shift operator and performing graph convolution. A deep GNN architecture is employed by concatenating multiple graph perceptrons. The output of the GNN is combined with a fully connected neural network to predict the zone. The parameters are optimized using cross entropy as the cost function. The proposed method improves generalization and reduces the required training samples by leveraging the graph structure. The GNN also provides node embeddings that can be further analyzed for localization purposes.

In [4], authors propose a GCN-based localization scheme for indoor positioning. The system model consists of APs and reference points (RPs). In the offline training stage, an RSSI fingerprint database is constructed using sampled RSSIs from APs at different locations. In the online deployment stage, the location is estimated based on the fingerprint database and real-time observations. GCN is used to extract features from the RSSI observations, and a neural network architecture is designed for classification. The problem is formulated as cross-entropy minimization. The adjacency matrix for the GCN is constructed based on the statistical profile of the training dataset or the reciprocal of the distance between APs. The proposed scheme is evaluated using the mean absolute error (MAE) and cross-entropy metrics. The neural network architecture includes GCN layers and MLP layers, and ReLU and softmax activation functions are used. Different adjacency matrix construction methods are proposed for different scenarios. The performance of the proposed scheme is analyzed and compared with existing methods.

Deep Sets Model:

- ϕ Network:
- Input: The input features of the APs are denoted as X_{AP}, and the input features of the waypoints are denoted as X_{WP}.
- Embedding Layer: The embedding layer transforms the bssid features of the APs into embeddings, denoted as E_{AP}.
- Fully-Connected Encoding Layer: The encoding layer processes the RSSI values of the APs and transforms them into a feature matrix, denoted as M_{RSSI}.
- Output: The output of the ϕ network is the combined feature matrix X = [E_{AP}; M_{RSSI}].
- ρ Network:
- Input: The input to the ρ network is the feature matrix X.
- Summation Operation: The ρ network applies a permutation invariant operation, such as summation, to combine the features of the APs and waypoints. It sums the features along the set elements axis.
- Output: The output of the ρ network is the predicted coordinate of the waypoint.

WiDAGCN Model:

- WiAGCN Model:
- Graph Feature Extractor $G(x)$:
- Input: The input subgraph contains AP nodes V_{AP} and waypoint nodes V_{WP}. It also includes the edges E_{WP→AP} representing the connections from waypoints to APs and the edges E_{AP→WP} representing the connections from APs to waypoints.
- Heterogeneous Graph Convolutional Layers: The graph feature extractor $G(x)$ uses heterogeneous graph convolutional layers to obtain node embeddings for the APs and waypoints.
- Graph-Attention Neural Network (GAT) Layer: The GAT layer captures attention weights for different nodes in the graph, enhancing the representation learning process.
- Output: The output of the graph feature extractor $G(x)$ is a set of node embeddings representing the APs and waypoints.
- WiDAGCN Model:
- Graph Feature Extractor $G(x)$:
- The WiDAGCN model utilizes the same graph feature extractor as the WiAGCN model, $G(x)$.
- Regressor $R(x)$:
- The regressor $R(x)$ takes the output of $G(x)$ and predicts the coordinates of the waypoints.
- Domain Discriminator $D(x)$:
- The domain discriminator $D(x)$ aims to classify whether the input data comes from the source domain or the target domain.
- Gradient Reversal Layer (GRL):
- The GRL is used to reverse the gradient during the backpropagation, making the features aligned between the source and target domains.
- Training Objectives:
- The model is trained using a combination of supervised and semi-supervised adversarial training.
- The feature extractor $G(x)$ and regressor $R(x)$ are trained to minimize the localization loss while the discriminator $D(x)$ is trained to correctly classify the domains.
- The GRL is used to update the parameters of $G(x)$ and $R(x)$ in a way that the features become domain-invariant.

3. Methodology

3.1. Dataset

The dataset is provided as 'csv' files to facilitate data processing, and no specific software is needed to read the 'csv' files. The 'csv' file consists of the following columns:

1. **Coordinates**: Three columns in the dataset shows the GPS coordinates (latitude, longitude, and floor) of the classrooms where the measurements were taken. Example: (x, y, z) = (36.89672737982672, 30.649524638866378, 1) for a measurement in the dataset.

2. **RSSI and Mac Address**: There are 85 columns named as all MAC addresses seen during the total measurement time. These columns are sorted in numerical and alphabetical order. In each row, the RSSI information taken from the Wi-Fi AP with that MAC address is shown in the dataset. Each row corresponds to one measurement. The non-heard Aps are set to 0 dBm. For instance, in the dataset, Wi-Fi AP with MAC address '04:bd:88:84:ac:a0' was heard at -66 dBm. The RSSI values are interpolated between the timestamps of each measurement. It is important to mention how these RSSI values are distributed in the database. Figure x introduces the histogram and KDE of all MAC addresses in the database.
3. **Timestamp**: The timestamp column represents interpolated timestamps of each measurement in UNIX time format. The timestamps provided are recorded in a mobile device between starting and ending times of each measurement.
4. **Room**: The room column represents the room's identification number where the measurements were done. Data collection was done in the Engineering Faculty Building's classrooms, and these room identification numbers are set before measurements were taken in the mobile application. There are a total number of 20 classrooms in the dataset.

3.2. Data Collection Procedure

The data were collected with an Android application coded in Flutter. The server has been written using C#. The model of the phone used for data collection is Samsung Galaxy J200F with Android version Android 7.1.2. In order to obtain maximum efficiency in the data collection process, the device charge was kept at maximum with powerbank. Measurements were taken in all classrooms of the Engineering Faculty Building for one minute duration. Since the exact location of the access points in the building is not known and some of them are mobile access points of the people in the building, as a result of one-minute measurements, less than 15 Wi-Fi devices were filtered and the final result obtained was 85 Wi-Fi Access Points. Measurements were not taken in line-of-sight since fingerprinting does not require line-of-sight. In the mobile application used, the faculty is selected first. Thereafter, if there is more than one building in the faculty, the building selection is made and the floor selection can be made on the screen that opens afterwards. The floor plan of the building is loaded from the database according to the selected floor. A point is selected on the plotted areas on the map to start the measurement. Room ID, room type and category are displayed in the window that opens at the top. Pressing the yellow arrow button in this window starts a one-minute measurement. The measurements are recorded in the database.

3.3. Graph Construction

In this project, the graph construction step is crucial for capturing the relationships between access points (APs) and waypoints. The graph is represented as a heterogeneous graph consisting of two types of nodes: AP nodes (V_AP) and waypoint nodes (V_WP). The edges (E) in the graph include AP-to-waypoint edges (E_WP→AP) and waypoint-to-AP edges (E_AP→WP).

To construct the graph, the features of the nodes and edges are defined. The node features (F_V) contain the RSSI (Received Signal Strength Indicator) values and bssid (basic service set identifier) identifiers. These features represent the signal strengths of different APs and enable the identification of important APs.

The edge features (F_E) capture the RSSI values between connected APs and waypoints. These values reflect the signal propagation between the APs and devices, forming the connection relationship in the

graph. The graph construction process involves creating subgraphs for each waypoint. The subgraphs are constructed by selecting the neighboring nodes up to a certain order, ensuring that the complexity of the graph is reduced.

3.3.1. Node Types

- **AP Nodes (V_AP):** These nodes represent the access points in the indoor environment. Each AP node is associated with a specific bssid (basic service set identifier), which serves as a unique identifier for the AP. The bssid is transformed into an embedding or encoding to capture the characteristics of the AP.
- **Waypoint Nodes (V_WP):** These nodes represent the waypoints in the indoor environment. Waypoints are specific locations that need to be localized accurately. The waypoint nodes can be labeled with known coordinates (in the source domain) or have unknown coordinates (in the target domain).

3.3.2. Edge Types:

- AP-to-Waypoint Edges (E_WP→AP): These edges represent the connections from APs to waypoints. They capture the signal propagation and strength between the APs and the waypoints. The edge features for these connections include the RSSI (Received Signal Strength Indicator) values, which indicate the signal strength received from the AP.
- Waypoint-to-AP Edges (E_AP→WP): These edges represent the connections from waypoints to APs. They reflect the relationship between waypoints and the APs they are associated with. The edge features for these connections can also include RSSI values, representing the signal strength from the waypoint to the AP.

3.3.3. Graph Structure

The constructed graphs are heterogeneous graphs with multiple types of nodes and edges. They are represented as G = (V, E, F_V, F_E), where V represents the set of nodes (V = {V_WP, V_AP}), E represents the set of edges (E = {E_WP→AP, E_AP→WP}), F_V represents the node features, and F_E represents the edge features.

It's important to note that the graph construction process involves creating subgraphs for each waypoint, considering neighboring nodes up to a certain order (such as 1st-order or 2nd-order neighbors). The subgraph construction focuses on selecting relevant nodes and maintaining the connectivity between them.

3.4. Model Development

3.4.1. Graph Convolutional Recurrent Network

This section presents the Graph Convolutional Recurrent Network (GCRN) model for indoor localization. The GCRN model combines graph-based techniques, deep learning architectures, and transfer learning to accurately predict indoor coordinates or room labels. The model exploits a graph structure to capture the relationships between access points and waypoints, while incorporating recurrent layers to model the

temporal dependencies in sequential RSSI measurements. Transfer learning is employed to adapt the model to different domains, enhancing its ability to generalize to unseen environments.

Graph Convolutional Network Layer

The graph convolutional layers aim to learn node embeddings that capture the relationships between nodes in the graph. Given an input node feature matrix X, the output node feature matrix H is computed as:

$H = \sigma(D^{-1} * A * X * W)$,

where σ is an activation function, D is the diagonal degree matrix of A, and W is the weight matrix for the graph convolution operation.

Recurrent Neural Network Layer

In the context of the GCRN model for indoor localization, the RNN component is used to model the temporal dependencies in the sequential measurements of RSSI values. Given a sequence of input RSSI measurements $X_{seq} = [x_1, x_2, ..., x_T]$, where T is the sequence length, the recurrent layers capture the hidden states H_{rec} at each time step t. At each time step t, the hidden state $H_{rec}[t]$ is computed based on the current input x_t and the previous hidden state $H_{rec}[t-1]$ using the RNN operation (either LSTM or GRU):

$H_{rec}[t] = RNN(x_t, H_{rec}[t-1])$.

During the training of the GCRN model, the parameters of the RNN layers (LSTM or GRU) are updated through backpropagation and gradient descent optimization. The goal is to learn the optimal weights that capture the temporal dependencies in the sequential RSSI measurements and improve the localization accuracy.

Fusion Layer

The fusion layer is a crucial component in the GCRN (Graph Convolutional Recurrent Network) model that combines the outputs of the graph convolutional layers and the recurrent layers to obtain a fused representation of the input data. This fused representation captures both the graph structure information and the temporal dependencies present in the sequential measurements.

Inputs for Fusion Layer:

The outputs of the graph convolutional layers, denoted as H, represent the learned node embeddings that capture the relationships between access points (APs) and waypoints in the graph structure. The outputs of the recurrent layers, denoted as H_{rec}, represent the hidden states that capture the temporal dependencies in the sequential measurements of RSSI values.

Concatenation in Fusion Layer:

The fusion layer concatenates the output features from the graph convolutional layers (H) and the recurrent layers (H_{rec}) to create a fused representation, denoted as F. This concatenation operation combines the graph-based information captured by H and the temporal information captured by H_{rec}, creating a comprehensive representation of the input data.

Mathematically, the fusion layer can be represented as:

F = [H, H_rec],

where [., .] denotes the concatenation operation.

Output for Fusion Layer:

The fused representation F contains information from both the graph convolutional layers and the recurrent layers. This fused representation serves as an integrated feature representation that captures the combined knowledge of the graph structure and temporal dynamics of the sequential measurements.

Localization Layer

The localization layer is responsible for predicting the coordinates or room labels of the waypoints based on the fused representation obtained from the fusion layer in the GCRN (Graph Convolutional Recurrent Network) model. It takes the fused representation as input and produces the final predictions.

Inputs:

The fused representation F, obtained from the fusion layer, contains the combined information from the graph convolutional layers and the recurrent layers. It represents a comprehensive feature representation that captures both the graph structure information and the temporal dependencies in the sequential measurements.

Coordinate Prediction:

If the task is to predict the coordinates of the waypoints, the localization layer utilizes a weight matrix W_coord. The fused representation F is multiplied by the weight matrix W_coord to obtain the predicted coordinates Y_coord. Mathematically, the coordinate prediction can be represented as:

Y_coord = F * W_coord,

where Y_coord represents the predicted coordinates.

Room Label Classification:

If the task is to classify the room labels of the waypoints, the localization layer utilizes a weight matrix W_label. The fused representation F is multiplied by the weight matrix W_label, and a softmax activation function is applied to obtain the predicted probabilities for each room label.

Mathematically, the room label classification can be represented as:

Y_label = softmax(F * W_label),

where Y_label represents the predicted probabilities for each room label.

Output:

The output of the localization layer depends on the specific task. For coordinate prediction, the output is the predicted coordinates Y_coord. For room label classification, the output is the predicted probabilities for each room label Y_label.

The localization layer takes the fused representation as input and applies appropriate operations (e.g., matrix multiplication and activation functions) to produce the final predictions for the indoor localization task. It leverages the learned representations and information from the previous layers to make accurate predictions of the coordinates or room labels for the waypoints. By using the fused representation from the fusion layer, the localization layer effectively combines the graph-based relationships, temporal dependencies, and other relevant information to provide accurate predictions for indoor localization.

3.4.2. Transfer Learning

Pretraining on Source Domain: The model is initially trained on a labeled dataset from a source domain, optimizing the parameters of all layers.

Feature Extraction: During transfer learning, the graph convolutional layers and recurrent layers are frozen, and only the fusion and localization layers are fine-tuned.

Domain Adaptation: The pretrained model is further fine-tuned on the target domain dataset, updating the parameters of the fusion and localization layers using a smaller amount of labeled data from the target domain.

The model is trained using a suitable loss function, such as mean squared error (MSE) for coordinate prediction or categorical cross-entropy for room label classification. The parameters of the model are optimized using gradient-based optimization algorithms, such as stochastic gradient descent (SGD) or Adam. The model's performance is evaluated using appropriate evaluation metrics, such as mean absolute error (MAE) or accuracy, on a validation or test set.

References

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