Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

Domain Background

The dataset I plan to use for the project was used in the article published in IEEE journal called "Enabling Cognitive Smart Cities Using Big Data and Machine Learning: Approaches and Challenges." The article discusses the challenges faced by the generation of unlabeled bigdata from smart cities.
The smart equipment used in the smart cities generates the tremendous amount of data. However, most of the data generated are not labeled; therefore, all the unlabeled data, which accounts for the eighty percent of the total data, get thrown out and not used in the machine learning to predict the outcome or to find a pattern in the data.

Most of the current methods that use the data from the smart cities utilize the method of sampling to make the predictions or to find a general pattern in the data. Even though sampling method produces good estimates in some cases, the sampling method is not the most effective way to utilize the data since the preference of the people living in different parts of the cities matters more. To use sampling and predict the data well, the sampling of the data needs to be large and, it is not possible to use unlabeled data for the sampling.
The article gives an example of criminal activities detection through the social media sites like Facebook and Twitter. To detect a criminal with high accuracy, the data needs to be sufficiently large. Therefore, the sampling methods are not useful in such scenarios.

The article talks about many related works toward the solution of the problem stated above. The related work discussed in the article include IBM Watson, Google Now, HPE Haven OnDemand, Cognitive IoT, Intelligent gateway, etc.

Google Now is among the important related works discussions in the article. Google Now service helps user provide suggestions and essential information at the right time and right place. Google Now uses the reinforced learning among many other methodologies to learn from the user data.

I like to investigate the problem posed in the articles because I am a communications engineer with the focus on IoT innovations. The problem relates to the filed I am passionate about.

Problem Statement

The indoor navigation of a user using the information collected by the smart IoT devices is the goal of the project. The dataset contains the information about a discrete floor map and the readings from IoT devices with which disabled or blind users can be navigated. The project aims to navigate the user from one location to another location within the floor map with minimum distance traveling. The initial and final position of the user will be set in advance. The path to travel from the initial to target location is the challenge that needs to be solved. The problem can have different initial and final positions that are within the floor map.

The unlabeled data needs to be used to travel from initial position to the target position efficiently. The solution model should be able to utilize the unlabeled data to increase the performance of the model compare to the model that uses only labeled data.

Datasets and Inputs

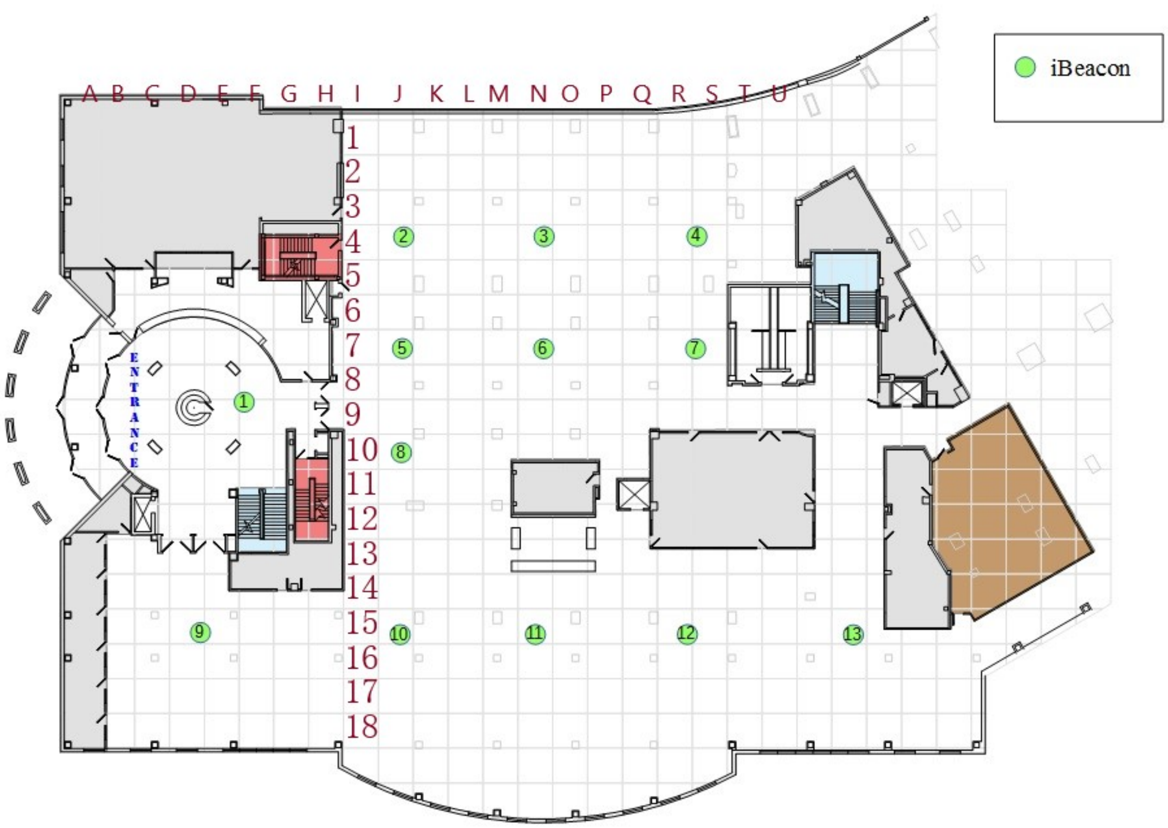

Figure 1 Floor map of library locating beacons and positions (Mohammadi, Al-Fuqaha, Guizani, & Oh, 2018)

Figure 1 shows the first floor of Waldo Library in Western Michigan University with the markings iBeacons in green color and a grid consisting little squares. IBeacons are low power Bluetooth devices that send a signal to a user. The closer a user to a beacon, the stronger the signal from the beacon.

As shown in figure 1, there are thirteen iBeacons set up on the first floor of the library. Each beacon transmits the signal which is picked up by the nearby user Bluetooth device. The strength of the signal from the beacon to the user is measured by the user device in RSSI. RSSI is the short form of Received Signal Strength Indicator. RSSI is a value indicating the strength of the signal from an iBeacon to the user device. The RSSI values measured are negative with minimum being -200. The RSSI value -200 suggests that the iBeacon is not in the range of the user device. A bigger value of RSSI from an iBeacon like -75 suggests that the iBeacon is closer to the user device. Since there are thirteen iBeacon devices, there are thirteen data variables, one data variable for each iBeacon. The data variables of the iBeacon are called as b3001, b3002, …, b3013. The iBeacon data variables contain only negative integers indicating RSSI values.

Figure 1 is divided into small rectangles of which columns are named by a letter and rows are named by a number. The little squares are the position of the library mapped by the letters and the numbers shown in figure 1. Each position, square, in the figure, is named as the ColumnRow format. For example, the iBeacon 3 is the square named N03 where N is the column and 03 is the row of the square location. In the dataset, each location has been assigned thirteen iBeacon RSSI values and a date.

The dataset also contains the time and date upon which location name and thirteen iBeacon data variables are captured. The format of the date variable is MM-DD-YYYY HH:MM:SS.

The dataset has fourteen input variables and one output variable. The fourteen-input variable includes all the thirteen iBeacon RSSI values data variables and date variable. The output variable is the symbolic location (square).

There are two sets. One set contains the symbolic location values and the other set do not contain the location values. There are 1420 labeled and 5200 unlabeled data points. However, both set contains all the values of the fourteen input variables with no missing data.

Solution Statement

The combination of Deep Neural Network (DNN), Reinforced Learning (RL), and semi-supervised learning is used as the solution to the problem created by a significant amount of unlabeled data.

DNN is a learning based on the neural nets, and it is a part of supervised learning. Reinforced learning is part of unsupervised learning which is a good match for the smart city data since many of the smart city data does not need an output but need an action to do a specific task. RL is a reward-based system where each action taken by the system has a reward, and the RL is trained in such a way that it maximizes the reward.

Similarly, semi-supervised learning uses the combination of labeled and unlabeled data to make decisions. Since there are many data points without the label, the semi-supervised learning is an excellent solution to the problem.

The solution contains the use of deep reinforcement learning using variational autoencoder (VAE). The agent designed for the problem observes the environment parameters and takes action to maximize the rewards earned. The goal of the agent is to travel from initial position to the final position with minimum distance while maximizing the rewards. The variational autoencoder neural net is used to predict state or the location label based on the RSSI readings from the IoT devices or iBeacons.

Benchmark Model

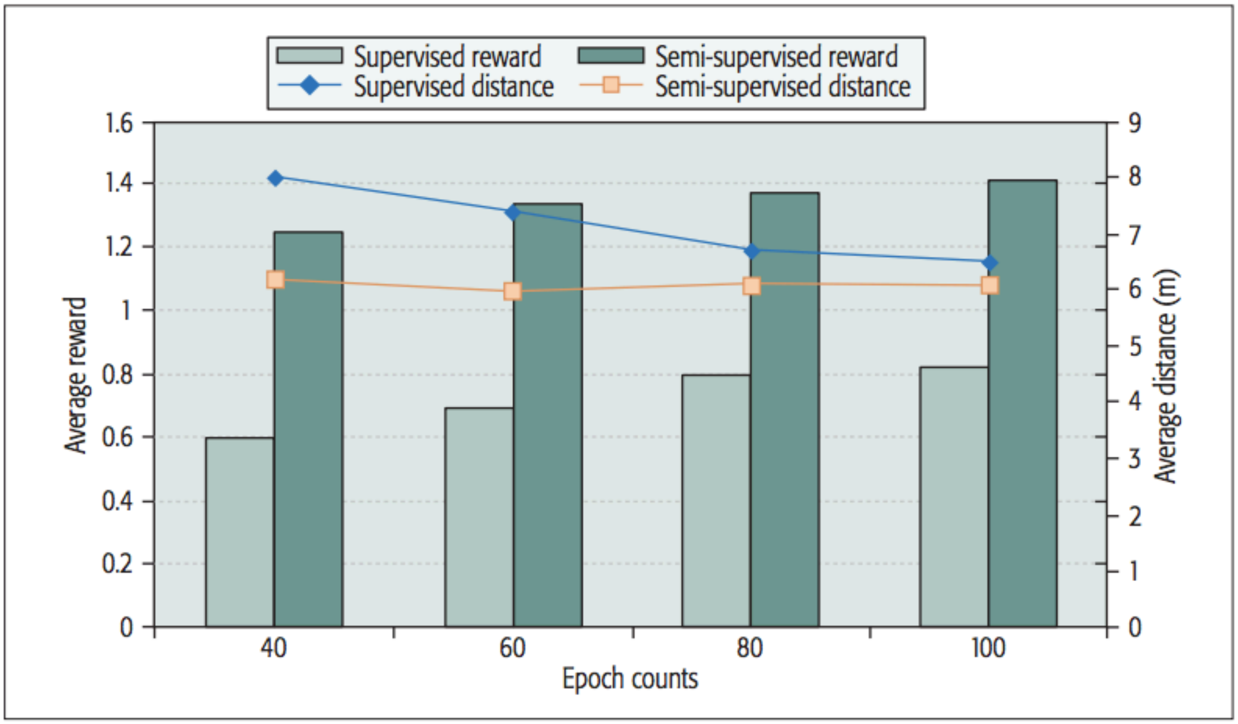

Figure 2 Performance of the proposed semi-supervised DLR model (Mohammadi, Al-Fuqaha, Guizani, & Oh, 2018)

The authors of the article used two datasets to train a semi-supervised DLR model. The fundamental reason for including semi-supervised learning is to provide the navigation service for indoor environments. The reward function for the reinforced learning is set to the reciprocal of the distance to the reference position. The model gets trained based on the RSSI readings from the low energy Bluetooth beacons and guides the user based on the best action like a move to the right, a move to the left, etc. As the user gets close to the referenced position, the reward value increases as the distance between the user and the reference location decreases.

The author of the article trained the model for both supervised and semi-supervised learning scenario. The figure 2 shows the bar graph comparing the performance of the supervised and semi-supervised learning over increasing number of epochs. As we can see in figure 2, the semi-supervised model gives the high amount of the rewords in very few cycles of epochs than the supervised model. The supervised model needs about one hundred epochs to reach the average reward amount of 0.8 while the semi-supervised model reaches the average reword of 1.2 in just forty epochs. Therefore, the semi-supervised DLR model performs much better than the supervised learning model. Also, the model also solves the problem of unlabeled data by using them in semi-supervised learning.

Evaluation Metrics

As discussed in the benchmark model, the solution model will be evaluated based on the distance traveled toward the target per step or epoch. As the agent trains, the agent should be able to get to the target position faster or with fewer time steps. The supervised learning model has only labeled dataset to train from and decide the path to the destination while semi-supervised learning model has both labeled and unlabeled data. Therefore, the semi-supervised learning model should be able to learn better than the supervised learning model and get to the target position in more optimized manner.

The rewards and the distance traveled by the agent will be calculated and stored at each time step for both supervised and semi-supervised learning models. If the agent goes more distance or takes fewer steps to get to the destination in semi-supervised model compare to the supervised model, the semi-supervised model has performed better than the supervised learning model. Therefore, better performance of the semi-supervised model proves that the unlabeled data help increase the efficiency of the model.

Project Design

The algorithm shown in figure 3 will be used to implement the deep reinforcement learning agent. The data from the labeled and unlabeled set will be cleaned if needed and additional feature set will be added if the feature set improves the outcome. Figure 4 shows the general architecture of the variational encoder (VAE). The variation encoder will be implemented for the semi-supervised learning model. The supervised learning model will be applied using a deep neural network consisting of several dense layers.

Algorithm 1 Semisupervised DRL Algorithm

Input: A dataset of labeled and unlabeled data $\{(X_l, Y_l), X_u\}$
Initialize the model parameters θ, ϕ, environment, state space, and replay memory $\mathcal{D}$
for *episode* $\leftarrow 1$ to M **do**
  for each sample (x, y) or x in dataset **do**
    $s_0 \leftarrow$ make observation of sample x
    for $t \leftarrow 0$ to T **do**
      Take an action a_t using ϵ-greedy strategy
      Perform action a_t to change the current state s_t to the next state s_{t+1}
      if sample is unlabeled **then**
        Infer the label based on (4): $q_\phi(y|x)$ and get approximate reward $r_t = closeness(s_{t+1}, y)$
      else
        Observe reward r_t that corresponds to label y
      Store transition (s_t, a_t, r_t, s_{t+1}) in $\mathcal{D}$
      Take a random minibatch of transitions (s_k, a_k, r_k, s_{k+1}) from $\mathcal{D}$; $0 < k \leq length(minibatch)$
      if s_{k+1} is a terminal state **then**
        $\xi_k = r_k$
      else
        $\xi_k = r_k + \gamma \max_{a'} Q(s_{k+1}, a'; \theta)$
      Apply gradient descent on $(\xi_k - Q(s_k, a; \theta))^2$ based on (13)
    end for
  end for each
end for

Figure 3 Semi-supervised DRL Algorithm to be used in the solution

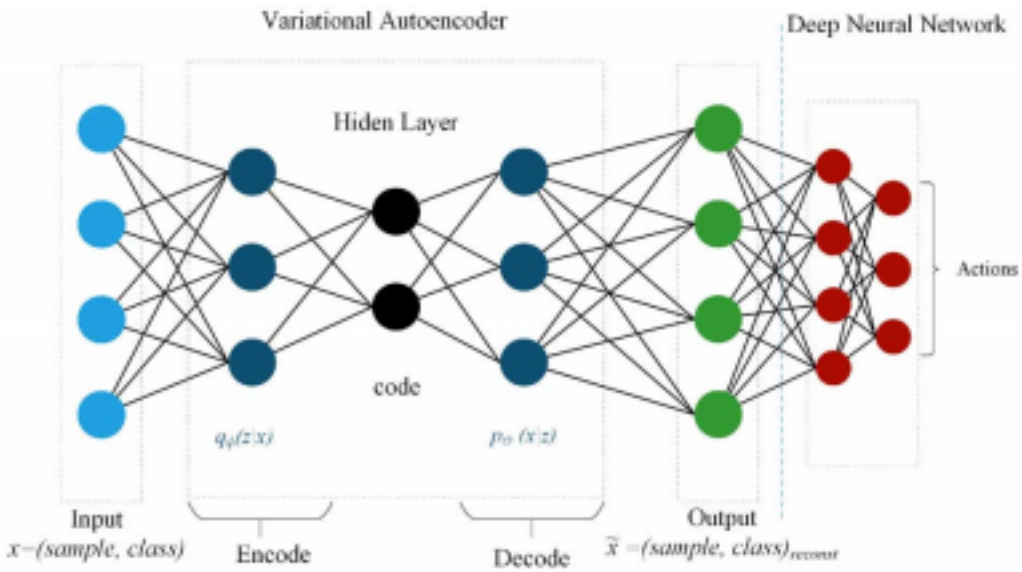

Figure 4 variational autoencoder (VAE) model

References

[1] M. Mohammadi, A. Al-Fuqaha, S. Sorour and M. Guizani, "Deep Learning for IoT Big Data and Streaming Analytics: A Survey," in *IEEE Communications Surveys & Tutorials*. doi: 10.1109/COMST.2018.2844341
URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8373692&isnumber=5451756

[2] M. Mohammadi, A. Al-Fuqaha, M. Guizani and J. S. Oh, "Semisupervised Deep Reinforcement Learning in Support of IoT and Smart City Services," in *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 624-635, April 2018.
doi: 10.1109/JIOT.2017.2712560
URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7945258&isnumber=8334665

[3] Link to the dataset:
URL:https://archive.ics.uci.edu/ml/datasets/BLE+RSSI+Dataset+for+Indoor+localization+and+Navigation