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Efficient User Localization in Wireless Networks Using Active Deep Learning

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***Abstract*—In this paper, we investigate the problem of user localization in wireless networks using Active Deep Learning. We constructed a deep neural network to learn the channel state information collected by antennas, and implemented active learning mechanism to improve the efficiency of utilizing labeled data. The performance and behavior of different active learning query strategies are compared and analyzed. We propose a location based query strategy that considers both spatial density and model uncertainty when selecting samples to label. Experimental results show that the active learning methodology is capable of achieving a same level of performance as traditional models using far less labeled samples. In addition, the location based strategy outperforms all the other query strategies for the location prediction problem.**

I. Introduction

The problem of user localization is increasingly drawing attentions from wireless communication researchers, and its applications span across various scenarios such as navigation [1], surveillance, Internet of Things (IoT) [2], [3], and so on. With the rapid development of machine learning methodology, the theoretical foundation of leveraging machine learning in wireless channel modeling is studied and summarized [4]. Much research efforts have been made on building supervised learning models on the labeled channel state information (CSI) data for various purposes. For instance, neural network has been exploited to predict unobserved wireless channel features [5], and predict wireless channel statistical parameters from the location information between transmitters and receivers [6]. The authors in [7] proposed a method that synthesized multiple machine learning models to enhance the prediction on user locations.

In recent years, deep learning [8] has gained significant popularity due to its performance in complex machine learning scenarios such as image and video content extraction, cognitive modeling, autopilot, etc. The application of deep learning in wireless localization has also prevailed as hot research interests [9]. Different algorithms and model architectures have been explored in both indoor and outdoor localization problems. In [10], received signal strength (RSS) and CSI data are used to train convolutional deep networks that predict indoor object locations. Zhang et al. [11] proposed a deep neural network with a Hidden Markov Model (HMM) based localizer for wireless positioning. The authors in [12] compared the performance of common supervised learning and deep learning models on indoor localization, and found that deep learning model outperforms all the others.

While traditional machine learning models are broadly applied and have achieved state-of-the-art performance in these scenarios, the performance of supervised learning models largely depends on the amount of labeled training data. Large amounts of labeled data are typically required to train a well-fit model, while obtaining labeled data could involve immense manual labor and is therefore a considerably costly task. In addition, since the channel information data in our localization problem is in high dimensions, it could be time consuming to train models on the full dataset over a number of iterations.

To overcome the aforementioned drawbacks, in this paper we explore the use of active learning methodologies on the localization problem. Our goal is to improve the performance of traditional machine learning approaches in the following ways.

1) Less labeled data needed: The active learning approaches utilize a query strategy that iteratively determines the most valuable samples that could help improve model performance [13]. These samples are handed to an oracle for labeling and then fed into the model for training. This mechanism boosts the efficiency of utilizing the limited amount of labeled data, and as a result makes it possible to reduce the number of labeled data required to achieve the same performance.

2) Less model training time: Active learning typically works under scenarios of limited amount of labeled data, and functions by tactically finding the most valuable samples to label and to improve itself on. Thus, active learning models would fit less data samples than traditional models that trains on the entire training dataset at each iteration.

In this paper, we investigate the user localization problem based on active learning mechanisms. We compare the effectiveness of several commonly used query strategies, and propose a new location based query strategy to further boost the performance of location coordinate prediction.

The remainder of this paper is organized as follows. Section II provides an overview of the user localization problem definition and the high level structure of our solution model. Section III takes a deeper look into the active learning mechanism and its query strategies. The experimental setup, results and analysis are presented in Section IV. Finally, Section V concludes the paper.

II. Problem Statement and System Model

In this section we describe the localization problem this paper targets.

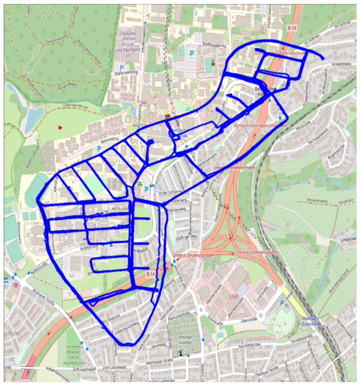

Fig. 1: Ground truth locations recorded by GPS.

A. Problem Definition

In our scenario, a transmitter, which is an SDR-equipped cart, moved randomly along campus roads inside a university residential area of several hundred square meters. At certain location spots, the channel responses were collected by an antenna array and recorded in the training data. The ground truth for each location, which is a 3-dimensional coordinate in the format of x, y and z, is provided by a differential GPS. Figure 1 shows the ground truth of all locations provided by GPS on a 2-D plane.

B. Data Sources and Format

The data used in this paper is from the IEEE CTW 2020 data competition on user localization. The dataset was acquired by the massive MIMO channel sounder [14] measuring outdoor channel responses between a moving transmitter and an 8x8 antenna array (only 56 out of the overall 64 antennas work properly). The channel information data collected for each location spot consists of 924 usable subcarriers, 56 functioning antennas and 5 channel measurements. There were 4979 location samples collected in total, forming into a dataset in the shape of $4979 \times 56 \times 924 \times 5$. Meanwhile, the signal-to-noise ratio data for each location, antenna and measurement was provided in a separate file. A ground truth file containing the x, y and z coordinates of all the 4979 locations was provided as labels.

Given the raw data files, our goal is to train a model that learns the pattern between the CSI input and location coordinates, and predicts user locations based on incoming CSI data.

C. System Model

In this paper, we build a data ingestion and modeling workflow to process the high dimensional CSI input and make location predictions using a deep learning model and active learning query strategies.

1) Dimensionality Reduction: In order to keep the model training process inside an acceptable period of time, the dimensionality reduction technique is applied to reduce the magnitude of our training data. We implemented an autoencoder [15], which consists of an encoder and a decoder, structured in Figure 2.

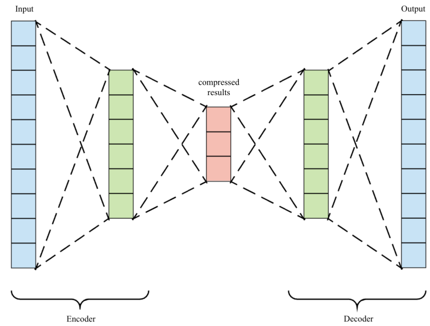

Fig. 2: The structure of autoencoder.

The encoder is a multi-layered neural network containing 3 convolutional 2D layers that gradually compress the input dimension of subcarriers from 925 to 37. While the subsequent decoder decodes the most compressed layer back to the original dimensions using a reversed network structure. The combined encoder-decoder model was trained to fit the original input data that is labeled by itself, so that the model would minimize the difference between the original input and the one going through our process of both compression and decompression. Finally after the training completes, the encoder part of the model was extracted and used to reduce the dimensionality of our input.

2) Neural Network Model: In our scenario, the localization problem could be formulated as a regression task based on the CSI input data and the coordinate labels. We adopt a multi-layered neural network as the basic learner of our regressor to fit the high dimensional CSI input, where all of our further active learning work is based.

The architecture of the basic model is illustrated in Figure 3, which takes the input data that already has its dimensionality reduced, and consists of 3 convolutional 1D layers and 3 dense layers to accept input and extract high level information. The output of the network consists of 3 nodes, representing the predicted coordinate in x, y and z axes, respectively. Based on the model tuning on our training data, we apply batch normalization for dense layers to stabilize training performance, and adopt ReLU activations for both convolutional and dense layers. The Adam optimizer is chosen as the best algorithm for calculating gradients.

III. Active Deep Learning Framework

In this section, we present our active learning framework.

A. Active Learning Preliminaries

For many real-world machine learning tasks, the number of unlabeled data could easily outmatch that of the labeled ones, while obtaining labels for the unlabeled data could often be of high cost. In recent years, active learning has evolved as an important branch of supervised learning to deal with scenarios where there are only limited amount of labeled data,

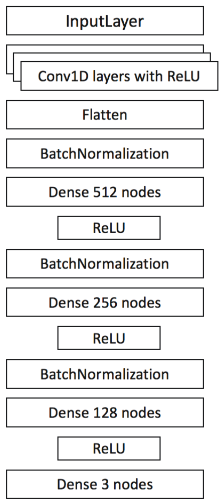

Fig. 3: The architecture of the basic learner.

while a large number of unlabeled data are available. Active learning improves the efficiency of utilizing labeled data and maximizes model performance by selecting certain samples from the unlabeled data pool to label before training. The selection is based on certain strategies that are called query strategies. The chosen samples are then labeled by an oracle or external human annotators, and fed back to the model to improve its performance. Figure 4 demonstrates the process of a typical active learning cycle.

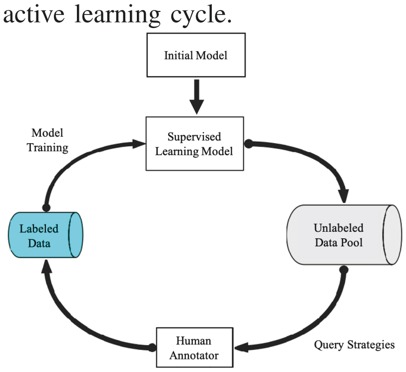

Fig. 4: Active learning cycle.

For each training iteration, the query strategy determines the most valuable samples for the model to learn, which is a decisive part in the active learning cycle. We will take a deeper look at different query strategies in the next section.

B. Query Strategies

There are several commonly used query strategies that aim at determining the most valuable samples for a human annotator to label.

1) Random Sampling: The random query strategy randomly selects samples from the unlabeled data pool without any preference. This strategy could typically serve as a benchmark and owns its advantage of being computationally efficient.

2) Least Confident: How uncertain the model is on the unlabeled samples could serve as a selection criterion [16]. Different measurements on model uncertainty result in different implementations of uncertainty query strategies. A commonly-used uncertainty measurement metric is based on the model's probability of its output, and selects samples with least confidence, as described in 1.

$$x_{LC} = \operatorname*{argmax}_x 1 - P(\hat{y}|x), \tag{1}$$

where $\hat{y}$ is the model's output with highest probability.

3) Margin Sampling: A variation of this strategy, which is called the margin sampling strategy, calculates the margin of each sample as the difference between its top probability and its second top probability, and selects samples with smallest margin as formulated in 2.

$$x_{MS} = \operatorname*{argmin}_x P(\hat{y1}|x) - P(\hat{y2}|x), \tag{2}$$

where $\hat{y1}$ and $\hat{y2}$ are the model's output with top and second top probability respectively.

4) Entropy Sampling: The entropy based strategy is a more generalized form of measuring uncertainty based on information theory, which calculates impurity in 3:

$$x_{ES} = \operatorname*{argmax}_x - \sum_i P(\hat{yi}|x) \log P(\hat{yi}|x), \tag{3}$$

where $\hat{yi}$ iterates through all possible model outputs.

5) Location Based Sampling: In this paper, based on the context and pattern of localization raw data, we propose a new query strategy described in 4.

$$x_{LB} = \operatorname*{argmax}_x (1 - P(\hat{y}|x)) * (\sum_i \|x - xc_i\|) \tag{4}$$

where xc is the set of all labeled samples, and $P(\hat{y}|x)$ is the model's probability output given an input x. This query strategy takes both model uncertainty and location density into consideration, and selects the sample that maximizes both the model's uncertainty, and the distance from any labeled samples in the space of input dimensions, with its measurement defined by the Euclidean distance. Compared with traditional uncertainty based strategies, the location based strategy adds the capability of selecting spatially balanced samples. This could help boost performance when the samples that the model is most uncertain of agglomerate together and cannot provide more global information.

In this paper, we refer to the least confident query strategy as "uncertainty sampling". We compare the performance of 5 active learning models that adopt these 5 query strategies respectively: random sampling, uncertainty sampling, margin sampling, entropy sampling and location based sampling.

IV. Numerical Results

A. Experimental Setup

We conduct data preprocessing, feature engineering and dimensionality reduction on the channel response data, and feed the processed data into our active learning architecture to analyze the effect of different query strategies and the pattern of samples chosen by different strategies.

1) Data Preprocessing: We calculate the Euclidean norm and the phase of each complex number in the channel response data, and stack them together with the provided signal noise ratio to form into a 4979×56×925×10 CSI dataset. This dataset then goes through the autoencoder dimensionality reduction process that reduces the dimension of subcarriers from 925 to 37. We split out 10 percent of overall data for test set, and within the training set, we further split out 80% for the labeled query pool that serves as the oracle, as shown in Figure 5. This means that the amount of labeled data for active learning is only 20% of that for a traditional supervised learning case.

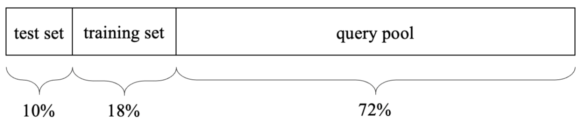

Fig. 5: The split of the dataset.

2) Learner Model: The base learner for our user location regression problem is a multi layer convolutional neural network. The architecture of the model is illustrated in Figure 3. The mean squared error (MSE) is used to evaluate model performance in our research, which can be denoted as following. Given that an input data has the true label $\mathbf{y}$ and predicted label is $\hat{\mathbf{y}}$, then the MSE is defined as:

$$\mathrm{MSE}(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{n} \sum_{n} ((\mathbf{y}_x - \hat{\mathbf{y}}_x)^2 + (\mathbf{y}_y - \hat{\mathbf{y}}_y)^2 + (\mathbf{y}_z - \hat{\mathbf{y}}_z)^2), \quad (5)$$

where $\mathbf{y_x}$, $\mathbf{y_y}$ and $\mathbf{y_z}$ are the true label coordinates on the x, y and z axis, respectively.

3) Active Learning Process: We customized an active learning architecture that pre-trains a basic learner using a given amount of labeled data. Then for each training iteration, the active learning mechanism chooses a batch of samples from our query pool according to different query strategies. The query pool comes from our labeled dataset so the samples automatically gets labeled, and the model then re-trains itself given these newly labeled data. Five query strategies are applied and compared here: random sampling, uncertainty sampling, margin sampling, entropy sampling and a proposed location based sampling. The changes of model performance over iterations under each query strategies were recorded for further analysis.

B. Performance Results

Figure 6 illustrates how the MSE changes over query iterations under all 5 query strategies. The gray horizontal line is the performance of a traditional model trained on the full labeled dataset using same iterations, which is a lower bound benchmark. It could be observed that most strategies tend to converge after around 500 queries, and the random sampling appears more unstable throughout the training. The proposed location-based strategy shows a fast convergence of 250 queries, with a rather good and stable prediction loss.

In addition, Figure 7 plots the cumulative distribution function of the MSE under each query strategy. The location based

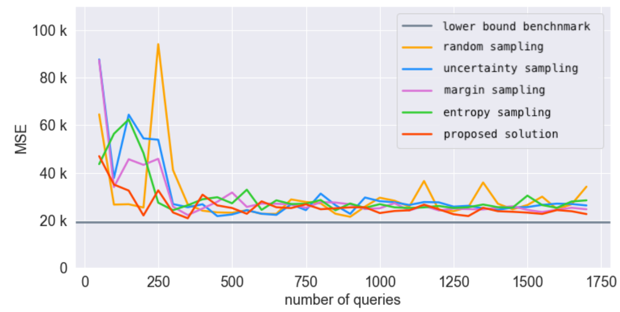

Fig. 6: MSE change over iterations under different query strategies.

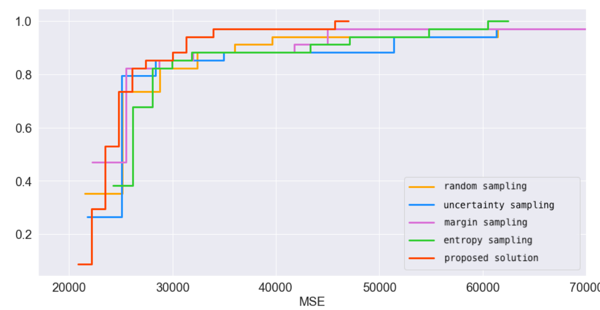

Fig. 7: The cumulative distribution function plot of MSE.

strategy outperforms all the others with a larger proportion of low MSE values. The random sampling strategy, on the other hand, contains larger amounts of big MSEs which indicates a more unstable fitting process.

Besides model performance, we explored into the samples chosen by each query strategy as well. Figure 8 visualizes all the chosen samples on a 2-d plane within the first 250 queries. The larger a dot is plotted, the earlier it is chosen by the strategy.

The margin and entropy sampling strategy display an early preference over the samples on the right and left part of the map respectively. While the early samples chosen by the uncertainty sampling and the proposed location based strategy turn out to fall into both left and right part of the map more evenly, demonstrating a more balanced behavior.

Figure 9 demonstrates the prediction results by both active learning and non active learning models after 25 epochs of training. The location based active learning methodology manages to control its prediction scope within a same level of non active learning results, given far less available labeled training samples. Moreover, the active learning model even generates comparatively more scattered predictions than the traditional method, thanks to its consideration for location density in the proposed query strategy.

The kernel density estimate(KDE) on the Euclidean distance between predictions and true labels is plotted in Figure 10. From the graph, the proposed location based strategy distributes closer to zero than all the other strategies, indicating the smallest prediction error on the test set.

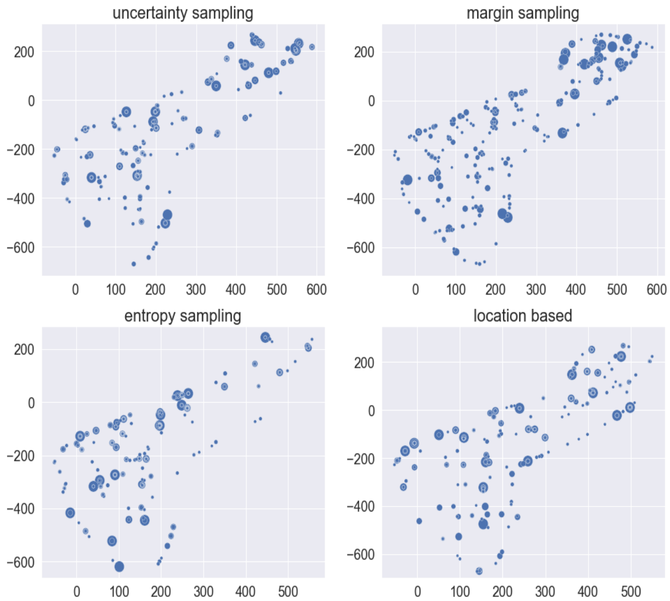

Fig. 8: The chosen samples by different query strategies.

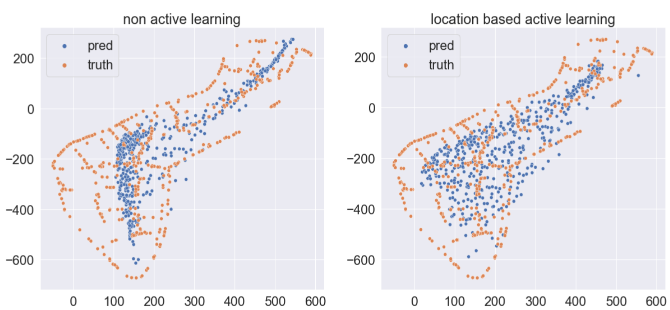

Fig. 9: Location predictions by both the active learning and non active learning method.

V. Conclusion

In this paper, we explored the use of active learning methodology in the user localization problem. We processed the raw channel state information data collected by antennas, trained an autoencoder to reduce the dimensionality of the CSI data, and applied active learning methodologies on top of a multi-layered 1D convolutional neural network. We applied several commonly used query strategies, and proposed the location based query strategy for choosing samples to label.

Experimental results demonstrate that active learning is capable of approaching a similar performance as traditional supervised learning models using much less labeled data. For query strategies, the location based strategy turns out to outperform all the other strategies with fast convergence and the lowest prediction error. We plotted and studied the pattern of chosen samples by each query strategy, which provides useful information on how they correlates with the model's final predictions. Future work includes studying the data behavior in certain areas of the route map to further improve the accuracy of prediction.

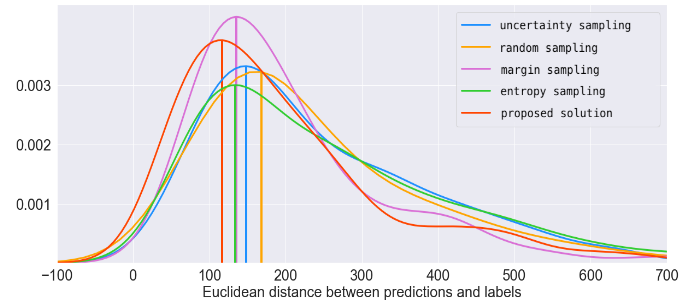

Fig. 10: KDE plot of the Euclidean distance between predictions and true labels.

Acknowledgements

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References

[1] R. Ayyalasomayajula, A. Arun, C. Wu, S. Sharma, A. R. Sethi, D. Vasisht, and D. Bharadia, *Deep Learning Based Wireless Localization for Indoor Navigation*. New York, NY, USA: Association for Computing Machinery, 2020. [Online]. Available: https://doi.org/10.1145/3372224.3380894

[2] F. Khelifi, A. Bradai, A. Benslimane, P. Rawat, and M. Atri, "A survey of localization systems in internet of things," *Mobile Networks and Applications*, vol. 24, no. 3, pp. 761–785, 2019.

[3] S. Sadowski and P. Spachos, "Rssi-based indoor localization with the internet of things," *IEEE Access*, vol. 6, pp. 30 149–30 161, 2018.

[4] S. Aldossari and K.-C. Chen, "Machine learning for wireless communication channel modeling: An overview," *Wireless Personal Communications*, vol. 106, 05 2019.

[5] S. Navabi, C. Wang, O. Y. Bursalioglu, and H. Papadopoulos, "Predicting wireless channel features using neural networks," in *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1–6.

[6] L. Bai, C.-X. Wang, J. Huang, Q. Xu, Y. Yang, G. Goussetis, J. Sun, and W. Zhang, "Predicting wireless mmwave massive mimo channel characteristics using machine learning algorithms," *Wireless Communications and Mobile Computing*, vol. 2018, 2018.

[7] L. Li, X. Guo, and N. Ansari, "Smartloc: Smart wireless indoor localization empowered by machine learning," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 8, pp. 6883–6893, 2020.

[8] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Networks*, vol. 61, pp. 85 – 117, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0893608014002135

[9] Y.-X. Ye, A.-N. Lu, M.-Y. You, K. Huang, and B. Jiang, "Wireless localization based on deep learning: State of art and challenges," *Mathematical Problems in Engineering*, vol. 2020, 2020.

[10] C. Hsieh, J. Chen, and B. Nien, "Deep learning-based indoor localization using received signal strength and channel state information," *IEEE Access*, vol. 7, pp. 33 256–33 267, 2019.

[11] W. Zhang, K. Liu, W. Zhang, Y. Zhang, and J. Gu, "Deep neural networks for wireless localization in indoor and outdoor environments," *Neurocomputing*, vol. 194, pp. 279–287, 2016.

[12] Z. Turgut, S. Üstebay, G. Z. G. Aydın, and A. Sertbaş, "Deep learning in indoor localization using wifi," in *International Telecommunications Conference*. Springer, 2019, pp. 101–110.

[13] P. Ren, Y. Xiao, X. Chang, P.-Y. Huang, Z. Li, X. Chen, and X. Wang, "A survey of deep active learning," 2020.

[14] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive mimo: Benefits and challenges," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 742–758, 2014.

[15] Y. Wang, H. Yao, and S. Zhao, "Auto-encoder based dimensionality reduction," *Neurocomputing*, vol. 184, pp. 232 – 242, 2016, roLoD: Robust Local Descriptors for Computer Vision 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925231215017671

[16] B. Settles and M. Craven, "An analysis of active learning strategies for sequence labeling tasks," in *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, 2008, pp. 1070–1079.