Signal Strength Prediction

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Abstract

In this report, we present a deep neural network approach based on RadioUNet: Fast Radio Map Estimation with Convolutional Neural Networks(CNN) to predict the received signal strength (RSS) values for the provided dataset. We begin with an introduction to the project statement and the possible techniques to answer it, along with our motivation for choosing our approach. We then introduce UNet, which is the architecture on which RadioUnet is based, providing background information about CNNs and the layers within it, along with the details of our RadioUNet-based approach. This is followed by the details regarding the model evaluation, where we explain how we have performed data preprocessing, testing, training, and validation. In the results section, we have included two plots; the first one shows the training and validation loss versus the epochs, and the second one is a bar plot showing the training error and validation error after the model is trained. We have also compared our approach with Linear Regression. In the discussion section, we have explained some of the challenges that we faced while implementing this approach, along with some of the solutions that we found to those problems. Finally, we presented the conclusions justifying whether it makes sense even to use Machine Learning for this problem statement.

Keywords: Received Signal Strength (RSS), RadioUNet, deep neural network, Linear Regression

1 Introduction

In the context of indoor positioning systems, accurate estimation of Received Signal Strength(RSS) plays an important role in several applications like localization and navigation. Simplistic methods like Linear Regression might not be able to extract all the necessary features and dependencies present in the RSS data collected from several sensors. Therefore, looking for a more sophisticated approach using Deep Learning(DL) is crucial.

The provided dataset with the project comprises RSS measurements from some of the 44 sensors distributed across a 14x13 (m) indoor office area. In such a spatially distributed environment, using a deep learning architecture allows us to fully explore the relationship between the RSS values and the physical location of the sensors. We have used a RadioUnet-based deep neural network approach to predict RSS values.

Our motivation for using this approach is its higher accuracy and efficiency compared to other DL prediction models. RadioUNet's U-Net-like architecture enables the preservation of spatial context during feature extraction and reconstruction. RadioUNet is a highly efficient and very accurate method for estimating the propagation path loss from point x to all points y on the 2D plane. RadioUNet generates path loss estimations that are very close to estimations given by physical simulation but much faster.

2 Related Works

UNet is a special CNN architecture, which is the original and core concept; it was initially developed for biomedical image sedimentation tasks and has been extended to a host of other applications, including video predicting, super-resolution, and medical image analysis.
UNets consist of convolution, pooling, upsampling, and activation function layers without fully connected layers.

3 Background

3.1 Convolutional Neural Networks

A Convolutional neural network (CNN) is a popular deep learning architecture typically used in machine learning applications. A CNN is defined by the following five basic computational steps as the layers of the network.

- The convolutional layer applies a set of filters/kernels to the input image, and each filter performs a convolution operation by sliding across the input image and computing the dot product between the filter weights and the pixel values of the image. This helps to generate feature maps that represent different paths or features learned by the network.

- The activation function layer introduces non-linearity into the network by applying an activation function to the output of the convolutional layer. One common activation function used is ReLU(Rectified Linear Unit). This function returns 0 if it receives any negative input, but for any positive value, it returns that value back.

- The pooling layer reduces the spatial dimensions(width and height) of the feature maps by applying a max pooling or average pooling operation.

- The upsampling layer upsamples lower-resolution feature maps to a higher resolution.

- The fully connected layer flattens the obtained feature maps into a one-dimensional vector.

3.2 RadioUNet

The RadioWNet model defined in our code is a variant of the U-Net architecture, modified for the task of predicting received signal strength (RSS) between transmitter/receiver pairs in an indoor environment. Let's have a look at the architecture.

- Encoder Path: The model starts with an encoder path composed of several convolutional layers (layer00, layer0, layer1, etc.), each followed by a ReLU activation function and max-pooling operation. These layers progressively reduce the spatial dimensions of the input while extracting higher-level features related to the received signal strength.

- Bottleneck: After several downsampling steps, the encoder path reaches a bottleneck layer (layer 5), where the spatial dimensions are significantly reduced, but the depth (number of channels) is increased, allowing the model to capture complex patterns in the input data.

- Decoder Path: The decoder path of the model consists of transposed convolutional layers, which perform upsampling to reconstruct the spatial dimensions of the feature maps gradually. At each step, the upsampling operation is followed by concatenation with feature maps from the corresponding encoder path layer to facilitate the recovery of spatial information lost during downsampling.

- Skip Connections: The concatenation of feature maps from the encoder path with those from the decoder path via skip connections allows the model to retain fine-grained spatial details throughout the upsampling process. This helps in better localization and prediction of received signal strength values.

- Final Output: The final output of the model is obtained after passing through additional convolutional layers. This output represents the predicted received signal strength values for the transmitter/receiver pairs.

4 METHODOLOGY

The RadioUNet model for RSS prediction is trained using PyTorch. Here is a sample input mask image followed by the steps in order.

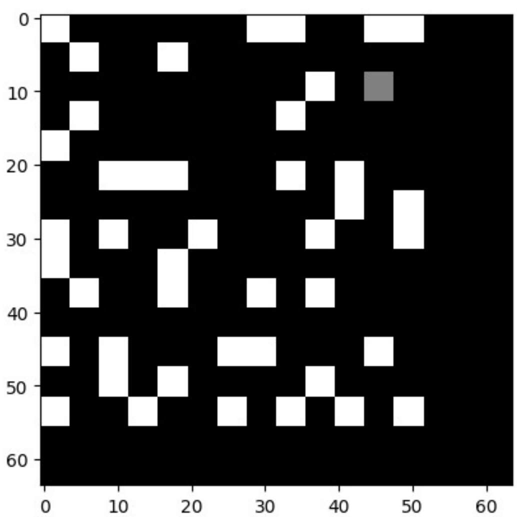

Figure 1: Mask for Linear Regression

1. Preprocessing: For preprocessing, initially, the distances between every transmitter-receiver pair are calculated based on the locations in the input file "location.txt." The "Inf" values in the RSS data are also set as zero. Then, the input images for the UNet are created by having one transmitter masked to one image. The images are also upscaled by a factor of 4 so that each pixel in the original input data (1x1 m in the indoor office space) is scaled to a 4x4 pixel square in the generated image. The purpose of this is to increase the resolution of the input images, allowing the UNet model to capture the spatial relationships. UNet decreases the size of the image and then increases it hence it is not possible to work with such a small image. If data augmentation is not performed, the model will overfit the data since the training size is so small. To avoid this, data augmentation is also performed to generate 20 images mapped to one single transmitter by taking into account eight receivers selected at random. So that makes 680 total images.

   The initial power values are in the dB scale, so they are negative. These values are normalized between 0 and 1 using min-max scaling by taking a minimum and maximum over the entire dataset and scaling by that.

2. Training: The code iterates over 10 epochs with batch size 1. Within each epoch, the model is set to training mode, and then batches of data are iterated from the training dataloader. For each batch, the input image and mask are moved to the GPU, and the gradients are zeroed. In the forward pass, the input image is passed to the model to get the output. Then, the loss between the predicted output and the ground truth mask is calculated using the defined MSELoss(Mean Squared Error) criterion. Finally, it backpropagates the gradients and updates the model parameters. The RadioUNet architecture passes the data through two cycles of UNet. That is, it has two cycles of upconv and downconv.

3. Validation: After each epoch, the model's performance is evaluated on the validation set without computing gradients. Similar to the training loop, it iterates over batches of validation data and calculates the validation loss. The input images and masks are split as a 95 percent training set and a 5 percent validation set. Our aim with this split is to have a large enough training dataset to avoid overfitting while avoiding test set bias as well.

4. Testing: To test the model, a testing script was created which outputs the value of the signal received at receivers, given as input by the user, by the transmitter, which is also given as input by the user.

5. Evaluation: The models were evaluated using R-squared score and MSE. The R^2 score represents the proportion of the variance in the dependent variable that is predictable from the independent variables in a regression model. It is simply a measure of how well the regression predictions approximate the actual data points. Its value ranges from 0 to 1 where a score of 1 indicates that the regression predictions perfectly fit the data and a score of 0 indicates that the regression predictions do not explain any of the variability of data. In general, a higher R^2 score indicates a better fit of the model to the data. The Mean Squared Error(MSE) measures the average squared difference between the actual values(or ground truth) and the predicted values produced by the model. It's always nonnegative, and smaller values indicate a better fit.

5 DISCUSSION

One of the primary challenges faced in developing the solution was creating suitable input and output images for the model. This involved preprocessing raw data, such as radio signal strength measurements and the locations, into a format suitable for training the deep learning model. Choosing and implementing different models to see what would give us the best results. Implementing the UNet architecture and adjusting it to suit the specific requirements of predicting radio signal strength was another challenge. It involved understanding the intricacies of UNet architecture, including encoder-decoder structure and appropriate layer configurations, and then adapting it to the problem domain of radio signal strength prediction. Multiple experiments and trials and errors with scaling and preprocessing techniques were performed to improve the model performance and obtain better results. Since the available dataset was too small, we needed to perform data augmentation to artificially increase the diversity of the training data without distorting the underlying patterns in the data.

6 RESULTS

The plots for training and validation Loss are as follows. As we can see, loss decreases per epoch. The fitted curve for linear regression

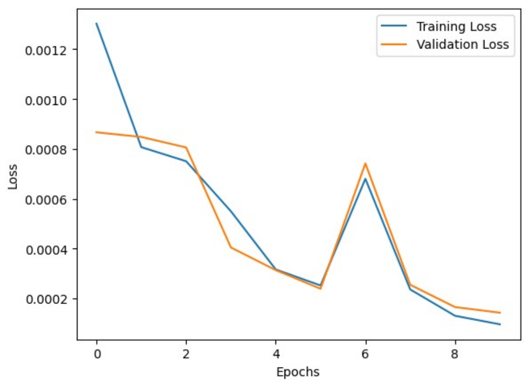

Figure 2: Training and Validation Loss versus Epochs

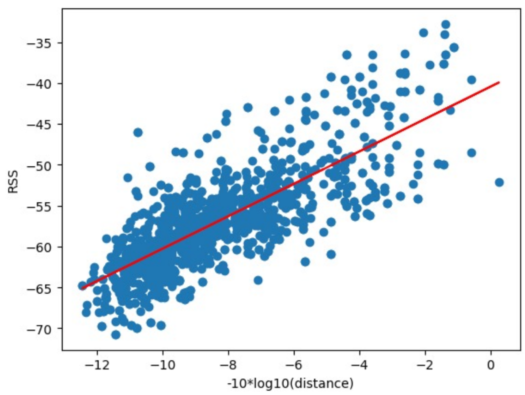

Figure 3: Linear Regression Fitted Curve

is shown below.

The R2 score for linear regression was 0.6, and MSE was 14.79. This shows that the line fitted by linear regression was not a very good estimator. The mean squared error between the predicted and actual points is very high, and an R2 score of 0.6 indicates that the model does not depict the relation between independent and dependent variables very well.

On the other hand, the R2 score for the deep learning-based approach (RadioUNet) was 0.87, and MSE was 0.0077. This indicates that the mean squared error between the predicted and actual signal strength values is very little. An R2 score of 0.87 also makes this a good regression model since it represents the relationship between the independent and dependent variables very well.

7 Conclusion

As we can see, the results with RadioUNet are better. Signal strength is affected by various factors, especially in an indoor environment; it can undergo small-scale fading and multipath. Due to varying channel conditions, it is difficult to accurately predict the signal strength using a linear equation or linear regression-based model. Hence, a deep learning-based approach can model these intricacies with greater precision and accuracy. Therefore, it makes sense to use DL-based approaches in such problems.

8 References

- Pytorch Tutorial
- RadioUNet Github Repo
- RadioUNet Paper