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Deep Transfer Learning Based Radio Map Estimation for Indoor Wireless Communications

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Abstract: This paper investigates the problem of transfer learning in radio map estimation for indoor wireless communications, which can be exploited for different applications, such as channel modelling, resource allocation, network planning, and reducing the number of necessary power measurements. Due to the nature of wireless communications, a radio map model developed under a particular environment can not be directly used in a new environment because of the changes in the propagation characteristics, thus creating a new model for every environment requires in general a large amount of data and is computationally demanding. To address these issues, we design an effective novel data-driven transfer learning procedure that transfers and fine-tunes a deep neural network (DNN)-based model for a radio map learned from an original indoor wireless environment to other different indoor wireless environments. Our method allows to predict the amount of training data needed in new indoor wireless environments when performing the operation of transfer learning using our similarity measure. Our simulation results illustrate that the proposed method achieves a saving of 60-70% in sensor measurement data and is able to adapt to a new wireless environment with a small amount of additional data.

A.1 Introduction

In wireless communications, accurate estimation of channel gain/path loss is important in network design for optimizing the distribution of towers, channel modelling, allocating resources and meeting the expected quality of service (QoS) requirements of the end user. Path loss measures the loss of signal strength (reduction in power, or attenuation) between a transmitter (Tx) and a receiver (Rx) due to large-scale effects. Different factors may cause the attenuation in signal power, for example, free-space propagation loss, reflections, diffractions, etc. from buildings, and objects blocking the line of sight (LOS) between Tx and Rx. Path loss is obtained for each Tx-Rx pair location and is sometimes referred to as path gain or radio map.

Wireless communication is dynamic in nature. For example, a good model for a radio map that is appropriate in a particular wireless environment, may not be appropriate for a new wireless environment due to changes in propagation characteristics. On the other hand, notice that knowing the strength of signal or received power in one wireless network area (source area) at several spatial locations (sampled radio map), one can make a smart utilization of a pre-developed model to estimate the radio map in another new wireless network area (target area) by exploiting transfer learning (TL) [19] and reduce the need of new measurements at the new environment.

The exploitation of knowledge acquired in the source area for the learning task in the target area is referred to as transfer learning (TL) [19]. It handles the data scarcity issue in the target area. In the context of radio map estimation, one may have configured or setup the wireless system in one indoor environment but need to perform deployment in another environment. TL can be exploited to achieve a good solution in the target area instead of learning a solution from the very beginning by exploiting the knowledge from the source model.

Some of the works that have successfully adopted TL include [3, 20–23, 32]. To capture traffic pattern diversity in cellular data of different cities, a spatial-temporal cross-domain neural network (STCNet) model is proposed in [20]. Model-based TL is exploited for similarities between different kinds of cellular traffic. In [21], TL is exploited to improve the robustness of deep neural network (DNN) based spectrum sensing in cognitive radio with the assumption that the data collected under different characteristics belong to different but related distributions/domains. A TL method via self-imitation is proposed in [32] to tackle the NP-hard mixed-integer nonlinear programming problems of resource allocation. In [22], downlink channel state information (CSI) prediction from uplink CSI using direct model-based TL, is proposed for frequency division duplexing (FDD) in a massive multiple-input multiple-output (MIMO) framework. A TL method based on Wasserstein distance [51] is applied to the wireless fingerprinting localization in [23]. In fact, [3] adopts a RadioUNet model which is a modified UNet architecture [14] (originally designed for biomedical image processing) for estimating radio maps in the urban environment. However, the work in [3] requires training the model from the very beginning for each new wireless environment.

Since users may experience different indoor wireless environments, data collection and training of DNN models from the very beginning are required in new wireless environments. Typically, a large amount of samples and training epochs are required for training a DNN, and thus training a new DNN for each new wireless environment may demand a substantial computational time and data acquisition cost.

In this work, we address the problem of estimating radio maps in indoor wireless communications using TL when the wireless environment changes. We assume that fast fading is averaged out in the measurements. The main contributions of this paper are the following:

- Design of an effective data-driven TL procedure that transfers and fine-tunes a DNN-based model for a radio map learned from an original indoor wireless environment to other different indoor wireless environments.

- Formulation of a data-driven similarity measure model that predicts the mean square error (MSE) that will be achieved for the estimated radio map in a new wireless environment when performing TL from a baseline (source) environment.

- Prediction of the amount of training data needed in new wireless environments depending on a certain criterion of the MSE threshold for the radio map estimation, when performing the operation of TL using our similarity measure model.

- Extensive testing of our algorithms using simulated data from the Remcom simulator [33]. Numerical experiments demonstrate that the proposed TL method achieves a high success-rate in estimating radio maps accurately for each new indoor wireless environment while using a small amount of training data. We also show experimentally that the Wasserstein distance (WD), widely used in TL, is not applicable to our radio map application.

The remainder of this paper is structured as follows: Section A.2 describes the environments for transfer learning. Section A.3 presents the proposed transfer learning-based radio map estimation. Section A.4 presents and discusses the results followed by concluding remarks in Section A.5.

A.2 Description of Environments for Transfer learning

In order to obtain power measurements that are sufficiently representative for real indoor wireless environments, we use the standard high accuracy ray-tracing *X3D*

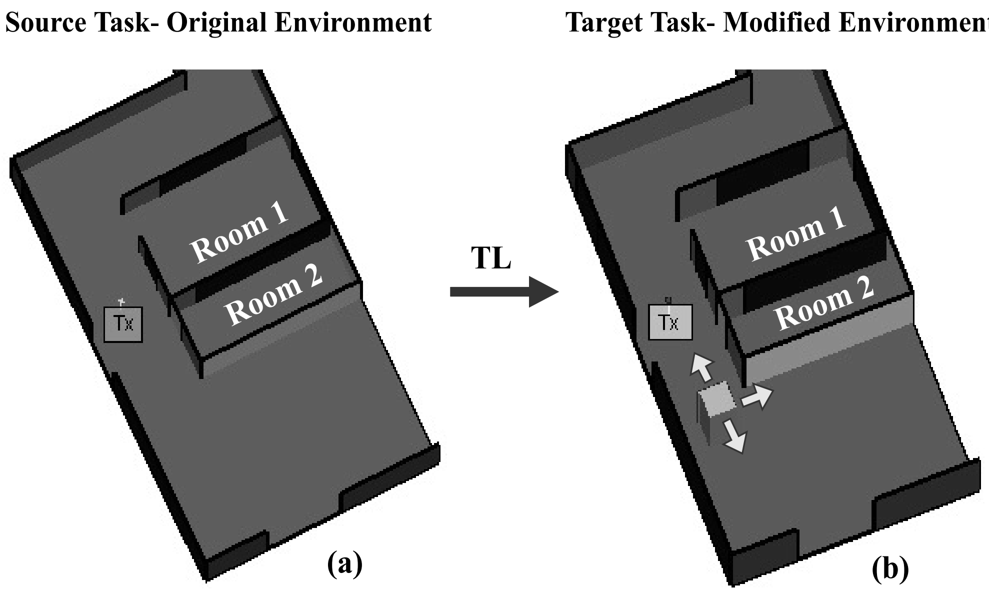


Figure A.1: Environments for TL: Original and modified environments.

Table A.1: Parameters used in Remcom for data generation.

Waveform	Narrow-band Sinusoidal
Carrier frequency	900 MHz
Bandwidth	1.0 MHz
Antenna type	Omni-directional
Tx location	(1.5, 10, 1.3)m
Tx height	1.3m
Tx power	27.73 dBm
Receiver threshold	-250 dBm
Voltage standing wave ratio (VSWR)	1.0
Transmission line loss	0 dB
Space between two Rx points	15cm
Space between two Rx routes	15cm
Noise figure	3 dB
Ray tracing	X3D ray model
Ray spacing	0.2°
Number of reflections	3
Number of transmissions	2
Number of diffractions	0
Volume of the object (single cube)	$1m^3$
Number of Rx locations	6678
Floor dimension (width x length x height)	(9.5 x 20.6 x 2.88)m
Number of wireless environments	250
Image size of floor environment (width x height)	(160 x 275) pixels

ray model [41], computed using the software Remcom [33]. We first consider an environment of a single floor which is comprised of two rooms, in order to obtain the radio map as shown in Figure A.1. We place a transmitter "Tx" at one fixed location (x^t) and then multiple receivers "Rx" at uniformly spaced locations (x_i^r) to obtain the power corresponding to each Rx location ($P(x_i^r)$), where i is the index of the receiver. This results in 6678 Rx locations and corresponding power values. Furthermore, to create different wireless environments, we incorporate an object at different locations, that is, a single solid cube block (made of metal) having volume $1m^3$ with the original environment[1]. The location of this object is changed horizontally, vertically, and diagonally as shown in Figure A.1(b), with an incremental spacing of 15cm. For each location, a new indoor wireless environment is created and the ray-tracing model provides the power for each particular environment with similar Rx locations. A total of 250 different indoor wireless environments are created by changing the location of the object in different directions and the images of each indoor wireless environment are saved as 160 x 275-pixel images. These images are later used also to investigate the suitability of the WD as a similarity

[1]The inclusion is made for the sake of simplicity to build different wireless environments conceptually.

measure for our problem and to develop a data-driven similarity measure between different indoor wireless environments. The parameters used in the Remcom for data generation are summarized in Table A.1.

A.3 Transfer Learning Based Radio Map Estimation

The TL system design proposed for radio map estimation from a source task to a target task is shown in Figure A.1. The arrows in Figure A.1(b) show the direction in which the object, that is, a cube, is moved. Each object location creates a new indoor wireless environment. The fundamental requirement in TL is the notion of similarity between the source and the target task over which TL is performed. Therefore, we now define the source task in which the baseline DNN model is trained and the target tasks in which the baseline/pre-trained model is transferred and fine-tuned, and then establish a similarity measure between the source and the target tasks.

A.3.1 Baseline DNN Model and TL Approach

We design and develop a DNN model with the power values obtained at multiple locations of receivers under the original indoor wireless environment (see Figure A.1(a)). For this purpose, we train a fully-connected DNN model (see Table A.2) and refer to it as "Baseline model", as shown in Figure A.2.

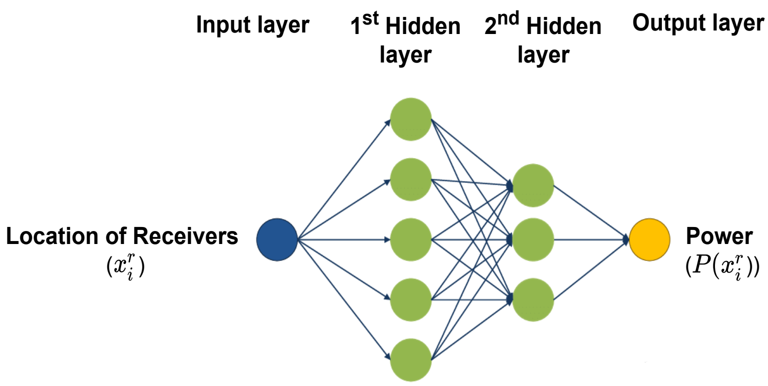


Figure A.2: Radio map estimation DNN model.

Next, we transfer the pre-trained (baseline) model to all new indoor wireless environments one-by-one (total 250) and fine-tune each of them individually. *Our hypothesis is that there is no sufficient amount of training data to train a DNN from the very beginning for the new wireless environments and hence, TL can be exploited to be able to train a DNN with a small amount of training data for estimating the radio map.*

We normalize the data to be between 0 and 1 for the faster training of DNN [3]. We use the rectified linear unit (ReLU) as an activation function and a minibatch of 32 samples. The usual MSE for the normalized data, defined as MSE $= \frac{\sum_{i=1}^{r}(P(x_i)-\hat{P}(x_i))^2}{r}$, is used as the loss function, where $P(x_i)$ and $\hat{P}(x_i)$ are the actual and the predicted power samples, respectively, and r is the number of Rx locations. Adam optimizer with a learning rate of 0.001 is used for stochastic optimization. Generally, the training data required to perform TL depends on the similarity, the more similar the environment, the less training data is required. In order to obtain the percentage of training data needed to perform the operation of TL, the whole data is split into eight different train-test split ratios, such as 0.05:0.95, 0.10:0.90, 0.15:0.85, 0.20:0.80, 0.25:0.75, 0.30:0.70, 0.35:0.65, and 0.40:0.60. Here, for instance, 0.05:0.95 specifies 5% training and 95% testing data. After training DNNs for each new indoor wireless environment, we store the test MSE obtained using TL and the number of epochs used in training the DNN model in order to establish the similarity between source and target tasks.

A.3.2 Similarity Measure using Wasserstein Distance

Similarity measures between the source and the target tasks such as Wasserstein distance (WD) [23] have been widely used in TL. WD computes the distance between two distributions. In our case, we compute WD between two images of different wireless environments. For two random variables U and V (U being the image of the environment with the cube present at the left-hand side bottom corner, and V being the image of remaining environments with the cube present at different locations) with respective cumulative distribution function (CDF) $F_U(u)$ and $F_V(v)$, the WD, which we denote as d, is defined as [51]

$$d(U,V) = \inf_{F_{UV} \in \mathcal{F}} \{\mathbb{E}_{F_{UV}} |U - V|\} \tag{A.1}$$

where, $\mathcal{F}$ is the collection of all joint CDFs, and $\mathbb{E}_{F_{UV}}$ is the expectation of joint CDF. In practice, the CDFs are computed empirically from the corresponding histograms.

A.3.3 Data-driven Similarity Measure

In order to formulate a data-driven similarity measure between the source and the target tasks, we train a convolutional neural network (CNN) regression model under two different cases and set a threshold empirically for its comparison with the obtained value.

Case A: In this case, the input of the CNN is composed of the images (first layer of Figure A.3) of different indoor wireless environments (total 250) and the output is the test MSE corresponding to TL obtained for each wireless environment when the baseline model is transferred and re-trained. The size of each image is 160 x 275 pixels. Each image is converted into a grayscale image before injecting it into the CNN.

Case B: In this case, the input of the CNN is the same, but the output is now both the test MSE corresponding to TL and the number of training epochs obtained for each wireless environment when the baseline model is transferred and re-trained.

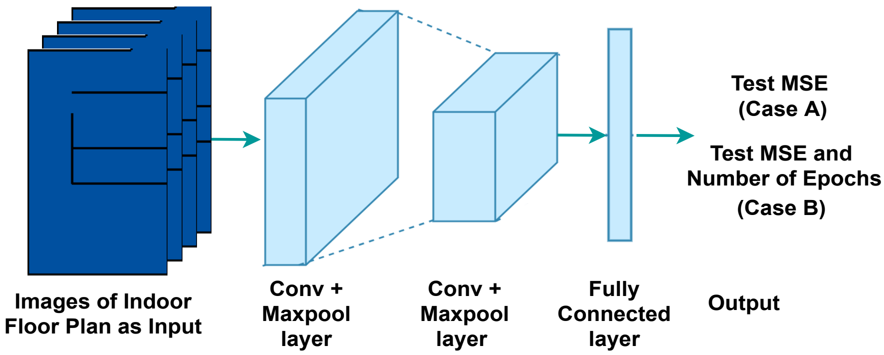


Figure A.3: Network structure for the CNN.

This case has a larger CNN model and it needs larger feature sets. This makes it computationally demanding. The network structure we consider in both cases is shown in Figure A.3.

Furthermore, to decide whether TL is beneficial or not between two tasks, in case A, we empirically set a threshold for the test MSE corresponding to TL as 1% (0.01) and compare it with the obtained test MSE using TL. If the value of obtained test MSE using TL is less than this threshold, then two tasks are recognized as similar and TL can be performed, otherwise, we assume that TL is not beneficial.

Similarly, in case B, we empirically set a threshold for the test MSE corresponding to TL as 1% (0.01) and the number of training epochs as 20, and compare the thresholds with both the obtained test MSE using TL and the obtained number of training epochs. If the obtained values of test MSE using TL and the number of training epochs are less than the thresholds, then two tasks are recognized as similar and TL can be performed, otherwise, it is assumed that TL is not beneficial.

A.4 Results and Discussions

The baseline DNN model used for TL is presented in Table A.2. It can be observed that the training of the baseline DNN model is satisfactory for the testing, that is, the test MSE is comparable to the training MSE, thus resulting in no over-fitting in the model.

Next, to check the potential usefulness of the WD, we first compute the WD between the floor image corresponding to the indoor wireless environment when the cube is positioned near the Tx (see Figure A.1(b)), and the different floor images (total 250) corresponding to indoor wireless environments when the cube is positioned at different locations. Similarly, we also compute the WD between the corresponding sampled radio map (power values) obtained when the cube is positioned near the Tx, and the sampled radio maps corresponding to the rest of the indoor wireless environments when the cube is positioned at different locations. However, if we measure the Pearson's correlation coefficient[2] (PCC), which is a widely adopted

[2]
$$\mathrm{PCC}(x,y) = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{A.2}$$

Table A.2: The Baseline DNN model

Number of neurons in input layer	2
Number of hidden layers	2
Number of neurons in each hidden layer	16, 8
Hidden layers activation function	ReLU
Dropout after each hidden layer	0.20
Number of neurons in output layer	1
Output layer activation function	ReLU
Optimizer used	Adam
Loss function	MSE
Batch size	32
Train-Test split ratio	80:20
Test MSE	0.0102
Train MSE	0.0101

metric for measuring correlations [20], between both types of WDs (floor images and associated sampled radio maps) across the various considered environments, then it results in a value of 0.08, reflecting poor correlation. This implies that the WD is not an effective similarity measure for our TL problem in the context of indoor wireless radio maps, which justifies further the use of our data-driven similarity measure for TL.

Along these lines, Table A.3 and Table A.4 present the model learning for the CNN regression models under case A and case B, respectively. In case B, the settings to train the CNN regression model are the same as in case A except for the number of neurons in the output layer of the neural network is 16 due to aggregation of the number of training epochs as well as the test MSE obtained using TL as output features of the CNN. Both tables show that the CNN is trained appropriately in both cases, that is, the test MSE, is comparable to training MSE.

Following our designed TL decision strategy described earlier for 250 different indoor wireless environments, we now obtain a decision for each of the two CNN cases.

Table A.5 and Table A.6 present the TL decisions for case A and case B, respectively. Each table demonstrates training data needed to perform TL following the proposed TL strategy and the corresponding number of indoor wireless environments.

It can be noticed from Table A.5 that 246 out of 250 different indoor wireless environments satisfy our criteria and are recommended for TL, resulting in a training data requirement of 30-40% only. This leads to a TL success-rate of 98.4%. Similarly, Table A.6 shows that 217 out of 250 different indoor wireless environments satisfy our criteria and are recommended for TL, resulting in a training data requirement of 20-35% only. This leads to a TL success-rate of 86.8%. Both results signify that TL can be used effectively to estimate the radio map in the new indoor wireless

x = WD of image, y = WD of power values, n = number of environments.

Table A.3: The CNN model in Case A

Total indoor wireless environments	250
Image size of floor environment (width x height)	160 x 275
Number of convolutional layers	2
Number of filters in first and second convolutional layer	32,64
Filter size in first and second convolutional layer	3 x 3
Number of max pooling layers	2
Filter/pool size in each max pooling layer	2 x 2
Number of strides in first and second convolutional layer	2
Activation function in first and second convolutional layer	ReLU
Dropout after second max pooling layer	0.3
Number of neurons in the output layer of neural network	8
Activation function in the output layer of neural network	ReLU
Optimizer used	Adam
Loss function	MSE
Batch size	32
Train-Test split ratio	80:20
Test MSE	0.0411
Train MSE	0.0314

Table A.4: The CNN model in Case B

Number of neurons in the output layer of neural network	16
Test MSE	0.0423
Train MSE	0.0348
All other parameters are the same as in Table A.3 (Case A).	

Table A.5: TL Performance in Case A

Training data needed	Number of environments
40%	23
35%	206
30%	17

Table A.6: TL Performance in Case B

Training data needed	Number of environments
35%	31
30%	152
25%	31
20%	3

environment where a small number of sensor measurements are available.

Furthermore, in order to see how good and reliable our proposed model is, we

Table A.7: Transferability, F1-score, and Accuracy

	Case A	Case B
TP	166	144
TN	19	17
FP	52	66
FN	13	23
Transferability	0.927	0.862
F1-score	0.836	0.763
Accuracy	0.740	0.644

calculate transferability[3], F1-score, and accuracy [69] in each case. Transferability shows how good our model is at recommending a correct TL. F1-score is a measure of the test accuracy of the model. Accuracy measures the degree of veracity of the model.

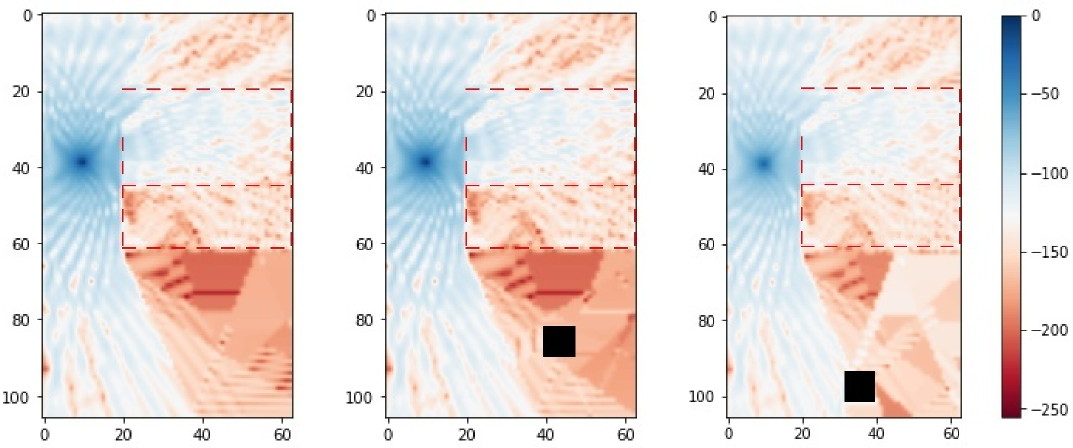
Table A.7 presents the true positive (TP), true negative (TN), false positive (FP), false negative (FN), transferability, F1-score, and accuracy for each case. It can be observed that the transferability and F1-score of our proposed model in case A are higher than in case B. Moreover, the accuracy of our proposed model in case A is 74%, which is higher than in case B. This means that for the different modified indoor wireless environments tested, the case A model provides a good performance. The reason for case B having lower accuracy is that the training epochs are not highly correlated with the test MSE corresponding to TL for the similarity measure. The analysis of results signifies that the data-driven similarity measure between the source and the target tasks is performing well and TL can be used effectively to estimate the radio map in the new indoor wireless environments requiring only a small number of sensor measurements.

As an illustration, Figure A.4 shows the radio maps corresponding to the original environment (no cube present) and two different indoor wireless environments (cube present). The cube in the radio maps is represented in black colour and the walls of the rooms in the radio maps are represented in dashed red colour. The radio maps in Figure A.4(b) and Figure A.4(c) represent the environments where only 20% and 30% of training data, respectively, are required when executing the operation of TL, as compared to the original radio map without executing the operation of TL in Figure A.4(a). The differences in the radio maps among the three environments can be easily visualized.

A.5 Conclusion

In this paper, we present a TL-based method to estimate the radio map for indoor wireless networks. Moreover, a data-driven similarity measure is developed to quantify the similarity between two tasks which is later used to decide whether

[3]Instead of the usual name of sensitivity in the context of medical diagnostic tests [69], we use the term "transferability" for the sake of clarity given the context of our work here.



(a) (b) (c)

Figure A.4: Radio map in (a) original indoor wireless environment, (b) environment where 20% of training data is required when executing the operation of TL, and (c) environment where 30% of training data is required when executing the operation of TL.

to recommend performing TL given only the image of the environment. A unique advantage of transfer learning is that it will reduce the number of training samples that are necessary for estimating the radio map in similar environments, saving a large amount of data acquisition requirements.