Semi-Supervised Learning with GANs for Device-Free Fingerprinting Indoor Localization

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Presentation Outline

I. Introduction

A. Indoor Localization Problem

B. Our Motivation

II. Proposed Method

A. Intro. to Generative Adversarial Networks (GANs)

B. Semi-Supervised with GANs

III. Experiment & Discussion

A. Performance Comparison

B. Discussion on Generator model

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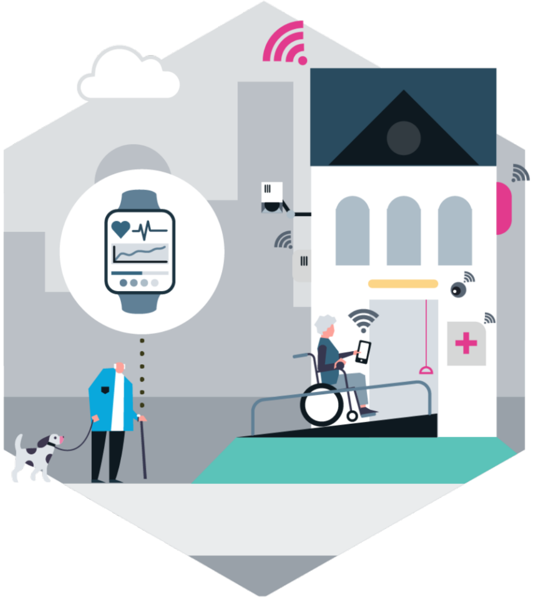
Indoor Localization Problem

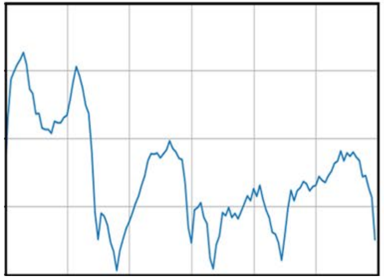
Many current and future **Internet of Things (IoT)** applications are enabled or facilitated by indoor location information.



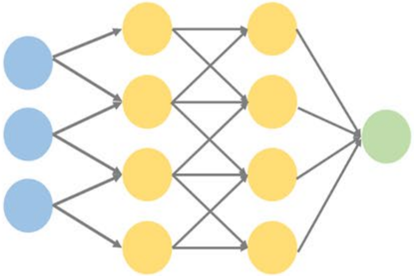
Indoor Localization Problem (cont.)

Solution =

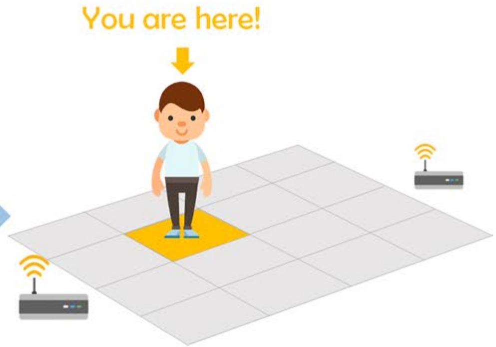
Collect Indoor Wireless Signal (CSI) + **Fingerprint (Deep Learning)**



Wireless Signal Measurement:
Channel State Information (CSI)



Deep Learning:
Neural Network (NN) Model



Online Testing

Motivation

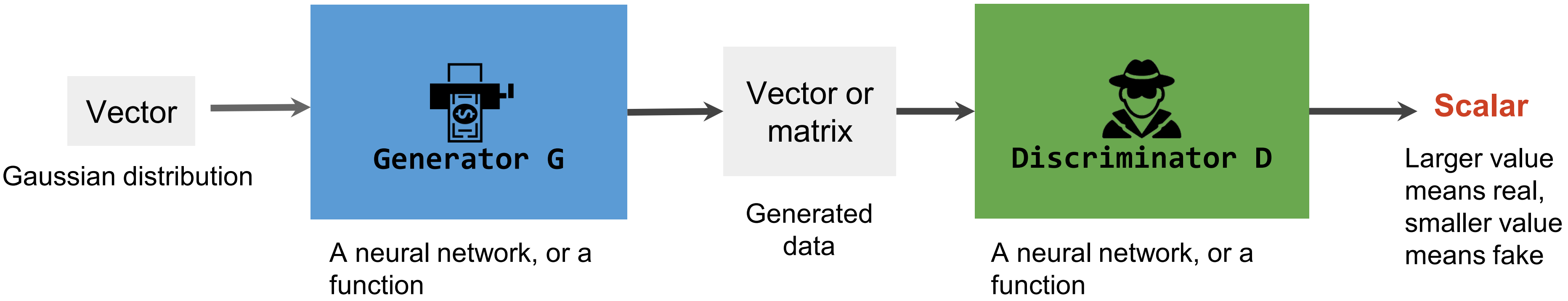
Many proposed deep learning-based solutions are based on **supervised learning**, which requires **numerous labeled data** collected in the site survey to train the fingerprinting localization system. However, data labeling is **labor-intensive** and **time-consuming**.

Motivation (cont.)

- **<u>Semi-Supervised Learning</u>,** which uses a small amount of labeled data and a large amount of unlabeled data for training, gives a possible solution to reduce labor effort.
- **<u>Generative Adversarial Network (GAN)</u>** has been proposed for Semi-Supervised Learning.

Generative Adversarial Network (GAN)

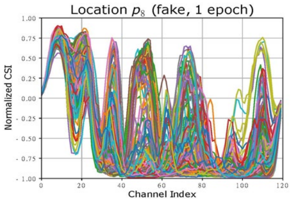
Basic idea of GAN:



Training a GAN is a ***minimax optimization***.

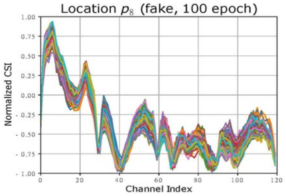
Semi-Supervised with GANs

If we want a GAN to ***generate fake CSI samples***...



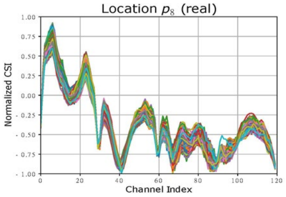
Fake CSI (1 epoch)

Training

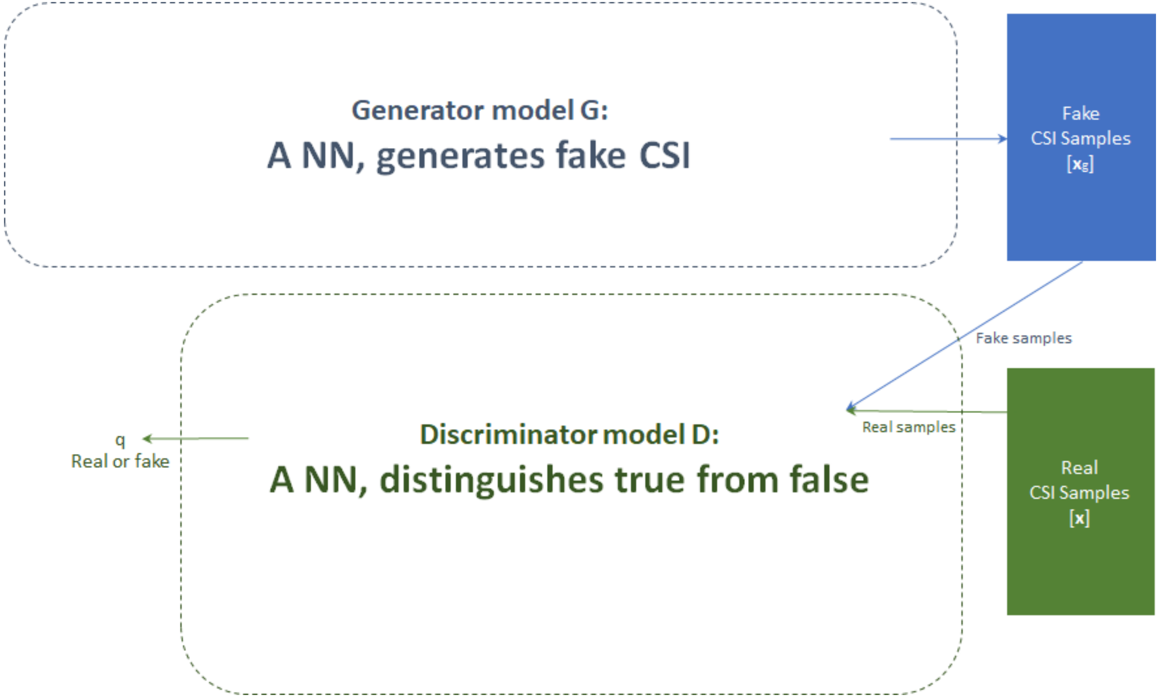


Fake CSI (100 epoch)

Resemblance



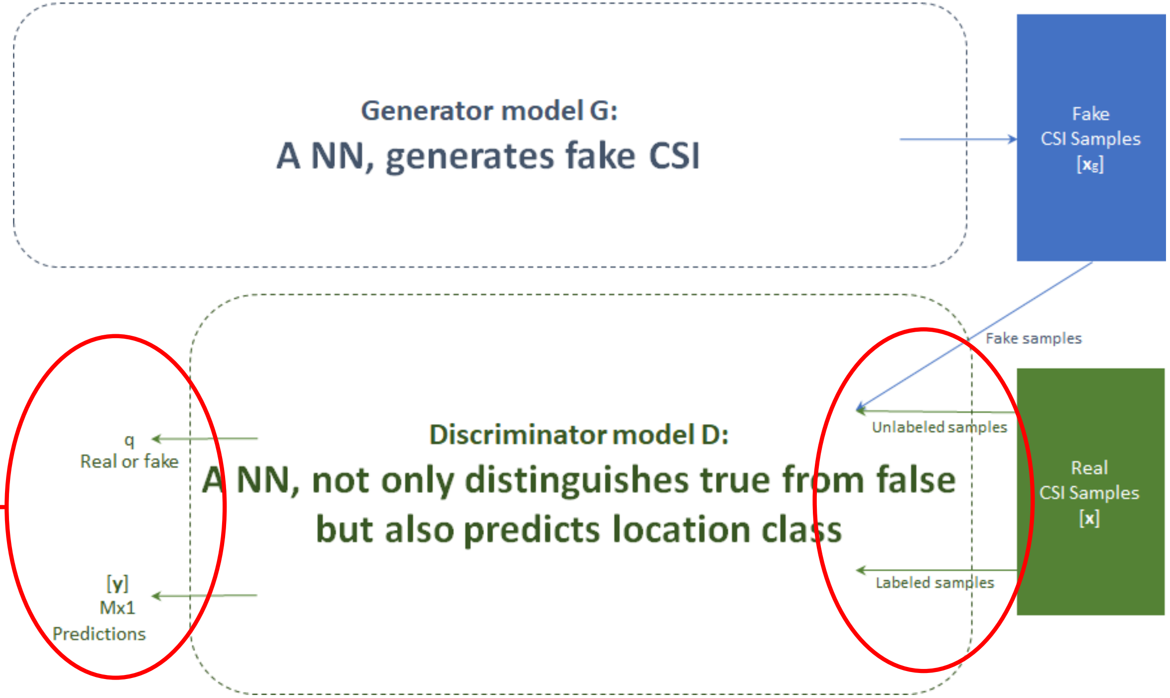
Real CSI



Semi-Supervised with GANs (cont.)

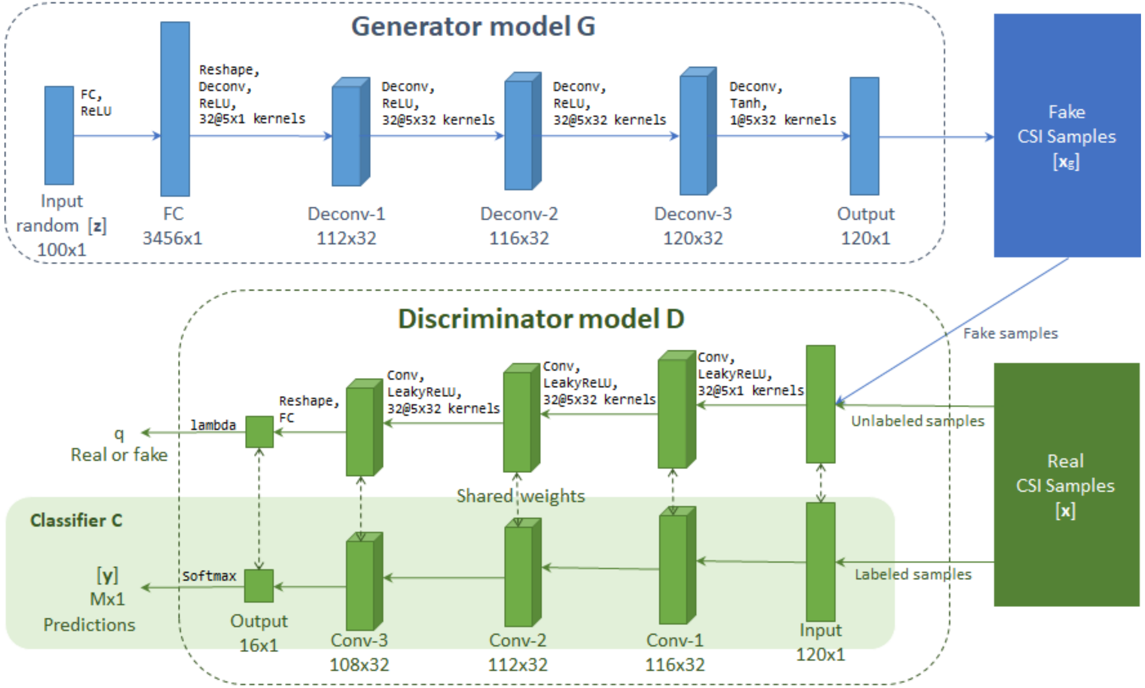
If we want a GAN to do ***semi-supervised learning with CSI samples***...

Make standard GAN's output from <u>1 to M+1</u> by making D become a dual model with shared weights.



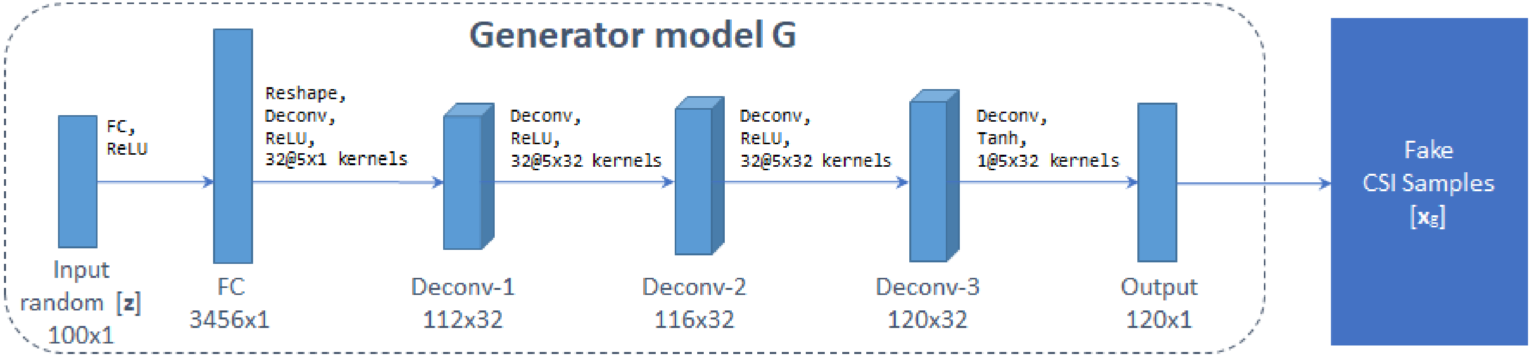
Semi-Supervised with GANs (cont.)

We apply **Deep Convolutional Generative Adversarial Network** (DCGAN) as our model's architecture.



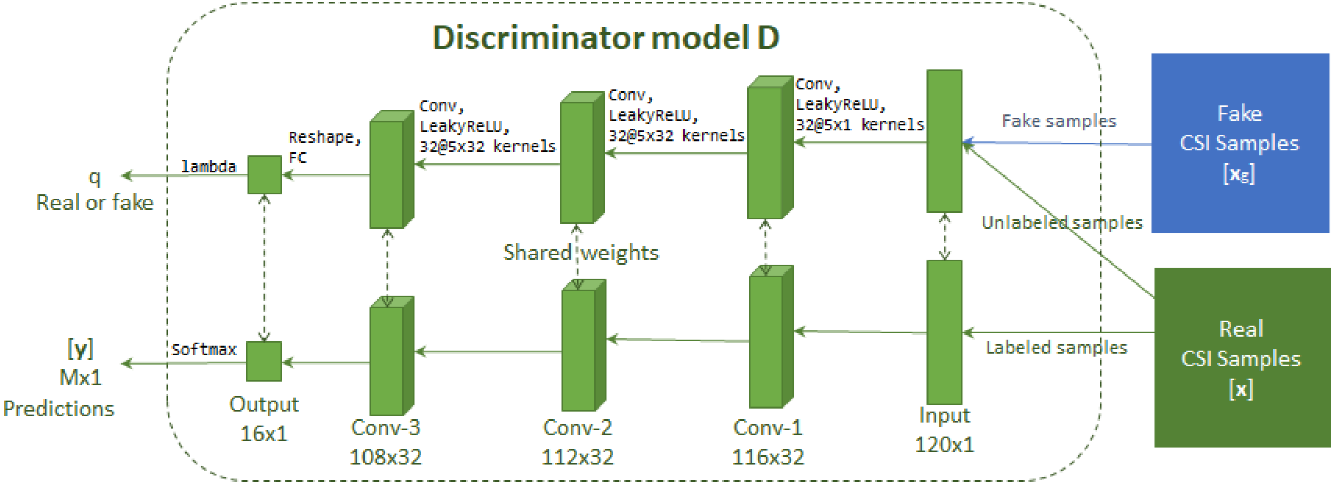
Note: The parameters of the model is determined by cross-validating the model performance with different configurations.

Generator Model



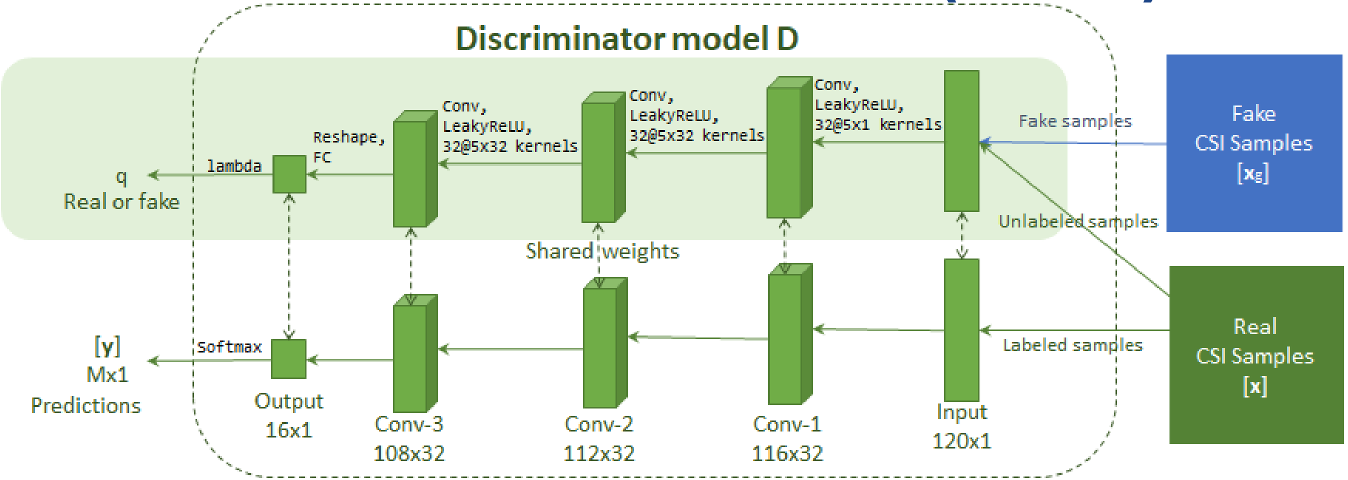
- **Input:** Random Gaussian distribution noise **z** (size 100x1)
- **Output:** Fake Generated CSI sample $\mathbf{x}_g$ (size 120x1)

Discriminator Model



- **Input:** Generated fake sample $\mathbf{x_g}$ (size 120x1); Real CSI sample **x** (size 120x1)
- **Output:** q, possibility the input is real (scalar); **y**, predictions on input (size Mx1)

Discriminator Model (cont.)

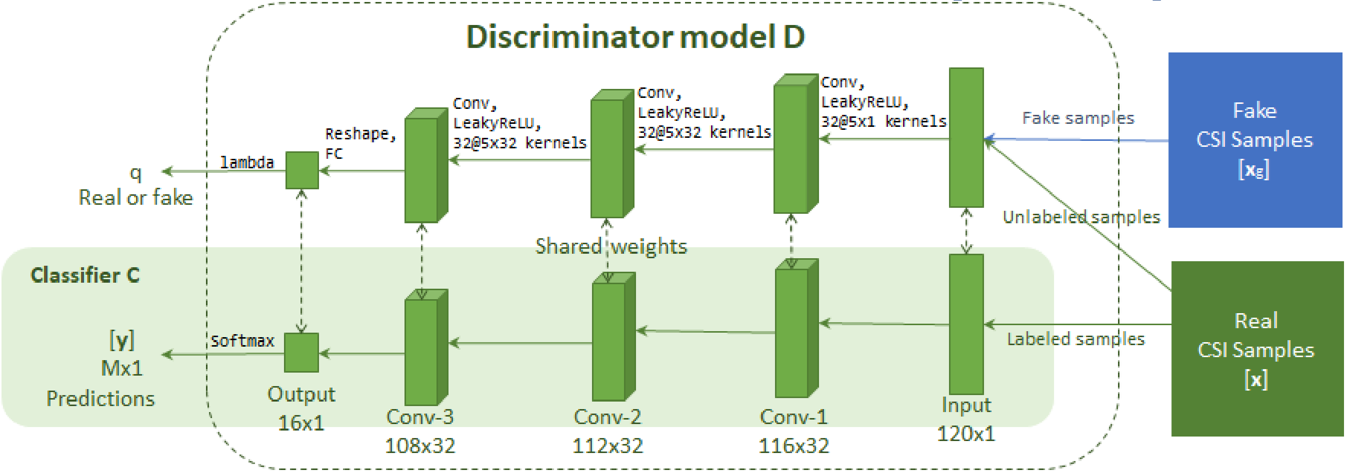


- **Seen as *Discriminator D***: Produce a scalar q which represents the probability of the input CSI sample being a real sample with a customized lambda function:

$$\lambda(\mathbf{c}) = \frac{\sum_{m=1}^{M} \exp(c_m)}{\sum_{m=1}^{M} \exp(c_m)+1}$$

[T. Salimans et al, "Improved techniques for training GANs, NIPS2016]

Discriminator Model (cont.)

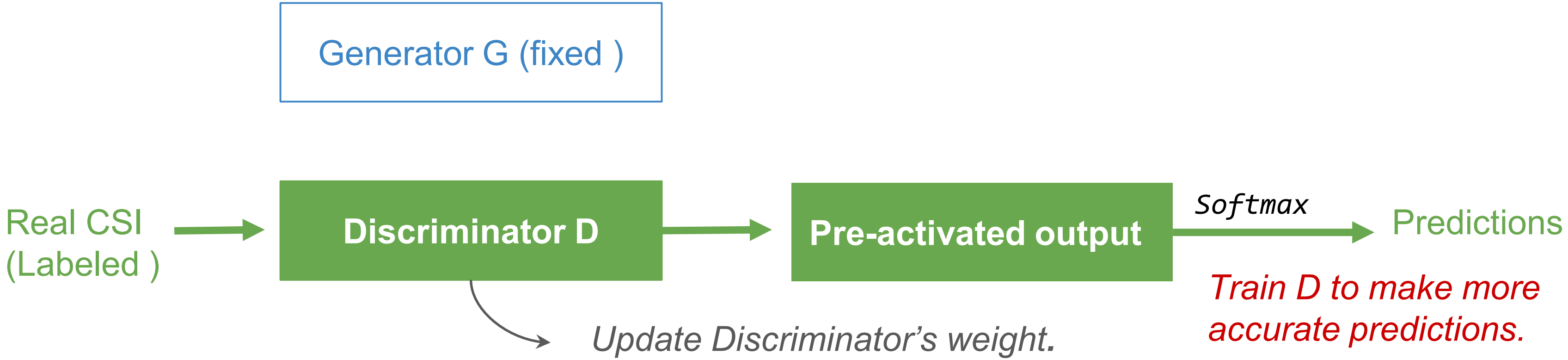


- **Seen as *Classifier C***: Produce a prediction vector **y** with Softmax activation and index of the largest component in **y** is the class prediction.
- ***<u>This model C is saved as the fingerprint</u>***.

Training DCGAN

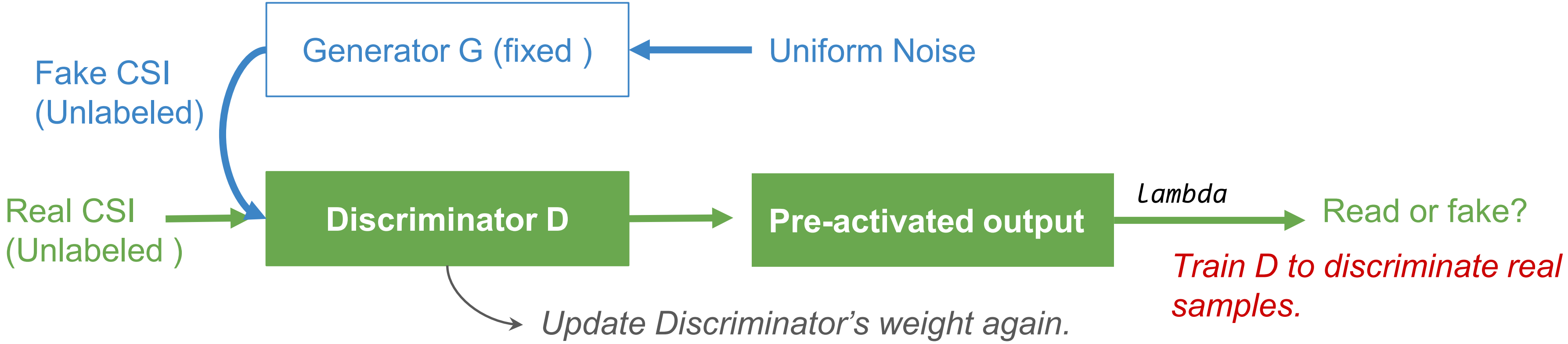
The training of the proposed DCGAN involves a **two-step** iterative process: (1)Training ***Discriminator*** and (2)Training ***Generator***. For each iteration:

First, we train Discriminator *as Classifier*, with ***few*** labeled CSI



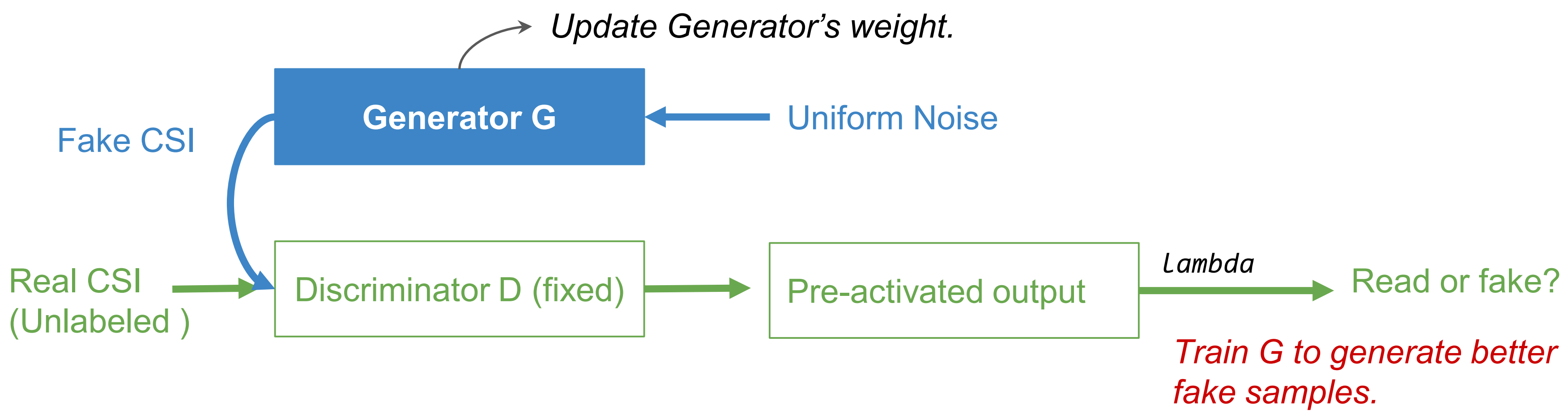
Training DCGAN (cont.)

Next, we train Discriminator D again, but with the fake CSI samples from ***fixed G*** plus real CSI samples:



Training DCGAN (cont.)

Finally, we turn to train Generator G, with the ***fixed and updated Discriminator D***:

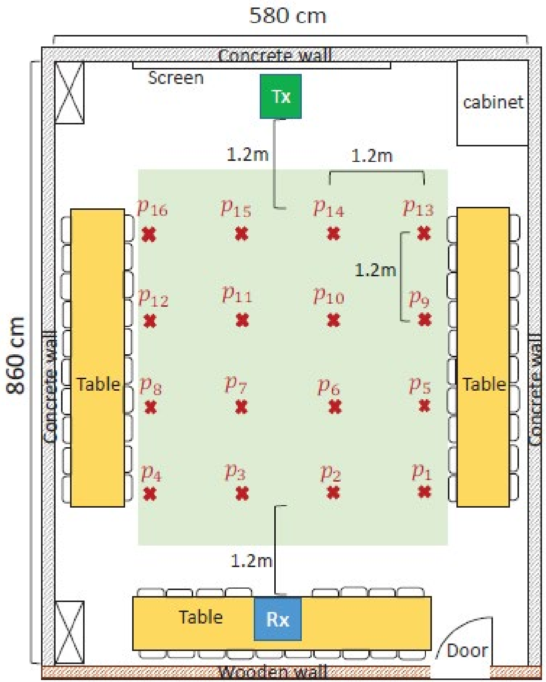


Note: The model is trained with Adam optimizer and categorical cross-entropy loss function in Tensorflow.

Experimental Environment

Dataset:

- **Training Set**: 400 CSI samples for each location (6400 for all locations)
- **Testing Set**: 200 CSI samples for each location (3400 for all locations)
- Unlabeled Set: the CSI is same as training set but without label



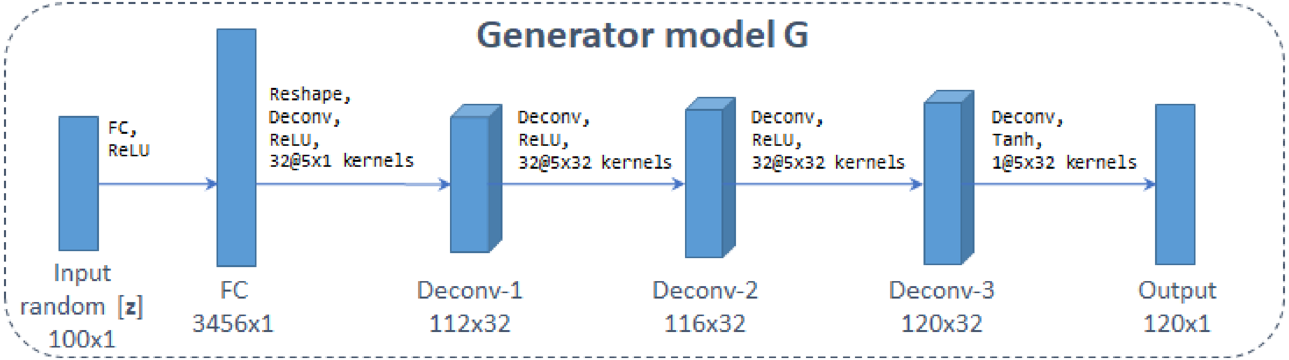
Conference room at the Research Center for Information Technology Innovation, Academia Sinica.

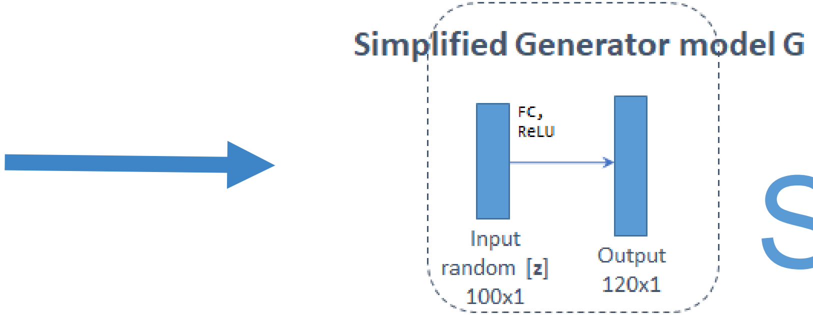
Experiment Result

Labeled CSI samples	Semi-Supervised DCGAN (%)	Supervised CNN (%) (same architecture as D of DCGAN)
16	**85.75**	**58.87**
32	85.78	68.78
64	87.28	82.47
128	87.41	81.25
1600	87.09	86.87
3200	86.72	88.31
6400	**87.84**	**87.71**

With semi-supervised DCGAN, the classification accuracy retains with reduced amount of labeled data.

Simplified G





Still Work ?

Simplified G (cont.)

Labeled CSI samples	Semi-Supervised DCGAN (%)	Semi-Supervised DCGAN With a Simplified G (%)
16	**85.75**	**64.40**
32	85.78	72.94
64	87.28	79.25
128	87.41	79.41
1600	87.09	81.41
3200	86.72	86.63
6400	**87.84**	**87.06**

A sophisticated G can help train a good D, and consequently a good C, in the considered DCGAN architecture.

Conclusion

1. We have presented a **GAN-based semi-supervised approach** to the device-free fingerprinting indoor localization problem.
2. We showed that the proposed scheme **achieves an increasingly advantageous performance when trained with an increasingly reduced number of labeled training samples**, as compared to the supervised approach.
3. The **interactions between the G, D, and C** of the proposed model were discussed.

Thank you for your attention!