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A Comparative Study of Deep-Learning-Based Semi-Supervised Device-Free Indoor Localization



Kevin M. Chen and Ronald Y. Chang

Research Center for Information Technology Innovation (CITI), Academia Sinica, Taipei, Taiwan



What is *device-free* indoor localization?





How to solve device-free indoor localization?





How to solve device-free indoor localization?





How to solve device-free indoor localization?



Introduction Methods Experiment Discussion Conclusi

What is *semi-supervised*?



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How to *semi-supervised*?





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Semi-Supervised Variational Auto-Encoder (VAE)

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This is an ordinary VAE*.



This is an ordinary classifier.



*D. P. Kingma and M. Welling, "Auto-encoding variational bayes," in Proc. 2nd International Conference on Learning Representations, ICLR, 2014.

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This is the *semi-supervised* VAE*.



*D. P. Kingma, S. Mohamed, D. J. Rezende, and M. Welling, "Semisupervised learning with deep generative models," in Proc. Neural Information Processing Systems ¹⁰ Conference, NeurIPS, 2014.

Introduction Methods Experiment Discussion Conclusion

Train the *semi-supervised* VAE with *labeled* CSI.



Introduction Methods Experiment Discussion Conclusion

Train the *semi-supervised* VAE with *labeled* CSI.





Train the *semi-supervised* VAE with *unlabeled* CSI.



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Semi-Supervised Generative Adversarial Network (GAN)

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This is an ordinary GAN*.



This is an ordinary classifier.



*I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in Proc. Advances in Neural Information Processing Systems 27, NeurIPS, 2014.



This is the *semi-supervised* GAN*.



*A. Odena, "Semi-supervised learning with generative adversarial networks," in Proc. Workshop on Data-Efficient Machine Learning, ICML, 2016



Consider the two model with *shared weights*.





Train the *semi-supervised* GAN with *labeled* CSI.





Train the semi-supervised GAN with unlabeled CSI.





Train the *semi-supervised GAN* with *unlabeled* CSI.



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Scenario 1 Conference Room Number of locations (M) 16 **Training CSI** 400 per location **Testing CSI** 200 per location





All the indoor environment are at Research Center for Information Technology Innovation, Academia Sinica, Taiwan.

Discussion **Experiment** 540 cm **Scenario 2** Concrete wall Door Counter Tx. p_{14} p_{11} *p*₁₃ p_{12} Lounge **DOO** Number of locations (M) p_{10} p_9 p_8 × X X 14 660 cm Wooden wall Couch Table e wall **Training CSI** p_5 p_7 p_6 X 768 per location 1.2m **Testing CSI** cabinet p_1 p_2 164 per location

1.2m

All the indoor environment are at Research Center for Information Technology Innovation, Academia Sinica, Taiwan.

Concrete wa

Experiment Discussion Door Cabinet **Scenario 3** 2.4m 5m Cabinet 0 p_2 p_3 Office × Cabinet AVAN V VIII 0.6m 1.8m × Number of locations (M) 0.7m p_5 p_4 p_7 p_8 p_9 18 ¥ 1305cm **Training CSI** 400 per location p_{11} p_{10} P12 p_{14} p₁₅ P13 **Testing CSI** × × Cabinet 100 per location × 6

^{660 cm} All the indoor environment are at Research Center for Information Technology Innovation, Academia Sinica, Taiwan.

Window

p16_

Window

ERXI

p17

4.2m

ndow Window



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Model semi-supervised VAE



Discussion **Experiment** Generator Reshape, Deconv Deconv. Conv, Reshape Conv, Deconv Conv. Conv. ReLU, ReLU, tanh, FC, ReLU. ReLU, ReLU, ReLU, 32@5x1 32@5x1 32@5x32 ReLU 32@5x32 32@5x32 32@5x1 MMM Fake noise **CSI Samples** Conv-2 Deconv-1 [n] Deconv-2 Deconv-3 Input Conv-1 112x32 112x32 116x32 [Xg] 120x32 120x1 120x1 116x32 FC 3456x1 Shared weights Classifier Real **CSI Samples** Conv.

Model semi-supervised GAN



More labels

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Comparison: Localization Performance

(Scena Conferen	ario 1 Ice Room	ı	Scenario 2 Lounge				Scenario 3 Office			
L	CNN	VAE	GAN	L	CNN	VAE	GAN	L	CNN	VAE	GAN
16	50.9%	61.7%	65.8%	14	39.9%	22.2%	35.6%	36	49.0%	64.4%	66.7%
32	63.2%	58.5%	67.0%	28	52.8%	31.4%	40.7%	72	66.9%	70.4%	70.4%
160	75.1%	73.5%	78.5%	140	70.5%	52.2%	55.4%	144	81.2%	78.9%	85.1%
3200	81.9%	72.7%	77.5%	5376	73.0%	50.5%	58.2%	3600	90.0%	81.1%	87.1%
6400	82.1%	73.0%	77.1%	10752	74.0%	62.7%	62.0%	7200	92.1%	87.1%	83.7%

*The performance is represented by the overall classification accuracy.

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160	75.1%	73.5%	78.5%	140	70.5%	52.2%	55.4%	144	81.2%	78.9%	85.1%
3200	81.9%	72.7%	77.5%	5376	73.0%	50.5%	58.2%	3600	90.0%	81.1%	87.1%
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160	75.1%	73.5%	78.5%	140	70.5%	52.2%	55.4%	144	81.2%	78.9%	85.1%	
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Comparison: Localization Performance

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Comparison: The Real CSI

Scenario 1 Conference Room



Scenario 2 Lounge



Comparison: Generative Performance

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Scenario 1 Conference Room

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Comparison: Generative Performance

Scenario 2 Lounge



Real CSI

VAE

GAN

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1. Semi-supervised VAE and GAN generally exhibit advantages over supervised CNN in the few labeled data regime, where GAN outperforms VAE.

2. Noisy CSI data could affect semi-supervised learning more negatively than supervised learning.

3. The comparative performance of semi-supervised VAE and GAN may be attributed to their different generative mechanisms and different generative results.

Thank you for your attention! Q&A



Kevin M. Chen and Ronald Y. Chang

Research Center for Information Technology Innovation (CITI), Academia Sinica, Taipei, Taiwan E-mail: [cwchen, rchang]@citi.sinica.edu.tw