Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation

Published In MICCAI 2021

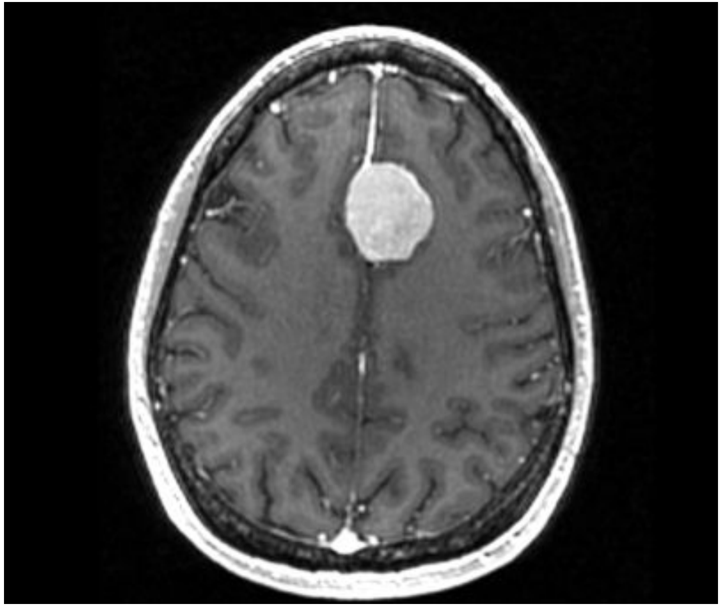
Presented By: Jatin Sachdeva

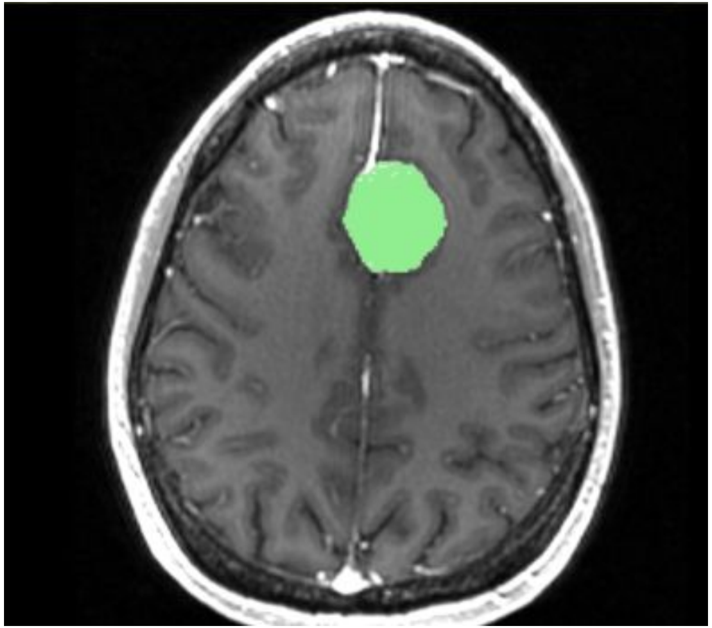
Course Instructor
Prof. Dr C Krishan Mohan

Mentor
Peketi Divya

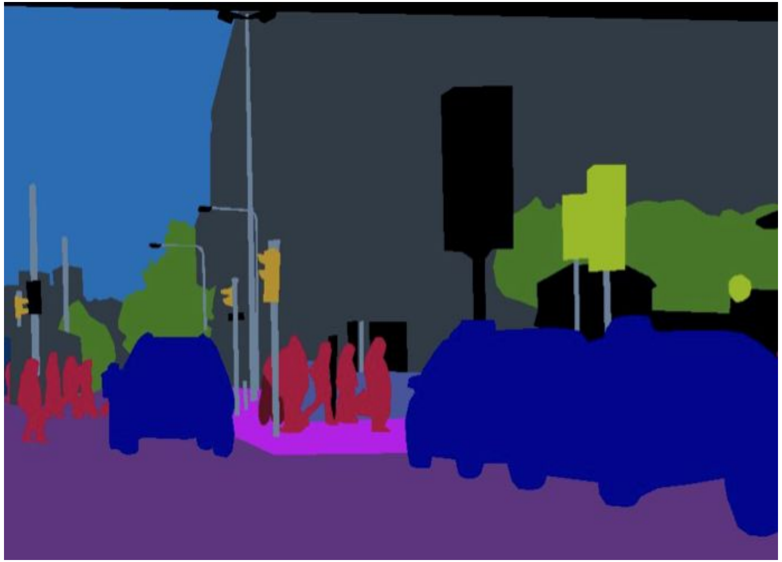
Table of Content

Motivation





Problem



Problem Statement

Getting Labeled data for medical image segmentation is challenging task. To address this issue we propose a semi-supervised image segmentation technique.

Challenges

- How to came up with good loss function

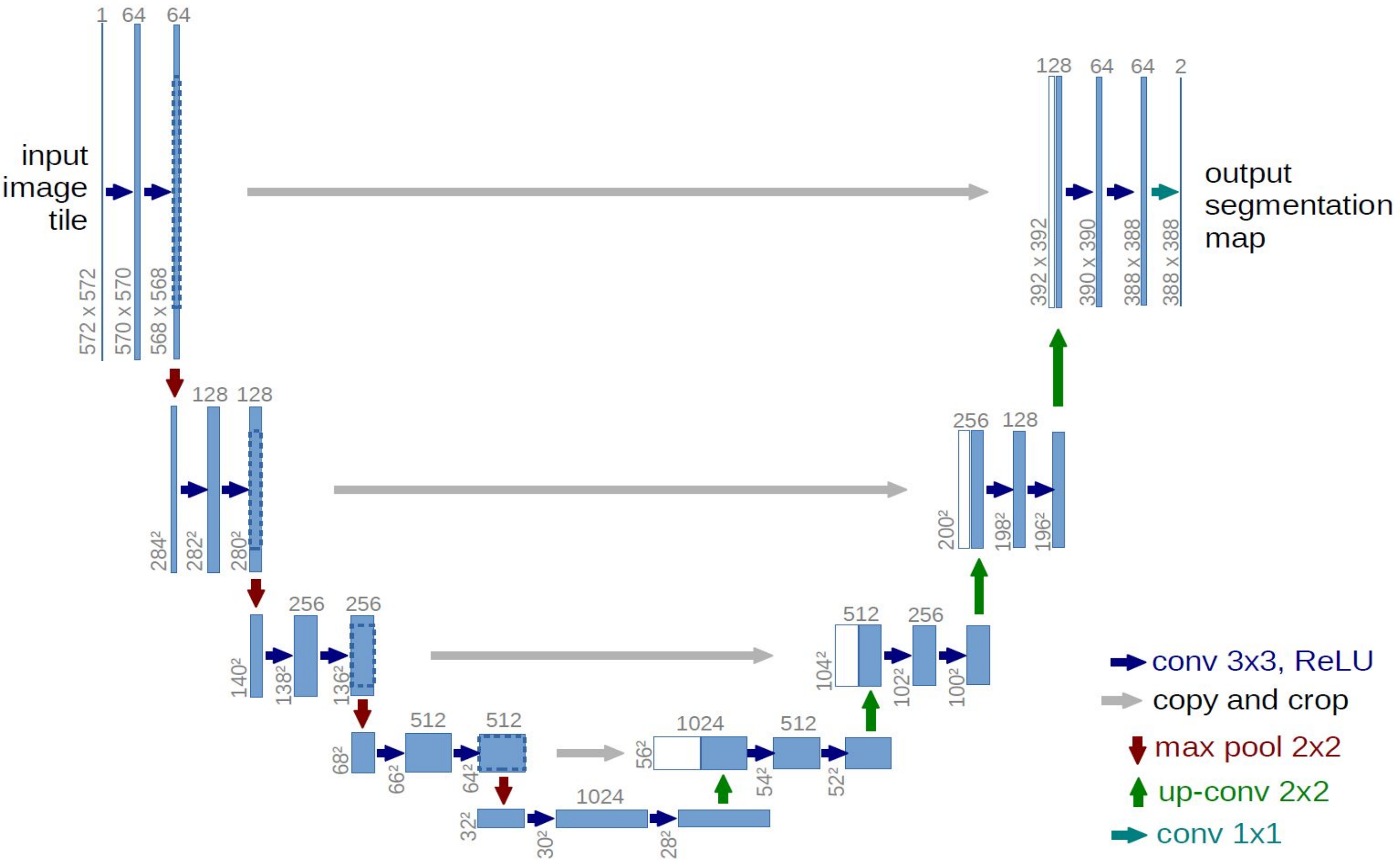
- How to come up with loss function for unlabeled data

Existing State of Arts

- Pseudo Labelling
- Mean Teacher
- VAT(virtual adversarial training)
- Deep Co-training

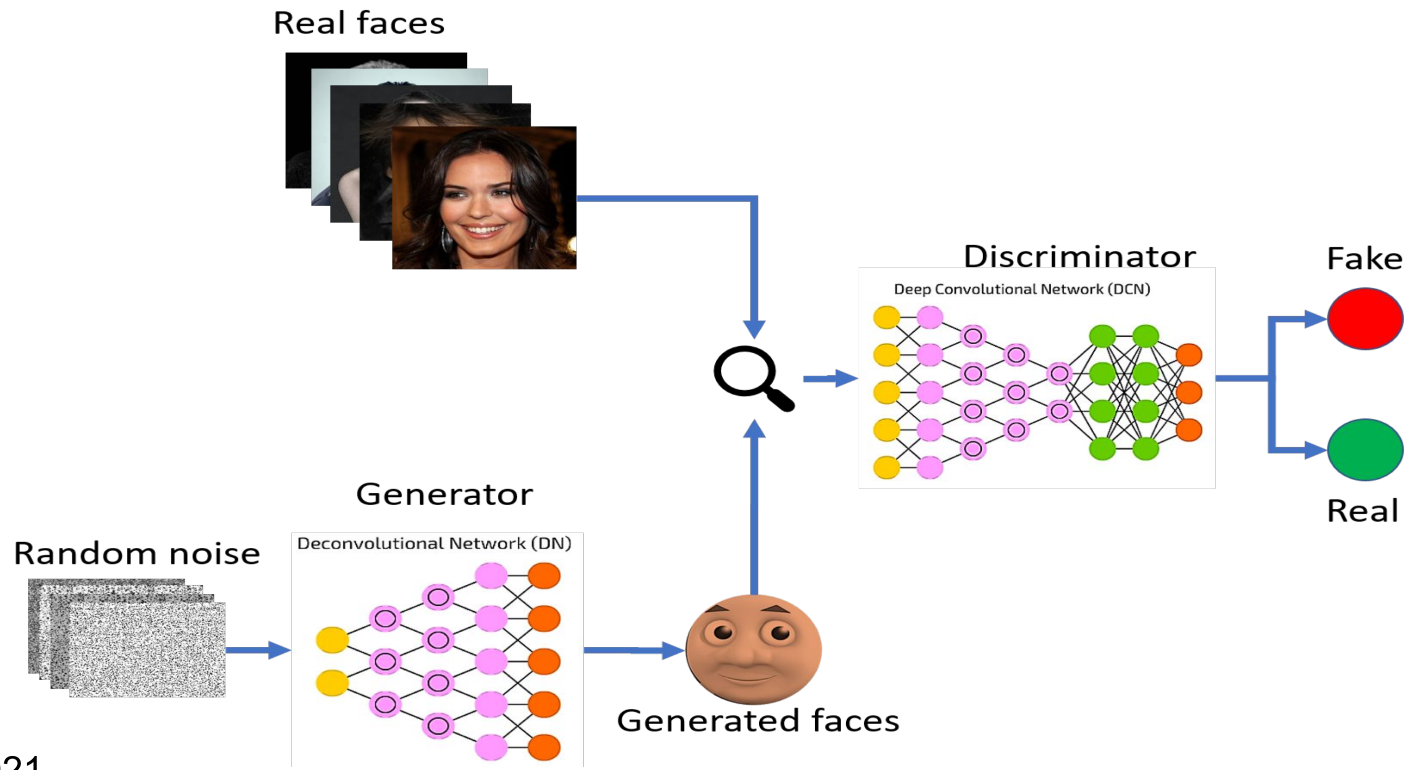
Unet and GAN

Unet



1
64
64
input image tile
572 x 572
570 x 570
568 x 568
128
128
284^2
282^2
280^2
256
256
140^2
138^2
136^2
512
512
68^2
66^2
64^2
1024
32^2
30^2
28^2
1024
512
56^2
54^2
52^2
512
256
104^2
102^2
100^2
256
128
200^2
198^2
196^2
128
64
64
2
392 x 392
390 x 390
388 x 388
388 x 388
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

Generative Adversarial Networks (GAN)



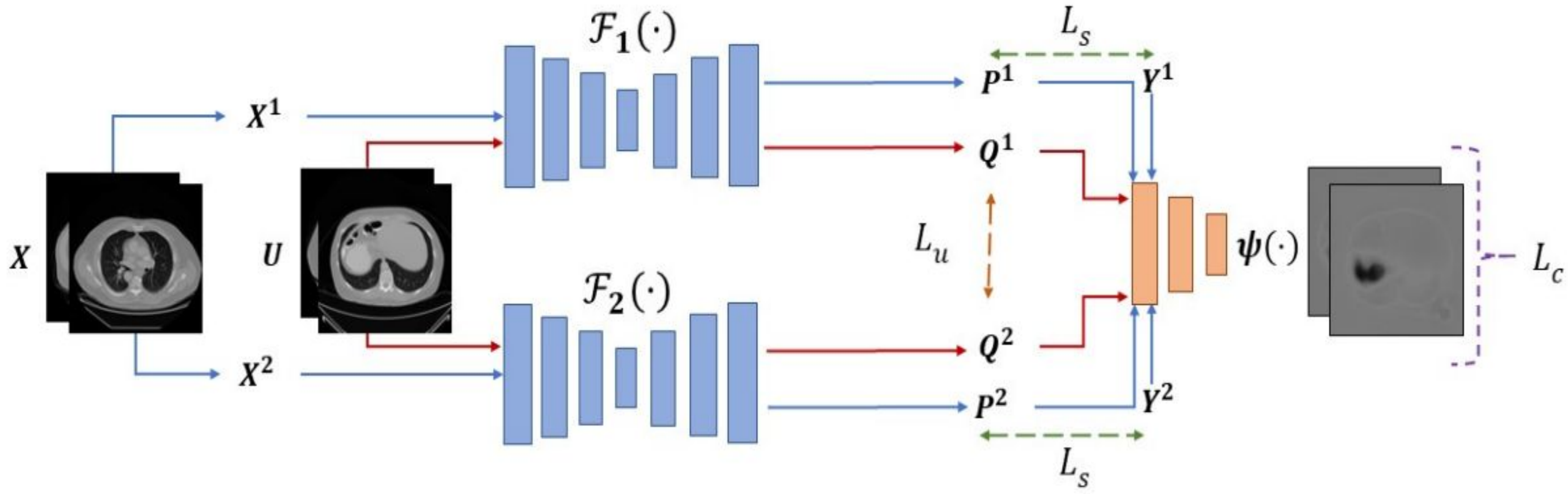
Loss Function for GAN

$$\min_{G} \max_{D} V(D, G)$$

$$V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

$$\mathbb{E}_{x \sim p_t}[1 - D(x)] + \mathbb{E}_{x \sim p_g}[D(x)] = \int_{\mathbb{R}} (1 - D(x))p_t(x) + D(x)p_g(x)dx$$

State of Art Experiment



Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

Multitask loss function

$$\min_{\boldsymbol{\Theta}} \max_{\theta_C} \mathcal{L}(\boldsymbol{\Theta}; \mathcal{D}) \ .$$

$$\mathcal{L}(\boldsymbol{\Theta}; \mathcal{D}) := \lambda_s \, \mathcal{L}_{\mathrm{s}}(\boldsymbol{\Theta}; \mathcal{X}) + \lambda_u \, \mathcal{L}_{\mathrm{u}}(\boldsymbol{\Theta}; \mathcal{U}) + \lambda_c \, \mathcal{L}_{\mathrm{c}}(\boldsymbol{\Theta}; \theta_C; \mathcal{D})$$

Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

Supervised Loss

$$\mathcal{L}_{\mathrm{ce}}(\theta_i;\mathcal{X}) = \mathbb{E}_{(\mathbf{X},\mathbf{Y})\sim\mathcal{X}}\left[\left\langle \mathbf{Y}, \log\left(\mathcal{F}_i(\mathbf{X})\right)\right\rangle\right]$$

$$\mathcal{L}_{\mathrm{dice}}(\theta_i;\mathcal{X}) = 1 - \mathbb{E}_{(\mathbf{X},\mathbf{Y})\sim\mathcal{X}}\left[\frac{2\langle \mathbf{Y}\ ,\ \mathcal{F}_i(\mathbf{X})\rangle}{\left\|\mathbf{Y}\right\|_1 + \left\|\mathcal{F}_i(\mathbf{X})\right\|_1}\right],$$

where we use $\langle \mathbf{A}, \mathbf{B}\rangle = \sum_{i,j} \mathbf{A}[i,j]\mathbf{B}[i,j]$ and $\|\mathbf{A}\|_1 = \sum_{i,j} |\mathbf{A}[i,j]|$.

Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

Unsupervised Loss

$$P(h^1 \neq h^2) \geq \max\left\{P_{\mathrm{err}}(h^1), P_{\mathrm{err}}(h^2)\right\}.$$

$$\mathcal{L}_{\mathrm{u}}(\mathbf{\Theta}; \mathcal{U}) \coloneqq \mathbb{E}_{\mathbf{U}\sim\mathcal{U}}\left[\left\langle \mathcal{F}_1(\mathbf{U}), \log\left(\mathcal{F}_2(\mathbf{U})\right)\right\rangle + \left\langle \mathcal{F}_2(\mathbf{U}), \log\left(\mathcal{F}_1(\mathbf{U})\right)\right\rangle\right].$$

Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

Critic Loss

$$\Psi : [0,1]^{H \times W} \rightarrow [0,1]^{H \times W}$$

$$\mathcal{L}_{adv1}(\mathbf{\Theta}; \theta_C; \mathcal{X}) := \mathbb{E}_{(\mathbf{X},\mathbf{Y}) \sim \mathcal{X}} \Bigg[- \sum_{a \in H} \sum_{b \in W} \Big\{ (1-\eta) \log \Big(\psi(\mathbf{Y})[a,b] \Big) + \eta \log \Big(1 - \psi(\mathcal{F}_i(\mathbf{X}))[a,b] \Big) \Big\} \Bigg] ,$$

$$\mathcal{L}_{adv2}(\mathbf{\Theta}; \theta_C; \mathcal{U}) := \mathbb{E}_{\mathbf{U} \sim \mathcal{U}} \Bigg[- \sum_{a \in H} \sum_{b \in W} \Big\{ \log \Big(1 - \psi(\mathcal{F}_i(\mathbf{U}))[a,b] \Big) \Big\} \Bigg]$$

$$\mathcal{L}_{\mathrm{c}}(\mathbf{\Theta}; \theta_C; \mathcal{D}) = \mathcal{L}_{\mathrm{adv1}}(\mathbf{\Theta}; \theta_C; \mathcal{X}) + \mathcal{L}_{\mathrm{adv2}}(\mathbf{\Theta}; \theta_C; \mathcal{U}) .$$

Dataset

- 670 Fluorescence Microscopy (FM) images from Nuclei
- 20 MRI volumes from Heart
- 41 CT volumes from Spleen
- 2D images are obtained by slicing the high-resolution MRI and CT volumes
- Heart (2271 slices)
- Spleen (3650 slices)
- Each slice is then resized to a resolution of 256 × 256.

Results

Dataset	Method	DSC			MAE		
	Fully Supervised	**91.36**			**2.25**		
		$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$	$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$
Nuclei	Mean Teacher	83.78	84.92	87.99	4.78	4.30	3.36
	Pseudo Labeling	60.90	72.46	85.91	8.40	6.37	3.84
	VAT	85.24	86.43	88.45	4.09	3.77	3.26
	Deep Co-training	85.83	87.15	89.20	4.08	3.80	3.08
	Duo-SegNet	**87.14**	**87.83**	**89.28**	**3.57**	**3.43**	**3.03**

Research Paper: Duo-SegNet: Adversarial Dual-Views for Semi-Supervised Medical Image Segmentation
Authors: Himashi Peiris, Zhaolin Chen, Gary Egan, Mehrtash Harandi

	Fully Supervised	**97.17**			**0.02**		
		$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$	$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$
Heart	Mean Teacher	71.00	87.59	93.43	0.22	0.09	0.05
	Pseudo Labeling	65.92	79.86	80.75	0.20	0.13	0.13
	VAT	85.33	91.60	94.83	0.11	0.06	0.04
	Deep Co-training	85.96	91.54	94.55	**0.10**	0.06	0.04
	Duo-SegNet	**86.79**	**93.21**	**95.56**	**0.10**	**0.05**	**0.03**
	Fully Supervised	**97.89**			**0.02**		
		$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$	$l_a = 5\%$	$l_a = 20\%$	$l_a = 50\%$
Spleen	Mean Teacher	75.44	90.76	92.98	0.20	0.08	0.06
	Pseudo Labeling	67.70	68.81	84.81	0.24	0.21	0.12
	VAT	78.31	91.37	94.34	0.19	0.07	0.05
	Deep Co-training	79.16	89.65	94.90	0.16	0.09	0.05
	Duo-SegNet	**88.02**	**92.19**	**96.03**	**0.10**	**0.07**	**0.03**

Ablation Study

(a) Network Structure Analysis.

Experiment	DSC	MAE
Duo-SegNet	88.02	0.10
w/o Critic	77.69	0.19
w/o Unlabeled Data	76.67	0.17
One Segmentation Network	82.44	0.16

(b) Hyper-parameter Analysis for λ_u.

λ_u	0.1	0.2	0.3	0.4	0.5
DSC	83.58	85.62	88.02	87.14	78.89
MAE	0.15	0.12	0.10	0.11	0.20

Conclusion

Inspired by Generative Adversarial Networks(GANs) and GAN based medical imaging applications including medical image segmentation , reconstruction and domain adaptation, Duoseg-net method graciously encloses the min-max formulation in dual-view learning for segmenting medical images where high-confidence predictions for unlabeled data are leveraged, which is simple and effective.

References

- Yi, Xin, Ekta Walia, and Paul Babyn. "Generative adversarial network in medical imaging: A review." Medical image analysis 58 (2019): 101552.

- Zhao, Jing, et al. "Multi-view learning overview: Recent progress and new challenges." Information Fusion 38 (2017): 43-54.

- Sivagami, S., et al. "Unet architecture based dental panoramic image segmentation." 2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET). IEEE, 2020.

- Miyato, Takeru, et al. "Virtual adversarial training: a regularization method for supervised and semi-supervised learning." IEEE transactions on pattern analysis and machine intelligence

Thank You