

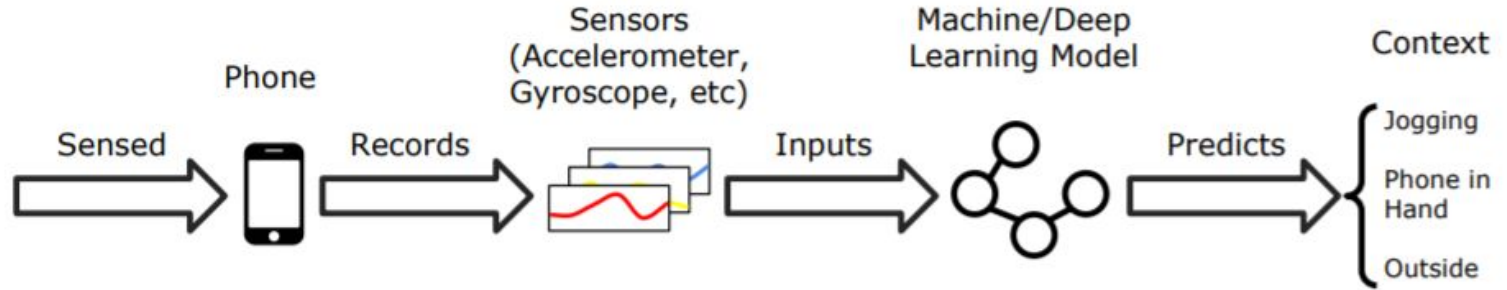
WPI

Human Context Recognition: A Controllable GAN Approach

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Project Overview



Use cases

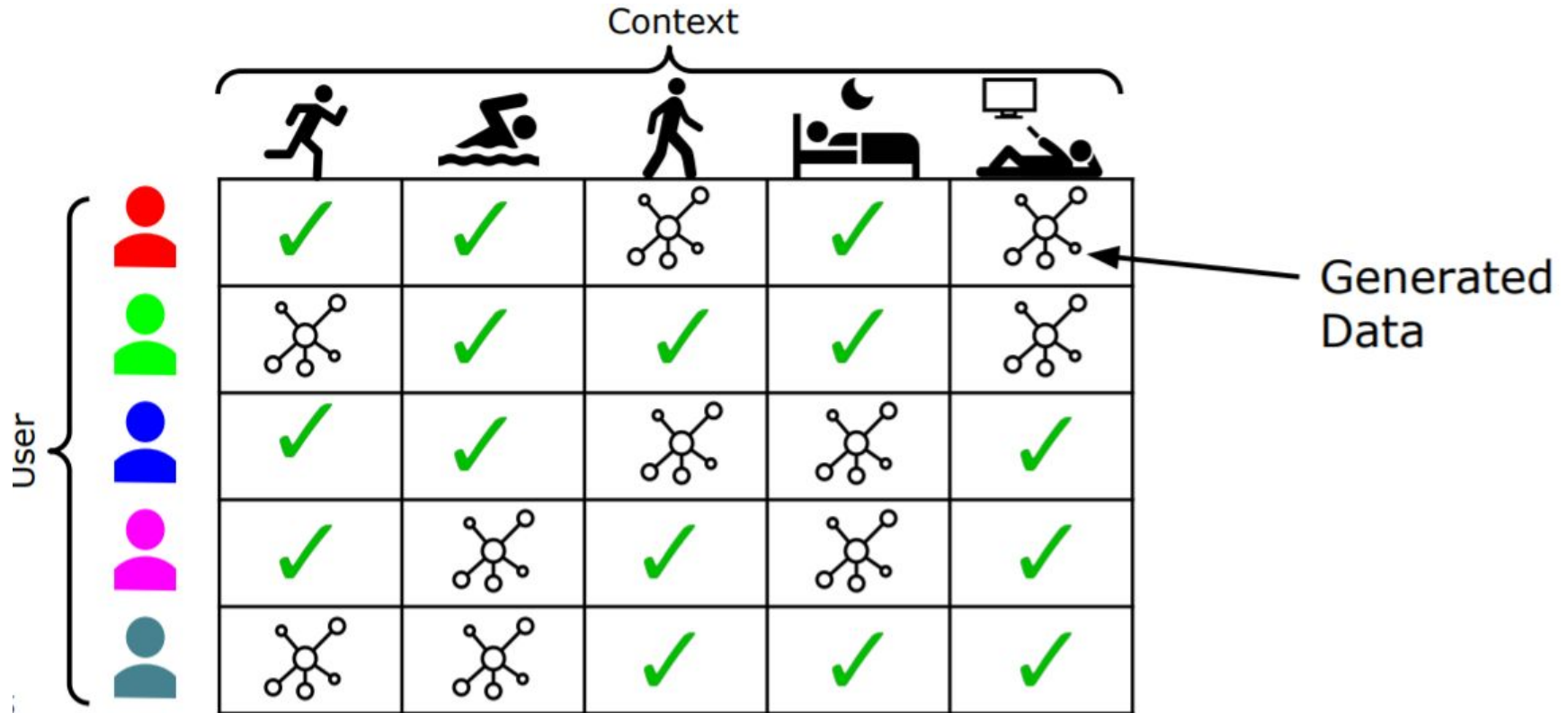
- Mobile healthcare
- Security/User Identification

Missing User-Context Pairs

		Context				
						
User		✓	✓		✓	
			✓	✓	✓	
		✓	✓			✓
		✓		✓		✓
				✓	✓	✓

We do not have data for every context data for every user

Missing User-Context Pairs

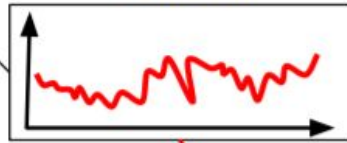


Idea: Generate Characteristic Data

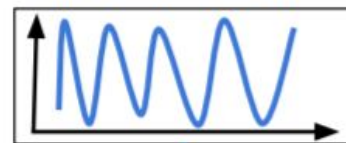
U0: User with no
'Running +
Phone-in-Hand' data



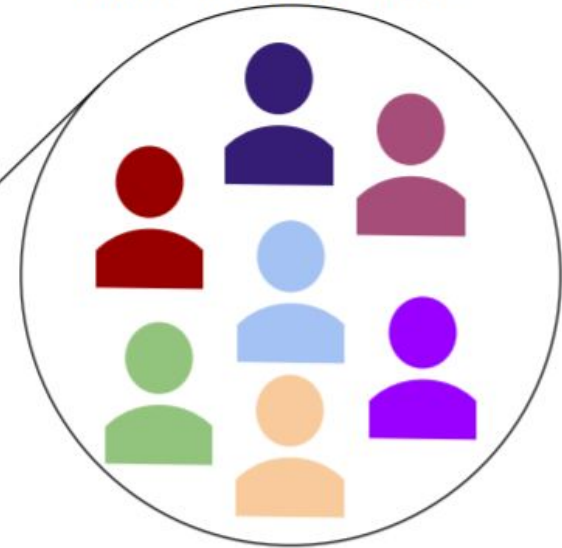
U0's typical
behavior



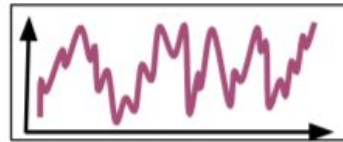
Typical 'Running +
Phone-in-Hand'



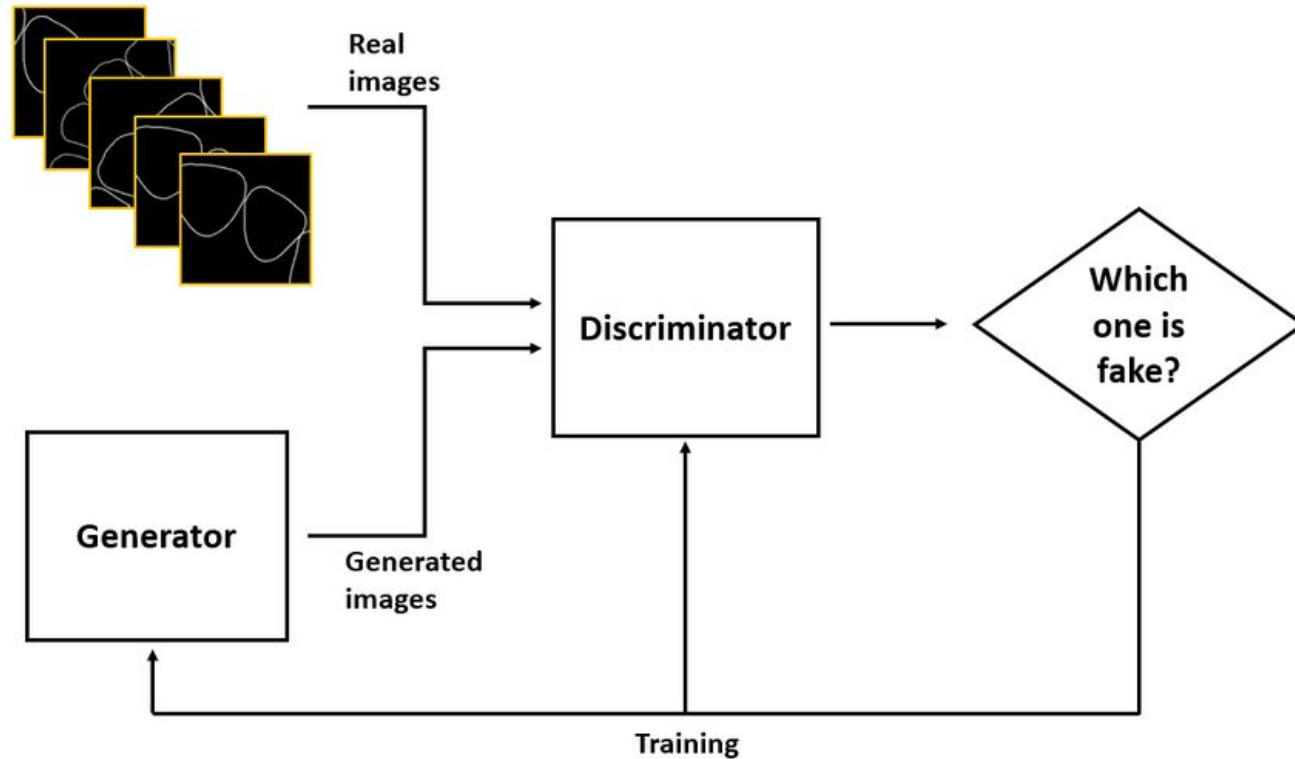
Users with 'Running +
Phone-in-Hand' data



Combined **style** of
U0 with 'Running +
Phone-in-Hand'
content



Approach: Generative Adversarial Network (GAN)



Simple GANs

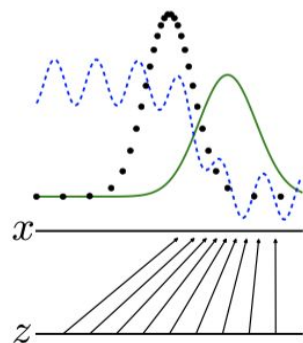
- **G** learns a transformation $f(z) = x$ such that all generated x converge towards the corpus.
- **D** should no longer be able to discern between **G**'s distribution and the corpus.

Legend:

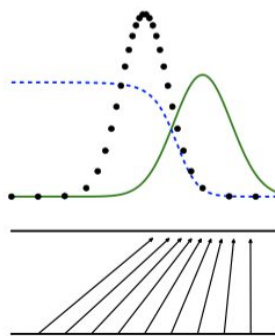
Discriminative distribution: — — —

Generative distribution: ———

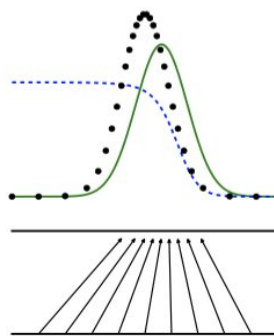
Corpus distribution: • • •



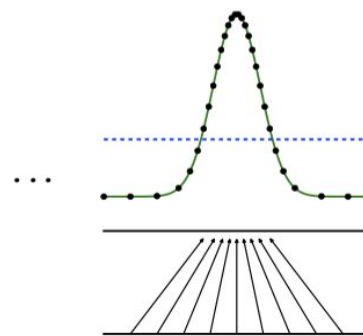
(a)



(b)



(c)



(d)

Conditional GANs

- Forces **G** to generate with a specific class/feature
- Reduces class imbalance during **G**'s training

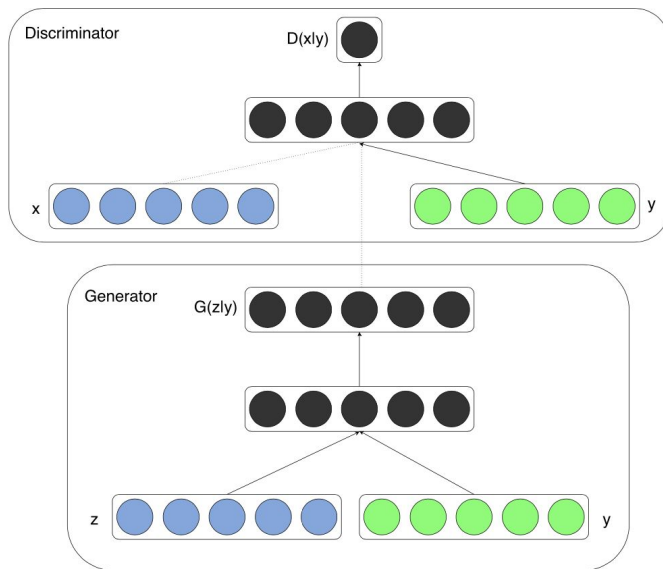
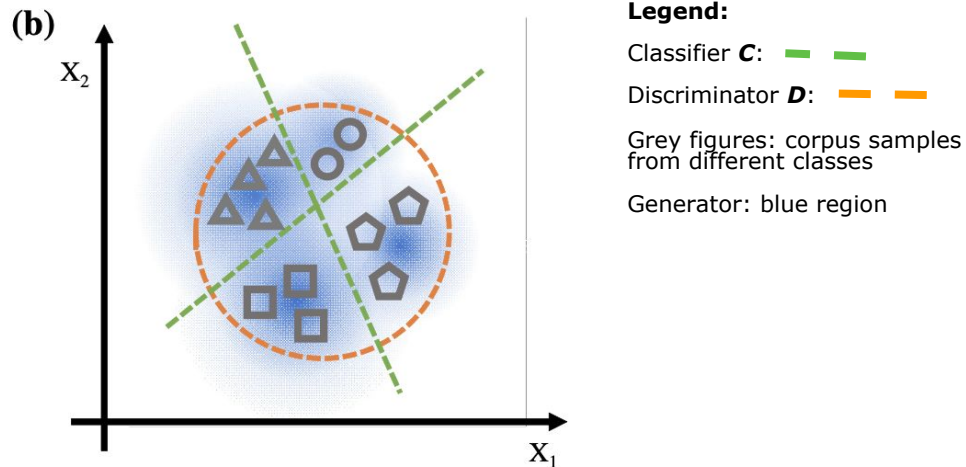
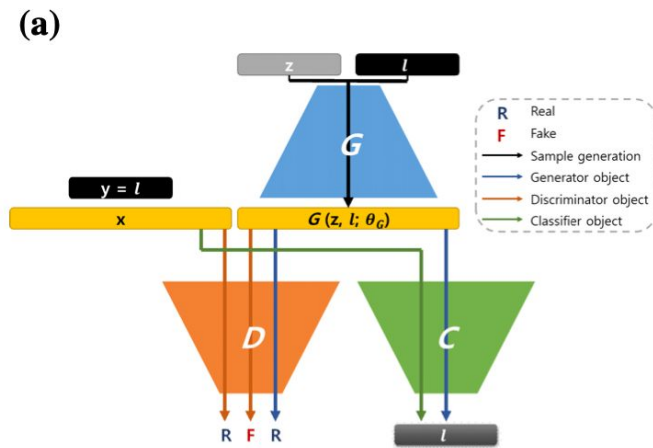


Figure 2: Generated MNIST digits, each row conditioned on one label

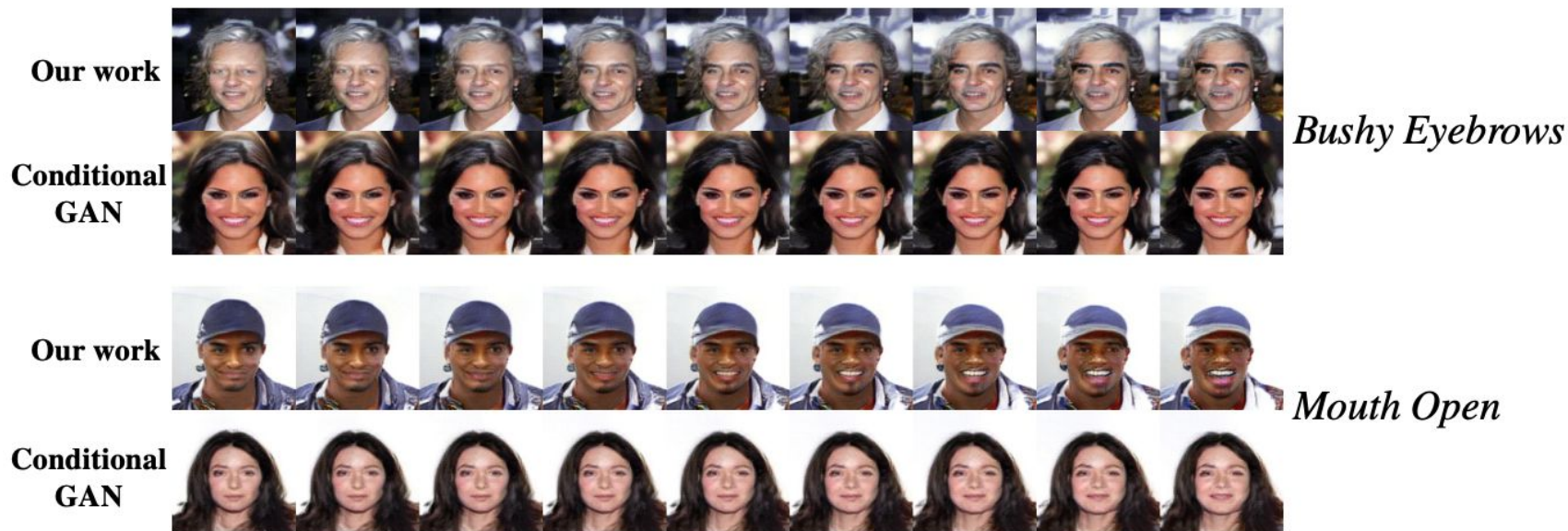
Controllable GANs

- Addition of third machine, classifier
- Alters discrete features



Controllable GANs

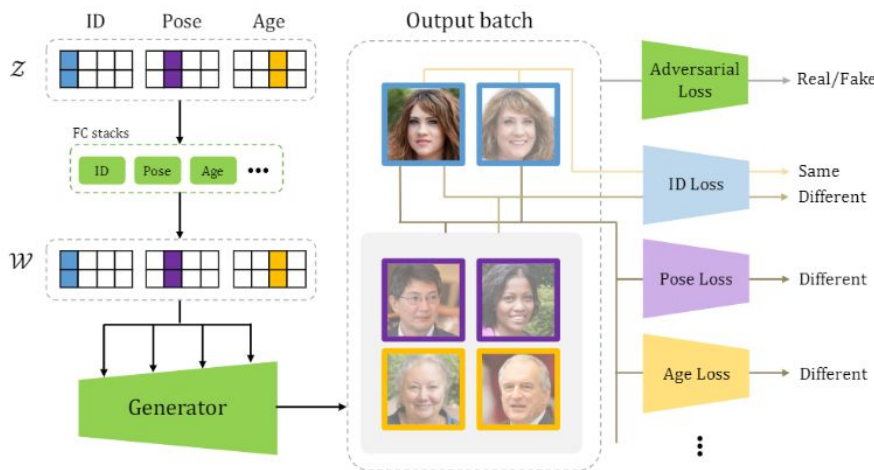
- Addition of third machine, classifier
- Alters discrete features



Explicitly Controllable GANs

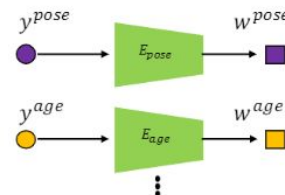
- Standard generator/discriminator models
- Alters a set of independent, continuous features

Training – Phase 1

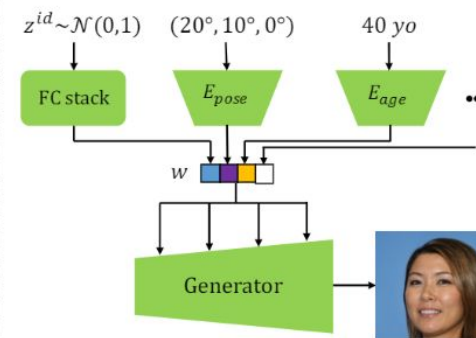


Training – Phase 2

Encoders are trained to map interpretable parameters y^k to w^k .

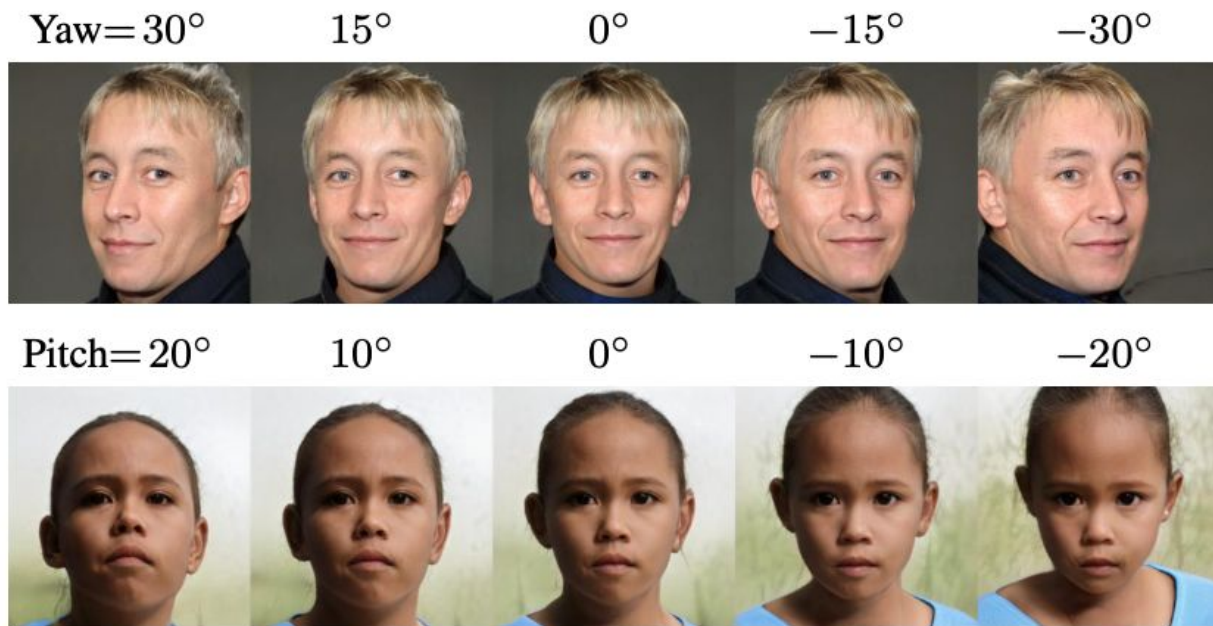


Inference



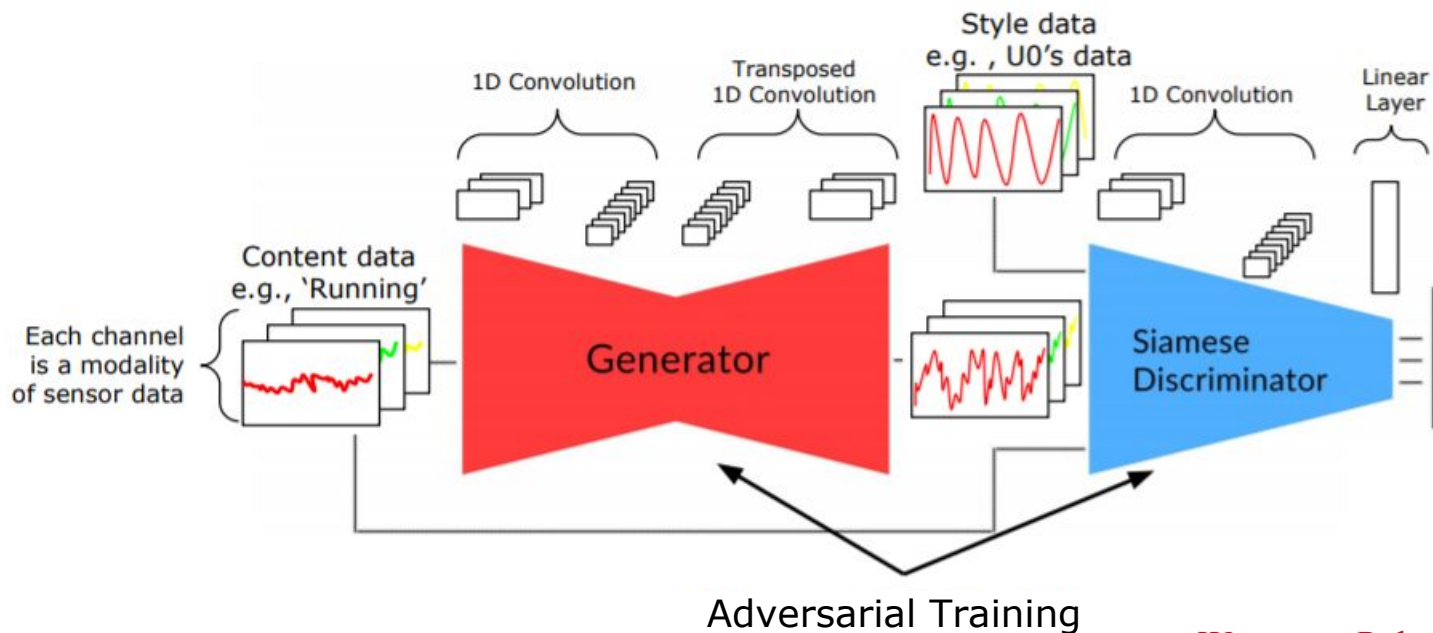
Explicitly Controllable GANs

- Standard generator/discriminator models
- Alters a set of independent, continuous features



Implementation for Mobile Sensor Data

- Smartphone data: 1D sequences with N channels
 - Channel: modality/sensor
- Generator: 1D convolution + transposed 1D convolution
 - Discriminator: 1D convolution + Linear



Completed Coding Tutorials



References

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- [2] I. J. Goodfellow et al., "Generative adversarial nets," in Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, Cambridge, MA, USA, Dec. 2014, pp. 2672–2680.
- [3] M. Mirza and S. Osindero, "Conditional Generative Adversarial Nets," ArXiv14111784 Cs Stat, Nov. 2014, Accessed: May 27, 2021. [Online]. Available: <http://arxiv.org/abs/1411.1784>
- [4] M. Lee and J. Seok, "Controllable Generative Adversarial Network," ArXiv170800598 Cs Stat, Mar. 2019, Accessed: May 27, 2021. [Online]. Available: <http://arxiv.org/abs/1708.00598>
- [5] A. Shoshan, N. Bhonker, I. Kviatkovsky, and G. Medioni, "GAN-Control: Explicitly Controllable GANs," ArXiv210102477 Cs, Jan. 2021, Accessed: May 27, 2021. [Online]. Available: <http://arxiv.org/abs/2101.02477>