

Human Context Recognition: A Controllable GAN Approach

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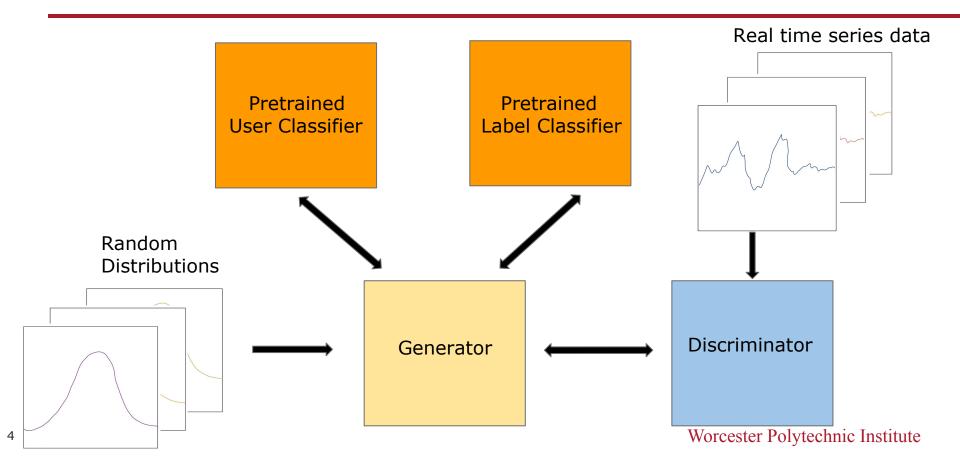
Progress Summary

- Cleaned our existing codebase by making our programs more modular.
- 2. Began implementing a Controllable GAN by building user and activity classifiers (explained later).
- Established a third metric for evaluating the performance of our GAN architectures.
- Continued exploring our novel methodology for training simple GANs by tuning hyperparameters.
- Gathered preliminary results demonstrating the benefits of our training methodology over existing practices.

Modularization of Vanilla GAN

- Broke GAN up into functions
- Added comments to specify parameters and return values
- GAN runs in 3 lines with easy specification of parameters

Controllable GAN



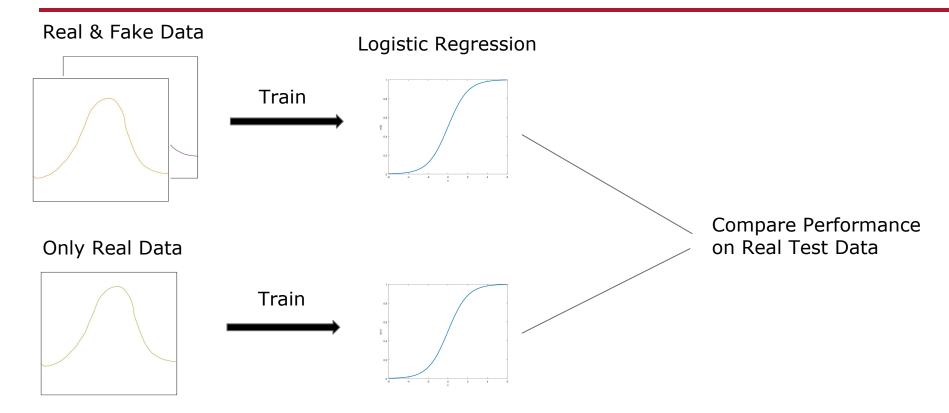
Controllable GAN Activity Classifier

Standard Classifier

SMOTE-Augmented Classifier

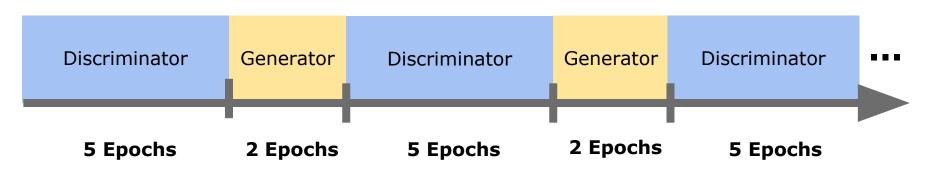
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	0.916	0.960	0.938	682	0	0.929	0.853	0.889	659
1	0.948	0.906	0.926	319	1	0.939	0.955	0.947	627
2	0.723	0.515	0.602	66	2	0.897	0.961	0.928	595
accuracy			0.917	1067	accuracy			0.921	1881
macro avg	0.862	0.794	0.822	1067	macro avg	0.921	0.923	0.921	1881
weighted avg		0.917	0.914	1067	weighted avg	0.922	0.921	0.921	1881

Evaluating Our GAN Architectures



Conventional GAN Training Methodology

5/2 Training Ratio



- [1] Lim et al. "Geometric GAN"
- [2] Lin, Muyang et. al "GAN Compression: Efficient Architectures for Interactive Conditional GANs"
- [3] Lei, Kai et. al "GCN-GAN: A Non-linear Temporal Link Prediction Model for Weighted Dynamic Networks"
- [4] Lee, Hyeungill et. al "Generative Adversarial Trainer: Defense to Adversarial Perturbations with GAN"
- [5] Mescheder, Lars et. al "Which Training Methods for GANs do actually Converge?"
- [6] Gao, Lianli et. al "Lightweight dynamic conditional GAN with pyramid attention for text-to-image synthesis"
- [7] Mirza Mehdi, "Conditional Generative Adversarial Nets"
- [8] Lee, Minhyeok et. al, "Controllable Generative Adversarial Network"
- [9] Goodfellow et. al, "Generative Adversarial Nets"
- [10] Shoshan et. al , "GAN-Control: Explicitly Controllable GANs"

Conventional GAN Training Methodology

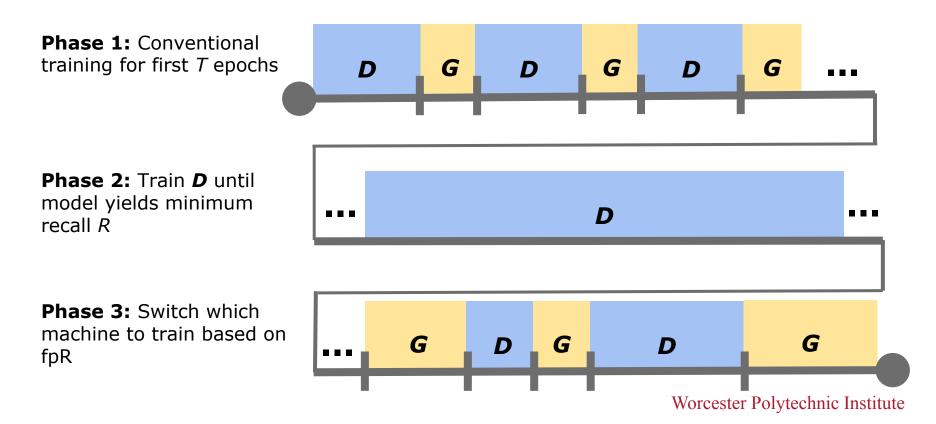
Original Motivation

- Stable training is an open problem
- Alternates training
- Simple to implement
- Involves only 2 hyper-parameters
- Ensures **D** is always better than **G**

Flaws

- D can be overtrained
- Leads to inefficient computation
- Minority of epochs spent training G
- Doesn't maintain a sense of fair competition between machines

Proposed Methodology: Dynamic Training



How Does Dynamic Training Add Value?

Assumptions:

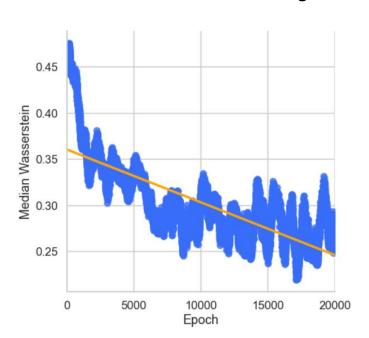
- 1. Similar runtime for training each machine for an epoch
- 2. Limited time and/or resources

Improvements on Conventional Training:

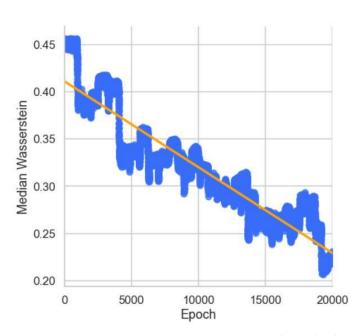
- Improves training stability
- 2. Reduces frequency of redundant/inefficient epochs
- 3. Leads to equal to or quicker convergence
- 4. Maximizes training of **G**
- 5. Negligibly additional computation

Preliminary Results: Median Wasserstein

Conventional Training



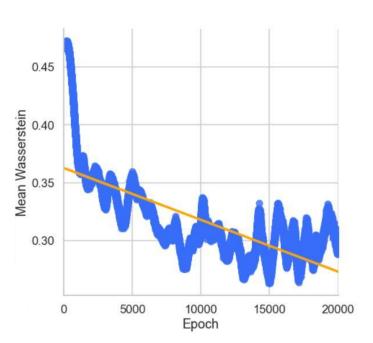
Dynamic Training



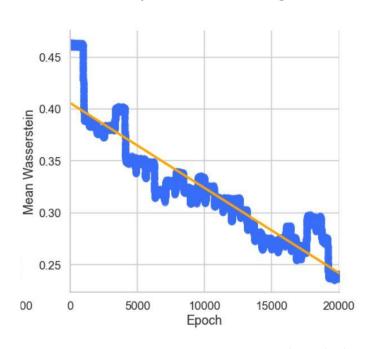
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Preliminary Results: Mean Wasserstein

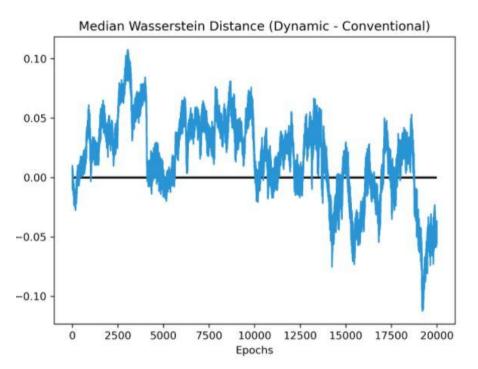


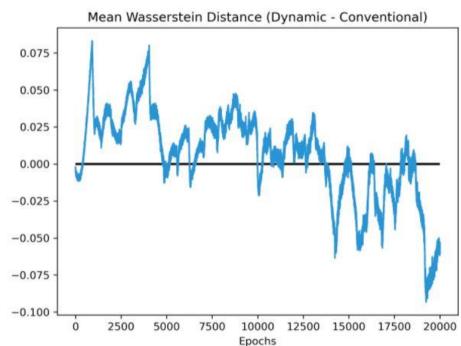


Dynamic Training



Preliminary Results: Wasserstein Difference





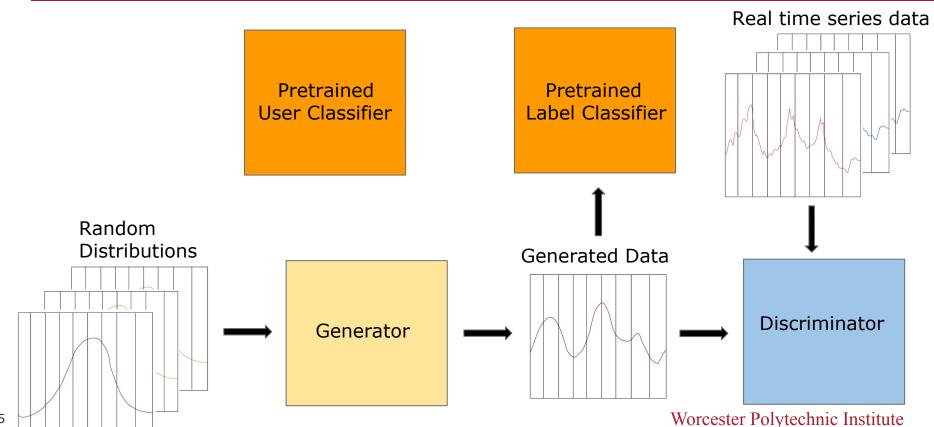
Next Steps

 Integrate user and activity classifiers into the main Controllable GAN architecture.

- 2. Train a Controllable GAN to generate 3 different types of activities undertaken by 3 users.
- 3. Expand the GAN to generate n different types of activities undertaken by m users.

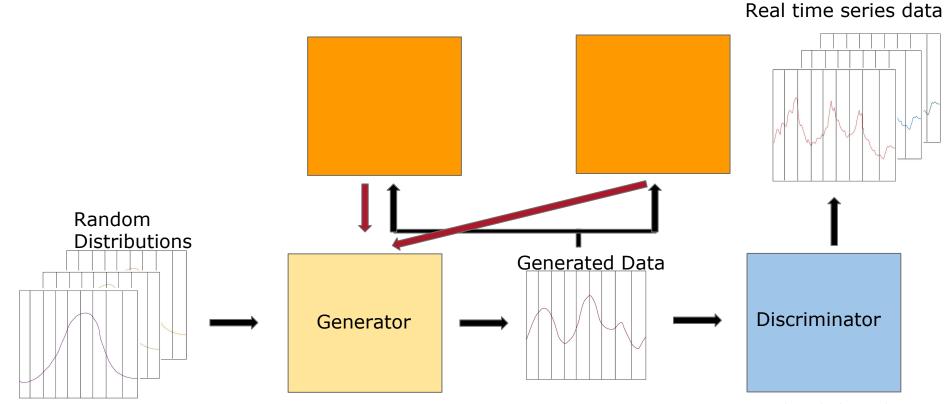
4. Begin updating the GAN for time-series data generation.

Controllable GAN





Pretrained Label Classifier



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