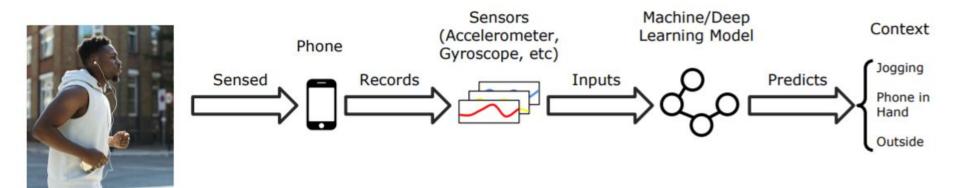


Human Context Recognition: A Controllable GAN Approach

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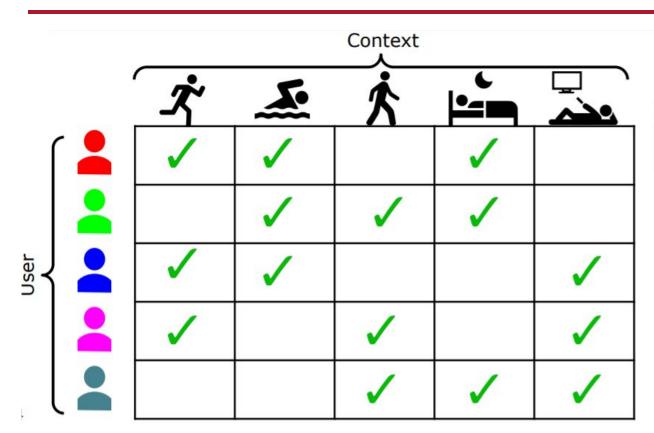
Project Overview



Use cases

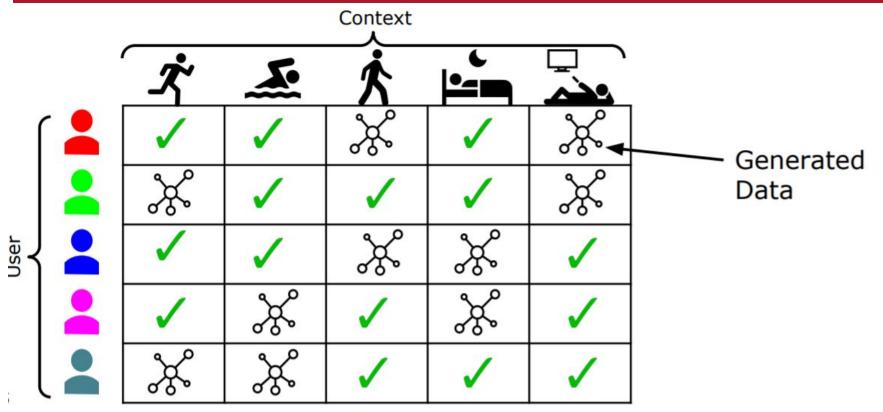
- Mobile healthcare
- Security/User Identification

Missing User-Context Pairs

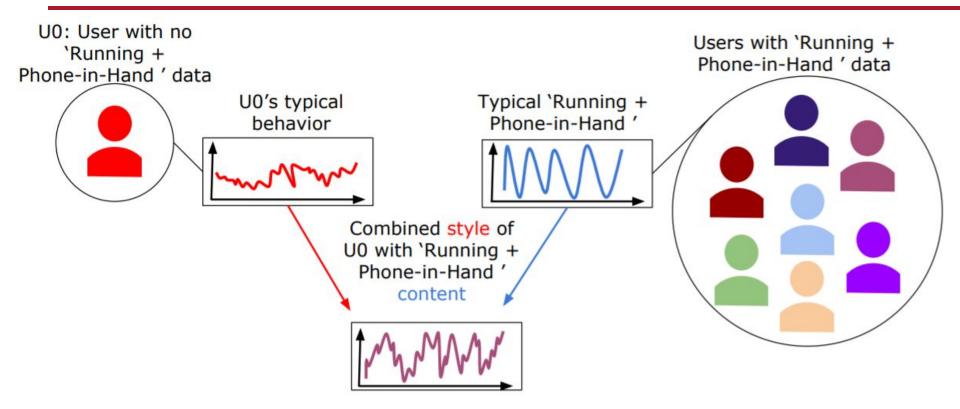


We do not have data for every context data for every user

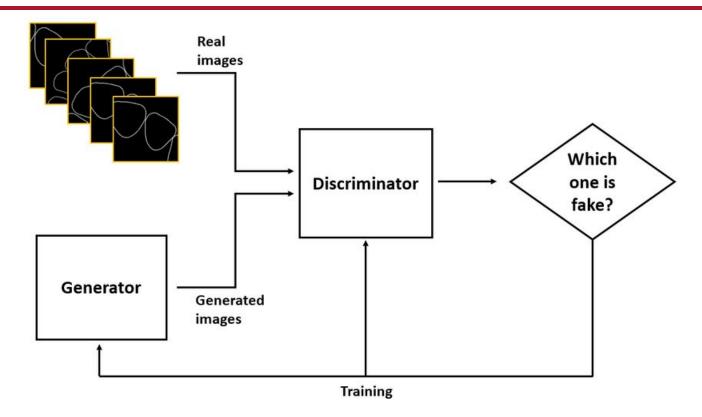
Missing User-Context Pairs



Idea: Generate Characteristic Data

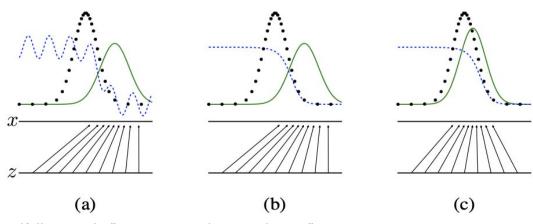


Approach: Generative Adversarial Network (GAN)



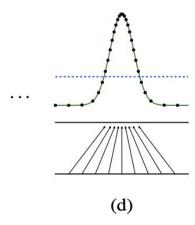
Simple GANs

- **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:

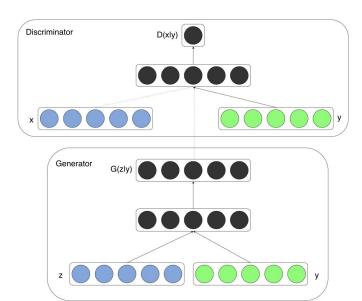
Discriminative distribution: — — Generative distribution: — — Corpus distribution: • • •



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Conditional GANs

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



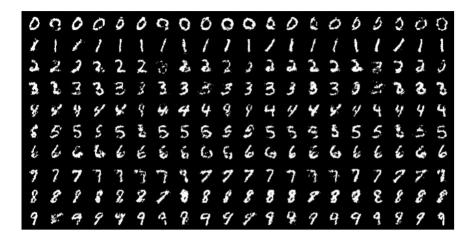
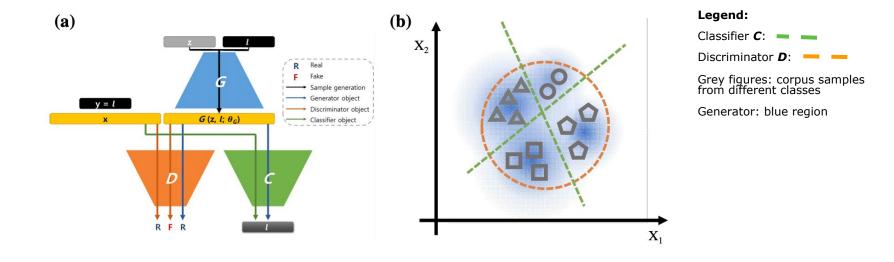


Figure 2: Generated MNIST digits, each row conditioned on one label

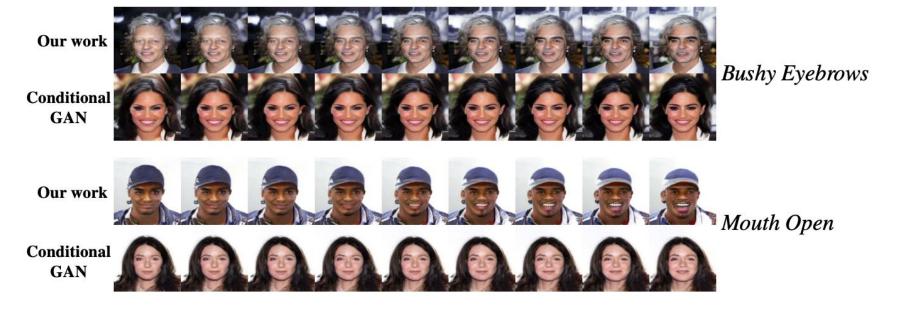
Controllable GANs

- Addition of third machine, classifier
- Alters discrete features



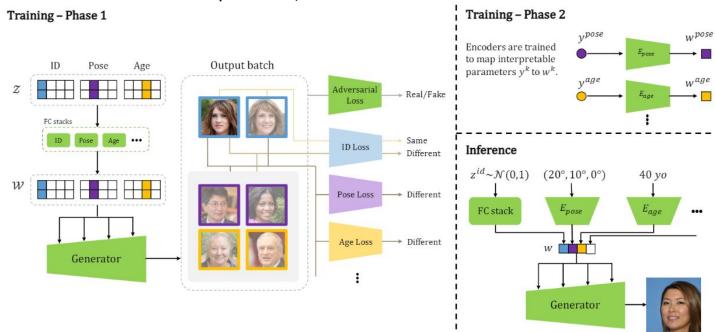
Controllable GANs

- Addition of third machine, classifier
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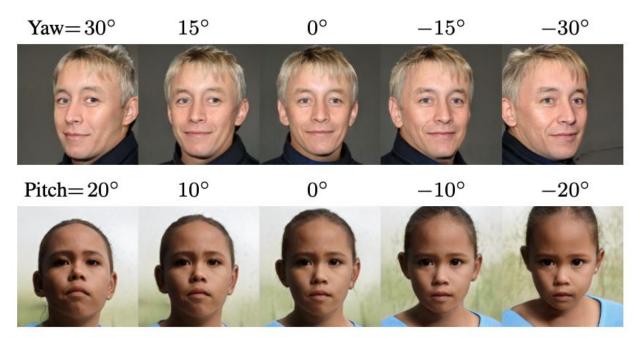
Explicitly Controllable GANs

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



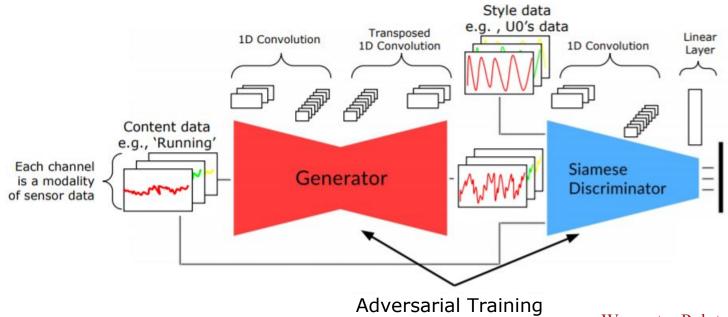
Explicitly Controllable GANs

- 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



- Deep Learning WithPyTorch: A 60 Minute Blitz
- Your First Machine
 Learning Project in
 Python Step-By-Step
- Introducing Scikit-Learn
- How to Develop a
 Conditional GAN (cGAN)

 From Scratch

Takeaways

- 1. Developed a basic understanding of the standard ML libraries and tools we'll use throughout our research.
- Read and analyzed the strengths and weaknesses of different GAN-based architectures rooted in image-based domains.
- Began looking into how to apply these related works into the time-series-based domain of mobile sensor data.

References

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