Generative Adversarial Networks	First article about GAN
How Generative Adversarial Networks and Their Variants Work: An **Overview**	In this article, we discuss the details of GANs for those readers who are familiar with, but do not comprehend GANs deeply or who wish to view GANs from various perspectives. In addition, we explain how GANs operates and the fundamental meaning of various objective functions that have been suggested recently. We then **focus on how the GAN can be combined with an autoencoder framework**. Finally, we enumerate the GAN variants that are applied to various tasks and other fields for those who are interested in exploiting GANs for their research.
Enforcing Statistical Constraints in Generative Adversarial Networks for **Modeling Chaotic Dynamical Systems**	Simulating complex physical systems often involves solving partial differential equations (PDEs) with some closures due to the presence of multi-scale physics that cannot be fully resolved. Therefore, reliable and accurate closure models for the unresolved physics remains an important requirement for many computational physics problems, e.g., turbulence simulation. Recently, several researchers have adopted generative adversarial networks (GANs), to generate solutions of PDEs-governed complex systems without having to numerically solve these PDEs. In this work, we present a statistical constrained generative adversarial network by enforcing constraints of covariance from the training data, which results in an improved machine-learning-based emulator to capture the statistics of the training data generated by solving fully resolved PDEs. Statistical regularization leads to better performance compared to standard GANs, measured by (1) the constrained model's ability to more faithfully emulate certain physical properties of the system and (2) the significantly reduced (by up to 80%) training time to reach the solution.
Enforcing constraints for time series prediction in supervised, **unsupervised** and reinforcement learning	We assume that we are **given a time series of data from a dynamical system and our task is to learn the flow map of the dynamical system.** We present a collection of results on how to enforce constraints coming from the dynamical system in order to accelerate the training of deep neural networks to represent the flow map of the system as well as increase their predictive ability. In general, the dynamic constraints need to include terms which are analogous to memory terms in model reduction formalisms. Such memory terms act as a restoring force which corrects the errors committed by the learned flow map during prediction. For the case of unsupervised learning, in particular generative adversarial networks, the constraints are introduced by augmenting the input of the discriminator. 2.2 3.2

Anomaly Detection with Generative Adversarial Networks for **Multivariate Time Series**	Today's **Cyber-Physical Systems** (CPSs) are large, complex, and affixed with networked sensors and actuators that are targets for cyber-attacks. Unsupervised machine learning techniques can be used to model the system behaviour and classify deviant behaviours as possible attacks. In this work, we proposed a novel Generative Adversarial Networks-based Anomaly Detection (GAN-AD) method for such complex networked CPSs. We used **LSTM-RNN** in our GAN to capture the distribution of the multivariate time series of the sensors and actuators under normal working conditions of a CPS. We model the time series of multiple sensors and actuators in the CPS concurrently to take into account of potential latent interactions between them. We used our GAN-AD to distinguish abnormal attacked situations from normal working conditions for a complex six-stage Secure Water Treatment (SWaT) system. Experimental results showed that the proposed strategy is effective in identifying anomalies caused by various attacks with high detection rate and low false positive rate as compared to existing methods.
MAD-GAN: **Multivariate Anomaly Detection** for **Time Series Data** with Generative Adversarial Networks	In this work, we propose an unsupervised multivariate anomaly detection method based on Generative Adversarial Networks (GANs), using the **Long-Short-Term-Memory Recurrent Neural Networks (LSTM-RNN)** as the base models (namely, the generator and discriminator) in the GAN framework to capture the temporal correlation of time series distributions. Instead of treating each data stream independently, our proposed Multivariate Anomaly Detection with GAN (MAD-GAN) framework considers the entire variable set concurrently to capture the latent interactions amongst the variables. We also fully exploit both the generator and discriminator produced by the GAN, using a novel anomaly score called DR-score to detect anomalies by discrimination and reconstruction. We have tested our proposed MAD-GAN using two recent datasets collected from real world CPS: the Secure Water Treatment (SWaT) and the Water Distribution (WADI) datasets. Our experimental results showed that the proposed MAD-GAN is effective in reporting anomalies caused by various cyberintrusions compared in these complex real-world systems.
C-RNN-GAN: Continuous **recurrent neural networks** with adversarial training	We propose a generative adversarial model that **works on continuous sequential data**, and apply it by **training it on a collection of classical music**. We conclude that it generates music that sounds better and better as the model is trained, report statistics on generated music, and let the reader judge the quality by downloading the generated songs.

GCN-GAN: A Non-linear Temporal Link Prediction Model for Weighted Dynamic Networks	In this paper, we generally formulate the **dynamics prediction problem of various network systems** (e.g., the prediction of mobility, traffic and topology) as the **temporal link prediction task**. We introduce a novel non-linear model GCN-GAN to tackle the challenging temporal link prediction task of weighted dynamic networks. The proposed model leverages the benefits of the **graph convolutional network (GCN)**, long short-term memory (**LSTM**) as well as the **GAN**. Thus, the dynamics, topology structure and evolutionary patterns of weighted dynamic networks can be fully exploited to improve the temporal link prediction performance. Concretely, we first utilize GCN to explore the local topological characteristics of each single snapshot and then employ LSTM to characterize the evolving features of the dynamic networks. Moreover, GAN is used to enhance the ability of the model to generate the next weighted network snapshot, which can effectively tackle the sparsity and the wide-value-range problem of edge weights in real-life dynamic networks.
Generative Adversarial Network Based **Autoencoder**: Application to **fault detection problem for closed-loop dynamical systems**	The fault detection problem for closed-loop, uncertain dynamical systems is investigated in this paper, using different deep-learning based methods. A novel generative-adversarial-based deep autoencoder is designed to classify data sets under normal and faulty operating conditions. This proposed network performs quite well when compared to any available classifier-based methods, and moreover, **does not require labeled fault-incorporated data sets for training purposes**.
Analysis of **Nonautonomous Adversarial Systems**	Generative adversarial networks are used to generate images but still their **convergence** properties are not well understood. There have been a few studies who intended to **investigate the stability properties of GANs as a dynamical system.** Among the proposed methods for stabilizing training of GANs, β-GAN was the first who proposed a complete **annealing strategy** to change high-level conditions of the GAN objective. In this note, we show by a simple example how annealing strategy works in GANs.
Nonstationary GANs: Analysis as Nonautonomous Dynamical Systems	Generative adversarial networks are used to generate images but still their convergence properties are not well understood. There have been a few studies who intended to **investigate the stability properties of GANs as a dynamical system.** Among the proposed methods for stabilizing training of GANs, some of them modify the data distribution during the course of training. We unify these methods under the name nonautonomous GAN and investigate their dynamical behaviour when the data distribution is not stationary.
Objective-Reinforced Generative Adversarial Networks (**ORGAN**) for **Sequence Generation Models**	This work proposes a method to guide the structure and quality of samples utilizing a **combination of adversarial training and expert-based rewards with reinforcement learning**. Building on SeqGAN, a sequence based Generative Adversarial Network (GAN) framework modeling the data generator as a stochastic policy in a reinforcement learning setting, we extend the training process to include domain-specific objectives additional to the discriminator reward. To improve training stability we utilize the **Wasserstein distance** as loss function for the discriminator. We demonstrate the effectiveness of this approach in two tasks: generation of molecules encoded as text sequences and musical melodies.

SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient	As a new way of training generative models, GAN that uses a discriminative model to guide the training of the generative model has enjoyed considerable success in generating real-valued data. However, it has **limitations** when the goal is for generating sequences of **discrete tokens.** In this paper, we propose a sequence generation framework, called SeqGAN, to solve the problems. **Modeling the data generator as a stochastic policy in reinforcement learning** (RL), SeqGAN bypasses the generator differentiation problem by directly performing gradient policy update. The RL reward signal comes from the GAN discriminator judged on a complete sequence, and is passed back to the intermediate state-action steps using Monte Carlo search.
Synthetic Dynamic PMU Data Generation: A Generative Adversarial Network Approach	This paper concerns with the production of synthetic phasor measurement unit (PMU) data for research and education purposes. Instead of constructing synthetic power grids and then producing synthetic PMU measurement data by time simulations, we propose a model-free approach to directly generate synthetic PMU data. we train the generative adversarial network (GAN) with real PMU data, which can be used to generate synthetic PMU data capturing the system dynamic behaviors.