Generative Adversarial Networks for Parallel Transportation Systems

Yisheng Lv, Yuanyuan Chen, Li Li, and Fei-Yue Wang

Abstract—Generative Adversaria Networks (GANs) have emerged as a promising and effective mechanism for machine learning due to its recent successful applications. GANs share the same idea of producing, testing, acquiring, and utilizing data as well as knowledge based on artificial systems, computational experiments, and parallel execution of actual and virtual scenarios, as outlined in the theory of parallel transportation. Clearly, the adversarial concept is embedded implicitly or explicitly in both GANs and parallel transportation systems. In this article, we first introduce basics of GANs and parallel transportation systems, and then present an approach of using GANs in parallel transportation systems for traffic data generation, traffic modeling, traffic prediction and traffic control. Our preliminary investigation indicates that GANs have a great potential and provide specific algorithm support for implementing parallel transportation systems.

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I. Introduction

Generative adversarial networks (GANs) were firstly introduced by Ian Goodfellow et al. in 2014 [1], where two competing models, a generator model G and a discriminator model D, are simultaneously trained as a minimax two-player game. The generator G learns to create samples that are drawn from the same distribution as the training data, while D learns to distinguish generated samples from real data. The solution to this game is a Nash equilibrium. Ideally, it should not be possible for D to make a right decision better than chance when G is well trained. The GANs paradigm provides a new framework for unsupervised learning. So far, GANs have become a hot research topic, and have been applied to single image super-resolution, image-to-image translation, video prediction, etc [2], [3].

Besides GANs, the idea of adversarial process has also shown power in (deep) reinforcement learning and some other artificial intelligence (AI) methods where they have different goals. For example, AlphaGo [4], a significant milestone in AI, achieves great success by playing against itself and learning from its mistakes. The adversarial concept has inspired many theoretical works and applications in different domains. Similarly, the adversarial idea can be generalized into parallel systems, and GANs have a great potential and provide specific algorithm support for the ACP based parallel system theory in terms of artificial systems modelling, computational experiments and virtual-real interaction and integration [5]–[8]. In this article, we introduce GANs and investigate the potential roles of GANs in ACP-based parallel transportation management and control systems (PtMS). PtMS was firstly proposed in [9], [10], and is a new mechanism for conducting operations of transportation systems.

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II. Basics of Generative Adversarial Networks

Before we get into GANs, we take a brief look at generative models and discriminative models. Discriminative models try to learn a function that maps the input x to an output y which is conditional probability $P(y|x)$. Generative models learn a joint probability distribution of the input x and the output y which is $P(x,y)$. GANs are a new example of generative models.

GANs consist of two models represented by differentiable functions, one generator G and one discriminator D, with conflicting objectives [2]. Typically, deep neural networks are used to represent G and D, respectively. D is trained to maximize the probability of assigning correct labels to both training data and samples from G, and G is simultaneously trained to minimize $\log(1-D(G(z)))$. This view can be formalized as the following two-player minimax game:

$$\min_G \max_D V(D,G) = E_{x\sim p_{\text{data}}}[\log D(x)] + E_{z\sim p_z}[\log(1-D(G(z)))],$$

where p_{data} is the training data distribution, and p_z is the prior noise distribution of the generative network.

GANs can be trained via stochastic gradient descent algorithms on two minibatches simultaneously. For each step, two minibatches are sampled from the training data and the noise prior distribution. Then two gradient steps are performed simultaneously. In practice, we can alternate between k steps of optimizing D and one step of optimizing G.

The flexibility of the GANs framework has enabled a lot of variations of the original GANs both in theory and applications such as the conditional GAN [11], WGAN [12], etc. Herein, we take the conditional GAN to more details.

The original GANs take noises as the input to the generator. There is no restriction on modes of data generated in such a way. Mirza et al. proposed the conditional version of GANs, named as the conditional GAN in which both the generator and the discriminator are conditional on extra information y like labels [11]. The objective function of a two-player minimax game in the conditional GAN is

$$\min_G \max_D V_c(D,G) = E_{x\sim p_{\text{data}}}[\log D(x|y)] + E_{z\sim p_z}[\log(1-D(G(z|y)))].$$

Let's take traffic flow prediction with the conditional GAN for an example. Given a sequence of observed traffic flow $(X_{t-n}, \ldots, X_{t-2}, X_{t-1})$, the problem is to predict traffic flow X_t at time t. Extra information, such as weather and local events, has impacts on traffic flow prediction. In the following, we use X to represent the input employed to make prediction, such as the combination of traffic flow series and weather, and Y is the target traffic flow value to be predicted. X is fed into the generator to produce the prediction $\bar{Y}$ of real data Y. The discriminator takes a series of traffic flow data, i.e. the concatenation of X and $\bar{Y}$ or the concatenation of X and Y, and outputs a probability that the last traffic flow values of the sequence is generated by the generator. This process is illustrated in Fig. 1. In addition, adding noise is optional. The well trained generator then can be used to predict traffic flow.

III. ACP and Parallel Transportation Systems

The ACP approach was originally proposed to model, analyze and control complex systems [8]. It consists of (A) "Artificial Systems", (C) "Computational Experiments", and (P) "Parallel Execution". The "Artificial Systems" is a collection of models of physical systems in the real world. The "Computational Experiments" is for data analytics based on artificial systems. The "Parallel Execution" is for decision-making and control based on A and C.

The framework of the ACP-based parallel transportation systems for management and control is illustrated in Fig. 2. Parallel transportation systems consist of artificial transportation systems and real transportation systems. The basic ideas of parallel transportation systems are: 1) modeling and representing real transportation systems using artificial transportation systems; 2) analysis and evaluation by computational experiments; and 3) control and management of transportation systems through parallel execution by connecting real and artificial transportation systems.

Urban transportation systems are typical complex systems with both engineering and social features. Various artificial transportation systems can be developed to model and represent urban transportation systems in terms of historical traffic conditions, traffic flow characteristics, traffic behavior, traffic scenarios, traffic policies, etc., at different levels of details. By performing computational experiments based on artificial transportation systems, behaviors and performance of actual transportation systems can be analyzed, predicted, and evaluated. Through interactions and parallel execution between actual transportation systems and artificial transportation systems,

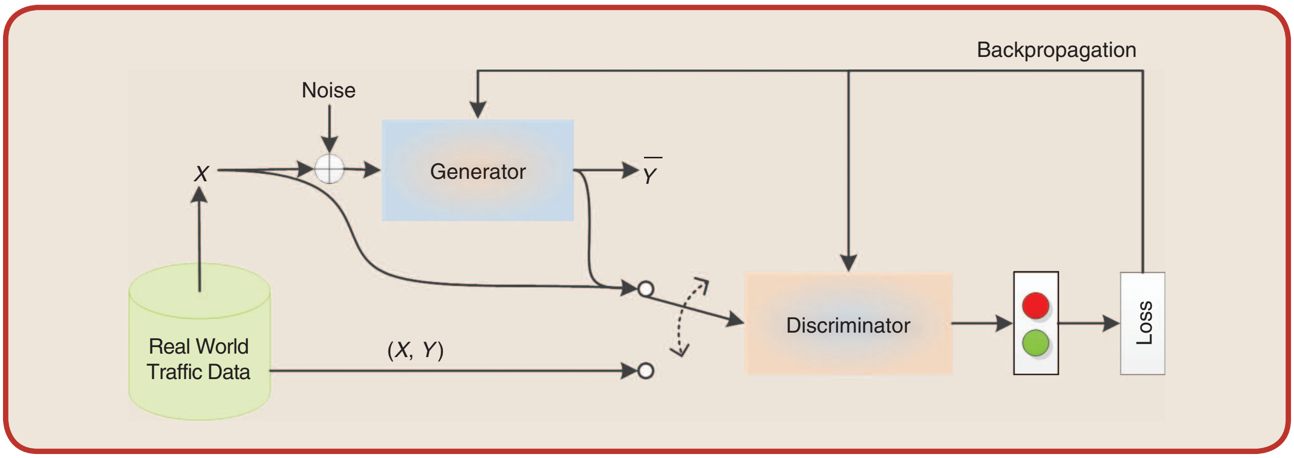

FIG 1 Example framework of the conditional GAN for traffic prediction.

different traffic strategies can be generated, optimized, and executed.

The ACP view on transportation system management and control does not just show a new kind of traffic management and control paradigm. More importantly, it provides an effective platform for use of almost all the concepts and methods developed in the fields of AI and computational intelligence [9], [10], [13]. Obviously, artificial transportation systems need to be calibrated and verified. Historical data and data generated with computational experiments on artificial transportation systems can be combined together to form the big data set. Thus, we can reduce such big data, extract rules, obtain knowledge and perform parallel control [14].

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IV. GANs in Parallel Transportation Systems

In this section we describe the potential use of GANs in parallel transportation systems. Clearly, the adversarial concept is embedded implicitly or explicitly in both GANs and parallel transportation systems. GANs share the same idea of producing, testing, and utilizing data as well as knowledge based on artificial systems, computational experiments, and parallel execution of actual and virtual scenarios, as outlined in the theory of parallel transportation systems. We present approaches of using GANs in parallel transportation systems for traffic data generation, traffic modeling, traffic prediction, and traffic control.

A. Data Generation

Traffic data are essential and fundamental for both traffic theory and applications. Typical traffic data include flow, speed, occupancy, origin-destination (OD) demand and queue length, etc. As is well known, traffic data can be collected via physical sensors like induction loops and videos. However, it is time-consuming and costly to collect traffic data. And often traffic data are corrupted and missing due to detector and communication malfunctions [15]. GANs have the ability to capture data distribution. Thus we can use GANs to generate realistic traffic data and traffic scenes.

Fig. 3 shows a simple example using the original GANs to learn distinct traffic flow distributions, which can recover

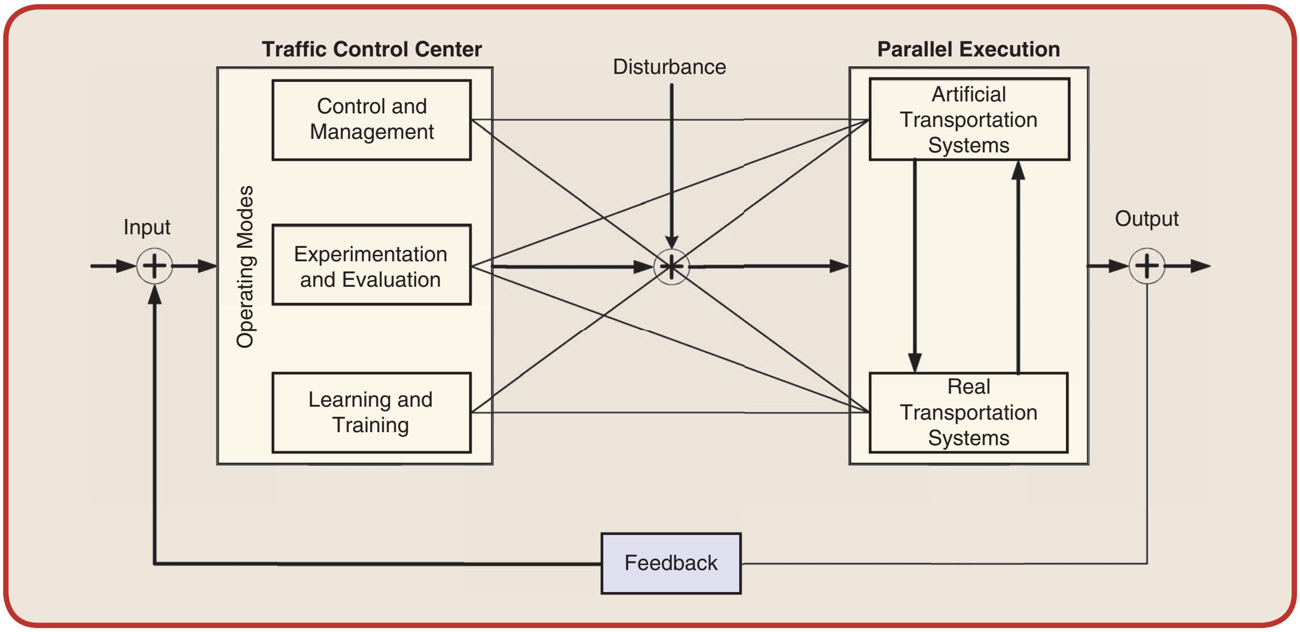

FIG 2 The ACP-based control and management of transportation systems.

> Under the framework of GANs and parallel transportation, such as software-defined transportation systems, computational experiments and virtual-real interaction, we present ways of applying GANs algorithms within parallel transportation system, from traffic generation, imputation, modeling, to traffic prediction and control.

original traffic flow data distributions effectively. The real data used were collected from a detector in the PeMS open-access traffic flow datasets (California Performance Measurement System). The sampling period is between January 1, 2013 and December 31, 2013. The generator and the discriminator are simple multilayer perceptron neural networks.

B. Traffic Modeling

Traffic modeling is to model behavior and process of transportation systems. Modeling transportation systems can have different levels of details from microscopic individual and vehicle dynamics to macroscopic crowd traffic dynamics. Similar to traffic data generation, GANs can be extended to simulate such multi-scale behavior of transportation systems for different purposes. For the microscopic level of transportation modeling, the framework of GANs can be used to describe vehicle following and lane-changing behavior. For the mesoscopic level of transportation system modeling, the framework of GANs can be used to simulate the cluster or platoon dynamics of individuals and vehicles. Also the framework of GANs can be utilized to model macroscopic traffic flow dynamics.

C. Traffic Prediction

Transportation systems are nonlinear and stochastic. Traffic variables can be seen as random variables. So far, a lot of parametric and nonparametric algorithms have been developed for traffic prediction [16], [17]. Recent studies show that deep learning methods have superior performance in traffic prediction [18], [19]. The framework of the conditional GAN can be easily extended to predict traffic variables.

Fig. 4 shows the predicted traffic flow time series (the red one) obtained via the LSTM-based conditional GAN in which the generator is long short term memory networks (LSTM) [20]. The observed data used for traffic flow prediction in this article were also collected from a detector in the PeMS with sampling period between October 1, 2009 and November 30, 2009. We also compare the conditional GAN with the autoregressive integrated moving average (ARIMA) model, seasonal ARIMA (SARIMA), support vector regression (SVR), and one hidden layer artificial neural network (ANN). Experiments demonstrate that the GAN framework can achieve comparable or better performance for traffic flow prediction against the compared methods.

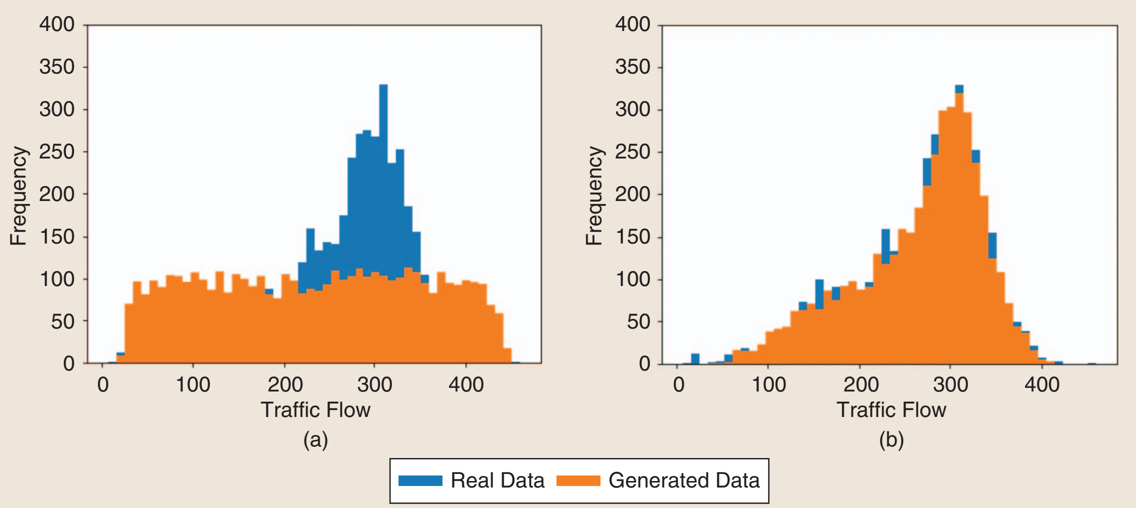

FIG 3 Traffic flow distribution during one morning hour (8:00–9:00). The horizontal axis is traffic flow (vehicles/5-min). The vertical axis is the frequency. (a) At the initial steps, the real distribution and the generated distribution are obviously different. (b) The final distribution learned captures the real data distribution.

D. Traffic Control

The GANs framework provides a new way to train generative models. Generative models can be used to model transportation systems, which lead to descriptive control. In real-world cases, relatively small data can be collected to make decisions. With generative models, much more data can be generated and be used to obtain optimal control polices. Generative models can simulate possible futures, which can be used to perform computational experiments to predict the future with certain actions. Such a mode leads to predictive control. No matter how many possible futures or actions there are, only one is selected and executed in real transportation systems. With the ability of data generation, modeling, and prediction with GANs, we can reduce the big data, extract knowledge, and create the real future through learning and adaptation. Prescriptive control is developed to find optimized polices from predictions through parallel execution, during which the real and artificial transportation systems interact with each other. The framework of GANs for traffic control is illustrated in Fig. 5.

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V. Conclusion

In this article, we introduce basics of GANs and investigate potential roles of GANs in parallel transportation systems. Under the framework of GANs and parallel transportation systems, such as software-defined transportation systems, computational experiments and virtual-real interaction, we present ways of applying GANs within parallel transportation systems, from traffic generation, traffic modeling, traffic prediction, to traffic control. Particularly, we show that the original GAN can recover traffic flow distribution effectively based on the data collected from PeMS. And we demonstrate that the conditional GAN with LSTM

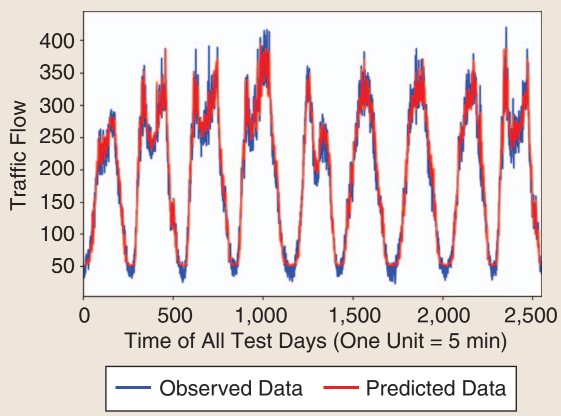

FIG 4 Traffic flow prediction with LSTM-based GAN. The horizontal axis is the time of all test days. The vertical axis is traffic flow (vehicles/5-min).

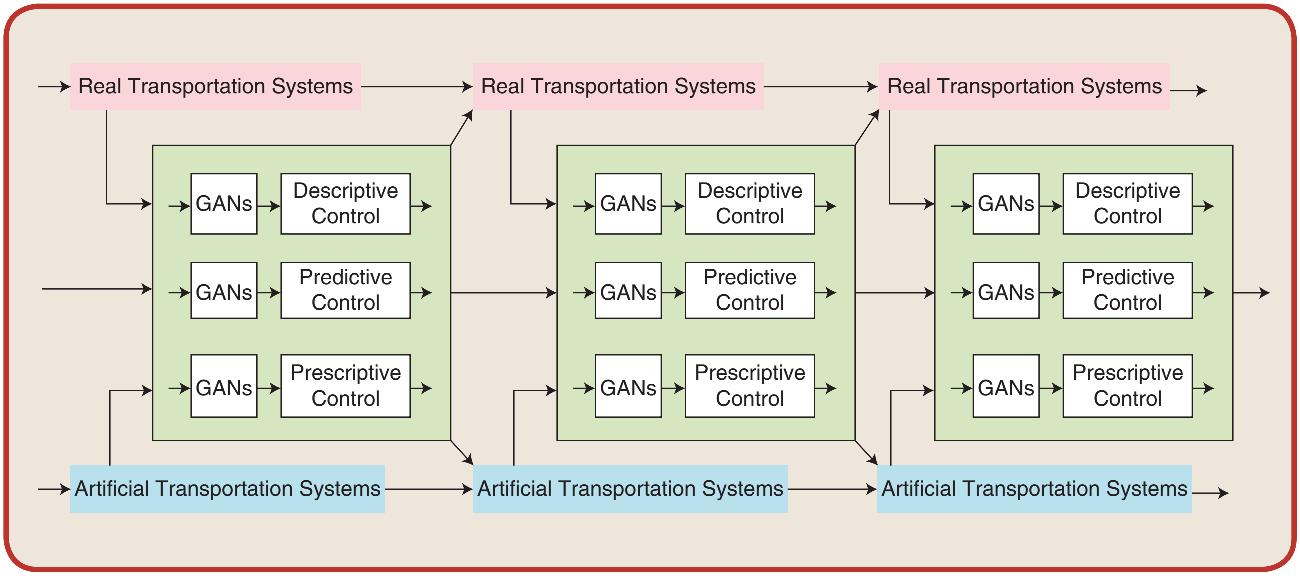

FIG 5 The framework of GANs for traffic control.

can have a comparable or better performance in predicting traffic flow against popular traffic prediction models such as ARIMA, SARIMA, SVR, and ANN models. Such preliminary investigations demonstrate the suitability of GANs for implementing parallel transportation systems. We believe that the combination of GANs and ACP-based parallel transportation could significantly promote the future developments and applications of intelligent transportation systems.

Still, there are more theoretical limitations of GANs and parallel transportation systems that need to be resolved. Currently, research and development in this direction are team-oriented and require large resources and effort. In a sense, we are constructing software defined transportation systems with a large number of algorithms, which then become traffic scenarios/data generators for powering data-driven analytics and decision-making for transportation. However, as new intelligent technologies emerging in big data, deep learning, GANs, knowledge automation, parallel transportation systems will be well grounded and provide a new mechanism to observe, describe, predict, and prescript dynamics of transportation systems, thus leading a new way in solving the real-world problems effectively.

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