GLOBAL RESEARCH IMMERSION PROGRAM FOR YOUNG SCIENTISTS

Generating Diverse and Realistic Traffic Simulation: A Survey

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1 Introduction

Fig 1: Overview of traffic simulation system [1]

- Simulation plays a crucial role in the development of **robotic systems**, with traffic simulation being one aspect at the **multi-agent interaction** level.
- Traffic simulation enables the creation of high-volume, realistic, and diverse traffic scenarios, which are essential for **developing** and **validating** self-driving systems, especially in terms of **safety evolution**, **interactive scenario design** and **data augmentation**.

2 Motivation

1. Realistic simulators are vital for autonomous vehicles (AVs) because testing new features and changes directly on the road is **costly** and **potentially dangerous.**
2. Modelling **human-like, controllable** and **multi-agent** traffic behaviour is challenging.
3. Simulating by replaying **recorded data** or controlling vehicle motions with predefined **rule-based** is **inefficient.**
4. On the other hand, **learning-based approaches**, by learning from real driving logs, enable the trained **end-to-end** network to directly predict **multimodal trajectories** and output proper **actions.**

3 Methods of Traffic Behaviors Modelling

3.1 Overview

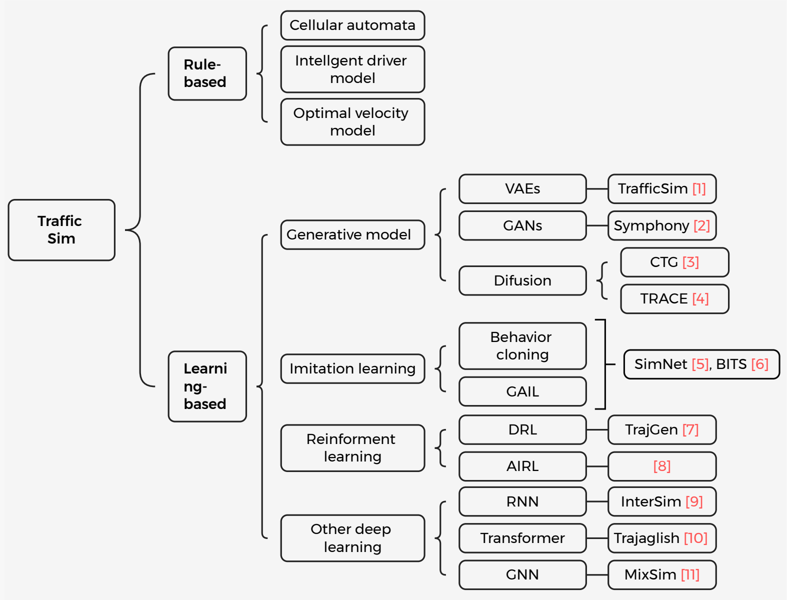

Fig 2: Categorization of methods

3.2 Problem formulation

The traffic simulation model aims to predict the future behaviour of traffic actors based on given semantic maps and dynamic environments. The map $M = \{M_s, M_d\}$ and states $S_t = \{s^1_{t-H:t}, s^2_{t-H:t}, \dots, s^N_{t-H:t}\}$ form a context $C = (M, S)$ that provides relevant information for agents. The model function:

$$f(M, S, A;\ \theta)$$

uses these inputs to generate actions $a_t = \{a^1_t, a^2_t, \dots, a^n_t\}$ from the action space A which can include high-level control commands. Based on this concept, the traffic simulation model can formulate the future multiagent behaviour action as:

$$a_{T'} \leftarrow f(M, S_{T-H:T}, A;\ \theta)$$

Where θ is a set of parameters in a learning-based model.

A. Imitation learning(IL) in Traffic Sim

The main idea of which is to use supervised learning with expert data to mimic the behaviour of demonstrators. There are two common ways to perform IL: behaviour cloning (BC) and Generative adversarial imitation learning (GAIL).

BC : faster training and more reliable policies. However, it is limited in novel situations and sensitive to noise (e.g. distribution shift). Classical objective function like:

$$\max \sum_{(s,a)\in D} \log(\pi_\theta(a|s))$$

GAIL: aim to uncover the hidden reward function of human driving behavior and acquire the driving policy by maximizing the learned reward. Robustness for noisy data but may suffer form mode collapse.

B. Generative models(GM) in Traffic Sim

Generative models identify probabilistic distributions of driving data and generate new samples from these distributions. They are used to learn and generate realistic traffic scenes, often focusing on long-tail scenarios. Some common types include Autoregressive Model (AR), Variational Auto-encoder(VAE), Generative Adversarial Network (GAN) and Diffusion Model

Diffusion Model [3]: Generates a vehicle's future trajectory by starting from Gaussian noise and iteratively denoising, using input context for guidance to ensure physical feasibility ,namely controllable traffic sim. Good at capturing complex relationships but challenging to interpret.

VAE[1] : VAE learns latent data representations using an encoder-decoder structure. The encoder transforms each agent's trajectory into latent variables, and the decoder maps back to high-dimensional space to generate new trajectory data.

3.3 BITS: Bi-level Imitation For TS (Case Analysis)

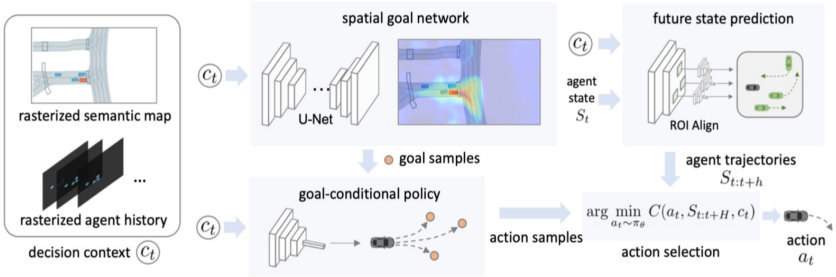

Fig 3: BITS Framework [5]

BITS is a Bi-level data-driven end2end traffic simulation model via **Imitation learning** technique. BITS decouples the AI model into a **high-level** intent inference and a **low-level** goal-conditioned control policy. The pipeline of this work shows below:

1. **Training a Spatial Goal Network to Find Potential Goals**: The input context includes a rasterized semantic map and kinematic history states. It generates a 2D BEV spatial distribution of possible short-term goals via a U-Net.
2. **Goal-Conditional Policy to Generate Trajectories**: Given a feature and a sampled goal pose, the policy uses an MLP-based decoder to generate a sequence of actions. Notably, it predicts control inputs (velocity, heading change) at each timestep.
3. **Nearby Agent Motion Prediction**: Using the RoIAlign technique, features of each neighbor's local and global scene context are extracted. These features are then concatenated for motion prediction.
4. **Cost based trajectory selection:** We choose a path a^*_t that minimized the cost function

$$a^*_t \leftarrow \arg\min_{a_t\sim\pi_\theta} C(a_t, S_{t:t+H}, c_t)$$

where the cost function considers two parts: collision and road departure cost functions, in the form:

$$C(a_t, S_{t:t+H}, c_t) = \alpha C_{collison} + \beta C_{road}$$

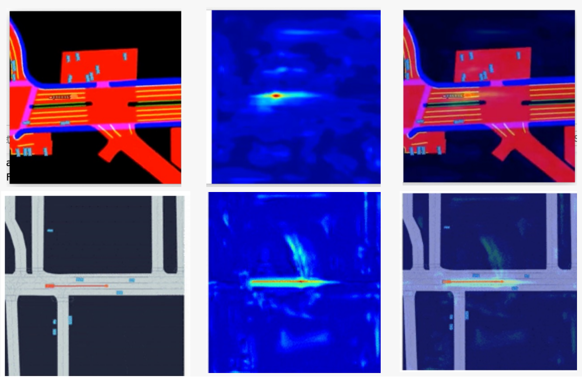

Fig 4: BITS decoupling, high-level and low-level [12]

4 Conclusion

This work overviews promising research in traffic simulation, focusing on the rise of learning-based methods over traditional rule-based ones. We briefly introduce various learning-based strategies, analyze their pros and cons, and present a case study on an imitation learning-based traffic simulation, showcasing the complete pipeline.

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