Biying WANG, Baosheng WANG, Shuang ZHAO, Jinshu SU, Shuhui CHEN, Minxin WANG, Zhengpeng LI, Ziling WEI, 2026. Representation levels and objective consistency of network traffic generation: a survey. *ENGINEERING Information Technology & Electronic Engineering,* 27(8):260095. https://doi.org/10.1631/ENG.ITEE.2026.0095

Representation levels and objective consistency of network traffic generation: a survey

Key words: Network traffic generation; Traffic representation levels; Task consistency; Protocol consistency

Corresponding author: Ziling WEI
E-mail: weiziling@nudt.edu.cn
ORCID: https://orcid.org/0000-0002-7858-1445

Motivation

1. Network traffic research requires large-scale and high-quality datasets, but real traffic collection is constrained by privacy policies, high annotation costs, outdated datasets, and class imbalance problems.
2. Existing surveys mainly organize traffic generation methods by model architectures, toolchains, or application scenarios, but overlook an essential question: what type of traffic is actually generated.
3. Most existing studies evaluate generated traffic through downstream task performance, but improved classification or detection performance does not necessarily indicate protocol validity or real-world replayability.

Main contributions

1. This survey proposes a two-dimensional framework to analyze network traffic generation from both generated traffic forms and supported objectives.
2. This survey reveals the trade-off between information preservation and learnability across different traffic representations.
3. This survey analyzes current evaluation practices and highlights the need for protocol-aware generation and engineering-oriented evaluation.

Methodology

This paper conducts a systematic literature review of network traffic generation studies published from 2019 to 2026. Relevant studies are collected from multiple academic databases using comprehensive search queries and screened according to predefined inclusion and exclusion criteria. From 113 candidate records, 39 representative studies are selected for detailed analysis. The selected studies are further categorized based on traffic representation levels, generation mechanisms, and objective consistency, enabling a comprehensive understanding of existing methods, evaluation practices, and future research directions.

Representation levels

Different traffic generation methods produce different forms of data, and each representation preserves different levels of protocol information and communication behavior. This survey categorizes generated traffic into four representation levels and analyzes their characteristics.

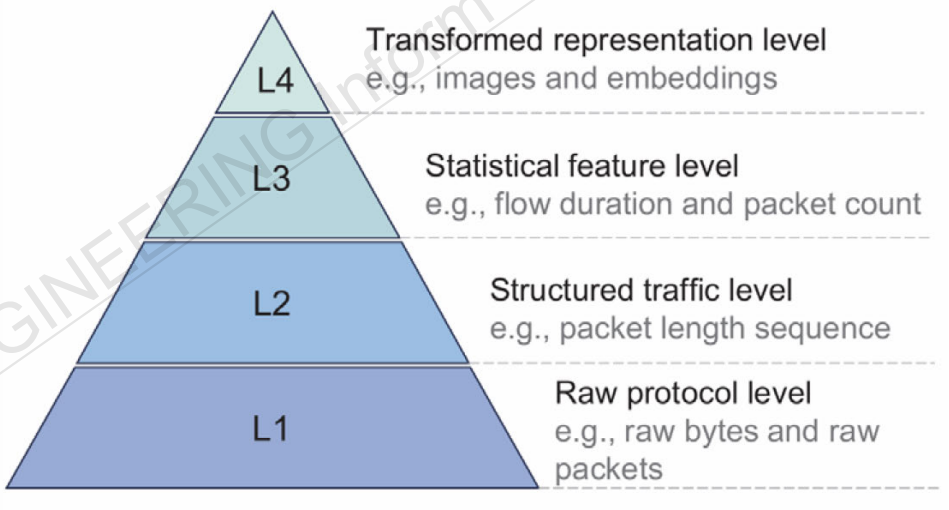

Fig. 2 Network traffic representation levels

Generation models

This paper reviews generation approaches from the perspective of model mechanisms and analyzes how different models relate to traffic representations and the consistency objectives they support.

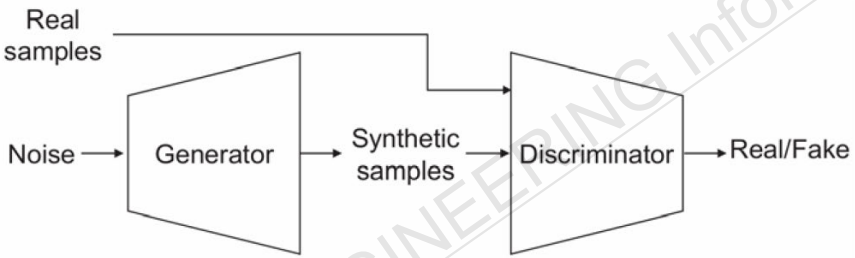

Fig. 3 Structure of a GAN

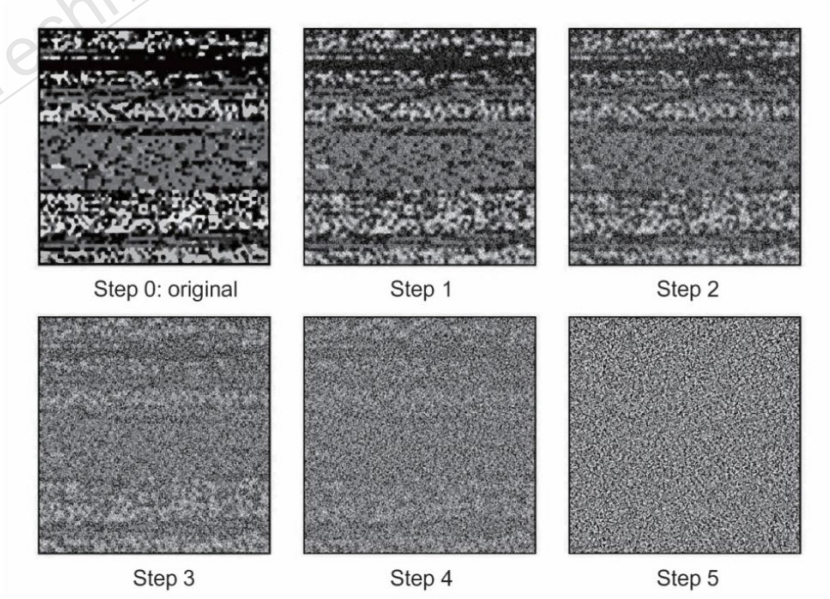

Fig. 4 Illustration of the forward noising and reverse denoising processes in DMs

Evaluation metrics

1. Similarity metrics generally follow three evaluation paths: distribution consistency, point-to-point error, and feature-space distance.

Table 4 Similarity metrics used in network traffic generation studies

Evaluation path	Metric	Description
Distribution consistency	JSD (Hui et al., 2022)	Measures the symmetric and bounded divergence between the distributions of y and $\hat{y}$
	TVD (Zhang SY et al., 2024)	Measures the statistical distance between the probability distributions of y and $\hat{y}$
	Wasserstein distance (Manocchio et al., 2021)	Measures the minimal transport cost between the probability distributions of y and $\hat{y}$
	CRPS (Chai et al., 2024)	Measures the accuracy of probabilistic forecasts by comparing the predicted CDF with the observed value
Point-to-point error	MAE (Li J and Li, 2022)	Average absolute error between the real and generated values: $\frac{1}{T}\sum_{t=1}^{T}\lvert y_t-\hat{y}_t\rvert$
	MSE (Li T et al., 2024)	Average squared error between the real and generated values: $\frac{1}{T}\sum_{t=1}^{T}(y_t-\hat{y}_t)^2$
	RMSE (Chai et al., 2024)	Square root of the mean squared error: $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t-\hat{y}_t)^2}$
	MAPE (Li J and Li, 2022)	Average relative error between the real and generated values: $\frac{1}{T}\sum_{t=1}^{T}\frac{\lvert y_t-\hat{y}_t\rvert}{\lvert y_t\rvert}$
Feature-space distance	FID (Cai et al., 2025)	Measures the Fréchet distance between the feature distributions of y and $\hat{y}$ in a pre-trained feature space
	Cosine similarity (Du et al., 2023)	Measures the cosine of the angle between two vectors
	Euclidean distance (Ring et al., 2019)	Measures the Euclidean distance between two vectors in the feature space

Evaluation metrics

2. In usability evaluation, generated data are assessed through downstream tasks.

Table 5 Usability metrics used in network traffic generation studies

Usability metric	Description
ASR (Sun PS et al., 2025)	Measures the proportion of the generated adversarial samples that successfully bypass the target detection model, reflecting the attack effectiveness of $\hat{y}$
Protocol compliance check (Sun PS et al., 2025)	Examines whether the generated packets satisfy protocol rules, such as field constraints, packet length, checksum validity, and state transition logic
Domain knowledge check (Ring et al., 2019)	Examines whether $\hat{y}$ is consistent with basic network protocol rules and the characteristics of the target dataset
Packet success rate (Delgado-Soto et al., 2025)	Measures the proportion of the generated packets that are transmitted correctly without errors. It reflects whether the generated packets can be processed by network devices

The metrics in this table are synthesized from the reviewed studies summarized in Table 1. Since a given metric may appear in multiple reviewed studies, only a few illustrative references are listed here for brevity rather than citing all relevant works listed in Table 1. ASR: attack success rate

Future directions

Although existing methods can generate traffic that improves downstream tasks, their ability to produce controllable, protocol-consistent, and practically usable traffic remains limited. Therefore, this paper identifies three future directions.

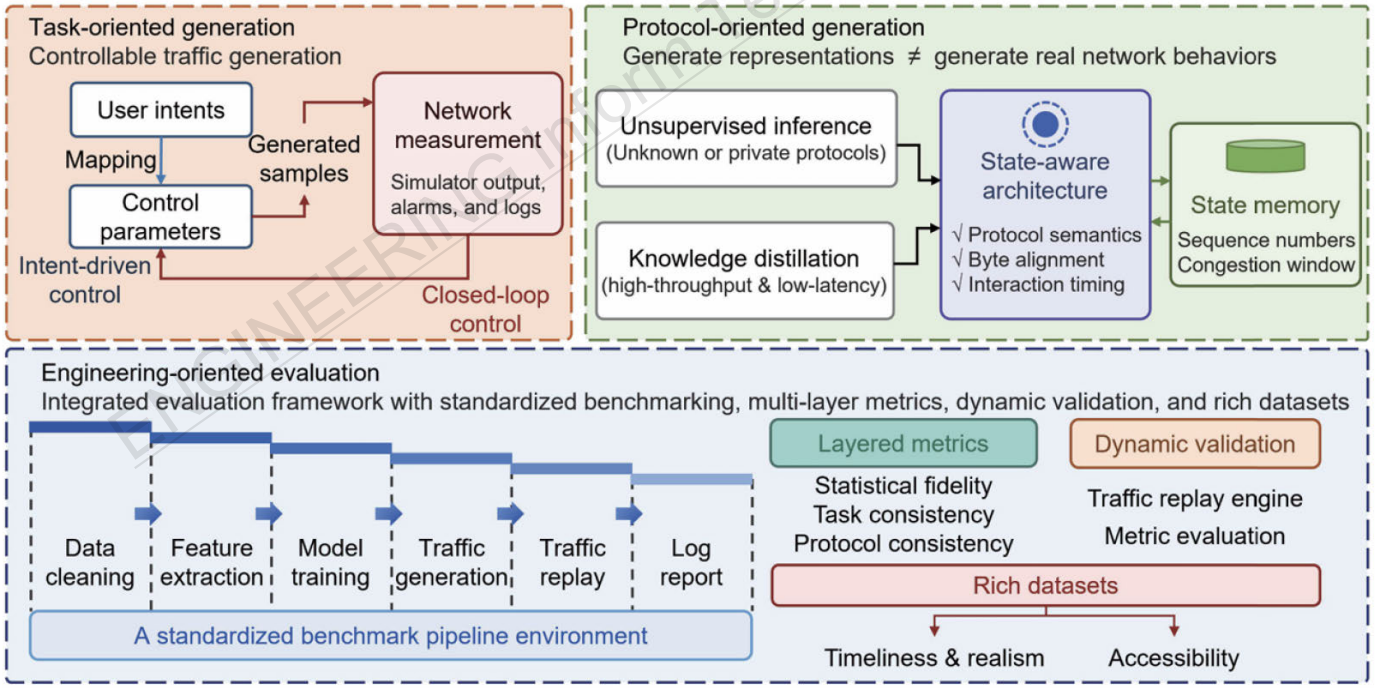

Fig. 5 Future directions of network traffic generation

Conclusions

1. Network traffic generation methods show a clear trade-off between learnability and practical usability. Lower-level representations preserve more protocol semantics, packet dependencies, and replayability, but are harder to generate accurately. In contrast, higher-level representations are easier to model but may lose important communication information.

2. Existing studies mainly focus on task consistency, where generated traffic improves downstream tasks, while protocol consistency remains insufficiently explored. Future research should move toward controllable generation, protocol-aware synthesis, and engineering-oriented evaluation to achieve more reliable and practical generated traffic.

Biying WANG received her B.S. degree in network and information security from the College of Computer Science and Technology, Jilin University, China. She is currently pursuing the Ph.D. degree in cyberspace security at the College of Computer Science and Technology, National University of Defense Technology, China. Her research interests include network traffic analysis and encrypted traffic intelligence.

Ziling WEI received his B.S. and M.S. degrees in computer science from the National University of Defense Technology (NUDT, China) in 2012 and 2014, respectively, and the Ph.D. degree in electrical engineering from the University of Alberta, Edmonton, AB, Canada, in 2019. He is currently an associate professor at NUDT. His research interests include network traffic analysis, mobile network security, and password security.