

Just-in-Time Logic Enforcement

A new paradigm of combining statistical and symbolic reasoning for network management

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Abstract

While ML can greatly aid network management, it often makes glaring mistakes that contradict common sense or domain-specific constraints, undermining its trustworthiness and hindering adoption. To address this mismatch, this paper advocates for enforcing logic during ML inference (or Just-In-Time), rather than during training or post-inference in prior work. We find that this approach offers correctness guarantees without sacrificing statistical fidelity, thereby maximizing the benefits of both ML and formal reasoning.

To achieve Just-In-Time Logic Enforcement, we interleave an SMT solver into the language model's inference process, which guides generation step by step to enforce domain-specific rules. Our proof-of-concept implementation, LeJIT, turns a generic GPT-2 model at inference time into either a synthetic data generator or a telemetry imputer by applying different sets of logic rules and performs on par with task-specific SOTA systems. LeJit paves the way for a networking foundation model networking that can be repurposed through logic rules, instead of costly retraining or fine-tuning.

CCS Concepts

• **Networks** → **Network manageability; Network management; Network measurement**; • **Computing methodologies** → **Inductive logic learning**; • **Theory of computation** → **Automated reasoning**.

Keywords

network management, LLM, formal methods, inference-time reasoning, SMT solver, neuro-symbolic AI

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1 Introduction

Machine learning (ML) has long shown potential for simplifying network management, powering automation in tasks such as router configuration [31], intent translation [50], incident response [18], and scheduling [20, 52]. Large language models (LLMs) have recently amplified this promise. Unlike traditional ML, LLMs can learn from vast amounts of unlabeled, multimodal data—ranging from traffic traces [7] and time series [29] to technical documents such as RFCs [40]. Massive investments in data and compute continue to accelerate their capabilities, making them increasingly powerful tools for reasoning and automation.

Despite this progress, network operators remain cautious. LLMs still hallucinate [11, 21, 41, 61], struggle to follow rules [3, 9, 23, 24], and are costly to train or fine-tune. As a result, the vision of a universal model for networking is giving way to specialized, task-specific designs [22, 27, 42, 59].

Unlike fields such as biology, networking is entirely human-engineered, not a natural phenomenon: almost every bit transmitted reflects deliberate choices in protocol design, hardware, and software. Solely relying on ML to infer all this structure from data (and then criticizing it when it fails to replicate or predict behaviors well-understood by experts) is ill-conceived at best. As prior work has noted, a natural solution is to combine ML with logic [6, 15, 60], *i.e.*, explicit rules. Existing approaches typically follow one of two design paradigms. At one paradigm, logic is taught through training. For example, Zoom2Net [16] augments the loss function with logic constraints inspired by physics-informed neural networks [8, 37]. While this approach imposes no inference overhead, it requires re-training hence white-box access to the model, limits rules to differentiable forms, and most importantly, does not guarantee rule compliance during inference. At the another design paradigm, logic is enforced *post inference*. NetDiffusion [24] takes this route, applying rule-based corrections after generation to fix invalid outputs. This method is model-agnostic and supports more expressive rules, but it may fail to find a valid correction [23], as often observed in NetDiffusion, which relies on a hard-coded one-pass algorithm.



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This paper argues that logic should guide ML autoregressive models with discrete output space. For example, LLMs are particularly well-suited to this approach, as their sequential token-by-token generation allows rules to be enforced step-by-step. Concretely, we propose to use rules to guide the model’s inference, dynamically pruning its token options at each step to enforce rule compliance. This approach enables easy repurposing of models by modifying the rules rather than retraining or fine-tuning. It also allows network operators to focus on defining useful rules without worrying whether they are differentiable, whether they appear enough in training, or whether they can be embedded in prompts. Finally, as we show in our evaluation (§4), enforcing rules during inference can be minimally invasive and preserve statistical fidelity.

While conceptually straightforward, intercepting and guiding an LLM’s inference using logic is highly challenging. First, network rules are complex, as they involve arithmetic constraints, conditional logic, and relationships across multiple input variables, making them incompatible with static token masking, which is recently supported by some LLMs to ensure syntactic compliance [2, 12, 13, 34, 38, 51]. To cope with this complexity and leverage rich networking knowledge, we posit that a true constraint solver must natively join the LLM’s inference process. To this end, we built LeJIT, a framework in which an SMT solver intersects the LLM’s token-by-token inference to guide it towards rule-compliant outputs. Before each token is generated, the solver dynamically computes the set of valid next tokens, based on a configurable set of logic rules, and the already generated tokens. Critically, the solver also looks ahead before computing the valid tokens to ensure that there is a path to a valid output, namely a rule-compliant token sequence. As a result, LeJIT is minimally invasive, gently nudging the LLM away from mistakes that lead to dead ends without overwriting decisions that would not have led to rule violations, thereby preserving the LLM’s original (valid) decisions.

The tight integration of the SMT solver brings LeJIT substantially more flexibility and power but comes with its own challenges. One such hurdle is the mismatch in granularity: LLMs operate over vocabularies of tokens, while SMT solvers reason over higher-level variables such as network measurements and packet header fields. To bridge this gap, LeJIT constructs a character-level transition system on the fly to exert finer-grained control than the granularity of variable-level network rules. Multiple challenges remain, particularly in automatically discovering meaningful and useful rules at scale and improving the performance of LeJIT.

Even in its proof-of-concept form, LeJIT shows significant promise. LeJIT turns the same GPT-2 model into either a synthetic data generator or a telemetry imputer by applying different sets of logic rules at inference time. Notably,

LeJIT-guided GPT-2 delivers performance on par with heavily engineered pipelines like Zoom2Net and NetShare, while producing outputs that are more accurate from a knowledge-consistency perspective. This result suggests a compelling vision: rather than pursuing ever-larger opaque models, we could develop a single reusable, task-adaptable foundation model for networking—one guided by logic instead of raw GPU power.¹

2 Motivation

We begin with a motivating use case introduced in recent work [16] to illustrate the benefits of combining ML with logic in networking. We use this use case to highlight why existing approaches fall short of fully realizing that potential and validate our intuition in our preliminary results (§4).

2.1 Why Networking Needs Logic

Example. A datacenter operator seeks to analyze fine-grained burst behavior [14], but only coarse-grained measurements (*e.g.*, ingress volume, ECN marked byte count) at 50 ms intervals are available. To recover missing millisecond-level ingress bytes $I_0..I_4$, the operator uses a telemetry imputer—an ML model trained to infer fine-grained signals from coarse-grained ones [16]. This task is feasible because many network metrics are correlated [14, 16].

As illustrated in Fig. 1a, the operator chooses to use a LLM, leveraging its recent advances. Given inputs such as $\text{TotalIngress}_T = 100$ and $\text{Congestion}_T = 8$ over a window $T = 5$, the LLM predicts $I_0, \dots, I_4 = [20, 15, 25, 70, 8]$. This output violates two key rules: $I_3 = 70$ exceeds the bandwidth limit ($\text{BW} = 60$), and the total sum (138) exceeds TotalIngress_T .

As prior work has noted [16, 24], rather than faulting an ML model for violating known rules, a better solution is to explicitly encode those rules into the model’s pipeline. In our example, these include

$$\forall t < T : 0 \leq I_t \leq \text{BW}, \quad (\text{R1})$$

$$\sum_{t=0}^{T-1} I_t = \text{TotalIngress}_T, \text{ and} \quad (\text{R2})$$

$$(\text{Congestion}_T > 0) \implies \max_{t=0}^{T-1} \{I_t\} \geq \frac{1}{2} \text{BW}. \quad (\text{R3})$$

R1 ensures that the ingress volume (I_t) at any given time is non-negative and does not exceed the bandwidth (BW). R2 states that the sum of all I_t within a time window T must equal the total observed ingress TotalIngress_T . R3 specifies that if ECN-markings (Congestion) are detected during the window T , there must be a burst event where at least one I_t exceeds half the bandwidth [14].

¹The authors have nothing against GPUs—only a shortage of them.

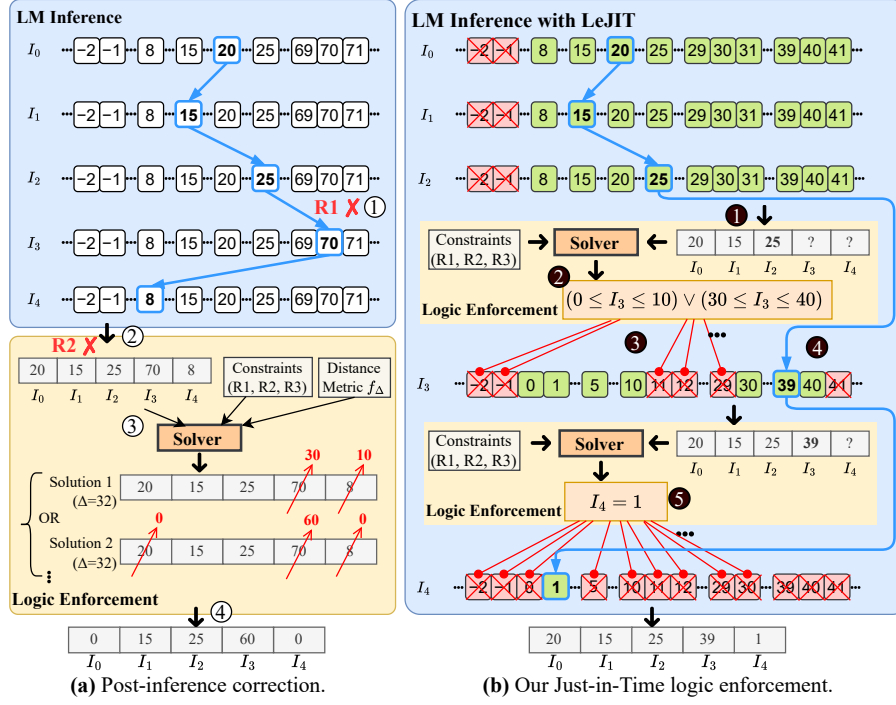


Figure 1: Example of using an LLM for network telemetry imputation under three rules R1–R3. (a) A pure LLM (blue frame) generates imputed samples $[I_0, \dots, I_4]$ that violate fundamental networking rules such as R1–R3. We can enforce logic post-inference (yellow frame), but not without hurting the statistical fidelity of the imputed sample. (b) Instead of enforcing rules post-inference, LeJIT invokes an SMT solver before every token generation to filter out tokens, that if selected by the LLM, will result in rule violations, effectively enforcing logic Just-In-Time.

2.2 Where Prior Methods Fall Short

Enforcing logical rules, such as R1–R3, on ML models in a way that leverages their complementary strengths without putting them at odds is challenging. To better understand this problem, we examine three fundamentally different strategies explored in prior networking and ML research: (1) correcting model outputs after inference, (2) teaching model rules at training time, and (3) constraining the model decoding process. We omit the discussion on prompt engineering for LLMs, which is inherently ad-hoc and provides no guarantees.

Enforcing rules post-inference. A natural way of integrating logic rules in any ML task is to allow the generative model to operate freely and then correct its output after generation to satisfy these rules. The correction can be done using a fast deterministic algorithm [24], an ILP [16], or a full constraint solver (e.g., an SMT solver) [5, 10, 45, 49].

We illustrate this post-inference approach in the lower part of Fig. 1a, where the LLM’s invalid output is fed to an SMT solver (③) together with R1–R3. We use an SMT solver because it is the most general, supporting a wide range of constraints. The solver’s job is to modify the LLM’s output to make it compliant with all provided rules. Unless provided with a specific optimization goal, the SMT solver would select an arbitrary solution among all compliant ones, not the most likely solution based on historical data. In other words, it will not respect the LLM’s learned distribution. One possible mitigation is to define a distance metric (f_Δ) and ask the solver to find a solution that satisfies the constraints

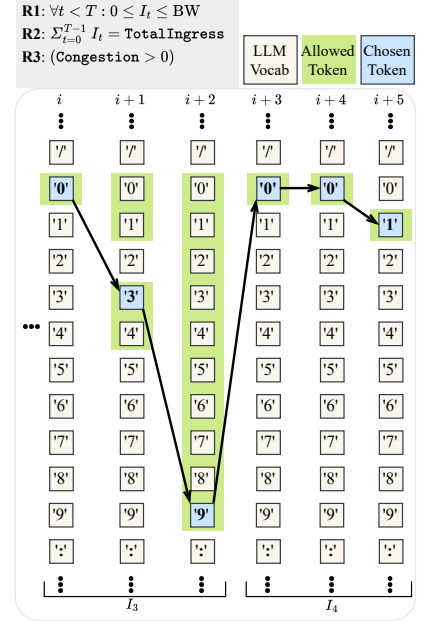


Figure 2: Character-level transition system constructed by LeJIT on the fly when imputing I_3 and I_4 . LeJIT operates on tokens, while the SMT solver on variables. Carefully aligning them allows LeJIT to be minimally invasive.

while remaining as close as possible to the original output of the LLM. While this method is relatively straightforward in domains like vision (where metrics like L2 distance often suffice), fields in network data are far more complex to compare. In networking, semantic meaning does not necessarily align with numerical distance [9, 23, 25], making it challenging to define a meaningful metric for each field of interest.

Teaching the model to follow rules. One way to encourage constraint satisfaction (R1–R3) is to embed rules into the training process, typically by adding them to the loss function as regularization terms [3, 16, 26, 39, 54]. The model is penalized for violations during training, with the hope that it generalizes rule compliance at inference time.

However, this approach has major drawbacks. It offers no guarantee of constraint satisfaction during inference, and applies only to differentiable rules or their approximations. This limitation is especially problematic in networking, where most rules are nondifferentiable. For instance, constraints R1–R3 require approximations such as sigmoid functions or fuzzy logic [58] to be included in the loss. Moreover, scaling to many constraints is difficult: each rule must be manually encoded and weighted, which complicates optimization [3, 26]. This issue is especially limiting in domains like networking, where describing a single protocol may involve hundreds of rules [19, 23, 28, 55]. Lastly, training-time approaches lack flexibility: any update to the rule set requires retraining or fine-tuning, making it ill-suited for dynamic network environments.

Enforcing rules during decoding. The inability of ML and LLMs in particular to follow explicit rules has prompted the ML research community to develop specialized techniques to help them adhere to structured output formats such as JSON or knowledge triplets [2, 12, 13, 34, 38, 51]. Specifically, constraint decoding developed for this purpose cannot be used to enforce networking rules because there is no theoretical foundation for converting them into forms compatible with such frameworks, such as context-free grammars, individual automata or their unions. In other words, constrained decoding typically filters tokens based on immediate validity (e.g., grammar-based parsing), but it cannot perform arithmetic calculations or ensure that a future token can satisfy the constraint model. For instance, encoding a constraint with \sum as rule R2 into a decoding process would mean tracking the running total and pruning any continuation that makes the final sum impossible—essentially doing search or backtracking. Even keeping track of a single such rule is far beyond the capability of standard token-by-token parsing.

3 Just-in-Time Logic Enforcement

Having shown that enforcing logic during training post-inference or compromises either correctness (compliance with rules) or statistical fidelity (learned distributions), and constraint encoding is inadequate to support network constraints, we propose LeJIT: a framework for Enforcing Logic Just-In-Time. LeJIT intersects the LLM’s token-by-token inference to guide it towards rule-compliant generation as shown in Fig. 1b. While incorporating the SMT solver introduces some inference delay, it provides a valuable collaboration between neural and symbolic reasoning. It maximizes the contribution of symbolic reasoning by enabling the enforcement of arbitrary network rules, including arithmetic, non-differentiable, and global constraints, without placing additional burden on the operator. Moreover, LeJIT preserves statistical fidelity by respecting the token distribution learned by the LLM.

To better understand how LeJIT works, let us revisit the example of imputing $[I_0, \dots, I_4]$ but now generated with LeJIT’s guidance. After generating a complete value (e.g., I_2 at ❶), LeJIT invokes the solver with the provided constraints, *instantiated using the values generated so far*. This dynamic partial instantiation is crucial for determining which constraints are active and what conditions must be met to ensure valid output going forward. For example, suppose the LLM had already produced values satisfying $\exists t < 3 : I_t \geq 30$; in that case, R3 would already be met and thus deactivated when determining the feasible region for I_3 . If no such value has been generated—as is the case in our example—the solver considers all three rules R1–R2 when computing the valid range for I_3 (❷). Then, LeJIT invalidates all candidate values of I_3 that fall outside this feasible region (❸), effectively guiding the model toward valid generation paths. As a result, the resulting model output $I_3 = 39$ is *always guaranteed* to satisfy all constraints (❹). Moreover, in the presence of global aggregation constraints such as R2, this guided inference process often concludes with only a single valid value remaining for the LLM to emit (❺).

LeJIT offers LLM-native generation with character-level control. A key challenge in guiding an LLM with the solver is the mismatch in granularity between the model’s generation process and the solver’s reasoning. LLMs produce output token by token, and these tokens, defined by the tokenizer, are often opaque and lack semantic clarity. In contrast, SMT solvers operate over well-defined, interpretable variables (such as ingress bytes or ECN markings) expressed through explicit logical constraints. This discrepancy makes it difficult to enforce constraints without interfering with the LLM’s native decoding behavior.

LeJIT addresses this issue by offering character-level guidance that is finer-grained than the symbolic variables on which

solvers operate. To achieve this level of control, LeJIT treats numeric values as plain text [36] and uses a character-level tokenization scheme [44], generating each number digit by digit. As shown in Fig. 2, LeJIT constructs a character-level transition system[4, 46, 48] on the fly during inference. Specifically, given a feasible range for a target variable as determined by the solver, LeJIT builds an unlabeled transition system where the current state reflects the last token selected by the LLM, and the set of next states includes all tokens that would maintain the value within the valid region.

LeJIT provides a little guidance, but it goes a long way. Over-constraining the LLM, for example, through partial completions or rigid templates, disrupts its natural reasoning path and undermines its generative strength. Still, even a well-trained model is highly likely to produce invalid outputs, since a single incorrect token can render the entire sequence invalid. As illustrated in Fig. 1a, the sequence becomes invalid as early as the generation of I_3 . LeJIT strikes a balance by filtering out rule-violating tokens at each generation step, intervening only when the model is about to make a critical mistake. This approach preserves the LLM’s natural behavior while enforcing compliance with constraints whenever necessary.

A single LLM to “rule” them all? A key side benefit of applying rules at inference time is that modifying the rules enables repurposing an existing LLM—originally trained for one task—for a different task, without retraining or fine-tuning. For example, an LLM trained to impute fine-grained ingress volumes can be readily adapted to generate synthetic coarse-grained signals by simply changing the constraints: instead of enforcing rules on fine-grained ingress values I_t that rely on access to coarse-grained signals, we can substitute rules that capture relationships among the coarse-grained signals themselves. In our preliminary evaluation (§4.2), we demonstrate that a generic LLM trained for telemetry imputation can, under the guidance of LeJIT, achieve competitive performance with SOTA specialized data generators.

4 Early Results

As a proof of concept, we prototype and empirically evaluate the effectiveness of LeJIT in experiments.

Dataset. We conduct all experiments using the data center data released by Meta [14], following the same evaluation setup as that of Zoom2Net [16]. We use measurements from the 10 random racks for testing and 80 racks for training. The test set contains over 30,000 data points.

Network rules. For the network telemetry imputation task (§4.1), we use 716 rules which describe relationships between coarse-grained signals (*e.g.*, retransmissions) and fine-grained ingress measurements I_t . For the synthetic network

data generation task (§4.2), we use 255 rules that capture relationships among the coarse-grained signals themselves. We obtain both sets of rules by applying NetNomos [23] on the training data.

LeJIT implementation. Since LeJIT is LLM-agnostic, its effectiveness does not rely on a specific language model architecture. Therefore, for LeJIT we deliberately employ a generic, less powerful LLM, GPT-2 [35], to demonstrate how LeJIT can instill networking knowledge into the model at inference time. We train GPT-2 from scratch on the aforementioned datacenter dataset [14] and adopt character-level tokenization [44] to enable fine-grained control. Importantly, we repurpose the same trained model for two distinct tasks by applying task-specific rule sets through LeJIT, without any retraining or fine-tuning.

Baselines. We use the following baselines for both use cases: (i) Vanilla GPT-2: The original GPT-2 model without LeJIT; (ii) Rejection Sampling: A naive approach that discards all outputs violating network rules and repeatedly samples from GPT-2 until a valid output is produced; (iii) “manual” rules: Instead of using the automatically discovered rules from NetNomos [23], this baseline enforces the four manually specified rules (C4–C7) used by Zoom2Net [16]. For each use case, we compare against SOTA task-specific frameworks. For network measurement imputation (§4.1), we evaluate against Zoom2Net [16]. For synthetic network data generation (§4.2), we compare against a diverse set of SOTA data generators: NetShare [56], E-WGAN-GP [17], CTGAN [53], TVAE [53], and the GPT-2-based REaLTabFormer [43]. For both tasks, we omit comparisons with traditional statistical methods such as kNN and regression, as previous studies have demonstrated that our task-specific baselines achieve superior performance [16, 43, 53, 56].

4.1 LeJIT for Network Telemetry Imputation

Finding 1: Unlike task-specific models, which (at best) comply with a few hand-picked rules, LeJIT comply with all 716 rules, while achieving on-par performance in imputation accuracy and downstream tasks with Zoom2net.

We apply LeJIT on the task of network telemetry imputation and evaluate its effectiveness in enforcing network rules, overhead and accuracy.

Rule violation. Fig. 3 (left) reports rule violation rates. Vanilla GPT-2, lacking any constraints, shows the highest violation rate at 18%. Zoom2Net, despite using a constraint enforcement module (CEM), relies on limited and soft manual rules, resulting in over 7% violations—similar to LeJIT when

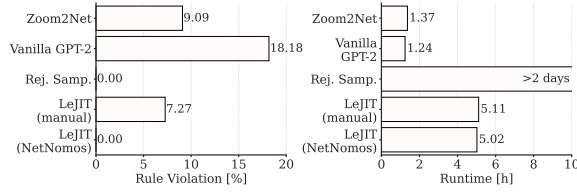


Figure 3: Rule violations in imputed time series (left) and runtime for 30K samples (right). LeJIT ensures 100% rule compliance with a moderate runtime overhead.

only manual rules are used. With the full set of NetNomos rules, LeJIT reduces violations to 0%.

Runtime overhead. As shown in Fig. 3 (right), rejection sampling achieves perfect compliance but takes over two days. As rejection sampling simply discards invalid outputs without guiding the model, the model repeatedly makes the same mistakes. In contrast, LeJIT completes over 30K imputations in 5 hours by guiding inference, achieving a more than 10× speedup compared to simple rejection sampling. Zoom2Net’s runtime performance is not directly comparable, since it enforces a much smaller set of handcrafted rules which allows post-inference enforcement. LeJIT trades inference performance for correctness guarantees which is a fair trade-off, in our view, given the importance of trustworthiness and correctness in network management. Of course, there also remain ample opportunities to improve the integration of the solver into the LLM to reduce the overhead as we discuss in §5.

Imputation accuracy. LeJIT with manual rules substantially improves GPT-2’s accuracy (Fig. 4, left), though it still trails Zoom2Net due to limited rule coverage. Rejection sampling hurts accuracy as it disrespects the LLM’s learned distribution, suppressing near-correct outputs and forcing sampling from unrelated regions. With full NetNomos rules, LeJIT matches and even surpasses Zoom2Net on EMD and p99 accuracy, while also improving burst analysis metrics across the board. When guided by LeJIT, GPT-2 outperforms Zoom2Net on all metrics except Burst Position. These results show that LeJIT enforces rules effectively at inference time, with performance improving as rule quality increases. The remaining gap on time-sensitive metrics (e.g., autocorrelation, Burst Position) likely stems from GPT-2’s generic architecture and the limited temporal expressiveness of the extracted rules by NetNomos [23]. Advancing methods for learning richer temporal constraints remains a key direction for future work and will unlock more benefits for LeJIT.

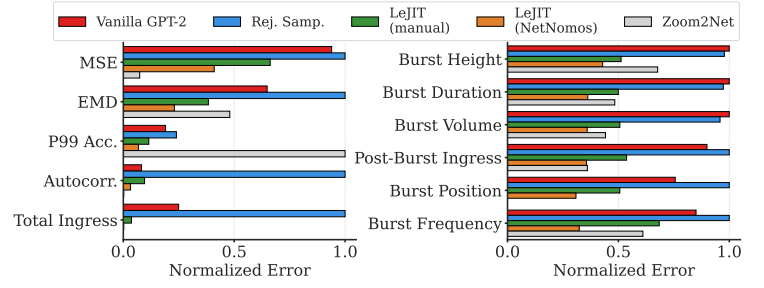


Figure 4: LeJIT improves both imputation accuracy (left) and downstream task performance (right) of the generic GPT-2 via logic enforcement, achieving on-par results with Zoom2Net [16].

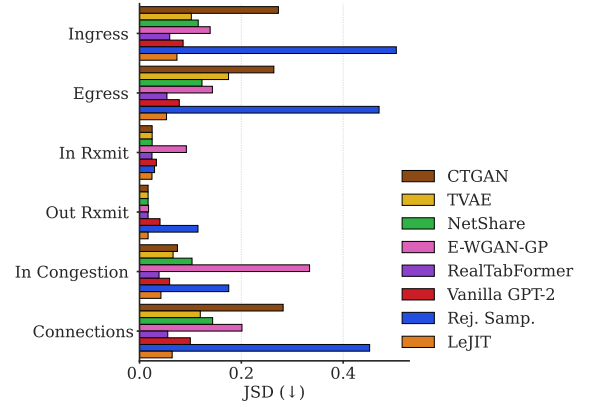


Figure 5: LeJIT generates samples of high fidelity (on-par with SOTA) while complying with all 171 rules (unlike SOTA)

4.2 LeJIT for Network Data Synthesis

Finding 2: LeJIT matches, and sometimes improves, the statistical fidelity of synthetic time series generated by tailored generators, while ensuring the time series follow hundreds of rules (unlike tailored data generators). Importantly, LeJIT’s underlying model is not task-specific.

We now apply LeJIT to the task of synthetic data generation and evaluate its effectiveness in enforcing network rules. Unlike the imputation, this generation task is unconditional: the models are not provided with any input signals (i.e., prompts no longer fed into GPT-2), and the data they generate depends solely on the learned input distributions.

As shown in Fig. 5, we compare various GPT-2 variants (vanilla, with rejection sampling, and with LeJIT’s guidance) against five aforementioned SOTA data generators. From each model, we draw 30K samples and compute the

Jensen–Shannon divergence (JSD) with respect to the original data distribution. The results demonstrate that LeJIT preserves the generative behavior of the base LLM while enforcing all 255 network rules. Rejection sampling significantly distorts the learned distribution, while the other data generators not only violate a large number of network rules [23], but also fail to offer clear advantages in approximating the target distribution. In contrast, LeJIT enables the base LLM to outperform its vanilla counterpart in most cases. This result suggests that enforcing domain knowledge during inference can improve the quality of generated data distributions.

5 Research Agenda

Logic-Guided Foundation Models for Networking. We envision a future where one LLM can power a broad range of networking tasks (e.g., configuration generation, security policy synthesis) simply by swapping in task-specific logic rules. Such a foundational, logic-guided model for networking would unify currently siloed ML efforts and vastly reduce engineering overhead [52]. Key questions include: (1) how to symbolically handle non-numeric or structured outputs (e.g., tables, topology graphs) in a single LLM, (2) how to tokenize heterogeneous networking knowledge in a way that does not create misalignment between the model output and symbolic rules, and (3) how to efficiently switch or compose rule sets for different tasks on the fly. Success in this direction would be transformative—instead of maintaining bespoke ML solutions for every networking problem, operators could rely on a single powerful model that is made context-specific and trustworthy via JIT logic “plug-ins.”

Constraint Learning and Solver Co-Design To improve JIT logic enforcement, two key directions are (1) improving LLM–solver integration and (2) improving the rule sets themselves. Current implementations depend on general-purpose SMT solvers external to the LLM, which introduces substantial inference delays [57]. This overhead makes large-scale deployment impractical. Future work should enable tighter coupling through token-level solvers, solver-aware decoding paths, or hybrid neural-symbolic architectures, making JIT enforcement feasible for latency-sensitive applications. In parallel, network rules—which are currently static and manually defined—must become more expressive (e.g., better support for temporal logic), data-driven, and adaptable. Systems could learn constraints from logs, refine them over time, or co-train them with model outputs. Ultimately, a LeJIT-like framework should evolve its constraints dynamically, improving accuracy while maintaining rule compliance in changing network environments.

Generalizing LeJIT beyond LLMs. While LeJIT currently targets autoregressive language models, many core networking tasks (e.g., traffic forecasting, anomaly detection, routing,

and protocol simulation) rely on non-language models like time-series regressors, GNNs, and diffusion models. However, this generalization is non-trivial. Unlike token-based LLMs, these models often produce continuous, high-dimensional outputs without an inherent notion of “next-step,” making it unclear how to insert constraint checks or prune invalid predictions. One promising direction is to rethink the inference process itself in networking as a constrained optimization problem: for instance, projecting a model’s unconstrained output onto the nearest point in the rule-compliant space via differentiable solvers [1, 32, 47] or gradient-based corrections. Similarly, generative models could be trained to emit semantic concepts [30, 33] that are easier to steer via symbolic logic, then decoded in a constraint-aware manner.

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