The Case For Language Model Approximated LIKE Predicate

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ABSTRACT

Modern databases often use the LIKE predicate to search text data. However, when the search condition is interrupted by wildcards, the existing search structure can degrade to a worst-case complexity linear to full table scale, resulting in poor performance. Traditional methods, such as B+-trees, fail to handle wildcards at both ends efficiently. Recent advances in language models offer a promising solution. These models can decode complex LIKE patterns into a small set of candidate values, which are then verified in dataset-size-invariant time via hash table lookups, greatly improving efficiency. However, integrating LLMs into databases faces challenges such as high latency, large storage requirements, and sensitivity to data distribution drifts.

To address these issues, we propose SMILE, a Small language Model Integrated LIKE Engine that learns column-local character distributions through small but exquisite parameters. Our SMILE acts as a neural translator that converts complex LIKE patterns into their corresponding result sets. Our approach achieves asymptotic complexity improvements while preserving SQL LIKE logic. We conduct comprehensive evaluation across diverse datasets to validate the efficacy of our approach. Our compact SMILE, with a parameter size 5 orders of magnitude smaller than large language models, achieves strong LIKE decoding efficiency and quality. Specifically, SMILE obtains high recall ability while accelerating LIKE by 3 orders of magnitude compared to large language models and sequential scans, 1.8-41.6 times faster than trigram indexes, and 2 orders of magnitude faster than B+-trees. Moreover, our model demonstrates robustness against potential data and query distribution drifts.

CCS CONCEPTS

• **Information systems** → **Query optimization**.

KEYWORDS

Query optimization

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1 INTRODUCTION

Modern database systems heavily rely on the LIKE predicate to efficiently retrieve and compute relevant textual information in relational tuples [14, 63, 75, 80]. This operator is crucial for various applications, including substring matching [66], data cleaning [46, 88, 133], and entity recognition [36].

Despite the widespread applications of the LIKE predicate, optimizing it remains a formidable challenge. Traditional B+-tree indexes work well for prefix/suffix patterns [33, 48] but struggle with wildcard-surrounded queries such as "%keyword%" [39, 124]. While trigram indexes support substring searches, they have high storage costs and limited wildcard flexibility [39]. When the queried keyword is interrupted by wildcards, or when the retrieving keyword is a "stop-word" present in all tuples [41], retrieval efficiency drops to $O(N \times \ell)$, where N represents the filtered table size, ℓ is the average string length. Furthermore, trigram indexes are not universally supported across databases [43, 98]. The fundamental limitation of existing approaches lies in their reliance on partial unmasked segments of the LIKE pattern for filtering and search operations, neglecting the holistic context of the query. This constraint significantly undermines their efficacy, particularly when dealing with complex wildcard patterns.

While exact evaluation for arbitrary LIKE patterns inherently requires $O(N \times \ell)$ complexity due to unavoidable full scans for high-cardinality cases (e.g., pure "%"), a critical class of interactive applications requires only a small set of guaranteed matches with sub-second latency. For instance, in data cleaning, in validating Pattern Functional Dependencies (PFDs) [102] such as `[Name LIKE "%John%"]` → `[gender = "M"]`, within a human-in-the-loop workflow [23, 45, 83]. In this setting, prohibitive scan latencies disrupt the interactive loop, while IR-style approximations are unsuitable as they return logically incorrect matches (e.g., "Joan"). This dilemma motivates an approach rooted in the principles of Approximate Query Processing [24, 100], where trading exhaustive completeness for interactive speed is a well-accepted compromise. We therefore propose a generate-and-validate strategy. If we have a near-oracle predictor to generate a constant-sized candidate set, we can then verify them in $O(\ell)$ time. This eliminates the dependency on dataset size N, delivering the performance expected in interactive systems that present constant-sized result sets [17, 26, 27, 62, 81]. We therefore investigate the feasibility of constructing such an oracle for efficient LIKE query processing.

Fortuitously, Large Language Models (LLMs) [22, 103, 104] approximately satisfy this oracle requirement. Thanks to their pre-trained masked prediction capabilities [37, 90, 115], LLMs can infer missing tokens from incomplete wildcard patterns, making them perfectly suitable for decoding LIKE wildcards into candidates. Figure 1 illustrates the core idea of our approach. For a query such as `SELECT * FROM T WHERE Conference LIKE "%IGMO%"`, we may apply prompt engineering to guide the LLM in understanding that the `Conference` column contains academic venue names. LLMs can then infer that the pattern `"%IGMO%"` likely corresponds to the name `SIGMOD`. We can then verify the presence of `SIGMOD` via a fast $O(\ell)$ hash lookup. Building on this potential, we proceed to evaluate whether we can significantly reduce the worst-case $O(N \times \ell)$ runtime of such interactive LIKE queries by using language models as efficient autocomplete keyboards—transforming patterns into

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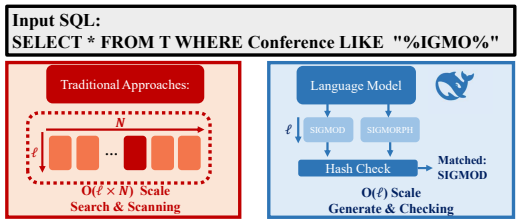


Figure 1: Example for language model Approximated LIKE.

a fixed set of candidate strings which are verified in $O(\ell)$ time via hash-based lookups.

However, deploying LLMs to accelerate the LIKE predicate faces a huge obstacle. LLMs are too **large** to fit into conventional DBMS [44, 91]. It therefore brings three barriers: (1) **Latency gap between DB applications and LLMs:** The LLM's response generation incurs second-level delays per query, conflicting with database's demands. For most OLAP scenarios with medium-sized data, a full-table scan (1 second) may be completed before LLMs finish their first sentence (10 seconds). (2) **Storage overheads of LLMs:** The storage space occupied by LLMs is astonishing. For example, DeepSeek-V3, with 671 billion parameters, requires nearly 1TB of storage [120]. This storage consumption can exceed the size of the entire database, significantly reducing the applicability of the method. (3) **Distribution drifts:** In database systems, data evolve continuously, necessitating frequent updates to model parameters [57, 86, 130]. However, fine-tuning LLMs is computationally expensive. To conclude, the "large" nature of existing LLMs presents challenges that hinder the direct deployment of translation LIKE predicates via LLMs. We have to explore whether it is possible to achieve similar LIKE translation functionality with a smaller model.

Fortunately, we observe that the distribution of characters within a single column can be regarded as a unique, special language with limited vocabulary combinations. This observation implies that translating LIKE templates into this column's sub-language can be learned via a small language model with limited parameters, obviating the need for resource-heavy LLMs. This insight motivates us to explore the use of lightweight Small Language Model(SLM) to learn the joint probability distribution of these characters. SLM, with smaller parameter scale, consumes significantly less memory and offers faster inference speed, making it well-suited for latency-sensitive database scenarios. Additionally, the lightweight nature of SLM makes it easier to manage through incremental finetuning in dynamic environments. Therefore, this observation inspires us to investigate whether we can **leverage small-scale language models to learn the language distribution of a single table** while retaining the functionality of LLMs for decoding LIKE predicate.

Based on the above discussions, we propose SMILE (Small language Model Integrated LIKE Engine), which leverages a lightweight character-level language model to translate LIKE queries into their result sets. This approach tackles the key challenges of LIKE predicate optimization. SMILE learns character distributions within specific column contexts, rather than across broad natural language domains. Coverage in this specific domain needs just a 16MB network, which is 5 orders of magnitude smaller than typical LLMs, yet it still translates LIKE patterns effectively. This small yet powerful model significantly boosts inference efficiency and reduces maintenance overhead. More importantly, SMILE transforms the inherently difficult LIKE matching problem into a more manageable string candidate verification task. During query optimization, SMILE generates candidate strings that match the LIKE pattern's logical constraints through autoregressive decoding. These candidates are then verified against the database using hash-based lookups. This hybrid approach converts the worst-case $O(N \times \ell)$ full table scans into $O(\ell)$ lookups for valid candidates, achieving substantial complexity improvements while preserving approximate SQL logic In summary, our work makes the following key contributions:

C1. A Novel Framework for LIKE Predicate Optimization: We introduce a new framework that recasts LIKE predicate optimization as a sequence translation task. This approach employs language models to directly generate candidate tuples from wildcard patterns, fundamentally shifting the execution paradigm from costly linear scans ($O(N \times \ell)$) to an efficient generate-and-validate process.

C2. Lightweight and Scalable SLM Architecture: To overcome the practical limitations of large language models (LLMs), we design and implement SMILE, a lightweight (16MB) and column-specific Small Language Model (SLM). SMILE acts as a specialized neural translator, efficiently learning data distributions to decode LIKE predicates into result sets. We further propose a hybrid strategy that enables our approach to scale to long text columns, which is a critical challenge for existing methods.

C3. Theoretical Framework with Probabilistic Guarantees: We establish a theoretical framework that provides probabilistic approximation guarantees for language-model-based LIKE decoding. By introducing the concept of pattern entropy to quantify query complexity, our framework formally bounds the sampling effort required to retrieve a target number of results with high confidence, establishing a principled link between model capacity, query structure, and performance.

C4. Evaluation Guided by Real-World Workload Analysis: To ensure a realistic evaluation, we first conducted a large-scale survey of 84,047 queries across 30 public databases to characterize real-world LIKE predicate usage. Guided by the identified patterns, we designed a representative benchmark on which SMILE achieves speedups of up to three orders of magnitude over sequential scans, and outperforms specialized trigram and B^+-tree indexes by 1.8-41.6× and two orders of magnitude, respectively, while using a model five orders of magnitude smaller than mainstream LLMs.

Roadmap: This paper is organized as follows. Section 2 formalizes the SQL LIKE predicate as a sequence-to-sequence task via neural machine translation. Section 3 evaluates state-of-the-art LLMs on LIKE pattern decoding, assessing accuracy, efficiency, and practical viability in database contexts. Section 4 introduces SMILE, a lightweight language model designed for efficient LIKE acceleration. In Section 5, we establish theoretical guarantees and extend the method's applicability. Section 6 presents experimental results comparing SMILE against baselines in accuracy, scalability, and robustness. Section 7 surveys related work, and Section 8 concludes with a summary, limitations, and future directions. Our Appendices provide more details about our collected workloads and experiments [].

2 PRELIMINARIES

In this section, we first provide an overview of the SQL LIKE predicate and language models in Section 2.1. Subsequently, we introduce a novel perspective on the optimization of the LIKE predicate from the viewpoint of neural language translation in Section 2.2. Section 2.3 explores practical interactive scenarios.

2.1 Basic Concepts

In this section, we introduce the SQL predicate LIKE and the definition of language models. Firstly, we delve into the definition of the LIKE predicate:

The LIKE predicate: The LIKE predicate facilitates the selection of tuples within a relational structure where attribute values match a specified pattern string. Formally, given a relation table T with attribute A, where the average string length of A is ℓ, and N tuples in total, the LIKE predicate $\mathcal{P}$ collects all tuples that satisfy $\mathcal{P}$ in result set $R_1 = \{t \in T \mid t[A] \text{ matches } \mathcal{P}\}$. As standardized in ISO/IEC 9075-2:2023 (Section 8.5, General Rule 3.b.ii) [7], the predicate recognizes two meta characters: (1) The percent symbol (%): Matches any substring of zero or more characters. (2) The underscore (_): Matches exactly one arbitrary character.

To illustrate the functionality of LIKE predicate, we provide the following examples. (E1): Pattern `LIKE "SIGMOD"` yields a condition where string matches `"SIGMOD"` string. (E2): Pattern `LIKE "SIG%"` matches all strings with the prefix `"SIG"` through left-anchored pattern matching. (E3): Pattern `LIKE "S_GMOD"` matches strings length of six with the first character being `"s"` and the last being `"GMOD"`.

Problem Definition: Given a LIKE predicate $\mathcal{P}$, we propose to optimize its approximate processing through dual objectives: minimizing query latency while maximizing recall of retrieved tuples. The recall metric is formally defined as: Recall $= \frac{|R_1 \cap R_2|}{|R_1|}$, where R_2 is the retrieved tuples, R_1 is $\mathcal{P}$'s ground truth result set.

Then, we proceed to provide the definition of language models.

Language model: Given vocabulary $V = \{x_1, x_2, \ldots, x_{|V|-2}, \langle SOS\rangle, \langle EOS\rangle\}$ and a sequence of preceding tokens $s_{<t} = (\langle SOS\rangle, x_{\pi 1}, x_{\pi 2}, \ldots, x_{\pi t-1})$, the language model $\mathcal{M}$ learns the conditional probability $\Pr(x_{\pi t} \mid x_{\pi 1}, x_{\pi 2}, \ldots, x_{\pi t-1})$ and samples the next token $x_{\pi t}$ based on this conditional probability distribution. That is:

$$x_{\pi t} \sim \Pr(x_{\pi t} \mid x_{\pi 1}, x_{\pi 2}, \ldots, x_{\pi t-1})$$

Given a fixed-length string input, the language model performs autoregressive decoding token-by-token iteratively. This iterative process begins with the start-of-sequence token $\langle SOS\rangle \in V$. In the t-th iteration, given the input $s_{<t} = (\langle SOS\rangle, x_{\pi 1}, x_{\pi 2}, \ldots, x_{\pi t-1})$, the language model generates the next token $x_{\pi t}$ based on $s_{<t}$. The generated token $x_{\pi t}$ is then appended to the historical input to form $s_{<t+1} = (s_{<t}, x_{\pi t})$. This updated string $s_{<t+1}$ serves as the input for the next iteration. The iterative process continues until $x_{\pi t}$ is the end-of-sequence token $\langle EOS\rangle \in V$.

2.2 LIKE Predicate Decoding: A Neuro-Linguistic Translation Perspective

We reconceptualize LIKE predicate evaluation as a specialized machine translation task. In this view, a LIKE pattern $\mathcal{P}$ is a source-language query that must be translated into its logical equivalents within the database's string domain (the target language). Formally, let A be the target column domain with N tuples. Conventional evaluation computes $\{s \in A \mid s \texttt{ matches } \mathcal{P}\}$ via deterministic approaches and faces a worst-case sequential scan for patterns like "%keyword%" in $O(N \times \ell)$ time. In contrast, our approach learns a translator $\mathcal{M} : \mathcal{P} \rightarrow \mathcal{A}" \subseteq A$, which translates the pattern into its results, where:

$$\mathcal{A}" = \arg\max_{s \in A} \Pr(s \mid \mathcal{P}) \quad \text{subject to} \quad s \texttt{ matches } \mathcal{P}$$

Here, $\Pr(s \mid \mathcal{P})$ represents the language model $\mathcal{M}$'s learned distribution. The verification condition s `matches` $\mathcal{P}$ ensures the correctness of the result, while the generation process leverages $\mathcal{M}$'s logical understanding to bypass exhaustive comparisons. This dual-phase approach achieves sublinear complexity by restricting pattern matching to a probabilistically generated candidate set $|\mathcal{A}"| \ll |A|$.

This paradigm shift overcomes the fundamental limitations of traditional indexes through logic-aware holistic decoding. While trigram indexes fail to fetch wildcard-broken or "stop-word" patterns, and B+-trees stumble on non-prefix alignment, the translation language model exploits distributional semantics to directly infer lexically valid matches. Our experimental validation in Section 6 demonstrates that this approach maintains SQL-standard logic while reducing asymptotic complexity from $O(N \times \ell)$ to $O(\ell) + \mathcal{M}_{decode}$, where $\mathcal{M}_{decode}$ represents the decoding overhead of modern Transformer architectures.

2.3 The Case for Instantaneous, Approximate LIKE Applications

Instantaneous feedback on LIKE predicates presents a dilemma in modern data systems. Traditional query processing guarantees completeness via exhaustive scans but suffers from high latency. Conversely, information retrieval techniques—such as full-text indexing [85] or embedding based reranking [58, 74] do not preserve the logical correctness of SQL LIKE patterns. We argue for a third paradigm for interactive applications: one that trades completeness for speed while strictly preserving logical correctness. These applications need a small, guaranteed-correct subset in interactive time—a capability current systems lack.

Rule Validation in Interactive Data Cleaning: Interactive data cleaning [32, 89, 105] relies on rapid, human-in-the-loop validation [23, 45, 83] of rules like Pattern Functional Dependencies (PFDs) [102]. For instance, when validating a rule such as `[name LIKE "%John%"] -> [gender="M"]`, an analyst needs immediate examples to check the logic. A slow full scan disrupts this cognitive flow, while IR-style approximate matching returns logically irrelevant hits (e.g., Joan" or Johnny Appleseed") that obscure logical correctness. Here, the trade-off is clear: sacrificing completeness for the interactive speed needed to validate rules is a small price to pay. Our system delivers a small set of guaranteed-correct matches, preserving the tight human-in-the-loop process.

Fast Maintenance of Learned Cardinality Estimators: Learned cardinality estimators for LIKE predicates [15, 76, 114] must be continuously retrained on evolving data to mitigate "catastrophic forgetting" [49, 68]. A cornerstone of this adaptation is experience replay [107, 145], which necessitates frequent acquisition of ground-truth labels—i.e., actual query results—for diverse LIKE patterns

from the current dataset. However, full-table scans to obtain these labels incur prohibitive latency, rendering online learning impractical. Our approach provides a remedy by generating a training-batch-sized, logically correct sample in sublinear time. For this task, completeness is unnecessary, but correctness is non-negotiable to avoid label noise, making the trade-off for speed ideal.

Pattern Induction in Information Extraction: Information Extraction (IE) relies on rapid "hypothesize-and-verify" cycles to refine patterns [21, 29, 140]. An engineer refining a pattern `LIKE "%John@%.edu%"` needs immediate feedback on its matches, but conventional query latency disrupts this iterative process. Our method provides millisecond-level, logically correct responses. Here, the goal is not completeness but to instantly receive a few logical witnesses to the pattern's behavior, allowing developers to validate and refine their logic without delay.

3 LARGE LANGUAGE MODELS: LESSONS LEARNED

In this section, we systematically evaluate the following hypothesis: *Since modern large language models(LLMs) have demonstrated remarkable zero-shot capabilities [40, 95, 131], could they serve as an "off-the-shelf" solution for decoding complex* `LIKE` *predicates, bypassing the need for specialized indexes or models?* In this section, we systematically investigate this possibility. We evaluate mainstream LLMs on both decoding quality and efficiency, treating them as a potential baseline. However, our findings reveal fundamental limitations that preclude their direct use: (1) substantial storage requirements, (2) prohibitive inference latency, and (3) a distributional mismatch leading to incomplete answers, which are unacceptable in a database context. These results thus serve as a crucial motivation, demonstrating that a specialized approach is not just an alternative, but a necessity.

Experimental Setup: We evaluate eight state-of-the-art open-source LLMs (ranging from 1.5B to 671B parameters) on `LIKE` predicate decoding. Our evaluation employs two real-world datasets: *TPC-H (lineitem)* [125], comprising 24M natural-language-like strings, and a recent snapshot of the *IMDB (name)* dataset [61], containing 15M real-world strings from the `primaryName` column.

To ensure practical relevance, our workload generation methodology is grounded in an analysis of 84,047 real-world `LIKE` patterns (see Appendix A). We focus on scenarios where conventional prefix/suffix indexes fail—specifically, patterns such as `LIKE "%Keyword%"` and `LIKE "%Key%Key%"`. We define two primary workloads:**W1 (Syllable-based):** Wildcards mask coherent phonetic syllables, simulating partial recall of word spellings where users reconstruct terms via pronunciation. **W2 (Morpheme-based):** Wildcards obscure morphemes—the smallest meaningful linguistic units—mimicking searches driven by semantic components. To enhance realism and complexity, we randomly replace 0 to 5 characters in the non-wildcard segments of each pattern with underscore ("_") wildcards. This process yields 2,000 test queries. Additional details are provided in Section 6.1.

Decoding Quality Analysis: We measure recall—the fraction of relevant strings correctly generated by each LLM for a given `LIKE` predicate. As illustrated in Figure 2, decoding accuracy correlates positively with model scale. However, a significant performance

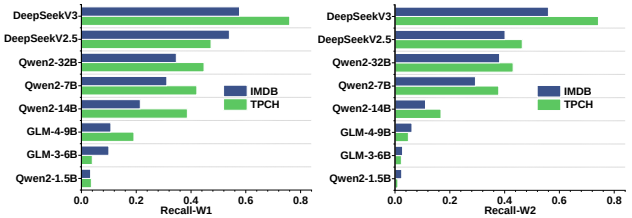


Figure 2: LLM recall performance across datasets and workloads. Left: W1. Right: W2.

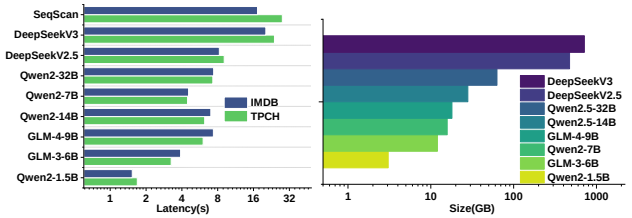


Figure 3: Computational cost of LLMs. Left: Inference latency. Right: Model size.

ceiling is evident, as no model approaches perfect recall. Even on the TPC-H dataset, where strings follow easier patterns, the state-of-the-art 671B-parameter model achieves a recall of only approximately 0.8. This persistent gap stems from a fundamental distributional mismatch, or more precisely, a bias mismatch. The open-world knowledge in an LLM's pre-training corpus instills an uncontrolled and undesirable bias towards general natural language. This generalist bias causes the LLM to generate numerous logically plausible strings that are valid in general language but do not exist within the target table's closed-world domain, thereby depressing recall. This issue is exacerbated on the IMDB dataset, whose structured strings deviate more sharply from natural language priors, leading to a more pronounced performance decline. Nevertheless, the core limitation persists even on linguistically coherent data, highlighting a systemic challenge in applying generalist models to specialized data retrieval tasks.

Computational Cost Analysis: Figure 3 quantifies the operational overhead of LLM-based decoding. High-performing models incur substantial latency; notably, DeepSeek-V3—the top performer in recall—exhibits inference times approaching those of a full sequential scan, rendering it unsuitable for latency-sensitive query processing. More critically, storage requirements pose an insurmountable barrier: state-of-the-art LLMs demand gigabytes to terabytes of parameter storage—often exceeding the size of the database itself. This inefficiency arises from the *generalist's burden*: LLMs are trained on diverse tasks (e.g., code generation [47], mathematical reasoning [144], dialogue [28]), resulting in a model whose parameters are overwhelmingly biased towards knowledge domains irrelevant to `LIKE` decoding. Although LLMs demonstrate zero-shot capability, their immense computational and storage demands are fundamentally incompatible with the efficiency constraints of database systems, where every CPU cycle and byte is carefully optimized.

Key Insights: *1. Foundational Decoding Capability:* LLMs can map wildcard patterns to logically plausible completions,

achieving high recall (up to 80%) on linguistically coherent data by leveraging learned language distributions.

2. The Prohibitive Cost of Scale: High accuracy requires massive models, incurring severe latency and storage overheads—a "success tax" that renders direct deployment economically and operationally infeasible.

3. The Generalist's Bias: General-purpose knowledge introduces an uncontrolled and inefficient bias; most model capacity is consequently irrelevant to LIKE decoding, violating core database design principles of specialization and resource frugality.

These results offer a crucial insight. The initial enthusiasm for general-purpose LLMs is met by the harsh reality of the "generalist's burden"—their vast knowledge introduces uncontrolled bias and prohibitive overhead, making them impractical for production database use. This realization motivates a deliberate shift in design philosophy: we argue that a workload-aware, specialized solution is a more principled and efficient engineering choice. Consequently, we propose a lightweight small language model designed to overcome the exact limitations identified in this section.

4 SMALL LANGUAGE MODELS: AN ECONOMICALLY VIABLE ALTERNATIVE

To overcome the limitations imposed by the LLMs' generalist bias, we propose SMILE (Small language Model Integrated LIKE Engine), a cost-effective solution that leverages SLMs to enhance the efficiency of LIKE predicate processing. SMILE is designed around a core principle: the intentional learning of a potent *inductive bias*. Instead of relying on open-world knowledge, SMILE learns the specific character-level distribution of a target column. This learned domain prior is the key to its efficiency and high recall, enabling it to act as a specialized neural translator that operates within the closed world of the database column.

4.1 SMILE Overview

As depicted in Figure 4, SMILE operates through three core stages: offline preparation of model and training workloads, online small language model driven translation of LIKE predicates, and hash-based validation of candidate strings. SMILE aims to optimize low-cardinality LIKE query patterns where dataset-size-independent decoding acceleration via SLM becomes feasible. This section provides a concise workflow overview. We formally introduce SMILE's SLM architecture and decoding strategies in Sections 4.2 and 4.3, respectively. Section 4.4 discusses decoding optimization techniques, while Section 4.5 details our query routing mechanism for identifying targetable low-cardinality queries.

1. Offline preparation: We initially prepare the training workloads offline. Subsequently, we train a classifier on the target column A and a character-level small language model using the prepared workloads. Inspired by prior works on learned database [111, 132], we first cluster historical queries into high-cardinality and low-cardinality types. We then train a binary classifier that classifies query patterns into these two categories. For low-cardinality patterns, we statistically model their wildcard distributions ("%" and "_" placements) to generate synthetic training data. We firstly sample N_s strings from A and obtain training sampling set $\mathcal{S} = \{s \mid s \in A\}$, $|\mathcal{S}| = N_s$. Then, we inject wildcards into the sampling set $\mathcal{S}$ to form supervised training information $\langle \mathcal{P}_i, s_i \rangle$ pairs where wildcard pattern $\mathcal{P}_i$ constitutes a source language and original tuples s_i form the target language. We employ teacher forcing with cross-entropy loss to train SMILE's SLM:

$$\mathcal{L} = -\sum_{\langle \mathcal{P}_i, s_i \rangle} \sum_{x_{ij} \in s_i} x_{ij} \log \mathcal{M}(\mathcal{P}_i)_j$$

Here, x_{ij} represents the true distribution of target string s_i's j-th token, and $\mathcal{M}(\mathcal{P}_i)_j$ represents the language model's output probability distribution for the j-th output token given wildcard input $\mathcal{P}_i$. The training approach mentioned above can be adapted for data updates. In scenarios where data undergoes periodic changes, we can similarly generate training samples and wildcard patterns from the new data distribution to fine-tune the model parameters. This training process makes SMILE acquires its inductive bias. By learning exclusively from the target column's data, the model internalizes a domain-specific prior that constrains its predictive distribution to the statistical patterns of this closed world, effectively eliminating the out-of-domain generation that plagues generalist models.

2. Online SLM translation: For unknown queries, we first utilize a character-level language classifier to route testing query workloads. Subsequently, based on the classification outcomes, we meticulously select wildcard patterns with low-cardinality from the testing workloads. These low-cardinality wildcard patterns can be efficiently translated into candidate sets in $O(\ell)$ time. For these low-cardinality queries, we employ a neural character Transformer to translate the source LIKE patterns into target strings in the database. However, if the query has high-cardinality (e.g., pure "LIKE %"), even if language model can successfully decode such queries, the number of samples generated by the language model is proportional to the scale of the entire database, which restricts the space for the language-model-based optimization. Therefore, we directly deliver these query patterns for the database to execute.

3. Hash verification: After we obtained the constant scale candidate set via the generation of our SLM, we verified our candidate set using hash index, allowing results to be checked in $O(\ell)$ time.

4.2 Transformer: The Efficient LIKE Translator

We find the Transformer architecture [16, 64, 127], originally developed for machine translation, is exceptionally well-suited for our LIKE predicate decoding task. This suitability stems from two of its inherent properties:

(A1). Intrinsic Seq2Seq Architecture: The "%" wildcard implies that the length of a matching string is independent of the pattern's length. This input-output length mismatch renders fixed-size architectures, such as standard MLPs, unsuitable for learning this mapping [16, 118]. The Transformer's encoder-decoder structure naturally addresses this challenge. The encoder maps the variable-length input pattern to a latent representation $\mathbf{H} \in \mathbb{R}^{m \times d}$. The decoder then autoregressively generates the output sequence y_t conditioned on $\mathbf{H}$, terminating upon generating an $\langle EOS \rangle$ token. This mechanism effectively decouples the input and output lengths, making it ideal for the variable-length translation required by LIKE predicates.

(A2). Dynamic Attention Mechanism: When decoding a LIKE predicate, different segments of the input pattern have varying importance for generating the output string. The attention mechanism

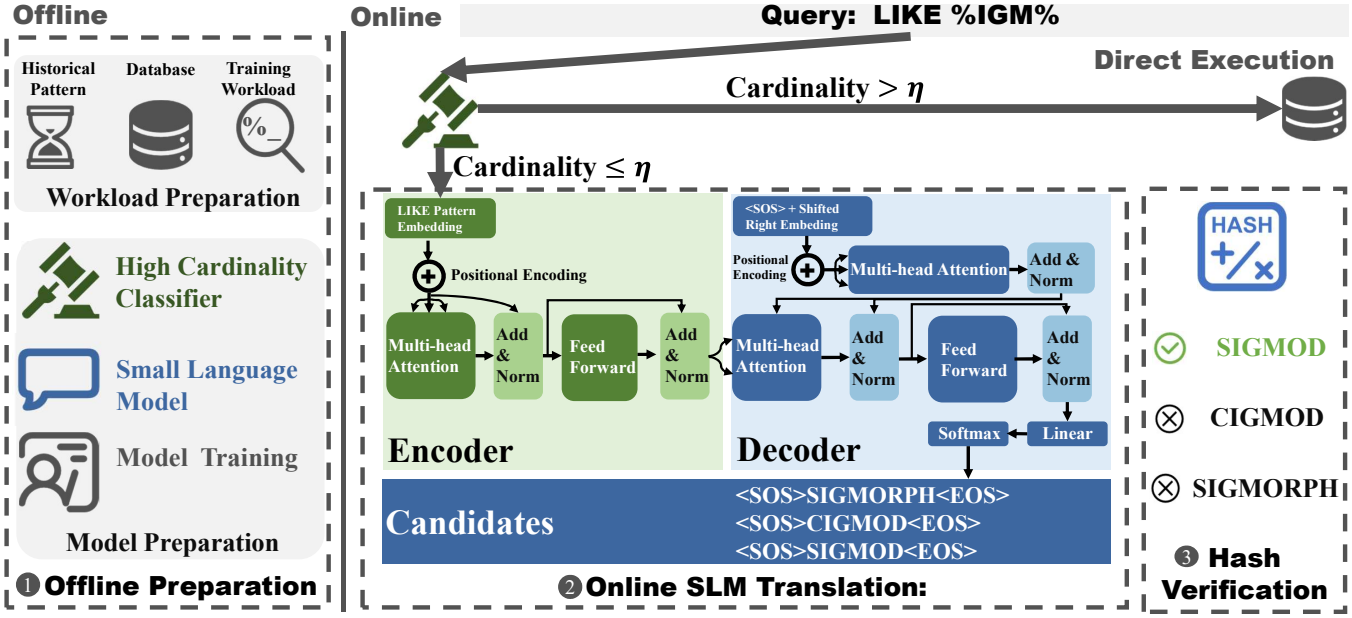


Figure 4: Overview on SMILE.

enables the model to dynamically focus on the most salient input tokens for each decoding step by adaptively weighting the input sequence. Formally, given an input sequence of d-dimensional embeddings $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m)$, attention computes Query, Key, and Value matrices via learnable linear projections: $\mathbf{Q} = \mathbf{X}\mathbf{W}_Q$, $\mathbf{K} = \mathbf{X}\mathbf{W}_K$, $\mathbf{V} = \mathbf{X}\mathbf{W}_V$, with projection matrices $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V \in \mathbb{R}^{d\times d}$. The rows of $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ represent the query, key, and value vectors, respectively. The core of the mechanism lies in computing relevance scores:

$$\boldsymbol{\alpha}_{i,j} = \frac{\exp\left(\mathbf{q}_i \mathbf{k}_j^\top / \sqrt{d}\right)}{\sum_{k=1}^{m} \exp\left(\mathbf{q}_i \mathbf{k}_k^\top / \sqrt{d}\right)}$$

where the scaled dot-product $\mathbf{q}_i \mathbf{k}_j^\top / \sqrt{d}$ measures feature compatibility. These normalized coefficients implement a soft reranking mechanism, where the attention coefficients assess the importance of the current feature contribution to LIKE decoding. Based on the attention weights, the context matrix $\mathbf{Z} \in \mathbb{R}^{m\times d}$ is computed via value aggregation as follows, where $\mathbf{z}_i$ denotes the i-th row of $\mathbf{Z}$:

$$\mathbf{z}_i = \sum_{j=1}^{m} \boldsymbol{\alpha}_{i,j} \mathbf{v}_j \quad \text{for } i = 1, \ldots, m,$$

This reweighting allows automatic emphasis on logically critical subpatterns (non-wildcard segments) while maintaining long-range dependency awareness - crucial for reconstructing masked segments between wildcards. For example, given a LIKE pattern "SIG_O_" to decode, we need to pay more attention to "SIG" than "O" as the prefix "Special Interest Group"("SIG") gives us more details of the underlying matched result than "O". Therefore, these architectural advantages make Transformers naturally suitable for LIKE predicate decoding: The dynamic length adaptation handles arbitrary wildcard expansions, while the attention mechanism automatically focuses on discriminative subpatterns to efficiently decode string patterns.

4.3 Capture LIKE pattern in a Seq2Seq manner

SMILE adapts Transformer to perform character-level translation of LIKE predicates. As illustrated in Figure 4, the model processes a LIKE pattern through distinct encoding and decoding stages.

Encoding Stage: The encoding stage transforms an input LIKE pattern $\mathcal{P}$ of length m into a dense vector representation $\mathbf{H} \in \mathbb{R}^{m\times d}$ via three sequential operations: (1) **Character-level Embedding**: Each character in the input pattern is mapped to a d-dimensional vector using a trainable embedding matrix $Emb \in \mathbb{R}^{|V|\times d}$, where V is a column-specific vocabulary. (2) **Positional Encoding**: To inform the model of the character sequence order, which is otherwise ignored by the self-attention mechanism, we inject positional information. This is achieved by summing the character embeddings with a standard sinusoidal positional encoding [127]:

$$PE_{(pos,2i)} = \sin\left(pos \times 10000^{-\frac{2i}{d}}\right),$$
$$PE_{(pos,2i+1)} = \cos\left(pos \times 10000^{-\frac{2i}{d}}\right),$$

where pos is the character's position and i is the dimension index ($i \le d$). This parameter-free approach facilitates generalization to variable-length patterns, which is crucial for robustly handling wildcards. (3) **Self-attention Encoding**: Finally, a Transformer encoder layer processes the resulting sequence. It employs a multi-head self-attention mechanism, followed by layer normalization and a residual connection, to capture long-range dependencies between characters in the pattern.

Decoding stage: The decoder learns a scoring function that maps the encoded LIKE pattern representation $\mathbf{H} \in \mathbb{R}^{m\times d}$ and the currently generated sequence $s_{<t} = (\langle SOS\rangle, x_{\pi 1}, x_{\pi 2}, \ldots, x_{\pi t-1})$ to

Algorithm 1 Temperature annealed decoding for LIKE patterns

Input: Encoded LIKE pattern $\mathbf{H} \in \mathbb{R}^{m \times d}$, temperature T, beam size K, decode length ℓ, Hash Verifier $Hash$
Output: Valid candidates $C_{\text{valid}} \subseteq C$

1: **procedure** DecodeLIKE($\mathbf{H}, T, K, \ell, Hash$)
2: $\mathbf{H}_{\text{tile}} \leftarrow \text{repeat}(\mathbf{H}, K)$ ▷ Tile pattern representation
3: $\mathbf{s_t} \leftarrow [\langle SOS \rangle]^{\times K}$; **done** $\leftarrow$ False^K; ▷ Init sequences
4: **for** $t = 1$ **to** ℓ **do**
5: $D_t \leftarrow \text{Decoder}(\mathbf{H}_{\text{tile}}, \mathbf{s_t})$ ▷ Decode
6: $\mathbf{P}_t \leftarrow \frac{\exp(D_t/T)}{\sum_{\epsilon \le |V|} \exp(D_t[\epsilon]/T)}$ ▷ Temperature scaling
7: $y_t \leftarrow \text{sample}(\mathbf{P}_t)$;
8: $\mathbf{s_t} \leftarrow \mathbf{s_t} + (y_t \cdot \neg\textbf{done})$; **done** $\leftarrow$ **done** $\vee (y_t == \langle EOS \rangle)$
9: **if** all(**done**) **then break**
10: $C_{\text{valid}} \leftarrow \{s_t \in \mathbf{s_t} \mid Hash[s_t] = 1\}$ ▷ Hash verification
11: **return** C_{valid}

the vocabulary score distribution D_t of the t-th token. This function is implemented via a Transformer-based architecture, maintaining dimensionality consistency across layers. The decoder then projects these hidden states to the score vector $D_t \in \mathbb{R}^{|V|}$:

$$D_t = \mathbf{W_o} \mathbf{h}_t^N + \mathbf{b_o}$$

where $\mathbf{h}_t^N \in \mathbb{R}^d$ denotes the final layer's hidden representation at step t, $\mathbf{W_o} \in \mathbb{R}^{|V| \times d}$ is the output weight matrix, and $\mathbf{b_o} \in \mathbb{R}^{|V|}$ is the bias vector with $|V|$ being the vocabulary size. The resulting weight vector from the decoder contains the likelihood scores for all tokens in the vocabulary. The subsequent section discusses an efficient decoding strategy based on these scores.

4.4 Translating LIKE Via Temperature Annealed Importance Sampling

Translating a LIKE predicate that matches multiple strings requires generating a diverse set of candidates. Standard greedy decoding, however, often yields repetitive outputs, as it consistently favors high-probability tokens and fails to explore the full solution space [146].

To address this, we employ a temperature-annealed sampling strategy, a technique adapted from large language model decoding [20, 22, 37, 146] to balance exploration and exploitation. Given a LIKE pattern $\mathcal{P}$ over column A with vocabulary V, SMILE's decoder computes a score distribution $D_t \in \mathbb{R}^{|V|}$ at each step t, conditioned on $\mathcal{P}$ and the prefix $s_{<t}$. We then apply temperature scaling to this distribution to promote diversity:

$$\Pr(x_{\pi t} = x_k) = \frac{\exp\left(D_t[k]/T\right)}{\sum_{\epsilon \le |V|} \exp\left(D_t[\epsilon]/T\right)}$$

Algorithm 1 outlines this process. To generate K candidates concurrently, the encoded LIKE pattern $\mathbf{H}$ is tiled, and each sequence is initialized with a $\langle SOS \rangle$ token (Lines 2-3). The algorithm then iteratively samples tokens. In each step, the decoder generates logits D_t, which are scaled by temperature T to form a probability distribution $\mathbf{P}_t$ (Line 5). A new token y_t is sampled from $\mathbf{P}_t$ and appended to each active sequence (Lines 6-7). The process terminates once all sequences have generated an $\langle EOS \rangle$ token. Finally, a hash-based verifier validates each candidate string in $O(\ell)$ time (Line 10). The overall time complexity is $O(D \cdot \ell)$, where D is the decoder's computational cost and ℓ is the decode length. This complexity is independent of the database size N, ensuring scalability.

4.5 Cardinality-Aware Classification

While SMILE achieves asymptotic acceleration for low-cardinality LIKE queries, high-cardinality patterns (e.g., pure LIKE "%") pose challenges. To decode type LIKE "%" predicate would require the sampling budget being linear to the table scale. Therefore, such exhaustive generation for non-selective patterns approaches $O(N \times \ell)$ complexity, negating our complexity improvements.

To resolve this tension, we introduce a cardinality-aware classifier that dynamically routes queries between the SLM translator and traditional execution methods. The classifier predicts whether a given LIKE pattern will exceed predefined cardinality thresholds proportional to the sampling budget, and we reuse the neural translator's pre-trained encoder (described in §4.3) to obtain $m \times d$ dimensional input patterns' hidden representation $\mathbf{H}$. We then use average pooling to map $\mathbf{H}$ into d dimensional summarization vectors. This summarization captures both syntactic features (wildcard positions, pattern length) and distribution characteristics (expected character distributions). A two-layer MLP with ReLU activation then maps these representations to cardinality class probabilities:

$$\Pr(\text{high-card}) = \sigma(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1 \cdot \text{Avg}(\mathbf{H}) + \mathbf{b}_1) + \mathbf{b}_2)$$

where $\text{Avg}(\mathbf{H})$ denotes average pooling of the input LIKE pattern's encoded representation $\mathbf{H}$, and σ represents the sigmoid function. The model trains on query logs annotated with true cardinality values, optimizing binary cross-entropy loss. In practice, this lightweight classifier (6MB parameters) introduces negligible overhead (0.1ms/query) while achieving accurate query routing in our experiments, enabling reliable fallback to full scans for low-selectivity patterns without compromising low-latency acceleration for targeted queries.

5 GUARANTEES AND EXTENSIONS

Having established the architecture of SMILE, we now turn to its theoretical underpinnings and practical extensibility. This section first develops a framework for probabilistic approximation guarantees, formally quantifying the relationship between the sampling effort of our SLM-based translator and the completeness of the query result. Building upon this theoretical foundation, we then explore practical extensions of our methodology.

5.1 Probabilistic Guarantees for Approximation

To develop a principled understanding of our language model based approach for LIKE predicate approximation, we construct a theoretical model. The goal of this model is to quantify the relationship between a query's complexity, the model's capacity, and the number of samples, n, required to retrieve at least K matching strings with confidence $1 - \delta$.

Our framework's central premise is to contrast the language model's objective with the conventional LIKE execution, which is a *discriminative* process: given a fixed, finite set of stored strings, the system identifies which ones satisfy the LIKE pattern. In contrast, our language model tackles this a *generative* task: it must infer the syntactic constraints implicit in the pattern and synthesize valid

strings *de novo*. Hence, the difficulty of this task depends not merely on the empirical data distribution of any specific database instance, but more on the intrinsic structural complexity of the pattern itself.

Assumption 1 (Task Complexity as Generative Entropy). We model the complexity of a LIKE pattern $\mathcal{P}$ by the difficulty of the generative task it represents. This difficulty is proportional to the size of its corresponding language, $L(\mathcal{P})$—the space of all possible valid strings. To formally quantify this *intrinsic generative complexity* while abstracting away from the contingent data distribution of any particular database, we employ the principle of maximum entropy. This leads us to assume a uniform distribution over all syntactically valid strings in $L(\mathcal{P})$, thereby isolating the complexity inherent in the pattern's structure.

Definition 1 (Pattern Entropy). Under this generative framework, for a LIKE pattern $\mathcal{P}$ over an alphabet Σ, we define the **pattern entropy**, $H(\mathcal{P})$, as the Shannon entropy of the uniform distribution over its language $L(\mathcal{P})$, measured in nats:

$$H(\mathcal{P}) = \ln |L(\mathcal{P})| \tag{1}$$

This value serves as a proxy for the syntactic learning difficulty posed to the generative model.

Theorem 5.1 (Entropy of a LIKE Pattern). *Given a* LIKE *pattern of length x with p underscore ("_") and q percent ("%") wildcards over alphabet Σ, no two percent signs adjacent, and a maximum generated-string length of m, the pattern entropy $H(\mathcal{P})$ is:*

$$H(\mathcal{P}) = p \ln |\Sigma| + \ln \left(\sum_{s=0}^{m-x+q} \binom{s+q-1}{q-1} |\Sigma|^s \right) \tag{2}$$

The proof is detailed in Appendix I.1. Theorem 5.1 provides a closed-form method to compute this complexity measure. The total entropy of a workload $\mathbb{W}$ is the sum of the entropies of its constituent patterns: $H(\mathbb{W}) = \sum_{\mathcal{P} \in \mathbb{W}} H(\mathcal{P})$. Next, we model the language model's capabilities in a simplified manner.

Assumption 2 (Model Information Capacity). We followed Meta AI's recent analyses [97], postulate that a model with $|\theta|$ parameters has an effective information capacity, M, that is proportional to its size, in a linear relationship:

$$M = \alpha |\theta| \tag{3}$$

where α is an architecture-dependent constant. Within our framework, M represents an abstracted upper bound on the total task complexity $H(\mathbb{W})$ that the model can reliably internalize.

Assumption 3 (Capacity-Limited Performance). We postulate a relationship between the model's capacity and its generative success probability, p. We conceptualize this as a resource allocation problem. If the model's capacity M meets or exceeds the task's complexity $H(\mathbb{W})$, its performance is primarily limited by other factors (e.g., training quality, decoding stochasticity), which we bound with a universal constant $c \in (0, 1]$. If the model is under-capacitated ($M < H(\mathbb{W})$), we assume its performance degrades proportionally to the ratio of available capacity to task demand. This leads to the following lower bound on the success probability:

$$p \geq c \cdot \min\left(1, \frac{M}{H(\mathbb{W})}\right) = c \cdot \min\left(1, \frac{\alpha|\theta|}{H(\mathbb{W})}\right) \tag{4}$$

This assumption provides a tractable, albeit simplified, link between model scale and task complexity, enabling the derivation of sampling bounds.

Theorem 5.2 (Sampling Complexity for LIKE Approximation). *Under the assumptions of our theoretical model, for a query workload with entropy $H(\mathbb{W})$, to retrieve at least K correct results with confidence $1 - \delta$, the required number of samples n from a model with $|\theta|$ parameters must satisfy:*

$$n \geq \begin{cases} \frac{1}{c}\left(K + \ln(1/\delta) + \sqrt{(2K + \ln(1/\delta))\ln(1/\delta)}\right) & \text{if } H(\mathbb{W}) \leq \alpha|\theta| \\ \frac{H(\mathbb{W})}{c \cdot \alpha|\theta|}\left(K + \ln(1/\delta) + \sqrt{(2K + \ln(1/\delta))\ln(1/\delta)}\right) & \text{otherwise} \end{cases} \tag{5}$$

The proof is detailed in Appendix I.2. Theorem 5.2 is the central result of our model, establishing a quantitative link between a workload's intrinsic complexity ($H(\mathbb{W})$), the model's abstracted capacity ($|\theta|, \alpha$), and the sampling budget (n) required for a given performance target (K, δ). Crucially, the generative viewpoint of our model implies that for a consistent query distribution, the syntactic rules learned from one data sample can generalize to entirely disjoint data partitions. This property is instrumental for handling evolving databases and enables rapid model deployment, a claim we validate empirically in Section 6.3 and 6.4.

5.2 Discussions

We discuss SMILE's extensibility to long text columns and its broader applications.

Scalability to Long Text Columns. Deep sequence models for LIKE optimization struggle with long text columns [15, 76, 114],[1] a limitation also present in our baseline full-string generation approach. The core challenges are twofold: (1) long text implies longer m in Theorem 5.1, thus greater entropy, impedes learning the data distribution for exact matches, and (2) the linear cost of autoregressive inference becomes prohibitive. To address this, we propose a hybrid strategy that reframes SMILE as a prefix-guided query rewriter. Instead of generating a full string, the SLM produces a fixed-length, high-selectivity prefix. This prefix is then used to probe a standard index (e.g., a B$^+$-tree), converting a `LIKE "%keyword%"` query into an efficient `LIKE "prefix%"` lookup. This design solves both issues: it lowers the target entropy ($H(x_{\text{prefix}}) < H(x_{\text{full}})$), improving sampling success per Theorem 5.2, and decouples inference cost from string length to ensure scalability. We believe this is the first practical deep learning approach for LIKE acceleration that scales to the maximum wildcard lengths (e.g., 8KB) supported by modern database systems.[2]

Generalization to Other Tasks. SMILE's core methodology is broadly applicable to other tasks. For instance, SMILE can accelerate approximate regular expression (regex) matching. By modeling regex as a sequence-to-sequence task, it can significantly improve performance in interactive data exploration and cleaning workflows. The approach also extends to optimizing fuzzy string joins (e.g., "Orders.CustomerName" with "Customers.Name"). A trained SLM

[1] Recent deep LIKE CardEst works use strings of 50–100 length in average, none exceeding 500. [14, 75, 76]

[2] For example, 255 bytes in SAP [110], 4KB in DB2 [60], and 8KB in SQL Server [93].

can act as a candidate generator, mapping an input like "J. Smith" to high-probability matches such as "John Smith". This transforms an expensive fuzzy join into a series of efficient, model-guided lookups. While primarily designed for single-column approximate queries, SMILE can be readily extended to optimize complex analytical queries, serving as a specialized form of Approximate Query Processing [24, 100]. We employ SMILE as a query rewriter for queries with non-sargable "LIKE" predicates: it generates a candidate set of matching strings and transforms the predicate into an equivalent "WHERE column IN (...)" clause. This simple yet powerful rewrite makes the predicate index-friendly, enabling the database optimizer to leverage efficient hash-based lookups instead of costly scans. If the cardinality estimator in the database predicts high selectivity for this predicate, SMILE can be enabled to perform the above rewriting. We validated this strategy end-to-end on relevant queries from TPC-H and IMDB-JOB benchmarks in Sec 6.2 and Appendix H.

6 EXPERIMENTS

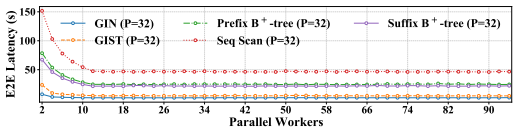
In this section, we provide an experimental analysis of SMILE in accelerating approximated LIKE pattern. We use our experiment results to answer the following questions:

(Q1) Effectiveness: Can the proposed language-model-based LIKE predicate decoding strategy significantly reduce the execution time and cost of LIKE predicates compared to traditional methods and state-of-the-art large language models across multiple datasets? Can it generate sufficiently high-quality candidate sets to recall potential query results? Can it play a useful optimization role in practical complex workloads? (Section 6.2)

(Q2) Scalability: Is the method's scalability in training and inference time sufficiently effective? Is the method's space occupancy sufficiently low? How does SMILE's performance and accuracy scale with increasing workload entropy and string length, particularly on billion-record and long-text datasets?(Section 6.3)

(Q3) Robustness: If data distribution drifts occur, can the method be updated in time to adapt to data changes? If the query template distribution changes, can the method still effectively support unknown query template estimation without retraining? (Section 6.4)

6.1 Experimental Setup



(a) Baseline Configuration Tuning(Partition=32).

(b) Hardware Hourly Rental Costs.

Hardware Configuration	Hourly Rental Cost ($)
1 × AMD EPYC 9654 CPU (96 Cores) [30]	$1.50
1 × AMD EPYC 9654 CPU (16 Cores) [30]	$0.25
1 × NVIDIA H20 GPU + 1 × AMD EPYC 9654 CPU (16 Cores) [13]	$0.98

Figure 5: Configuration analysis and hardware cost.

Datasets: We evaluate LIKE predicate performance on six diverse datasets, with detailed statistics summarized in Table 1. Four are standard benchmarks in string query research [14, 75, 137]: (1) **TPC-H** [125], comprising 24 million rows from the comment column of the lineitem table (SF=4); (2) **IMDB** [61], with 15 million entries from the primaryName column of the Name table of the **real-world** IMDB dataset; (3) **Reddit** [96], containing 2 million **real-world** reddit usernames; and (4) **WIKI** [129], consisting of 4 million **real-world** Wikipedia article titles. To further assess scalability and robustness, we use two large-scale, **real-world** datasets: (5) **RedPajama** [123], a set of 1 billion unique string windows (max length 40) extracted from a 1TB corpus; and (6) **News Room** [56], used for long-text evaluation with 1.2 million articles averaging 3962 characters in length.

Table 1: Statistics for the datasets used in our evaluation.

	Reddit	WIKI	IMDB	TPC-H	Redpajama	NewsRoom
Total	2,000,000	4,000,000	14,757,614	23,996,604	1,000,000,000	1,212,741
Unique	1,999,847	4,000,000	11,278,588	15,189,929	1,000,000,000	1,200,762
Min Length	1	1	1	8	1	27
Max Length	20	257	105	43	40	18386
Avg Length	11.00	19.91	13.51	26.23	36.61	3962.47

Workload Design. To evaluate the robustness of our method, we designed four LIKE workloads (W1-W4) that span from realistic to challenging scenarios. **Realism-Driven Workloads (W1 & W2).** We derived W1 and W2 from an analysis in Appendix A based on our collected 84,047 production LIKE queries(available at [8]). The analysis revealed that challenging infix searches (e.g., %Keyword%, %Key1%Key2%) are prevalent. We found that in such queries, the substrings masked by wildcards often correspond to linguistic units like morphemes or syllables, rather than arbitrary characters. Accordingly, we generate realistic patterns by splitting string into list of linguistic units using [9, 10] and replacing 0-2 consecutive linguistic units with a single "%" wildcard. This method covers over 50% of the production cases (Appendix A.3). We therefore define two specific workloads: **W1 (Syllable-based):** Simulates phonetic recall by masking syllables, the basic units of pronunciation [108]. For example, "SIGMOD CONFERENCE" can yield the pattern %MOD CON%EN%. **W2 (Morpheme-based):** Models semantic-driven searches by masking morphemes, the smallest meaningful units in a language [42, 50]. This simulates users searching for concepts embedded within larger words. The detailed construction algorithm of these workload is described in Appendix E. **Benchmark Workloads (W3 & W4).** To benchmark against established standards and test performance boundaries, we include two additional workloads: **W3 (CLIQUE Workload):** Adopts the standard suite of LIKE patterns from CLIQUE [75] (e.g., %Key, Key%, %Key%Key%) to evaluate performance on common predicate forms. **W4 (LPLM Workload):** Uses the generator from LPLM [14] to create challenging patterns with high wildcard density and low semantic content (e.g., S0%S1%S2%...Sn%).

Finally, our analysis in Appendix A.4 and A.6 shows that single-character "_" wildcards are statistically independent of "%" wildcards, and usually appear 0-5 times per query, with occurrences of 6-7 times being less than 0.1%. Based on this finding, we augment all generated patterns across W1-W4 by randomly replacing 0-5 characters in each key with a "_", enhancing the realism of the final query predicates.

Baseline competitors: We select the following baseline competitors as they have proven their effectiveness in realistic database LIKE pattern matching deployments of PostgreSQL, or achieved

state-of-the-art open-sourced text pattern understanding performance in relevant NLP tasks [34, 120, 121]. The baselines include:
1. Prefix B+-tree: Accelerates prefix LIKE patterns through prefix-optimized B+-tree structure.
2. Suffix B+-tree: Accelerates suffix LIKE patterns using reverse-ordered B+-tree structure.
3. Prefix+Suffix B+-tree: Accelerates suffix LIKE patterns using combined prefix and suffix B+-trees.
4. Sequential scan: Baseline full-table scanning approach.
5. GIST index [39]: Accelerates LIKE via Generalized Search Tree.
6. GIN index [101]: Accelerates LIKE through Generalized Inverted Index.
7. GIN index (Approximate) [39]: Approximate LIKE matching using inverted index, following a similarity filtering technique in [25, 55].
8. Qwen2.5-7B [121]: 7B-parameter LLM developed by Qwen-Team.
9. Qwen2.5-32B [121]: 32B-parameter LLM developed by Qwen-Team.
10. DeepSeek-V2.5 [34]: 236B-parameter LLM developed by Deepseek.
11. DeepSeek-V3 [120]: State-of-the-art open-sourced 671B LLM.

Experimental settings: The language model of SMILE is configured with a hidden layer size of 512 and a single attention layer. During training, we set the learning rate to 3×10^{-4} and the batch size to 16384. For the SMILE's classifier, we maintain the same hidden layer size of 512 but adjust the batch size to 2048 and the learning rate to 1×10^{-4}. We establish a classification threshold of 16 for the query workload cardinality. When training the small language model, we utilize 200 sampled batches to ensure effective learning and model convergence. During inference, we set the sampling number being 64. Our SMILE is trained and evaluated on a server with a Nvidia H20 GPU and a 96-core AMD EPYC 9654 CPU. The PostgreSQL version is 16.3. To ensure a fair comparison, we first tune the optimal configuration for baselines via W3 of the TPC-H dataset on the 96-core CPU. As shown in Figure 5(a), their performance saturates at 16 parallel workers due to Amdahl's Law [12]. Beyond this point, more cores offer no advantage. Consequently, we configured all CPU baselines with 16 workers and 32 partitions for the main experiments. Our 96-core server's resources can be partitioned, simulating a multi-tenant environment. Therefore, to provide a practical and equitable comparison of economic efficiency, our cost analysis for all methods is normalized to the price of a 16-core CPU setting, which represents the most cost-effective hardware configuration. This methodology ensures a fair comparison of economic efficiency (see Figure 5(b) and Appendix G).

Evaluation metrics: We assess method effectiveness along three principal dimensions. **End-to-end retrieval latency**: Total query processing time. **Recall**: Result quality, defined as Recall = $\frac{|R_1 \cap R_2|}{|R_1|}$, where R_1 denotes the ground-truth result set and R_2 the retrieved set. **Uniformed-Cost**: To enable hardware-agnostic comparison, we adopt the rental-cost normalization from [113]. Results are reported as estimated cost per one million queries ($/1M queries), using the hourly hardware rental rates in Fig. 5(b); our full cost model is detailed in Appendix G.

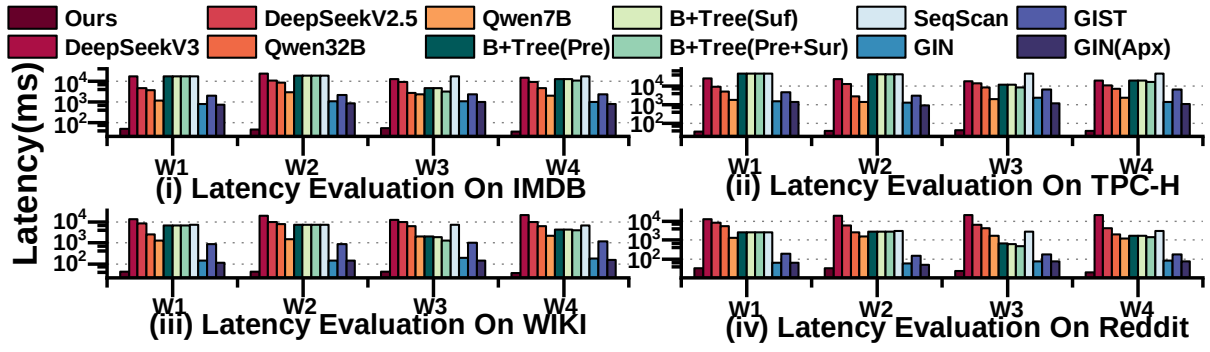
6.2 Effectiveness Evaluation

In this section, we evaluate the effectiveness of multiple LIKE retrieval methods across four datasets under four different workload patterns. We assess the effectiveness and quality of these methods from two perspectives: efficiency and quality.

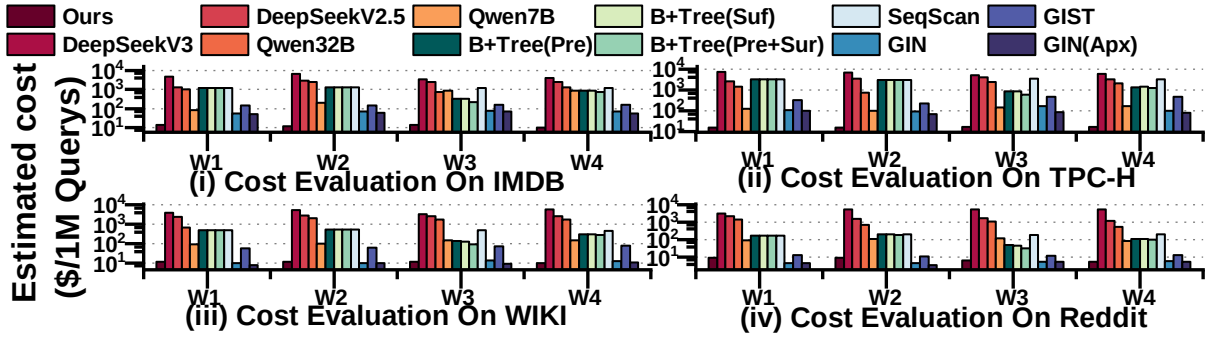
Efficiency Evaluation: We conducted a comprehensive efficiency evaluation on four diverse datasets (IMDB, TPC-H, WIKI, and Reddit), assessing performance through two key metrics: raw retrieval latency and a normalized query processing cost. As illustrated in Figure 6(a), SMILE consistently demonstrates superior retrieval latency. It achieves a $1.88 - 41.56\times$ speedup over trigram-based GIN indexes and surpasses both prefix/suffix B+-trees and full-table scans by two and three orders of magnitude, respectively. This performance stems from SMILE's design, which synergizes $O(\ell)$-time decoding with a lightweight, hash-based candidate validation mechanism. This approach effectively circumvents the inherent bottlenecks of traditional methods, such as the $O(\log N)$ complexity of tree-based indexes or the performance degradation of GIN when wildcards disrupt trigram extraction. To ensure a fair comparison, particularly given SMILE's use of GPU hardware, we also introduce a normalized cost metric (USD per million queries) that accounts for hardware and energy expenditure. This provides an equitable assessment against CPU-based baselines, with results shown in Figure 6(b). On large-scale, complex datasets like IMDB and TPC-H, SMILE's efficiency translates into a substantial cost advantage, proving to be one to two orders of magnitude more cost-effective than all baselines. For instance, its cost on IMDB is significantly lower than that of the GIN index. However, on smaller datasets like Reddit, where the overhead of our model is less amortized, the cost advantage narrows. Under such smaller dataset, the highly-optimized GIN index is 2× more cost effective than SMILE. In summary, while GIN remains a viable option for smaller workloads, SMILE's architecture delivers both superior speed and unparalleled cost-efficiency for the large-scale, complex pattern matching tasks that are the primary target of modern data systems.

Quality evaluation: Figure 7(a) evaluates LIKE search quality across four datasets and query patterns. While conventional deterministic indexes ensure perfect recall at a high computational cost, approximate methods like GIN(Apx) falter on most datasets. LLM-based approaches show performance scaling with model size; large models like DeepSeek-V3 (671B) achieve certain recall up to 0.8 on simple patterns (W1, W2), but their performance collapses (<0.1) on complex ones (W3, W4), revealing an inability to grasp data semantics in a database specific domain. In stark contrast, our compact SMILE model consistently delivers high recall (>0.9) across all workloads. This demonstrates the efficacy of a specialized, data-aware model for LIKE predicate evaluation, positioning SMILE as a robust solution where both accuracy and efficiency are critical.

End-to-End Performance on Realistic Workloads. Figure 7(b) presents a comprehensive end-to-end (E2E) evaluation of SMILE on complex queries from the TPC-H (T) and IMDB-JOB (J) benchmarks, selected for their challenging LIKE predicates. As shown in Figure 7(b)(i), SMILE consistently outperforms all baselines, achieving speedups of 1.18× to 9.51× over the next-best method. This demonstrates its practical utility in accelerating full query plans that include complex operations like joins and aggregations. Figure 7(b)(ii) confirms that this performance gain is achieved while maintaining a consistently high recall of over 95%. This evaluation also highlights the structural fragility of trigram-based approximate indexes. Notably, GIN(Apx) exhibits highly inconsistent

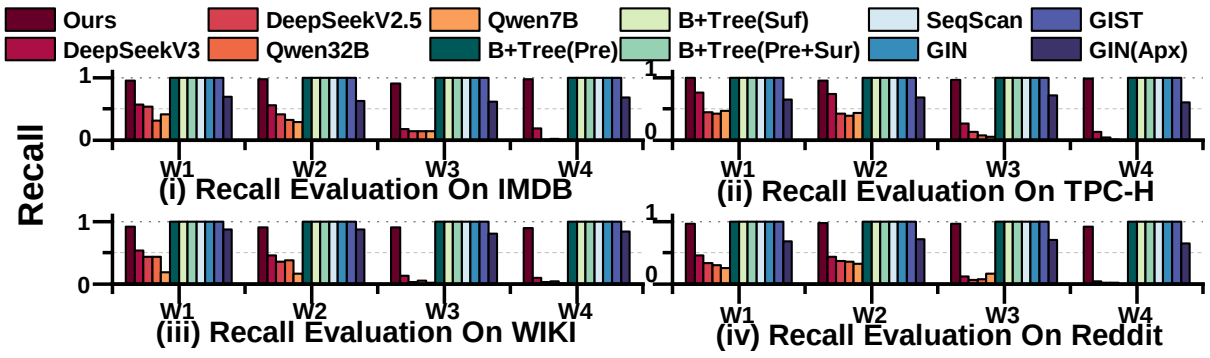


(a) Evaluation on retrieval latency.

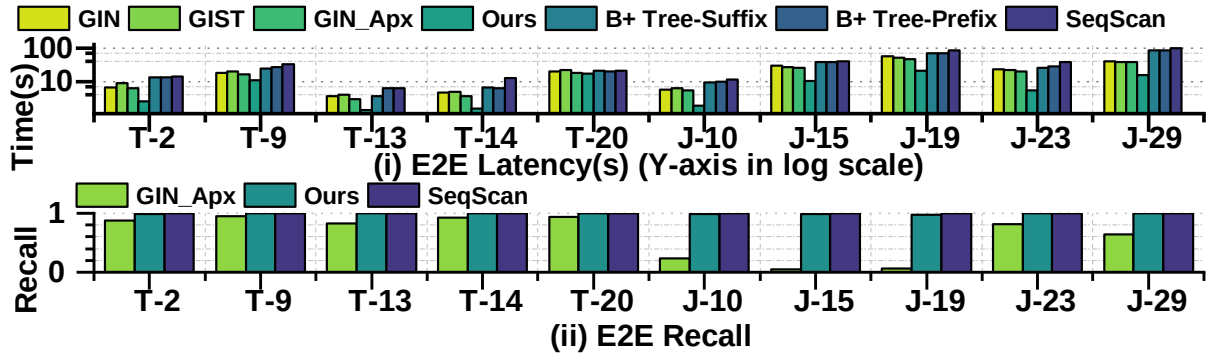


(b) Evaluation on uniformed retrieval cost

Figure 6: Evaluation on retrieval efficiency (Y-axis in log scale).



(a) Evaluation on retrieval quality.



(b) End-to-end evaluation on IMDB-JOB(J) and TPC-H(T) templates.

Figure 7: Evaluation on retrieval quality and end-to-end (E2E) performance.

recall—near-perfect on TPC-H queries but collapsing to near-zero on several IMDB-JOB templates. This discrepancy stems from the query structure: TPC-H queries often terminate with a `GROUP BY` operation, which can mask row-level filtering errors in the final

aggregated output. Conversely, the IMDB-JOB queries are direct selections where any filtering inaccuracy immediately impacts the final result set. SMILE's stable, high recall across both benchmarks underscores its robustness. While the substantial speedup from accelerating the LIKE predicate is naturally diluted by other system costs (e.g., I/O, joins) in E2E queries, the fundamental operator acceleration provides significant practical value. A more granular analysis is available in Appendix H.

Takeaway: SMILE delivers both high efficiency and high recall for LIKE retrieval across diverse workloads. *Efficiency-wise*, it outperforms trigram indexes, B$^+$-trees, and full scans, thanks to $O(\ell)$ decoding and lightweight hash-based validation—avoiding the bottlenecks of tree traversal, index degeneration, and LLM overhead. *Quality-wise*, SMILE achieves over 0.9 recall on all patterns, far surpassing LLMs while matching deterministic indexes. Its compact design enables sub-20 ms inference without sacrificing accuracy, making it practical for accelerating complex queries.

6.3 Scalability Evaluation

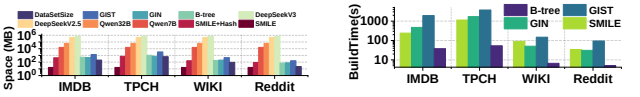
In this section, we empirically investigate the scalability of our approach through experiments, analyzing storage overhead, training cost, and inference cost.

Space scalability: Figure 8a evaluates the storage overhead of SMILE against state-of-the-art LLMs and traditional LIKE-optimized indexes. SMILE requires only ≈16MB of parameter storage, which is 3–5 orders of magnitude less than large LLMs (e.g., DeepSeek-V3, Qwen-32B). Compared to GIN, GIST, and B+-trees, SMILE reduces space consumption by 23×, 82×, and 28× in average. This efficiency arises from two factors: (1) our model's use of attention mechanisms to compactly encode workload distribution, and (2) its specialized design for database predicates, avoiding the domain-agnostic parameter bloat of general-purpose LLMs. These results confirm that SMILE achieves exceptional space efficiency without compromising task-specific effectiveness.

Training scalability: Fig. 8b evaluates SMILE's training-phase scalability against traditional indexes. On larger datasets (IMDB, TPC-H), SMILE's construction time is comparable to GIN and five times faster than GIST, though B+-tree remains fastest due to its batched, sorted-data indexing. GIN and GIST incur overhead from tokenizing column data into triplets and building inverted/general search trees over expanded token sets. SMILE exploits GPU parallelism via its attention mechanism, enabling concurrent gradient computation and updates for 10^4 tuple pairs per batch. Its compact parameter count further reduces convergence time. Consequently, SMILE achieves superior training scalability through hardware parallelism and attention efficiency.

Inference scalability: Fig. 9a shows end-to-end latency under varying sample budgets. Latency scales linearly with sample count: below 1ms for 8 samples, and close to 100ms for 512. At maximum sampling (512), this 0.1s latency is competitive with existing baselines under equivalent workloads, demonstrating superior throughput for high-volume inference.

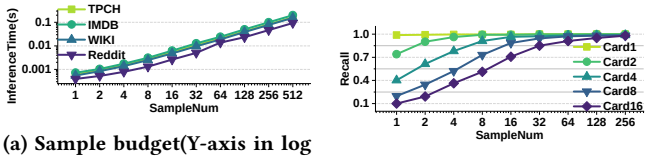
Scalability with Cardinality. Figure 9b evaluates SMILE's decoding scalability with respect to query cardinality on the TPC-H lineitem table. A fixed sample budget often suffices to achieve high recall (≥ 90%), confirming SMILE's efficiency. Moreover, the sample size needed to maintain high recall scales approximately linearly with result cardinality. This aligns with Theorem 5.2: higher-cardinality queries typically exhibit greater entropy and complexity, and the theorem predicts that the required sample size must scale accordingly—empirically observed here as a linear dependence on result size, thereby validating our theoretical bound.



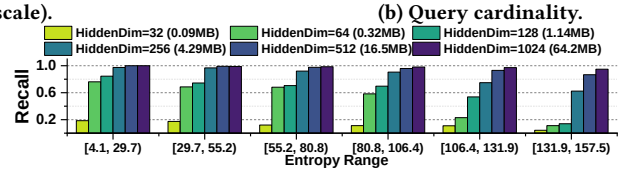
(a) Scalability on space. **(b) Scalability on building time.**

Figure 8: Scalability on space and building time(Y-axis in log scale).

Mitigating High-Entropy Challenges. High-entropy queries are inherently difficult, but our theory (Eq. 4) suggests a remedy: increasing model capacity, $|\theta|$. To validate this, we study the interplay among model size, query entropy, and recall. Figure 9c shows a representative result (Appendix C provide details). Entropy is calcualted using Eq. 2. Two insights emerge: (1) for a fixed model size, recall degrades as entropy increases, confirming entropy as a performance boundary, as predicted; and (2) this boundary is malleable—increasing model capacity significantly boosts recall, especially in high-entropy regimes. This reveals a practical scaling law: the performance penalty from high entropy can be effectively offset by larger models, offering a principled trade-off between capacity and robustness on complex workloads. See Appendix C for a comprehensive analysis.

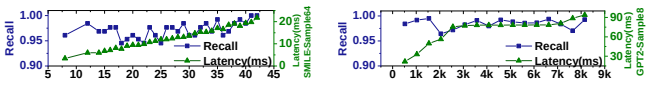


(a) Sample budget(Y-axis in log scale). **(b) Query cardinality.**



(c) Impact of model capacity across different query entropy regimes.

Figure 9: Scalability on budget, cardinality, entropy.



(a) SMILE (16MB) on TPC-H. **(b) GPT-2 (124M) on NewsRoom.**

Figure 10: Scalability with respect to string length.

Scalability with String Length. Figure 10 evaluates the scalability of our approach with respect to the length of the LIKE predicate. Figure 10a shows the performance of our standard 16MB SMILE model on the IMDB dataset for short predicates (up to 45 characters). As expected, latency scales linearly with predicate length, while recall remains consistently high. Figure 10b) demonstrates our system's ability to handle extremely long predicates, a significant challenge for traditional DBMS [93, 110]. This experiment,

conducted on W4 of the News Room dataset, utilizes an extension of our prefix generation technique (Section 5.2) with a fine-tuned 124M GPT-2 model. As detailed in Appendix B.2, we find that a remarkably small number of generated prefix samples is sufficient for high accuracy. With just 8 samples, we achieve recall above 0.95 for predicates up to 8192 characters. This result is achieved with modest overhead: latency remains under 100ms, showcasing a highly favorable trade-off between accuracy and performance. A comprehensive analysis of the interplay between sample count, latency, and recall is provided in Appendix B.2.

(a) Generalization from 1% data. (b) Varying data proportion(W4).
Figure 11: Scalability on the billion-scale RedPajama dataset.

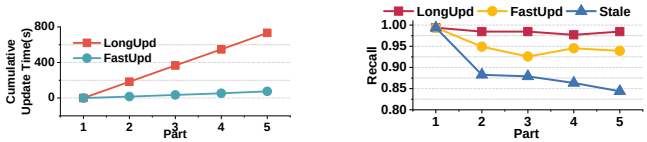
Scalability Across Billion-Scale Data. To evaluate the scalability and cost-effectiveness of our approach, we conducted experiments on the billion-record RedPajama dataset. First, we trained a 16MB SMILE model on 1% of the data and tested its generalization on an unseen, disjoint subset. As shown in Figure 11a, the model effectively learned the data distribution for simpler workloads, achieving over 0.9 recall for W2 with an inference sample size of 512. However, performance on the more complex workload W4 was lower, indicating the need for more training data. To determine the sufficient data scale, we trained models on progressively larger fractions of the dataset, focusing on the challenging W4 workload. Figure 11b shows that recall improves significantly as the training data proportion increases from 0.1% to 10%. Critically, we found that training on 10% of the data is sufficient to achieve excellent performance, yielding 0.9 recall with 512 samples. These results demonstrate that our method is both scalable and data-efficient. This finding corroborates that high performance does not require the full dataset or oversized models. Since query workload distributions are similar, the model can learn a generalizable mapping from a representative subset, making performance largely independent of absolute data scale once sufficiency is reached.

Takeaway: Our evaluation confirms SMILE is a practical and resource-efficient solution for LIKE queries, demonstrating superior scalability: **1. On Space:** 3–5 orders of magnitude smaller than LLMs. **2. On Time:** Achieves competitive build times and comparable inference latency to traditional methods, while scaling gracefully to long predicates. **3. On Data Efficiency:** Generalizes on billion-scale data by training on only a small fraction (e.g., 10%), validating its efficiency.

6.4 Robustness Evaluation

The effectiveness of SMILE primarily derives from two key factors: the learned joint character distribution across database columns and the query patterns extracted from historical workloads. To systematically evaluate the robustness of SMILE under deviations from normal conditions, we conduct controlled experiments simulating both query drift and data drift scenarios using the realworld IMDB dataset (15M tuples with maximum string length attributes). This dataset presents significant robustness challenges due to its complex string patterns and scale.

Robustness to Data Drifts. We evaluate SMILE's robustness to data drifts by simulating periodic data ingestion. The IMDB-name table is partitioned into five segments, and we test three variants: *Stale* (no updates), *FastUpd* (fine-tuned on 10 batches from each new partition), and *LongUpd* (fine-tuned on 100 batches).



(a) Update Scalability. (b) Recall Robustness.
Figure 12: Performance of SMILE under data drifts, showing the trade-off between update cost and recall.

As shown in Fig. 12, the results highlight an effective trade-off between performance and update cost. Remarkably, the *Stale* model maintains 84% recall on the final partition, demonstrating strong generalization from its initial training. The *FastUpd* strategy offers an efficient compromise, restoring recall close to 95% with a lightweight fine-tuning process that totals only 75 seconds. For maximum precision, *LongUpd* achieves near-perfect recall at a higher computational cost. This experiment confirms three key properties of SMILE: **(P1) Inherent Robustness:** It naturally generalizes to data with similar distributions, even without updates. **(P2) Efficient Adaptation:** Lightweight fine-tuning provides a cost-effective method to maintain high accuracy on evolving data. **(P3) Flexible Precision:** The architecture allows for more intensive retraining to achieve maximum precision when resources permit. These validate SMILE's suitability for dynamic environments.

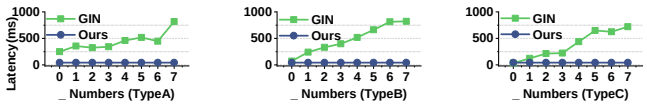
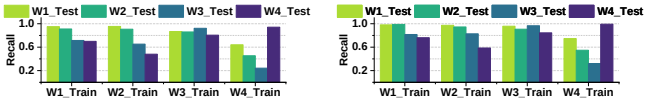


Figure 13: Robustness on wildcard patterns against inverted index.

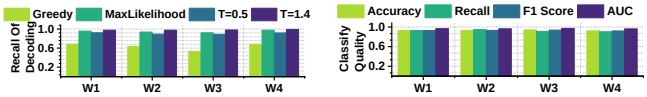
Robustness on patterns. To evaluate robustness, we compare our method against inverted index across three workloads shown in Figure 13. The workloads are designed around keyword selectivity, where a keyword is defined as high-selectivity if its data frequency is below 0.5% and low-selectivity if above 2%. **Type-A** queries ("%low%low%") conjoin two common keywords. **Type-B** ("%high%low%") contains at least one rare keyword. **Type-C** ("%word%") contains single keyword with equal mix of high and low selectivity keywords. To simulate real-world complexity, we inject a varying number of "_" wildcards (0-7) into each pattern. The results highlight a clear performance trade-off. For Type-A queries, our generative approach is substantially faster, as it holistically processes the pattern, bypassing the GIN index's expensive intersection of large posting lists. On Type-B and Type-C queries, performance is comparable since GIN can leverage a highly selective keyword or perform a direct lookup. Critically, Figure 13 shows that GIN's latency degrades significantly with more "_" wildcards, as they fragment the trigrams the index relies on. In contrast, our method's performance remains stable, demonstrating superior robustness to the complex and fragmented patterns that challenge traditional n-gram indexes. See Appendix D for a more analysis.

Robustness to Query Drifts. In Fig. 14, we investigate SMILE's OOD generalization by cross-evaluating on workloads with varying structural characteristics (W1-W4). Our analysis reveals two primary findings. First, a model trained on the diverse patterns of the W3 workload acts as a robust "generalist," adapting effectively to the realistic query structures of W1 and W2. This indicates that SMILE learns fundamental wildcard logic, not just template-specific features. However, generalization proves challenging when faced with the highly arbitrary and hard patterns of the W4 workload, which represents a significant structural shift and defines the model's performance boundaries. Second, and more importantly, this generalization gap can be substantially mitigated by increasing the inference-time sampling budget. As shown by comparing Fig. 14a and Fig. 14b, a larger sampling scale boosts recall by 10-20% on OOD templates. This highlights a key practical advantage of our approach: the ability to trade computational resources for enhanced robustness against unforeseen query drifts, effectively adapting to new patterns without retraining [35, 116, 120].



(a) Query OOD eval (S-32). (b) Query OOD eval (S-256).

Figure 14: Query drift evaluation.



(a) Decoding robustness. (b) Classification quality.

Figure 15: Decoding/Classification robustness.

Robustness of Different Decoding Methods. Fig. 15a evaluates the robustness of four decoding strategies for SMILE trained on templates from W1–W4 and tested on a disjoint set from the same wildcard workload distribution. Greedy decoding demonstrates poor generalization, frequently generating repetitive outputs and failing. Maximum likelihood and low-temperature ($T = 0.5$) decoding provide only slight improvements and remain ineffective on the more demanding W3 and W4 workloads. Conversely, high-temperature ($T = 1.4$) decoding achieves an optimal trade-off between quality and diversity, maintaining high recall across all workload patterns.

Robustness of the cardinality classifier: Fig. 15b assesses the classifier's ability to identify high-cardinality queries (threshold: 16) under varying wildcard patterns. Four classifier variants, each tuned to a specific workload pattern, achieve F1-scores >90% across all configurations. This performance arises from the SLM encoder's semantic representation, which maps query patterns into a latent space where high-cardinality queries become linearly separable. The resulting features enable the neural classifier to reliably identify and route such queries, enhancing processing efficiency.

Takeaway: SMILE exhibits strong robustness to both data and query drift. It generalizes effectively to evolving data, enabling a flexible trade-off between accuracy and fine-tuning cost. Unlike traditional inverted indexes, its performance remains stable across complex wildcard patterns. Meanwhile, SMILE mitigates query drift by trading inference-time computation for generalization: increasing the sampling budget significantly improves zero-shot recall on unseen query templates, offering a practical alternative to expensive retraining.

7 RELATED WORK

Learned cardinality estimation on `LIKE` predicates: Cardinality estimation refers to the problem of predicting the result size of a query without executing it [57], leveraging either data distributions [87, 138, 139] or query patterns [67, 86]. Recently, learned approaches have become prominent in this domain, offering superior accuracy compared to traditional histogram or sampling-based methods [139]. In terms of string `LIKE` predicates, many works target estimating the cardinality of such predicates using learned models [14, 63, 75, 80]. However, there exists a fundamental difference between the cardinality estimation problem studied in prior work and our focus on accelerating `LIKE` predicates. While cardinality estimation aims to predict the number of matching tuples, `LIKE` predicate acceleration focuses on optimizing the end-to-end execution efficiency of queries involving `LIKE` operations. Prior methods addressing `LIKE` cardinality estimation do not address the core challenge of reducing the computational overhead inherent in pattern-matching operations, which is the central objective of our proposed solution.

Learned query acceleration: Recent research efforts increasingly replace traditional data structures with machine learning components [38, 51, 70, 71, 109, 126, 130]. Learned indexes revolutionize query processing by substituting logarithmic-time tree traversals with constant-time ML model inference [51, 70, 130]. For relational data, the Recursive Model Index (RMI) [70] employs multi-layer perceptrons to predict record locations, while the Fitting-Tree [51] achieves error-bounded performance through piecewise linear regression. Current learned string indexing approaches [117, 128, 137] optimize for variable-length storage and full/prefix matches, but they fail to support arbitrary `LIKE` wildcard patterns (e.g., `%keyword%`). This limitation arises from the complex challenge of modeling substring distributions under variable wildcard configurations. Our solution bridges this gap by adapting neural sequence-to-sequence models from NLP [16, 64, 118, 127]. Rather than relying on recursive tree structures, our approach resembles neural machine translation, transforming complex `LIKE` wildcard templates into candidates that are easy to verify. This also fundamentally differs from generative retrieval in NLP [54], which generates hypothetical documents for high-quality dense retrieval; in contrast, our work performs constrained database-specific generation to accelerate matching of complex LIKE patterns.

Efficient `LIKE` Processing & Approximate String Matching: The `LIKE` predicate is ubiquitous in databases [14, 65, 75] but hard to optimize, especially for wildcard-surrounded patterns (e.g., "%keyword%") [39, 124]. While B^+-trees support prefix/suffix matches [33, 48], n-gram-based indexes (e.g., trigrams) are commonly used for general patterns via inverted [65, 101, 147] or tree structures [39]. Approximate substring matching, often based on edit distance [18, 25, 55, 82, 84, 136], addresses vague queries in interactive systems [17, 27, 62, 81]. Unlike prior work focusing on fixed-threshold, wildcard-free patterns [82], we accelerate `LIKE` execution by adopting Approximate Query Processing principles [24, 100], trading

completeness for speed. Our method returns a high-quality subset of guaranteed-correct matches, avoiding costly full scans on string columns when prefix-index optimization fails, especially given LIKE's prevalence in benchmarks like TPC-H (Q2,9,13,14,20) [125].

8 CONCLUSION

This paper introduces SMILE, a novel framework that leverages a small language model to accelerate complex LIKE queries with complex wildcards. Our evaluation shows that SMILE outperforms traditional indexing structures by up to three orders of magnitude in execution time and remains robust to shifts in both data and query distributions, highlighting its potential for modern DBMS. Our work suggests several promising directions for future research. First, the core idea: casting complex query execution as neuron translation—can be extended beyond wildcard matching to other costly operations, such as regular expression evaluation and similarity joins. Second, while our current transformer-based SLM is effective against LLMs, more lightweight or database-native architectures may reduce inference overhead, particularly for high-entropy workloads where existing decoding struggles. In the future, we aim to develop more effective learned structures, enabling controllable trade-offs between performance and accuracy across diverse situations.

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APPENDIX NAVIGATION

This appendix provides a comprehensive suite of empirical analyses, scalability studies, and implementation details that underpin the claims and contributions of our paper. To help readers navigate this rich supplementary material, we offer the following roadmap:

(1) **Section A (An Empirical Analysis of Real-World LIKE Predicate Usage)** presents the foundational study of 84,047 real-world LIKE predicates across 30 diverse datasets. It characterizes the distribution of wildcards (% and _), validates the semantic nature of masked substrings, and analyzes selectivity and positional correlations—providing the empirical motivation for our approach.

(2) **Section B (In-depth Scalability Analysis)** investigates how our method scales to billion-record datasets and long-text predicates. It demonstrates that high performance can be achieved with modest training data fractions and that a fine-tuned GPT-2 model enables efficient, high-recall prefix generation for inputs up to 8,192 characters with sub-100ms latency.

(3) **Section C (Empirical Validation of Theoretical Guarantees)** offers experimental evidence for our theoretical framework, confirming that pattern entropy predicts query difficulty and that increasing model capacity yields a clear scaling law for recall—especially for high-entropy patterns.

(4) **Section D (In-Depth Performance Analysis against Trigram-based Indexes)** conducts a fine-grained comparison with GIN indexes across three workload types, revealing SMILE's superiority on conjunctive low-selectivity queries and its robustness to underscore (_) fragmentation.

(5) **Section E (Workload Construction)** details the algorithmic procedure used to generate linguistically grounded synthetic workloads (W1 and W2), ensuring realism through syllable- and morpheme-level masking.

(6) **Section F (Optimizing Baselines via Parallelism and Partitioning)** documents our rigorous effort to maximize baseline performance through CPU parallelism and data partitioning, establishing a strong and fair performance ceiling governed by Amdahl's Law.

(7) **Section G (Cost-Effectiveness Model)** introduce the unified cost model.

(8) **Section H (An In-depth Study of End-to-End Performance)** validates SMILE's practical impact on full query execution in standard benchmarks (TPC-H and IMDB-JOB), demonstrating consistent latency reduction and over 95% recall while contextualizing the relationship between predicate-level acceleration and end-to-end gains.

(9) **Section I (Theoretical results)** provides the detailed derivations for the theoretical results presented in Section 5.1.

Together, these sections provide rigorous, reproducible, and multi-dimensional validation of our system's design, efficacy, and practicality in real-world database environments.

A AN EMPIRICAL ANALYSIS OF REAL-WORLD LIKE PREDICATE USAGE

This chapter presents a comprehensive empirical study on the usage patterns of LIKE predicates in real-world scenarios. Our primary objective is to uncover and characterize the prevalent patterns that emerge from a large-scale analysis of diverse datasets.

Our investigation is structured to answer several key research questions: (1) How does this large-scale survey differ from and extend previous work in this area? (2) What is the statistical distribution of the percentage sign ("%") wildcard in typical "LIKE" predicates? (3) Similarly, what is the distribution of the underscore ("_") wildcard? (4) What is the interplay and co-occurrence relationship between the "%" and "_" wildcards within the same predicate?

A.1 Comparison with Prior Work

While our study is the most extensive to date, we build upon foundational work that first highlighted the importance of "LIKE" predicate analysis. A notable example is the work presented in [75], which investigated patterns within the well-known IMDB Join Order Benchmark (JOB). The authors made a key observation that: "LIKE predicates appearing in the Join Order Benchmark (JOB) workload have typically 2 or 3 %s, and there is a single or two words between two contiguous %s."

However, while this seminal study provided valuable initial insights, its conclusions are drawn from the relatively narrow context of the JOB workload, which comprises only 195 "LIKE" predicates from a single domain. The benchmark's primary focus on join order optimization means it may not fully represent the diverse ways "LIKE" predicates are utilized across the broader spectrum of database applications. To establish a more general and robust understanding, our research broadens this scope significantly. We perform a large-scale analysis of 84,047 "LIKE" predicates extracted from 30 distinct and diverse datasets, offering substantial advantages in scale, diversity, and the breadth of application contexts. The details of the workloads we collected are shown in Table 2. The complete workload, including all datasets link and predicates, is publicly available at "https://anonymous.4open.science/r/SMILE-0D8B/Realworld_84047LIKE.csv". Details are summarized in Table 2.

Grounded in this extensive and diverse corpus, our study systematically dissects the characteristics of real-world "LIKE" predicates. We begin by analyzing the distribution and structure of the most common wildcards, then delve into the semantic meaning of the enclosed keywords, and finally investigate their impact on query selectivity and execution complexity. This multi-faceted analysis validates our core hypotheses and reveals key characteristics that motivate our proposed approach.

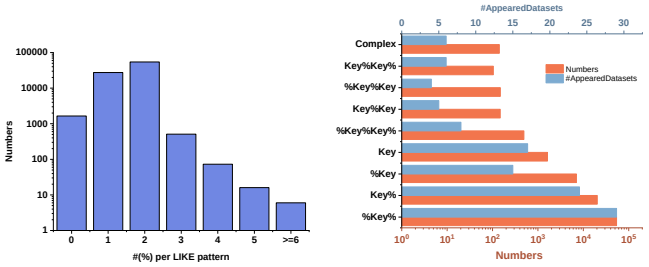
A.2 Distribution and Patterns of the % Wildcard

We begin by investigating the usage of the most common wildcard, "%". Our analysis aims to validate that patterns with leading and/or trailing wildcards, such as "%key%" and "%key1%key2%", are the most prevalent forms that challenge traditional prefix-based indexing.

Figure 16(a) illustrates the frequency of "%" occurrences within a single "LIKE" predicate. The y-axis is on a logarithmic scale to accommodate the wide distribution. It is evident that queries containing one or two "%" wildcards are overwhelmingly dominant,

Table 2: Overview of realistic SQL workloads employed in our evaluation

Dataset Source	Num of LIKEs	Avg. Num of % Signs per LIKE	Number of LIKEs Containing _	Length Distribution Of LIKEs 50%	75%	90%	100%	Category	Avg.Table.Rows
AMBI-QT [122]	1142	1.80	0	5	7	10	21	Fine-tuning Analysis	1838
ST2S [92]	3383	1.65	24	8	12	16	38	Pretraining / Text-to-SQL	2
SQL-Advising [73]	271	0.90	12	6	13	14	14	Fine-tuning Analysis	8807
BULL [1]	159	1.39	0	5	11	17.2	35	General LLM DB Reasoning	3294
CSS [2]	390	1.87	0	4	5	5	6	Chinese Domain SQL	7421
Cpiser [94]	207	0.56	0	2	3	6	18	Chinese Domain SQL	17
JOB [3]	194	2.00	0	8	10	13	35	Query Optimization	3526284
KaggleDBQA [78]	18	1.88	0	9	12.5	17.5	24	Fine-tuning Analysis	280035
EHRSQL [79]	1479	2.00	0	8	8	8	8	Medical SQL QA	108000
LogicCat [4]	66	1.87	0	8.5	14	16	27	Logical Reasoning	20
SQL-NLP [99]	24	1.58	0	9	10	14	14	Educational Demo	24441
SocialMediaQueries [119]	21	1.95	4	10	15	19	23	Social Media SQL QA	45649087
SpiderSS [5]	188	1.81	0	5	7.25	11	21	Data Augmentation	1838
TPCH [31]	7	1.71	0	4	6.5	12.6	21	SQL Engine Benchmark	3400000(SF=1)
Advising [72]	126	1.80	0	8	13	14	14	Fine-tuning Analysis	8807
Beaver [6]	31	1.03	0	3	3	8	17	Enterprise SQL QA	46108
Bird [19]	833	0.76	7	6	10	22	178	Complex JOIN Reasoning	707332
Chase [134]	627	1.69	0	4	6	8	21	Logical Parsing	999
Cosql [141]	21	2.00	0	6	10	11	16	Conversational SQL QA	1838
Dusql [106]	119	0.00	0	2	2	3	5	Chinese SQL QA	5
Sciencebench [69]	51	1.82	0	5	7	11	19	Scientific Domain SQL QA	1256108
Sede [59]	6275	1.84	70	9	13	18	104	NL2SQL	40903150
Sesql [77]	614	1.66	5	4	4	5	8	Chinese SQL QA	5
Sparc [143]	8	2.00	0	5.5	7.75	10	10	Multi-turn SQL Generation	1838
Spider [142]	281	1.62	0	6	9	13	42	Generalization and Schema Linking	1838
Spider-DK [53]	14	1.57	0	5	5.75	6.7	7	Data Augmentation	10
Spider2 [135]	90	1.67	0	8	10	12	21	Large scale DB QA	5273M
Spidersyn [52]	176	1.80	0	5	8	11	21	Data Augmentation	1838
OmniSQL [112]	67058	1.62	1467	8	11	16	110	Pretraining / Text-to-SQL	16
Vanna [11]	174	2.16	0	12	21	43	91	Fine-tuning Analysis	98339



(a) Frequency of "%" per query (log scale). **(b) Top-5 most frequent LIKE patterns.**

Figure 16: Distribution analysis of the "%" wildcard in LIKE predicates. (a) shows the number of "%" characters per query, highlighting the dominance of 1- and 2-wildcard queries. (b) shows the absolute frequency (blue) and dataset prevalence (orange) of the most common patterns.

accounting for 27,485 and 54,309 instances, respectively. This confirms that multi-keyword substring searches are a widespread phenomenon.

Figure 16(b) delves deeper into the structural patterns of these queries. The "%key%" pattern is, by a significant margin, the most frequent, appearing over 34,000 times across 29 distinct datasets. The "key%" pattern follows, with over 20,000 occurrences. Notably, patterns with multiple keywords, such as "%key1%key2%", are also highly common, ranking fifth in frequency. The dataset prevalence (orange bars) further underscores that these index-unfriendly patterns are not artifacts of a single application but are a pervasive feature across diverse database workloads.

Takeaway: The "%key%" and "%key1%key2%" patterns are one of the most common and widespread structures in real-world "LIKE" queries, confirming and highlighting the critical need for solutions that can efficiently handle leading wildcards.

A.3 Empirical Validation of Workload Generation

To substantiate the rationale behind our realism-driven workloads (W1 and W2), we conducted an empirical study to analyze the semantic nature of substrings masked by wildcards in real-world queries. The central hypothesis is that for the most challenging LIKE patterns (i.e., those with leading wildcards), the masked portions are not arbitrary character sequences but typically correspond to a small number of fundamental linguistic units. Validating this hypothesis is crucial, as it ensures our synthetic workloads accurately reflect the challenging yet meaningful search patterns encountered in production environments.

Our investigation analyzed a corpus of 84,047 production LIKE queries, focusing on the most prevalent patterns. We employed Deepseek V3 to perform a statistical analysis, classifying the content masked by the wildcard ("%") into three categories: *morphemes* (the smallest meaningful units in a language), *syllables* (units of pronunciation), and *others*. The "Others' category encompasses substrings with low semantic or phonetic significance, such as numerical sequences, punctuation, or arbitrary character fragments. It is important to note that the morpheme and syllable categories are not mutually exclusive; a substring can represent both. For instance, in a query like "%MOD%" against the string "SIGMOD",

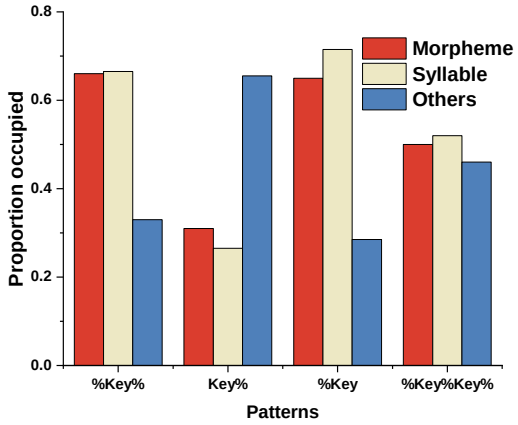


Figure 17: Statistical analysis of wildcard-masked content in common LIKE patterns from realistic patterns. The bars show the proportion of masked substrings that can be described by morphemes, syllables, or other content types.

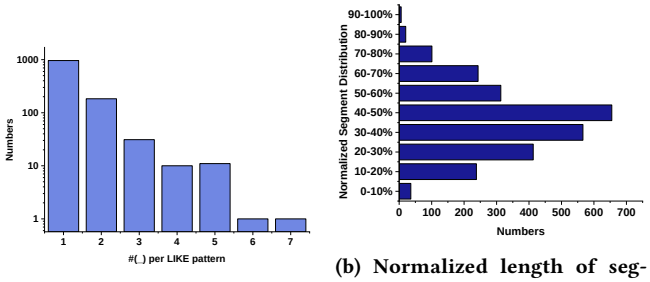
the masked prefix "SIG" can be interpreted both as a syllable for pronunciation and as a morpheme representing a 'special Interest Group". Figure 17 presents the results of this analysis. The findings strongly support our hypothesis for the most index-unfriendly patterns:

- For infix patterns such as %Key% and %Key%Key%, a significant majority of the masked substrings correspond to morphemes (approx. 66% and 50%, respectively) and syllables (approx. 67% and 53%). This indicates that users frequently formulate infix searches by omitting one or two meaningful or pronounceable chunks from the beginning, end, or middle of a string.
- Similarly, for suffix queries (%Key), the masked prefixes are predominantly morphemes (65%) and syllables (72%). This pattern suggests users often know the ending of a string but are uncertain about a well-defined prefix, which might be a name, a category, or another semantic unit.
- Conversely, for prefix patterns (Key%), the "Others' category dominates (65%). This is an insightful result, suggesting that when users know the beginning of a string, the unknown suffix is often not a clean linguistic unit but rather an arbitrary truncation. However, prefix queries are efficiently handled by traditional indexes like B+-trees and are not the primary focus of our work on accelerating challenging LIKE queries.

Takeaway: Empirical analysis of 84,047 production queries reveals that wildcards in challenging infix and suffix LIKE patterns predominantly mask a small number of semantic (morphemes) or phonetic (syllables) units. This finding validates our principled, linguistics-based approach to generating realistic and challenging workloads.

A.4 Analysis of the _ Wildcard

While the "%" wildcard is dominant, the single-character wildcard, "_", also appears in real-world queries, introducing distinct challenges due to its fixed-length matching semantics.



(a) Frequency of "_" per query. **(b) Normalized length of segments delimited by "_".**

Figure 18: Usage characteristics of the "_" wildcard. (a) shows that most queries use "_" sparingly. (b) reveals that segments created by "_" are predominantly short.

As shown in Figure 18(a), the absolute frequency of "_" is substantially lower than that of "%". Most queries that use this wildcard contain only one or two instances. However, its impact on query complexity is disproportionate. Figure 18(b) reveals a critical characteristic: the length distribution of substrings (segments) delimited by "_". A vast majority of these segments are extremely short. This proliferation of short, often low-selectivity segments (e.g., single characters or stop words) poses a significant challenge for optimization.

Takeaway: "_" wildcard, though less frequent than "%", fragments query patterns into very short substrings. This fragmentation can drastically increase the optimization difficulty.

A.5 Selectivity Analysis of Keyword Conjunctions

A key question is whether %Key%Key% queries commonly feature a conjunction of low-selectivity keywords that collectively yield a high-selectivity result. Such queries may be notoriously difficult for traditional systems. To investigate this, we approximated keyword selectivity by measuring word frequencies in the large-scale sample from Common Crawl text corpus with ten billion tokens [123]. This choice is motivated by the observation that most LIKE-based predicates in practice operate over relatively small datasets. If we were to estimate selectivity directly from such small datasets, we would encounter significant statistical instability: for databases with fewer than 100 tuples, the estimated selectivity of a rare keyword would be either $1/|D|$ or 0, leading to unreliable and highly variable estimates. To avoid this circular dependency and ensure consistent, statistically robust frequency estimates, we instead adopt the Common Crawl corpus—a large, publicly available, and representative text corpus—as a unified source for approximating keyword frequencies.

Table 3: Prevalence of queries where all individual keywords have low selectivity (frequency > threshold) but their conjunction has high selectivity (frequency < threshold).

Individual Keyword Selectivity Threshold (>)	Joint Pattern Selectivity Threshold (<)	Qualifying Queries	Total Queries	Proportion (%)
1e-05	1e-07	590	1009	58.47
1e-05	1e-06	687	1009	68.09
1e-04	1e-07	190	1009	18.83
1e-04	1e-06	237	1009	23.49
1e-04	1e-05	257	1009	25.47

Table 3 quantifies this phenomenon. The results are striking. For instance, when defining "low selectivity" as a keyword frequency greater than 1e-05 and "high selectivity" as a joint pattern frequency less than 1e-07, we find that a remarkable **58.47%** of multi-keyword queries fit this profile. This proportion rises to **68.09%** when the joint selectivity threshold is relaxed to 1e-06.

> **Takeaway:** A majority of real-world multi-keyword "LIKE" queries are composed of individually common terms whose intersection is highly selective. This is a common user behavior for filtering large datasets and represents a critical workload characteristics.

A.6 Positional Correlation of % and _ Wildcards

Finally, we investigate the relationship between the positions of "%" and "_" wildcards when they co-occur in a query. Understanding this relationship is important for building a realistic workload.

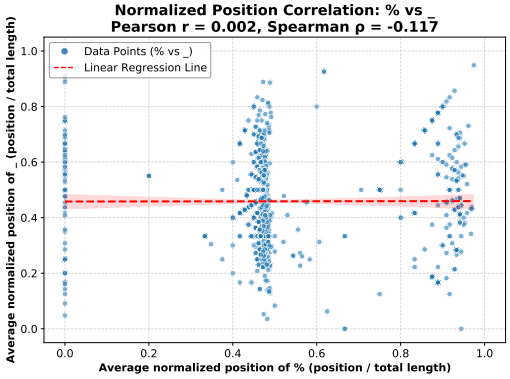


Figure 19: Positional correlation between "%" and "_" wildcards in co-occurring queries. The near-zero correlation coefficients (Pearson $r = 0.002$, Spearman $\rho = -0.117$) indicate a lack of relationship between their normalized positions.

Figure 19 plots the average normalized position of "_" against the average normalized position of "%" for each query containing both. The scatter plot reveals no discernible pattern, appearing as a random cloud of points. This visual observation is statistically confirmed by the Pearson and Spearman correlation coefficients, which are both extremely close to zero.

> **Takeaway:** The positions of "%" and "_" wildcards within a query are close to statistically independent. This suggests that users employ them as orthogonal tools to specify different and unrelated constraints on a string's structure, rather than using them in a coordinated, patterned way. Consequently, a system claiming full LIKE support have to prepare for the simultaneous presence of "%" and "_" and optimize accordingly by treating their positional constraints as independent variables.

B IN-DEPTH SCALABILITY ANALYSIS

In this section, we conduct a more in-depth analysis of the scalability of our proposed method. We focus on two critical aspects:

(1) How does our methodology scale to billion-scale datasets?

(2) How does our methodology support long text inputs?

To address these questions, we selected two appropriate datasets for a comprehensive evaluation.

- **RedPajama** [123]: We utilized a 1TB corpus from the RedPajama dataset. We segmented the data into words, extract a dataset of 1 billion unique string windows, each with a maximum length of 40.
- **News Room** [56]: This dataset was used for evaluating long-text performance. Containing 1,212,741 articles with average string length being 3962.

B.1 Scalability to Billion-Scale Datasets

Training models on billion-scale datasets presents significant computational and financial challenges. This section addresses a fundamental question in large-scale data modeling: how can our method be applied to datasets comprising a billion or more records in a cost-effective manner? Specifically, we investigate several key subquestions: Can a compact model, such as SMILE, effectively learn the data distribution and converge when trained on such massive datasets? What level of generalization performance can be expected? More importantly, is it necessary to train on the entire billion-record corpus, a process that entails significant computational and financial expenditure? Or, can we achieve high performance by training on only a small fraction of the data, thereby enabling a more cost-effective scaling strategy? In this section, we conduct two targeted experiments on the billion-record RedPajama dataset to explore these questions and demonstrate the scalability and data efficiency of our approach.

Experiment 1: Generalization on a Data Subset. This experiment evaluates the generalization performance of our model when trained on a small subset of a billion-scale dataset. We sampled two disjoint 10-million-record subsets, denoted as A and B, from the full RedPajama dataset. We trained our 16MB SMILE model on subset A and evaluated its performance on a 4,096-record sample drawn from subset B. This setup ensures that the test data was strictly held-out and entirely unseen during the training phase. The results are presented in Figure 20.

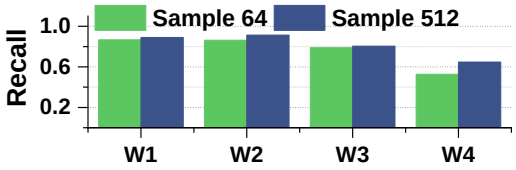


Figure 20: Generalization performance on the RedPajama billion-scale dataset. The model is trained on only 1% of the data and tested on an independent, unseen subset.

As shown in the figure, the model demonstrates strong generalization capabilities, particularly for the less complex workloads W1, W2, and W3. Specifically, with an inference sample size of 512, the recall for W1, W2, and W3 exceeds 0.88, 0.90, and 0.80, respectively. This result indicates that the model can effectively capture the underlying data distribution even when trained on a small fraction (in this case, 1%) of the total dataset. Moreover, increasing the inference sample size from 64 to 512 consistently improves recall across all

workloads, highlighting the model's ability to leverage larger sample sets at inference time to refine its predictions. Conversely, the recall for the more complex workload W4 is comparatively lower. This suggests that capturing its more intricate data patterns likely necessitates a larger training set, a hypothesis we investigate in the next experiment.

Experiment 2: Determining Sufficient Data Scale. To quantify the relationship between training data volume and model performance, we conducted a focused experiment on the challenging W4 workload from the RedPajama dataset. The objective was to identify the minimum training data fraction required to achieve high performance, thereby determining a cost-effective training strategy. We trained separate models on incrementally larger subsets of the data, ranging from 0.01% to 15% of the full dataset. The results are depicted in Figure 21.

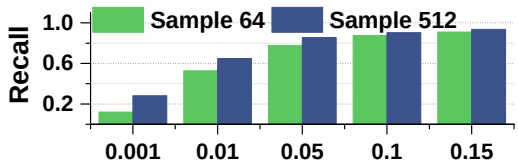


Figure 21: Impact of training data size on generalization for the W4 workload.

The results, depicted in Figure 21, reveal a clear trend: model performance improves substantially as the training data fraction increases. Training on only 0.1% of the data yields low recall (below 0.3 for a sample size of 512), although performance can still be improved by increasing the sample size during inference. As the training data proportion grows, recall steadily climbs. For workload W4, we observe that training on approximately 10% of the data achieves excellent results: recall surpasses 0.87 with an inference sample size of 64 and reaches 0.9 with a sample size of 512. This finding is significant: it demonstrates that our method not only scales to billion-record datasets but also achieves high performance cost-effectively. By training on a strategically chosen subset (e.g., 10% for complex workloads), we can avoid the prohibitive costs associated with full-corpus training while still attaining excellent generalization.

B.2 Scalability on Long Text Predicates

To rigorously evaluate our method's performance on long text predicates, a known challenge for traditional database systems, we conducted a scalability analysis using the "News Room" dataset and our most challenging workload, W4. Many commercial DBMSs impose strict length limitations on "LIKE" patterns; for instance, SQL-Server [93] has a limit of 8192 characters, while SAP HANA's is 128 [110]. We adopted the 8192-character limit as the upper bound for our tests to demonstrate our system's ability to operate well beyond typical industrial constraints.

In this experiment, we employed a fine-tuned GPT-2-Small (124M) model, as detailed in Section 5.2, to generate 40-character prefixes for given "LIKE" patterns. A key parameter in our approach is the number of generated prefix samples, which we denote as k. To understand the trade-off between accuracy and performance, we systematically varied k from 1 to 8. The inference overhead for this process is O(|Prefill| + $k\times$ |Output|). Since the output length is a fixed-size prefix, latency is primarily influenced by the input string length (|Prefill|) and the number of samples k. The results, showcasing the interplay between recall, latency, input length, and sample count, are presented in Figure 22 and Figure 23.

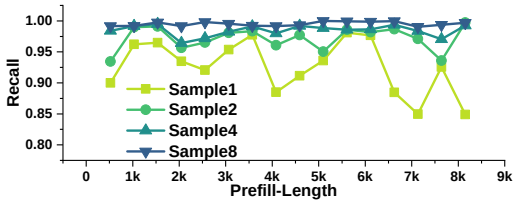


Figure 22: Recall vs. Input String Length for a varying number of generated samples (k). Increasing k significantly improves and stabilizes recall, with $k = 4$ consistently achieving over 95% and $k = 8$ approaching near-perfect accuracy.

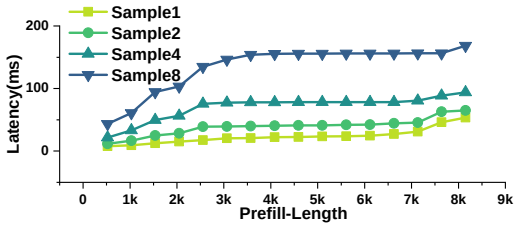


Figure 23: Latency vs. Input String Length for a varying number of generated samples (k). Latency scales linearly with both input length and k, but remains well under 100ms for the highly effective $k = 4$ configuration.

The results reveal two critical insights. First, as depicted in Figure 22, our method demonstrates exceptional prefix generation efficiency. While a single sample ($k = 1$) yields volatile recall, performance dramatically improves and stabilizes as k increases. Notably, with just $k = 4$ samples, the recall consistently surpasses the 95% threshold across all tested input lengths up to 8192 characters. Increasing to $k = 8$ further pushes the recall to near-perfect levels, offering a configuration for applications demanding maximum accuracy. This underscores the superior generative capability of the GPT-2 model in this task; it achieves high coverage with a remarkably small number of samples, a stark contrast to the standard SMILE(16MB) which require 64 samples to attain similar coverage in shorter text length.

Second, this high recall is achieved with minimal latency overhead, as shown in Figure 23. The latency scales linearly and predictably with both the input length and the number of samples k. While generating more samples naturally incurs a higher computational cost, the overhead remains modest and practical. For the $k = 4$ setting, which delivers excellent recall, the end-to-end latency stays comfortably below 100ms even for the longest inputs. Even in the most demanding $k = 8$ scenario, the latency remains under 180ms. This demonstrates a highly favorable trade-off, allowing practitioners to tune the parameter k to meet specific application requirements for accuracy without incurring prohibitive performance penalties.

Takeaway: Our method exhibits outstanding scalability for long text queries, effectively overcoming the stringent length limitations of conventional DBMSs. By leveraging a fine-tuned GPT-2 model, it achieves over 95% recall with as few as 4 generated prefix samples, maintaining low latency (under 100ms) even for inputs up to 8192 characters. This highlights a powerful and practical trade-off between near-perfect accuracy and high performance.

C EMPIRICAL VALIDATION OF THEORETICAL GUARANTEES

In Section 5.1, we established a theoretical framework that links a `LIKE` pattern's intrinsic complexity, quantified by its entropy $H(\mathcal{P})$, and a model's capacity, represented by its parameters $|\theta|$, to the expected query performance. This section presents a series of targeted experiments designed to empirically validate the core hypotheses derived from our theory. Specifically, we aim to verify two key predictions: (1) that query recall is inversely correlated with pattern entropy, and (2) that increasing model capacity systematically improves recall, particularly for high-entropy queries, suggesting a scaling law for neural `LIKE` decoding.

C.1 Impact of Pattern Entropy on Recall

Hypothesis. Our theoretical model, particularly Eq. 4, posits an inverse relationship between a pattern's entropy $H(\mathcal{P})$ and the model's success probability, which directly translates to recall. Higher entropy implies greater uncertainty in the generative process, making it inherently more challenging for the model to produce correct values. This increased uncertainty should manifest as a performance boundary, leading to lower recall for high-entropy patterns.

Experimental Setup. To test this hypothesis, we conducted an experiment on the real-world IMDB-Name dataset. We generated a workload of 2,000 queries based on the W1 template. For each query, we calculated its pattern entropy based on the data distribution. Subsequently, we partitioned the queries into fine-grained clusters based on their entropy values and measured the average recall for each cluster.

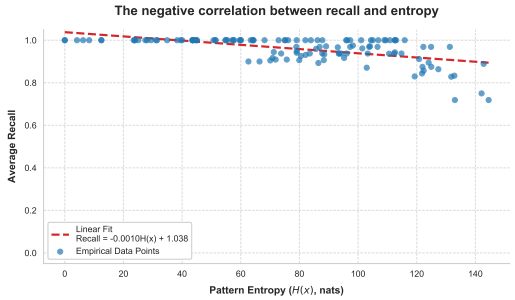


Figure 24: Negative correlation between average recall and average pattern entropy per cluster on the IMDB dataset. Each blue dot represents a cluster: its x-coordinate is the mean entropy of the cluster's patterns, and its y-coordinate is the cluster's mean recall. The red dashed line shows the linear regression fit.

Results and Analysis. Figure 24 presents the scatted results on each cluster centroid, plotting average recall as a function of pattern entropy. The empirical data points clearly demonstrate a strong negative correlation between the two variables. As pattern entropy increases, the average recall systematically decreases. The superimposed linear regression line (Recall $\approx -0.0010 \cdot H(\mathcal{P}) + 1.038$) quantitatively confirms this downward trend, providing strong evidence for our hypothesis.

This result empirically validates our theoretical assertion. Patterns with low entropy (e.g., `"John%"`), correspond to states in the generative FSM with low branching factors and highly skewed transition probabilities, making them easy for SMILE to decode. Conversely, high-entropy patterns (e.g., `"%son%"`), introduce significant uncertainty at multiple decision points within the FSM. This inherent ambiguity acts as a performance boundary for the model. Nevertheless, it is noteworthy that even for patterns with entropy exceeding 120 nats, SMILE maintains a respectable recall above 0.8, demonstrating its resilience and ability to retain fundamental decoding capabilities even for the most challenging queries.

C.2 Scaling Model Capacity for High-Entropy Patterns

Hypothesis. While high entropy poses a challenge, our theory (Eq. 4) also predicts that this challenge can be mitigated by increasing the model's capacity $|\theta|$. A larger model possesses greater capacity M to memorize and generalize the complex transition rules of the data's underlying FSM. Therefore, we hypothesize that increasing model size will enhance its decoding capability, leading to improved recall across all entropy levels, with the most significant gains observed in the high-entropy regimes.

Experimental Setup. We extended our experiment on the IMDB W1 workload to investigate the relationship between model size, pattern entropy, and recall. We trained and evaluated six variants of SMILE with different hidden dimensions, corresponding to parameter sizes ranging from 0.09MB (HiddenDim=32) to 64.2MB (HiddenDim=1024). We then measured their recall performance across six distinct entropy ranges, from low ([4.1, 29.7)) to very high ([131.9, 157.5]).

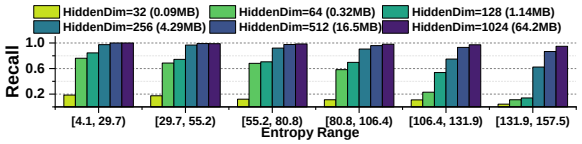


Figure 25: Impact of model size on recall across different entropy ranges. Within each entropy bracket, larger models consistently achieve higher recall. The performance advantage of larger models becomes more pronounced as entropy increases. Notably, for the highest entropy regime (Entropy > 137), maintaining recall above 0.9 requires scaling model capacity to HiddenDim=1024 (64.2MB).

Results and Analysis. Figure 25 illustrates the results of this experiment. The findings are threefold and strongly support our hypothesis.

(1) **Consistent Improvement:** Within any given entropy bracket, recall consistently and monotonically increases

with model size. For instance, in the moderate entropy range [55.2, 80.8), the recall improves from approximately 0.12 for the 0.09MB model to over 0.95 for the 16.5MB model.

(2) **Widening Performance Gap:** More importantly, the performance gap between smaller and larger models widens as entropy increases. For low-entropy queries ([4.1, 29.7)), even the smallest model achieves a reasonable recall of nearly 0.2, and the largest models quickly approach perfect recall. However, for the highest-entropy queries ([131.9, 157.5]), the smallest models are nearly ineffective (recall < 0.05), whereas the largest 64.2MB model maintains a robust recall of over 0.9.

(3) **Capacity-Entropy Coupling:** Crucially, our extended experiments reveal a quantitative relationship between model complexity and workload entropy. To maintain recall above 0.9 in high-entropy regimes (Entropy > 106), model capacity must scale accordingly to HiddenDim=1024 (64.2MB). This phenomenon directly validates the core claim of Theorem 5.2: model complexity couples with workload entropy $H(W)$. This quantitative relationship provides clear guidance for system deployment, enabling appropriate model configuration based on specific workload characteristics.

These results provide compelling evidence for the second part of our theory. Larger models, with their greater parameter count $|\theta|$, are better equipped to learn the intricate character-level distributions required to navigate the high-uncertainty state transitions defined by complex LIKE patterns. This phenomenon suggests the existence of a *scaling law for neural LIKE predicate decoding*: investing more model parameters yields predictable and significant improvements in decoding accuracy, especially for the most ambiguous and difficult segments of the query workload. This validates the crucial role of model capacity, $M = \alpha|\theta|$, in our theoretical framework and demonstrates a practical path to enhancing performance by scaling the model architecture.

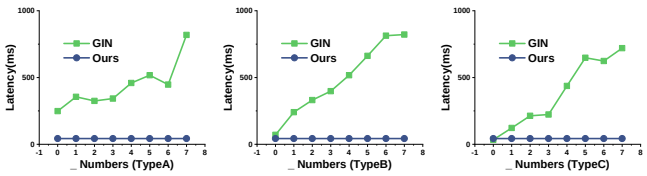
Takeaway. In summary, our empirical validation yields three critical insights that directly support our theoretical framework. First, we confirm that pattern entropy is a robust and accurate predictor of query difficulty, establishing a clear performance boundary dictated by the inherent uncertainty of the LIKE pattern. Second, we demonstrate that this boundary is not static—by systematically increasing the model's parameter count, we can enhance its capacity to learn complex data distributions, thereby improving recall, especially for the most challenging high-entropy queries. Third, and most importantly, we establish a quantitative scaling relationship: to achieve certain degree of recall, model complexity is determined by workload entropy $H(\mathbb{W})$. This reveals a promising scaling law for neural LIKE predicate decoding, providing a principled approach for trading model size for query performance to meet specific application requirements.

D IN-DEPTH PERFORMANCE ANALYSIS AGAINST TRIGRAM-BASED INDEXES

To provide a more nuanced understanding of SMILE's performance characteristics, we conduct a head-to-head comparison against a highly optimized trigram-based GIN (Generalized Inverted Index), a standard and powerful baseline for accelerating LIKE queries in modern database systems like PostgreSQL. The objective of this analysis is to delineate the specific query scenarios where each approach excels, focusing on the interplay between the selectivity of individual keywords within a pattern and the selectivity of their combined intersection.

Workload Design. We designed three distinct query workloads (Type-A, Type-B, and Type-C) to probe the performance of both systems under controlled conditions. We define a keyword as high-selectivity if its occurrence frequency is below 0.5% and low-selectivity if its frequency is above 2%. Furthermore, to simulate the complexity of real-world _ patterns, based on the findings in Section A.4, we synthetically introduced a variable number of single-character wildcards (_), ranging from 0 to 7, into each pattern independently. This range is based on our analysis of 84,047 real-world querys, where seven was the maximum observed number of such wildcards.

- **Type-A (Low-Selectivity Conjunction):** Queries follow the pattern `"%low_sel1%low_sel2%"`. Each keyword by itself is common (low selectivity), but their combined occurrence is rare (high selectivity). This represents the ideal scenario for methods that can efficiently compute intersections.
- **Type-B (High-Selectivity Dominant):** Queries follow the pattern `"%high_sel%low_sel%"`. The pattern contains at least one highly selective keyword that can be used by an index to dramatically prune the search space.
- **Type-C (Single Keyword):** Queries contain only a single keyword, `"%word%"`, which can be of either high or low selectivity. This workload evaluates the baseline performance without the advantage of intersection.



(a) Type-A: Low-Sel Conjunction. (b) Type-B: High-Sel Dominant. (c) Type-C: Single Keyword.

Figure 26: Performance comparison of SMILE and a GIN index across three query workloads with varying keyword selectivity and an increasing number of single-character "_" wildcards. Latency is shown on a linear scale.

Results and Analysis. Figure 26 presents the latency comparison between SMILE and the GIN index across the three workloads.

In the **Type-A workload** (Figure 26a), SMILE demonstrates a significant performance advantage, outperforming the GIN index by orders of magnitude. This is because the GIN index must first retrieve the large posting lists for both low-selectivity keywords and then perform a costly intersection operation. In contrast, SMILE holistically decodes the entire pattern, directly generating candidates that satisfy the conjunctive constraint without materializing large intermediate result sets.

For the **Type-B workload** (Figure 26b), the performance of SMILE and the GIN index is largely comparable. The GIN index can

effectively leverage the high-selectivity keyword to immediately filter the dataset down to a very small number of candidates, making its strategy highly efficient. SMILE's generative approach remains competitive, but its relative advantage is diminished when a simple and highly effective index path is available to the baseline.

In the **Type-C workload** (Figure 26c), the GIN index performs on par with or slightly better than SMILE. For a single-keyword search, the GIN index reduces to a direct lookup, which is its most efficient operational mode. SMILE's generative process, while fast, incurs a baseline overhead that makes it less suitable for these simple patterns where its "intersection" advantage is nullified.

A crucial observation across all workloads is the **impact of the _ wildcard**. As the number of _ wildcards increases, the performance of the GIN index degrades noticeably. This is because each _ can break up the trigrams that the index relies on. For example, a search for `"SI_M_D"` cannot use trigrams like `"SIG"` or `"MOD"`. The index must fall back to a less efficient strategy of scanning for all possible trigram combinations, leading to higher latency. Conversely, SMILE's performance remains remarkably stable. As a generative model, it treats _ as just another token in the sequence to be generated. Its latency is therefore insensitive to the number of such wildcards, showcasing its robustness to complex and fragmented patterns.

Takeaway. This detailed analysis reveals a clear performance trade-off between SMILE and traditional trigram-based indexes. SMILE's strength lies in its ability to holistically interpret complex patterns, making it exceptionally efficient for queries involving a conjunction of low-selectivity keywords. While its performance is competitive for queries dominated by a high-selectivity term, traditional indexes are slightly more efficient for simple, single-keyword lookups. Critically, SMILE exhibits superior robustness to patterns fragmented by single-character wildcards (_), a scenario where the structural assumptions of trigram indexes break down. This suggests that SMILE is not a universal replacement but a powerful complementary engine, particularly suited for workloads rich in complex, conjunctive, and fragmented search patterns.

E WORKLOAD CONSTRUCTION

In the following section of this chapter, we describe the process of creating our loads W1 and W2. Our pseudocode can be found in Algorithm 2:

The algorithm in Algorithm 2 proceeds as follows. In line 2, the input string is decomposed into its minimal semantic units: syllables for W_1 and morphemes for W_2. We use the Pyphen [10] to segment the syllables and morfessor [9] to segment the morphemes. For instance, the string "SIGMOD CONFERENCE" is split into S = ["SIG", "MOD ", "CON", "FER", "EN", "CE"], and $n = |S|$ (e.g., $n = 6$) is computed. In line 4, a binary random decision determines whether to generate a single-field (`%Keyword%`) or dual-field (`%Key%key%`) fuzzy pattern, thereby diversifying the structural complexity of the generated queries.

In the single-field branch (lines 5–15), the algorithm samples two integers $f, b \in \{0, 1, 2\}$ to specify how many segments at the beginning and end of S are to be obscured with the multi-character wildcard `%`. To ensure genuine fuzziness, if $f = b = 0$, one of them is set to 1. The pattern P is initialized with a leading `%`, then constructed by iterating over all segments: those in the first f or last b positions are replaced by `%`, while the intervening segments are appended verbatim. A trailing `%` is appended to complete the pattern. For example, with $f = 1$ and $b = 2$, the resulting pattern is `%MOD CONFER%`, which matches any string containing the exact substring "MOD CONFER".

In the dual-field branch (lines 17–29), three integers $f, m, b \in \{0, 1, 2\}$ control fuzziness at the front, a potential middle gap, and the back, with the constraint that at least one of them is non-zero. If $m > 0$, a valid middle position mid_pos is randomly selected from the range $[f, n - b - 2]$ to avoid overlap with the front and back regions. During pattern construction, wildcards are inserted at the front, back, and—if $m > 0$—at mid_pos. For example, with $f = 1$, $m = 1$, $b = 1$, and $mid\_pos = 3$ (corresponding to the segment "FER"), the resulting pattern is `%MOD CON%EN%`, which requires the non-contiguous substrings "MOD CON" and "EN" to appear in order, separated by arbitrary characters.

Algorithm 2 Fuzzy LIKE Pattern Generation

Input: Text T, Options O
Output: Fuzzy LIKE pattern P

1: **procedure** GenerateFuzzyPattern(T, O)
2: $S \leftarrow \text{Segment}(T, O)$ ▷ Extract syllables/morphemes
3: $n \leftarrow |S|$
4: **if** rand() < 0.5 **then**
5: /* **Single-field pattern** */
6: $f \leftarrow \text{rand}(0, 2)$; $b \leftarrow \text{rand}(0, 2)$
7: **if** $f + b = 0$ **then**
8: $f \leftarrow 1$ **or** $b \leftarrow 1$ ▷ Ensure fuzziness
9: $P \leftarrow$ "%"
10: **for** $i = 0$ **to** $n - 1$ **do**
11: **if** $i < f$ **or** $i \geq n - b$ **then**
12: $P \leftarrow P +$ "%"
13: **else**
14: $P \leftarrow P + S[i]$
15: $P \leftarrow P +$ "%"
16: **else**
17: /* **Dual-field pattern** */
18: $f \leftarrow \text{rand}(0, 2)$; $m \leftarrow \text{rand}(0, 2)$; $b \leftarrow \text{rand}(0, 2)$
19: **if** $f + m + b = 0$ **then**
20: $f \leftarrow 1$ **or** $m \leftarrow 1$ **or** $b \leftarrow 1$
21: **if** $m > 0$ **then**
22: $mid\_pos \leftarrow \text{rand}(f, n - b - 2)$ ▷ Middle position
23: $P \leftarrow$ "%"
24: **for** $i = 0$ **to** $n - 1$ **do**
25: **if** $i < f$ **or** $i \geq n - b$ **or** $(m > 0$ **and** $i = mid\_pos)$ **then**
26: $P \leftarrow P +$ "%"
27: **else**
28: $P \leftarrow P + S[i]$
29: $P \leftarrow P +$ "%"
30: $P \leftarrow \text{ReplaceRandomChars}(P, \text{"\_"}, \text{rand}(0, 5))$ ▷ Add "_'s
31: **return** P

Finally, in line 30, the algorithm invokes `ReplaceRandomChars` to substitute up to six randomly selected characters in the constructed pattern P with the single-character wildcard _. This independent random underscore replacement step simulates the pattern of load occurrence in real-world scenarios.

F OPTIMIZING BASELINES VIA PARALLELISM AND PARTITIONING

In this section, we detail our efforts to maximize the performance of the baseline methods through the strategic use of CPU parallelism and data partitioning. Our goal is to establish a robust performance benchmark, ensuring that each baseline is configured to its optimal potential before comparison. We utilize the W3 on TPC-H lineitem table as a representative workload to illustrate the outcomes of our extensive tuning process.

The core of our optimization strategy revolves around two primary axes: scaling the degree of parallelism by increasing the number of parallel workers and varying the data fragmentation by adjusting the number of partitions. Figure 27 presents the end-to-end latency of five baseline methods—GIN, GIST, Prefix B$^+$-tree, Sequential Scan, and Suffix B$^+$-tree—as a function of the number of parallel workers, across four distinct partitioning schemes (P=4, 8, 16, and 32).

A key observation across all subfigures is the initial sharp decline in latency as the number of parallel workers increases from one. This demonstrates the inherent parallelizability of the tasks and the effectiveness of distributing the workload across multiple CPU cores. However, this performance gain is not linear and quickly reaches a point of diminishing returns. For instance, in Figure 27(a) with 4 partitions, the latency for most baselines stabilizes after approximately 16 parallel workers. Beyond this threshold, the addition of more workers yields negligible performance improvements and, in some cases, introduces minor performance jitter.

This phenomenon is a classic illustration of Amdahl's Law [12], which posits that the speedup of a program using multiple processors is limited by its sequential fraction. In our context, factors such as I/O bottlenecks, data synchronization overhead, and the inherent sequential components of the query processing algorithms constrain the achievable speedup. Despite our best efforts to parallelize every possible aspect of the baselines, these fundamental limitations dictate a ceiling on performance scalability.

Furthermore, we systematically increased the number of data partitions from 4 to 32, as shown in subfigures (a) through (d), to further enhance the potential for parallel execution. Data partitioning can significantly improve query performance by dividing a large dataset into smaller, more manageable chunks, allowing queries to run in parallel across these segments. As depicted, increasing the partition count generally lowers the overall latency floor for the index-based methods. For example, the latency for GIN and GIST methods at 32 partitions (Figure 27(d)) is visibly lower than at 4 partitions (Figure 27(a)) when using a high degree of parallelism. This is because a higher partition count allows for a finer-grained distribution of work, reducing contention and improving load balancing among the parallel workers.

However, even with 32 partitions, the performance of all baselines eventually plateaus, reinforcing the constraints imposed by Amdahl's Law. The sequential scan, being the most fundamentally I/O-bound operation, benefits the least from increased parallelism and partitioning, exhibiting a relatively flat performance curve after an initial small dip. This comprehensive tuning process confirms that we have pushed the conventional baselines to their practical performance limits under this parallel execution model. The observed performance saturation underscores the necessity for a more advanced approach to overcome these inherent scalability challenges.

Takeaway Our exhaustive tuning demonstrates that the performance of traditional methods is fundamentally constrained by Amdahl's Law. Despite aggressive parallelism and data partitioning, their scalability quickly reaches a point of diminishing returns due to sequential bottlenecks. This establishes a practical performance ceiling, confirming that merely adding more hardware resources is an insufficient strategy and motivating the need for architecturally superior solutions.

G DETAILED COST MODEL

Our cost estimation is based on prevailing cloud computing rental prices, which reflect the real-world deployment costs of database systems. We established two primary hardware configurations for our experiments, with rental rates sourced from public cloud providers [13, 30] and detailed in Table 4.

A critical aspect of our cost model is the selection of CPU core counts to ensure a fair and cost-effective comparison. As demonstrated in our analysis in Section F, the performance of all traditional baselines (B+-Tree, GIN, GIST, and SeqScan) saturates when the degree of parallelism reaches approximately 16 workers. Allocating additional CPU cores beyond this threshold yields negligible latency improvements due to inherent bottlenecks, as dictated by Amdahl's Law. Consequently, to model a realistic and economically rational deployment, we benchmark the traditional methods on a 16-core CPU configuration. This represents the most cost-effective setup, as provisioning the full 96-core CPU would not enhance their performance but would unfairly inflate their cost. Our method and other deep learning-based baselines, which are designed for such hardware, utilize the CPU+GPU configuration.

Table 4: Hardware Configurations and Hourly Rental Costs.

Hardware Configuration	Hourly Rental Cost ($)
1 × AMD EPYC 9654 CPU (96 Cores)	$1.50
1 × AMD EPYC 9654 CPU (16 Cores)	$0.25
1 × NVIDIA H20 GPU + 1 × AMD EPYC 9654 CPU (16 Cores)	$0.98

We calculate the cost to process one million queries, denoted as C_{1M}, based on the total execution time. Specifically, if a method takes T_{1M} seconds to execute one million queries on a hardware configuration with an hourly rate of R, the cost is computed as:

$$C_{1M} = \frac{T_{1M}}{3600} \times R$$

This metric provides a normalized and direct comparison of the economic efficiency of each method.

H AN IN-DEPTH STUDY OF END-TO-END PERFORMANCE

In this section, we conduct a comprehensive analysis of the end-to-end (E2E) performance of SMILE on complex queries, as extended in Sec. 5.2. The primary objective is to quantify its practical impact on full query execution and to validate its efficacy against established indexing techniques across disparate data domains. To this end, we perform experiments on two standard benchmarks: TPC-H [125] and IMDB-JOB [3]. We compare SMILE against a sequential scan baseline and several state-of-the-art index structures, including GIN, GIST, and B+ Tree variants tailored for prefix and suffix matching.

Specifically, we selected five representative query templates from TPC-H (Q2, Q9, Q13, Q14, Q20) and five from IMDB-JOB (Q10, Q15, Q19, Q23, Q29). These queries were chosen for their reliance on complex `LIKE` predicates. The TPC-H queries target the `part.name`, `part.type`, and `order.comment` columns (abbreviated as `partName`, `partType`, and `orderComment`). The IMDB-JOB queries focus on the `cast_info.note` and `movie_info.info` columns (abbreviated as `castInfo` and `movieInfo`). We measure E2E latency and conduct a granular analysis of SMILE's core filtering efficacy and predicate evaluation speed.

Figure 29 presents the E2E query latency results. As illustrated, SMILE consistently and substantially outperforms all baselines across all tested queries on both benchmarks. The performance gap is particularly pronounced on complex queries like TPC-H Q9 and IMDB-JOB Q13, where SMILE achieves up to an order of magnitude reduction in latency compared to the traditional index-based approach. These results confirm the practical utility and superiority of SMILE in reducing overall query execution time. The consistent improvements on both the structured data of TPC-H and the varied textual data in IMDB-JOB underscore the robustness and generalizability of our learned approach.

While these E2E results are compelling, a more granular analysis is necessary to isolate the core contribution of our method. The true potency of SMILE lies in its ability to drastically accelerate the evaluation of the `LIKE` predicate itself, which is often a primary bottleneck. To quantify this effect, we conducted a micro-benchmark to measure the predicate evaluation latency and the corresponding recall rate.

Figure 28 provides this detailed breakdown. Figure 28a isolates the performance of `LIKE` predicate evaluation, revealing that SMILE is faster than all baselines by a significant margin. Compared to a sequential scan, SMILE achieves an acceleration of up to two orders of magnitude across all targeted columns. For instance, on the TPC-H `partType` and IMDB-JOB `castInfo` columns, SMILE's latency is orders of magnitude lower than that of SeqScan and substantially better than other specialized indexes like GIN. This demonstrates SMILE's efficacy as a specialized accelerator for pattern matching. Concurrently, Figure 28b confirms that this remarkable speedup does not come at a great cost to accuracy. SMILE maintains a high recall rate, typically exceeding 90% for most TPC-H queries. While it demonstrates some variability on the more heterogeneous IMDB-JOB dataset (e.g., JOB-Q15), its recall remains effective for pre-filtering, ensuring that the vast majority of qualifying rows are correctly identified.

The stark contrast between the multi-order-of-magnitude speedup at the predicate level (Figure 28a) and the more modest, albeit still substantial, gains in E2E queries (Figure 29) is an important and expected finding. SMILE functions as a highly specialized accelerator for `LIKE` predicates, analogous to how a B-tree or learned index accelerates point/range lookups. By transforming a linear-time scan for pattern matching into a near-constant-time operation, it removes a critical bottleneck. However, in a complex analytical query, this predicate evaluation is just one component of a larger execution plan. The total query time is still heavily influenced by other substantial costs, such as I/O for data retrieval, CPU cycles for join processing, and final aggregations. These factors, which are orthogonal to our contribution, can dominate the overall execution time and thus dilute the exponential gains achieved at the single-predicate level. Nonetheless, by fundamentally accelerating the `LIKE` operator, SMILE delivers tangible and crucial value to the performance of modern database systems.

Takeaway: SMILE delivers consistent and practical end-to-end query performance improvements, significantly outperforming both sequential scans and traditional index structures across diverse datasets. Its core strength lies in accelerating single-column `LIKE` predicates by up to two orders of magnitude over sequential scans while maintaining high recall (often >90%), making it a potent pre-filter. The dilution of this effect in E2E queries is an expected outcome attributable to other system bottlenecks (e.g., I/O, joins), but the fundamental acceleration of the pattern-matching operator remains a significant and valuable contribution.

I PROOFS OF THEORETICAL RESULTS

This appendix provides the detailed derivations for the theoretical results presented in Section 5.1.

I.1 Proof of Theorem 5.1

Proof. The theorem aims to compute the pattern entropy $H(\mathcal{P}) = \ln |L(\mathcal{P})|$, where $|L(\mathcal{P})|$ is the cardinality of the language $L(\mathcal{P})$ generated by a `LIKE` pattern $\mathcal{P}$. The proof proceeds by enumerating the number of unique strings that can match the pattern.

A `LIKE` pattern $\mathcal{P}$ of length x consists of literal characters, p underscore wildcards ("_"), and q percent wildcards ("%"). The alphabet is Σ, and the maximum length of a generated string is m. The cardinality $|L(\mathcal{P})|$ is the product of the number of combinations for each component of the pattern.

(1) **Literal Characters:** The non-wildcard characters are fixed and each contributes a multiplicative factor of 1 to the total cardinality.

(2) **Underscore Wildcards ("_"):** Each of the p underscore wildcards matches exactly one character from the alphabet Σ. As these choices are independent, they collectively contribute a factor of $|\Sigma|^p$.

$$C_{\_} = |\Sigma|^p \tag{6}$$

(3) **Percent Wildcards ("%"):** Each of the q percent wildcards can match a sequence of characters of any length, including zero. Let s be the total number of characters matched by all q percent wildcards combined. The length of a generated

string is determined by the length of the fixed parts of the pattern plus the total length s. The fixed part (literals and underscores) has a length of $x - q$. Thus, the total string length is $(x - q) + s$. Given the maximum length constraint m, we have $(x-q)+s \leq m$, which implies that $s \leq m-x+q$. The minimum value for s is 0.

For a fixed total length s, we determine the number of ways these s characters can be generated. This involves two steps: first, we partition the total length s among the q wildcards. This is a classic combinatorial problem solvable with stars and bars, yielding $\binom{s+q-1}{q-1}$ ways to distribute the lengths. Second, for each such partition, the s character positions can be filled with any character from Σ, giving $|\Sigma|^s$ possible sequences.

To find the total contribution from the percent wildcards, we sum over all possible values of s:

$$C_{\%} = \sum_{s=0}^{m-x+q} \binom{s+q-1}{q-1} |\Sigma|^s \tag{7}$$

The total cardinality of the language $L(\mathcal{P})$ is the product of the contributions from the underscore and percent wildcards:

$$|L(\mathcal{P})| = C_{\_} \cdot C_{\%} = |\Sigma|^p \left(\sum_{s=0}^{m-x+q} \binom{s+q-1}{q-1} |\Sigma|^s \right) \tag{8}$$

Finally, the pattern entropy $H(\mathcal{P})$ is the natural logarithm of this cardinality. Using the logarithm property $\ln(ab) = \ln(a) + \ln(b)$, we arrive at the final expression:

$$\begin{aligned} H(\mathcal{P}) &= \ln\left(|\Sigma|^p\right) + \ln\left(\sum_{s=0}^{m-x+q} \binom{s+q-1}{q-1} |\Sigma|^s \right) \\ &= p \ln|\Sigma| + \ln\left(\sum_{s=0}^{m-x+q} \binom{s+q-1}{q-1} |\Sigma|^s \right) \end{aligned} \tag{9}$$

This completes the proof. □

I.2 Proof of Theorem 5.2

Proof. The theorem provides the minimum number of samples, n, required to retrieve at least K matching strings with a confidence of $1 - \delta$. We model the sampling process as a sequence of n independent Bernoulli trials. Let $X_i = 1$ if the i-th sample is a correct match (with probability p) and $X_i = 0$ otherwise. The total number of successes is $S_n = \sum_{i=1}^{n} X_i$, which follows a Binomial distribution, $S_n \sim \text{Binomial}(n, p)$, with expectation $\mathbb{E}[S_n] = np$.

Our goal is to find the minimum n such that $P(S_n \geq K) \geq 1 - \delta$, which is equivalent to bounding the lower tail probability: $P(S_n < K) \leq \delta$. We apply a standard multiplicative Chernoff bound, looking for the smallest n satisfying $np > K$, which for any $K < \mathbb{E}[S_n]$ states:

$$P(S_n \leq K) \leq \exp\left(-\frac{(\mathbb{E}[S_n] - K)^2}{2\mathbb{E}[S_n]} \right) \tag{10}$$

To satisfy the confidence requirement, we set the right-hand side to be at most δ, which after taking logarithms and rearranging gives $(np - K)^2 \geq 2np \ln(1/\delta)$. We take the positive square root to find a lower bound on the expected number of successes, leads to:

$$np \geq K + \ln\left(\frac{1}{\delta}\right) + \sqrt{\ln\left(\frac{1}{\delta}\right)\left(2K + \ln\left(\frac{1}{\delta}\right)\right)} \tag{11}$$

We now derive the bound on n by considering the two cases for the success probability p, which is lower-bounded by $p \geq c \cdot \min\left(1, \frac{\alpha|\theta|}{H(\mathbb{W})}\right)$ from Eq. (4).

Case 1: Model capacity is sufficient ($H(\mathbb{W}) \leq \alpha|\theta|$). In this regime, the model's capacity $M = \alpha|\theta|$ meets or exceeds the workload entropy. We substituting $p \geq c$ into Eq. (11):

$$n \cdot c \geq K + \ln\left(\frac{1}{\delta}\right) + \sqrt{\ln\left(\frac{1}{\delta}\right)\left(2K + \ln\left(\frac{1}{\delta}\right)\right)} \tag{12}$$

This directly yields the bound for the first case.

Case 2: Model capacity is limited ($H(\mathbb{W}) > \alpha|\theta|$). Here, the workload entropy exceeds the model's capacity, and the success probability is bounded by $p \geq \frac{\alpha|\theta|}{H(\mathbb{W})}$. To guarantee that the condition in Eq. (11) is met, we must provision for the worst-case (lowest) possible success probability. We therefore substitute $p = \frac{c \cdot \alpha|\theta|}{H(\mathbb{W})}$:

$$n\left(\frac{c \cdot \alpha|\theta|}{H(\mathbb{W})}\right) \geq K + \ln\left(\frac{1}{\delta}\right) + \sqrt{\ln\left(\frac{1}{\delta}\right)\left(2K + \ln\left(\frac{1}{\delta}\right)\right)} \tag{13}$$

Solving for n gives the bound for the second case:

$$n \geq \frac{H(\mathbb{W})}{c \cdot \alpha|\theta|}\left(K + \ln\left(\frac{1}{\delta}\right) + \sqrt{\ln\left(\frac{1}{\delta}\right)\left(2K + \ln\left(\frac{1}{\delta}\right)\right)}\right) \tag{14}$$

Combining both cases completes the proof of the theorem. □

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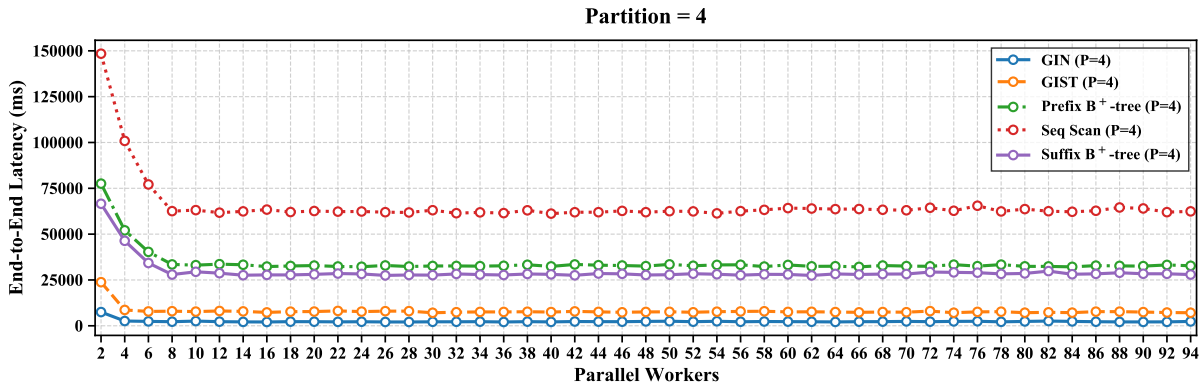
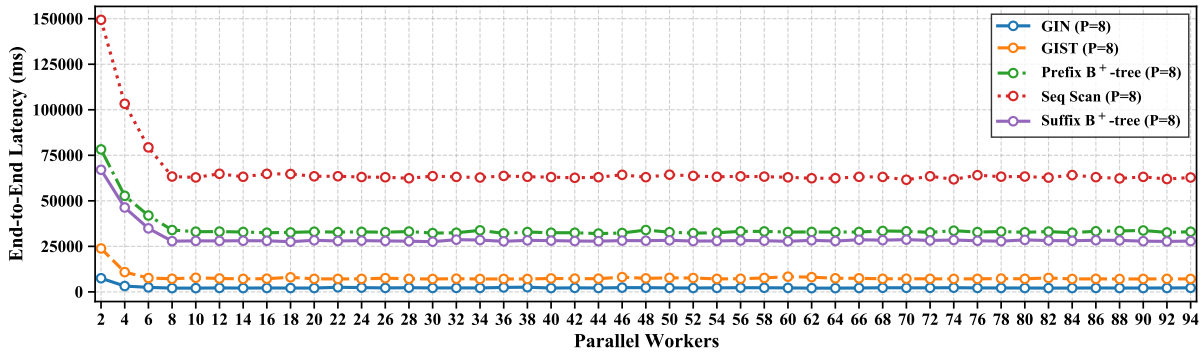
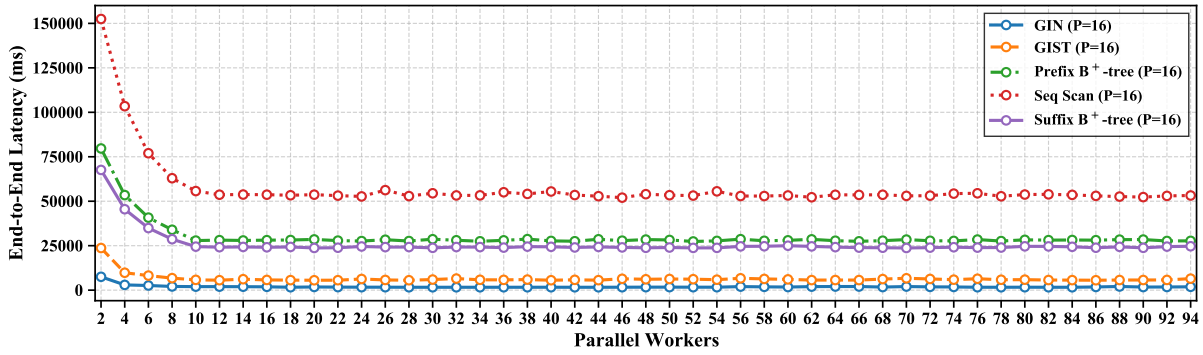


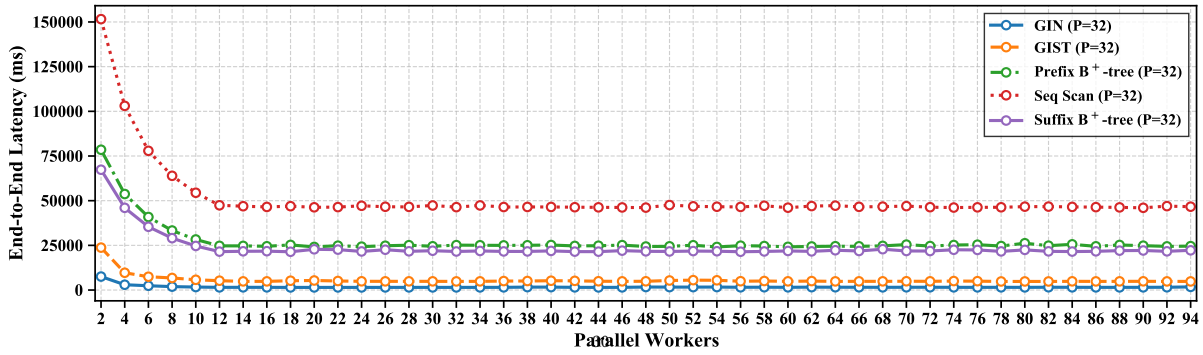
(a) End-to-End Latency with 4 Partitions.



(b) End-to-End Latency with 8 Partitions.

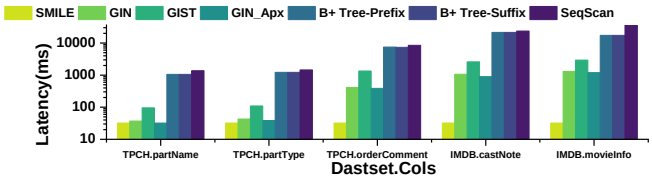


(c) End-to-End Latency with 16 Partitions.

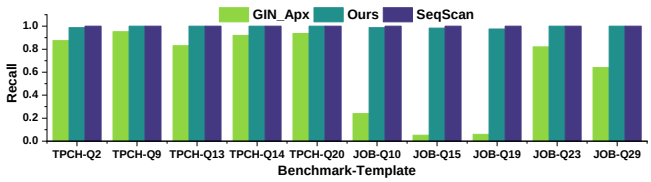


(d) End-to-End Latency with 32 Partitions.

Figure 27: End-to-end latency as a function of the number of parallel workers for different partitioning schemes on the TPC-H lineitem table. The performance of all baselines plateaus after a certain number of workers, illustrating the limits of parallelization as described by Amdahl's Law.

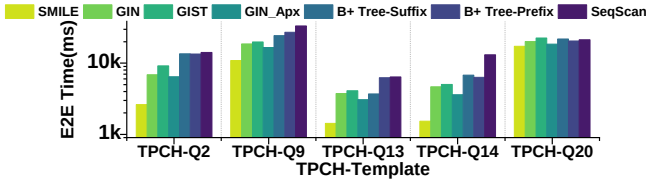


(a) Predicate evaluation latency per column.



(b) Recall rate per query template.

Figure 28: A detailed breakdown of SMILE's performance against baselines. (a) The latency (log-scale) of LIKE predicate evaluation on individual columns. (b) The recall rate achieved by SMILE's filtering mechanism for each query template. Together, these results show that SMILE achieves orders-of-magnitude acceleration over sequential scans while maintaining high recall.



(a) E2E query latency on TPC-H (Queries: 2, 9, 13, 14, 20).

(b) E2E query latency on IMDB-JOB (Queries: 10, 15, 19, 23, 29).

Figure 29: End-to-end query performance of SMILE against baselines. The figures show total execution time (log-scale) for selected queries on TPC-H and IMDB-JOB. SMILE consistently outperforms not only the sequential scan but also established index structures like GIN, GIST, and B+ Tree variants, demonstrating its superior effectiveness in accelerating real-world analytical queries.