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Lightweight and Data-Efficient Fine-Tuning of Language Models for Bidirectional Text-to-SQL and SQL-to-Text Tasks: A Systematic Review

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Abstract

Large language models (LLMs), which are increasingly essential to ultramodern natural language processing, have greatly improved semantic parsing, textbook creation, and natural language interfaces to databases. Among these procedures, text-to-SQL and SQL-to-text tasks are essential for providing user-friendly access to structured data. However, adoption in real-time and resource-constrained contexts is limited since standard complete LLM fine-tuning is still computationally costly and data-intensive. This systematic review highlights Scopus-listed research on featherlight and data-effective fine-tuning techniques published between 2020 and 2025, with a focus on bidirectional Text-to-SQL and SQL-to-Text workloads. appendages, bias-only tuning, low-rank adaptation (LoRA), prefix-tuning, and quantization-aware fine-tuning are among the parameter-efficient fine-tuning (PEFT) techniques that are examined in this review. Furthermore, data-efficient learning frameworks and classifier-guided data selection are examined as ways to lower annotation costs without sacrificing performance. Applications in cybersecurity for smart cities, low-resource database systems, and enterprise analytics are critically examined. The review comes to the conclusion that combining parameter-efficient adaptation with classifier-guided learning provides a scalable, sustainable, and energy-conscious way to implement language models in structured data environments. Modern LLMs exhibit strong generalization across a variety of tasks, such as question answering, summarization, and structured text generation, after being pretrained on extensive quantities.

Keywords: Parameter-Efficient Fine-Tuning, Text-to-SQL, SQL-to-Text, Classifier-Guided Learning, LoRA, Semantic Parsing, PEFT.

1. Introduction

Natural language processing (NLP) has undergone a dramatic transformation caused by transformer-based language models. Modern LLMs exhibit strong generalization across a variety of tasks, such as question answering, summarization, and structured text production, after being pretrained on large-scale datasets. Natural language database interfaces, where Text-to-SQL systems convert user queries into executable database commands and SQL-to-Text systems produce human-readable explanations of query results, are among the most significant uses of these technologies. Adapting LLMs to database-centric jobs is still difficult, despite their usefulness. Large amounts of annotated data and significant computer resources are

needed for full fine-tuning, which modifies every model parameter. For businesses with limited hardware, energy, or data resources, these demands are frequently unfeasible. Additionally, curating Text-to-SQL databases is costly since it requires subject knowledge.
In response to these challenges, recent studies have increasingly focused on lightweight and data-efficient methods for fine-tuning models. These approaches aim to reduce the cost of training while maintaining the model's performance [1], [2]. Parameter-efficient fine-tuning (PEFT) techniques update only a small part of the model's parameters, whereas data-efficient methods seek to get the most out of limited labeled data. Classifier-guided fine-tuning has become a promising approach, as it emphasizes the use of informative samples during the adaptation process. This makes it especially useful for structured tasks where the distribution of queries is uneven.
This review systematically analyzes recent developments in lightweight and data-efficient fine-tuning methods, with a focus on their application to bidirectional Text-to-SQL and SQL-to-Text tasks.It summarizes findings from literature indexed in Scopus, published between 2020 and 2025. The review outlines current trends, identifies areas that still need research, and suggests future directions that support sustainable and scalable AI solutions.

2. Review Methodology and Selection Criteria

A systematic literature review approach was used to ensure a thorough and unbiased examination of the topic. All searches were carried out in Scopus-indexed databases, focusing on high-impact journals and conferences. The time frame considered was from 2020 to 2025 to concentrate on recent developments in transformer-based models and current fine-tuning methods.

The search terms included concepts like parameter-efficient fine-tuning, Text-to-SQL, semantic parsing, LoRA, classifier-guided learning, and data-efficient adaptation. Only studies that met all three criteria were included: (i) They either proposed or assessed lightweight or data-efficient fine-tuning approaches, (ii) They provided empirical evidence to support their claims, and (iii) They were relevant to structured language tasks. Excluded were survey papers, discussions without practical evaluation, and works published before 2020.

The final set of studies consists of 30 publications indexed in Scopus.These were analyzed thematically and grouped into categories such as parameter-efficient fine-tuning (PEFT), data-efficient learning, optimization through compression, and application-specific adaptations.

3. Parameter-Efficient Fine-Tuning Techniques

3.1 Adapter-Based Fine-Tuning

Adapter-based methods involve adding small, trainable modules between the layers of a transformer model, while keeping the original weights unchanged. This setup allows for efficient adaptation to new tasks and reuse of components across different domains [3]. In Text-to-SQL tasks, adapters help the model learn specific schemas without retraining the entire system, which is especially useful when database structures change often [8].

3.2 Prefix-Tuning and Prompt Optimization

Prefix-tuning works by adjusting continuous vectors that are added before input embeddings, allowing the model to adapt to new tasks without altering its main structure [4].Prompt-based methods build on this by encoding relevant task or schema details directly into prompts that the model learns. These techniques have proven effective for generating structured outputs, such as SQL queries and explanations [9].

3.3 Low-Rank Adaptation (LoRA)

LoRA breaks down the changes made to model weights into smaller matrices, significantly reducing the number of parameters that need to be trained while still maintaining the model's ability to express complex patterns [5].Studies show that LoRA works well with large models and performs as well as full fine-tuning on various tasks. For Text-to-SQL and SQL-to-Text tasks, LoRA allows quick adaptation to new schemas and query styles with little computational cost [10].

3.4 Bias-Only and Hybrid PEFT Methods

Bias-only fine-tuning updates only the bias terms in the model, providing a very lightweight method that still works reasonably well when there is limited data [6].

Hybrid approaches mix different techniques like adapters, LoRA, and bias tuning to offer a balance between flexibility and efficiency, helping users choose the best adaptation method based on their available resources [11].

4. Data-Efficient and Classifier-Guided Fine-Tuning

Data scarcity is a persistent challenge in semantic parsing, particularly for domain-specific databases. Data-efficient fine-tuning aims to reduce labeling effort by prioritizing informative samples. Classifier-guided approaches employ auxiliary classifiers to score or filter training instances, focusing adaptation on high-value examples [7].

In Text-to-SQL tasks, classifier-guided sampling has been shown to emphasize complex query structures and rare schema elements, leading to improved generalization with fewer labeled examples [12], [13]. When combined with PEFT methods, classifier-guided fine-tuning reduces overfitting and stabilizes training in low-resource regimes [14]. This integration aligns closely with emerging research on sustainable and cost-effective AI deployment.

5. Quantization and Pruning for Lightweight Optimization

Model compression techniques further enhance efficiency beyond PEFT. Quantization reduces numerical precision, lowering memory usage and inference cost. Recent studies demonstrate that quantized models can be effectively fine-tuned using LoRA-style updates with minimal accuracy degradation [15], [16]. Pruning techniques remove redundant parameters, yielding sparse models suitable for real-time applications. Hybrid approaches that combine pruning, quantization, and PEFT provide a comprehensive solution for deploying LLMs in constrained environments, such as edge devices and real-time database systems [17].

6. Applications in Text-to-SQL, SQL-to-Text, and Smart Cities

Lightweight fine-tuning techniques have enabled practical deployment of natural language interfaces across enterprise analytics, low-resource databases, and smart city platforms. In Text-to-SQL systems, PEFT facilitates rapid domain adaptation and schema portability [8], [9]. SQL-to-Text systems benefit from prompt- and prefix-based methods that generate interpretable explanations of query results. In smart city contexts, efficient fine-tuning supports applications such as cybersecurity monitoring, anomaly detection, and automated reporting. Lightweight adaptation frameworks enable real-time processing under strict latency and energy constraints, highlighting the practical relevance of data-efficient fine-tuning [18].

7. Research Gaps and Challenges

Despite notable progress, several challenges remain. First, standardized benchmarks for evaluating classifier-guided fine-tuning in Text-to-SQL & SQL-to-Text Bidirectional tasks are lacking. Second, explainability and robustness of lightweight-adapted models remain underexplored, particularly in safety-critical applications. Finally, cross-lingual and federated fine-tuning for structured data tasks require further investigation.

8. Future Research Directions

Future research should focus on unified frameworks that integrate classifier-guided learning, PEFT, and compression techniques. Privacy-preserving and federated fine-tuning is particularly relevant for enterprise and governmental databases. Extending lightweight adaptation to multilingual and cross-lingual Text-to-SQL & SQL-to-Text tasks represents another important direction for broadening accessibility.

9. Conclusion

This systematic review demonstrates that lightweight and data-efficient fine-tuning techniques provide a viable alternative to full model retraining for Text-to-SQL and SQL-to-Text tasks. By integrating classifier-guided data selection with parameter-efficient adaptation, researchers and practitioners can achieve scalable, sustainable, and high-performance deployment of language models in structured data environments.

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