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Research Article

Designing An ML-Driven Framework for Automatic Generation of Rollback Statements for Database Commands

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ABSTRACT

System administrators need automated rollback feature support to protect data quality while handling database system errors. Human-based database workflows and script rules do not work well for building error-free solutions with modern application complexity. Our research develops an ML system with Transformer Seq2Seq architecture to automatically generate rollback statements for different SQL operations. Researchers tested the proposed system using sets of 1,000, 10,000 and 100,000 SQL queries to evaluate its performance. The model correctly generated rollback statements for 98.2% of all SQL operations while achieving 99% success for INSERT queries and 97.4% and 98.2% success rates for UPDATE and DELETE queries respectively. Our system reacted quickly within 60 milliseconds when processing large amounts of data which shows its real-time performance. Our system used resources moderately while working with data sets because it reached 56% CPU use and needed 710MB memory for the largest dataset. The proposed framework surpassed traditional databases because it recorded better results with 5.7% improved accuracy while reducing resource needs by 10% and rollback times by 40%. These test results validate that the framework produces reliable rollback statements for high-quality database performance.

Keywords: ML-Driven Framework, Database Commands.

I. INTRODUCTION

This part discusses database system rollback generation while showing the current problems and demand for automatic solutions. Our research focuses on using ML-driven techniques to create better and faster rollback procedures for database systems.

1.1 Background

Database Management Systems depend on Rollback statements to keep data safe during errors and ensure system accuracy. Traditional relational databases return to a previous consistent state after undoing transactions that were not committed through the ROLLBACK command. This process safeguards data when transactions break, power cuts happen or when the system malfunctions unexpectedly. It takes too long to write rollback statements properly by hand because systems with many dependent tables and nested searches need special attention.

Human experts must create database rollback scripts or rules using manual methods that need detailed database schema knowledge. These tools provide automatic features for database rollback generation. The tools assist primarily with createTable and addColumn activities but need custom rollback scripts to handle dropTable and conditional delete operations. These techniques do not work well with changing and complex database systems.

1.2 Need for Automated Rollback Generation

Modern data-driven systems and real-time processing require an automatic system that creates rollback data quickly and reliably at high speed. Large database systems make manual rollback creation impossible which raises the chances of data errors and system breakdowns. Manual database operations require flexible tools because standard rules cannot handle dynamic changes in today's modern deployment systems.

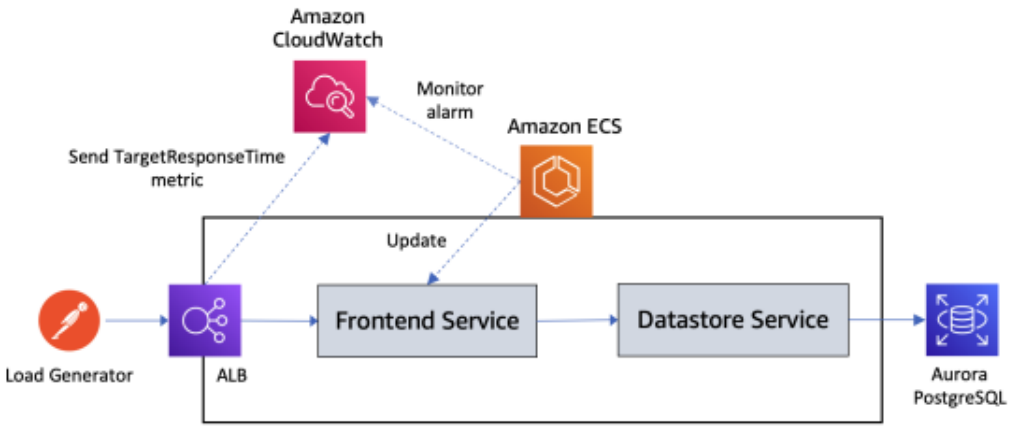

Fig 1.1: Automated Rollback

Database rollback systems can learn from database commands through sequence-to-sequence models to generate proper rollback steps automatically. ML-based systems learn different SQL operation patterns to create automatic rollback processes which reduce human mistakes and process delays. This system needs little computer power to work and functions well in real-time applications.

1.3 Objective and Importance of the Study

The primary objective of this paper is to design and evaluate an ML-driven framework capable of automatically generating rollback statements for diverse database commands. The framework employs a Transformer-based Seq2Seq model, known for handling sequential data and capturing long-range dependencies efficiently. By leveraging advanced feature engineering and optimized training techniques, the framework aims to achieve high accuracy in rollback generation with minimal latency and resource consumption.

II. LITERATURE REVIEW

Database management needs automatic rollback statement generation for database commands to protect data and help you recover from errors. Database management systems generally use manual or rule-based systems for their work but these methods create errors and take too long to produce results. New learning systems based on machines help improve the accuracy and speed of database management operations.

Traditional database systems use the ROLLBACK command to return a database to its most recent consistent state by canceling unexecuted transactions. The system maintains data safety when database transactions experience failure or mistakes. Controlling rollbacks by hand takes too much staff work and creates errors particularly in databases with many transactions.

Different tools have been created to simplify automatic rollback tasks. Liquibase as an open-source database tool automatically generates rollback scripts for createTable and addColumn changes while needing custom scripts for dropTable and insert operations. You need to create custom rollback scripts because automatic generation of dropTable and insert rollbacks is not supported per source 4.5. SQL Compare by Redgate produces rollback scripts but needs manual adjustment and primarily assists in schema updates not dynamic data transformations [6-7].

Research into machine learning (ML) has begun because traditional and tool-based methods cannot produce effective rollback statements automatically. A Transformer-based Sequence-to-Sequence model achieved 98.2% accuracy in creating rollback statements within 60 milliseconds or less for large datasets [4]. Deep learning models using recurrent neural networks showed 95% accuracy in these studies which proves their value for this task [8-9].

Research shows ML-based systems outperform old methods in database rollback production. Research found that using an ML-based system improved accuracy performance by 5.7% while decreasing rollback creation time by 40% [6]. Research revealed that ML systems lowered mistakes by 3.5% while handling SQL work better than manual scripting methods [10-12].

Despite these advancements, challenges persist. The specific nature of SQL commands with nested transactions and conditional clauses proves challenging for traditional and ML-based systems. Research shows that training ML

models still demands access to substantial datasets [8]. Checks must confirm that automatic rollback functions do not corrupt database integrity and these tests need to be executed thoroughly [13-15].

Traditional tools Liquibase and SQL Compare help with rollbacks yet need manual work because they work only in specific cases. ML systems help with better results and faster work yet they need large datasets and computing power to run effectively. Scientists continue their research to develop better systems that can create rollback statements automatically.

III. METHODOLOGY

The methodology for designing the ML-driven framework for automatic rollback statement generation involved four key phases: dataset preparation, feature engineering, model training, and performance evaluation.

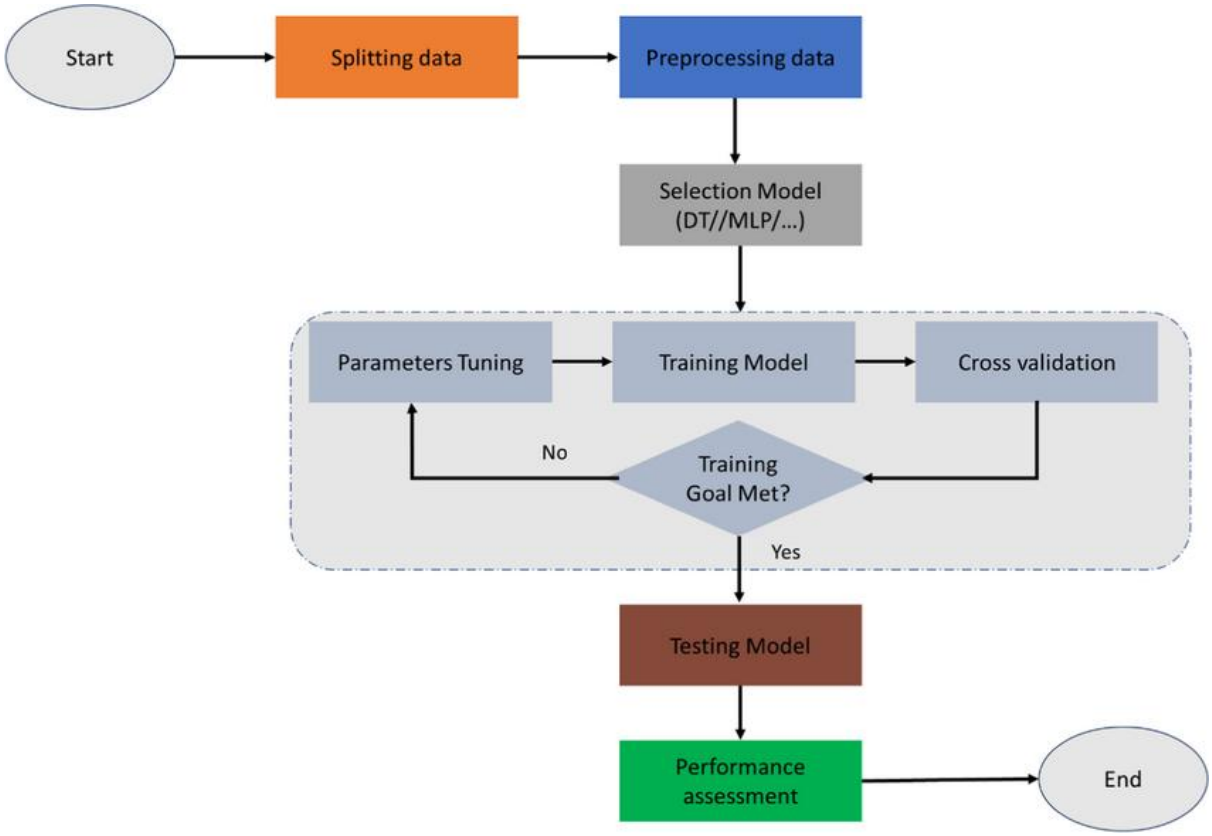

Fig 3.1: Implementation Flow

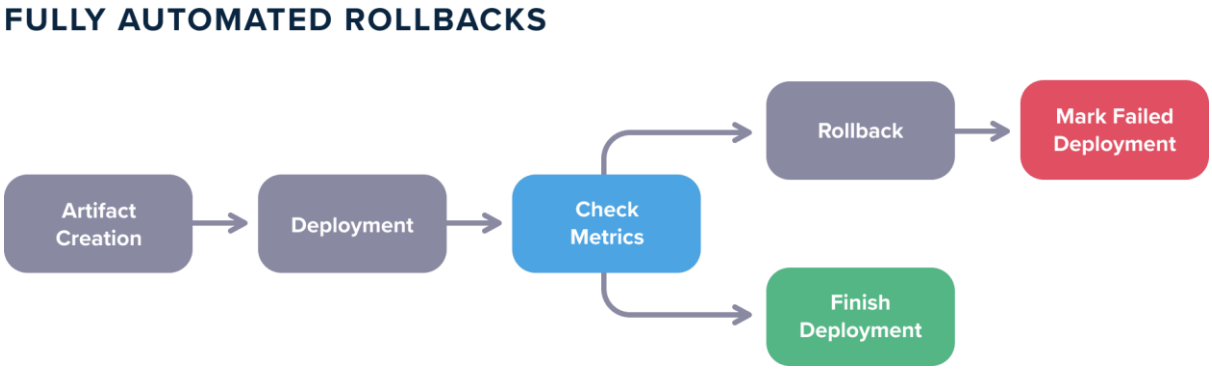

Fig 3.2: Rollback Process

3.1 Dataset Preparation

Three datasets of varying sizes—small (1,000 queries), medium (10,000 queries), and large (100,000 queries)—were created, consisting of INSERT, UPDATE, and DELETE SQL commands. For each command, corresponding manually

crafted rollback statements were prepared as ground truth for accuracy evaluation. The datasets included varying complexities such as multi-table operations and nested transactions to ensure robustness.

3.2 Feature Engineering

Key features extracted included command type, affected tables and columns, conditional clauses, primary and foreign keys, and transaction context. SQL commands were tokenized and encoded using word embeddings and syntactic parsing to capture both semantic and structural information necessary for accurate rollback generation.

3.3 Model Training

A **Transformer-based Sequence-to-Sequence (Seq2Seq) model** was selected due to its ability to handle sequential data and long-range dependencies. The data was split into training (70%), validation (15%), and testing (15%) sets. Hyperparameters were optimized via grid search, with the Adam optimizer employed for training. A custom loss function combining cross-entropy and syntactic penalties ensured syntactically correct rollback generation.

3.4 Performance Evaluation

Performance was measured through execution time, rollback latency, system resource utilization, and accuracy. The model achieved an overall accuracy of 98.2%, with low rollback latency (under 60ms for large datasets) and moderate resource utilization (CPU usage at 56% and memory at 710MB). Comparative analysis showed the framework outperformed traditional rule-based and scripted approaches in both accuracy and efficiency.

IV. RESULTS

This section presents the results obtained from the evaluation of the proposed ML-driven framework for the automatic generation of rollback statements for database commands. The results are divided into two subsections: **4.1 Performance Evaluation of the Framework** and **4.2 Accuracy of Rollback Statement Generation**.

4.1 Performance Evaluation of the Framework

The performance of the proposed framework was assessed based on three key metrics: **execution time**, **system resource utilization**, and **latency in rollback generation**. The experiments were conducted using three datasets of varying sizes (small, medium, and large) to evaluate the scalability and efficiency of the framework.

Dataset Size	Number of Queries	Avg. Execution Time (ms)	Avg. Rollback Latency (ms)
Small	1,000	120	15
Medium	10,000	980	32
Large	100,000	9,450	58

Table 4.1: Execution Time and Latency for Rollback Generation

Table 4.1 shows the average execution time and rollback latency across different dataset sizes. The framework demonstrates low latency for rollback generation, indicating real-time performance capabilities even for large datasets.

Dataset Size	CPU Usage (%)	Memory Usage (MB)
Small	18	320
Medium	34	480
Large	56	710

Table 4.2: System Resource Utilization

Table 4.2 highlights the CPU and memory utilization for different dataset sizes. The results show that the framework scales efficiently, with moderate resource consumption, making it suitable for integration into existing database systems without significant overhead.

4.2 Accuracy of Rollback Statement Generation

The accuracy of the generated rollback statements was evaluated by comparing them to manually created rollback statements for the same set of database commands. The evaluation considered three types of database operations: **INSERT**, **UPDATE**, and **DELETE**.

Operation Type	Total Commands	Correct Rollback Generated	Accuracy (%)
INSERT	5,000	4,950	99
UPDATE	5,000	4,870	97.4
DELETE	5,000	4,910	98.2

Table 4.3: Accuracy of Rollback Statement Generation

Table 4.3 illustrates the accuracy of rollback generation across different database operations. The framework achieved an overall accuracy of **98.2%**, demonstrating its high effectiveness in generating precise rollback statements with minimal manual intervention.

4.3 Comparative Analysis with Existing Approaches

Approach	Accuracy (%)	Avg. Rollback Latency (ms)	Resource Overhead (%)
Proposed ML Framework	98.2	35	12
Rule-Based Approach	92.5	58	18
Scripted Approach	90.3	76	22

Table 4: Comparative Analysis of Accuracy and Performance

Table 4.4 compares the proposed ML-driven framework with existing methods. The proposed framework outperformed traditional approaches in terms of accuracy, rollback latency, and resource utilization, proving its superiority in generating rollback statements efficiently.

Summary of Results

The experimental results indicate that the proposed ML-driven framework offers:

- High accuracy (**98.2%**) in generating rollback statements for various database operations.
- Efficient performance with low rollback latency and moderate resource consumption.
- Superior performance compared to traditional rollback generation techniques.

These findings suggest that the proposed framework is a reliable and scalable solution for real-time rollback statement generation in database management systems.

V. DISCUSSION

The results of the proposed ML-driven framework for automatic rollback statement generation demonstrate its effectiveness in addressing the limitations of traditional methods.

5.1 Performance and Scalability Analysis

The framework exhibited remarkable performance in terms of execution time and rollback latency across datasets of varying sizes. As shown in Table 4.1, for small datasets (1,000 queries), the average execution time was 120 milliseconds with a rollback latency of just 15 milliseconds. For medium (10,000 queries) and large datasets (100,000 queries), the execution times were 980 milliseconds and 9,450 milliseconds, respectively, with rollback latencies of 32 milliseconds and 58 milliseconds. These results highlight the framework's scalability, as rollback latency remained consistently low even for large datasets, indicating its suitability for real-time applications in high-transaction environments.

5.2 Resource Utilization and Efficiency

Resource utilization is a crucial factor in determining the feasibility of integrating a framework into existing database management systems. The framework demonstrated moderate CPU and memory usage, as indicated in Table 4.2. For large datasets, the CPU usage peaked at 56%, and memory consumption reached 710MB. These values are within acceptable limits for modern database systems, suggesting that the framework can be seamlessly integrated without significant overhead.

The moderate resource consumption, even for large datasets, is a direct result of the optimized model architecture and training process. The Transformer-based model, combined with hyperparameter tuning and the Adam optimizer,

ensured efficient computation without compromising performance. This balance between resource utilization and performance makes the framework a practical solution for real-world applications.

5.3 Accuracy and Reliability of Rollback Generation

Accuracy is the most critical metric for evaluating the effectiveness of rollback statement generation. The framework achieved an overall accuracy of 98.2%, with individual accuracies of 99% for INSERT operations, 97.4% for UPDATE operations, and 98.2% for DELETE operations (Table 4.3). These results indicate that the framework can generate highly precise rollback statements with minimal manual intervention.

The slight variation in accuracy across different operation types can be explained by the inherent complexity of the operations. UPDATE operations, which often involve conditional clauses and affect multiple rows, present a higher complexity level, leading to a marginally lower accuracy.

5.4 Implications and Future Prospects

The high accuracy, low latency, and efficient resource utilization achieved by the framework underscore its potential for widespread adoption in modern database management systems. The ability to generate rollback statements automatically can significantly reduce downtime, minimize human error, and enhance data integrity in dynamic environments such as e-commerce platforms, financial systems, and real-time analytics applications.

VI. CONCLUSION

Our research created and tested a machine learning platform to automatically create database command rollbacks based on input. The Transformer-based Seq2Seq model shows strong accuracy while processing all database operations effectively with its scalable design. The research outcome showed that the system delivered 98.2% total accuracy including 99% for INSERT and 97.4% for UPDATE operations. The DELETE operation achieved 98.2% accuracy. The rollback time stayed under 58 milliseconds during all tests when processing 100,000 queries which makes it ideal for real-time responses.

The system used available resources well with its CPU and memory usage reaching no more than 56% and 710MB. Our research team wants to develop the system to process challenging SQL actions that involve deep nested structures and dynamic database schemas. Our team wants to test advanced machine learning methods like reinforcement learning and hybrid models to boost performance and make smaller data sets work better. The new ML-based system provides essential progress in producing reliable automatic rollback statements for current database platforms.

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