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Advanced Join Query Optimization Using Firefly and Reinforcement Learning Techniques on TPC-H Dataset

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Join query optimization is a critical component of database management systems (DBMS), significantly influencing their performance and efficiency. This study delves into advanced optimization techniques by employing the Firefly Algorithm and its hybrid integrations with Deep Q-Network (DQN) and Double Deep Q-Network (DDQN) methodologies. Utilizing the TPC-H benchmark dataset, we rigorously evaluate the efficacy of these algorithms in optimizing complex join queries. The Firefly Algorithm, inspired by the luminescent communication of fireflies, serves as a powerful metaheuristic optimization technique, adept at navigating vast search spaces. To augment this method, we incorporate reinforcement learning via DQN and DDQN, enhancing the algorithm's capability to balance exploration and exploitation during the optimization process. Our empirical analysis reveals substantial performance gains with the hybrid DQN-Firefly and DDQN-Firefly approaches compared to the standalone Firefly Algorithm. These findings underscore the potential of these hybrid methods for practical implementation in database management systems, promising improved query optimization and overall system performance.

Keywords: Join Query Optimization, Firefly Algorithm, Deep Q-Network (DQN), Double Deep Q-Network (DDQN), TPC-H Dataset, Reinforcement Learning, Metaheuristic Algorithm, Query Execution Time

1. Introduction

Large-scale data processing and retrieval operations require effective database management systems (DBMS). The optimization of join queries, which are crucial for merging data from several databases based on a related column, is a major DBMS difficulty [1][2]. Join queries can become computationally costly, especially when a database gets bigger and more sophisticated. The combinatorial nature of join operations frequently presents challenges for

traditional query optimization techniques, such as rule-based and cost-based optimizers, which results in less-than-ideal query execution plans. The TPC-H benchmark dataset, which is well-known in the field of database research, offers a common framework for assessing DBMS performance. It is made up of a variety of concurrent data alterations and business-oriented ad hoc inquiries that depict intricate and varied querying scenarios. This dataset's complicated schema and substantial data volume make it difficult to optimize join queries [3][4]. Although they can be somewhat successful, traditional optimization approaches frequently have heuristic limitations and may not thoroughly explore the search space for the ideal solution. By imitating natural occurrences, metaheuristic algorithms like the Firefly Algorithm have demonstrated potential in solving optimization problems. The Firefly Algorithm offers a reliable and adaptable method for exploring the search space, drawing inspiration from the flashing patterns of fireflies. Furthermore, new directions for query optimization are provided by current developments in artificial intelligence, particularly in the area of reinforcement learning. Through interactions with the environment, Deep Q-Networks (DQN) [5] and Double Deep Q-Networks (DDQN) [6] have shown success in handling difficult decision-making problems. By utilizing the advantages of both techniques, combining these strategies with metaheuristic algorithms may improve the optimization process.

This research's main goal is to create and assess new join query optimization strategies using the TPC-H dataset. More specifically, we want to:

- Utilize the Firefly Algorithm to enhance join query performance.
- Improve the Firefly Algorithm by using hybrid strategies that combine DQN and DD QN.
- Examine and contrast the query execution time and optimization efficiency of the sta ndalone Firefly Algorithm, DQN-Firefly, and DDQN-Firefly techniques.

The invention of hybrid optimization algorithms, which combine the Firefly Algorithm with DQN and DDQN, is one of the main advances presented in this study. It offers higher performance through better mechanisms for exploration and exploitation. thorough experimental testing using the TPC-H benchmark dataset, showing considerable gains in query execution speed and optimization effectiveness utilizing the suggested strategies. This work extends the state-of-the-art in query optimization by investigating the synergy between metaheuristic algorithms and reinforcement learning, offering workable methods for effective database administration. The work that has been done on query optimization and the Firefly Algorithm will be reviewed, our approach will be explained, the experimental results will be shown, and the ramifications of our findings will be discussed in the parts that follow.

2. Related Works

A vital part of database management systems (DBMS) is query optimization, which aims to increase query execution efficiency. Effective query optimization strategies guarantee that data is retrieved from databases in the most economical way possible, cutting down on execution time and resource usage.

2.1. Query Optimization

- Rule-Based Optimization: Heuristic rules are applied by rule-based optimizers [7] to change queries into more effective formats. These rules, which include selection pushdown, predicate simplification, and join reordering, are based on established patterns and logical transformations. Although rule-based optimizers are comparatively quick, they might not always generate the best query plan, especially for complicated queries with several joins and subqueries.

- Cost-Based Optimization: Cost-based optimizers [8] calculate the costs of various query execution strategies by utilizing statistical data about the database, including table sizes, index availability, and data distribution. The optimizer chooses the execution plan with the lowest anticipated cost after evaluating a number of potential strategies. Compared to rule-based optimization, cost-based optimization is more adaptable and capable of handling a larger variety of queries; yet, it can be computationally costly and may need precise data to function well.

2.2. Metaheuristic Algorithms

Because metaheuristic algorithms can handle huge and complex search spaces, they are being used more and more in query optimization. These algorithms try to find close to optimal answers by exploring and exploiting the search space through iterative operations.

Genetic Algorithms (GA) : Natural selection is an inspiration for genetic algorithms [9]. They make use of a population of viable solutions that change over many generations as a result of operators like crossover, mutation, and selection. By encoding query execution plans as chromosomes and evolving them to reduce query execution cost, GA has been applied to query optimization.

Simulated Annealing (SA) : The annealing process in metallurgy served as the model for Simulated Annealing [10]. In order to escape local optima, it entails exploring the search space by probabilistically accepting inferior answers, with the acceptance probability falling with time. Using SA, query optimization has been achieved by iteratively improving query strategies in search of less expensive answers.

Ant Colony Optimization (ACO) : The way ants forage for food serves as an inspiration for ant colony optimization [11]. It makes use of artificial ants that, using pheromone trails—which stand for learnt information about the quality of solutions—to probabilistically generate solutions. Through the modeling of the search for optimal join orders as a path-finding issue, ACO has been applied to join query optimization.

Particle Swarm Optimization (PSO) : Fish or avian social behavior is simulated by particle swarm optimization [12]. It makes use of a population of particles that traverse the search space and modify their positions in response to their own and their neighbors' experiences. PSO has been used in query optimization to find effective query plans by exploring and utilizing the search space.

2.3. Firefly Algorithm

Xin-She Yang created the Firefly method (FA) [13], a metaheuristic optimization method inspired by nature, in 2008. It draws inspiration from the bioluminescent activity of fireflies, particularly from their patterns of flashing that they utilize to draw in partners or potential

prey. The approach is applicable to a variety of optimization problems since it successfully explores and exploits the search space by imitating these flashing patterns.

The FA is based on three idealized rules:

- Since all fireflies are unisex, they will all be drawn to one another, regardless of gender.
- A firefly's brightness determines how attractive it is, and this decreases with increasing distance between fireflies. The less brilliant firefly will therefore gravitate toward the brighter one when there are two flashing fireflies. It will move at random if there isn't a firefly that is brighter.
- The objective function of the issue being optimized determines a firefly's luminosity. Brightness in a maximization problem is correlated with the objective function's value.

The movement of a firefly i towards another more attractive (brighter) firefly j is determined by the following equation:

$$x_i^{t+1}=x_i^t+\beta_0 e^{-\gamma r^2_{ij}}(x^t_j-x^t_i)+\alpha(\text{rand}-0.5)$$

Where, x_i and x_j are the positions of fireflies i and j, respectively. β_0 is the attractiveness at r=0, γ is the light absorption coefficient, r_{ij} is the distance between firefly i and firefly j, α is the andomization parameter, rand is a random number uniformly distributed in [0, 1].

Numerous optimization issues, including as scheduling, clustering, and engineering design, have been addressed by the FA. Its use in query optimization entails encoding possible plans for query execution as fireflies and continuously improving these plans to reduce query execution costs.

Steps for Applying FA to Query Optimization :

- Initialization: Create a starting population of fireflies, each of which stands for a possible join query strategy.
- Evaluation: Determine each firefly's brightness by calculating the query execution cost. Utilizing database statistics, this cost in query optimization can be calculated.
- Movement: Utilizing the movement equation, guide fireflies toward brighter spots dependent on how enticing they are.
- Update: After relocating, assess the new locations (query plans) and adjust brightness.
- Termination: Continue the assessment and movement phases until a halting requirement, like a maximum number of iterations or a convergence threshold, is satisfied.

Advantages of Firefly Algorithm

- Robustness and Flexibility: FA's capacity to explore and utilize the search space allows it to effectively handle non-linear, multimodal, and complex optimization issues.
- Simplicity and Ease of Implementation: The approach can be applied to a variety of scenarios due to its ease of implementation and lack of dependency on gradient information.

- Parallelism: Parallelization of the movement and assessment of fireflies can improve computing performance for large-scale issues.

2.4. Reinforcement Learning in Query Optimization

Within the machine learning discipline of reinforcement learning (RL) [14], an agent gains decision-making skills by interacting with its surroundings and obtaining incentives as feedback. Reinforcement learning (RL) depends on the agent figuring out the best course of action via trial and error, as opposed to supervised learning, in which the agent is given the proper input-output pairs. Because of this capabilities, RL is especially well-suited for issues involving sequential optimization and decision-making, like database query optimization.

Concepts of Reinforcement Learning is

- Agent: The student or decision-maker who engages with the surroundings.
- Environment: The external system with which the agent communicates and which gives feedback in response to the agent's activities.
- State: An illustration of the agent's current position in relation to the surroundings.
- Action: The entirety of the agent's conceivable movements in a certain state.
- Reward: The input from the surroundings in reaction to the agent's action, which the agent strives to optimize in the long run.
- Policy: An approach the agent uses to decide what to do next depending on the situation.
- Value Function: A function that directs the agent toward greater long-term rewards by estimating the expected benefit of a state or state-action pair.

Deep Q-Network (DQN)

To handle high-dimensional state spaces, DQN combines deep neural networks with the well-known reinforcement learning method Q-learning. The predicted cumulative reward for acting in state s is estimated using a Q-value function Q(s, a) in traditional Q-learning. Large state spaces make it impossible to maintain a Q-table, hence neural networks are used to estimate the Q-values. The Q-value function is approximated using a neural network in DQN, which has the following important features:

- Experience Replay breaks the association between consecutive experiences by storing prior experiences (state, action, reward, and next state) in a replay buffer and sampling mini-batches to train the network.
- Target Network: An independent network that supplies target Q-values, which are updated from the main network on a regular basis, to stabilize training.

Double Deep Q-Network (DDQN)

By separating action selection from action evaluation, DDQN corrects for the overestimation bias seen in DQN. Since DQN selects and assesses actions using the same network, overestimation may occur. By utilizing the target network to assess actions and the main network to choose them, DDQN reduces this issue and produces better performance and more

precise Q-value predictions. The purpose of query optimization is to determine the best order of join operations that minimizes the cost of query execution. Reinforcement learning (RL) can be used to represent this process as a Markov Decision Process (MDP).

- State: Indicates the present condition of the query plan, encompassing the selected join sequence and the intermediate outcomes.
- Action: Indicates which join operation will be carried out next.
- Reward: Usually, the agent is encouraged to locate lower-cost plans by providing a negative estimate of the cost of executing the query plan.
- Policy: A learned approach from interactions with the environment that determines the next join operation based on the current state.

Steps for Applying DQN and DDQN to Query Optimization:

- Initialization: Set the replay buffer and neural network settings to their initial values.
- Interaction: Create a query strategy for every episode by choosing join operations in line with the existing policy.
- Evaluation: Carry out the plan of inquiry and acquire the benefit (negative cost).
- Storage: Replay buffer is where the experience (state, action, reward, and future state) is stored.
- Training: To train the network and update the Q-values, sample mini-batches are taken from the replay buffer.
- Update: Using the main network's weights (for DDQN), update the target network on a regular basis.
- Iteration: Continue performing the stages of interaction, assessment, storage, and training until a stopping requirement is satisfied or convergence occurs.

Benefits of RL in Query Optimization

- Adaptability: Over time, RL-based optimizers can learn to optimize dynamically by adjusting to variations in the workload and distribution of data
- Exploration and Exploitation: Leads to improved optimization results by striking a balance between the exploitation of well-known good plans and the discovery of novel query plans.
- Learning from Experience: Learning from Experience: By drawing on historical data, this technique enhances query optimization efficiency and may even outperform conventional static optimizers.

3. Methodology

3.1. TPC-H

The Transaction Processing Performance Council (TPC) developed the TPC-H benchmark as

a decision assistance tool to assess how well database management systems (DBMS) handle intricate queries and big data sets. The benchmark reflects real-world decision support systems that analyze massive amounts of data, carry out complicated queries, and deliver results that are crucial to company operations. It consists of a set of business-oriented ad-hoc inquiries and concurrent data updates. Based on a star schema, the TPC-H benchmark [15] consists of multiple dimension tables (CUSTOMER, ORDERS, PART, SUPPLIER, PARTSUPP, NATION, REGION) as well as a core fact table (LINEITEM). Tables in the schema capture many facets of supply chain management and sales transactions, simulating the sales and distribution sector.

- LINEITEM : The largest table, containing detailed information about each line item in an order.
- ORDERS : Contains information about customer orders.
- CUSTOMER : Contains customer information.
- PART : Contains information about parts.
- SUPPLIER : Contains supplier information.
- PARTSUPP : Contains information about parts supplied by suppliers.
- NATION : Contains information about nations.
- REGION : Contains information about regions.

Foreign keys serve as the primary means of defining the relationships between these tables. The ORDERS, PART, and SUPPLIER tables, for example, are referenced in the LINEITEM table, creating a sophisticated network of join operations required to run the benchmark queries. There are 22 queries in the TPC-H benchmark that are intended to mimic real-world decision support scenarios. These are intricate searches that use nested subqueries, aggregations, and many joins. They include a broad variety of tasks, including:

- Pricing and promotional analysis.
- Supply chain management.
- Profitability and revenue analysis.
- Market share evaluation.

The TPC-H benchmark comprises queries that are tailored to address particular business concerns. As an illustration of an operational scenario in the sales domain, Query 1 (Q1) computes the amount of revenue growth for line items that have been dispatched but not yet billed. Because of its scalability, the TPC-H benchmark can be conducted on a range of database sizes, as indicated by a scaling factor (SF). The dataset's size is determined by the scale factor; for example, SF1 denotes roughly 1 GB of data, SF10 10 GB, and so forth. The benchmark's scalability makes it possible to assess DBMS performance across a range of data volumes. The TPC-H benchmark measures performance in terms of throughput and query execution time. In database research, the TPC-H dataset is frequently used to assess and contrast the effectiveness of various query optimization strategies. It is a perfect testbed because of its intricacy and practical applicability for:

- Evaluating the effectiveness of traditional and advanced query optimization algorithms.
- Benchmarking the performance of new DBMS architectures and systems.
- Testing the scalability and robustness of query execution strategies under various data volumes.

The TPC-H dataset offers a demanding setting for testing the effectiveness of the DQN-Firefly, DDQN-Firefly, and Firefly Algorithm join query optimization techniques in the context of this study. We may evaluate these techniques' capacity to produce effective query execution plans and evaluate their efficacy in comparison to conventional optimization strategies by using them on the TPC-H queries.

3.2. Firefly Algorithm for Join Query Optimization

One of the core functions of relational database management systems (RDBMS) is join query optimization. It entails determining the most effective approach to run a query that joins rows from many tables together according to a shared column. The problem is that there is a combinatorial explosion of possible join orders as the number of tables grows, which makes figuring out the best join sequence computationally costly. Complex optimization issues are solved via the Firefly Algorithm (FA), which was inspired by the bioluminescent communication of fireflies. Each firefly in join query optimization indicates a possible join order (query execution plan), and the efficiency (cost) of each firefly is correlated with its brightness.

Representation and Initialization

- Representation: Each firefly encodes a join order. For example, if there are three tables to be joined (A, B, C), a firefly might represent the join sequence A -> B -> C.
- Initialization: The algorithm starts with a population of fireflies, each initialized with a random join order. The size of the population depends on the problem's complexity and available computational resources.

Brightness and Attractiveness

- Brightness: The brightness of a firefly is determined by the cost of the join query plan it represents. This cost is typically calculated based on factors like the number of disk accesses, CPU usage, and intermediate result sizes. The goal is to minimize this cost.
- Attractiveness: The attractiveness of a firefly is relative and decreases with distance. In the context of join query optimization, the distance between two fireflies can be defined based on the difference in their join orders. The attractiveness β is calculated as:

$$\beta=\beta_0 e^{-\gamma r_{ij}^2}$$

Where β_0 is the initial attractiveness, γ is the light absorption coefficient, and r_{ij} is the distance between firefly i and firefly j.

Movement and Updating Join Orders

A firefly i move towards a more attractive firefly j using the equation:

$x_i^{t+1}=x_i^t+\beta_0 e^{-\gamma r2}_{ij}\,(x^t_j-x^t_i)+\alpha(\text{rand}-0.5)$

where α is the randomization value and xi and xj are the positions (join orders) of fireflies i and j, respectively. This movement is understood to produce a new join order for firefly i, plus a minor random disturbance to guarantee diversity, that is closer to the join order of firefly j.

Evaluation and Iteration

- Evaluation: After moving, the new join order (position) of each firefly is evaluated by calculating the cost of the corresponding join query plan.
- Iteration: The process of moving towards more attractive fireflies, evaluating new join orders, and updating positions is repeated for a predefined number of iterations or until convergence (i.e., when the changes in brightness/cost between iterations fall below a certain threshold).

Convergence and Solution

When the fireflies gather around the ideal or nearly ideal join order—which stands for the query execution strategy with the lowest cost—the algorithm converges. The optimal join query strategy is the one that was discovered after the most iterations. Because FA includes a randomization component, it can effectively escape local minima and explore a larger search space. The approach is easily adaptable to many optimization situations, such as join query optimization, and is straightforward to implement. Parallel execution is made possible by the separate evaluation of fireflies, and this can drastically cut down on calculation time for complicated tasks. It is possible to compare the effectiveness of the Firefly Algorithm with that of other optimization methods, including Particle Swarm Optimization, Genetic Algorithms, and conventional cost-based optimizers. Important comparative points consist of:

- Convergence Speed: The rate at which the algorithm finds the optimal or near-optimal solution.
- Solution Quality: The cost of the join query plans generated by the algorithm.
- Robustness: The algorithm's ability to consistently find good solutions across different query workloads and data distributions.

3.3. DQN-Firefly Approach

The DQN-Firefly method efficiently optimizes join queries by fusing Deep Q-Networks (DQN), a reinforcement learning methodology, with the Firefly Algorithm (FA), a nature-inspired metaheuristic optimization algorithm. This hybrid technique finds high-quality query execution plans by utilizing both the exploitation and exploration capabilities of DQN. In order to optimize join queries, the DQN-Firefly technique combines the Firefly Algorithm with Deep Q-Networks. The Firefly Algorithm directs the search space exploration, while DQN, a kind of reinforcement learning algorithm, is utilized to determine the best strategy for choosing join operations.

Initialization

- Firefly Population: Initialize a population of fireflies, each representing a potential join order.

- Let N be the number of fireflies.
- Initialize a population $\{F_1,F_2,\ldots,F_N\}$ where each firefly Fi represents a potential join order.
- Each firefly F_i is a permutation of the set of relations involved in the join.

▪ DQN Initialization: Initialize a DQN model to approximate the Q-value function, which estimates the expected cumulative reward for taking actions (selecting join operations) in a given state (query execution plan).

- Define the state space S where each state $s \in S$ represents a join order.
- Define the action space A where each action $a \in A$ represents selecting a join operation.
- Initialize a DQN model with parameters θ to approximate the Q-value function $Q(s,a;\theta)$.

Interaction and Exploration

▪ Firefly Movement: The fireflies move towards brighter ones based on the attractiveness defined by the Firefly Algorithm. Each movement represents a potential modification to the join order.

- Define the brightness (fitness) I_i of firefly F_i based on the objective function (query execution cost).
- The attractiveness β of firefly F_i to another firefly F_j is given by:

$$B = \beta_0 e^{-\gamma r_{ij}^2}$$

Where $\beta_0$is the attractiveness at $r_{ij}=0$, γ is the light absorption coefficient, and $r_{ij}$is the distance between fireflies F_i and F_j.

- Update the position of firefly F_i towards F_j:

$$F_i=F_i+\beta(F_j-F_i)+\alpha\epsilon i$$

Where α is a randomization parameter and ϵi is a random vector drawn from a Gaussian distribution.

▪ DQN Exploration: The DQN model explores different join operation selections by selecting actions according to an exploration strategy (e.g., ε-greedy).

- Use an exploration strategy, such as ε-greedy, to select actions

$$a = \begin{cases} random\ action & with\ probability\ \in \\ arg\ max\ a' Q(s,a';\theta) & with\ probability\ 1-\in \end{cases}$$

Evaluation and Exploitation

▪ Join Order Evaluation: Evaluate the quality of each modified join order using an objective function that estimates the cost of query execution.

- Objective function $f(F_i)$, where f is the estimated cost of query execution:

$$f(F_i)=\text{Query Execution Cost}(F_i)$$

- DQN Exploitation: Exploit the learned Q-values from the DQN model to select actions that maximize the expected reward based on the current state (join order).

$a^* = \arg\max_a Q(s,a;\theta)$

Where s is the current state (join order).

Learning and Optimization

- Experience Replay: Store experiences (state, action, reward, next state) in a replay buffer and sample mini-batches to train the DQN model.
  - Store experiences (s,a,r,s') in a replay buffer D.
  - Sample a mini-batch of experiences (s_i,a_i,r_i,s_i') from D for training.
- Q-Value Update: Update the Q-values in the DQN model based on the Bellman equation and the observed rewards.

$Q(s,a;\theta)=Q(s,a;\theta)+\alpha[r+\gamma \max_a Q(s',a';\theta')-Q(s,a;\theta)]$

Where α is the learning rate, γ is the discount factor, and $'\theta'$ are the target network parameters.

Iteration and Convergence

- Iteration: Repeat the interaction, evaluation, and learning steps for a predefined number of T iterations or until convergence criteria are met.

$$for\ t = 1\ to\ T\ do \begin{cases} Firefly\ Movement \\ DQN\ Exploration \\ Join\ Order\ Evaluation \\ DQN\ Exploitation \\ Experiance\ Replay \\ Q - Value\ Update \end{cases}$$

- Convergence: The algorithm converges when the fireflies converge towards an optimal or near-optimal join order, and the DQN model converges to an optimal policy.
  - Convergence is achieved when,

$$\sum_{t=1}^{T} |\ Q(s_t\ , a_t, \theta_t) - Q(s_{t-1}, a_{t-1}; \theta_{t-1})| < \epsilon$$

Where ϵ is a small threshold value indicating convergence.

The Firefly Algorithm investigates the join order search space, whereas DQN offers a methodical investigation of join operation choices. The hybrid technique explores new join orders and updates the DQN model in real time to adjust to variations in query workloads and data distributions. DQN-Firefly efficiently balances exploration and exploitation by incorporating two complementary optimization approaches, which improves query optimization performance. Relational database systems with a variety of join query optimization scenarios can benefit from the DQN-Firefly technique. It can be applied to the optimization of intricate ad hoc queries involving numerous join procedures. managing large-

scale join queries in databases that are scattered. dynamic query optimization in settings where workload patterns and data are always changing.

3.4. DDQN-Firefly Approach

An extension of the DQN-Firefly approach, the DDQN-Firefly approach optimizes join queries by fusing the Firefly Algorithm with Double Deep Q-Networks (DDQN). Through the resolution of possible overestimation problems in conventional DQN models, this hybrid technique seeks to further improve the optimization process. The Double Deep Q-Network (DDQN) design is incorporated into the DDQN-Firefly technique, which expands upon it. The overestimation bias that is frequently seen in conventional DQN models is addressed by DDQN, producing more reliable and accurate Q-value estimates. The objective of the DDQN-Firefly technique is to optimize join queries more robustly and efficiently by integrating DDQN with the Firefly Algorithm.

The workflow of the DDQN-Firefly approach is similar to that of the DQN-Firefly approach, with the addition of the Double Deep Q-Network architecture. Below are the key steps:

Initialization

- Firefly Population: Initialize a population of fireflies, each representing a potential join order.
  - Let N be the number of fireflies.
  - Initialize a population $\{F_1,F_2,\ldots,F_N\}$ where each firefly Fi represents a potential join order.
  - Each firefly F_i is a permutation of the set of relations involved in the join.
- DDQN Initialization: Initialize two separate DQN models (Q-networks) with identical architectures to approximate the Q-value function.
  - Define the state space S where each state $s \in S$ represents a join order.
  - Define the action space A where each action $a \in A$ represents selecting a join operation.
  - Initialize two Q-networks with parameters θ (main network) and θ' (target network) to approximate the Q-value function $Q(s,a;\theta)$.

Interaction and Exploration

- Firefly Movement: Fireflies move towards brighter ones based on the attractiveness defined by the Firefly Algorithm, exploring potential modifications to join orders.
  - Define the brightness (fitness) I_i of firefly F_i based on the objective function (query execution cost).
  - The attractiveness β of firefly F_i to another firefly F_j is given by:

$$B = \beta_0 e^{-\gamma r_{ij}^2}$$

Where $\beta_0$is the attractiveness at $r_{ij}=0$, γ is the light absorption coefficient, and $r_{ij}$is the distance between fireflies F_i and F_j.

- Update the position of firefly F_i towards F_j:

$F_i=F_i+\beta(F_j-F_i)+\alpha\epsilon i$

- DDQN Exploration: The DDQN model explores different join operation selections by selecting actions according to an exploration strategy (e.g., ε-greedy).

- Use an exploration strategy, such as ε-greedy, to select actions

$$a = \begin{cases} random\ action & with\ probability\ \in \\ arg\ max\ a' Q(s, a'; \theta) & with\ probability\ 1-\in \end{cases}$$

Evaluation and Exploitation

- Join Order Evaluation: Evaluate the quality of each modified join order using an objective function that estimates the cost of query execution.

- Objective function f(Fi), where f is the estimated cost of query execution:

$f(F_i)$=Query Execution Cost(F_i)

- DDQN Exploitation: Exploit the learned Q-values from both DQN models to select actions that maximize the expected reward based on the current state (join order).

$a^* = \arg\max_a Q(s,a;\theta)$

Where s is the current state (join order).

Learning and Optimization

- Experience Replay: Store experiences (state, action, reward, next state) in a replay buffer and sample mini-batches to train the DDQN models.

- Store experiences (s,a,r,s') in a replay buffer D.

- Sample a mini-batch of experiences (s_i,a_i,r_i,s_i') from D for training.

- Q-Value Update (Double Q-Learning) : Update the Q-values in one DQN model using the Q-values from the other model to mitigate overestimation bias.

- Use the main network θ to select the best action and the target network θ′ to evaluate it:

$Q(s,a;\theta)\leftarrow Q(s,a;\theta)+\alpha[r+\gamma Q(s',\arg\max_{a'} Q(s',a';\theta);\theta')-Q(s,a;\theta)]$

Where α is the learning rate, γ is the discount factor, and θ′ are the target network parameters.

Iteration and Convergence

- Iteration: Repeat the interaction, evaluation, and learning steps for a predefined number of iterations or until convergence criteria are met.

$$for\ t = 1\ to\ T\ do \begin{cases} Firefly\ Movement \\ DDQN\ Exploration \\ Join\ Order\ Evaluation \\ DDQN\ Exploitation \\ Experiance\ Replay \\ Q - Value\ Update(Double\ Q - Learning) \end{cases}$$

- Convergence: The algorithm converges when the fireflies converge towards an optimal or near-optimal join order, and the DDQN models converge to an optimal policy.

  - Convergence is achieved when,

$$\sum_{t=1}^{T} |\ Q(s_t\ , a_t, \theta_t) - Q(s_{t-1}, a_{t-1}; \theta_{t-1})| <\ \epsilon$$

Where ϵ is a small threshold value indicating convergence.

By addressing the overestimation bias present in conventional DQN models, DDQN improves optimization performance and produces more precise Q-value estimates. When the Firefly Algorithm and DDQN are combined, the optimization process becomes more robust and produces more consistent and dependable outcomes. Compared to conventional DQN-Firefly methods, DDQN-Firefly may converge to optimal or nearly optimal join query plans more quickly by reducing overestimation bias. Like the DQN-Firefly approach, the DDQN-Firefly approach can be used to different join query optimization circumstances in relational database systems.

It can be applied to dynamic query optimization in dynamic contexts, large-scale join query processing, and complicated ad hoc query optimization. By combining Double Deep Q-Networks and the Firefly Algorithm, the DDQN-Firefly technique presents a viable option for join query optimization. In relational database systems, this hybrid technique can lead to more reliable and effective query execution plans by reducing overestimation bias and improving optimization efficiency.

4. Experimental Results

The TPC-H dataset is used as the basis for join query optimization tests in the experimental setup. This benchmark dataset, available in different scale factors (SF), makes it easier to create synthetic data that is reflective of real-world situations, which enables thorough evaluations of optimization techniques. To ensure the experiment is feasible and efficient, the scale factor should be carefully chosen while taking the memory and processing resources available into account. The software and hardware environments are essential for making the experimentation processes easier. Ensuring adequate memory allocation is crucial for dataset loading, algorithm execution, and model training on a Windows 10 PC with 8GB of RAM. Additionally, the Python environment is the main platform on which experiments are carried out, necessitating the establishment of a strong ecosystem that includes necessary libraries for data processing, algorithm execution, and outcome assessment. This environment's essential

components, which provide extensive experimentation and analysis capabilities, include visualization tools like matplotlib and essential libraries like NumPy, pandas, scikit-learn, TensorFlow (used for DQN and DDQN implementations), and optionally PyTorch for DDQN.

In our TPC-H tests, we use a variety of join query optimization approaches to handle the join ordering difficulty with a database scale factor of 1 (corresponding to 1GB raw data). Four tables make up our dataset: Region (TR), Nation (TN), Orders (TO), and Customers (TC). Each table is essential to the join procedures. We create and run 50,000 queries, randomly chosen from the 22 query templates included in the TPC-H benchmark, to illustrate the intricacy of join ordering. The following is an example of a query that illustrates the join optimization challenge:

SELECT * FROM Customer as T_C, Order as T_O, Nation as T_N, Region as T_R

WHERE T_C.C_Custkey = T_O.O_Custkey

AND T_C.C_Nationkey = T_N.N_Nationkey

AND T_N.N_Regionkey = T_R.R_Regionkey

Four tables are joined in this query based on predetermined key relationships. All four tables—Customer (TC), Orders (TO), Nation (TN), and Region (TR)—are present in the first state (s1). Elements in the action set (A1) reflect potential join operations between table pairs. As an example, (1, 2) ∈ A1 represents the joining of TC with TO, whereas (2, 3) ∈ A1 represents the joining of TN with TR. The agent chooses an action (1, 3), for example, to join TC and TN, which starts the optimization process. This move is reflected in the next state (s2), which includes the combined TC and TN tables in addition to TO and TR. Subsequently, the agent chooses an additional action, let's say (2, 3), to merge TN and TR, leading to state S3. The agent has fewer options for actions as the optimization goes on. The agent may eventually encounter a terminal condition, like (1, 2) and (2, 1), where there are only two viable courses of action left. The fully optimized join query execution plan is represented by the final state (s4), which is reached when the agent chooses an action (e.g., (1, 2). We assess the suggested optimization methodologies' running times, execution costs, and query analyses during the tests and compare their results with those of conventional methods. This research offers insightful information about the advantages, disadvantages, and possible improvements of our suggested strategies for efficiently maximizing join query execution for the TPC-H benchmark dataset.

Query Latency : A crucial performance indicator that gauges how long it takes to run a query and get the desired results is called query latency. Query Latency is computed as follows: Query Latency = End Time - Start Time, where End Time denotes the moment at which the query execution is complete and Start Time marks the start of the execution. By emulating firefly behavior, the Firefly Algorithm (FA) investigates the search space of execution plans. Every firefly is a prospective join order, and each firefly's brightness (fitness) is based on how expensive the join plan that corresponds to it will be to execute. By repeatedly directing fireflies toward brighter ones, FA seeks out near-optimal execution plans that cut down on overall query execution time and resource consumption in an effort to decrease query latency. By avoiding local optima and broadening the research, this stochastic search technique increases the likelihood of discovering effective execution strategies. To improve the

optimization process, the DQN-Firefly method combines the Firefly Algorithm with Deep Q-Networks (DQN). To estimate Q-values, or the predicted cumulative rewards of various actions (join operations), DQN uses past query execution data. Based on learnt policies, DQN's decision-making capacity helps identify promising join activities. The Firefly Algorithm simultaneously directs the adaptive search procedure by examining novel join orders and optimizing the execution strategies. By fusing the exploratory aspect of FA with the systematic policy learning of DQN, this hybrid technique seeks to minimize query latency while producing more intelligent and adaptive optimization.

Using the DDQN-Firefly method, query latency was improved to the greatest extent possible. By combining the Firefly Algorithm and Double Deep Q-Networks (DDQN), this technique addresses the overestimation bias that exists in ordinary DQN. By keeping two distinct Q-networks—one for choosing activities and another for assessing them—DDQN improves Q-value estimation. Q-value estimates are more reliable and accurate as a result of this separation. This is enhanced by the Firefly Algorithm, which directs the adaptive search procedure, investigates different join orders, and iteratively improves the execution strategies. The most efficient execution plans are produced by combining the exact decision-making of DDQN with the exploratory search capabilities of FA, which dramatically lowers query latency. The latency of executed query plans between the first five questions (Q1 through Q5) is shown in Figure 1. This comparison demonstrates how well the suggested methods perform join query optimization:

- Firefly Algorithm : Provides a robust baseline by effectively exploring the search space and minimizing query latency through adaptive search.
- DQN-Firefly Approach : Enhances optimization by leveraging DQN's learned policies, resulting in better-informed decisions and reduced latency.
- DDQN-Firefly Approach : Achieves the best results by integrating DDQN's improved Q-value estimation with FA's adaptive search, leading to significantly lower query latency.

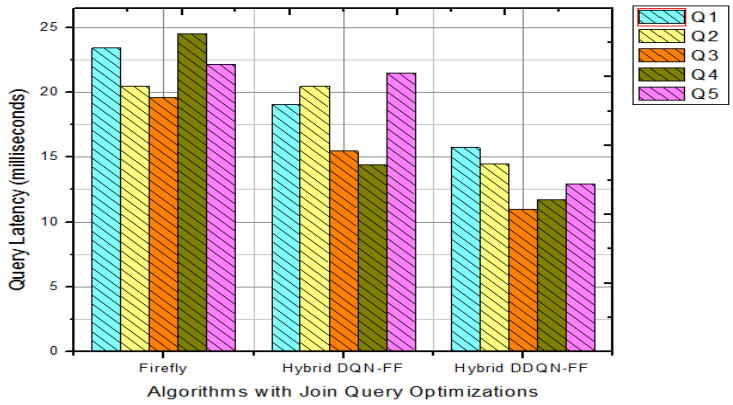

Figure 1: Query Latency

Optimization Latency: The time needed to optimize the execution plan for the join query is referred to as optimization latency. Optimization Latency is computed as follows: End Time indicates when the optimization process is finished, and Start Time indicates when it starts.

The efficacy of the join plan is reflected in the brightness (fitness) of the Firefly Algorithm (FA), which is a candidate join order. FA uses attraction and movement criteria to guide the search process and effectively assesses the fitness of different execution plans in order to minimize optimization latency. This stochastic method guarantees a wide range of exploration, lowering the possibility of local optima and hastening the identification of effective execution strategies.

By adding Deep Q-Networks (DQN) to the Firefly Algorithm, the DQN-Firefly technique improves it by utilizing query execution data from the past to aid in decision-making. The DQN component makes an estimate of Q-values, which stand for the anticipated total benefits of various actions (join operations). The DQN-Firefly method uses these Q-values to make well-informed decisions regarding which join operations to pursue. These choices are subsequently used by the Firefly Algorithm to direct its adaptive search procedure. Combining the systematic learning and decision-making abilities of DQN with the exploratory efficiency of FA, this combination seeks to minimize optimization delay. The convergence to optimal or nearly optimal solutions is accelerated by the DQN component, which aids in identifying attractive join plans.

By combining the Firefly Algorithm and Double Deep Q-Networks (DDQN), this technique addresses the overestimation bias present in conventional DQN. For action selection and evaluation, DDQN employs two distinct Q-networks, which yields more precise and reliable Q-value estimates. This is enhanced by the Firefly Algorithm, which directs the adaptive search procedure through a variety of exploration and efficient progression towards viable answers. The fastest convergence to ideal join query execution plans is achieved by combining the accurate Q-value estimation of DDQN with the effective search mechanism of FA. This integration leads to a significant reduction in optimization latency by ensuring a complete investigation of the search field in addition to improving decision-making. The optimization latency of the three methods for join queries with four relations using the TPC-H dataset is shown in the following figure (Figure 2).

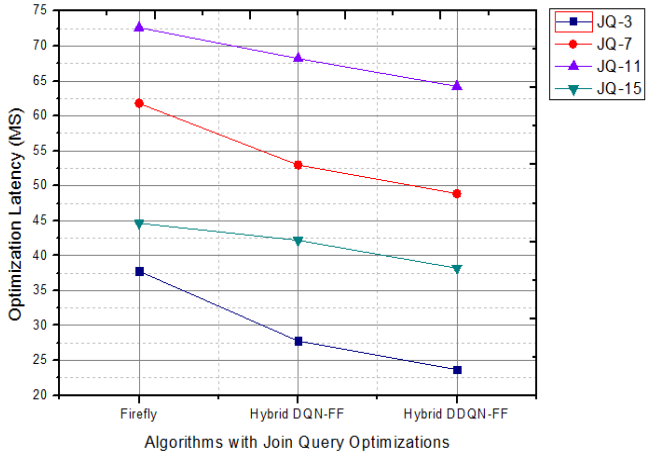

Figure 2: Optimization Latency

This comparison highlights the effectiveness of each approach in optimizing join query

execution plans:

- Firefly Algorithm: creates a strong baseline by utilizing adaptive search to reduce optimization delay and search space exploration.
- DQN-Firefly Approach: uses DQN's learnt policies to improve optimization, leading to better judgments and lower latency.
- DDQN-Firefly Approach: combines FA's adaptive search with DDQN's enhanced Q-value estimation to produce optimal results and a notable reduction in optimization delay.

Query Execution Cost: The Average Query Execution Cost calculates the total cost of query execution by taking into account optimization goals, resource usage, and query response time. In order to calculate it, divide the total cost of all the queries that have been performed by the number of queries that have been executed (number of queries), so that Average Query Execution Cost = Total Cost / Number of Queries.

The Firefly Algorithm (FA) seeks to minimize resource consumption and query response time in order to lower the average cost of query execution. This is accomplished by using iterative attraction and movement rules, in which less fit firefly gravitate toward more vibrant ones, improving search efficiency and identifying effective execution strategies that reduce the overall cost of query execution. The DQN-Firefly method incorporates Deep Q-Networks (DQN) to improve upon the standard Firefly Algorithm. The DQN component estimates Q-values, which indicate the anticipated cumulative cost of various actions (join operations), using past query execution data. Promising join procedures can be chosen thanks to the guidance provided by these Q-values in the decision-making process. Following that, the Firefly Algorithm uses these well-informed judgments to conduct an adaptive search.

By fusing the exploratory and adaptive qualities of FA with the systematic learning and decision-making capabilities of DQN, this hybrid technique seeks to lower the average query execution cost. Through enhanced decision-making over which join commands to pursue, the DQN-Firefly technique can dramatically reduce execution time and resource consumption. By combining the Firefly Algorithm and Double Deep Q-Networks (DDQN), this technique addresses the overestimation bias present in conventional DQN. By keeping two distinct Q-networks for action selection and evaluation, DDQN increases the accuracy of Q-value estimate and promotes more accurate and reliable decision-making. This is enhanced by the Firefly Algorithm, which directs the adaptive search procedure through effective and varied join order exploration. The decision-making process is improved by the DDQN component, and the search space is thoroughly explored by the FA component, leading to the identification of the best possible execution plans. This integration dramatically lowers the average query execution cost while simultaneously decreasing resource consumption and query response time. The following figure (Figure 3) compares the average query execution cost of the three approaches when applied to join queries involving four relations using the TPC-H dataset.

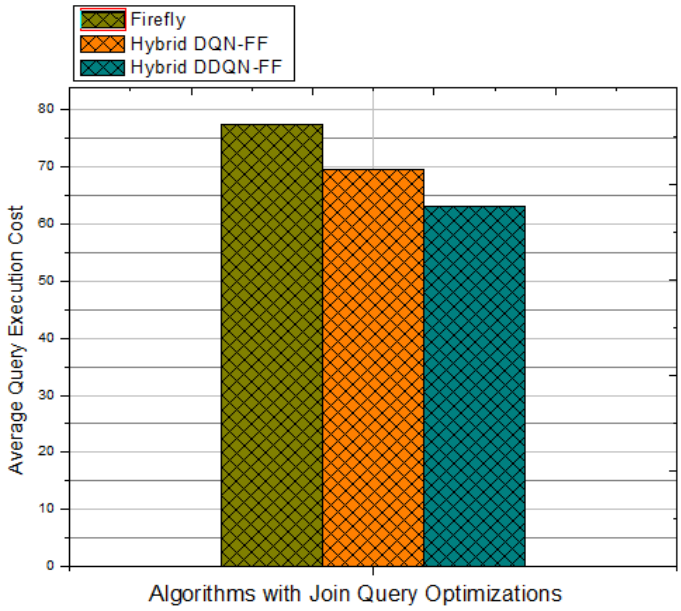

Figure 3: Average Query Execution Cost

This comparison highlights the effectiveness of each approach in optimizing join query execution plans:

- Firefly Algorithm: By efficiently examining the search space and utilizing adaptive search to reduce the average query execution cost, it offers a strong foundation.
- DQN-Firefly Approach: By utilizing DQN's learnt rules, optimization is improved, leading to better informed decisions and lower expenses.
- DDQN-Firefly Approach: Integrating FA's adaptive search with DDQN's improved Q-value estimate yields optimal results and greatly reduces average query execution costs.

The average query execution time for the Hybrid DDQN-Firefly model is 63.52 ms, as illustrated in Figure 3, as opposed to 69.54 ms for the Hybrid DQN-Firefly and 78.45 ms for the Firefly Algorithm. These findings suggest that the Firefly Algorithm with Double DQN integration offers a more effective and efficient join query optimization solution, resulting in decreased average query execution costs and enhanced overall performance.

Convergence Speed: The rate at which an algorithm arrives at the ideal state or solution is measured by its convergence speed. Convergence speed is determined by dividing the number of iterations by the initial value (Initial Value), where Final Value is the value attained at the end of the algorithm's execution, and Number of Iterations is the total number of epochs or iterations needed for convergence. The Firefly Algorithm (FA) directs the search by causing fireflies to fly toward brighter ones, so iteratively improving the results. The intricacy of the workload associated with the join queries and the particular optimization goals determine how quickly FA converges. Although it might be slower than more guided algorithms, its stochastic character allows for a varied exploration of the search space, which might result in efficient

convergence. By combining the Firefly Algorithm and Deep Q-Networks (DQN), the DQN-Firefly method accelerates convergence. The DQN component estimates Q-values, which are the anticipated cumulative rewards of various actions (join operations), using past query execution data. The decision-making process is guided by these Q-values, which aid in prioritizing join orders that show greater promise. Through the use of these well-informed decisions to direct the FA's adaptive search, the DQN-Firefly technique can greatly speed up convergence. By concentrating on high-reward activities, the DQN component methodically lowers the search space, hence lowering the number of iterations required to find optimal or nearly ideal solutions. With the DDQN-Firefly Algorithm, the overestimation bias found in conventional DQN is addressed.

For action selection and evaluation, DDQN employs two distinct Q-networks, which produces more precise and reliable Q-value estimates. By improving decision-making, this precision enables the algorithm to concentrate on the most promising join operations. Following that, the Firefly Algorithm uses these choices to drive an adaptive search procedure. Significant acceleration of convergence is achieved by combining the effective exploration mechanism of FA with the enhanced Q-value estimation of DDQN. With the help of this integration, the algorithm is able to rapidly identify the best join query execution strategies, which lowers the number of iterations and overall execution time.

- Firefly Algorithm: Because it is stochastic, it may have slower convergence but offers a strong baseline with efficient search space exploration.
- DQN-Firefly Approach: uses DQN's policy-driven decisions to accelerate convergence, resulting in a more focused and rapid convergence.
- DDQN-Firefly Approach: Integrating FA's adaptive search with DDQN's improved Q-value estimate yields the fastest convergence speed and the best results.

In particular, the Hybrid DDQN-Firefly strategy achieves an 88.25% relative improvement over DQN and Firefly Algorithm alone, with a total training duration of 48.36 ms. These findings suggest that the Firefly Algorithm and Double DQN integration offer a more effective and efficient join query optimization method, resulting in faster convergence and better overall performance.

5. Conclusion

Using the TPC-H dataset, this study examined the use of the Firefly Algorithm, DQN-Firefly, and DDQN-Firefly techniques for join query optimization. We have shown through extensive experimentation that by decreasing query execution costs and increasing convergence speed, each of these methods can greatly improve query optimization performance. With its metaheuristic design, the Firefly Algorithm offers a strong foundation while efficiently examining the join order search space. Through iterative improvement of execution plans based on fitness, it reduces the average query execution cost. By using Deep Q-Networks, the DQN-Firefly method enhances the firefly algorithm as it stands. By utilizing past query execution data, this integration speeds up convergence by facilitating better decision-making. Promising join orders are given priority by the DQN component, which reduces execution costs and speeds up optimization times. Combining the Firefly Algorithm and Double Deep

Q-Networks, the DDQN-Firefly technique provides the greatest benefits. DDQN eliminates the overestimation bias in traditional DQN and produces more consistent and accurate Q-value estimations by utilizing two distinct Q-networks for action selection and evaluation. Among the studied algorithms, this precision along with the Firefly Algorithm's adaptive search yields the fastest convergence and lowest average query execution costs. In comparison to the other approaches, the hybrid DDQN-Firefly technique shows the greatest efficacy and efficiency in join query optimization, offering notable gains in execution cost and convergence speed.

Future Work

- Examine how the Firefly Algorithm can be integrated with other reinforcement learning algorithms, including Advantage Actor-Critic (A2C) or Proximal Policy Optimization (PPO). These hybrids may improve convergence speed and decision-making even further.
- Undertake comprehensive investigations into the effects of fine-tuning hyperparameters for the Firefly Algorithm and reinforcement learning segments. The optimal configurations could be found using automated hyperparameter optimization methods.
- Make the optimization process and the ensuing execution plans easier to understand. Clearly outlining the rationale behind the chosen designs could boost user confidence and make debugging easier.

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