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Abstract

This technical report extends the SIGMOD 2025 paper "A Modular Graph-Native Query Optimization Framework" by providing a comprehensive exposition of GOpt 's advanced technical mechanisms, implementation strategies, and extended evaluations. While the original paper introduced GOpt 's unified intermediate representation (GIR) and demonstrated its performance benefits, this report delves into the framework's implementation depth: (1) the full specification of GOpt 's optimization rules; (2) a systematic treatment of semantic variations (e.g., homomorphism vs. edgedistinct matching) across query languages and their implications for optimization; (3) the design of GOpt's Physical integration interface, enabling seamless integration with transactional (Neo4j) and distributed (GraphScope) backends via engine-specific operator customization; and (4) a detailed analysis of plan transformations for LDBC benchmark queries.

1 Introduction

Graph databases have become indispensable tools for managing interconnected data across domains such as social networks, fraud detection, and recommendation systems. At the heart of these systems lies the need to efficiently execute Complex Graph Patterns (CGPs), which combine graph pattern matching with relational operations like projection, aggregation, and filtering. While existing graph databases like Neo4j [3] and GraphScope [11] provide foundational support for CGPs, their monolithic architectures impose critical limitations: (1) tight coupling with single query languages (e.g., Cypher [12] or Gremlin [17]), hindering cross-language interoperability, and (2) fragmented optimization strategies that lack integration of state-of-the-art techniques like worst-case optimal joins or high-order statistics. These constraints impede performance and flexibility in real-world applications, where evolving query requirements and industrial-scale datasets demand modular, graph-native optimization.

In our SIGMOD 2025 paper, "A Modular Graph-Native Query Optimization Framework" [14], we introduced GOpt, a unified optimization framework designed to address these challenges. GOpt decouples query parsing, optimization, and execution through a graph intermediate representation (GIR), enabling support for multiple query languages (Cypher, Gremlin) and seamless integration with diverse backend engines (Neo4j, GraphScope). By combining heuristic rule-based optimizations (RBO), automatic type inference, and a cost-based optimizer (CBO) leveraging high-order statistics, GOpt achieves significant performance gains – up to $48.6\times$ speedup on Neo4j and $78.7\times$ on GraphScope.

This technical report expands on the SIGMOD work by delving into GOpt 's architectural nuances and practical implementations. Key contributions include:

- In-Depth Optimization Strategies: We detail GOpt 's rule-based optimizations (e.g., FilterIntoPattern, Pattern-Join), cost-model-driven physical operator selection, and hybrid join strategies (binary joins, vertex expansion) tailored for backend engines.
- (2) Semantic Adaptations: We formalize GOpt 's handling of diverse pattern-matching semantics (homomorphism, edge-distinct) across query languages, ensuring correctness while preserving optimization opportunities.
- (3) Physical Interface for Multiple Backends: We demonstrate how GOpt 's PhysicalConverter allows engines to covert their own executable operators (e.g., Neo4j's ExpandInto, GraphScope's ExpandIntersect), enabling backend-specific optimizations without compromising modularity.
- (4) Industrial Validation: Through a granular analysis of GOpt 's optimization impact on the LDBC Social Network Benchmark (SNB) [13], we dissect how and why specific plan transformations – such as pattern order refinement, common pattern removal, and aggregation/filter pushdown – enable significant performance gains. These case studies provide actionable insights for the community, offering a blueprint for optimizing complex graph queries.

The report is structured as follows: Section 2 gives background knowledge of graph pattern matching. Section 3 and Section 4 revisit GOpt 's GIR abstraction and core architecture, respectively. We detail the optimization strategies in Section ??, and their applications to optimizing both simple and complex graph queries in Section ?? and Section 6. Section 7 details the design principles of GOpt's physical integration interface, formalizing two backend-specific methodologies for seamless integration with Neo4j and GraphScope, tailored to their Java-native and distributed execution models, respectively.

By bridging the gap between academic advancements and industrial demands, GOpt establishes a new paradigm for graph query optimization—one that is modular, extensible, and graph-native. This report serves as a comprehensive guide for practitioners seeking to leverage GOpt 's full potential in real-world graph analytics pipelines.

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Notation	Definiton
$G(V_G, E_G)$	A data graph with V_G and E_G
$P(V_P, E_P)$	A pattern graph with V_P and E_P
$N_G(v), N_G^E(v)$	Out neighbors and out edges of v in graph G
$\lambda_G(v), \lambda_G(e)$	The type of vertex v and edge e in graph G
$ au_P(v), au_P(e)$	The type constraint of vertex v and edge e in pattern
	P, can be BasicType, UnionType or AllType
$\mathcal{F}_{P,G}$	The number of mappings of pattern P in graph G

Table 1: Frequently used notations.

2 Preliminaries

2.1 The Definitions

Data graph $G = (V_G, E_G)$ in this report adheres to the definition of the property graph model [9]. V_G and E_G are the sets of vertices and edges, where $|V_G|$ and $|E_G|$ represent the number of vertices and edges. Given $u, v \in V_G$, $(u, v) \in E_G$ is an edge directed from u to v, and all the out neighbors and out edges of u are denoted as $N_G(v)$ and $N_G^E(v)$, respectively. Each vertex or edge in G is associated with a type, denoted as $\lambda_G(v)$ and $\lambda_G(e)$ respectively. Both vertices and edges can carry properties, which are key-value pairs. Note that if no ambiguity arises, we omit G from the subscript in the notations, and so as the follows. Considering two graphs G_1 and G_2 , we assert that G_2 is a subgraph of G_1 , symbolized as $G_2 \subseteq G_1$, if and only if $V_{G_2} \subseteq V_{G_1}$, and $E_{G_2} \subseteq E_{G_1}$.

A pattern $P = (V_P, E_P)$ is a small *connected* graph. Note that if P is not connected, matching the pattern is equivalent to taking the Cartesian product of the matches for its connected components, which is naturally the problem of CGPs in the following. Each vertex and edge in the pattern graph is associated with a set of types as a type constraint, denoted as $\tau_P(v)$ and $\tau_P(e)$, respectively. Besides, predicates can be specified to vertices and edges in the pattern graph as well.

Finding matches of *P* in *G* involves identifying all subgraphs *G'* in *G* where *P* can be mapped to *G'* via a homomorphism preserving edge relations and type constraints. The mapping function $h: V_P \rightarrow V_{G'}$ ensures that $\forall e = (u, v) \in E_P$, there is a corresponding edge $(h(u), h(v)) \in E_{G'}$. Additionally, the types of vertices and edges in *G'* must align with the type constraints specified in *P*: (1) $\forall v \in V_P, \lambda_{G'}(h(v)) \in \tau_P(v)$, and (2) $\forall e = (u, v) \in E_P, \lambda_{G'}((h(u), h(v))) \in$ $\tau_P(e)$. The number of mappings of *P* in *G* is called *pattern frequency*, denoted as $\mathcal{F}_{P,G}$, or simply \mathcal{F}_P when *G* is clear.

A complex graph pattern, termed as CGP, extends patterns with further relational operations. Optimizing CGPs is challenging due to their hybrid semantics. A straightforward way is to first identify matches of P in G, and then subject the matched subgraphs to the remaining relational operators in CGPs for further analysis, such as projecting the properties of matched vertices and edges and selecting the matched subgraphs that satisfy certain conditions.

In the realm of pattern matching, the *pattern matching order* is pivotal, significantly influencing the overall efficiency and execution time of the process. Consider the matching order for a pattern *P* as a sequence of vertices $v^{(1)}, v^{(2)}, \ldots, v^{(|V_P|)}$, where each $v^{(i)} \in V_P$ and i < j indicates that in the matching order, vertex $v^{(i)}$ is mapped to a vertex in the data graph *G* before vertex $v^{(j)}$. We can enumerate matching orders for pattern *P* by permuting

the vertices in V_P . Additionally, there may be different matching strategies for each order. For example:

- Start with the first vertex v⁽¹⁾, and then iteratively match the subsequent vertices v⁽²⁾,...,v^(|V_P|) to form the complete match.
 First match the vertices v⁽¹⁾...v⁽ⁱ⁾, then match the vertices
- First match the vertices $v^{(1)} \dots v^{(i)}$, then match the vertices $v^{(i)} \dots v^{(|V_P|)}$, where $i \in [1, |V_P|]$, and finally join the matching results of these two parts to generate the final matches.
- A hybrid approach that combines the above two methods.

Each matching order, along with its associated matching strategies, is referred to as a PatternOrder. For a given pattern P, different PatternOrders guarantee the same final results based on the equivalent pattern transformation rule PatternJoin (detailed in Section 5.2), but involve different execution costs. In Section 5.2, we will show how GOpt determine the best PatternOrder for a given pattern using cost-based optimization techniques.

2.2 Pattern Matching Semantics

It is important to note that in our framework, pattern matching is conducted under homomorphism semantics, which is useful due to its transformability. However, different query languages may adopt different semantics for pattern matching. Generally, the semantics can be categorized as follows:

- Homomorphism Semantics: Allows duplicates of vertices or edges in matching results.
- Edge-Distinct Semantics: Allows duplicate vertices but not edges.
- Vertex-Distinct Semantics: Allows duplicate edges but not vertices.
- Vertex-Edge-Distinct Semantics: Disallows duplicates of both vertices and edges.

REMARK 2.1. Different query languages may adopt different semantics for pattern matching, which can lead to different matching results. Currently, Apache TinkerPop adopts homomorphism semantics in Gremlin [17], while Neo4j uses edge-distinct semantics in Cypher [12]. In GOpt, we primarily focus on homomorphism semantics for pattern matching as it is the most general. When integrating with different query languages, we apply the corresponding filters to ensure the matching results are consistent with the semantics of the respective query language.

Example 2.1. We illustrate the differences among various semantics in Fig. 1, with a particular emphasis on homomorphism and edge-distinct semantics, which are employed by Gremlin and Cypher, respectively. Fig. 1(a) presents a data graph G, while Fig. 1(b) depicts a pattern P. Fig. 1(c) shows the pattern matching results of pattern P within the data graph G under homomorphism semantics. In this context, the matching results can include duplicated vertices and edges. For example, in R_1 , all matched vertices are duplicates (u_1), and all matched edges are duplicates (e_1). In contrast, under edge-distinct semantics, duplicate edges are not allowed. To comply with this, a further all-edge-distinct filter is applied to the results of pattern matching (i.e., the results in Fig. 1(c)), to generate edge-distinct results in Fig. 1(d).



R1	u1	e1	u1	e1	u1	e1	u1	e1
R2	u1	e1	u1	e1	u1	e2	u2	e3
R3	u1	e1	u1	e2	u2	e4	u3	e5
R4	u1	e2	u2	e4	u3	e5	u1	e1

(c) Matching Results of P in G under Homomorphism Semantics

Results	v1	v1->v2	v2	v2->v3	v3	v3->v4	v4	v4->v
R1	u1	e1	u1	e2	u2	e4	u3	e5
R2	u1	e2	u2	e4	u3	e5	u1	e1
R3	u2	e4	u3	e5	u1	e1	u1	e2
R4	u3	e5	u1	e1	u1	e2	u2	e4

(d) Matching Results of P in G under Edge-Distinct Semantics

Figure 1: An example of pattern matching semantics.

	Results	v4	v4->v1	v1	v1->v2	v2
v4 → v1 → v2	R1	u1	e1	u1	e2	u2
Graph Pattern P1	R2	u1	e2	u2	e4	u3
м	R3	u2	e4	u3	e5	u1
	R4	u2	e3	u1	e1	u1
v2 → v3 → v4	R5	u3	e5	u1	e2	u2
Graph Pattern P2	R6	u3	e5	u1	e1	u1

(a) Complex Pattern P' (b) Matching Results of P1 in G under Edge-Distinct Semantics

Results	v1	v1->v2	v2	v2->v3	v3	v3->v4	v4	v4->v1
R1	u1	e1	u1	e2	u2	e4	u3	e5
R2	u1	e2	u2	e4	u3	e5	u1	e1
R3	u2	e4	u3	e5	u1	e1	u1	e2
R4	u3	e5	u1	e1	u1	e2	u2	e4
R5	u1	e2	u2	e3	u1	e1	u1	e1
R6	u1	e1	u1	e1	u1	e2	u2	e3

(c) Join Results of Matches of P1 and P2 in G under Edge-Distinct Semantics

Figure 2: An example of joining two patterns under Edge-Distinct semantics.

In our framework, we carefully design optimization rules to be consistent with the query language semantics. For example, the Join-ToPattern (which will be discussed in details in Section 5.1.2) aims to merge two patterns P_1 and P_2 , initially connected by a Join operator, into a single pattern P where the join keys (i.e., vertices and/or edges) serves as the common vertices or edges in P. Conversely, the PatternJoin (which will be discussed in details in Section 5.2.1) attempts to decompose a pattern into two sub-patterns, match them separately, and then join the results to generate the final matches. These two rules operate correctly under homomorphism semantics, making them suitable for Gremlin, since duplications are allowed in both pattern-based and join-based queries. However, under nonhomomorphism semantics, these rules must be applied with caution. For example, when supporting Cypher, we cannot apply the Join-ToPattern to merge P_1 and P_2 into P, since the original join-based query results may contain duplicate edges, but after merging, the matchings of P will not, which is inconsistent with the original results. For the PatternJoin to decompose P into P_1 and P_2 , after matching P_1 and P_2 separately and joining the matching results, we will further apply an edge-distinct filter to the results to ensure no duplicate edges are present.

Example 2.2. We illustrate an example of a join-based query under edge-distinct semantics in Fig. 2 The CGP P' joins two patterns P_1 and P_2 , as shown in Fig. 2(a). The results of matching P_1 in G (Fig. 1(a)) are shown in Fig. 2(b). For brevity, the results for P_2 are omitted for brevity as they are the same to P_1 's. The results of CGP P' in G are displayed in Fig. 2(c), highlighting that joining the matching results of P_1 's and P_2 's can generate duplicate edges.

First, let us consider the JoinToPattern. If we directly apply the JoinToPattern to merge P_1 and P_2 into P (Fig. 1(b)), and match the merged pattern P in G, we will eliminate duplicate edges in results as shown in Fig. 1(d). This outcome is inconsistent with the original join-based query results shown in Fig. 2(c). Therefore, the JoinToPattern should not be directly applied in Cypher.

Next, let us consider the PatternJoin. If we apply the Pattern-Join to decompose P (Fig. 1(b)) into P_1 and P_2 (Fig. 2(a)), match them separately, and then join the results, we will obtain the results shown in Fig. 2(c). However, the results contain duplicate edges, which contradict the matching results of P in Fig. 1(d) under edgedistinct semantics. Therefore, we should apply an edge-distinct filter to the joined results (Fig. 2(c)) to ensure consistency with edge-distinct semantics.

3 GIR Abstraction

In this section, we introduce the query-language-agnostic graph intermediate representation (GIR) for GOpt to capture both graph and relational operations. The GIR abstraction defines a data model \mathcal{D} that describes the structure of the intermediate results during query execution, and a set of operators Ω .

3.1 Data Model

The data model \mathcal{D} presents a schema-like structure in which each data field has a String-typed name, accompanied by a designated datatype. The supported datatypes encompass both graph-specific datatypes and general datatypes. Graph-specific datatypes include *Vertex, Edge,* and *Path,* as shown below:

- *Vertex* is a datatype to represent the vertices in data graph. It typically consists of: ID that serves as a unique identifier for the vertex; TYPE that characterizes the vertex class; and *properties* that includes property names and property values as a set of attributes associated with the vertex's type.
- *Edge* is a datatype to represent the edges in data graph. It usually includes: EID that acts as a unique identifier for the edge, which is a triplet of (edge_id, src_id, dst_id), with src_id and dst_id pinpointing the source and destination vertices; ETYPE that represents the edge kind, which is also a triplet of (edge_type, src_type, dst_type), with src_type and

dst_type specifying the source and destination vertex types; and *properties* that consist of property names and property values as a set of attributes associated with the edge's type.

• *Path* is a datatype of an array of vertices and edges that represents a sequence of connected vertices and edges in the data graph. It is denoted as $p = [v_1, e_1, v_2, e_2, ..., v_n]$, where v_i and e_i are the *i*-th vertex and edge in the path respectively. Specifically, *Path* includes PID as a unique identifier; and a specific property of length, denoting the number of edges in the path.

General datatypes comprise *Primitives* including *Integer*, *Float*, *String* etc., and *Collections* representing a group of elements, e.g., *List*, *Set*, and *Map*. Notice that the properties in vertices and edges are of general datatypes. For instance, a vertex with *type* PERSON may have *properties* of name (*String*), age (*Integer*), and hobbies (*List*).

3.2 Operators

The operators in Ω operate on data tuples extracted from \mathcal{D} , and produce a new set of data tuples as a result. The set Ω is composed of graph operators and relational operators. For clarity, we introduce only the parameters that are essential to understanding each operator's functionality, omitting those that are not critical to its core purpose.

3.2.1 Graph Operators

The graph operators are specifically for the retrieval of graph data. They include GET_VERTEX, EXPAND_EDGE, EXPAND_PATH, and MATCH_PATTERN. **GET_VERTEX**. The GET_VERTEX operator is designed to retrieve vertices from the data graph, or to retrieve source or destination vertices from specified edges.

Parameters: (*tag*, *alias*, *types*, *opt*)

- *tag*: The identifier from which to obtain vertices. If it is tagged with an edge, it retrieves the source or target vertices from the tagged edge with the specified type constraints. If the *tag* parameter is unspecified (NA), it retrieves vertices directly from the data graph.
- *alias*: A name to indicate the retrieved vertices in \mathcal{D} .
- *types*: The type constraints for the vertices.
- *opt*: The vertex option (if retrieving vertices directly from the data graph, this parameter will be ignored.):
 - SRC: Source vertices of the tagged edges.
 - *DST*: Destination vertices of the tagged edges.
 - OTHER: The other vertices of the tagged edges, which is in line with the following EXPAND_EDGE operator when the edge is expanded in BOTH directions.

EXPAND_EDGE. The EXPAND_EDGE operator is used to retrieve edges from the data graph, or to retrieve adjacent edges from specified vertices.

Parameters: (*tag*, *alias*, *types*, *opt*)

- *tag*: The identifier from which to expand edges. If it is tagged with vertices, it expands either outgoing (OUT) or incoming (IN) edges from the tagged vertices with specified type constraints. If the *tag* parameter is unspecified (NA), it retrieves edges directly from the data graph.
- *alias*: A name to indicate the retrieved edges in \mathcal{D} .
- *types*: The type constraints for the edges.

- *opt*: The edge option (if retrieving edges directly from the data graph, this parameter will be ignored.):
 - OUT: Outgoing edges from the tagged vertices.
 - *IN*: Incoming edges to the tagged vertices.
 - *BOTH*: Both outgoing and incoming edges from the tagged vertices.

EXPAND_PATH. The EXPAND_PATH operator is designed to retrieve paths from specified source vertices.

Parameters: (*tag*, *alias*, *expand_base*, *length*, *opt*)

- *tag*: The identifier for the source vertices.
- *alias*: A name to indicate the retrieved paths in \mathcal{D} .
- *expand_base*: A composite of EXPAND_EDGE and GET_VERTEX operators defining what is each hop in the path.
- *length*: The number of hops in the path expansion.
- *opt*: The path option:
 - ARBITRARY: No constraints.
 - *SIMPLE*: No repeated nodes in the path.
 - TRAIL: No repeated edges in the path.

MATCH_PATTERN. The MATCH_PATTERN operator is used to describe a series of operations to match a complex pattern within the data graph.

Parameters: (*expand_base*)

• *expand_base*: A composite of GET_VERTEX, EXPAND_EDGE, and EXPAND_PATH operators defining a pattern graph.

Notice that the types parameter in the graph operators specifies type constraints to filter out desired classes of graph elements, where we allow either a single type constraint or a union of multiple type constraints, depending on the query requirements. The alias parameter indicates a name under which intermediate results are stored, allowing subsequent operations to reference these results using the *taq* parameter. We provide a special empty string tag to refer to the result of the immediate previous operation, thereby avoiding unnecessary data storage during execution. Filter conditions can be integrated into these operators using optimization rules from GOpt, specifically the FilterIntoPattern. In the EXPAND PATH operator, the number of hops is a specific positive integer. Ranged hop or even arbitrary hop (using Kleene star) will be handled in the future. For the MATCH_PATTERN operator, to facilitate illustration, we use MATCH_START and MATCH_END to denote the beginning and end of a pattern match. Alternatively, within this paper, a pattern may be depicted to represent the MATCH_PATTERN.

3.2.2 Relational Operators

We briefly discuss the essential relational operators in Ω , which are widely used in RDBMS, including PROJECT, SELECT, ORDER, LIMIT, GROUP, UNFOLD, JOIN, and UNION.

PROJECT. The PROJECT operator is used for projection, allowing the selection of specific columns and computation of additional values if necessary.

Parameters: (columns_expressions)

• *columns_expressions*: A list of columns or expressions to be included in the projection. The input columns (or those for these expressions) are specified by tags, and each output column can be given an alias for reference in subsequent operations.

SELECT. The SELECT operator filters rows (i.e., data) based on specific conditions in the data.

- **Parameters:** (condition_expression)
- *condition_expression*: An expression defining the filter condition.

ORDER. The ORDER operator sorts the results according to specified columns and ordering options.

- **Parameters:** (*order_by_columns*)
- order_by_columns: A list of columns, specified by tags, with options for sorting order (ASC or DESC).

LIMIT. The LIMIT operator restricts the number of results returned. **Parameters:** (*limit_count*)

• *limit_count*: The maximum number of results to be returned.

GROUP. The GROUP operator groups the results by specific columns and applies aggregation functions.

Parameters: (group_by_columns, aggregation_functions)

- *group_by_columns*: A list of columns, specified by tags, on which to group the results.
- aggregation_functions: Functions applied for aggregation, such as COUNT, SUM, AVG, MIN, MAX, FIRST. Aggregated result can be assigned an alias for reference.

UNFOLD. The UNFOLD operator transforms a collection of nested results into a flat structure, where each element in the collection becomes a separate row.

Parameters: (collection_column)

 collection_column: The column, specified by a tag, containing the collection to be unfolded. The flattened results can be assigned an alias for reference.

JOIN. The JOIN operator is used to join the results of two subqueries based on specific conditions, supporting multiple join types.

Parameters: (*left*, *right*, *join_keys*, *join_type*)

- *left*: The left sub-query for the join.
- *right*: The right sub-query for the join.
- *join_keys*: The column keys, specified by tags, on which the join operation is performed, determining how rows from the two sub-queries are matched.
- *join_type*: The type of join, such as INNER, LEFT OUTER, RIGHT OUTER, FULL OUTER, SEMI, or ANTI. The results can be assigned an alias for reference.

UNION. The UNION operator merges results from two sub-queries into a single result set.

Parameters: (*left*, *right*)

- *left*: The left sub-query to be merged.
- right: The right sub-query to be merged.

These operators can be applied on graph-specific data as well, e.g., to project properties of vertices, to select edges with specific conditions, to join two sub-paths into a longer one with the join key as the end vertices of the two sub-paths, or to union the results of two sub-matching clauses.

3.3 Applications of GIR

We have designed GIR as a query-language-agnostic intermediate representation capable of expressing queries from diverse graph



Figure 3: The GIR Representations of Cypher queries. In the following, the MATCH_PATTERN operator in an GIR will be illustrated as a graph view for simplicity.

query languages. Currently, we have implemented the construction of GIR [2] for two of the most popular graph query languages, Cypher [12] and Gremlin [17], enabling the broader application of optimization techniques based on GIR. As a result, with GOpt, GraphScope [11] seamlessly supports queries from both query languages, optimizing them using the same unified set of optimization strategies that will be elaborated in the following sections.

Fig. 3 illustrates the GIR representation of the query example in Cypher and Gremlin languages. In Fig. 3, each Match clause is transformed into a MATCH_PATTERN operator, which captures the vertexedge relationships defined nested in the pattern. The two Match clauses are organized into a Join operator (with an INNER join type), which combines the results of each MATCH_PATTERN. Notably, if the second Match clause is OPTIONAL, which means the pattern matching is optional, the Join operator will be the LEFT OUTER join type. The relational clauses following the Match clause are then converted into corresponding relational operators of SELECT, GROUP, and ORDER.

REMARK 3.1. The definition of GIR is inspired by existing work on graph relational algebra [18] and is enhanced with MATCH_PATTERN to handle complex patterns. Moreover, GIR's development follows an engineer-oriented approach, prioritizing support for commonly used functionalities over theoretical completeness. It continuously evolves to meet new requirements from real applications.

4 Architecture

The system overview of GOpt is illustrated in Fig. 4, which is composed of three primary layers: Query Parser, GIR Optimizer and Physical Converter. The Physical Converter provides a modular interface for integrating GOpt with different graph backends (detailed in Section Section 7). In this section, we focus primarily on introducing the Query Parser and GIR Optimizer.

4.1 Query Parser

The Query Parser serves as the top layer of GOpt to transform user queries into a logical plan in the GIR format, to facilitate the following optimization process.

First, the parser performs syntax validation on the input graph queries using the ANTLR Tool [1]. For queries that do not comply



Figure 4: GOpt System Overview.

with the syntax rules, ANTLR errors are thrown immediately. As aforementioned, GOpt supports both Cypher and Gremlin. The current implementation focuses on the key components of the query language, primarily involving query clauses for graph pattern matching and relational operations. The supported grammars can be found in [8].

Next, for valid queries, the GIRBuilder tool is used to construct the GIR plan. The GIR plan represents a unified intermediate structure that is independent of the query syntax and serves as the foundation for all optimizations in GOpt. We provide a code snippet to demonstrate how to construct the logical plan in Fig. 3 using the GIRBuilder:

```
GraphIrBuilder irBuilder = new GraphIrBuilder();
pattern1 = irBuilder.patternStart()
.getV(Alias("v1"),AllType())
.expandE(Tag("v1"),Alias("e1"),AllType(),Dir.OUT)
.getV(Tag("e1"),Alias("v2"),AllType(),Vertex.END)
.expandE(Tag("v2"),Alias("e2"),AllType(),Dir.OUT)
.getV(Tag("e2"),Alias("v3"),AllType(),Vertex.END)
.patternEnd();
pattern2 = irBuilder.patternStart()
.getV(Alias("v1"),AllType())
.expandE(Tag("v1"),Alias("e3"),AllType(),Dir.OUT)
.getV(Tag("e3"),AllType())
.expandE(Tag("v1"),Alias("e3"),AllType(),Dir.OUT)
.getV(Tag("e3"),Alias("v3"),BasicType("Place"),Vertex.END)
.patternEnd();
query = irBuilder.join(pattern1,pattern2,
    Keys([Tag("v1"), Tag("v3")]), JoinType.INNER)
.select(Expr("v3.name='China'"))
.order(Keys(Tag("cnt")), Order.ASC, Limit(10));
```

Here, Alias() defines an alias for results, accessible via Tag() in later operations. With the GIRBuilder, the logical plan is constructed in a language-agnostic manner, facilitating the subsequent optimization process. Henceforth, when mention optimizing a query, we are referring to optimizing based on its GIR.

4.2 GIR Optimizer

In this phase, GOpt unfolds the GIR structure, composed of a hybrid of patterns and relational operations, and transforms it into a physical plan that can be executed by the engine. The intermediate structure generated during the transformation is referred to as the GIR plan. The input to this phase is the intermediate representation (GIR) of the query, and the final output is the optimized GIR plan,



Figure 5: DAG of Optimization Process.

which is ready for integration with the underlying engine. The entire optimization process within GOpt can be conceptualized as a Directed Acyclic Graph (DAG), where each node embodies certain optimization Strategy. A Strategy encapsulates the application of either a single rule or a group of related rules within GOpt. The edges in the DAG represent dependencies between strategies, similar to the optimization phases in traditional database systems, where certain rules depend on the outputs of others. GOpt applies the strategies in the topological order of the DAG, ensuring that the applications of strategies does not conflict with one another. The DAG formed by the various strategies that have been adopted by GOpt is shown in Fig. 5.

At the core of GOpt , there lies the Strategy interface that guides the optimization process of each node in the DAG as follows:

interface Strategy {
 GIRPlan transform(GIRPlan input);
}

The transform function defines how the input GIR plan is transformed into the optimized GIR plan. Depending on the implementation of transform, optimizations can be executed based on heuristic or top-down search approaches. Internally, GOpt provides two main types of Strategy implementations – RuleBasedStrategy and PatternStrategy.

RuleBasedStrategy includes a series of heuristic rules, where each rule specifically implements the transform function to perform equivalent transformations on the input GIR plan and output the transformed GIR plan. These rules are partly reused from Calcite [10], including: FilterIntoJoin [6], FieldTrim [5], SortProjectTrans [7], and AggJoinTrans [4]. Additionally, to handle specific optimizations related to graph data and operations, GOpt has implemented specialized rules for graph data models, including: FilterIntoPattern, JoinToPattern, ComSubPattern, EVFusion, Deg-Fusion, PKIndex, and LateProject. We will discuss these rules in detail in Section 5.

PatternStrategy primarily optimizes the execution sequence of graph operators within Patterns, referred to as PatternOrders . The transform function takes a GIR plan as input, composed of MATCH_PATTERN and other relational operators, as shown in Fig. 6(a); it outputs an optimized GIR plan representing the PatternOrder , consisting of a series of physical operators, as shown in Fig. 6(b). The transform function executes a top-down search algorithm as described in the GOpt paper [14], obtaining a series of PatternOrders along with their respective costs, and selects the PatternOrder with the lowest cost as the most optimized GIR plan,



Figure 6: The GIR Optimization.

5 Details of Optimization Strategies

In this section, we provide a detailed overview of the optimization strategies implemented in GOpt, which consists of two core components: RuleBasedStrategy and PatternStrategy.

The RuleBasedStrategy encompasses a series of heuristic rules. GOpt utilizes a heuristic-driven approach where these rules are applied immediately upon meeting specific preconditions, thus removing the necessity for cost-based estimation. Some of these rules are adopted from Calcite, such as FilterIntoJoin [6], FieldTrim [5], SortProjectTrans [7], and AggJoinTrans [4]. Given that these rules have concrete implementations within Calcite, we will not delve into their introductions here. Furthermore, to address particular optimizations pertinent to graph data and operations, GOpt has introduced specialized rules tailored for graph data models. These include FilterIntoPattern , JoinToPattern , ComSubPattern , EVFusion , DegFusion , PKIndex , and LateProject. Detailed explanations of these rules will be provided in the following sections.

The second component, PatternStrategy, focuses on optimizing the order of graph operations within a single pattern. Unlike RuleBasedStrategy, the application of PatternStrategy relies on the availability of external metadata for cost estimation, which allows GOpt to determine whether to use a heuristic approach or a dynamic programming (DP) strategy for optimization. We will explore the implementation of PatternStrategy through three key interfaces: (1) logicalOrder: Determines the logical sequence of operations; (2) physicalSpec: Specifies the physical execution plan; (3) getCost: Estimates the cost of a given plan.

5.1 RuleBasedStrategy

5.1.1 FilterIntoPattern

FilterIntoJoin [6] is a relational rule that implemented in Calcite, which aims to push filter conditions into a Join condition and into the inputs of the Join . Built upon the idea, we implement Filter-IntoPattern to further push down filter conditions into the graph operations nested in the Pattern. The following code snippet illustrates the preconditions before applying the rule:

Considering the following example, we illustrate the transformation of this rule in detail. For the query:

```
Match (v1)-[e1]->(v2),
    (v2)-[e2]->(v3),
    (v1)-[e3]->(v3)
Where v3.name = "China"
Return v1.name, count(v2);
```

After the application of FilterIntoPattern , the optimization effect is equivalent to rewriting the query as follows:

```
Match (v1)-[e1]->(v2),
// the filter conditions has been pushed into the pattern
       (v2)-[e2]->(v3 {name: "China"}),
       (v1)-[e3]->(v3 {name: "China"})
Return v1.name, count(v2);
```

5.1.2 JoinToPattern

For two patterns connected by a JOIN operator, the JoinToPattern aims to merge them into a single one, when the join keys (i.e., vertices and/or edges) serving as the common vertices and/or edges in the resulted pattern. This rule is effective under the homomorphismbased matching semantics as discussed in Section 2.2. It is applicable when the two patterns are connected by a JOIN operator with JoinType.INNER. The following code snippet demonstrates the precondition checks:

<pre>public interface JoinToPatternRuleConfig extends {</pre>
JoinToPatternRuleConfig DEFAULT =
new Config()
.withOperandSupplier(b0 ->
<pre>b0.operand(Join.class)</pre>
predicate(
<pre>join -> join.getJoinType() == JoinType.INNER)</pre>
)
.inputs(
<pre>b1 -> b1.operand(AbstractLogicalMatch.class).</pre>
anyInputs(),
<pre>b2 -> b2.operand(AbstractLogicalMatch.class).</pre>
anyInputs());
}
For example, consider the following query:

Match (v1)-[e1]->(v2), (v2)-[e2]->(v3) Match (v1)-[e3]->(v3) Return v1, v2, v3;

After applying the JoinToPattern under homomorphism-based matching semantics, the two patterns are merged into a single one, resulting in the following query:

Match (v1)-[e1]->(v2),	
(v2)-[e2]->(v3),	
(v1)-[e3]->(v3)	
Return v1, v2, v3;	

5.1.3 ComSubPattern

For two patterns connected by binary operators such as UNION and JOIN, we design the ComSubPattern to identify common subpatterns in the two patterns, and save the computation cost by matching the common subpattern only once. This rule is applicable when the two patterns are connected by a binary operator, such as UNION or JOIN, as shown in the following code snippet (UNION as an example, and JOIN is similar):

```
public interface ComSubPatternRuleConfig extends ... {
   ComSubPatternRuleConfig DEFAULT =
    new Config()
   .withOperandSupplier(b0 ->
    b0.operand(UNION.class))
    .inputs(
        b1 -> b1.operand(AbstractLogicalMatch.class).
            anyInputs(),
        b2 -> b2.operand(AbstractLogicalMatch.class).
            anyInputs());
}
```

By identifying the patterns connected by a UNION or JOIN, the ComSubPattern will further detect the common subpattern in the two patterns, and merge the common subpattern into a single one if it exists. For example, consider the following query:

```
Match (v1:PERSON)-[]->(v2:PERSON)-[]->(v3:PLACE)
Union
Match (v1:PERSON)-[]->(v2:PERSON)-[]->(v4:COMMENT)
Return v1, v2, v3, v4;
```

After applying the ComSubPattern, it identifies the common subpattern (v1:PERSON)-[]->(v2:PERSON) in the two patterns, and merges the common subpattern into a single one and computes it only once, resulting in the following query:

```
Match (v1:PERSON)-[]->(v2:PERSON)
with v1, v2
Match (v2)-[]->(v3:PLACE)
Union
Match (v2)-[]->(v4:COMMENT)
Return v1, v2, v3, v4;
```

5.1.4 EVFusion

The EVFusion is a specific optimization implemented for graph operators within patterns. Traversal is one of the most commonly used query patterns in graph databases, typically composed of multi-hop expansions along different edge and vertex types. Each hop generally involves two main operations: (1) EXPAND_EDGE : Expanding edges of a specific type from the starting vertex, which may include edge filtering operations. (2) GET_VERTEX : Extracting the target vertex of a specified type from the edges, which may also involve further filtering of the target vertices. However, in practical graph storage systems, target vertices are stored alongside their corresponding edges. This allows the operators of EXPAND_EDGE and GET_VERTEX to be merged into a new operator, EXPAND , which serves as the motivation behind our rule design.

Before applying this rule, several constraints must be satisfied: (1) No alias operations on EXPAND_EDGE : Aliases typically indicate that subsequent operators will perform additional operations on the edges generated by EXPAND EDGE operator. If any alias remains after applying the FieldTrim, the edges must be preserved separately and cannot be merged. (2) No further type filtering on the target vertex: The target vertex's type must be directly inferable from the pair types of the source vertex and the expand edge. For example, in (a: PERSON)-[b: KNOWS]->(c: PERSON), according to the LDBC schema specification [13], the type of vertex c can be determined as PERSON based on the pair types of (a: PERSON) and (b:KNOWS), eliminating the need for additional type filtering. In contrast, consider (a:PERSON)<-[:HASCREATOR]-(b:POST), POST and COMMENT are both valid target vertex types induced from the source vertex (a: PERSON) and the expand edge [: HASCREATOR]. In this case, the target vertex b requires further type filtering by POST,

making the merging operation inapplicable. (3) No additional property filtering on the target vertex: EXPAND operator only supports filtering on edges, while separate property filtering on the target vertex would necessitate an extra filtering operation. Consequently, the merging operation would not yield any performance benefits in such cases.

In Fig. 7, we demonstrate how the FieldTrim and DegFusion work together to optimize a query example.

5.1.5 DegFusion

The DegFusion is an advanced fusion optimization that builds upon the EVFusion, specifically tailored for optimizing graph operators. The GROUP operator, which functions as a reducer, can potentially become a performance bottleneck due to synchronization overhead. To address this, we have identified a specific pattern within GROUP operations where aggregations are performed over single edges. These operations can be transformed into the EXPAND DEGREE operator, effectively converting them into degree computations. This transformation allows the execution layer to utilize pre-maintained adjacent edge sizes, directly computing the results without incurring the performance penalties associated with the reducer operation. The preconditions before applying the rule include: (1) The GIR consists of an EXPAND operator followed by an GROUP operator. (2) The GROUP operation is semantically equivalent to computing the degree of the input EXPAND. Concretely, the condition checks whether the GROUP key is the starting vertex of the EXPAND operator, and the GROUP function performs a distinct-count computation on the target vertices generated by EXPAND .

As shown in Fig. 7, we demonstrate the combined optimization effect of FieldTrim and DegFusion on the following query.

<pre>Match (v1:PERSON)-[:KNOWS]->(v2)</pre>	
Return v1, count(distinct v2);	

5.1.6 PKIndex

In graph databases, it's common to maintain primary key indexes on vertices or edges to enhance the performance of graph-specific operations. We leverage the indexing capabilities provided by the execution layer to optimize graph operators through the use of primary key indexes. Given the following Cypher query:

Match	(v1:	PERSON)	WHERE	v1.id	=	933	Return	v1.name;
-------	------	---------	-------	-------	---	-----	--------	----------

After application of the FilterIntoPattern , the filtering condition will be fused into the source operation (v1: PERSON), and is equivalent to rewriting the query as:

Match (v1: PERSON {id: 933}) Return v1	.name;
--	--------



Figure 7: Transformations of FieldTrim and DegFusion .

The (v1: PERSON id: 933) is represented by the physical operator Scan v1(PERSON, id=933) after PatternStrategy. Without a primary key index on the id attribute, the execution layer has to scan all vertices of type PERSON and then sequentially apply predicate filtering to identify the single vertex with id=933. This approach can be inefficient, especially when dealing with large datasets. To optimize this, GOpt generates a hint by introducing the IndexScan v1(PERSON, id=933) operator, to guide the execution layer to use the primary key index on the id attribute, thereby optimizing the efficiency of Scan operation.

5.1.7 LateProject

There are two primary strategies for retrieving property data in graph databases: (1) Prefetch: In this approach, when a graph operator retrieves vertex or edge data, it simultaneously fetches the associated property data. During subsequent operations, if property data is needed, it can be accessed from cached values stored within the graph-specific data. This method reduces the latency of on-demand property data access and is particularly suitable for distributed scenarios. Prefetching helps mitigate costly communication overhead that would otherwise be incurred when accessing property data across machine nodes. (2) Lazy Retrieval: This strategy defers the retrieval of property data until it is explicitly required by relational operations. When fetching graph-specific data types, the graph operator only retains minimal information, such as the internal ID or type for each vertex or edge. The key advantage of lazy retrieval is its ability to minimize the size of intermediate data



Figure 8: Examples of Pattern Transformation.

during execution, which makes it ideal for single-node scenarios where there is no risk of additional communication overhead.

The LateProject is designed based on the concept of Lazy Retrieval. Currently, this rule is applied exclusively in single-node system settings.

5.2 PatternStrategy

5.2.1 Pattern Transformation

We optimize the query pattern by transforming it into various equivalent forms to facilitate the selection of the most efficient search order. The correctness of these pattern transformations is ensured by the PatternJoin as follows:

Given data graph *G* and pattern P_t , with P_{s_1} and P_{s_2} where $P_t = P_{s_1} \bowtie_k P_{s_2}$ and \bowtie_k is the join operator with join key $k = V_{P_{s_1}} \cap V_{P_{s_2}}$. Let R(P, G), or R(P) for brevity, represent the results of matching *P* in *G*. Under homomorphism-based matching semantics, $R(P_t)$ can be computed by:

$$R(P_t) = R(P_{s_1}) \bowtie_k R(P_{s_2}) \tag{1}$$

It should be noted that, for other non-homomorphic semantics, additional filters can be applied to the results of $R(P_t)$ to ensure compliance with the query semantics, as we have discussed in Section 2.2.

Based on this equivalent rule in pattern matching, we introduce two build-in strategies in GOpt, to perform pattern transformations while ensuring the correctness:

- BinaryJoin: denoted as JOIN(P_{s1}, P_{s2} → P_t), this strategy decomposes a query pattern P_t into two sub-patterns P_{s1} and P_{s2} where P_t = P_{s1} ⋈_k P_{s2}. In this case, we can find matchings of P_{s1} and P_{s2} separately, and then using a binary join operator to join the results of P_{s1} and P_{s2} to generate the final results.
- VertexExpansion: denoted as EXPAND(P_s, P_v → P_t), this strategy applies when V_{Pv} = V_{Pt} \V_{Ps} = {v}. We can firstly find matchings of P_s, then match vertex v by expanding edges directly from P_s's matchings, to obtain the final results of P_t.

Example 5.1. We show an example of the pattern transformation process in Fig. 8. The initial query pattern, P_t , is depicted in Fig. 8(a), while three equivalent transformations of P_t are illustrated in Fig. 8(b)-(d). In Fig. 8(b), the pattern results from applying the BinaryJoin to decompose P_t into two sub-patterns, P_{s_1} and P_{s_2} , where $P_t = P_{s_1} \bowtie_k P_{s_2}$ and the join key $k = v_2$. Figures Fig. 8(c) and Fig. 8(d) demonstrate the application of the VertexExpansion, expanding a single vertex from P_s to P_t . Specifically, in Fig. 8(c), a single edge, e_5 , along with its adjacent vertex v_5 , is expanded from P_s to P_t , while Fig. 8(d) illustrates that multiple edges, e_1 and e_3 , with the common adjacent vertex v_3 , are expanded from P_s to P_t .

5.2.2 PhysicalCostSpec

Note that certain operations can have rather different computational costs in different engines. To address the issue, we introduce the PhysicalCostSpec interface to allow the backend engine to register their implementation costs for the pattern transformations. Below, we demonstrate the details of PhysicalCostSpec of the two different pattern transformation strategies, BinaryJoin and VertexExpansion, when integrated with GraphScope and Neo4j.

• BinaryJoinCostSpec: The JOIN may have different implementations such as HashJoin, NestedLoopJoin and SortMergeJoin. When integrated with GraphScope and Neo4j, they both adopt the HashJoin implementation. So the cost of executing the JOIN is defined as:

$$\operatorname{Cost}_{\operatorname{Join}} = \alpha_{\operatorname{Join}} \times (\mathcal{F}_{P_{s_1}} + \mathcal{F}_{P_{s_2}}) \tag{2}$$

where α_{Join} is a normalized factor for the JOIN operation, and so as the other operations.

• VertexExpansionCostSpec: If the vertex v only has one adjacent edge to P_s , i.e., $E(P_t) \setminus E(P_s) = \{e\}$, both Neo4j and Graph-Scope implement it by getting the neighbors through the edge e. However, if the vertex v has multiple adjacent edges to P_s , i.e., $E(P_t) \setminus E(P_s) = \{e_1, \ldots, e_n\}$, where $e_i = (v_i, v)$ and $v_i \in V(P_s)$, Neo4j and GraphScope adopt different implementations. Specifically, Neo4j implements an ExpandInto operation, which first expands the edge e_1 from v_1 to get candidate set of matchings for v, and then expands the edge e_2 from v_2 , filtering out those are not in the candidate set, and so on so forth until the last edge e_n , and finally returns the matchings of P_t . Therefore, the cost of executing the EXPAND operation when integrating Neo4j is defined as:

$$Cost_{EXPAND} = \alpha_{EXPAND} \times \sum_{i=1}^{n} \mathcal{F}_{P_i}$$
(3)

In contrast, GraphScope adopts a more efficient implementation, called ExpandIntersect, which is based on the worst-case optimal join algorithm. In this case, GraphScope expands edges from v_1, \ldots, v_n simultaneously, and then intersect the candidate sets to get the final matchings. The cost of executing the EXPAND operation when integrating GraphScope is defined as:

$$Cost_{EXPAND} = \alpha_{EXPAND} \times n \times \mathcal{F}_{P_s}$$
(4)

With these cost estimations, along with those of other physical operators omitted here for brevity, GOpt can employ a general cost model to select the most efficient physical plan by minimizing the total operator costs within the plan. Please note that during pattern optimization, it is not necessary to specify the implementations of the operators in different backends, e.g., ExpandInto or ExpandIntersect, which, we refer them as ExecOps. Instead, our focus is on the cost of executing these operators, which influences the physical plan GOpt selects. Once optimization is complete, GOpt converts the optimized physical plan into a format executable by the integrated backend engine, which will then convert each GIROp to the corresponding ExecOp of the backend engine. We will discuss this process in detail in Section 7. Additionally, defining these cost functions is optional; if a cost function is not specified, GOpt can still apply RuleBasedStrategy to optimize the patterns.



Figure 9: An Example of Vertex Expansion Implementations

Example 5.2. We illustrate the different vertex expansion implementations of Neo4j and GraphScope when multiple edges are expanded in Fig. 9. Initially, pattern P_s matches to (u_1, u_2) in the data graph (Fig. 9(a)). To match P_t by expanding e_3 and e_2 , Neo4j first expands e_3 , yielding three mappings (Fig. 9(b)), and then performs ExpandInto to find matches for e_2 connecting u_2 to u_3, u_4 and u_5 , respectively. As ExpandInto flattens the intermediate matching results, the cost is the sum of frequencies of intermediate patterns, as shown in Eq. 3. In contrast, GraphScope uses ExpandIntersect, which begins by finding the match set $R(P_1)$ by expanding e_3 , yielding one intermediate result. It then expands e_2 and intersects the matched set with $R(P_1)$ to obtain $R(P_t)$, and finally unfolds the match set after expanding all the edges (Fig. 9(c)). ExpandIntersect reduces computation by avoiding flattening intermediate results, with the cost defined in Eq. 4.

6 Optimizing Complex Queries

In this section, we demonstrate how query optimization can be achieved through the combination of multiple Strategies. We select several queries from IC and BI query sets to illustrate the optimization process. For each query, we first register the Strategies DAG with GOpt . The DAG specifies the application order of the Strategies, which GOpt follows sequentially. Before applying a Strategy, GOpt evaluates whether the query satisfies the preconditions of the Strategy. If the preconditions are not met, the Strategy is skipped, and the next Strategy is applied. If the preconditions are satisfied, the Strategy is applied to optimize the current GIR Plan, and its output serves as the input for the subsequent Strategy. The following examples provide a detailed view of how these queries are optimized.

6.1 Single-Pattern Heuristic Optimization.

As illustrated in FigureFig. 11(a), the IC_2 query consists of a single MATCH clause combined with a series of relational clauses. The query pattern represents a straightforward 2-hop traversal, where the (p:PERSON) node is filtered using a primary key lookup based on its property id. The pattern itself does not involve complex optimizations, and the final PatternOrders can be directly derived from the order specified in the user-provided query. The primary optimization focus lies in the combined application of PatternStrategy and other RuleBasedStrategy. During the optimization process, only a subset of the registered Strategies is

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Figure 10: Strategies DAG of IC₂.

effectively applied, which are highlighted in blue in Fig. 10. GOpt follows the specified order of these Strategies to apply the optimizations as follows:

- GOpt translates the Cypher query into a GIR using the GIRBuilder tool.
- The GIR consists of a Pattern structure along with relational operations that correspond to the WHERE, RETURN, and OR-DER clauses in the original Cypher query. Due to page size constraints, the initial structure of the GIR is omitted from the figure. The GIR after the application of FilterIntoPattern, Field-Trim, and SortProjectTrans is shown in Fig. 11(b). By applying FilterIntoPattern, the filtering conditions in the WHERE clause are pushed down into the MATCH clause, specifically onto the (:PERSON) node and the (:HASCREATOR) relationship. Field-Trim eliminates redundant columns generated by the MATCH clause, such as columns k and h derived from the [:KNOWS] and [:HASCREATOR] relationships, respectively. Additionally, this rule retains only the minimal required set of node and edge properties, which, when combined with LateProject, maximizes optimization benefits, as will be discussed in the next step. By leveraging Calcite's SortProjectTrans, the TopK operation-comprising ORDER and LIMIT-is pushed up before the **PROJECT** operation.
- The physical plan after PatternStrategy is shown in Fig. 11(c), which aligns with the user-specific order, namely (p:PERSON)
 → (friend:PERSON) → (msg:POST|COMMENT).
- Subsequently, GOpt continues to optimize the query by applying EVFusion and DegFusion . The EVFusion is applied to merge the EXPAND_EDGE and GET_VERTEX operations into a single EXPAND operation, reducing intermediate data pipeline overhead. PKIndex is applied when a primary key indexing is available, enabling direct lookups instead of full scans, significantly reducing the amount of data processed. The physical plan after optimization is shown in Fig. 11(d).
- Finally, LateProject further enhances the physical plan, as illustrated in Fig. 11(e). After FieldTrim application, the (friend:PERSON) node retains only the properties id, firstName, and lastName, while (msg:POST|COMMENT) node retains only the properties id, creationDate, content, and imageFile. However, Field-Trim does not determine when these properties should be retrieved—whether they should be prefetched at node/edge retrieval or lazily fetched at the final Projection. LateProject ensures that properties are always retrieved lazily at projection time. This rule is particularly beneficial in single-node system

Table 2: Ablation Results for IC ₂ .					
Rules	Execution Time (ms)				
None	10599				
+FilterIntoPattern	371				
+FieldTrim	301				
+SortProjectTrans	251				
+EVFusion	208				
+LateProject	156				
+PKIndex	134				

scenario, where accessing local properties incurs no additional network overhead.

In order to further validate the efficiency of these Strategies, we conducted the ablation experiment to assess their individual contributions. To mitigate the impact of Strategy dependencies on the ablation outcomes, We incrementally added the rules in their intended application order and measured the execution time after each addition. The results, as illustrated in Table 2, provide insights into the effectiveness of each rule within the optimization process.

For most rules (excluding FilterIntoPattern), the addition of each rule reduces the execution time by 15% to 25%, with an average reduction of approximately 22%. While the individual impact of each rule is moderate, their cumulative effect significantly enhances performance, reducing the overall execution time from 371 ms to 134 ms—a speedup of nearly 3x.

Among all the rules, FilterIntoPattern stands out as the most impactful. When this rule is applied, the execution time drops dramatically from 10,599 ms to 371 ms, representing a 30x improvement in performance. This substantial gain is expected, as FilterIntoPattern performs critical data pruning at an early stage of execution, drastically reducing the number of nodes and edges that need to be processed in subsequent stages. This early filtering minimizes unnecessary computations, leading to a significant boost in efficiency.

6.2 Multi-Patterns Heuristic Optimizaiton.

The query BI_5 , shown in Fig. 13(a), contains multiple MATCH clauses, some of which are optional, along with additional relational operations between these MATCH clauses. The complexity of the query stems from the interaction between the MATCH and relational clauses. While each individual pattern is relatively simple, the overall query becomes significantly more complex. To optimize such queries effectively, GOpt employs advanced optimization Strategies, such as ComSubPattern , DegFusion , and others, which are highlighted in blue in Fig. 12, and optimizes the query as follows:

Bingqing Lyu, Xiaoli Zhou, Longbin Lai, Yufan Yang, Yunkai Lou, Wenyuan Yu, Ying Zhang[‡], Jingren Zhou



Figure 12: Strategies DAG of BI5.

- GOpt first converts the query into a GIR . The multiple MATCH clauses (*P*₁, *P*₂, *P*₃, *P*₄) are organized by Join operations. If the right MATCH is optional, the Join type is LEFT OUTER; otherwise, it is an INNER. The structure of the Join is followed by subsequent relational operations, which form the left branch of the next Join. The GIR representation after FilterIntoPattern is shown in Fig. 13(b).
- Next, GOpt applies PatternStrategy for each pattern. The PatternStrategy preserves the user-defined order. For pattern P_1 , the operations are output in the order of $(tag:TAG) \rightarrow (msg:POST|COMMENT)$. The same optimization is applied to other patterns. Then, ComSubPattern is applied, it identifies that P_1 and P_2 share the intermediate results of (msg:POST|COMMENT), and since P_1 directly outputs the msg as the final result, the pattern operations in P_2 can be expanded from P_1 's output. As a result, the Join between P_1 and P_2 can be flattened into an expansion. The same reasoning applies to P_2 , P_3 , and P_4 , resulting in the physical plan shown in Fig. 13(c).
- Finally, GOpt applies two additional rules: EVFusion and Deg-Fusion . The EVFusion fuses EXPAND_EDGE and GET_VERTEX into a single EXPANDoperation. This fusion enables the application of DegFusion . The DegFusion identifies that GET_VERTEX is followed by a GROUP operation, where the GROUP key corresponds to the start vertex of EXPAND, and the GROUP value is the distinctly-aggregated count of the target vertex of EXPAND, which implies that the GROUP operation performs degree aggregation. Consequently, EXPAND and GROUP can be merged into a single EXPAND_DEGREE operation. The final physical plan is shown in Fig. 13(d).

Additionally, we provide an ablation experiment to demonstrate the contribution of each rule in this optimization process. The results are shown in Table 3. The execution time decreases from 386 ms to 286 ms after incorporating both DegFusion and EVFusion , demonstrating that these two rules together can achieve a 25% speedup. Upon adding ComSubPattern , there is a significant reduction in execution time from 114,678 ms down to 386 ms, marking a remarkable 400x performance improvement. This substantial enhancement is anticipated because ComSubPattern optimizes the process by maximizing the reuse of intermediate results from previously identified common patterns and eliminating unnecessary

Table 3: Ablation Results for BI ₅ .					
Rules	Execution Time (ms)				
None	400414				
+FilterIntoPattern	114678				
+ComSubPattern	386				
+EVFusion	359				
+DegFusion	286				

Table 4: Time Costs for IC12.		
Execution Time (ms)		
175		
252		
438		

Plan	Execution Time (s)
GOpt -plan with High-Order Statistics	1163
GOpt -plan with Low-Order Statistics	OT (>3600)

Join operations, thus preventing superfluous data exploration. Additionally, FilterIntoPattern contributes to an approximate 3x performance improvement, as evidenced by the reduction in execution time from 400,414 ms to 114,678 ms upon its introduction.

6.3 Path Optimization.

We illustrate the optimization of a path query IC_{12} in Fig. 14, with corresponding execution times for each plan shown in Table 4. The query aims to find the path between two vertices: a PERSON p_1 with specified id, and a TAGCLASS t with specified name. The Cypher query and the query pattern are shown in Fig. 14(a) and Fig. 14(b), respectively.

The optimized plan generated by

gopt is displayed in Fig. 14(c), with the corresponding number of intermediate results marked at each expansion step. Similarly, the alternative plans in Fig. 14(d) and Fig. 14(e) are also annotated with the number of intermediate results. In the optimized plan, the path is decomposed into two patterns: P_1 , starting from PERSON p_1 , and P_2 , starting from TAGCLASS t. The results of P_1 and P_2 are joined on the TAG vertex to produce the final results. This optimized plan effectively reduces the number of intermediate results generated during query execution, thereby enhancing overall performance. For comparison, we provide two alternative plans in Fig. 14(d) and Fig. 14(e), each joining on different vertices. These alternative plans are shown to be suboptimal as they generate more intermediate results compared to the optimized plan in Fig. 14(c).

As demonstrated in Table 4, the optimized plan generated by gopt achieves the lowest execution time of 175 ms, outperforming the alternative plans by 30% and 60%, respectively. This case study underscores the effectiveness of gopt in optimizing path queries.

6.4 Cyclic Pattern Optimization.

In Fig. 15, we present a case study on optimizing a cyclic query *C*, with the corresponding execution times for each plan shown in Table 5. The primary objective of this study is to determine the

	1 2 1
Applied Rule	Execution Time (ms)
None	770573
FilterIntoPattern	234313
AggJoinTrans	214955
JoinToPattern	64466
ComSubPattern	7014

Table 6: Ablation Results for Complex Query Q.

optimal search order for a cyclic pattern using cost-based optimization techniques. The Cypher query is illustrated in Fig. 15(a), with the corresponding query pattern shown in Fig. 15(b).

In Fig. 15(c) and Fig. 15(d), we present two optimized plans generated by

gopt, utilizing high-order and low-order statistics, respectively, and mark the number of intermediate results generated at each expansion step. The comparison reveals that the optimized plan in Fig. 15(c) with high-order statistics is more efficient than the one in Fig. 15(d), as it generates fewer intermediate results during query execution. Specifically, although the search order in the first four expansion steps is identical for both plans, as the pattern expands and grows larger, the optimized plan using low-order statistics produces significantly more intermediate results. This inefficiency arises from substantial deviations in the estimated cardinality compared to the actual values, leading to a suboptimal search order. In contrast, the high-order statistics enable more accurate cardinality estimations in the optimizer, resulting in a more efficient search order. The execution times in Table 5 further confirm the superiority of the optimized plan with high-order statistics, which completes the query in 1163 s, while the plan with low-order statistics exceeds the timeout threshold of 3600 s. This case study demonstrates the importance of utilizing high-order statistics in cost-based optimization techniques to enhance query performance.

6.5 Complex Pattern Optimization.

We present a complex query Q, which combines IC_5 and IC_6 , to demonstrate a comprehensive optimization process in Fig. 16. This process involves both the RuleBasedStrategy and PatternStrategy.

RuleBasedStrategy. The query pattern is depicted in Fig. 16(a). Initially, we outline the logical plan in

gopt as shown in Fig. 16(b), where the query is translated into three patterns M_1 , M_2 , and M_3 , followed by relational operators JOIN, SELECT, and GROUP.

The optimization process begins by attempting to push down the SELECT operator. This technique reduces computational costs by minimizing the number of intermediate results. The optimized plan is presented in Fig. 16(c). Here, we initially apply the existing relational rule FilterIntoJoin from Calcite, which integrates the SELECT operator into the inputs of the join operations. Following this, we implement the FilterIntoPattern, which further advances the pushdown of the SELECT operator into the patterns M_1 , M_2 and M_3 . By pushing the SELECT operator to the pattern level, unnecessary graph elements are filtered out at earlier stages in the query processing, thereby enhancing performance.

Subsequently, we apply the AggJoinTrans to push an aggregate (i.e., GROUP) pass a JOIN, which is also an existing relational rule in Calcite, as shown in Fig. 16(d). This rule focuses on pushing

Table 7: Time Costs for Q, with different searching order ofM4.

Plan	Execution Time (ms)
GOpt -plan	7014
Alt-plan1	22211
Alt-plan2	194047

GROUP operations further down the plan to limit intermediate results. In our case, the GROUP shares the same key as the JOIN (the one with the key=p2), which allows the GROUP to progress through this join, with an additional GROUP to accumulate the _cnt attribute after the join, as the join operator may generate duplicate matches of p2. This is a standard optimization in relational query processing, reducing intermediate results prior to joining the patterns M_3 .

Following these adjustments, we employ the JoinToPattern to remove unnecessary join operators and merge the patterns. It is important to note that the JoinToPattern is applicable only under homomorphism semantics (as we have discussed in Section 2.2), though for demonstration purposes, we apply this rule assuming such semantics, despite Cypher's use of edge-distinct semantics. As illustrated in Fig. 16(e), patterns M_1 and M_2 are merged into a singular pattern, M_4 , with the join keys (p2, f) as the common vertices in the merged pattern.

After pattern merging, we utilize cost-based optimization techniques to further refine the patterns, seeking the most efficient query execution order. The resulting optimized order is specified in Fig. 16(f). It is noteworthy that within the cyclic pattern M_4 , we apply a WcoJoin strategy based on the backend GraphScope, leveraging PhysicalCostSpec, ensuring execution efficiency with worst-case optimality.

Finally, we apply the ComSubPattern, as shown in Fig. 16(g), which further eliminates the join operator between M_4 followed by GROUP, and M_3 . This rule can be applied since: (1) the GROUP operation outputs (p2,_cnt), (2) the following join operator has join key p2, which is the subset of the output of the GROUP, and (3) the search order of pattern M_3 starts from the p2. We eliminate the join operator and directly search the pattern M_3 by starting from the common vertices (i.e., matches of p2) in the output of the GROUP, to accelerate the query processing.

To validate the efficiency of these strategies further, we conducted an ablation experiment to assess their individual contributions, as shown in Table 6. The results indicate that without any optimization rules, executing the query takes 770573 ms. Applying the FilterIntoPattern achieves a 70% improvement, reducing the execution time to 234313 ms. The AggJoinTrans further enhances performance by 8%. The JoinToPattern achieves a 71% improvement. Finally, the ComSubPattern provides the most significant performance boost, achieving a 97% improvement and reducing the execution time to 7014 ms. This case study demonstrates the effectiveness of

gopt in optimizing complex queries through RuleBasedStrategy.

PatternStrategy. Beyond the overall RuleBasedStrategy process discussed above, we delve into the detailed optimization process of PatternStrategy, particularly focusing on the cyclic pattern M_4 in the query Q. The query pattern is illustrated in Fig. 17(a), while Fig. 17(b)-(d) present the optimized plan generated by gopt and two alternative plans, respectively. Each plan indicates the

number of intermediate results produced at each expansion step. The

gopt optimized plan shown in Fig. 17(b) produces the fewest intermediate results compared to the alternatives in Fig. 17(c) and Fig. 17(d), resulting in a more efficient query execution.

Additionally, Table 7 provides execution times for Q using different search orders of M_4 . These results confirm the superiority of the

gopt optimized plan, which achieves the lowest execution time of 7014 ms, outperforming the alternative plans by $3 \times$ and $27 \times$, respectively. This case study underscores the effectiveness of gopt in optimizing complex queries with cyclic patterns, particularly in enhancing query performance through cost-based optimization techniques.

7 Backend Integration

The Physical Converter layer of GOpt (see Section 4) is responsible for transforming the optimized physical plan into a plan that is compatible with the underlying backend engine. This layer serves as a bridge between GOpt and various backend engines, enabling seamless integration and execution of the optimized plans.

We offer two ways for integration. The first one is through a PhysicalConverter interface, which defines the methods for converting each physical operator in the GOpt-optimized plan to the corresponding executable operator in the backend engine. This allows GOpt to traverse and convert the optimized physical plan into a backend-compatible executable plan. We have integrated GOpt with Neo4j using this approach. The second one provides a Google Protocol Buffers (protobuf) [15] based physical plan output to facilitate cross-platform integration. This allows GOpt to submit the optimized plan directly to the backend engine in protobuf format, enabling the backend engine to parse and transform it into its native execution plan. We have integrated GOpt with Alibaba's GraphScope platform using this approach [2], enabling execution on the distributed dataflow engine Gaia [16].

7.1 PhysicalConverter Interface

We define the PhysicalConverter interface as follows:

```
interface PhysicalConverter {
    // Convert methods for GIR's physical operators
    ExecOp convert(JOIN op);
    ExecOp convert(EXPAND op);
    ExecOp convert(PROJECT op);
    // Additional conversions for other physical operators
        are omitted for brevity
    ...
}
```

Backends can implement the PhysicalConverter interface to convert each GIROp from the optimized physical plan into an ExecOp that is executable by the backend engine. For example, we implement the PhysicalConverter for Neo4j as follows:

```
public class Neo4jConverter implements PhysicalConverter {
    // Context for logical planning in Neo4j
    private final LogicalPlanningContext context;
    // The logical plan producer in Neo4j,
    // which can construct the plan that is executable by Neo4j
```

private final LogicalPlanProducer planProducer;

```
// A mapper to transform GOpt's expressions to Neo4j's
private final ExpressionMapper exprMapper;
```

// Converts a JOIN into a Neo4j HashJoinPipe, // an executable plan node for Neo4j's query engine. @Override public HashJoinPipe convert(JOIN op) { Transform the input plans into LogicalPlan nodes LogicalPlan left = op.getLeft().accept(this).getNode(); LogicalPlan right = op.getRight().accept(this).getNode(); // Convert the join condition to Neo4j's Variables Set<Variable> condition = toNeoVar(op.getCondition()); // Use the plan producer to create a Neo4j HashJoinPipe return (HashJoinPipe) planProducer.planNodeHashJoin(condition, left, right, context); 3 // Converts a EXPAND into a Neo4j ExpandPipe, // an executable plan node for Neo4j's query engine. @Override public ExpandPipe convert(EXPAND op) { '/ Transform the input plan into a LogicalPlan node LogicalPlan input = op.getInput().accept(this).getNode(); // The vertexExpansion can contain multiple edgeExpands List<EdgeExpand> edgeExpands = op.getExpands(); // The first edgeExpand is converted into a
// ExpandAll mode, expanding all the edges EdgeExpand first = edgeExpands.get(0); // Convert op fields to Neo4j structures String tag = op.getTag(); String alias = op.getAlias(); SemanticDirection dir = toNeoDir(op.getDir()); List<RelType> relTypes = toNeoRelType(op.getRelTypes()); Relationship rel = toNeoRel(tag, alias, dir, relTypes);
// Define the ExpandAll mode for the first edgeExpand ExpansionMode expandAllMode = ExpandAll\$.MODULE\$; // Update the plan by adding the executable op ExpandPipe node = (ExpandPipe) planProducer. planSimpleExpand(input, tag, alias, rel, expandAllMode, context); // For the rest edgeExpands, we use the ExpandInto mode, // meaning that they are expanded and confirmed // to be existed in the first edgeExpand results for (int i = 1; i < edgeExpands.size(); i++) {</pre> EdgeExpand edgeExpand = edgeExpands.get(i); // Convert each field in edgeExpand, omit here // Use the ExpandInto mode ExpansionMode expandIntoMode = ExpandInto\$.MODULE\$; // Update the plan node = planProducer.planSimpleExpand(node, tag, alias. rel. expandIntoMode. context): } return node; } // Converts a PROJECT into a Neo4j ProjectPipe, // an executable plan node for Neo4j's query engine. @Override public ProjectPipe convert(PROJECT op) { / Transform the input plan into a LogicalPlan node LogicalPlan inputPlan = op.getInput().accept(this). getNode(); // Transform the expression to Neo4j's expression List<Expression> exprs = op.getExprs().stream() .map(expr -> expr.accept(this)) collect(Collectors.toList()); // Use the plan by adding the executable op return (ProjectPipe) planProducer.planRegularProjection(

// other conversion methods omitted for brevity \ldots

inputPlan, exprs, context);

}

}

By implementing the PhysicalConverter interface, we observe that Neo4j's executable plan is incrementally constructed by the LogicalPlanProducer class (provided by Neo4j) through converting each physical operator in the GOpt-optimized plan in to the

corresponding operator (named XOpPipe, which is a subclass of ExecOp) that is executable by Neo4j's query engine.

7.2 Protobuf-based Physical Plan

The second approach for backend integration utilizes a protobufbased physical plan. This design enables cross-platform integration and provides the complete view of the optimized physical plan to backend engines in a more flexible manner. In this approach, GOpt outputs the optimized physical plan in a serialized format using Google Protocol Buffers (protobuf) [15], comprising all necessary information about the physical operators, their configurations, and the data flow between them. By submitting the protobuf-based physical plan to the backend engines, these engines can parse the protobuf representation and transform it into their native execution plan format. We have used this approach to integrate GOpt with Alibaba's GraphScope platform, facilitating execution on the distributed dataflow engine Gaia [16]. We show an example as follows.

Firstly, in GOpt, we provide a build-in implementation of the PhysicalConverter interface that serializes the physical plan into a protobuf-based representation:

```
public class ProtobufConverter implements PhysicalConverter
    {
      The protobuf builder for the physical plan
   private final PhysicalPlanPB.Builder planBuilder;
    // Convert methods for protobuf-based physical operators
   @Override
   public ExecOp convert(EXPAND op) {
       // Convert EXPAND to protobuf representation
       ExpandPB expandPB = ExpandPB.newBuilder()
           .addAllExpands(op.getExpands().stream()
               .map(expand -> transformEdgeExpandPb(expand))
               .collect(Collectors.toList()))
           .build();
       planBuilder.addOps(expandPB);
       return op:
   }
   // Additional conversions for other physical operators
         are omitted for brevity
}
```

Then we submit the protobuf-based physical plan to the integrated backend engine Gaia in GraphScope:

```
// Serialize the physical plan to protobuf format
PhysicalPlanBp physicalPlan = planBuilder.build();
byte[] serializedPlan = physicalPlan.toByteArray();
// Submit the serialized plan to the backend engine
GaiaClient gaiaClient = new GaiaClient();
gaiaClient.submit(serializedPlan);
```

In the engine side, Gaia (which is developed in Rust) receives the serialized protobuf-based physical plan and further construct its native execution plan:

```
// GAIA is a dataflow-based engine for distributed graph
    processing
```

- worker.dataflow(move |input, output| {
 - // Deserialize the protobuf-based physical plan
 let physicalPlan = PhysicalPlanPb::decode(serializedPlan)
 - // Retrieve source data from the graph based on the Source operator
 - let sources = get_source_data(graph, physicalPlan. getSource());
 - let mut stream = input.input_from(sources);

```
// Iterate through the protobuf operators and convert
         them to native operator:
    for op : physicalPlan.getOpsList() {
       let op_kind = op.getOpKind();
       match op_kind {
           OpKind::Expand(expand) -> {
                / parse the pb operator and generate the udf
               let func = gen_expand_udf(edge)?;
               // add a flat_map operator with the udf
               stream = stream.flat_map(move |input| func.
                    exec(input))?;
           OpKind::Project(project) -> {
               // parse the pb operator and generate the udf
               let func = gen_project_udf(project)?;
               // add a map operator with the udf
               stream = stream.map(move |input| func.exec(
                    input))?;
           // Additional cases for other physical operators
                are omitted for brevity
       }
   }
// Finally, sink the stream into the output
    stream.sink_into(output)?;
});
```

In this way, the protobuf-based physical plan offers a flexible and efficient approach for Gaia integration, allowing GOpt to seamlessly interact with cross-platform backend engines.

8 Conclusion

In this paper, we extends the SIGMOD 2025 paper "A Modular Graph-Native Query Optimization Framework" by offering an indepth exploration of GOpt's advanced technical mechanisms, implementation Strategies, and extended evaluations. Our focus lies on detailing the optimization Strategies that GOpt utilizes to enhance the efficiency of complex graph queries, specifically highlighting RuleBasedStrategy and PatternStrategy methodologies. Through the utilization of query cases derived from the LDBC Social Network Benchmark (SNB), we illustrate the potent capabilities of these combined Strategies in optimizing such queries. Empirical experiments conducted further elucidate the individual and collective contributions of each Strategy towards overall optimization efficacy. Finally, we introduce the physical converter layer in GOpt, showcasing its role in facilitating seamless integration with different backend engines.

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A APPENDIX

Г				
MATCH (p:PERSON)-[k:KNOWS]-(friend:PERSON)<-[h:HASCREATOR]-(msg: POST COMMENT) WHERE p.id = \$id AND h.creationDate <= \$date Return friend.id AS fid, friend.firstName AS firstName, friend.lastName AS lastName, msg.id AS mid, msg.content AS content, msg.imageFile AS imageFile, msg.creationDate AS date ORDER BY msg.creationDate DESC,				
LIMIT 20; (a) IC2 in Cynher Queny				
p: PERSON id=\$id KNOWS Friend: PERSON HASCREATOR creationDate <= \$date COMMENT				
ORDER (key1=msg.creationDate, cmp1=desc, key2=msg.id, cmp2=asc, limit=20)				
PROJECT (friend.id AS fid, friend.firstName AS firstName,)				
(b) Logical Plan After FilterIntoPattern FieldTrim SortProjectTrans				
Scan p PERSON ExpandE GetV friend ExpandE GetV msg id=\$id KNOWS PERSON HASCREATOR POST COMMENT				
ORDER (key1=msg.creationDate, cmp1=desc,				
keyz=msg.id, cmpz=asc, imit=20)				
•				
PROJECT (friend.id AS fid,				
mend.irstivarie AS irstivarie,)				
(c) Physical Plan After PatternStrategy				
IndexScan p PERSON id=\$id → ExpandV friend KNOWS -> PERSON → HASCREATOR -> POST COMMENT				
ORDER (key1=msg.creationDate, cmp1=desc,				
keyz=msg.id, cmpz=asc, imm=20)				
PROJECT (triend.id AS tid, friend firstName AS firstName				
(d) Physical Plan After EVFusion, PKIndex.				
IndexScan D				
PERSON → ExpandV friend id=\$id KNOWS -> PERSON → HASCREATOR -> POST COMMENT				
Property Prefetch Property Prefetch				
id false id true				
firstName false creationDate true				
lastName false content false				
imageFile false				
ORDER (key1=msg.creationDate, cmp1=desc, key2=msg.id, cmp2=asc, limit=20)				
LAZYF ETCH (friend.id, friend.firstName.				
friend.lastName, msg.content, msg.imageFile)				
PROJECT (friend.id AS fid,				
friend.firstName AS firstName,)				



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Figure 13: Optimization Process of BI₅.



Figure 14: Case Study on IC₁₂

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Figure 15: Case Study on Cyclic Query C



Figure 16: Case Study on Complex Query Q

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Figure 17: CBO on Cyclic Query M4