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Cypher: An Evolving Query Language for Property Graphs

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ABSTRACT

The Cypher property graph query language is an evolving language, originally designed and implemented as part of the Neo4j graph database, and it is currently used by several commercial database products and researchers. We describe Cypher 9, which is the first version of the language governed by the openCypher Implementers Group. We first introduce the language by example, and describe its uses in industry. We then provide a formal semantic definition of the core read-query features of Cypher, including its variant of the property graph data model, and its "ASCII Art" graph pattern matching mechanism for expressing subgraphs of interest to an application. We compare the features of Cypher to other property graph query languages, and describe extensions, at an advanced stage of development, which will form part of Cypher 10, turning the language into a compositional language which supports graph projections and multiple named graphs.

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1 INTRODUCTION

In the last decade, property graph databases [34] such as Neo4j, JanusGraph and Sparksee have become more widespread in industry and academia. They have been used in multiple domains, such as master data and knowledge management, recommendation engines, fraud detection, IT operations and network management, authorization and access control [52], bioinformatics [39], social networks [17], software system analysis [25], and in investigative journalism [11]. Using graph databases to manage graph-structured data confers many benefits such as explicit support for modeling graph data, native indexing and storage for fast graph traversal operations, built-in support for graph algorithms (e.g., Page Rank, subgraph matching and so on), and the provision of graph languages, allowing users to express complex pattern-matching operations.

In this paper we describe Cypher, a well-established language for querying and updating property graph databases, which began life in the Neo4j product, but has now been implemented commercially in other products such as SAP HANA Graph, Redis Graph, Agens Graph (over PostgreSQL) and Memgraph. Neo4j [52] is one of the most popular property graph databases1 that stores graphs natively on disk and provides a framework for traversing graphs and executing graph operations. The language therefore is used in hundreds of production applications across many industry vertical domains. Cypher is also used in several research projects (e.g., Ingraph [41], Gradoop [29], and Cytosm [55]) as well as in recent or incubating open-source projects, such as Cypher for Apache Spark and Cypher over Gremlin.

Since 2015 the openCypher project2 has sought to enable the use of Cypher as a standardized language capable of multiple independent implementations, and to provide a framework for cross-implementer collaborative evolution of new language features. The goal is that Cypher will mature into an industry standard language for property graph querying, playing a complementary role to that of the SQL standard for relational data querying. Here we present Cypher 9 [47], the first version of the language governed by openCypher. We give an introduction to the language, describe its uses in industry, provide a formal definition of its data model and the semantics of its queries and clauses, and then describe current work that will lead to Cypher 10, a compositional language supporting graph projections and multiple named graphs.

The data model of Neo4j that is used by Cypher is that of property graphs. It is the most popular property graph data model in industry, and is becoming increasingly prevalent in academia [38]. The model comprises nodes, representing entities (such as people, bank accounts, departments and so on), and relationships (synonymous with edges), representing the connections or relationships between the entities. In the graph model, the relationships are as important as the entities themselves. Moreover, any number of attributes (henceforth termed properties), in the form of key-value pairs, may be associated

1https://db-engines.com/en/ranking/graph+dbms
2https://www.opencypher.org
with the nodes and relationships. This allows for the modeling and querying of complex data.

The language comes with a fully formalized semantics of its core constructs. The need for it stems from the fact that Cypher, in addition to being implemented in an industrial product with a significant customer base, has been picked up by others, and several implementations of it exist. Given the lack of a standard for the language (which can take many years to complete, as it did for SQL), it has become pressing to agree on the formal data model and the meaning of the main constructs. A formal semantics has other advantages too; for example, it allows one to reason about the equivalence of queries, and prove correctness of existing or discover new optimizations. The need of the formal semantics has long been accepted in the field of programming languages [43] and for several common languages their semantics has been fully worked out [1, 22, 42, 49]. Recently similar efforts have been made for the core SQL constructs [12, 13, 20, 57] with the goal of proving correctness of SQL optimizations and understanding the expressiveness of its features. The existence of the formal semantics of Cypher makes it possible for different implementations to agree on its core features, and paves a way to a reference implementation against which others will be compared. We also note that providing semantics for an existing real-life language like Cypher that accounts for all of its idiosyncrasies is much harder than for theoretical calculi underlying main features of languages, as has been witnessed by previous work on SQL [20] and on many programming languages.

Organization. We provide a high-level overview of Cypher features in Section 2. In Section 3 we illustrate the semantics of the major clauses by means of a step-by-step analysis of an example query, and give further examples of queries used in industrial applications. The formal specification of the core of Cypher is given in Section 4. The historical context of Cypher is presented in Section 5, followed by a description of current developments in Cypher, such as query composition and support for multiple graphs, in Section 6. In Section 7 we cover related work on other graph data models and graph query languages. Future work and conclusions are given in Sections 8 and Section 9.

2 THE CYPHER LANGUAGE

Cypher is a declarative query language for property graphs. Cypher provides capabilities for both querying and modifying data, as well as specifying schema definitions.

Linear queries. A Cypher query takes as input a property graph and outputs a table. These tables can be thought of as providing bindings for parameters that witness some patterns in a graph, with some additional processing done on them.

Cypher structures queries linearly. This allows users to think of query processing as starting from the beginning of the query text and then progressing linearly to the end. Each clause in a query is a function that takes a table and outputs a table that can both expand the number of fields and add new tuples. The whole query is then the composition of these functions. This linear order of clauses is understood purely declaratively – implementations are free to re-order the execution of clauses if this does not change the semantics of the query. Thus, rather than declaring the projection at the beginning of the query like SQL does with SELECT, in Cypher the projection goes at the end of the query as RETURN.

The linear flow of queries in Cypher extends to query composition. By using WITH, the query continues with the projected table from the query part before WITH as the driving table for the query part after WITH. The WITH clause allows the same projections as RETURN, including aggregations. It also supports filtering based on the projected fields, as we shall see in Section 3.

In addition to this linear way of composing queries, Cypher also supports nested subqueries such as UNION queries.

Pattern matching. The central concept in Cypher queries is pattern matching. Patterns in Cypher are expressed in a visual form as "ASCII art", such as (a ~ [x] ~> (b)). The MATCH clause in Cypher uses such a pattern and introduces new rows (synonymous with records) with bindings of the matched instances of the pattern in the queried graph.

Cypher’s functionality was influenced by XPath [30] and SPARQL [58], and its patterns express a restricted form of regular path queries: the concatenation and disjunction of single relationship types, as well as variable length paths (essentially, transitive closure). Cypher also supports matching and returning paths as values.

Data modification. Cypher supports a rich update language for modifying the graph. Updating clauses re-use the visual graph-pattern language and provide the same simple, top-down semantic model as the rest of Cypher. The basic clauses for updates include CREATE for creating new nodes and relationships, DELETE for removing entities, and SET for updating properties. Additionally, Cypher provides a clause called MERGE which tries to match the given pattern, and creates the pattern if no match was found. An implementation of Cypher can use database synchronization primitives such as locking to ensure that patterns matched by MERGE are unique within the database.

Pragmatic. Cypher is intentionally similar to SQL in order to help users transition between the two languages. It follows the same clause syntax structure and implements the established semantics for many functions. Cypher has built-in support for query parameters, making it easy to eliminate the problems of query injection. The choice of defaults aligns with common usage. The syntax for grouping and aggregation is simple, and the expression language includes powerful features such as list slicing and list comprehensions, existential subqueries, and working with paths.

Neo4j implementation. Query execution in Neo4j follows a conventional model, outlined by the Volcano Optimizer Generator [19]. The query planning in Neo4j is based on the IDP algorithm [44, 54], using a cost model described in [21]. The final query compilation uses either a simple tuple-at-a-time iterator-based execution model, or compiles the query to Java bytecode with a push-based execution model based on [46].

An execution plan for a Cypher query in Neo4j contains largely the same operators as in relational database engines and an additional operator called Expand. Semantically Expand is very similar to a relational join. It finds pairs of nodes that are connected through an edge. In terms of implementation it utilizes the fact that the data representation of Neo4j contains direct references from each node via its edges to the related nodes. This means that Expand never
needs to read any unnecessary data, or proceed via an indirection such as an index in order to find related nodes.

3 CYPER BY EXAMPLE

Figure 1 shows a data graph $G$ consisting of researchers, students and publications. For each researcher we show the students they supervise, and the publications they have authored, and for each publication, we show which other publications it cites.

The following Cypher query returns the name of each researcher in $G$, the number of students they currently supervise, and the number of times a publication they have authored has been cited – both directly and indirectly – by other publications.

| 1 MATCH (r:Researcher) |
| 2 OPTIONAL MATCH (r)-[:SUPERVISES]->(s:Student) |
| 3 WITH r, count(s) AS studentsSupervised |
| 4 MATCH (r)-[:AUTHORS]->(p1:Publication) |
| 5 OPTIONAL MATCH (p1)<-[[:CITES*]]-.(p2:Publication) |
| 6 RETURN r.name, studentsSupervised, |
| 7 count(DISTINCT p2) AS citedCount |

The pattern given in the first MATCH clause in line 1 matches all researchers, i.e., nodes with the label Researcher. This produces three bindings for the variable $r$, namely $n_1$, $n_6$, and $n_{10}$ represented as three rows in a table with a single attribute $r$, that correspond to the researchers Nils, Elin and Thor.

The MATCH clause has an optional variant: OPTIONAL MATCH, which is analogous to the outer join construct in SQL. This clause produces rows for all matches in the same way that MATCH does, providing the entire pattern is found in the data graph. However, in cases where no data matching the entire pattern is found, a single row will be produced in which the bindings for all variables introduced in OPTIONAL MATCH will be set to null.

<table>
<thead>
<tr>
<th>$r$</th>
<th>$s$</th>
<th>$r$</th>
<th>studentsSupervised</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_1$</td>
<td>null</td>
<td>$n_1$</td>
<td>0</td>
</tr>
<tr>
<td>$n_6$</td>
<td>$n_7$</td>
<td>$n_6$</td>
<td>2</td>
</tr>
<tr>
<td>$n_6$</td>
<td>$n_8$</td>
<td>$n_{10}$</td>
<td>1</td>
</tr>
<tr>
<td>$n_{10}$</td>
<td>$n_7$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(a)

Figure 2: Variable bindings

The OPTIONAL MATCH clause in line 2 matches all the students supervised by each researcher. This yields a binding of the newly-introduced variable $s$ for each value to which $r$ was bound by the MATCH clause in line 1, producing the table in Figure 2a. When $r$ is bound to $n_1$ (Nils, who does not supervise any students), the corresponding binding for $s$ is null. For the researcher Elin ($n_6$), who supervises two students, both $n_7$ and $n_8$ are bound.

The WITH clause in line 3 is used both to project a subset of the variables currently in scope and their bindings to the query part succeeding WITH, and to compute an aggregation. The WITH clause has two expressions, the second of which is an aggregation, functioning in a very similar way to SQL. The first expression, $r$, is a non-aggregating expression and therefore acts as an implicit grouping key for the aggregating function count(s). Taking the results shown in the above table, we count all the non-null values of $s$ for each unique binding of $r$, aliasing it as studentsSupervised. The WITH clause will project all the bindings produced for $r$ and studentsSupervised, as shown in Figure 2b. We note that the variable $s$ is no longer in scope after line 3, as it was not projected by WITH, and may no longer be used in the remainder of the query.

This table now acts as the driving table for the MATCH clause in line 4. Here, we define a pattern which matches all the publications authored by the researchers. The researcher Thor has not authored any publications, which means $n_{10}$ will not be matched. As a result, $n_{10}$ is not produced as a binding for $r$, and therefore no row containing these bindings will be added to the intermediate result table.

The variable bindings produced by line 4 include all researchers who have authored at least one publication, the number of students they supervise, and the publication they authored:

<table>
<thead>
<tr>
<th>$r$</th>
<th>studentsSupervised</th>
<th>$p_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_1$</td>
<td>0</td>
<td>$n_2$</td>
</tr>
<tr>
<td>$n_6$</td>
<td>2</td>
<td>$n_5$</td>
</tr>
<tr>
<td>$n_{10}$</td>
<td>2</td>
<td>$n_9$</td>
</tr>
</tbody>
</table>

The OPTIONAL MATCH clause in line 5 matches, for each publication authored by one of the researchers in $G$, all the publications which cite it, both directly and indirectly. This is achieved through the use of a pattern containing the variable-length relationship CITES*, indicating that one or more CITES relationships must be traversed. The results produced are:

<table>
<thead>
<tr>
<th>$r$</th>
<th>studentsSupervised</th>
<th>$p_1$</th>
<th>$p_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_1$</td>
<td>0</td>
<td>$n_2$</td>
<td>$n_4$</td>
</tr>
<tr>
<td>$n_6$</td>
<td>0</td>
<td>$n_5$</td>
<td></td>
</tr>
<tr>
<td>$n_{10}$</td>
<td>0</td>
<td>$n_9$</td>
<td></td>
</tr>
<tr>
<td>$n_6$</td>
<td>2</td>
<td>$n_5$</td>
<td>$n_9$</td>
</tr>
</tbody>
</table>

When $p_1$ is bound to $n_9$, which is not cited by any publication, the corresponding binding for $p_2$ is null. In addition, we note that there are two identical rows, indicated with †. The existence of these duplicate rows is due to the variable-length relationship pattern: $n_9$ is reachable from $n_2$ through the intermediate nodes $n_5$ and $n_4$.

RETURN is the last clause in the query (lines 6 and 7) and, much like the WITH clause in line 3, computes and projects expressions. The value of the name property of each researcher is projected, along with the value of studentsSupervised. The aggregation expression, in contrast to the one in line 3, counts the distinct values of $p_2$ (excluding null values) and aliases the results as citedCount, denoting the number of publications citing a publication authored by the researcher. The table consisting of the rows containing the result of the expressions is projected by RETURN:

<table>
<thead>
<tr>
<th>$r$.name</th>
<th>studentsSupervised</th>
<th>citedCount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nils</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Elin</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Examples from industry. Bioinformatics [3, 61] and pharmaceuticals [45] are major areas where graph storage and analytics are
widely used. There is a strong overlap between graph processing and machine learning [27]. Several specific application domains have played a large role in the expansion of property graphs and the use of the Cypher language: fraud detection, knowledge management, network and IT operations, real-time recommendation engines, master data management, social networks, and identity and access management.

A real-world query from the network management domain is shown below. In a data center, entities such as services, firewalls, servers, routers and network switches are modeled as nodes, with relationships representing the dependencies between them. The query returns the component that is depended upon – both directly and indirectly – by the largest number of entities.

```
MATCH (svc:Service)<-[DEPENDS_ON*]-(dep:Service)
RETURN svc, count(DISTINCT dep) AS dependents
ORDER BY dependents DESC LIMIT 1
```

Our second example shows a query in the domain of fraud detection. It returns details regarding a potential fraud ring, in which distinct account holders share personal information, such as social security number (SSN), telephone number and address.

```
MATCH (accHolder:AccountHolder)-[HAS]->(pInfo)
WHERE pInfo:SSN OR pInfo:PhoneNumber OR pInfo:Address
WITH pInfo,
    collect(accHolder.uniqueId) AS accountHolders,
    count(*) AS fraudRingCount
WHERE fraudRing > 1
RETURN accountHolders,
    labels(pInfo) AS personalInformation,
    fraudRingCount
```

The `collect` function returns a list containing the values returned by the expression, and the `labels` function returns a list containing all the labels of a node. Thus, in the query above, these functions will return, respectively, a list containing the unique identifiers of all the account holders, and a list containing all the labels of the nodes bound to the variable `pInfo`.

4 FORMAL SPECIFICATION

We now provide a formal specification of the core of Cypher. Formal specifications of languages have multiple advantages over documentation written in natural language. They can be used to reason about the language and prove optimizations correct, they can lead to a reference implementation that could be used to verify whether a particular implementation of the language adheres to its specification, and they leave much less room for ambiguity compared to natural language descriptions. While common in the programming language community, formal specifications of query languages have recently appeared in the database literature [12, 13, 20, 57].

The key elements of Cypher are as follows:

- data model, that includes values, graphs, and tables;
- query language, that includes expressions, patterns, clauses, and queries.

Values could be simple or composite, such as lists and maps; we have already seen property graphs, and tables that are the outputs of queries. Expressions denote values; patterns occur in `MATCH` clauses; and queries are sequences of clauses. Each clause denotes a function from tables to tables.

To provide a formal semantics of Cypher, we need to define one relation and two functions:

- The `pattern matching relation` checks if a path $p$ in a graph $G$ satisfies a pattern $\pi$, under an assignment $u$ of values to the free variables of the pattern. This is written as $(p, G, u) \models \pi$. 

Figure 1: Example data graph showing supervision and citation data for researchers, students and publications
We consider three disjoint sets \( \mathcal{K} \) of property keys, \( \mathcal{N} \) of node identifiers and \( \mathcal{R} \) of relationship identifiers (ids for short). These sets are all assumed to be countably infinite (so we never run out of keys and ids). For this presentation of the model, we assume two base types: the integers \( \mathbb{Z} \), and the type of finite strings over a finite alphabet \( \Sigma \) (this does not really affect the semantics of queries; these two types are chosen purely for illustration purposes).

The set \( \mathcal{V} \) of values is inductively defined as follows:

- Identifiers (i.e., elements of \( \mathcal{N} \) and \( \mathcal{R} \)) are values;
- Base types (elements of \( \mathbb{Z} \) and \( \Sigma^* \)) are values;
- \texttt{true}, \texttt{false} and \texttt{null} are values;
- \texttt{list()} is a value (empty list), and if \( v_1, \ldots, v_m \) are values, for \( m > 0 \), then \( \text{list}(v_1, \ldots, v_m) \) is a value.
- \texttt{map()} is a value (empty map), and if \( k_1, \ldots, k_m \) are distinct property keys and \( v_1, \ldots, v_m \) are values, for \( m > 0 \), then \( \text{map}(k_1, v_1, \ldots, k_m, v_m) \) is a value.
- If \( n \) is a node identifier, then path(\( n \)) is a value. If \( n_1, \ldots, n_m \) are node ids and \( r_1, \ldots, r_{m-1} \) are relationship ids, for \( m > 1 \), then path(\( n_1, r_1, n_2, \ldots, n_{m-1}, r_{m-1}, n_m \)) is a value. We shall use shorthands \( n \) and \( n_1 r_1 n_2 \ldots n_{m-1} r_{m-1} n_m \).

In the Cypher syntax, lists are \( \{v_1, \ldots, v_m\} \) and maps are \( \{k_1 : v_1, \ldots, k_m : v_m\} \); we use explicit notation for them to make clear the distinction between the syntax and the semantics of values.

We use the symbol \( \langle \cdot \cdot \cdot \rangle \) to denote concatenation of paths, which is possible only if the first path ends in a node where the second starts, i.e., if \( p_1 = n_1 r_1 \ldots r_j n_j \) and \( p_2 = n_j r_j \ldots r_m n_m \) then \( p_1 \cdot p_2 = n_1 r_1 r_2 \ldots r_m n_m \).

Every real-life query language will have a number of functions defined on its values, e.g., concatenation of strings and arithmetic operations on numbers. To model this, we assume a finite set \( \mathcal{F} \) of predefined functions that can be applied to values (and produce new values). The semantics is parameterized by this set, which can be extended whenever new types and/or basic functions are added to the language.

**Property graphs.** Let \( \mathcal{L} \) and \( \mathcal{T} \) be countable sets of node labels and relationship types, respectively. A property graph is a tuple \( G = (\mathcal{N}, \mathcal{R}, \mathcal{T}, \text{tgt}, \lambda, \tau, \rho) \) where:

- \( \mathcal{N} \) is a finite subset of \( \mathcal{N} \), whose elements are referred to as the \textit{nodes} of \( G \).
- \( \mathcal{R} \) is a finite subset of \( \mathcal{R} \), whose elements are referred to as the \textit{relationships} of \( G \).
- \( \text{src} : \mathcal{R} \rightarrow \mathcal{N} \) is a function that maps each relationship to its \textit{source} node.
- \( \text{tgt} : \mathcal{R} \rightarrow \mathcal{N} \) is a function that maps each relationship to its \textit{target} node.
- \( \lambda : \mathcal{N} \rightarrow \mathcal{L} \) is a partial function from names to values, e.g., concatenation of strings and arithmetic operations on numbers. To model this, we assume a finite set \( \mathcal{F} \) of predefined functions that can be applied to values (and produce new values). The semantics is parameterized by this set, which can be extended whenever new types and/or basic functions are added to the language.

**Example 4.1.** We now refer to the property graph in Figure 1 and show how, for a sample of its nodes and relationships, it is formally represented in this model as a graph \( G = (\mathcal{N}, \mathcal{R}, \text{src}, \text{tgt}, \lambda, \tau, \rho) \).

\[
\begin{align*}
\text{N} & = \{n_1, \ldots, n_{10}\}; \\
\text{R} & = \{r_1, \ldots, r_{11}\}; \\
\text{src} & = \{r_1 \mapsto n_1, r_4 \mapsto n_5, r_7 \mapsto n_8, r_{10} \mapsto n_6\}; \\
\text{tgt} & = \{r_2 \mapsto n_3, r_5 \mapsto n_6, r_8 \mapsto n_{10}, r_{11} \mapsto n_9\}; \\
\lambda(n_1, \text{name}) & = \text{Nils}, \lambda(n_2, \text{acmid}) = 220, \lambda(n_3, \text{acmid}) = 190, \ldots, \\
\lambda(n_{10}, \text{name}) & = \text{Thors}; \\
\tau(r) & = \begin{cases}
\text{authors} & \text{for } r \in \{r_1, r_5, r_{10}\}, \\
\text{supervises} & \text{for } r \in \{r_6, r_7, r_8\}, \\
\text{cites} & \text{for } r \in \{r_2, r_3, r_4, r_9, r_{11}\}.
\end{cases}
\end{align*}
\]

**Tables.** Let \( \mathcal{A} \) be a countable set of names. A record is a partial function from names to values, conventionally denoted as a tuple with named fields \( u = (a_1 : v_1, \ldots, a_n : v_n) \) where \( a_1, \ldots, a_n \) are
It is important to remember that the Cypher pattern whose domain is empty.

are both represented as \((\ast, \ast, \{\ast\}, \{\ast\})\) (since \(\Rightarrow \ast\)). As highlighted by this example, \(I\) is nil if the optional grammar token \(\text{list}\) does not appear in the pattern syntax (see Figure 3). Otherwise, \(I\) is equal to \((\ast, \ast, \{\ast\}, \{\ast\})\) if \(\text{list}\) derives to \(\ast\), and \(I\) is equal to \((d, d), (d_1, \ast), (d_1, d_2), (d_1, d_2)\) if other derivations rules are applied, respectively.

In general, \(I\) defines the range of the relationship pattern. The range is \([m, n]\) where \(m\) is replaced by 1 and \(n\) in the place of the lower and upper bounds. The range is \([1, 1]\) if \(I = \text{nil}\). A relationship pattern is said rigid if its range \([m, n]\) satisfies \(m = n \in \mathbb{N}\).

A path pattern is an alternating sequence of the form

\[
\chi_1 \rho_1 \chi_2 \cdots \rho_{n-1} \chi_n
\]

where each \(\chi_i\) is a node pattern and each \(\rho_i\) is a relationship pattern. A path pattern \(\pi\) can be optionally given a name \(a\), written as \(\pi; a\); we then refer to a named pattern. A path pattern is rigid if all relationship patterns in it are rigid, and variable length otherwise.

We shall now define the satisfaction relation for path patterns w.r.t. a property graph \(G = (N, R, \text{src}, \text{tgt}, i, \lambda, \tau)\), a path \(p\) with node ids from \(N\) and relationship ids from \(R\), and an assignment \(u\).

We consider rigid patterns first as a special case, because they – unlike variable length patterns – uniquely define both the length and the possible variable bindings of the paths satisfying them. The satisfaction of variable length patterns will then be defined in terms of a set of rigid patterns.

**Satisfaction of rigid patterns.** As a precondition for a path \(p\) to satisfy any pattern, it is necessary that all relationships in \(p\) are distinct. Then, the definition is inductive, with the base case given by node patterns (which are rigid path patterns). Let \(\chi\) be a node pattern \((x, \mathcal{P}, \mathcal{T})\); then \((n, G, u) \models \chi\) if all of the following hold:

- \(\ast\) either \(a\) is nil or \(u(a) = n\);
- \(L \subseteq \lambda(n)\);
- \(\|s(n, k)\|_{G, u} = \text{true}\) for each \(k\) s.t. \(P(k)\) is defined.

Example 4.2. Consider the property graph \(G\) in Figure 4 and the node patterns \(\chi_1 = (x, \{\text{Teacher}, \varnothing\})\) and \(\chi_2 = (y, \varnothing, \varnothing)\). Then,

\[
\begin{align*}
(n_1, G, u) & \models \chi_1 & \text{if } u \text{ is an assignment that maps } x \text{ to } n_1, \\
(n_2, G, u) & \not\models \chi_1 & \text{for any assignment } u, \\
(n_3, G, u) & \models \chi_1 & \text{if } u \text{ is an assignment that maps } x \text{ to } n_3, \\
(n_4, G, u) & \models \chi_1 & \text{if } u \text{ is an assignment that maps } x \text{ to } n_4.
\end{align*}
\]

For \(i = 1, \ldots, 4\) we have that \((n_i, G, u_i) \models \chi_2\) whenever \(u_i\) is an assignment that maps \(y\) to \(n_i\).

\(\Box\)

For the inductive case, let \(\chi\) be a node pattern, let \(\pi\) be a rigid path pattern, and let \(\rho\) be the relationship pattern \((d, a, T, P, I)\). First we assume that \(I \neq \ast\); since \(\rho\) is rigid, \(I = (m, m)\) with \(m \in \mathbb{N}\). For \(m = 0\), we have that \((n \cdot p, G, u) \models \chi_\rho \pi\) if

\[
\begin{align*}
\text{(a)} & \text{ either } a \text{ is nil or } u(a) = \text{list}(); \\
\text{(b)} & \text{ } (n, G, u) \models \chi_\rho \pi, \text{ and } (p, G, u) \models \pi.
\end{align*}
\]

For \(m \geq 1\), we have that \((n_1 r_1 n_2 \cdots r_m n_{m+1} \cdot p, G, u) \models \chi_\rho \pi\) if all of the following hold:

\[
\begin{align*}
\text{(a')} & \text{ either } a \text{ is nil or } u(a) = \text{list}(r_1, \ldots, r_m); \\
\text{(b')} & \text{ } (n_1, G, u) \models \chi_\rho, \text{ and } (p, G, u) \models \pi; \\
\text{and, for every } i \in \{1, \ldots, m\}, \text{ all of the following hold:}
\end{align*}
\]
Informally, a variable length pattern is a compact representation for a possibly infinite set of rigid patterns; e.g., a pattern of length at least 1 will represent patterns of length 1, patterns of length 2, and so on.

To make this idea precise, let \( \rho = (d, a, T, P, I) \) be a variable length relationship pattern, and \( \rho' = (d, a, T, (m', m'')) \) be a rigid relationship pattern. We say that \( \rho \) subsumes \( \rho' \), and write \( \rho \sqsupseteq \rho' \), if \( m' \) belongs to the range \([m, n]\) defined by \( I \). If \( \rho \) is rigid, then it only subsumes itself. This subrelation is easily extended to path patterns. Given a variable length pattern \( \pi = \chi_1 \rho_1 \chi_2 \cdots \rho_{k-1} \chi_k \) and a rigid pattern \( \pi' = \chi_1 \rho'_1 \chi_2 \cdots \rho'_{k-1} \chi_k \), we say that \( \pi \) subsumes \( \pi' \) (written \( \pi \sqsupseteq \pi' \)) if \( \rho_i \sqsupseteq \rho'_i \) for every \( i \in \{1, \ldots, k-1\} \).

Then, we define the rigid extension of \( \pi \) as

\[
\text{rigid}(\pi) = \{ \pi' \mid \pi' \text{ is rigid and } \pi \sqsupseteq \pi' \}
\]

that is, the (possibly infinite) set of all rigid patterns subsumed by \( \pi \). For a named pattern, rigid(\( \pi/a \)) = \( \{ \pi'/a \mid \pi' \in \text{rigid}(\pi) \} \). Finally, \( (p, G, u) \models \pi \) if \( (p, G, u) \models \pi' \) for some \( \pi' \in \text{rigid}(\pi) \), and similarly for named patterns.

**Example 4.4.** Consider the following variable length pattern \( \pi \):

\[
(x: \text{Teacher}) \rightarrow [\text{KNOWS}\star 1..2] \rightarrow (y: \text{Teacher})
\]

That is, \( \pi \) is the pattern \( \chi_1 \rho_1 \chi_2 \rho_3 \chi_3 \chi_2 \) with

\[
\chi_1 = (x, \{ \text{Teacher} \}, \varnothing), \quad \chi_3 = (y, \{ \text{Teacher} \}, \varnothing), \quad \chi_2 = (\varnothing, \varnothing, \varnothing)
\]

and \( \rho = (\rightarrow, \text{nil}, \{ \text{KNOWS} \}, \varnothing, (1, 2)) \).

Then, rigid(\( \pi \)) is the set

\[
\{ \chi_1 p_1 \chi_2 p_1 \chi_3, \chi_1 p_1 \chi_2 p_2 \chi_3, \chi_1 p_2 \chi_1 \chi_2 p_3 \chi_3, \chi_1 p_2 \chi_2 p_2 \chi_3 \}
\]

where

\[
\rho_1 = (\rightarrow, \text{nil}, \{ \text{KNOWS} \}, \varnothing, (1, 1)), \quad \rho_2 = (\rightarrow, \text{nil}, \{ \text{KNOWS} \}, \varnothing, (2, 2))
\]

Consider again the property graph \( G \) in Figure 4. Let

\[
p_1 = n_1 r_1 n_2 r_2 n_3 \quad u_1 = \{ x \mapsto n_1, y \mapsto n_3, z \mapsto n_2 \}
\]

\[
p_2 = n_1 r_1 n_2 r_2 n_3 r_4 n_4 \quad u_2 = \{ x \mapsto n_1, y \mapsto n_4, z \mapsto n_2 \}
\]

Then, \( (p_1, G, u_1) \models \pi_1 \) and \( (p_2, G, u_2) \models \pi_2 \); therefore, \( \pi \) is satisfied in \( G \) by \( p_1 \) under \( u_1 \) and by \( p_2 \) under \( u_2 \). This shows the ability of a variable length pattern to match paths of varying length.

In addition, variable length patterns may admit several assignments even for a single given path. To see this, note that \( p_2 \) satisfies \( \pi \) in \( G \) also under the assignment \( u_2' \) that agrees with \( u_2 \) on \( x \) and \( y \) but maps \( z \) to \( n_3 \), because \( (p_2, G, u'_2) \models \pi_3 \).
In Cypher, we want to return the “matches” for a pattern in a graph, not simply check whether the pattern is satisfied (i.e., there exists a match). This is captured formally next.

**Pattern matching.** The set of free variables of a node pattern \( \pi = (a, L, P) \), denoted by free(\( \pi \)), is \( \{a\} \) whenever \( a \) is not nil, and empty otherwise. For a relationship pattern \( \rho \), the set free(\( \rho \)) is defined analogously. Then, for a path pattern \( \pi \) we define free(\( \pi \)) to be the union of all free variables of each node and relationship pattern occurring in it. For example, for the pattern of Example 4.4 we have free(\( \pi \)) = \{x, y, z\}. For named patterns, free(\( \pi/a \)) = free(\( \pi \)) \cup \{a\}. Then, for a path pattern \( \pi \) (optionally named), a graph \( G \) and an assignment \( u \), we define

\[
\text{match}(\pi, G, u) = \bigcup_{\rho \in \text{rigid}(\pi)} \bigcup_{u' \in \text{dom}(u') \setminus \text{free}(\pi)} \left\{ \text{match}(\pi|_u, G, u') \mid (p(G, u \cdot u')) \models \pi' \right\}
\]

(1)

Note that, even though both \( u' \) and \( \pi' \) range over infinite sets, only a finite number of values contribute to a non-empty set in the final union. Thus \( \text{match}(\pi, G, u) \) is finite.

In (1), \( \bigcup \) stands for bag union: whenever a new combination of \( \pi' \) and \( \rho \) is found such that \( (p(G, u \cdot u')) \models \pi' \), a new occurrence of \( u' \) is added to \( \text{match}(\pi, G, u) \). This is in line with the way Cypher combines the MATCH clause and bag semantics, which is not captured by the satisfaction relation alone.

**Example 4.5.** Consider once again the graph \( G \) in Figure 4, and let \( \pi \) be the following variable length pattern:

\[
(x:Teacher) -[:KNOWS*1..2]-> ()
\]

This is similar to the pattern in Example 4.4, but the middle node pattern is not given any name here: free(\( \pi \)) = \{x, y\}. Indeed, rigid(\( \pi \)) is the same as in the previous example, with \( y_1 = (\{\}, \{\}, \{\}) \).

Let \( \rho = n_1p_1n_2p_2n_3p_3n_4 \) and \( u = \{x \mapsto n_1, y \mapsto n_4\} \); it is easy to see that \( (p(G, u)) \models \pi \), \( \pi \in \text{rigid}(\pi) \). However, observe that \( (p(G, u)) \models \pi_2 \) as well (whereas \( \pi_1 \) and \( \pi_4 \) are not satisfied by any path of \( G \)). This shows that there may be multiple ways for a single path to satisfy a variable length pattern even under the same assignment. In our example, two copies of \( u \) will be added to \( \text{match}(\pi, G, \{\}) \).

**Matching tuples of path patterns.** Cypher allows one to match a tuple \( \bar{\pi} = (\pi_1, \ldots, \pi_n) \) of path patterns, each optionally named. We say that \( \bar{\pi} \) is rigid if all its components are rigid, and rigid(\( \bar{\pi} \)) is defined as rigid(\( \pi_1 \) \( \times \cdots \times \) rigid(\( \pi_n \)). The set of free variables of \( \bar{\pi} \) is defined as free(\( \bar{\pi} \)) = \( \bigcup_{\pi_i} \) free(\( \pi_i \)). Let \( \bar{\rho} = (p_1, \ldots, p_n) \) be a tuple of paths; we write \( (\bar{\rho}(G, u)) \models \bar{\pi} \) if no relationship id occurs in \( \bar{\pi} \) more than once in its path in \( \bar{\rho} \) and \( (p_i(G, u)) \models \pi_i \) for each \( i \) in \{1, \ldots, n\}.

Then, for a tuple of patterns \( \pi \), a graph \( G \) and an assignment \( u \), match(\( \pi, G, u \)) is defined as in (1), with the difference that the bag union is now over tuples \( \bar{\pi} \in \text{rigid}(\pi) \) and \( \bar{\rho} \) of paths.

**Complexity.** Graph homomorphism is the notion commonly used in graph querying [6, 9, 16]. At first, the pattern matching mechanism of Cypher might seem an extension of it that accounts for additional features such as values associated with nodes and relationships. However, on a more careful examination one may notice that Cypher actually departs from graph homomorphism. Indeed, in defining how rigid patterns are satisfied, we only looked at paths in which relationship ids occur at most once. In other words, a path cannot traverse the same relationship (i.e., edge) more than once.

Why do we have such a restriction, and how does it affect the complexity of pattern matching? Graph pattern matching is a canonical NP-complete problem: for a graph \( G \) and a pattern \( \pi \), checking whether there is a match for \( \pi \) in \( G \) is NP-complete. Note that this is consistent with finding patterns in relational querying: for instance, given a join query \( Q \) and a relational database \( D \), checking if \( Q(D) \) returns a tuple is NP-complete as well [2].

However, Cypher goes beyond simple matching, by returning paths. This is where the problem occurs. Suppose we have a graph with a single node \( n \) a single relationship \( r \), whose source and target are \( n \), and let \( \pi \) be the pattern \( x \rightarrow \{*\ldots\} \rightarrow (x) \). What would it return under homomorphism semantics? Since there are infinitely many paths from \( n \) to \( n \), it appears that such a pattern will match infinitely many times, i.e., for each \( m \geq 0 \), it will produce a match that traverses the unique edge in the graph \( m \) times.

To avoid this situation, Cypher chose to disallow repeating relationship edges while matching patterns. In the above example, two matches will be returned: one for traversing the unique edge zero times, one for traversing it a single time. The question now is: how different is the complexity of this pattern matching?

By using the problem of the existence of two disjoint paths in a graph, one can prove that checking whether there is a match for \( \pi \) in \( G \) according to the Cypher semantics remains NP-complete. In fact, differently from the case of homomorphism-based matching, there is even a fixed path for which this is true. Nonetheless, such fixed patterns are of rather peculiar shape and they are not, based on many years of experience, a common occurrence in practice.

### 4.3 Formal Syntax and Semantics

We now present the key components of Cypher, namely expressions, clauses, and queries, and define their formal semantics. Together with pattern matching defined in the previous section, they will constitute the formalization of the core of Cypher.

The syntax of Cypher patterns was given in Figure 3. The syntax of Cypher expressions, clauses, and queries is provided in Figure 5.

**Semantics of expressions.** The semantics of an expression \( \text{expr} \) is a value \([\text{expr}]_{G, u} \in V\) determined by a property graph \( G \) and an assignment \( u \) that provides bindings for the names used in \( \text{expr} \).

The rules here are fairly straightforward and given in full detail in [18]. Below we explain them briefly.

**Values and variables.** The semantics of \( v \in V \) is \( v \) itself, and the semantics of \( a \in A \) is given by \( u(a) \).

**Maps.** Here \( \text{expr}.k \) is the value associated with key \( k \); \( \{\} \) is the empty map, and every prop list, which is of the form \( \{k_1 : e_1, \ldots, k_m : e_m\} \) (see Section 4.2) can be seen as a map.

**Lists.** These expressions either test if a value is in the list, or form a list from a sequence of values, or select elements and sublists of a list, given by their positions.

**Strings.** We have some basic operations on strings such as looking for prefix, suffix, and subword (starts-with, ends-with, contains).

**Logic.** Just like SQL, Cypher uses 3-value logic for dealing with nulls. The values are \text{true}, \text{false}, and \text{null} (unknown), and the rules for connectives and, or, not, and xor, are exactly the same as in SQL. Also one can test if a value is null.
A query is either a sequence of clauses.

Semantics of clauses. Both OPTIONAL and WHERE could be omitted. The key to their semantics is pattern matching, in particular match(\(\pi, G, u\)) described in Section 4.2 (see Equation 1).

Similarly to the description of the semantics of queries in Figure 6, we make the assumption that the fields of \(T\) are \(b_1, \ldots, b_p\). Our convention about the names \(a_i'\) are exactly the same as for queries (see above), except that \(a_i' = \alpha(e_i)\) only if \(e_i\) is a name.

The MATCH clause extends the set of field names of \(T\) by adding to it field names that correspond to names occurring in the pattern but not in \(u\). It also adds tuples to \(T\), based on matches of the pattern that are found in graphs. UNWIND is another clause that expands the set fields, and WITH clauses can change the set of fields to any desired one.

Example 4.6. Let \(G\) be the property graph defined in Figure 4. Consider the clause MATCH \(\pi\), where \(\pi\) is the pattern

\[(x) \rightarrow [x \text{\ interacts } y] \rightarrow (y)\]

Let \(T\) be the table \(\{(x: n_1), (x: n_3)\}\) with a single field \(x\). We show how to compute \(\text{match}(\pi, G)\).

Note that rigid(\(\pi\)) is the (infinite) set of all rigid paths \(\pi_m = (\rightarrow, \text{nil}, \{\text{knocks}\}, m, m)\), for \(m > 0\). These can only be satisfied by paths with exactly \(m\) distinct relationships. Since \(G\) only contains 3 relationships, only \(\pi_1, \pi_2\) and \(\pi_3\) can contribute to the result.

Let \(u = (x: n_1, y: n_3)\), \(\pi' = \pi_1\) and \(p = n_1r_1n_2\). Then free(\(\pi_1\)) \(\subseteq\) \(\text{dom}(u) = \{y\}\), and thus \(u'\) must be a record over the field \(y\). One can easily check that \((n_1r_1n_2, G, (x: n_1, y: n_3)) \models \pi_1\). In fact \(n_2\) is the only suitable value for \(y\), and thus the contribution of this specific triple \(u, \pi', p\) to the final result is precisely \(\{(x: n_1, y: n_3)\}\).

No path \(p\) other than \(n_1r_1n_2\) can contribute a record in the case where \(u = (x: n_1)\) and \(p = \pi_1\). Indeed, \(\pi_1\) requires \(p\) to be of length 1, and start at \(x\), which \(u\) evaluates to \(n_1\). By a similar reasoning, we can compute the contribution of the following triples:

\[\bullet (x: n_1, y: n_3), n_2, n_1r_1n_2p_2n_3\]
The Cypher query language emerged from the evolution of the Neo4j graph database, which in turn originated from a data model that was first conceived of in 2000 by the founders of Neo4j in the course of building a media asset management system. The system’s data model changed frequently, and had complex data structures and access control views which inspired the idea of tagging network elements with ‘captions’ or property sets. The high emphasis on relationship information (modeled as graph edges) coupled with the need to support variable-length path traversals led away from the schema-rigid relational database initially used, to the creation of a native property graph database system.

From 2007 onwards this technology began to be provided for general use as an open-source database management system. Initially Neo4j was embedded as a Java library: the Tinkerpop Blueprints and Gremlin APIs, now part of the Apache project, originated in the early incarnations of Neo4j. Increased usage led to the inception of a property graph query language which would occupy the same ecological niche as SQL. The development of this language went hand in hand with changes in the database implementation that increasingly automated search optimizations through indexing of node data, which in turn drove the addition of node labels to the original scheme of relationship types.

From these influences emerged the current Cypher data model and the predominance of the Cypher language, which became the primary way of interacting with the graph. Cypher was largely an invention by André Taylor, engineer at Neo4j and co-author of this paper, in early 2011, and is a syntactic and feature level inspired by SQL, and also incorporates concepts from functional programming.

![Figure 6: Semantics of Cypher queries](image)

![Figure 7: Semantics of Cypher clauses](image)

- $(x : n_1, y : n_2)$, $n_3, n_1r_1n_2r_2n_3r_3n_4$ yields $(x : n_1, y : n_4)$;
- $(x : n_3, y : n_4)$, $n_1, n_3r_3n_4$ yields $(x : n_3, y : n_4)$;

and show that the contributions of all other possible combinations of records, paths and patterns are empty. This tells us that $\text{MATCH } \pi \|_G(T)$ is the table with the rows $(x : n_1, y : n_2)$, $(x : n_1, y : n_3)$, $(x : n_1, y : n_4)$, and $(x : n_3, y : n_4)$.

5 HISTORICAL REMARKS

The Cypher query language emerged from the evolution of the Neo4j graph database, which in turn originated from a data model that was first conceived of in 2000 by the founders of Neo4j in the course of building a media asset management system. The system’s data model changed frequently, and had complex data structures and access control views which inspired the idea of tagging network elements with ‘captions’ or property sets. The high emphasis on relationship information (modeled as graph edges) coupled with the need to support variable-length path traversals led away from
Cypher 9 assumes an implicit single global graph. Passing multiple graph references requires an extension of the formal semantics presented here. Three subqueries forms a graph. In contrast to the property graph model, RDF [59], a W3C recommendation, models resources using a directed labeled graphs are presented in [4, 23, 24, 26], and work undertaken on the hypergraph data model is detailed in [28, 35–37, 51]. Semi-structured data models closely related to graph data models include XML [10] and OEM [48]. RDF [59], a W3C recommendation, models resources using a graph model, and forms the foundation of the Semantic Web. Its basic building block is a triple, consisting of a subject, which describes the resource and is modeled as a node; a predicate which is a property of the resource and is modeled as an edge; and an object, which is the value of the property. A triple is therefore a statement of the relationship between the subject and the object, and a set of triples forms a graph. In contrast to the property graph model, RDF only supports a single value on a node or edge.

6 CURRENT DEVELOPMENTS

A consensus-driven openCypher Implementers Group (oCIG) now governs the evolution of the Cypher language. For most of 2017 it has been working on the definition of Cypher 10, which will be described in a complete natural language specification, combined with an extension of the formal semantics presented here. Three new features are being added to this next version of the language: multiple graphs, query composition, and temporal data types (e.g. date-time). These reflect industrial usage experience of Cypher, particularly in Neo4j and SAP HANA Graph [50].

Multiple graphs. Cypher 9 assumes an implicit single global graph that is used both for querying and for updating operations. Applications sometimes work with multiple disconnected subcomponents of this global graph. Such components may be understood as distinct property graphs themselves. However, Cypher does not yet include a mechanism for referencing such graphs explicitly and therefore the language does not easily allow operations to be applied to specific graphs.

The Cypher 10 proposal for multiple graphs introduces named graph references, which represent externally located graphs, graphs created by the query, or graphs created by a previous query in a composition of queries. Graph references may be passed as arguments to, and returned as results from, Cypher 10 queries, and can be used in set operations. These capabilities broadly match comparable functionality already present in SPARQL 1.1 [58]. Named graphs contribute to natural partitioning and graph transformations (which in turn enable graph-compositional queries).

Query composition. Passing multiple graph references requires extending the existing tabular composition mechanism in Cypher 9, where the WITH projection clause turns the output of a query into an input driving table for a following query. The Cypher 10 proposal for multiple graphs adds the ability to instead pass a “table-graphs” construct, consisting of a single table and multiple named graphs as query arguments. A table-graphs may additionally pass information relating to which of these graphs is being used for reading (source graph) and updating operations (target graph). Similarly a query result is a table-graphs. This enables Cypher queries to be composed as a chain of elementary queries. With the addition of subqueries such query chains can also be formed into a tree.

This parallels the advocacy of a similar feature by the LDBC Query Language Task Force in their description of the G-CORE research language [5]. The two proposals differ in that G-CORE describes queries that output only a single graph. In Cypher the projection of tabular results is recognized as necessary for applications to access property values, and consequently Cypher 10 is closed under table-graphs.

As part of these new query composition features, Cypher 10 also introduces named queries. Named queries simplify the creation of libraries of re-usable queries which can be composed in different query trees. They also form the basis for offering graph views.

Example 6.1. The following graph transformation query first finds all pairs of persons that have at least a single friend in common and then returns a new graph where they are connected directly:

```
FROM GRAPH soc_net AT "hdfs://.../soc_network"
MATCH (a)-[r1:FRIEND]->(b)
WHERE abs(r2.since-r1.since) < $duration
WITH DISTINCT a, b
RETURN GRAPH friends OF (a)-[:SHARE_FRIEND]-(b)
```

The result of this query may then be composed with a follow-up query, e.g. for further filtering for friend-sharing-friends that live in the same city:

```
QUERY GRAPH friends
MATCH (a)-[:SHARE_FRIEND]-(b)
FROM GRAPH register AT "bolt://.../citizens"
MATCH (a)-[:IN]->(c:City)<-[:IN]-(b)
RETURN *
```

Drafts of the Cypher 10 proposal for compositional graph queries have already been implemented in Cypher for Apache Spark.

Temporal types. A detailed proposal specifies support for temporal instant types (DateTime, LocalDateTime, Date, Time, and LocalTime) and a duration type.

7 RELATED WORK

Graph data models. These in general have been a topic of research since the 1990s. We provide here a summary and refer the reader to the surveys [6, 7] for further reading.

Variations of simple directed labeled graphs are presented in [4, 23, 24, 26], and work undertaken on the hypergraph data model is detailed in [28, 35–37, 51]. Semi-structured data models closely related to graph data models include XML [10] and OEM [48].

RDF [59], a W3C recommendation, models resources using a graph model, and forms the foundation of the Semantic Web. Its basic building block is a triple, consisting of a subject, which describes the resource and is modeled as a node; a predicate which is a property of the resource and is modeled as an edge; and an object, which is the value of the property. A triple is therefore a statement of the relationship between the subject and the object, and a set of triples forms a graph. In contrast to the property graph model, RDF only supports a single value on a node or edge.

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1https://github.com/thobe/openCypher/blob/date-time/cip/CIP2015-08-06-date-time.adoc
Graph query languages. Some graph navigation can be expressed in SQL using recursive queries. Basic properties such as reachability in a graph can be expressed fairly easily, but complex graph patterns that involve both data and navigation become very cumbersome using SQL's recursion. In addition, some features of Cypher, such as non-repeatability of edges in pattern matching, cannot in general be expressed in SQL. Deficiencies of SQL as a graph query language led to a large body of research on proper graph query languages. We briefly summarize the main contributions here and refer the reader to comprehensive surveys [6–8, 60].

Regular path queries (RPQs) – the ability to express a path between any two nodes as a regular expression over the edge labels – were first proposed by in 1987 in [16], and extended to conjunctive RPQs by means of taking joins in [14]; these classes of queries form the basis of languages studied in the theoretical literature [8, 60]. RPQs and related languages were extended to a theoretical model of data graphs that resemble property graphs in [38], which also described GXPath, a graph extension of XPath with node tests.

SPARQL [58] is the standard language used for querying RDF data [59], and support for RPQs was added in SPARQL 1.1 through the introduction of property paths [33].

There are other industrial property graph query languages. Oracle's PGQL [56] uses the SELECT-FROM-WHERE form from SQL and the graph pattern syntax from Cypher. It allows for RPQs through the use of the PATH clause defining a regular path pattern. It does not support data insertion or updating. Gremlin [53] is a property graph dataflow language designed by Apache Tinkerpop, which supports procedural pattern matching and traversals embedded in general purpose languages, but does not allow independent statement of a declarative query in the style of SQL and Cypher. The U.S. standards body INCITS recently created a working group to examine potential extensions to the SQL standard to allow relational data to be viewed and queried as property graph data.

8 FUTURE WORK

Major topics under discussion for language changes beyond the current developments around Cypher 10 include: richer path patterns, allowing selection of additional semantics of pattern matching (homomorphism, node isomorphism, edge isomorphism), enlarging the schema model, expanding the underlying data model, and clarifying theoretical vs real-life complexity of Cypher queries.

Path patterns. Cypher 9 supports a more limited form of regular path queries than for example SPARQL [58] and does not support full regular expression composition. A future version of Cypher will add an extended form of regular path patterns that allows data tests on nodes and relationships and path cost declarations. In addition, it will be possible to define named path patterns which can be referenced in other path patterns. This latter change was first proposed in PGQL [56].

Configurable morphisms. Cypher 9 matches patterns using relationship (edge) isomorphism, i.e. each matched instance of a given pattern never binds the same relationship from the underlying data graph to more than one relationship variable or path variable. This restriction reduces the number of pattern matches and ensures that variable length relationship patterns never produce infinite result sets. In some applications this rule is insufficient: it is envisioned that Cypher will also allow the writer of a query to specify the use of homomorphism or node isomorphism pattern matching semantics.

Schema model. Cypher was originally conceived in a dynamically typed, schema-less context. Neo4j nowadays is schema-optional, i.e. it supports an additional schema constraint language (e.g. for requiring nodes with a given label to have certain properties). Other implementations of Cypher assume a more strict schema (e.g., Cypher for Apache Spark, or SAP HANA Graph). Standardizing a schema model will improve data modeling capabilities and help portability of queries while also enabling implementations to type check queries more rigidly up-front as well as optimize them better.

Data model. Current industry trends indicate the need for supporting both spatial and temporal (time-evolving) graph data as well as stream processing applications. These trends point towards future evolutions of the core data model and underlying type system together with other related language changes.

Theoretical vs real-life complexity. We have seen that pattern matching under the Cypher semantics can be NP-complete, even for a fixed pattern, and thus unlikely to be tractable in general. Theoretically, this could be viewed as a reason to look for an alternative semantics. However, in practice this works well: people do not write queries that look like reductions from NP-complete problems. While in databases, high theoretical complexity has usually been seen as a show stopper, in other fields this is not so: very fast industrial strength SAT solvers routinely solve NP-complete problems of large size [40]. Typechecking in some popular languages could provably take exponential time in the worst case [31], and problems of astronomical complexity or even undecidable ones have been successfully tackled [15, 32]. The reason is the same as in the case of Cypher queries: examples from the worst case analysis very rarely arise in practice. This observation leads to a new research program on analyzing real-life practical complexity of queries and its differences with the theoretical complexity of languages.

9 CONCLUSION

The property graph data model is increasingly prevalent across a wide variety of application domains, where data is represented naturally as a graph structure and there is a requirement for the query language to allow for graph-oriented operations (e.g., transitive closure) to be expressed directly. This has also fueled the use of native graph data structures to optimize storage and query processing for such operations.

Cypher is a solidly-established declarative query language for the property graph model, with increasing adoption in multiple products and projects. The language is evolving with new features – saliently support for multiple graphs and query composition. Under the aegis of the openCypher Implementers Group it is now being documented as a fully-specified standard that can be independently implemented using different architectures, and varying storage and query optimization strategies.

All this work – including the formal semantics described in this paper – will contribute towards the goal of establishing Cypher alongside SQL as complementary languages, enabling integrated use of the graph and relational data models.
REFERENCES


1995.

Property graph vs RDF triple store: A comparison on gyan substructure search.


of modern query languages for graph databases. ACM Comput. Surv., 50(3):68:1–


SIGACT-SIGART Symposium on Principles of Database Systems, PODS 2013, New


[10] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,


[12] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[13] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[14] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[15] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[16] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[17] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[18] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[19] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[20] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[21] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[22] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[23] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[24] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[25] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[26] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[27] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[28] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,

[29] M. Cabra. How the ICIJ used Neo4j to unravel the Panama Papers. Neo4j Blog,