Karlsruhe Institute of Technology

Benchmarking of Graph Databases - Suitability for the Industrial Environment

Bachelor's Thesis
by

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Karlsruhe, den TODO: date

Zusammenfassung

TODO: Zusammenfassung (Deutsch)

Abstract

TODO: Zusammenfassung (Englisch)

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1. Introduction

TODO: Fix url in bibliography

1.1 Problem Statement

TODO: Highlight that current graph database benchmark papers are not covering our field. With the growing digitalisation of the industry more data is available and can be used to improve production processes. The amount of data created depends on the individual use case, but still it needs to be stored to be useful. Since there are multiple databases available it can be difficult to choose the right one for an individual scenario.

1.1.1 Use Case - Industry 4.0

There are multiple analytic algorithms to run on data to extract certain features. In the industry those algorithms play an important role too, but in this thesis we are looking at different aspects of the industrial use case, mainly inserting data and reading data.

In section 2.2 we will show an example given by the industry. There is no industrial data available publicly so we have to base our design on that given example which is visualised in figure 2.2.

1.1.1.1 Inserting Data

To digitalise the production processes the data produced by every machine in the production line should be stored for future analysis. And to store that data it needs to be written into a database. Since most factories running 24 hours a day the machines are producing a lot of data during the day. That will be the base load for the underlying database, to store all that data from the production machines.

1.1.1.2 Reading Data

Besides using the stored data for analysis algorithms, simply reading data from the database is another common use case. An example would be to get the time at which a specific product was processes by a specific machine to check if all parameters were set correctly.

1.2 Question

This thesis should give an answer to the question, if graph databases are suitable for an industrial application. Suitable in this case means that the database can withstand the amount of data written to it during production. In section 3.1 we analyse how much data could be written to a database and of which structure that data is. We motivate graphs and the use of graph databases in section 2.2 and section 2.3 respectively and will concentrate on those in this thesis, because of the structure of the data from production.

1.3 Methodology

We will chose the databases to use for our testing from other studies covering benchmarking graph databases to be able to compare the results and look to similarities in behaviour. To evaluate different databases we first will look up existing benchmarks and choose the best fitting one for our research. In the benchmarking program we need to look at the creation of data and how it can be stored and retrieved. The same exact dataset should be used for all databases equally to eliminate the variation that comes with generating data during each benchmark run. Next the workloads should be customisable and be able cover our goals. Also the measurements taken during the benchmark need to be useful for us. The databases should be able to connect to the benchmark in the same way.

1.4 Goal of this Thesis

With this thesis we want to examine whether and if so, how well graph databases are able to stand the load of an production line. Because every manufacturer is different and we cannot cover all scenarios we try to cover the most important parameters so that the suitability for the individual case can be estimated.

1.5 Structure

In chapter 2 we are motivating graph and the use of graph databases. The different kinds of graph databases are explained and an example database which we are testing is mentioned and shortly described. Also in this chapter we are comparing the different available benchmarking programs and their features. NOTE: Maybe mention related work

In chapter 3 the industrial data is modelled and its structure is analysed as well as a reasonable amount of data is determined. Then we are figuring out how a workload could look like in an industrial environment. At last we further analyse out chosen benchmarking program and give an overview of its procedure.

Chapter 4 is focused on the design of the different extensions for the benchmark and also the concrete data structure. For the extension we cover the design of the specific workloads, the design of classes to create and recreate the dataset, the graph workload class managing the graph databases and the graph data and finally the database bindings which are responsible for connecting the database to the benchmarking program.

In chapter 5 the implementation of the single components is described. First we cover the graph data generator which includes the class for creating the graph data as well as the class for recreating it from files. Next the bindings are implemented and their individual adaptions to the benchmark are highlighted. And lastly we explain the graph workload class which is the mediator between the created graph data and the database bindings.

Chapter 6 focuses on running the benchmark and evaluating the results. First, we define our objective during evaluation. Then the configuration of our system is stated, as well as the hardware as the software side. Next the procedure of running the benchmarks sequentially is explained following be the different aspects we are testing. These are grouped into ”maximum load” in section 6.4, ”throughput” in section 6.5 and ”responsiveness” in section 6.6. Each group includes multiple benchmarks in which we changed on variable at a time. The results are presented directly after each benchmark followed by a discussion to interpret the results.

In chapter 7 we draw a conclusion over out work and give the answer to our question from above. Also ideas for future research and development in this field are presented.

Finally in chapter 8 with give a short summary of our work.

2. Background & Related Work

In this chapter we will give a introduction into the different fields touched by our research. Related work is mentioned primarily in section 2.4 as it covers the different benchmarks and their findings.

2.1 Graphs

A graph as the literature tells us [26, p. 89] is a tuple of sets $G = (V, E)$ with $E \subseteq V \times V$. Elements of V are called vertices and elements of E are called edges. The set of vertices has to be not empty, but the edge set can be. In this thesis we are focusing on directed graphs only, although some graph databases are capable of handling undirected graphs too not all are. Also there would be no benefit in using undirected edges since our model also uses directed edges. In general graphs can have labels or weights on their edges as stated in [26, p. 99]. For our purposes we will use labels on the vertices and edges to ease the understanding of our data structure. In section 2.3 we will give reasons why having labels on the graph components is useful.

Figure 2.1 shows an example of a directed graph with labels on its vertices. An equivalent representation of that graph would be

$$\begin{aligned} V &= \{1, 2, 3\} \\ E &= \{(1, 2), (1, 3), (2, 3), (3, 2)\}. \end{aligned} \tag{2.1}$$

2.1.1 Trees

TODO: Explain tree graphs shortly.

2.2 Industrial Data

Under the term ”industrial data” we understand data that is produced by machines during the production. That could be the current settings of the machine, temperatures or tolerances measured during processing or what product is currently worked on. In chapter 3.1 the possible structure of this data is analysed.

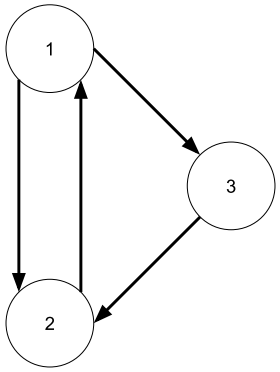

Figure 2.1: A directed graph with three labeled vertices and four edges.

As there is no publicly available information about how industrial data should look like we will use the example given by our partners at SICK AG [21] as an inspiration for our test data.

Listing 2.1 shows the graph excerpt of our given example.

Listing 2.1: An excerpt showing the observation of components.

```
"@graph": [
  {
    "@id": "http://localhost:3000/observations/185",
    "@type": "ssn:Observation",
    "featureOfInterest": "aoi:Feature",
    "observationSamplingTime": "2016-05-18T12:55:27.954Z",
    "observedProperty": [
      "aoi:twisting",
      "aoi:y-shift",
      "aoi:x-shift"
    ],
    "observationResult": "http://localhost:3000/observations/185/sensor-output",
    "observationResultTime": "2016-05-18T12:55:27.954Z",
    "observedBy": "http://localhost:3001/AOI_SMD407",
    "dataClass": "Testdata"
  },
  {
    "@id": "http://localhost:3000/observations/185/sensor-output",
    "@type": "ssn:SensorOutput",
    "isProducedBy": "http://localhost:3001/equipment/AOI_SMD407",
    "hasValue": "http://localhost:3000/observations/185/result"
  },
  {
    "@id": "http://localhost:3000/observations/185/result",
    "@type": "ssn:ObservationValue, shopfloor:Panel",
    "orderNo":"http://localhost:3000/order#0",
    "partNr": "http://localhost:3000/part#2060817",
    "hasPart": "http://localhost:3000/observations/185/board#3827581",
    "startTime": "2016-05-18T12:55:27.954Z",
    "endTime": "2016-05-18T12:56:27.954Z"
  },
  {
    "@id": "http://localhost:3000/observations/185/board#3827581",
    "@type": "shopfloor:Board",
    "hasPart": ["http://localhost:3000/observations/185/component#C1-1","http://
        localhost:3000/observations/185/component#C2-1"],
    "boardUID":"3827581",
    "isBadBoard": false
  },
  {
    "@id": "http://localhost:3000/observations/185/component#C1-1",
    "@type": "shopfloor:Component",
    "componentType": "C0603",
    "position":0,
    "testFeature":[
```

```
      {
        "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-
            TWISTING",
        "feature": "aoi:twisting1",
        "analysisMode": [
          {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
              -901-TWISTING",
            "windowNumber": "901",
            "featureFlag": "0",
            "mode":"MENI"
          }
        ],
        "hasValue": {
          "@type": "xsd:integer",
          "@value": "10"
        }

      },
      {
        "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-Y-
            Shift",
        "feature": "aoi:y-shift1",
        "analysisMode": [
          {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
              -901-Y-Shift",
            "windowNumber": "901",
            "featureFlag": "0",
            "mode":"MENI"
          }
        ],
        "hasValue": {
          "@type": "xsd:integer",
          "@value": "-17"
        }
      },
      {
        "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-X-
            Shift",
        "feature": "aoi:x-shift1",
        "analysisMode": [
          {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
              -901-X-Shift",
            "windowNumber": "901",
            "featureFlag": "0",
            "mode":"MENI"
          }
        ],
        "hasValue": {
          "@type": "xsd:integer",
          "@value": "20"
        }
      }
    ]
  },
  {
    "@id": "http://localhost:3000/observations/185/component#C2-1",
    "@type": "aoi:Component",
    "componentType": "C0603",
    "position":0,
    "testFeature":[
      {
        "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-
            TWISTING",
        "feature": "aoi:twisting1",
        "analysisMode": [
          {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
              -901-TWISTING",
            "windowNumber": "901",
            "featureFlag": "0",
            "mode":"MENI"
          }
        ],
        "hasValue": {
          "@type": "xsd:integer",
```

```
            "@value": "12"
          }
        },
        {
          "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-Y-
              Shift",
          "feature": "aoi:y-shift1",
          "analysisMode": [
            {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
                -901-Y-Shift",
              "windowNumber": "901",
              "featureFlag": "0",
              "mode":"MENI"
            }
          ],
          "hasValue": {
            "@type": "xsd:integer",
            "@value": "14"
          }
        },
        {
          "@id": "http://localhost:3000/observations/185/component#C0603-MENI-901-X-
              Shift",
          "feature": "aoi:x-shift1",
          "analysisMode": [
            {"@id": "http://localhost:3000/observations/185/AnalysisMode#C0603-MENI
                -901-X-Shift",
              "windowNumber": "901",
              "featureFlag": "0",
              "mode":"MENI"
            }
          ],
          "hasValue": {
            "@type": "xsd:integer",
            "@value": "11"
          }
        }
      ]
    }
]
```


In figure 2.2 the provided example is visualised partially, it shows the observation of a product.

2.3 Graph Databases

TODO: Write about available versions of the databases There is a variety of database types available the main categories are SQL and NoSQL databases. A short description of SQL databases would be "A relational database organizes data in tables (or relations). A table is made up of rows and columns. A row is also called a record (or tuple). A column is also called a field (or attribute). A database table is similar to a spreadsheet." ([11])

NoSQL databases on the other hand are able to store any kind of data in any record, they don't rely on a specified schema. Also they are able to scale horizontally for the cost of consistency. [28]

Graph databases are a type of NoSQL databases. They use graph theory to store their data as described in 2.1 with vertices and edges. Every vertex has a unique identifier (id) in the database, the edges coming from or going to that vertex and it can have properties assigned to it as key/value pairs. Edges also have a unique id, a start and end vertex and properties just as vertices. [20]

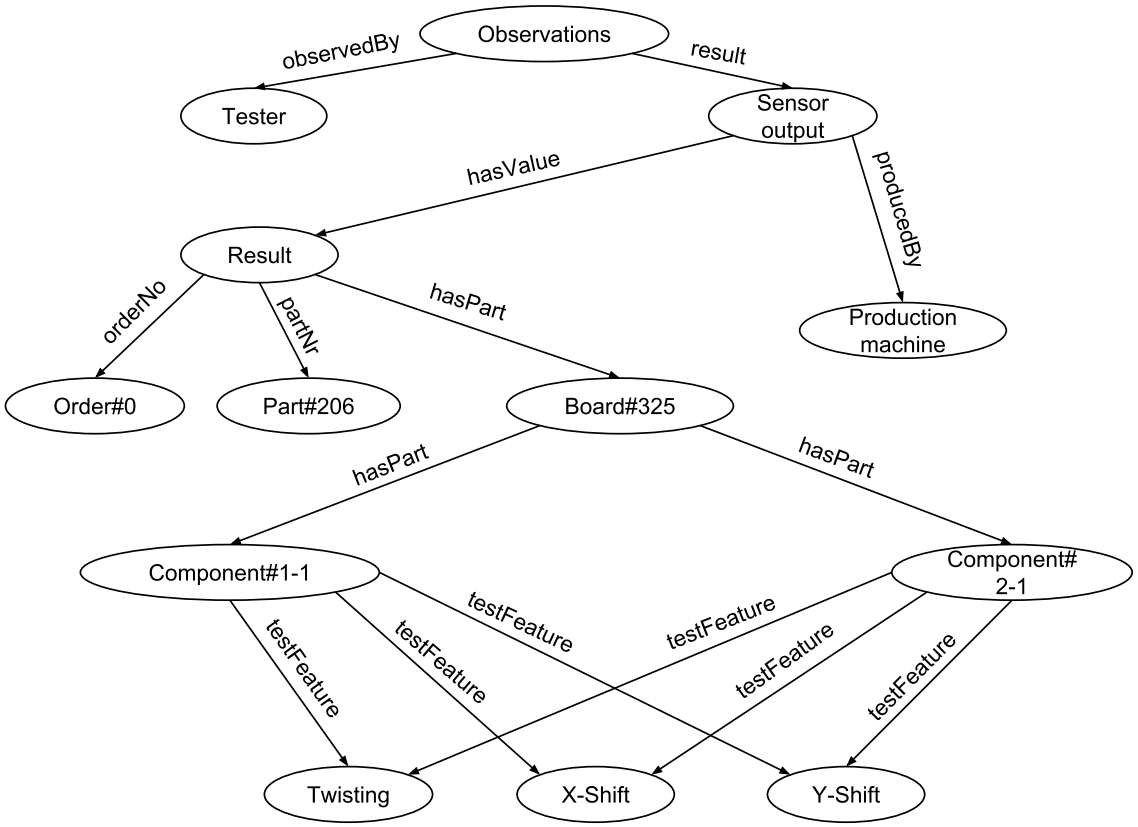

Figure 2.2: An example graph representing the observation of test features in the components of a board.

The labels mentioned at the end of section 2.1 can be seen as the properties assigned to a vertex or edge. To map a production line in which the elements like machines and products might have their own real world ids these properties can be used to store these real world ids as a key/value pair. Later a particular machine for example can be looked up by its id. That is critical to find the data stored in the database.

In the following subsections 2.3.1 through 2.3.3 we will discuss the different types of graph databases and give examples of real databases which operate by that type. All databases used in this thesis support the ACID[1] principle with transactions to ensure data consistency.

2.3.1 RDF/Triplestores

First in our list are RDF stores also known as triple stores.

RDF (Resource Description Framework) is a model for data interchange on the Web. It is able to merge data even with different schemas, it also support the evolution of a schema over time. The linking strucutre of the Web is extended by RDF by it using URIs[2] to name relationships and resources connected by those. [18, p. 4]

> This linking structure forms a directed, labeled graph, where the edges represent the named link between two resources, represented by the

[1] short for atomicity, consistency, isolation, durability. It should guarantee data validity.
[2] abbreviation of Universal Resource Identifier, used to identify abstract of physical resources. [5]

> graph nodes. This graph view is the easiest possible mental model for RDF and is often used in easy-to-understand visual explanations. ([25])

Triplestores store semantic facts as subject - predicate - object triples, also referred to as statements using RDF. These statements form a network of data, which can also be seen as a graph. [18, p. 4]

2.3.1.1 Apache Jena TDB

"Apache Jena (or Jena in short) is a free and open source Java framework for building semantic web and Linked Data applications. The framework is composed of different APIs interacting together to process RDF data." ([4])

The TDB component in Jena is responsible to store and query RDF data. [2]

In section 2.4 we will discuss recent studies investigating Apache Jena, among others.

2.3.2 Document Stores

As the name suggests the data model of document stores consist of documents which can have fields without depending on a defined schema [19]. Its aggregates data in those documents and transforms them internally into an searchable form [24].

2.3.2.1 OrientDB

OrientDB is a mix of a document store and a graph store, as stated in their manual "OrientDB is a document-graph database, meaning it has full native graph capabilities coupled with features normally only found in document databases." ([19]) Its designed as a robust, highly scalable database with a wide possible set of use cases. [19]

2.3.3 Graph Stores

Graph stores organise their data as graphs. References with foreign keys known from relational databases are mapped as relationships in graph databases. Each node in the database model contains a list of relationship-records to represent their connection to other nodes. [16]

2.3.3.1 Neo4j

Neo4j is a native graph database and was build as such from the ground up. In their introduction they say "The architecture is designed for optimizing fast management, storage, and traversal of nodes and relationships. In Neo4j, relationships are first class citizens that represent pre-materialized connections between entities." ([17])

2.3.3.2 Sparksee

The user manual describes Sparksee as follows, "Sparksee is an embedded graph database management system tightly integrated with the application at code level." ([22]) Sparksee is implemented in C++ but provides a low level Java API.

2.4 Graph Database Benchmarks

TODO: Add benchmark results As the need to compare similar programs exists benchmarks are needed to hand results over certain parameters to aid decision making. In the field of graph databases that is no different. There exist multiple benchmarks for graph databases and some are outlined shortly in the following subsections 2.4.1 to 2.4.3. In in section 3.3 we choose a benchmark for our work.

2.4.1 LDBC: Graphalytics

Benchmark specifications, practices and results for graph data management systems are established by an industry council called The Linked Data Benchmark Council. The Graphalytics benchmark facilitates a choke-point design to evaluate the crucial technological challenges present in system design, one example would be the ”large graph memory footprint” as mentioned in [6, p. 2].

Graphalytics uses Datagen to create social network graphs, which are easy to understand for their users [6, p. 3].

The workloads implemented in Graphalytics represent common graph algorithms such as breadth-first search, weakly connected components or single-source shortest paths to name just a few [12, p. 7].

Neo4j was used among others in the study of Capotă et al. [6], which we will refer to in our evaluation in chapter 6.

2.4.2 XGDBench

Is a graph database benchmark for cloud computing systems. It is designed to work in the cloud and in future exascale clouds. XGDBench is an extension of the Yahoo! Cloud Serving Benchmark for graph databases. This benchmark is written in X10, a “programming language that is aimed for providing a robust programming model that can withstand the architectural challenges posed by multi-core systems, hardware accelerators, clusters, and supercomputers” ([8]).

XGDBench also focuses on social networks for their data structure, that is generated by a procedure called Multiplicative Attribute Graph (MAG), see [13] for more information.

It specifically targets read, update and graph traversal operations for its performance aspects [8, p. 366].

This study featured following graph databases which we are also testing Fuseki, Neo4j and OrientDB [8, p. 364]. Fuseki is a SPARQL[3] server providing a HTTP interface to Jena [3], so that research covers three of our four databases.

2.4.3 YCSB

The Yahoo! Cloud Serving Benchmark (YCSB) was not designed specifically for graph databases, but rather for key-value and cloud stores. The project consists of the YCSB client which is responsible for generating the data, as well as the Core

[3]SPARQL is a language to query and manipulate RDF data. [10]

workloads those are a set of workloads executed by the client. The client is extensible to that new workloads, new databases and new generators can be integrated. [27]

The core workload is designed to use simple CRUD[4] operations on any database with no special structure of the generated data.

TODO: maybe add [1]

2.5 Other Related Work TODO: Add if more present/needed

2.5.1 Graph Database: Anna

2.5.2 TODO: Add more

[4]CRUD stands for the basic operations on persistent storage, these are Create, Read, Update, Delete.

3. Analysis

In this chapter we will analyse the data which could occur in an industrial use case, that includes its structure and amount. Further we will examine possible workloads for our graph databases in section 3.2.

At the end of this chapter in section 3.3 we will chose one benchmark for our research.

3.1 Data

As described in section 2.2 we have to work with the data coming from production machines. Figure 2.2 shows us how that data could look like.

Additionally our partners at SICK AG [21] gave us the following key data for a product example. A component carrier with up to 64 circuit boards on it each with up to 128 components is produced every three minutes. Each component has up to 128 test features.

3.1.1 Data Structure

Looking at the graph in figure 2.2 and the example given by SICK we can see that the data looks much like a tree with some cross edges, a root node at the top and multiple children connected to it with multiple children each. The given excerpt from figure 2.2 shows a part of a testing procedure for a board with components. Three properties of each component were observed.

We keep this structure in mind for our design in section 4.1, where we will compose the structure for our implementation and finally our evaluation.

3.1.2 Data Amount

To evaluate the amount of data created during production we need to know how much is produced per time unit. With the parameters mentioned in 3.1 we can calculate the maximum number of data points produced every three minutes.

$$\begin{aligned}
n_{total} &= n_{componentCarrier} \\
&\quad + n_{componentCarrier} \times n_{circuitBoard} \\
&\quad + n_{componentCarrier} \times n_{circuitBoard} \times n_{component} \\
&\quad + n_{componentCarrier} \times n_{circuitBoard} \times n_{component} \times n_{test} \\
\iff &= 1 + 1 \times 64 + 1 \times 64 \times 128 + 1 \times 64 \times 128 \times 128 \\
\iff &= 1 \times (1 + 64 + 64 \times 128 + 64 \times 128 \times 128) \\
\iff &= 1 + 64 + 64 \times 128 + 64 \times 128 \times 128 \\
\iff &= 1 + 64 \times (1 + 128 + 128 \times 128) \\
\iff &= 1 + 64 \times (1 + 128 \times (1 + 128)) \\
\iff &= 1 + 64 \times (1 + 128 \times 129) \\
\iff &= 1 + 64 \times 16.513 \\
\iff &= 1.056.833
\end{aligned} \tag{3.1}$$

Over the course of a hour 3.2, day 3.3, week 3.4, month 3.5 and year 3.6 we get the following number of nodes created by the machines.

$$\begin{aligned}
n_{hourTotal} &= n_{total} \times \frac{n_{minutesPerHour}}{n_{timeForSingleComponentCarrier}} \\
\iff &= 1.056.833 \times \frac{60min}{3min} \\
\iff &= 1.056.833 \times 20 \\
\iff &= 21.136.660
\end{aligned} \tag{3.2}$$

$$\begin{aligned}
n_{dayTotal} &= n_{hourTotal} \times n_{hoursPerDay} \\
\iff &= 21.136.660 \times 24 \\
\iff &= 507.279.840
\end{aligned} \tag{3.3}$$

$$\begin{aligned}
n_{weekTotal} &= n_{dayTotal} \times n_{daysPerWeek} \\
\iff &= 507.279.840 \times 7 \\
\iff &= 3.550.958.880
\end{aligned} \tag{3.4}$$

$$\begin{aligned}
n_{monthTotal} &= n_{dayTotal} \times n_{daysPerMonth} \\
\iff &= 507.279.840 \times 30 \\
\iff &= 15.218.395.200
\end{aligned} \tag{3.5}$$

$$\begin{aligned}
n_{yearTotal} &= n_{dayTotal} \times n_{daysPerYear} \\
\iff &= 507.279.840 \times 365 \\
\iff &= 185.157.141.600
\end{aligned} \tag{3.6}$$

In section 4.2.2 we will use these numbers for our workload design.

We can extract the size of each data point from our given example, each measurement is only two to three characters long, however the other values range from 1 to around 75 characters. The size for our workload should therefore be in that range.

3.2 Workloads

Workloads should represent the mix of operations executed on a database. There are two main uses for our database in an industrial environment, the first one is described in section 3.2.1. Another one is illustrated in section 3.2.2. The given examples are based on what we think would represent the industrial use of databases.

In section 4.2 we will specify our workloads for our evaluation, the following subsections should only motivate the use for these specific use cases.

3.2.1 Inserting Data into the Database

It is not rare that production runs 24h a day, therefore data is produced all around the clock. This shows, that the ability to store data quickly is a decisive point in choosing a database. As the machines operate data is continuously written to the database.

3.2.2 Retrieving Data from the Database

Besides the previous mentioned continuous writing of data into the database, retrieving data from the database would be the next natural use for it. That could be in the form of looking up a certain product produced in the past to get its test parameter values or to get all products made by a specific machine to check if some are faulty.

3.3 Benchmark Comparison

To chose a benchmark for our upcoming research we will look at the following aspects of each benchmark.

- Data Structure - Of what structure is the generated data?
- Workloads - How are the workloads designed?
- Programming Language - Is it written in a well known programming language or do we have to learn it first.
- Community - Is there a community for support?

The results of our comparison are shown in the following table 3.1.

Since we are not using a social network structure for our data the graph generators in Graphalytics and XGDBench do not aid us much, as the generators would be difficult to extend because of their use of complex algorithms to create that structure in the created data ([9], [8]). YCSB on the other hand does not serve any particular

Table 3.1: Aspects of the different databases

Benchmark	Data Strucutre	Workloads	Programming Language	Community
Graphalytics	Social Network	Algorithm based	Java	small[1]
XGDBench	Social Network	Read, Update and Graph Traversal	X10	none[2]
YCSB	No specific structure	CRUD based	Java	big[3]

[1] 8 contributors and 16 forks on GitHub [14]
[2] 1 contributor and 1 fork (which is from us) on GitHub [15]
[3] 108 contributors and 1278 forks on GitHub [7]

structure presumably as they are not designed for graph databases and therefore don't need a particular structure on their data. So YCSB should be easy to extend with out data model.

For the workload aspect Graphalytics uses common algorithms which does not represent out workload scenario. XGDBench fits our needs better but not quite well, as inserting data is very important for us. YCSB supports inserting, reading and scanning[4] so it fulfils all our requirements for a benchmark.

Only XGDBench uses another programming language then the other benchmarks namely X10, which could take some time to learn.

Lastly the community aspect in which YCSB stands out with many contributors and an overall more active community than the other two.

All observed aspects indicate that YCSB would suit our goal the best. The generator and the workloads should be easily extendable, since they has an open design[5].

3.4 YCSB

TODO: Reference figure in explanation of aspects, maybe do subsections and move figure up. Go in more detail about the flow, reading inputs, creating which classes executing what over what class TODO: show how values are generated in the generator class In this section we will describe the internal workflow of a benchmark run in YCSB.

YCSB separated the execution into two parts. The first part is the load phase in which the initial data is written to the database. Then comes the transaction phase where database operation are performed.

A wrapper class[6] is used to start and end the measurements for each operation executed on the database.

[4] See com.yahoo.ycsb.DB class in the code of [7]
[5] See com.yahoo.ycsb.Workload and com.yahoo.ycsb.generator.Generator in the code of [7]
[6] See com.yahoo.ycsb.DBWrapper in [7]

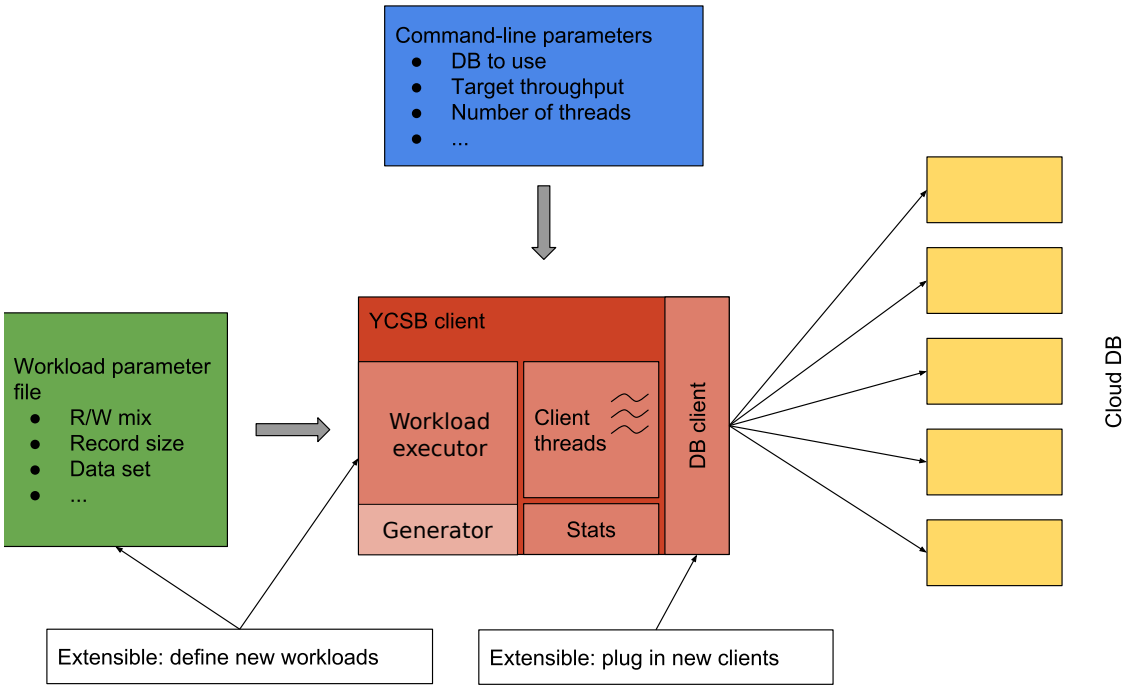

Figure 3.1: The rough architecture of YCSB. Recreated and modified from [1, p. 25]

To start a benchmark run you need to specify certain parameters, such as the database to use and the workload file to use. The client then loads the database, sets up the specified workload class and executes the specified amount and kind of operations on the database.

YCSB uses a workload file to specify some parameters about the workload. These are among others the workload class to use, how much data should be added in the load phase, how much operations should be executed in the transaction phase and what percentage of the operations should be inserts, reads, updates, scans or deletes respectively.

The measurements can be saved as histograms each covering on particular operation. There is also a summary printed out to the console or a file depending on the parameters you set that additionally lists the overall time for the benchmark, operations per second and some more meta information.

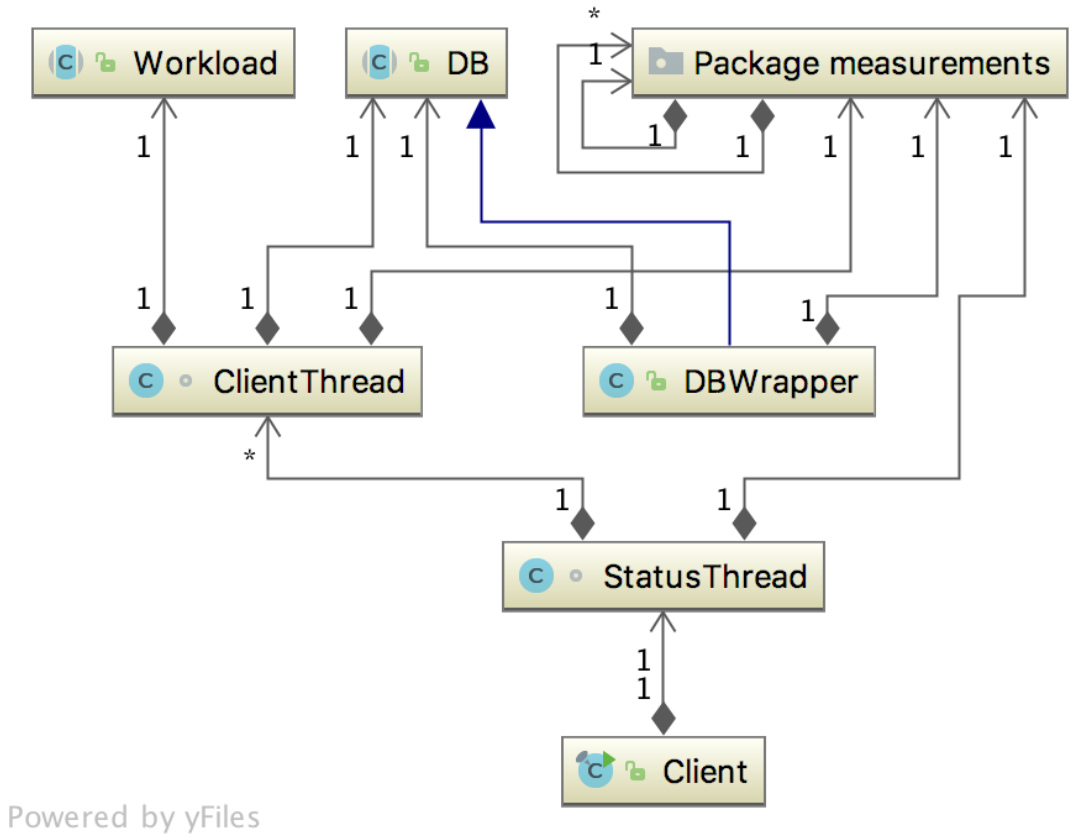

Figure 3.2: Class diagram about the main classes involved in a benchmark run.TODO: reference and explain

4. Design

In this chapter we will design the data structure of our test data, as well as the workloads to simulate a typical industrial use of our examined databases.

After that we will plan our extension for YCSB in section 4.3, both for the internals of the benchmark and the bindings to connect the databases.

In the end in section 4.4 and 4.5 we will outline tools to support execution of the benchmark and evaluation of the results.

4.1 Data Structure

To create a schema for our data structure we had a meeting with other researchers at our institute. The result of out session can be seen in figure 4.1. In the centre left we see "Features of Interest" which could be mapped to the "testFeature" edge in the industrial example of figure 2.2 as it depicts an observation of some product. At the bottom we see a "M" which stands for "Machine", its connection to "P. Schritte"[1] shows that this machine does one to n production steps. Every production step is associated with a component which consists of a PCB[2] what has different parts, a version and a file after which it was created.

As the model shows too much detail in some areas without giving a good overview of an industrial data schema, we had to reiterate over it and get rid of some complexity where we don't need it for our purposes.

The meeting gave us a better understanding of how a production facility could handle its data and with that in mind and the objective to design a simpler schema that includes to most necessary parts of production the model shown in figure 4.2 was created.

TODO: create graphic and describe its content. Graphic should have numbers on its edges, maybe use puml

[1] german for production steps
[2] short for printed circuit board

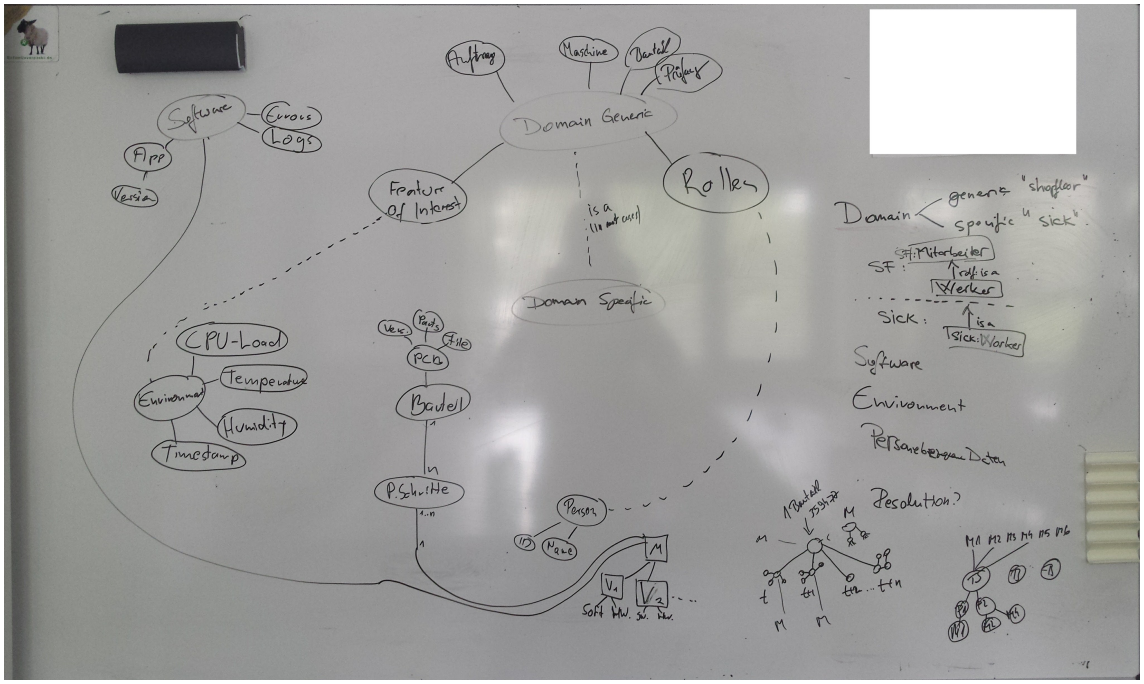

Figure 4.1: The first design of a data schema for industrial data. Created by researchers at our institute.

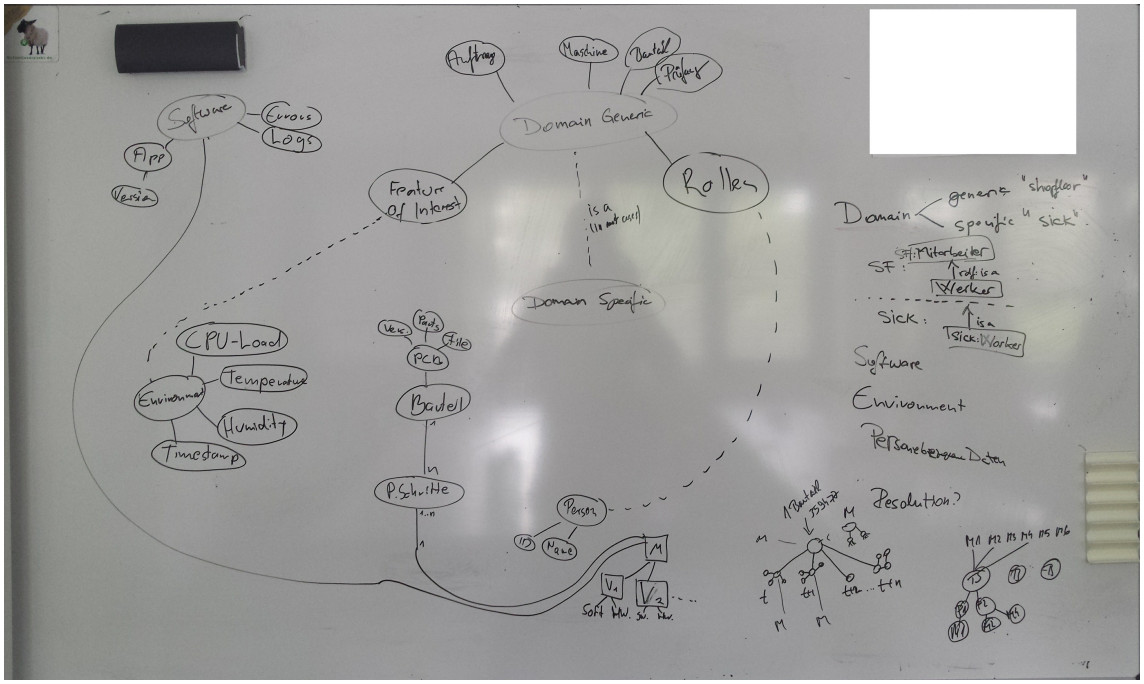

Figure 4.2: The final design of the data schema.TODO: figure with final data structure as implemented

4.2 Workloads

Our workload design will be separated into three part. In subsection 4.2.1 we discuss the design of workloads aimed to uncover the ability to store large amounts of data. Subsection 4.2.2 will directly investigate the suitability of a database to be used in an industrial use case for storing data. We will design workloads to examine the other industrial use case of retrieving data under load in subsection 4.2.3. Finally we will give a summary over all workloads we are going to run on the databases in subsection 4.2.4

4.2.1 Throughput

To explore the throughput of the databases we will have some variables we will change over the course of the different workloads. These variables are

- using an index on the key
- the size of a single property of the node
- using no edges with an index.

The last variable sound counter intuitive, since edges add meaning to the data, but by eliminating them we want so see if edges could be a cause of delay, because to add an edge the start and end node need to be known and therefore be retrieved at first.

We will go over the different variables in the following subsections and motivate their purpose.

4.2.1.1 Index

For this category we will use different data set sizes in terms of their number of nodes. We will use steps of multiplication by 10 from 1.000 nodes to 10.000.000 nodes, to examine if there is a linear correlation between the number of nodes and the time needed to store them.

Switching from indexed to not indexed we want to inspect how write speed or operations per second are effected. Indexing is important to retrieve data more quickly for the cost of write speed, with this workload we will see if the sacrifice in write speed is reasonable. We will only use an index on the node and edge key, which will be used to search that graph component[3] in the database. Indexing the other properties would have no benefit in our example. NOTE: would have, e.g. temperature of component. Results could be mapped to those.

For this workload we will use a node property size of 10B, that is small enough to not have an impact on performance but large enough to represent most of the data stored in the properties of our example.

[3] a node or an edge of the graph

4.2.1.2 Node Property Size

After retrieving a number of nodes that represents a acceptable execution time we will vary the next variable which is the property size. We will go from 10B used in the index benchmarks to up to 1MB, again in steps of multiplying by 10 (10B, 100B, 1KB, ..., 1MB).

The typical property size is between 1B (1 character) and roughly 75B (75 characters) according to our example in listing 2.1.

The use of properties is not limited to short strings, that is why we will investigate if larger amounts of data influence the throughput more than linearly.

We will use an index on the keys, because using an index would represent the use in the industry and since we are not indexing the growing values there will be no impact from using it.

4.2.1.3 No Edges

NOTE: maybe remove index, as it has no real purpose. Underline importance of investigating the speed difference without edges. Maybe indexing helps, make sure to compare both with the workloads with edges to see if index helps with edges. In subsection 4.2.1 we already justified why we will investigate the throughput with an exclusive use of nodes in the data set.

As this workload does not allow for much variation besides using an index or not, it will only include these two workloads.

As in subsection 4.2.1.2 we will use a suitable large data set in terms of node count resulting from the first workloads. We will use the same node size as in 4.2.1.1 to be able to compare the results directly to the corresponding ones from that workload.

4.2.2 Production Simulation

Related to production we will investigate the impact of the structure and the general suitability for an industrial use. The next two subsection will cover those aspects in more detail.

The property size will be set to 50B, which should be enough to cover on average most values stored in the database.

4.2.2.1 Structure

For production we have some variables to investigate which mainly effect the structure of our data. We have three layers which we can blow up horizontally by increasing the corresponding parameters, which are

- NOTE: maybe link to figure if suitable
- productsperorder, this spreads the data graph apart at a level closer to the root
- componentsperproduct, this changed the width in the middle of the graph

- testparametercount, which widens the graph at the lowest level.

For production simulation we will first examine if the data structure impacts performance of the databases. To investigate this aspect we will change the width of the graph with the variables mentioned above. We will use the numbers from section 3.1 as the maximum width, which would be $productsperorder = 64$, $componentsperproduct = 128$ and $testparametercount = 128$. In the first workload we will set all variables to one, the next one will use $productsperorder = 16$, $componentsperproduct = 32$ and $testparametercount = 32$. The third and last one will use the maximum width mentioned above. By this variation we will cover the minimum and maximum with an additional result in the middle to see if there are any changes in performance.

The keys of the graph components will be indexed, because indexing these values should be done to later work on that data more efficiently, which is necessary for the industry.

4.2.2.2 Suitability

To examine if a database is suitable for the industry it should be able to store the data faster then it is coming from the machines. In section 3.1.2 we calculated that 1.056.833 nodes would be written to the database every three minutes. First we will set up a data set with that amount of nodes and insert it into the database, that will allow us to compare the time needed to store all data with our three minute limit. If the database should take more than three minutes it would not be suitable, since data is produced faster than it can be stored.

The next steps would be to repeat that procedure with a node amount that represents a whole hour, day, week, month and year, iff the databases are storing the data fast enough to not take up an unreasonable amounts of time in running the benchmark.

We will use the structure with the maximum width, because it represents the industrial use case best regarding the information given by our partners at SICK AG [21].

4.2.3 Retrieving under load

TODO: mention potential to compare to other studies. There would be no point in storing data if it is not retrieved at some point. To investigate on the performance of reading and scanning (more on that in subsection 4.2.3.2) data from the database the following workloads are designed.

As mentioned in section 4.2.1.1 indexing is important for retrieving data, therefore we will us it as a variable for this workload category. By doing so we want to examine if the price we pay while writing is justified by the performance gain in retrieving data.

The node amount will be determined by the first workload investigating the throughput, to not take up too much time testing these features.

We want to retrieve both nodes and edges, because either could be useful, since the edges can also store properties in them.

4.2.3.1 Reading

Reading single values is the basic operation when it comes to retrieving data from a database. Since the database will be under constant load, because of production delivering data all the time, we will use 5% of the total operations executed in this workload for read operations, the rest will be inserting data.

4.2.3.2 Scanning

Scanning a graph can be done in multiple ways, the simplest being depth first search [23], to retrieve values associated with connected nodes. For example you could scan from a machine to get the test features of their produced products.

As in subsection 4.2.3.1 we will use a mix of 5% scan operations with 95% insert operations, to simulate the constant load present in an industrial environment.

The number of steps to do during scanning will be 1000 as that was the default value set in YCSB and it should also represent a good amount of data to read.

4.2.4 Summary

In this subsection we will give an overview over all workloads and their variables.

For the workloads measuring the throughput ”Products per Order”, ”Components per Product” and ”Test Parameter Count” will all be set to 1. Their overview is shown in table 4.1

The workloads to investigate the suitability for the industry are shown in table 4.2. For these workloads the property size is fixed to 50B and an index is used on all workloads. Edges are also used in these workloads to reflect the use in the industry.

The remaining workloads to examine the ability to retrieve data are shown in table 4.3. These workloads will use a appropriate data set size regarding execution time and a property size as in the production simulation of 50B. A simple structure is used to investigate the basic capabilities of data retrieval, that means ”Products per Order”, ”Components per Product” and ”Test Parameter Count” are set to 1.

4.3 Extension of the Benchmark

To be able to execute the introduced workloads and use the data structure designed above, we need to extend the YCSB benchmark. For the benchmark to be able to execute our workloads the way we want them to be executed the following parts of the benchmark need to be extended

- Generation of the dataset
- Class to store the order of operations
- Class to get random graph component identifiers
- Workload to use the generated dataset
- Database bindings.

In the following subsections we will go in more detail over the different areas we are planing to modify.

Aspect	Node Count	Node Size	Index	Only Nodes
1. With Index	1.000	10B	True	False
2. With Index	10.000	10B	True	False
3. With Index	100.000	10B	True	False
4. With Index	1.000.000	10B	True	False
5. With Index	10.000.000	10B	True	False
1. Without Index	1.000	10B	False	False
2. Without Index	10.000	10B	False	False
3. Without Index	100.000	10B	False	False
4. Without Index	1.000.000	10B	False	False
5. Without Index	10.000.000	10B	False	False
1. Node Size	x	100B	True	False
2. Node Size	x	1KB	True	False
3. Node Size	x	10KB	True	False
4. Node Size	x	100KB	True	False
5. Node Size	x	1MB	True	False
1. No Edges	x	10B	True	True
2. No Edges	x	10B	False	True

Table 4.1: Workloads to investigate the throughput. x is a placeholder for a suitable data set size in terms of execution time.

4.3.1 Graph Data Generator

YCSB does not include a graph data generator, therefore we need to create one that fulfils our needs.

The generator should create a data set with the structure mentioned in section 4.1 and store the data for future reproduction when using the benchmark with the next database.

The two parts of the generator, which are creating together with storing the data and recreating the data are designed in subsection 4.3.1.1 and 4.3.1.2 respectively.

Generally to represent a graph in YCSB we need some classes to represent nodes, edges and the graph. In section 2.1 we mentioned that a graph is a tuple of a set of nodes and a set of edges. That can be directly mapped to a class with two lists, one for nodes and the other one for edges. We want the nodes to have a key for identification, a label to match it with an object that could exist in the real world and a value, which will represent the data stored in the node, the size of this value should be directly linked the the property size from 4.2.1.2. An edge should also have a key for identification, a label to add meaning to it and a start and an end node, represented by their keys.

The generator of the dataset should decide if it should create a new one or recreate it by looking at the existing files.

Aspect	Node Count	Products per Order	Components per Product	Test Parameter Count
1. Structure	x	1	1	1
2. Structure	x	16	32	32
3. Structure	x	64	128	128
1. Suitability (three minutes)	1.056.833	64	128	128
2. Suitability (hour)	21.136.660	64	128	128
3. Suitability (day)	507.279.840	64	128	128
4. Suitability (week)	3.550.958.880	64	128	128
5. Suitability (month)	15.218.395.200	64	128	128
6. Suitability (year)	185.157.141.600	64	128	128

Table 4.2: Workloads to simulate production. Again x represents a placeholder for a suitable data set size.

Aspect	Index	Insert Proportion	Read Proportion	Scan Proportion
1. Reading	True	95%	5%	0%
2. Reading	False	95%	5%	0%
1. Scanning	True	95%	0%	5%
2. Scanning	False	95%	0%	5%

Table 4.3: Workloads to investigate capability to retrieve data under load.

4.3.1.1 Storing the Dataset

TODO: Activity diagram of *GraphDataRecorder* :: *createGraph*() We want to control the size of the dataset with our variables mentioned in the workload section 4.2 so this generator should create small subgraphs with only one node and its corresponding edges every time it is asked for a new value. By storing the current state of the created graph in the generator class, we can always determine the next subgraph to create.

The modify the structure of the graph with our three variables, these need to be parsed in this class and used during subgraph creation.

An activity diagram is shown in figure 4.3 to illustrate the creation process with usage of the parameters for tweaking the width of the graph.

Figure 4.3: Activity diagram of the creation process for the dataset.TODO: create and describe

Figure 4.4: Activity diagram of the *RandomGraphComponentGenerator* showing the process of storing and restoring.TODO:

To restore that data also one node at a time we will store each created subgraph in a file, for that we will serialise the graph and deserialise it when we are restoring the data.

To disable edges for the workload from subsection 4.2.1.3 we can simply skip the step of creating and adding them to the graph.

4.3.1.2 Restoring the Dataset

The restoring of the data should be easily done by deserialising it from the created file during creation of the dataset. Since the single subgraphs were stored in the file, we can pass the to the workload just after deserialising them.

For larger datasets we should read the subgraphs from the file as needed and not at the beginning, because that could fill up the RAM with the dataset and leave less memory for the database to work with.

4.3.2 Random Graph Component Generator

Reading and scanning operations require a point to start with in the data, that's why we need the key of some component in the graph. The kay can be randomly chosen, but the node or edge associated with it has to be present in the database. Therefore we need to somehow store the keys of the graph components we have already put into the database, that could be done in the *GraphDataGenerator* created for subsection 4.3.1.1, because it anyway touches all created values.

Because we want to retrieve edges and nodes randomly we have to pick one of the two randomly every time a random component is required. As in 4.3.1.1 and its subsections, every created value needs to be stored to be retrieved later on. The data needed for this generator is not as complex as a graph and can therefore be stored directly in a file line by line for easy storing and restoring. That also means, that we can read the files at the beginning of the run so it is faster accessible during the benchmark without using to much memory.

For the workload which requires the absents of edges a method should be defined to return only a randomly chosen node.

Figure 4.4 shows an activity diagram of the generator.

4.3.3 Operation Order Generator

To fix the execution order of inserting and retrieving data to and from the graph, we need to store the operations too. That can be done by simply storing the name of each operation in a file as it appears and reading it from there when running the benchmark.

In YCSB there is already a *DiscreteGenerator*[4] which take a value and a weight and returns distributed according to the weights a value, this can be used to get the operations to run on the database.

Figure 4.5 visualises the procedure of storing the operation order.

[4]com.yahoo.ycsb.generator.DiscreteGenerator

Figure 4.5: Activity diagram of the operationOrderGenerator.TODO:

4.3.4 Graph Workload

NOTE: Graph Workload functionality TODO: Activity diagram of the workflow with graph data. Create Activity diagram with database from workload view. The *GraphWorkloads* task is to coordinate the different generators and to execute the workload as specified. To be able to store the generated dataset in a specific folder on the system the workload class should take a path to a folder and instrument the generators to store their data in that folder or recreate it from there respectively.

This class will be the interface between the client calling $Workload :: doInsert$ and $Workload :: doTransaction$ and the database. The $Workload :: doInsert$ method will only insert a subgraph into the database, to do so the workload class needs to get the subgraph from the GraphDataGenerator and redirect its value to the database. For the $Workload :: doTransaction$ method the workload has to be able to call the available methods on a database which are

- DB::insert(String table, String key, Map<String, ByteIterator> values)
- DB::read(String table, String key, Set<String> fields, Map<String, ByteIterator> result)
- DB::scan(String table, String key, int recordcount, Set<String> fields, Vector<HashMap<String, ByteIterator>> result)
- DB::update(String table, String key, Map<String, ByteIterator> values)
- DB::delete(String table, String key).

We will only use the first three for our workloads, but the other ones should be implemented too, to support future workloads. To determine which operation should be executed the *OperationOrderGenerator* from subsection 4.3.3 will be used.

In general we see, that a *table* is given as an argument, in a graph database we don't have tables as in relational databases, so we can use it to distinguish between nodes and edges, by simply passing the string "node" or "edge" to the database. Next is a *key*, which we can use to pass the key identifier of the graph component to the database. The *values* map will contain the values of the graph components to insert parsed into a map for compatibility and vice versa for the *result* map and vector. Our data design does not focus to much on the individual properties the nodes and edges could have, therefore we will simply read all *fields* of the graph component.

DB::insert
As described above the $DB :: insert$ method will get a value from the *GraphDataGenerator* and insert it into the database.

DB::read
The read operation will pick a random graph component with the *RandomGraphComponentGenerator* and use its kind (node or edge) as the *table* argument and the key identifier as the *key* argument.

DB::scan
Scanning also requires a random component which will be chosen by the *RandomGraphComponentGenerator*. The mapping is also the same as with DB :: *read* for the *table* and *key* arguments. *recordcount* will be set to 1000 as that is the default value specified by the $CoreWorkload$[5] and that value represents a good amount for scanning.

DB::update
For this operation we also need an existing graph component picked by the *RandomGraphComponentGenerator* to get a valid key identifier and the kind of graph component we are going to update. Only the property value should be changed during update, not the identifier nor the label.

DB::delete
This takes a random graph component via the *RandomGraphComponentGenerator* and calls the *delete* method of the database.

To avoid calling these methods with edges when the workload specifies to not use them, a parameter which can be set should determine if a random graph component or a random node should be picked by the *RandomGraphComponentGenerator*.

Since the client only calls $Workload$ :: $doTransaction$ to execute one of the various database operations the *OperationOrderGenerator* should be called to generate the next operation.

4.3.5 Bindings

To ensure compatibility with other workloads present in YCSB we will extend the DB class and implement the methods used for other databases. Because graph databases are slightly different we will explain how each database will map the arguments of the DB methods to their own API in the following subsections.

The basic functions we need from our database are

1. creating a node
2. creating an edge
3. adding properties to a node
4. adding properties to an edge
5. getting a node by its identifier
6. getting an edge by its identifier
7. getting the values of a node
8. getting the values of an edge
9. getting the outgoing edges of a node
10. getting the start node of an edge

[5] com.yahoo.ycsb.workloads.CoreWorkload

11. removing a node
12. removing an edge

Generally the *DB* operations can then be implemented using these functions. A common implementation is shown in listing 4.1.

We will cover the implementation of the single methods in section 5.2.

The following subsections will only mention specialities regarding the corresponding database.

Listing 4.1: Generic example of a database implementation with the use of graph data.

```
public class Database extends DB {
  private Node creatingANode(String key);
  private Edge creatingAnEdge(String key, Node startNode, Node endNode);
  private void addingPropertiesToANode(Node node, Map<String, ByteIterator> values)
      ;
  private void addingPropertiesToAnEdge(Edge edge, Map<String, ByteIterator> values
      );
  private Node gettingANodeByItsIdentifier(String key);
  private Edge gettingAnEdgeByItsIdentifier(String key);
  private HashMap<String, ByteIterator> gettingTheValuesOfANode(Node node);
  private HashMap<String, ByteIterator> gettingTheValuesOfAnEdge(Edge edge);
  private List<Edge> gettingTheOutgoingEdgesOfANode(Node node);
  private Node gettingTheStartNodeOfAnEdge(Edge edge);
  private void removingANode(String key);
  private void removingAnEdge(String key);

  private void doDepthFirstSearchOnNodes(Node node, int recordcount, Vector<HashMap
      <String, ByteIterator>> result) {
    if (result.size() >= recordcount) {
      return;
    }

    result.add(gettingTheValuesOfANode(node));

    List<Edge> edges = gettingTheOutgoingEdgesOfANode(node);

    for (Edge edge : edges) {
      Node startNode = gettingTheStartNodeOfAnEdge(edge);
      doDepthFirstSearchOnNodes(startNode, recordcount, result);
    }
  }

  private void doDepthFirstSearchOnEdges(Node node, int recordcount, Vector<HashMap
      <String, ByteIterator>> result) {
    if (result.size() >= recordcount) {
      return;
    }

    List<Edge> edges = gettingTheOutgoingEdgesOfANode(node);

    for (Edge edge : edges) {
      result.add(gettingTheValuesOfAnEdge(edge));

      Node startNode = gettingTheStartNodeOfAnEdge(edge);
      doDepthFirstSearchOnNodes(startNode, recordcount, result);
    }
  }

  @Override
  public Status insert(String table, String key, Map<String, ByteIterator> values)
      {
    switch(table) {
    case "Node":
      Node node = creatingANode(key);
      addingPropertiesToANode(node, values);
```

```
      break;
    case "Edge":
      Node startNode = gettingANodeByItsIdentifier(values.get("startNode").toString
          ());
      Node endNode = gettingANodeByItsIdentifier(values.get("endNode").toString());
      Edge edge = creatingAnEdge(key, startNode, endNode);
      addingPropertiesToAnEdge(edge, values);
      break;
    default:
      return Status.NOT_FOUND;
    }
    return Status.OK;
  }

  @Override
  public Status read(String table, String key, Set<String> fields, Map<String,
      ByteIterator> result) {
    switch(table) {
    case "Node":
      Node node = gettingANodeByItsIdentifier(key);
      result = gettingTheValuesOfANode(node);
      break;
    case "Edge":
      Edge edge = gettingAnEdgeByItsIdentifier(key);
      result = gettingTheValuesOfAnEdge(edge);
      break;
    default:
      return Status.NOT_FOUND;
    }
    return Status.OK;
  }

  @Override
  public Status scan(String table, String startkey, int recordcount, Set<String>
      fields, Vector<HashMap<String, ByteIterator>> result) {
    switch(table) {
    case "Node":
      Node node = gettingANodeByItsIdentifier(startkey);
      doDepthFirstSearchOnNodes(node, recordcount, result);
      break;
    case "Edge":
      Edge edge = gettingAnEdgeByItsIdentifier(startkey);
      Node startNode = gettingTheStartNodeOfAnEdge(edge);
      doDepthFirstSearchOnEdges(startNode, recordcount, result);
      break;
    default:
      return Status.NOT_FOUND;
    }
    return Status.OK;
  }

  @Override
  public Status update(String table, String key, Map<String, ByteIterator> values)
      {
    switch(table) {
    case "Node":
      Node node = gettingANodeByItsIdentifier(key);
      addingPropertiesToANode(node, values);
      break;
    case "Edge":
      Edge edge = gettingAnEdgeByItsIdentifier(key);
      addingPropertiesToAnEdge(edge, values);
      break;
    default:
      return Status.NOT_FOUND;
    }
    return Status.OK;
  }

  @Override
  public Status delete(String table, String key) {
    switch(table) {
    case "Node":
      removingANode(key);
```

```
        break;
      case "Edge":
        removingAnEdge(key);
        break;
      default:
        return Status.NOT_FOUND;
      }
      return Status.OK;
    }
}
```

TODO: Extend what information will be given TODO: Also extend over sections to exactly tell what information will be given and adapt subsections accordingly.

4.3.5.1 Apache Jena

Apache Jena uses transactions to work on the database, therefore we will need to open and close them as we insert or retrieve data from the database. Transactions can be opened for either read or write operations, to guarantee data validity.

To get access to the data over Jena we can use the $TDBFactory :: createDataset$ method.

Jena has no option to use an index, so we can't use it for the workloads which have the index as their variable, but we still can compare its performance to the indexed and not indexed results of the other databases.

In Jena we will use the following mapping for the method arguments.

key
Should be used on the model retrieved from the dataset to create a resource, which would represent a node or create a property to form an edge. To retrieve data the create resource or property method can be used as well, because if the passed key is already used on another node the returned node will be equal to the already existing node.

values
Properties can be stored as so called *Statement*s, which represent a triple as mentioned above. The subject will be the graph component itself, the predicate will be the identifier of the value in the map and the value will be the object of the statement.

4.3.5.2 Neo4j

To index the keys of the nodes and edges we have to create an index with an $IndexManager$. Over this $Index$ the graph components have to be inserted and retrieved.

Neo4j also uses transactions, but we can not set them as read or write transactions. That is no disadvantage, because it will mark it accordingly after the called methods.

The mapping for this database will be as follows.

key
Nodes will use the key as a native label and also set it as a specific property, that is needed to retrieve the nodes easily as we have to find a node by passing a label, the property key and the property value to the database. Edges should use the key

as the edge type, that way they can be retrieved more easily, as the type can be directly returned by an edge to compare it to the key we are looking up.

values
Neo4j directly supports setting properties with a key and a value, therefore we can directly store the values as properties in the graph components of Neo4j.

4.3.5.3 OrientDB

4.3.5.4 Sparksee

4.3.6 Summary

TODO: Parameters!!, where used general workflow.

4.4 Execution Tool

4.5 Evaluation Tool

5. Implementation of your Project

5.1 Graph Data Generator

5.1.1 Graph Data Creator

5.1.2 Graph Data Recreator

5.2 Graph Database Bindings

NOTE: Highlight the mapping of data and other specialities

5.2.1 Apache Jena

5.2.2 Neo4j

5.2.3 OrientDB

5.2.4 Sparksee

5.3 Graph Workload

5.3.1 Parameters

5.4 Random Graph Data Generator

5.5 Operation Order Generator

6. Evaluation

6.1 Objective

6.2 Setup

6.2.1 Hardware

6.2.2 Software

6.3 ExecutionNOTE: Scripts to run all benchmarks successively

6.4 Maximum Load

6.4.1 Probing Node CountNOTE: Comparing indexed to not indexed

6.4.1.1 Results

6.4.1.2 Discussion

6.4.2 Probing Node SizeNOTE: See change over increasing node size

6.4.2.1 Results

6.4.2.2 Discussion

6.5 Throughput

6.5.1 Difference without Edges

6.5.1.1 Results

6.5.1.2 Discussion

6.5.2 Product ComplexityNOTE: More child nodes.

6.5.2.1 Results

6.5.2.2 Discussion

6.5.3 Production SuitabilityNOTE: Testing production like workload

6.5.3.1 Results

6.5.3.2 Discussion

6.6 Responsiveness

6.6.1 Reading under load

6.6.1.1 Results

6.6.1.2 Discussion

6.6.2 Scanning under load

6.6.2.1 Results

6.6.2.2 Discussion

7. Conclusion and Future Work

7.1 Conclusion

7.1.1 Suitability

7.1.2 General Performance of Databases

7.2 Future Work

7.2.1 More Bindings

7.2.2 Concurrency

7.2.3 Other input methodsNOTE: I only used native Java APIs, to directly test the database.

7.2.4 WorkloadsTODO: what kind?

NOTE: Vary RAM amount.

8. Summary

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