Alexander Krause, Thomas Kissinger, Dirk Habich, Wolfgang Lehner

NeMeSys - A Showcase of Data Oriented Near Memory Graph Processing

Erstveröffentlichung in / First published in:

SIGMOD/PODS '19: International Conference on Management of Data, Amsterdam 30.06. – 05.07.2019. ACM Digital Library, S. 1945–1948. ISBN 978-1-4503-5643-5

DOI: https://doi.org/10.1145/3299869.3320226

NeMeSys - A Showcase of Data Oriented Near Memory Graph Processing

Alexander Krause, Thomas Kissinger, Dirk Habich, Wolfgang Lehner
[firstname.lastname]@tu-dresden.de
Technische Universität Dresden
Dresden, Saxony, Germany

ABSTRACT

NeMeSys is a NUMA-aware graph pattern processing engine, which uses the Near Memory Processing paradigm to allow for high scalability. With modern server systems incorporating an increasing amount of main memory, we can store graphs and compute analytical graph algorithms like graph pattern matching completely in-memory. Our system blends state-of-the-art approaches from the transactional database world together with graph processing principles. We demonstrate, that graph pattern processing – standalone and workloads – can be controlled by leveraging different partitioning strategies, applying Bloom filter-based messaging optimization and, given performance constraints, can save energy by applying frequency scaling of CPU cores.

CCS CONCEPTS

• **Information systems → Graph-based database models**; **Main memory engines**; *Data scans*; *Point lookups*; *Relational parallel and distributed DBMSs.*

KEYWORDS

Graph, In-memory, Bloom filter, NUMA

ACM Reference Format:
Alexander Krause, Thomas Kissinger, Dirk Habich, Wolfgang Lehner. 2019. NeMeSys - A Showcase of Data Oriented Near Memory Graph Processing. In *2019 International Conference on Management of Data (SIGMOD '19), June 30-July 5, 2019, Amsterdam, Netherlands.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3299869.3320226

1 INTRODUCTION

Processing the ever-growing data volume demands for continuously increasing server capacities. These are usually achieved by implementing several multiprocessor inside one scale-up system which exhibit a *non-uniform memory access (NUMA)*, where the processors memory domains are still accessible through an interconnect network. Modern relational database systems are capable to exploit such server systems by employing the state-of-the-art *data-oriented architecture (DORA)*, which has been proven to show superior scalability. Another key finding of recent research is the application of online energy controling mechanisms as described in [5]. Following these findings, relational in-memory database can achieve energy savings under given performance constraints by scaling the core- and uncore-frequencies or turning off cores completely.

A still emerging use case for in-memory databases is the processing of graphs. Aside many other algorithms, *graph pattern matching* is an important application as described in [6]. Graph pattern matching (GPM) is a declarative, topology-based querying mechanism [4] with considerable complexity. Queries are usually entered as a graph itself and the systems task is to find all combinations of vertices, which match to the constraints of the query vertices. Computing GPM on NUMA systems is challenging, due to its inherent random memory accesses and thus an efficient processing management is needed to maintain performance.

To overcome these challenges, we present NeMeSys, a DORA based graph processing engine, which leverages well known principles from the relational to efficiently process GPM queries on NUMA systems. In addition to the DORA, NeMeSys features *(I)* graph specific partitioning methods, *(II)* specifically tailored graph operators such as *Vertex-Bound* or *Edge-Bound* and *(III)* a fine tunable messaging optimization.

In our demonstration, we want to showcase how different configurations take effect on the systems performance. We will not only show isolated effects but the combined influence of the set of graph specific system characteristics. This way we aim to underline the importance of careful system tuning, which is yet still prone to workload changes. Additionally, we can show that our previously developed energy adaptivity

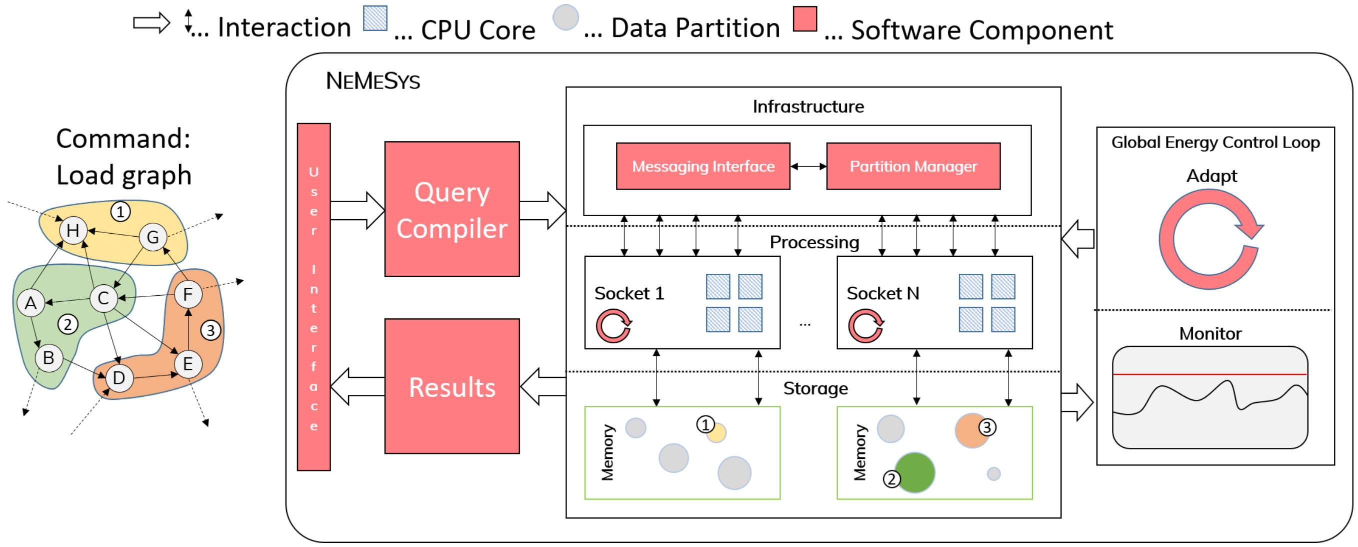


Figure 1: NeMeSys system design

mechanisms for *relational* in-memory databases from [5] are general enough to be seamlessly integrated into NeMeSys, which specifically targets graph processing.

2 SYSTEM

From a hardware perspective, the scale-up approach is mainly characterized by the separate memory domains and the resulting NUMA behavior. NeMeSys is built upon the well-known DORA and leverages *near-memory computing (NMC)* principles with its basic architecture being portrayed in Figure 1. NMC means, that we limit the scope of each worker to memory domains, which are directly connected to their socket (local instead of remote accesses).

2.1 NeMeSys Storage Layer

Generally, we store a *directed edge-labeled multigraph* in NeMeSys as a set of triples containing only the source vertex, the target vertex and the label of the edge between these two vertices[1]. This layout can be efficiently stored in a relational table with exactly these three columns. Considering only *outgoing edges* is quite sufficient to fully represent the topology of the graph on the storage layer, thus leading to the naming of our data container: the *outgoing edge table*.

The core concept of DORA is that all data objects are implicitly partitioned and partitions are exclusively accessed by the assigned worker thread. That means, we have to partition our *outgoing edge table* and we decided to partition this table based on the source vertices, wherefore we apply our guidelines from [6]. On the one hand, the advantage is that a worker thread is able to exclusively process several vertices with all of its outgoing edges within a partition without using latches or locks for synchronization. On the other hand, a disadvantage is that we implicitly replicate vertices, but the overhead is negligible due to dictionary encoded vertices. Of course, in addition to our *outgoing edge table*, we also need to store the partitioning information as presented in Section 2.3.

2.2 NeMeSys Processing Layer

Conjunctive queries (CQ) are a well-studied mechanism for expressing graph patterns [7] and NeMeSys uses this mechanism. A CQ decomposes the pattern into a set of *edge predicates* each consisting of a pair of vertices and an edge label. An easy example for a CQ would be a query containing three vertices and two edges: $(A) \rightarrow_{\text{knows}} (B) \rightarrow_{\text{livesIn}} (C)$. This query wants to find all combinations of vertices, where *A knows B* and *B lives in* a place *C*.

NeMeSys accepts a query string of multiple triples as CQ, where each triple represents an edge predicate. Each triple contains a comma delimited list of source vertex, target vertex and an edge label and all three positions can be either a variable as placeholder or a previously known *id*, if a specific vertex or label shall be part of the query pattern.

We identified three graph specific operators, which are necessary to execute conjunctive queries:

Scan Operator. The Scan operator performs a parallel vertex scan over all partitions in the case that the starting as well as the target vertex of a CQ triple are unknown. By specifying a certain edge label predicate, the operator

[1] Property graphs can also be expressed as directed edge-labeled multigraphs by introducing additional vertices and edges for every property and its value.

Final edited form was published in "SIGMOD/PODS '19: International Conference on Management of Data. Amsterdam 2019", S. 1945–1948, ISBN 978-1-4503-5643-5
https://doi.org/10.1145/3299869.3320226

returns only edges with the specific label. The `Scan` operator is always the first operator in the pattern matching process.

Vertex-Bound (VB) Operator. The `VB` operator takes an intermediate *GPM* result as input and tries to match new vertices in the query pattern according to the following CQ triple. The operator has to be only applied when either the source vertex or target vertex is known and thus bound.

Edge-Bound (EB) Operator. This operator ensures the existence of additional edge predicates between known vertex matching candidates of the CQ. It performs a data lookup with a given source and target vertex as well as a given edge label. If the lookup fails, both vertices are eliminated from the matching candidates. Otherwise the matching state is passed to the next operator or is returned as final result.
During query processing, workers will continuously process all of their partitions incoming messages with the applicable operator. Moreover, each operator in NeMeSys is asynchronously processed in parallel and generates new intermediate results that invoke the next operator in the pattern matching query. Hence, NeMeSys allows for intra- and inter-query parallelism as well as pipelining to fully exploit the high number of cores in scale-up systems.

2.3 NeMeSys Infrastructure Layer

To efficiently support the above described pattern matching processing, NeMeSys provides two important components at the infrastructure layer:

Partition Manager: The *partition manager* keeps track of the edge-to-partition assignments and exploits, that all outgoing edges of one vertex are always stored in the same partition. Basically, the *partition manager* is maintaining a one dimensional index, which contains all *vertex ids* as keys and the target partitions as values. This allows NeMeSys to easily identify the correct partitions, on which a worker needs to apply the next query operator. Because of very frequent index requests, its size should fit in the CPU cache.

Message Interface: Because of the enforced locality and the asynchronous execution, workers need to communicate the query pattern matching state (intermediate results) via messages instead of directly enqueuing it at target partitions. In NeMeSys, every partition has an incoming and outgoing message queue. A coordinator is continuously performing cross socket copy operations, to move the messages of one worker to all corresponding target partitions. The messaging itself can also become a performance bottleneck, because not all CQs contain only forward oriented edges. Since we only index the source vertex of an edge, targets of backward oriented edge predicate requests can not be answered through an index lookup. In such cases, we need to send a broadcast targeting all data partitions to scan through their *target* column and search for the requested vertex.

Bloom filter optimization. Since NeMeSys is an asynchronous system, communication is performed via messages through the aforementioned *Messaging Interface*. Generally speaking, avoiding communication, such as the previously mentioned broadcasts, as much as possible can only increase the performance. Hence, we employ a Bloom filter-based message optimization, which serves as a secondary index to prevent unnecessary messages, like vertex- or edge-requests targeting partitions, which do not actually contain them. Since we use dictionary encoded integer keys for our partitioning, we can employ a fast and simple hash function inside the Bloom filter. Usually, a modulo operator is used to hash integer ids to a bucket. However, the modulo operator is very costly [1]. Thus we exploit the residue class ring property, where:

$$(x)_{\text{base}} \pmod{\text{base}^k} = \text{last } k \text{ digits of } (x)_{\text{base}} \quad . \tag{1}$$

For 64 bit unsigned integer *vertex ids*, which are of base 2, the last k digits of $(x)_2$ are given by applying a bitmask, or *bitwise and*, of $(2^k - 1)$ to $(x)_2$.

Following this approach, we can replace the modulo operator by *bitwise and* while selecting prime numbers for a_i, since they yield best uniformity results [2], and use (2) as our Bloom filter hash function.

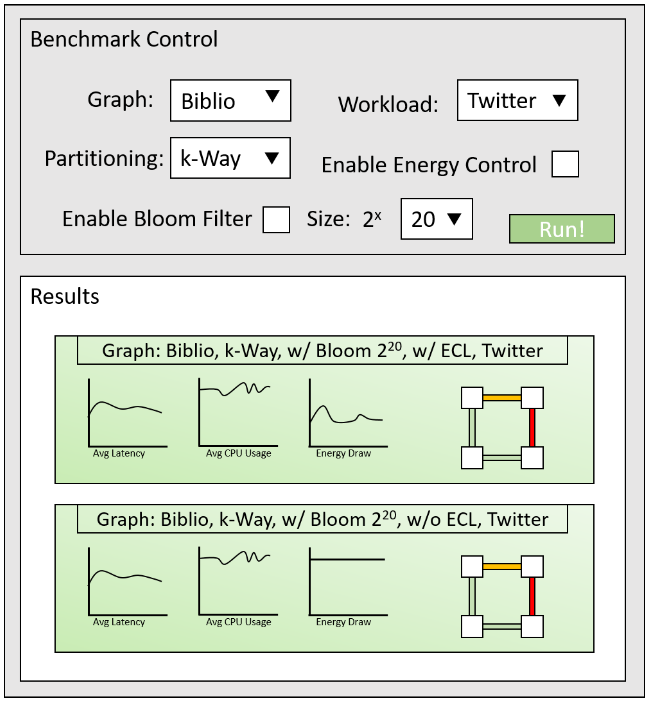
$$H'_i(x) = y = (a_i \cdot x) \wedge (M - 1) \quad . \tag{2}$$

2.4 Energy adaptivity

As stated in Section 1, we integrate the energy management from [5]. For this purpose, NeMeSys implements software sensors, which measure the time spent performing different tasks, e.g. actual computing time or query latency and the energy consumption is measured through the processor integrated RAPL counters [3]. We are able to specify a performance constraint, i.e. a maximum query latency and allow NeMeSys to set the frequencies of all cores accordingly. Turning off cores, when there is just not enough computational demand, is allowed by the loosely coupled DORA approach, which was introduced in [5]. In a strict DORA, workers are only allowed to touch their very own data partition, but we allow them to process any data partition, which is currently not being processed.

3 DEMONSTRATION SETUP

With our demo, we will showcase our DORA based graph processing system NeMeSys. The demo itself is split into two parts. First, we want to show the influence of graph partitioning and the resulting data allocation on the intra-query parallelism of graph pattern matching inside NeMeSys. We will explain the query generation and justify the graph specific operators by showcasing applicable scenarios. Following the basics, we will highlight the importance of the



Benchmark Control

Graph: Biblio ▼ Workload: Twitter ▼

Partitioning: k-Way ▼ Enable Energy Control □

Enable Bloom Filter □ Size: 2^x 20 ▼

Results

Graph: Biblio, k-Way, w/ Bloom 2^{20}, w/ ECL, Twitter

Graph: Biblio, k-Way, w/ Bloom 2^{20}, w/o ECL, Twitter

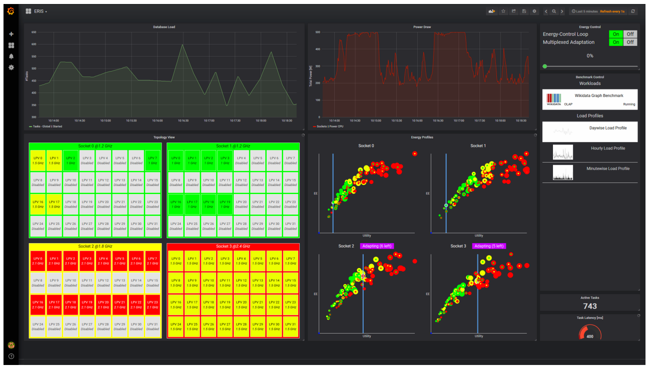
Figure 2: Demo UI with benchmark tuning knobs

messaging interface and the performance impact of unnecessary messages. Demo visitors can play with all knobs and observe the corresponding system behavior (cf. Fig 2).

Adjusting the control knobs. The performance of graph processing is influenced by the underlying partitioning, as shown in [6]. Thus, we allow the user to apply different graph partitionings like e.g. Hash or Multilevel k-Way. In addition, we provide multiple datasets based on bibliographic, social or protein network characteristics. We will present allocation mappings, which underline and explain the differences between certain partitioning strategies. For optimizing the messaging, we consider Bloom filters. Their false positive rate is tightly bound to the size of the internal bitfield. Users can change the number of available bits to trade off memory consumption for messaging efficiency.

Controling Energy. Within this second part of our demo, we allow the user to play around with the aforementioned control knobs and view their influence on the energy consumption of the system. This includes starting different workload scenarios for a given configuration while allowing for online adaption for energy efficiency, as introduced in [5].

After selecting the desired configuration including the workload pattern, the benchmark can be executed and its results will be presented below. We visualize inter-socket communication as well as computational demand of the sockets themselves for better comparability. Furthermore, key characteristics like energy demand or average query latency



Energy Control

Energy-Control Loop On Off

Multiplexed Adaptation On Off

0%

Benchmark Control

Workloads

Wikidata Graph Benchmark OLAP Running

Load Profiles

Daywise Load Profile

Hourly Load Profile

Minutewise Load Profile

Active Tasks 743

Task Latency [ms] 400

Topology View

Socket 0 @1.2 GHz

LPV 0 1.5 GHz	LPV 1 1.5 GHz	LPV 2 1 GHz	LPV 3 Disabled	LPV 4 Disabled	LPV 5 Disabled	LPV 6 Disabled	LPV 7 1 GHz
LPV 8 Disabled	LPV 9 Disabled	LPV 10 Disabled	LPV 11 Disabled	LPV 12 Disabled	LPV 13 Disabled	LPV 14 Disabled	LPV 15 Disabled
LPV 16 1.5 GHz	LPV 17 1.5 GHz	LPV 18 Disabled	LPV 19 Disabled	LPV 20 Disabled	LPV 21 Disabled	LPV 22 Disabled	LPV 23 Disabled
LPV 24 Disabled	LPV 25 Disabled	LPV 26 Disabled	LPV 27 Disabled	LPV 28 Disabled	LPV 29 Disabled	LPV 30 Disabled	LPV 31 Disabled

Socket 1 @1.2 GHz

LPV 0 1 GHz	LPV 1 1 GHz	LPV 2 1 GHz	LPV 3 1 GHz	LPV 4 Disabled	LPV 5 Disabled	LPV 6 Disabled	LPV 7 Disabled
LPV 8 Disabled	LPV 9 Disabled	LPV 10 Disabled	LPV 11 Disabled	LPV 12 Disabled	LPV 13 Disabled	LPV 14 Disabled	LPV 15 Disabled
LPV 16 1 GHz	LPV 17 1 GHz	LPV 18 1 GHz	LPV 19 1 GHz	LPV 20 Disabled	LPV 21 Disabled	LPV 22 Disabled	LPV 23 Disabled
LPV 24 Disabled	LPV 25 Disabled	LPV 26 Disabled	LPV 27 Disabled	LPV 28 Disabled	LPV 29 Disabled	LPV 30 Disabled	LPV 31 Disabled

Socket 2 @1.8 GHz

LPV 0 2.1 GHz	LPV 1 2.1 GHz	LPV 2 2.1 GHz	LPV 3 2.1 GHz	LPV 4 2.1 GHz	LPV 5 2.1 GHz	LPV 6 2.1 GHz	LPV 7 2.1 GHz
LPV 8 Disabled	LPV 9 Disabled	LPV 10 Disabled	LPV 11 Disabled	LPV 12 Disabled	LPV 13 Disabled	LPV 14 Disabled	LPV 15 Disabled
LPV 16 2.1 GHz	LPV 17 2.1 GHz	LPV 18 2.1 GHz	LPV 19 2.1 GHz	LPV 20 2.1 GHz	LPV 21 2.1 GHz	LPV 22 2.1 GHz	LPV 23 2.1 GHz
LPV 24 Disabled	LPV 25 Disabled	LPV 26 Disabled	LPV 27 Disabled	LPV 28 Disabled	LPV 29 Disabled	LPV 30 Disabled	LPV 31 Disabled

Socket 3 @2.4 GHz

LPV 0 1.5 GHz	LPV 1 1.5 GHz	LPV 2 1.5 GHz	LPV 3 1.5 GHz	LPV 4 1.5 GHz	LPV 5 1.5 GHz	LPV 6 1.5 GHz	LPV 7 1.5 GHz
LPV 8 1.5 GHz	LPV 9 1.5 GHz	LPV 10 1.5 GHz	LPV 11 1.5 GHz	LPV 12 1.5 GHz	LPV 13 1.5 GHz	LPV 14 1.5 GHz	LPV 15 1.5 GHz
LPV 16 1.5 GHz	LPV 17 1.5 GHz	LPV 18 1.5 GHz	LPV 19 1.5 GHz	LPV 20 1.5 GHz	LPV 21 1.5 GHz	LPV 22 1.5 GHz	LPV 23 1.5 GHz
LPV 24 1.5 GHz	LPV 25 1.5 GHz	LPV 26 1.5 GHz	LPV 27 1.5 GHz	LPV 28 1.5 GHz	LPV 29 1.5 GHz	LPV 30 1.5 GHz	LPV 31 1.5 GHz

Socket 2 Adapting (6 left)

Socket 3 Adapting (5 left)

Figure 3: Demo UI for energy efficiency

are displayed. This allows the user to run a plethora of different benchmark workloads and compare the impact of the applied optimization strategies.

4 CONCLUSION AND FUTURE WORK

With our demo, we present NeMeSys, which allows for NUMA-aware, energy-adaptive graph processing on modern multiprocessor systems. Furthermore, we underline the importance of a careful yet workload dependent parameter selection. Our vision is to build an adaptive system, which can decide the optimal data partitioning as well as Bloom filter sizes for a given graph and workload and adapt to it on the fly. However, graph partitioning is a hard problem. Thus, we need to identify suitable heuristics and transformation methods, to change one partitioning layout to another, which requires intensive future research.

5 ACKNOWLEDGEMENTS

This work is partly funded within the CRC 912 (HAEC).

REFERENCES

[1] T. Granlund. 2017. Instruction latencies and throughput for AMD and Intel x86 processors. https://gmplib.org/~tege/x86-timing.pdf.

[2] T. E. Hull and A. R. Dobell. 1962. Random Number Generators. *SIAM Rev.* 4 (1962).

[3] Intel. 2016. Intel 64 and IA-32 Architectures Software Developer's Guide. http://www.intel.com/content/dam/www/public/us/en/documents/manuals/64-ia-32-architectures-software-developer-vol-3b-part-2-manual.pdf. (2016).

[4] M. Junghanns, M. Kießling, A. Averbuch, A. Petermann, and E. Rahm. 2017. Cypher-based Graph Pattern Matching in Gradoop. In *Proceedings of the Fifth International Workshop on Graph Data-management Experiences & Systems, GRADES@SIGMOD/PODS.* 3:1–3:8.

[5] T. Kissinger, D. Habich, and W. Lehner. 2018. Adaptive Energy-Control for In-Memory Database Systems. In *SIGMOD.*

[6] A. Krause, T. Kissinger, D. Habich, H. Voigt, and W. Lehner. 2017. Partitioning Strategy Selection for In-Memory Graph Pattern Matching on Multiprocessor Systems. In *Euro-Par.*

[7] P. T. Wood. 2012. Query Languages for Graph Databases. *SIGMOD Rec.* 41, 1 (April 2012). https://doi.org/10.1145/2206869.2206879