Seminar Large-scale Data Engineering (LDE)
01 Structure of Scientific Papers

Dr.-Ing. Patrick Damme
Technische Universität Berlin
Berlin Institute for the Foundations of Learning and Data
Big Data Engineering (DAMS Lab)

Last update: Apr 26, 2026

[**Credit:** Based on “Introduction to Scientific Writing”/ ”01 Structure of Scientific Papers” by Matthias Boehm (TU Graz, winter 2021/22)]

Announcements/Org

- **Hybrid Setting with Optional Attendance**
  - In-person in MAR 0.008
  - Virtual via zoom
    https://tu-berlin.zoom-x.de/j/67376691490?pwd=NmlvWTM5VUVWRjU0UGI2bXhBVkxzQT09

- **Delayed Start of Introductory Lectures**
  - Due to participation in **Dagstuhl Seminar** on
    “Managing Vector Data for Retrieval Augmented Generation”
  - **But:** **No impact** on your total working time, submission deadlines, etc.

About Me

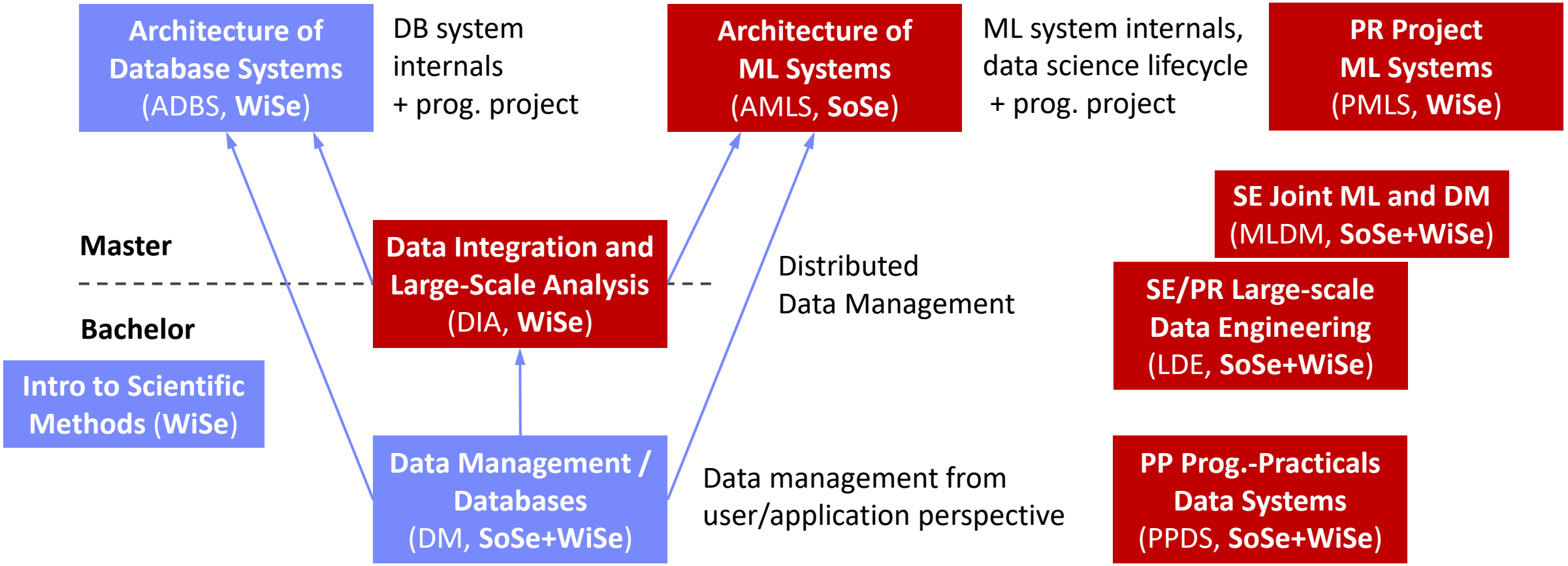
- **Since 10/2022: Postdoc at TU Berlin**, Germany
  - FG Big Data Engineering (DAMS Lab) headed by Prof. Matthias Böhm
  - Continuing work on integrated data analysis pipelines
  - Research interests in the fields of database and ML systems (especially compiler & runtime techniques, extensibility)

- **2021-2022: Postdoc at TU Graz & Know-Center GmbH**, Austria
  - Data Management group headed by Prof. Matthias Böhm
  - Started work on integrated data analysis pipelines

- **2015-2020: PhD student at TU Dresden**, Germany
  - Dresden Database Research Group headed by Prof. Wolfgang Lehner
  - PhD thesis on making complex analytical database queries more efficient through lightweight compression of intermediate results

FG Big Data Engineering (DAMS Lab) – Teaching

Successfully Established TUB Teaching Portfolio (modules, slides)



Agenda

- **Course Organization, Outline, and Deliverables**
- **Structure of Scientific Papers**
- **List of Seminar Topics**

Course Organization, Outline, and Deliverables

Large-scale Data Engineering: Module Overview

20 seats in total

master + bachelor

#41086: LDE Seminar + Project (12 ECTS)

10 students

10 students

#41095: Seminar LDE (3)

#41183: Project LDE (9 ECTS)

11 students

bachelor-only

bachelor-only

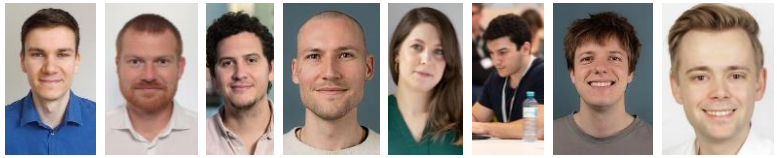
Mon, 14:00-16:00
MAR 0.008 & zoom

Seminar LDE

- Reading & writing scientific papers
- Giving presentations on papers
- Summary paper
- Presentation
- Lecturer & seminar mentor

Project LDE

- Building & evaluating prototypes
- Giving presentations on prototypes
- Prototype design/impl/tests/doc/eval
- Presentation
- Project mentors



Mon, 16:00-18:00
MAR 0.008 & zoom

→ In the context of systems for data engineering, data management, machine learning

→ In combination: Ideal preparation for a bachelor/master thesis with our group

Course Organization

- **General Contact Person**
  - Dr.-Ing. Patrick Damme (patrick.damme@tu-berlin.de)
- **Course Website**
  - https://pdamme.github.io/teaching/2026_summer/lde/lde_summer2026.html
  - One site for seminar and project
  - All material, schedule, **deadlines**
- **ISIS course**
  - https://isis.tu-berlin.de/course/view.php?id=46572
  - Announcements, discussion forum, topic selection poll, submission of summary paper and presentation slides
- **Language**
  - Lectures and slides: **English**
  - Communication: **English**/**German**
  - Submitted paper and presentation: **English**
  - **Informal language** (first name is fine), immediate feedback is welcome

Semester Schedule & Deadlines

- **Three Introductory Lectures** (optional)
  - Apr 27: Structure of Scientific Papers
  - May 04: Scientific Reading and Writing
  - May 11: Experiments, Reproducibility, and Giving Presentations
- **Self-organized Seminar Work**
  - Consultation hours for any questions (optional) (FR 768 and zoom)
- **Final Presentations** (mandatory, in-person)
  - Jun 29, 14:00-18:00: Session #1
  - Jul 06, 14:00-18:00: Session #2

- **List of Seminar Topics**
  - Presented today, take your time to select afterwards
- **Topic Selection**
  - **Deadline: May 04, 23:59** (in 1 week)
  - Ranked list of **5 topics** via poll on the ISIS course
  - Global topic assignment based on preferences
  - **Notification of assigned topics: May 06** (in 1^+ week)
- **Submission of Summary Paper**
  - **Deadline: Jun 15, 23:59** (in 7 weeks)
  - Upload PDF in the ISIS course
- **Submission of Presentation Slides**
  - **Deadline: The day before you present, 23:59**
  - Upload PDF in the ISIS course

Portfolio Exam Registration

- **Registration: May 11 – Jun 08**
  - Binding registration in Moses/MTS
  - Including selection of seminar presentation date (first-come-first-serve)
- **De-registration**
  - **Until 3 days before the first graded exam part**
    - De-register yourself in Moses/MTS
    - Modules “LDE”/”Seminar LDE”: until **Jun 12**
    - Module “Project LDE”: until **Jul 30**
  - **With sufficient reason: Until the day of the exam**
    - In case of sickness etc.
    - Modules “LDE”/”Seminar LDE”: until **Jun 15/Jun 29/Jul 06**
    - Module “Project LDE”: until **Aug 02/Aug 03**
- **Missing Deadlines/Exam Without De-registration**
  - Zero points in the respective exam part (!)
  - **Approach us early in case of problems**
- **If You Don’t Want to Take LDE Anymore**
  - Let me know asap to give students in the queue a chance to fill in

Seminar Deliverables: Summary Paper

- **Individual Seminar Work**
  - 1 student = 1 paper, no teamwork
- **Step 1: Understand the Topic**
  - Read and understand your selected paper
  - Read up on any unclear concepts
  - Search for related work to understand the context (at least 3-5 more papers, at least skim them)
- **Step 2: How Would You Explain the Topic?**
  - How would you structure the information?
  - Which helpful illustrations would you draw?
  - What key take-aways do you want to convey?
- **Step 3: Write the Summary Paper**
  - English, full text (sentences/paragraphs)
  - **4 pages** + unlimited references

- **FAQ**
  - **Title of the summary paper?**
    => Feel free to choose your own (e.g., “A Summary of XYZ”)
  - **Author(s) of the summary paper?**
    => Just you (not the original authors)
  - **Structure of the summary paper: Stick with the given paper’s?**
    => Use your own, but adhere to the prototypical paper structure
  - **Summary == copy the most important sentences?**
    => No, use your own words!
  - **Summary == slightly rephrase the text?**
    => No, present the topic in your own way!
  - **Writing perspective?**
    => “we” + ”the authors”
  - **Where to reference the given paper?**
    => Reference after each sentence/paragraph usually unnecessary
    => Ensure that source of information is always clear,
    e.g., ref once at the beginning of the section
  - **Copying figures, tables, listings, etc. from the given paper?**
    => Create your own illustrations, tables, listings etc.
    => Exception (if necessary for accuracy): reuse plots (with ref)

Seminar Deliverables: Summary Paper: LaTeX Paper Template

- **Obtain the Template**
  - https://www.acm.org/publications/proceedings-template
  - Download the ZIP archive **`acmart-primary.zip`** and unpack it
- **Select the Right Template**
  - The archive contains **all** ACM templates
  - Use the **sigconf document class**
- **The Easiest Way to Set up Your Own Document**
  - Copy just the required files to a new directory
  - Rename the .tex and .bib file as you like
    (and adapt the **`\bibliography{}`**)
  - Open the .tex file in a text/LaTeX editor
  - Remove example contents, replace it by yours
    (title, authors, sections, paragraphs, figures, etc.)
  - Replace the .bib contents by your BibTeX entries

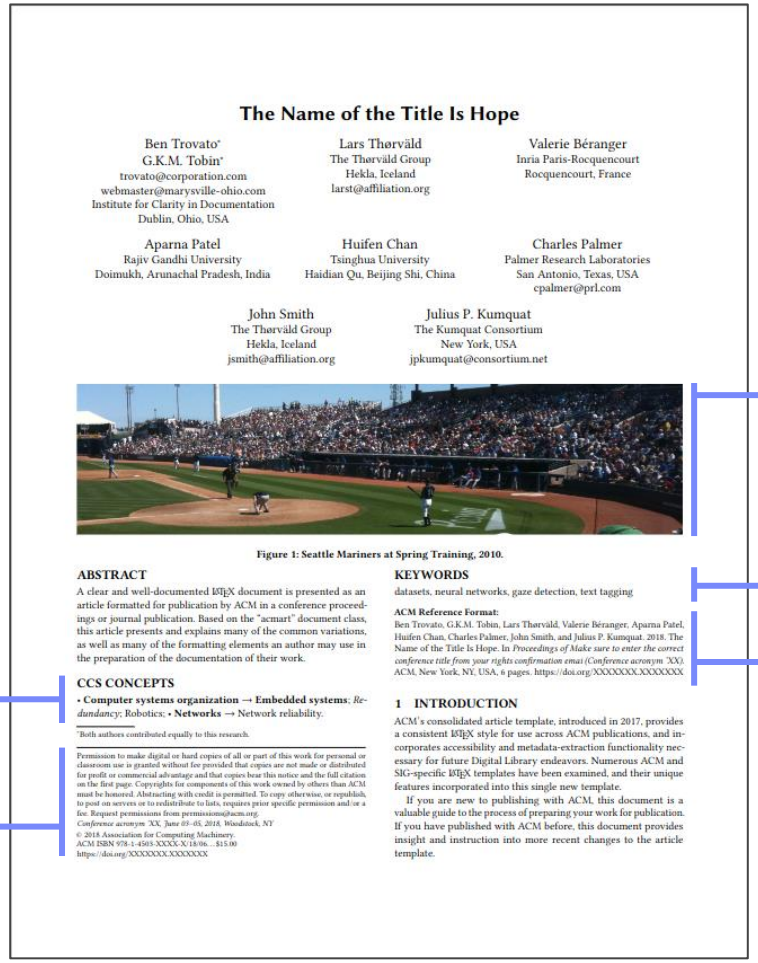
```
acmart-primary/
  samples/
    sample-base.bib
    sample-sigconf.tex
    …
  acmart.cls
  ACM-Reference-Format.bst
  …
```

```
lde-summary-paper/
  literature.bib
  summary-paper.tex
  acmart.cls
  ACM-Reference-Format.bst
```

Seminar Deliverables: Summary Paper: LaTeX Paper Template

ACM acmart template

document class sigconf (double-column)



The Name of the Title Is Hope

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Figure 1: Seattle Mariners at Spring Training, 2010.

ABSTRACT

A clear and well-documented LaTeX document is presented as an article formatted for publication by ACM in a conference proceedings or journal publication. Based on the "acmart" document class, this article presents and explains many of the common variations, as well as many of the formatting elements an author may use in the preparation of the documentation of their work.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

datasets, neural networks, gaze detection, text tagging

ACM Reference Format:

1 INTRODUCTION

ACM's consolidated article template, introduced in 2017, provides a consistent LaTeX style for use across ACM publications, and incorporates accessibility and metadata-extraction functionality necessary for future Digital Library endeavors. Numerous ACM and SIG-specific LaTeX templates have been examined, and their unique features incorporated into this single new template.

If you are new to publishing with ACM, this document is a valuable guide to the process of preparing your work for publication. If you have published with ACM before, this document provides insight and instruction into more recent changes to the article template.

CCS concepts

(ACM Computing Classification System)
Select concepts at https://dl.acm.org/ccs
and insert generated code:

```
%%
%% The code below is generated by the tool at http://dl.acm.org/ccs.cfm.
%% Please copy and paste the code instead of the example below.
%%
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 </concept>
 <concept>
```

Copyright notice

Just keep as it is (ignore the dummy data)

Teaser image

Not required (especially no photograph)

Keywords

Specify meaningful keywords

```
%% Keywords. The author(s) should pick words that accurately describe
%% the work being presented. Separate the keywords with commas.
\keywords{datasets, neural networks, gaze detection, text tagging}
```

ACM reference format

Just keep as it is (ignore the dummy data)

Seminar Deliverables: Presentation & Grading

- **Presentation**
  - **Speaker:** Explain the topic to your fellow students, such that **they** can **understand** it
  - Create appropriate slide deck
  - Clear motivation, background, approach, experiments, conclusions, etc.
  - **15 min talk + 5 min discussion** (stay in time)
  - **Audience:** **engage in the discussion**

- **Academic Honesty / No Plagiarism**
  - Develop **your own** reading/writing/pres skills
  - Use of **generative AI** (ChatGPT etc.) **is prohibited**

- **Graded Portfolio Exam**
  - **#41086 (seminar + project)**
    - 25 pts: summary paper
    - 15 pts: presentation
    - 50 pts: design/impl/tests/doc/exps
    - 10 pts: presentation
  - **#41095 (seminar-only)**
    - 65 pts: summary paper
    - 35 pts: presentation

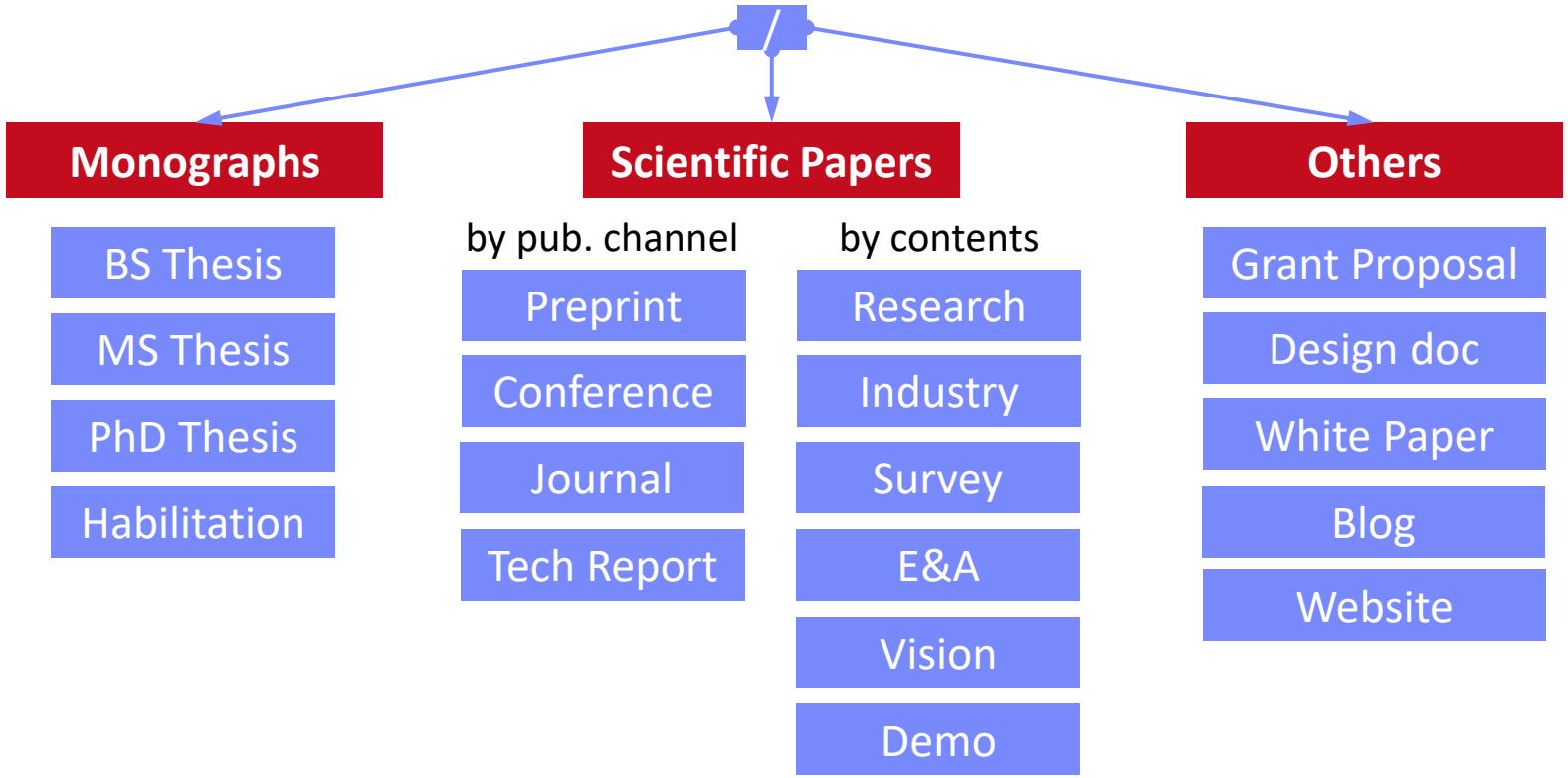
Structure of Scientific Papers

In Computer Science (Data Management)

[**Credit:** Based on “Introduction to Scientific Writing”/ ”01 Structure of Scientific Papers” by Matthias Boehm (TU Graz, winter 2021/22)]

Overview Types of Scientific Writing

- **Classification of Scientific/Technical Documents**
  - Formal vs informal writing, cumulative?, single vs multi-author, archival vs non-archival publications
- **Scientific Reading/Writing Skills Are Crucial**
  - Different types of docs share many similarities



Paper Writing and Publication Process

- **Research – Writing Cycle**
  - Read lots of papers
  - ~~Idea → Research → Writing → Document~~
  - Idea → Writing/Research → Document
  - Incremental refinement of drafts

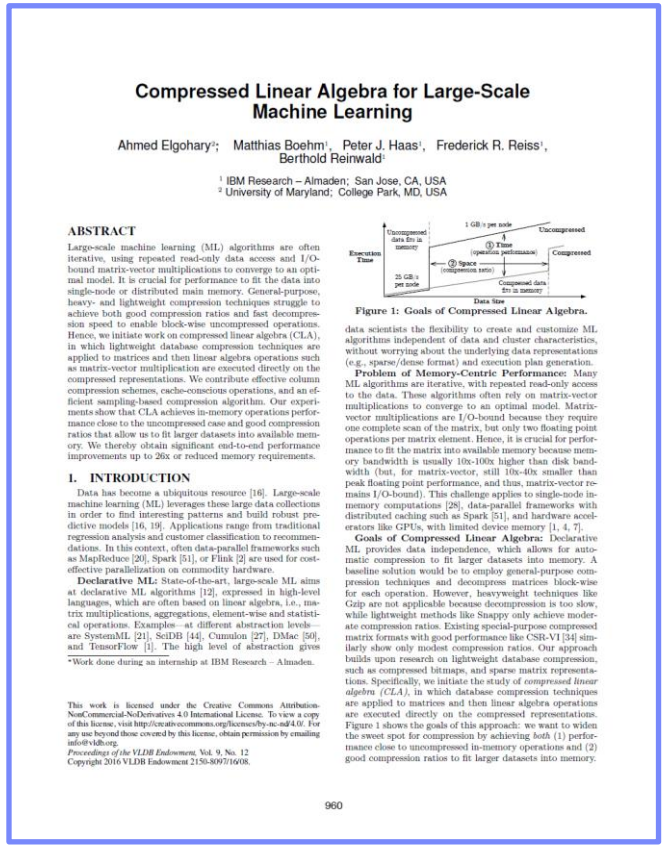
- **Paper Submission Cycle**
  - Blind vs double-blind submission
  - Revisions and Camera-ready
  - **Similar: bachelor/master** thesis
    → drafts to advisor / final version

- **Example: SIGMOD 2025: Paper Submission Round 4**
  - **Oct 10, 2024:** Abstract Submission & Declaration of COIs
  - **Oct 17, 2024:** Paper Submission
  - **Nov 28, 2024:** Notification of Accept/Review/Reject
  - **Dec 05, 2024:** Submission of Revision Plan
  - **Dec 19, 2024:** Revision Feedback
  - Submission of Revised Paper
  - **Jan 30, 2025:** Final Notification
  - Submission of Camera-ready Version

[Eamonn Keogh: How to do good research, get it published in SIGKDD and get it cited!, **KDD 2009**]

[Simon Peyton Jones: How to write a great research paper, MSR Cambridge]

Running Example



Compressed Linear Algebra for Large-Scale Machine Learning

Ahmed Elgohary[2]; Matthias Boehm[1], Peter J. Haas[1], Frederick R. Reiss[1], Berthold Reinwald[1]

[1] IBM Research – Almaden; San Jose, CA, USA
[2] University of Maryland; College Park, MD, USA

ABSTRACT

Large-scale machine learning (ML) algorithms are often iterative, using repeated read-only data access and I/O-bound matrix-vector multiplications to converge to an optimal model. It is crucial for performance to fit the data into single-node or distributed main memory. General-purpose, heavy- and lightweight compression techniques struggle to achieve both good compression ratios and fast decompression speed to enable block-wise uncompressed operations. Hence, we initiate work on compressed linear algebra (CLA), in which lightweight database compression techniques are applied to matrices and then linear algebra operations such as matrix-vector multiplication are executed directly on the compressed representations. We contribute effective column compression schemes, cache-conscious operations, and an efficient sampling-based compression algorithm. Our experiments show that CLA achieves in-memory operations performance close to the uncompressed case and good compression ratios that allow us to fit larger datasets into available memory. We thereby obtain significant end-to-end performance improvements up to 26x or reduced memory requirements.

1. INTRODUCTION

Data has become a ubiquitous resource [16]. Large-scale machine learning (ML) leverages these large data collections in order to find interesting patterns and build robust predictive models [16, 19]. Applications range from traditional regression analysis and customer classification to recommendations. In this context, often data-parallel frameworks such as MapReduce [20], Spark [51], or Flink [2] are used for cost-effective parallelization on commodity hardware.

Declarative ML: State-of-the-art, large-scale ML aims at declarative ML algorithms [12], expressed in high-level languages, which are often based on linear algebra, i.e., matrix multiplications, aggregations, element-wise and statistical operations. Examples—at different abstraction levels—are SystemML [21], SciDB [44], Cumulon [27], DMac [50], and TensorFlow [1]. The high level of abstraction gives

*Work done during an internship at IBM Research – Almaden.

Proceedings of the VLDB Endowment, Vol. 9, No. 12

Figure 1: Goals of Compressed Linear Algebra.

data scientists the flexibility to create and customize ML algorithms independent of data and cluster characteristics, without worrying about the underlying data representations (e.g., sparse/dense format) and execution plan generation.

Problem of Memory-Centric Performance: Many ML algorithms are iterative, with repeated read-only access to the data. These algorithms often rely on matrix-vector multiplications to converge to an optimal model. Matrix-vector multiplications are I/O-bound because they require one complete scan of the matrix, but only two floating point operations per matrix element. Hence, it is crucial for performance to fit the matrix into available memory because memory bandwidth is usually 10x-100x higher than disk bandwidth (but, for matrix-vector, still 10x-40x smaller than peak floating point performance, and thus, matrix-vector remains I/O-bound). This challenge applies to single-node in-memory computations [28], data-parallel frameworks with distributed caching such as Spark [51], and hardware accelerators like GPUs, with limited device memory [1, 4, 7].

Goals of Compressed Linear Algebra: Declarative ML provides data independence, which allows for automatic compression to fit larger datasets into memory. A baseline solution would be to employ general-purpose compression techniques and decompress matrices block-wise for each operation. However, heavyweight techniques like Gzip are not applicable because decompression is too slow, while lightweight methods like Snappy only achieve moderate compression ratios. Existing special-purpose compressed matrix formats with good performance like CSR-VI [34] similarly show only modest compression ratios. Our approach builds upon research on lightweight database compression, such as compressed bitmaps, and sparse matrix representations. Specifically, we initiate the study of *compressed linear algebra (CLA)*, in which database compression techniques are applied to matrices and then linear algebra operations are executed directly on the compressed representations. Figure 1 shows the goals of this approach: we want to widen the sweet spot for compression by achieving *both* (1) performance close to uncompressed in-memory operations and (2) good compression ratios to fit larger datasets into memory.

960

- **Example paper used in the following**
  - Ahmed Elgohary, **Matthias Boehm**, Peter J. Haas, Frederick R. Reiss, Berthold Reinwald: **Compressed Linear Algebra** for Large-Scale Machine Learning. **PVLDB 2016**

[Ahmed Elgohary, Matthias Boehm, Peter J. Haas, Frederick R. Reiss, Berthold Reinwald: Scaling Machine Learning via Compressed Linear Algebra. **SIGMOD Record 2017 46(1)**]

[Ahmed Elgohary, Matthias Boehm, Peter J. Haas, Frederick R. Reiss, Berthold Reinwald: Compressed Linear Algebra for Large-Scale Machine Learning. **VLDB Journal 2018 27(5)**]

[Ahmed Elgohary, Matthias Boehm, Peter J. Haas, Frederick R. Reiss, Berthold Reinwald: Compressed Linear Algebra for Large-Scale Machine Learning. **Commun. ACM 2019 62(5)**]

Prototypical Structure of a Scientific Paper

- **Title & Authors**
- **Sections and Subsections**
  - Abstract → short overview of problem and solution (part of meta data)
  - Introduction → context, problem, contributions
  - Background / Preliminaries → necessary background for understanding
  - Main Part → technical core contributions
  - Main Part 2
  - Experiments → setting, micro benchmarks, end-to-end benchmarks
  - Related Work → areas of related work, differences to your own work
  - Conclusions → summary, conclusions, and future work
  - Acknowledgments → funding agencies, helpful people beyond co-authors
  - References → list of other works referenced throughout the paper
  - (Appendix) → any additional contents (e.g., proves of theorems, more results)

Title and Authors

Compressed Linear Algebra for Large-Scale Machine Learning

Ahmed Elgohary[2]*, Matthias Boehm[1], Peter J. Haas[1], Frederick R. Reiss[1], Berthold Reinwald[1]

[1] IBM Research – Almaden; San Jose, CA, USA
[2] University of Maryland; College Park, MD, USA

- **Title**
  - Descriptive yet concise
  - Short name if possible → easier to cite and discuss
- **List of Authors**
  - E.g., by contribution (main, …, advisor)
  - E.g., by last name
  - Affiliations, contact (corresponding author)

SPOOF: Sum-Product Optimization and Operator Fusion for Large-Scale Machine Learning

Tarek Elgamal[2]; Shangyu Luo[3]; Matthias Boehm[1], Alexandre V. Evfimievski[1], Shirish Tatikonda[4]; Berthold Reinwald[1], Prithviraj Sen[1]

[1] IBM Research – Almaden; San Jose, CA, USA
[2] University of Illinois; Urbana-Champaign, IL, USA
[3] Rice University; Houston, TX, USA
[4] Target Corporation; Sunnyvale, CA, USA

MNC: Structure-Exploiting Sparsity Estimation for Matrix Expressions

Johanna Sommer, IBM Germany
Matthias Boehm, Graz University of Technology
Alexandre V. Evfimievski, IBM Research – Almaden
Berthold Reinwald, IBM Research – Almaden
Peter J. Haas, UMass Amherst

SliceLine: Fast, Linear-Algebra-based Slice Finding for ML Model Debugging

Svetlana Sagadeeva*, Graz University of Technology
Matthias Boehm, Graz University of Technology

[**Credit:** sliceline, Silicon Valley, HBO]

Abstract

% 1. State the problem

Large-scale machine learning (ML) algorithms are often iterative, using repeated read-only data access and I/O-bound matrix-vector multiplications to converge to an optimal model. It is crucial for performance to fit the data into single-node or distributed main memory.

% 2. Say why it's an interesting problem

General-purpose, heavy- and lightweight compression techniques struggle to achieve both good compression ratios and fast decompression speed to enable block-wise uncompressed operations.

% 3. Say what your solution achieves

Hence, we initiate work on compressed linear algebra (CLA), in which lightweight database compression techniques are applied to matrices and then linear algebra operations such as matrix-vector multiplication are executed directly on the compressed representations. We contribute effective column compression schemes, cache-conscious operations, and an efficient sampling-based compression algorithm. Our experiments show that CLA achieves in-memory operations performance close to the uncompressed case and good compression ratios that allow us to fit larger datasets into available memory.

% 4. Say what follows from your solution

We thereby obtain significant end-to-end performance improvements up to 26x or reduced memory requirements.

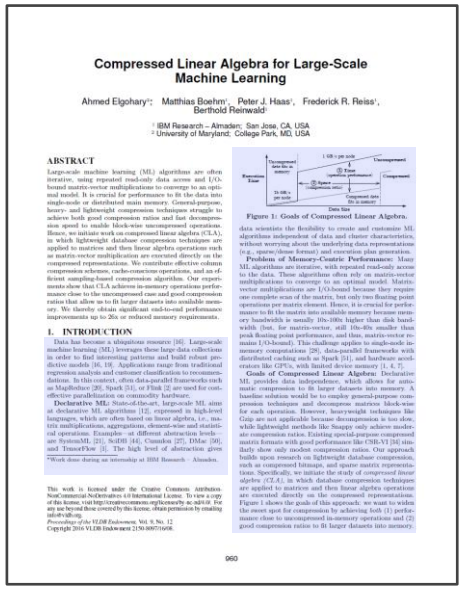
[Simon Peyton Jones: How to write a great research paper, MSR Cambridge]

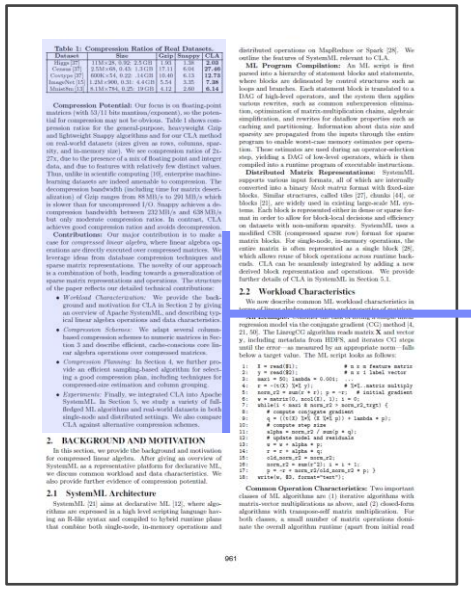
ABSTRACT

Large-scale machine learning (ML) algorithms are often iterative, using repeated read-only data access and I/O-bound matrix-vector multiplications to converge to an optimal model. It is crucial for performance to fit the data into single-node or distributed main memory. General-purpose, heavy- and lightweight compression techniques struggle to achieve both good compression ratios and fast decompression speed to enable block-wise uncompressed operations. Hence, we initiate work on compressed linear algebra (CLA), in which lightweight database compression techniques are applied to matrices and then linear algebra operations such as matrix-vector multiplication are executed directly on the compressed representations. We contribute effective column compression schemes, cache-conscious operations, and an efficient sampling-based compression algorithm. Our experiments show that CLA achieves in-memory operations performance close to the uncompressed case and good compression ratios that allow us to fit larger datasets into available memory. We thereby obtain significant end-to-end performance improvements up to 26x or reduced memory requirements.

Introduction

- **Prototypical Structure**
  - Context (1 paragraph)
  - Problems (1-3 paragraphs)
  - [Existing Work (1 paragraph)]
  - [Idea (1 paragraph)]
  - Contributions (1 paragraph)


Compressed Linear Algebra for Large-Scale Machine Learning



Contributions: Our major contribution is to make a case for *compressed linear algebra*, where linear algebra operations are directly executed over compressed matrices. We leverage ideas from database compression techniques and sparse matrix representations. The novelty of our approach is a combination of both, leading towards a generalization of sparse matrix representations and operations. The structure of the paper reflects our detailed technical contributions:

- *Workload Characterization:* We provide the background and motivation for CLA in Section 2 by giving an overview of Apache SystemML, and describing typical linear algebra operations and data characteristics.
- *Compression Schemes:* We adapt several column-based compression schemes to numeric matrices in Section 3 and describe efficient, cache-conscious core linear algebra operations over compressed matrices.
- *Compression Planning:* In Section 4, we further provide an efficient sampling-based algorithm for selecting a good compression plan, including techniques for compressed-size estimation and column grouping.
- *Experiments:* Finally, we integrated CLA into Apache SystemML. In Section 5, we study a variety of full-fledged ML algorithms and real-world datasets in both single-node and distributed settings. We also compare CLA against alternative compression schemes.

- **Introduction Matters**
  - **Anchoring:** most reviewers reach their opinion after reading introduction and motivation and then look for evidence

[Eamonn Keogh: How to do good research, get it published in SIGKDD and get it cited!, **KDD 2009**]

Main Part & Experiments

- **Main Part: Core Technical Contributions**
  - Make it easy to skim the paper
    → paragraph labels, self-explanatory figures (close to text), and structure
  - Avoid unnecessary formalism → as simple as possible
  - Shortening the text in favor of structure improves readability

→ 02 Scientific Reading and Writing

- **Solid, Reproducible Experiments**
  - Experimental setup and methodology
  - Experimental results (visual presentation, interpretation/conclusions)
  - Different kinds of experiments for different aspects of the problem

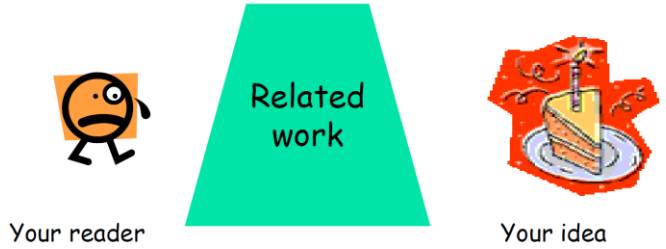
→ 03 Experiments, Reproducibility, and Giving Presentations

Related Work

- **Purpose of a “Related Work”-Section**
  - **Not** a mandatory task or to show you know the field
  - Put you work in context of related areas (~ 1 paragraph each)
  - Discuss closely related work
  - **Crisp separation from existing work** (what are the differences)

[Simon Peyton Jones: How to write a great research paper, MSR Cambridge]

- **Placement**
  - Section 2 or **Section n-1**
  - Throughout the paper



- **Give Credit**
  - Cite broadly, **give credit to inspiring ideas**, create connections
  - Honestly acknowledge **limitations of your approach**

References

- **Setup**
  - Use LaTeX **\cite**{} and BibTeX
  - Use a consistent source of bibtex entries (e.g., DBLP)

```
inproceedings{StonebrakerBPR11,
  author    = {Michael {Stonebraker et al.}},
  title     = {{The Architecture of SciDB}},
  booktitle = {{SSDBM}},
  year      = {2011}
}
```

VLDB2016.bib

\bibliographystyle{abbrv}
\bibliography{VLDB2016}

- **Different References Styles**
  - But, **not in footnotes** (unless required)
  - **8. REFERENCES**

    [1] M. Abadi et al. TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. *CoRR*, 2016.

    [2] A. Alexandrov et al. The Stratosphere Platform for Big Data Analytics. *VLDB J.*, 23(6), 2014.

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Jaume Amores. 2013. Multiple instance classification: Review, taxonomy and comparative study. *Artificial Intelligence.*

List of Seminar Topics

See list at https://pdamme.github.io/teaching/2026_summer/lde/SeminarTopics.pdf

Summary and Q&A

- **Course Organization, Outline, and Deliverables**
- **Structure of Scientific Papers**
- **List of Seminar Topics (Topic Selection by May 04)**

- **Remaining Questions?**

- **Next Lectures**
  - 02 Scientific Reading and Writing [May 04]
  - 03 Experiments, Reproducibility, and Giving Presentations [May 11]