Data Integration and Large-scale Analysis (DIA)
01 Introduction and Overview

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Technische Universität Berlin
Berlin Institute for the Foundations of Learning and Data
Big Data Engineering (DAMS Lab)

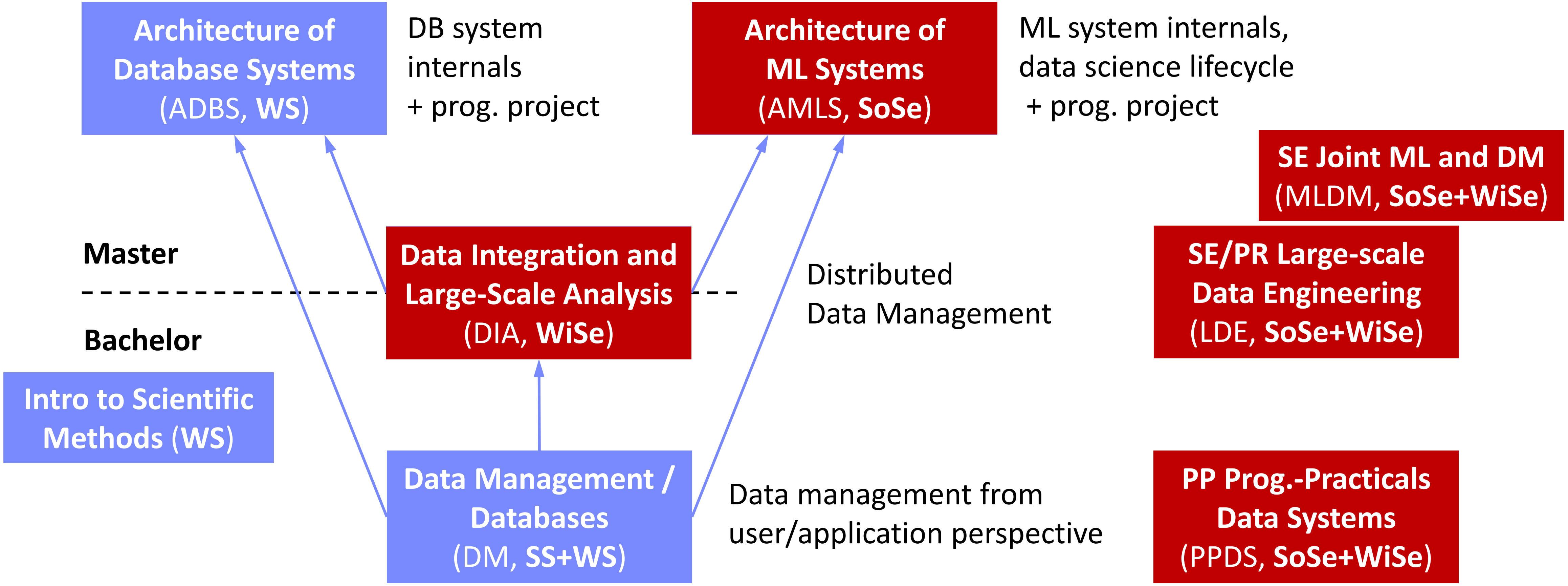
 Last update: Oct 19, 2023

FG Big Data Engineering (DAMS Lab) – About Me

- **Since 09/2022 TU Berlin**, Germany
  - University professor for Big Data Engineering (DAMS)
- **2018-2022 TU Graz**, Austria
  - BMK endowed chair for data management + research area manager
  - **Data management for data science** (DAMS), **SystemDS & DAPHNE**
- **2012-2018 IBM Research – Almaden**, CA, USA
  - Declarative large-scale machine learning
  - Optimizer and runtime of **Apache SystemML**
- **2007-2011 PhD TU Dresden**, Germany
  - Cost-based optimization of integration flows
  - Time series forecasting / in-memory indexing & query processing

DB group

FG Big Data Engineering (DAMS Lab) – Teaching

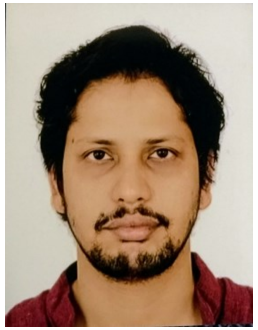


Agenda

- Course Organization
- Course Motivation and Goals
- Course Outline and Projects/Exercise
- Excursus: Apache SystemDS

Course Organization

Course Logistics

- **Staff**
  - **Lecturer:** Prof. Dr. Matthias Boehm, DAMS
  - **Teaching Assistant:** M.Tech. Arnab Phani, DAMS
- **Language**
  - Lectures and slides: **English**
  - Communication and examination: **English**/**German**
- **Course Format**
  - VL/UE 3/2 SWS, **6 ECTS** (3 ECTS + 3 ECTS), bachelor/master; no capacity restrictions
  - **Weekly lectures** (**Thu 4.15pm sharp**, in-person & zoom livestreaming/recording), **optional attendance**
  - **Mandatory exercises or programming project** (3 ECTS)
  - **Recommended papers** for additional reading on your own
- **Prerequisites**
  - Basic understanding of SQL / RA (or willingness to fill gaps)
  - Basic programming skills (Python, R, Java, C++)

204 Reg (as of Oct 17)

Course Logistics, cont.

- **Website / ISIS Course / Zoom**
  - https://mboehm7.github.io/teaching/ws2324_dia/index.htm (public)
  - https://isis.tu-berlin.de/course/view.php?id=35037 (TUB-internal)
  - https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09
- **Communication**
  - **Informal language** (first name is fine); **immediate feedback** welcome
  - ISIS Forum for offline Q&A on projects/exercises as well as
  - **TA Office hours:** TBD second week
- **Academic Honesty / No Plagiarism** (incl LLMs like ChatGPT)
- **Exam**
  - **Exam Prerequisite: Completed exercises or project** (checked by teaching assistants)
  - **Final written exam** (oral exam if <35 students take the exam): **Feb 08, 4pm** / **Feb 15, 4pm**
  - **Grading** (project/exercises pass/fail, 100% exam) → **5 extra points in exam** if exercises with >= 90%

Course Applicability

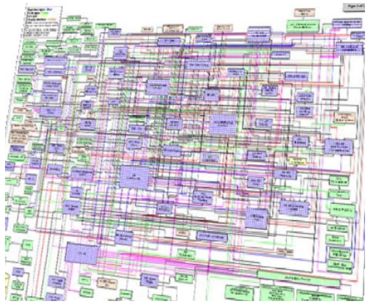
- **Bachelor study programs computer science, information systems management, computer engineering, and electrical engineering**
- **Master study programs computer science, information systems management, computer engineering, and electrical engineering**
  - Data and software engineering
  - Cognitive systems
  - Distributed systems and networks
- **Free subject course in any other study program or university**

Course Motivation and Goals

Data Sources and Heterogeneity

- **Terminology**
  - **Integration** (Latin integer = whole): consolidation of data objects / sources
  - **Homogeneity** (Greek homo/homoios = same): similarity
  - **Heterogeneity**: dissimilarity, different representation / meaning

[**Credit:** Albert Maier]

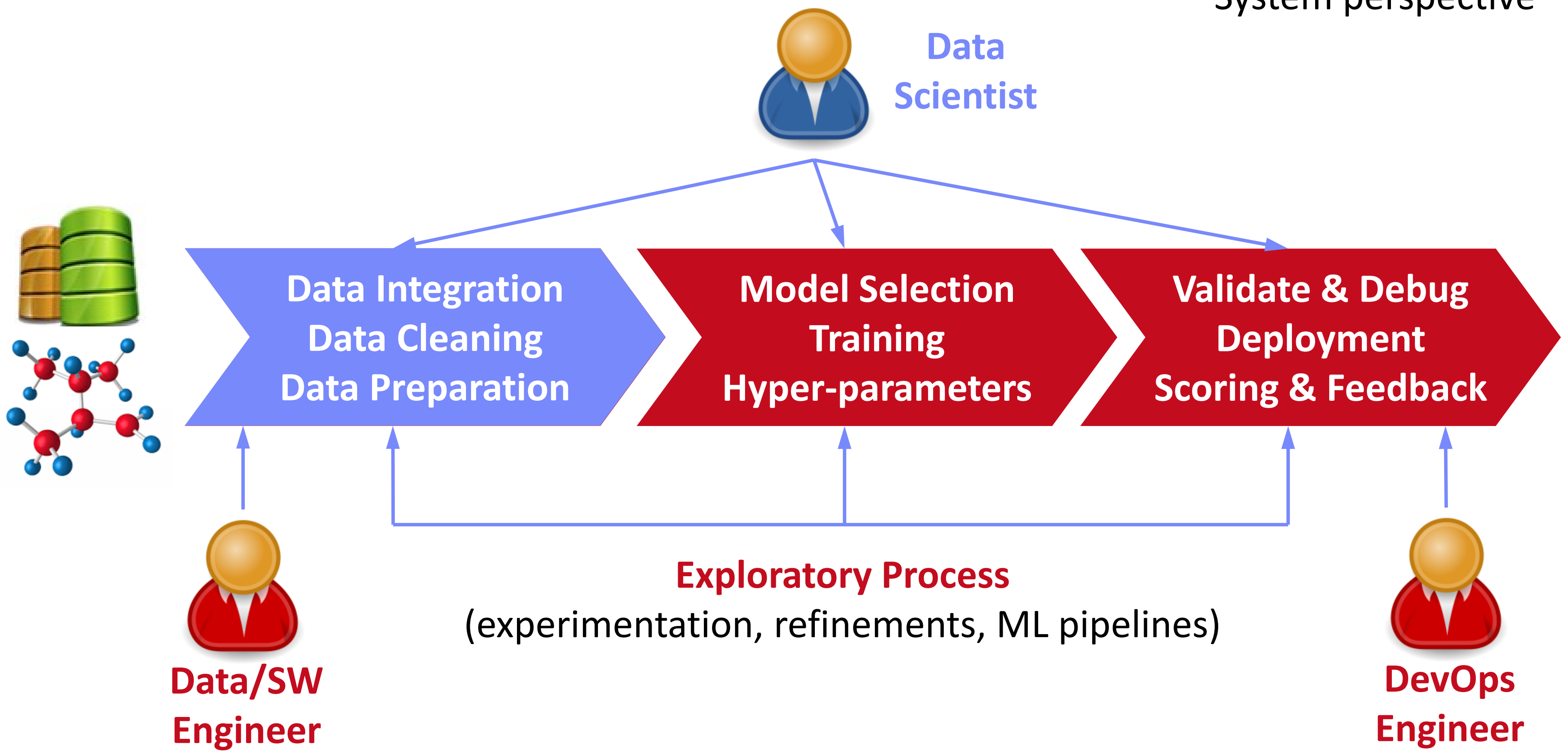


- **Heterogeneous IT Infrastructure**
  - Common enterprise IT infrastructure contains >100s of **heterogeneous and distributed systems and applications**
  - E.g., health care data management: 20 - 120 systems

- **Multi-Modal Data (example health care)**
  - **Structured patient data**, patient records incl. prescribed drugs
  - **Knowledge base** drug APIs (active pharmaceutical ingredients) + interactions
  - **Doctor notes** (text), diagnostic codes, outcomes
  - **Radiology images** (e.g., MRI scans), **patient videos**
  - **Time series** (e.g., EEG, ECoG, heart rate, blood pressure)

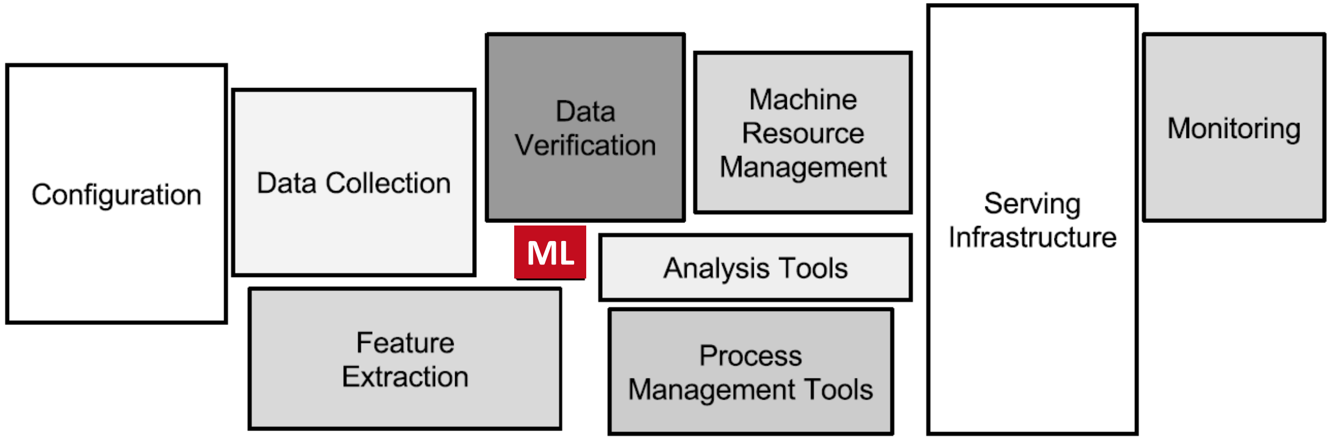
Recap: The Data Science Lifecycle (aka KDD Process, aka CRISP-DM)

Data-centric View:
Application perspective
Workload perspective
System perspective



The 80% Argument

- **Data Sourcing Effort**
  - Data scientists spend **80-90% time** on finding, integrating, cleaning datasets
- **Technical Debts in ML Systems**

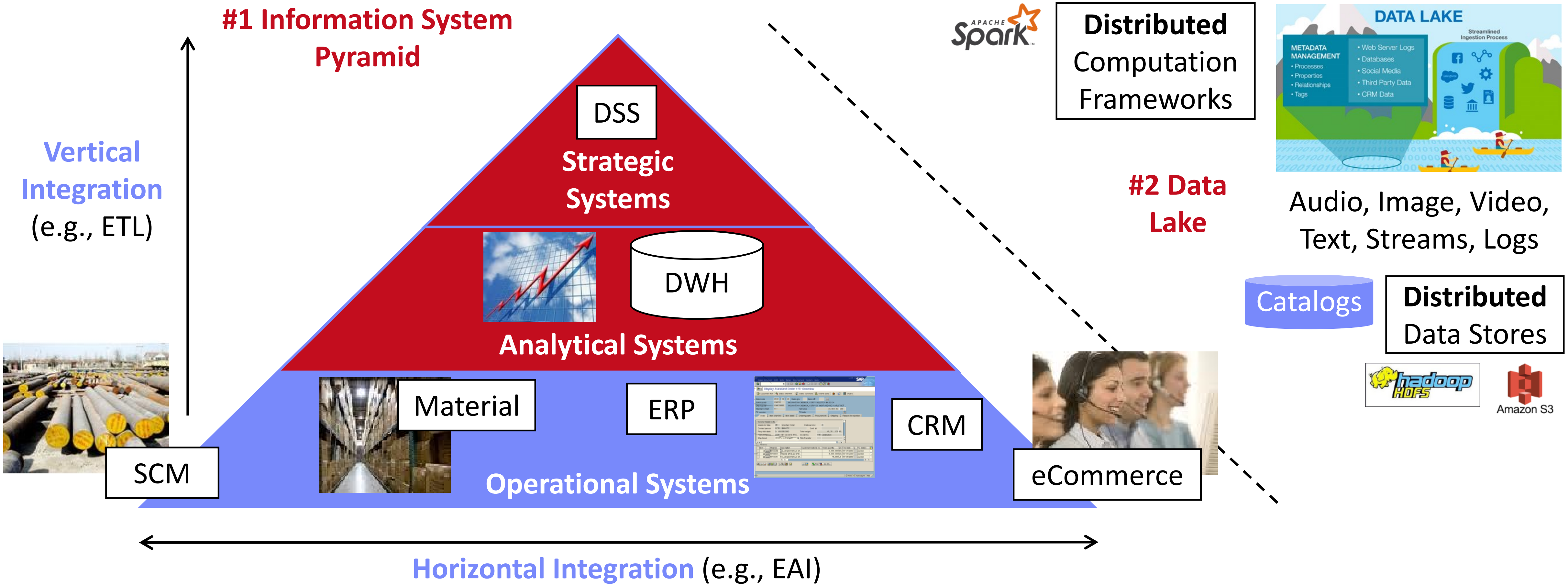


  - Glue code, pipeline jungles, dead code paths
  - Plain-old-data types (arrays), multiple languages, prototypes
  - Abstraction and configuration debts
  - Data testing, reproducibility, process management, and cultural debts

[Michael Stonebraker, Ihab F. Ilyas: Data Integration: The Current Status and the Way Forward. **IEEE Data Eng. Bull. 41(2) (2018)**]

[D. Sculley et al.: Hidden Technical Debt in Machine Learning Systems. **NeurIPS 2015**]

Complementary System Architectures



Course Goals

- **Common Data and System Characteristics**
  - **Heterogeneous** data sources and formats, often distributed
  - **Large** data collections → **distributed** data storage and analysis

- **#1 Major data integration architectures**

- **#2 Key techniques for data integration and cleaning**

- **#3 Methods for large-scale data storage and analysis**

Course Outline and Projects/Exercise

Part A: Data Integration and Preparation

Data Integration Architectures

- **01 Introduction and Overview** [Oct 19]
- **02 Data Warehousing, ETL, and SQL/OLAP** [Oct 26, **virtual**]
- **03 Message-oriented Middleware, EAI, and Replication** [Nov 02]

Key Integration Techniques

- **04 Schema Matching and Mapping** [Nov 09]
- **05 Entity Linking and Deduplication** [Nov 16]
- **06 Data Cleaning and Data Fusion** [Nov 23]
- **07 Data Provenance and Catalogs** [Nov 30]

Part B: Large-Scale Data Management & Analysis

Cloud Computing

- **08 Cloud Computing Foundations** [Dec 07]
- **09 Cloud Resource Management and Scheduling** [Dec 14]
- **10 Distributed Data Storage** [Jan 11]

Large-Scale Data Analysis

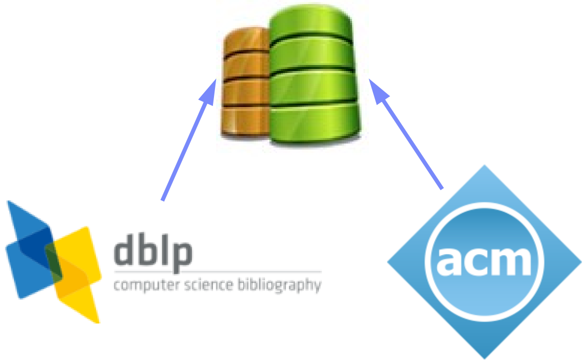
- **11 Distributed, Data-Parallel Computation** [Jan 18]
- **12 Distributed Stream Processing** [Jan 25]
- **13 Distributed Machine Learning Systems** [Feb 01]

Overview Projects or Exercises

- **Team**
  - **1-3 person teams** (w/ clearly separated responsibilities)
  - In exceptions, also larger teams (e.g., **Data Cleaning / TPCx-AI** Benchmarks)

- **Objectives**
  - Non-trivial programming project in DIA context (**3 ECTS → 80-90 hours**)
  - **Preferred:** Open source contribution to **Apache SystemDS**
    https://github.com/apache/systemds (from HW to high-level scripting)
  - **Alternative Exercise:** Data engineering and ML pipeline for
    "Entity Resolution of Publication Data"

Creating a deduplicated publication dataset

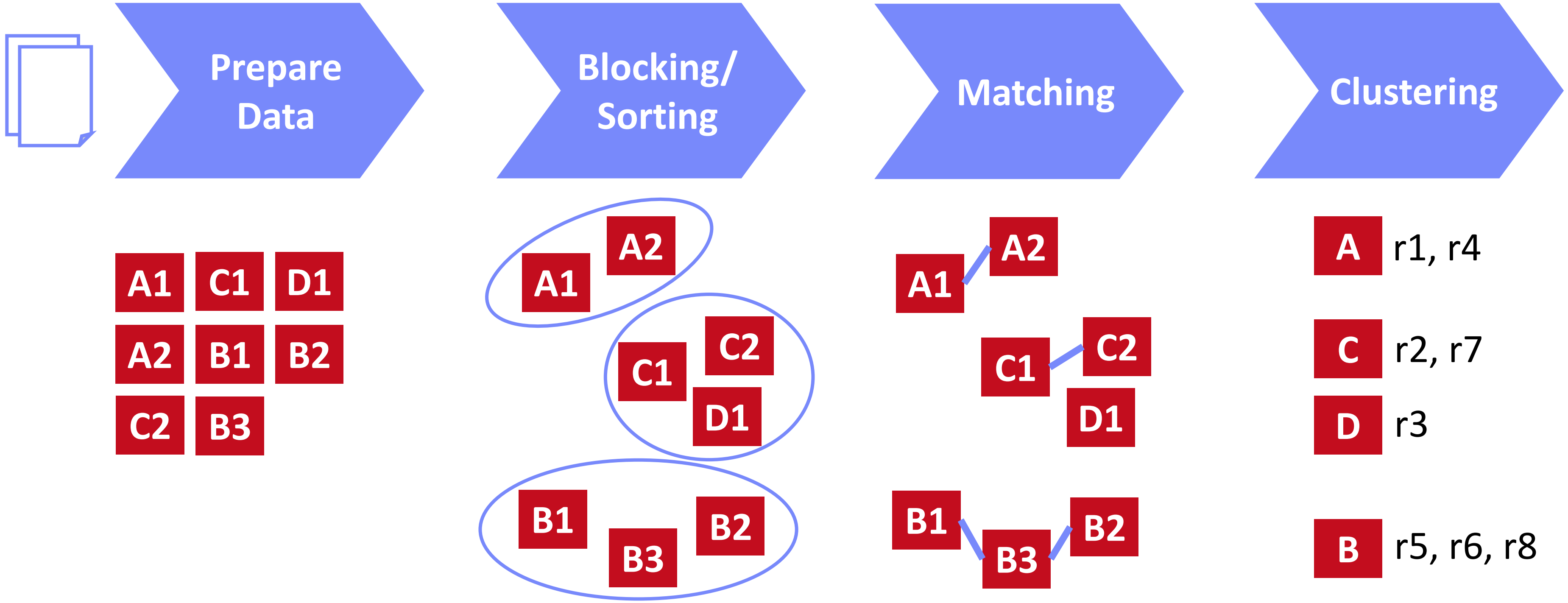


- **Timeline**
  - **Nov 03:** Binding project/exercise selection (via email to matthias.boehm@tu-berlin.de)
  - **Feb 02:** Project/exercise submission deadline

DIA Exercise (alternative to projects)

- **Task: Entity Resolution of Publication Data**
  - **1-3 person teams**; data: subsets of **DBLP** and **ACM** publication datasets
  - Perform data acquisition and **data preparation**, develop an **entity resolution pipeline** (local operations), reimplement a **data-parallel entity resolution pipeline** on **Spark/Flink/Dask** (distributed operations)
  - https://mboehm7.github.io/teaching/ws2324_dia/DIA_2023_Exercise.pdf

- **Preview**
  05 Entity Linking and Deduplication



DIA Exercise (alternative to projects), cont.

1 DIA WiSe2023: Exercise – Entity Resolution of Publication Data

Published: Oct 19, 2023 (last update: Oct 19)
Deadline: Feb 02, 2023, 11.59pm

This exercise is an alternative to the DIA programming projects, and aims to provide practical experience in the development of data engineering and ML pipelines. The task is to construct an Entity Resolution (ER) pipeline for deduplication of research publication datasets. You may use any programming language(s) of your choosing, and utilize existing open-source ML frameworks and libraries. The expected result is a zip archive named DIA_Exercise_<student_ID>.zip (replace <student_ID> by your student ID) of max 5 MB, containing:

- The source code used to solve the individual sub-tasks
- A PDF report of up to 8 pages (10pt), including the names of all team members, a brief summary of how to run your code, and a description of the solutions to the individual sub-tasks.

Data: Obtain the DBLP and ACM datasets from here and here respectively. A description of the data can be found at `https://www.aminer.org/citation`.

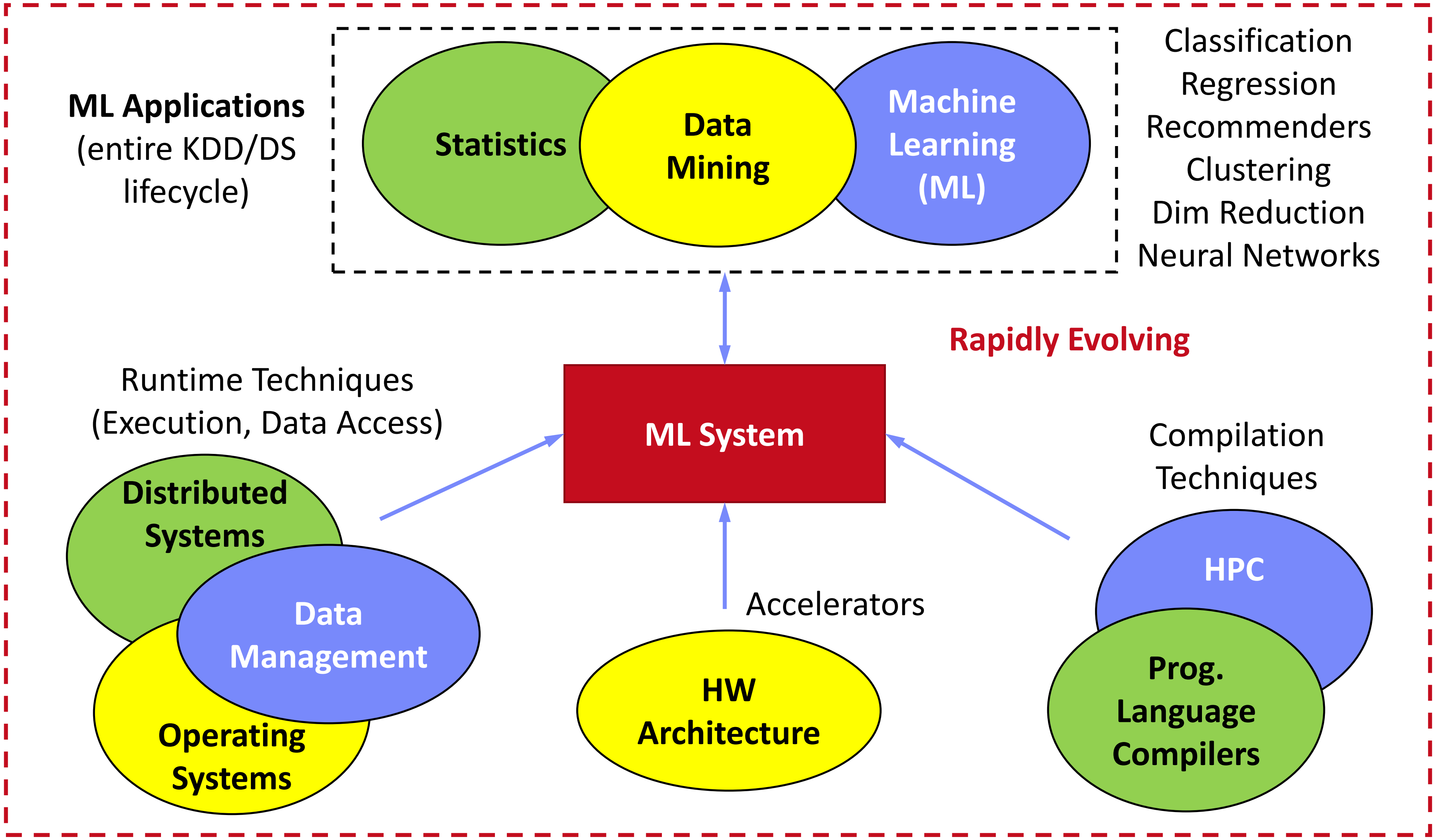
Grading: This exercise can be pursued in teams of 1 to 3 persons (one submission, scale quality expectations). The overall grading is a *pass/fail* for the entire team. Exercises with $\geq 50/100$ points are a pass, and with $\geq 90/100$ points we receive 5 extra points in the exam.

[https://mboehm7.github.io/teaching/ws2324_dia/DIA_2023_Exercise.pdf]

Apache SystemDS: A Declarative ML System for the End-to-End Data Science Lifecycle

https://github.com/apache/systemds

What is an ML System?



Landscape of ML Systems

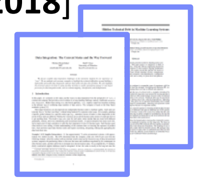
- **Existing ML Systems**
  - **#1 Numerical computing** frameworks
  - **#2 ML Algorithm libraries** (local, large-scale)
  - **#3 Linear algebra ML systems** (large-scale)
  - **#4 Deep neural network** (DNN) frameworks
  - **#5 Model management, and deployment**

- **Exploratory Data-Science Lifecycle**
  - **Open-ended problems** w/ underspecified objectives
  - Hypotheses, data integration, run analytics
  - **Unknown value** → lack of system infrastructure
    → **Redundancy of manual efforts and computation**

- **Data Preparation Problem**
  - **80% Argument:** 80-90% time for finding, integrating, cleaning data
  - Diversity of tools → boundary crossing, lack of optimization

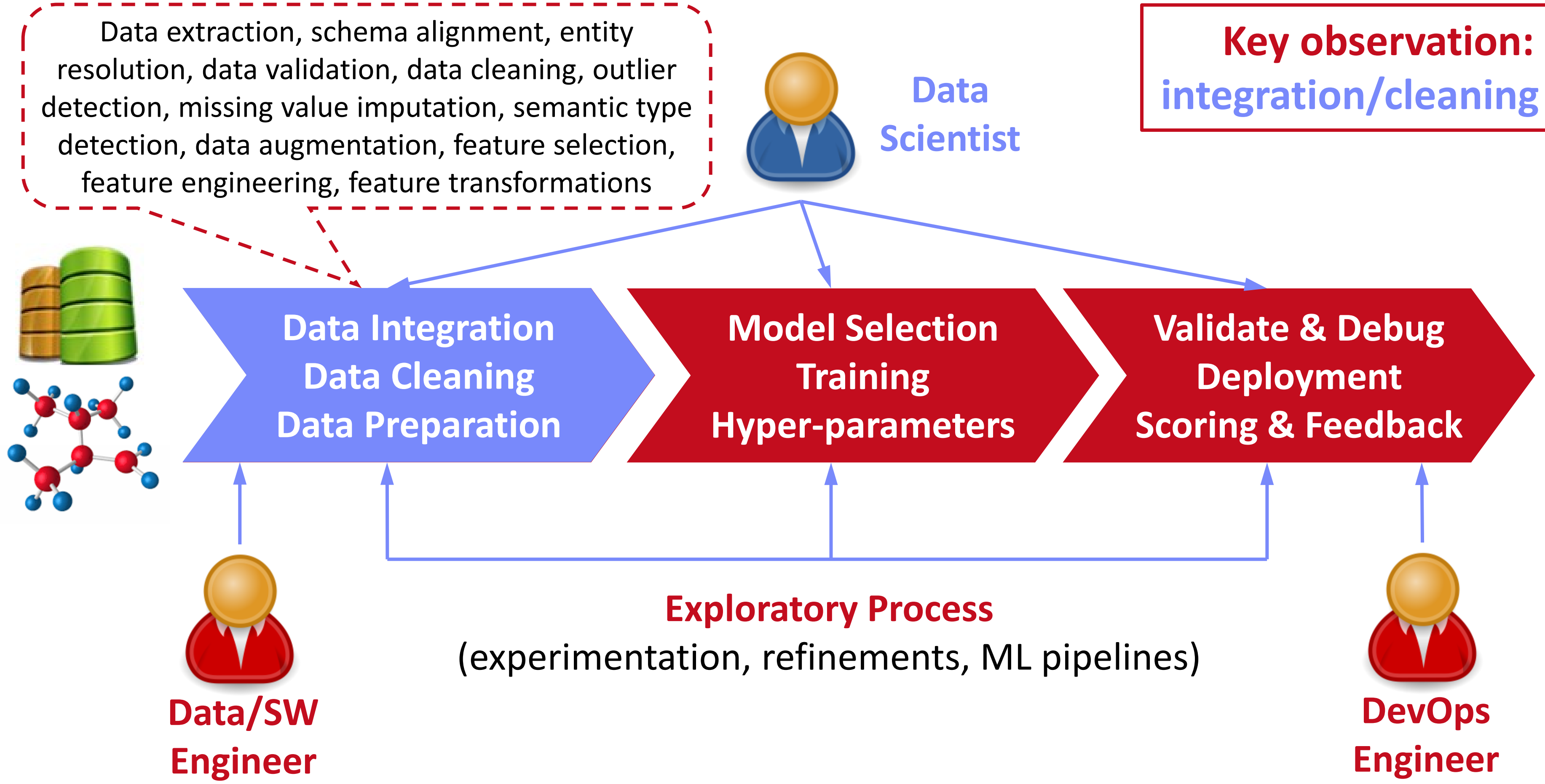
"Take these datasets and show value or competitive advantage"

[NIPS 2015]
[DEBull 2018]

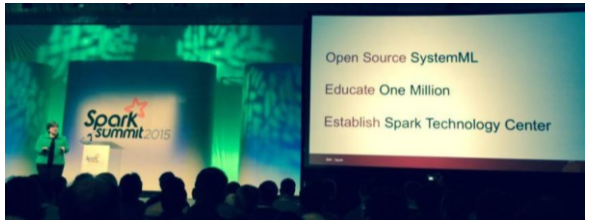


The Data Science Lifecycle
(aka KDD Process, aka CRISP-DM)

Key observation: SotA data integration/cleaning based on ML



Apache SystemDS [https://github.com/apache/systemds]



APIs: Command line, JMLC, Python
Spark MLContext, Spark ML,
(Scalable Algorithms + Primitives)

DML Scripts

Language

Compiler

Runtime

Write Once,
Run Anywhere

[SIGMOD’15,’17,’19,’21abc,’23abc,’24a]
[PVLDB’14,’16ab,’18,’22]
[ICDE’11,’12,’15]
[CIDR’17,’20]
[VLDBJ’18]
[CIKM’22]
[DEBull’14]
[PPoPP’15]

Apache SystemML™

07/2020 Renamed to **Apache SystemDS**
05/2017 Apache Top-Level Project
11/2015 Apache Incubator Project
08/2015 Open Source Release

In-Memory Single Node
(scale-up)

Hadoop or Spark Cluster
(scale-out)

Federated
(LA progs, PS)

Others:
Netezza
Apache Flink

In-Progress:
GPU

since 2014/16

Java

since 2012

hadoop

since 2010/11

Apache Spark

since 2015

exdra

since 2019

Language Abstractions and APIs

Data Independence + Impl-Agnostic Ops
➔ **"Separation of Concerns"**

- **Example:** Stepwise Linear Regression

User Script

```
X = read('features.csv')
Y = read('labels.csv')
[B,S] = steplm(X, Y,
  icpt=0, reg=0.001)
write(B, 'model.txt')
```

Built-in Functions

```
m_steplm = function(...) {
  while( continue ) {
    parfor( i in 1:n ) {
      if( !fixed[1,i] ) {
        Xi = cbind(Xg, X[,i])
        B[,i] = lm(Xi, y, ...)
    } }
    # add best to Xg
    # (AIC)
} }
```

Feature Selection

```
m_lm = function(...) {
  if( ncol(X) > 1024 )
    B = lmCG(X, y, ...)
  else
    B = lmDS(X, y, ...)
}
```

ML Algorithms

```
m_lmCG = function(...) {
  while( i<maxi&nr2>tgt ) {
    q = (t(X) %*% (X %*% p))
      + lambda * p
    beta = ... }
}
```

```
m_lmDS = function(...) {
  l = matrix(reg,ncol(X),1)
  A = t(X) %*% X + diag(l)
  b = t(X) %*% y
  beta = solve(A, b) ...}
```

Linear Algebra Programs

Facilitates optimization across data science lifecycle tasks

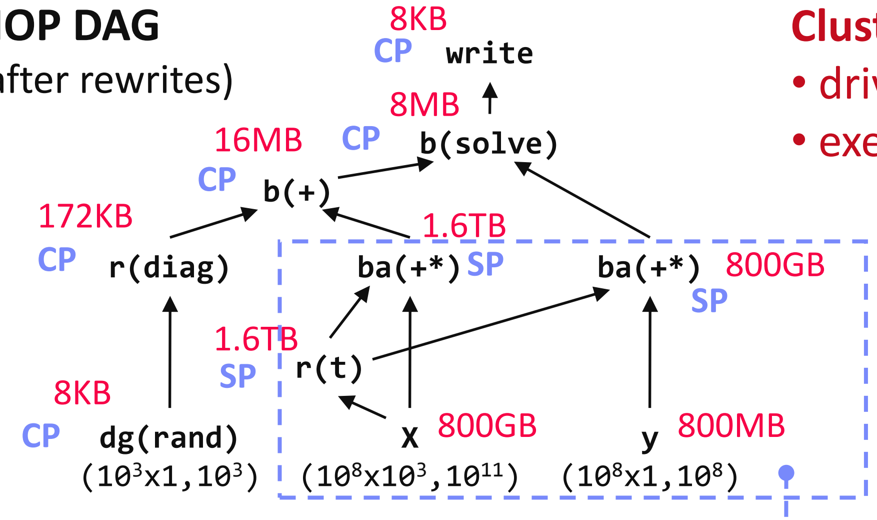
Basic HOP and LOP DAG Compilation

LinregDS (Direct Solve)

```
X = read($1);
y = read($2);
intercept = $3;
lambda = 0.001;
...
if( intercept == 1 ) {
  ones = matrix(1, nrow(X), 1);
  X = append(X, ones);
}
I = matrix(1, ncol(X), 1);
A = t(X) %*% X + diag(I)*lambda;
b = t(X) %*% y;
beta = solve(A, b);
...
write(beta, $4);
```

Scenario:
X: $10^8 \times 10^3$, 10^{11}
y: $10^8 \times 1$, 10^8

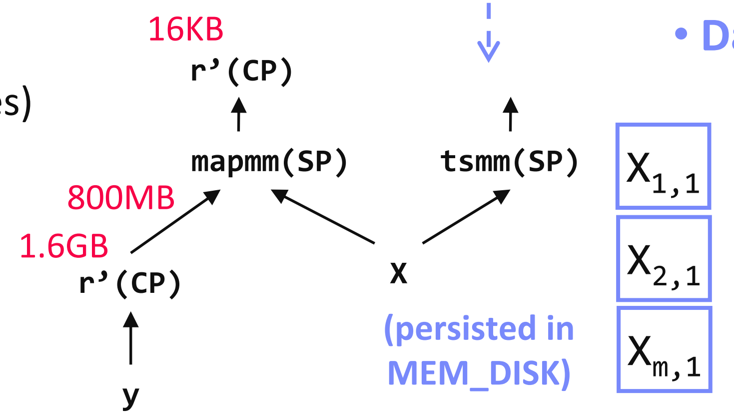
HOP DAG
(after rewrites)



Cluster Config:

- driver mem: 20 GB
- exec mem: 60 GB

LOP DAG
(after rewrites)



➔ Distributed Matrices

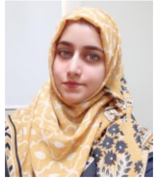
- Fixed-size matrix blocks
- Data-parallel operations

➔ Hybrid Runtime Plans:

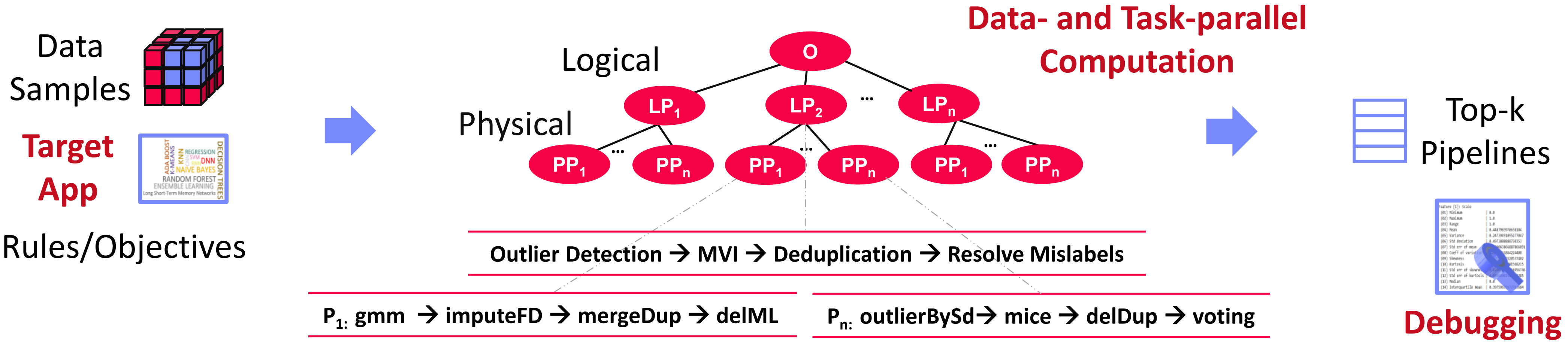
- Size propagation / memory estimates
- Integrated CP / Spark runtime
- Dynamic recompilation during runtime

Data Cleaning Pipelines [SIGMOD'24a]

[WIP] **WashHouse**: Data Cleaning Benchmark



- **Automatic Generation of Cleaning Pipelines**
  - Library of robust, parameterized **data cleaning primitives**,
  - **Enumeration of DAGs** of primitives & **hyper-parameter optimization** (evolutionary, HB)



University	Country
TU Graz	Austria
TU Graz	Austria
TU Graz	Germany
IIT	India
IIT	IIT
IIT	Pakistan
IIT	India
SIBA	Pakistan
SIBA	null
SIBA	null

Dirty Data

University	Country
TU Graz	Austria
TU Graz	Austria
TU Graz	Austria
IIT	India
IIT	India
IIT	India
IIT	India
SIBA	Pakistan
SIBA	Pakistan
SIBA	Pakistan

After **imputeFD(0.5)**

A	B	C	D
0.77	0.80	1	1
0.96	0.12	1	1
0.66	0.09	null	1
0.23	0.04	17	1
0.91	0.02	17	null
0.21	0.38	17	1
0.31	null	17	1
0.75	0.21	20	1
null	null	20	1
0.19	0.61	20	1
0.64	0.31	20	1

Dirty Data

A	B	C	D
0.77	0.80	1	1
0.96	0.12	1	1
0.66	0.09	17	1
0.23	0.04	17	1
0.91	0.02	17	1
0.21	0.38	17	1
0.31	0.29	17	1
0.75	0.21	20	1
0.41	0.24	20	1
0.19	0.61	20	1
0.64	0.31	20	1

After **MICE**

SliceLine for Model Debugging [SIGMOD'21b]

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

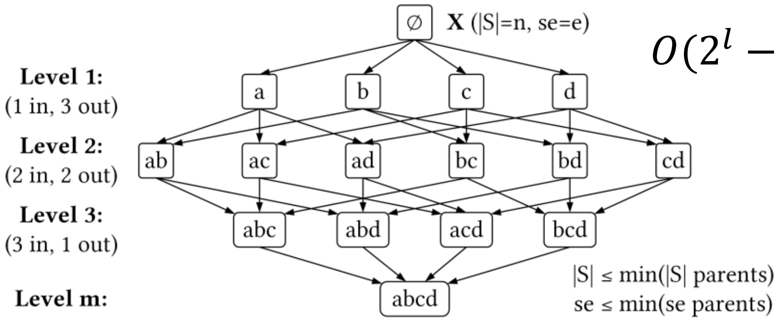
- **Problem Formulation**
  - **Intuitive slice scoring function**
  - Exact **top-k slice finding**
  - $|S| \geq \sigma \wedge sc(S) > 0,\ \alpha \in (0,1]$

$$sc = \alpha\left(\frac{\bar{e}(S)}{\bar{e}(X)} - 1\right) - (1-\alpha)\left(\frac{|X|}{|S|} - 1\right)$$

$$= \alpha\left(\frac{|X|}{|S|} \cdot \frac{\sum_{i=1}^{|S|} es_i}{\sum_{i=1}^{|X|} e_i} - 1\right) - (1-\alpha)\left(\frac{|X|}{|S|} - 1\right)$$

slice error **slice size**

- **Properties & Pruning**
  - Monotonicity of slice sizes, errors
  - **Upper bound sizes/errors/scores**
    → pruning & termination



$$O\left(2^l - \sum_{j=1}^{m} 2^{d_j} + l + m\right)$$

- **Linear-Algebra-based Slice Finding**
  - Recoded/binned matrix **X**, error vector e
  - **Vectorized implementation in linear algebra** (join & eval via sparse-sparse matmult)
  - Local and distributed task/data-parallel execution

Candidate Slices

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

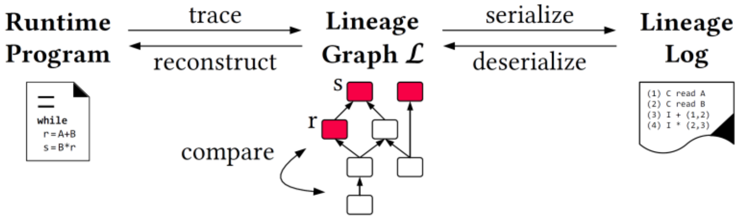
Data

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 2 & 0 \\ 0 & 2 & 0 \\ 2 & 0 & 1 \\ 0 & 2 & 0 \\ 1 & 1 & 1 \\ 2 & 0 & 1 \end{bmatrix}$$

== Level

Multi-level Lineage Tracing & Reuse [CIDR'20, SIGMOD'21a]

- **Lineage as Key Enabling Technique**
  - Trace lineage of ops (incl. non-determinism), dedup for loops/funcs
  - Model versioning, data reuse, incr. maintenance, autodiff, debugging

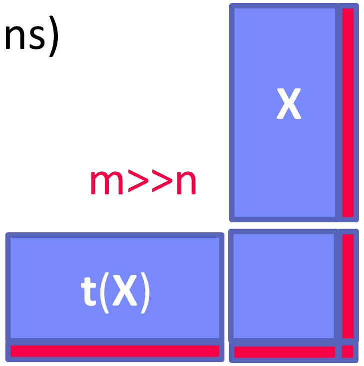


- **Full Reuse of Intermediates**
  - Before executing instruction, probe output lineage in cache `Map<Lineage, MatrixBlock>`
  - Cost-based/heuristic caching and eviction decisions (compiler-assisted)

```
for( i in 1:numModels )
  R[,i] = lm(X, y, lambda[i,], ...)
```

```
m_lmDS = function(...) {
  l = matrix(reg,ncol(X),1)
  A = t(X) %*% X + diag(l)
  b = t(X) %*% y
  beta = solve(A, b) ...}
```

- **Partial Reuse of Intermediates**
  - **Problem:** Often partial result overlap
  - Reuse partial results via dedicated rewrites (compensation plans)
  - Example: steplm

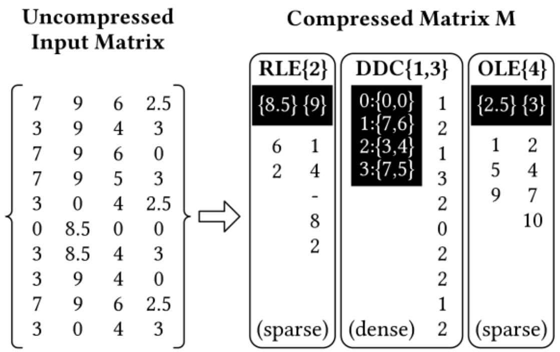



```
m_steplm = function(...) {
  while( continue ) {
    parfor( i in 1:n ) {
      if( !fixed[1,i] ) {
        Xi = cbind(Xg, X[,i])
        B[,i] = lm(Xi, y, ...)
    } }
    # add best to Xg (AIC)
} }
```

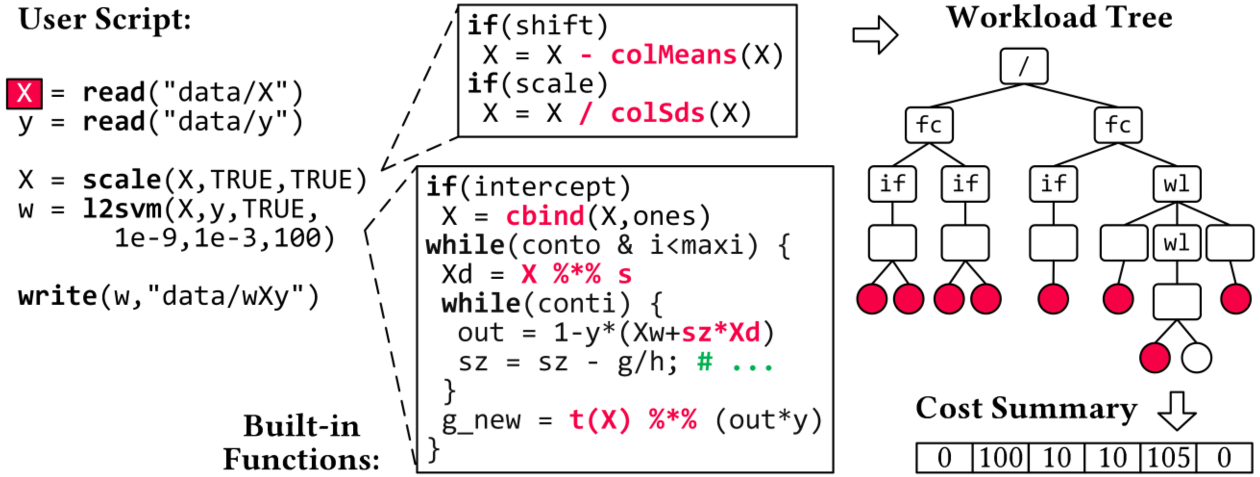
- **Next Steps:** multi-backend, unified mem mgmt

Compressed Linear Algebra Extended [PVLDB'16a, VLDBJ'18, SIGMOD'23a]

- **Lossless Matrix Compression**
  - **Improved general applicability** (adaptive compression time, new compression schemes, new kernels, intermediates, workload-aware)
  - Sparsity → **Redundancy exploitation** (data redundancy, structural redundancy)

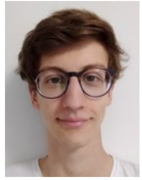


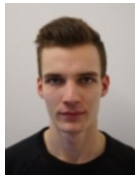
- **Workload-aware Compression**
  - Workload summary → compression
  - Compressed Representation → execution planning

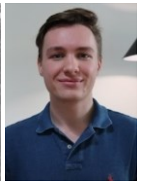


- **Next Steps**
  - Frame compression, compressed I/O
  - Compressed feature transformations
  - Morphing of compressed data

Federated Learning [SIGMOD'21c]

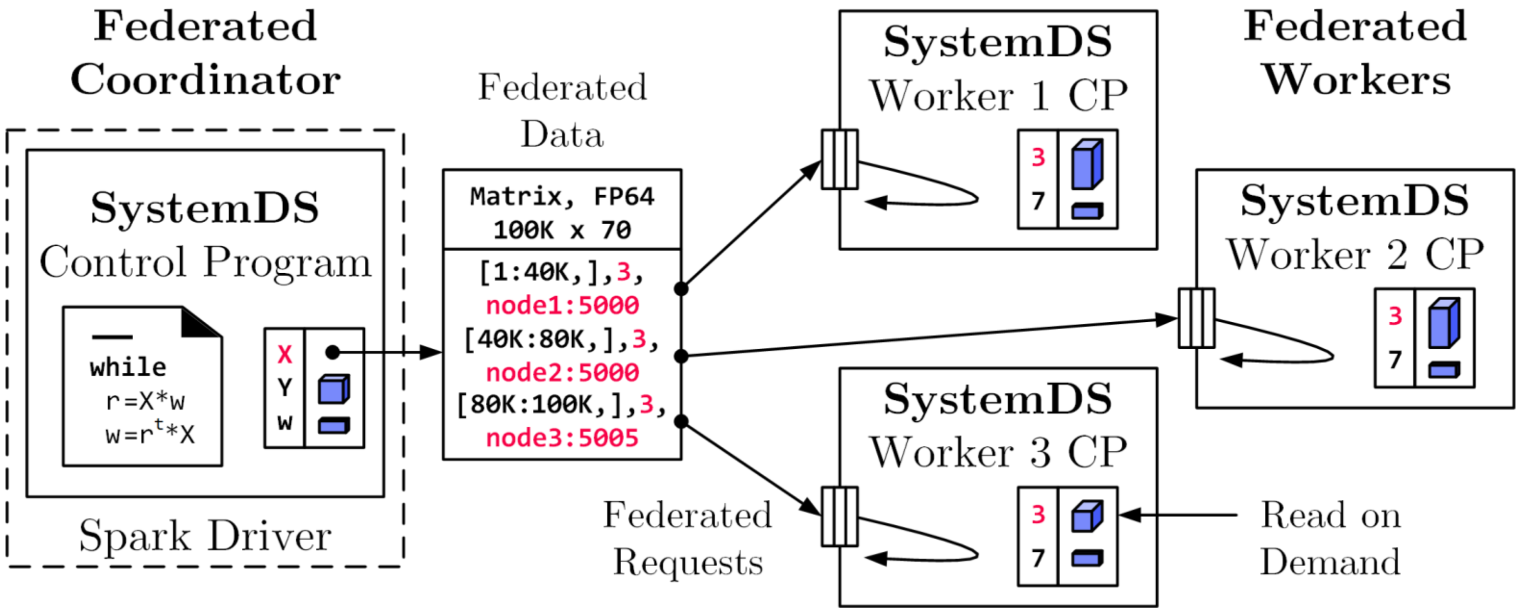







- **Federated Backend**
  - **Federated data** (matrices/frames) as meta data objects
  - **Federated linear algebra**, (and **federated parameter server**)

```
X = federated(addresses=list(node1, node2, node3),
  ranges=list(list(0,0), list(40K,70), ..., list(80K,0), list(100K,70)));
```



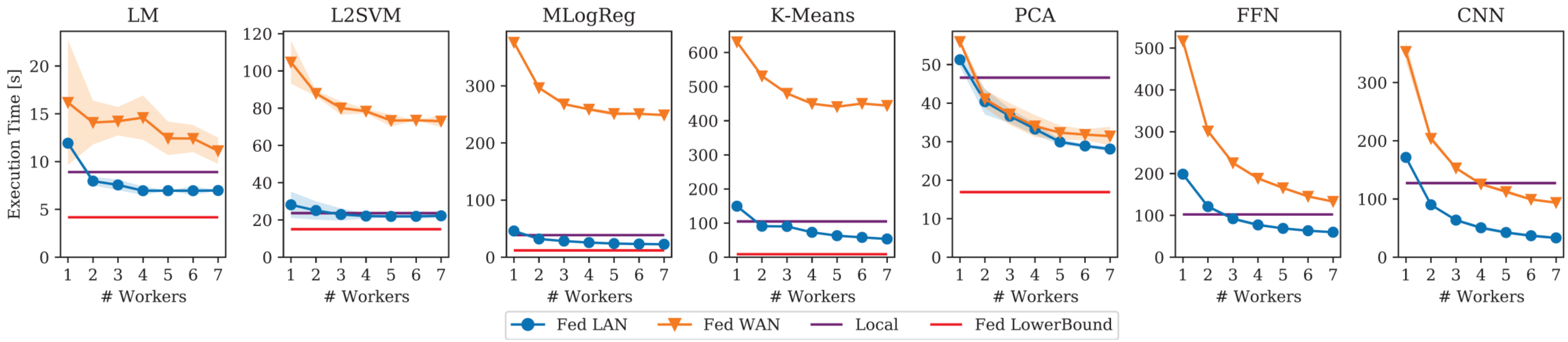
Federated Requests:
`READ, PUT, GET, EXEC_INST, EXEC_UDF, CLEAR`

➔ **Design Simplicity:**
(1) reuse instructions
(2) federation hierarchies

Federated Learning – Experiments

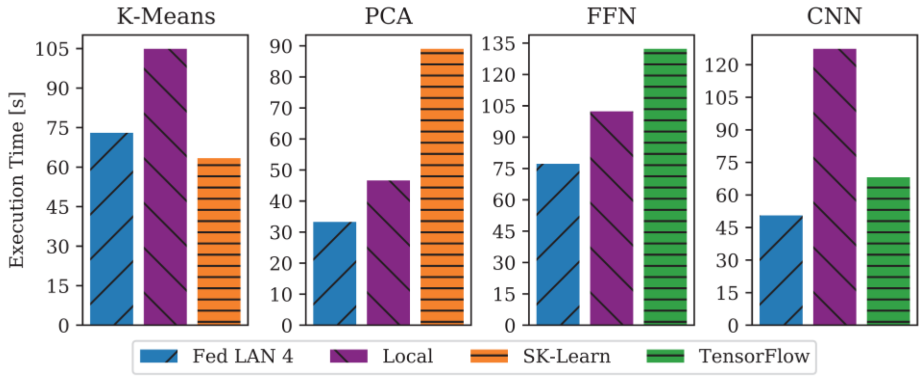
Reproducible Results

OPEN ACCESS



- **Workloads and Baselines**
  - **LM:** linear regression, lmCG
  - **L2SVM:** l2-regularized SVM
  - **MLogReg:** multinomial logreg
  - **K-Means:** Lloyd's alg. w/ K-Means++ init
  - **PCA:** principal component analysis
  - **FFN:** fully-connected feed-forward NN
  - **CNN:** convolutional NN

Comparisons w/ **Scikit-learn** and **TensorFlow**



Summary and Q&A

- **Course Goals**
  - **#1** Major data integration architectures
  - **#2** Key techniques for data integration and cleaning
  - **#3** Methods for large-scale data storage and analysis

- **Programming Projects**
  - Unique project in **Apache SystemDS** (teams or individuals), **or**
  - Exercise on **data engineering and ML pipeline**

- **Next Lectures**
  - **02 Data Warehousing, ETL, and SQL/OLAP** [Oct 26, **virtual only**]
  - **03 Message-oriented Middleware, EAI, and Replication** [Nov 02]

Thanks