Architecture of ML Systems
01 Introduction and Overview

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Agenda

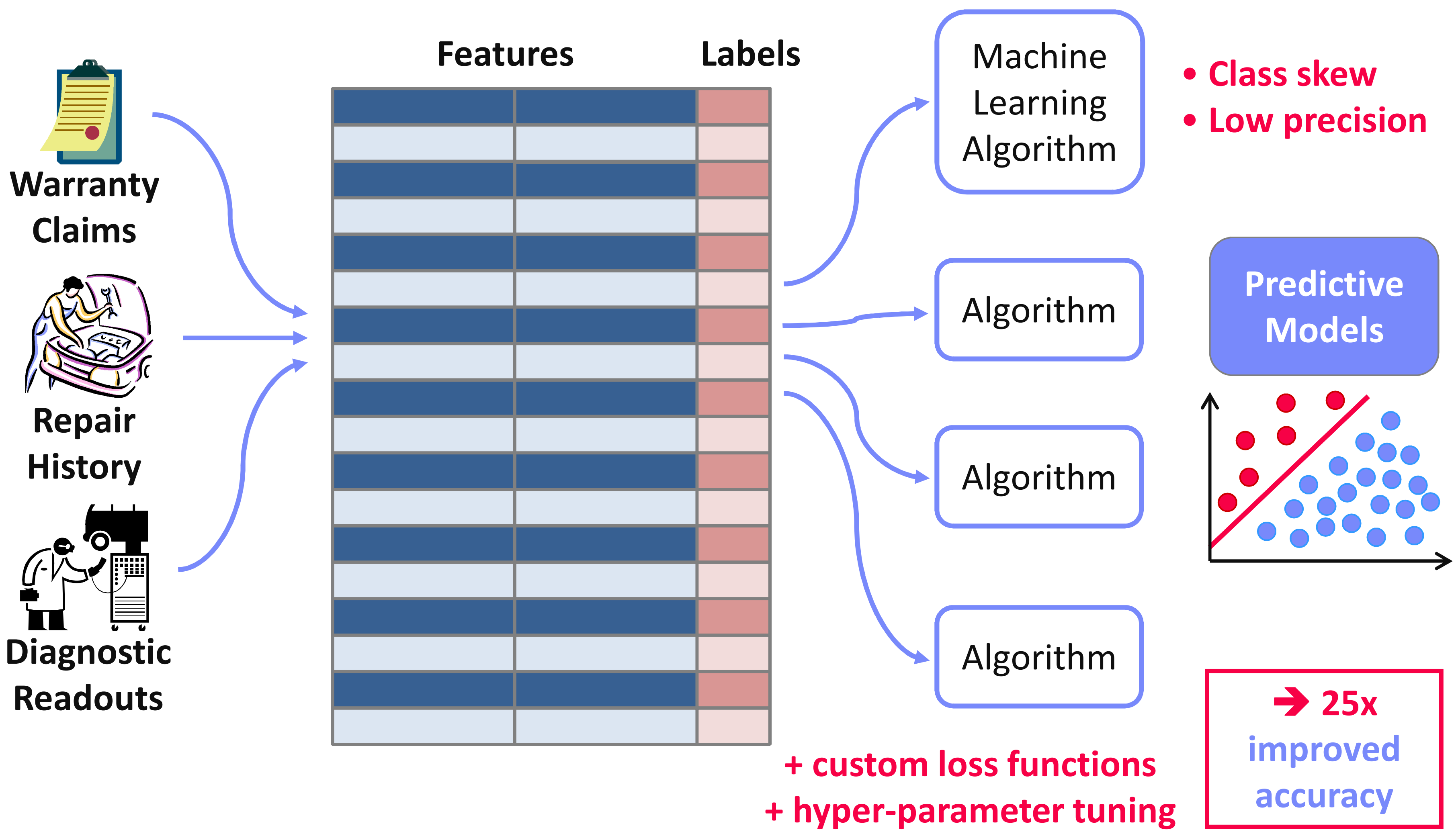
- **Motivation and Goals**
- **Data Management Group**
- **Course Organization**
- **Course Outline and Projects**
- **Overview Apache SystemML**

Motivation and Goals

Example ML Applications (Past)

- **Transportation / Space**
  - **Lemon car detection and reacquisition** (classification, seq. mining)
  - **Airport passenger flows from WiFi data** (time series forecasting)
  - Satellite senor analytics (regression and correlation)
- **Finance**
  - Water cost index based on various influencing factors (regression)
  - **Insurance claim cost per customer** (model selection, regression)
  - **Financial analysts survey correlation** (bivariate stats w/ new tests)
- **Health Care**
  - **Breast cancer cell grow from histopathology images** (classification)
  - **Glucose trends and warnings** (clustering, classification)
  - Emergency room diagnosis / patient similarity (classification, clustering)
  - Patient survival analysis and prediction (Cox regression, Kaplan-Meier)

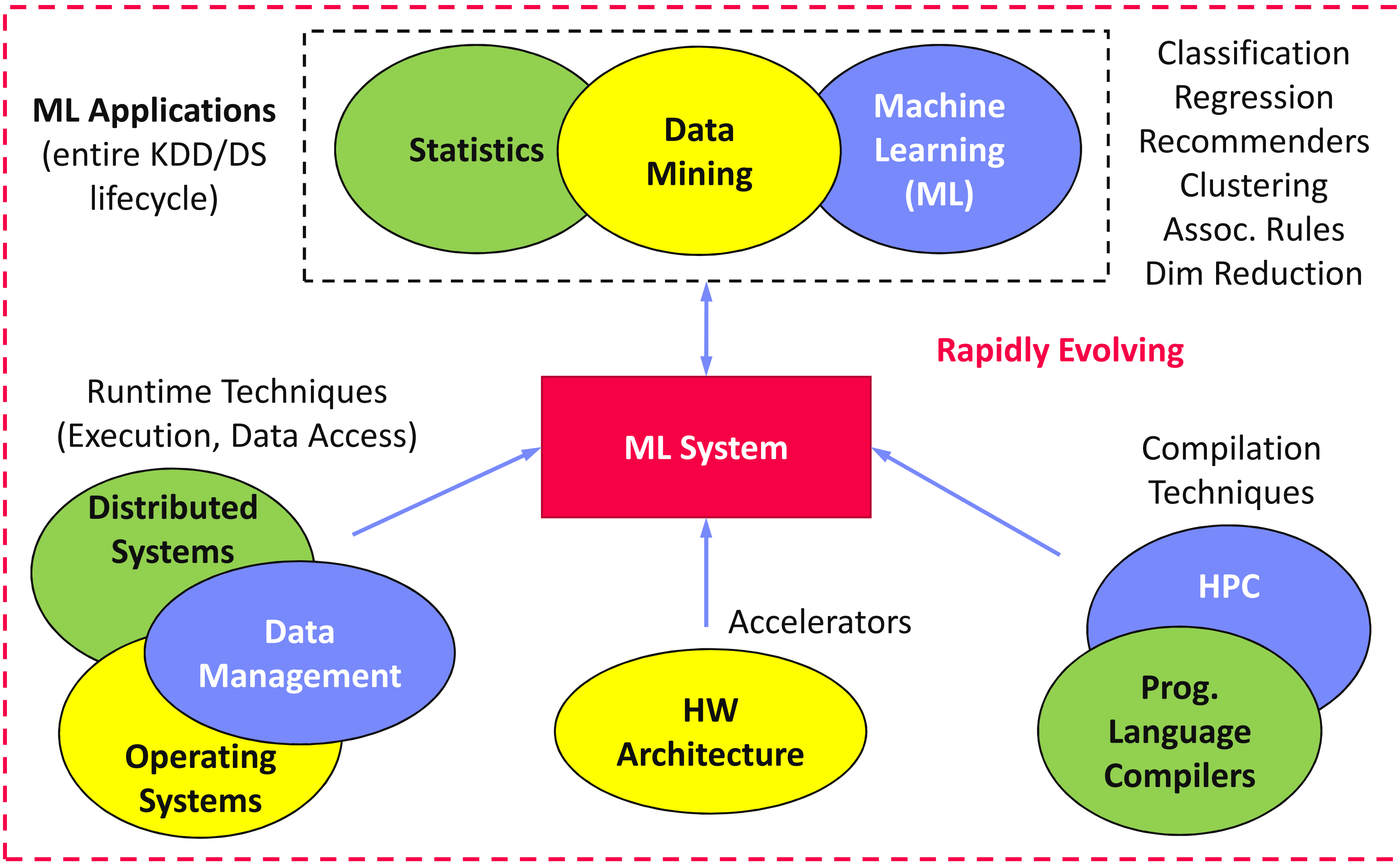
A Car Reacquisition Scenario



Example ML Applications (Past), cont.

- **Other Domains**
  - **Machine data: errors and correlation** (bivariate stats, seq. mining)
  - Smart grid: energy demand/RES supply, weather models (forecasting)
  - Visualization: dimensionality reduction into 2D (auto encoder)
- **Information Extraction**
  - **NLP contracts → rights/obligations** (classification, error analysis)
  - **PDF table recognition and extraction** (NMF clustering, custom)
  - OCR: optical character recognition (preprocessing, classification)
- **Algorithm Research** (+ various state-of-the art algorithms)
  - **User/product recommendations** via various forms of NMF
  - Localized, supervised metric learning (dim reduction and classification)
  - Learning word embeddings via orthogonalized skip-gram
  - Learning first-order rules for explainable classification

What is an ML System?



What is an ML System?

- **ML System**
  - **Narrow focus:** SW system that executes ML applications
  - **Broad focus:** Entire system (HW, compiler/runtime, ML application)

  → Trade-off **runtime/resources** vs **accuracy**

  → Early days: no standardizations, lots of different languages and system architectures, but many shared concepts

- **Course Objectives:**
  - Architecture and internals of modern (large-scale) ML systems
  - **#1** Understanding of characteristics → **better evaluation / usage**
  - **#2** Understanding of effective techniques → **build/extend ML systems**

Data Management Group

About Me

- **09/2018 TU Graz**, Austria
  - BMVIT endowed chair for data management
  - **Data management for data science**
    (ML systems internals, end-to-end data science lifecycle)
- **2012-2018 IBM Research – Almaden**, USA
  - Declarative large-scale machine learning
  - Optimizer and runtime of **Apache SystemML**
- **2011 PhD TU Dresden**, Germany
  - Cost-based optimization of integration flows
  - Systems support for time series forecasting
  - In-memory indexing and query processing

https://github.com/tugraz-isds/systemds

DB group

Data Management Courses

- **SS: Databases / Databases 1 (DM)**
  - Data management from user/application perspective
  - VU 1.5/1.5 (4 ECTS), and VU 1/1 (3 ECTS)
- **SS: Architecture of ML Systems (AMLS)**
  - Internals of machine learning systems
  - VU 2/1 (5 ECTS), master, github.com/tugraz-isds/systemds

- **WS: Data Integration and Large-Scale Analysis (DIA)**
  - Distributed data and information systems
  - VU 2/1 (5 ECTS), bachelor/master
- **WS: Architecture of Database Systems (ADBS)**
  - Internals of database management systems
  - VU 2/1 (5 ECTS), master

Course Organization

Basic Course Organization

- **Staff**
  - Lecturer: Univ.-Prof. Dr.-Ing. Matthias Boehm, ISDS
  - Assistant: M. Tech. Arnab Phani, ISDS

- **Language**
  - Lectures and slides: **English**
  - Communication and examination: **English**/**German**

- **Course Format**
  - VU 2/1, **5 ECTS** (2x 1.5 ECTS + 1x 2 ECTS), master only
  - **Weekly lectures** (**start 12.15pm**, including **Q&A**), **attendance optional**
  - **Mandatory programming project** (2 ECTS)
  - **Recommended papers** for additional reading on your own

Course Logistics

- **Exam**
  - **Completed project** (merged PRs and project presentation)
  - **Final oral exam** (by appointment)
  - **Grading** (40% project, 60% exam)

- **Communication**
  - **Informal language** (first name is fine)
  - Please, **immediate feedback** (unclear content, missing background)
  - Newsgroup: news://news.tugraz.at/tu-graz.lv.amls (email for private issues)
  - Office hours: by appointment or after lecture

- **Website**
  - https://mboehm7.github.io/teaching/ss19_amls/index.htm
  - All course material (lecture slides, list of projects) and dates

Course Logistics, cont.

- **Open Source Projects**
  - Programming project in context of open source projects
    - SystemDS: https://github.com/tugraz-isds/systemds
    - SystemML: https://github.com/apache/systemml
    - Other open source projects possible, **but harder to merge PRs**
  - Commitment to **open source and open communication** (discussion on PRs, mailing list, etc)
  - **Remark:** Don't be afraid to ask questions / develop code in public

Course Outline

Part A-C: Architecture, Compiler, Runtime

A: Introduction

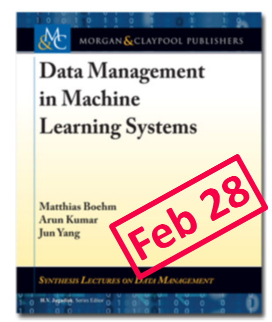
- **01 Introduction and Overview** [Mar 15]
- **02 Languages, Architectures, and System Landscape** [Mar 22]

B: Rewrites and Optimization

- **03 Size Inference, Rewrites, and Operator Selection** [Mar 29]
- **04 Operator Fusion and Runtime Adaptation** [Apr 05]

C: Execution Strategies

- **05 Data- and Task-Parallel Execution** [Apr 12]
- **06 Parameter Servers** [May 03]
- **07 Hybrid Execution and HW Accelerators** [May 10]



Part D-F: Data Access and ML Lifecycle

D: Data Storage and Access

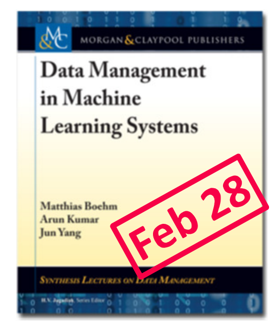
- **08 Formats, Caching, Partitioning, and Indexing** [May 17]
- **09 Lossy and Lossless Compression** [May 24]

E: ML Lifecycle Systems

- **10 Data Acquisition, Cleaning, and Preparation** [Jun 07]
- **11 Model Selection and Management** [Jun 14]
- **12 Model Deployment and Serving** [Jun 21]

F: Wrap-Up

- **14 Project Presentations, Conclusions, Q&A** [Jun 28]



Project Overview

- **Team**
  - Individuals or two-person teams (w/ clearly separated responsibilities)
- **Objectives**
  - Non-trivial feature in an open source ML system (**2 ECTS → 50 hours**)
  - OSS processes: Break down into 3-7 tasks, code/tests/docs, PR per task, code review, incorporate review comments, etc
- **Target Systems**
  - Preferred: **SystemDS**, or **Apache SystemML**
  - Other options: Julia, TensorFlow, PyTorch, <your_favorite_project>
- **Timeline**
  - **Mar 22:** List of projects and discussions
  - **Apr 05:** Project selection
  - Last lecture: 5-10min **project presentation**, including demo!

Example Projects

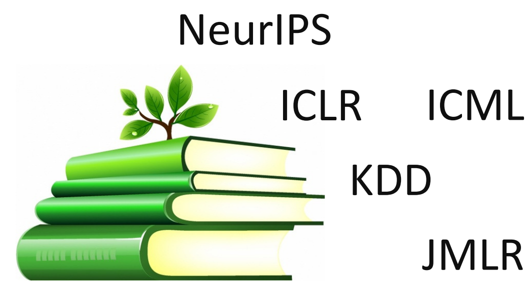
- **#1: Auto Differentiation**
  - Implement auto differentiation for deep neural networks
  - Integrate auto differentiation framework in compiler or runtime
- **#2: Sparsity-Aware Optimization of Matrix Product Chains**
  - Integrate sparsity estimators into DP algorithm
  - Extend DP algorithm for DAGs and other operations
- **#3 Parameter Server Update Schemes**
  - New PS update schemes: e.g., stale-synchronous, Hogwild!
  - Language and local/distributed runtime extensions
- **#4 Extended I/O Framework for Other Formats**
  - Implement local readers/writers for NetCDF, HDF5, libsvm, and/or Arrow
- **#5: LLVM Code Generator**
  - Extend codegen framework by LLVM code generator
  - Native vector library, native operator skeletons, JNI bridge

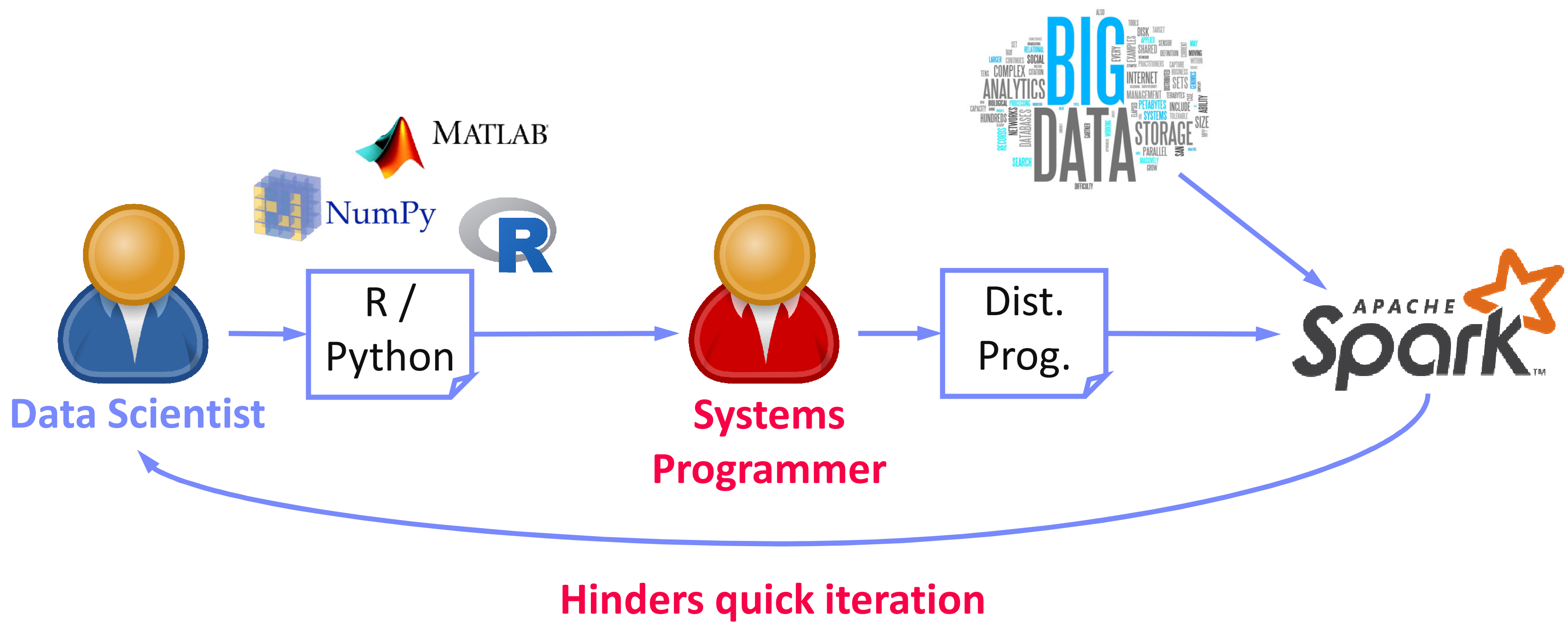
Overview Apache SystemML

Declarative Large-Scale Machine Learning

Common Large-Scale ML Challenges

- **#1 Custom ML Algorithms**
  - Huge diversity of existing ML algorithms
  - Cutting- / bleeding-edge algorithms
  - Domain-specific extensions init/loss





Common Large-Scale ML Challenges

- **#1 Custom ML Algorithms**
  - Huge diversity of existing ML algorithms
  - Cutting- / bleeding-edge algorithms
  - Domain-specific extensions init/loss

- **#2 Changing Environment**
  - Sample vs large-scale datasets (data size)
  - Dense/sparse, #features (data characteristics)
  - Single-node vs cluster (cluster characteristics)

"Hellerstein's Inequality"

$$\frac{\Delta env}{\Delta t} \gg \frac{\Delta app}{\Delta t}$$

- **#3 Integration and Deployment**
  - Data preparation and feature engineering
  - **Batch** and mini-batch training/scoring
  - Low-latency scoring (streaming)
  - Scale-up, **scale-out**, GPUs (hardware)

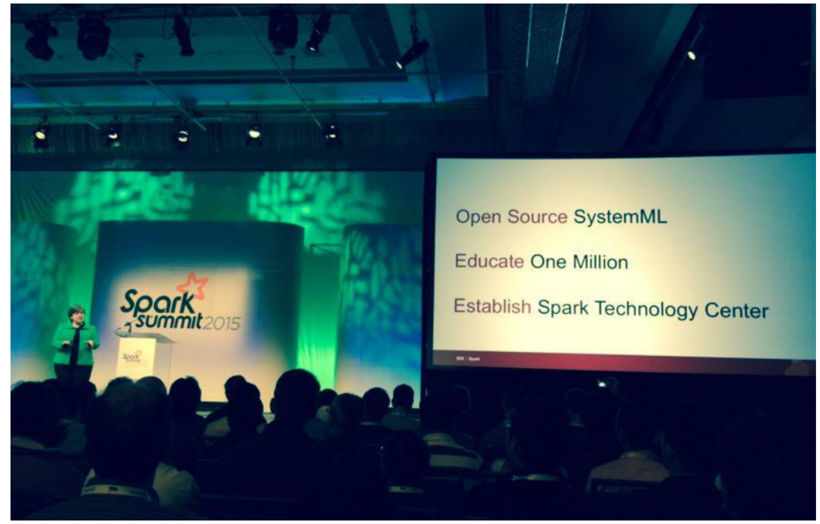
R / Python

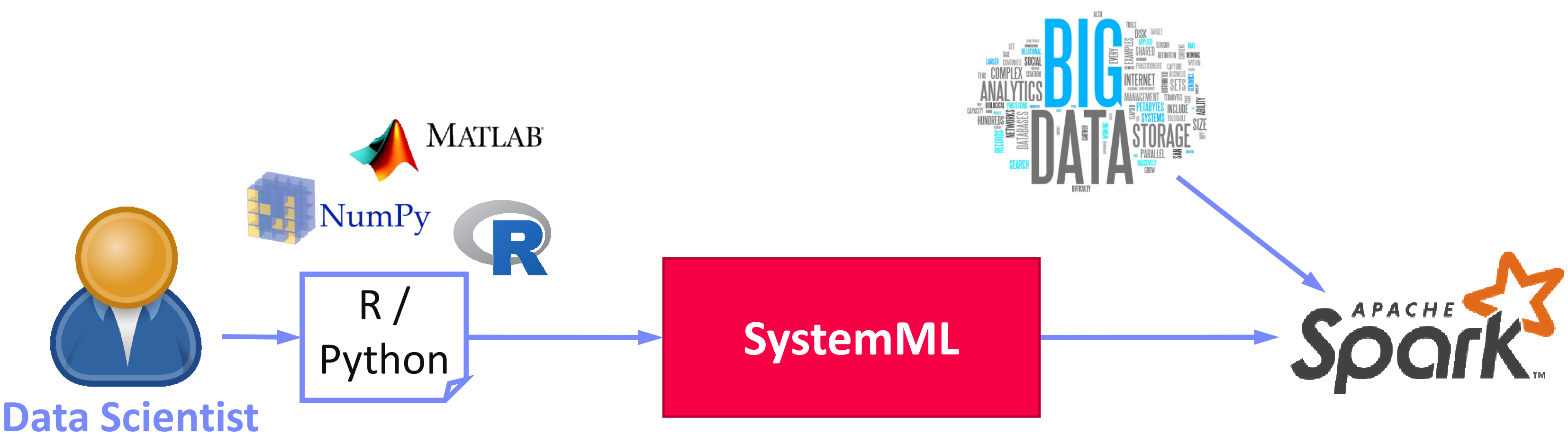
"Write Once, Run Anywhere"

Apache SystemML

Apache SystemML™

05/2017 Apache Top-Level Project
11/2015 Apache Incubator Project
08/2015 Open Source Release
01/2012 Integration in IBM BigInsights
01/2010 Project Kickoff





Example: Linear Regression Conjugate Gradient

Note:
#1 Data Independence
#2 Implementation-Agnostic Operations

```
X = read($1); # n x m matrix
y = read($2); # n x 1 vector
maxi = 50; lambda = 0.001;
intercept = $3;
...
r = -(t(X) %*% y);
norm_r2 = sum(r * r); p = -r;
w = matrix(0, ncol(X), 1); i = 0;
while(i<maxi & norm_r2>norm_r2_trgt)
{
   q = (t(X) %*% (X %*% p))+lambda*p;
   alpha = norm_r2 / sum(p * q);
   w = w + alpha * p;
   old_norm_r2 = norm_r2;
   r = r + alpha * q;
   norm_r2 = sum(r * r);
   beta = norm_r2 / old_norm_r2;
   p = -r + beta * p; i = i + 1;
}
write(w, $4, format="text");
```

Read matrices from HDFS

Compute initial gradient

Compute conjugate gradient

Compute step size

Update model and residuals

➔ "Separation of Concerns"

High-Level SystemML Architecture

APIs: Command line, JMLC, Spark MLContext, Spark ML, (20+ scalable algorithms)

DML Scripts

Language

Compiler

Runtime

DML (**D**eclarative **M**achine **L**earning **L**anguage)

Apache SystemML™

05/2017 Apache Top-Level Project
11/2015 Apache Incubator Project
08/2015 Open Source Release

[SIGMOD'15,'17,'19]
[PVLDB'14,'16a,'16b,'18]
[ICDE'11,'12,'15]
[CIDR'17]
[VLDBJ'18]
[DEBull'14]
[PPoPP'15]

In-Memory Single Node
(scale-up)

Hadoop or Spark Cluster
(scale-out)

In-Progress:

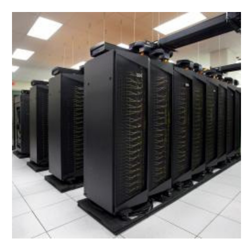
GPU

since 2014/16

Java

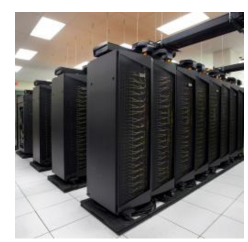
since 2012

hadoop



since 2010/11

APACHE Spark



since 2015

Basic HOP and LOP DAG Compilation

LinregDS (Direct Solve)

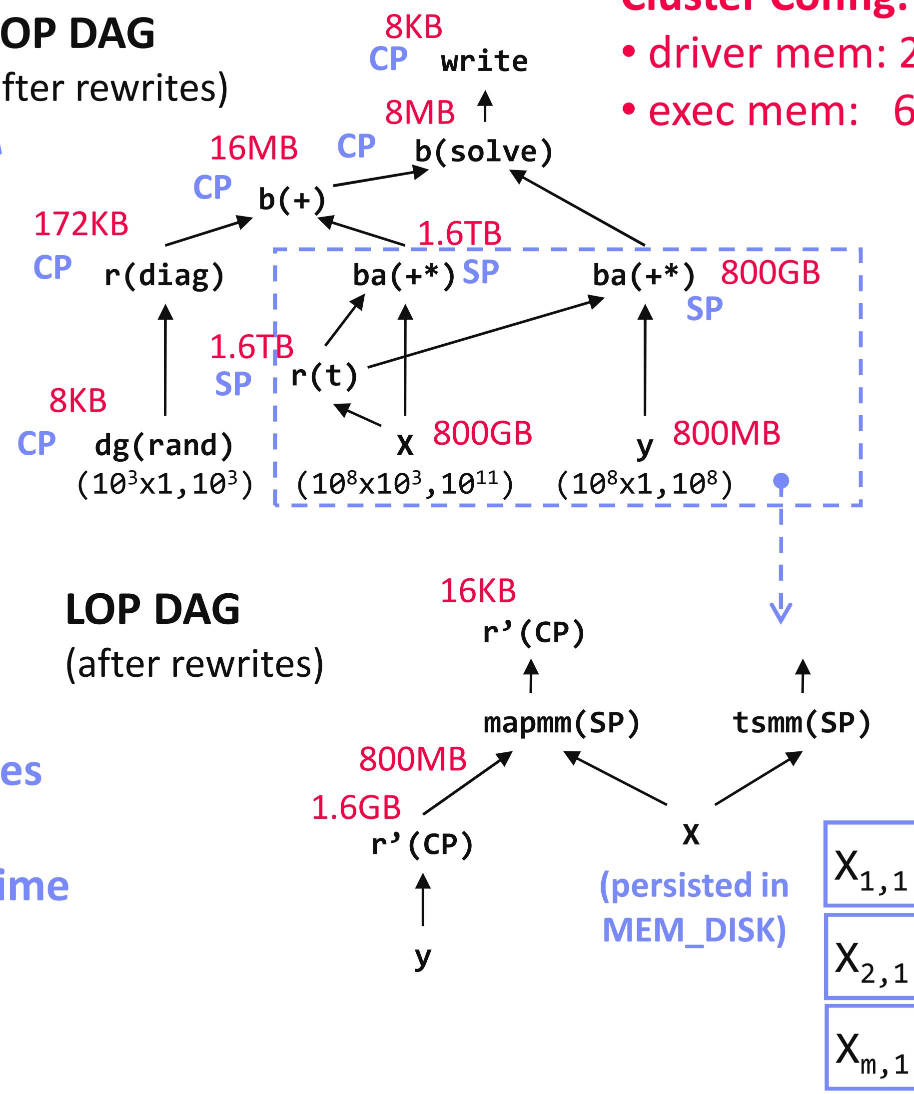
```
X = read($1);
y = read($2);
intercept = $3;
lambda = 0.001;
...
if( intercept == 1 ) {
  ones = matrix(1, nrow(X), 1);
  X = append(X, ones);
}
I = matrix(1, ncol(X), 1);
A = t(X) %*% X + diag(I)*lambda;
b = t(X) %*% y;
beta = solve(A, b);
...
write(beta, $4);
```

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

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

HOP DAG
(after rewrites)

LOP DAG
(after rewrites)



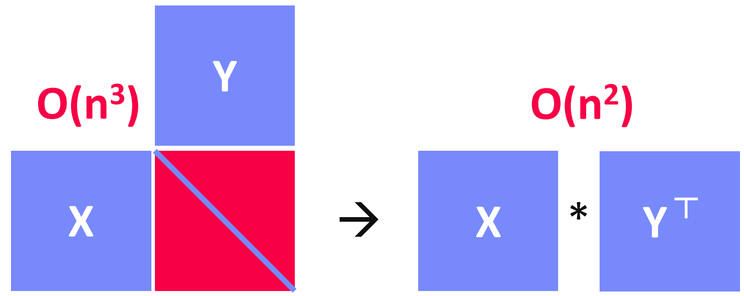
➔ Hybrid Runtime Plans:
- Size propagation / memory estimates
- Integrated CP / Spark runtime
- Dynamic recompilation during runtime

➔ Distributed Matrices
- Fixed-size (squared) matrix blocks
- Data-parallel operations

Static and Dynamic Rewrites

- **Example Static Rewrites** (size-indep.)
  - Common Subexpression Elimination
  - Constant Folding / Branch Removal / Block Sequence Merge
  - Static Simplification Rewrites
  - Right/Left Indexing Vectorization
  - For Loop Vectorization
  - Spark checkpoint/repartition injection

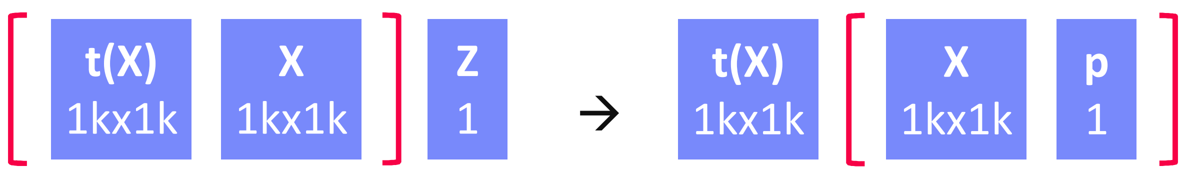
`trace(X%*%Y) → sum(X*t(Y))`



`sum(λ*X) → λ*sum(X)`
`sum(X+Y) → sum(X)+sum(Y)`

- **Example Dynamic Rewrites** (size-dep.)
  - Dynamic Simplification Rewrites
  - Matrix Mult Chain Optimization

`rowSums(X) → X, iff ncol(X)=1`
`sum(X^2) → X%*%t(X), iff ncol(X)=1`

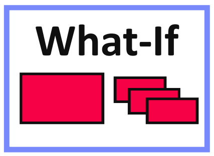


2,002 MFLOPs

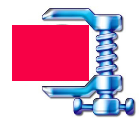
4 MFLOPs

Size propagation and sparsity estimation

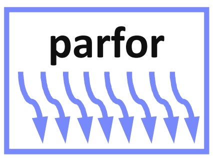
Selected Research Results



#3 Resource Optimization
for automatic resource provisioning
(SIGMOD'15)

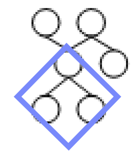


#4 Compressed Linear Algebra
(PVLDB'16,
SIGMOD Record'17,
VLDB Journal'18, CACM'19)



#2 Task-Parallel Parfor Loops
hybrid parallelization strategies
(PVLDB'14)

Apache SystemML™



#5 Optimizing Operator Fusion Plans
(PPoPP'15, CIDR'17,
PVLDB'18)

#1 SystemML's Optimizer
rewrites, operator selection, size propagation, memory estimates,
dynamic recompilation (DEBull'14)

ΣΠ

#6 Advanced Optimization
sum-product (CIDR'17),
sparsity estimation (SIGMOD'19)

GPU, meta learning, numerical stability,
parameter servers, etc

Lessons on Declarative Specification

- **L1: Importance of Data Independence and Logical Operations**
  - **Protection of investments** (adaptation to changing technology stack)
  - Simplification of **development** (especially libs) and **deployment**
  - Adaptation to **data/cluster characteristics**, **but** harder to optimize
  - Allows optimizations such as **resource op**, **compression** and **fusion**

- **L2: User Categories** (|Alg. Users| **>>** |Alg. Developers|)
  - Algorithm developers/researchers → Linear algebra
  - Algorithm users → ML libraries
  - Domain experts → ML tasks / AutoML

Alg. Users

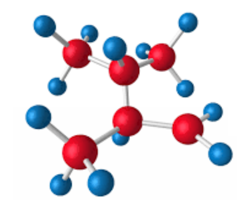
- **L3: Importance of Real Applications and Users**
  - Language for ML is wild west, **no standards** (PMML, PFA, ONNX)
  - **Unseen data and algorithm characteristics**
  - **Source of new APIs, features and optimizations**
  - Variety of apps / use cases → **balance generality / specialization**

Lessons on Data Model

- **L4:** Diversity of ML Algorithms / Applications
  - Broad range of algorithms (stats, ML, 2^{nd}-order optim)
  - Model choice often a **cost-benefit tradeoff**
  - Complex ML applications (rules, models, etc)
  - Opportunities of data programming and augmentation

- **L5: Users want Consolidated Lifecycle / Structured Data**
  - **Boundary crossing** for data integration, cleaning, feature engineering, training, and scoring is obstacle
  - **Heterogeneous input/output data**, with **structure**
  - Poor support for **provenance and model versioning**
  - APIs for embedded, low-latency scoring

TFX



Incl. Meta Data

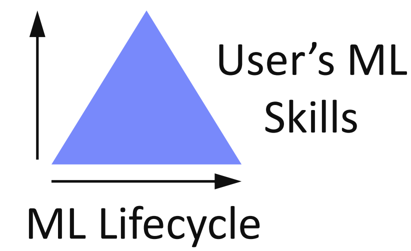
- **L6: Data Model very Difficult to Change**
  - Internal format extensions (e.g., dense/sparse, type) are major efforts
  - All combinations of data representations virtually impossible to test
  - **Deep integration of tensors** equivalent to new system

SystemDS™ Overview

https://github.com/tugraz-isds/systemds

- **Overview**
  - Open source **System** for end-to-end **D**ata **S**cience lifecycle
  - Data integration/cleaning, ML training, serving

- **Stack of Declarative Languages**
  - **Language hierarchy for tasks and users**
  - **Unified DSL and layering** for interop., reuse, opt
  - **Data model:** Heterogeneous tensors (w/ schema)



- **Key Features**
  - **#1: Data integration and cleaning**, outliers, feature engineering
  - **#2: ML model training**, tuning, validation, and **serving**
  - **#3: Data provenance and model versioning** → explainability
  - **#4: ML+Rules:** incorporate domain-expert and compliance rules
  - **Hybrid runtime plans**: local/distributed, data/task/PS/federated
  - **Horizontal and vertical optimization; sparsity exploitation**