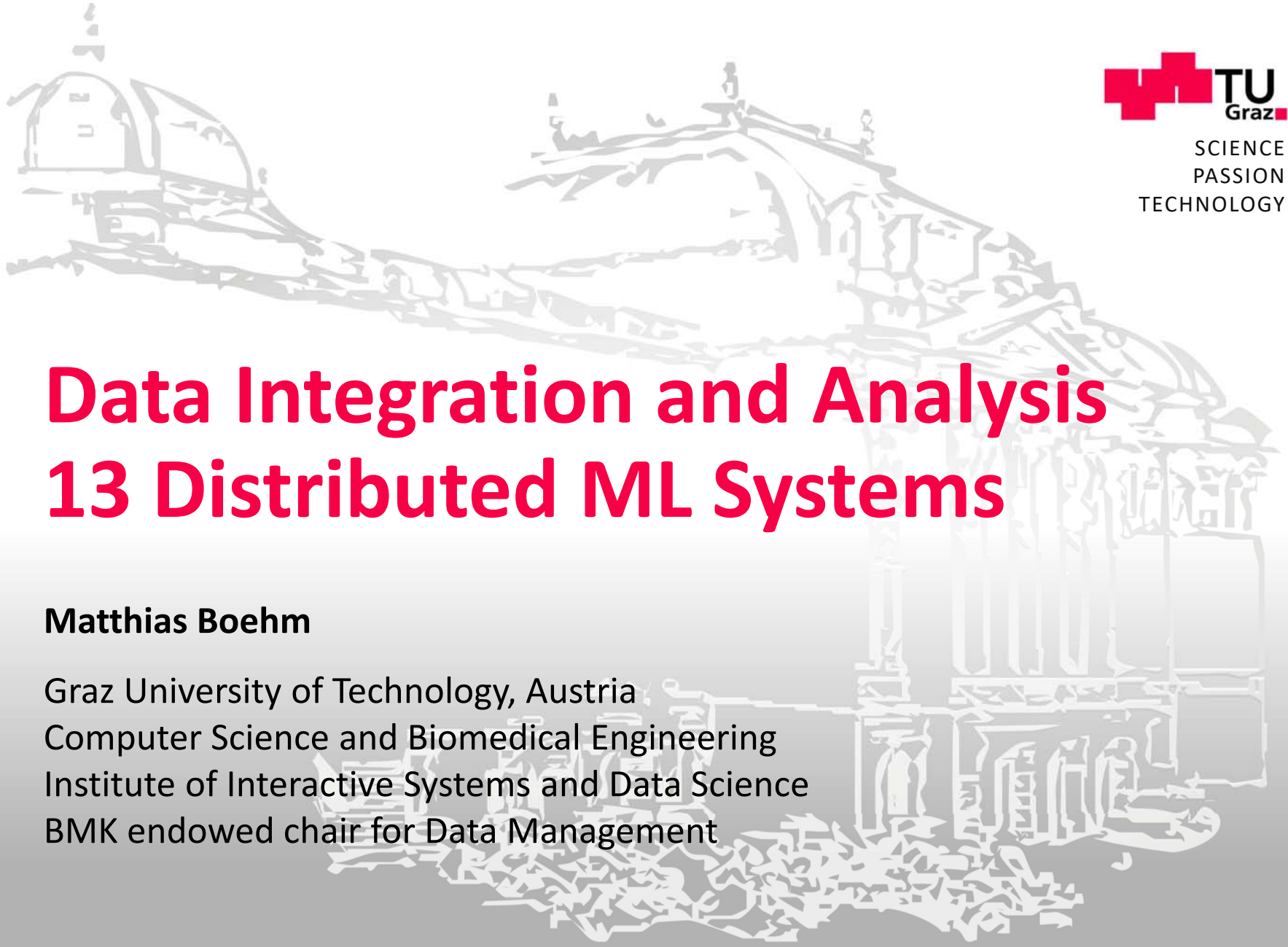

SCIENCE
PASSION
TECHNOLOGY

Data Integration and Analysis
13 Distributed ML Systems

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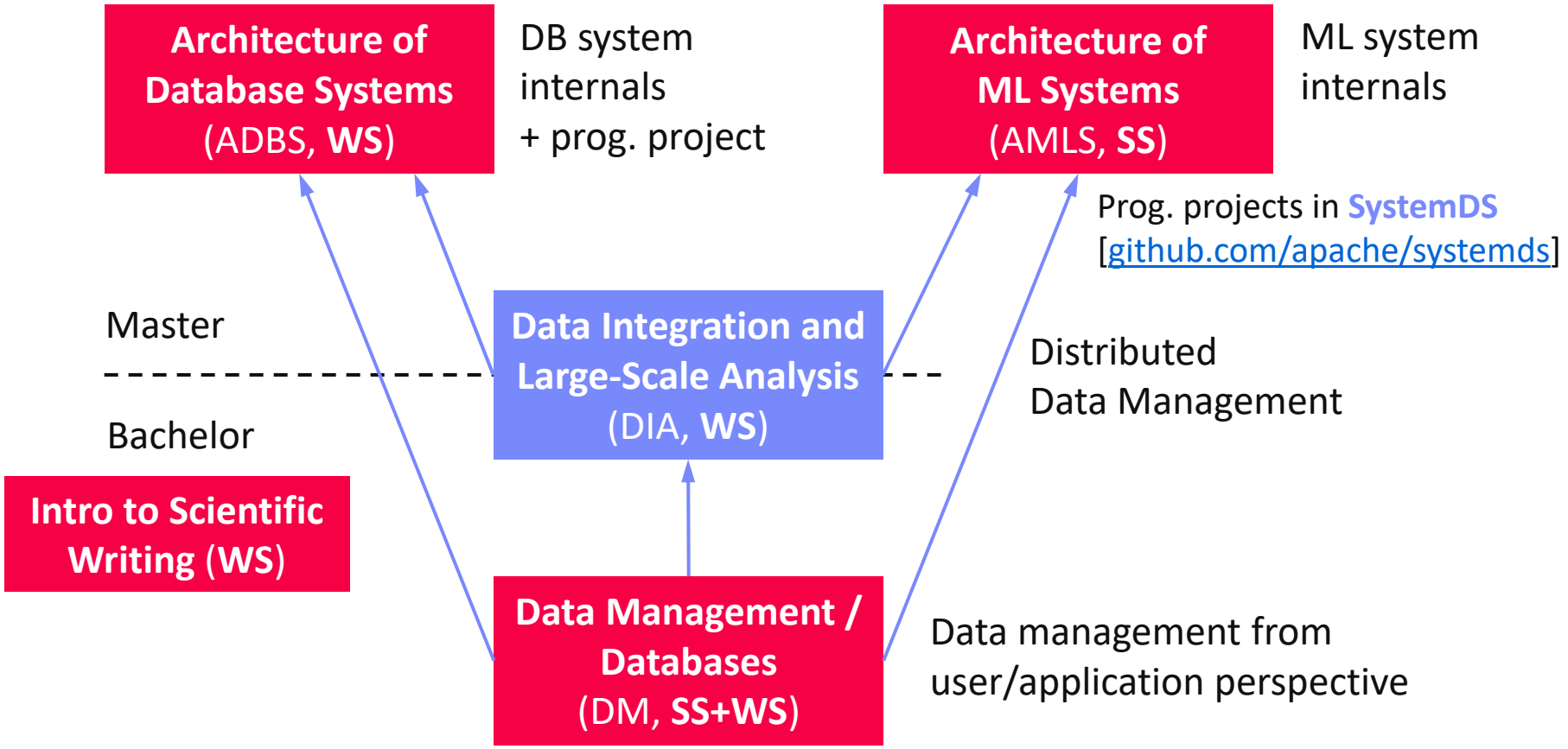
Last update: Jan 22, 2021

ISDS

Announcements/Org

- **#1 Video Recording**
  - Link in TeachCenter & TUbe (lectures will be public)
  - Optional attendance (independent of COVID)
- **#2 COVID-19 Restrictions** (HS i5)
  - Corona Traffic Light: **RED**
  - Temporarily webex lectures until end of semester
- **#3 Course Evaluation and Exam**
  - Evaluation period: **Dec 15 – Jan 31** (1/98)
  - Exam date: **Feb 08** (i13, 5.30pm-7.30pm) (53/76)
    - FFP2 masks provided by TU Graz

Data Management Courses

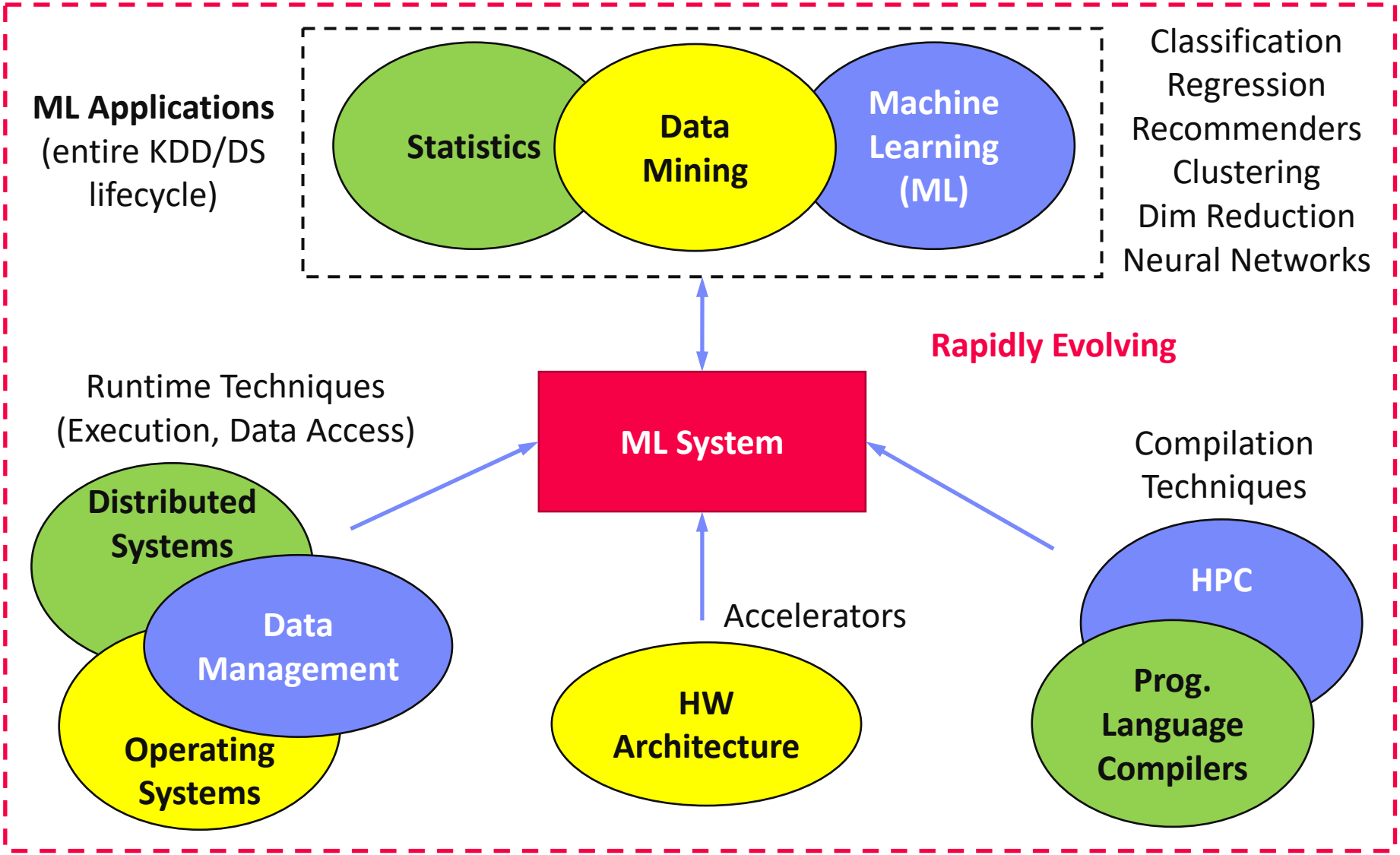


Agenda

- **Landscape of ML Systems**
- **Distributed Linear Algebra**
- **Distributed Parameter Servers**
- **Q&A and Exam Preparation**

Landscape of ML Systems

What is an ML System?

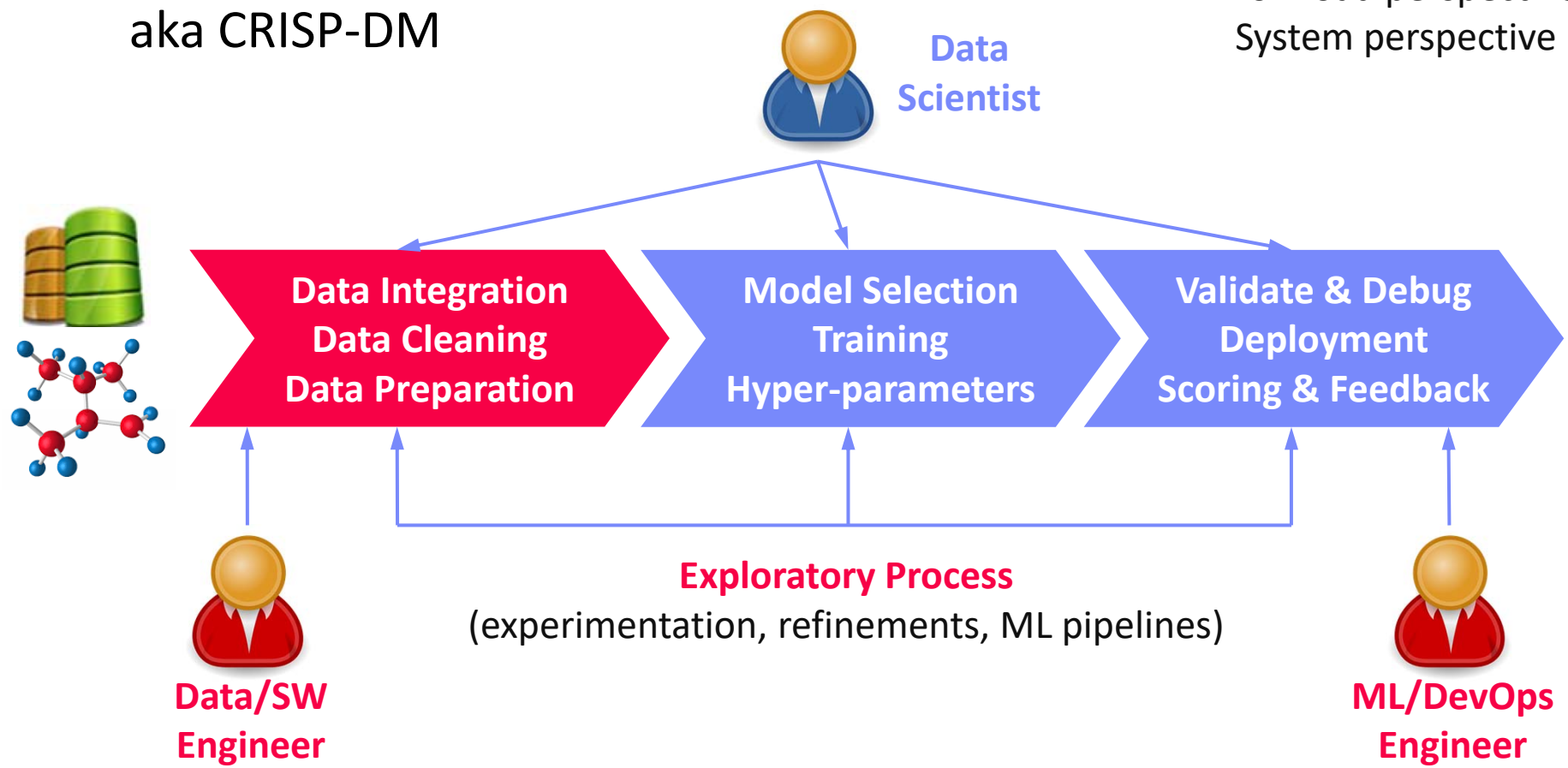


The Data Science Lifecycle

aka KDD Process

aka CRISP-DM

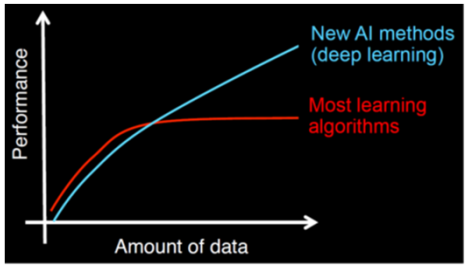
Data-centric View:
Application perspective
Workload perspective
System perspective



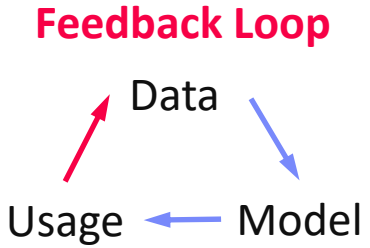
Driving Factors for ML

- **Improved Algorithms and Models**
  - Success across data and application domains (e.g., health care, finance, transport, production)
  - More complex models which leverage large data

[**Credit:** Andrew Ng'14]



- **Availability of Large Data Collections**
  - Increasing automation and monitoring ➔ data (simplified by cloud computing & services)
  - Feedback loops, data programming/augmentation



- **HW & SW Advancements**
  - Higher performance of hardware and infrastructure (cloud)
  - Open-source large-scale computation frameworks, ML systems, and vendor-provides libraries

Stack of ML Systems

Deployment & Scoring

Validation & Debugging

Training

Hyper-parameter Tuning

Model and Feature Selection

Data Programming & Augmentation

Data Preparation (e.g., one-hot, binning)

Data Integration & Data Cleaning

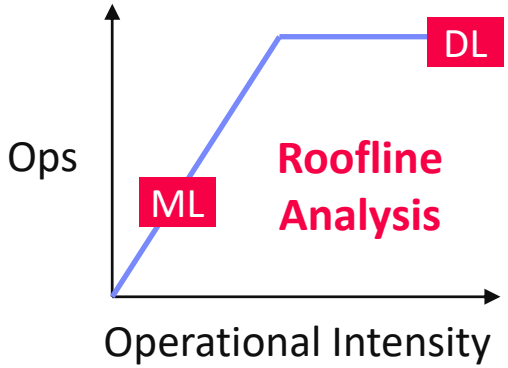
ML Apps & Algorithms	Supervised, unsupervised, RL linear algebra, libs, AutoML
Language Abstractions	Eager interpretation, lazy evaluation, prog. compilation
Fault Tolerance	Approximation, lineage, checkpointing, checksums, ECC
Execution Strategies	Local, distributed, cloud (data, task, parameter server)
Data Representations	Dense & sparse tensor/matrix; compress, partition, cache
HW & Infrastructure	CPUs, NUMA, GPUs, FPGAs, ASICs, RDMA, SSD/NVM

Improve **accuracy** vs. **performance** vs. **resource requirements**

➔ **Specialization & Heterogeneity**

Accelerators (GPUs, FPGAs, ASICs)

- **Memory- vs Compute-intensive**
  - **CPU:** dense/sparse, large mem, high mem-bandwidth, moderate compute
  - **GPU:** dense, small mem, slow PCI, very high mem-bandwidth / compute



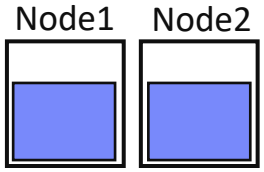
- **Graphics Processing Units (GPUs)**
  - Extensively used for deep learning training and scoring
  - NVIDIA Volta: "tensor cores" for 4x4 mm → 64 2B FMA instruction
- **Field-Programmable Gate Arrays (FPGAs)**
  - Customizable HW accelerators for prefiltering, compression, DL
  - Examples: Microsoft Catapult/Brainwave Neural Processing Units (NPUs)
- **Application-Specific Integrated Circuits (ASIC)**
  - Spectrum of chips: DL accelerators to computer vision
  - Examples: Google TPUs (64K 1B FMA), NVIDIA DLA, Intel NNP

Data Representation

- **ML- vs DL-centric Systems**
  - **ML:** dense and sparse matrices or tensors, different sparse formats (CSR, CSC, COO), frames (heterogeneous)
  - **DL:** mostly dense tensors, embeddings for NLP, graphs

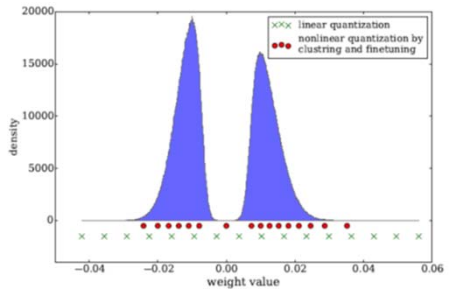
```
vec(Berlin) – vec(Germany)
+ vec(France) ≈ vec(Paris)
```

- **Data-Parallel Operations for ML**
  - Distributed matrices: RDD<MatrixIndexes,MatrixBlock>
  - Data properties: **distributed caching**, **partitioning**, **compression**



- **Lossy Compression ➔ Acc/Perf-Tradeoff**
  - Sparsification (reduce non-zero values)
  - Quantization (reduce value domain), learned
  - New data types: Intel Flexpoint (mantissa, exp)

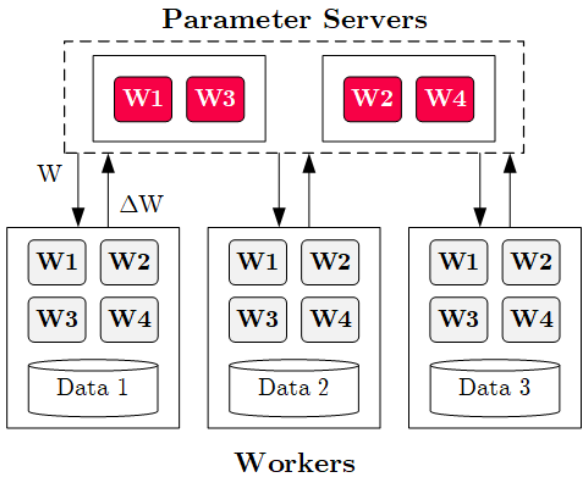
[**Credit:** Song Han'16]



Execution Strategies

- **Batch Algorithms: Data and Task Parallel**
  - Data-parallel operations
  - Different physical operators

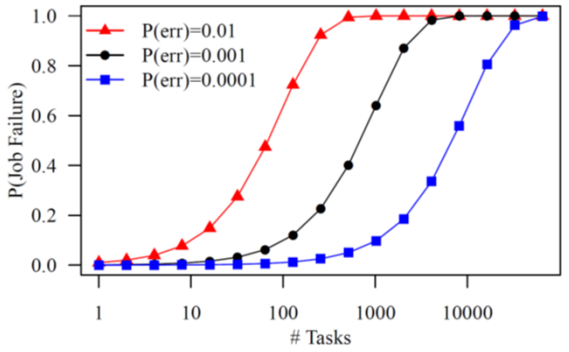
- **Mini-Batch Algorithms: Parameter Server**
  - Data-parallel and model-parallel PS
  - Update strategies (e.g., async, sync, backup)
  - Data partitioning strategies
  - Federated ML (trend 2018)



- **Lots of PS Decisions ➔ Acc/Perf-Tradeoff**
  - Configurations (#workers, batch size/param schedules, update type/freq)
  - Transfer optimizations: lossy compression, sparsification, residual accumulation, layer-wise all-reduce, gradient clipping, momentum corrections

Fault Tolerance & Resilience

- **Resilience Problem**
  - Increasing error rates at scale (soft/hard mem/disk/net errors)
  - Robustness for preemption
  - **Need cost-effective resilience**



- **Fault Tolerance in Large-Scale Computation**
  - Block replication (min=1, max=3) in distributed file systems
  - ECC; checksums for blocks, broadcast, shuffle
  - Checkpointing (MapReduce: all task outputs; Spark/DL: on request)
  - Lineage-based recomputation for recovery in Spark

- **ML-specific Schemes** (exploit app characteristics)
  - Estimate contribution from lost partition to avoid strugglers
  - Example: user-defined “compensation” functions

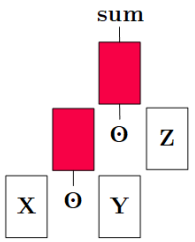
Language Abstractions

- **Optimization Scope**
  - **#1 Eager Interpretation** (debugging, no opt)
  - **#2 Lazy expression evaluation** (some opt, avoid materialization)
  - **#3 Program compilation** (full opt, difficult)

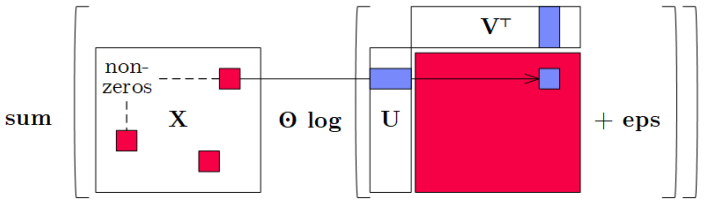
NumPy, R, PYTORCH, TensorFlow, MAHOUT, Apache Spark, Apache SystemML™, Apache SystemDS

- **Optimization Objective**
  - Most common: **min time** s.t. memory constraints
  - Multi-objective: **min cost** s.t. time, **min time** s.t. acc, **max acc** s.t. time

- **Trend: Fusion and Code Generation**
  - Custom fused operations
  - Examples: SystemDS, Weld, Taco, Julia, TF XLA, TVM, TensorRT



Sparsity-Exploiting Operator



ML Applications

- **ML Algorithms (cost/benefit – time vs acc)**
  - Unsupervised/supervised; batch/mini-batch; first/second-order ML
  - Mini-batch DL: variety of NN architectures and SGD optimizers
- **Specialized Apps: Video Analytics in NoScope (time vs acc)**
  - Difference detectors / specialized models for "short-circuit evaluation"

[**Credit:** Daniel Kang'17]

- **AutoML (time vs acc)**
  - Not algorithms but tasks (e.g., `doClassify(X, y)` + search space)
  - Examples: MLBase, Auto-WEKA, TuPAQ, Auto-sklearn, Auto-WEKA 2.0
  - AutoML services at Microsoft Azure, Amazon AWS, Google Cloud
- **Data Programming and Augmentation (acc?)**
  - Generate noisy labels for pre-training
  - Exploit expert rules, simulation models, rotations/shifting, and labeling IDEs (Software 2.0)

[**Credit:** Jonathan Tremblay'18]

Landscape of ML Systems

Apache SystemML™

#1 Language Abstraction

- Linear Algebra Programs
- Computation Graphs
- Algorithm Libraries
- Operator Libraries
- Collections
- Graphs
- Matrices
- Tensors
- Frames

#2 Execution Strategies

- Parameter Server (Modell-Parallel)
- Task-Parallel Constructs
- Data-Parallel Operations
- Local (single node)
- HW accelerators (GPUs, FPGAs, ASICs)
- Distributed

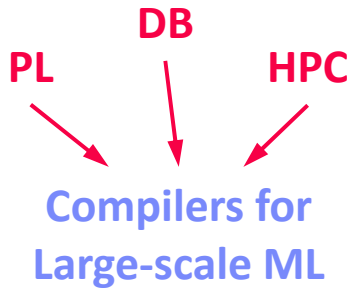
#3 Distribution

#4 Data Types

Distributed Linear Algebra

Linear Algebra Systems

- **Comparison Query Optimization**
  - Rule- and cost-based rewrites and operator ordering
  - Physical operator selection and query compilation
  - Linear algebra / other ML operators, DAGs, control flow, sparse/dense formats



- **#1 Interpretation** (operation at-a-time)
  - Examples: R, PyTorch, Morpheus [PVLDB'17]
- **#2 Lazy Expression Compilation** (DAG at-a-time)
  - Examples: RIOT [CIDR'09], Mahout Samsara [MLSystems'16]
  - Examples w/ control structures: Weld [CIDR'17], OptiML [ICML'11], Emma [SIGMOD'15]
- **#3 Program Compilation** (entire program)
  - Examples: SystemML [PVLDB'16], Julia Cumulon [SIGMOD'13], Tupleware [PVLDB'15]

Optimization Scope

```
1:  X = read($1); # n x m matrix
2:  y = read($2); # n x 1 vector
3:  maxi = 50; lambda = 0.001;
4:  intercept = $3;
5:  ...
6:  r = -(t(X) %*% y);
7:  norm_r2 = sum(r * r); p = -r;
8:  w = matrix(0, ncol(X), 1); i = 0;
9:  while(i<maxi & norm_r2>norm_r2_trgt)
10: {
11:    q = (t(X) %*% X %*% p)+lambda*p;
12:    alpha = norm_r2 / sum(p * q);
13:    w = w + alpha * p;
14:    old_norm_r2 = norm_r2;
15:    r = r + alpha * q;
16:    norm_r2 = sum(r * r);
17:    beta = norm_r2 / old_norm_r2;
18:    p = -r + beta * p; i = i + 1;
19: }
20: write(w, $4, format="text");
```

Linear Algebra Systems, cont.

Note: TF 2.0

[Dan Moldovan et al.: AutoGraph: Imperative-style Coding with Graph-based Performance. **SysML 2019**.]

- **Some Examples …**

Apache SystemML™

```
X = read("./X");
y = read("./y");
p = t(X) %*% y;
w = matrix(0,ncol(X),1);

while(...) {
  q = t(X) %*% X %*% p;
  ...
}
```

(Custom DSL w/ R-like syntax; program compilation)

MAHOUT

```
var X = drmFromHDFS("./X")
val y = drmFromHDFS("./y")
var p = (X.t %*% y).collect
var w = dense(...)
X = X.par(256).checkpoint()

while(...) {
  q = (X.t %*% X %*% p)
      .collect
  ...
}
```

(Embedded DSL in Scala; lazy evaluation)

TensorFlow (1.x)

```
# read via queues
sess = tf.Session()
# ...
w = tf.Variable(tf.zeros(...,
  dtype=tf.float64))

while ...:
  v1 = tf.matrix_transpose(X)
  v2 = tf.matmul(X, p)
  v3 = tf.matmul(v1, v2)
  q = sess.run(v3)
  ...
```

(Embedded DSL in Python; lazy [and eager] evaluation)

ML Libraries

- **Fixed algorithm implementations**
  - Often on top of existing linear algebra or UDF abstractions

Single-node Example (Python)

```
from numpy import genfromtxt
from sklearn.linear_model \
  import LinearRegression

X = genfromtxt('X.csv')
y = genfromtxt('y.csv')

reg = LinearRegression()
  .fit(X, y)
out = reg.score(X, y)
```

SparkML/
MLlib

Distributed Example (Spark Scala)

```
import org.apache.spark.ml
.regression.LinearRegression

val X = sc.read.csv('X.csv')
val y = sc.read.csv('y.csv')
val Xy = prepare(X, y).cache()

val reg = new LinearRegression()
  .fit(Xy)
val out reg.transform(Xy)
```

DL Frameworks

- **High-level DNN Frameworks**
  - Language abstraction for DNN construction and model fitting
  - Examples: Caffe, Keras


```
model = Sequential()
model.add(Conv2D(32, (3, 3),
padding='same',

input_shape=x_train.shape[1:]))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(
  MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
...
```

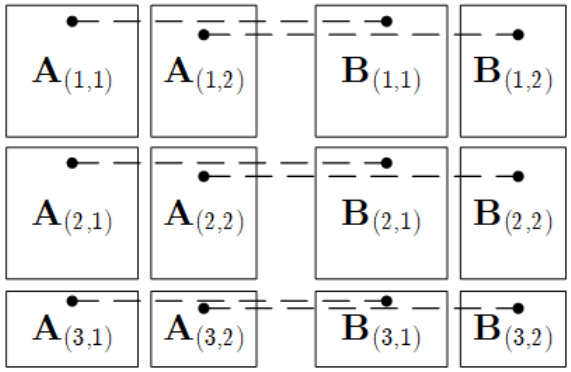
```
opt = keras.optimizers.rmsprop(
  lr=0.0001, decay=1e-6)

# Let's train the model using RMSprop
model.compile(loss='cat…_crossentropy',
  optimizer=opt,
  metrics=['accuracy'])

model.fit(x_train, y_train,
  batch_size=batch_size,
  epochs=epochs,
  validation_data=(x_test, y_test),
  shuffle=True)
```

- **Low-level DNN Frameworks**
  - Examples: TensorFlow, MXNet, PyTorch, CNTK

Distributed Matrix Operations

Elementwise Multiplication
(Hadamard Product)

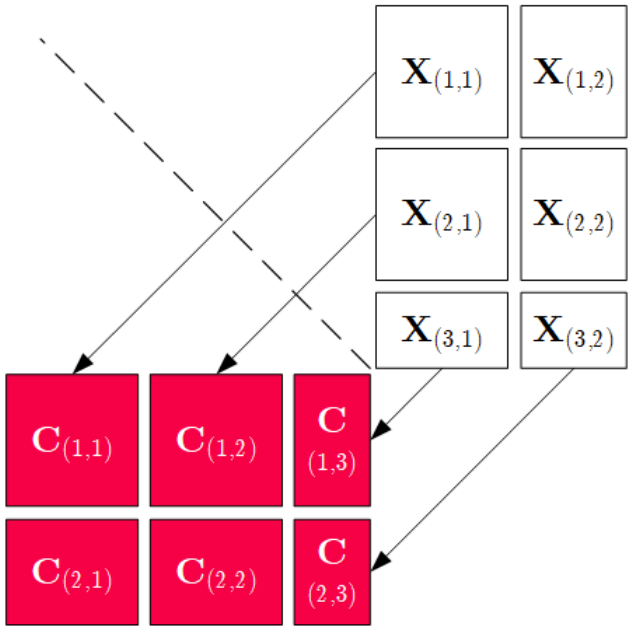
```
C = A * B
```



Note: also with row/column vector rhs

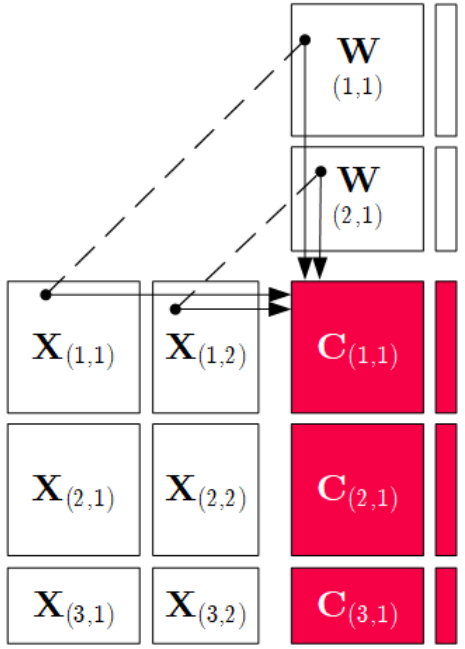
Transposition

```
C = t(X)
```



Matrix Multiplication

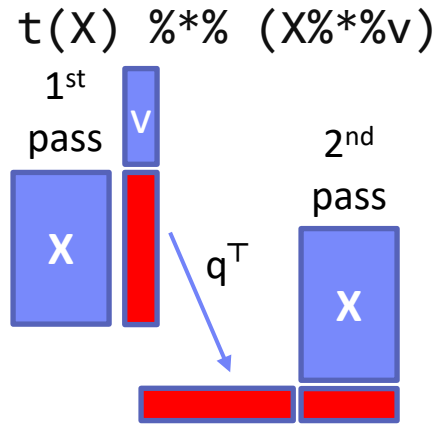
```
C = X %*% W
```



Note: 1:N join

Physical Operator Selection

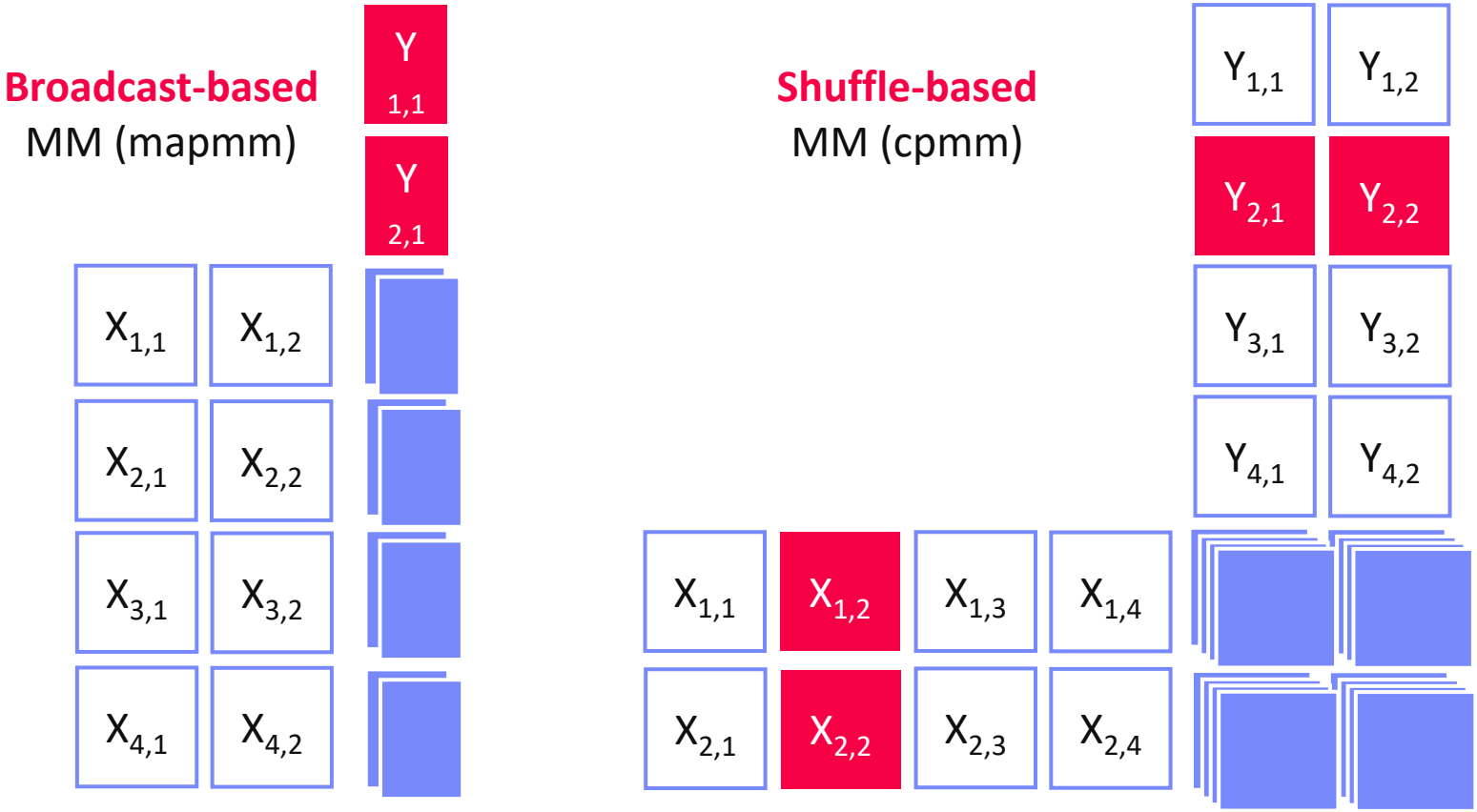
- **Common Selection Criteria**
  - Data and cluster characteristics (e.g., data size/shape, memory, parallelism)
  - Matrix/operation properties (e.g., diagonal/symmetric, sparse-safe ops)
  - Data flow properties (e.g., co-partitioning, co-location, data locality)
- **#0 Local Operators**
  - SystemML mm, tsmm, mmchain; Samsara/Mllib local
- **#1 Special Operators** (special patterns/sparsity)
  - SystemML **tsmm**, **mapmmchain**; Samsara AtA



- **#2 Broadcast-Based Operators** (aka broadcast join)
  - SystemML **mapmm**, **mapmmchain**
- **#3 Co-Partitioning-Based Operators** (aka improved repartition join)
  - SystemML **zipmm**; Emma, Samsara OpAtB
- **#4 Shuffle-Based Operators** (aka repartition join)
  - SystemML **cpmm**, **rmm**; Samsara OpAB

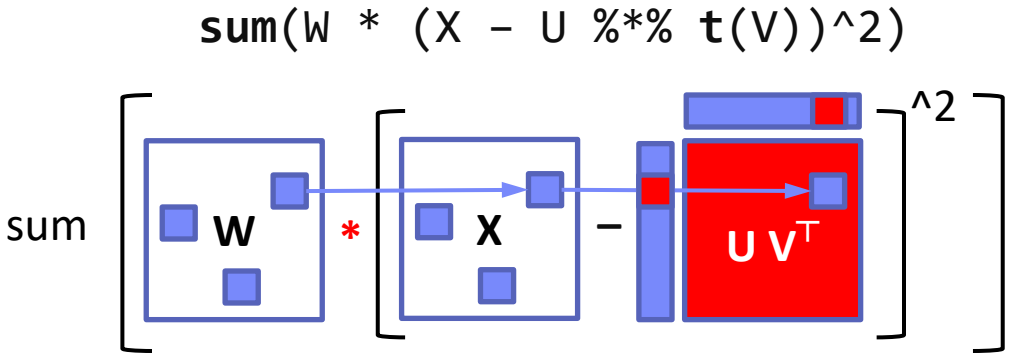
Physical Operator Selection, cont.

- **Examples Distributed MM Operators**

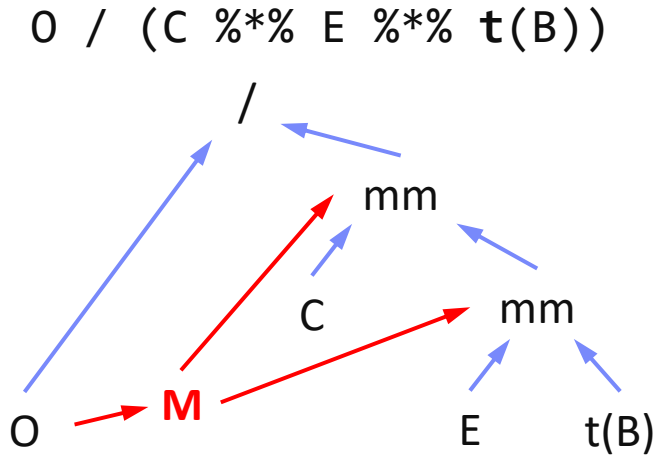


Sparsity-Exploiting Operators

- **Goal:** Avoid dense intermediates and unnecessary computation
- **#1 Fused Physical Operators**
  - E.g., SystemML [PVLDB'16] wsloss, wcemm, wdivmm
  - Selective computation over non-zeros of "sparse driver"

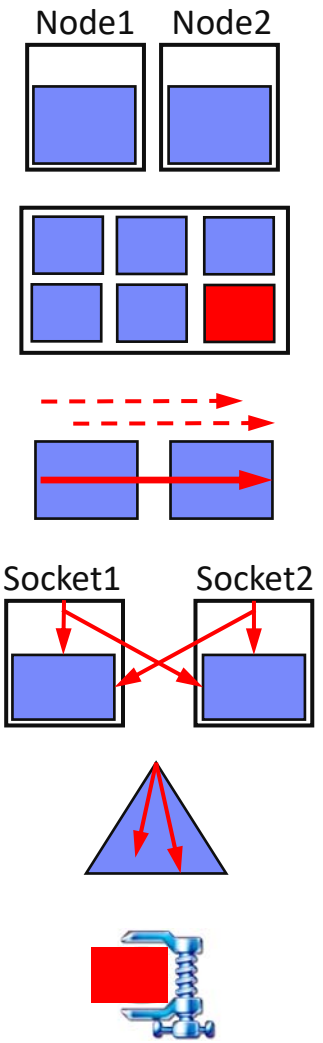


- **#2 Masked Physical Operators**
  - E.g., Cumulon MaskMult [SIGMOD'13]
  - Create mask of "sparse driver"
  - Pass mask to single masked matrix multiply operator



Overview Data Access Methods

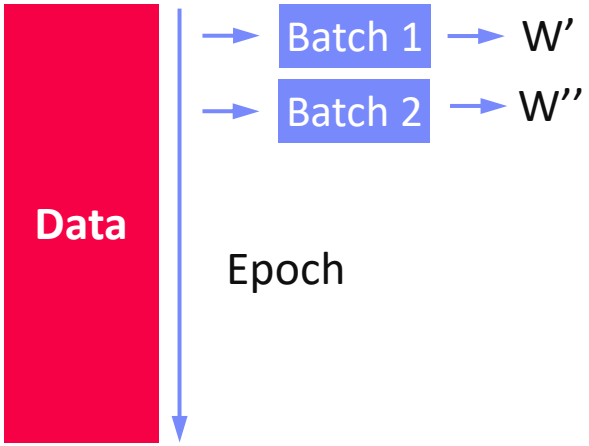
- **#1 (Distributed) Caching**
  - Keep read only feature matrix in (distributed) memory
- **#2 Buffer Pool Management**
  - Graceful eviction of intermediates, out-of-core ops
- **#3 Scan Sharing (and operator fusion)**
  - Reduce the number of scans as well as read/writes
- **#4 NUMA-Aware Partitioning and Replication**
  - Matrix partitioning / replication → data locality
- **#5 Index Structures**
  - Out-of-core data, I/O-aware ops, updates
- **#6 Compression**
  - Fit larger datasets into available memory



Distributed Parameter Servers

Background: Mini-batch ML Algorithms

- **Mini-batch ML Algorithms**
  - Iterative ML algorithms, where each iteration only uses a **batch of rows** to make the next model update (in **epochs** or w/ **sampling**)
  - For large and **highly redundant training sets**
  - **Applies to almost all iterative**, model-based ML algorithms (LDA, reg., class., factor., DNN)
  - **Stochastic Gradient Descent** (SGD)



- **Statistical vs Hardware Efficiency** (batch size)
  - **Statistical efficiency:** # accessed data points to achieve certain accuracy
  - **Hardware efficiency:** number of independent computations to achieve high hardware utilization (parallelization at different levels)
  - **Beware higher variance / class skew for too small batches!**

➔ **Training Mini-batch ML algorithms sequentially is hard to scale**

Background: Mini-batch DNN Training (LeNet)

[Yann LeCun, Leon Bottou, Yoshua Bengio, and Patrick Haffner: Gradient-Based Learning Applied to Document Recognition, **Proc of the IEEE 1998**]

```
# Initialize W1-W4, b1-b4
# Initialize SGD w/ Nesterov momentum optimizer
iters = ceil(N / batch_size)

for( e in 1:epochs ) {
   for( i in 1:iters ) {
      X_batch = X[((i-1) * batch_size) %% N + 1:min(N, beg + batch_size - 1),]
      y_batch = Y[((i-1) * batch_size) %% N + 1:min(N, beg + batch_size - 1),]

      ## layer 1: conv1 -> relu1 -> pool1
      ## layer 2: conv2 -> relu2 -> pool2
      ## layer 3:  affine3 -> relu3 -> dropout
      ## layer 4:  affine4 -> softmax
      outa4 = affine::forward(outd3, W4, b4)
      probs = softmax::forward(outa4)

      ## layer 4:  affine4 <- softmax
      douta4 = softmax::backward(dprobs, outa4)
      [doutd3, dW4, db4] = affine::backward(douta4, outr3, W4, b4)
      ## layer 3:  affine3 <- relu3 <- dropout
      ## layer 2: conv2 <- relu2 <- pool2
      ## layer 1: conv1 <- relu1 <- pool1

      # Optimize with SGD w/ Nesterov momentum W1-W4, b1-b4
      [W4, vW4] = sgd_nesterov::update(W4, dW4, lr, mu, vW4)
      [b4, vb4] = sgd_nesterov::update(b4, db4, lr, mu, vb4)
   }
}
```

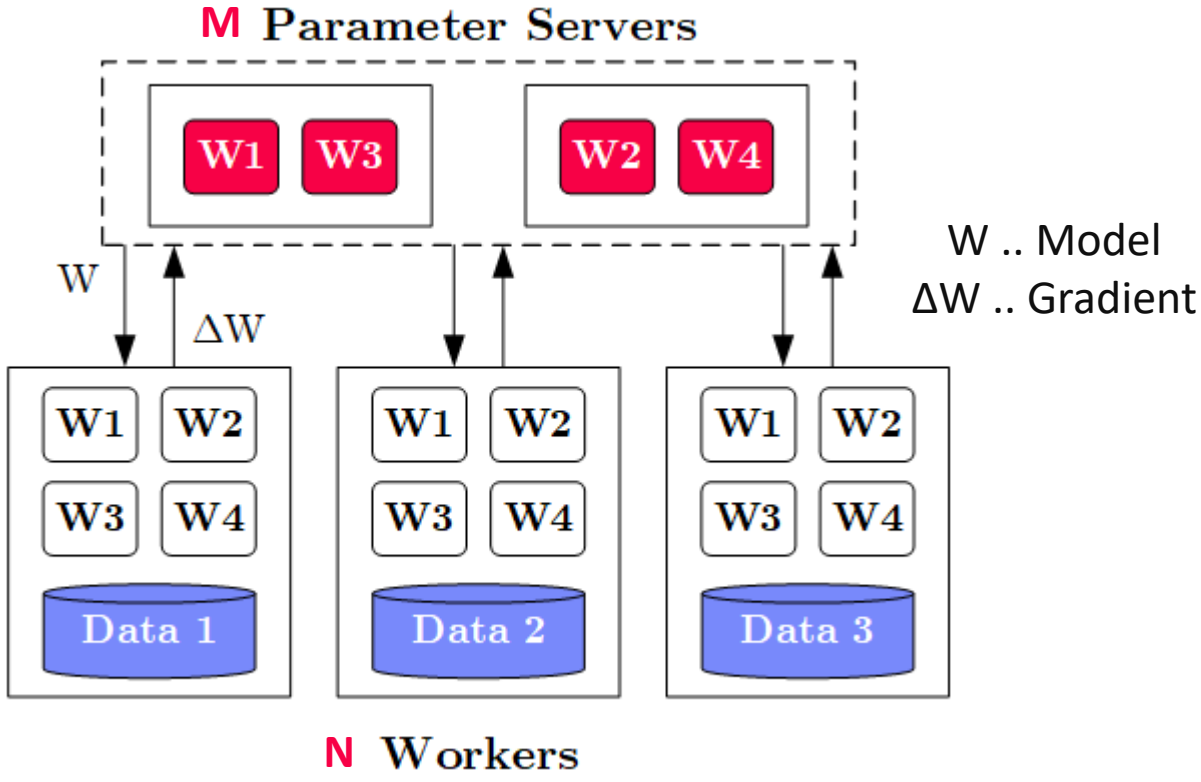
NN Forward Pass

NN Backward Pass
→ Gradients

Model Updates

Overview Data-Parallel Parameter Servers

- **System Architecture**
  - M Parameter Servers
  - N Workers
  - Optional Coordinator



- **Key Techniques**
  - Data partitioning D → workers Di (e.g., disjoint, reshuffling)
  - Updated strategies (e.g., synchronous, asynchronous)
  - Batch size strategies (small/large batches, hybrid methods)

History of Parameter Servers

- **1st Gen: Key/Value**
  - **Distributed key-value store** for parameter exchange and synchronization
  - Relatively high overhead
- **2nd Gen: Classic Parameter Servers**
  - **Parameters as dense/sparse matrices**
  - Different **update/consistency strategies**
  - Flexible configuration and fault tolerance
- **3rd Gen: Parameter Servers w/ improved data communication**
  - Prefetching and range-based pull/push
  - Lossy or lossless compression w/ compensations
- **Examples**
  - TensorFlow, MXNet, PyTorch, CNTK, Petuum

[Alexander J. Smola, Shravan M. Narayanamurthy: An Architecture for Parallel Topic Models. **PVLDB 2010**]

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

[Mu Li et al: Scaling Distributed Machine Learning with the Parameter Server. **OSDI 2014**]

[Jiawei Jiang, Bin Cui, Ce Zhang, Lele Yu: Heterogeneity-aware Distributed Parameter Servers. **SIGMOD 2017**]

[Jiawei Jiang et al: SketchML: Accelerating Distributed Machine Learning with Data Sketches. **SIGMOD 2018**]

Basic Worker Algorithm (batch)

```
for( i in 1:epochs ) {
   for( j in 1:iterations ) {
      params = pullModel(); # W1-W4, b1-b4 lr, mu
      batch = getNextMiniBatch(data, j);
      gradient = computeGradient(batch, params);
      pushGradients(gradient);
   }
}
```

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

Extended Worker Algorithm (nfetch batches)

```
gradientAcc = matrix(0,...);
for( i in 1:epochs ) {
   for( j in 1:iterations ) {
      if( step mod nfetch = 0 )
         params = pullModel();
      batch = getNextMiniBatch(data, j);
      gradient = computeGradient(batch, params);
      gradientAcc += gradient;
      params = updateModel(params, gradients);
      if( step mod nfetch = 0 ) {
         pushGradients(gradientAcc); step = 0;
         gradientAcc = matrix(0, ...);
      }
      step++;
} }
```

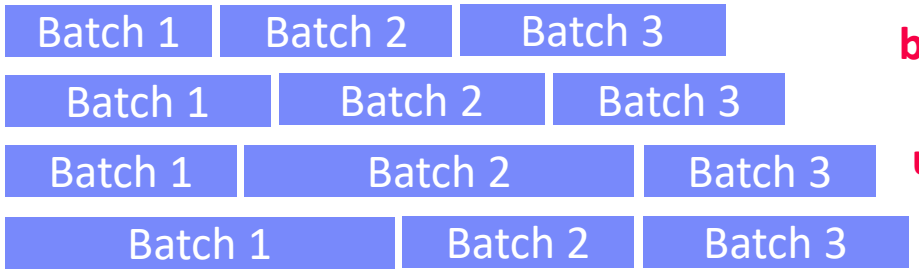
nfetch batches require **local gradient accrual** and **local model update**

[Jeffrey Dean et al.: Large Scale Distributed Deep Networks. **NIPS 2012**]

Update Strategies

- **Bulk Synchronous Parallel (BSP)**
  - Update model w/ accrued gradients
  - Barrier for N workers

- **Asynchronous Parallel (ASP)**
  - Update model for each gradient
  - No barrier



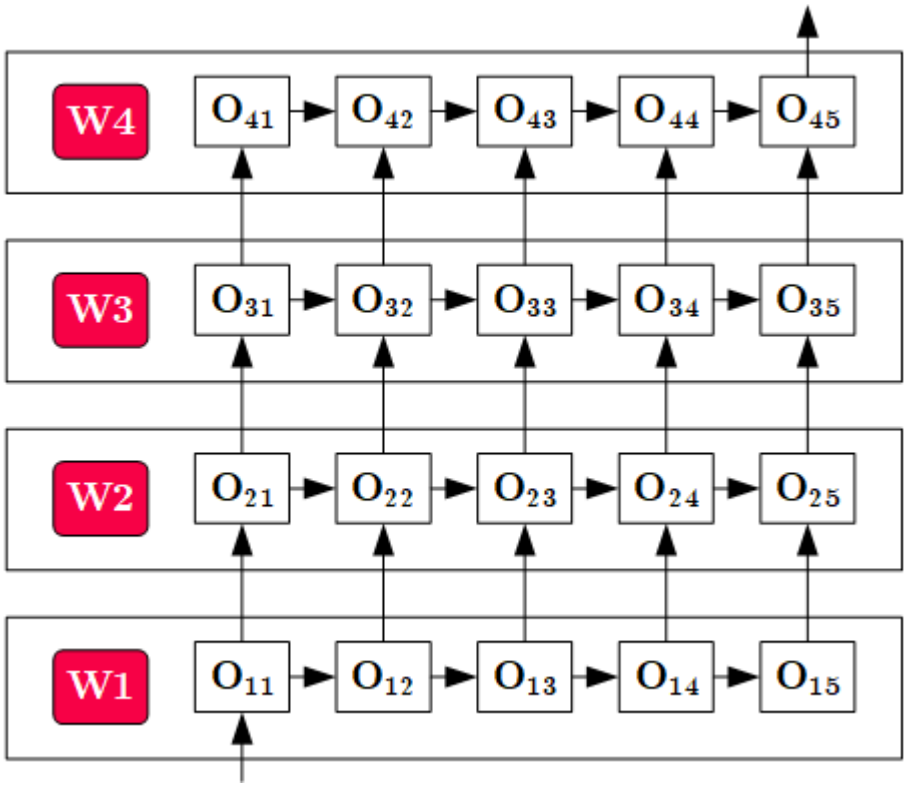
but, stale model updates

- **Synchronous w/ Backup Workers**
  - Update model w/ accrued gradients
  - Barrier for N of N+b workers

[Martín Abadi et al: TensorFlow: A System for Large-Scale Machine Learning. **OSDI 2016**]

Overview Model-Parallel Execution

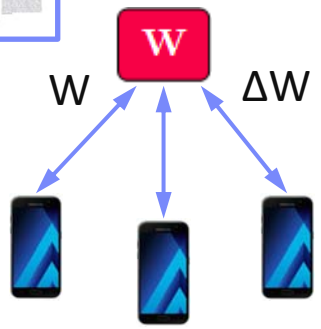
- **System Architecture**
  - Nodes act as workers and parameter servers
  - Data Transfer for boundary-crossing data dependencies
- **Pipeline Parallelism**



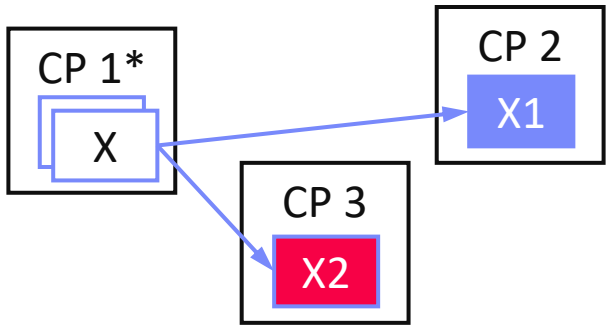
Workers w/ disjoint network/model partitions

Federated ML

[Keith Bonawitz et al.: Towards Federated Learning at Scale: System Design. **MLSys 2019**]



- **Motivation Federated ML**
  - Learn model **w/o central data consolidation**
  - **Privacy + data/power caps** vs **personalization and sharing**
- **Data Ownership → Federated ML in the enterprise**
  (machine vendor – middle-person – customer equipment)
- **Federated ML Architecture**
  - Multiple control programs w/ single master
  - Federated tensors (metadata handles)
  - **Federated instructions** and **parameter server**



- **ExDRa Project** (Exploratory Data Science over Raw Data)
  - **Basic approach:** Federated ML + ML over raw data
  - System infra, integration, data org & reuse, Exp DB, geo-dist.

Bundesministerium Verkehr, Innovation und Technologie
FFG Forschung wirkt.

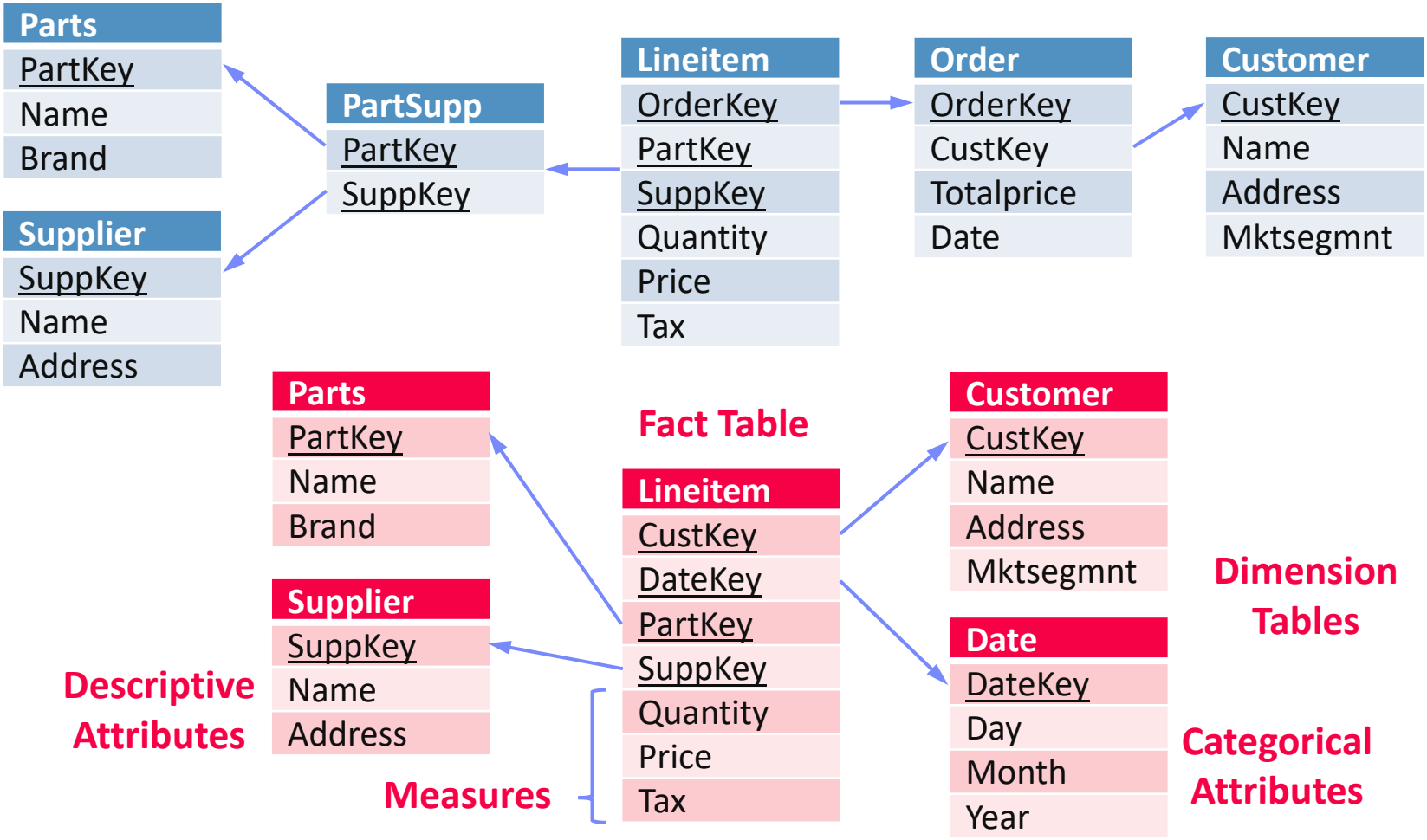
Gefördert im Programm "IKT der Zukunft" vom Bundesministerium für Verkehr, Innovation, und Technologie (BMVIT→BMK)

Q&A and Exam Preparation

Selected Example Questions
(for 80/100 pointers)

Data Warehousing

- **Given the following normalized schema, create a Star Schema that covers all information. Annotate the key concepts.** [15/100 points]



Data Warehousing, cont.

- **Given student registrations in CS/SWE per year, which of the following aggregations are valid (MAX, SUM, AVG)?** [6/100 points]

# Stud	16/17	17/18	18/19	19/20	20/21	Total
CS	1,153	1,283	1,321	1,343	(1252)	**Y?**
SEM	928	970	939	944	(907)	**Y?**
Total	**X?**	**X?**	**X?**	**X?**	**X?**	

STOCK

	MAX	SUM	AVG
X	OK	OK	OK
Y	OK	NOT OK	OK

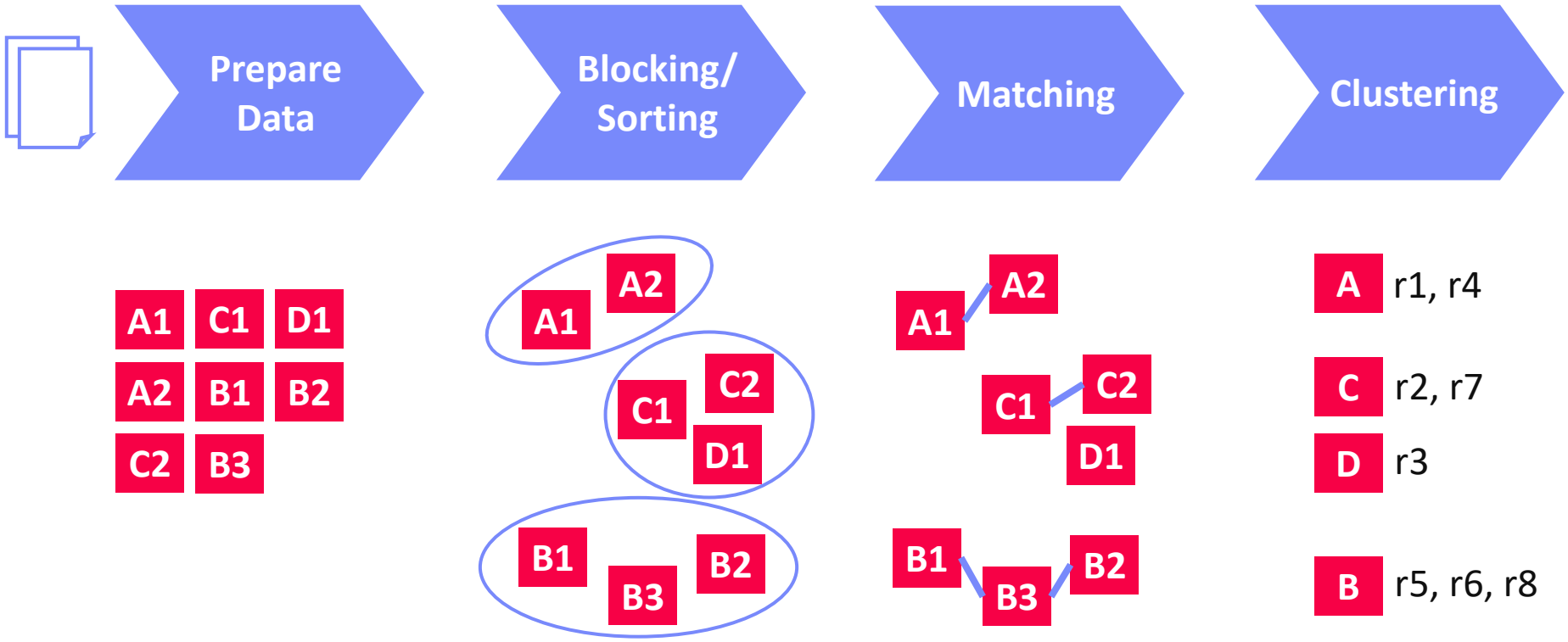
Message-oriented Middleware

- **Describe the Message Delivery Guarantees At-Most-Once, At-Least-Once and Exactly-Once, and indicate which of them require persistent storage before sending.** [6/100 points]

Name	Description	Storage
At-Most-Once	Send and forget, never sent message twice (even on failures)	No
At-Least-Once	Store and forward, replay stream from (acknowledged) checkpoint	Yes
Exactly-Once	Store and forward, replay stream from (acknowledged) checkpoint, transactional delivery	Yes

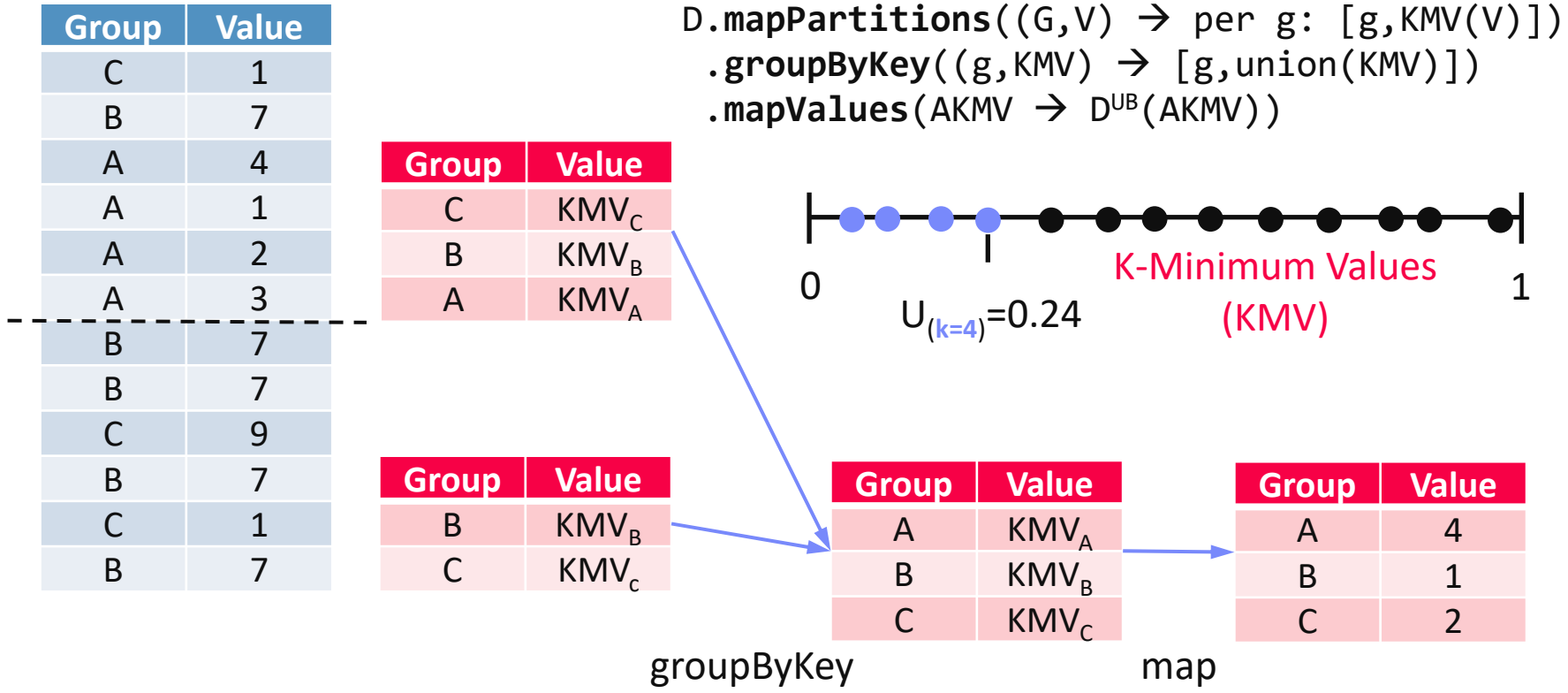
Schema Matching / Entity Linking

- **Explain the phases of a typical Entity Resolution Pipeline with example techniques for the individual phases.** [20/100 points]



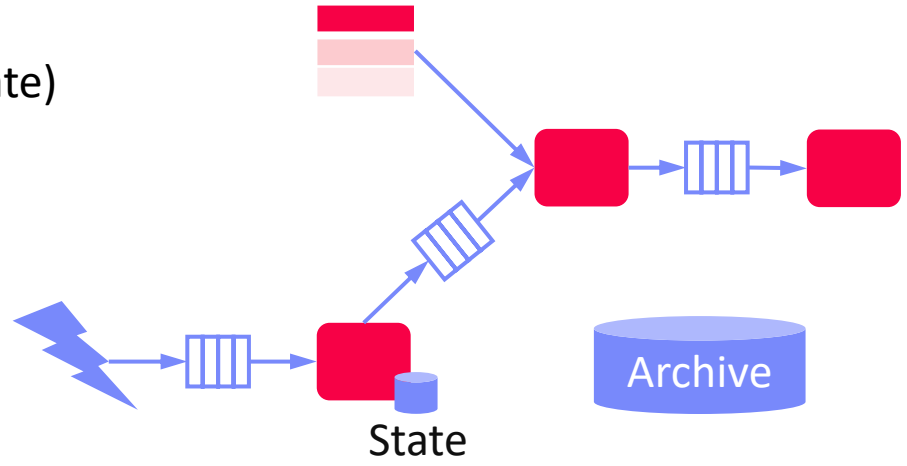
Data Parallel Computation / Stream Mining

- **Given a distributed collection of key-value pairs D (Group, value), describe an efficient, data-parallel implementation that approximates the number of distinct items per group.** [15/100 points]

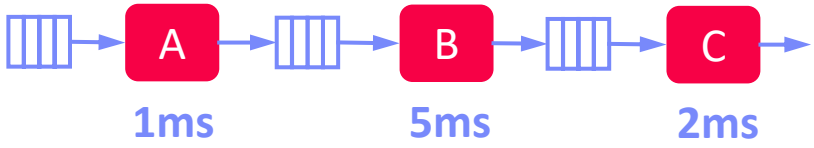


Stream Processing

- **Describe the concept of Continuous Queries and a Basic System Infrastructure to process them over incoming data streams.** [8/100 points]
  - Deployed Data flow graphs
  - **Nodes:** asynchronous ops (w/ state) (e.g., separate threads / queues)
  - **Edges:** data dependencies (tuple/message streams)
  - **Push model:** data production controlled by source



- **Given the continuous query A-B-C, what are the resulting perf characteristics?** [4 points]
  - Max throughput
  - Min tuple latency



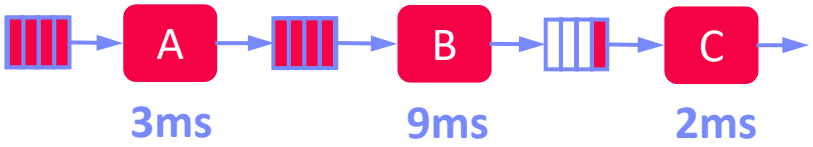
$1/\max(C(op_i)) = 1/5 \text{ tuples/ms} = 200 \text{ tuples/s}$

$\text{sum}(C(op_i)) = 1\text{ms} + 5\text{ms} + 2\text{ms} = 8\text{ms}$

Stream Processing, cont.

- **Describe the three classes of techniques for handling overload situations in continuous queries?** [6/100 points]

- **#1 Back Pressure**
  - Graceful handling of overload w/o data loss
  - Slow down sources
  - E.g., blocking queues



Self-adjusting operator scheduling
Pipeline runs at rate of slowest op

- **#2 Load Shedding**
  - #1 Random-sampling-based load shedding
  - #2 Relevance-based load shedding
  - #3 Summary-based load shedding (synopses)
- **#3 Distributed Stream Processing** (see last part)
  - Data flow partitioning (distribute the query)
  - Key range partitioning (distribute the data stream

Summary and Q&A

- **Landscape of ML Systems**
- **Distributed Linear Algebra**
- **Distributed Parameter Servers**
- **Q&A and Exam Preparation**

Thanks

(please, participate in the course evaluation)

- **#1 Projects and Exercises**
  - 7 (team) projects merged, many projects in PR pipeline
  - 3 (team) exercises submitted → **grace period: end of Feb**
  - In case of problem: ask for help + re-scoping possible

- **#2 Course Evaluation and Exam**
  - Evaluation period: **Dec 15 – Jan 31** (1/98)
  - Exam date: **Feb 08** (i13, 5.30pm-7.30pm) (53/98)