SCIENCE
PASSION
TECHNOLOGY

Architecture of ML Systems
02 Languages, Architectures, and System Landscape

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Last update: Mar 10, 2022

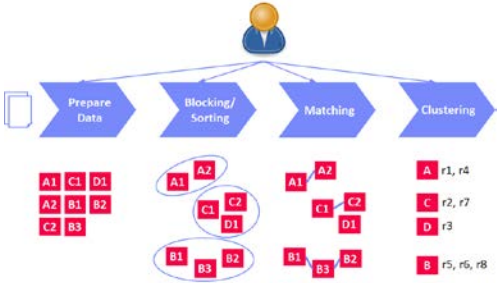
Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - https://tugraz.webex.com/meet/m.boehm

- **#2 Course Registrations** (as of Mar 10)
  - **Architecture of Machine Learning Systems** (AMLS)

  113 (9)

- **#3 SIGMOD Programming Context 2022**
  - **Task: entity resolution blocking** (recall, runtime limit)
  - http://sigmod2022contest.eastus.cloudapp.azure.com/index.shtml
  - **Submission deadline: Apr 30**
  - **Organized by:** Georgia Tech / University of Modena
  - **Awards:** XXX USD sponsored by Microsoft



Projects / Exercises (project selection by **Mar 31**)

- **#1 Apache SystemDS Projects**
  - https://issues.apache.org/jira/secure/Dashboard.jspa?selectPageId=12335852#Filter-Results/12365413 (to be cleaned up by Mar 18)
  - Features across the stack (built-in scripts, APIs, compiler, runtime)
- **#2 DAPHNE Projects**
  - https://mboehm7.github.io/teaching/ss22_amls/AMLS_DAPHNE_projects.pdf
  - OSS end 03/2022; Features at level of runtime, compiler, tools
- **#3 Alternative 1: SIGMOD Programming Contest**
  - http://sigmod2022contest.eastus.cloudapp.azure.com/index.shtml
  - Participate and build an **ML-based ER blocking system**
- **#4 Alternative 2: Exercise on ML Pipelines**
  - https://mboehm7.github.io/teaching/ss22_amls/AMLS_2022_Exercise.pdf

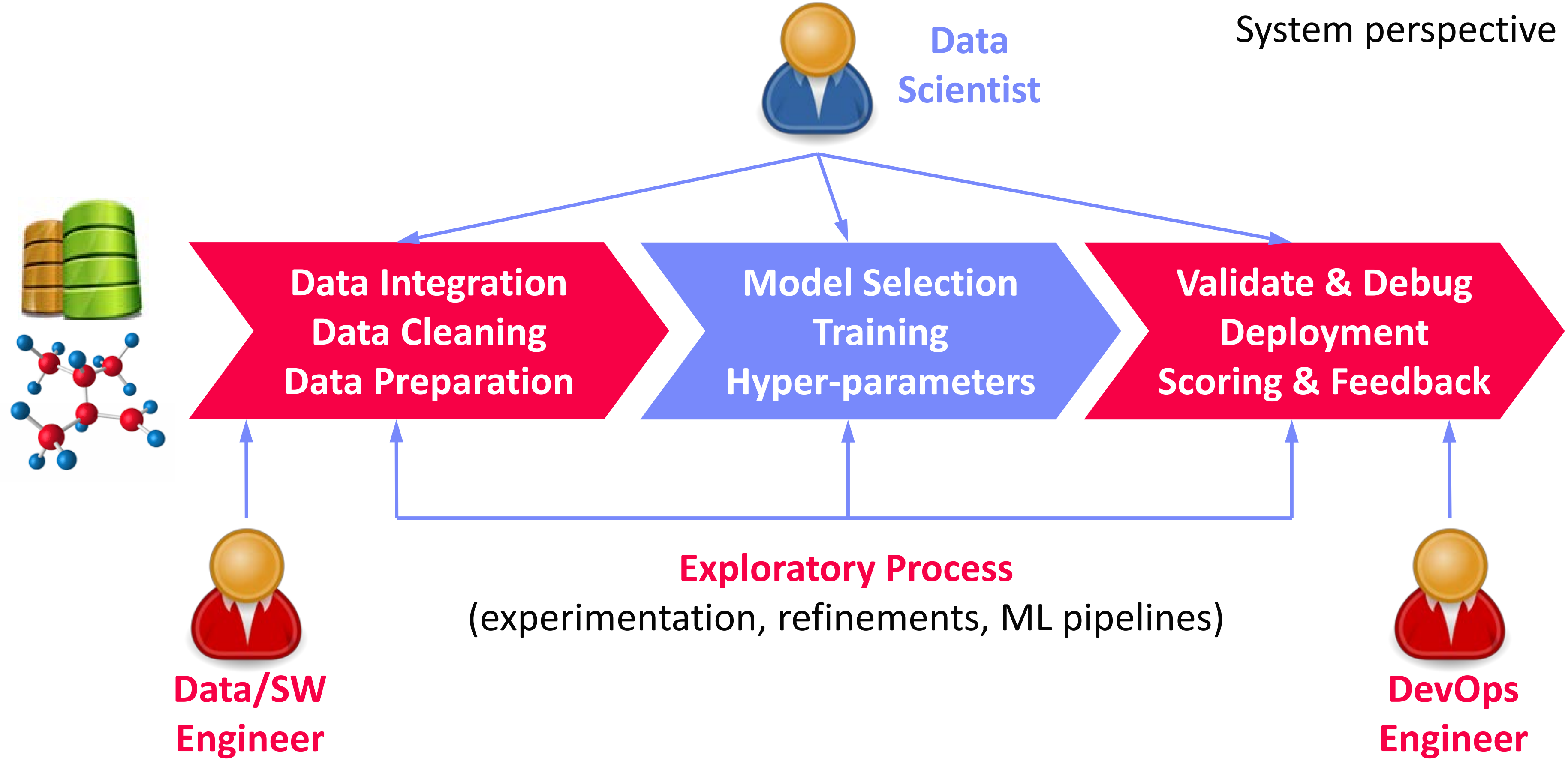
Agenda

- **Data Science Lifecycle**
- **ML Systems Stack**
- **Language Abstractions**
- **ML Systems Benchmarks**

Data Science Lifecycle

The Data Science Lifecycle

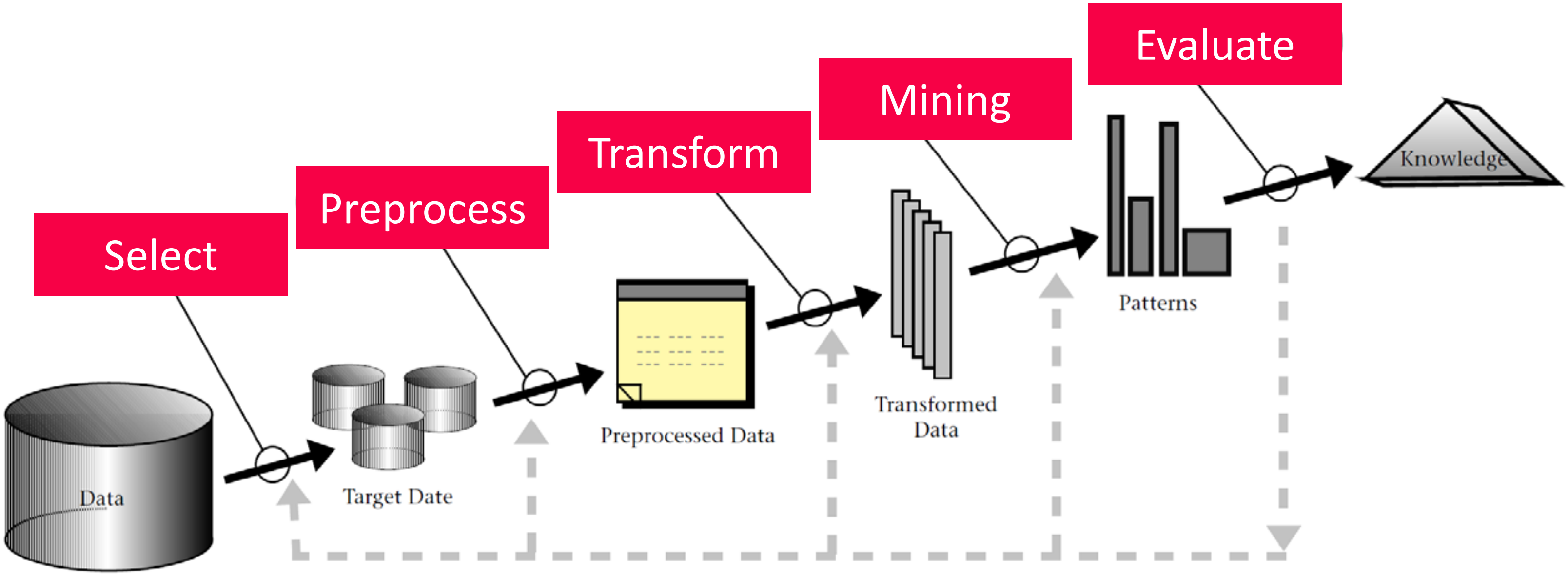
Data-centric View:
Application perspective
Workload perspective
System perspective



Exploratory Process
(experimentation, refinements, ML pipelines)

The Data Science Lifecycle, cont.

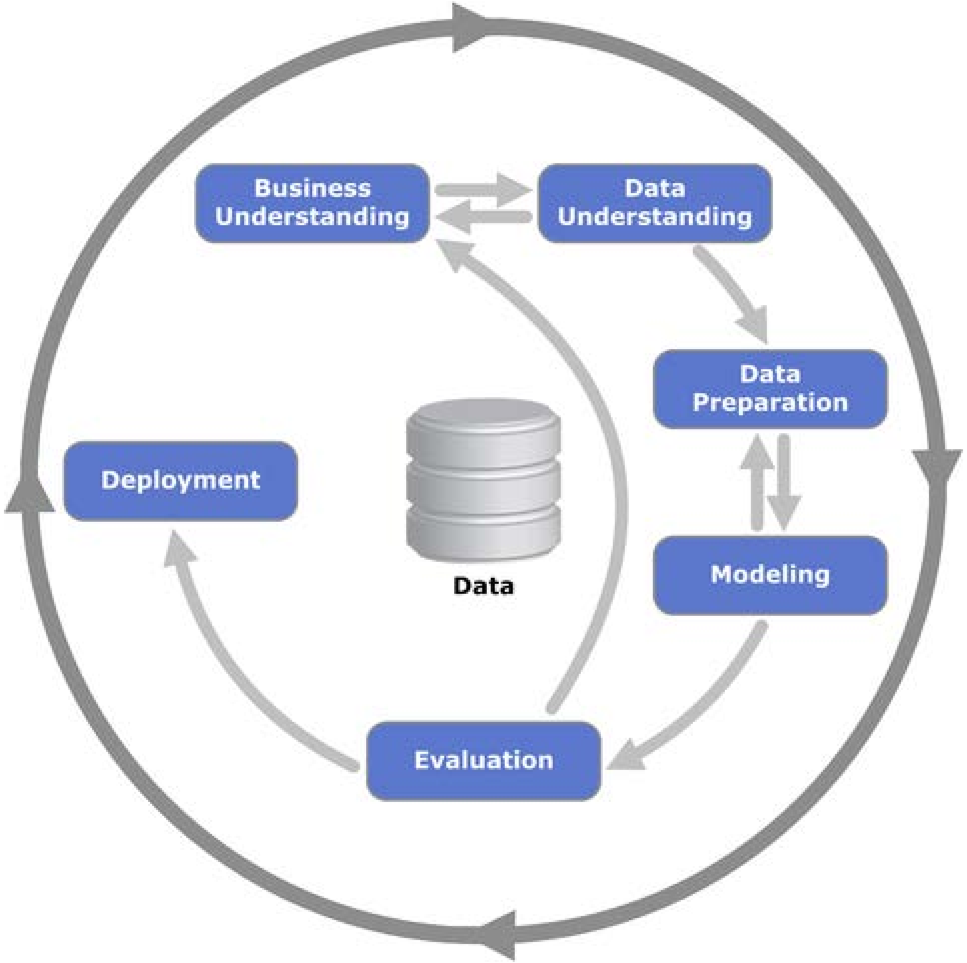
- **Classic KDD Process** (Knowledge Discovery in Databases)
  - Descriptive (association rules, clustering) and predictive



[Usama M. Fayyad, Gregory Piatetsky-Shapiro, Padhraic Smyth: From Data Mining to Knowledge Discovery in Databases. **AI Magazine 17(3) (1996)**]

The Data Science Lifecycle, cont.

- **CRISP-DM**
  - **CR**oss-**I**ndustry **S**tandard **P**rocess for **D**ata **M**ining
  - Additional focus on business understanding and deployment



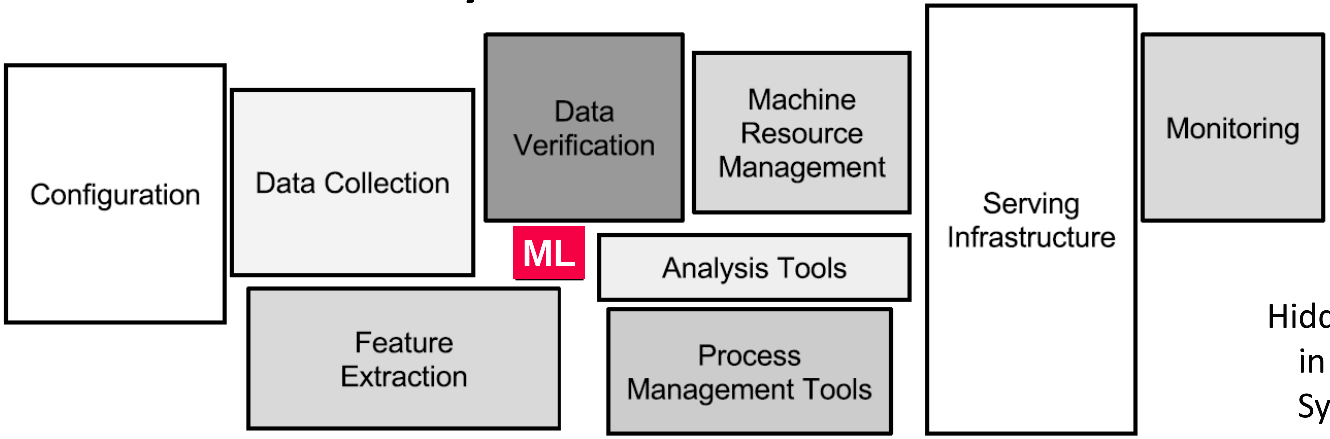
[https://statistik-dresden.de/archives/1128]

The 80% Argument

- **Data Sourcing Effort**
  - Data scientists spend **80-90% time** on finding relevant datasets and data integration/cleaning.

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

- **Technical Debts in ML Systems**

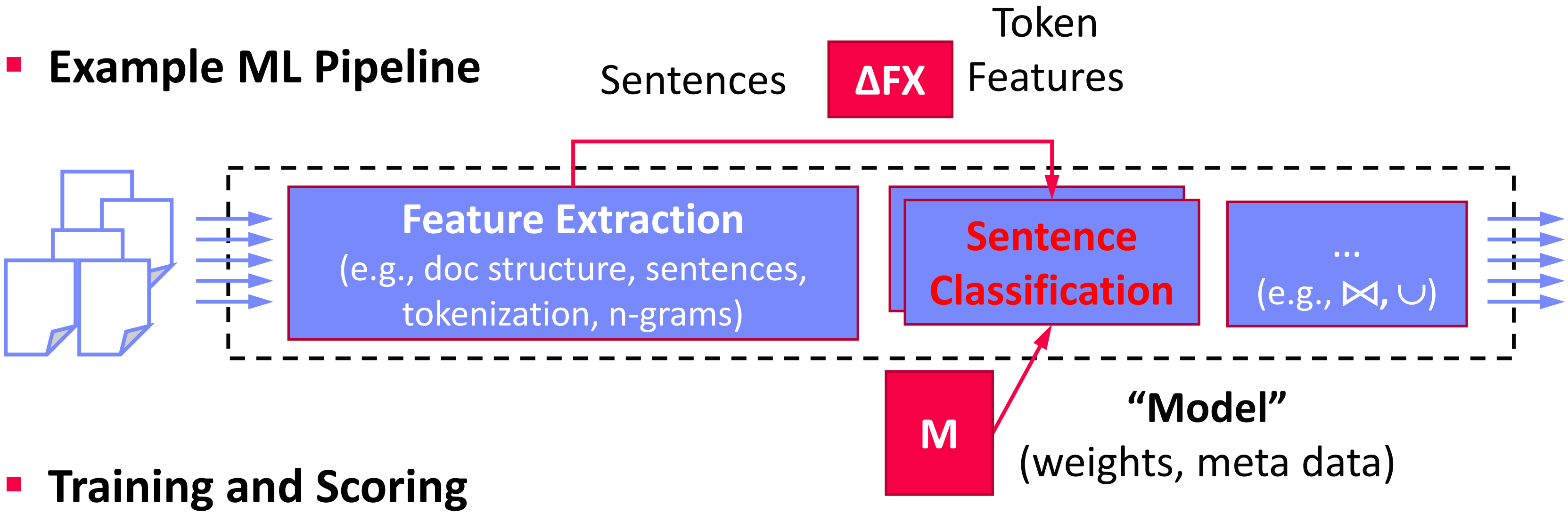


[D. Sculley et al.: Hidden Technical Debt in Machine Learning Systems. **NIPS 2015**]

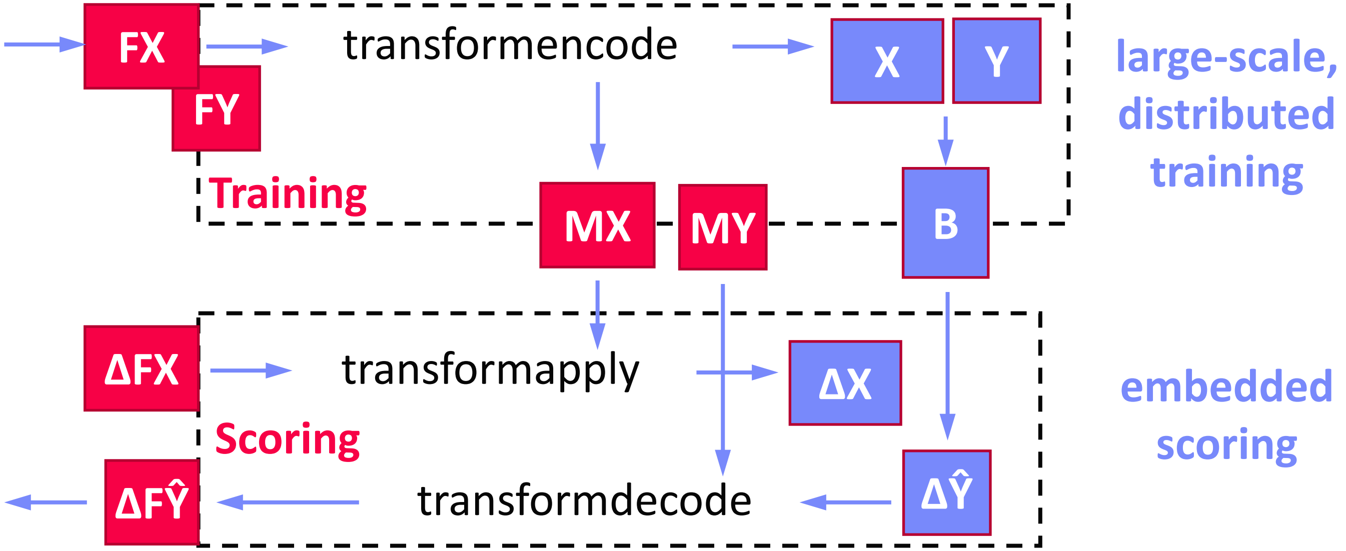
  - Glue code, pipeline jungles, dead code paths
  - Plain-old-data types, multiple languages, prototypes
  - Abstraction and configuration debts
  - Data testing, reproducibility, process management, and cultural debts

A Text Classification Scenario

- **Example ML Pipeline**

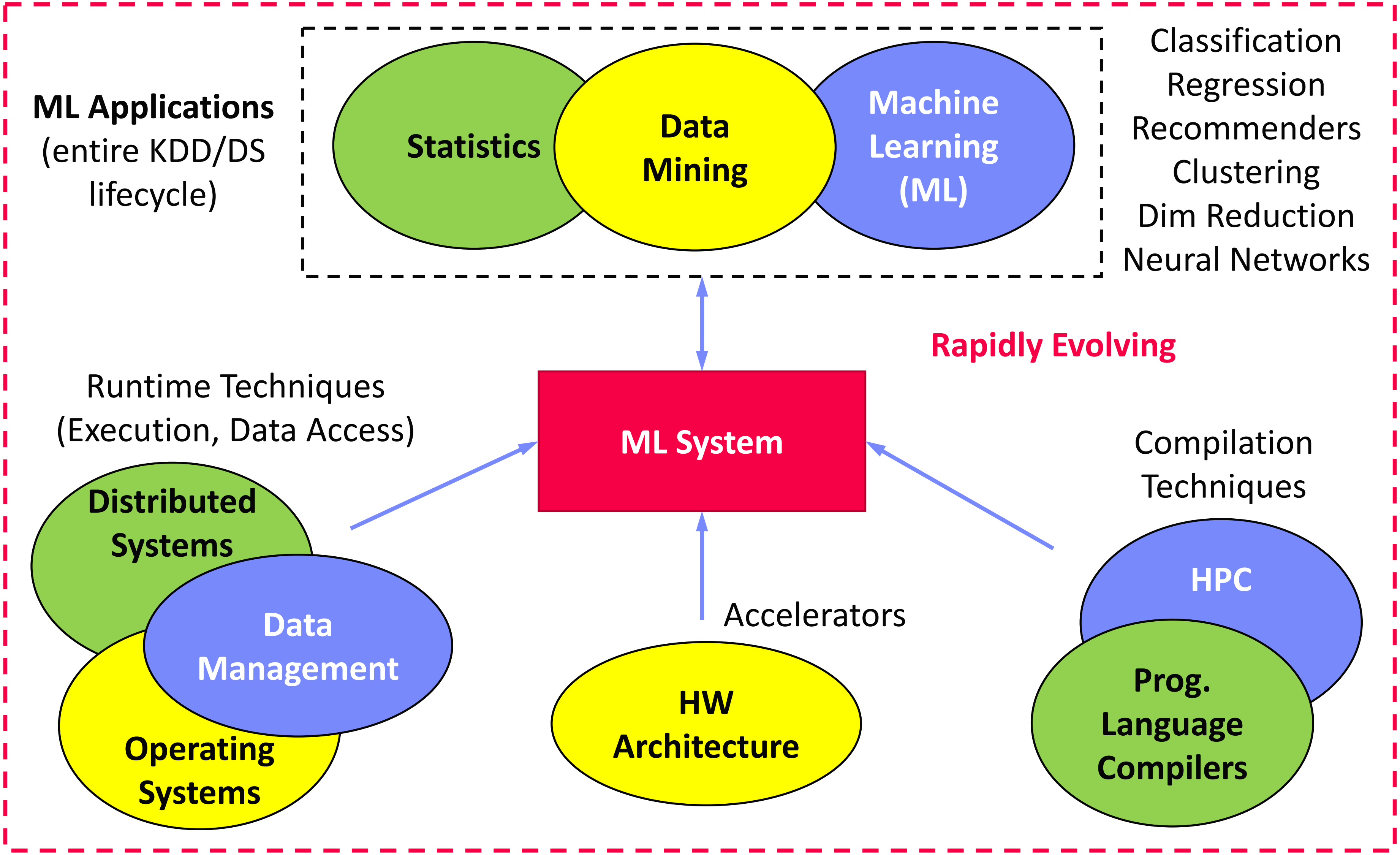


- **Training and Scoring**



ML Systems Stack

What is an ML System?



ML Applications
(entire KDD/DS lifecycle)

Statistics

Data Mining

Machine Learning (ML)

Classification
Regression
Recommenders
Clustering
Dim Reduction
Neural Networks

Rapidly Evolving

ML System

Runtime Techniques
(Execution, Data Access)

Distributed Systems

Data Management

Operating Systems

Accelerators

HW Architecture

Compilation Techniques

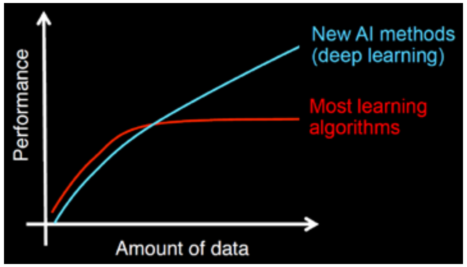
HPC

Prog. Language Compilers

Driving Factors for ML

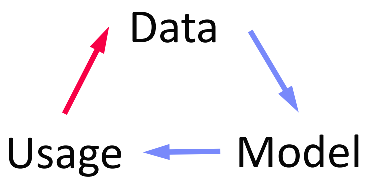
- **Improved Algorithms and Models**
  - Success across data and application domains (e.g., health care, finance, transport, production)
  - More complex models which leverage large data

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



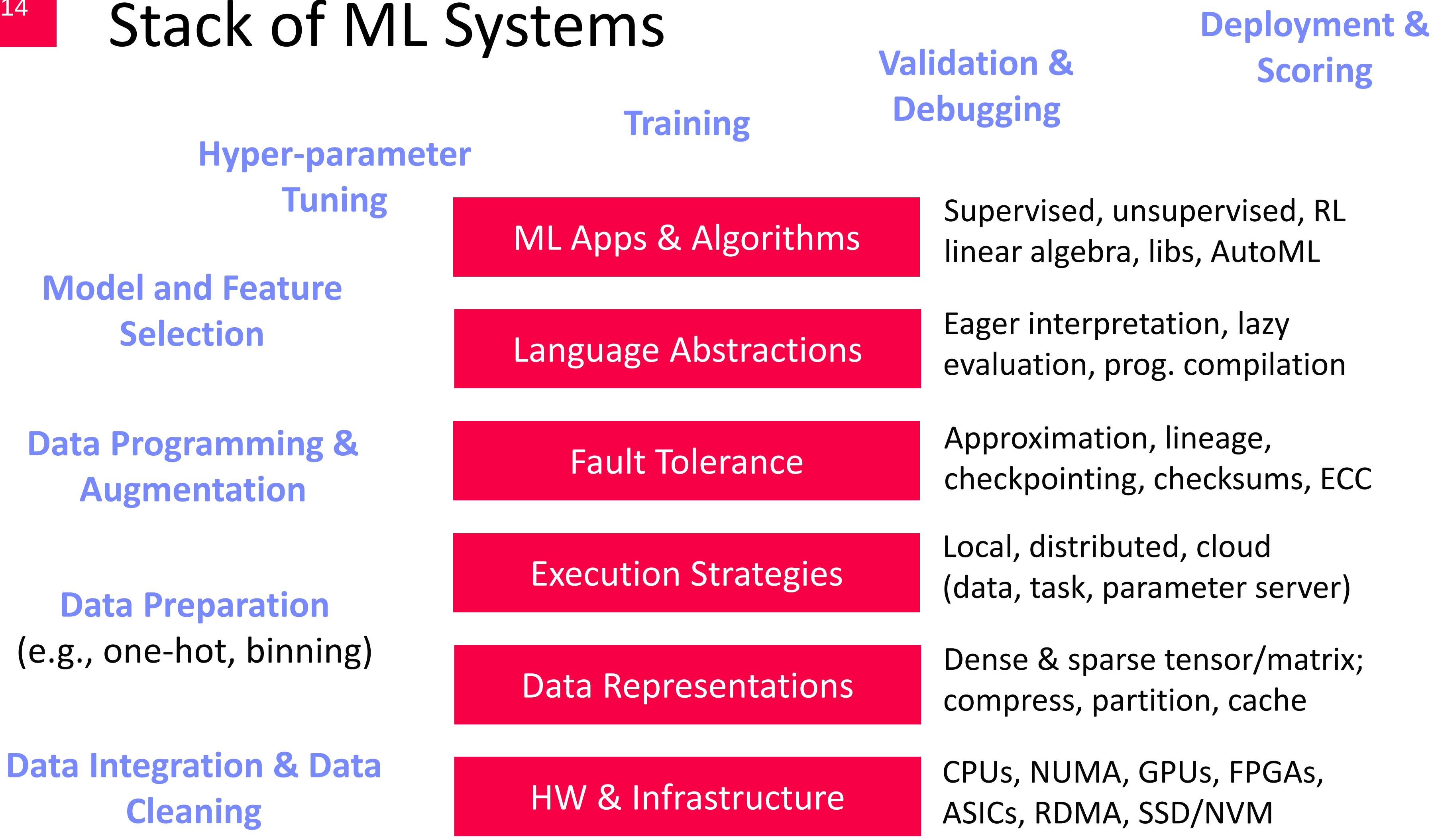
- **Availability of Large Data Collections**
  - Increasing automation and monitoring ➔ data (simplified by cloud computing & services)
  - Feedback loops, **simulation/data prog./augmentation** → Trend: **self-supervised learning**

Feedback Loop



- **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

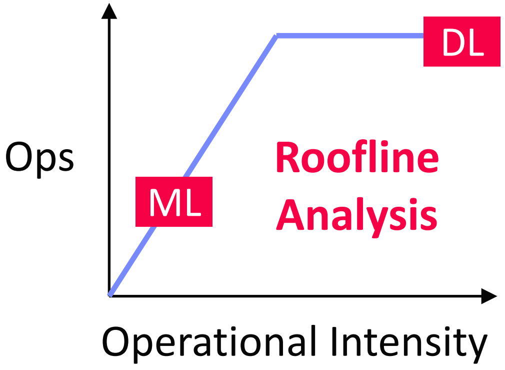
ML Apps & Algorithms	Supervised, unsupervised, RL linear algebra, libs, AutoML
Language Abstractions	Eager interpretation, lazy evaluation, prog. compilation
Fault Tolerance	Approximation, lineage, checkpointing, checksums, ECC
Execution Strategies	Local, distributed, cloud (data, task, parameter server)
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 2B FMA), NVIDIA DLA, Intel NNP, IBM TrueNorth
- **Quantum Computers?**
  - Examples: IBM Q (Qiskit), Google Sycamore (Cirq → TensorFlow Quantum)

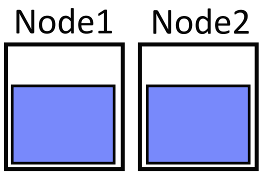
Data Representation

Apps
Lang
Faults
Exec
Data
HW

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

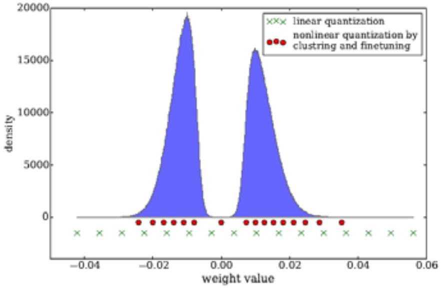
```
vec(Berlin) – vec(Germany)
+ vec(France) ≈ vec(Paris)
```

- **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
  - Data types: **bfloat16**, Intel Flexpoint (mantissa, exp)

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

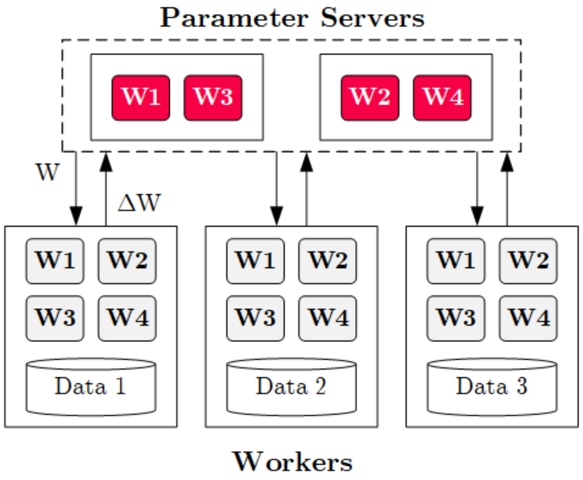


Execution Strategies

Apps
Lang
Faults
Exec
Data
HW

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

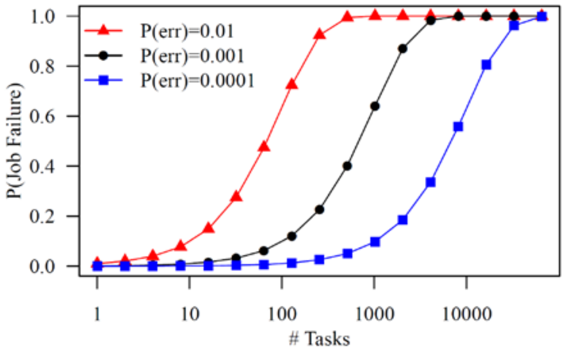
- **Mini-Batch Algorithms: Parameter Server**
  - Data-parallel and model-parallel PS
  - Update strategies (e.g., async, sync, backup)
  - Data partitioning strategies
  - Federated ML (trend 2018)



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

Fault Tolerance & Resilience

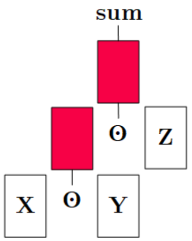
- **Resilience Problem**
  - Increasing error rates at scale (soft/hard mem/disk/net errors)
  - Robustness for preemption
  - **Need cost-effective resilience**



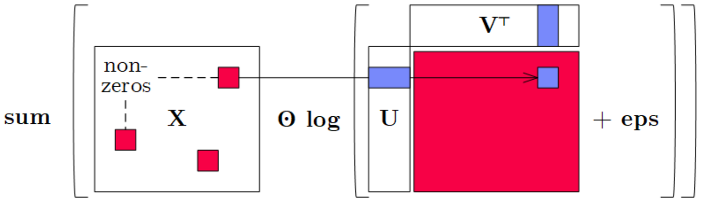
- **Fault Tolerance in Large-Scale Computation**
  - Block replication (min=1, max=3) in distributed file systems
  - ECC; checksums for blocks, broadcast, shuffle
  - Checkpointing (MapReduce: all task outputs; Spark/DL: on request)
  - Lineage-based recomputation for recovery in Spark
- **ML-specific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

Language Abstractions and System Architectures

Landscape of ML Systems

JAX

AIDA

Ludwig

Dask

Mlbase

Tupleware

TUPAQ

GraphLab

HP Distributed R

Kasen

Emma

Cümülön(-D)

OptiML

Glade

RIOT-DB

Cumulon

SystemDS

DMac

LINVIEW

Photon ML

RIOT

SystemML

SAP HANA

Hemingway

Mahout Samsara

MS (Rev) R

Velox

SciDB

BigR

Brainwash

F

ORE

TensorDB

Longview

Fa

DeepDive

AzureML

R4ML

Columbus

SimSQL

Orion

Zombie

ScalOps

MXNet

BUDS

R

Santoku

LibFM

Torch

PyTorch

Matlab

KeystoneML

scikit-learn

Sherlock

Julia

ModelHub

TensorFlow

BigDL

Hamlet

ModelDB

Weka

Mahout

Theano

CNTK

Spark ML

SPSS

MADlib

Bismarck

VW

Singa

Keras

Spark R

DL4J

SAS

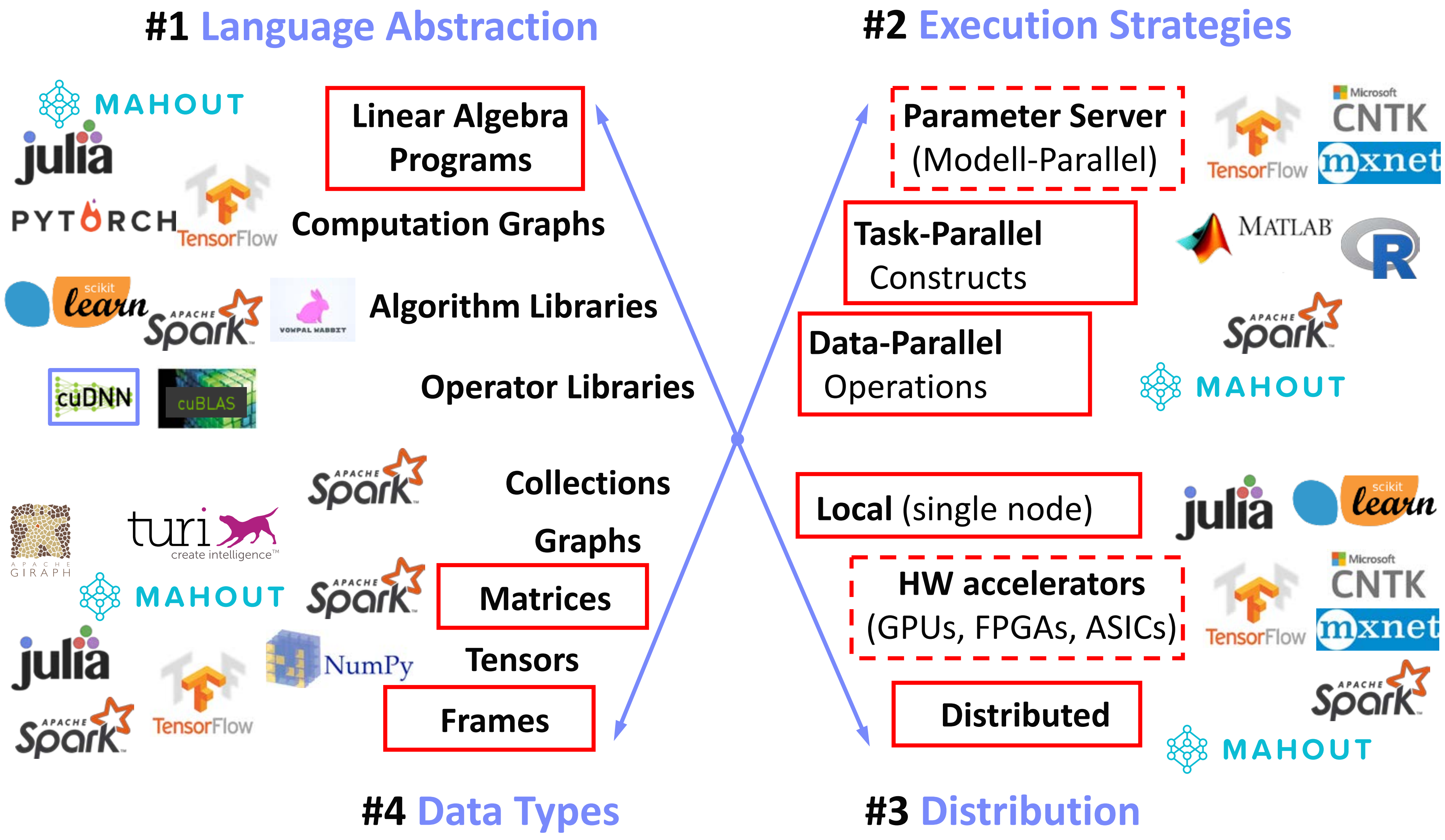
Flink ML

RAPIDS

Caffe

Landscape of ML Systems, cont.

Apache SystemML™



#1 Language Abstraction

- Linear Algebra Programs
- Computation Graphs
- Algorithm Libraries
- Operator Libraries

#2 Execution Strategies

- Parameter Server (Modell-Parallel)
- Task-Parallel Constructs
- Data-Parallel Operations

#3 Distribution

- Local (single node)
- HW accelerators (GPUs, FPGAs, ASICs)
- Distributed

#4 Data Types

- Collections
- Graphs
- Matrices
- Tensors
- Frames

UDF-based Systems

- **User-defined Functions (UDF)**
  - Data type: Input usually collections of cells, **rows, or blocks**
  - Implement loss and overall optimizer by yourself / UDF abstractions
  - Examples: **data-parallel** (e.g., Spark MLlib) or **In-DBMS analytics** (MADlib, AIDA)

- **Example SQL**

Matrix Product in SQL

```
SELECT A.i, B.j,
  SUM(A.val*B.val)
FROM A, B
WHERE A.j = B.i
GROUP BY A.i, B.j;
```

Matrix Product w/ UDF

```
SELECT A.i, B.j,
  dot(A.row, B.col)
FROM A, B;
```

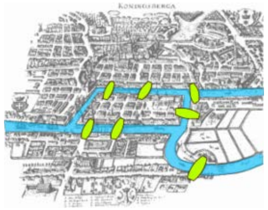
Optimization w/ UDA

```
Init(state)
Accumulate(state,data)
Merge(state,data)
Finalize(state,data)
```

Graph-based Systems

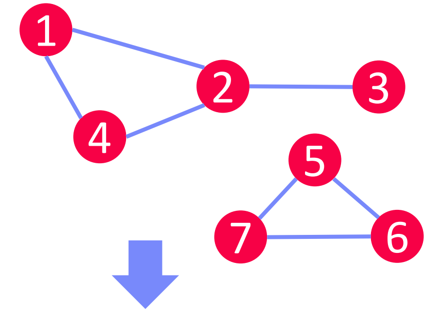
[Grzegorz Malewicz et al: Pregel: a system for large-scale graph processing. **SIGMOD 2010**]

- **Google Pregel**
  - Name: Seven Bridges of Koenigsberg (Euler 1736)
  - **“Think-like-a-vertex”** (vertex-centric processing)
  - Iterative processing in super steps, comm.: message passing



- **Programming Model**
  - Represent graph as collection of vertices w/ edge (adjacency) lists
  - Implement algorithms via Vertex API
  - Terminate if all vertices halted / no more msgs

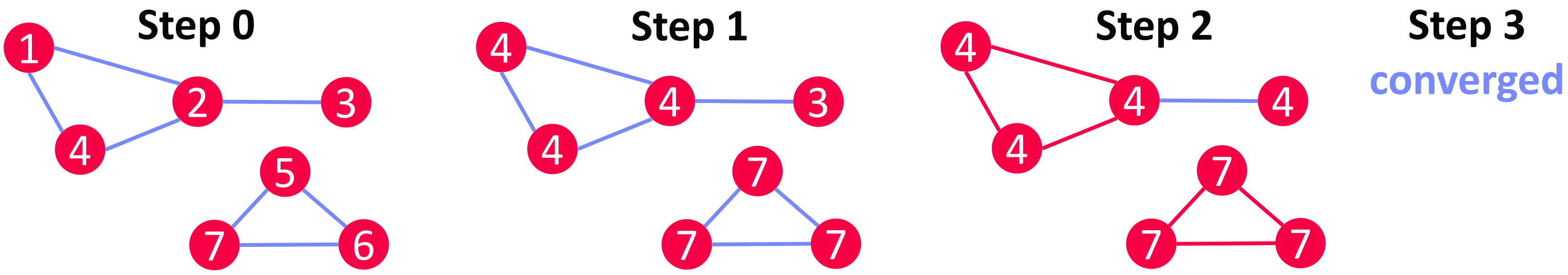
```
public abstract class Vertex {
  public String getID();
  public long superstep();
  public VertexValue getValue();

  public compute(Iterator<Message> msgs);
  public sendMsgTo(String v, Message msg);
  public void voteToHalt();
}
```



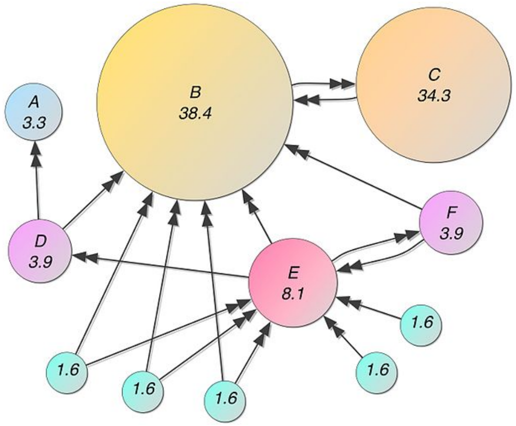
2	[1, 3, 4]	Worker 1
7	[5, 6]	
4	[1, 2]	
1	[1, 2, 4]	
5	[6, 7]	Worker 2
3	[2]	
6	[5, 7]	

Graph-based Systems, cont.

- **Example1: Connected Components**
  - Determine connected components of a graph (subgraphs of connected nodes)
  - Propagate max(current, msgs) if != current to neighbors, terminate if no msgs



- **Example 2: Page Rank**
  - Ranking of webpages by importance / impact
  - **#1:** Initialize vertices to 1/numVertices()
  - **#2:** In each super step
    - Compute current vertex value:
      `value = 0.15/numVertices()+0.85*sum(msg)`
    - Send to all neighbors:
      `value/numOutgoingEdges()`



[**Credit:** https://en.wikipedia.org/wiki/PageRank]

Graph-based Systems, cont.

- **Excursus: Graph Processing via Sparse Linear Algebra**
  - SystemDS' components()

```
# initialize state with vertex ids
c = seq(1,nrow(G));
diff = Inf;
iter = 1;
# iterative computation of connected components
while( diff > 0 & (maxi==0 | iter<=maxi) ) {
  u = max(rowMaxs(G * t(c)), c);
  diff = sum(u != c)
  c = u; # update assignment
  iter = iter + 1;
}
```

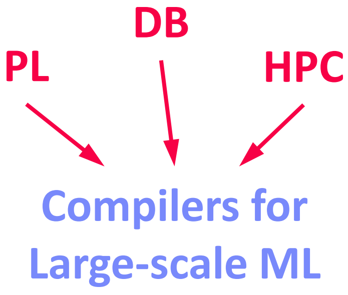
  - SystemDS' pageRank()

```
alpha = ifdef(argAlpha, 0.85);
while( i < maxi ) {
  # power iteration on G w/ Gij = 1/degree
  p = alpha*(G %*% p) + (1-alpha)*(e %*% u %*% p);
  i += 1;
}
```

[Jure Leskovec, Anand Rajaraman, Jeffrey D. Ullman: Mining of Massive Datasets, **Stanford 2014**]

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], **TensorFlow** [OSDI'16] **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

```
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");
```

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)

```
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.matmult(X, p)
  v3 = tf.matmult(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

SparkML/
MLlib

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)
```

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)
```

DNN 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

Feature-centric Tools

- **DeepDive**
  - Knowledge base construction via SQL/MLNs
  - Grounding: SQL queries → factor graph
  - Inference: statistical inference on factor graph
  - Incremental maintenance via sampling / variational approach

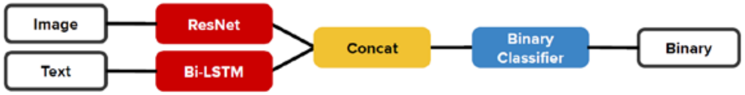
[Jaeho Shin et al: Incremental Knowledge Base Construction Using DeepDive. **PVLDB 2015**]

- **Overton (Apple)**
  - Building, monitoring, improving ML pipelines
  - High-level abstractions: tasks and payloads
  - Data slicing, multi-task learning, data augmentation

[Christopher Ré et al: Overton: A Data System for Monitoring and Improving Machine-Learned Products, **CIDR 2020**]

- **Ludwig (Uber AI)**
  - Data types and configuration files
  - Encoders, combiners, decoders
  - **Example** "visual question answering":

[Piero Molino, Yaroslav Dudin, Sai Sumanth Miryala: Ludwig: a type-based declarative deep learning toolbox. **CoRR 2019**]



ML Systems Benchmarks

“Big Data” Benchmarks w/ ML Components

- **BigBench**
  - 30 workloads (6 statistics, 17 data mining)
  - Different data sources, processing types
  - **Note:** TPCx-BB, TPCx-HS [TPCTC 2016]

[Ahmad Ghazal et al: **BigBench:** towards an industry standard benchmark for big data analytics. **SIGMOD 2013**]

- **HiBench (Intel)**
  - MapReduce Micro benchmarks (WC, TeraSort)
  - IR/ML (e.g., PageRank, K-means, Naïve Bayes)

[Lan Yi, Jinquan Dai: Experience from Hadoop Benchmarking with **HiBench:** From Micro-Benchmarks Toward End-to-End Pipelines. **WBDB 2013**]

- **GenBase**
  - Preprocessing and ML in array databases

[Rebecca Taft et al: **GenBase:** a complex analytics genomics benchmark. **SIGMOD 2014**]

- **SparkBench**
  - Existing library algorithms (ML, Graph, SQL, stream)
  - ML: LogReg, SVM, matrix factorization, PageRank

[Dakshi Agrawal et al: **SparkBench** - A Spark Performance Testing Suite. **TPCTC 2015**]

Linear Algebra and DNN Benchmarks

- **SLAB: Scalable LA Benchmark (UCSD)**
  - **Ops:** TRANS, NORM, GRM, MVM, ADD, GMM
  - **Pipelines/Decompositions:** MMC, SVD
  - **Algorithms:** OLS, LogReg, NMF, HRSE

[Anthony Thomas, Arun Kumar: A Comparative Evaluation of Systems for Scalable Linear Algebra-based Analytics. **PVLDB 2018**]

- **DAWNBench (Stanford)**
  - Image Classification ImageNet: 93% top-5 val err
  - Image Classification CIFAR10: 94% test accuracy
  - Question Answering SQuAD: 0.75 F1 measure

[Cody Coleman et al.: DAWNBench: An End-to-End Deep Learning Benchmark and Competition, **ML Systems Workshop 2017**]

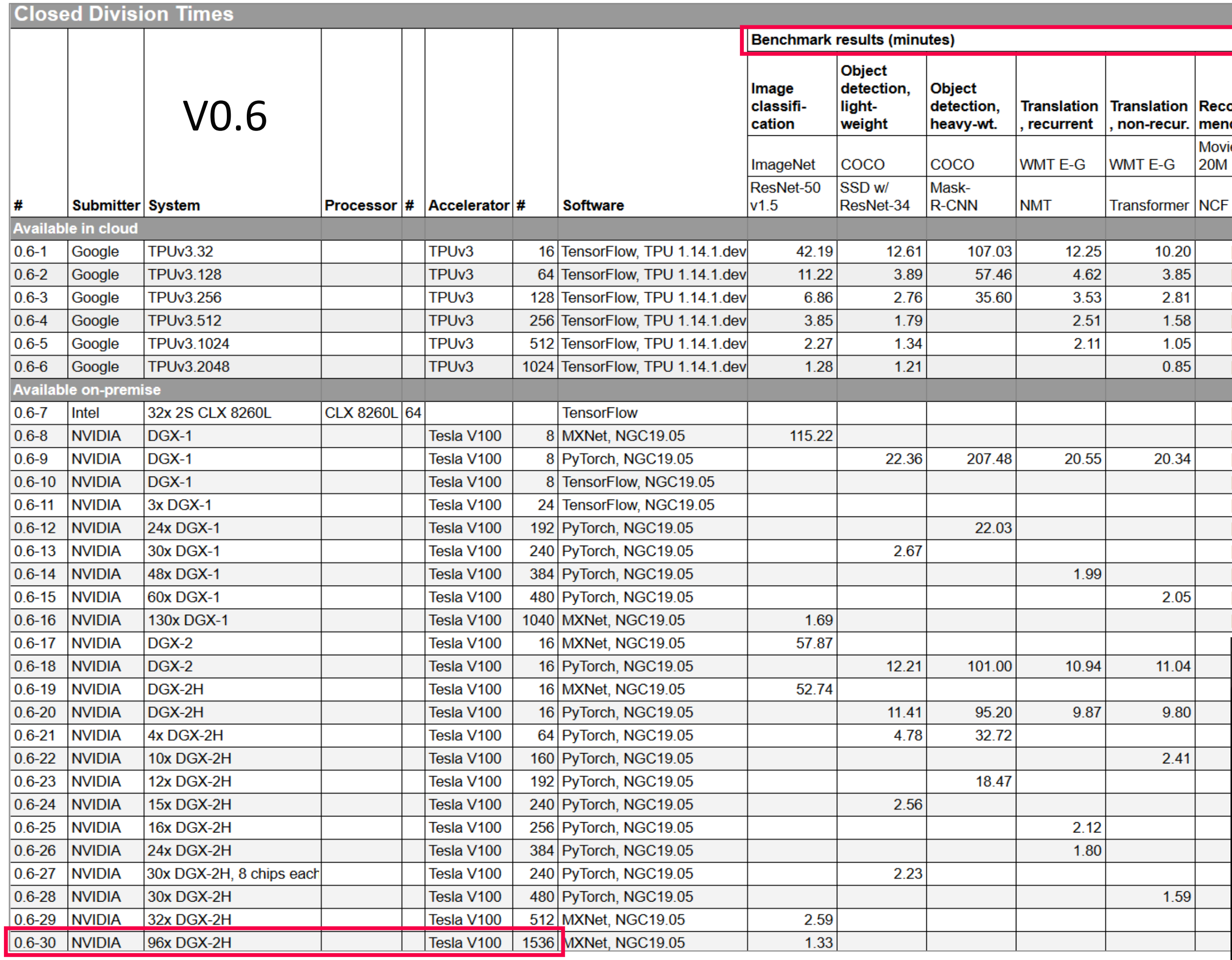
- **MLPerf**
  - Image classification ImageNet, object detection COCO, translation WMT En-Ger, recommendation MovieLens, reinforcement learning GO
  - **Train to target accuracy**
  - Open (diff model) vs closed divisions

[Peter Mattson et al.: MLPerf Training Benchmark, **MLSys 2020**]

[https://mlcommons.org/en/training-normal-11/, https://mlcommons.org/en/training-hpc-10/]

DNN Benchmarks, cont.

[**MLPerf** v0.6: https://mlperf.org/training-results-0-6/,
MLPerf v0.7: https://mlperf.org/training-results-0-7]



Closed Division Times

		V0.6						Benchmark results (minutes)									
								Image classifi-cation	Object detection, light-weight	Object detection, heavy-wt.	Translation, recurrent	Translation, non-recur.	Recom-mendation	Reinforce-ment Learning			
								ImageNet	COCO	COCO	WMT E-G	WMT E-G	MovieLens-20M	Go			
#	**Submitter**	**System**	**Processor**	**#**	**Accelerator**	**#**	**Software**	ResNet-50 v1.5	SSD w/ ResNet-34	Mask-R-CNN	NMT	Transformer	NCF	Mini Go	**Details**	**Code**	**Notes**
Available in cloud																	
0.6-1	Google	TPUv3.32			TPUv3	16	TensorFlow, TPU 1.14.1.dev	42.19	12.61	107.03	12.25	10.20	[1]		details	code	none
0.6-2	Google	TPUv3.128			TPUv3	64	TensorFlow, TPU 1.14.1.dev	11.22	3.89	57.46	4.62	3.85	[1]		details	code	none
0.6-3	Google	TPUv3.256			TPUv3	128	TensorFlow, TPU 1.14.1.dev	6.86	2.76	35.60	3.53	2.81	[1]		details	code	none
0.6-4	Google	TPUv3.512			TPUv3	256	TensorFlow, TPU 1.14.1.dev	3.85	1.79		2.51	1.58	[1]		details	code	none
0.6-5	Google	TPUv3.1024			TPUv3	512	TensorFlow, TPU 1.14.1.dev	2.27	1.34		2.11	1.05	[1]		details	code	none
0.6-6	Google	TPUv3.2048			TPUv3	1024	TensorFlow, TPU 1.14.1.dev	1.28	1.21			0.85	[1]		details	code	none
Available on-premise																	
0.6-7	Intel	32x 2S CLX 8260L	CLX 8260L	64			TensorFlow						[1]	14.43	details	code	none
0.6-8	NVIDIA	DGX-1			Tesla V100	8	MXNet, NGC19.05	115.22					[1]		details	code	none
0.6-9	NVIDIA	DGX-1			Tesla V100	8	PyTorch, NGC19.05		22.36	207.48	20.55	20.34	[1]		details	code	none
0.6-10	NVIDIA	DGX-1			Tesla V100	8	TensorFlow, NGC19.05						[1]	27.39	details	code	none
0.6-11	NVIDIA	3x DGX-1			Tesla V100	24	TensorFlow, NGC19.05						[1]	13.57	details	code	none
0.6-12	NVIDIA	24x DGX-1			Tesla V100	192	PyTorch, NGC19.05			22.03			[1]		details	code	none
0.6-13	NVIDIA	30x DGX-1			Tesla V100	240	PyTorch, NGC19.05		2.67				[1]		details	code	none
0.6-14	NVIDIA	48x DGX-1			Tesla V100	384	PyTorch, NGC19.05				1.99		[1]		details	code	none
0.6-15	NVIDIA	60x DGX-1			Tesla V100	480	PyTorch, NGC19.05					2.05	[1]		details	code	none
0.6-16	NVIDIA	130x DGX-1			Tesla V100	1040	MXNet, NGC19.05	1.69					[1]		details	code	none
0.6-17	NVIDIA	DGX-2			Tesla V100	16	MXNet, NGC19.05	57.87									
0.6-18	NVIDIA	DGX-2			Tesla V100	16	PyTorch, NGC19.05		12.21	101.00	10.94	11.04					
0.6-19	NVIDIA	DGX-2H			Tesla V100	16	MXNet, NGC19.05	52.74									
0.6-20	NVIDIA	DGX-2H			Tesla V100	16	PyTorch, NGC19.05		11.41	95.20	9.87	9.80					
0.6-21	NVIDIA	4x DGX-2H			Tesla V100	64	PyTorch, NGC19.05		4.78	32.72							
0.6-22	NVIDIA	10x DGX-2H			Tesla V100	160	PyTorch, NGC19.05					2.41					
0.6-23	NVIDIA	12x DGX-2H			Tesla V100	192	PyTorch, NGC19.05			18.47							
0.6-24	NVIDIA	15x DGX-2H			Tesla V100	240	PyTorch, NGC19.05		2.56								
0.6-25	NVIDIA	16x DGX-2H			Tesla V100	256	PyTorch, NGC19.05				2.12						
0.6-26	NVIDIA	24x DGX-2H			Tesla V100	384	PyTorch, NGC19.05				1.80						
0.6-27	NVIDIA	30x DGX-2H, 8 chips each			Tesla V100	240	PyTorch, NGC19.05		2.23								
0.6-28	NVIDIA	30x DGX-2H			Tesla V100	480	PyTorch, NGC19.05					1.59					
0.6-29	NVIDIA	32x DGX-2H			Tesla V100	512	MXNet, NGC19.05	2.59									
0.6-30	NVIDIA	96x DGX-2H			Tesla V100	1536	MXNet, NGC19.05	1.33									

DGX SUPERPOD
Autonomous Vehicles | Speech AI | Healthcare | Graphics | HPC
• 96 DGX-2H
• 10 Mellanox EDR IB per node
• 1,536 V100 Tensor Core GPUs
• 1 megawatt of power

96 x DGX-2H = 96 * 16 = 1536 V100 GPUs
➔ ~ 96 * $400K = **$35M – $40M**

[https://www.forbes.com/sites/tiriasresearch/2019/06/19/nvidia-offers-a-turnkey-supercomputer-the-dgx-superpod/#693400f43ee5]

AutoML and Data Cleaning

- **MLBench**
  - Compare **AutoML** w/ human experts (Kaggle)
  - Classification, regression; AUC vs Runtime

[Yu Liu et.al: MLBench: Benchmarking Machine Learning Services Against Human Experts. **PVLDB 2018**]

- **(Open Source) AutoML Benchmark**
  - 39 classification datasets, AUC metric, 10-fold CV
  - Extensible metrics, OS **AutoML** frameworks, datasets

[Pieter Gijsbers et al.: An Open Source AutoML Benchmark. **Automated ML Workshop 2019**]

- **CleanML**
  - Train/Test on **dirty vs clean data** (2x2)
  - Missing values, outliers, duplicates, mislabels

[Peng Li et al: CleanML: A Benchmark for Joint Data Cleaning and Machine Learning, **ICDE 2021**]

- **Meta Worlds Benchmark**
  - **Meta-reinforcement** and **multi-task learning**
  - 50 robotic tasks (e.g., get coffee, open window)

[Tianhe Yu et al: Meta-World: A Bench-mark and Evaluation for Multi-Task and Meta Reinforce-ment Learning, **CoRL 2019**]

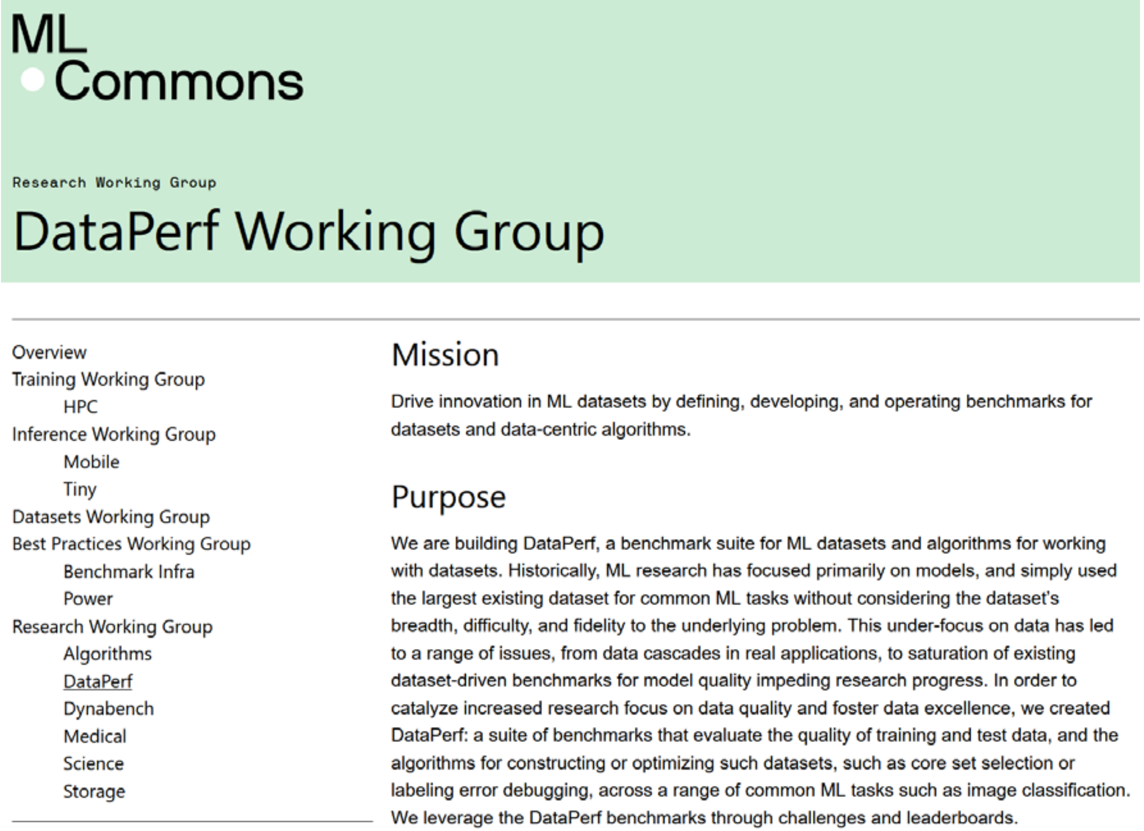
- **Feature Type Inference**
  - Dirty/clean ML model training/test

[Vraj Shah et al.: Towards Benchmarking Feature Type Inference for AutoML Platforms, **SIGMOD 2021**]

AutoML and Data Cleaning, cont.

- **Excursus: ML-Commons Working Groups**
  - Including DataPerf Working Group

[https://mlcommons.org/en/groups/research-dataperf/]



Research Working Group

DataPerf Working Group

Mission

Drive innovation in ML datasets by defining, developing, and operating benchmarks for datasets and data-centric algorithms.

Purpose

We are building DataPerf, a benchmark suite for ML datasets and algorithms for working with datasets. Historically, ML research has focused primarily on models, and simply used the largest existing dataset for common ML tasks without considering the dataset's breadth, difficulty, and fidelity to the underlying problem. This under-focus on data has led to a range of issues, from data cascades in real applications, to saturation of existing dataset-driven benchmarks for model quality impeding research progress. In order to catalyze increased research focus on data quality and foster data excellence, we created DataPerf: a suite of benchmarks that evaluate the quality of training and test data, and the algorithms for constructing or optimizing such datasets, such as core set selection or labeling error debugging, across a range of common ML tasks such as image classification. We leverage the DataPerf benchmarks through challenges and leaderboards.

Summary and Q&A

- **Data Science Lifecycle**
- **ML Systems Stack**
- **Language Abstractions**
- **ML System Benchmarks**

- **Recommended Reading** (a critical perspective on a broad sense of ML systems)
  - [M. Jordan: SysML: Perspectives and Challenges. Keynote at **SysML 2018**]
  - ***"ML […] is far from being a solid engineering discipline that can yield robust, scalable solutions to modern data-analytic problems"***
  - https://www.youtube.com/watch?v=4inIBmY8dQI

- **Others:** https://nautil.us/deep-learning-is-hitting-a-wall-14467/ (Mar 10, 2022)