SCIENCE
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TECHNOLOGY

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

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Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Streaming: https://tugraz.webex.com/meet/m.boehm
- **#2 Course Registrations AMLS** (as of Mar 06)
  - COVID-19 precautions **March 11 – April 19**
  - **Project selection** by **Apr 03**
- **#3 Study Abroad Fair** (**Mar 18, 10am-3pm**, INF 25d HS i4)
  - Info booths and short presentations on study abroad programs (e.g., exchange, research, summer)
- **#4 Catalyst Coding Contest** (**Apr 03, 3-8pm**)
  - **Hosted by: IT Community Styria**
  - INF 18, HS i1 (117 seats)
  - https://register.codingcontest.org/

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IT Community Styria

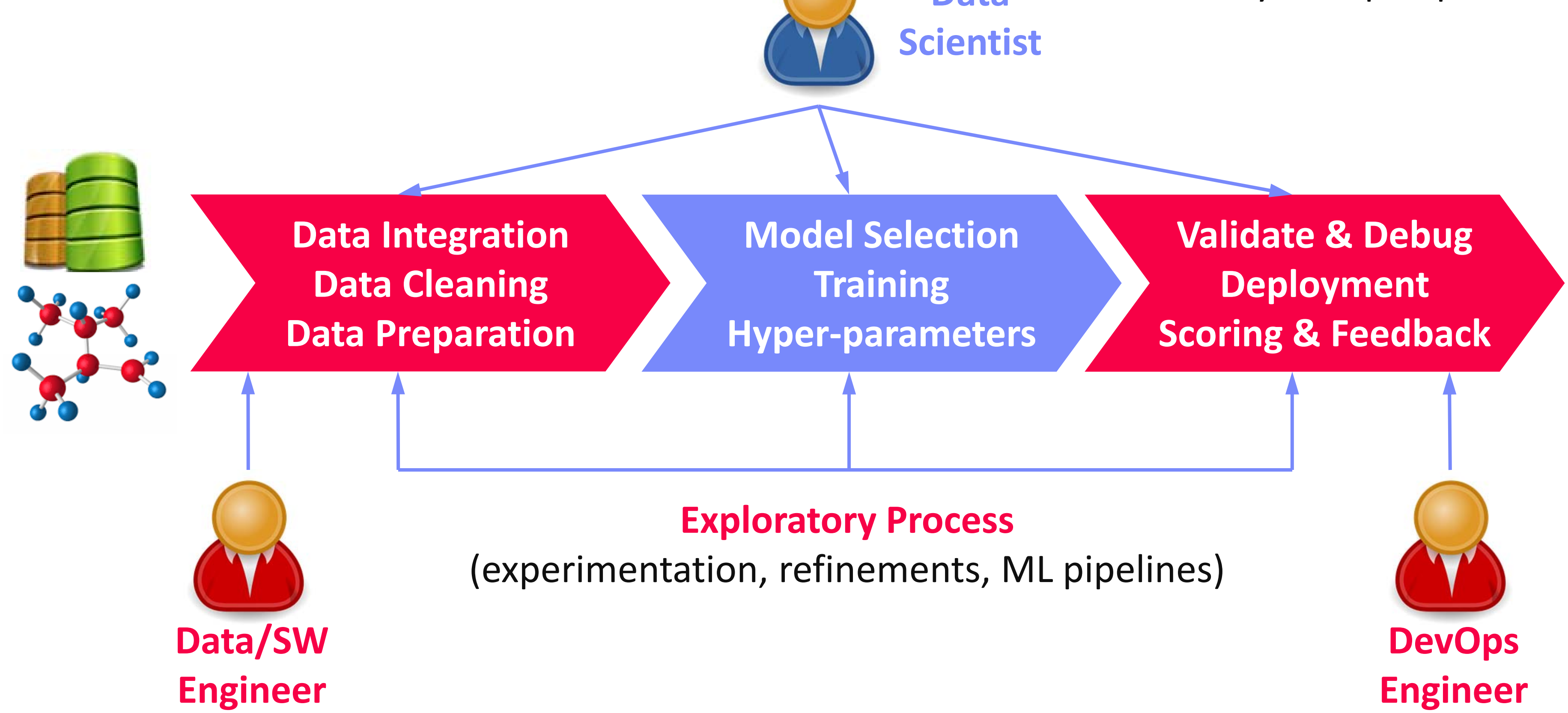
Agenda

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

Data Science Lifecycle

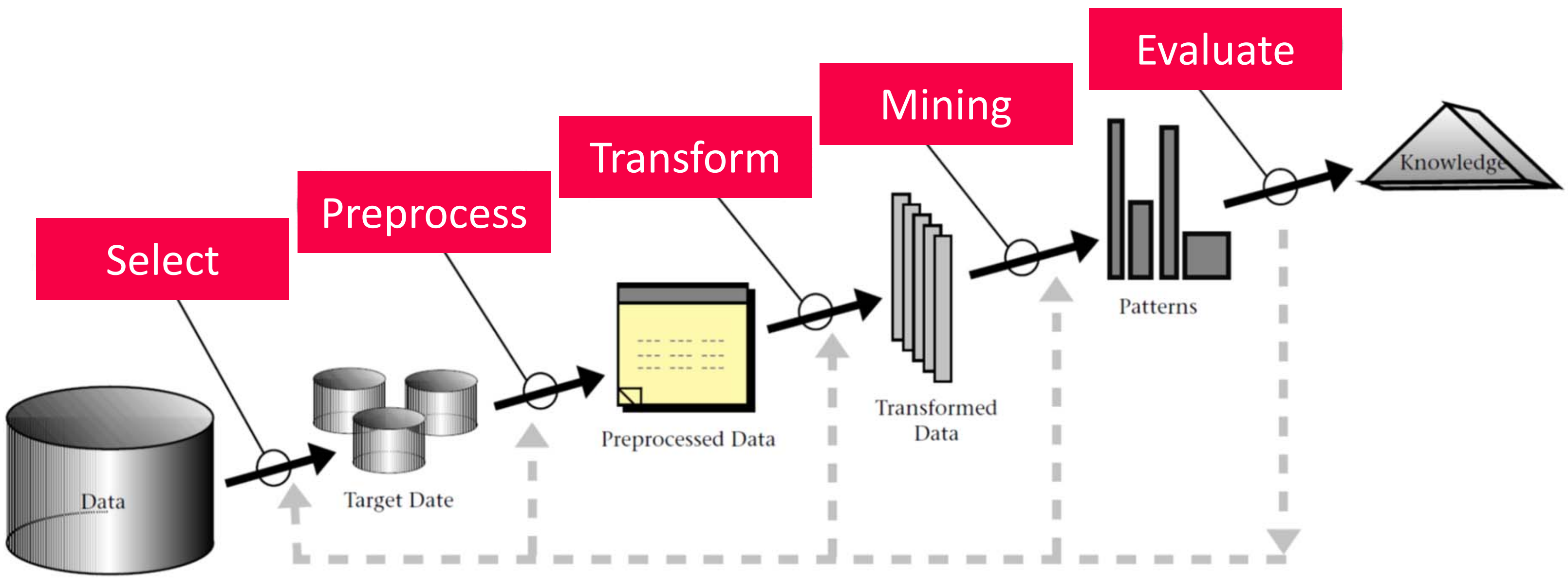
The Data Science Lifecycle

Data-centric View:
Application perspective
Workload perspective
System perspective



The Data Science Lifecycle, cont.

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



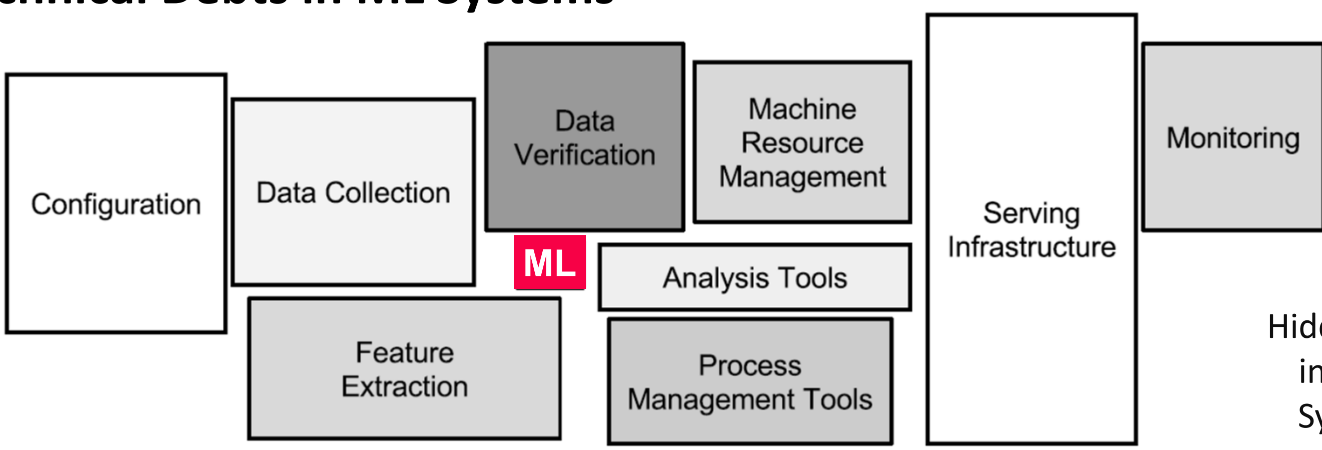
[Usama M. Fayyad, Gregory Piatetsky-Shapiro, Padhraic Smyth: From Data Mining to Knowledge Discovery in Databases. **AI Magazine 17(3) (1996)**]

The 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**

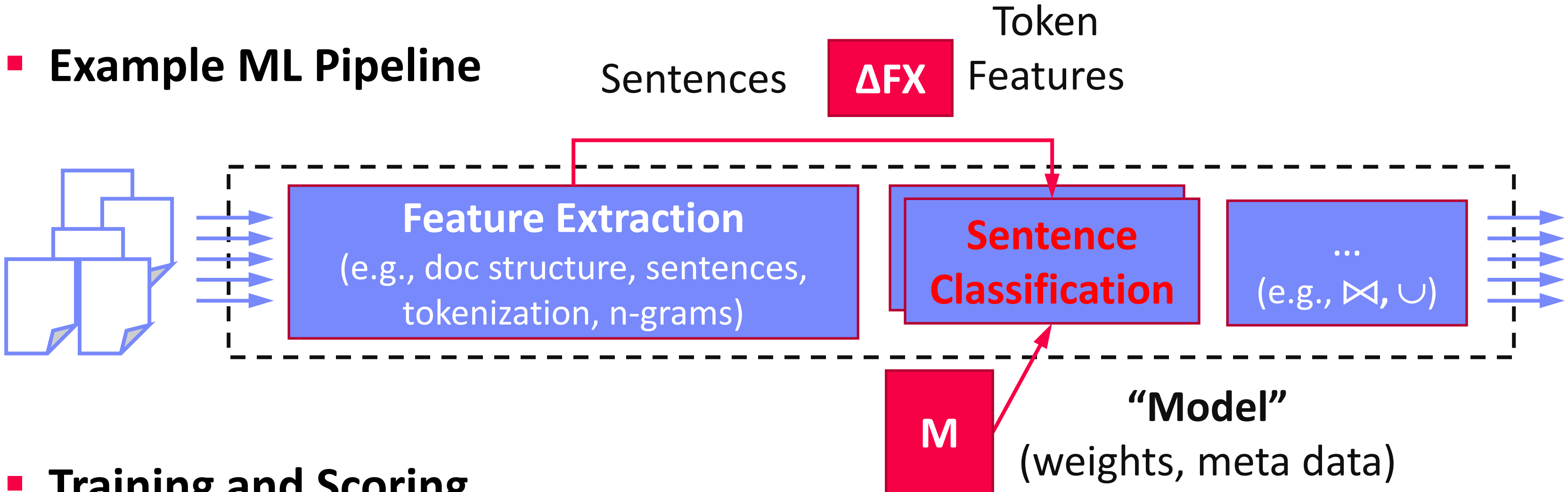


[D. Sculley et al.: Hidden Technical Debt in Machine Learning Systems. **NIPS 2015**]

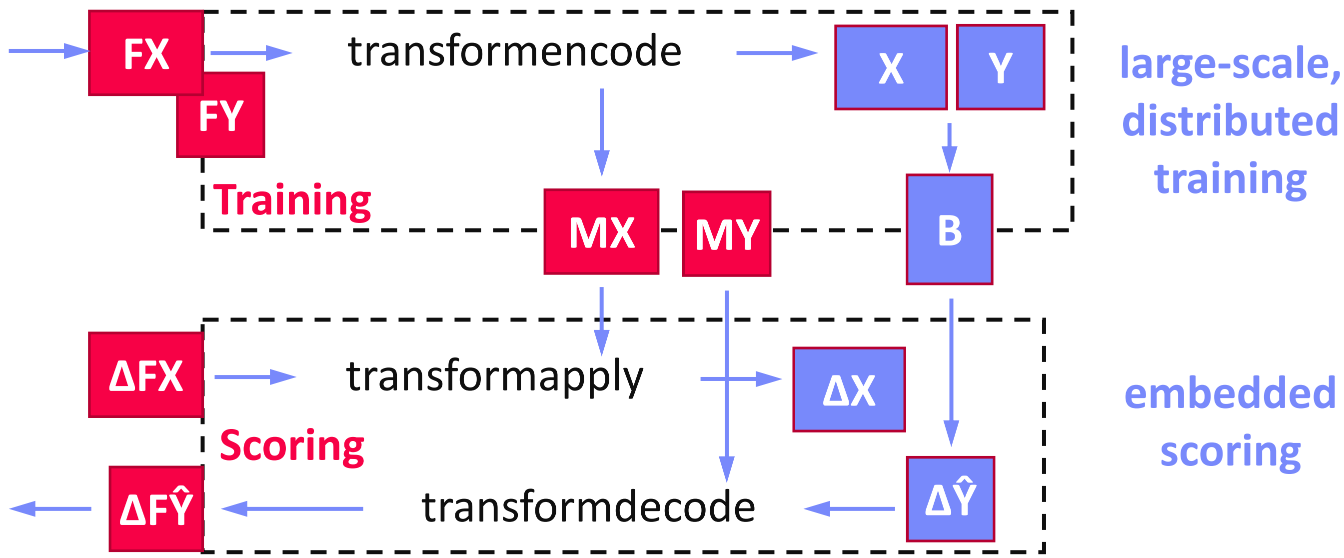
  - Glue code, pipeline jungles, dead code paths
  - Plain-old-data types, multiple languages, prototypes
  - Abstraction and configuration debts
  - Data testing, reproducibility, process management, and cultural debts

A Text Classification Scenario

- **Example ML Pipeline**

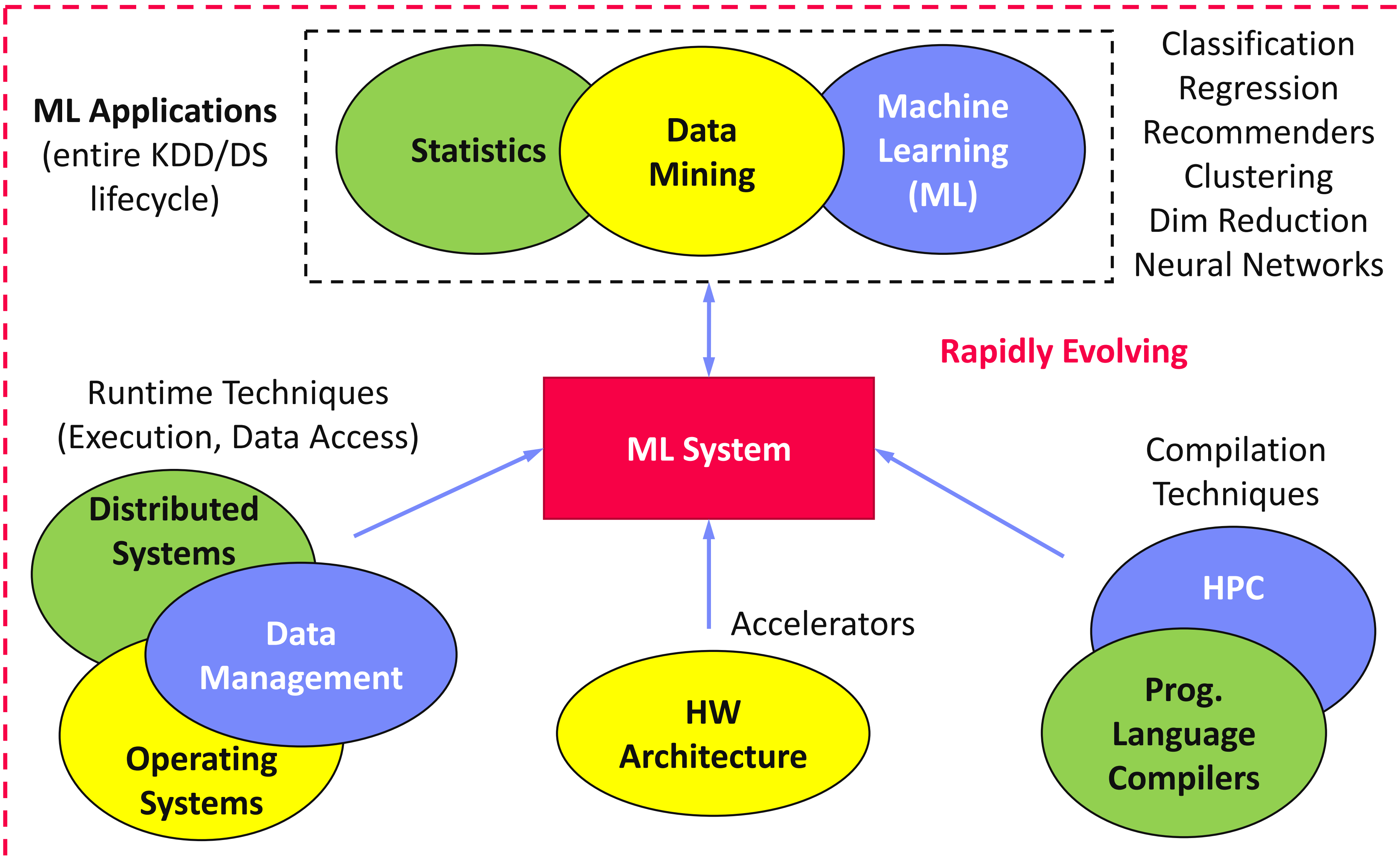


- **Training and Scoring**



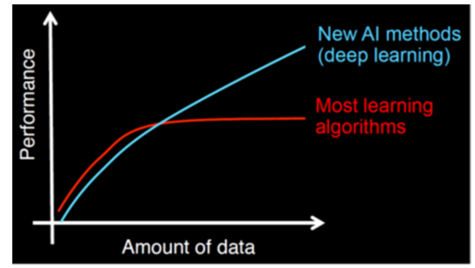
ML Systems Stack

What is an ML System?



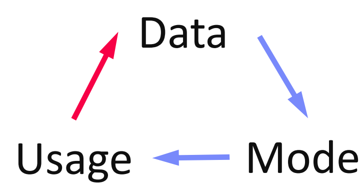
Driving Factors for ML

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



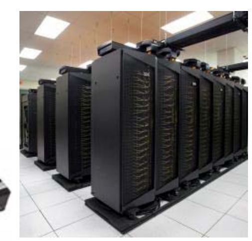
- **Improved Algorithms and Models**
  - Success across data and application domains (e.g., health care, finance, transport, production)
  - More complex models which leverage large data

Feedback Loop



- **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

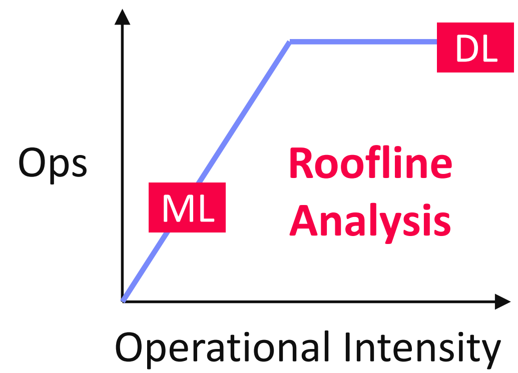
Concern	Layer	Examples
Hyper-parameter Tuning	ML Apps & Algorithms	Supervised, unsupervised, RL linear algebra, libs, AutoML
Model and Feature Selection	Language Abstractions	Eager interpretation, lazy evaluation, prog. compilation
Data Programming & Augmentation	Fault Tolerance	Approximation, lineage, checkpointing, checksums, ECC
Data Preparation (e.g., one-hot, binning)	Execution Strategies	Local, distributed, cloud (data, task, parameter server)
	Data Representations	Dense & sparse tensor/matrix; compress, partition, cache
Data Integration & Data Cleaning	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



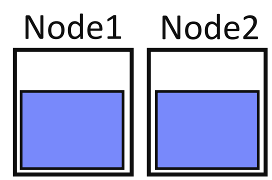
- **Graphics Processing Units (GPUs)**
  - Extensively used for deep learning training and scoring
  - NVIDIA Volta: "tensor cores" for 4x4 mm → 64 2B FMA instruction
- **Field-Programmable Gate Arrays (FPGAs)**
  - Customizable HW accelerators for prefiltering, compression, DL
  - Examples: Microsoft 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

- **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

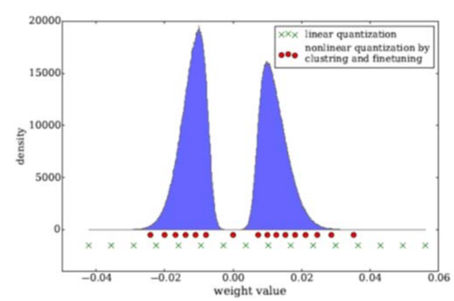
```
vec(Berlin) – vec(Germany)
+ vec(France) ≈ vec(Paris)
```

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



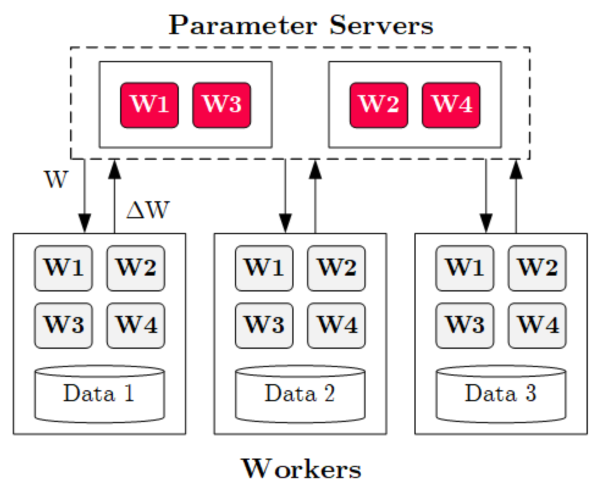
- **Lossy Compression → Acc/Perf-Tradeoff**
  - Sparsification (reduce non-zero values)
  - Quantization (reduce value domain), learned
  - New data types: Intel Flexpoint (mantissa, exp)

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



Execution Strategies

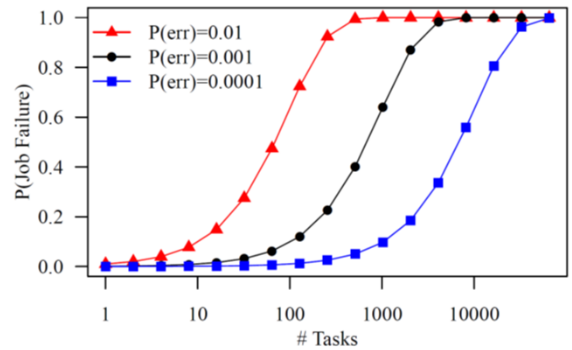
- **Batch Algorithms: Data and Task Parallel**
  - Data-parallel operations
  - Different physical operators
- **Mini-Batch Algorithms: Parameter Server**
  - Data-parallel and model-parallel PS
  - Update strategies (e.g., async, sync, backup)
  - Data partitioning strategies
  - Federated ML (trend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



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

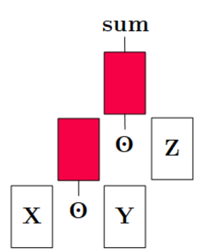
- **ML-specific Schemes** (exploit app characteristics)
  - Estimate contribution from lost partition to avoid strugglers
  - Example: user-defined "compensation" functions

Language Abstractions

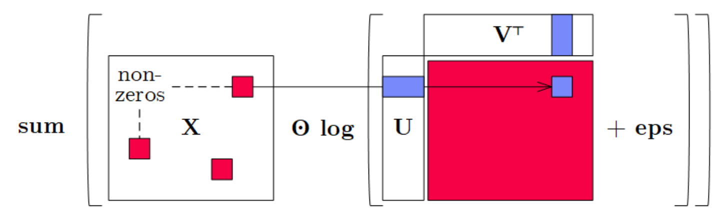
- **Optimization Scope**
  - **#1 Eager Interpretation** (debugging, no opt)
  - **#2 Lazy expression evaluation** (some opt, avoid materialization)
  - **#3 Program compilation** (full opt, difficult)

- **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 Dask Ludwig

TUPAQ Mlbase Tupleware GraphLab HP Distributed R

Kasen Emma Cümülön(-D) OptiML

Glade Cumulon **SystemDS** DMac RIOT-DB

LINVIEW Photon ML **SystemML** RIOT

Hemingway Mahout Samsara SAP HANA MS (Rev) R

Velox F Brainwash ORE **BigR** SciDB

Longview TensorDB DeepDive AzureML Fa R4ML

Columbus SimSQL Orion Zombie ScalOps MXNet

R BUDS

Matlab Santoku LibFM KeystoneML Torch PyTorch

Julia scikit-learn Sherlock ModelHub BigDL TensorFlow

Weka ModelDB Hamlet

Mahout CNTK Theano

SPSS VW Spark ML MADlib

SAS Spark R Flink ML Bismarck Keras Singa DL4J Caffe

Landscape of ML Systems, cont.

#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;
```

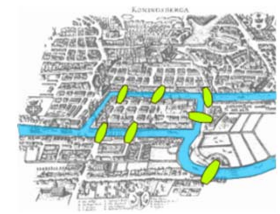
Optimization w/ UDA

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

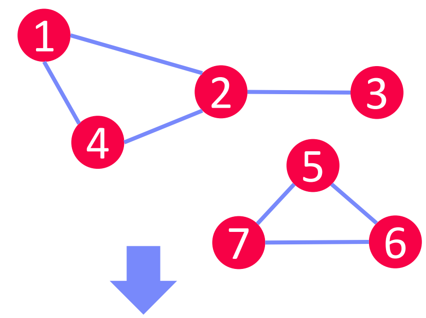
Graph-based Systems

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

Worker 1

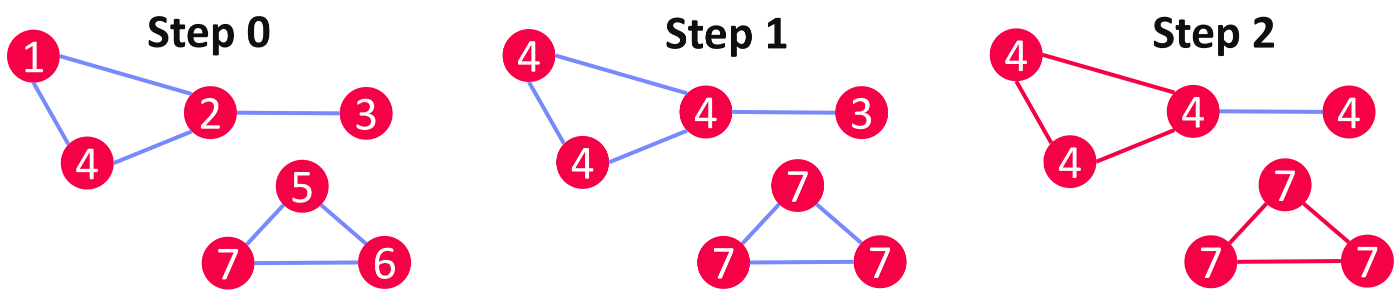
---

5 [6, 7]
3 [2]
6 [5, 7]

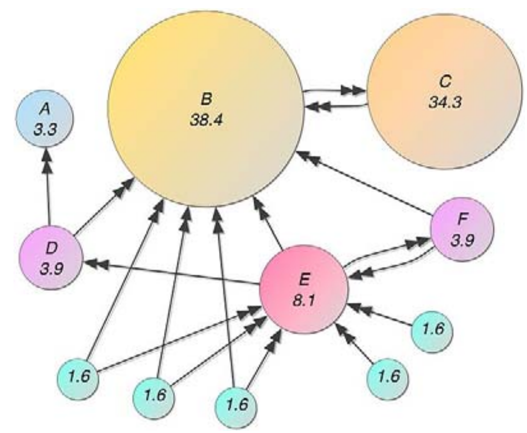
Worker 2

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]

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

DB

PL **HPC**

Compilers for Large-scale ML

- **#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)

```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)

```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**

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

DNN Benchmarks, cont.

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

Closed Division Times

#	Submitter	System	Processor	#	Accelerator	#	Software	Benchmark results (minutes): Image classification, ImageNet, ResNet-50 v1.5	Object detection, light-weight, COCO, SSD w/ ResNet-34	Object detection, heavy-wt., COCO, Mask-R-CNN	Translation, recurrent, WMT E-G, NMT	Translation, non-recur., WMT E-G, Transformer	Recom-mendation, MovieLens-20M, NCF	Reinforce-ment Learning, Go, 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									

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, Hantian Zhang, Luyuan Zeng, Wentao Wu, Ce Zhang: 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, **CoRR 2019**]

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

[Tianhe Yu et al: Meta-World: A Benchmark and Evaluation for Multi-Task and Meta Reinforcement Learning, **CoRL 2019**]

Programming Projects

Refinement until March 27

(bring you own if you want)

Project Selection by April 03

Example Projects APIs/Tools

- **#1 Extended Python and Java Language Bindings**
- **#2 Auto Differentiation** (builtin function and compiler)
- **#3 Built-in Functions for Regression, Classification, Clustering**
- **#4 Built-in Functions for Time Series Missing Value Imputation**
- **#5 DL-based Entity Resolution Primitives** (baseline implementation)
- **#6 Model Selection Primitives** (BO, multi-armed bandit, hyperband)
- **#7 Neural Collaborative Filtering** (see MLPerf benchmark)
- **#8 Quantum Neural Networks** (Grover's Quantum Search, Qiskit/TFQ)

- **#9 SLAB Benchmark** (benchmark driver, summary)
- **#10 Documentation and Tutorials** (for different target users)
- **#11 Extended Test Framework** (comparisons, caching, remove redundancy)
- **#12 Performance Testsuite** (extend algorithm-level suite)
- **#13 ONNX Graph Importer/Exporter** (DML script / HOP DAG generation)

Example Projects Compiler/Runtime

- **#14** Loop Vectorization Rewrites (more general framework)
- **#15** Canonicalization Rewrite Framework (refactoring, new rewrites)
- **#16** Extended CSE & Constant Folding (commutativity, one-shot)
- **#17** Extended Matrix Multiplication Chain Opt (sparsity, rewrites)
- **#18** Extended Update In-Place Framework (reference counting)
- **#19** Operator Scheduling Algorithms (baselines)

- **#20** Lazy / Asynchronous Instruction Evaluation
- **#21** SLIDE Operators and Runtime Integration (Sub-LInear DL Engine)
- **#22** Compression Planning Extensions (co-coding search algorithm)
- **#23** Feature Transform: Equi-Height/Custom Binning (local, distributed)
- **#24** Extended Intel MKL-DNN Runtime Operations (beyond conv2d)
- **#25** Extended I/O Framework for Other Formats (e.g., NetCDF, HDF5, Arrow)
- **#26** Protobuf reader/writer into Data Tensor (local, distributed)

Summary and Q&A

- **Data Science Lifecycle**
- **ML Systems Stack**
- **Language Abstractions**
- **ML System Benchmarks**
- **Programming Projects** (first come, first serve)

- **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