Architecture of ML Systems
04 Adaptation, Fusion, and JIT

Matthias Boehm

Graz University of Technology, Austria
Computer Science and Biomedical Engineering
Institute of Interactive Systems and Data Science
BMK endowed chair for Data Management

PUBLIC DOMAIN

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Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Hybrid: HSi5 / https://tugraz.webex.com/meet/m.boehm

- **#2 AMLS Project Selections**
  - **Project selection** by **Mar 31** (see **Lecture 02** for four alternatives)
  - Discussion current status project selection (~18 students assigned)

- **#3 DAPHNE OSS Release**
  - Public code repository since Mar 31 EOD
  - https://github.com/daphne-eu/daphne
  - Apache v2 license

Agenda

- **Motivation and Terminology**
- **Runtime Adaptation**
- **Operator Fusion & JIT Compilation**

Motivation and Terminology

Recap: 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

PL **DB** **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], **Dask**
  - Examples w/ control structures: **Weld** [CIDR'17], **OptiML** [ICML'11], **Emma** [SIGMOD'15]
- **#3 Program Compilation** (entire program)
  - Examples: **SystemML** [ICDE'11/PVLDB'16], **Julia**, **Cumulon** [SIGMOD'13], **Tupleware** [PVLDB'15]

Optimization Scope

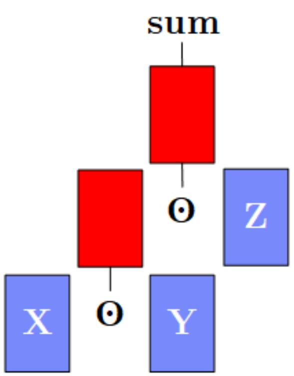
```
X = read($1); # n x m matrix
y = read($2); # n x 1 vector
maxi = 50; lambda = 0.001;
intercept = $3;
...
r = -(t(X) %*% y);
norm_r2 = sum(r * r); p = -r;
w = matrix(0, ncol(X), 1); i = 0;
while(i<maxi & norm_r2>norm_r2_trgt)
{
   q = (t(X) %*% X %*% p)+lambda*p;
   alpha = norm_r2 / sum(p * q);
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

Major Compilation/Runtime Challenges

- **#1 Unknown/Changing Sizes**
  - Sizes inference crucial for cost-estimation and validity constraints (e.g., rewrites)
  - **Tradeoff:** optimization scope vs size inference effort
  - **Challenge:** Unknowns ➔ conservative fallback plans

```
Y = foo(X)
Z = Y[Ix,]
# nrow(Z)?
```

- **#2 Operator Runtime Overhead**
  - Operators great for **programmability**, size inference, simple compilation, and **efficient kernel implementations** (sparse, dense, compressed)
  - **Tradeoff:** general-purpose vs specialization
  - **Challenges:** intermediates, parallelization, complexity of operator combinations



Terminology Ahead-of-Time / Just-in-Time

- **Ahead-of-Time Compilation**
  - Originating from compiled languages like C, C++
  - **#1** **Program compilation** at different abstraction levels
  - **#2** **Inference program compilation** & packaging

Apache SystemML™ TensorFlowLite PYTORCH

- **Just-In-Time Compilation** (at runtime for specific data/HW)
  - Originating from JIT-compiled languages like Java, C#
  - **#1** **Lazy expression evaluation** + optimization
  - **#2** Program/function compilation **with recompilation**

MAHOUT TensorFlow Apache SystemML™ julia (LLVM)

- **Excursus: Java JIT**
  - **#1** Start w/ Java bytecode interpretation by JVM ➔ **fast startup**
  - **#2** **Tiered JIT compile** (cold, warm, hot, very hot, scorching) ➔ **performance**
  - Trace statistics (frequency, time) at method granularity
  - Note: `-XX:+PrintCompilation`

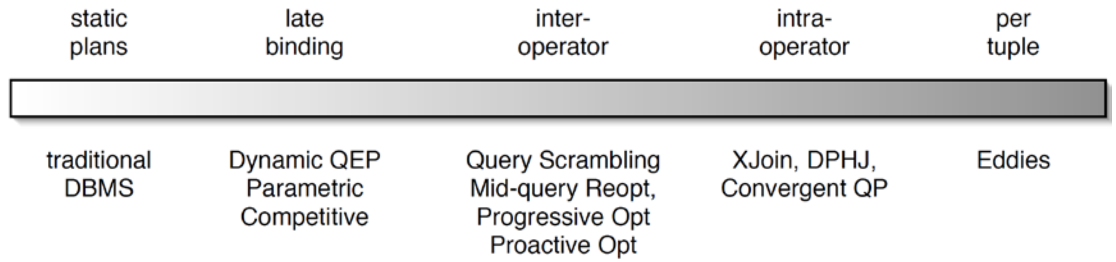
PL

Terminology Runtime Adaptation & JIT

DB

- **Excursus: Adaptive Query Processing**
  - **Spectrum of Adaptivity**

[Amol Deshpande, Joseph M. Hellerstein, Shankar Raman: Adaptive query proc-essing: why, how, when, what next. **SIGMOD 2006**]



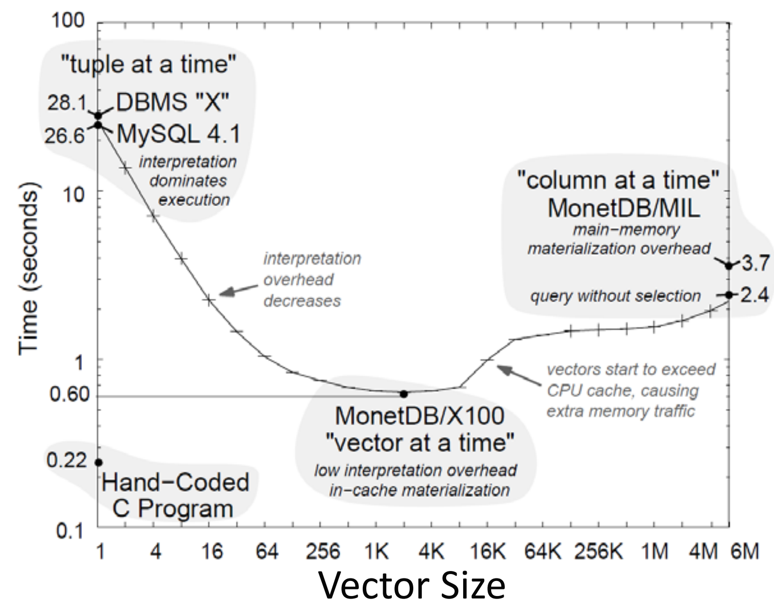
DB

- **Excursus: Query Execution Strategies**
  - **#1 Volcano Iterator Model**
  - **#2 Materialized Intermediates**
  - **#3 Vectorized (Batched) Execution**
  - **#4 Query Compilation**

HPC

  - Similar: Loop fusion, fission, tiling

[Peter A. Boncz, Marcin Zukowski, Niels Nes: MonetDB/X100: Hyper-Pipelining Query Execution. **CIDR 2005**]



Runtime Adaptation

ML Systems w/ Optimizing Compiler

Apache SystemML™

Issues of Unknown or Changing Sizes

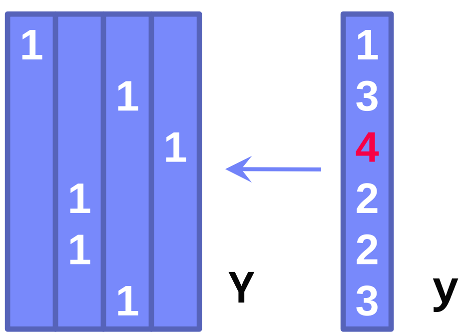
- **Problem of unknown/changing sizes**
  - Unknown or changing sizes and sparsity of intermediates
    These unknowns lead to very conservative fallback plans (distributed ops)
- **#1 Control Flow**
  - Branches and loops
  - Complex function call graphs
  - User-Defined Functions

```
X = read('/tmp/X.csv');
if( intercept )
  X = cbind(X, matrix(1,nrow(X),1));

Z = foo(X) + X; # size of + and Z?
```

- **#2 Data-Dependencies**
  - Data-dependent operators
    (e.g., table, rmEmpty, aggregate)
  - Computed size expressions

```
Y = table(seq(1,nrow(X)), y);
grad = t(X) %*% (P - Y);
```

```
d = dout[,(t-2)*M+1:(t-1)*M];

cur_Q = matrix (0, 1, 2*ncur);
cur_S = matrix (0, 1, ncur*dist);
```



Ex.: Multinomial Logistic Regression

Issues of Unknown or Changing Sizes, cont.

- **#3 Changing Dims and Sparsity**
  - Iterative feature selection workloads
  - Changing dimensions or sparsity
  - ➔ Same code with different data
- **#4 API Limitations**
  - Precompiled scripts/programs (inputs unavailable)
- **(#5 Compiler Limitations)**

Ex: Stepwise LinReg

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

➔ Dynamic recompilation techniques as robust fallback strategy

- Shares goals and challenges with adaptive query processing
- However, ML domain-specific techniques and rewrites

Recompilation

Script

~100 ms

Language

Parsing (syntactic analysis)

Live Variable Analysis

Validate (semantic analysis)

~10 ms

HOPs

Multiple Rounds

Construct HOP DAGs

Static/Dynamic Rewrites

Intra-/Inter-Procedural Analysis

~1 ms

Static/Dynamic Rewrites

Compute Memory Estimates

LOPs

Construct LOP DAGs
(incl operator selection, hop-lop rewrites)

Generate Runtime Program

Execution Plan

[Matthias Boehm et al: SystemML's Optimizer: Plan Generation for Large-Scale Machine Learning Programs. **IEEE Data Eng. Bull 2014**]

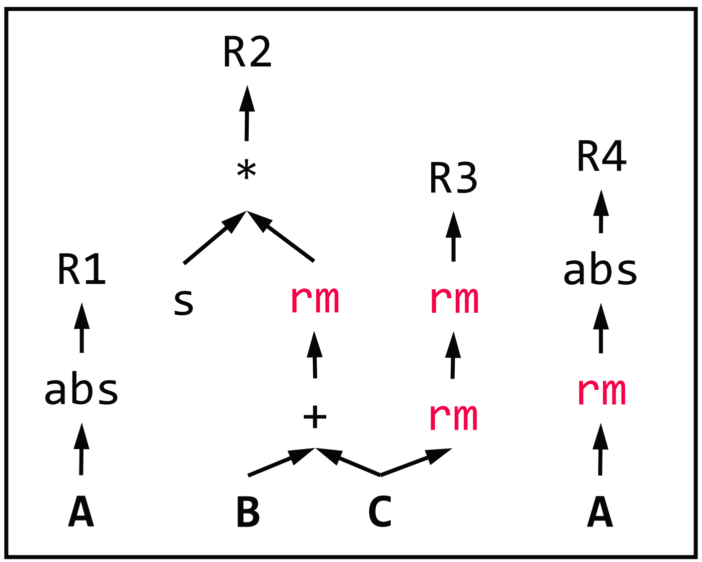
Dynamic Recompilation

Other systems w/ recompile: **SciDB**, **MatFast**

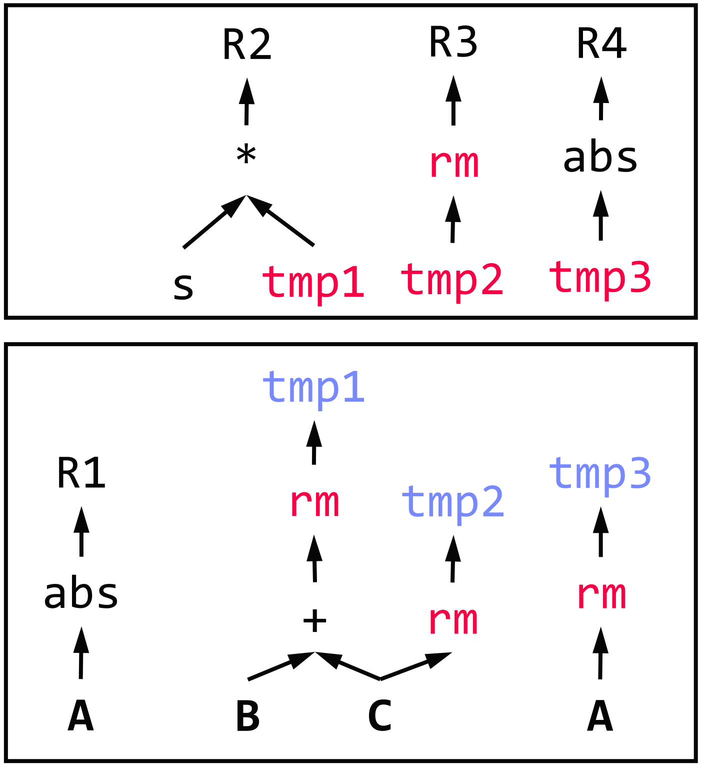
Dynamic Recompilation

- **Compile-time Decisions**
  - **Split HOP DAGs for recompilation:** prevent unknowns but keep DAGs as large as possible; split after reads w/ unknown sizes and specific operators
  - **Mark HOP DAGs for recompilation:** Spark due to unknown sizes / sparsity

Control flow → statement blocks
→ initial recompilation granularity



(recursive rewrite)



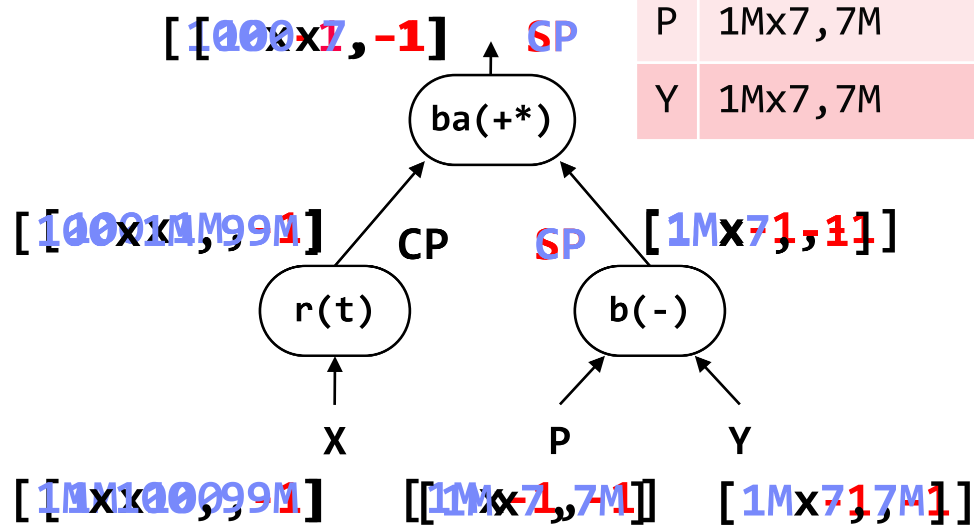
`rm .. removeEmpty(X, [margin="rows",select=I])`

Dynamic Recompilation, cont.

- **Dynamic Recompilation at Runtime** on recompilation hooks (last level program blocks, predicates, recompile once functions)
  - **Deep Copy DAG**
  - Replace Literals
  - **Update DAG Statistics**
  - **Dynamic Rewrites**
  - **Recompute Memory Estimates**
  - **[Codegen]**
  - **Generate Runtime Instructions**

Symbol Table

X	1Mx100,99M
P	1Mx7,7M
Y	1Mx7,7M



Dynamic Recompilation, cont.

- **Recompile Once Functions**
  - Unknowns due to inconsistent or unknown call size information
  - IPA marks functions as “recompile once”, if it contains loops
  - **Recompile the entire function on entry + disable unnecessary recompile**

```
foo = function(Matrix[Double] A)
    # recompiled w/ size of A
    return (Matrix[Double] C)
{
    C = rand(nrow(A),1) + A;
    while(...)
      C = C / rowSums(C) * s
}
```

- **Recompile parfor Loops**
  - Unknown sizes and iterations
  - **Recompile parfor loop on entry + disable unnecessary recompile**
  - Create independent DAGs for individual parfor workers

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

Operator Fusion & JIT Compilation

(aka Code Generation)

Many State-of-the-Art ML Systems,
especially for DNNs and numerical computation

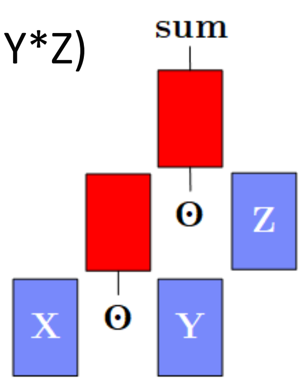
Motivation: Fusion

[Matthias Boehm et al.: On Optimizing Operator Fusion Plans for Large-Scale ML in SystemML. **PVLDB 2018**]

- **Data Flow Graphs** (better data access)
  - DAGs of linear algebra (LA) operations and statistical functions
  - Materialized intermediates → ubiquitous fusion opportunities

a) Intermediates

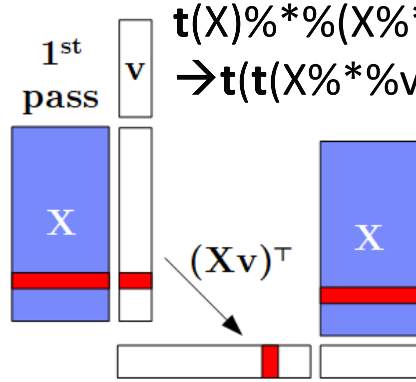
sum(X*Y*Z)



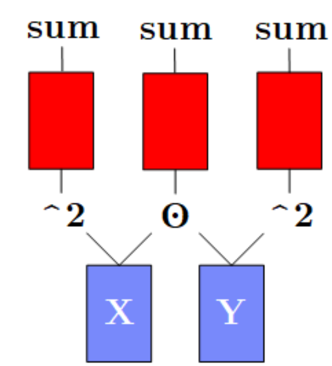
b) Single-Pass

t(X)%*%(X%*%v)

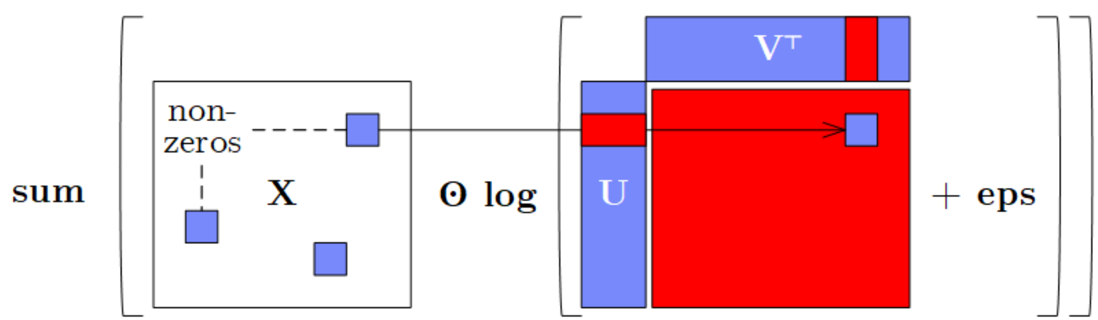
→**t**(**t**(X%*%v)%*%X)



c) Multi-Aggregates



d) Sparsity Exploitation

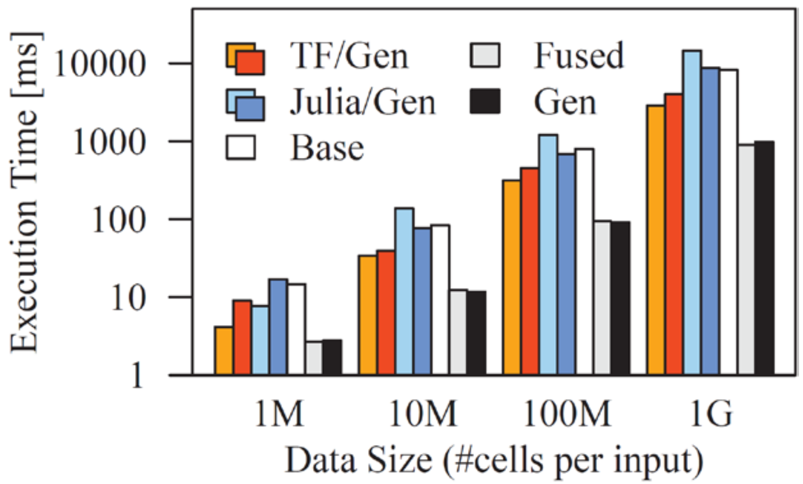


Motivation: Fusion, cont.

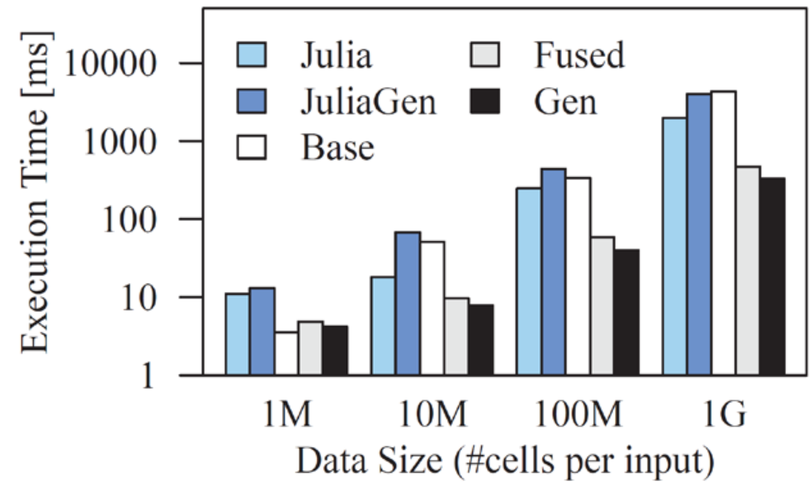
Beware: SystemML 1.0, Julia 0.6.2, TensorFlow 1.5

Cell Template: `sum(X*Y*Z)`

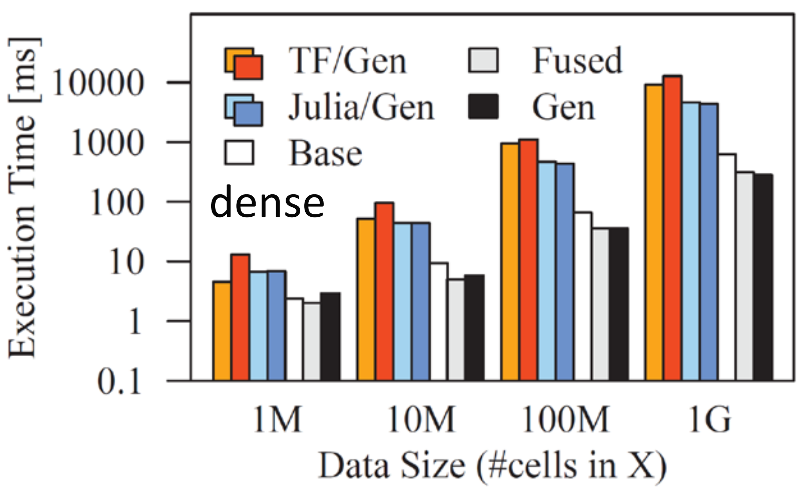
dense



sparse (0.1)

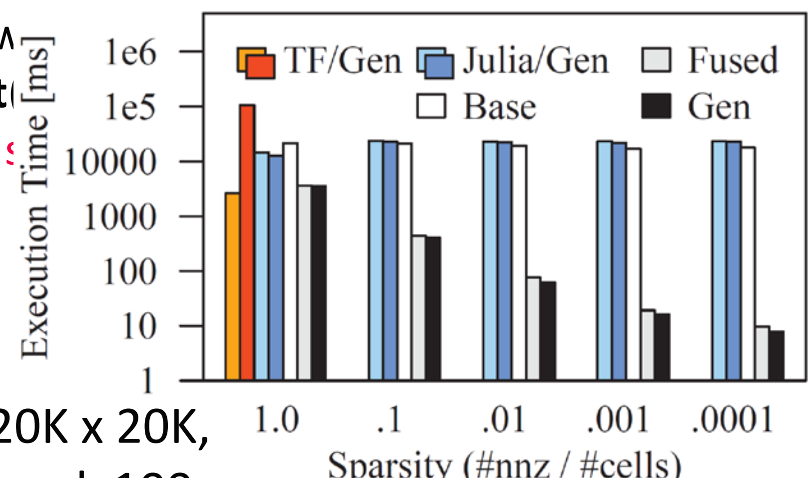


Row: `t(X)%*%(w*(X%*%v))`



Outer: `sum(X*log(U%*%t(V)+1e-15))`

TF w
→ t(
9.2 s



20K x 20K, rank 100

Motivation: Just-In-Time Compilation

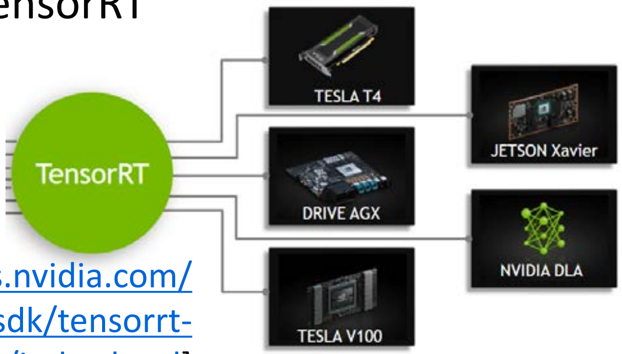
- **Operator Kernels (better code)**
  - Specialization opportunities: data types, shapes, and operator graphs
  - Heterogeneous hardware: CPUs, GPUs, FPGAs, ASICs x architectures
- **#1 CPU Architecture**
  - Specialize to available instructions sets
  - Register allocation and assignment, etc

Examples: x86-64, sparc, amd64, arm, ppc

- **#2 Heterogeneous Hardware**
  - JIT compilation for custom-build ASICs with HW support for ML ops
  - Different architectures of devices

Example: NVIDIA TensorRT

GPU Platforms



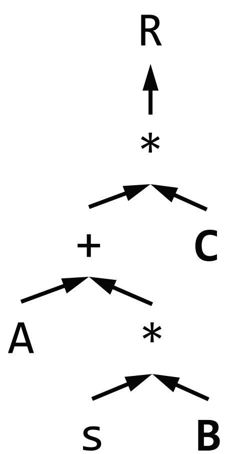
[https://docs.nvidia.com/deeplearning/sdk/tensorrt-developer-guide/index.html]

- **#3 Custom ML Program**
  - Operator graphs and sizes

Operator Fusion Overview

- **Related Research Areas**
  - DB: **query compilation**
  - HPC: **loop fusion, tiling, and distribution** (**NP complete**)
  - ML: **operator fusion** (dependencies given by data flow graph)

- **Example Operator Fusion**




```
for( i in 1:n )
  tmp1[i,1] = s * B[i,1];
for( i in 1:n )
  tmp2[i,1] = A[i,1] + tmp1[i,1];
for( i in 1:n )
  R[i,1] = tmp2[i,1] * C[i,1];
```

```
for( i in 1:n )
  R[i,1] = (A[i,1] + s*B[i,1]) * C[i,1];
```

Memory Bandwidth:
L1 core: 1TB/s
L3 socket: 400GB/s
Mem: 100 GB/s

[https://software.intel.com/en-us/articles/memory-performance-in-a-nutshell]

Evolution of Operator Fusion in ML Systems

- **1st Gen: Handwritten Fused Operators**
  - [BLAS (since 1979): e.g., `alpha * X + Y` → `AXPY`]
  - Rewrites: e.g., A+B+C → `AddN(A, B, C)`, `t(X) %*% (w * (X %*% v))` → `MMCHAIN`
  - Sparsity exploiting fused ops: e.g., `sum(X*log(U%*%t(V)+eps))`

[Arash Ashari: On optimizing machine learning workloads via kernel fusion. **PPOPP 2015**]

[Matthias Boehm: SystemML: Declarative Machine Learning on Spark. **PVLDB 2016**]

- **2nd Gen: Fusion Heuristics**
  - Automatic operator fusion via elementary ops
  - Heuristics for replacing sub-DAGs w/ fused ops

[Tarek Elgamal et al: SPOOF: Sum-Product Optimization and Operator Fusion for Large-Scale Machine Learning. **CIDR 2017**]

- **3rd Gen: Optimized Fusion Plans**
  - Greedy/exact fusion plan (sub-DAG) selection
  - [Greedy/evolutionary kernel implementations]

[Matthias Boehm et al.: On Optimizing Operator Fusion Plans for Large-Scale ML in SystemML. **PVLDB 2018**]

Automatic Operator Fusion System Landscape

System	Year	Approach	Sparse	Distr.	Optimization
BTO	2009	Loop Fusion	No	No	k-Greedy, cost-based
Tupleware	2015	Loop Fusion	No	Yes	Heuristic
Kasen	2016	Templates	(Yes)	Yes	Greedy, cost-based
SystemML	**2017**	**Templates**	**Yes**	**Yes**	**Exact, cost-based**
Weld	2017	Templates	(Yes)	Yes	Heuristic
Taco	2017	Loop Fusion	Yes	No	Manuel
Julia	2017	Loop Fusion	Yes	No	Manuel
Tensorflow XLA	2017	Loop Fusion	No	No	Manuel/Heuristic
Tensor Comprehensions	2018	Loop Fusion	No	No	Evolutionary, cost-based
TVM	2018	Loop Fusion	No	No	ML/cost-based
PyTorch	2019	Loop Fusion	No	No	Manual/Heuristic
JAX	2019	N/A	No	No	See TF XLA

JIT

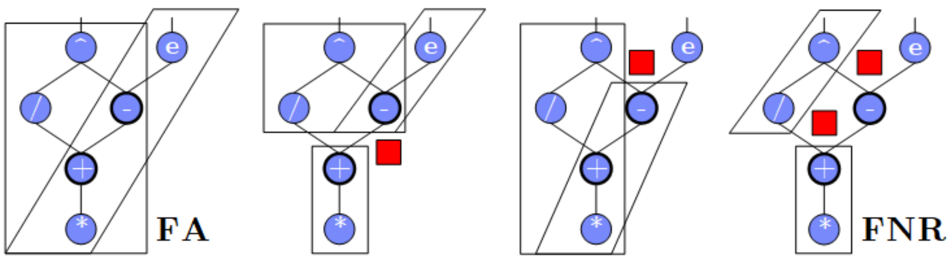
A Case for Optimizing Fusion Plans

Apache SystemML™

- **Problem:** Fusion heuristics → **poor plans** for complex DAGs (cost/structure), sparsity exploitation, and local/distributed operations
- **Goal: Principled approach for optimizing fusion plans**

$$C = A + s * B$$
$$D = (C/2)\hat{}(C\text{-}1)$$
$$E = \exp(C\text{-}1)$$

- **#1 Materialization Points**
  (e.g., for multiple consumers)
- **#2 Sparsity Exploitation**
  (and ordering of sparse inputs)
- **#3 Decisions on Fusion Patterns**
  (e.g., template types)
- **#4 Constraints**
  (e.g., memory budget and block sizes)

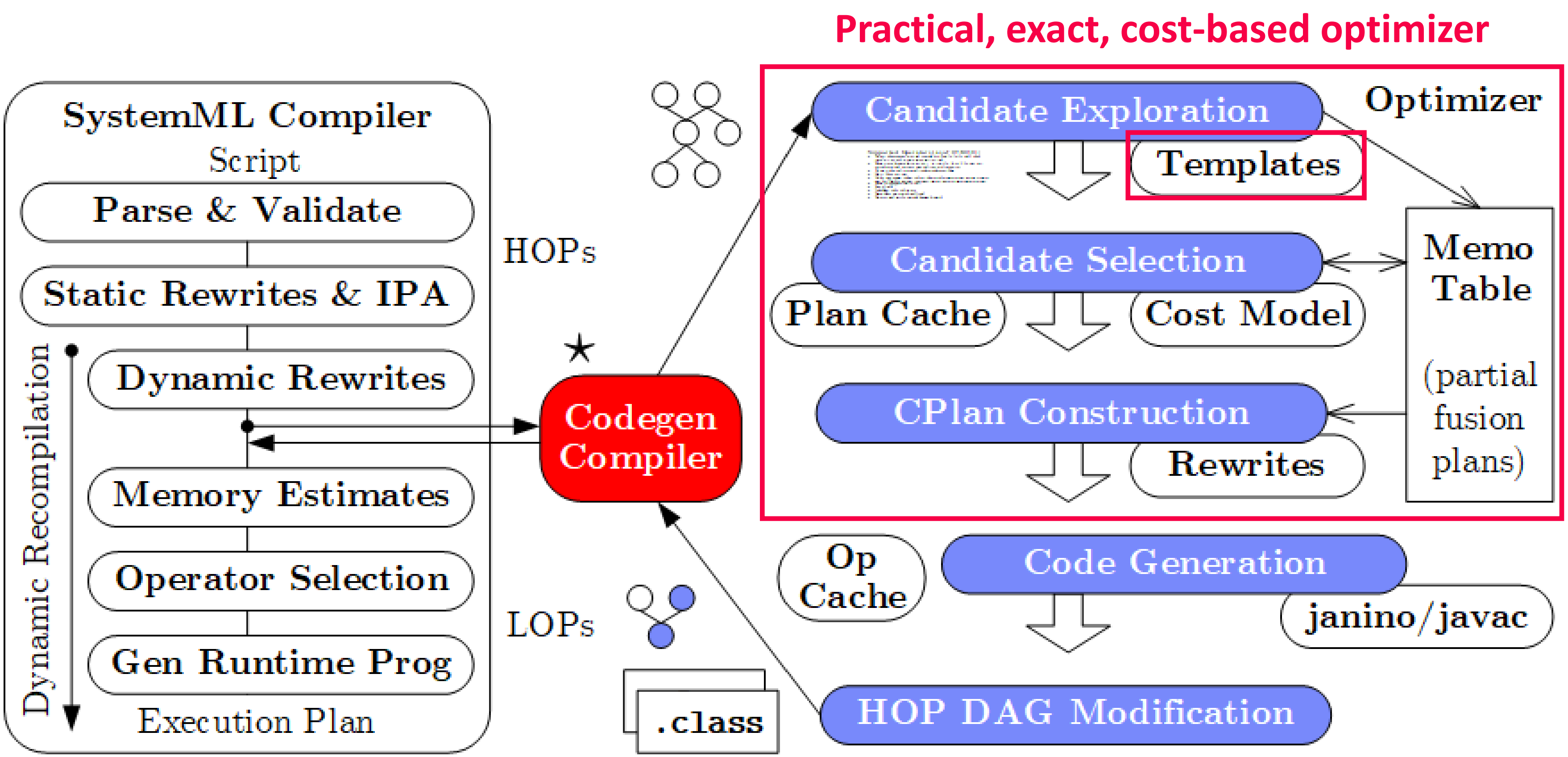



```
Y + X * (U %*% t(V))
```

sparse-safe over X

→ **Search Space that requires optimization**

System Architecture (Compiler & Codegen Architecture)

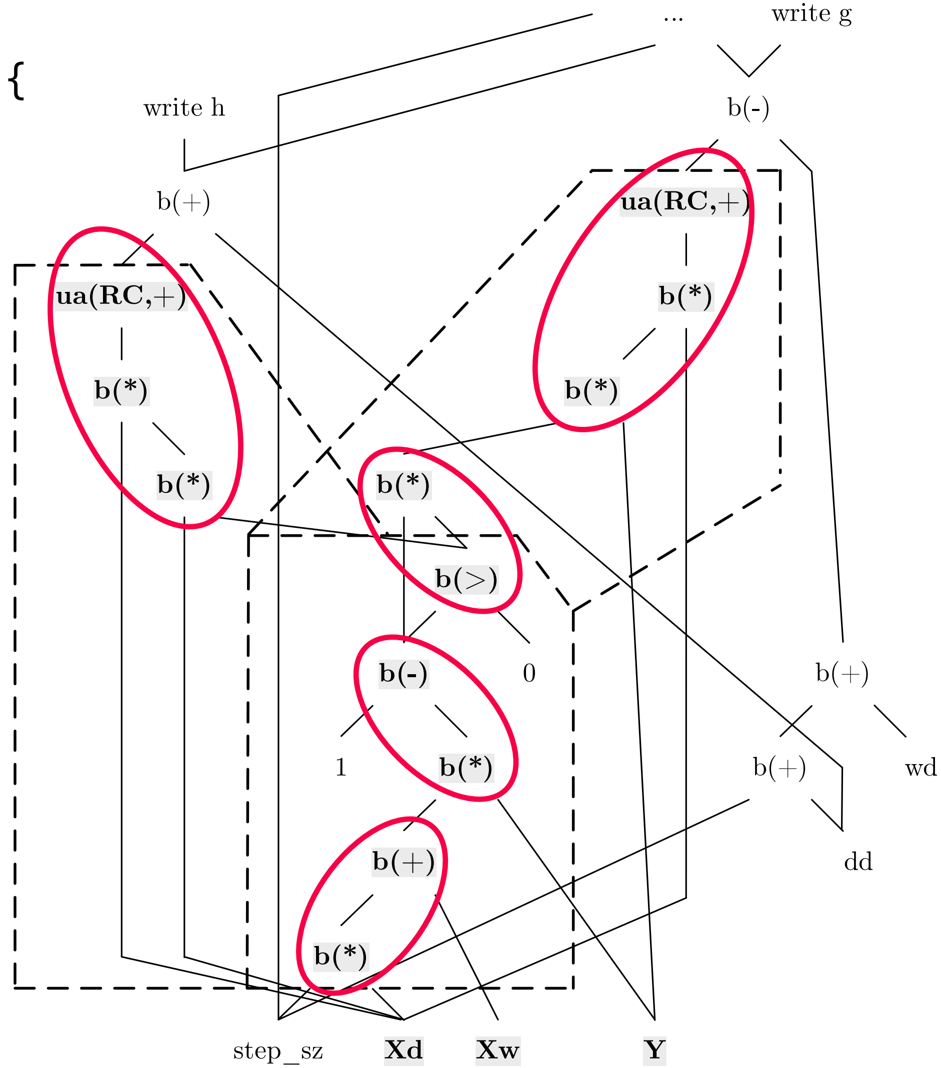


- CPlan representation/construction and codegen similar in TF XLA (HLO primitives, pre-clustering of nodes, caching, LLVM codegen)
- **Templates:** Cell, Row, MAgg, Outer w/ different data bindings

Codegen Example L2SVM (Cell/MAgg)

- **L2SVM Inner Loop**

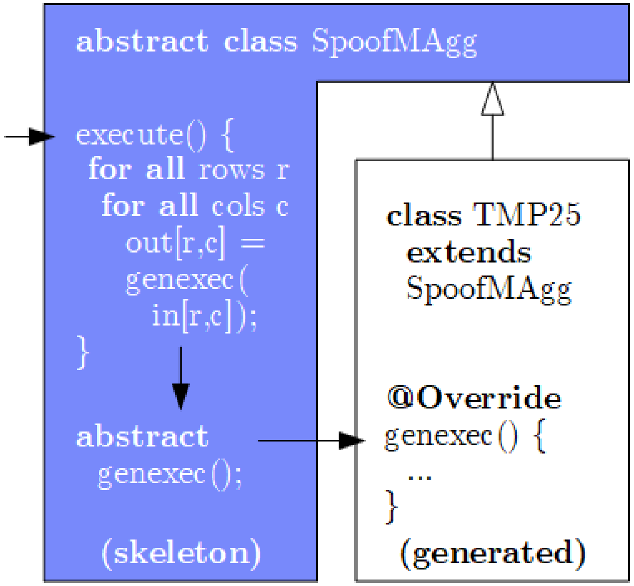
```
while(continueOuter & iter < maxi) {
  #...
  while(continueInner) {
    out = 1-Y* (Xw+step_sz*Xd);
    sv = (out > 0);
    out = out * sv;
    g = wd + step_sz*dd
      - sum(out * Y * Xd);
    h = dd + sum(Xd * sv * Xd);
    step_sz = step_sz - g/h;
}} ...
```



- **# of Vector Intermediates**
  - Base (w/o fused ops): **10**
  - Fused (w/ fused ops): **4**

Codegen Example L2SVM, cont. (Cell/MAgg)

- **Template Skeleton**
  - Data access, blocking
  - Multi-threading
  - Final aggregation



- **# of Vector Intermediates**
  - Gen (codegen ops): 0

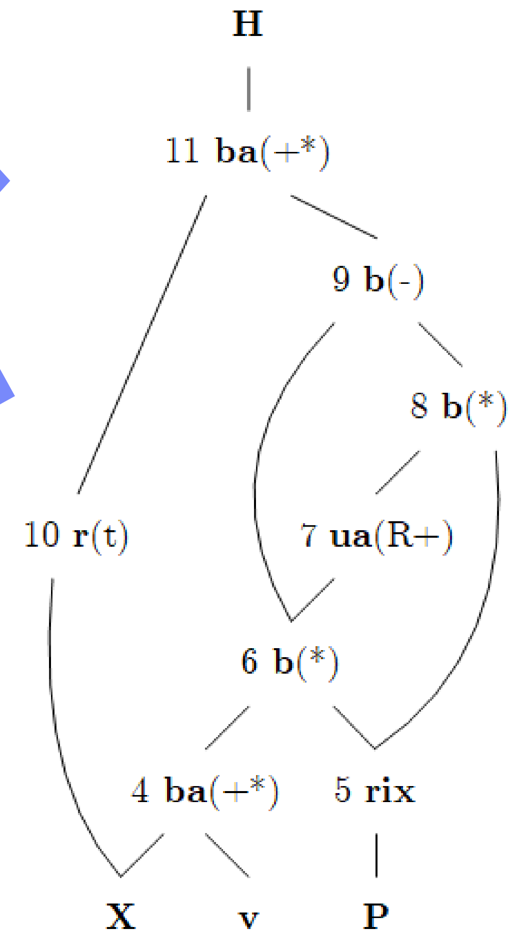
```
public final class TMP25 extends SpoofMAgg {
  public TMP25() {
    super(false, AggOp.SUM, AggOp.SUM);
  }
  protected void genexec(double a, SideInput[] b,
   double[] scalars, double[] c, ...) {
    double TMP11 = getValue(b[0], rowIndex);
    double TMP12 = getValue(b[1], rowIndex);
    double TMP13 = a * scalars[0];
    double TMP14 = TMP12 + TMP13;
    double TMP15 = TMP11 * TMP14;
    double TMP16 = 1 - TMP15;
    double TMP17 = (TMP16 > 0) ? 1 : 0;
    double TMP18 = a * TMP17;
    double TMP19 = TMP18 * a;
    double TMP20 = TMP16 * TMP17;
    double TMP21 = TMP20 * TMP11;
    double TMP22 = TMP21 * a;
    c[0] += TMP19;
    c[1] += TMP22;
  }
}
```

Codegen Example MLogreg (Row)

- **MLogreg Inner Loop**
  (main expression on feature matrix X)

```
1: Q = P[, 1:k] * (X %*% v)
2: H = t(X) %*% (Q - P[, 1:k] * rowSums(Q))
```

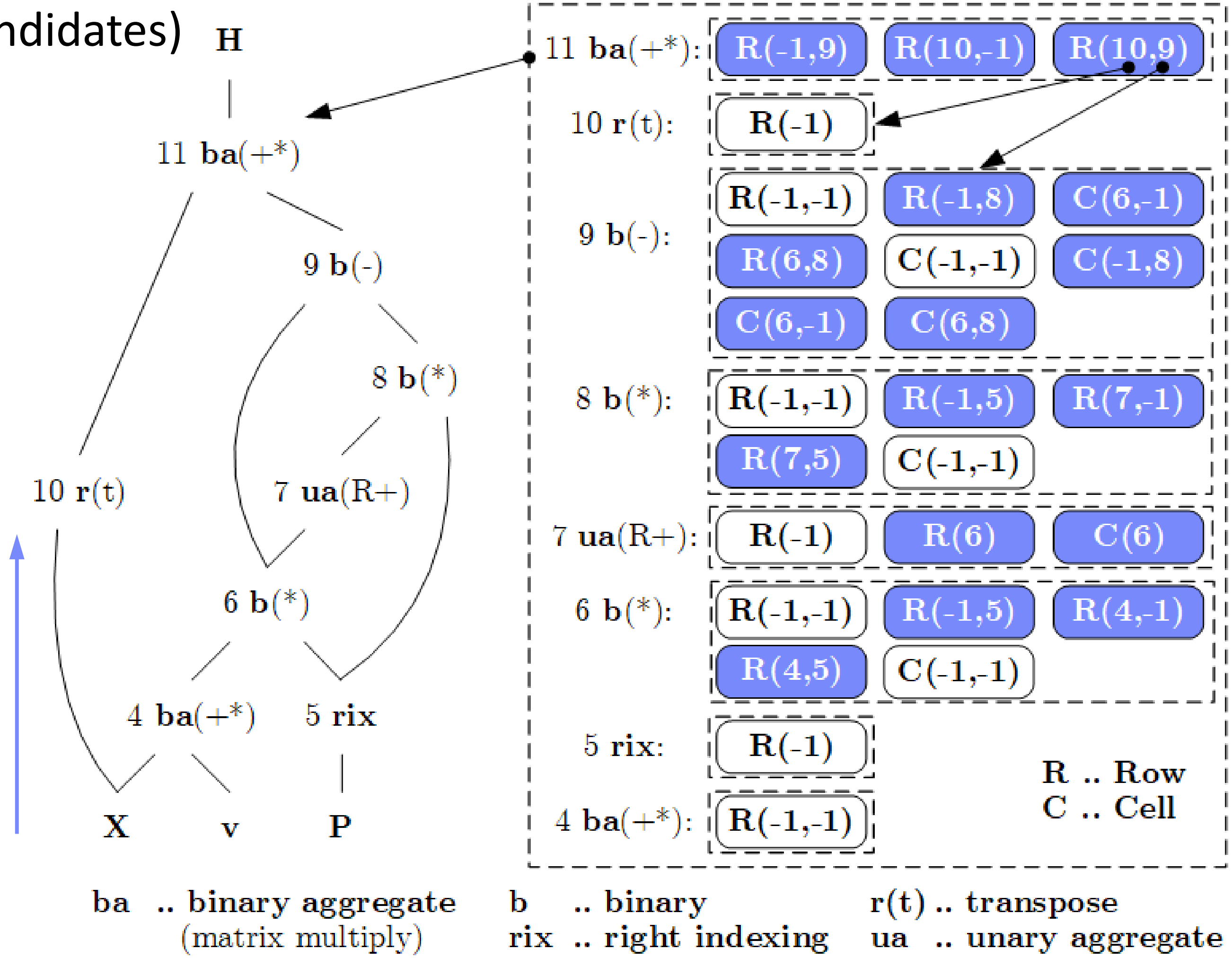
```
public final class TMP25 extends SpoofRow {
  public TMP25() {
    super(RowType.COL_AGG_B1_T, true, 5);
  }
  protected void genexecDense(double[] a, int ai,
   SideInput[] b, double[] c,..., int len) {
    double[] TMP11 = getVector(b[1].vals(rix),...);
    double[] TMP12 = vectMatMult(a, b[0].vals(rix),...);
    double[] TMP13 = vectMult(TMP11, TMP12, 0, 0,...);
    double TMP14 = vectSum(TMP13, 0, TMP13.length);
    double[] TMP15 = vectMult(TMP11, TMP14, 0,...);
    double[] TMP16 = vectMinus(TMP13, TMP15, 0, 0,...);
    vectOuterMultAdd(a, TMP16, c, ai, 0, 0,...); }
  protected void genexecSparse(double[] avals, int[] aix,
   int ai, SideInput[] b, ..., int len) {...}
}
```



Candidate Exploration (by example MLogreg)

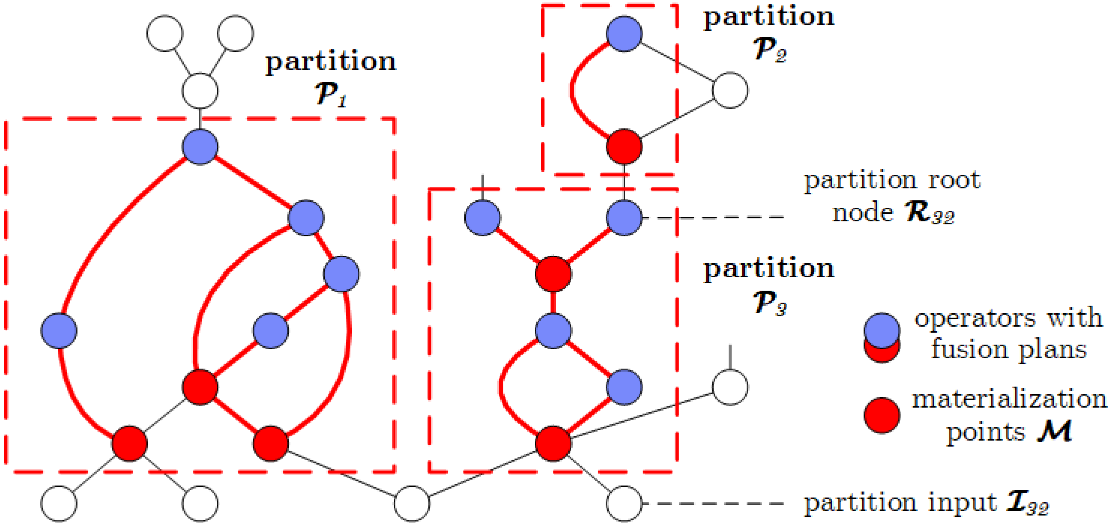
- **Memo Table for partial fusion plans** (candidates)
- **OFMC Template Fusion API**
  - Open
  - Fuse, Merge
  - Close
- **OFMC Algorithm**
  - **Bottom-up Exploration** (single-pass, template-agnostic)
  - Linear space and time

Memo Table



Candidate Selection (Partitions and Interesting Points)

- **#1 Determine Plan Partitions**
  - Materialization Points M
  - Connected components of fusion references
  - Root and input nodes
  - → **Optimize partitions independently**



- **#2 Determine Interesting Points**
  - **Materialization Point Consumers:** Each data dependency on materialization points considered separately
  - **Template / Sparse Switches:** Data dependencies where producer has templates that are non-existing for consumers
  - → **Optimizer considers all $2^{|M'_i|}$ plans** (with $|M'_i| \geq |M_i|$) per partition

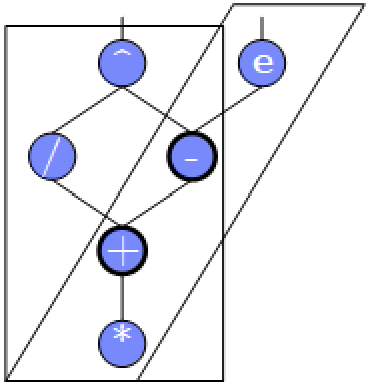
Candidate Selection, cont. (Costs and Constraints)

- **Overview Cost Model**
  - Cost partition with **analytical cost model** based on peak memory and compute bandwidth
  - Plan comparisons / fusion errors don't propagate / dynamic recompilation

$$C(\mathcal{P}_i|\mathbf{q}) = \sum_{p \in \mathcal{P}_i|\mathbf{q}} \left(\hat{T}_p^w + \max\left(\hat{T}_p^r, \hat{T}_p^c\right)\right)$$

- **#3 Evaluate Costs**
  - #1: Memoization of already processed sub-DAGs
  - #2: Account for shared reads and CSEs within operators
  - #3: Account for redundant computation (overlap)

  → **DAG traversal** and **cost vectors** per fused operator (with memoization of pairs of operators and cost vectors)

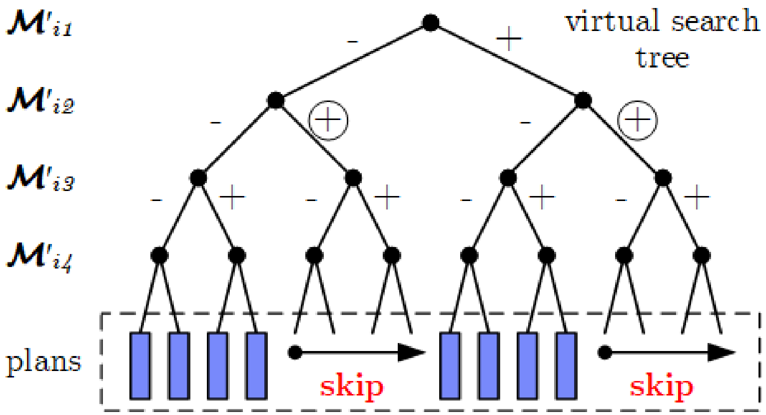


- **#4 Handle Constraints**
  - **Prefiltering** violated constraints (e.g., row template in distributed ops)
  - Assign **infinite costs for violated constraints** during costing

Candidate Selection, cont. (MPSkipEnum and Pruning)

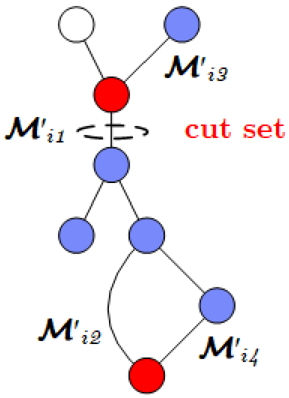
- **#5 Basic Enumeration**
  - Linearized search space: from - to *

```
for( j in 1:pow(2,|M'_i|) )
   q = createAssignment(j)
   C = getPlanCost(P_i, q)
   maintainBest(q, C)
```



- **#6 Cost-Based Pruning**
  - **Upper bound:** cost C^U of best plan q* (monotonically decreasing)
  - **Opening heuristic:** evaluate FA and FNR heuristics first
  - **Lower bound:** C^{LS} (read input, write output, min compute) + dynamic C^{LD} (materialize intermediates q) ➔ **skip subspace** if $C^U \leq C^{LS} + C^{LD}$

- **#7 Structural Pruning**
  - **Observation:** Assignments can create independent sub problems
  - Build **reachability graph** to determine **cut sets**
  - During enum: probe cut sets, recursive enum, combine, and skip



Ahead-of-Time Compilation

- **TensorFlow `tf.compile`**
  - Compile entire TF graph into binary function w/ low footprint
  - **Input:** Graph, config (feeds+fetches w/ fixes shape sizes)
  - **Output:** x86 binary and C++ header (e.g., inference)
  - **Specialization for frozen model and sizes**

[Chris Leary, Todd Wang: XLA – TensorFlow, Compiled!, **TF Dev Summit 2017**]

- **PyTorch Compile**
  - Compile Python functions into ScriptModule/ScriptFunction
  - Lazily collect operations, optimize, and JIT compile
  - Explicit `jit.script` call or `@torch.jit.script`

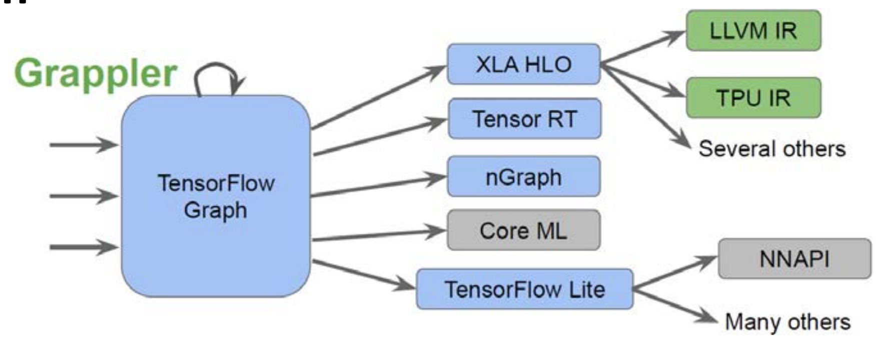
```
a = torch.rand(5)
def func(x):
  for i in range(10):
    x = x * x # unrolled into graph
  return x

jitfunc = torch.jit.script(func) # JIT
jitfunc.save("func.pt")
```

[Vincent Quenneville-Bélair: How PyTorch Optimizes Deep Learning Computations, **Guest Lecture Stanford 2020**]

Excursus: MLIR

[Rasmus Munk Larsen, Tatiana Shpeisman: TensorFlow Graph Optimizations, **Guest Lecture Stanford 2019**]

- **Motivation TF Compiler Ecosystem**
  - Different IRs and compilation chains for runtime backends
  - **Duplication of infrastructure** and fragile error handling
  - Adoption: PYTORCH [https://github.com/llvm/torch-mlir]



- **MLIR (Multi-level, Machine Learning IR)**
  - SSA-based IR, similar to LLVM
  - Hierarchy of modules, functions, regions, blocks, and operations
  - **Dialects for different backends** (defined ops, customization)
  - **Systematic lowering**

```
func @testFunction(%arg0: i32) {
  %x = call @thingToCall(%arg0)
    : (i32) -> i32
  br ^bb1
^bb1:
  %y = addi %x, %x : i32
  return %y : i32
}
```

[Chris Lattner et al.: MLIR: Scaling Compiler Infrastructure for Domain Specific Computation. **CGO 2021,** https://arxiv.org/pdf/2002.11054.pdf]

Excursus: MLIR, cont.

(DAPHNE pre-project prototype)

```
while(i < max_iter) { # PageRank
  p = alpha*(G%*%p) + (1-alpha)*(e%*%u%*%p);
  i += 1;
}
```

After Several Optimization Passes

```
module  {
  func @main() {
    %0 = daphne.constant 5.000000e-01 : f64
    %1 = daphne.constant 0 : i64
    %2 = daphne.constant 1.000000e+00 : f64
    %3 = daphne.constant 1 : i64
    %4 = daphne.constant 10 : i64
    %5 = daphne.rand  {cols = 50 : i64, rows = 50 : i64, seed = -1 : i64, sparsity = 7.000000e-02 : f64} : () -> ...
    %6, %7, %8 = ...
    %9 = daphne.sub %2, %0 : (f64, f64) -> f64
    %10:2 = daphne.while (%arg0 = %6, %arg1 = %1) : (!daphne.matrix<50x1xf64>, i64) -> (same) condition: {
      %11 = cmpi "ult", %arg1, %4 : i64
      daphne.yield %11 : i1
    } body: {
      %11 = daphne.mat_mul %5, %arg0 : (!daphne.matrix<50x50xf64>, !daphne.matrix<50x1xf64>) -> !daphne.matrix<50x1xf64>
      %12 = daphne.mul %11, %0 : (!daphne.matrix<50x1xf64>, f64) -> !daphne.matrix<50x1xf64>
      %13 = daphne.mat_mul %8, %arg0 : (!daphne.matrix<1x50xf64>, !daphne.matrix<50x1xf64>) -> !daphne.matrix<1x1xf64>
      %14 = daphne.mat_mul %7, %13 : (!daphne.matrix<50x1xf64>, !daphne.matrix<1x1xf64>) -> !daphne.matrix<50x1xf64>
      %15 = daphne.mul %9, %14 : (f64, !daphne.matrix<50x1xf64>) -> !daphne.matrix<50x1xf64>
      %16 = daphne.add %12, %15 : (!daphne.matrix<50x1xf64>, !daphne.matrix<50x1xf64>) -> !daphne.matrix<50x1xf64>
      %17 = daphne.add %arg1, %3 : (i64, i64) -> i64
      daphne.yield %16, %17 : !daphne.matrix<50x1xf64>, i64
    }
    daphne.print %10#0 : !daphne.matrix<50x1xf64>
    daphne.return
  }
}
```

3) Code motion outside loop

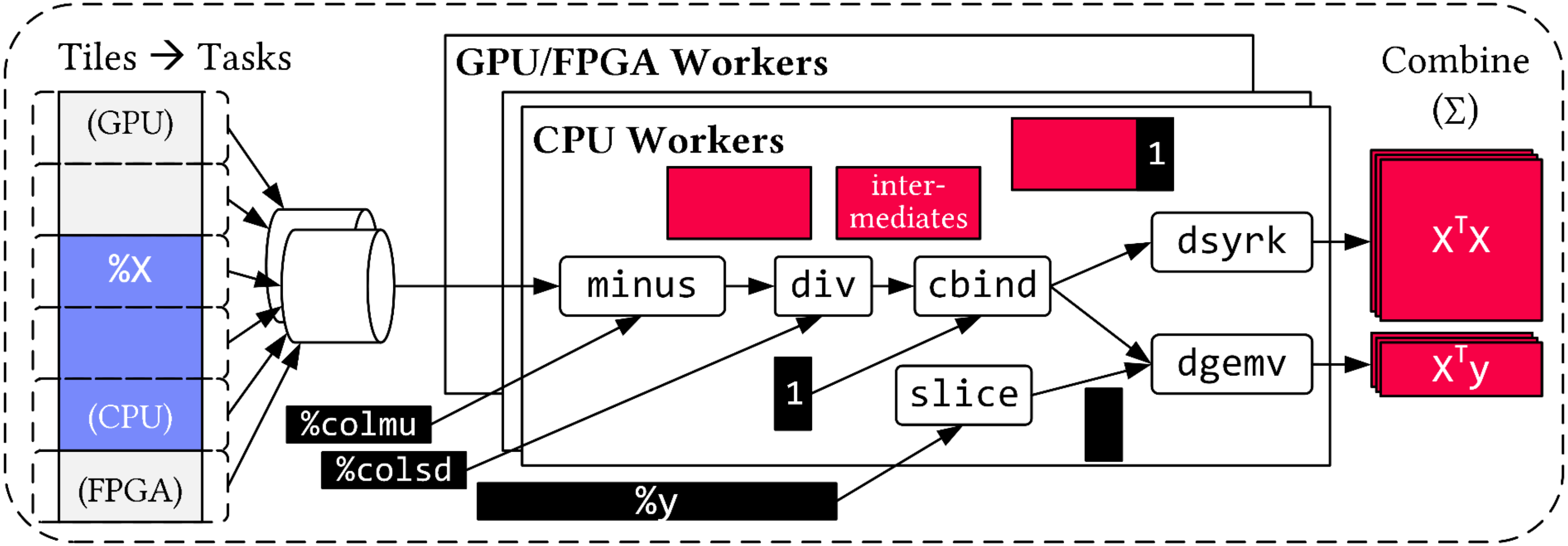
1) Shape inference of dimensions

2) Matrix multiplication chain reordered

DAPHNE – Vectorized Execution

AH
AK

```
(%9, %10) = fusedPipeline1(%X, %y, %colmu, %colsd) {
```



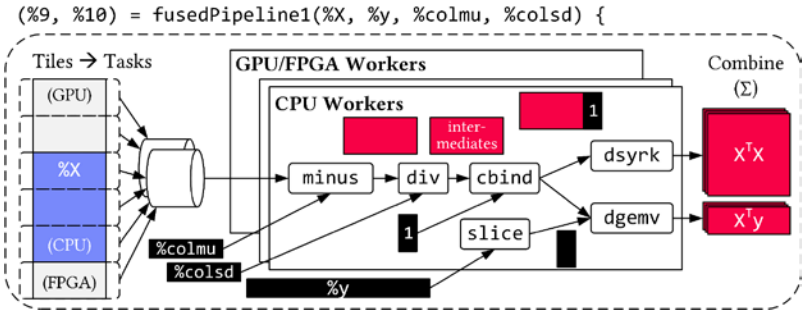
Default Parallelization Frame & Matrix Ops

Locality-aware, Multi-device Scheduling

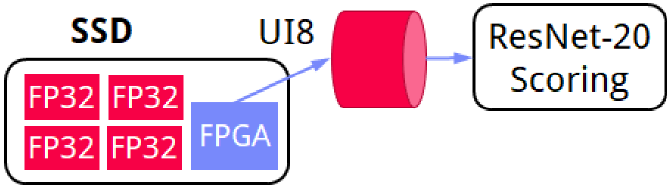
Fused Operator Pipelines on Tiles/Scalars + Codegen

DAPHNE – Vectorized Execution, cont.

- **#1 Zero-copy Input Slicing**
  - Create view on sliced input (no-op)
  - All kernels work on views



- **#2 Sparse Intermediates**
  - Reuse dense/sparse kernels
  - Sparse pipeline intermediates for free
- **#3 Fine-grained Control**
  - Task sizes (dequeue, data access) vs data binding (cache-conscious ops)
  - Scheduling for load balance (e.g., sparse operations)
- **#4 Computational Storage**
  - Task queues connect eBPF programs, async I/O into buffers, and op pipelines



Conclusions

- **Summary**
  - Motivation and Terminology
  - Runtime Adaptation
  - Operator Fusion & JIT

Recommended Reading

[Chris Leary, Todd Wang: XLA – TensorFlow, Compiled!, **TF Dev Summit 2017,** https://www.youtube.com/watch?v=kAOanJczHA0]

→ **Impact of Size Inference and Costs (lecture 03)**

→ **Ubiquitous Rewrite, Fusion, and Codegen/JIT Opportunities**

- **Next Lectures** (Runtime Aspects)
  - **05 Data- and Task-Parallel Execution** (batch/prog) [Apr 08]
  - **Easter break**
  - **06 Parameter Servers** (mini-batch) [Apr 29]
  - **07 Hybrid Execution and HW Accelerators** [May 06]
  - **08 Caching, Partitioning, Indexing and Compression** [May 13]