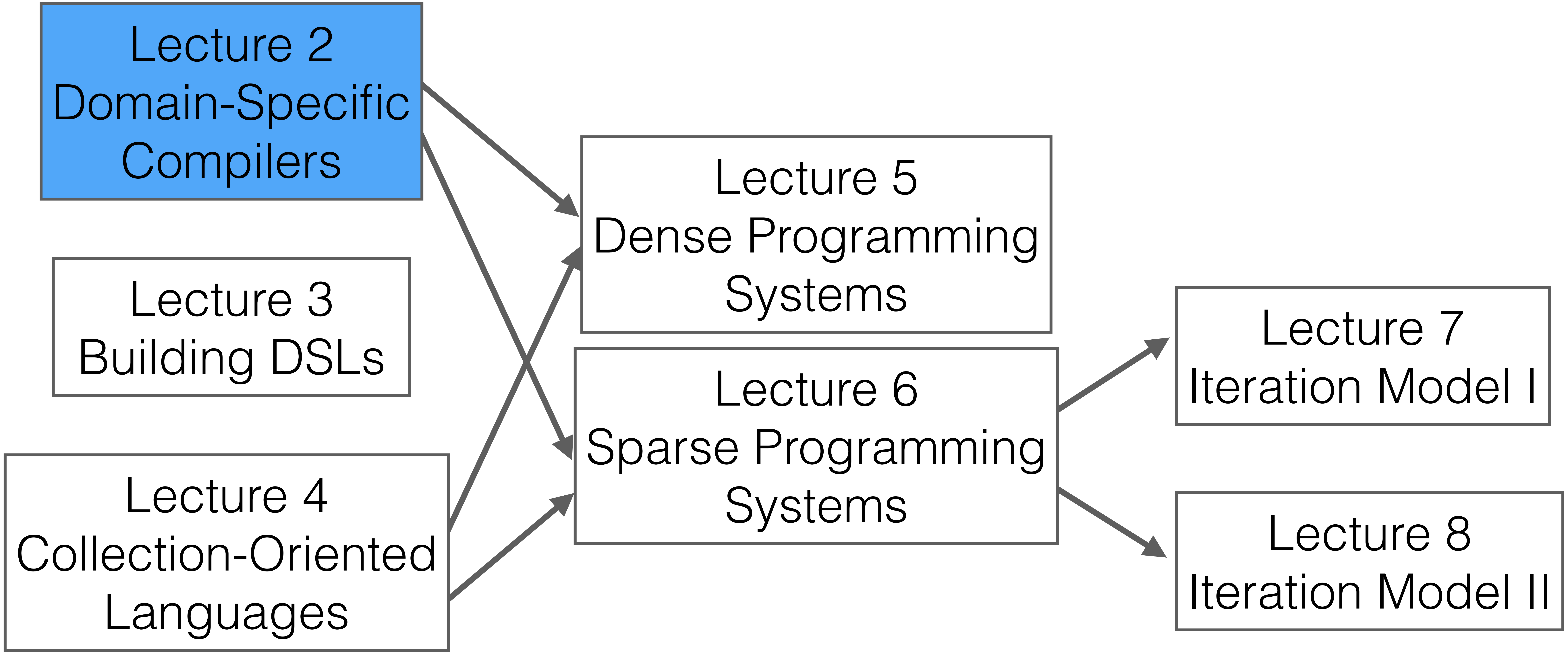
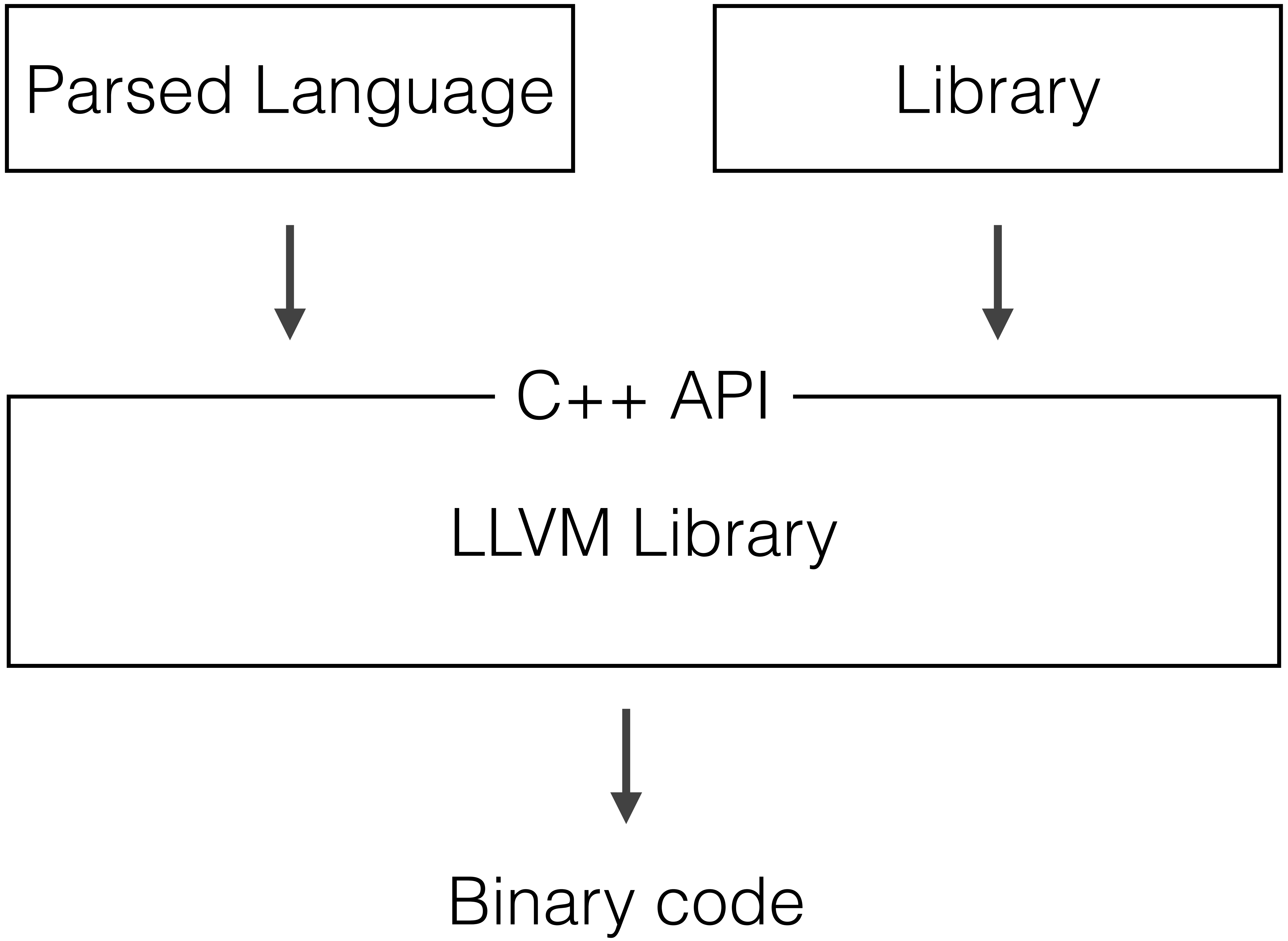
Lecture 2 — Why Domain-Specific Compilers

Stanford CS343D (Winter 2025)
Fred Kjolstad


Lecture 2
Domain-Specific
Compilers
Lecture 3
Building DSLs
Lecture 4
Collection-Oriented
Languages
Lecture 5
Dense Programming
Systems
Lecture 6
Sparse Programming
Systems
Lecture 7
Iteration Model I
Lecture 8
Iteration Model II

Languages vs libraries: LLVM is a compiler for general languages, yet it is a library that does not require a parser




```
// a*b
Value* mul = builder.CreateMul(a, b);
```

https://llvm.org

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- The History of Fortran (Backus 1982)

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- Simple loop parallelization
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2010-2020s - DSLs and Synthesis
- Halide, TensorFlow/XLA, Taco
- Code generation for SQL

Automatic programming

The compiler as an optimizer

```
for (int i = 0; i < M; i++) {
  double t = 0.0;
  for (int j = 0; j < N; j++) {
    int pB2 = i*N + j;
    t += B[pB2] * c[j];
  }
  a[i] = t;
}
```

optimize →

```
for (int i = 0; i < M; i++) {
  double t = 0.0;
  for (int p = B_pos[i]; p < B_pos[i+1]; p++) {
    int j = B_crd[p];
    t += B[p] * c[j];
  }
  a[i] = t;
}
```

The compiler as generator

$$a = Bc$$

↓ lower

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"In short, automatic programming always has been a euphemism for programming with a higher-level language than was then available to the programmer. Research in automatic programming is simply research in the implementation of higher-level programming languages."
- David Parnas

Granularity of generated code

$$A = B \odot (CD)$$

$\downarrow$ select

```
Matrix T = gemm(C,D);
Matrix A = spelmul(B,T);
```

Kernel Library

```
gemm    ttv    mttkrp    matadd
spelmul    spmv    ttm    ...
```

$$A = B \odot (CD)$$

$\downarrow$ compile

```
int pA2 = 0;
for (int pB1 = B1_pos[0];
     pB1 < B1_pos[1]; pB1++) {
  int i = B1_crd[pB1];
  for (int pB2 = B2_pos[pB1];
       pB2 < B2_pos[pB1+1]; pB2++) {
    int j = B2_crd[pB2];
    double t = 0.0;
    for (int k = 0; k < O; k++) {
      int pC2 = i * O + k;
      int pD2 = k * N + j;
      t += C[pC2] * D[pD2];
    }
    A[pA2++] = B[pB2] * t;
  }
}
```

What does a compiler do for you?

1. Lets you program a different machine than the one you actually have
    - A high-level language is an imaginary machine (virtual machine)
    - The compiler automatically programs the actual machine for you
2. Lets you know if you are using the language incorrectly
3. Optimizes the performance of your program

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Every programmer was a Performance Engineer

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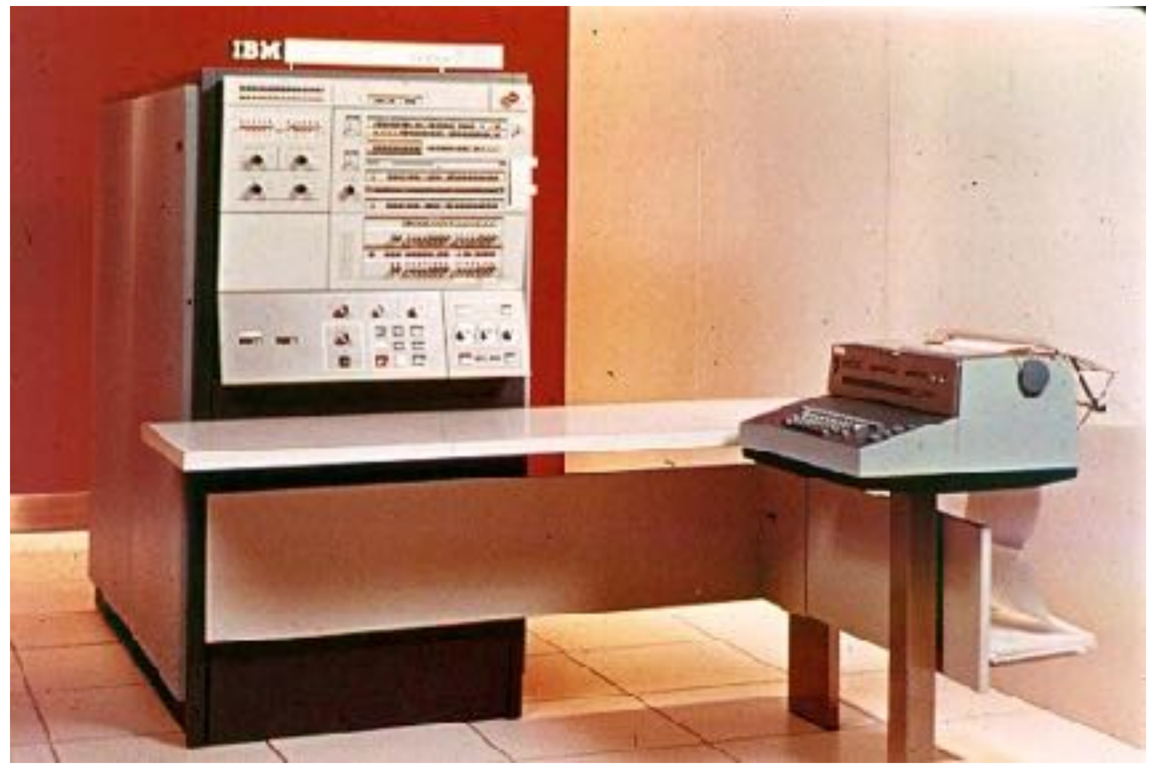
IBM System/360



Launched: 1964
Clock rate: 33 KHz
Data path: 32bits
Memory: 524 Kbytes
Cost: $5,000 per month

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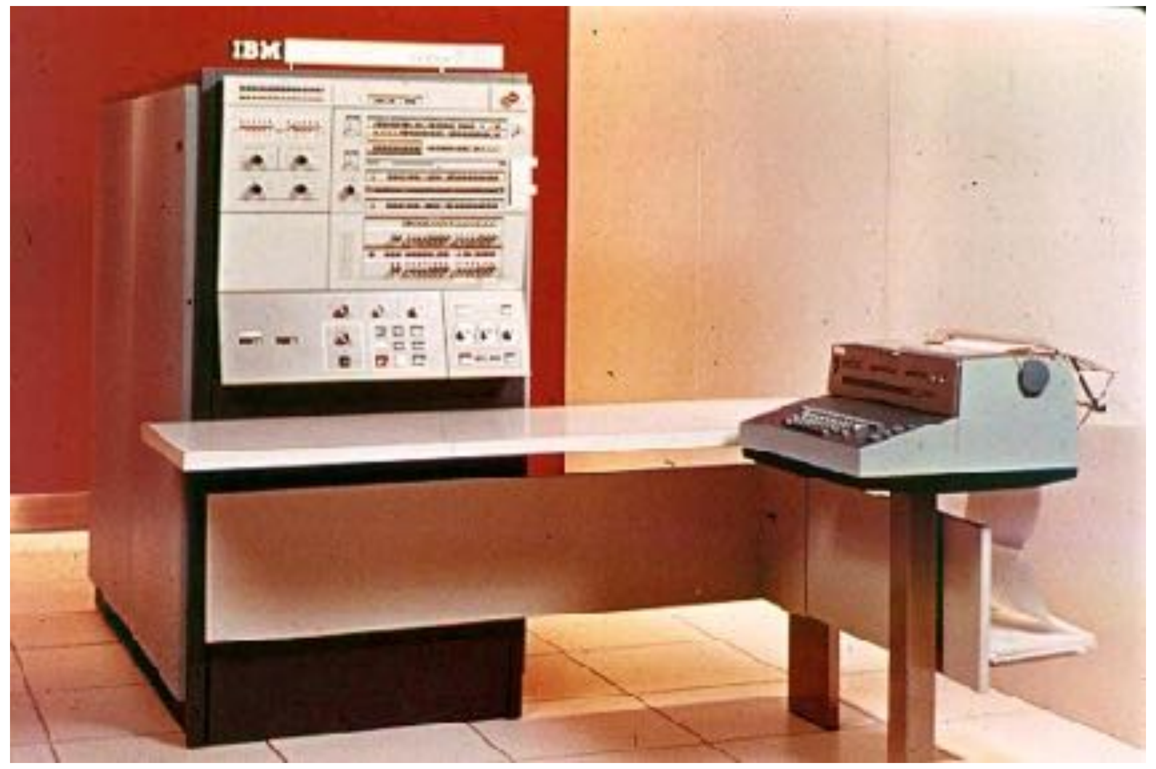

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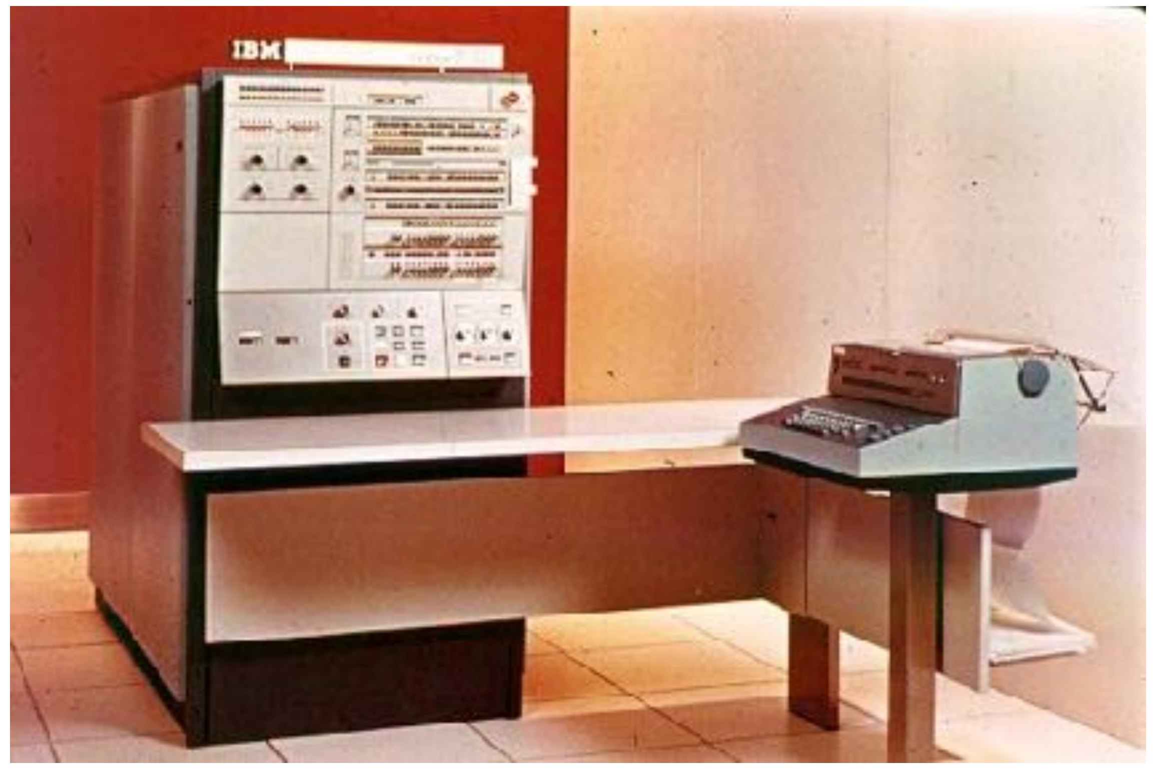

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Any useful program would stretch the machine resources
- Program had to be planned around the machine
- Many would not ‘fit’ without intense performance hacks

Software Properties

What do programmers want to add?

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- Functionality

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… and…

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… and…

- Scalability
- Compatibility
- Correctness
- Clarity
- Low Power
- Maintainability
- Modularity
- Portability
- Reliability
- Robustness
- Testability
- Usability

… and more.

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… and more.

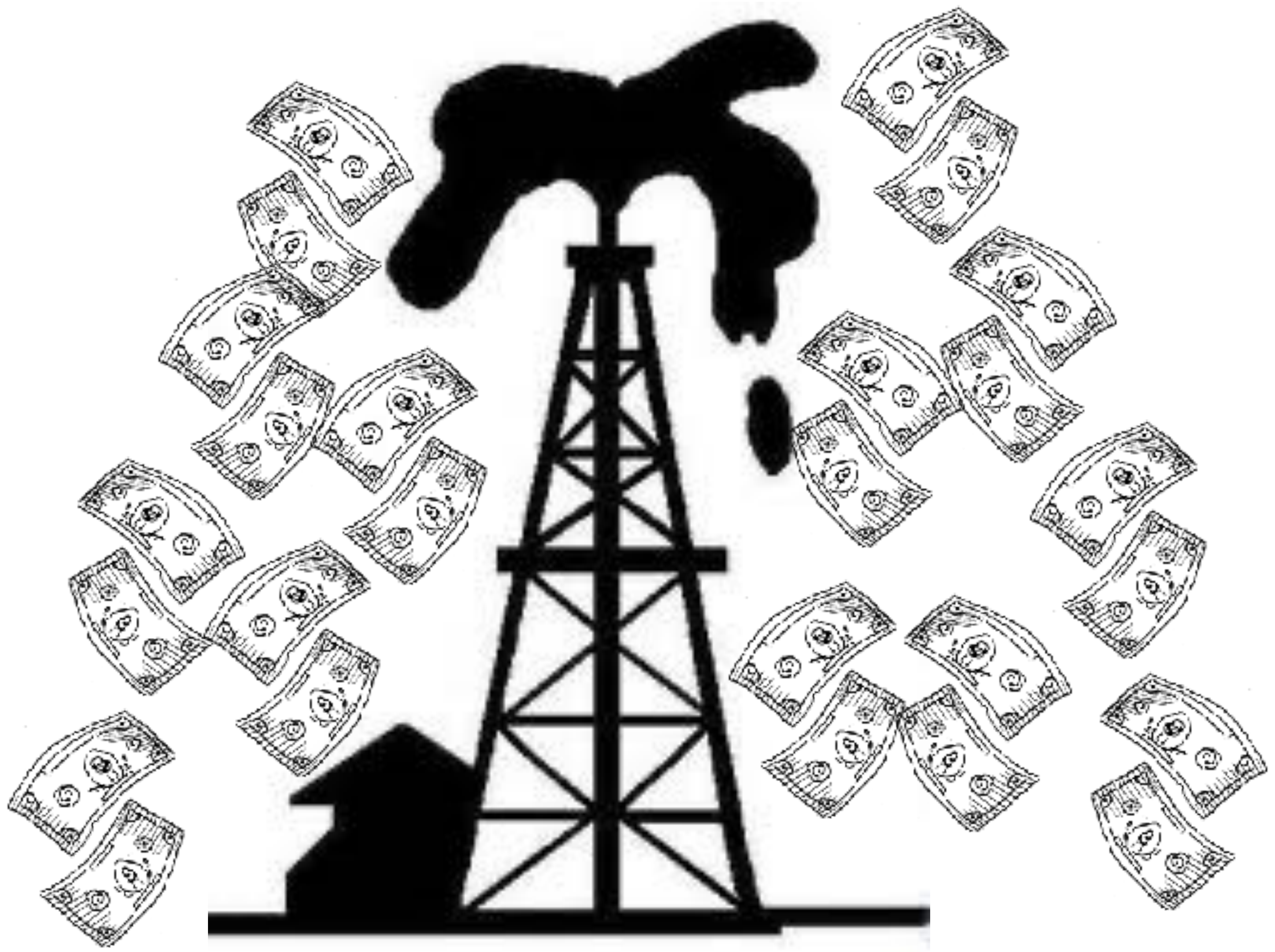
Performance is the currency of computing. You can often "buy" needed properties with performance.

In the Dominant Era of Computing, Performance became Free

The currency was free

Only need to wait a few months

Performance doubled every 2 years



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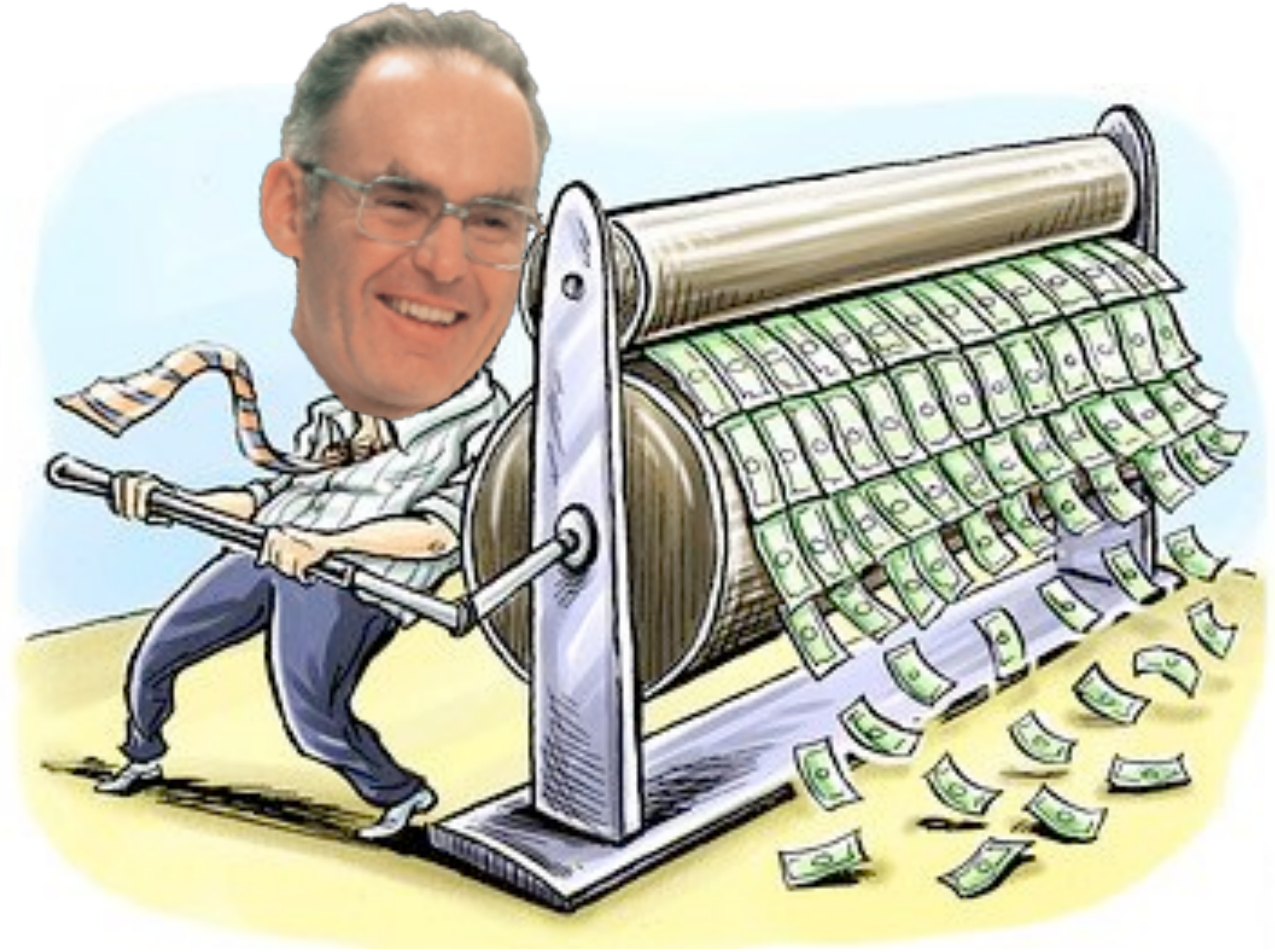
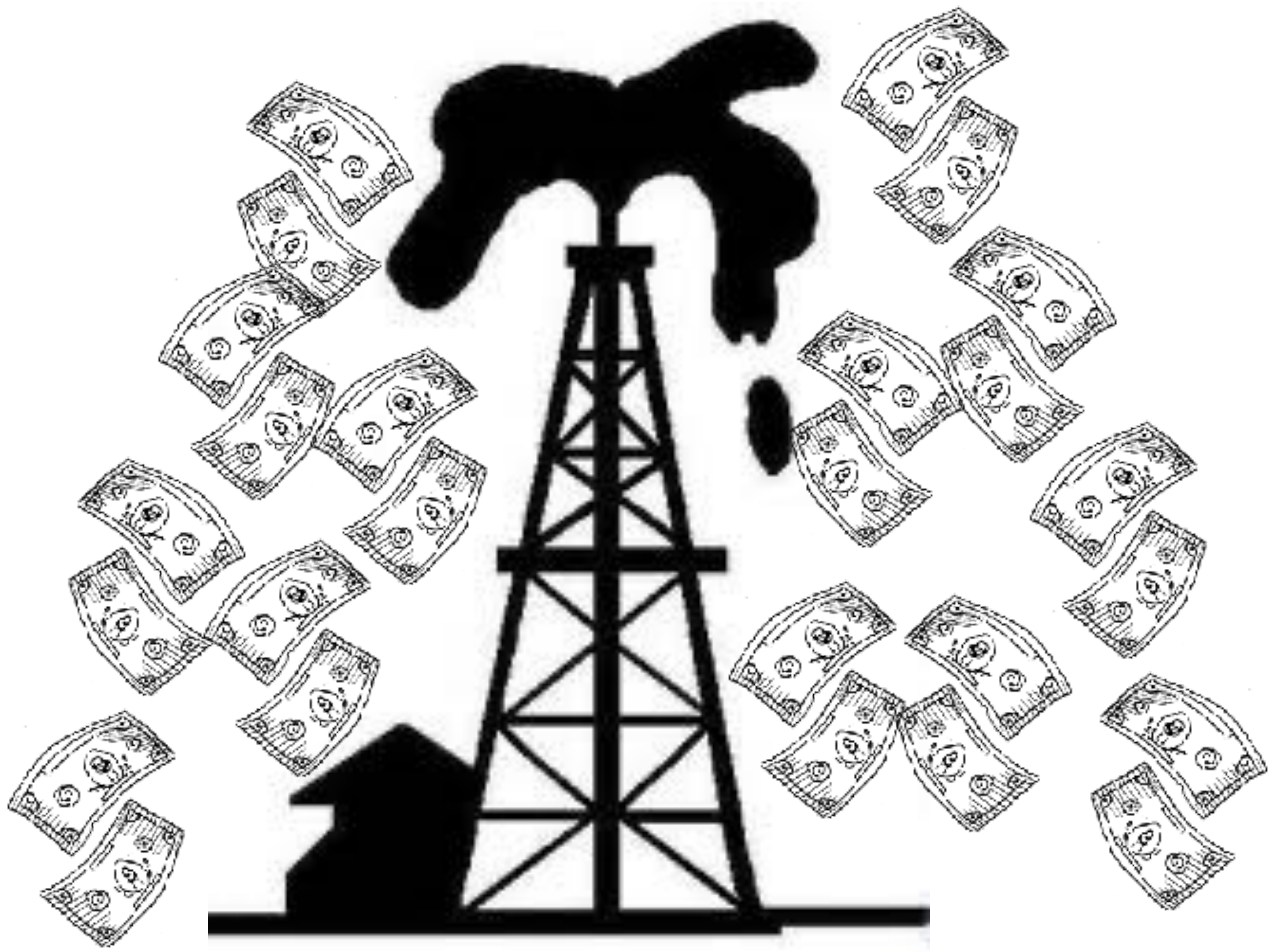
In the Dominant Era, Performance was Free

Moore's Law and the scaling of clock frequency
= printing press for the currency of performance



In the Dominant Era, Performance was Free

Performance engineering was
'optional' at best and
'irrelevant' for most programmers



Performance is the currency of computing. You can often "buy" needed properties with performance.

The Age of Free Performance is Over

Moore's law is not giving free performance any more

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The Age of Free Performance is Over

Two ways to get better performance:

1. Remove software abstractions costs

2. Build domain-specific hardware

Both requires specialization. A compiler is a generator of specialized code.

Inefficient abstractions mechanisms in software and inefficient use of hardware

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- Andrew Koenig

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Figure from “There’s plenty of room at the Top: What will drive computer performance after Moore’s law?” Leiserson et al., Science 368

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17h vs 1s!

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Parallelism

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Locality

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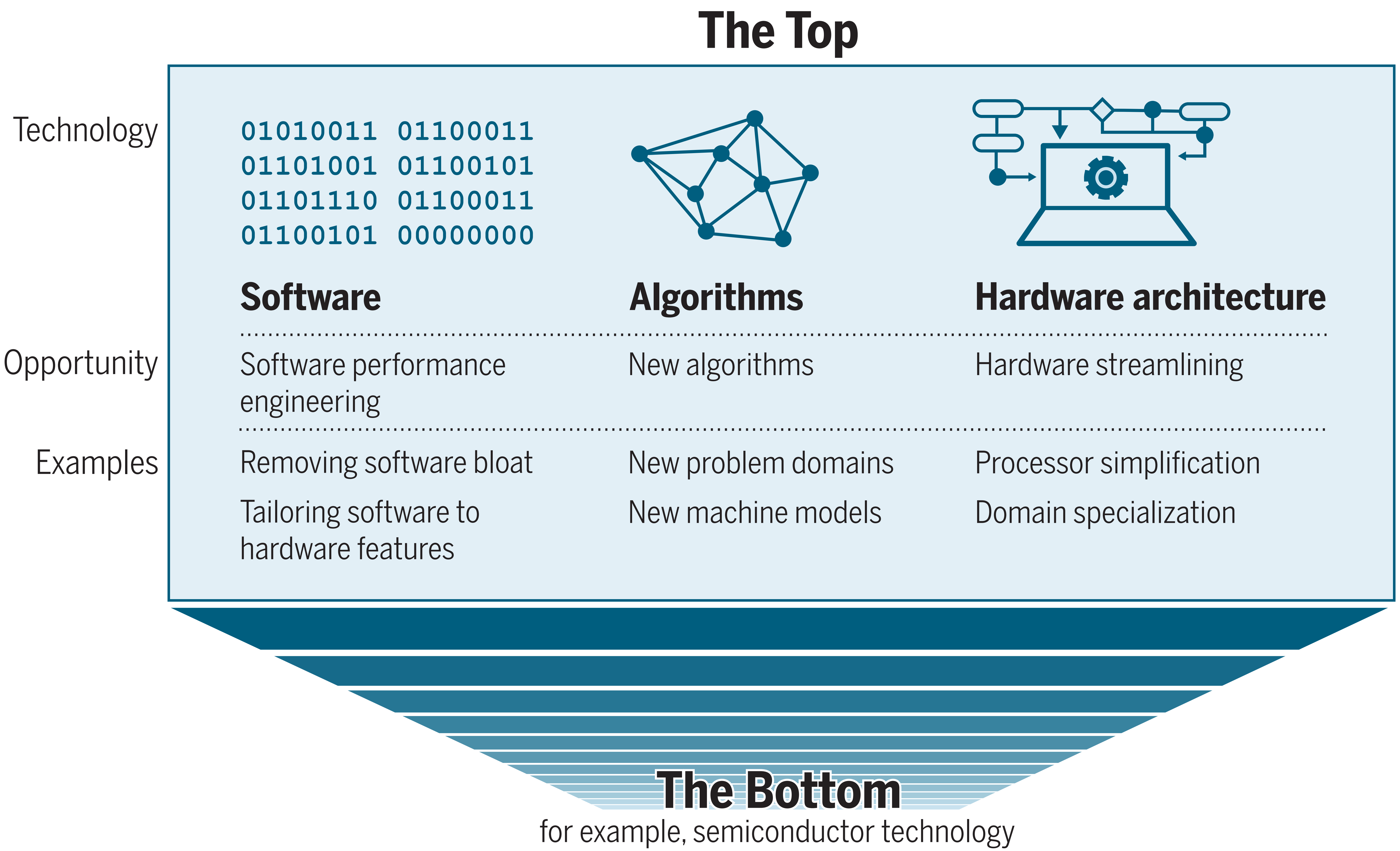
1	Python	25,552.48	0.005	1	—	0.00
2	Java	2,372.68	0.058	11	10.8	0.01
3	C	542.67	0.253	47	4.4	0.03
4	Parallel loops	69.80	1.969	366	7.8	0.24
5	Parallel divide and conquer	3.80	36.180	6,727	18.4	4.33
6	plus vectorization	1.10	124.914	23,224	3.5	14.96
7	plus AVX intrinsics	0.41	337.812	62,806	2.7	40.45

17h vs 1s!

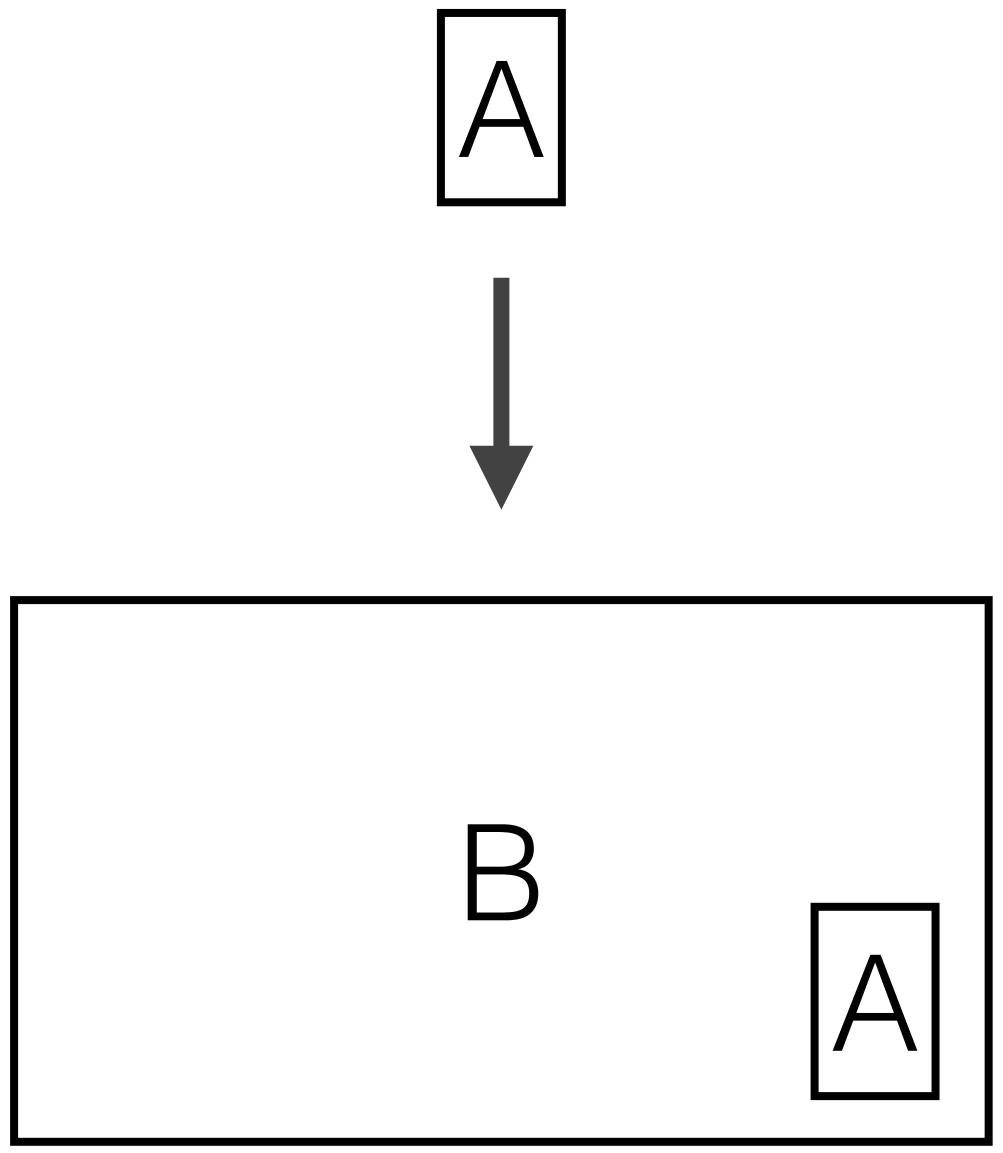
Figure from “There’s plenty of room at the Top: What will drive computer performance after Moore’s law?” Leiserson et al., Science 368

Parallelism Locality Specialization

There’s plenty of room at the top



Problem reduction



Abstraction with friction from traditional library composition

$$A = B \odot (CD)$$

Traditional Library Composition

```
T = matmul(C, D);
A =  elmul(B, T);
```

Three pitfalls:

1. Loose temporal locality
2. Data structures must match what functions expect
3. May cause asymptotic slow-down

Example 1: Sampled Dense-Dense Matrix Multiplication with Linear Algebra

$$A = B \odot (CD)$$

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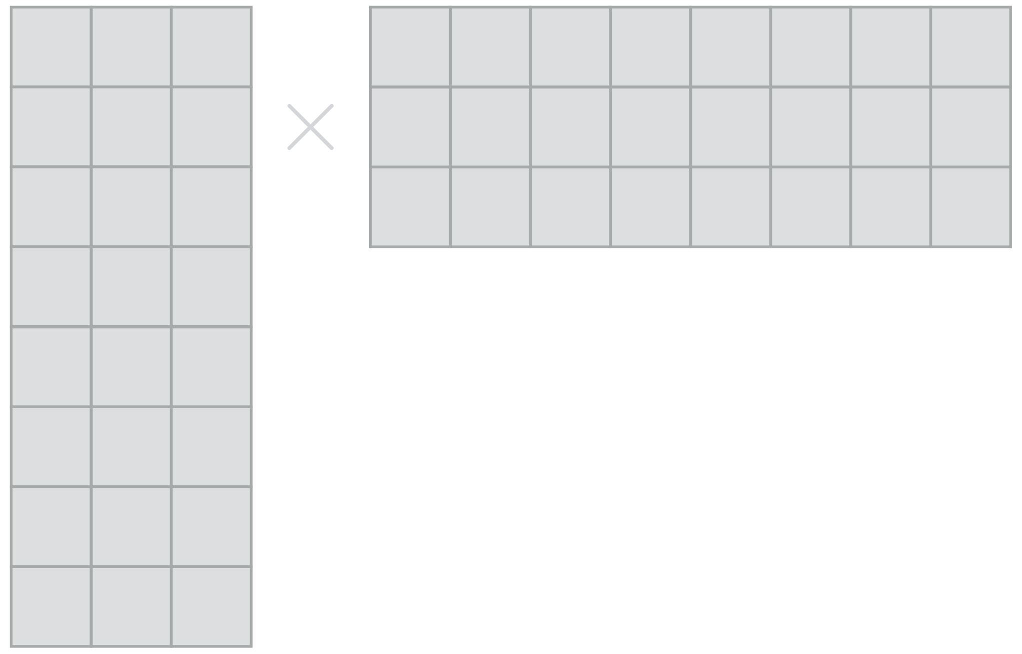

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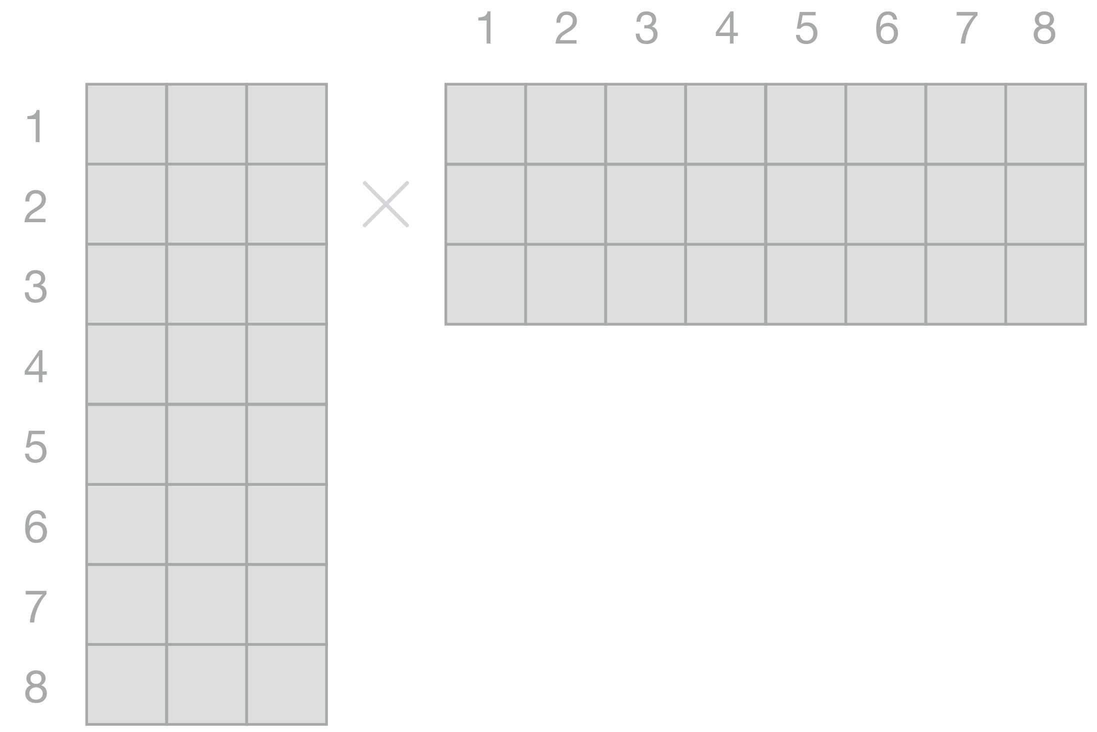

64 inner product

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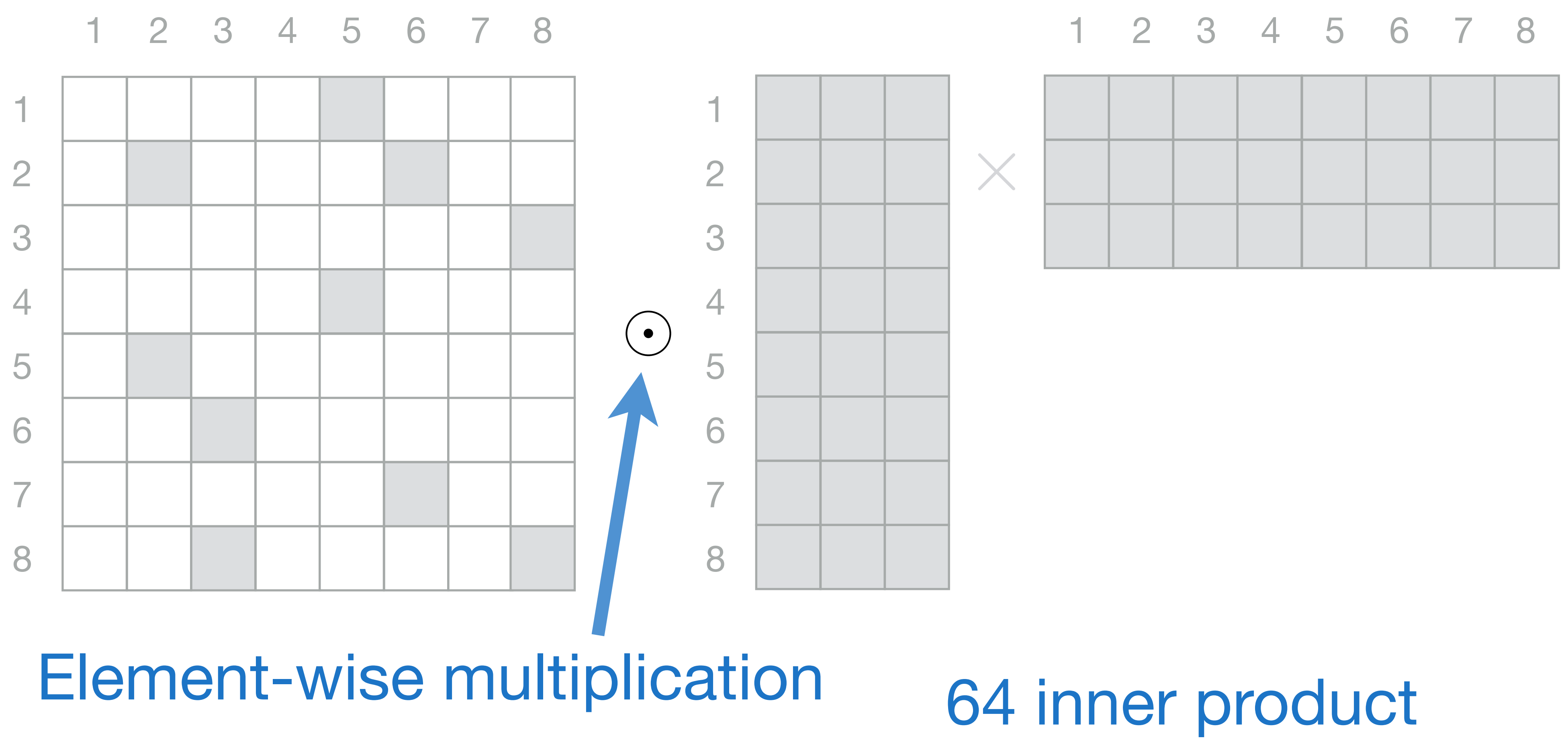

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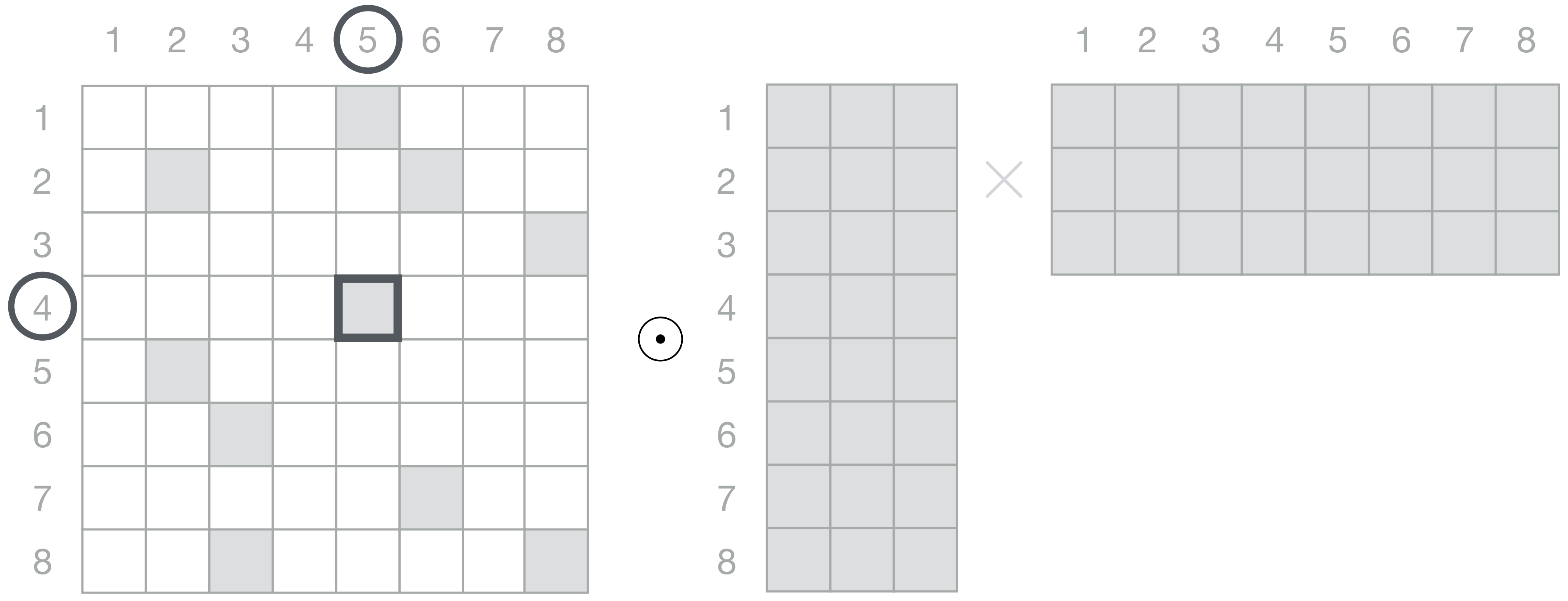

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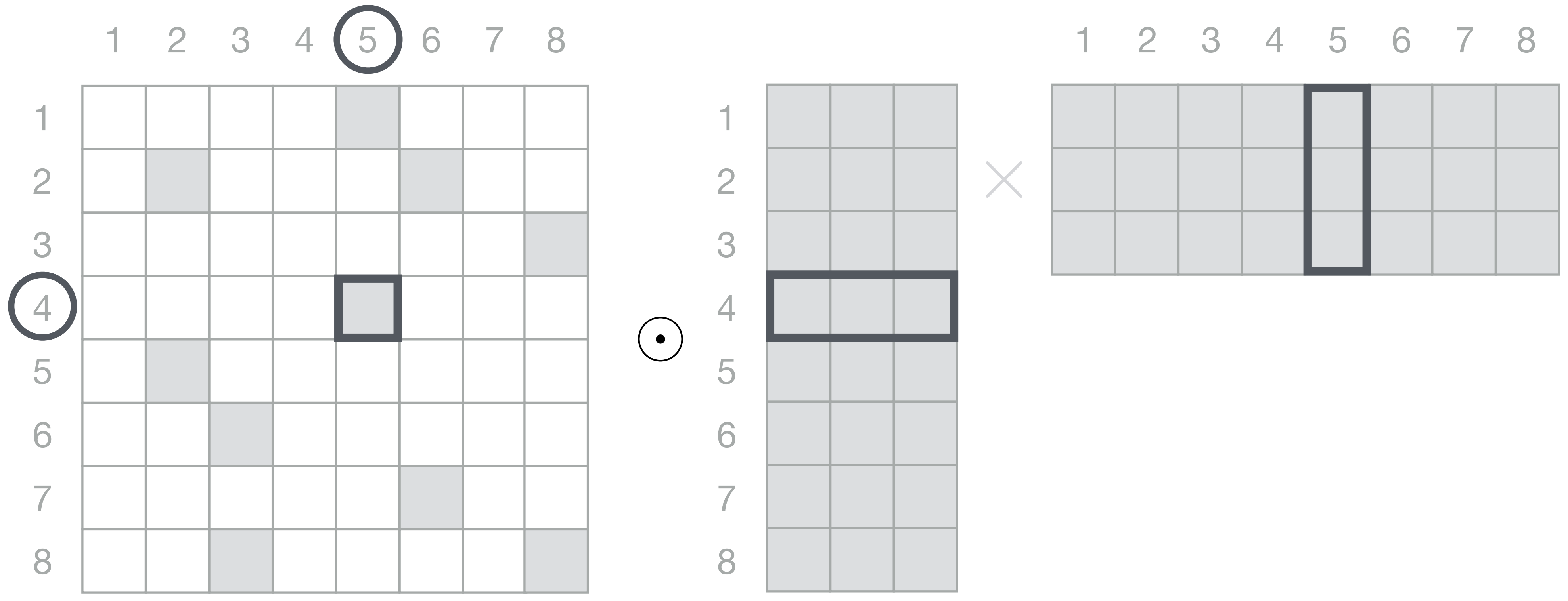

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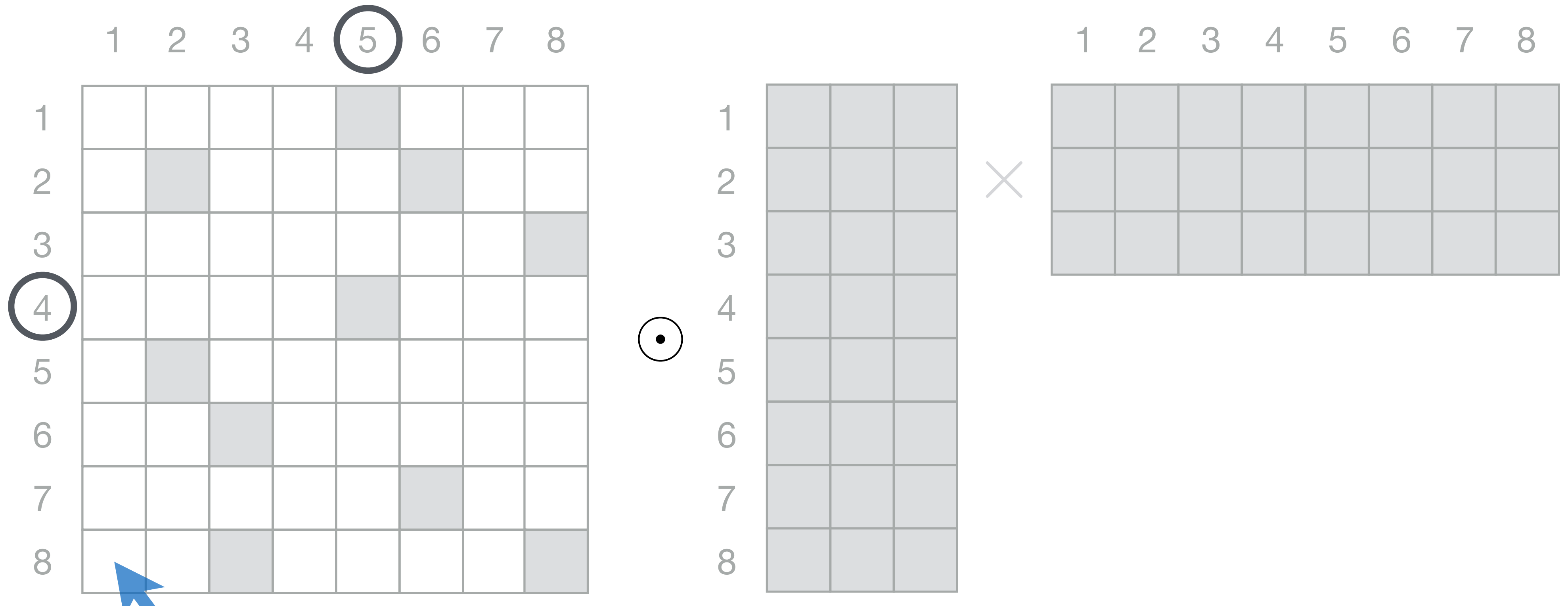

This dot product need not be computed

~~64 inner product~~
10 inner product

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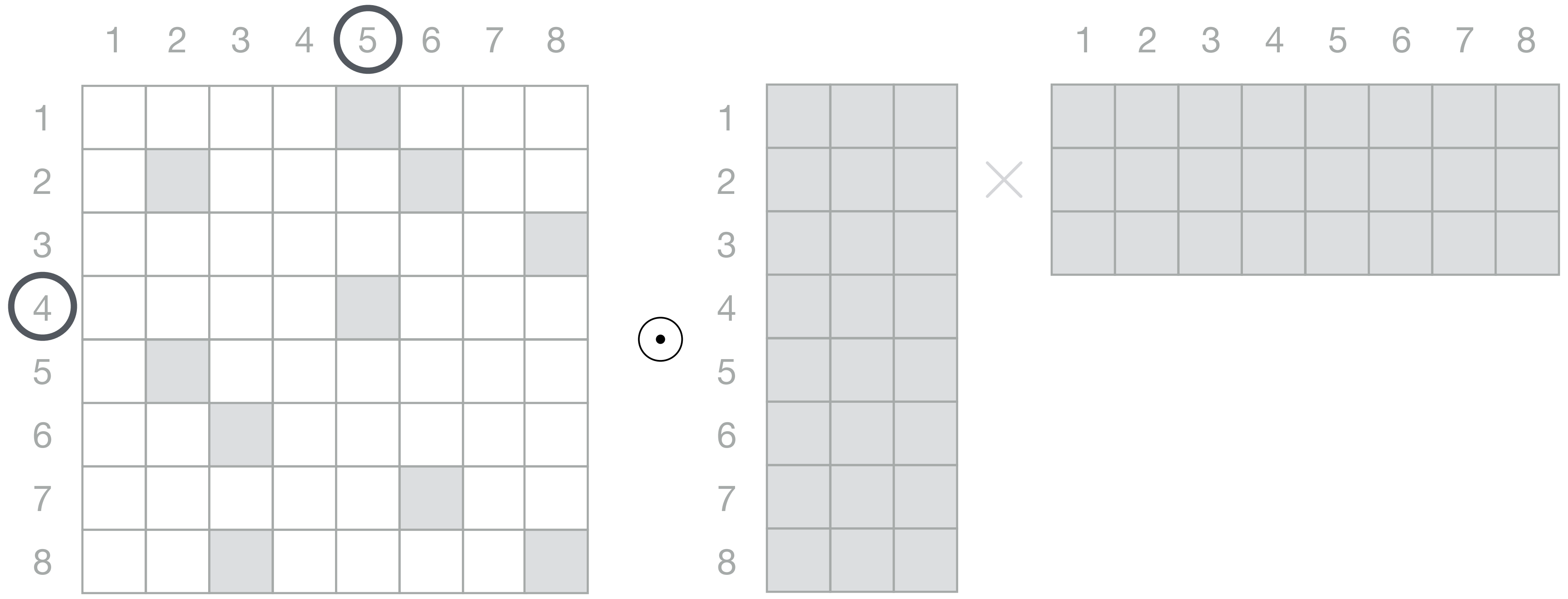

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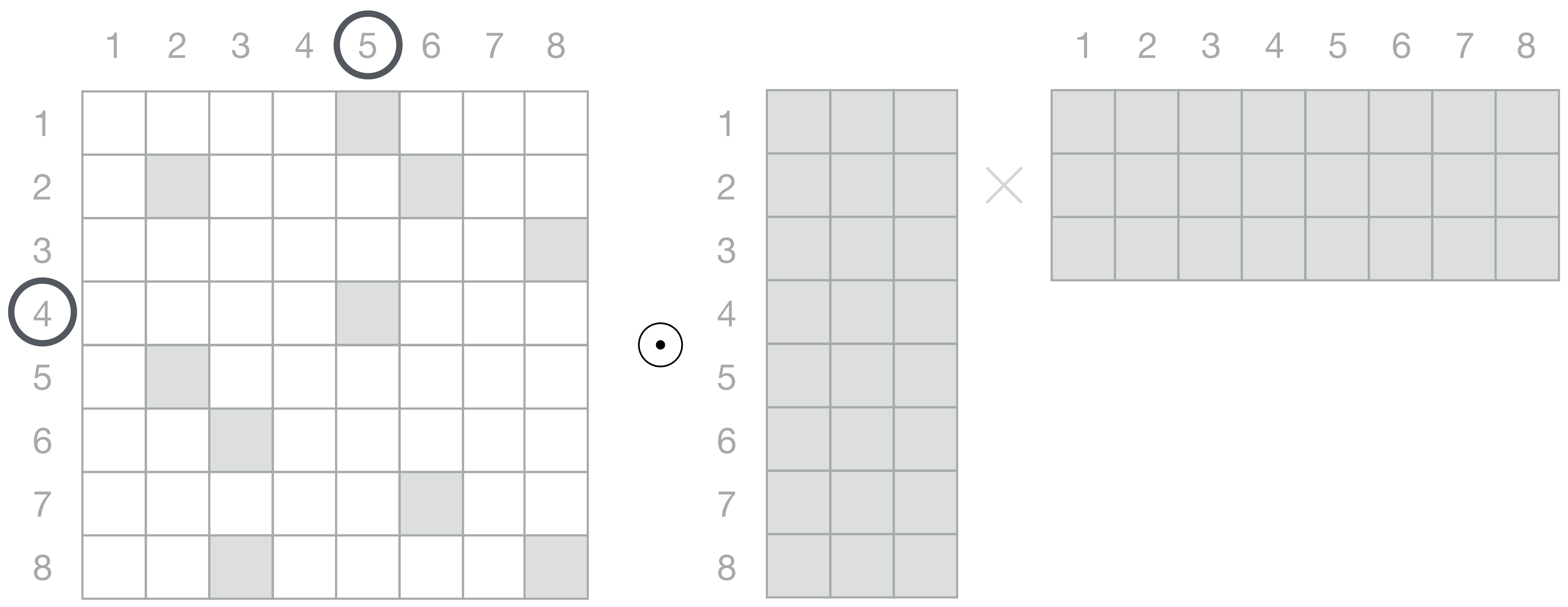

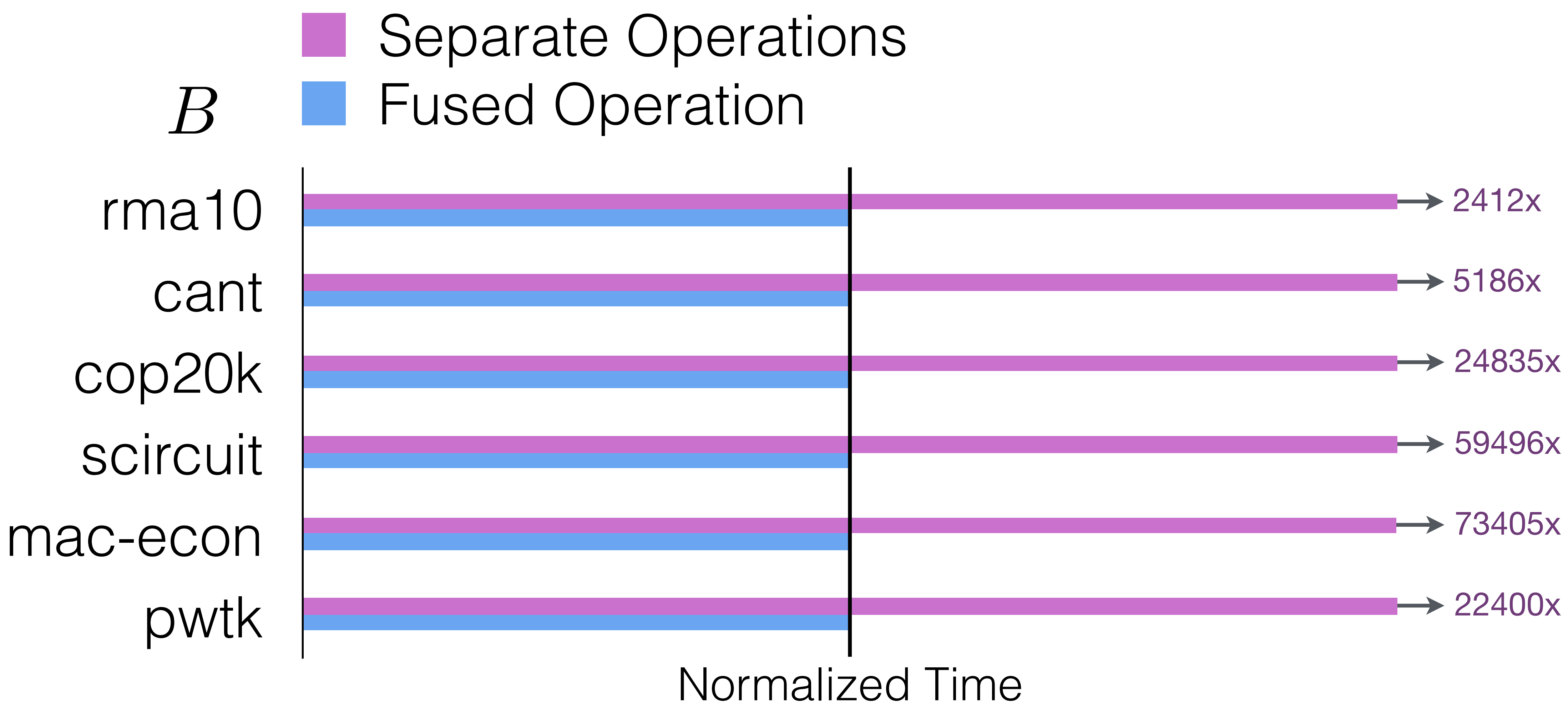

Example 2: Triangle Query with Relational Algebra

$$Q_{\triangle} = R(A,B) \bowtie S(B,C) \bowtie T(A,C)$$

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$$Q_{\triangle} = R(A, B) \bowtie S(B, C) \bowtie T(A, C) \qquad O(N^{3/2})$$

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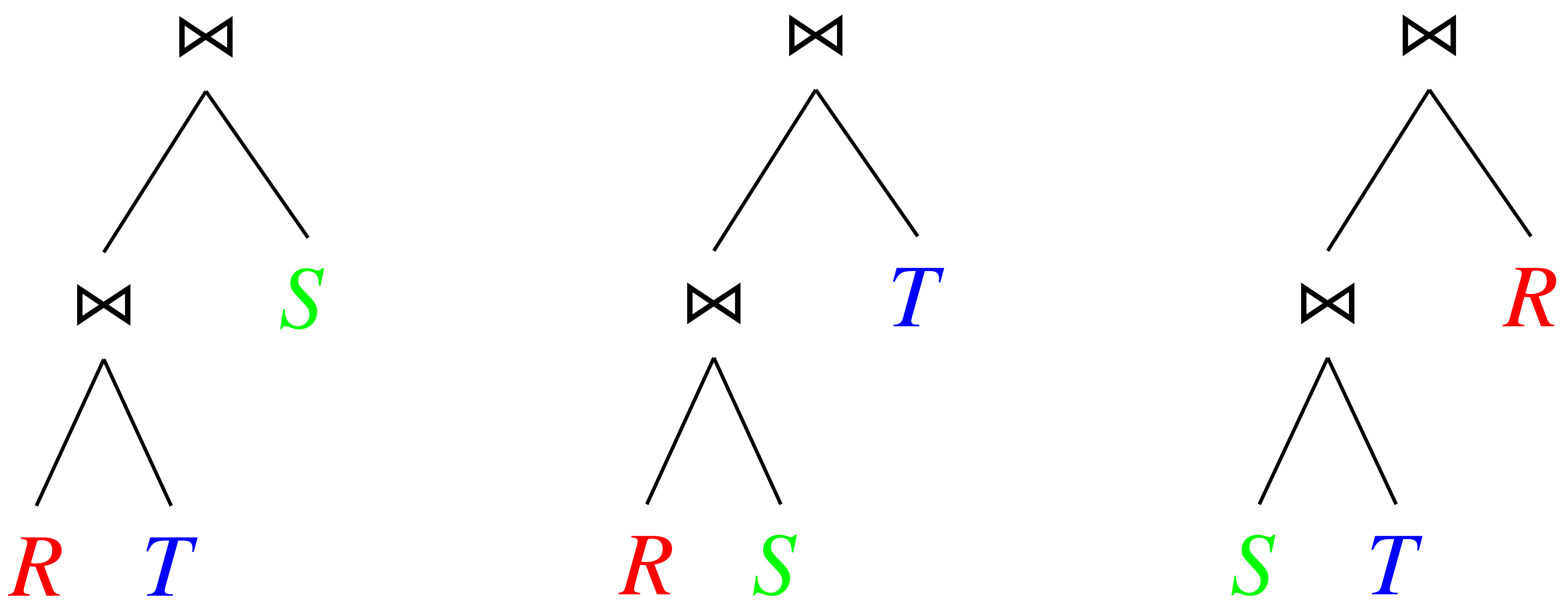

$O(N^2)$

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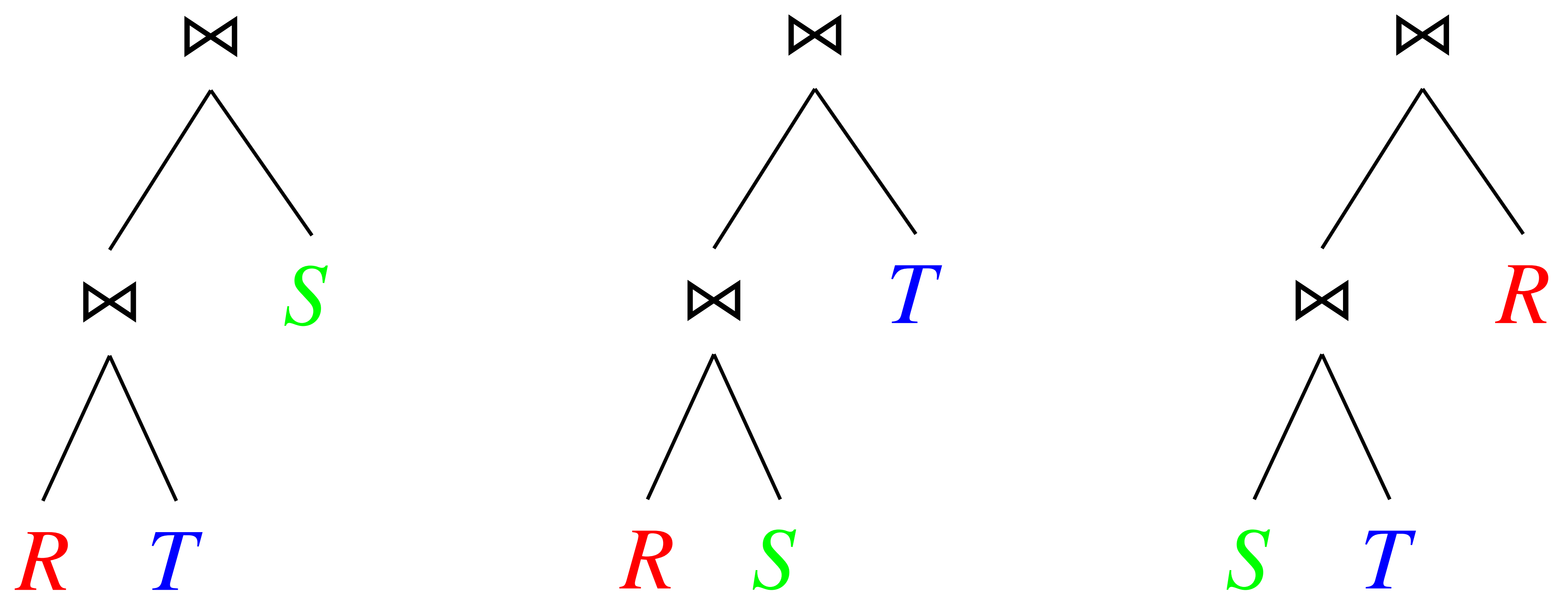

$O(N^2)$

Algorithm 2 Computing $Q_{\triangle}$ by delaying computation.

Input: $R(A,B), S(B,C), T(A,C)$ in sorted order

- $Q \leftarrow \emptyset$
- $L_A \leftarrow \pi_A(R) \cap \pi_A(T)$
- **For** each $a \in L_A$ **do**
  - $L_B^a \leftarrow \pi_B(\sigma_{A=a}(R)) \cap \pi_B(S)$
  - **For** each $b \in L_B^a$ **do**
    - $L_C^{a,b} \leftarrow \pi_C(\sigma_{B=b}(S)) \cap \pi_C(\sigma_{A=a}(T))$
    - **For** each $c \in L_C^{a,b}$ **do**
      - Add (a,b,c) to Q
- **Return** Q

Figures from Ngo, Ré and Rudra (2013), with algorithm from Veldhuizen (2014)

$O(N^{3/2})$

Example 3: Simulation with Meshes and Linear Algebra

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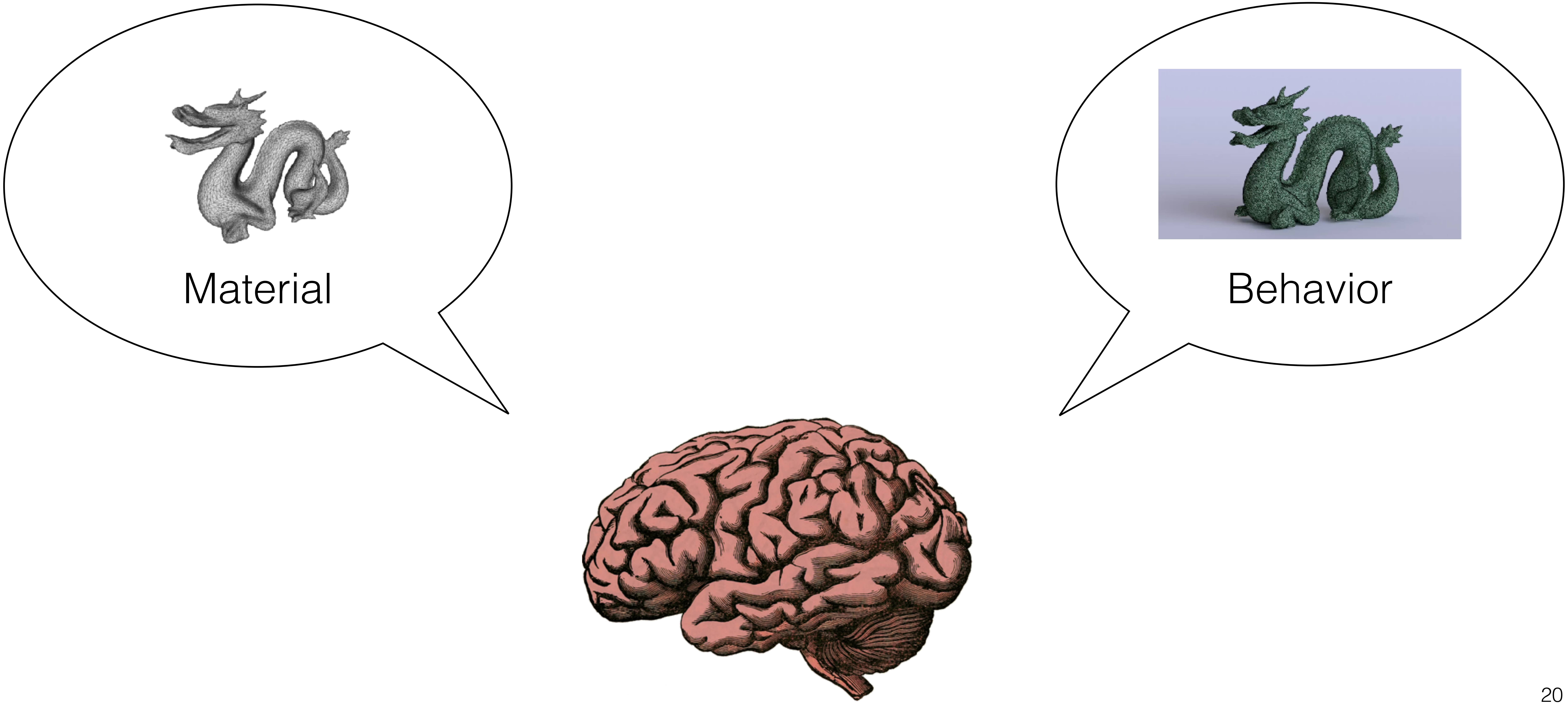
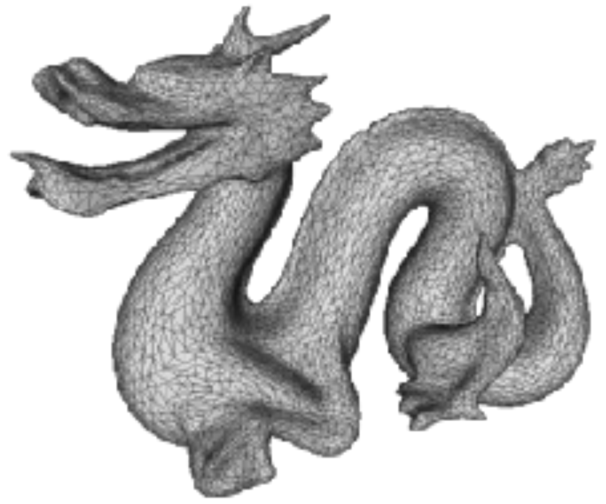
Behavior

Example 3: Simulation with Meshes and Linear Algebra



Example 3: Simulation with Meshes and Linear Algebra

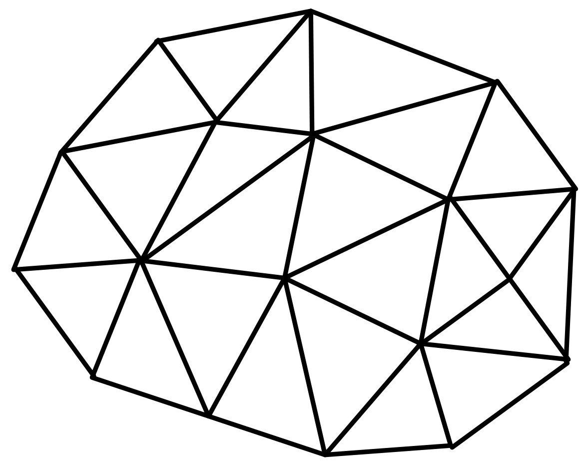


Material

$$f = Ma$$

Linear Algebra

Example 3: Simulation with Meshes and Linear Algebra



Mesh

$$f = Ma$$

Linear Algebra

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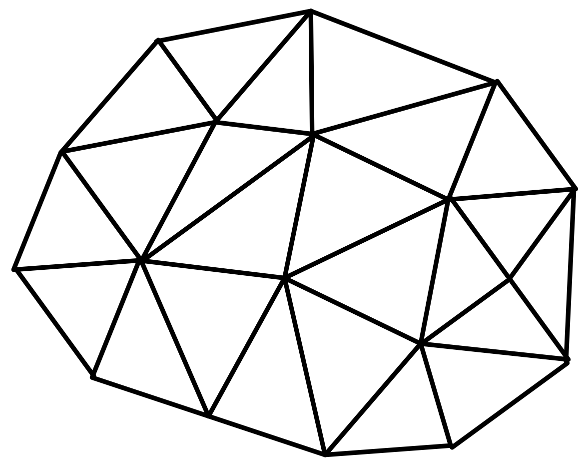

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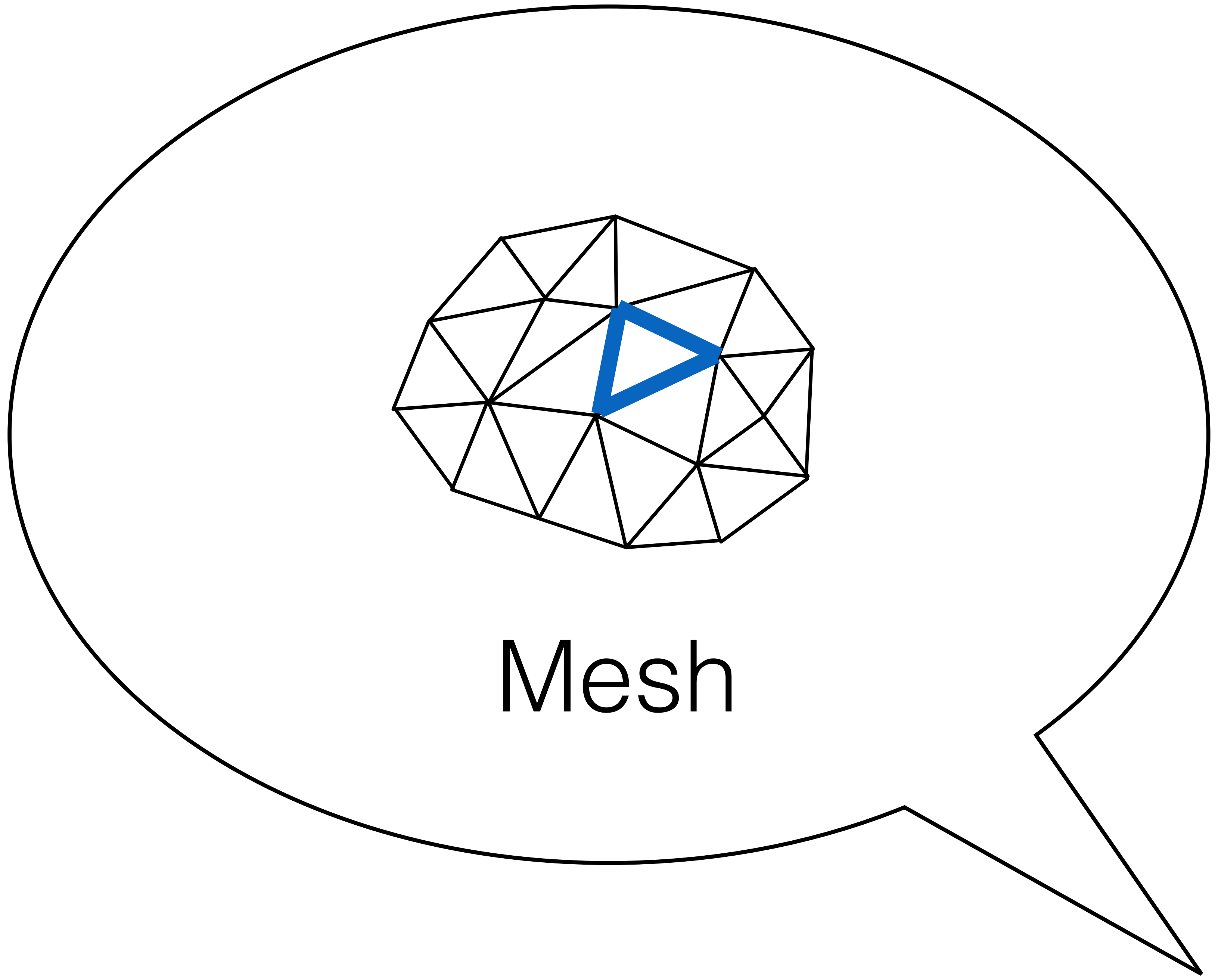
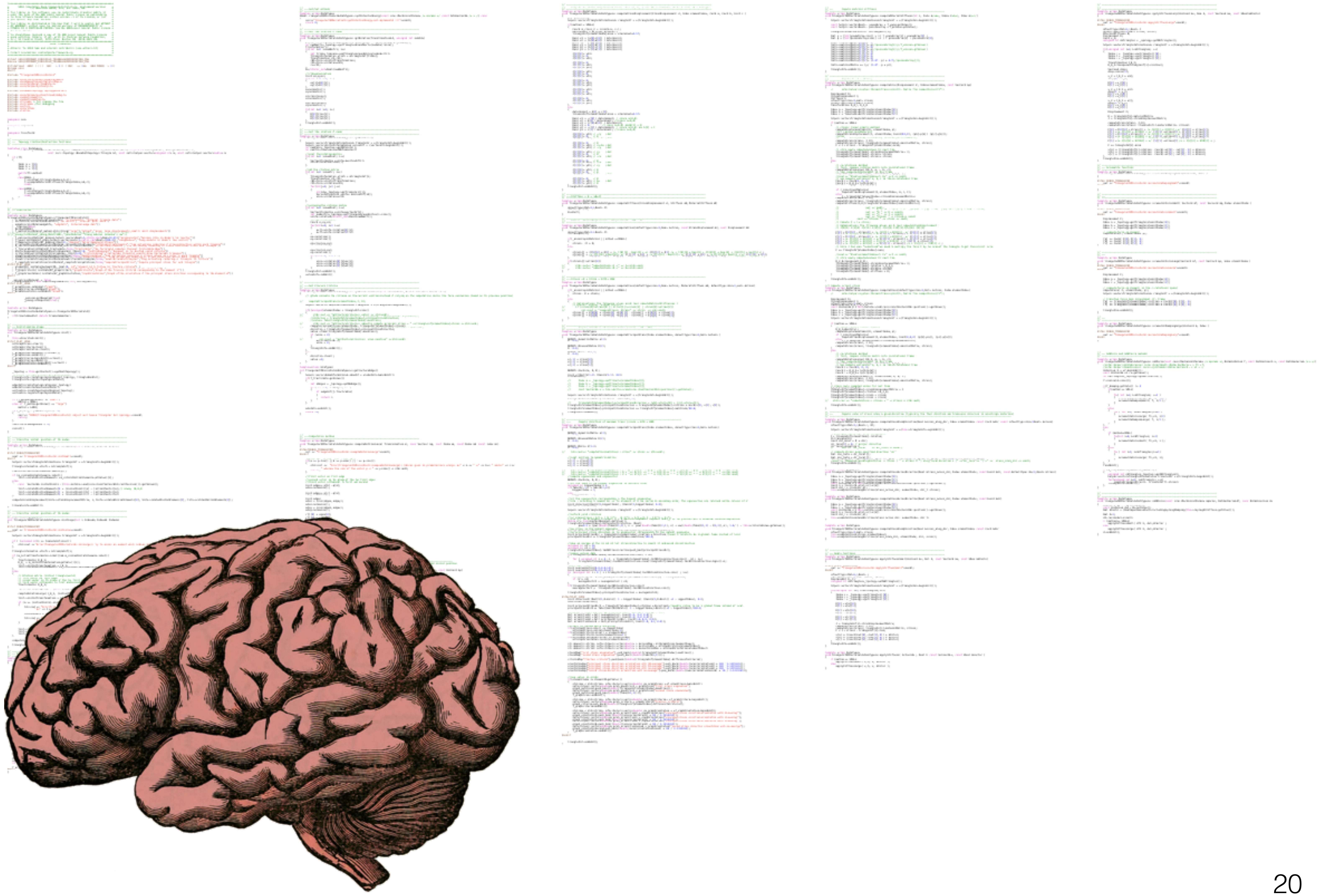
Linear Algebra

Example 3: Simulation with Meshes and Linear Algebra

Matrix-free in-place stencil computation





Example 3: Simulation with Graphs and Linear Algebra

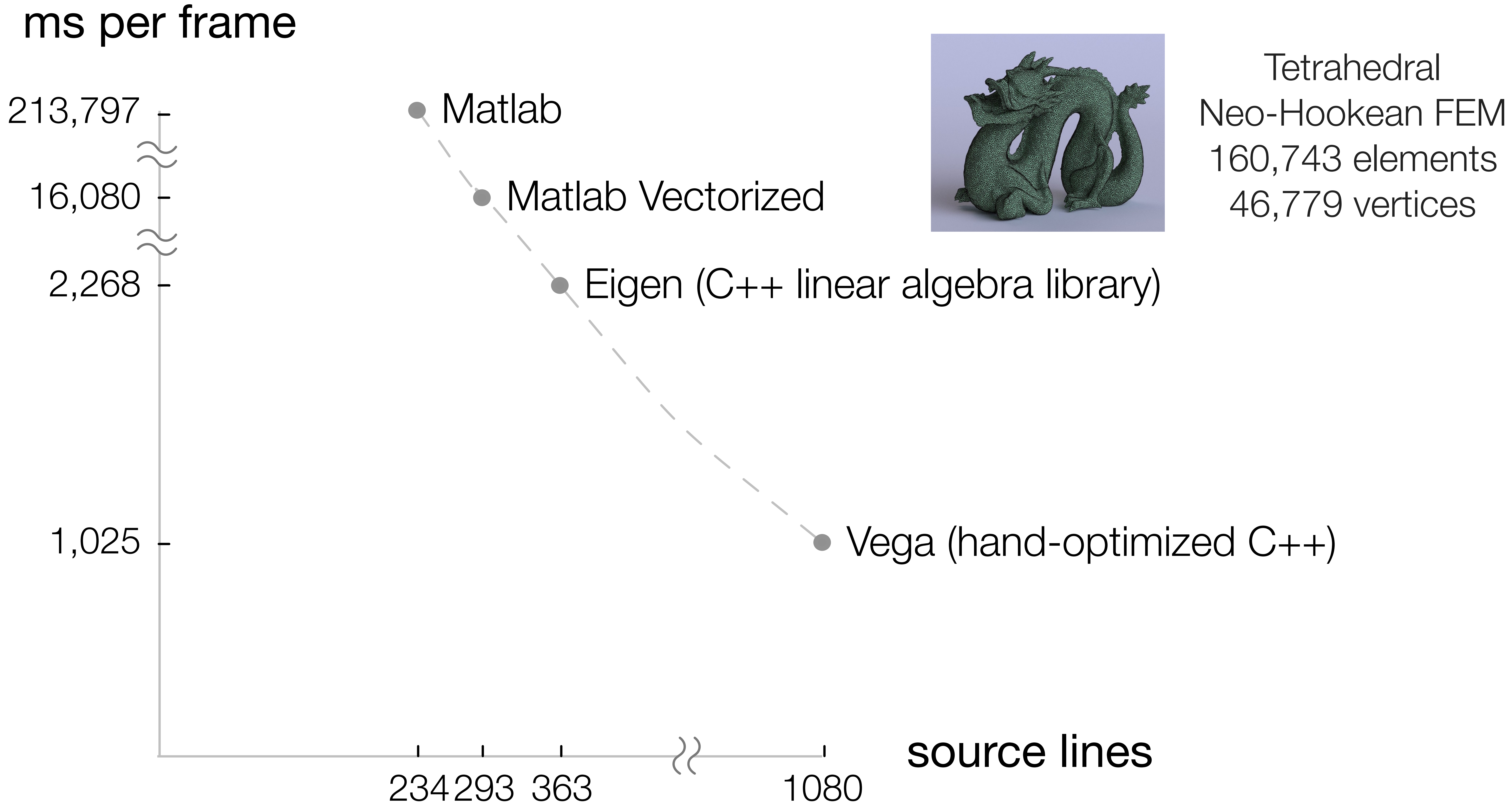


Figure from Kjolstad et al (2016)

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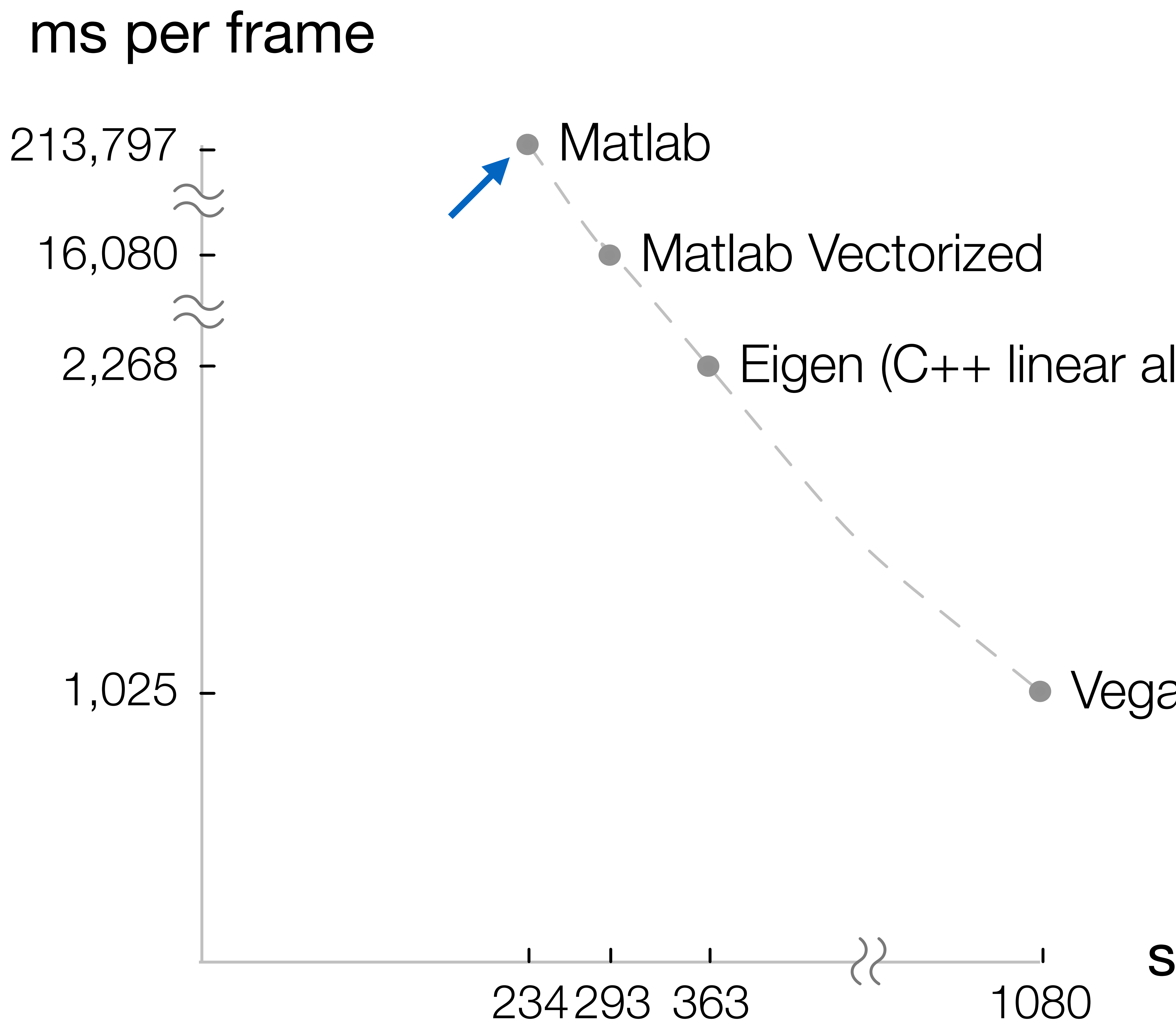

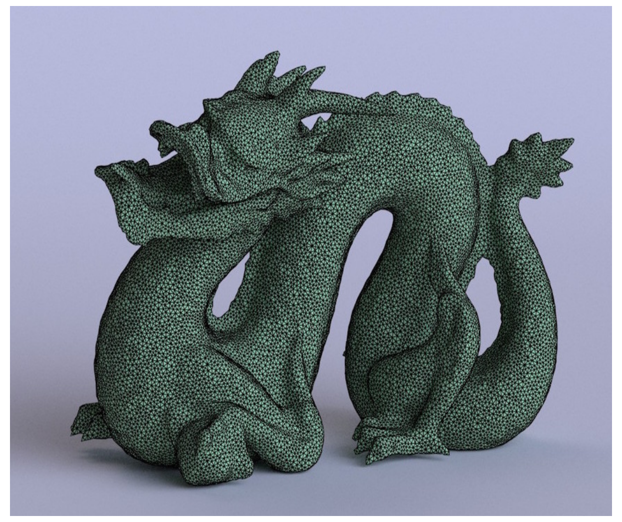

Tetrahedral
Neo-Hookean FEM
160,743 elements
46,779 vertices

Figure from Kjolstad et al (2016)

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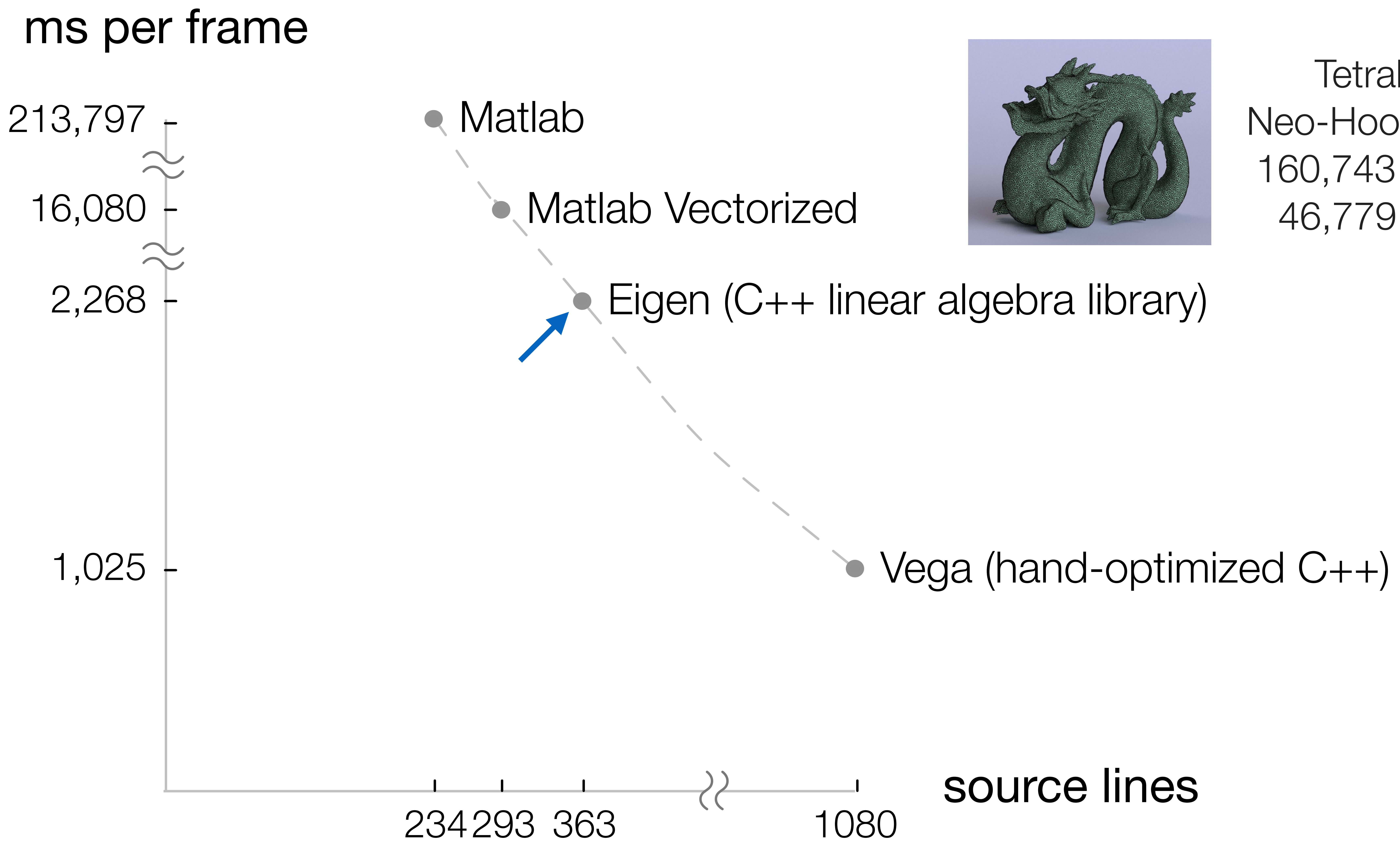

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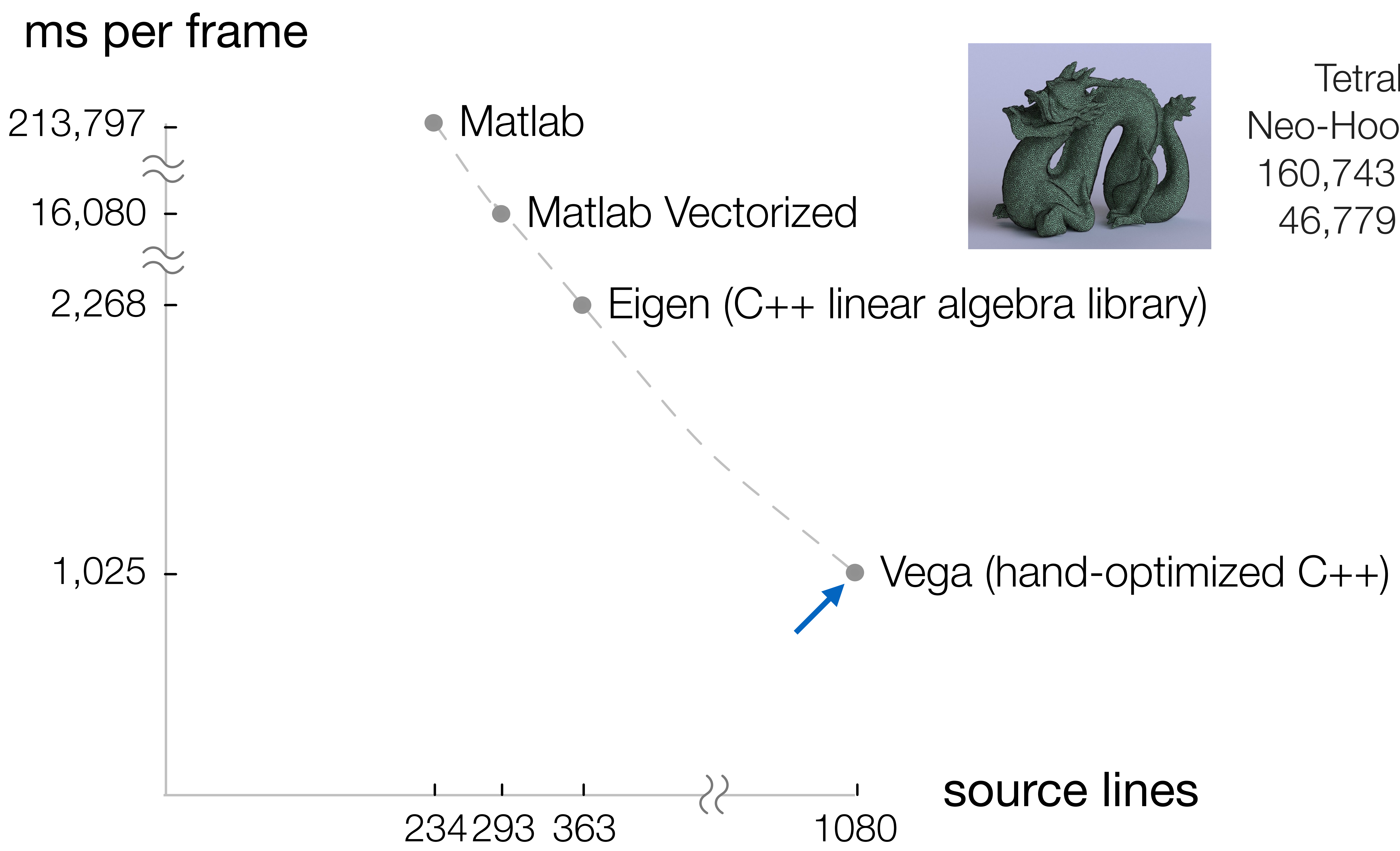

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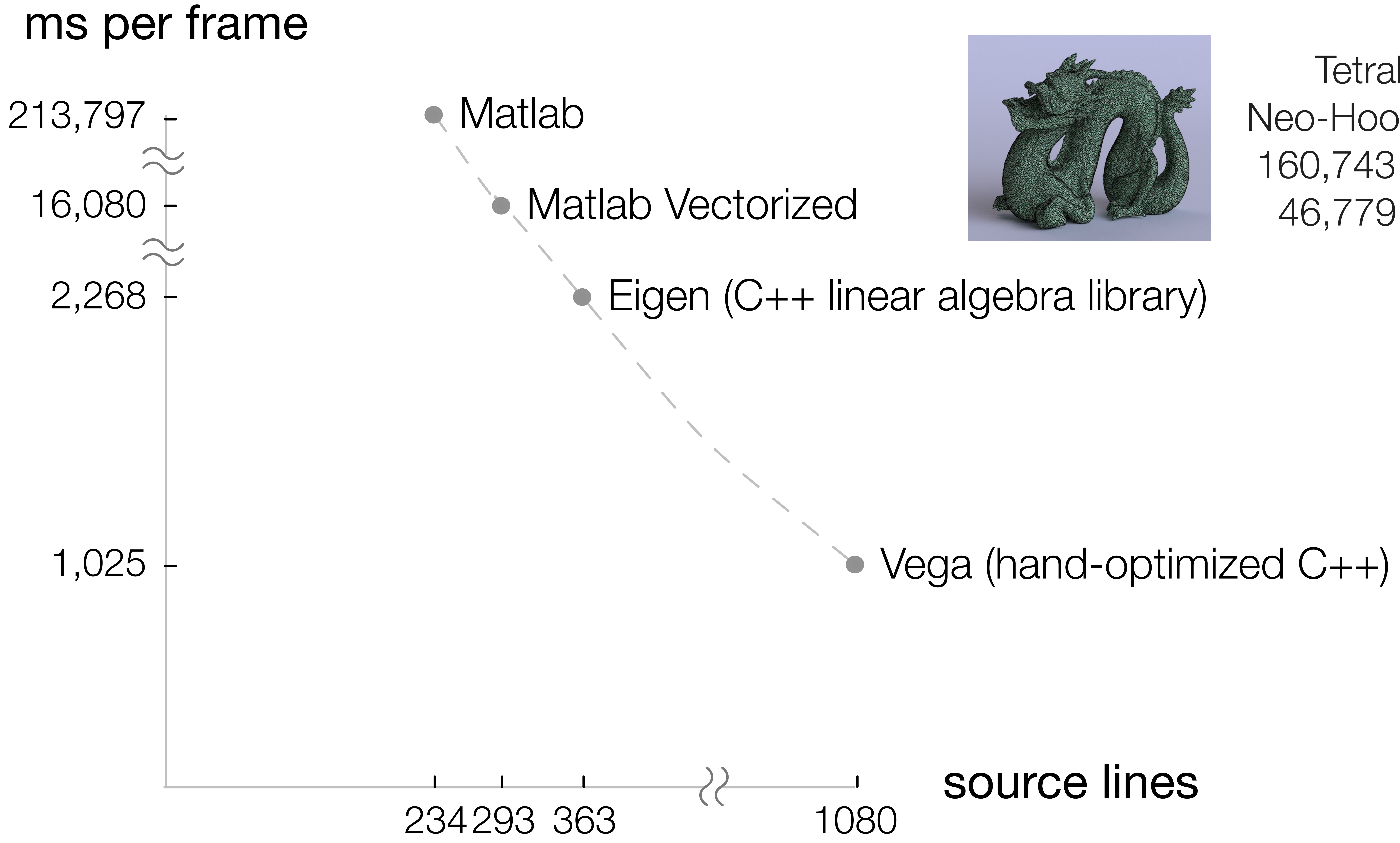

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Too many combinations for a fixed-function library

$a = Bc$

$a = Bc + a$

$a = Bc + b$ $\quad A = B + C$ $\quad a = \alpha Bc + \beta a$

$a = B^T c$ $\quad A = \alpha B$ $\quad a = B(c + d)$

$a = B^T c + d$ $\quad A = B + C + D$ $\quad A = BC$

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Data analytics
(tensor factorization)

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Quantum Chromodynamics

Too many combinations for a fixed-function library

CSparse

Eigen (SpMV)

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OSKI

$a = Bc + b$

$A = B + C$

$a = \alpha Bc + \beta a$

PETSc

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Eigen (SpMV): $a = Bc$

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OSKI: $a = \alpha Bc + \beta a$ — OSKI has 282 specialized variants of this expression

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$\times$

Dense Matrix

CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

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$A = BCd$ $\quad A = B^T$ $\quad a = B^T Bc$

$a = b + c$ $\quad A = B$ $\quad K = A^T CA$

$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $\quad A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$

$A_{lj} = \sum_{ik} B_{ikl} C_{ij} D_{kj}$ $\quad A_{ij} = \sum_{k} B_{ijk} c_k$

$A_{ijk} = \sum_{l} B_{ikl} C_{lj}$ $\quad A_{ik} = \sum_{j} B_{ijk} c_j$

$A_{jk} = \sum_{i} B_{ijk} c_i$ $\quad A_{ijl} = \sum_{k} B_{ikl} C_{kj}$

$\tau = \sum_{i} z_i (\sum_{j} z_j \theta_{ij})(\sum_{k} z_k \theta_{ik})$

$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$

$a = \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} P_{no} \overline{M_{po}}\, \overline{P_{ip}}$

$\times$

Dense Matrix

Thermal Simulation CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

Too many combinations for a fixed-function library

$a = Bc$

$a = Bc + a$

$a = Bc + b$ $\quad A = B + C$ $\quad a = \alpha Bc + \beta a$

$a = B^T c$ $\quad A = \alpha B$ $\quad a = B(c + d)$

$a = B^T c + d$ $\quad A = B + C + D$ $\quad A = BC$

$A = B \odot C$ $\quad a = b \odot c$ $\quad A = 0$ $\quad A = B \odot (CD)$

$A = BCd$ $\quad A = B^T$ $\quad a = B^T Bc$

$a = b + c$ $\quad A = B$ $\quad K = A^T C A$

$$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj} \qquad A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$$

$$A_{lj} = \sum_{ik} B_{ikl} C_{ij} D_{kj} \qquad A_{ij} = \sum_{k} B_{ijk} c_k$$

$$A_{ijk} = \sum_{l} B_{ikl} C_{lj} \qquad A_{ik} = \sum_{j} B_{ijk} c_j$$

$$A_{jk} = \sum_{i} B_{ijk} c_i \qquad A_{ijl} = \sum_{k} B_{ikl} C_{kj}$$

$$\tau = \sum_i z_i \Big(\sum_j z_j \theta_{ij}\Big)\Big(\sum_k z_k \theta_{ik}\Big)$$

$$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$$

$$a = \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} P_{no} \overline{M_{po}}\, \overline{P_{ip}}$$

$\times$

Web matrix [BG 2008]

Dense Matrix

Thermal Simulation: CSR

DCSR

BCSR: Finite Elements Method, Block-Sparse NN Weights [GRK 2017]

Data Analytics: COO

ELLPACK

CSB

Blocked COO

CSC: Mesh Simulations on GPUs [BG 2009]

Convolutions: DIA

Blocked DIA

DCSC

Eulerian Simulations

Too many combinations for a fixed-function library

$a = Bc$

$a = Bc + a$

$a = Bc + b$ $A = B + C$ $a = \alpha Bc + \beta a$

$a = B^T c$ $A = \alpha B$ $a = B(c + d)$

$a = B^T c + d$ $A = B + C + D$ $A = BC$

$A = B \odot C$ $a = b \odot c$ $A = 0$ $A = B \odot (CD)$

$A = BCd$ $A = B^T$ $a = B^T Bc$

$a = b + c$ $A = B$ $K = A^T CA$

$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$

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$A_{ijk} = \sum_{l} B_{ikl} C_{lj}$ $A_{ik} = \sum_{j} B_{ijk} c_j$

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$\tau = \sum_{i} z_i (\sum_{j} z_j \theta_{ij})(\sum_{k} z_k \theta_{ik})$

$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$

$a = \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} P_{no} \overline{M_{po}}\, \overline{P_{ip}}$

$\times$

Dense Matrix

CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

Sparse vector Hash Maps

Too many combinations for a fixed-function library

$a = Bc$

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$a = B^T c + d$ $A = B + C + D$ $A = BC$

$A = B \odot C$ $a = b \odot c$ $A = 0$ $A = B \odot (CD)$

$A = BCd$ $A = B^T$ $a = B^T Bc$

$a = b + c$ $A = B$ $K = A^T CA$

$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$

$A_{lj} = \sum_{ik} B_{ikl} C_{ij} D_{kj}$ $A_{ij} = \sum_{k} B_{ijk} c_k$

$A_{ijk} = \sum_{l} B_{ikl} C_{lj}$ $A_{ik} = \sum_{j} B_{ijk} c_j$

$A_{jk} = \sum_{i} B_{ijk} c_i$ $A_{ijl} = \sum_{k} B_{ikl} C_{kj}$

$\tau = \sum_{i} z_i (\sum_{j} z_j \theta_{ij})(\sum_{k} z_k \theta_{ik})$

$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$

$a = \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} P_{no} \overline{M_{po}}\, \overline{P_{ip}}$

$\times$

Dense Matrix

CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

Sparse vector Hash Maps

Coordinates

Dense Tensors

CSF

Blocked Tensors

Too many combinations for a fixed-function library

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$A_{ijk} = \sum_{l} B_{ikl} C_{lj}$ $\quad A_{ik} = \sum_{j} B_{ijk} c_j$

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$\tau = \sum_{i} z_i (\sum_{j} z_j \theta_{ij})(\sum_{k} z_k \theta_{ik})$

$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$

$a = \sum_{ijklmnop} M_{ij} P_{jk} M_{kl} P_{lm} \overline{M_{nm}} P_{no} \overline{M_{po}}\, \overline{P_{ip}}$

$\times$

Dense Matrix

CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

Sparse vector Hash Maps

Coordinates

Dense Tensors

CSF

Blocked Tensors

Linked Lists Database

Compression Schemes

Cloud Storage

Too many combinations for a fixed-function library

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$A_{ij} = \sum_{kl} B_{ikl} C_{lj} D_{kj}$ $\quad A_{kj} = \sum_{il} B_{ikl} C_{lj} D_{ij}$

$A_{lj} = \sum_{ik} B_{ikl} C_{ij} D_{kj}$ $\quad A_{ij} = \sum_{k} B_{ijk} c_k$

$A_{ijk} = \sum_{l} B_{ikl} C_{lj}$ $\quad A_{ik} = \sum_{j} B_{ijk} c_j$

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$C = \sum_{ijkl} M_{ij} P_{jk} \overline{M_{lk}}\, \overline{P_{il}}$

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$\times$

Dense Matrix

CSR DCSR BCSR

COO ELLPACK CSB

Blocked COO CSC

DIA Blocked DIA DCSC

Sparse vector Hash Maps

Coordinates

Dense Tensors

CSF

Blocked Tensors

Linked Lists Database

Compression Schemes

Cloud Storage

$\times$

CPU

GPUs TPUs

FPGA

Sparse Tensor Hardware

Cloud Computers

Supercomputers

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k B_{ijk} c_k$$

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k B_{ijk} c_k$$

dense dense

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k \underbrace{B_{ijk}}_{\text{dense}} \underbrace{c_k}_{\text{dense}}$$

```
for (int i = 0; i < m; i++) {

  for (int j = 0; j < n; j++) {
    int pB2 = i*n + j;
    int pA2 = i*n + j;
    double t = 0.0;
    for (int k = 0; k < o; k++) {
      int pB3 = pB2*o + k;
      t += B[pB3] * c[k];
    }
    A[pA2] = t;
  }
}
```

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k B_{ijk} c_k$$

CSF dense

```
for (int pA = 0; pA < m*n; pA++) {
  A[pA] = 0.0;
}
for (int pB1 = B1_pos[0]; pB1 < B1_pos[1]; pB1++) {
  int i = B1_crd[pB1];
  for (int pB2 = B2_pos[pB1]; pB2 < B2_pos[pB1+1]; pB2++) {
    int j = B2_crd[pB2];
    int pA2 = i*n + j;
    double t = 0.0;
    for (int pB3 = B3_pos[pB2]; pB3 < B3_pos[pB2+1]; pB3++) {
      int k = B3_crd[pB3];
      t += B[pB3] * c[k];
    }
    A[pA2] = t;
  }
}
```

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k B_{ijk} c_k$$

CSF compressed

```
for (int pA = 0; pA < m*n; pA++) {
  A[pA] = 0.0;
}
for (int pB1 = B1_pos[0]; pB1 < B1_pos[1]; pB1++) {
  int i = B1_crd[pB1];
  for (int pB2 = B2_pos[pB1]; pB2 < B2_pos[pB1+1]; pB2++) {
    int j = B2_crd[pB2];
    int pA2 = i*n + j;
    double t = 0.0;
    int pB3 = B3_pos[pB2];
    int pc1 = c1_pos[0];
    while (pB3 < B3_pos[pB2+1] && pc1 < c1_pos[1]) {
      int kB = B3_crd[pB3];
      int kc = c1_crd[pc1];
      int k = min(kB, kc);
      if (kB == k && kc == k) {
        t += B[pB3] * c[pc1];
      }
      pB3 += (int)(kB == k);
      pc1 += (int)(kc == k);
    }
    A[pA2] = t;
  }
}
```

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ij} = \sum_k B_{ijk} c_k$$

CSF   hash map

```
for (int pA = 0; pA < m*n; pA++) {
  A[pA] = 0.0;
}
for (int pB1 = B1_pos[0]; pB1 < B1_pos[1]; pB1++) {
  int i = B1_crd[pB1];
  for (int pB2 = B2_pos[pB1]; pB2 < B2_pos[pB1+1]; pB2++) {
    int j = B2_crd[pB2];
    int pA2 = i*n + j;
    double t = 0.0;
    for (int pB3 = B3_pos[pB2]; pB3 < B3_pos[pB2+1]; pB3++) {
      int k = B3_crd[pB3];
      int pc1 = k % c_size;
      if (c_crd[pc1] != k && c_crd[pc1] != -1) {
        int end = pc;
        do {
          pc = (pc+1) % c_size;
        } while (c_crd[pc1] != k &&
                 c_crd[pc1] != -1 && pc1 != end);
      }
      if (c_crd[pc1] == k) {
        t += B[pB3] * c[pc1];
      }
    }
    A[pA2] = t;
  }
}
```

Optimized code is often complex, especially when it iterates over irregular data structures

$$A_{ijk} = \underset{\text{CSF}}{\underset{\uparrow}{B_{ijk}}} + \underset{\text{COO}}{\underset{\uparrow}{C_{ijk}}}$$

```
int iB = 0;
int C0_pos = C0_pos[0];
while (C0_pos < C0_pos[1]) {
  int iC = C0_crd[C0_pos];
  int C0_end = C0_pos + 1;
  if (iC == iB)
    while ((C0_end < C0_pos[1]) && (C0_crd[C0_end] == iB)) {
      C0_end++;
    }
  if (iC == iB) {
    int B1_pos = B1_pos[iB];
    int C1_pos = C0_pos;
    while ((B1_pos < B1_pos[iB + 1]) && (C1_pos < C0_end)) {
      int jB = B1_crd[B1_pos];
      int jC = C1_crd[C1_pos];
      int j = min(jB, jC);
      int A1_pos = (iB * A1_size) + j;
      int C1_end = C1_pos + 1;
      if (jC == j)
        while ((C1_end < C0_end) && (C1_crd[C1_end] == j)) {
          C1_end++;
        }
      if ((jB == j) && (jC == j)) {
        int B2_pos = B2_pos[B1_pos];
        int C2_pos = C1_pos;
        while ((B2_pos < B2_pos[B1_pos + 1]) && (C2_pos < C1_end)) {
          int kB = B2_crd[B2_pos];
          int kC = C2_crd[C2_pos];
          int k = min(kB, kC);
          int A2_pos = (A1_pos * A2_size) + k;
          if ((kB == k) && (kC == k)) {
            A[A2_pos] = B[B2_pos] + C[C2_pos];
          } else if (kB == k) {
            A[A2_pos] = B[B2_pos];
          } else {
            A[A2_pos] = C[C2_pos];
          }
          if (kB == k) B2_pos++;
          if (kC == k) C2_pos++;
        }
        while (B2_pos < B2_pos[B1_pos + 1]) {
          int kB0 = B2_crd[B2_pos];
          int A2_pos0 = (A1_pos * A2_size) + kB0;
          A[A2_pos0] = B[B2_pos];
          B2_pos++;
        }
        while (C2_pos < C1_end) {
          int kC0 = C2_crd[C2_pos];
          int A2_pos1 = (A1_pos * A2_size) + kC0;
          A[A2_pos1] = C[C2_pos];
          C2_pos++;
        }
      } else if (jB == j) {
        for (int B2_pos0 = B2_pos[B1_pos];
                 B2_pos0 < B2_pos[B1_pos + 1]; B2_pos0++) {
          int kB1 = B2_crd[B2_pos0];
          int A2_pos2 = (A1_pos * A2_size) + kB1;
          A[A2_pos2] = B[B2_pos0];
        }
      } else {
        for (int C2_pos0 = C1_pos; C2_pos0 < C1_end; C2_pos0++) {
          int kC1 = C2_crd[C2_pos0];
          int A2_pos3 = (A1_pos * A2_size) + kC1;
          A[A2_pos3] = C[C2_pos0];
        }
      }
      if (jB == j) B1_pos++;
      if (jC == j) C1_pos = C1_end;
    }
    while (B1_pos < B1_pos[iB + 1]) {
      int jB0 = B1_crd[B1_pos];
      int A1_pos0 = (iB * A1_size) + jB0;
      for (int B2_pos1 = B2_pos[B1_pos];
               B2_pos1 < B2_pos[B1_pos + 1]; B2_pos1++) {
        int kB2 = B2_crd[B2_pos1];
        int A2_pos4 = (A1_pos0 * A2_size) + kB2;
        A[A2_pos4] = B[B2_pos1];
      }
      B1_pos++;
    }
    while (C1_pos < C0_end) {
      int jC0 = C1_crd[C1_pos];
      int A1_pos1 = (iB * A1_size) + jC0;
      int C1_end0 = C1_pos + 1;
      while ((C1_end0 < C0_end) && (C1_crd[C1_end0] == jC0)) {
        C1_end0++;
      }
      for (int C2_pos1 = C1_pos; C2_pos1 < C1_end0; C2_pos1++) {
        int kC2 = C2_crd[C2_pos1];
        int A2_pos5 = (A1_pos1 * A2_size) + kC2;
        A[A2_pos5] = C[C2_pos1];
      }
      C1_pos = C1_end0;
    }
  } else {
    for (int B1_pos0 = B1_pos[iB];
             B1_pos0 < B1_pos[iB + 1]; B1_pos0++) {
      int jB1 = B1_crd[B1_pos0];
      int A1_pos2 = (iB * A1_size) + jB1;
      for (int B2_pos2 = B2_pos[B1_pos0];
               B2_pos2 < B2_pos[B1_pos0 + 1]; B2_pos2++) {
        int kB3 = B2_crd[B2_pos2];
        int A2_pos6 = (A1_pos2 * A2_size) + kB3;
        A[A2_pos6] = B[B2_pos2];
      }
    }
  }
  if (iC == iB) C0_pos = C0_end;
  iB++;
}
while (iB < B0_size) {
  for (int B1_pos1 = B1_pos[iB];
           B1_pos1 < B1_pos[iB + 1]; B1_pos1++) {
    int jB2 = B1_crd[B1_pos1];
    int A1_pos3 = (iB * A1_size) + jB2;
    for (int B2_pos3 = B2_pos[B1_pos1];
             B2_pos3 < B2_pos[B1_pos1 + 1]; B2_pos3++) {
      int kB4 = B2_crd[B2_pos3];
      int A2_pos7 = (A1_pos3 * A2_size) + kB4;
      A[A2_pos7] = B[B2_pos3];
    }
  }
  iB++;
}
```

Can we get abstractions *without* friction by moving the abstractions into the compiler?

Can we get abstractions *without* friction by moving the abstractions into the compiler?

Domain-Specific
Language
Constructs

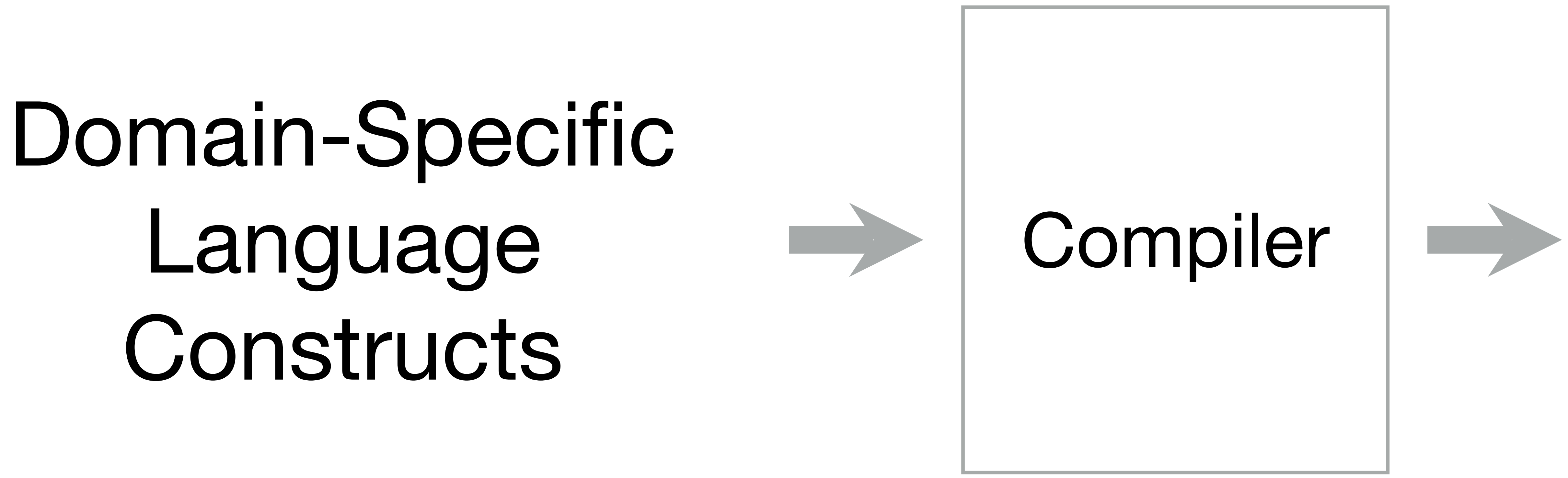
Can we get abstractions *without* friction by moving the abstractions into the compiler?

Domain-Specific Language Constructs

Generated Code

```c
int iB = 0;
int C0_pos = C0_pos_arr[0];
while (C0_pos < C0_pos_arr[1]) {
  int iC = C0_idx_arr[C0_pos];
  int C0_end = C0_pos + 1;
  if (iC == iB)
    while ((C0_end < C0_pos_arr[1]) && (C0_idx_arr[C0_end] == iB)) {
      C0_end++;
    }
  if (iC == iB) {
    int B1_pos = B1_pos_arr[iB];
    int C1_pos = C0_pos;
    while ((B1_pos < B1_pos_arr[iB + 1]) && (C1_pos < C0_end)) {
      int jB = B1_idx_arr[B1_pos];
      int jC = C1_idx_arr[C1_pos];
      int j = min(jB, jC);
      int A1_pos = (iB * A1_size) + j;
      int C1_end = C1_pos + 1;
      if (jC == j)
        while ((C1_end < C0_end) && (C1_idx_arr[C1_end] == j)) {
          C1_end++;
        }
      if ((jB == j) && (jC == j)) {
        int B2_pos = B2_pos_arr[B1_pos];
        int C2_pos = C1_pos;
        while ((B2_pos < B2_pos_arr[B1_pos + 1]) && (C2_pos < C1_end)) {
          int kB = B2_idx_arr[B2_pos];
          int kC = C2_idx_arr[C2_pos];
          int k = min(kB, kC);
          int A2_pos = (A1_pos * A2_size) + k;
          if ((kB == k) && (kC == k)) {
            A_val_arr[A2_pos] = B_val_arr[B2_pos] + C_val_arr[C2_pos];
          } else if (kB == k) {
            A_val_arr[A2_pos] = B_val_arr[B2_pos];
          } else {
            A_val_arr[A2_pos] = C_val_arr[C2_pos];
          }
          if (kB == k) B2_pos++;
          if (kC == k) C2_pos++;
        }
        while (B2_pos < B2_pos_arr[B1_pos + 1]) {
          int kB0 = B2_idx_arr[B2_pos];
          int A2_pos0 = (A1_pos * A2_size) + kB0;
          A_val_arr[A2_pos0] = B_val_arr[B2_pos];
          B2_pos++;
        }
        while (C2_pos < C1_end) {
          int kC0 = C2_idx_arr[C2_pos];
          int A2_pos1 = (A1_pos * A2_size) + kC0;
          A_val_arr[A2_pos1] = C_val_arr[C2_pos];
          C2_pos++;
        }
      } else if (jB == j) {
        for (int B2_pos0 = B2_pos_arr[B1_pos];
                 B2_pos0 < B2_pos_arr[B1_pos + 1]; B2_pos0++) {
          int kB1 = B2_idx_arr[B2_pos0];
          int A2_pos2 = (A1_pos * A2_size) + kB1;
          A_val_arr[A2_pos2] = B_val_arr[B2_pos0];
        }
      } else {
        for (int C2_pos0 = C1_pos; C2_pos0 < C1_end; C2_pos0++) {
          int kC1 = C2_idx_arr[C2_pos0];
          int A2_pos3 = (A1_pos * A2_size) + kC1;
          A_val_arr[A2_pos3] = C_val_arr[C2_pos0];
        }
      }
      if (jB == j) B1_pos++;
      if (jC == j) C1_pos = C1_end;
    }
    while (B1_pos < B1_pos_arr[iB + 1]) {
      int jB0 = B1_idx_arr[B1_pos];
      int A1_pos0 = (iB * A1_size) + jB0;
      for (int B2_pos1 = B2_pos_arr[B1_pos];
               B2_pos1 < B2_pos_arr[B1_pos + 1]; B2_pos1++) {
        int kB2 = B2_idx_arr[B2_pos1];
        int A2_pos4 = (A1_pos0 * A2_size) + kB2;
        A_val_arr[A2_pos4] = B_val_arr[B2_pos1];
      }
      B1_pos++;
    }
    while (C1_pos < C0_end) {
      int jC0 = C1_idx_arr[C1_pos];
      int A1_pos1 = (iB * A1_size) + jC0;
      int C1_end0 = C1_pos + 1;
      while ((C1_end0 < C0_end) && (C1_idx_arr[C1_end0] == jC0)) {
        C1_end0++;
      }
      for (int C2_pos1 = C1_pos; C2_pos1 < C1_end0; C2_pos1++) {
        int kC2 = C2_idx_arr[C2_pos1];
        int A2_pos5 = (A1_pos1 * A2_size) + kC2;
        A_val_arr[A2_pos5] = C_val_arr[C2_pos1];
      }
      C1_pos = C1_end0;
    }
  } else {
    for (int B1_pos0 = B1_pos_arr[iB];
             B1_pos0 < B1_pos_arr[iB + 1]; B1_pos0++) {
      int jB1 = B1_idx_arr[B1_pos0];
      int A1_pos2 = (iB * A1_size) + jB1;
      for (int B2_pos2 = B2_pos_arr[B1_pos0];
               B2_pos2 < B2_pos_arr[B1_pos0 + 1]; B2_pos2++) {
        int kB3 = B2_idx_arr[B2_pos2];
        int A2_pos6 = (A1_pos2 * A2_size) + kB3;
        A_val_arr[A2_pos6] = B_val_arr[B2_pos2];
      }
    }
  }
  if (iC == iB) C0_pos = C0_end;
  iB++;
}
while (iB < B0_size) {
  for (int B1_pos1 = B1_pos_arr[iB];
           B1_pos1 < B1_pos_arr[iB + 1]; B1_pos1++) {
    int jB2 = B1_idx_arr[B1_pos1];
    int A1_pos3 = (iB * A1_size) + jB2;
    for (int B2_pos3 = B2_pos_arr[B1_pos1];
             B2_pos3 < B2_pos_arr[B1_pos1 + 1]; B2_pos3++) {
      int kB4 = B2_idx_arr[B2_pos3];
      int A2_pos7 = (A1_pos3 * A2_size) + kB4;
      A_val_arr[A2_pos7] = B_val_arr[B2_pos3];
    }
  }
  iB++;
}
```

Can we get abstractions *without* friction by moving the abstractions into the compiler?



Generated Code

```c
int iB = 0;
int C0_pos = C0_pos_arr[0];
while (C0_pos < C0_pos_arr[1]) {
  int iC = C0_idx_arr[C0_pos];
  int C0_end = C0_pos + 1;
  if (iC == iB)
    while ((C0_end < C0_pos_arr[1]) && (C0_idx_arr[C0_end] == iB)) {
      C0_end++;
    }
  if (iC == iB) {
    int B1_pos = B1_pos_arr[iB];
    int C1_pos = C0_pos;
    while ((B1_pos < B1_pos_arr[iB + 1]) && (C1_pos < C0_end)) {
      int jB = B1_idx_arr[B1_pos];
      int jC = C1_idx_arr[C1_pos];
      int j = min(jB, jC);
      int A1_pos = (iB * A1_size) + j;
      int C1_end = C1_pos + 1;
      if (jC == j)
        while ((C1_end < C0_end) && (C1_idx_arr[C1_end] == j)) {
          C1_end++;
        }
      if ((jB == j) && (jC == j)) {
        int B2_pos = B2_pos_arr[B1_pos];
        int C2_pos = C1_pos;
        while ((B2_pos < B2_pos_arr[B1_pos + 1]) && (C2_pos < C1_end)) {
          int kB = B2_idx_arr[B2_pos];
          int kC = C2_idx_arr[C2_pos];
          int k = min(kB, kC);
          int A2_pos = (A1_pos * A2_size) + k;
          if ((kB == k) && (kC == k)) {
            A_val_arr[A2_pos] = B_val_arr[B2_pos] + C_val_arr[C2_pos];
          } else if (kB == k) {
            A_val_arr[A2_pos] = B_val_arr[B2_pos];
          } else {
            A_val_arr[A2_pos] = C_val_arr[C2_pos];
          }
          if (kB == k) B2_pos++;
          if (kC == k) C2_pos++;
        }
        while (B2_pos < B2_pos_arr[B1_pos + 1]) {
          int kB0 = B2_idx_arr[B2_pos];
          int A2_pos0 = (A1_pos * A2_size) + kB0;
          A_val_arr[A2_pos0] = B_val_arr[B2_pos];
          B2_pos++;
        }
        while (C2_pos < C1_end) {
          int kC0 = C2_idx_arr[C2_pos];
          int A2_pos1 = (A1_pos * A2_size) + kC0;
          A_val_arr[A2_pos1] = C_val_arr[C2_pos];
          C2_pos++;
        }
      } else if (jB == j) {
        for (int B2_pos0 = B2_pos_arr[B1_pos];
                 B2_pos0 < B2_pos_arr[B1_pos + 1]; B2_pos0++) {
          int kB1 = B2_idx_arr[B2_pos0];
          int A2_pos2 = (A1_pos * A2_size) + kB1;
          A_val_arr[A2_pos2] = B_val_arr[B2_pos0];
        }
      } else {
        for (int C2_pos0 = C1_pos; C2_pos0 < C1_end; C2_pos0++) {
          int kC1 = C2_idx_arr[C2_pos0];
          int A2_pos3 = (A1_pos * A2_size) + kC1;
          A_val_arr[A2_pos3] = C_val_arr[C2_pos0];
        }
      }
      if (jB == j) B1_pos++;
      if (jC == j) C1_pos = C1_end;
    }
    while (B1_pos < B1_pos_arr[iB + 1]) {
      int jB0 = B1_idx_arr[B1_pos];
      int A1_pos0 = (iB * A1_size) + jB0;
      for (int B2_pos1 = B2_pos_arr[B1_pos];
               B2_pos1 < B2_pos_arr[B1_pos + 1]; B2_pos1++) {
        int kB2 = B2_idx_arr[B2_pos1];
        int A2_pos4 = (A1_pos0 * A2_size) + kB2;
        A_val_arr[A2_pos4] = B_val_arr[B2_pos1];
      }
      B1_pos++;
    }
    while (C1_pos < C0_end) {
      int jC0 = C1_idx_arr[C1_pos];
      int A1_pos1 = (iB * A1_size) + jC0;
      int C1_end0 = C1_pos + 1;
      while ((C1_end0 < C0_end) && (C1_idx_arr[C1_end0] == jC0)) {
        C1_end0++;
      }
      for (int C2_pos1 = C1_pos; C2_pos1 < C1_end0; C2_pos1++) {
        int kC2 = C2_idx_arr[C2_pos1];
        int A2_pos5 = (A1_pos1 * A2_size) + kC2;
        A_val_arr[A2_pos5] = C_val_arr[C2_pos1];
      }
      C1_pos = C1_end0;
    }
  } else {
    for (int B1_pos0 = B1_pos_arr[iB];
             B1_pos0 < B1_pos_arr[iB + 1]; B1_pos0++) {
      int jB1 = B1_idx_arr[B1_pos0];
      int A1_pos2 = (iB * A1_size) + jB1;
      for (int B2_pos2 = B2_pos_arr[B1_pos0];
               B2_pos2 < B2_pos_arr[B1_pos0 + 1]; B2_pos2++) {
        int kB3 = B2_idx_arr[B2_pos2];
        int A2_pos6 = (A1_pos2 * A2_size) + kB3;
        A_val_arr[A2_pos6] = B_val_arr[B2_pos2];
      }
    }
  }
  if (iC == iB) C0_pos = C0_end;
  iB++;
}
while (iB < B0_size) {
  for (int B1_pos1 = B1_pos_arr[iB];
           B1_pos1 < B1_pos_arr[iB + 1]; B1_pos1++) {
    int jB2 = B1_idx_arr[B1_pos1];
    int A1_pos3 = (iB * A1_size) + jB2;
    for (int B2_pos3 = B2_pos_arr[B1_pos1];
             B2_pos3 < B2_pos_arr[B1_pos1 + 1]; B2_pos3++) {
      int kB4 = B2_idx_arr[B2_pos3];
      int A2_pos7 = (A1_pos3 * A2_size) + kB4;
      A_val_arr[A2_pos7] = B_val_arr[B2_pos3];
    }
  }
  iB++;
}
```

Separation of Algorithm, Data Representation, and Schedule

Algorithm Language

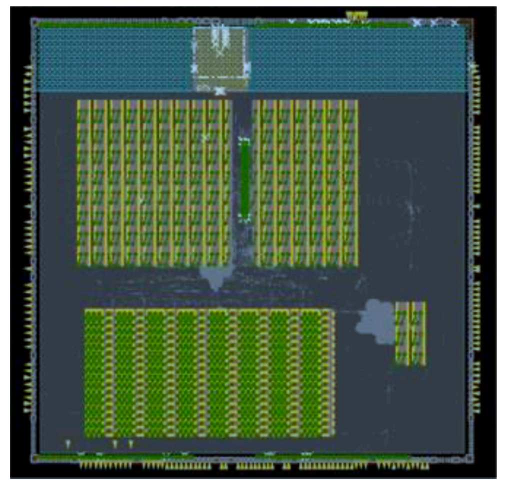
Data Representation Language

Scheduling Language

Compiler

CPUs

GPUs



DSAs

Most of HW retargeting is about changing schedules and data representations

How do you develop new language and compiler abstractions

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"Hitching our research to someone else's driving problem,
and solving those problems on the owners' terms
leads us to richer computer science research."
— Fred Brooks

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"Like other great software, great little languages are grown, not built. Start with a solid simple design, expressed in a notation like Backus-Naur form. Before implementing the language, test your design by describing a wide variety of objects in the proposed language. After the language is up and running, iterate designs to add new features as dictated by real use."
— Jon Bentley (Little Languages)

A process for developing DSLs

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  - Best to work closely with application people
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A process for developing DSLs

- Study applications to find patterns in their computations
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- Then you generalize
  - Deductively from examples to a natural coherent class
  - Inductively from new examples and observed patterns
  - Generalization must work for observed cases
  - Generalization must work for something new
- Look for ways to build abstractions into the compiler
  - Lets you separately describe different concerns
  - E.g., describe data structures independently of program

For Discussion

```
c := 0
for i := 1 step 1 until n do
    c := c + a[i]×b[i]
```

```
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for i := 1 step 1 until n do
   c := c + a[i]×b[i]
```

Def Innerproduct
≡ (Insert +)∘(ApplyToAll ×)∘Transpose

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for i := 1 step 1 until n do
   c := c + a[i]×b[i]
```

Def Innerproduct

$$\equiv (\text{Insert} +)\circ(\text{ApplyToAll} \times)\circ\text{Transpose}$$

IP:<<1,2,3>, <6,5,4>> =	
Definition of IP	⇒ (/+)∘(α×)∘Trans: <<1,2,3>, <6,5,4>>
Effect of composition, ∘	⇒ (/+):((α×):(Trans: <<1,2,3>, <6,5,4>>))
Applying Transpose	⇒ (/+):((α×): <<1,6>, <2,5>, <3,4>>)
Effect of ApplyToAll, α	⇒ (/+): <×: <1,6>, ×: <2,5>, ×: <3,4>>
Applying ×	⇒ (/+): <6,10,12>
Effect of Insert, /	⇒ +: <6, +: <10,12>>
Applying +	⇒ +: <6,22>
Applying + again	⇒ 28