



Introducing the Cambridge Architecture

The evolution of the Stored Program Machine

Problem statement

Modern computing workloads

- exhibit high memory intensity
- are becoming progressively structured
- when data sets grow,
caches become less effective
- memory access is becoming
dominant energy consumer

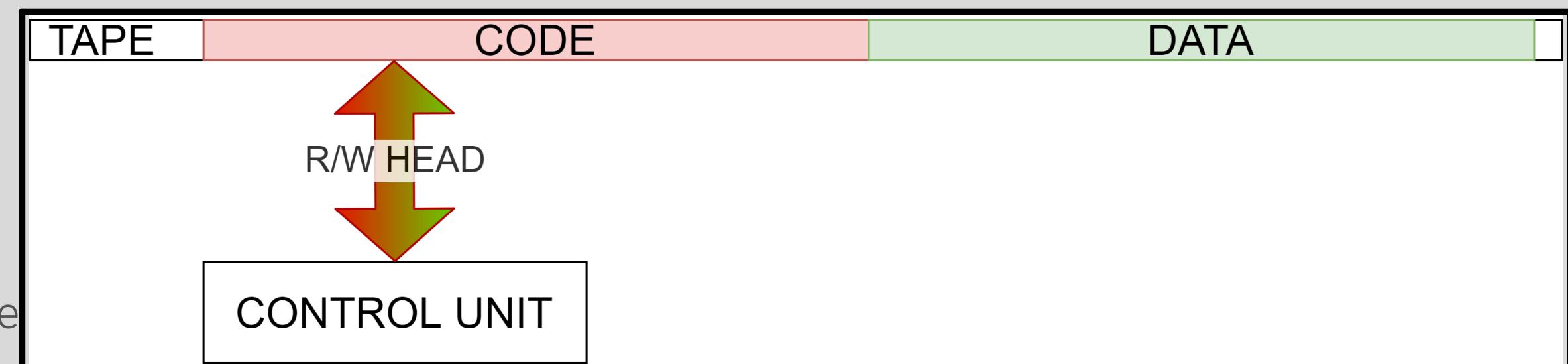
Generation 0 Turing Machine

ABSTRACTION

Computing is code and data -
both could be stored

ADVANTAGE

Creation of stored program machine
The base of Computing



1936

Generation 1 Harvard Architecture

ABSTRACTION

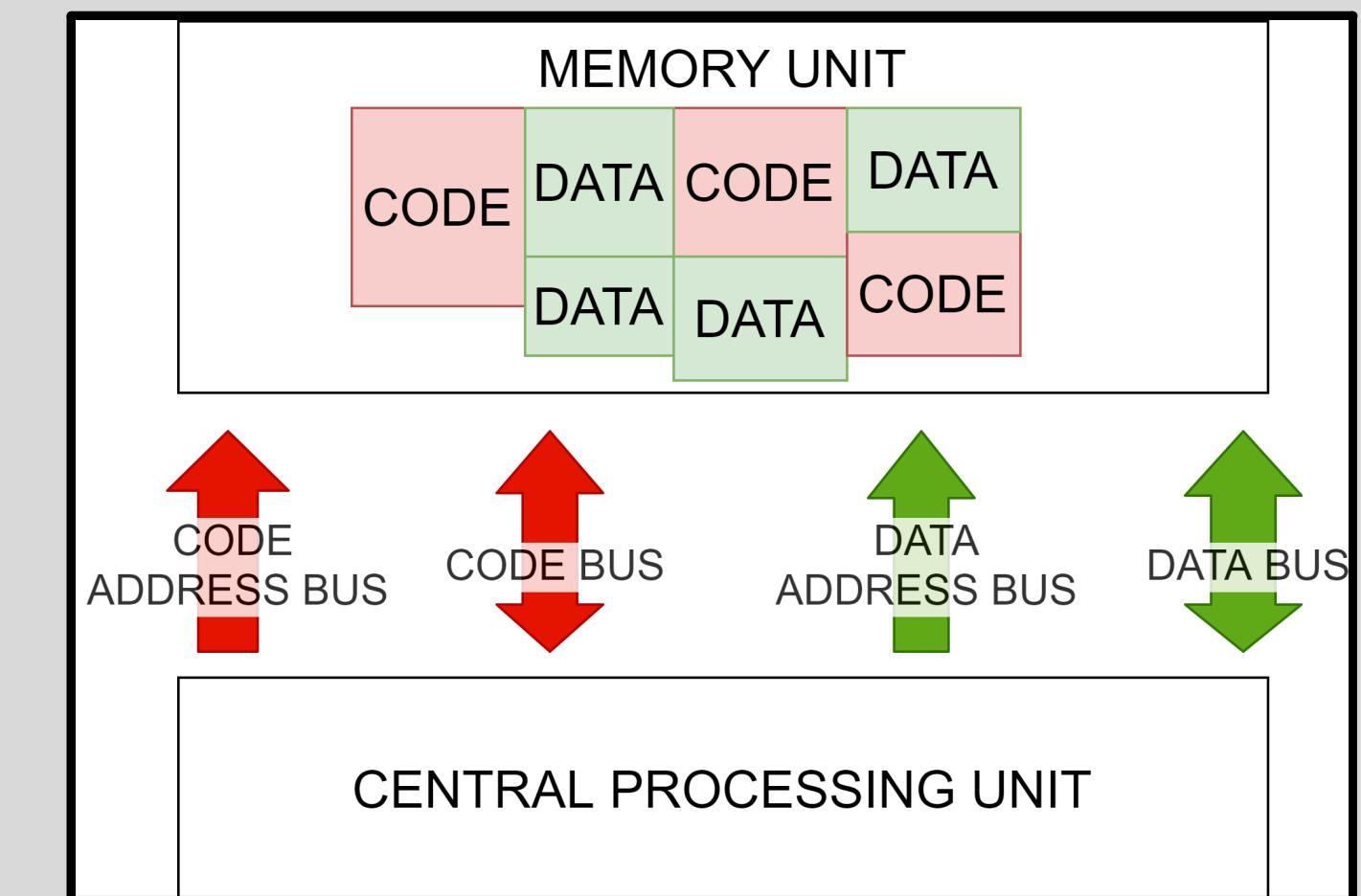
Code and Data separation

RAM Machine

ADVANTAGE

Different infrastructure for code and data

handling improved performance



1944

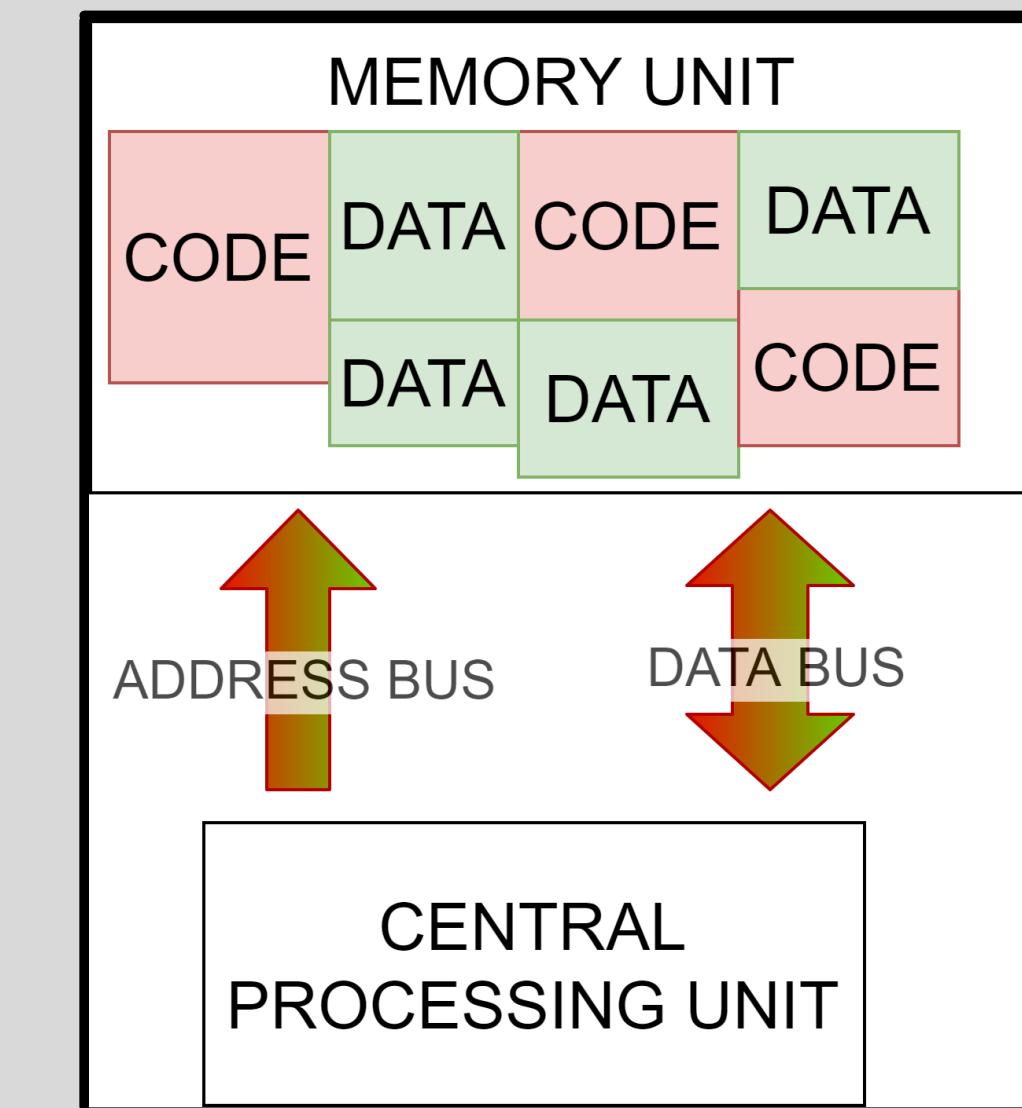
Generation 1 von Neumann/Princeton architecture

ABSTRACTION

CPU usage
Code/Data stored in Random Access Memory
RAM uses addresses to store/access data

ADVANTAGE

Shared infrastructure for code and data reduced costs
Address manipulation (pointers)
Birth of data structures



1945

Generation 2 Cache systems

ABSTRACTION

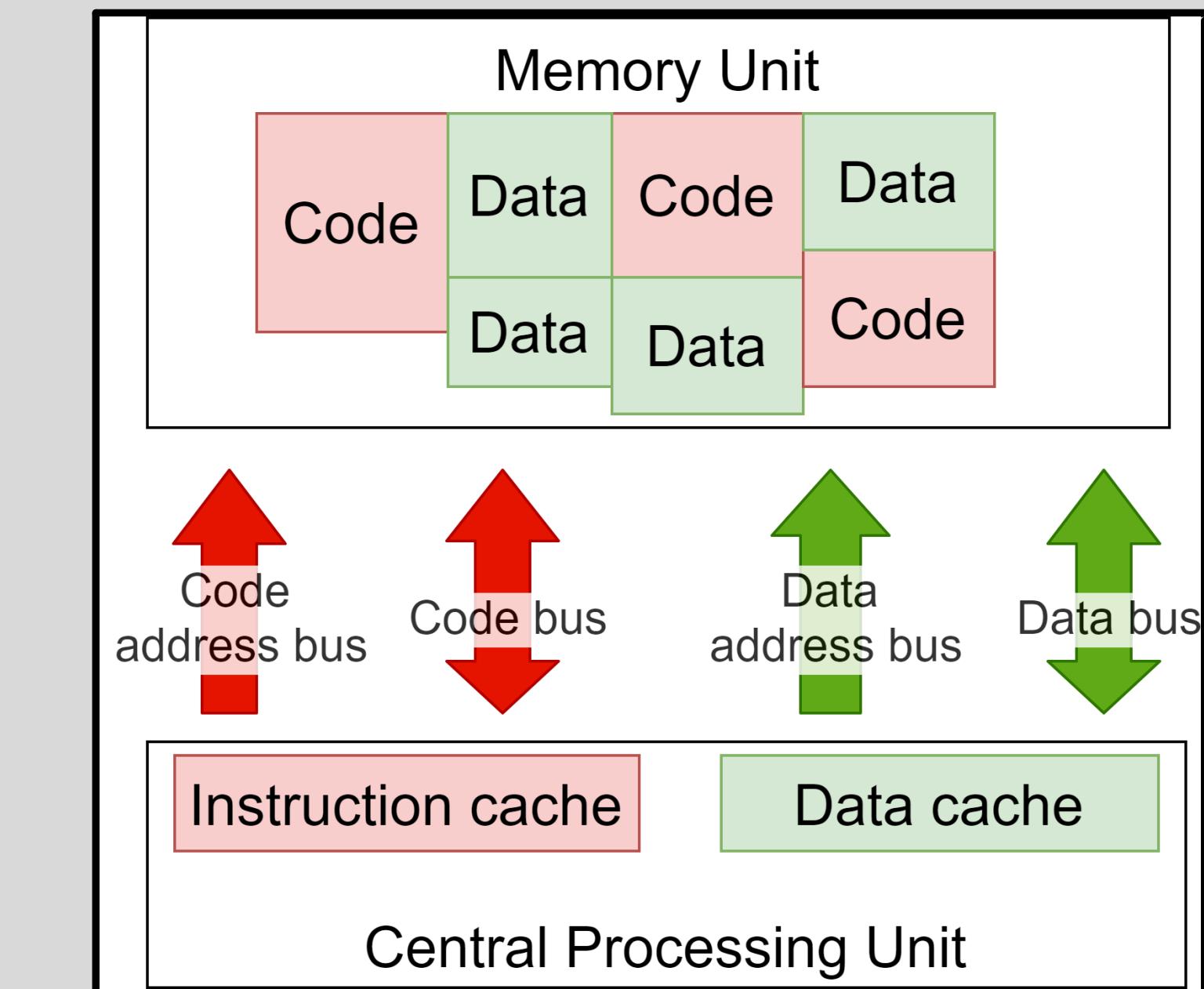
Working sets for code and data

ADVANTAGE

Lower average latency of memory accesses

Improved cycle time/performance

Better resource utilization on external I/O



1976

Back to our Problem statement

Modern computing workloads

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Foreach and map-reduce

```

6  public static void main(String[] args) {
7
8      List<String> nameList = new ArrayList<String>();
9
10     nameList.add("Java");
11     nameList.add("Kotlin");
12     nameList.add("Android");
13
14     // only single statement to be executed for each i
15     nameList.forEach(name -> System.out.println(name))
16 }
17

```

```

2
3  var numbers = map[int]string{1: "one", 2: "two", 3: "three"}
4
5  func countValue(numbers map[int]string, value string) (count int) {
6      for _, v := range numbers {
7          if value == v {
8              count++
9          }
10     }
11     return
12 }
13

```

```

4  template<typename Real>
5      int countValue(const std::vector<Real>& V, const Real& ref) {
6          int c = 0;
7          for (auto v: V) {
8              if (v == ref) ++c;
9          }
10         return c;
11     }
12

```

```

4
5  names = ['tom', 'john', 'simon']
6
7  for element in names:
8      operate(element)
9
10
11 const companies = ["Apple", "Google", "Facebook"];
12
13 companies.forEach(company => {
14     console.log(company);
15 });

```

```

1 #include <vector>
2
3 template<typename Real>
4 int countValue(std::vector<Real>& values, Real value)
5 {
6     int c = 0;
7     for (Real r : values)
8         if (r == value)
9             ++c;
10    return c;
11 }
12
13 #define ARRSIZE 1000000
14 int main()
15 {
16     std::vector<double> values(ARRSIZE);
17     // for (int i = 0; i < ARRSIZE; i++)
18     //     values[i] = (rand() + 1) / 17.0;
19     countValue(values, 42.0);
20 }
21

```

Benchmark your code online at [Quick Bench!](#)

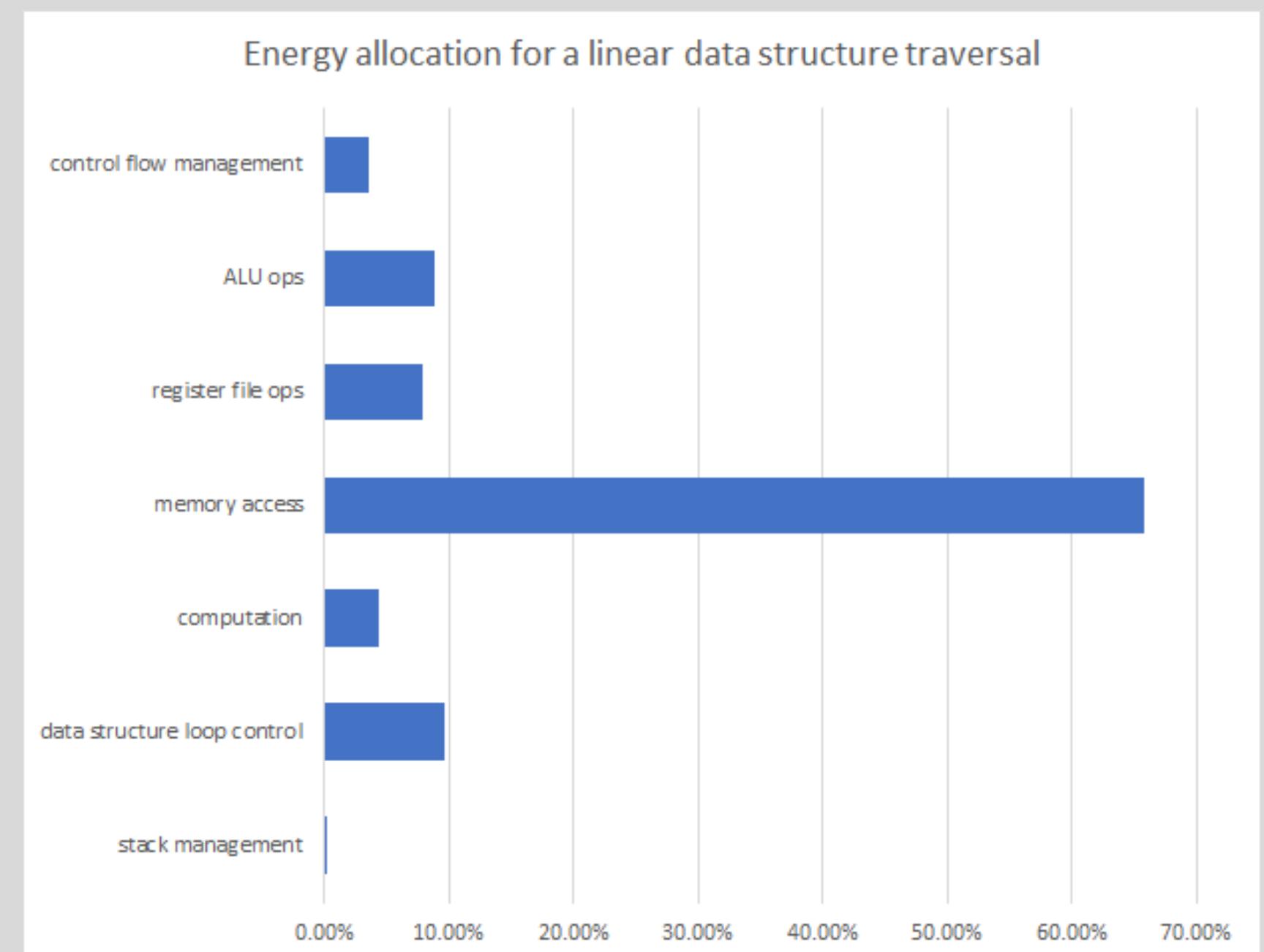
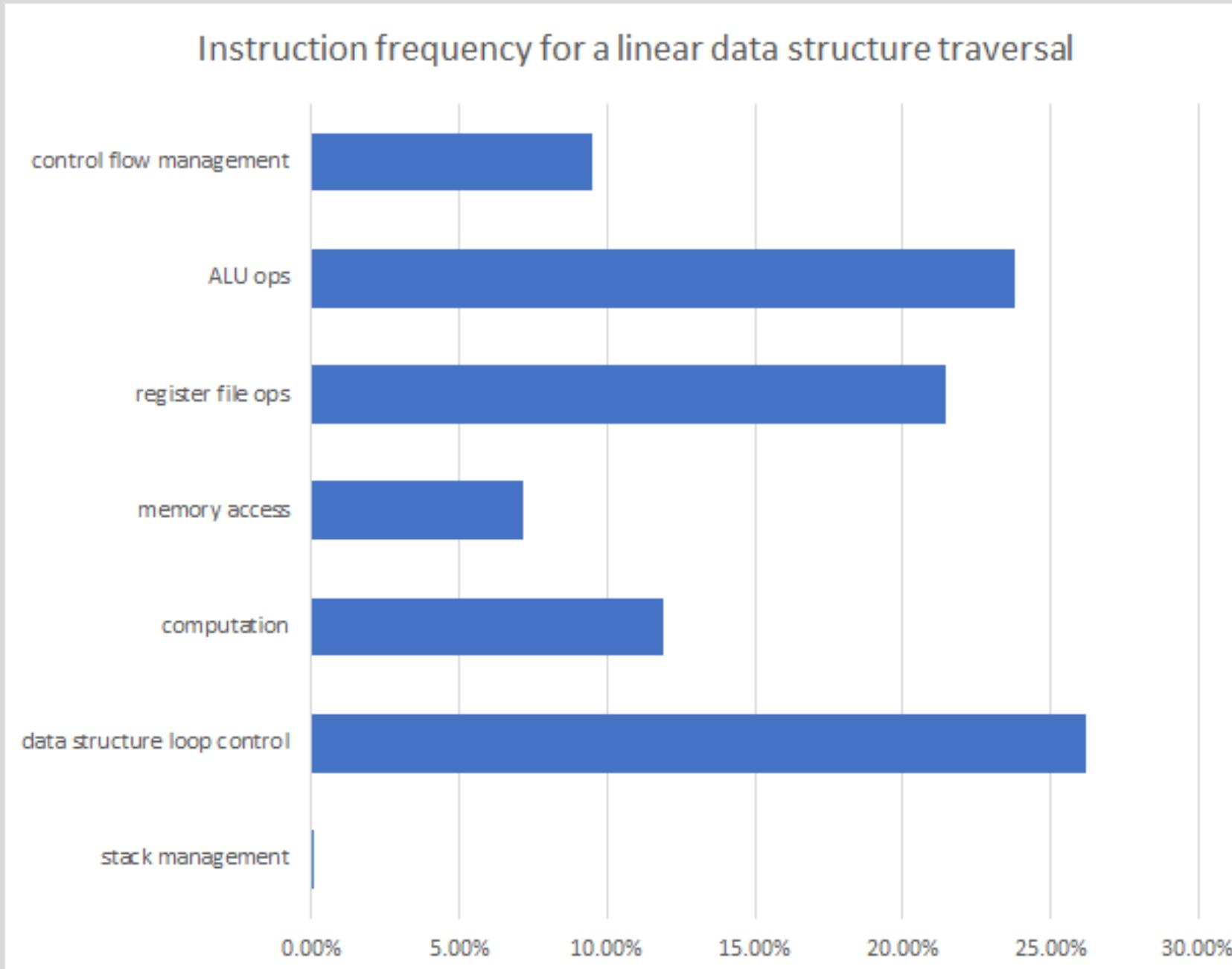
```

RISC-V rv64gc clang 11.0.0 (Editor #1, Compiler #1) C++ x
RISC-V rv64gc clang 11.0.0 ✓ Compiler options...

A Output... Filter... Libraries + Add new... Add tool...
100    int countValue(double)(std::vector<double>, std::allocator<double> &, double): # @int countValue(double)(std::vector<double>, std::allocator<double> &, double)
101        addi    sp, sp, -80
102        sd     ra, 72(sp)
103        sd     s0, 64(sp)
104        addi    s0, sp, 80
105        sd     a0, -24(s0)
106        fsd    fa0, -32(s0)
107        mv     a0, zero
108        sw     a0, -36(s0)
109        ld     a0, -24(s0)
110        sd     a0, -48(s0)
111        ld     a0, -48(s0)
112        call   std::vector<double>, std::allocator<double> ::begin()
113        sd     a0, -56(s0)
114        ld     a0, -48(s0)
115        call   std::vector<double>, std::allocator<double> ::end()
116        sd     a0, -64(s0)
117        j      .LBB4_1
118 .LBB4_1:          # =>This Inner Loop Header: Depth=1
119        addi    a0, s0, -56
120        addi    a1, s0, -64
121        call   __gnu_cxx::operator!=<double*, std::vector<double>, std::allocator<double> >(<__gnu_cxx:: normal_iterator<double*>, std::vector<double>, std::allocator<double> > const&
122        mv     a1, zero
123        beq    a0, a1, .LBB4_6
124        j      .LBB4_2
125 .LBB4_2:          # in Loop: Header=BB4_1 Depth=1
126        addi    a0, s0, -56
127        call   __gnu_cxx:: normal_iterator<double*>, std::vector<double>, std::allocator<double> ::operator*() const
128        fld    ft0, 0(a0)
129        fsd    ft0, -72(s0)
130        fld    ft0, -72(s0)
131        fld    ft1, -32(s0)
132        feqd   a0, ft0, ft1
133        xor    a0, a0, 1
134        bnez   a0, .LBB4_4
135        j      .LBB4_3
136 .LBB4_3:          # in Loop: Header=BB4_1 Depth=1
137        lw     a0, -36(s0)
138        addi   a0, a0, 1
139        sw     a0, -36(s0)
140        j      .LBB4_4
141 .LBB4_4:          # in Loop: Header=BB4_1 Depth=1
142        j      .LBB4_5
143 .LBB4_5:          # in Loop: Header=BB4_1 Depth=1
144        addi    a0, s0, -56
145        call   __gnu_cxx:: normal_iterator<double*>, std::vector<double>, std::allocator<double> ::operator++()
146        j      .LBB4_1
147 .LBB4_6:
148        lw     a0, -36(s0)
149        ld     s0, 64(sp)
150        ld     ra, 72(sp)
151        addi   sp, sp, 80
152        ret

```

Big Data/Streaming workloads



Data Structure	Time Complexity							
	Average				Worst			
	Access	Search	Insertion*	Deletion**	Access	Search	Insertion	Deletion
Array	O(1)	O(n)	O(n)	O(n)	O(1)	O(n)	O(n)	O(n)
Stack	O(n)	O(n)	O(1)	O(1)	O(n)	O(n)	O(1)	O(1)
Singly-Linked List	O(n)	O(n)	O(1)	O(1)	O(n)	O(n)	O(1)	O(1)
Doubly-Linked List	O(n)	O(n)	O(1)	O(1)	O(n)	O(n)	O(1)	O(1)
Skip List	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(n)	O(n)	O(n)	O(n)
Hash Table	-	O(1)	O(1)	O(1)	-	O(n)	O(n)	O(n)
Binary Search Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(n)	O(n)	O(n)	O(n)
Cartesian Tree	-	O(log(n))	O(log(n))	O(log(n))	-	O(n)	O(n)	O(n)
B-Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))
Red-Black Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))
Splay Tree	-	O(log(n))	O(log(n))	O(log(n))	-	O(log(n))	O(log(n))	O(log(n))
AVL Tree	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))	O(log(n))

Graph Operations							
Node / Edge Management	Storage	Add Vertex	Add Edge	Remove Vertex	Remove Edge	Query*	
Adjacency list	O(V + E)	O(1)	O(1)	O(V + E)	O(E)	O(V)	
Incidence list	O(V + E)	O(1)	O(1)	O(E)	O(E)	O(E)	
Adjacency matrix	O(V ^2)	O(V ^2)	O(1)	O(V ^2)	O(1)	O(1)	
Incidence matrix	O(V · E)	O(V · E)	O(E)				

Heap Operations						
Type	Time Complexity					
	Find Max	Extract Max	Increase Key	Insert	Delete	Merge
Linked List (sorted)	O(1)	O(1)	O(n)	O(n)	O(1)	O(m+n)
Linked List (unsorted)	O(n)	O(n)	O(1)	O(1)	O(1)	O(1)
Binary Heap	O(1)	O(log n)	O(log n)	O(log n)	O(log n)	O(m+n)
Binomial Heap	O(1)	O(log n)	O(log n)	O(1)	O(log n)	O(log n)
Fibonacci Heap	O(1)	O(log n)	O(1)	O(1)	O(log n)	O(1)



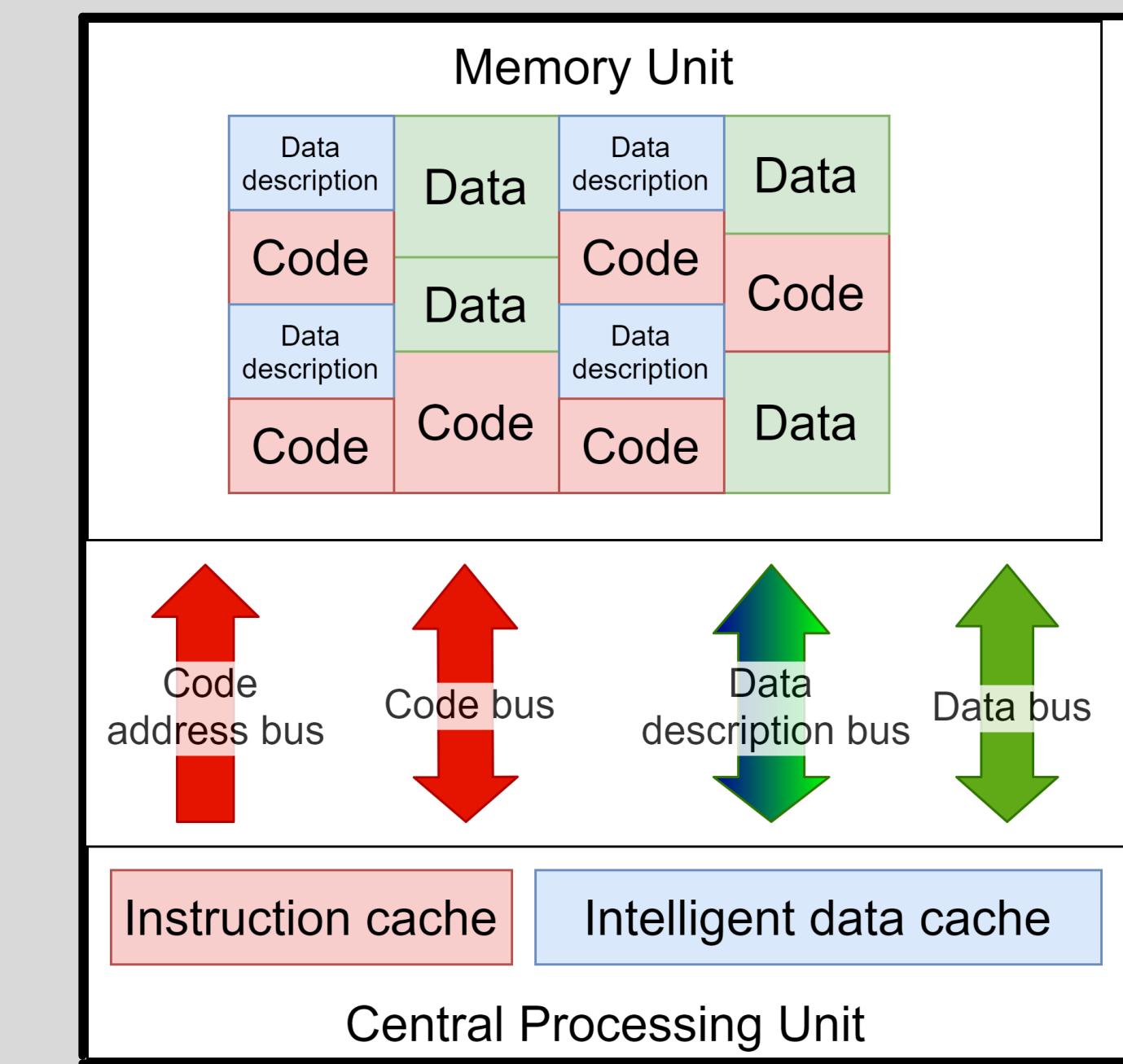
Data structure management has become a service.
Custom hardware can dramatically improve energy efficiency.

Cambridge Architecture
makes memory responsible for data
structure management

Next Generation Cambridge Architecture

ABSTRACTION

Most memory accesses are not random
 Memory becomes aware of data structure
 Data structure traversal and scheduling are moved to memory
 Memory becomes an active data structure management service

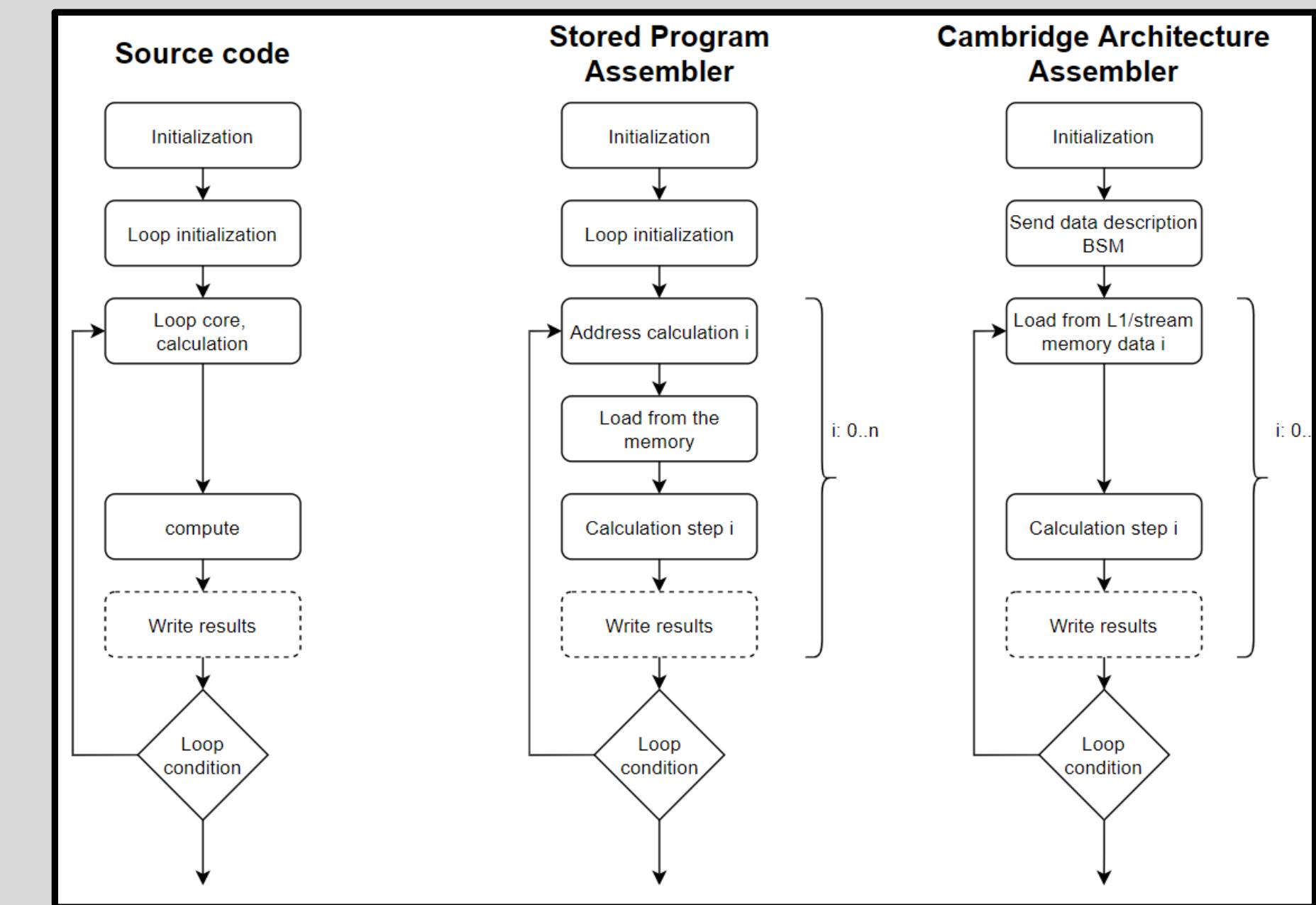


Cambridge Architecture

OPERATION

Data structure traversal and schedule owned by memory transformed into a stream

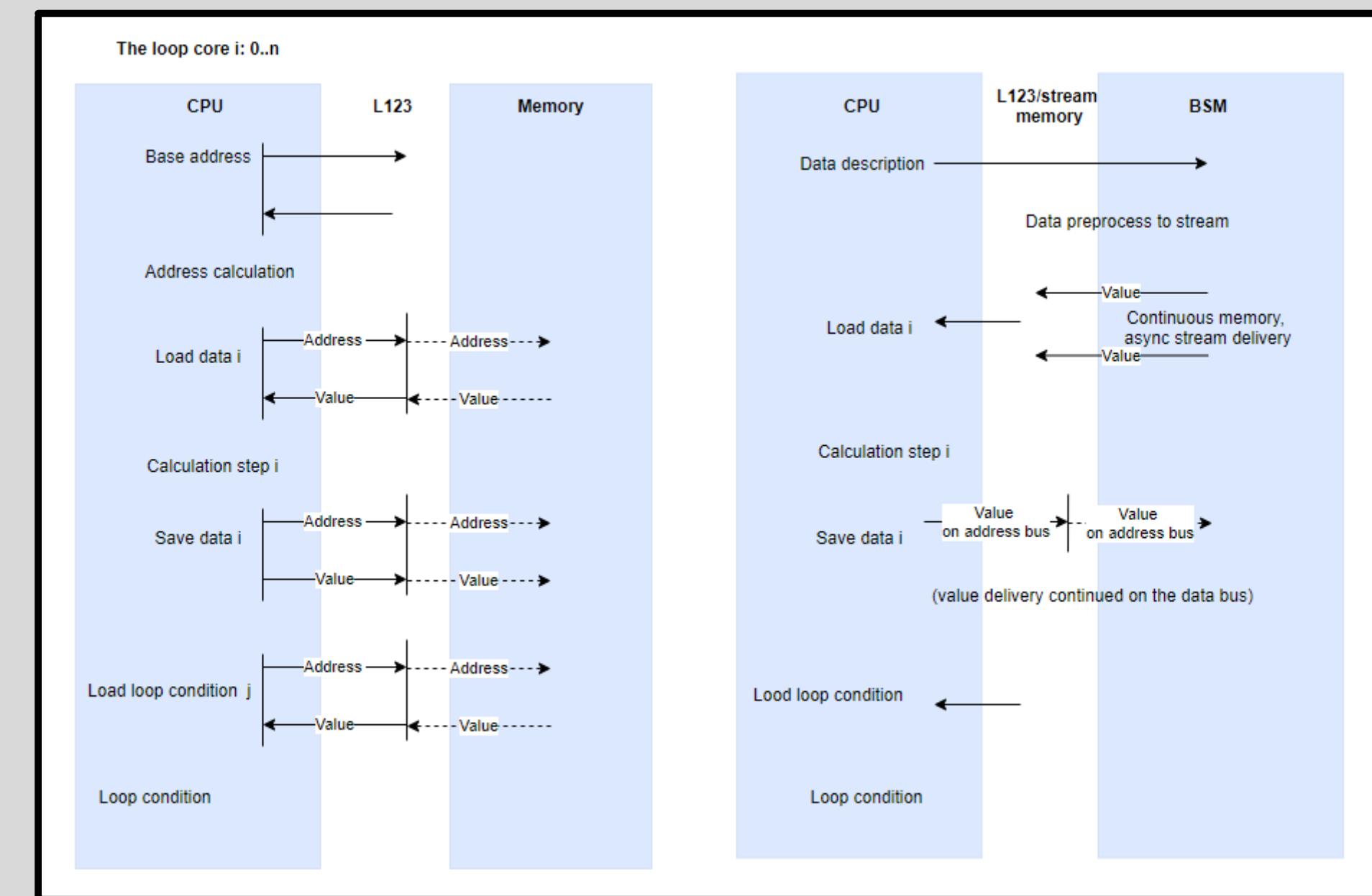
Processor execution transition from request/reply to data-driven stream bypasses caches

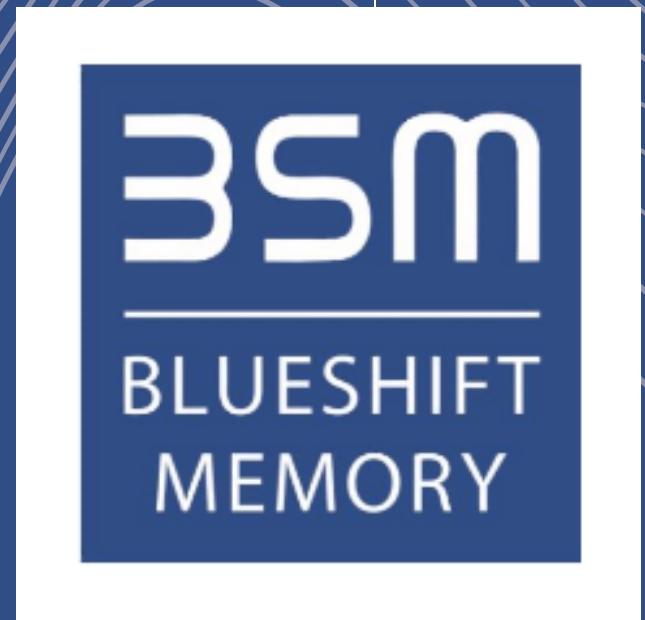


Cambridge Architecture BlueShift Memory streaming

OPERATION

- BlueShift Memory receives data descriptor
- Preprocesses the schedule
- Transform data access into streams
Send to CPU
- Receive update stream
Update data in memory





BLUESHIFT MEMORY

Cambridge Architecture benefits

Cambridge Architecture benefits

Zero-latency memory
media workloads
big data operators

Energy Efficiency Improvements

50%+

Performance Improvements

2-1000x

≡ Article Navigation

Exposing Memory Access Patterns to Improve Instruction and Memory Efficiency in GPUs

NEAL C. CRAGO, MARK STEPHENSON, and STEPHEN W. KECKLER, NVIDIA

ACM Trans. Archit. Code Optim., Vol. 15, No. 4, Article 45, Publication date: October 2018.

DOI: <https://doi.org/10.1145/3280851>

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The banner features a dark blue background with a glowing blue circuit board pattern. In the center is a white square containing a blue infinity symbol logo. Above the banner, the MemComputing logo is visible. Below the banner, the text "Breakthrough Computing Performance" is displayed in large, bold, white letters.

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Sorting

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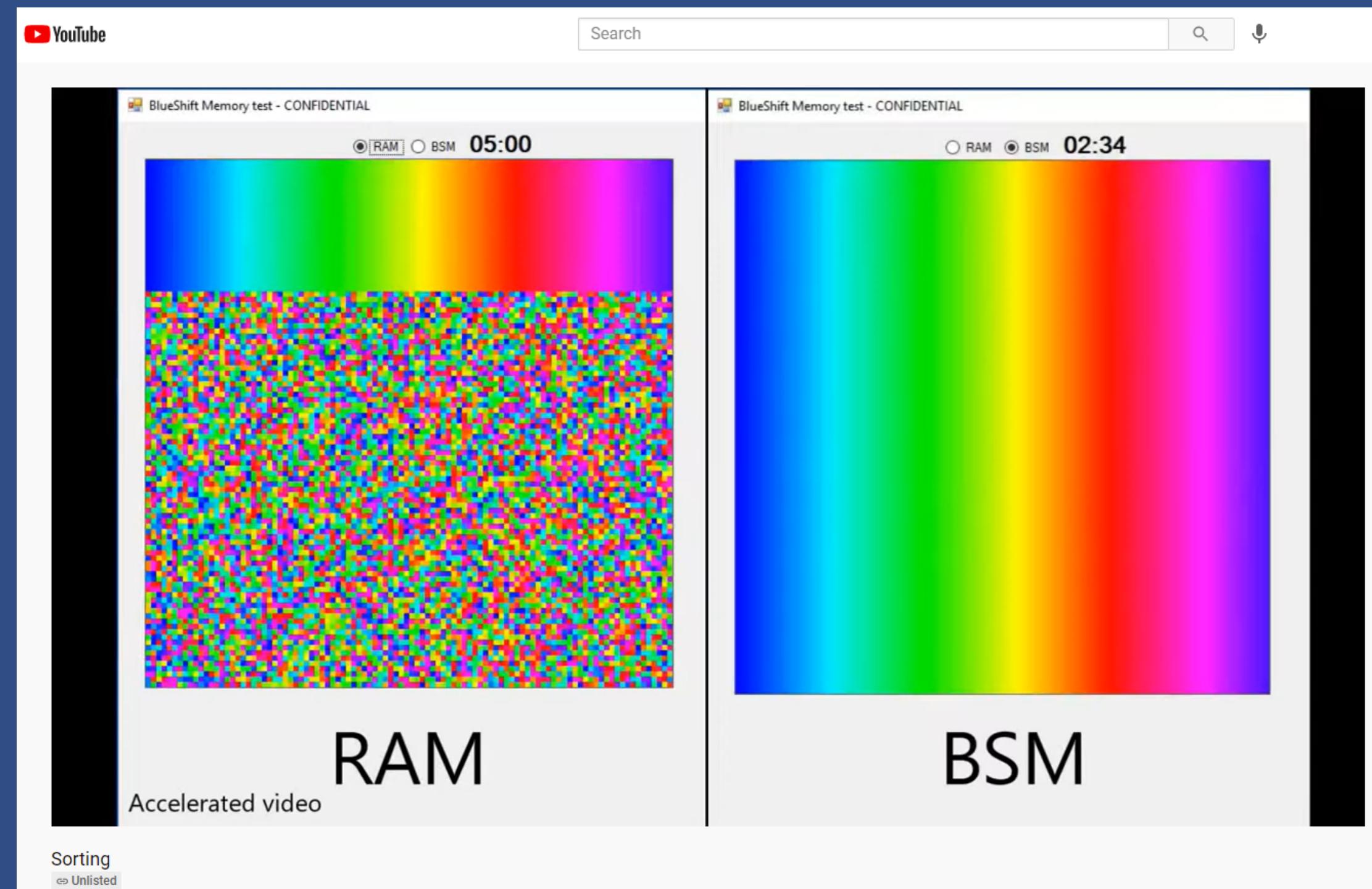
Image Processing

<https://www.youtube.com/watch?v=hSOMwG8hDDM>

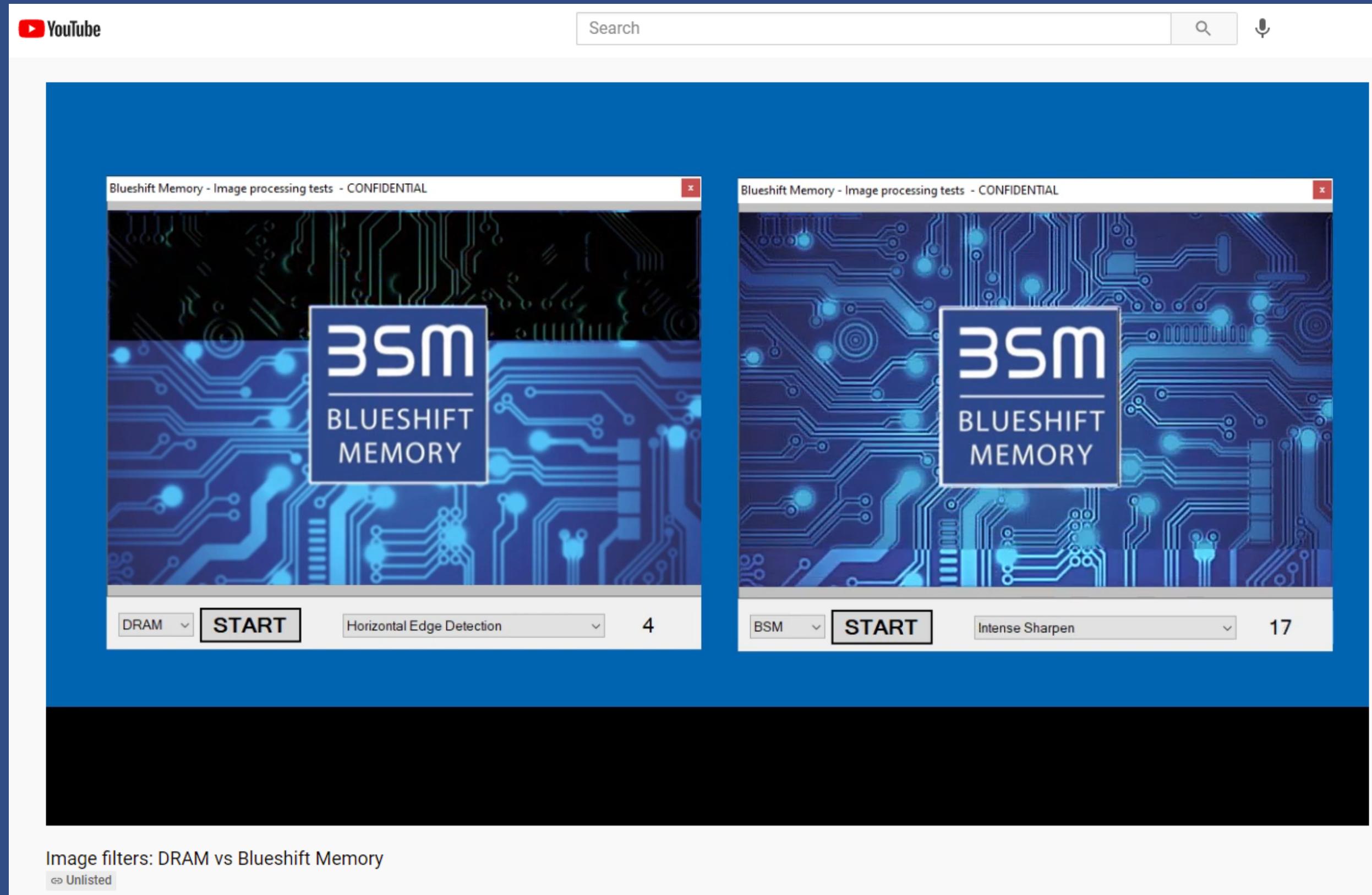
Computer Vision

<https://www.youtube.com/watch?v=fT-s-BppSFY>

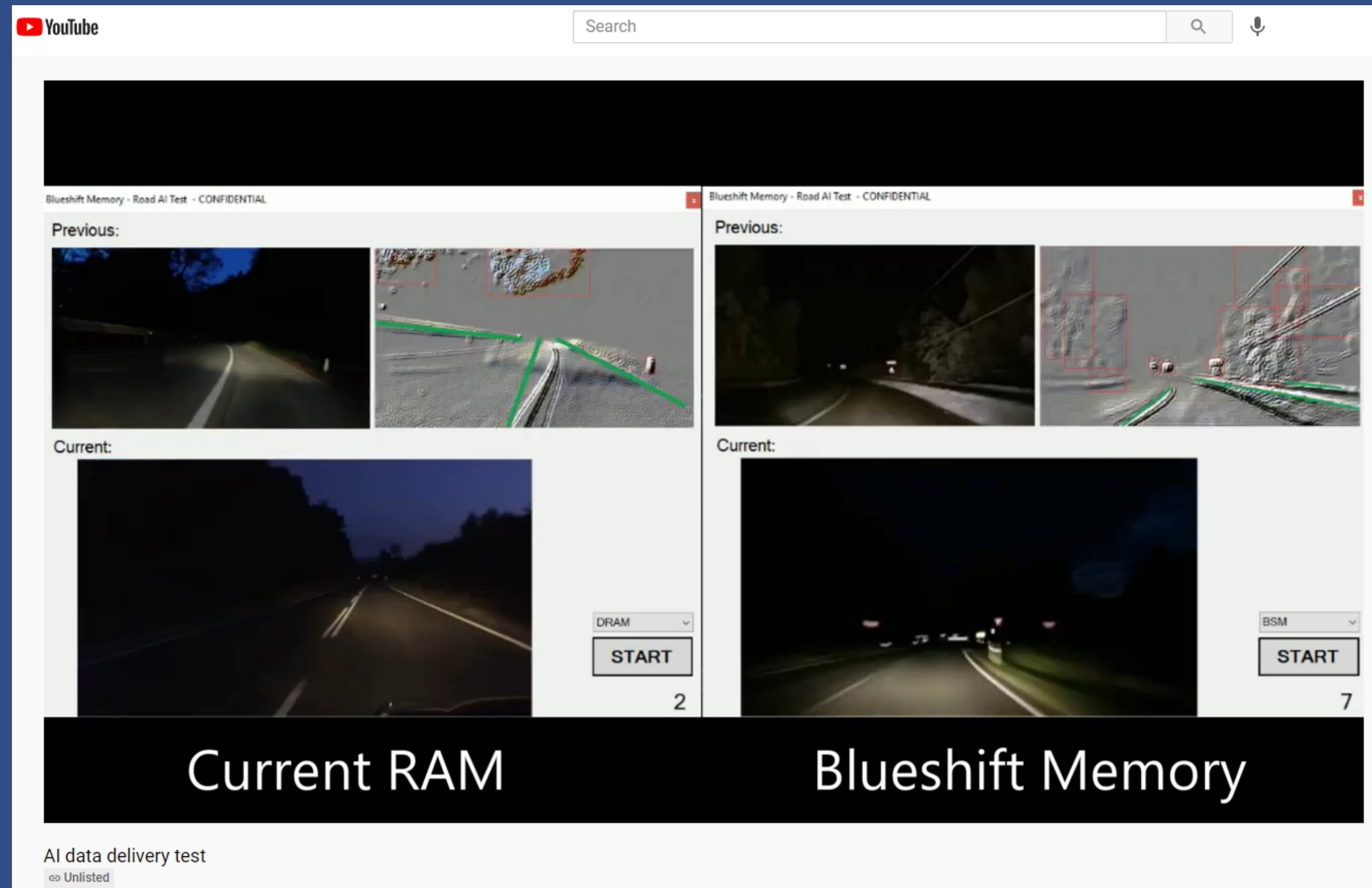
BSM speed-up 10x



BSM speed-up 2x



BSM speed-up 4x





Conclusion

Modern big data and media workloads benefit from active memory

Cambridge Architecture enables performance and energy efficiency improvements as a natural evolution



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