## Von Neumann Execution Model

Fetch:
- send PC to memory
- transfer instruction from memory to CPU
- increment PC

Decode & read ALU input sources

Execute
- an ALU operation
- memory operation
- branch target calculation

Store the result in a register or memory



## Von Neumann Execution Model

Program is a linear series of addressable instructions
- next instruction to be executed is pointed to by the PC
- send PC to memory
- next instruction to execute depends on what happened during the execution of the current instruction

Instruction operands reside in a centralized processor memory (GPRs)

## Dataflow Execution Model

Instructions are already in the processor:

Operands arrive from a producer instruction via a network

Check to see if all an instruction's operands are there

Execute
- an ALU operation
- memory operation
- branch target calculation

Send the result
- to the consumer instructions or memory



## Dataflow Execution Model

Execution is driven by the availability of input operands
- operands are consumed
- output is generated
- **no PC**

Result operands are passed directly to consumer instructions
- **no register file**

## Dataflow Computers

Motivation:

- exploit **instruction-level parallelism** on a massive scale
- more fully utilize all processing elements

Believed this was possible if:

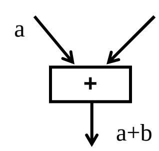
1. expose instruction-level parallelism by using a functional-style programming language
    - no side effects; only restrictions were producer-consumer
2. scheduled code for execution on the hardware greedily
3. hardware support for data-driven execution



## Dataflow Execution

All computation is **data-driven**.

- binary is represented as a directed graph
    - nodes are operations
    - values travel on arcs




- WaveScalar instruction

| opcode | destination1 | destination2 |
|---|---|---|

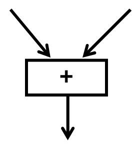
## Dataflow Execution

Data-dependent operations are connected, producer to consumer

Code & initial values loaded into memory

Execute according to the **dataflow firing rule**

- when operands of an instruction have arrived on all input arcs, instruction may execute
- value on input arcs is removed
- computed value placed on output arc

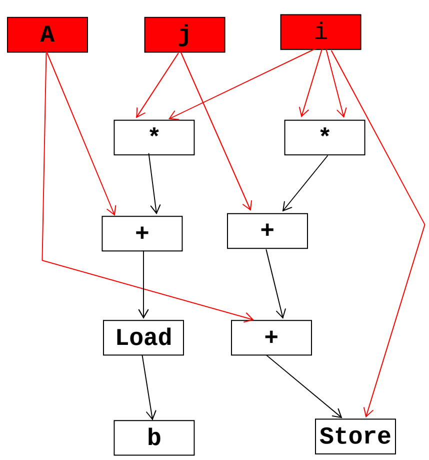





## Dataflow Example

```
A[j + i*i] = i;

b = A[i*j];
```



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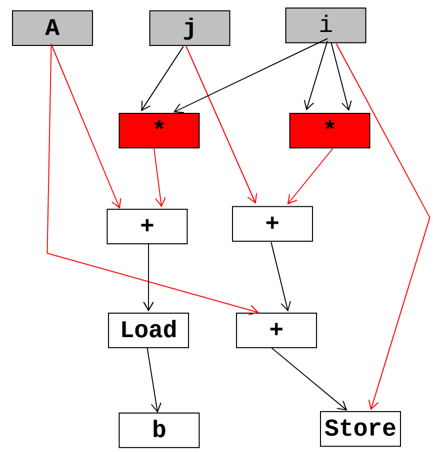




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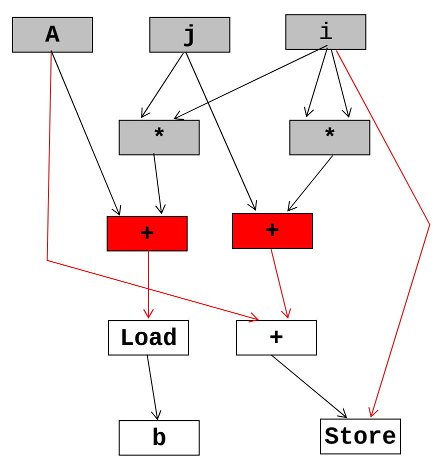
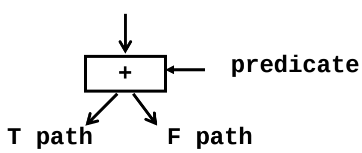


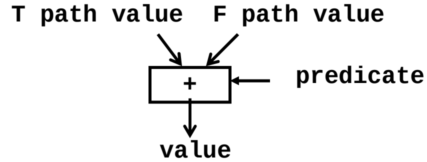
# Dataflow Execution

Control

- steer (ρ)




merge (ϕ)



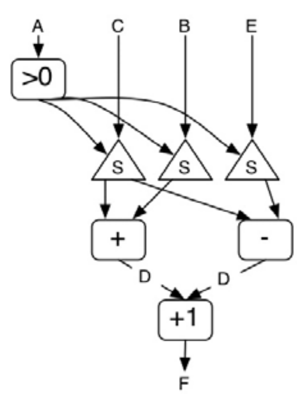

- convert control dependence to data dependence with value-steering instructions
- execute one path after condition variable is known (steer)
  
  or
- execute both paths & pass values at end (merge)



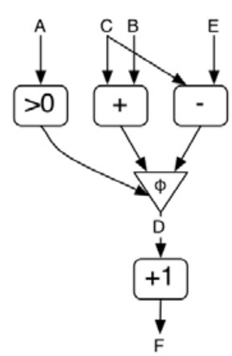
# WaveScalar Control

```
if (A > 0)
     D = C + B;
else
     D = C - E;
F = D + 1;
```

ρ (steer)




ϕ (merge)



## Dataflow Computer ISA

Instructions
- operation
- names of destination instructions

Data packets, called **Tokens**
- value
- tag to identify the operand instance & match it with its fellow operands in the same dynamic instruction instance
  - architecture dependent
    - instruction number
    - iteration number
    - activation/context number (for functions, especially recursive)
    - thread number
- Dataflow computer executes a program by receiving, matching, computing & sending out tokens.



## Types of Dataflow Computers

**static**:
- one copy of each instruction
- no simultaneously active iterations, no recursion

## Types of Dataflow Computers

**dynamic**

- multiple copies of each instruction
- better performance
- gate counting technique to prevent instruction explosion

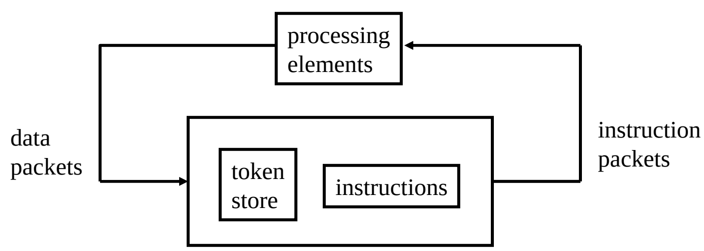
**k-bounding**

- extra instruction with K tokens on its input arc; passes a token to 1st instruction of loop body
- 1st instruction of loop body consumes a token (needs one extra operand to execute)
- last instruction in loop body produces another token at end of iteration
- limits active iterations to k



## Prototypical Early Dataflow Computer

Original implementations were centralized.




Performance cost

- large token store (long access)
- long wires
- arbitration both for PEs and storing of result

## Problems with Dataflow Computers

Language compatibility

- dataflow cannot guarantee a correct ordering of memory operations
- dataflow computer programmers could not use mainstream programming languages, such as C
- developed special languages in which order didn't matter

Scalability: large token store

- side-effect-free programming language with no mutable data structures
  - each update creates a new data structure
  - 1000 tokens for 1000 data items even if the same value
- aggravated by the state of processor technology at the time
  - delays in processing (only so many functional units, arbitration delays, etc.) meant delays in operand arrival
  - associative search impossible; accessed with slower hash function



## Dataflow Example

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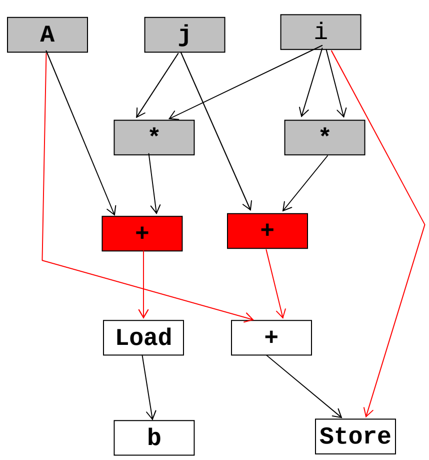

## Example to Illustrate the Memory Ordering Problem

A[j + i*i] = i;

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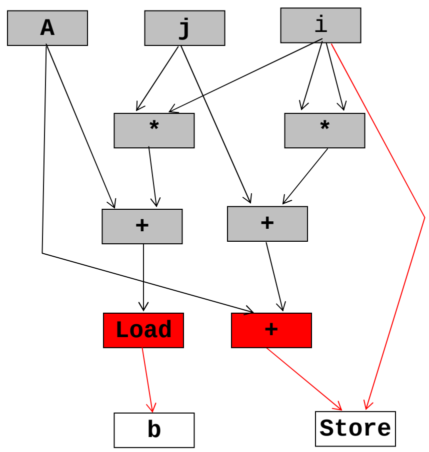




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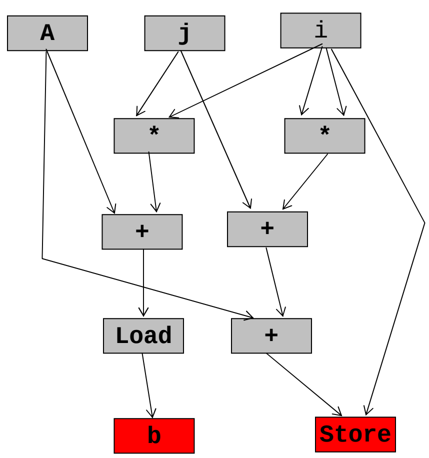

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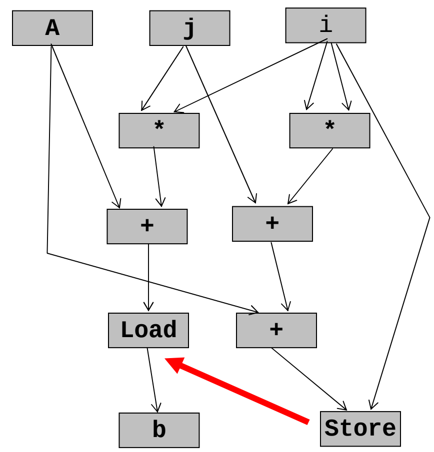
Load-store ordering issue






## Partial Solutions

Solutions led away from pure dataflow execution

Data representation in memory
- **I-structures**:
  - write once; read many times
  - early reads are deferred until the write
- **M-structures**:
  - multiple reads & writes, but they must alternate
  - reusable structures which could hold multiple values

## Partial Solutions

Local (register) storage for back-to-back instructions

Frames for distinct sequential instruction execution within the token store

- create “frames”, each of which stored the data for one iteration or one thread
- not have to search entire token store (offset to frame)

Physically partition token store & place each partition with a PE

- dataflow execution within coarse-grain threads