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
- from the ALU 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

Operands reside in a centralized, global 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:
- expose instruction-level parallelism by using a functional-style programming language
  - no side effects; only restrictions were producer-consumer
- scheduled code for execution on the hardware greedily
- hardware support for data-driven execution

Brief Review of Instruction-Level Parallelism (ILP)

Fine-grained parallelism

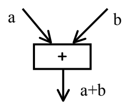
Obtained by:
- – instruction overlap
- – executing instructions in parallel

In contrast to:
- – **loop-level** parallelism (medium-grained)
- – **process-level** or **task-level** or **thread-level** parallelism (coarse-grained)

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

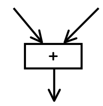
Dataflow Execution

Data-dependent operations are connected, producer to consumer

Code & initial values loaded into memory

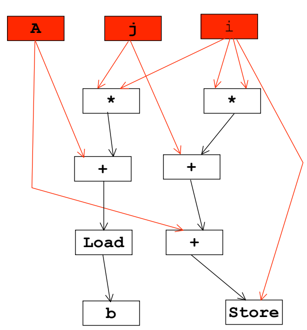
Execute according to the **dataflow firing rule**

- 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



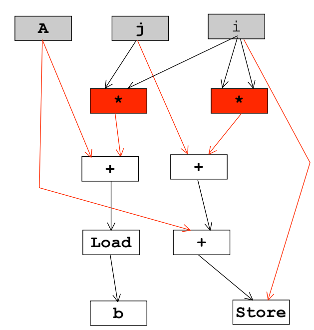
Dataflow Example

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

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



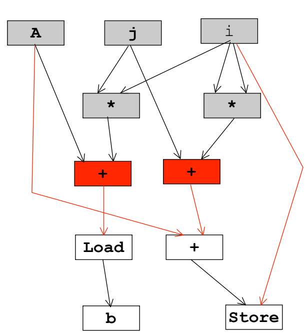
Dataflow Example

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

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



Dataflow Example

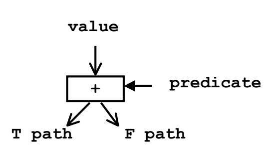
```
A[j + i*i] = i;

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

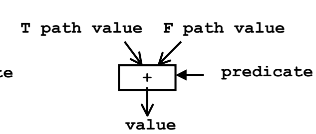


Dataflow Execution

Control

- steer (ρ) merge (ϕ)





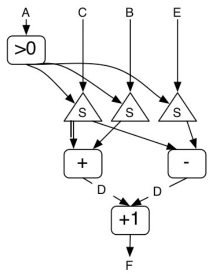
- convert control dependence to data dependence with value-steering instructions
- execute one path after condition variable is known (steer)

  or
- execute both paths & pass values at end (merge)

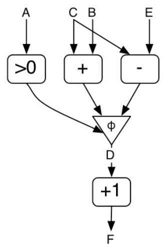
WaveScalar Control

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

ρ (steer)



φ (merge)



Dataflow Computer ISA

Instructions
- operation
- 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 & sending out tokens.

Types of Dataflow Computers

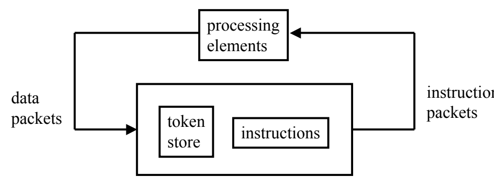
static:
- one copy of each instruction
- no simultaneously active iterations, no recursion

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 global 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
- delays in processing (only so many functional units, arbitration delays, etc.) meant delays in operand arrival
- associative search impossible; accessed with slower hash function
- aggravated by the state of processor technology at the time

Partial Solutions

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

Local (register) storage for back-to-back instructions in a single thread

Cycle-level multithreading

Partial Solutions

Frames of sequential instruction execution

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

Partition token store & place each partition with a PE

Many solutions led away from pure dataflow execution