

Lecture 7. Instruction-Level Parallelism

Introductions to Data Systems and Data Design

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What is ILP?

Instruction-Level Parallelism

ILP = the potential to execute multiple instructions simultaneously

Sequential: → →

Parallel:

	Same work, 3x faster!

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Sequential: → →

Parallel:

	Same work, 3x faster!

Key question: When can instructions execute in parallel?

Answer: When they are *independent* — no data dependencies between them.

Why ILP Matters for Data Systems

Modern CPUs can execute 4–8 operations per cycle:

Processor	Issue Width	ALU Ports	Load Ports
Intel Skylake	4 µOPs/cycle	4	2
Apple M1	8 µOPs/cycle	6	3
AMD Zen 4	6 µOPs/cycle	4	3

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But: Typical programs achieve only **1.5–2.5 IPC** (instructions per cycle).

Why? Dependencies between instructions prevent parallel execution.

The Data Systems Connection

Many data operations are inherently parallel:

- **Map:** Apply function to each element independently
- **Filter:** Test each element independently
- **Reduce:** Combine elements... *but how?*

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- **Reduce:** Combine elements... *but how?*

```
// Map: embarrassingly parallel
for (int i = 0; i < n; i++)
    b[i] = f(a[i]); // Each iteration independent!
```

```
// Reduce: sequential?
for (int i = 0; i < n; i++)
    sum += a[i]; // Each iteration depends on previous!
```

This lecture: How to expose ILP in reductions and similar operations.

Data Dependencies

Three Types of Dependencies

// Given these instructions:

```
r1 = r2 + r3      // I1  
r4 = r1 + r5      // I2: uses r1 from I1  
r1 = r6 + r7      // I3: writes r1 again  
r8 = r1 + r9      // I4: uses r1 from I3
```

Type	Name	Example	Real Dependency?
RAW	Read After Write	I1 → I2	Yes (true)
WAR	Write After Read	I2 → I3	No (name only)
WAW	Write After Write	I1 → I3	No (name only)

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r1 = r6 + r7      // I3: writes r1 again  
r8 = r1 + r9      // I4: uses r1 from I3
```

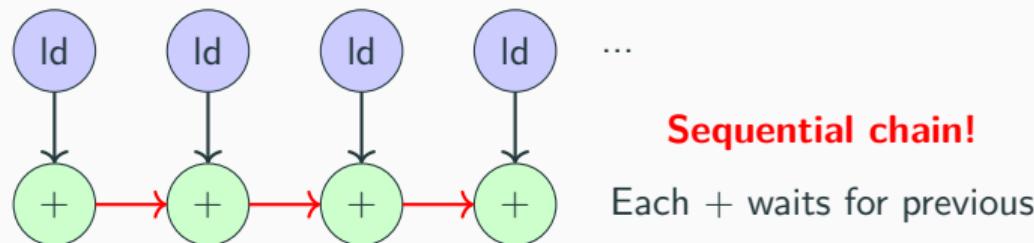
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RAW	Read After Write	$I1 \rightarrow I2$	Yes (true)
WAR	Write After Read	$I2 \rightarrow I3$	No (name only)
WAW	Write After Write	$I1 \rightarrow I3$	No (name only)

RAW = True dependency: I2 must wait for I1's result. Cannot be avoided.

WAR, WAW = False dependencies: CPU eliminates these via register renaming.

The Reduction Problem

```
long sum = 0;  
for (int i = 0; i < n; i++) {  
    sum += a[i];  
}
```



ILP = 1 for the additions — complete serialization!

Breaking the Chain

Let's Measure It

```
// sum_v1.cpp - naive reduction (100M doubles)
double sum = 0;
for (int i = 0; i < n; i++) {
    sum += a[i]; // Dependency chain: each add waits for previous
}
$ cd examples && make sum_v1 && ./sum_v1
```

Baseline Performance

```
$ cd examples && make sum_v1 && ./sum_v1  
Sum: 1e+08, Time: 152 ms
```

Why so slow?

- 100M additions at 3 GHz = should be ~33 ms if 1 add/cycle
- But we're getting ~150 ms — about **0.2 adds/cycle!**

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- But we're getting ~150 ms — about **0.2 adds/cycle!**

The bottleneck: Each addition has 4-cycle latency.

With a single accumulator, we execute 1 add every 4 cycles → 0.25 IPC.

Loop Unrolling: The Idea

Instead of one accumulator, use **multiple independent accumulators**:

// Before: one chain

```
sum += a[0]; sum += a[1]; sum += a[2]; sum += a[3]; ...
```

// After: four parallel chains

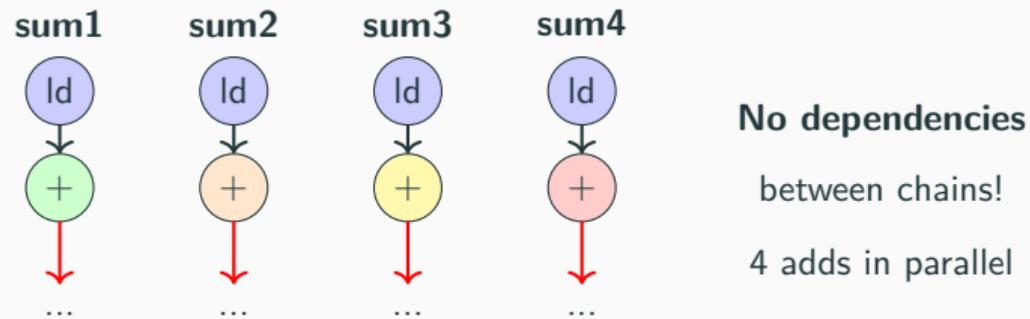
```
sum1 += a[0]; sum2 += a[1]; sum3 += a[2]; sum4 += a[3];
```

```
sum1 += a[4]; sum2 += a[5]; sum3 += a[6]; sum4 += a[7];
```

...

```
sum = sum1 + sum2 + sum3 + sum4;
```

Visualizing Parallel Chains



No dependencies

between chains!

4 adds in parallel

Each chain has internal dependencies, but **chains are independent!**

4x Unrolled Code

```
// sum_v2.cpp - 4x unrolled
double sum1 = 0, sum2 = 0, sum3 = 0, sum4 = 0;
for (int i = 0; i < n; i += 4) {
    sum1 += a[i];
    sum2 += a[i+1];
    sum3 += a[i+2];
    sum4 += a[i+3];
}
double sum = sum1 + sum2 + sum3 + sum4;

$ cd examples && make sum_v2 && ./sum_v2
Sum: 1e+08, Time: 42 ms      # 3.6x speedup!
```

Why Not 4× Speedup?

Theoretical: 4 independent chains \rightarrow 4× speedup

Actual: 3.6× speedup

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Reasons:

1. Loop overhead (increment, compare, branch)
2. Memory bandwidth starting to matter
3. Not perfectly overlapped

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Theoretical: 4 independent chains → 4× speedup

Actual: 3.6× speedup

Reasons:

1. Loop overhead (increment, compare, branch)
2. Memory bandwidth starting to matter
3. Not perfectly overlapped

Let's try more unrolling...

8x Unrolled

```
// sum_v3.cpp - 8x unrolled
double s1=0, s2=0, s3=0, s4=0, s5=0, s6=0, s7=0, s8=0;
for (int i = 0; i < n; i += 8) {
    s1 += a[i];    s2 += a[i+1]; s3 += a[i+2]; s4 += a[i+3];
    s5 += a[i+4]; s6 += a[i+5]; s7 += a[i+6]; s8 += a[i+7];
}
double sum = (s1+s2) + (s3+s4) + (s5+s6) + (s7+s8);

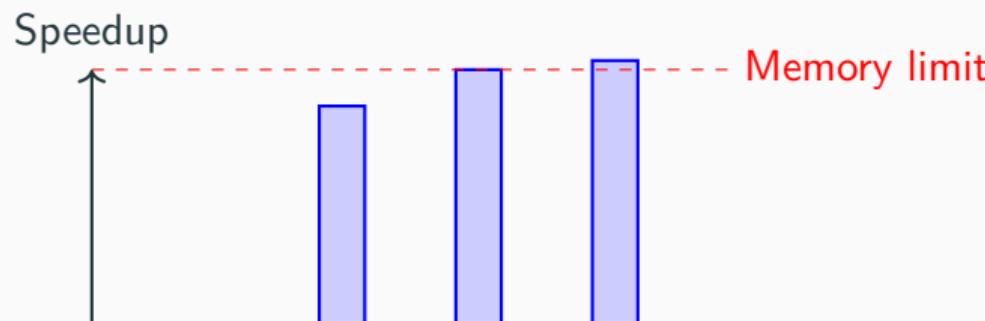
$ cd examples && make sum_v3 && ./sum_v3
Sum: 1e+08, Time: 38 ms      # Only 4x - hitting memory bandwidth!
```

Performance Summary

```
$ cd examples && make sum      # Run all three versions
```

Version	Accumulators	Time	Speedup
Naive	1	152 ms	1×
4× unrolled	4	42 ms	3.6×
8× unrolled	8	38 ms	4.0×

Diminishing returns: Beyond 4–8 accumulators, memory bandwidth dominates.



More Examples

Example: Dot Product

```
// Naive dot product (dot_v1.cpp)
double dot = 0;
for (int i = 0; i < n; i++) {
    dot += a[i] * b[i]; // multiply then add to accumulator
}
```

Same problem: Single accumulator creates a dependency chain.

Example: Dot Product

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double dot = 0;
for (int i = 0; i < n; i++) {
    dot += a[i] * b[i]; // multiply then add to accumulator
}
```

Same problem: Single accumulator creates a dependency chain.

```
// 4x unrolled dot product (dot_v2.cpp)
double d1=0, d2=0, d3=0, d4=0;
for (int i = 0; i < n; i += 4) {
    d1 += a[i] * b[i];
    d2 += a[i+1] * b[i+1];
    d3 += a[i+2] * b[i+2];
    d4 += a[i+3] * b[i+3];
```

Dot Product Performance

```
$ cd examples && make dot && ./dot_v1 && ./dot_v2
Dot: 1e+08, Time: 168 ms    # naive
Dot: 1e+08, Time: 56 ms     # 4x unrolled
```

3× speedup — same pattern as sum!

Example: Finding Maximum

```
// Naive max (max_v1.cpp)
double max_val = a[0];
for (int i = 1; i < n; i++) {
    if (a[i] > max_val) max_val = a[i];
}
```

```
$ cd examples && make max_v1 && ./max_v1
```

Two problems: (1) Dependency chain on `max_val`, (2) Unpredictable branch!

Max: Branchless + Unrolled

```
// Branchless max (max_v2.cpp) - ternary → cmov
double max_val = a[0];
for (int i = 1; i < n; i++)
    max_val = (a[i] > max_val) ? a[i] : max_val;

// 4x unrolled branchless max (max_v3.cpp)
double m1=a[0], m2=a[1], m3=a[2], m4=a[3];
for (int i = 4; i < n; i += 4) {
    m1 = (a[i]     > m1) ? a[i]     : m1;
    m2 = (a[i+1]   > m2) ? a[i+1]   : m2;
    m3 = (a[i+2]   > m3) ? a[i+2]   : m3;
    m4 = (a[i+3]   > m4) ? a[i+3]   : m4;
}
double max_val = max(max(m1,m2), max(m3,m4));
```

Max Performance

```
$ cd examples && make max  
Max: 1, Time: 312 ms      # v1: Branch mispredictions!  
Max: 1, Time: 156 ms      # v2: Branchless, 2x faster  
Max: 1, Time: 45 ms       # v3: Branchless + unrolled, 7x faster!
```

Combining branchless + unrolling = massive speedup on random data.

Example: Count Elements

```
// Count elements > threshold (count.cpp has all versions)
int count = 0;
for (int i = 0; i < n; i++) {
    if (a[i] > threshold) count++; // Naive: branch
}
```

```
count += (a[i] > threshold); // Branchless: 0 or 1
```

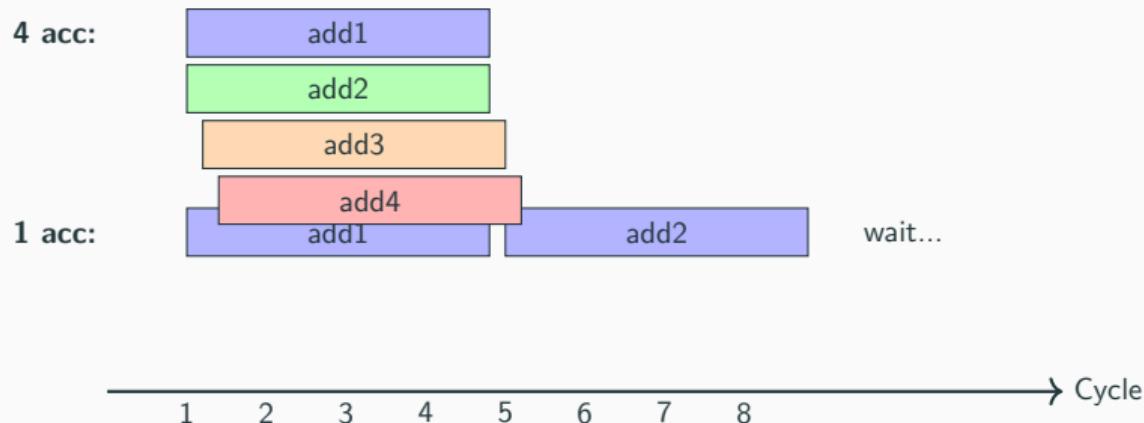
```
// Branchless + unrolled
int c1=0, c2=0, c3=0, c4=0;
for (int i = 0; i < n; i += 4) {
    c1 += (a[i] > threshold);
    c2 += (a[i+1] > threshold);
    c3 += (a[i+2] > threshold);
    c4 += (a[i+3] > threshold);
```

Understanding the Hardware

Why Does Unrolling Help?

Add latency: 4 cycles (Skylake)

Add throughput: 2 per cycle (ports P0, P1)



With 1 accumulator: 1 add every 4 cycles = **0.25 adds/cycle**

With 4 accumulators: 4 adds in 4 cycles = **1 add/cycle** (4× better!)

Latency vs Throughput

Operation	Latency	Throughput
Integer add	1 cycle	4/cycle
FP add	4 cycles	2/cycle
FP multiply	4 cycles	2/cycle
FP divide	10-20 cycles	1/14 cycles
Load (L1 hit)	4 cycles	2/cycle

Latency vs Throughput

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Key insight:

- **Latency** = time for one operation to complete
- **Throughput** = how many operations can be *in flight*

To achieve throughput, you need **latency × throughput** independent operations!

The Magic Number

FP add: 4 cycles latency \times 2/cycle throughput = **8 operations in flight**

→ Need at least 8 independent adds to saturate the FP adders!

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FP multiply: 4 cycles \times 2/cycle = **8 operations in flight**

Load: 4 cycles \times 2/cycle = **8 operations in flight**

Rule of thumb: Unroll by **latency \times throughput** to maximize ILP.

For most FP operations: **4–8× unrolling** is the sweet spot.

Compiler Optimizations

Does the Compiler Do This Automatically?

```
// Will -O3 unroll this for us?  
double sum = 0;  
for (int i = 0; i < n; i++) {  
    sum += a[i];  
}  
  
$ cd examples && make fast      # Compare -O1 vs -O3 vs -O3 -ffast-math  
Time: 152 ms      # -O1  
Time: 152 ms      # -O3: Same!
```

No! The compiler cannot change the order of FP additions (not associative).

Enabling Compiler Optimizations

```
$ cd examples && make sum_v1_fast && ./sum_v1_fast  
Time: 25 ms      # -O3 -ffast-math works!
```

-ffast-math tells the compiler:

- FP operations are associative (can reorder)
- No NaN/Inf checks needed
- Allows aggressive optimizations

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Time: 25 ms      # -O3 -ffast-math works!
```

-ffast-math tells the compiler:

- FP operations are associative (can reorder)
- No NaN/Inf checks needed
- Allows aggressive optimizations

Warning: May change numerical results slightly!

What Does -O3 -ffast-math Generate?

```
$ cd examples  
$ g++ -O3 -ffast-math -std=c++14 -S sum_v1.cpp  
$ cat sum_v1.s | grep -A 20 "\.L3:"
```

The compiler generates **SIMD code** with multiple accumulators!

- Uses vaddpd (vectorized add, 4 doubles at once)
- Unrolls the loop
- Multiple vector accumulators

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- Uses vaddpd (vectorized add, 4 doubles at once)
- Unrolls the loop
- Multiple vector accumulators

But: Understanding manual unrolling helps you:

1. Know when compiler can't help (complex reductions)
2. Debug performance issues
3. Write code the compiler can optimize

Practical Guidelines

When to Unroll Manually

Do unroll when:

- Reduction over large arrays (sum, max, dot product)
- Compiler can't optimize (no `-ffast-math`, complex operations)
- Performance-critical inner loops

Don't unroll when:

- Code is not in a hot path
- Loop body is already complex
- Memory bandwidth is the bottleneck (unrolling won't help)

How Much to Unroll

Data Type	Latency	Throughput	Unroll Factor
int add	1	4/cycle	4×
int64 add	1	4/cycle	4×
float add	4	2/cycle	8×
double add	4	2/cycle	8×
double mul	4	2/cycle	8×

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float add	4	2/cycle	8×
double add	4	2/cycle	8×
double mul	4	2/cycle	8×

Practical advice: Start with 4×, measure, try 8×.

Beyond 8× rarely helps (memory becomes bottleneck).

The Complete Pattern

```
// Template for any associative reduction
T reduce(T* a, int n, T init, T (*op)(T, T)) {
    // Multiple accumulators
    T acc1 = init, acc2 = init, acc3 = init, acc4 = init;

    int i = 0;
    for (; i + 4 <= n; i += 4) {
        acc1 = op(acc1, a[i]);
        acc2 = op(acc2, a[i+1]);
        acc3 = op(acc3, a[i+2]);
        acc4 = op(acc4, a[i+3]);
    }

    // Handle remainder
}
```

Diagnosing ILP with PMU Counters

The First Metric: IPC

IPC (Instructions Per Cycle) = instructions retired / cycles

```
$ cd examples && make sum_v1 sum_v2
$ perf stat ./sum_v1
    481,234,567      cycles
    125,012,345     instructions # 0.26 IPC

$ perf stat ./sum_v2
    132,456,789      cycles
    175,023,456     instructions # 1.32 IPC
```

The First Metric: IPC

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    132,456,789      cycles
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```

Low IPC (< 1) often indicates ILP problems!

- Modern CPUs can retire 4+ instructions/cycle
- IPC of 0.26 means we're leaving ~90% performance on the table

Intel's Top-Down Analysis

Intel CPUs provide **topdown** counters that categorize where cycles go:

```
$ cd examples && perf stat -M TopdownL1 ./sum_v1
 48.2% backend_bound          # ← ILP problem!
 12.1% frontend_bound
  8.3% bad_speculation
 31.4% retiring
```

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```

Category	Meaning
Backend Bound	Waiting for data or execution resources
Frontend Bound	Instruction fetch/decode stalls
Bad Speculation	Wasted work from mispredicted branches
Retiring	Useful work (higher is better!)

Backend Bound: Digging Deeper

```
$ cd examples && perf stat -M TopdownL2 ./sum_v1
```

Backend Bound:

42.1%	core_bound	# ← Execution unit stalls
6.1%	memory_bound	# ← Memory access stalls

Backend Bound: Digging Deeper

```
$ cd examples && perf stat -M TopdownL2 ./sum_v1
```

Backend Bound:

42.1%	core_bound	# ← Execution unit stalls
6.1%	memory_bound	# ← Memory access stalls

Core Bound = waiting for execution resources

- Could be port contention (not enough ALUs)
- Could be **dependency chains** (our problem!)

Memory Bound = waiting for data from cache/memory

Specific Counters for ILP

```
$ cd examples  
$ perf stat -e cycles,instructions,uops_executed.thread,\  
uops_issued.any,resource_stalls.any ./sum_v1
```

Counter	Meaning
uops_executed.thread	μ OPs actually executed
uops_issued.any	μ OPs sent to execution
resource_stalls.any	Cycles stalled on resources
cycle_activity.stalls_total	Total stall cycles

Specific Counters for ILP

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cycle_activity.stalls_total	Total stall cycles

Key ratio: uops_executed / cycles

- Should be 2–4 on modern CPUs
- If < 1, you have an ILP problem

Example: Diagnosing Our Sum

```
$ cd examples && make perf    # Runs all perf comparisons

$ perf stat -e cycles,uops_executed.thread ./sum_v1
 480,000,000      cycles
 125,000,000      uops_executed.thread  # 0.26 uops/cycle!

$ perf stat -e cycles,uops_executed.thread ./sum_v2
 130,000,000      cycles
 180,000,000      uops_executed.thread  # 1.38 uops/cycle
```

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$ perf stat -e cycles,uops_executed.thread ./sum_v2
 130,000,000      cycles
 180,000,000      uops_executed.thread # 1.38 uops/cycle
```

Diagnosis: Naive version executes only 0.26 μ ops/cycle

Cause: Dependency chain — each add waits 4 cycles for previous

Solution: Multiple accumulators \rightarrow 1.38 μ ops/cycle ($5\times$ better!)

Port Utilization

For advanced diagnosis, check which execution ports are busy:

```
$ cd examples  
$ perf stat -e uops_dispatched_port.port_0,\  
uops_dispatched_port.port_1,uops_dispatched_port.port_5 ./sum_v2
```

Port Utilization

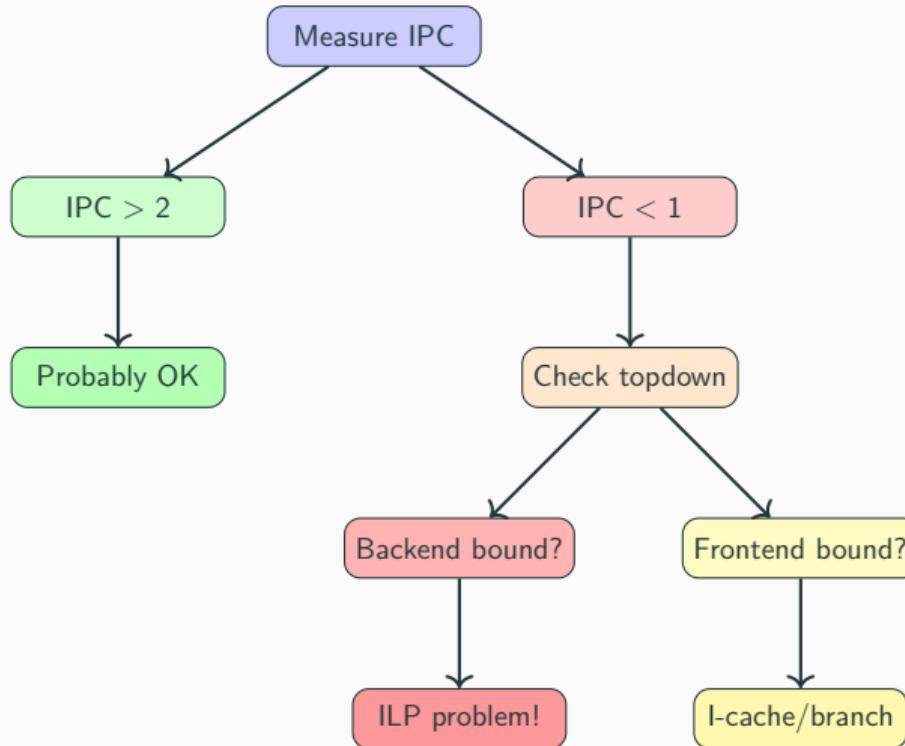
For advanced diagnosis, check which execution ports are busy:

```
$ cd examples  
$ perf stat -e uops_dispatched_port.port_0,\  
uops_dispatched_port.port_1,uops_dispatched_port.port_5 ./sum_v2
```

If one port is saturated while others are idle → restructure code

If all ports have low utilization → dependency problem (our case!)

Quick Diagnosis Flowchart



Practical Commands

```
$ cd examples

# Quick IPC check
$ perf stat ./sum_v1

# Top-down analysis (Intel)
$ perf stat -M TopdownL1 ./sum_v1

# Detailed execution metrics
$ perf stat -e cycles,instructions,uops_executed.thread ./sum_v1

# Compare two versions
$ perf stat ./sum_v1 && perf stat ./sum_v2
```

Practical Commands

```
$ cd examples

# Quick IPC check
$ perf stat ./sum_v1

# Top-down analysis (Intel)
$ perf stat -M TopdownL1 ./sum_v1

# Detailed execution metrics
$ perf stat -e cycles,instructions,uops_executed.thread ./sum_v1

# Compare two versions
$ perf stat ./sum_v1 && perf stat ./sum_v2
```

Rule of thumb: If $IPC \leq 1$ and backend bound $\geq 40\%$, try loop unrolling!

Summary

Key Takeaways

1. **ILP** = executing multiple instructions per cycle
 - Limited by data dependencies between instructions
2. **Reductions create dependency chains** — single accumulator = serialization
3. **Loop unrolling with multiple accumulators** breaks the chain
 - 4–8 accumulators typically optimal
 - Matches latency × throughput
4. **Compiler may help** with `-O3 -ffast-math`
 - But understanding the technique helps write better code

Performance Checklist

When optimizing a reduction:

1. **Measure baseline** — is it actually slow?
2. **Check for branches** — make branchless if unpredictable
3. **Unroll with multiple accumulators** — $4\times$ or $8\times$
4. **Measure again** — did it help?
5. **Check memory bandwidth** — if no improvement, you're memory-bound

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When optimizing a reduction:

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Same patterns apply to:

- Database aggregations (SUM, COUNT, AVG, MAX)
- ML operations (dot products, norms, reductions)
- Compression (checksums, hashing)

Try It Yourself!

All examples available in the examples/ folder:

```
$ cd examples  
$ make run          # Run all examples  
$ make sum          # Compare sum versions  
$ make dot          # Compare dot product versions  
$ make max          # Compare max versions  
$ make fast         # Compare -O1 vs -O3 -ffast-math  
$ make perf         # Run with perf stat (Linux)
```

Next lecture: SIMD — doing 4–8 operations with *one* instruction!