面向目标机器的代码优化
——指令并行与调度

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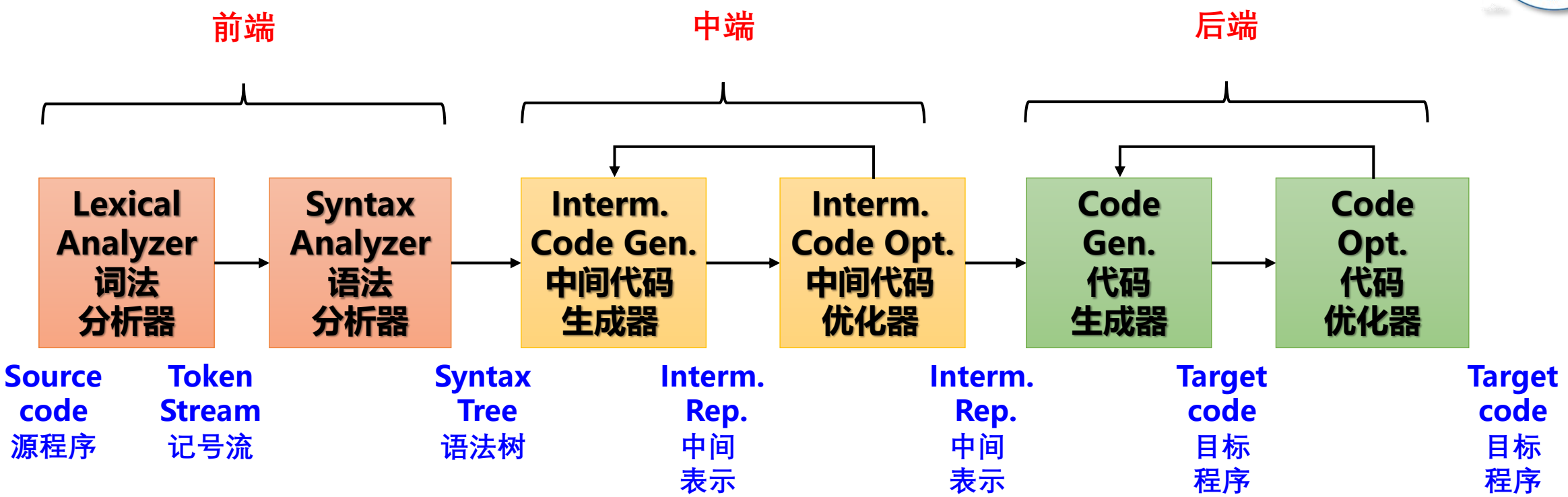
计算机科学与技术学院

2025年12月01日

前情回顾



- 编译器的基本步骤

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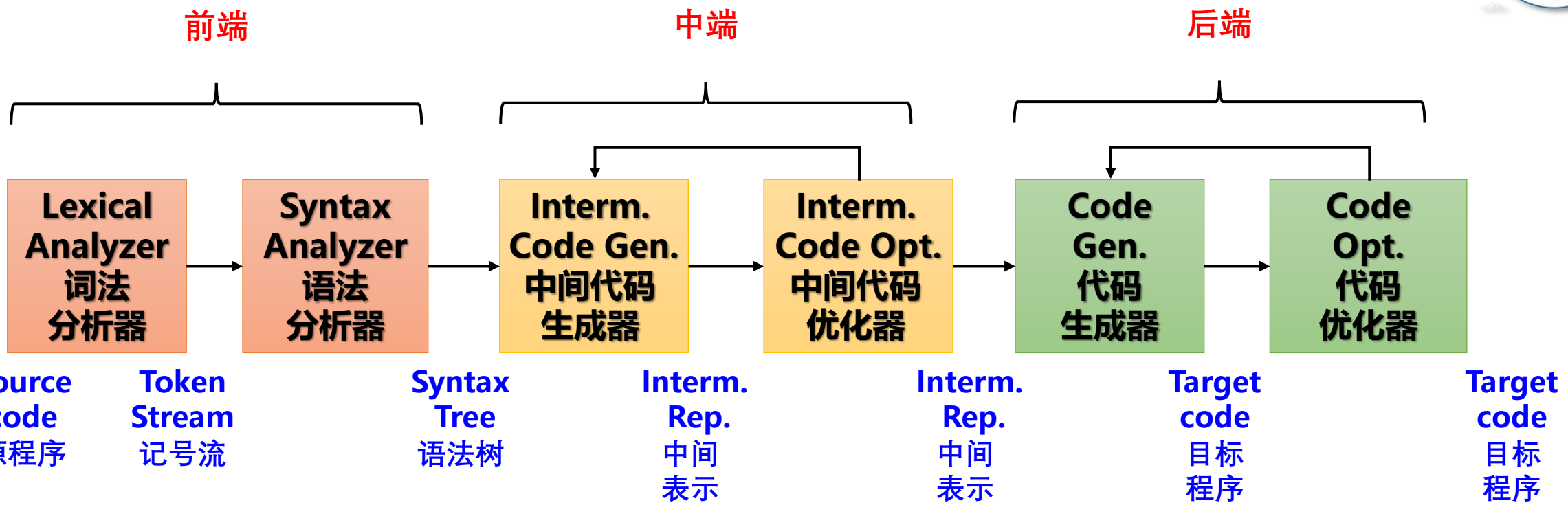

技术方案 Flex → Bison → LLVM/LightIR → LoongArch64

实验 Lab0 → Lab1 → Lab2 → Lab3 → Lab4

- 编译器的基本步骤与实验安排

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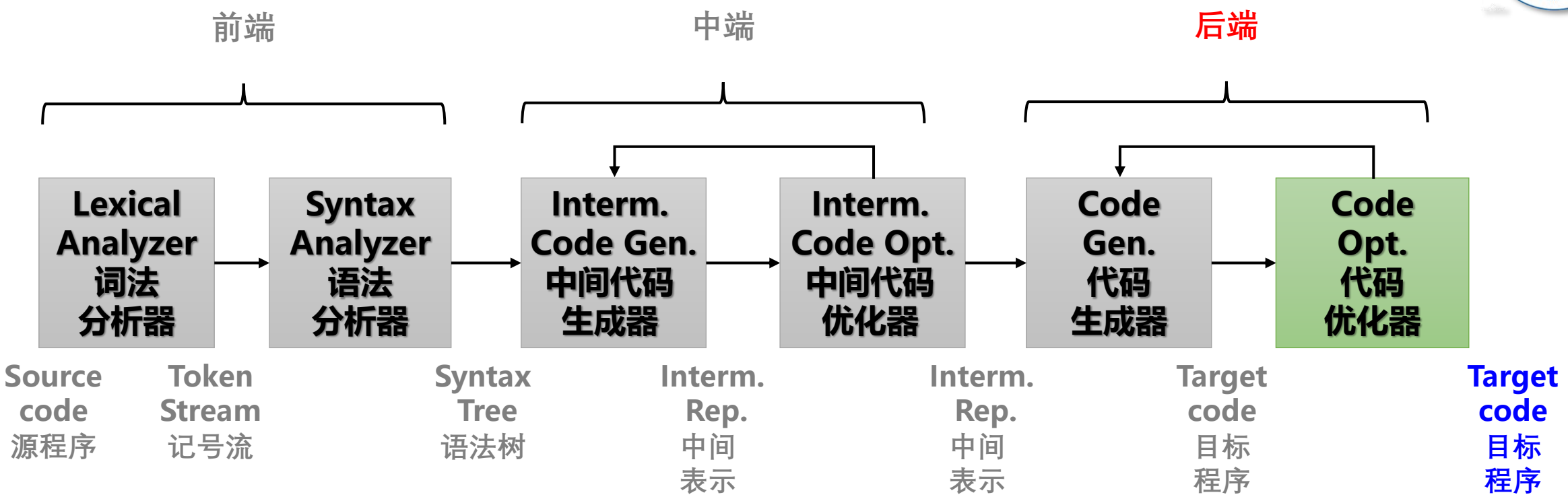

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面向目标机器的代码优化

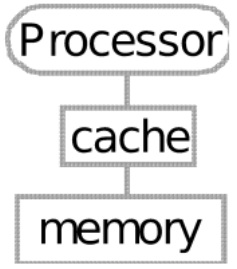
- 目标：优化生成的机器代码，与机器无关的优化不同，这一层级的信息是IR层无法获取的。
- 面向目标机器的代码优化十分重要，但往往很难实现:
  - 难以跨机器架构复用
  - 难以跨语言复用

面向目标机器的代码优化 – 种类

- 减少操作数量
  - 算术操作、内存访问等
- 用代价小的操作替换代价高的操作
  - 例如：4-cycle 乘法 与 1-cycle 移位运算
- 降低缓存缺失（Cache miss）
  - 覆盖数据和指令的访问
- 并行计算
  - 单线程内部的指令调度
  - 跨线程的并行执行

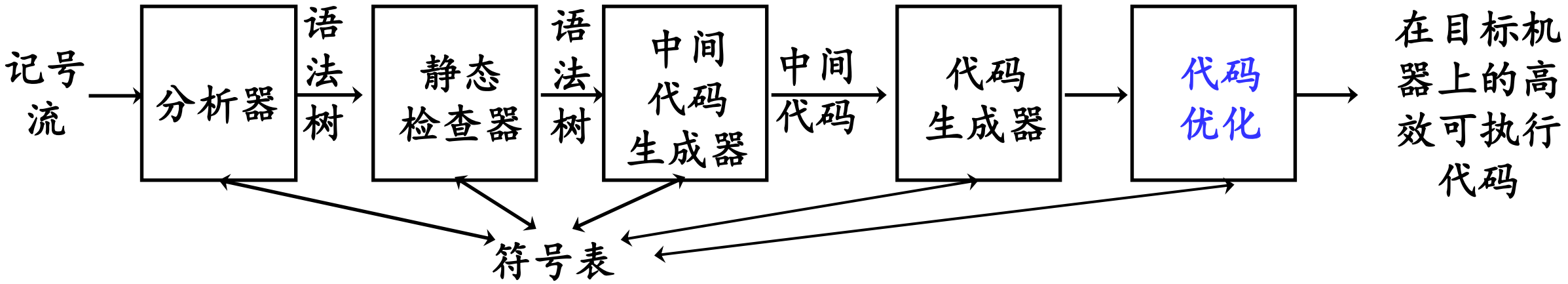
执行时间的计算公式:

Execution time = Operation count * Machine cycles per operation



冯诺依曼体系结构

本节提纲



- 现代处理器架构
- 流水线并行的例子
- 指令调度与数据依赖分析
- 数据依赖指导下的指令调度
- 科技前沿——大模型的流水并行训练

现代处理器架构

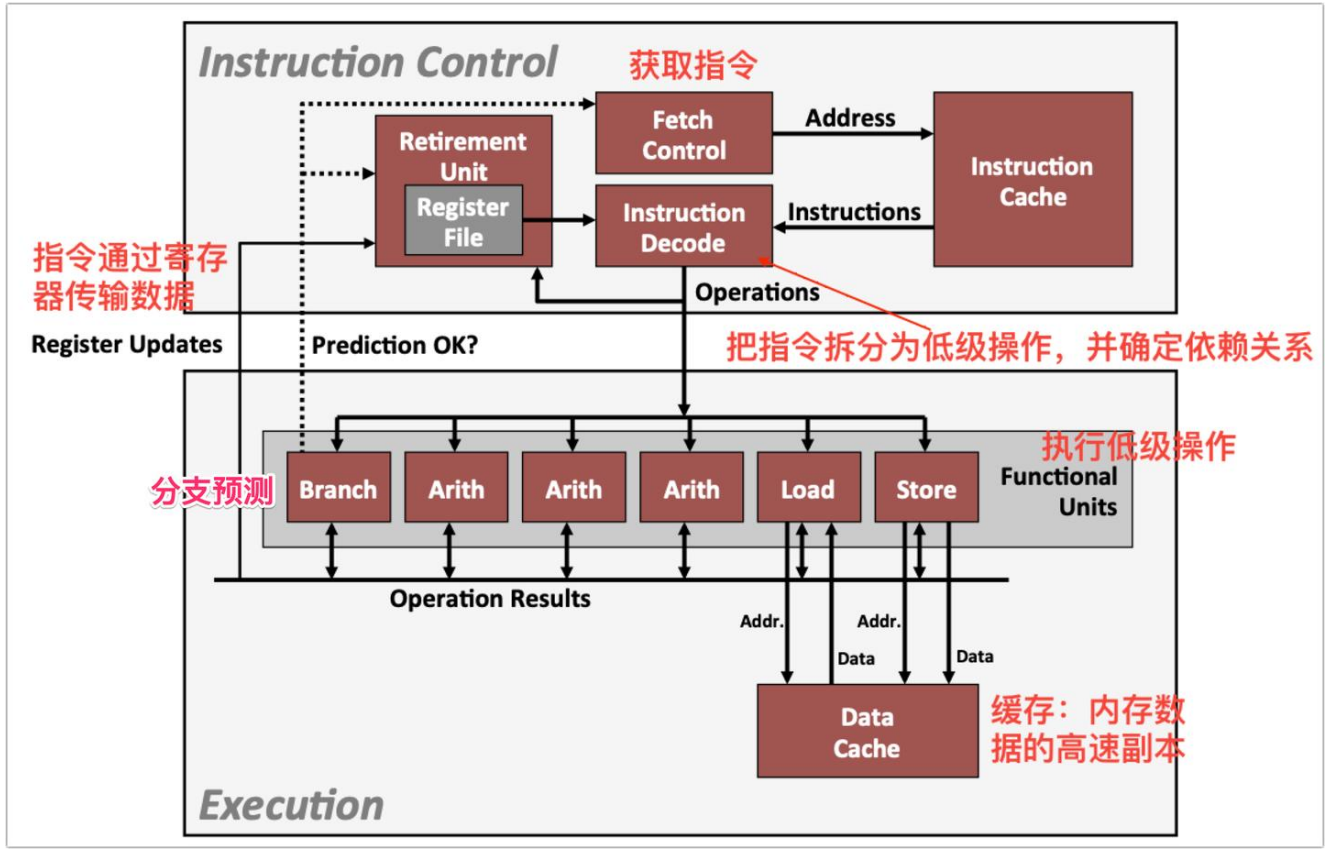
指令控制单元(ICU)

Fetch control

- 包含分支预测的功能

Instruction decode

- 从instruction cache (icache)中读取指令，然后翻译为一组微操作
- 例如，addq %rax, %rdx转换为单个微操作
- 例如，addq %rax, 8(%rdx)转换为内存读取、加法和内存写入三个微操作。

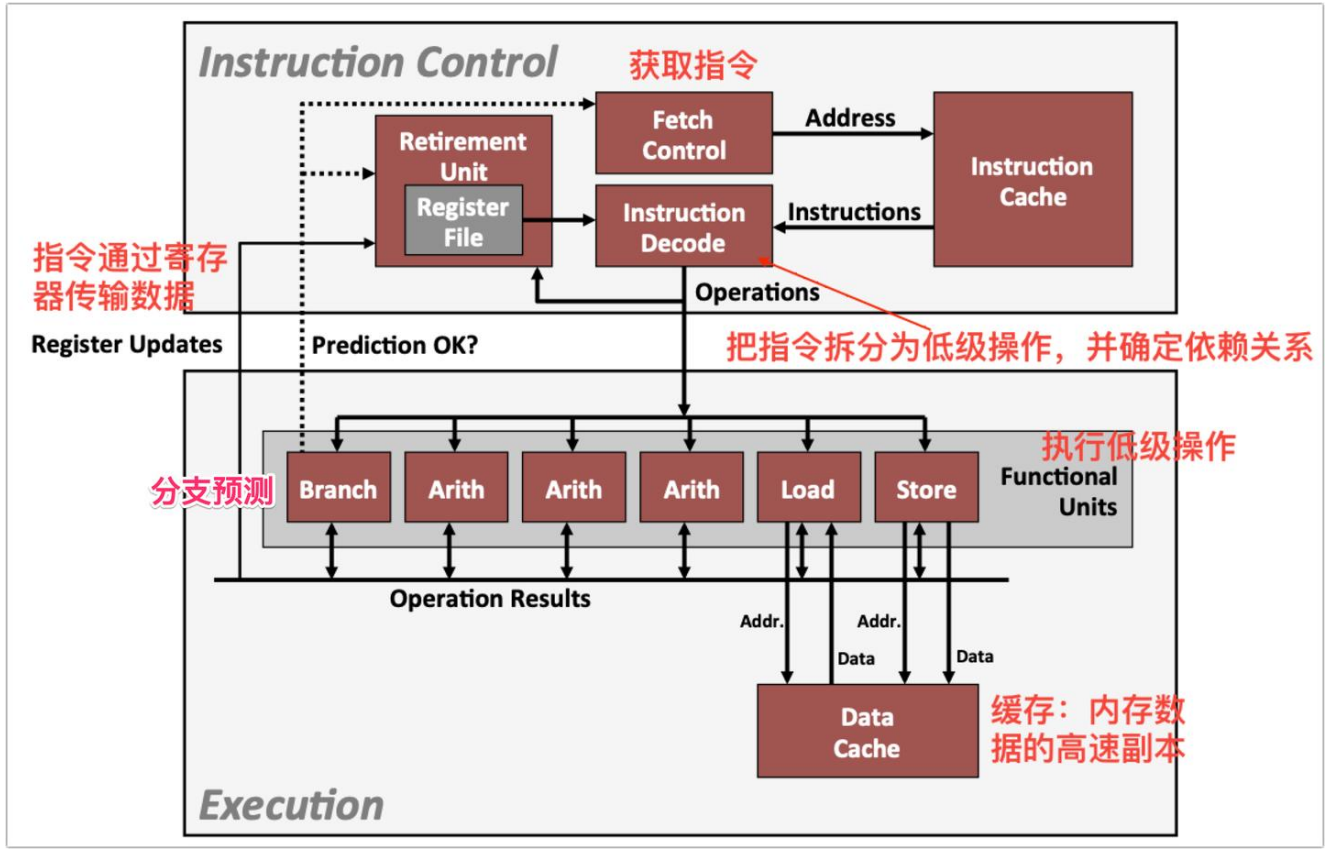


现代处理器架构

现代处理器架构

执行单元(EU, Execution Unit)

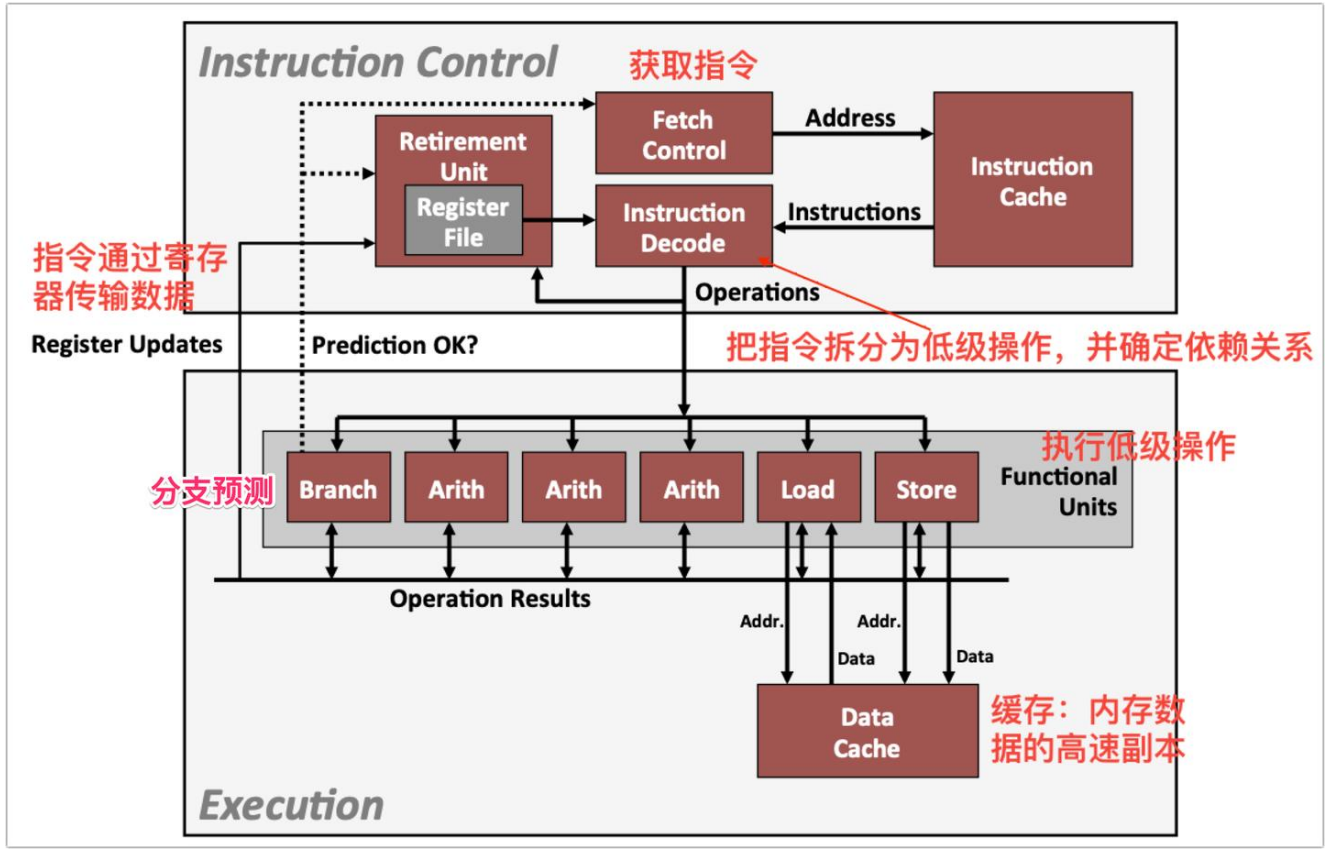
- 接收来自ICU的微操作，分发到各个功能单元执行。
- Load和Store单元
  - 包含一个加法器计算地址，和data cache (dcache)交互
- Branch单元
  - 预测结果会保存在EU内的队列中，若预测错误，则会丢弃保存的执行结果，并通知Fetch Control单元，之后才能获取正确的指令
- 其它各种功能单元
  - 整数运算、浮点乘、整数乘、分支等等



现代处理器架构

现代处理器架构：乱序 + 超标量

- 现代处理器一般是乱序且是超标量的。
  - 超标量：通过实现多个硬件单元，可以在每个时钟周期执行多个操作
  - 乱序：指令执行的顺序和二进制代码中的顺序不一定相同



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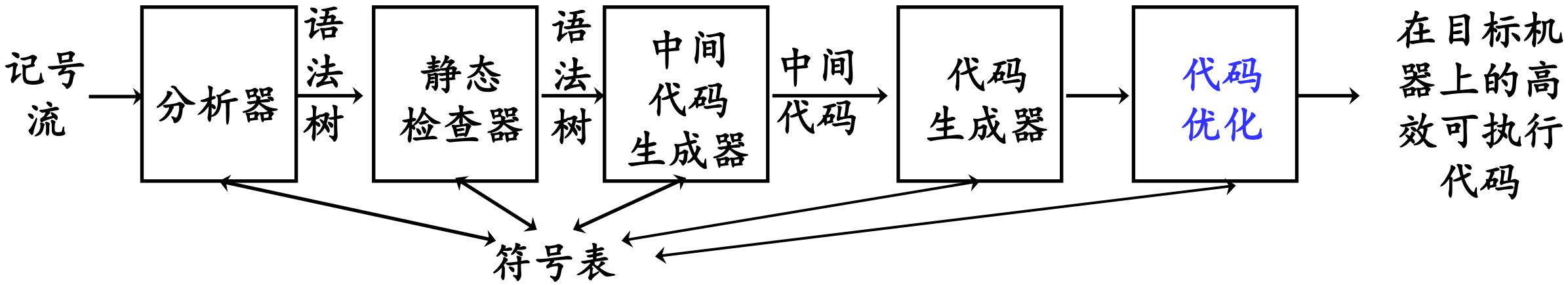

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处理器流水线

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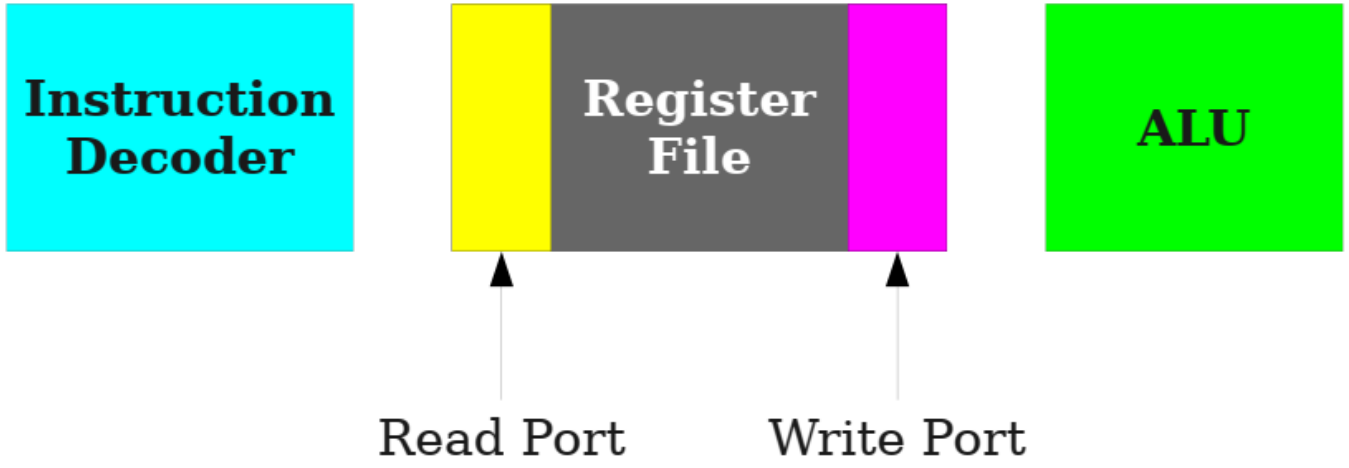


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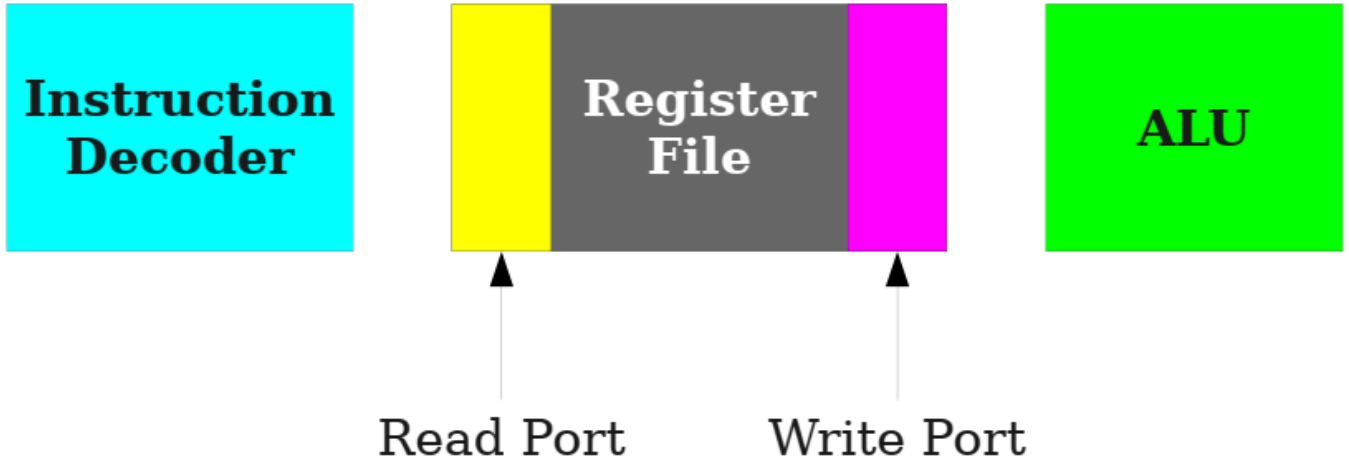


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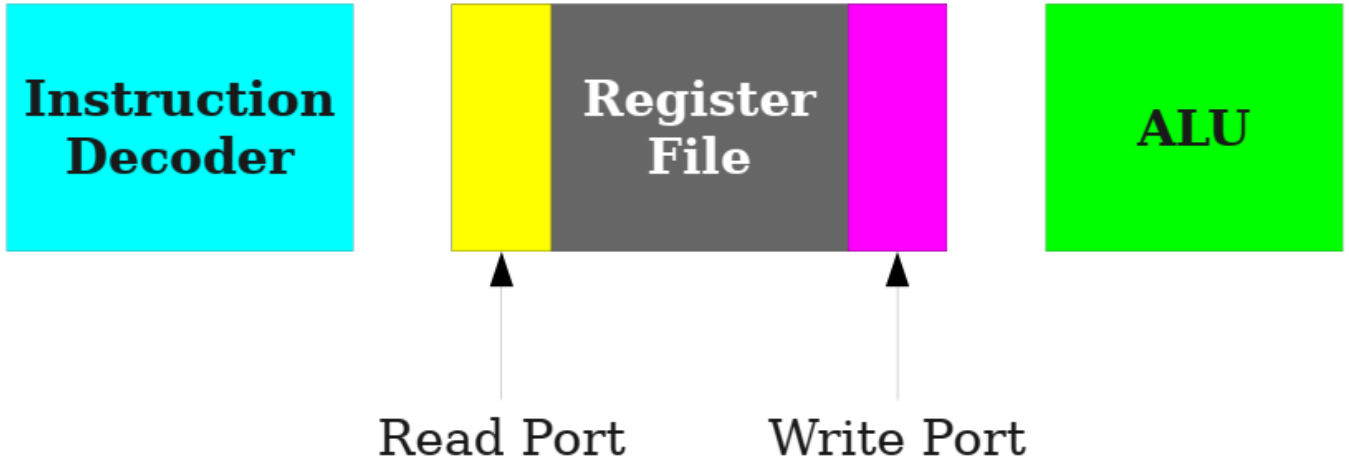


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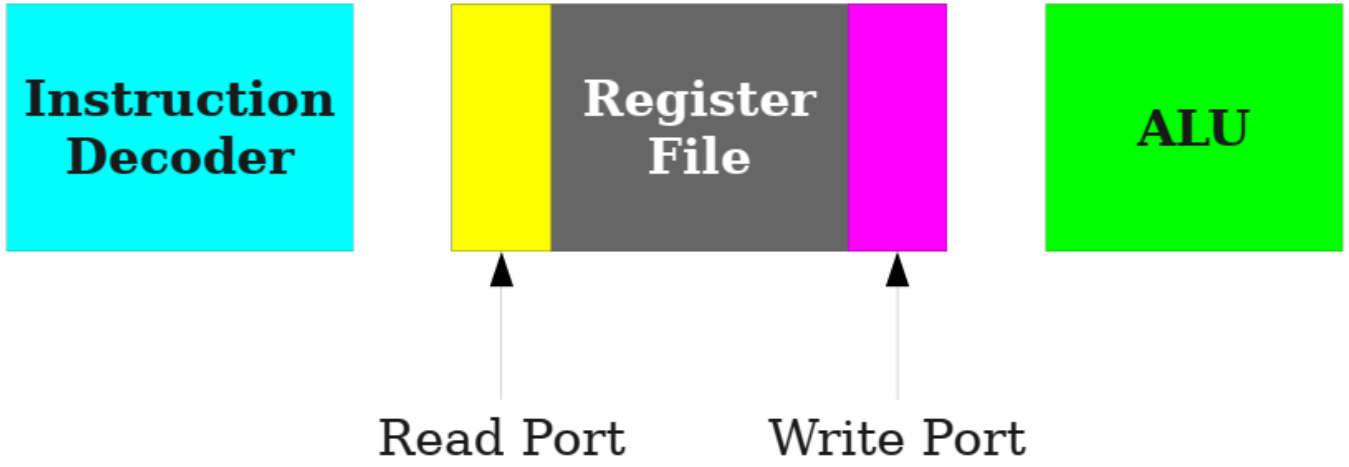

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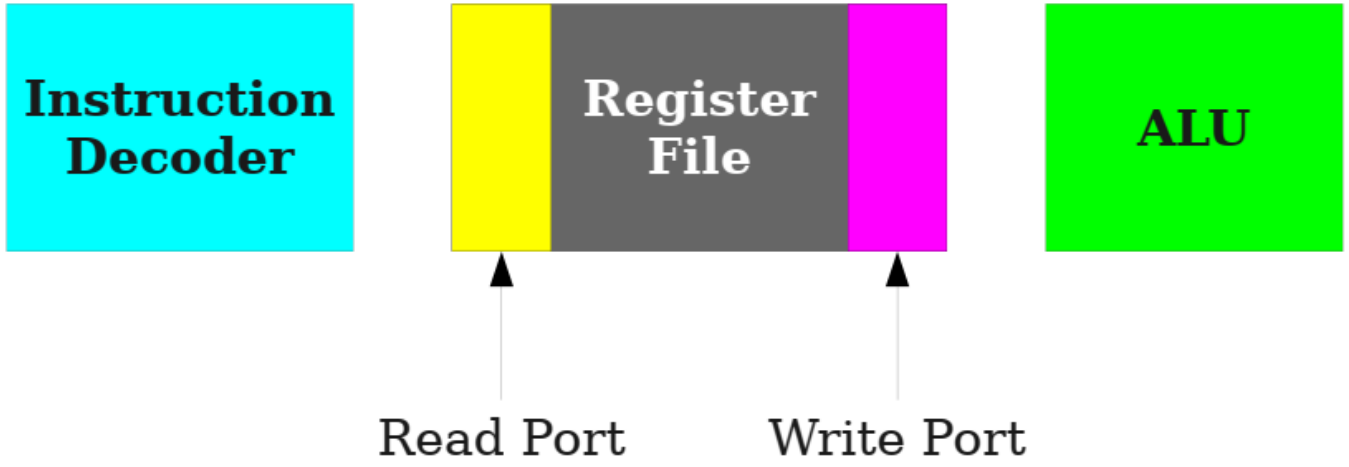

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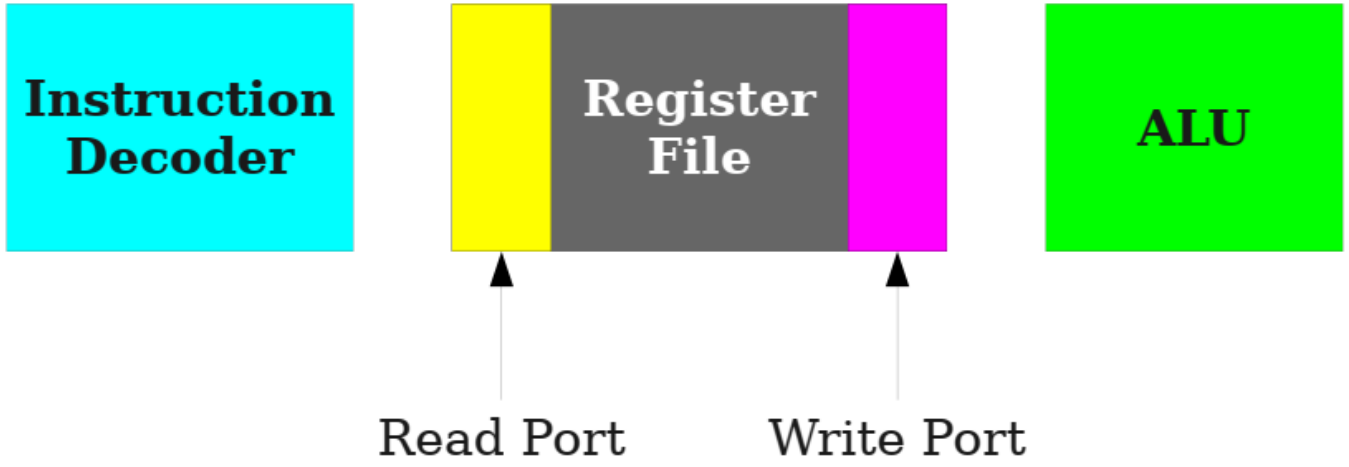

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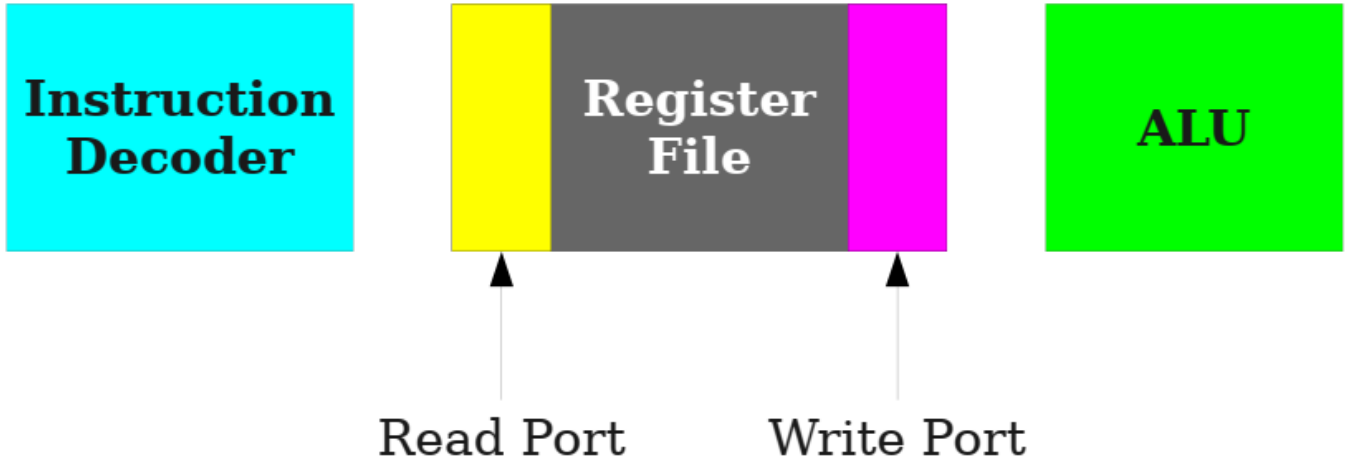

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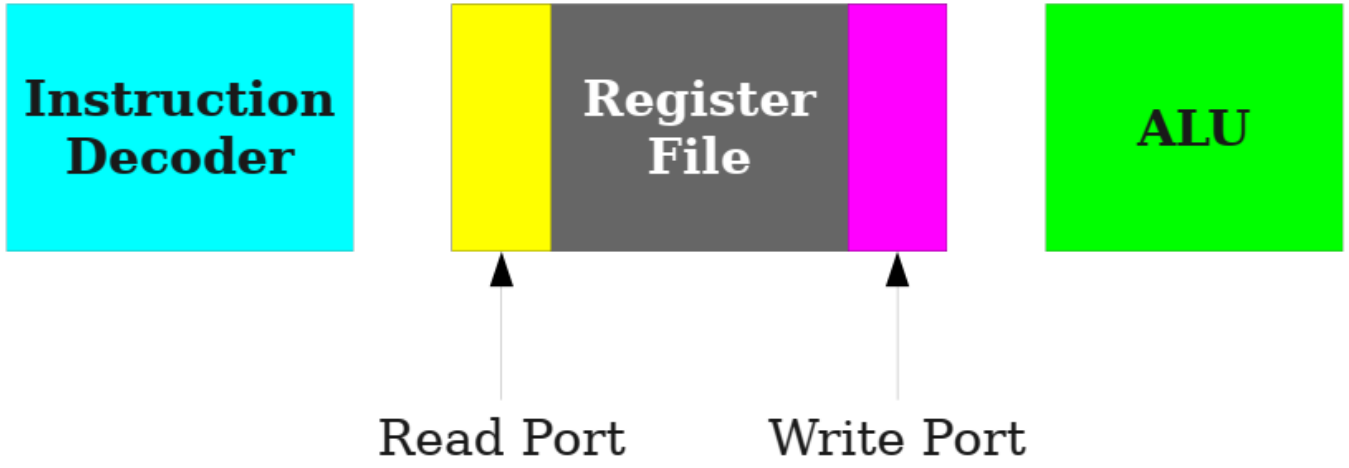


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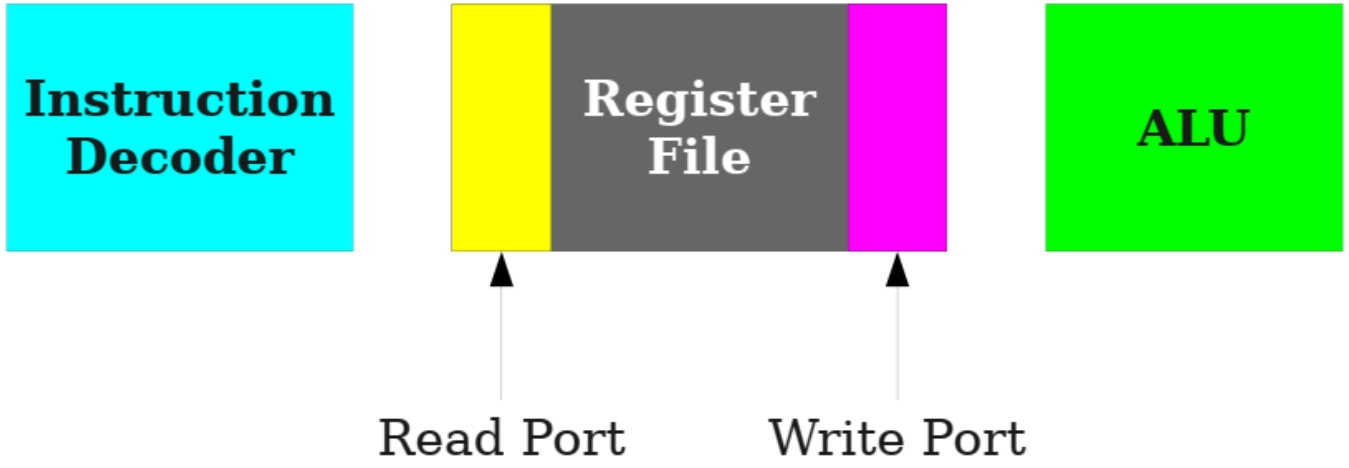


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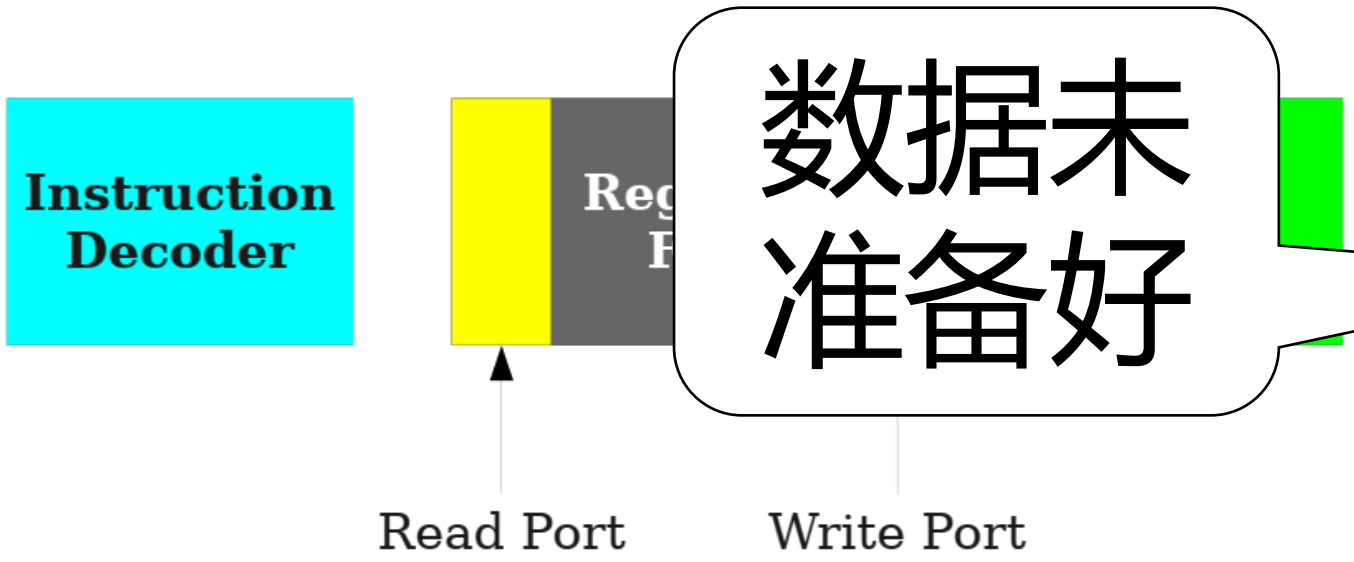


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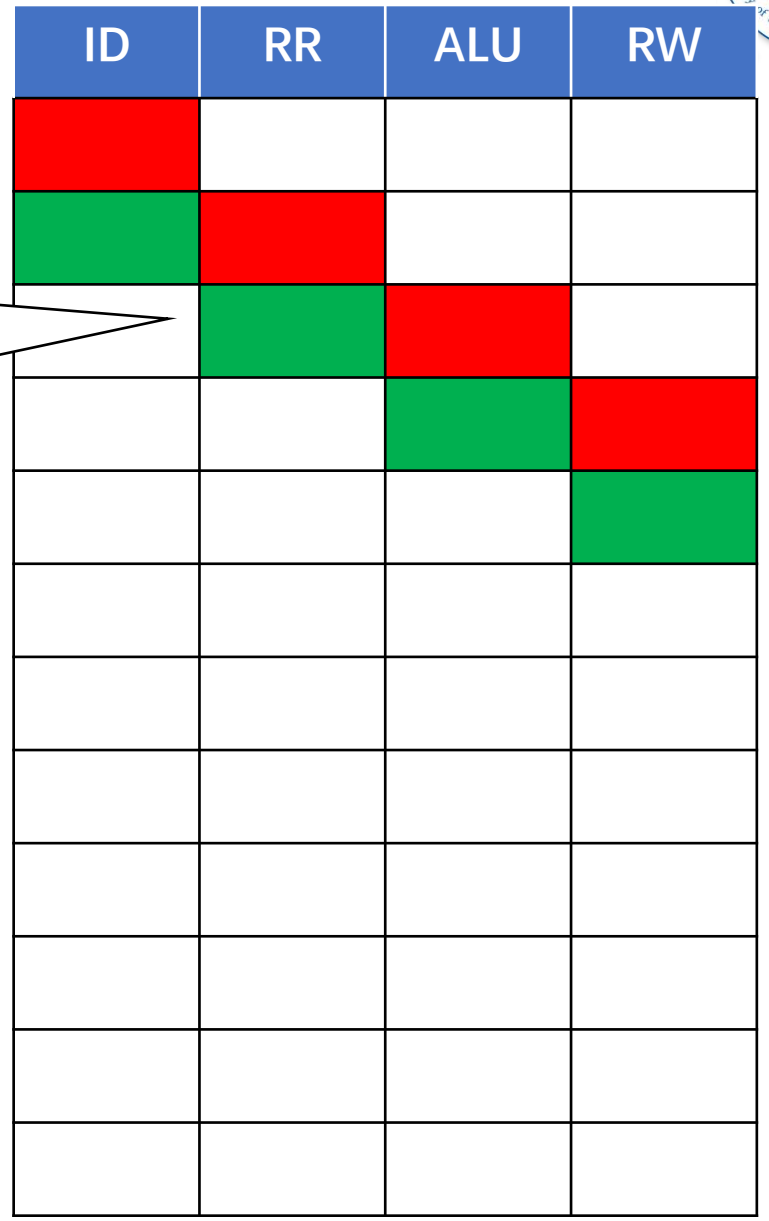

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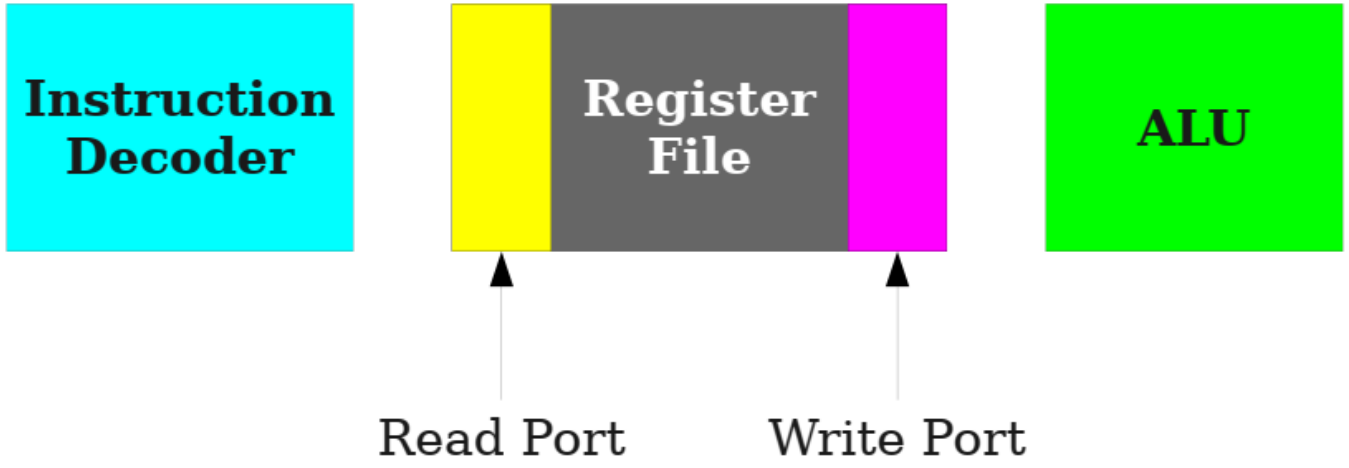


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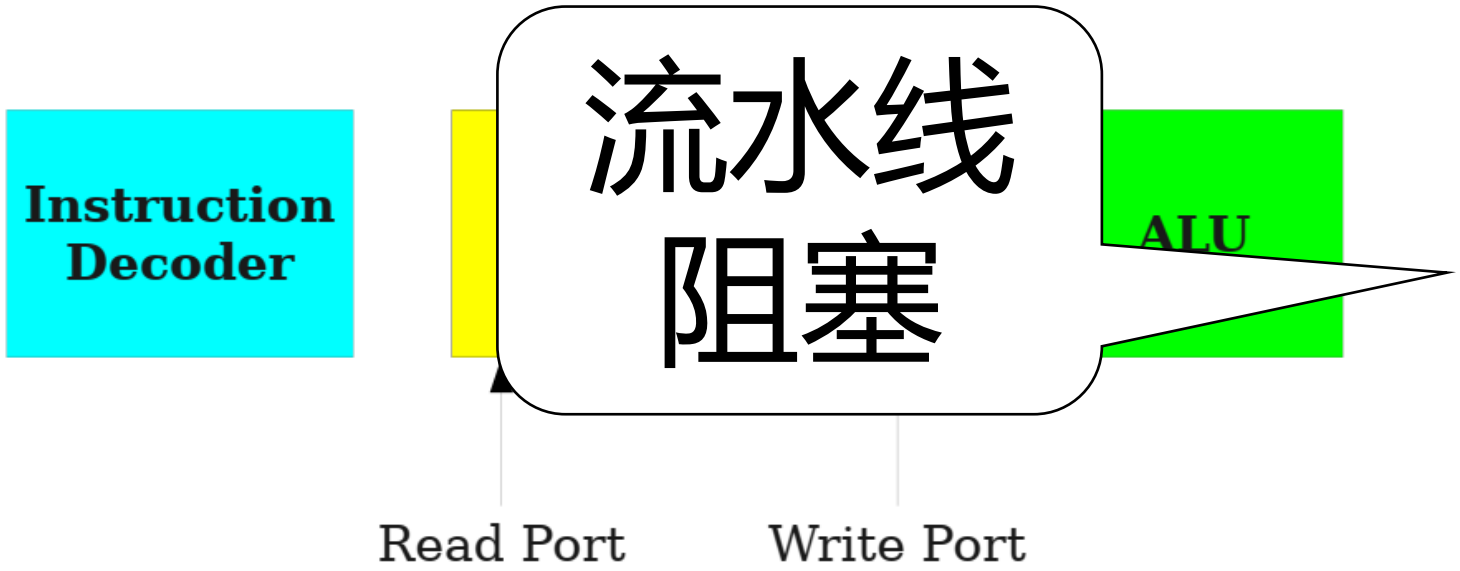

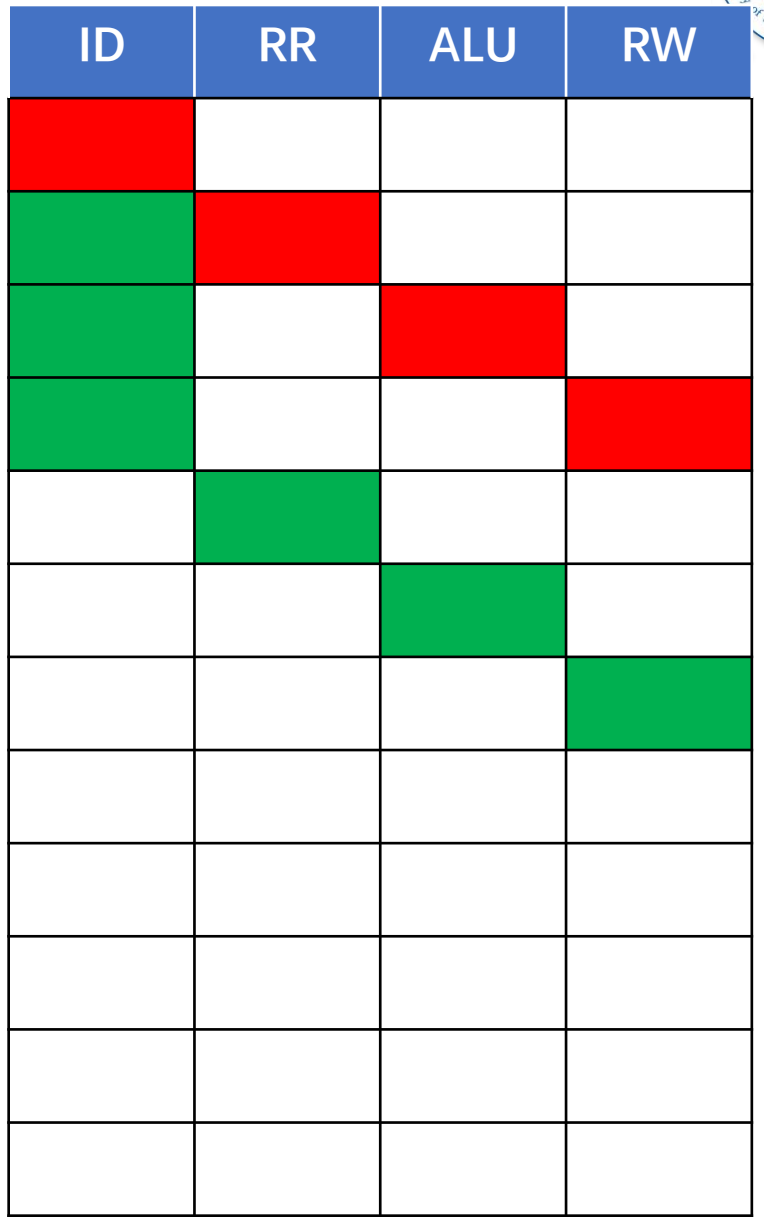


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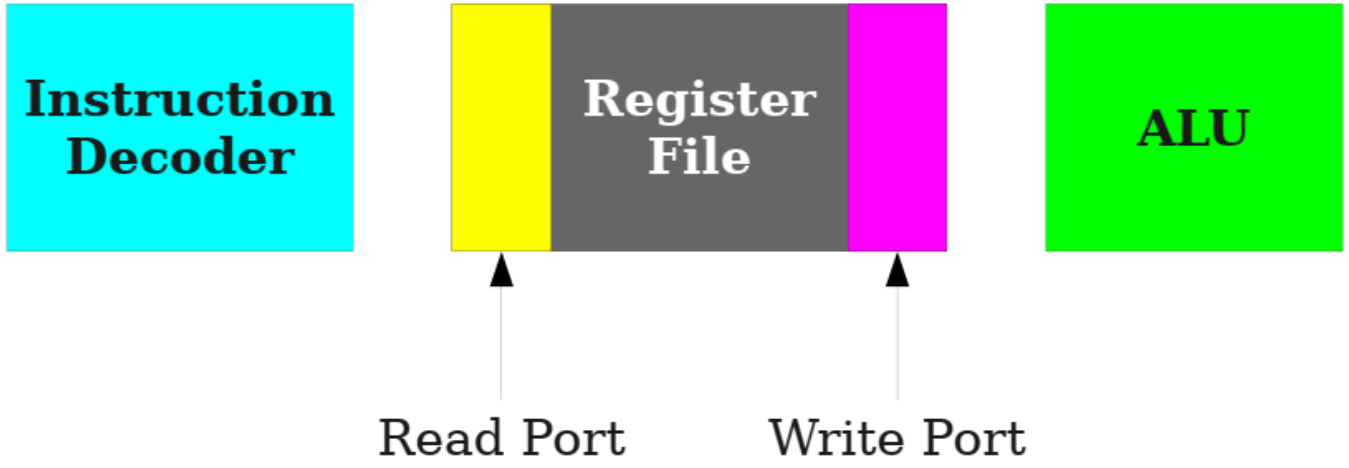


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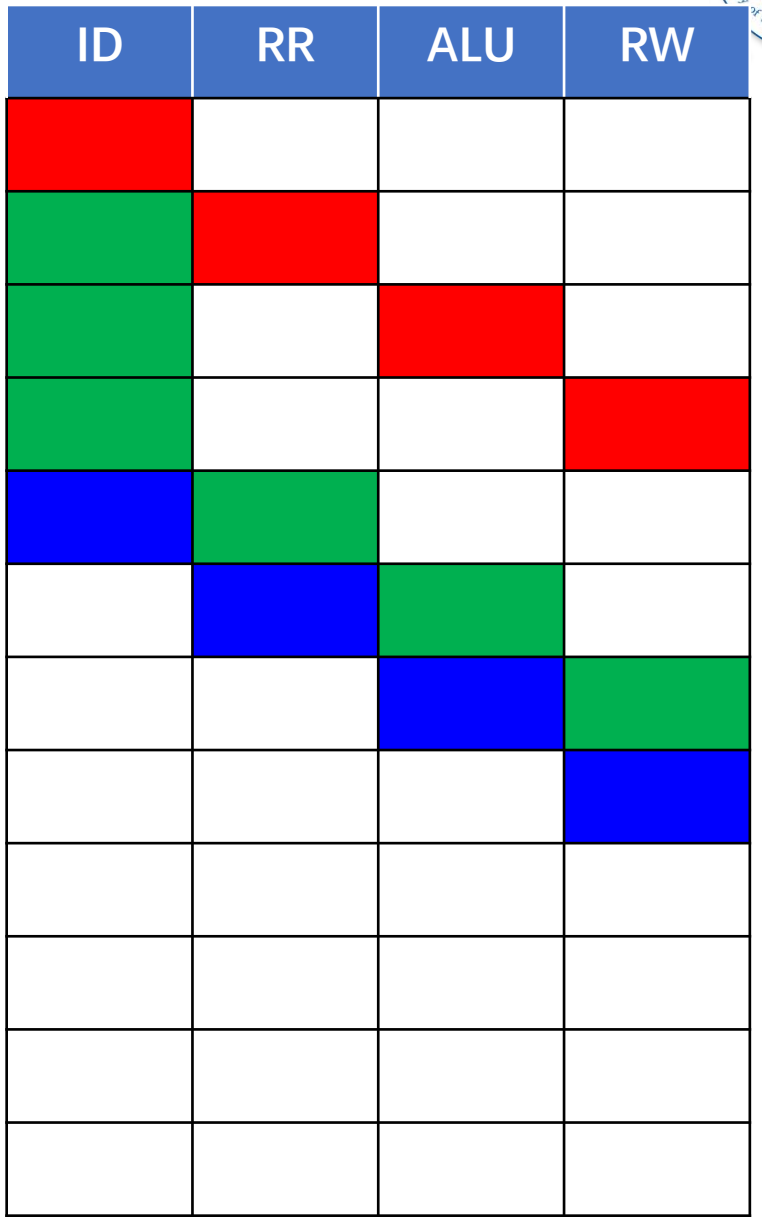

复杂的流水线并行

流水线阻塞

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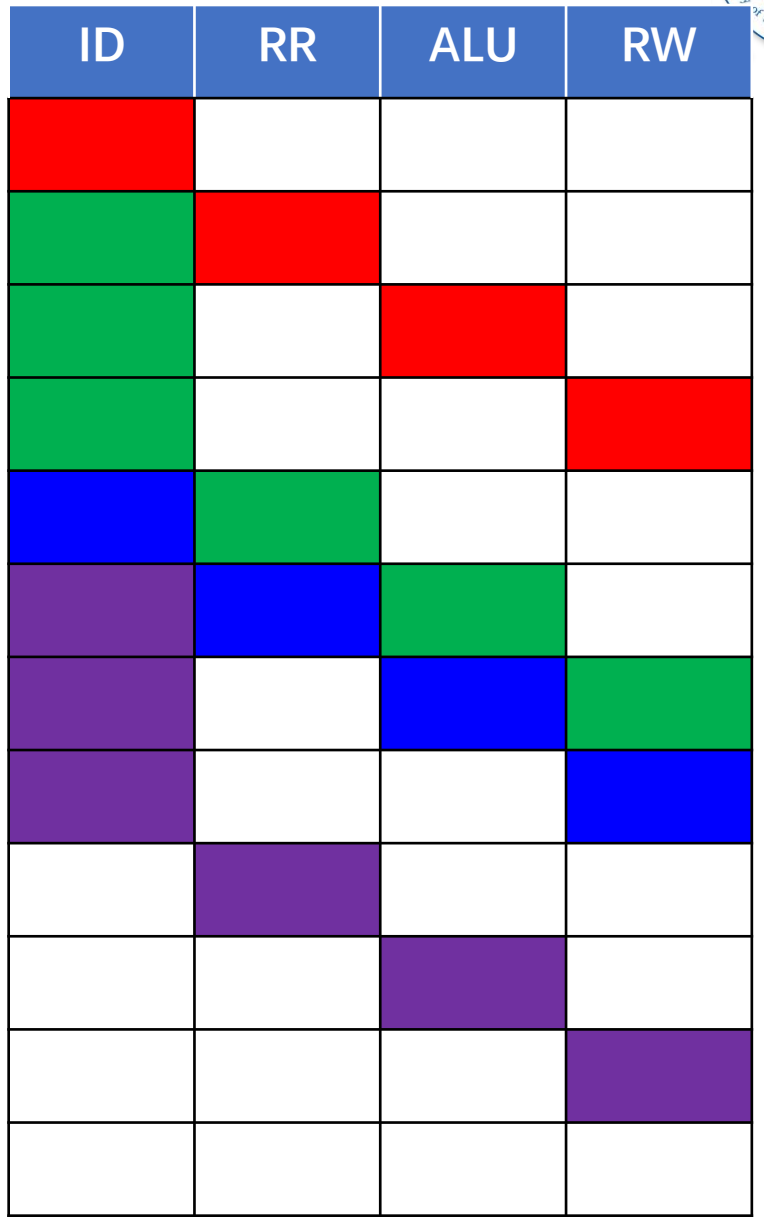
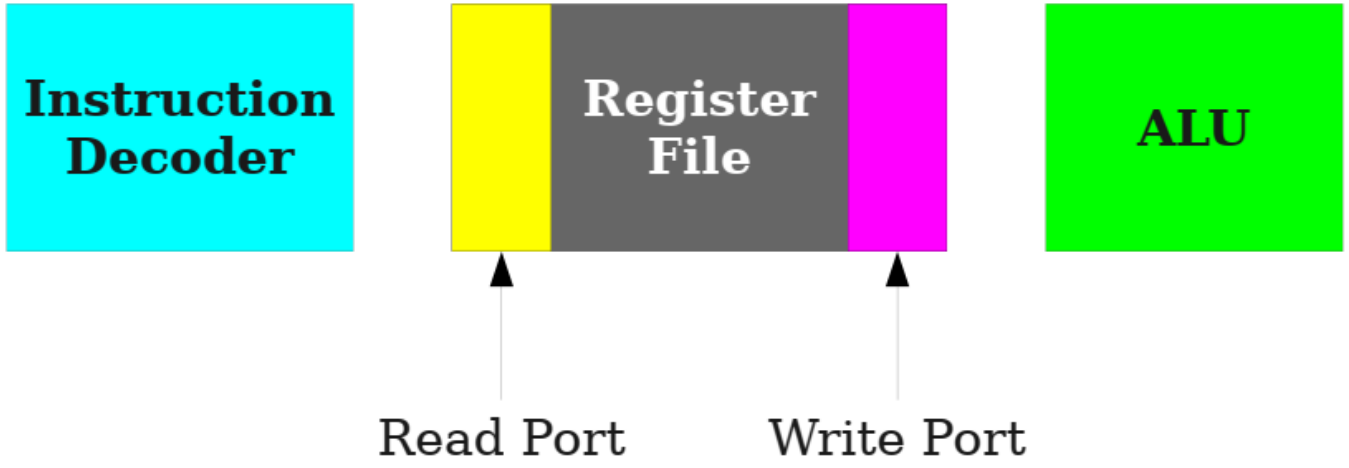


可能的优化

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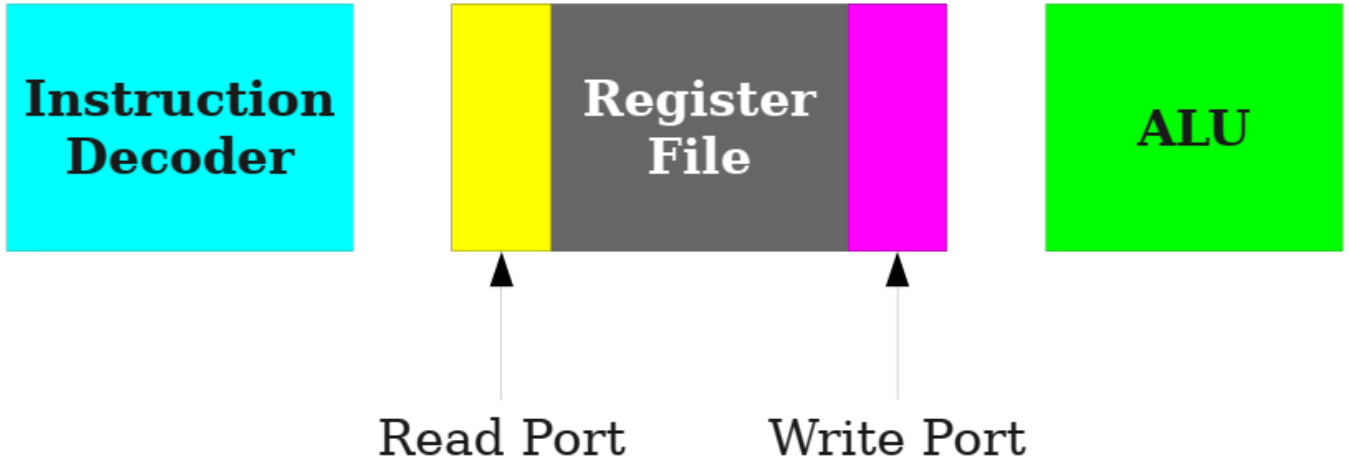


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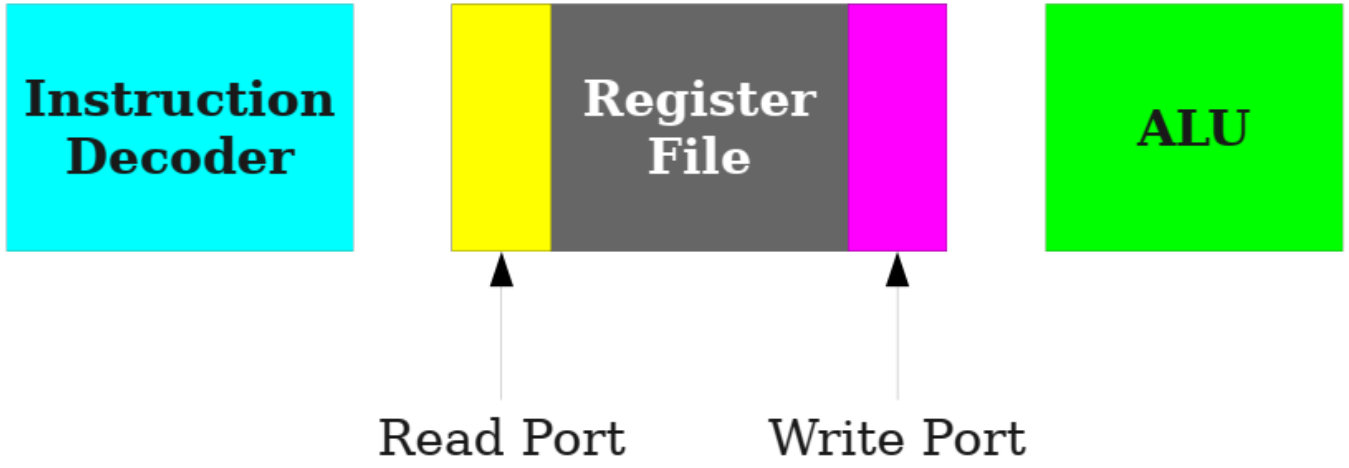


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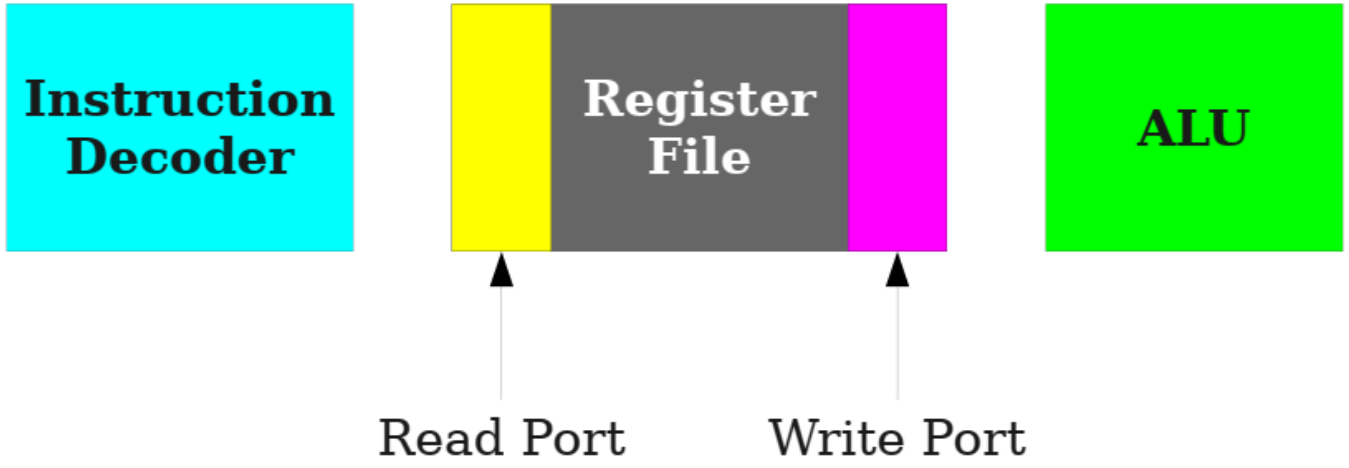


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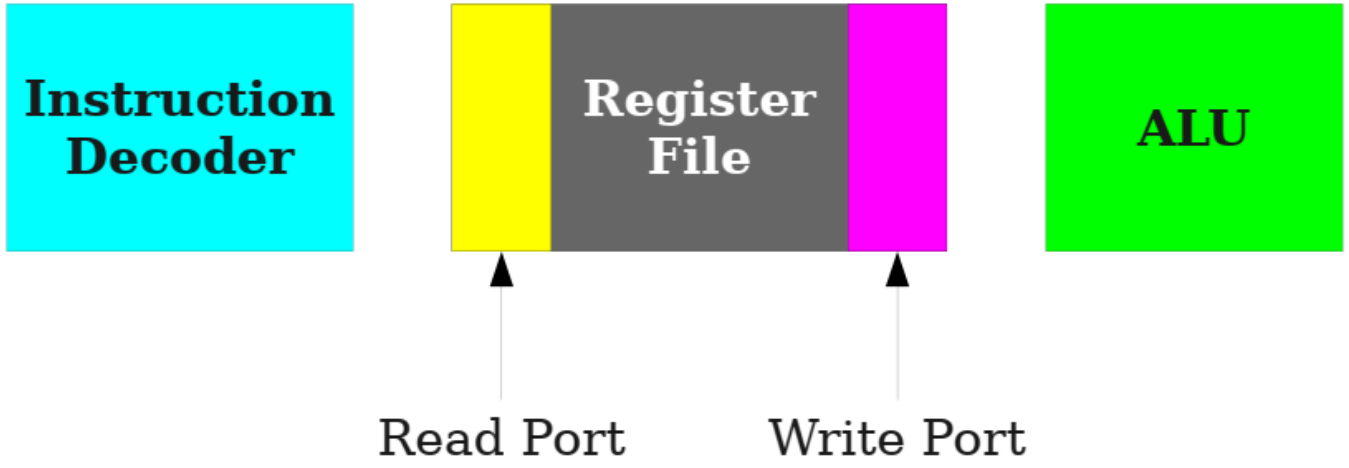


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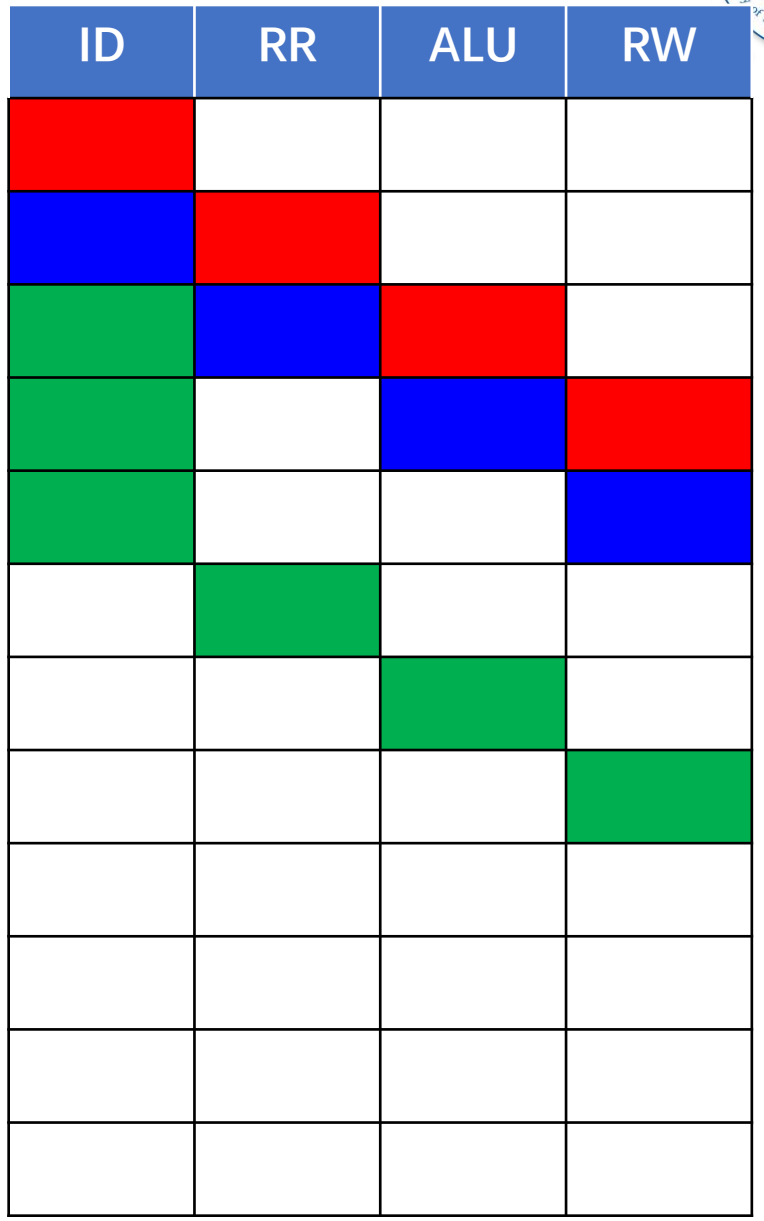
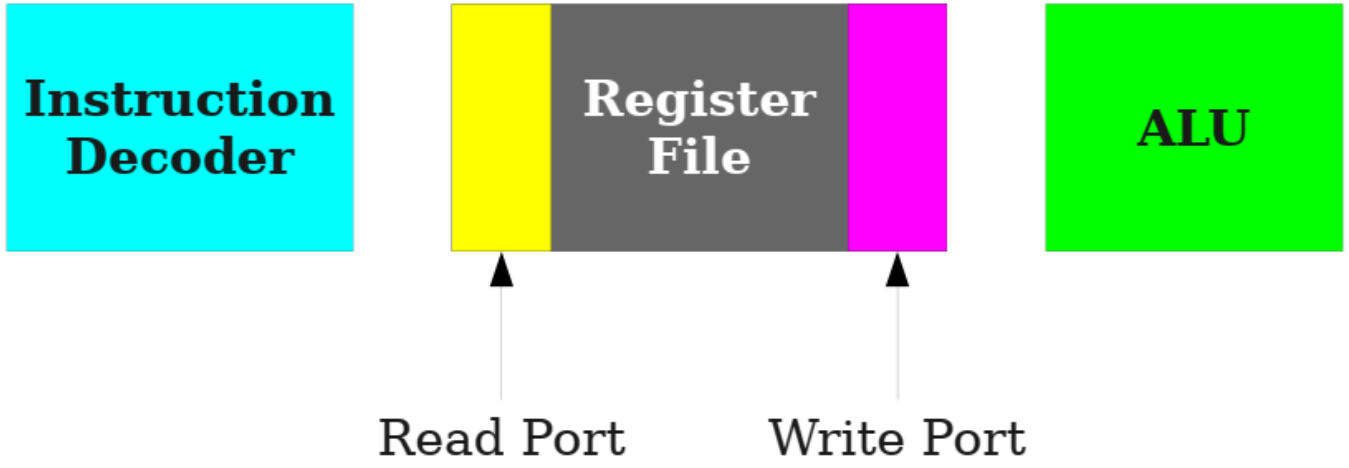
add $t2, $t0, $t1      # $t2 = $t0 + $t1
add $t7, $t5, $t6      # $t7 = $t5 + $t6
add $t4, $t3, $t2      # $t4 = $t3 + $t2
add $t0, $t0, $t7      # $t0 = $t0 + $t7
```



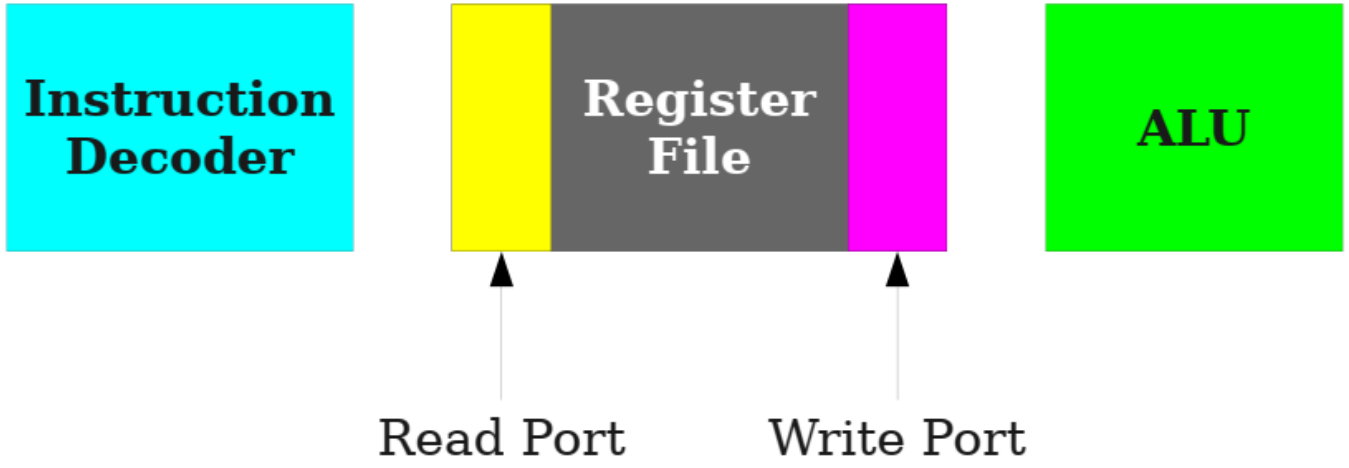
可能的优化




```
add $t2, $t0, $t1      # $t2 = $t0 + $t1
add $t7, $t5, $t6      # $t7 = $t5 + $t6
add $t4, $t3, $t2      # $t4 = $t3 + $t2
add $t0, $t0, $t7      # $t0 = $t0 + $t7
```

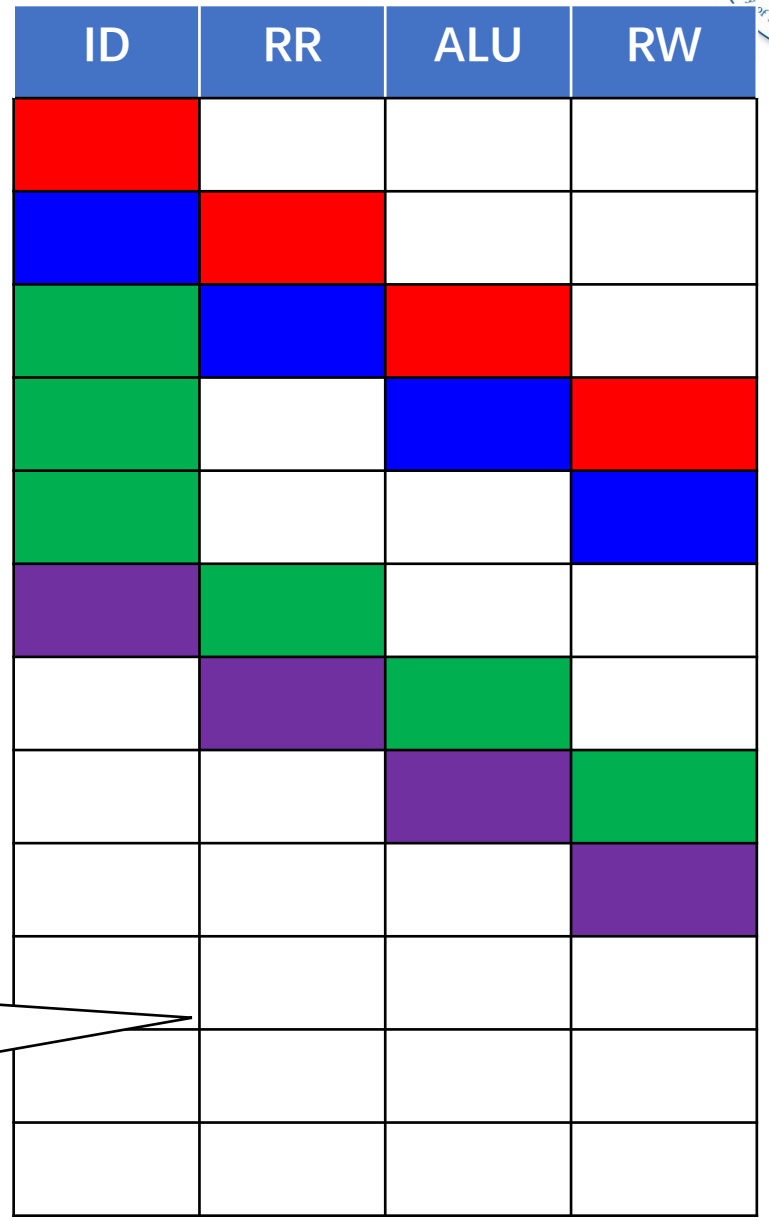
ID	RR	ALU	RW

可能的优化

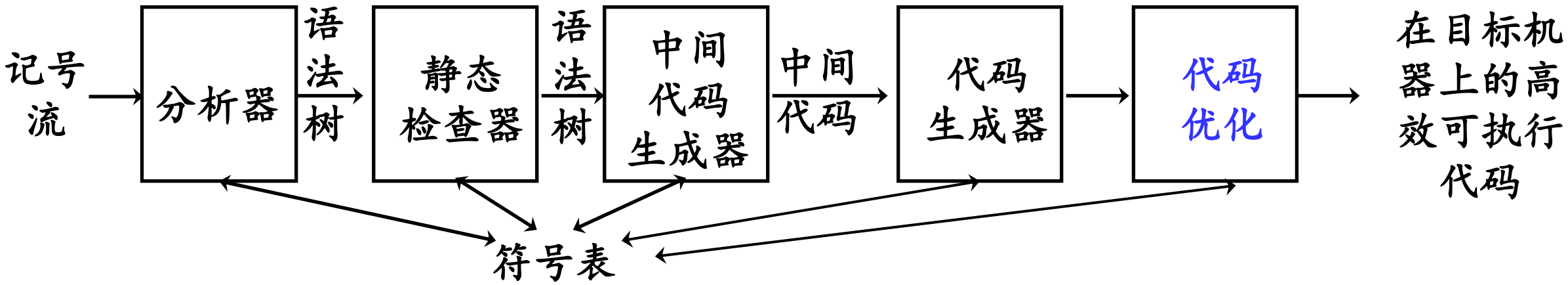



```
add $t2, $t0, $t1      # $t2 = $t0 + $t1
add $t7, $t5, $t       6
add $t4, $t3, $t       2
add $t0, $t0, $t7      # $t0 = $t0 + $t7
```

节省两个时钟周期



本节提纲



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指令调度(Instruction scheduling)

优化的起源

- 由于处理器流水线并行机制，指令的执行顺序对性能有较大影响。

指令调度

- 重排机器代码指令，旨在最小化执行特定指令序列所需的时钟周期数。
- 任意编译器均支持指令调度。

理论和技术挑战

- 然而，在处理器流水线上执行的顺序代码内含着一些指令之间的依赖关系，在指令调度期间执行的任何转换都必须保留这些依赖关系，以维护被调度代码的逻辑。

三种数据依赖关系

read-after-write，RAW

- 当一条指令读取另一条指令写入的结果时，会产生写后读相关性，读指令必须在写指令一定时钟周期后再读取而不会产生阻塞。

```
x = ...
... = x
```

write-after-read，WAR

- 当一条指令写在另一条指令的操作数上时，会产生反向依赖或称读后写依赖。 读指令必须在写指令之前经过适当的周期数才能安全读取，而不阻塞写指令。

```
... = x
x = ...
```

write-after-write，WAW

- 如果两条指令写入同一个目标，就会产生单个输出或写后写依赖关系

```
x = ...
x = ...
```

分析数据依赖关系

t0 = t1 + t2

t1 = t0 + t1

t3 = t2 + t4

t0 = t1 + t2

t5 = t3 + t4

t6 = t2 + t7

分析数据依赖关系

t0 = t1 + t2

t1 = t0 + t1

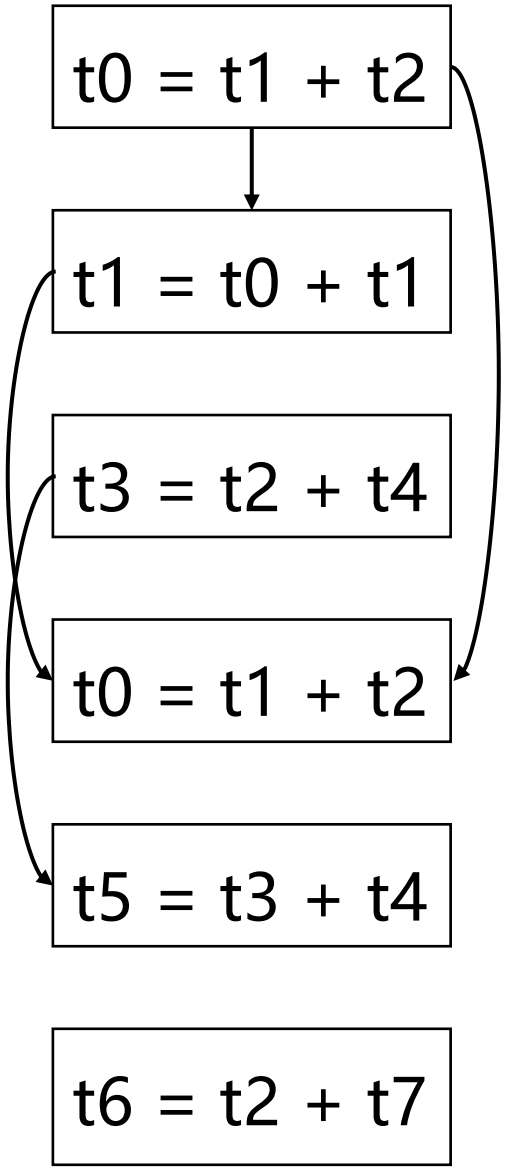
t3 = t2 + t4

t0 = t1 + t2

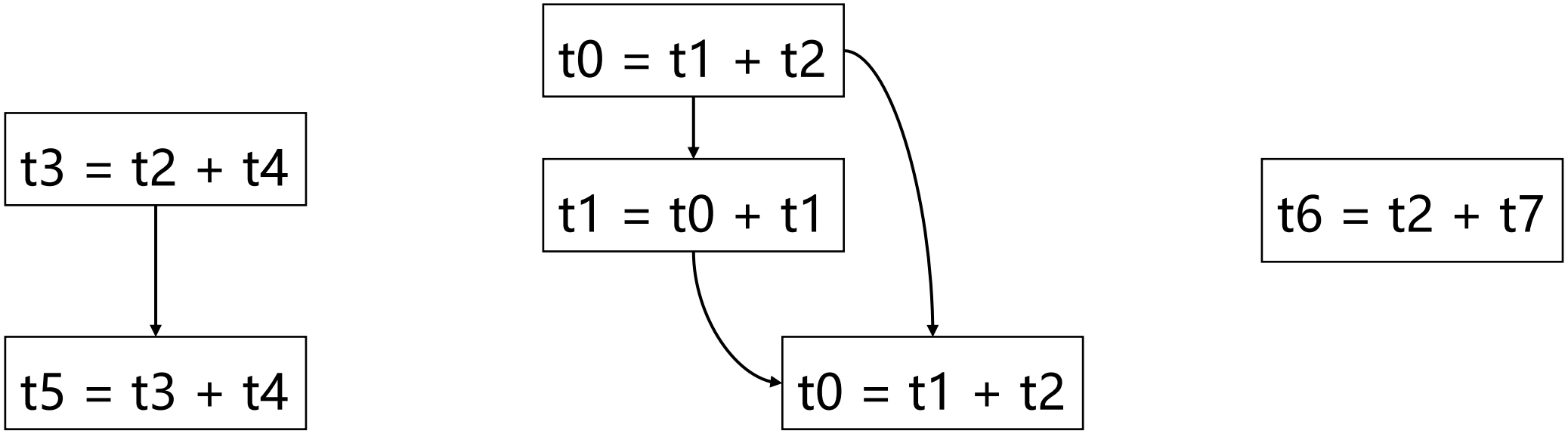
t5 = t3 + t4

t6 = t2 + t7

分析数据依赖关系



分析数据依赖关系

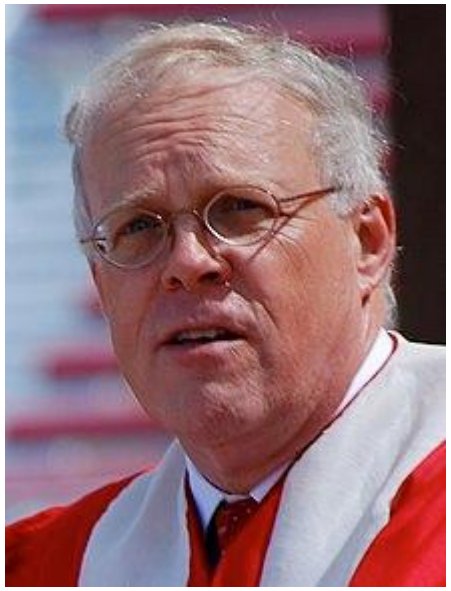


指令数据依赖图[HennessyGross，1983]

- 一个基本块的指令数据依赖图：
  - 每个节点表示单个机器指令
  - 每一条边代表了两条指令间存在数据依赖，否则就没有依赖
- 依赖图是一个有向无环图，directed acyclic graph (DAG)
  - Directed: 代表了计算的顺序
  - Acyclic: 不能存在环状依赖（why？）
- 合法的指令调度
  - 条件：一条指令不能先于他的祖先节点执行
- 实现方法
  - 对依赖图进行拓扑排序(topological sort)

延伸阅读

- John L. Hennessy and Thomas Gross. 1983. **Postpass Code Optimization of Pipeline Constraints**. ACM Trans. Program. Lang. Syst. 5, 3 (July 1983), 422–448. https://doi.org/10.1145/2166.357217

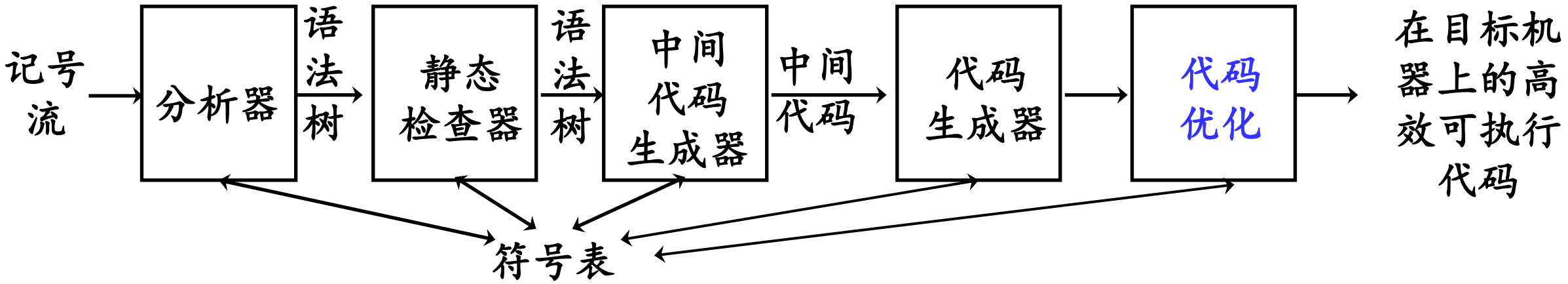


John L. Hennessy

David Patterson

- 2017年，Hennessy和Patterson共同获得图灵奖。
- 获奖演说：
  - A New Golden Age for Computer Architecture: Domain-Specific Hardware/Software Co-Design, Enhanced Security, Open Instruction Sets, and Agile Chip Development

本节提纲



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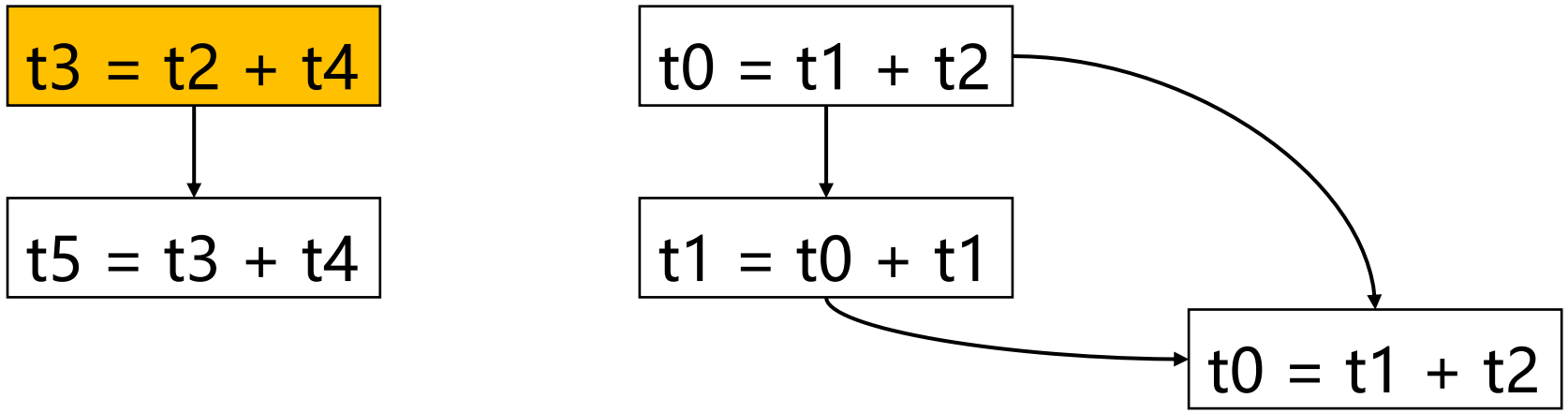
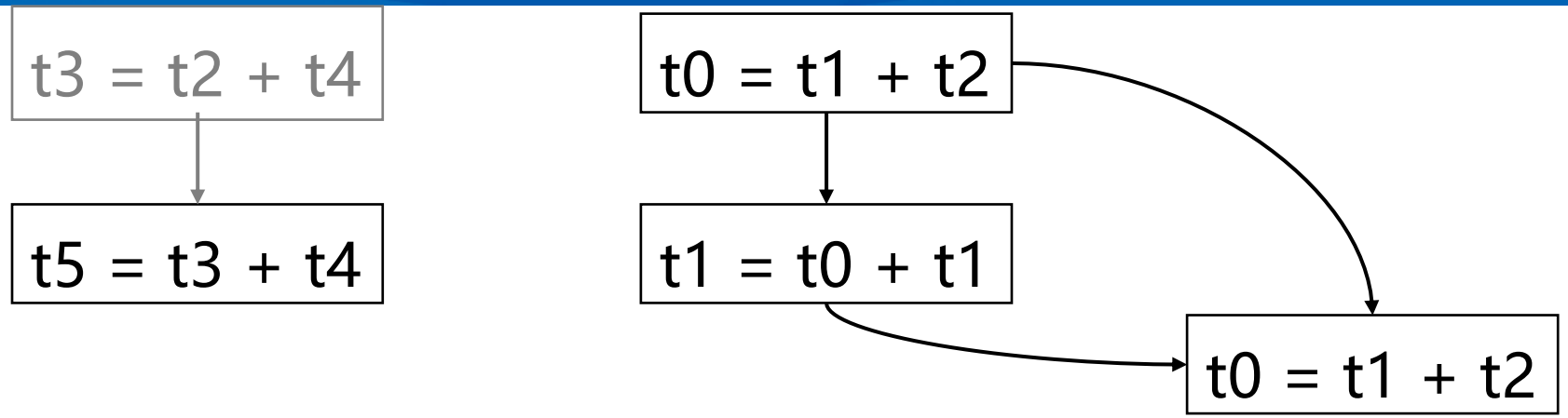
数据依赖指导下的指令调度

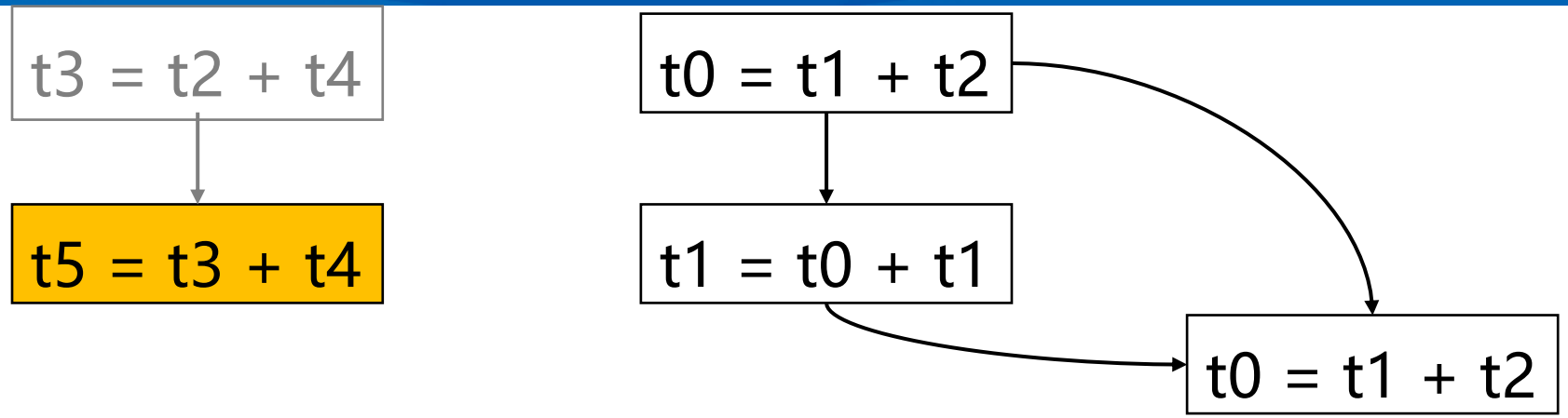


数据依赖指导下的指令调度



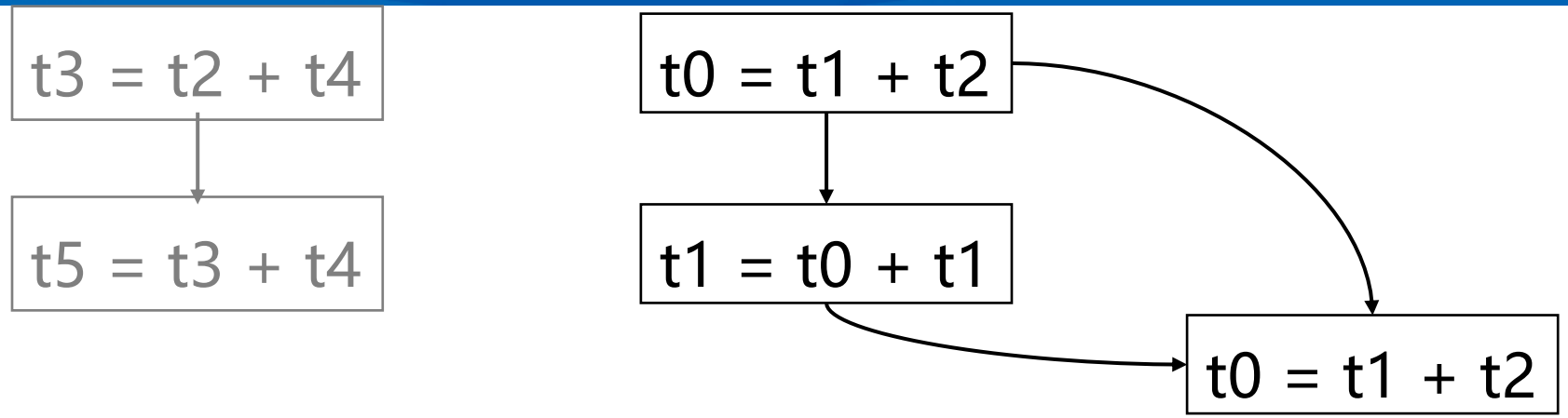
t3 = t2 + t4

数据依赖指导下的指令调度



t3 = t2 + t4

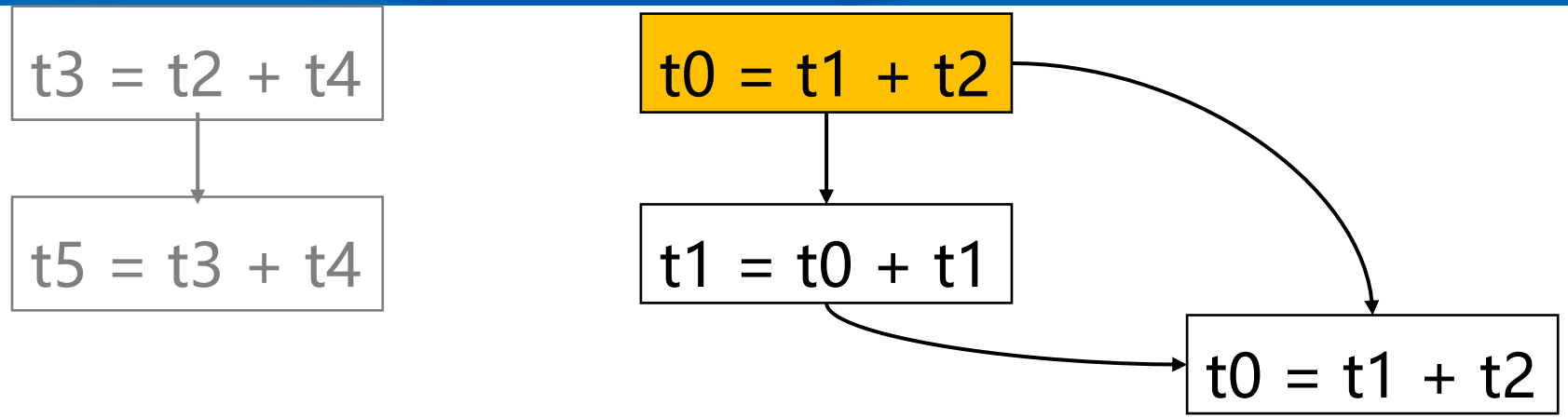
数据依赖指导下的指令调度



t3 = t2 + t4

t5 = t3 + t4

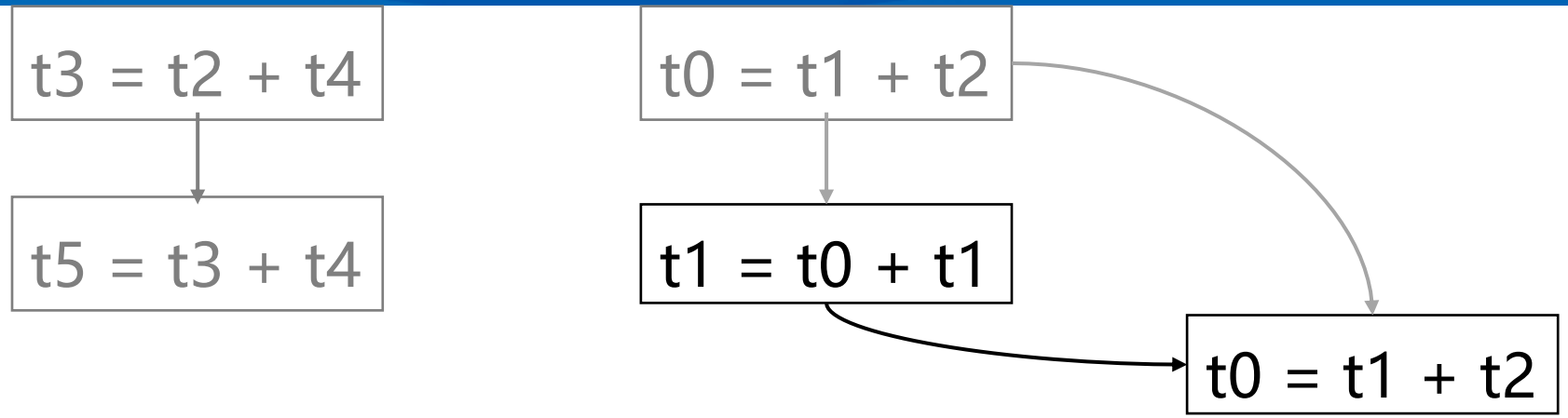
数据依赖指导下的指令调度



t3 = t2 + t4

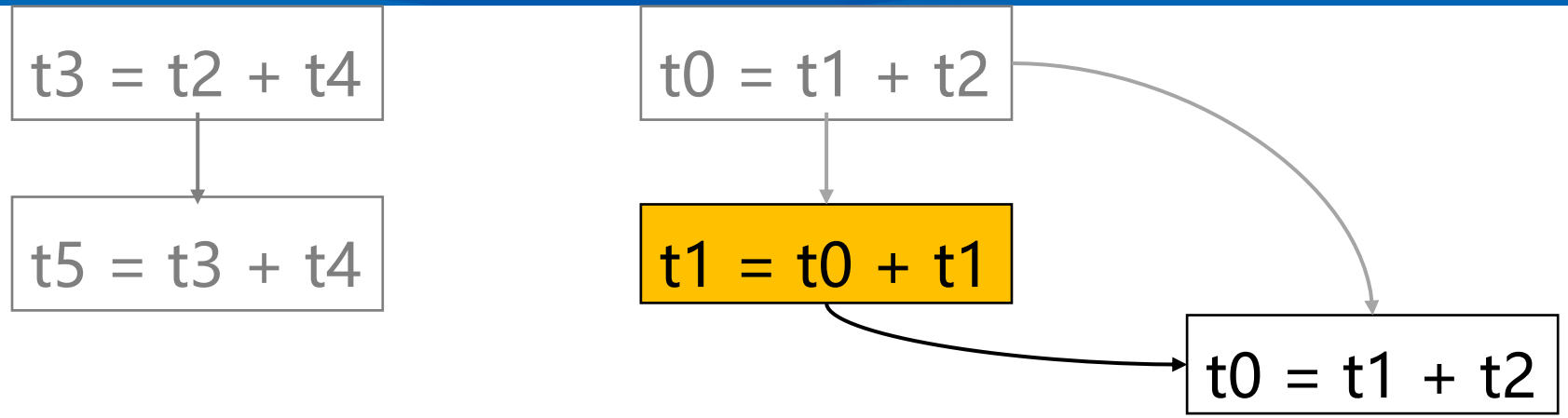
t5 = t3 + t4

数据依赖指导下的指令调度



t3 = t2 + t4
t5 = t3 + t4
t0 = t1 + t2

数据依赖指导下的指令调度

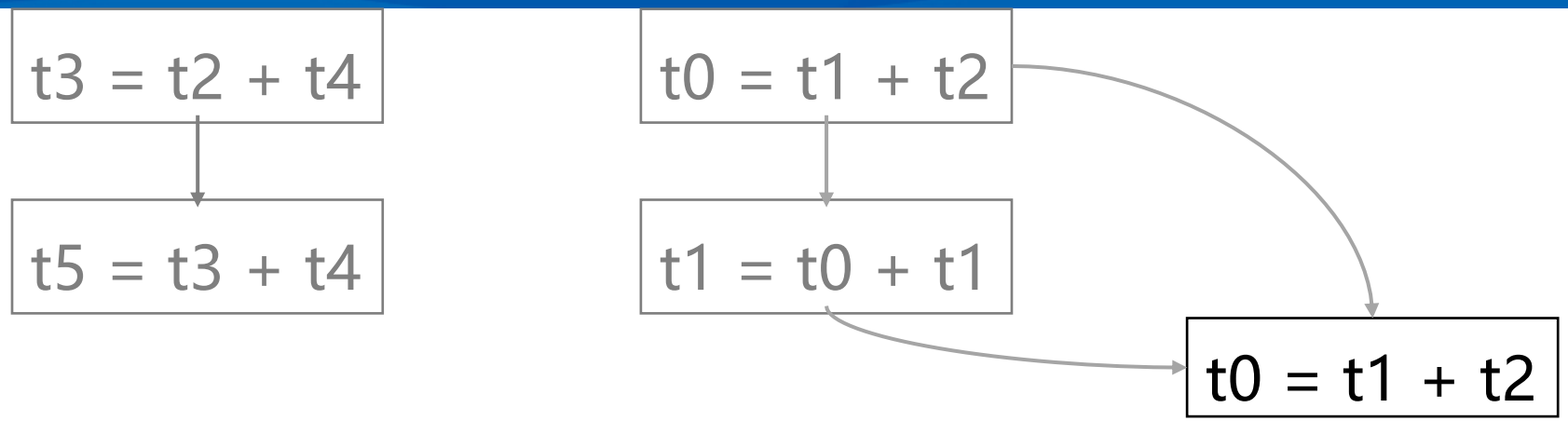


t3 = t2 + t4

t5 = t3 + t4

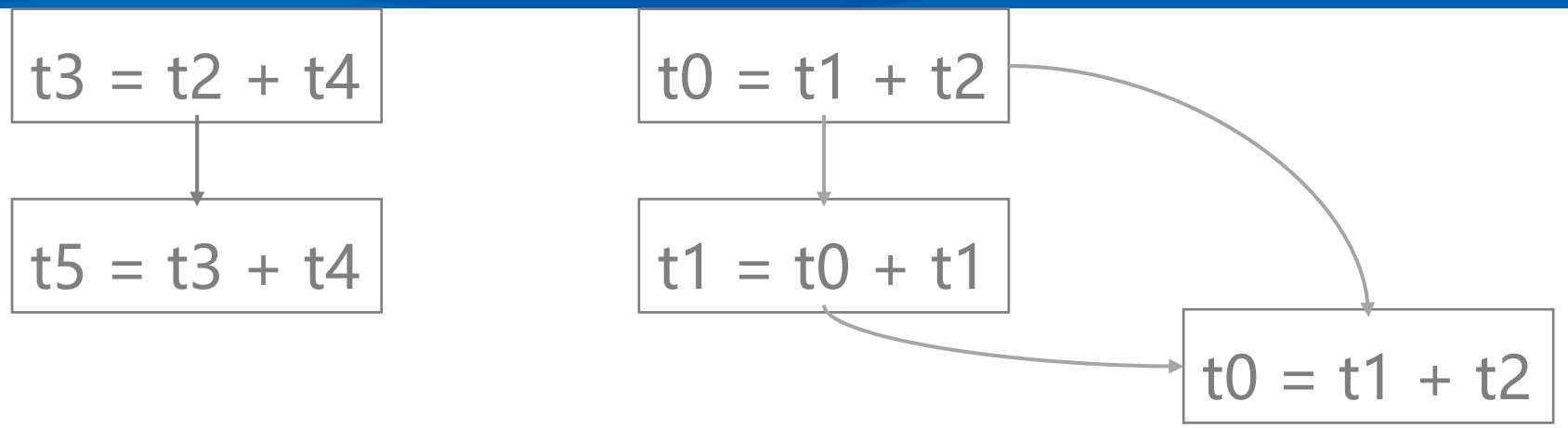
t0 = t1 + t2

数据依赖指导下的指令调度



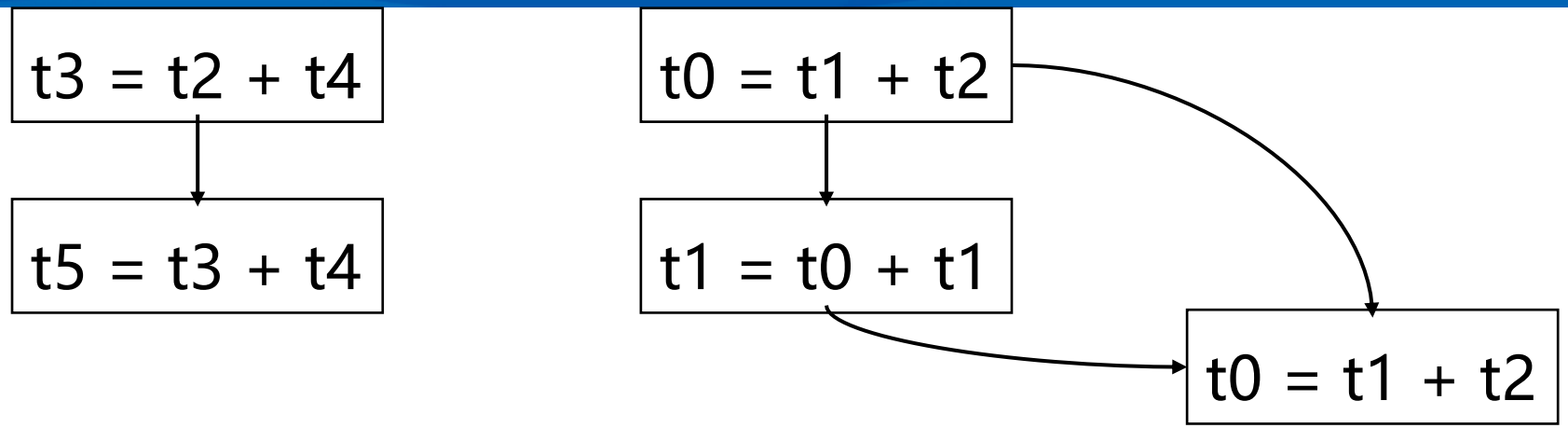
t3 = t2 + t4
t5 = t3 + t4
t0 = t1 + t2
t1 = t0 + t1

数据依赖指导下的指令调度



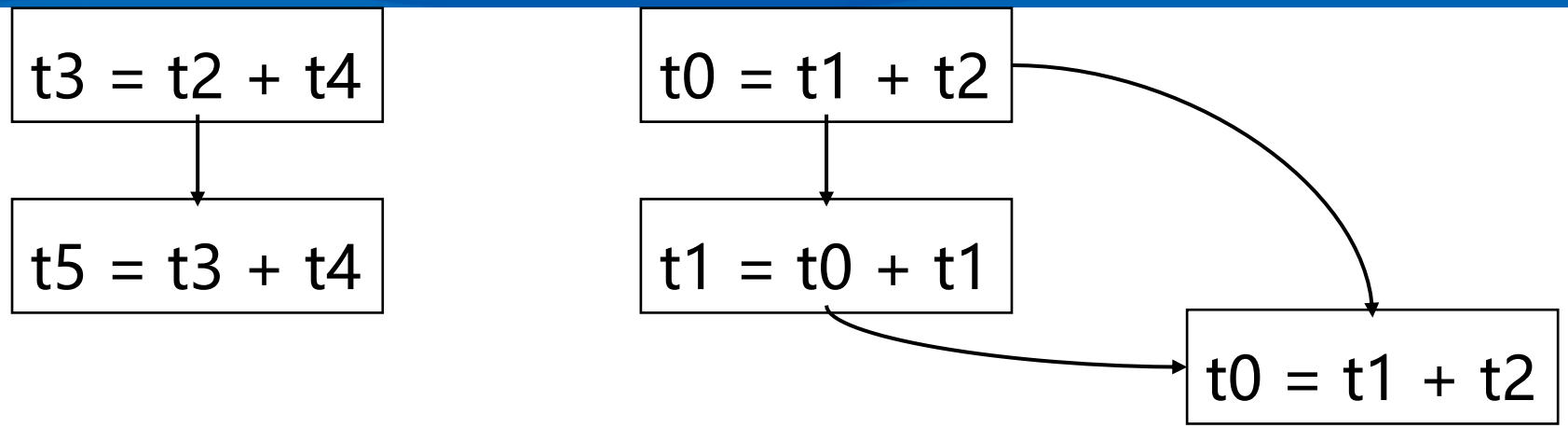
t3 = t2 + t4
t5 = t3 + t4
t0 = t1 + t2
t1 = t0 + t1
t0 = t1 + t2
t6 = t2 + t7

数据依赖指导下的指令调度



t3 = t2 + t4
t5 = t3 + t4
t0 = t1 + t2
t1 = t0 + t1
t0 = t1 + t2
t6 = t2 + t7

数据依赖指导下的指令调度



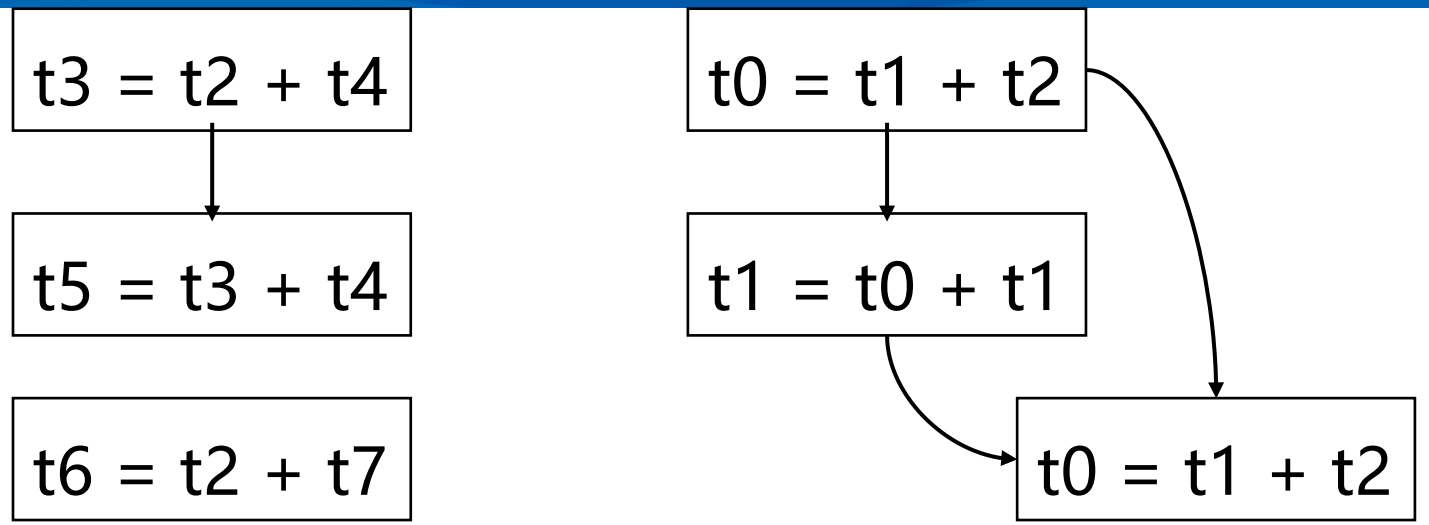
t3 = t2 + t4
t5 = t3 + t4
t0 = t1 + t2
t1 = t0 + t1
t0 = t1 + t2
t6 = t2 + t7

t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1
t5 = t3 + t4
t0 = t1 + t2

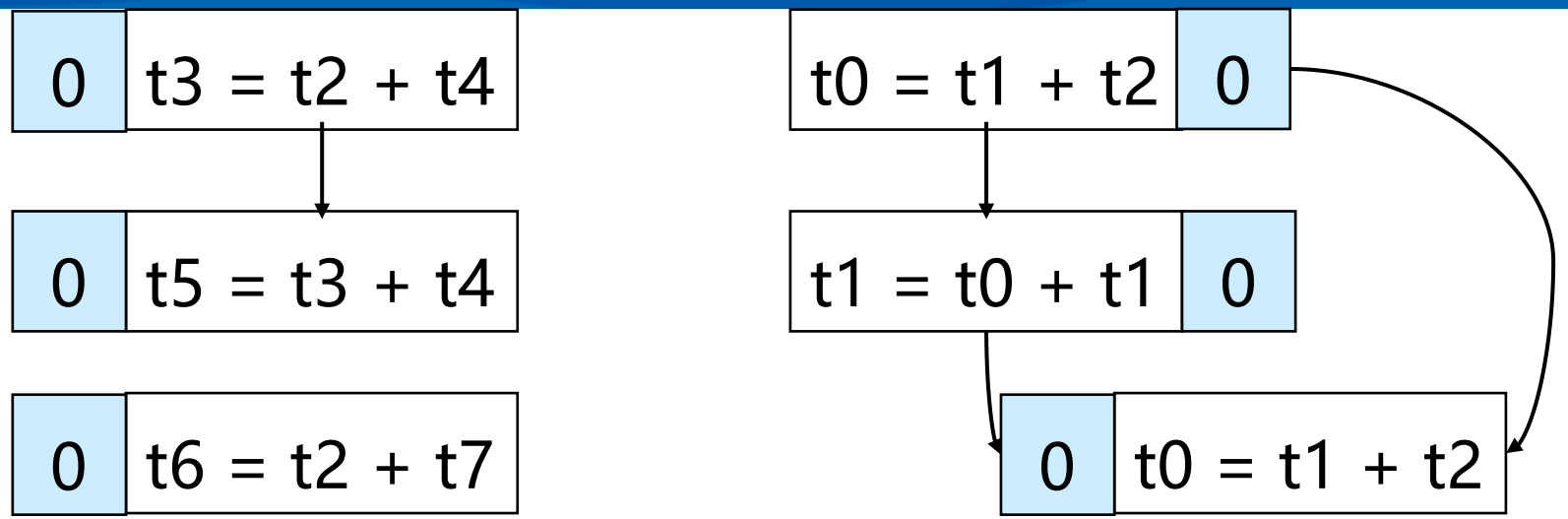
指令调度的空间

- 数据依赖图可能有许多有效的拓扑排序。
  - 该如何选择一种能与流水线完美配合的排序方式呢？
- 寻找最快的指令时间表是众所周知的 NP 难题。
  - 不要指望很快就能找到多项式时间算法！
- 在实践中使用启发式方法
  1. 将可以不受干扰地运行完成的指令安排在会造成干扰的指令之前。
  2. 将依赖关系较多的指令安排在依赖关系较少的指令之前。
  3. 对 DAG 进行加权调整！(边的权重为指令等待时间)

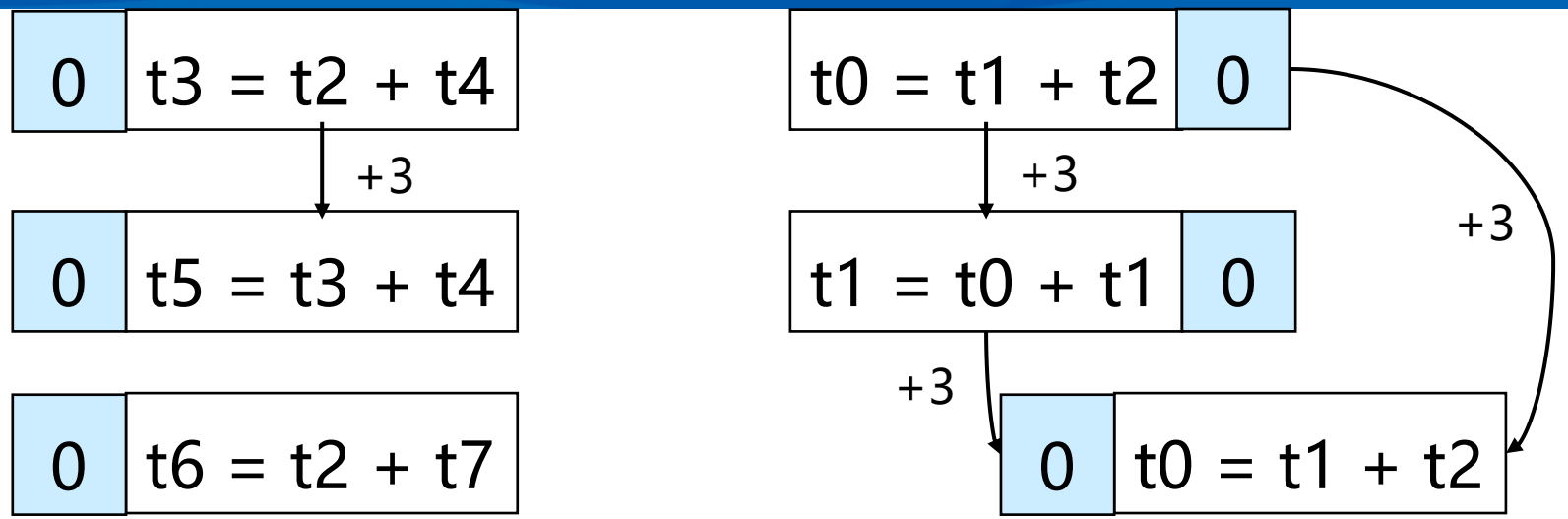
升级版的指令调度



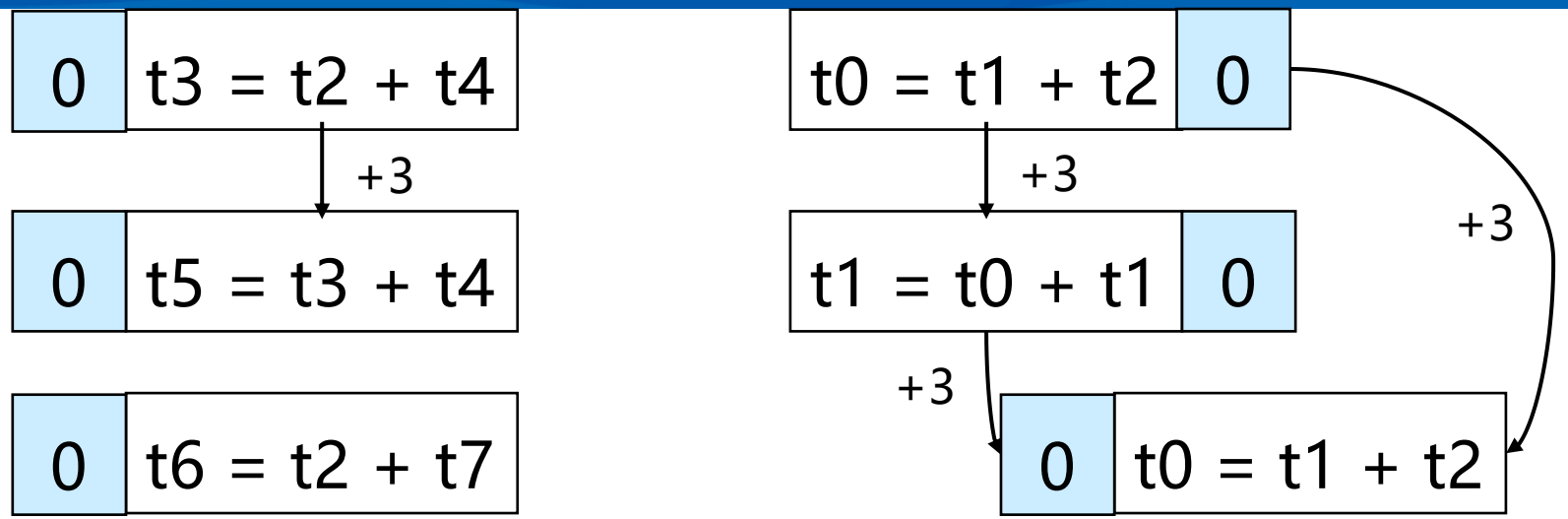
升级版的指令调度



升级版的指令调度

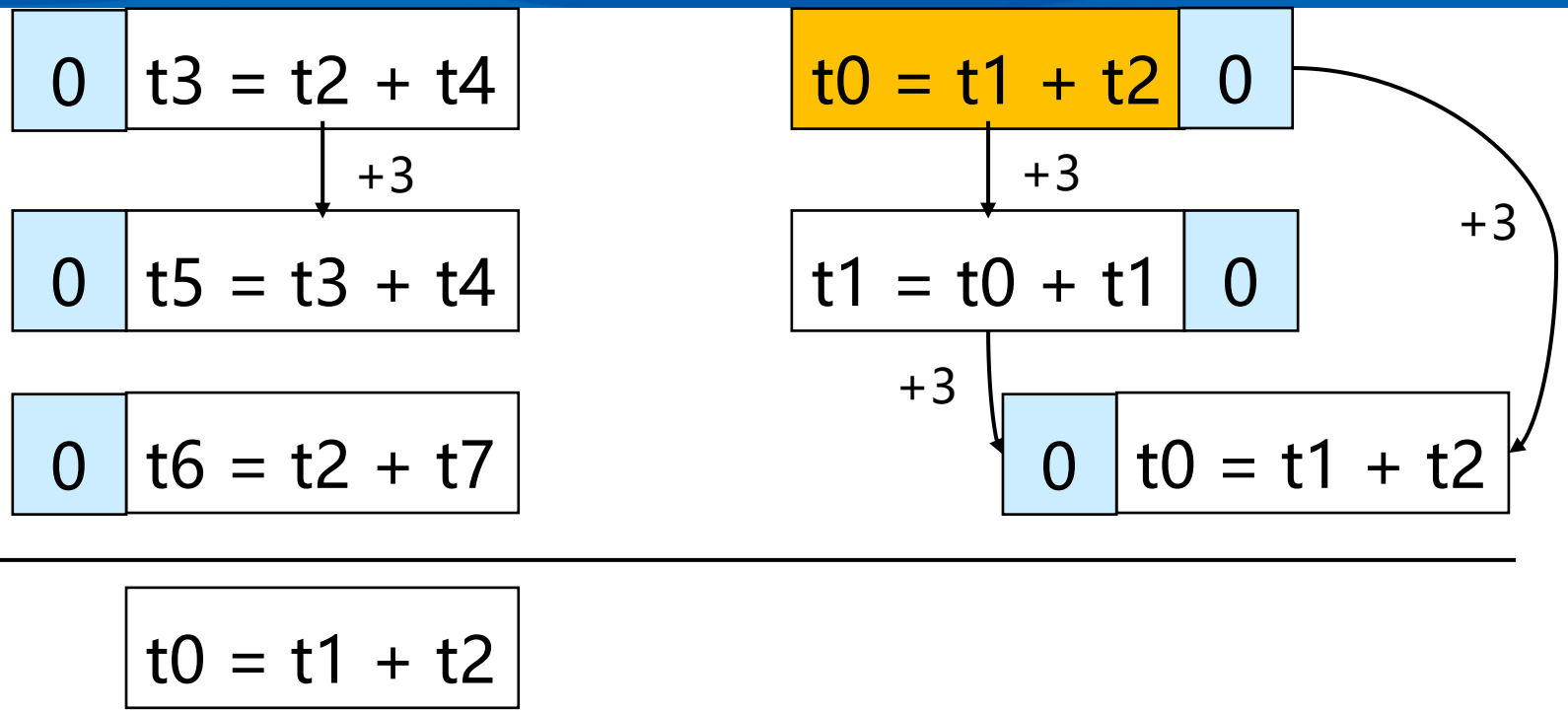


升级版的指令调度



ID	RR	ALU	RW

升级版的指令调度



ID	RR	ALU	RW

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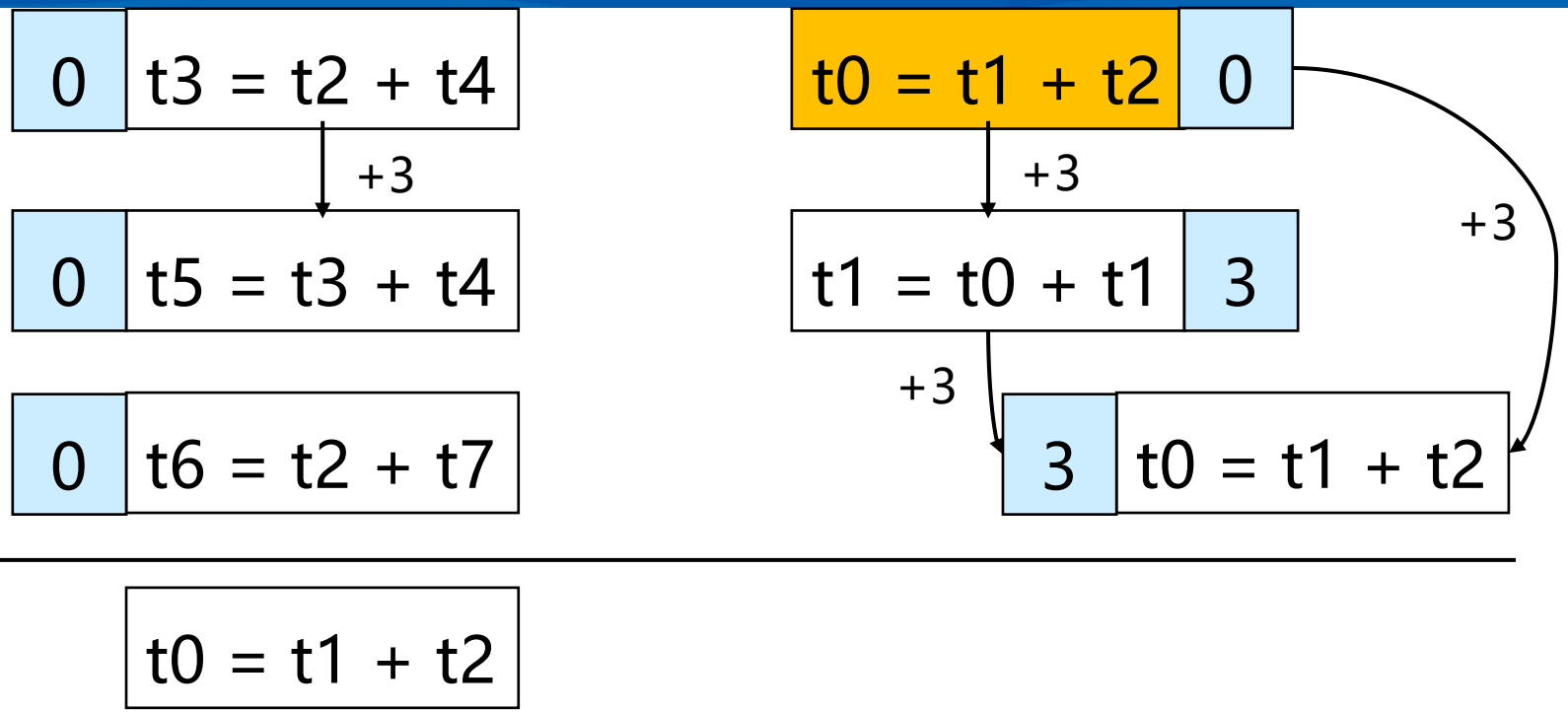
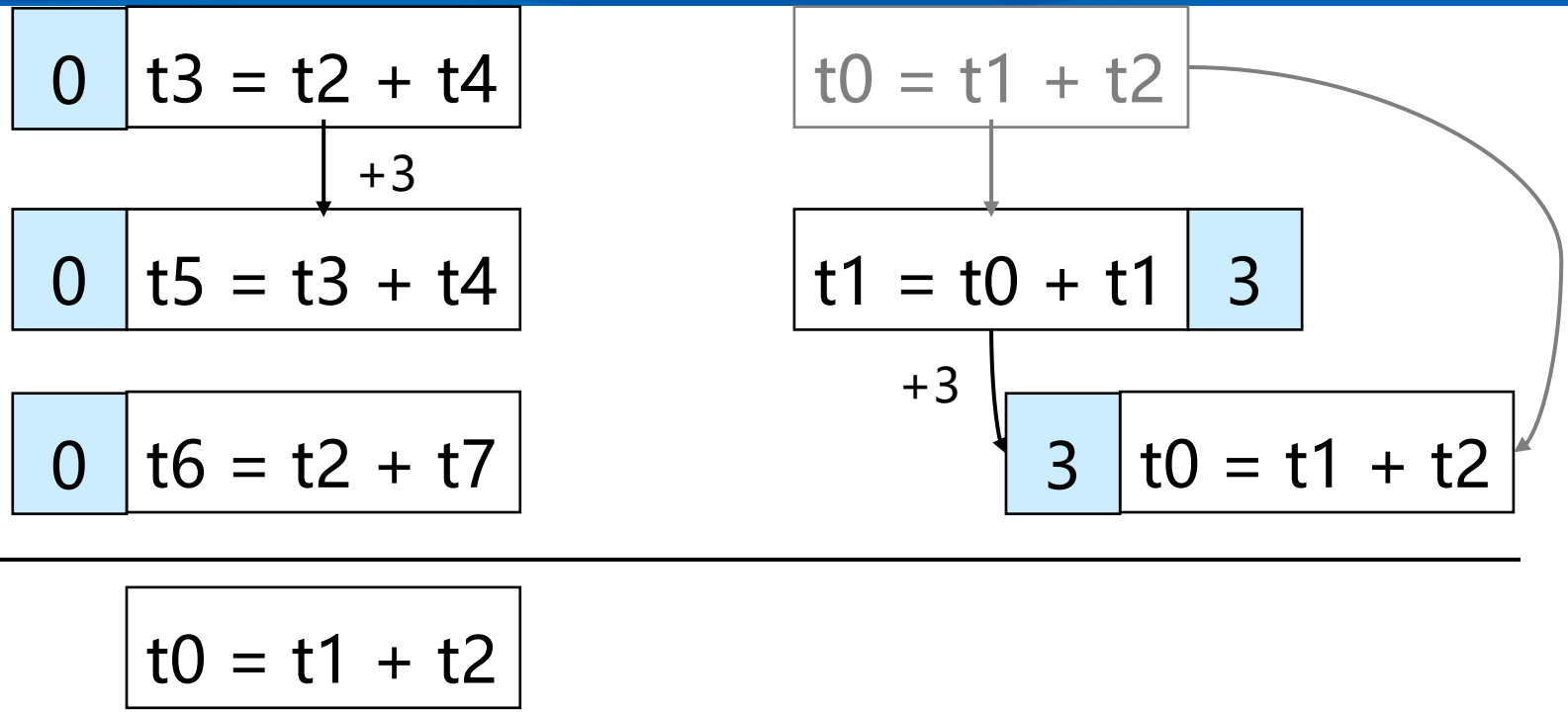


ID	RR	ALU	RW

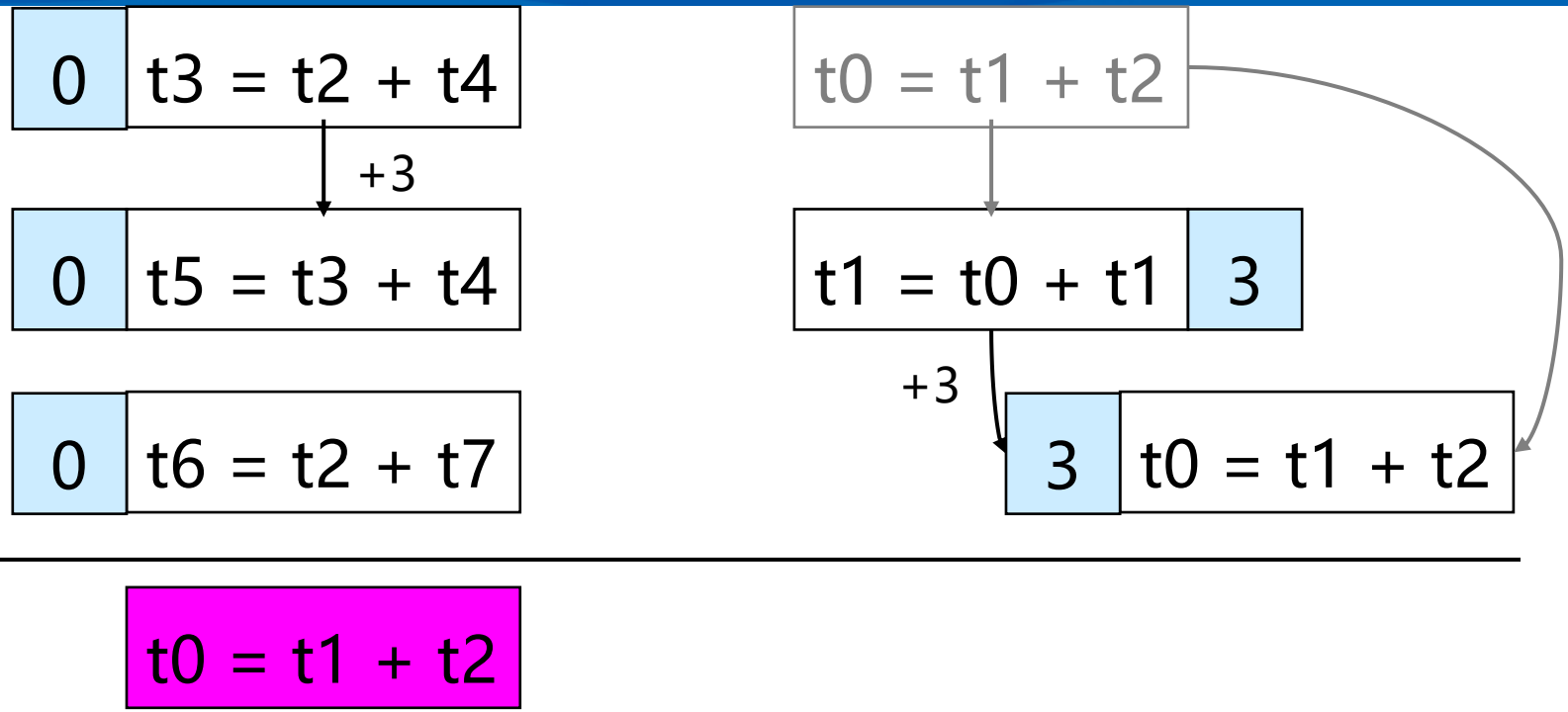
升级版的指令调度



t0 = t1 + t2

ID	RR	ALU	RW

升级版的指令调度



ID	RR	ALU	RW

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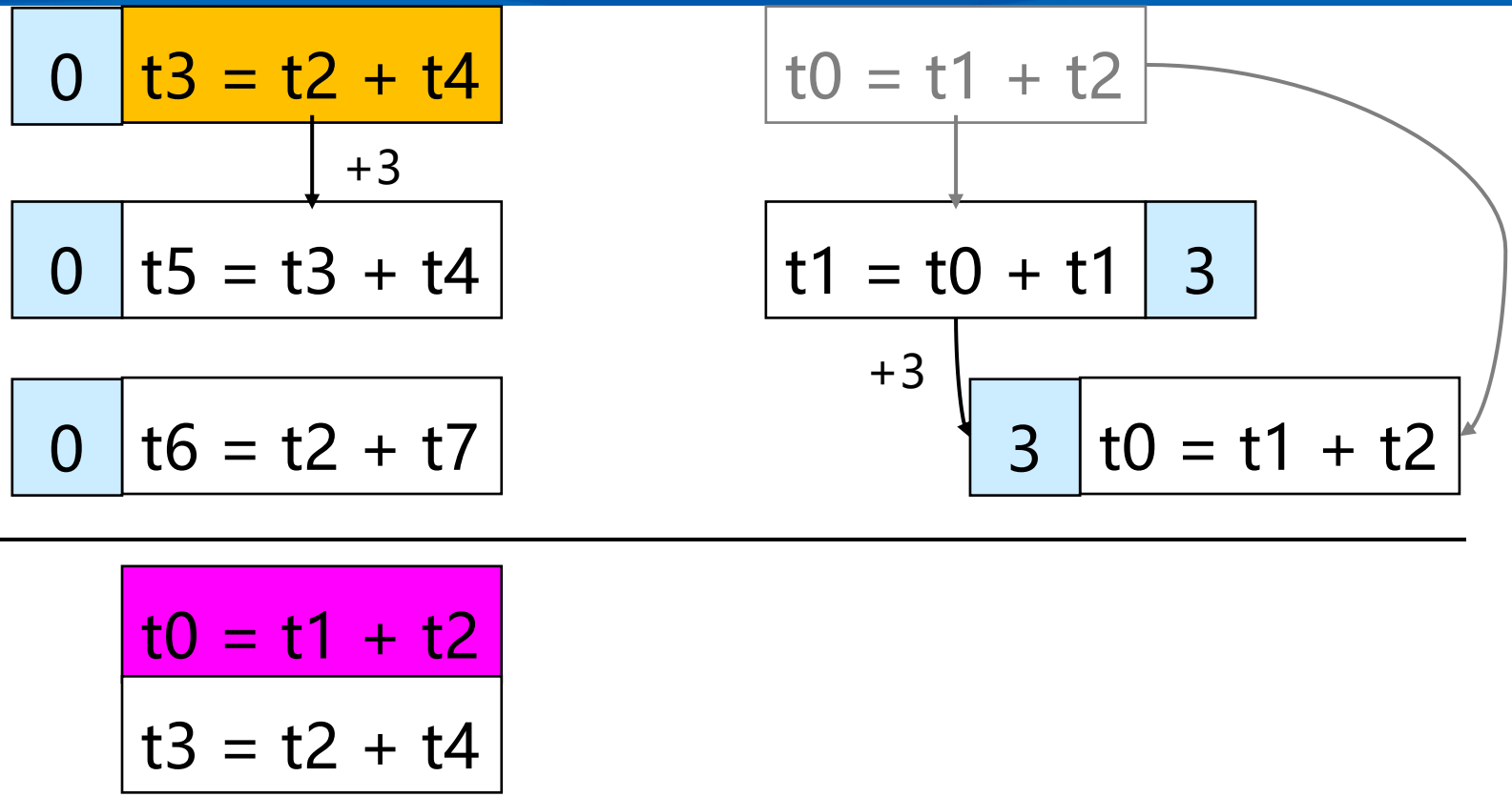
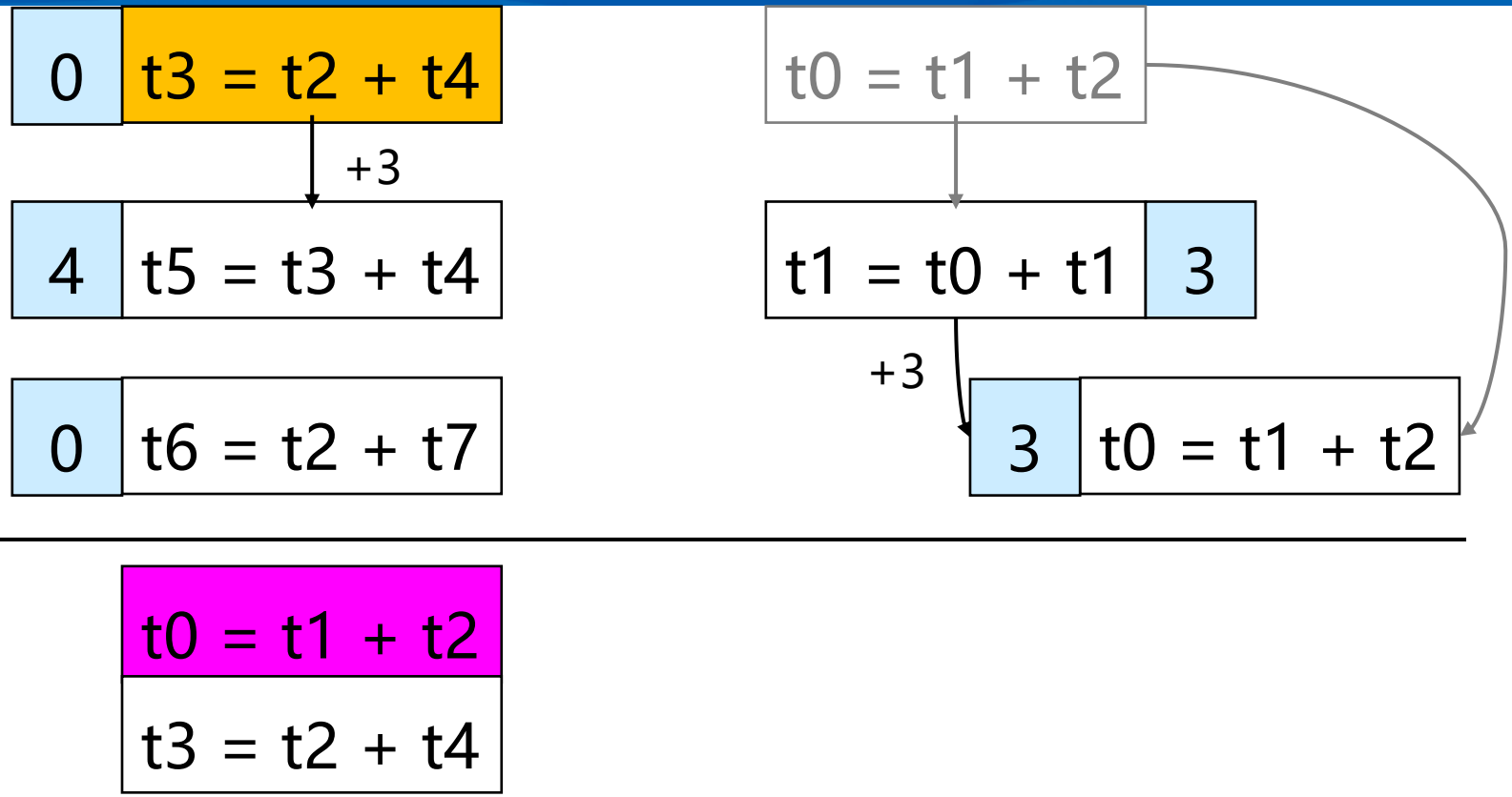


ID	RR	ALU	RW

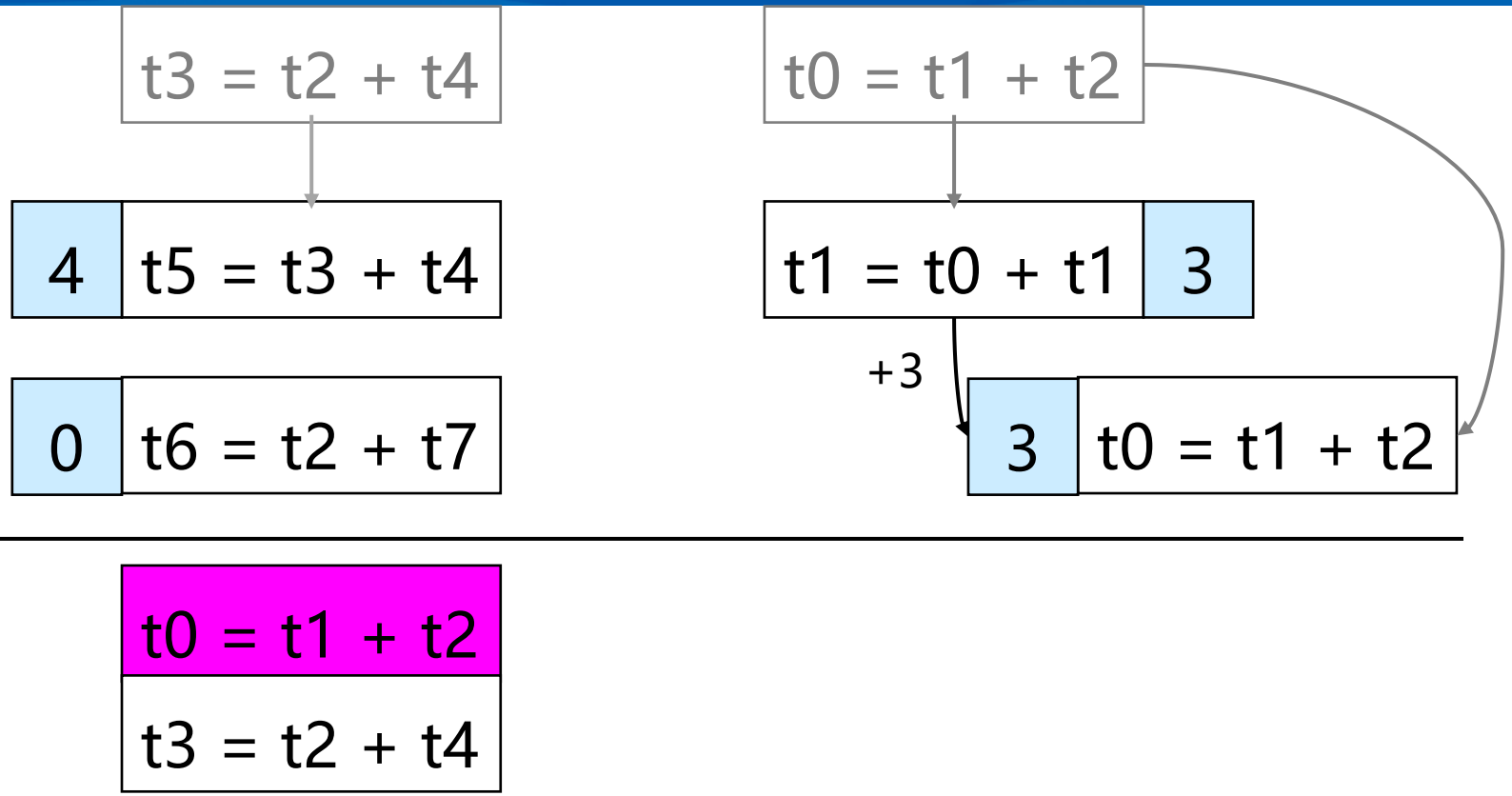
升级版的指令调度



t0 = t1 + t2
t3 = t2 + t4

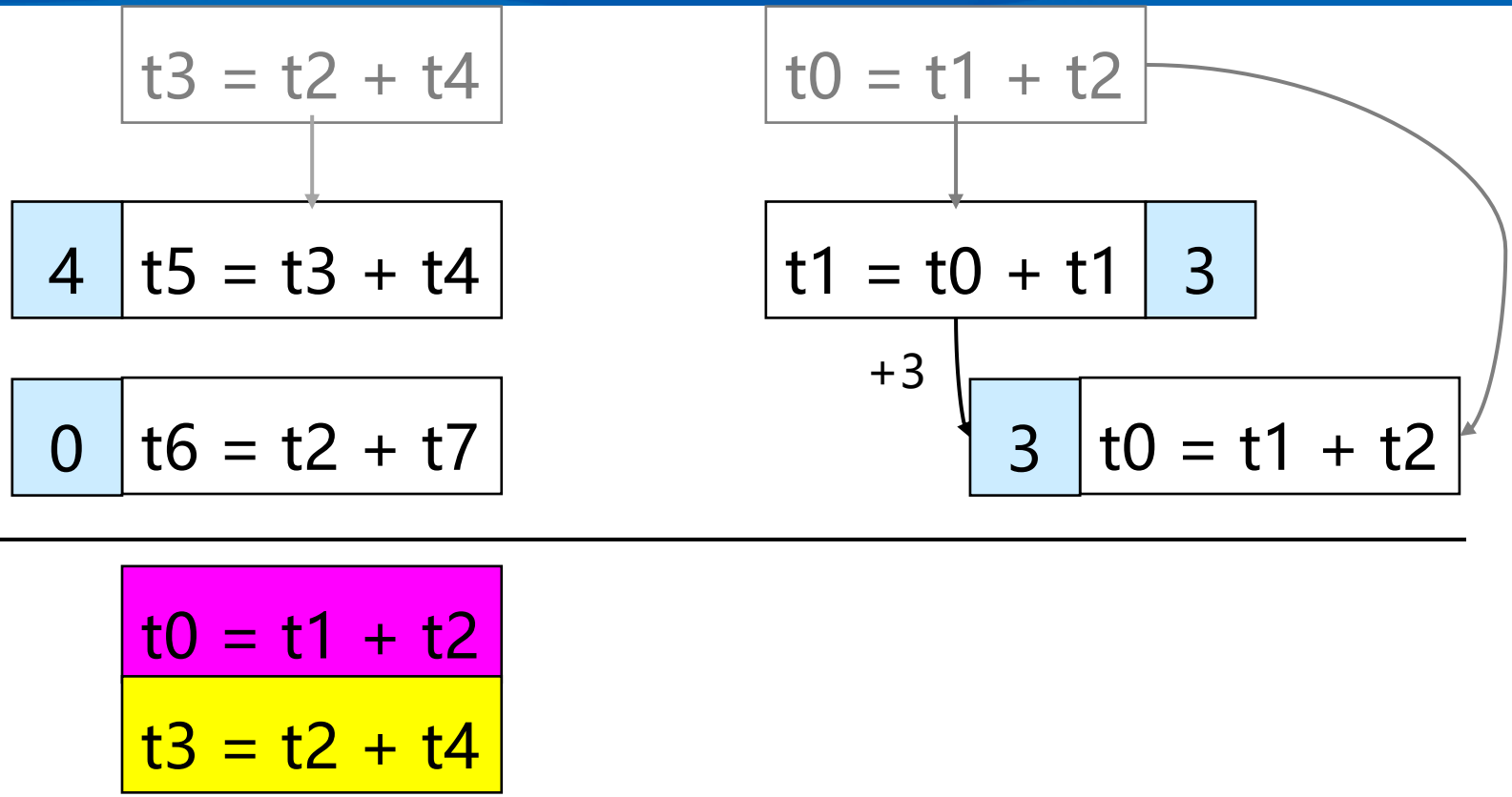
ID	RR	ALU	RW

升级版的指令调度



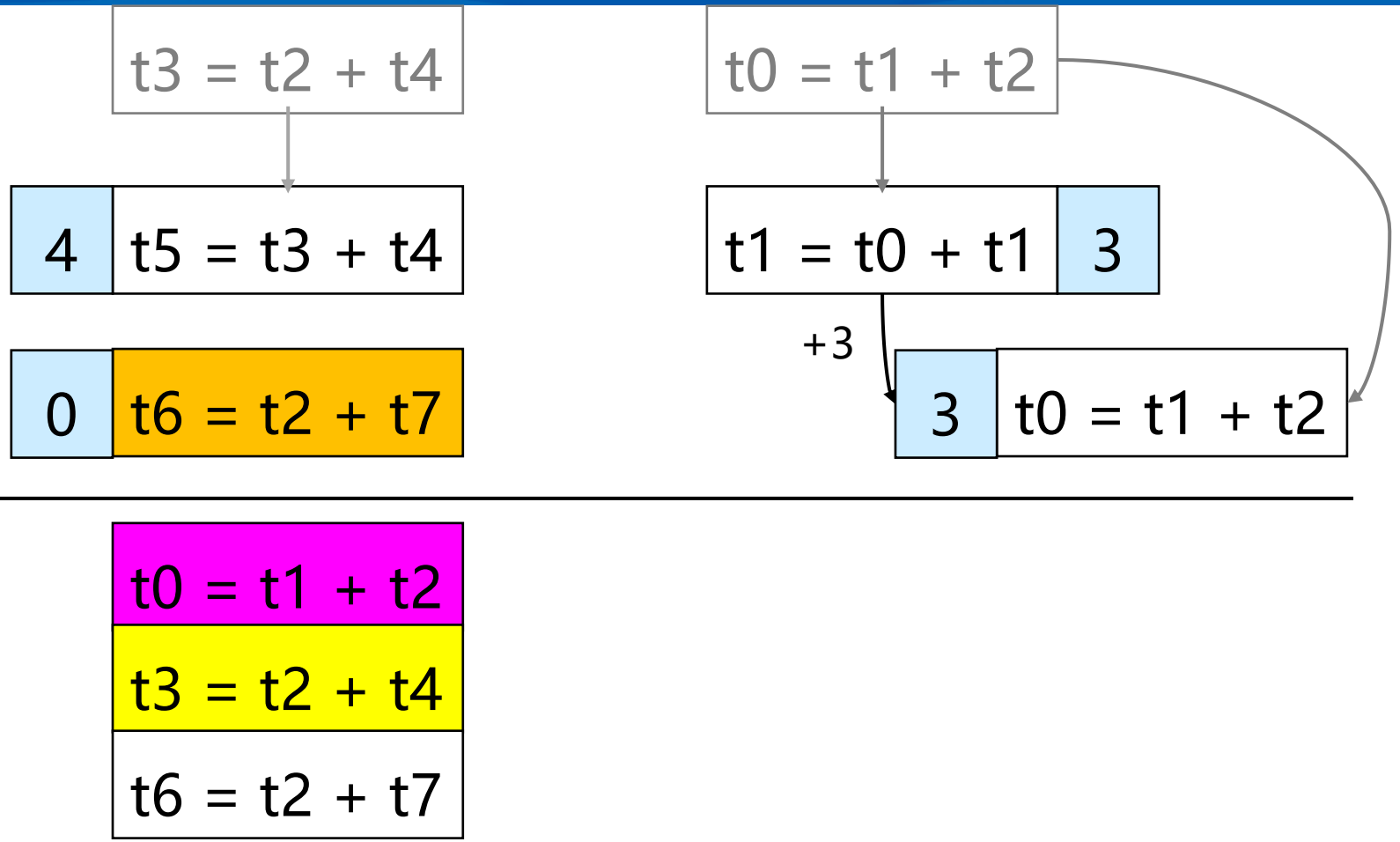
ID	RR	ALU	RW

升级版的指令调度



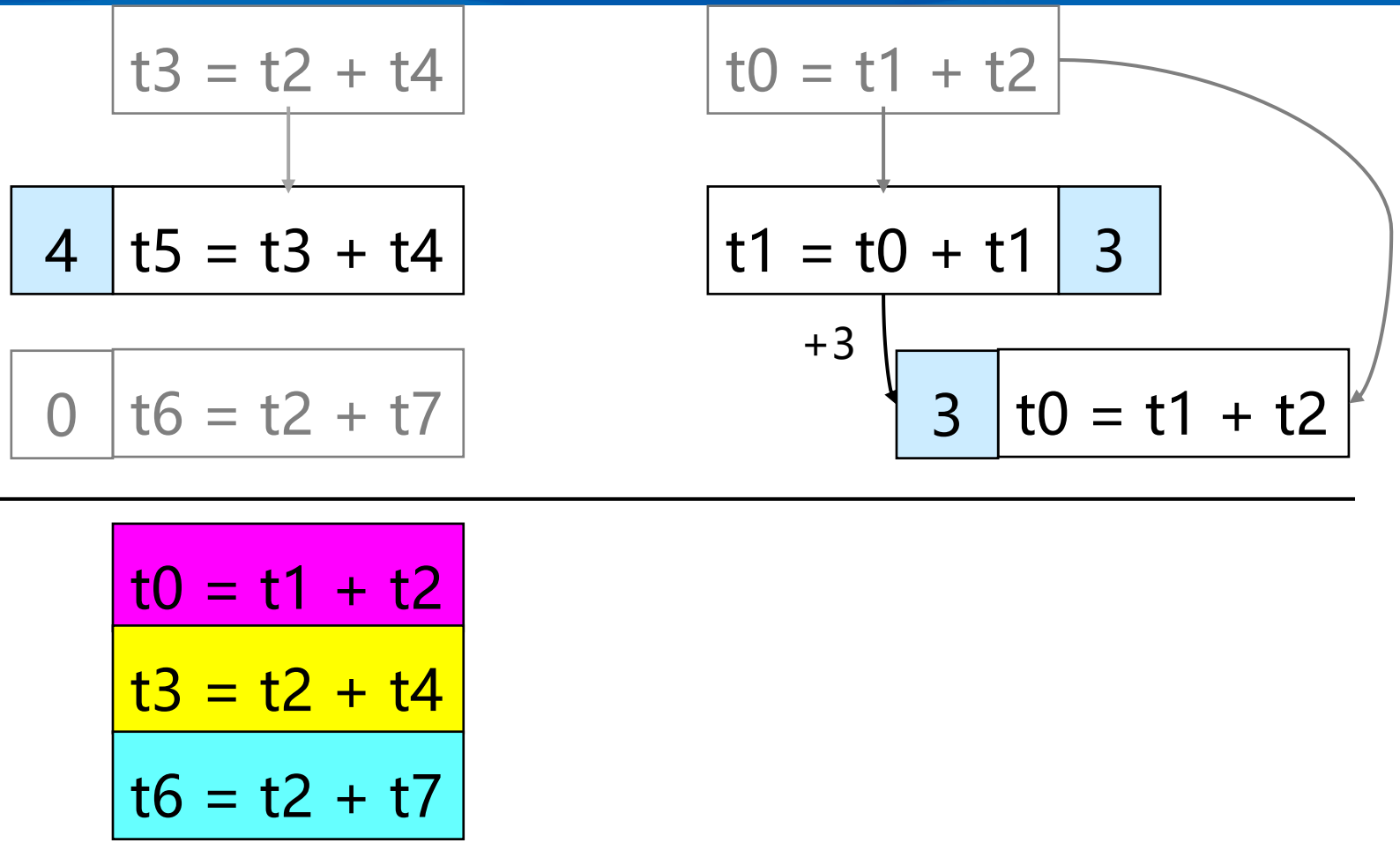
ID	RR	ALU	RW

升级版的指令调度



ID	RR	ALU	RW

升级版的指令调度



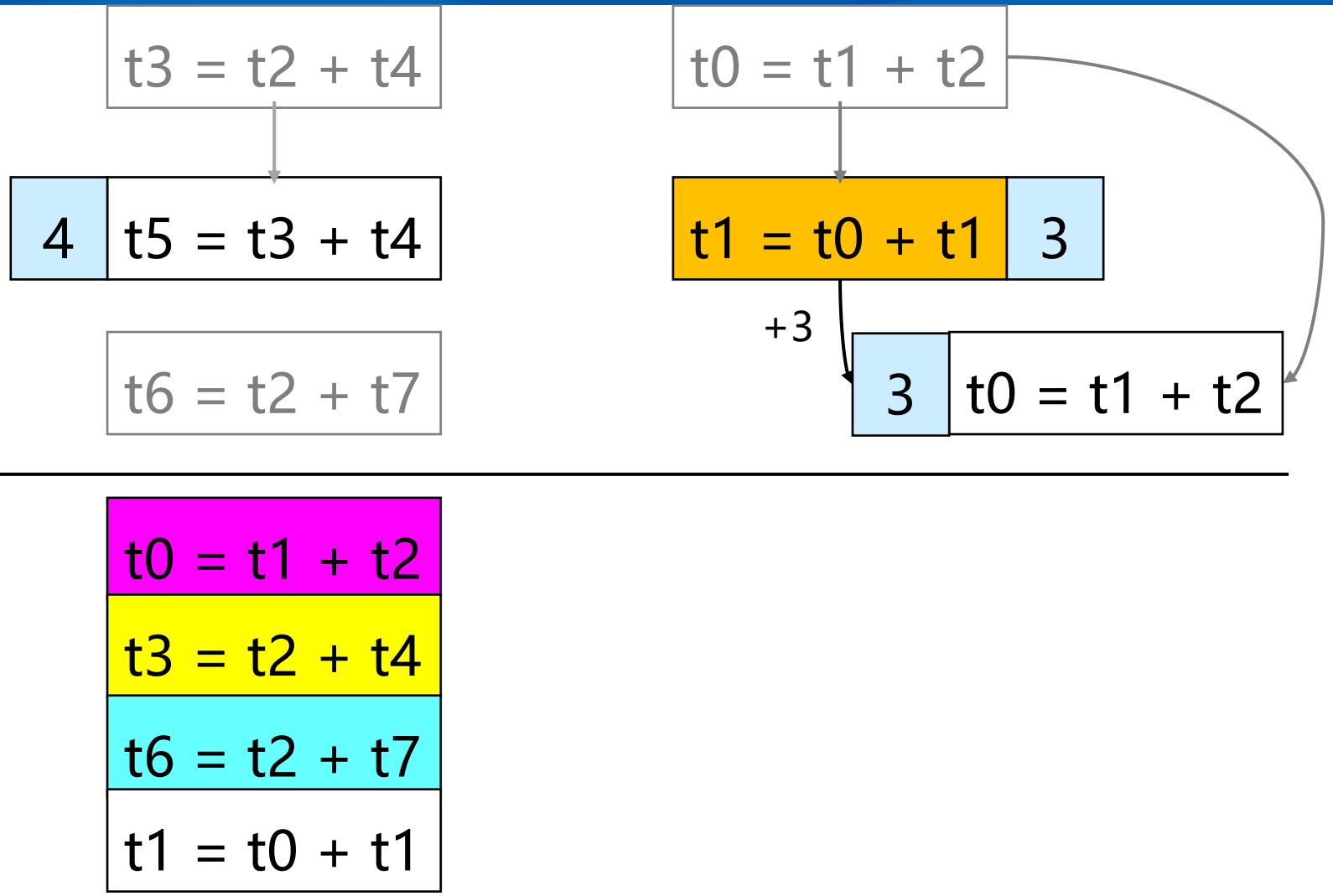
t0 = t1 + t2

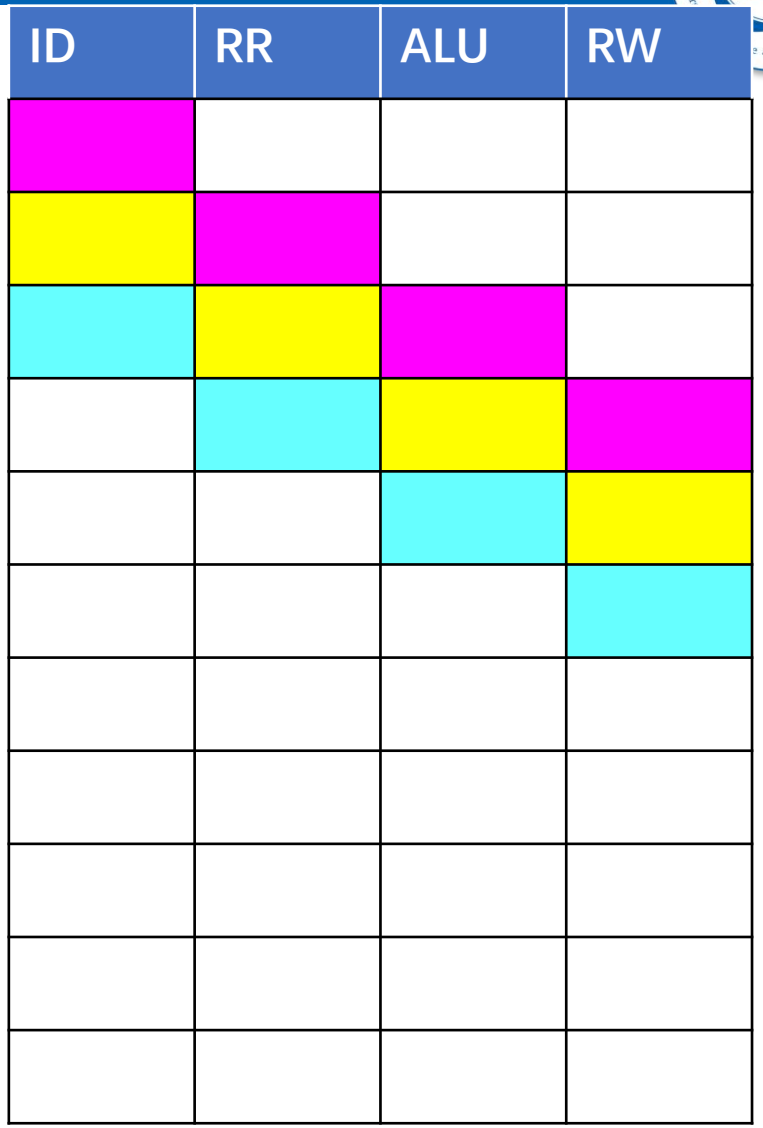
t3 = t2 + t4

t6 = t2 + t7

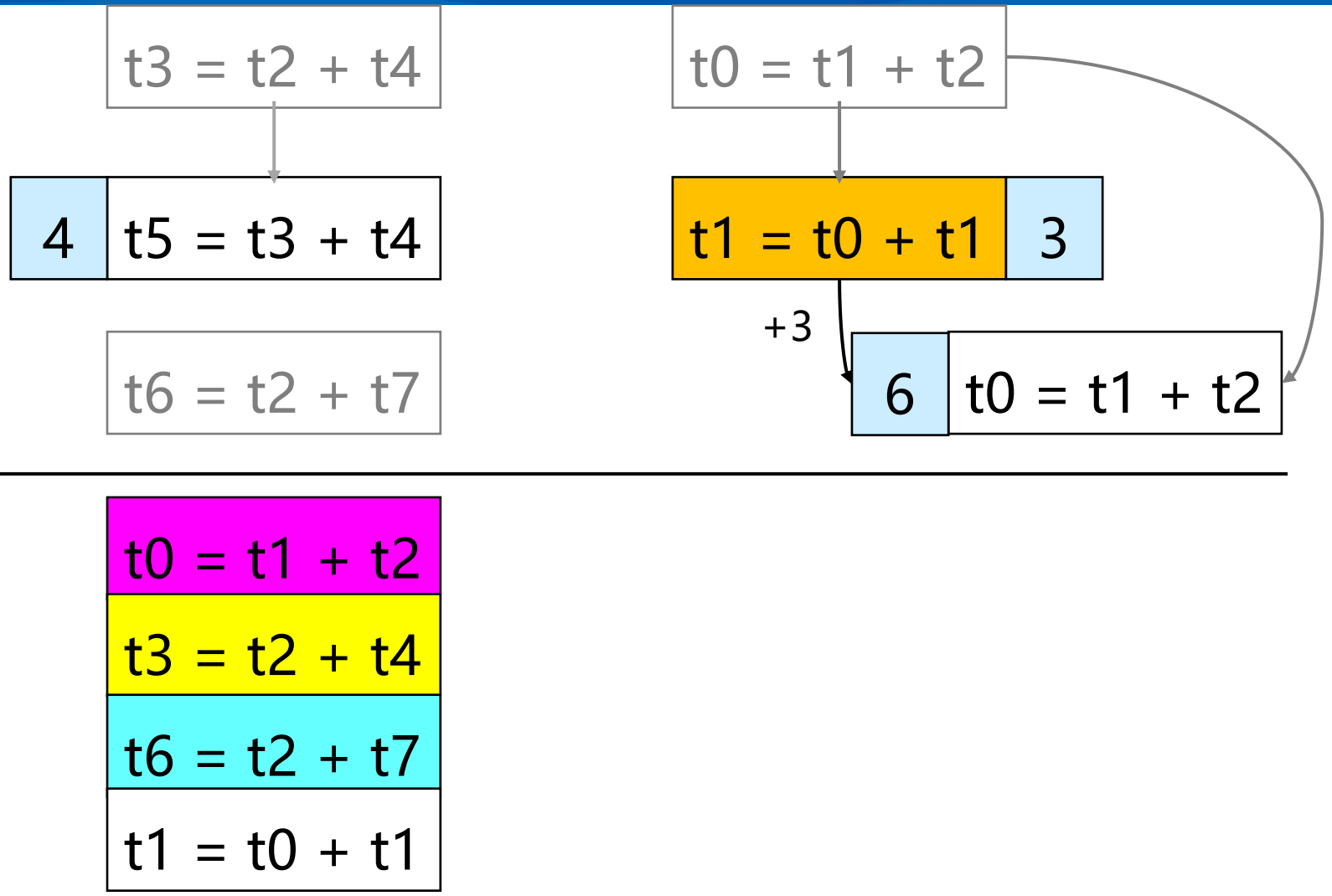
ID	RR	ALU	RW

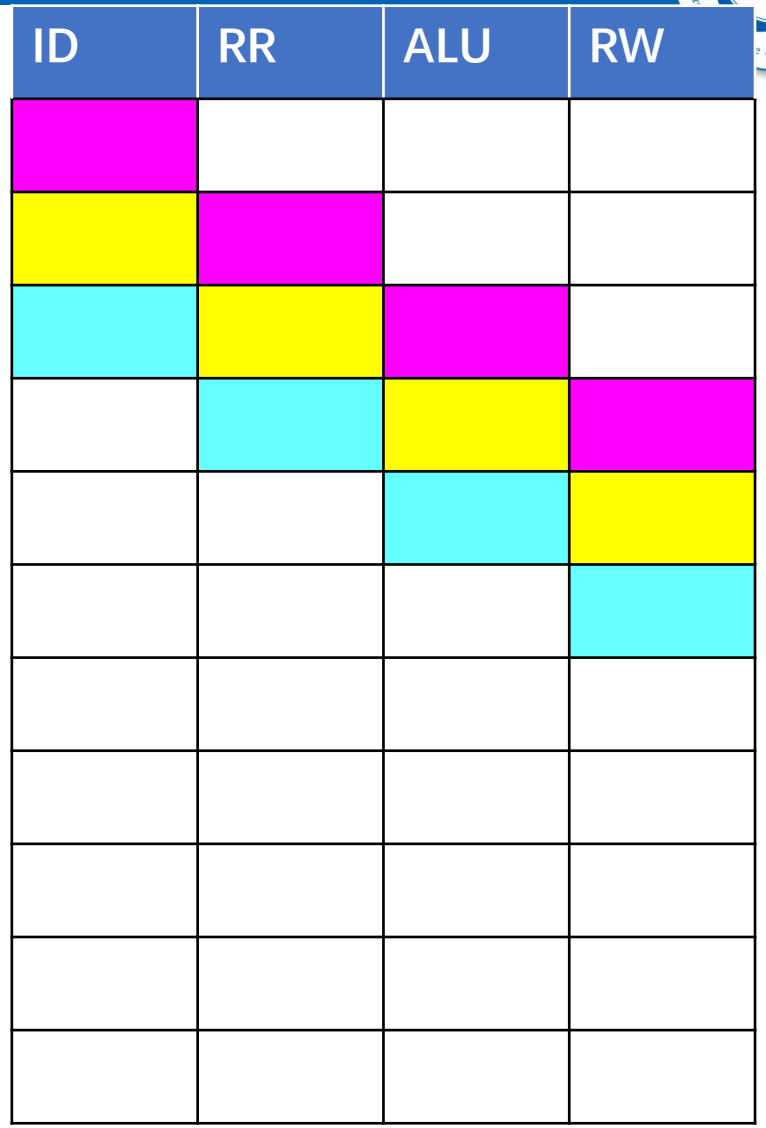
升级版的指令调度


t3 = t2 + t4
t0 = t1 + t2
4
t5 = t3 + t4
t1 = t0 + t1
3
+3
t6 = t2 + t7
3
t0 = t1 + t2
t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1


ID
RR
ALU
RW

升级版的指令调度


t3 = t2 + t4
t0 = t1 + t2
4
t5 = t3 + t4
t1 = t0 + t1
3
+3
t6 = t2 + t7
6
t0 = t1 + t2
t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1


ID
RR
ALU
RW

升级版的指令调度

t3 = t2 + t4

t0 = t1 + t2

4 | t5 = t3 + t4

t1 = t0 + t1

t6 = t2 + t7

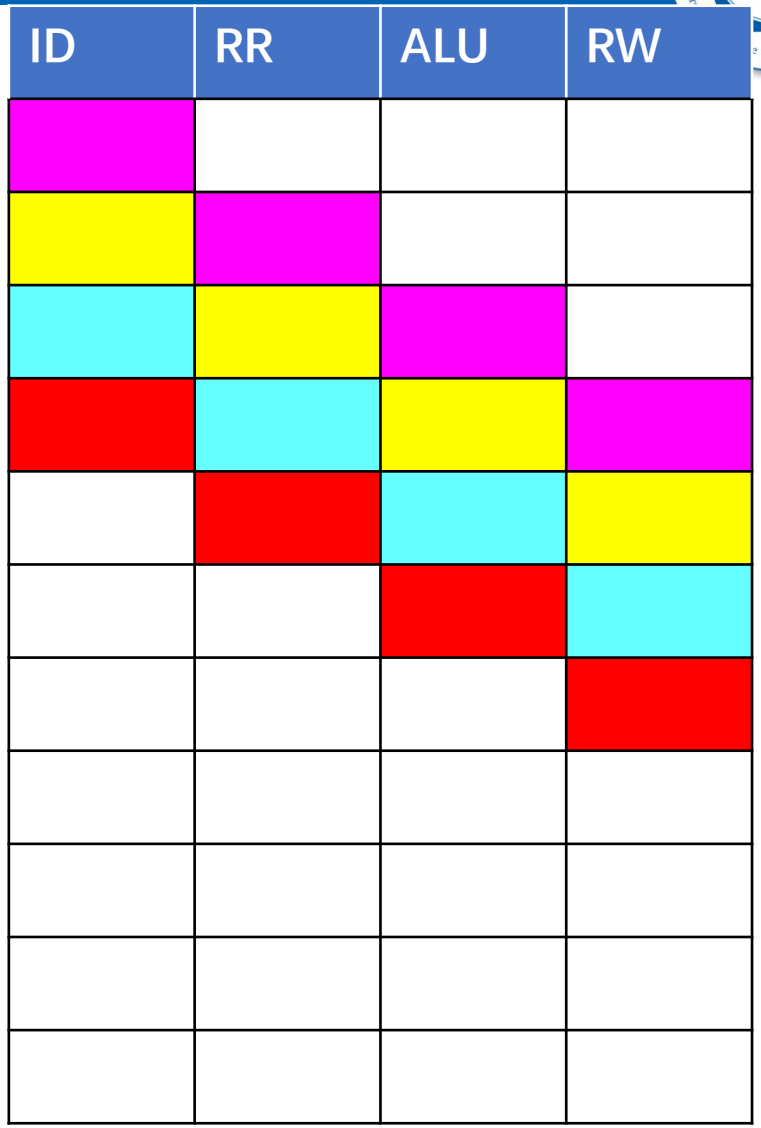
6 | t0 = t1 + t2

t0 = t1 + t2

t3 = t2 + t4

t6 = t2 + t7

t1 = t0 + t1



升级版的指令调度

t3 = t2 + t4

4 | t5 = t3 + t4

t6 = t2 + t7

t0 = t1 + t2

t1 = t0 + t1

6 | t0 = t1 + t2

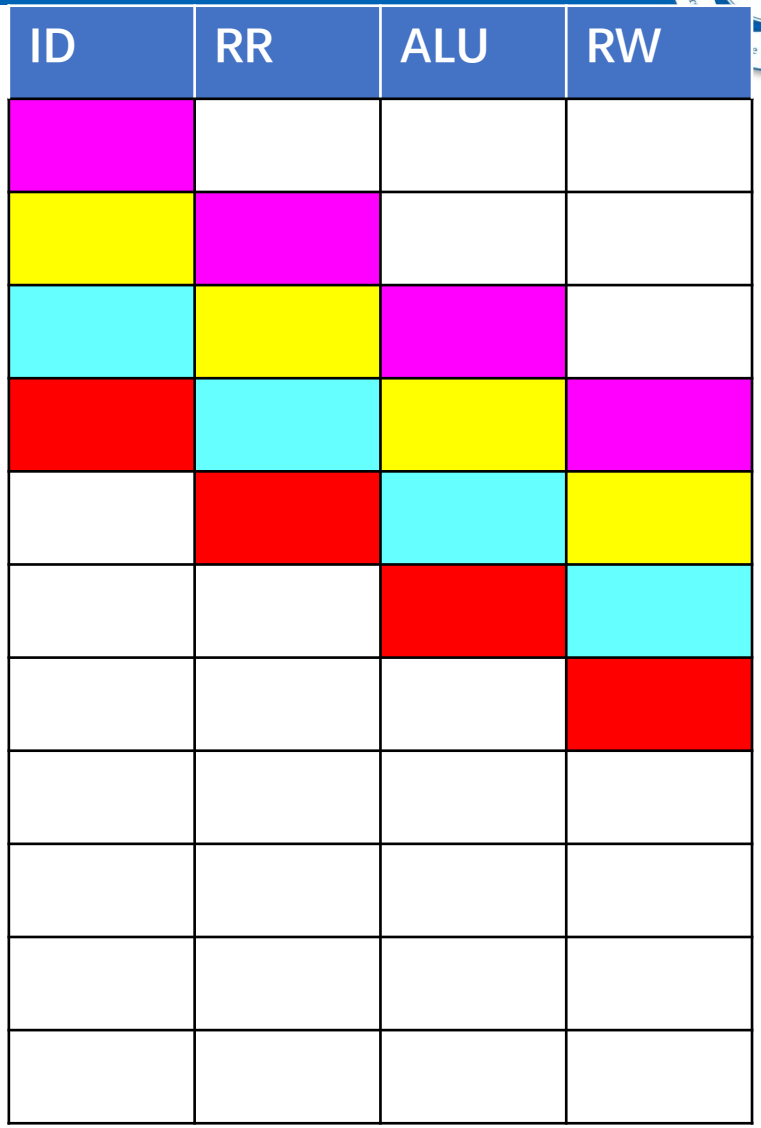
t0 = t1 + t2

t3 = t2 + t4

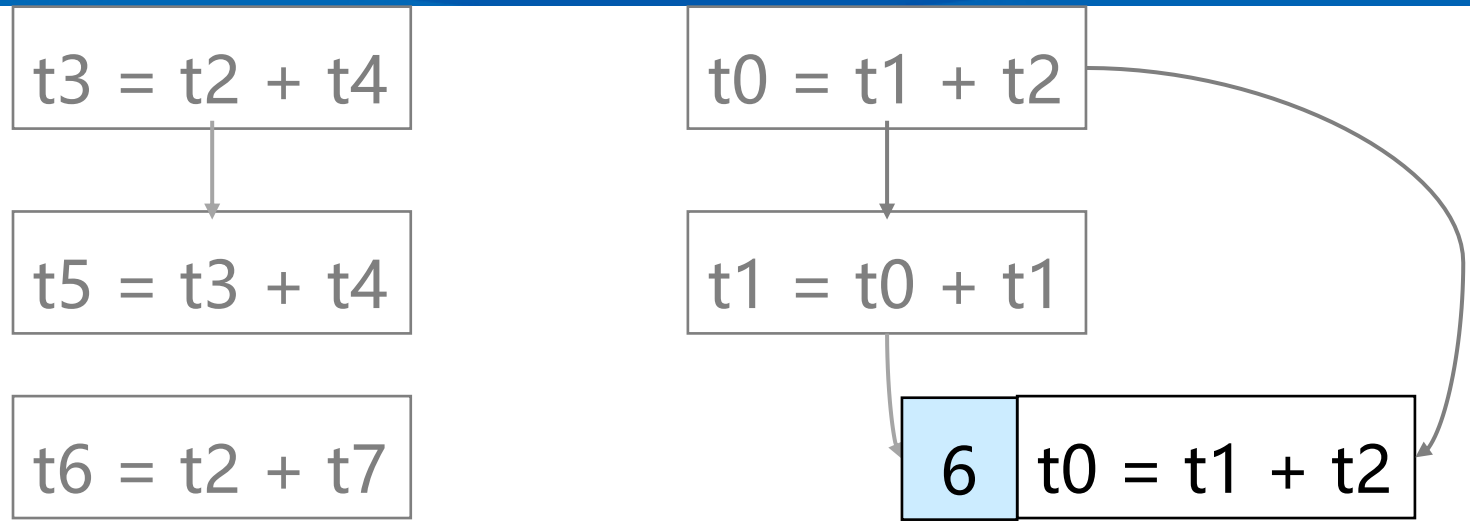
t6 = t2 + t7

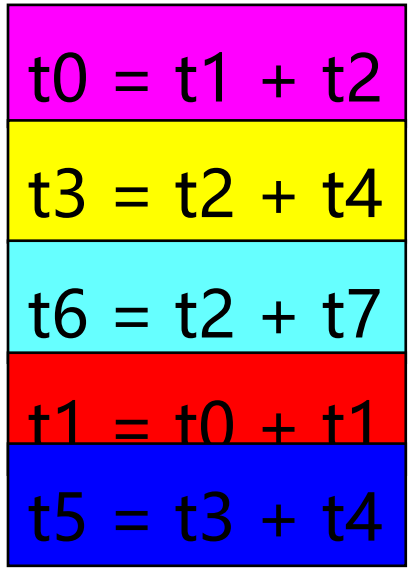
t1 = t0 + t1

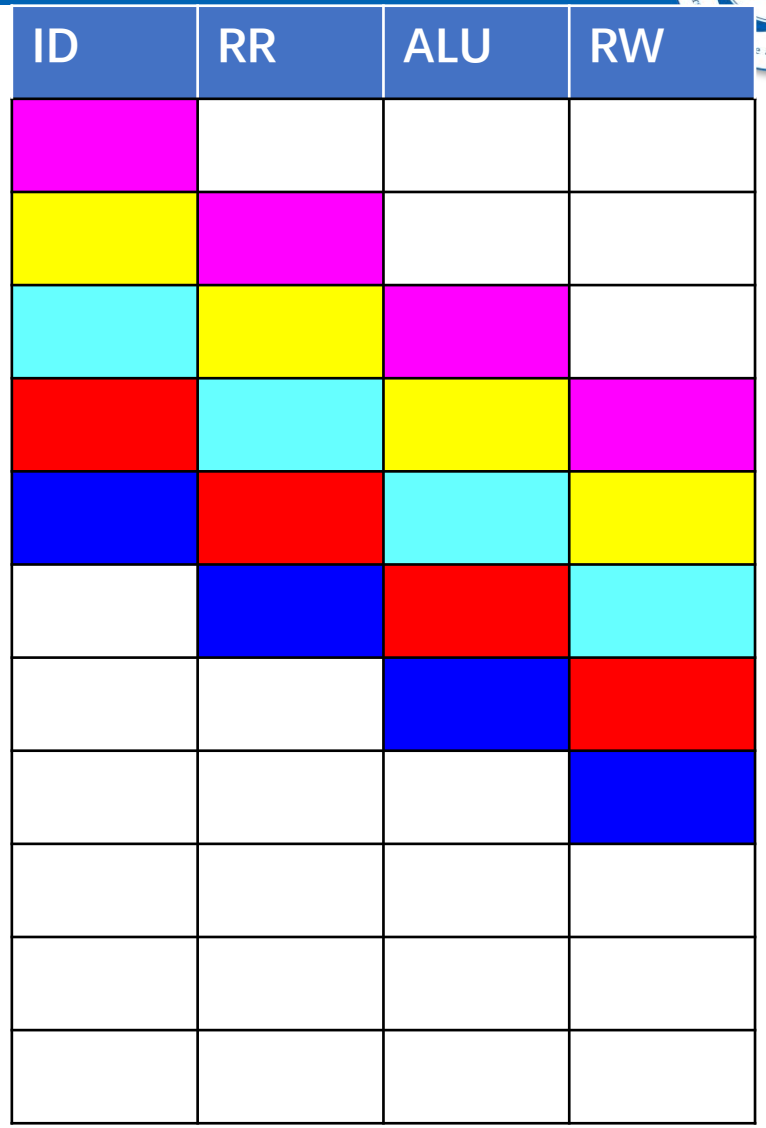
t5 = t3 + t4



升级版的指令调度


t3 = t2 + t4
t5 = t3 + t4
t6 = t2 + t7
t0 = t1 + t2
t1 = t0 + t1
6
t0 = t1 + t2


t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1
t5 = t3 + t4


ID
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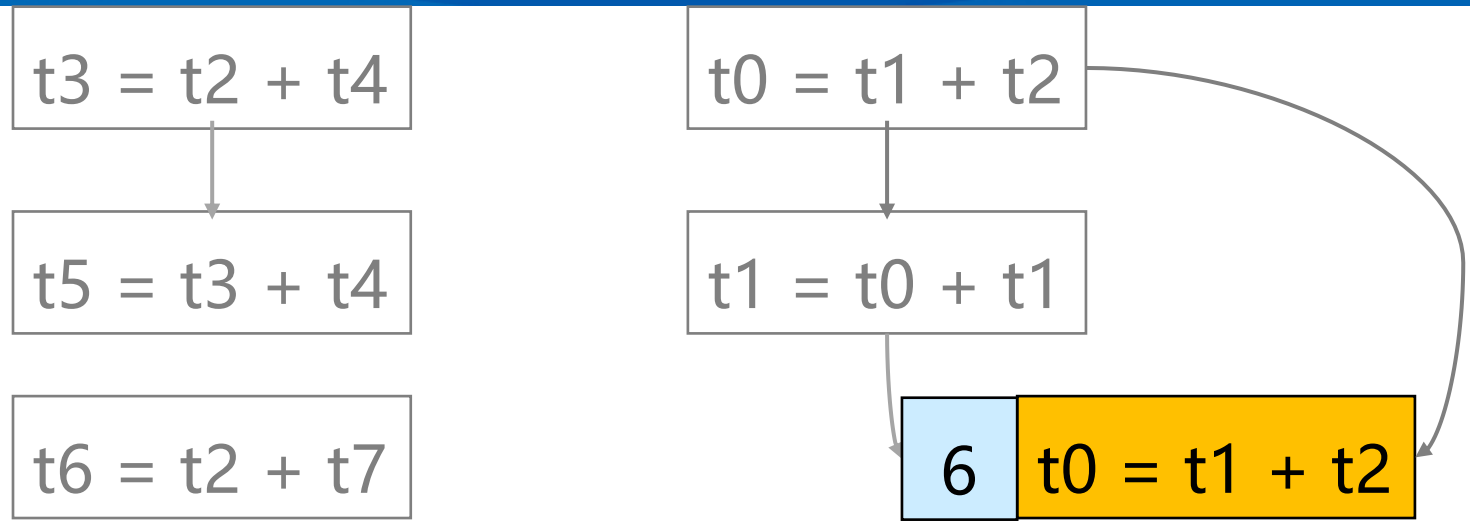
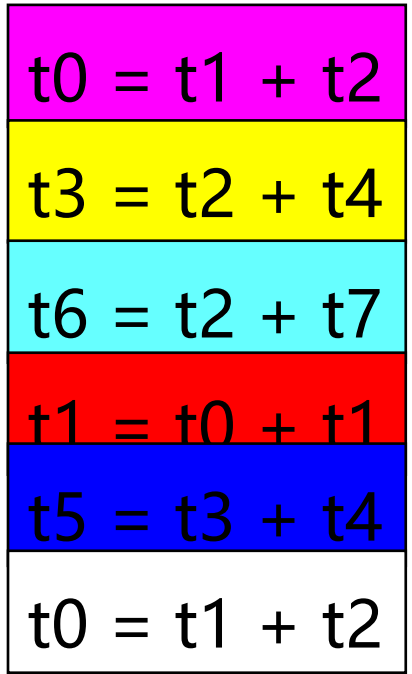
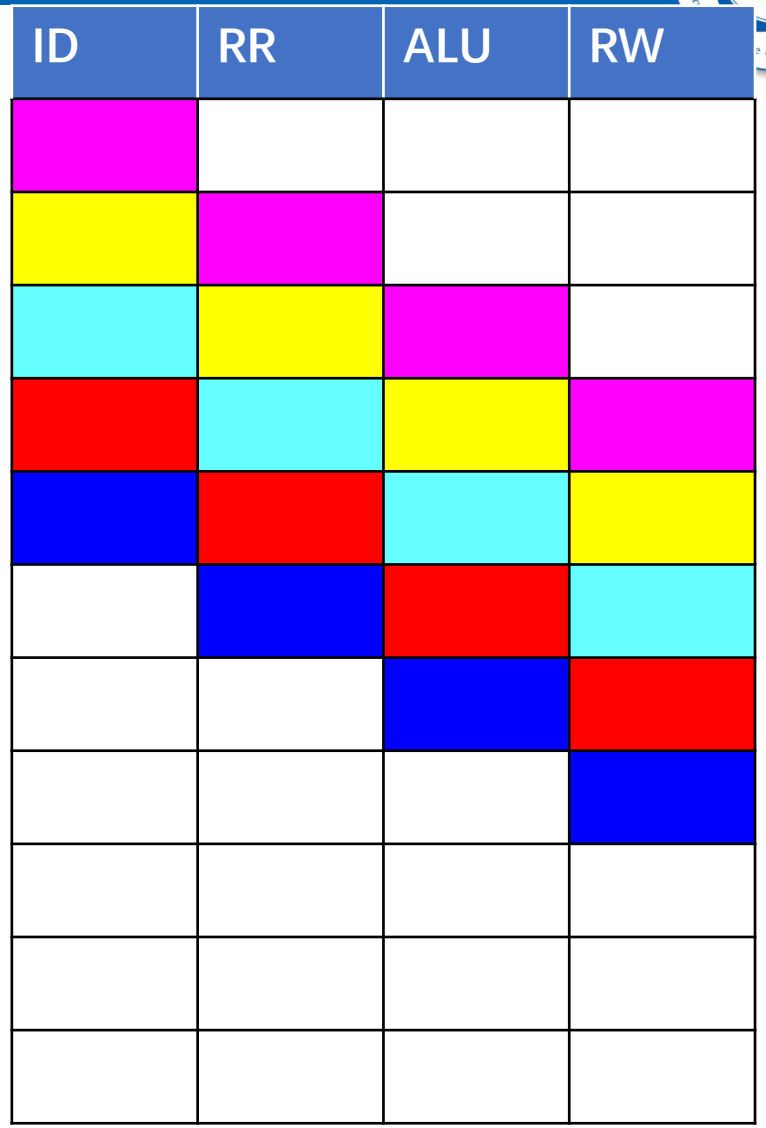
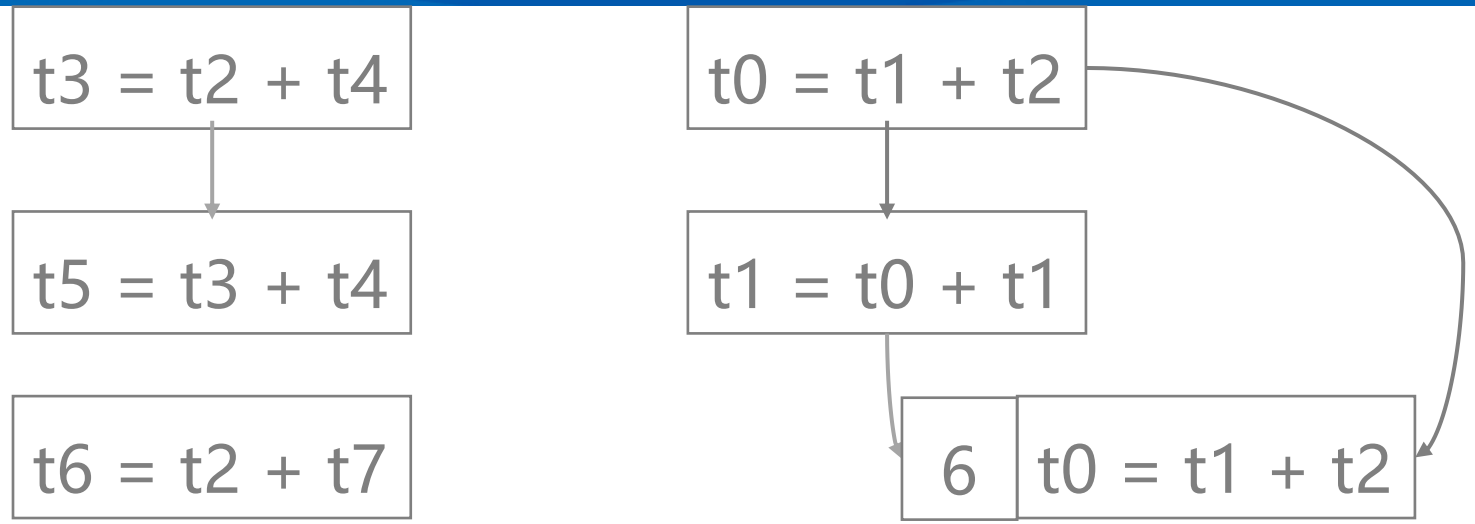
升级版的指令调度

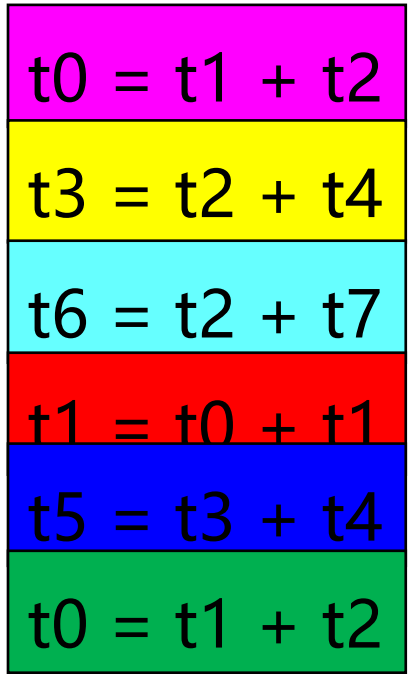

t3 = t2 + t4
t5 = t3 + t4
t6 = t2 + t7
t0 = t1 + t2
t1 = t0 + t1
6
t0 = t1 + t2

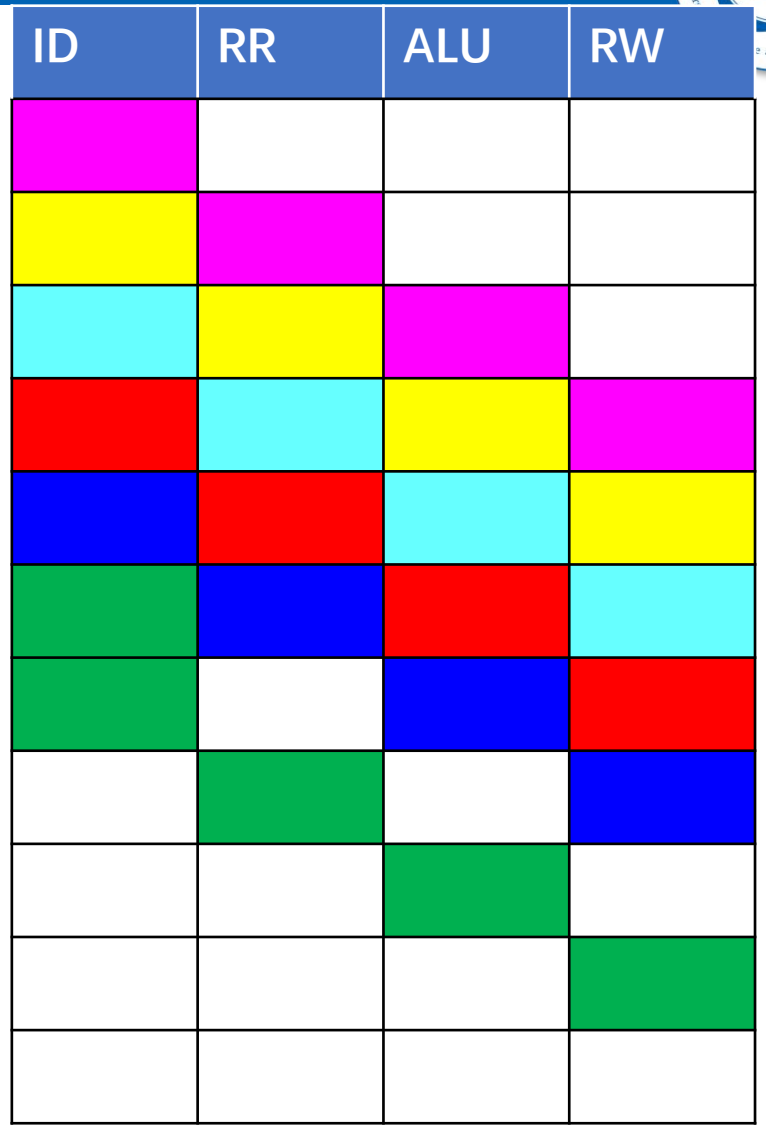

t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1
t5 = t3 + t4
t0 = t1 + t2


ID
RR
ALU
RW

升级版的指令调度


t3 = t2 + t4
t5 = t3 + t4
t6 = t2 + t7
t0 = t1 + t2
t1 = t0 + t1
6
t0 = t1 + t2


t0 = t1 + t2
t3 = t2 + t4
t6 = t2 + t7
t1 = t0 + t1
t5 = t3 + t4
t0 = t1 + t2


ID
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ALU
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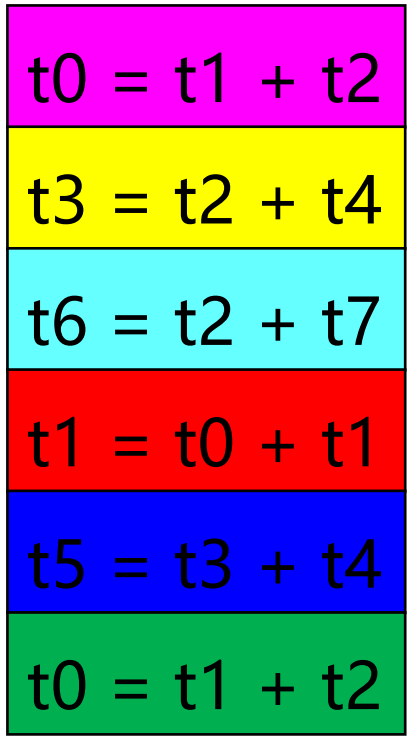
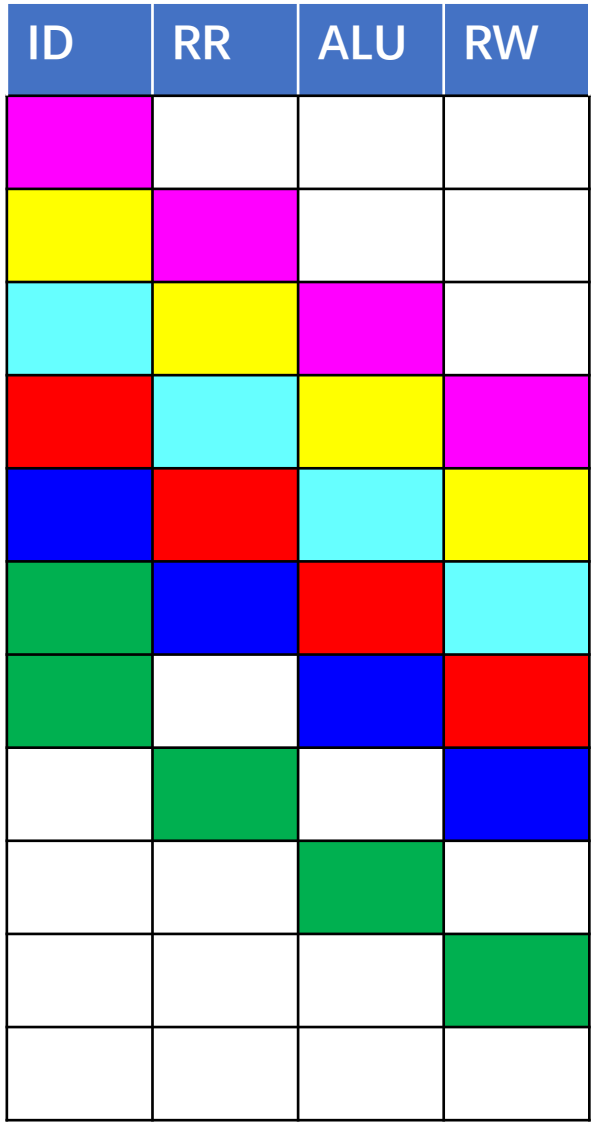
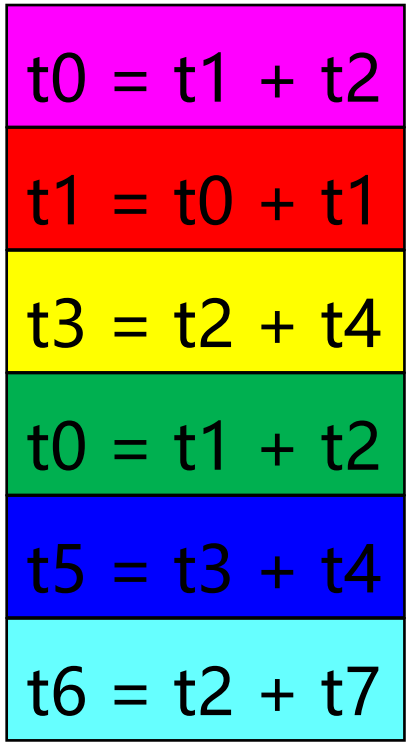
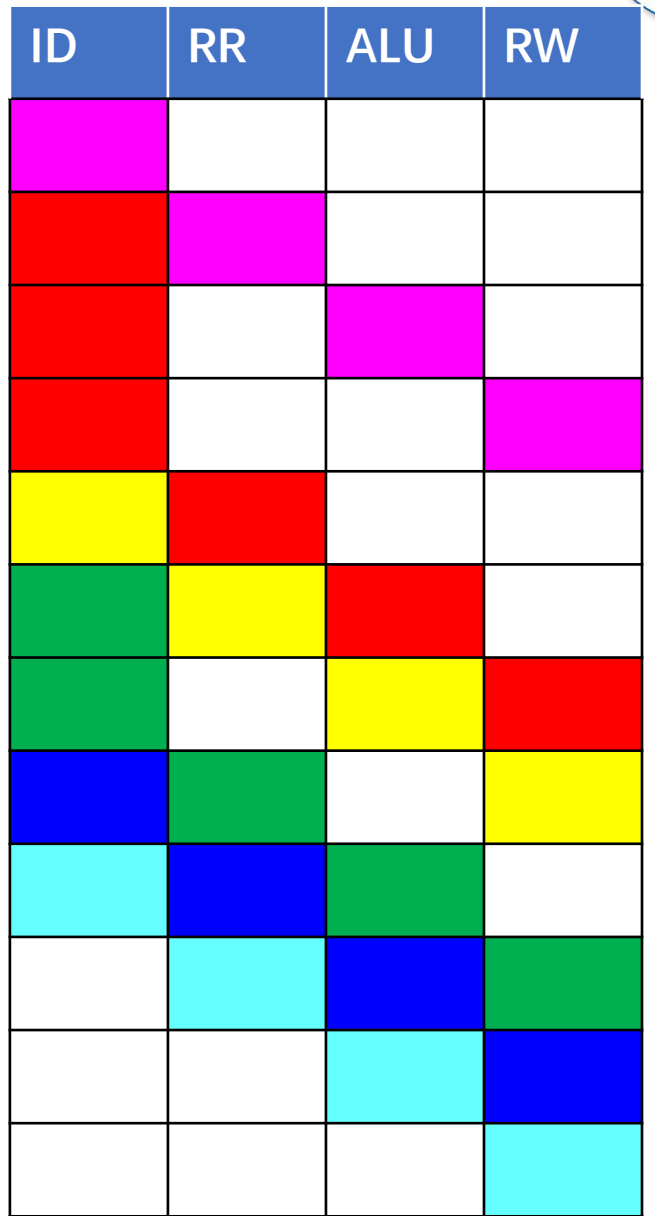
不同调度之间的性能差距









更多高级的调度

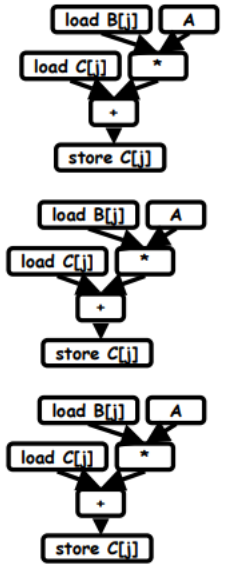
- 现代优化编译器可以进行更积极的调度，以获得巨大的性能提升。
- 一种强大的技术：循环展开(loop unrolling)
  - 一次展开多个循环迭代。
  - 使用前面介绍的调度算法更智能地调度指令。
  - 可以在循环迭代中找到流水线级并行性。

软件流水线(Software pipeline)

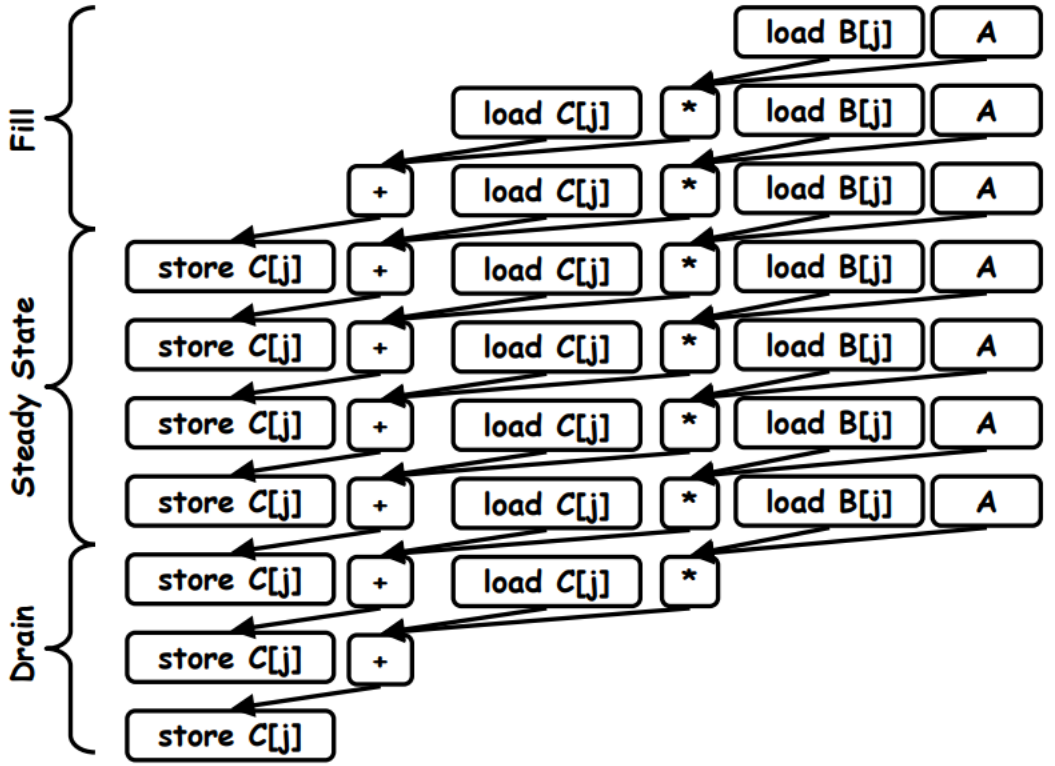
- 通过并行执行来自不同循环体的指令来加快循环程序的执行速度;
- 在前一个循环体未结束前启动下一个新的循环体，来达成循环体时间上的并行性;
- 相比于简单的展开循环,软件流水线在优化资源使用的同时保持代码的简洁。

```
for(j = 0; j < MAX; j++)
  C[j] += A * B[j];
```

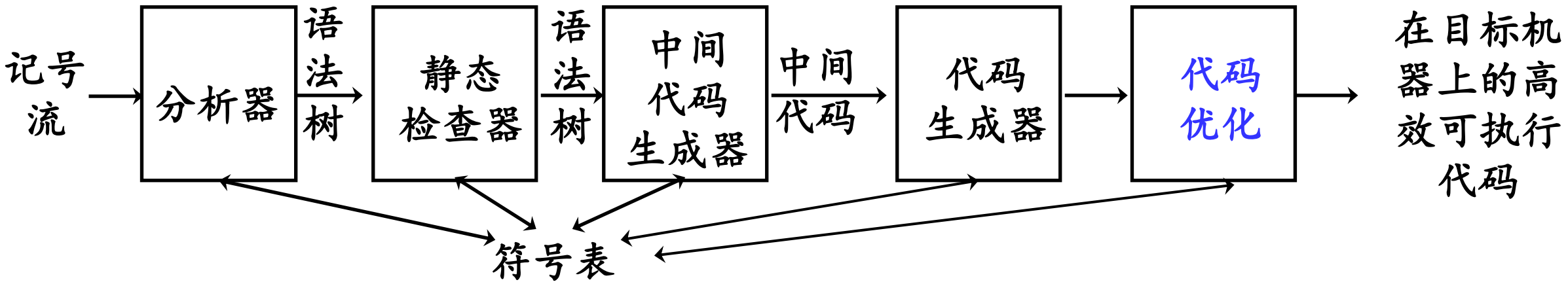
Not pipelined:



Pipelined:

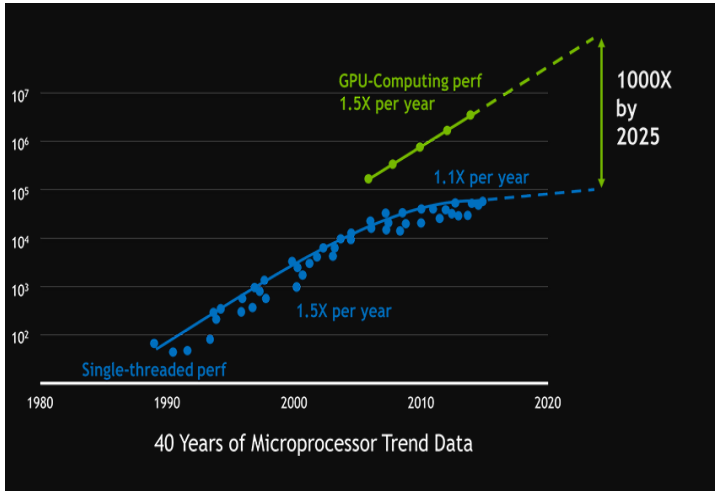


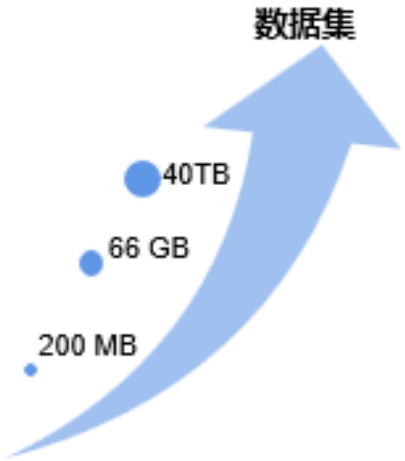
本节提纲

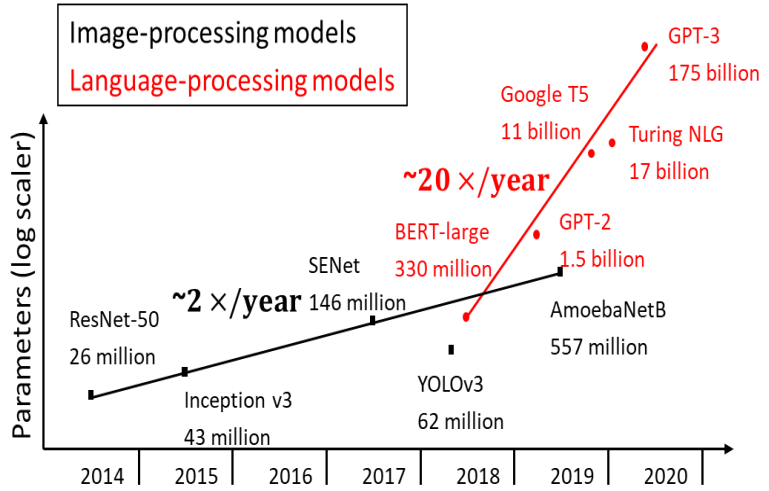


- 现代处理器架构
- 流水线并行的例子
- 指令调度与数据依赖分析
- 数据依赖指导下的指令调度
- **科技前沿——大模型的流水并行训练**

科技前沿——大模型并行训练







持续增长的算力

在后摩尔时代，GPU依然保持每年50%的算力增长幅度

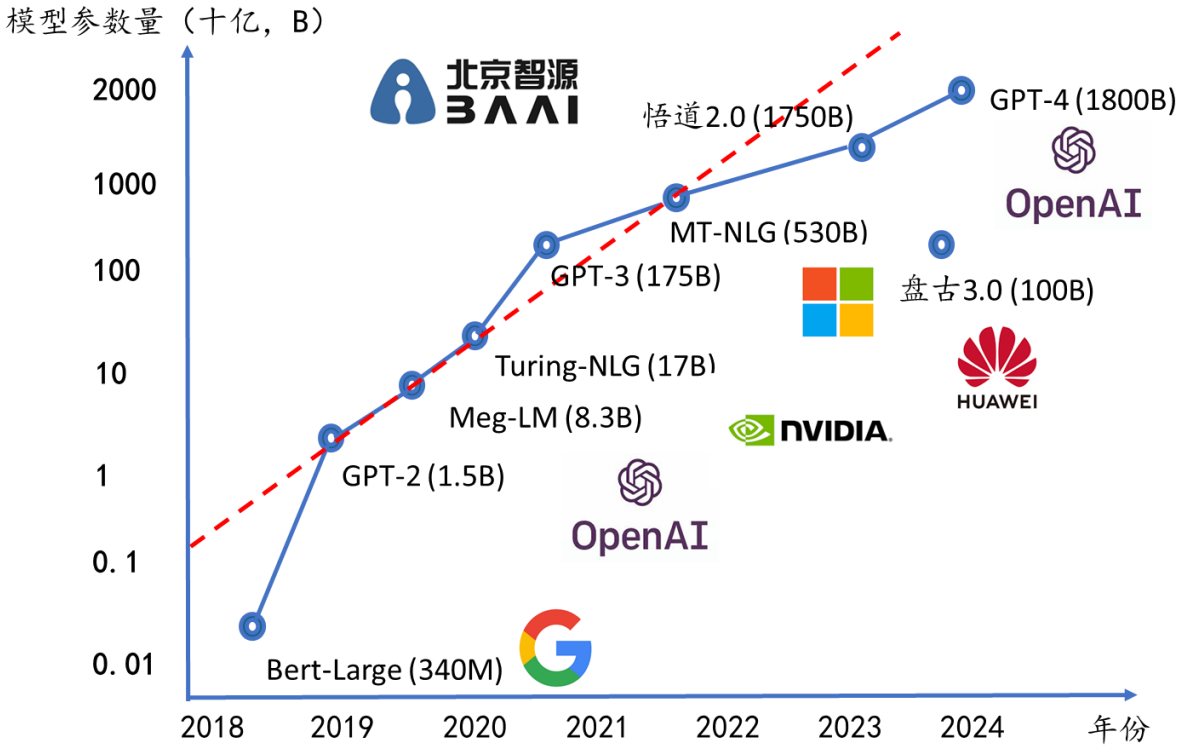
爆发式增长的数据

自然语言处理领域的训练数据集，从200MB增长到40TB

爆发式变大的模型

自然语言处理领域的模型，大小以每年20倍的速度增长

参数规模与任务复杂度的快速增长



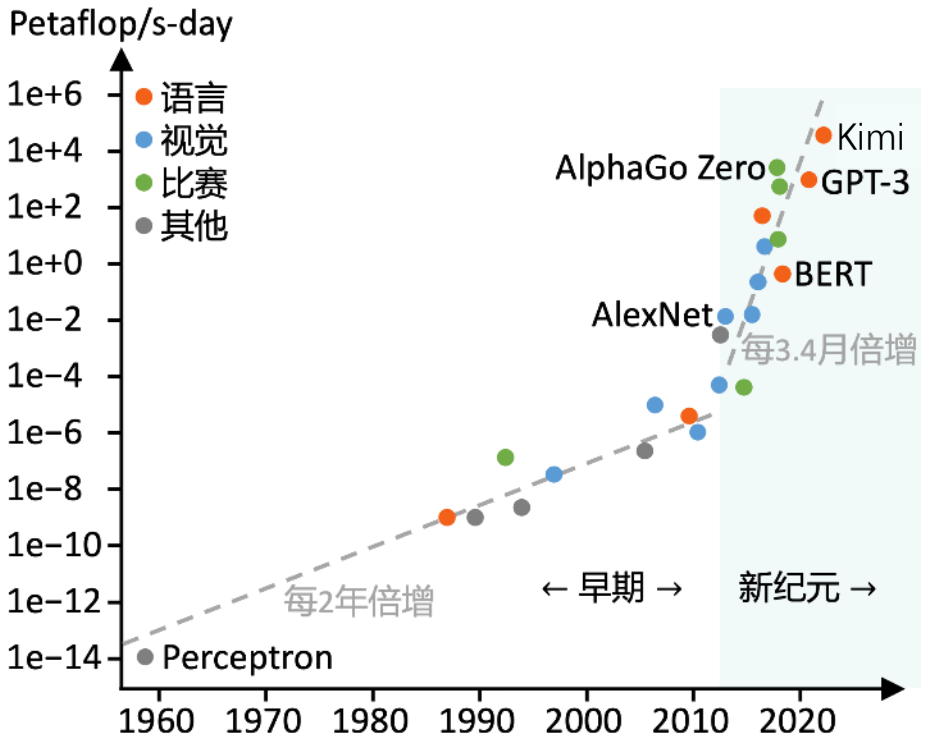
世界范围内千模涌起、竞争激烈
大模型体量已突破**万亿参数**

模型	上下文长度（token数）	约合汉字	发布时间
GPT-4.1	100万	70万	2025年4月
Gemini 1.5 Pro	200万	150万	2024年2月
Claude	20万	15万	2024年
DeepSeek	12.8万	12.8万	2025年
Kimi	200万	200万	2025年
通义千问	1000万	1000万	2025年

长上下文窗口增强模型推理能力
最新模型可一次性处理10部《红楼梦》的信息量

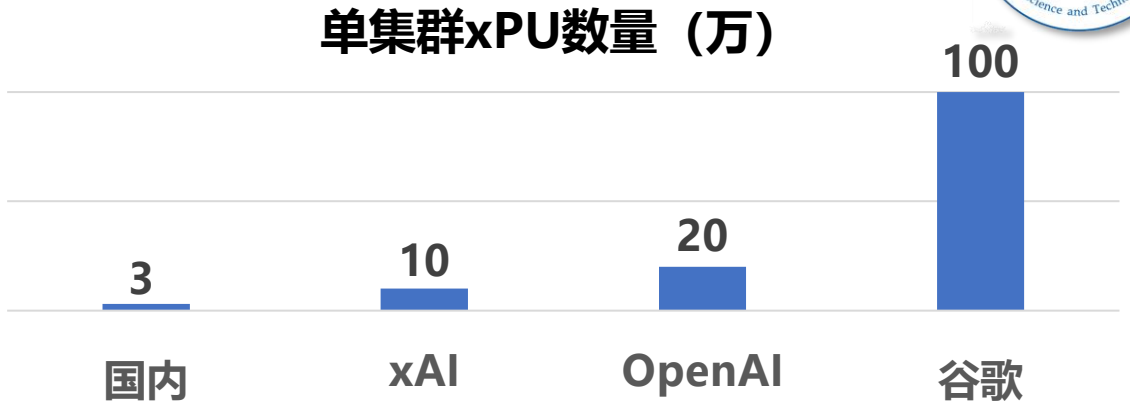
大模型功能的提升伴随着大模型参数和上下文长度的指数级增长

第三次AI浪潮催生智能算力需求爆发

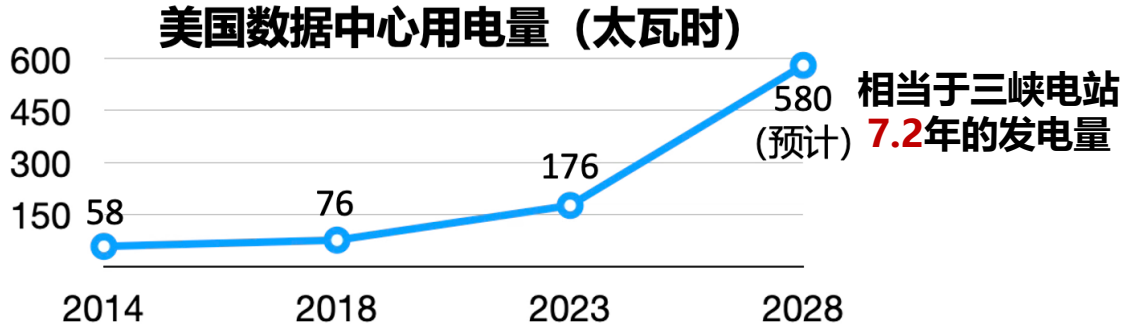


智能算力需求每3.4月翻一倍

增幅远超摩尔定律



全球范围内的AI基础设施军备竞赛

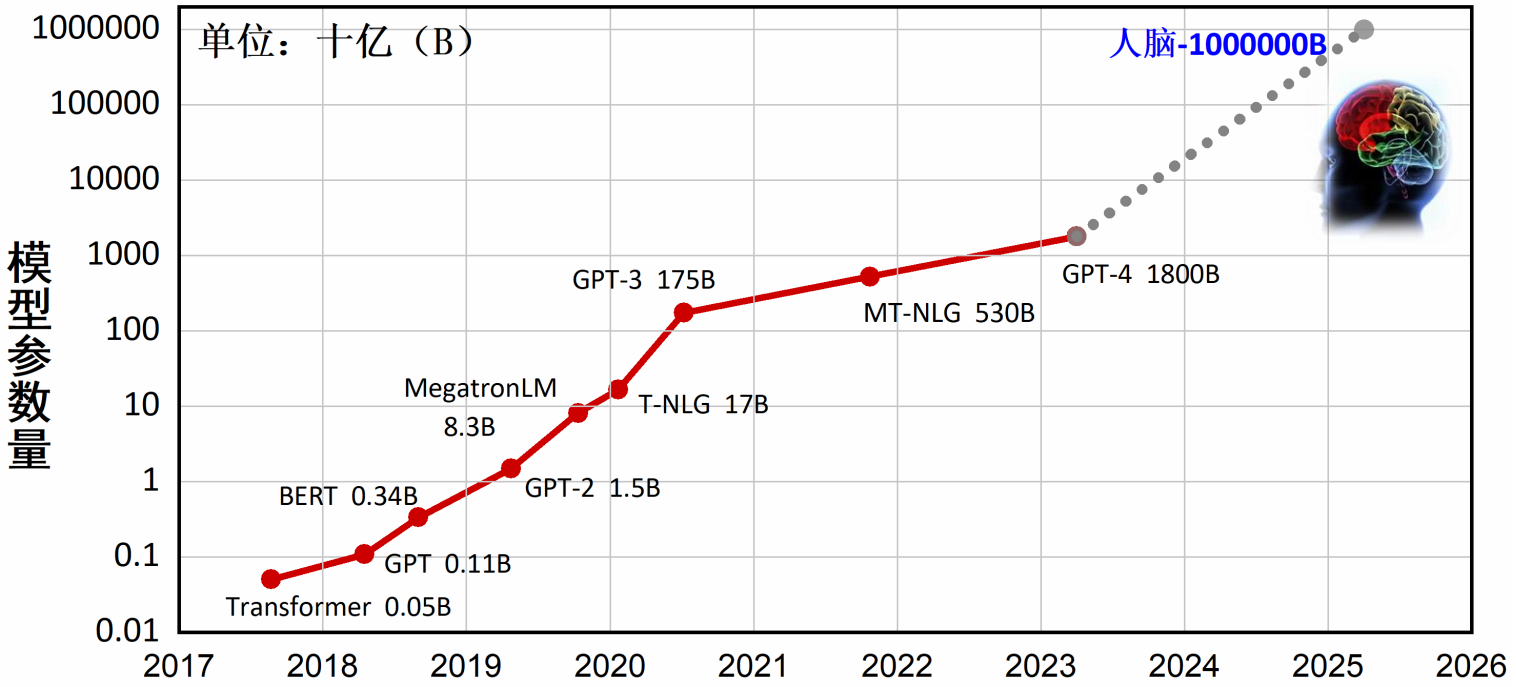


能源挑战：电力需求指数级攀升

大模型对智能算力需求爆炸式增长，算力已经成为发展AI大模型的制约

实现通用人工智能AGI的算力困境

- 人脑信息处理：千万亿（1000，000 B）突触（类比于参数）



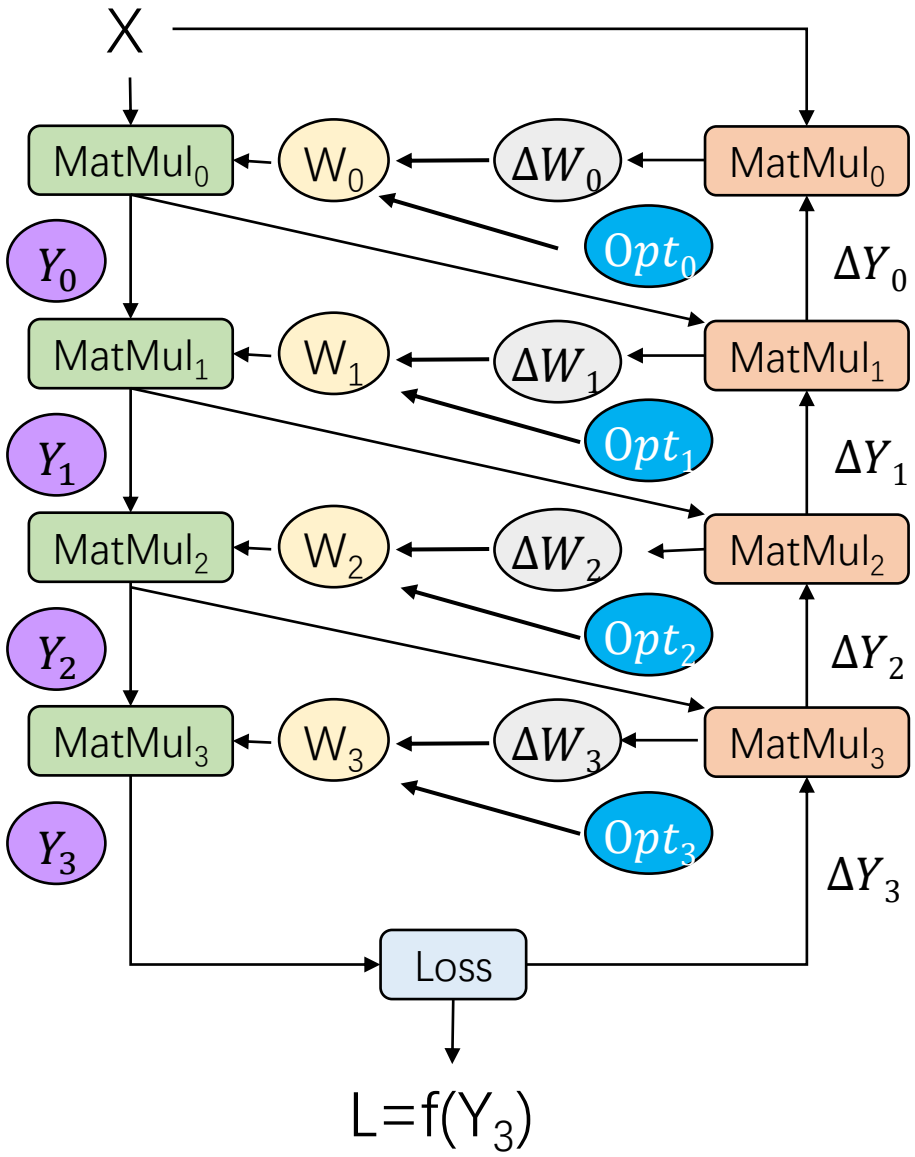
观点1：OpenAI认为，模型参数量与计算量增幅的最佳比值为1:2 [1]。

观点2：DeepMind认为，模型参数量与计算量增幅的最佳比值为1:3 [2]。

现有AI大模型的参数量与人脑的参数量还有三个数量级的差距
未来智能算力规模还要提升至少三个数量级

[1] Scaling laws for neural language models[J]. arXiv preprint arXiv:2001.08361, 2020.
[2] Training compute-optimal large language models[J]. arXiv preprint arXiv:2203.15556, 2022.

训练过程中“四大”内存占用



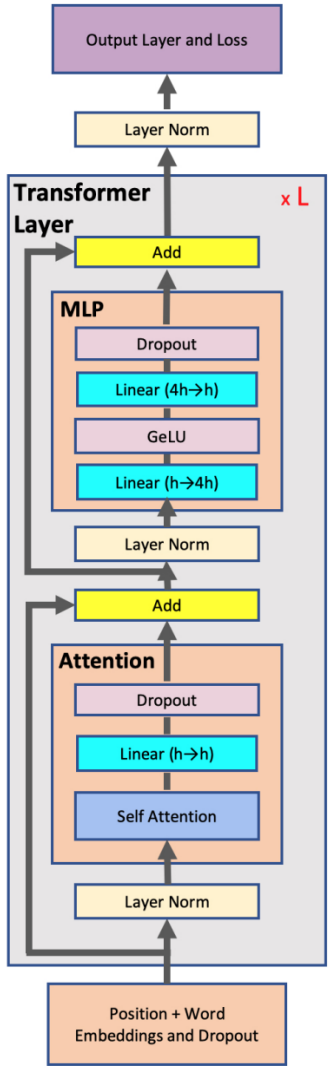
参数

梯度

中间数据

优化器状态

以GPT为例分析训练内存占用情况

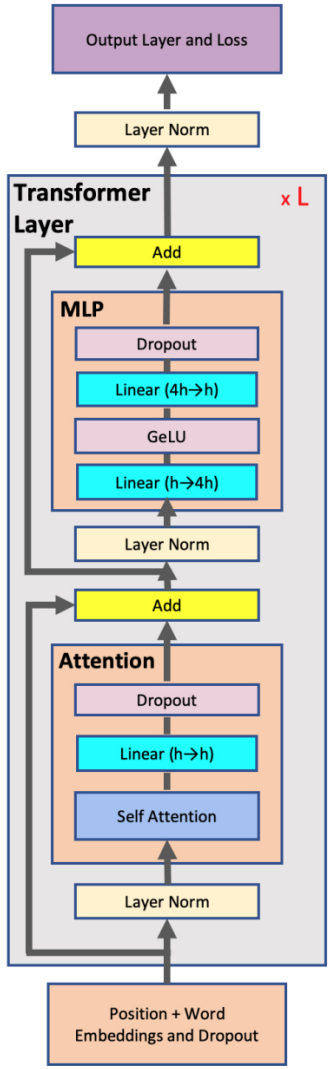


用于计算Loss的输出层

重复堆叠的Transformer层

→ Embedding层

以GPT为例分析训练内存占用情况



用于计算Loss的输出层

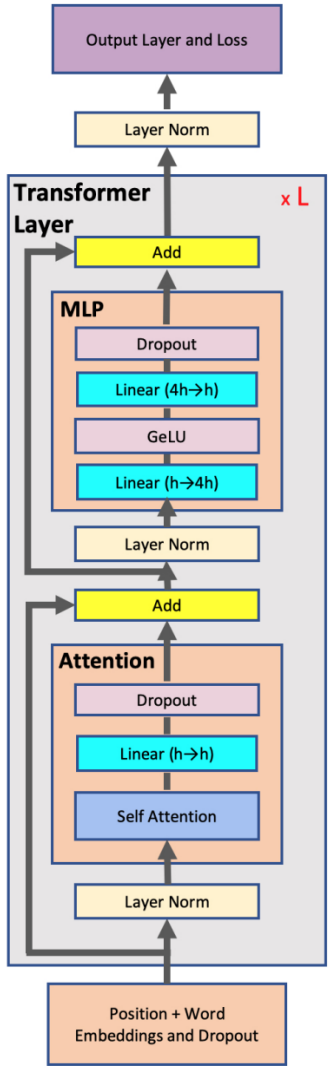
重复堆叠的Transformer层

→ Embedding层

训练1750亿参数的GPT-3的配置

参数	缩写	参考值
hidden size	h	12288
sequence length	s	2048
number of layers	L	96
number of attention heads	a	96
mini-batch size	b	128
vocabulary size	v	50000

以GPT为例分析训练内存占用情况



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训练1750亿参数的GPT-3的内存占用

内存占用类型	占用大小	参考值
参数 + 梯度	$(L(12h^2+13h)+hv+h(s+1))\times 4$	650 GB
优化器状态量	$(L(12h^2+13h)+hv+h(s+1))\times 12$	1950 GB
中间数据	$(L(5as^2+34hs)+5hs+4sv)\times 4b$	32895 GB

以GPT为例分析训练内存占用情况

显卡型号	发售年份	显存容量	参考价格
H100	2023	80GB	$36550
A100	2020	40/80GB	$9745 (40GB)
V100	2017	16/32 GB	$4392 (16GB)
P100	2016	16GB	$557

需要至少440/880张A100才能满足GPT-3训练过程中的内存占用

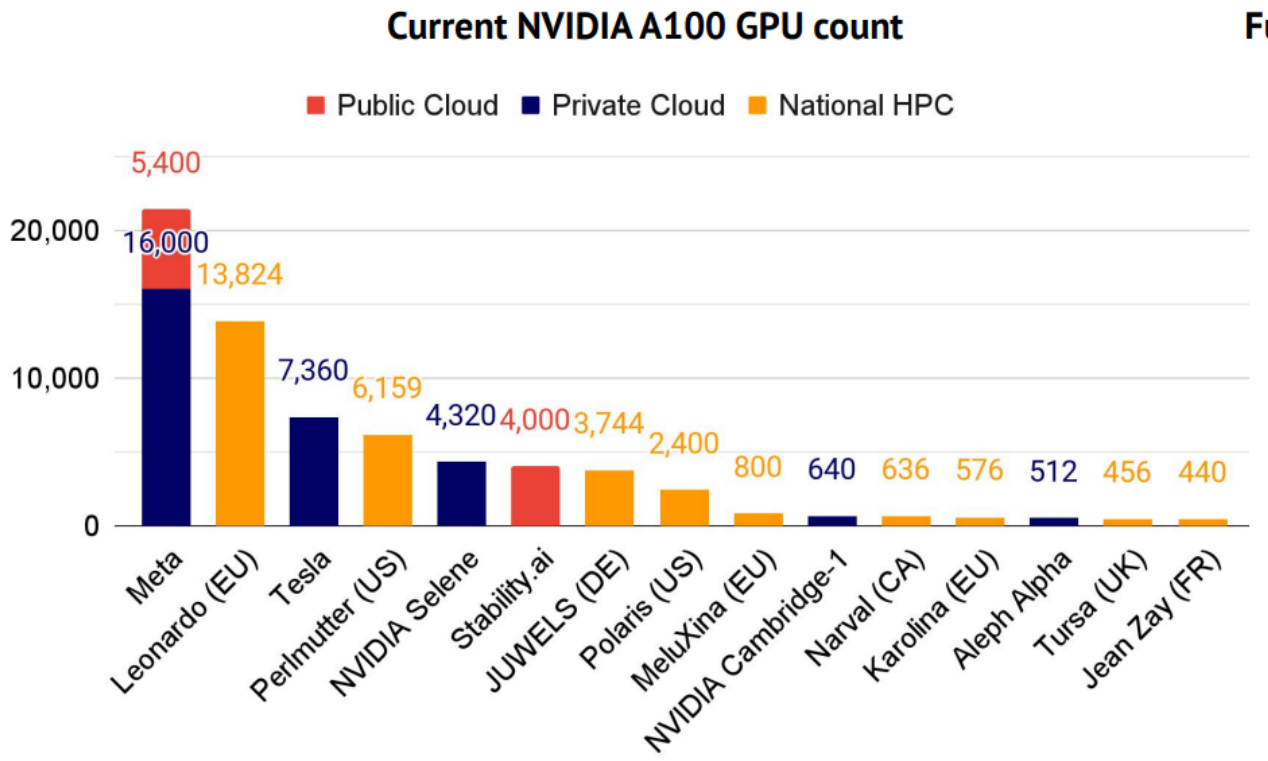
训练1750亿参数的GPT-3的内存占用

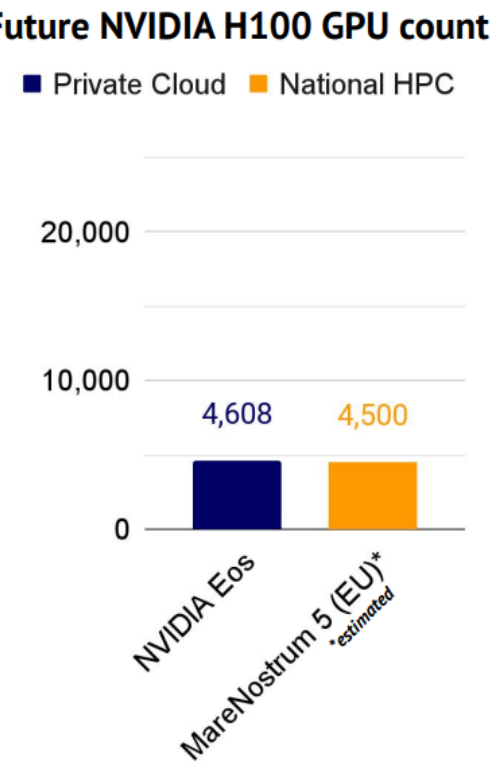
内存占用类型	占用大小	参考值
参数 + 梯度	$(L(12h^2+13h)+hv+h(s+1))\times 4$	650 GB
优化器状态量	$(L(12h^2+13h)+hv+h(s+1))\times 12$	1950 GB
中间数据	$(L(5as^2+34hs)+5hs+4sv)\times 4b$	32895 GB

国外各大机构的A100卡数

In a gold rush for compute, companies build bigger than national supercomputers

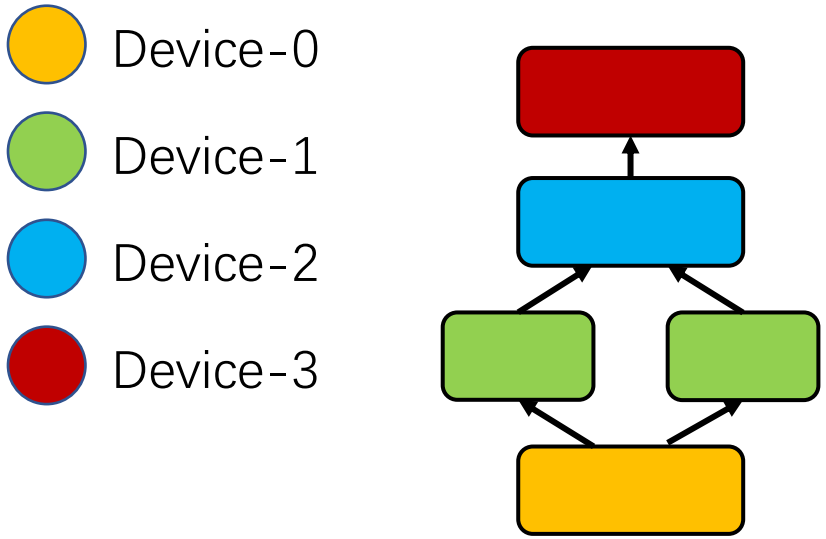
"We think the most benefits will go to whoever has the biggest computer" – Greg Brockman, OpenAI CTO





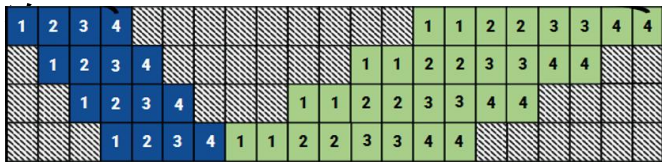
如何用更少的硬件资源训练大模型成为关键问题之一?

相关工作--流水线并行

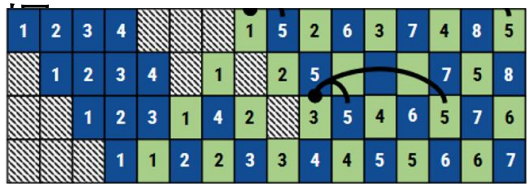


- **优点**：
  - 能有效减少单个设备的内存占用量
- **缺点**：
  - 不可避免地引入通信，且通信在关键路径上
  - 扩展上限受到模型本身层数的限制

GPipe, NIPS 2019, Google：将mini-batch进一步拆分为若干micro-batch，但仍有大量气

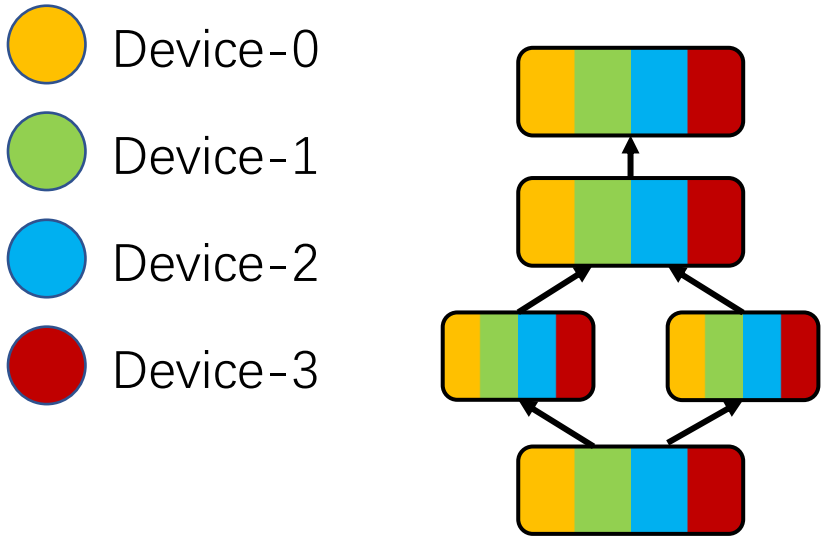


PipeDream, SOSP 2019, Microsoft：允许后续micro-batch异步提前执行，但使用的参数比较陈



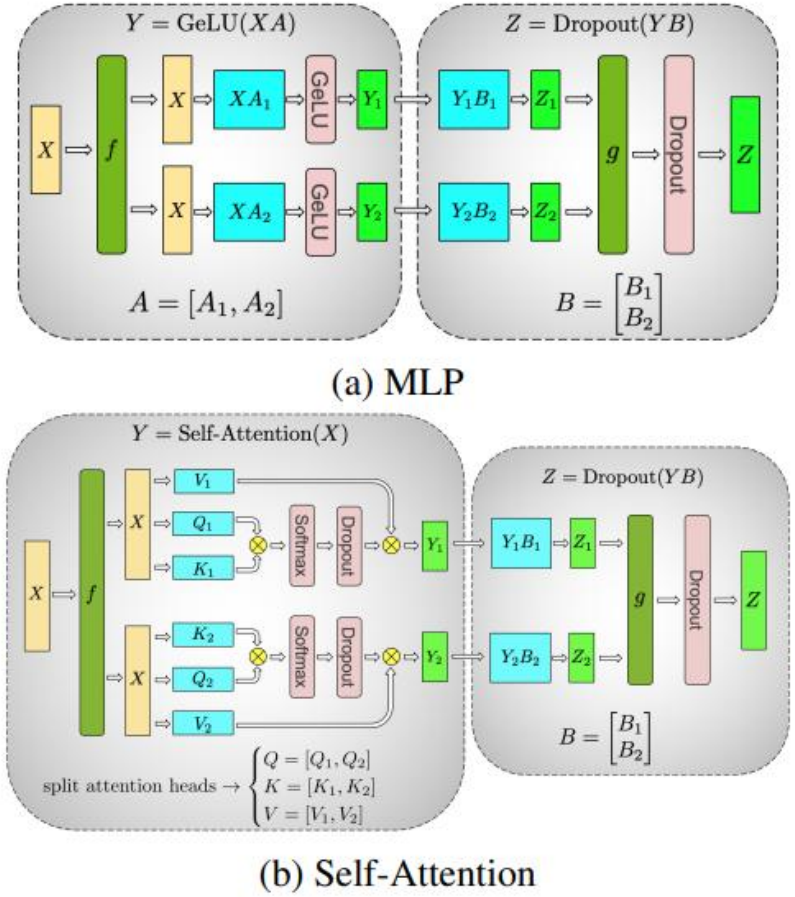
DAPPLE, PPoPP 2021, Alibaba：修改执行序，交叉执行不同micro-batch的前向和反向计算，减少气泡，减少保存的中间数据数量

相关工作--张量并行

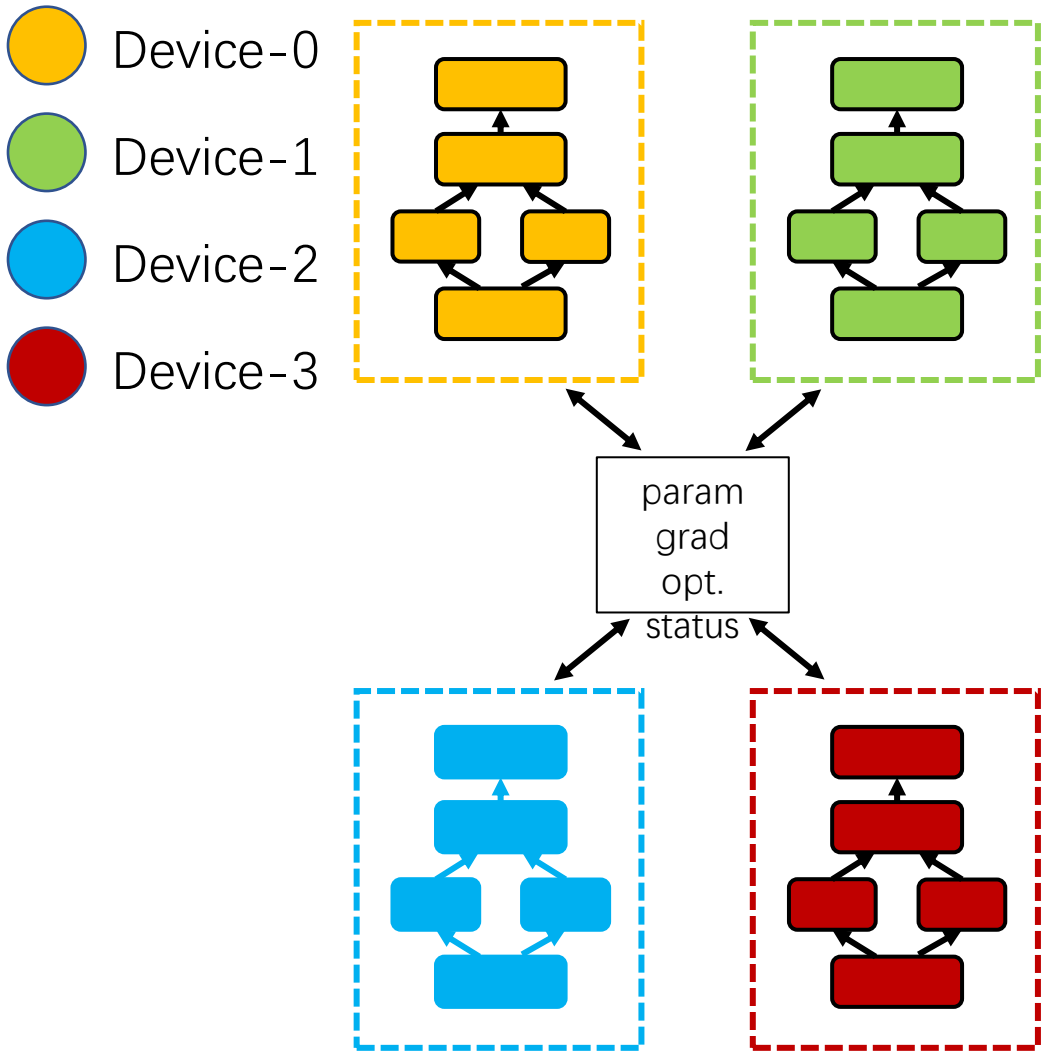


- **优点**:
  - 有效减少单个设备的内存占用
  - 可以训练单个设备无法训练的层
- **缺点**:
  - 需要实现分布式算子，以及插入相应通信算子，即重构代码
  - 计算和传输顺序执行，无法相互隐藏
  - 通信量大，对机内带宽需求高

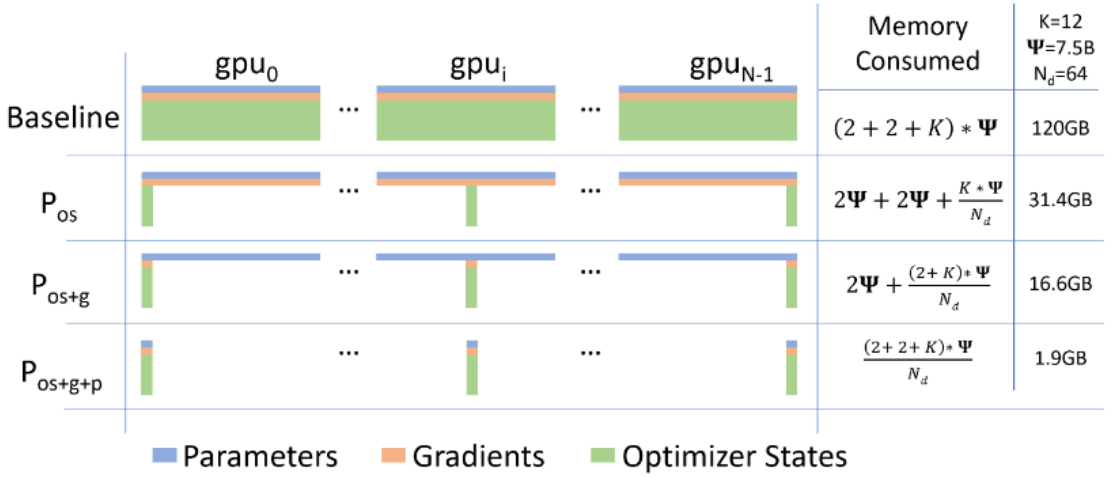
Megatron-LM, arXiv 2020, NVIDIA:
通过先验知识对Transformer层切分做张量并行



相关工作--数据并行+去冗余



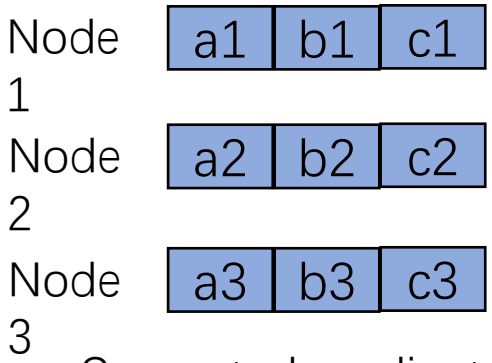
ZeRO, arXiv 2020, Microsoft：对多种数据做切分，做到了数据并行时零数据冗余

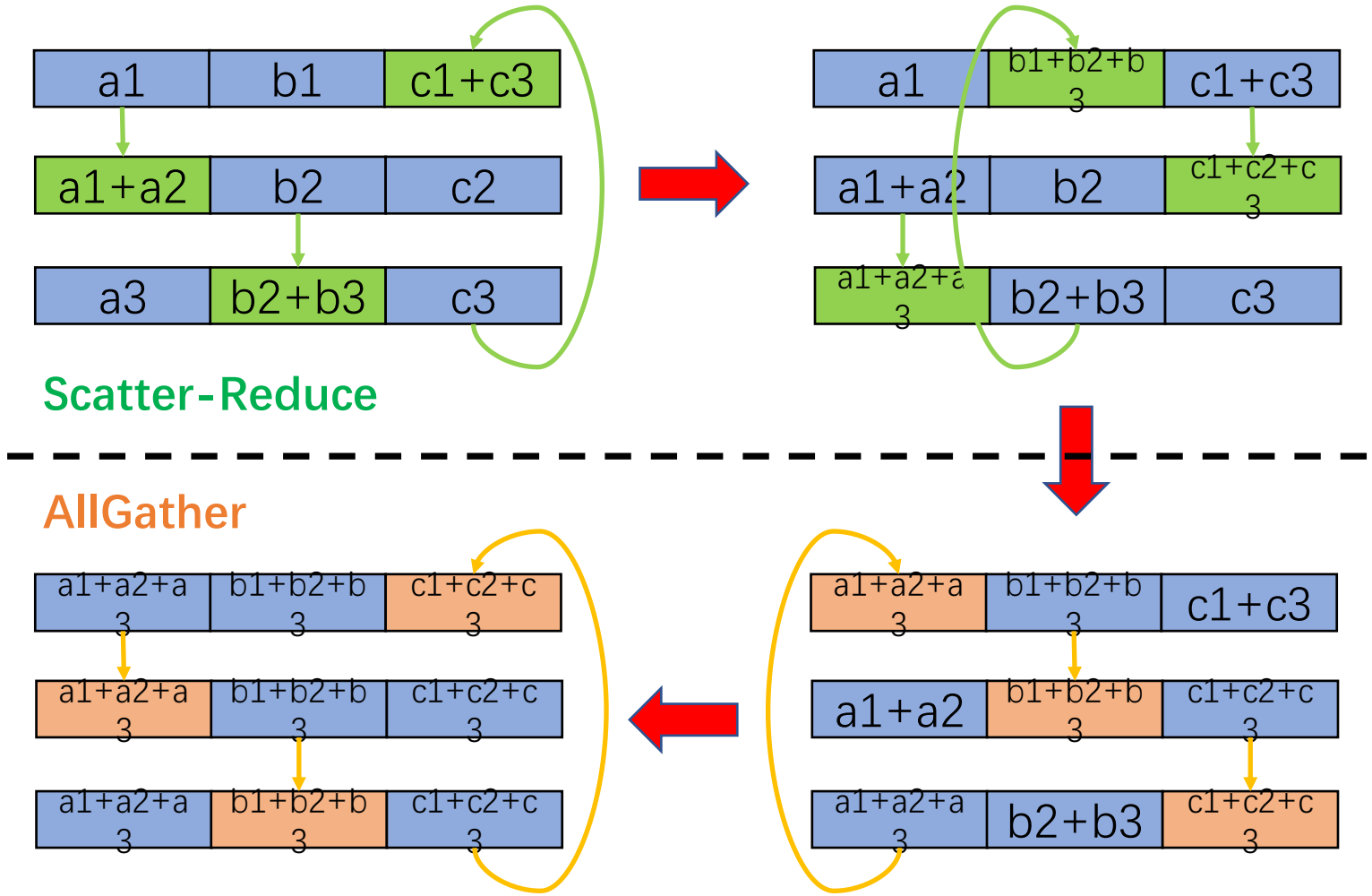


其中，φ表示模型大小，K表示优化器状态重复度，N_d是数据并行度

- **优点**：
  - 数据并行简单易扩展
  - ZeRO带来的通信不在关键路径上，可以隐藏在计算之下
- **缺点**：
  - 通信量大，对机内、机间带宽需求大

相关工作--Ring AllReduce



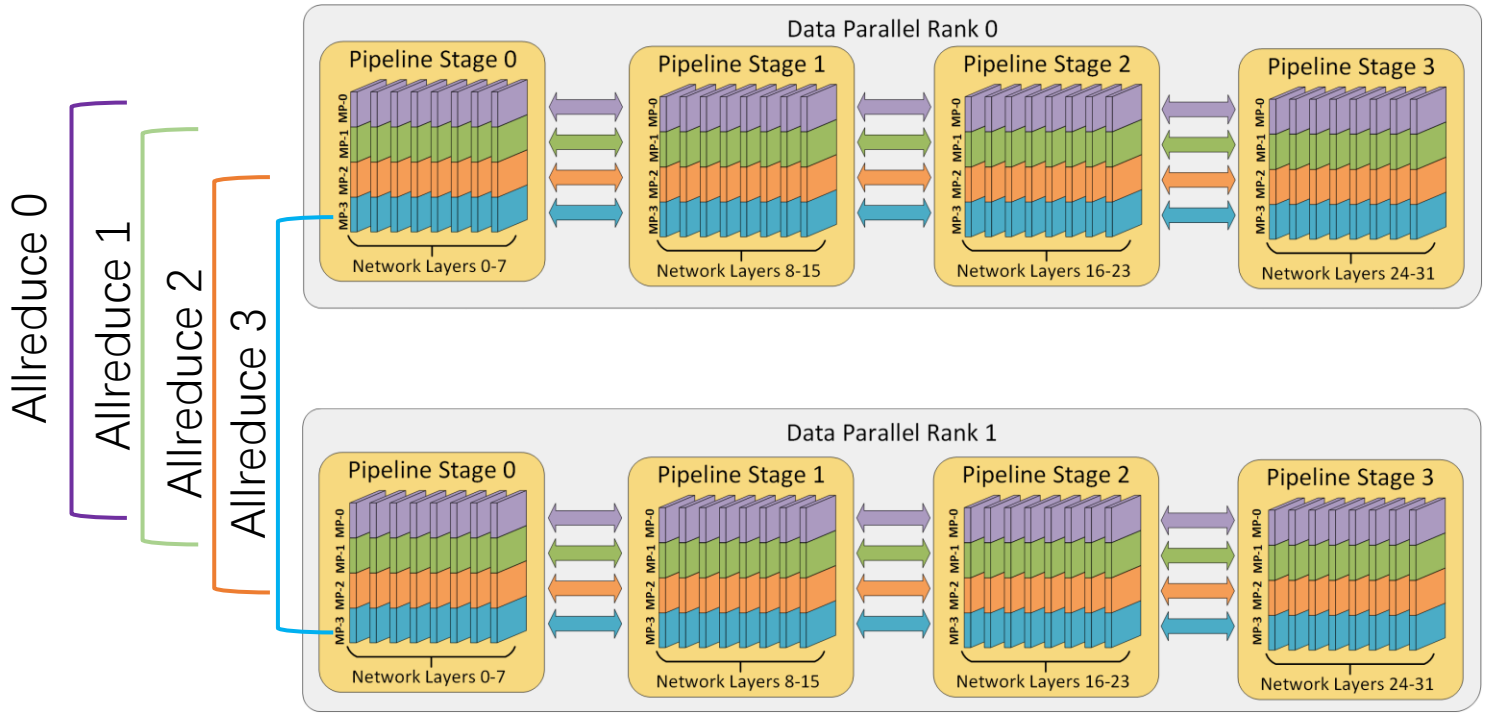


p: 计算节点数量
m: 传输数据量
每个节点的传输开销:

$$\frac{\boldsymbol{m}}{\boldsymbol{p}} \cdot \boldsymbol{2(p-1)}$$

[1] Bringing HPC Techniques to Deep Learning, https://andrew.gibiansky.com/blog/machine-learning/baidu-allreduce/

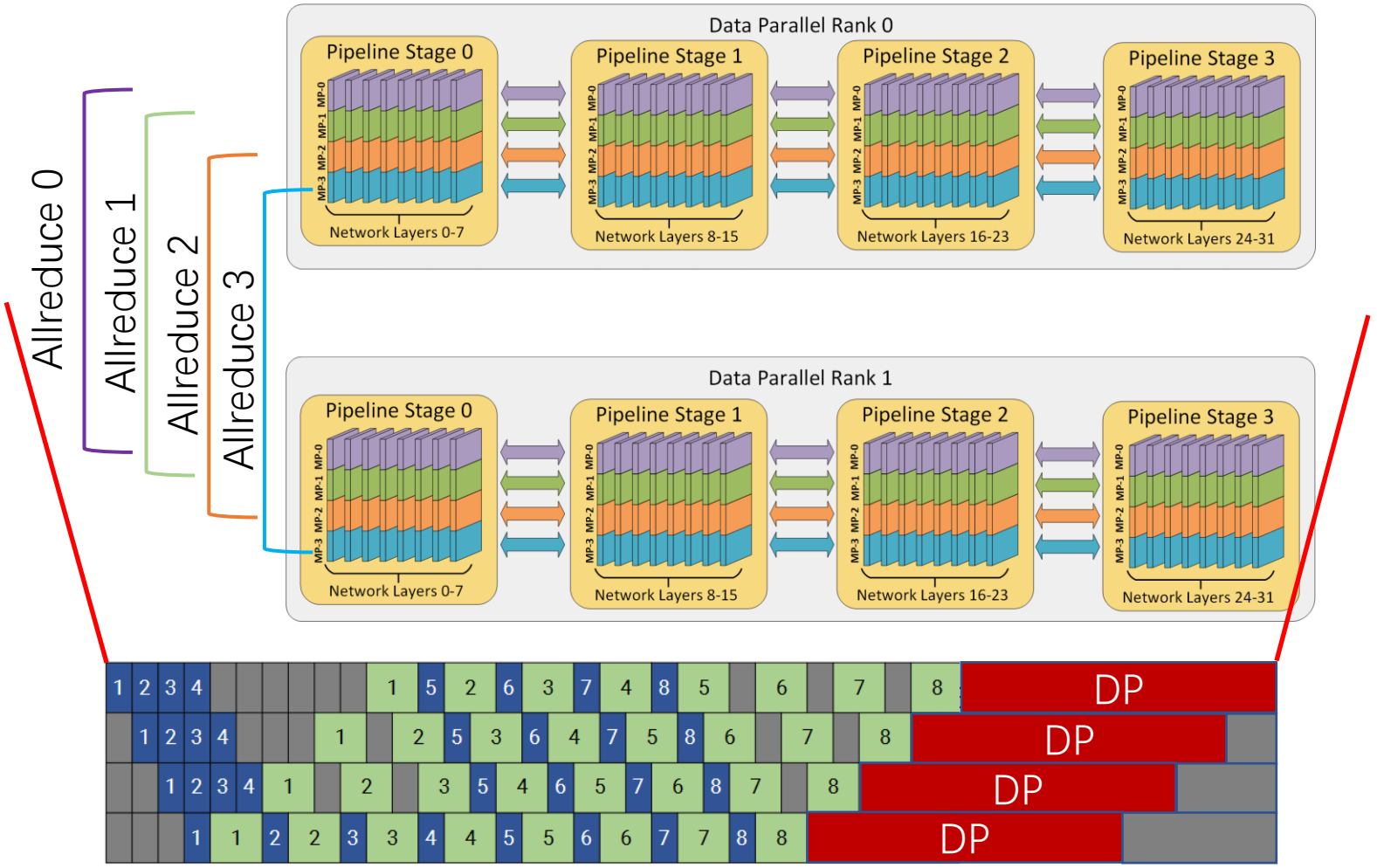
3D并行训练



训练参数设定

- 数据并行维度：2路
- 流水并行维度：4个stage
- 张量并行维度：4个partition

3D并行训练

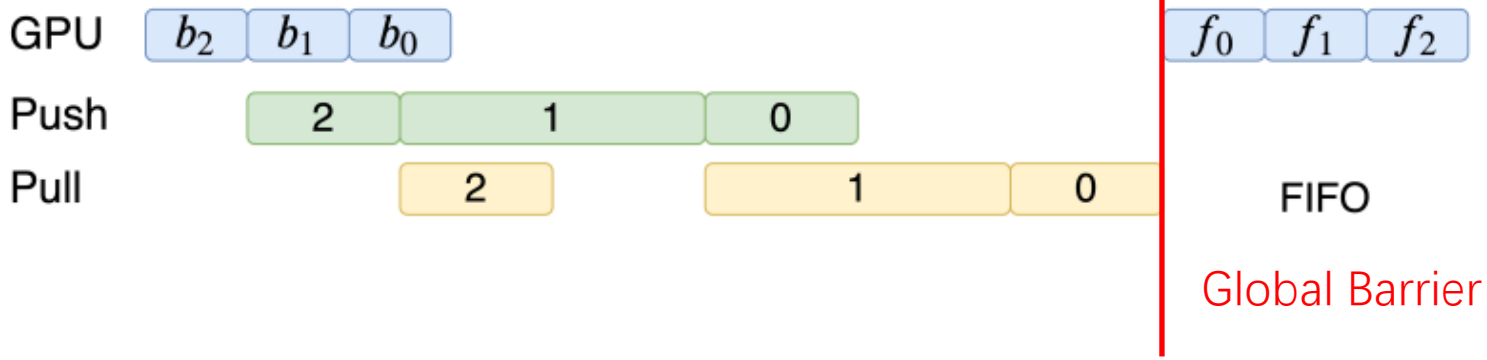


训练参数设定

- 数据并行维度：2路
- 流水并行维度：4个stage
- 张量并行维度：4个partition

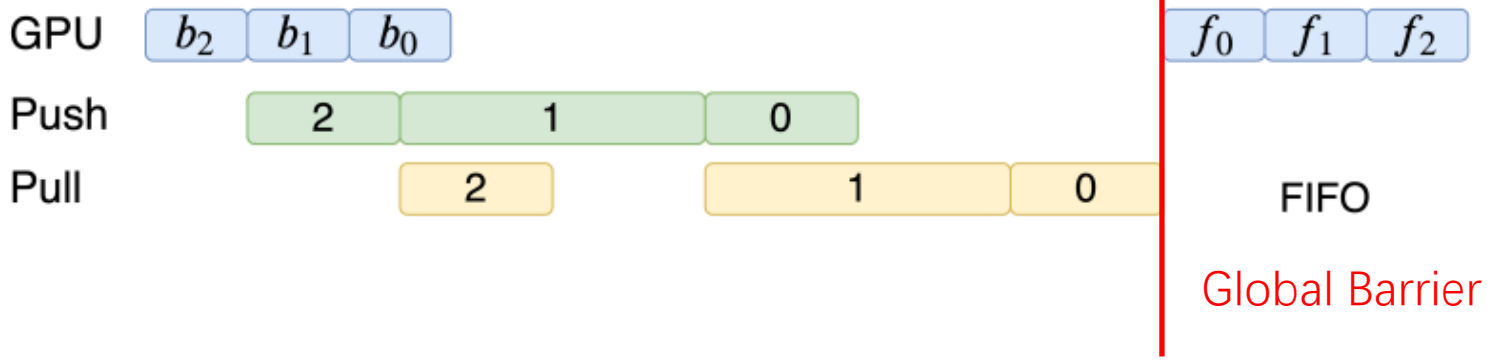
相关工作--优先级调度

- 问题：梯度通信不足以被反向计算完全隐藏

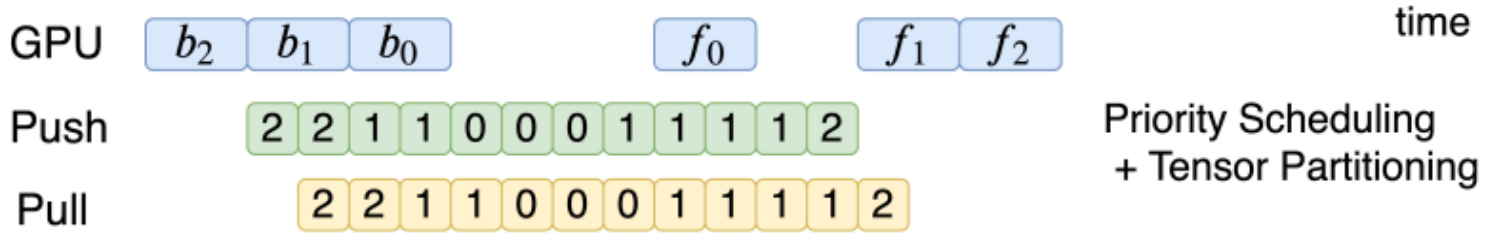


相关工作--优先级调度

- 问题：梯度通信不足以被反向计算完全隐藏



- Byt

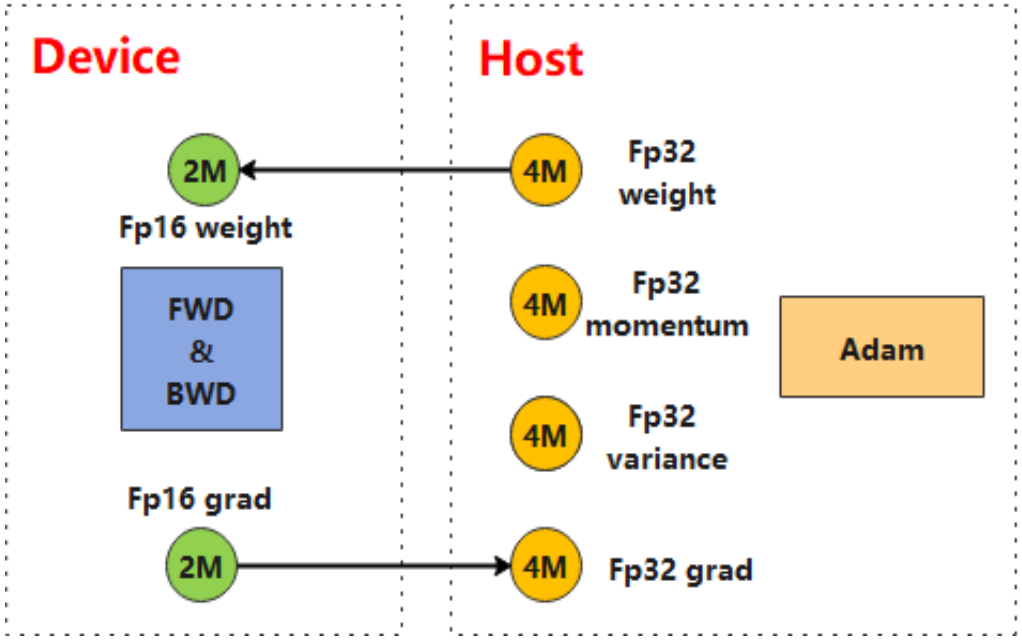


核心技术：梯度切分、抢占式优先级调度，打破每轮迭代的Global Barrier

技术优势：

- 先使用的梯度优先抢占网络资源
- 下一轮前向计算提前触发

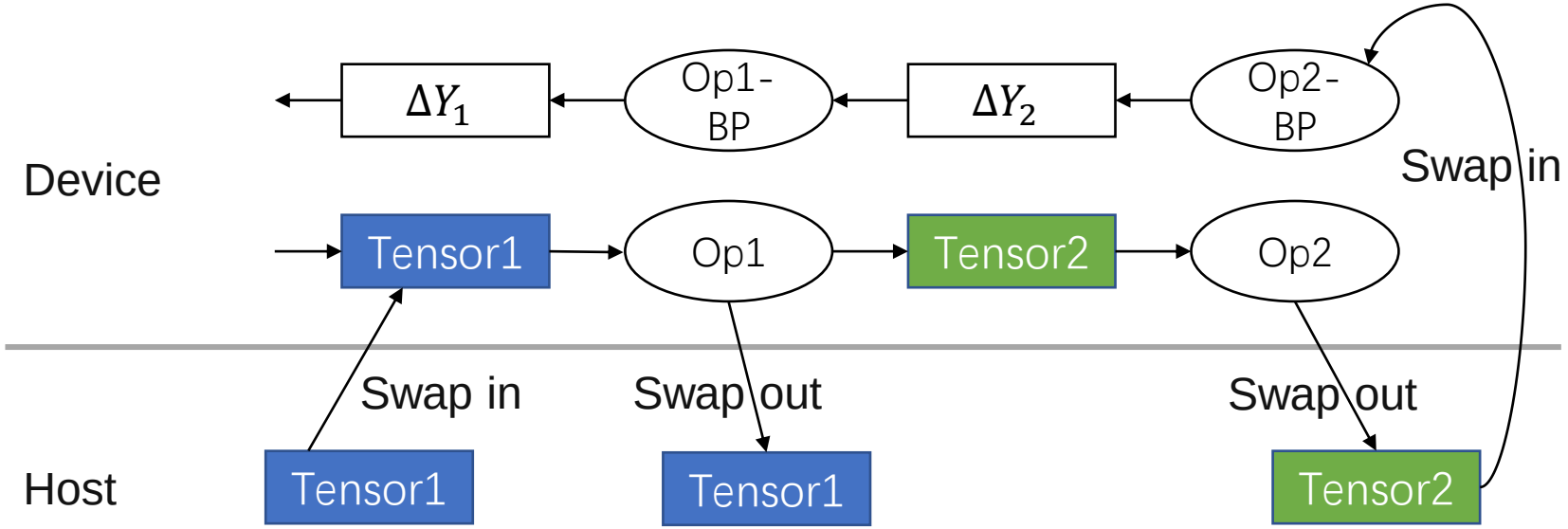
相关工作--优化器卸载



- 优点：
  - 能将显卡上大量的优化器状态量
  - 卸载到CPU侧
- 缺点：
  - CPU侧内存可能会成为可训练模型大小的瓶颈
  - 显著增加了参数更新的开销

ZeRO-Offload, ATC 2021, Microsoft：
将优化器的状态与计算卸载到CPU

相关工作--内存交换



vDNN, MICRO 2016, NVIDIA：将张量交换到CPU侧内存以降低GPU侧的显存负载

- **优点**:
  - 适用于所有类型的张量
  - 可显著增加可训练模型的大小
- **缺点**:
  - 受限于PCIe带宽，交换过多内存会影响端到端训练速度

我们课题组围绕AI并行计算的科研成果

以数据为中心的大模型高性能并行训练系统

挑战

核心任务
提升并行效率

分解

关键问题
- ③ 通信墙
- ② 存储墙
- ① 内存墙

完成

驱动

③ 针对大模型数据搬运的并行通信优化技术

基于特征缓存的局部性通信优化方法	基于细粒度一致性的强弱混合同步机制	基于压缩的传算协同集合通信方法
FAST23,VLDB24	VLDB21,EuroSys24	NSDI25,SOSP21

② 针对大模型训练数据的高效存取技术

面向海量小文件的分布式元数据服务	基于异构介质的高性能单机存储引擎	支持快速原地更新的单机向量索引
EuroSys23,SOSP25	FAST21,EuroSys23	SOSP23

① 针对大模型状态数据的高效内存管理机制

内存节省的流水并行训练方法	内存感知的模型切分与调度方法	基于混合介质的分离式内存管理方法
HPCA23,SOSP23	HPCA24,OSDI24	VLDB21,ASPLOS23

学术创新：

- 厘清了数据组织、分布、搬运、同步对并行的影响机理
- 提出了以数据为中心的算存网多维协同新系统架构

能力突破：

- 高速内存不足时仍可以算
- 训练数据太多时仍管得好
- 网络带宽不高时仍同步快

应用场景：

H3C　中科类脑　趋动科技 VirtAI Tech　Baidu 百度　Alibaba Group　oppo

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2025 Fall

Specific Requirements

- We focus on the latest papers from SOSP and OSDI, as well as papers released on arXiv. Each time presenters select one paper from SOSP or OSDI and one from arXiv.
- The presentation follows a "1+N" format, where one person delivers the main content while supporting members assist with preparation and manage the Q&A session. These supporting members are also encouraged to contribute to the presentation.
- The discussion should provide a thorough analysis of the paper's strengths and weaknesses, along with a comprehensive review of related work from the past three years. The presentation must be at least 45 minutes long.

Other Information

The playback video and text summary will be uploaded to bilibili and zhihu as soon as possible.

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计算机科学与技术学院

2025年12月01日