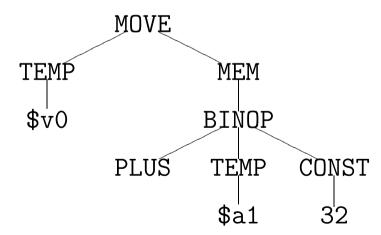
8 Instruction Selection

- The **IR code instructions** were designed to do exactly *one* operation: load/store, add, subtract, jump, etc.
- The **machine instructions** of a real CPU often perform *several* of these primitive operations.

Example: The MIPS machine instruction lw \$v0, 32(\$a1) corresponds to the following IR tree:



- Finding the appropriate machine instructions to implement a given IR tree is called **instruction selection**.
- The instruction selection phase is supplied with a **machine description**, a set of IR **tree patterns** describing the machine instructions of the target CPU.

Instruction selection then amounts to **tiling** the IR tree with a (minimal) set of tree patterns.

• In this chapter we will use a hypothetical target CPU, the *Jouette*³² architecture.

N.B.

- In the following, we abbreviate the IR tree



³²French: toy.

• Machine description for *Jouette*:³³

Instruction	Effect	IR Tree Pattern
	r_i	$TEMP \atop r_i$
add	$r_i \leftarrow r_j + r_k$	+
mul	$r_i \leftarrow r_j * r_k$	*
sub	$r_i \leftarrow r_j - r_k$	
div	$r_i \leftarrow r_j/r_k$	
addi	$r_i \leftarrow r_j + c$	CONST CONST
subi	$r_i \leftarrow r_j - c$	CONST

³³In the *Jouette* CPU, register r_0 always contains the value 0 (MIPS: \$zero).

• Machine description for *Jouette* (continued):³⁴

Instruction	Effect	IR Tree Pattern			
load	$r_i \leftarrow M[r_j + c]$	MEM MEM MEM CONST			
store	$M[r_j+c] \leftarrow r_i$	MOVE MOVE MOVE MOVE MEM MEM MEM CONST CONST CONST			
movem	$M[r_j] \leftarrow M[r_i]$	MOVE MEM MEM			

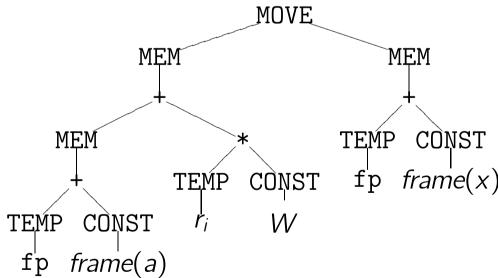
 $^{^{34}}M[x]$ denotes the memory word at address x.

- Instruction selection means tiling the IR tree.
 - The **tiles** are the tree patterns available in the machine description.
 - The fundamental goal is to cover the tree with non-overlapping tiles.

Example: The Tiger assignment statement

$$a[i] := x$$

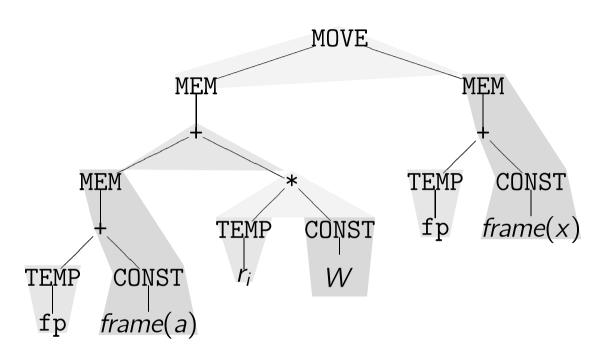
is translated into the following IR tree³⁵ (variables a and x are frame-resident, i lives in register r_i):



 $[\]frac{35}{\text{frame}(v)}$ denotes the offset of variable v's slot in the frame, cf. access, Chapter 6.

• This tree has several valid tilings:

(1)



Jouette machine instructions

```
1 load r_1, frame(a)(fp)

2 addi r_2, r_0, W

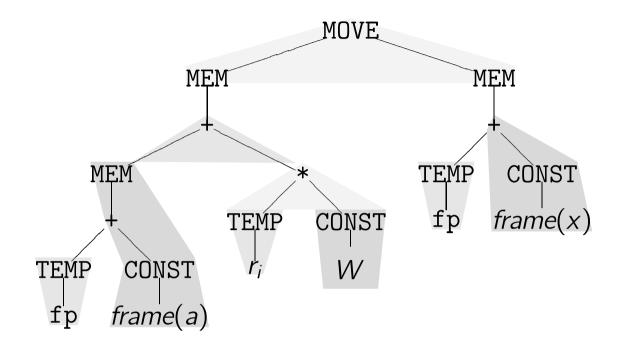
3 mul r_2, r_i, r_2

4 add r_1, r_1, r_2

5 load r_2, frame(x)(fp)

6 store O(r_1), r_2
```





Jouette machine instructions

```
1 load r_1, frame(a)(fp)

2 addi r_2, r_0, W

3 mul r_2, r_i, r_2

4 add r_1, r_1, r_2

5 addi r_2, fp, frame(x)

6 movem r_1, r_2
```

- Can we always find a tiling such that the given IR tree can be covered?
 - Yes, if the machine instruction set is "reasonable", we can at least produce a tiling such that each tile covers one IR tree node only.

Example: naive tiling for the previous IR tree:

```
Jouette machine instructions

addi r_1, r_0, frame(a)

add r_1, fp, r_1

load r_1, 0(r_1)

addi r_2, r_0, W

mul r_2, r_i, r_2

addi r_1, r_1, r_2

addi r_2, r_0, frame(x)

load r_2, 0(r_2)

store 0(r_1), r_2
```

• It is expected that the execution cost ($\approx \#$ of instructions) of the naive tiling is higher than for the two previous tilings.

8.1 Algorithms for Instruction Selection

• A number of reasonable algorithms exist to solve the IR tree tiling problem. We will first discuss an algorithm that produces an *optimal tiling:*

In an **optimal tiling**, no two adjacent tiles can be combined into a single tile of lower cost.

 For simplicity, we can just set the cost of each instruction to 1 unit. For a modern CPU, nearby instructions interact in many ways such that a good cost function will actually be quite complicated to design.

Example: for the Intel Pentium 4, *instruction latency* is influenced by the following CPU features:

- branch prediction, speculative execution
- non-blocking memory access
- pipelining
- multiple cache levels, temporal/spatial locality of data access

8.1.1 Maximal Munch

- The simple algorithm **Maximal Munch** always finds an optimal tiling:
 - (1) Start at the root of the IR tree.
 - (2) Find the largest (maximum number of covered IR tree nodes) tile t that fits.
 - (3) Record the machine instruction corresponding to t.
 - 4 t covers the root and (perhaps) several other nodes below the root. Tile t leaves several subtrees uncovered.
 - (5) Invoke Maximal Munch recursively on all subtrees.
 - 6 Emit the machine instructions recorded in step 3 in order of a postorder traversal of the tiled IR tree.
 - Why does the algorithm order the machine instructions in a postorder fashion?

• Step ② of **Maximal Munch** involves **tree pattern matching**. In a C implementation, one will typically find code fragments like

C implementation of Maximal Munch _ void maximal munch (T stm s) 1 ₹ ... 3 switch (s->kind) { case T_MOVE: { 4 $T_{exp} dst = s->u.MOVE.dst;$ T_exp src = s->u.MOVE.src; 6 8 if (dst->kind == T_MEM) { if (dst->u.MEM->kind == T BINOP && 10 dst->u.MEM->u.BINOP.op == T_PLUS && dst->u.MEM->u.BINOP.right->kind == T_CONST) { 11 12 T_exp e1 = dst->u.MEM->u.BINOP.left; 13 $T_{exp} = 2 = src;$ 14 /* detected: MOVE (MEM (BINOP (PLUS, e1, CONST (c))), e2) */ 15 16 17 maximal_munch (e1); maximal_munch (e2); 18 19 emit ("store"); 20 21 } 22 else 23

8.1.2 Dynamic Programming

- Maximal Munch makes a local decision when it selects and places the next tile.
- A more ambitious approach, based on **dynamic programming** techniques, takes a global view and can produce an **optimum tiling**:

In an optimum tiling, the sum of the overall tile costs is minimum.

- The basic idea of dynamic programming is that an optimum solution of a problem p is based on optimum solutions of the subproblems of p.
 - If p = instruction selection for an IR tree, then the solutions to **subproblems** of p are tilings for the tree's **subtrees**.
 - Tiling based on dynamic programming thus proceeds bottom-up.

• The **cost** of placing a tile *t* is

$$c + \sum_{i=1}^{\#leaves(t)} c_i$$

where c denotes the cost for the tile itself (remember: we assume c = 1 for simplicity) and c_i is the cost of the ith tiled subtree attached to t.

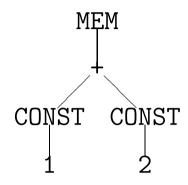
– Note:

We have, for example,
$$\#leaves\left(\begin{array}{c} + \\ \end{array}\right)=2$$
 and $\#leaves\left(\begin{array}{c} \text{MEM} \\ + \\ \end{array}\right)=1.$

• Instruction selection by dynamic programming:

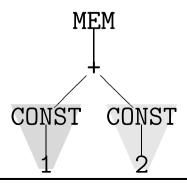
Of all the tiles that match at a node n—starting from the leaves of the IR tree—the one with **minimum cost** is chosen and the (minimum) cost of node n is remembered.

• **Example:** Select the optimum *Jouette* instructions to implement the IR tree



① Start at the leaves (the two CONST nodes). For both leaves, the only matching tile is an addi instruction with total cost

$$1 + \sum_{i=1}^{0} c_i = 1$$
.



② Proceed up the IR tree. At the + node, several tiles match:

Tile	Instruction	Tile Cost c	Leaves Cost $\sum_i c_i$	Total Cost
MEM CONST CONST	add	1	1+1	3
MEM CONST CONST	addi	1	1	2
MEM CONST CONST	addi	1	1	2

③ Proceed up the IR tree. Again, at the MEM node, several tiles match:

Tile	Instruction	Tile Cost c	Leaves Cost $\sum_i c_i$	Total Cost
MEM CONST CONST	load	1	2	3
MEM CONST CONST	load	1	2	3
MEM CONST CONST	load	1	1	2
MEM CONST CONST	load	1	1	2

When the tiling process has covered the IR tree root with tile t, switch to code emission:

```
emit(t):

foreach tile t_i attachted to tile t do

\_emit(t_i);

write instruction for tile t;
```

(5) The final *Jouette* assembly program is

```
Jouette machine instructions

1 addi r_1, r_0, 1
2 load r_1, 2(r_1)
```