Accelerators (II)

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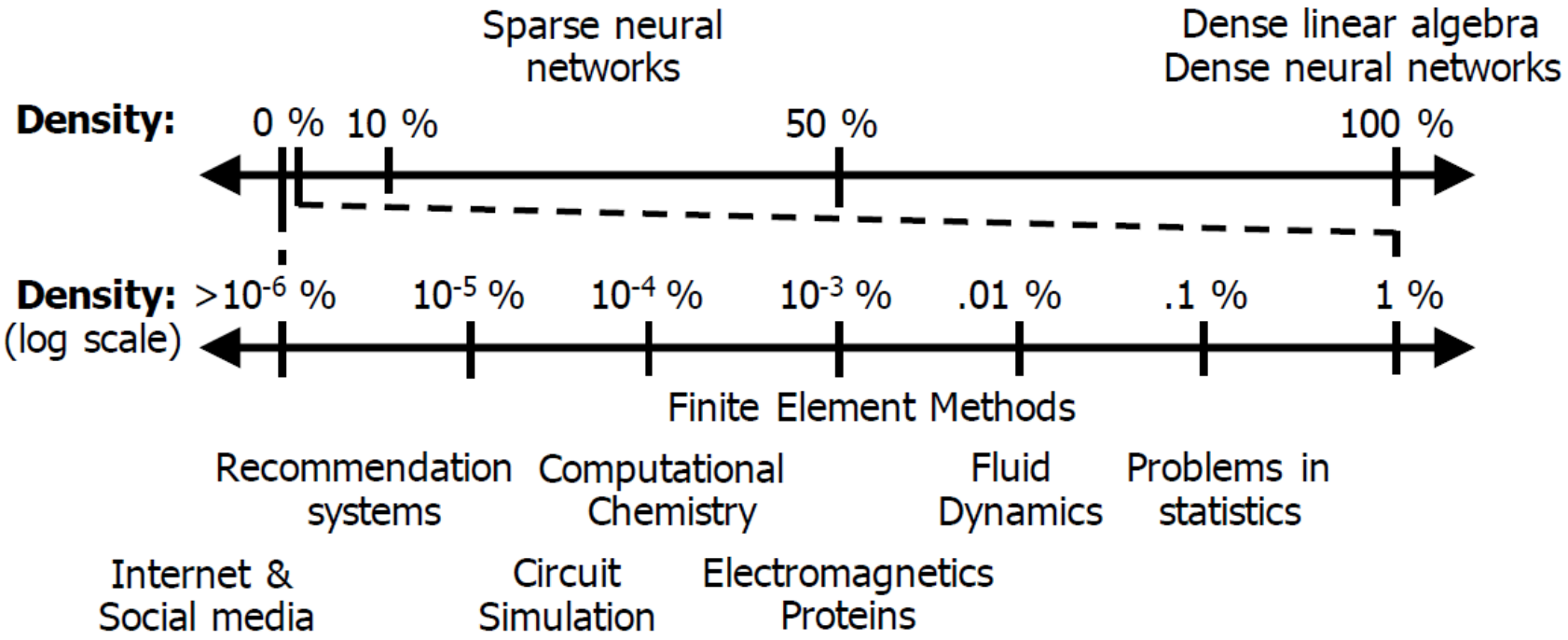
Many problems use Sparse Tensors



[Extensor, Hegde, et.al., MICRO 2019]

Exploiting Sparsity

Sparse data can be compressed

Can save space and energy by avoiding manipulation of zero values

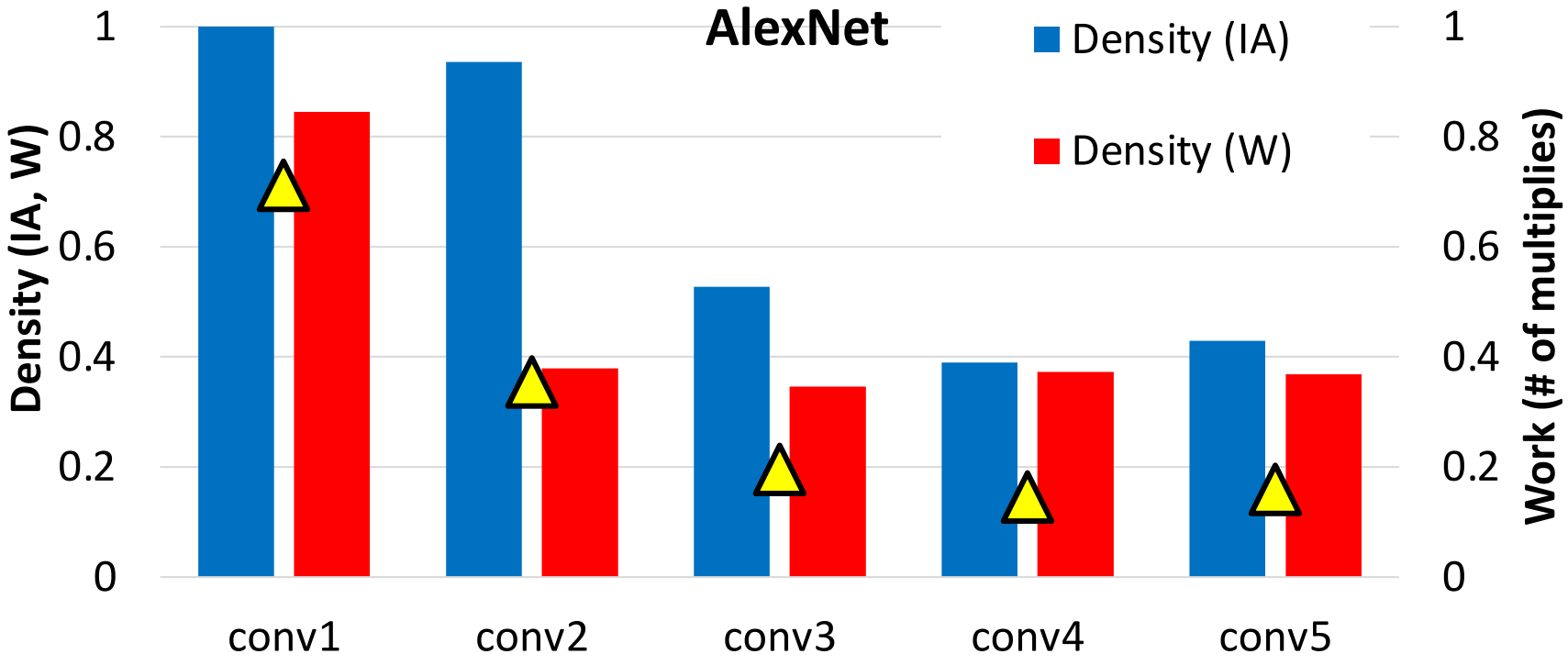
$$anything \times 0 = 0$$

$$anything + 0 = anything$$

Can save time and energy by avoiding fetching unnecessary operands and avoiding **ineffectual** computations

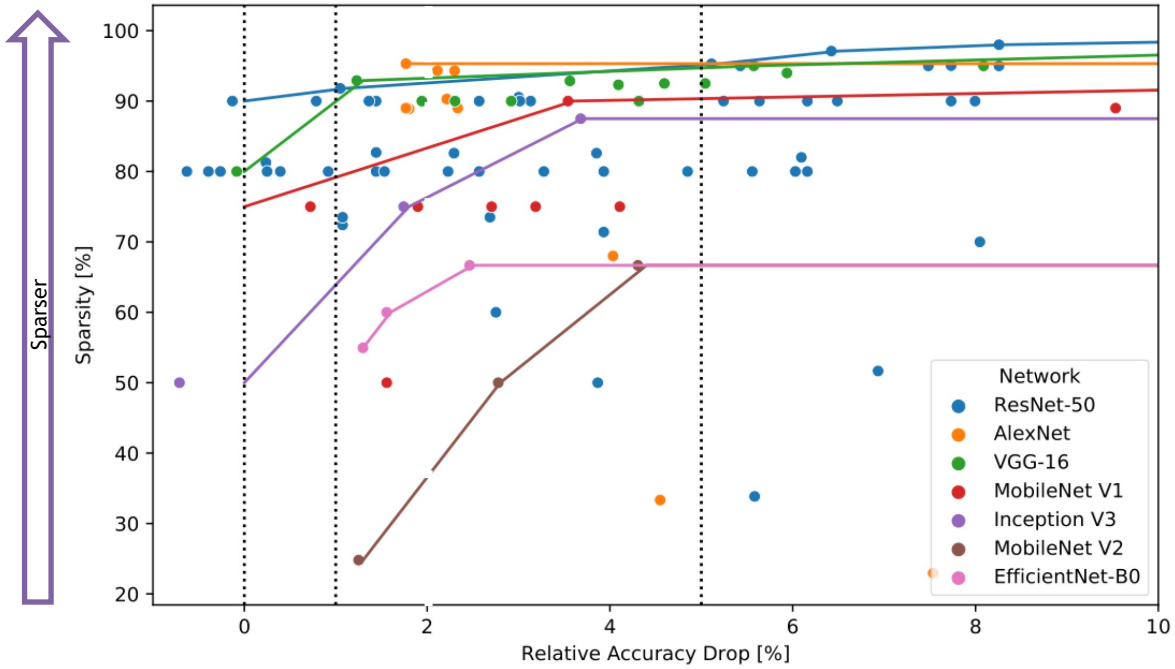
Motivation in DNNs

- Leverage CNN sparsity to improve energy-efficiency



Exploitable Sparsity

Acceptable sparsity depends on target task and error tolerance



Hoefler et al. arXiv, 2021

	Error Tolerance		
	≤0%	≤1%*	≤2%
ResNet-50	~90%	~90%	~91%
AlexNet			~93%
VGG-16	~80%	~88%	~92%
MobileNet V1	~72%	~79%	~82%
Inception V3	~50%	~62%	~73%
EfficientNet-B0			~52%
MobileNet V2			~25%

**MLPerf error tolerance*

Hardware Sparse Acceleration Features

Format:
Choose tensor representations to save necessary storage spaces and energy associated zero accesses

Gating:
Explicitly eliminate ineffectual storage accesses and computes by letting the hardware unit staying idle for the cycle to save energy

Skipping:
Explicitly eliminate ineffectual storage accesses and computes by skipping the cycle to save energy and time

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What is the chosen format?

Do all tensors share the same format?

When is a storage access gated?

How much is the compute able to skip ahead?

At which storage level is the skipping performed?

What is the criteria for skipping?

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1-D Output-Stationary Convolution


```
int i[W];      # Input activations
int w[S];      # Filter weights
int o[Q];      # Output activations

for q in [0..Q):
       for s in [0…S):
          o[q] += i[q+s]*f[s];
}}
```

What opportunity(ies) exist if some of the filter weights are zero?

Can avoid reading operands, doing multiply and updating output

† Assuming: 'valid' style convolution

1-D Output-Stationary Convolution

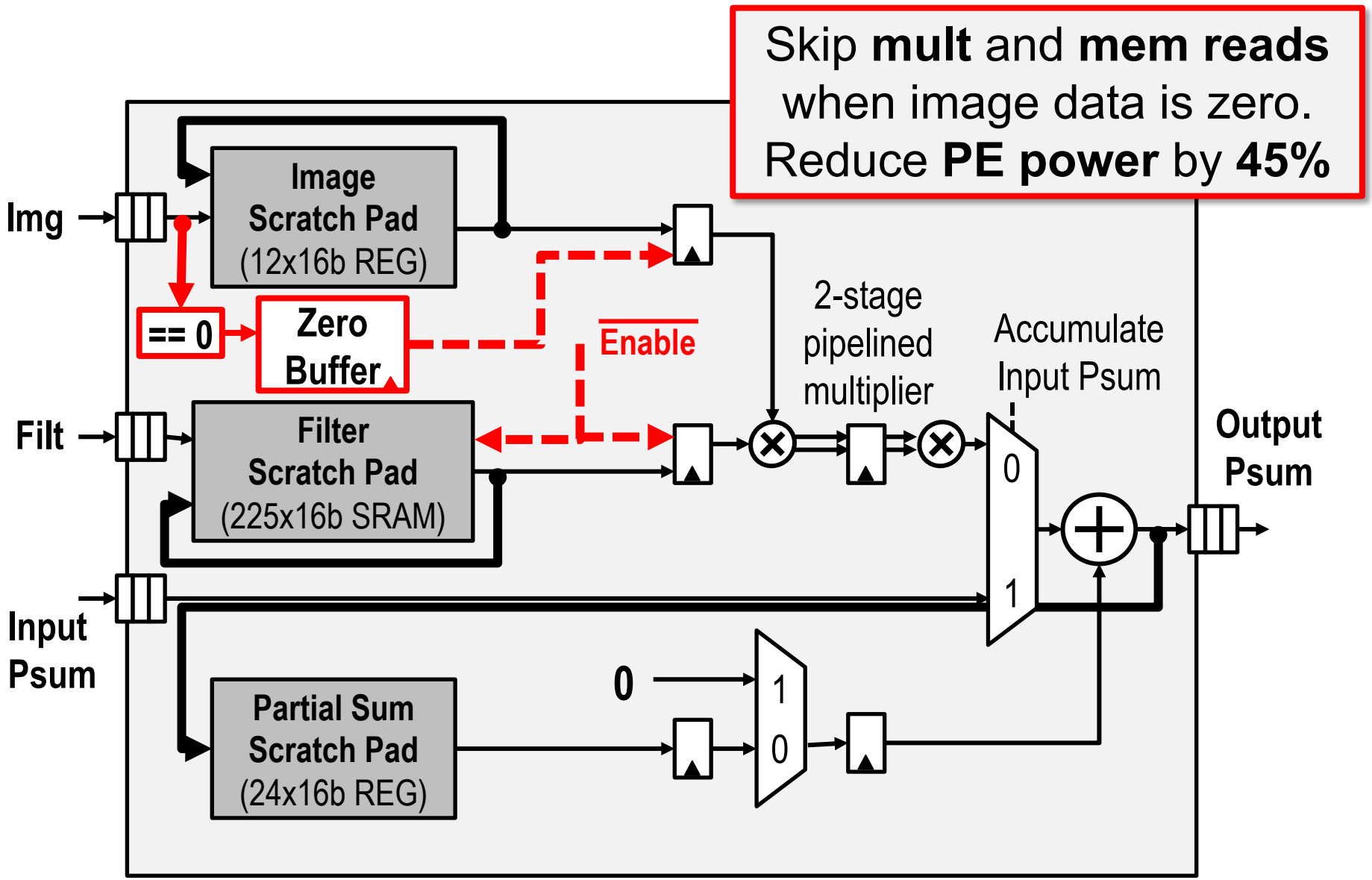

```
int i[W];      # Input activations
int f[S];      # Filter weights
int o[Q];      # Output activations

for q in [0..Q):
        for s in [0..S):
            if (!f[s]) o[q] += i[q+s]*f[r];
}}
```

What did we save using the conditional execution? Energy

What didn't we save using the conditional execution? Time

† Assuming: 'valid' style convolution

Eyeriss – Clock Gating



Sparse Tensor Representation

Hardware Sparse Acceleration Features

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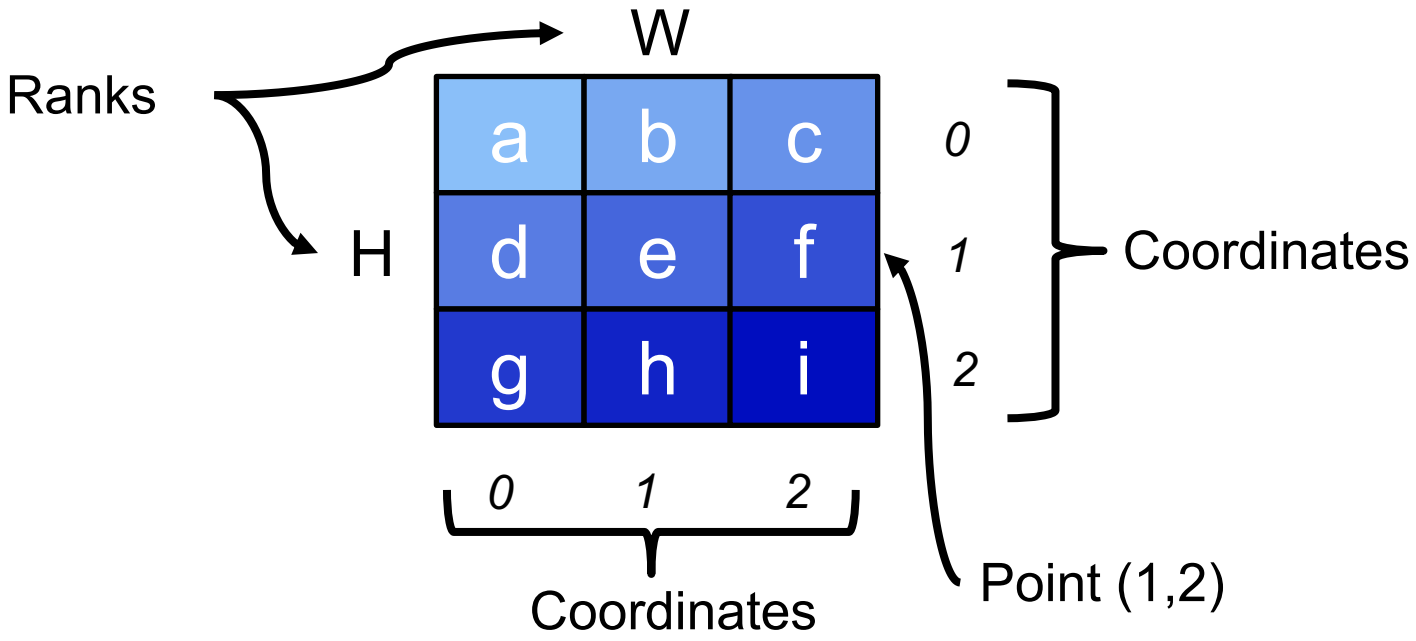
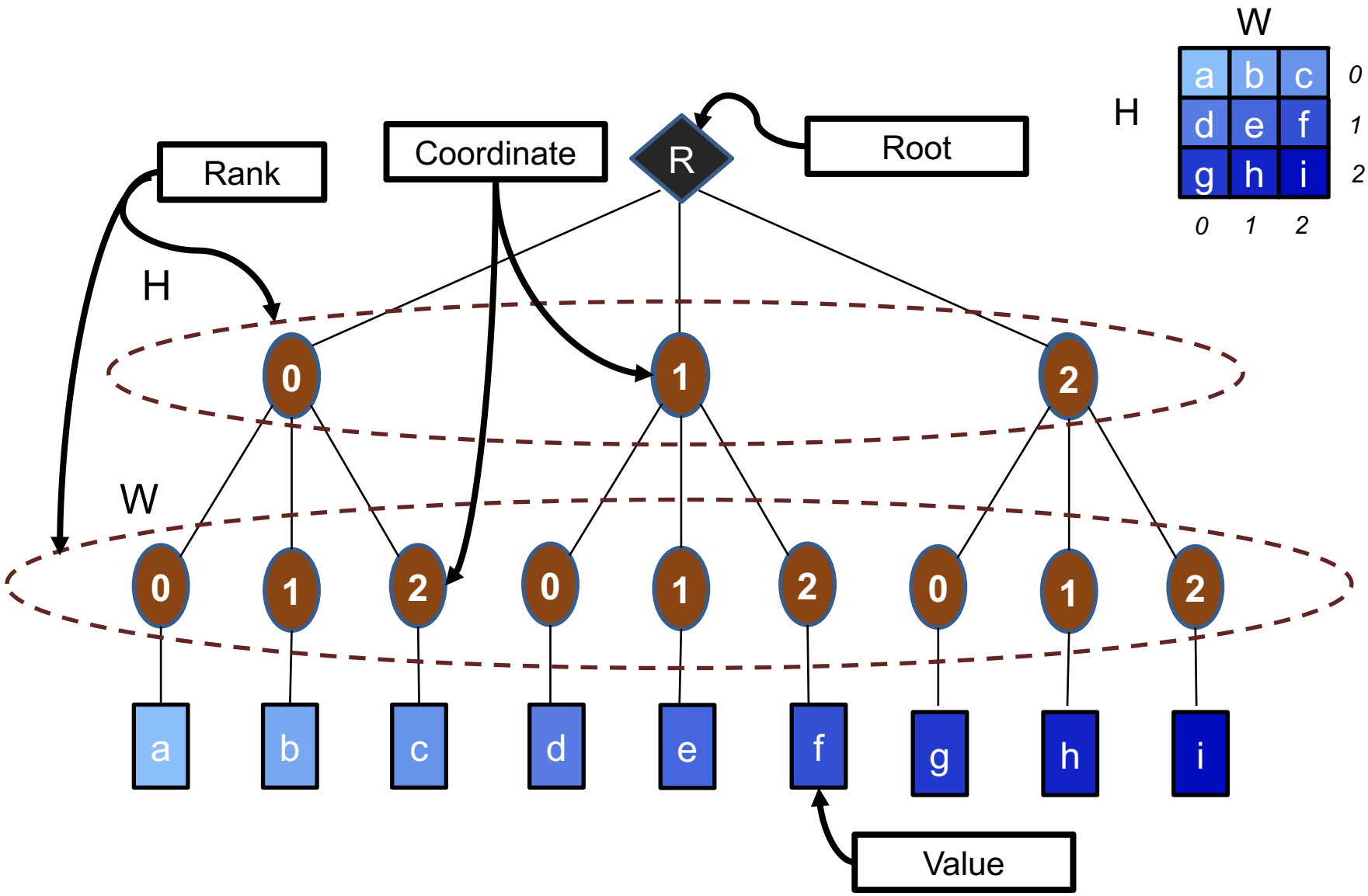
Tensor Data Terminology



- The elements of each “rank” (dimension) are identified by their “coordinates”, e.g., rank H has coordinates 0, 1, 2

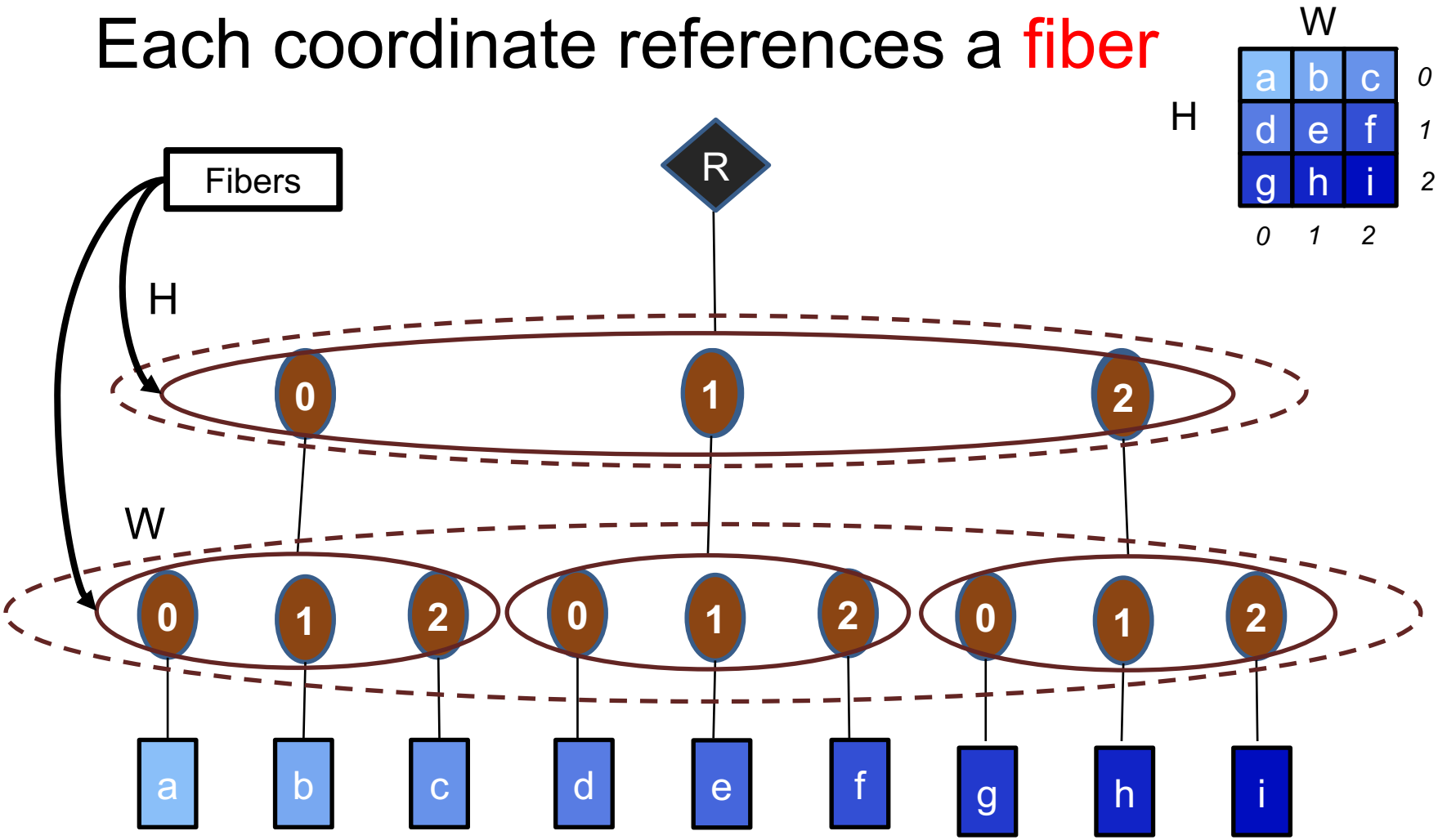
- Each element of the tensor is identified by the tuple of coordinates from each of its ranks, i.e., a “point”.
  So (1,2) -> “f”

Tree-based Tensor Abstraction



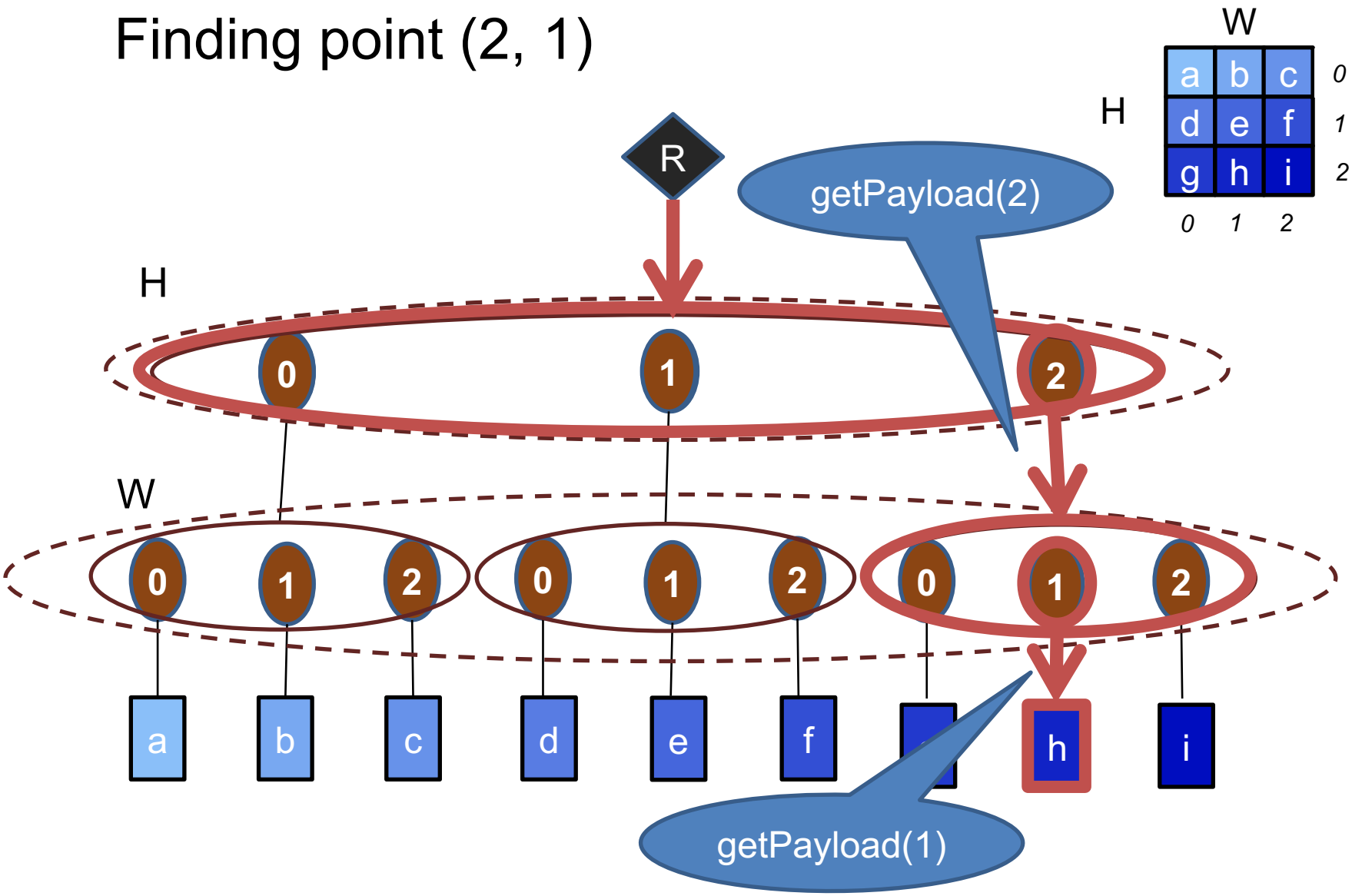
Fibertree Tensor Abstraction

Each coordinate references a fiber



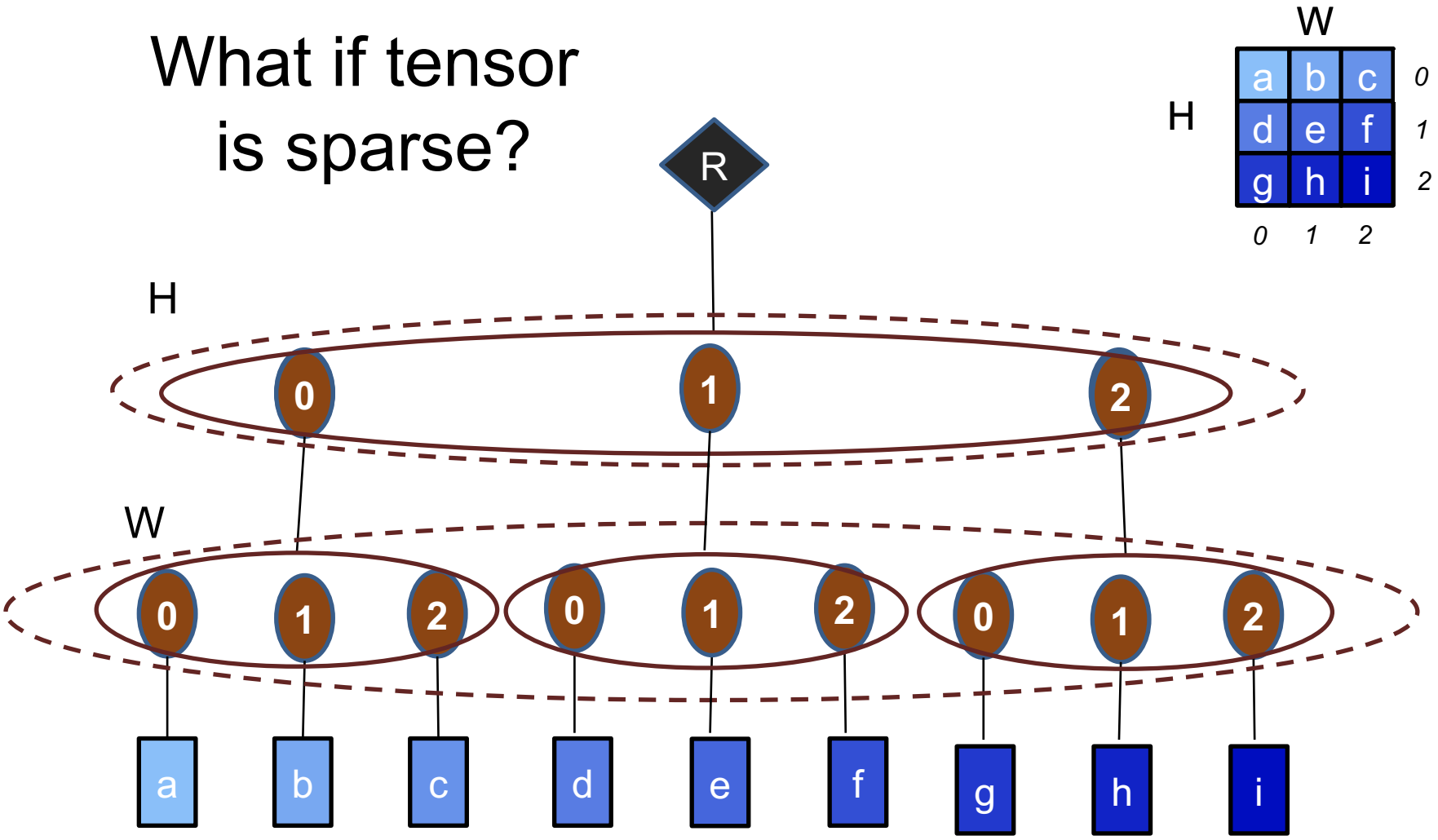
Fibertree Tensor Abstraction

Finding point (2, 1)



Fibertree Tensor Abstraction

What if tensor is sparse?



Fibertree Tensor Abstraction

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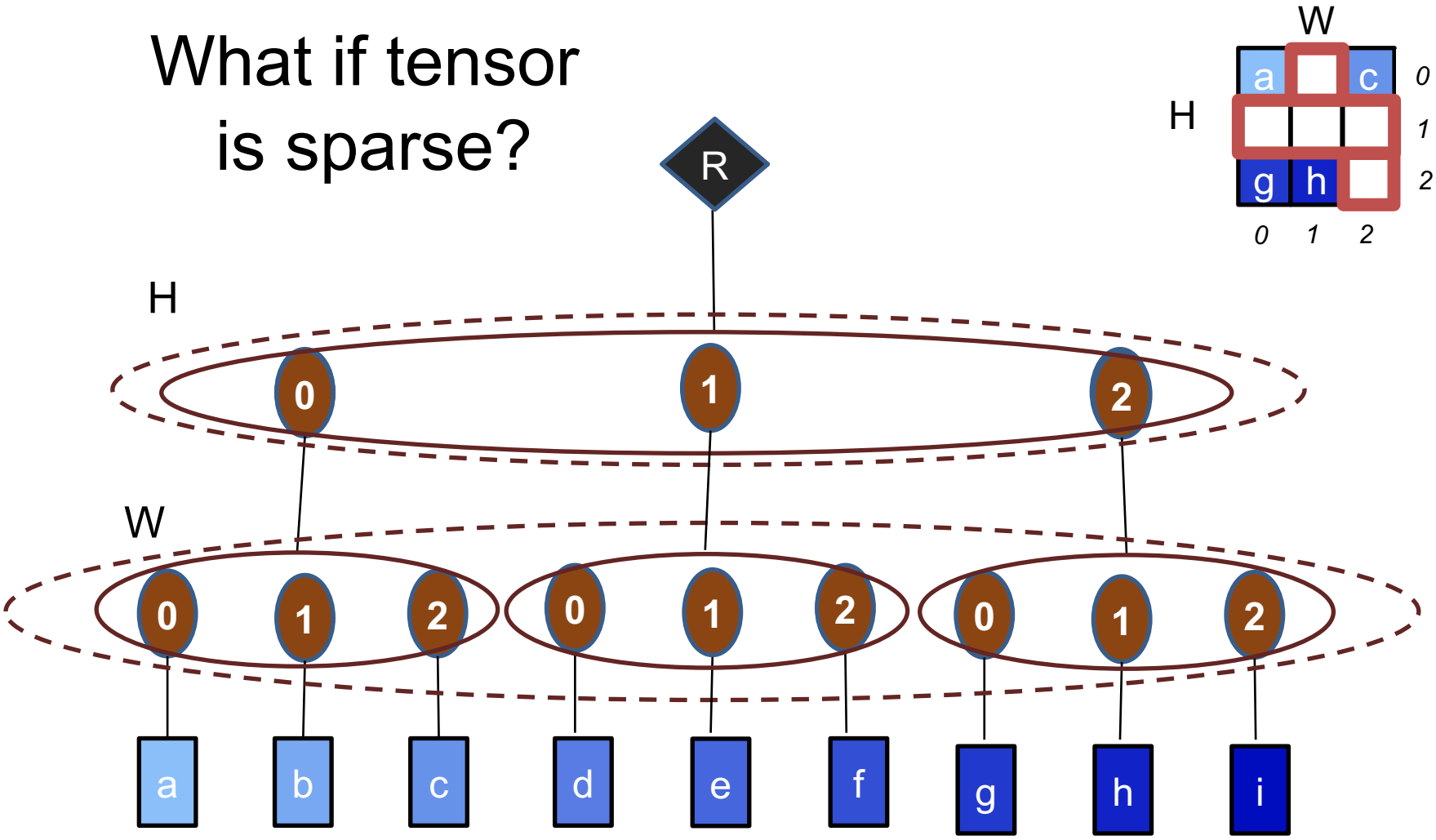
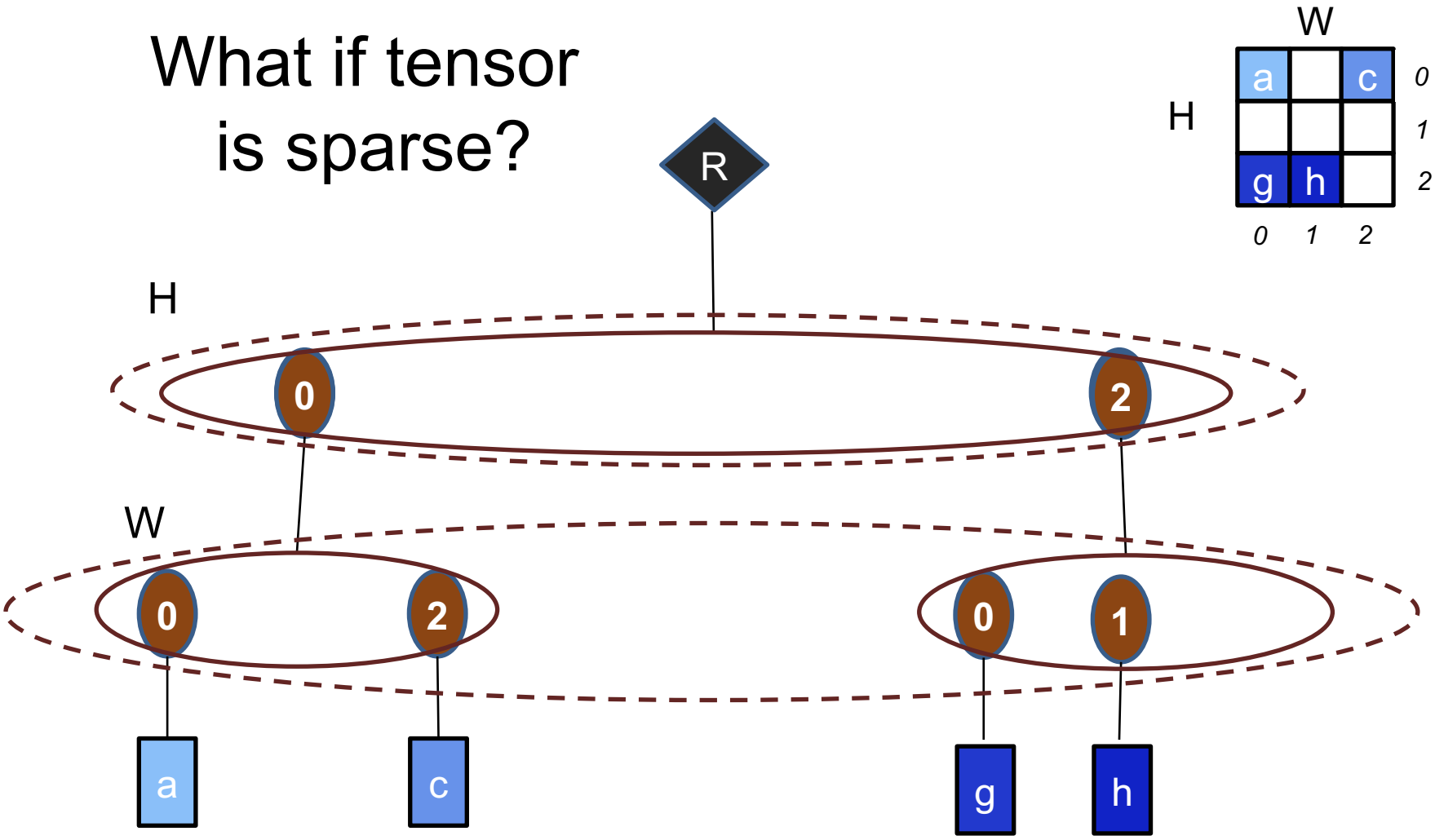


Fibertree Tensor Abstraction

What if tensor is sparse?



Fibertree Tensor Abstraction

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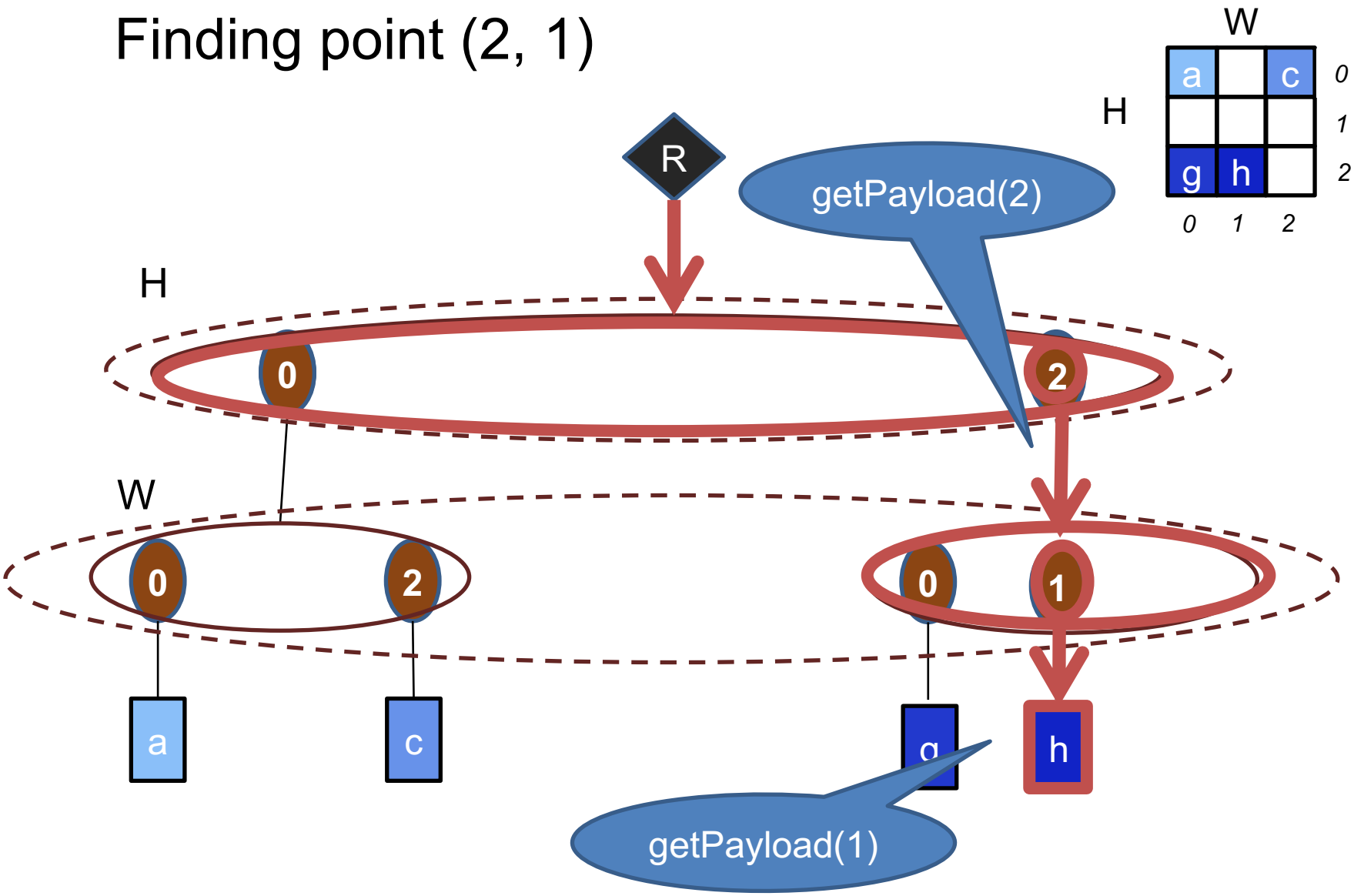


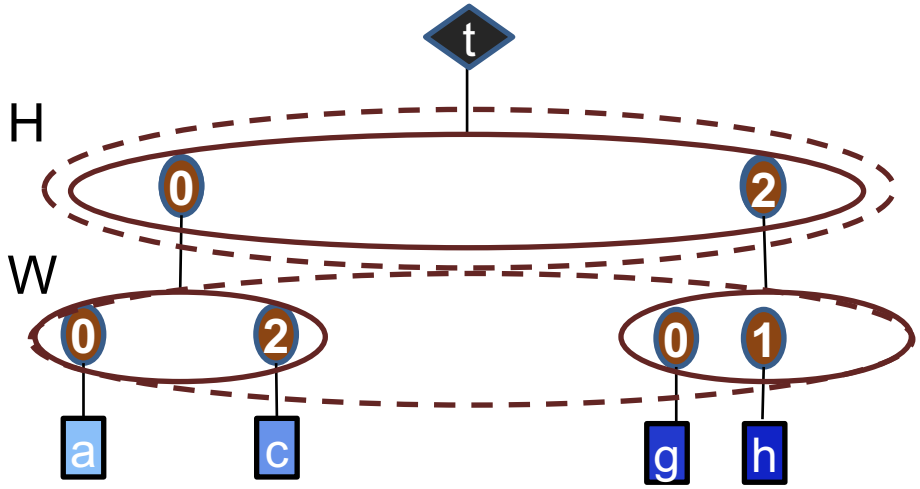
Tensor Traversal (2-D)

```
# 2-D Tensor Traversal

t = Tensor(H,W)

sum = 0
for (h, t_h) in t:
  for (w, t_val) in t_h:
      sum += t_val
```

Each iteration returns a (coordinate, payload) tuple



t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

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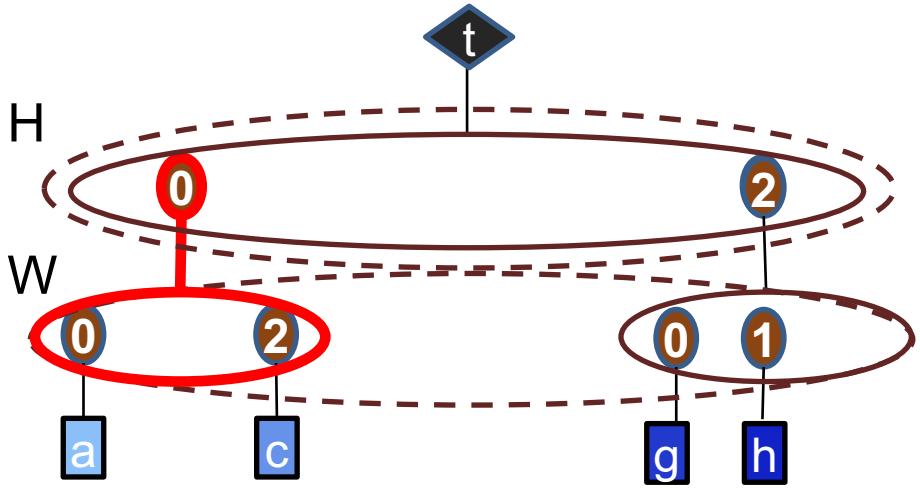
```



t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

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```

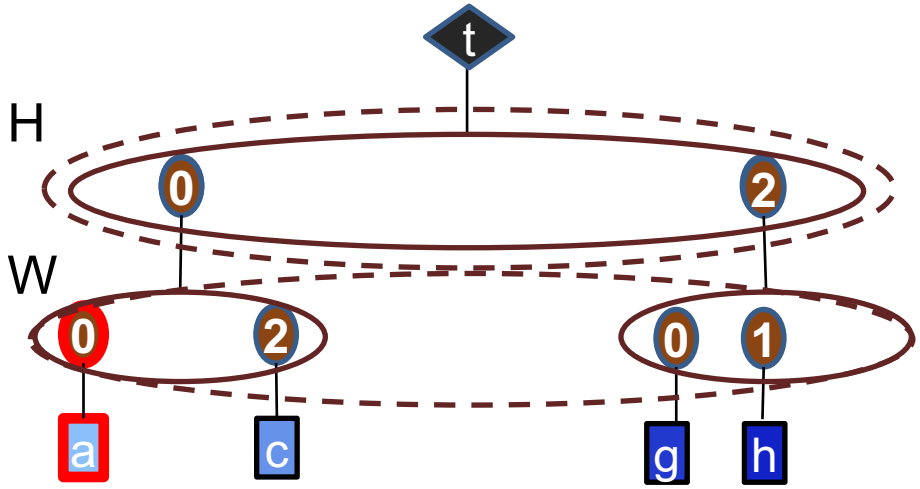

t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

Tensor Traversal (2-D)

```
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```

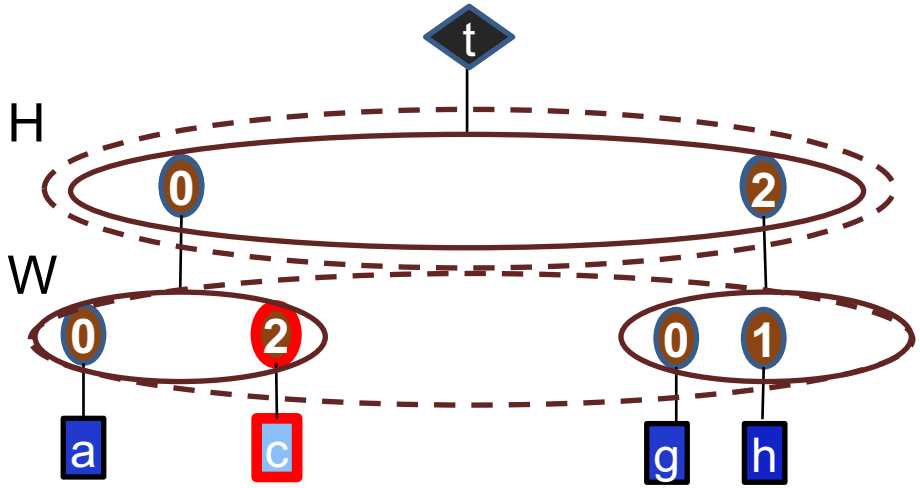

t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

Tensor Traversal (2-D)

```
# 2-D Tensor Traversal

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sum = 0
for (h, t_h) in t:
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```
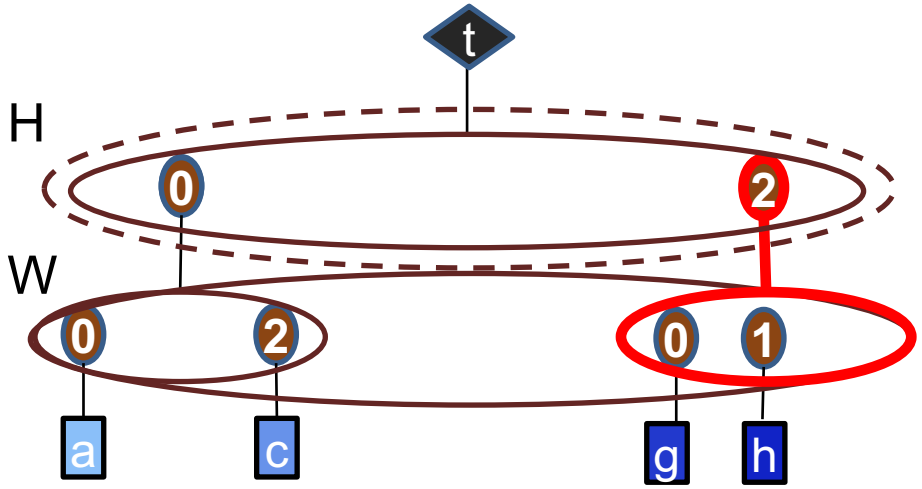
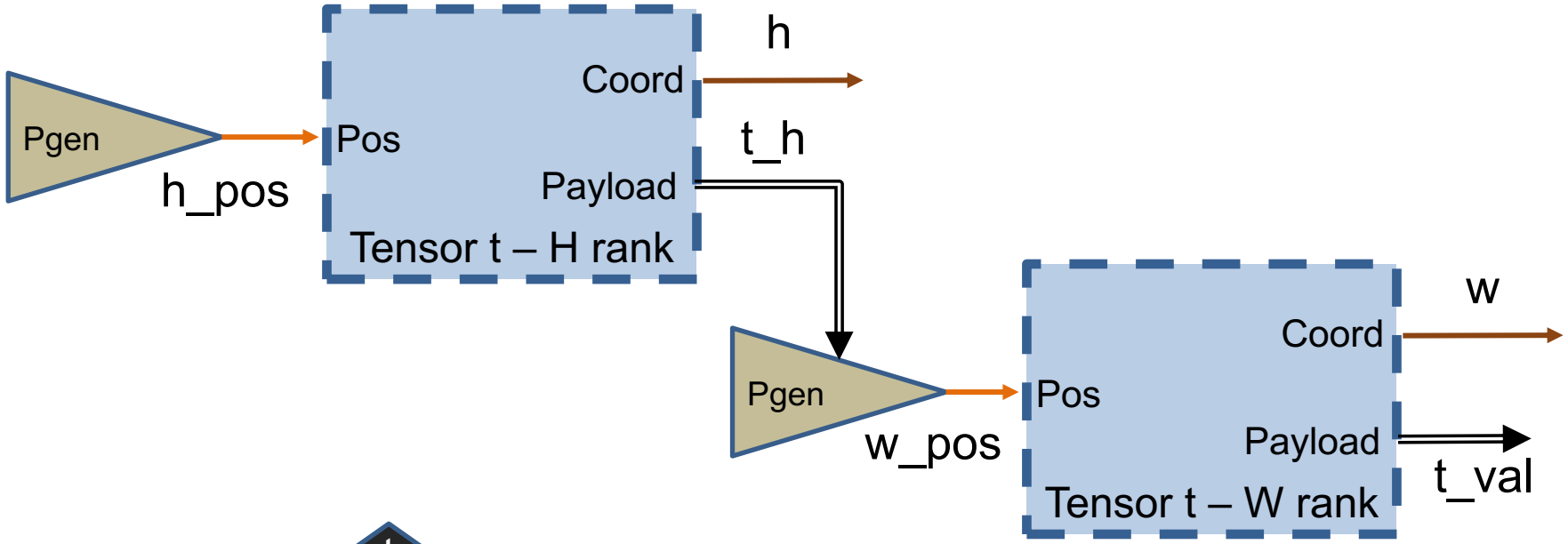
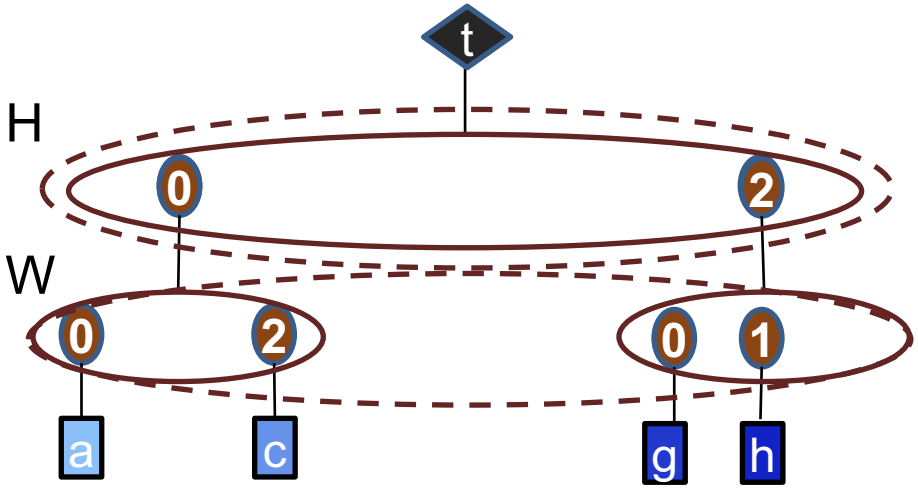



t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

Tensor Traversal (2-D)



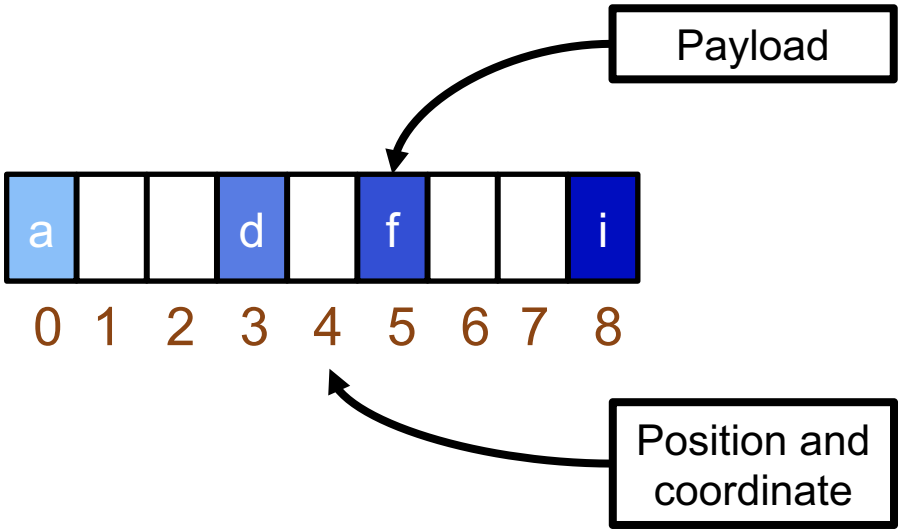


Concordant Traversal

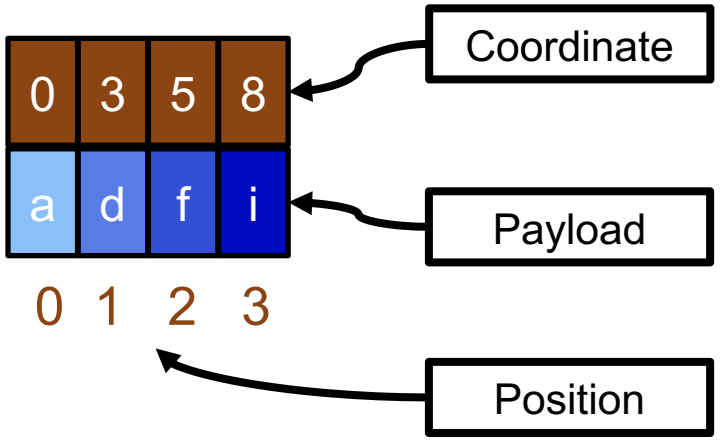
Example Fiber Representations

Each fiber has a set of (coordinate, “payload”) tuples

Array



Coordinate/Payload List



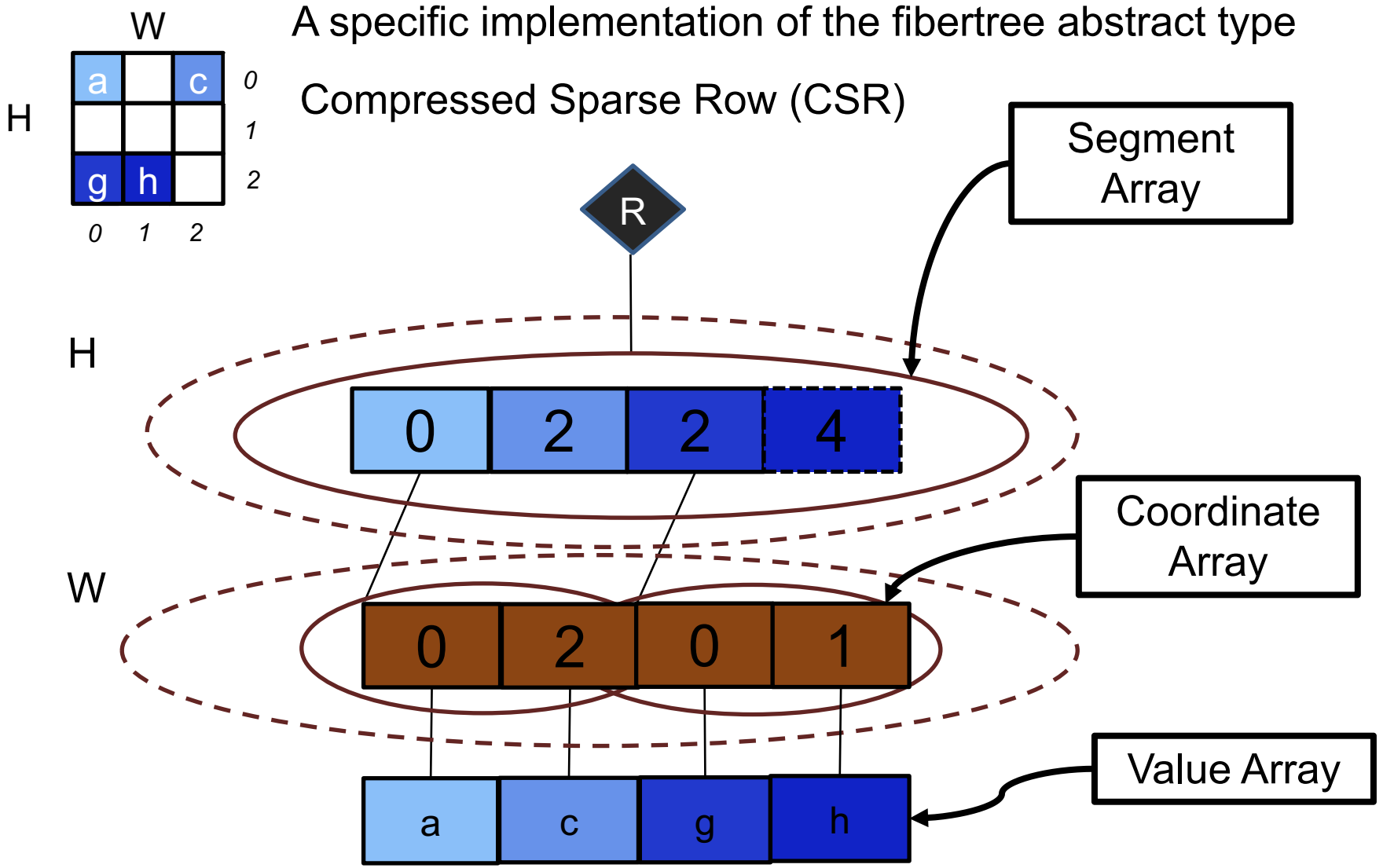
Data in a fiber is accessed by its position or offset in memory

Fiber Representation Choices

- Implicit Coordinates
  - Uncompressed (no metadata required)
  - Compressed – e.g., run length encoded
- Explicit Coordinates
  - E.g., coordinate/payload list
- Compressed vs Uncompressed
  - Compressed/uncompressed is an attribute of the representation*.
  - Uncompressed means size is proportional to maximum coordinate value
  - Compressed formats will have metadata overhead relative to uncompressed formats. For dense data, this may cost more than just using an uncompressed format.
  - Space efficiency of a representation depends on sparsity

*Note: sparsity/density is an attribute of the data.

Uncompressed/Compressed Representation



Tensor Traversal (CSR Style)

```
# 2-D Tensor Traversal (CSR)

t_segs = Array(H)
t_coords = Array(W)
t_vals = Array(W)

sum = 0
for t_h_pos in [0,H):
  h = t_h_pos
  t_w_start = t_segs[t_h_pos]
  t_w_len = t_segs[t_h_pos+1]-t_w_start
  for t_w_pos in [t_w_start, t_w_len):
     h = t_coords[t_w_pos]
     t_val = t_vals[t_w_pos]
     sum += t_val
```

For uncompressed rank coordinate equals position

Coordinates not actually used in this example

CONV: Exploiting Sparse Weights

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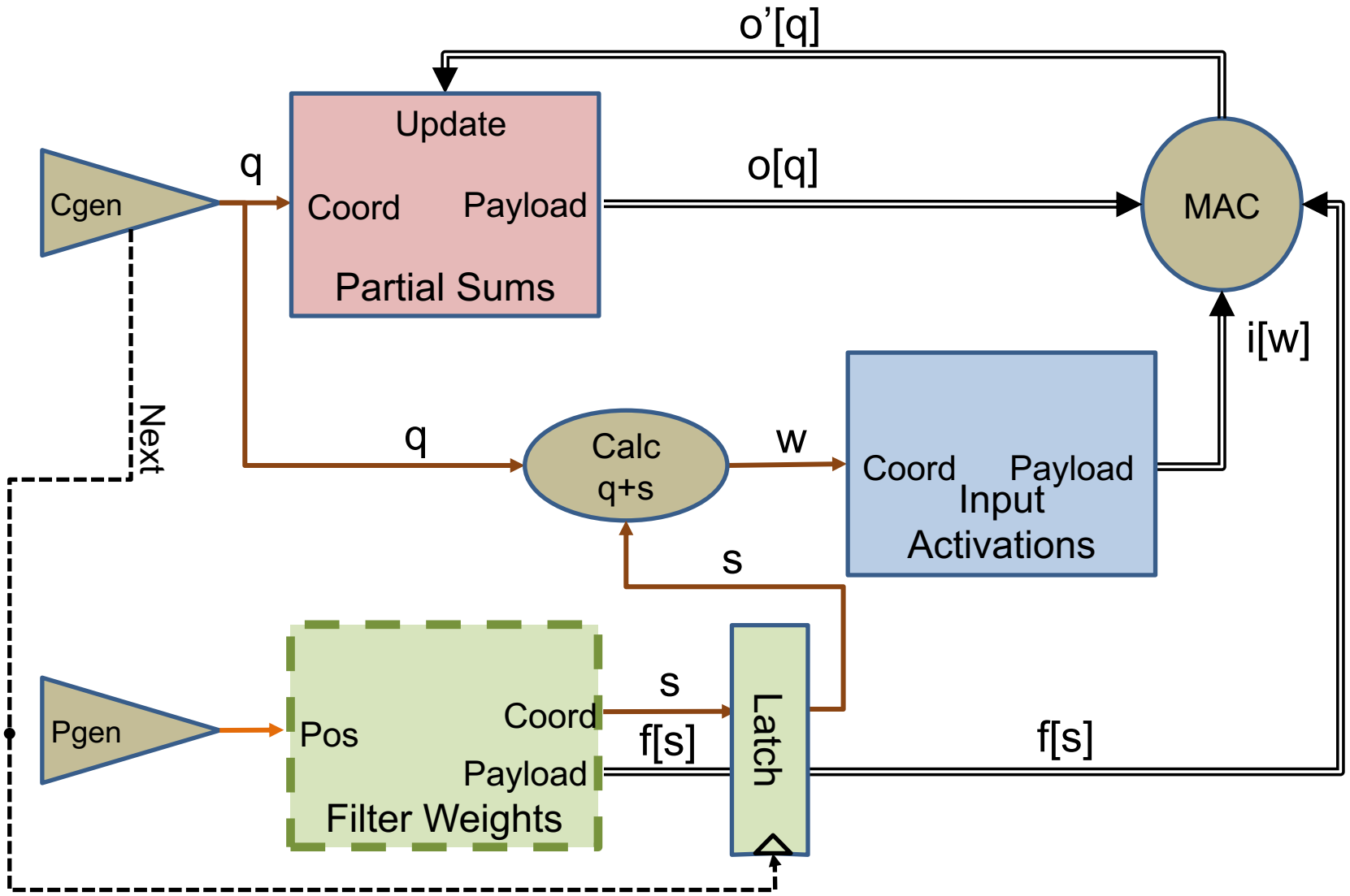
Weight Stationary - Sparse Weights

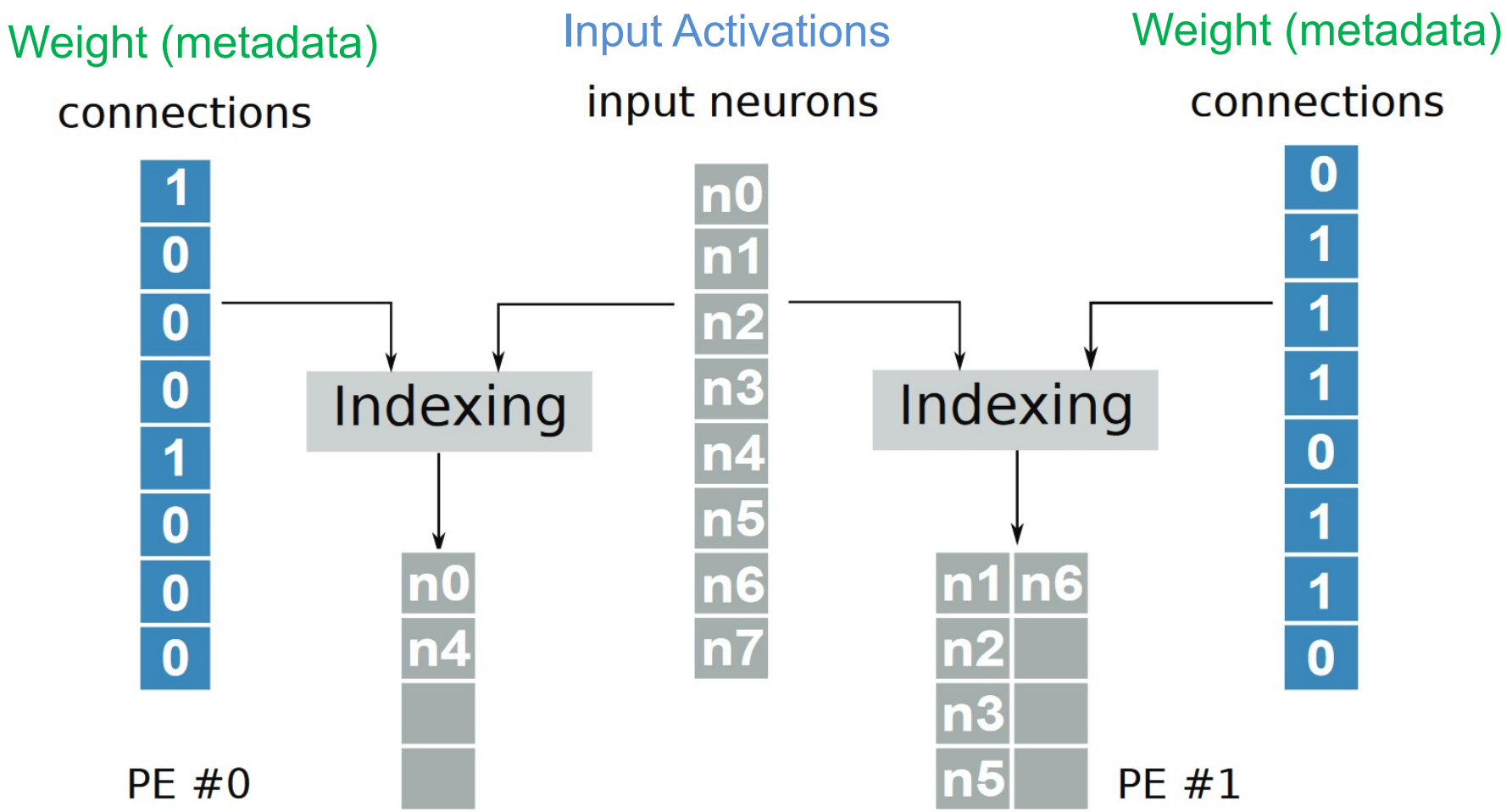
```
i = Array(W)          # Input activations
f = Tensor(S)         # Filter weights
o = Array(Q)          # Output activations

for (s, f_val) in f:
  for q in [0, Q):
    w = q + s
    o[q] += i[w] * f_val
```

Concordant traversal

Weight Stationary - Sparse Weights



Cambricon-X – Activation Access



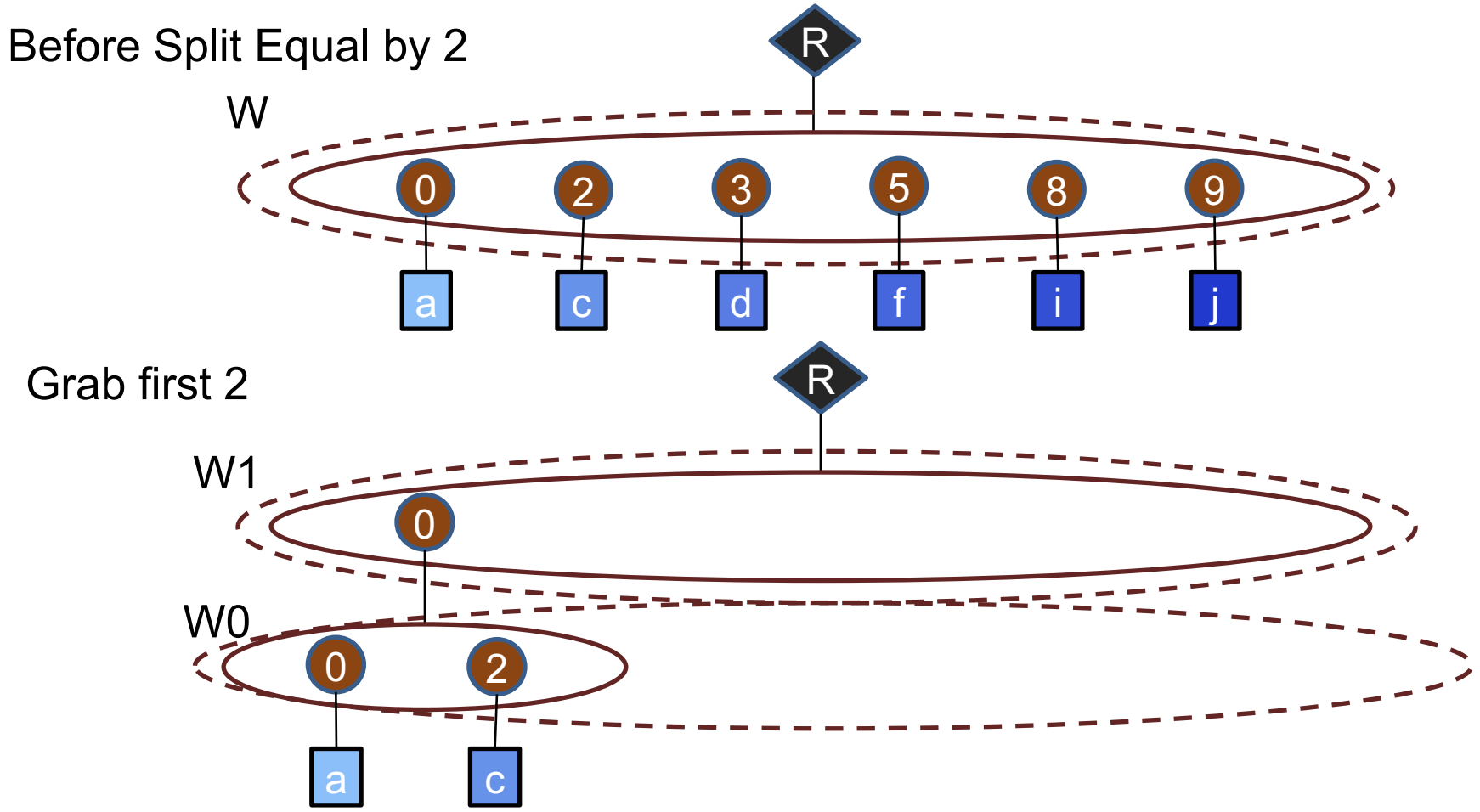
Cambricon-X – Zhang et.al., Micro 2016

To Extend to Other Dimensions of DNN

- **Need to add loop nests for:**
  - **2-D input activations and filters**
  - **Multiple input channels**
  - **Multiple output channels**

- **Add parallelism…**

Fiber Splitting Equally in Position Space



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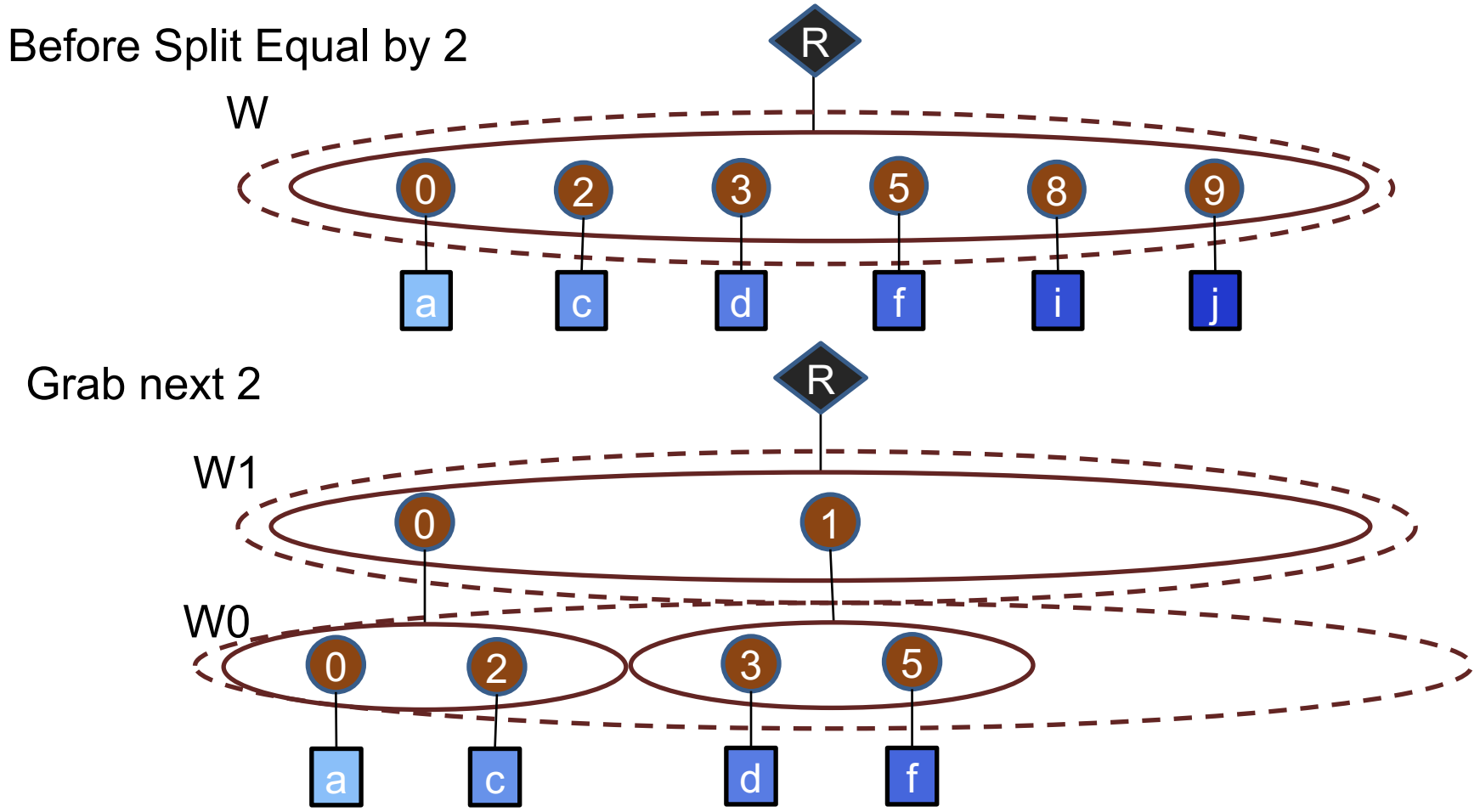
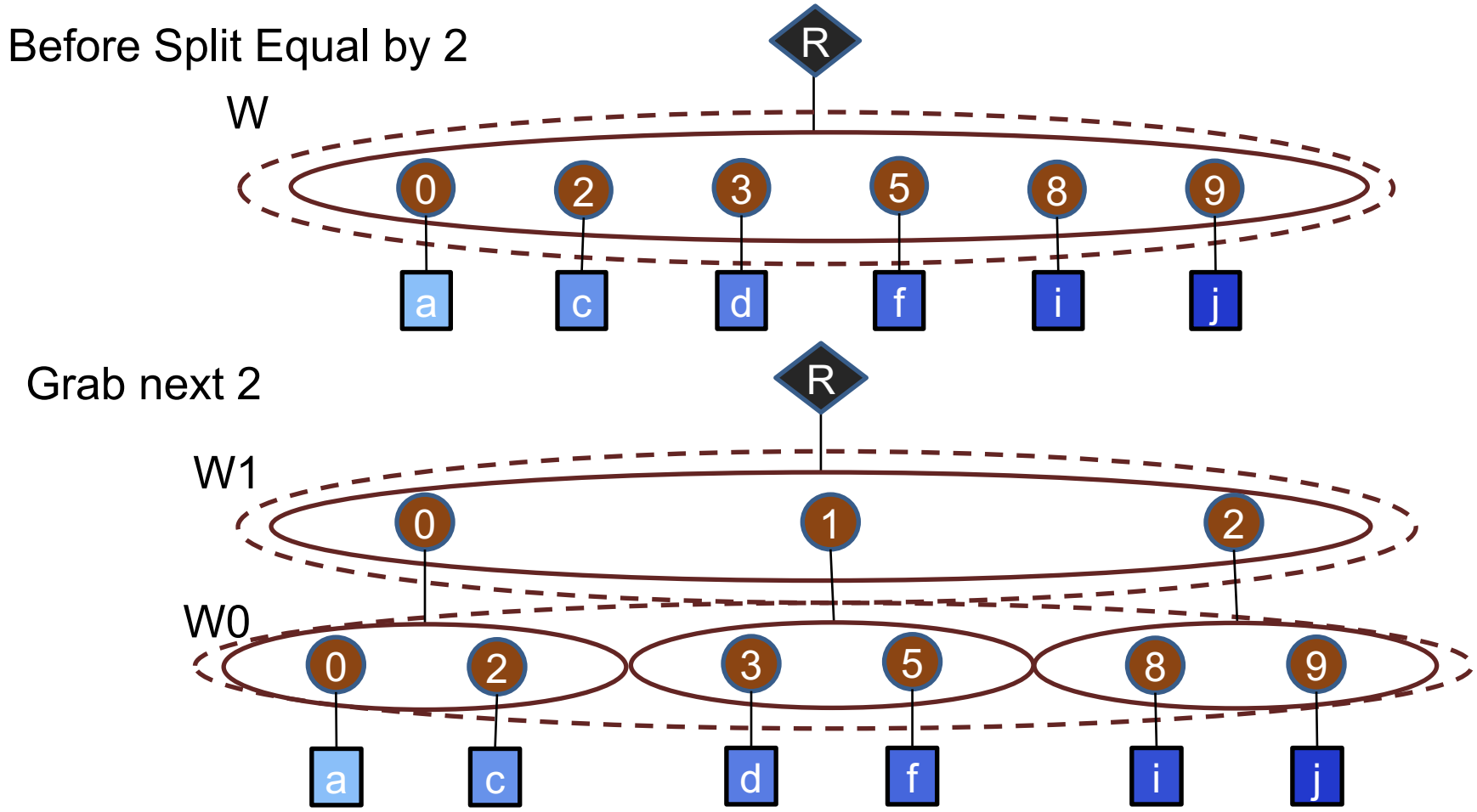
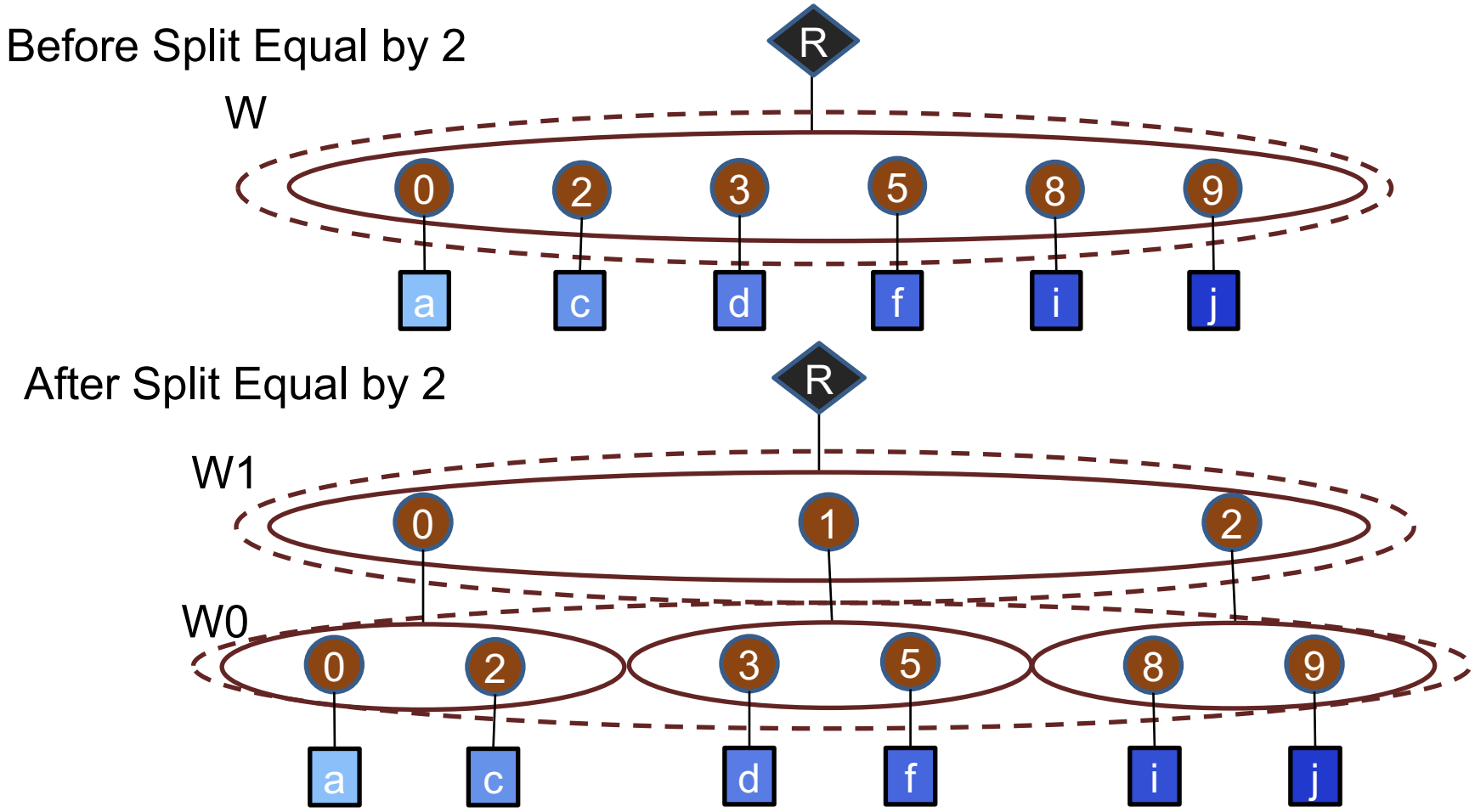


Fiber Splitting Equally in Position Space



Fiber Splitting Equally in Position Space



Parallel Weight Stationary - Sparse Weights

```
i = Array(W)          # Input activations
f = Tensor(S)         # Filter weights
o = Array(Q)          # Output activations

for (s1, f_split) in f.splitEqual(2):
  for q1 in [0, Q/4):
    parallel-for (s0, f_val) in f_split:
      parallel-for q0 in [0, 4):
        q = q1*4 + q0
        w = q + s
        o[q] += i[w] * f_val
```

Get groups of two weights

Work on two weights in parallel

Work on four outputs at once

Calculate coordinates

Look up input activation

Accumulate multiple outputs each spatially

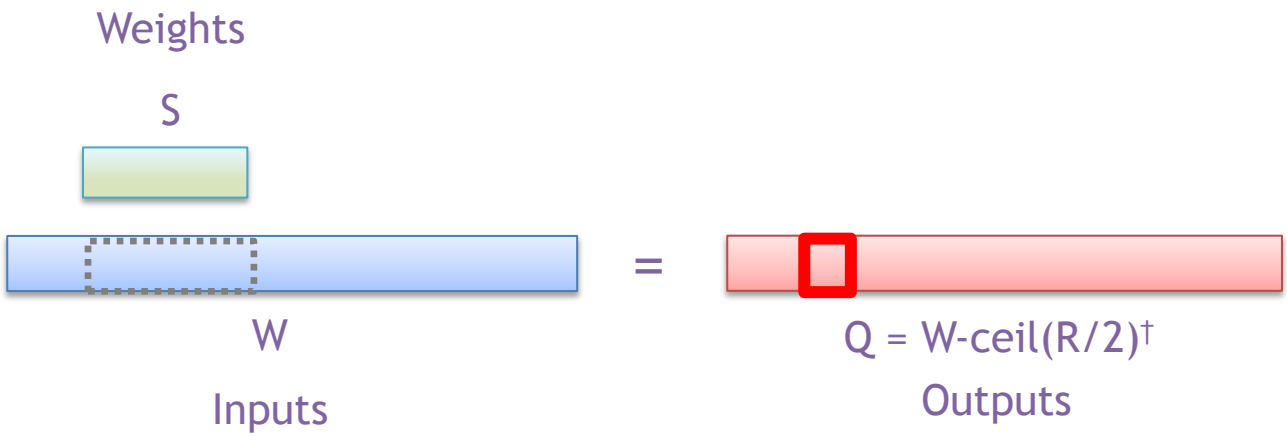
CONV: Exploiting Sparse Inputs & Sparse Weights

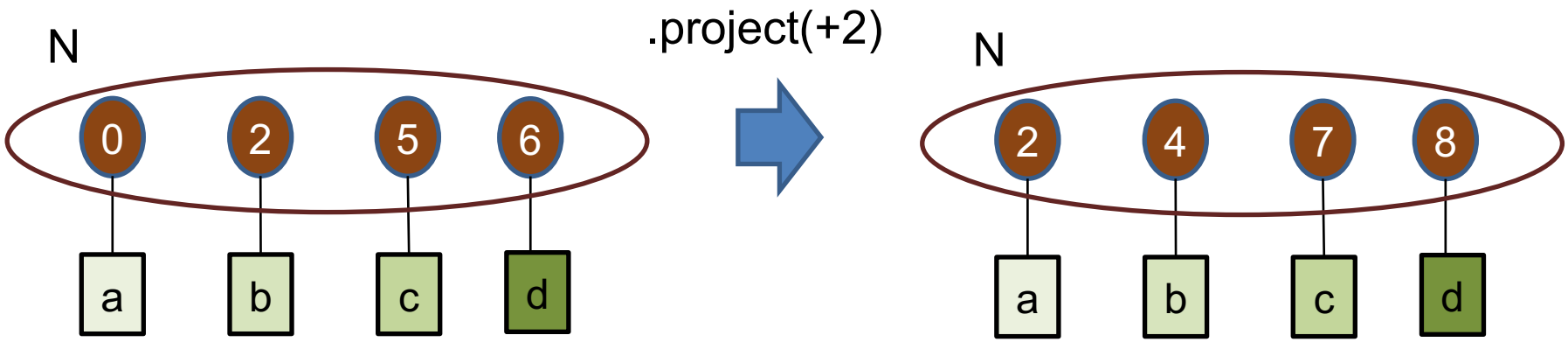
Output Stationary - Sparse Weights & Inputs

```
i = Tensor(W)          # Input activations
f = Tensor(S)          # Filter weights
o = Array(Q)           # Output activations

for q in [0,Q):
  for (s, (f_val, i_val)) in f.project(+q) & i:
    o[q] += i_val * f_val
```

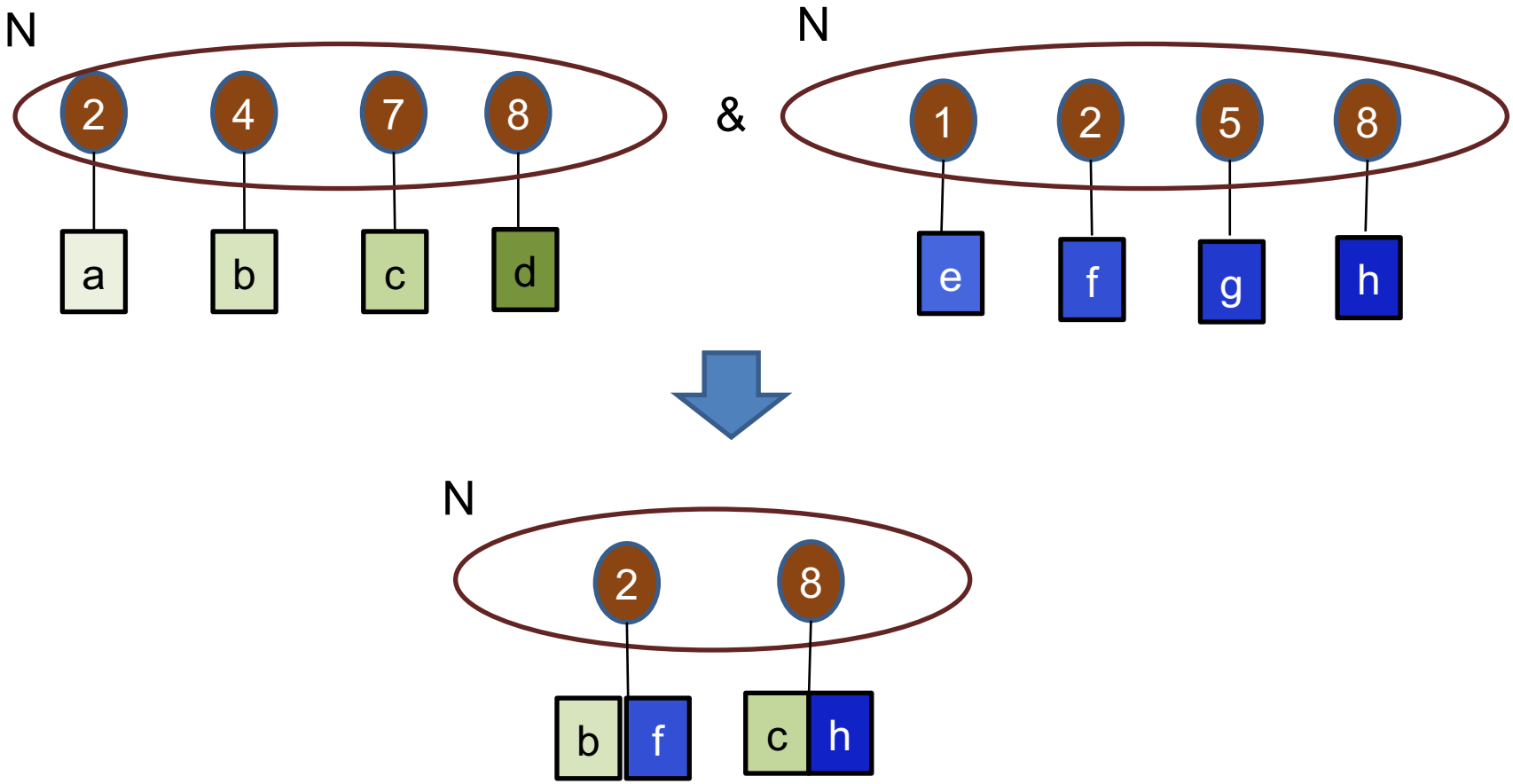
Fiber Coordinate Projection



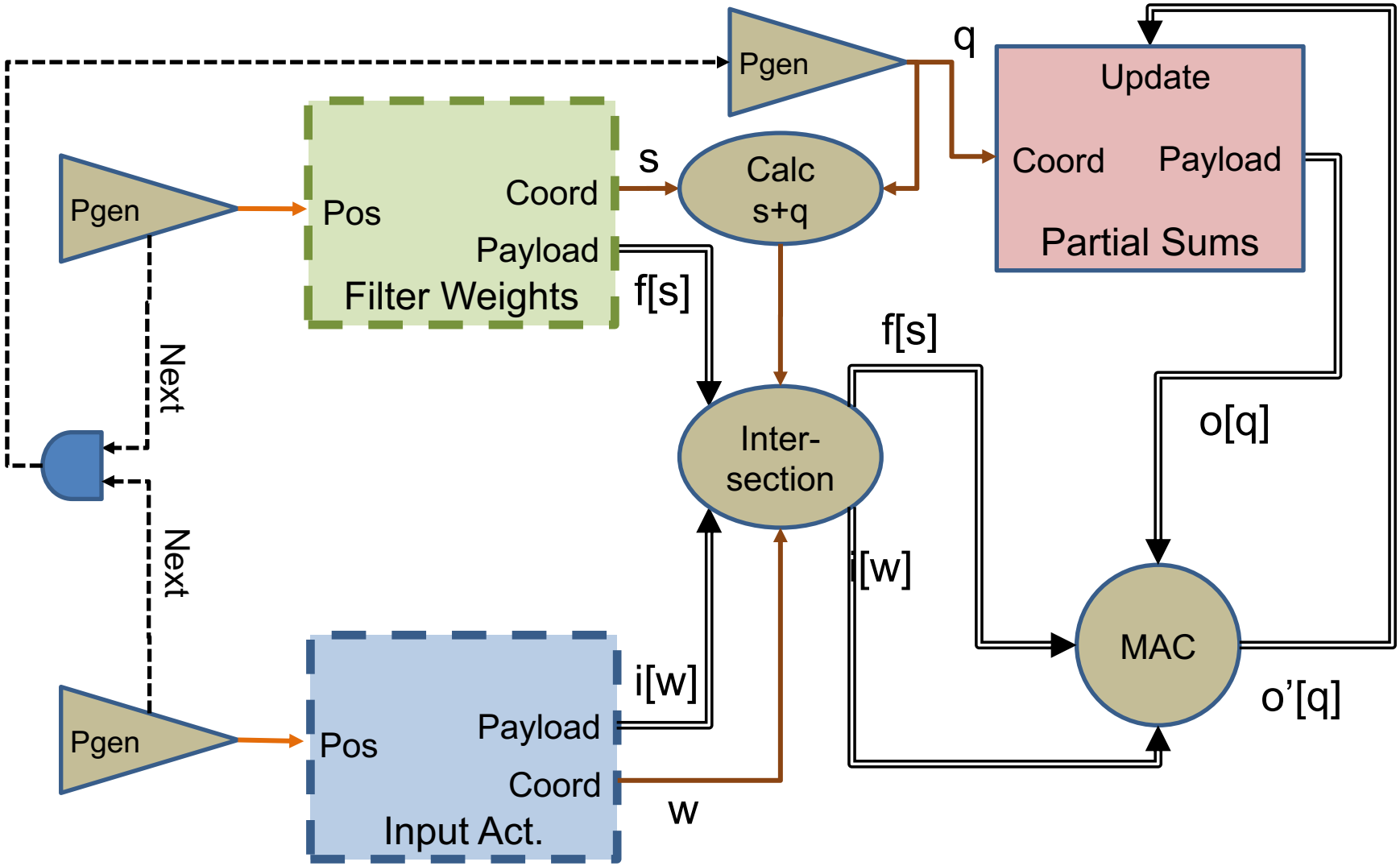


fiber-projection

Fiber Intersection



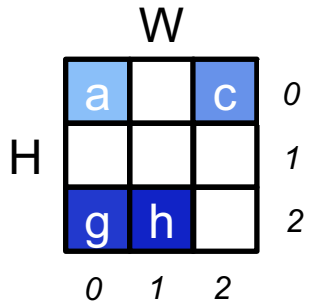
Output Stationary - Sparse Weights & Inputs



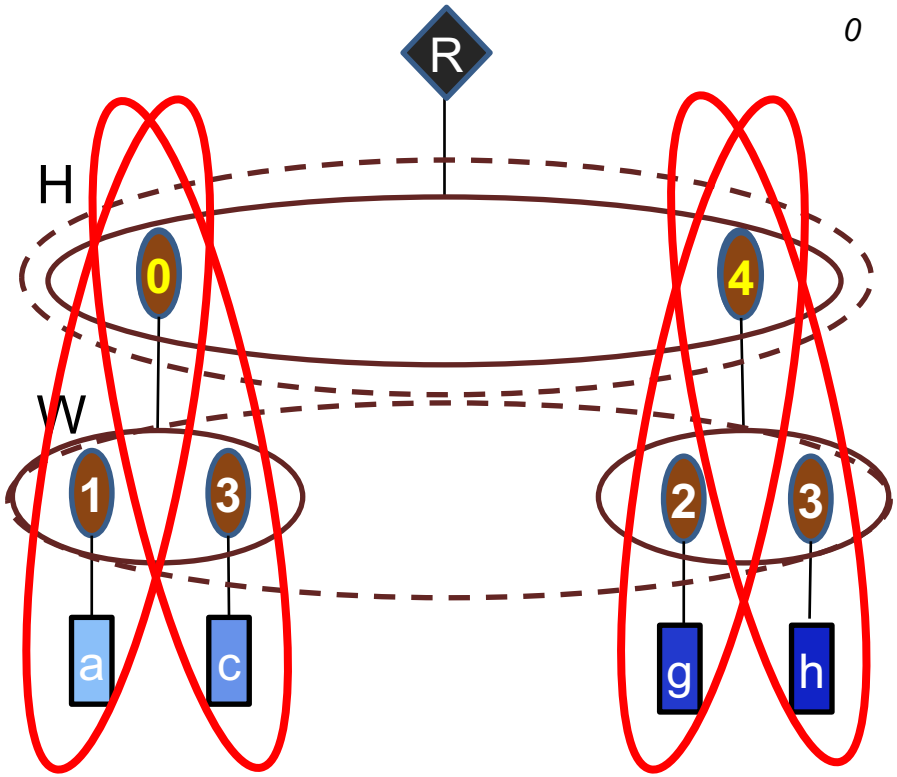
Flattening Ranks

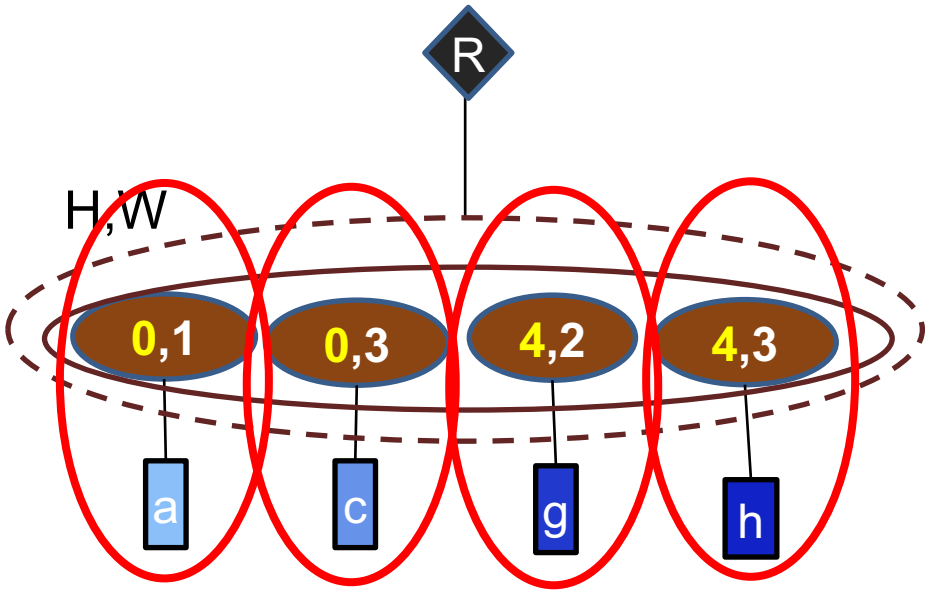
For efficiency one can form new representations where the data structure for two or more ranks are combined.

Tensor-<CC>(HW)



Tensor-<C^2>(HW)





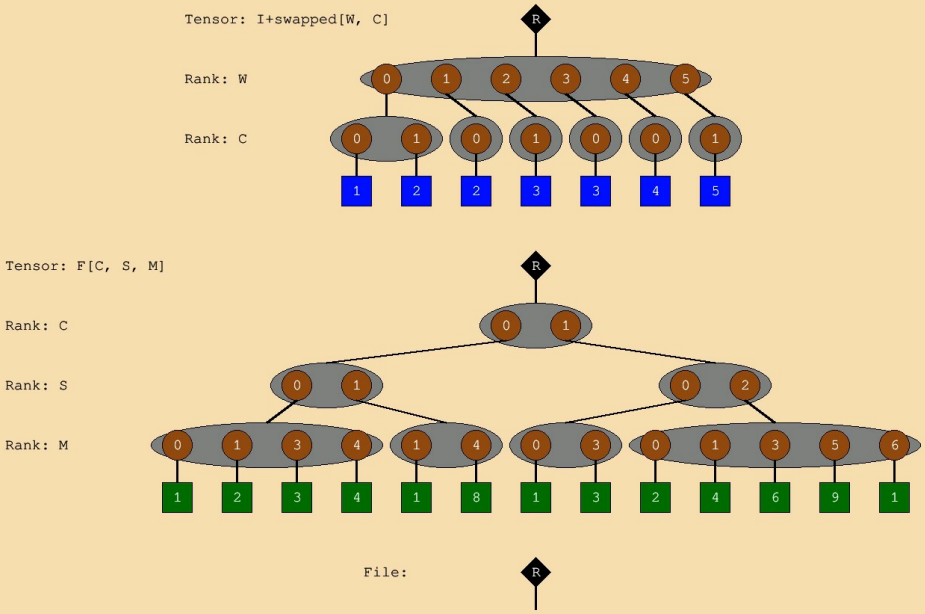
Row Stationary – Sparse Inputs & Activations

```
i = Tensor(CW)        # Input activations (CW flattened)
f = Tensor(C,SM)      # Filter weights (SM flattened)
o = Array(M, Q)       # Output activations

for ((c, w), i_val) in i:
  f_c = f.getPayload(c)
  f_c_split = f_c.splitEven(2)
  parallel-for (_, f_sm) in f_c_split:
    for ((s, m), f_val) in f_sm if w-Q <= s < w:
      q = w - s
      o[m, q] += i_val * f_val
```

Eyeriss V2 – Chen et.al., JETCAS 2018

Row Stationary – Sparse Inputs & Activations



Eyeriss V2 – Chen et.al., JETCAS 2018

Thank you!

Next Lecture:
Transactional Memory