Accelerators (II)

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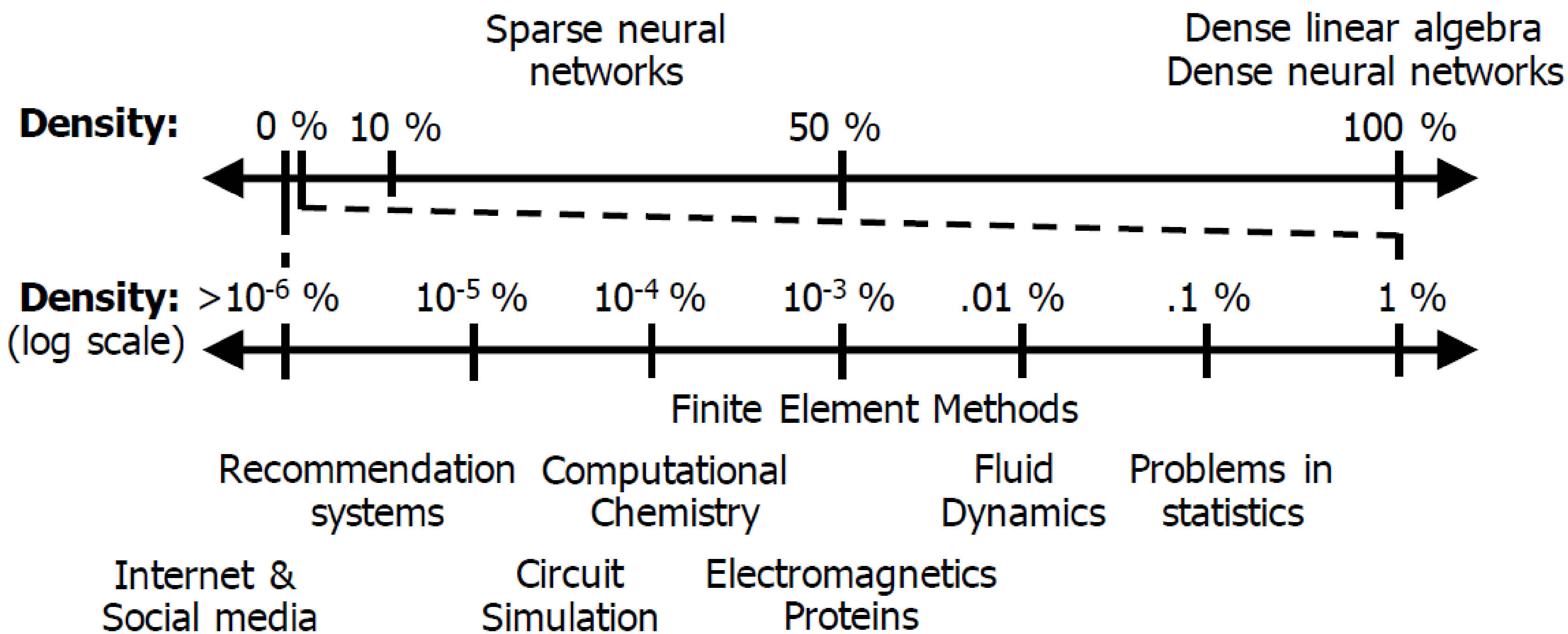
Many problems use Sparse Tensors



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

Exploiting Sparsity

Sparse data can be compressed

Can save space and energy by avoiding manipulation of zero values

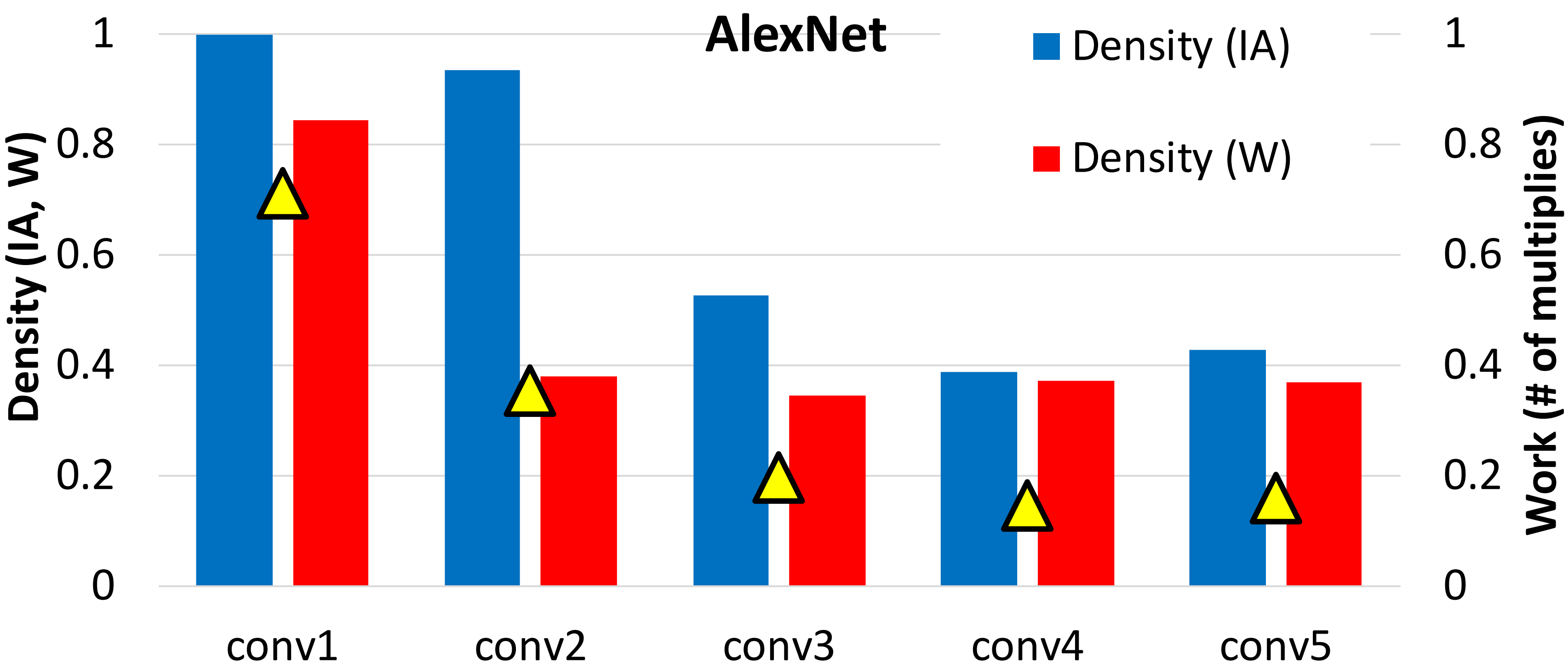
$$\boldsymbol{anything} \times \mathbf{0} = \mathbf{0}$$

$$\boldsymbol{anything} + \mathbf{0} = \boldsymbol{anything}$$

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

Motivation in DNNs

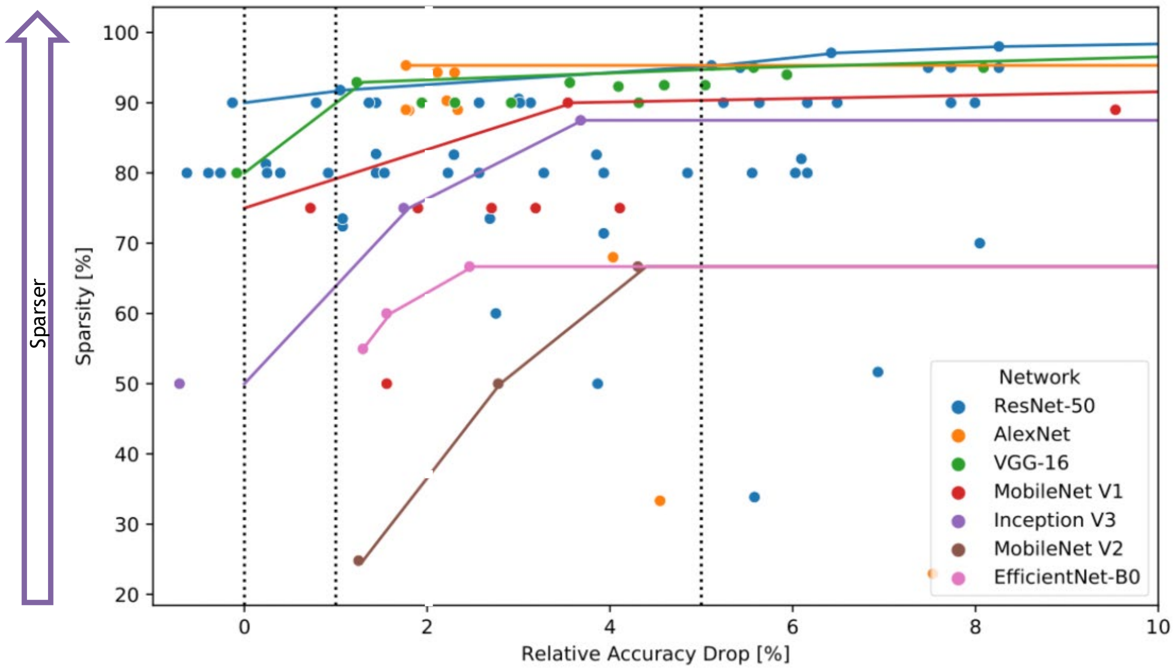
- Leverage CNN sparsity to improve energy-efficiency



SCNN, Parashar et.al., ISCA 2017

Exploitable Sparsity

Acceptable sparsity depends on target task and error tolerance



	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*

Hoefler et al. arXiv, 2021

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?

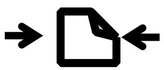
When is a storage access gated?

How much is the compute able to skip ahead?

At which storage level is the skipping performed?

What is the criteria for skipping?

Hardware Sparse Acceleration Features



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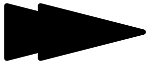
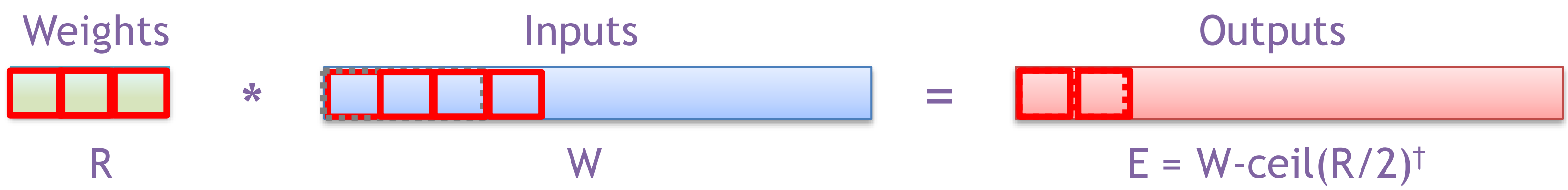


Skipping:
Explicitly eliminate ineffectual storage accesses and computes by skipping the cycle to save energy and time

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):
          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]
}}
```

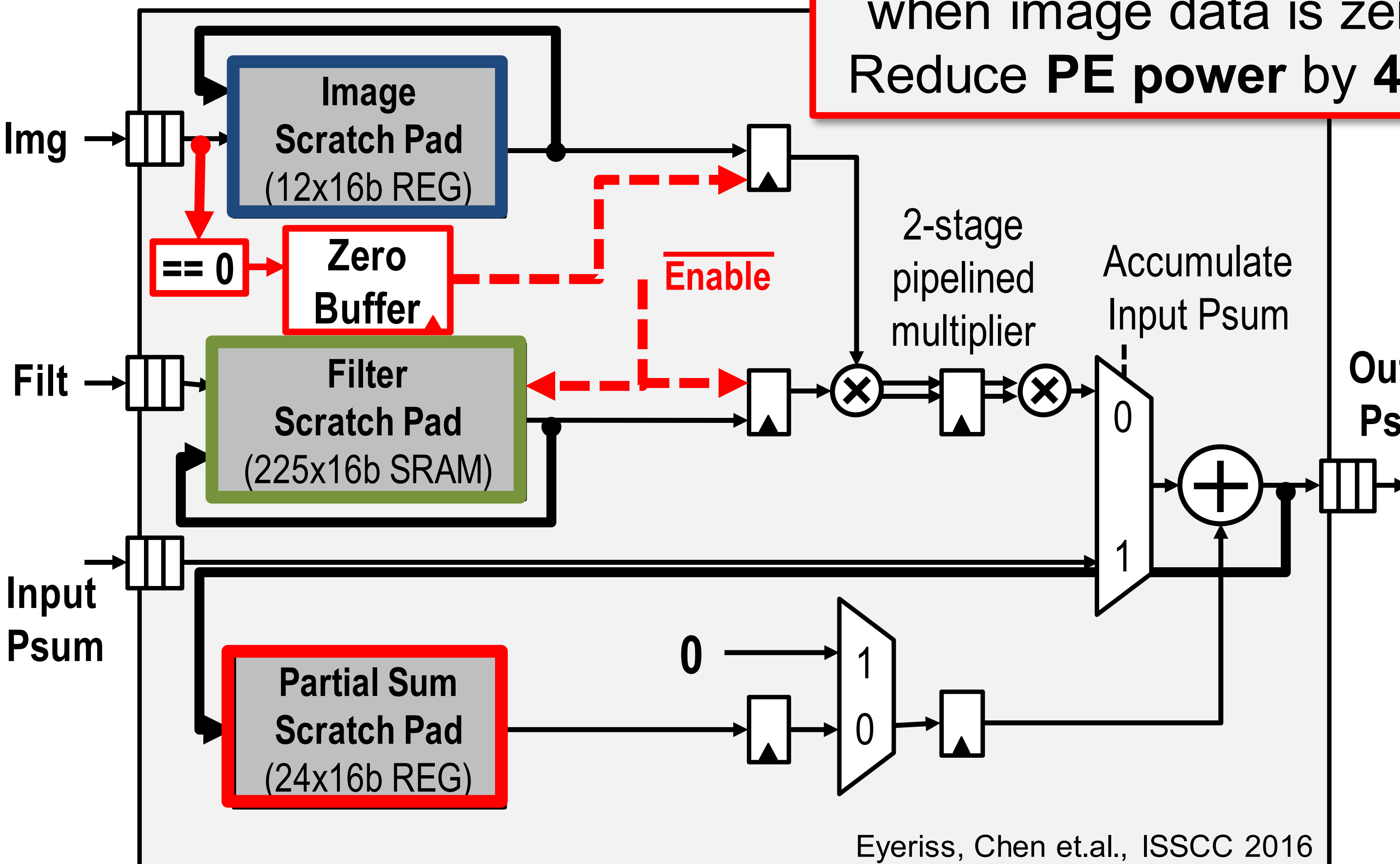
What did we save using the conditional execution? Energy

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

† Assuming: 'valid' style convolution

Eyeriss – Clock Gating

Gate **mult** and **mem reads** when image data is zero. Reduce **PE power** by **45%**



Sparse Tensor Representation

Hardware Sparse Acceleration Features

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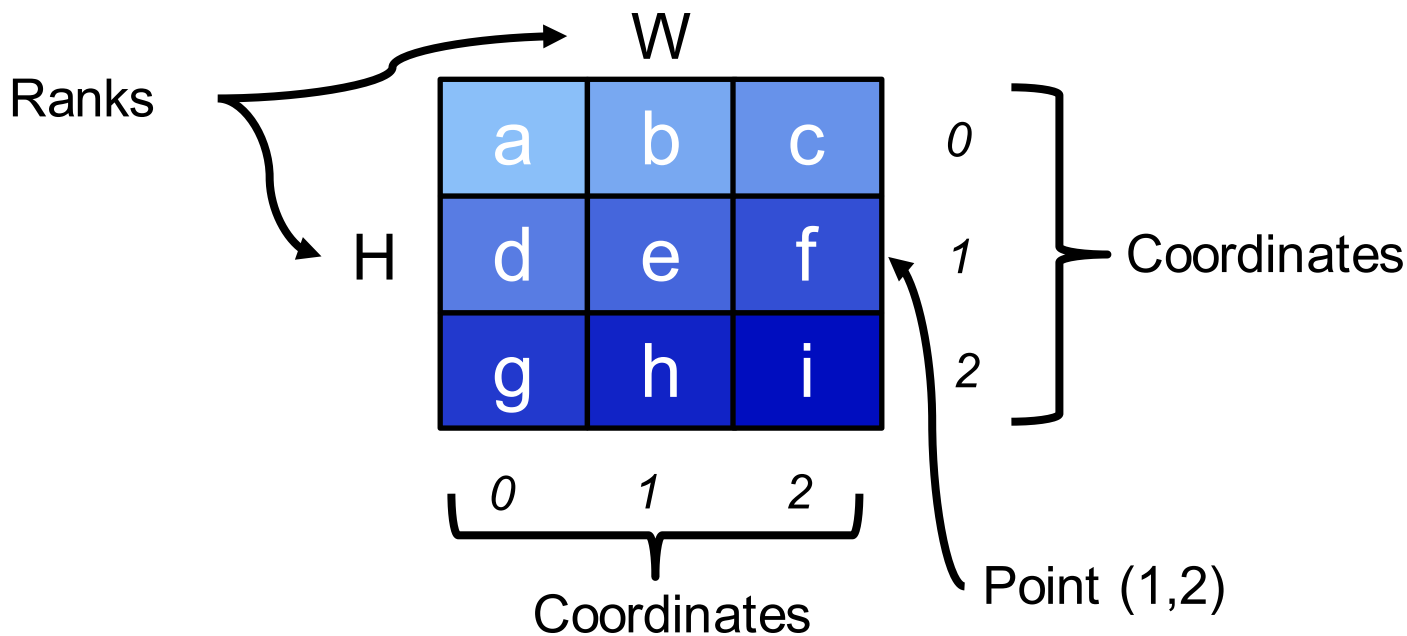
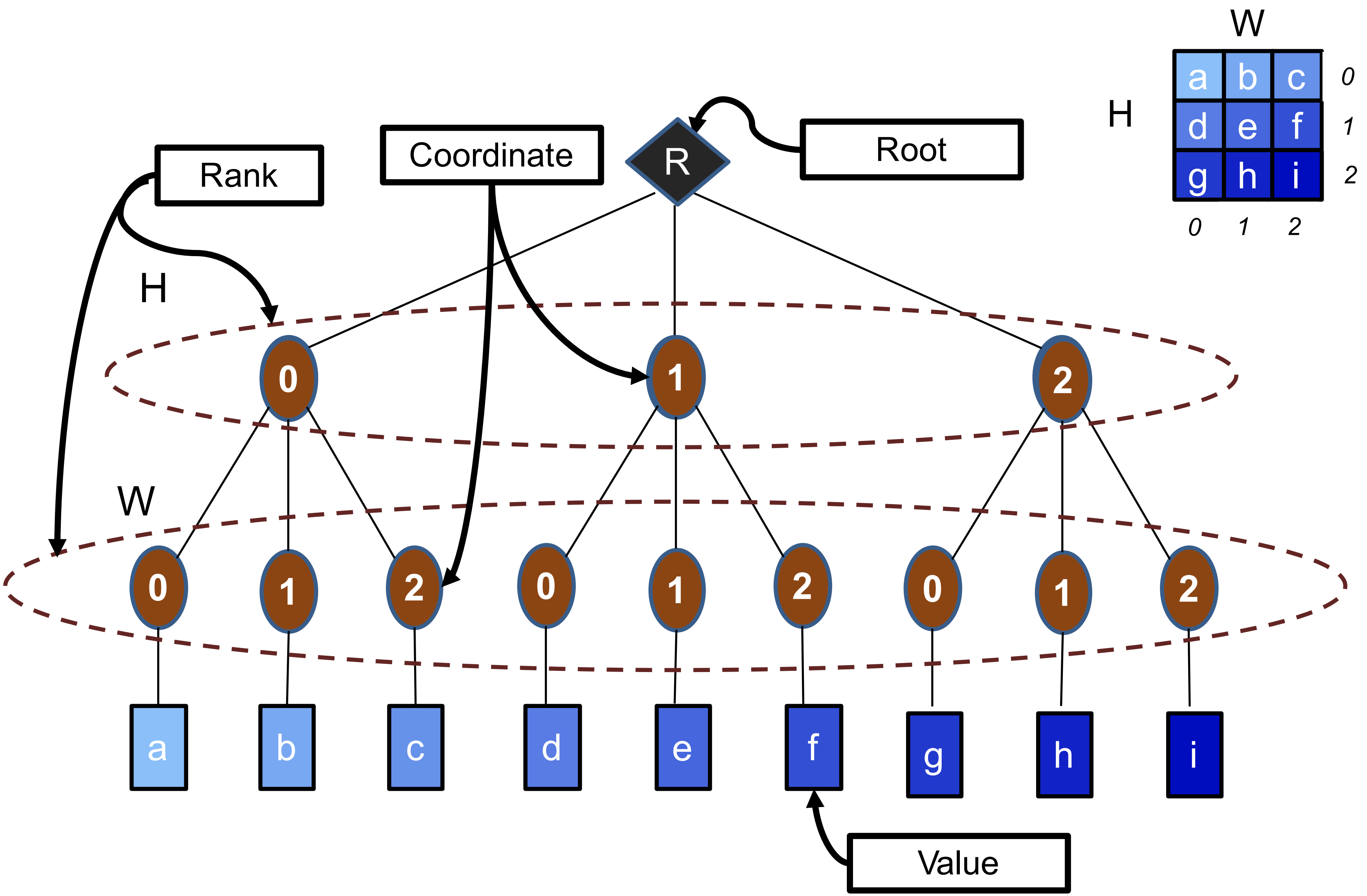
Tensor Data Terminology



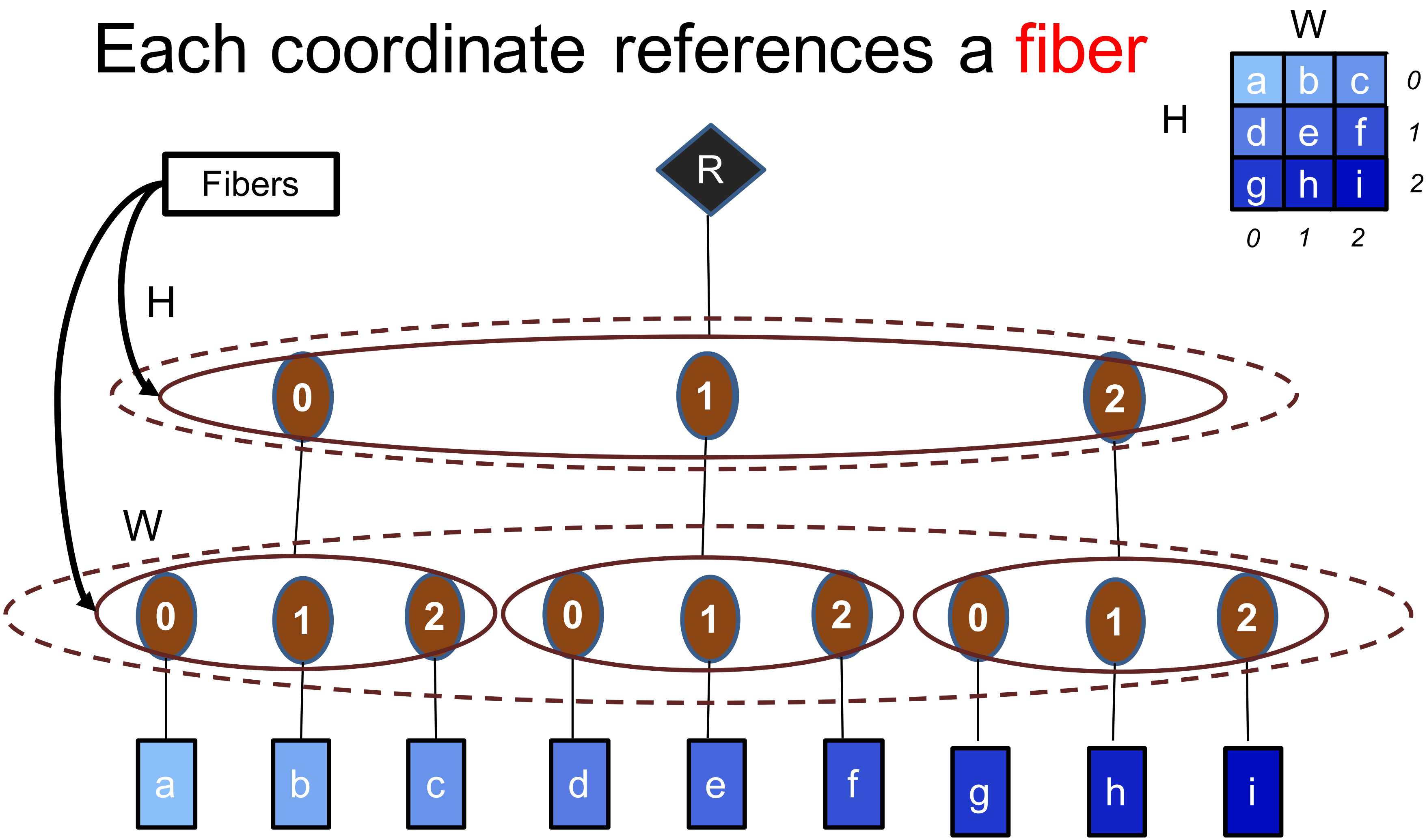
- The elements of each “rank” (dimension) are identified by their “coordinates”, e.g., rank H has coordinates 0, 1, 2
- Each element of the tensor is identified by the tuple of coordinates from each of its ranks, i.e., a “point”.
  So (1,2) -> “f”

Tree-based Tensor Abstraction



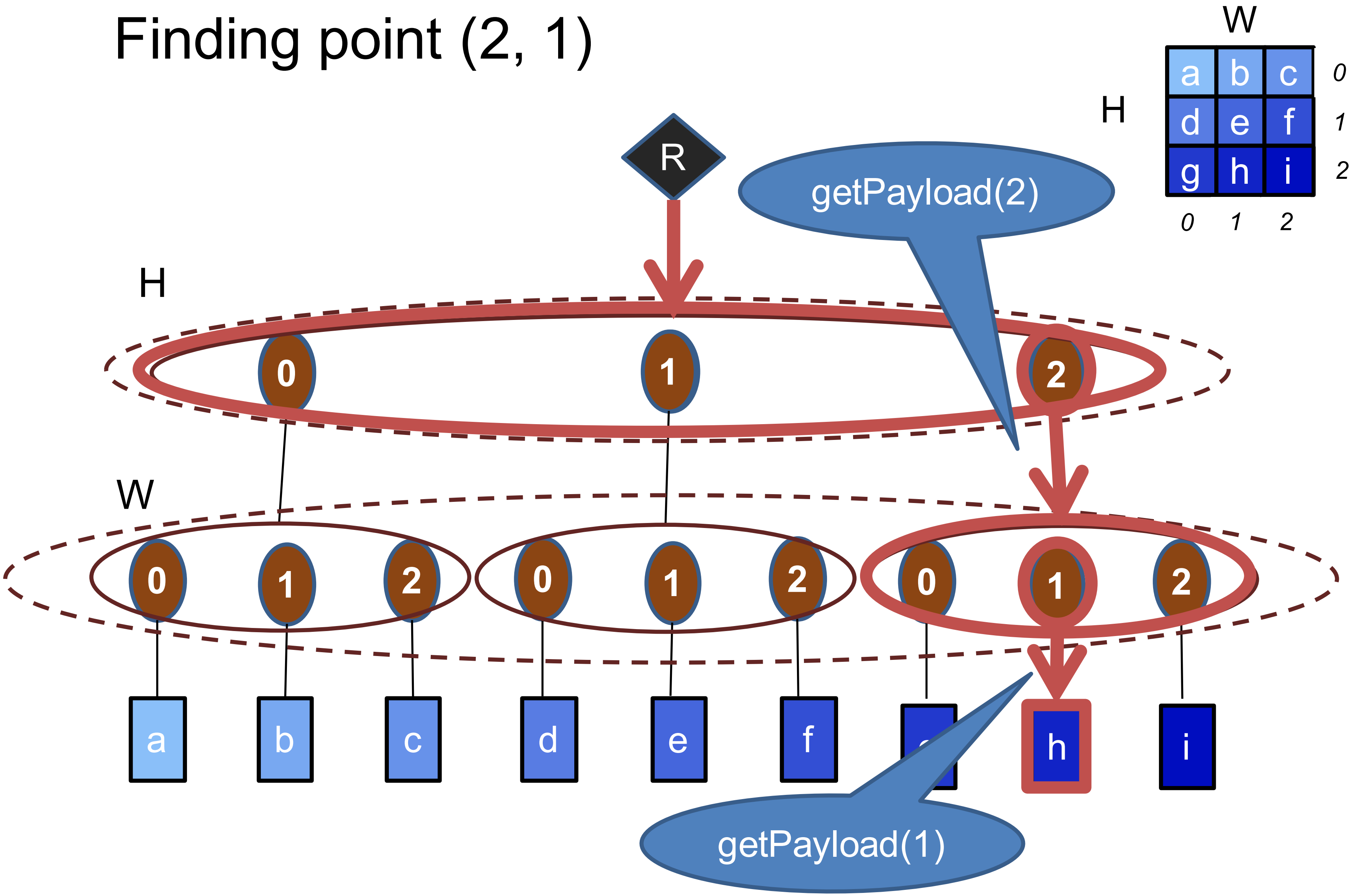
Fibertree Tensor Abstraction

Each coordinate references a fiber



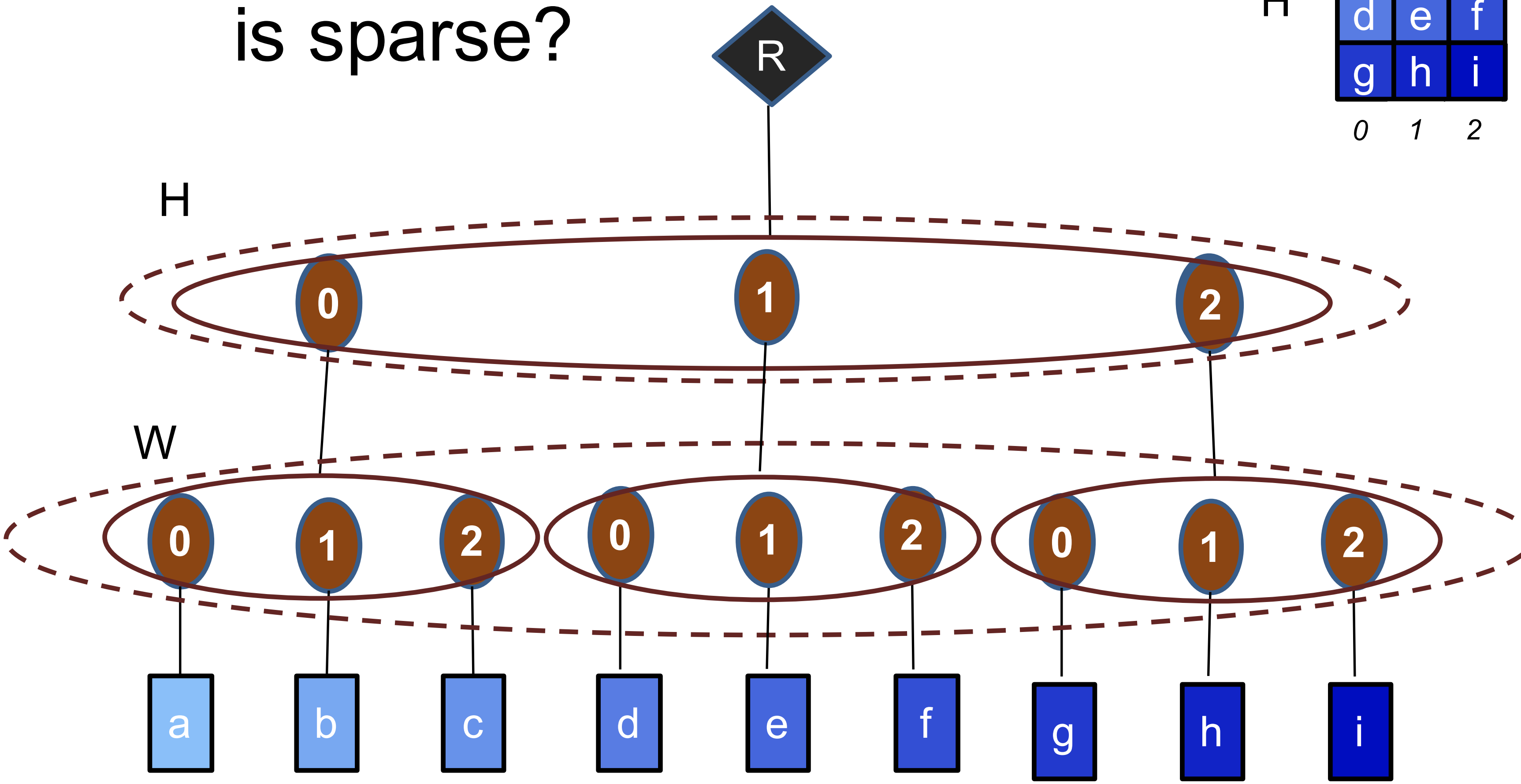
Fibertree Tensor Abstraction

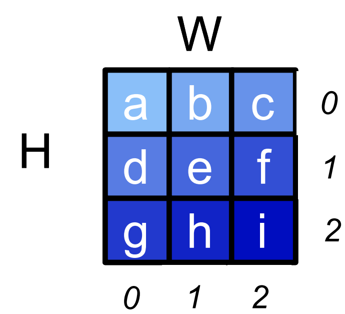
Finding point (2, 1)



Fibertree Tensor Abstraction

What if tensor
is sparse?





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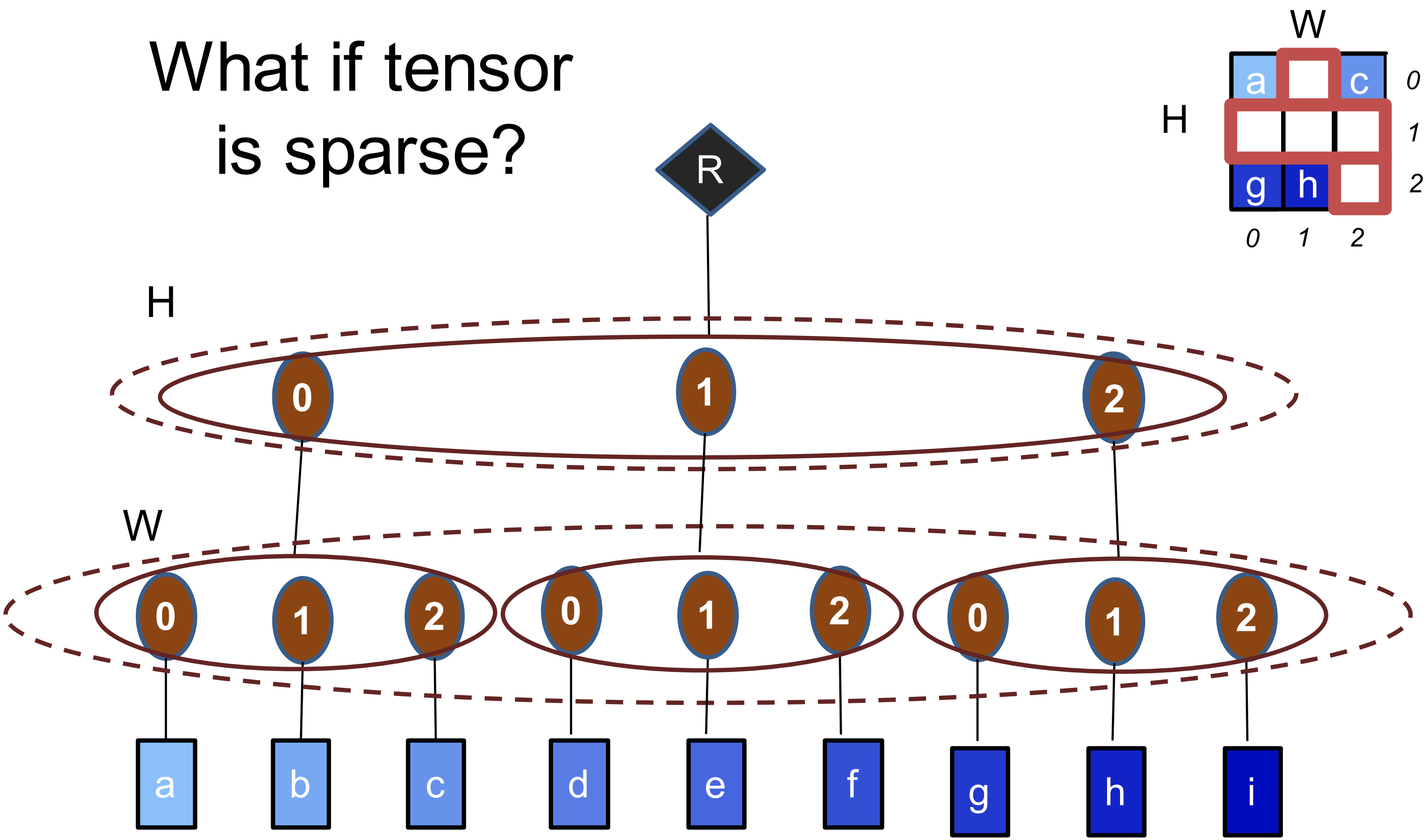

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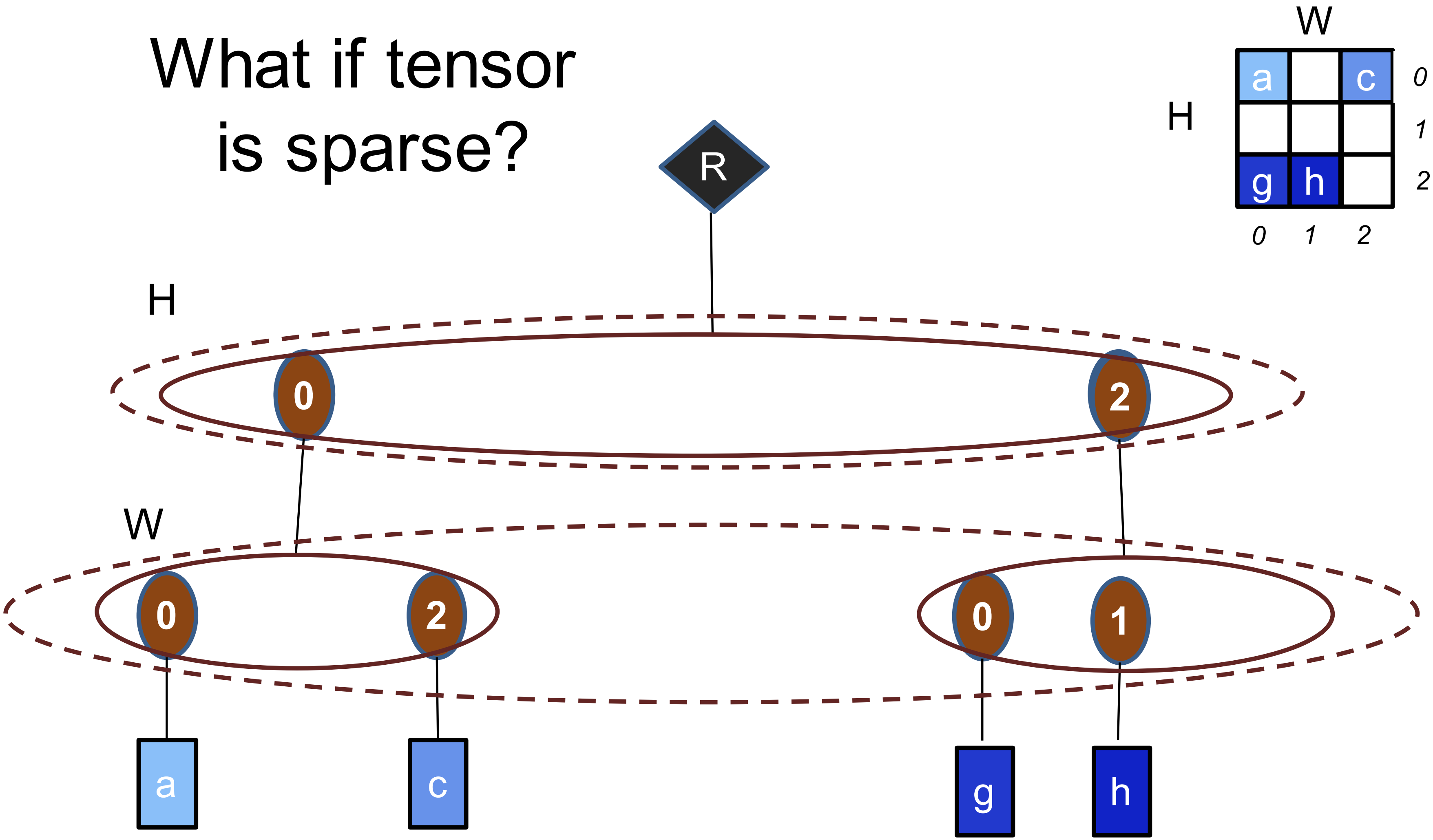

Fibertree Tensor Abstraction

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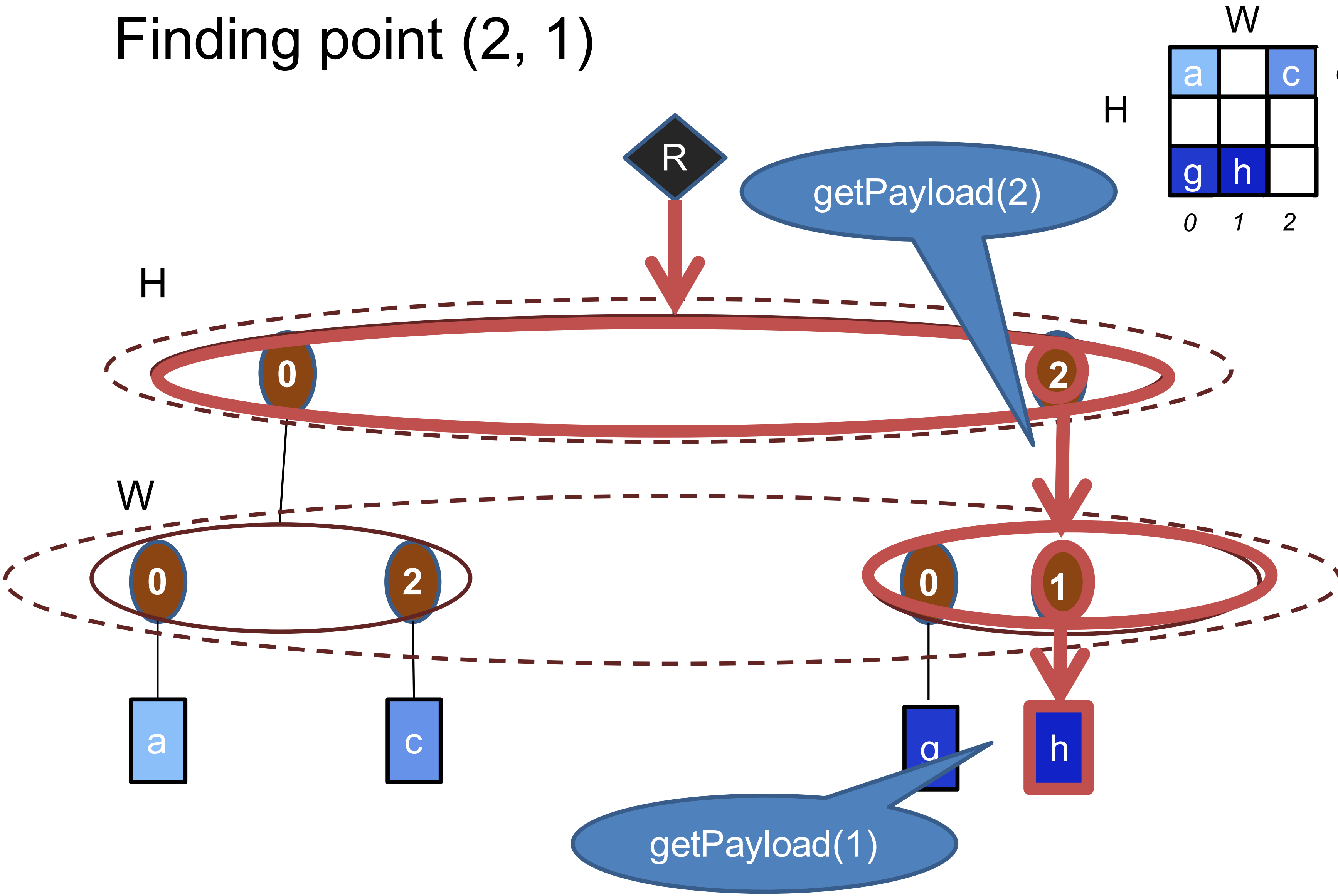


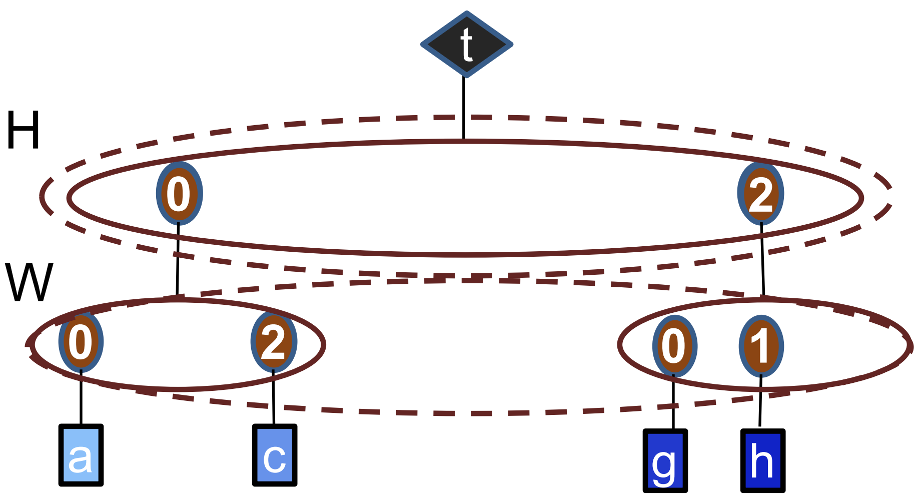
Tensor Traversal (2-D)

```
# 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	?	?	?
…	…	…	…	…

Tensor Traversal (2-D)

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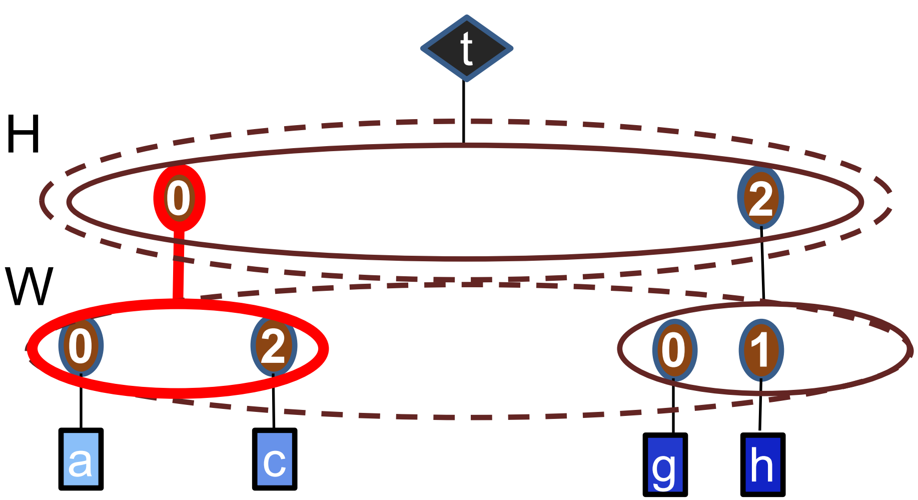
```



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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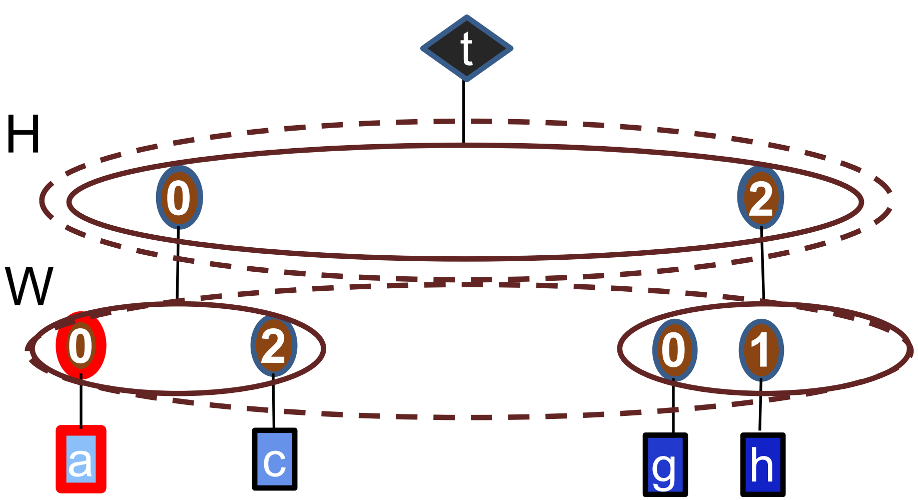

t_pos	h	t_h_pos	w	t_val
0	0	?	?	?
0	0	0	0	a
0	0	1	2	c
1	2	?	?	?
…	…	…	…	…

Tensor Traversal (2-D)

```
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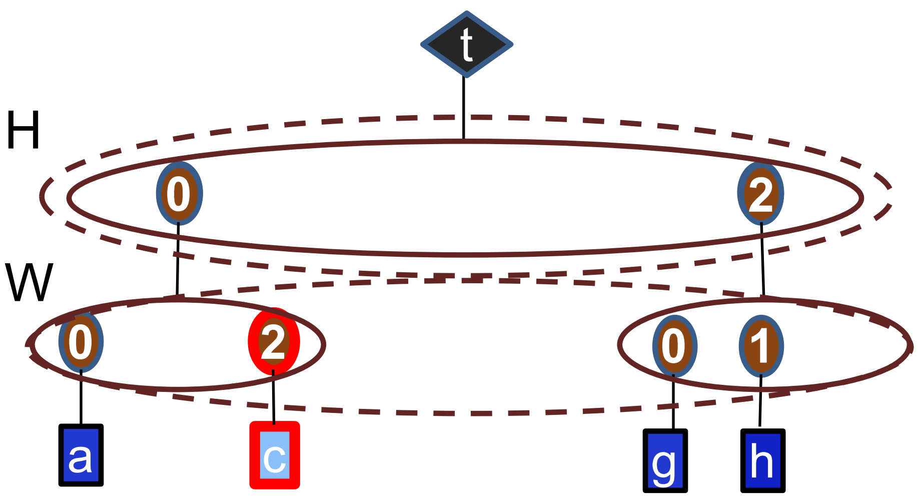
```



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

t = Tensor(H,W)

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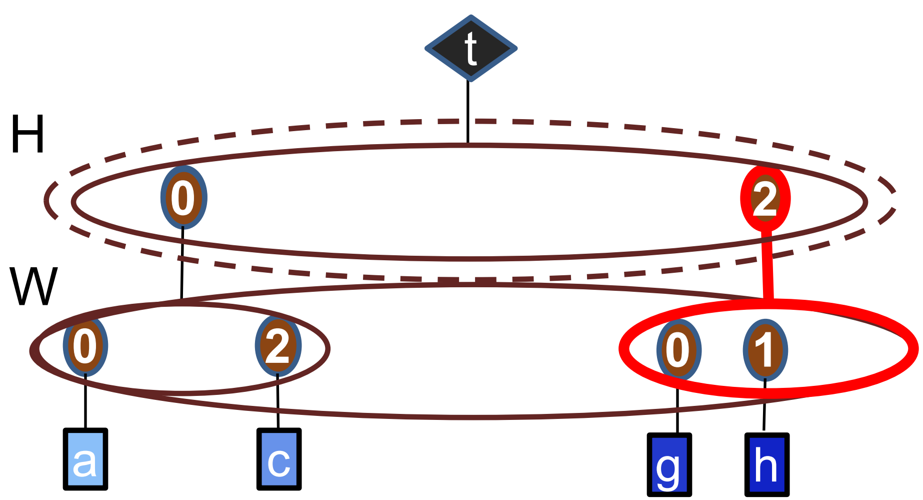
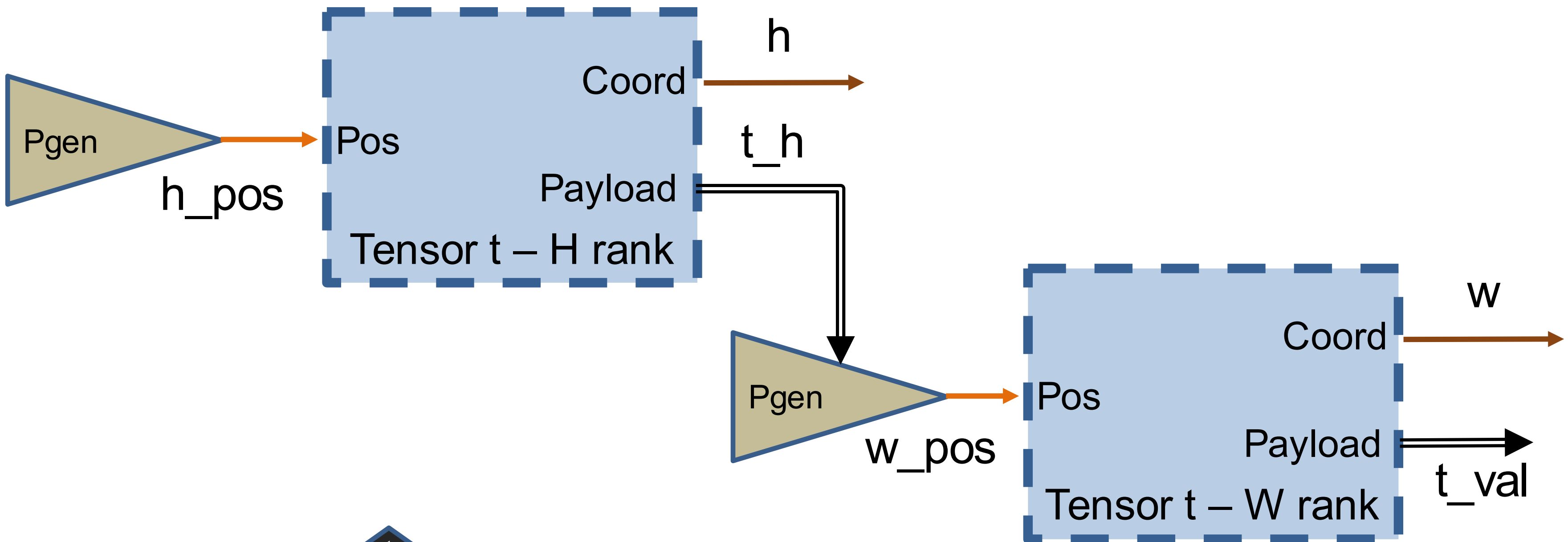
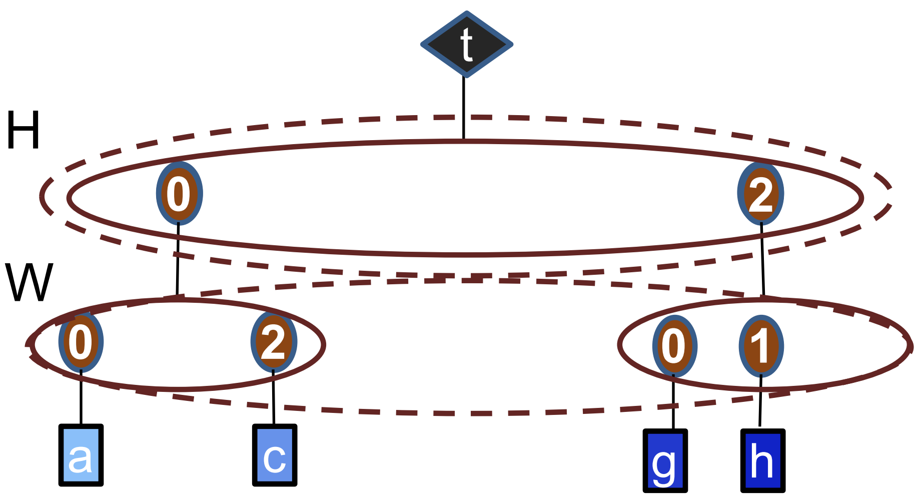
```



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)



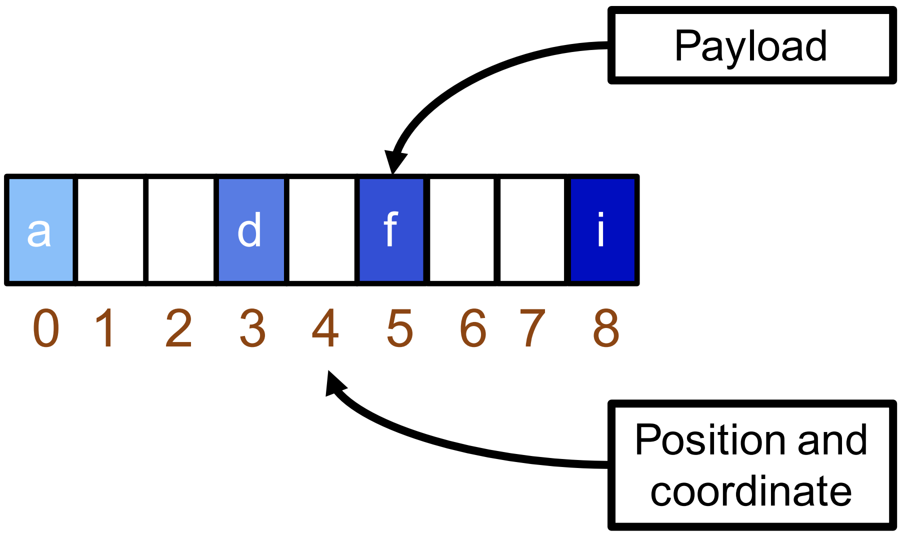


Concordant Traversal

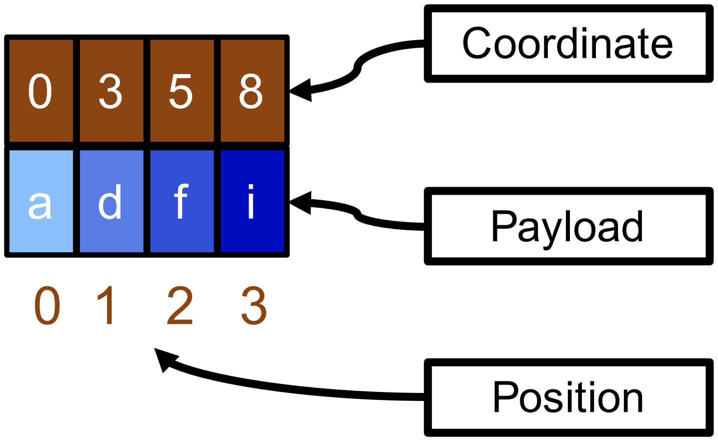
Example Fiber Representations

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

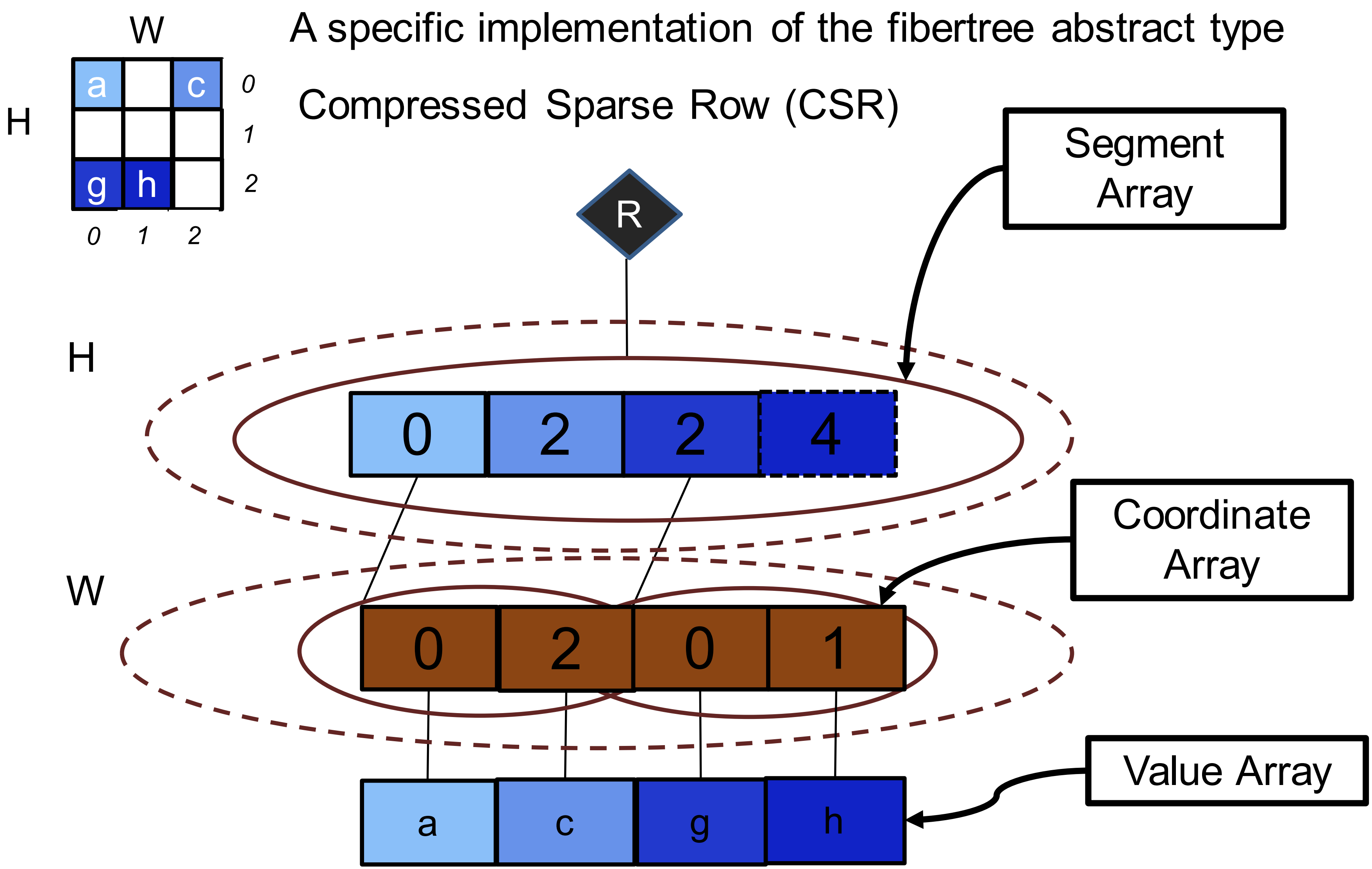
- Implicit Coordinates
  - Uncompressed (no metadata required)
  - Compressed – e.g., run length encoded
- Explicit Coordinates
  - E.g., coordinate/payload list
- Compressed vs Uncompressed
  - Compressed/uncompressed is an attribute of the representation*.
  - Uncompressed means size is proportional 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

A specific implementation of the fibertree abstract type

Compressed Sparse Row (CSR)



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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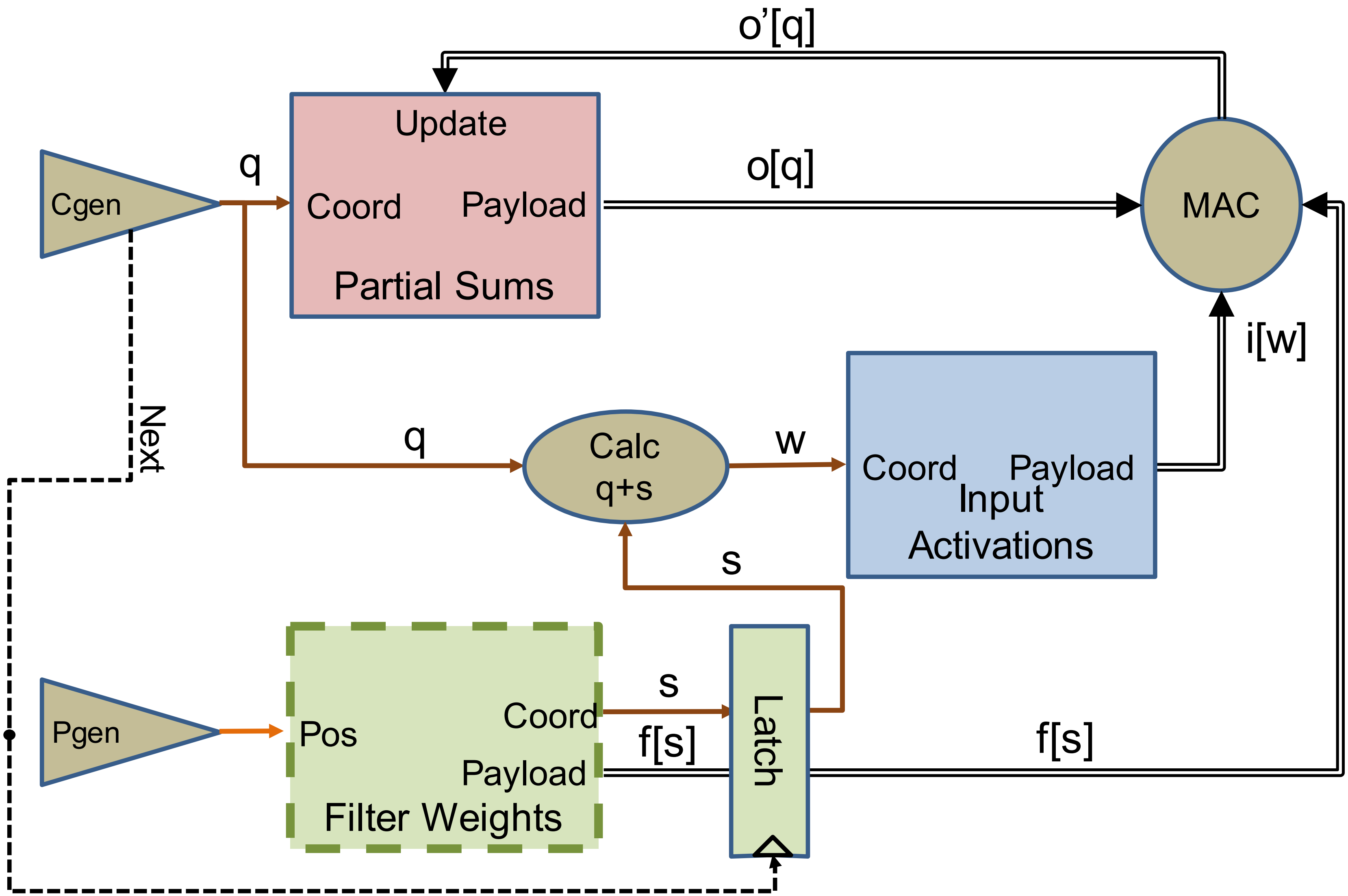
Weight Stationary - Sparse Weights

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

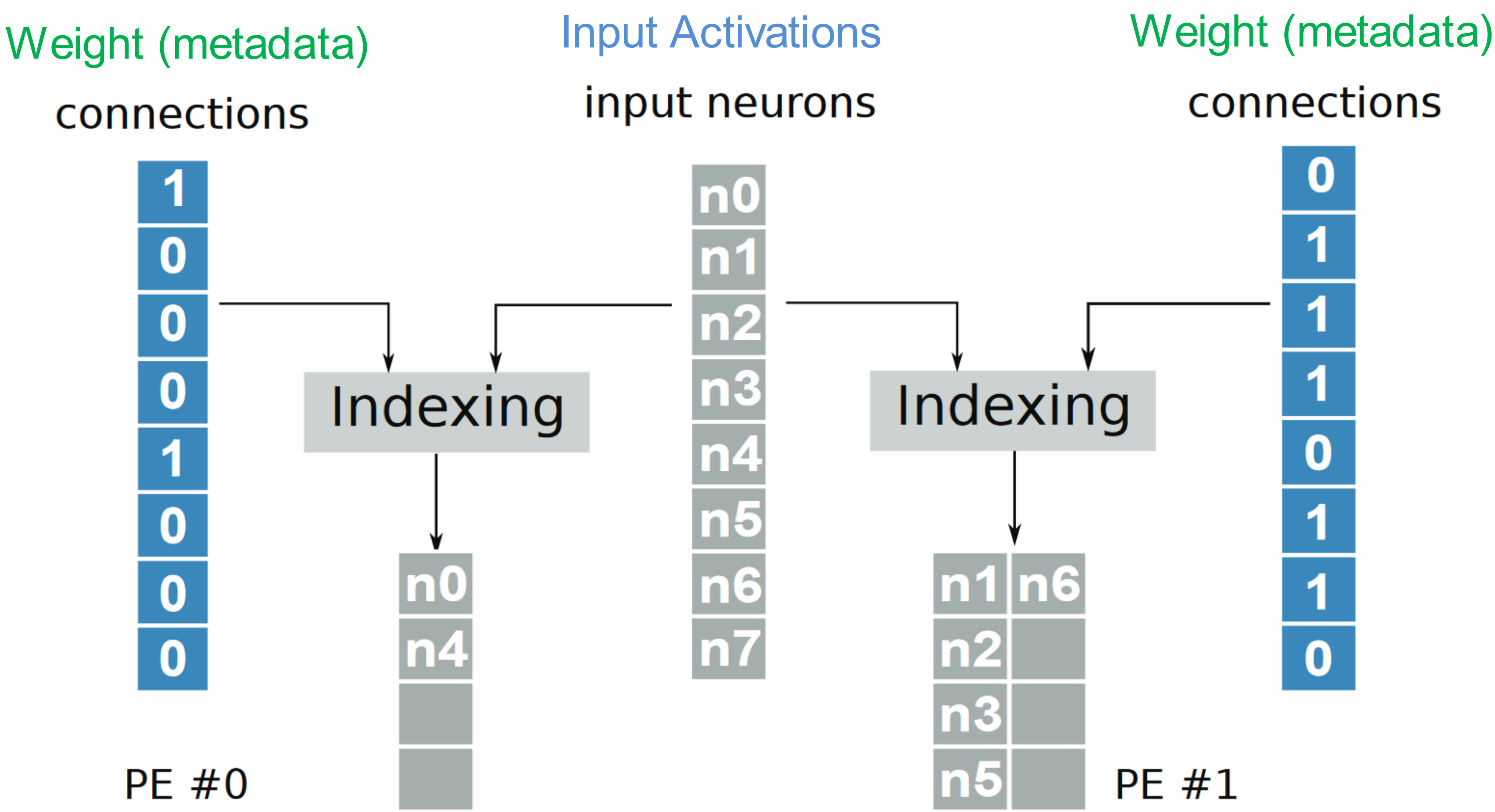
for (s, f_val) in f:
  for q in [0, Q):
    w = q + s
    o[q] += i[w] * f_val
```

Concordant traversal

Weight Stationary - Sparse Weights



Cambricon-X – Activation Access



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

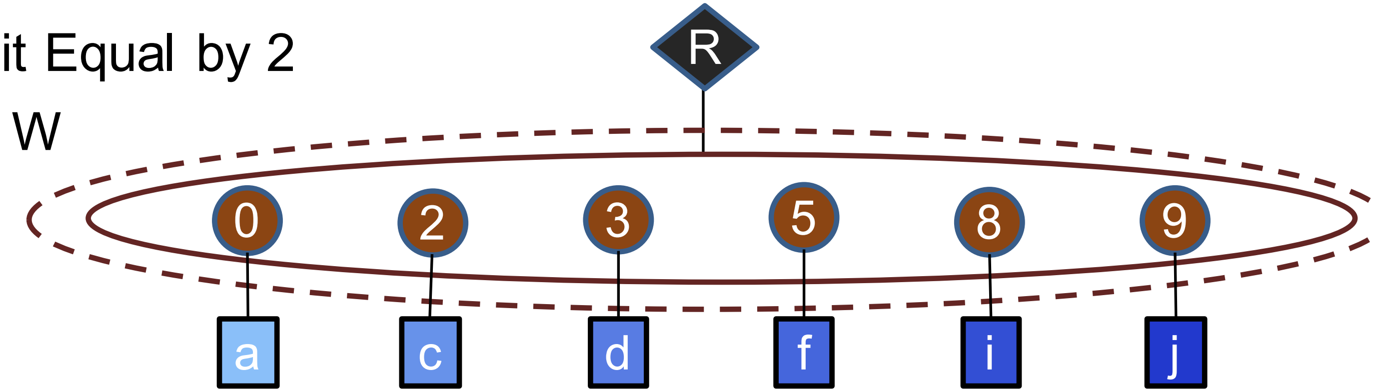
To Extend to Other Dimensions of DNN

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

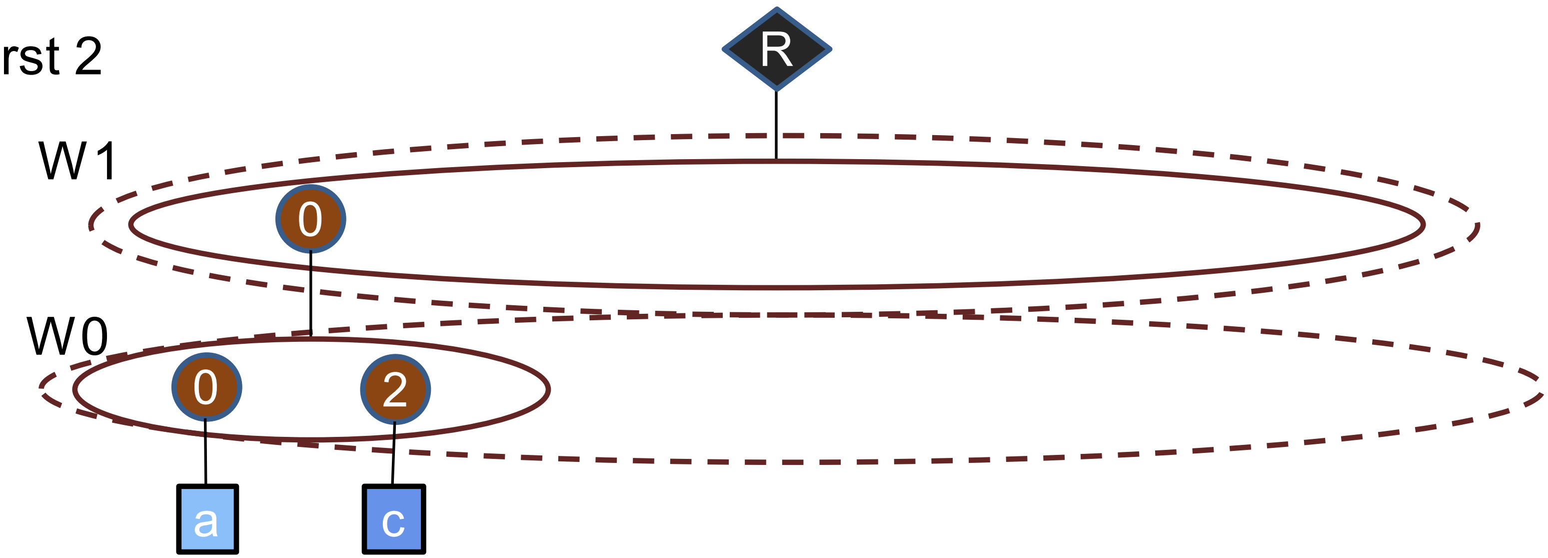
- **Add parallelism…**

Fiber Splitting Equally in Position Space

Before Split Equal by 2



Grab first 2



Fiber Splitting Equally in Position Space

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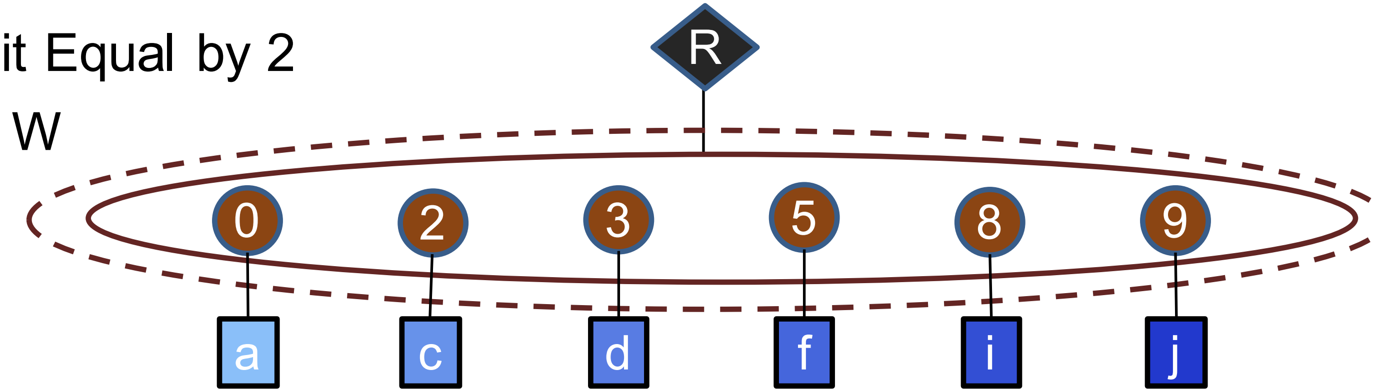
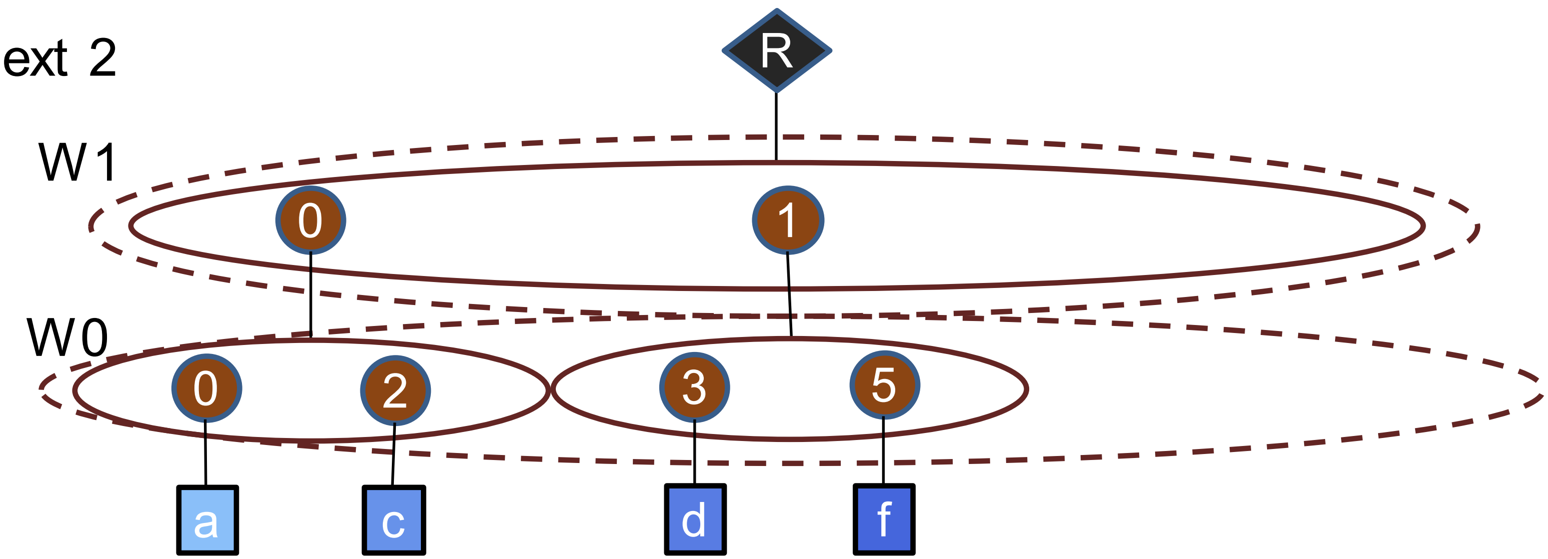


Grab next 2



Fiber Splitting Equally in Position Space

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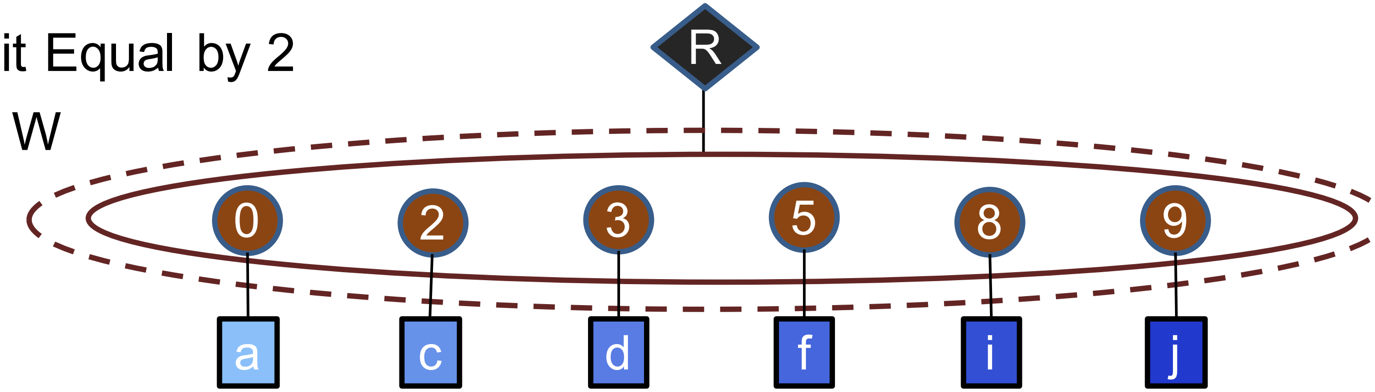
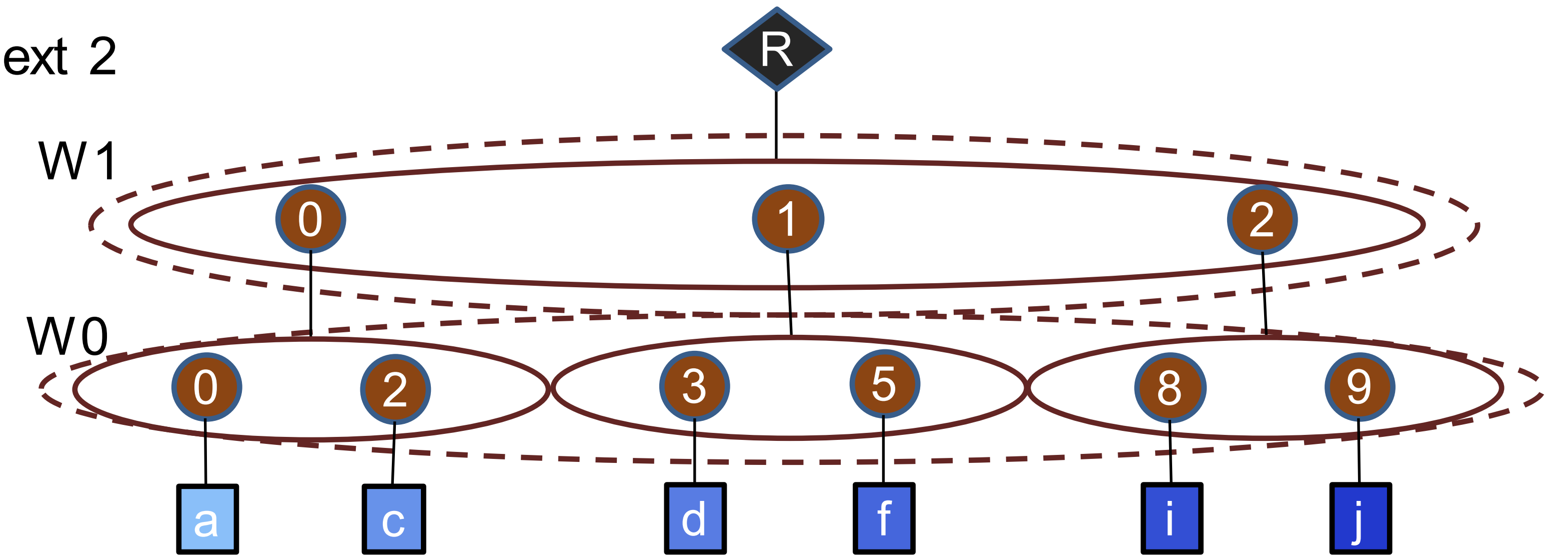
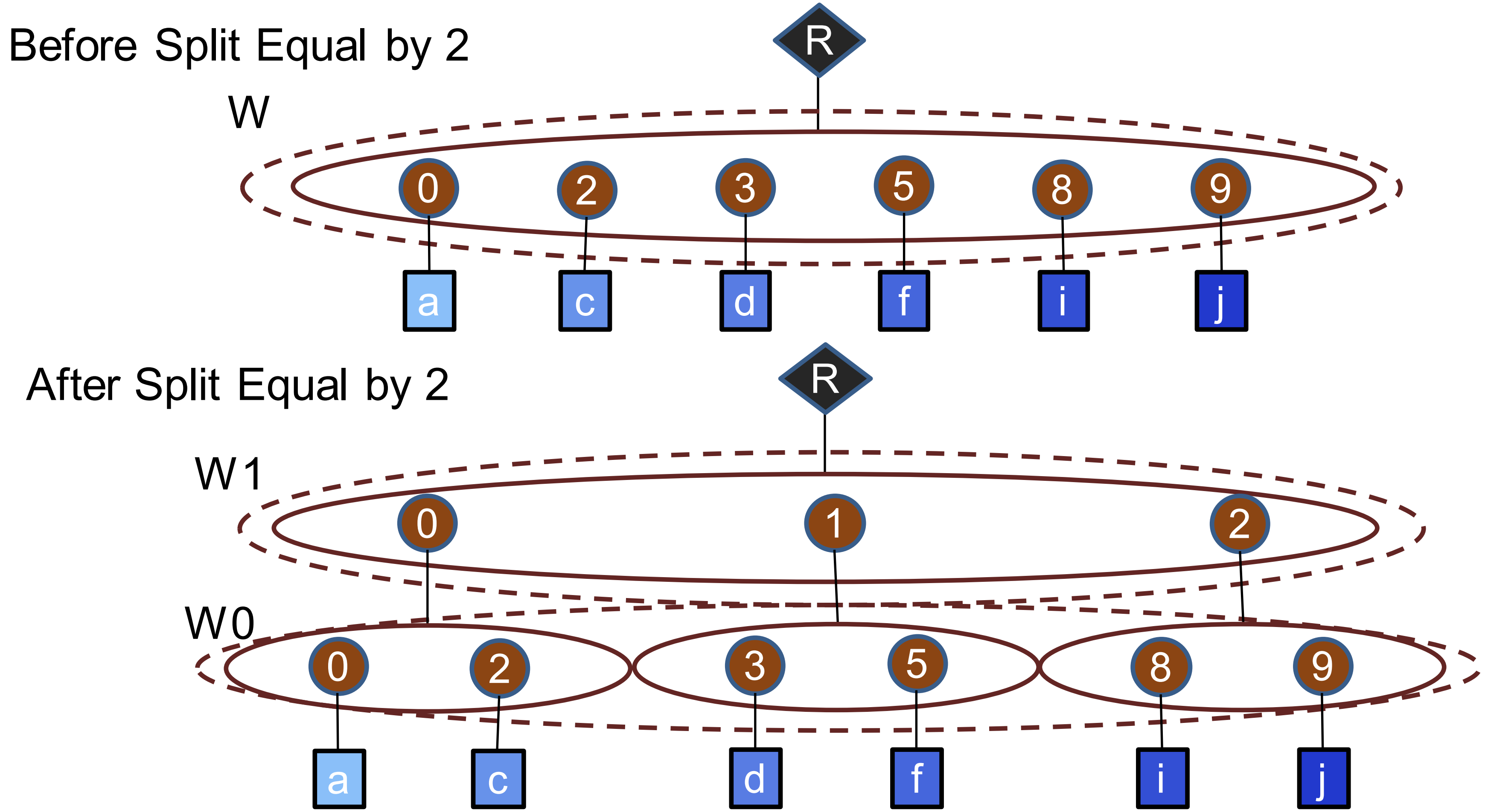


Grab next 2



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

Accumulate multiple outputs each spatially

Look up input activation

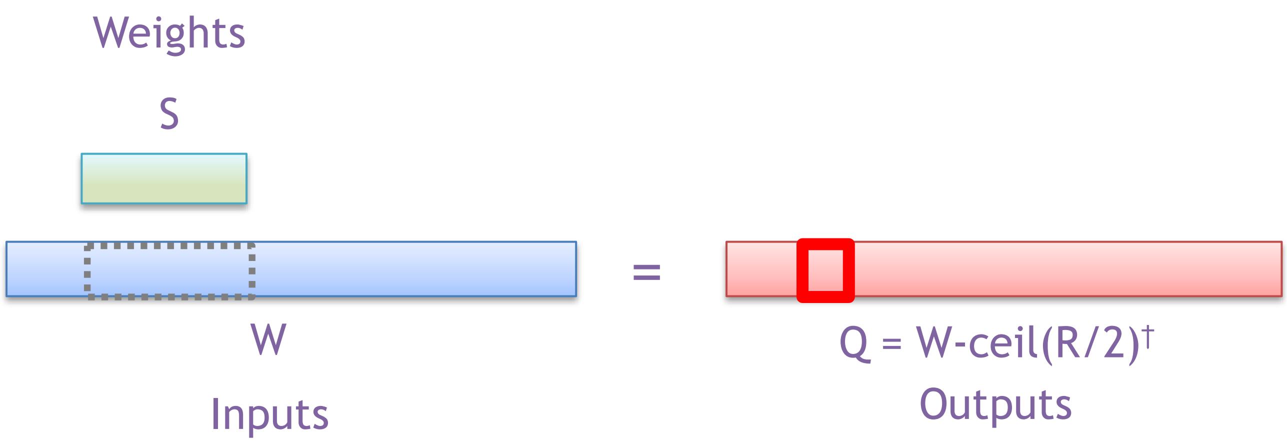
CONV: Exploiting Sparse Inputs & Sparse Weights

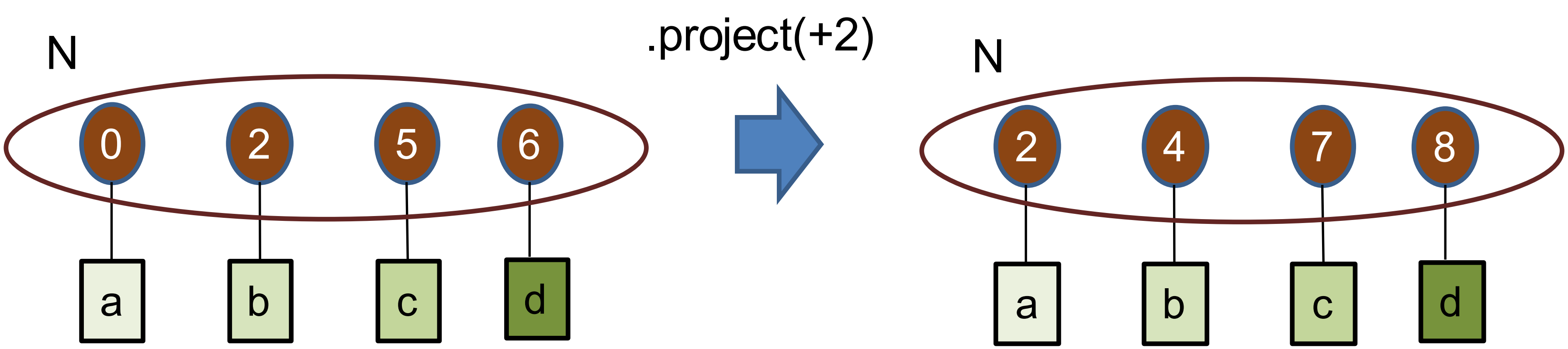
Output Stationary - Sparse Weights & Inputs

```
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
```

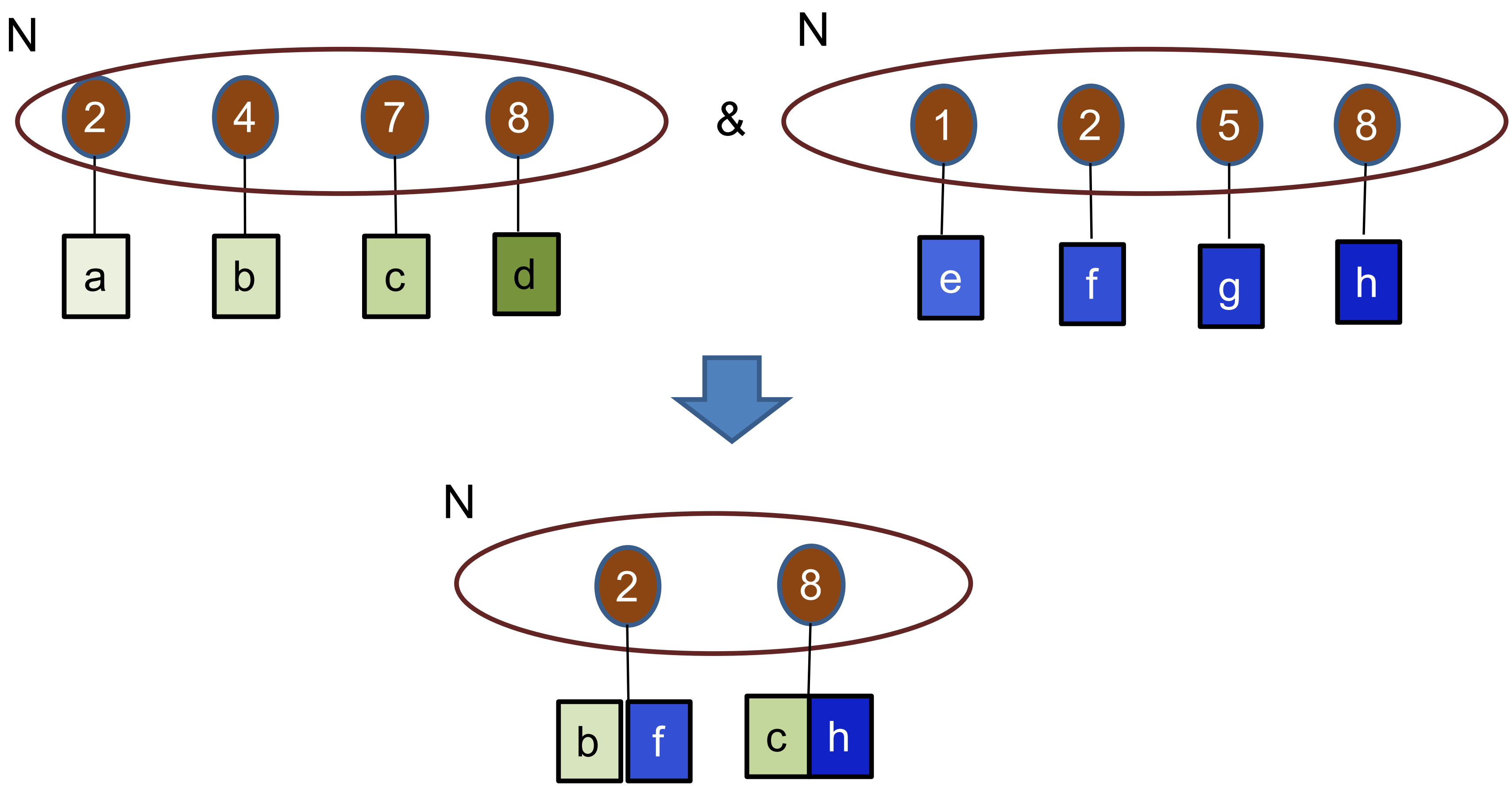
Fiber Coordinate Projection



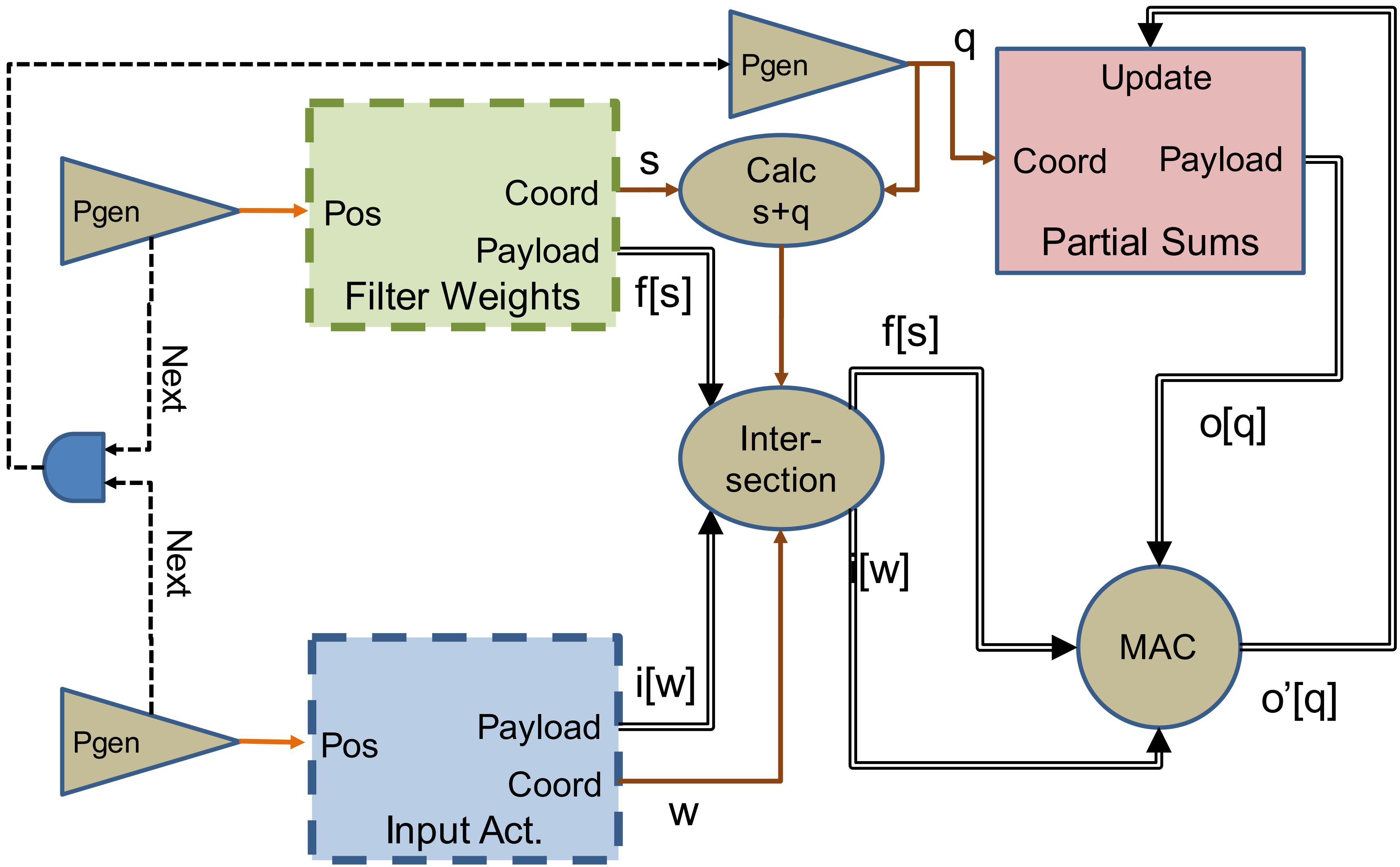


fiber-projection

Fiber Intersection



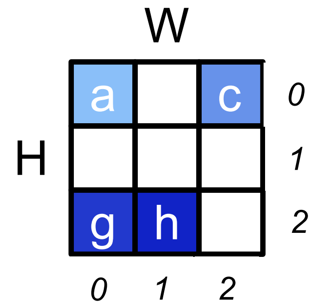
Output Stationary - Sparse Weights & Inputs



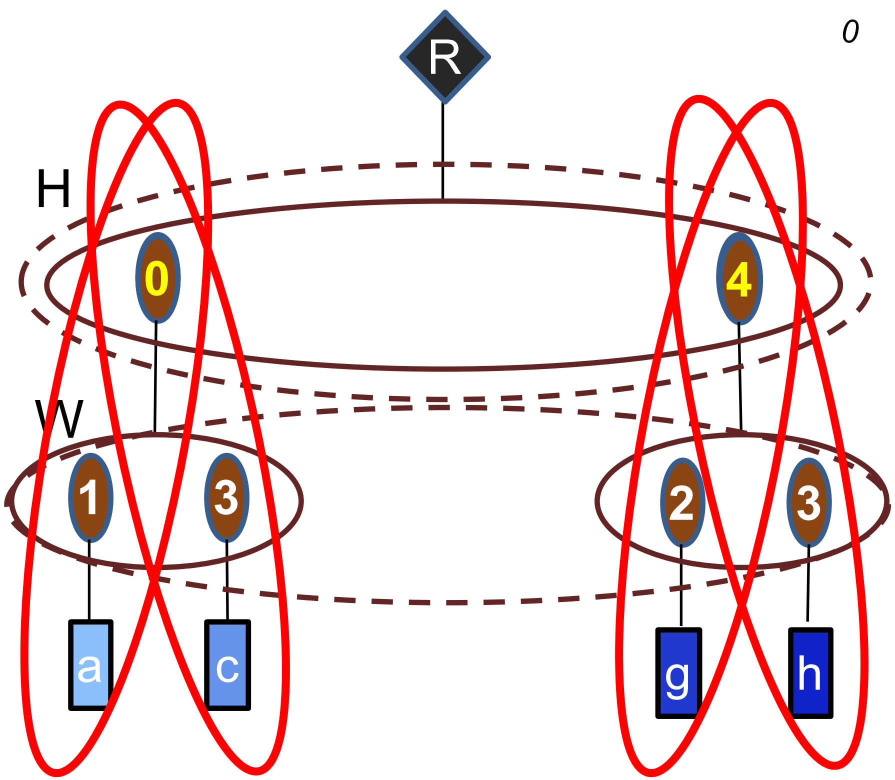
Flattening Ranks

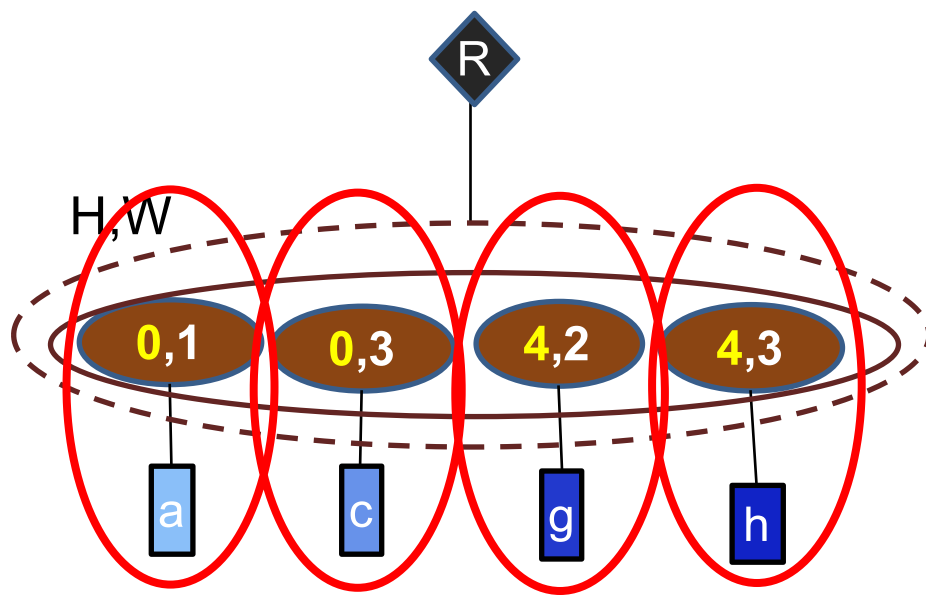
For efficiency one can form new representations where the data structure for two or more ranks are combined.

Tensor-<CC>(HW)



Tensor-<C^2>(HW)





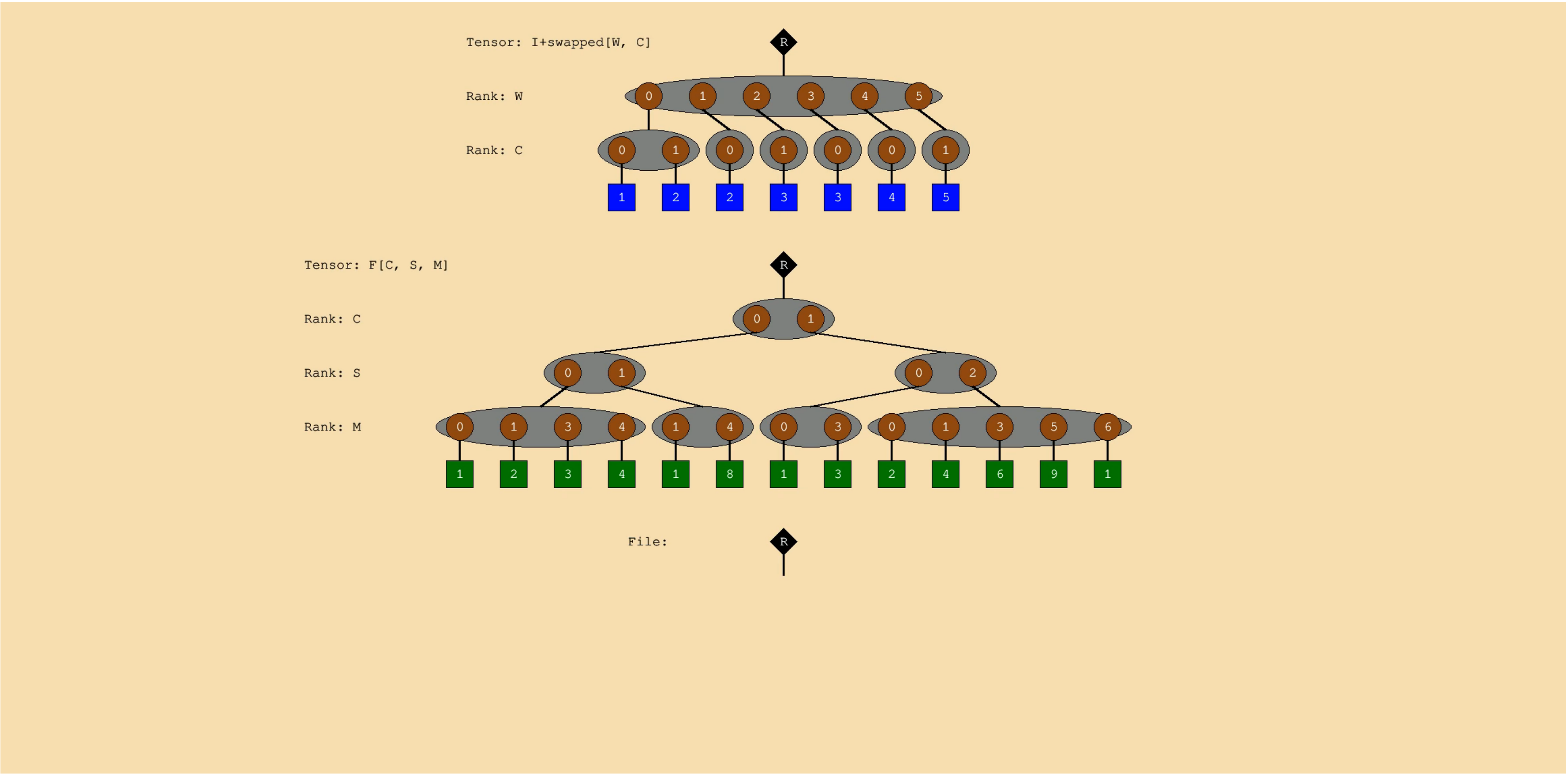
Row Stationary – Sparse Inputs & Activations

```
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
```

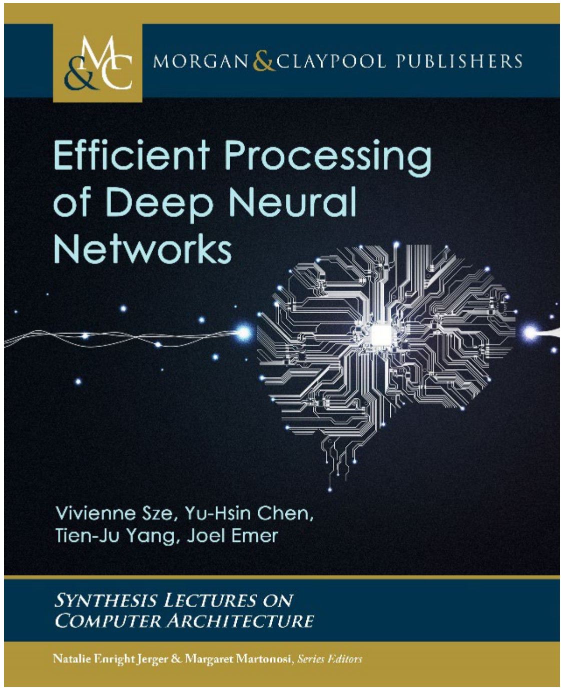
Eyeriss V2 – Chen et.al., JETCAS 2018

Row Stationary – Sparse Inputs & Activations



Eyeriss V2 – Chen et.al., JETCAS 2018

Hardware Architecture for Deep Learning



Part I Understanding Deep Neural Networks
Introduction
Overview of Deep Neural Networks

Part II Design of Hardware for Processing DNNs
Key Metrics and Design Objectives
Kernel Computation
Designing DNN Accelerators
Operation Mapping on Specialized Hardware

Part III Co-Design of DNN Hardware and Algorithms
Reducing Precision
Exploiting Sparsity
Designing Efficient DNN Models
Advanced Technologies

6.593[01] – Coming Spring 2023

Thank you!

Next Lecture:
Virtualization and Security