



Dynamic Filters (Quotient & InfiniFilter)

Research Topics in Database Management

Niv Dayan

What is a Filter?

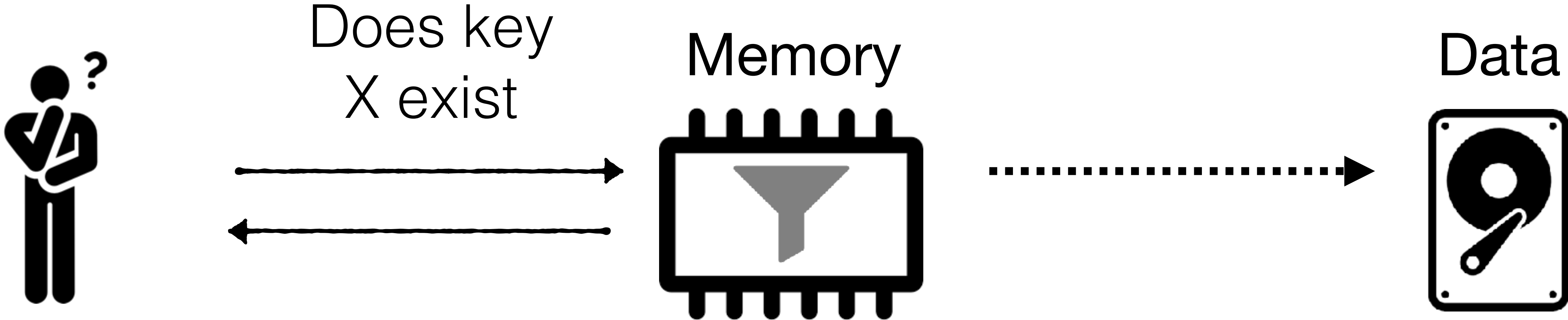
Does X exist?



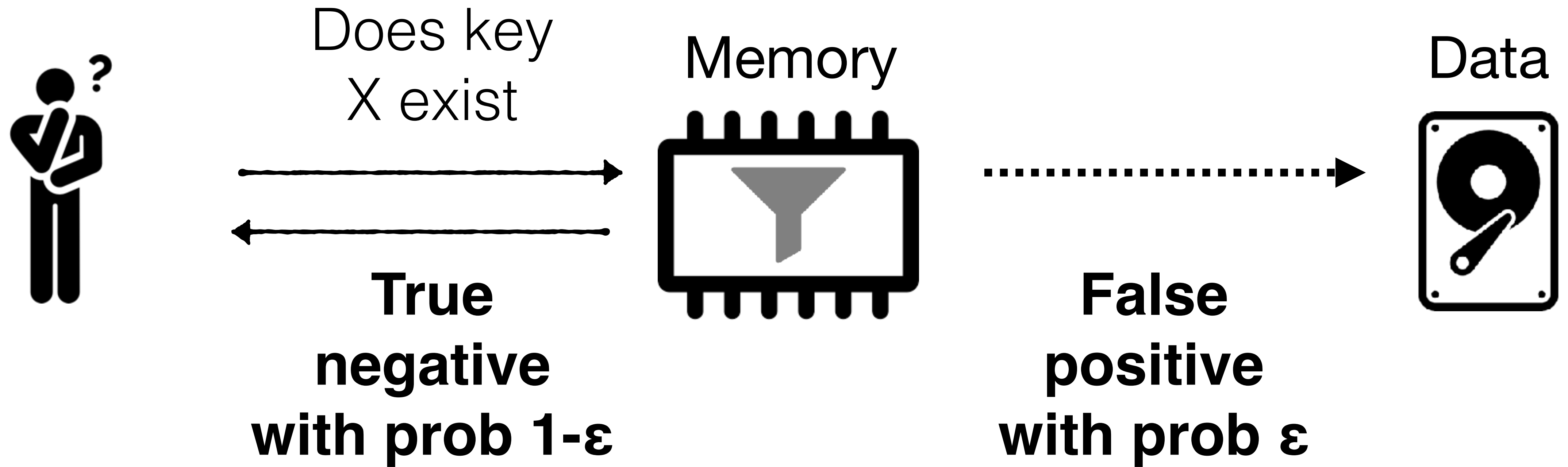
Set

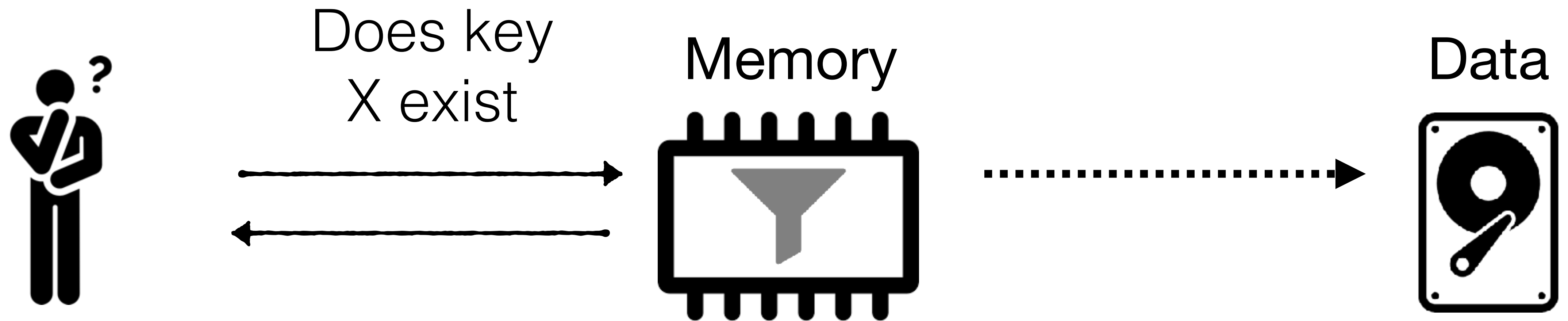


If key X does not exist



If key X does not exist



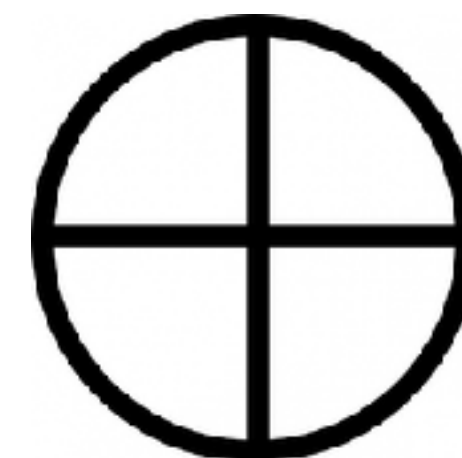


Saves storage accesses & network hops

Blocked
Bloom



XOR



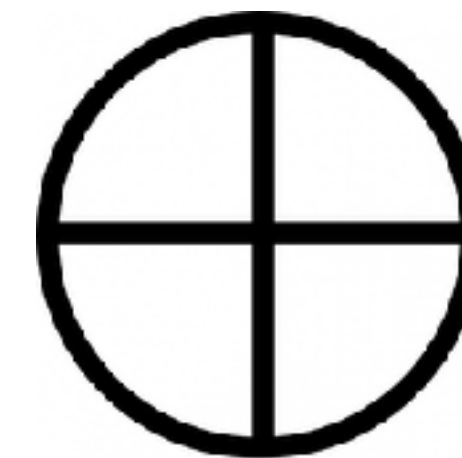
Faster

Lower FPR

Blocked
Bloom



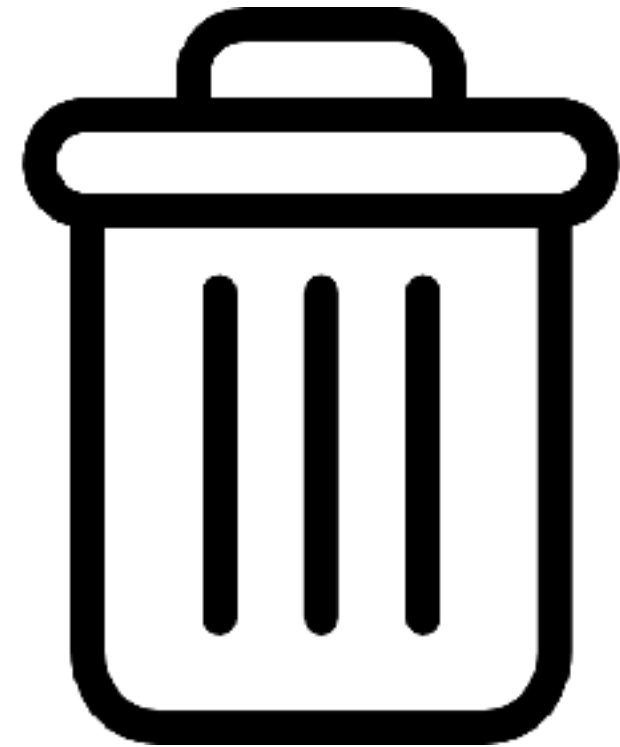
XOR



Static - no deletes or resizing

Supporting Dynamic Data

Supporting Dynamic Data



Deletes

(First hour)



Resizing

(Second hour)

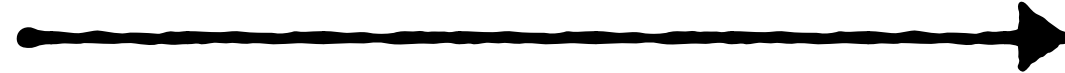
Why Support Deletes?



Why Support Deletes?



Query(X)

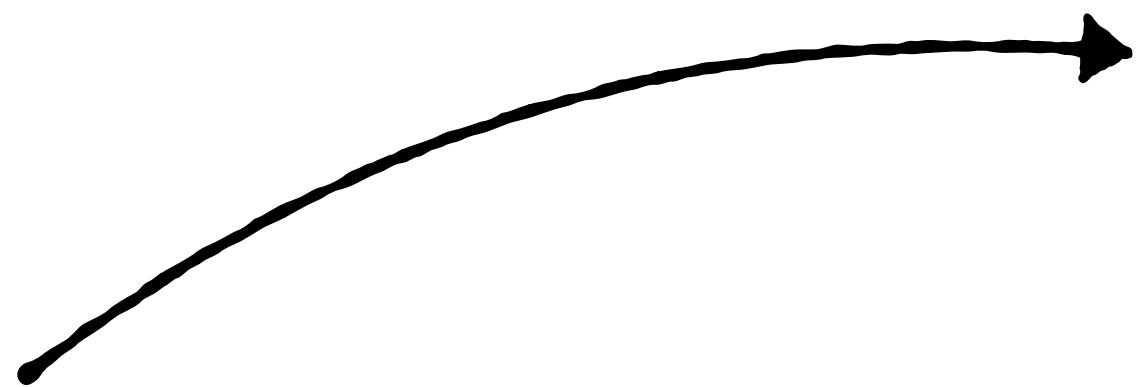


**True
positive**



Key X



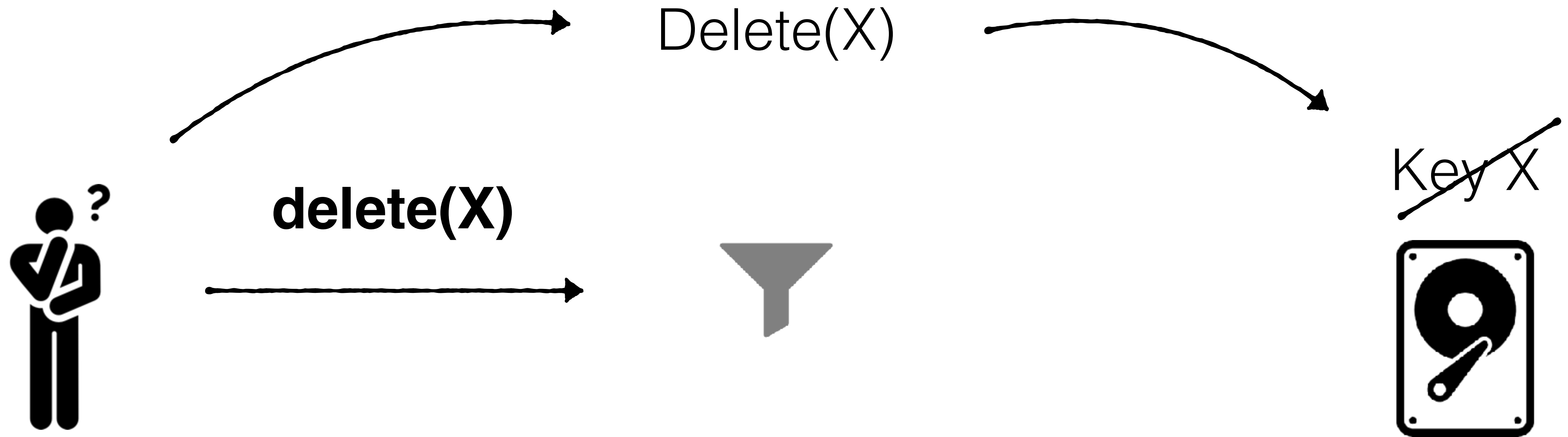


Delete(X)



~~Key X~~



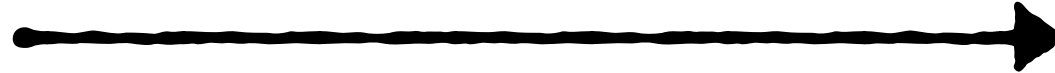


Why should we also delete from filter?

Desired Outcome



Query(X)



Negative



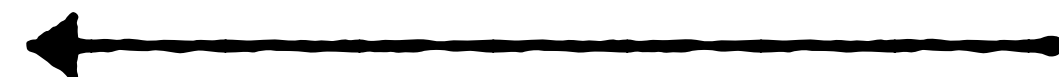
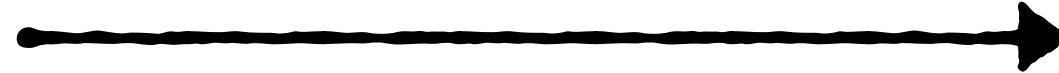
~~**Key X**~~



Desired Outcome



Query(X)



Negative



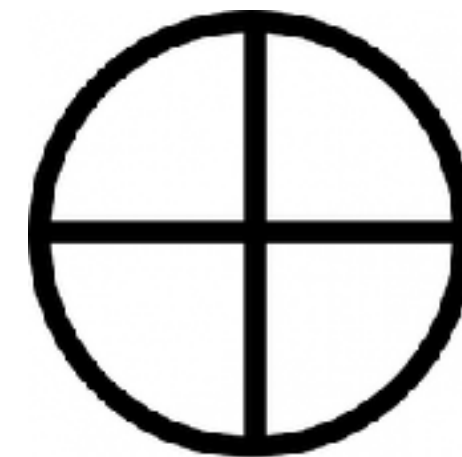
Only possible if filter supports deletes

Why do last week's filters not support deletes?

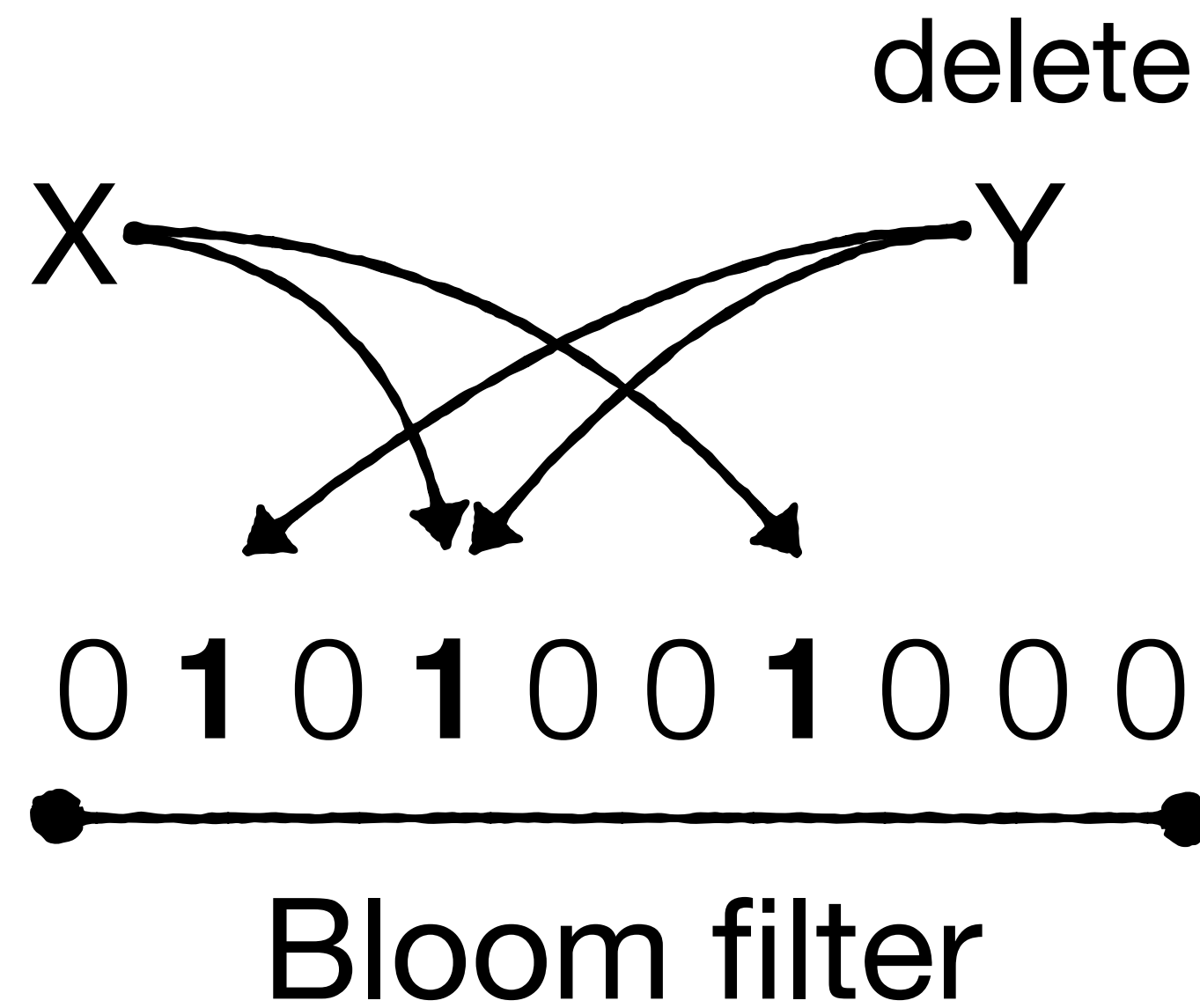
Bloom



XOR

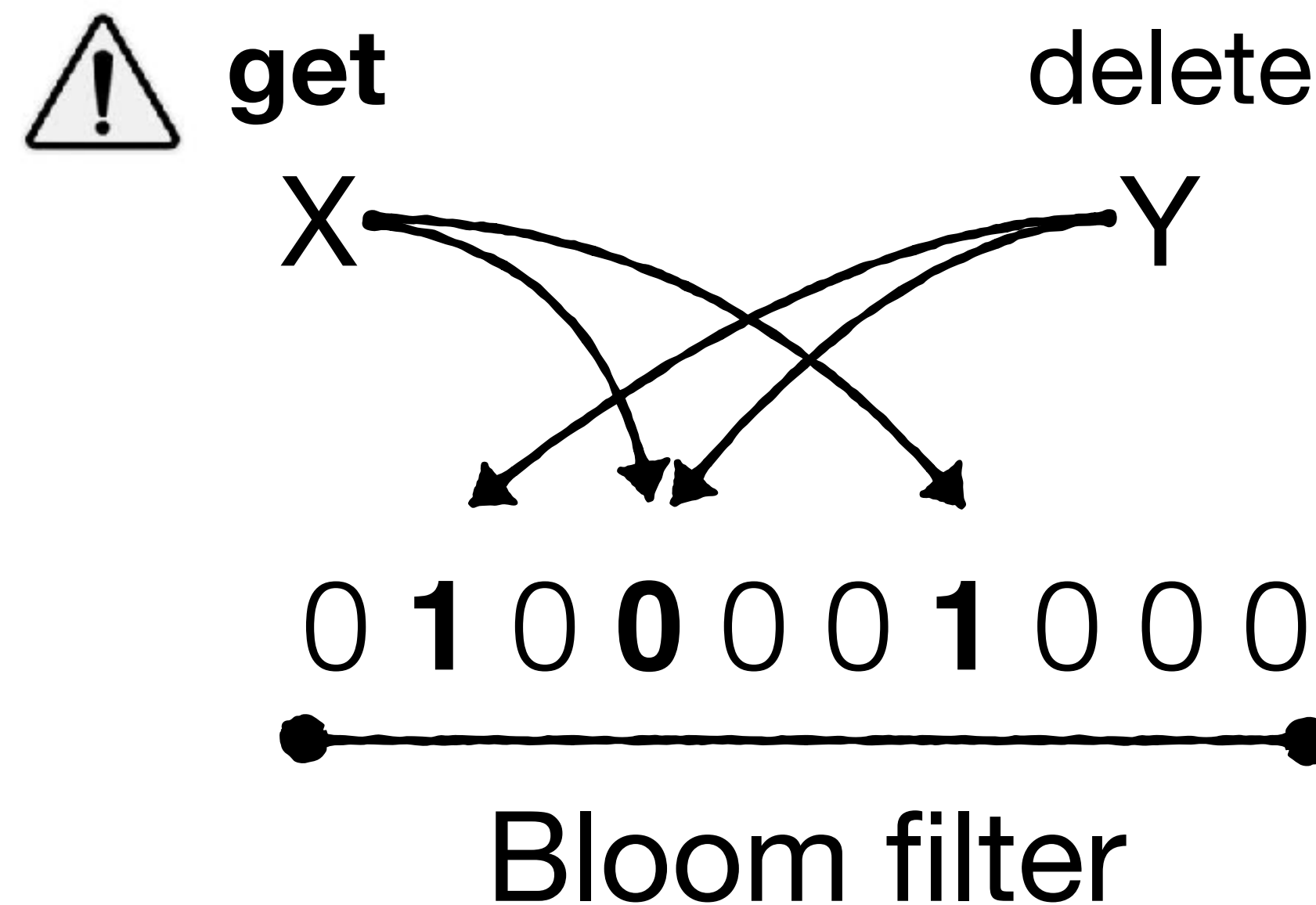


Multiple keys may map to each bit




Multiple keys may map to each bit

Setting bits back to 0s can lead to false negatives

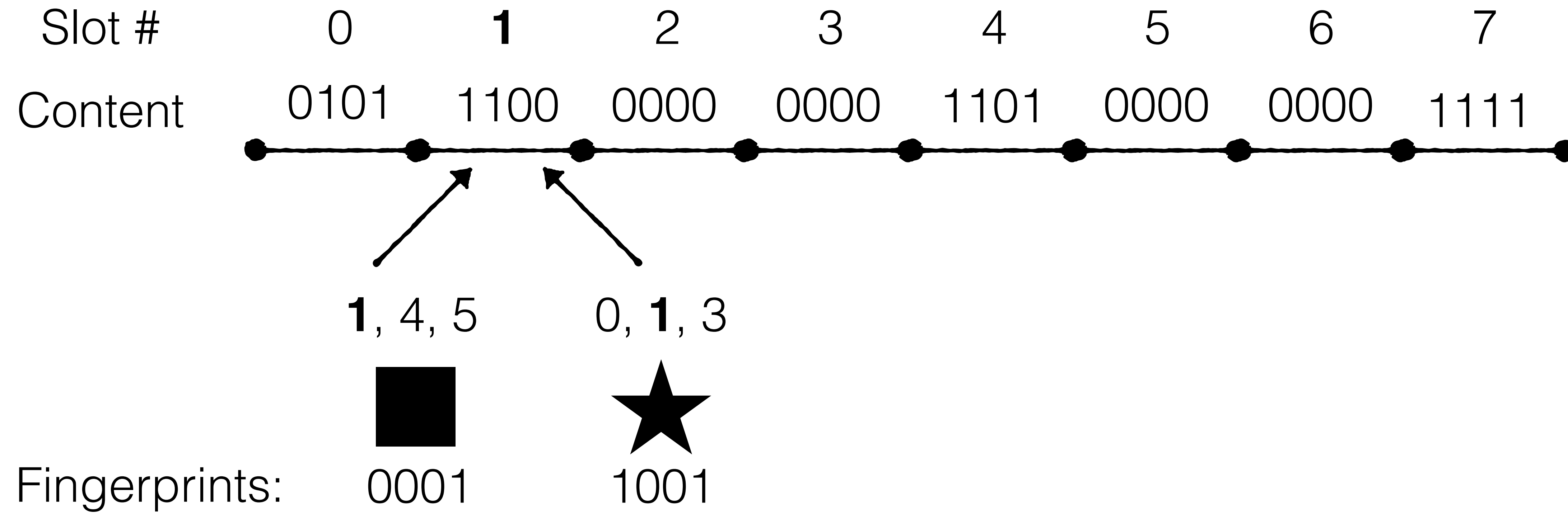


Slot #	0	1	2	3	4	5	6	7
Content	0101	1100	0000	0000	1101	0000	0000	1111

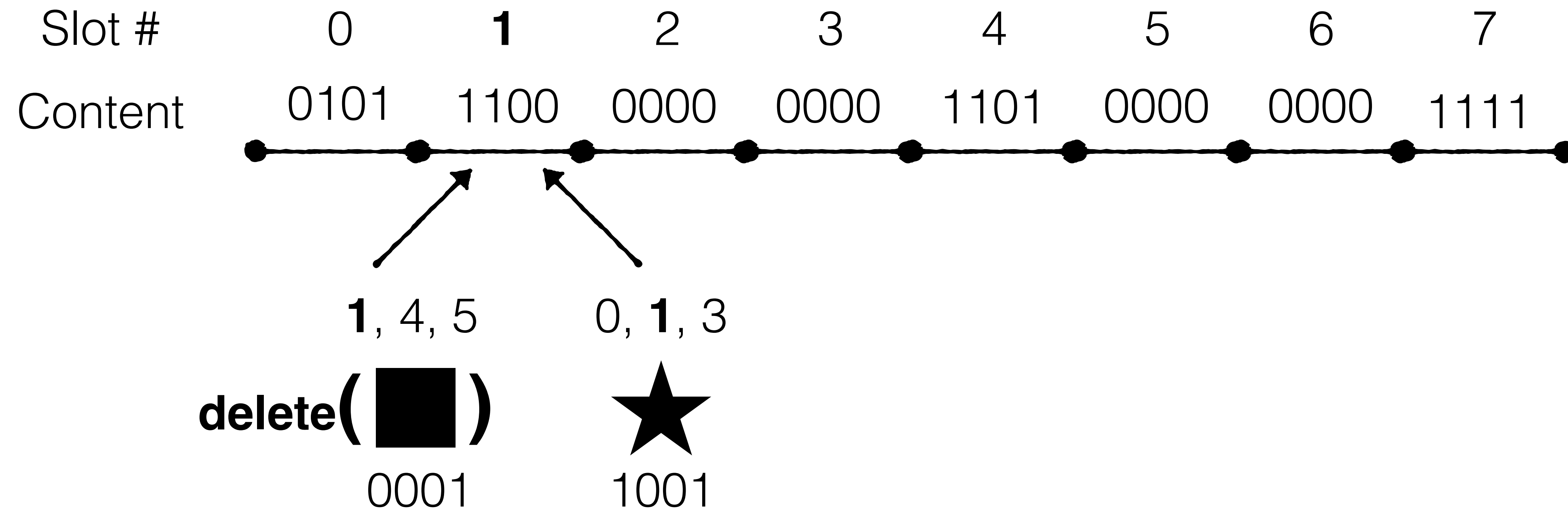


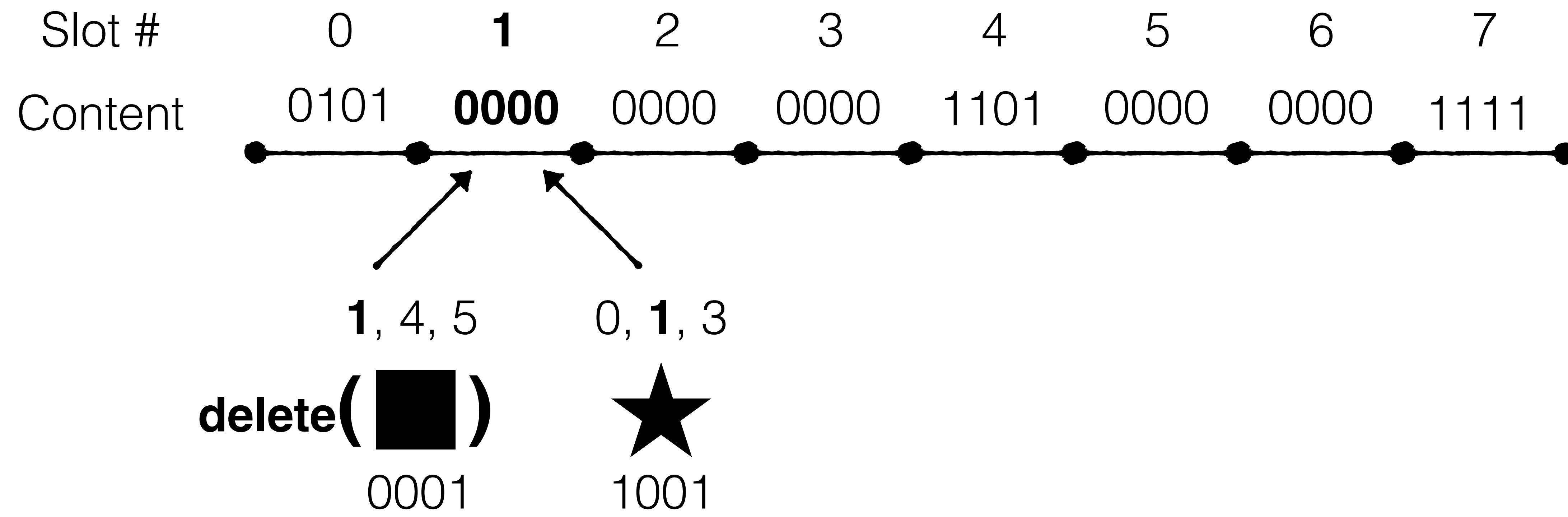
XOR filter

Multiple keys share slots

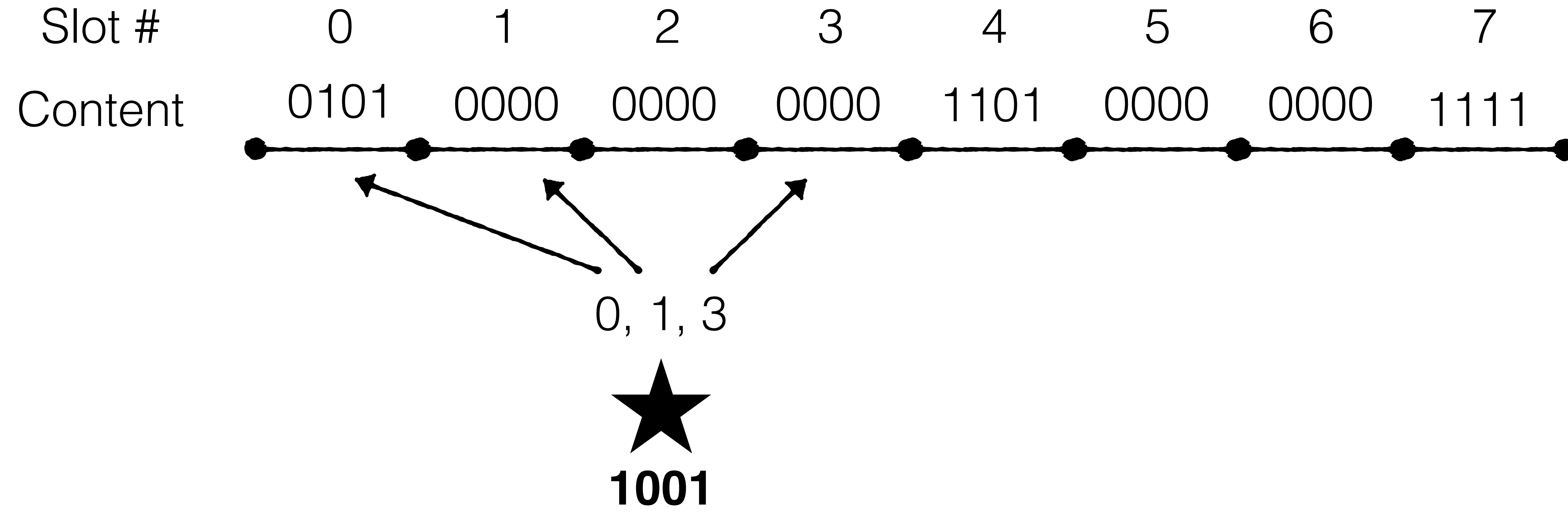


Multiple keys share slots



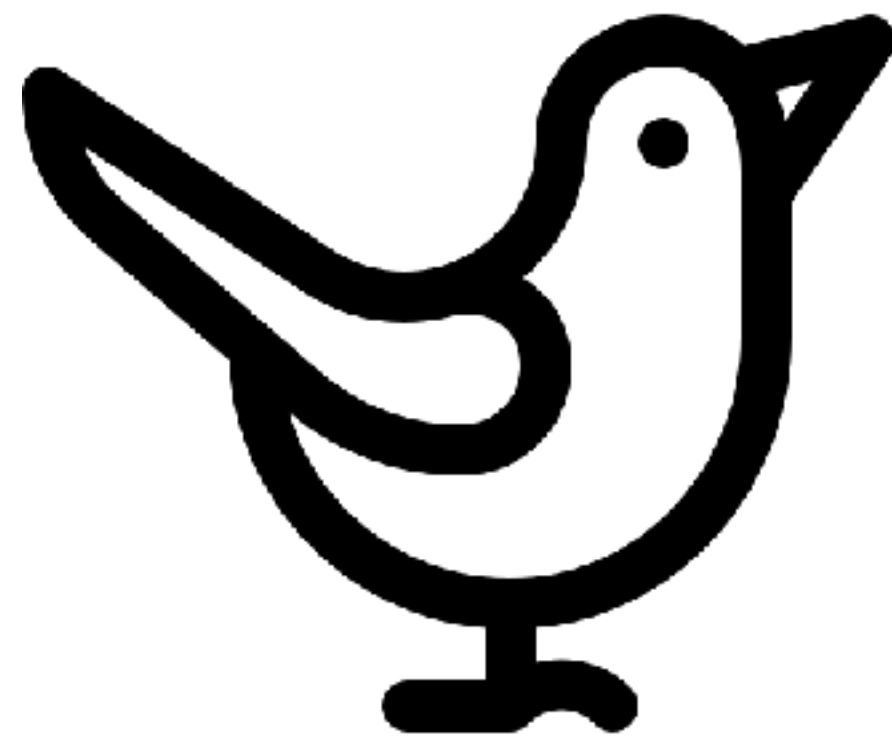


Resetting a slot for one entry will cause false negatives over other entries



How to support deletes without false negatives?

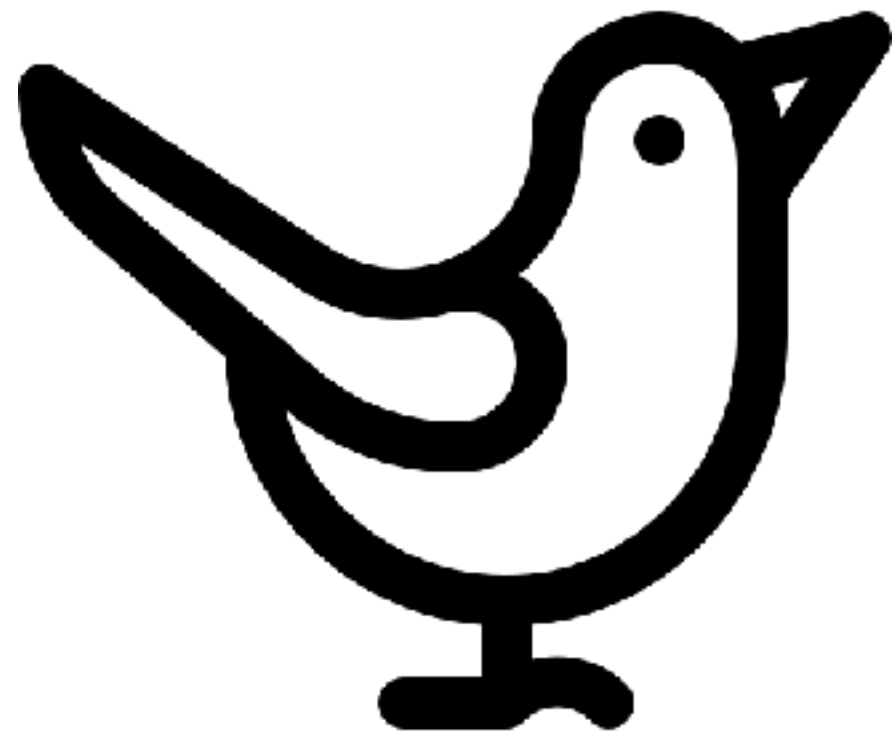
How to support deletes without false negatives?



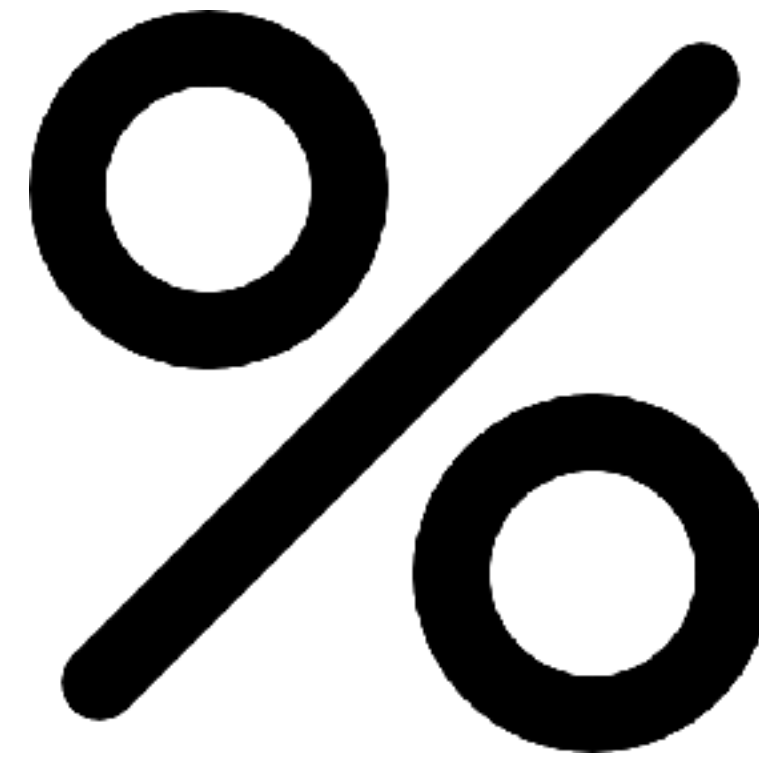
Cuckoo Filters

(Last semester)

How to support deletes without false negatives?

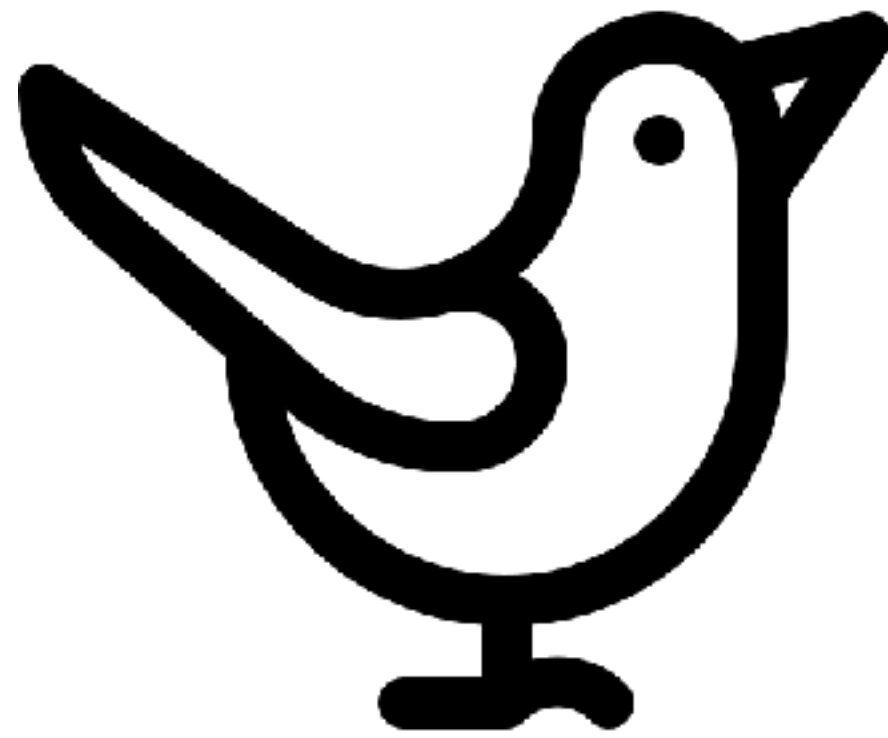


Cuckoo Filters
(Last semester)

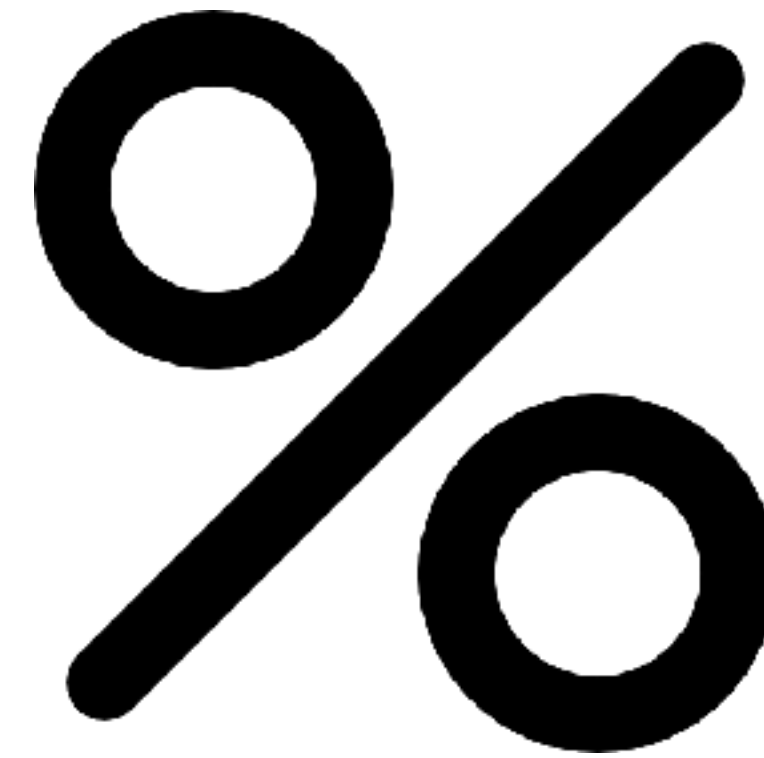


Quotient Filters
(Today)

Why cover another filter that supports deletes?

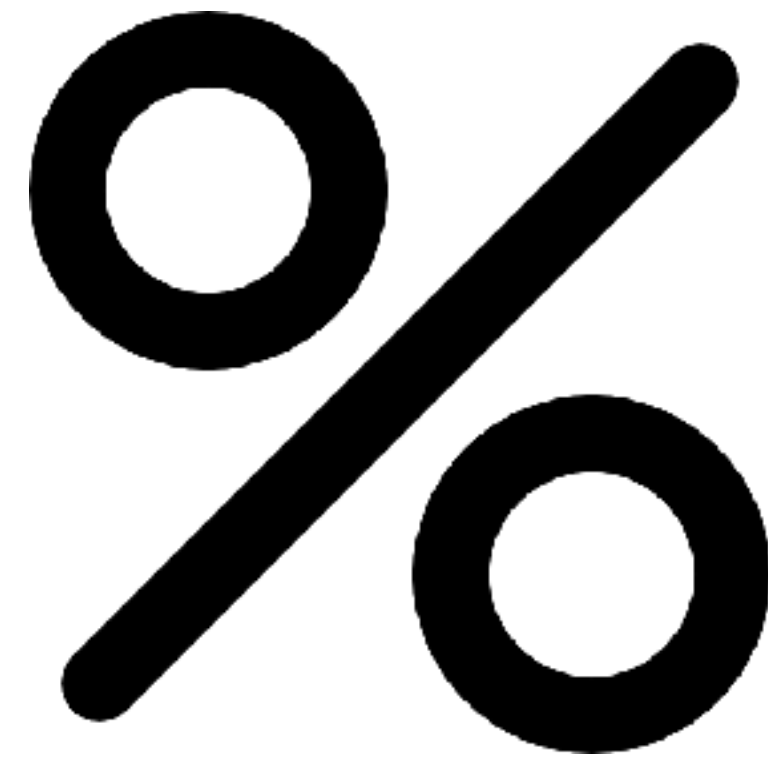


Cuckoo Filters
(Last semester)



Quotient Filters
(Today)

Showcase cool encoding/decoding techniques



Quotient Filters

Quotient Filters

Don't Thrash: How to Cache Your Hash on Flash. VLDB 2012.

Michael A Bender, Martin Farach-Colton, Rob Johnson, Bradley C Kuszmaul, Dzejla Medjedovic, Pablo Montes, Pradeep Shetty, Richard P Spillane, Erez Zadok.

A General-Purpose Counting Filter: Making Every Bit Count. SIGMOD 2017.

Prashant Pandey, Michael A Bender, Rob Johnson, Rob Patro.

Vector Quotient Filters: Overcoming the Time/Space Trade-Off in Filter Design. SIGMOD 2021.

Prashant Pandey, Alex Conway, Joe Durie, Michael A. Bender, Martin Farach-Colton, Rob Johnson.

Which to focus on?

Don't Thrash: How to Cache Your Hash on Flash. VLDB 2012.

A General-Purpose Counting Filter: Making Every Bit Count. SIGMOD 2017.

Vector Quotient Filters: Overcoming the Time/Space Trade-Off in Filter Design. SIGMOD 2021.

Don't Thrash: How to Cache Your Hash on Flash. VLDB 2012.
Worse memory & query efficiency

A General-Purpose Counting Filter: Making Every Bit Count. SIGMOD 2017.

Vector Quotient Filters: Overcoming the Time/Space Trade-Off in Filter Design.
SIGMOD 2021.

Don't Thrash: How to Cache Your Hash on Flash. VLDB 2012.

Worse memory & query efficiency

A General-Purpose Counting Filter: Making Every Bit Count. SIGMOD 2017.

Vector Quotient Filters: Overcoming the Time/Space Trade-Off in Filter Design.
SIGMOD 2021.

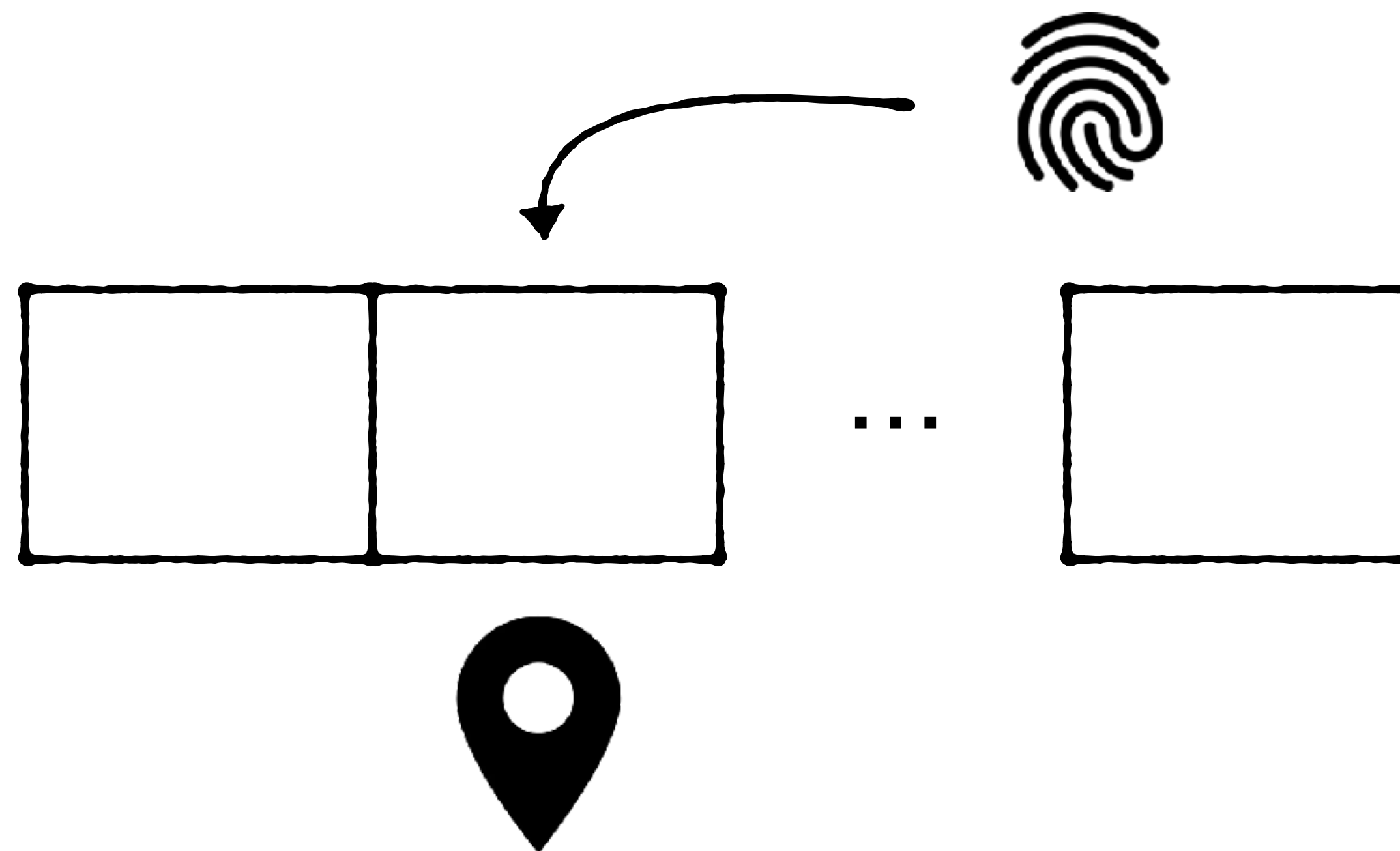
Uses SIMD & less tunable

Our focus

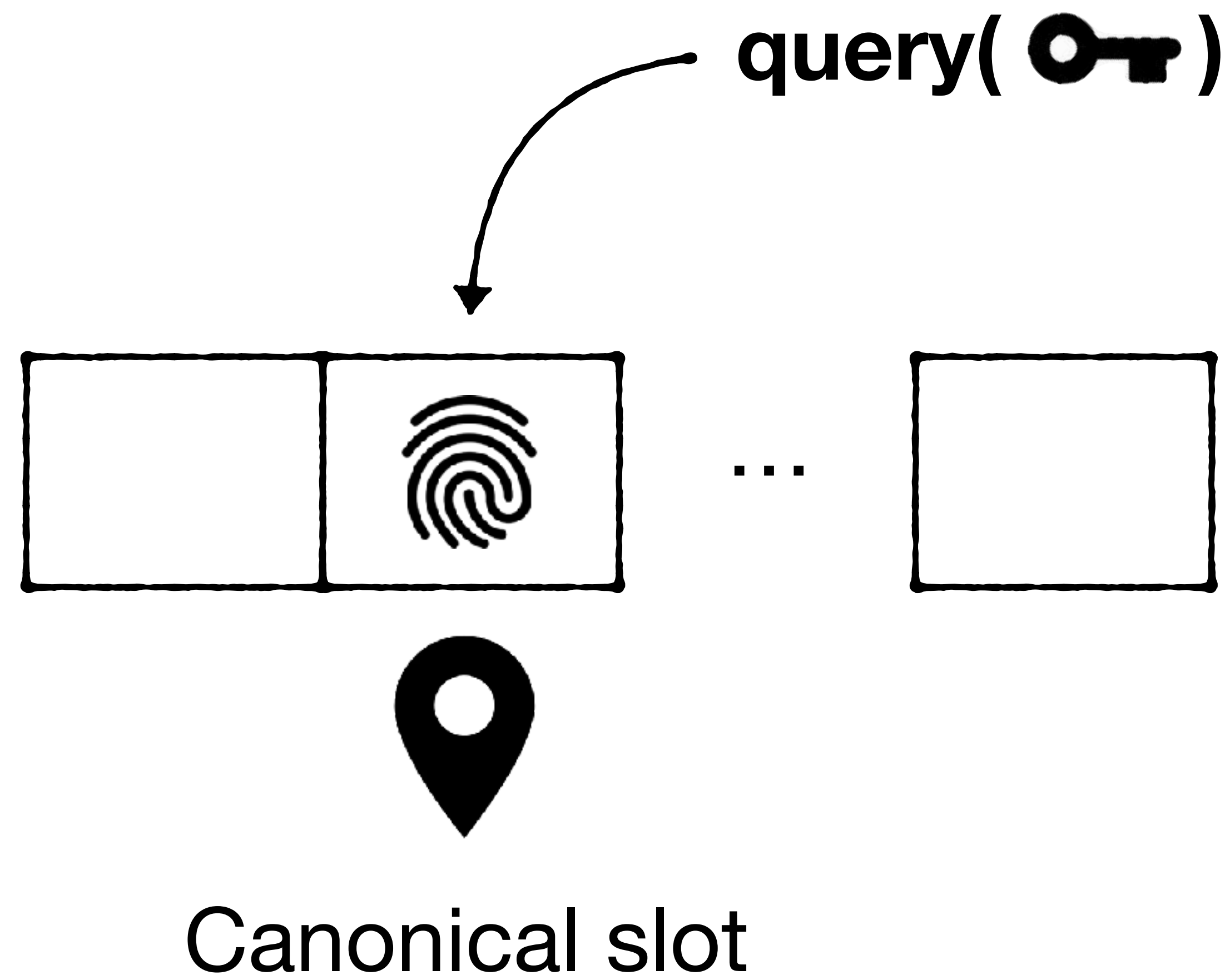
A General-Purpose Counting Filter: Making Every Bit Count. 2017.

hash() = 0 1 0 1 0 0 1 1 0 1 0 1 1 0 1 1 0 0

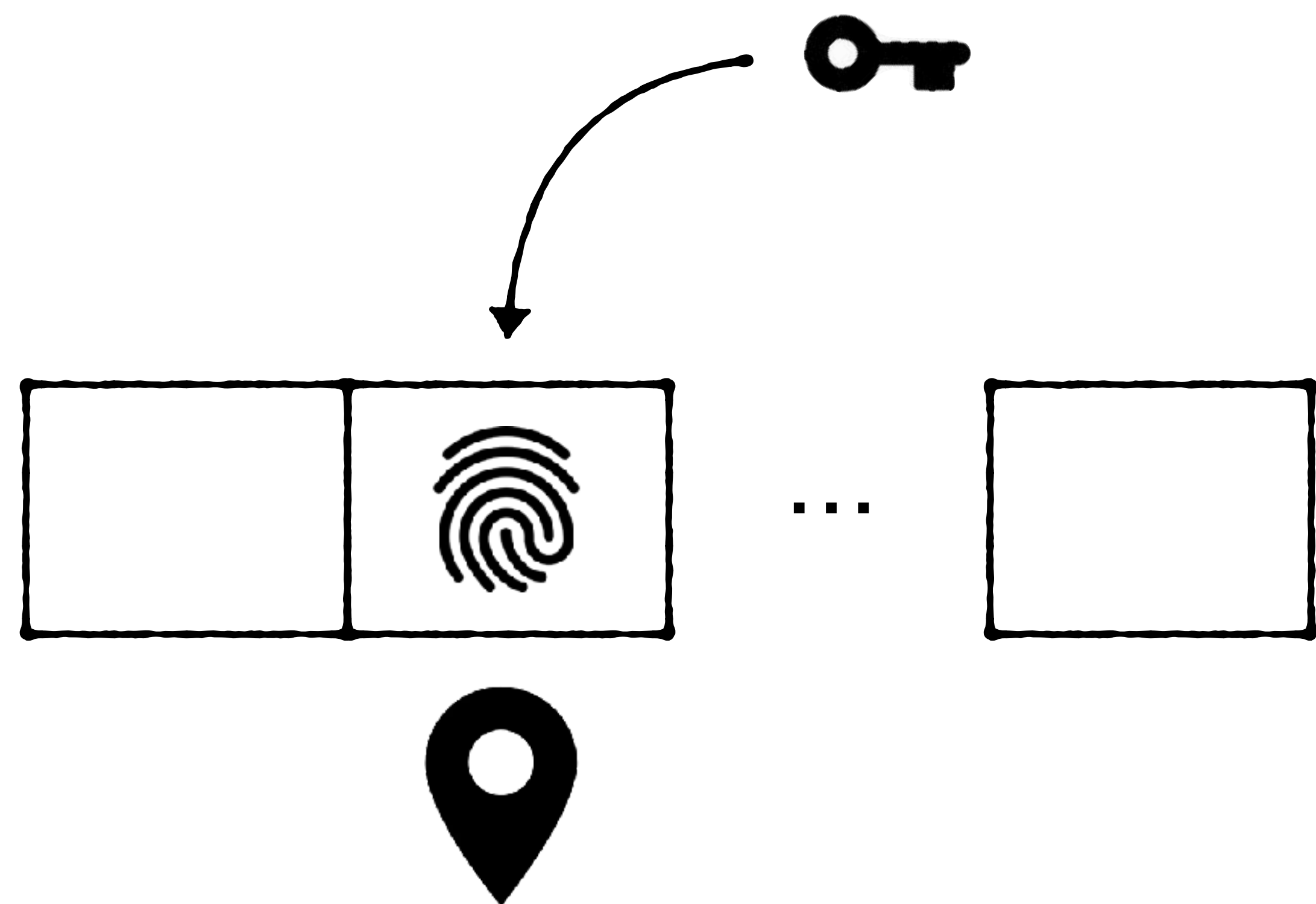




Canonical slot

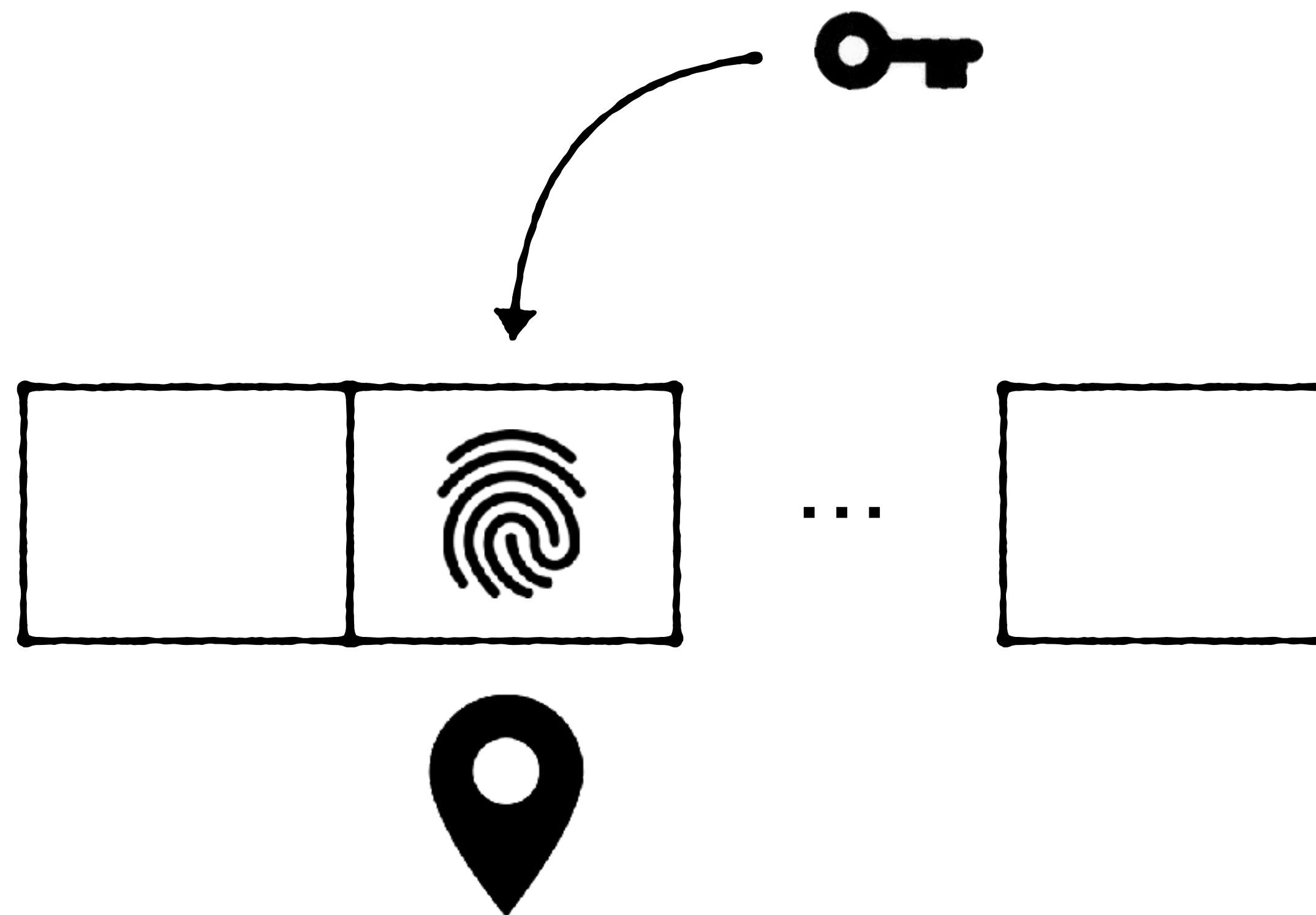


Each inserted fingerprint corresponds to exactly one entry

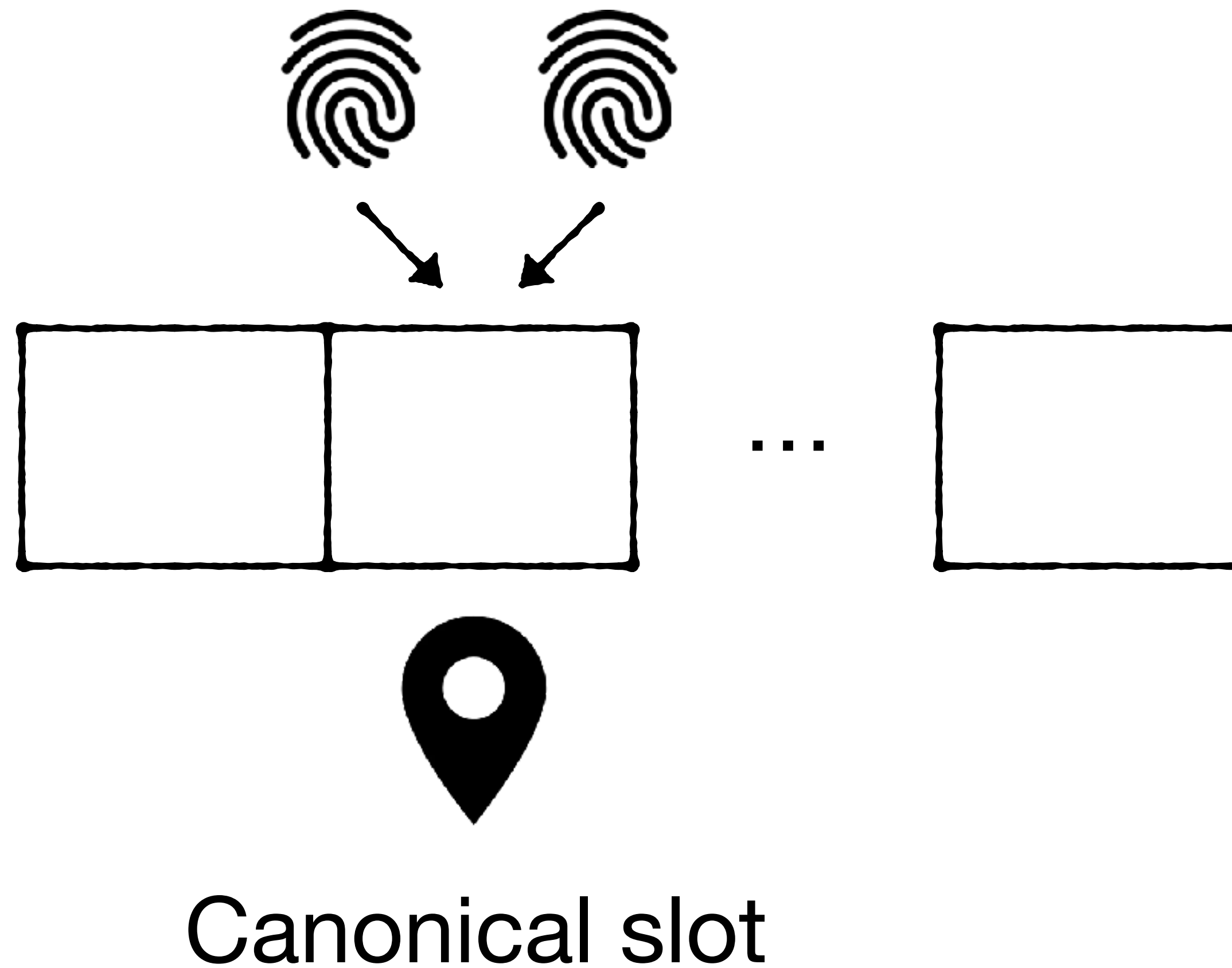


Each inserted fingerprint corresponds to exactly one entry

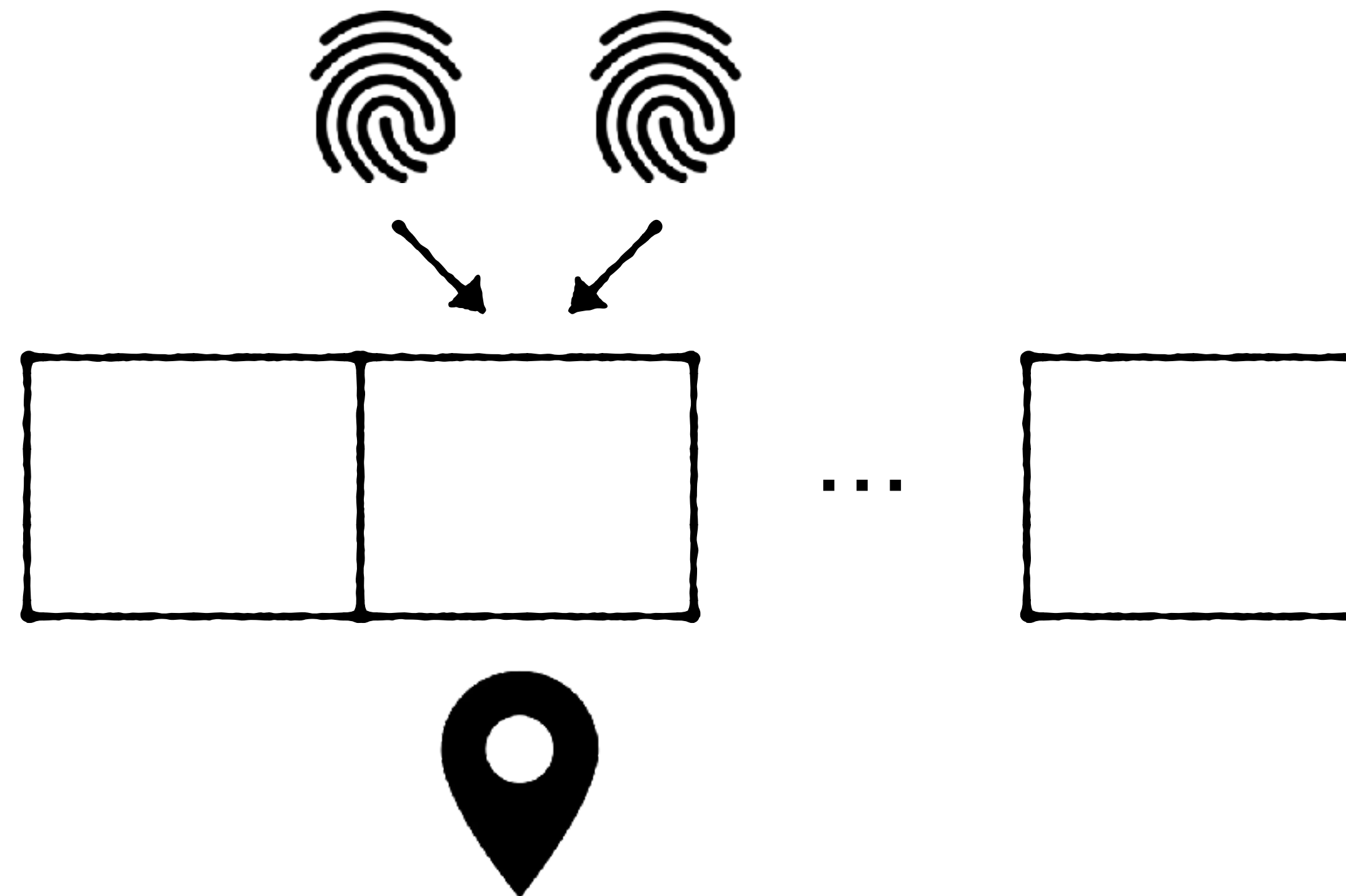
Removing it won't introduce false negatives for other entries



Hash collisions - multiple fingerprints map to same canonical slot

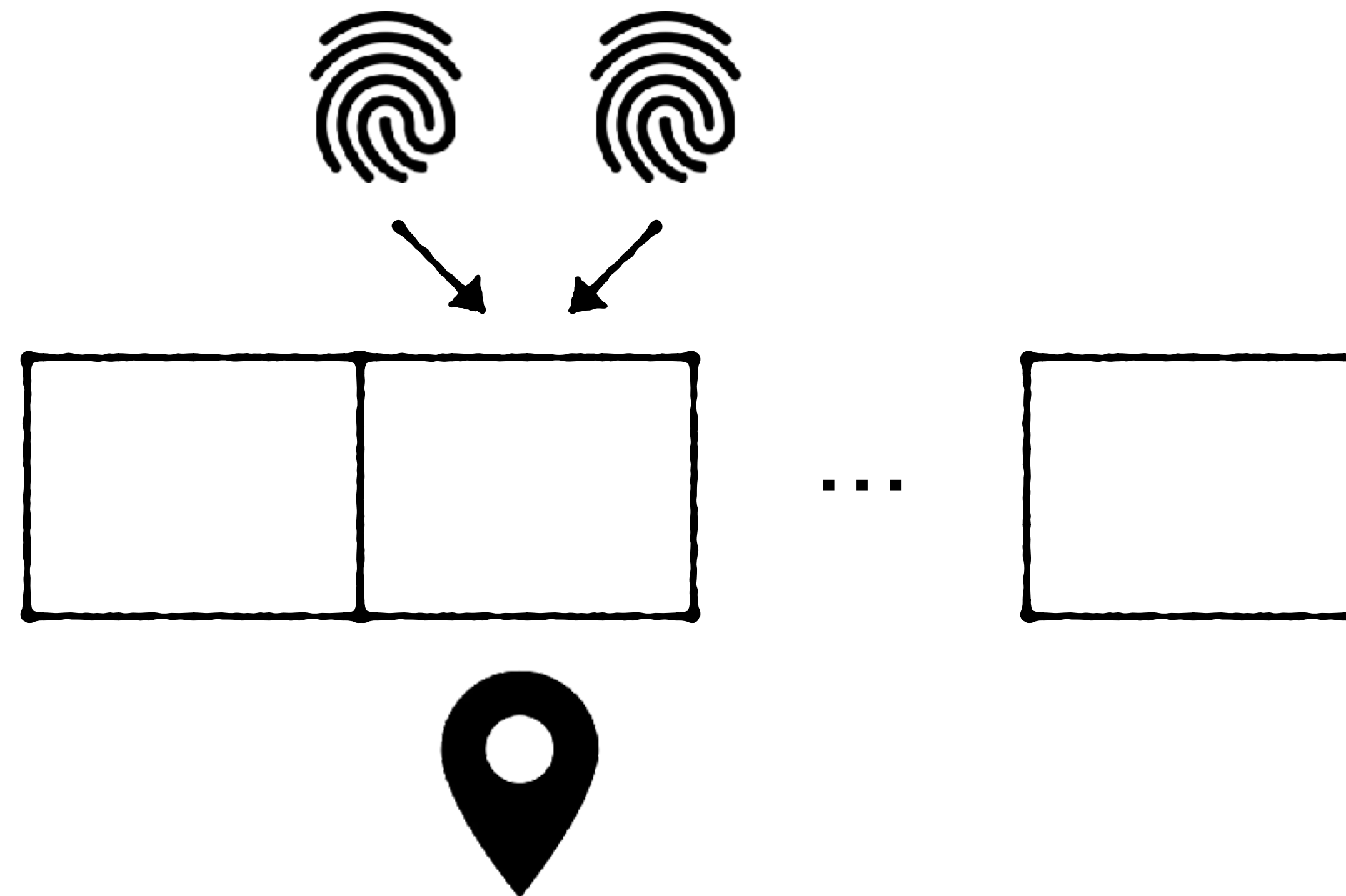


Address using Robin Hood Hashing

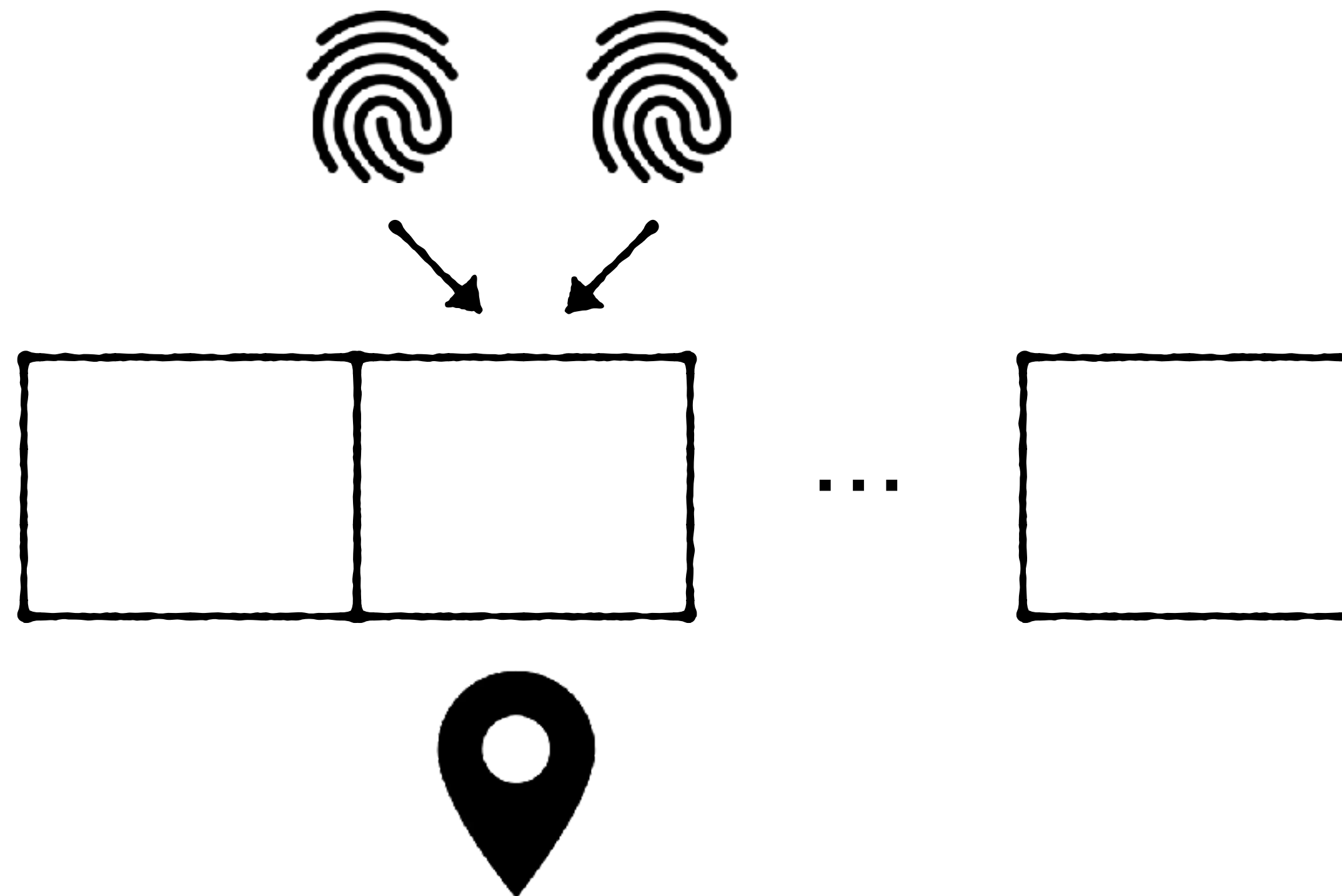


Address using Robin Hood Hashing

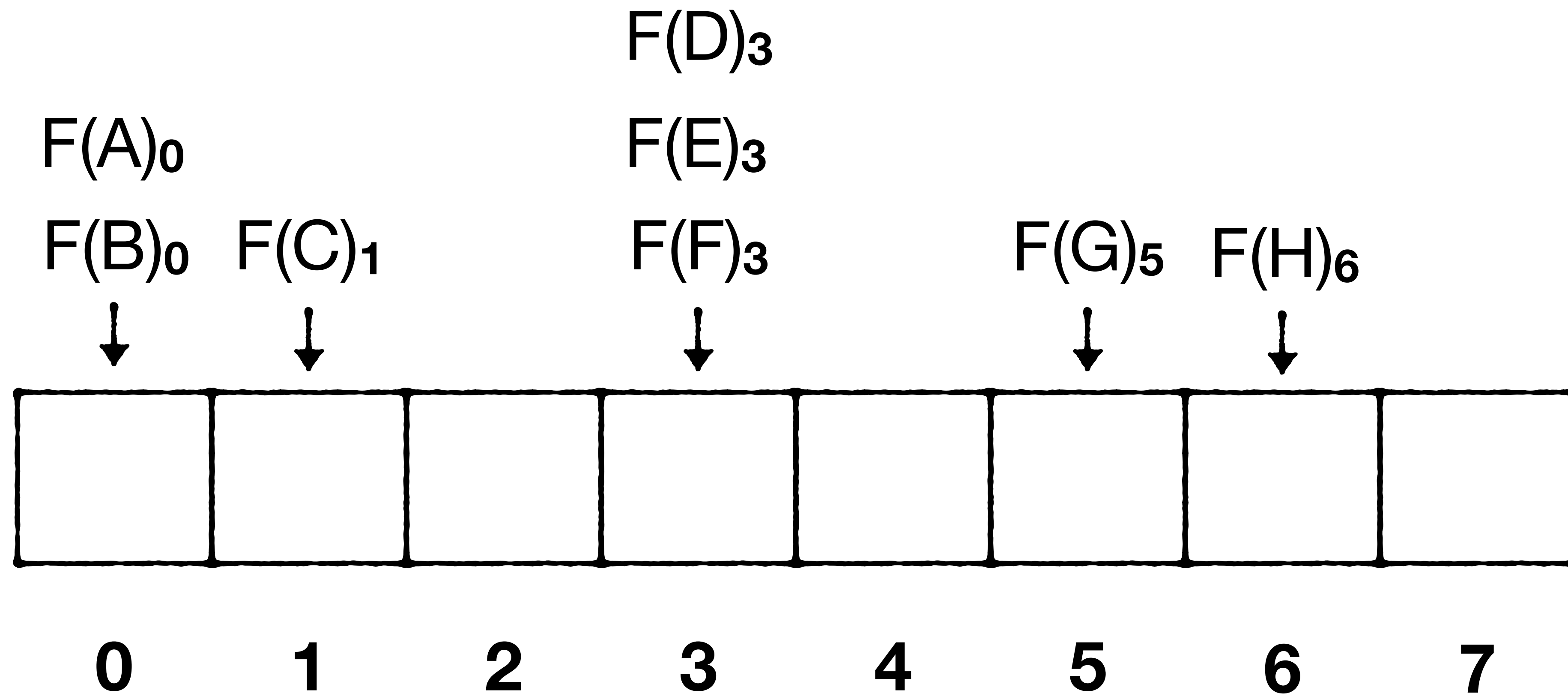
Variant of linear probing

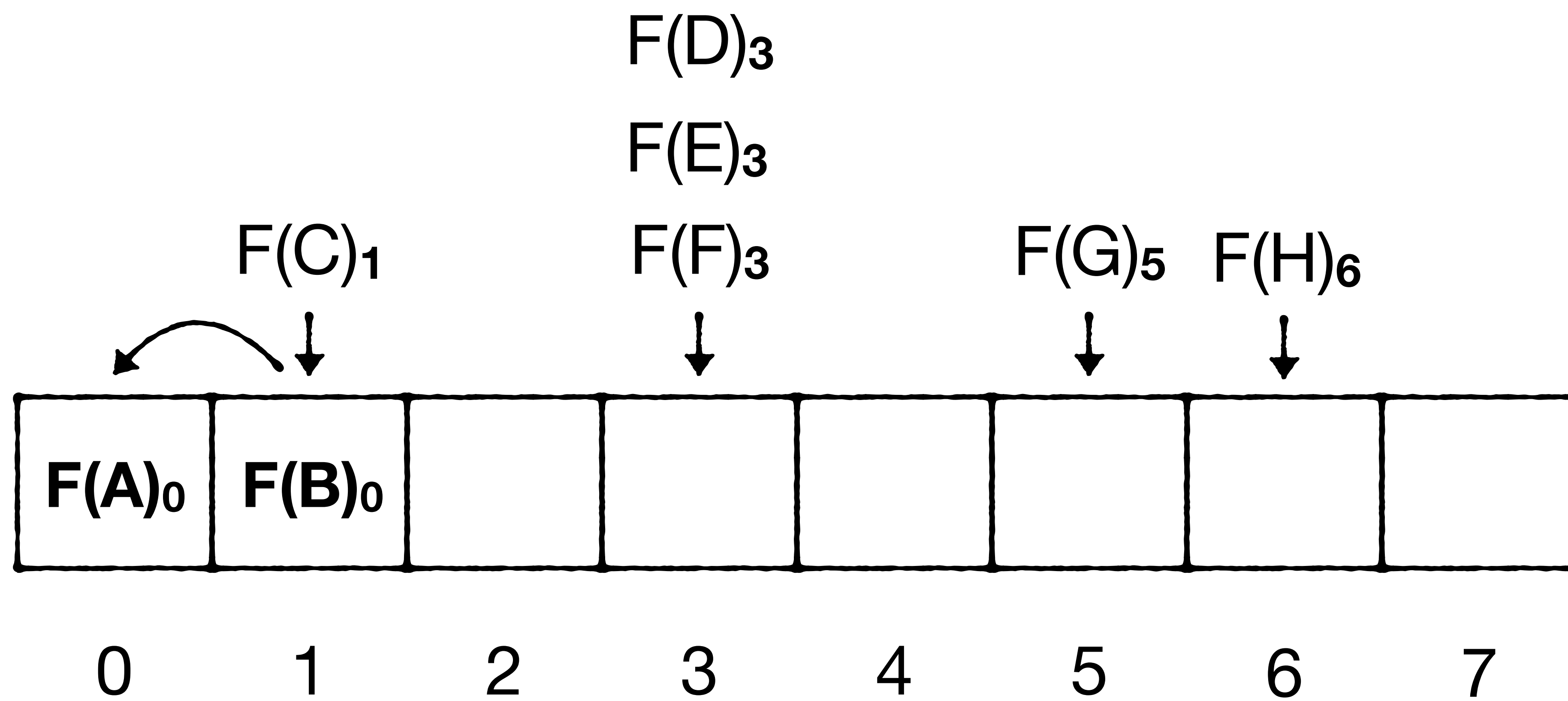


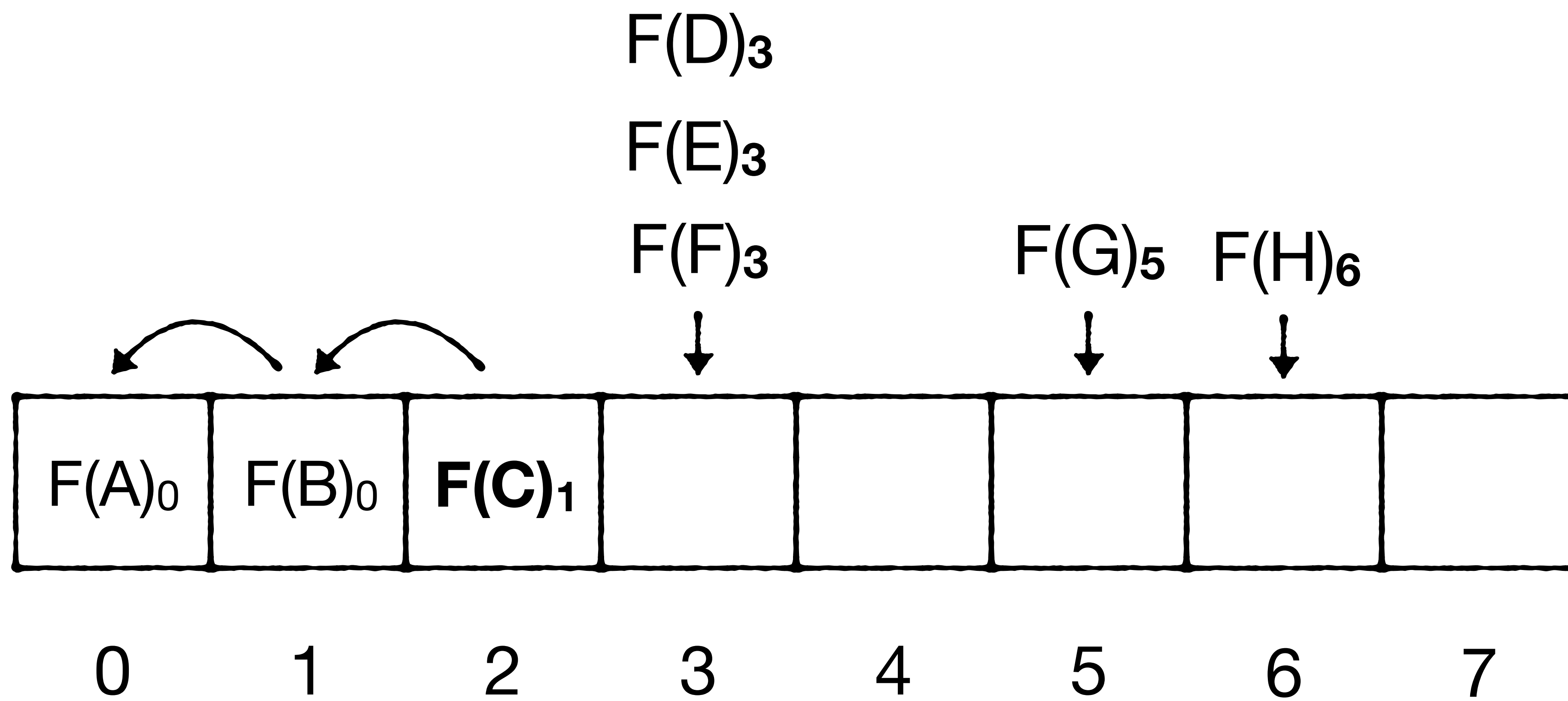
Each fingerprint is pushed rightwards yet stays as close as possible to its “canonical slot”

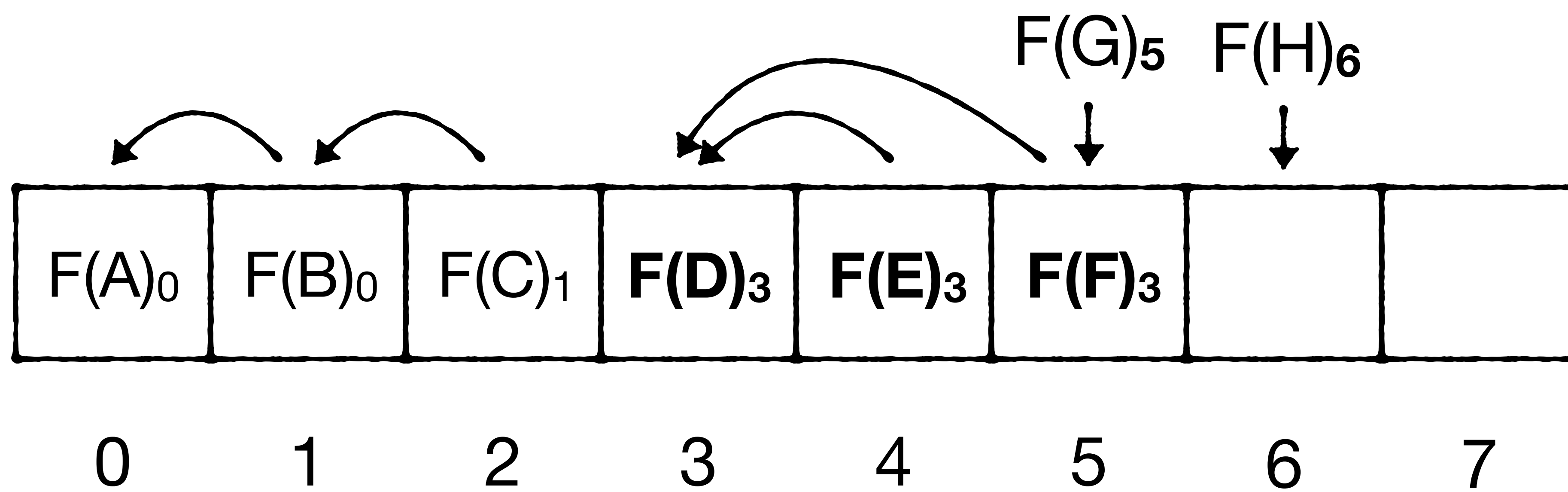


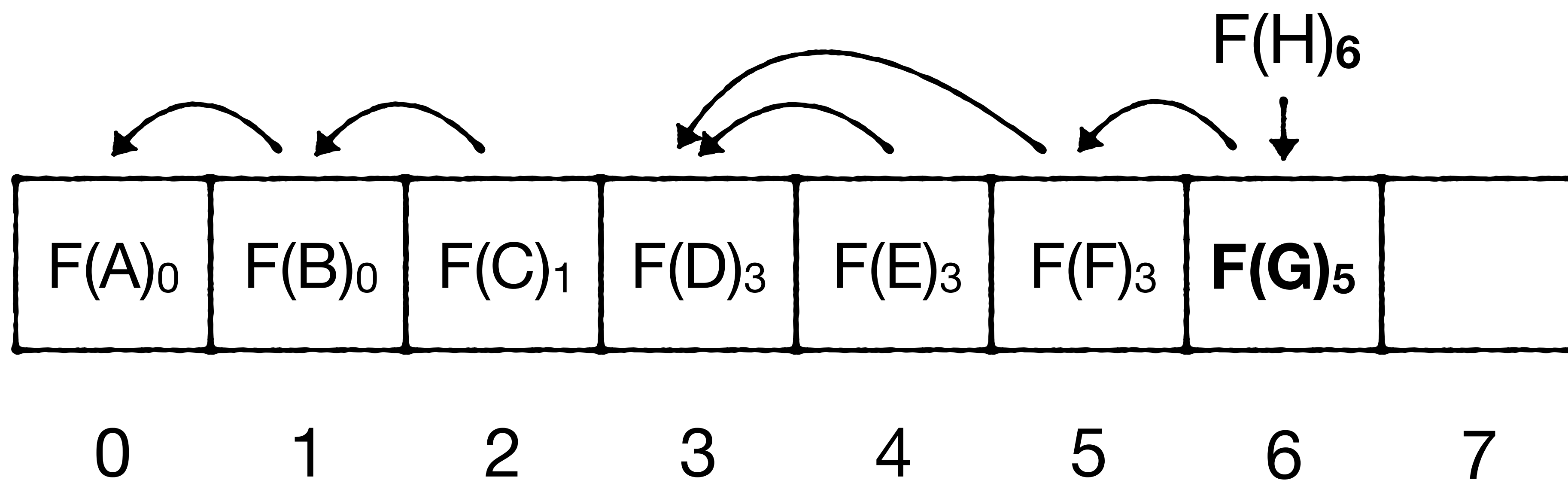
Each fingerprint is pushed rightwards yet stays as close as possible to its “canonical slot”

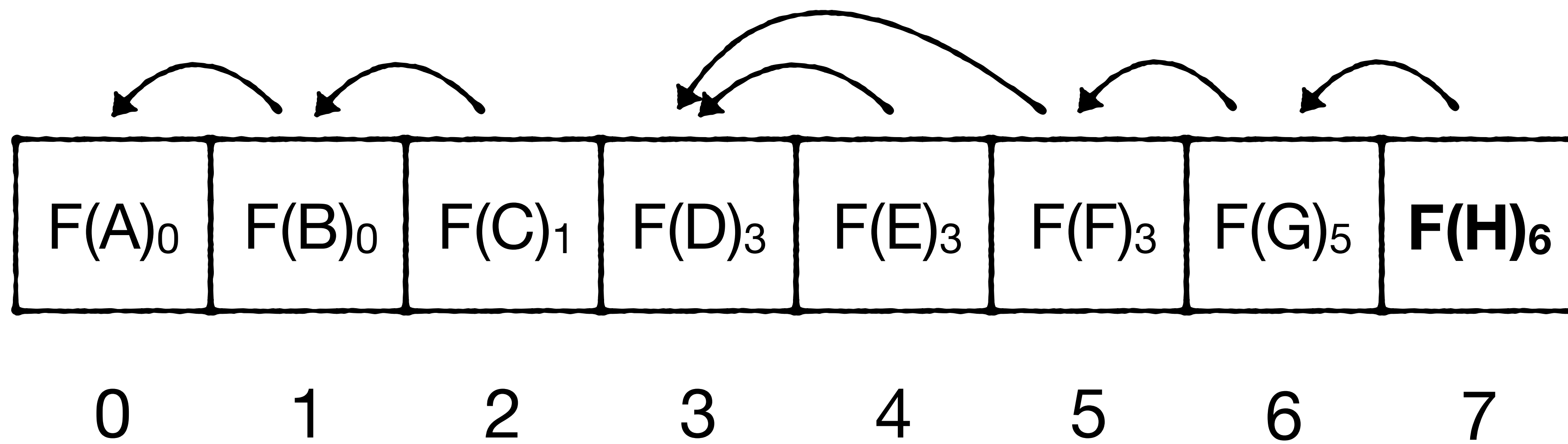




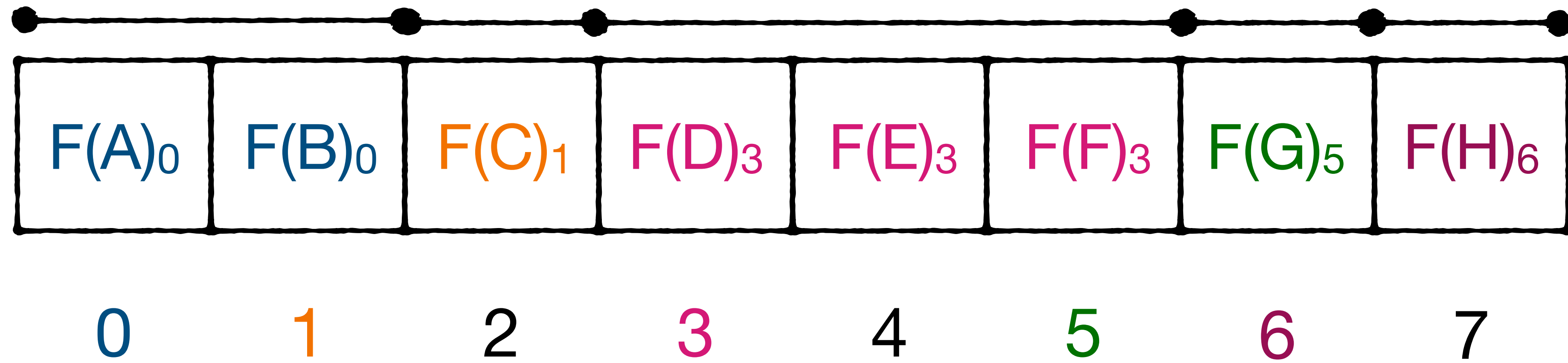




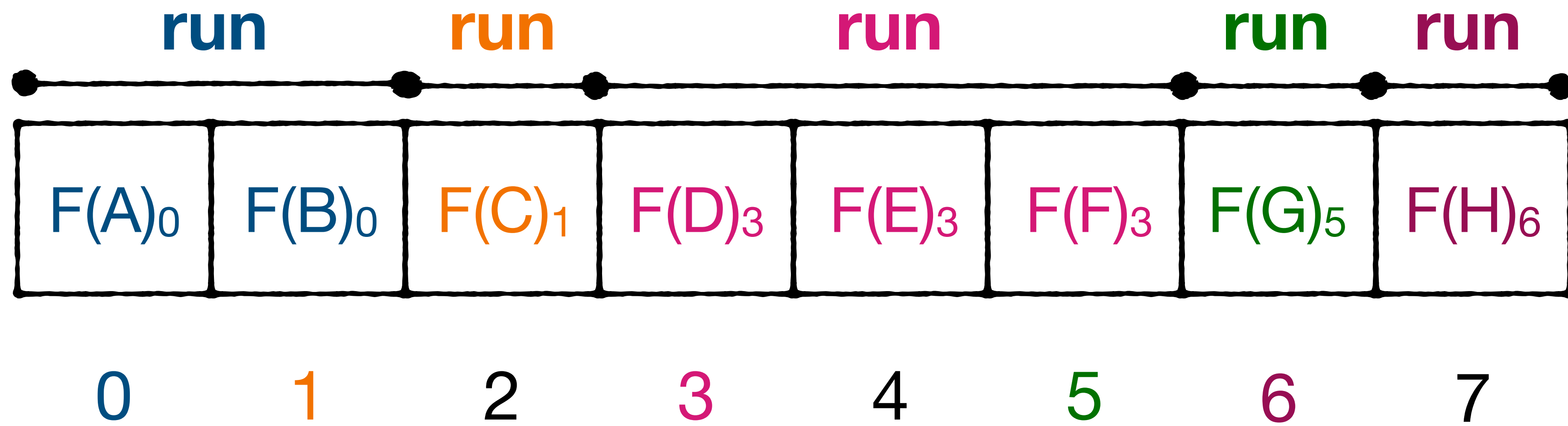




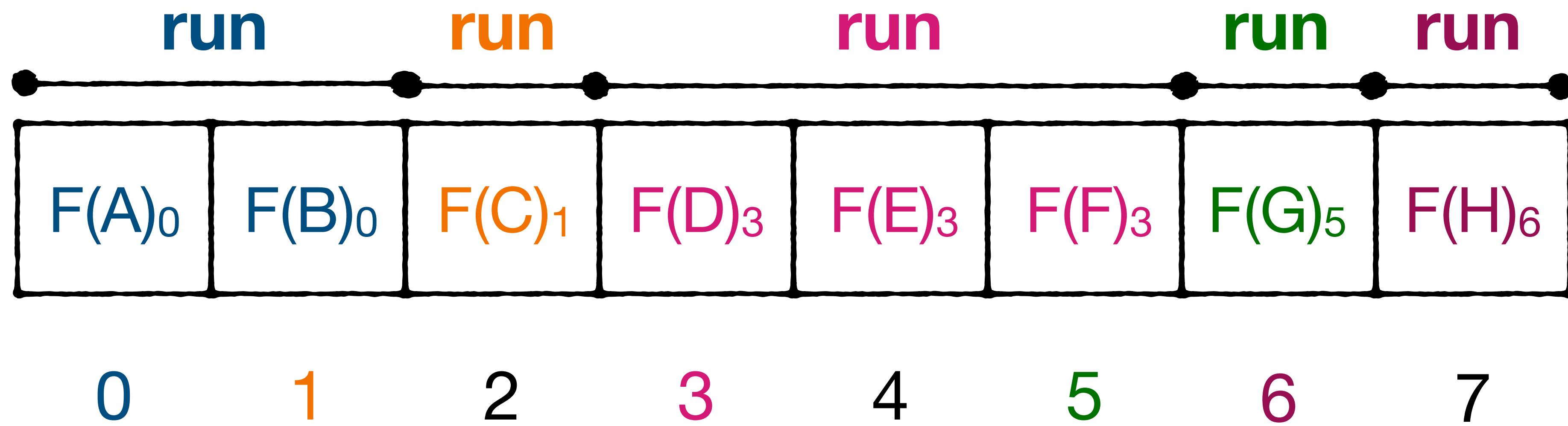
Note: fingerprints belonging to same canonical slot are contiguous

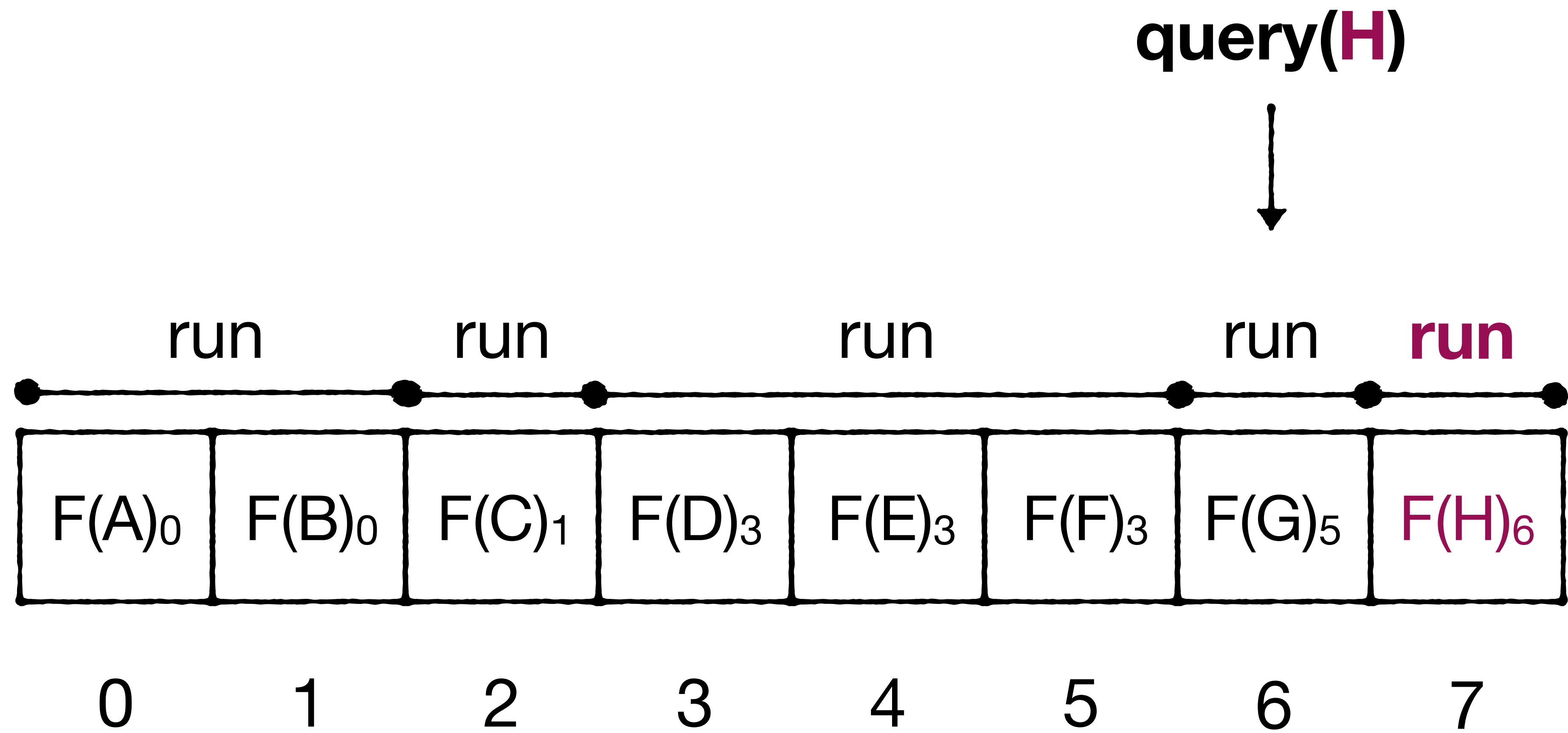


Note: fingerprints belonging to same canonical slot are contiguous

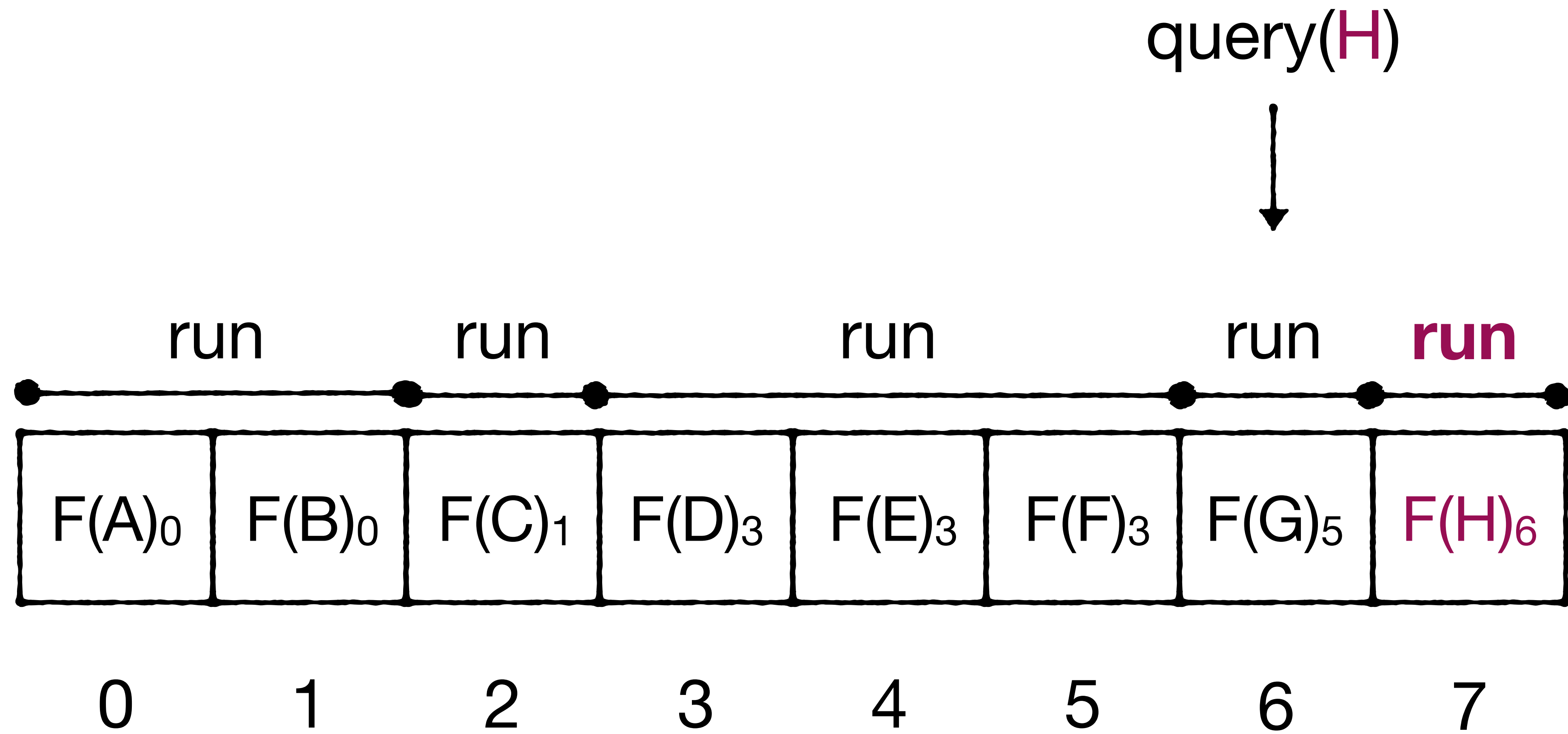


On average, each run consists of ≈ 1 slot

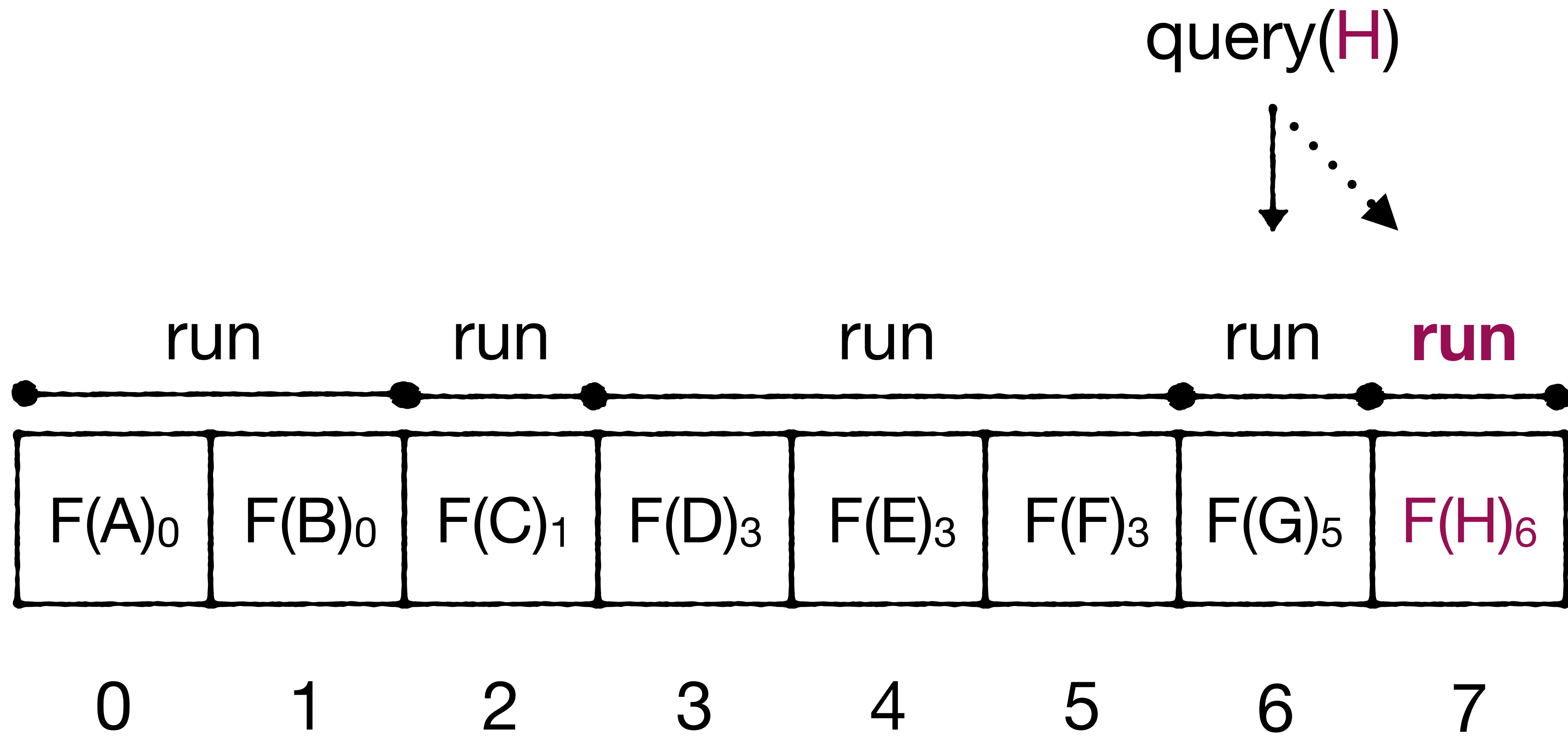




Problem?



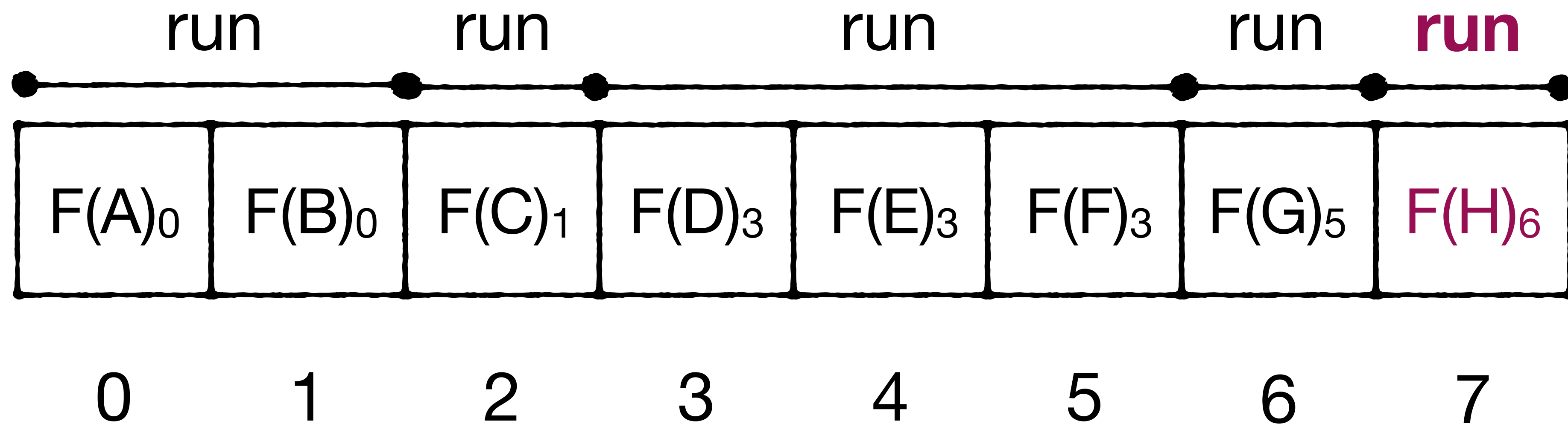
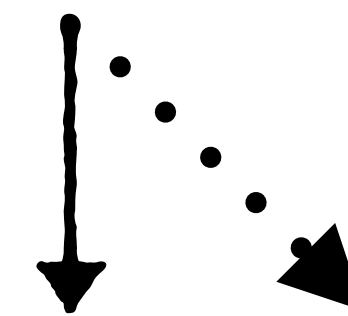
Problem? **Fingerprint** might have shifted to the right



Problem? Fingerprint might have shifted to the right

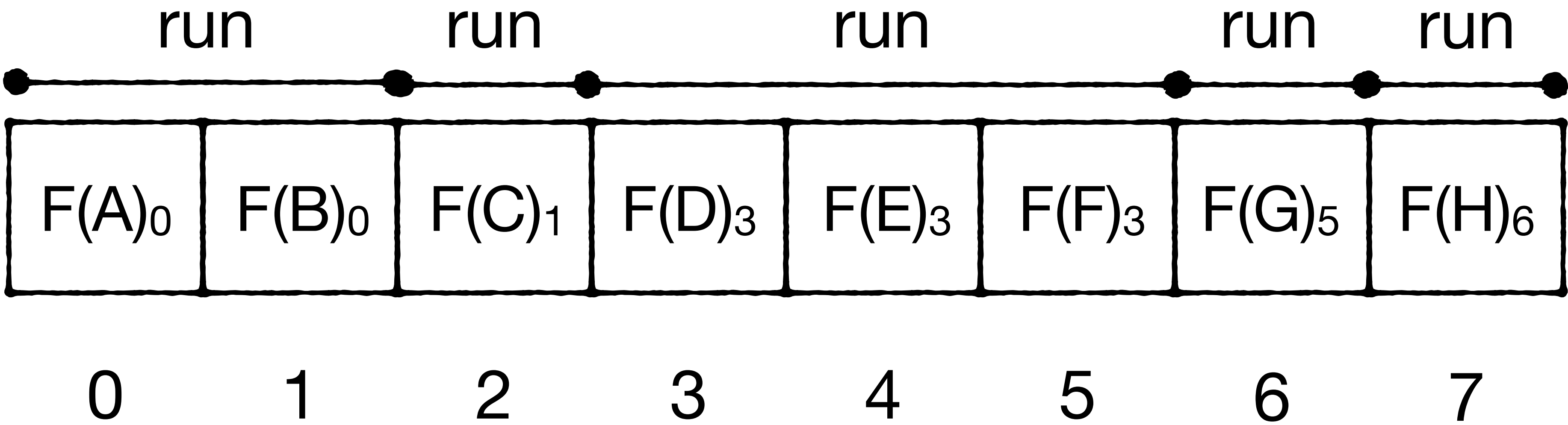
Solution?

query(**H**)

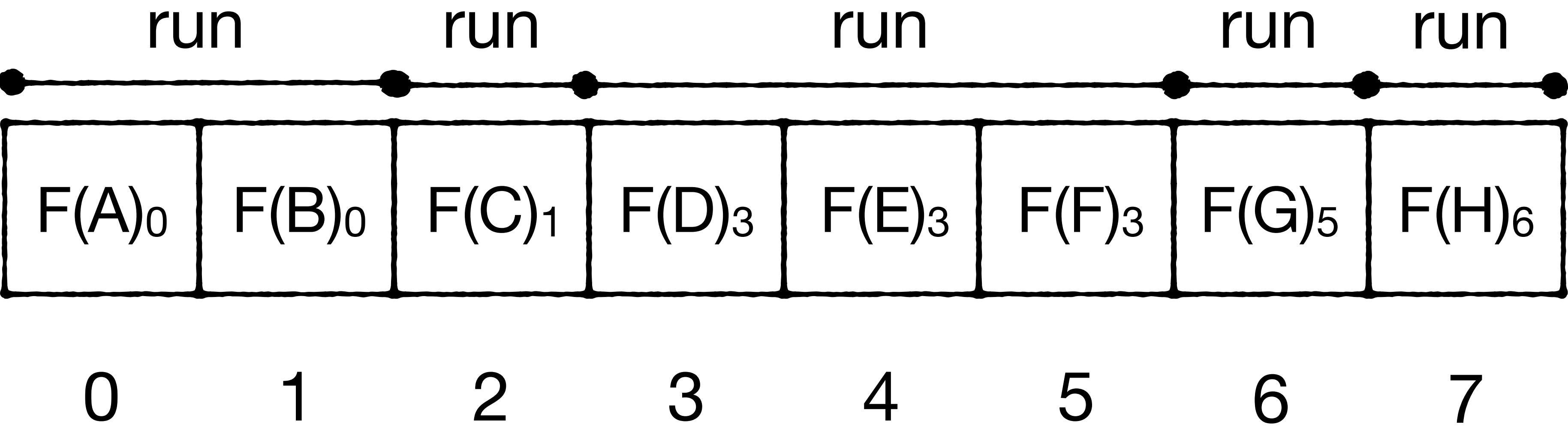


Solution: delineate runs using 2 bitmaps

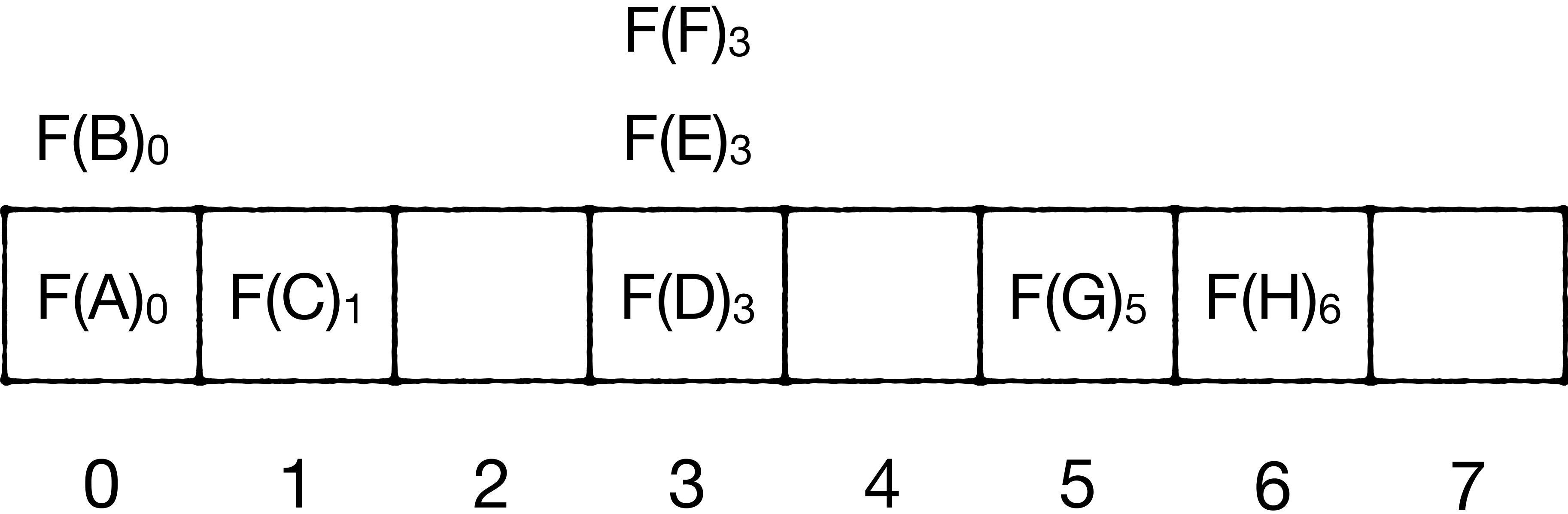
Occupied:
End:



Occupied: **1 if there is a run belonging to this slot**
End:



Occupied: **1 if there is a run belonging to this slot**
End:



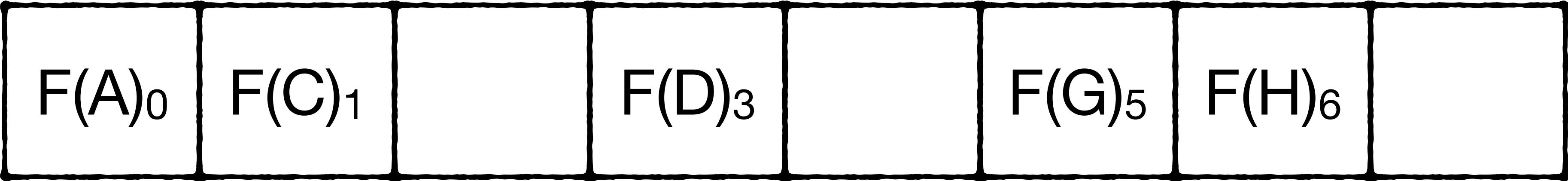
Occupied:
End:

1 1 0 1 0 1 1 0

F(B)₀

F(F)₃

F(E)₃

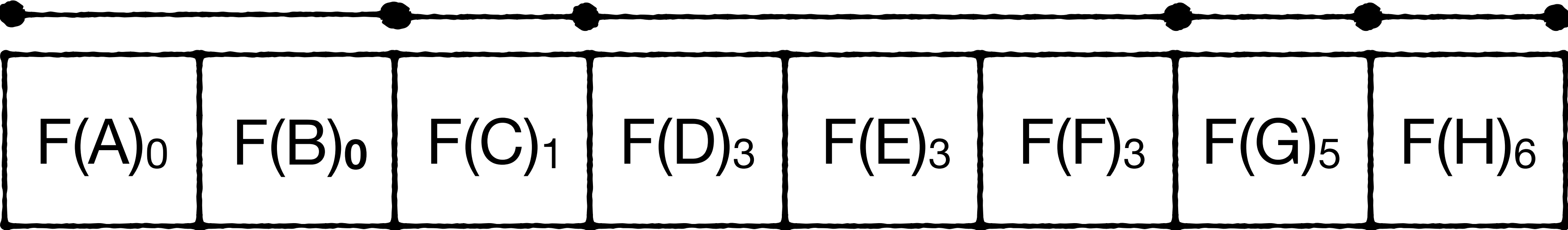


0 1 2 3 4 5 6 7

Occupied:
End:

1 1 0 1 0 1 1 0

run run run run run



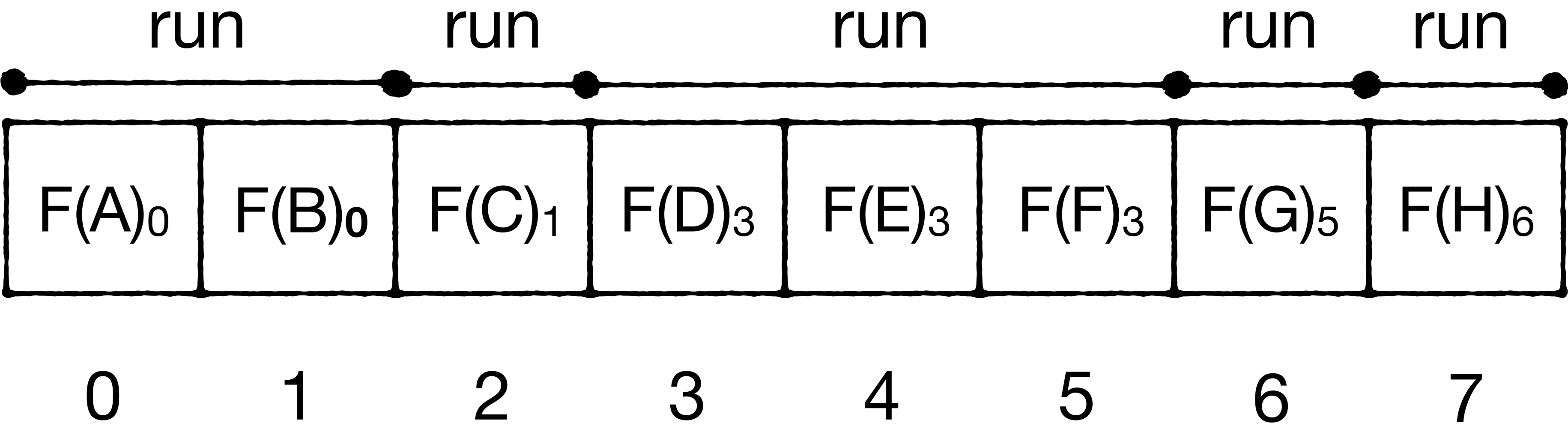
0 1 2 3 4 5 6 7

Occupied:

1 1 0 1 0 1 1 0

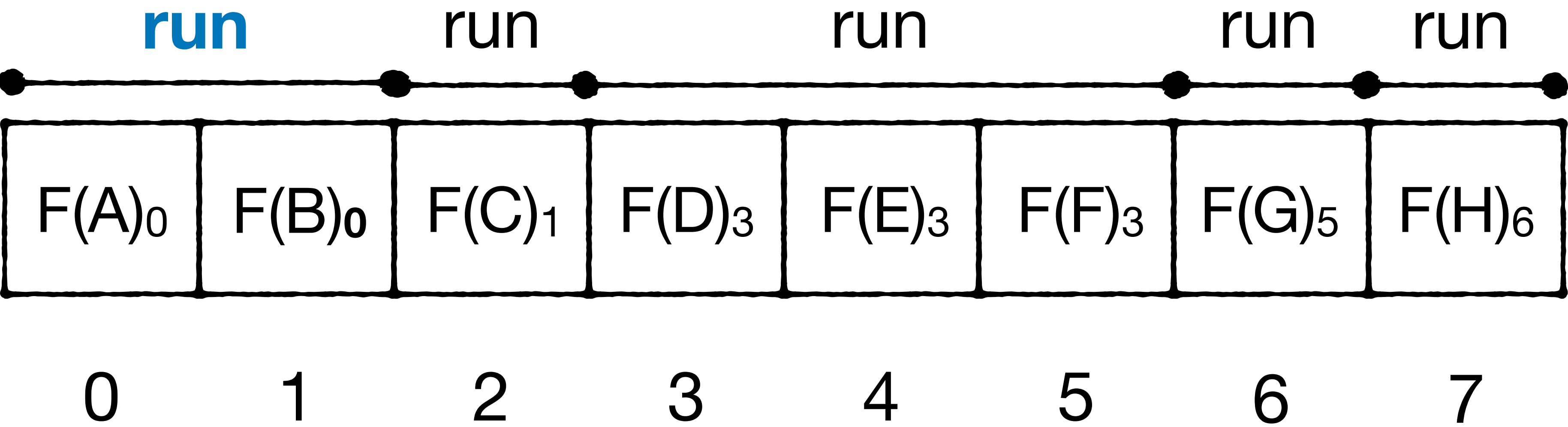
End:

1 for each slot where a run ends



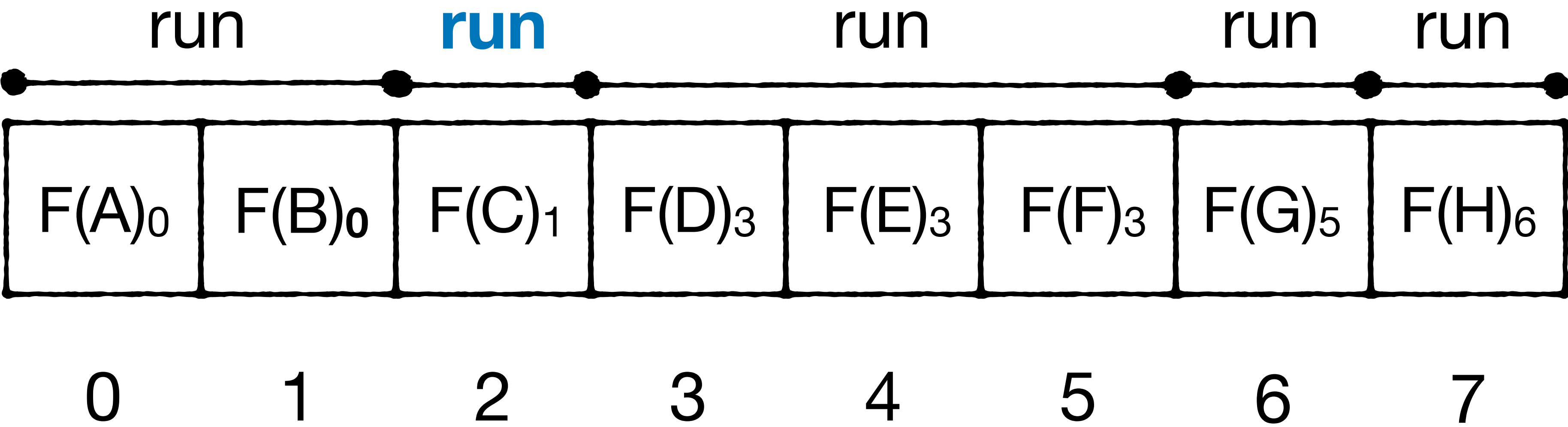
Occupied:
End:

1	1	0	1	0	1	1	0
0	1						



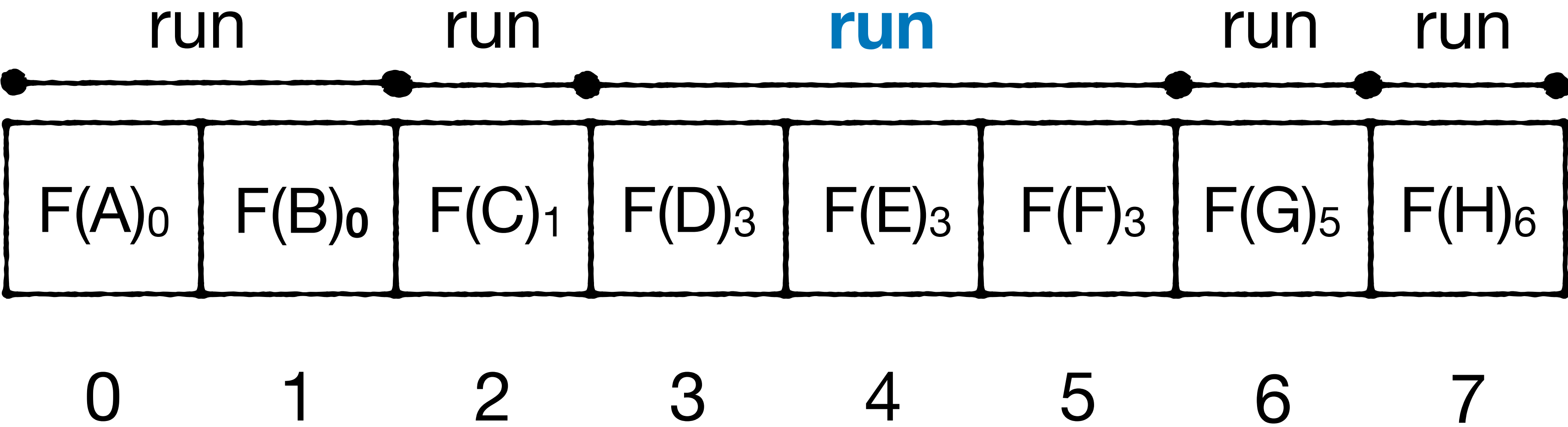
Occupied:
End:

1	1	0	1	0	1	1	0
0	1	1					



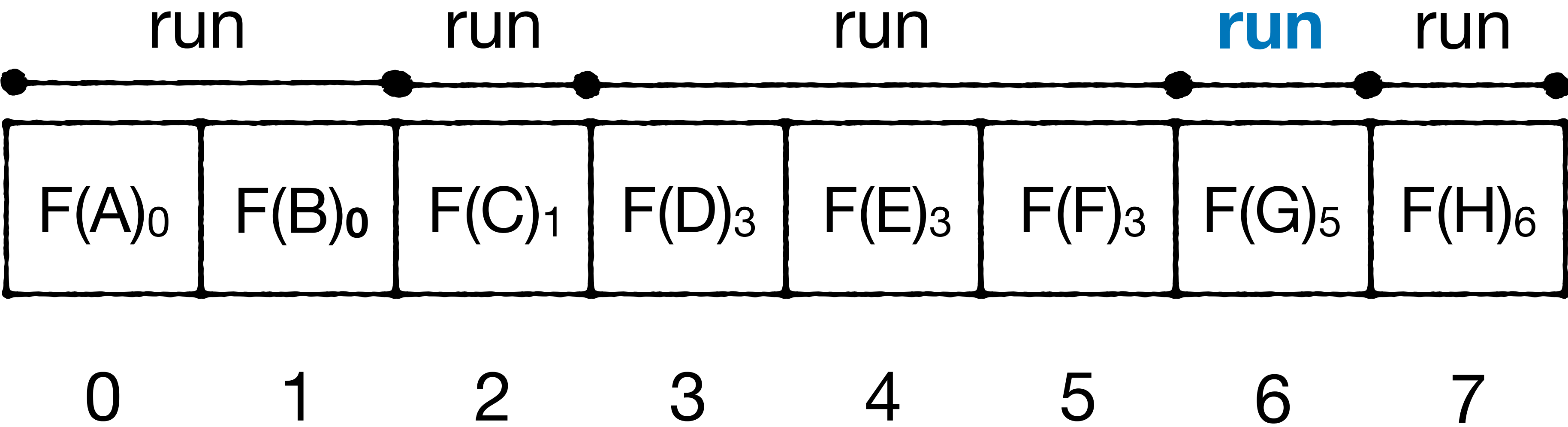
Occupied:
End:

1	1	0	1	0	1	1	0
0	1	1	0	0	1		



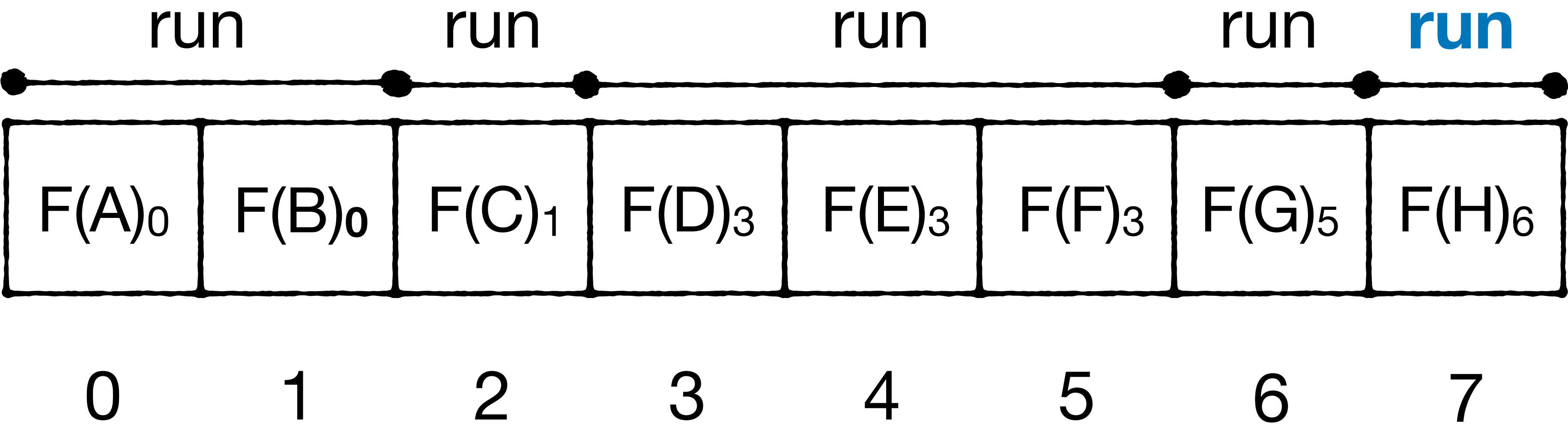
Occupied:
End:

1	1	0	1	0	1	1	0
0	1	1	0	0	1	1	



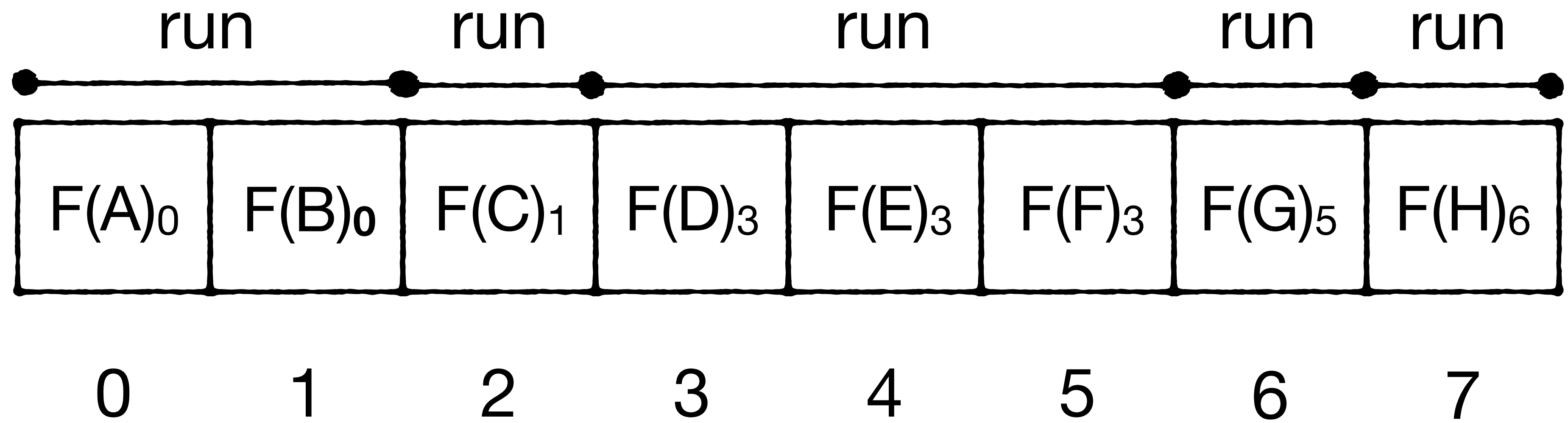
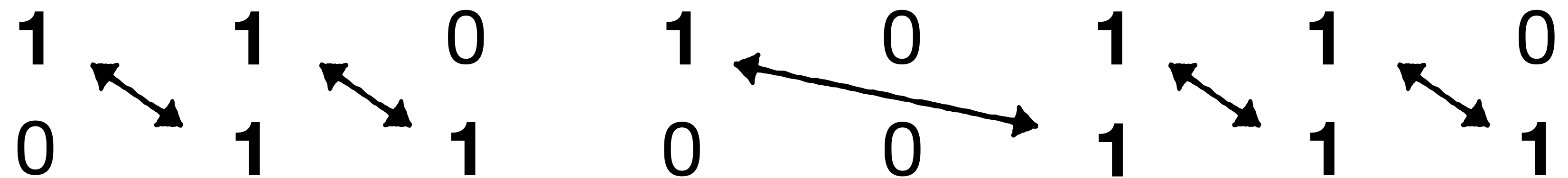
Occupied:
End:

1	1	0	1	0	1	1	0
0	1	1	0	0	1	1	1



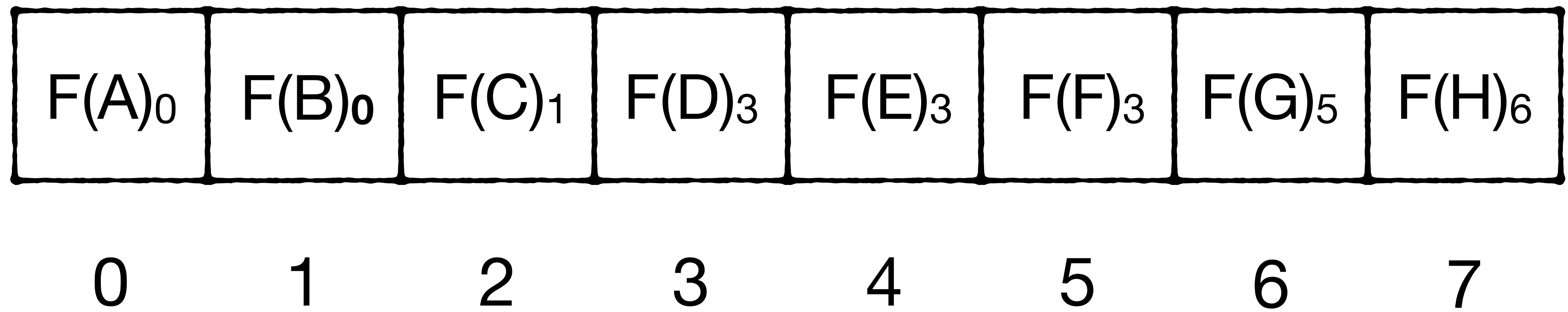
i^{th} set occupied bit corresponds to i^{th} set end bit

Occupied: 1 1 0 1 0 1 1 0
End: 0 1 1 0 0 1 1 1



How to query?

Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1



get(Z)

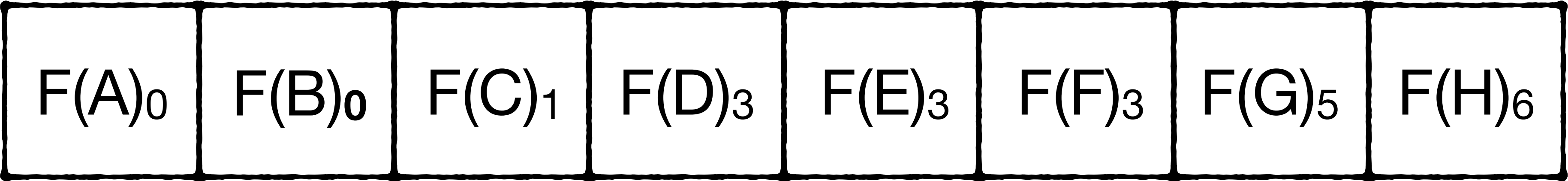


Occupied:

1 1 0 1 0 1 1 0

End:

0 1 1 0 0 1 1 1

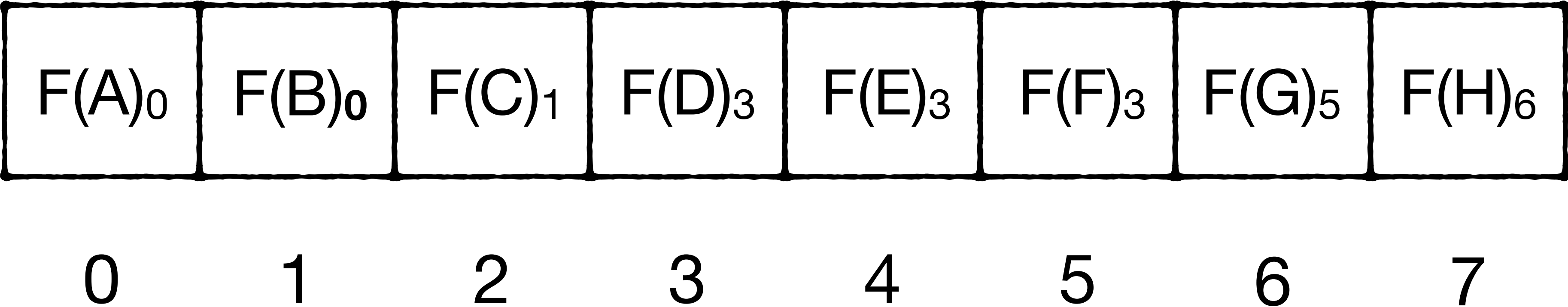


0 1 2 3 4 5 6 7

get(Z) return negative



Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1



get(H)

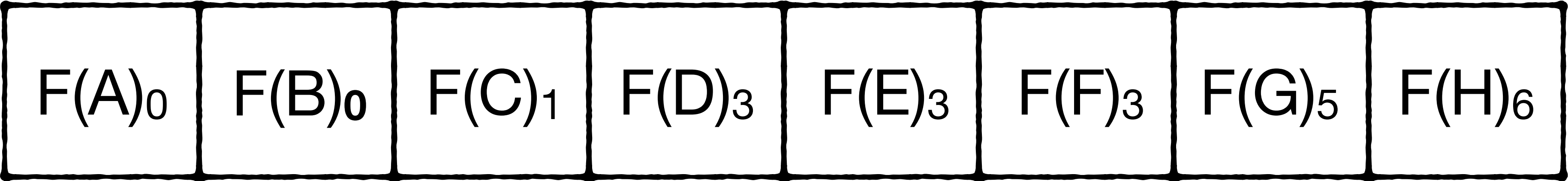


Occupied:

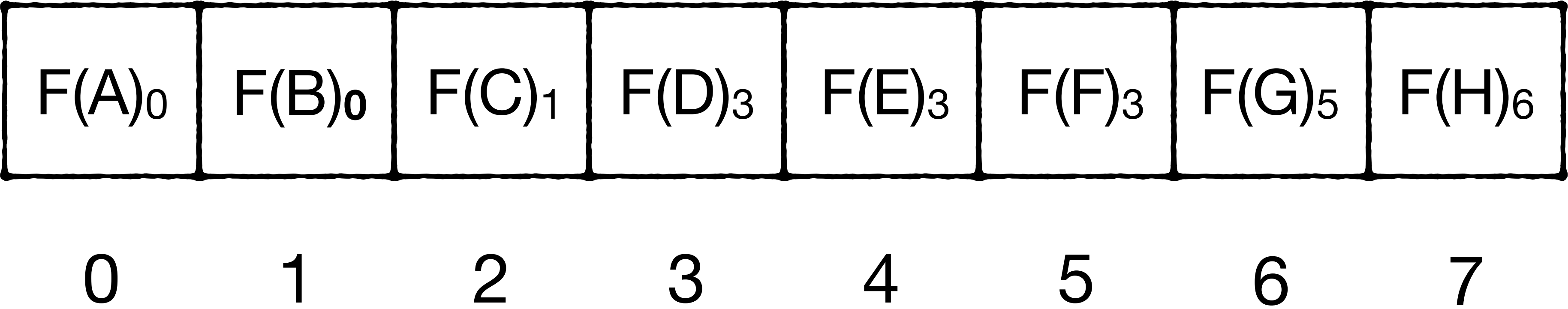
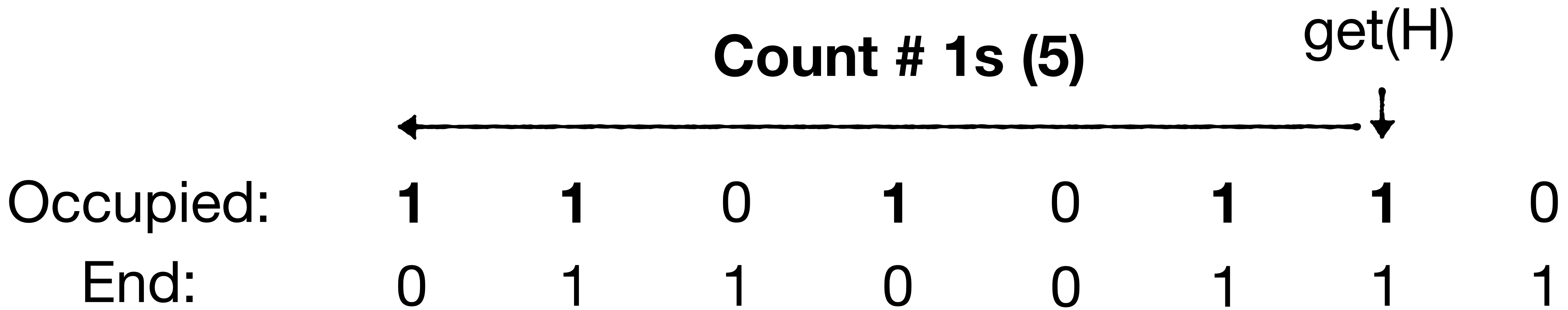
1 1 0 1 0 1 **1** 0

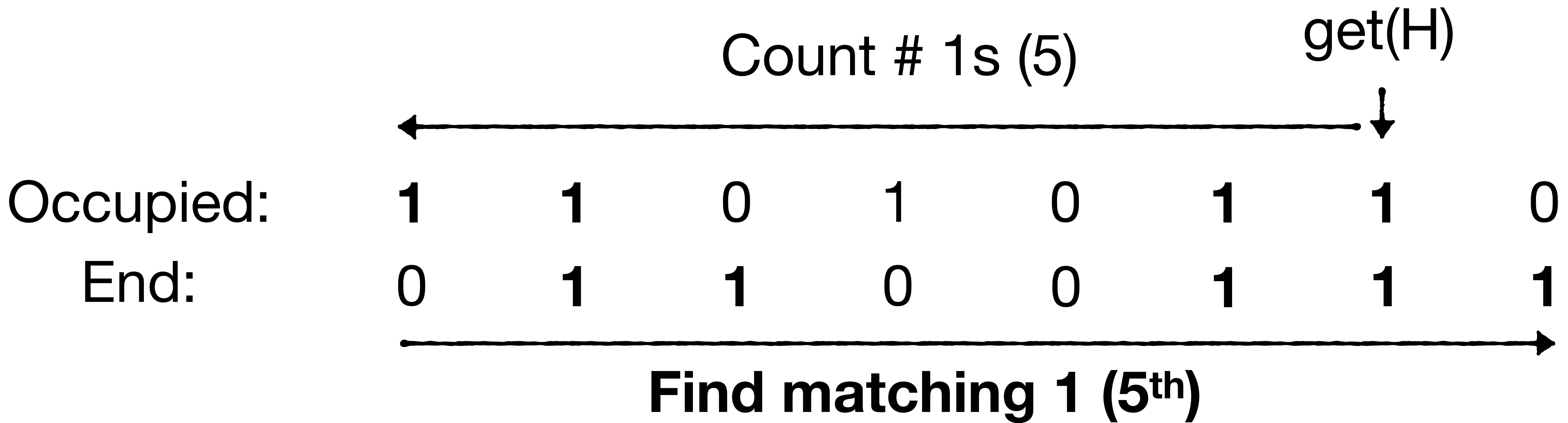
End:

0 1 1 0 0 1 1 1

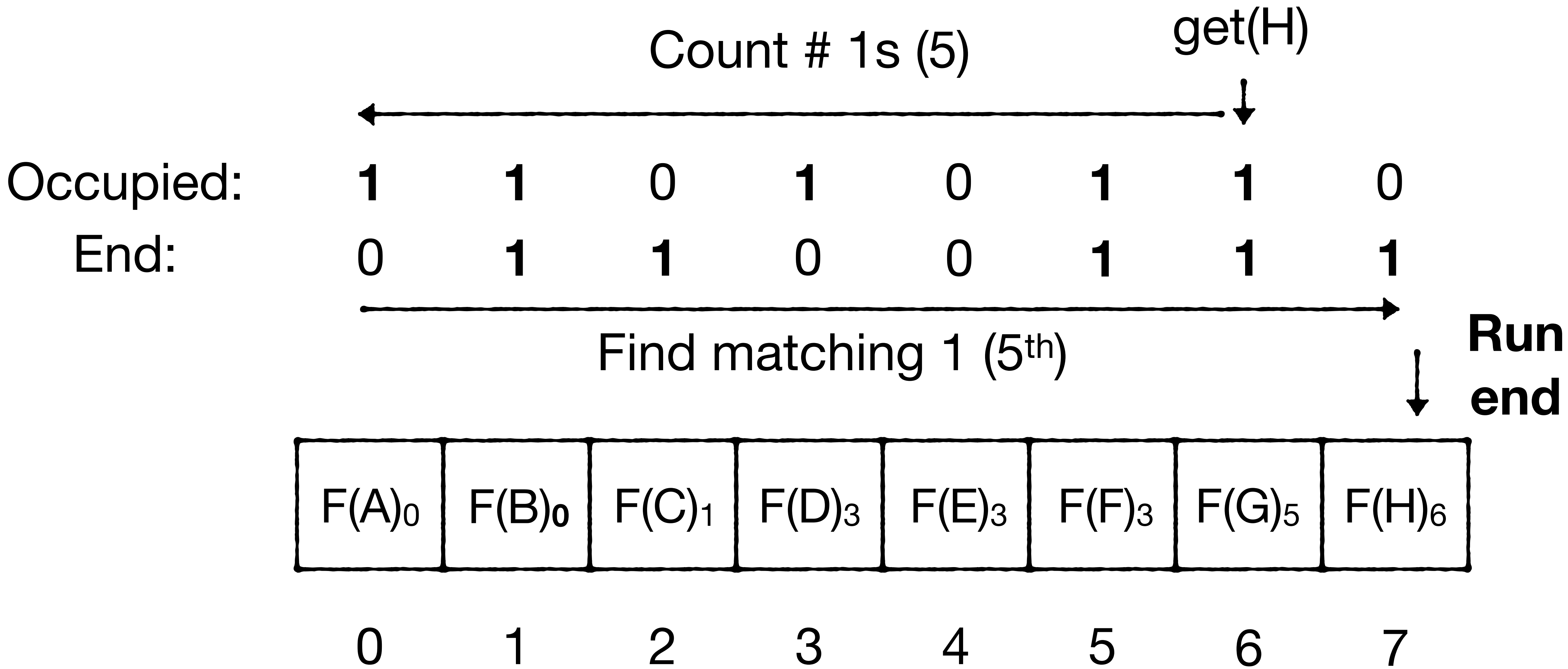


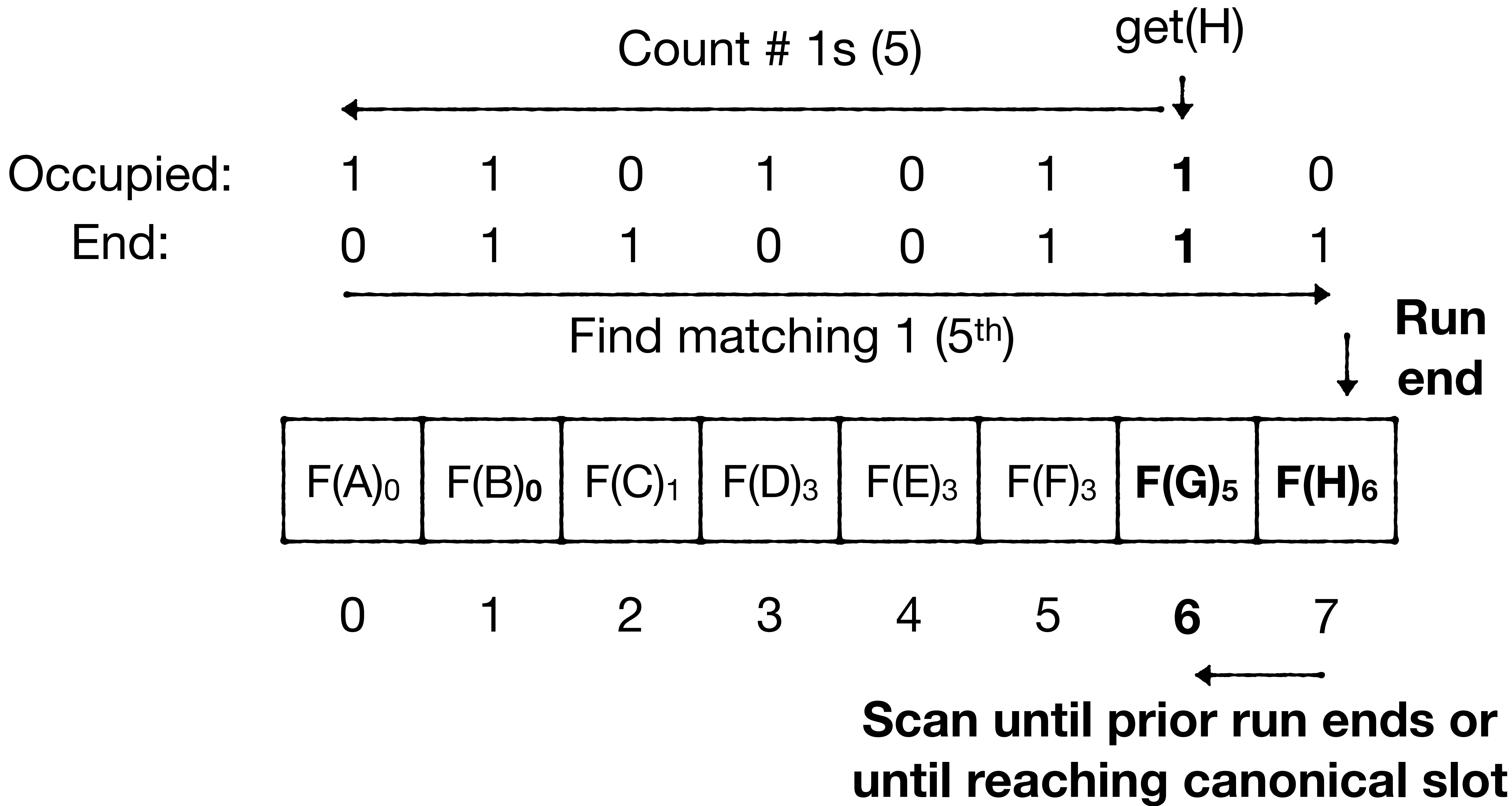
0 1 2 3 4 5 6 7





F(A) ₀	F(B) ₀	F(C) ₁	F(D) ₃	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
0	1	2	3	4	5	6	7





Can handle queries :)

Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1

F(A) ₀	F(B) ₀	F(C) ₁	F(D) ₃	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
0	1	2	3	4	5	6	7

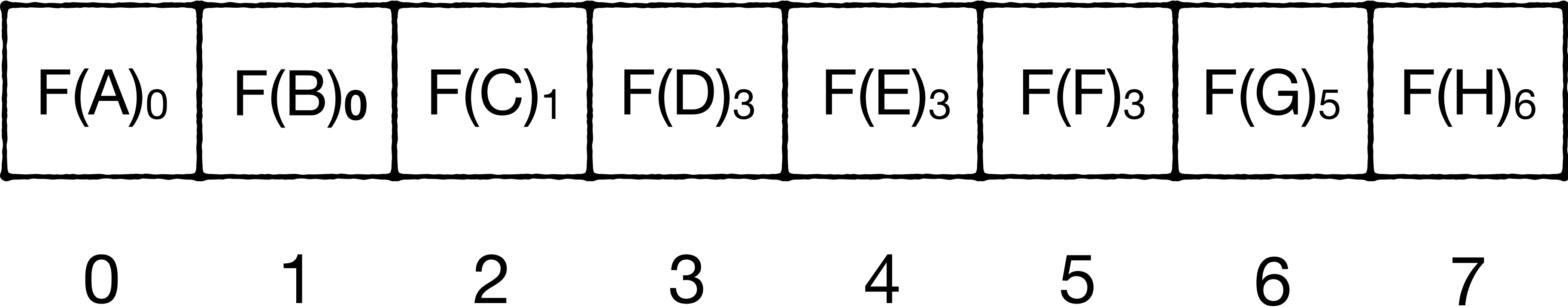
Can handle queries :) **problem?**

Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1

F(A) ₀	F(B) ₀	F(C) ₁	F(D) ₃	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
0	1	2	3	4	5	6	7

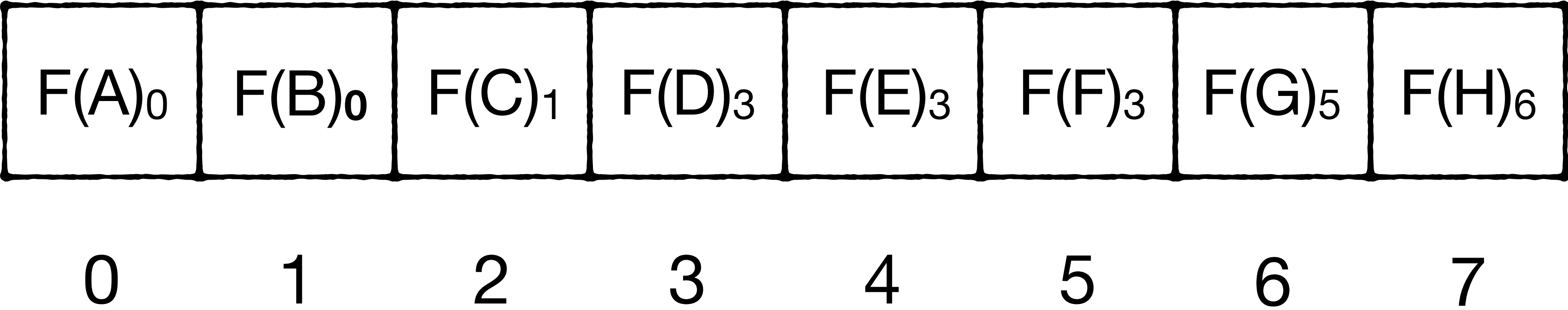
Scanning bitmaps takes $O(N)$

Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1



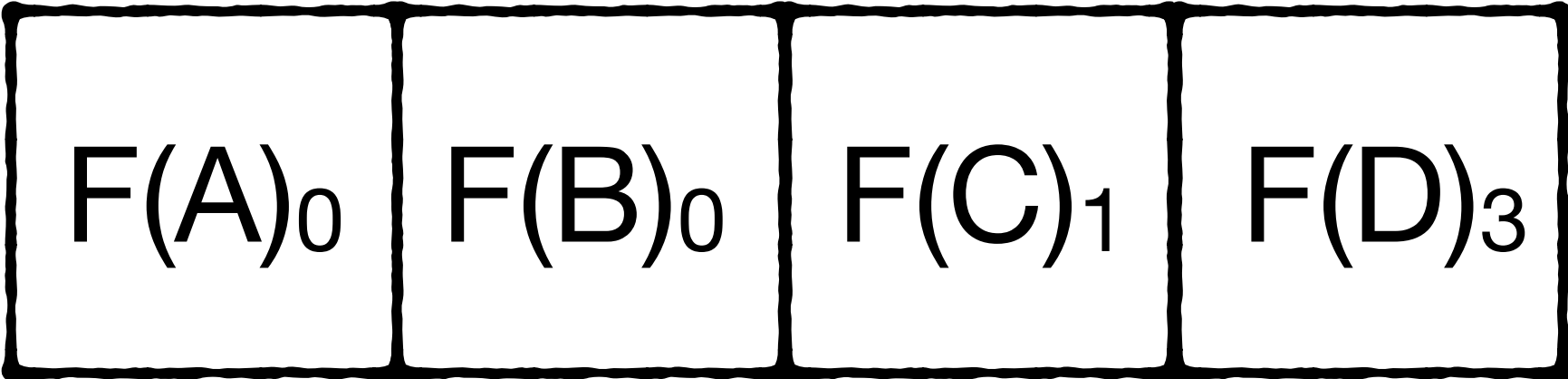
Scanning bitmaps takes $O(N)$
Ideas?

Occupied:	1	1	0	1	0	1	1	0
End:	0	1	1	0	0	1	1	1

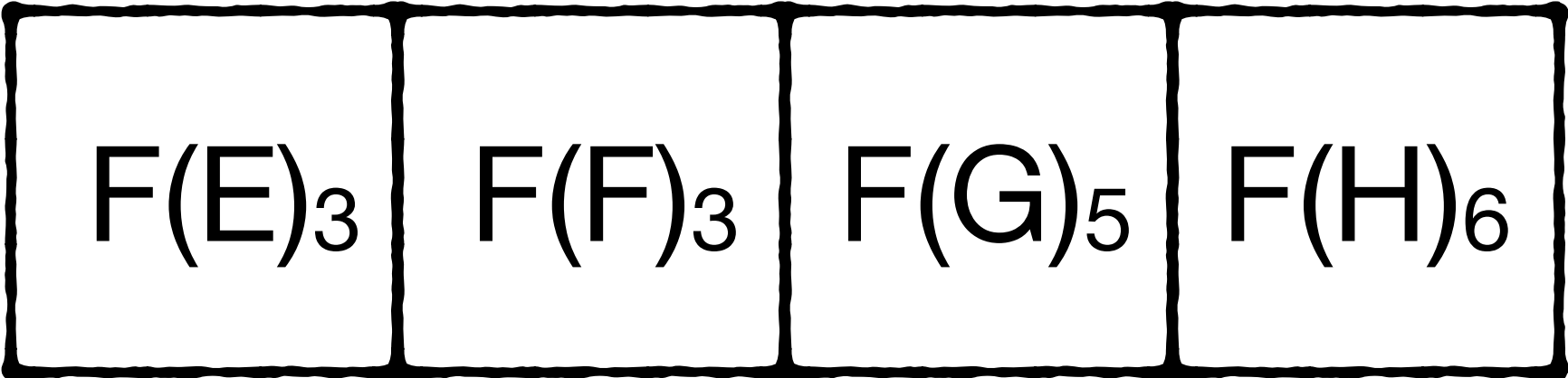


Split filter into chunks (64 slots in practice)

Occupied:	1	1	0	1		0	1	1	0
End:	0	1	1	0		0	1	1	1



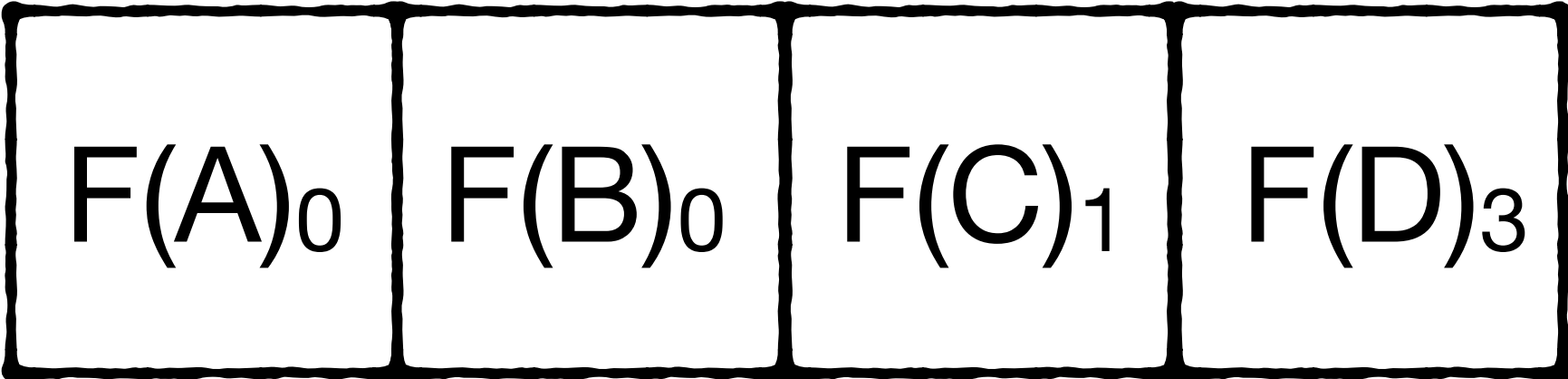
0 1 2 3



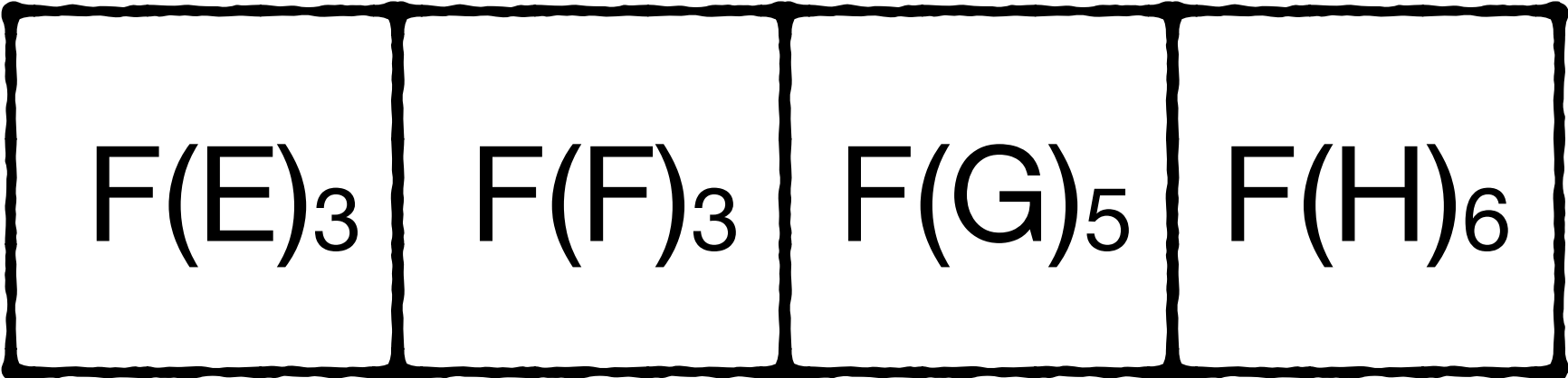
4 5 6 7

Split filter into chunks (64 slots in practice)
≈ 1-2 cache lines

Occupied:	1	1	0	1		0	1	1	0
End:	0	1	1	0		0	1	1	1



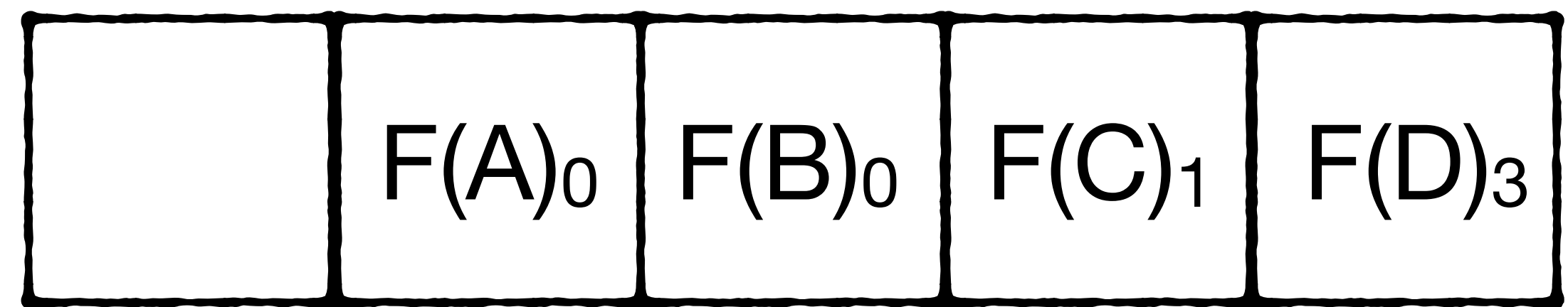
0 1 2 3



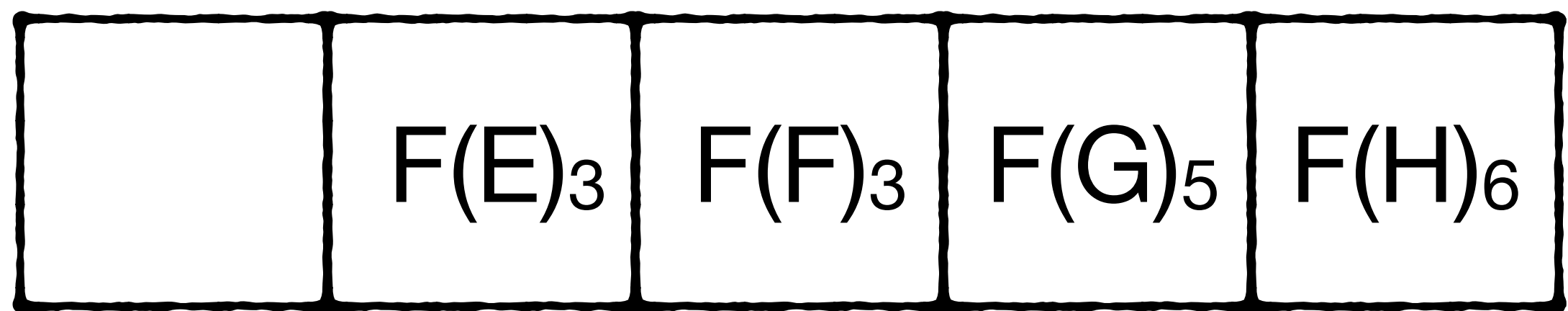
4 5 6 7

Each chunk has offset field (8 bits)

Occupied:	1	1	0	1		0	1	1	0
End:	0	1	1	0		0	1	1	1



Offset 0 1 2 3

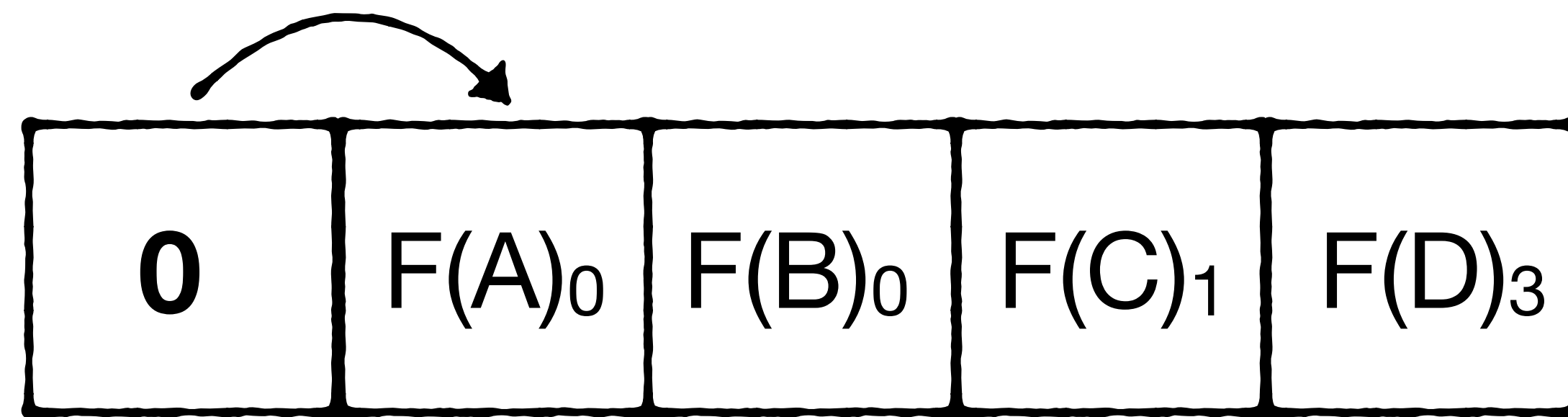


Offset 4 5 6 7

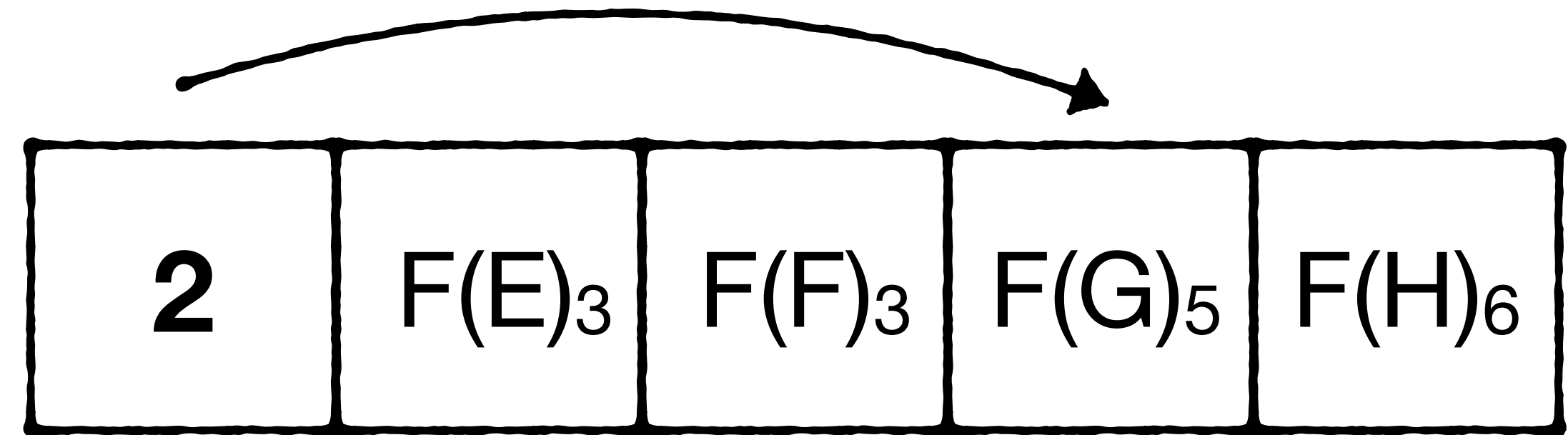
Each chunk has offset field

Measures distance to first entry of chunk

Occupied:	1	1	0	1		0	1	1	0
End:	0	1	1	0		0	1	1	1



Offset 0 1 2 3

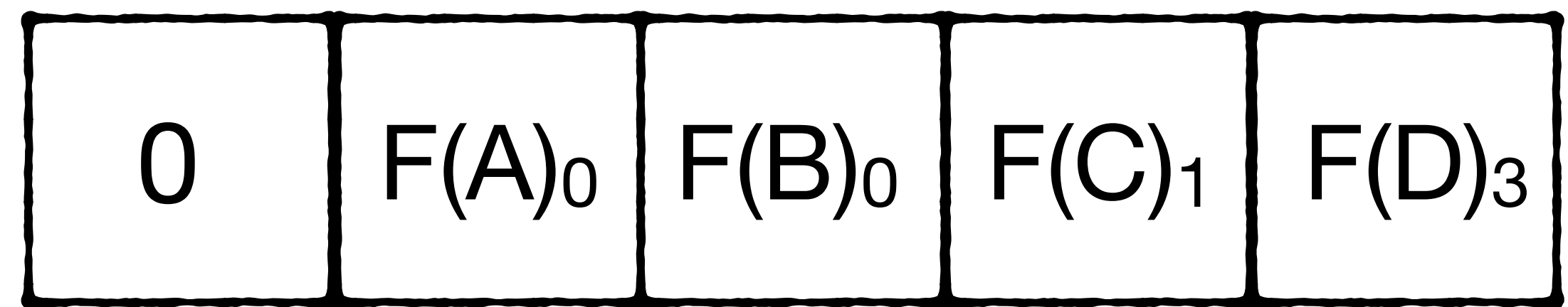


Offset 4 5 6 7

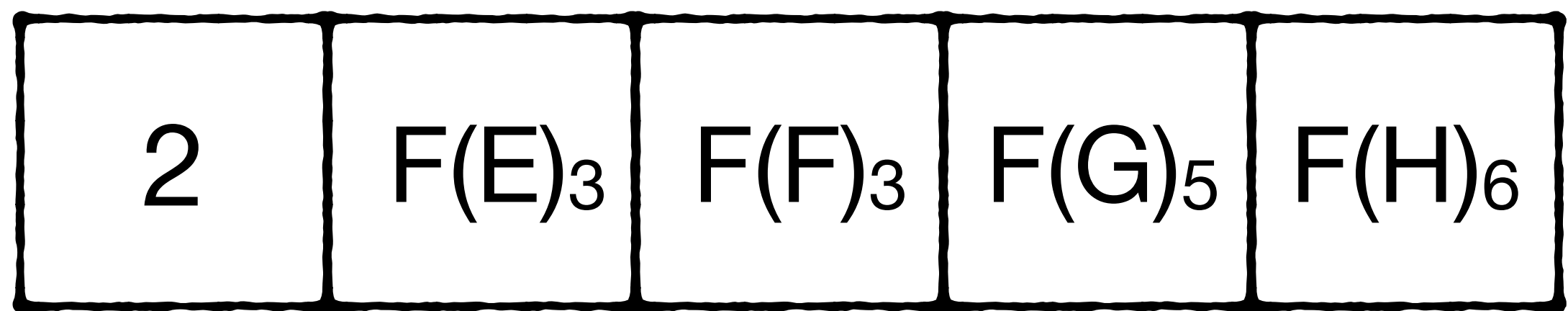
Back to Example

get(H)
↓

Occupied:	1	1	0	1		0	1	1	0
End:	0	1	1	0		0	1	1	1



Offset 0 1 2 3



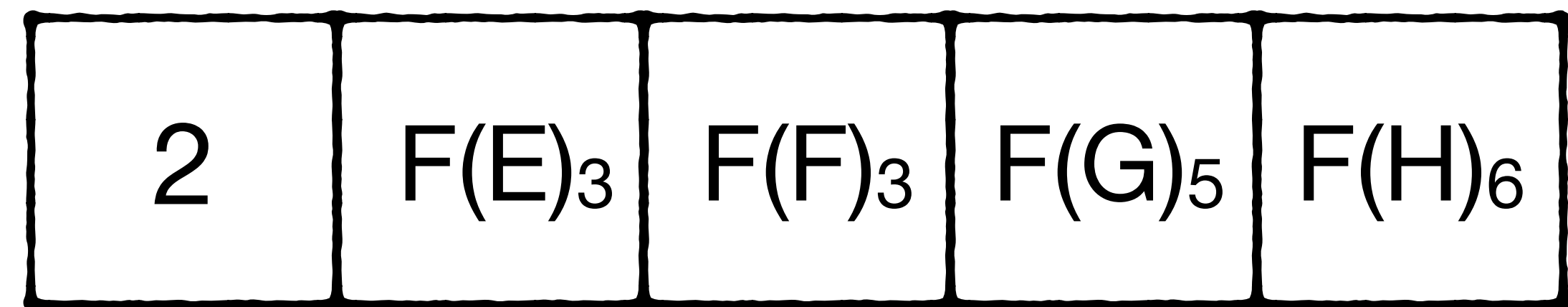
Offset 4 5 6 7

Back to Example

get(H)



0	1	1	0
0	1	1	1

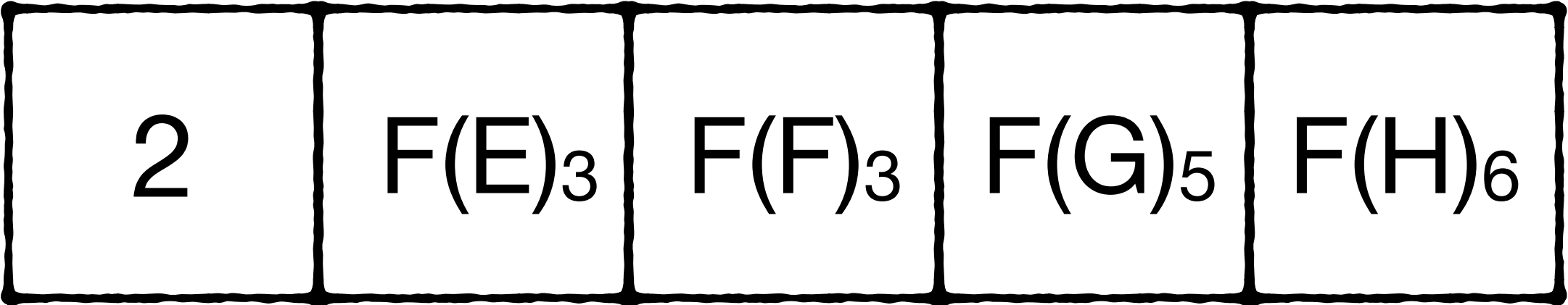


Offset	4	5	6	7
--------	---	---	---	---

get(H)

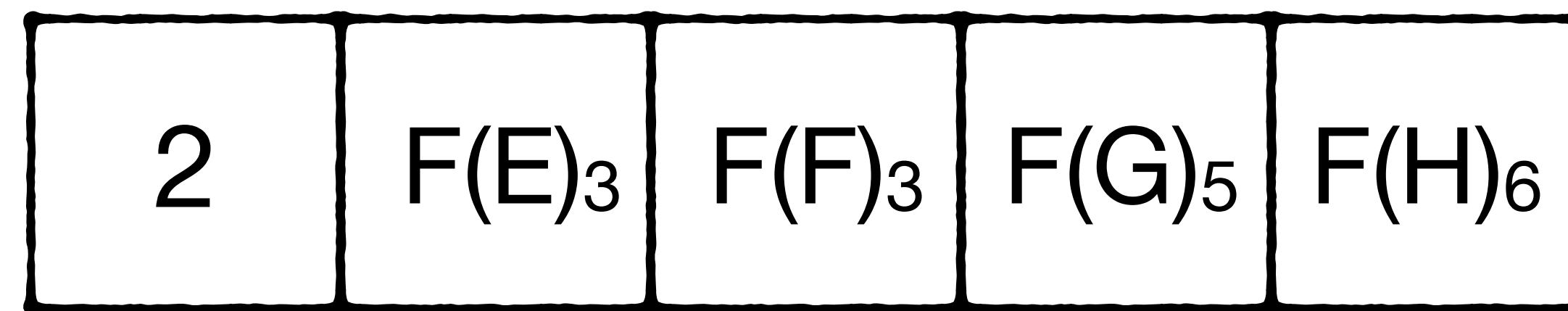


Occupied:	0	1	1	0
End:	0	1	1	1

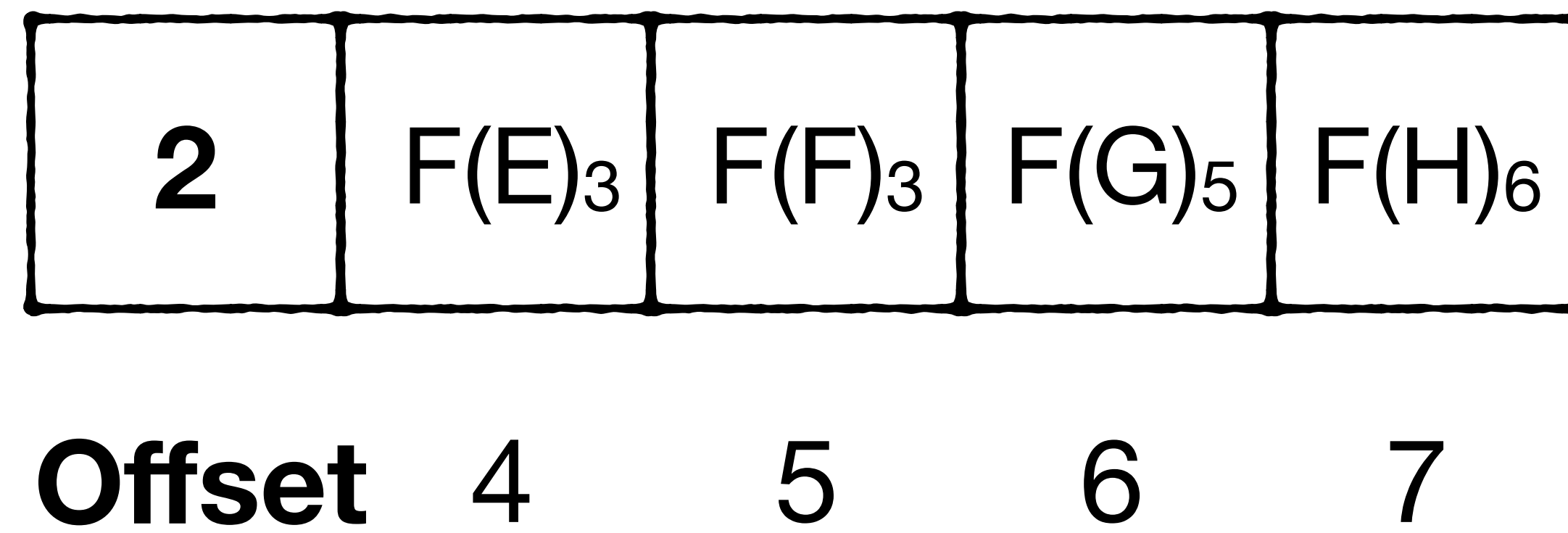
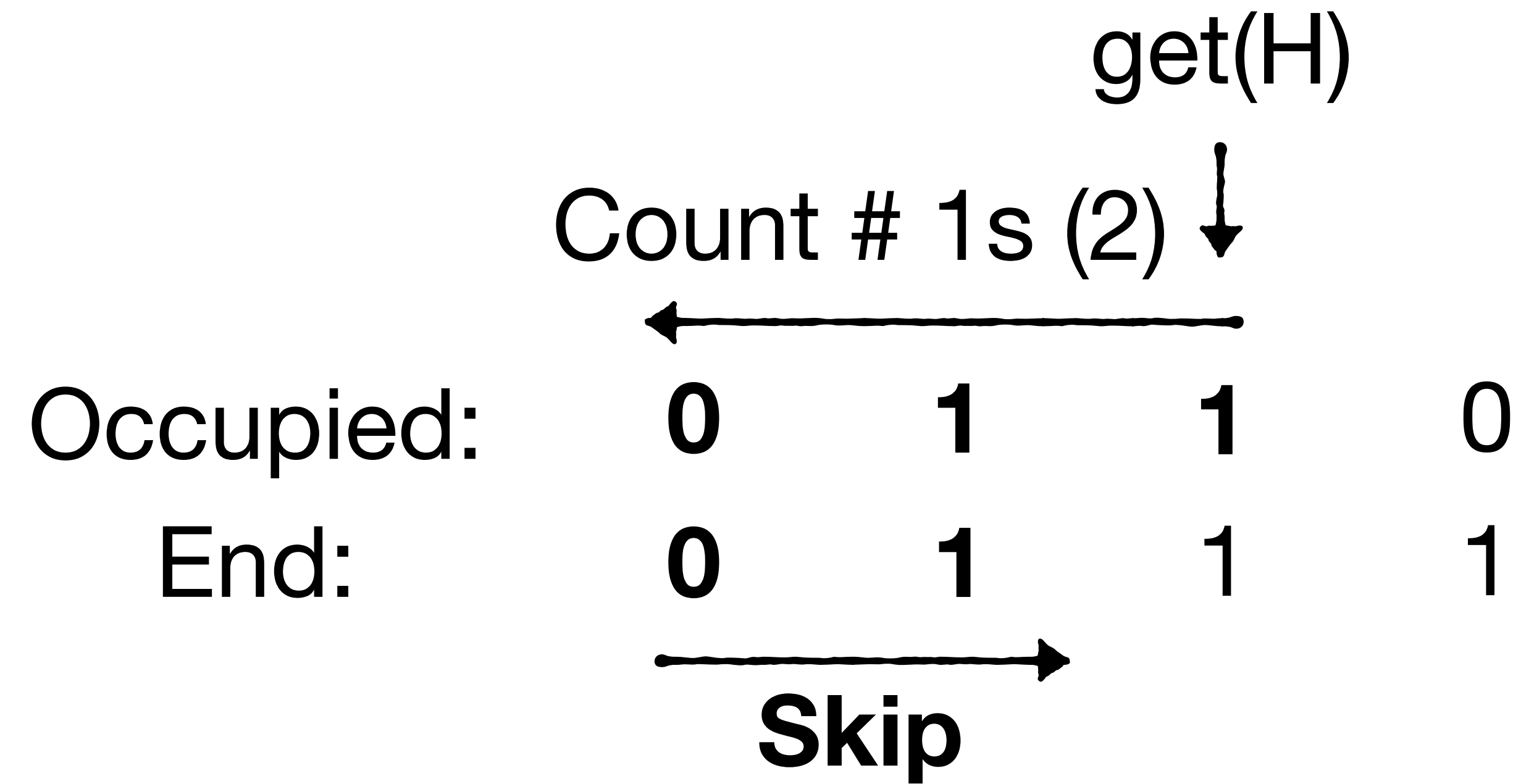


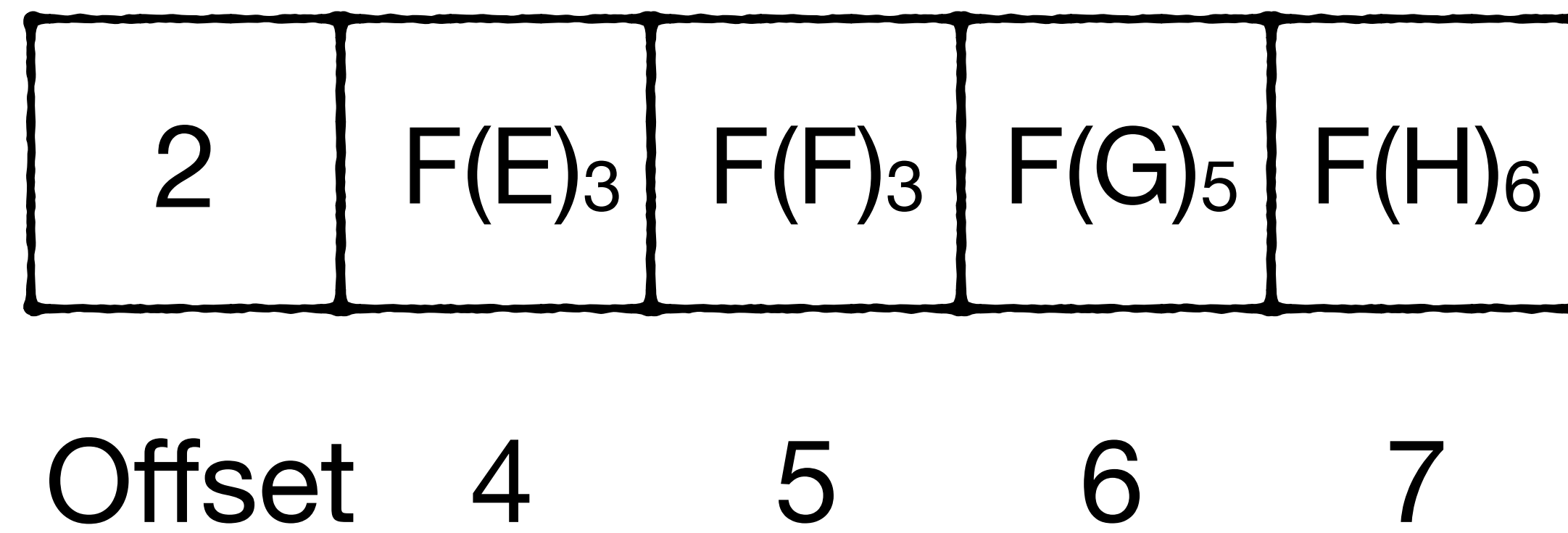
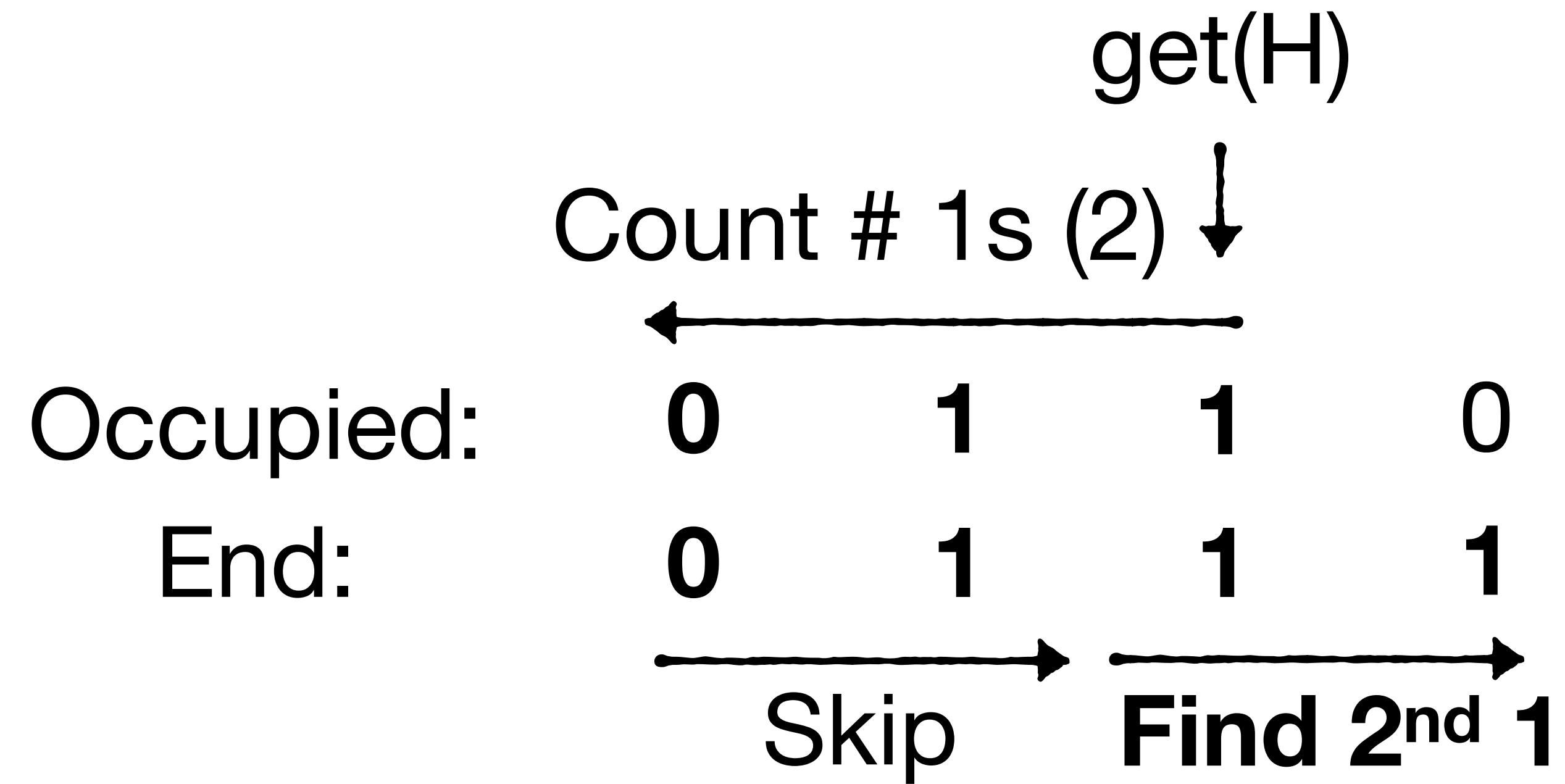
Offset	4	5	6	7
--------	---	---	---	---

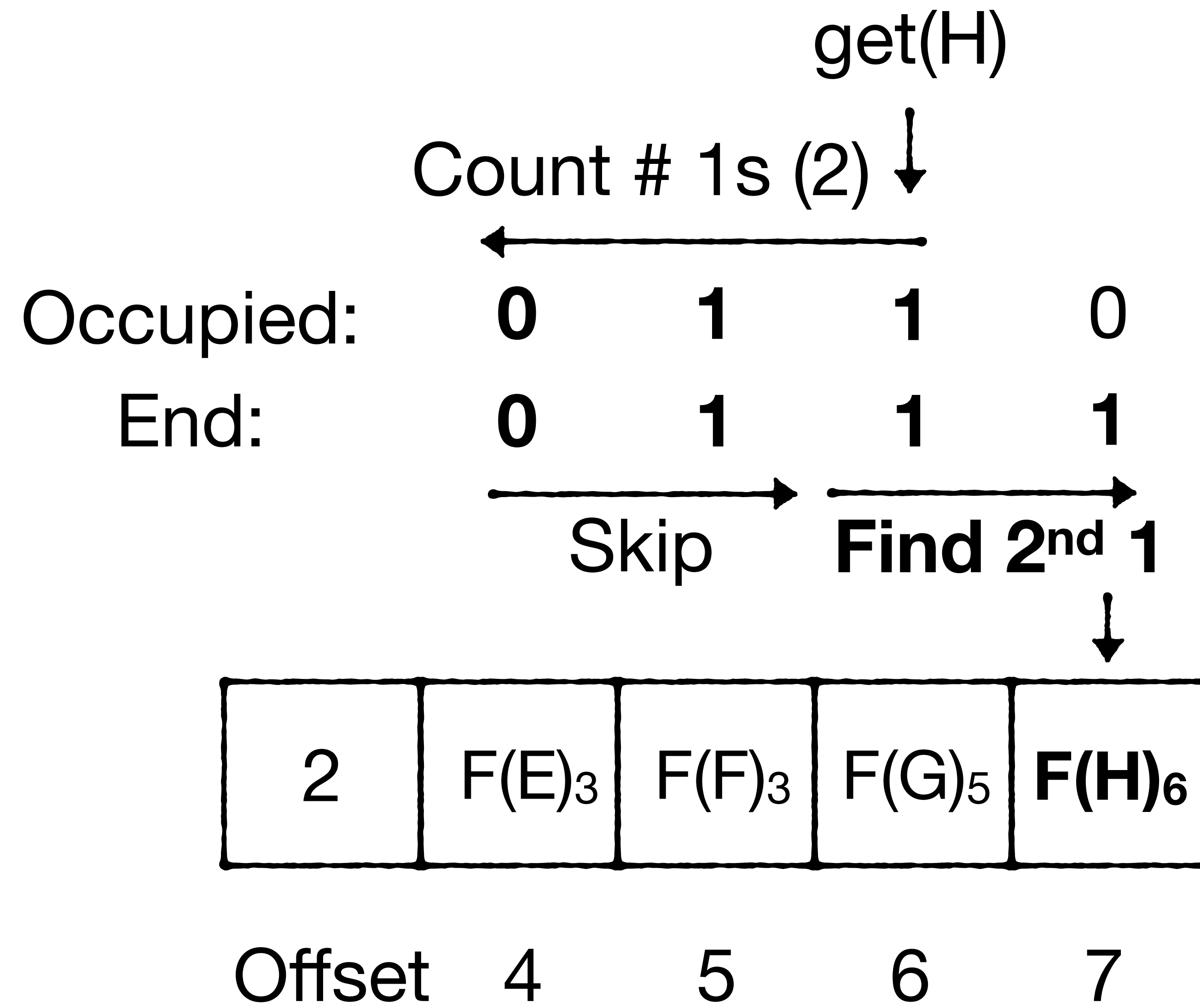
get(H)
↓
Count # 1s (2) ←
Occupied: 0 1 1 0
End: 0 1 1 1

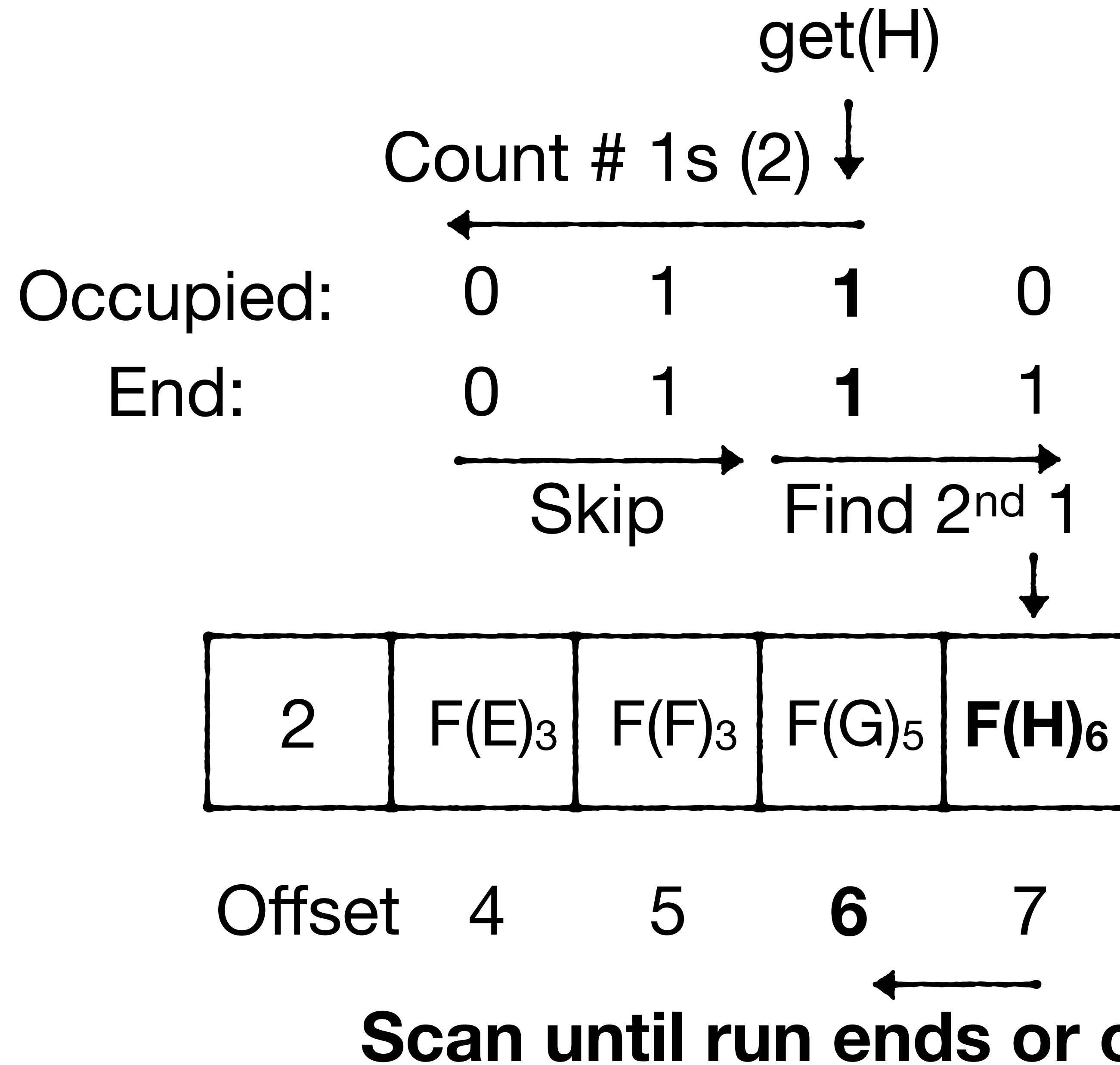


Offset 4 5 6 7



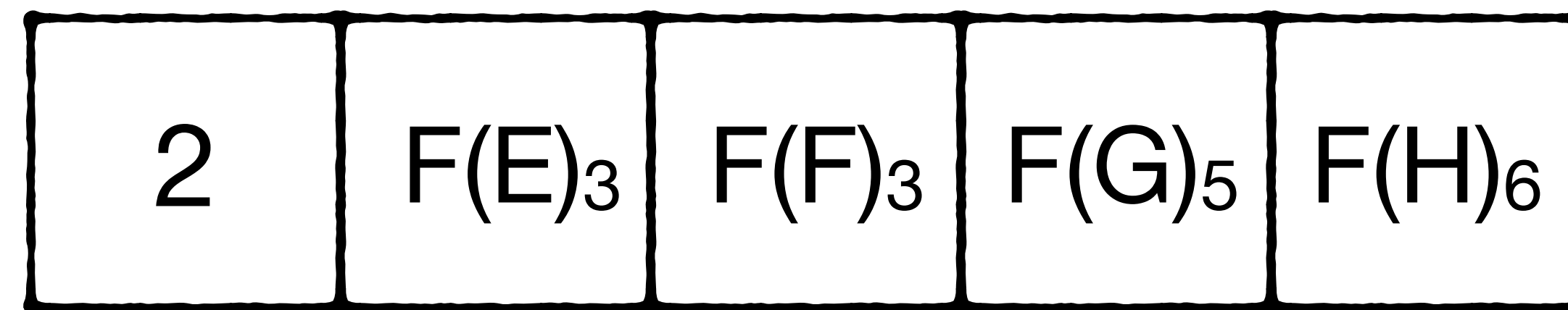






Target run may have been pushed to next chunk

Occupied:	0	1	1	0
End:	0	1	1	1



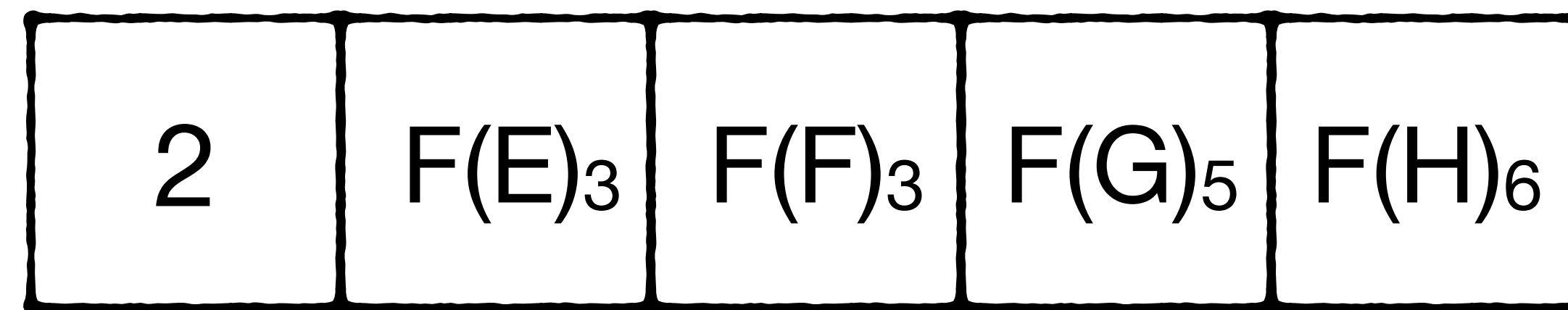
Offset	4	5	6	7
--------	---	---	---	---

Target run may have been pushed to next chunk

get(l)

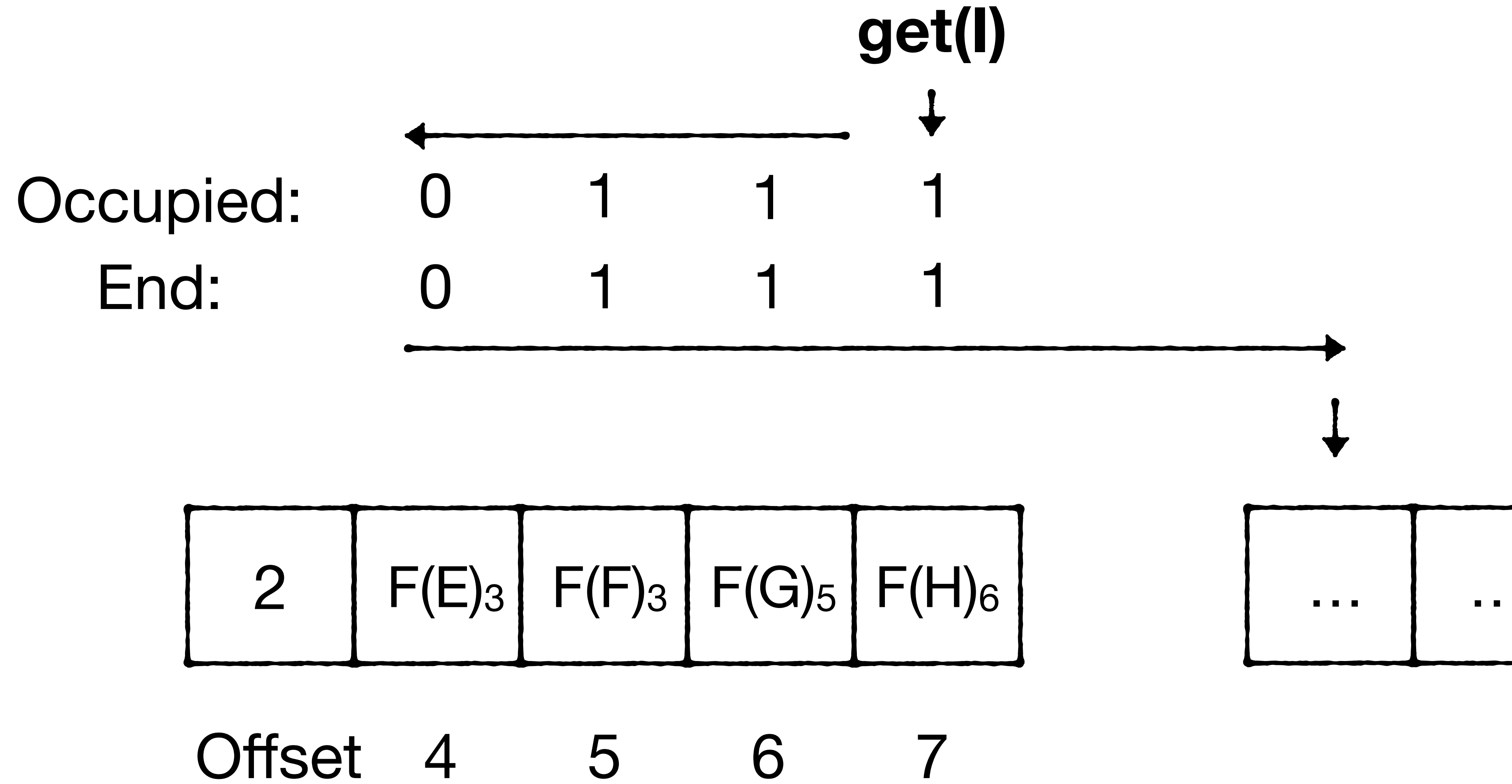


Occupied:	0	1	1	1
End:	0	1	1	1

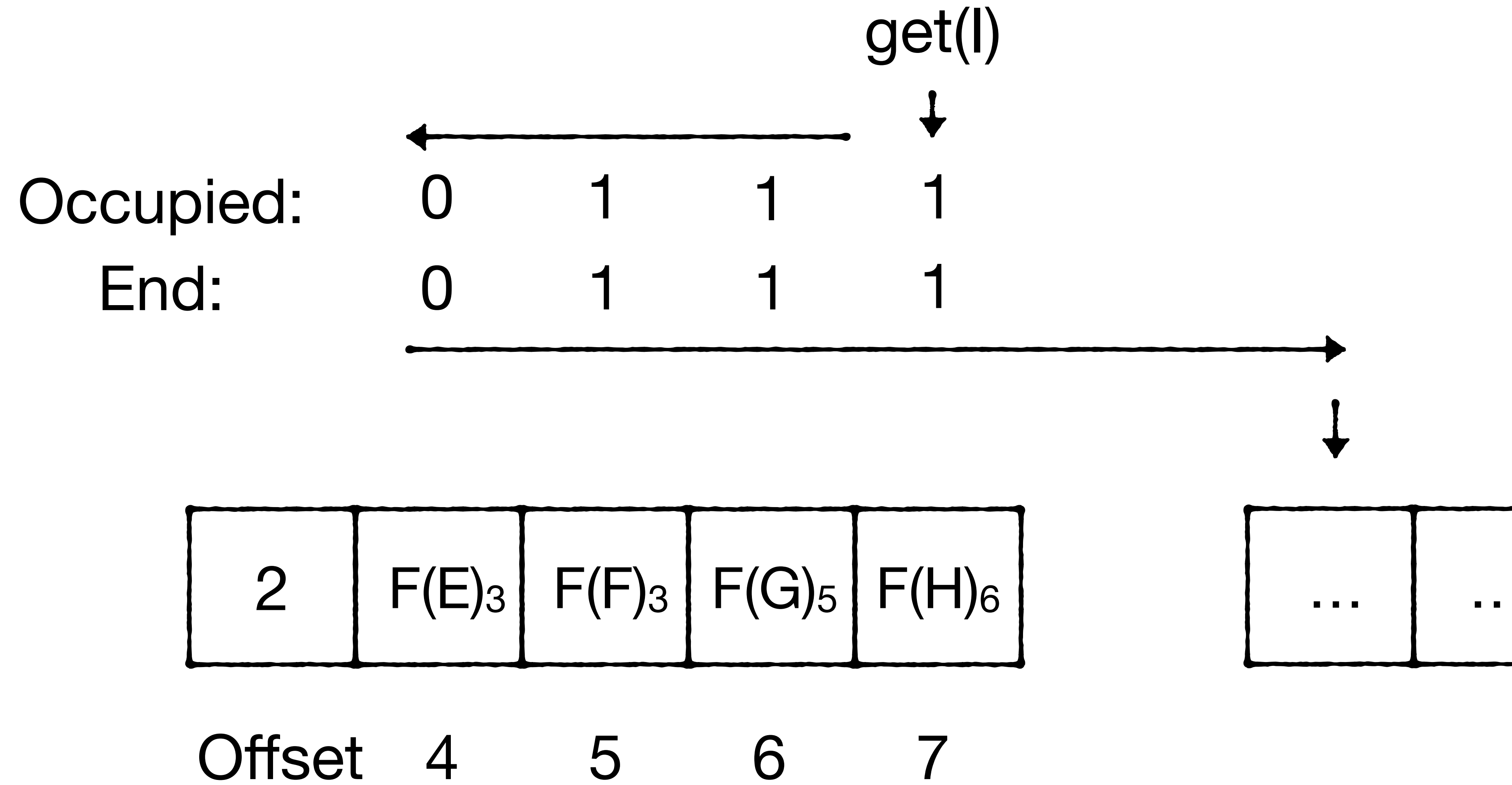


Offset	4	5	6	7
--------	---	---	---	---

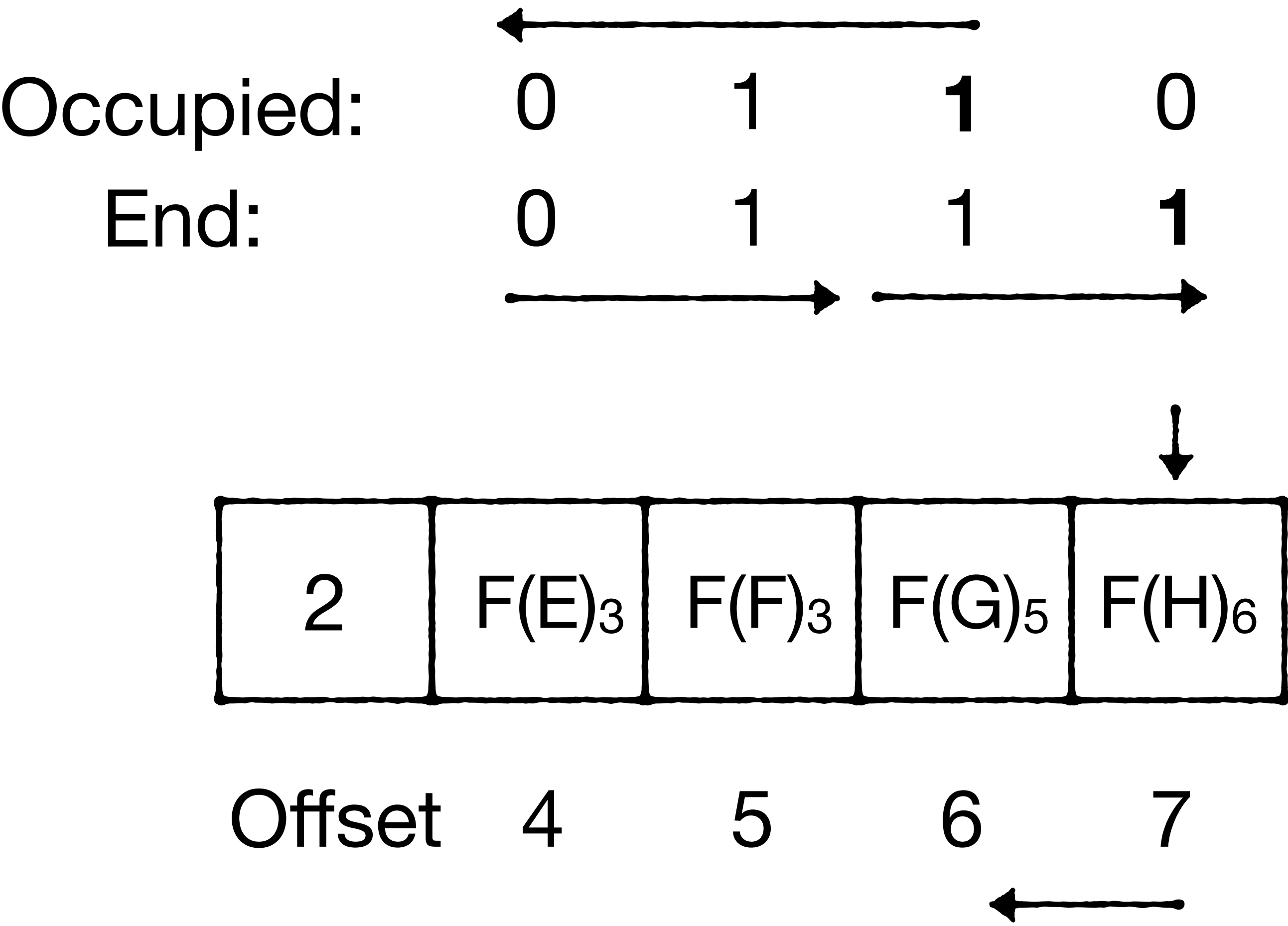
Target run may have been pushed to next chunk



Sequential cache misses, since chunks are adjacent (not too shabby)



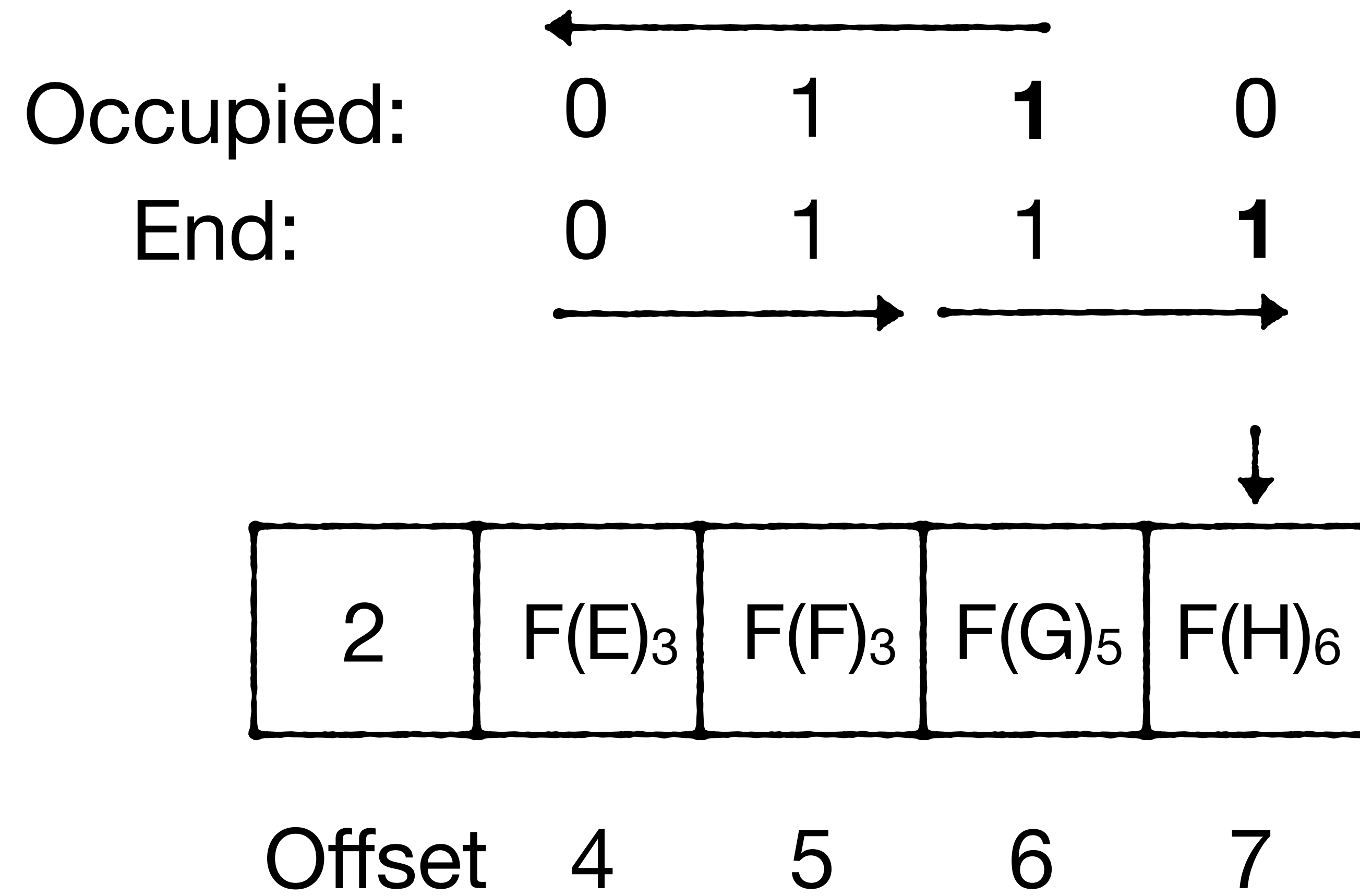
Queries in expected $O(C)$, where $C=64$ is chunk size



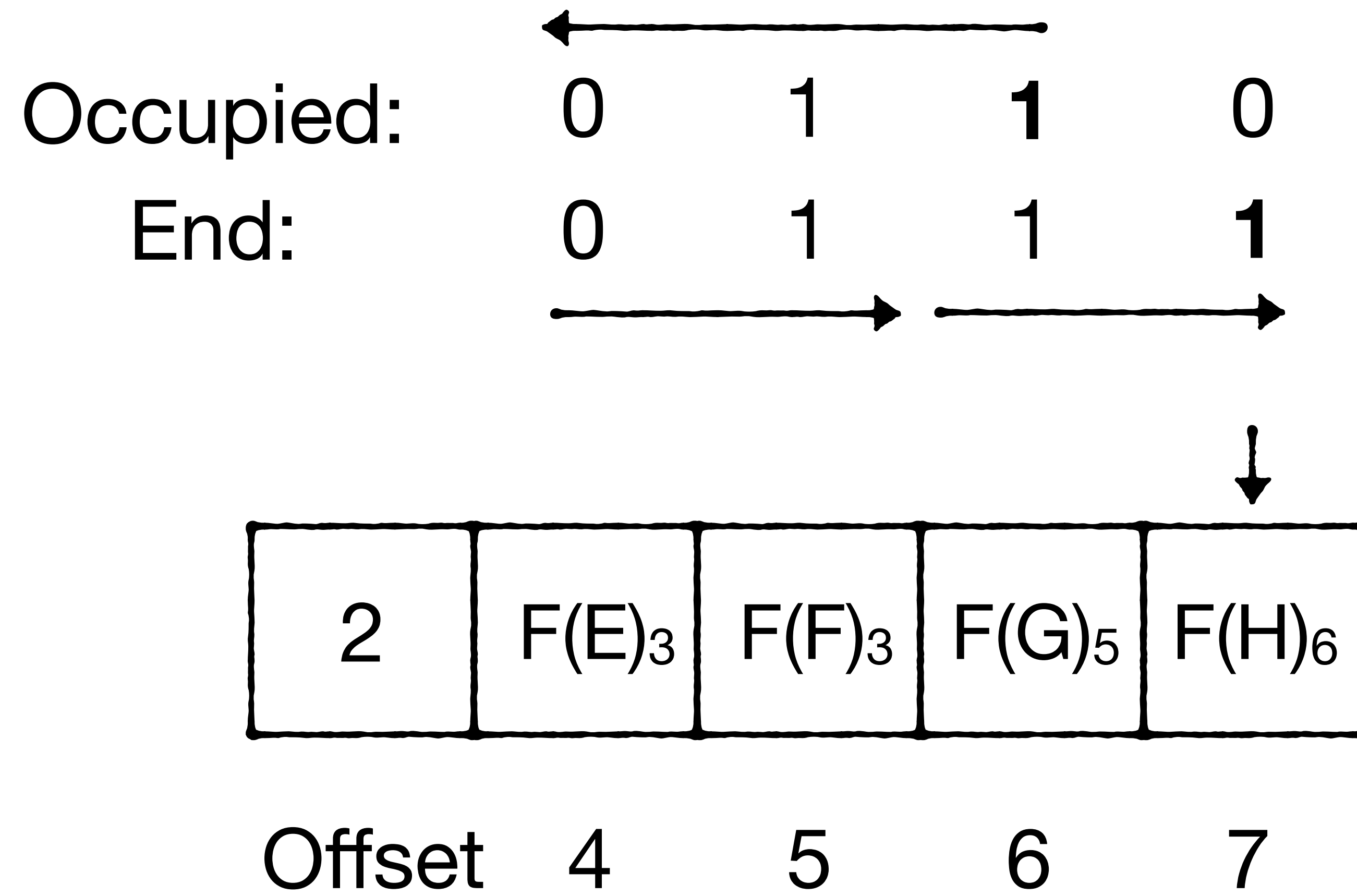
Queries in expected $O(C)$, where $C=64$ is chunk size



Can we do $O(1)$?



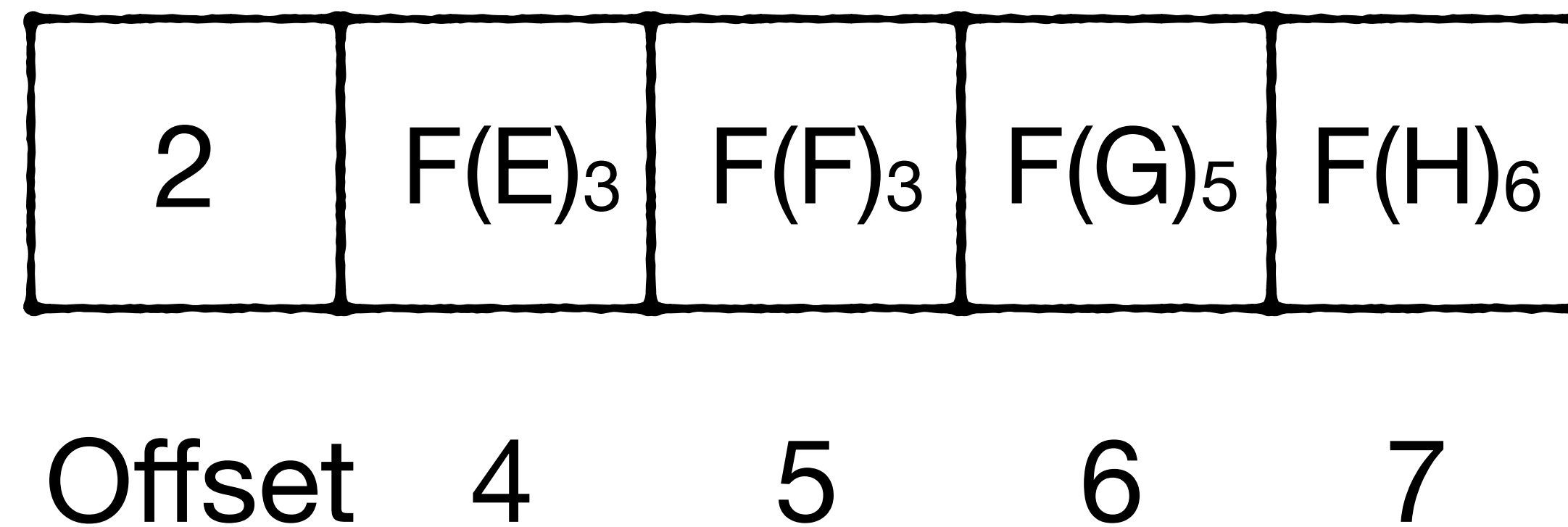
Rank & Select



Rank & Select

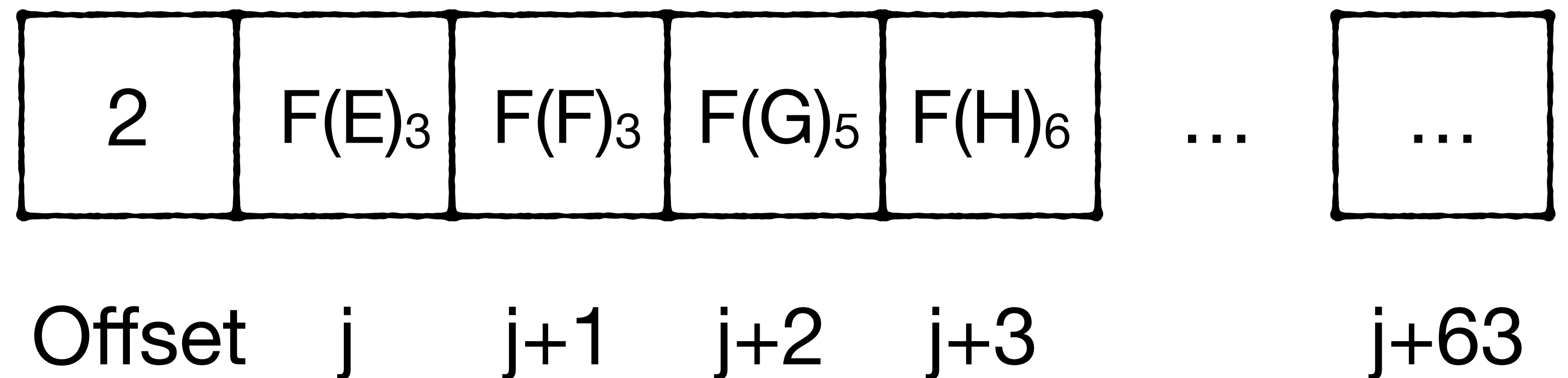
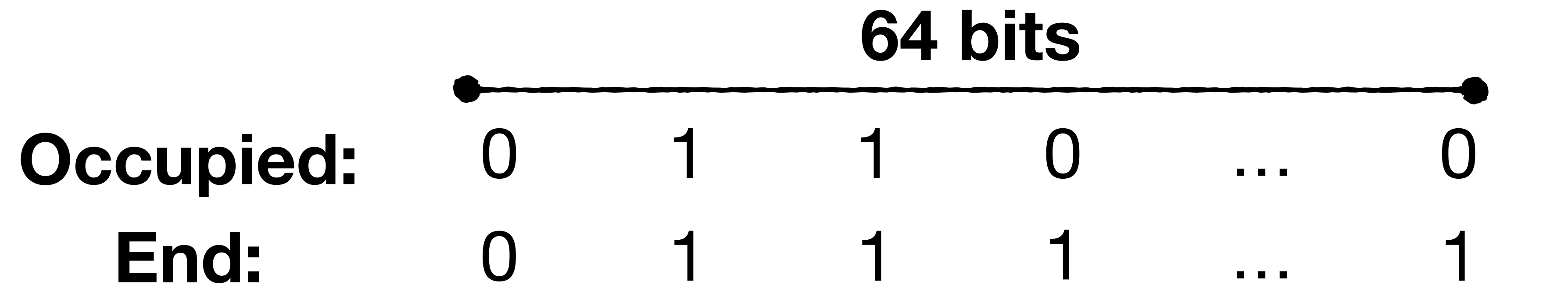
Can parse a 64-bit bitmap in constant time

Occupied:	0	1	1	0
End:	0	1	1	1



Rank & Select

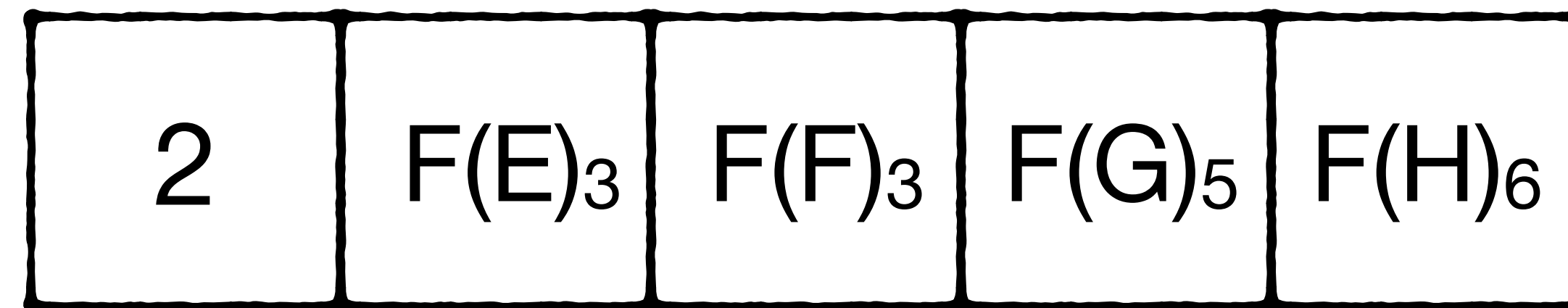
Can parse a 64-bit bitmap in constant time



Rank(i) counts # 1s before the i^{th} bit

Select (i)

Occupied:	0	1	1	0
End:	0	1	1	1

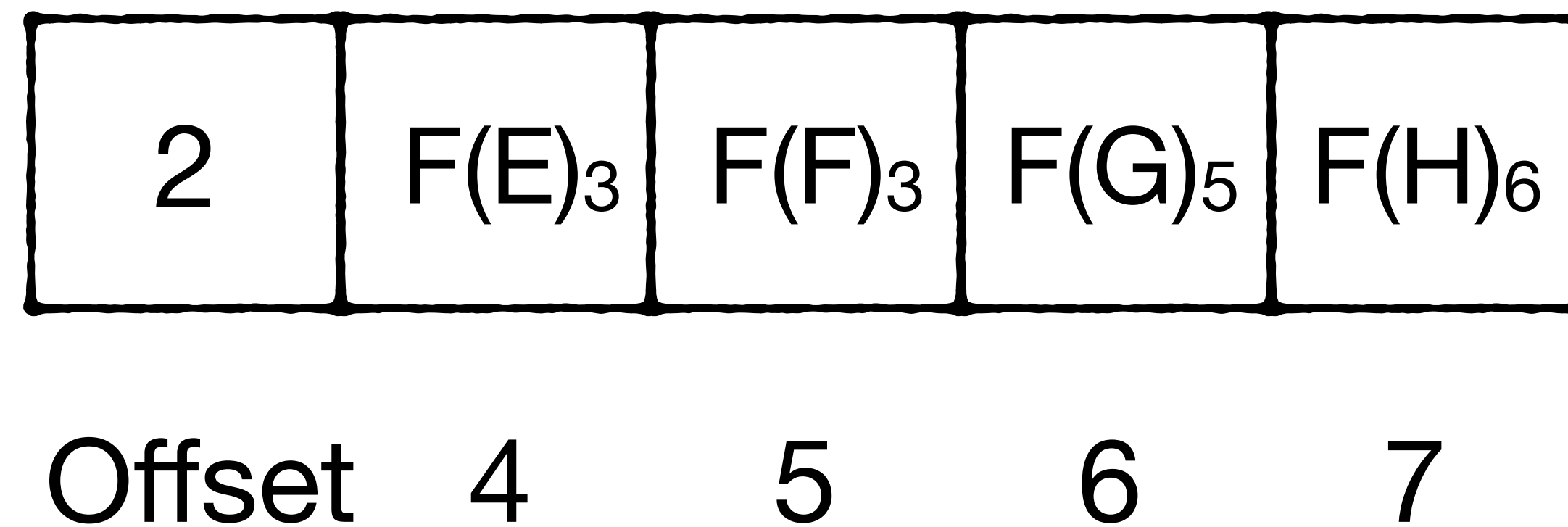


Offset	4	5	6	7
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Rank (i) counts # 1s before the i^{th} bit

Select(i) returns the offset of the i^{th} 1

Occupied:	0	1	1	0
End:	0	1	1	1



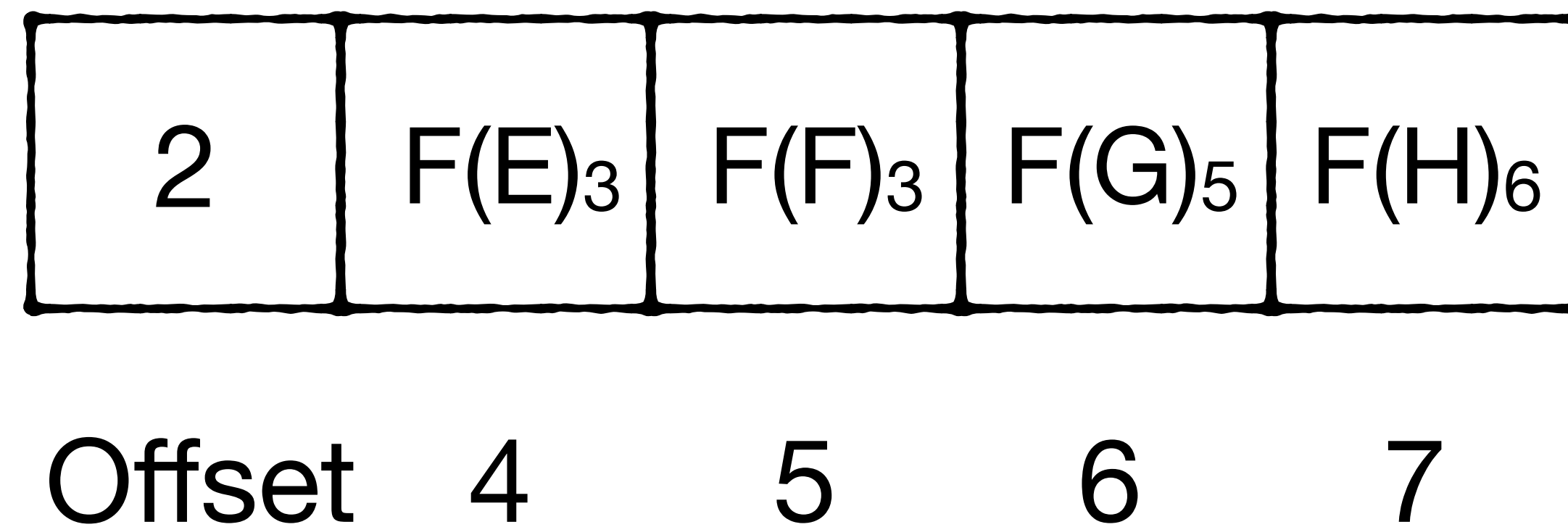
Rank (i) counts # 1s before the i^{th} bit

(1) How to use?

Select (i) returns the offset of the i^{th} 1

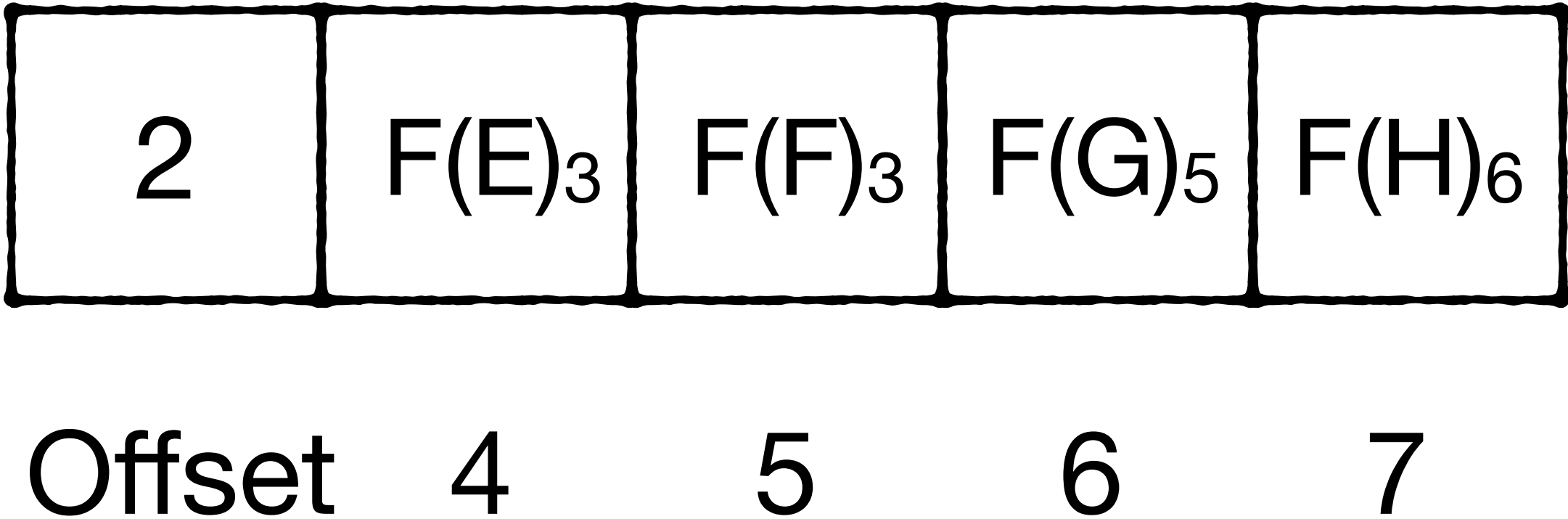
(2) How to implement?

Occupied:	0	1	1	0
End:	0	1	1	1




Back to example: get(H)

Occupied:	0	1	1	0
End:	0	1	1	1



(A) Count # of runs ends belonging to previous chunks

Occupied:	0	1	1	0
End:	0	1	1	1



$a = \text{Rank}(\text{Offset})$

2	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
---	-------------------	-------------------	-------------------	-------------------

Offset	4	5	6	7
--------	---	---	---	---

(A) Count # of runs ends belonging to previous chunks

Occupied:	0	1	1	0
End:	0	1	1	1



$$a = \text{Rank}(2) = 1$$

2	F(E)₃	F(F)₃	F(G) ₅	F(H) ₆
----------	-------------------------	-------------------------	-------------------	-------------------

Offset	4	5	6	7
--------	---	---	---	---

(B) Count # of run ends belonging to this chunk before target

Occupied:	0	1	1	0
End:	0	1	1	1



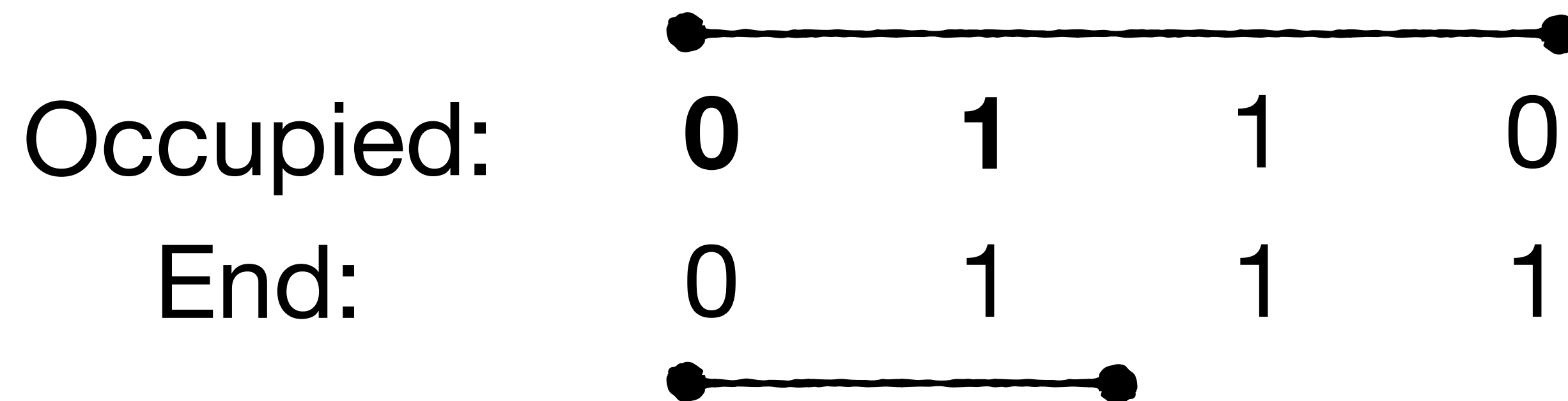
$a = \text{Rank}(2) = 1$

2	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
---	-------------------	-------------------	-------------------	-------------------

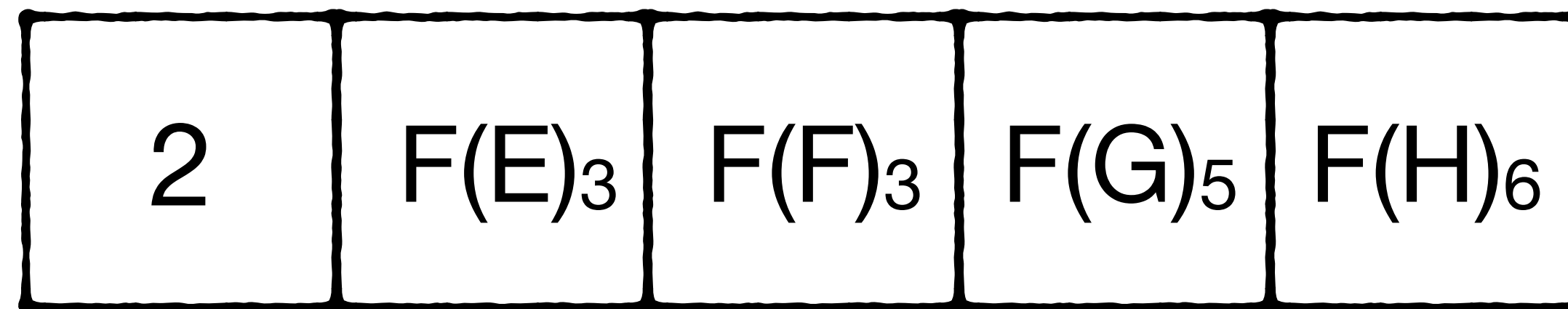
Offset 4 5 6 7

(B) Count # of run ends belonging to this chunk before target

$$b = \text{Rank}(\text{targetSlot} - \text{firstChunkSlot})$$

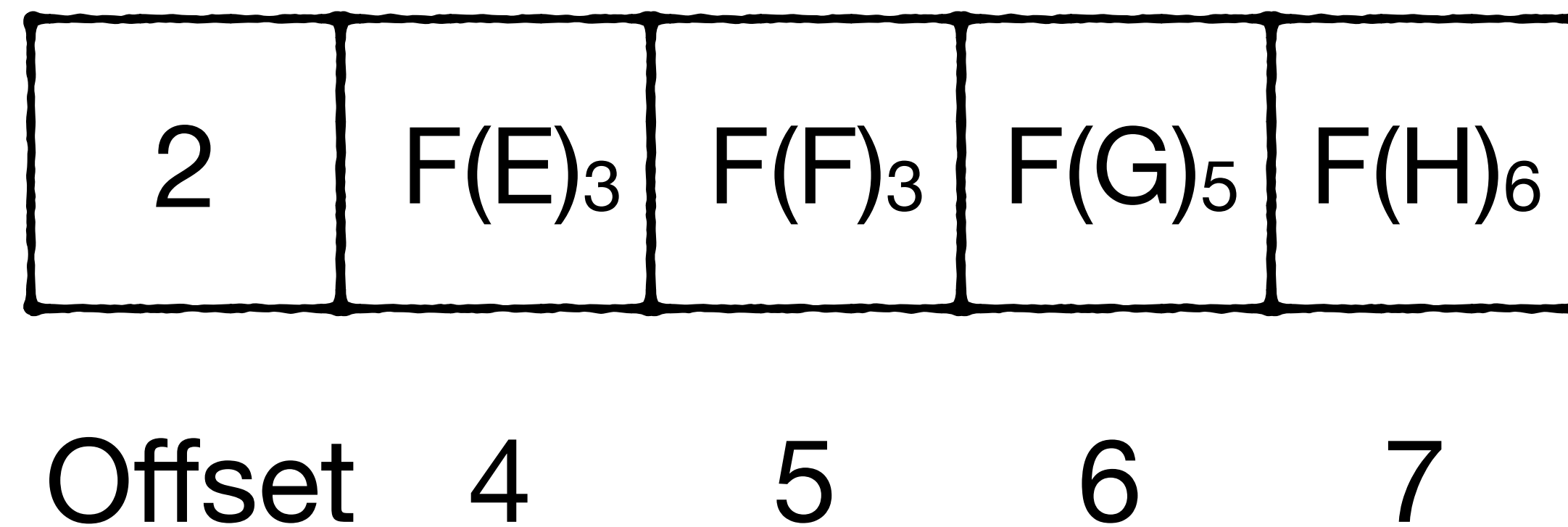
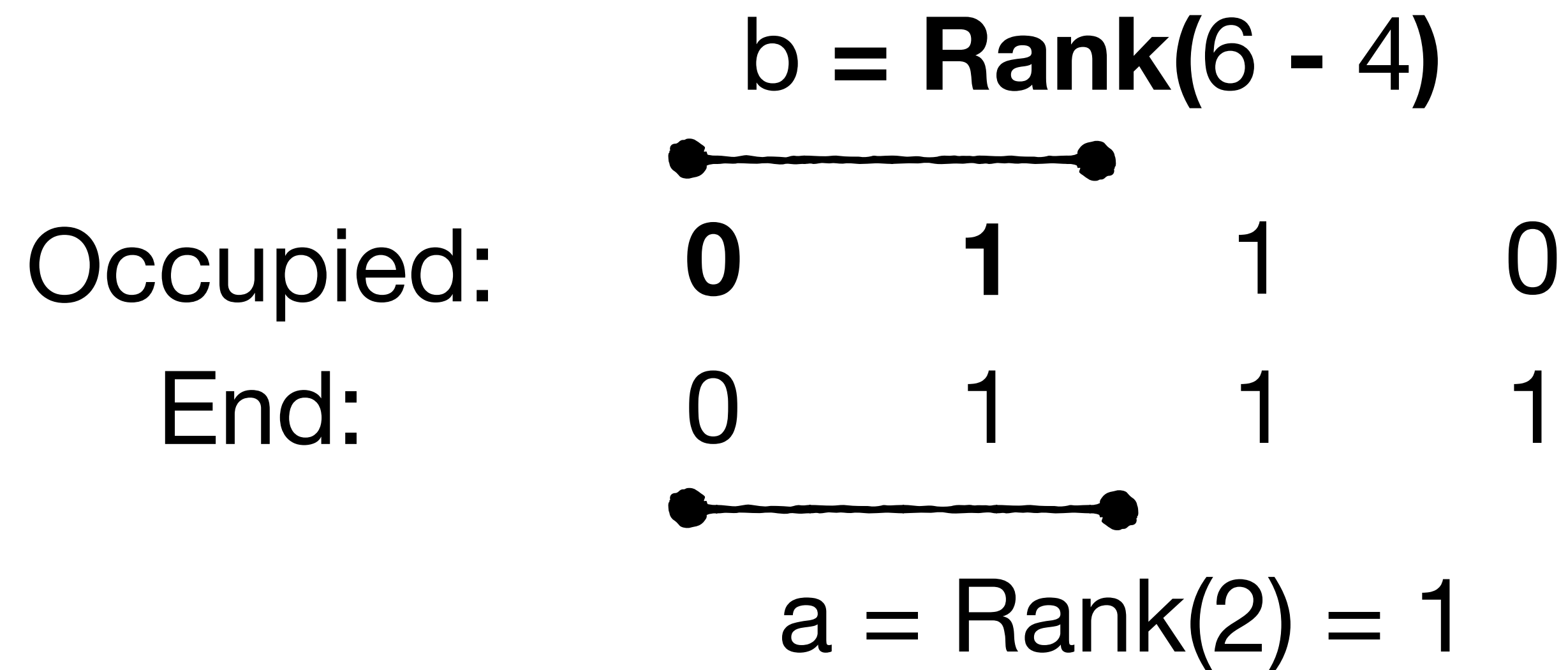


$$a = \text{Rank}(2) = 1$$

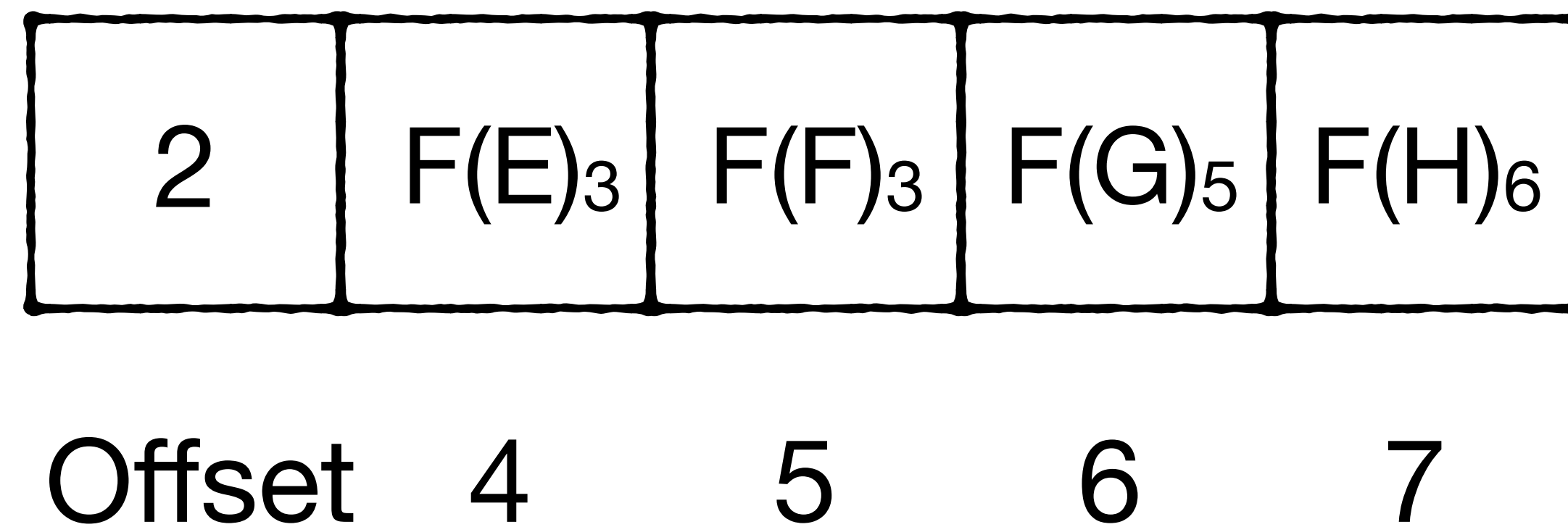
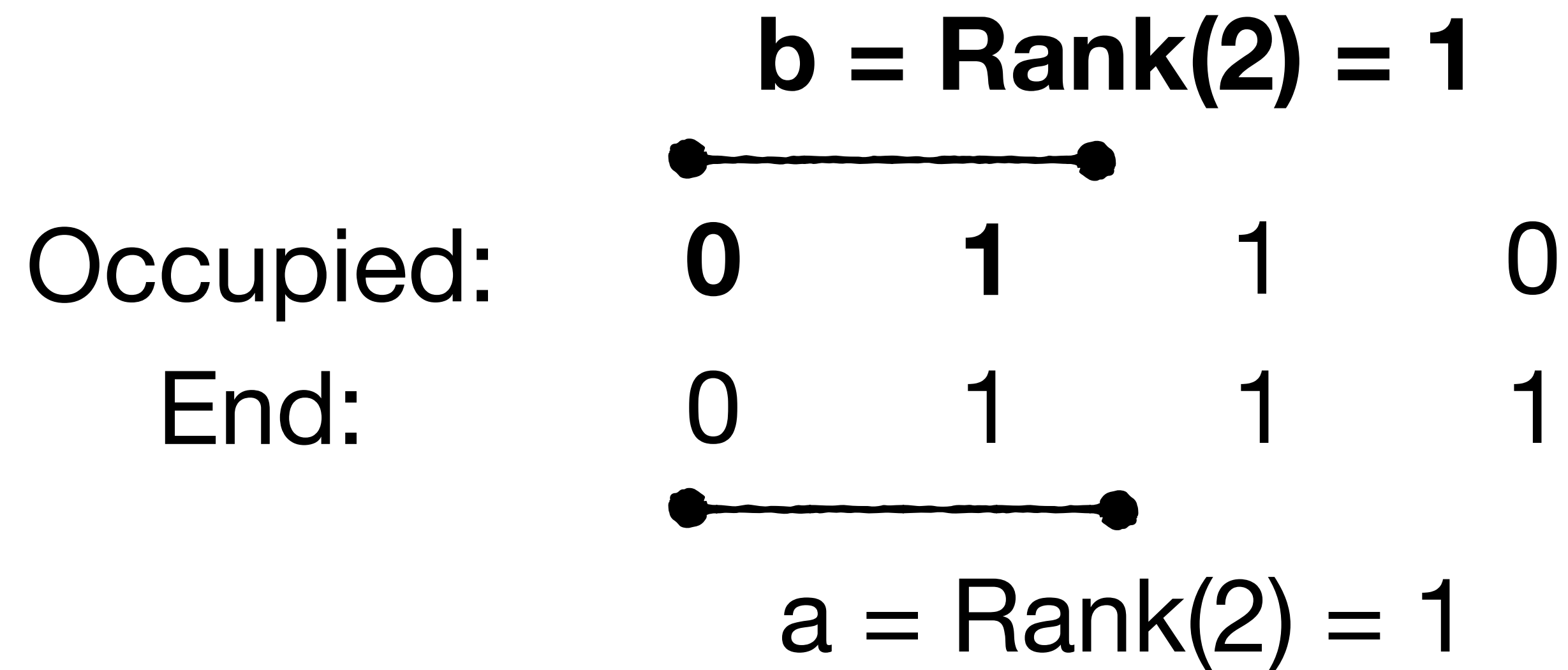


Offset 4 5 6 7

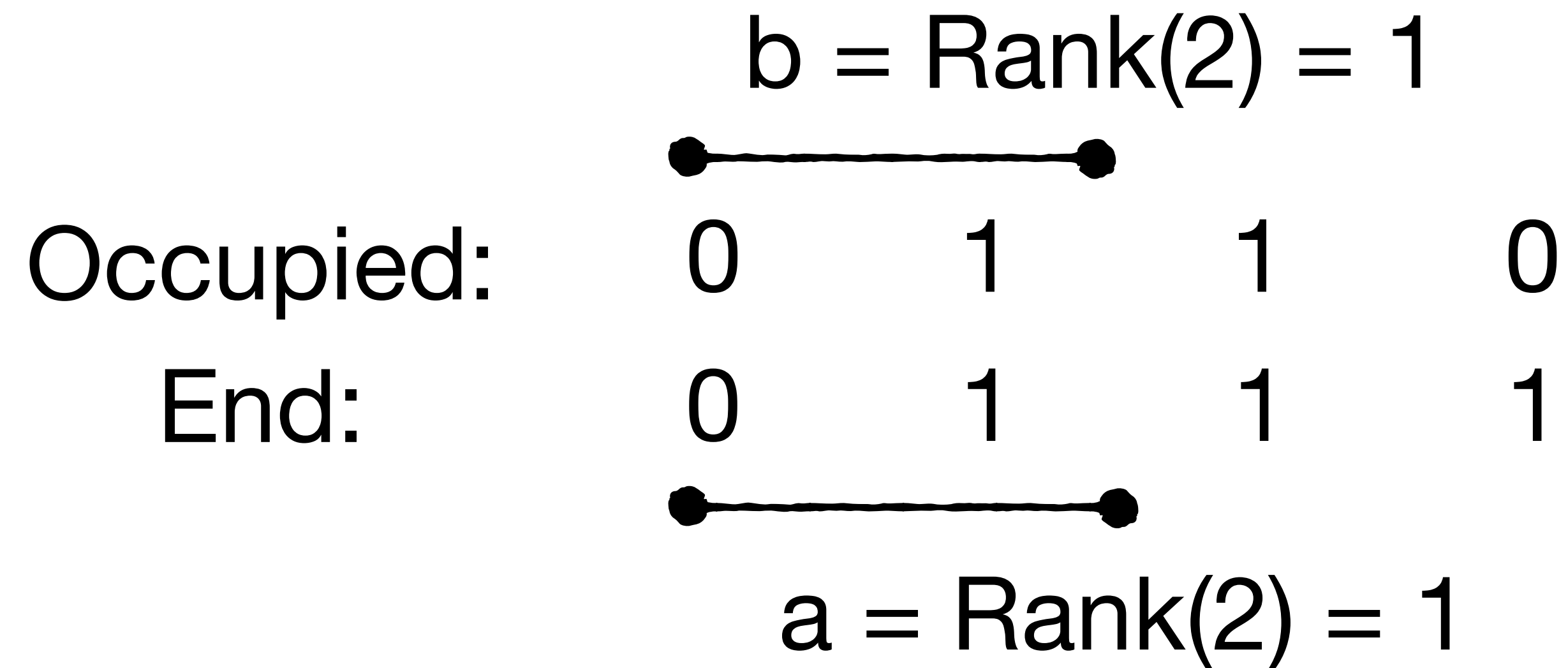
(B) Count # of run ends belonging to this chunk before target



(B) Count # of run ends belonging to this chunk before target




(C) skip to the $(a+b)^{\text{th}}$ run end



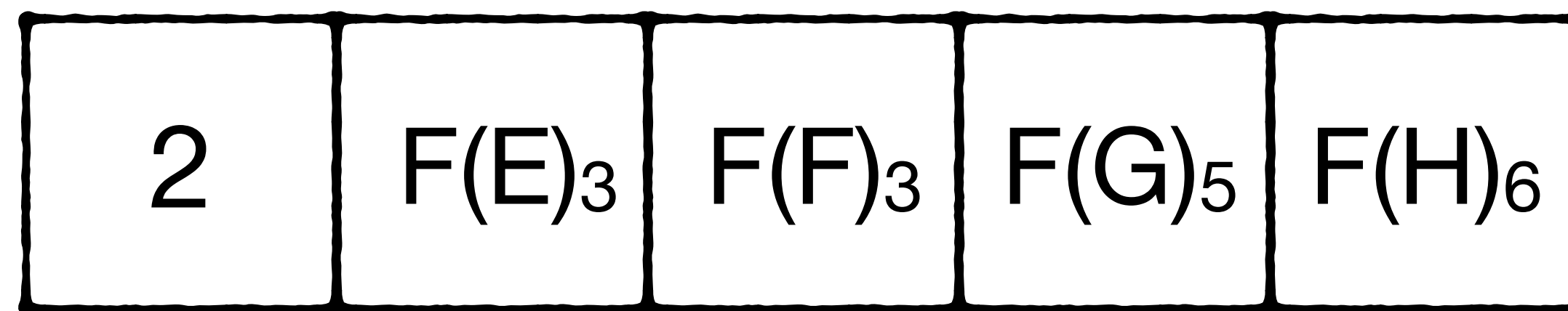
2	F(E) ₃	F(F) ₃	F(G) ₅	F(H) ₆
Offset	4	5	6	7

(C) skip to the $(a+b)^{\text{th}}$ run end

Occupied:	0	1	1	0
End:	0	1	1	1

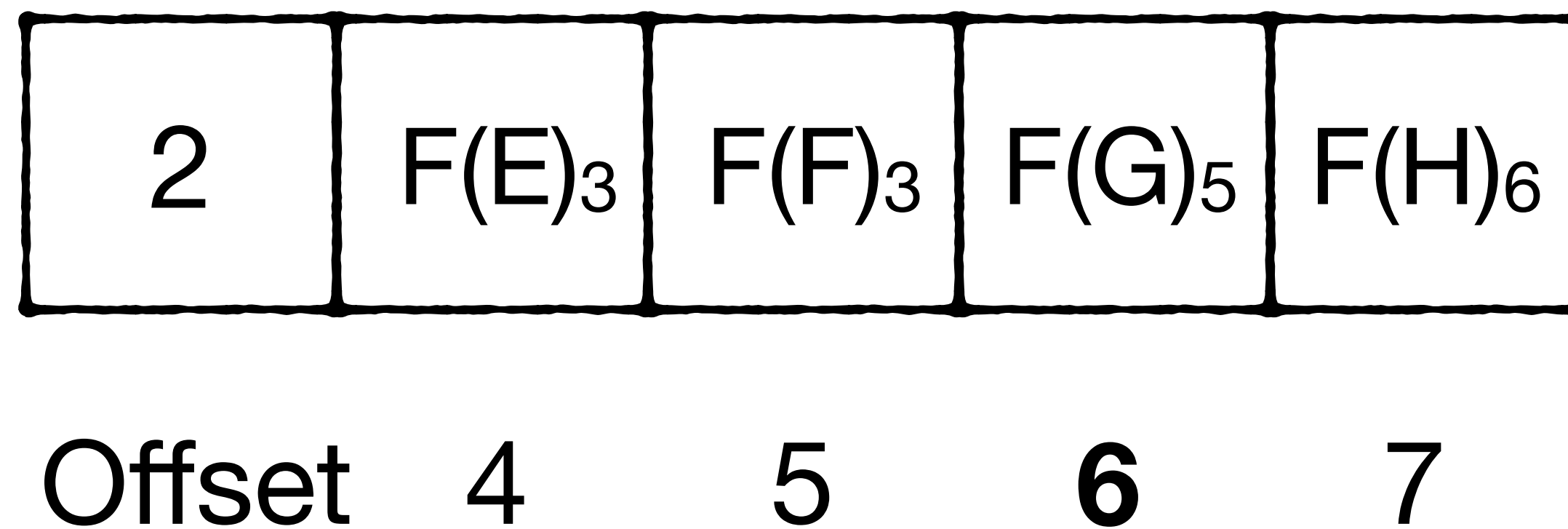


Select(a + b)




Offset	4	5	6	7
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(C) skip to the $(a+b)^{\text{th}}$ run end



(C) skip to the $(a+b)^{\text{th}}$ run end

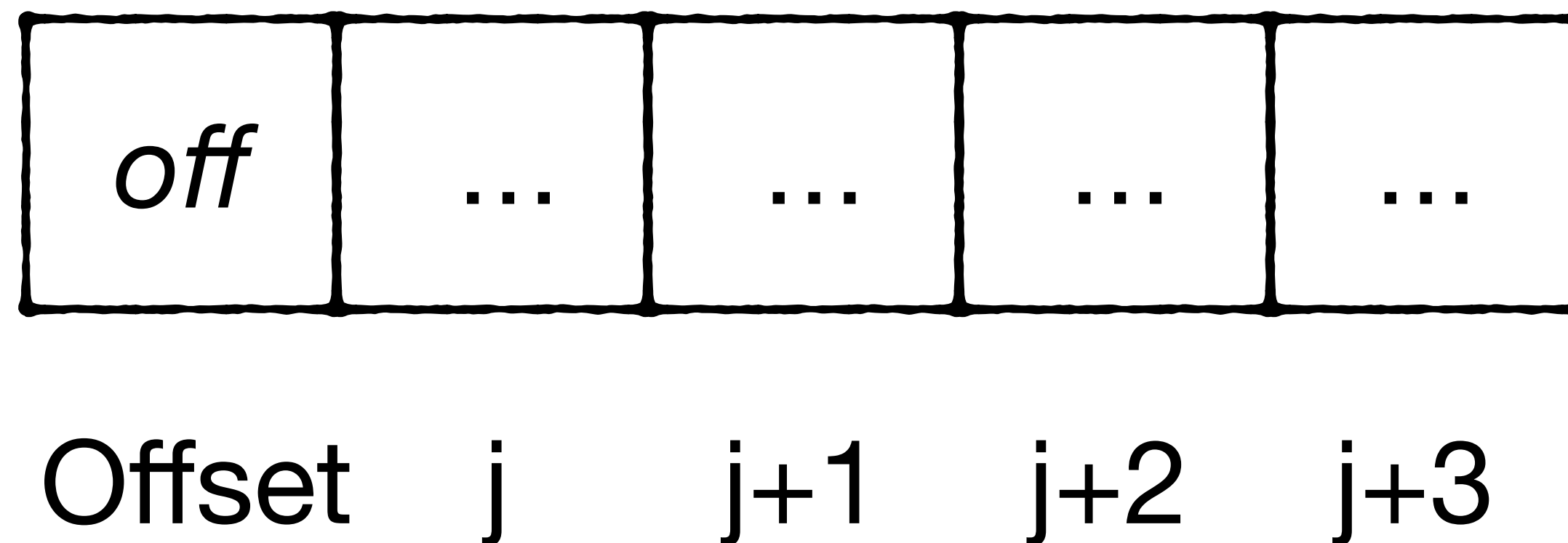
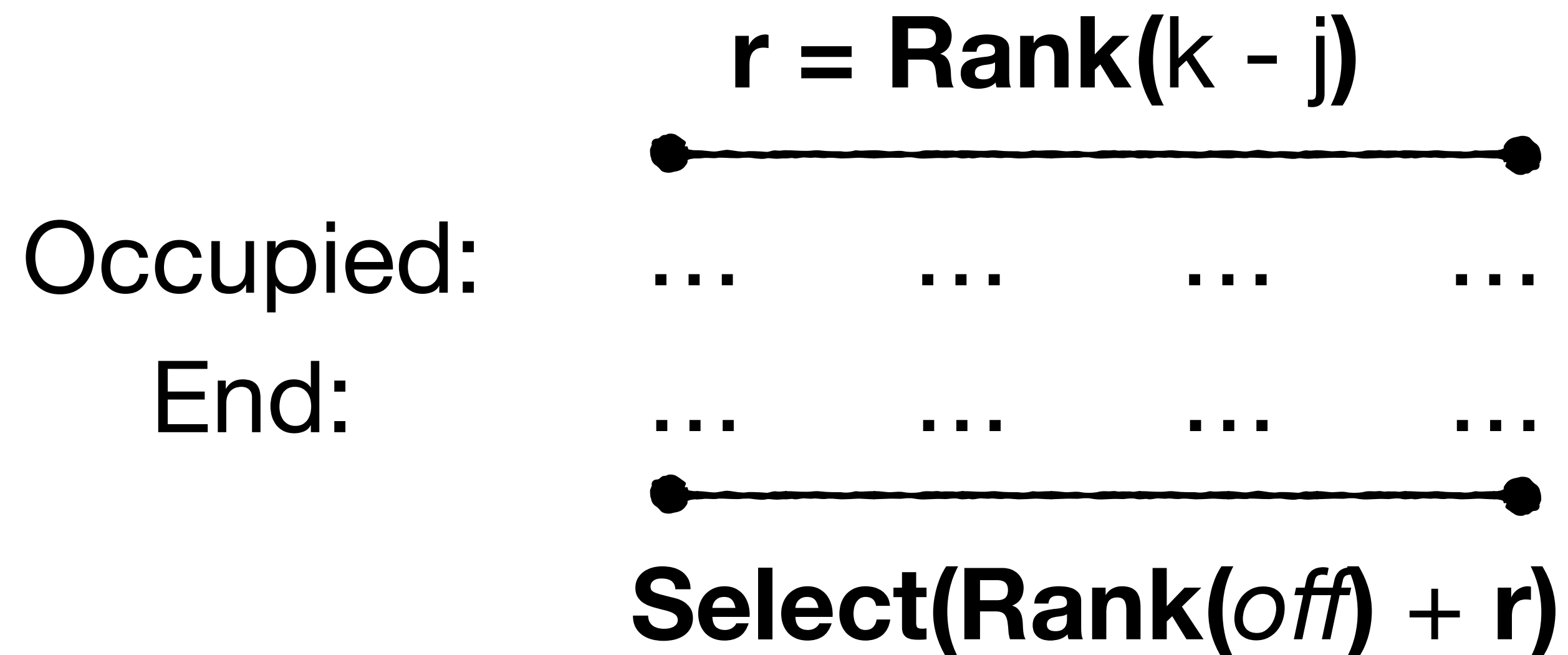
Occupied:	0	1	1	0
End:	0	1	1	1



2	F(E) ₃	F(F) ₃	F(G) ₅	F(H)₆
---	-------------------	-------------------	-------------------	-------------------------

Offset	4	5	6	7
--------	---	---	---	---

General algorithm to bring us to end of slot k's run



Implementing Rank and Select Efficiently

Implementing Rank and Select Efficiently



No looping

Implementing Rank Efficiently

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$

Implementing Rank Efficiently

$$\text{rank}(i) = \text{popcount}(\mathbf{B} \& (2^i - 1))$$



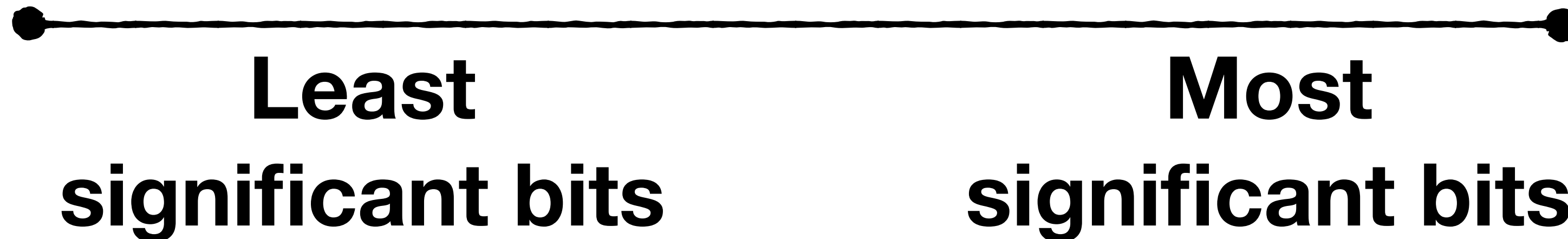
Bitmap (64 bits long)

Implementing Rank Efficiently

$$\text{rank}(i) = \text{popcount}(\mathbf{B} \ \& \ (2^i - 1))$$



Bitmap (64 bits long)



Implementing Rank Efficiently

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$



Total # of 1s

Implementing Rank Efficiently

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$



Mask out irrelevant more significant bits

$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$

e.g.,

$B = 0 \ 1 \ 1 \ 0 \ 1 \ 0 \ 1 \ 1$

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$

e.g.,

B = 0 1 1 0 1 0 1 1



rank(6) = 3

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$

e.g.,

$$B = 0 \ 1 \ 1 \ 0 \ 1 \ 0 \ 1 \ 1$$

$$\text{rank}(6) = 3$$

mask: $2^6 - 1 = 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 0 \ 0$

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$

e.g.,

B = 0 1 1 0 1 0 1 1

&

1 1 1 1 1 1 0 0

=

0 1 1 0 1 0 0 0

rank(6) = 3

$$\text{rank}(i) = \text{popcount}(B \ \& \ (2^i - 1))$$

e.g.,

$$B = 0 \ 1 \ 1 \ 0 \ 1 \ 0 \ 1 \ 1$$

$$\text{rank}(6) = 3$$

$$\text{popcount}(0 \ 1 \ 1 \ 0 \ 1 \ 0 \ 0 \ 0) = 3$$

Implementing Select Efficiently

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, \mathbf{B}))$



Bitmap (64 bits long)

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, \mathbf{B}))$



Count trailing zeros

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, \mathbf{B}))$



Count trailing zeros

$\text{tzcnt}(\underline{000}11101) = 3$

Implementing Select Efficiently

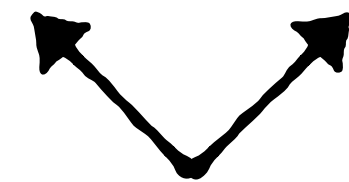
$$\text{select}(i) = \text{tzcnt}(\mathbf{pdep}(2^i, B))$$



Scatter bits in first operand at 1s in second operand

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$



Available on x86

<https://www.felixcloutier.com/x86/>

Implementing Select Efficiently

$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$

e.g.,

$B = 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1$

Implementing Select Efficiently

$$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$$

e.g.,

B = 0 1 1 0 1 0 1 1



Select(2) = 4

Implementing Select Efficiently

$$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$$

e.g.,

$$B = 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1$$

$$\text{Select}(2) = 4$$

$$2^2 = 0\ 0\ 1\ 0\ 0\ 0\ 0\ 0$$

Implementing Select Efficiently

$$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$$

e.g.,

$B = 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1$

$\text{Select}(2) = 4$

$\text{pdep}(\begin{array}{ccccccc} & & \nearrow & \nearrow & & \nearrow & \nearrow & \nearrow \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{array} , B) = 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0$

Scatter bits in first operand at 1s in second operand

Implementing Select Efficiently

$$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$$

e.g., $B = 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1$ $\text{Select}(2) = 4$

$\text{pdep}(00100000, B) = 00001000$



**Only the 1 at relevant
position is now set**

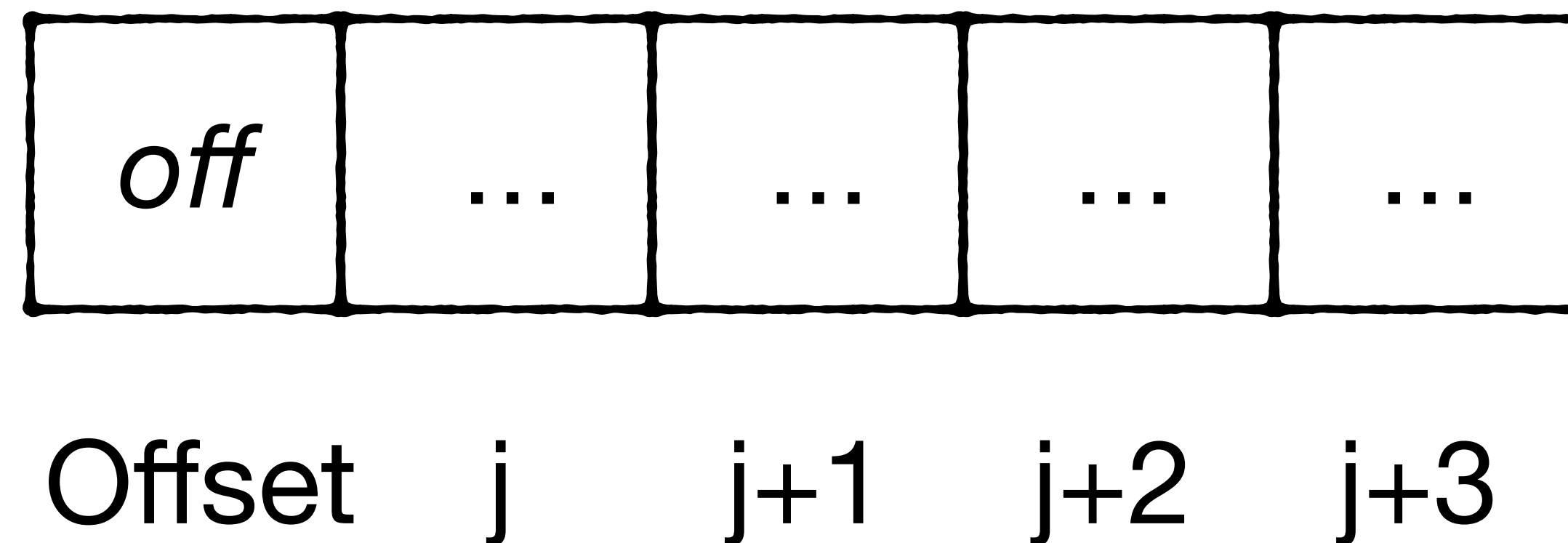
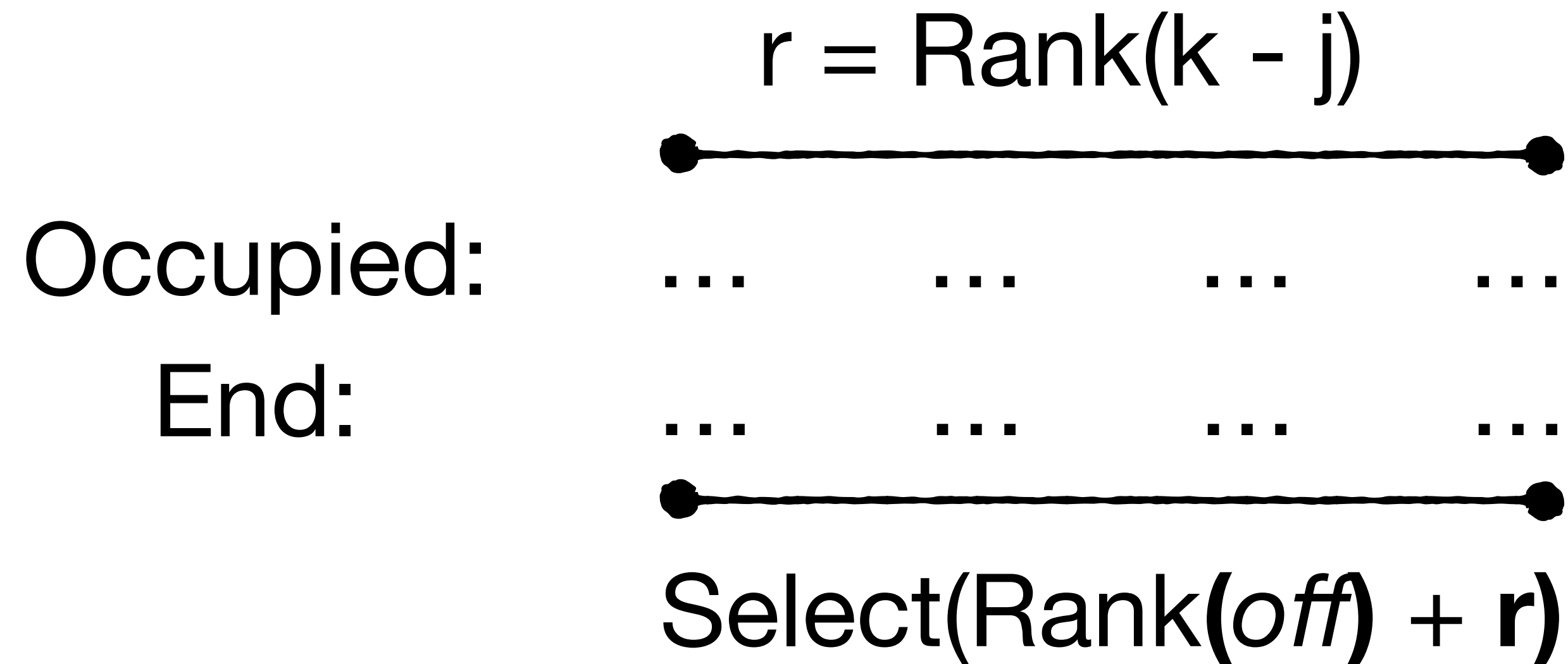
Implementing Select Efficiently

$$\text{select}(i) = \text{tzcnt}(\text{pdep}(2^i, B))$$

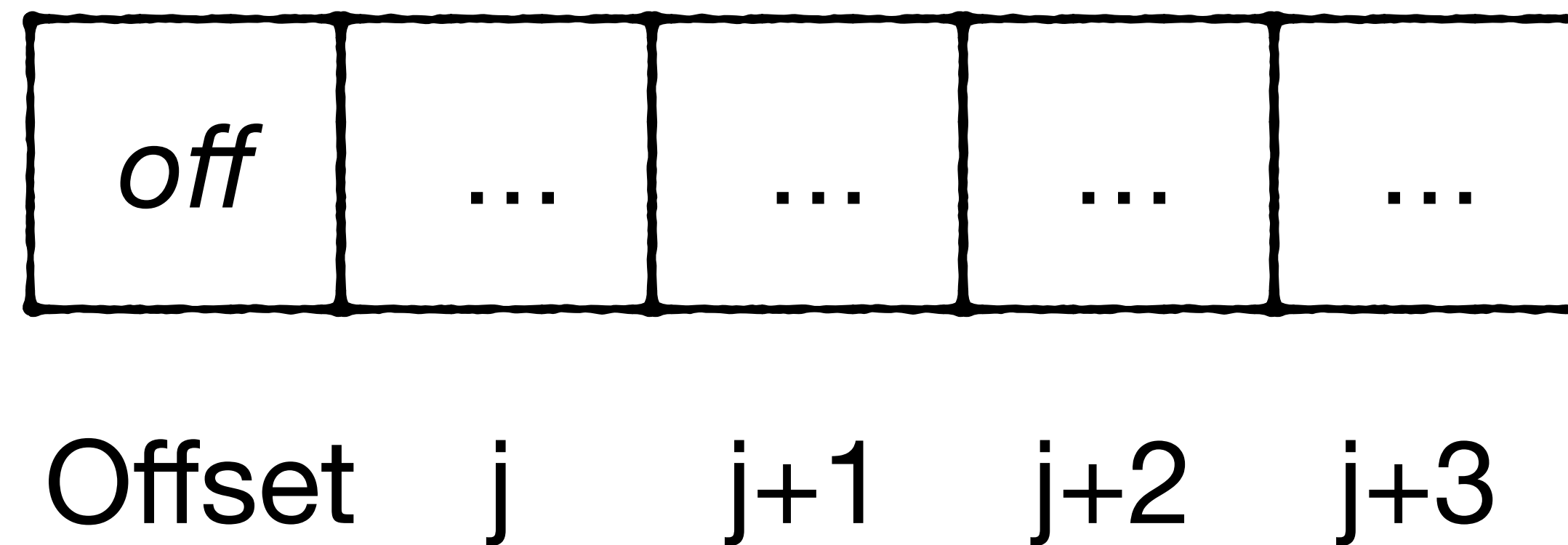
e.g., $B = 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1$ $\text{Select}(2) = 4$

$$\text{tzcnt}(0\ 0\ 0\ 0\ 1\ 0\ 0\ 0) = 4$$

queries in $O(1)$ due to fast rank and select

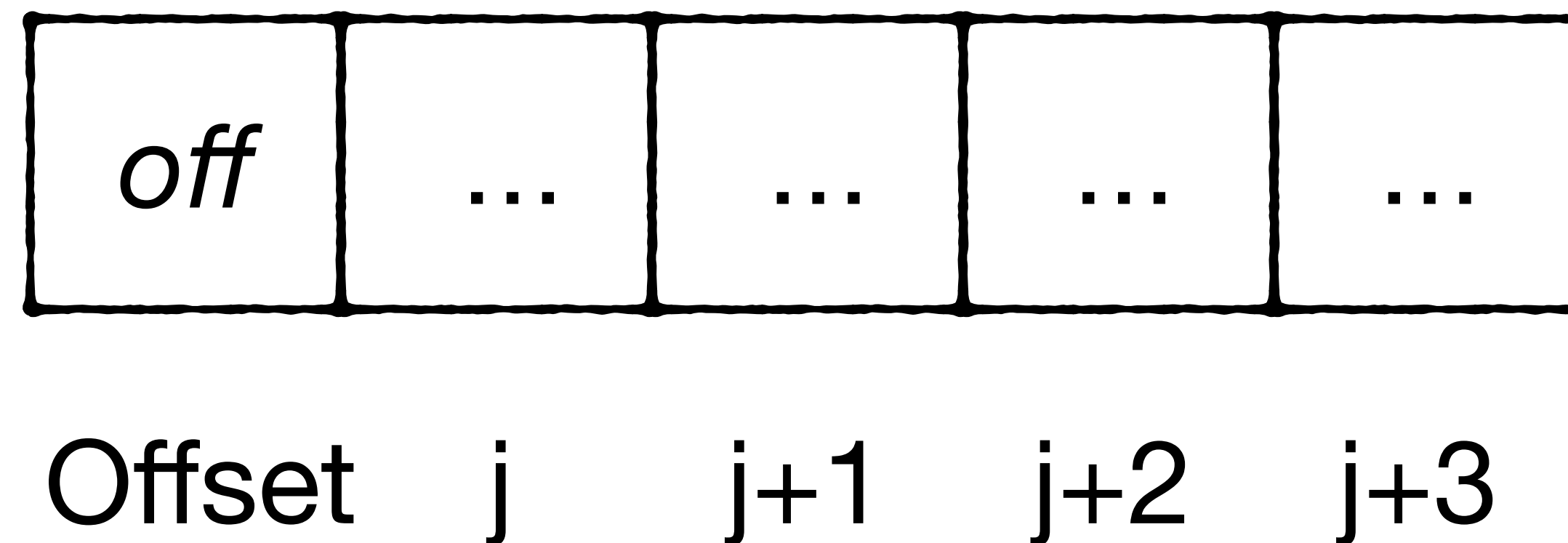


Insertions?



Insertions

Find target run, push colliding entries to right, insert



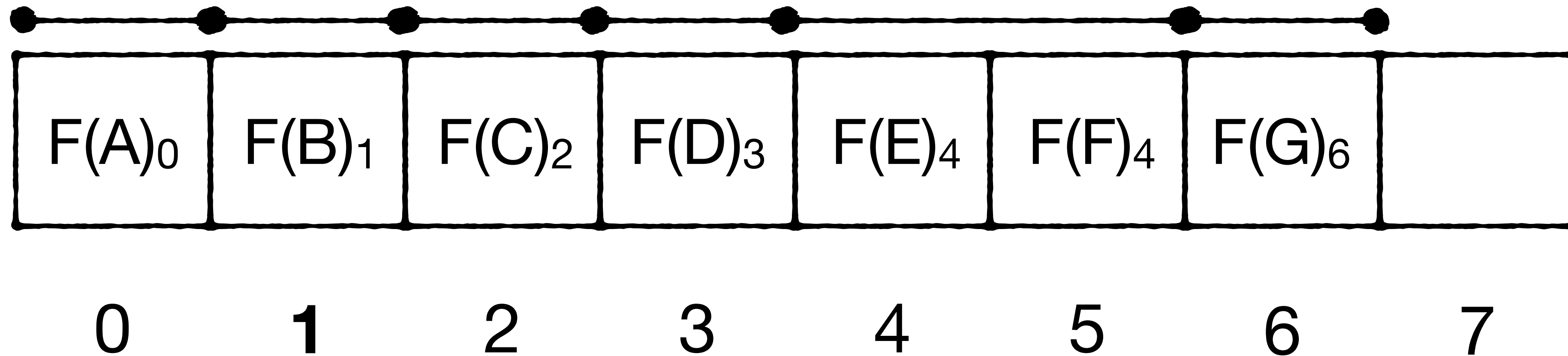
Insertions

Find target run, push colliding entries to right, insert

Insert $F(X)_1$



run



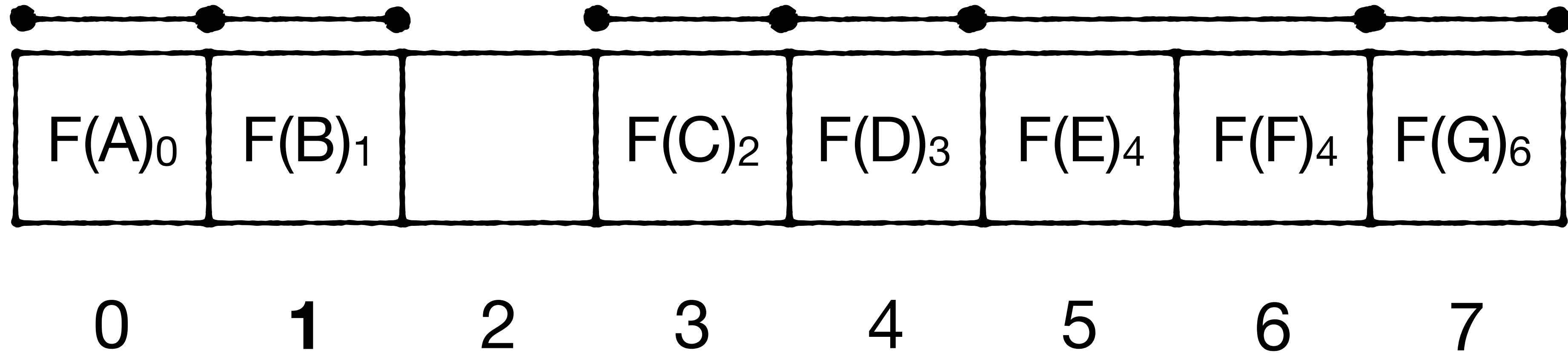
Insertions

Find target run, push colliding entries to right, insert

Insert $F(X)_1$



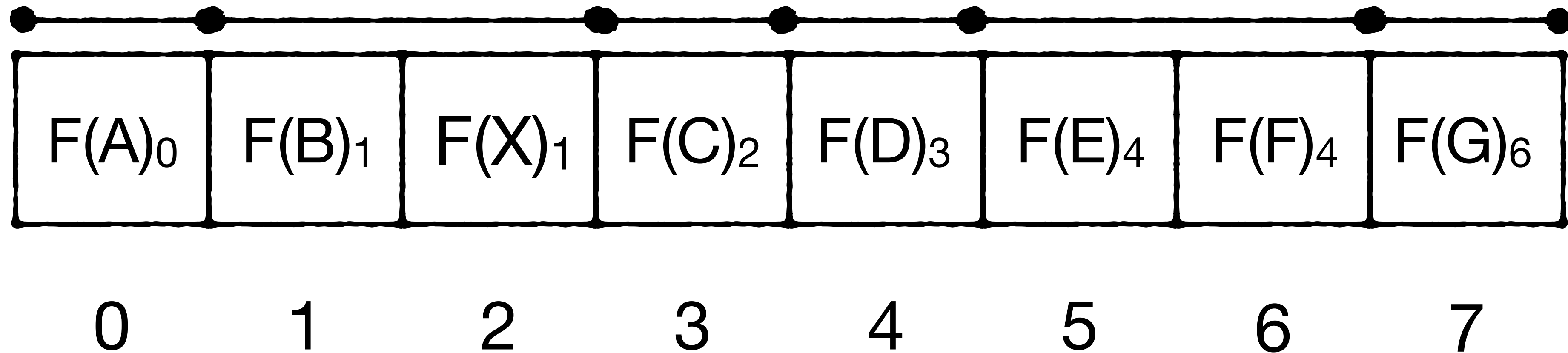
run



Insertions

Find target run, push colliding entries to right, insert

run

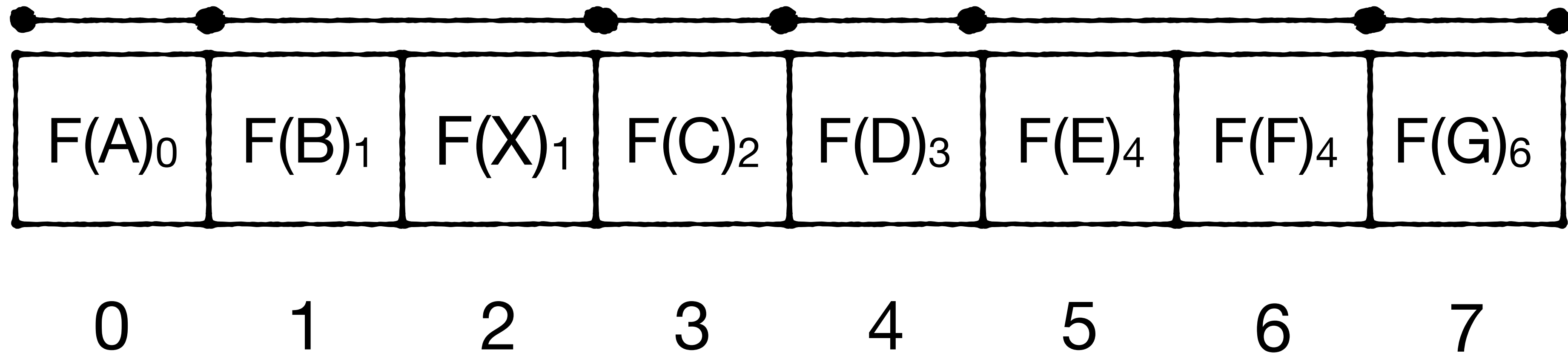


Insertions

Find target run, push colliding entries to right, insert

Problem?

run



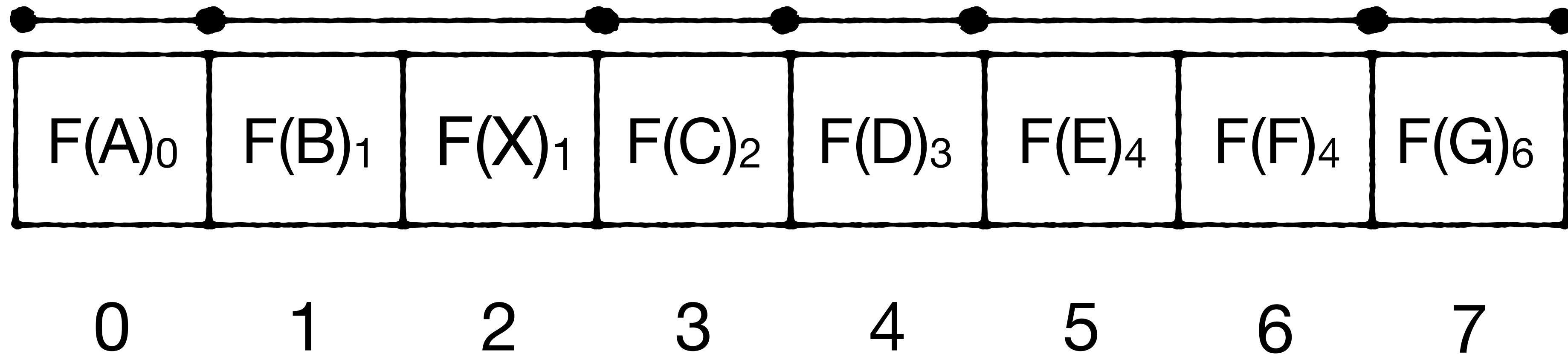
Insertions

Find target run, **push colliding entries to right**, insert



potentially $O(N)$

run



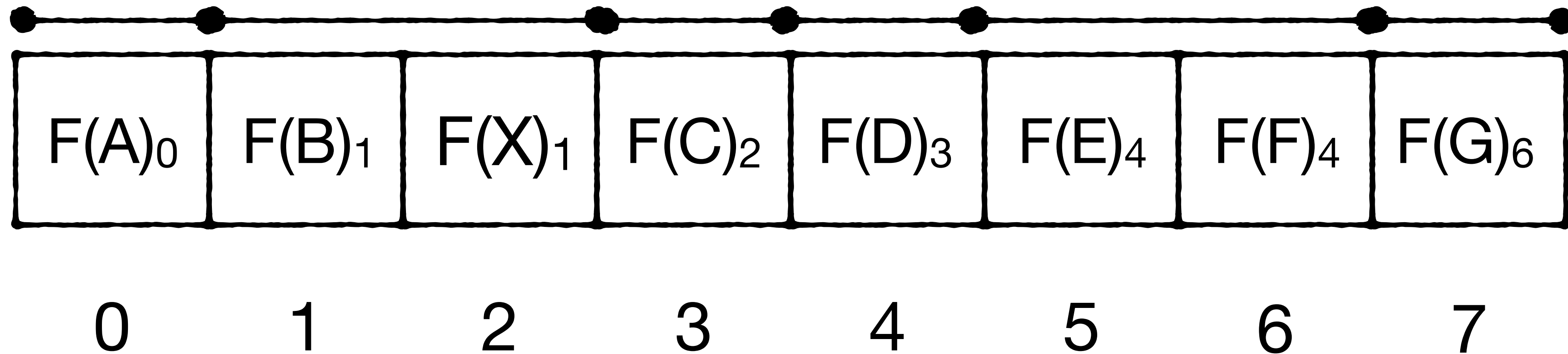
Insertions

Find target run, **push colliding entries to right**, insert



potentially $O(N)$ - **solution?**

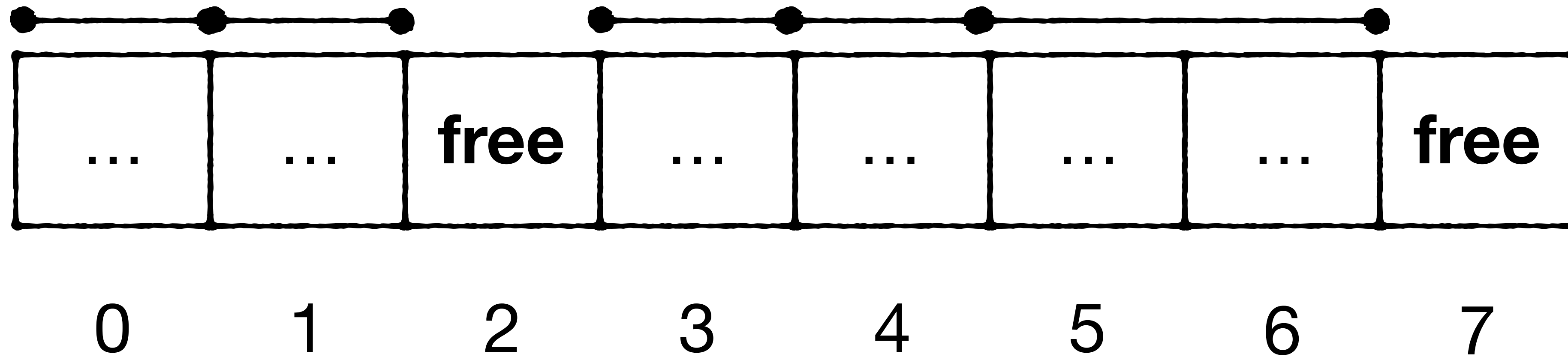
run



Insertions

Keep at least 5% spare capacity

run

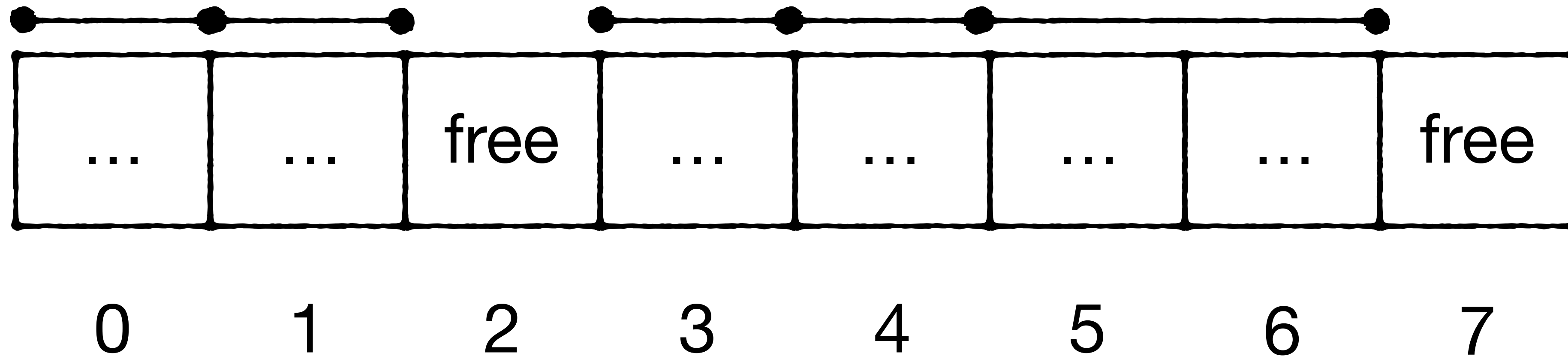


Insertions

Keep at least 5% spare capacity

Push on avg. 20 entries on avg due to hashing

run

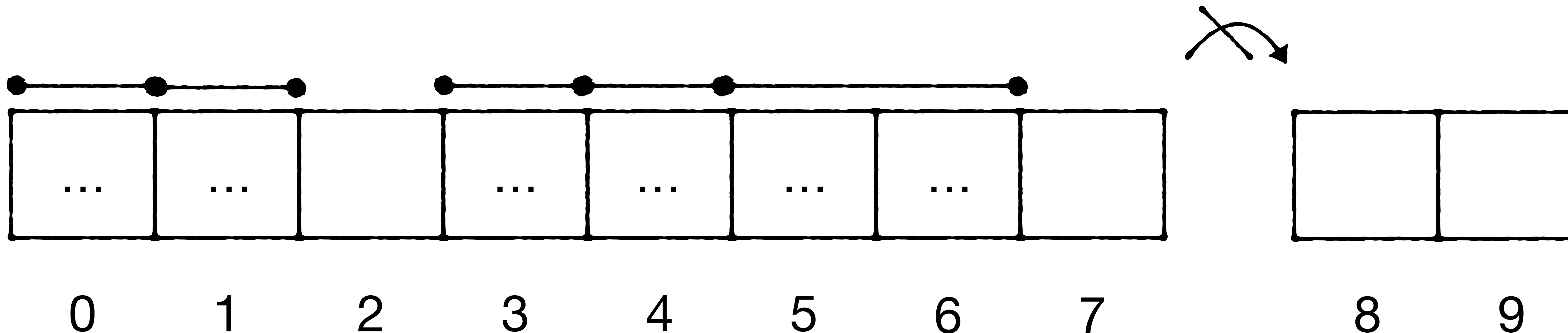


Insertions

Keep at least 5% spare capacity

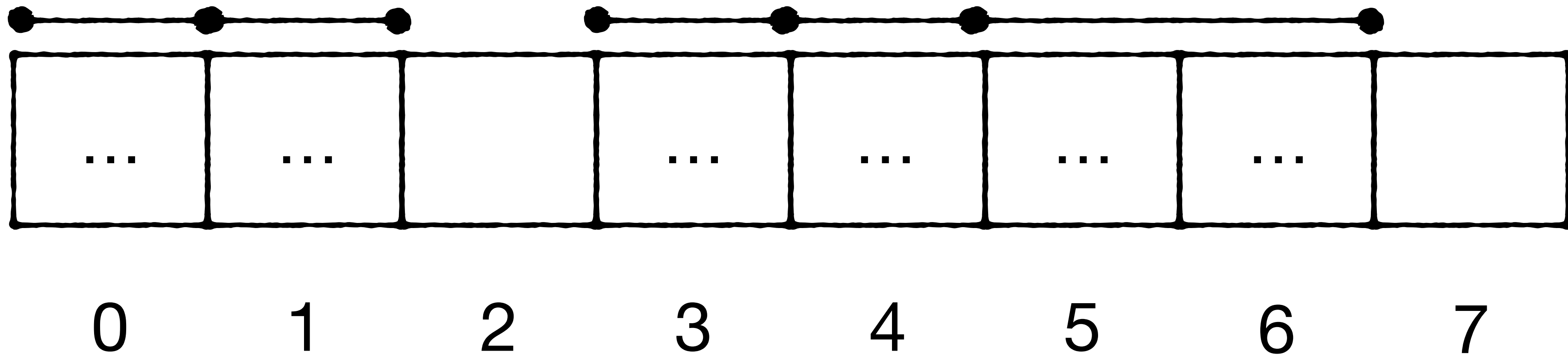
Push on avg. 20 entries on avg due to hashing

Most insertions don't spill to the next chunk



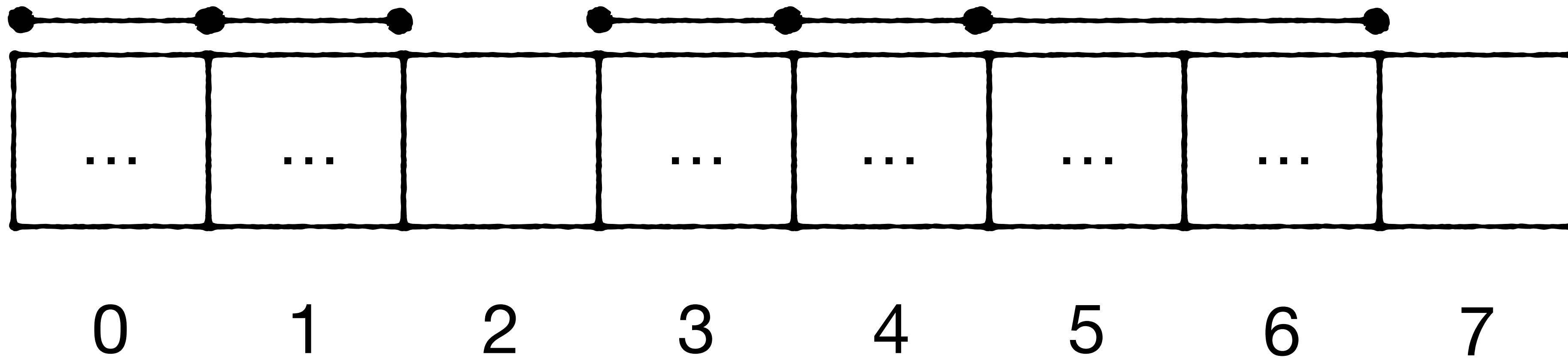
deletes?

run

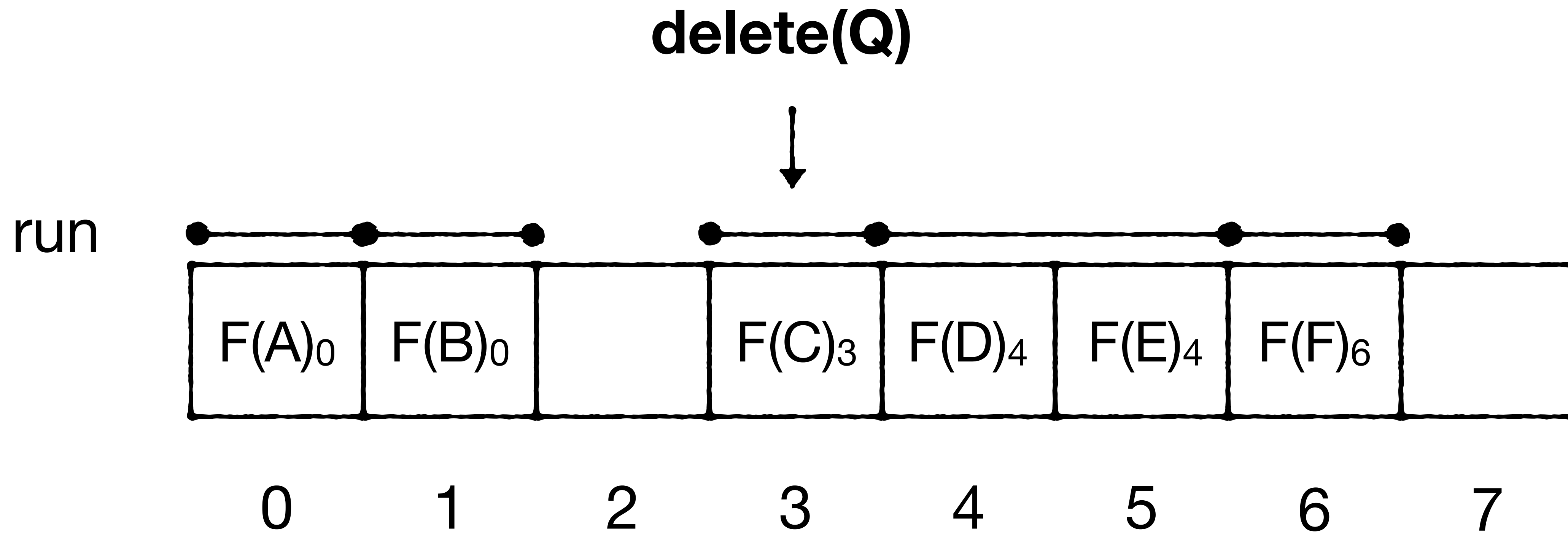


Can only delete entry we know exists. Why?

run

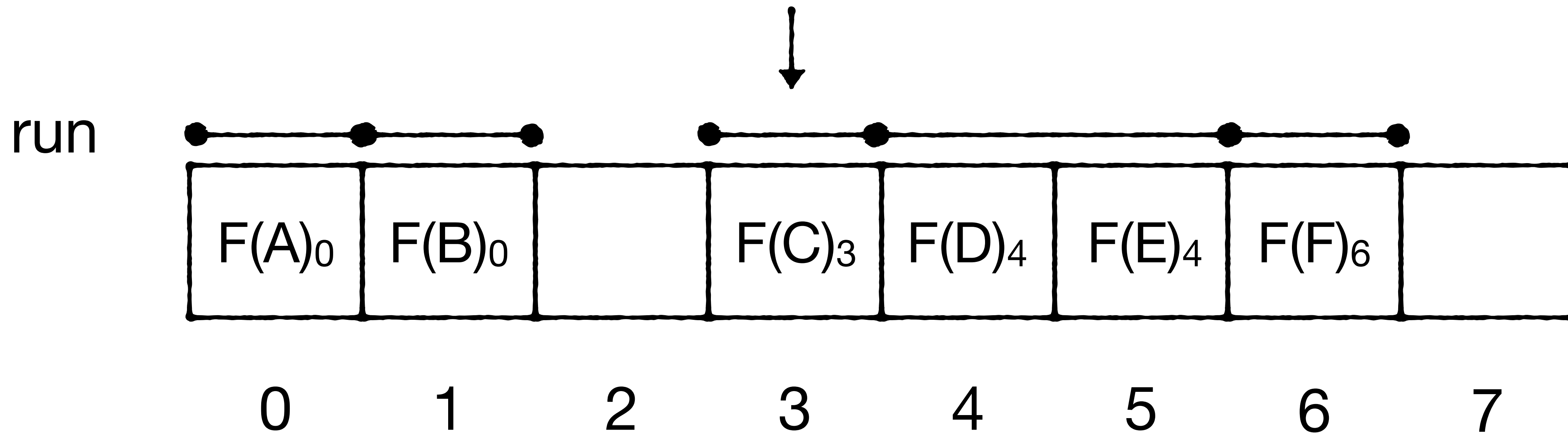


Can only delete entry we know exists. Why?



Can only delete entry we know exists. Why?

delete(Q) - matches C's FP at slot 3

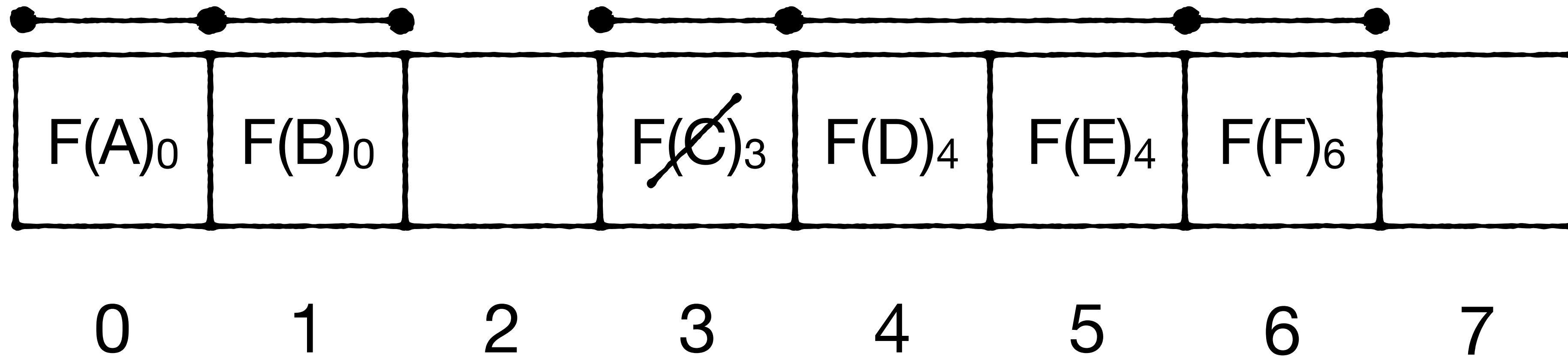


Can only delete entry we know exists. Why?

**Subsequent get(C) return
false negatives**

delete(Q)

run

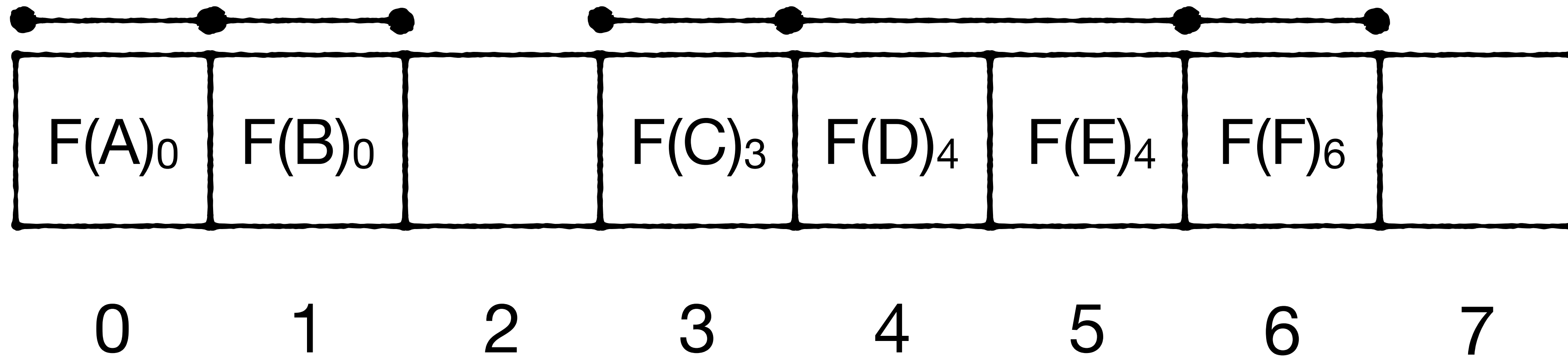


How to delete an entry we know exists?

delete(D)

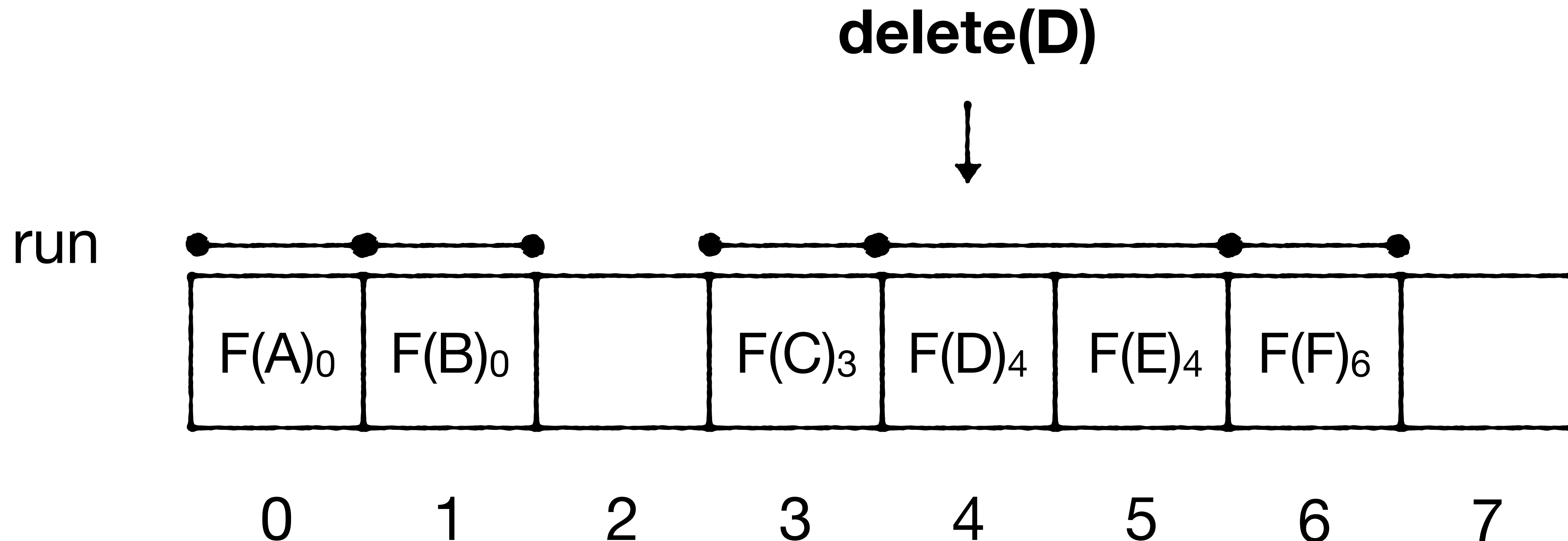


run



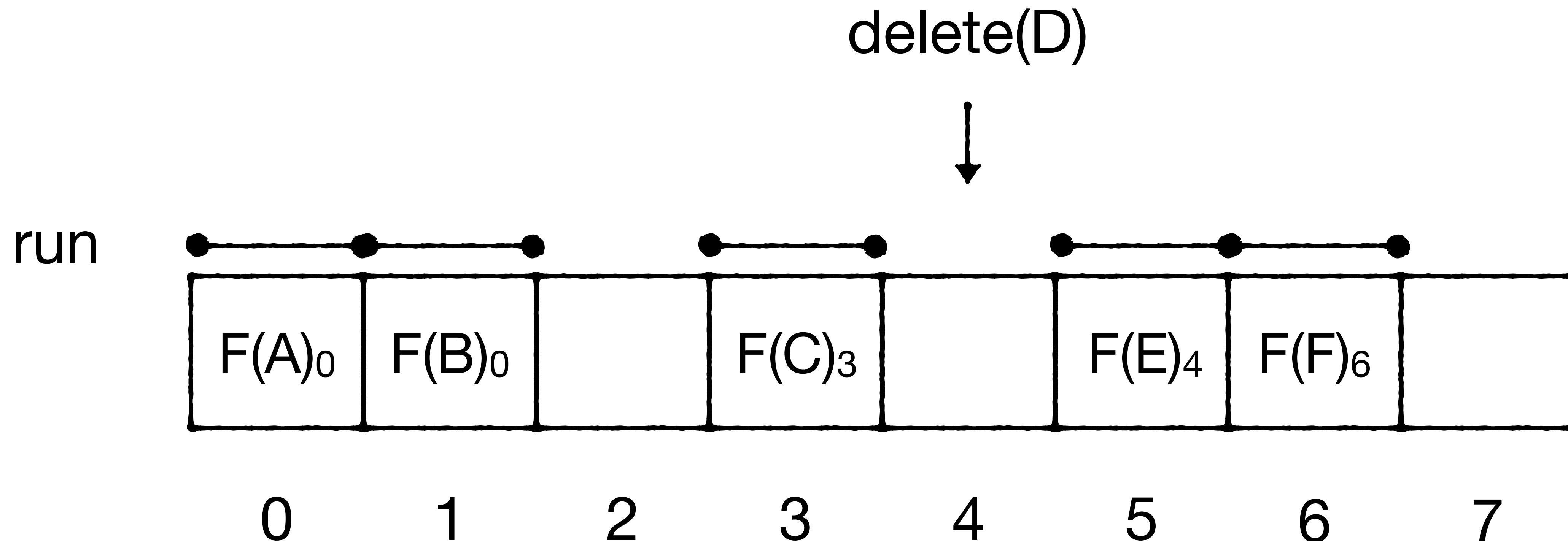
How to delete an entry we know exists?

(1) Find run, remove matching fingerprint



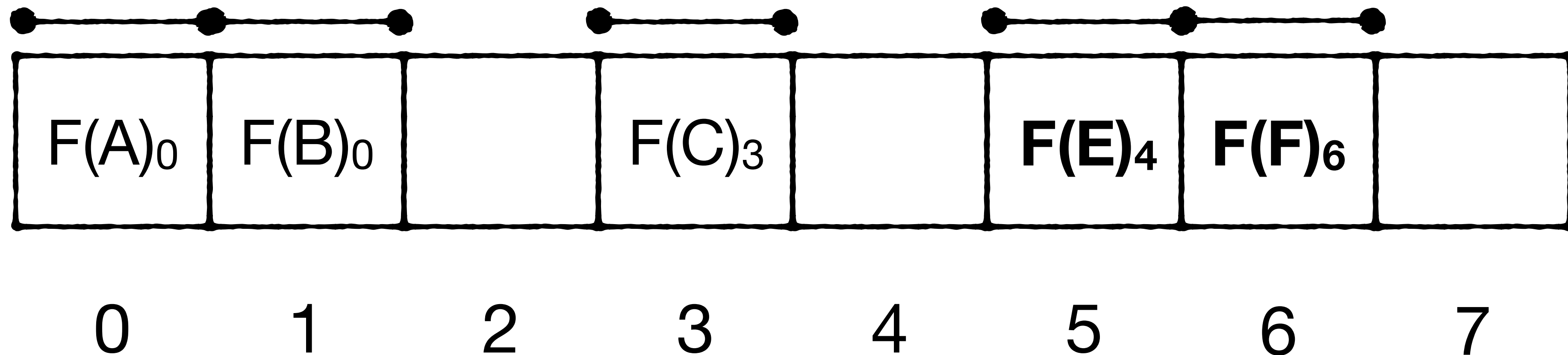
How to delete an entry we know exists?

(1) Find run, remove matching fingerprint



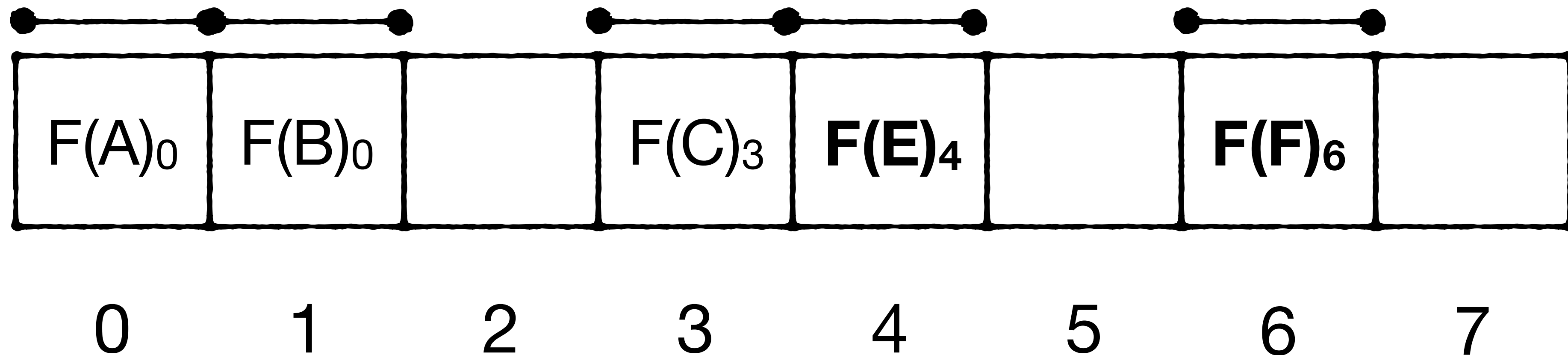
(2) shift entries leftwards if needed to maintain contiguous runs as close as possible to their canonical slot

run



(2) shift entries leftwards if needed to maintain contiguous runs as close as possible to their canonical slot

run



Analysis

Query/insert/delete

False positive rate

Analysis

Query/insert/delete

$O(1)$

expected time

False positive rate

Analysis

Query/insert/delete

$O(1)$

expected time

False positive rate

$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$

Analysis

Query/insert/delete

$O(1)$

False positive rate

$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$



Bits / entry budget

Analysis

Query/insert/delete

$O(1)$

False positive rate

$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$



Metadata bits

(2 bitmaps and offsets field)

Analysis

Query/insert/delete

$O(1)$

False positive rate

$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$



Load factor, $\alpha < 0.95$

Analysis

Query/insert/delete

$O(1)$

False positive rate

$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$



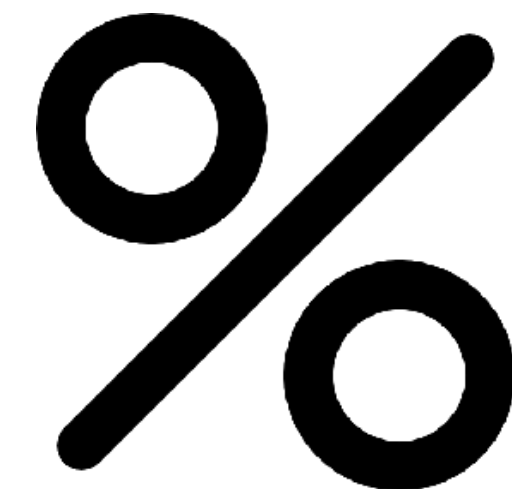
Avg run length

Bloom



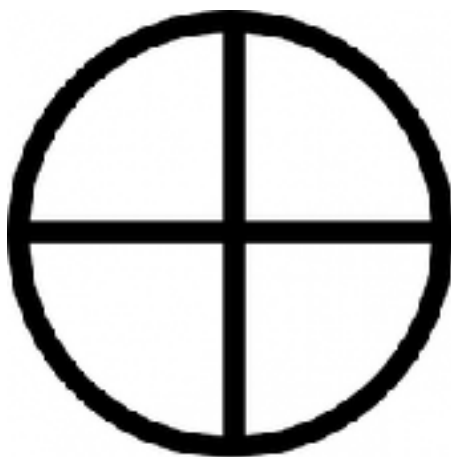
$$\approx 2^{-M/N \cdot 0.69}$$

Quotient



$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$

XOR



$$\approx 2^{-M/N \cdot 0.81}$$

Idealized



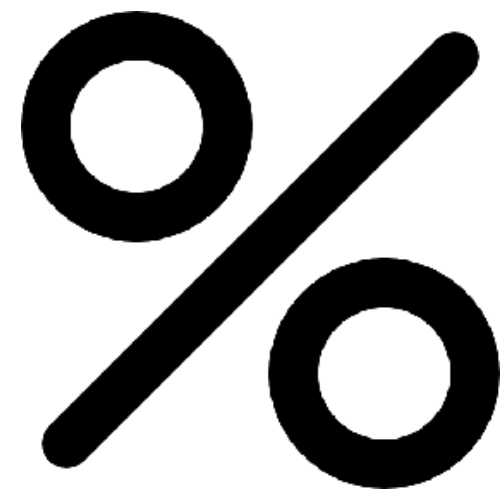
$$\approx 2^{-M/N}$$

Bloom



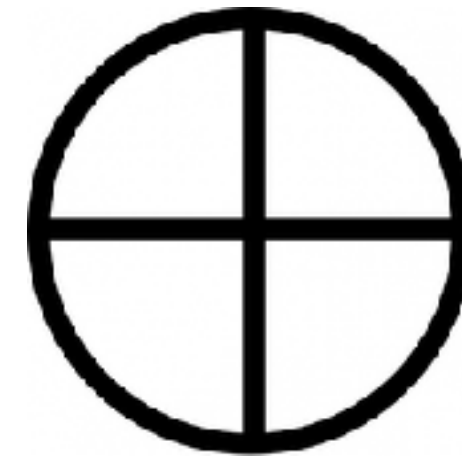
$$\approx 2^{-M/N \cdot 0.69}$$

Quotient



$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$

XOR



$$\approx 2^{-M/N \cdot 0.81}$$

Idealized



$$\approx 2^{-M/N}$$

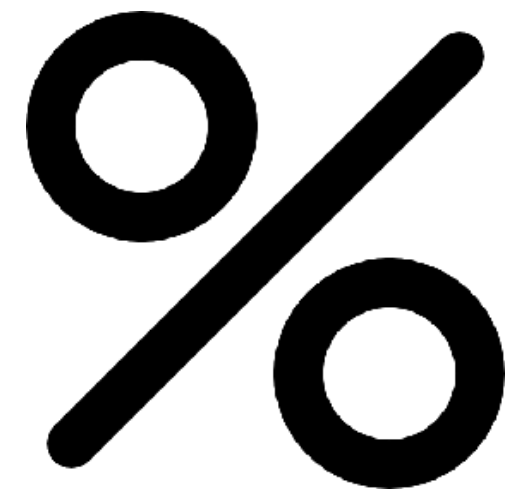
Lower than Bloom for $M/N > 10$

Bloom



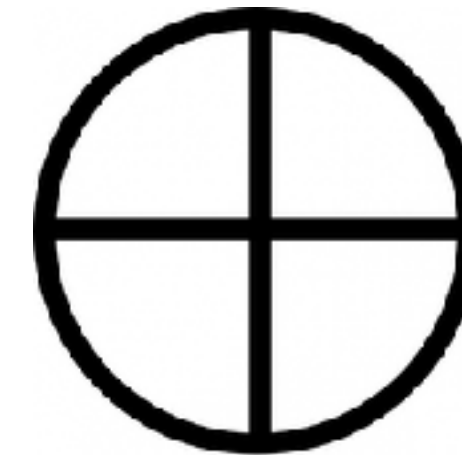
$$\approx 2^{-M/N \cdot 0.69}$$

Quotient



$$\approx \alpha \cdot 2^{-(M/N - 2.125)/\alpha}$$

XOR



$$\approx 2^{-M/N \cdot 0.81}$$

Idealized



$$\approx 2^{-M/N}$$

Lower than Bloom for $M/N > 10$

Supports deletes :)

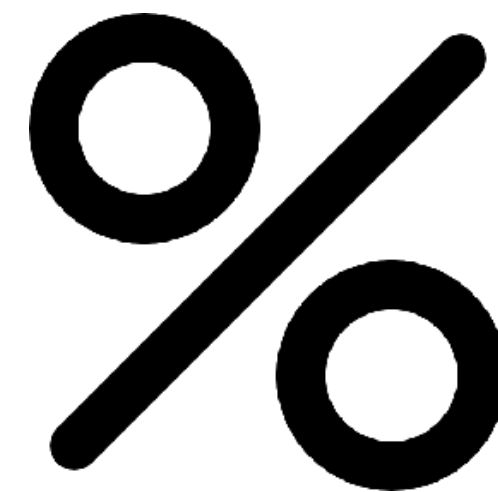
Performance (cache misses)

Blocked Bloom



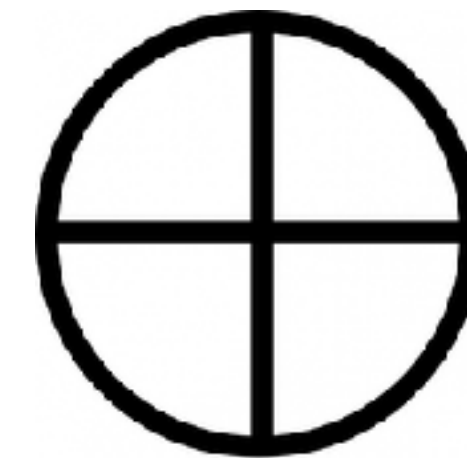
1

Quotient

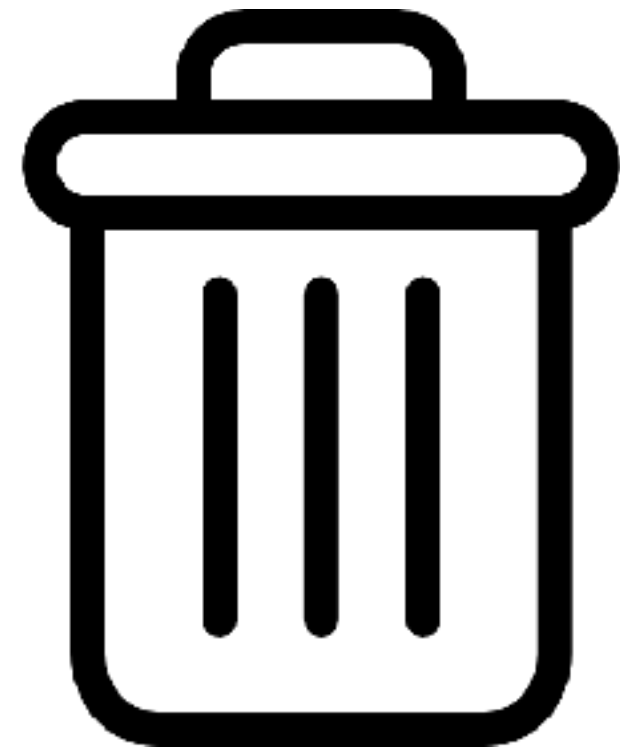


$\approx 1-2$ on avg
sequential

XOR



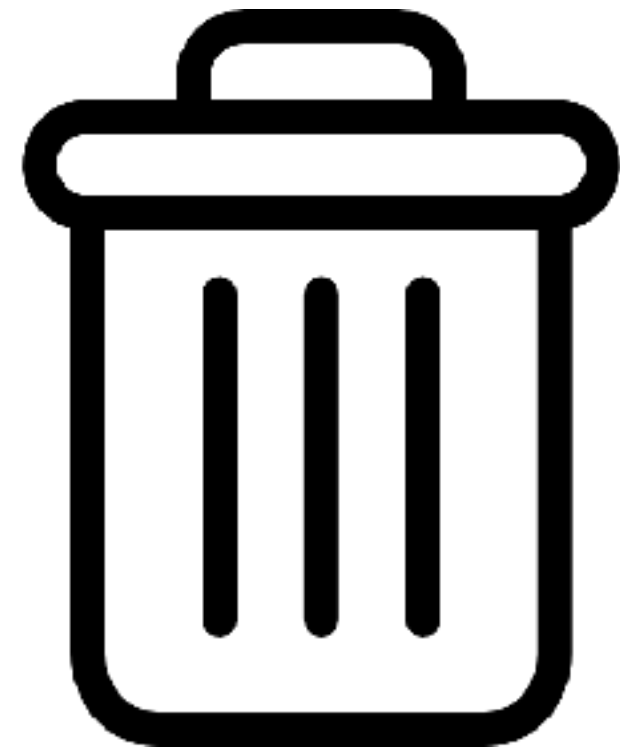
3
random



Deletes



Resizing



Deletes

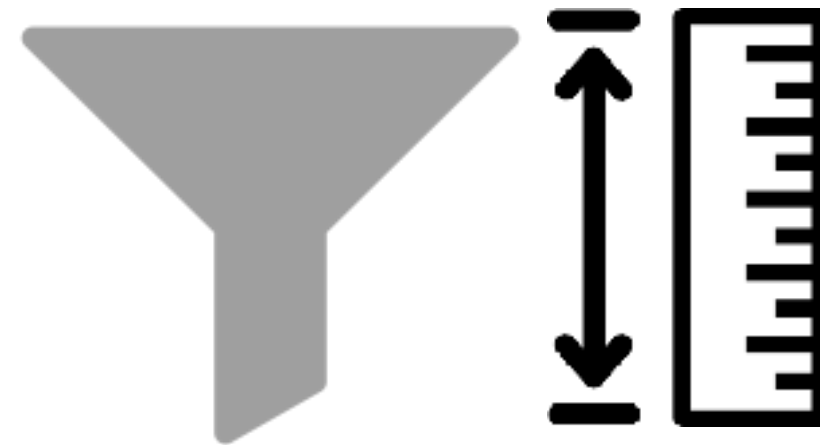


Resizing

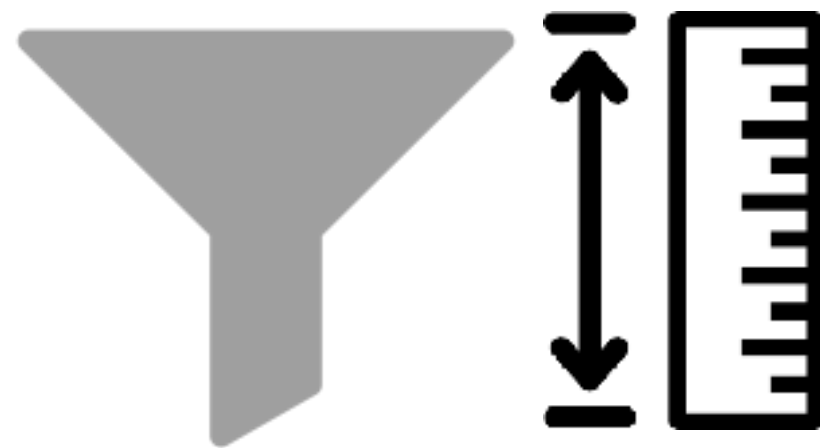


Break

Allocated with fixed capacity



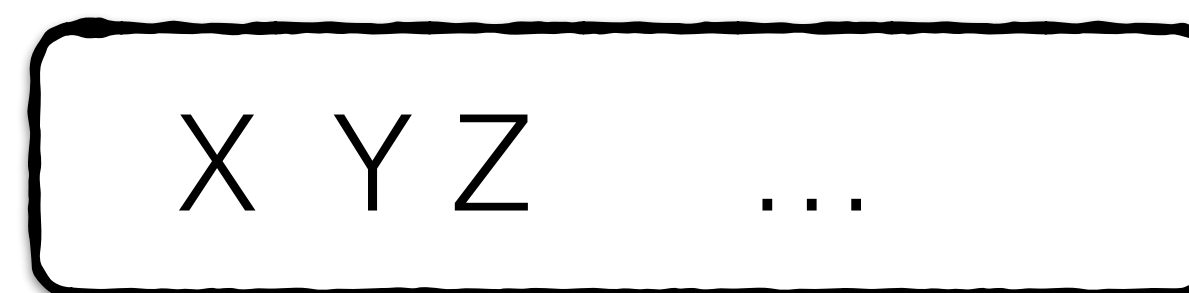
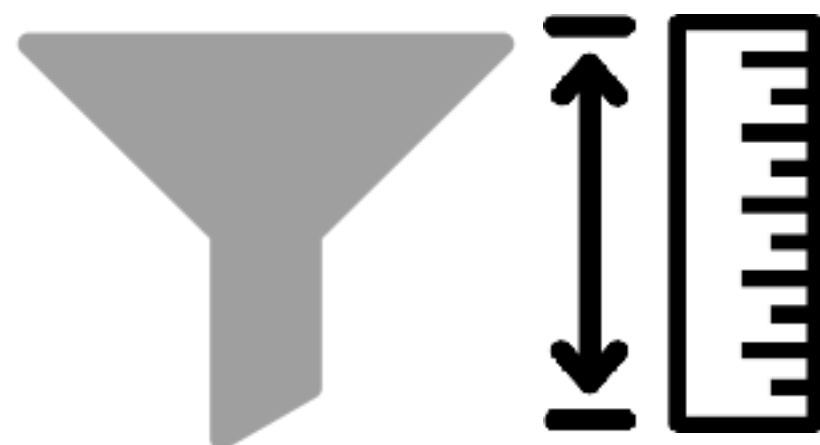
Allocated with fixed capacity



**False positive
rate**



**Insertion/query/
delete cost**



Data growth

How to Expand Filters Efficiently?



?



Data growth

How to Expand Filters Efficiently?



?

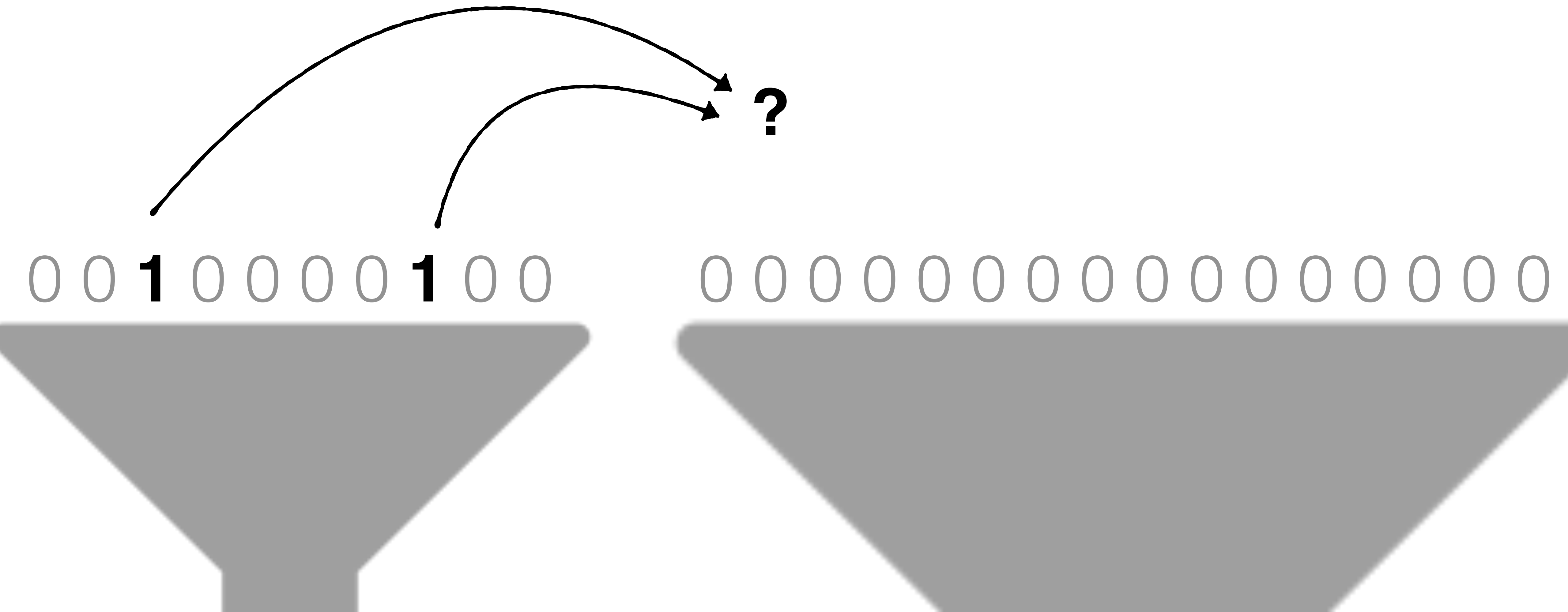


Data growth

Without rereading the original data

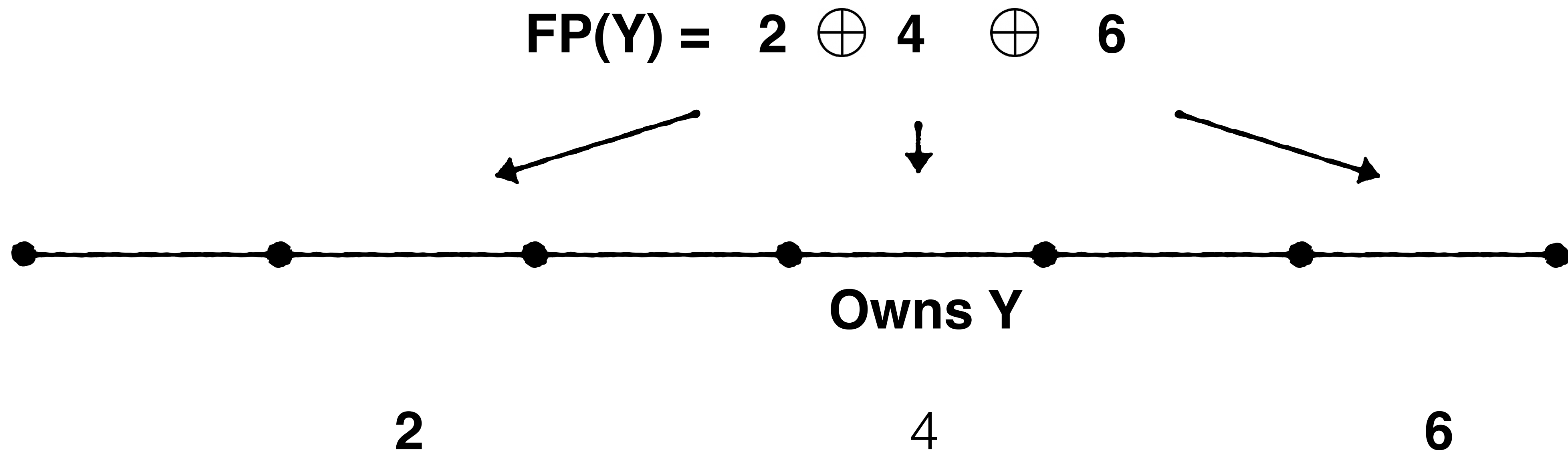


Bloom Filters: unexpandable



XOR Filters: unexpandable

Can't recover original fingerprints without
accessing the original data



Expansion Workarounds

Expansion Workarounds

Pre-Allocation



Memory



Expansion Workarounds

Pre-Allocation



Memory



Reconstruction



Full scan



Agenda

Chaining



Quotient Filter



InfiniFilter &
Aleph Filter



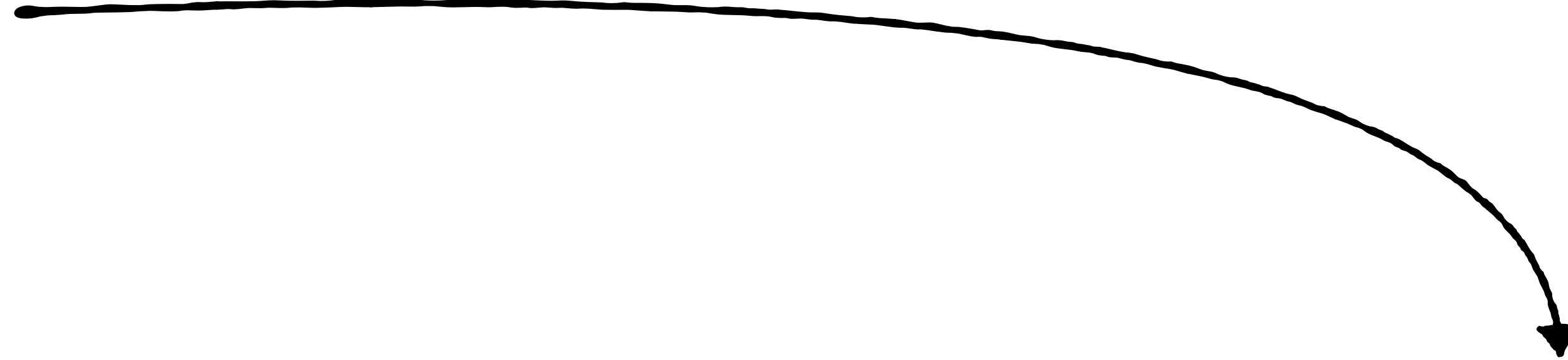
Chaining

Create 2x larger filter when former reaches capacity



Chaining

Insertions



Chaining

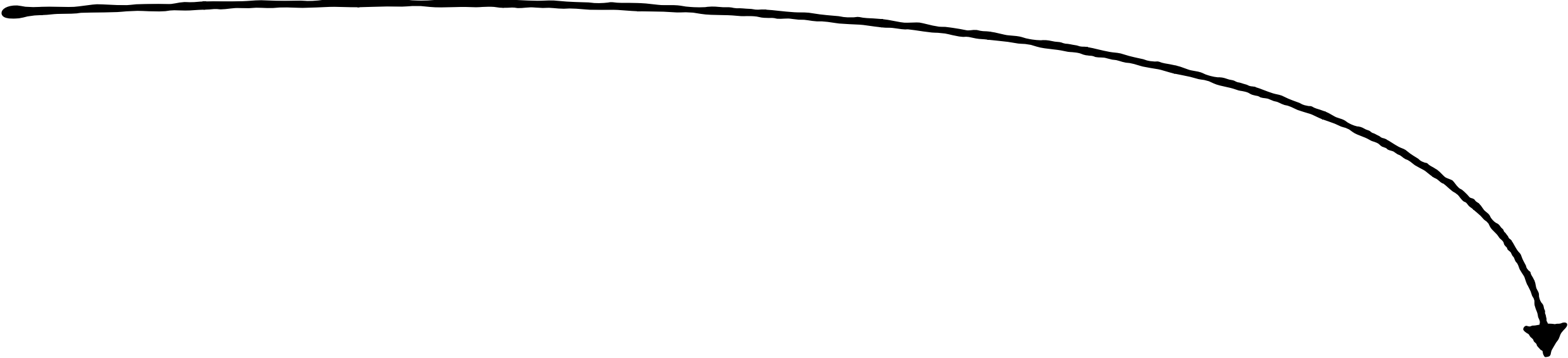
Insertions

**Create 2x
larger**

Full

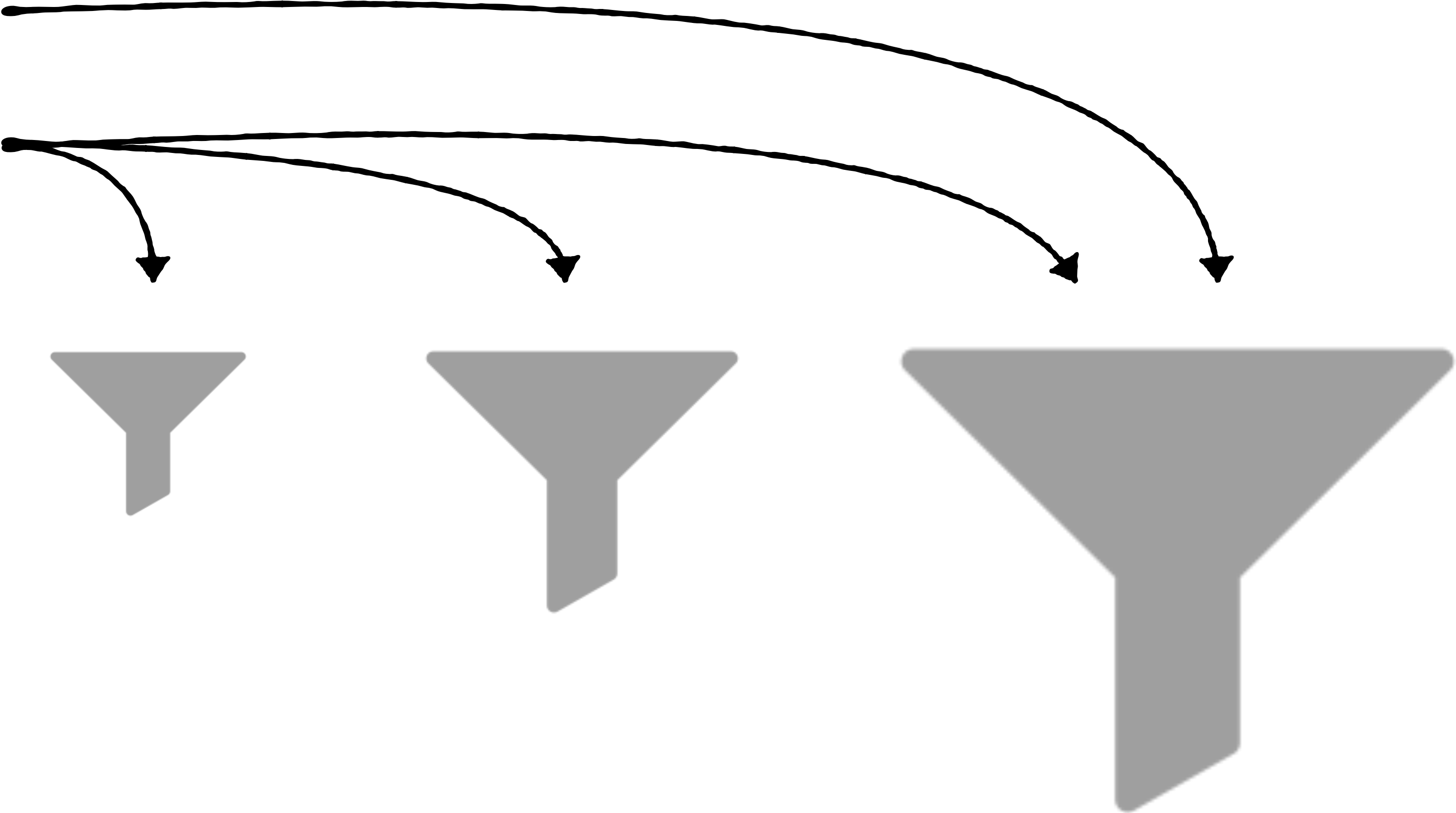


Insertions



Insertions

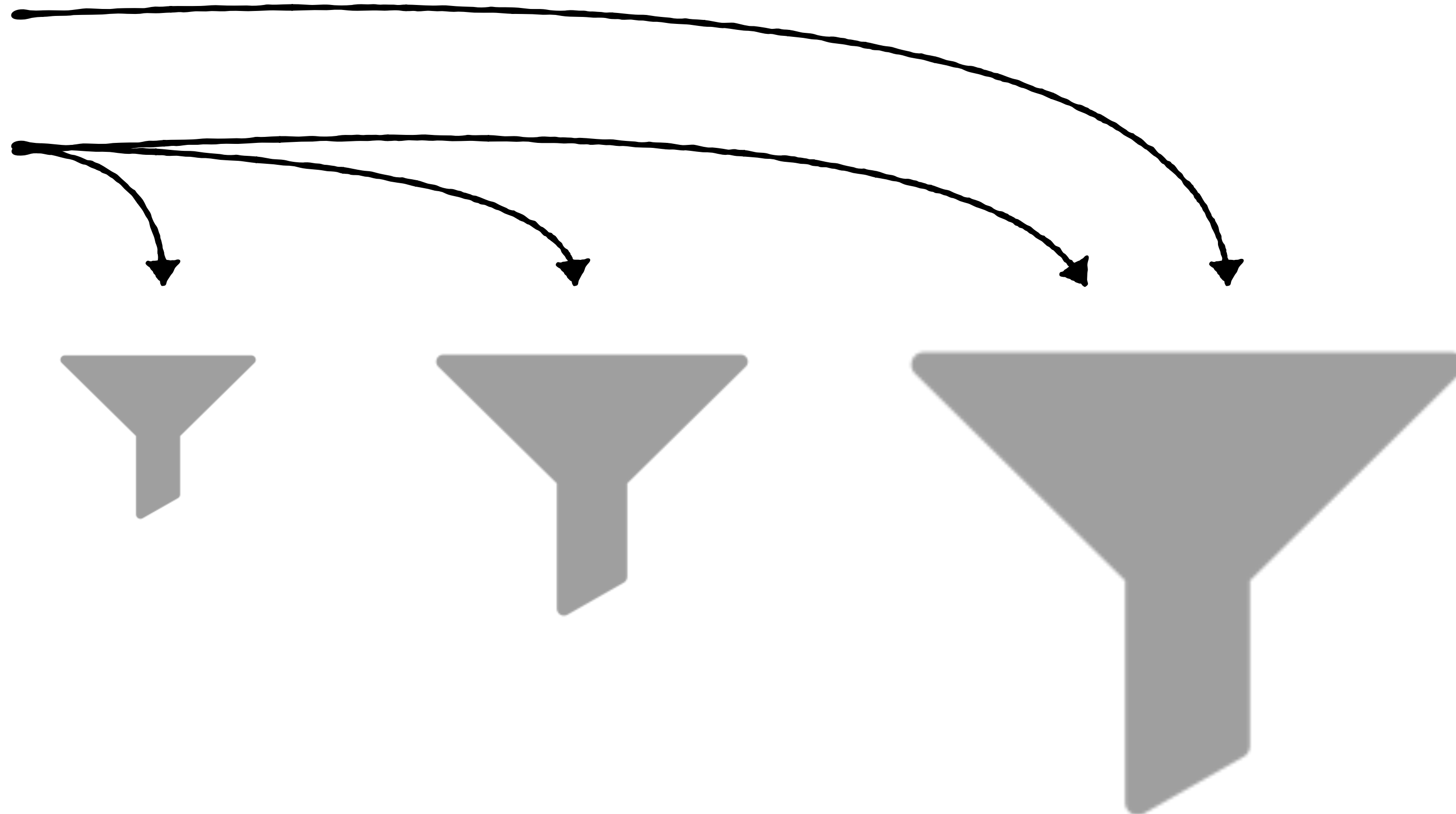
Queries



Works with any filter

Insertions

Queries

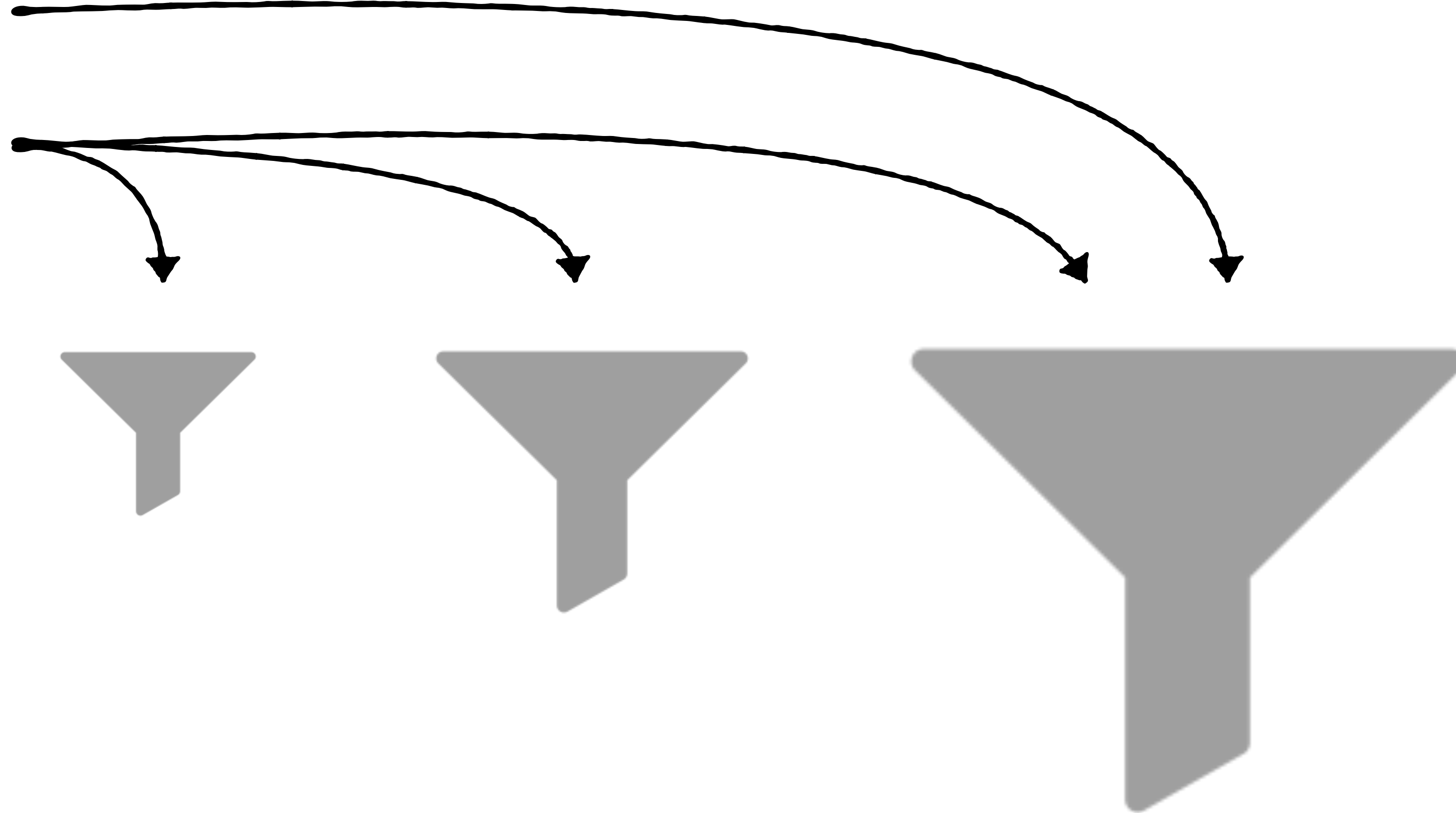


Works with any filter

Downsides?

Insertions

Queries



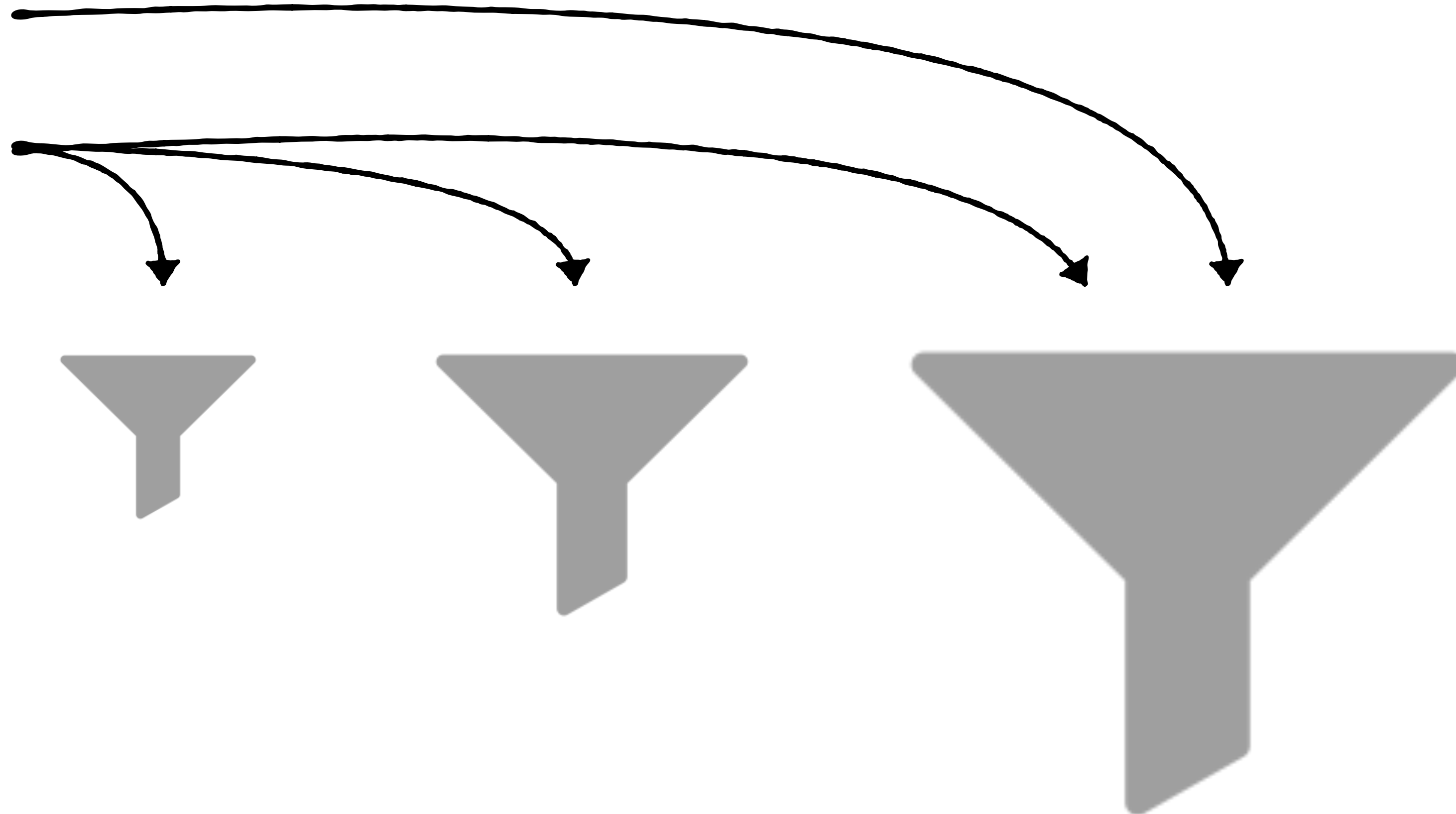
Works with any filter

Downsides?

Insertions

Queries

$O(\log_2 N)$



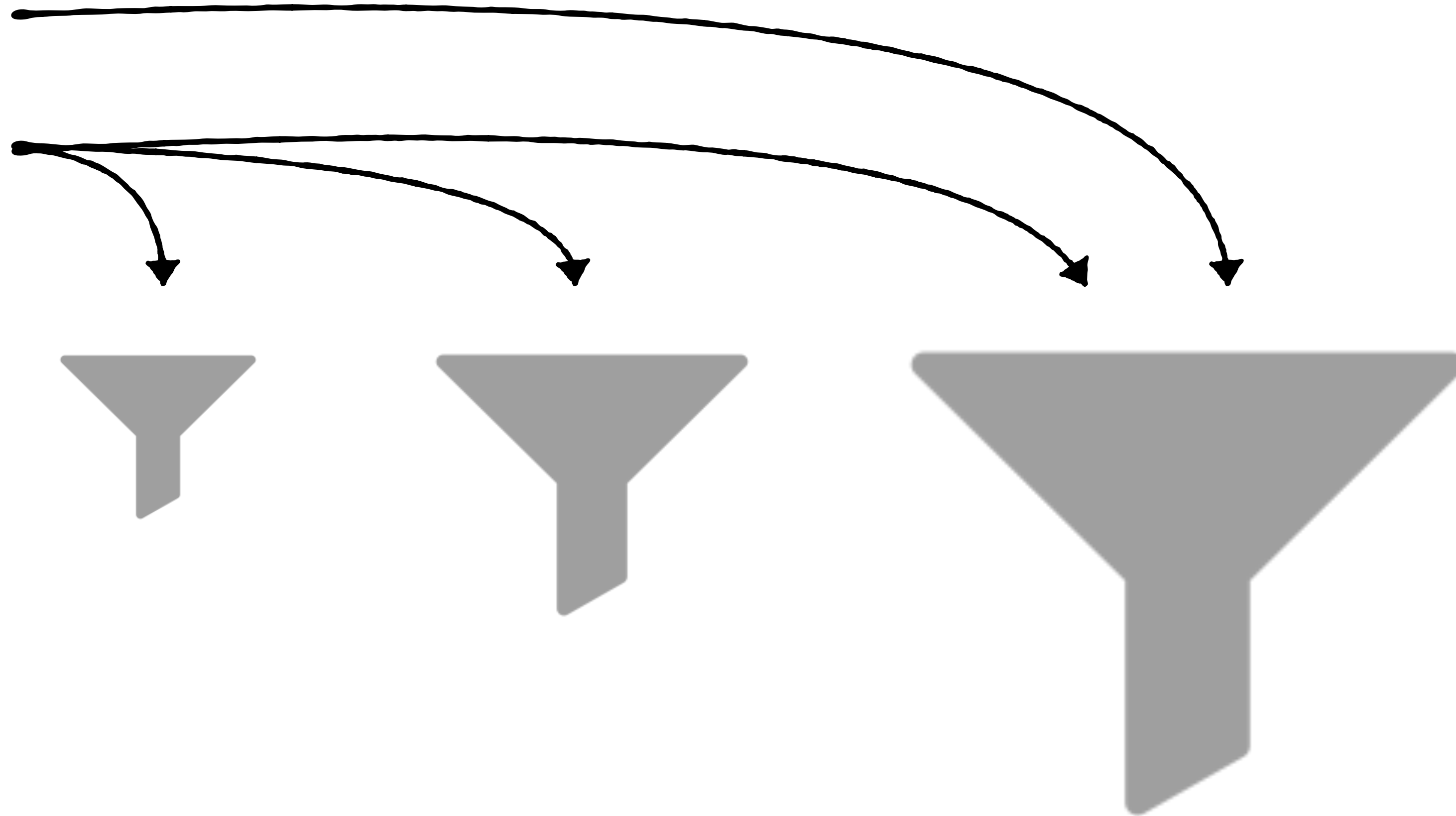
Works with any filter

Downsides?

Insertions

Queries

$O(\log_2 N)$



FPR?

$$\mathbf{FPR} \approx \epsilon + \epsilon + \epsilon = O(\epsilon \cdot \log_2 N)$$



Suppose we want to keep it ϵ ?



$$\mathbf{FPR} \approx \epsilon + \epsilon + \epsilon = O(\epsilon \cdot \log_2 N)$$

Suppose we want to keep it ε ?



$$\text{FPR} \approx \underbrace{\varepsilon + \varepsilon + \varepsilon}_{\text{Set lower FPRs for newer filters}} = O(\varepsilon \cdot \log_2 N)$$

Set lower FPRs for newer filters

Geometrically decreasing. Any issue?



$$\text{FPR} \approx \epsilon + \epsilon/2 + \epsilon/4 = O(\epsilon \cdot \log_2 N)$$



$$\text{FPR} \approx \varepsilon + \varepsilon/2 + \varepsilon/4 = O(\varepsilon)$$



Most Memory
Most data, lowest FPR



$$\text{FPR} \approx \varepsilon + \varepsilon/2 + \varepsilon/4 = O(\varepsilon)$$

Bits / entry:

$$\log(4/\varepsilon)$$



$$\text{FPR} \approx \varepsilon + \varepsilon/2 + \varepsilon/4 = O(\varepsilon)$$

Bits / entry:

$$\log(2^{\log N / \varepsilon})$$

Can we better scale memory?



$$\text{FPR} \approx \varepsilon + \varepsilon/2 + \varepsilon/4 = O(\varepsilon)$$

Bits / entry:



$\log_2 N + \log(1/\varepsilon)$

The FPRs should decrease more slowly but still converge



$$\text{FPR} \approx \varepsilon + \varepsilon/2 + \varepsilon/4 = O(\varepsilon)$$

Bits / entry:



$$\log_2 N + \log(1/\varepsilon)$$

Reciprocal of square numbers

$$1/1^2 + 1/2^2 + 1/3^2 + \dots = ?$$



**Solved by Euler
in 1734**

$$1/1^2 + 1/2^2 + 1/3^2 + \dots = \pi^2/6$$



**Solved by Euler
in 1734**

$$\begin{aligned} 1/1^2 + 1/2^2 + 1/3^2 + \dots &= \pi^2/6 \\ &= 1.645 \end{aligned}$$



Solved by Euler
in 1734

$$1/1^2 + 1/2^2 + 1/3^2 + \dots = \pi^2/6$$

Polynomially decreasing yet still convergent



$$\mathbf{FPR} \approx \mathbf{\varepsilon/1^2} \mathbf{+} \mathbf{\varepsilon/2^2} \mathbf{+} \mathbf{\varepsilon/3^2} \mathbf{=} \mathbf{\varepsilon \cdot \pi^2/6}$$



$$\text{FPR} \approx \varepsilon/1^2 + \varepsilon/2^2 + \varepsilon/3^2 = \varepsilon \cdot \pi^2/6$$

Bits / entry:

$$\log(3^2/\varepsilon)$$



$$\text{FPR} \approx \varepsilon/1^2 + \varepsilon/2^2 + \varepsilon/3^2 = \varepsilon \cdot \pi^2/6$$

Bits / entry:

$$\log(\log(N)^2/\varepsilon)$$



$$\text{FPR} \approx \varepsilon/1^2 + \varepsilon/2^2 + \varepsilon/3^2 = \varepsilon \cdot \pi^2/6$$

Bits / entry:

$$2 \log_2 \log_2(N) + \log(1/\varepsilon)$$



$$\mathbf{FPR} \approx \varepsilon$$

$$\text{Bits / entry:} \quad \mathbf{2 \log_2 \log_2(N) + \log(1/\varepsilon)} \quad < \quad \mathbf{\log N + \log(1/\varepsilon)}$$

$$\text{FPR} \approx \varepsilon$$

Bits / entry:

$$\frac{2 \log_2 \log_2 (N) + \log(1/\varepsilon)}{\text{Close to lower bound}}$$



How to Approximate A Set Without Knowing Its Size In Advance

Rasmus Pagh, Gil Segev, Udi Wieder. **FOCS 2013.**

$$\text{FPR} \approx \varepsilon$$

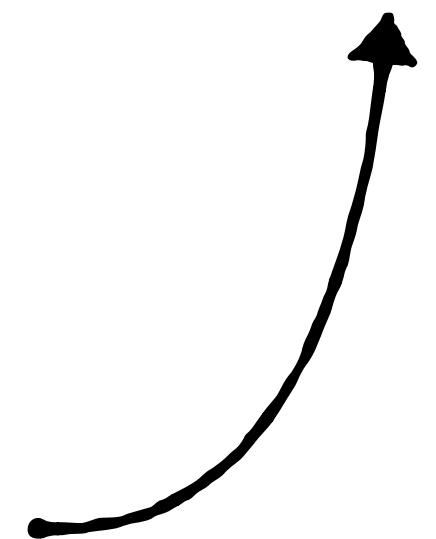
Bits / entry:

$$\frac{2 \log_2 \log_2 (N) + \log(1/\varepsilon)}{\text{Close to lower bound}}$$

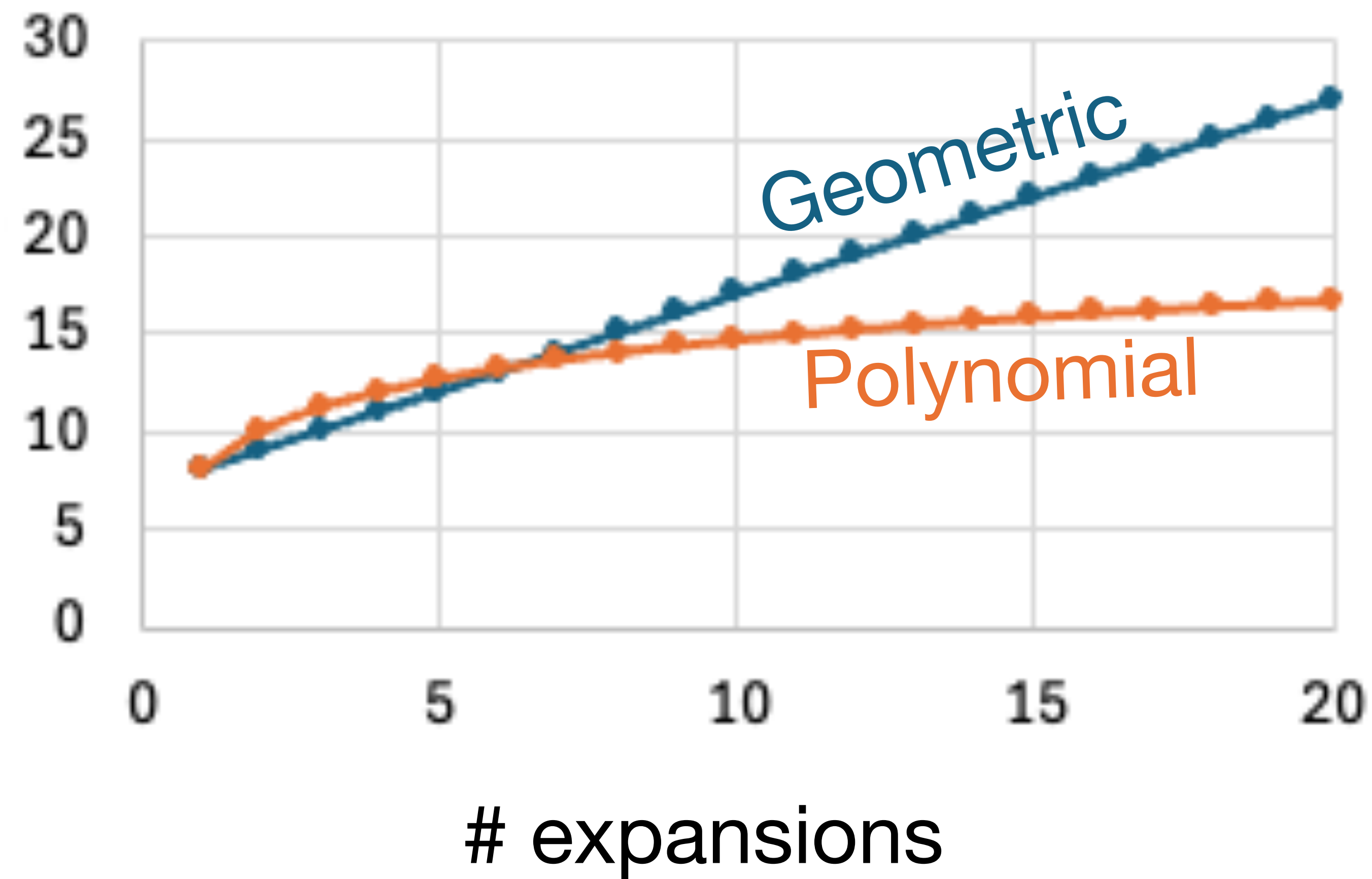


How to Approximate A Set Without Knowing Its Size In Advance
Rasmus Pagh, Gil Segev, Udi Wieder. FOCS 2013.

Much of what follows originates from here :)



Bits / entry



Chaining



queries

Quotient Filters



InfiniFilter &
Aleph Filter



Quotient Filters are Semi-Expandable



Semi-Expandable





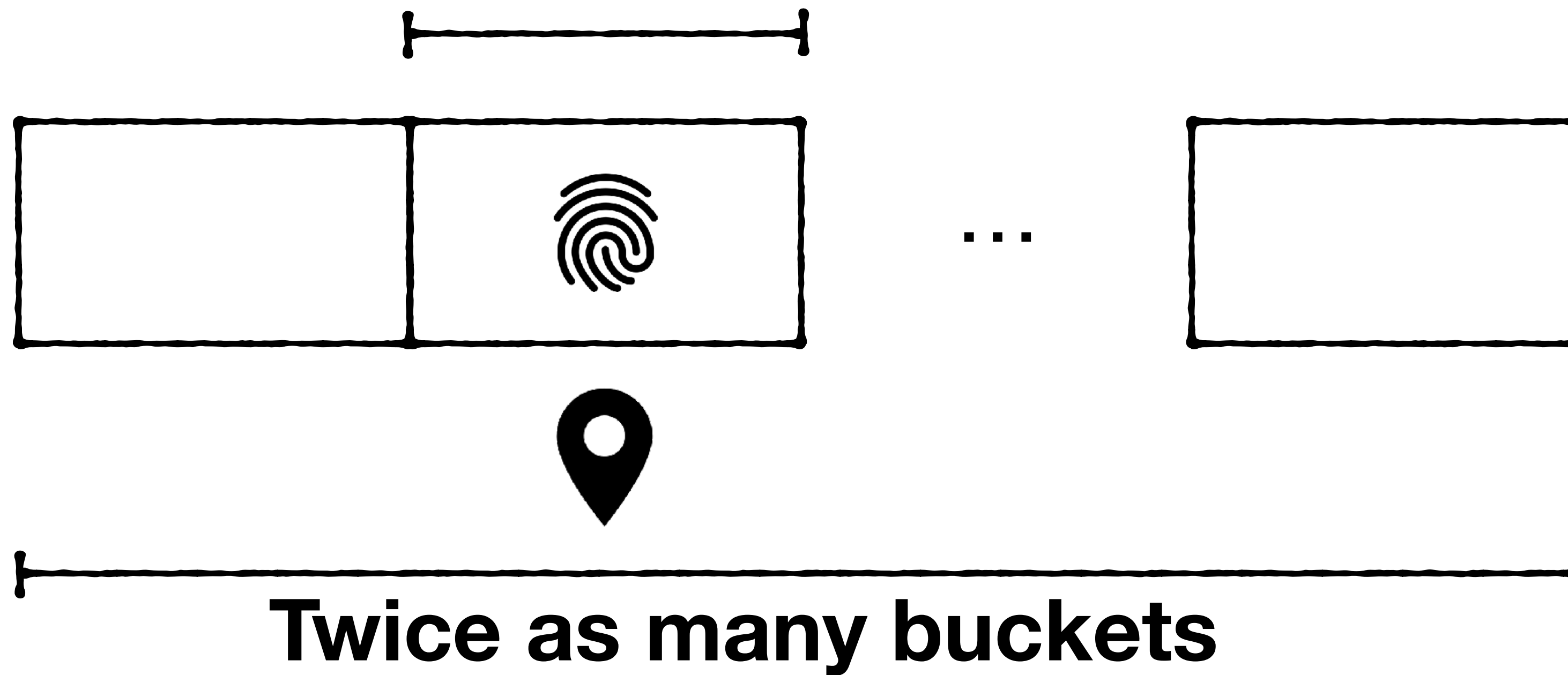
hash() = 0 1 0 1 0 0 1 1 **0** 1 0 1 1 0 1 1 0 0



One bit narrower



One bit narrower



$$\text{False positive rate (FPR)} \approx \alpha \cdot 2^{-(M/N + 2.125) / \alpha}$$

$$\text{False positive rate (FPR)} \approx \alpha \cdot 2^{-(M/N - \log_2(N) + 2.125) / \alpha}$$



**Lose 1 fingerprint bit in
each expansion**

$$\text{False positive rate (FPR)} \approx \alpha \cdot 2^{-(M/N - \log_2(N) + \mathbf{2.125}) / \alpha}$$

Remove constants



$$\text{False positive rate (FPR)} \approx 2^{-(M/N - \log_2(N))}$$



Simplify

False positive rate (FPR) $\approx N \cdot 2^{-M/N}$



Supports up to M/N expansions



False positive rate (FPR) $\approx N \cdot 2^{-M/N}$



Supports up to M/N expansions



$O(1)$ operations



Chaining



queries

Quotient Filters



FPR

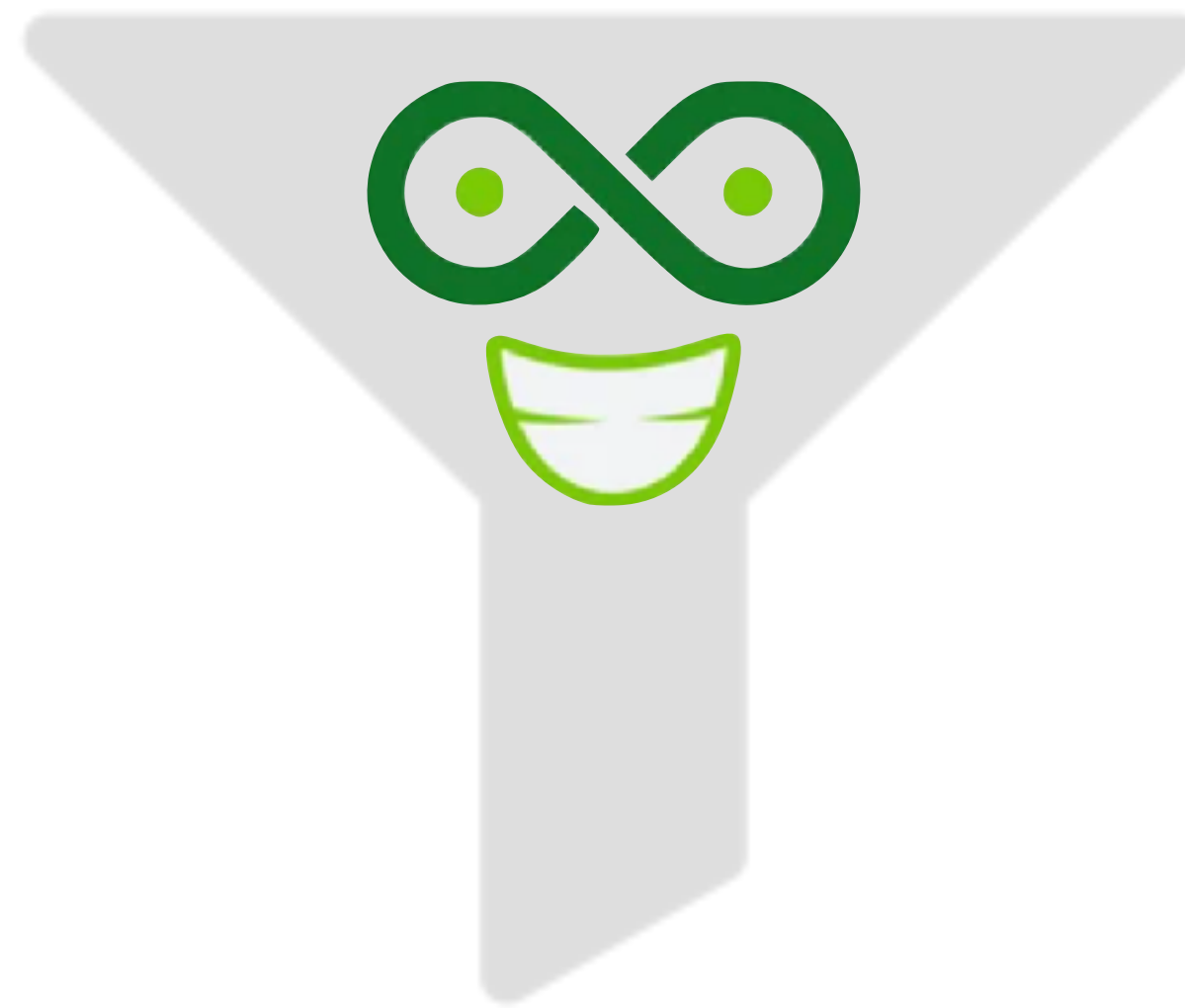
expansions

**InfiniFilter &
Aleph Filter**

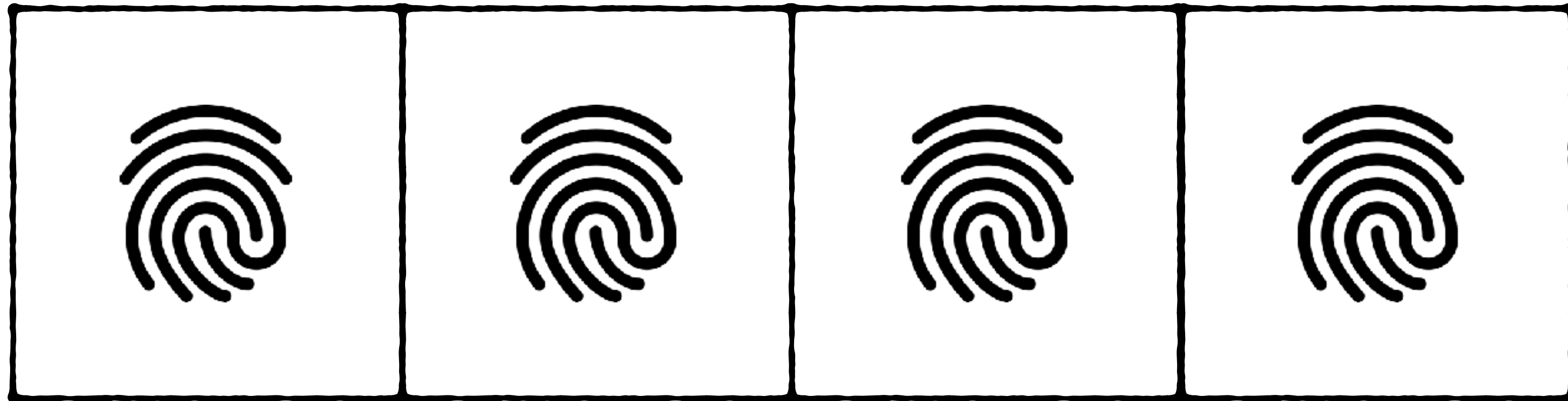


InfiniFilter: Expanding Filters to Infinity and Beyond

Niv Dayan, Ioana Bercea, Pedro Reviriego, Rasmus Pagh. SIGMOD 2023

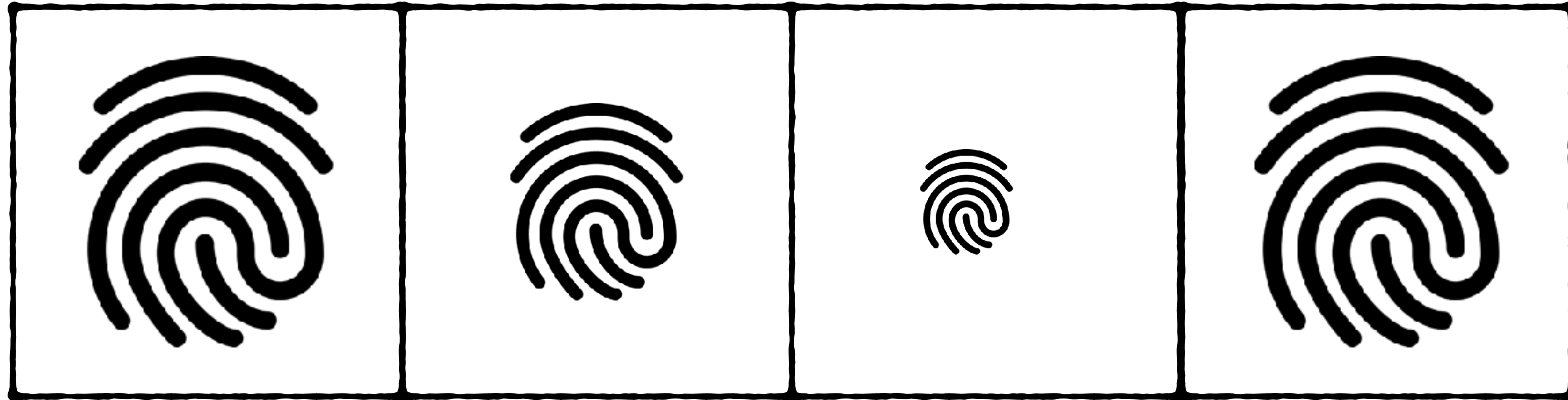


InfiniFilter



Quotient filter

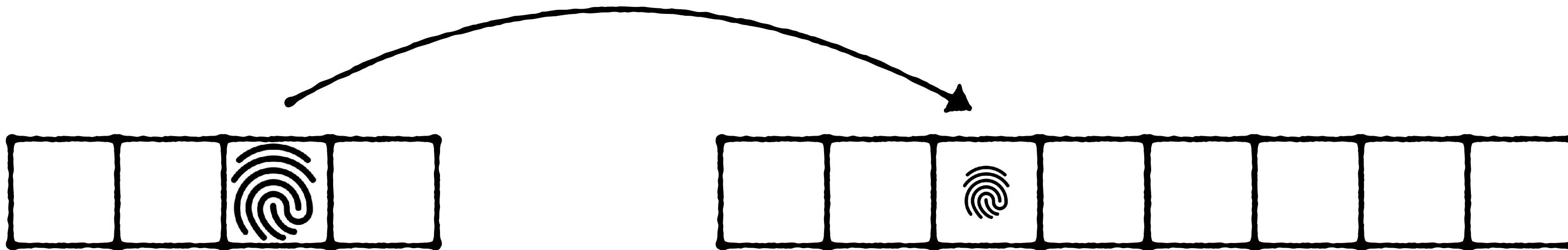
InfiniFilter



Variable-sized fingerprints

InfiniFilter

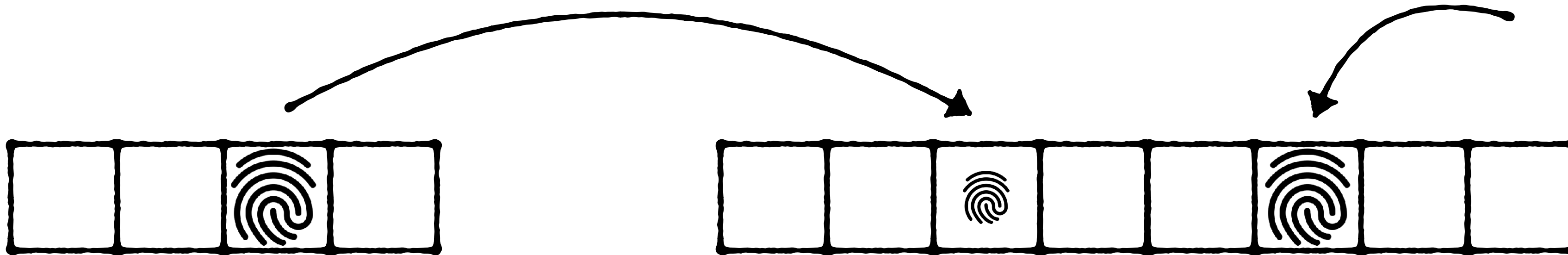
**(1) sacrifice one bit
during expansion**



InfiniFilter

(1) sacrifice one bit
during expansion

**(2) Newer entries get
longer fingerprints**



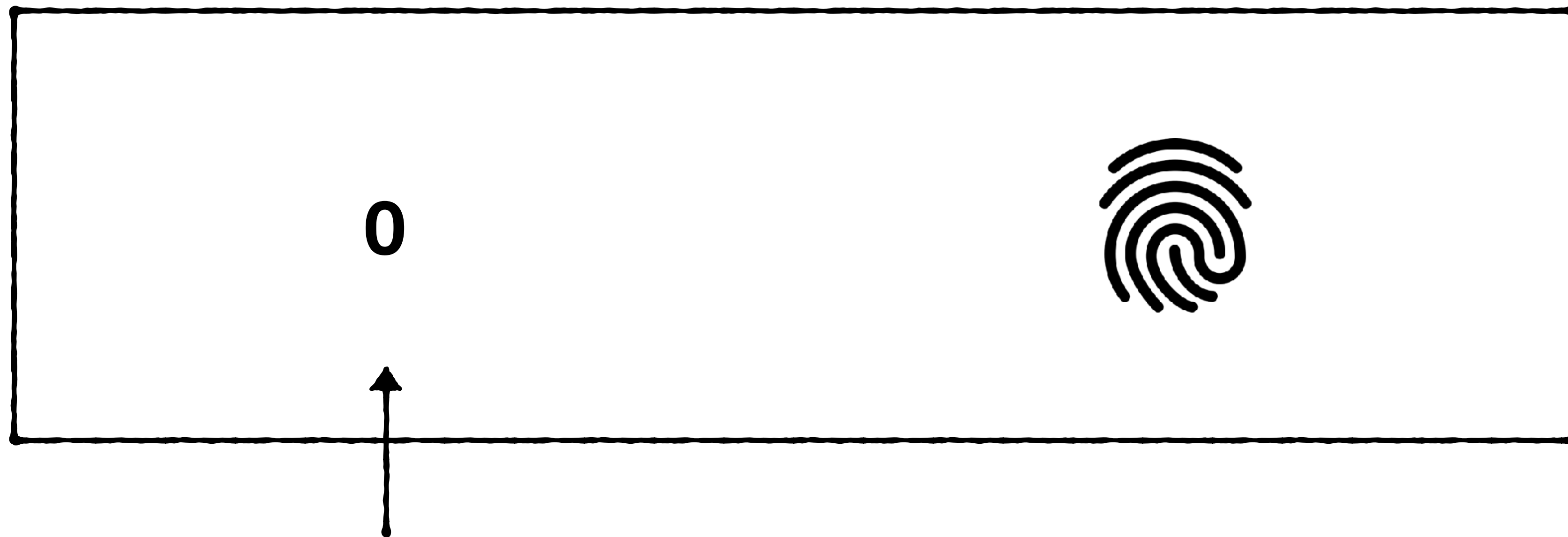
Unary age counter

Fingerprint



Unary age counter

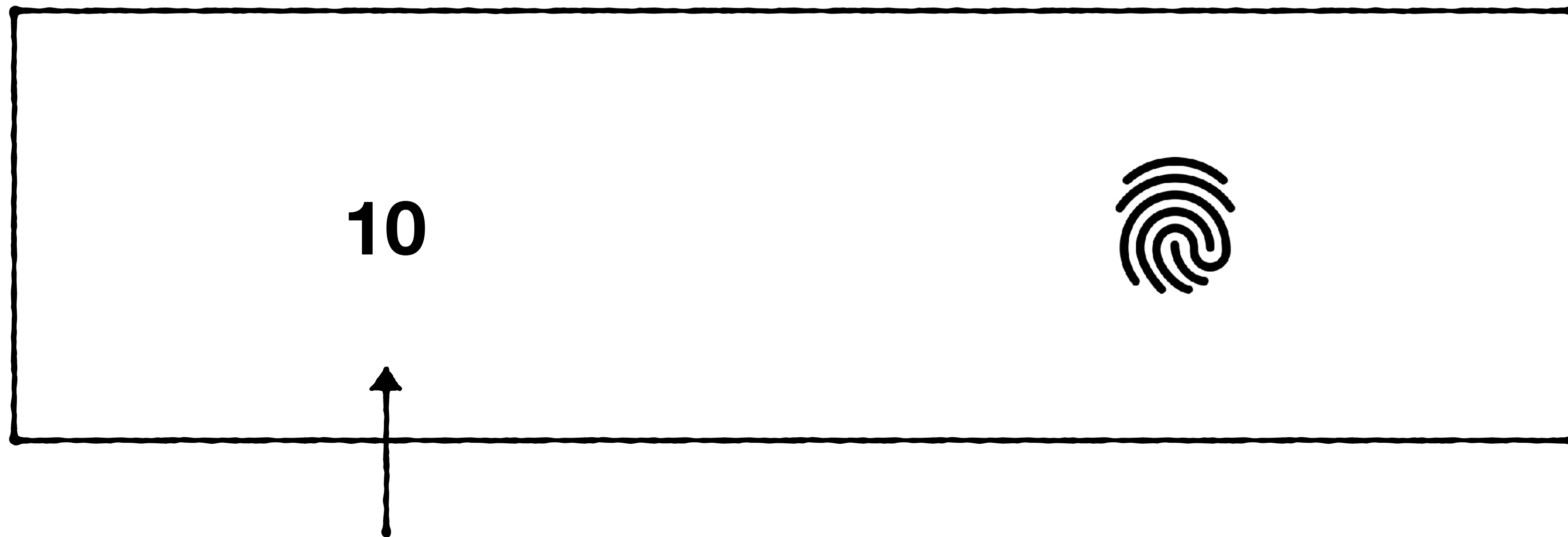
Fingerprint



0 expansions ago

Unary age counter

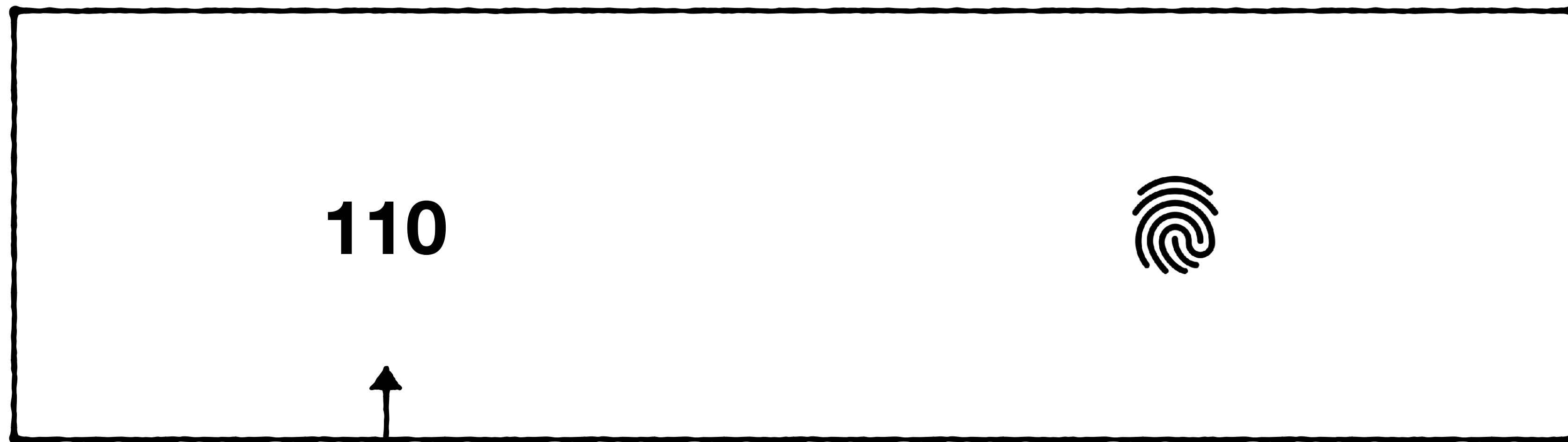
Fingerprint



1 expansions ago

Unary age counter

Fingerprint



2 expansions ago

Unary age counter

Fingerprint

110



Delimiter



Unary age counter

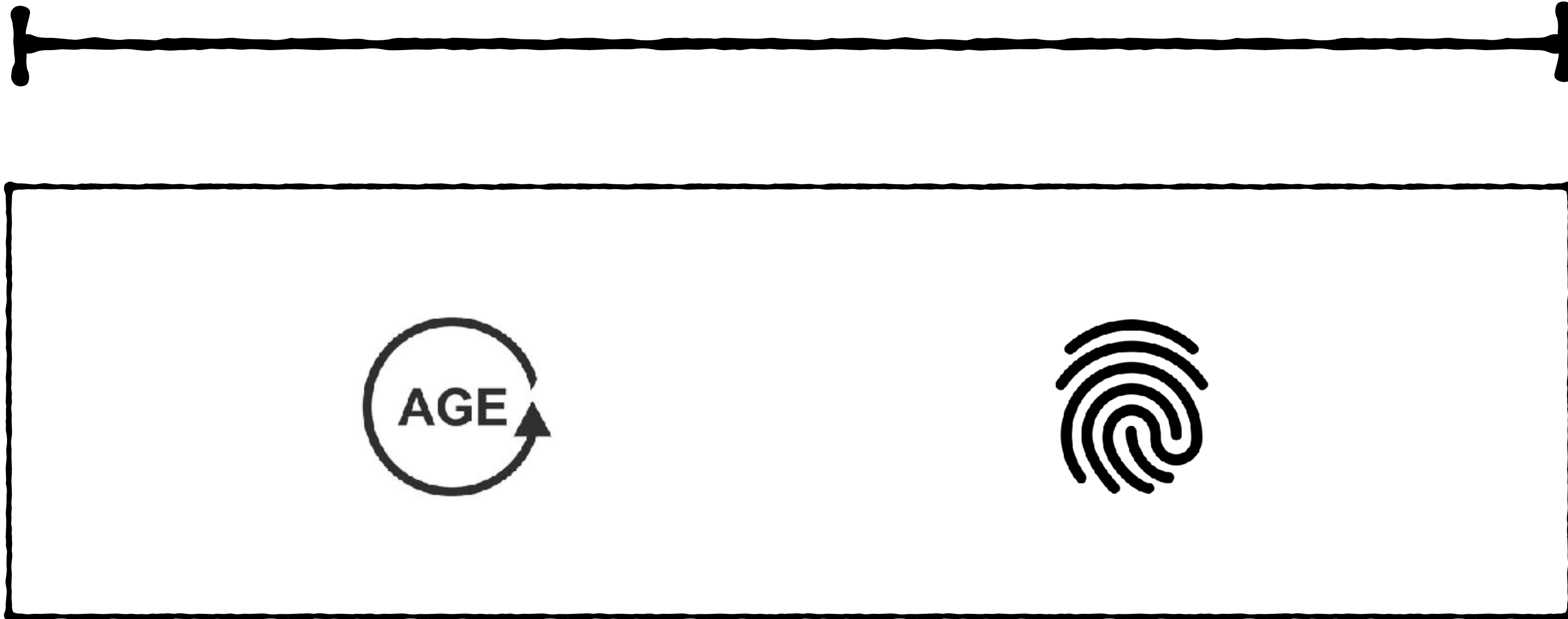
Fingerprint

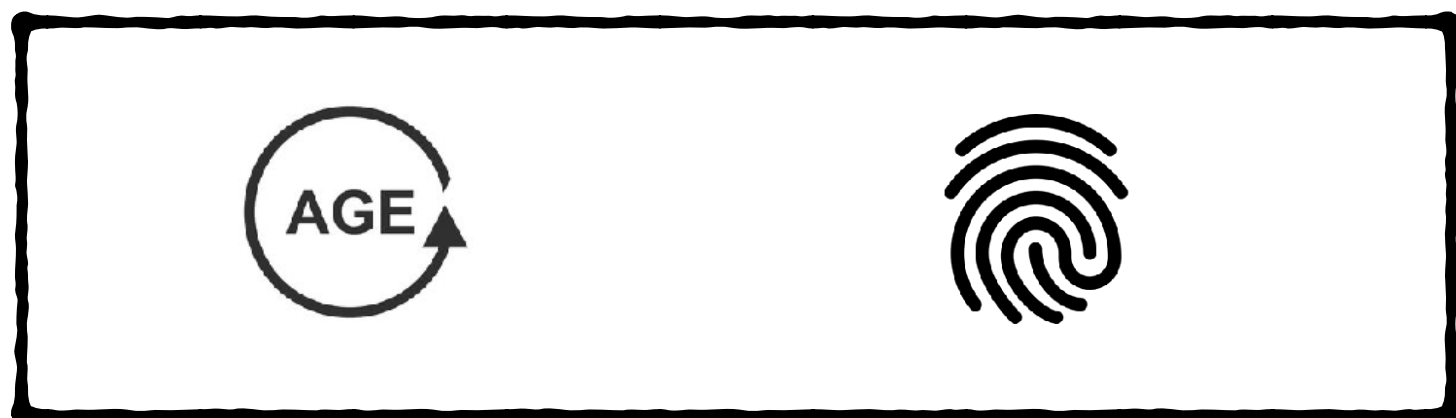
110



All remaining slot bits

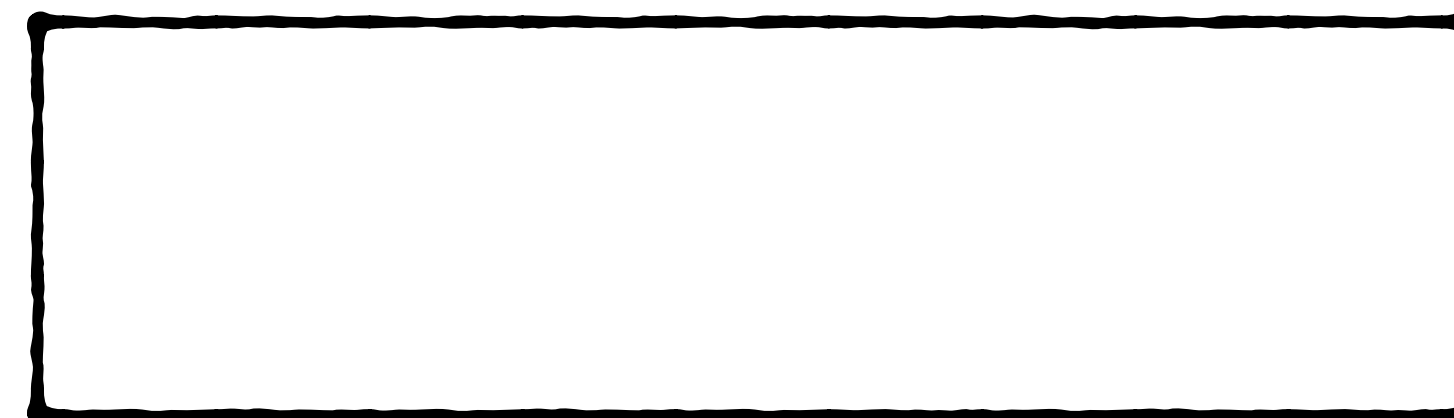
Fixed-length

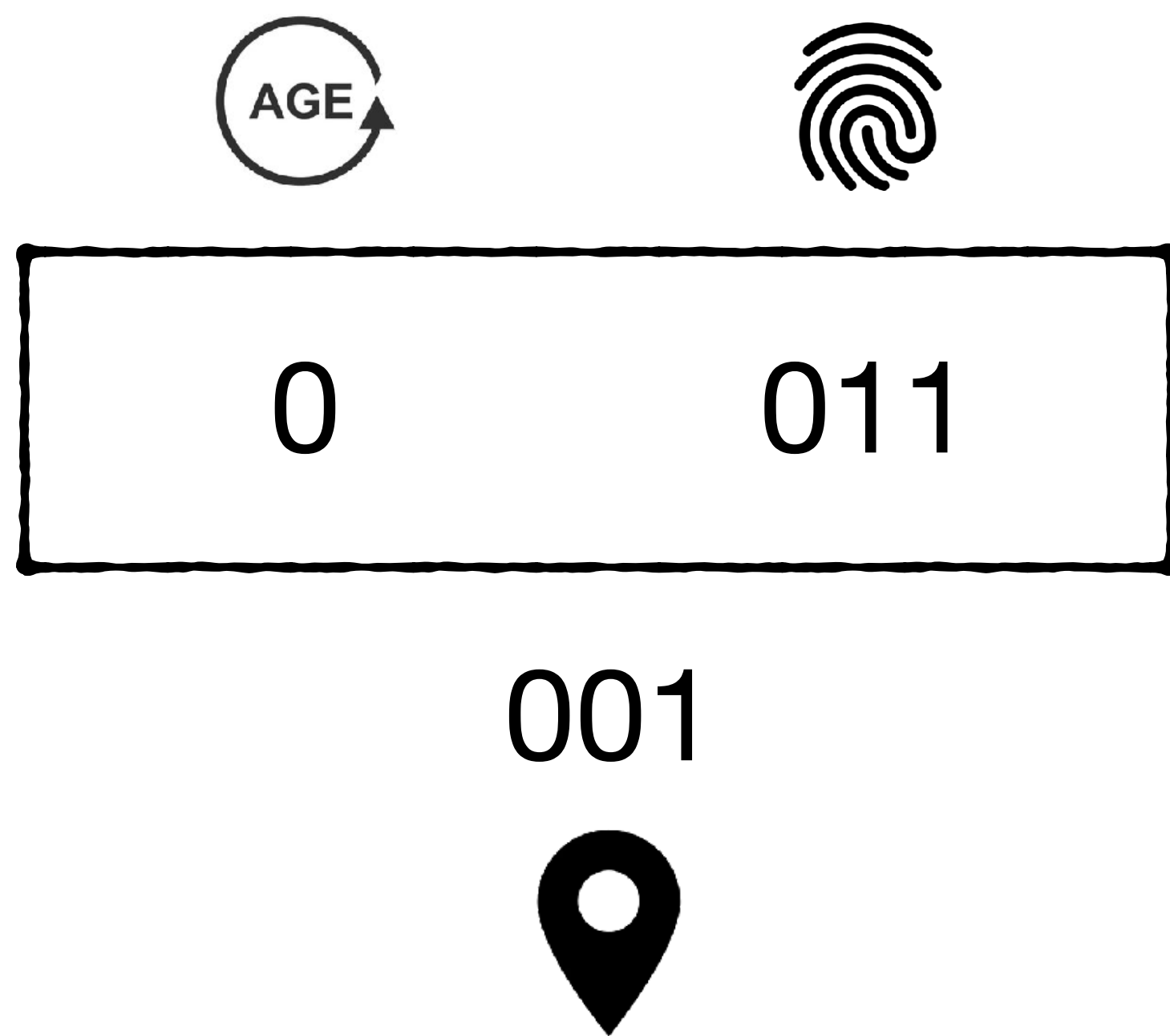




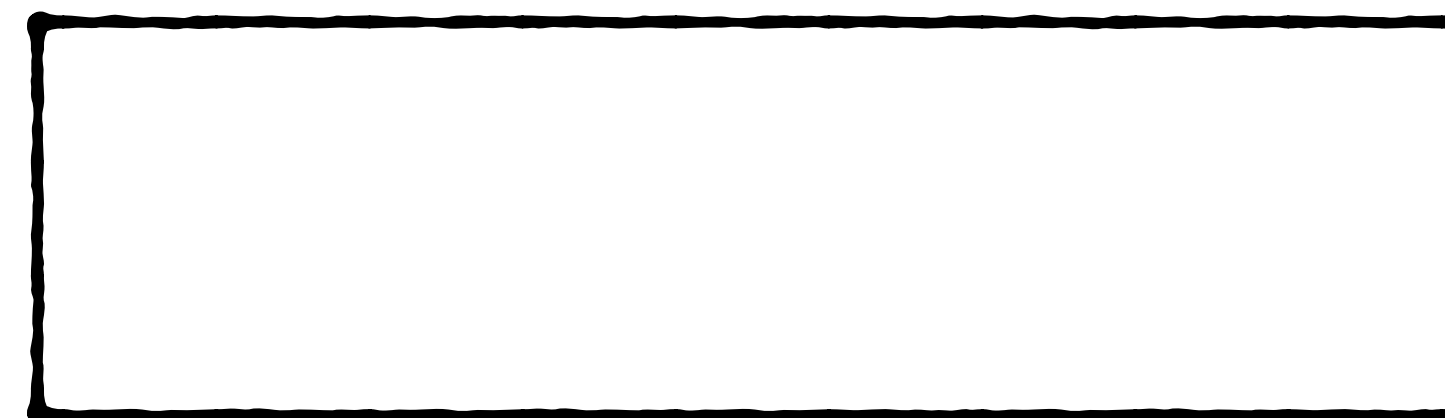
Expansion

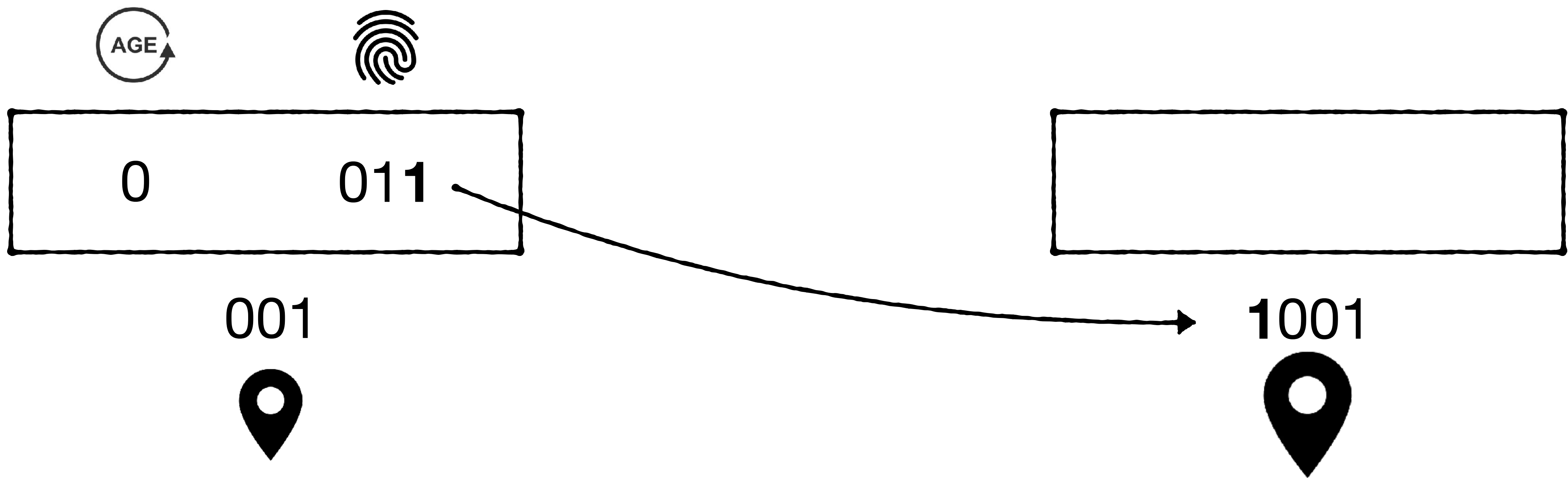
A horizontal arrow pointing from the left box to the right box, with the word "Expansion" written above it.

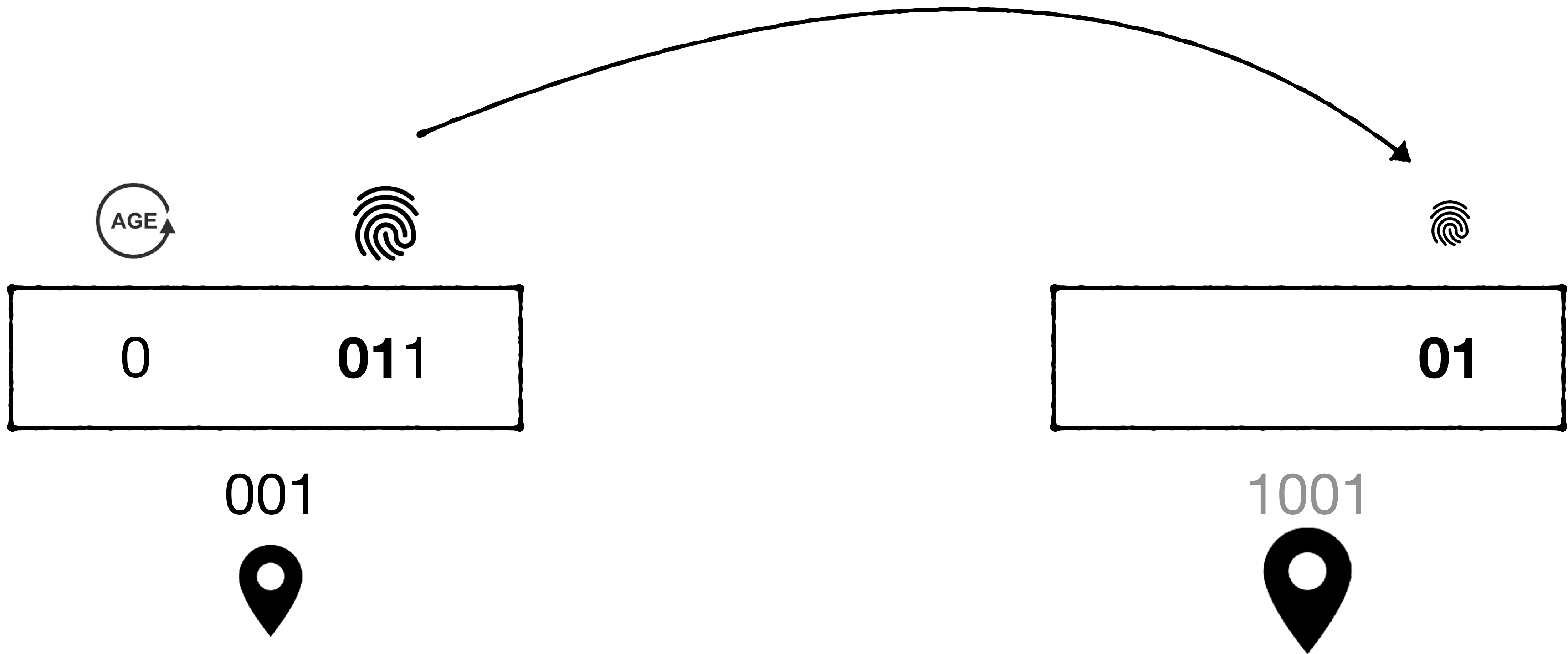


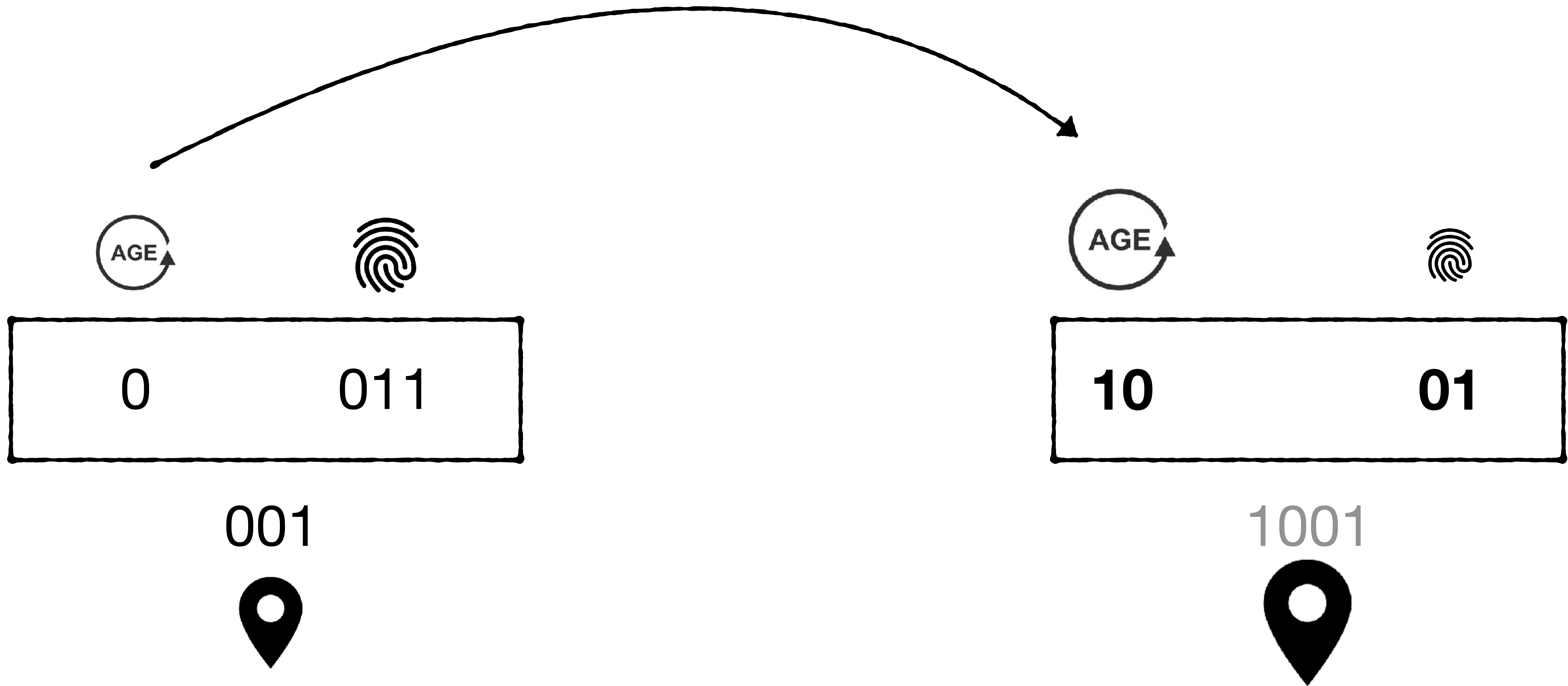


Expansion →

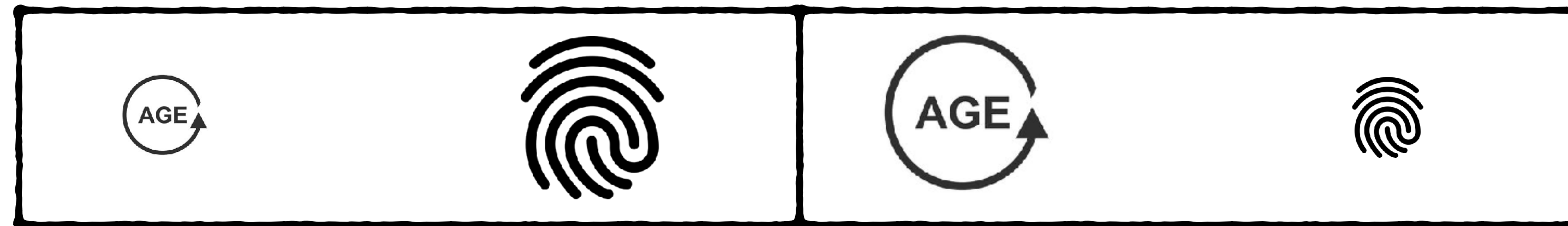




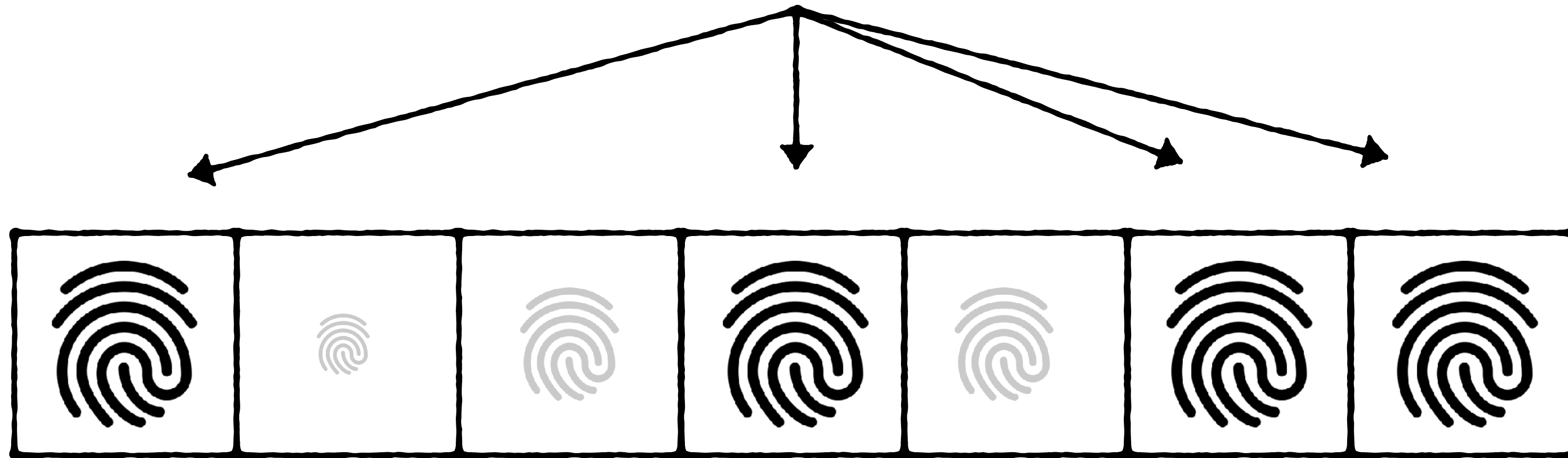




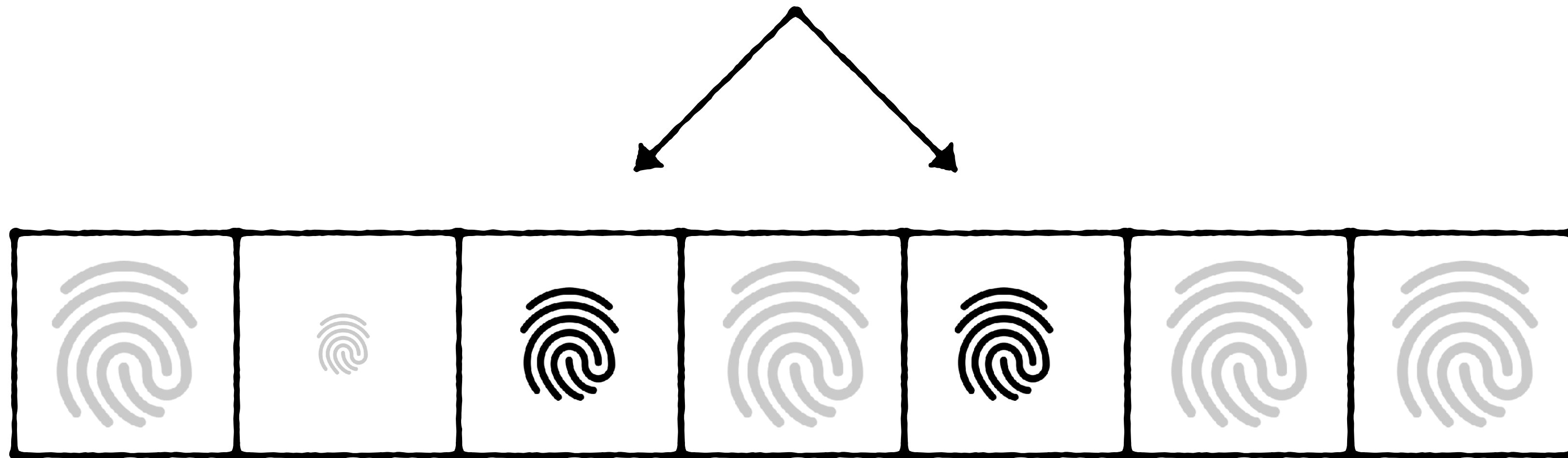
**Longer fingerprints can be inserted
after expansion**



Half of entries have F bit fingerprints



Quarter have $F-1$ bit fingerprints



Eighth have $F-2$ bit fingerprints






weighted false positive rate $\approx \log_2(N) \cdot 2^{-F}$



$$\text{false positive rate} = \log_2(N) \cdot 2^{-M/N} < N \cdot 2^{-M/N}$$

**with quotient
filter**

Query()



fetch  ↓



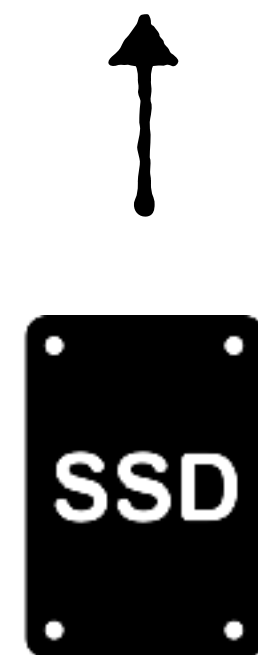


**Rehash() &
rejuvenate
fingerprint**





Rehash() &
rejuvenate
fingerprint



FPR

$$\log N \cdot 2^{-M/N} \longrightarrow 2^{-M/N}$$

Increase slot width at rate of $\approx 2 \log_2 \log_2 N$



$$\text{FPR} \approx \log N \cdot 2^{-M/N}$$



$$\text{FPR} \approx \cancel{\log N} \cdot 2^{-M/N} - 2 \log_2 \log_2 N$$



$$\text{FPR} \approx 2^{-M/N}$$

After F expansions, oldest fingerprints run out of bits





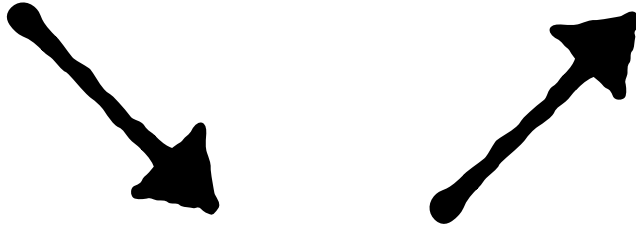
Unary padding occupies whole slot



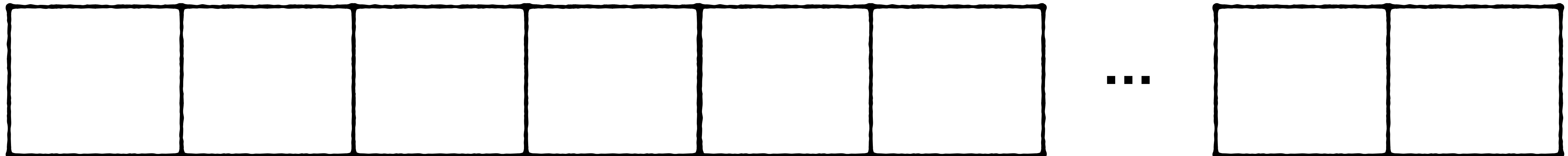
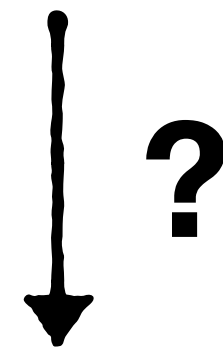
Unary padding occupies whole slot

Any query

Positive

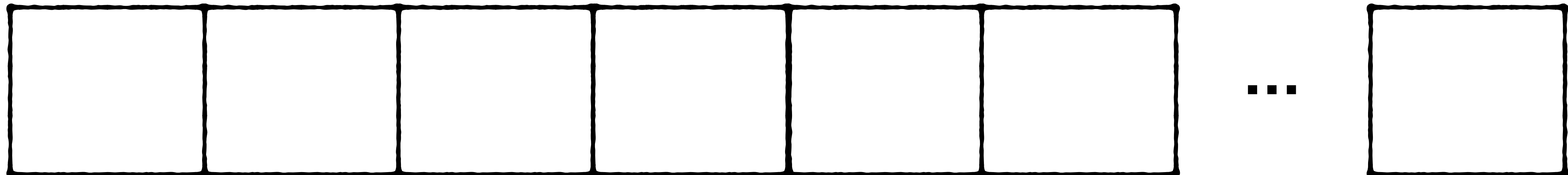
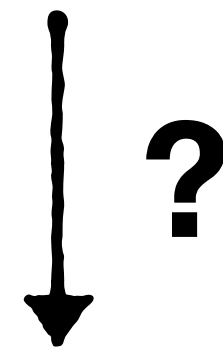
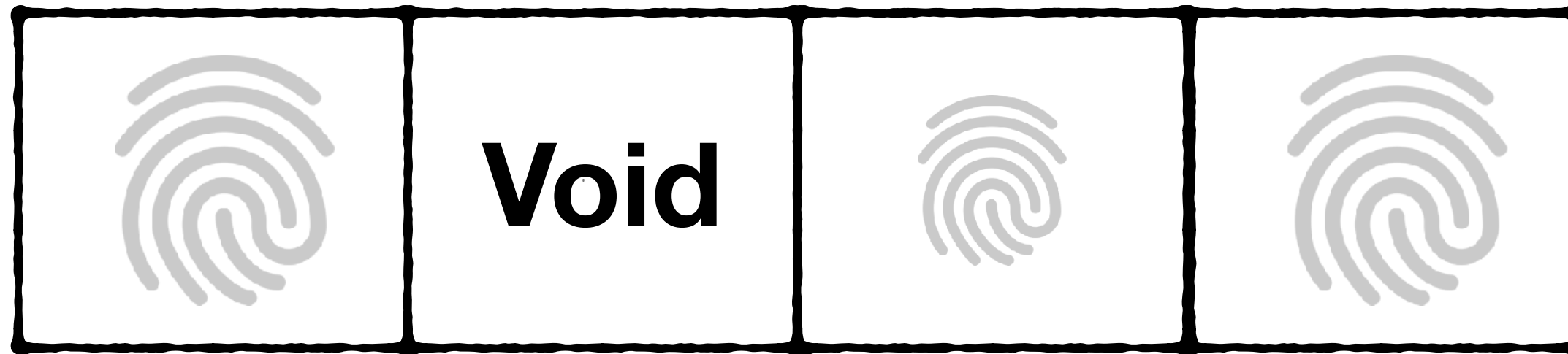


How to continue expanding?

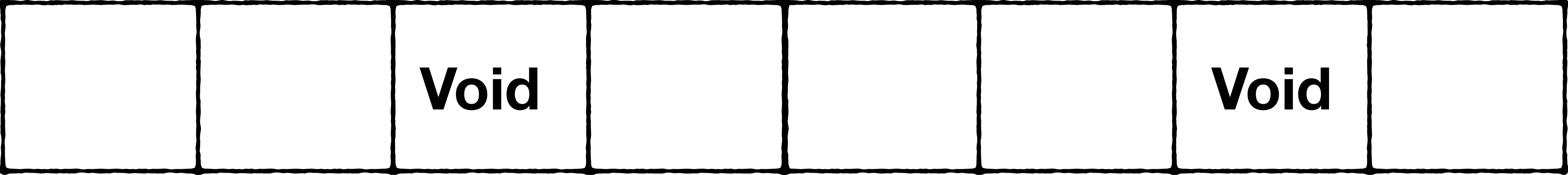
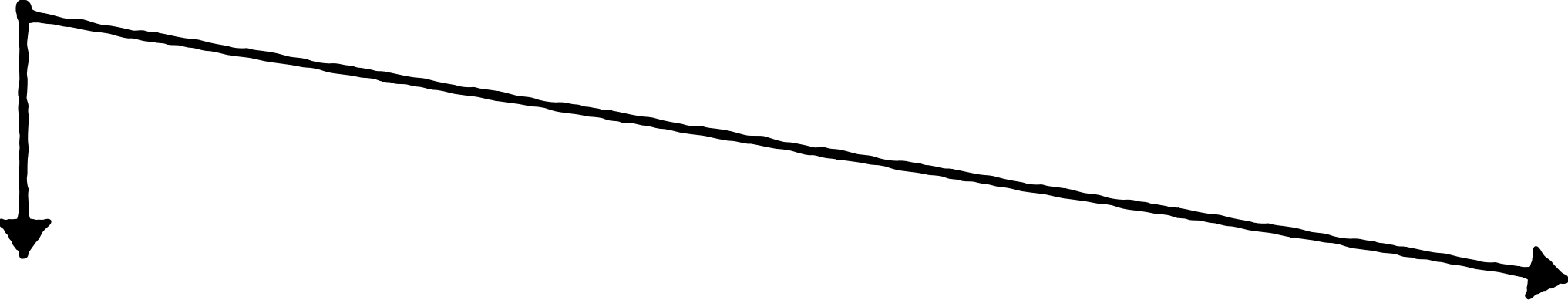
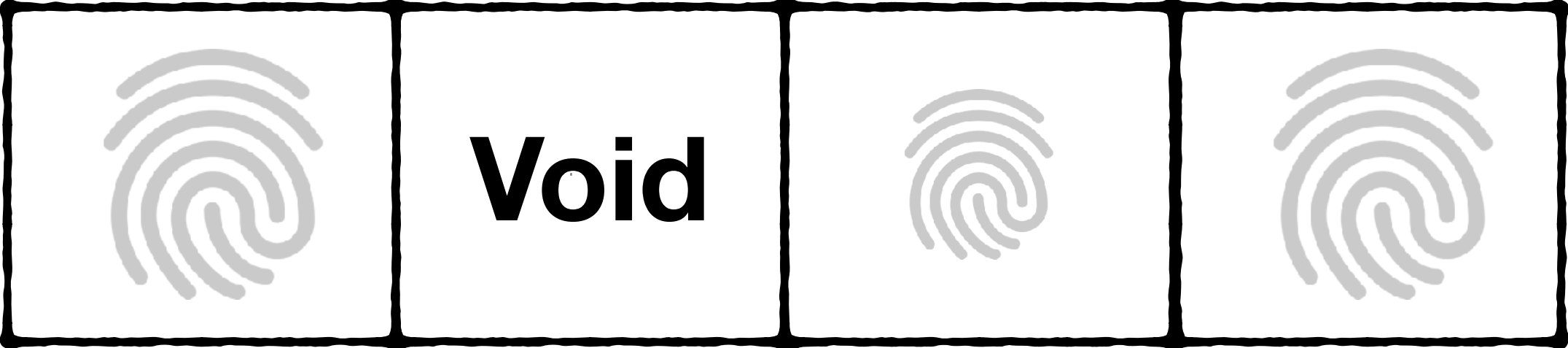


Aleph Filter: To Infinity in Constant Time

Niv Dayan, Ioana Bercea, Rasmus Pagh. VLDB 2024

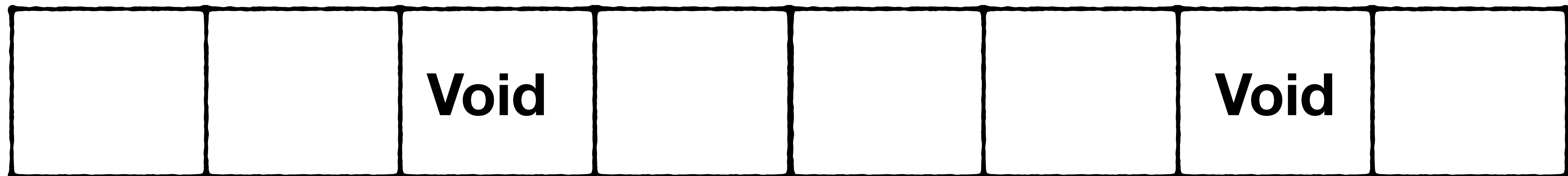
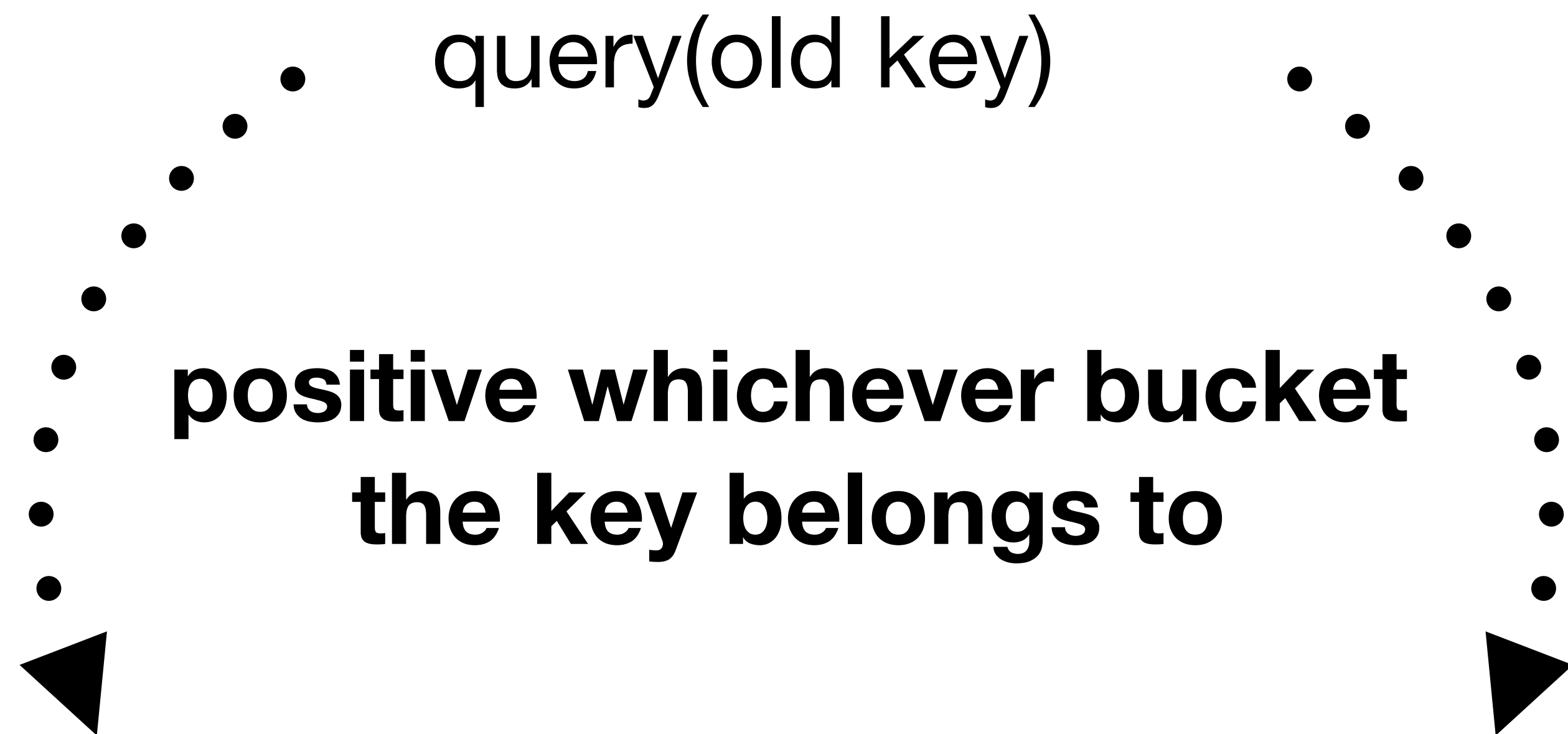


Duplicate

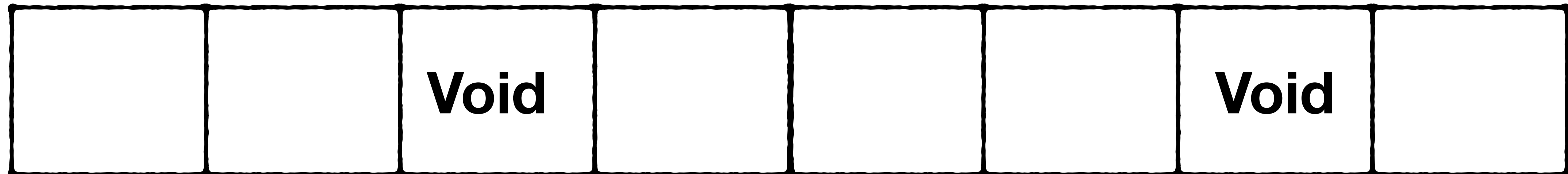
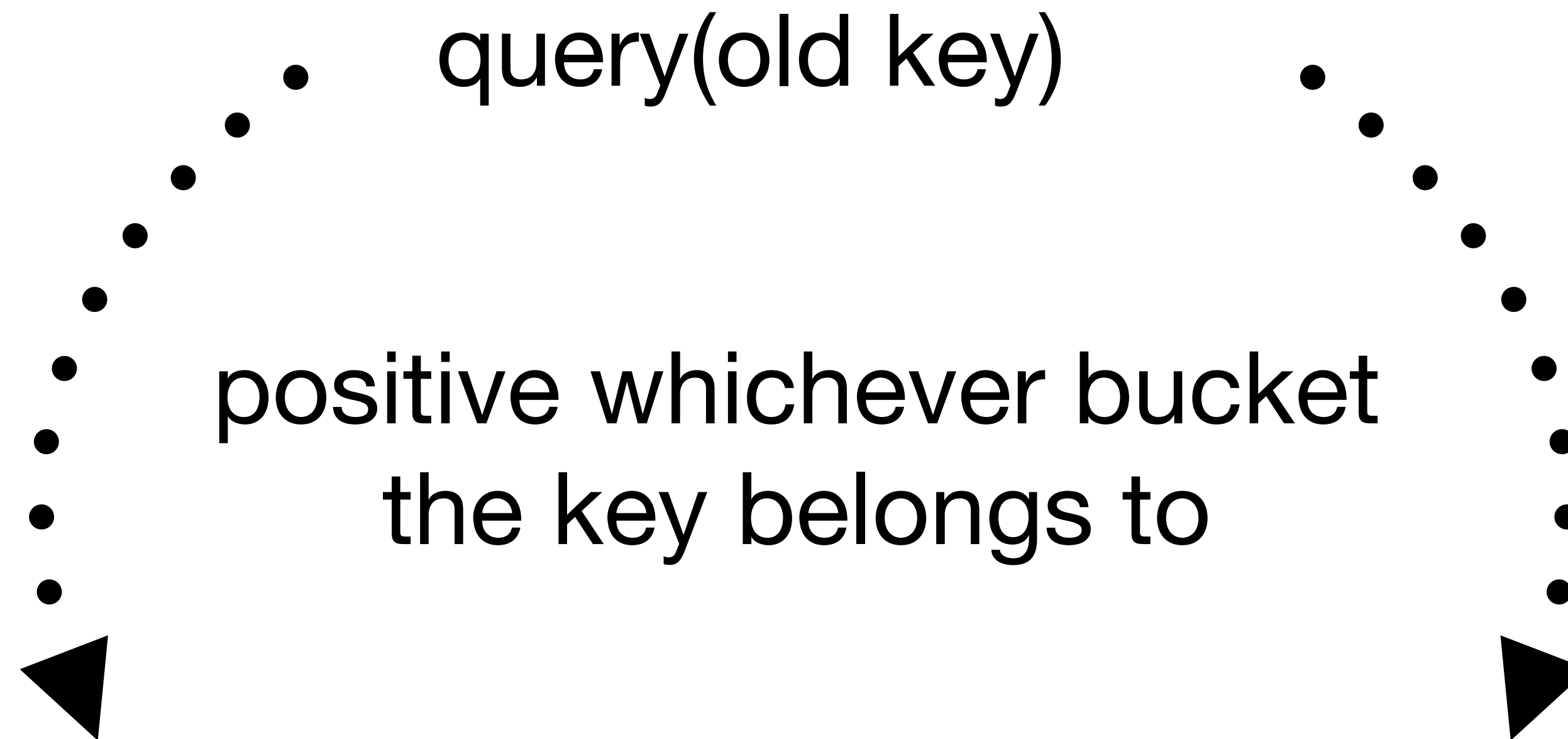


query(old key)

		Void				Void	
--	--	-------------	--	--	--	-------------	--

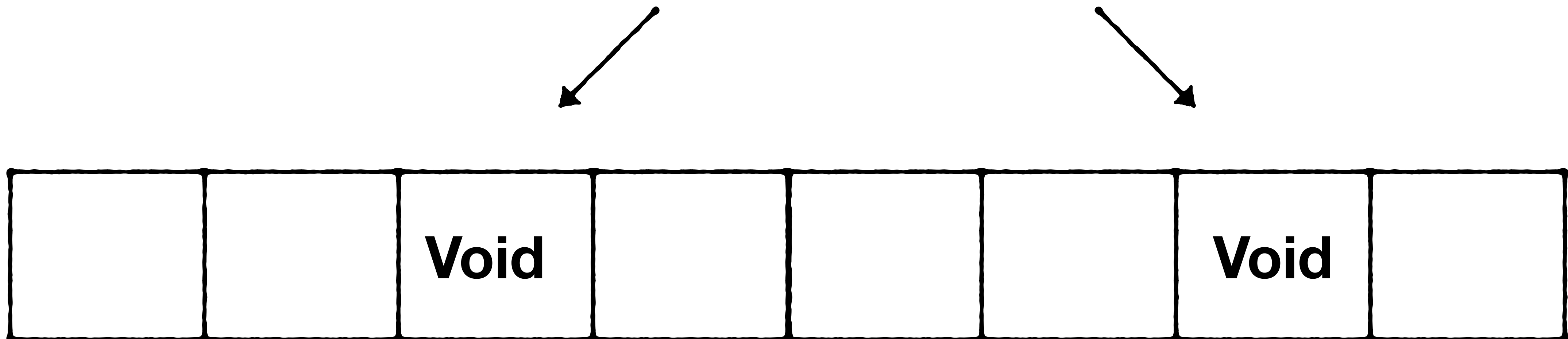


Expand Indefinitely with $O(1)$ performance



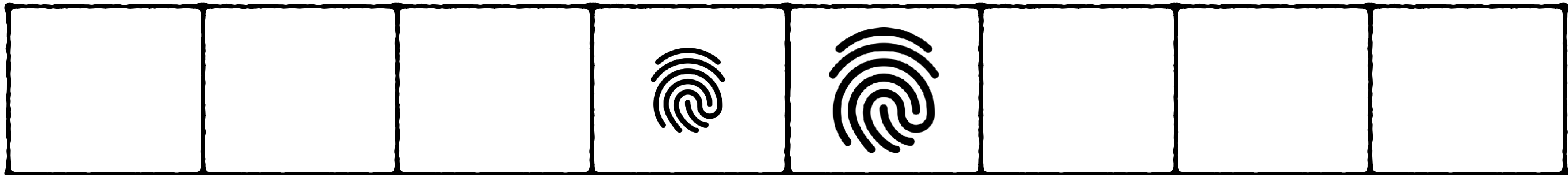
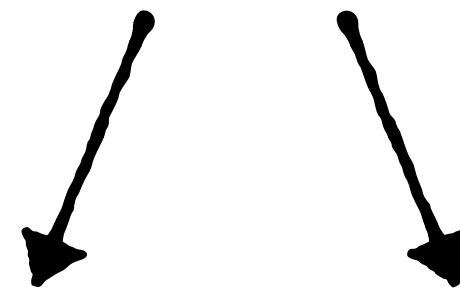
Expandable Filters Complicate Deletes

Identify how many void entries to remove



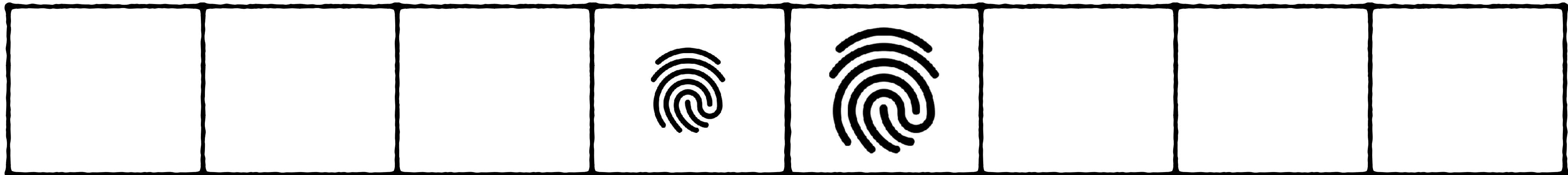
Expandable Filters Complicate Deletes

Multiple fingerprints of diff lengths may match key to delete



Expandable Filters Complicate Deletes

Solutions exist in the papers :)



Thank you!