Tutorial on Indexes & Filters

Database System Technology

Niv Dayan

Who can’t make office hours due to conflicts ?

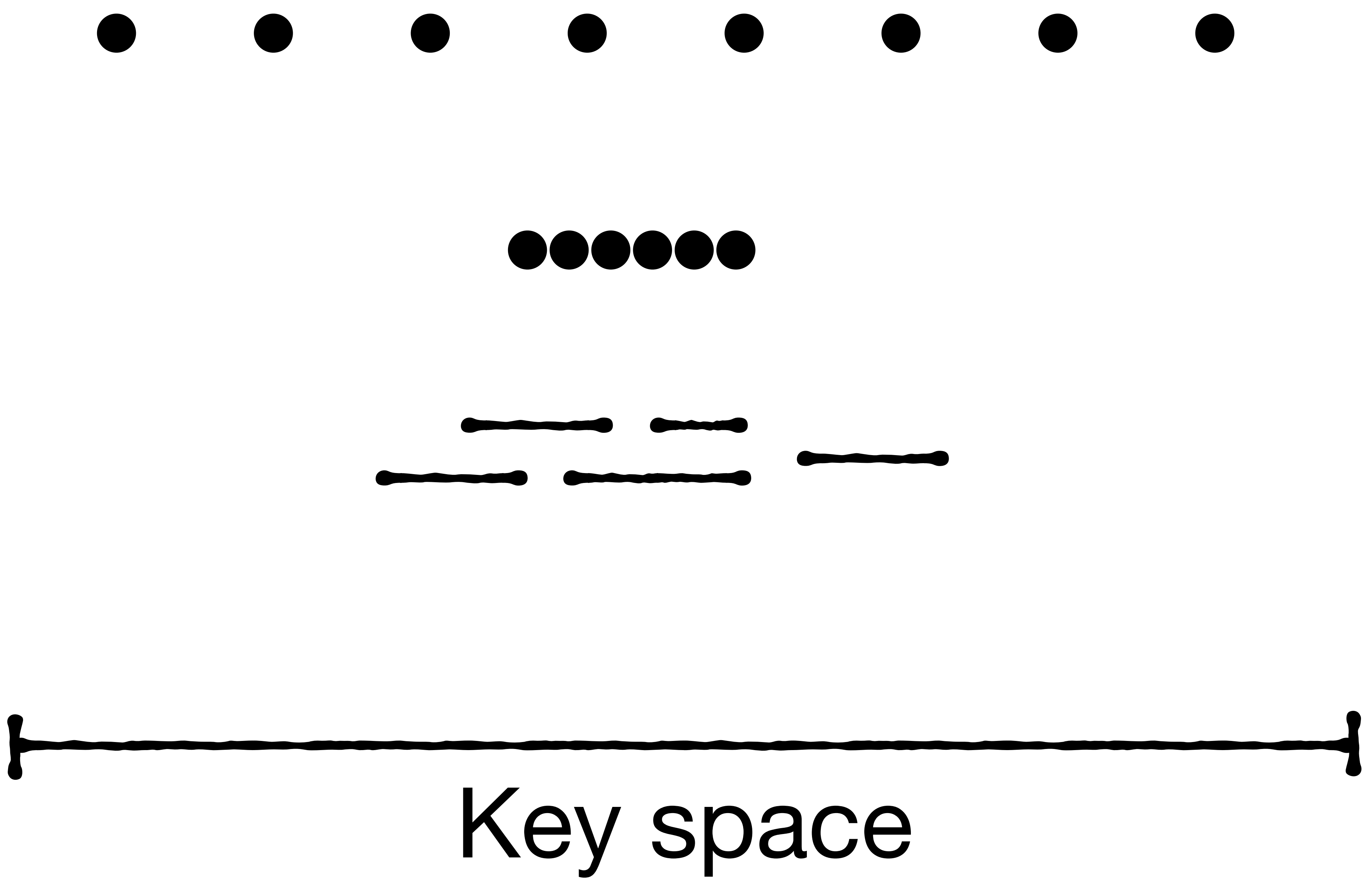
Question 1

Consider an LSM-tree and the three query workloads below. For each workload, comment on the usefulness of having Bloom filters and/or a buffer pool (block cache).

(1) uniformly randomly distributed get queries

(2) get queries with lots of spatial locality

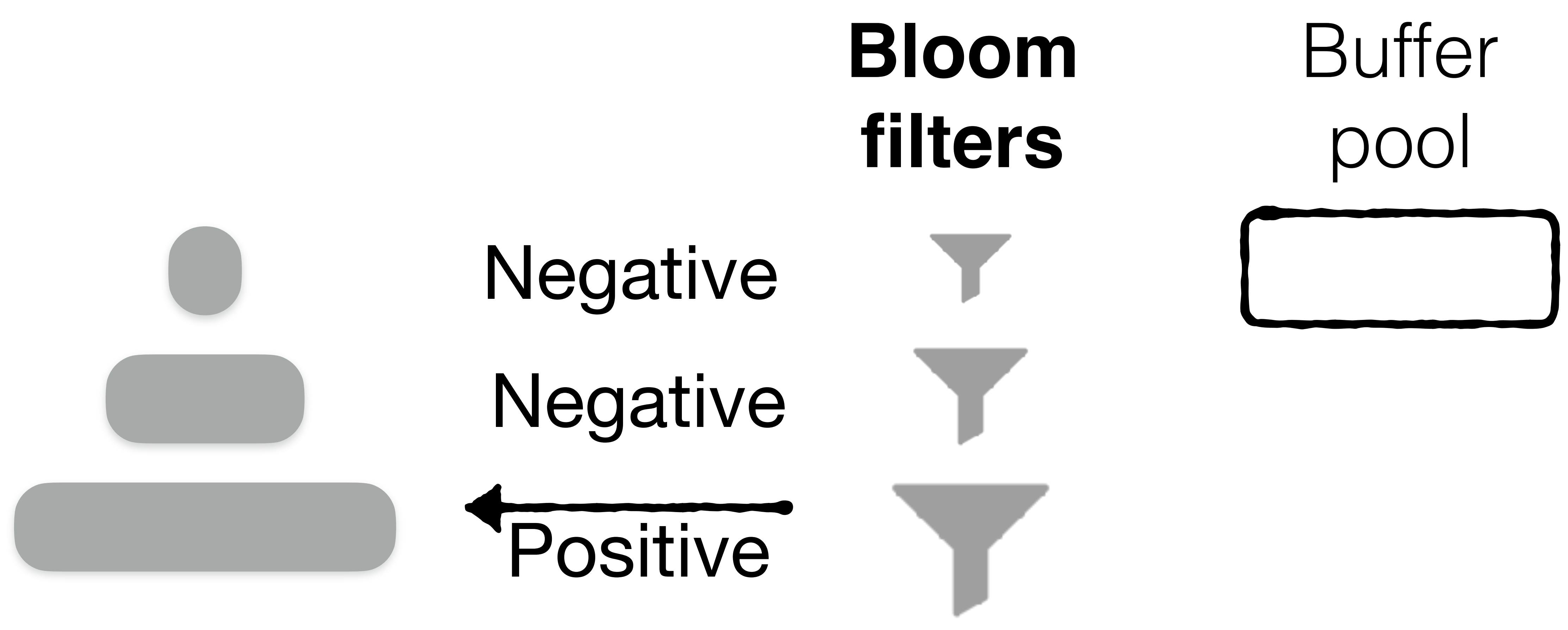
(3) scan queries with lots of spatial locality



Question 1

Consider an LSM-tree and the three query workloads below. For each workload, comment on the usefulness of having Bloom filters and/or a buffer pool (block cache).

(1) uniformly randomly distributed get queries • • • • • • • •



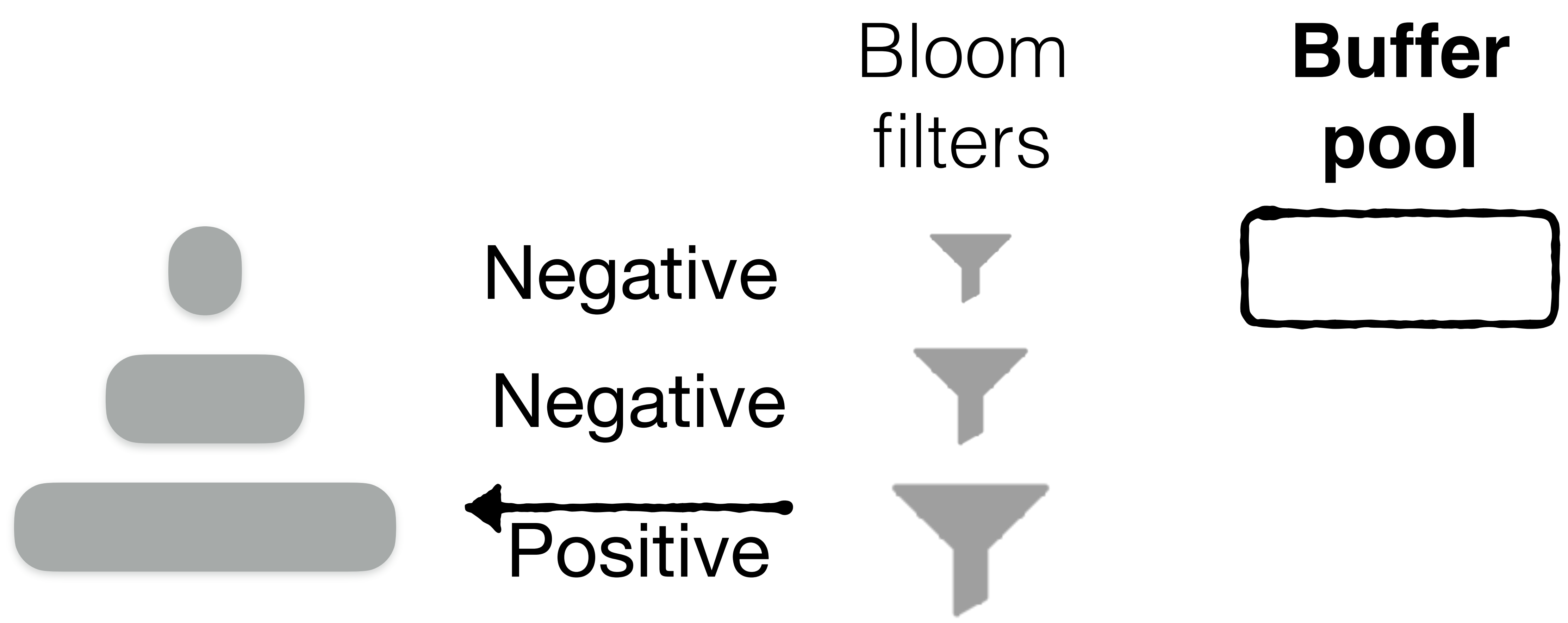
Data recently accessed isn't more likely be accessed again, so a buffer pool isn't so useful, unless it is large enough to fit a high percentage of the data.

In contrast, Bloom filters eliminate storage accesses that do not retrieve the target entry, so they help a lot.

Question 1

Consider an LSM-tree and the three query workloads below. For each workload, comment on the usefulness of having Bloom filters and/or a buffer pool (block cache).

(2) get queries with lots of spatial locality



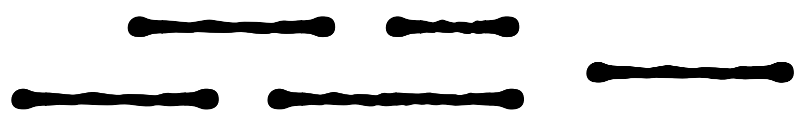
A buffer pool is very useful here to keep hot data pages in memory.

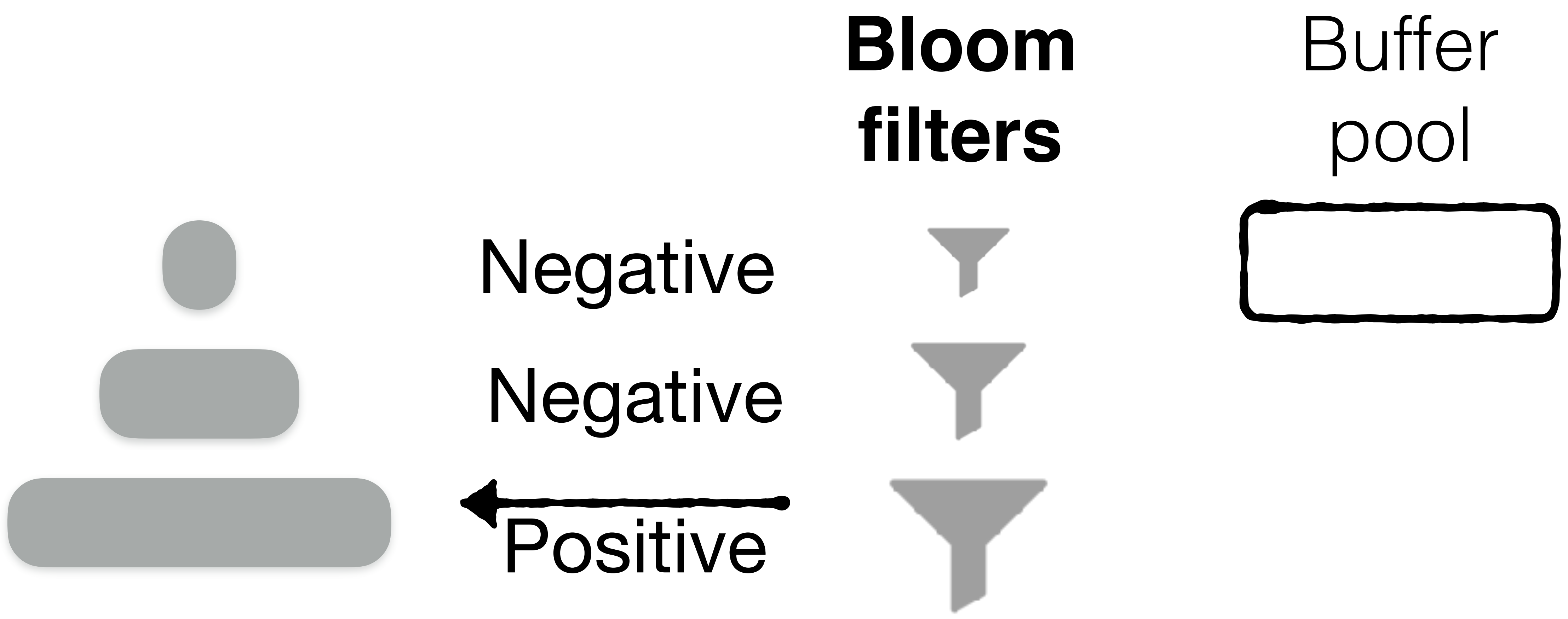
If the working set does not fit entirely in memory, the Bloom filters would also help by fetching data into memory using fewer I/Os.

Question 1

Consider an LSM-tree and the three query workloads below. For each workload, comment on the usefulness of having Bloom filters and/or a buffer pool (block cache).

(3) scan queries with lots of spatial locality





A buffer pool is also useful to keep hot scanned data pages in memory.

The Bloom filters do not help at all as they do not support range queries.

Question 2

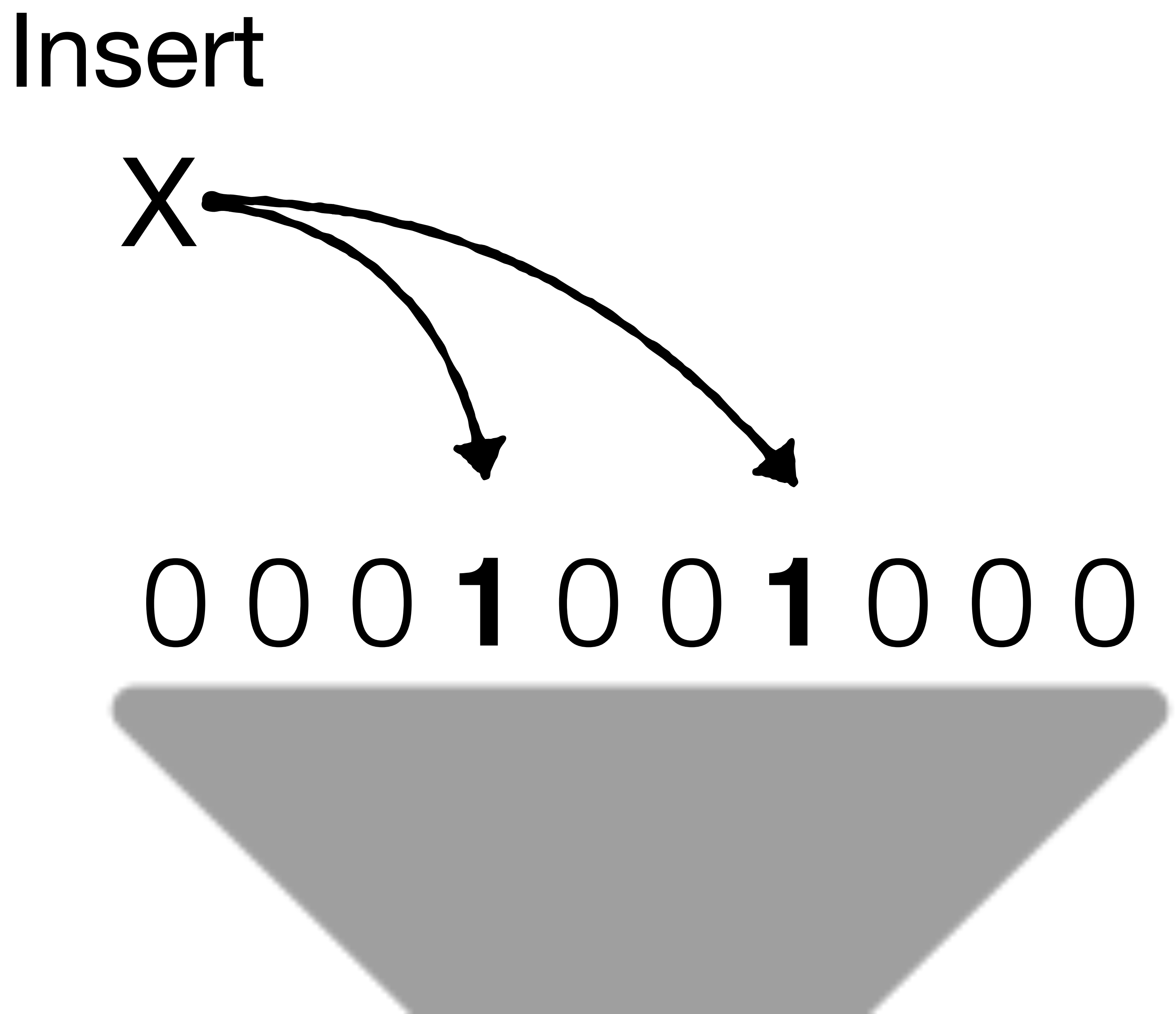
Can a Bloom filter handle deletes? Why or why not?

0 0 0 0 0 0 0 0 0 0

Question 2

Can a Bloom filter handle deletes? Why or why not?

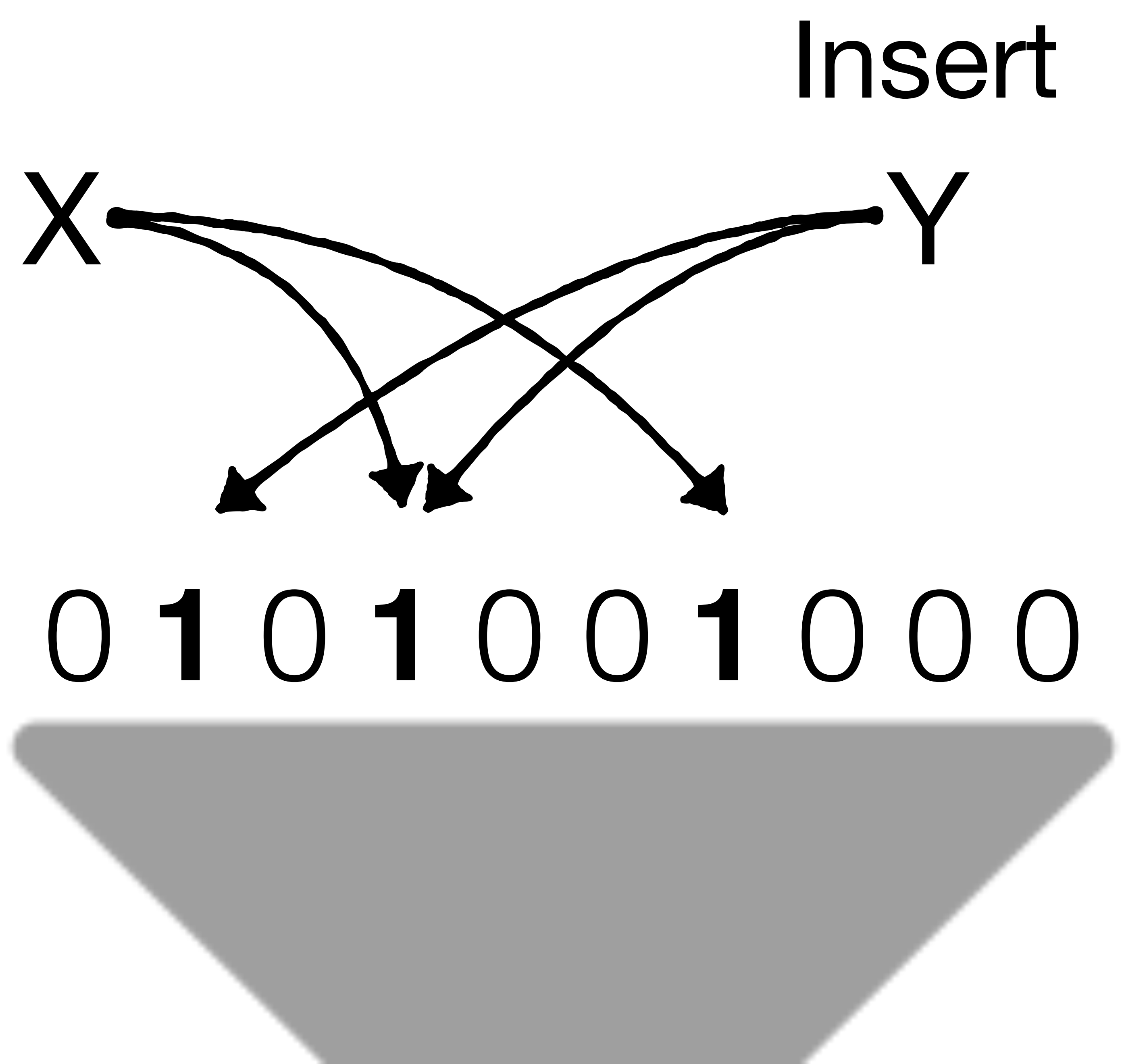
No, as this could lead to false negatives.



Question 2

Can a Bloom filter handle deletes? Why or why not?

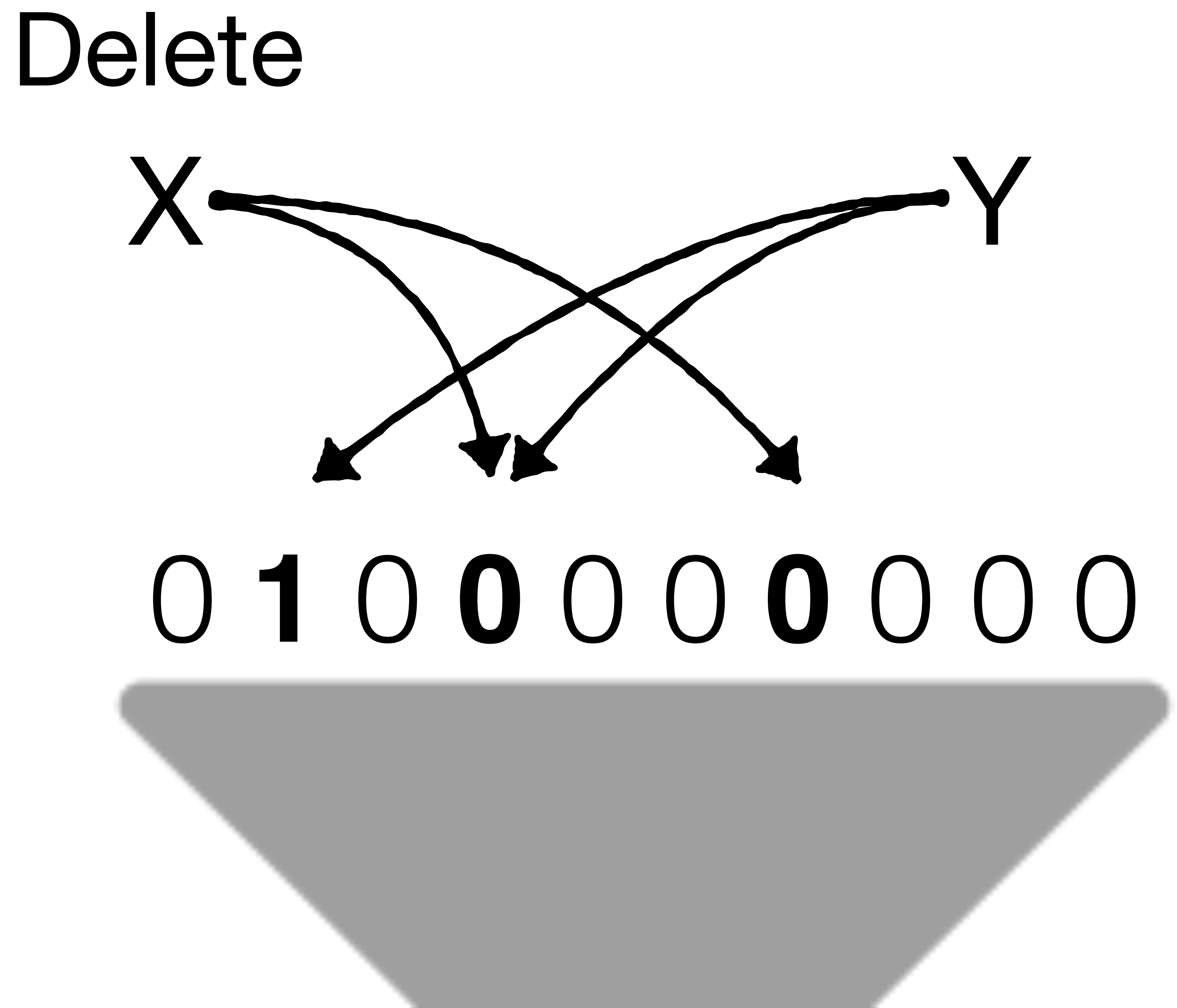
No, as this could lead to false negatives.



Question 2

Can a Bloom filter handle deletes? Why or why not?

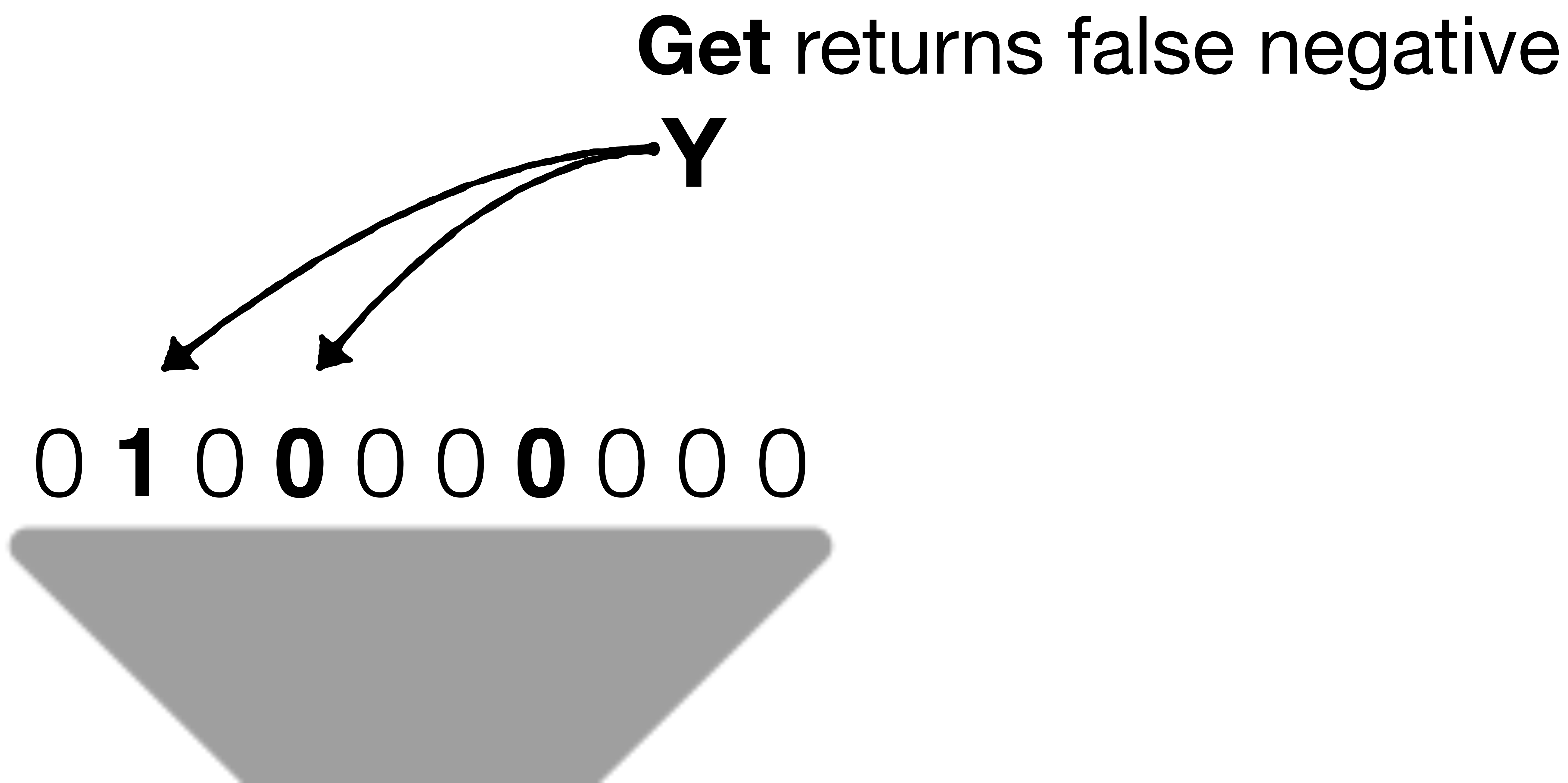
No, as this could lead to false negatives.



Question 2

Can a Bloom filter handle deletes? Why or why not?

No, as this could lead to false negatives.



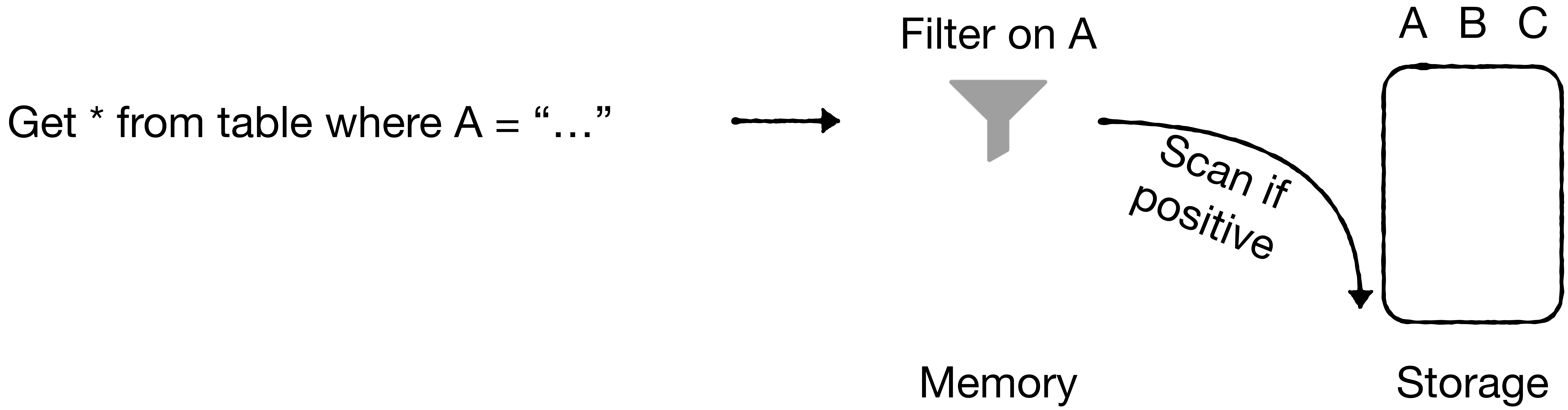
Question 2

Can a Bloom filter handle deletes? Why or why not?

Good exam answer: While it’s possible to set the corresponding bits for a given key from 1’s back to 0’s in a Bloom filter to reflect a deletion, this can lead to false negatives when querying for other keys that had also mapped to at least one of the same bits. This is not acceptable in DB applications as it would lead to data loss (not finding relevant existing data for queries searching for it).

Question 3

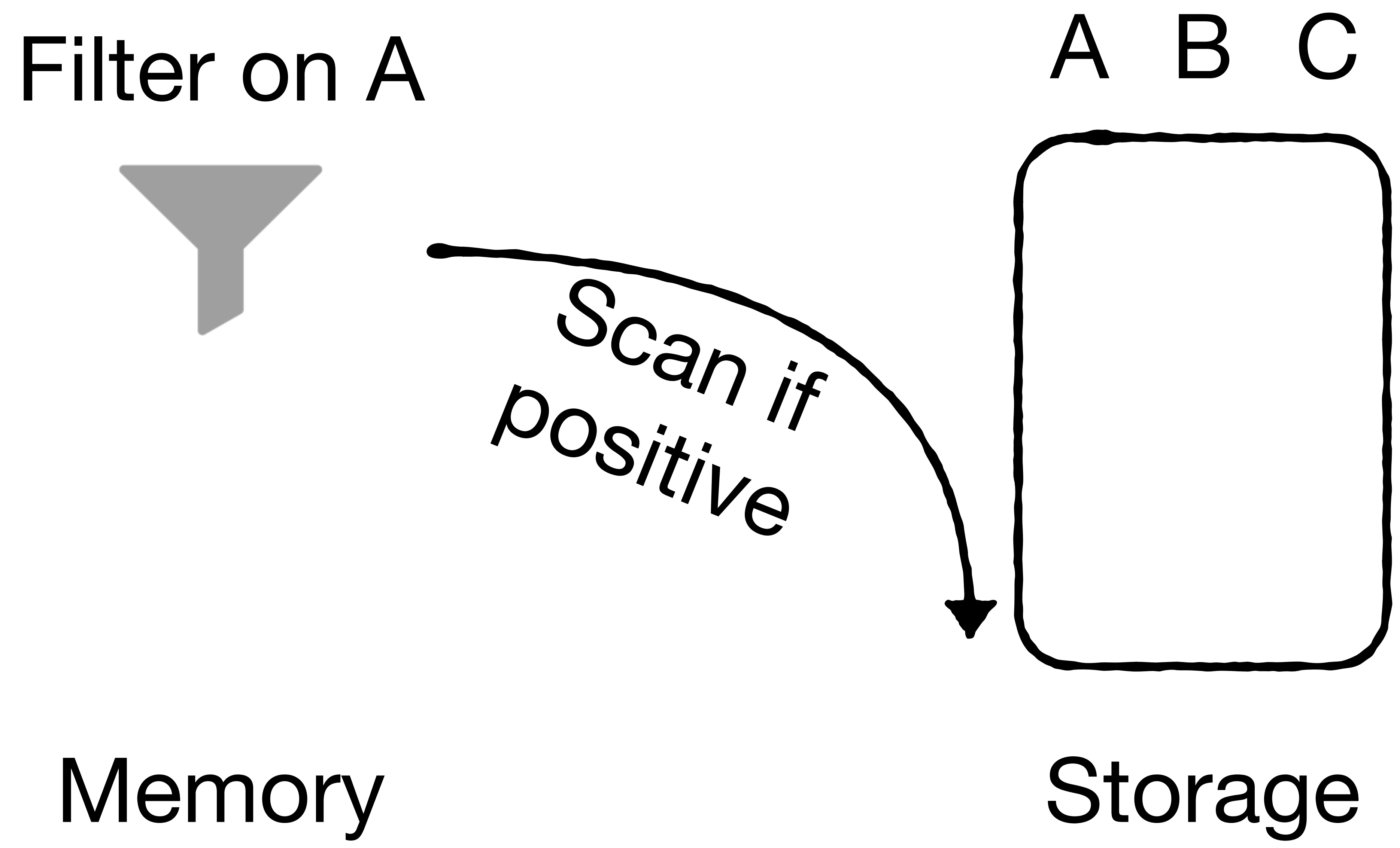
Suppose we apply a Bloom filter on a given column in a DB table. What’s the impact on the filter as more non-unique vs. unique values of A are added. What can be done to address any issues?



Question 3

Suppose we apply a Bloom filter on a given column in a DB table. What's the impact on the filter as more non-unique vs. unique values of A are added. What can be done to address any issues?

Insertions of non-unique values have no effect.

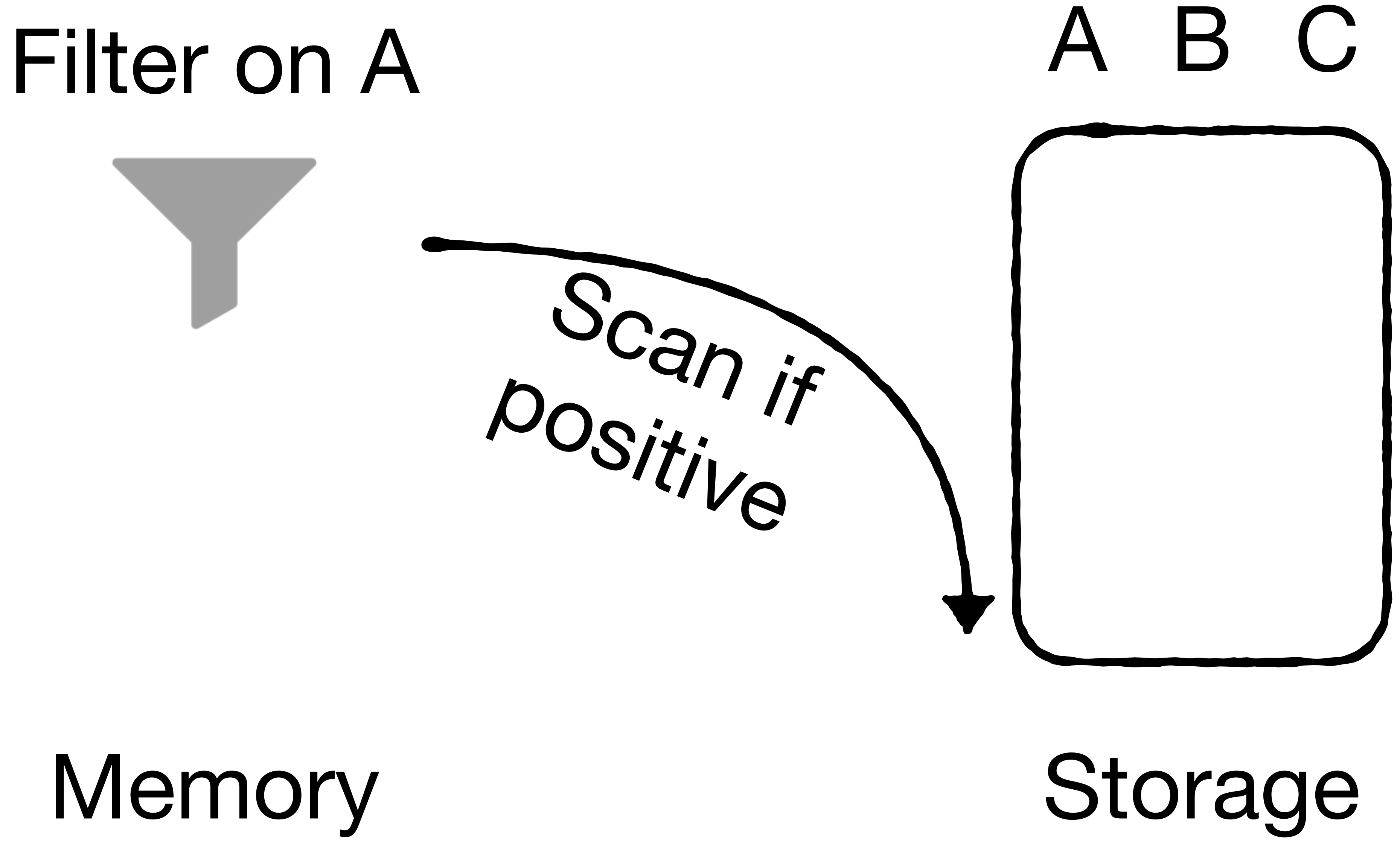


Question 3

Suppose we apply a Bloom filter on a given column in a DB table. What's the impact on the filter as more non-unique vs. unique values of A are added. What can be done to address any issues?

Insertions of non-unique values have no effect.

If more unique values of column A are inserted, the false positive rate for the filter would increase, perhaps beyond our expectation.



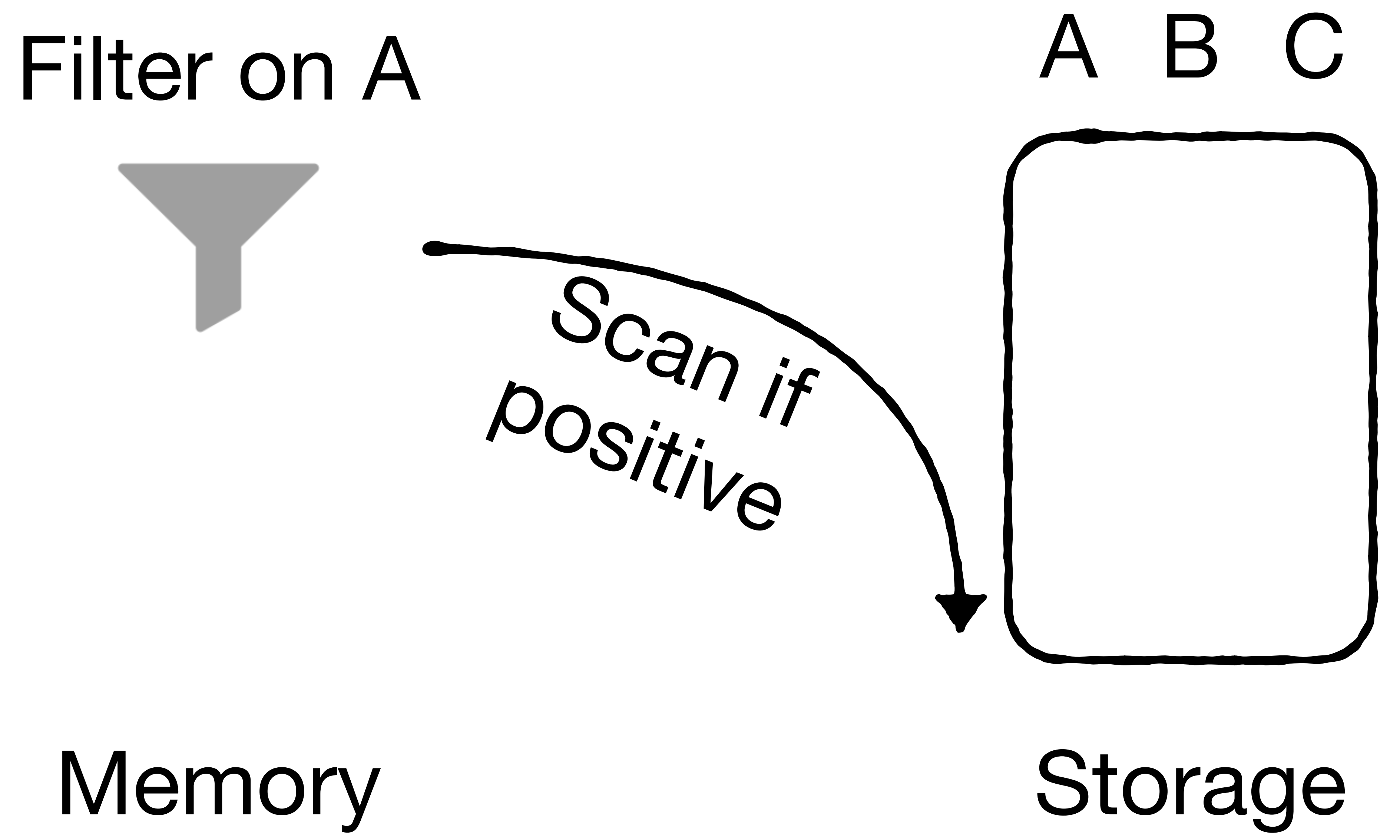
Question 3

Suppose we apply a Bloom filter on a given column in a DB table. What's the impact on the filter as more non-unique vs. unique values of A are added. What can be done to address any issues?

Insertions of non-unique values have no effect.

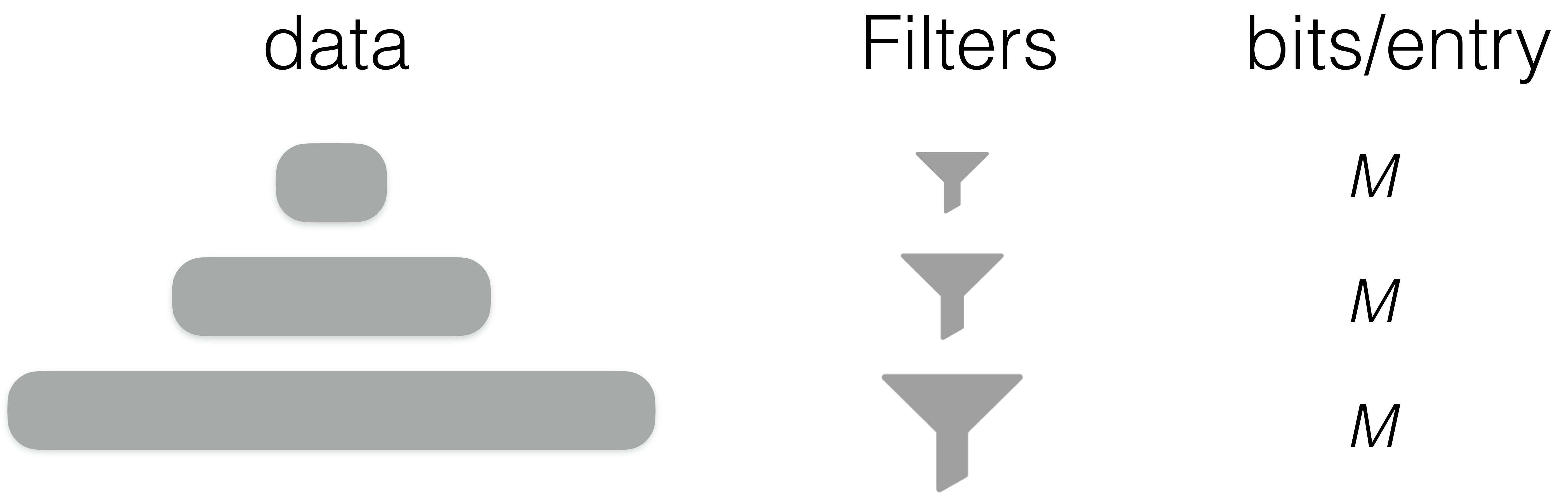
If more unique values of column A are inserted, the false positive rate for the filter would increase, perhaps beyond our expectation.

To compensate, we can rebuild a filter with a larger capacity by scanning the table whenever the FPR crosses some threshold. In fact, we can do this opportunistically while scanning the table to process a query.



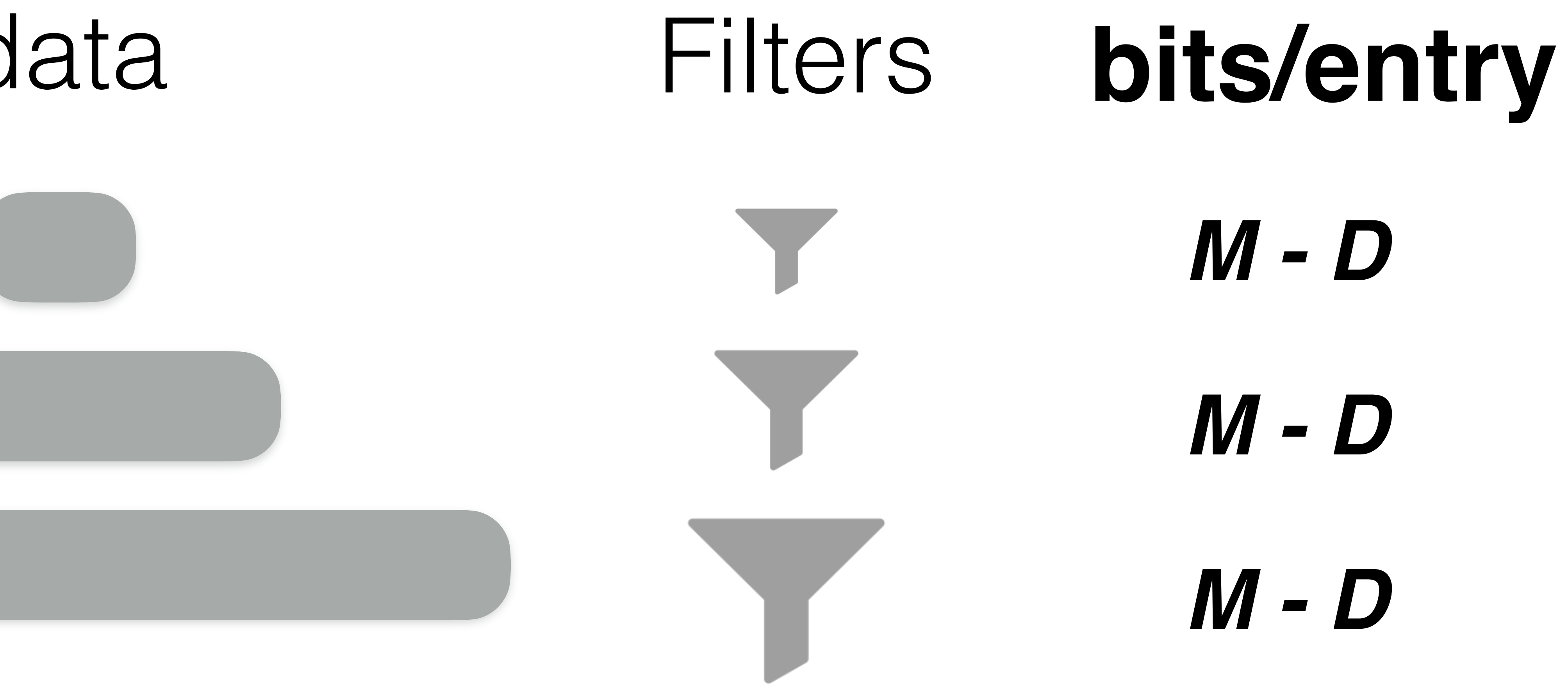
Question 4

We have a leveled LSM-tree with a Bloom filter with M bits/entry for every level. Our query workload consists of point queries to keys that exist, usually at the largest level. Suppose we are near our memory capacity and must free some space used by the filters. Option 1 is to reduce the number of bits/entry for each filter. Option 2 is to drop the filter for the largest level. Compare and contrast these approaches.



Question 4

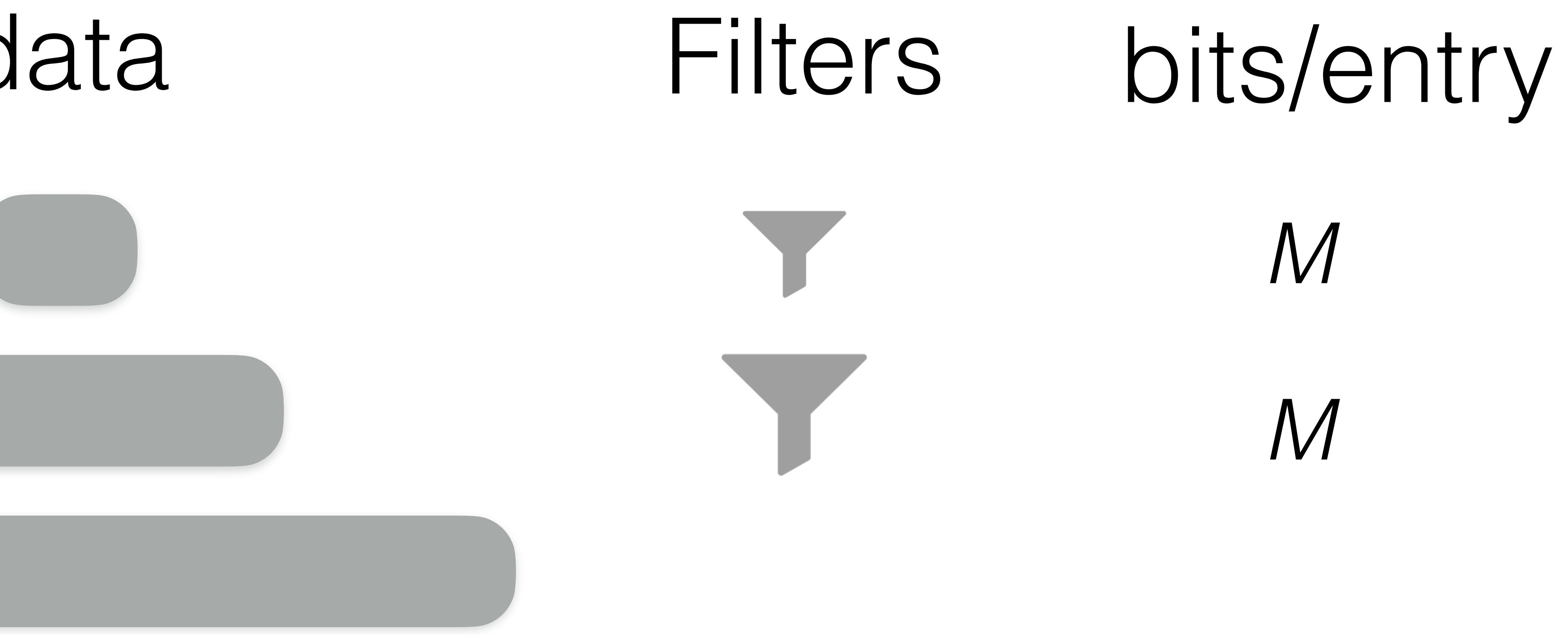
We have a leveled LSM-tree with a Bloom filter with M bits/entry for every level. Our query workload consists of point queries to keys that exist, usually at the largest level. Suppose we are near our memory capacity and must free some space used by the filters. Option 1 is to reduce the number of bits/entry for each filter. Option 2 is to drop the filter for the largest level. Compare and contrast these approaches.



Option 1 would lead to more false positives and thus worse query performance. Furthermore, if we need this change immediately, it requires scanning the data to build new smaller filters.

Question 4

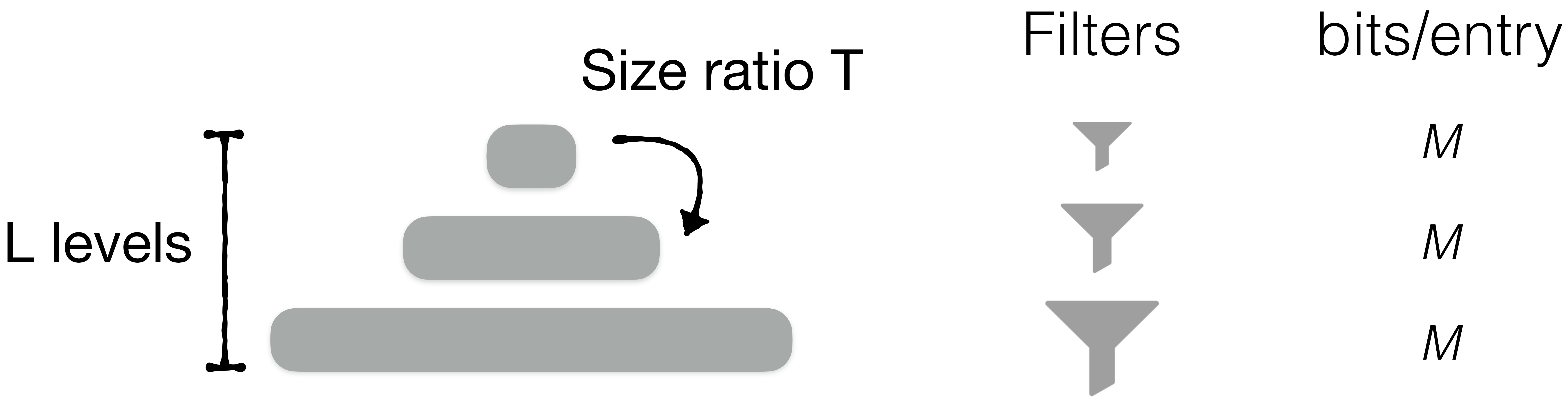
We have a leveled LSM-tree with a Bloom filter with M bits/entry for every level. Our query workload consists of point queries to keys that exist, usually at the largest level. Suppose we are near our memory capacity and must free some space used by the filters. Option 1 is to reduce the number of bits/entry for each filter. Option 2 is to drop the filter for the largest level. Compare and contrast these approaches.



Option 2 would immediately reduce the filters' memory footprint by a factor of T, the size ratio. It would not impact query performance as the largest level's bloom filter only helps with queries to non-existing entries, of which there are none in our workload. This is the better choice.

Question 5

What is the cost of building Bloom filters for a leveled LSM-tree, measured in worst-case memory accesses per insertion? Assume the same number of bits per entry M is assigned to filters at all levels.

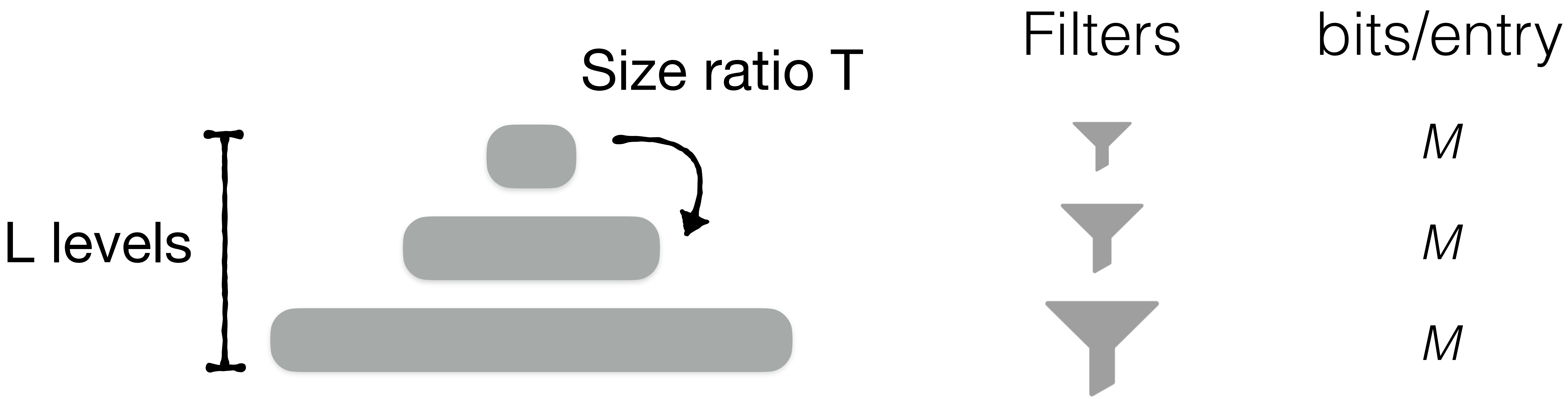


Question 5

What is the cost of building Bloom filters for a leveled LSM-tree, measured in worst-case memory accesses per insertion? Assume the same number of bits per entry *M* is assigned to filters at all levels.

The optimal number of hash functions is ln(2) · M.

So each insertion into a Bloom filter costs O(M) memory accesses.



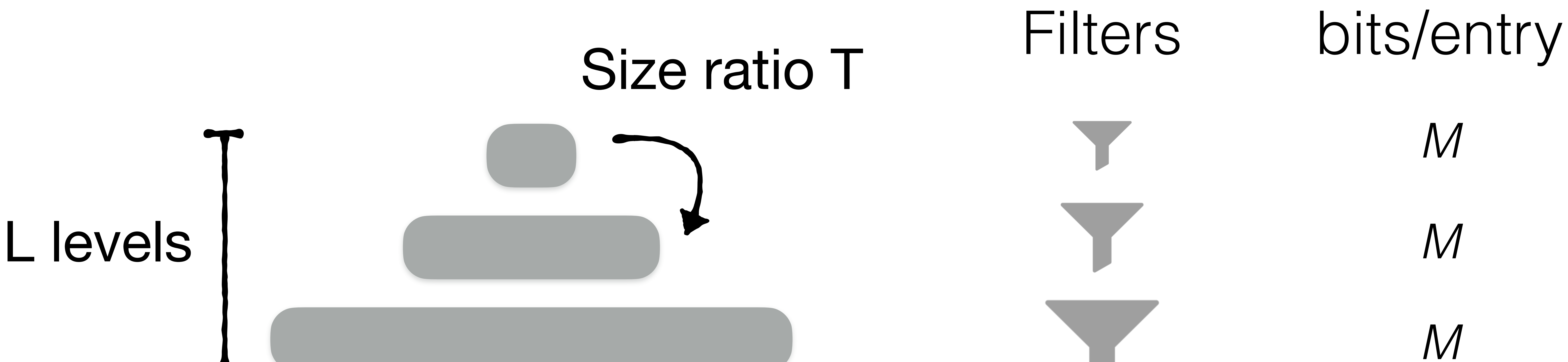
Question 5

What is the cost of building Bloom filters for a leveled LSM-tree, measured in worst-case memory accesses per insertion? Assume the same number of bits per entry *M* is assigned to filters at all levels.

The optimal number of hash functions is $\ln(2) \cdot M$.

So each insertion into a Bloom filter costs $O(M)$ memory accesses.

An entry is merged $O(L \cdot T)$ times across the tree. For each merge, the entry is inserted in a Bloom filter.



Question 5

What is the cost of building Bloom filters for a leveled LSM-tree, measured in worst-case memory accesses per insertion? Assume the same number of bits per entry *M* is assigned to filters at all levels.

The optimal number of hash functions is $\ln(2) \cdot M$.

So each insertion into a Bloom filter costs $O(M)$ memory accesses.

An entry is merged $O(L \cdot T)$ times across the tree. For each merge, the entry is inserted in a Bloom filter.

Hence, the overall cost is $O(L \cdot T \cdot M)$.