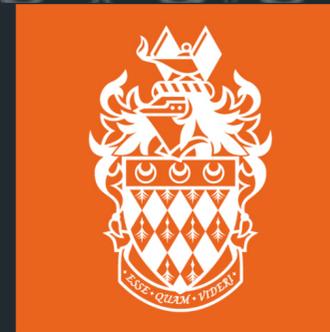


Improved Reconstruction Attacks on Encrypted Data Using Range Query Leakage

Marie-Sarah Lacharité, **Brice Minaud**, Kenny Paterson

Information Security Group



ROYAL
HOLLOWAY
UNIVERSITY
OF LONDON

IEEE Symposium on Security and Privacy, May 21, 2018

Outsourcing Data with Search Capabilities

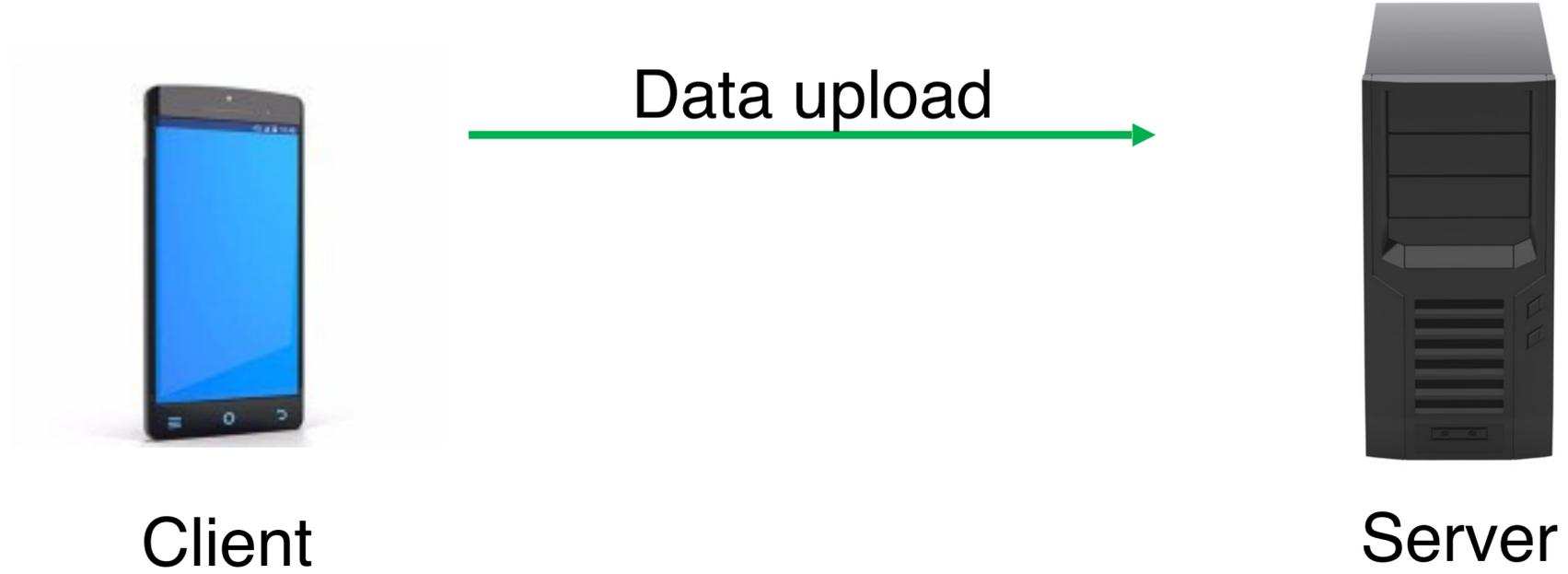


Client

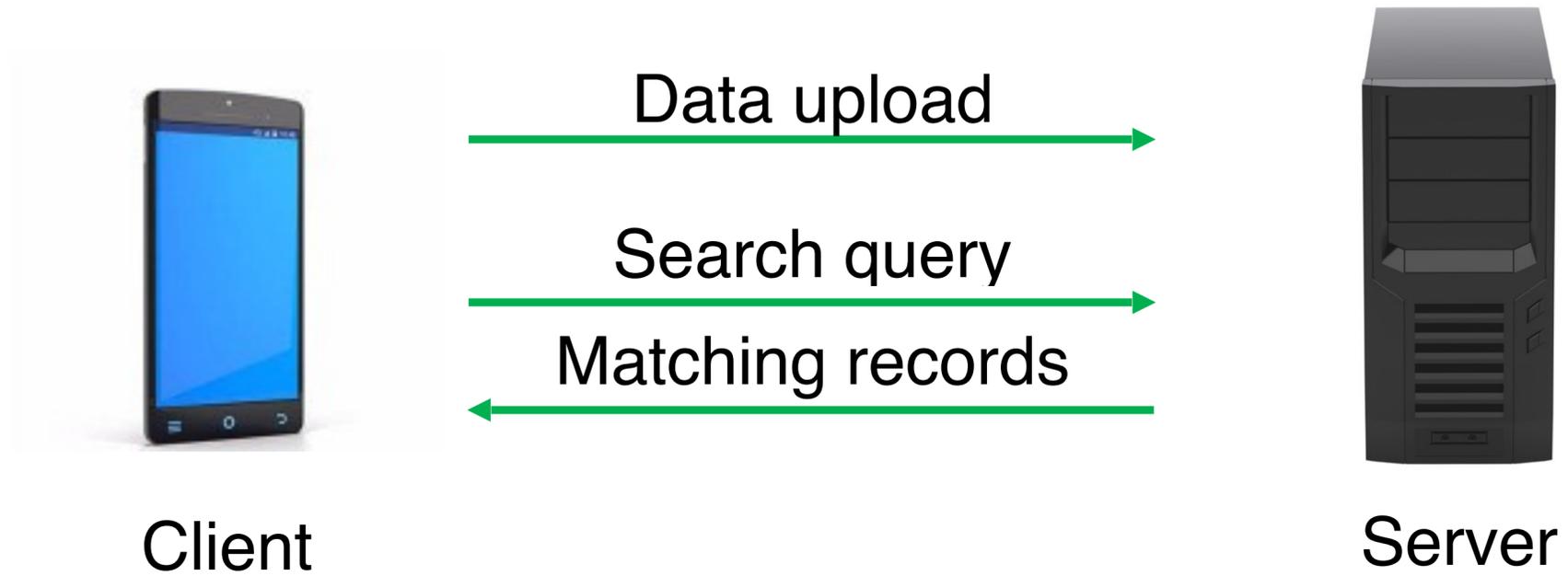


Server

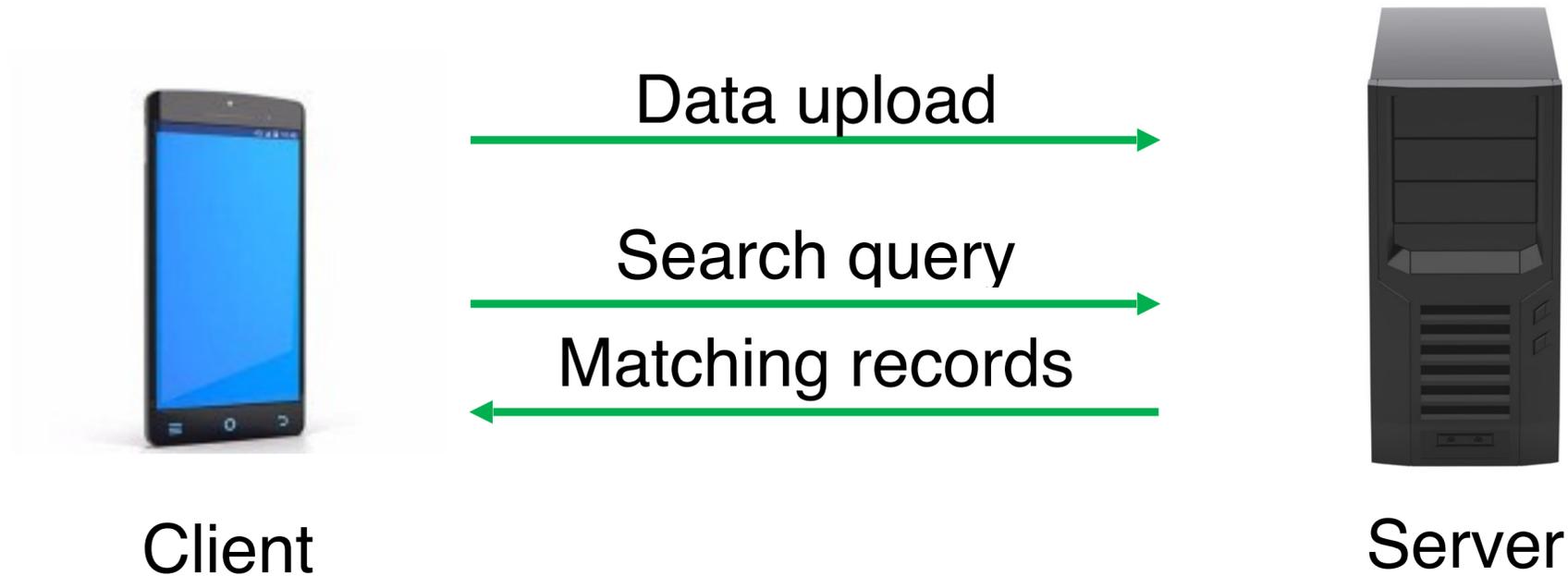
Outsourcing Data with Search Capabilities



Outsourcing Data with Search Capabilities



Outsourcing Data with Search Capabilities



For an **encrypted database management system**:

- Data = collection of records in a database. *e.g. health records.*
- Search query examples:
 - find records with given value. *e.g. patients aged 57.*
 - find records within a given range. *e.g. patients aged 55-65.*

Security of Data Outsourcing Solutions



Adversaries:

- **Snapshot:** breaks into server, gets snapshot of memory.
- **Persistent:** corrupts server, sees all communication transcripts.
Can be server itself.

Security goal = privacy.

→ Adversary learns as little as possible about the client's data and queries.

- **Structure-preserving encryption.**
Vulnerable to **snapshot** attackers.

Solutions

- **Structure-preserving encryption.**
Vulnerable to **snapshot** attackers.
- **Second-generation schemes:**
Aim to protect against **snapshot** and **persistent** attackers.

Solutions

- **Structure-preserving encryption.**

Vulnerable to **snapshot** attackers.

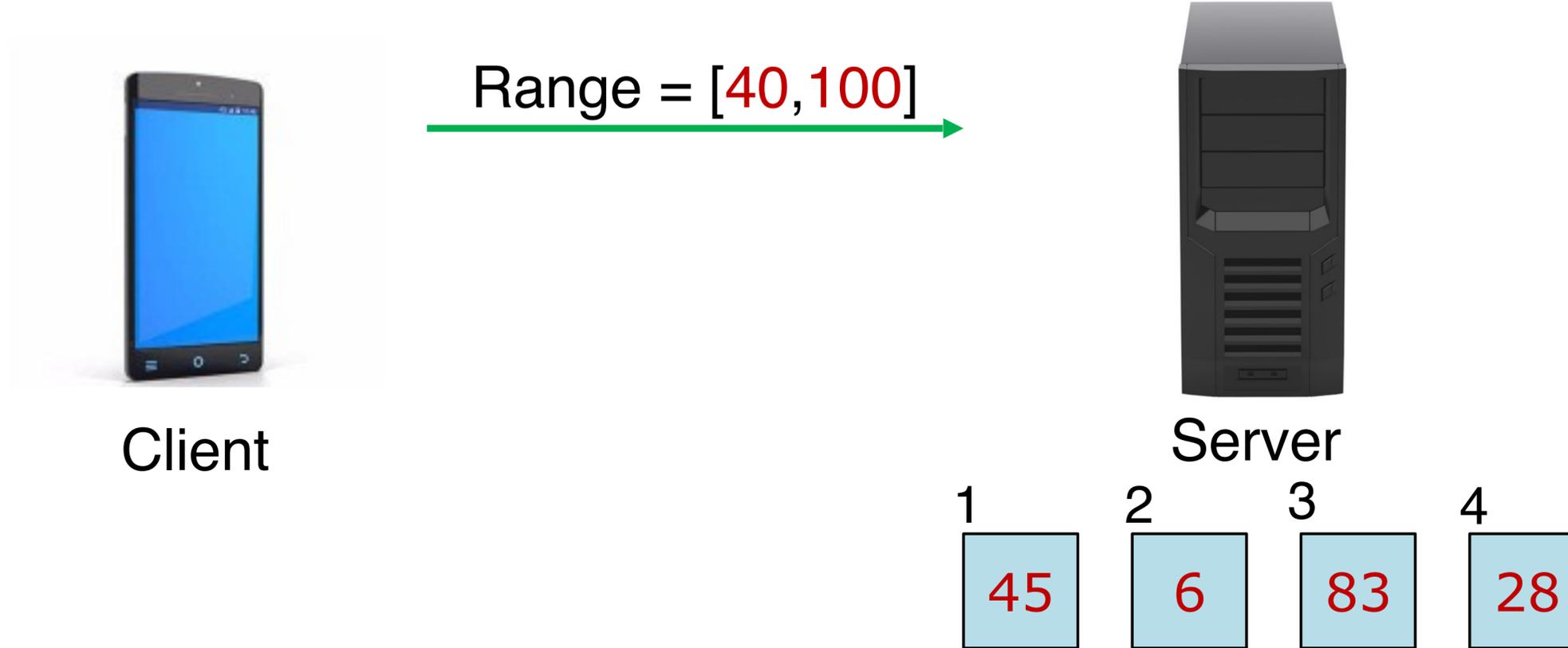
- **Second-generation schemes:**

Aim to protect against **snapshot** and **persistent** attackers.

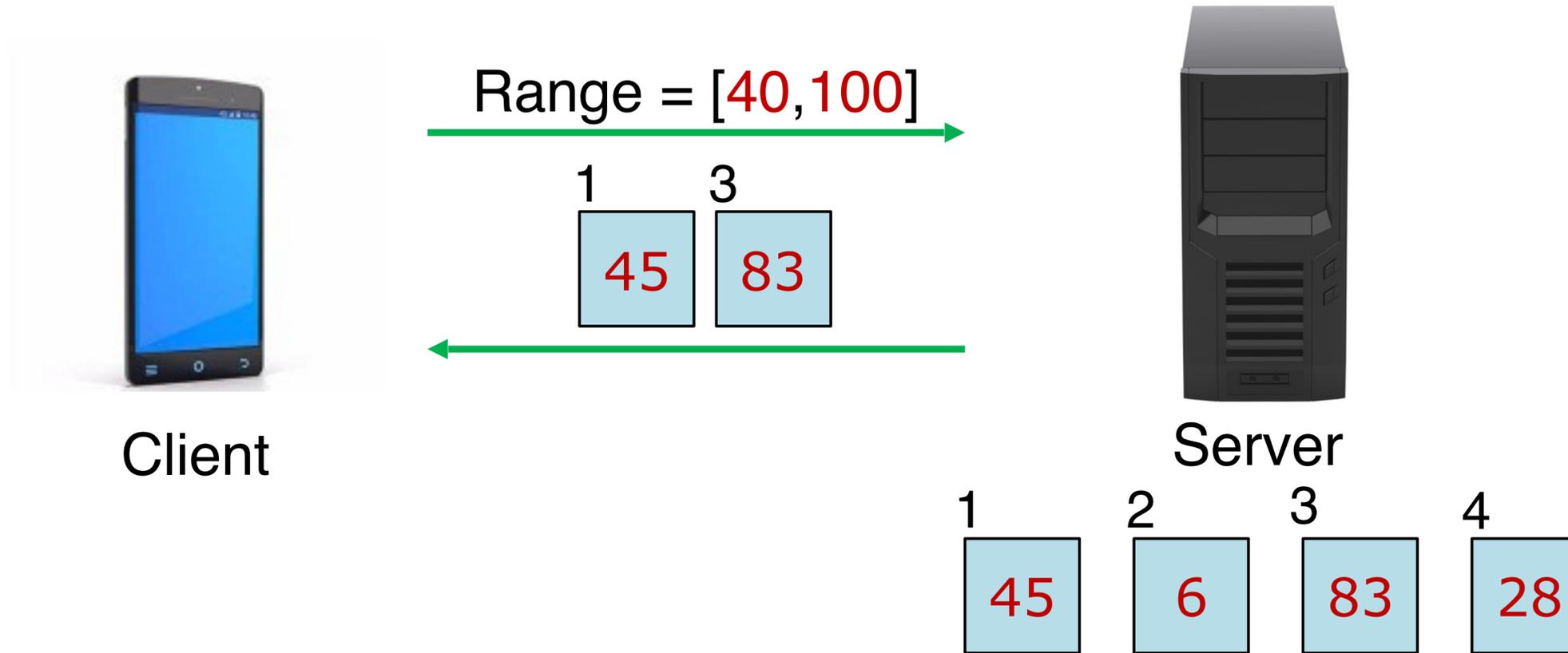
- **Very active research topic.**

[AKSX04], [BCLO09], [PKV+14], [BLR+15], [NKW15], [KKNO16], [LW16], [FVY+17], [SDY+17], [DP17], [HLK18], [PVC18], [MPC+18]...

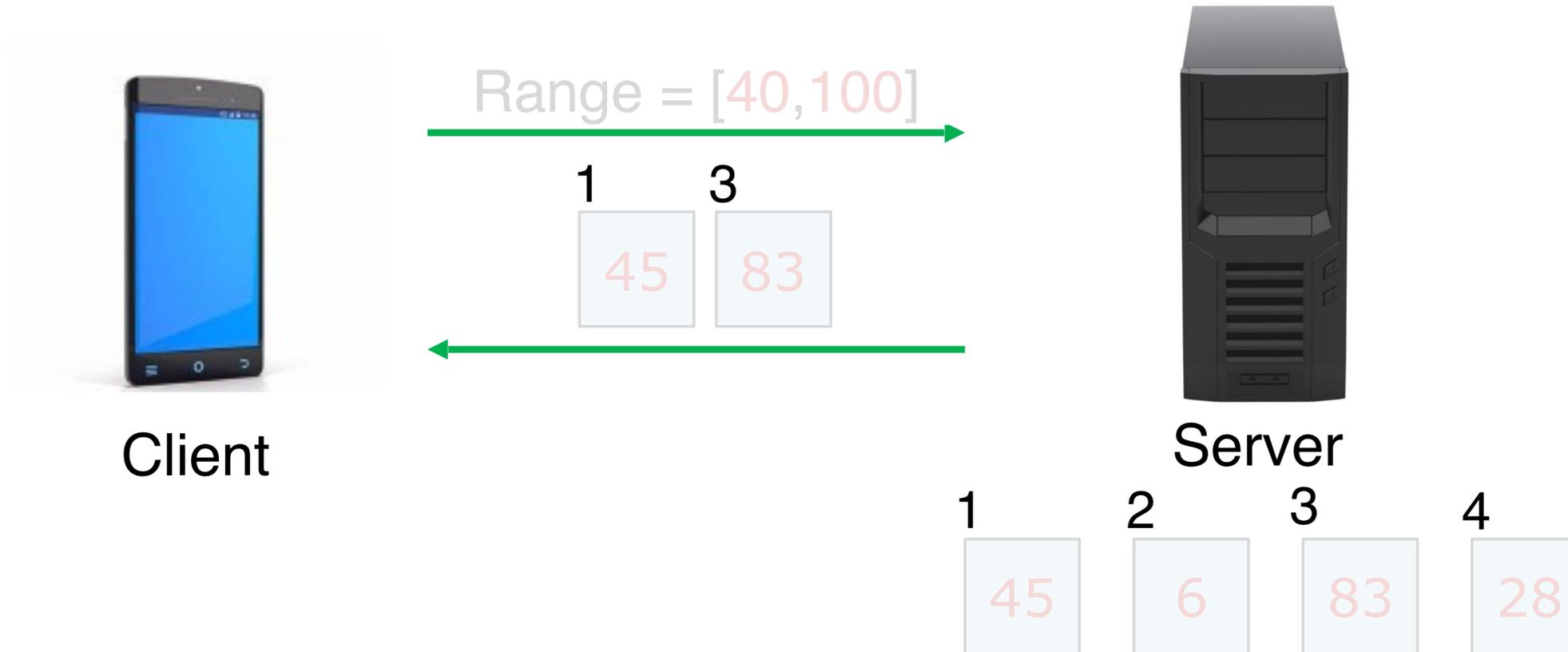
Schemes Supporting Range Queries



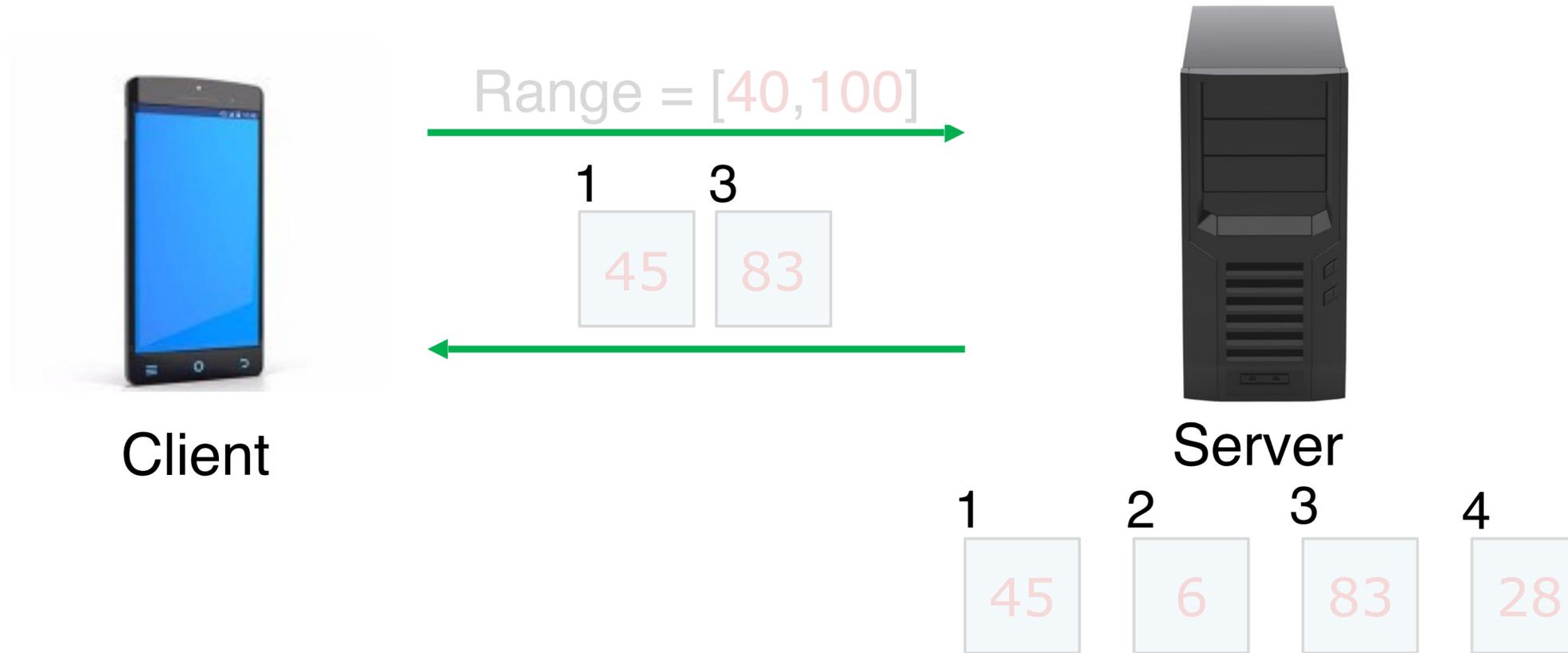
Schemes Supporting Range Queries



Schemes Supporting Range Queries

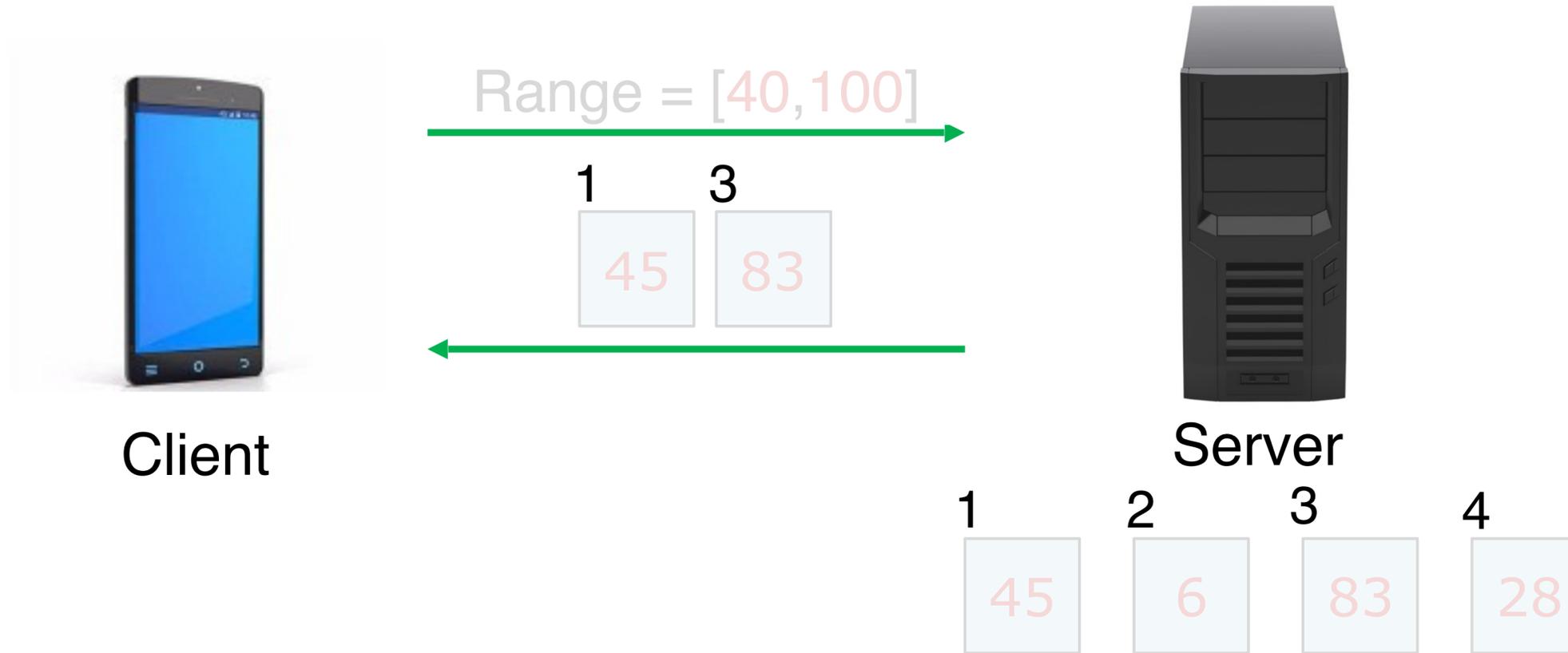


Schemes Supporting Range Queries



- Most schemes leak set of matching records = **access pattern** leakage.
OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJ+15], ...

Schemes Supporting Range Queries



- Most schemes leak set of matching records = **access pattern** leakage.

OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJ+15], ...

- Some schemes also leak #records below queried endpoints = **rank** leakage.

FH-OPE, Lewi-Wu, Arx, Cipherbase, EncKV, ...

Exploiting Leakage

- Most schemes prove that nothing more leaks than their leakage model allows.

For example, leakage = **access pattern + rank**.

What can we really learn from this leakage?

Exploiting Leakage

- Most schemes prove that nothing more leaks than their leakage model allows.
For example, leakage = **access pattern + rank**.
What can we really learn from this leakage?
- **Our goal: full reconstruction** = recovering the exact value of every record.

Exploiting Leakage

- Most schemes prove that nothing more leaks than their leakage model allows.
For example, leakage = **access pattern + rank**.
What can we really learn from this leakage?
- **Our goal: full reconstruction** = recovering the exact value of every record.
- **[KKNO16]**: $O(N^2 \log N)$ queries suffice for full reconstruction using only access pattern leakage!
 - where N is the number of possible values (e.g. 125 for age in years).

Assumptions for our Analysis

- Data is **dense**: all values appear in at least one record.
- Queries are **uniformly distributed**.
Our algorithms don't actually care though – the assumption is for computing data upper bounds.

Our Main Results

- **Full reconstruction** with $O(N \cdot \log M)$ queries from **access pattern** leakage
 - in fact, $N \cdot (3 + \log M)$.

Our Main Results

- **Full reconstruction** with $O(N \cdot \log N)$ queries from **access pattern** leakage
 - in fact, $N \cdot (3 + \log N)$.
- **Approximate reconstruction** with relative accuracy ε with $O(N \cdot (\log 1/\varepsilon))$ queries.

Our Main Results

- **Full reconstruction** with $O(N \cdot \log N)$ queries from **access pattern** leakage
 - in fact, $N \cdot (3 + \log N)$.
- **Approximate reconstruction** with relative accuracy ε with $O(N \cdot (\log 1/\varepsilon))$ queries.
- **Approximate reconstruction** using an *auxiliary distribution* and **access pattern + rank** leakage.

Our Main Results

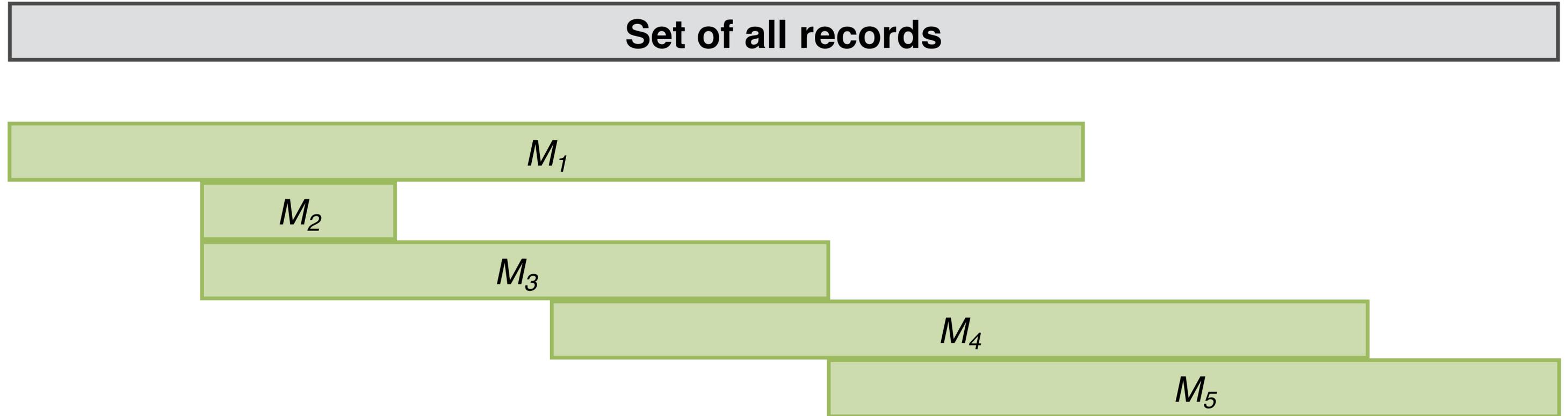
- **Full reconstruction** with $O(N \cdot \log M)$ queries from **access pattern** leakage
 - in fact, $N \cdot (3 + \log M)$.
- **Approximate reconstruction** with relative accuracy ε with $O(N \cdot (\log 1/\varepsilon))$ queries.
- **Approximate reconstruction** using an *auxiliary distribution* and **access pattern + rank** leakage.



Full reconstruction



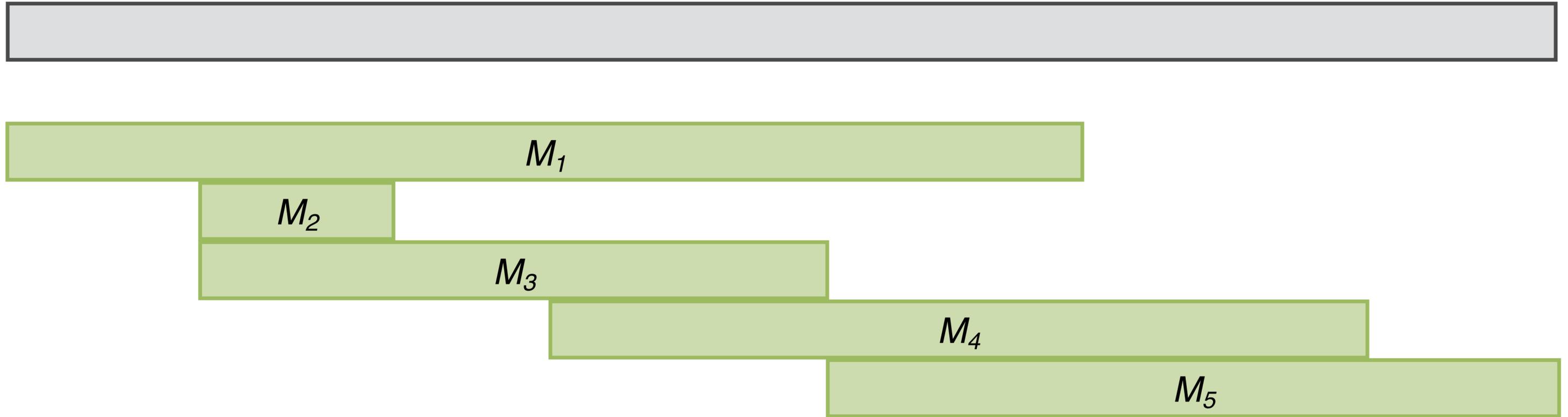
Full Reconstruction Algorithm



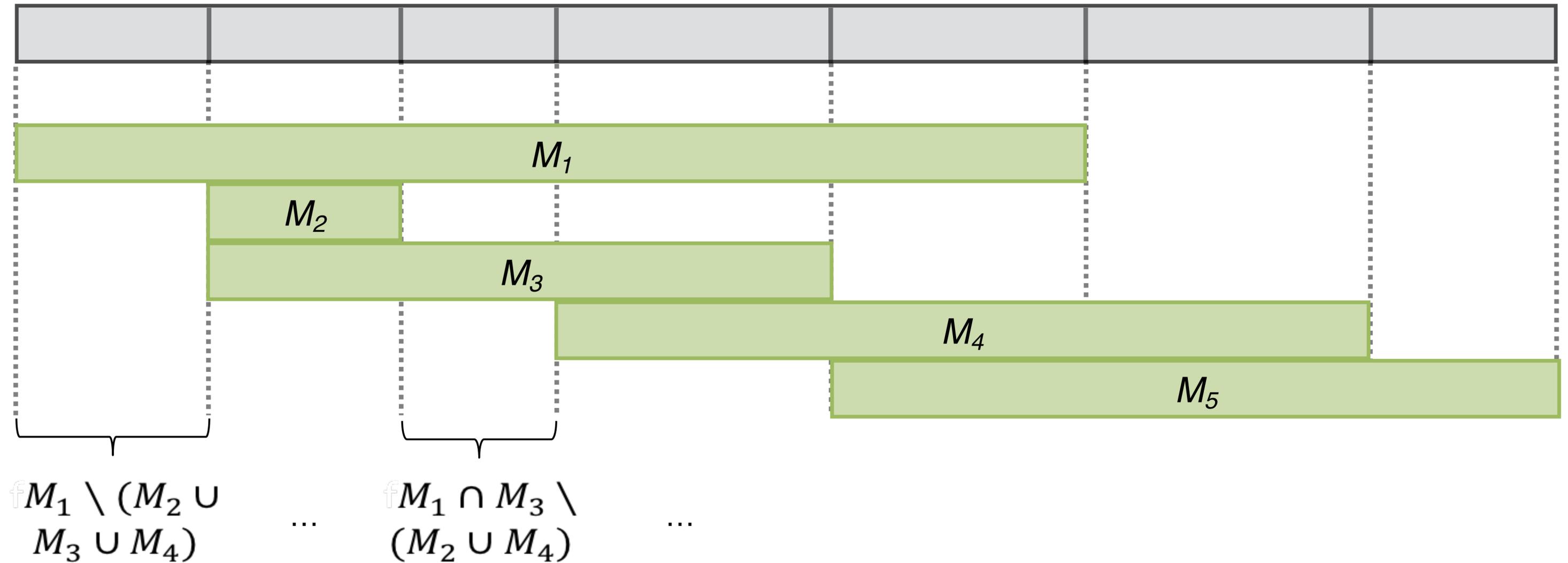
Assume $N = 7$ values, and 5 queries.

M_i = set of records matched by i -th query.

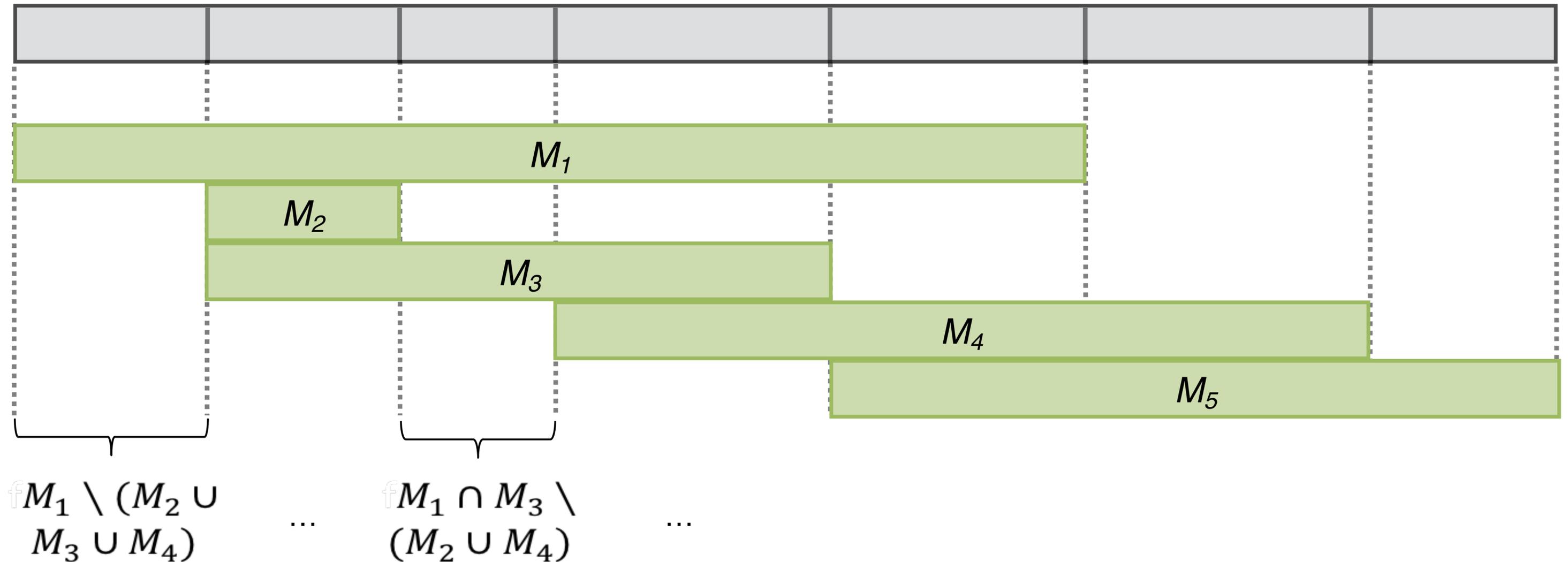
Step 1: Partitioning



Step 1: Partitioning

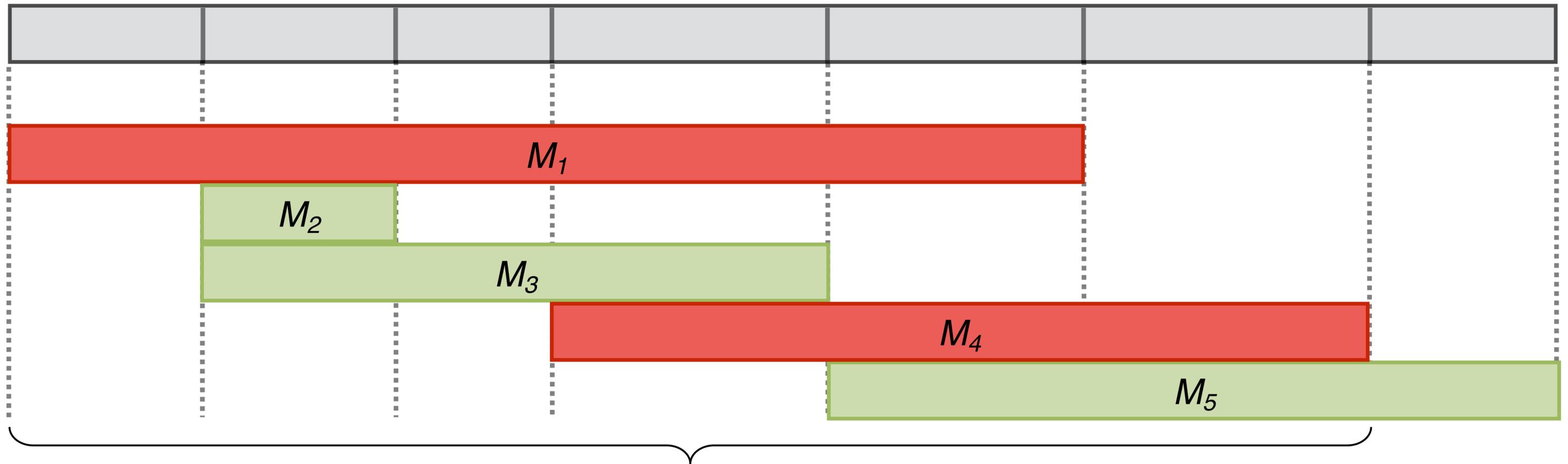


Step 1: Partitioning



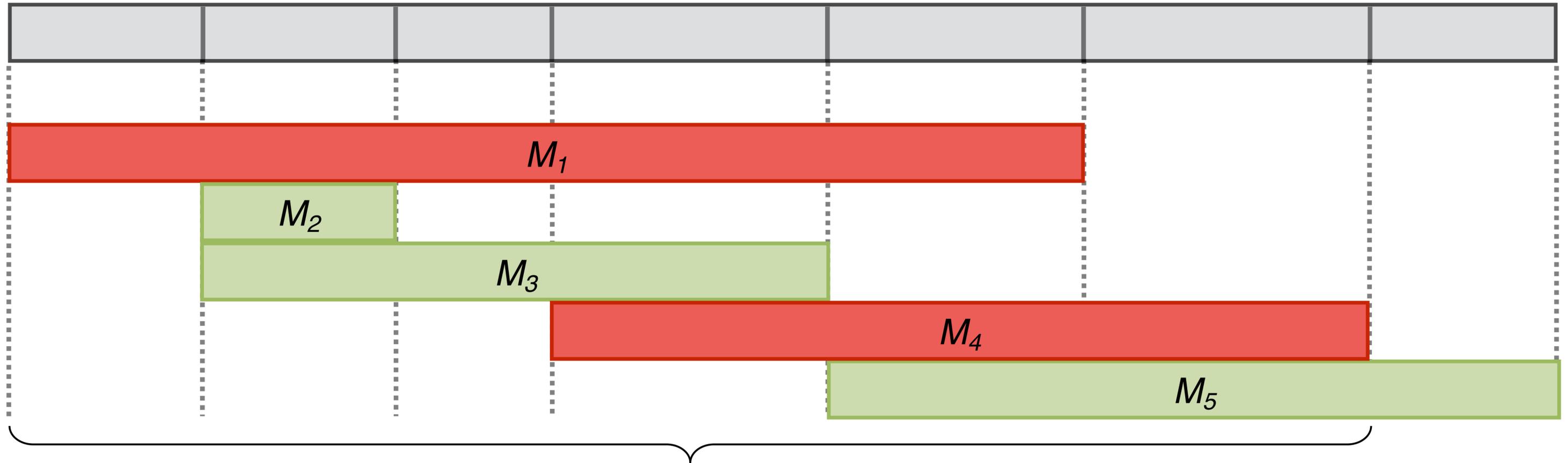
If there are N minimal subsets \rightarrow each of them correspond to a single value.

Step 2a: Finding an Endpoint



$M_1 \cup M_3$ cover all but 1 minimal set

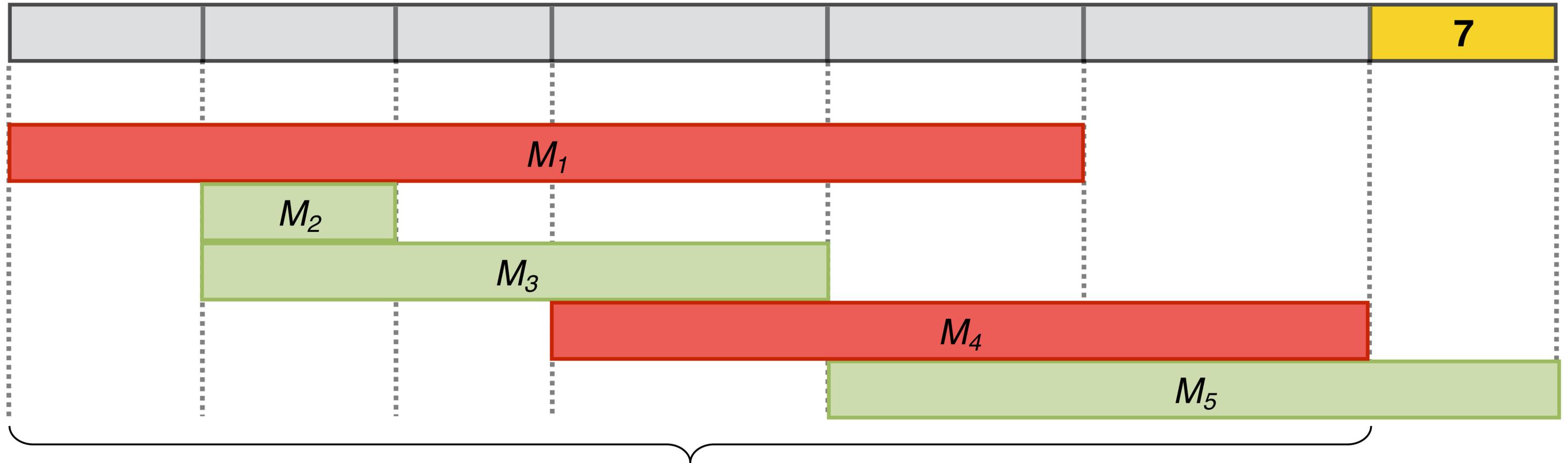
Step 2a: Finding an Endpoint



$M_1 \cup M_3$ cover all but 1 minimal set

Endpoint!

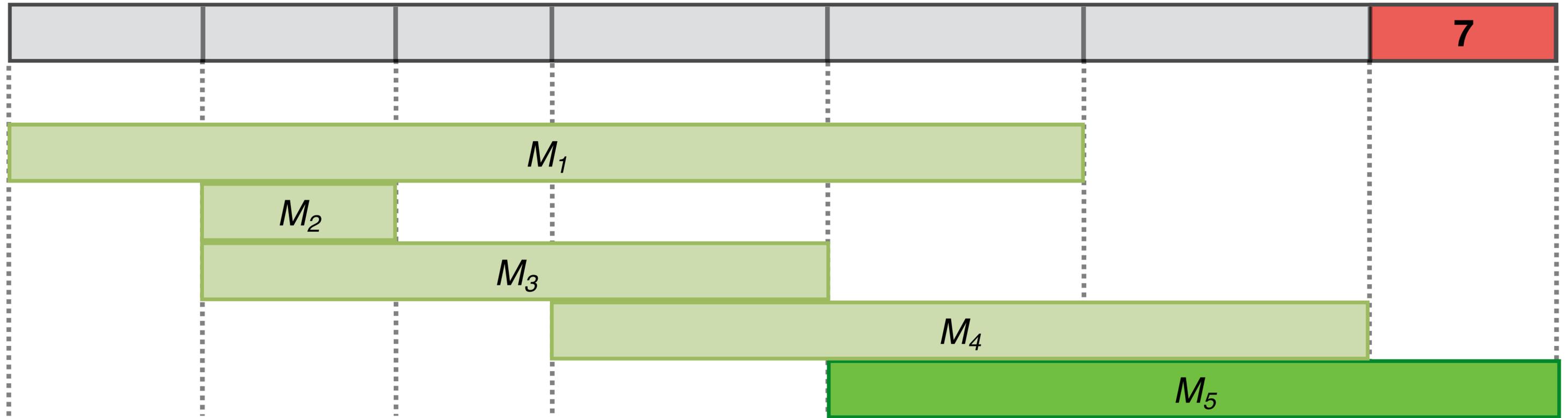
Step 2a: Finding an Endpoint



$M_1 \cup M_3$ cover all but 1 minimal set

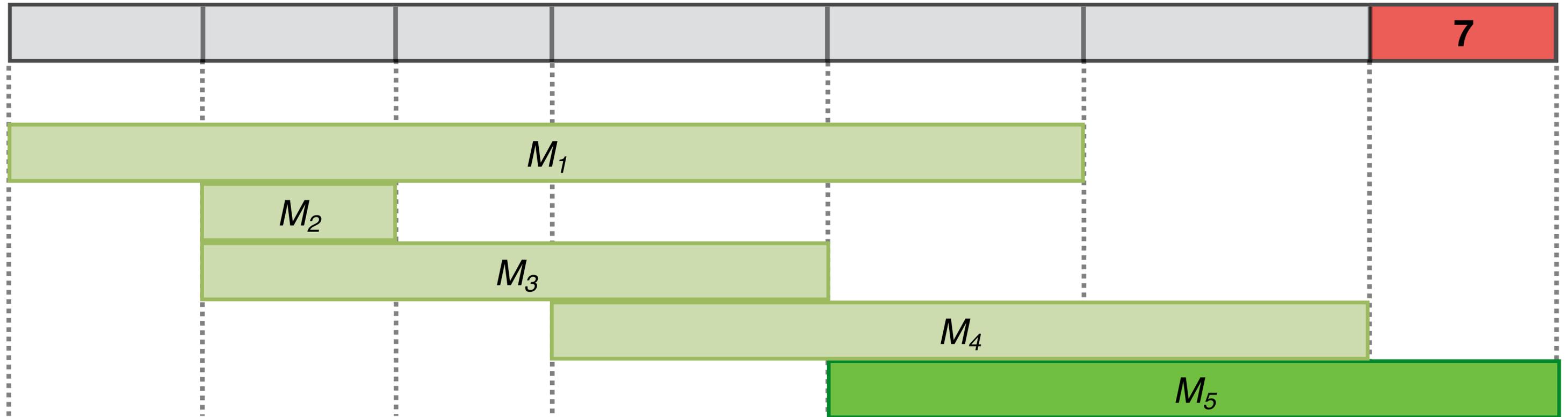
Endpoint!

Step 2b: Propagating



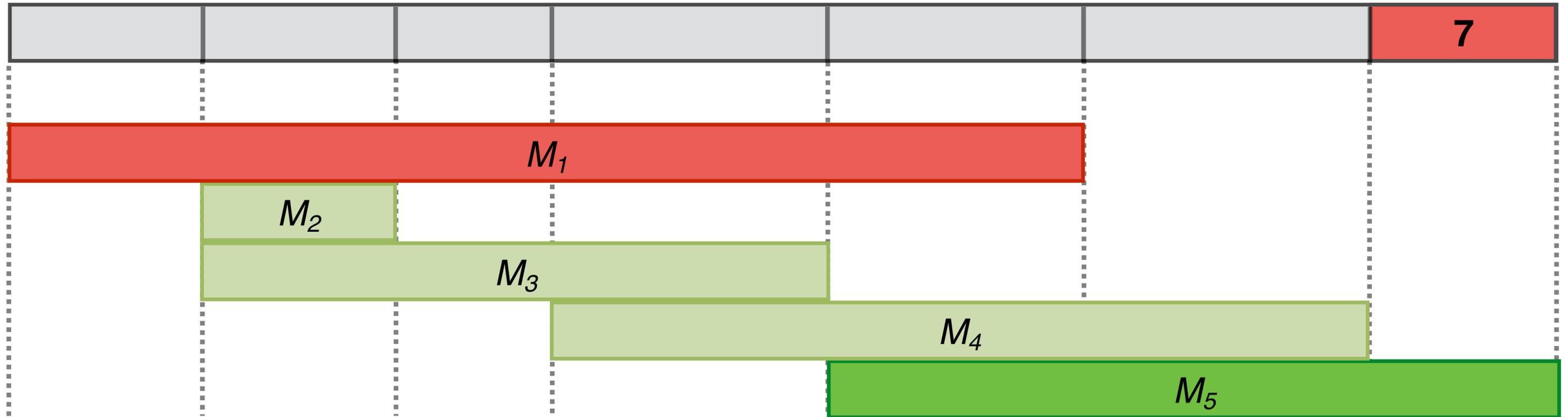
- Intersect

Step 2b: Propagating



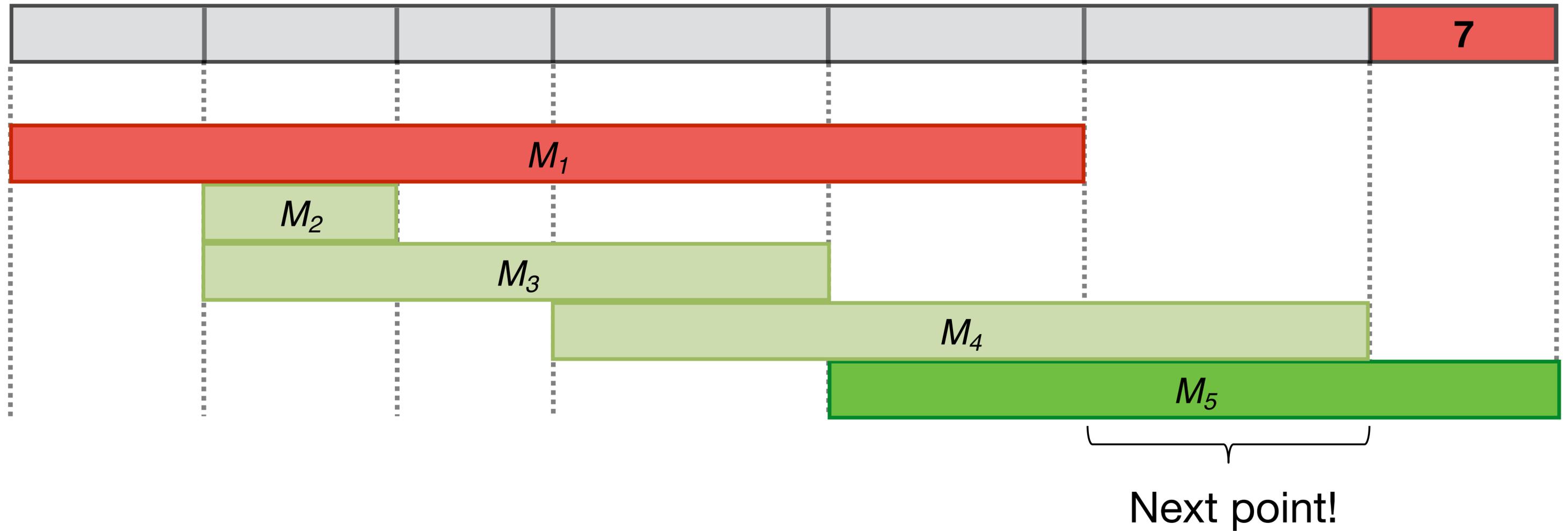
- Intersect
- Trim

Step 2b: Propagating



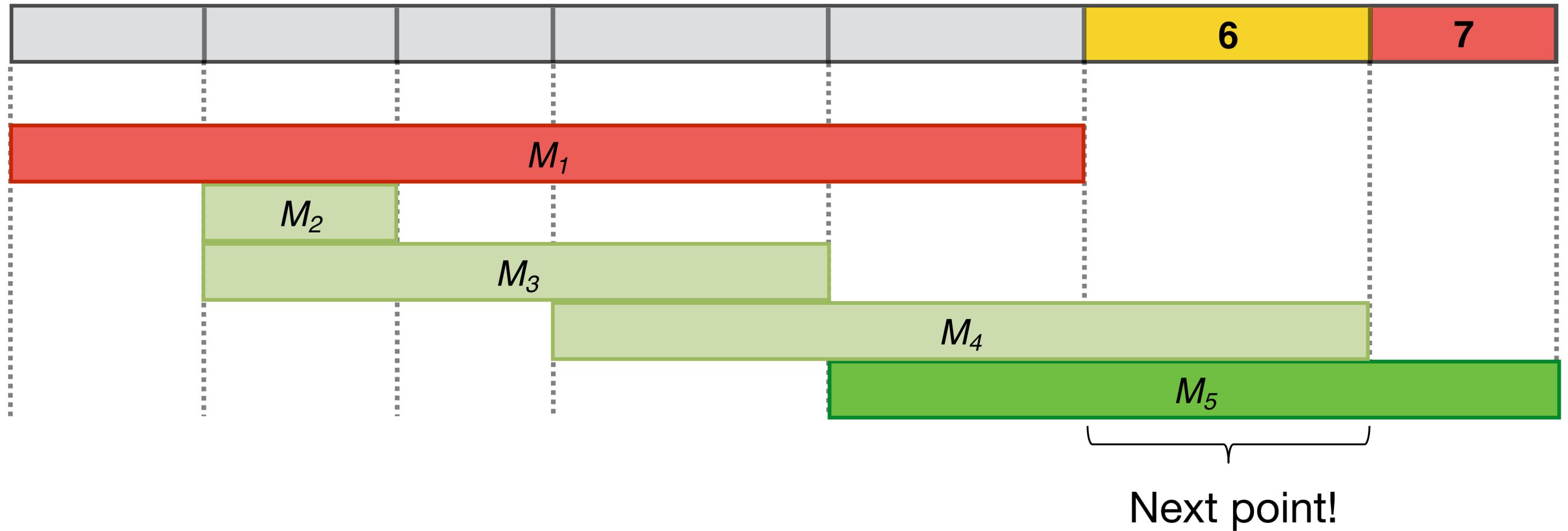
- Intersect
- Trim

Step 2b: Propagating



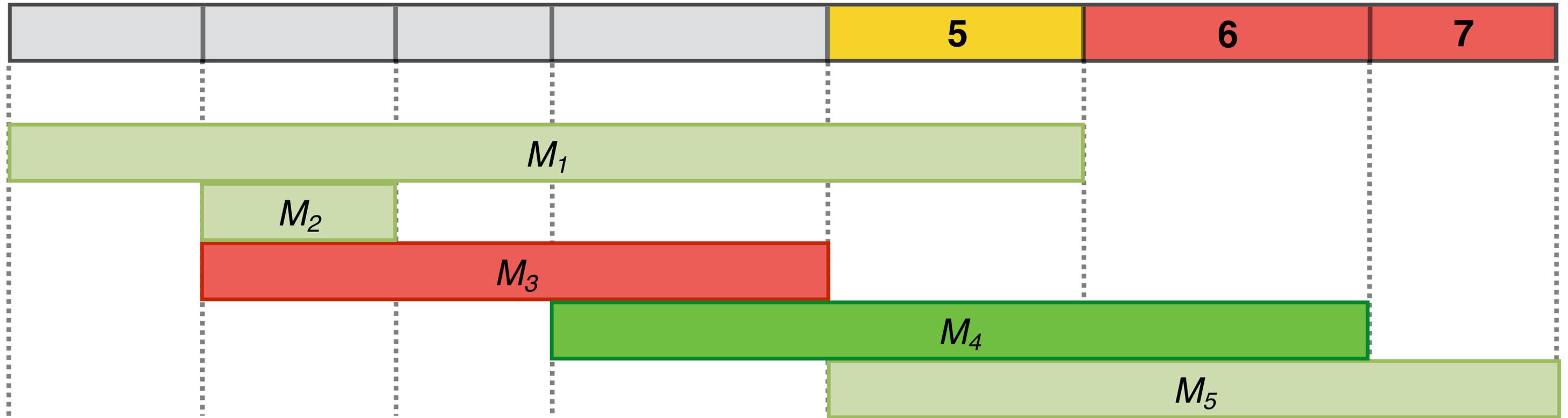
- Intersect
- Trim

Step 2b: Propagating



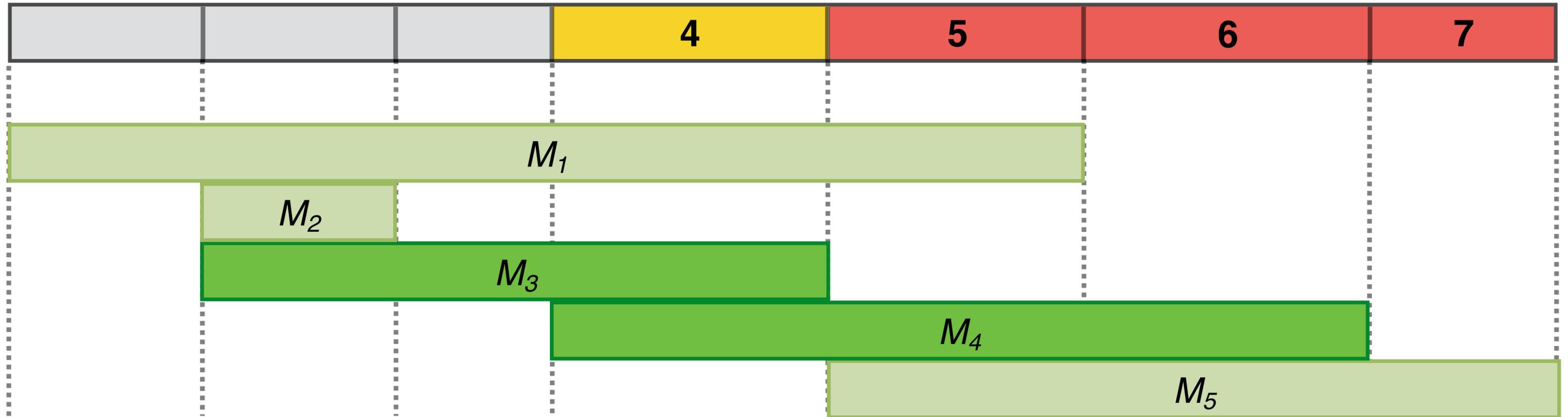
- Intersect
- Trim

Step 2b: Propagating



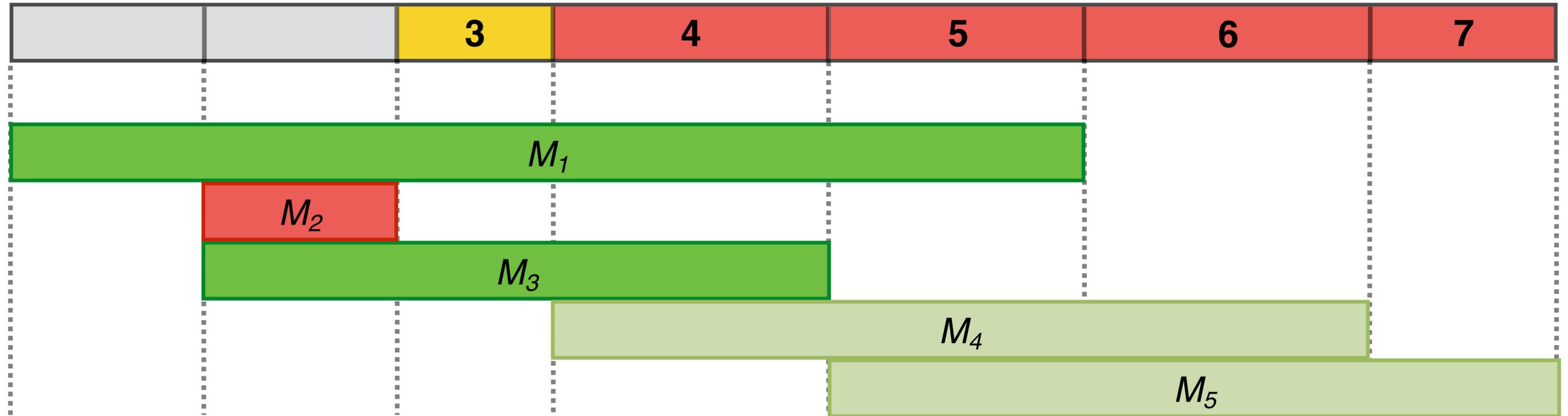
- Intersect
- Trim

Step 2b: Propagating



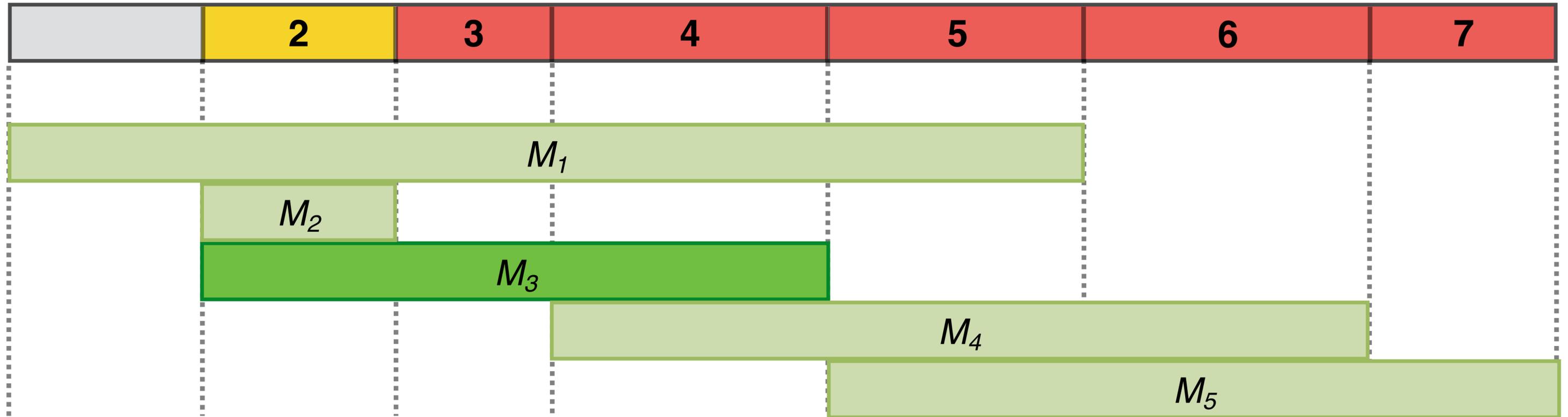
- Intersect
- Trim

Step 2b: Propagating



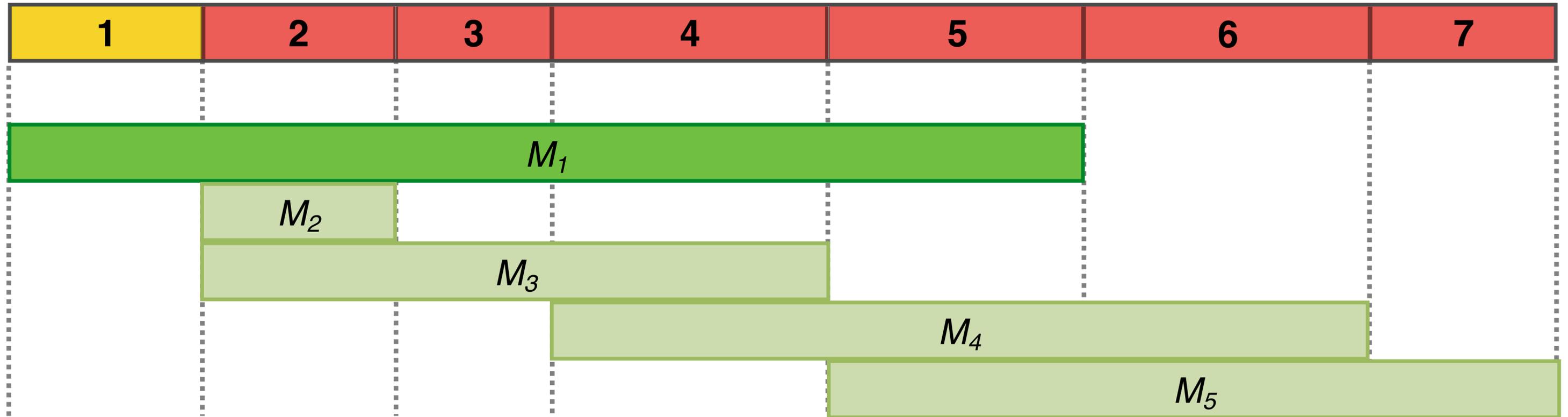
- Intersect
- Trim

Step 2b: Propagating



- Intersect
- Trim

Done!



- Intersect
- Trim

Full Reconstruction: Conclusion

- **Generic setting:** only **access pattern** leakage.
- **Partitioning**, then **sorting** steps.
- Expectation of #queries **sufficient** for reconstruction:
$$N \cdot (3 + \log N) \quad \text{for } N \geq 26$$
- Expectation of #queries **necessary** for reconstruction:
$$1/2 \cdot N \cdot \log N - O(N)$$

for *any* algorithm.
- Our algorithm is **data-optimal**.

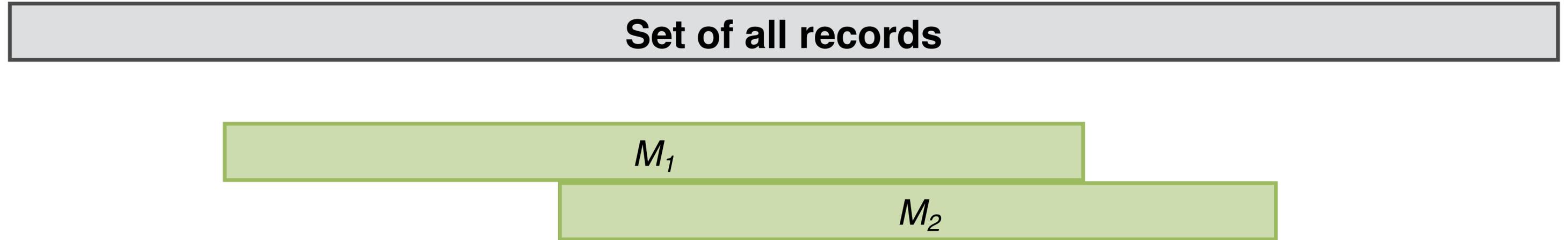


Reconstruction with Auxiliary Data +
Rank Leakage

Auxiliary Data Attack with Rank Leakage

- Assume **access pattern** + **rank** leakage.
- Also assume an **approximation to the distribution on values** is known.
 - “Auxiliary distribution”.
 - From aggregate data, or from another reference source.
- We show experimentally that, under these assumptions, **far fewer queries** are needed.

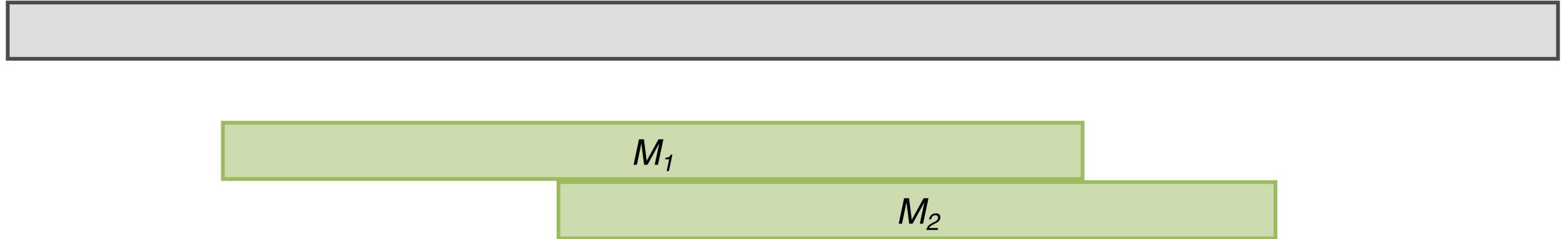
Auxiliary Data Attack Algorithm



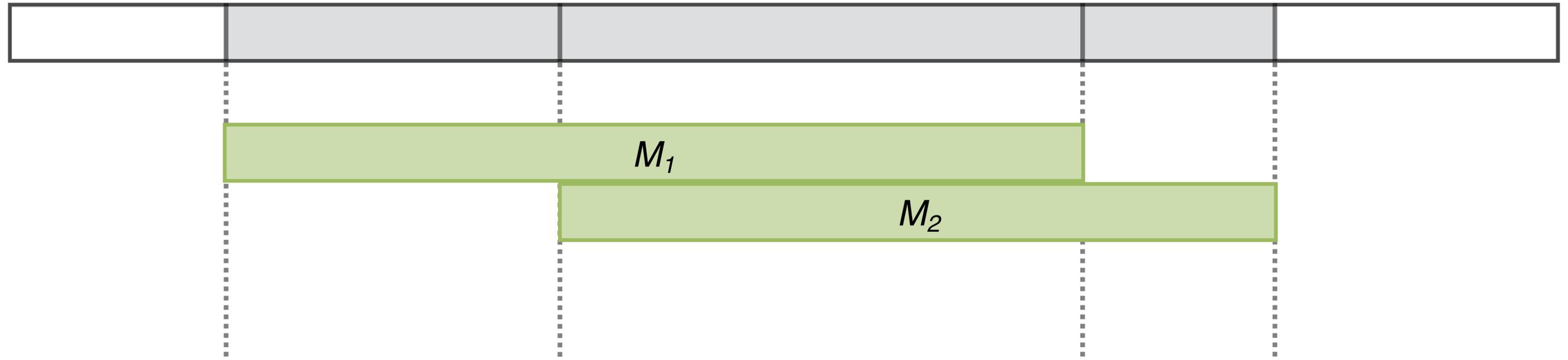
Assume $N = 125$ values, and 2 queries.

M_i = set of records matched by i -th query.

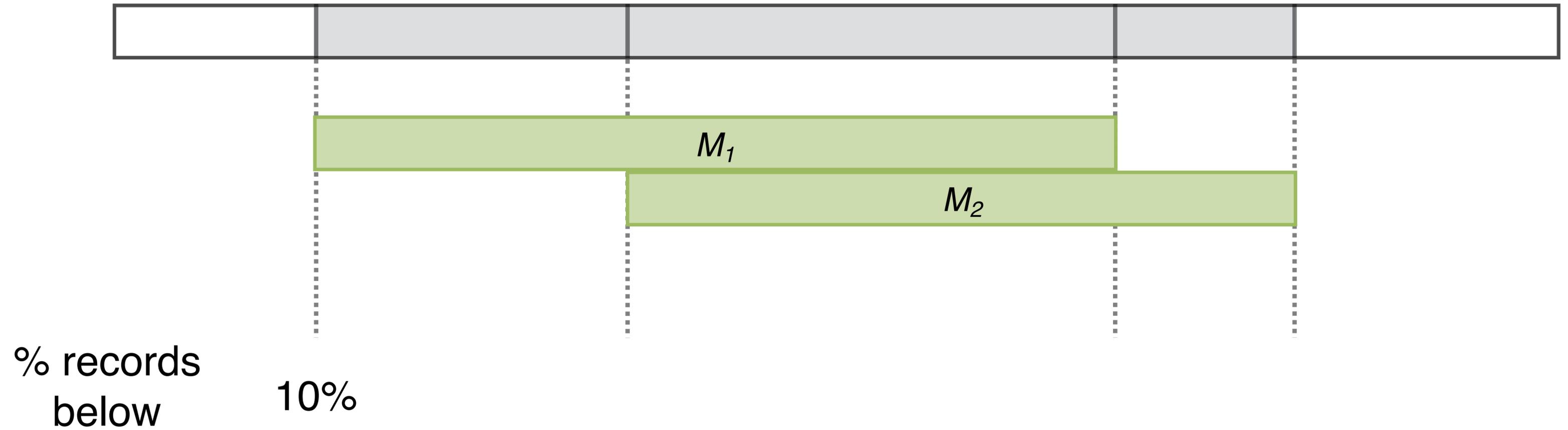
Partitioning and Matching



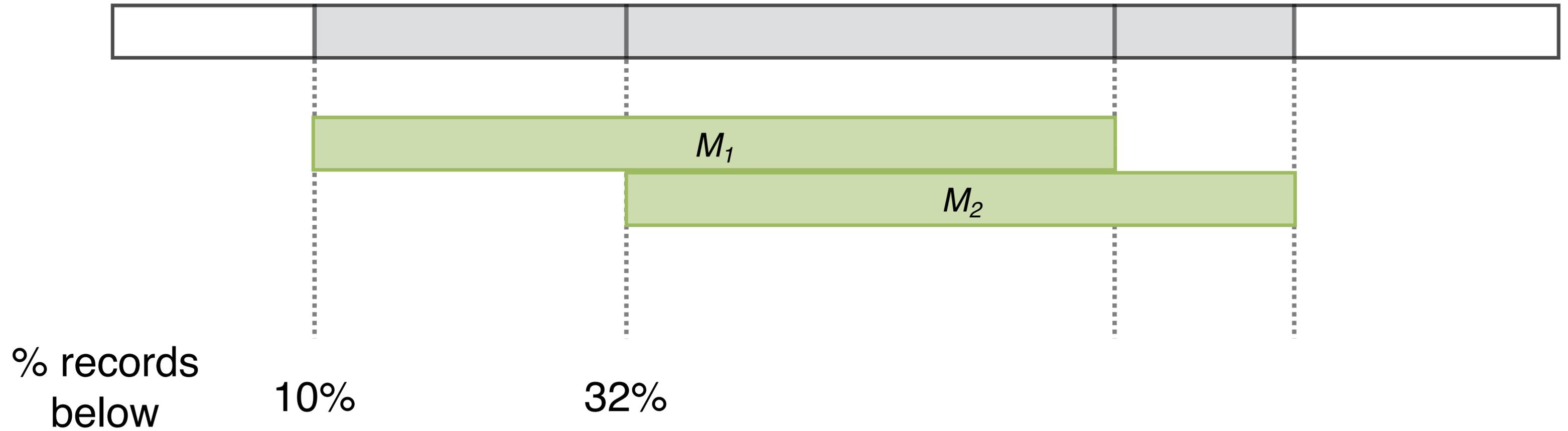
Partitioning and Matching



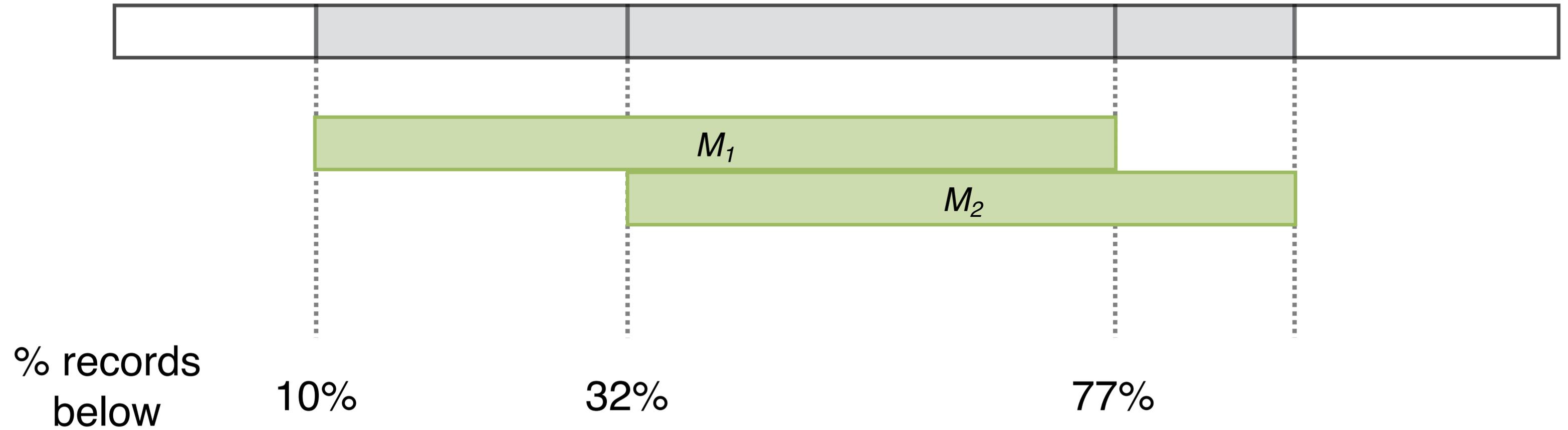
Partitioning and Matching



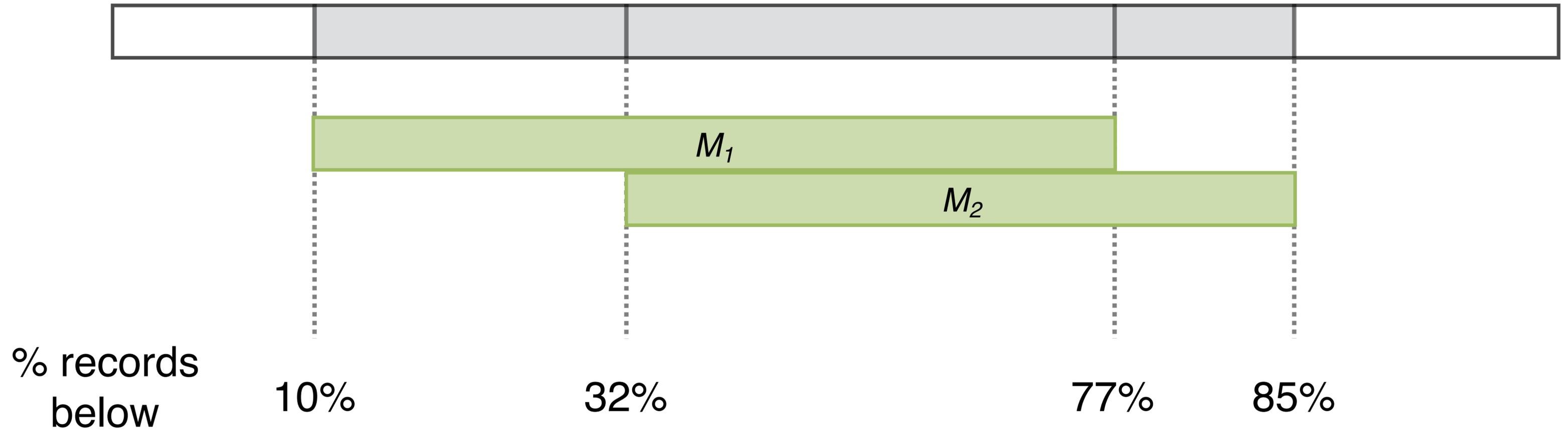
Partitioning and Matching



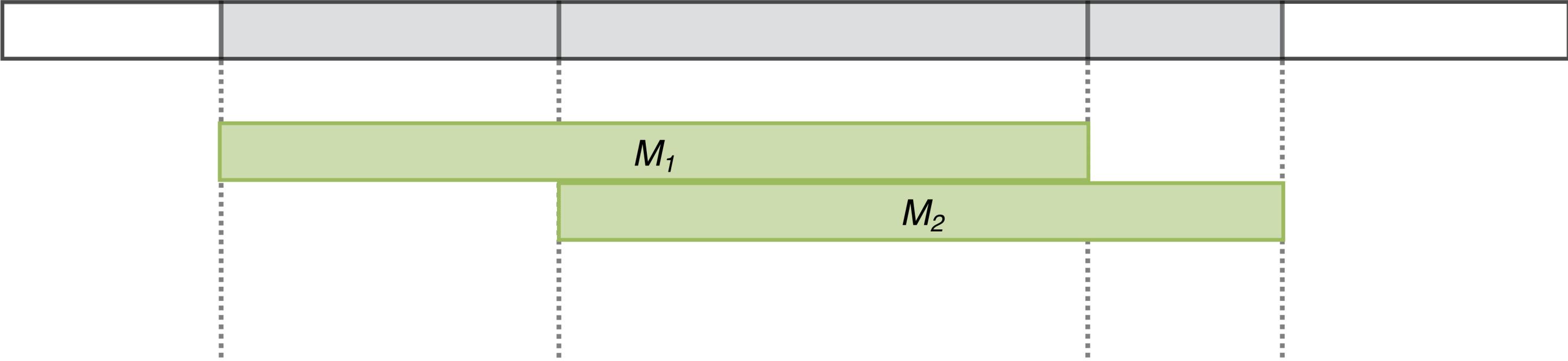
Partitioning and Matching



Partitioning and Matching



Partitioning and Matching



% records below

10%

32%

77%

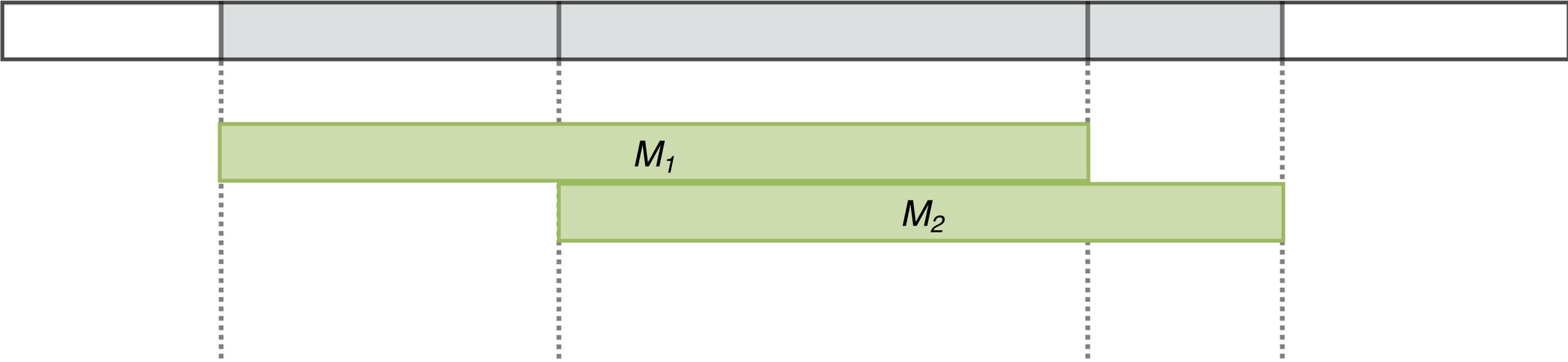
85%

Matching with aux. distribution



Age 12

Partitioning and Matching



% records below

10%

32%

77%

85%

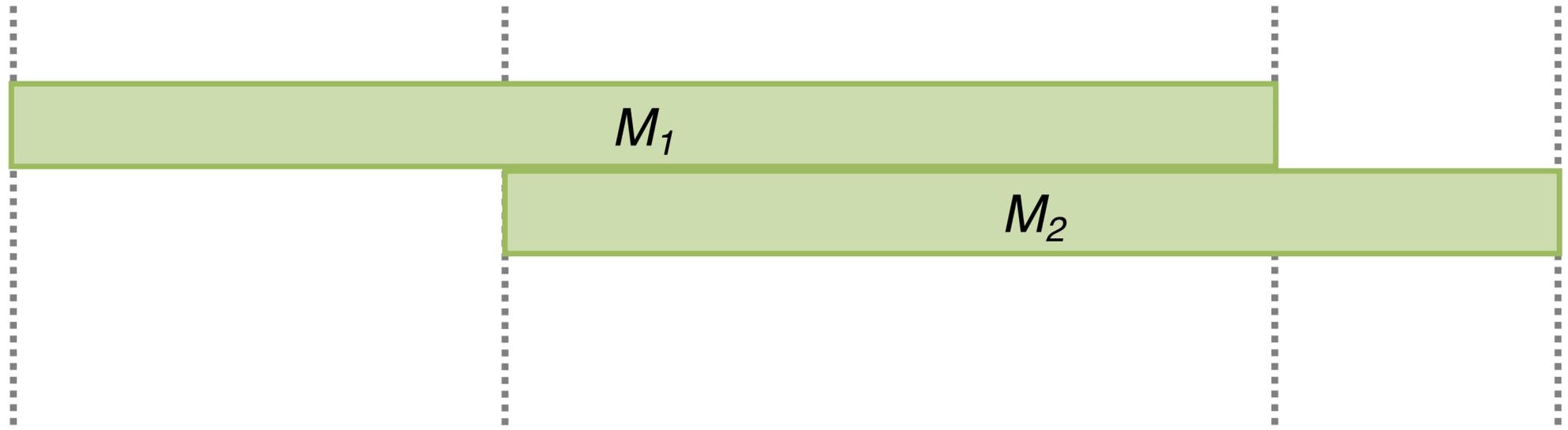
Matching with aux. distribution

Age

12

43

Partitioning and Matching



M_1

M_2

% records
below

10%

32%

77%

85%

Matching with
aux. distribution



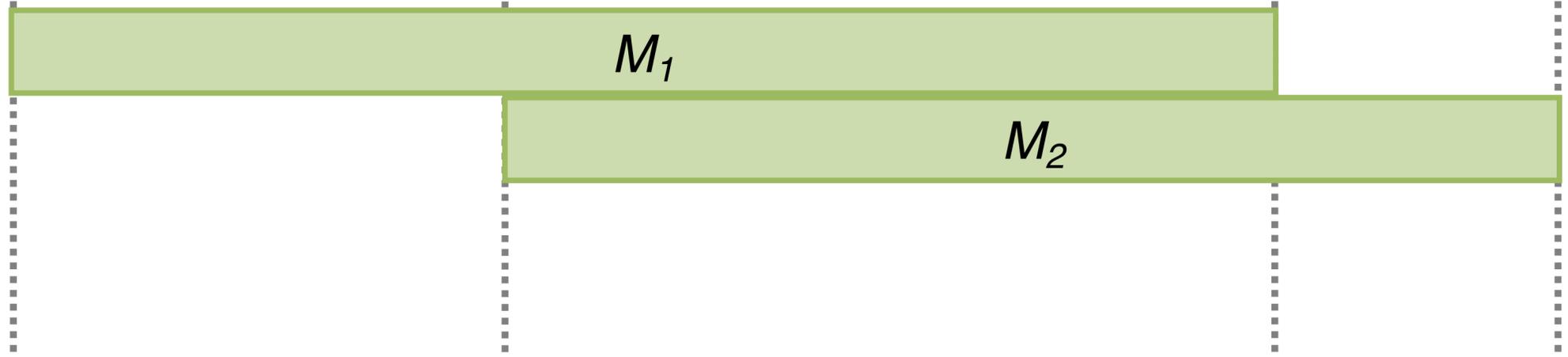
Age

12

43

60

Partitioning and Matching



% records below

10%

32%

77%

85%

Matching with
aux. distribution



Age

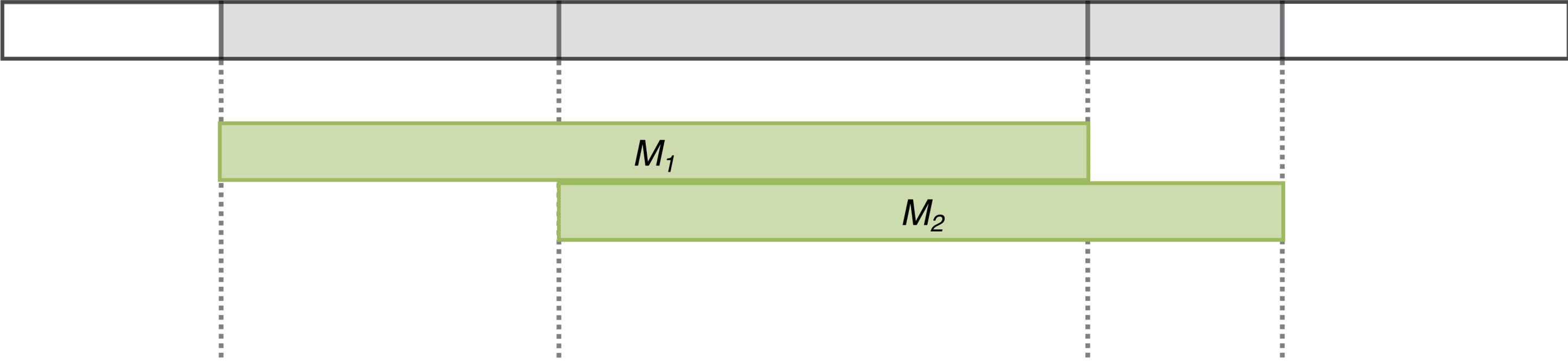
12

43

60

72

Partitioning and Matching



% records below

10%

32%

77%

85%

Matching with aux. distribution

Age

12

43

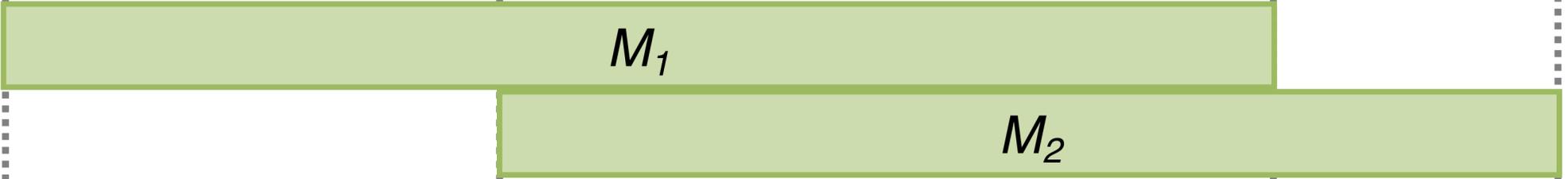
60

72

Expectation

19

Partitioning and Matching



% records below

10%

32%

77%

85%

Matching with aux. distribution



Age

12

43

60

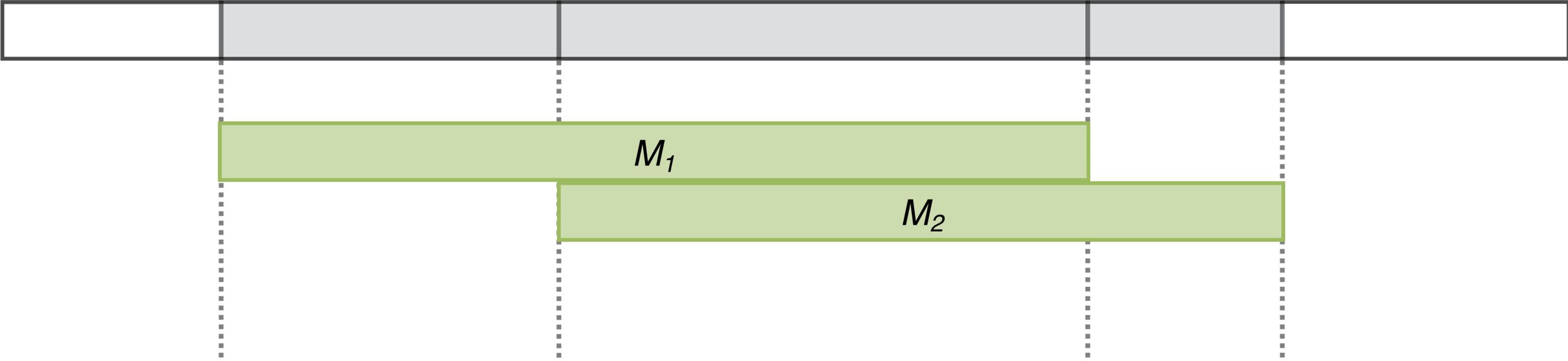
72

Expectation

19

50

Partitioning and Matching

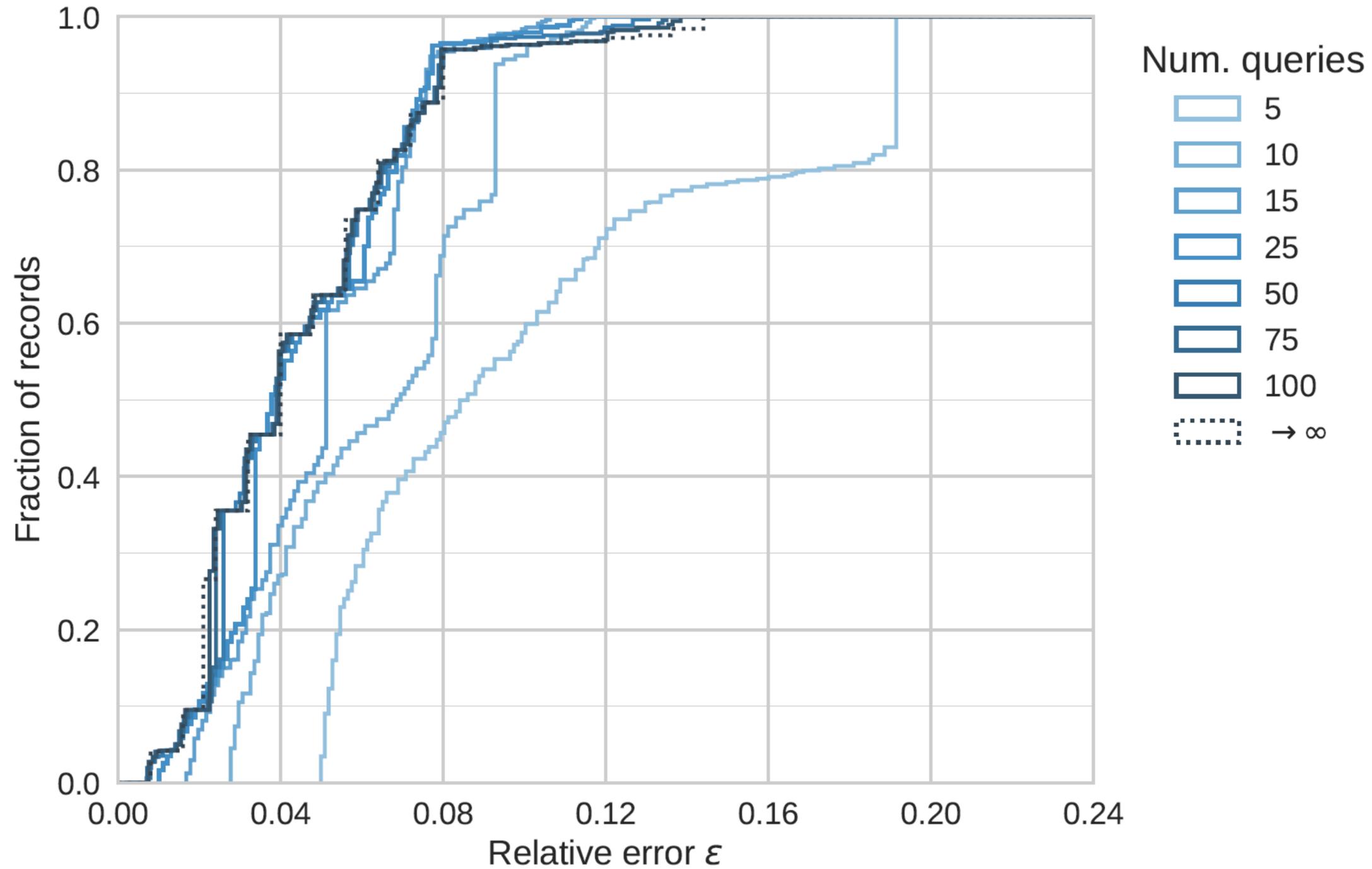


| | 10% | 32% | 77% | 85% |
|---------------------------------|-----|-----|-----|-----|
| % records below | | | | |
| Matching with aux. distribution | ↓ | ↓ | ↓ | ↓ |
| Age | 12 | 43 | 60 | 72 |
| Expectation | | 19 | 50 | 65 |

Auxiliary Data Attack: Experimental Evaluation

- Ages, $N = 125$.
- Health records from US hospitals (NIS HCUP 2009).
- **Target:** age of individual hospitals' records.
- **Auxiliary data:** aggregate of 200 hospitals' records.
- **Measure of success:** proportion of records with value guessed within ϵ .

Results with Imperfect Auxiliary Data





Conclusions



Reconstruction Attacks: Conclusions

| Attack | Leakage | Other req'ts | Suff. # queries |
|--------------------------------------|-----------|-----------------|--|
| KKNO16 | AP | Density | $O(N^2 \log N)$ |
| Full | AP + rank | Density | $N \cdot (\log N + 2)$ |
| | AP | Density | $N \cdot (\log N + 3)$ |
| ϵ-approx. | AP | Density | $5/4 N \cdot (\log 1/\epsilon) + O(N)$ |
| Auxiliary | AP + rank | Auxiliary dist. | Experimental |

- **Full reconstruction** $\approx N \log N$ queries with only **access pattern!**
Efficient, data-optimal algorithms + matching lower bound.
- For $N = 125$:
 - **800 queries** \rightarrow full reconstruction.
 - **25 queries** \rightarrow majority of records within 5%, using *auxiliary distribution* + **rank**.

Reconstruction Attacks: Conclusions

- Many clever schemes have been designed, enabling range queries on encrypted data.

OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJKNRS15], FH-OPE, Lewi-Wu, Arx, Cipherbase, EncKV,...

- Second-generation schemes **defeat the *snapshot* adversary** (with caveats).
- But as our attacks show, **no known scheme offers meaningful privacy vs. a *persistent* adversary** (including server itself).
- More research needed!