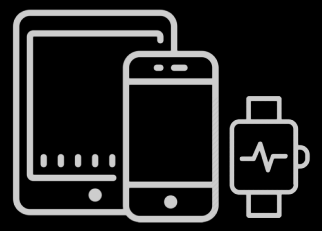
Scaling time-series stores via approximation

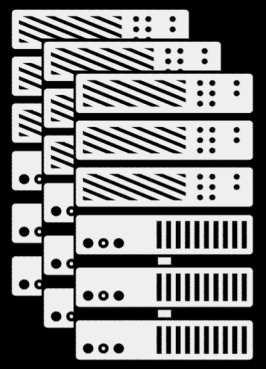
Ashish Vulimiri

“Colossal” streaming data

4 TB /car /day
x 100s thousands cars



10 MB /device /day
x millions devices



10 TB /data center /day
x 10s data centers

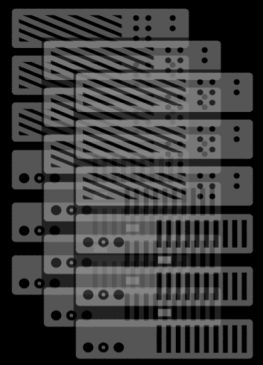
20 GB /home /day
x 100s thousands homes

“Colossal” streaming data

4 TB /car /day
x 100s thousands cars

10 MB /device /day
x millions devices

Hundreds of **TB** to **PB** /day



10 TB /data center /day
x 10s data centers

20 GB /home /day
x 100s thousands homes

Data stores for “colossal” streaming data

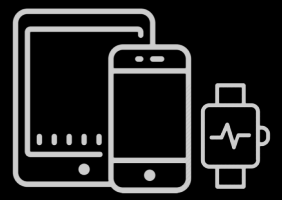
Storing and analyzing data at this scale is a major operational burden

- For the best ingest throughput & query latency, need in-memory stores
  - E.g. Facebook Gorilla
  - Best performance, but expensive
  - Need secondary system for persistence
- Alternately, can use conventional time-series stores
  - Worse performance
  - Still quite resource-intensive: high storage footprint, replication bandwidth

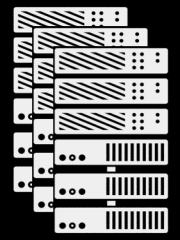
Data stores for “colossal” streaming data

Streams are mainly consumed by analytics and learning workloads

- Forecasting [Facebook Prophet]
- Recommender systems [SoundCloud, Spotify]
- Outlier detection [Etsy Kale]
- Telemetry analytics [Splunk, Twitter Observability]



Primary goal is to extract aggregate properties of data



Theme: Scaling stream analytics via approximation

Build data stores that use approximate data representations to

- Reduce storage and network footprint
- Increase size of in-memory working set
- Reduce query latency

by up to orders of magnitude in real applications

Part 1: SummaryStore [SOSP'17, open-source]

- Low-cost, low-latency approximate single node store

Part 2: Timely Approximate Replicas [WIP]

- Using approximation to scale network use in distributed stores

PART 1: SummaryStore

Approximate single-node time-series store

SummaryStore: 1000-foot overview

Approximate single-node store for “colossal” time-series data

Built around novel data approximation scheme designed for time-series analytics

In real applications (forecasting, outlier analysis, SQL analytics ...) and microbenchmarks:

scale	**1 PB** on commodity node (compacted **100x**)
latency	**< 1s** at 95th %ile
error	**< 10%** at 95th %ile

SummaryStore: Key insight

We make the following observation:

many stream analyses favor newer data over older
existing stores are oblivious, hence costly and slow

Examples:

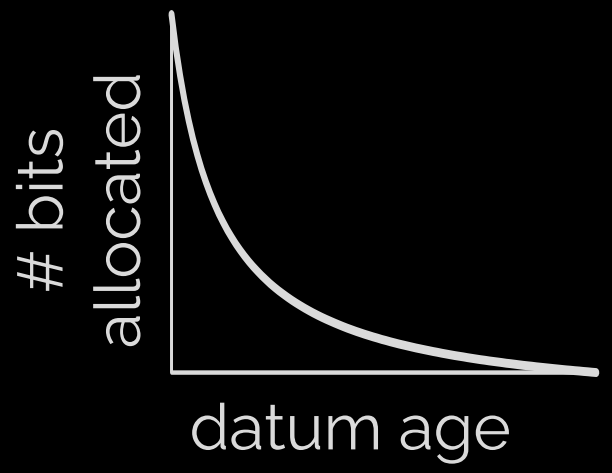
Spotify, SoundCloud	Time-decayed weights in song recommender
Facebook EdgeRank	Time-decayed weights in newsfeed recommender
Twitter Observability	Archive data past an age threshold at lower resolution
Smart-home apps	Decaying weights in e.g. HVAC control, energy monitor

...

SummaryStore: approximate store for stream analytics

Our system, **SummaryStore**

- Approximates data leveraging observation that analyses favor newer data
- Allocates fewer bits to older data than new: each datum decays over time

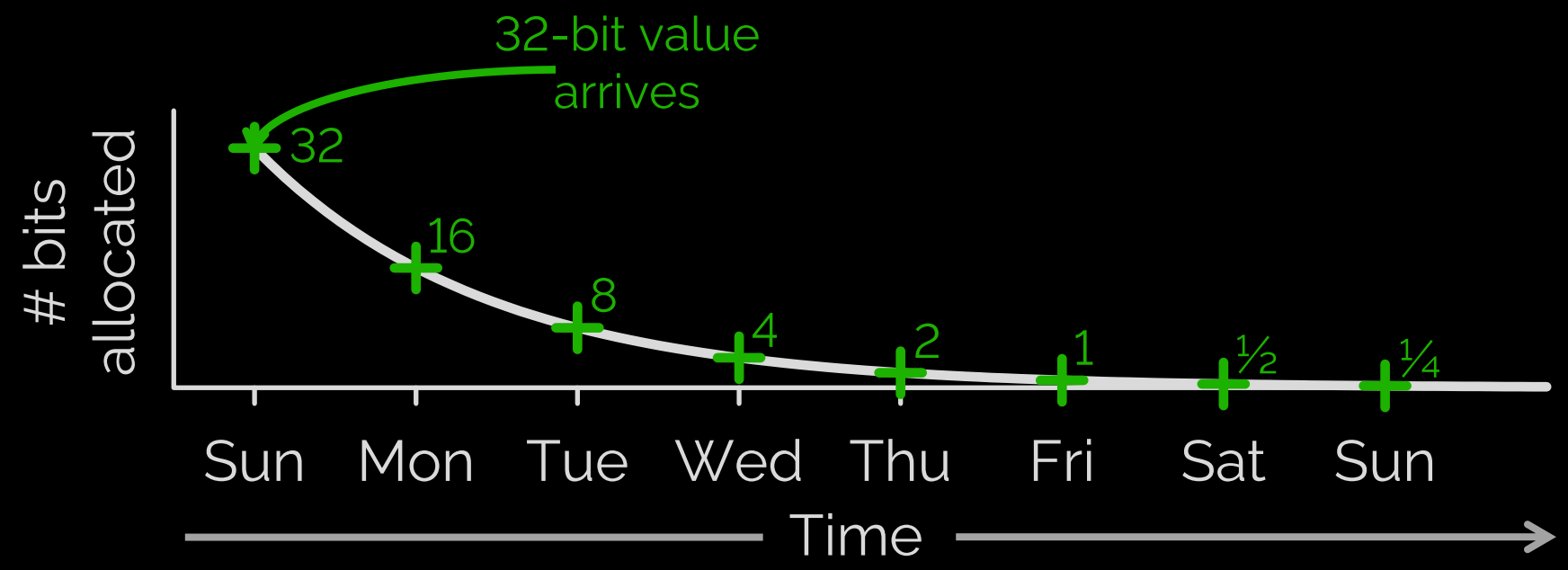


SummaryStore: approximate store for stream analytics

Our system, **SummaryStore**

- Allocates fewer bits to older data than new: each datum decays over time

Example decay policy: halve number of bits each day

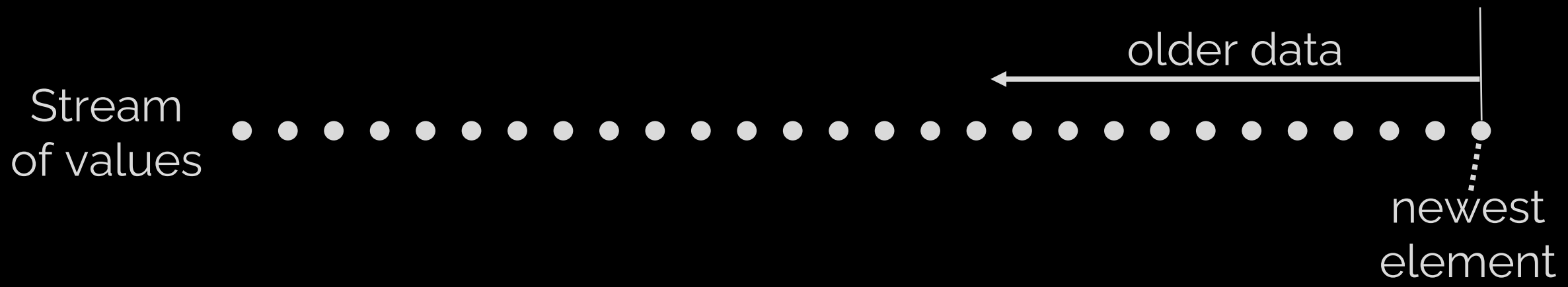


SummaryStore: Outline

1. Time-decayed stream approximation
2. Processing writes
3. Handling queries
4. Evaluation

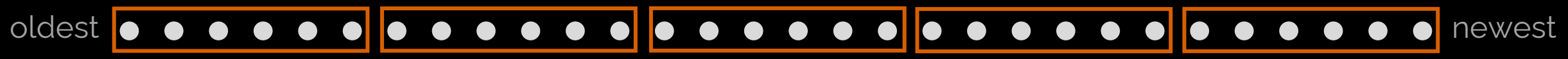
Time-decayed stream approximation

through windowed summarization



Time-decayed stream approximation

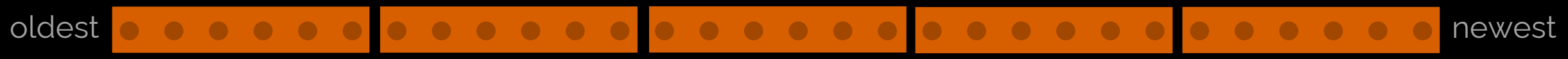
through windowed summarization



1. Group values in windows

Time-decayed stream approximation

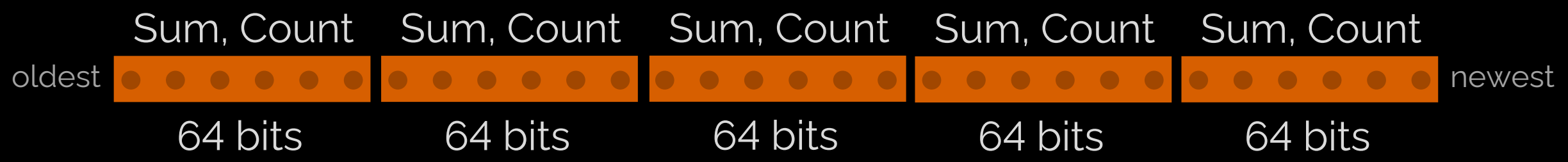
through windowed summarization



1. Group values in windows. Discard raw data

Time-decayed stream approximation

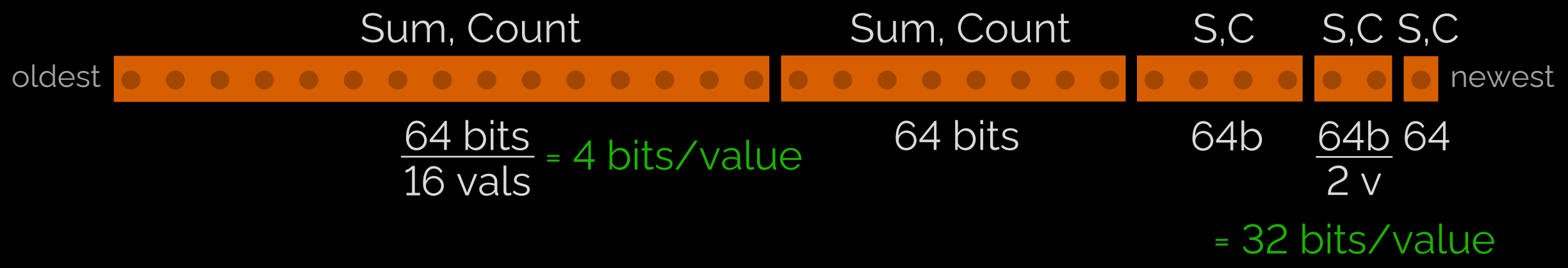
through windowed summarization



1. Group values in windows. Discard raw data, keep only window summaries
   - e.g. Sum, Count, Histogram, Bloom filter, Sample ...
   - Each window is given same storage footprint

Time-decayed stream approximation

through windowed summarization



1. Group values in windows. Discard raw data, keep only window summaries
   - e.g. Sum, Count, Histogram, Bloom filter, Sample ...
   - Each window is given same storage footprint
2. To achieve decay, use longer timespan windows over older data

SummaryStore: Outline

1. Time-decayed stream approximation
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3. Handling queries
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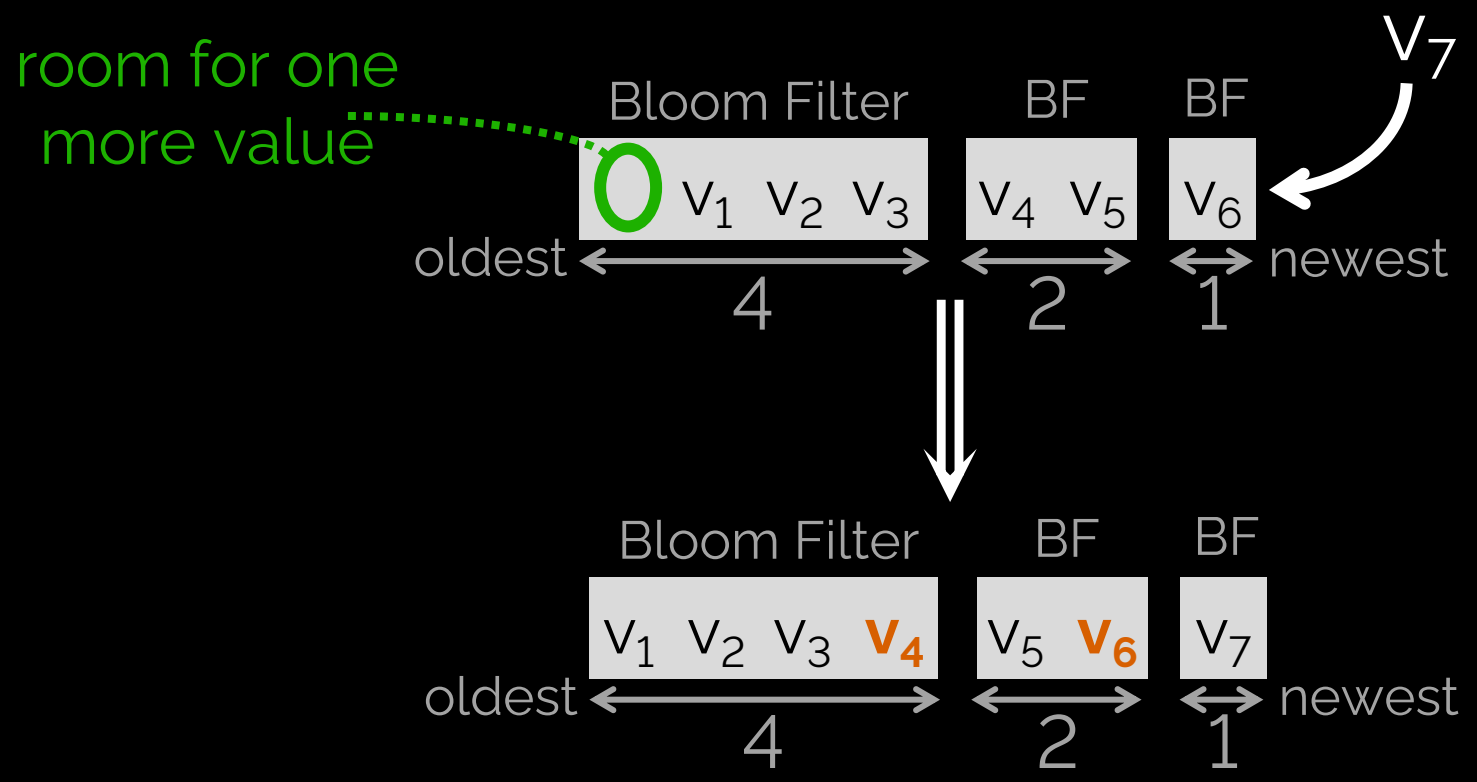
Processing writes: Challenge



Configuration:

Window lengths
1, 2, 4, 8, ...

Each window has
1000-bit
Bloom Filter

Don't have raw values, only window summaries (Bloom Filters)

How do we "move" v_4, v_6 between windows?

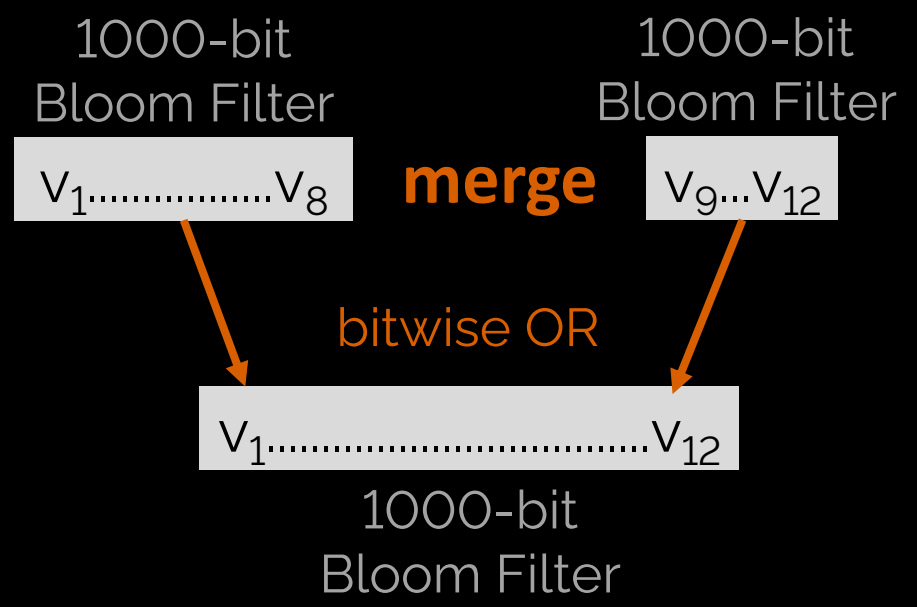
Ingest algorithm

Not possible to actually move values

Instead, use a different technique, building on work by Cohen & Wang†

- Ingest new values into new windows
- Periodically compact data by **merging** consecutive window pairs
  - Merge all summary data structures
  - Halve storage budget for window values

† E. Cohen, J. Wang, "Maintaining time-decaying stream aggregates", J. Alg. 2006



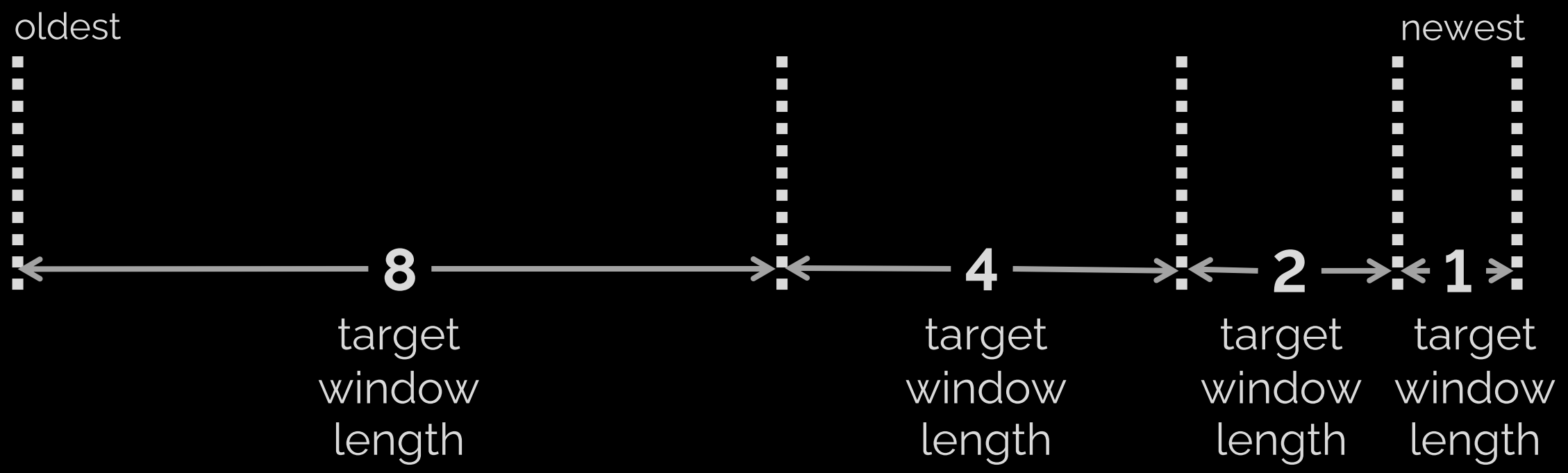
merge operation for

Bloom Filter	:	bitwise OR
Count	:	add
Histogram	:	combine & rebin
		etc

Ingest algorithm

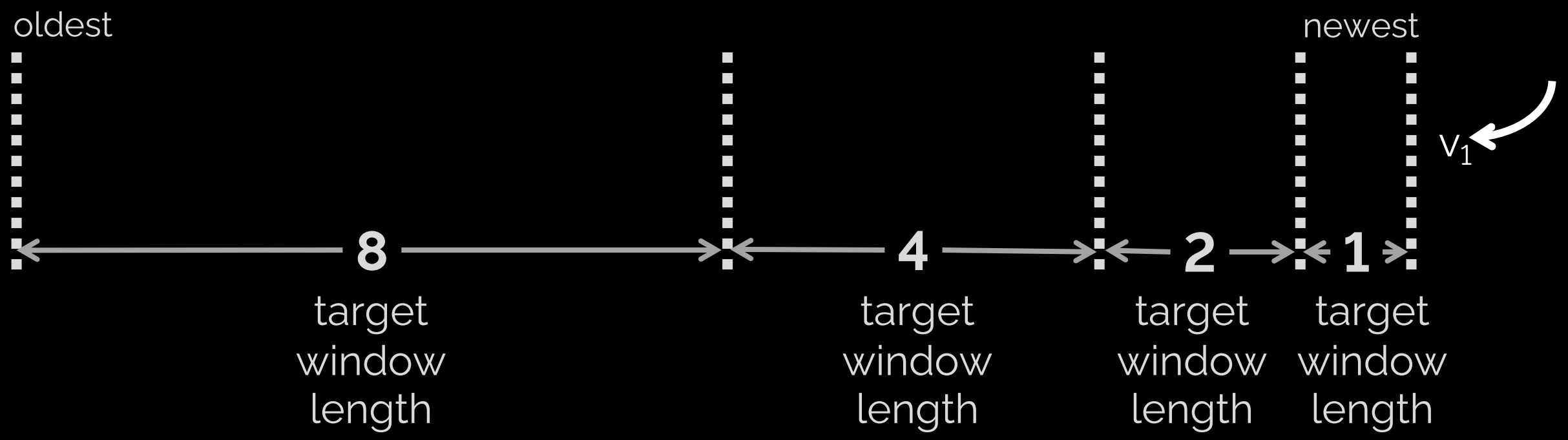
Configure a target sequence of window lengths (choice affects decay)

- Example below uses 1, 2, 4, 8, 16, ...



Ingest algorithm

1. When a value arrives, create new window of length 1 to hold it
2. Merge any consecutive windows contained in same pair of dotted lines



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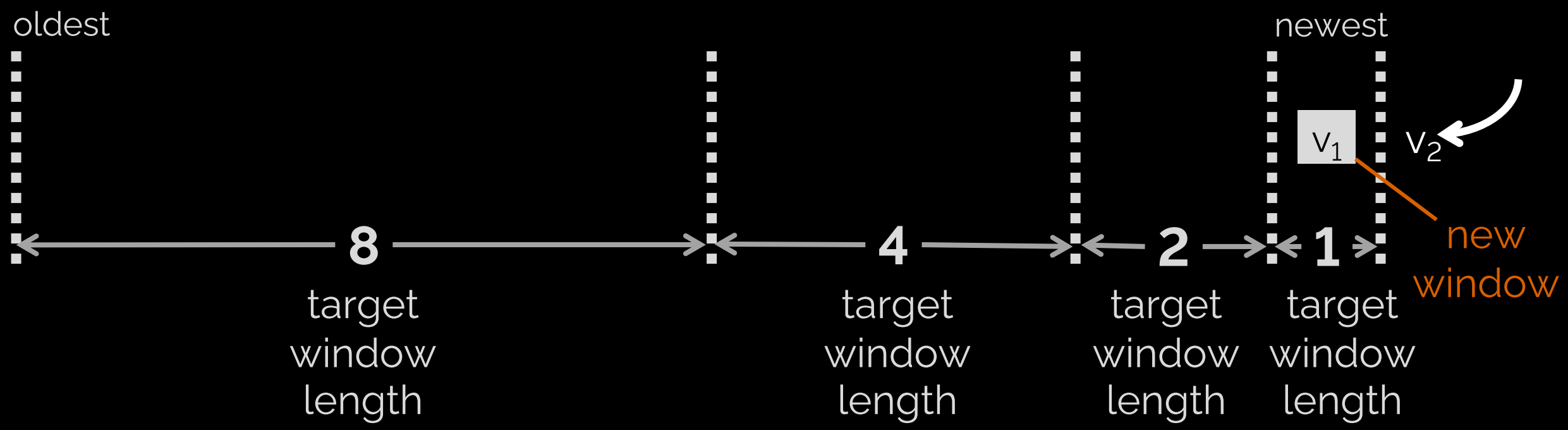

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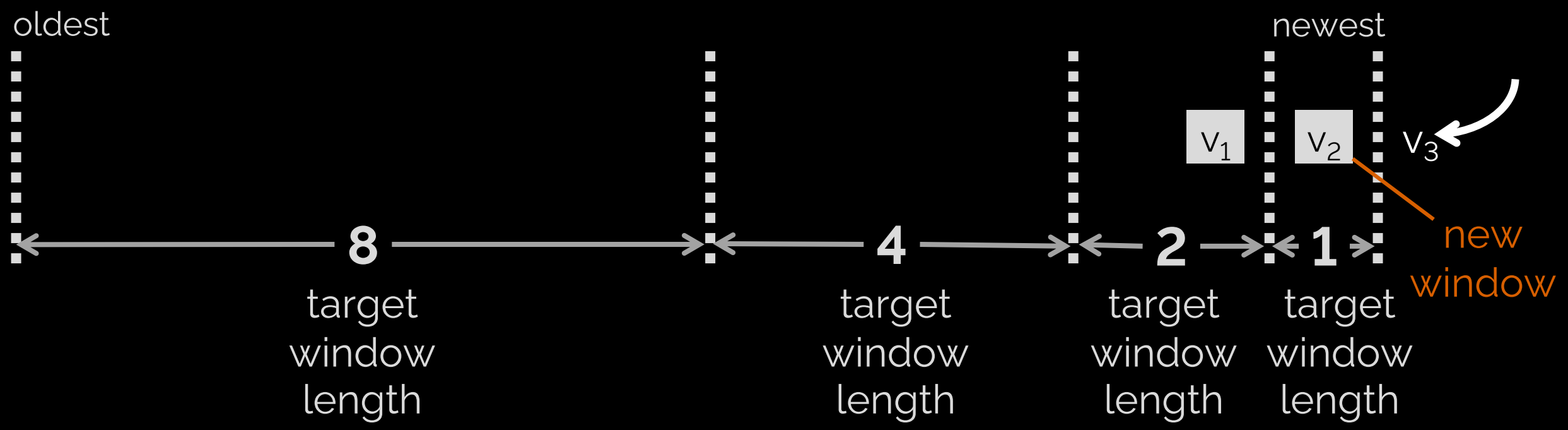

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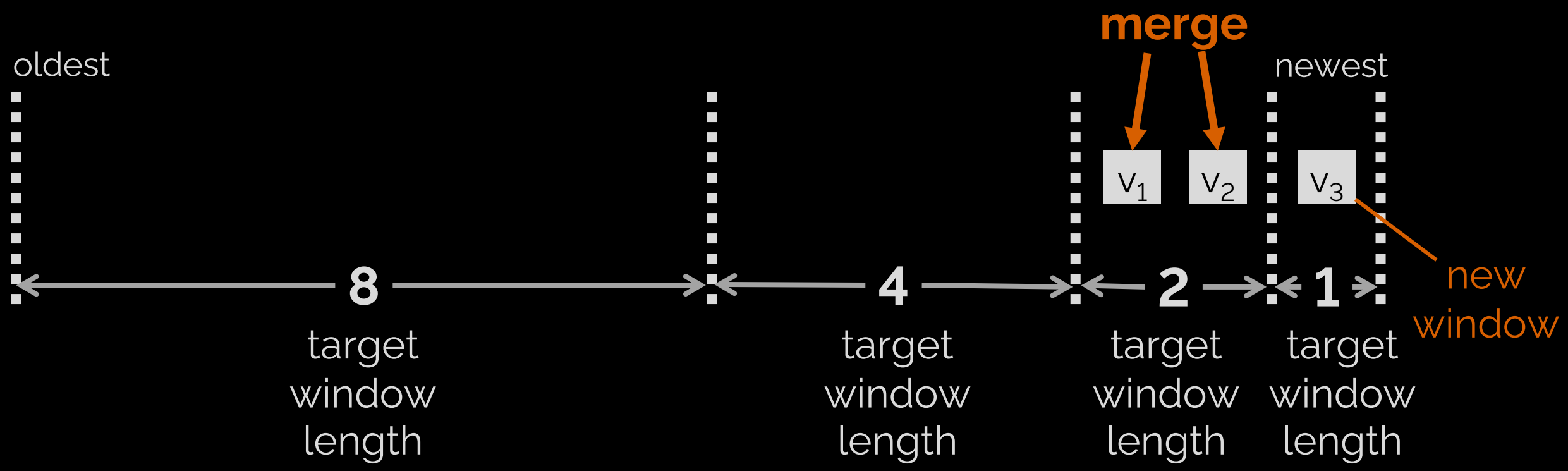

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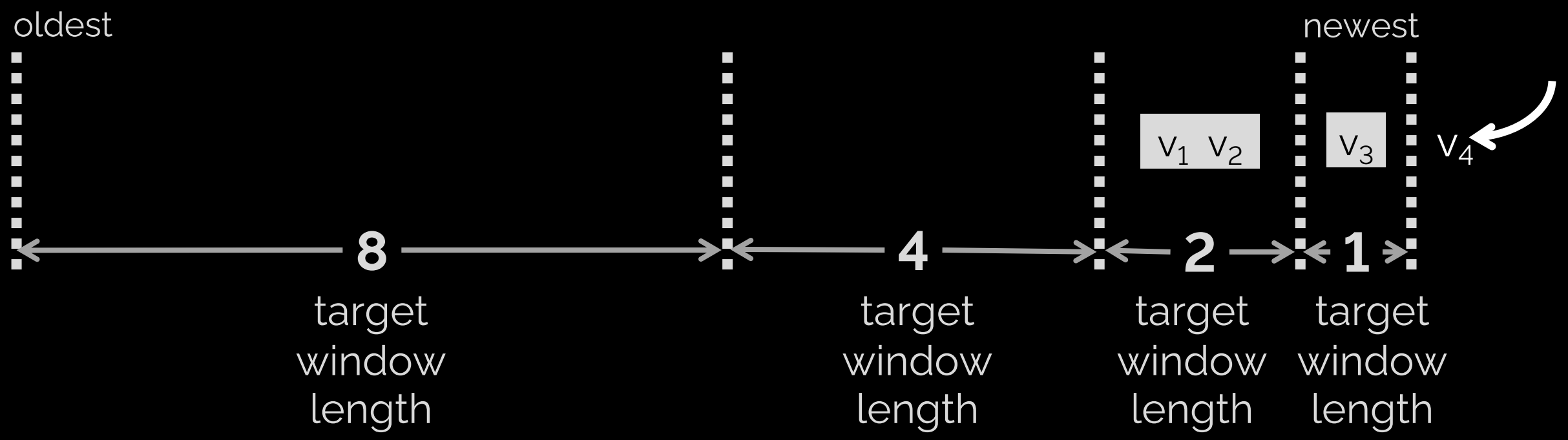

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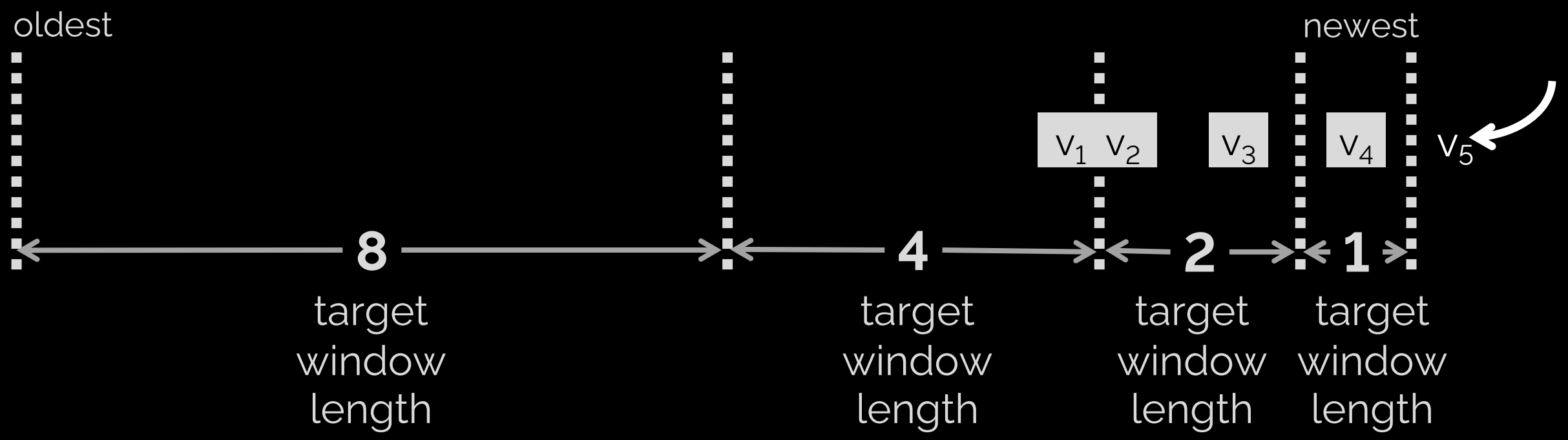

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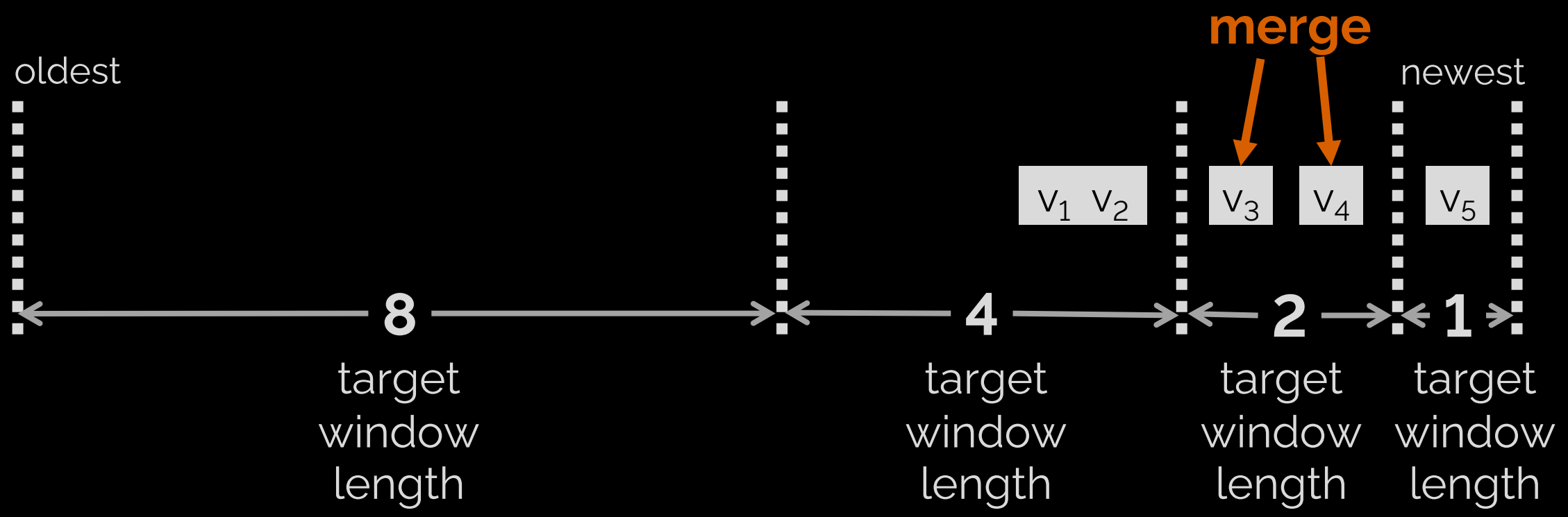

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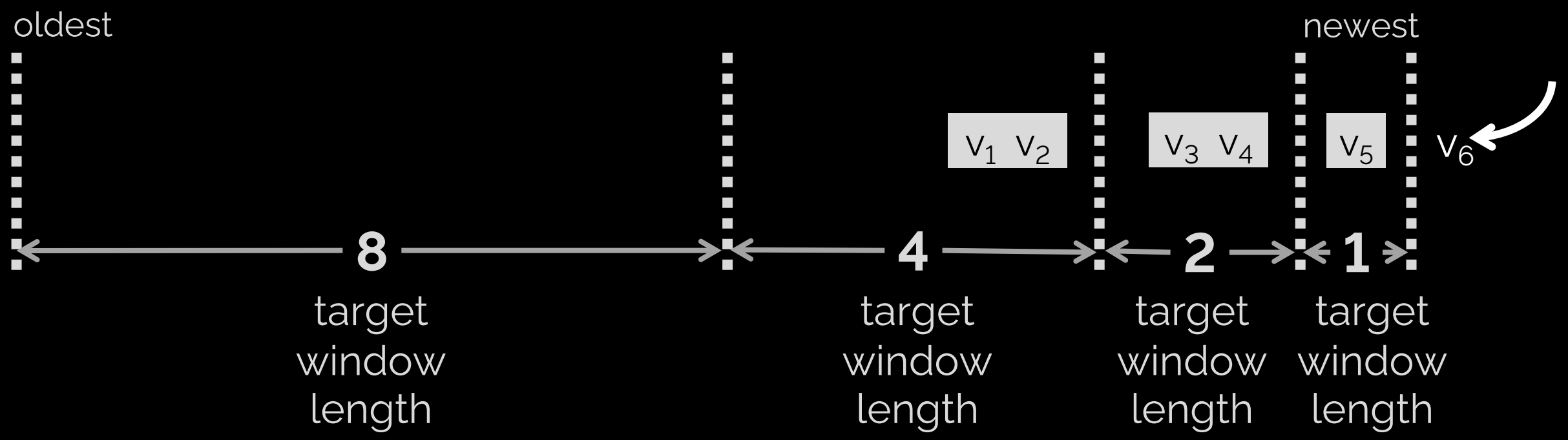

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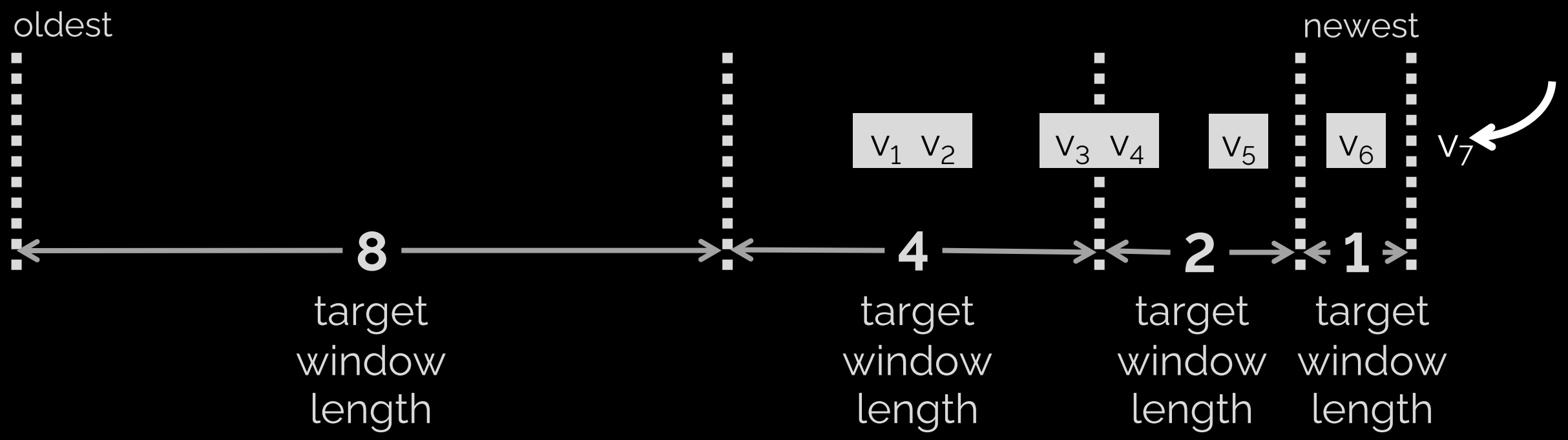

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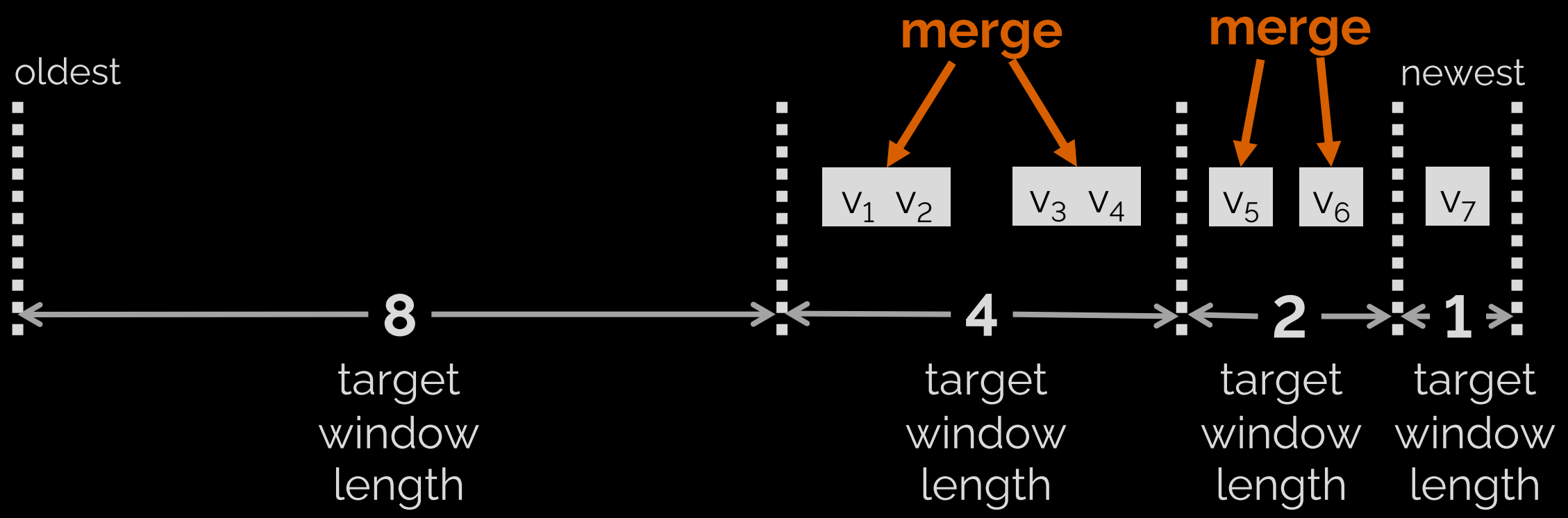

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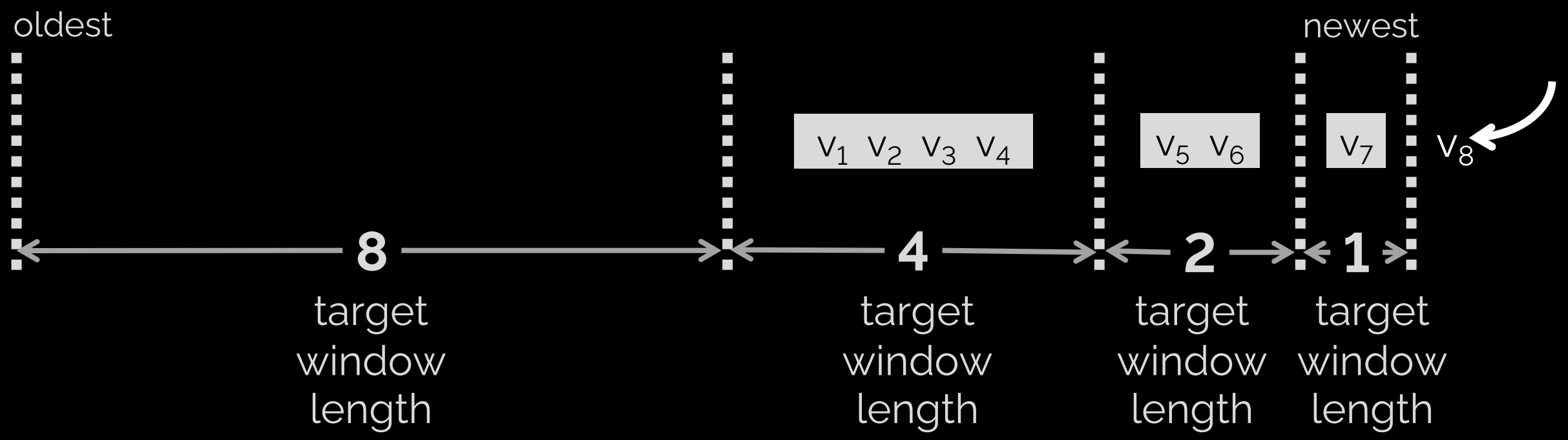

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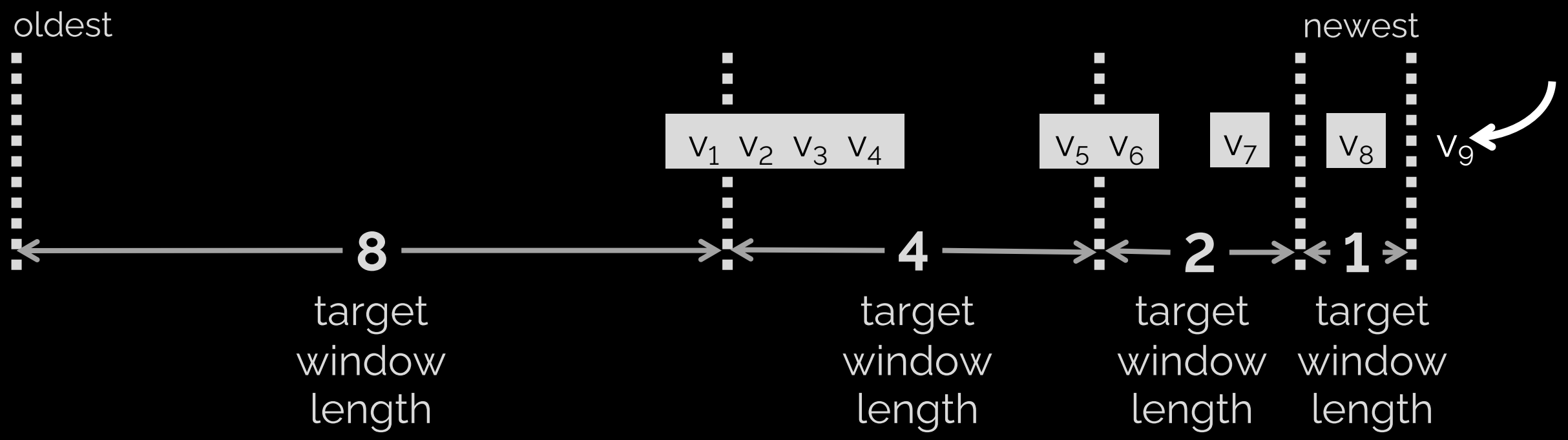

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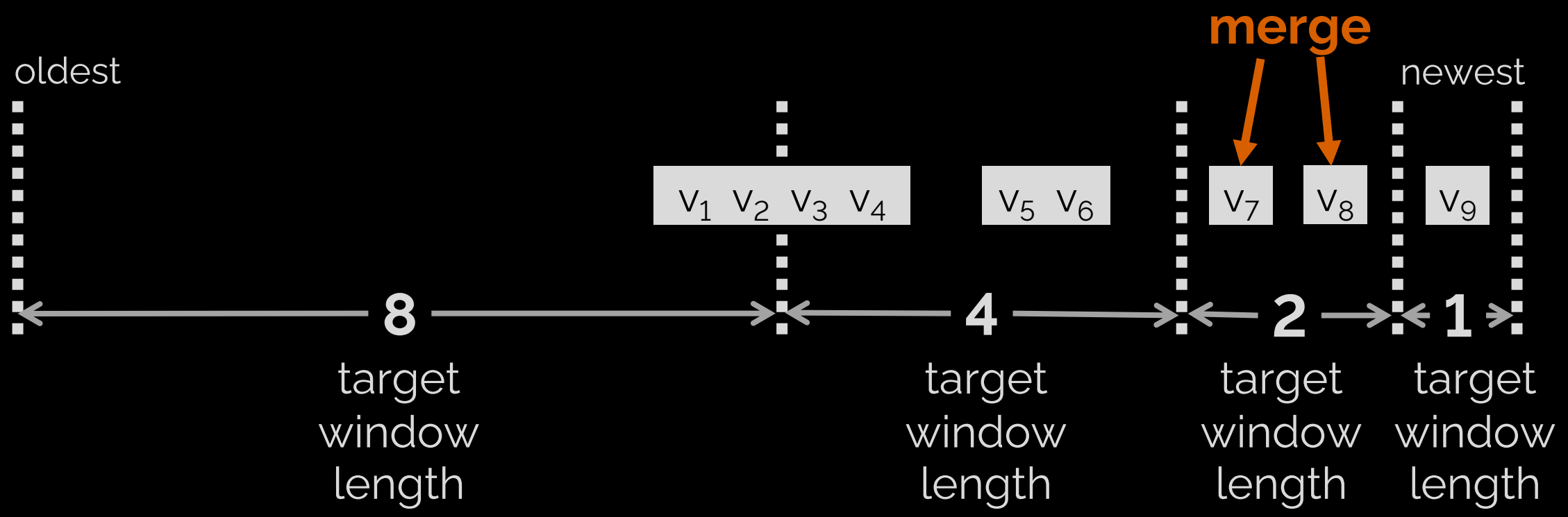

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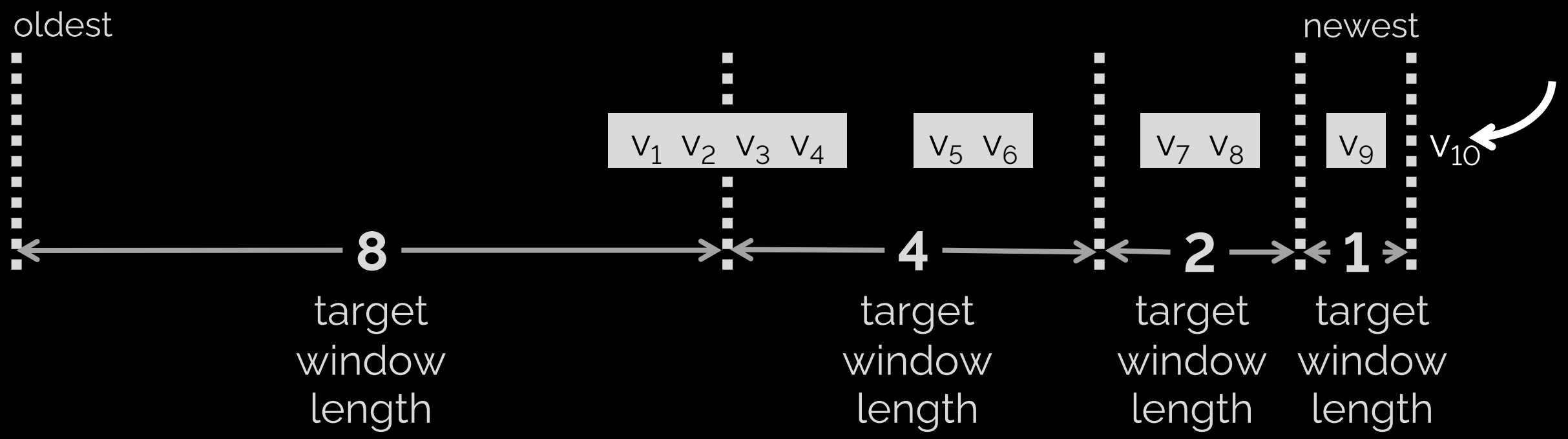

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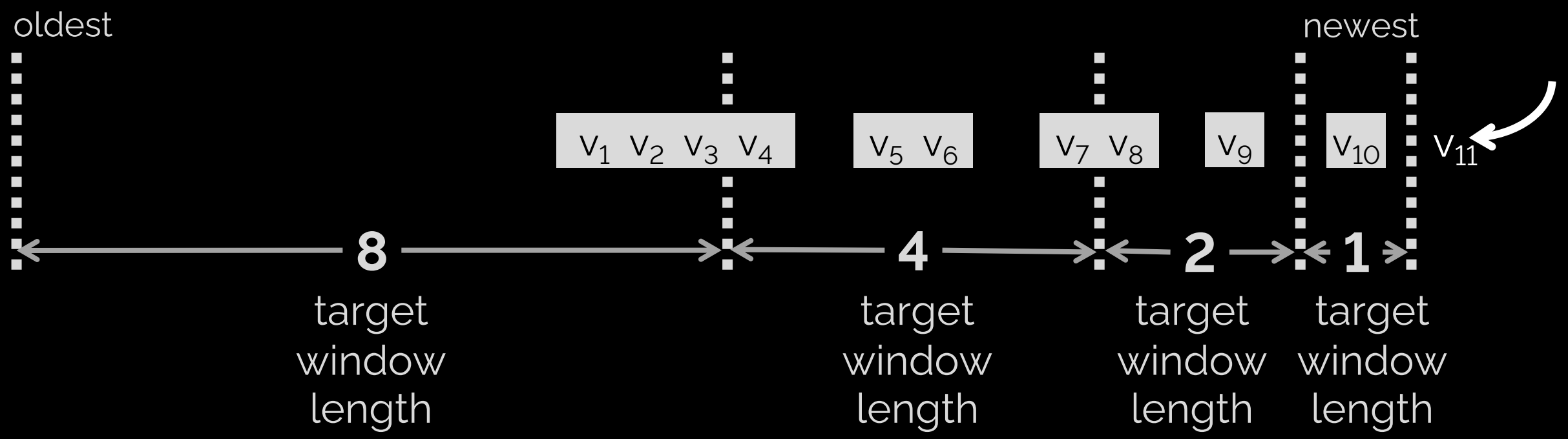

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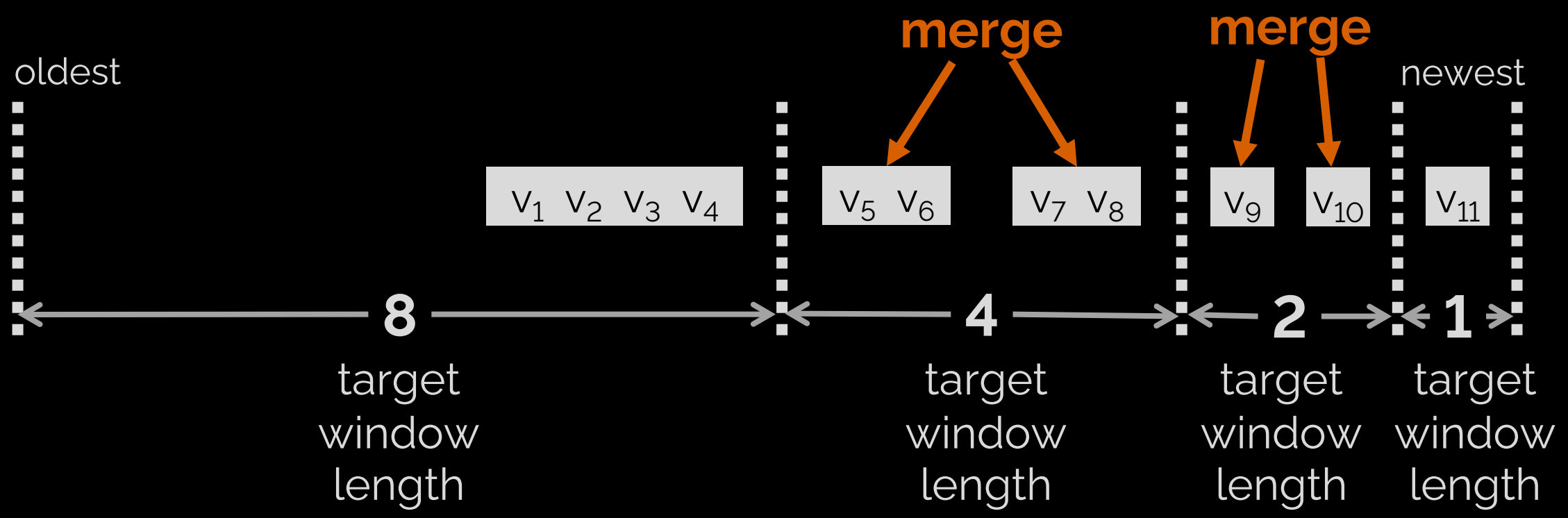

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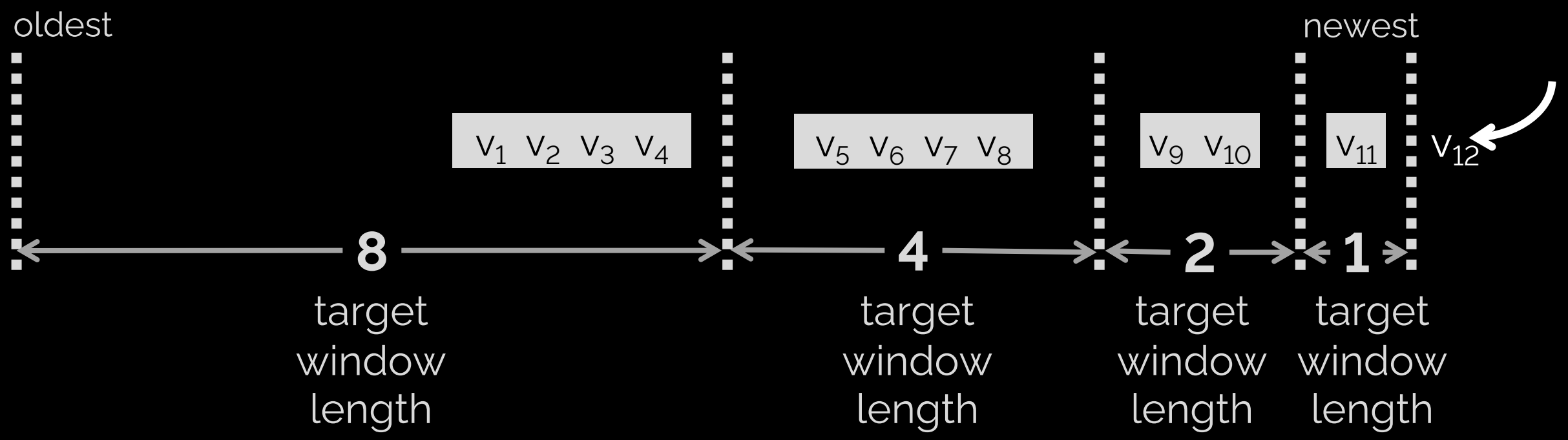

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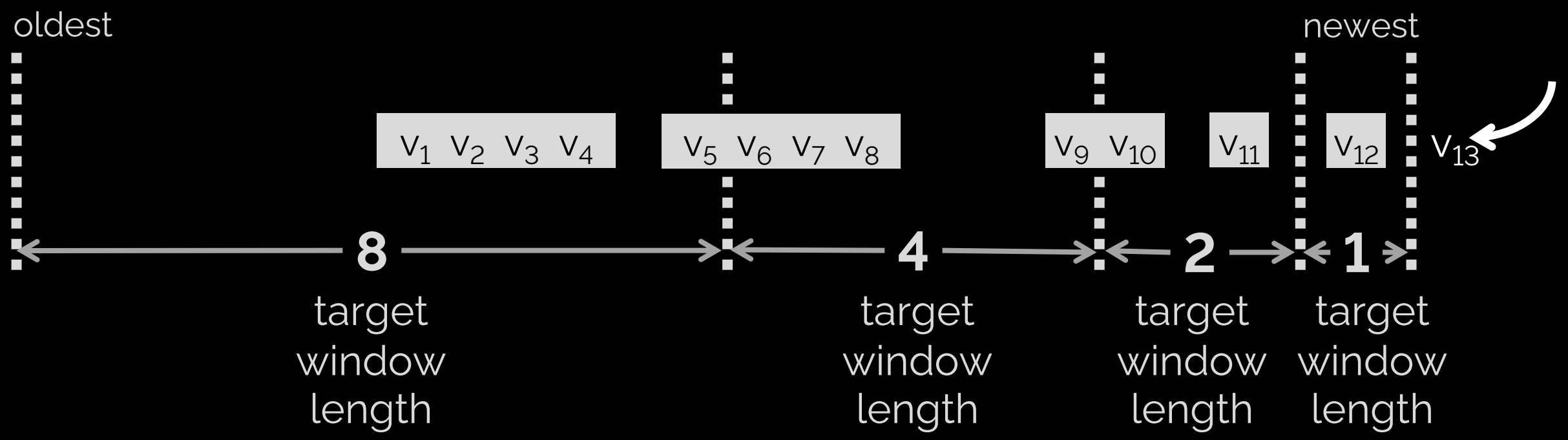

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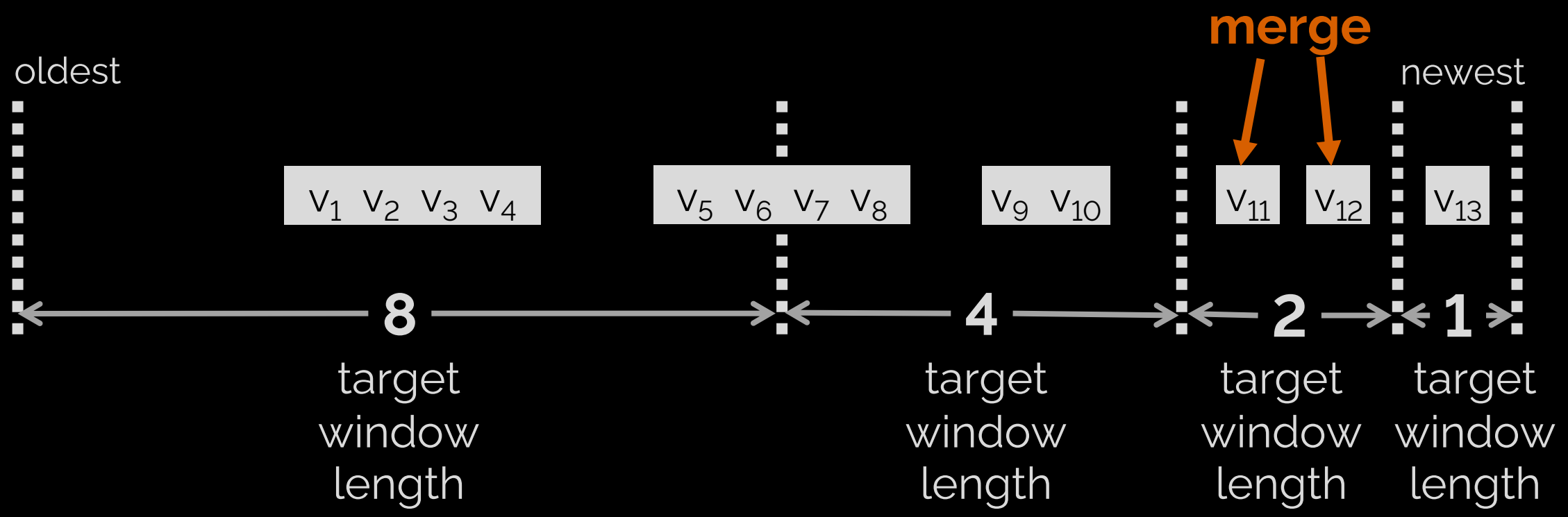

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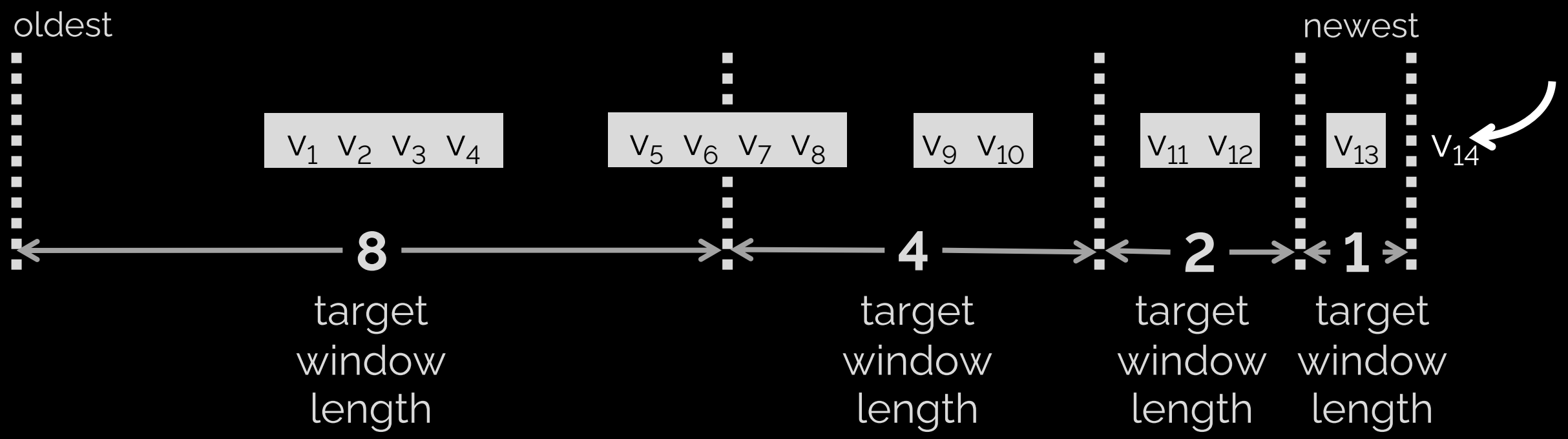

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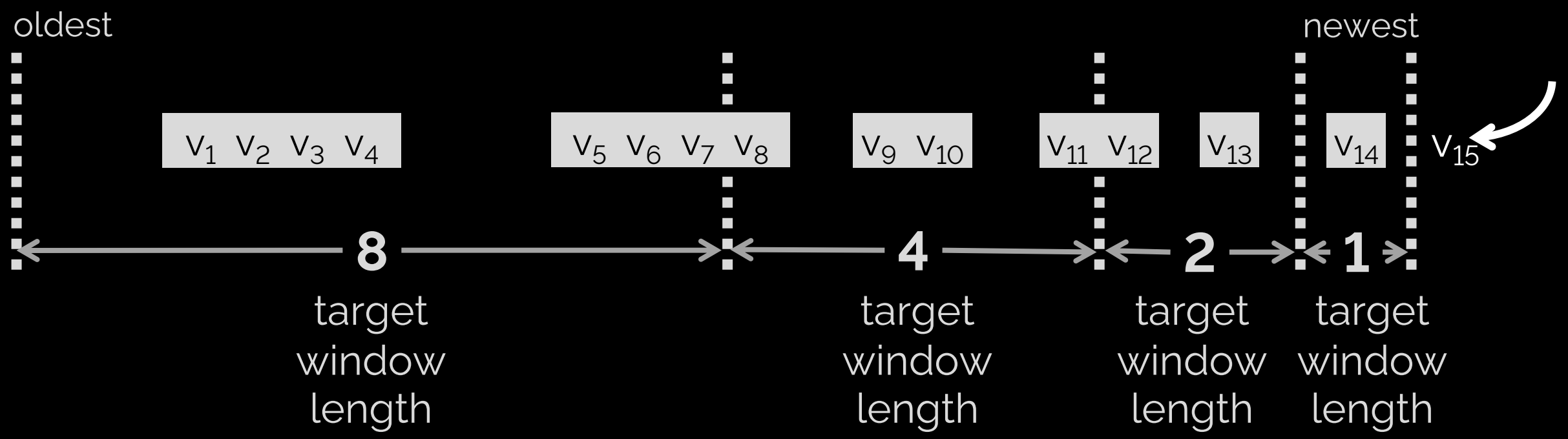

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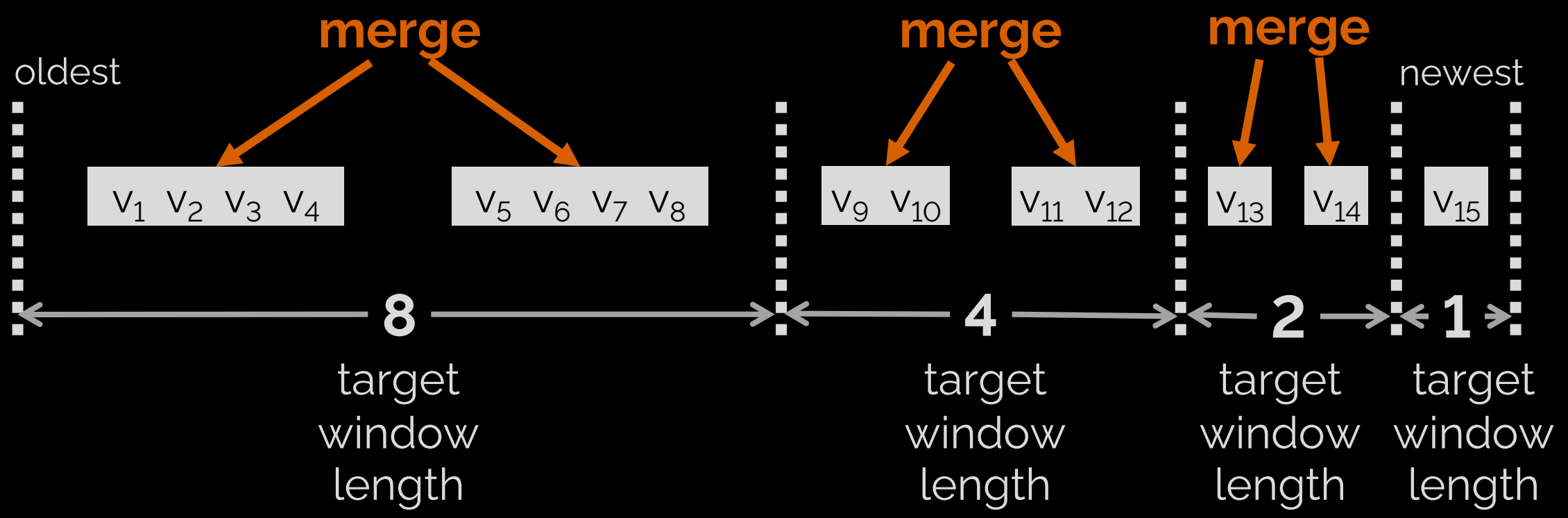

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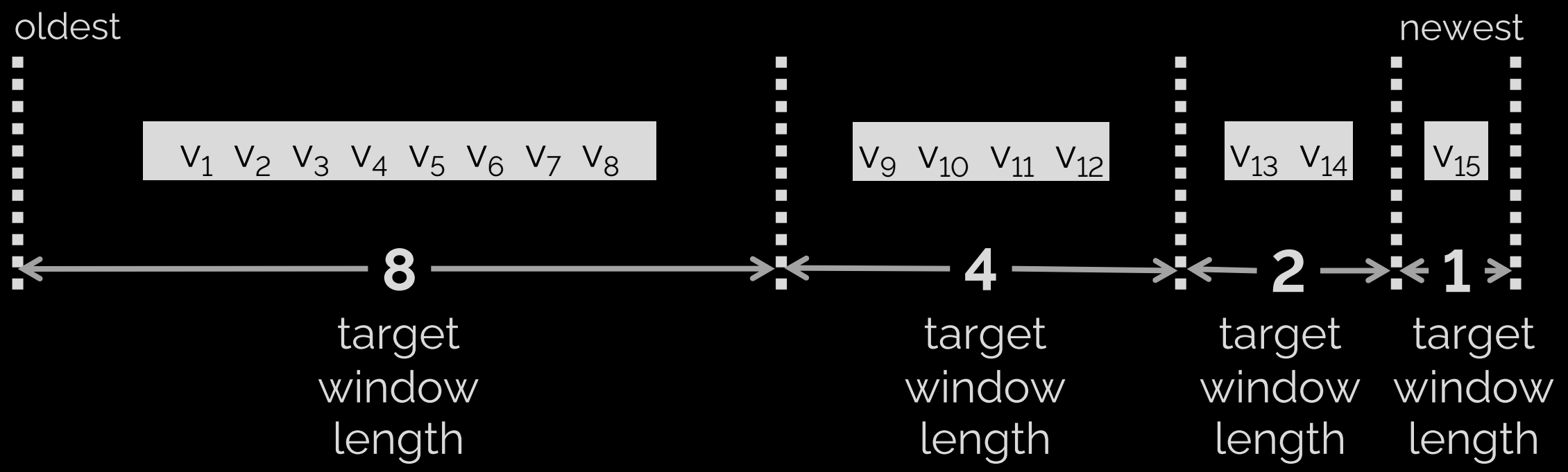

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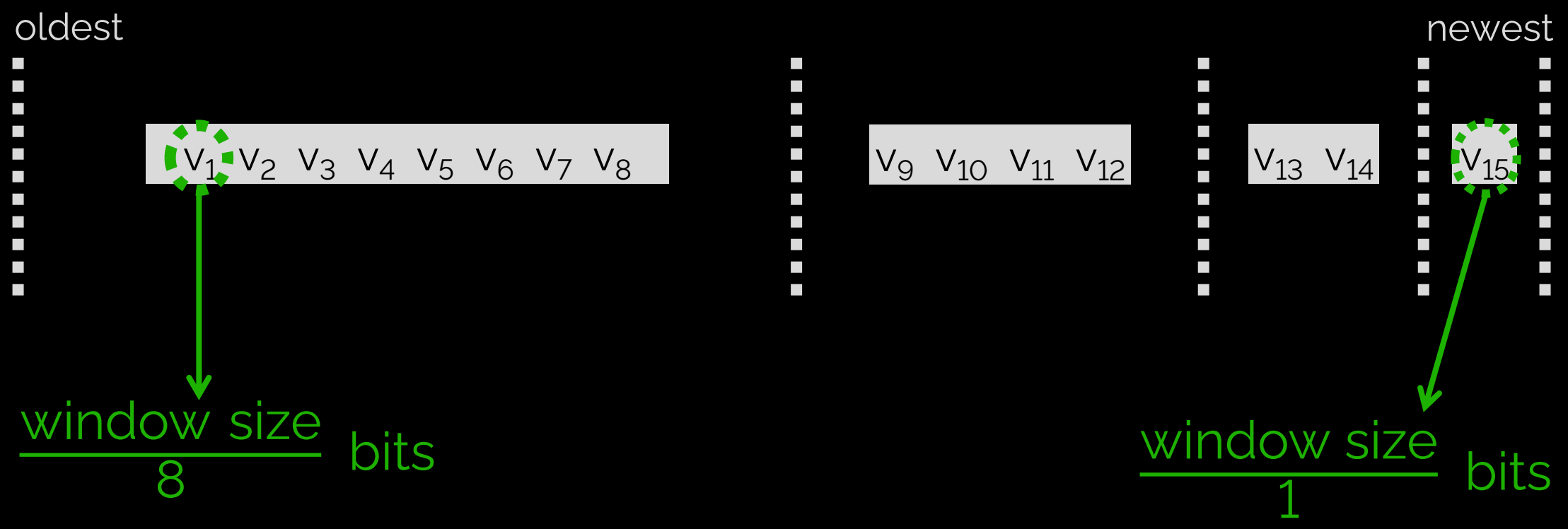

Ingest algorithm

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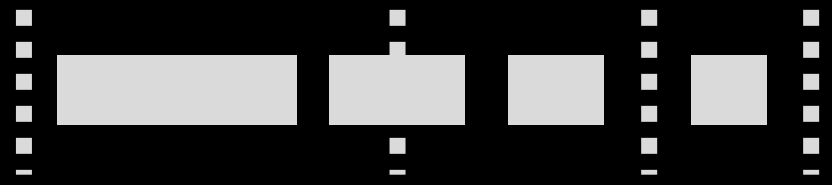
Why this algorithm works:

- At any point in time:
  - No more than one actual window inside any target window (between a pair of dotted lines)



  - Thus number of actual windows ≤ 2 x number of target windows
- By induction: # bits allocated to any datum is always within 2x of target

SummaryStore: Outline

1. Time-decayed stream representation
2. Processing writes
3. Handling queries
4. Evaluation

Query interface: Time-range queries

query a summary over
the time-range $[T_1, T_2]$

Examples

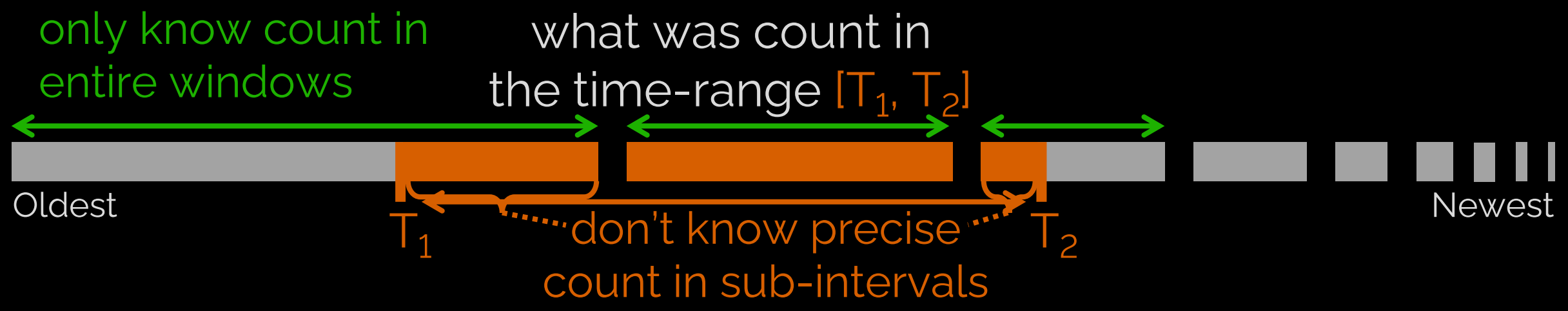
- What was average energy usage in Sep 2015?
- Fetch a random (time-decayed) sample over the last 1 year

Query interface: Time-range queries

query a summary over
the time-range $[T_1, T_2]$

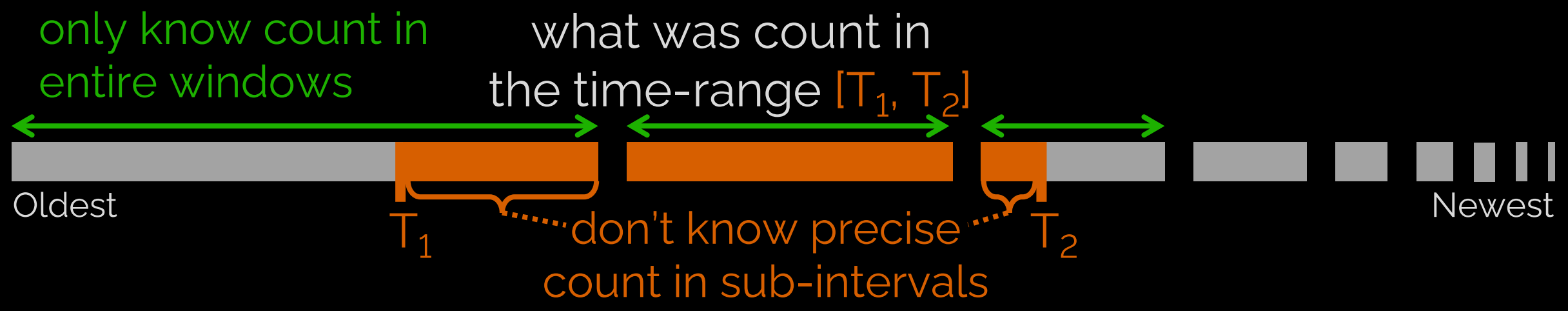
Time-ranges are allowed to be arbitrary, need not be window-aligned

Query interface: Time-range queries



Time-ranges are allowed to be arbitrary, need not be window-aligned

Query interface: Time-range queries



Time-ranges are allowed to be arbitrary, need not be window-aligned

Lack of window alignment introduces error

We use novel low-overhead statistical techniques to estimate answer & confidence interval

Query accuracy

Age = how far back in time query goes

- Lower age ⇒ more recent data, so better accuracy

Length = time-span query covers

- Longer length ⇒ more windows spanned, so better

Not suited for large age + small length

- e.g. query over the time range
  [10 years ago, 10 years ago + 3 seconds]

length \ age	new	med	old
long	✓	✓	✓
med	✓	✓	–
short	✓	–	×

not suited

SummaryStore: Outline

1. Time-decayed stream representation
2. Processing writes
3. Handling queries
4. Evaluation

Evaluation

On a single node: 224 GB RAM, 10 x 1 TB disk

Microbenchmarks: 1 PB on single node

Real applications

- Forecasting
- Outlier analysis
- Analyzing network traffic and data backup logs

Evaluation

On a single node: 224 GB RAM, 10 x 1 TB disk

Microbenchmarks: 1 PB on single node

Real applications

- Forecasting
- Outlier analysis
- Analyzing network traffic and data backup logs

1. Microbenchmarks: 1 PB on a single node

1 PB on a single node: Setup

Dataset: 1024 x 1 TB streams, each randomly generated

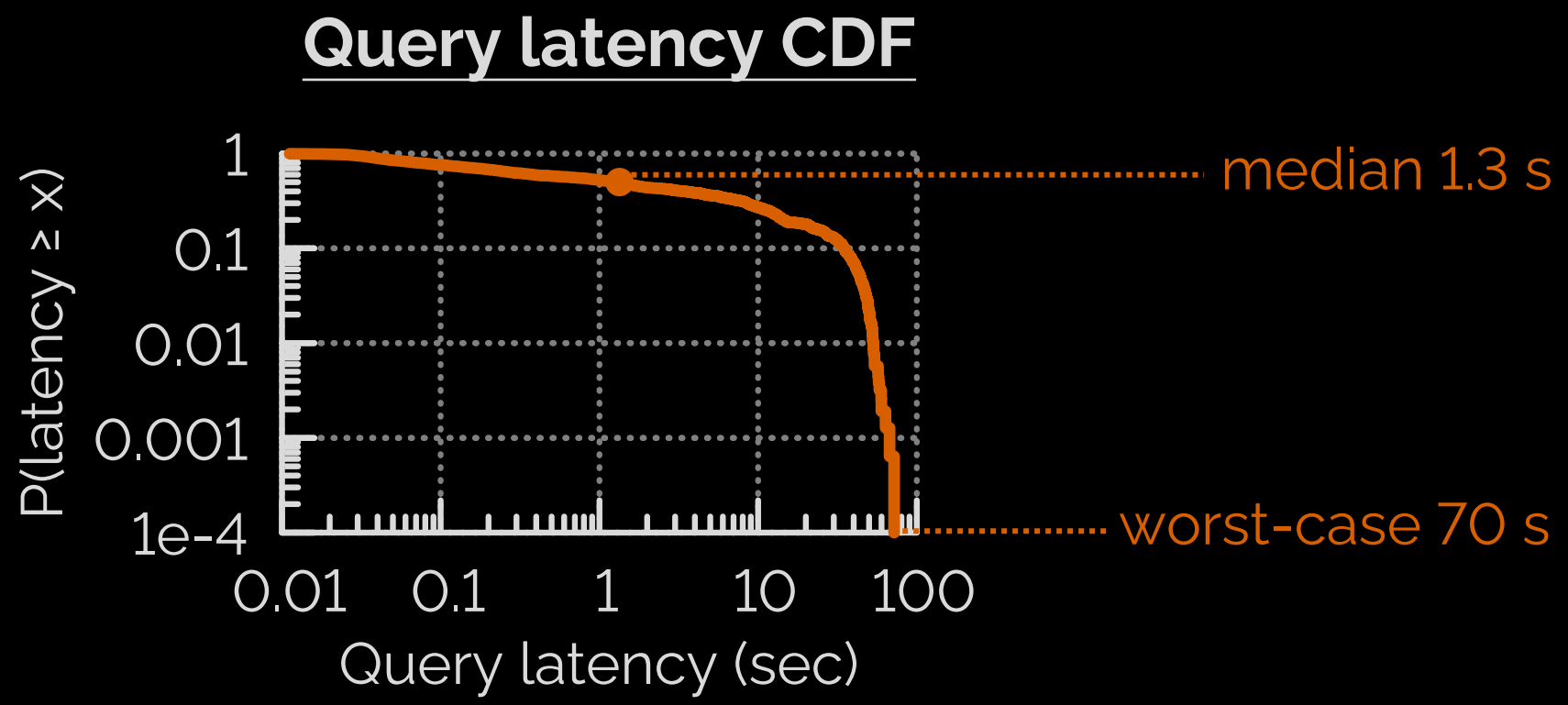
- Poisson, Pareto arrival process
- Uniform random values

Compacted 100x (down to 10 TB)

Queries: randomly generated

- Count, Sum, Frequency, Existence
- Each query picks a random stream and a random time interval
  - Spans up to 1 TB raw data

1 PB on a single node: Latency

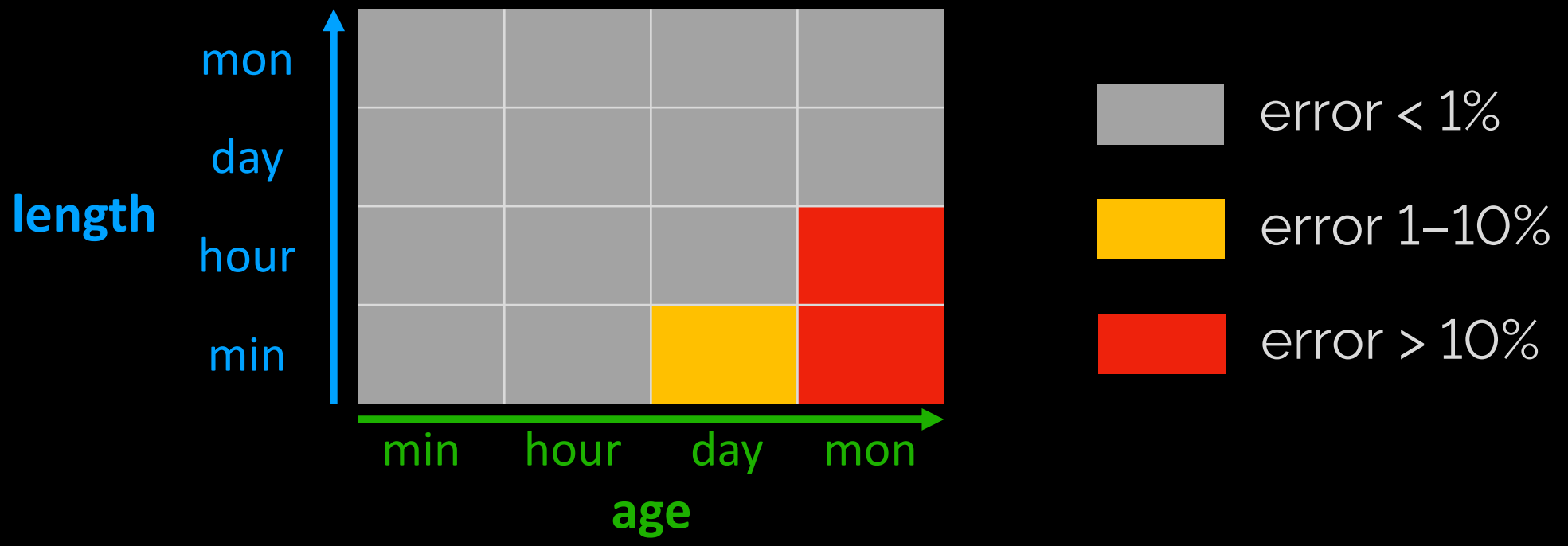


Above latencies were with all caches disabled (conservative bound)

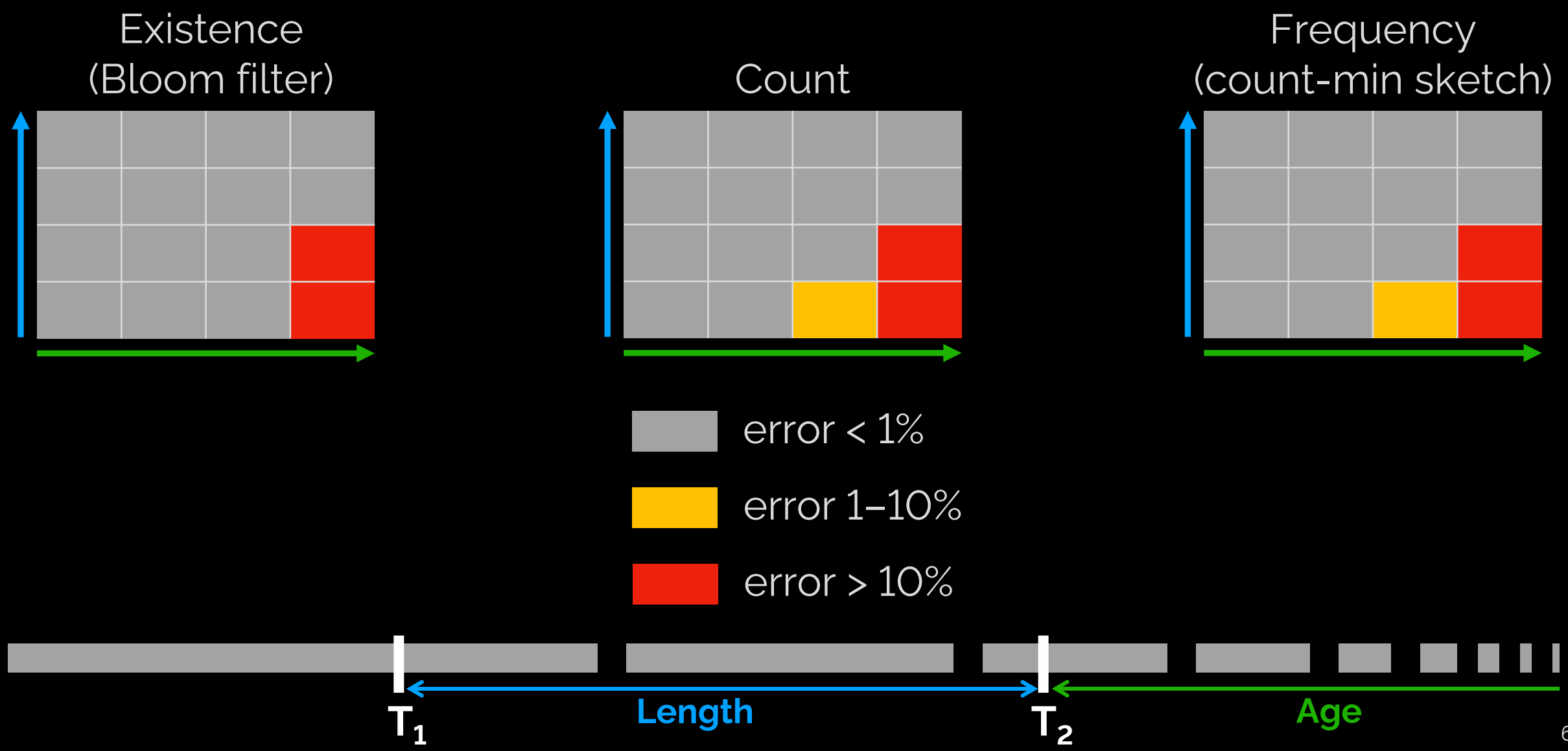
With caching: varies, < 1s 95th %ile w/ reasonable locality

1 PB on a single node (compacted 100x): Accuracy

95th %ile error in
$[T_1, T_2]$ Count



1 PB on a single node (compacted 100x): Accuracy



2. Real application: Time-series forecasting w/ Prophet

Time-series forecasting w/ Prophet

Prophet: open-source forecasting library from Facebook

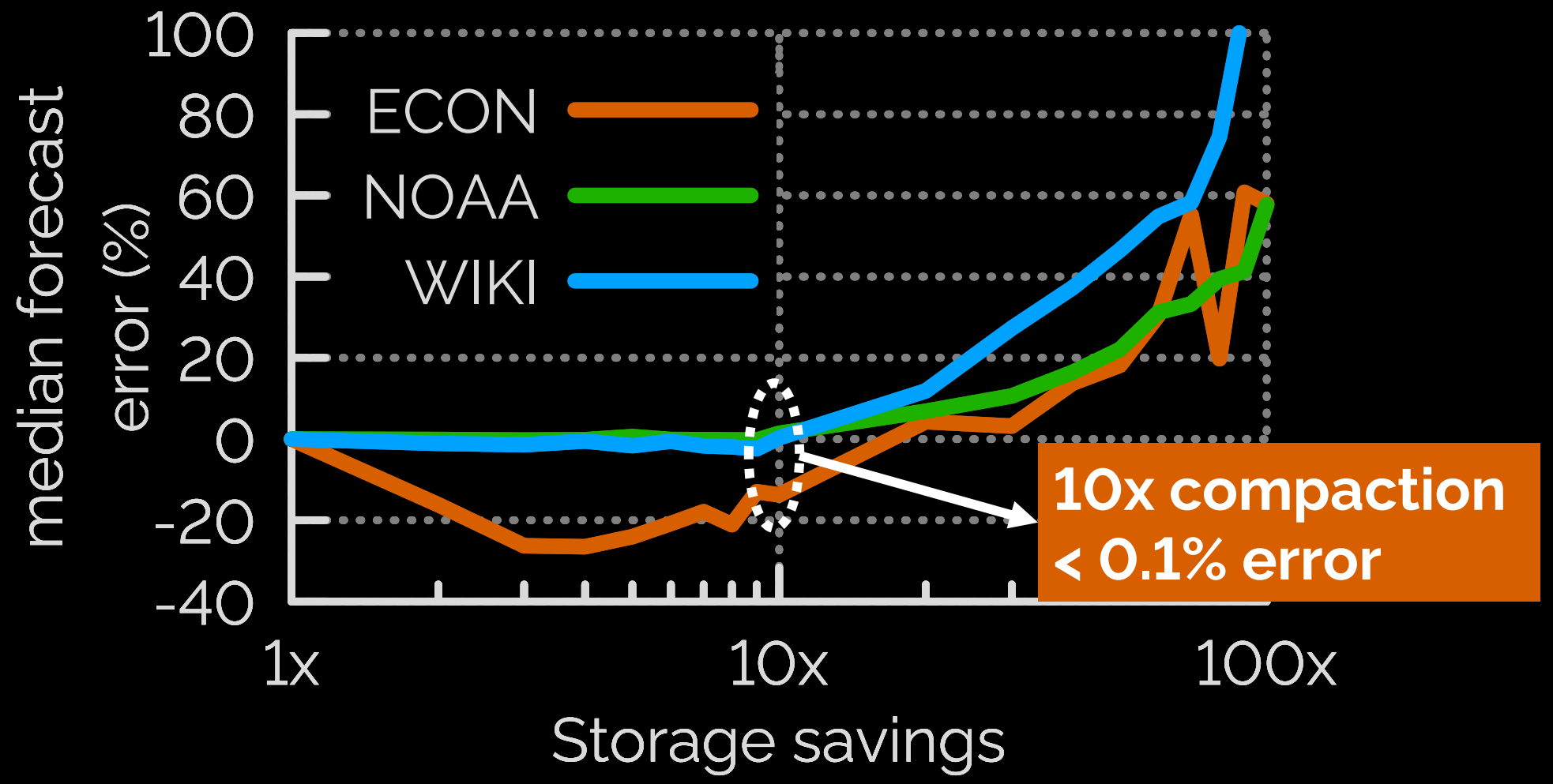
Tested three datasets

- WIKI: visit counts for Wikipedia pages
- NOAA: global surface temperature readings
- ECON: log of US economic indicators

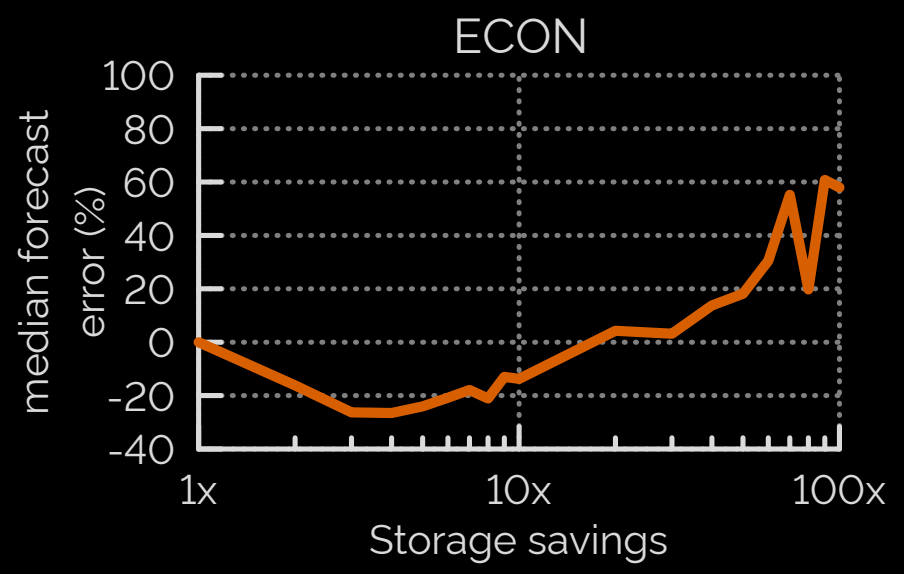
On each time-series in each dataset, compared forecast accuracy of

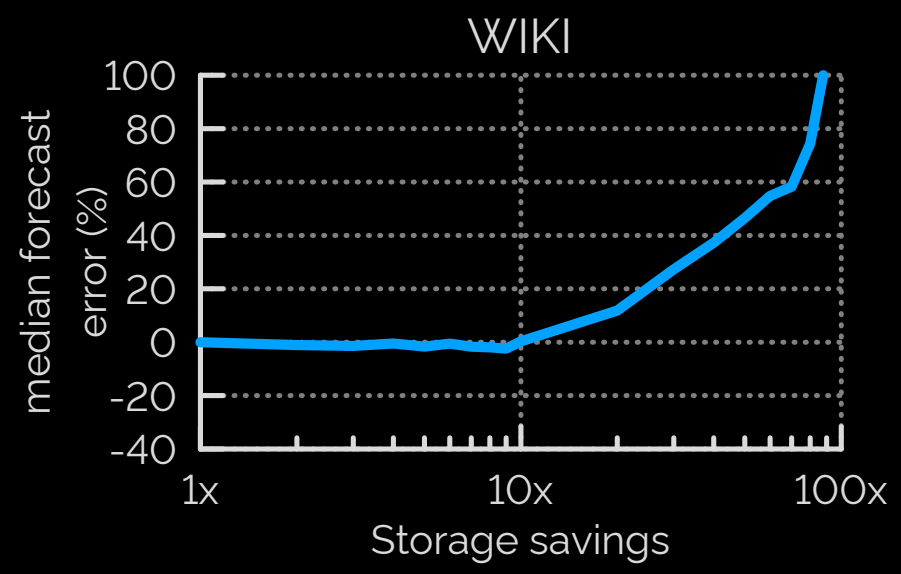
- Model trained on all data
- Model trained on time-decayed sample of data

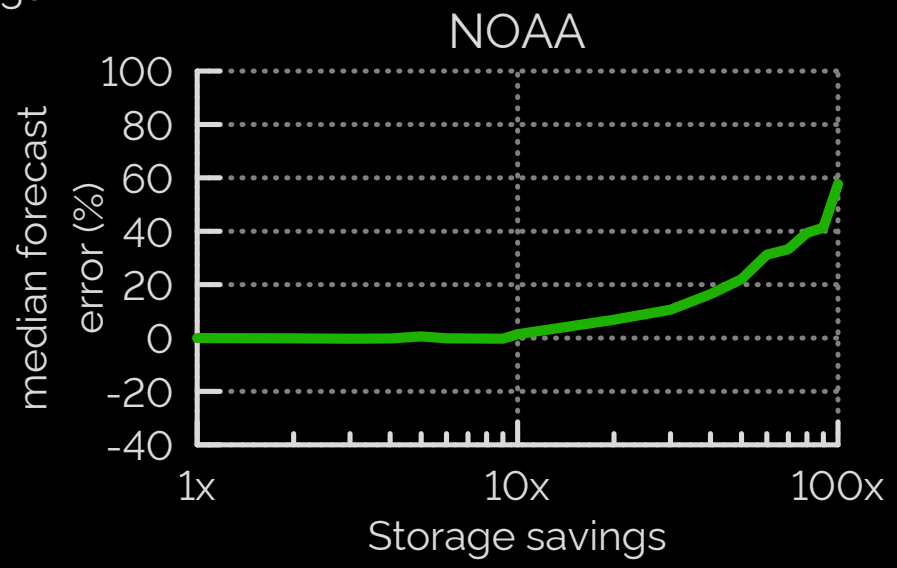
Time-series forecasting w/ Prophet



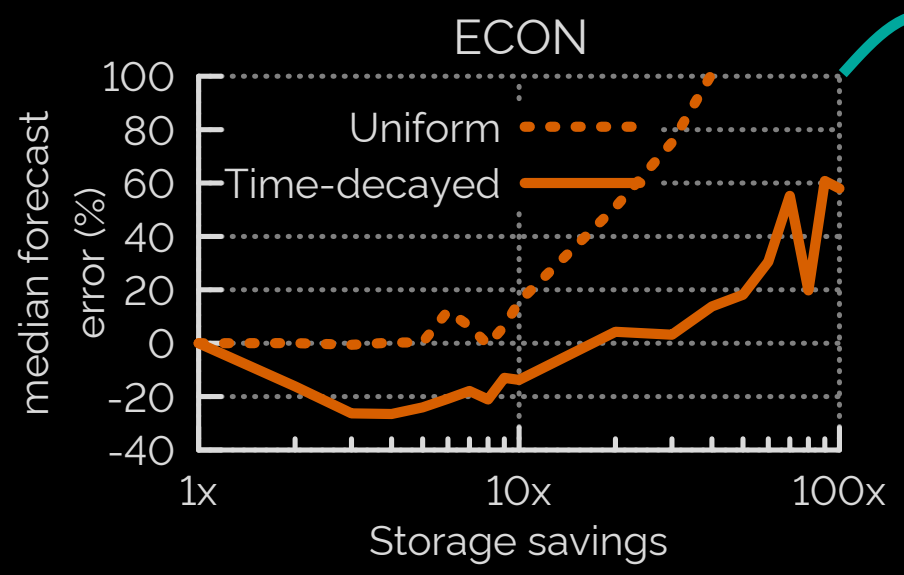
Time-series forecasting w/ Prophet



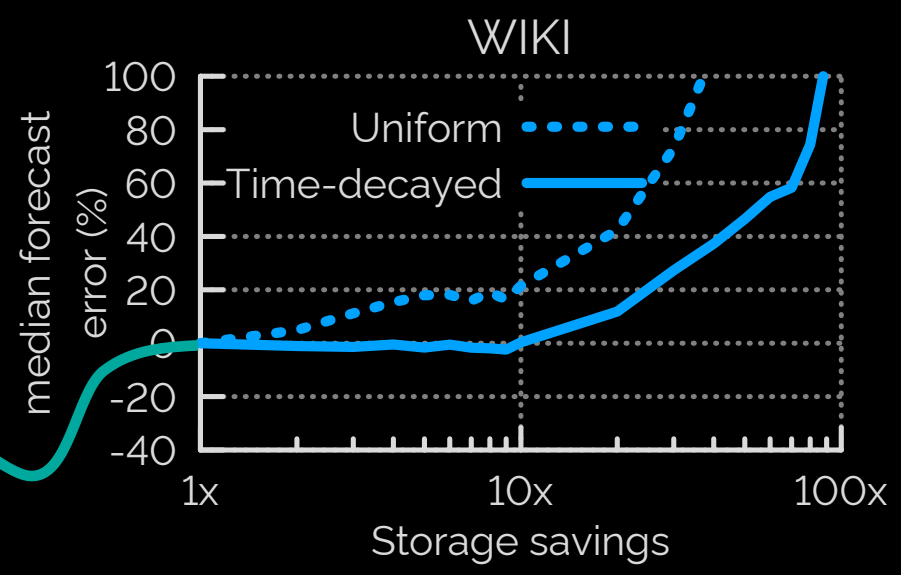


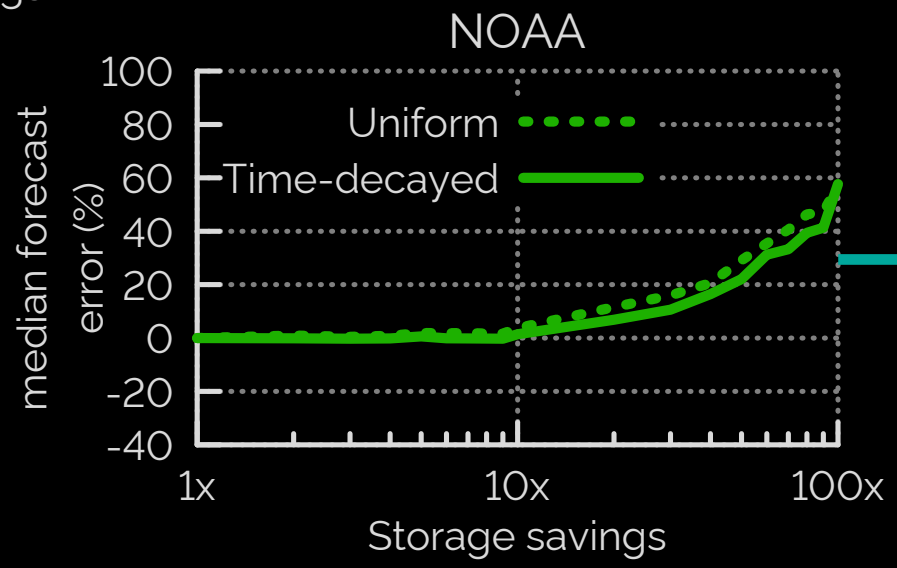


Time-series forecasting w/ Prophet



substantial improvement





difference not as stark because of predictable dataset

Skipped details [see SOSP'17]

Landmarks

System design

System configuration

Statistical techniques for sub-window queries

Skipped details [see SOSP'17]

Landmarks

System design

System configuration

Statistical techniques for sub-window queries

Landmarks

Mechanism for protecting specific values from decay

Values declared as landmarks are

- Always stored at full resolution
- Seamlessly combined with decayed data when answering queries

Example application: outlier analysis

SummaryStore: approximate store for stream analytics

Contributions

- Abstraction: time-decayed summaries + landmarks
- Data ingest mechanism
- Low-overhead statistical techniques bounding query error

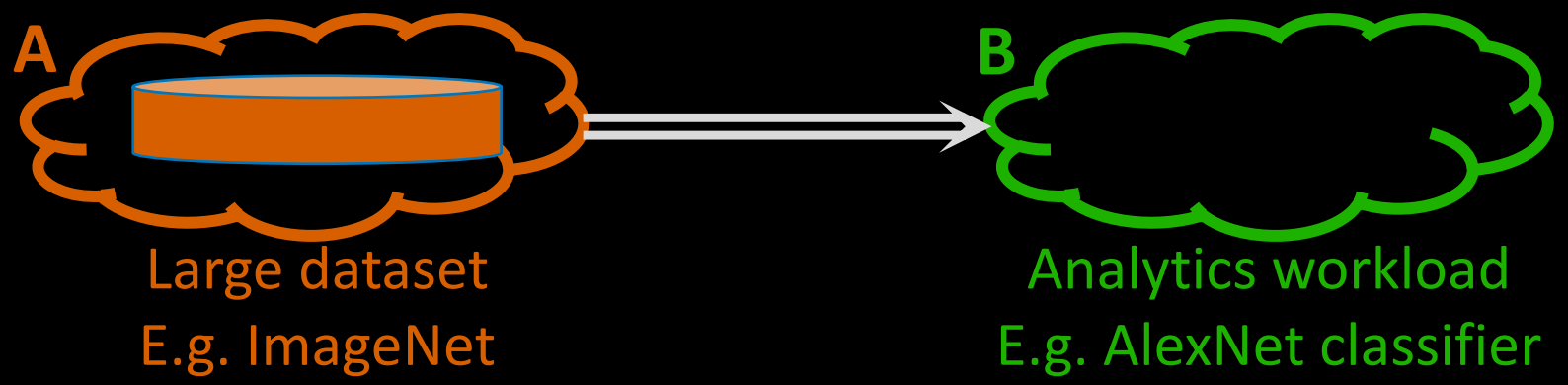
Works well in real applications and microbenchmarks:

- 10-100x compaction, warm-cache latency < 1s, low error
- 1 PB on a single node (summarized down to 10 TB)

PART 2: Timely Approximate Replicas

Scaling network use in distributed data stores

Motivating Example



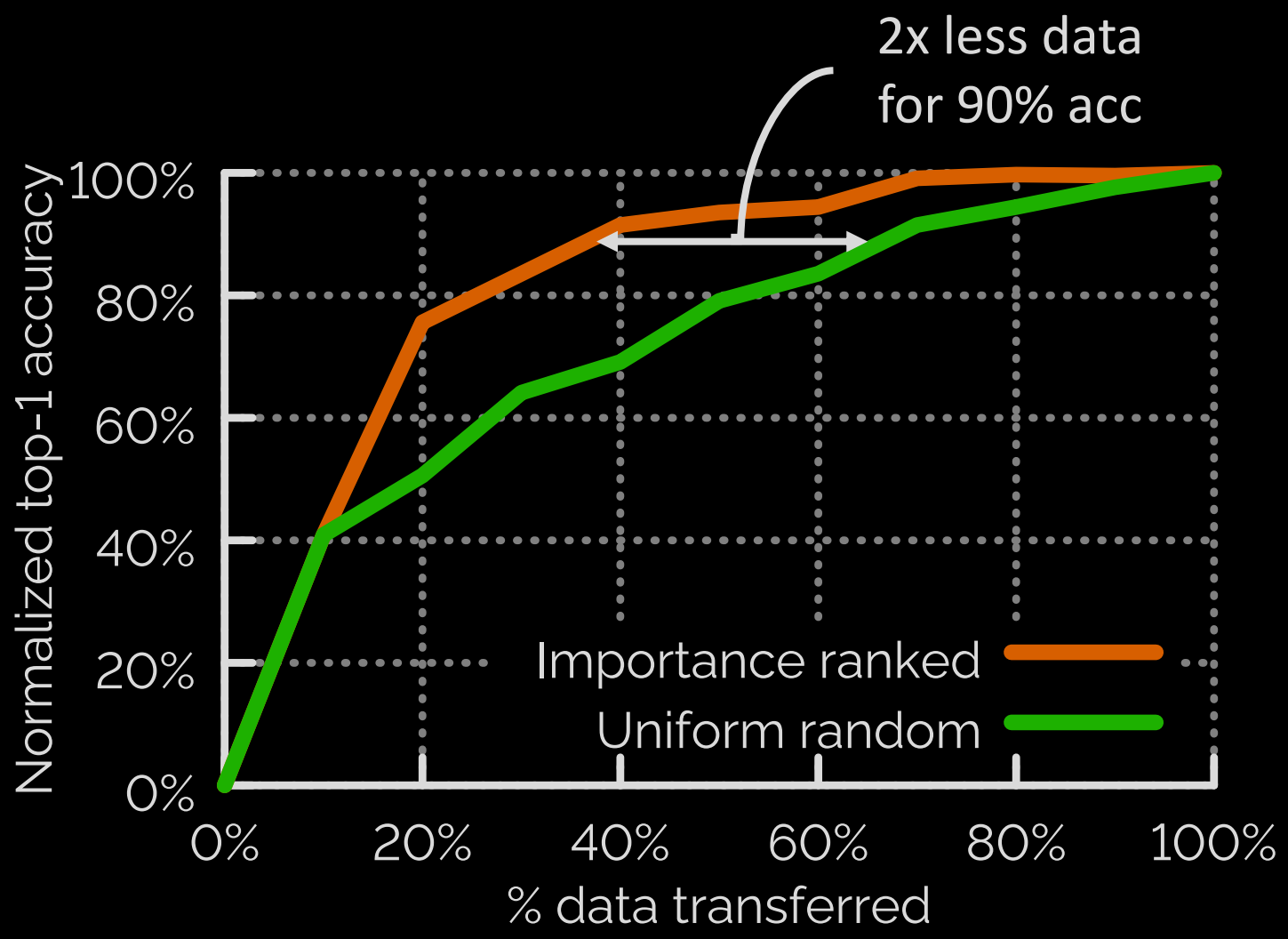
Need to transfer large dataset from A to B so B can run analytics

Option 1: transfer data in (uniform) random order

Option 2: "importance" ranking

a. A sends B a small random subset of the data (say 10%)
b. B trains a crude initial model on the data subset, sends model to A
c. A uses the initial model to prioritize the remaining data

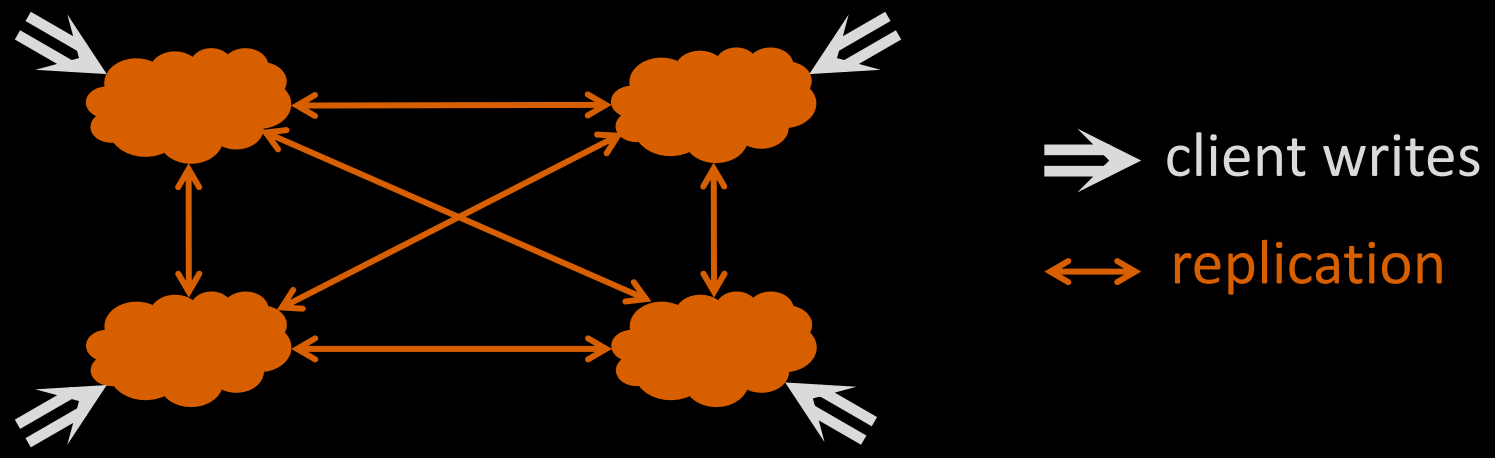
Motivating Example



Motivating Example

Takeaway: can significantly reduce time to insight by intelligently ordering data transmission

Speeding up replication in distributed stores



Consider a system of replica nodes receiving updates in parallel

Wish to replicate all updates to all nodes eventually

Key idea: reduce time to replica convergence by carefully ordering update propagation

- Send the “most important bits” first

Speeding up replication in distributed stores

We control replication such that every node ends up with a useful **summary** of all data ingested by system, while ensuring:

1. Summaries are *useful*
   - Goal: summaries are tailored to expected query workload
   - Current prototype: summaries are statistically correct summary structures (e.g. uniform, stratified, universe samples; scalable Bloom filters)
2. Summaries are *monotonic*
   - In a quiet system, summaries keep improving over time
3. Summaries don't *diverge* across nodes
   - Query answers are roughly similar at every node
   - Ensure nodes are true ~replicas of each other

Challenge: Coordinating summary construction

Suppose we want each node to have a stratified sample of all ingested data

Problem: constructing a true stratified sample needs global view of *all* data

True of most summary structures

- In general, most summaries are usually constructed offline, processing all data in a batch

Challenge: need efficient distributed, online summarization

Solution: Split-plane architecture

Provide lightweight primitive statistics in statistics plane

- Coarse, low overhead to maintain

Use to orchestrate more complex summaries in data plane

Identified a small family of primitives enough to implement a number of more sophisticated data plane summaries. Currently:

- Primitives: Counters (sum, count, avg.); Quantile digest (quantiles and frequencies); HyperLogLog (count distinct)
- Data plane: uniform, stratified & universe samples; histograms; heavy hitters; scalable Bloom Filters

Example: Implementing stratified sampling

Each node

1. Periodically pushes counter updates to statistics plane, based on local data arrival pattern
   - Global stats: per-stratum value mean, variance
   - Per-node stats: per-node per-stratum arrival rate
2. Subscribes to updates from statistics plane
3. Periodically plugs stats into a linear program to choose sampling policy

Initial Evaluation

Deployments:

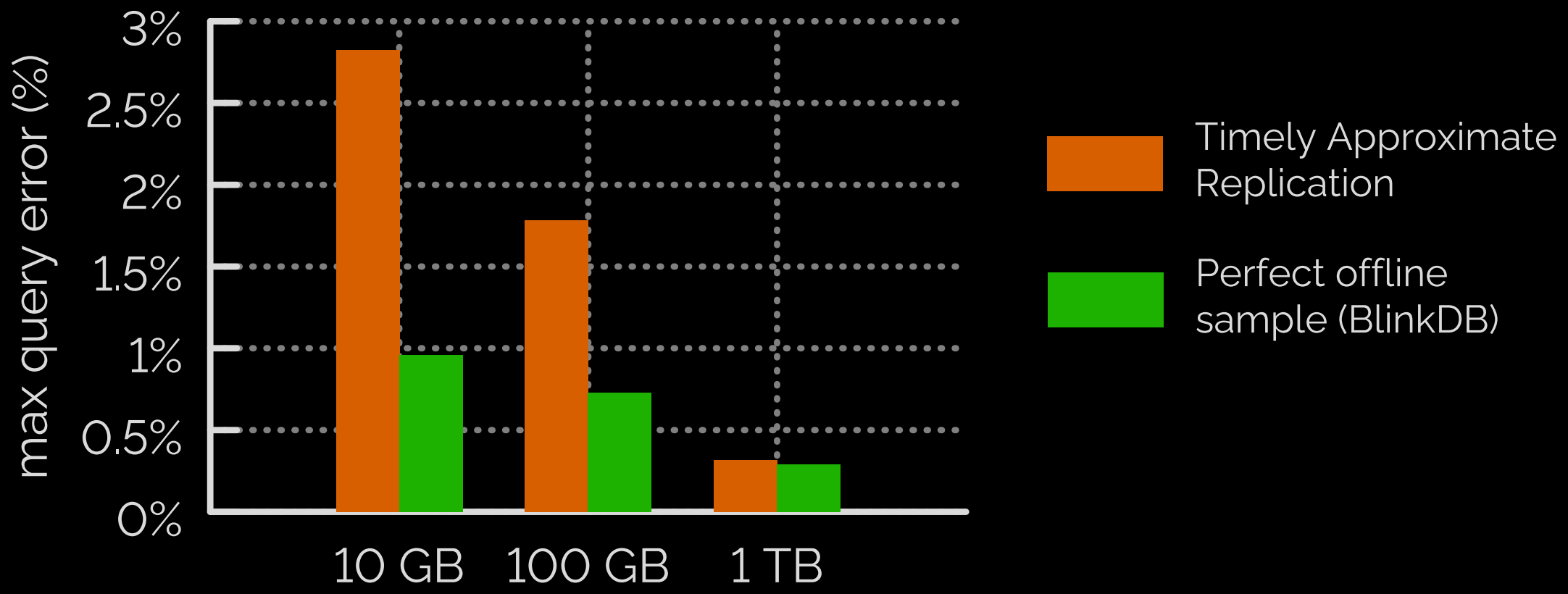
- Geo-distributed: 3 nodes in US, Europe, Japan (R = 3)
- Single DC: 100 nodes (R = 30)

Workload:

- Instacart sales DB, scaled up to 1 TB
- Bag of 15 OLAP queries

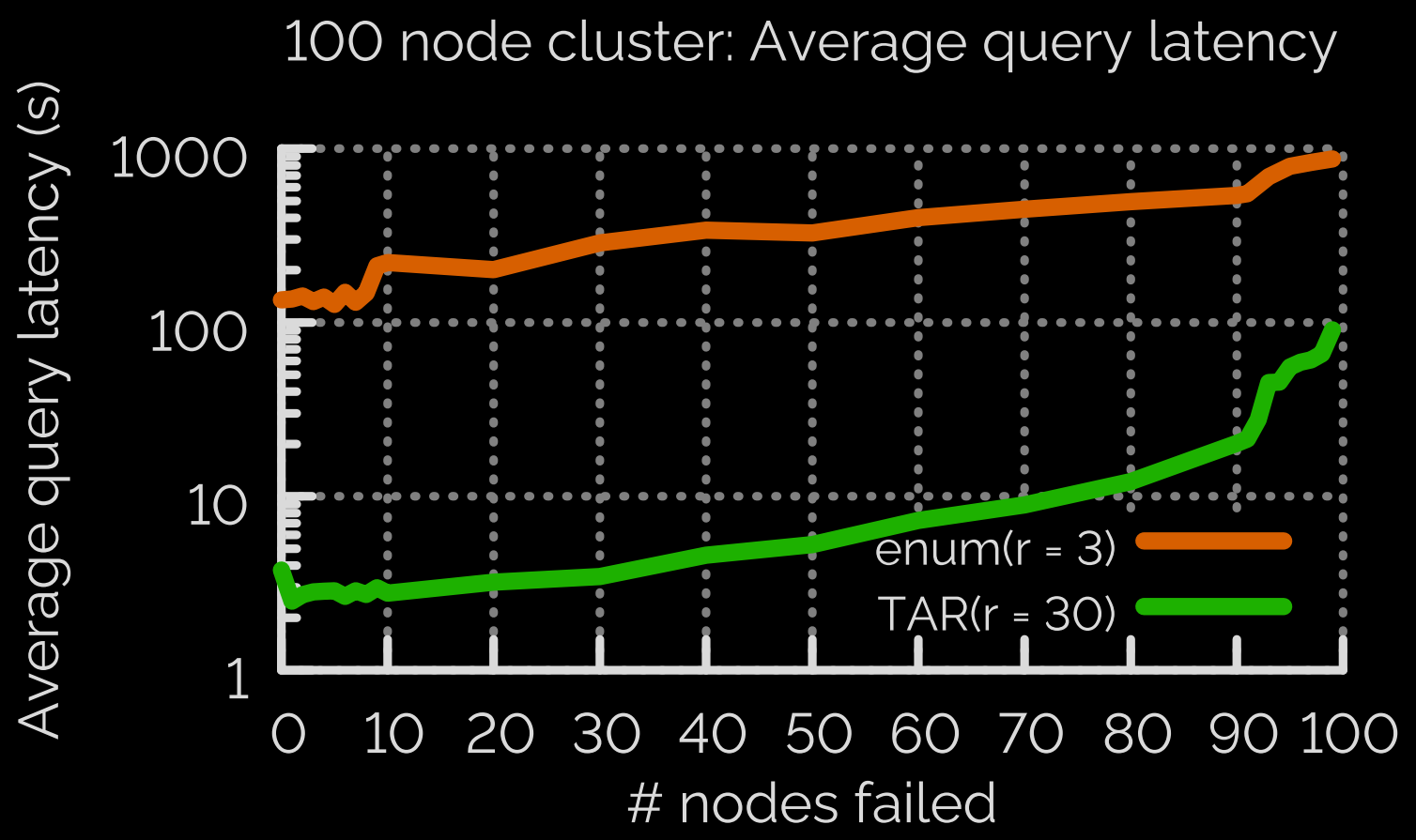
Config: build stratified sample @ 10x compaction

Geo-distributed: 10x compacted replication



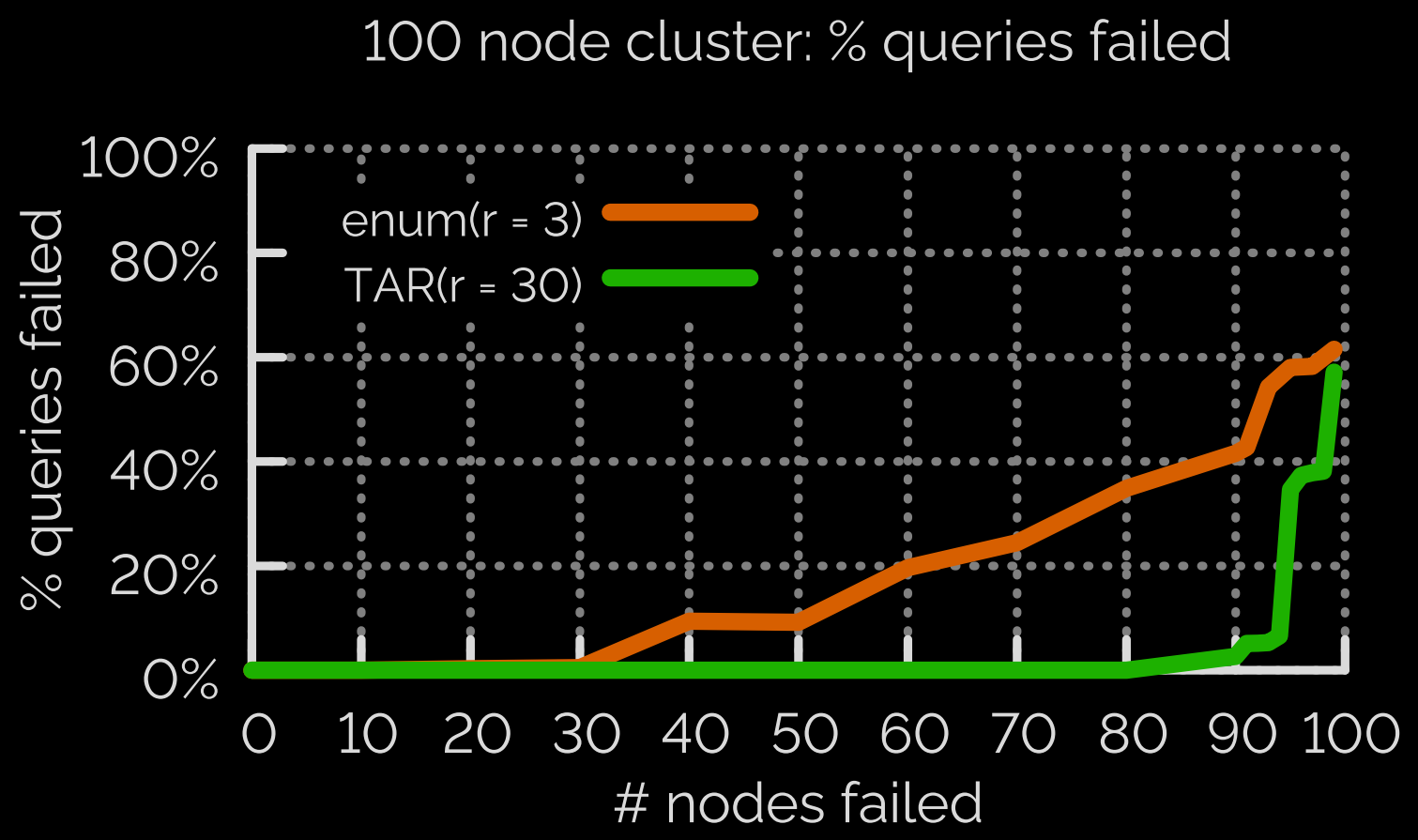
Value prop: can get good accuracy 10x faster than conventional replication

In a data center: R=30 with 10x compaction



Value prop: can increase availability 10x with same replication cost

In a data center: R=30 with 10x compaction



Value prop: can increase availability 10x with same replication cost

Summary: Timely Approximate Replication

Approach:

- Control data replication so nodes quickly obtain good summary of all data
- Coordinate to ensure summaries provide correct global view
- Split-plane approach: provide low-cost primitive shared statistics,
  use to orchestrate more complex summaries

In initial experiments:

- Good accuracy with 10x less data transfer
- 10x higher availability with same replication cost

Future Work

Zero-touch configuration

- Both systems presented have number of config parameters: choice of summaries, compaction rate, decay function etc.
- Primary barrier to ease of deployment
- Working on deriving config automatically from workload or hints

Scaling ML training

- Know how to distribute and simplify ML inference tasks
- Scaling training is much harder
- Working on approaches to: identify most relevant training data, federate training implementation

Summary

SummaryStore

- Single-node approximate time-series store
- Novel time-decayed approximation scheme
- 10-100x improved storage cost, query latency, ingest throughput

Timely Approximate Replication

- Improving data replication in distributed data stores
- Coordinated data replication to quickly provide useful data summary
- Promising initial results: 10x lower replication bandwidth, or
  10x higher replication factor with same bandwidth

Backup slides

SummaryStore Configuration

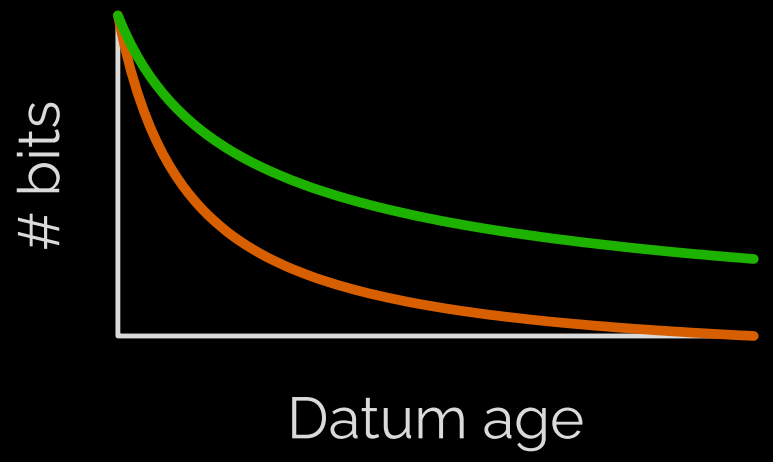
For each stream, users configure

1. List of summaries to maintain per-window
   - Built-in: Sum, Count, Histogram, Bloom Filter, Random Sample, ...
   - Pluggable interface to add more
     - Allows adapting existing non-streaming summarization techniques

SummaryStore Configuration

For each stream, users configure

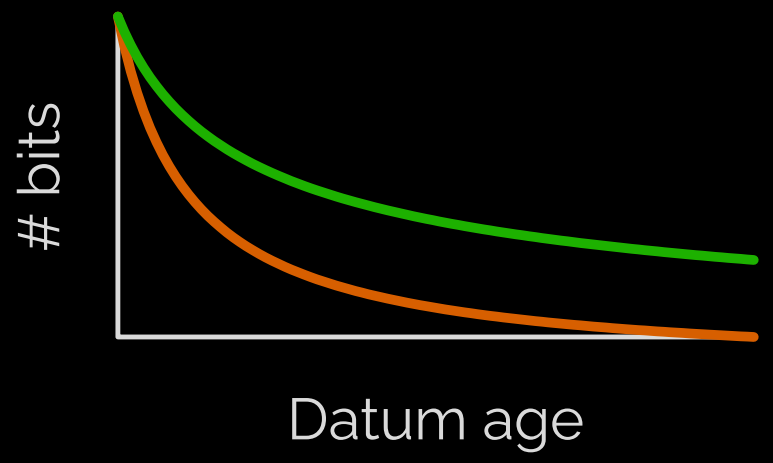
1. List of summaries to maintain per-window
2. Sequence of window lengths: controls decay
   - With window lengths = 1, 2, 4, 8, 16, 32, ...; after N inserts
     - Storage footprint = $O(\log_2 N)$
     - # bits to nth oldest element = $O(1 / n)$
   - With window lengths = 1, 2, 3, 4, 5, 6, ...; after N inserts
     - Storage footprint = $O(\sqrt{N})$
     - # bits to nth oldest element = $O(1 / \sqrt{n})$
   - Choice affects storage compaction, accuracy



SummaryStore Configuration

For each stream, users configure

1. List of summaries to maintain per-window
2. Sequence of window lengths: controls decay
   - Don't actually need to provide full list of window lengths
   - Parametric family of **power-law decay** functions
   - Simple 4 parameter API



SummaryStore Configuration

	Individual stream size		
PowerLaw (p, q, R, S)	*10 GB*	*100 GB*	*1000 GB*
(1, 1, 88, 1)	1.1x	3.4x	11x
(1, 1, 16, 1)	2.5x	7.9x	25x
(1, 1, 8, 1)	3.5x	11x	35x
(1, 1, 4, 1)	5x	16x	50x
(1, 1, 1, 1)	10x	32x	100x
(1, 2, 48, 1)	22x	100x	480x
(1, 2, 5, 1)	100x	460x	2200x
Exponential (b, R, S)	*10 GB*	*100 GB*	*1000 GB*
(2, 88, 1)	120x	1100x	9700x
(2, 32, 1)	320x	2800x	25000x
(2, 1, 1)	8600x	77000x	700000x
(3, 1, 1)	14000x	120000x	1100000x

Table 5: Storage compaction evolution w/ decay configurations. **Column name = size of raw data, increasing over time; compaction = (size of raw data)/(size of SummaryStore). The parameters of the power-law decay function map to different window lengths and consequently different compactions; admins can refer to table as rule-of-thumb for configuring.**

SummaryStore API

CreateStream(decay function, [list of summary operators])

DeleteStream(streamID)

Append(streamID, [timestamp], value)

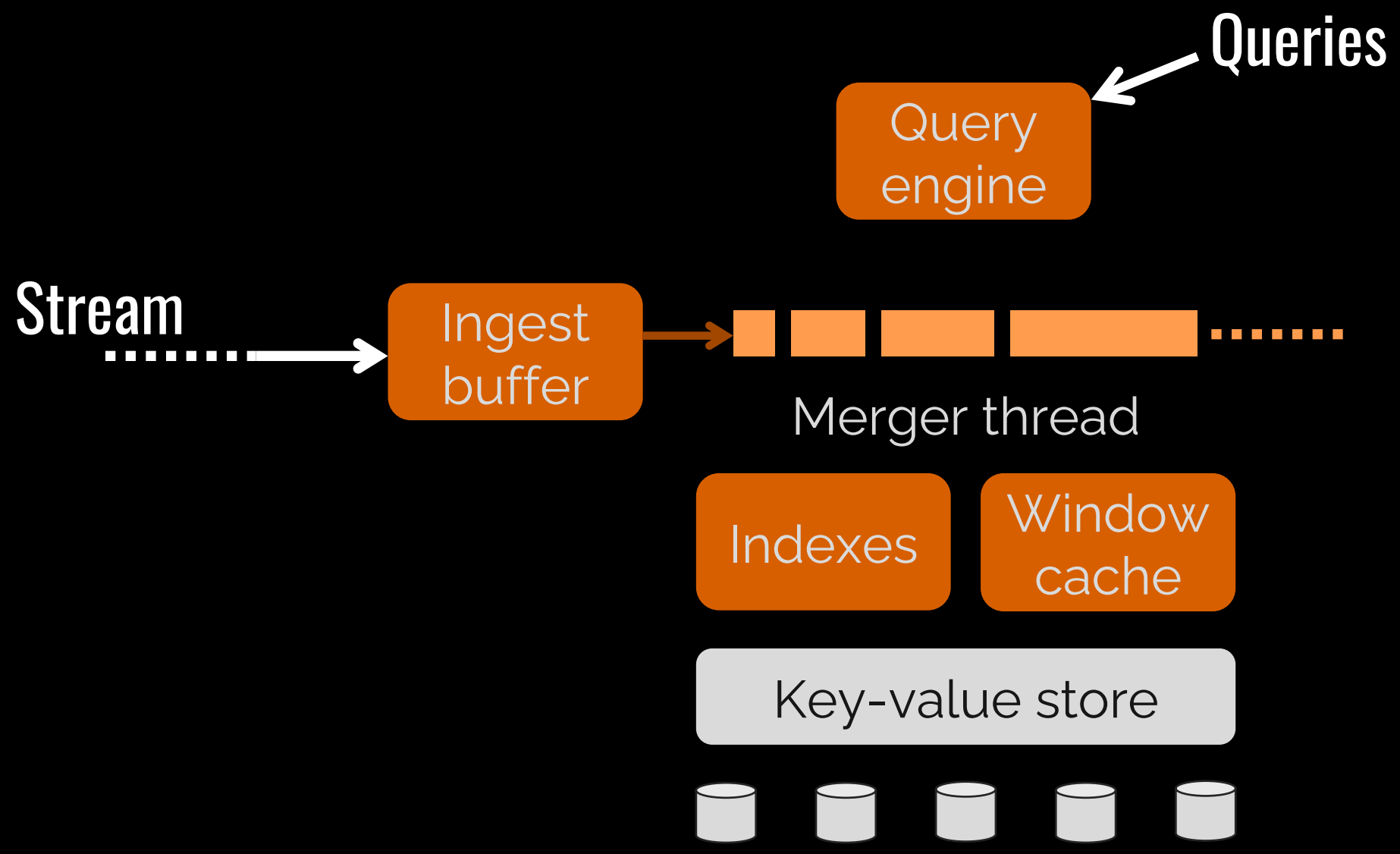
BeginLandmark(streamID)

EndLandmark(streamID)

Query(stream, T_1, T_2, operator, params)

QueryLandmark(stream, T_1, T_2)

SummaryStore Architecture

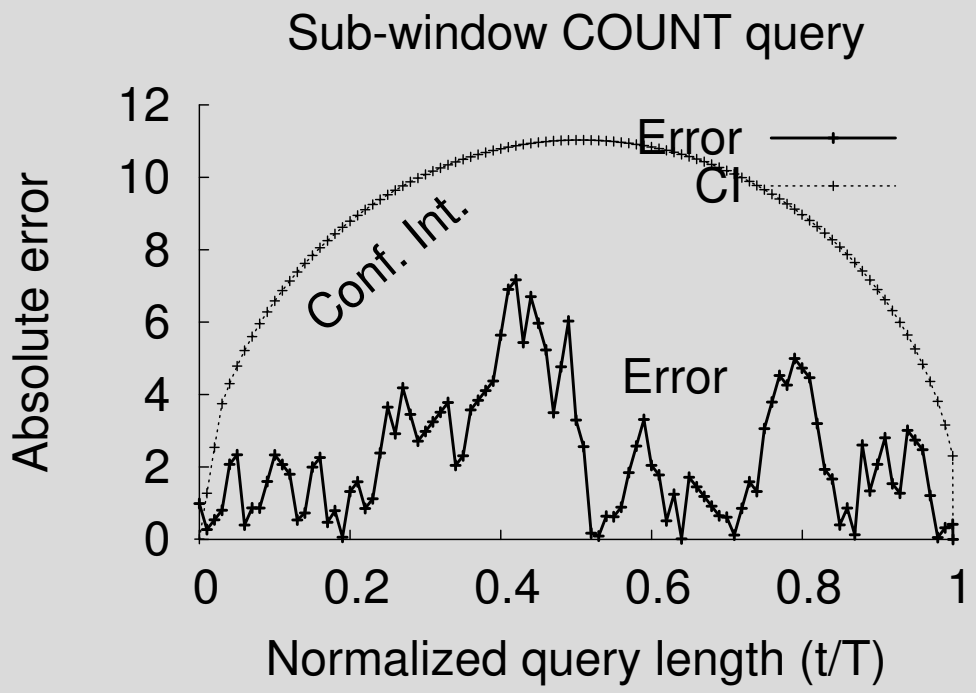


Statistical techniques for sub-window queries

Query	Method for Error Estimation
count[a, a+t] (generic)	$N\left(C\frac{t}{T}, \left(\frac{\sigma_t}{\mu_t}\right)^2 \frac{T}{\mu_t}\frac{t}{T}\left(1-\frac{t}{T}\right)\right)$
count[a, a+t] (Poisson)	Binomial $\left(C, \frac{t}{T}\right)$
sum[a, a+t]	$N\left(S\frac{t}{T}, \left(\frac{\sigma_t^2}{\mu_t^2}+\frac{\sigma_v^2}{\mu_v^2}\right)\frac{T\mu_v^2}{\mu_t}\frac{t}{T}\left(1-\frac{t}{T}\right)\right)$
membership(v)[a, a+t]	For Bloom filter with FP probability p: $p\frac{t}{T}$
membership(v)[a, a+t]	For CMS: Pr (Hypergeom$(C, S, V) > 0$)
frequency(v)[a, a+t]	Hypergeom(C, S, V)
S = normal distribution of count[a, a+t] (generic) in first row V = distribution over frequency(v)[entire window]; v refers to values	

Table 6: Statistical methods for sub-window queries.

Statistical techniques for sub-window queries



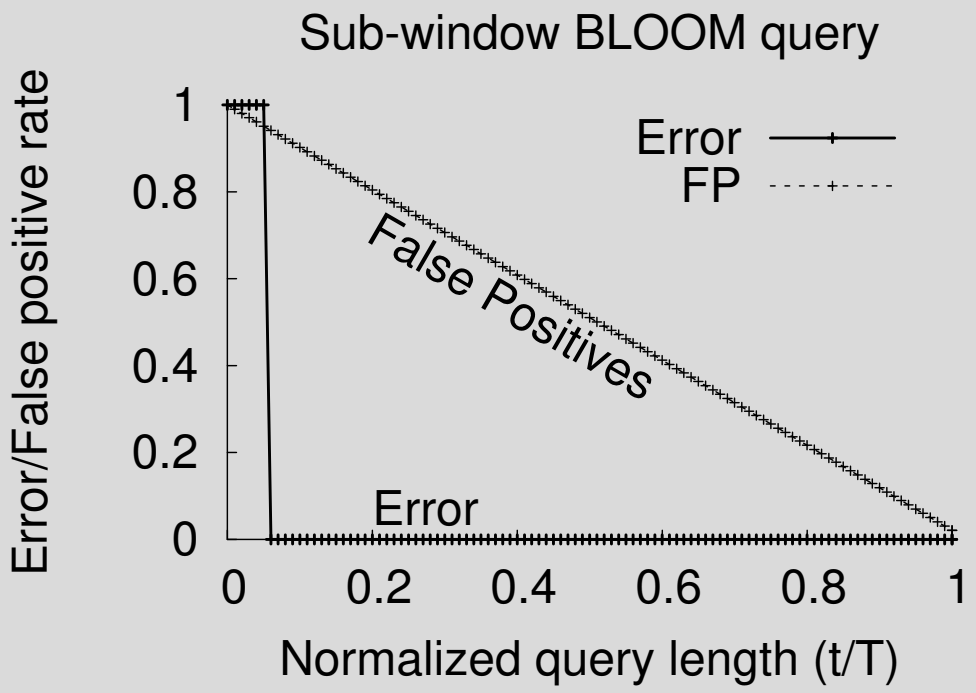


Figure 12: Sub-window answers and error estimates.

Combining decayed and landmark data when answering queries

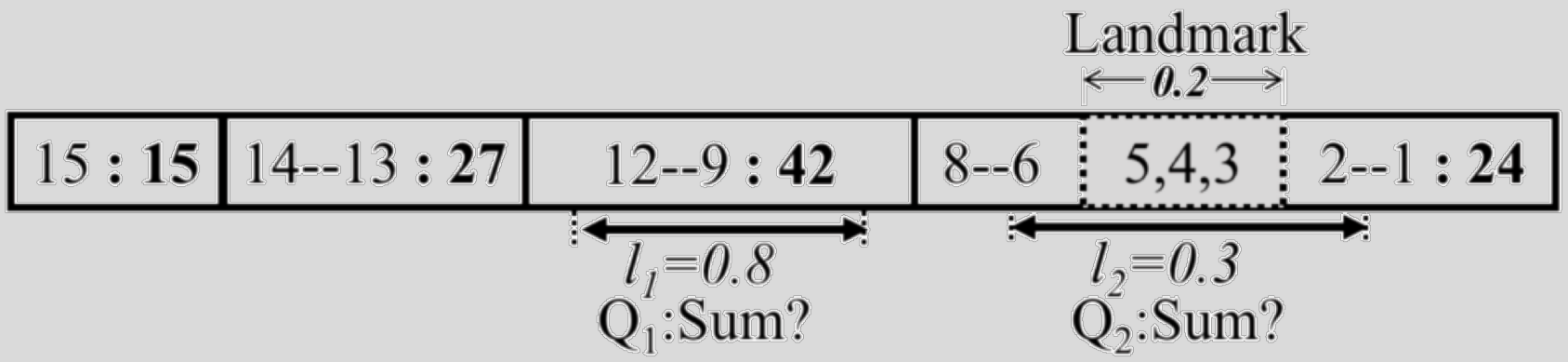


Figure 4: Challenge in answering sub-window queries for Summarized and Landmark windows. Q_1 **asks Sum over summarized only,** Q_2 **over summarized and landmark. For the first window, 24 refers to the sum for 8—6 and 2—1; {3,4,5} are excluded from summaries and included in the landmark window.**

Evaluation: 1 PB at 100x compaction

Error with infinite variance Pareto arrivals

Error in $[T_1, T_2]$ Count

	min	hour	day	mon
mon	0.0	0.0	0.0	0.0
day	0.0	0.0	0.0	0.0
hour	0.0	0.0	0.0	5.2e4
min	0.001	0.003	0.01	7.7e4

not suited

Evaluation: 1 PB at 100x compaction

Error with Poisson arrivals

Error in $[T_1, T_2]$ Count

	min	hour	day	mon
mon	0.0	0.0	0.0	0.0
day	0.0	0.0	0.0	0.0
hour	0.0	0.0	0.0	0.0
min	0.0	0.0	0.002	0.001

Evaluation: 1 PB at 100x compaction

Latency breakdown

Latency (seconds)

	min	hour	day	mon
mon	54	50	47	34
day	15	14	9	4.5
hour	1.8	1.2	0.6	0.2
min	0.3	0.1	0.05	0.03

Evaluation: Smaller dataset, lower compaction

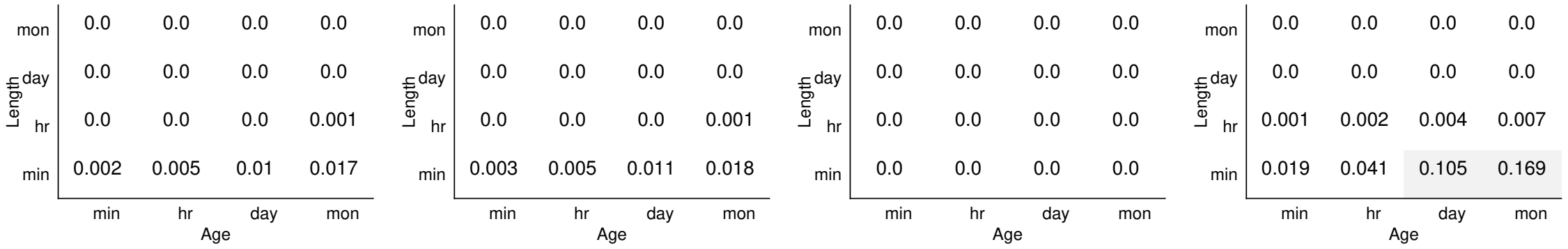
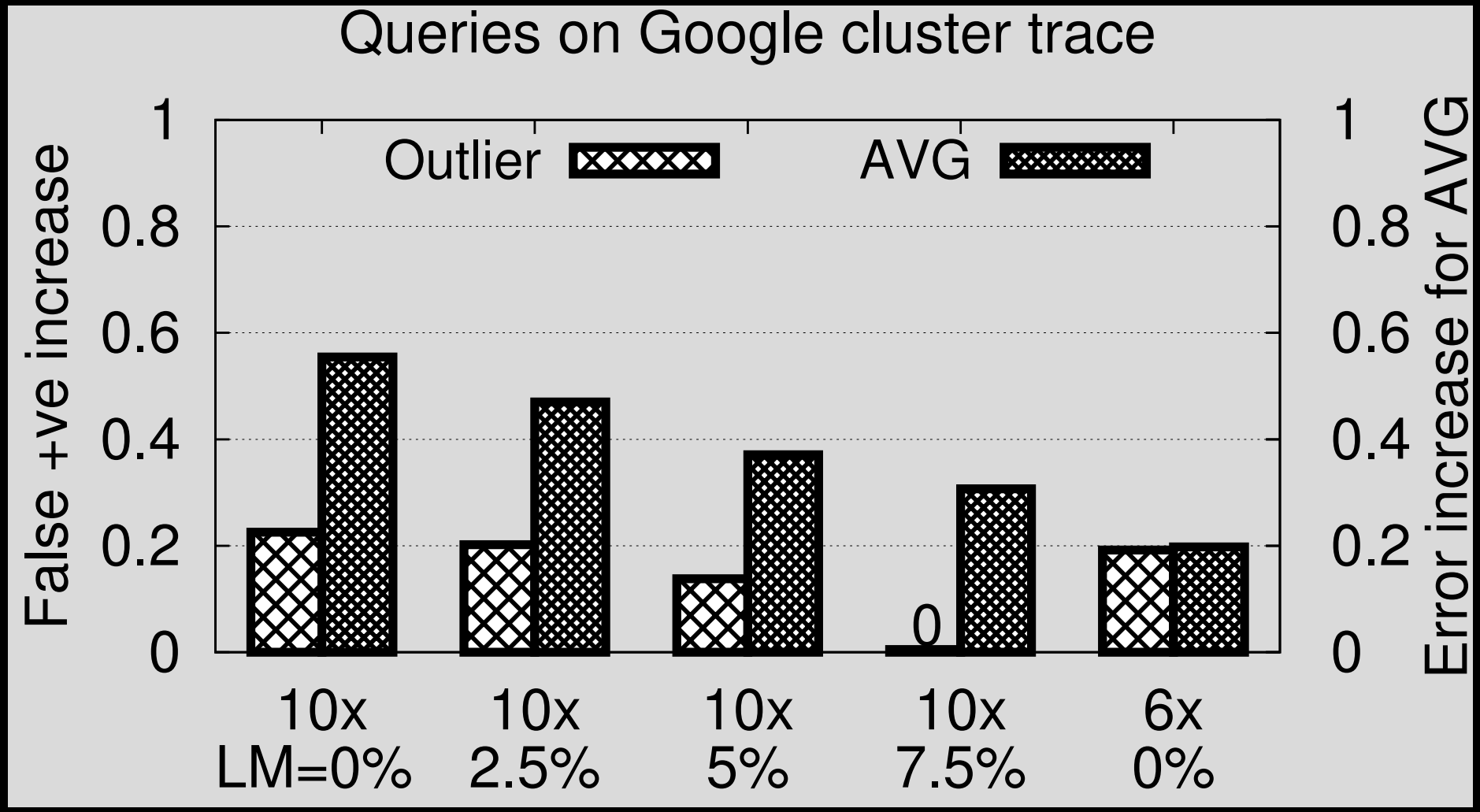


Figure 11: Error heatmap. **Slow Velocity Poisson(λ = 10), 5 GB/stream, Lower Compaction (5x)**

Evaluation: Outlier analysis on Google cluster trace



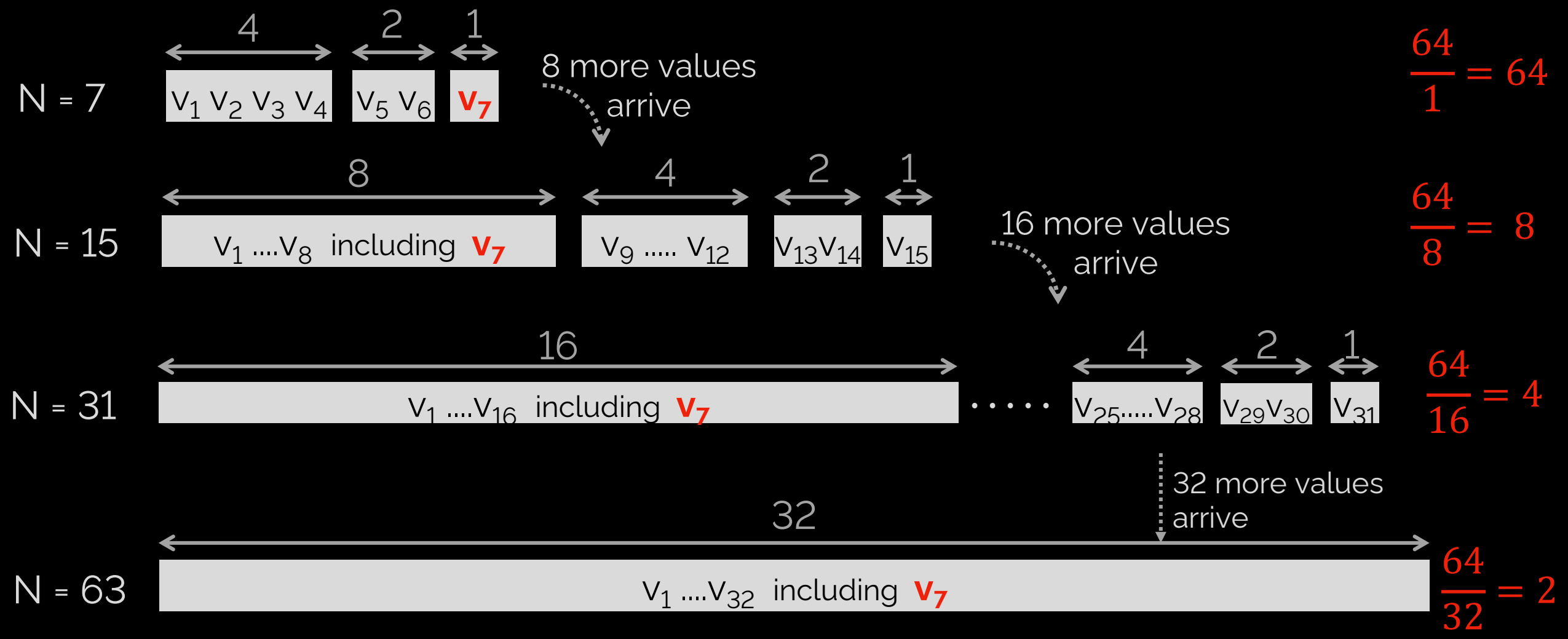
Deleted slides

Design goals

1. Allow reusing work on non-streaming approx
   - Substantial body of work on approximating static datasets
   - E.g. sampling [BlinkDB, QuickR], histograms [SQL DBs], other sketches, …
   - No clear winner, each suitable for different applications
   - Orthogonal to policy on time

2. Support configurable time-decay
   - Tune storage, accuracy

Our solution: decay through **windowed summarization**

Data decays as it ages

Assuming each window is 64 bits, # bits used for v_7 =