Read as Needed: Building WiSER, a Flash-Optimized Search Engine

FAST '20

Jun He, Kan Wu, Sudarsun Kannan ,Andrea C. Arpaci-Dusseau, Remzi H. Arpaci-Dusseau

Department of Computer Sciences, University of Wisconsin–Madison

Department of Computer Science, Rutgers University

Presented by Zhexin Jin and Yuming Xu, USTC, ADSL

April 24th, 2020

Outline

- Motivation
- Background
- Design
- Implementation
- Evaluation
- Conclusion

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USTC, CHINA ADSLAB

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Motivation

SSDs provide

- High throughput
- Low latency
- High read bandwidth
- Inexpensive

Many applications/systems have been optimized for SSDs

- Key-value stores: RocksDb, Wisckey, ...
- Graph stores: FlashGraph, Mosaic, ...
- File systems: SFS, F2FS, ...

But search engines are overlooked!

Motivation

Search engines require

- Low data latency: queries are interactive
- High data throughput: engines retrieve info from a large amount of data
- High scalability: data grows over time

Just use more RAM?

- Cost prohibitive at large scale
- Data grows fast
- may waste bandwidth: rarely read and process 100GB/s

Motivation

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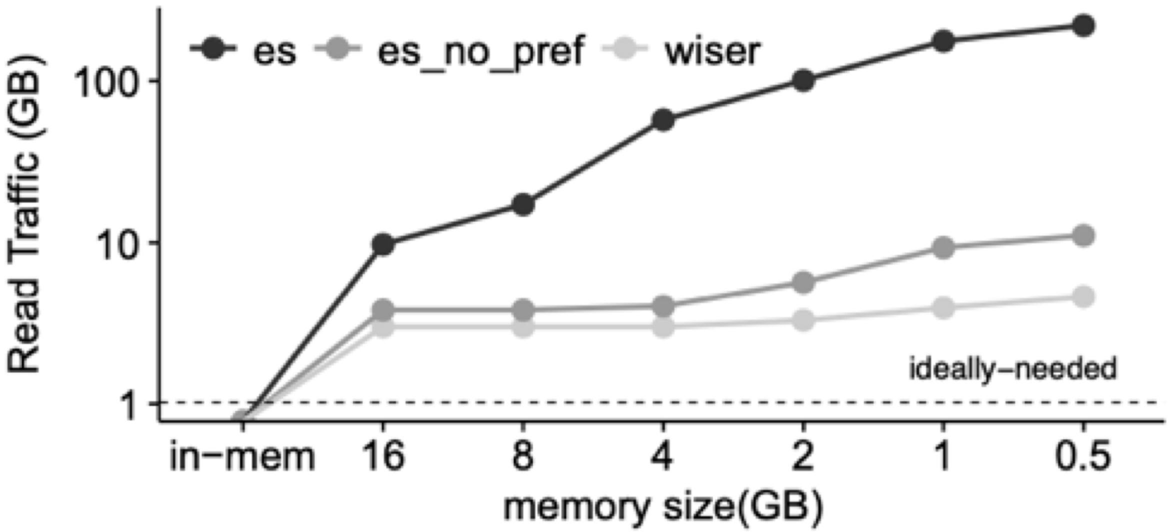
Can search engines perform well with a small memory and a fast SSD?



Outline

USTC, CHINA ADSLAB

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Inverted index

ID	Text
1	I thought about naming the engine CHEESE, but I could not explain CHEE.
2	Fried cheese curds, cheddar cheese sale.
3	Tofu, also known as bean curd, may not pair well with cheese.

1. The indexer splits a document into tokens.
2. The indexer transforms the tokens.
3. The location information of the term is inserted to a list, called a postings list.

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Term Map

…
cheese
…
curd
…

Postings Lists

ID	TF	POS	OFF
1	1	7	(34, 39)
2	2	2, 5	(6, 11), (28, 33)
3	1	12	(52, 57)

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ID	TF	POS	OFF
2	1	3	(13, 17)
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TF: Term frequency

Term Map

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POS: Position

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OFF: Byte offset

Term Map

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cheese
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…

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Query processing

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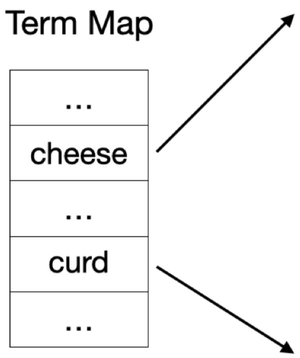
Single-term query: cheese



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1. Document matching: iterating document IDs in a term's postings list.
2. Phrase matching: use positions to perform phrase matching.
3. Ranking: calculating the relevance score of each document, which usually uses TF.
4. Highlighting: highlighting queried terms in the top documents.

Query processing

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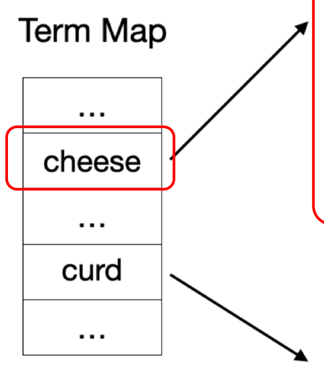

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Query processing

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Single-term query: cheese

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ID	TF	POS	OFF	Score
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Query processing

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Single-term query: cheese

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Postings Lists

ID	TF	POS	OFF	Score
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2	2	2, 5	(6, 11), (28, 33)	highest
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Fried cheese curds, cheddar cheese sale.

1. Document matching: iterating document IDs in a term's postings list.
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Single-term query: cheese

Two-term query:

- cheese AND curd
- cheese OR curd

1. Document matching: iterating document IDs in a term's postings list.
2. Phrase matching: use positions to perform phrase matching.
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Query processing

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Single-term query: cheese

Two-term query:

- cheese AND curd
- cheese OR curd

Phrase query:

- cheese curd

1. Document matching: iterating document IDs in a term's postings list.
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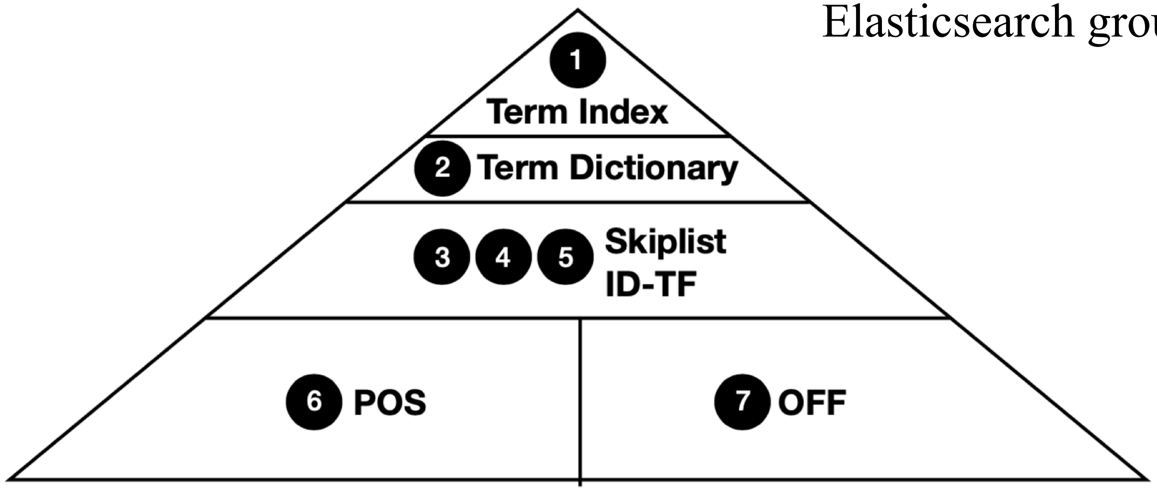
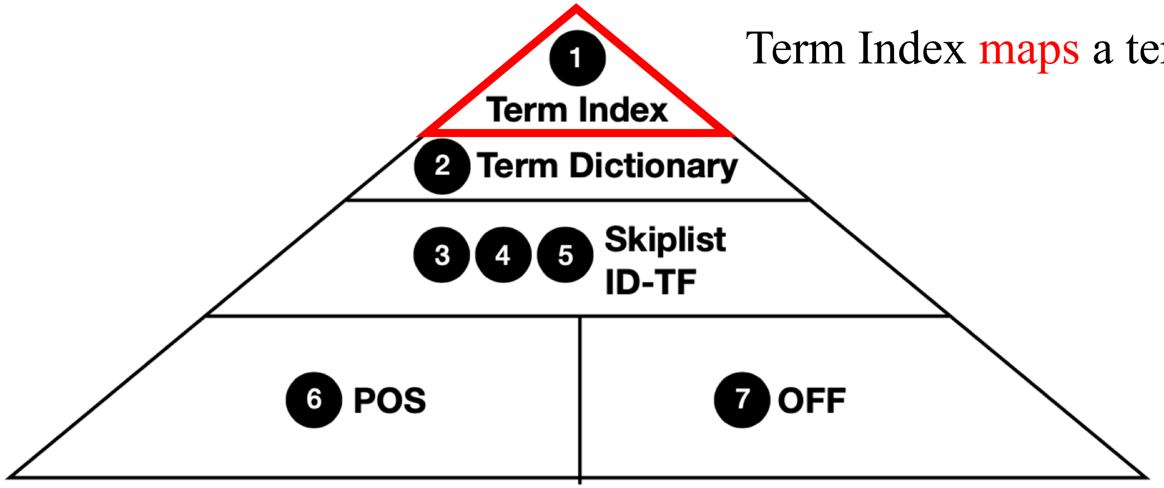
Elasticsearch



Elasticsearch groups data of different stages into multiple locations.

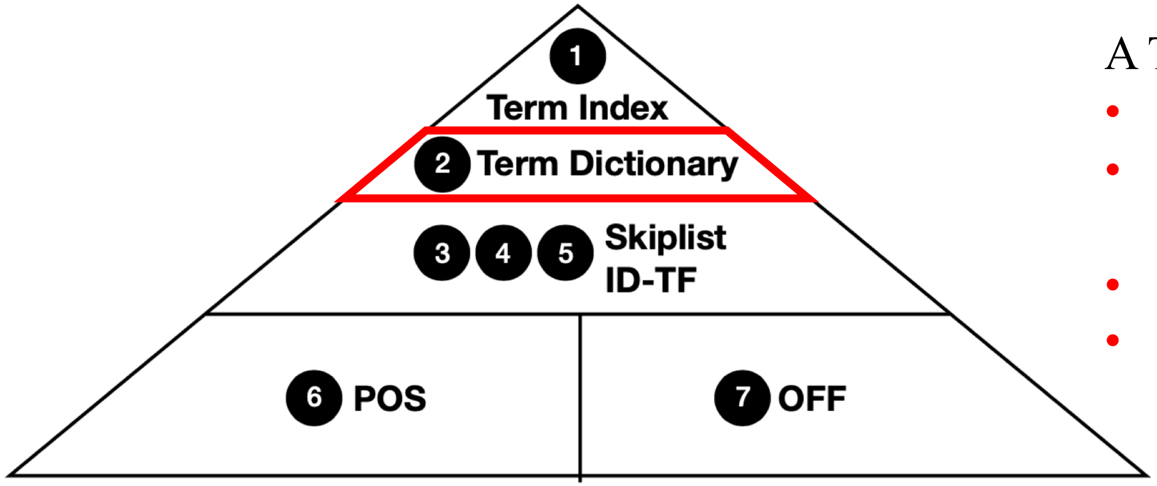
For Wikipedia
- Term Index: 4 MB
- Term Dictionary: 200 MB
- Skiplist, ID-TF: 2.7 GB
- POS: 4.8 GB
- OFF: 2.8 GB

Elasticsearch



Term Index maps a term to an entry in Term Dictionary.

Elasticsearch



A Term Dictionary entry contains

- metadata about a term (e.g., doc frequency)
- pointer pointing to document IDs and Term Frequencies (ID-TF)
- pointer pointing to positions (POS)
- pointer pointing to byte offsets (OFF).

Outline

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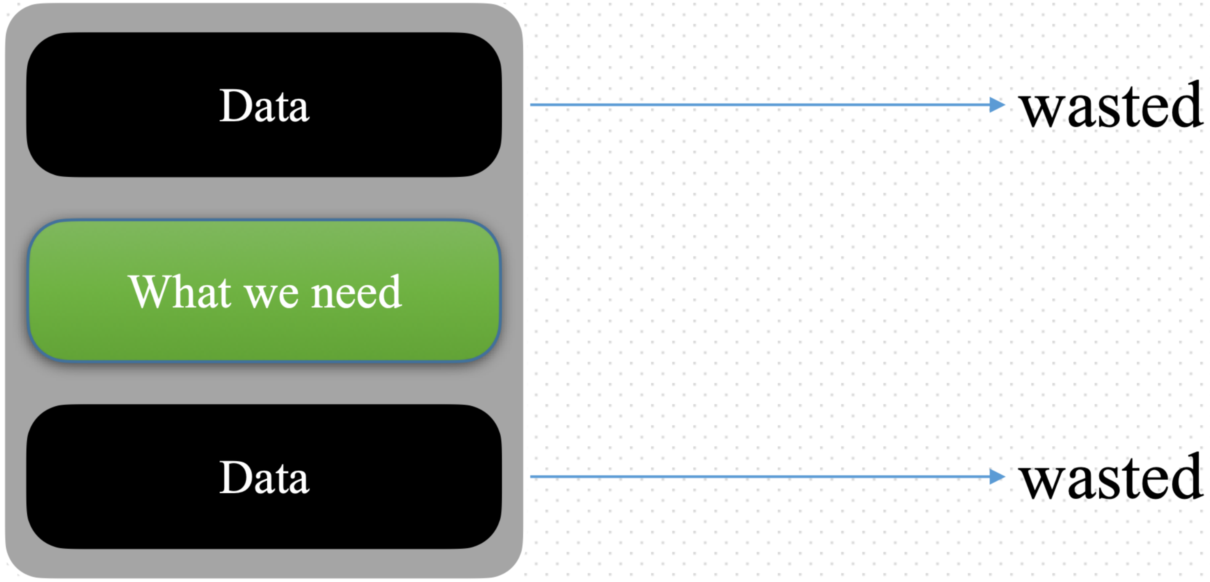
Design

- **Read amplification**

In a word, read what we don’t need



File

Actually we fetch the whole file from disk

Design

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Four techniques to reach our goals

Cross-stage data grouping

- reduce read amplification
- make I/O requests be large

Two-way Cost-aware Bloom Filter

- also reduce read amplification

Adaptive prefetching

- hide I/O latency

Trade Disk Space for I/O

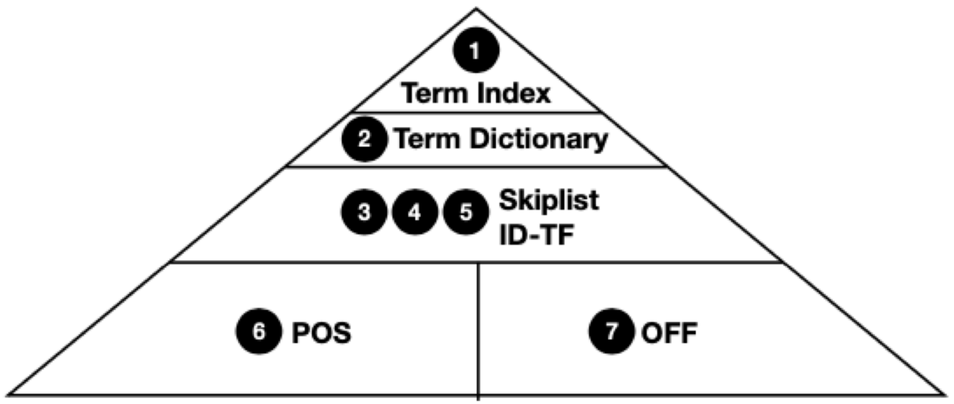
- reduce read amplification

Cross-stage data grouping

USTC, CHINA ADSLAB

In the Background part, we have known the process of a query

In single term query or phrase query, we all need to read 1-6



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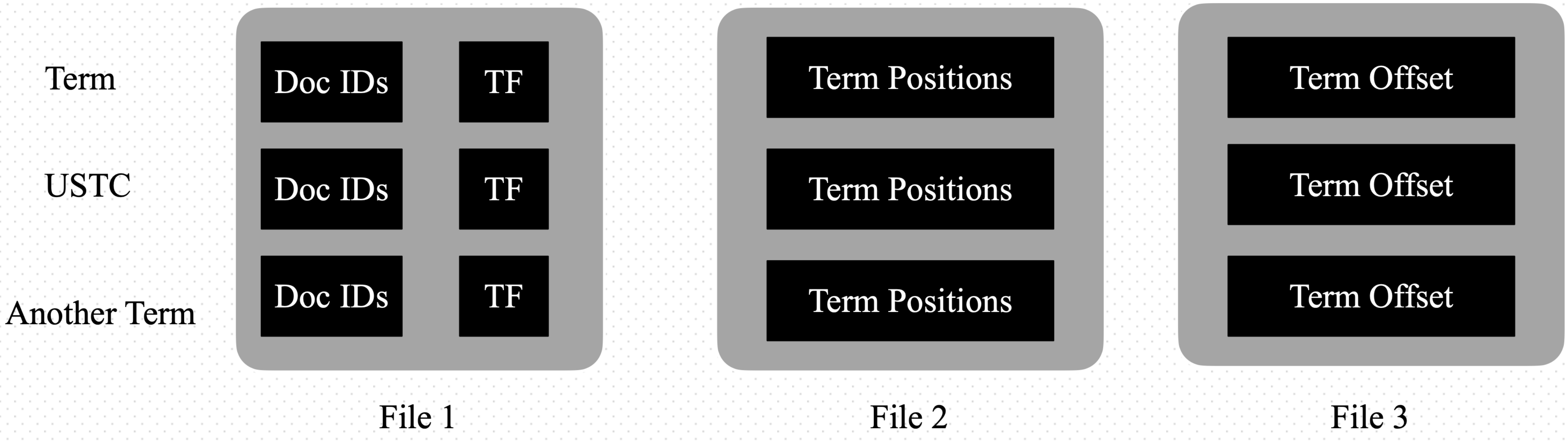
Cross-stage data grouping

USTC, CHINA ADSLAB

In the previous design, we need to read disk many times

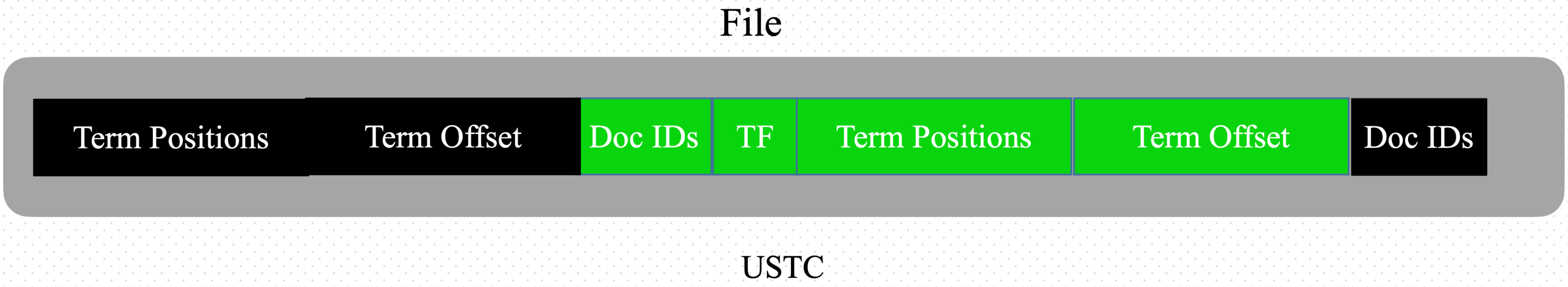
For term ‘USTC’, IO count:3 or more (TF:Term Frequencies)



Cross-stage data grouping

WISER change the grouping way

For term ‘USTC’, IO count:1

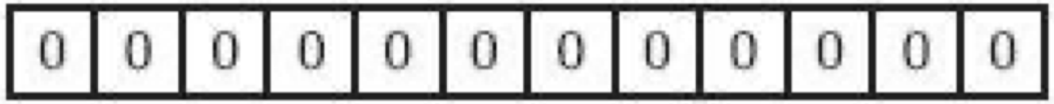


Two-way Cost-aware Bloom Filter

Bloom Filter

- **A type of Data Structure**
- **Use hash to test whether a element is in the set**

At first, Bloom Filter is a bit-array containing m bits,
and all bits are set to 0

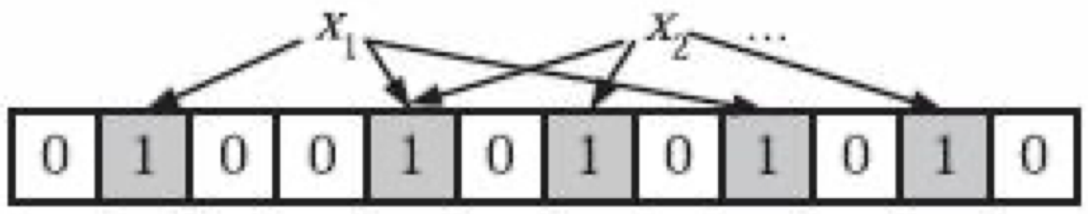


Two-way Cost-aware Bloom Filter

Bloom Filter

- **A type of Data Structure**
- **Use hash to test whether a element is in the set**

S = {x1,x2,…,xn}
Using k individual hash functions to map the element



For example, if we want to present $x_1 \in BF$, $BF[h_i(x)], i = 1,...,k$ should be set to 1

Two-way Cost-aware Bloom Filter

Bloom Filter

- **A type of Data Structure**
- **Use hash to test whether a element is in the set**

S = {x1,x2,…,xn}
Using k individual hash functions to map the element

Check whether $y \in BF$:
check $BF[h_i(y)]$, $i = 1,\ldots,k$, if
$\forall i, BF[h_i(y)] = 1$, then $y \in BF$

Two-way Cost-aware Bloom Filter

Bloom Filter

- **For phrase query like ‘Distributed System’**
- **100% recall but precision<100%**
- **For each term in each document**
- **In this case Bloom Filter aim at optimizing negative result**

Two conditions: 1. the percentage of negative tests must be high

2. Reading Bloom Filter must be faster than directly reading position

Two-way Cost-aware Bloom Filter

Using plain Bloom Filter

- Two conditions are conflict!
- One way is slow while another way is fast
- May be larger than positions

Two-way Cost-aware Bloom Filter

USTC, CHINA ADSLAB

Using plain Bloom Filter

- **Two conditions are conflict!**
- **One way is slow while another way is fast**
- **May be larger than positions**

the percentage of negative tests must be high :
Bloom Filter should be large
Reading Bloom Filter must be faster than directly reading position :
Bloom Filter should be small

Two-way Cost-aware Bloom Filter

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Using plain Bloom Filter

- Two conditions are conflict!
- **One way is slow while another way is fast**
- May be larger than positions

60KB < 50KB + 500KB

Using two-way Bloom Filter is better

Distributed

Filter after:60KB

Positions:50KB

Systems

Filter Before:600KB

Positions:500KB

600KB > 50KB + 500KB

Two-way Cost-aware Bloom Filter

Using plain Bloom Filter

- Two conditions are conflict!
- One way is slow while another way is fast
- **May be larger than positions**

Two-way doesn't work, cost-aware is added

Distributed	Filter before:600KB	Filter after:600KB	Positions:200KB
Systems	Filter before:600KB	Filter after:600KB	Positions:200KB

600KB > 200KB + 200KB

Two-way Cost-aware Bloom Filter

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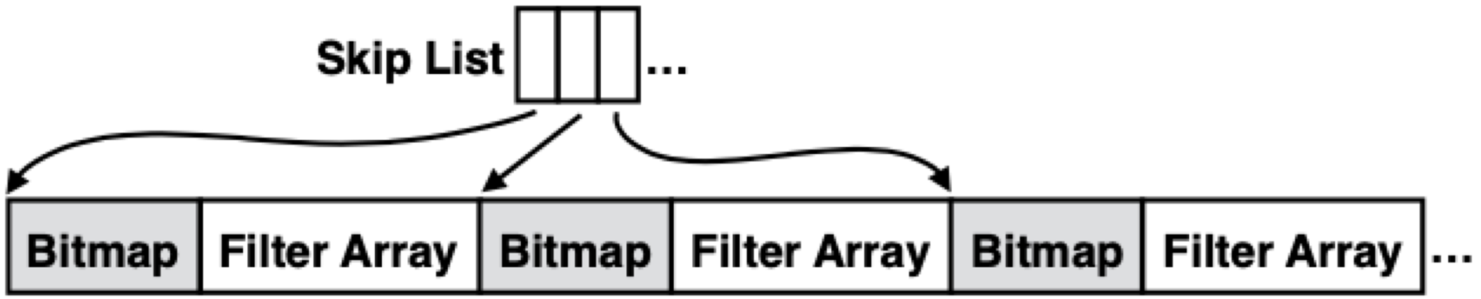
- **Allocate Bloom Filter**

  To further reduce the size of BFs, using bitmap-based data layout to store BFs



  Using skip list to avoid reading large chunks of filters

  Using bitmap to reduce the space usage of empty BFs

Adaptive Prefetch

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- **Elasticsearch using native prefetch**
  - Linux unconditionally prefetches data of a fixed size(default:128KB)
  - But data sizes are different
  - Cause high read amplification

Adaptive Prefetch

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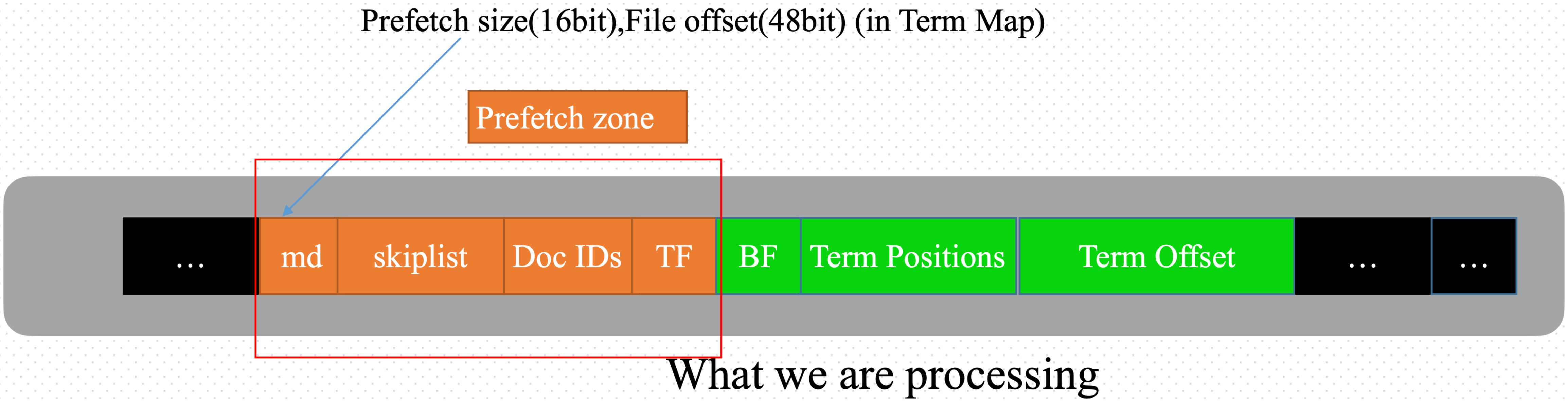
WISER adaptively prefetches frequently-used data to hide I/O latency

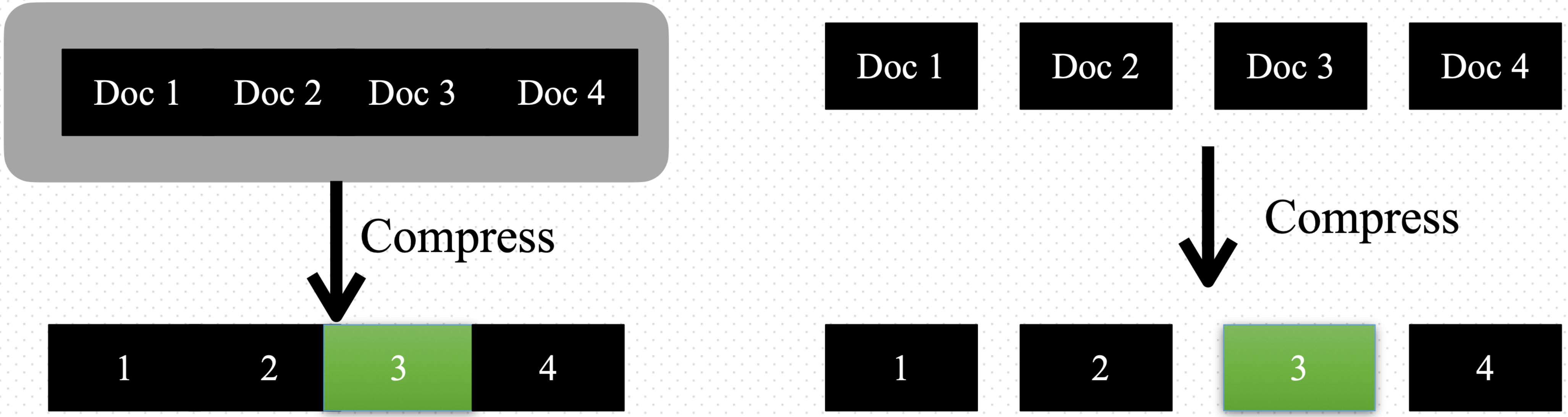


Adaptive: only when all prefetch zones in a query are larger than a threshold(e.g.,128KB), and divide prefetch zone to avoid access to much data at a time

Trade Disk Space for I/O

WISER compresses documents individually to reduce read amplification

4KB align(just as the size of one SSD page)



Need to fetch all data

Only to fetch 3

Impact on Indexing

- **Focus on optimizing query processing instead of index creation**

  query processing is performed far more frequently

- **Cross-stage data grouping**

  Does not add overhead, data is just placed in different place

- **Adaptive prefetching**

  Employs existing info, does not add any overhead

- **Trading space for I/O**

  Adds I/O overhead for indexing because document need more space

Impact on Indexing

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- **Bloom Filter**

  Requires extra computation: building BF

  Although many filters are empty, the accumulative cost can be high.

  Currently, haven't optimize the process of building

  todo: 1. Parallelize the building process

  2. cache the hash values of popular terms to avoid hashing the same term frequently

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Implementation

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- **11000 lines of C++ code (es is based on Java)**

- Using mmap( ) to map data file
- Switch from class virtualization to templates
- Use case-specific functions to allow special optimizations
- Reusing preallocated std::vector to avoided frequent memory allocation

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Setup

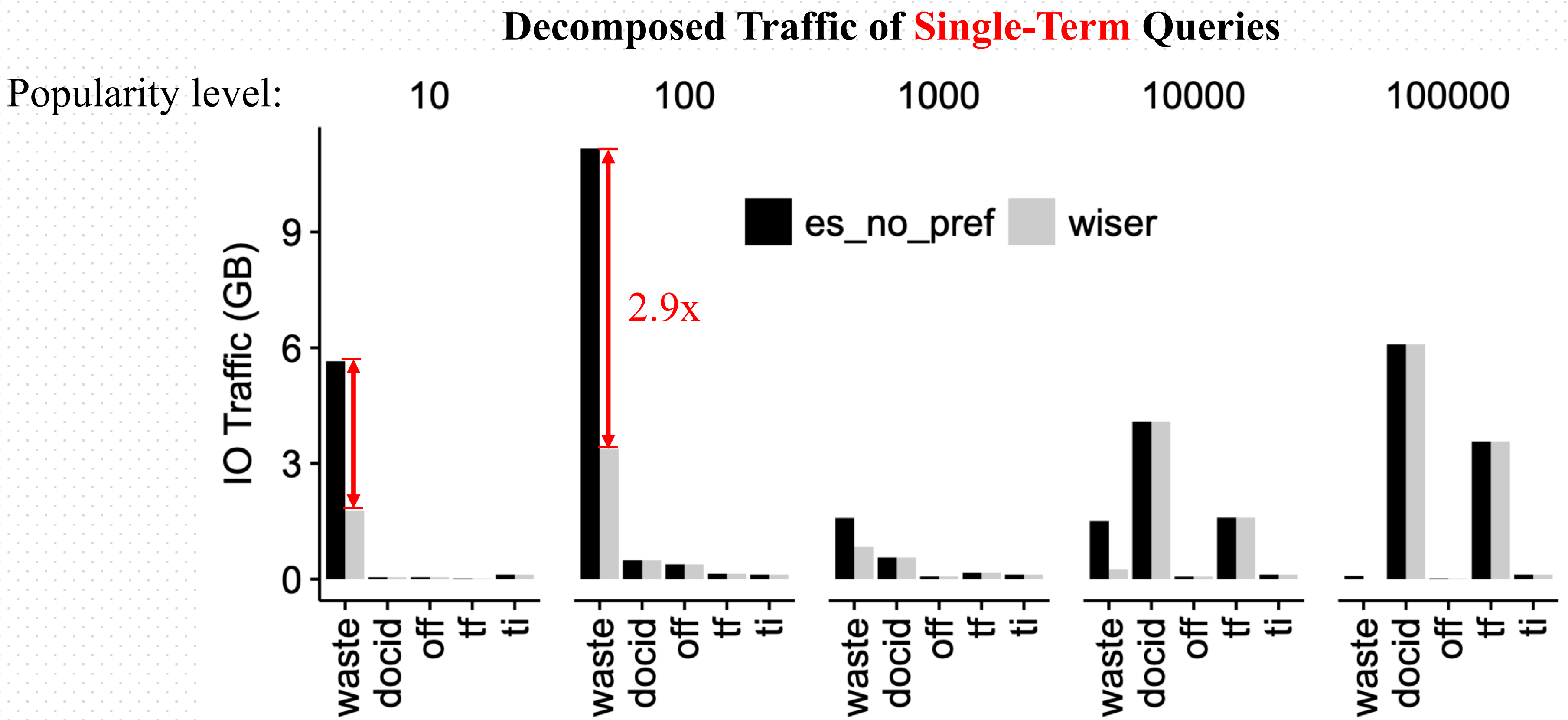
- 16 CPU cores
- 64-GB RAM
- 256-GB NVMe SSD
  - Peak read bandwidth is 2.0 GB/s
  - Peak IOPS is 200,000
- Ubuntu with Linux 4.4.0
- Use only 512 MB of memory (using a Linux container)

WSBench

- Dataset: Wikipedia
  - Total size: 18 GB
  - 6 million documents, 6 million unique terms
- Queries:
  - single term queries, “and” queries, “phrase” queries, real queries
  - vary term popularities in wikipedia

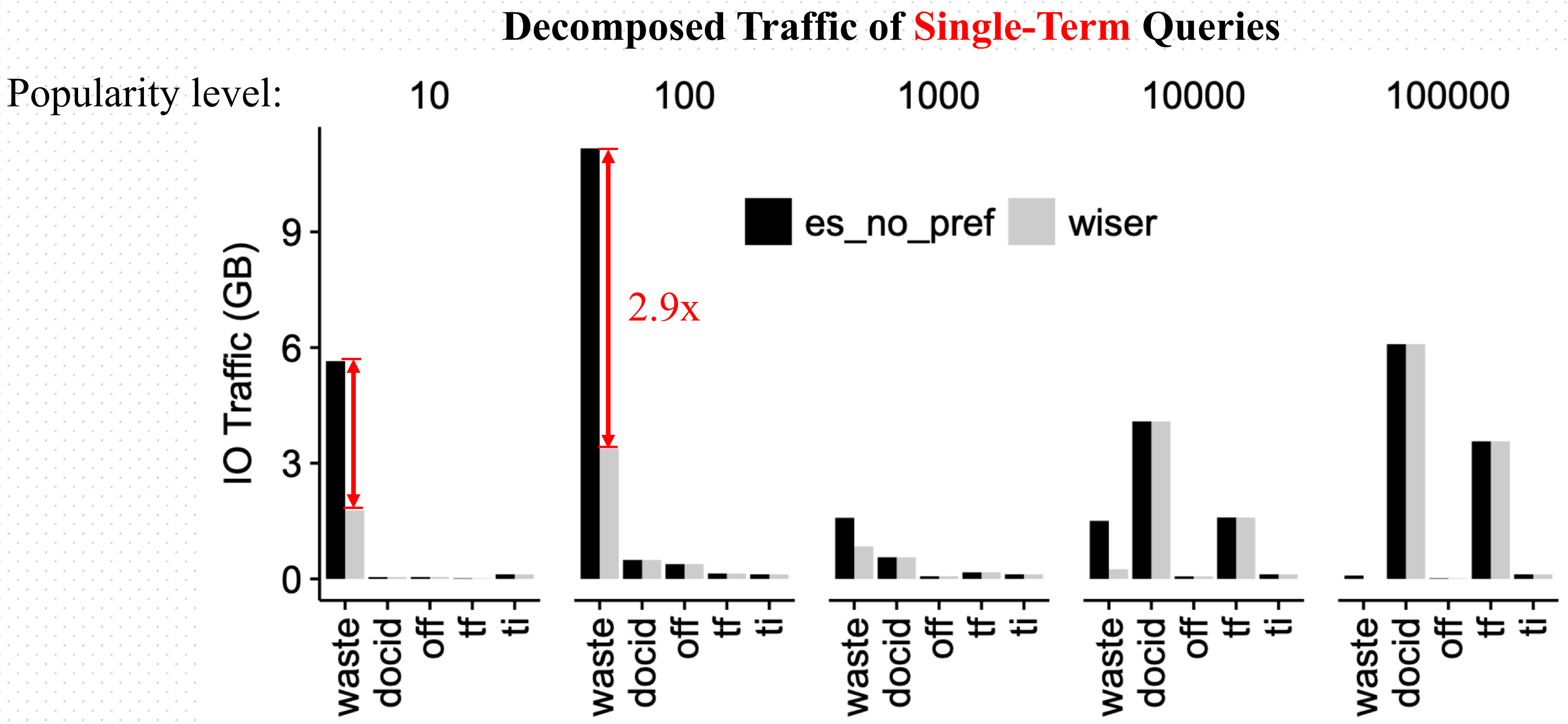
popularity level = document frequency = the number of documents in which a term appears

Cross-stage Data Grouping



- waste: the data that is unnecessarily read
- docid: the ideally needed data of document ID
- off: offset
- tf: term frequency
- ti: term index/dictionary
- es_no_pref: Elasticsearch without prefetch

Cross-stage Data Grouping



Elasticsearch needs three separate I/O requests:

1. Term index   2. ID, TF   3. Offsets

WiSER only needs one I/O request!

Cross-stage Data Grouping

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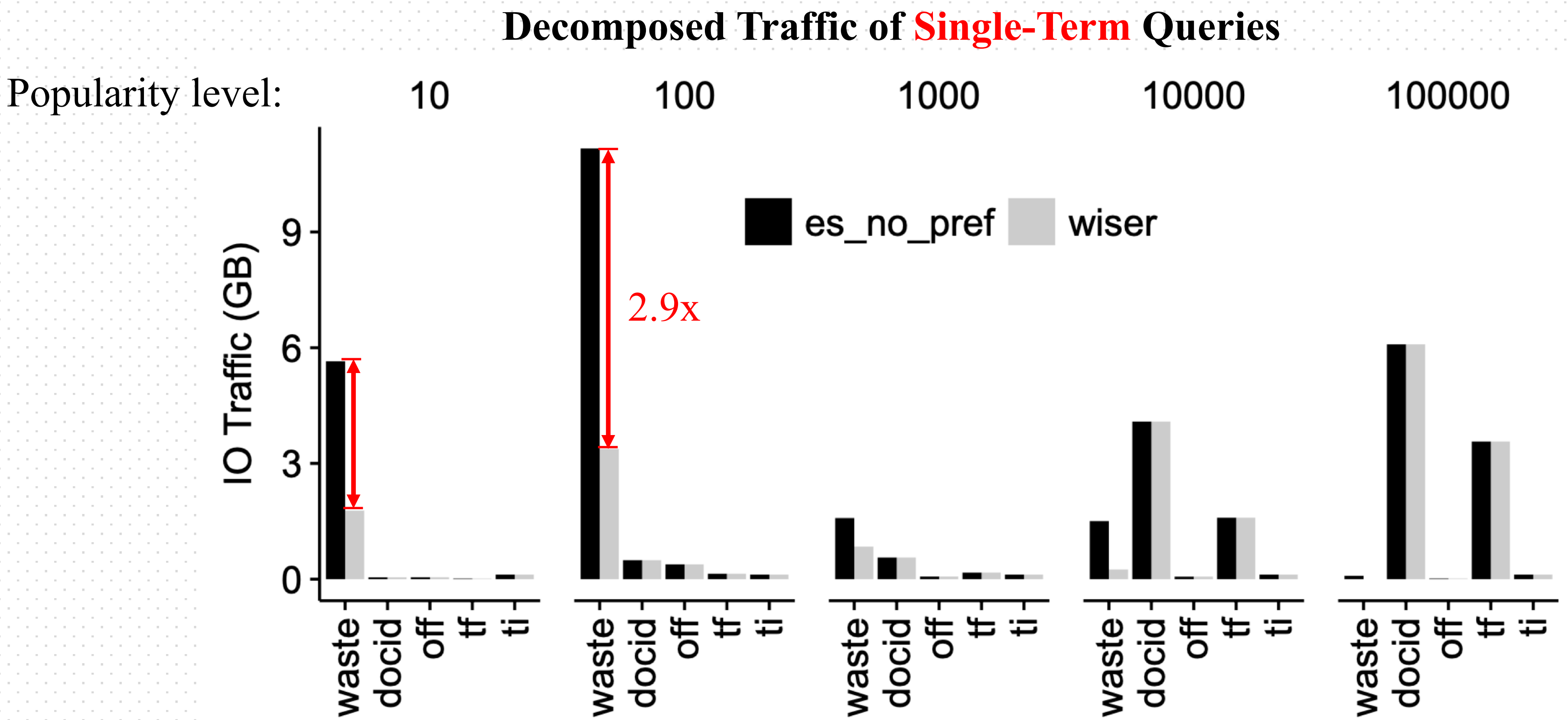

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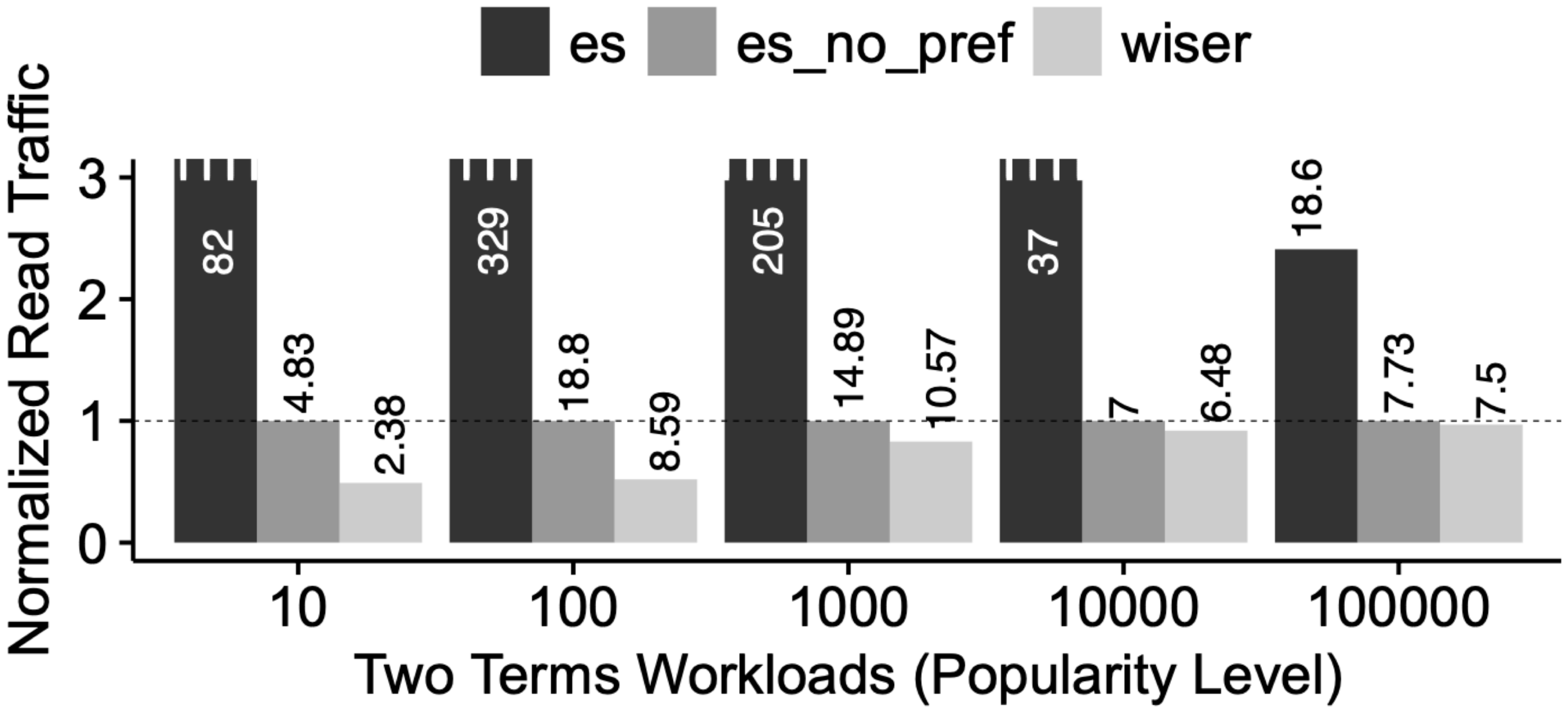
Reduce read amplification!

Cross-stage Data Grouping

I/O Traffic of Two-term Match Queries



Cross-stage Data Grouping

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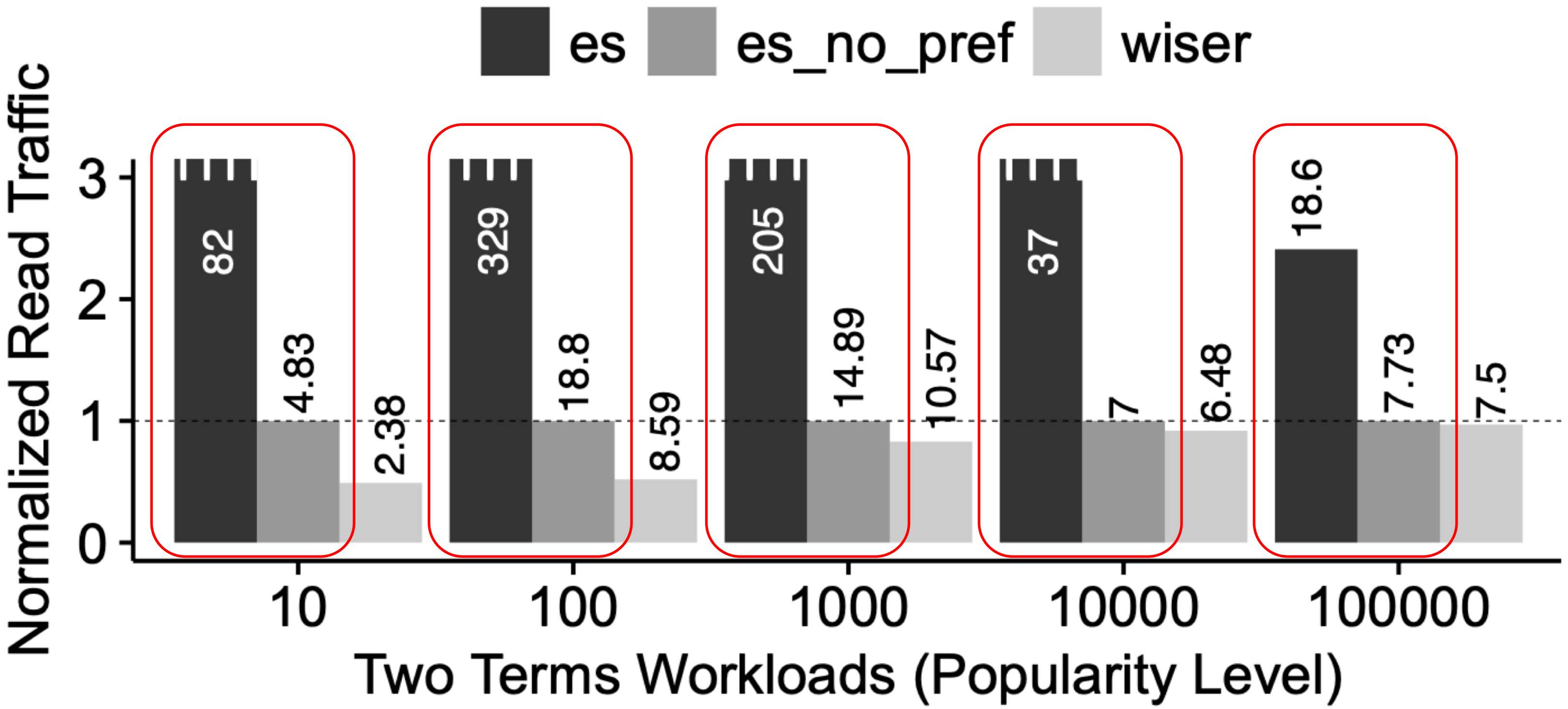
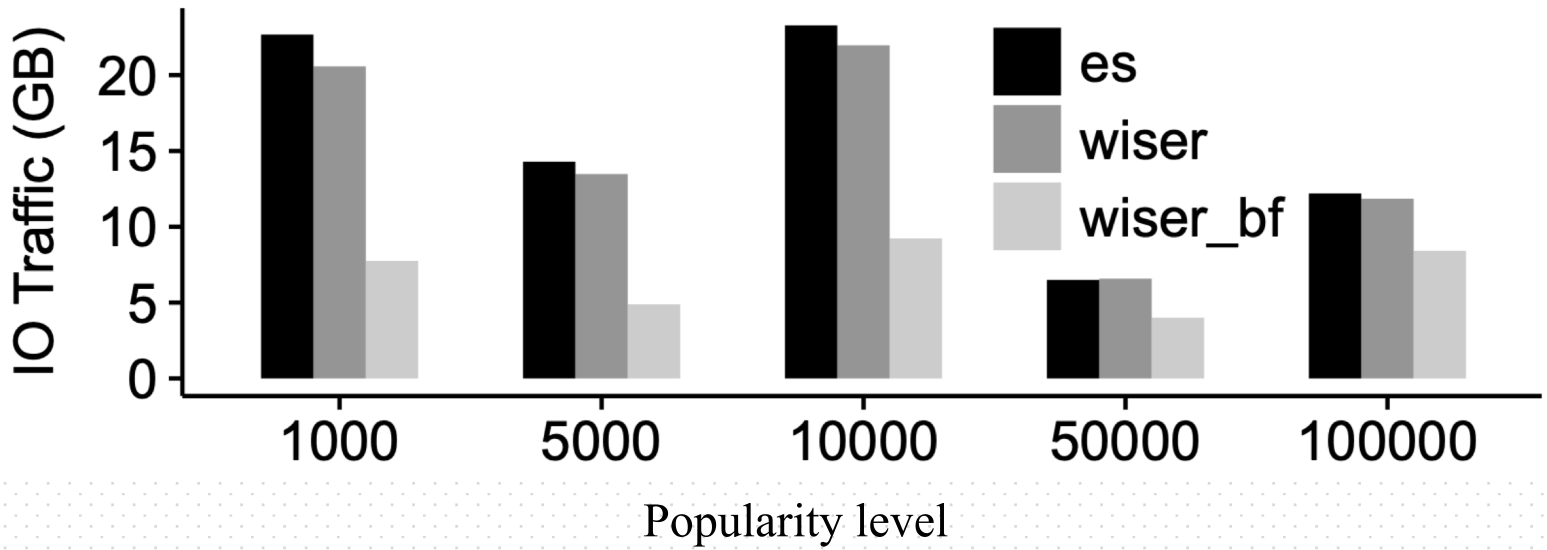
I/O Traffic of Two-term Match Queries



Naive prefetch in Elasticsearch can increase read amplification significantly!

Two-Way Cost-Aware Bloom Filters

I/O Traffic of Phrase Queries



- es: Elasticsearch without prefetch
- wiser: WiSER without Bloom filters
- wiser_bf: WiSER with Bloom filters

Two-Way Cost-Aware Bloom Filters

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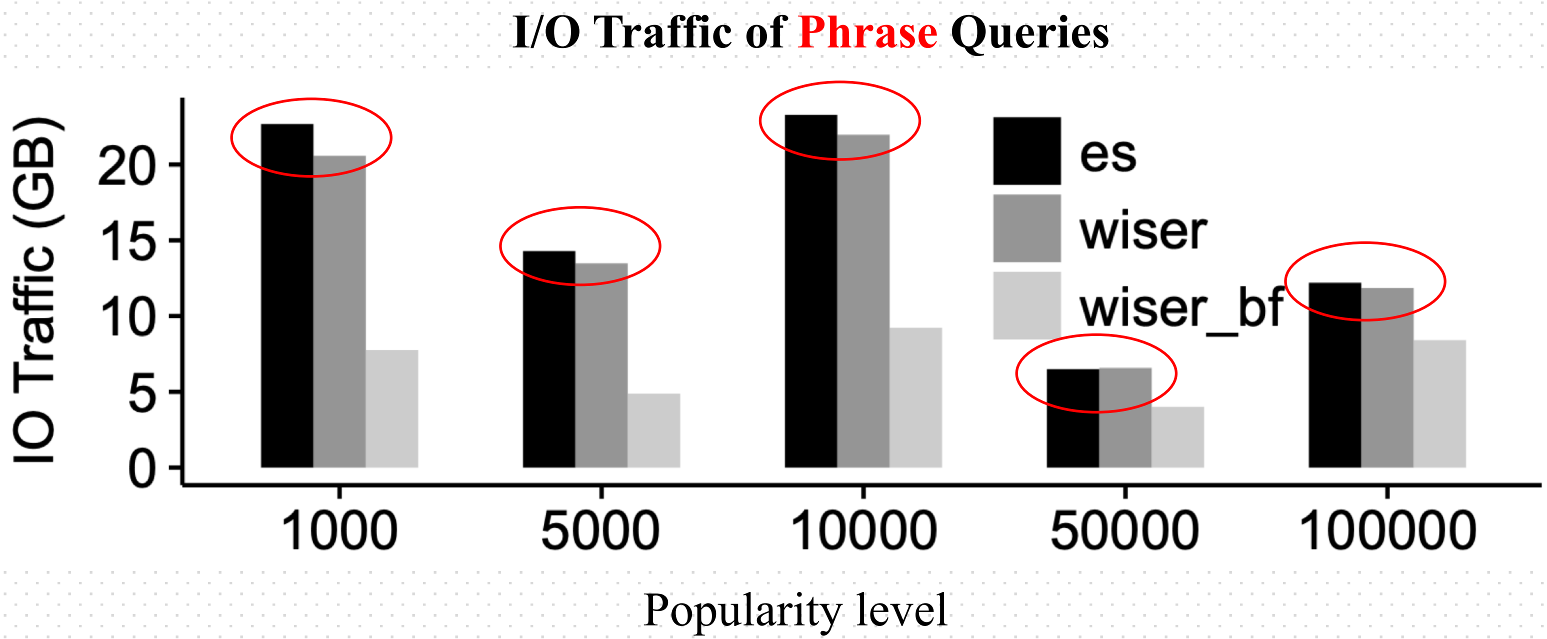

- es: Elasticsearch without prefetch
- wiser: WiSER without Bloom filters
- wiser_bf: WiSER with Bloom filters

WiSER without our Bloom filters demands a similar amount of data as Elasticsearch.

Two-Way Cost-Aware Bloom Filters

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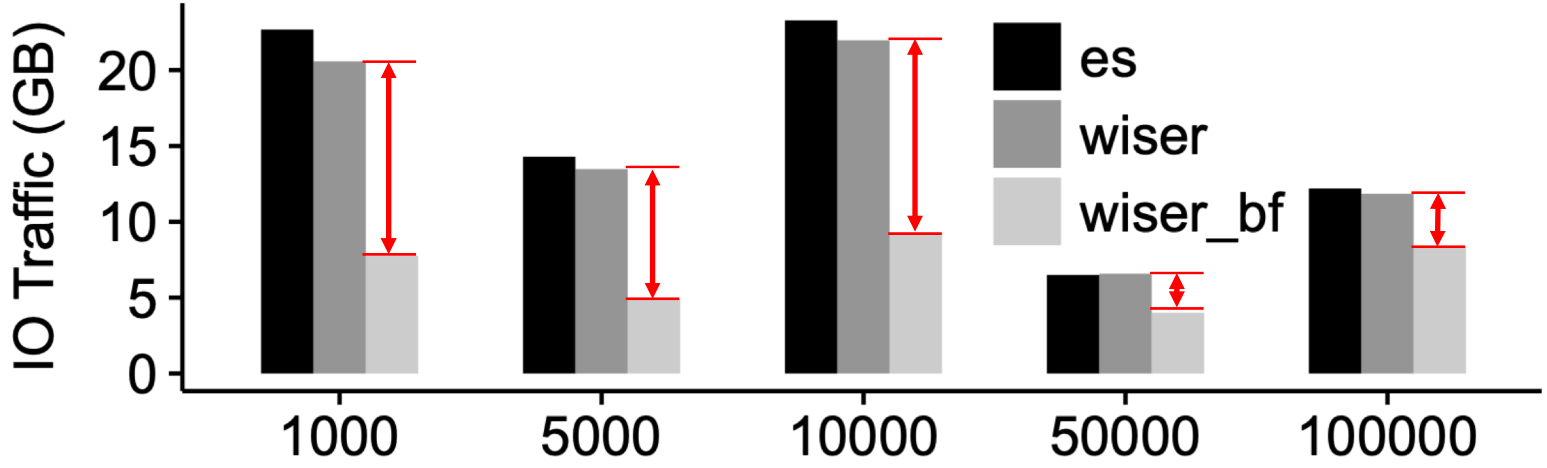
I/O Traffic of Phrase Queries



Popularity level

- es: Elasticsearch without prefetch
- wiser: WiSER without Bloom filters
- wiser_bf: WiSER with Bloom filters

WiSER with Bloom filters incurs much less I/O traffic!

Two-Way Cost-Aware Bloom Filters

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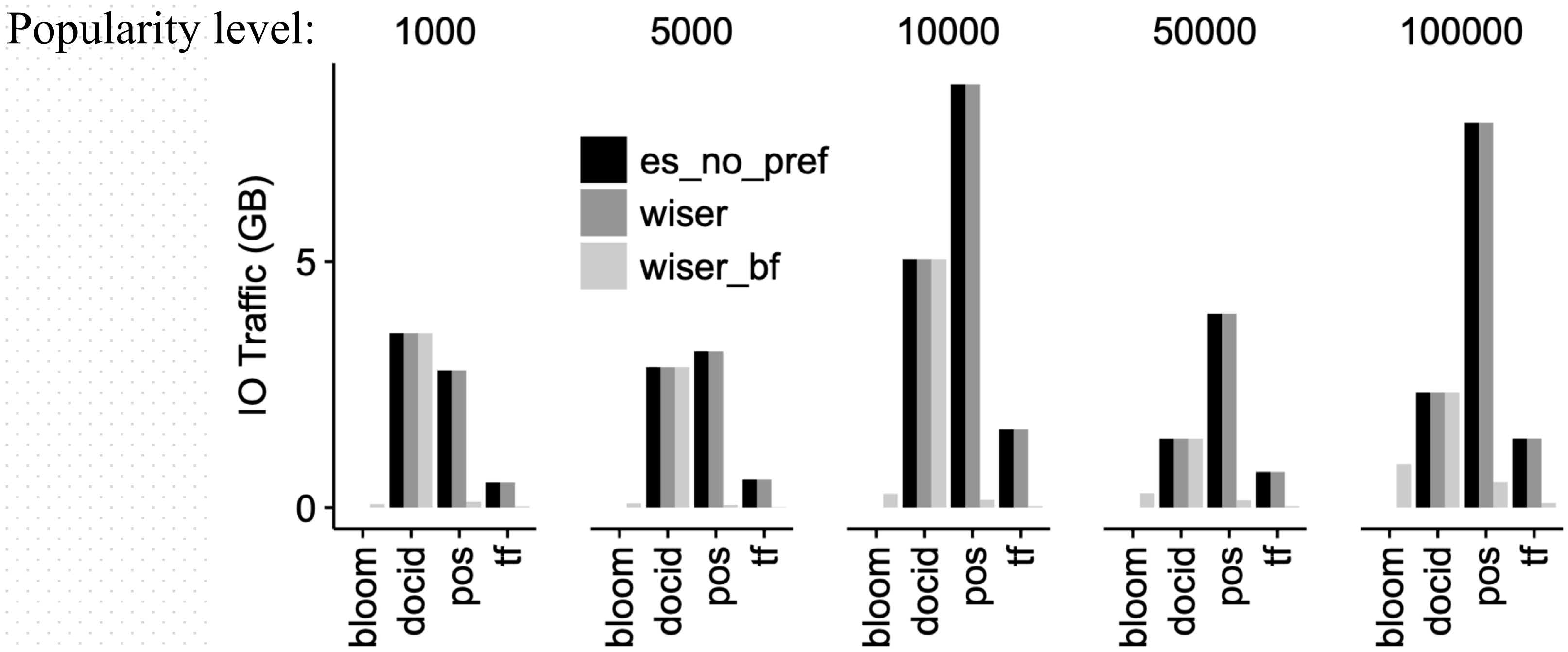
Decomposed Traffic Analysis of Phrase Queries



- bloom: the ideally needed data of Bloom filters
- docid: document ID
- pos: positions
- tf: term frequencies

- es_no_pref: Elasticsearch without prefetch
- wiser: WiSER without Bloom filters
- wiser_bf: WiSER with Bloom filters
- ideally: byte-addressable

Two-Way Cost-Aware Bloom Filters

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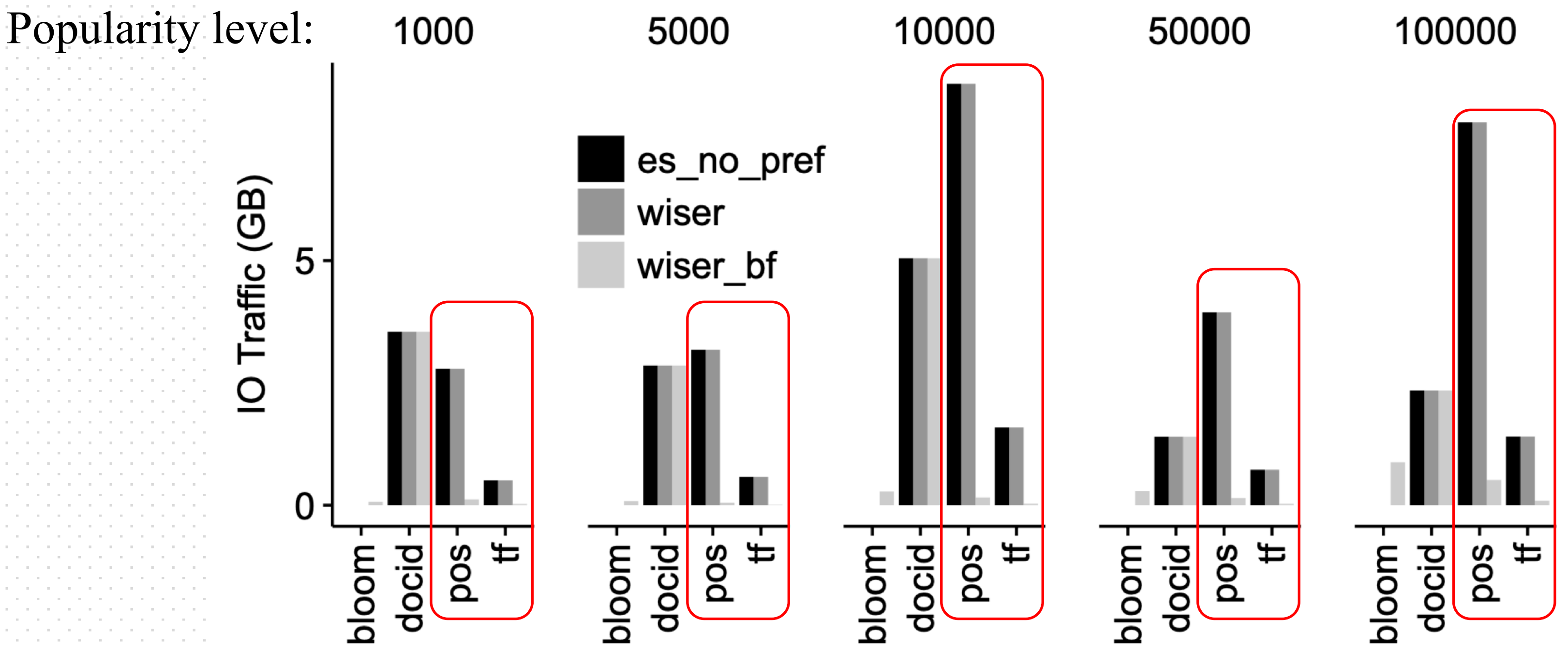
Decomposed Traffic Analysis of Phrase Queries



Reduce the traffic from positions and term frequencies!

Adaptive Prefetching

Trade Disk Space for Less I/O

End-to-end Performance

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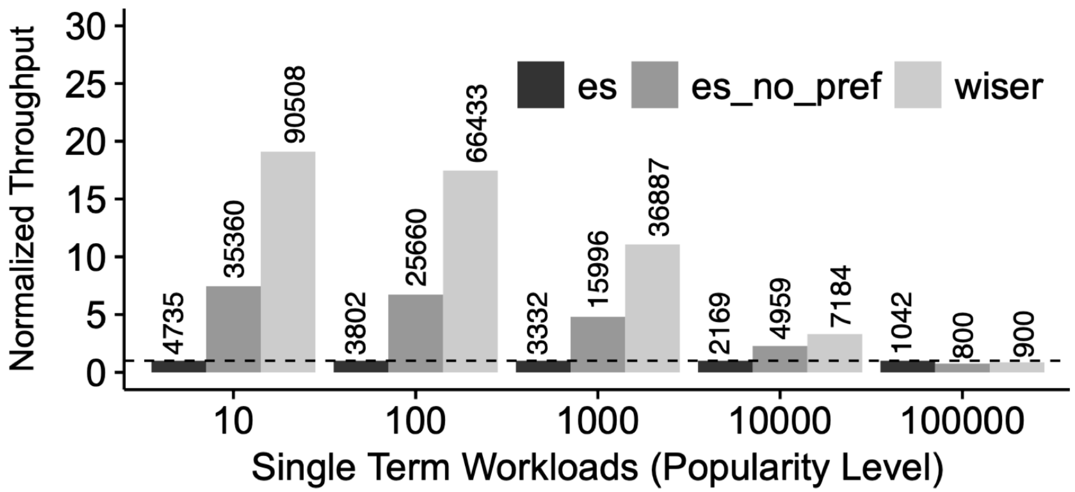
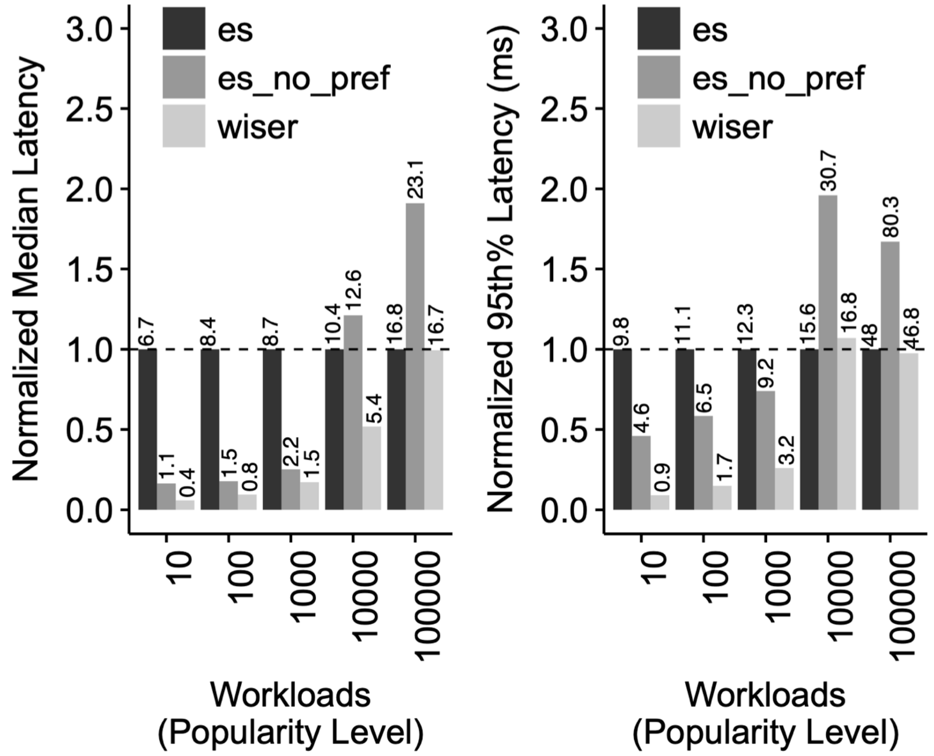
Single Term Matching Throughput



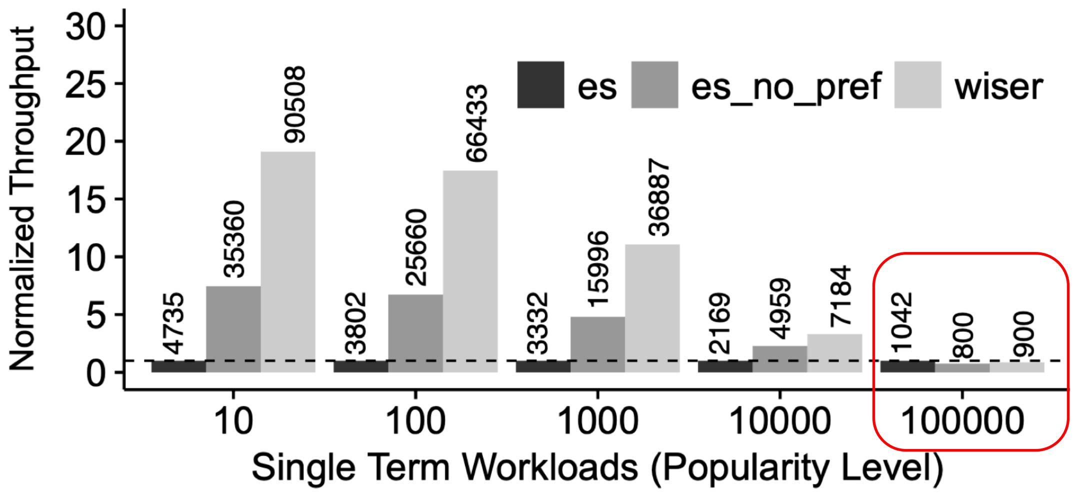
Single Term Matching Latency



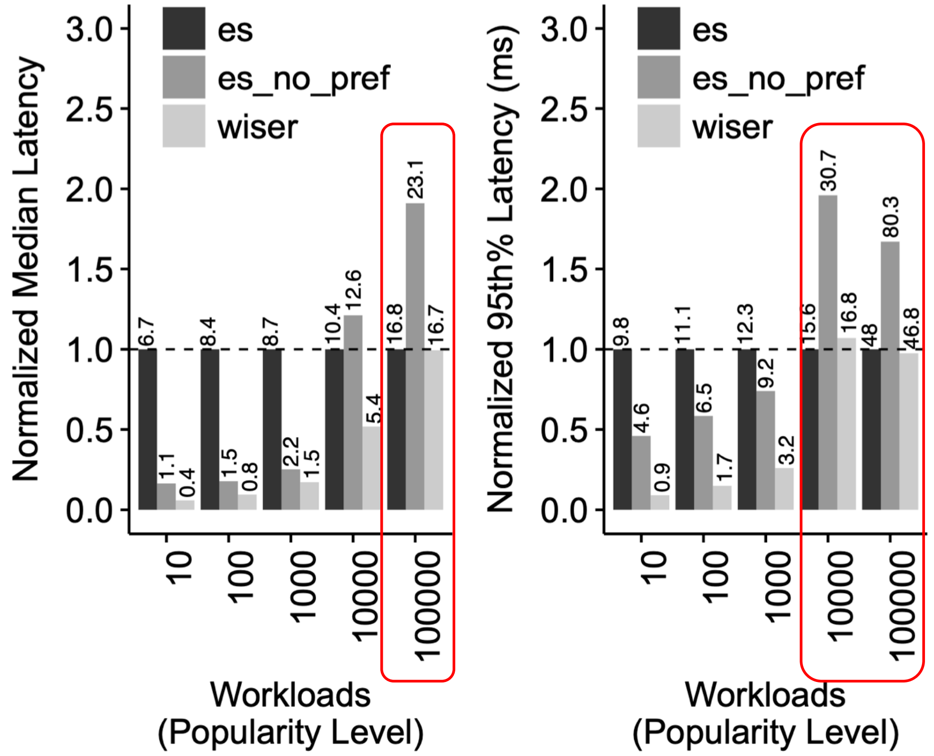
- Throughput: QPS (Queries Per Second)
- es: Elasticsearch with prefetch (128 KB)
- es_no_pref: Elasticsearch without prefetch
- wiser: WiSER

End-to-end Performance

Single Term Matching Throughput



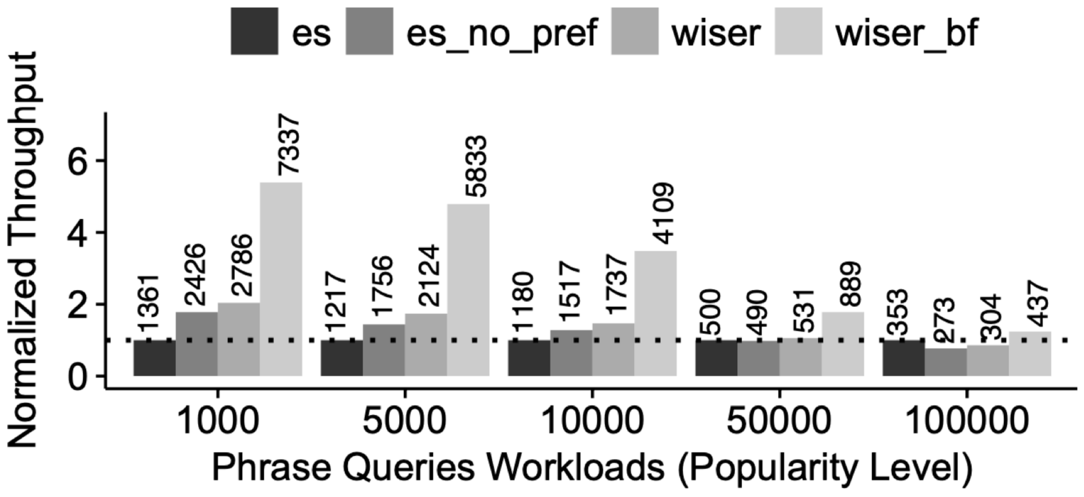
Single Term Matching Latency



Due to WiSER's less efficient score calculation.

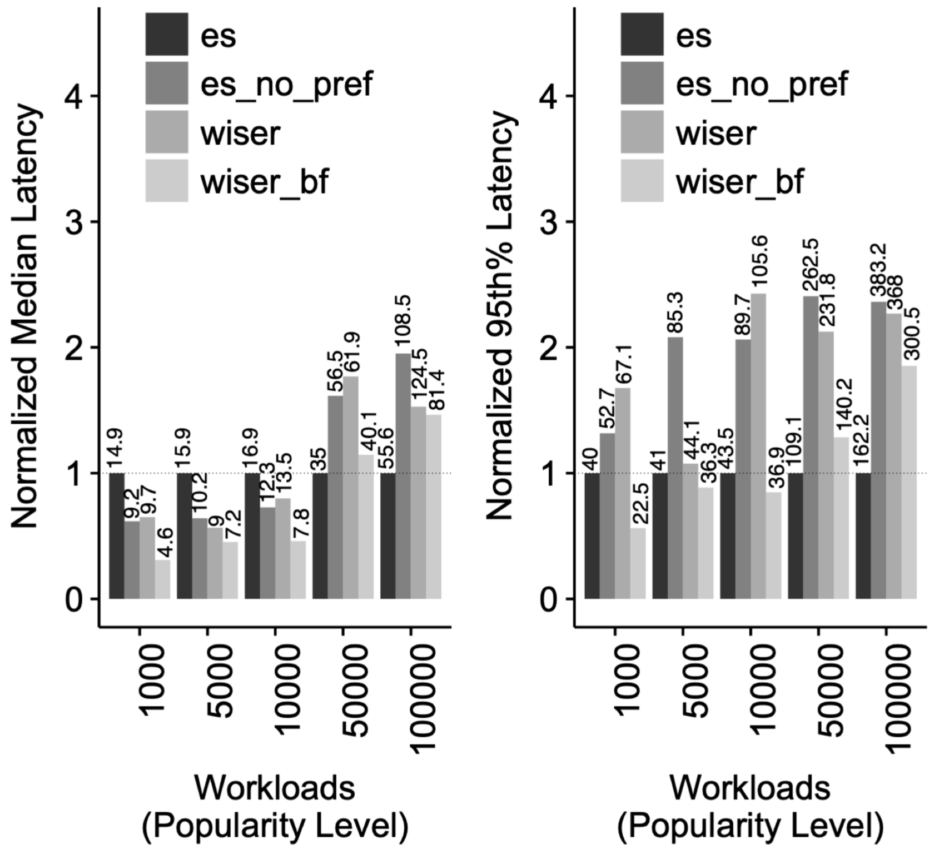
End-to-end Performance

Phrase Query QPS



- Throughput: QPS (Queries Per Second)
- es: Elasticsearch with prefetch (128 KB)
- es_no_pref: Elasticsearch without prefetch
- wiser: WiSER without Bloom filters
- wiser_bf: WiSER with Bloom filters

Phrase Queries Latency



End-to-end Performance

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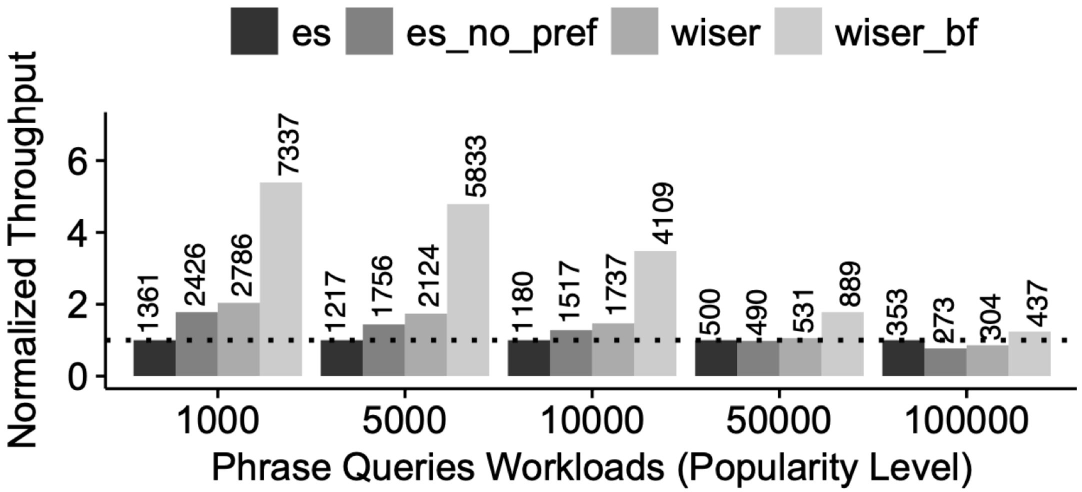
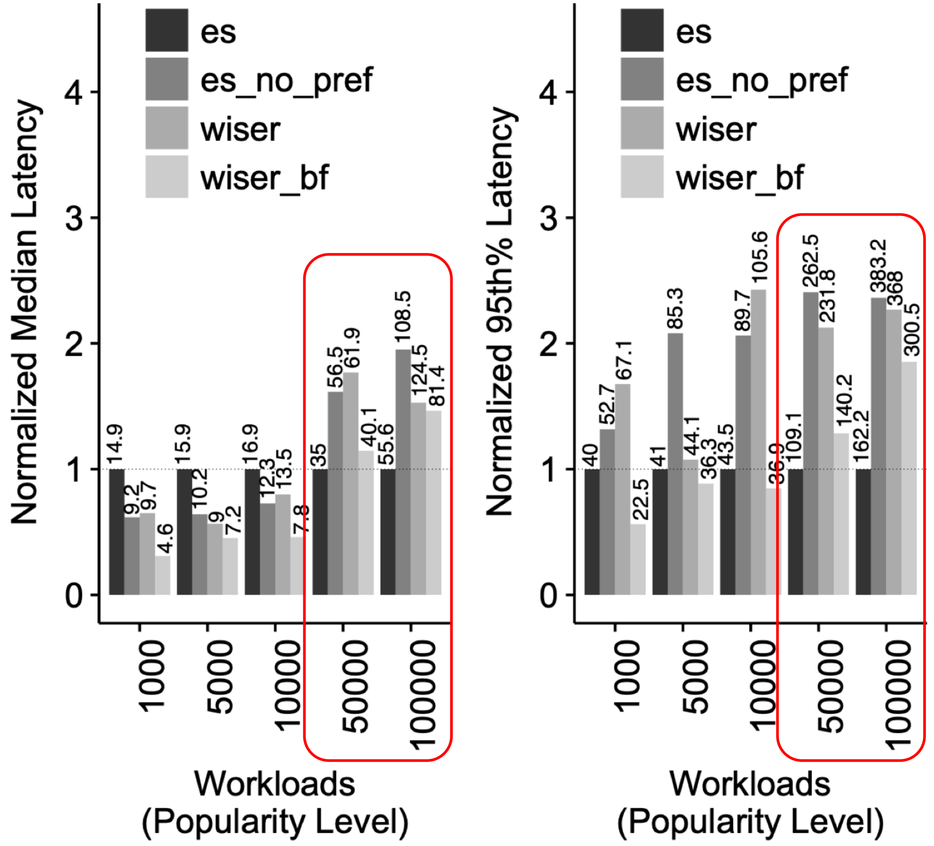
Phrase Query QPS



Phrase Queries Latency



- Elasticsearch with OS prefetch (es) achieves the lower latency because the OS prefetches 128 KB of positions data and avoids waiting for many page faults.
- Although the latency of individual queries is lower, the query throughput is also lower due to the read amplification caused by prefetch.

End-to-end Performance

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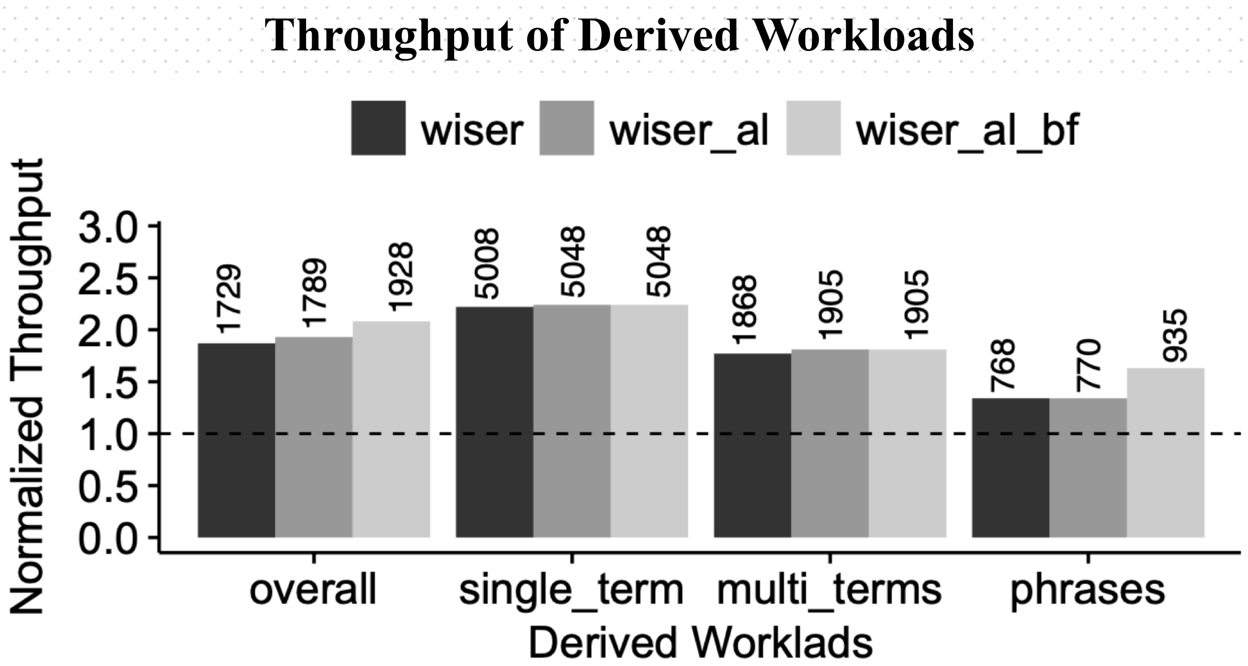

- wiser: unknown
- wiser_al: unknown
- wiser_al_bf: unknown
- Normalized to the throughput of Elasticsearch without Prefetching

- For single-term queries, WiSER achieves as high as 2.2x throughput compared to Elasticsearch.
  - Around 60% queries in the real workload are of popularity less than 10,000.
- For multi-term match queries, grouped data layout also helps to increase throughput by more than 60%.
- For phrase queries, WiSER with Bloom filters increases throughput by more than 60%.

Scaling with Memory

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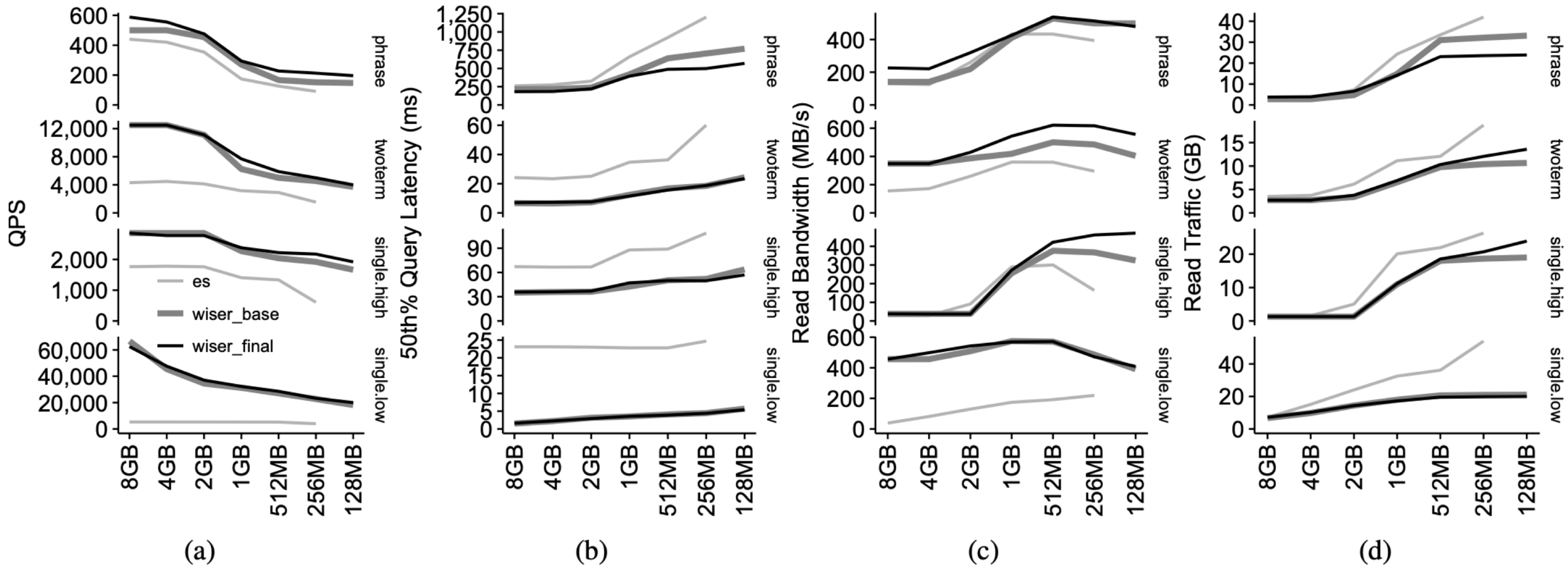
Performance over a range of memory sizes



- es: Elasticsearch without prefetch
- wiser_base: WiSER with only cross-stage grouping
- wiser_final: fully-optimized WiSER
- single.high: high popularity level
- single.low: low popularity level

Scaling with Memory

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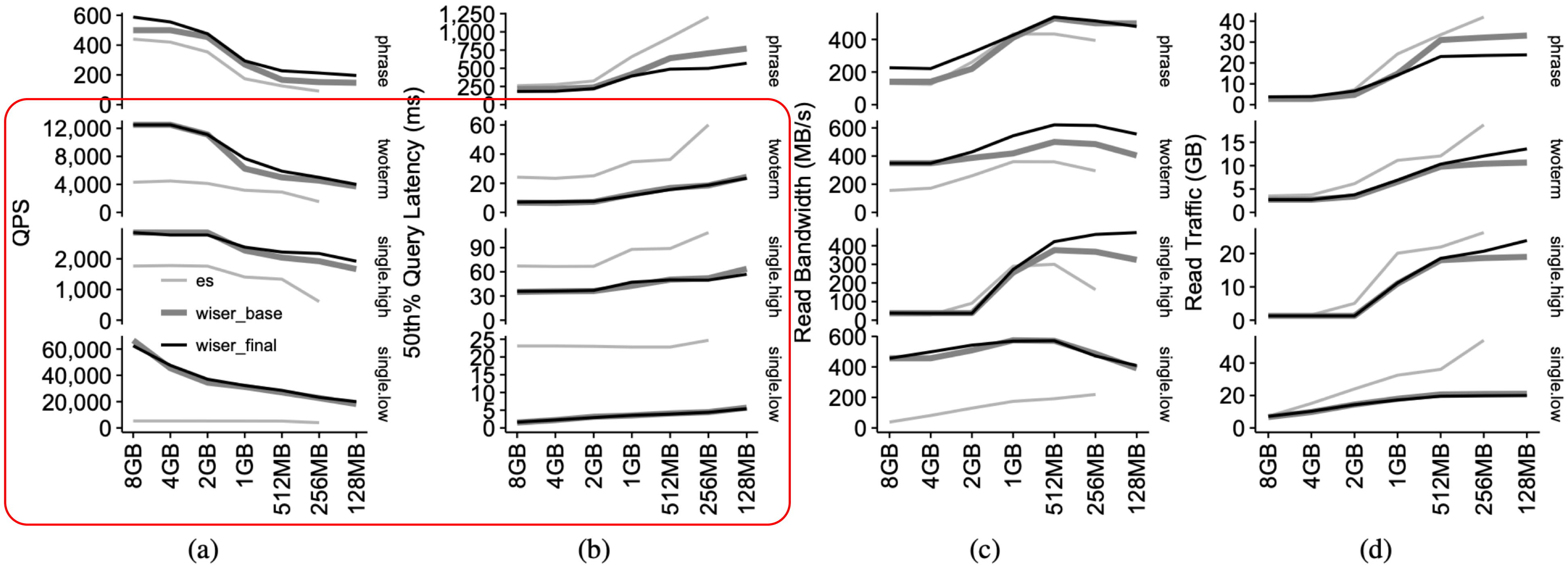
Performance over a range of memory sizes



Due to the network issue of Elasticsearch.

Scaling with Memory

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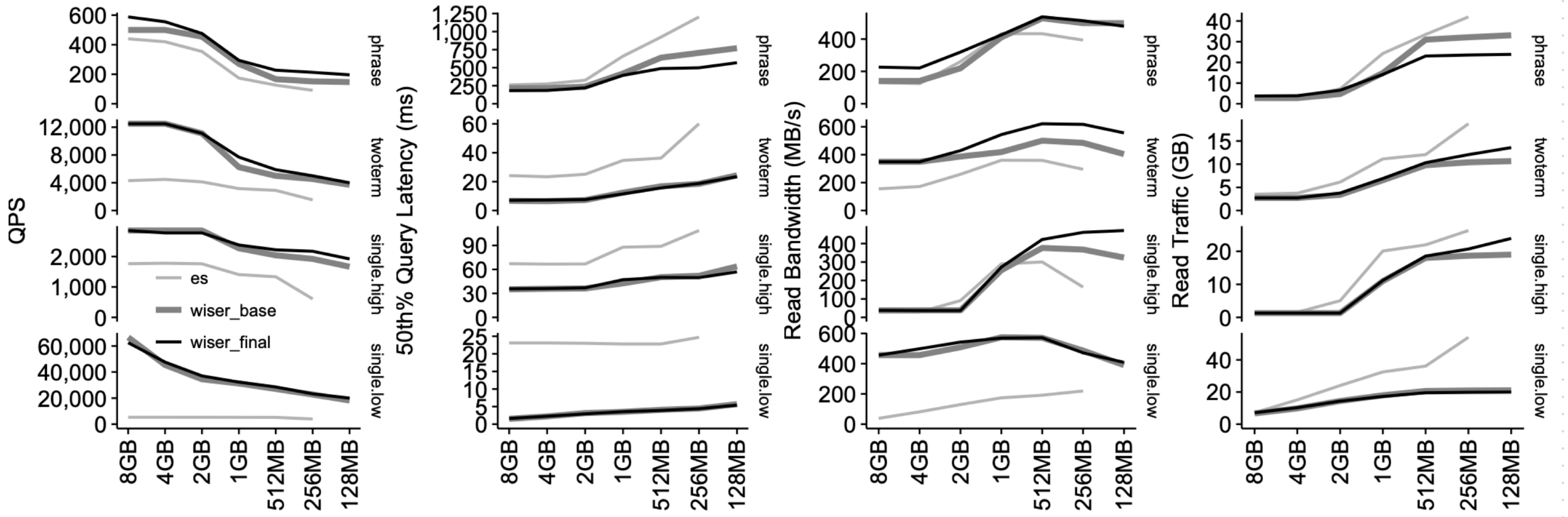
Performance over a range of memory sizes



(a) (b) (c) (d)

- As expected, query throughput is higher, and latency is lower, when more memory is available.
- WiSER has much higher query throughput and much lower query latency than Elasticsearch across all workloads and memory sizes.
- WiSER's traffic sizes increase much slower than Elasticsearch's as we reduce memory sizes.

Outline

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- Motivation
- Background
- Design
- Implementation
- Evaluation
- **Conclusion**

Conclusion

IO is the bottleneck

Conclusion

IO is the bottleneck

Cross-stage
Data Grouping

Two-Way Cost-Aware
Bloom Filters

Adaptive Prefetching

Trade Disk Space
for Less I/O

Conclusion

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IO is the bottleneck

- Cross-stage Data Grouping → Reduce read amplification → Reduce I/O traffic
- Two-Way Cost-Aware Bloom Filters → Reduce I/O traffic for phrase
- Adaptive Prefetching → Reduce latency
- Trade Disk Space for Less I/O → Reduce read amplification → Reduce I/O traffic

Conclusion

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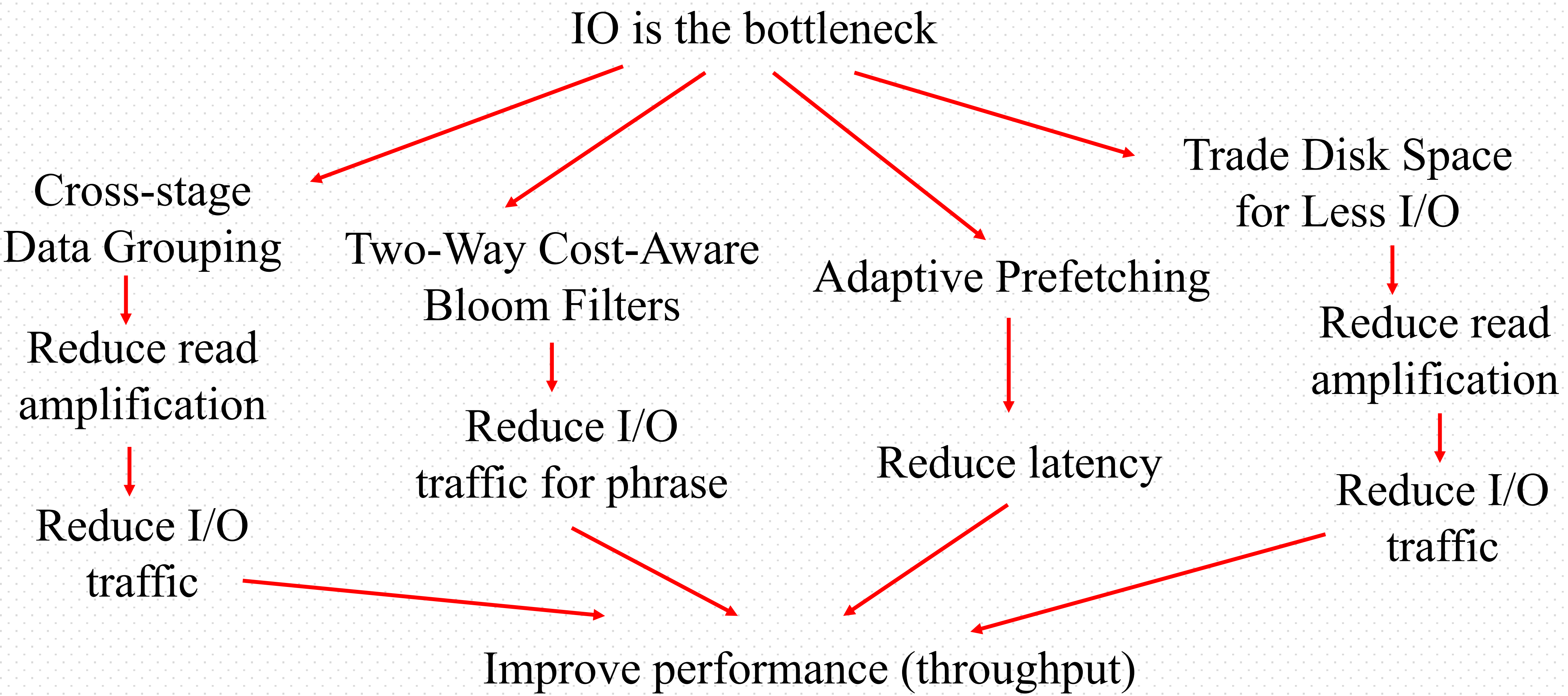

Read as Needed: Building WiSER, a Flash-Optimized Search Engine

Thanks & QA!

USTC, CHINA
ADSLAB
先进数据系统实验室

April 24th, 2020