Parallel & Distributed Operating Systems Group

Cryptography at Scale: Designing a Private Web Search Engine

Alexandra Henzinger

Committee: Henry Corrigan-Gibbs, Yael Kalai, Vinod Vaikuntanathan, and Nickolai Zeldovich

We trust web servers with our secrets

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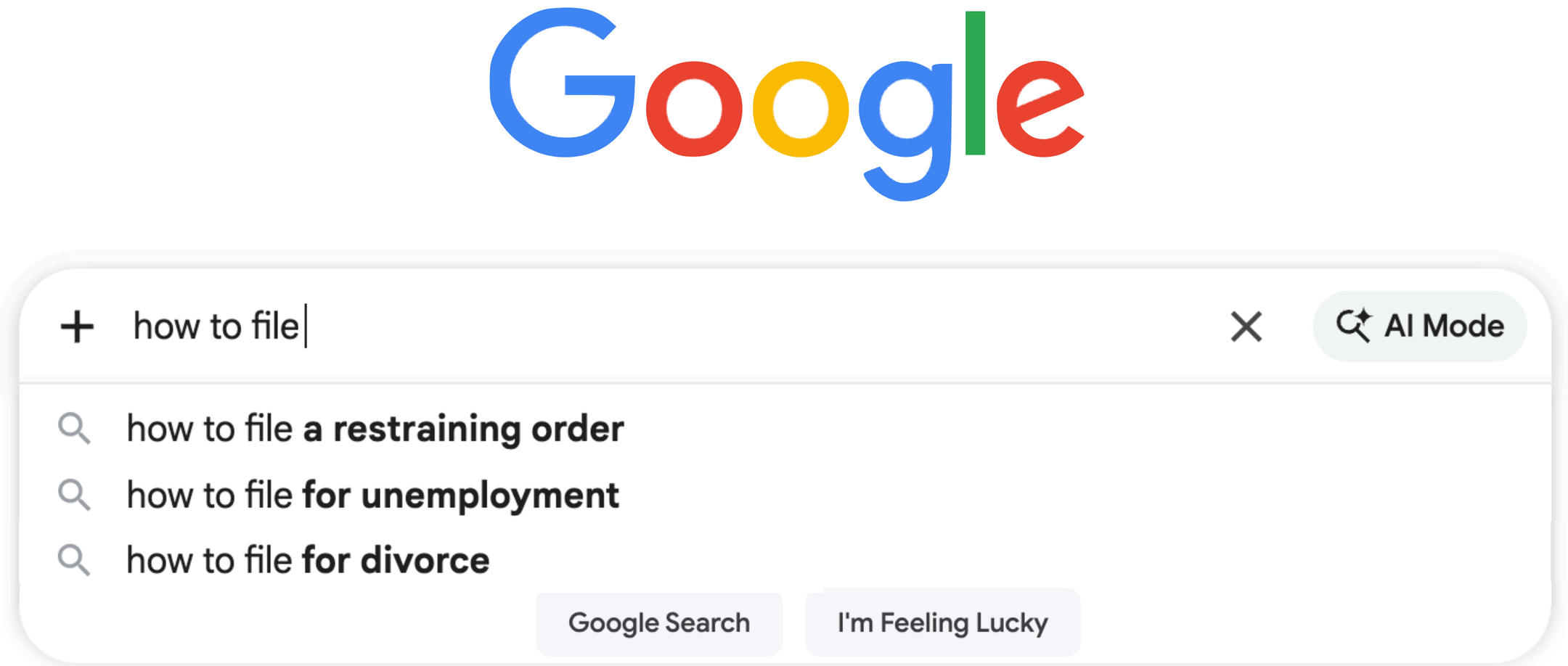

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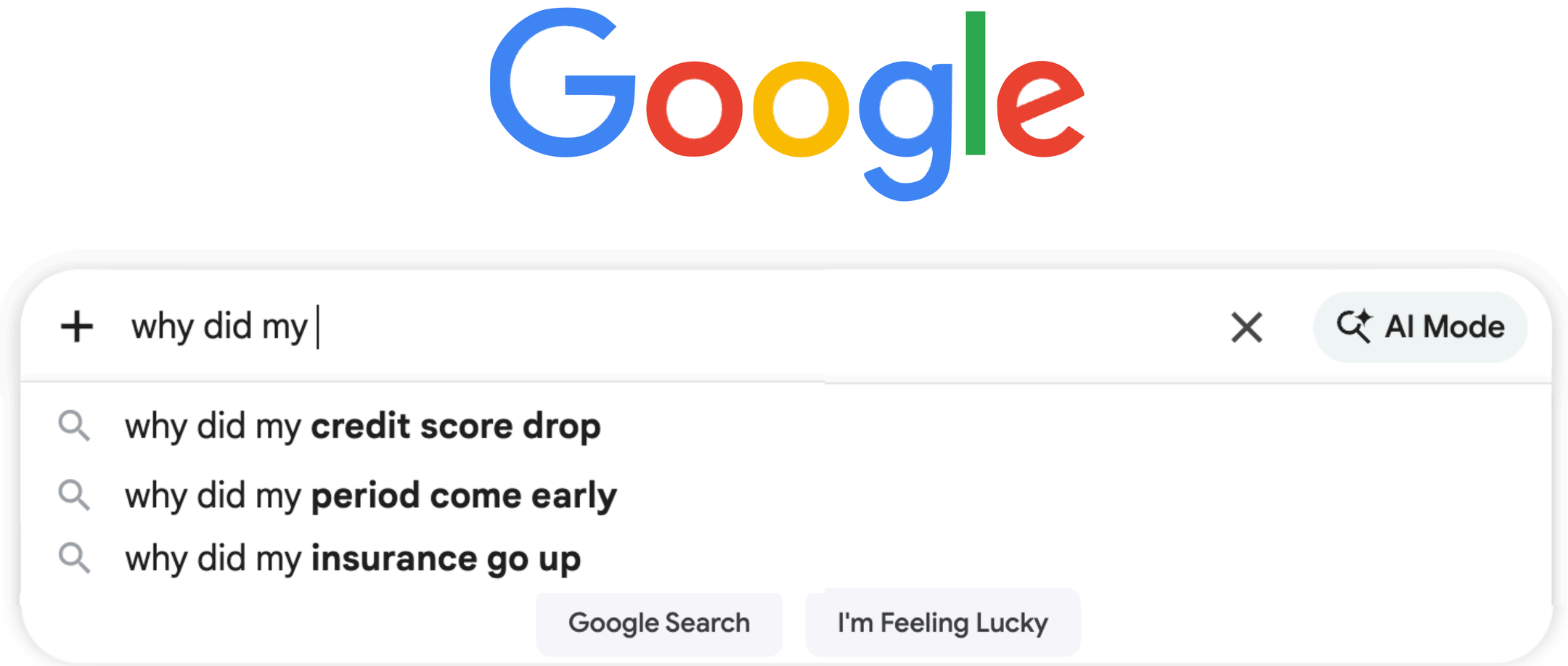

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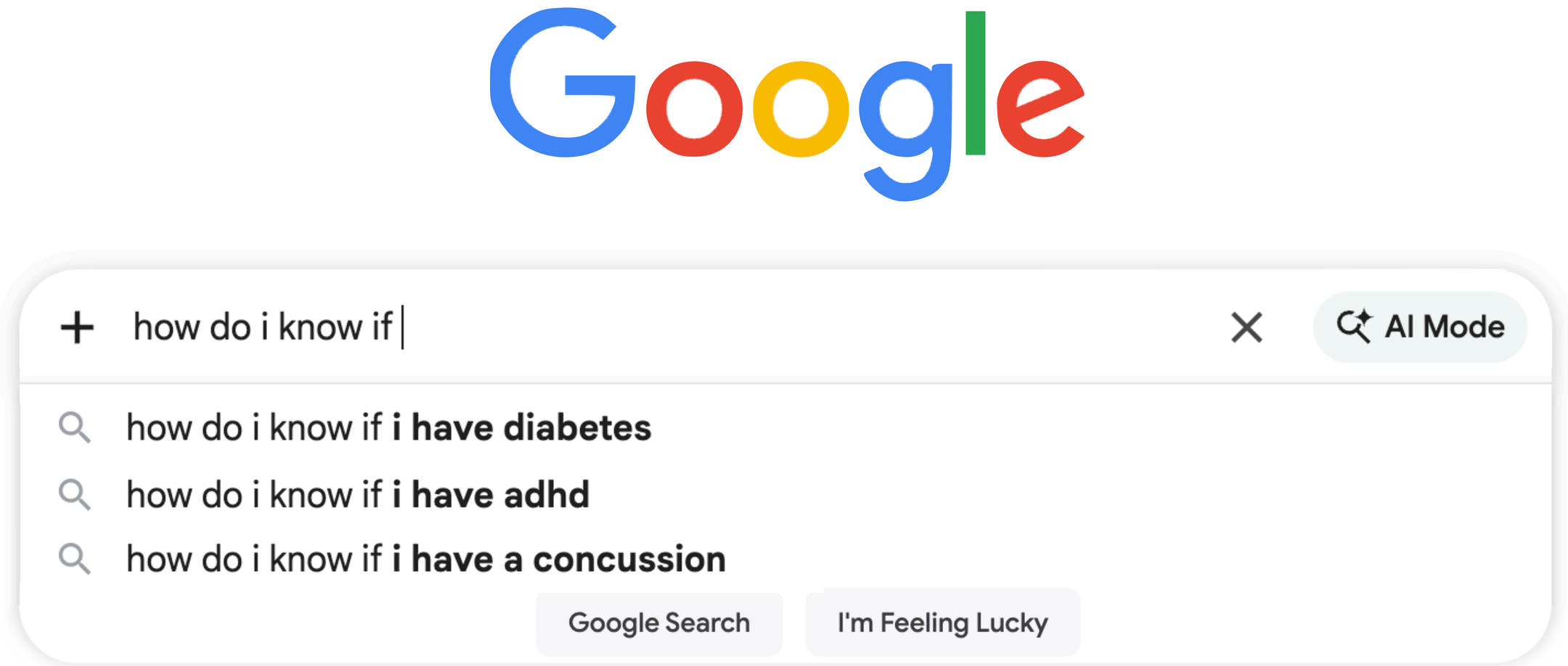

Web servers leak our secrets

Breach

Unsecured Microsoft Bing Server Exposed Users' Search Queries and Location

The Hacker News, Sep 2020

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Sale

Health Insurers Are Vacuuming Up Details About You — And It Could Raise Your Rates

NPR, July 2018

Dream: Web servers never see our secrets

~~Breach~~

~~Reuse~~

~~Sale~~

[RAD78, Gentry09, BV11]

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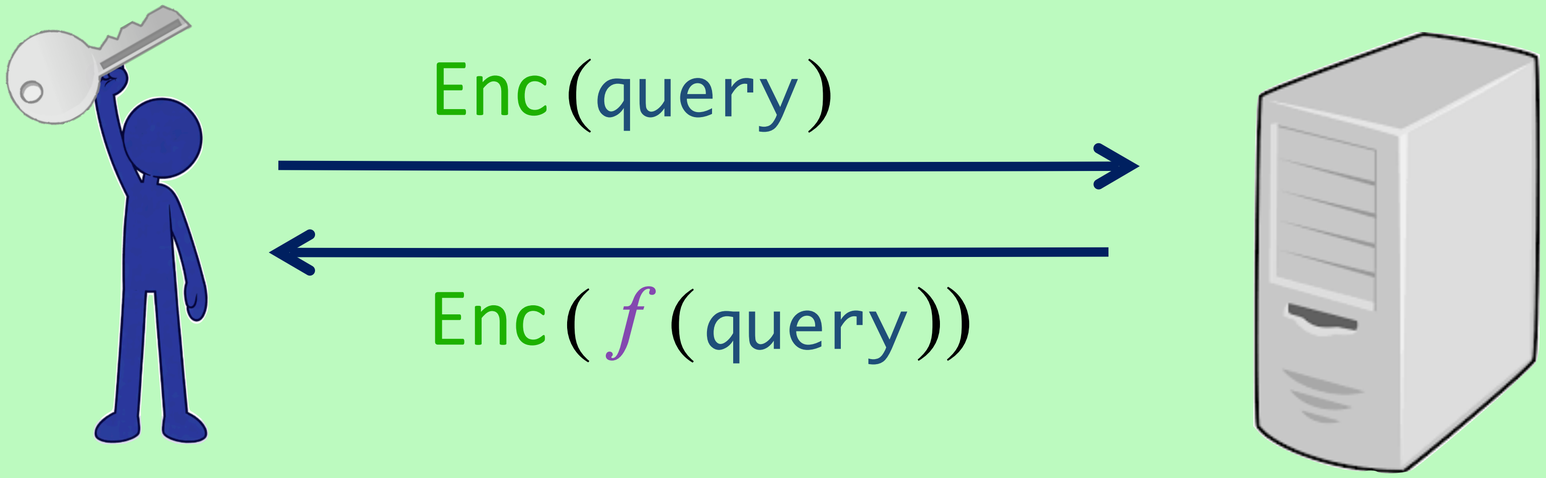

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… why aren't we using them?

[RAD78, Gentry09, BV11]

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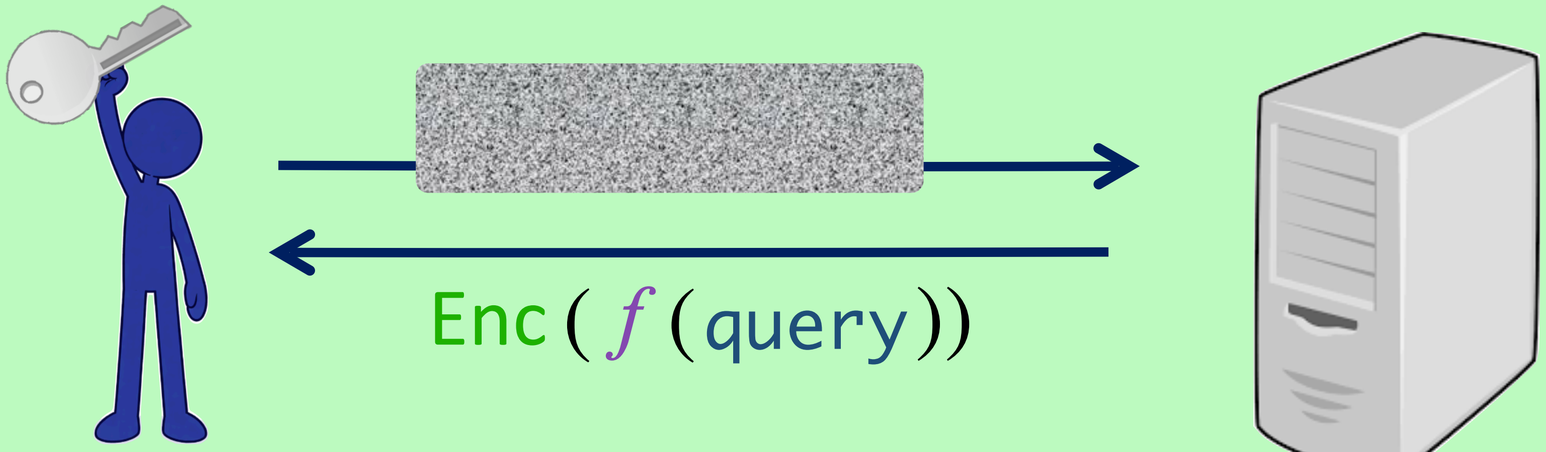

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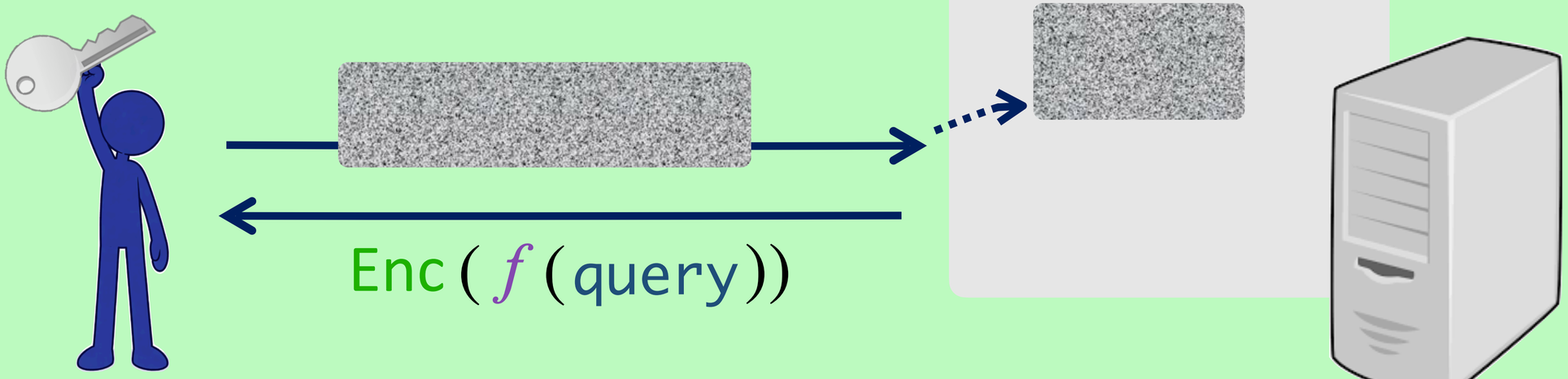

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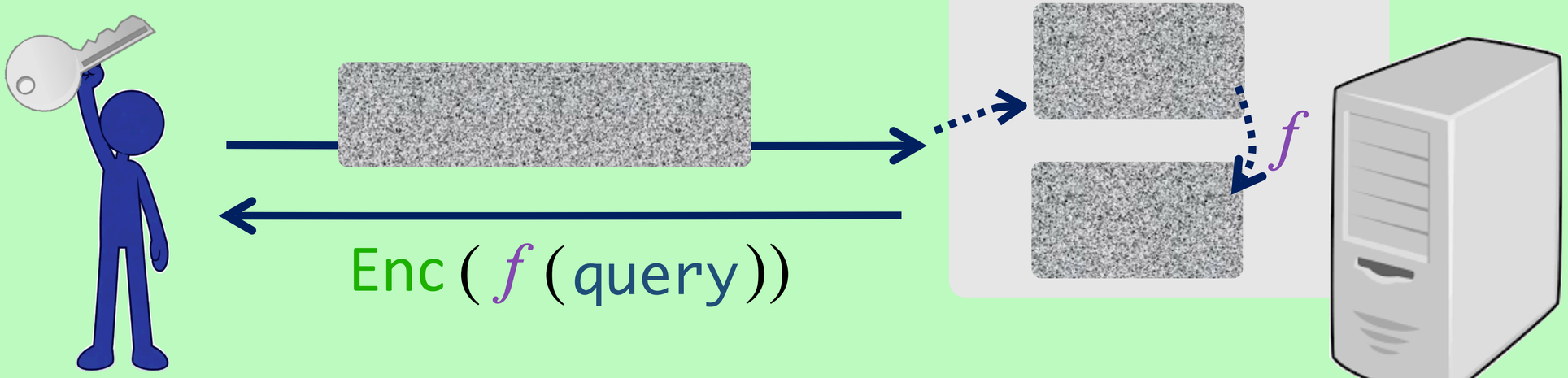

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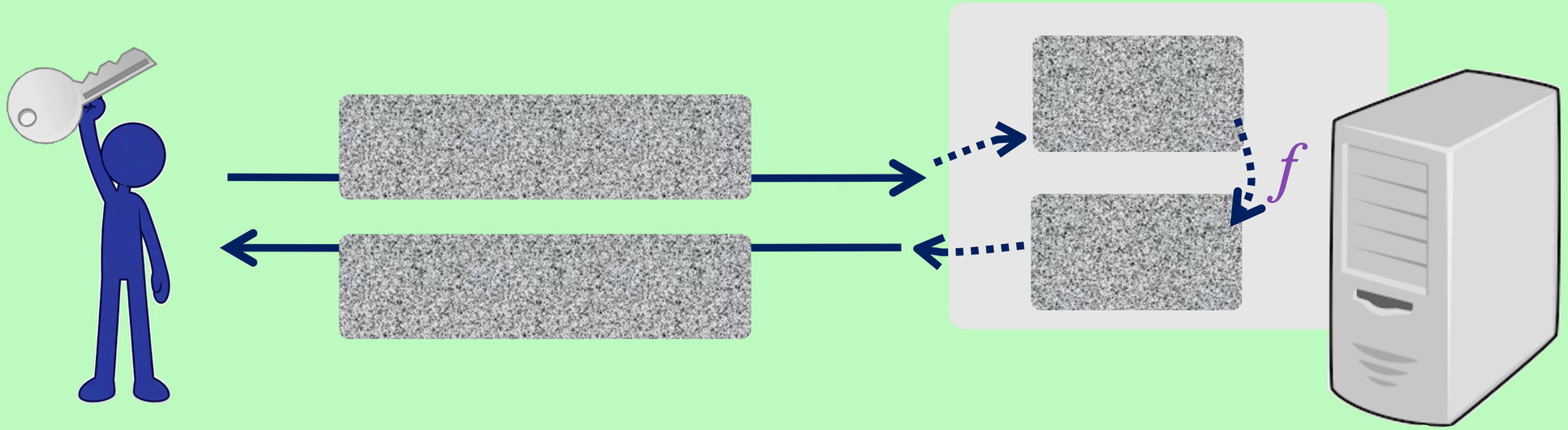

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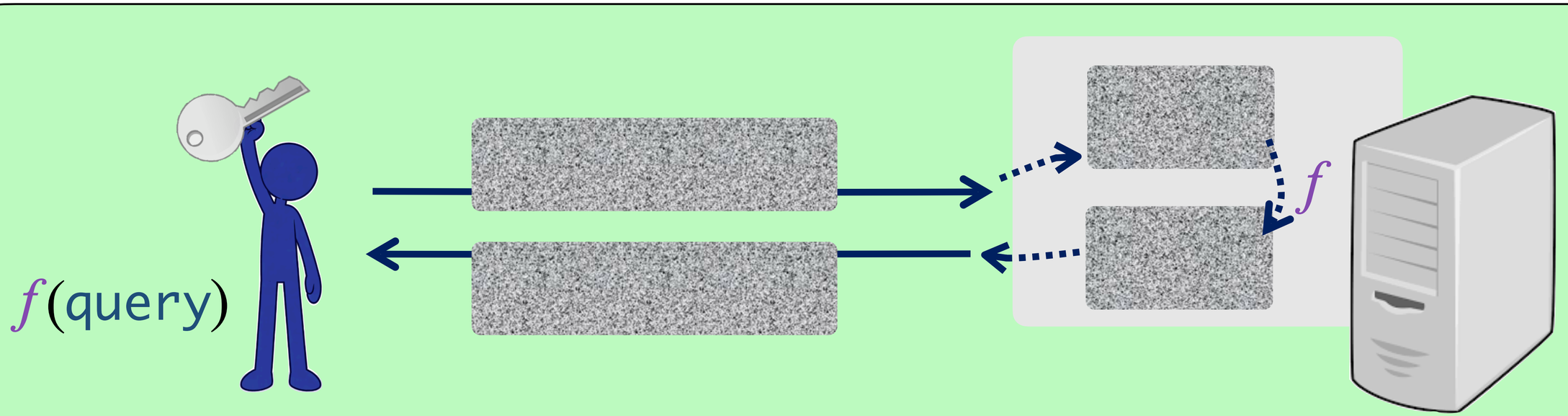

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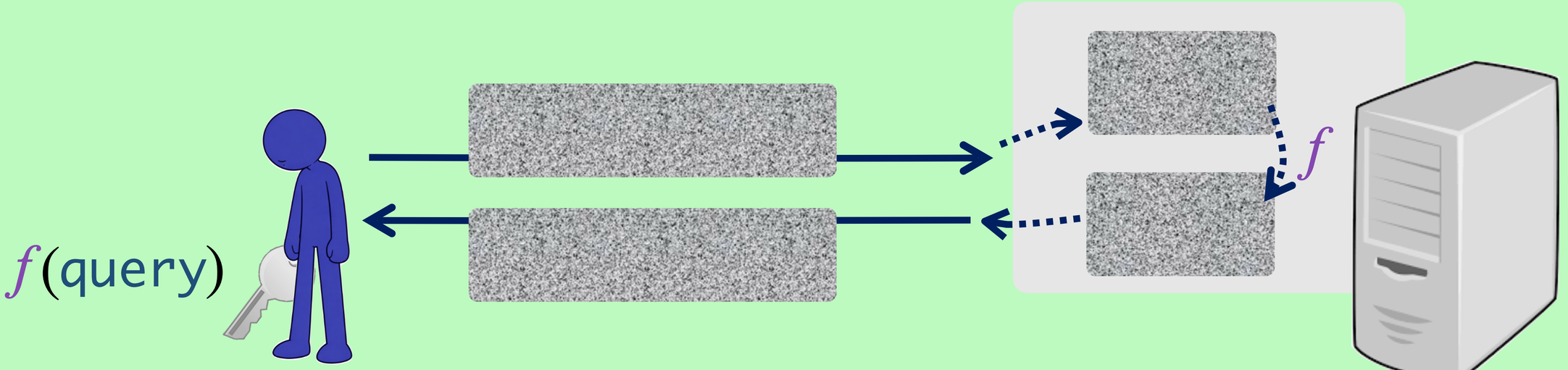

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e.g., add and multiply on encrypted data

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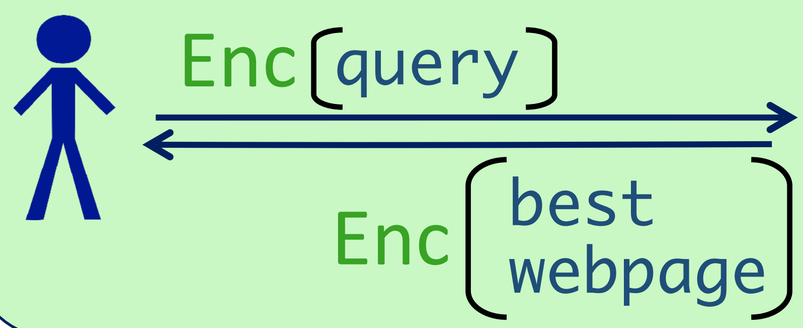

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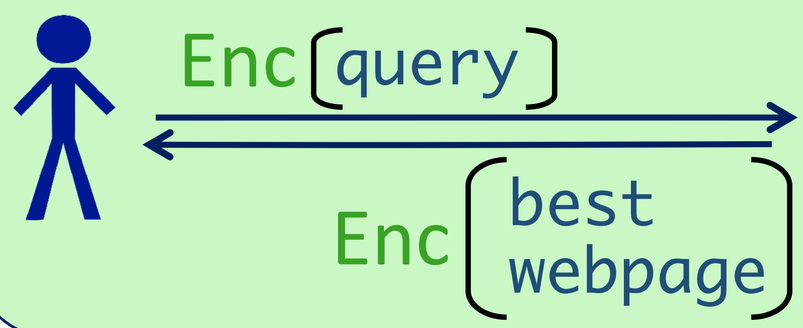

Wildly intractable:
Compile down to + and ×?

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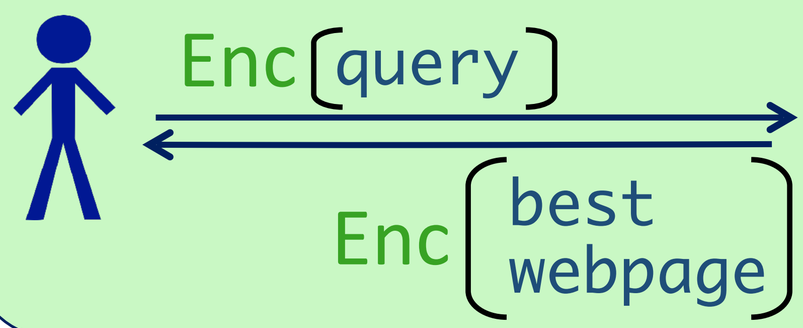

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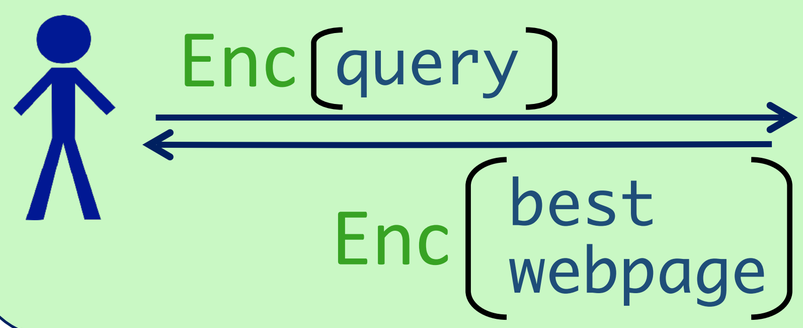

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Design fast cryptography

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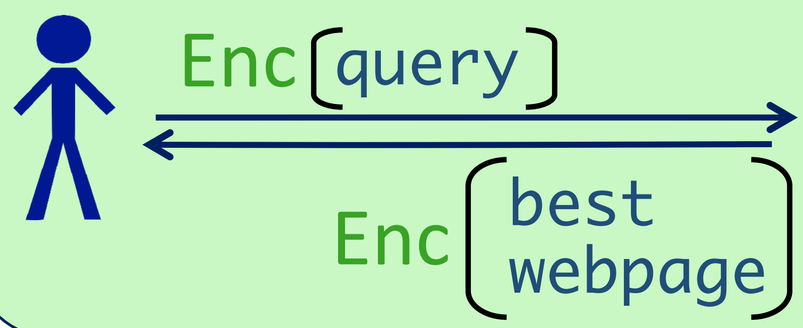

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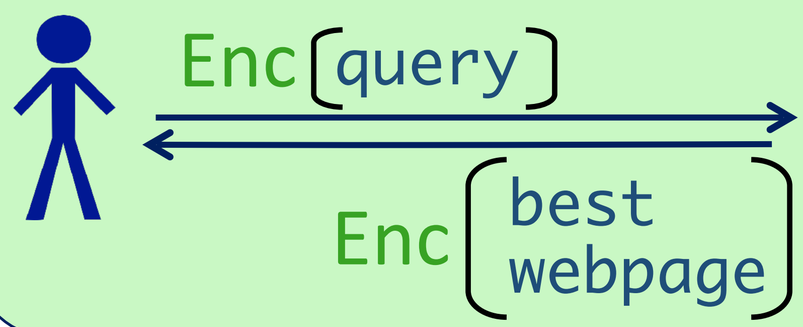

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Design fast cryptography

Re-architect systems

My research: A privacy-preserving software stack

Applications

Libraries

Cryptographic operations

Privacy-preserving systems

- Protect high-impact applications

Algorithms on encrypted data

- Reorganize computation and data in a way that scales

Fast cryptography

- Design efficient encrypted operations

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- **Private matrix multiplication**
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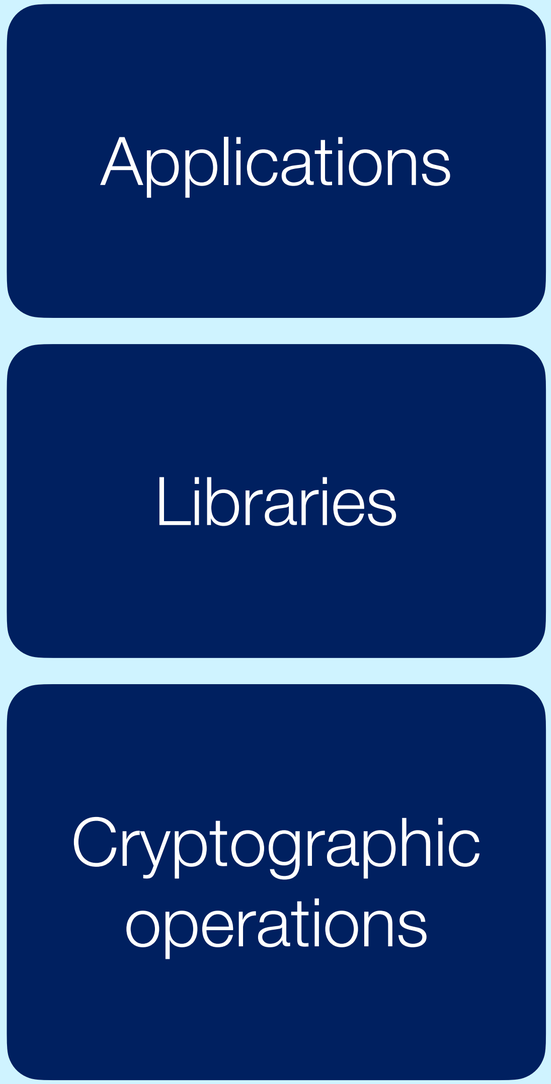

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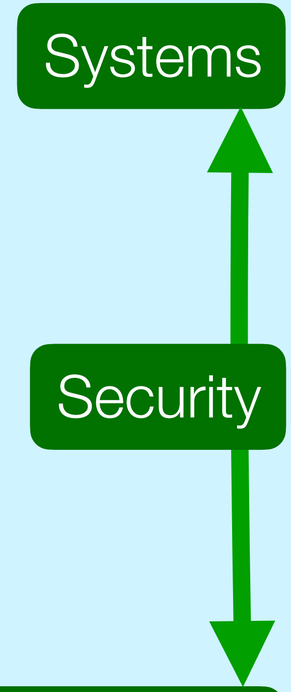

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Systems

ML

Distributed computing

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Security

Data mining

Differential privacy

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Cryptography

Complexity

Coding theory

Data structures

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This Talk: The design of a private search engine

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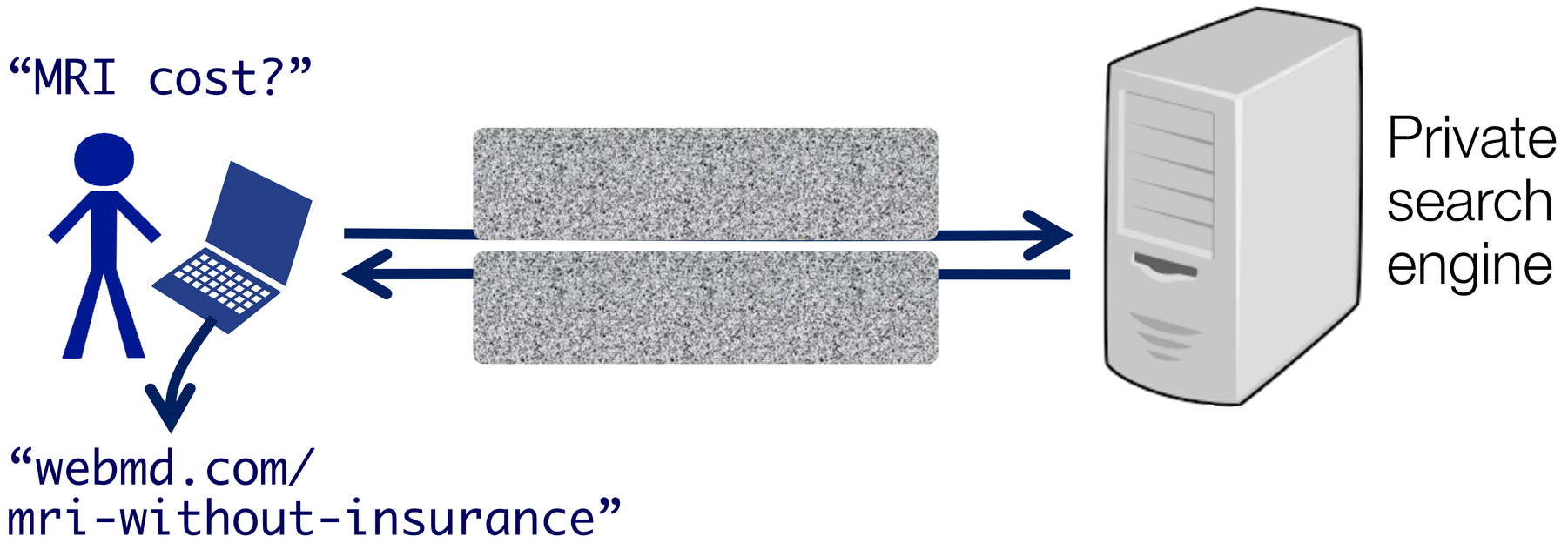

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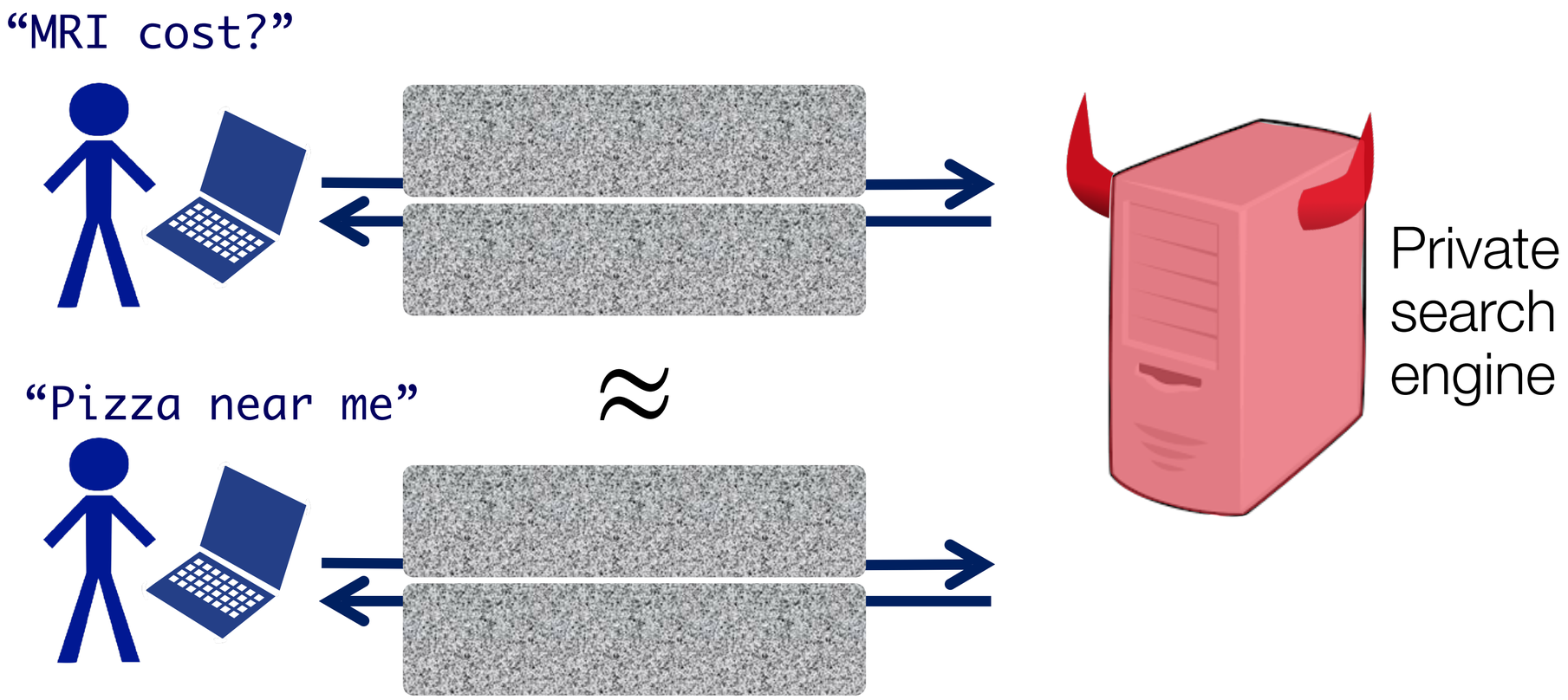

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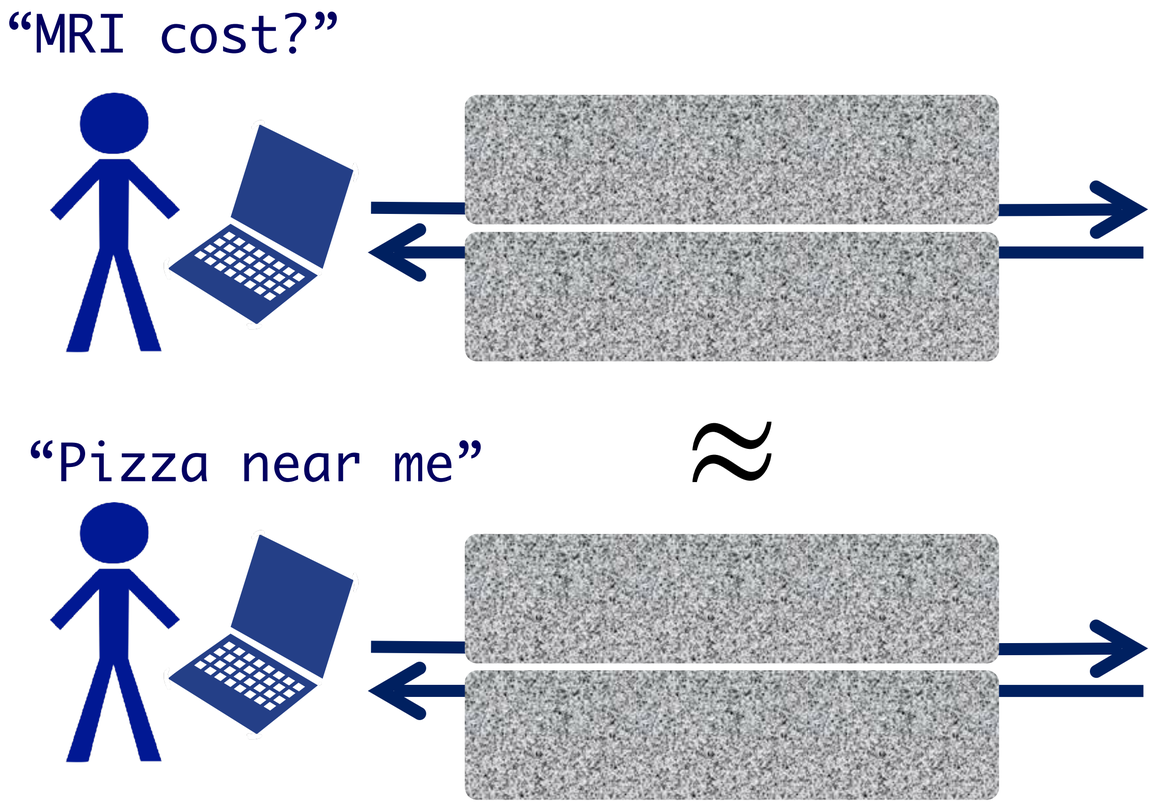

Private search engine

Limitations, for now:

- won’t hide *when* the client searches
- won’t guarantee integrity
- won’t hide HTTP(S) requests after search

Tiptoe: A private search engine

Henzinger, Dauterman, Corrigan-Gibbs, and Zeldovich (SOSP'23)

Privacy: Search engine learns no information about queries

Scale: Searches over public web crawl (360M pages) in 2.7s of latency
using 145 core-seconds of compute and 57 MiB of traffic per query

Quality: Ranks the best search result in the top 10, on average
though less accurate than best non-private search

The first private search engine to work at this scale

Prior work in private search:

Relaxed privacy guarantees

- Anonymize queries

  [DMS04, MC09, YWP09, BTD12, GSSCL14, ADE15]

- Obfuscate queries

  [MC09, ND09, YWPC09, RF10, ADE15, BTD12, PCMBK15]

- Trust hardware (SGX)

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Limited scale

- Coeus (SOSP'21) hides queries to Wikipedia

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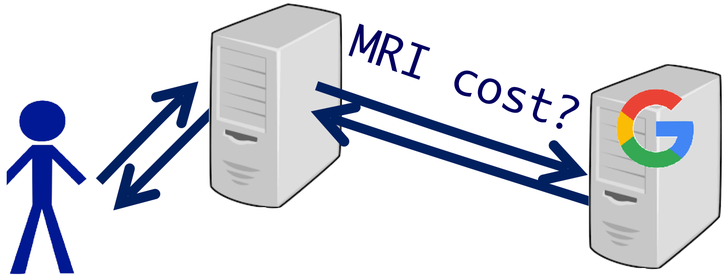

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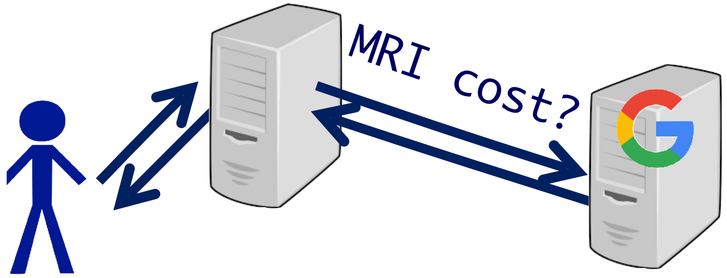

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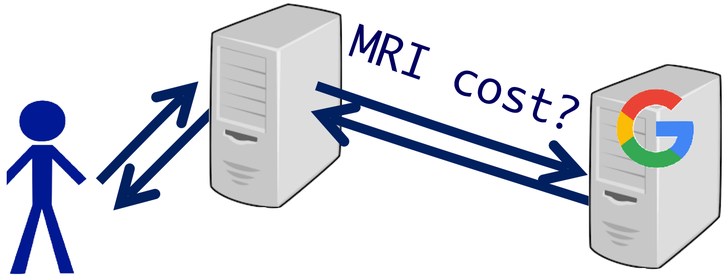

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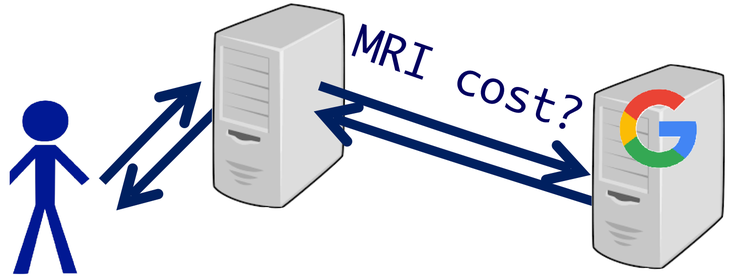

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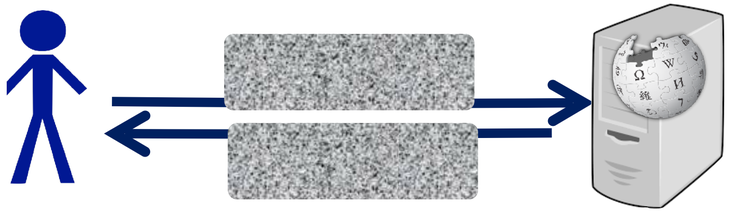

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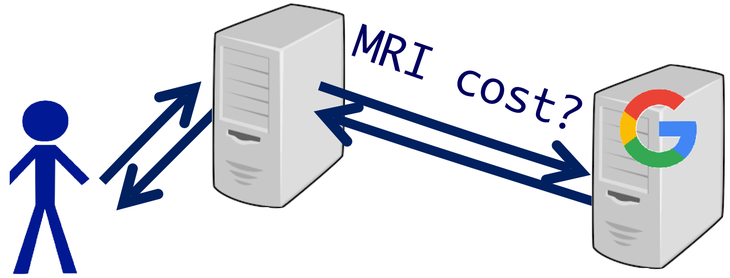

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Why?

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Challenge: Build search from encrypted `ADD` and `MUL`

Coeus (SOSP'21): count appearances of query words in each doc* (TF-IDF search) [RS76,SM86]

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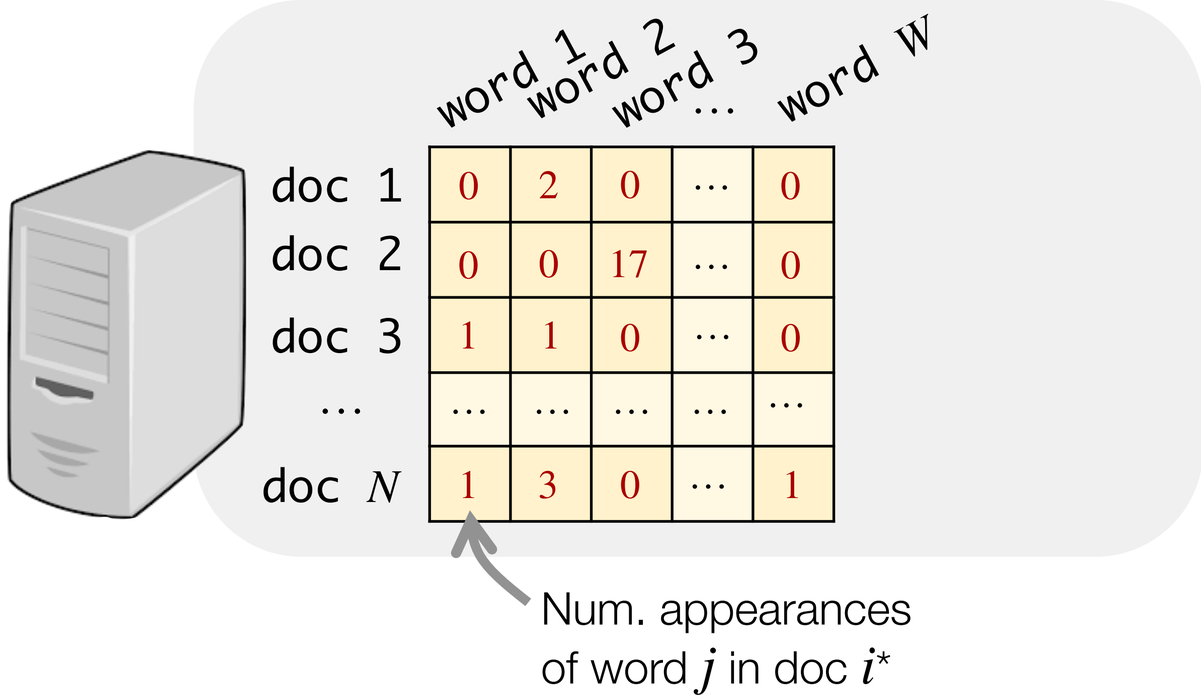

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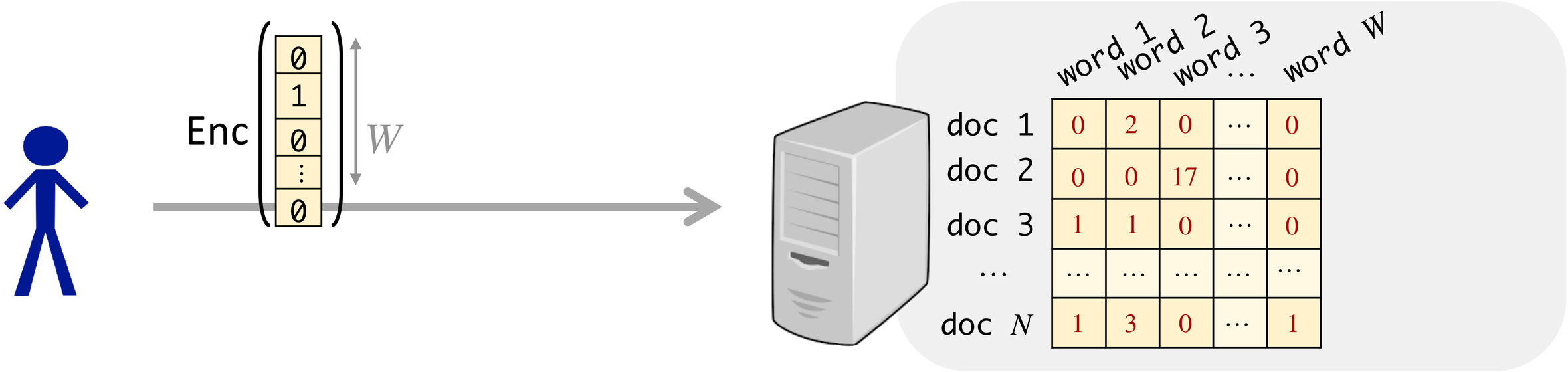

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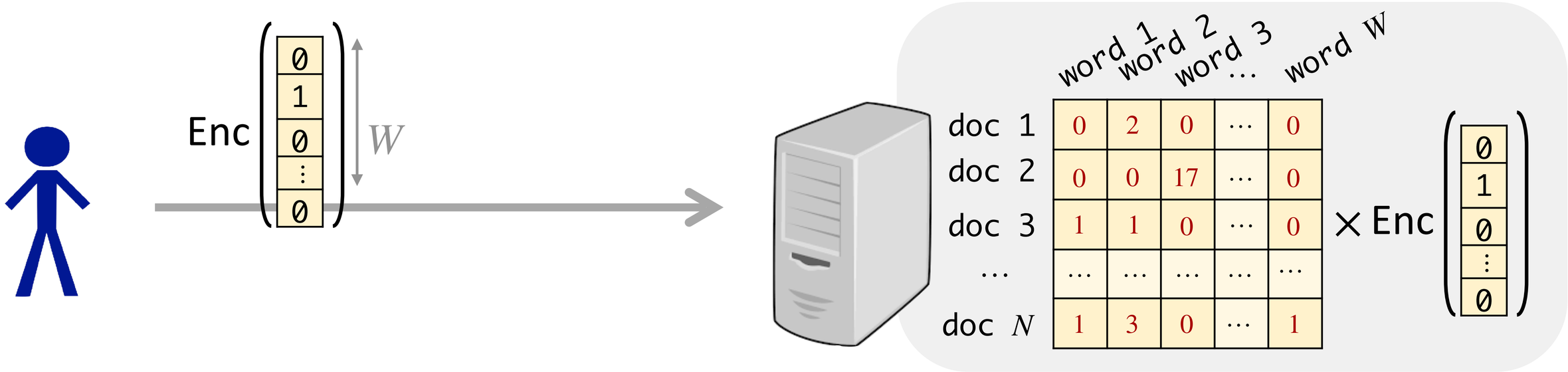
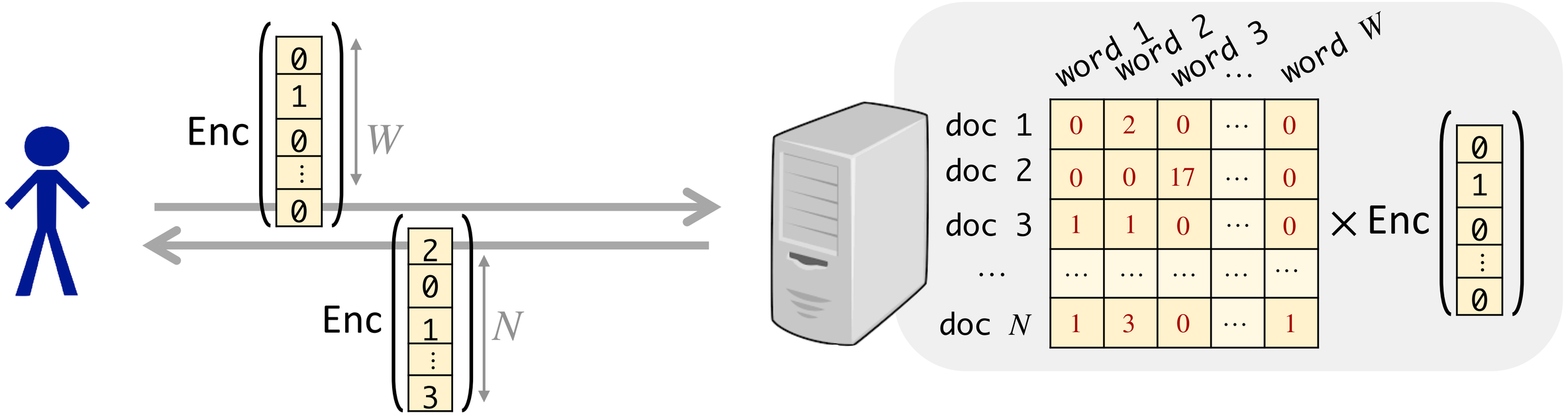


using encrypted ops

Challenge: Build search from encrypted **ADD** and **MUL**

Coeus (SOSP'21): count appearances of query words in each doc* (TF-IDF search) [RS76,SM86]



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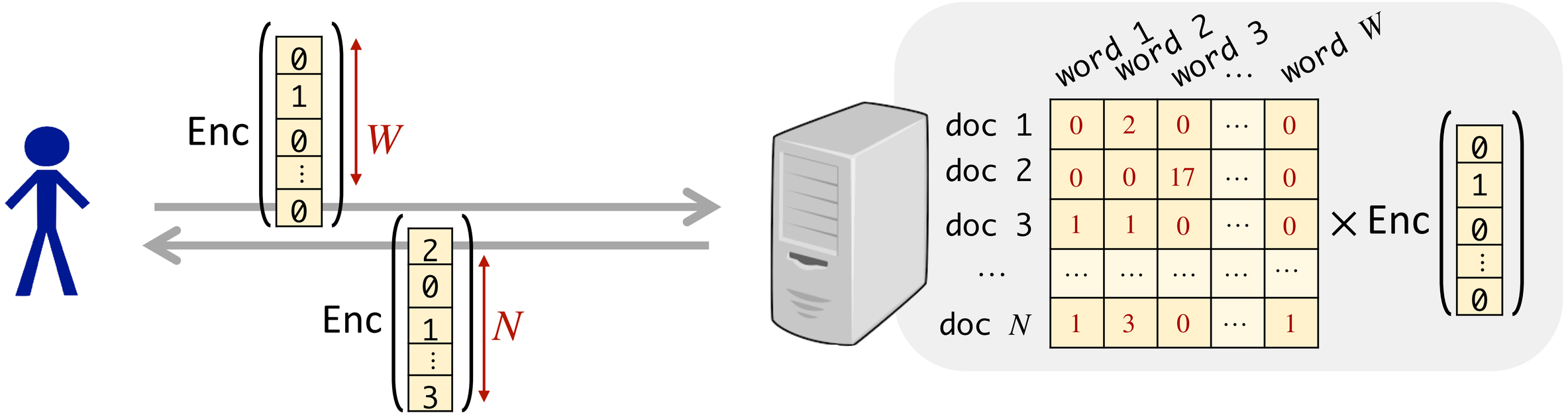

On every query,

- communication: $\geq N + W$ bytes

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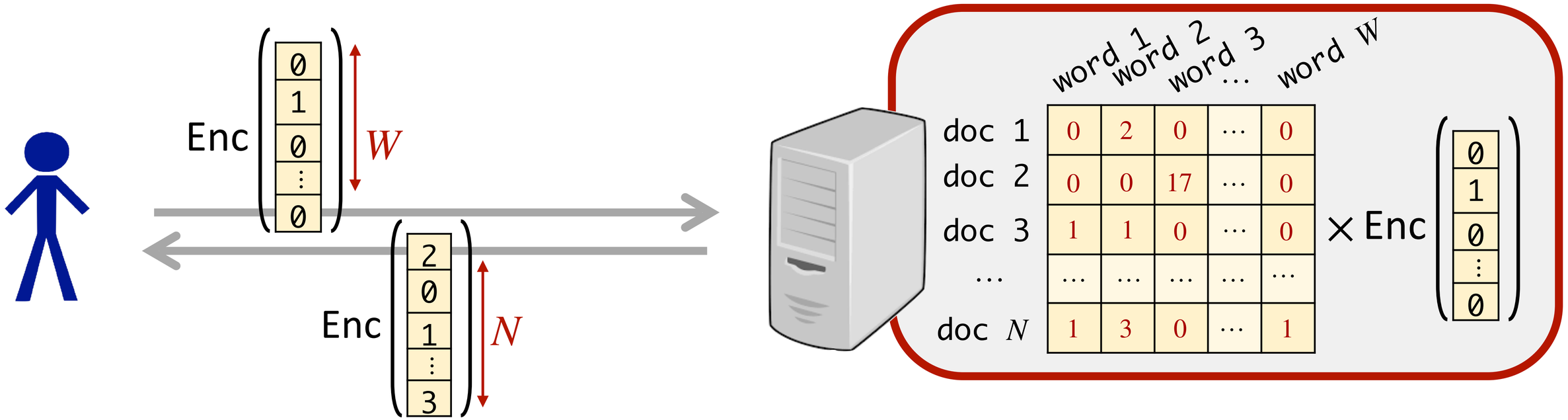

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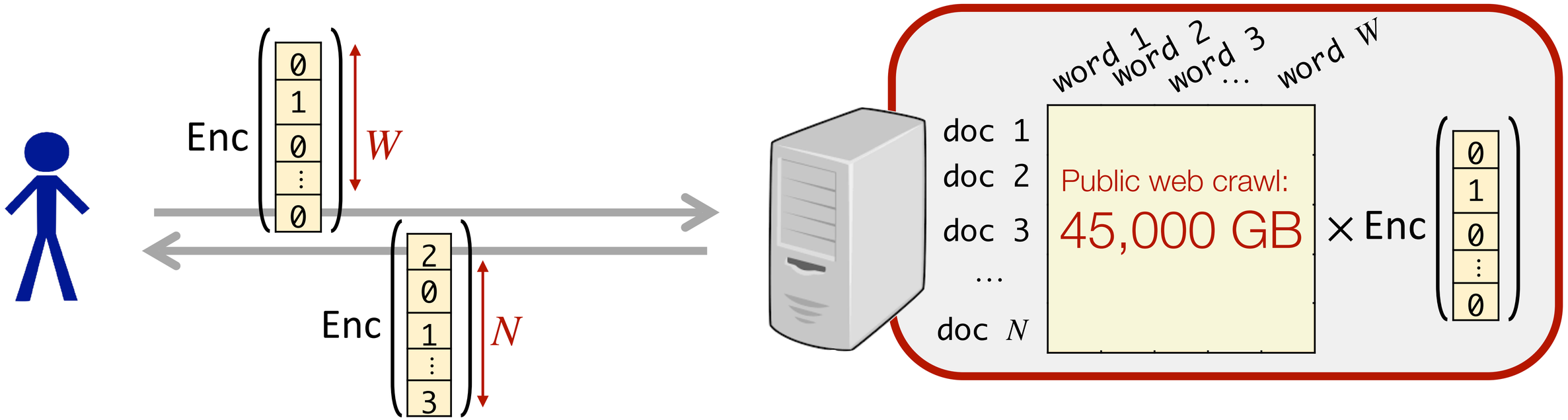

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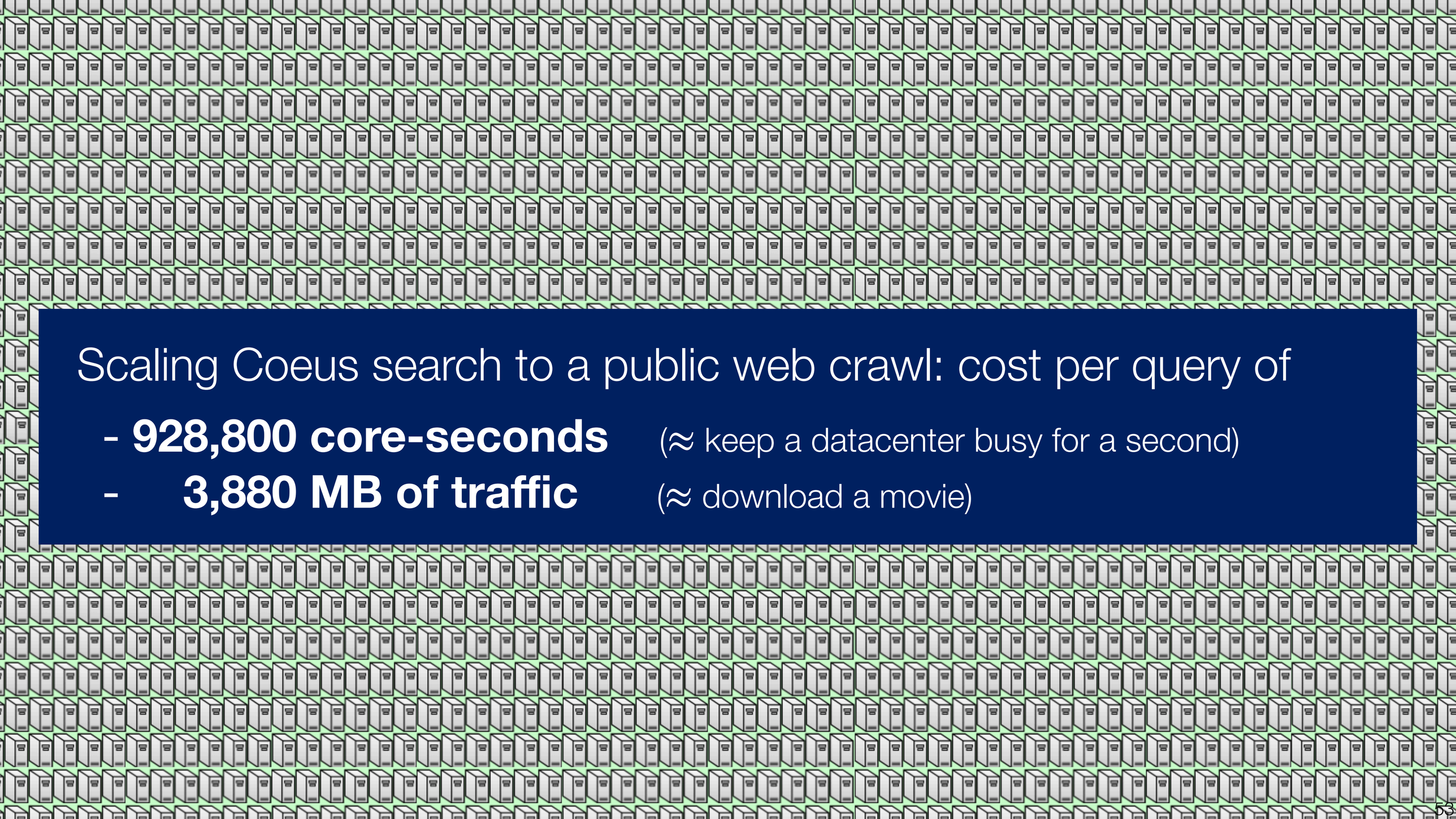
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$\Longrightarrow$ Need new system design

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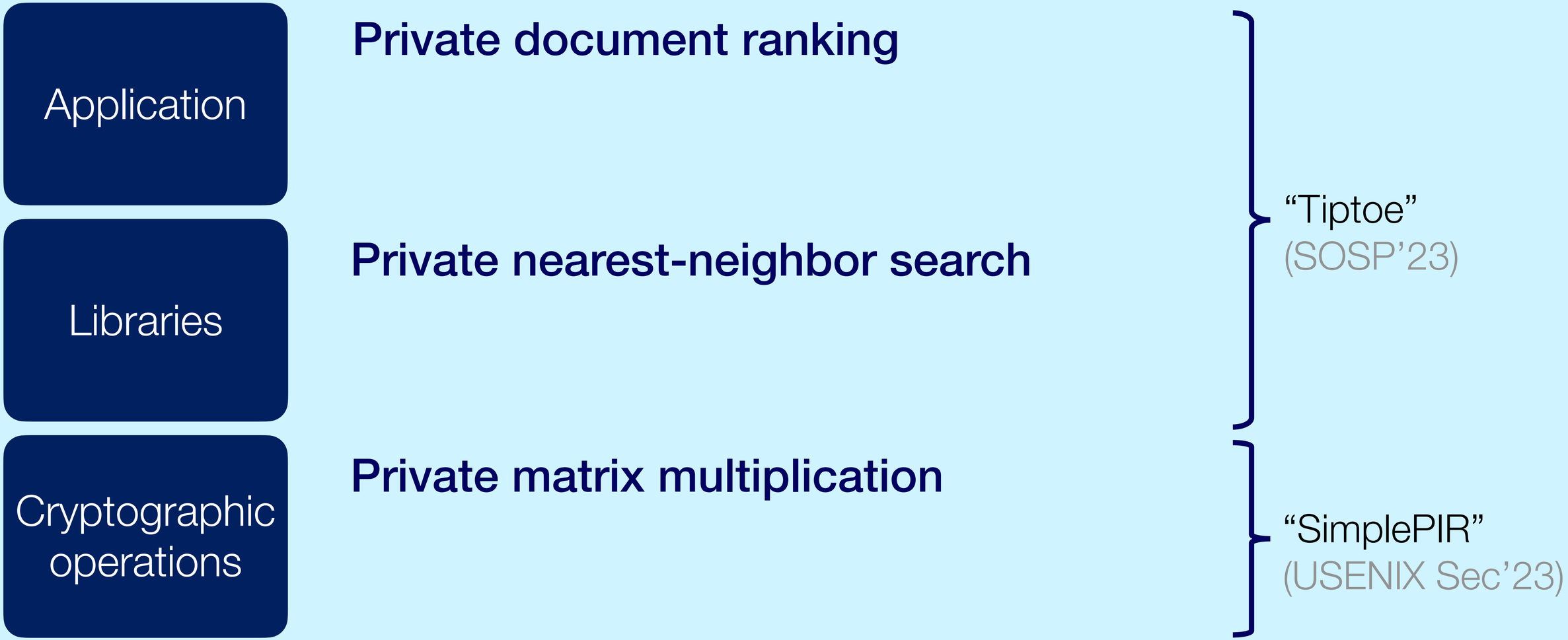

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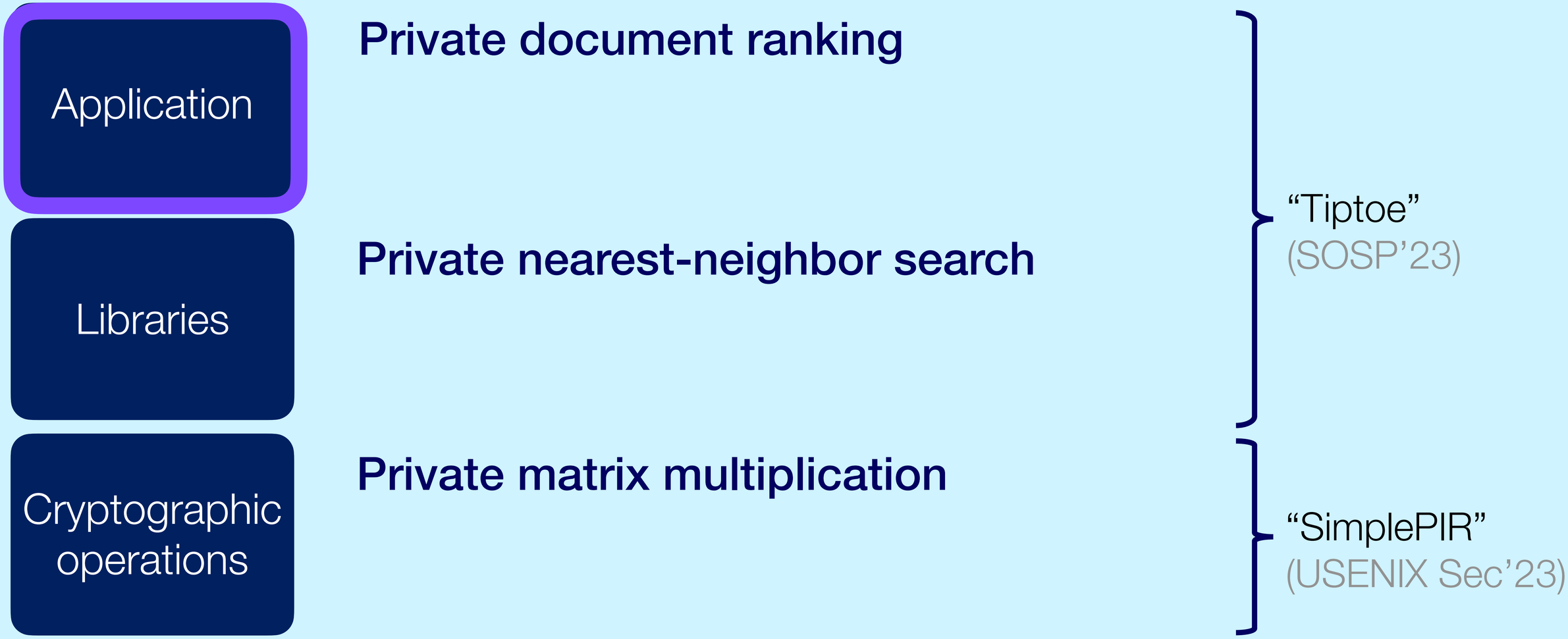

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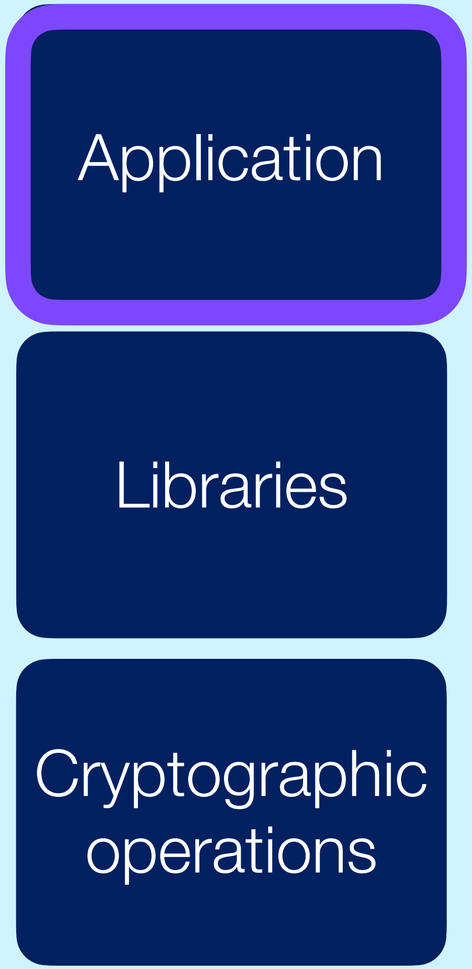

Private document ranking

Idea: exploit new data representations with semantic embeddings

Private nearest-neighbor search

Private matrix multiplication

"Tiptoe" (SOSP'23)

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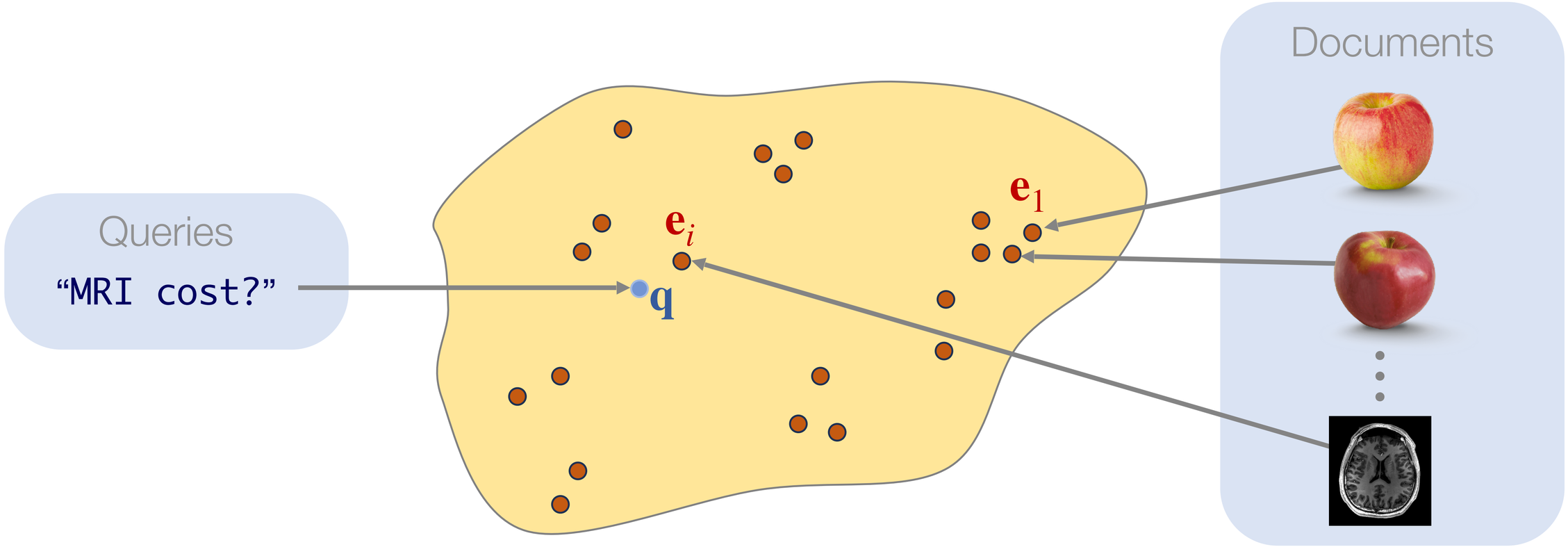
New approach: Private search via semantic embeddings

- Used widely in non-private search (Google, Spotify, YouTube) [Osgood'57, DC'19, MYCG'19, YYZL'19, …]
- Embeddings map inputs into $\mathbb{R}^d$ such that "similar" inputs are "close"
- This talk: inner-product distance for "closeness" and $d \approx 192$



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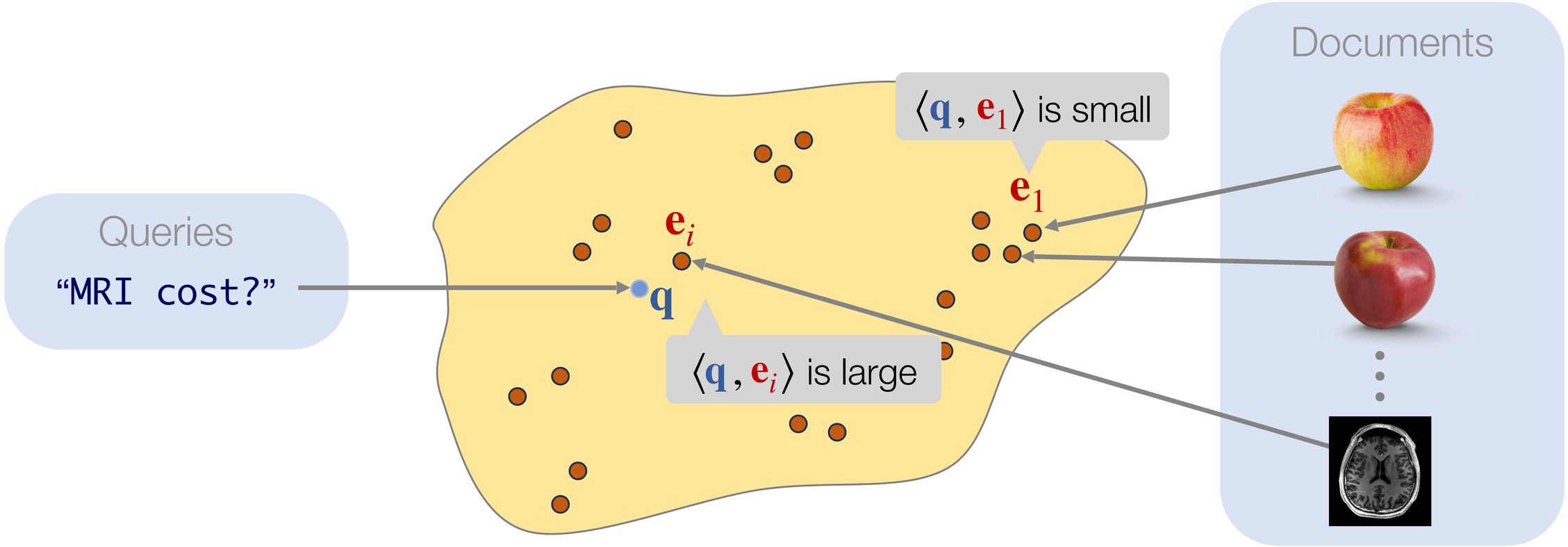
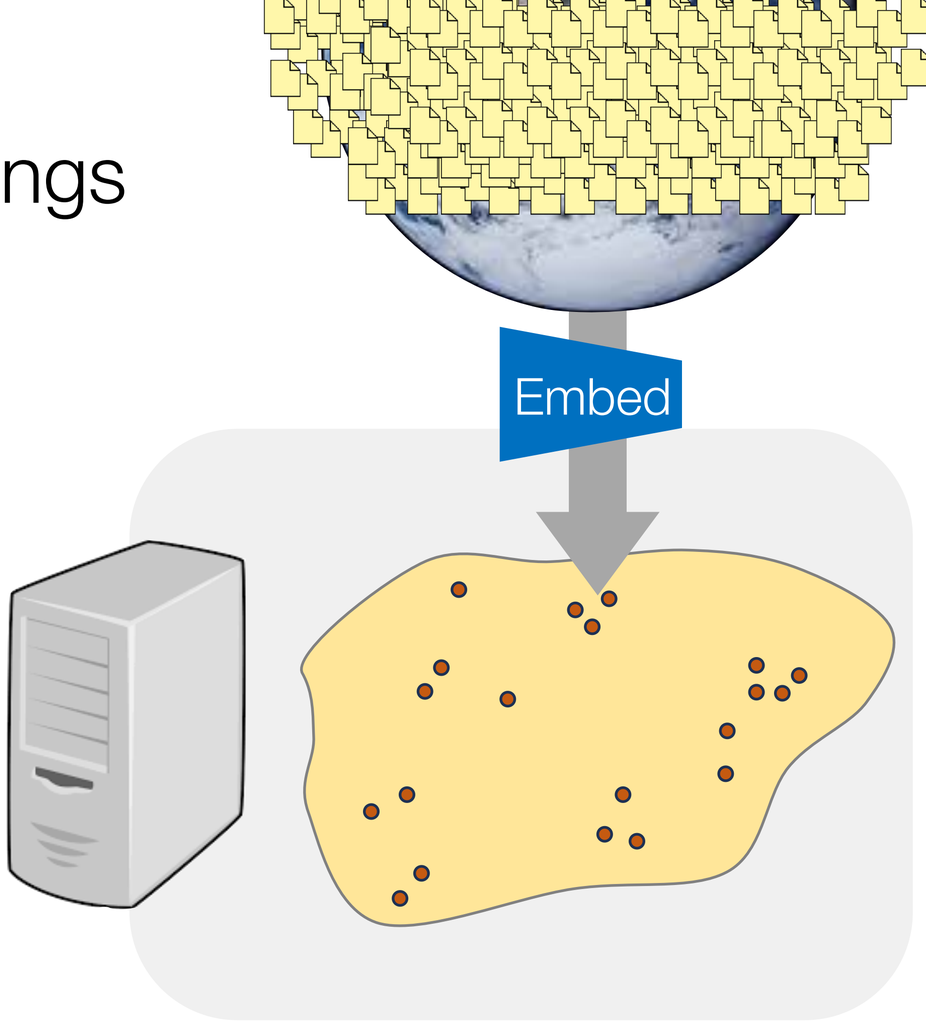


Goal: Private search via semantic embeddings



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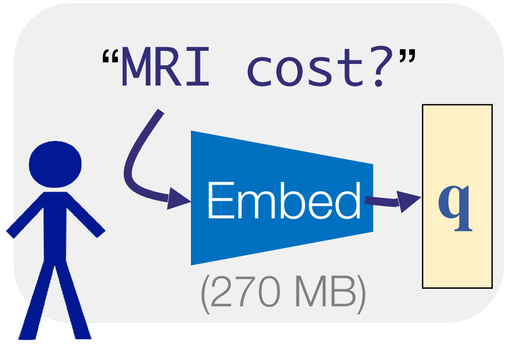

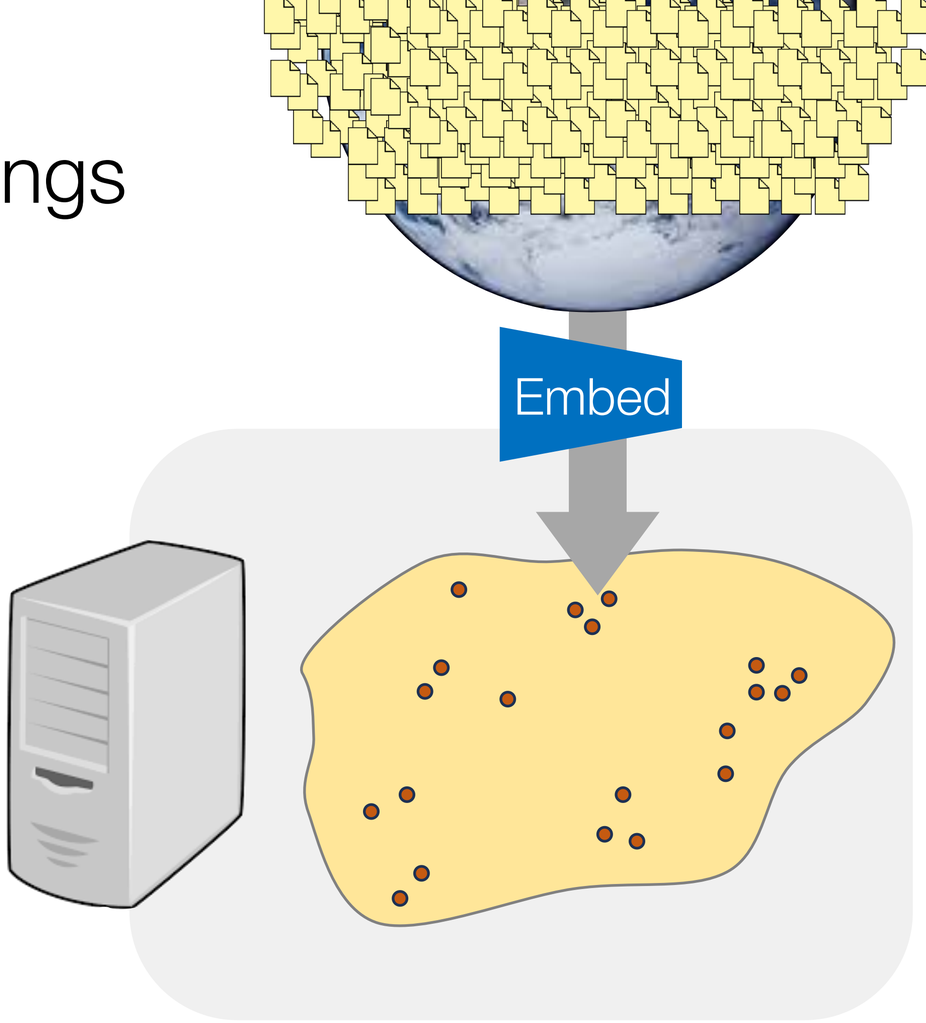

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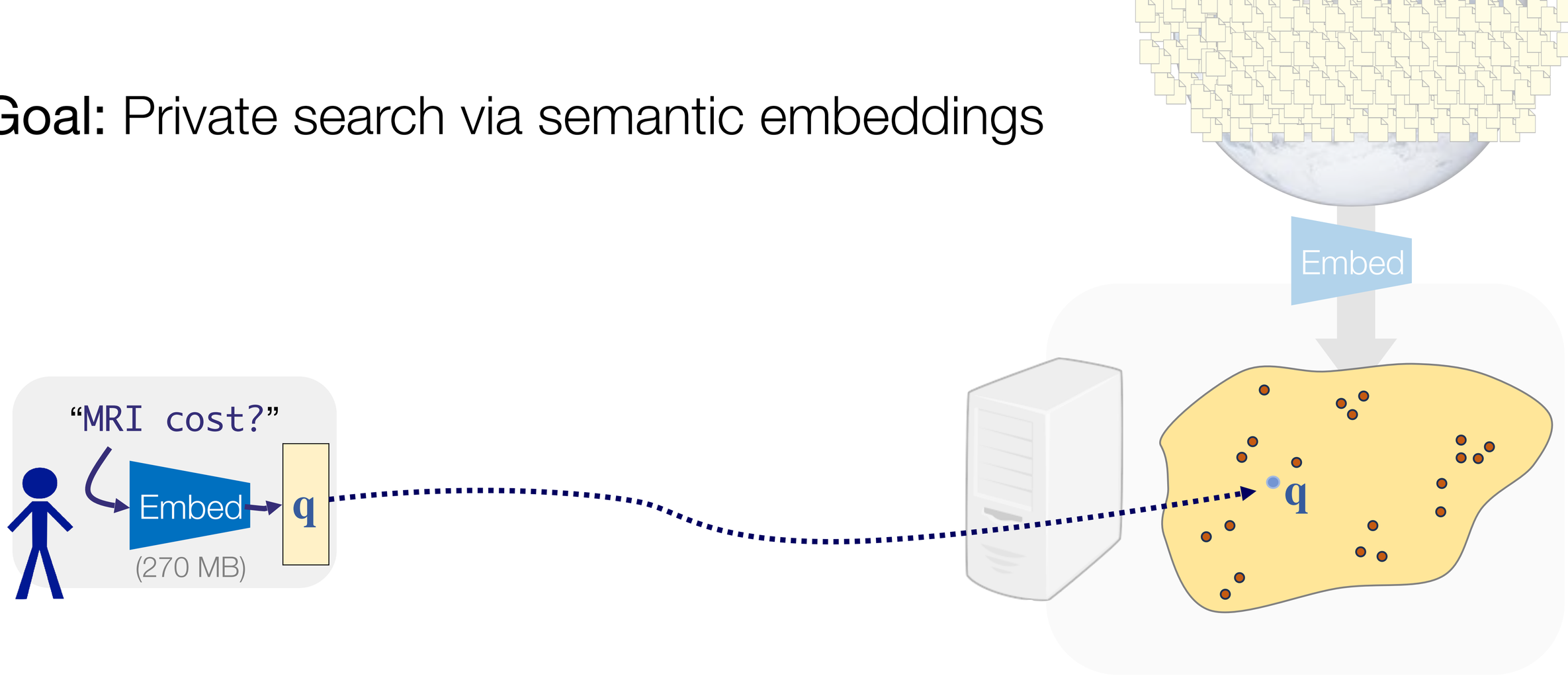
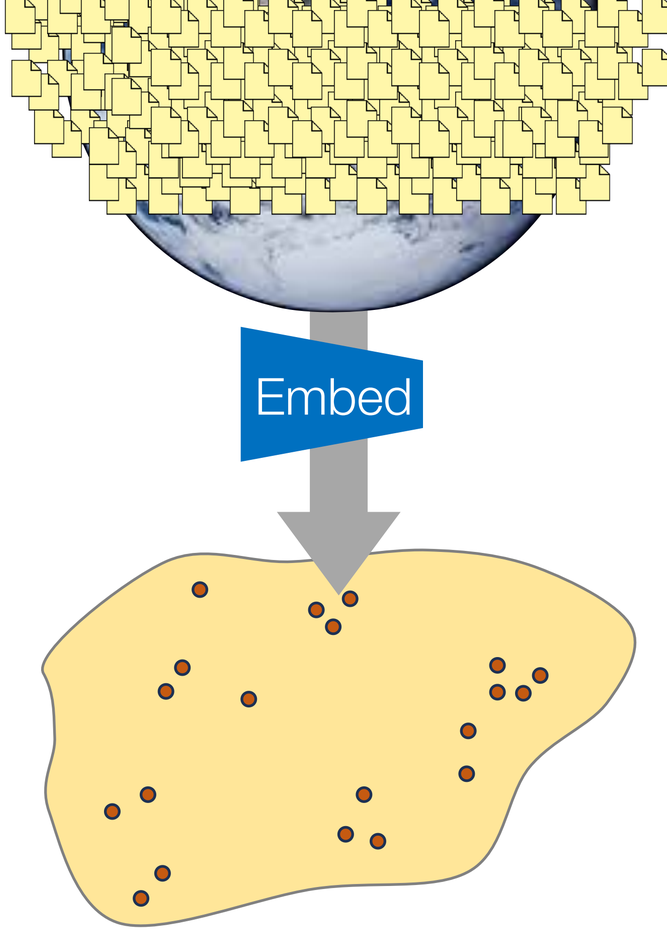


↳ **Updated goal:** private nearest-neighbor search

i.e., privately find the server-held vector with max inner-product $\langle \mathbf{q}, \mathbf{e} \rangle$

Why embeddings are useful



As in non-private search,

+ Expressive: can perform semantic search
+ General: exist for text, code, images, …

In private search, a **key benefit to scalability**:

+ Embeddings "linearize" the computation:
  produce crypto-friendly operations, without large doc representations

Tiptoe: Design in layers

Application

Libraries

Cryptographic operations

Private document ranking

Idea: exploit new data representations with semantic embeddings

Private nearest-neighbor search

Private matrix multiplication

"Tiptoe" (SOSP'23)

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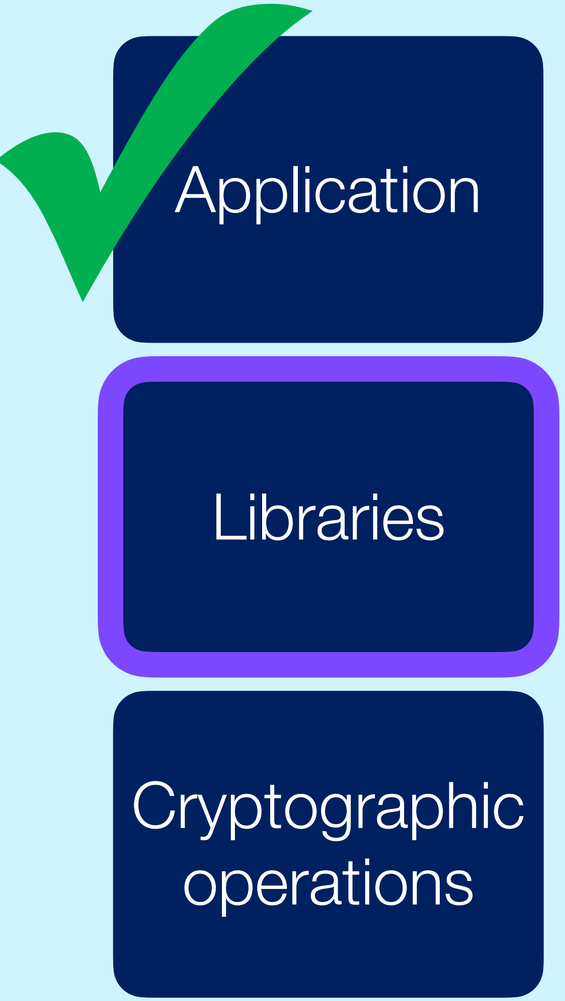

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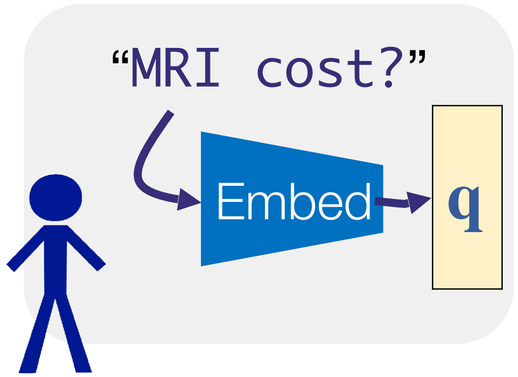
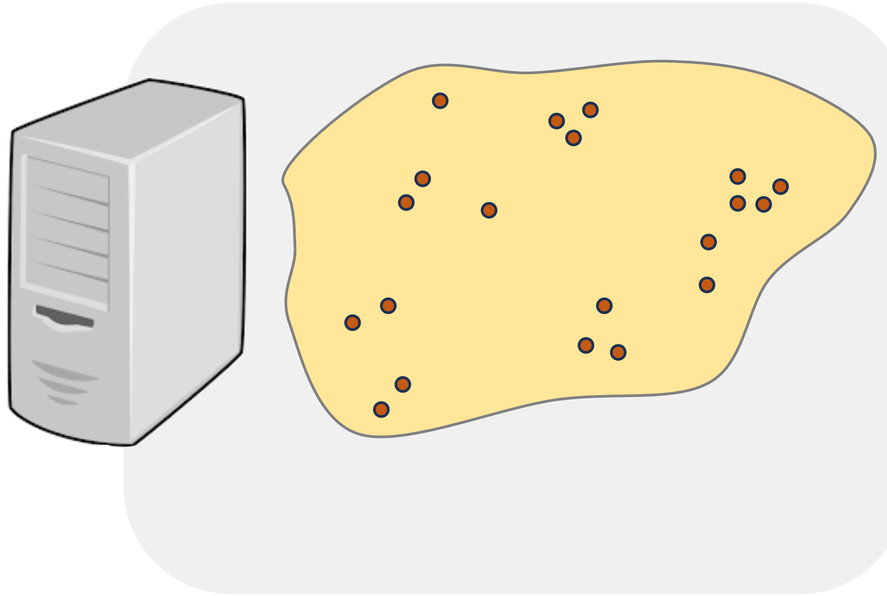
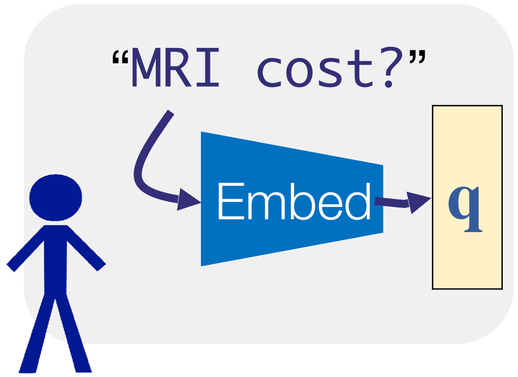
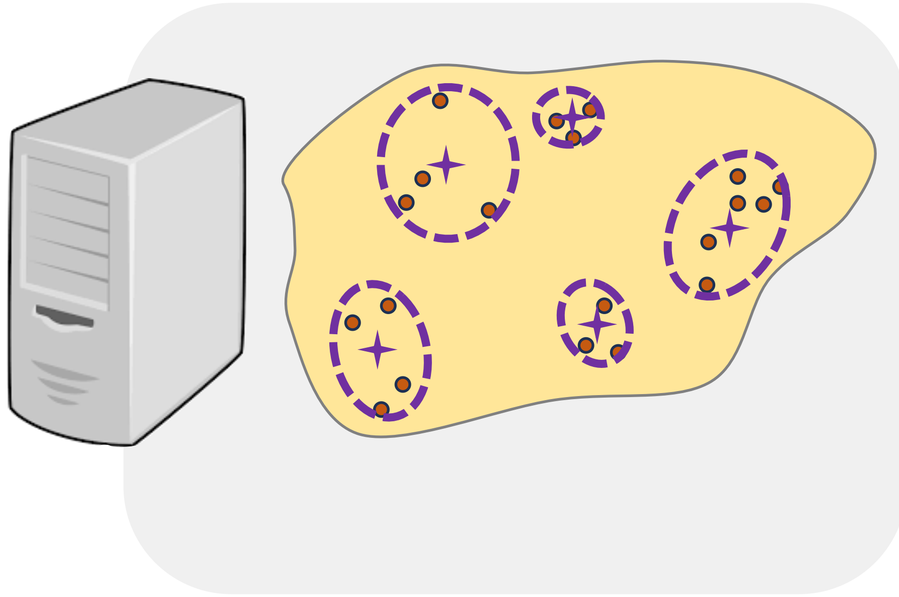




Goal: Private nearest-neighbor search

Plan: Structure the user's search with clustering





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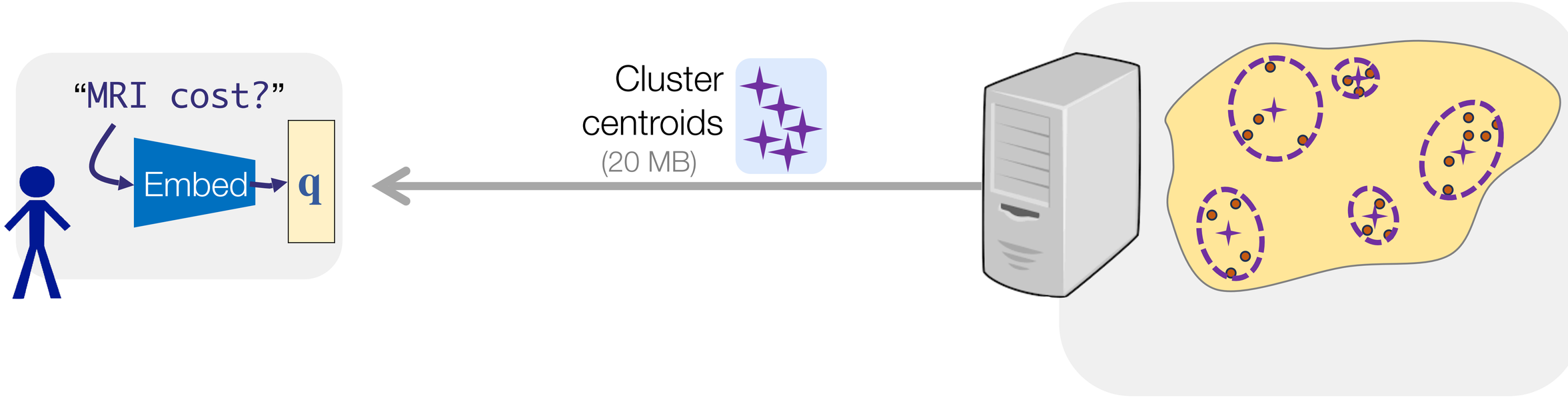

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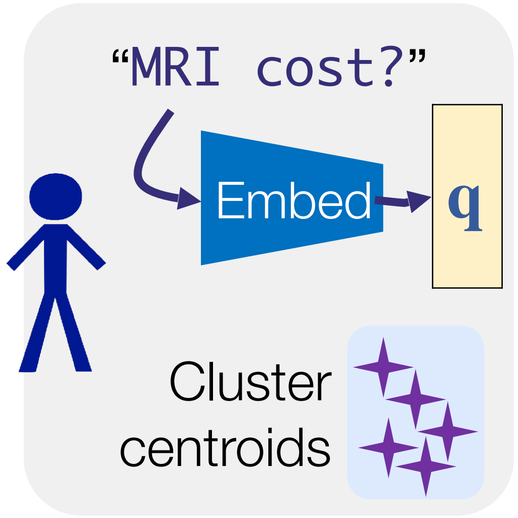

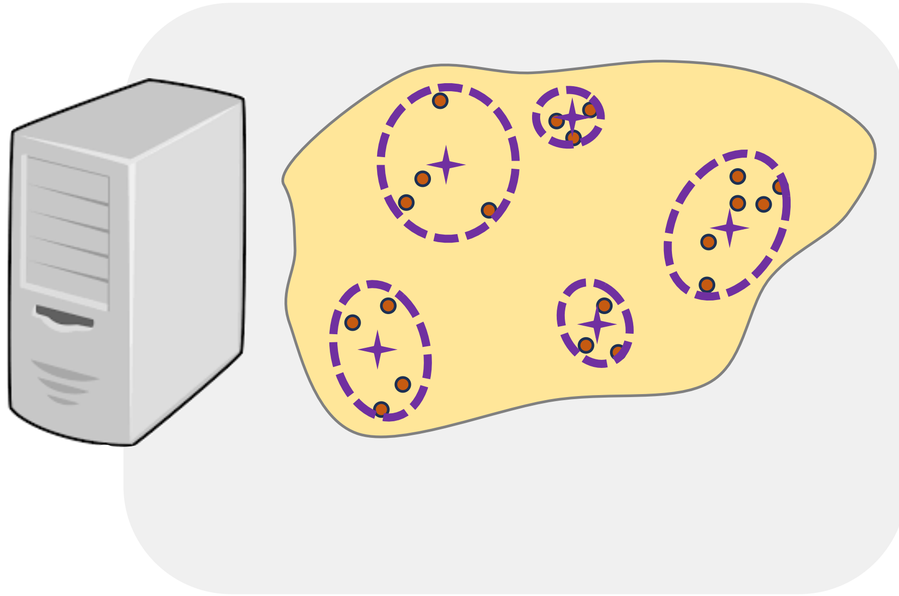

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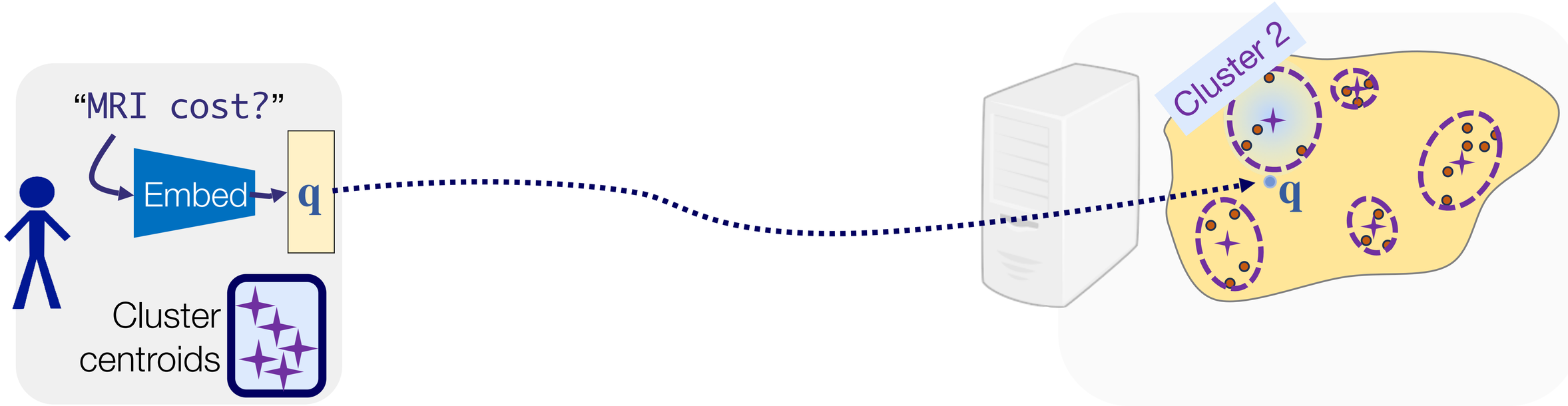

↳ **Updated goal:** exact search over Cluster 2

i.e., privately fetch inner-product scores $\langle \mathbf{q}, \mathbf{e} \rangle$ for docs in Cluster 2

Goal: Private nearest-neighbor search

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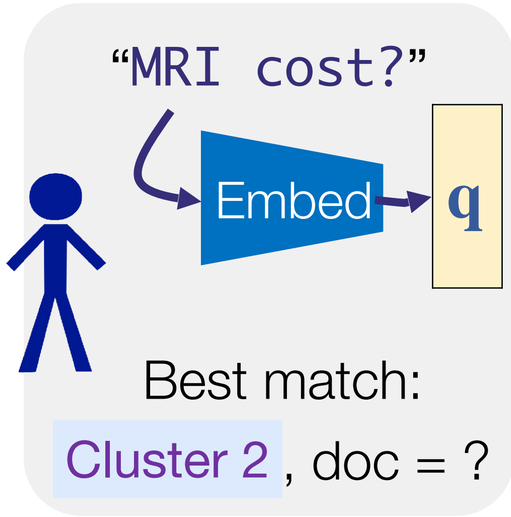

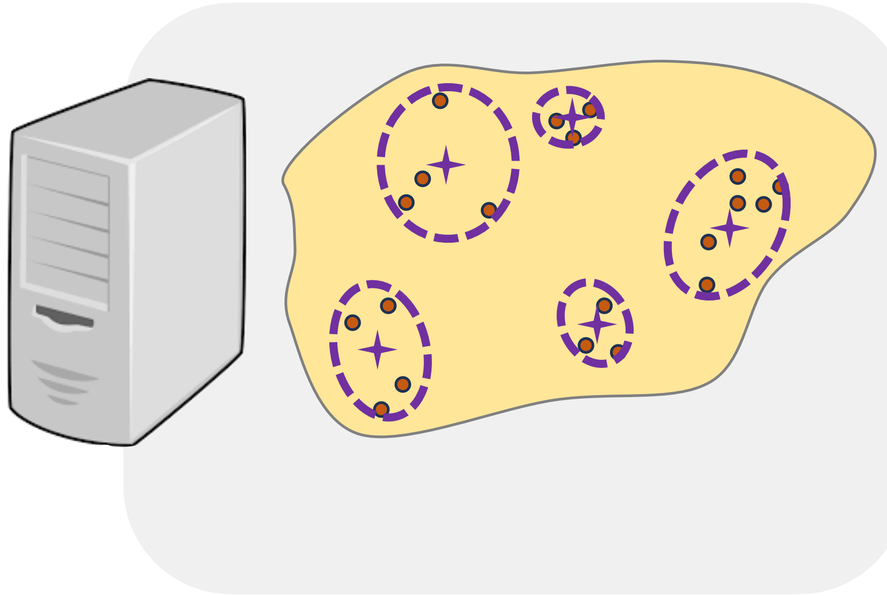

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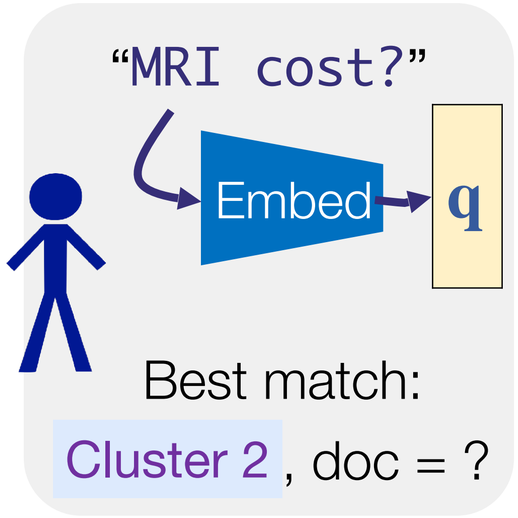

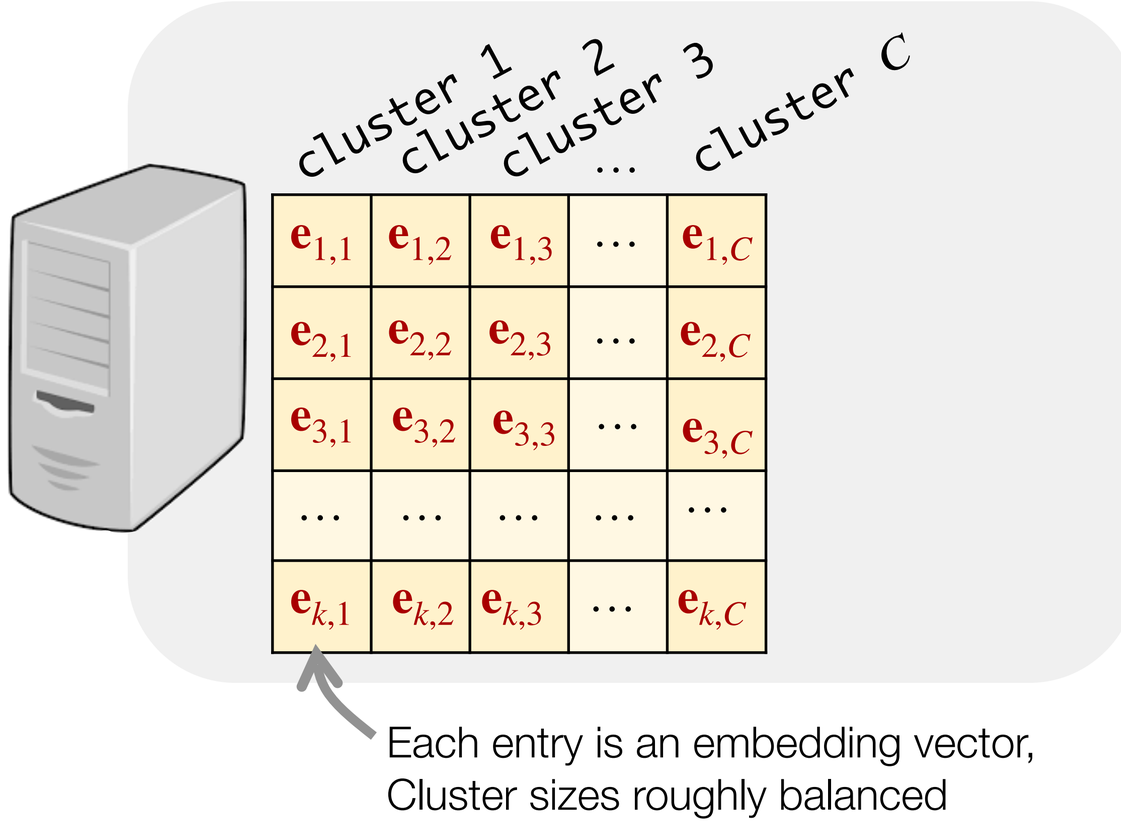

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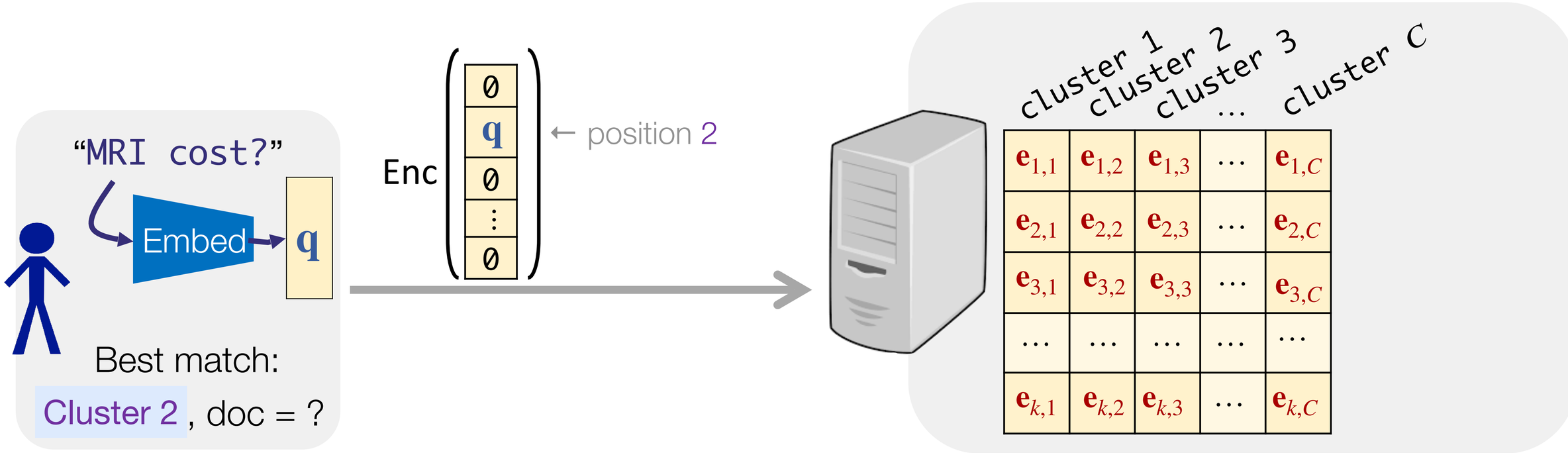

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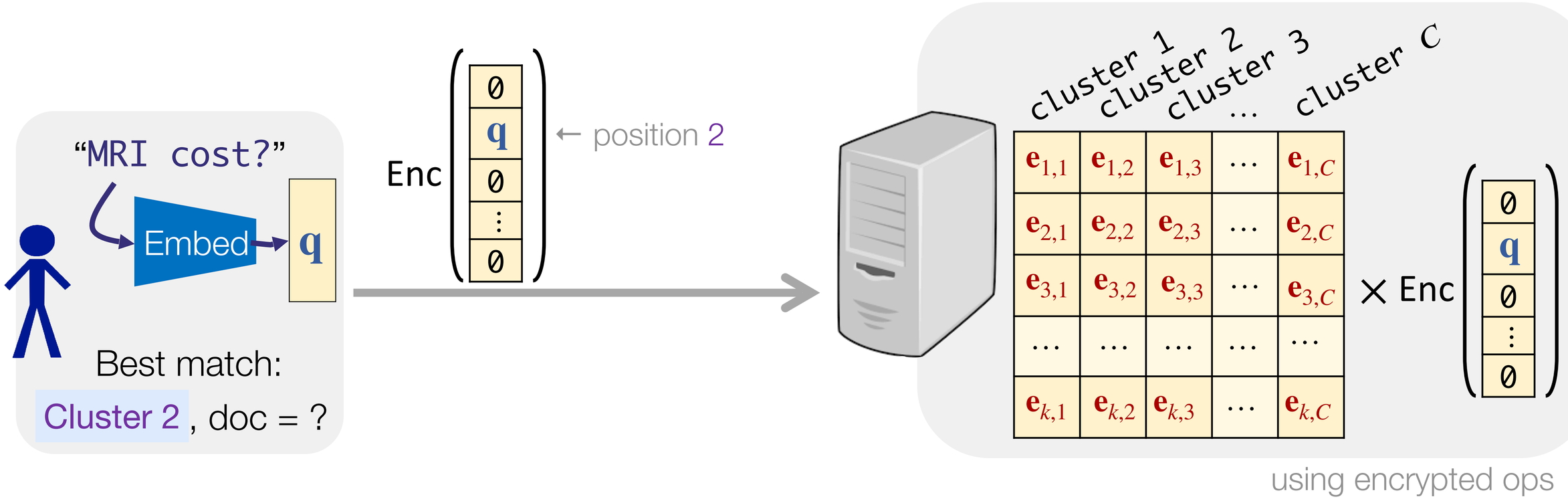

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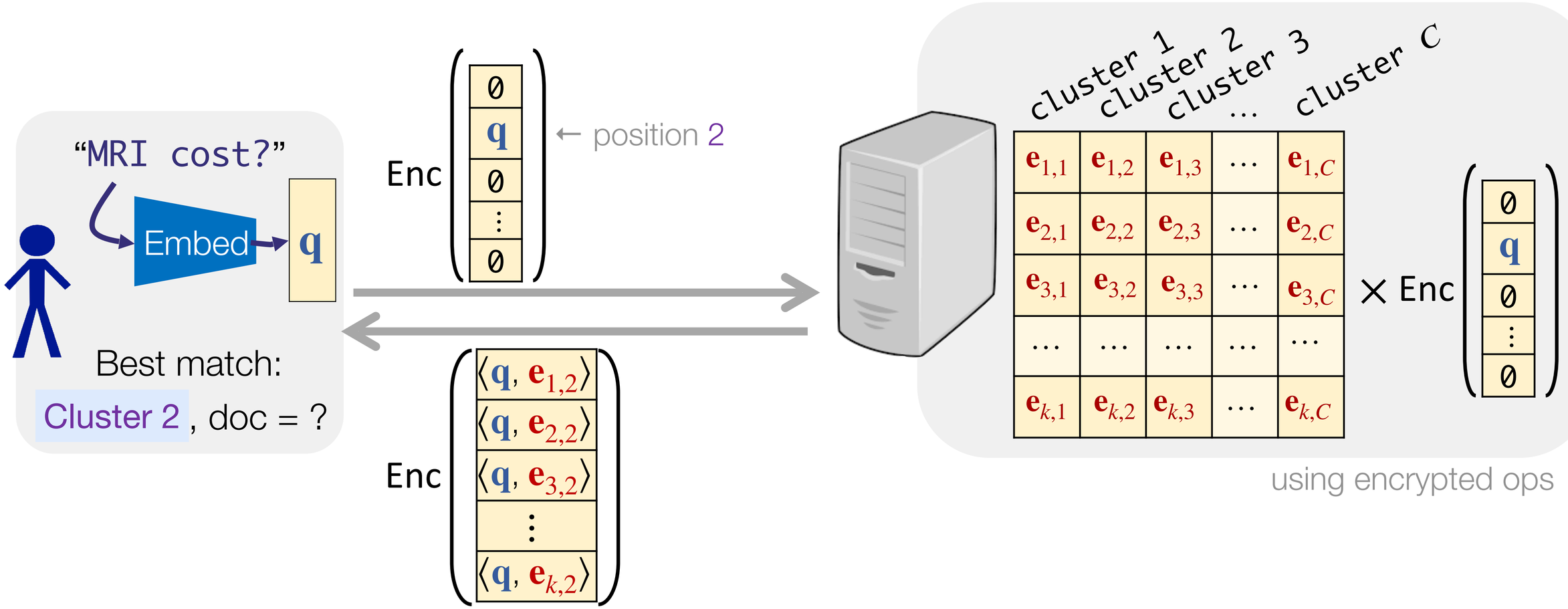

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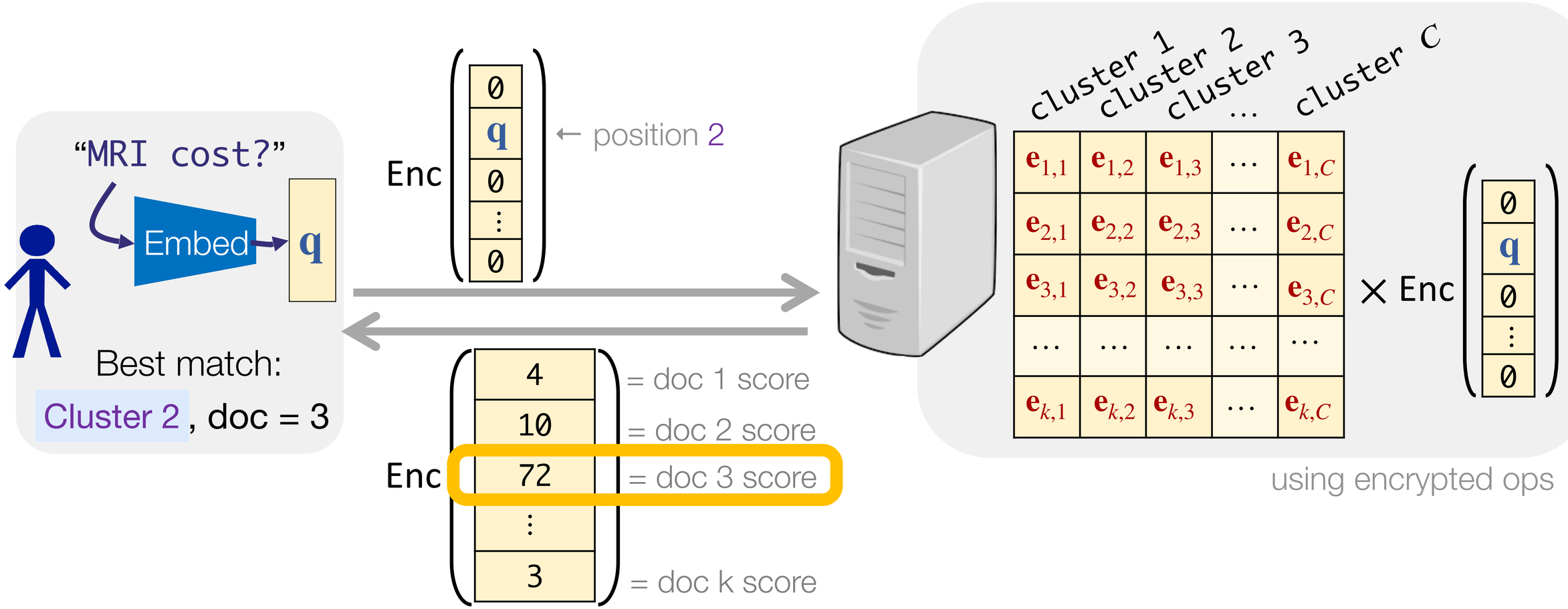

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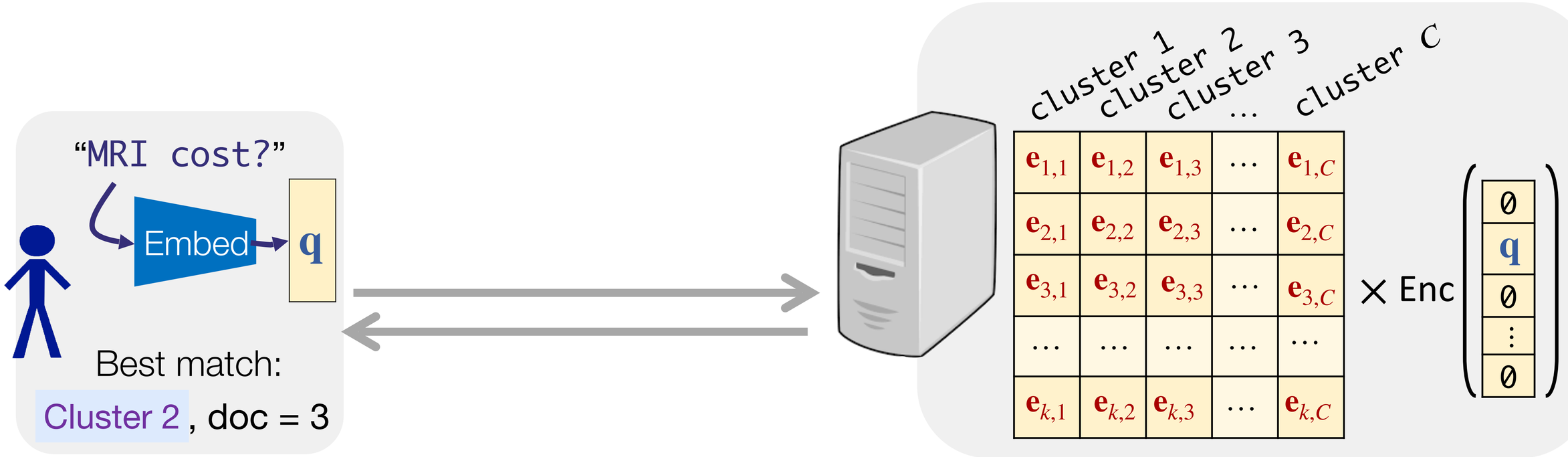

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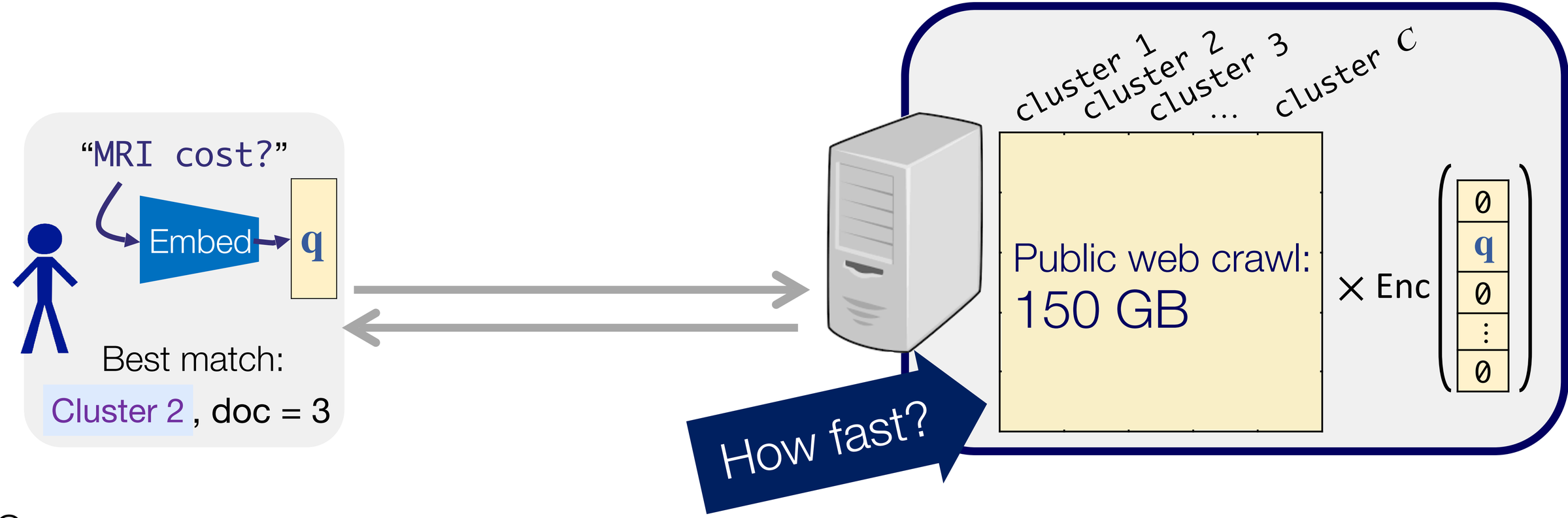

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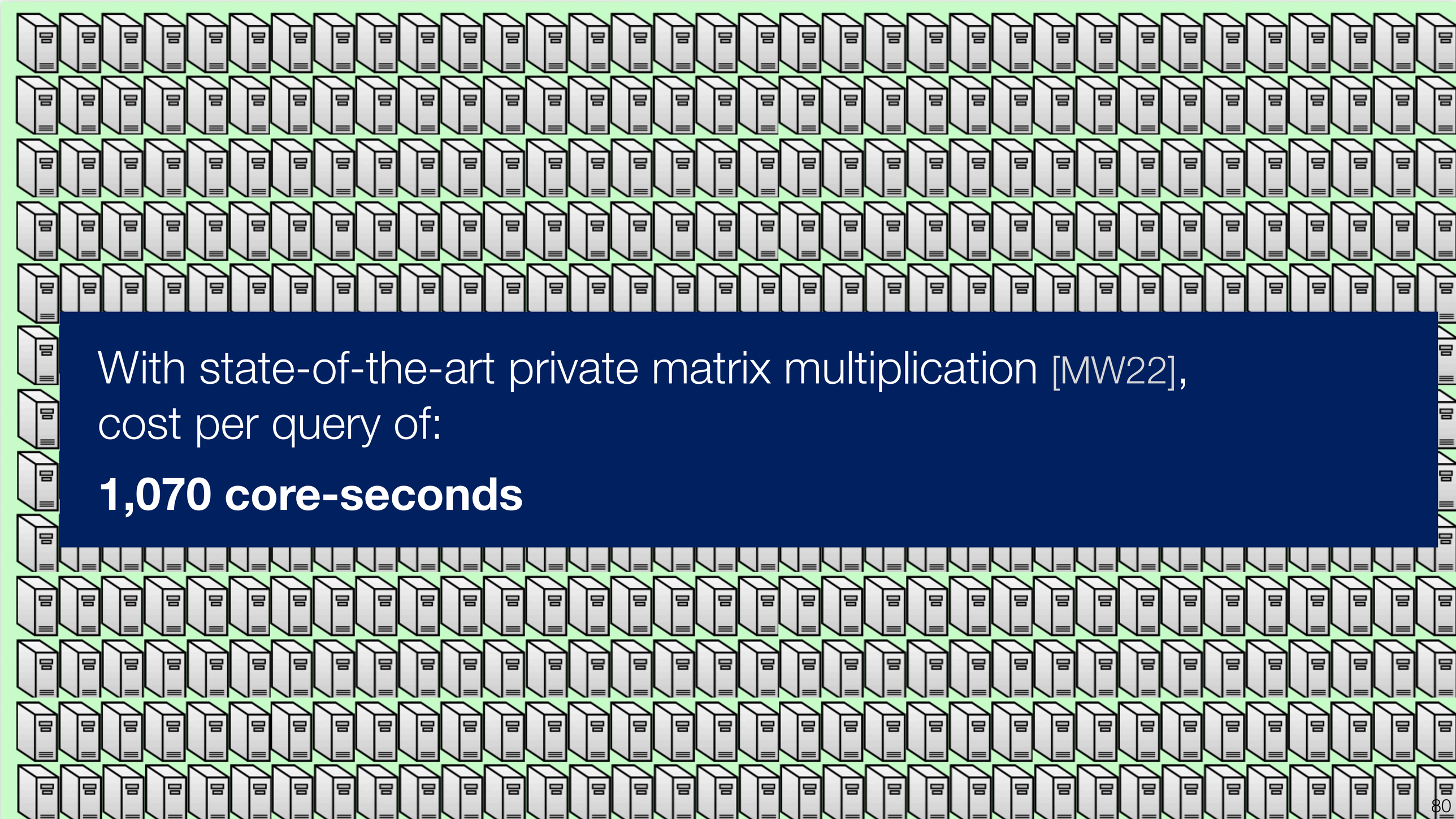
- computation: one large private matrix multiplication



With state-of-the-art private matrix multiplication [MW22],
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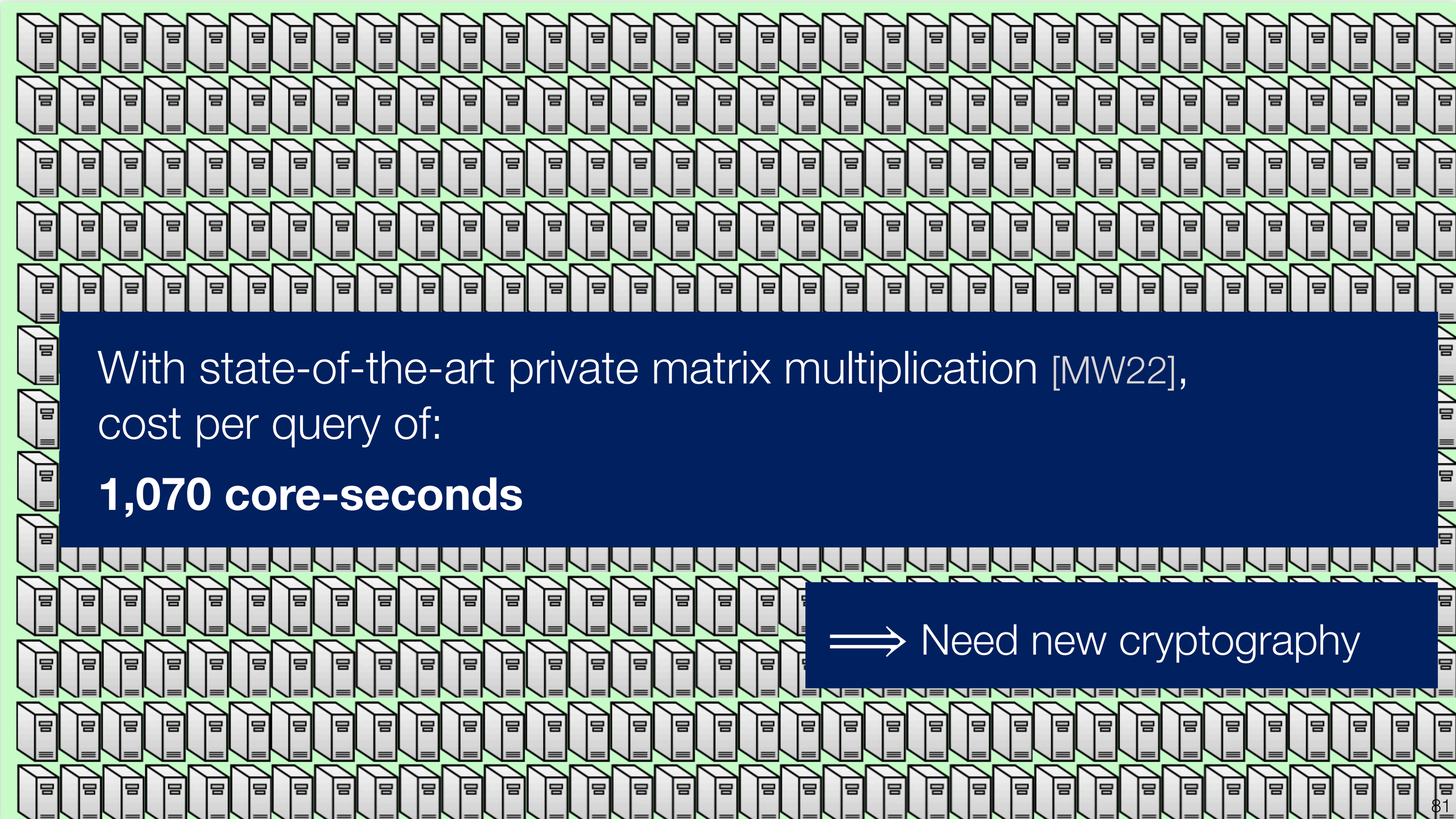

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$\Longrightarrow$ Need new cryptography

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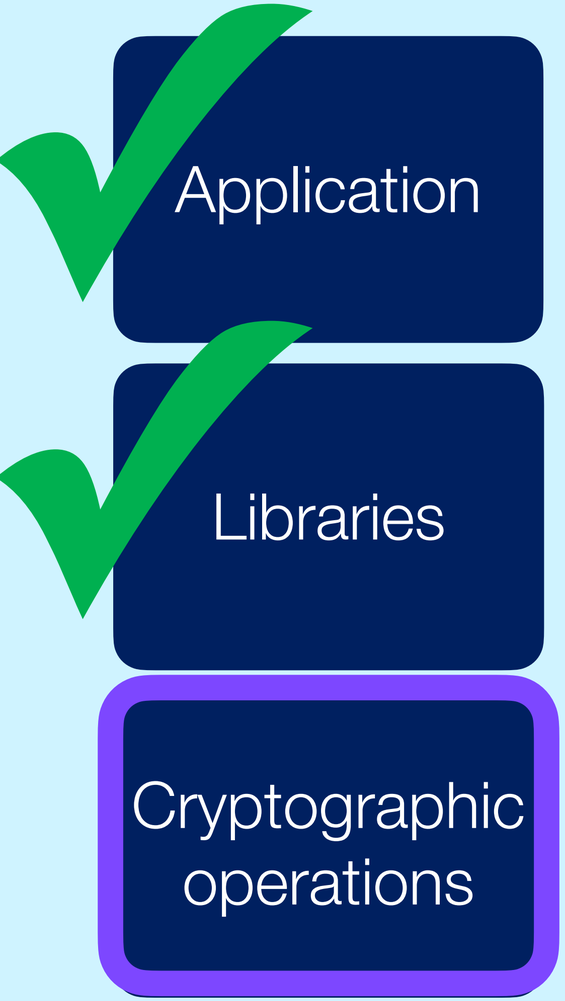

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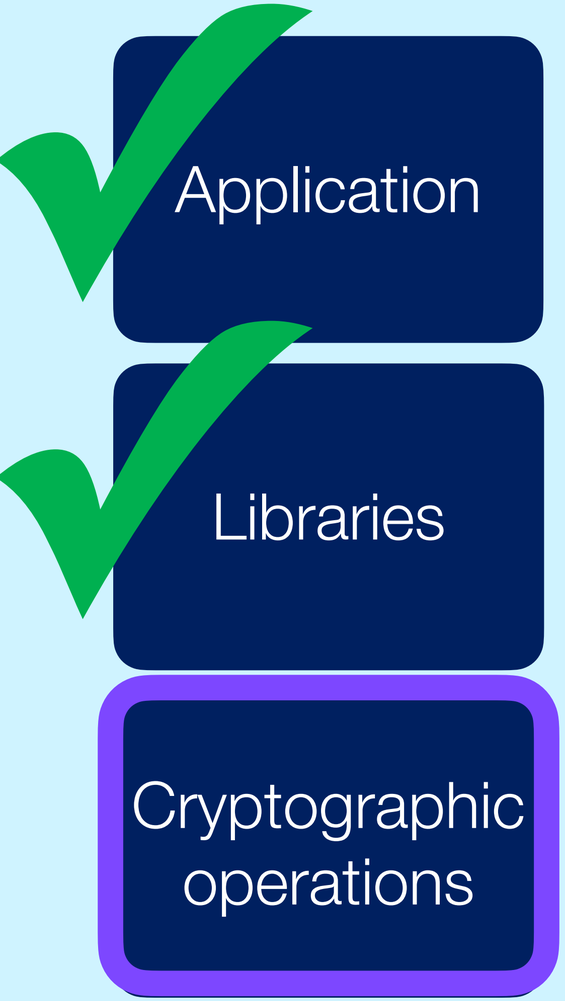

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Idea: enable aggressive preprocessing

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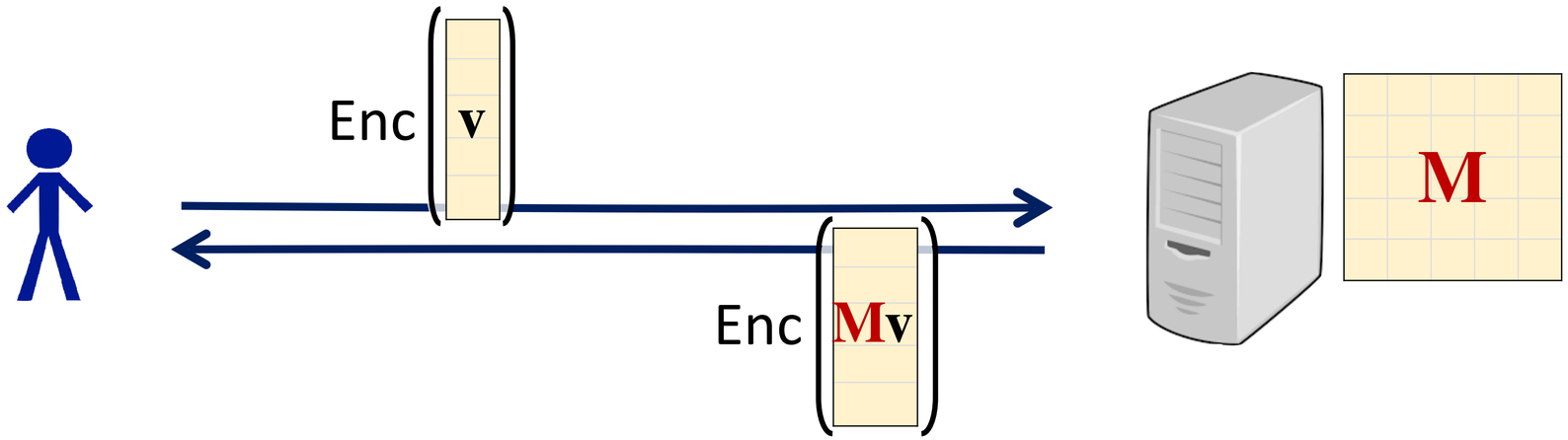
SimplePIR: Fast private matrix multiplication

Henzinger, Hong, Corrigan-Gibbs, Meiklejohn, and Vaikuntanathan (USENIX Sec'23)



+ New encryption that supports preprocessing any matrix $\mathbf{M}$ for fast multiplication

+ Per-query server work (on n-by-n matrix of 16-bit ints):

  No privacy: n^2 16-bit adds and muls

  Our scheme: n^2 64-bit adds and muls

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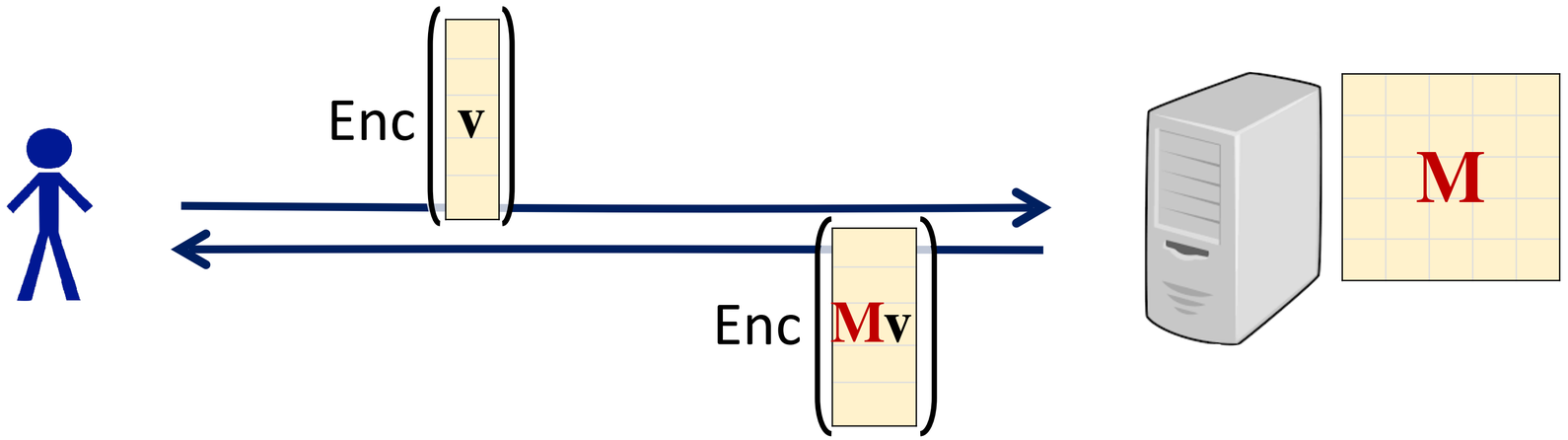

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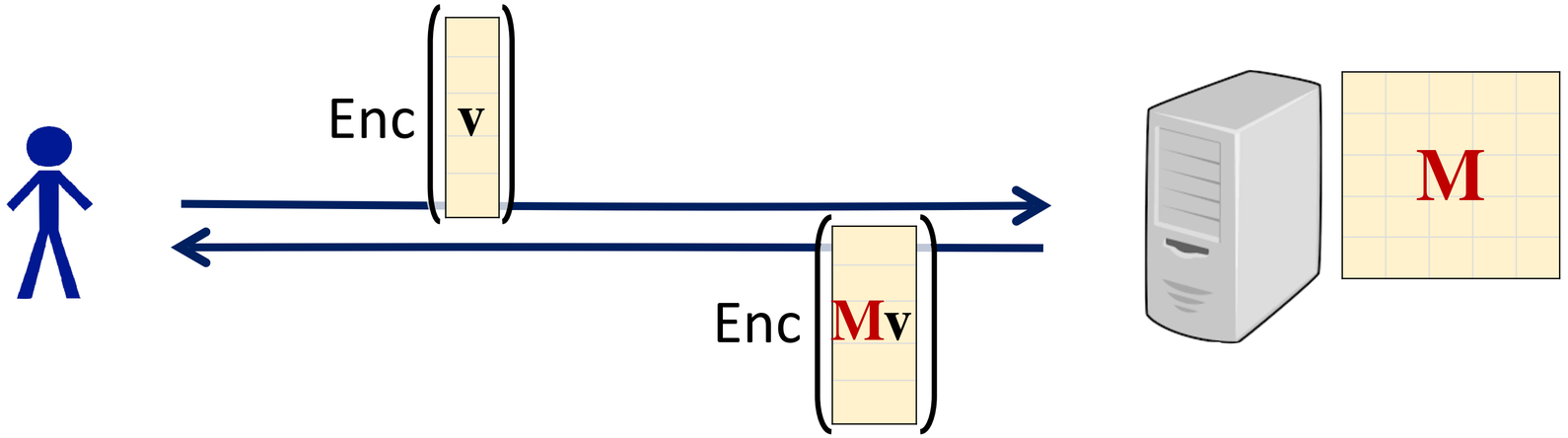

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Hard problem: “Learning with errors” [Reg’09]

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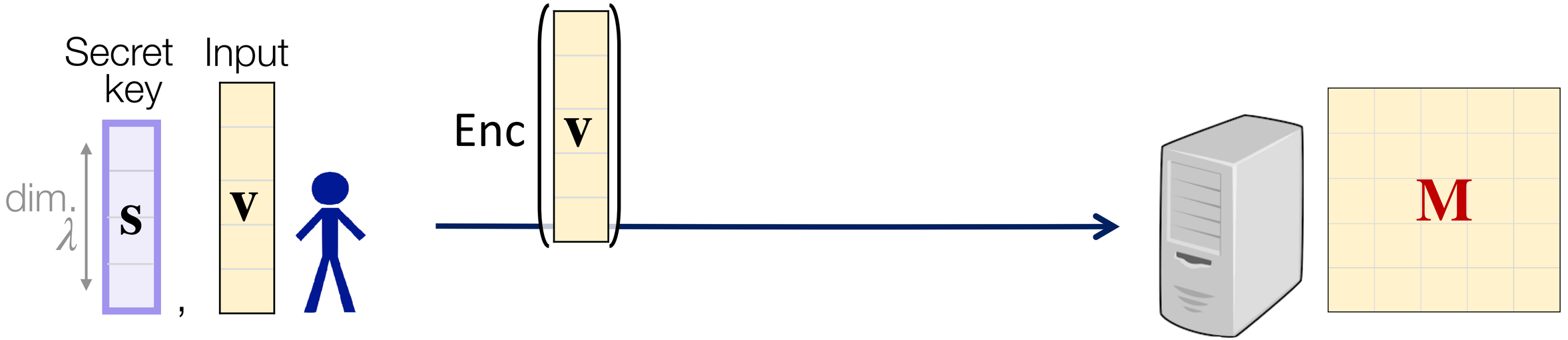

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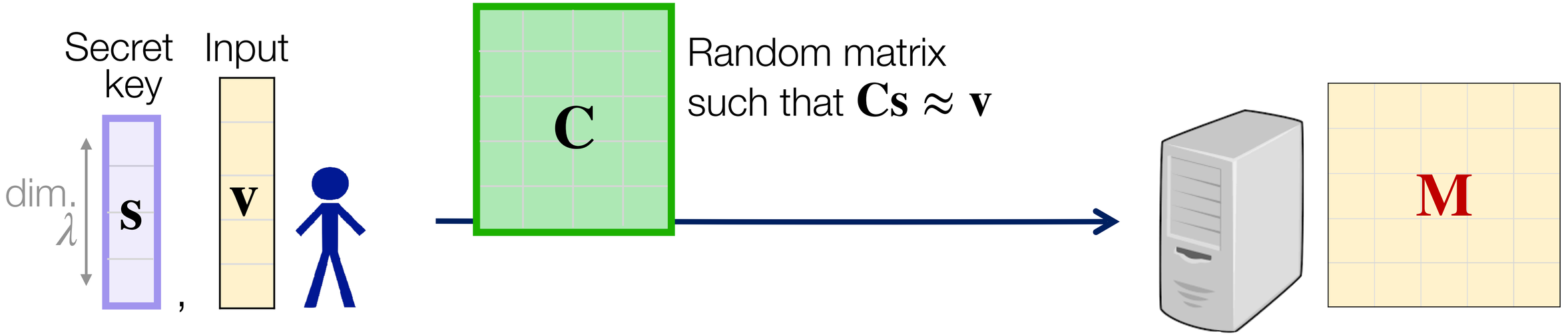

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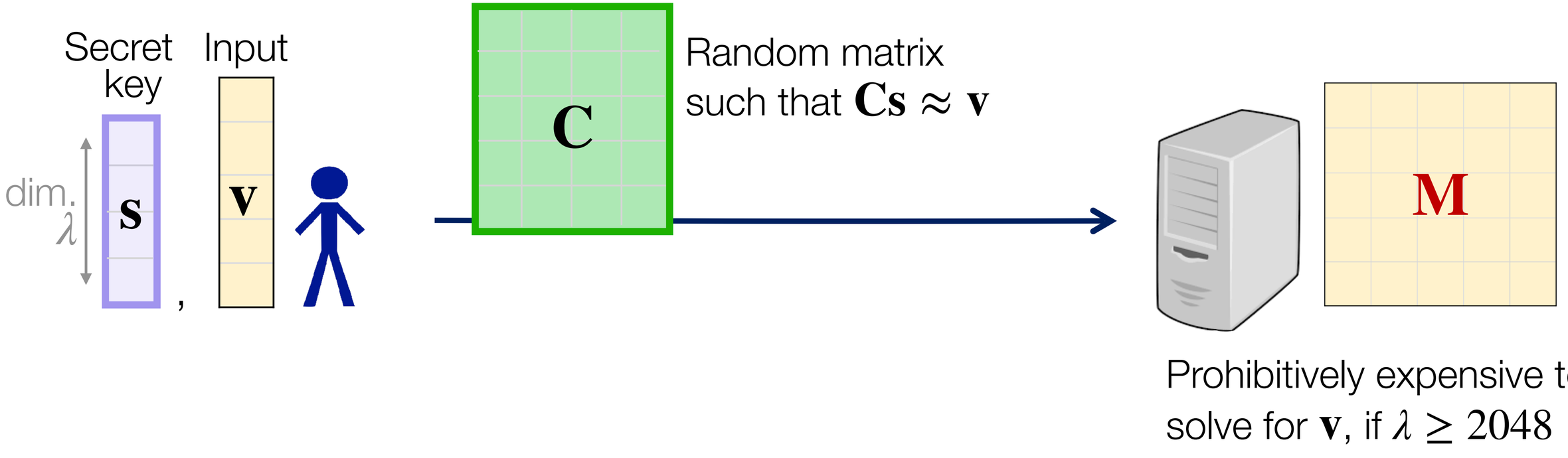

Prohibitively expensive to solve for $\mathbf{v}$, if $\lambda \geq 2048$

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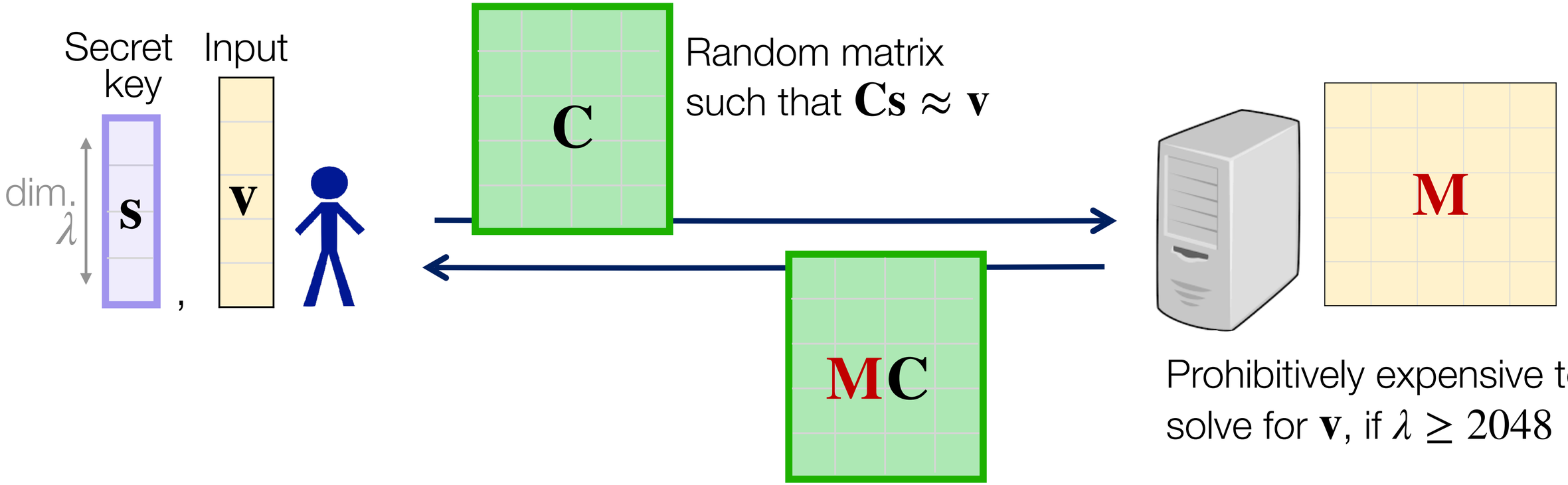

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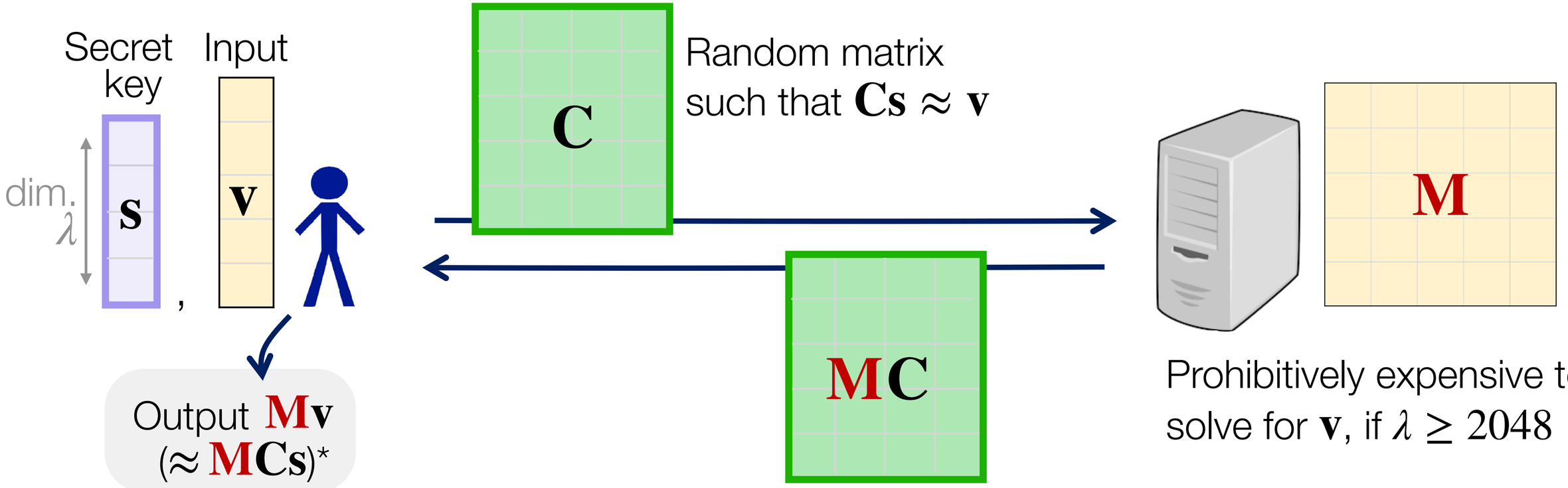
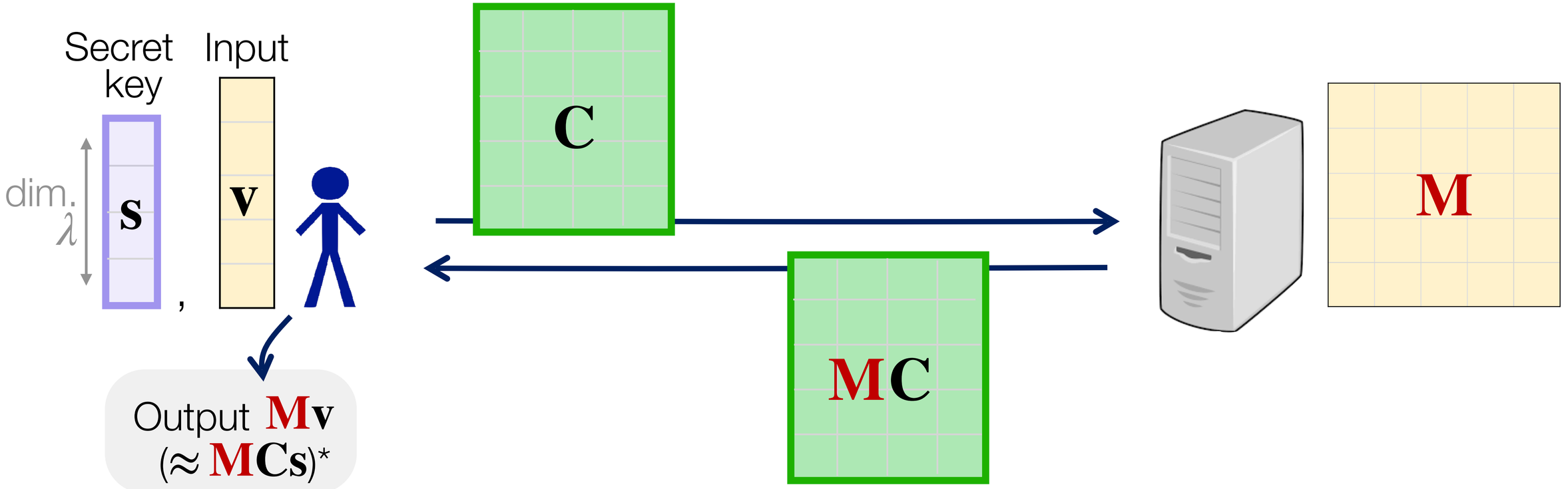


Result: Private matrix multiplication … at high cost

For security: $\lambda \geq 2048$



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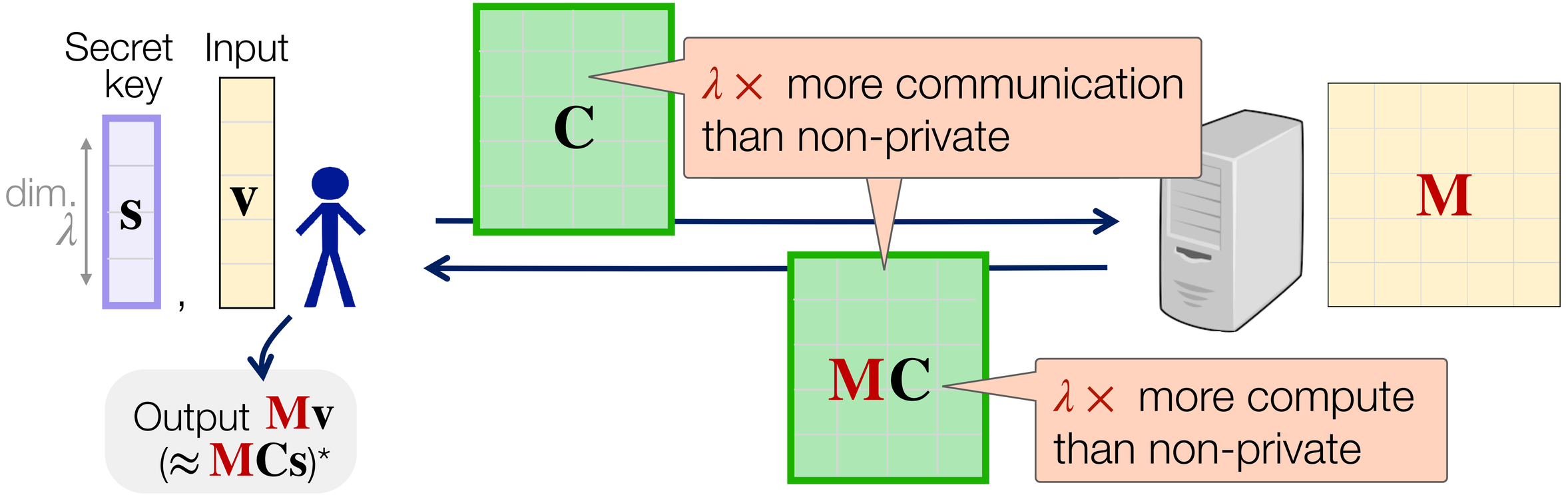
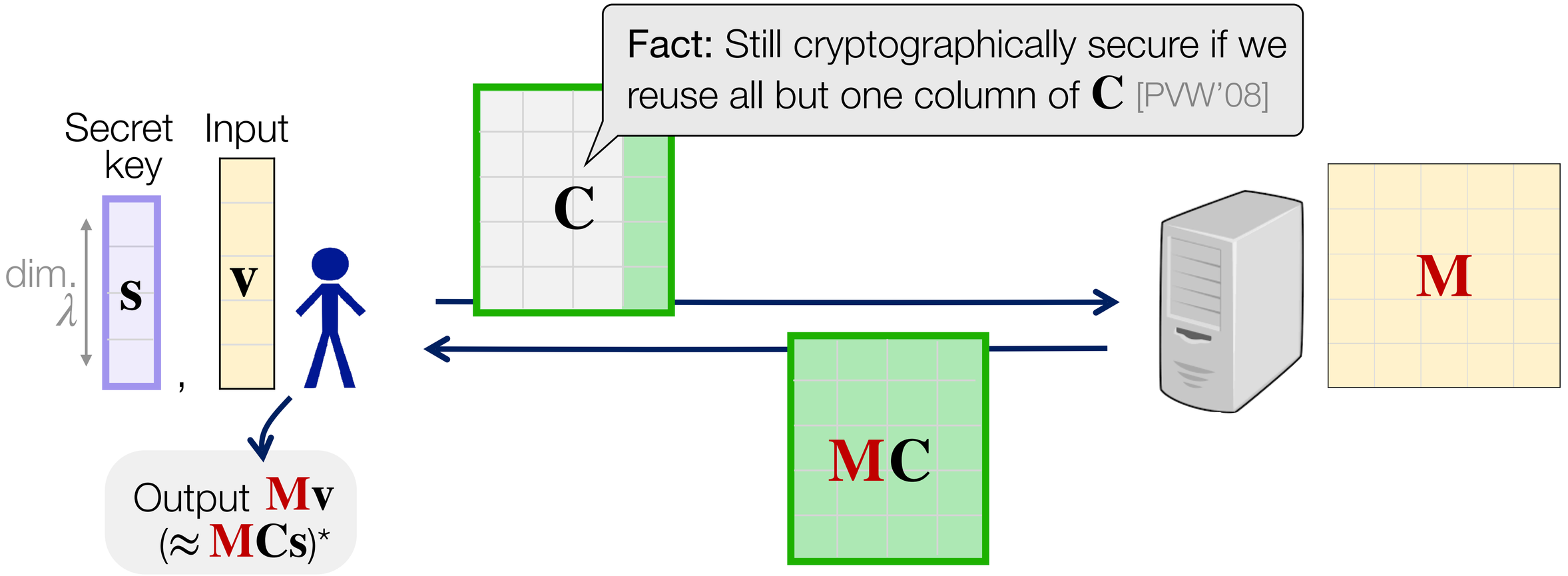


Idea: Expose useful structure for preprocessing



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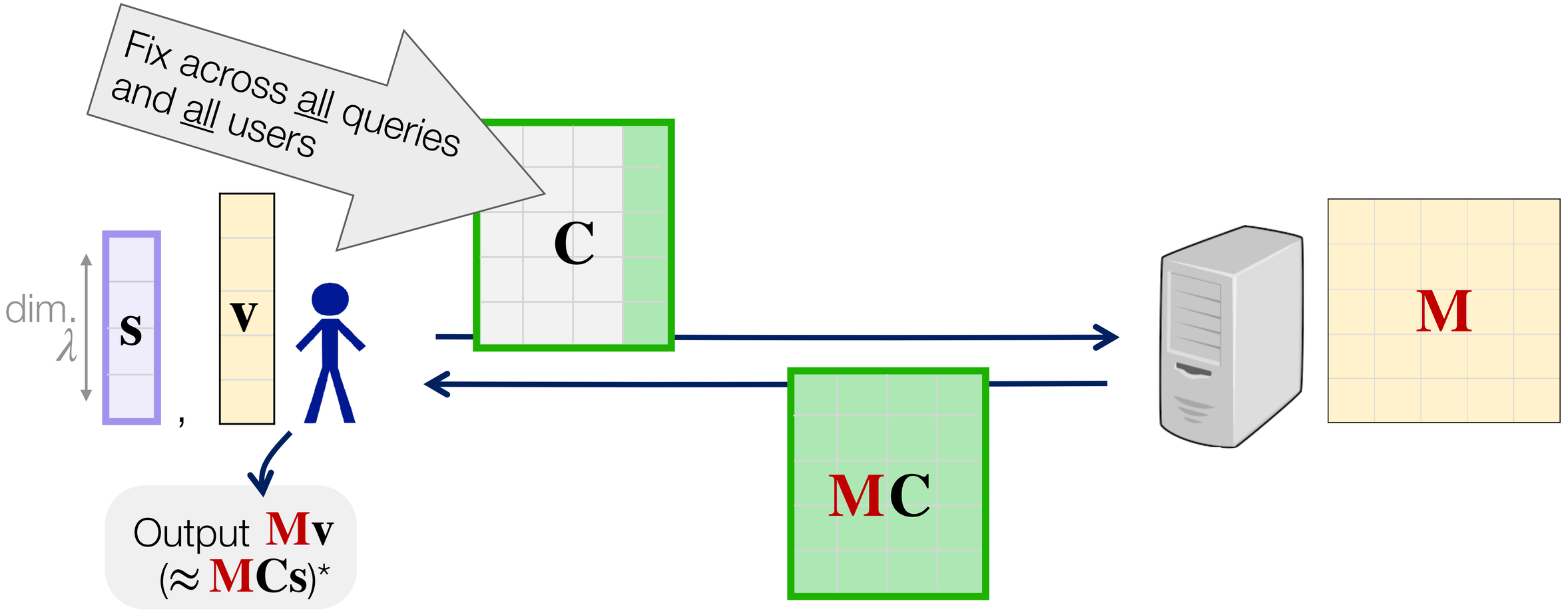

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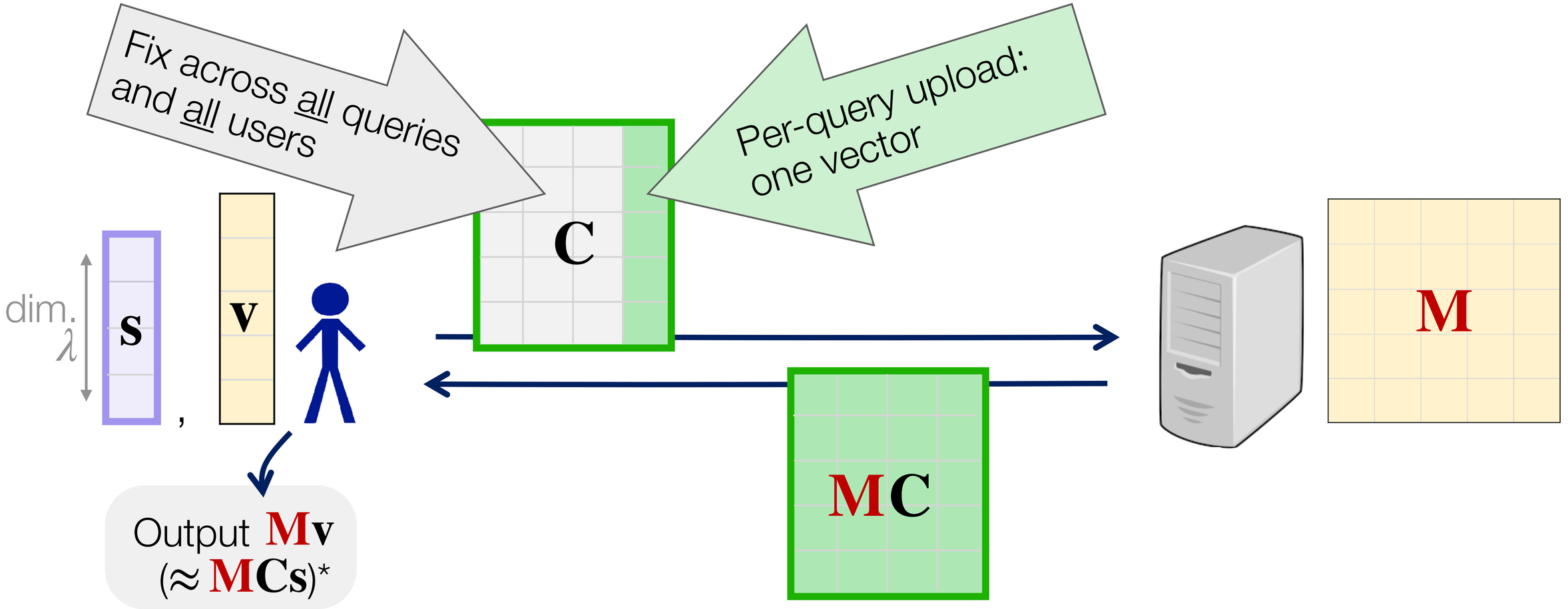

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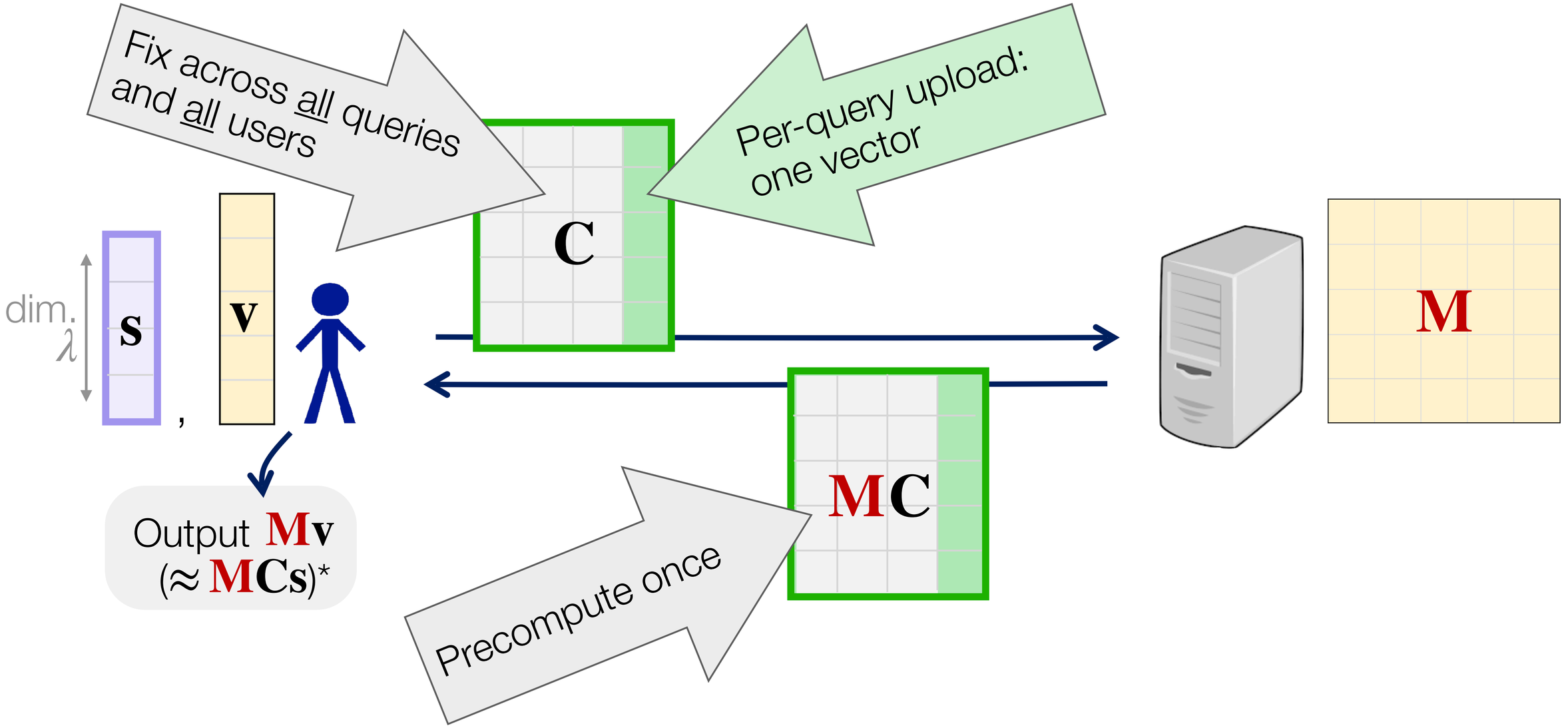

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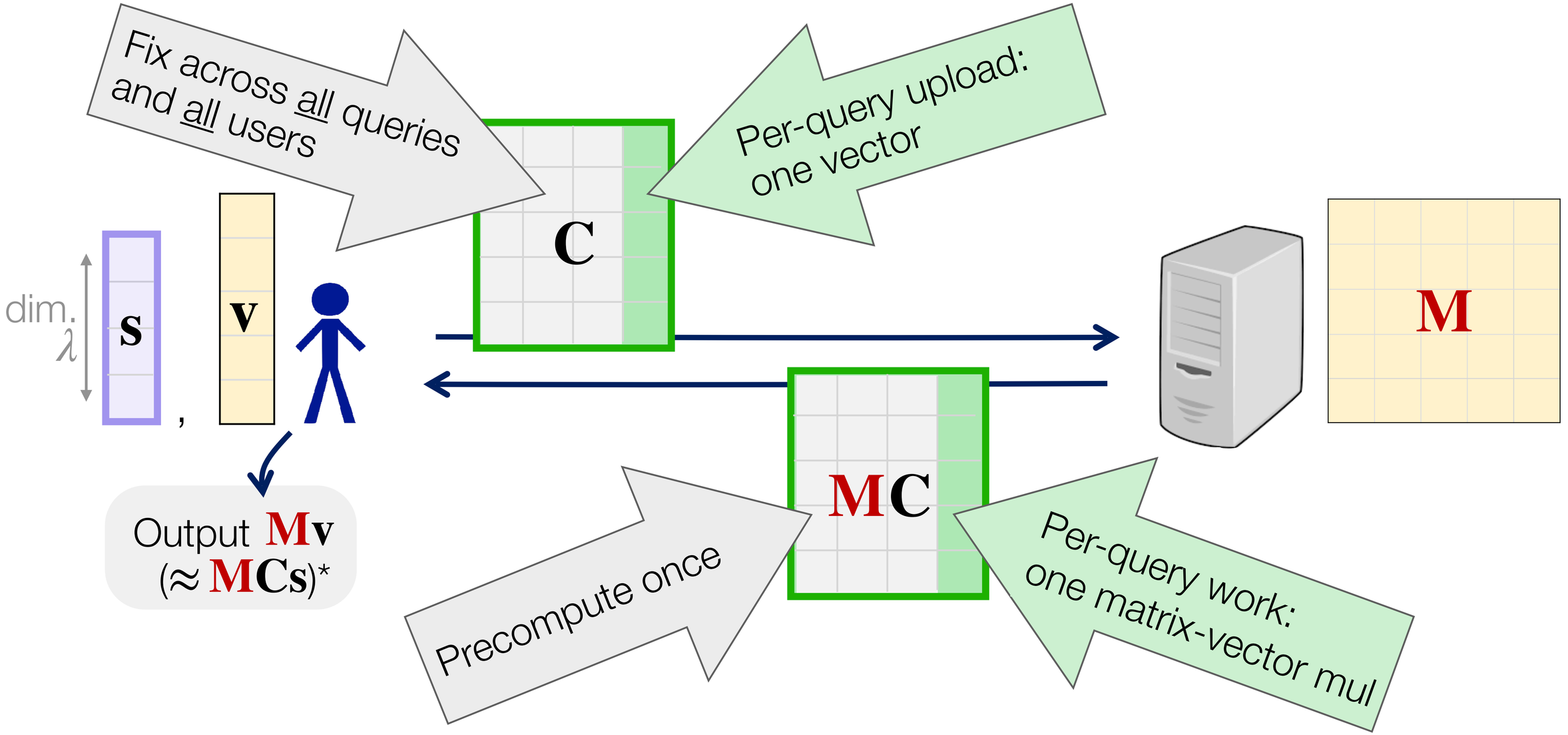

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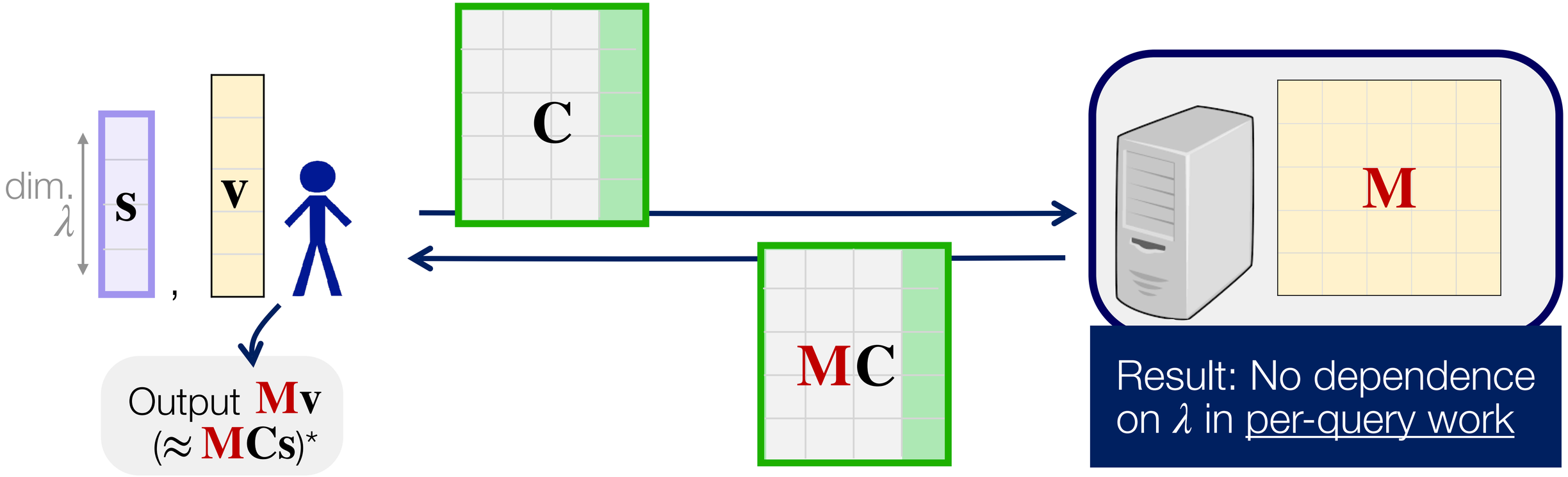

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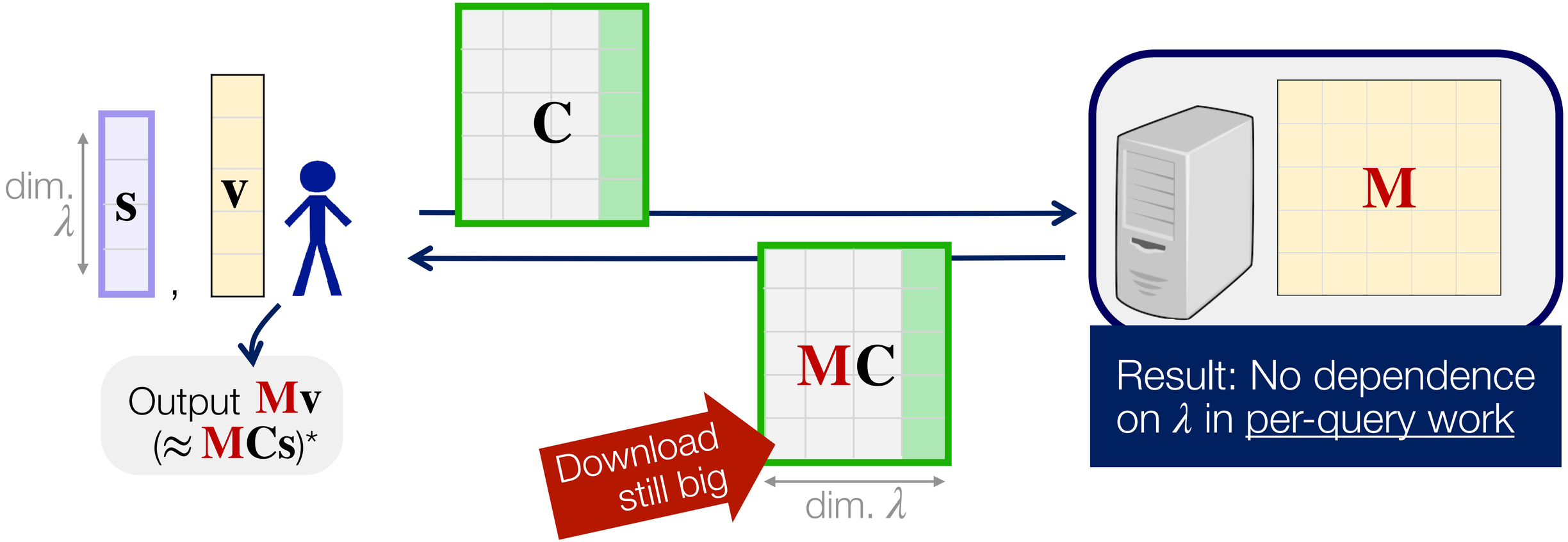
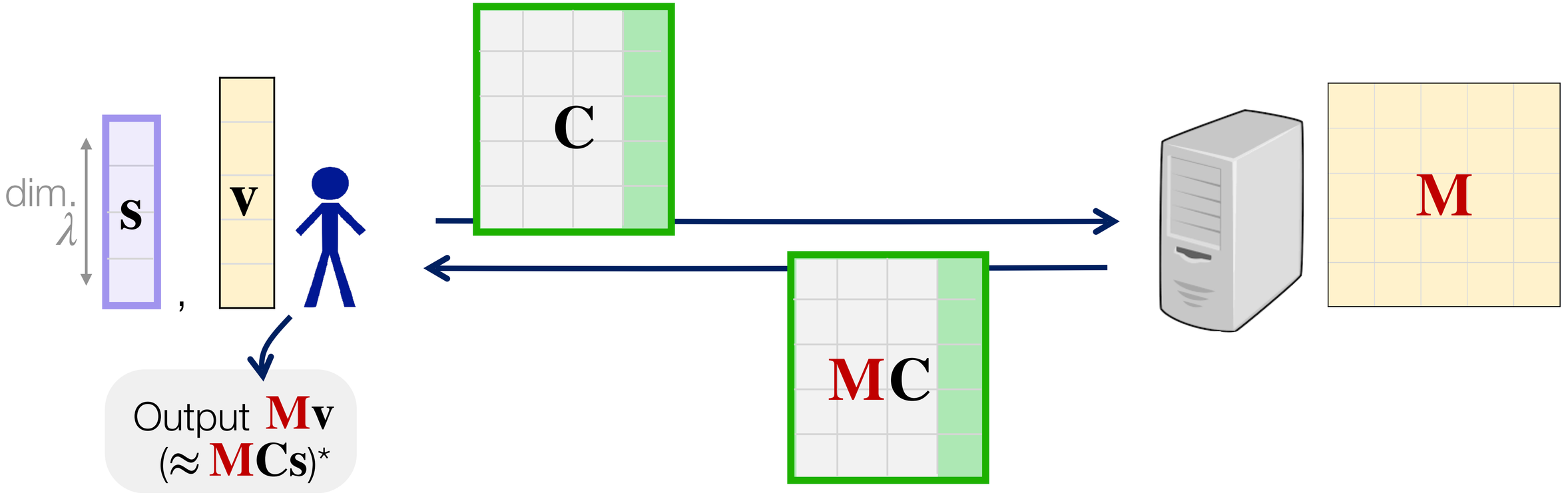


Extension: Repeat to shrink communication

Strategy: decrypt under encryption, inspired by fully-homomorphic schemes [Gen09, BV11]



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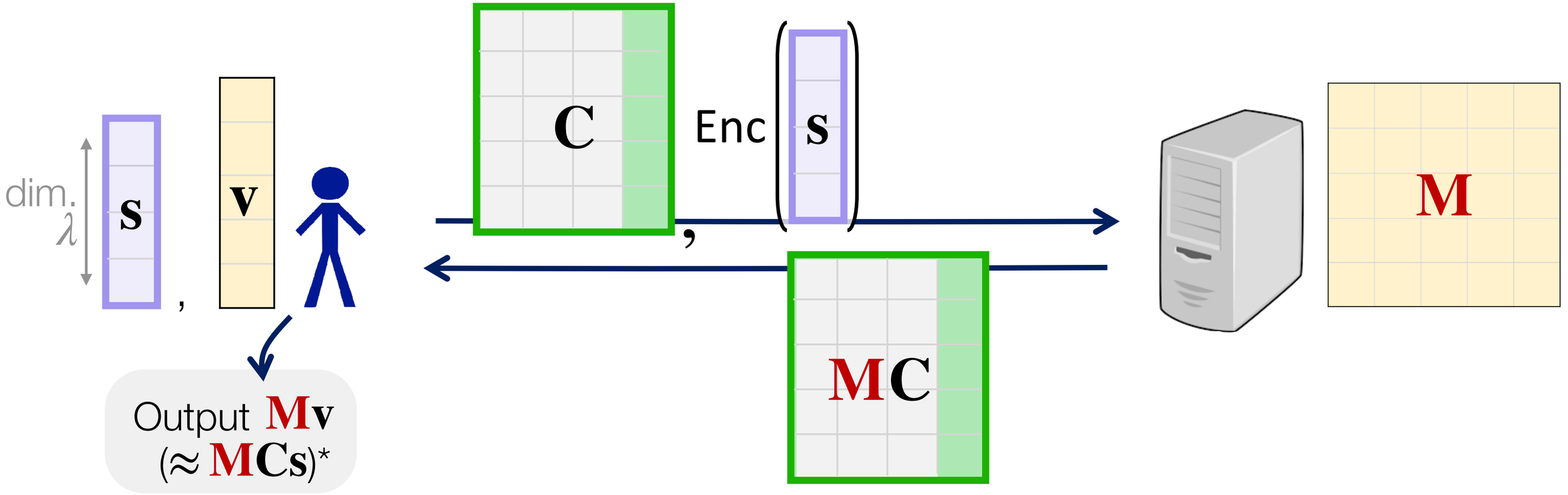

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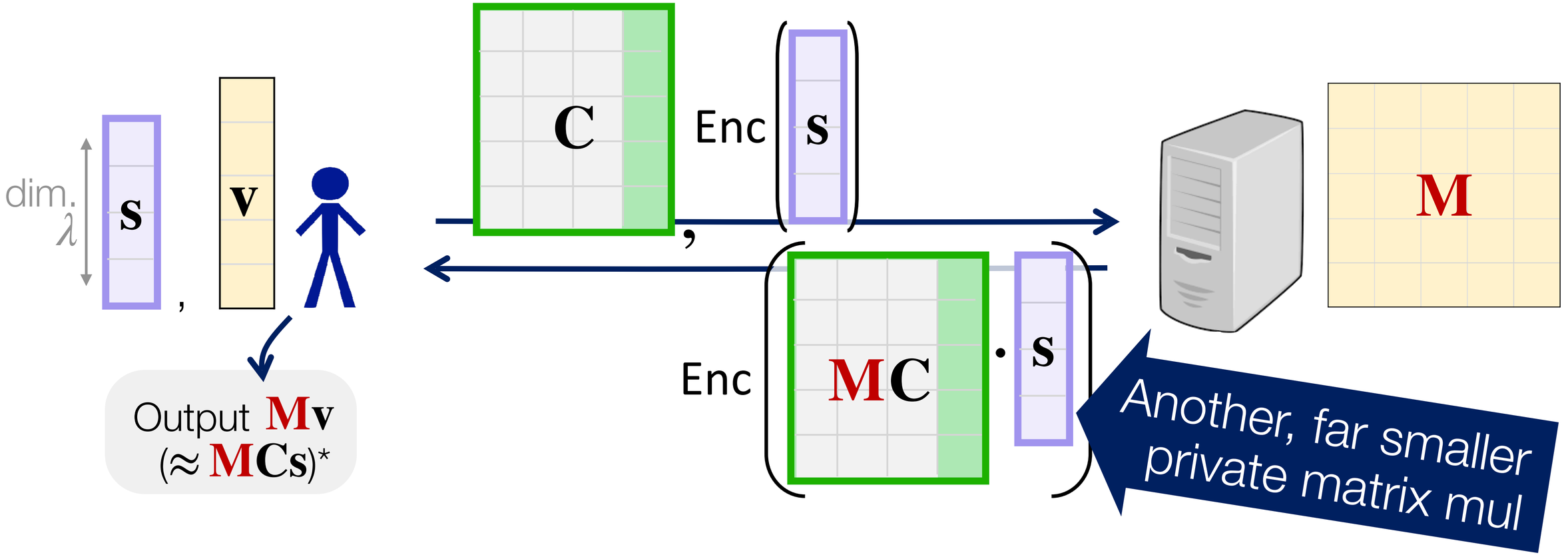

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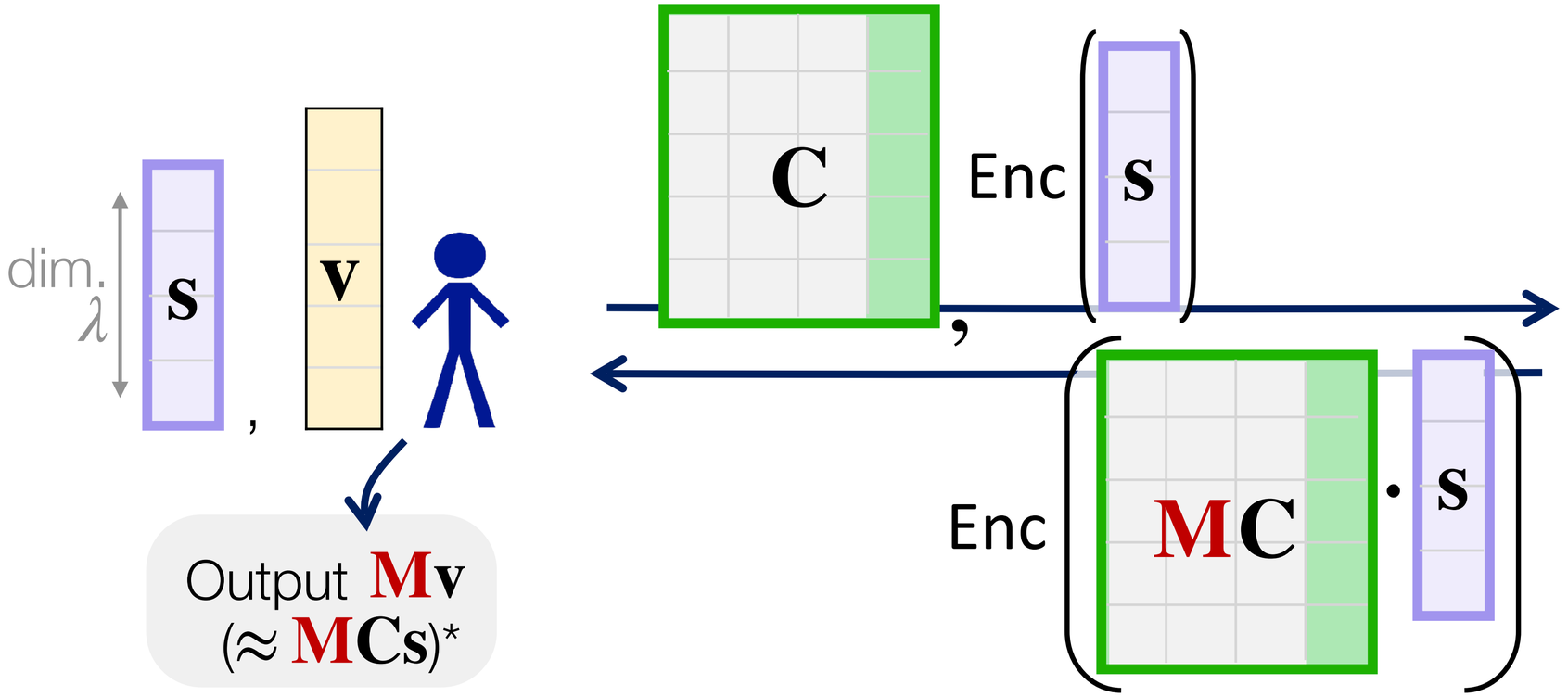
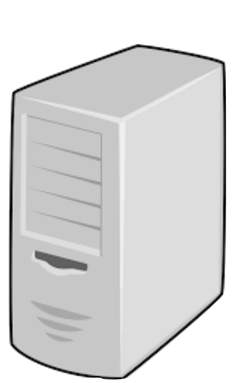
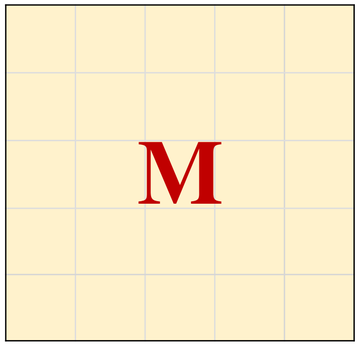


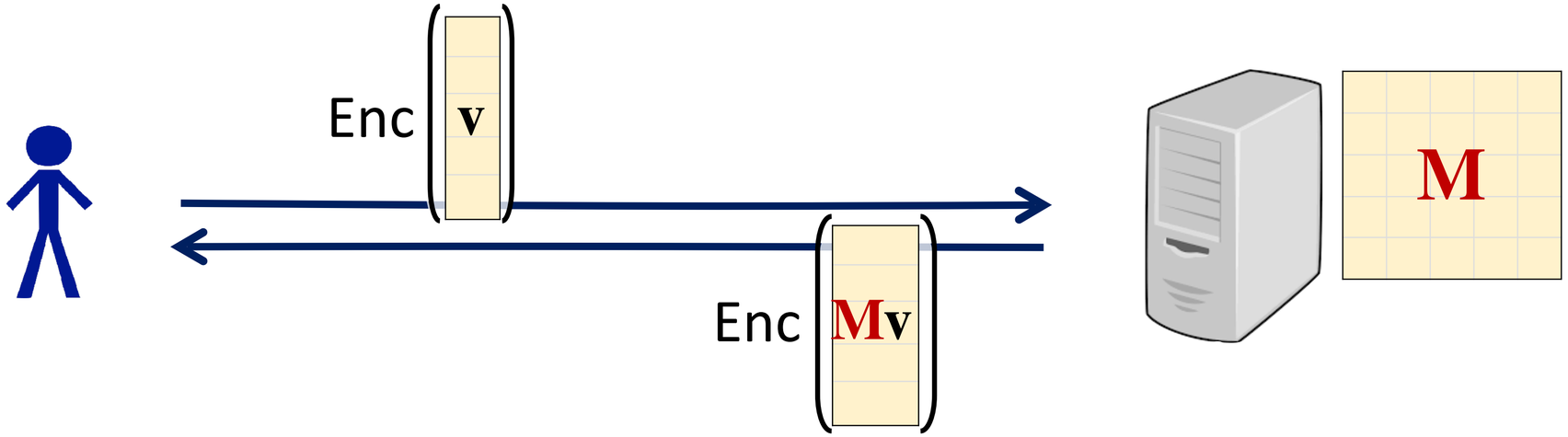




Result: No dependence on λ in leading term in communication

SimplePIR: The bottom line

With preprocessing, can multiply a matrix by encrypted vector at near-unencrypted speed



Protocol extensions
- VeriSimplePIR [CL24, RLP26]
- HintlessPIR [LMRS24]
- YPIR [MW24], InspPIRe [MPSY26]
- "Barely doubly efficient" SimplePIR [Lee25]
- Run on GPUs [LHC25]

Applications
- Private information retrieval
- Private key-value lookups [CD24, HLPZ+25]
- Private retrieval-augmented-generation [Z24, WLZZ25]
- Private set intersection [LLMT25]
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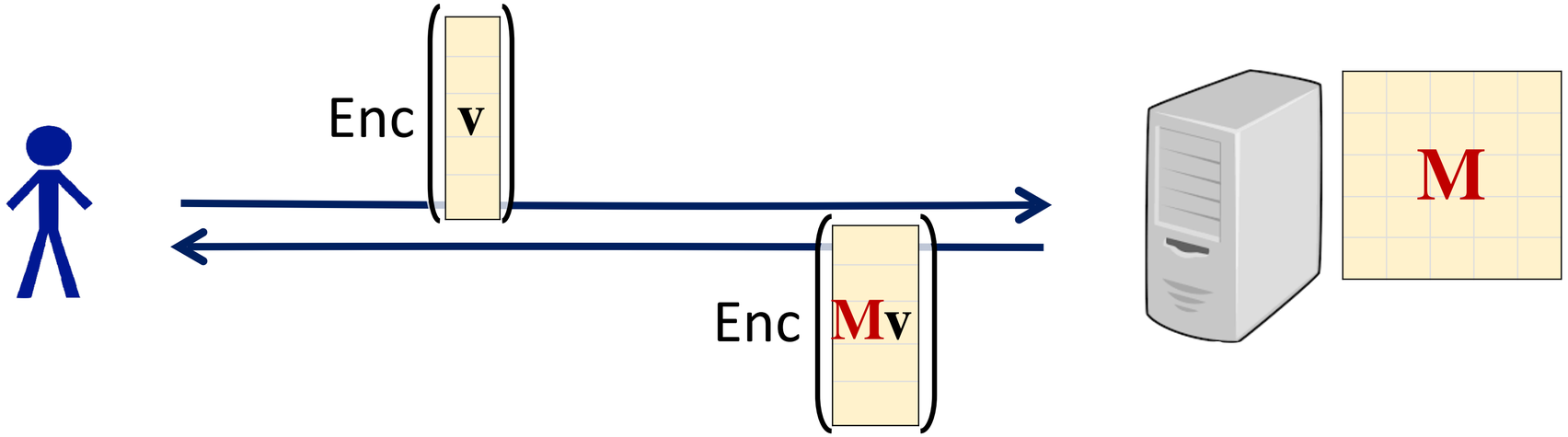

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Tiptoe: Design in layers

Private document ranking

Idea: exploit new data representations with semantic embeddings

Private nearest-neighbor search

Idea: expose structure in the computation with clustering

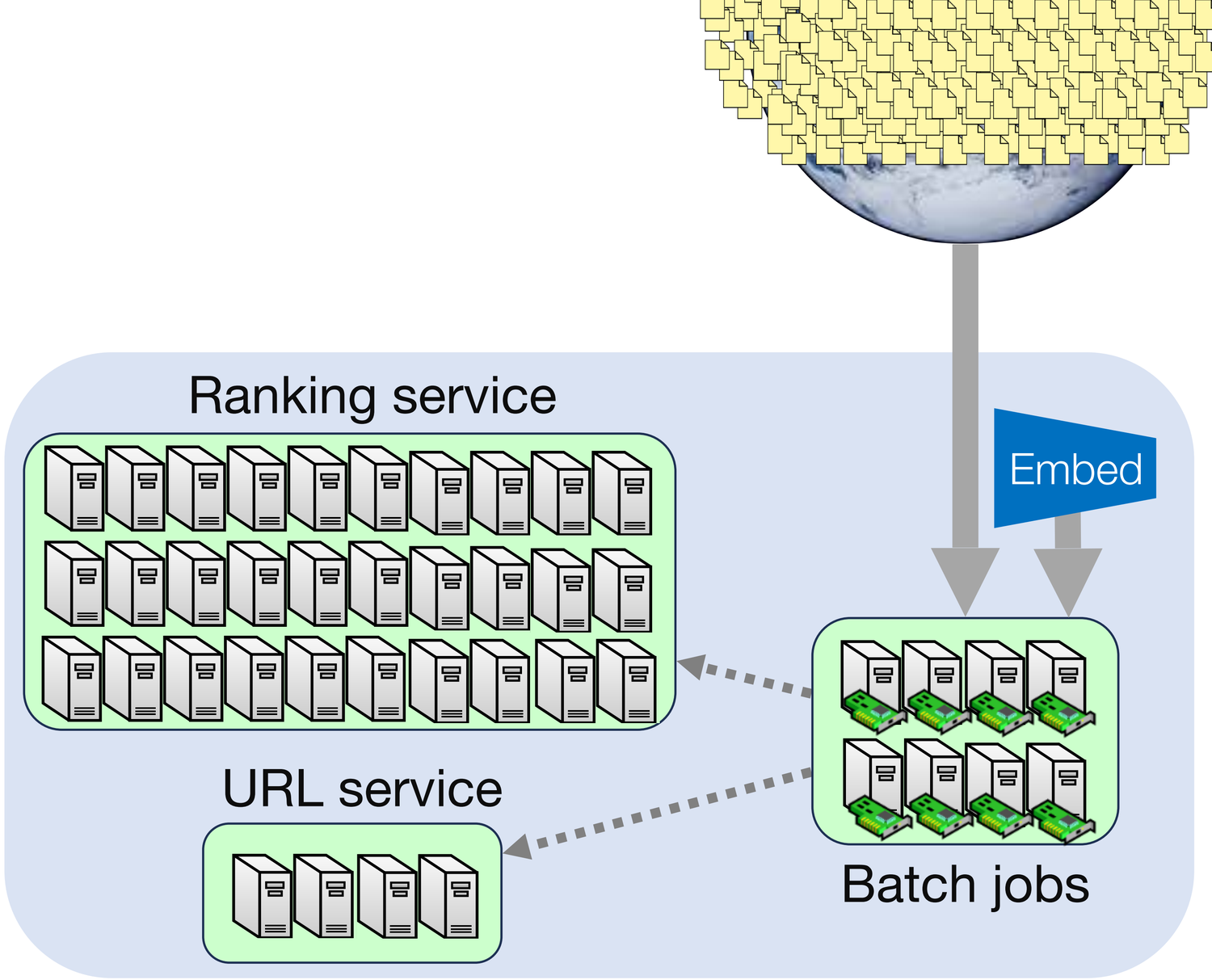
Private matrix multiplication

Idea: enable aggressive preprocessing

"Tiptoe" (SOSP'23)

"SimplePIR" (USENIX Sec'23)

Tiptoe: The full system

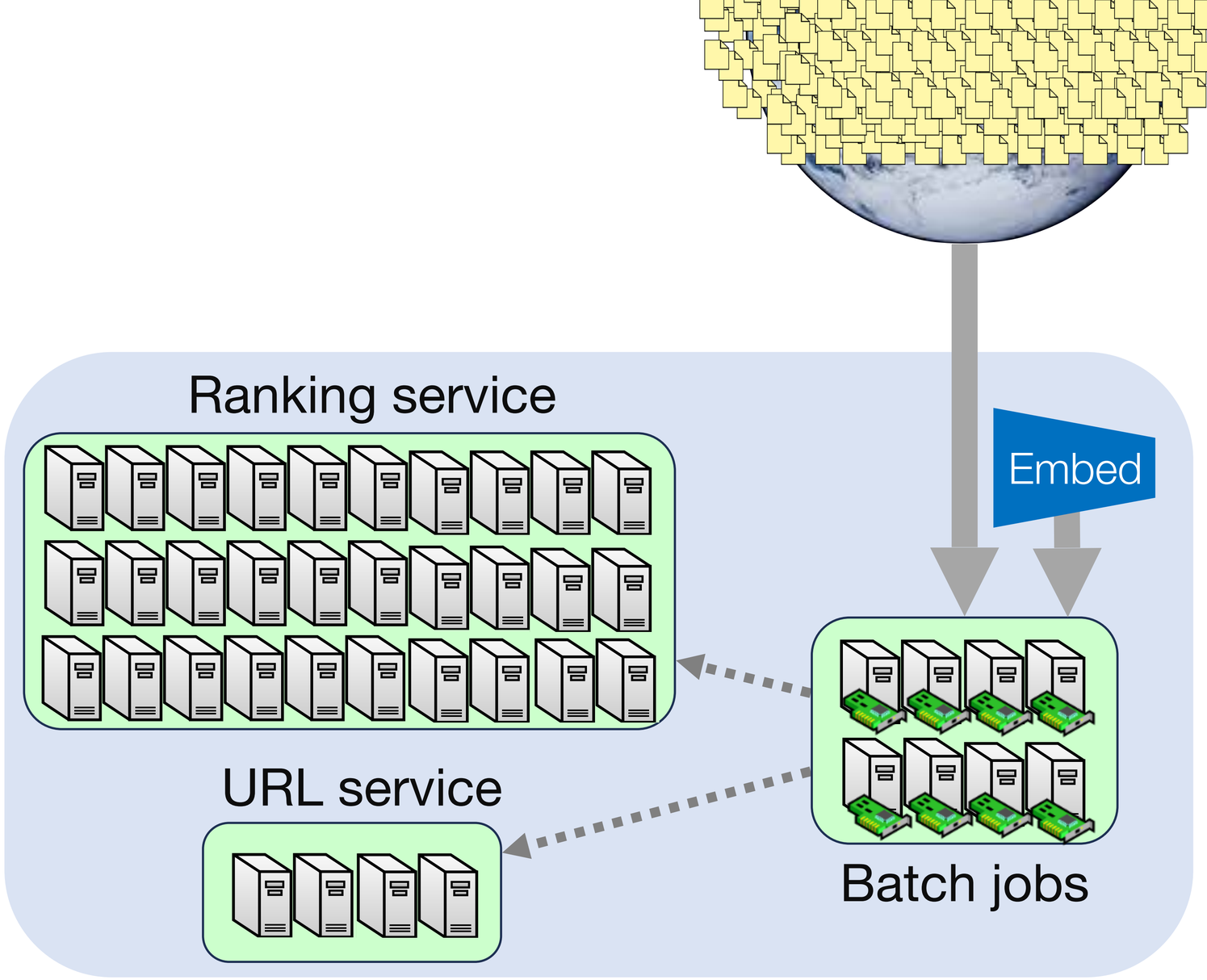


`github.com/ahenzinger/tiptoe`
`github.com/ahenzinger/simplepir`

Tiptoe: The full system

Batch jobs:

1. Embed documents
2. Cluster embeddings
3. Preprocess crypto



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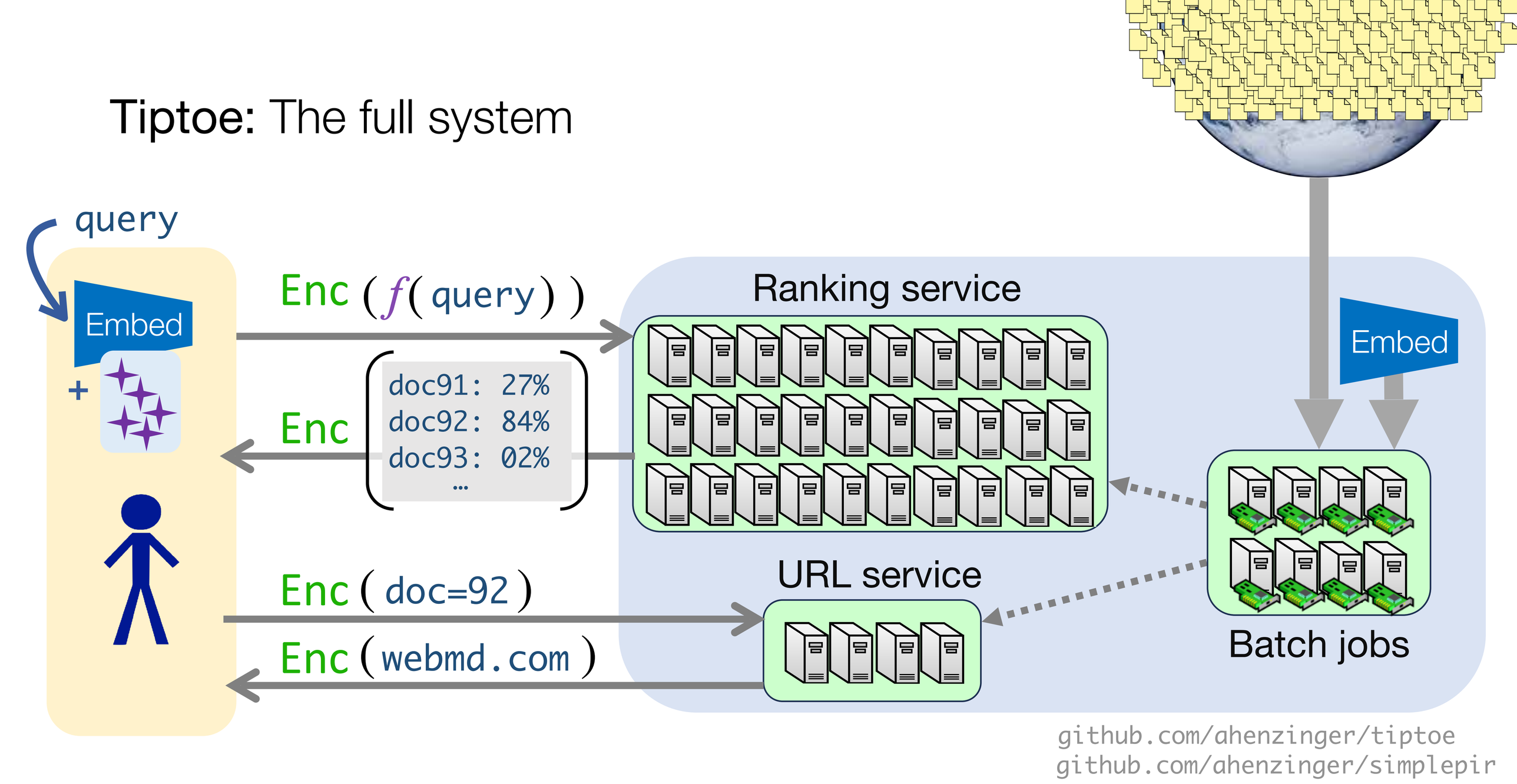

github.com/ahenzinger/tiptoe
github.com/ahenzinger/simplepir

Tiptoe is cheaper than state-of-the-art private search

On English Common crawl with 364M pages

	Coeus, scaled up (SOSP'21)	Tiptoe (SOSP'23)	Gain
Client storage	-	0.3 GiB	
Server compute (per query)	928,800 core-s	145 core-s	6,400×
Communication (per query)	3,880 MiB	57 MiB	62×
Latency (per query)	-	2.7 s	

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SimplePIR: $10\times$ less computation

Semantic embeddings: $100\times$ smaller than a bag-of-words representation

Clustering: communication sublinear in N

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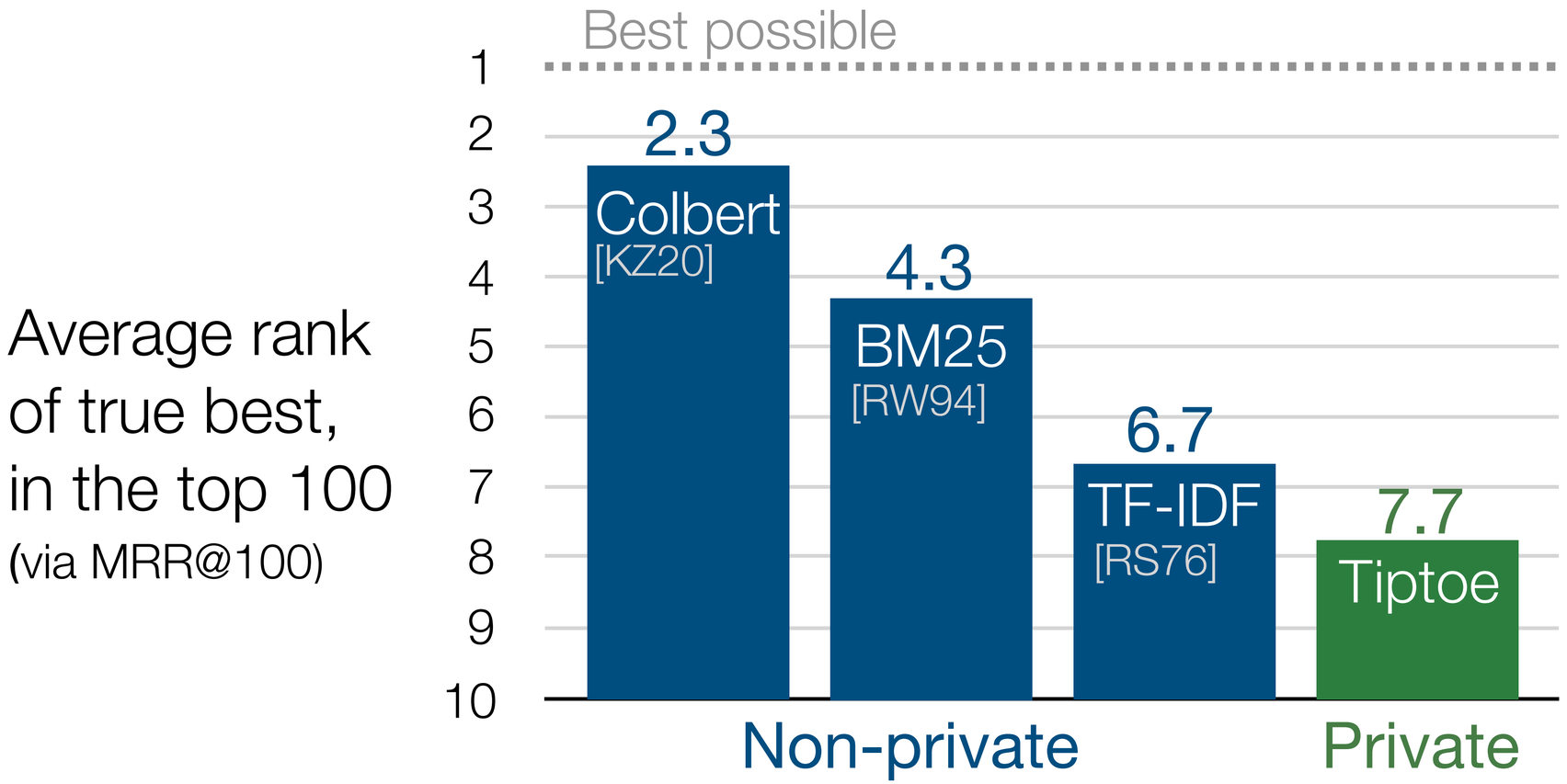
Tiptoe ranks the best result in the top 10, on average

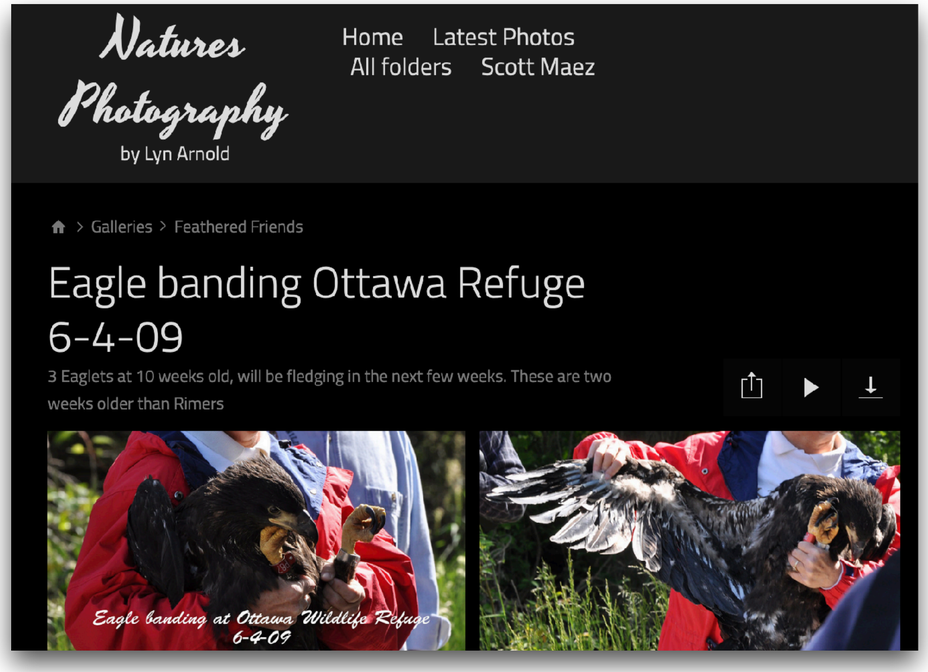
On MS MARCO document ranking data set



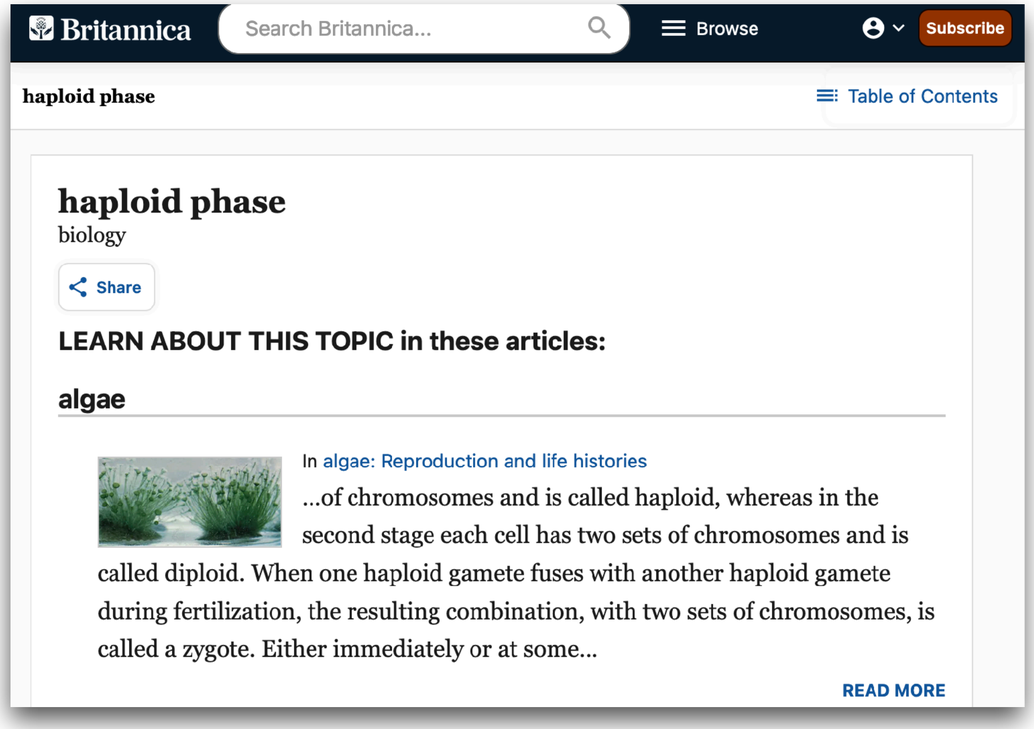
Embedding model: `msmarco-distilbert-base-tas-b`

Examples: Tiptoe's text search

`Q: how long before eagles get feathers`



`Q: the meaning of haploid cell`



On the Common crawl data set

Examples: Tiptoe's text search

```
Q: Advice on writing a doctoral thesis
```

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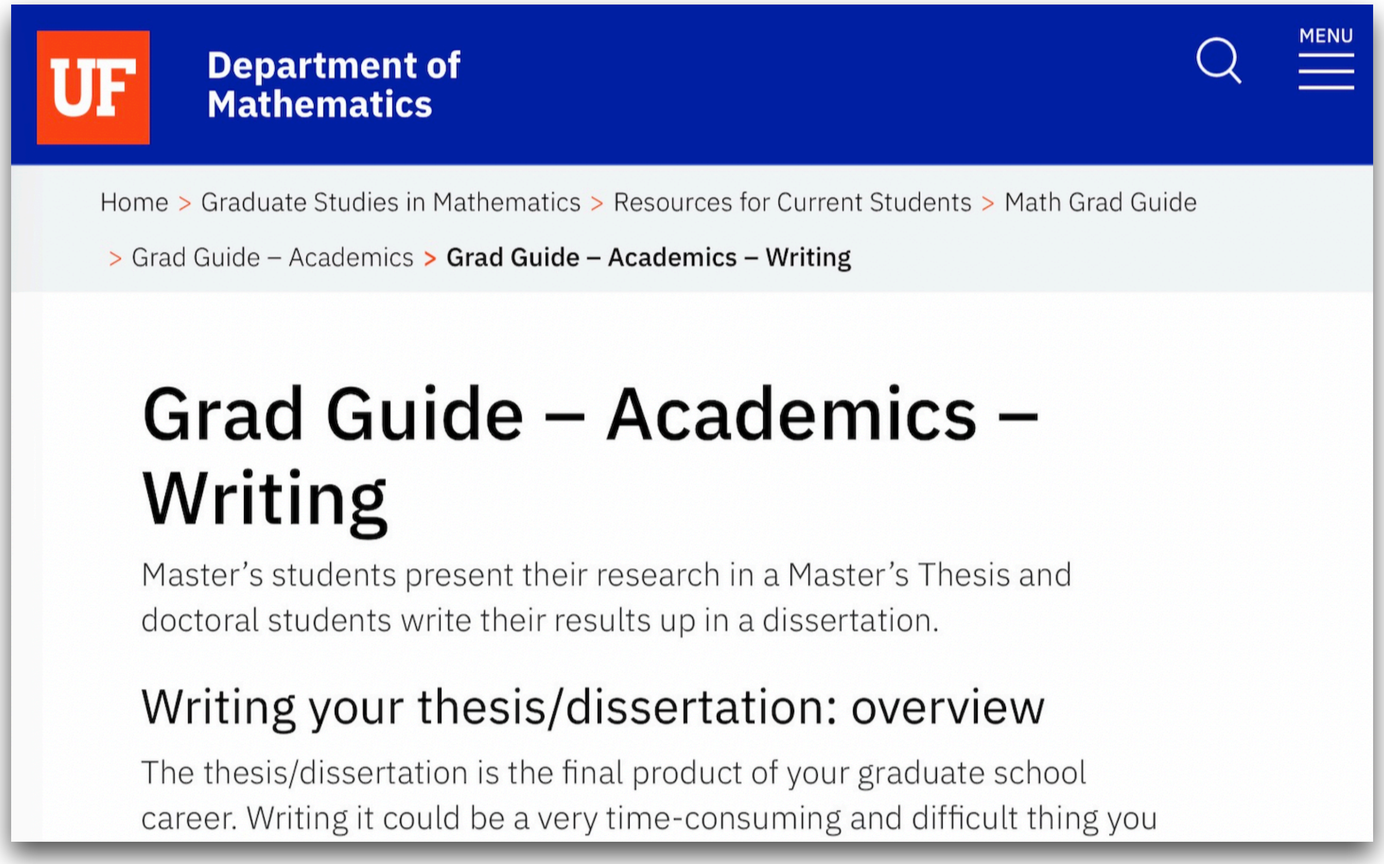

Examples: Tiptoe's text search

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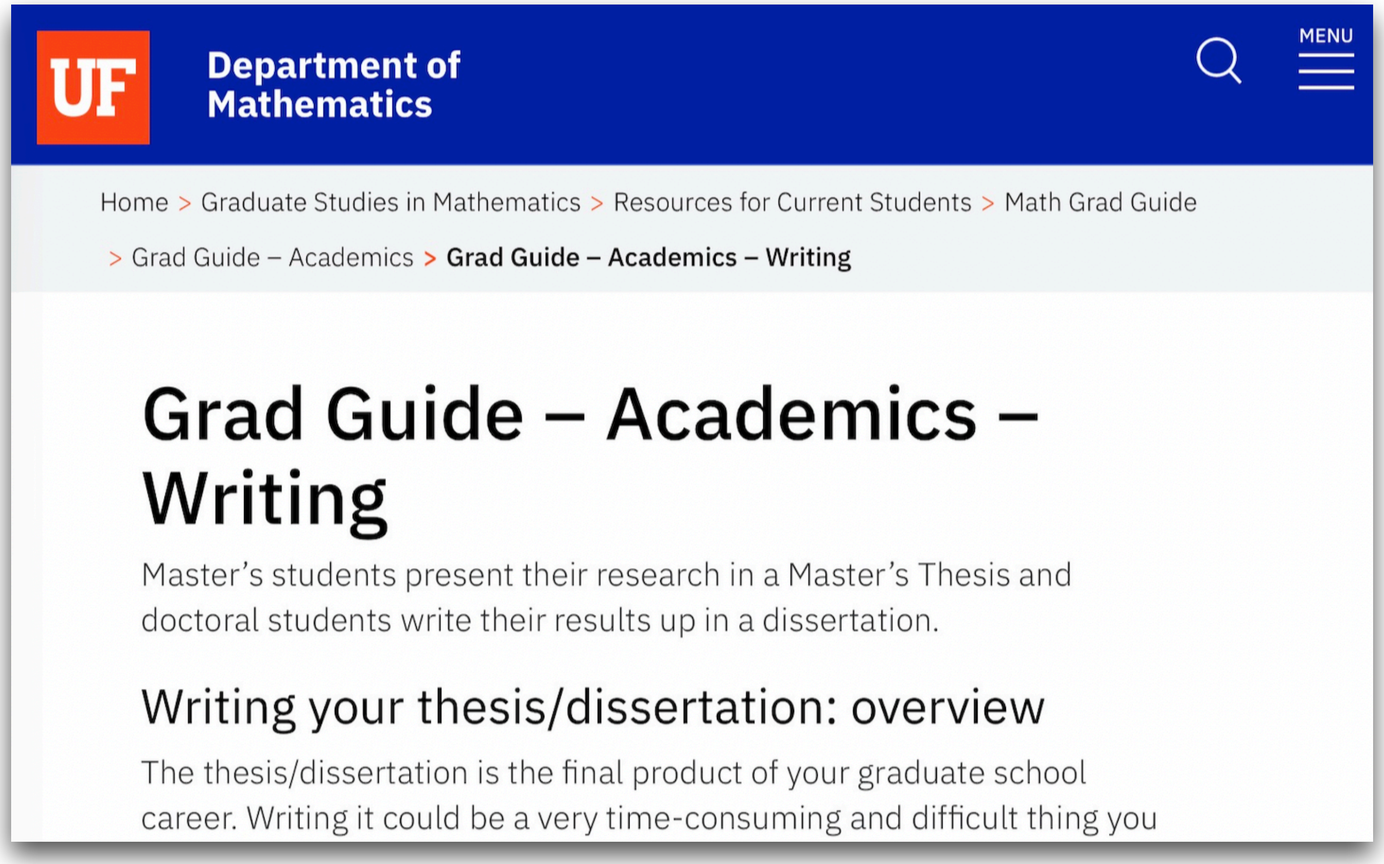

`Q: Advice on writing a doctoral thesis in Computer Science`

Examples: Tiptoe's text search

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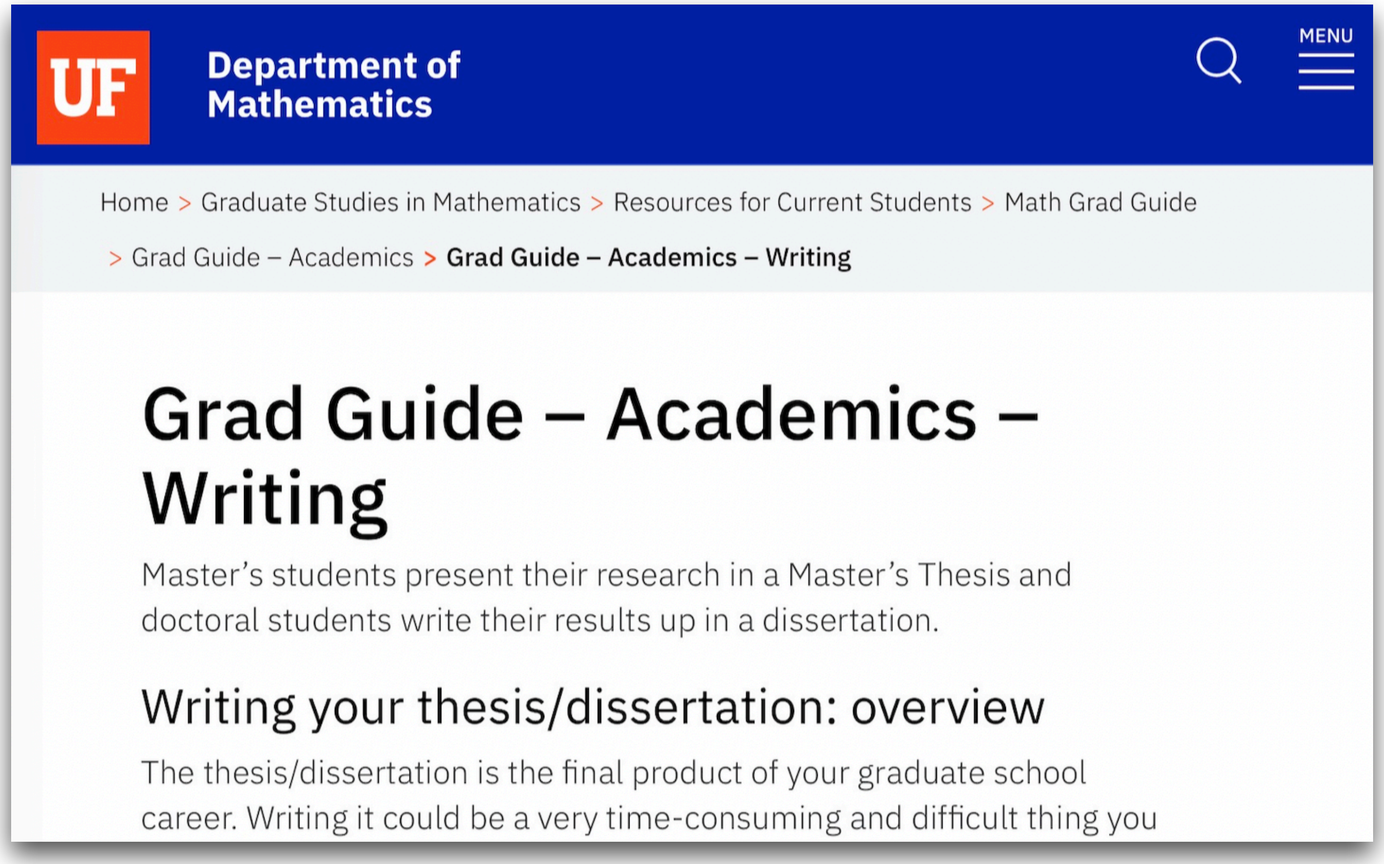
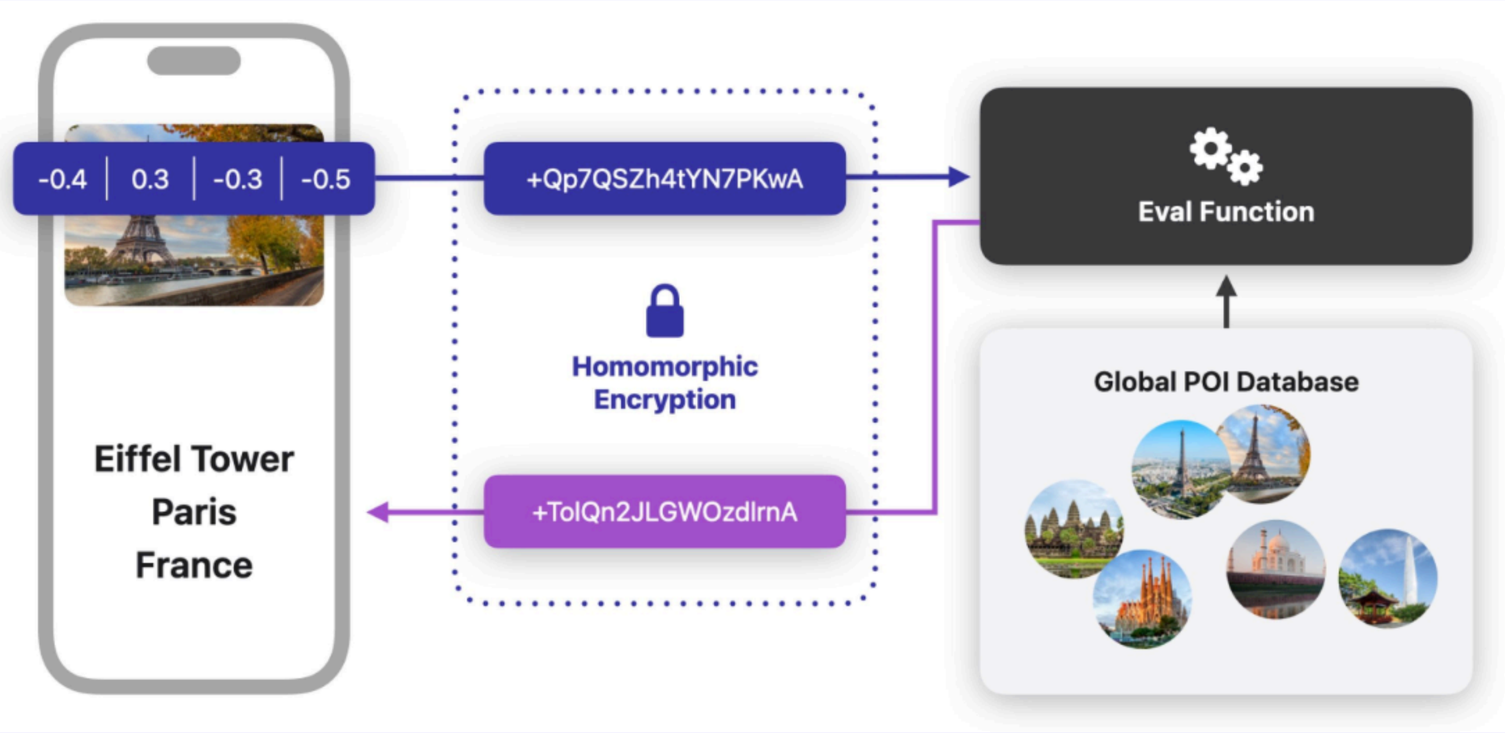


Q: Advice on writing a doctoral thesis in Computer Science

A: buydissertations.com/computer-science.html

Apple adopted Tiptoe's private nearest-neighbor search in **iOS 18 and macOS "Enhanced Visual Search"**

Goal: label landmarks in photos without revealing the photos to Apple servers



machinelearning.apple.com/research/wally-search
machinelearning.apple.com/research/homomorphic-encryption

My research: A privacy-preserving software stack

Applications

Libraries

Cryptographic operations

Privacy-preserving systems (SOSP'23, USENIX Sec'26)

- **Private web search**
- Private recommendations

Algorithms on encrypted data (USENIX Sec'23, '25)

- **Private nearest-neighbor search**
- Private matrix factorization

Fast cryptography (EUROCRYPT'22, '25, '26, '26)

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- Private information retrieval
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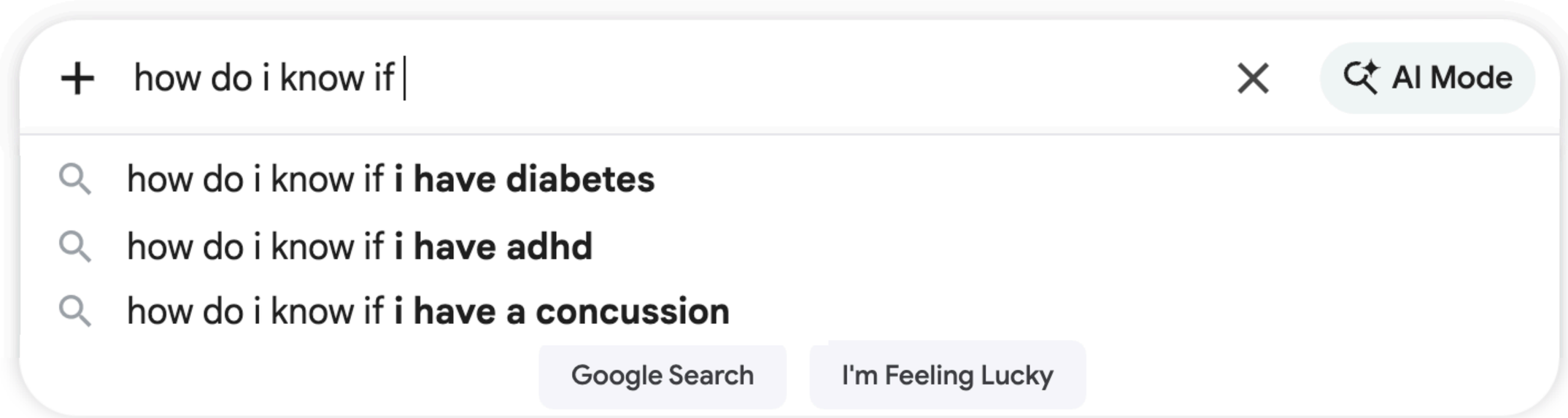

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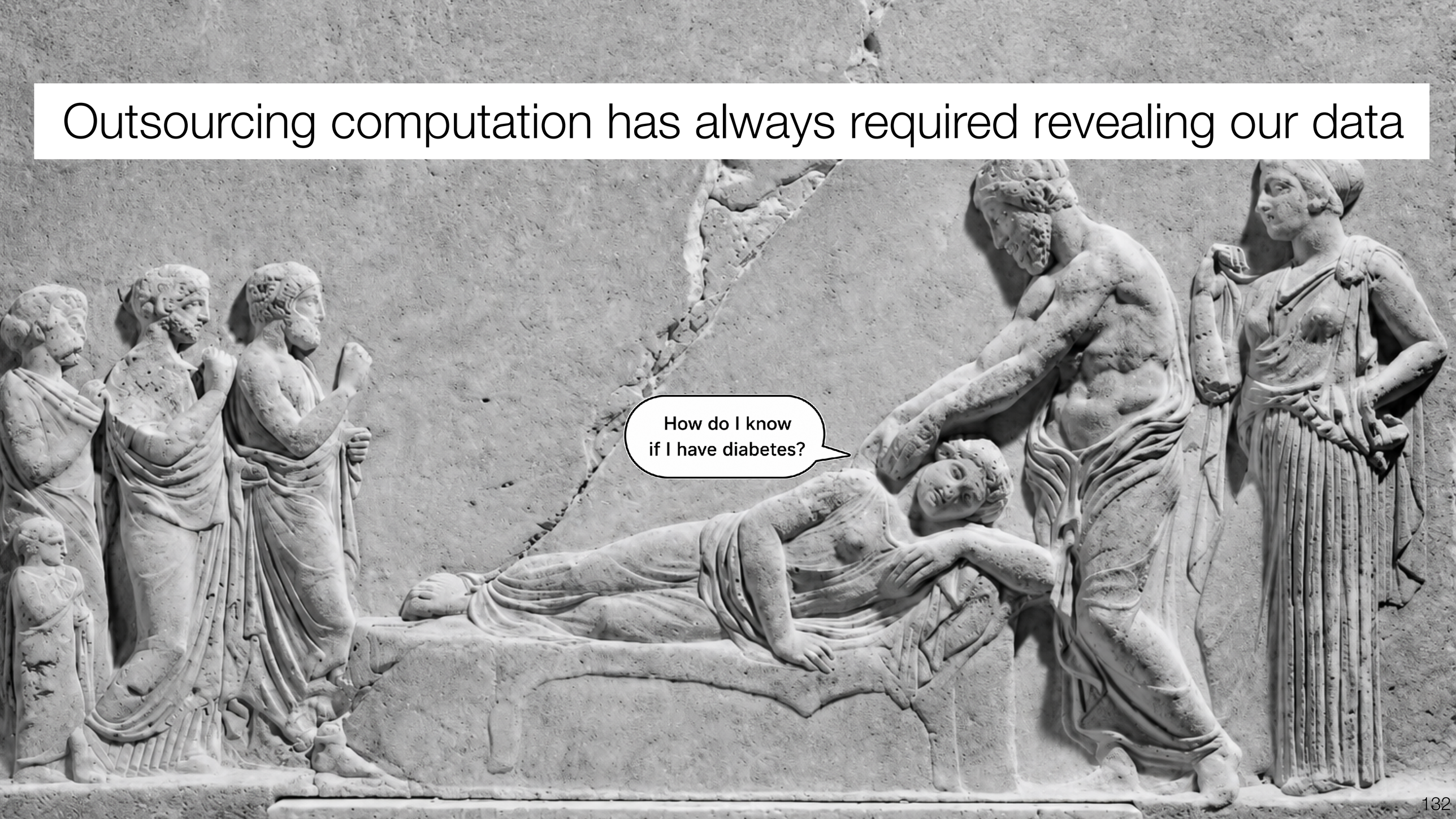
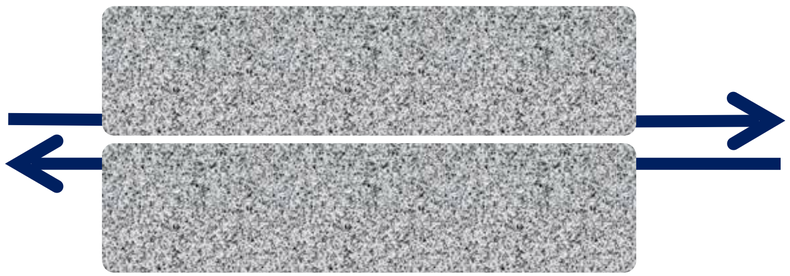


Computer science can give us **more**: functionality and privacy

"How do I know if I have diabetes?"

"Pizza near me"



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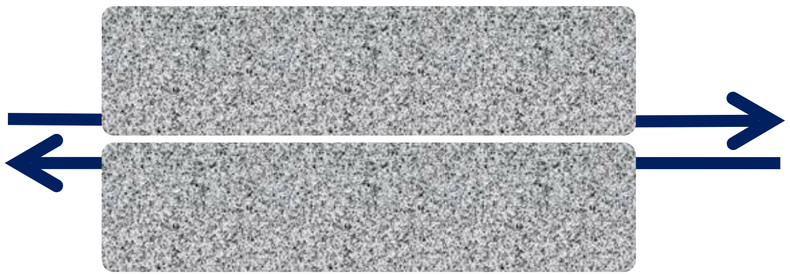

Private search engine

Conclusion

Today, computer systems see our secrets. They don't have to.

We can build privacy-protecting systems by re-thinking the stack:

- new system architectures
- new algorithms on encrypted data
- new cryptography

Privacy at scale is in reach, if we design it right.

Thank you!