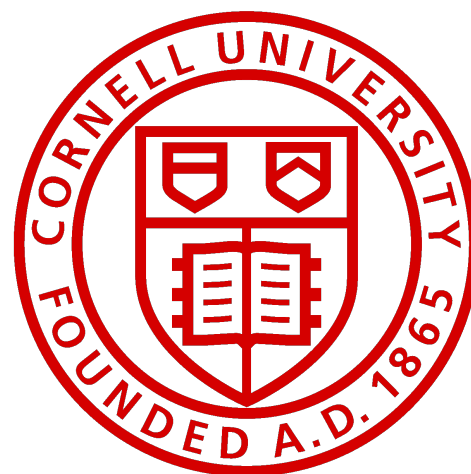
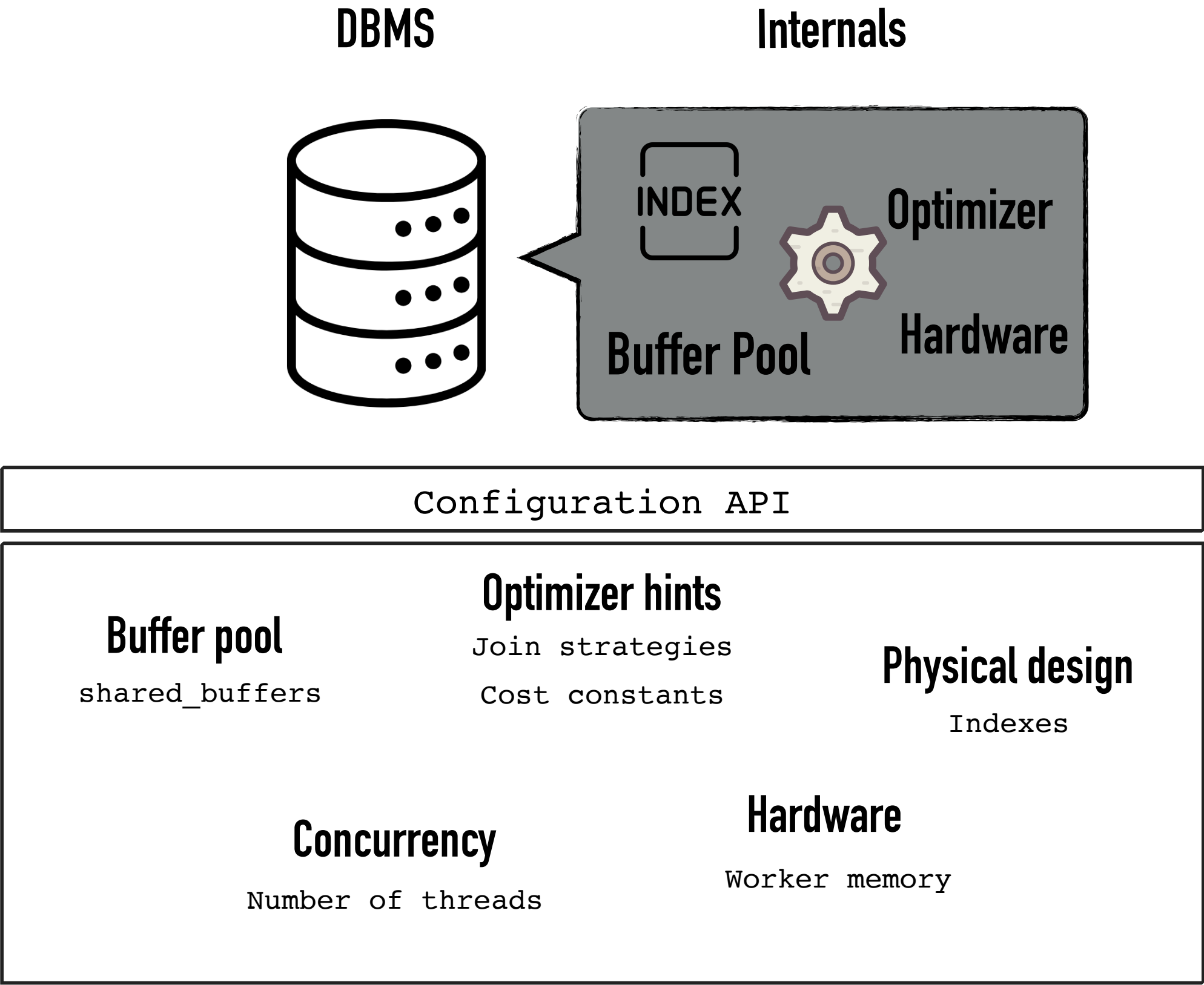


λ -TUNE: HARNESSING LARGE LANGUAGE MODELS FOR AUTOMATED DATABASE SYSTEM TUNING

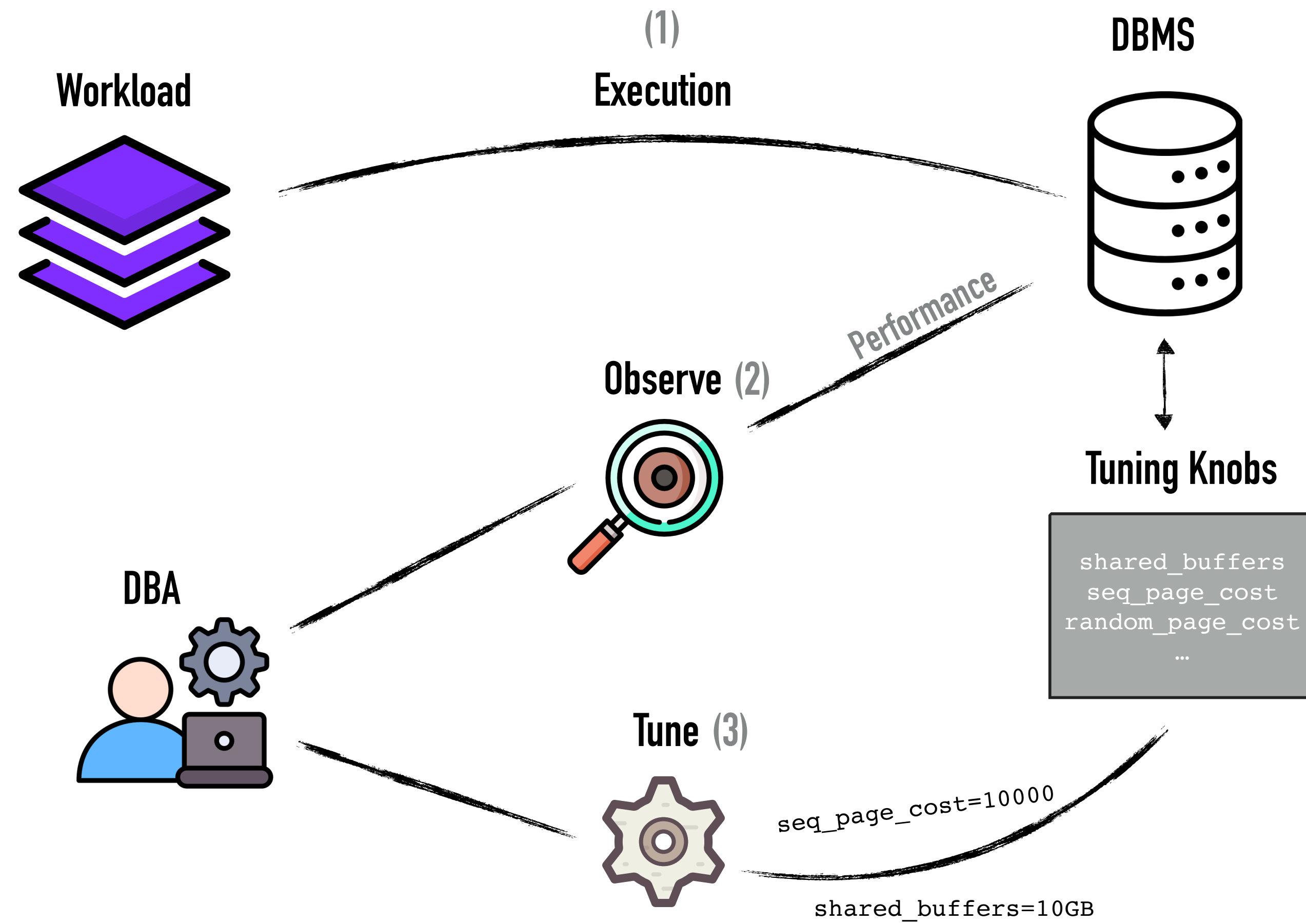
Victor Giannakouris, Immanuel Trummer
Computer Science Department
Cornell University



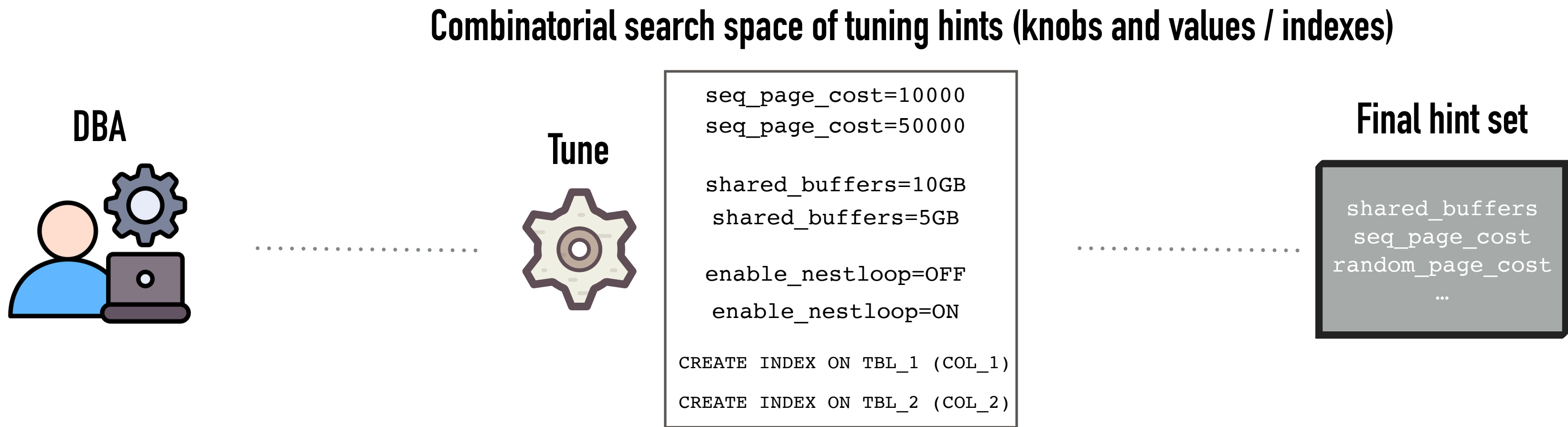
HOW TO TUNE A DATABASE SYSTEM



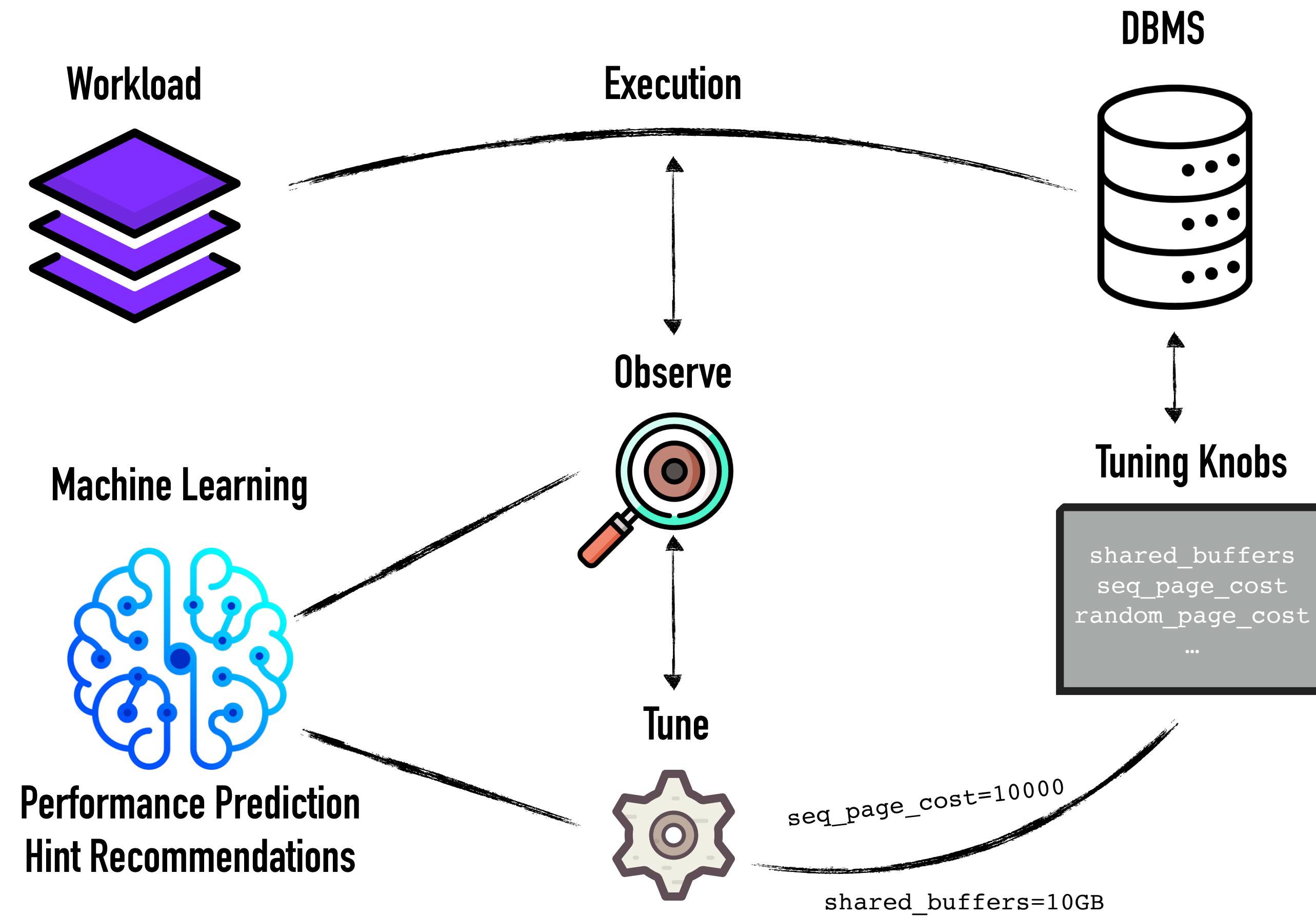
TUNING PIPELINE



TUNING DATABASE SYSTEMS IS HARD



TUNING USING LEARNED SOLUTIONS



LANGUAGE MODEL BASED SOLUTIONS

► DB-BERT

- Language model: BERT
- Approach: Reinforcement Learning

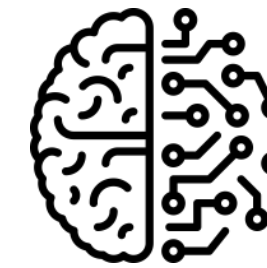
► GPTuner

- Language model: GPT-4
- Bayesian Optimization

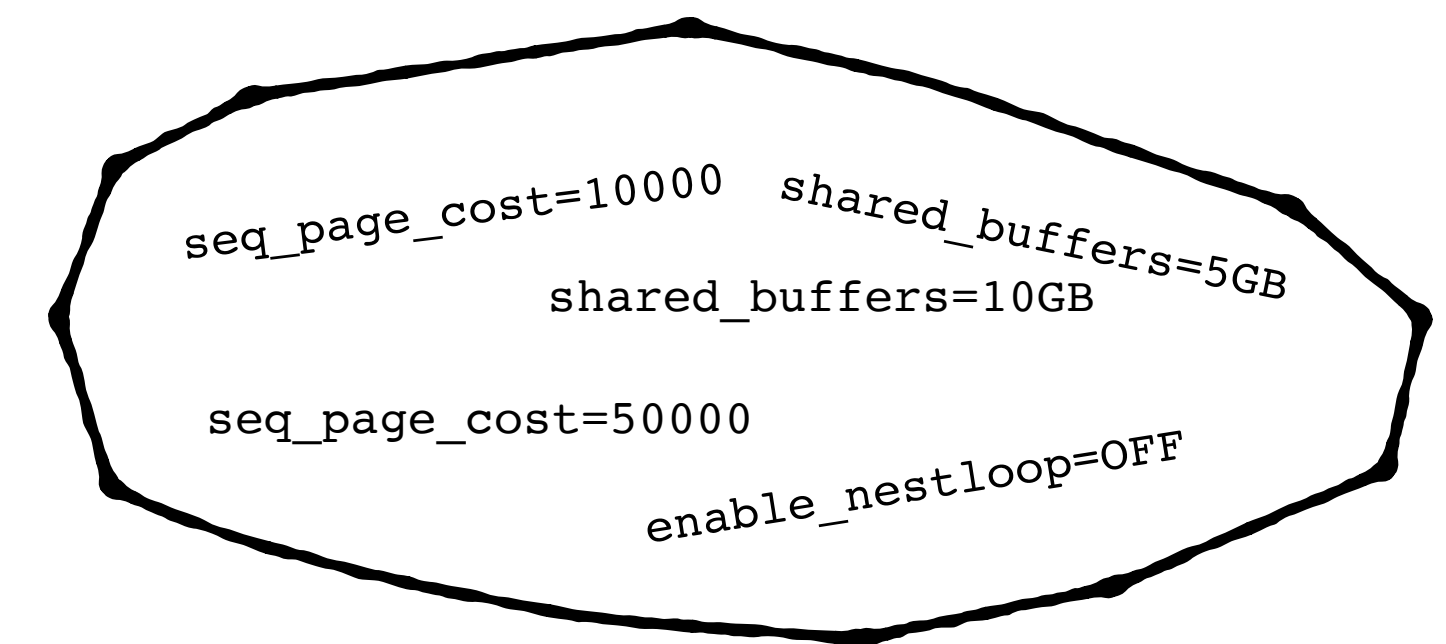
► LLM Usage

- Extract ***individual tuning hints*** from documents
- Still have to deal with a vast search space of ***hint combinations***

LLM



Extract individual hints



Explore Combinations

EXPLOITING THE LATEST ADVANCES OF LARGE LANGUAGE MODELS

- ▶ Latest Language Models support large prompt & response sizes
 - ▶ Not possible with BERT
- ▶ LLMs can be exploited further
 - ▶ Domain-specific tuning practices are *already included in their pre-trained weights*
- ▶ Instead of extracting single hints
 - ▶ Ask the LLM directly for *only a few sets* of full configurations

EXPLOITING THE LATEST ADVANCES OF LARGE LANGUAGE MODELS

BERT

Model

512 Tokens
Input



No generative output
Output

365M Parameters

EXPLOITING THE LATEST ADVANCES OF LARGE LANGUAGE MODELS

BERT

Model

512 Tokens
Input

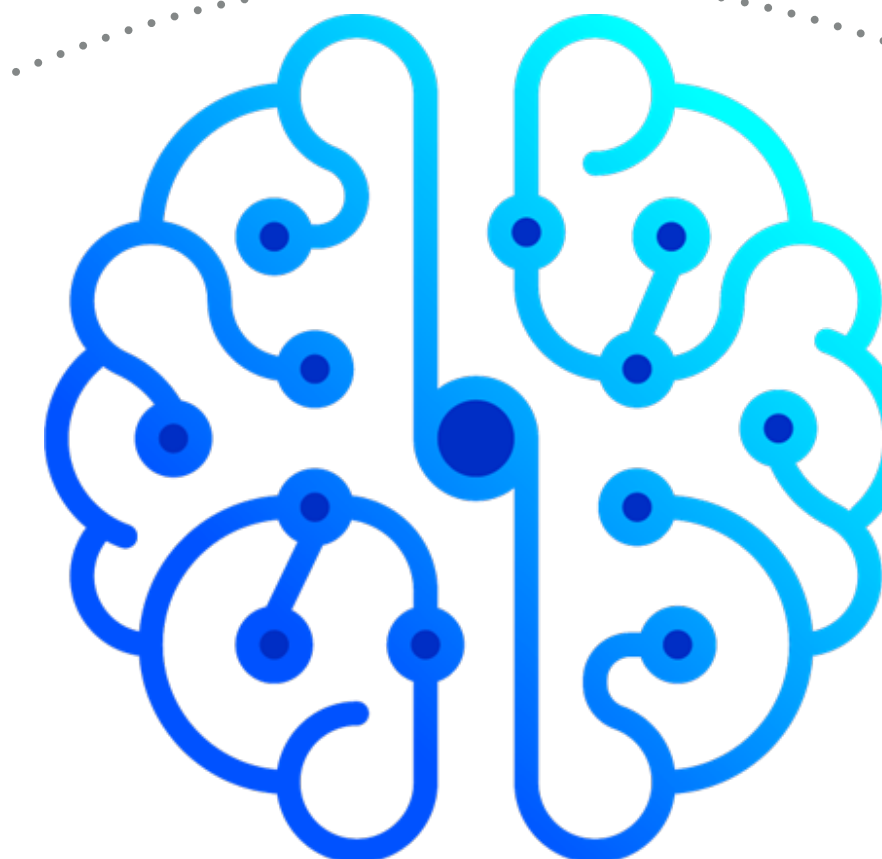


No generative output
Output

365M Parameters

GPT-4

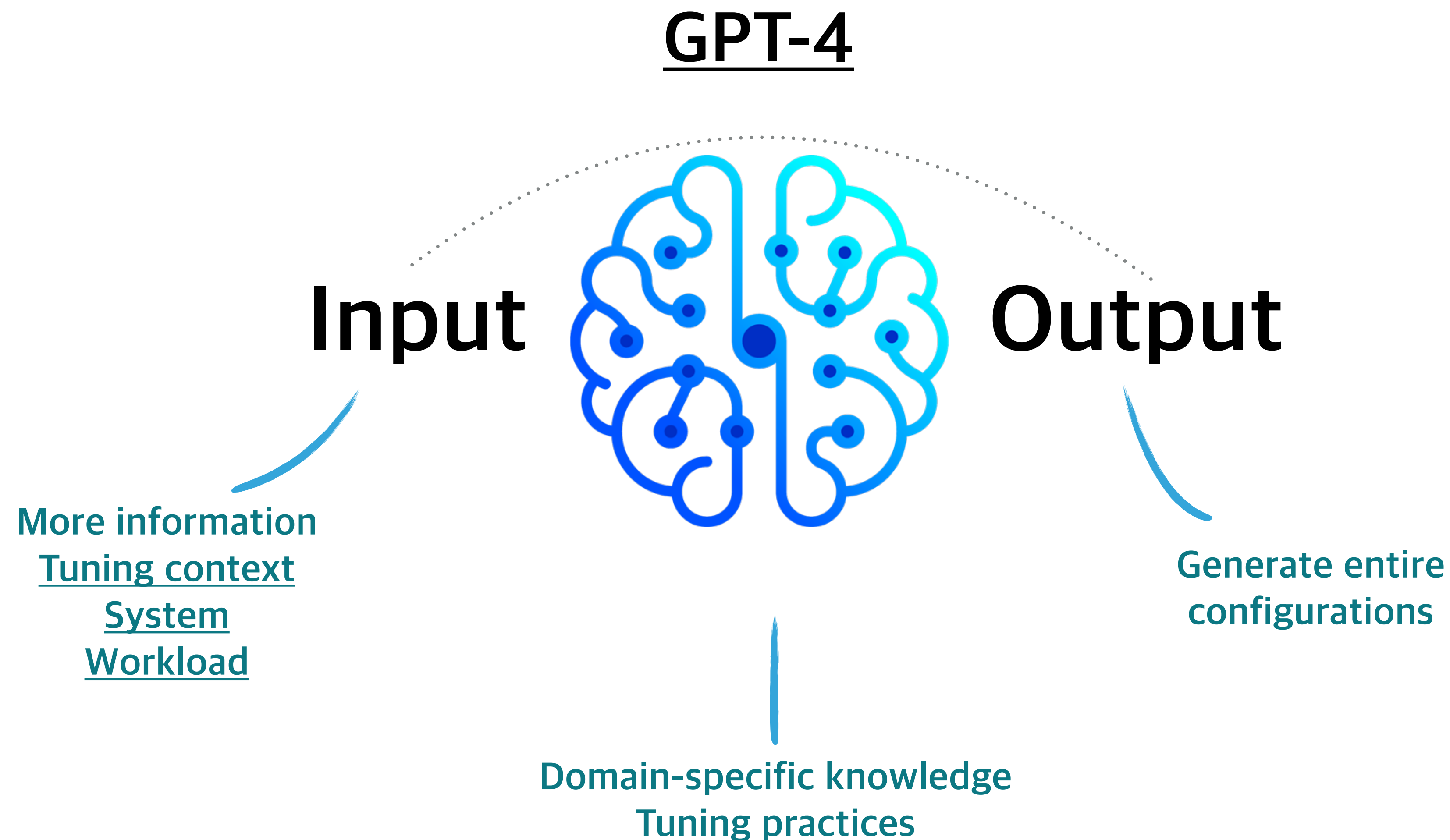
Input



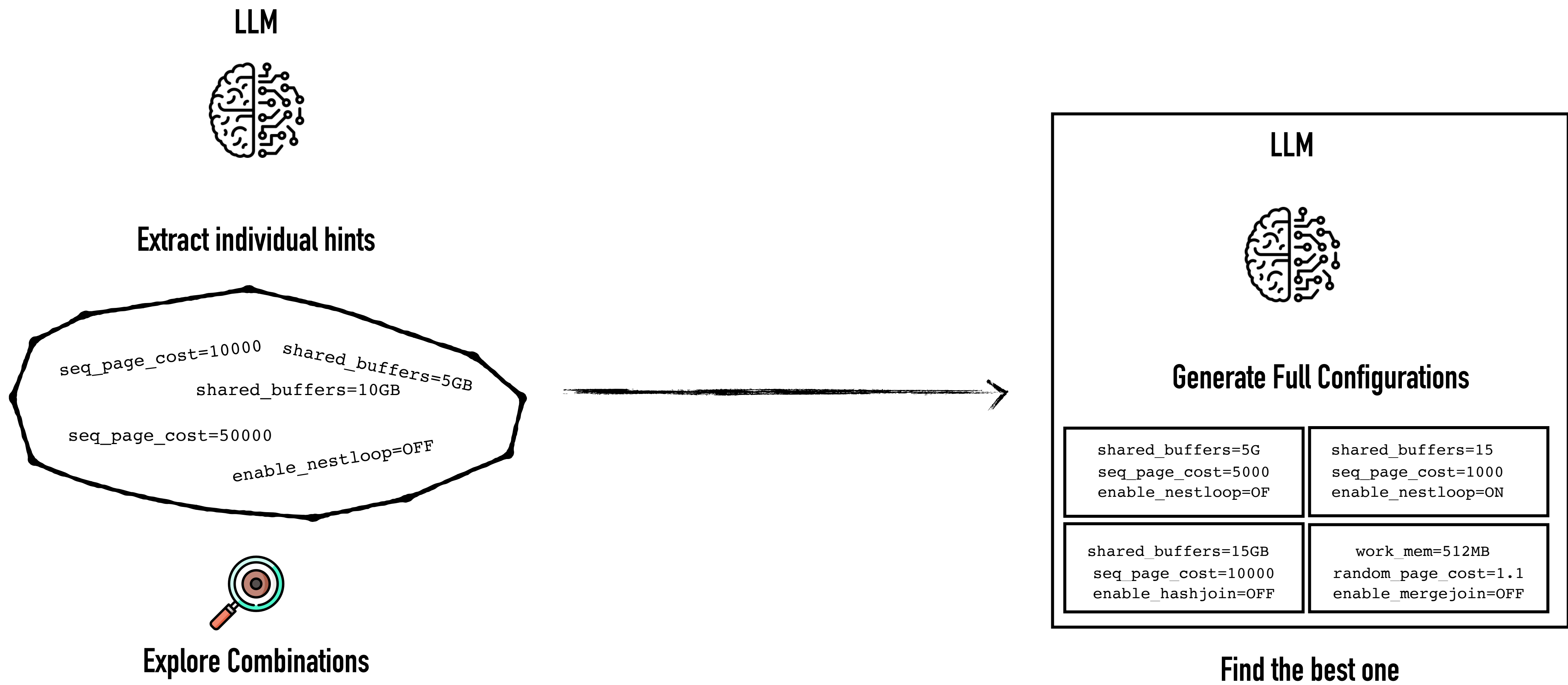
Output

Generative Output

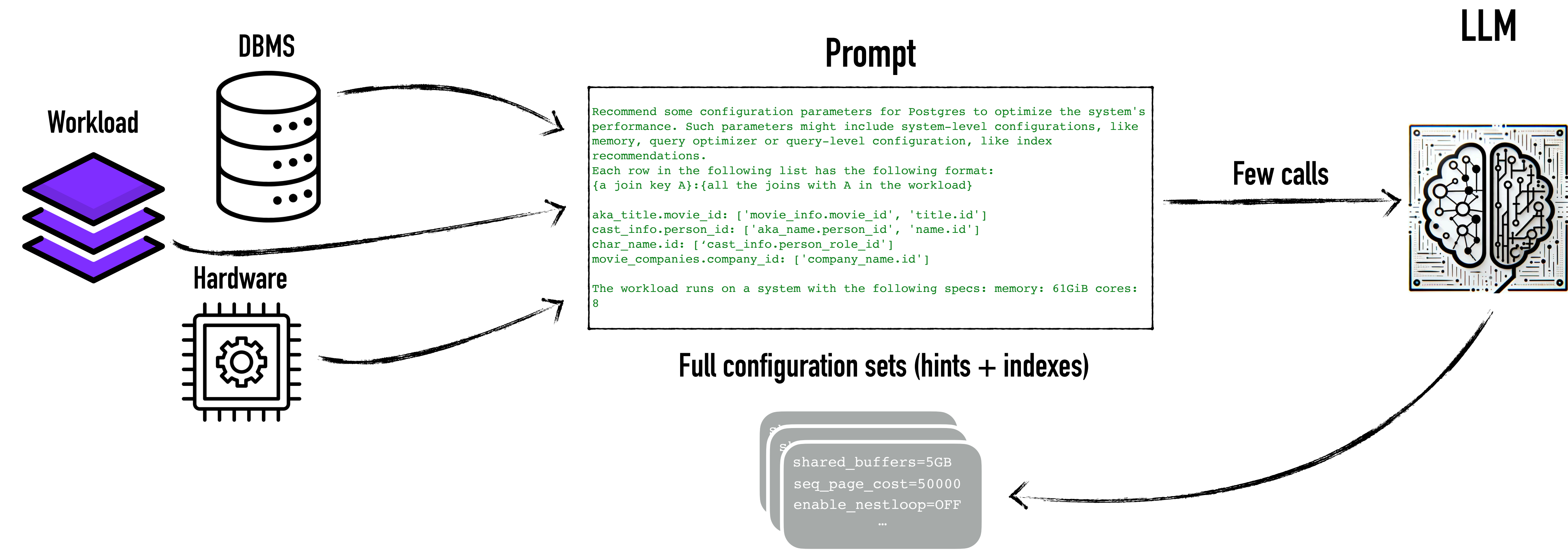
EXPLOITING THE LATEST ADVANCES OF LARGE LANGUAGE MODELS



EXPLOITING THE LATEST ADVANCES OF LARGE LANGUAGE MODELS



λ-Tune



λ-Tune

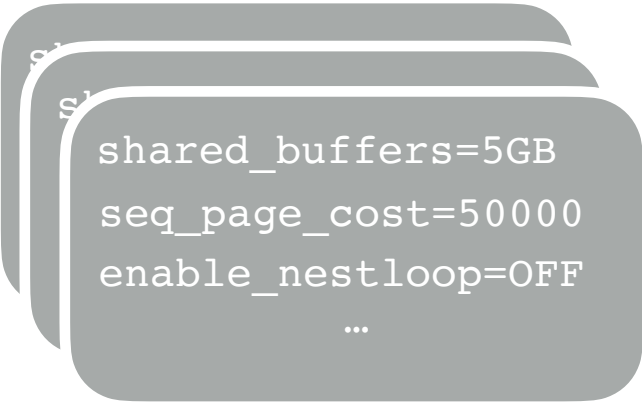
How to generate a good prompt?

```
Recommend some configuration parameters for Postgres to optimize the system's
performance. Such parameters might include system-level configurations, like
memory, query optimizer or query-level configuration, like index
recommendations.
Each row in the following list has the following format:
{a join key A}:{all the joins with A in the workload}

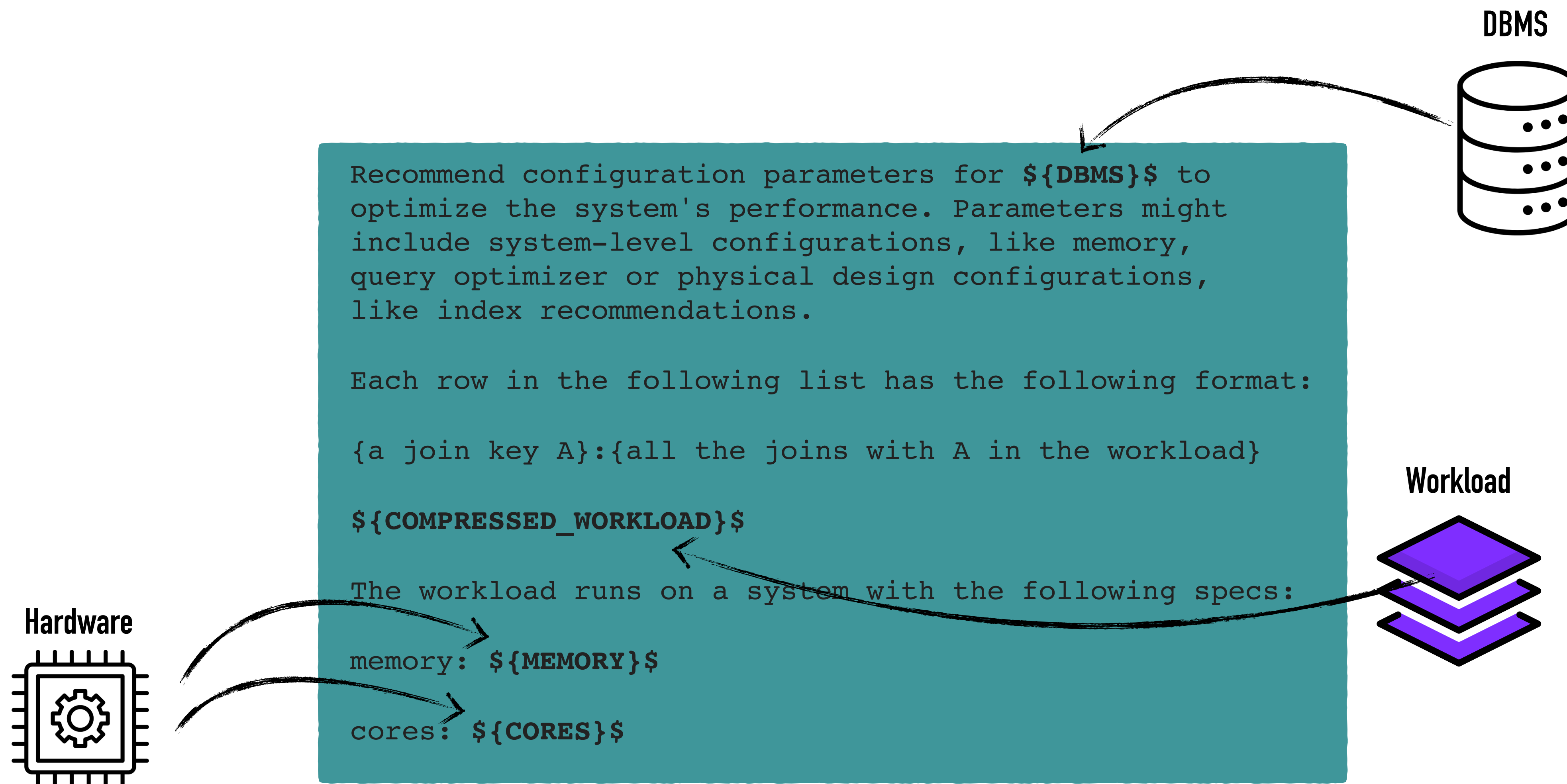
aka_title.movie_id: ['movie_info.movie_id', 'title.id']
cast_info.person_id: ['aka_name.person_id', 'name.id']
char_name.id: ['cast_info.person_role_id']
movie_companies.company_id: ['company_name.id']

The workload runs on a system with the following specs: memory: 61GiB cores:
8
```

How to select among the retrieved configurations?



PROMPT GENERATION – PROMPT TEMPLATE



PROMPT GENERATION – COMPRESSION

Recommend configuration parameters for `${DBMS}$` to optimize the system's performance. Parameters might include system-level configurations, like memory, query optimizer or physical design configurations, like index recommendations.

Each row in the following list has the following format:

`{a join key A}:{all the joins with A in the workload}`

`${COMPRESSED_WORKLOAD}$`

The workload runs on a system with the following specs:

memory: `${MEMORY}$`

cores: `${CORES}$`

PROMPT GENERATION – COMPRESSION

- ▶ Naive approach
 - ▶ Include all the SQL queries of the workload
- ▶ High monetary costs
 - ▶ Pay per token to the LLM provider
 - ▶ Lengthy queries
 - ▶ Redundant information
 - ▶ Queries might be similar (e.g. joins)
- ▶ Large workloads do not even fit in the prompt
 - ▶ Model prompt size limitations

PROMPT GENERATION – COMPRESSION

- ▶ Decompose input queries into smaller components
 - ▶ e.g. joins
- ▶ Select the most important components (operators) with respect to
 - ▶ A user-defined token budget
 - ▶ A computational cost – how expensive an operator is

PROMPT GENERATION – COMPONENT SELECTION

- ▶ Assign each component p to
 - ▶ An execution cost $V(p)$ (the optimizer's estimated cost)
 - ▶ A token size H
- ▶ Integer Linear Program (ILP)
 - ▶ Maximize the value $V(p)$
 - ▶ With a token budget B

Maximize:
$$\sum_{p \in P} V(p) \cdot R_p$$

Subject to:
$$\sum_{\langle c_1, c_2 \rangle \in P} H_{c_2} \cdot R_{\langle c_1, c_2 \rangle} + \sum_{c \in C} H_c \cdot L_c \leq B$$

Query execution plan

```

tpch=# explain select * from orders o, customer c where o_custkey = c_custkey;
                                QUERY PLAN
-----
Hash Join  (cost=69577.00..519864.11 rows=15000000 width=265)
  Hash Cond: (o.o_custkey = c.c_custkey)
    -> Seq Scan on orders o  (cost=0.00..410912.00 rows=15000000 width=107)
    -> Hash  (cost=50827.00..50827.00 rows=1500000 width=158)
          -> Seq Scan on customer c  (cost=0.00..50827.00 rows=1500000 width=158)

JIT:
  Functions: 10
  Options: Inlining true, Optimization true, Expressions true, Deforming true
(8 rows)

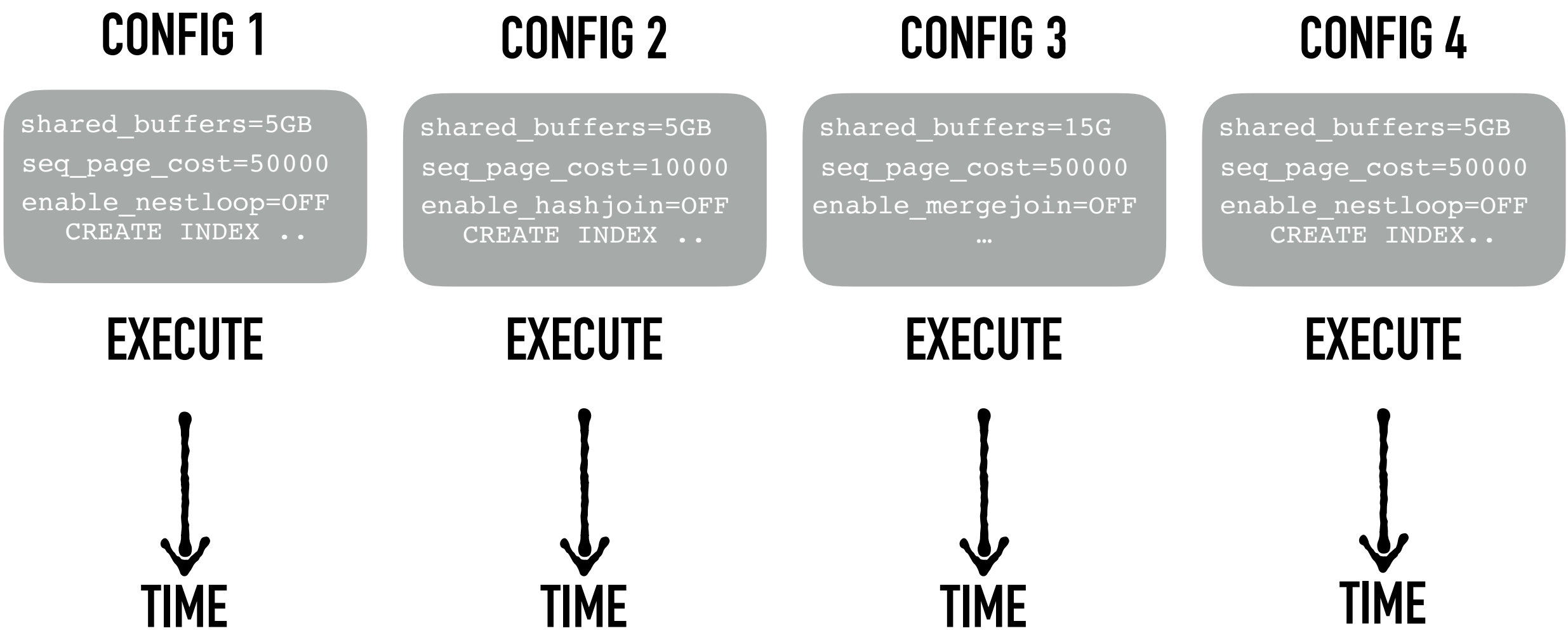
```

(Obtained using the EXPLAIN clause)

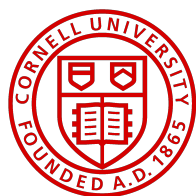
CONFIGURATION SELECTION

Evaluate all configurations in a random order

- 1. Reconfigure the system
- 2. Run all queries
- 3. Find the optimal configuration

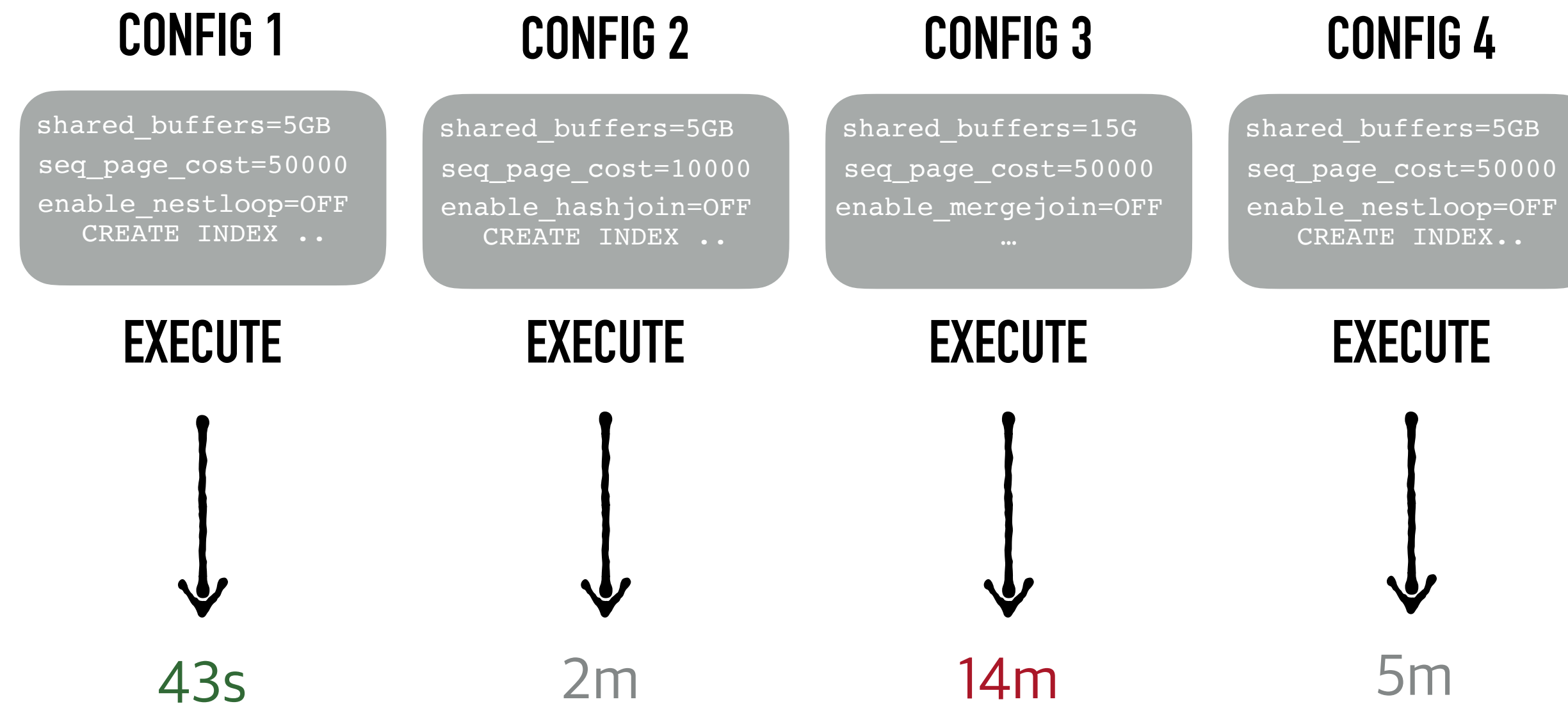


PICK THE CONFIGURATION THAT ACHIEVES THE MINIMUM EXECUTION TIME



CONFIGURATION SELECTION

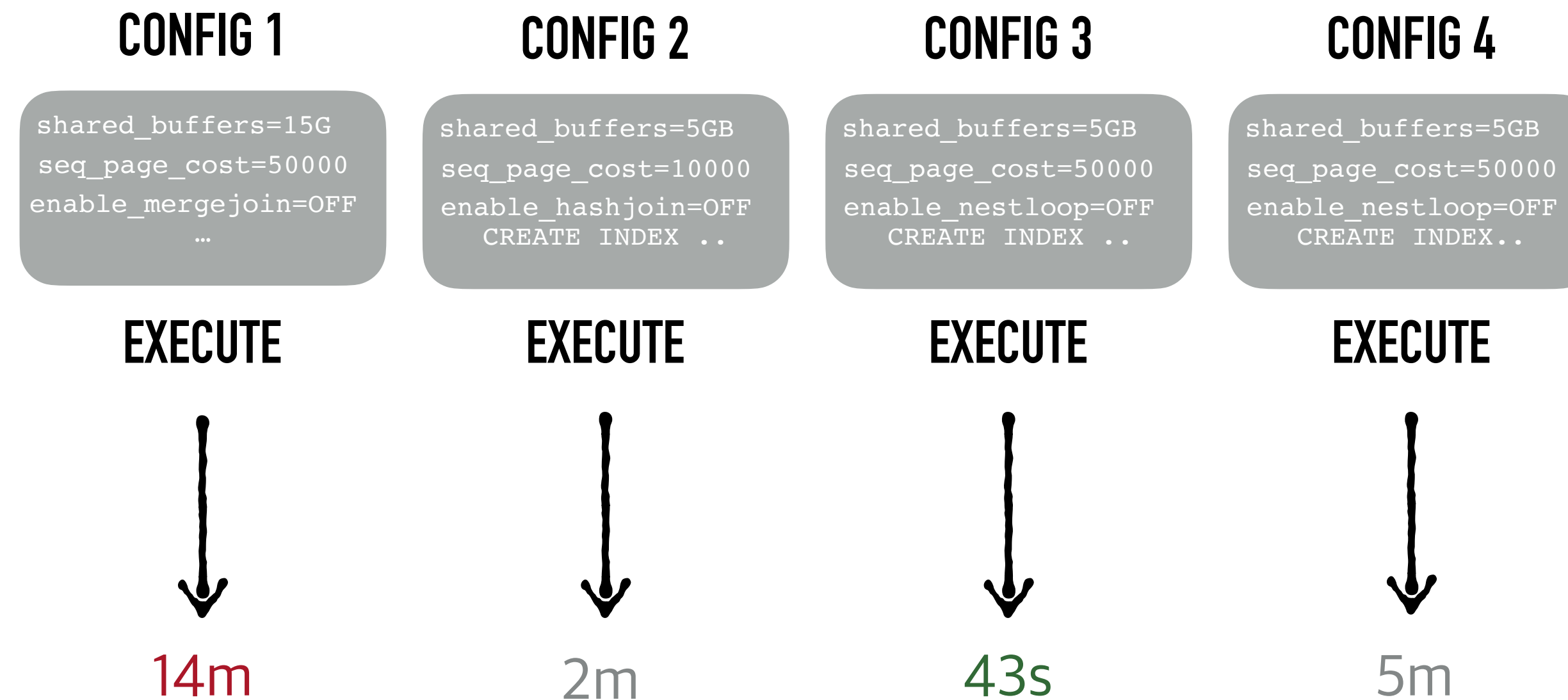
The execution order matters



Set 43s as the timeout for the rest

CONFIGURATION SELECTION

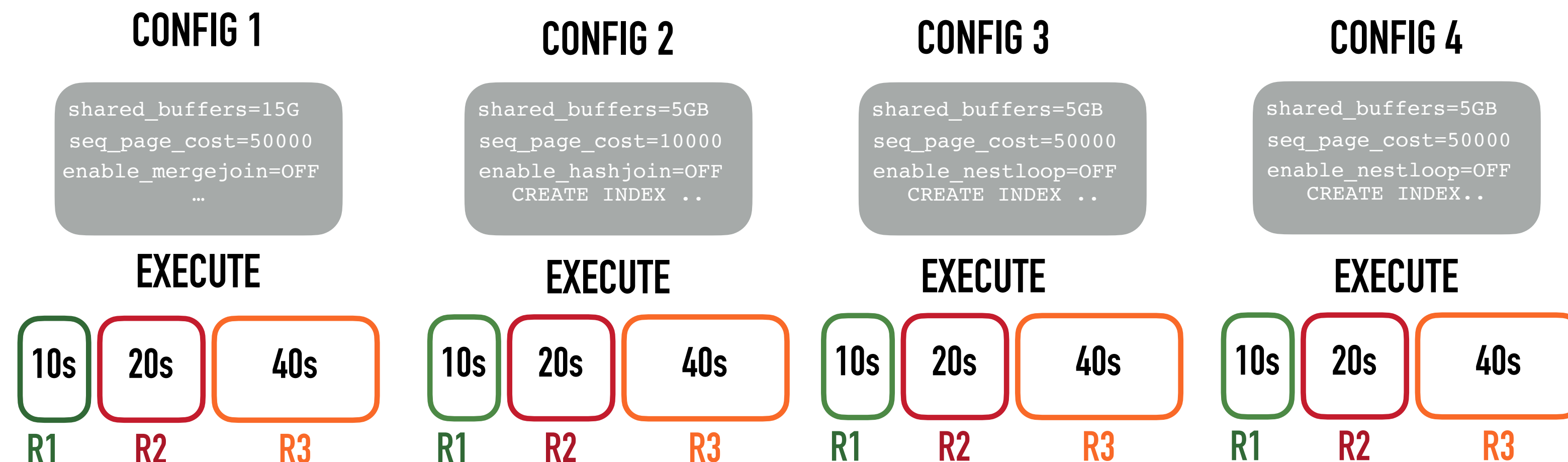
The execution order matters



Need to spend 14 minutes before finding a good configuration

CONFIGURATION SELECTION – EVALUATION ROUNDS

Allocate each configuration equal execution time per round

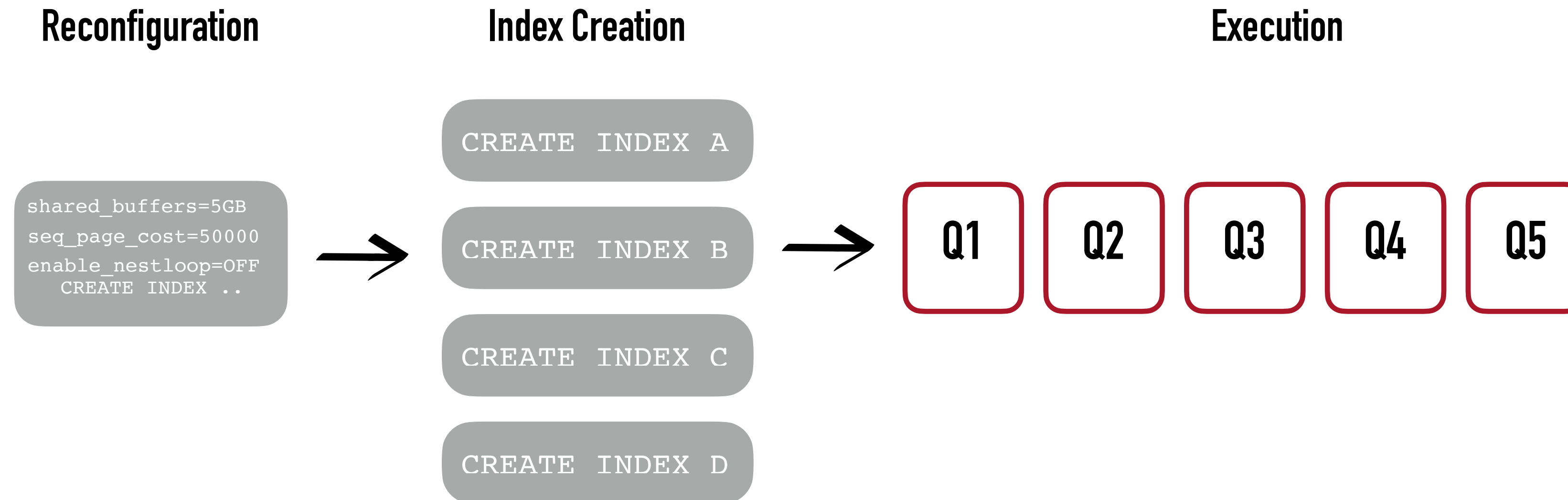


Execution time follows a geometric progression

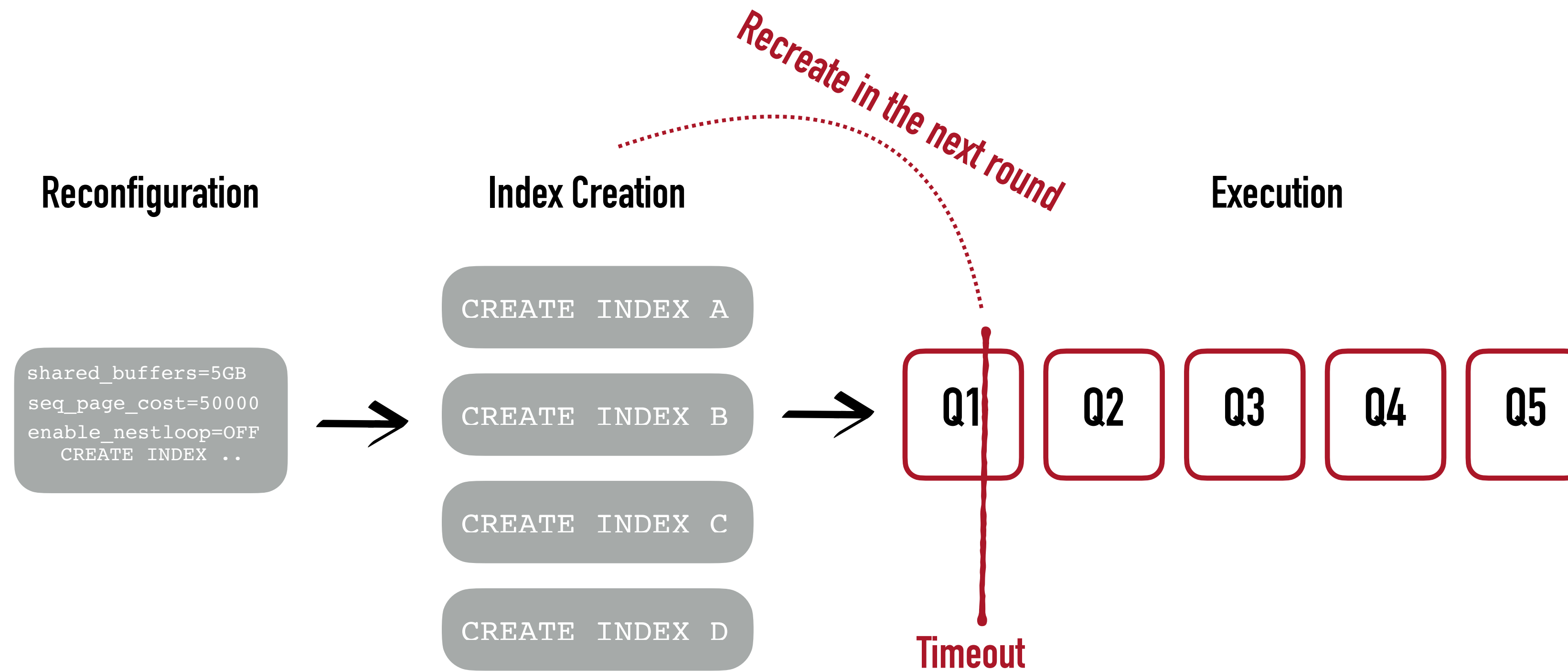
Given an initial timeout \underline{r} and a factor \underline{a}

$$R_1 = r \cdot a^0, R_2 = r \cdot a^1, R_3 = r \cdot a^2, \dots, R_n = r \cdot a^{n-1}$$

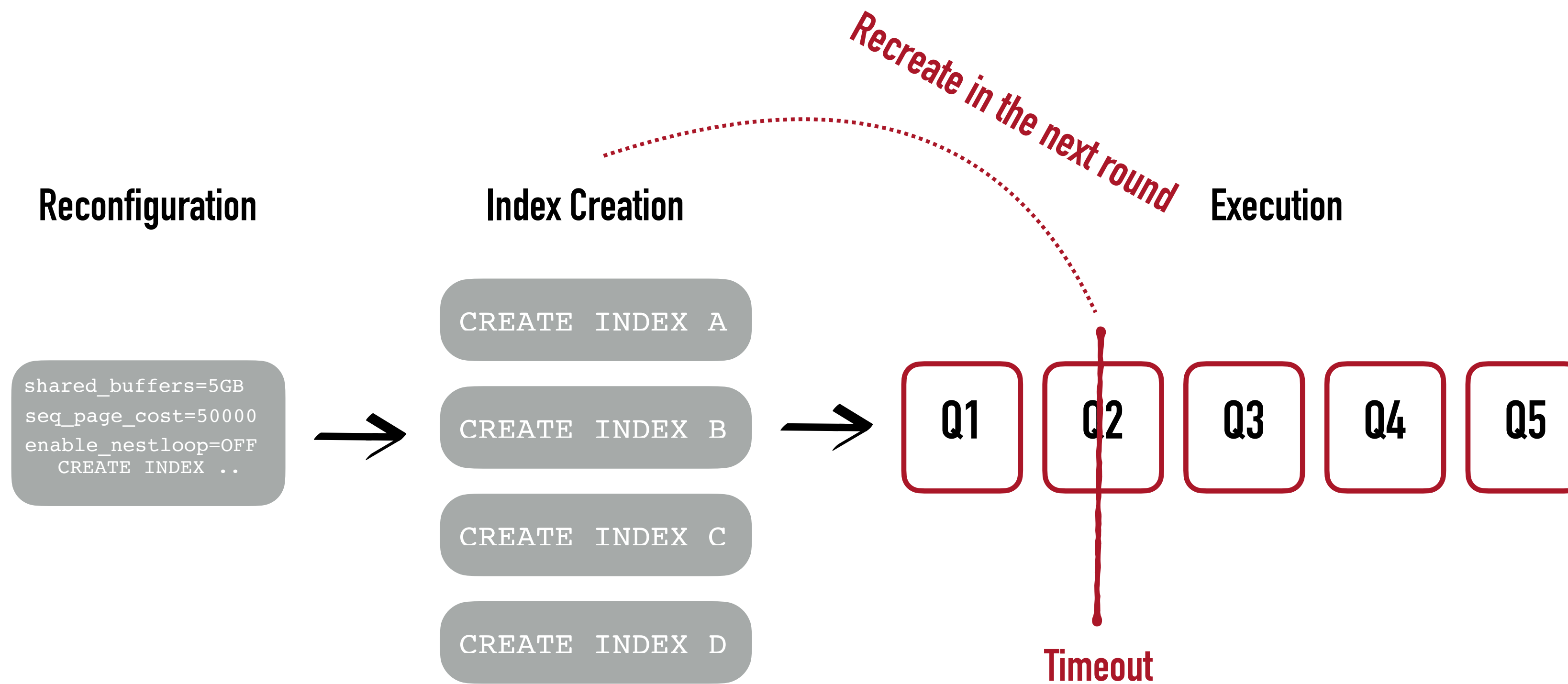
QUERY SCHEDULING



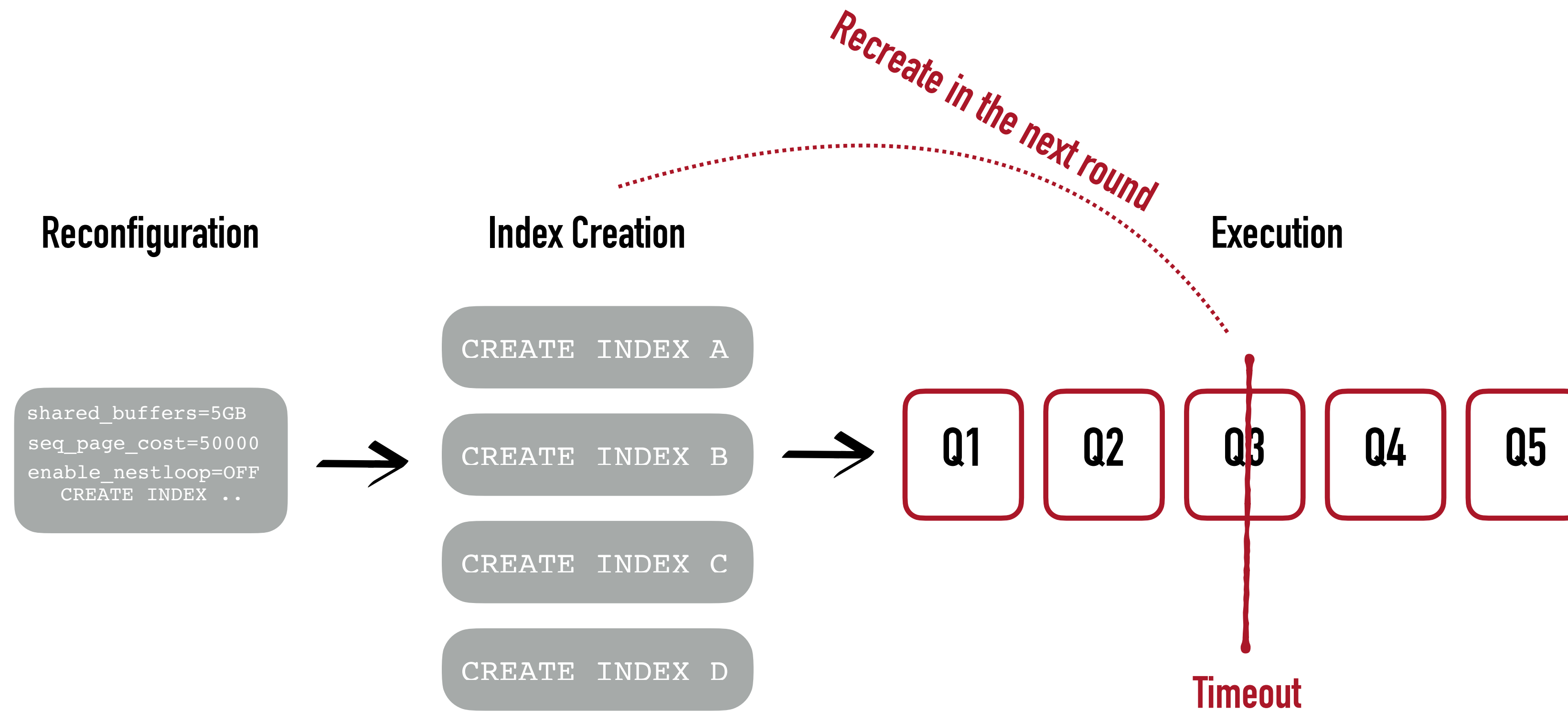
QUERY SCHEDULING



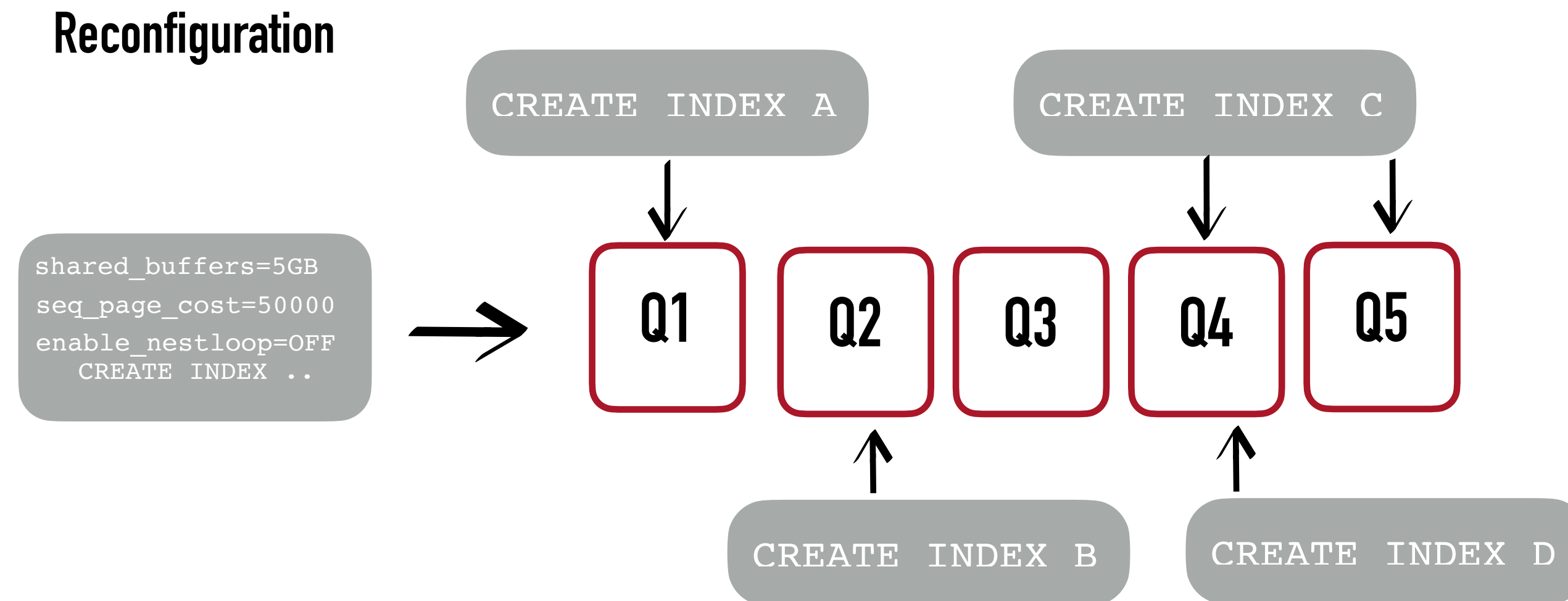
QUERY SCHEDULING



QUERY SCHEDULING



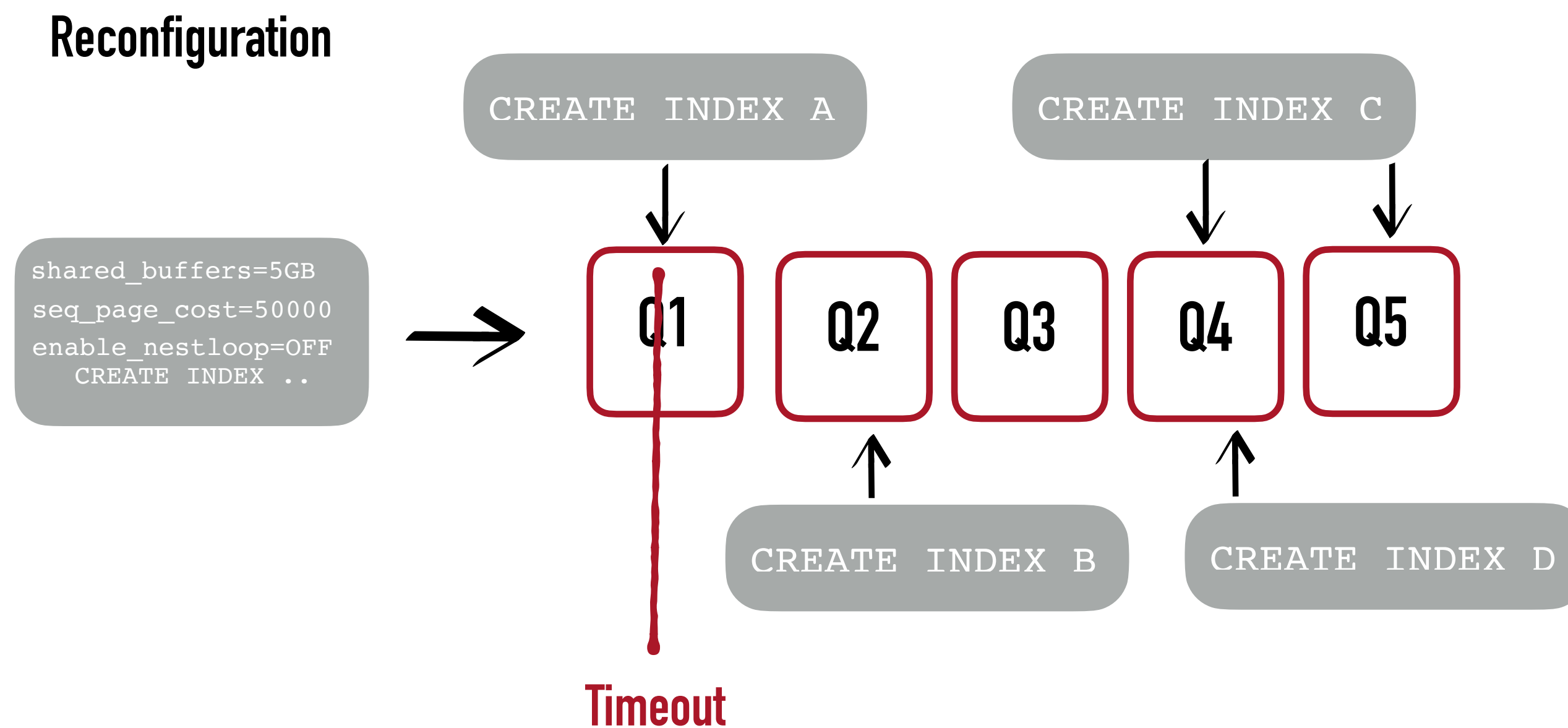
QUERY SCHEDULING



Interleave query execution with index creation

Lazy index creation

QUERY SCHEDULING



If the timeout is exceeded, we only pay the cost of the necessary indexes in each round

According to the index creation cost, we optimally order the queries using a dynamic programming approach

EXPERIMENTAL EVALUATION

▸ Setup

- p3.2xlarge EC2 Instance (AWS) with GPU
 - 8 vCPUs
 - 61 GiB Memory

▸ Benchmarks

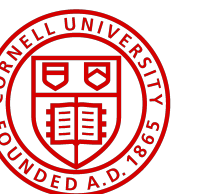
- Join Order Benchmark (JOB)
- TPC-H 1GB / 10GB
- TPC-DS

▸ Database Systems

- Postgres
- MySQL

▸ Baselines

- DB-BERT, GPTuner
- UDO, MLOS (LlamaTune), ParamTree,
- Indexes
 - Dexter
 - DB2Advisor

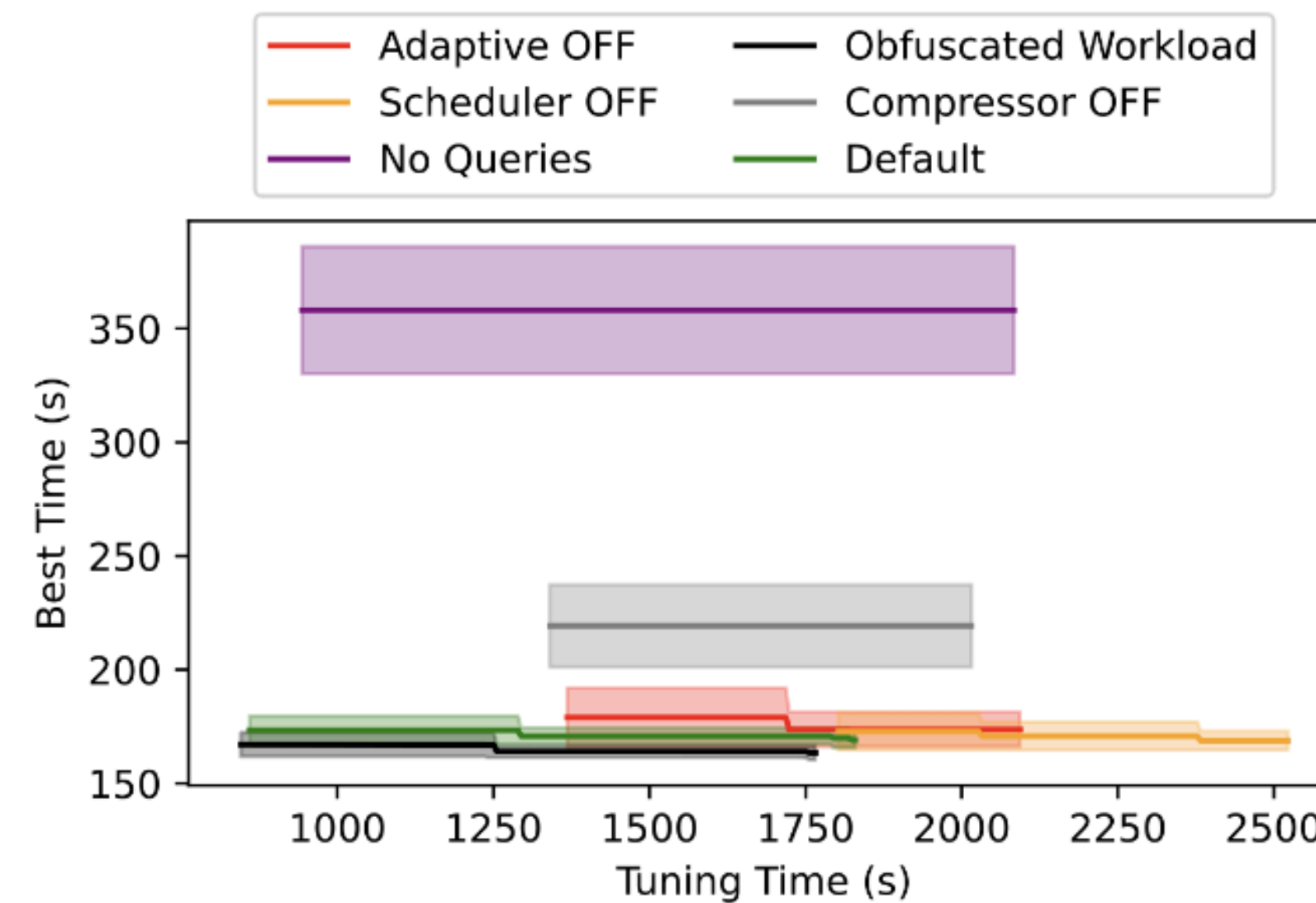


ABLATION STUDY

Is the LLM aware of the input workload? (— Obfuscated Workload)

Is the compression important? (— Compressor OFF)

Does the scheduler accelerates the tuning process? (— Scheduler OFF)

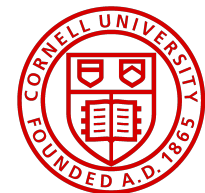


Join Order Benchmark (JOB) over Postgres

EXPERIMENTAL EVALUATION – SUMMARY

COST OF THE BEST CONFIGURATION FOUND BY EACH APPROACH, SCALED TO THE BEST CONFIGURATION OVERALL

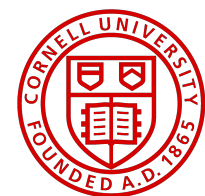
Benchmark	DBMS	Initial Indexes	λ-Tune	UDO	DB-Bert	GPTuner	LlamaTune	ParamTree
TPC-H 1GB	PG	Yes	1.07	1.96	1.13	1	2.08	3.23
TPC-H 1GB	MS	Yes	1.06	1	1.02	1.73	1.39	3.24
TPC-H 10GB	PG	Yes	1.03	1	1.05	1.04	2.38	3.18
TPC-H 10GB	MS	Yes	4.98	1	5.16	5.84	2.86	15.2
JOB	PG	Yes	1	1.32	1.05	1.1	3.48	3.48
JOB	MS	Yes	1	1.07	3.69	3.69	3.22	3.22
TPC-H 1GB	PG	No	1.05	3.76	1	1.06	1.43	4.24
TPC-H 1GB	MS	No	1.2	2.83	1.02	1	1.61	3.64
TPC-H 10GB	PG	No	1.65	1.54	2.45	2.52	1	1.54
TPC-H 10GB	MS	No	1.04	3.2	1.09	1	1.88	3.2
JOB	PG	No	1	1.69	1.08	1.13	3.09	3.26
JOB	MS	No	1	3.07	3.07	3.07	3.07	3.07
TPC-DS	PG	No	1	1.37	1.67	1.66	3.33	3.33
TPC-DS	MS	No	1.79	3.25	1	1.03	1.05	3.25
Average			1.41	2	1.82	1.91	2.27	4.07



EXPERIMENTAL EVALUATION – SUMMARY

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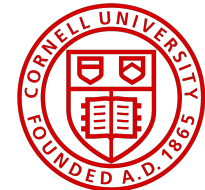
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Average			1.41	2	1.82	1.91	2.27	4.07



CONCLUSIONS

- ▶ Large Language Models can significantly enhance the tuning process
 - ▶ Can speed-up automated tuning
- ▶ Latest advancements in LLMs motivate design changes
 - ▶ Full configuration generation
- ▶ λ -Tune
 - ▶ Prompting – workload compression with ILP
 - ▶ Efficient evaluation – minimize time spent in inefficient configurations

QUESTIONS?

