

RocksDB Festival

RF5_Team_Key_Value

Supported by IITP, StarLab.

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Docks

- 1. Team
- 2. db_bench Experiment
 - ✓ 1. key_size
 - ✓ 2. value_size
 - ✓ 3. data_size
- 3. Topic: Key-value
- 4. Goals
 - ✓ 1. Latest research trends
 - Characterizing, Modeling, and Benchmarking RocksDB Key-Value Workloads at Facebook
 - ✓ 2. Research topic
 - ✓ 3. Final goal

1. Team

■ Team: Docks

■ Member

- ✓ Minguk Choi 최민국 [Leader]
 - koreachoi96@gmail.com
 - www.github.com/korea-choi
- ✓ Jungwon Lee 이정원
 - gardenlee960828@gmail.com
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- ✓ Guangxun shin 좌오꾸와썬
 - guangxun0621@naver.com
 - www.github.com/GUANG32194441



2. db_bench Experiment

■ 0. Experiment subject

- ✓ Check out read/write throughput when [key/value/data] size changes
 - Just to be familiar with rocksdb & db_bench
 - Just simple experiment

```
Initializing RocksDB Options from the specified file
Initializing RocksDB Options from command-line flags
RocksDB: version 6.22
Date: Sun Jul 18 16:50:59 2021
CPU: 4 * Intel(R) Core(TM) i3-2100 CPU @ 3.10GHz
CPUCache: 3072 KB
Keys: 16 bytes each (+ 0 bytes user-defined timestamp)
Values: 100 bytes each (50 bytes after compression)
Entries: 10000000
Prefix: 0 bytes
Keys per prefix: 0
RawSize: 1106.3 MB (estimated)
FileSize: 629.4 MB (estimated)
Write rate: 0 bytes/second
Read rate: 0 ops/second
Compression: Snappy
Compression sampling rate: 0
Memtablerep: skip_list
Perf Level: 1
WARNING: Assertions are enabled; benchmarks unnecessarily slow
```

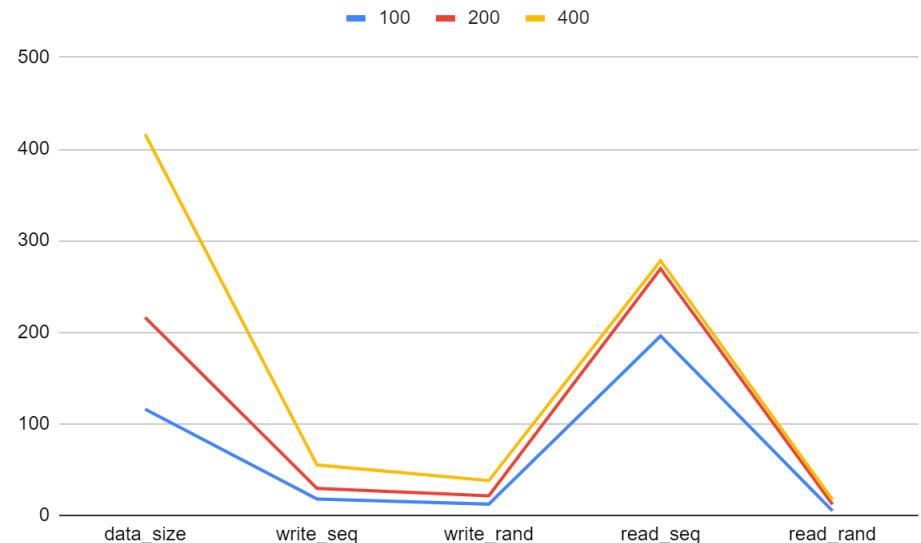
2. db_bench Experiment

■ 1. Value_size

✓ Workload

- Key_size = 16 Byte / Data_number = 10,000,000
- Value_size = 100/200/400Byte
- write_seq / write_rand / read_seq / read_rand

value_size (B)	data_size	write_seq	write_rand	read_seq	read_rand
100	116	17.8	12.3	195.9	5
200	216	29.4	21.3	269.2	12.1
400	416	55	38	278	17
Ratio (/K16-V100)					
K16-V100	1.00	1.00	1.00	1.00	1.00
K16-V200	1.86	1.65	1.73	1.37	2.42
K16-V400	3.59	3.09	3.09	1.42	3.40



✓ value size \propto throughput ? Yes

- the bigger value size, the better performance? Maybe Not.
- More flush/compactions, longer total execution time

2. db_bench Experiment

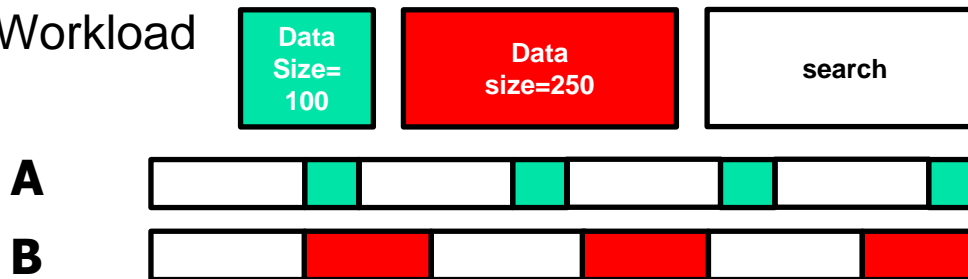
■ 1. Value_size

✓ Why?

- Data size is different.

✓ EX.

- Workload



- $\text{Throughput} = \frac{\text{read_data}}{\text{time}}$ -> $T_a < T_b$
-> B's performance is better than A?

✓ Data size \propto throughput

✓ If data size is different, how about comparing performance with...

- Compaction number
- Total execution time

Ratio = [K16, V100/200/400] value / [K16, V100] value

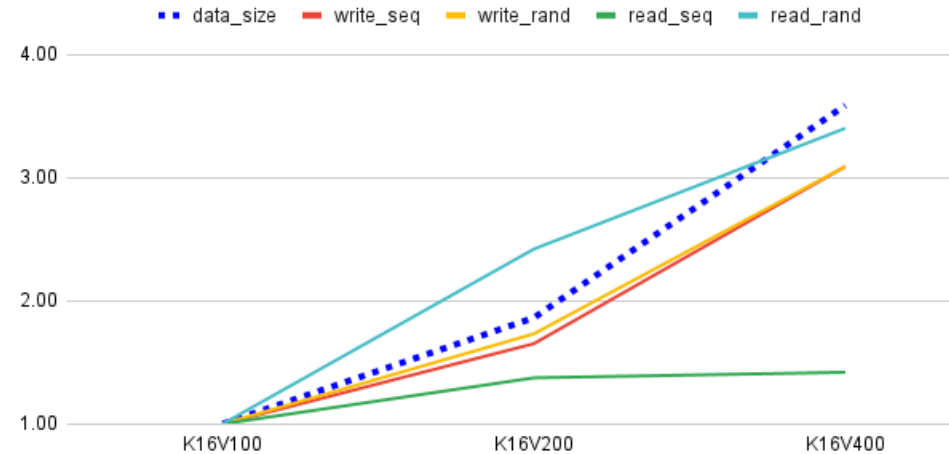
2. db_bench Experiment

■ 1. Value_size

✓ Ratio

- [K16/32/64, V100/200/400] value / [K16, V100] value

value_size (B)	data_size	write_seq	write_rand	read_seq	read_rand
100	116	17.8	12.3	195.9	5
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K16-V400	3.59	3.09	3.09	1.42	3.40



✓ data size \propto throughput ? Yes

✓ if data size is different,

- maybe throughput would **not be the appropriate metrics.**

2. db_bench Experiment

■ 2. Key_size

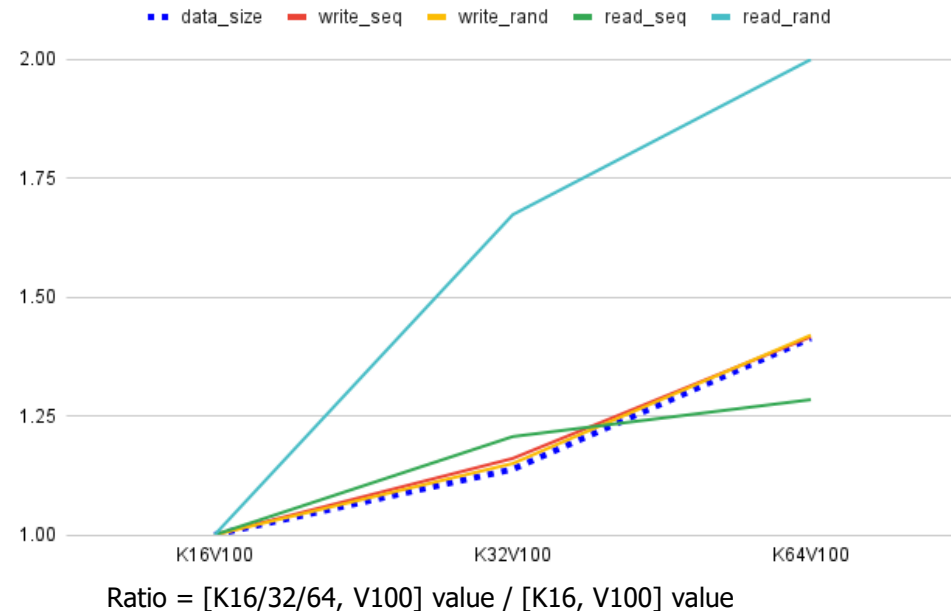
✓ Workload

- Key_size = 16/32/64 Byte
- Value_size = 100 Byte / Data_number = 10,000,000
- write_seq/write_rand/read_seq/read_rand

✓ The bigger the key size, the bigger **overhead**? Maybe yes

-> But **data size is much more critical**

value_size	data_size	write_seq	write_rand	read_seq	read_rand
16 B	116	16.8	11.8	193.1	4.9
32 B	132	19.5	13.7	233	8.2
64 B	164	23.8	16.7	248	9.8
Ratio (/K16-V100)	data_size	write_seq	write_rand	read_seq	read_rand
K16-V100	1.00	1.00	1	1.00	1.00
K32-V100	1.14	1.16	1.15	1.21	1.67
K64-V100	1.41	1.42	1.42	1.28	2.00



2. db_bench Experiment

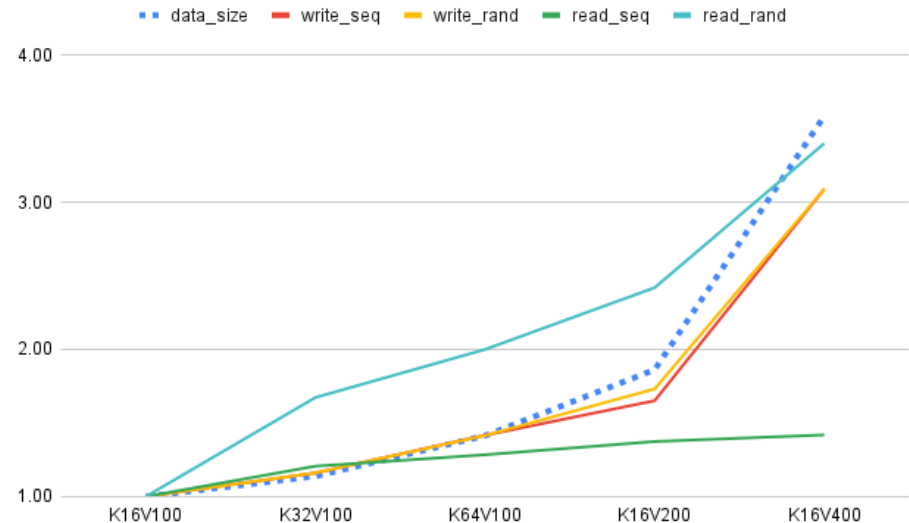
■ 3. Data_size

✓ Workload

- Key_size = 16/32/64 Byte / Value_size = 100/200/400 Byte
- Data_number = 10,000,000
- write_seq/write_rand/read_seq/read_rand

data_size (B)	write_seq	write_rand	read_seq	read_rand
116	17.8	12.3	195.9	5
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K64-V100	1.41	1.42	1.42	1.28	2.00
K16-V200	1.86	1.65	1.73	1.37	2.42
K16-V400	3.59	3.09	3.09	1.42	3.40



Ratio = [K16/32/64, V100/200/400] value / [K16, V100] value

✓ Why read_ratio is not directly proportional?

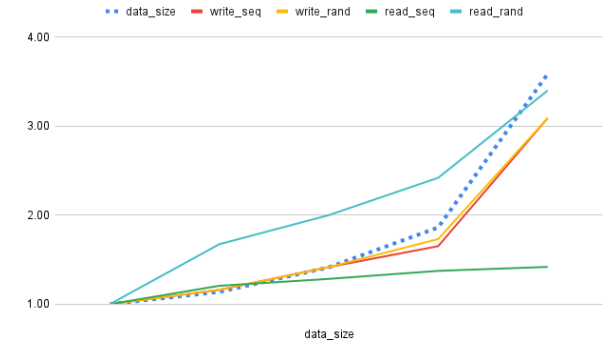
2. db_bench Experiments

■ 4. Why read_ratio is not directly proportional

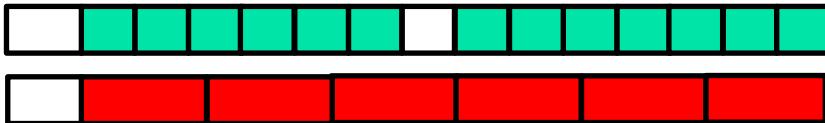
✓ **Workload**



✓ **Throughput** = $\frac{\text{read_data}}{\text{time}}$

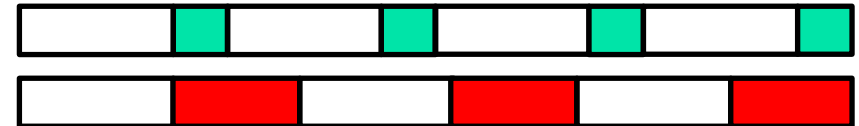


✓ **read_sequential: iterator**



```
void ReadSequential(ThreadState* thread, DB* db) {
    Iterator* iter = db->NewIterator(options);
    int64_t i = 0;
    int64_t bytes = 0;
    for (iter->SeekToFirst(); i < reads_ && iter->Valid(); iter->Next()) {
        bytes += iter->key().size() + iter->value().size();
        thread->stats.FinishedOps(nullptr, db, 1, kRead);
        ++i;
    }
}
```

✓ **read_random: Get**



```
void ReadRandom(ThreadState* thread) {
    if (FLAGS_num_column_families > 1) {
        s = db_with_cfh->db->Get(options, db_with_cfh->GetCfh(key_rand), key,
                                &pinnable_val, ts_ptr);
    } else {
        s = db_with_cfh->db->Get(options,
                                db_with_cfh->db->DefaultColumnFamily(), key,
                                &pinnable_val, ts_ptr);
    }
}
```

2. db_bench Experiments

■ 5. Summary

- ✓ data size \propto throughput
 - the higher **throughput**, the better **performance**? **Maybe Not.**
- ✓ if data size is different,
 - throughput would **may not be the appropriate metrics.**
 - compare with Compaction number/Total execution time
- ✓ Why read_ratio is not directly proportional?
 - read_sequential: **Iterator**
 - read_random: **Get**

3. Topic: Key/Value

■ RocksDB is Key/Value DB

Welcome to RocksDB

RocksDB is a storage engine with key/value interface, where keys and values are arbitrary byte streams. It is a C++ library. It was developed at Facebook based on LevelDB and provides backwards-compatible support for LevelDB APIs.

RocksDB supports various storage hardware, with fast flash as the initial focus. It uses a Log Structured Database Engine for storage, is written entirely in C++, and has a Java wrapper called RocksJava. See [RocksJava Basics](#).

RocksDB can adapt to a variety of production environments, including pure memory, Flash, hard disks or remote storage. Where RocksDB cannot automatically adapt, highly flexible configuration settings are provided to allow users to tune it for them. It supports various compression algorithms and good tools for production support and debugging.

4. Goal

■ 1. Latest research trends: Key Trace

Characterizing, Modeling, and Benchmarking RocksDB Key-Value Workloads at Facebook

Zhichao Cao, *University of Minnesota, Twin Cities, and Facebook*;

Siying Dong and Sagar Vemuri, *Facebook*;

David H.C. Du, *University of Minnesota, Twin Cities*

<https://www.usenix.org/conference/fast20/presentation/cao-zhichao>

The slide is a presentation slide from FAST '20. On the left, it features the **usenix** logo (THE ADVANCED COMPUTING SYSTEMS ASSOCIATION) and the **FAST '20** logo. Below these is the text "Open Access Sponsor" followed by the **NetApp** logo. A small inset image shows a speaker at a podium. The main content area is titled "Real World Workload" in red. It contains a diagram with a blue box at the top labeled "Production Workloads from Different Applications" and a white box at the bottom labeled "RocksDB" with a yellow cheetah logo. An arrow points from the RocksDB box up to the Production Workloads box. The **facebook** logo is at the bottom left of the main content area. In the bottom right corner, there are logos for **M** (University of Minnesota) and **CRTS** (Center for Research in Technology and Society).

Source: FAST '20 - Characterizing, Modeling, and Benchmarking RocksDB Key-Value Workloads at Facebook (<https://youtu.be/MZTSjBERXVc>)

4. Goal

■ 1. Latest research trends: Key Trace

Characterizing, Modeling, and Benchmarking RocksDB Key-Value Workloads at Facebook

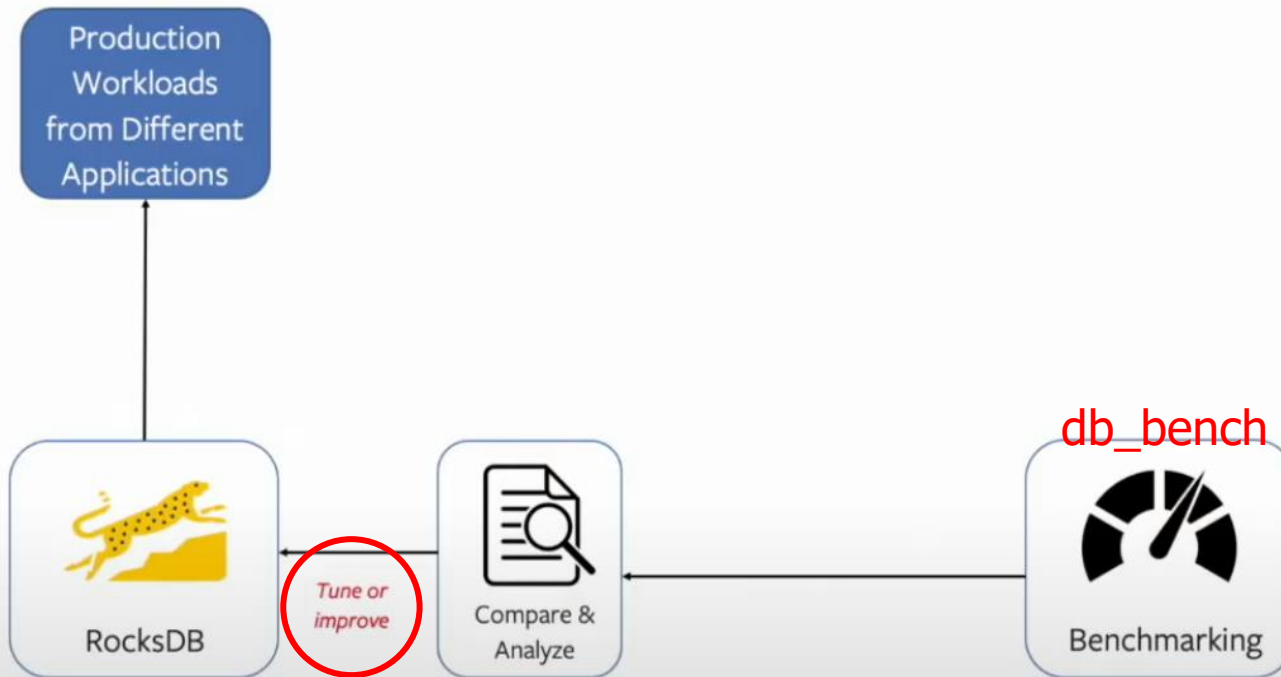
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Real World
Workload



4. Goal

■ 1. Latest research trends: Key Trace

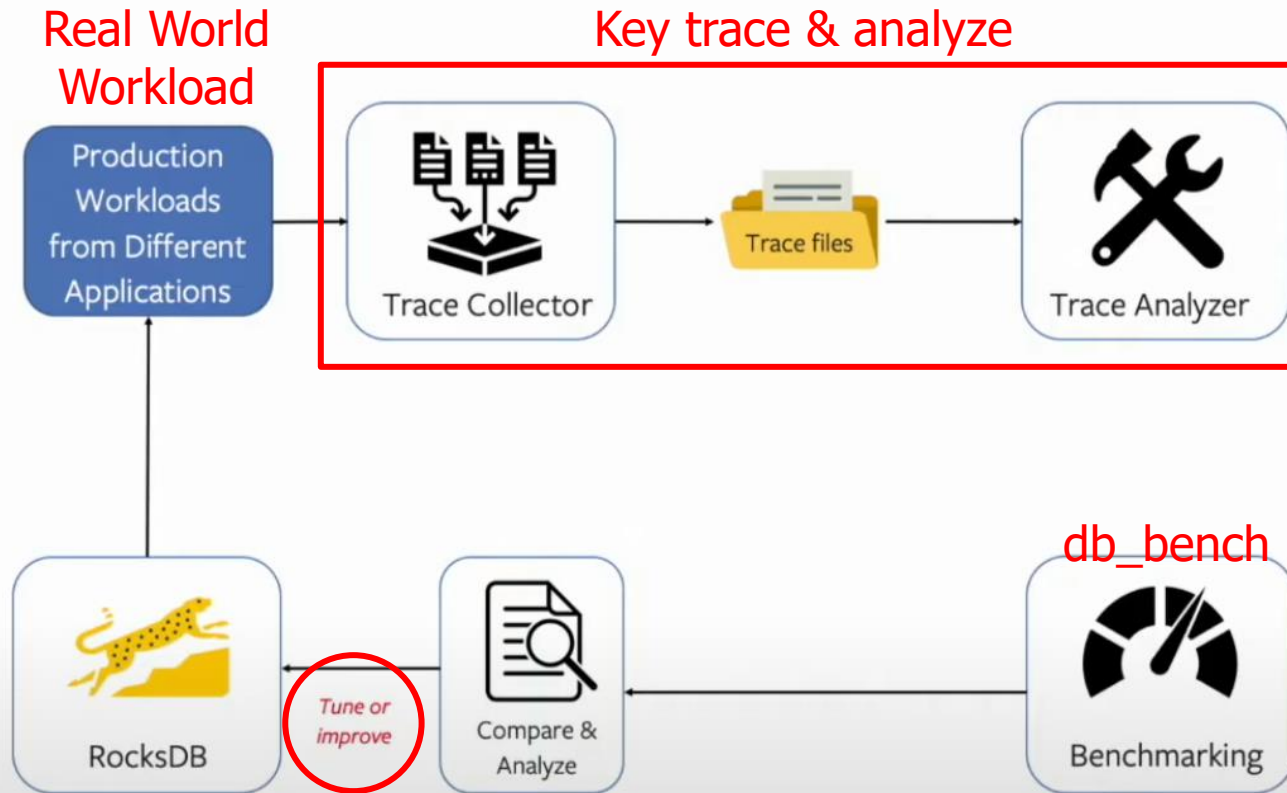
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4. Goal

■ 1. Latest research trends: Key Trace

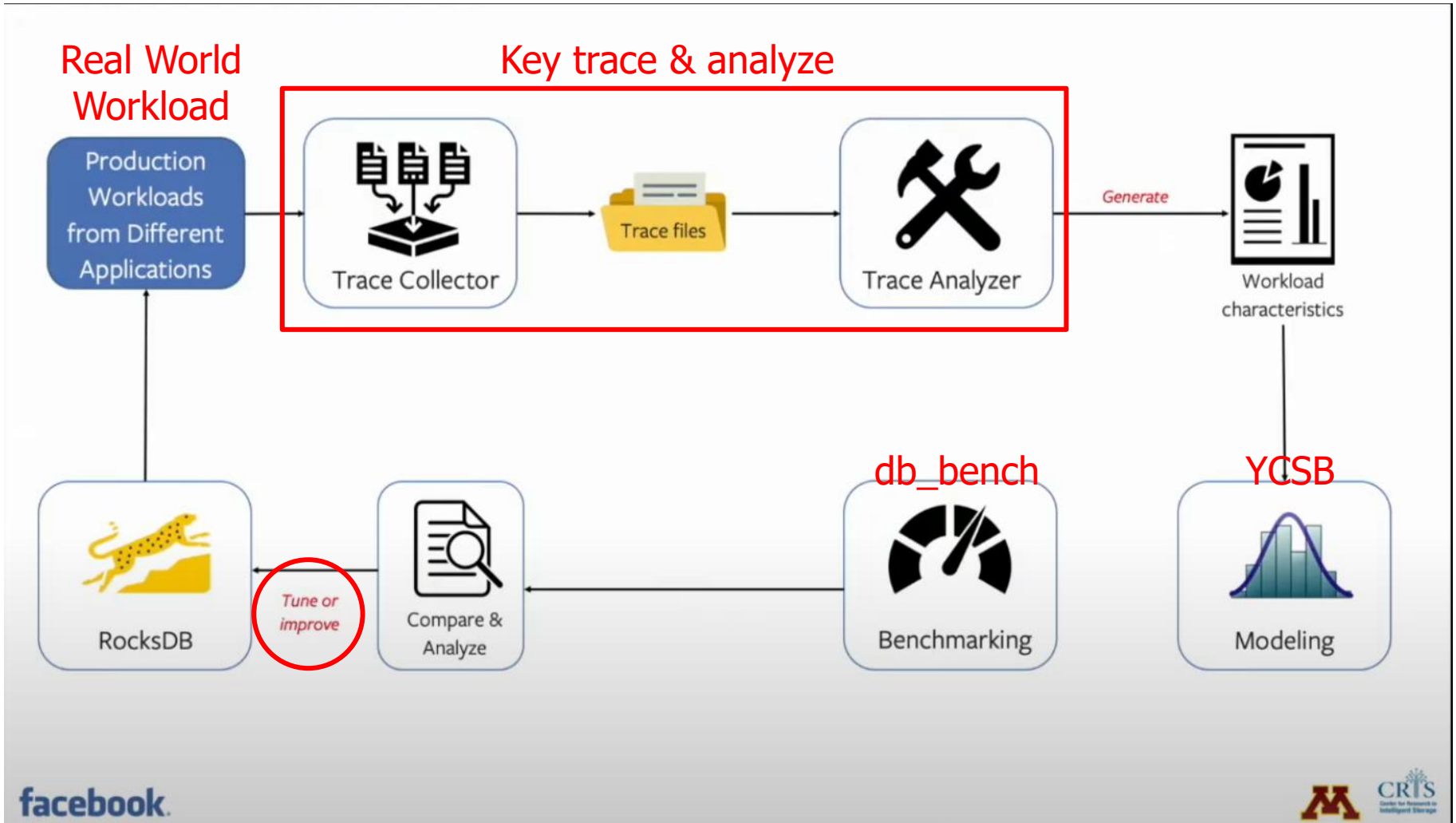
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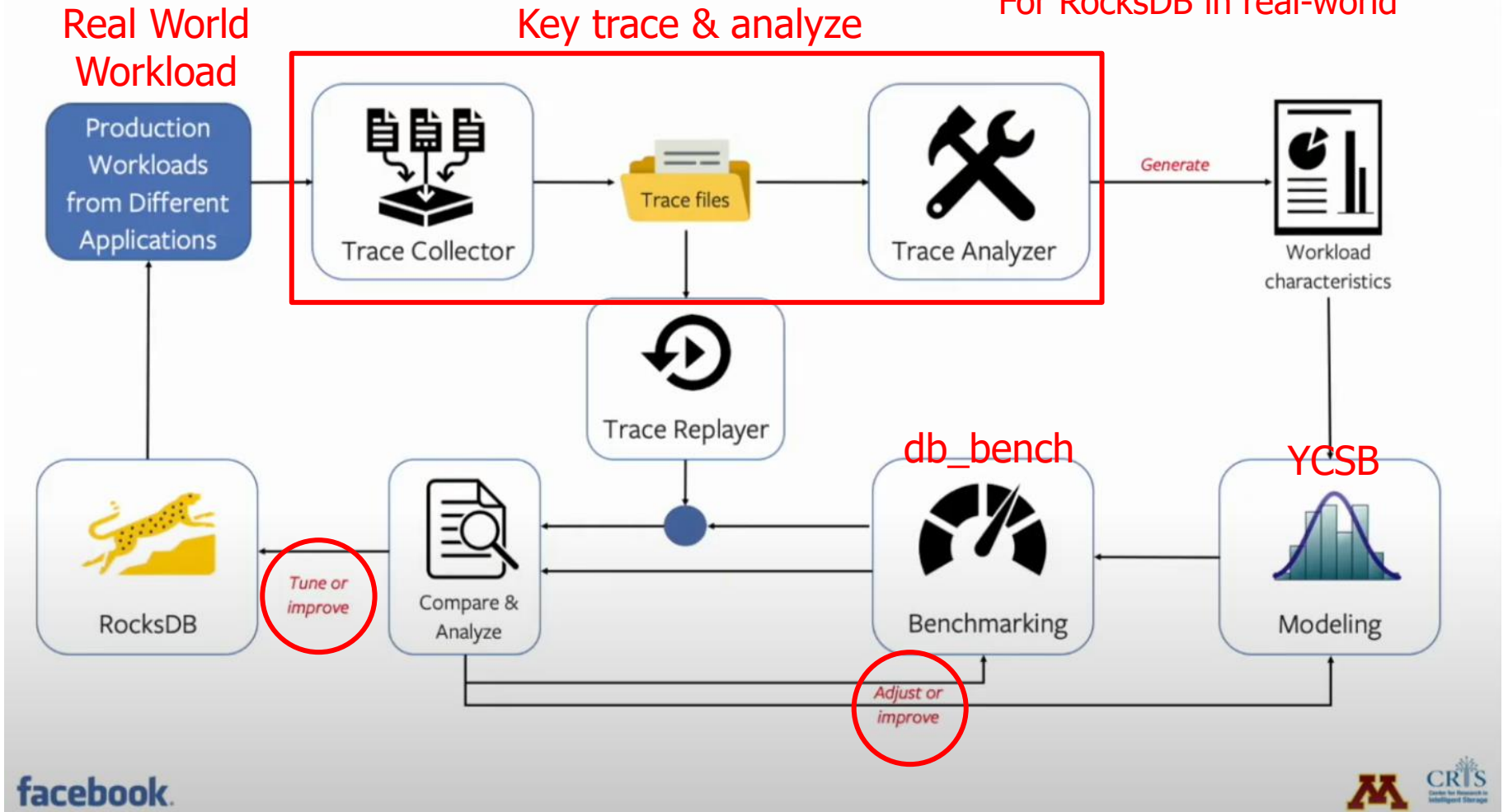
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4. Goal

■ 1. Latest research trends: Key Trace

By tracing/analyzing real-world workload
Adjust/improve benchmark/virtual workload
For RocksDB in real-world



4. Goal

■ 2. Research topic: One(Two) step forward

- ✓ Analyze real-world workload
 - Getting real-world workload is much harder than analyzing it
- ✓ Analyze virtual workload
 - It's already analyzed (maybe)
- ✓ Generate/Adjust virtual workload
 - Based on open-source real-world workload
- ✓ Adjust/Improve rocksdb/db_bench
 - Based on open-source real-world workload
- ✓ Other open issues/questions



■ 3. Final Goal: KSC 2021 submission

Q & A

