

# RTune: A RocksDB Tuning System with Deep Genetic Algorithm

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과제명: IoT 환경을 위한 고성능 플래시 메모리  
스토리지 기반 인메모리 분산 DBMS 연구개발

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# CONTENTS

1

## Introduction

2

## Related Work

3

## Background

- 2.1 LSM-Tree, WA and SA
- 2.2 Mahalanobis Distance

4

## Method

- 3.1 Data Generation
- 3.2 Design

5

## Evaluation

- 4.1 Experimental Setup
- 4.2 Results

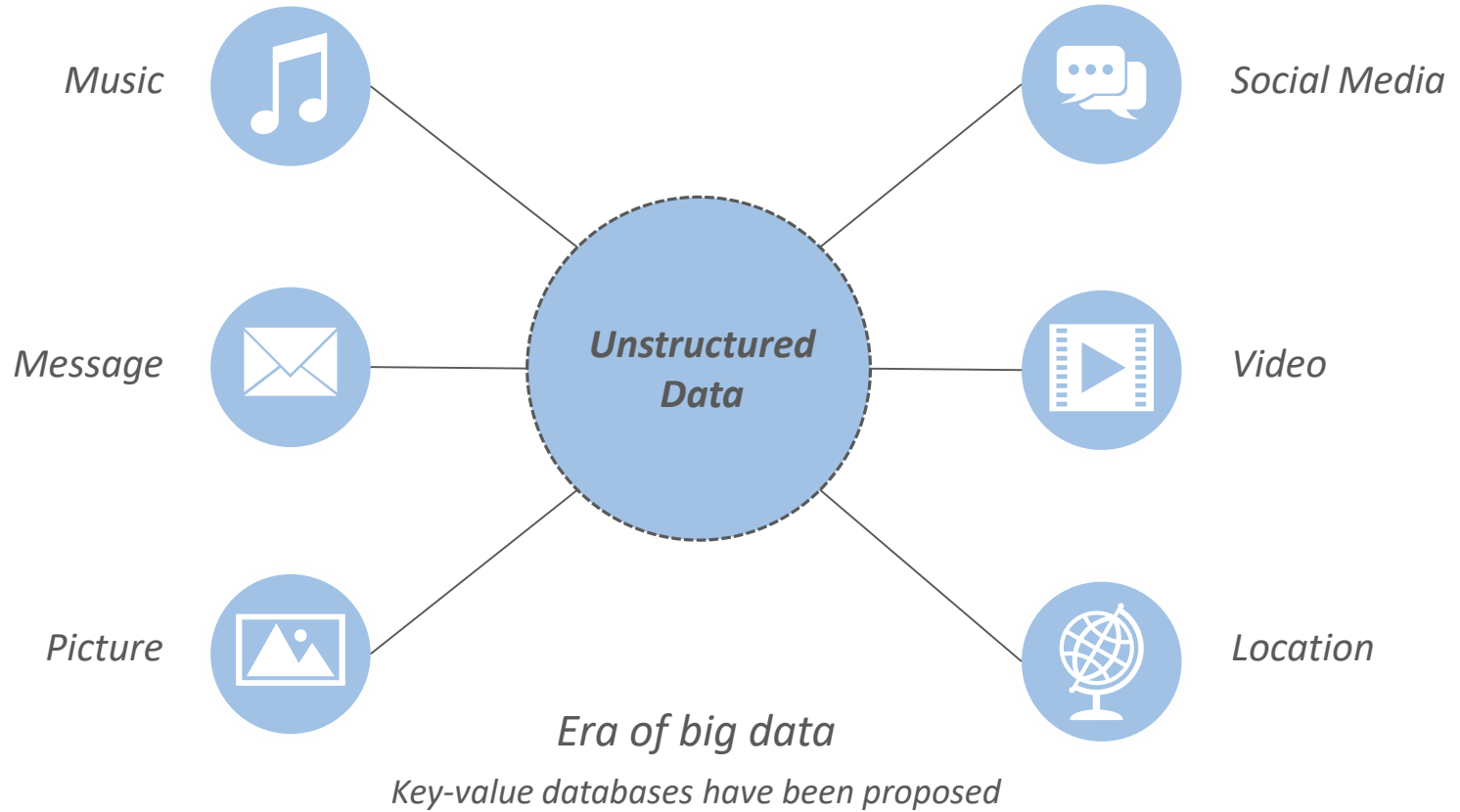
6

## Conclusion



# Introduction

# Introduction



# Introduction



## **RocksDB**

- *Disk-based key-value database*
- *Use Log-structured Merge-tree (LSM-tree)*

## **LSM-Tree**

- **Write amplification (WA)**
  - *Decrease data processing performance*
  - *Decline the lifespan*
- **Space amplification (SA)**
  - *Increasing space usage*

## **Reduce WA and SA by tuning RocksDB knobs**

- *Too many factors for performance tuning*
  - *Knobs, workload, hardware*

# RTune : RocksDB tuning system

- **Contributions:**

- *Generated RocksDB data repository.*
- *New workload representation for dimension reduction.*
- *Created **combined workloads** that are as close to the target workload as possible.*
- *Novel score function to train a DNN model.*
- *Use a **genetic algorithm** with a trained **DNN** model to find the best solutions.*



## Related Work

# Related Work

| <i>Model</i>             | <i>Optimization Target</i>     | <i>Total Tuning time</i>                 | <i>Data Repository Dependency</i> | <i>Main Techniques</i>             | <i>Target Database</i>                | <i>Workload Mapping</i>       |
|--------------------------|--------------------------------|--|-----------------------------------|------------------------------------|---------------------------------------|-------------------------------|
| <i>OtterTune (2017)</i>  | <i>Throughput<br/>Latency</i>  | <i>60 min</i>                            | <i>O</i>                          | <i>Lasso<br/>repression<br/>GP</i> | <i>MySQL<br/>Postgres<br/>Vector</i>  | <i>Euclidean<br/>distance</i> |
| <i>BestConfig (2017)</i> | <i>Throughput</i>              | <i>-</i>                                 | <i>X</i>                          | <i>DDS<br/>RBS</i>                 | <i>MySQL<br/>Cassandra<br/>Hive</i>   | <i>X</i>                      |
| <i>CDBTune (2019)</i>    | <i>Throughput<br/>Latency</i>  | <i>Offline: 2.3 h<br/>Online: 25 min</i> | <i>X</i>                          | <i>DDPG</i>                        | <i>MySQL<br/>Postgres<br/>MongoDB</i> | <i>X</i>                      |
| <i>Multi-Task (2021)</i> | <i>IOPS</i>                    | <i>10 iterations</i>                     | <i>X</i>                          | <i>Multitask<br/>Clustering</i>    | <i>RocksDB</i>                        | <i>X</i>                      |
| <i>RTune</i>             | <i>TIME, RATE,<br/>WAF, SA</i> | <i>15 min</i>                            | <i>X</i>                          | <i>DNN, GA</i>                     | <i>RocksDB</i>                        | <i>Combined<br/>Workload</i>  |



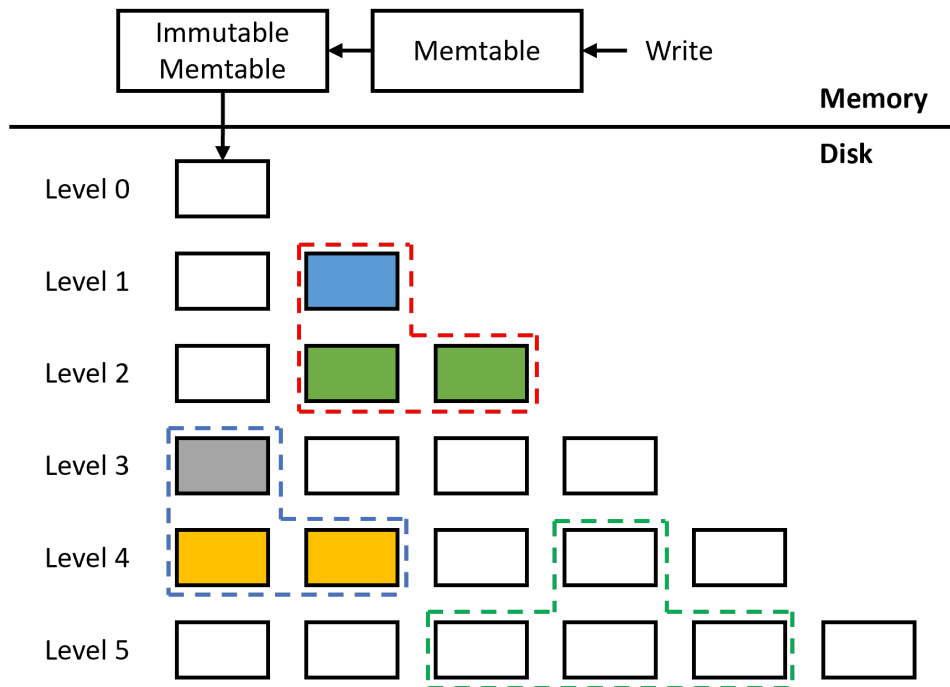
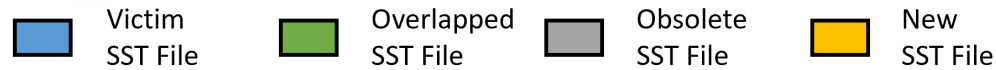


3

## Background

- 1. LSM-Tree, WA and SA*
- 2. Mahalanobis Distance*

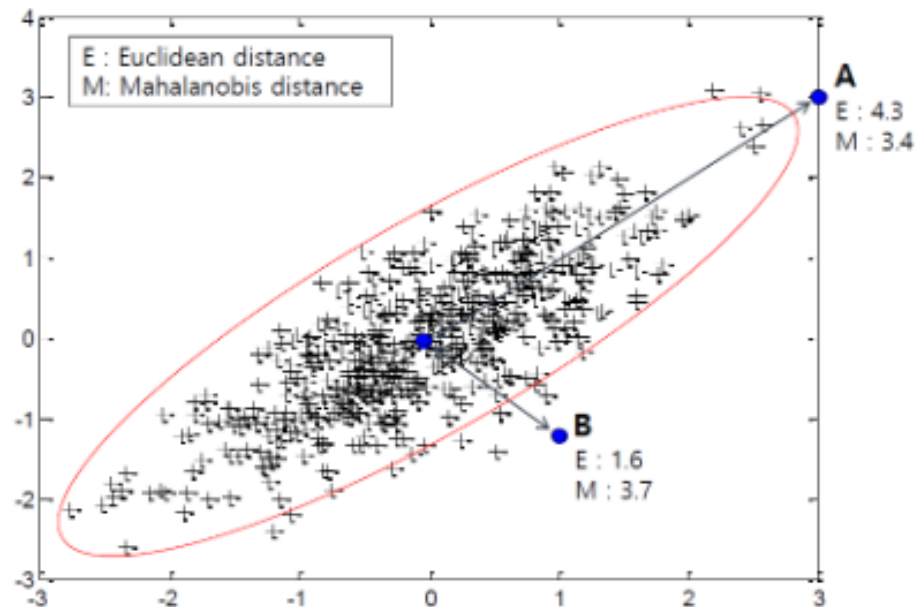
# LSM-Tree, WA and SA



**Figure 1. LSM-Tree and compaction**

- **Write Amplification (WA)**
  - Additional write operations
  - **Overlapped SST File**
  
- **Space Amplification (SA)**
  - Additional space occupancy
  - **Obsolete SST File**
  
- **Issues**
  - Multi-threaded
  - Important to reduce **WA** and **SA**

# Mahalanobis Distance



- **Euclidean Distance**

- $D_E(\vec{x}) = (\vec{x} - \vec{\mu})^T (\vec{x} - \vec{\mu})$

- **Mahalanobis Distance (MD)**

- Consider the **variance** between data

- $D_M(\vec{x}) = \sqrt{(\vec{x} - \vec{\mu})^T \mathbf{S}^{-1} (\vec{x} - \vec{\mu})}$



4

# Method

*1. Architecture*

*2. Data Generation*

*3. Design*

# Architecture of proposed model

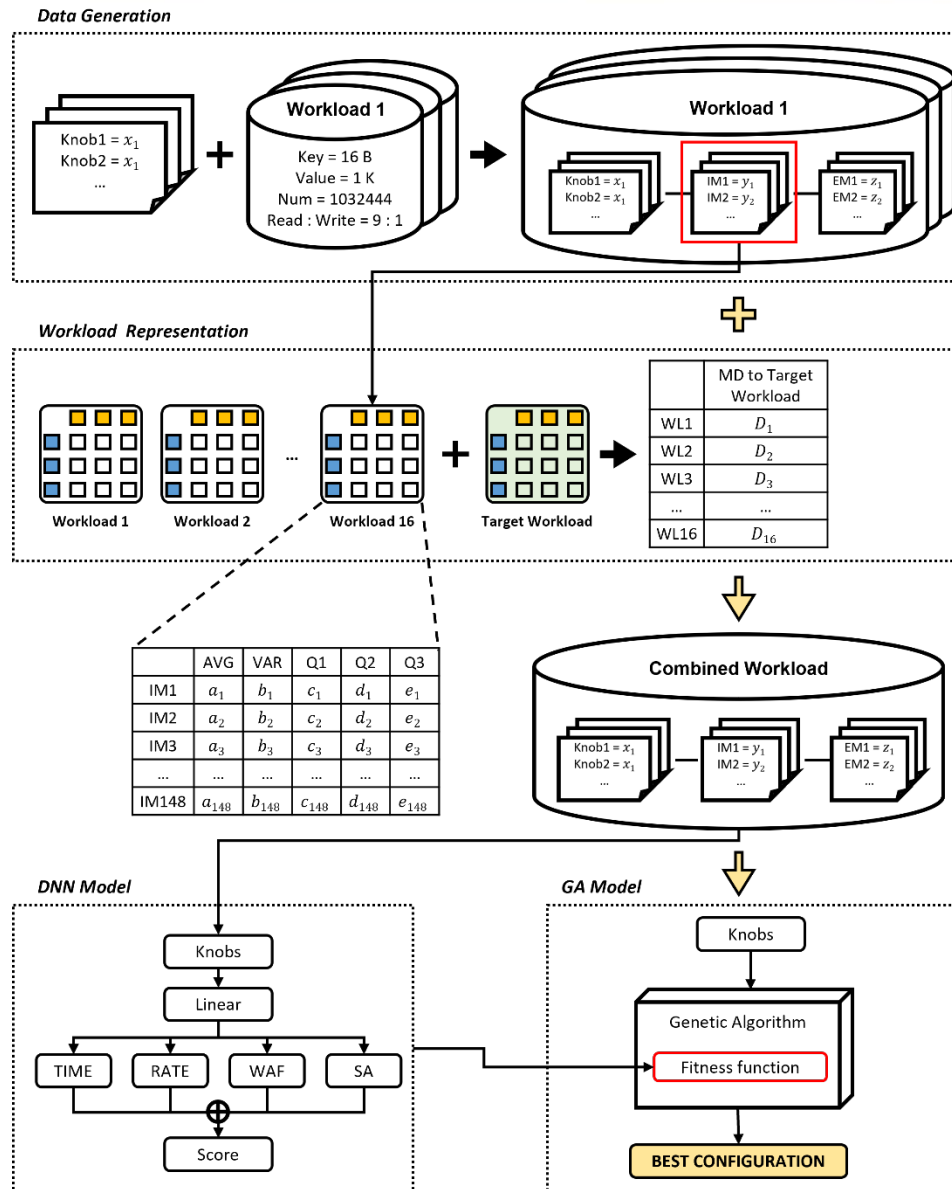


Figure 2. Overview of proposed model architecture

# Data Generation

- **DB\_Bench** : RocksDB benchmarking tool.
  - Internal Metrics(IM) : Configuration, **workload**, I/O status, etc.
  - External Metrics(EM) : TIME, RATE, WAF, SA
  
- **Knobs**
  - Selected **22 knobs** refer to official sites.
  - Generated 20,000 random **configurations** (set of knobs).
  
- **Workload**
  - **16 workloads** with size of **1 GB** each.
  - Different value sizes, # of entries, read-write ratio, update.
  - Key size : **16 B**

# Data Generation

**Table 1. Basic workloads.**

| Workload Index | Value Size (B), # of Entry | Read : Write | Update |
|----------------|----------------------------|--------------|--------|
| 0              | 1024, 1032444              | 9 : 1        | -      |
| 1              | 1024, 1032444              | 1 : 1        | -      |
| 2              | 1024, 1032444              | 1 : 9        | -      |
| 3              | 1024, 1032444              | -            | TRUE   |
| 4              | 4096, 261124               | 9 : 1        | -      |
| 5              | 4096, 261124               | 1 : 1        | -      |
| 6              | 4096, 261124               | 1 : 9        | -      |
| 7              | 4096, 261124               | -            | TRUE   |
| 8              | 16384, 65472               | 9 : 1        | -      |
| 9              | 16384, 65472               | 1 : 1        | -      |
| 10             | 16384, 65472               | 1 : 9        | -      |
| 11             | 16384, 65472               | -            | TRUE   |
| 12             | 65536, 16380               | 9 : 1        | -      |
| 13             | 65536, 16380               | 1 : 1        | -      |
| 14             | 65536, 16380               | 1 : 9        | -      |
| 15             | 65536, 16380               | -            | TRUE   |

# Workload Representation

- 20,000 [**Configuration** – **IM** – **EM**] pairs for each workload.
- **IM** include information for a workload.
- Represent a workload by **IM**.
  
- **Disadvantages** :
  - **Huge** size of table.
  - **Expensive** to proceed with various calculations.

**Table 2. Original workload representation.**

| <b>Configuration #</b> | <b>1</b> | <b>2</b> | <b>...</b> | <b>20000</b> |
|------------------------|----------|----------|------------|--------------|
| <b>IM 1</b>            | 12965    | 13040    | ...        | 14586        |
| <b>IM 2</b>            | 1239     | 837      | ...        | 297          |
| <b>...</b>             | ...      | ...      | ...        | ...          |
| <b>IM n</b>            | 44       | 63       | 78         | 208          |



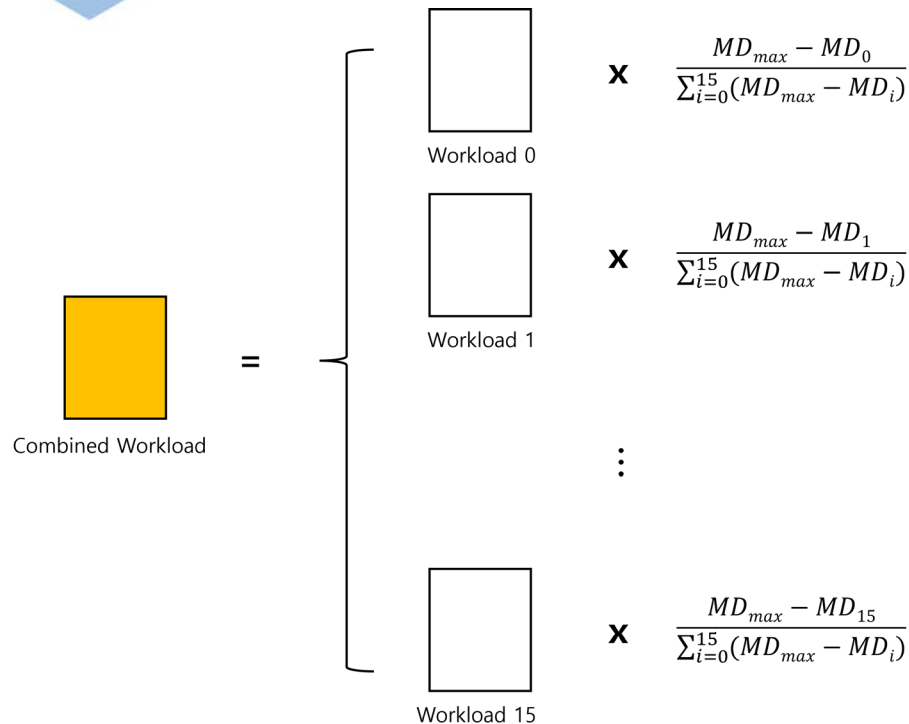
# Workload Representation

- Use 5 statistics [*Average, Variance, 1<sup>st</sup> Quartile, 2<sup>nd</sup> Quartile, 3<sup>rd</sup> Quartile*] of 20,000 data of each internal metrics.
  
- *Advantages :*
  - *Dimension reduction*
  - *Easy to proceed with various calculations.*

**Table 3. New workload representation.**

|             | Average | Variance | 1st Quartile | 2nd Quartile | 3rd Quartile |
|-------------|---------|----------|--------------|--------------|--------------|
| <b>IM 1</b> | 13544   | 55615    | 10513        | 13448        | 15798        |
| <b>IM 2</b> | 834     | 2315     | 564          | 912          | 1132         |
| ...         | ...     | ...      | ...          | ...          | ...          |
| <b>IM n</b> | 80      | 1213     | 68           | 81           | 121          |

# Combined Workload



- *Distance*  $\rightarrow$  *similarity*
- Calculate the **proportion** of each basic workload data to be included in CW
- 20,000 [**Configuration – IM – EM**] pairs in CW

**Figure 3. Combined workload calculation process**

# Deep Neural Network Model

- Train **DNN** model with CW

- Input : **Configurations**
- Output : Prediction for 4 EM.

- Score function**

- $Score = \alpha_1 \frac{TIME_D}{TIME_P} + \alpha_2 \frac{RATE_P}{RATE_D} + \alpha_3 \frac{WAF_D}{WAF_P} + \alpha_4 \frac{SA_D}{SA_P}$
- $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0.25$

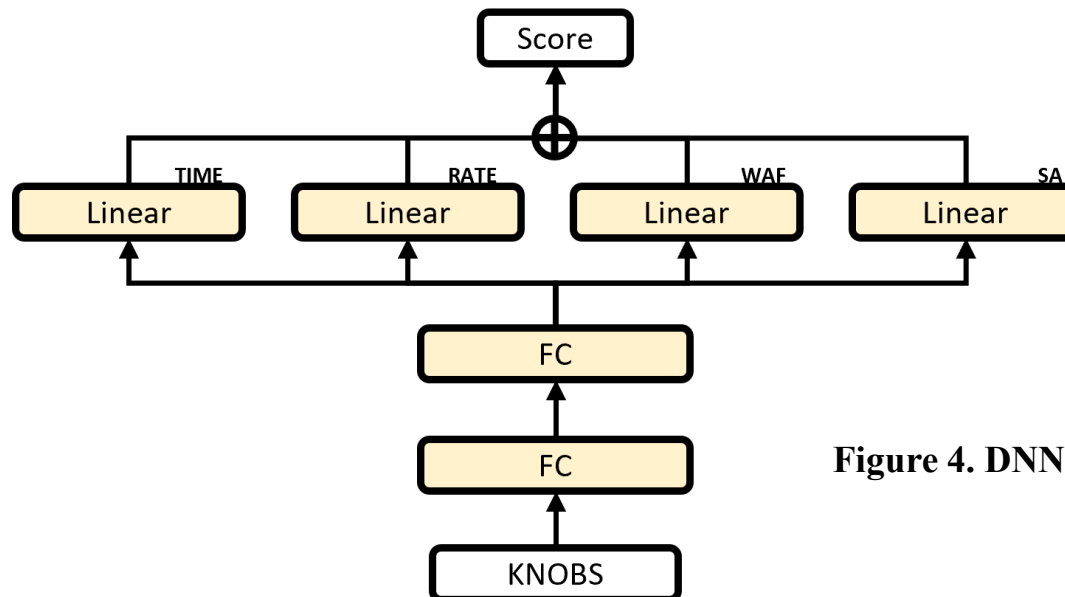


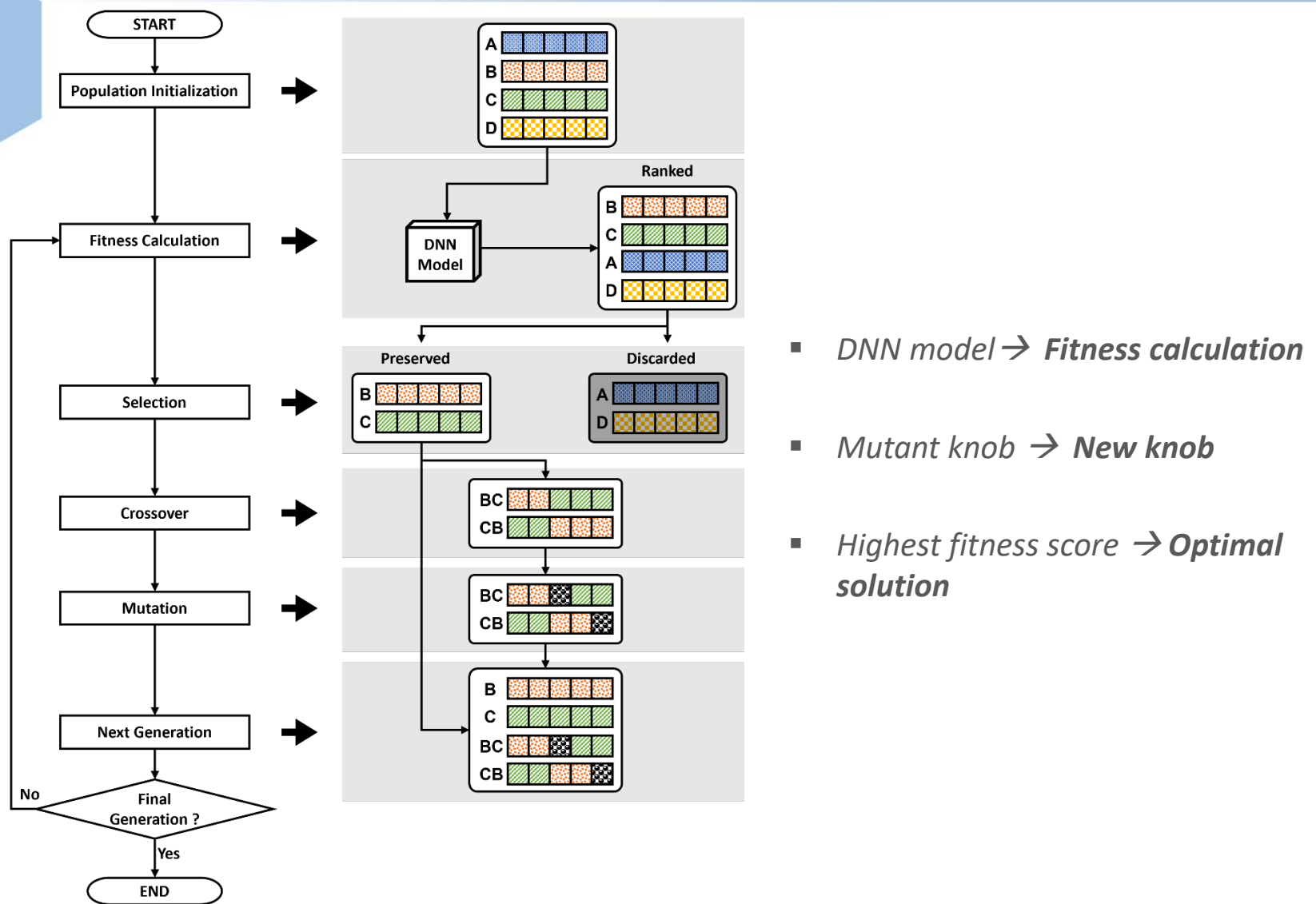
Figure 4. DNN model structure

# Deep Neural Network Model

**Table 4. Hyperparameters of DNN model.**

| <b>Optimizer</b>           | <b>Adamw</b>    |
|----------------------------|-----------------|
| <b>Learning Rate</b>       | 0.0002          |
| <b>Epoch</b>               | 300             |
| <b>Loss Function</b>       | MSE             |
| <b>X Scaler</b>            | MinMaxScaler    |
| <b>Y Scaler</b>            | StandardScaler  |
| <b>Layer</b>               | (22, 64, 16, 1) |
| <b>Activation Function</b> | ReLU            |

# Genetic Algorithm



- *DNN model* → *Fitness calculation*
- *Mutant knob* → *New knob*
- *Highest fitness score* → *Optimal solution*

**Figure 5. Genetic Algorithm**

# Genetic Algorithm

**Table 5. Hyperparameters of GA model.**

|                            |                |
|----------------------------|----------------|
| <b>Mutation Ratio</b>      | 0.4            |
| <b>Crossover Ratio</b>     | 0.5            |
| <b>Population Size</b>     | 128            |
| <b>Generation</b>          | 1000           |
| <b>Selection Algorithm</b> | Rank Selection |
| <b>Selection Size</b>      | 64             |



5

# Evaluation

*1. Experimental Setup*

*2. Results*

# Target Workload Information

- *Generated 6 target workloads*
  - *16 workloads with size of 1 GB each.*
  - *Different value sizes, # of entries, read-write ratio, update.*
  - *Key size : 16 B*
  
- *Generate 20 data pair for target workloads.*

**Table 6. Target workloads.**

| <b>Workload Index</b> | <b>Value Size (B), # of Entry</b> | <b>Read : Write</b> | <b>Update</b> |
|-----------------------|-----------------------------------|---------------------|---------------|
| <b>16</b>             | 8192, 130816                      | 7 : 3               | -             |
| <b>17</b>             | 8192, 130816                      | 3 : 7               | -             |
| <b>18</b>             | 8192, 130816                      | -                   | True          |
| <b>19</b>             | 32768, 32752                      | 7 : 3               | -             |
| <b>20</b>             | 32768, 32752                      | 3 : 7               | -             |
| <b>21</b>             | 32768, 32752                      | -                   | True          |



# External Metrics

- *External Metrics: TIME, RATE, WAF, SA*
  - *TIME (s): Total execution time*
    - *Time interval from the start of the data recording to the end.*
  - *RATE (MB/s): Data processing rate*
    - *The number of operations processed by RocksDB per second.*
  - *WAF : WA factor*
    - *Ratio of **physical data size** and **logical data size** written to the storage.*
    - $$WAF = \frac{\text{Physical data size}}{\text{Logical data size}}$$
  - *SA (MB): Space amplification*
    - *The size of the data recorded in the actual **LSM-Tree**.*

# Results

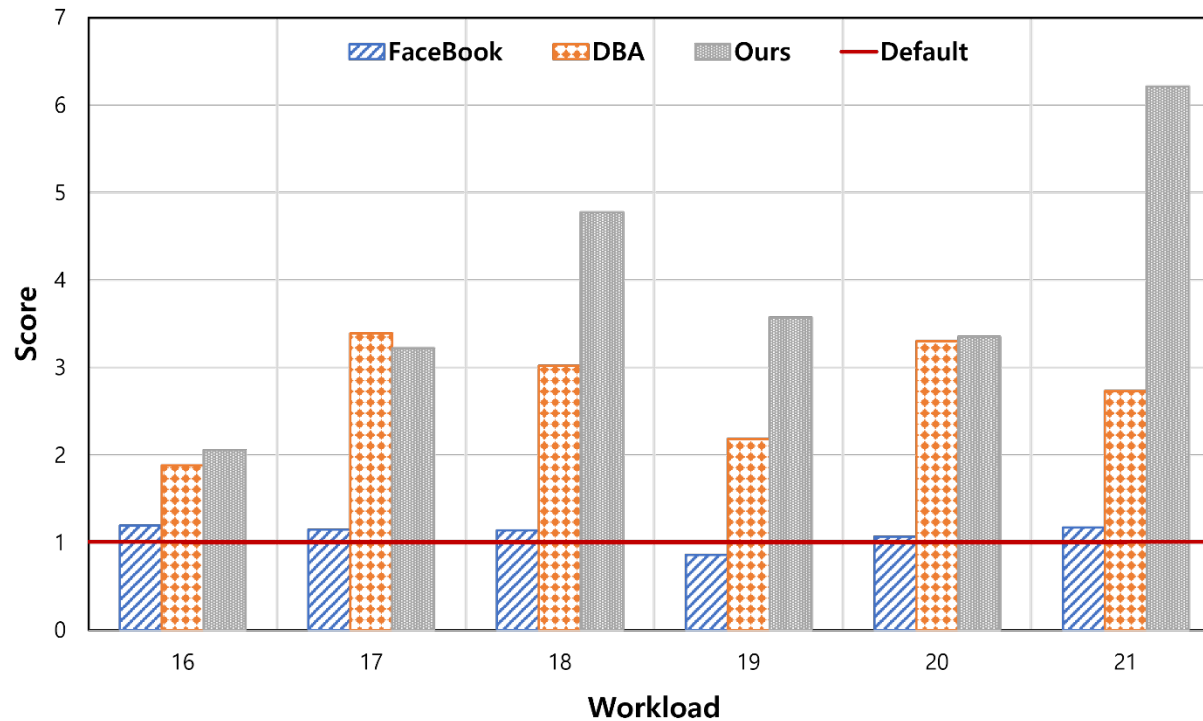
- Apply *geometric mean* to the EM.

- $$\text{Score} = \sqrt[4]{\frac{\text{TIME}_D}{\text{TIME}_A} \times \frac{\text{RATE}_A}{\text{RATE}_D} \times \frac{\text{WAF}_D}{\text{WAF}_A} \times \frac{\text{SA}_D}{\text{SA}_A}}$$

- *Performance of default setting is described as a red line pointing to 1.*

# Overall Comparison

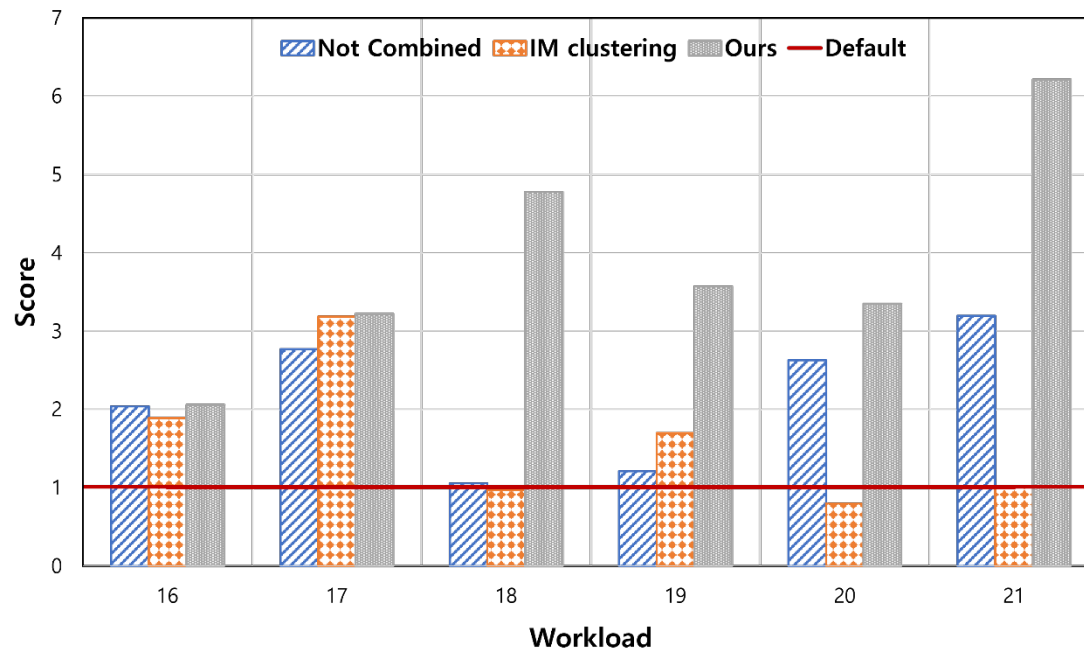
- Overall comparison among **default settings**, **Facebook** recommended configuration, **database administrator (DBA)**, and **RTune**.
- Best performance among the **5 target workloads**.
- Slightly lower than **DBA** in the **17th** workload.



**Figure 6. Overall performance comparison**

# Combined Workload & Pruning Internal Metrics

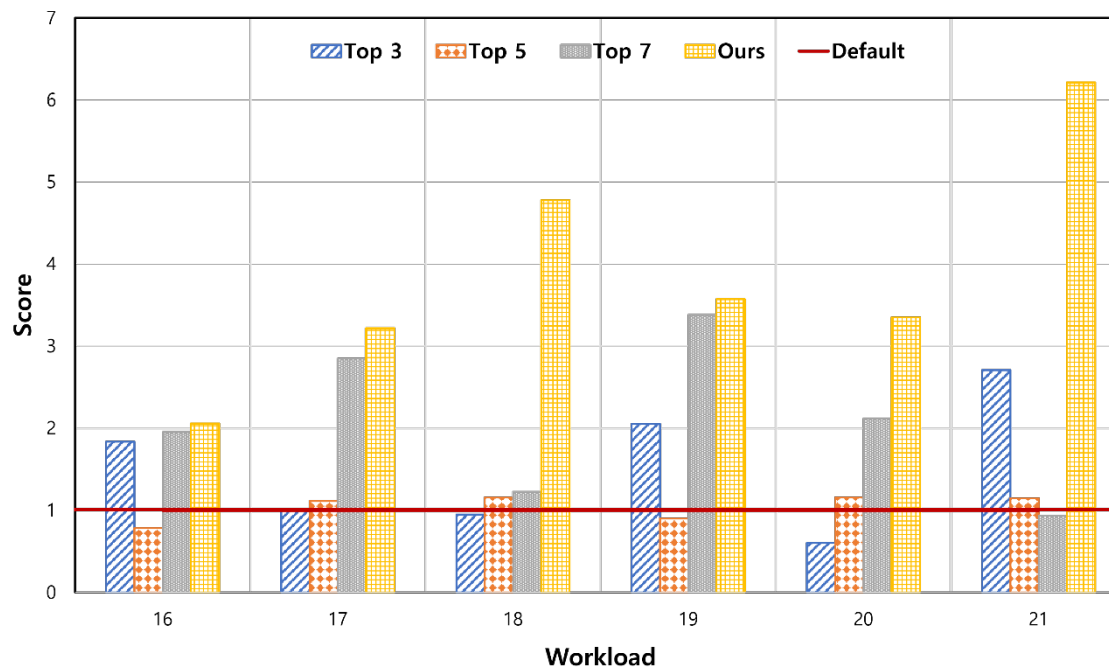
- **“Not Combined”** : Use the *closest* workload as the CW.
- **“IM Clustering”** : Use pruned IM by k-means clustering.
- **Best performance in *all target workloads*.**
- **Better to describe a workload using *CW* and *full IM*.**



**Figure 7. Workload combining and internal metrics pruning comparison**

# Number of Knobs

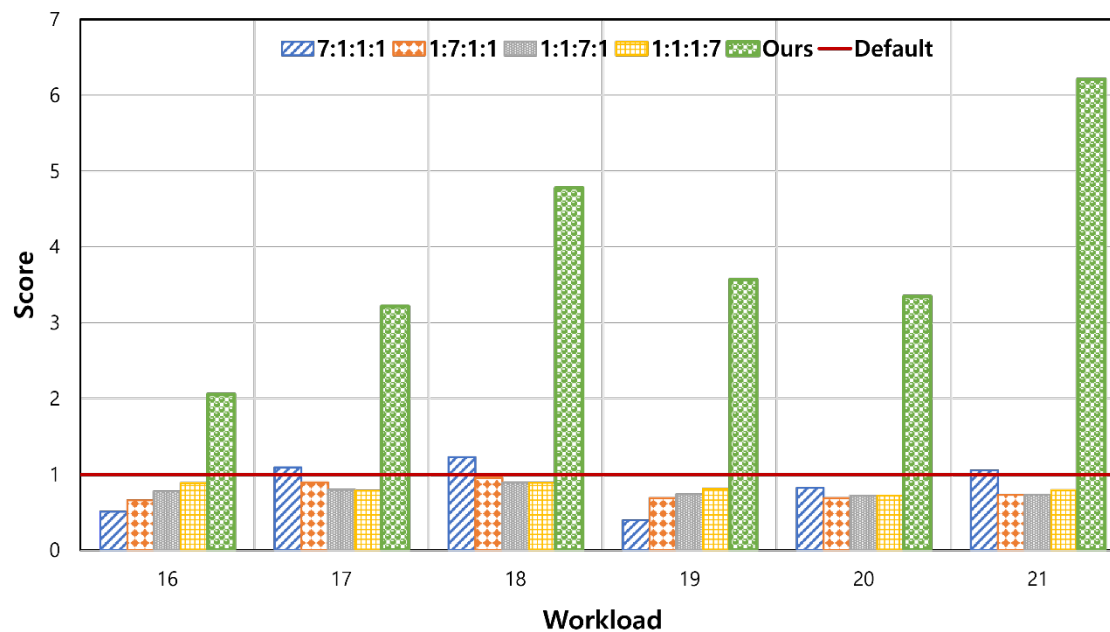
- Difference in the *number of knobs*.
- Pruning knobs with **3, 5, and 7 knobs** with a random forest.
- Best performance in *all target workloads*.
- Top 7 model achieved good performance in workload 16, 17, and 19, but it is *not stable*.



**Figure 8. Comparison of number of knobs**

# Weight Comparison

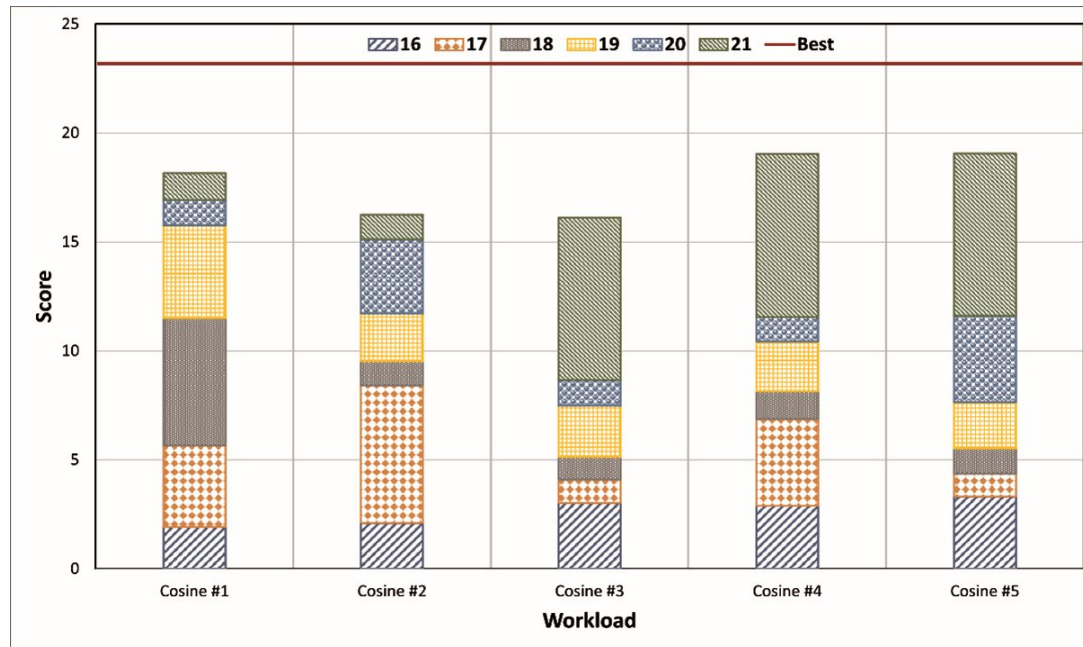
- Comparison of using **4 different weight pairs** to the score function.
- Best performance in **all target workloads**.
- The rest of 4 models hard to reach the default setting.



**Figure 9. Different weight comparison**

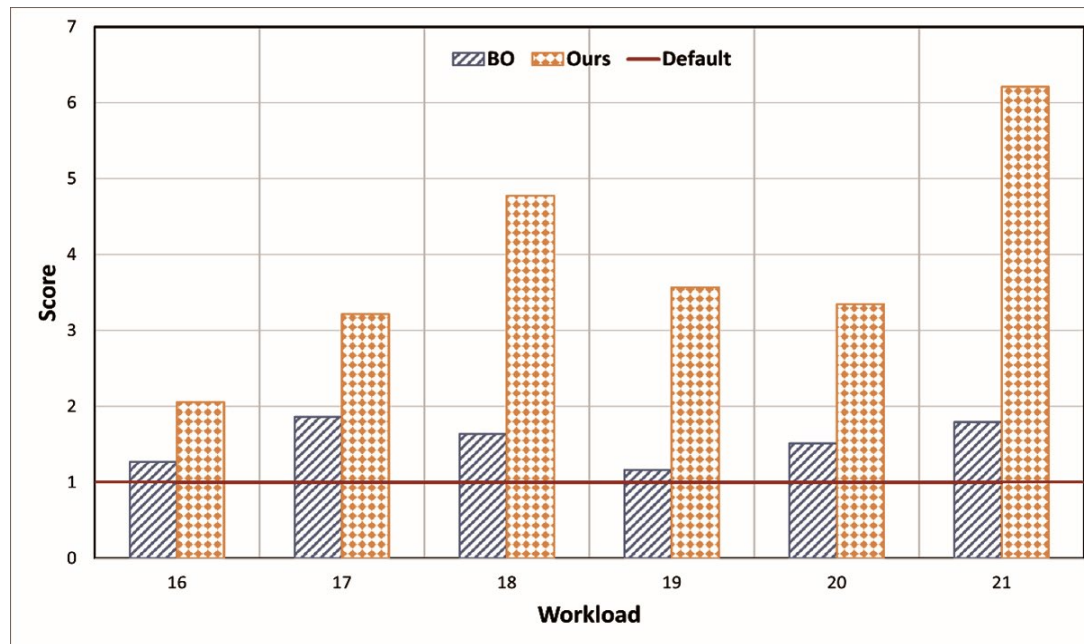
# Cosine similarity & Mahalanobis distance

- *Comparison of cosine similarity and Mahalanobis distance.*
- *The sum of the performance was good but not the best.*
- *Performance is not stable especially in the case of Cosine #3.*



# Bayesian optimization comparison

- *Comparison of Bayesian optimization with GA.*
- *BO cannot overperform our model.*
- *The score barely exceeds the default line in workload 19.*







6

## Conclusion

# Conclusion and Future Works

- **Conclusion**

- *Generated **RocksDB** data repository.*
- *Applied **MD** and **new workload representation** to create **CW**.*
- ***Novel score function** to train **DNN** model with 4 **EM** **simultaneously**.*
- *Use **GA** with **DNN** model to find the **optimal solutions**.*
- *Proved the optimal solutions yields the **best performance** through comparative experiments.*

# THANK YOU

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