DeepLog: Anomaly Detection and Diagnosis from System Logs through Deep Learning

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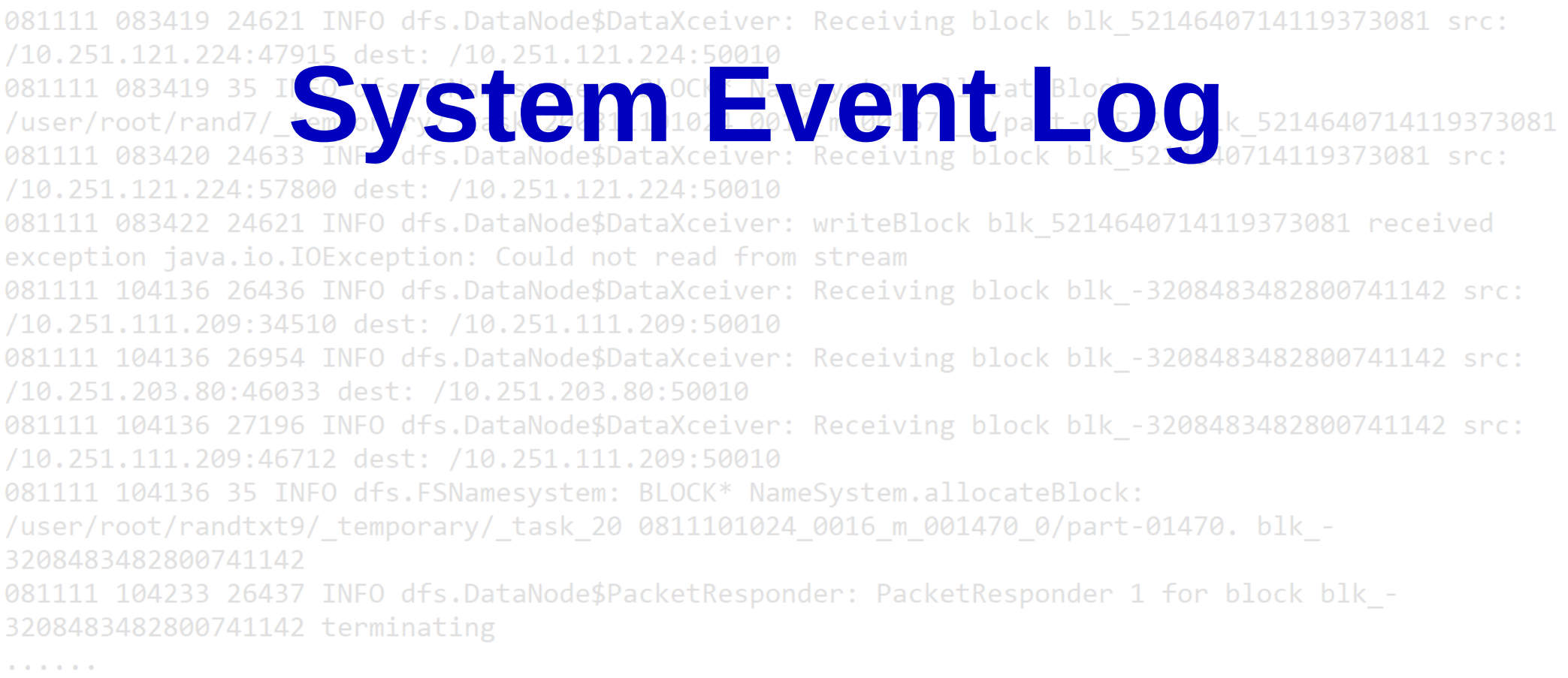
University of Utah

THE UNIVERSITY OF UTAH

Background

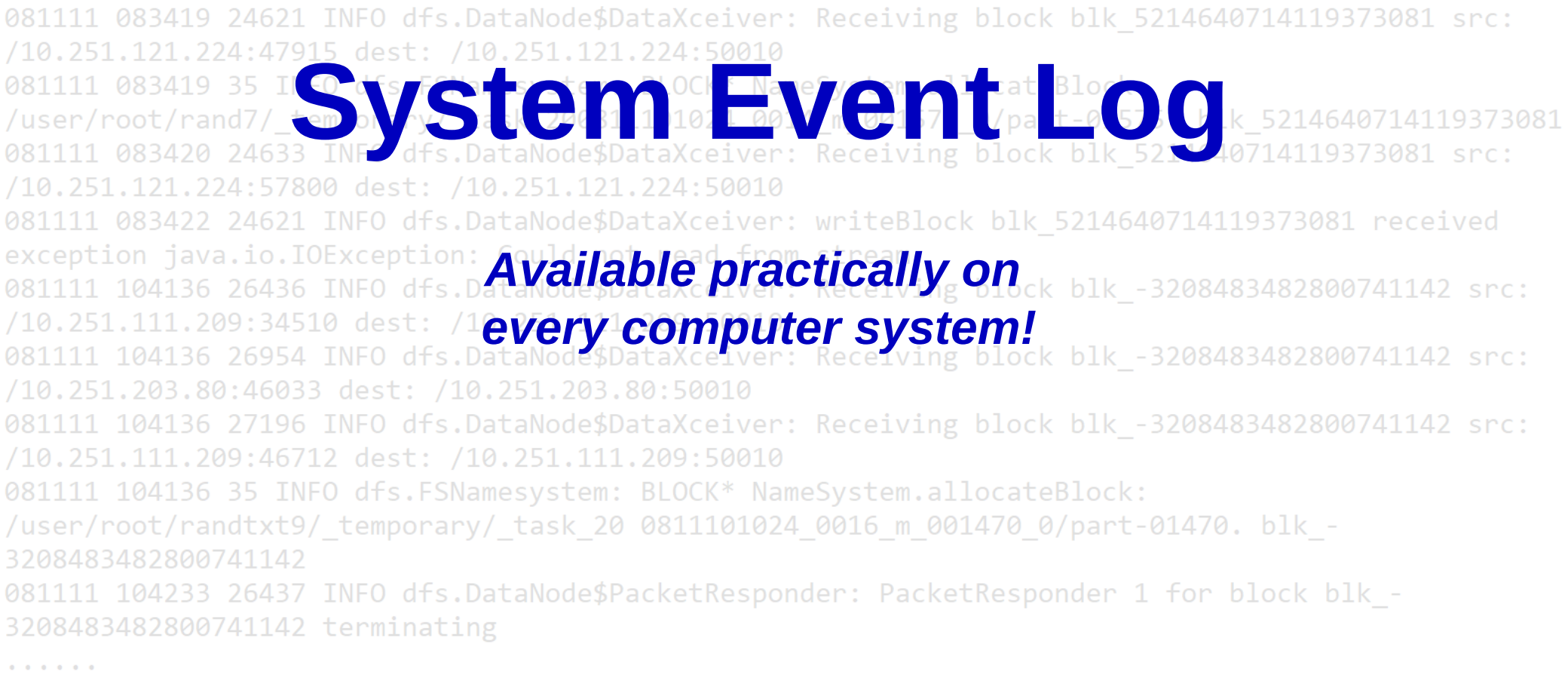
```
081111 083419 24621 INFO dfs.DataNode$DataXceiver: Receiving block blk_5214640714119373081 src:
/10.251.121.224:47915 dest: /10.251.121.224:50010
081111 083419 35 INFO dfs.FSNamesystem: BLOCK* NameSystem.allocateBlock:
/user/root/rand7/_temporary/_task_200811101024_0014_m_001575_0/part-01575. blk_5214640714119373081
081111 083420 24633 INFO dfs.DataNode$DataXceiver: Receiving block blk_5214640714119373081 src:
/10.251.121.224:57800 dest: /10.251.121.224:50010
081111 083422 24621 INFO dfs.DataNode$DataXceiver: writeBlock blk_5214640714119373081 received
exception java.io.IOException: Could not read from stream
081111 104136 26436 INFO dfs.DataNode$DataXceiver: Receiving block blk_-3208483482800741142 src:
/10.251.111.209:34510 dest: /10.251.111.209:50010
081111 104136 26954 INFO dfs.DataNode$DataXceiver: Receiving block blk_-3208483482800741142 src:
/10.251.203.80:46033 dest: /10.251.203.80:50010
081111 104136 27196 INFO dfs.DataNode$DataXceiver: Receiving block blk_-3208483482800741142 src:
/10.251.111.209:46712 dest: /10.251.111.209:50010
081111 104136 35 INFO dfs.FSNamesystem: BLOCK* NameSystem.allocateBlock:
/user/root/randtxt9/_temporary/_task_20 0811101024_0016_m_001470_0/part-01470. blk_-
3208483482800741142
081111 104233 26437 INFO dfs.DataNode$PacketResponder: PacketResponder 1 for block blk_-
3208483482800741142 terminating
......
```

Background



System Event Log

Background



System Event Log

Available practically on every computer system!

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Automatic Analysis?

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Automatically detected anomaly

Background

Started service A on port 80
Executor updated: app-1 is now LOADING
……

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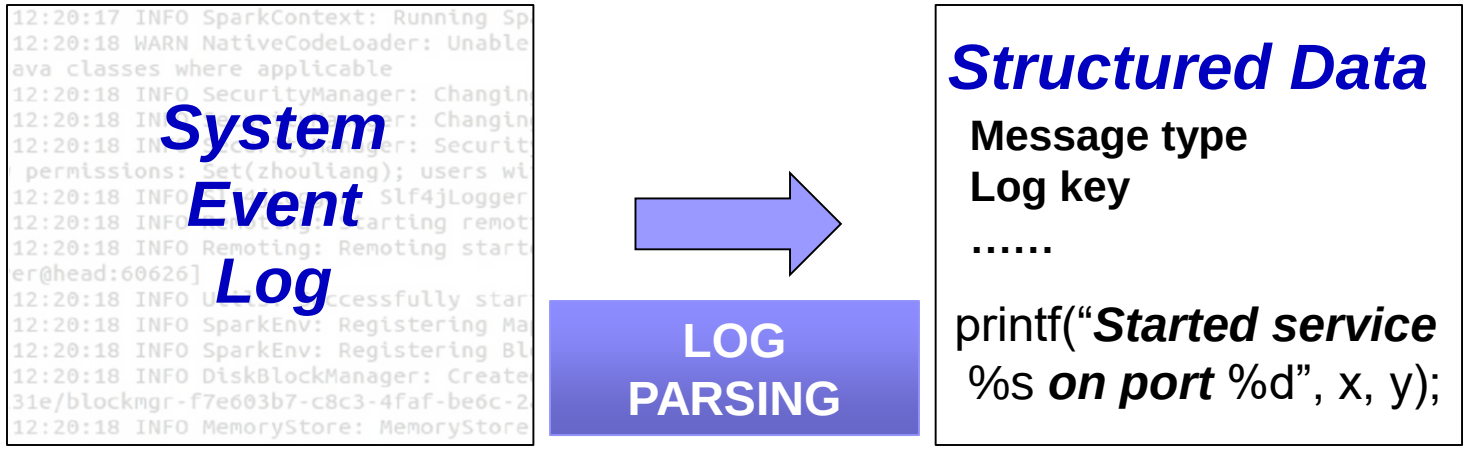

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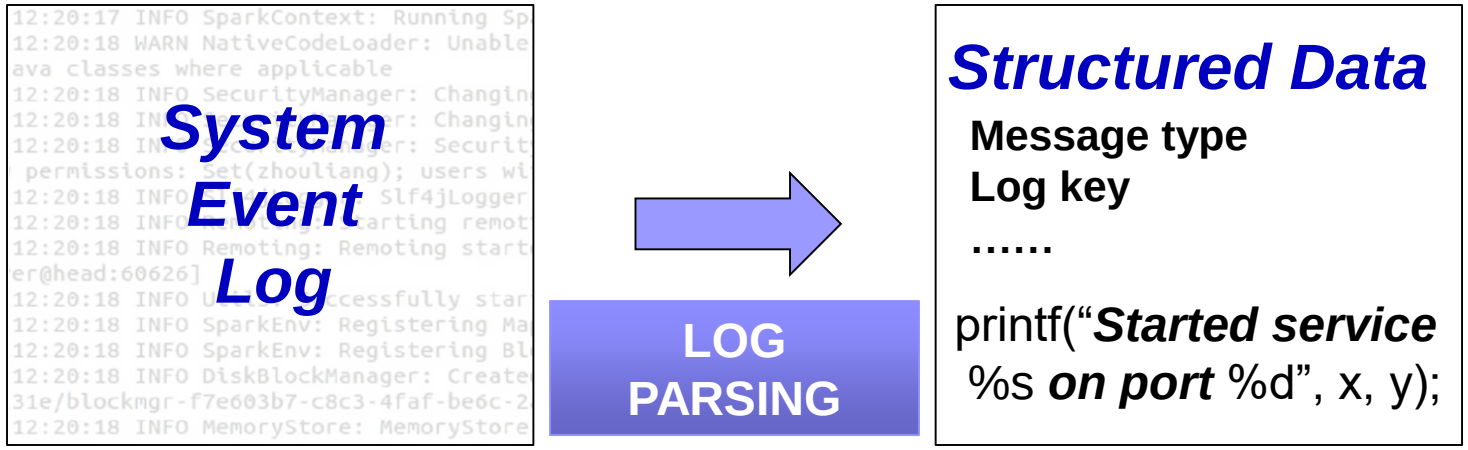


Started service A on port 80
Executor updated: app-1 is now LOADING
……

***Started service** * **on port** ** *(log key ID: 1)*
***Executor updated:** * **is now LOADING** *(log key ID: 2)*
……

Background

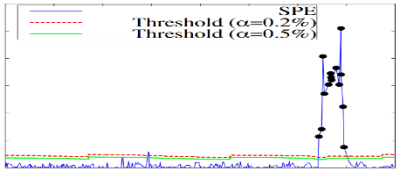
LOG PARSING

Structured Data

Message type
Log key
……

printf("***Started service*** %s ***on port*** %d", x, y);

Anomaly Detection



LOG ANALYSIS

Background

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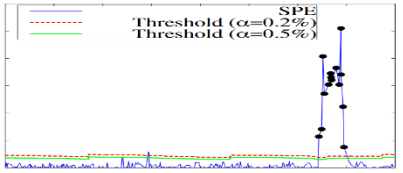

LOG ANALYSIS

❑**Message count vector:**
Xu'SOSP09, Lou'ATC10, etc.

Background

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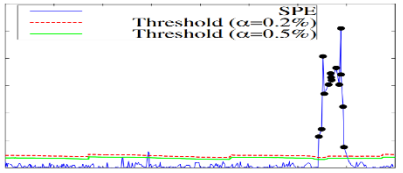

LOG ANALYSIS

❑**Message count vector:**
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Problem: Offline batched processing

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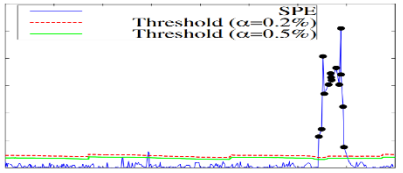

LOG ANALYSIS

❑**Message count vector:**
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Problem: Offline batched processing

❑**Build workflow model:**
Lou'KDD10, Beschastnikh'ICSE14, Yu'ASPLOS16, etc.

Background

LOG PARSING

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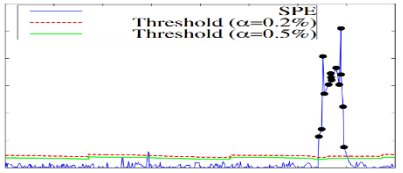

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Problem: Only for simple execution path anomalies

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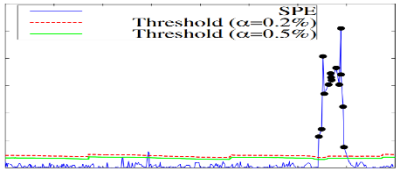

LOG ANALYSIS

Common problem: Only Log keys (Message types) are considered.

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Xu'SOSP09, Lou'ATC10, etc.
Problem: Offline batched processing

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DeepLog

log message (log key underlined)	log key	parameter value vector
t_1 Deletion of file1 complete	k_1	[t_1 - t_0, file1]
t_2 Took 0.61 seconds to deallocate network …	k_2	[t_2 - t_1, 0.61]
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SPELL
A streaming log parser published in ICDM'16

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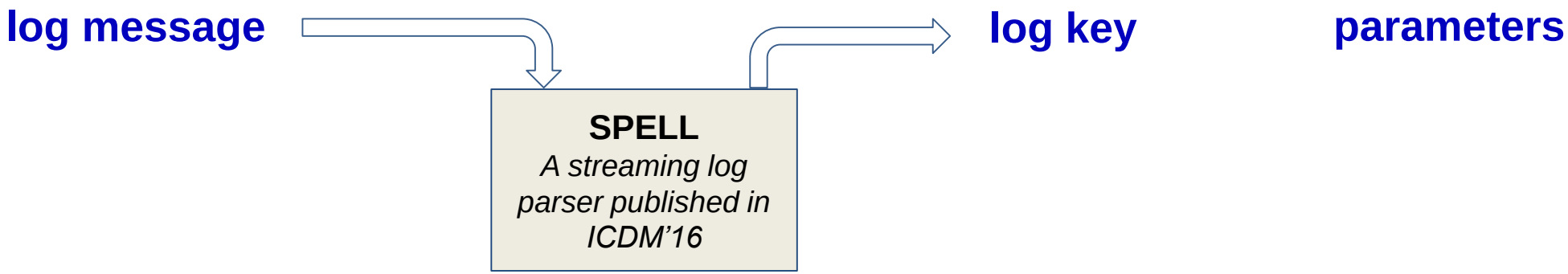

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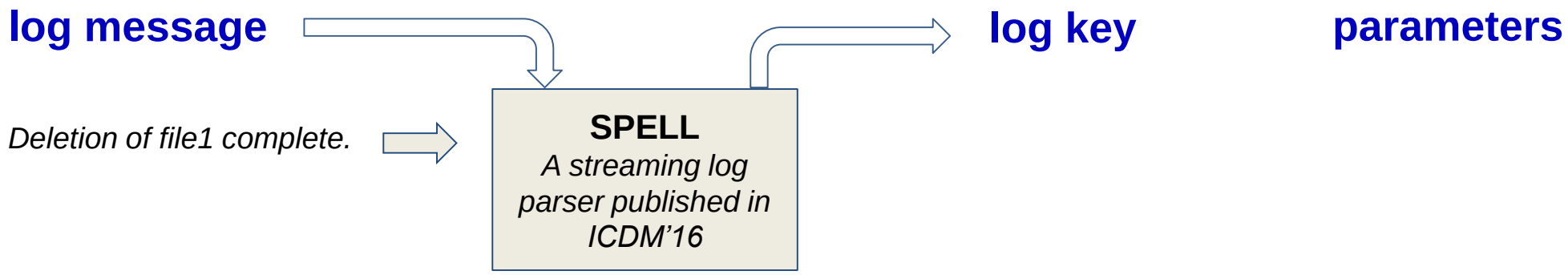

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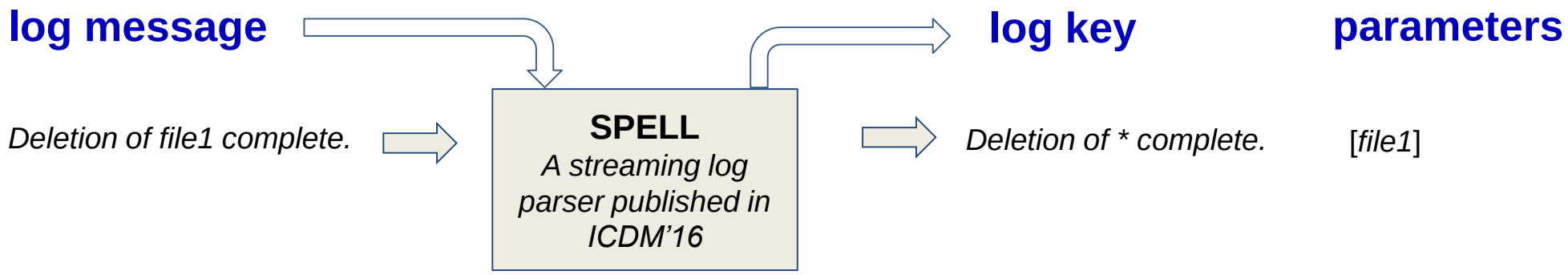

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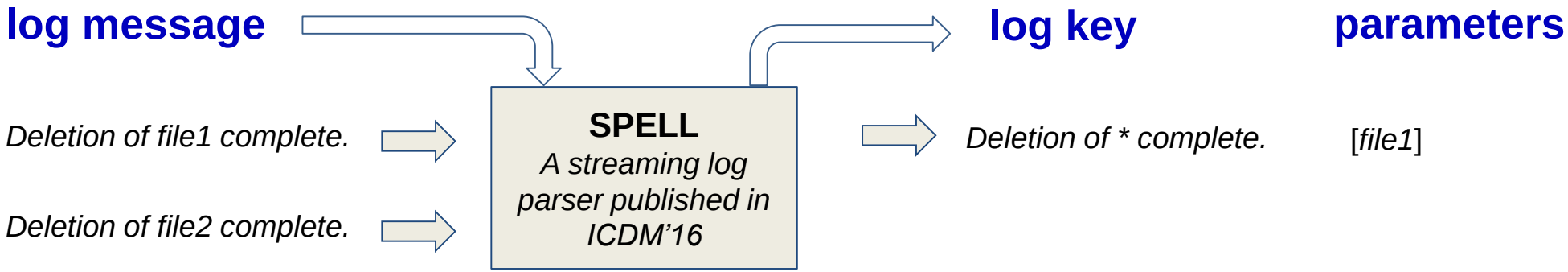

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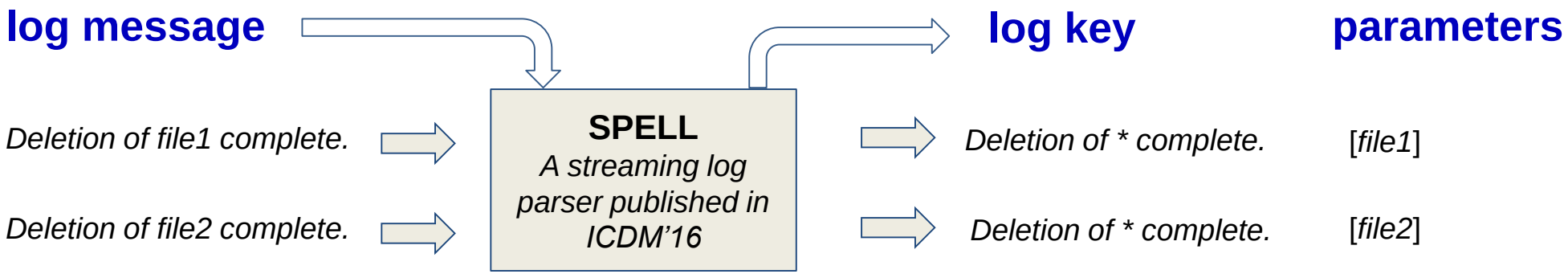

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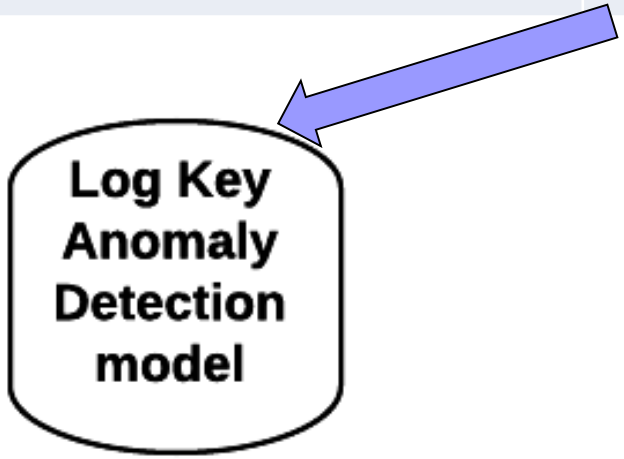

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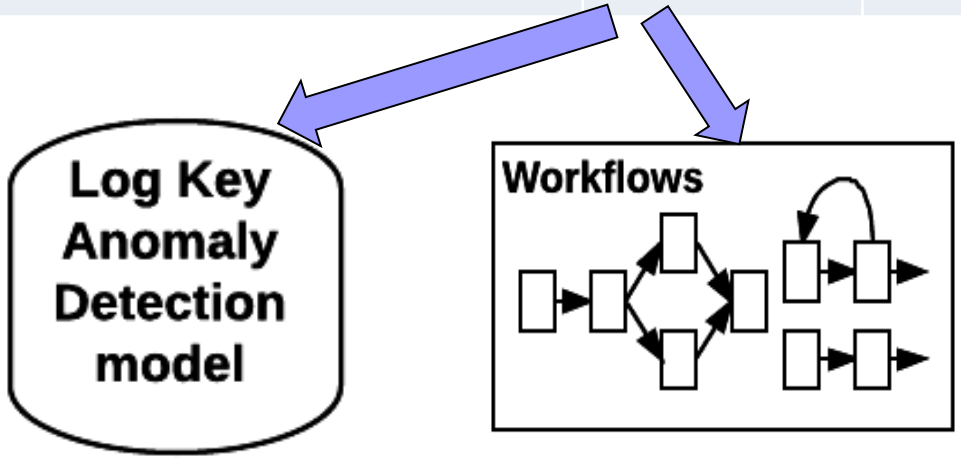

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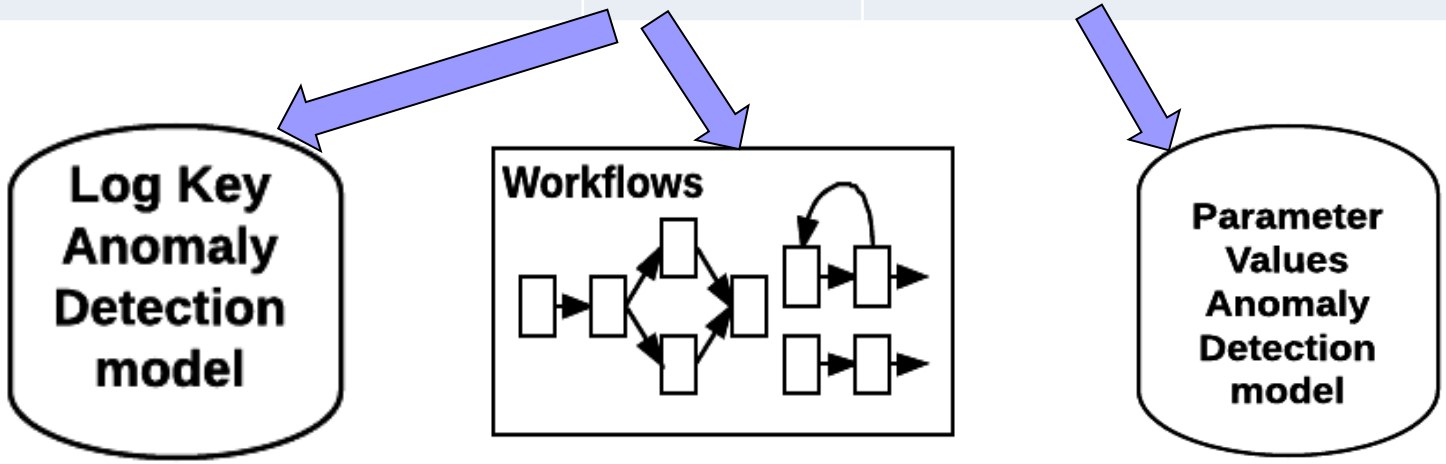

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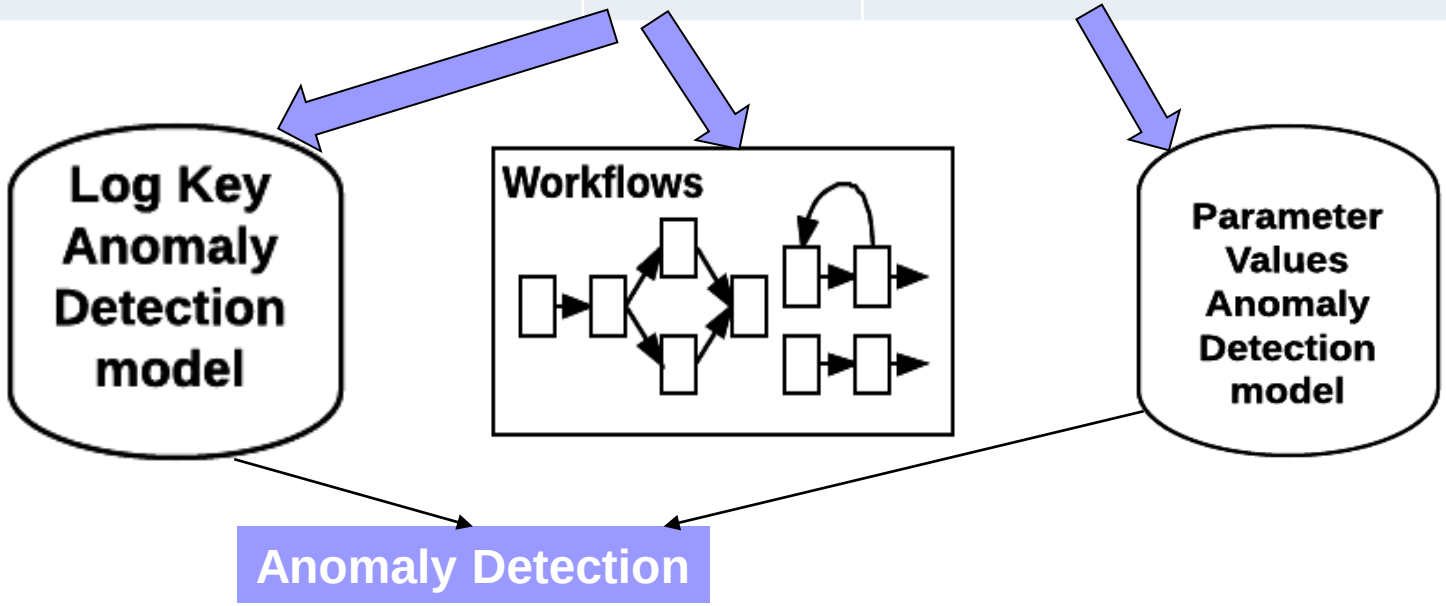

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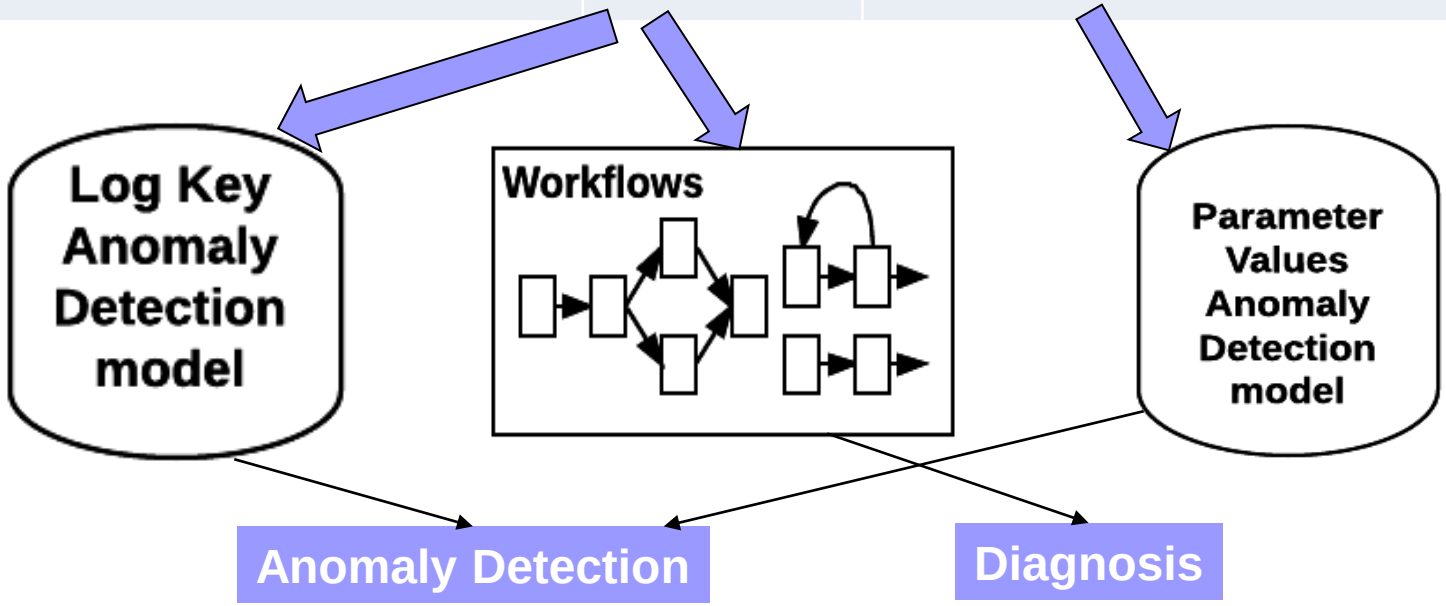

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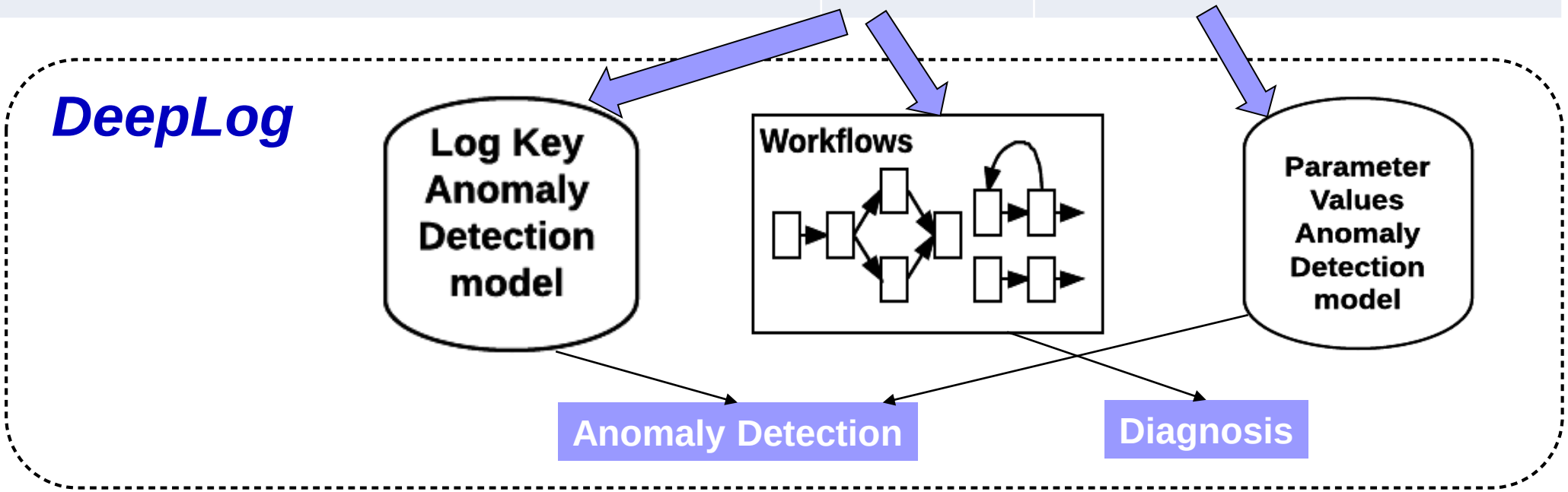
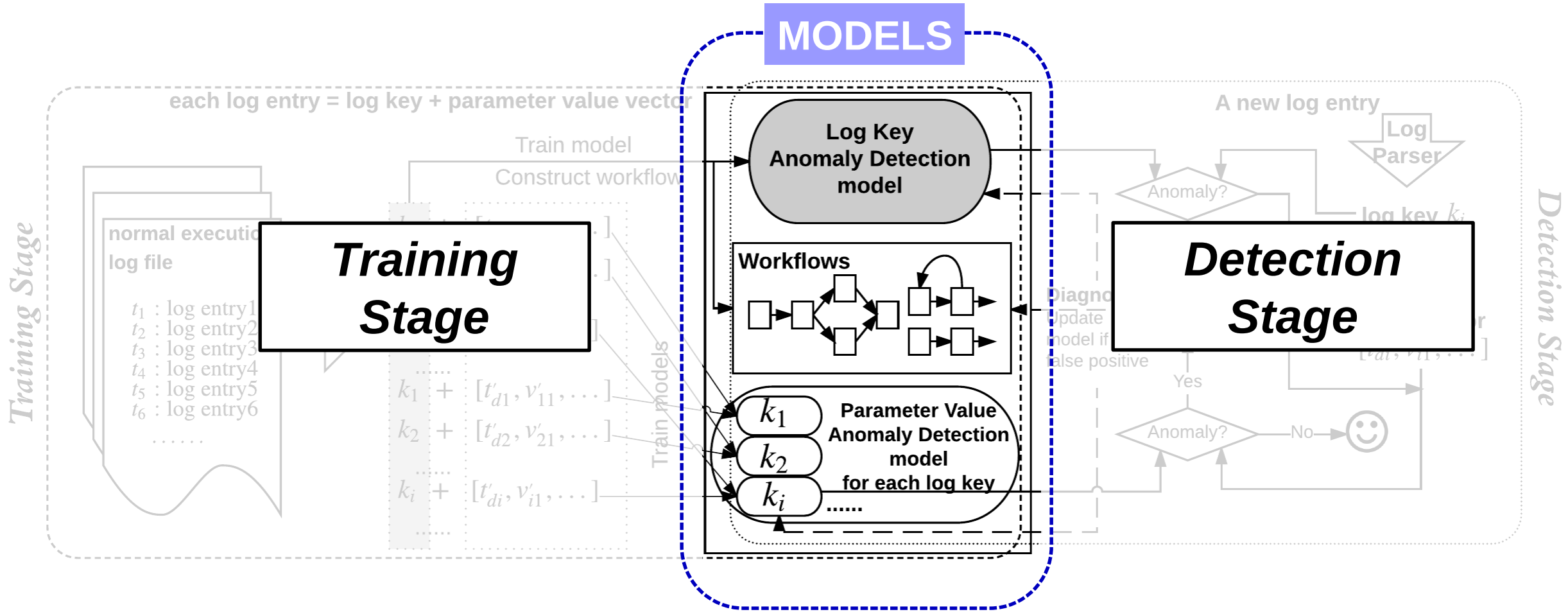


DeepLog Architecture



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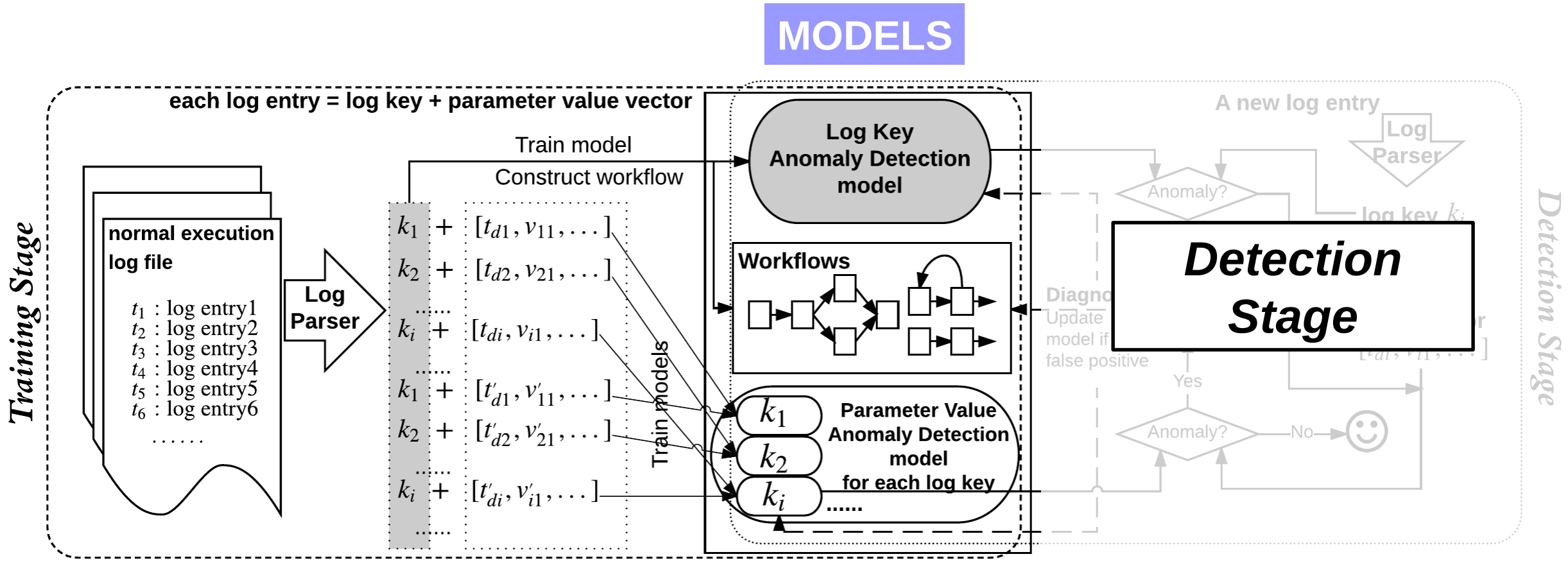

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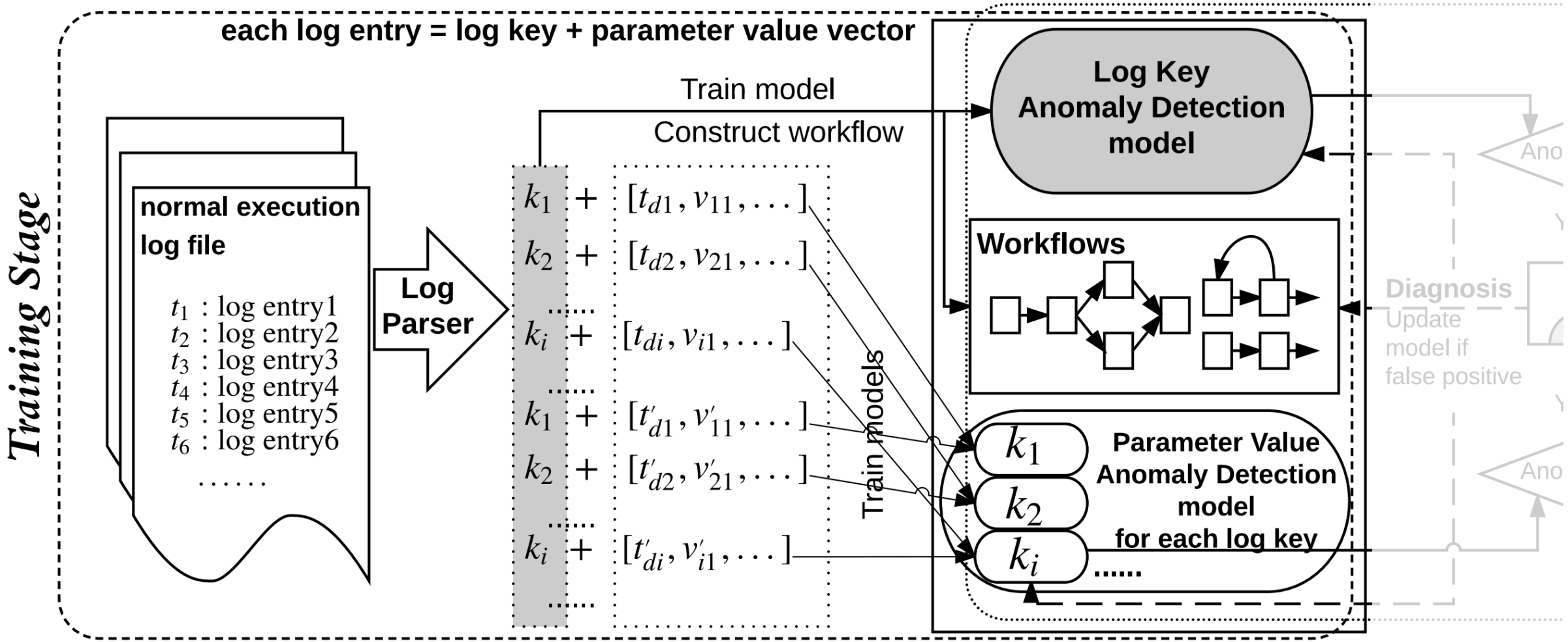
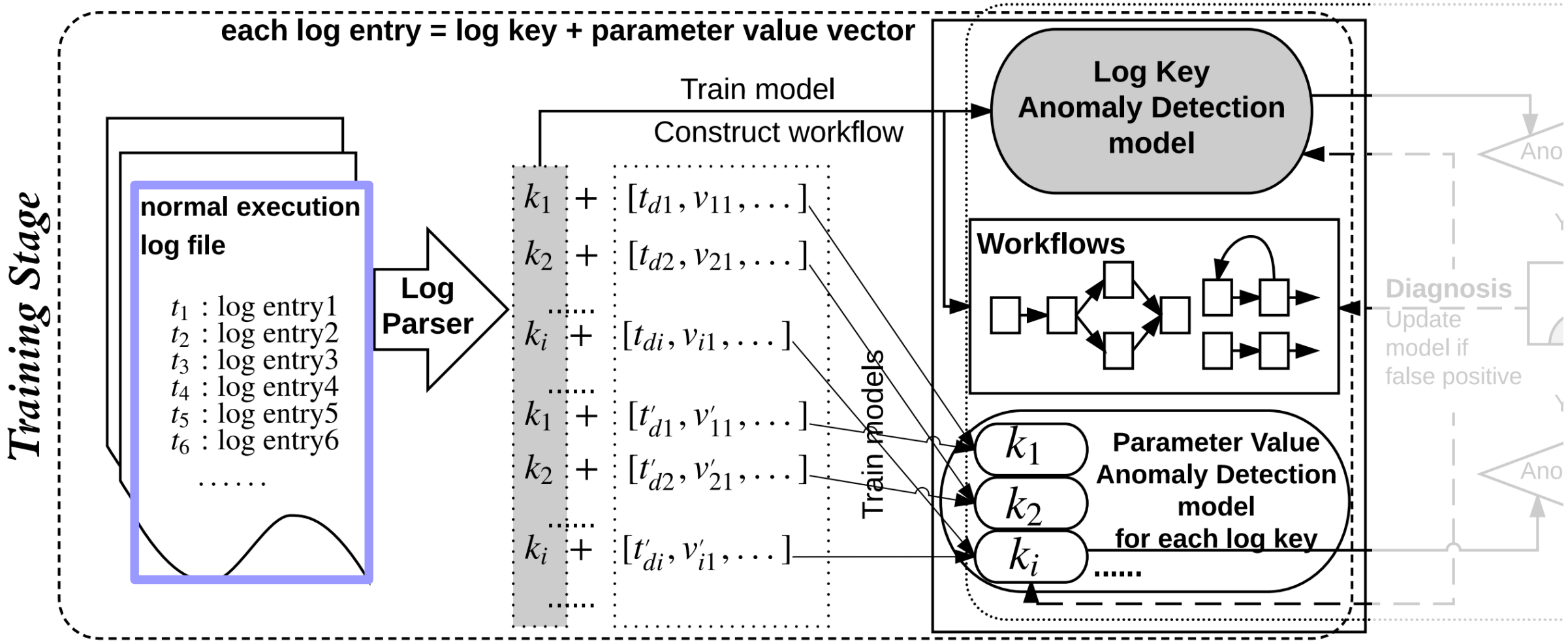


DeepLog Architecture



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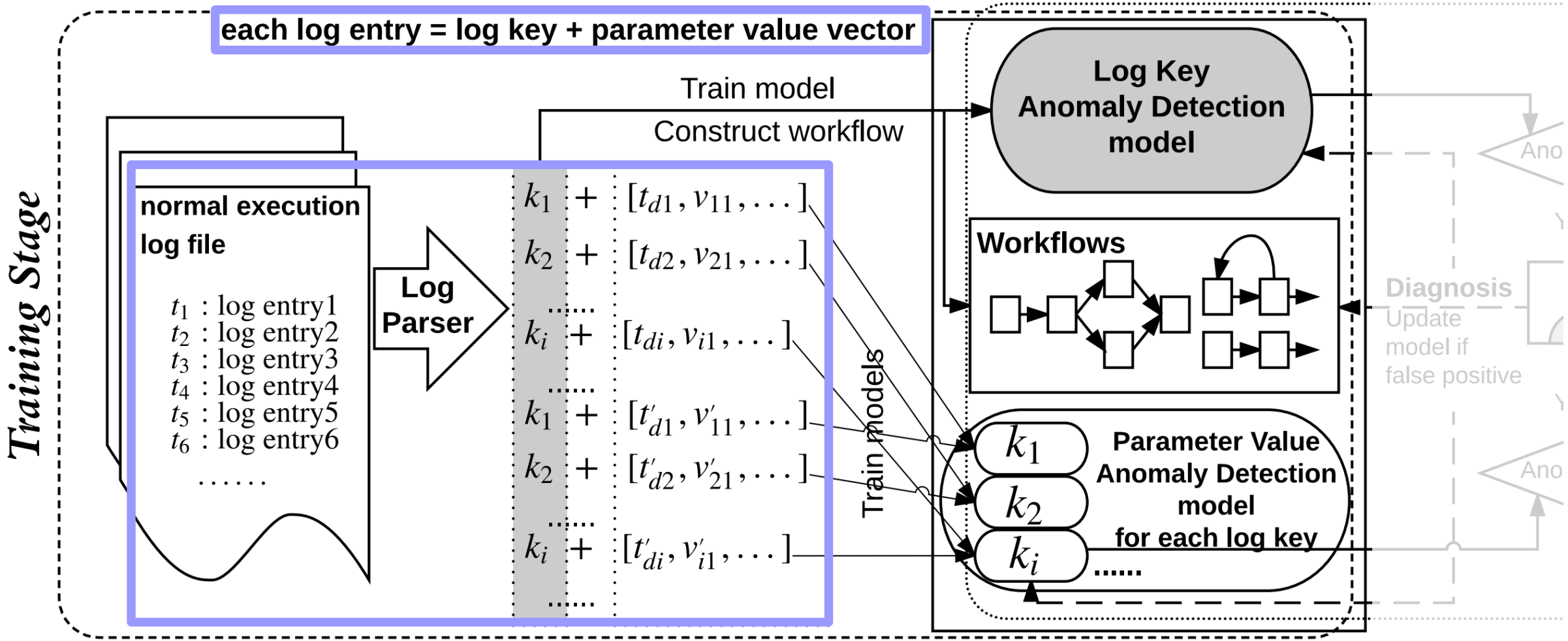

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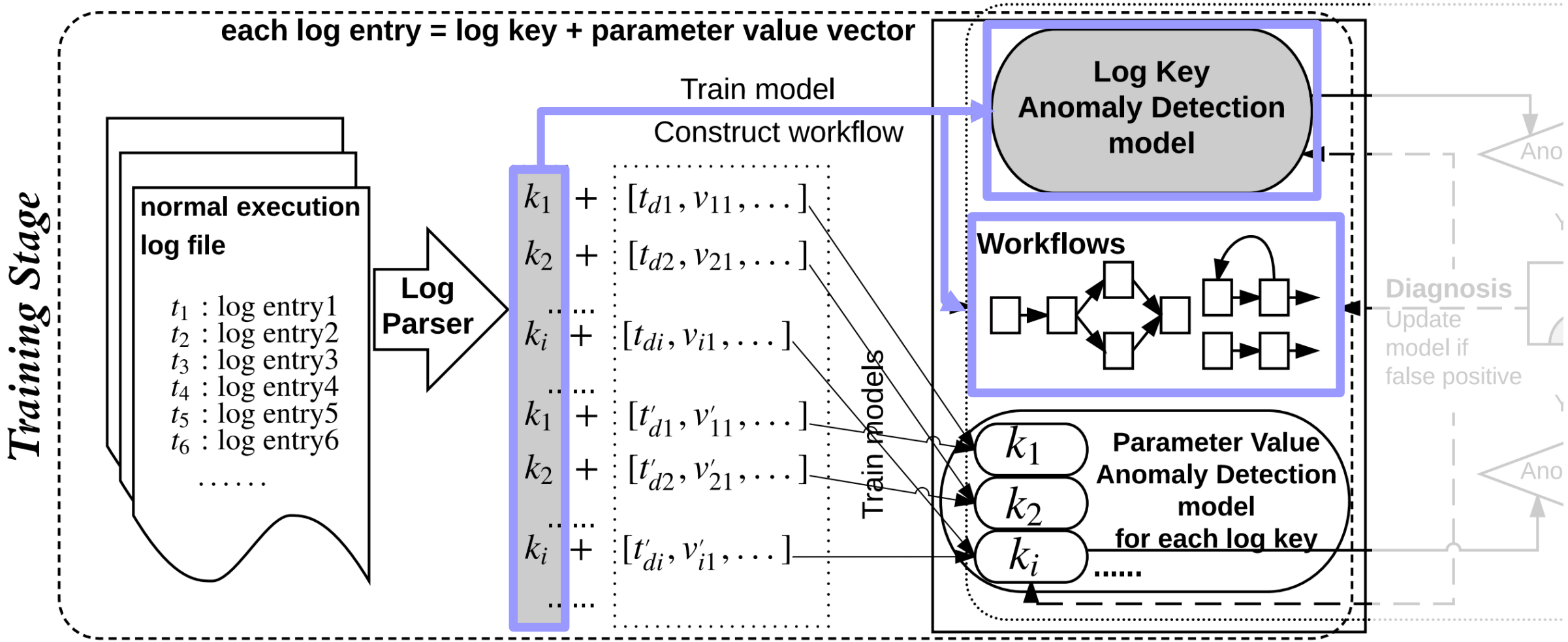

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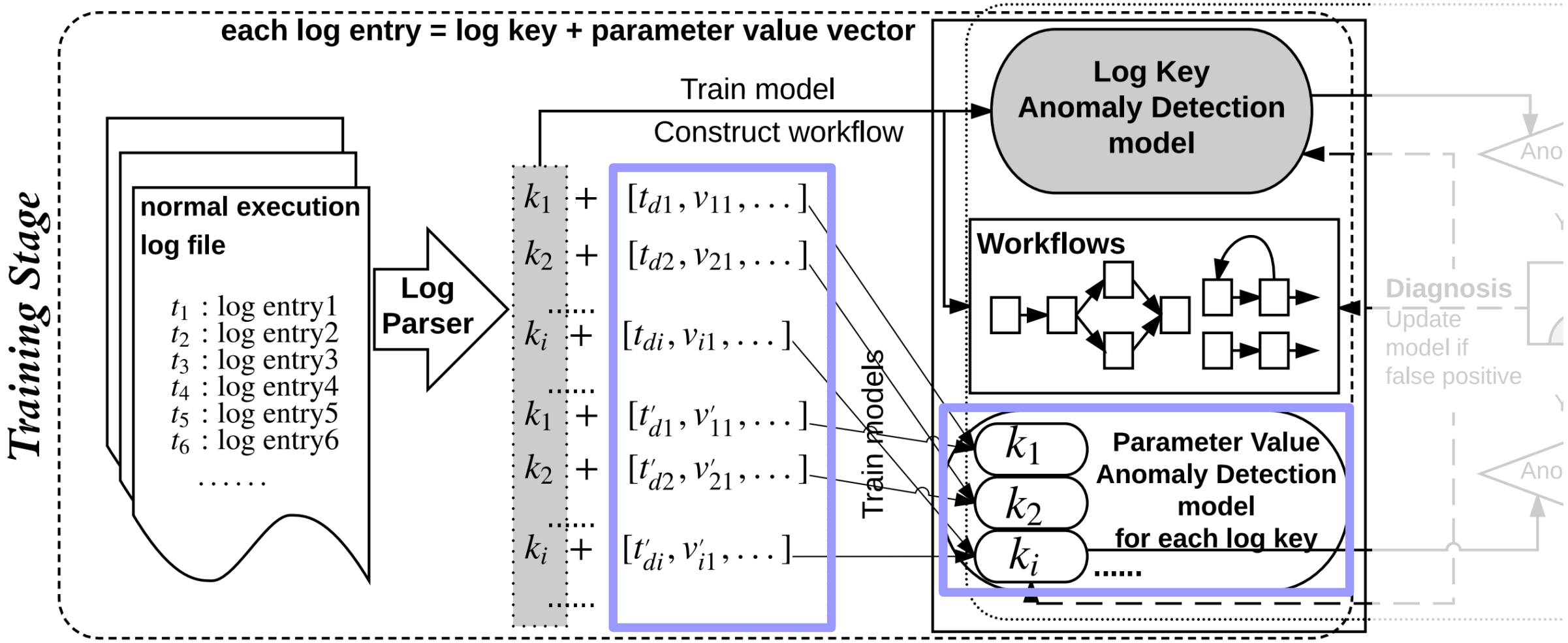

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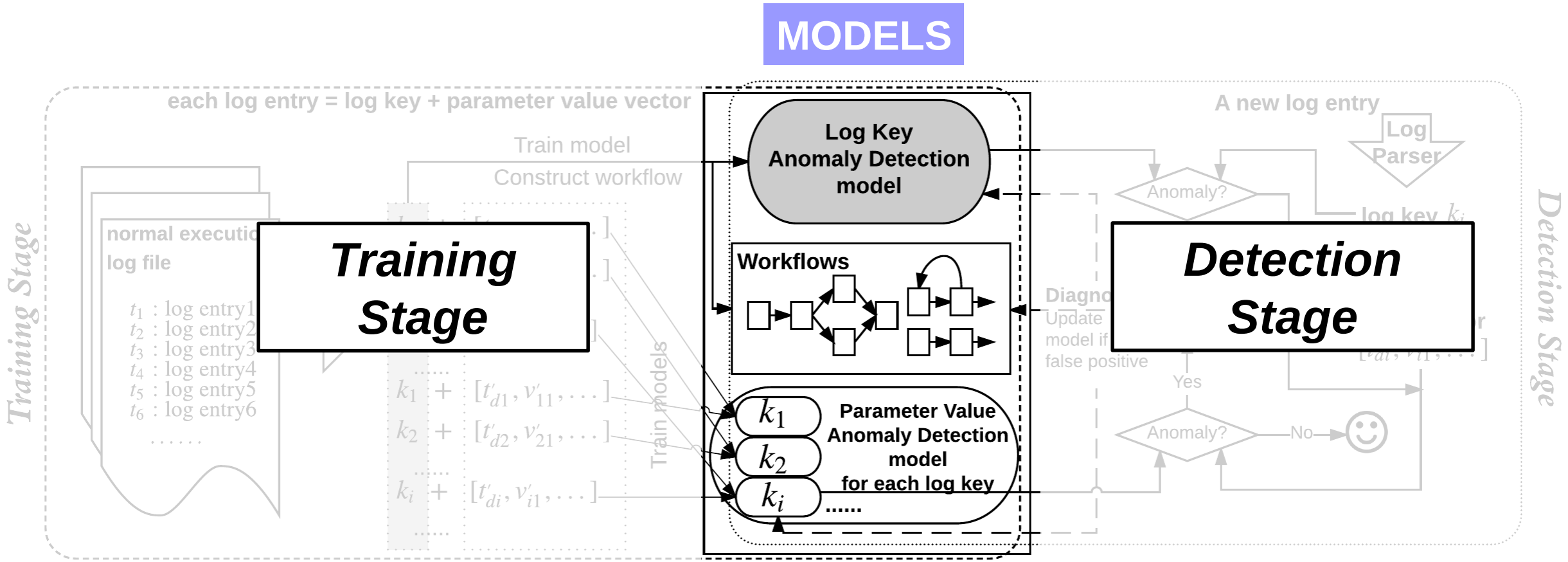

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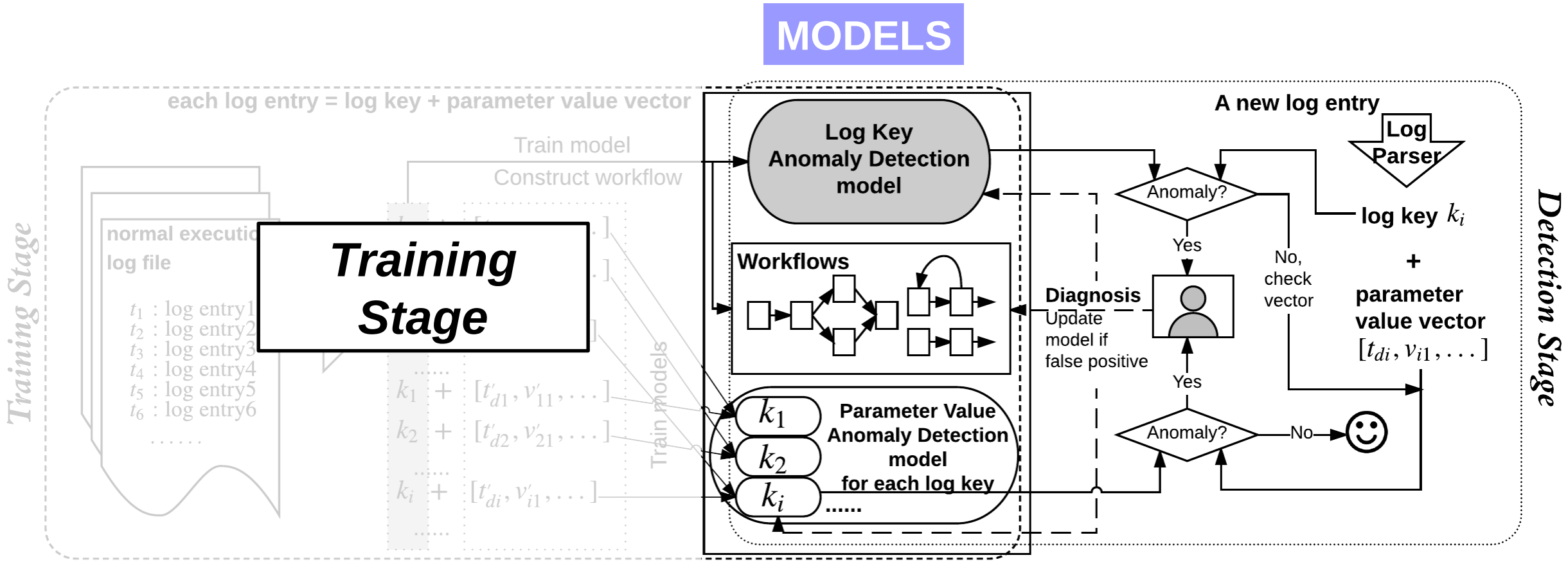

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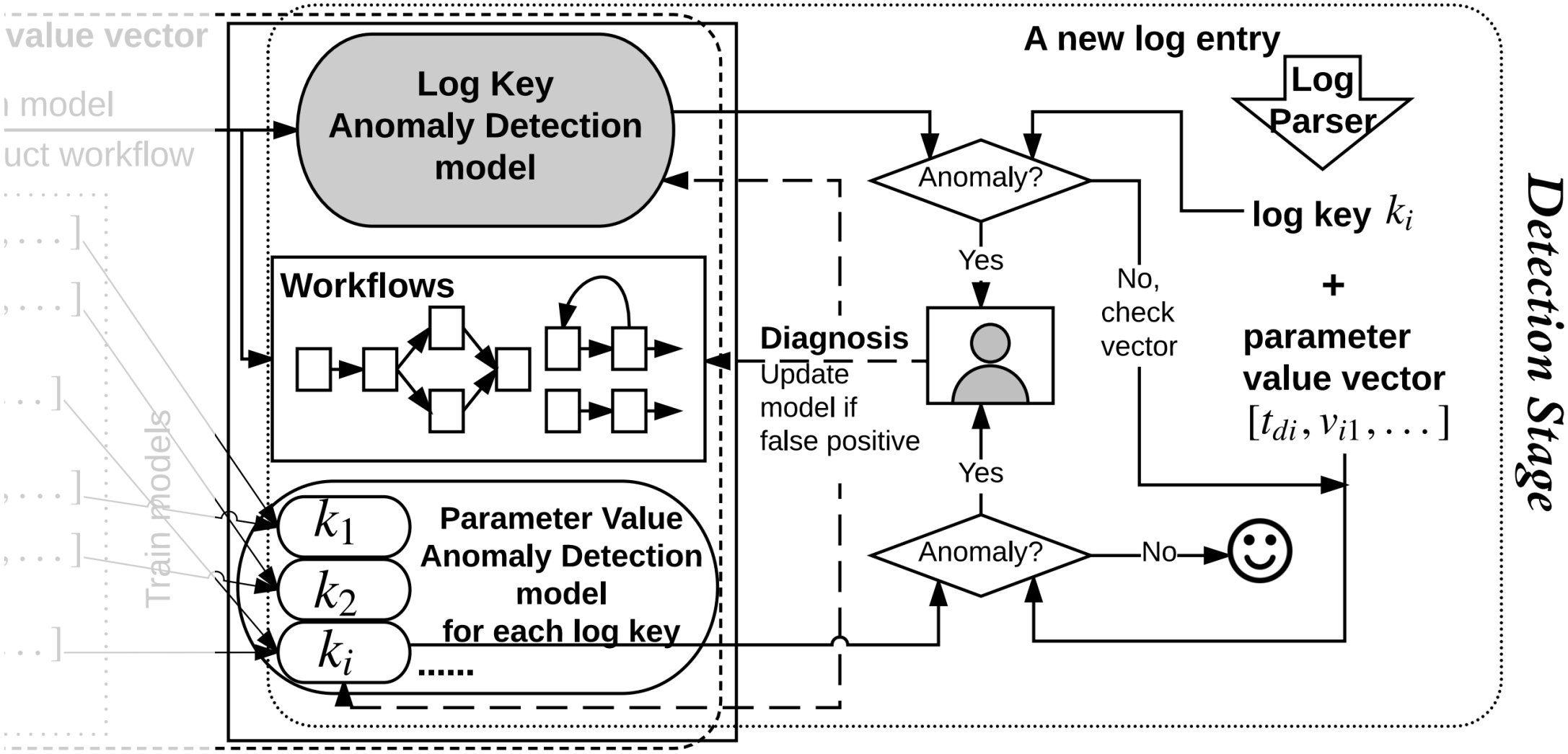

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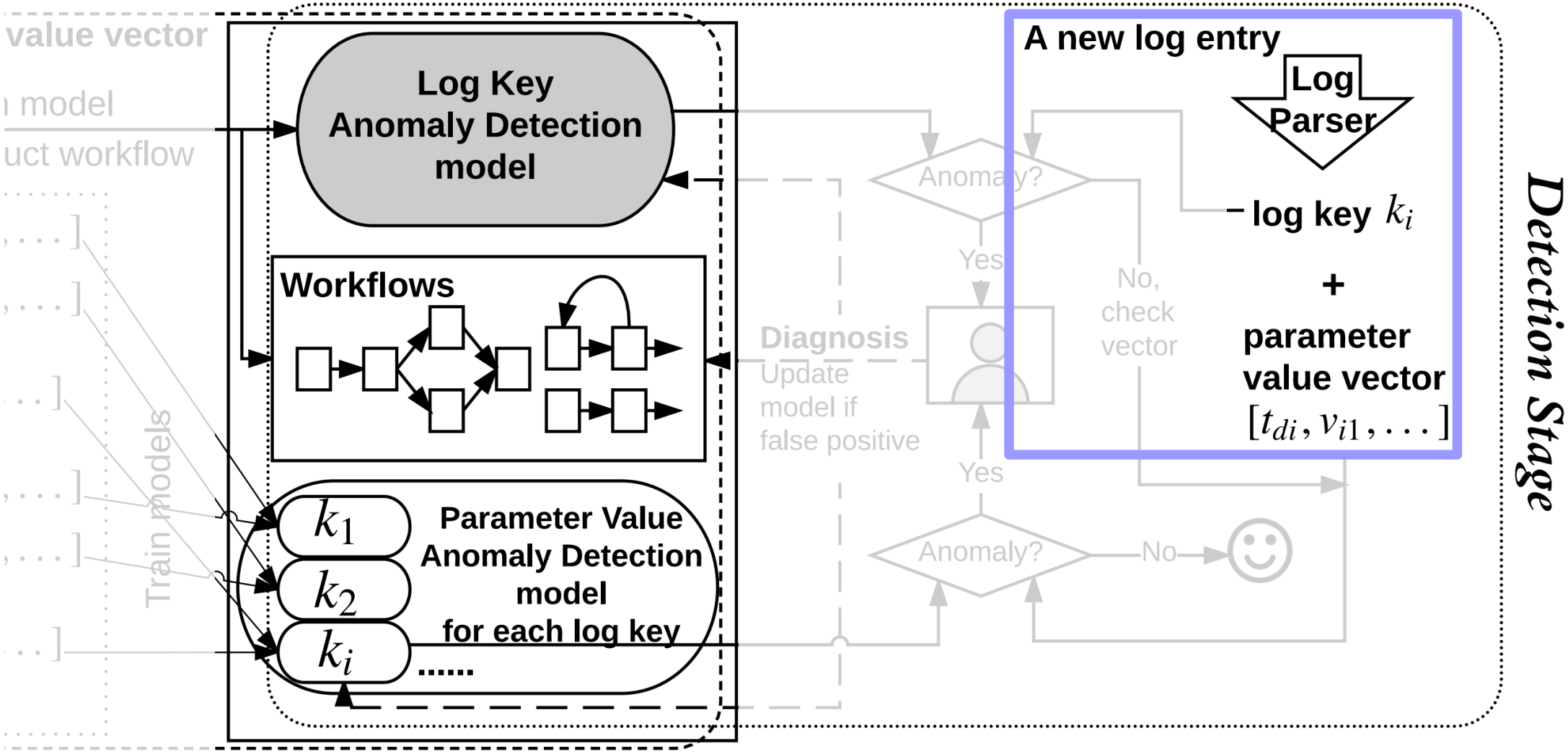
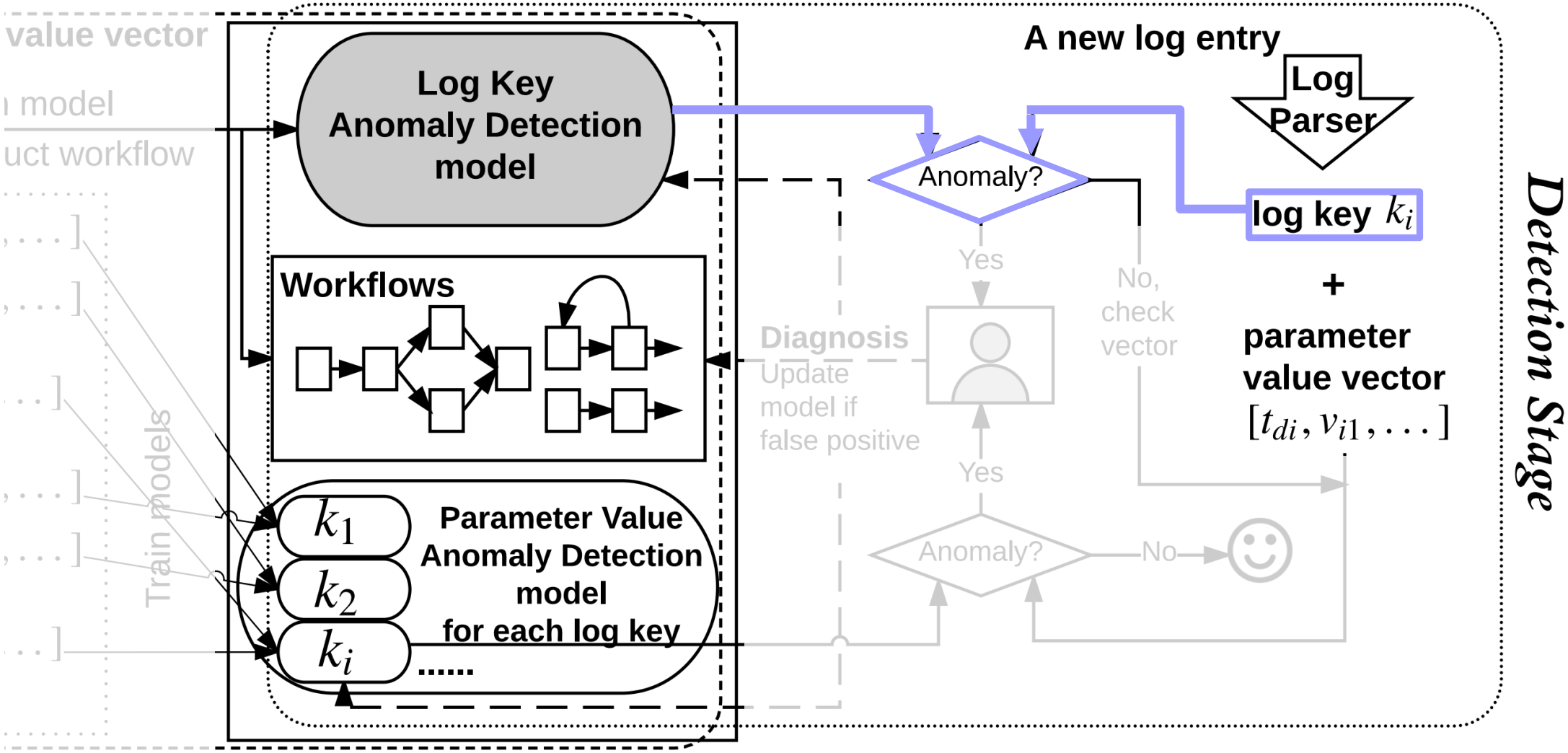


DeepLog Architecture



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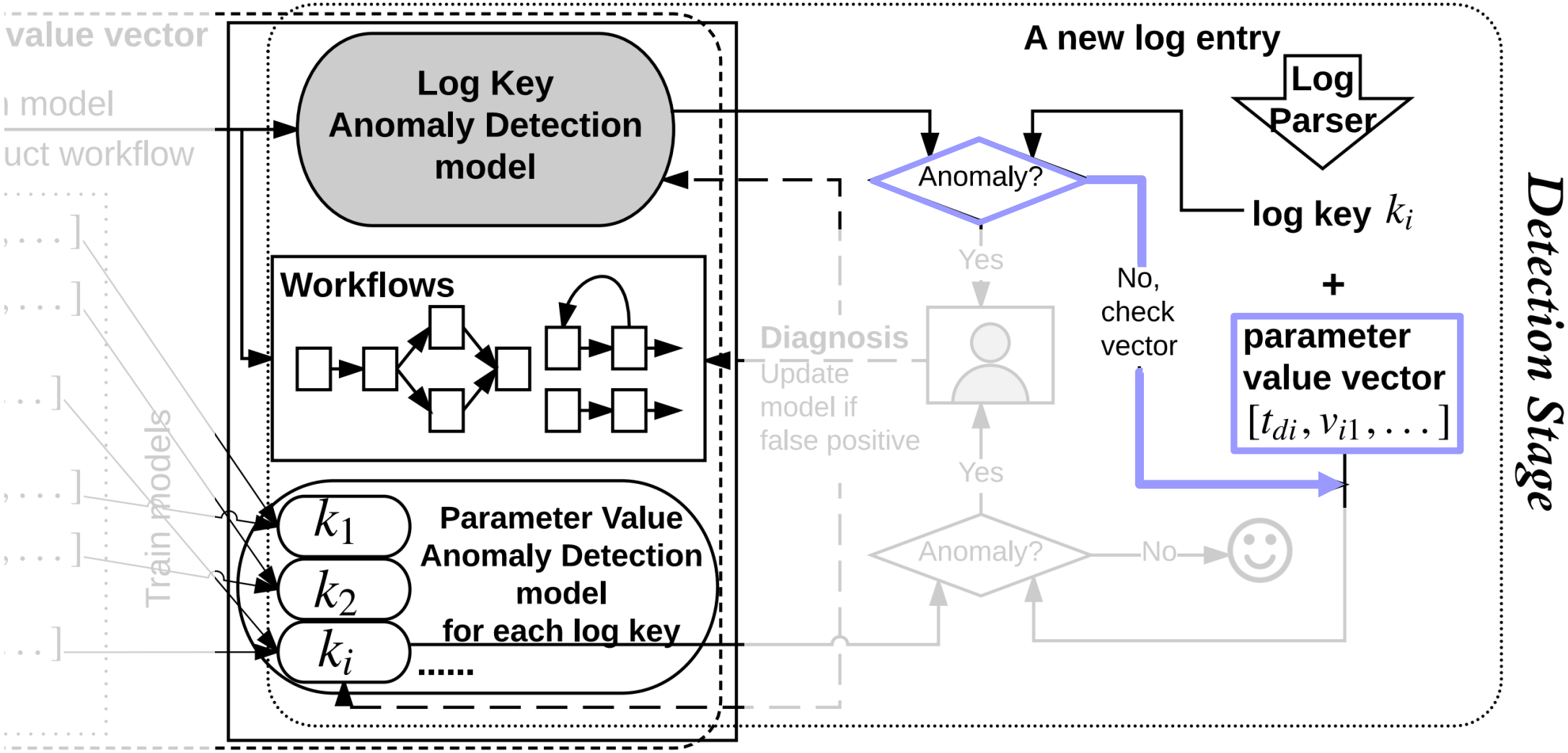

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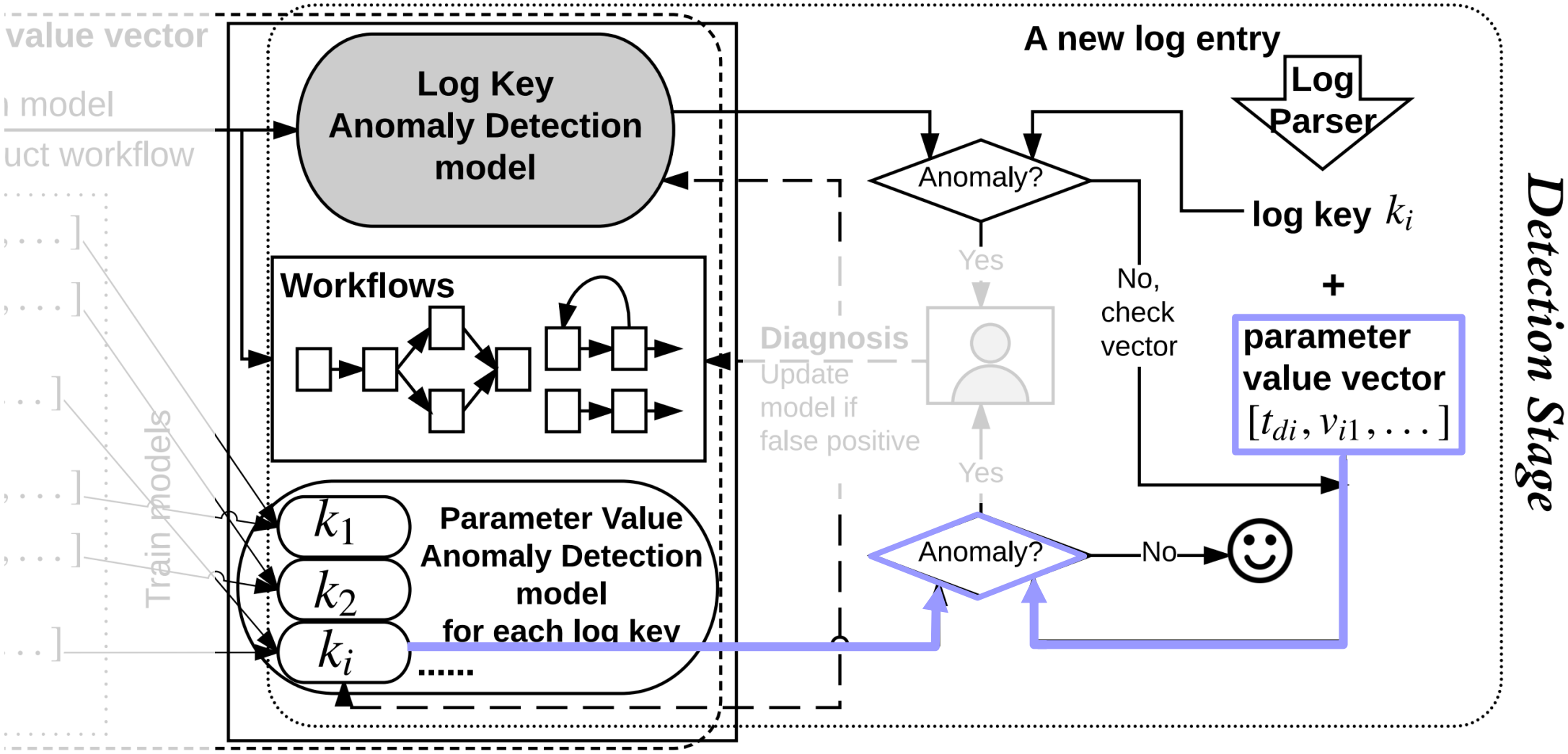

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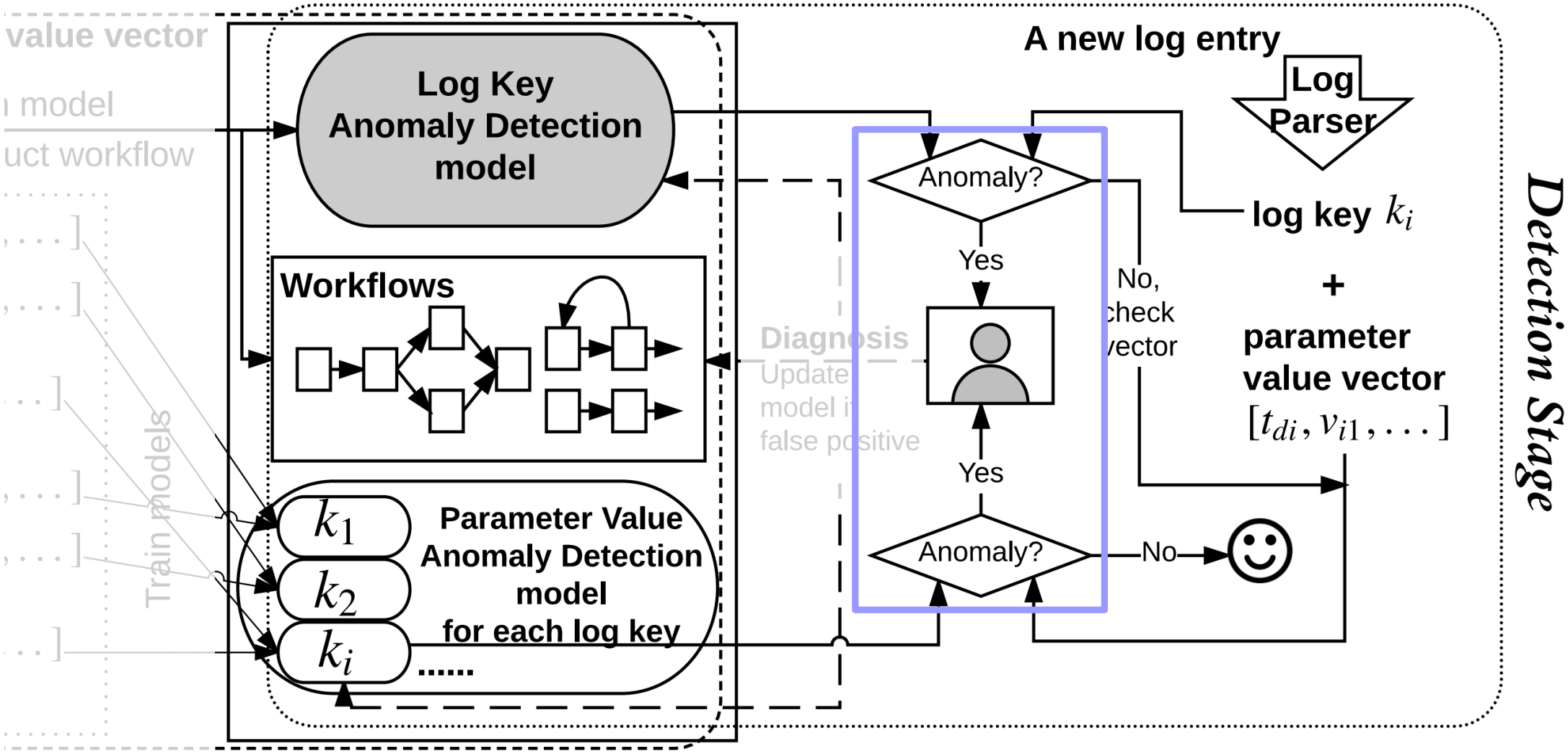

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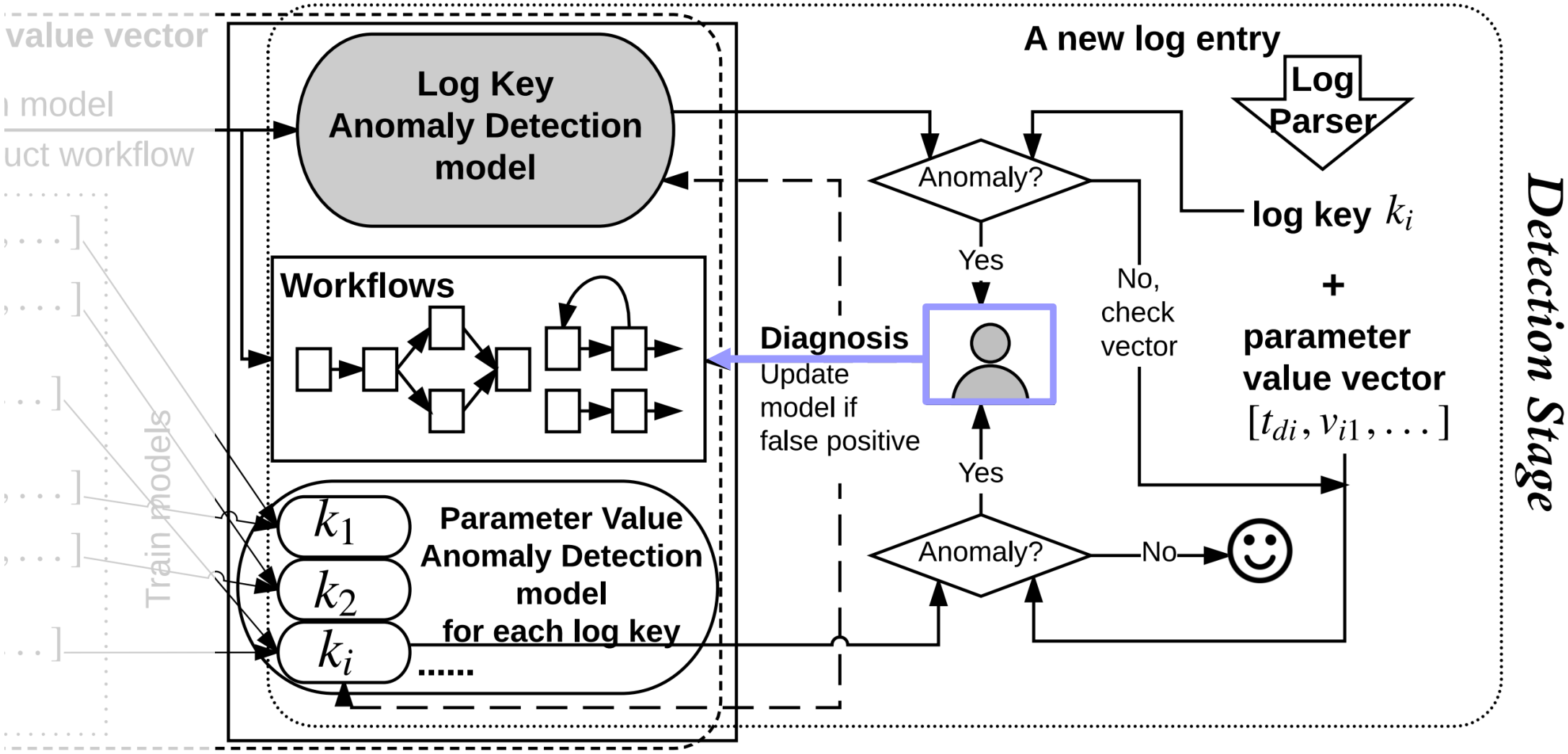

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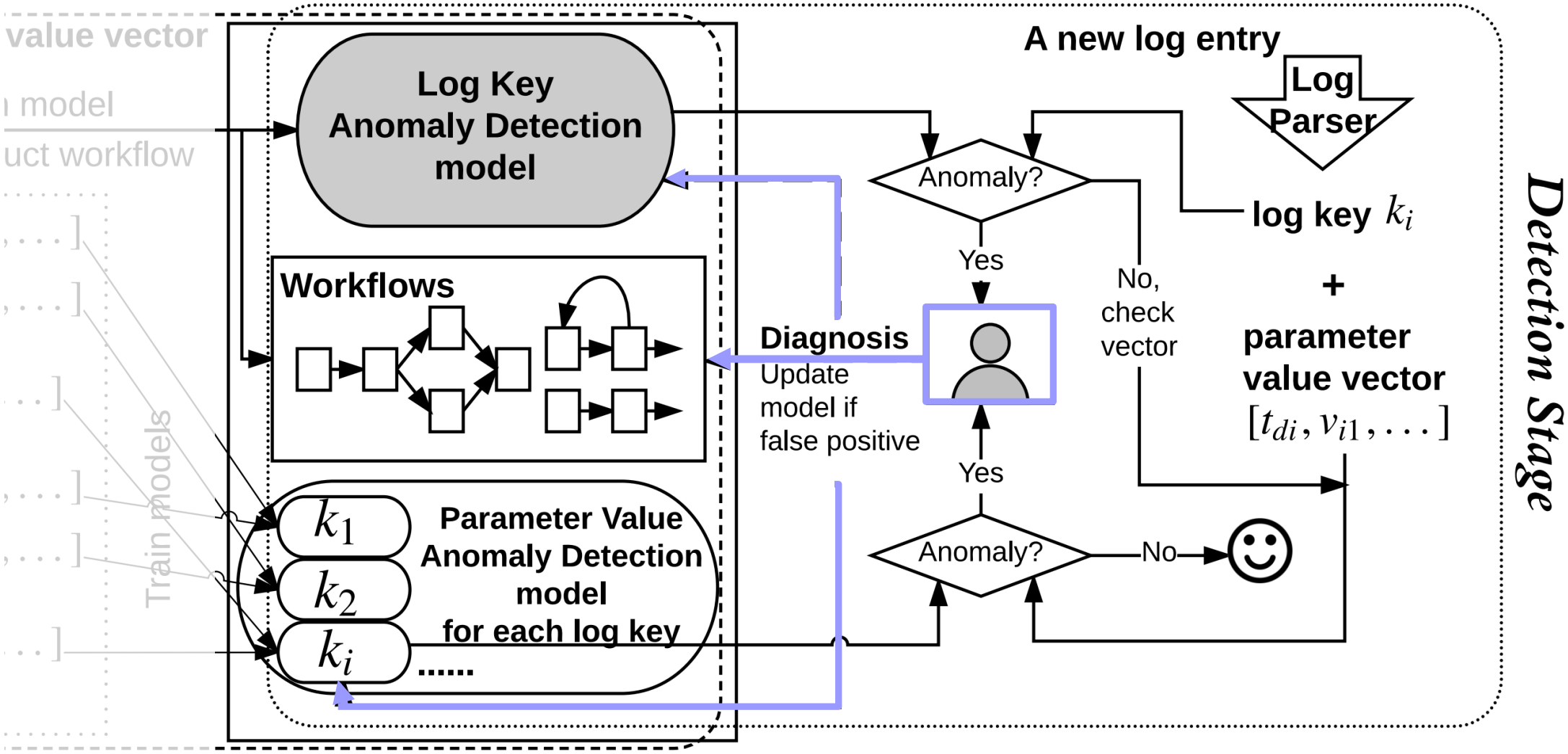

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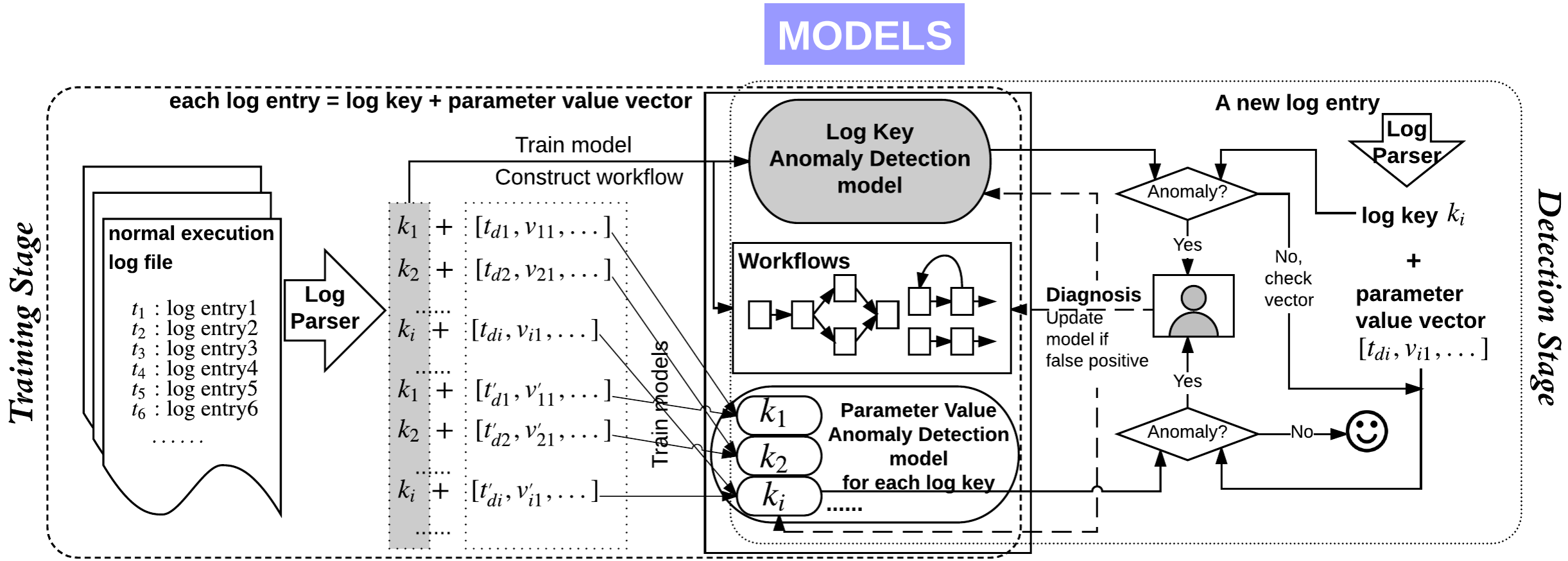

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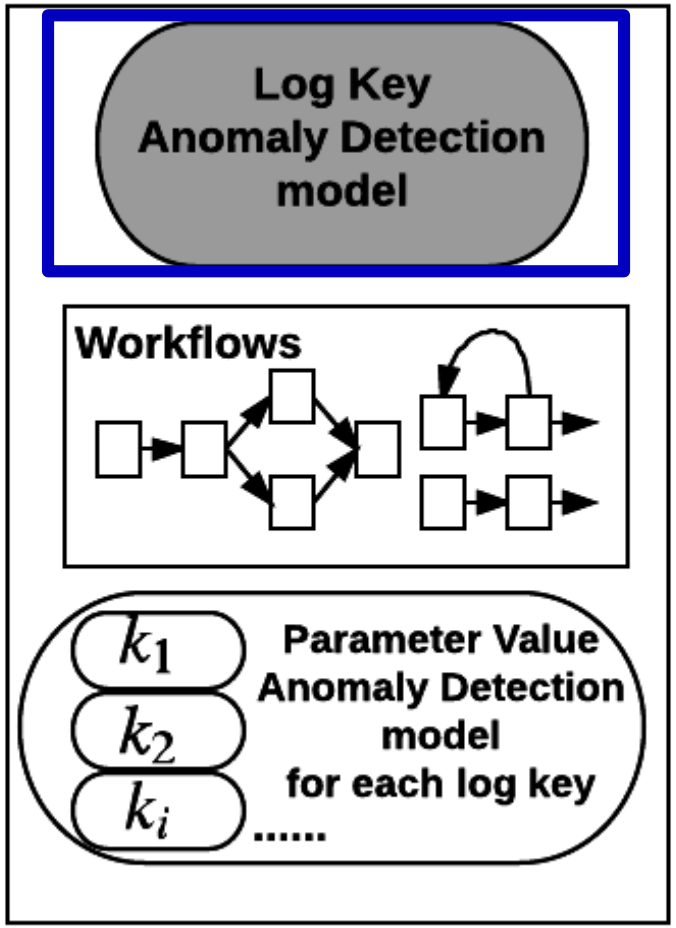

Example log key sequence:

25 18 54 57 18 56 … 25 18 54 57 56 18 …

- a rigorous set of logic and control flows
- a (*more structured*) natural language

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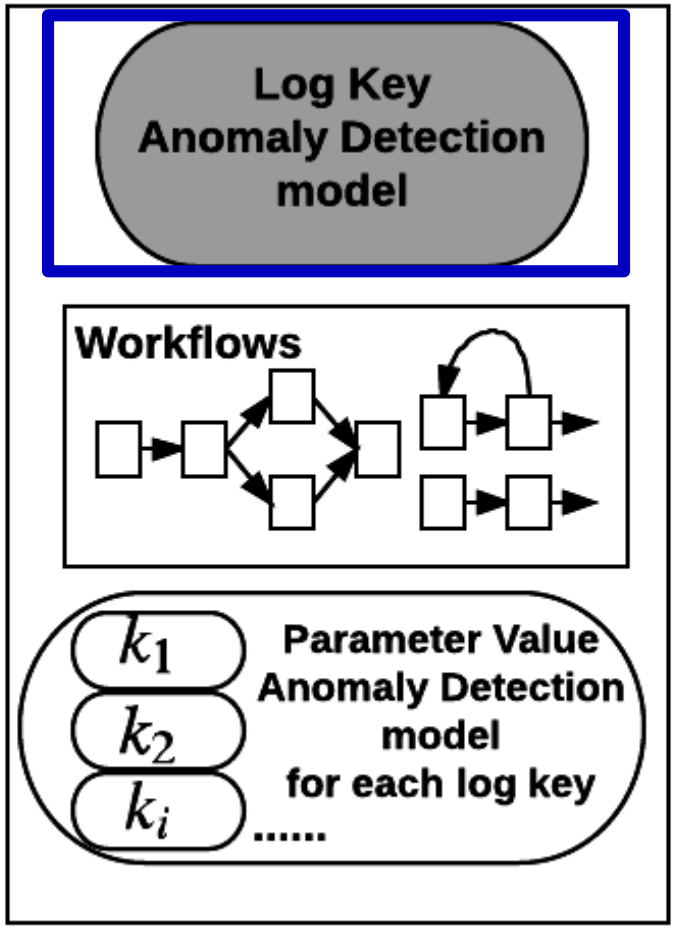

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multi-class classifier: *history sequence => next key to appear*

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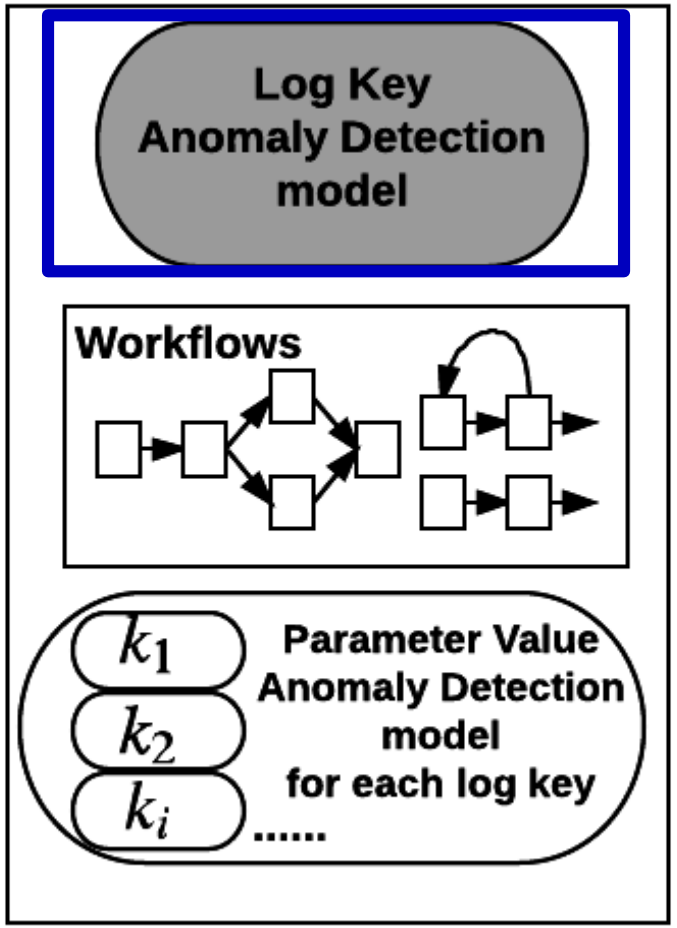

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A log key is detected to be abnormal if it does not follow the prediction.

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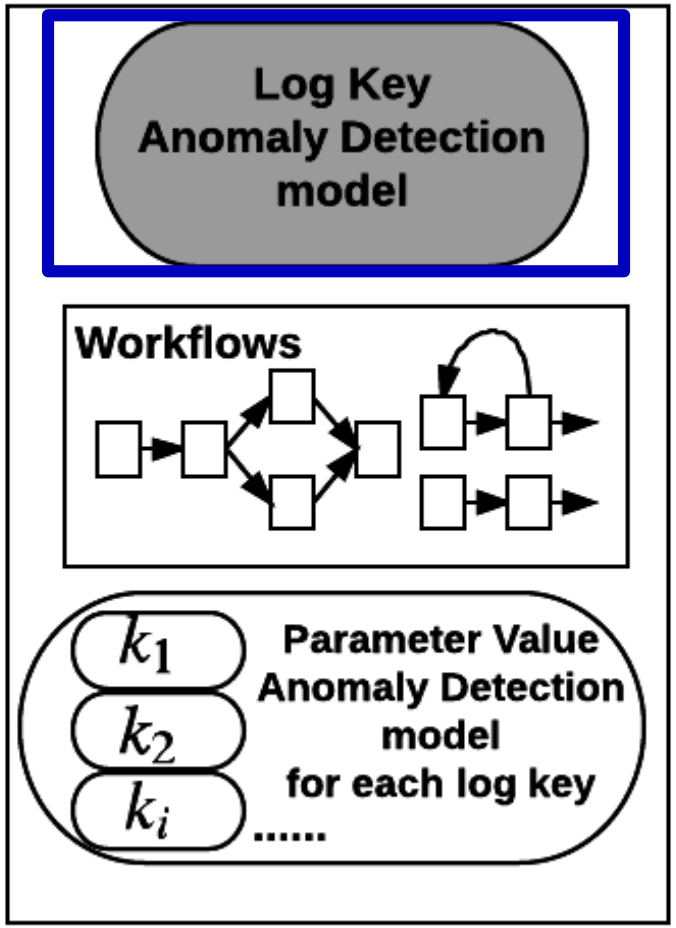

Use long short-term memory (LSTM) architecture

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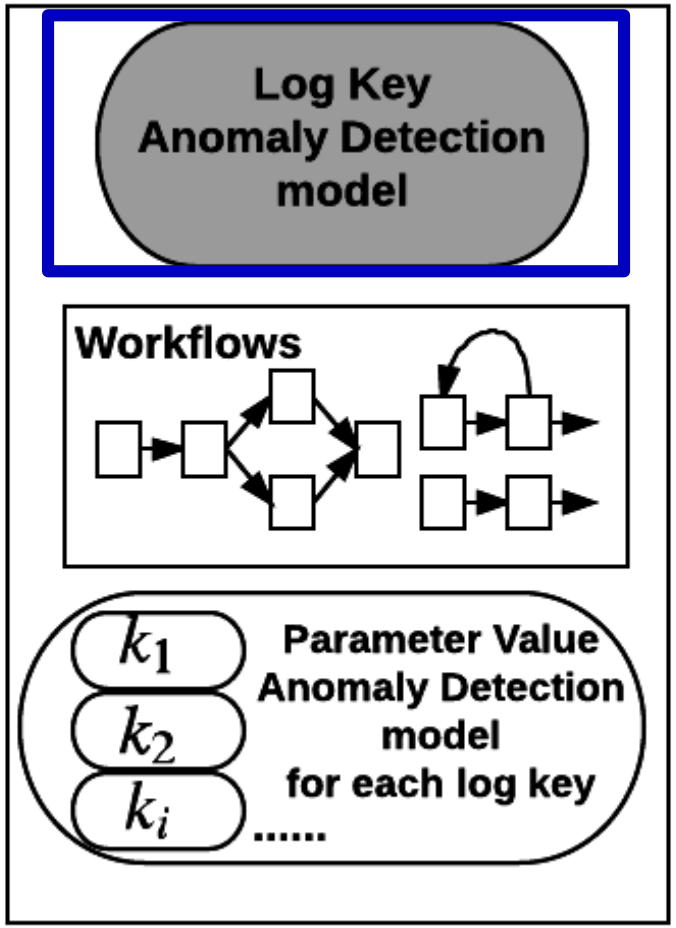

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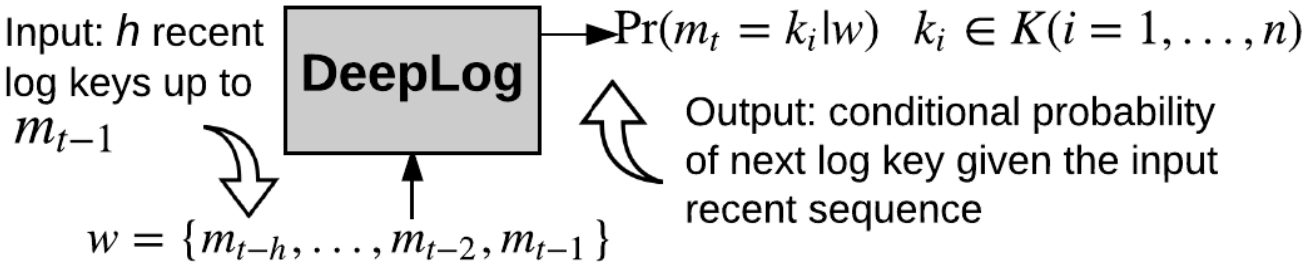

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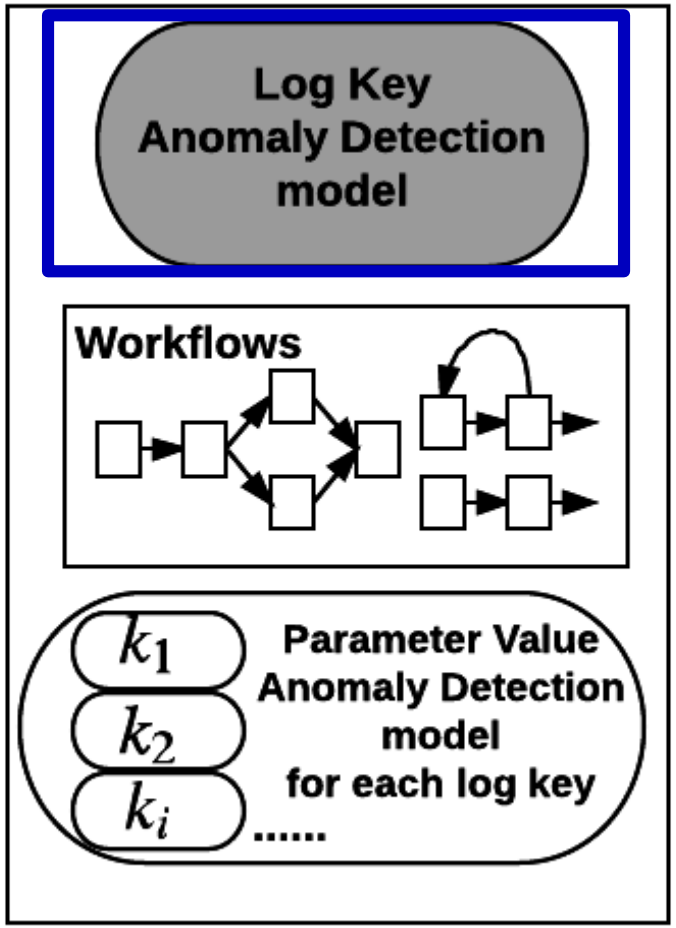

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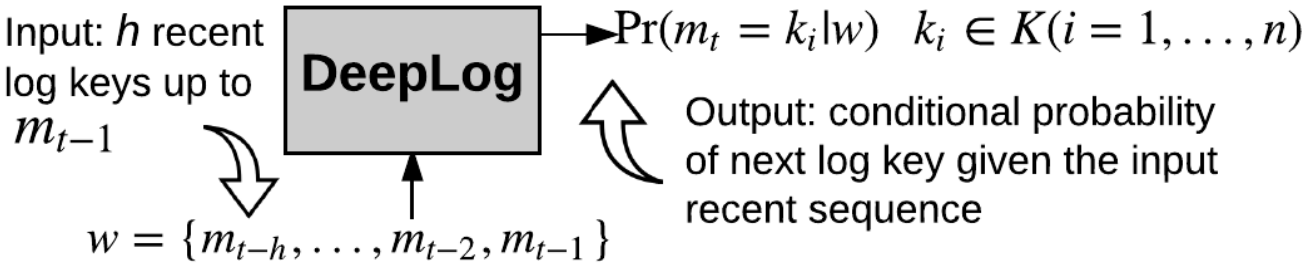

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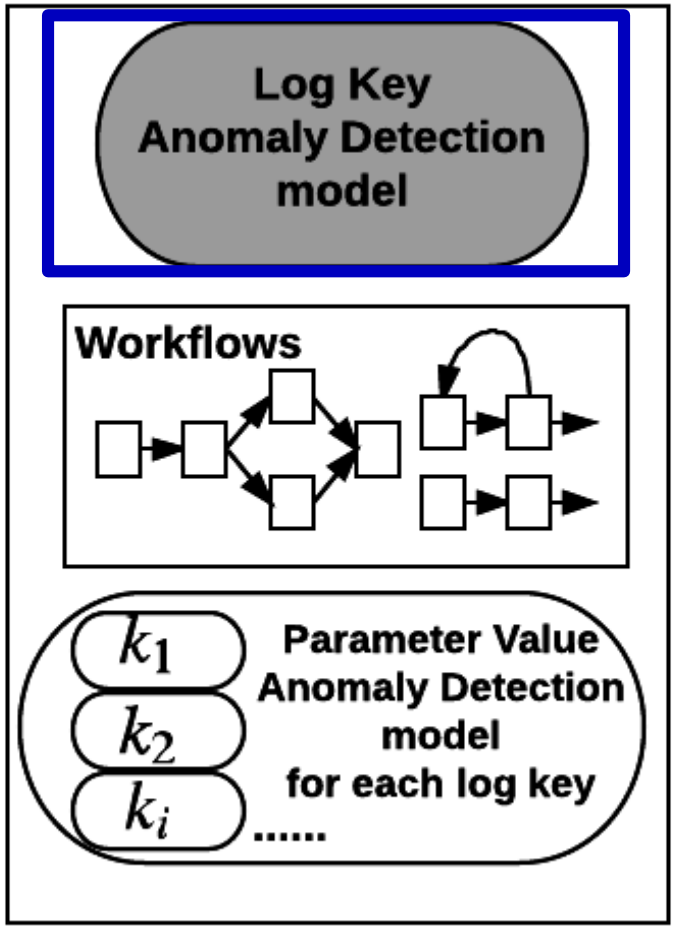

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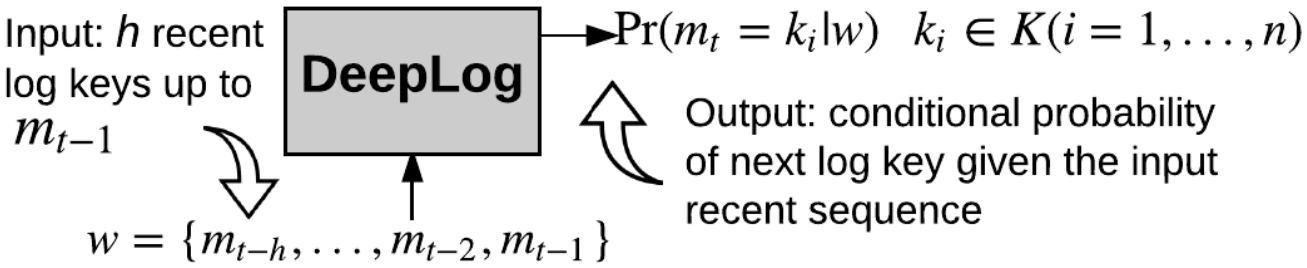

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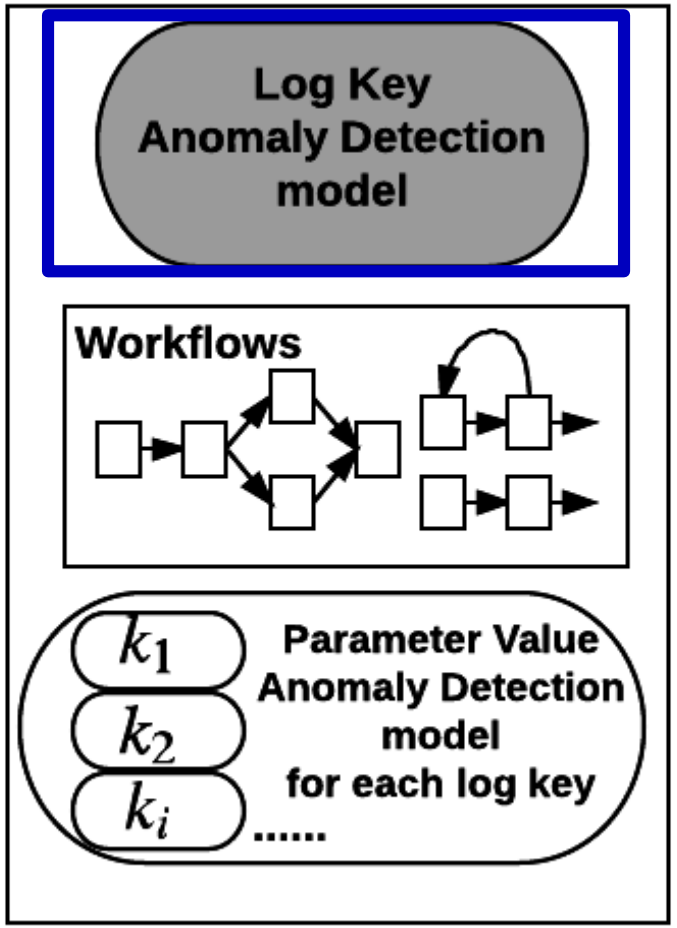

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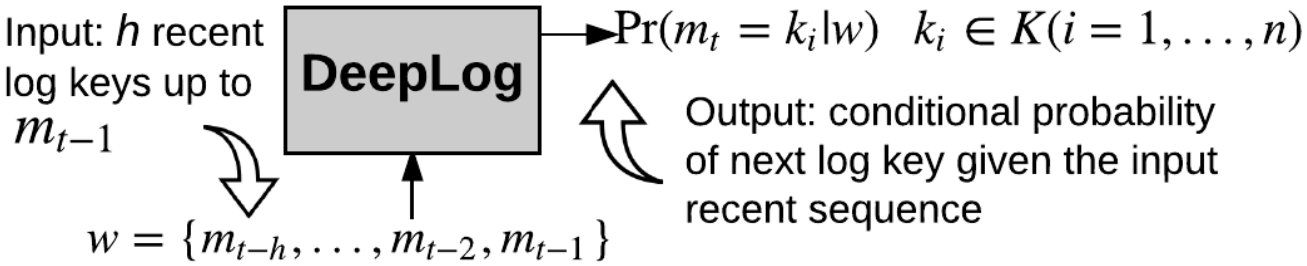

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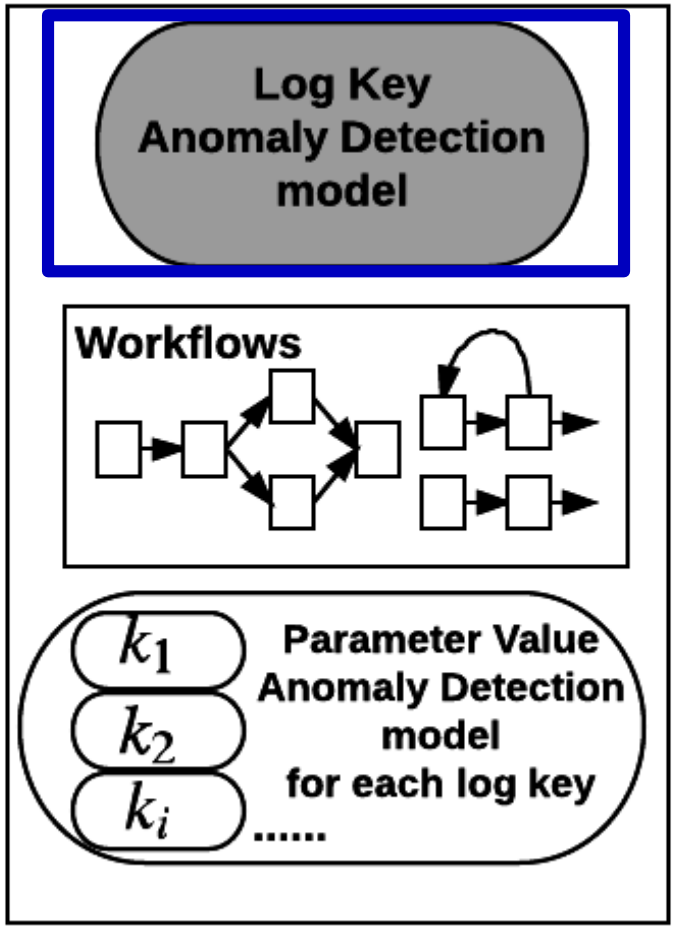

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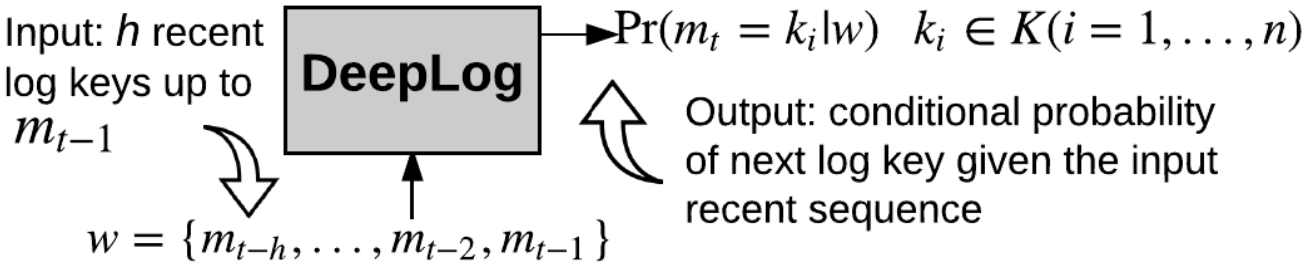

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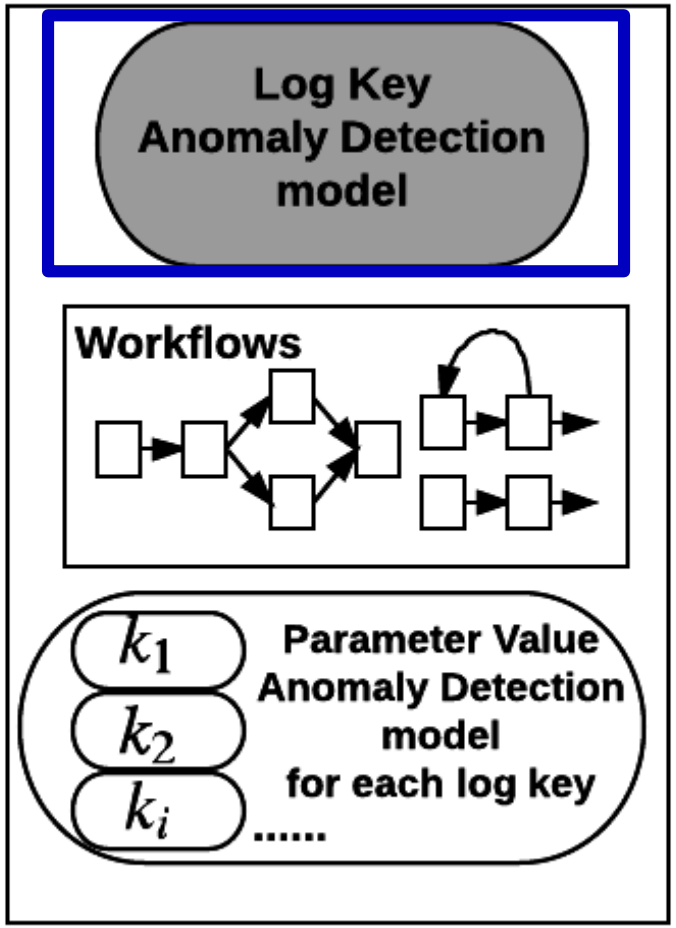

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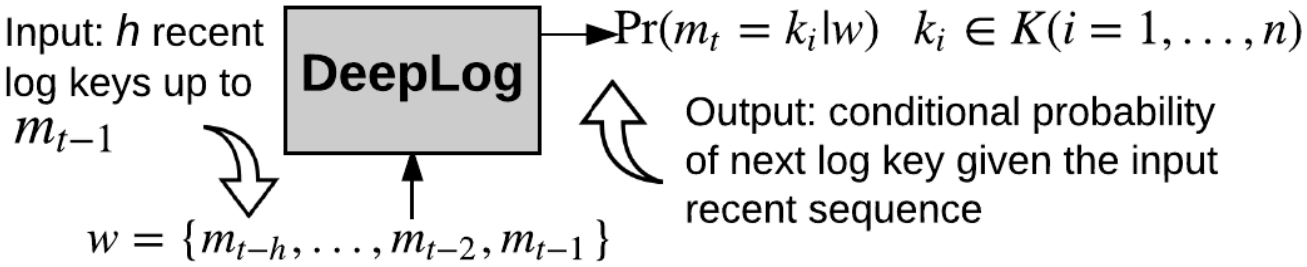
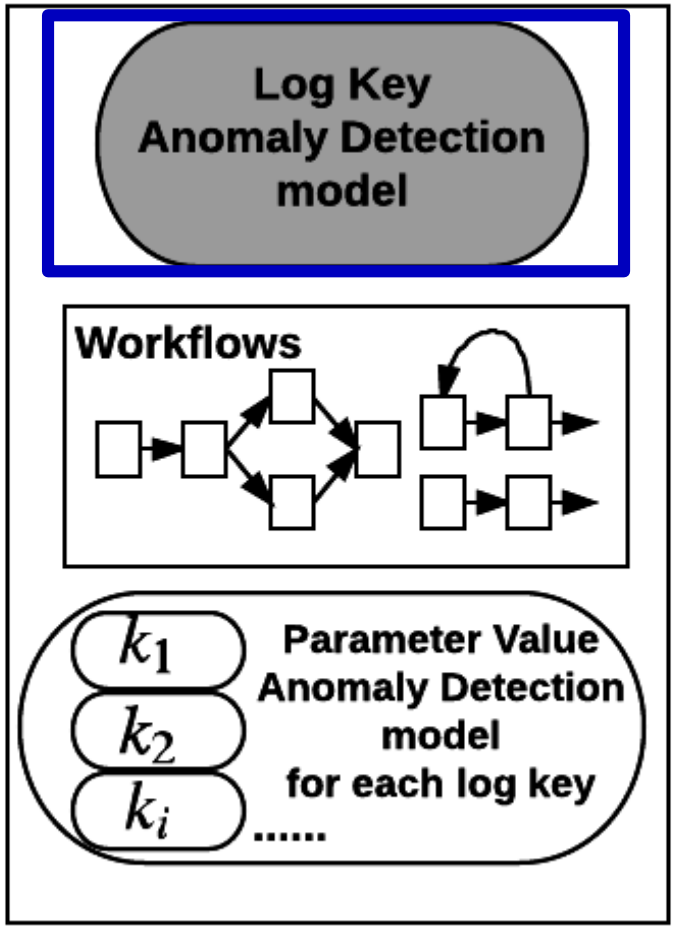
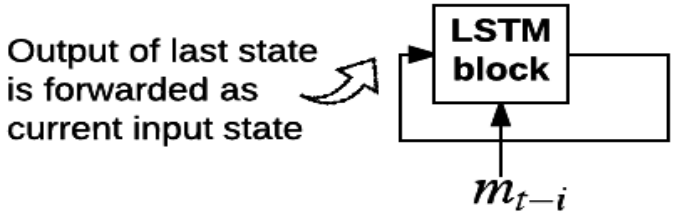


Detection:

In detection stage, DeepLog checks if the actual next log key is among its top *g* probable predictions.

Log Key Anomaly Detection model





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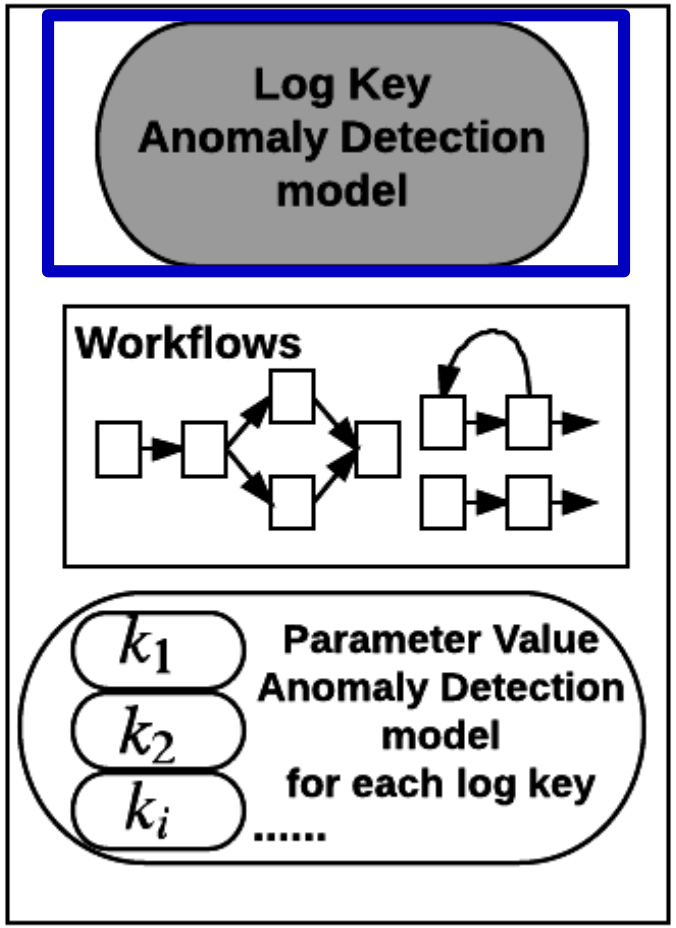

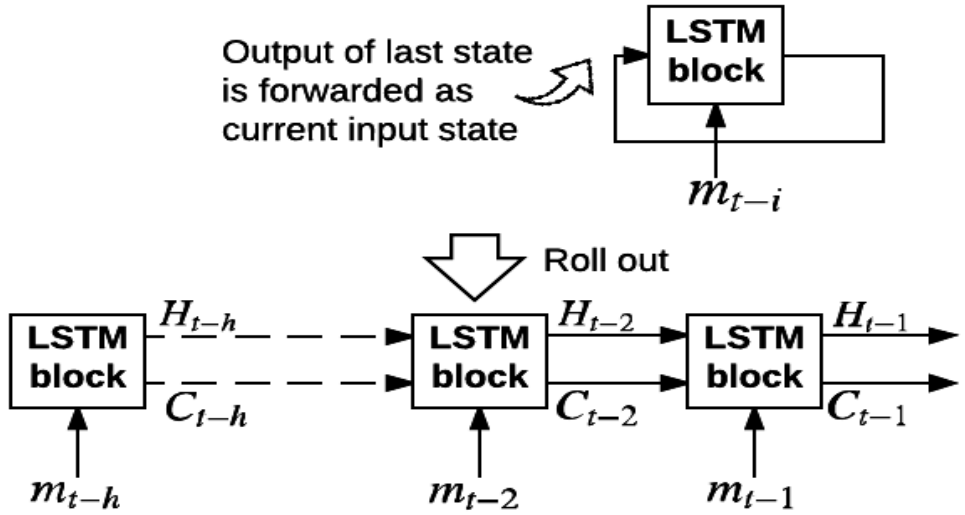

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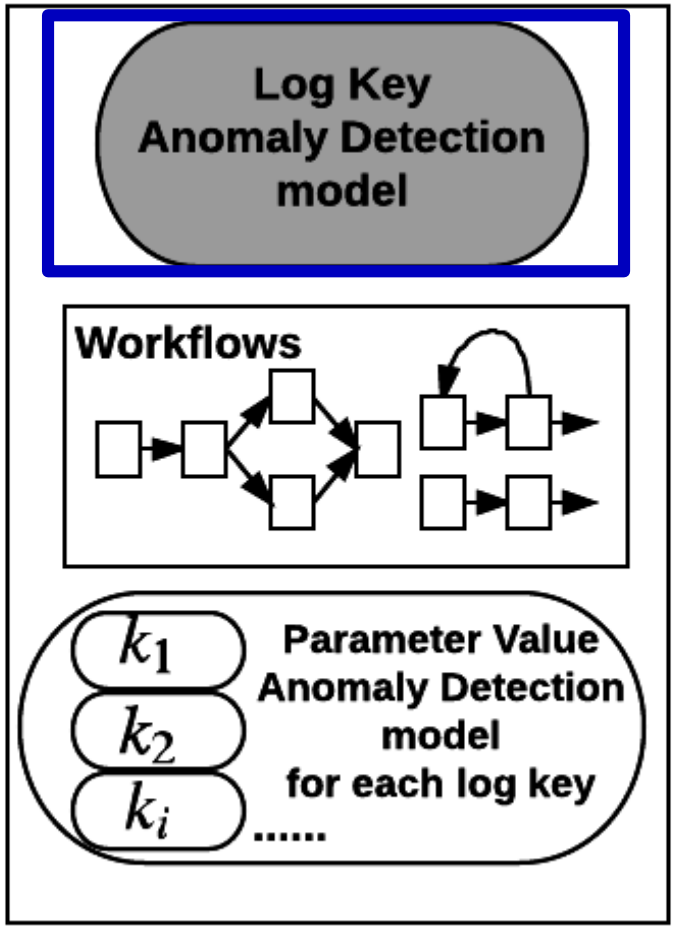
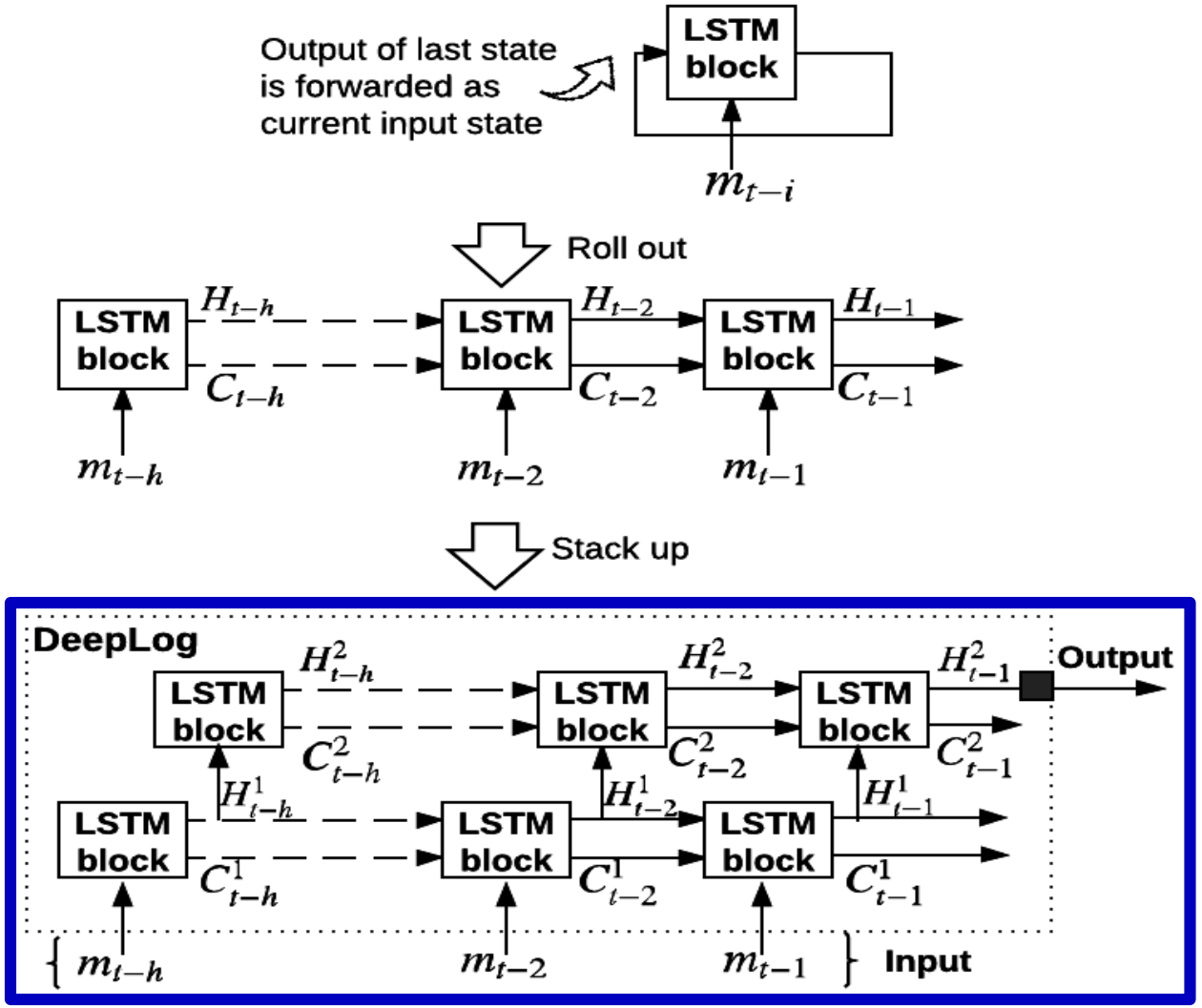
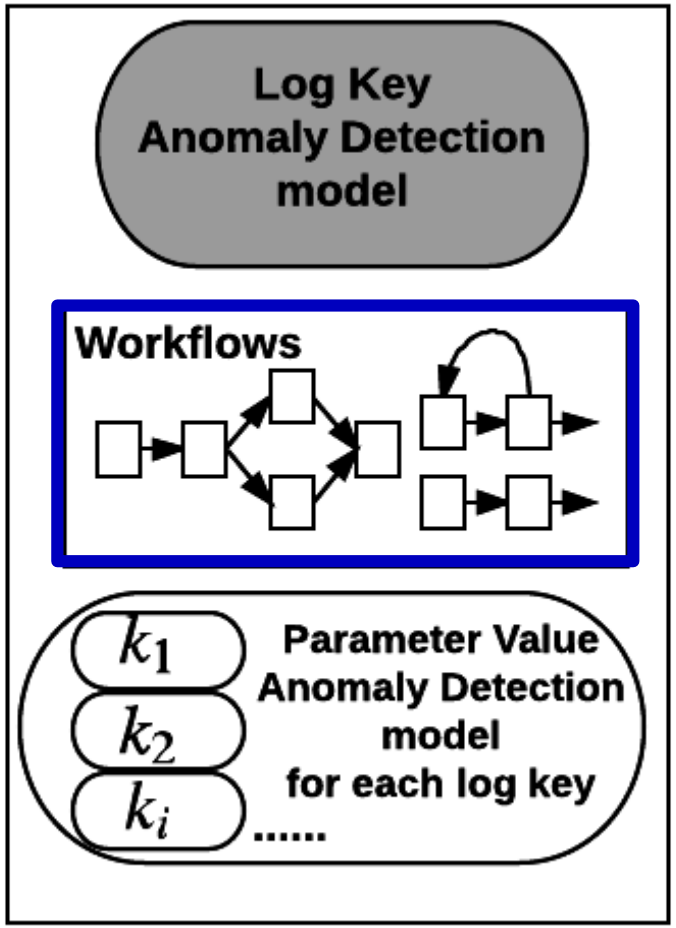




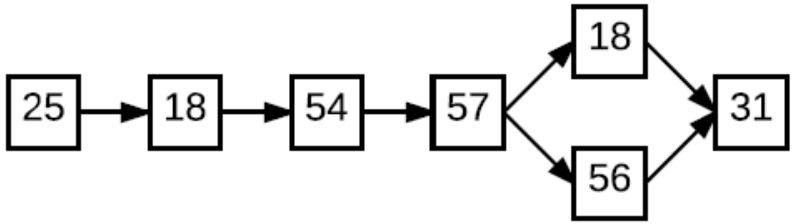
Workflow Construction



Input: log key sequence

25 18 54 57 18 56 … 25 18 54 57 56 18 …

Output:



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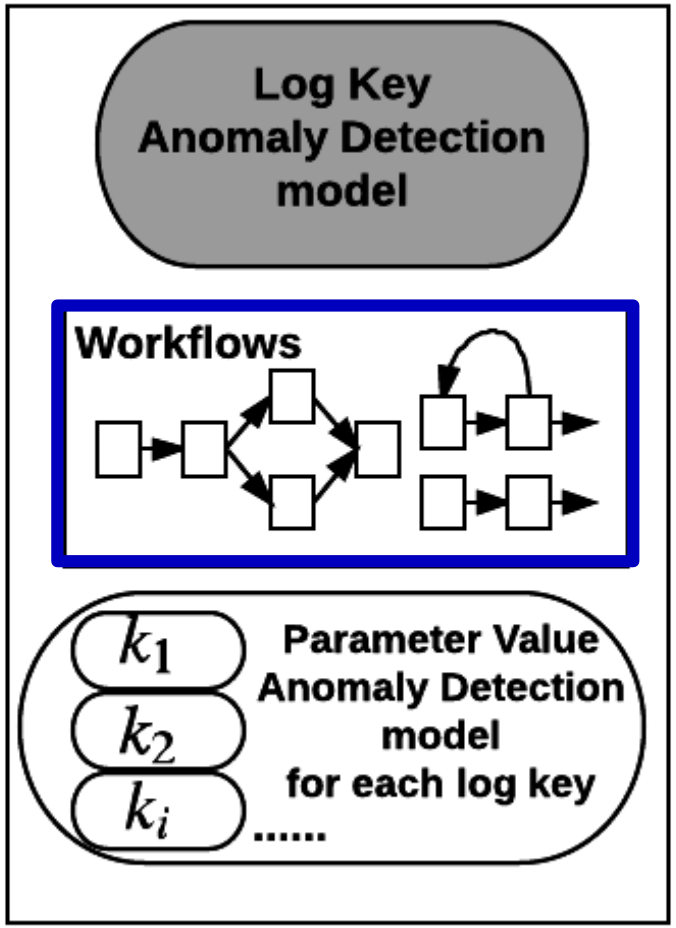

Method 1: Using Log Key Anomaly Detection model

--- LSTM prediction probabilities

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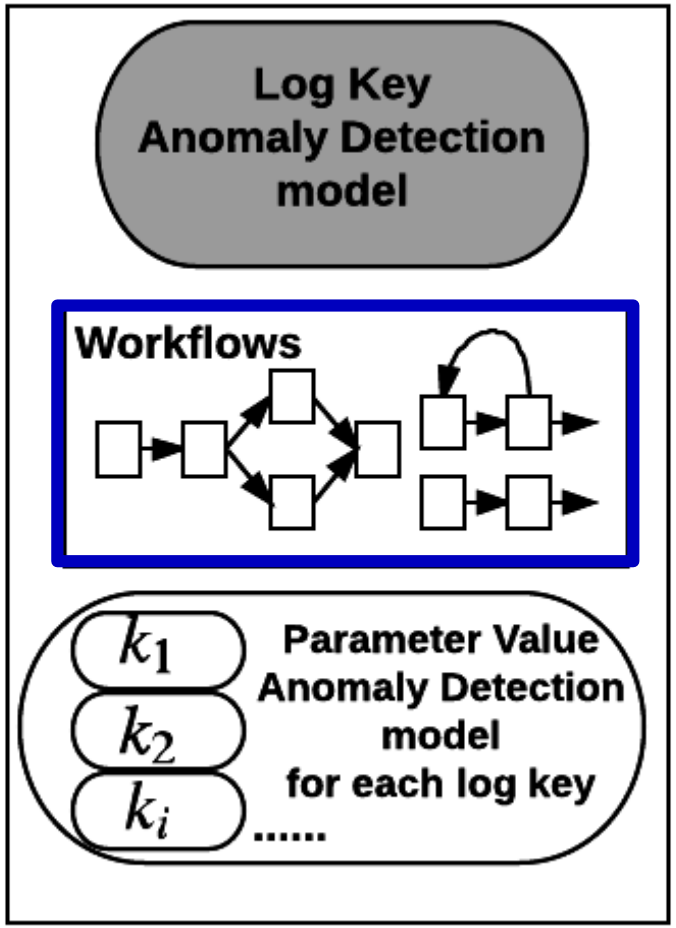

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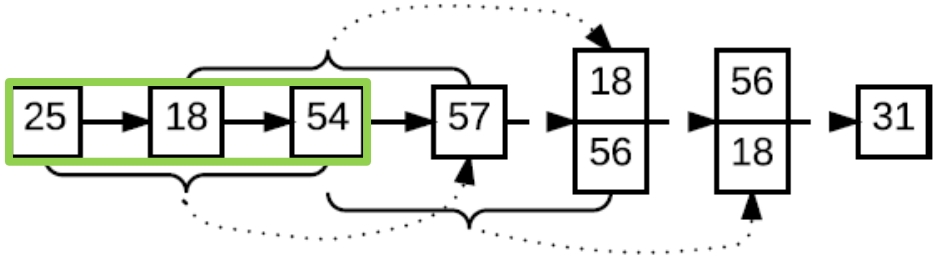
An example of concurrency detection:



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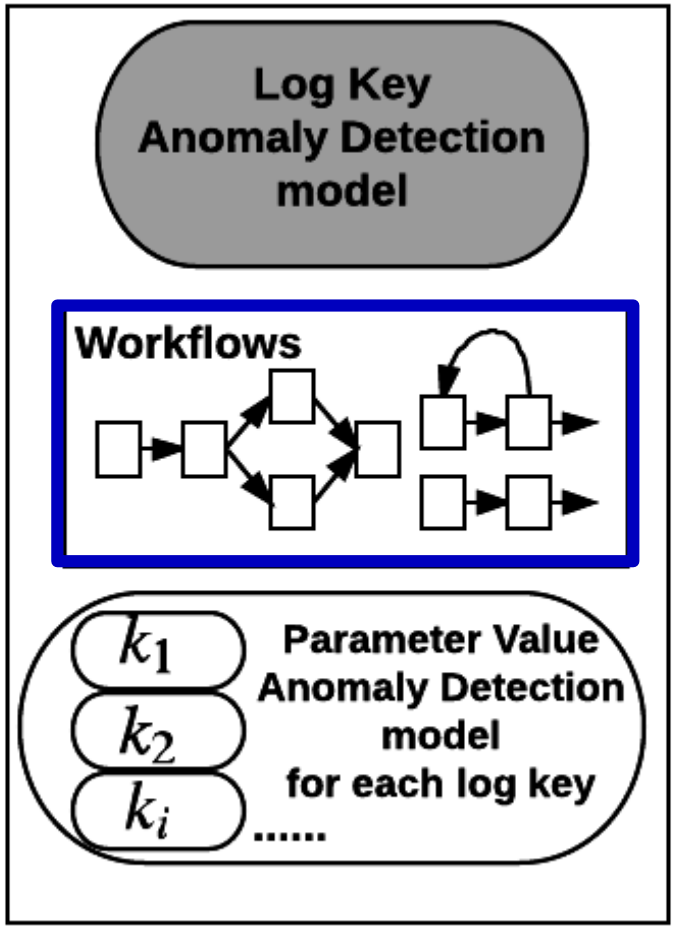

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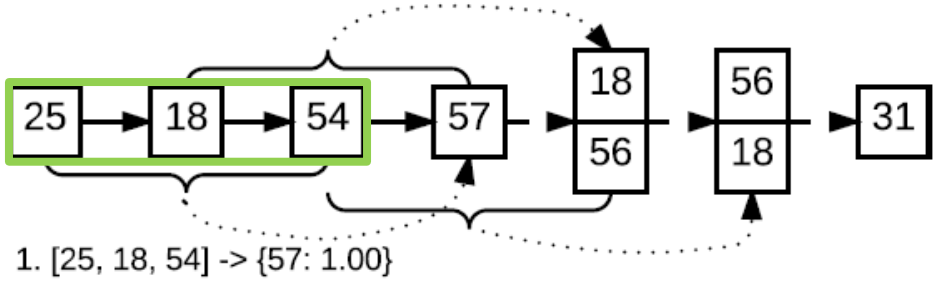

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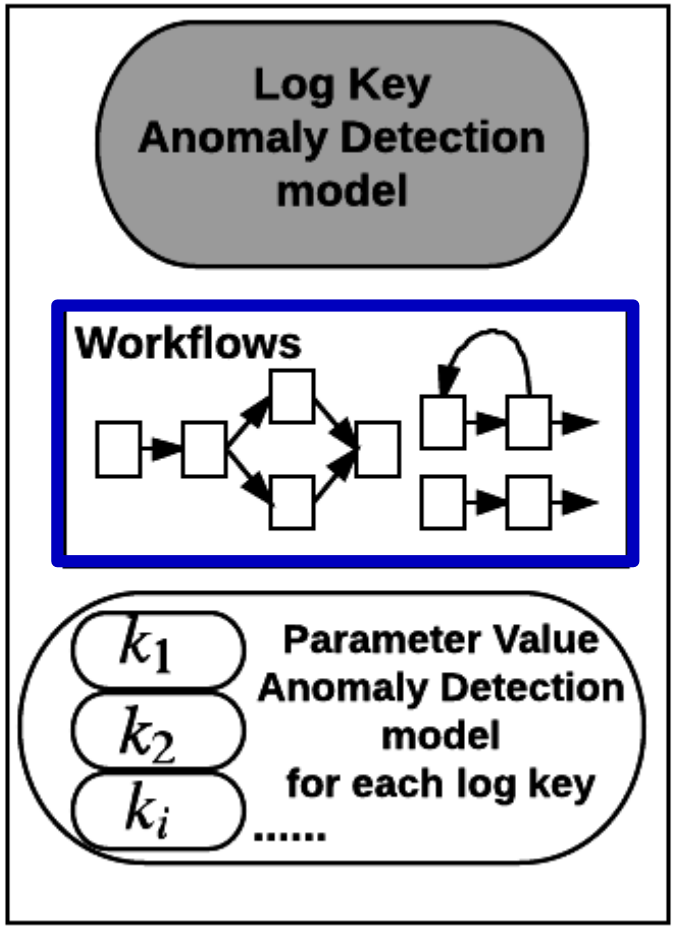

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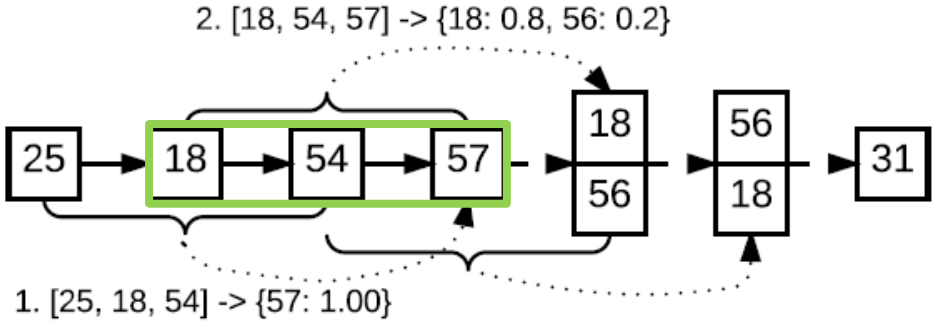

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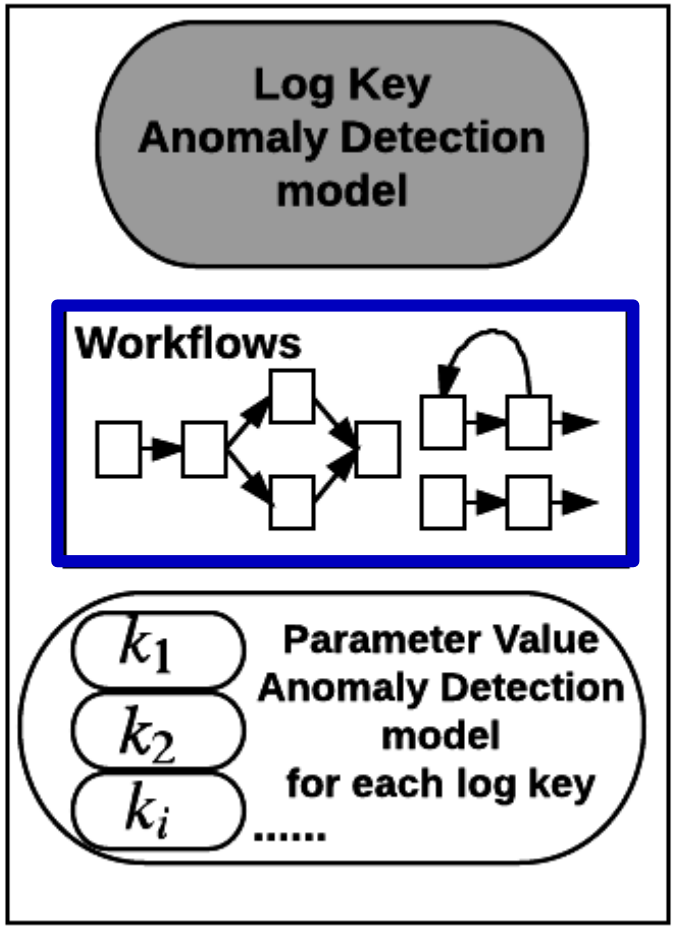

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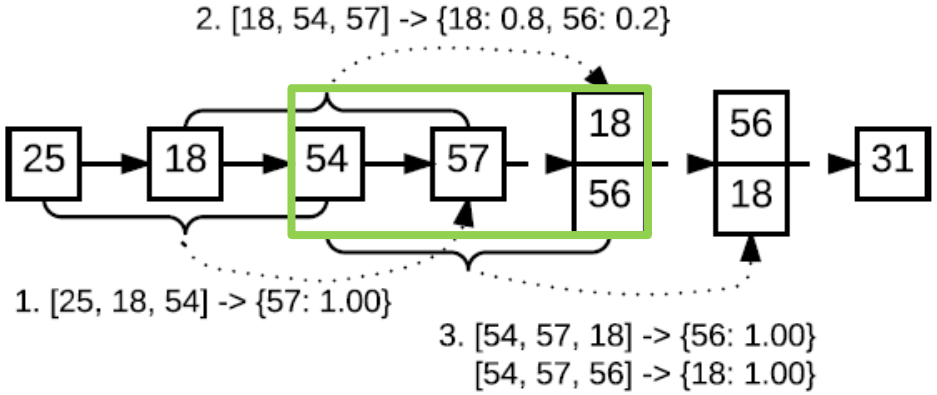

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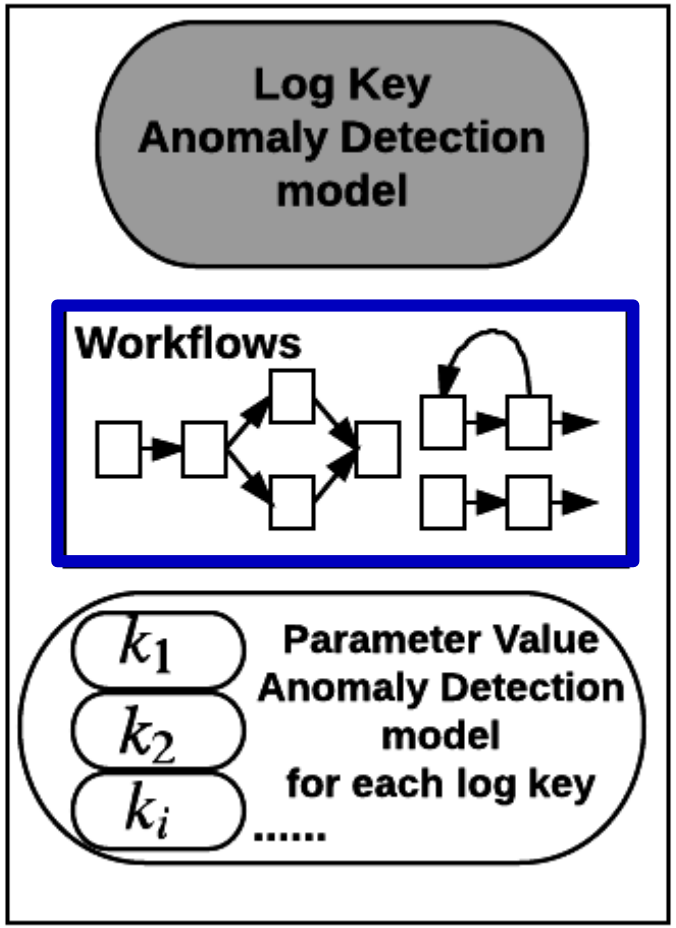

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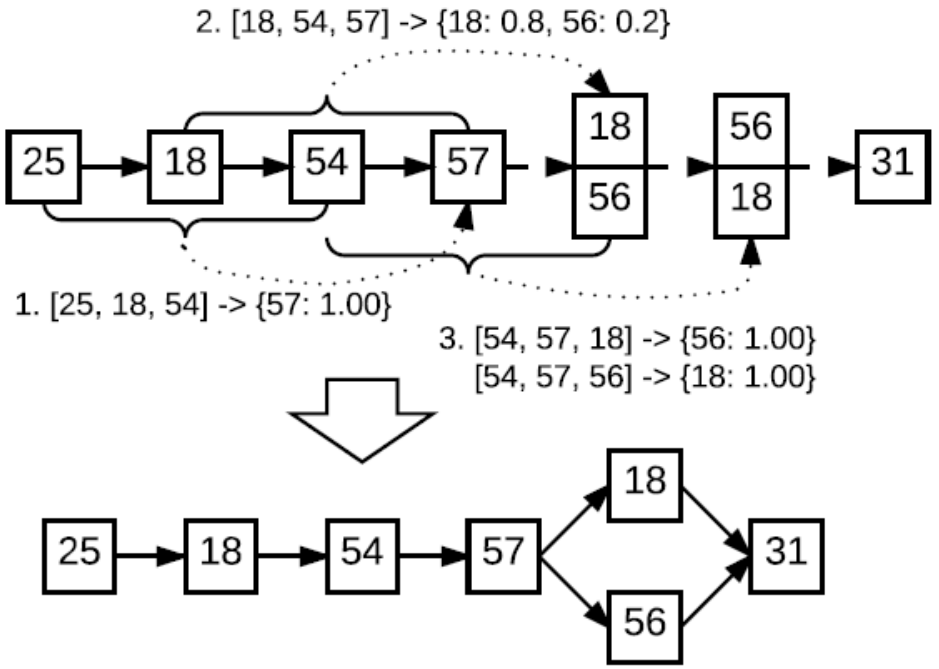

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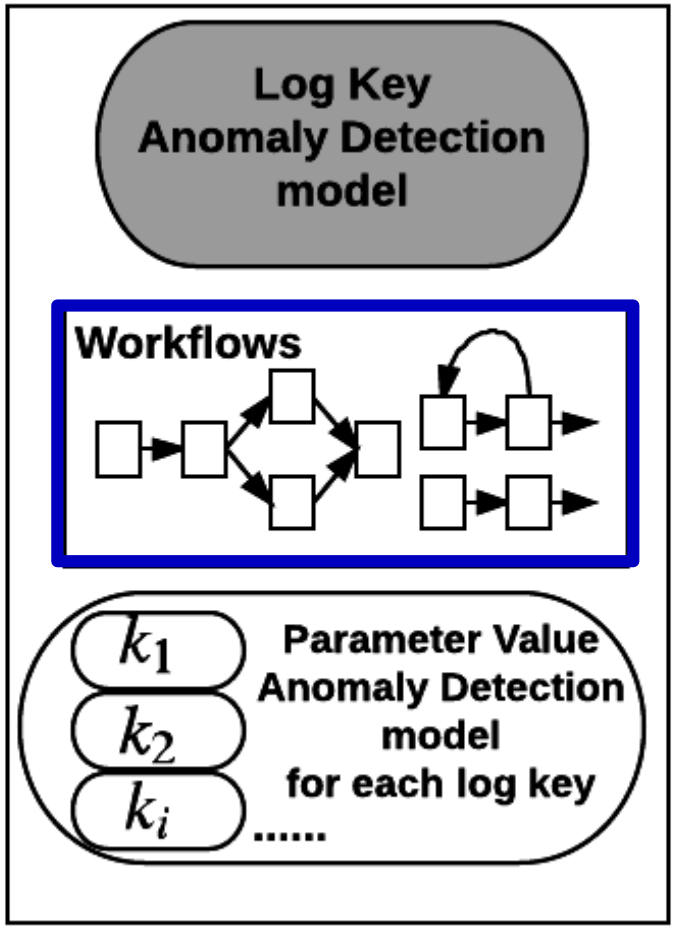

Method 2: A density-based clustering approach

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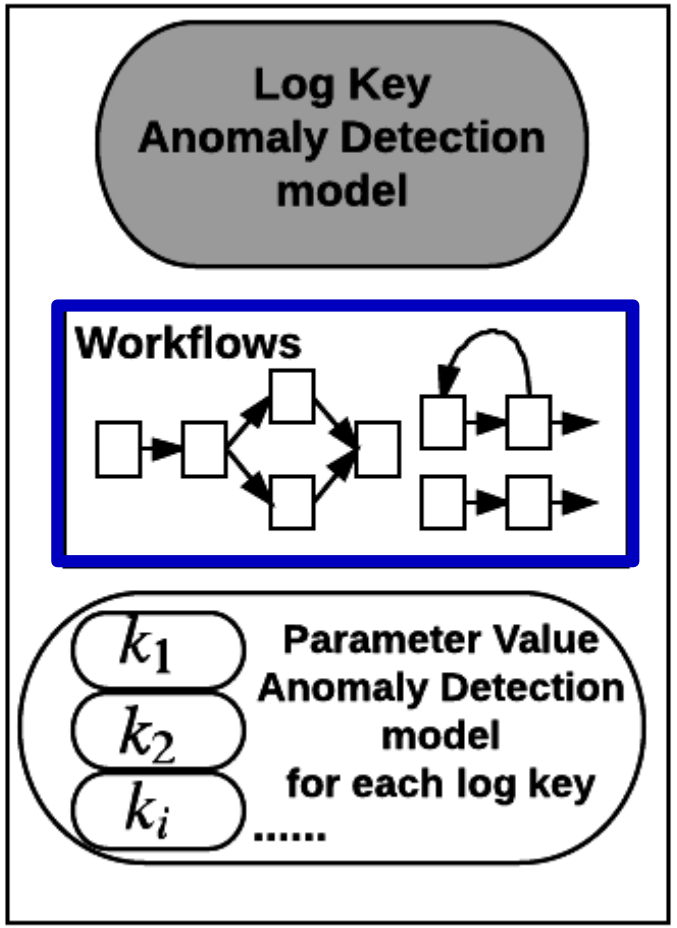


Method 2: A density-based clustering approach

Co-occurrence matrix of log keys (k_i, k_j) within distance d

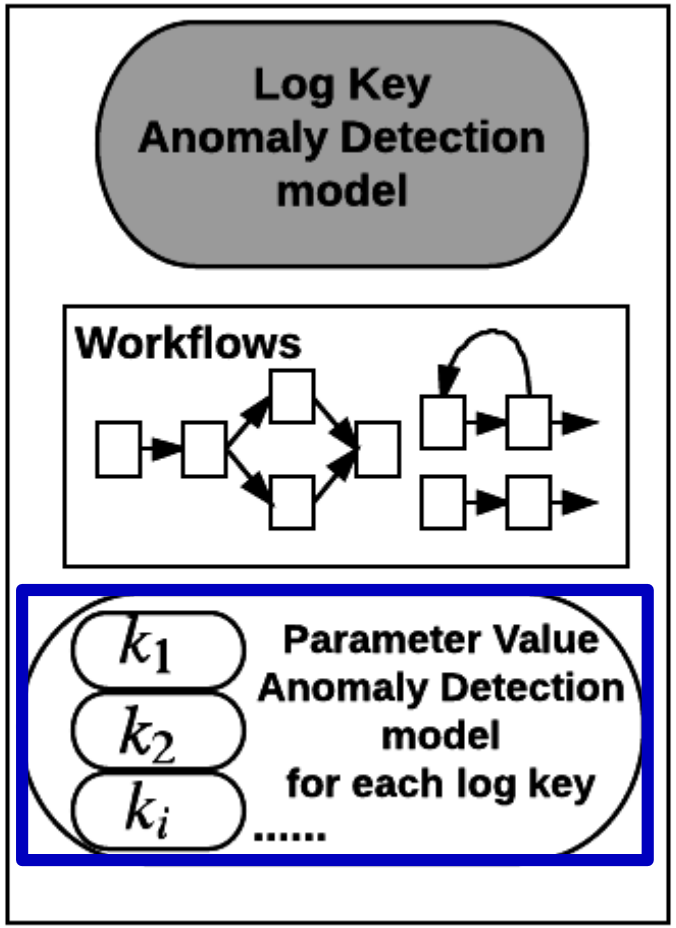
	k_1	...	k_j	...	k_n
k_1	$p_d(1, 1)$		$p_d(1, j)$		
...					
k_i	$p_d(i, 1)$		$p_d(i, j) = \frac{f_d(k_i, k_j)}{d \cdot f(k_i)}$		
...					
k_n	$p_d(n, 1)$		$p_d(n, j)$		

$f_d(k_i, k_j)$: the frequency of (k_i, k_j) appearing together within distance d

$f(k_i)$: the frequency of k_i in the input sequence

$p_d(i, j)$: the probability of (k_i, k_j) appearing together within distance d

Parameter Value Anomaly Detection model



Example:

Log messages of a particular log key:

t_2: $Took\ 0.61\ seconds\ to\ deallocate\ network$ ...

t'_2: $Took\ 1.1\ seconds\ to\ deallocate\ network$ ...

....

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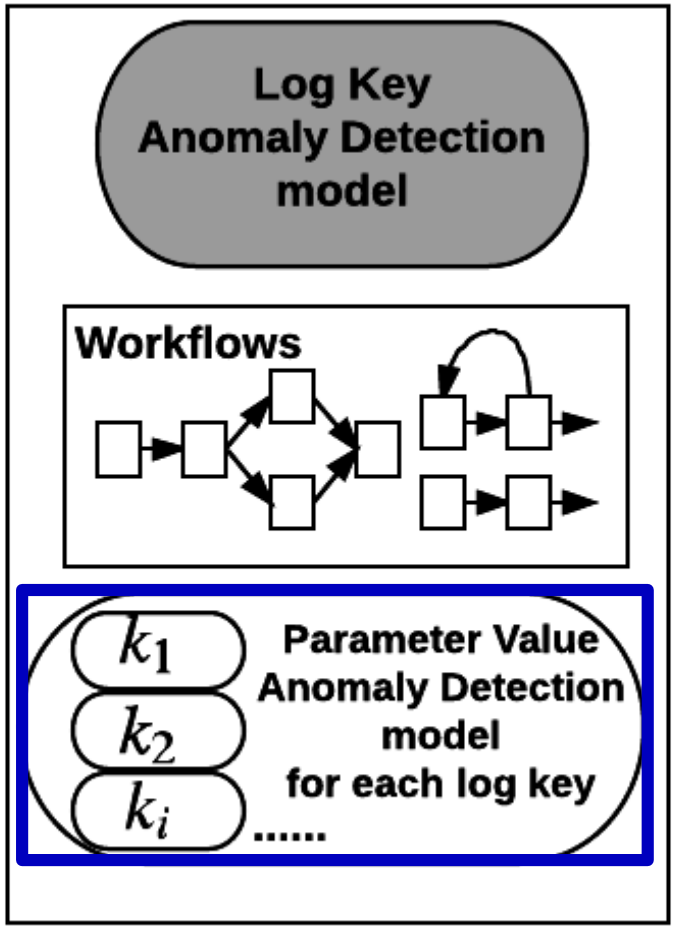

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Parameter value vectors overtime:

[t_2- t_1, 0.61], [t'_2- t'_1, 1.1], ...

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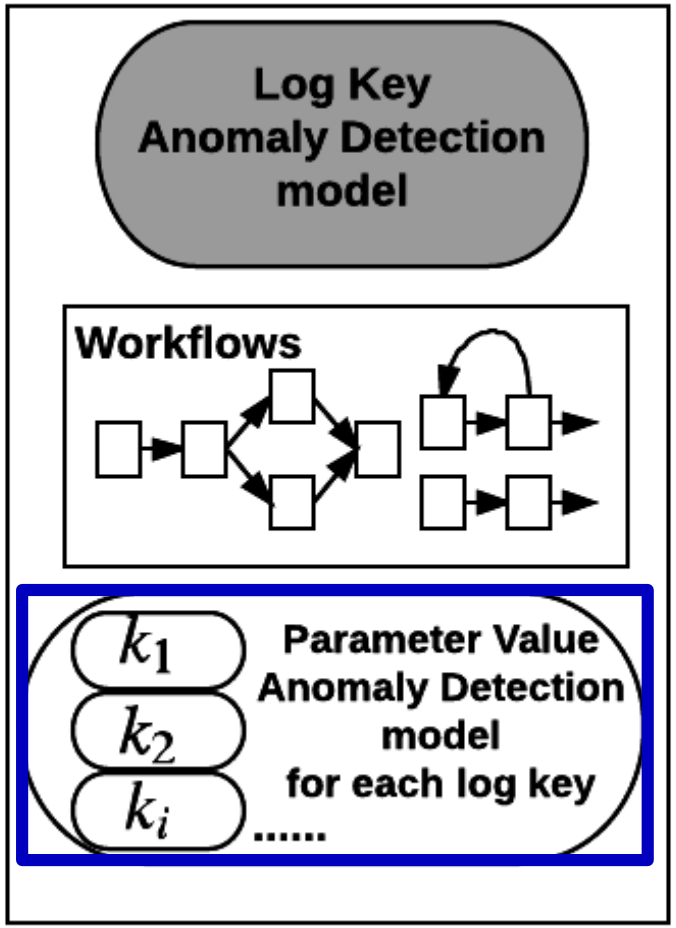

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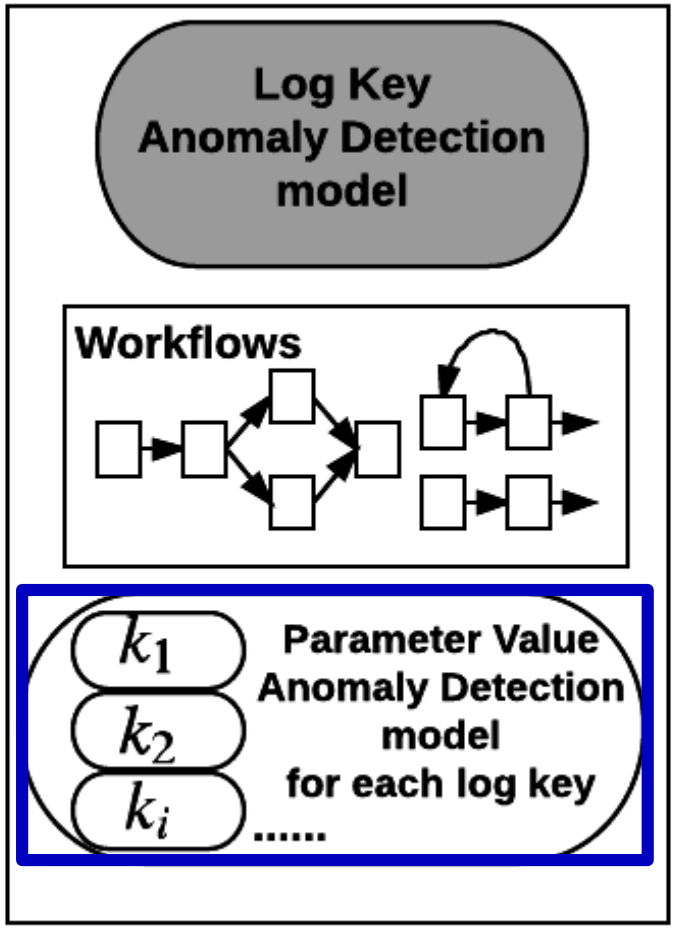
The time difference between current log and preceding log (they might have different log keys)

Multi-variate time series data anomaly detection problem!

Parameter Value Anomaly Detection model



Multi-variate time series data anomaly detection problem

- ✓ Leverage LSTM-based approach;
- ✓ A parameter value vector is given as input at each time step;
- ✓ An anomaly is detected if the mean-square-error (MSE) between prediction and actual data is too big.

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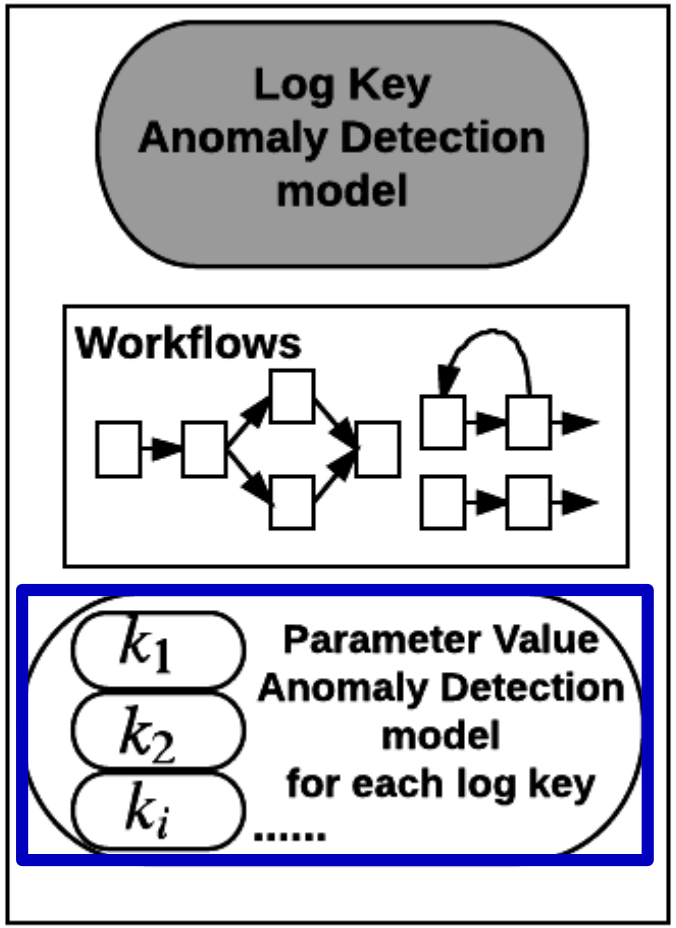

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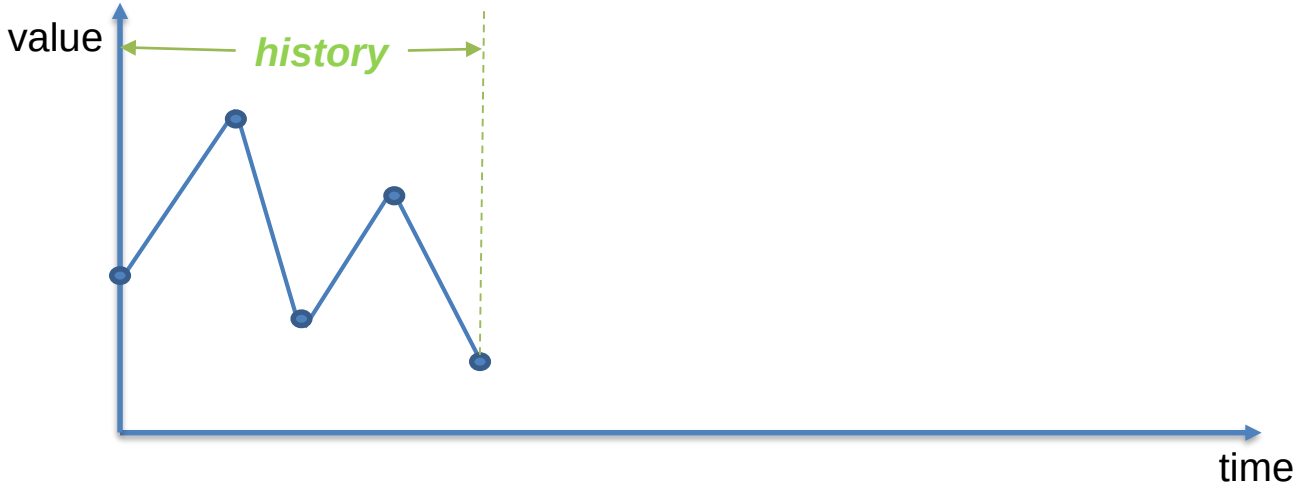

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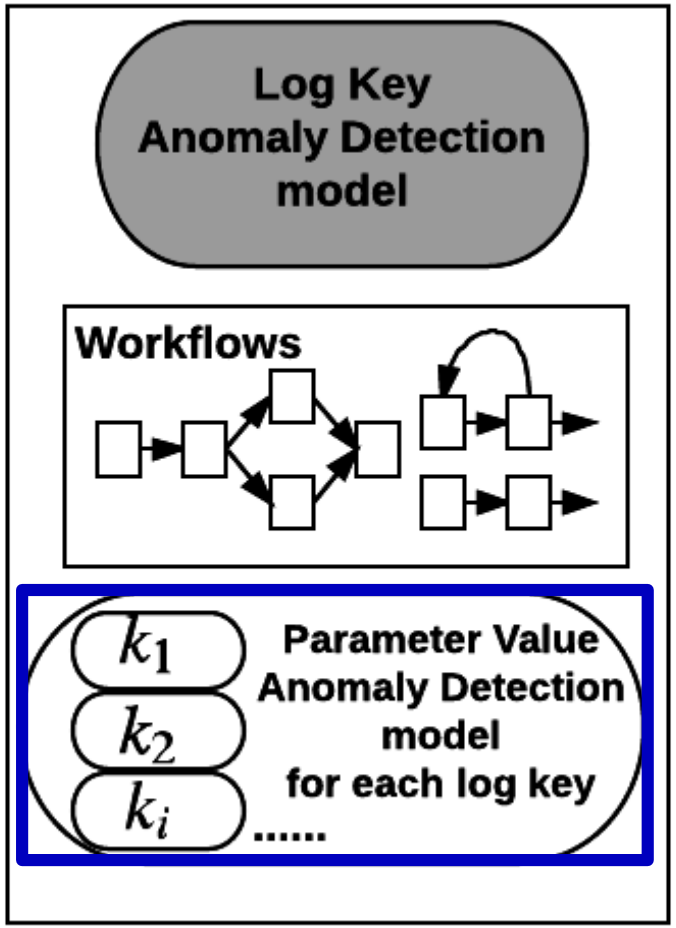

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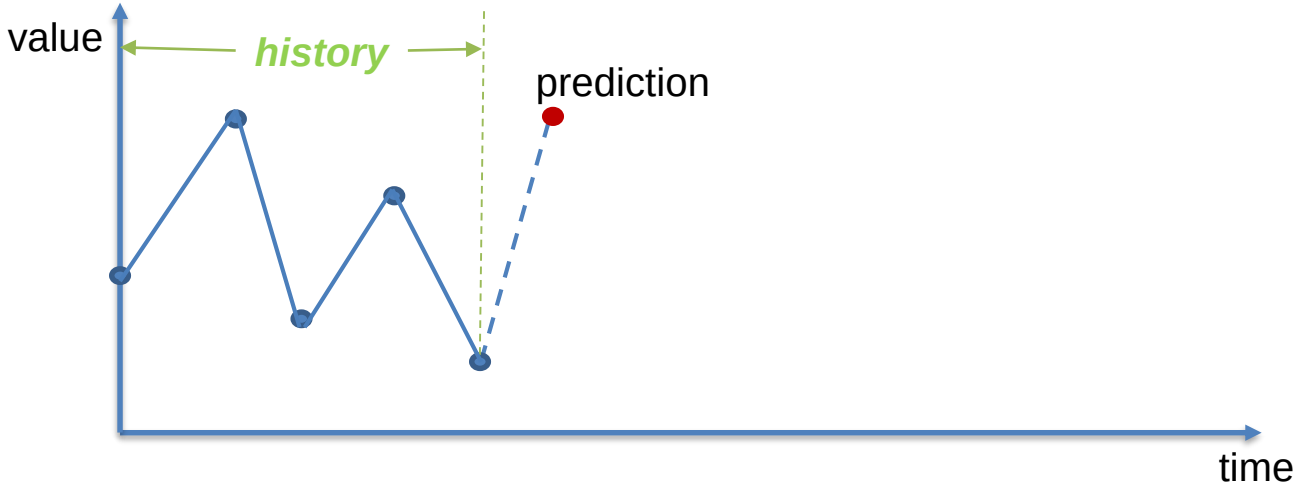
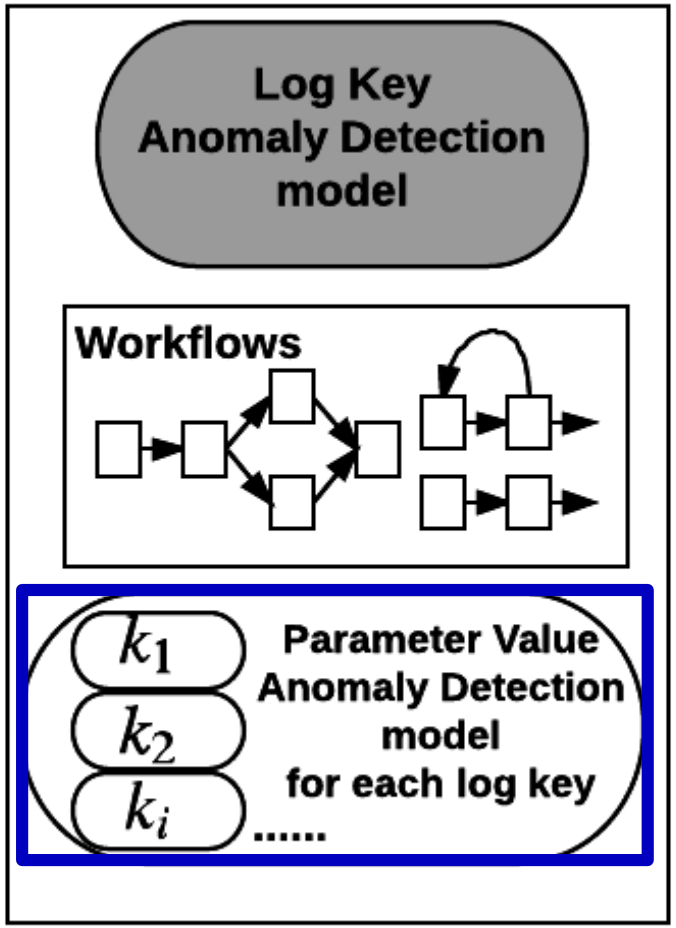


Parameter Value Anomaly Detection model



Multi-variate time series data anomaly detection problem

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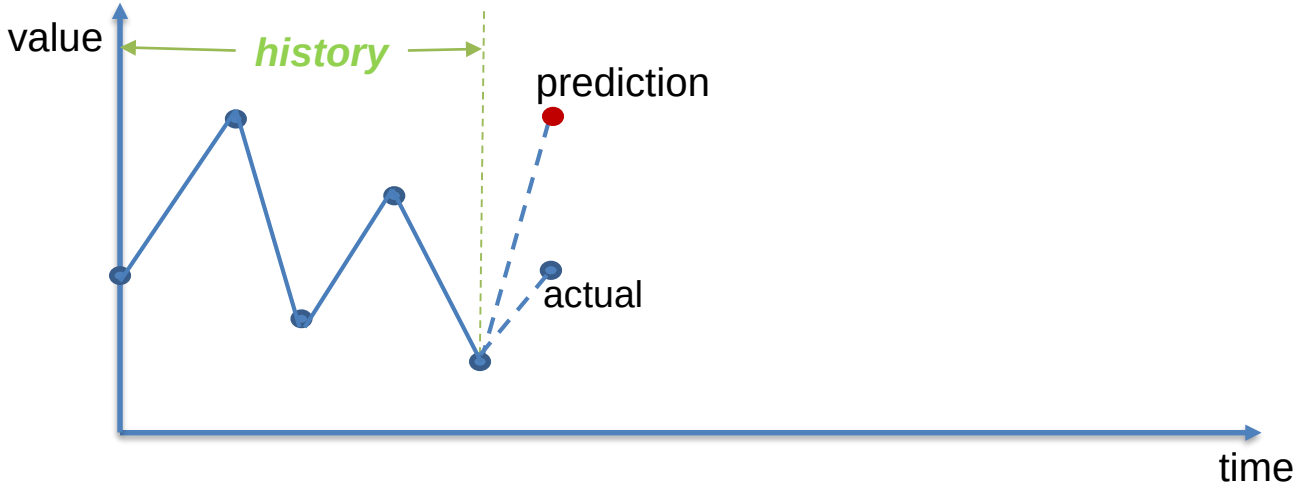

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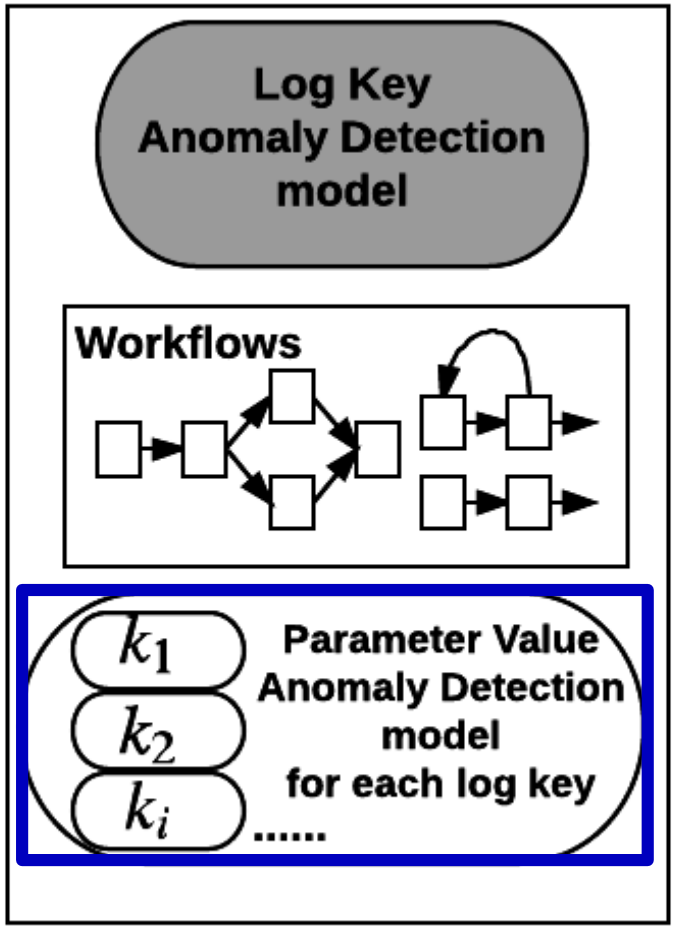

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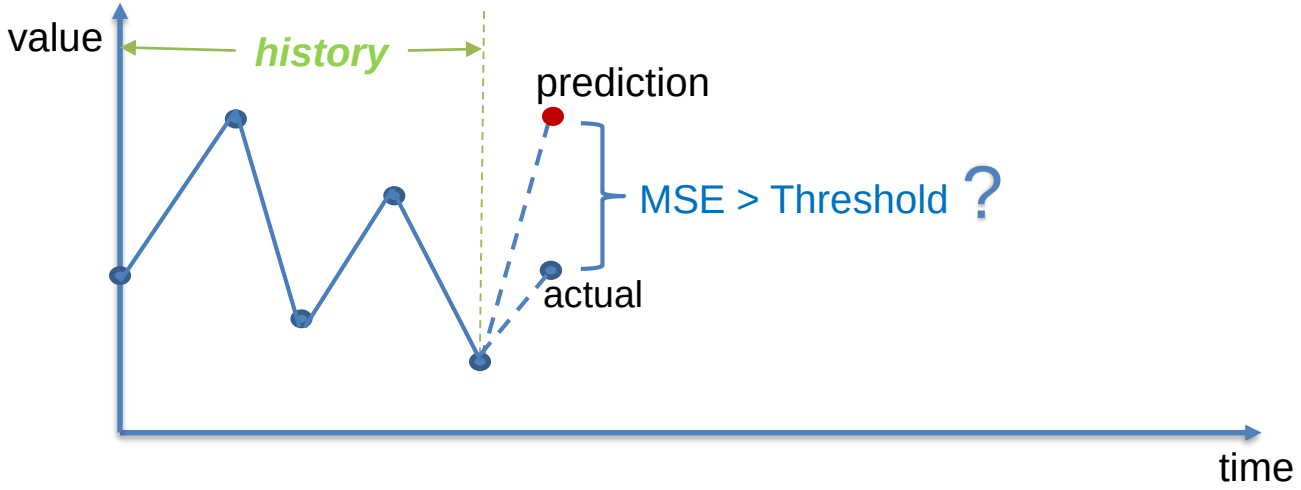

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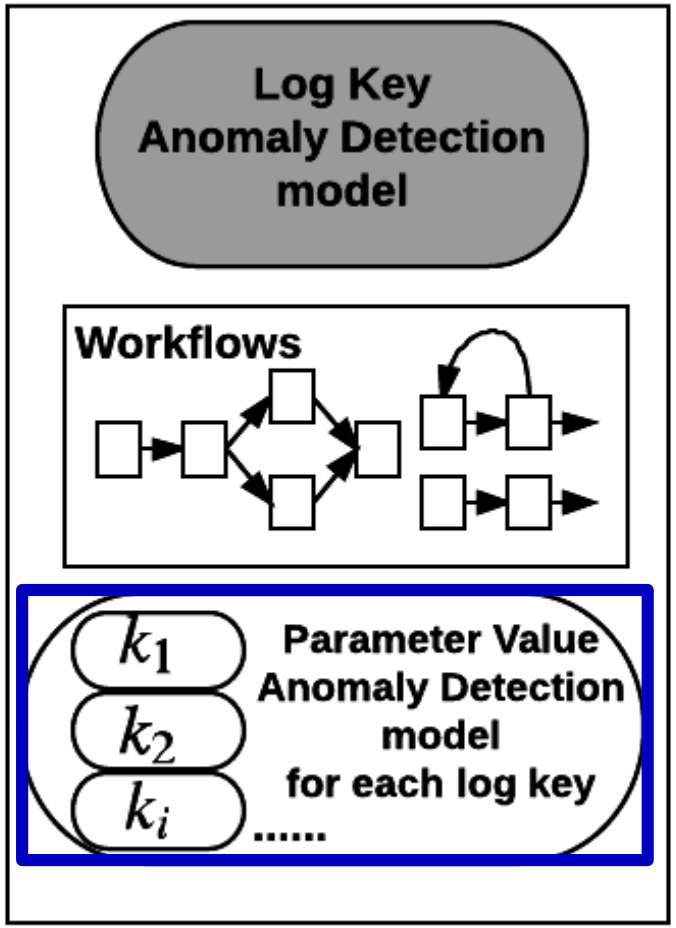

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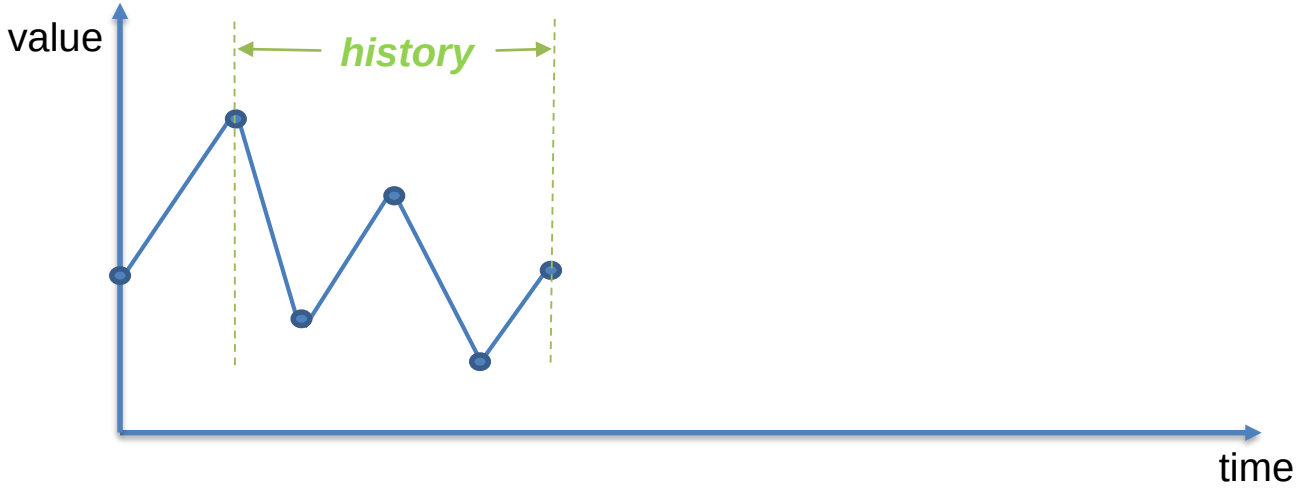

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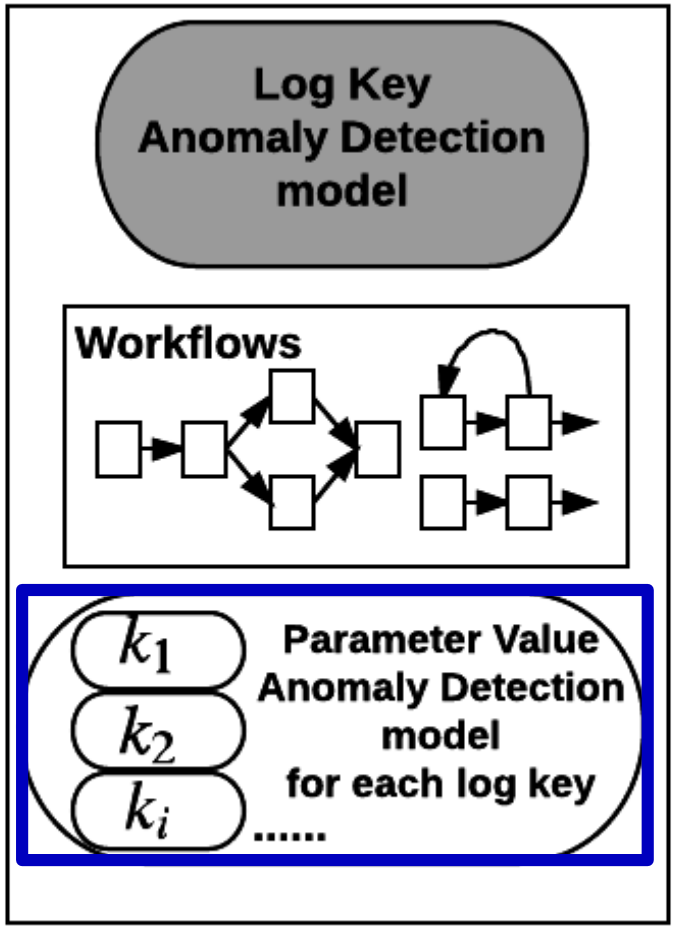

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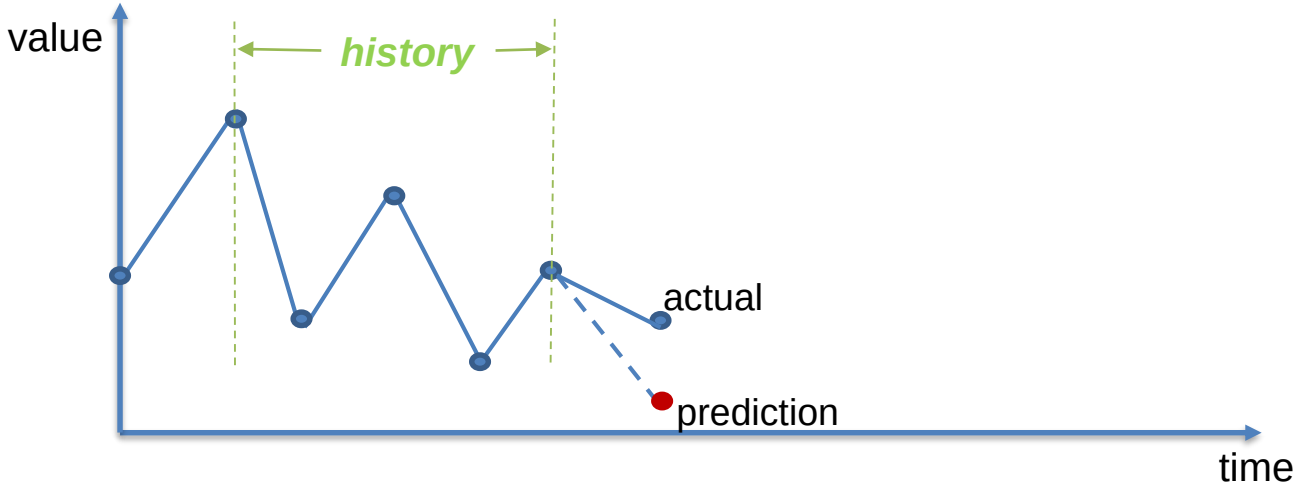

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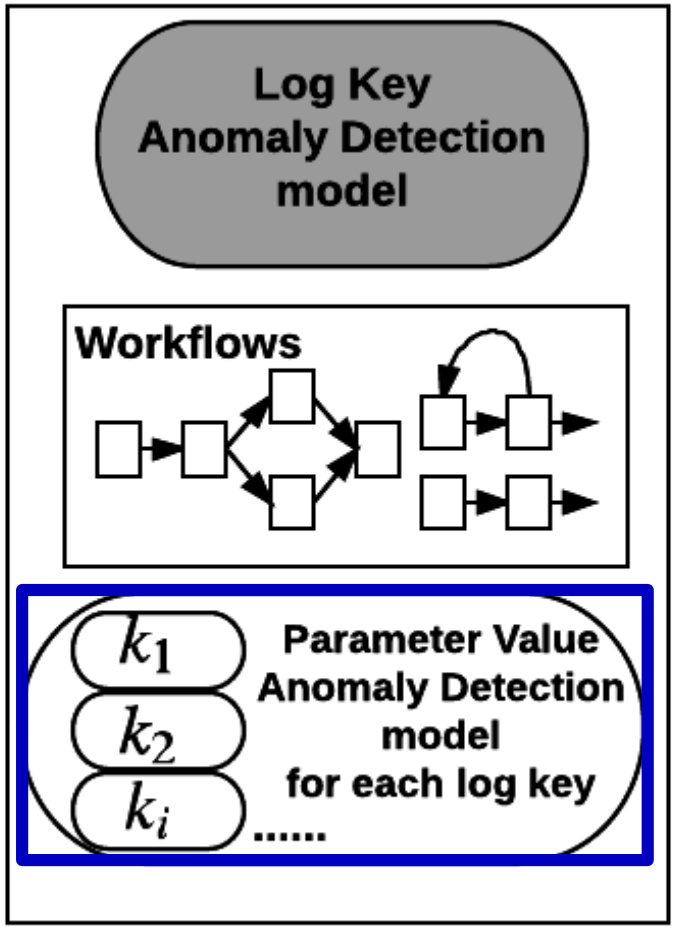

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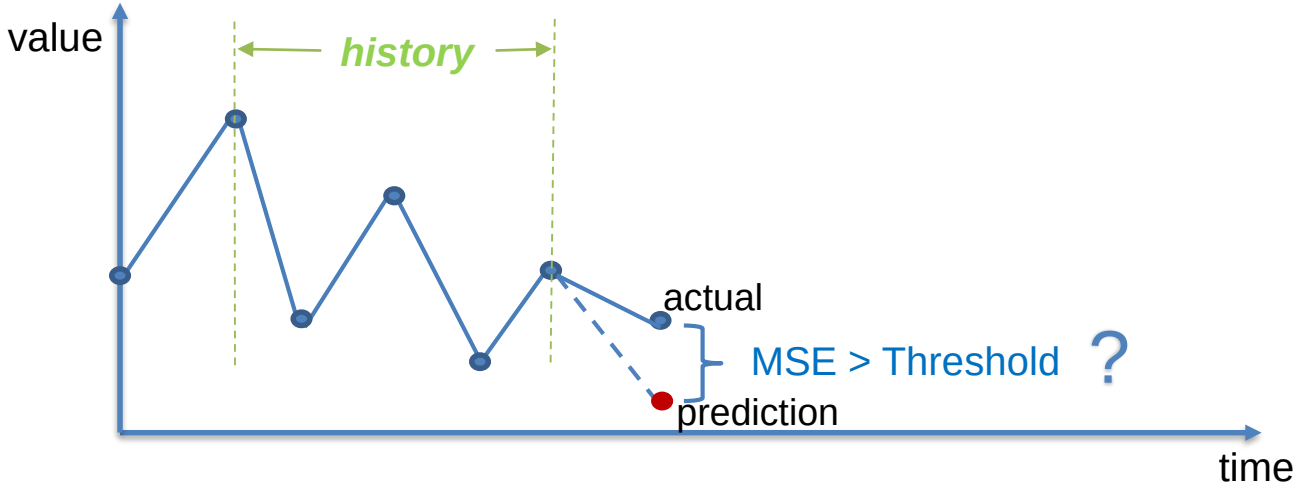

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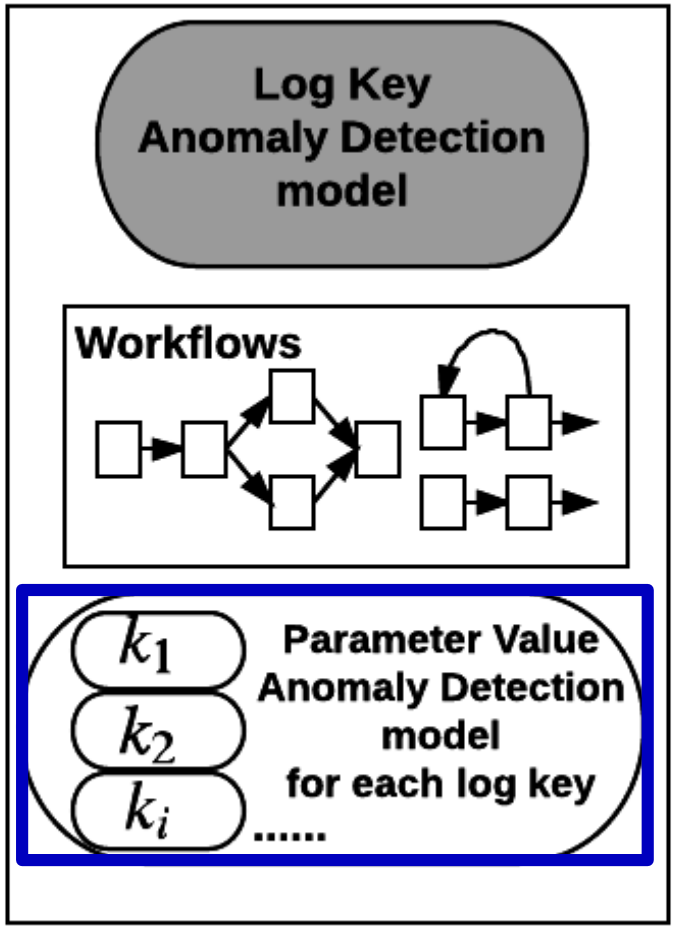

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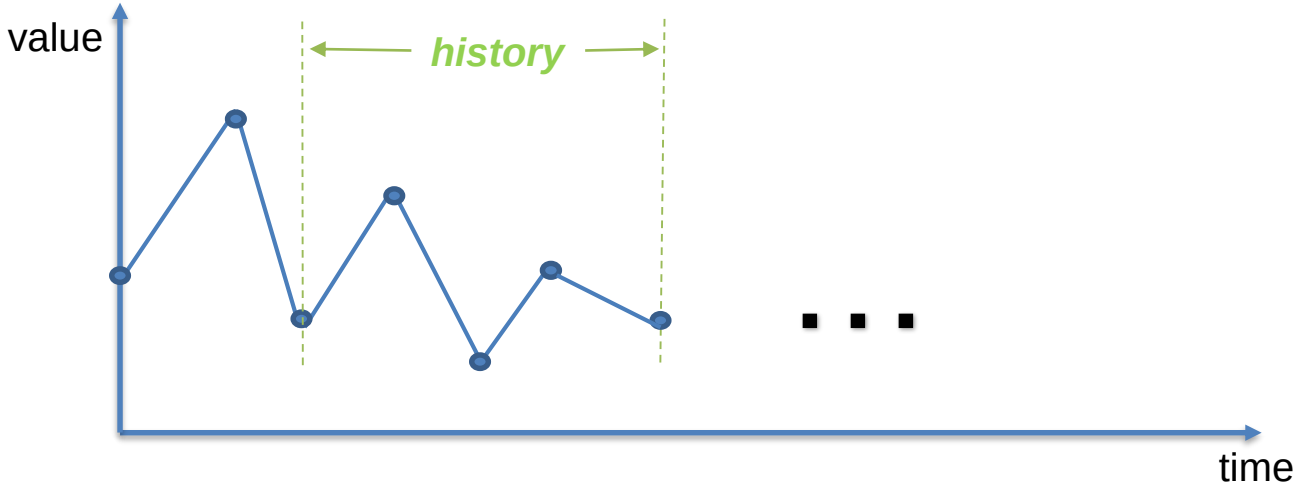

LSTM model online update

Q: How to handle false positive?

LSTM model online update

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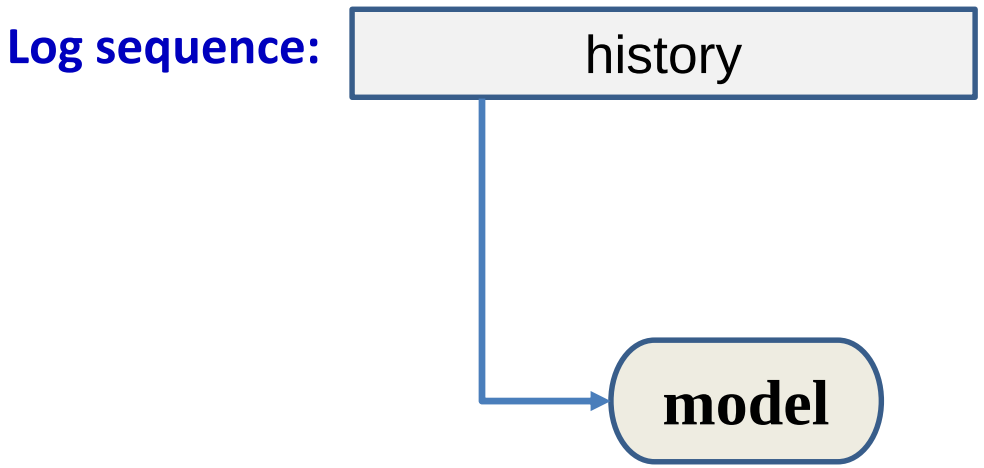
Log sequence: history

LSTM model online update

Q: How to handle false positive?



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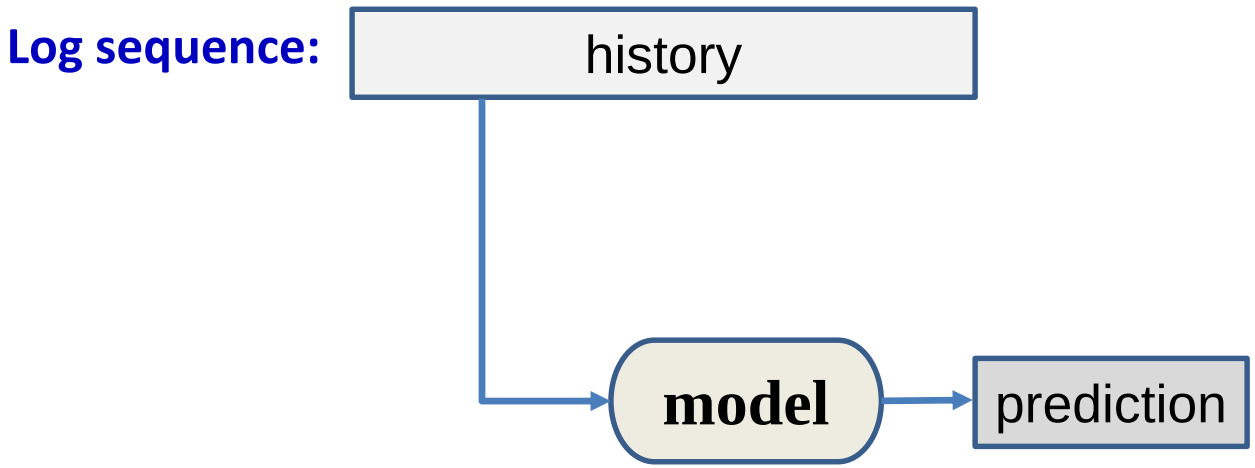

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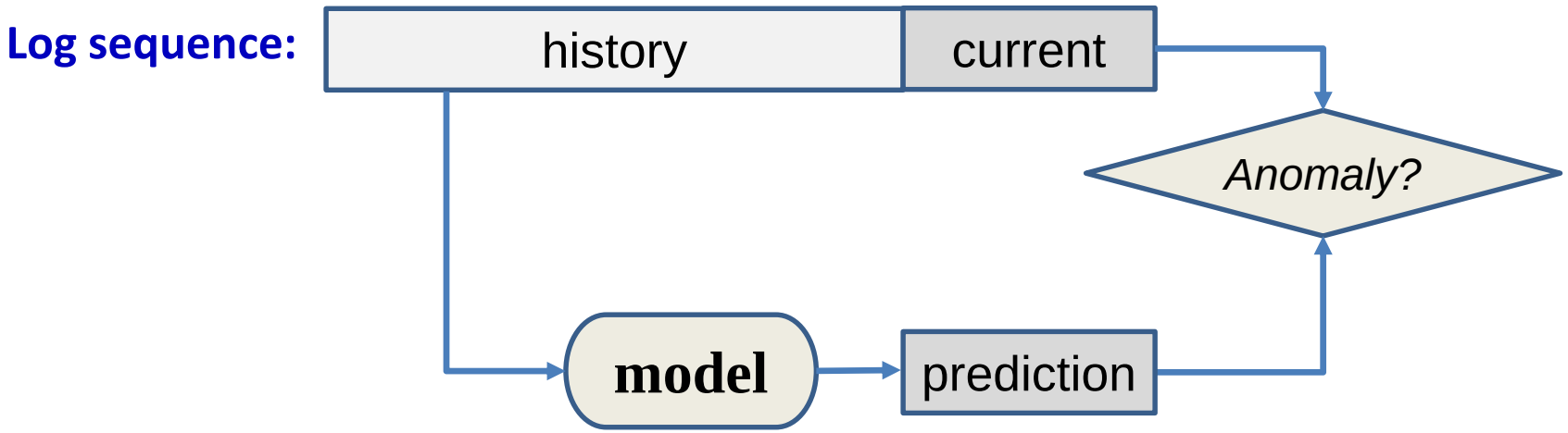

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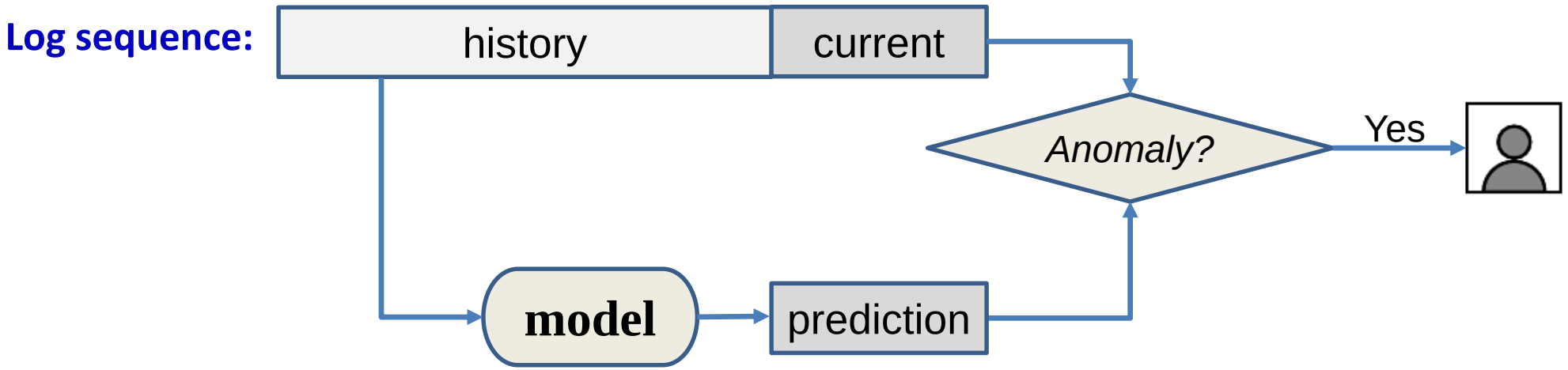

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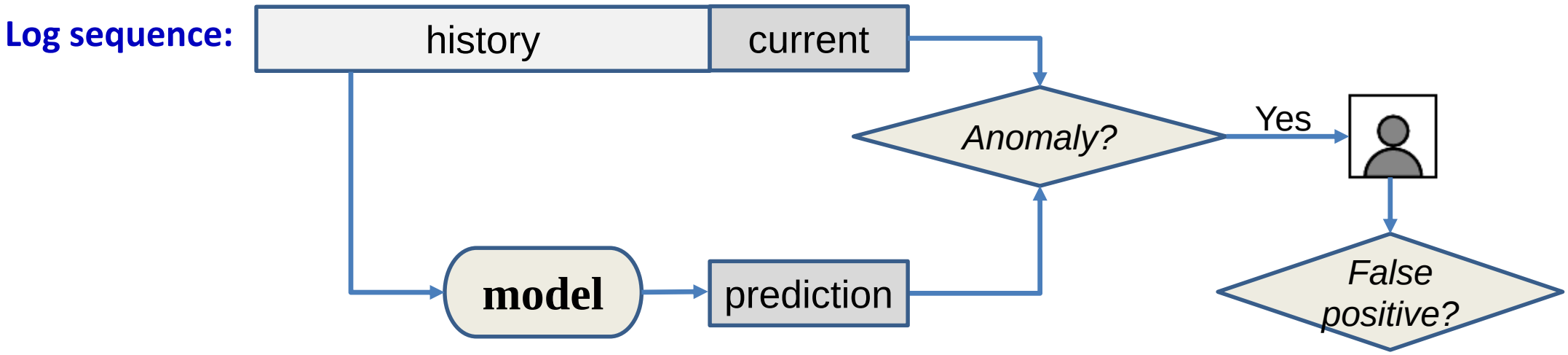

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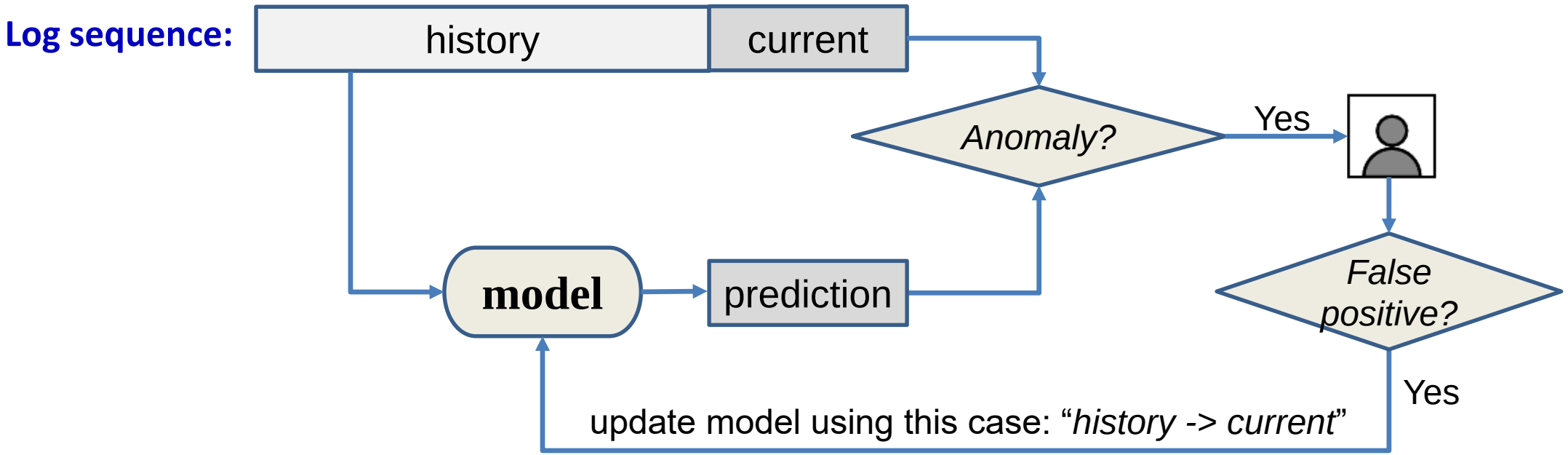
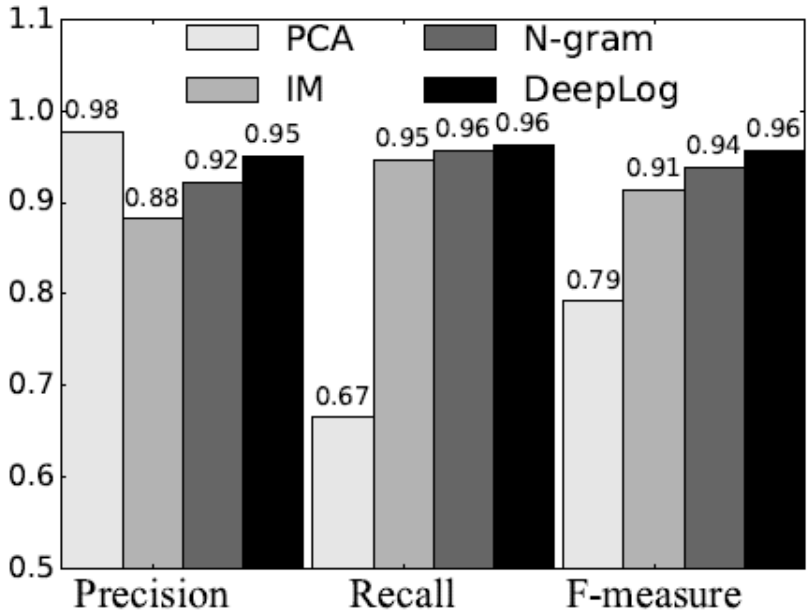


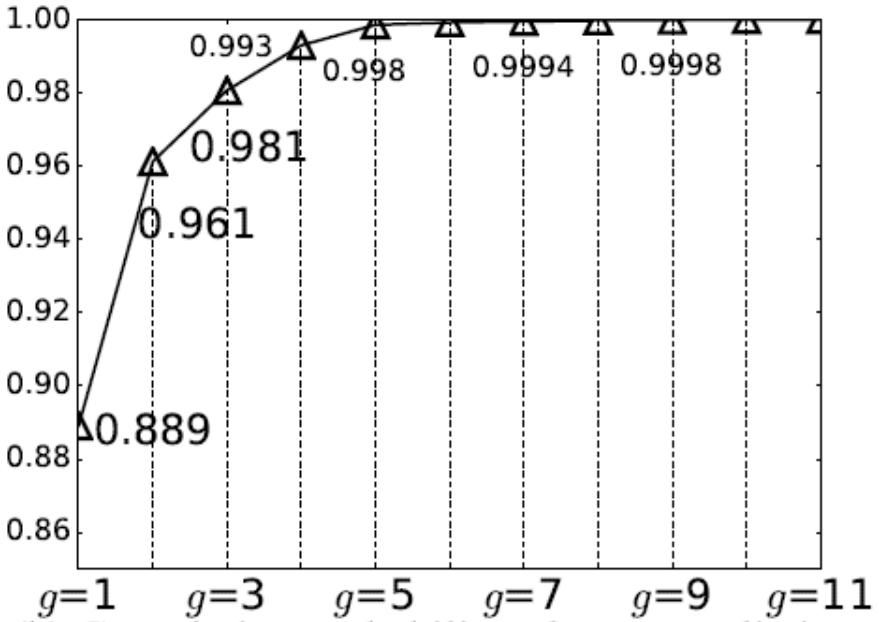
adjusts the weights to minimize the error between model output and actual observed values from the false positive cases.

Evaluation – log key anomaly detection

Up is good



(a) Accuracy on HDFS.



(b) Cumulative probability of top g predictions.

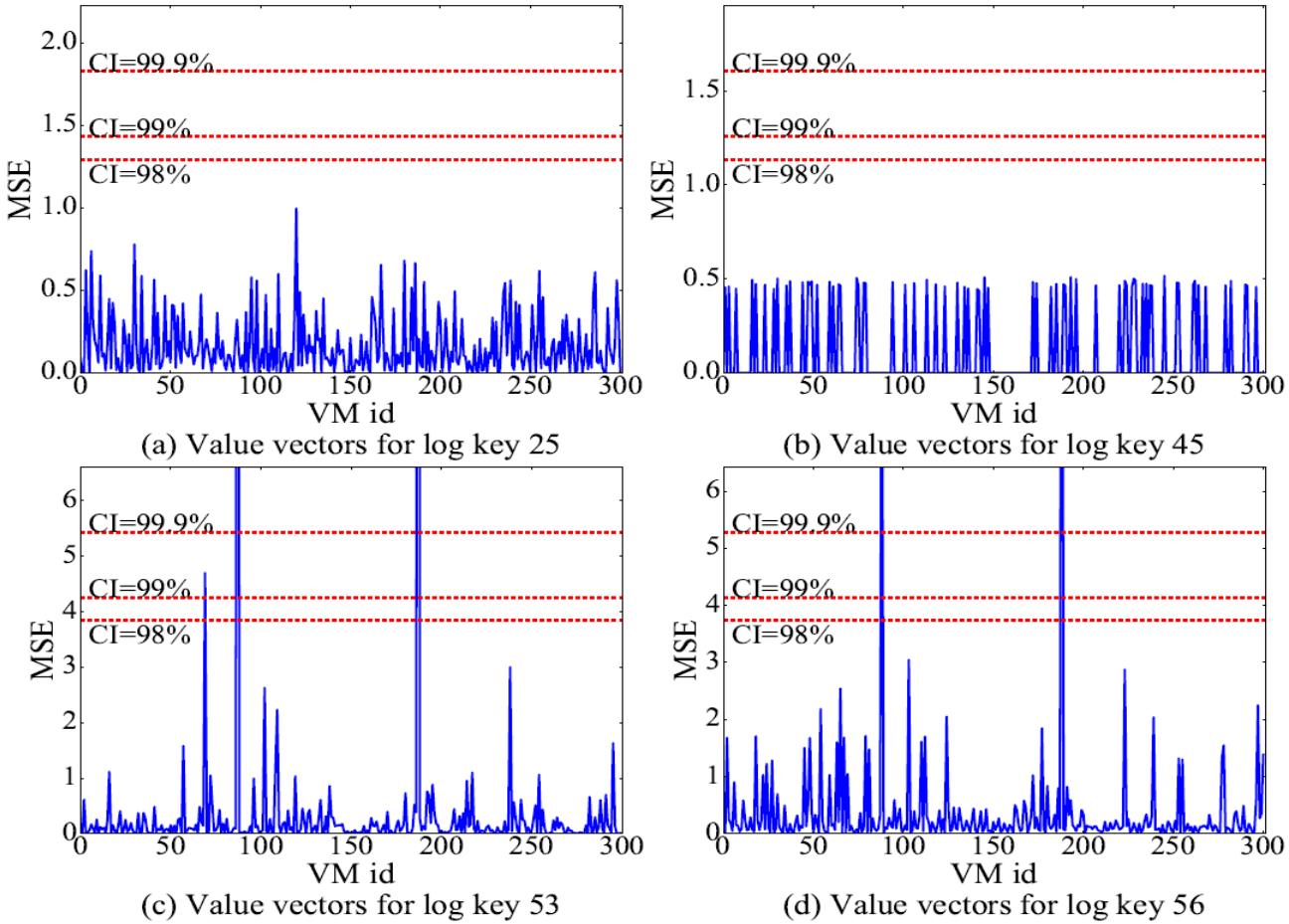
Evaluation results on HDFS log data [1].

(over a million log entries with labeled anomalies)

[1] PCA (SOSP'09), IM (UsenixATC'10), N-gram (baseline language model)

Evaluation – parameter value anomaly detection

MSE:
mean square error



Evaluation results on OpenStack cloud log with different confidence intervals (CIs)

Evaluation – parameter value anomaly detection

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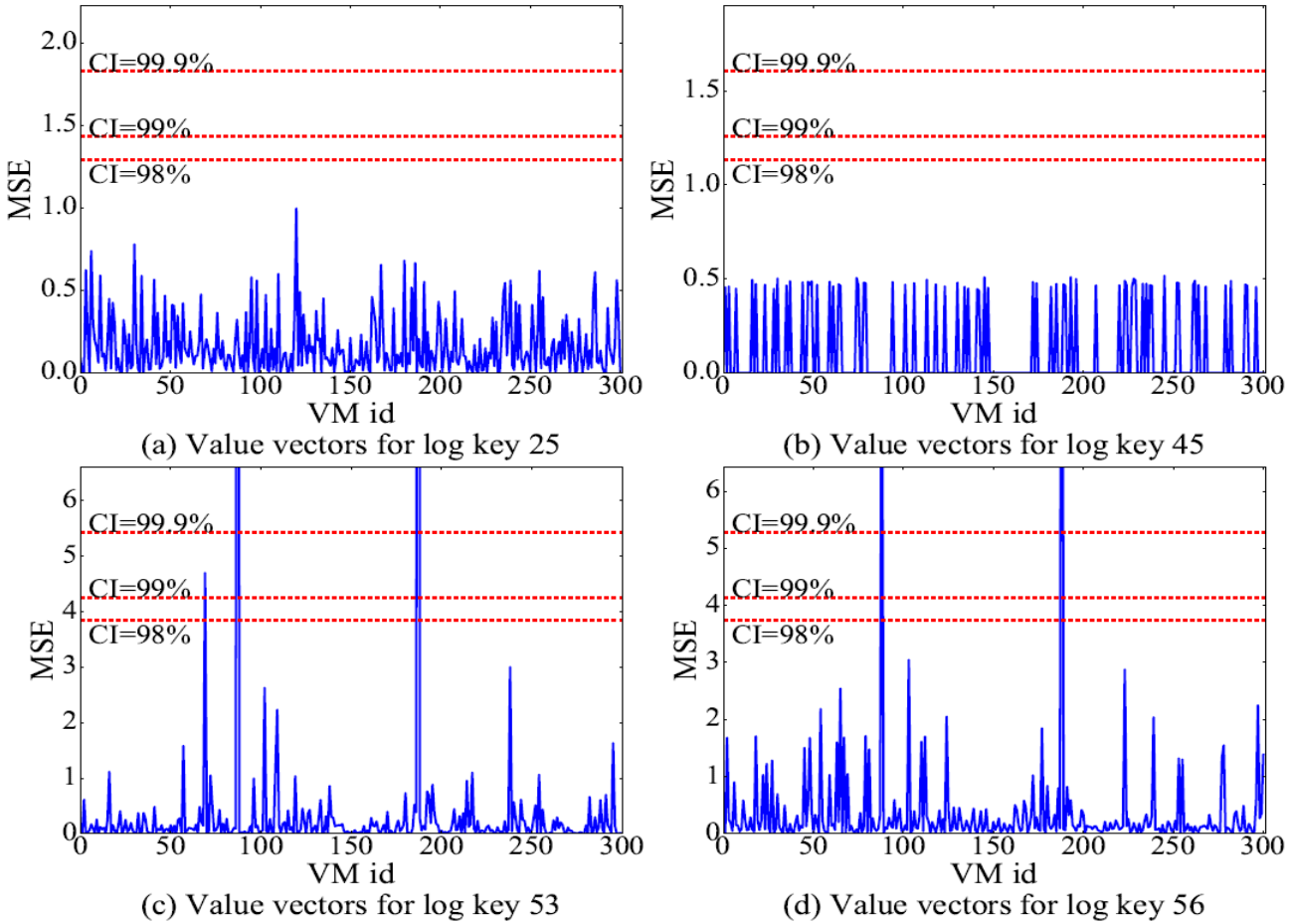

Evaluation results on OpenStack cloud log with different confidence intervals (CIs)

generated on CloudLab;
VM creation/deletion operations;
injected performance anomalies.

Evaluation – parameter value anomaly detection

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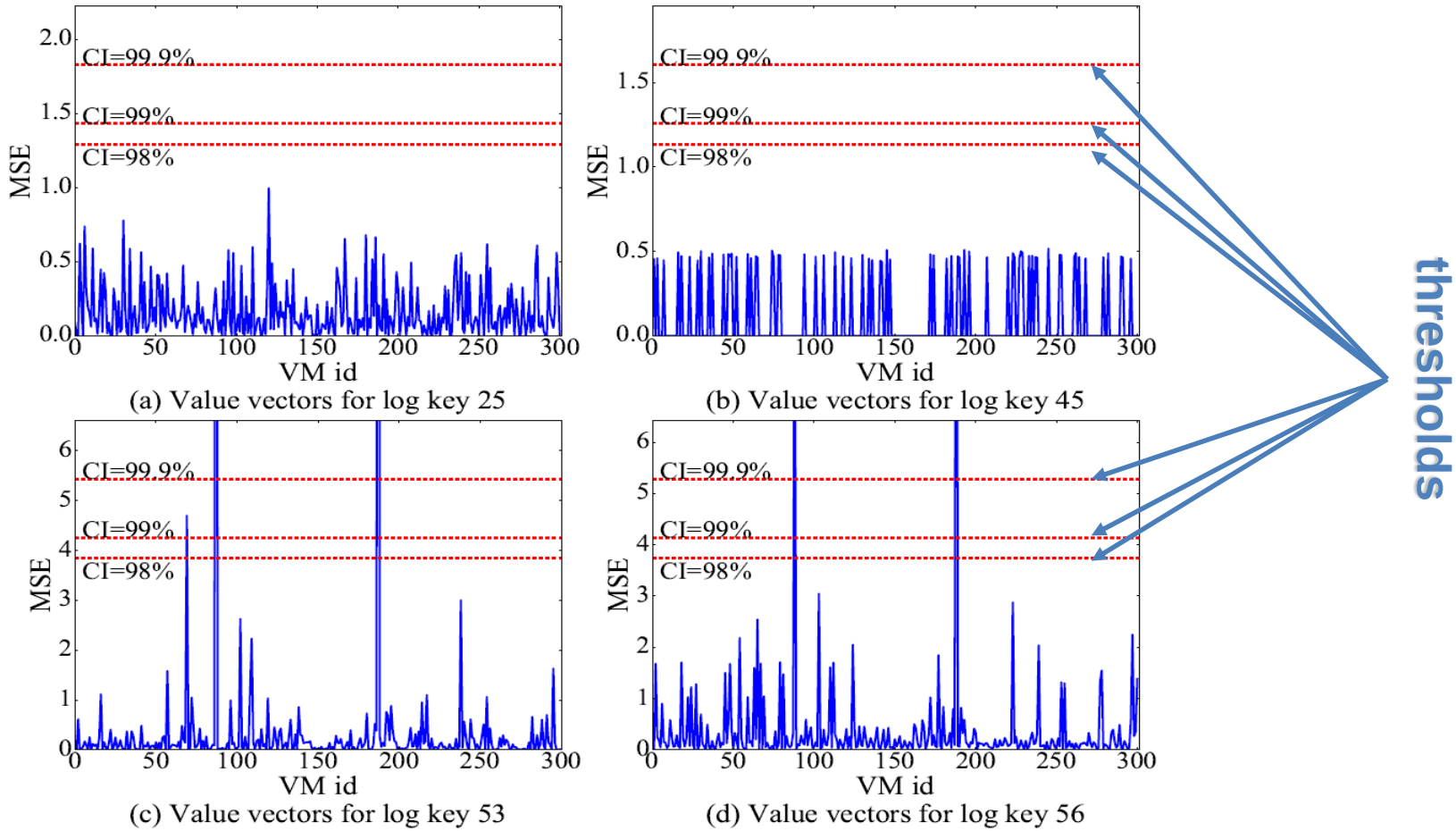

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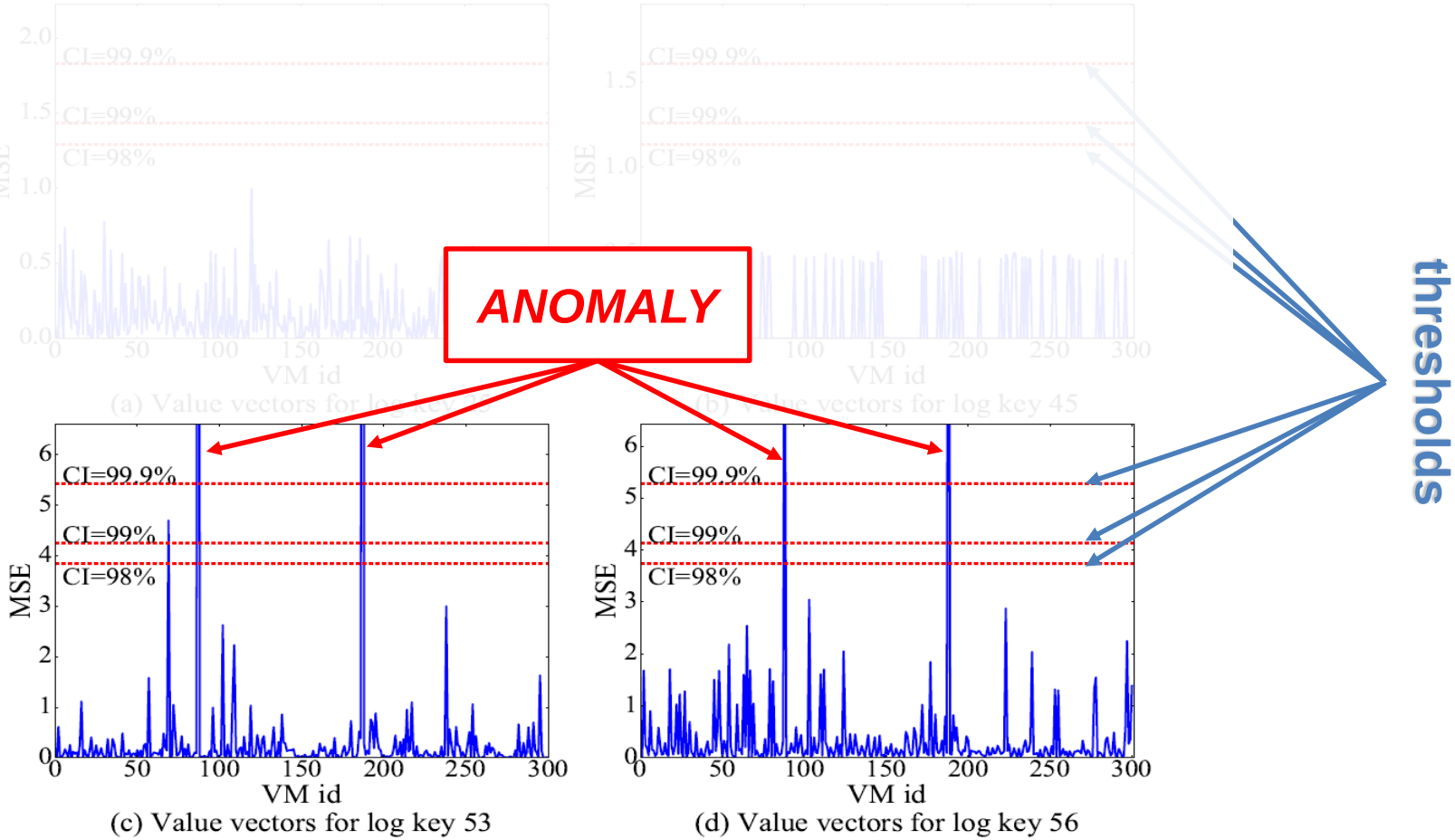

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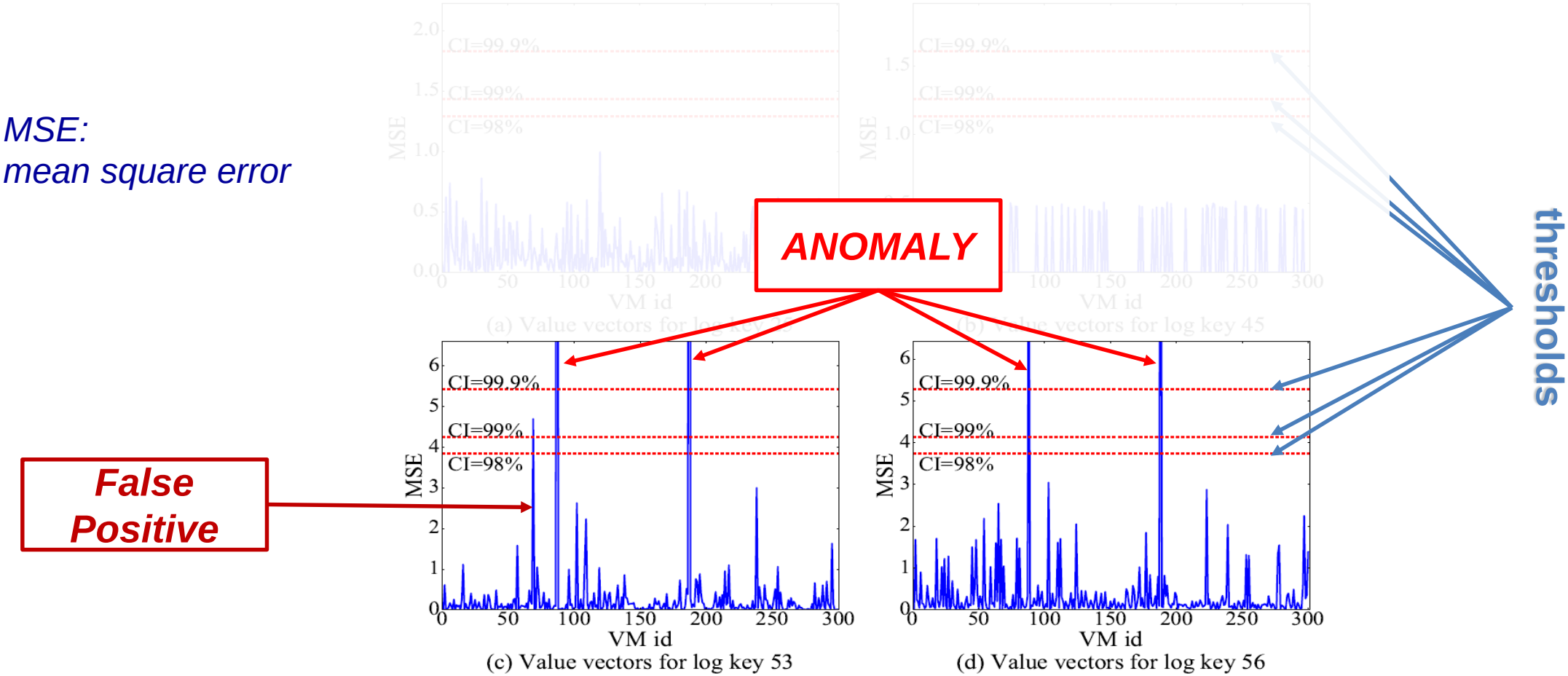
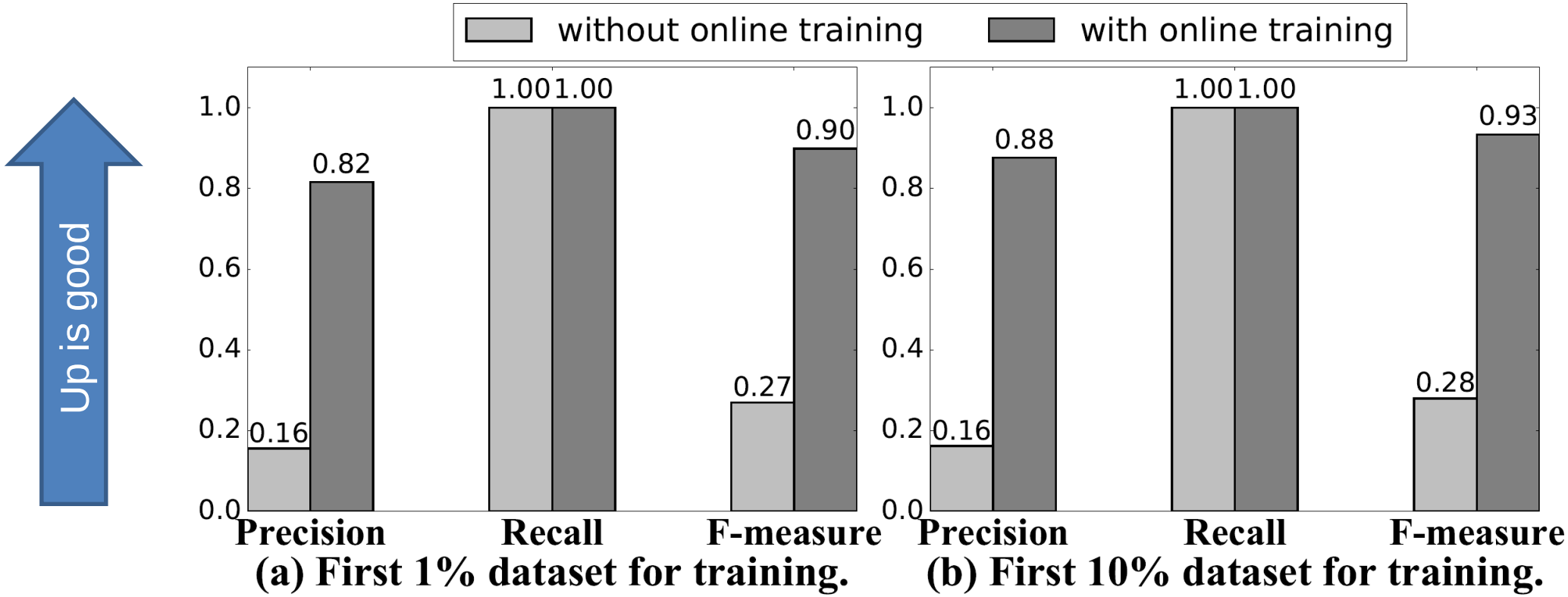


Evaluation results on OpenStack cloud log with different confidence intervals (CIs)

Evaluation – LSTM model online update

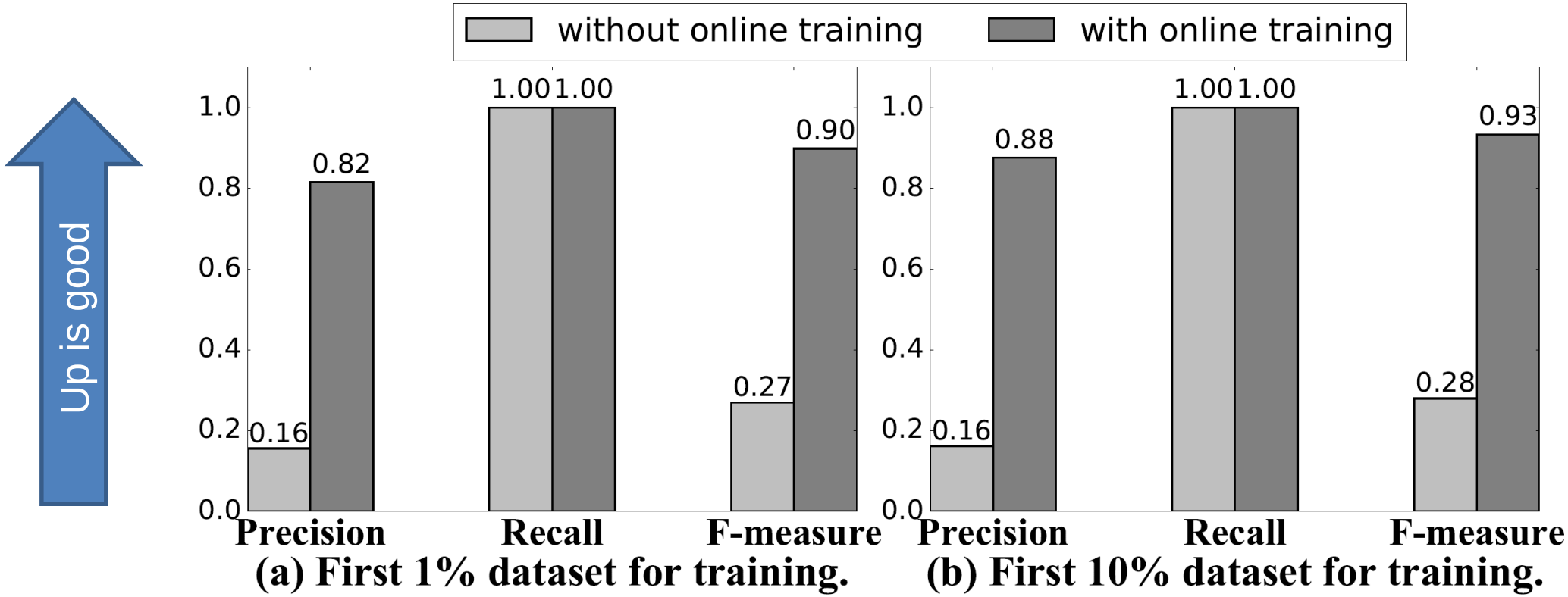


(a) First 1% dataset for training.

(b) First 10% dataset for training.

Evaluation on Blue Gene/L log,
with and without online model update.

Evaluation – LSTM model online update



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Evaluation on Blue Gene/L log, with and without online model update.

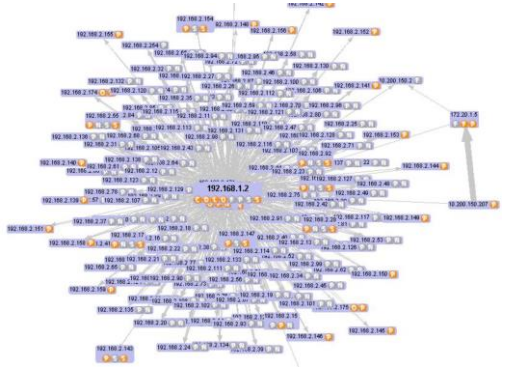
HPC log with labeled anomalies; Available at https://www.usenix.org/cfdr-data

Evaluation – case study: network security log

Dataset: IEEE VAST Challenge 2011

(Mini Challenge 2 – Computer Networking Operations)

The dataset contains firewall log, IDS log, etc.



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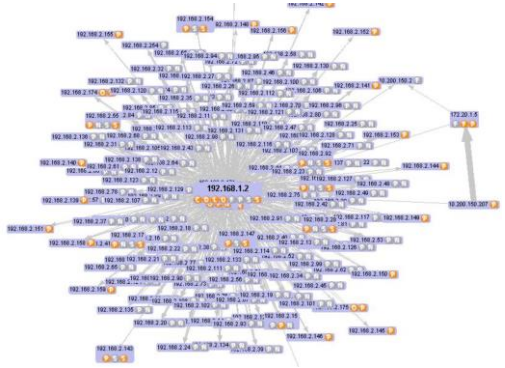

suspicious activity	detected?
Day 1: Denial of Service attack	Yes, log key anomaly in IDS log
Day 1: port scan	Yes, log key anomaly in IDS log
Day 2: port scan 1	Yes, log key anomaly in IDS log
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Day 2: socially engineered attack	Yes, log key anomaly in firewall log
Day 3: undocumented IP address	No

Detection results.

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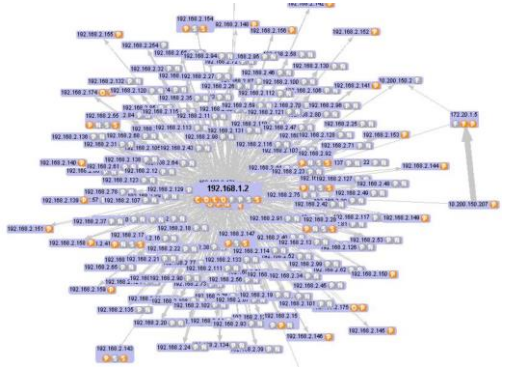

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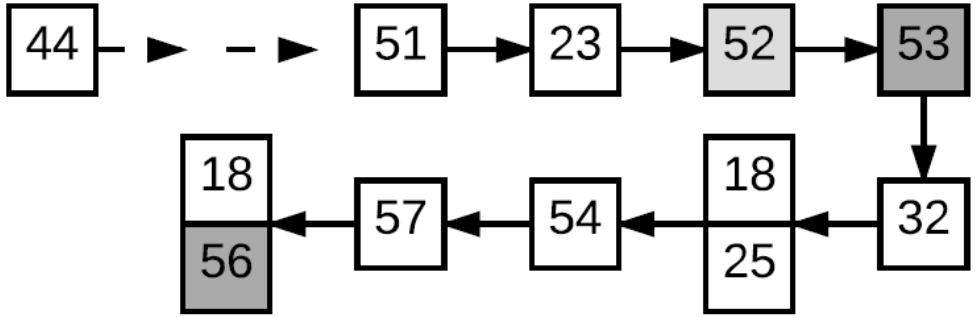
Detection results.

Could be fixed with prior knowledge of "documented IP"

Evaluation – workflow construction



44: instance: * Attempting claim: memory * disk * vcpus * CPU
51: instance: * Claim successful
23: instance: * GET * HTTP/1.1" status: * len: * time: *
*52: instance: * Creating image*
53: instance: * VM Started (Lifecycle Event)
32: instance: * VM Paused (Lifecycle Event)
18: instance: * VM Resumed (Lifecycle Event)
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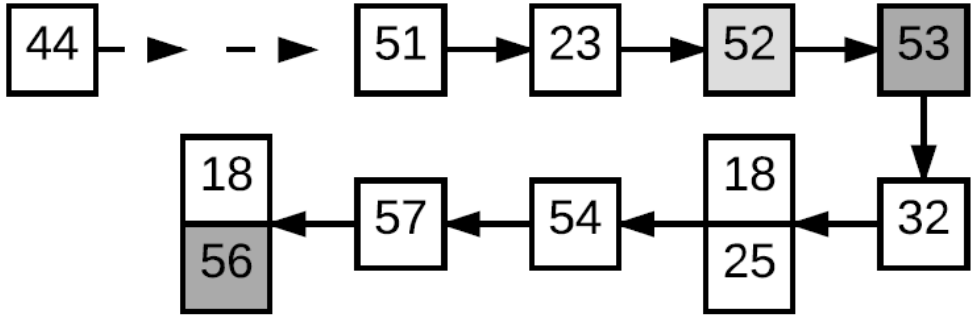
56: instance: * Took * seconds to build instance

Constructed workflow of *VM Creation*.

(previously generated OpenStack cloud log)

Evaluation – workflow construction

How does it help to diagnose anomalies?



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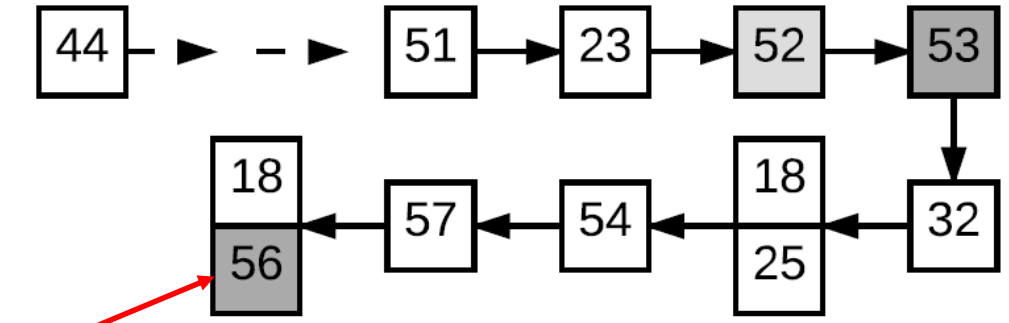

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Parameter value anomaly

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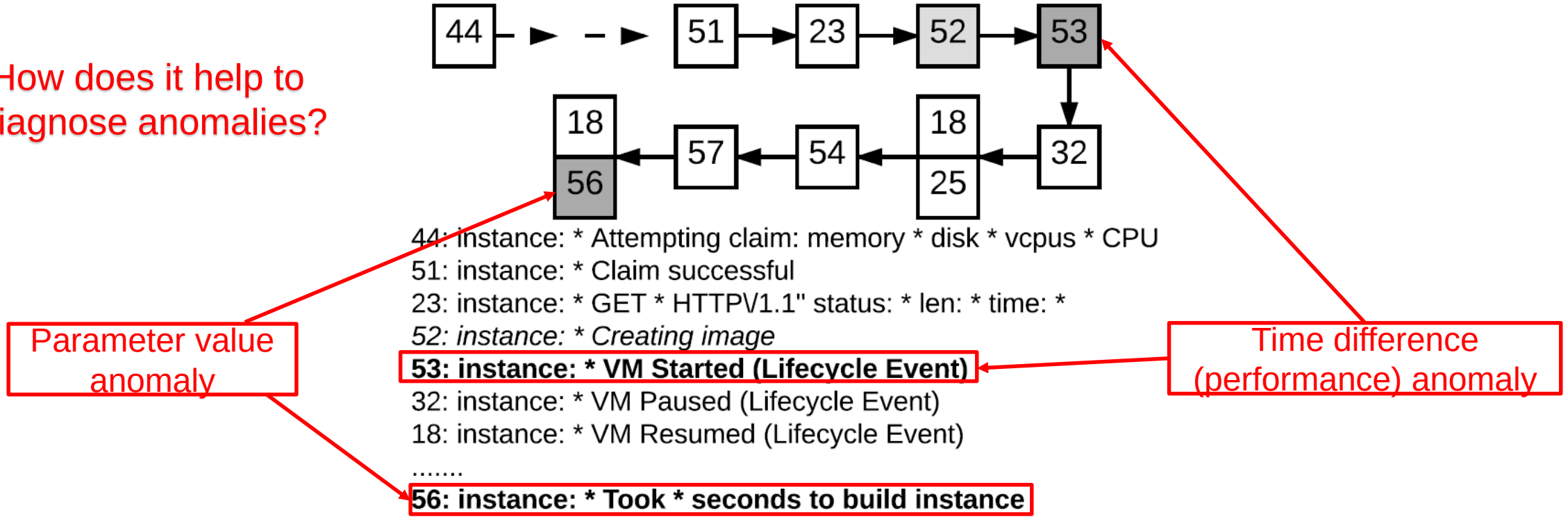

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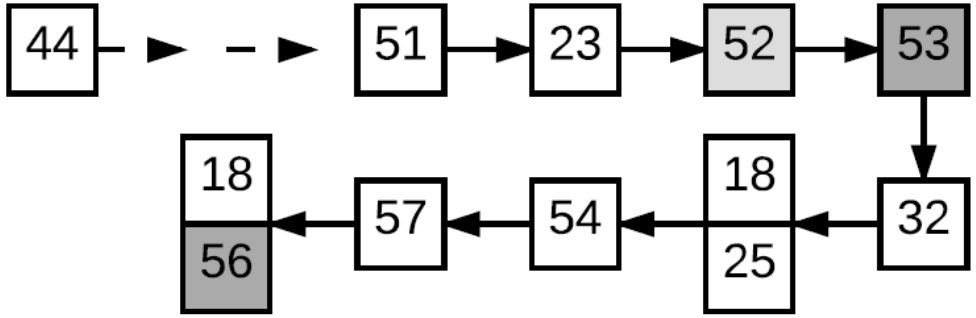

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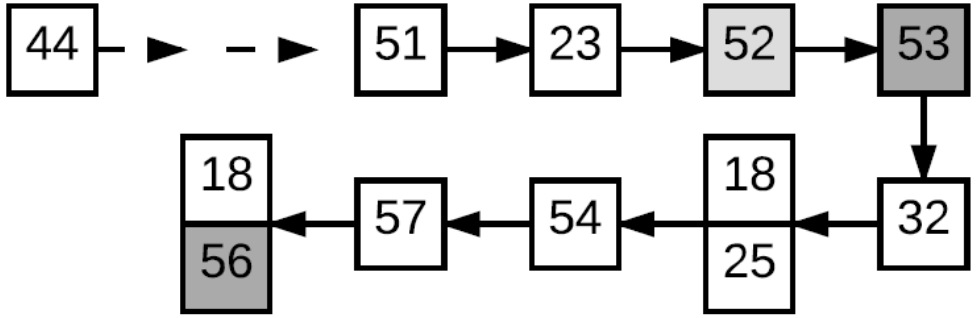
Identified anomaly:
Instance took too long to build because of the transition from 52 -> 53

Constructed workflow of *VM Creation*.
(previously generated OpenStack cloud log)

Evaluation – workflow construction

How does it help to diagnose anomalies?



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Constructed workflow of *VM Creation*.

(previously generated OpenStack cloud log)

Identified anomaly:

Instance took too long to build because of the transition from 52 -> 53

Injected anomaly:

During VM creation, network speed from controller to compute node is throttled.

Summary

DeepLog

- A realtime system log anomaly detection framework.
- LSTM is used to model system execution paths and log parameter values.
- Workflow models are built to help anomaly diagnosis.
- It supports online model update.

Thank you!

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Feifei Li
lifeifei@cs.utah.edu