

FuzzGuard: Filtering out Unreachable Inputs in Directed Grey-box Fuzzing through Deep Learning

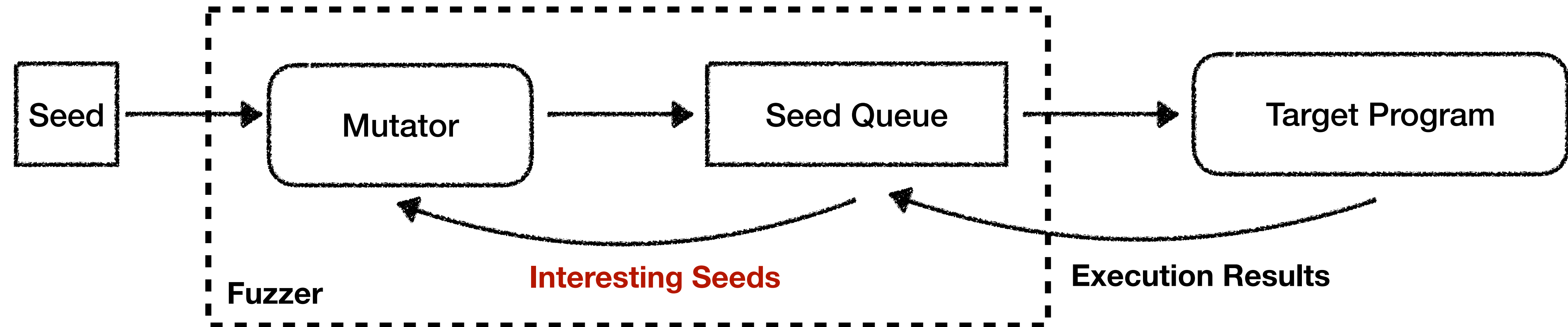
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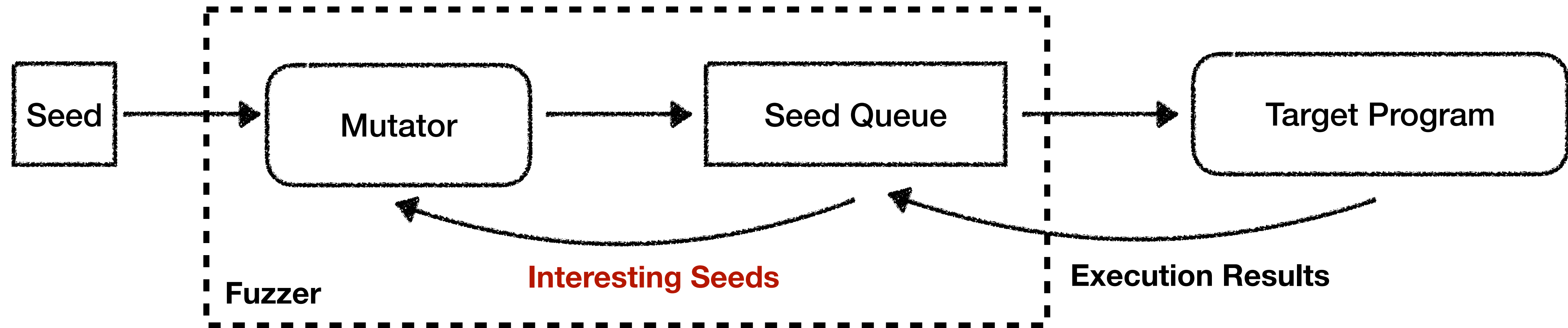
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Mutation based Grey-box Fuzzing Overview

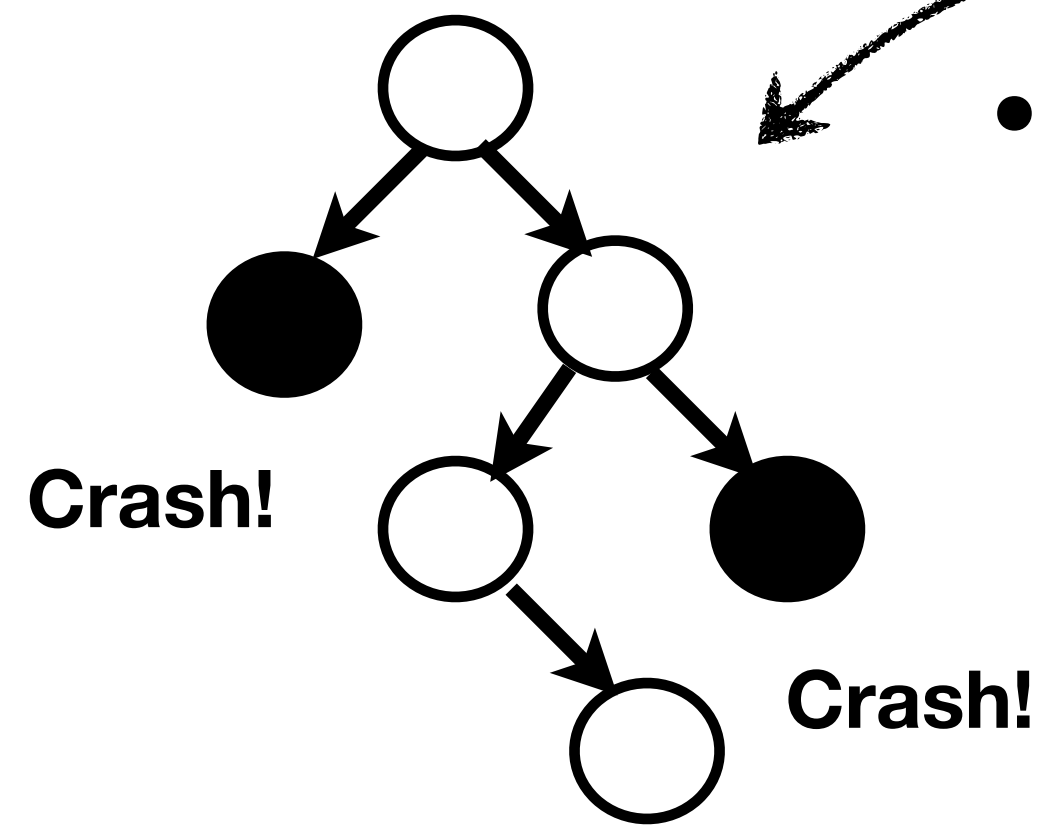


- Coverage-based Grey-box Fuzzing (CGF)
- Directed Grey-box Fuzzing (DGF)

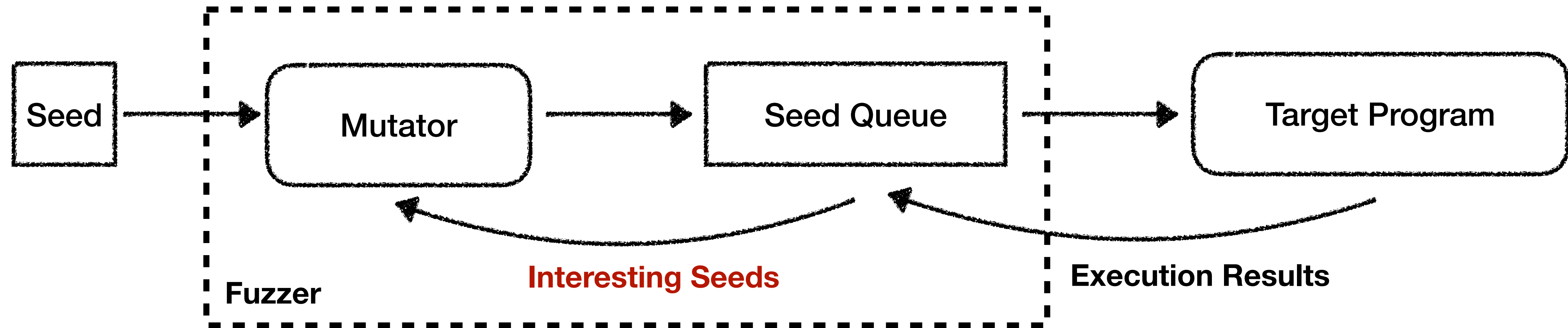
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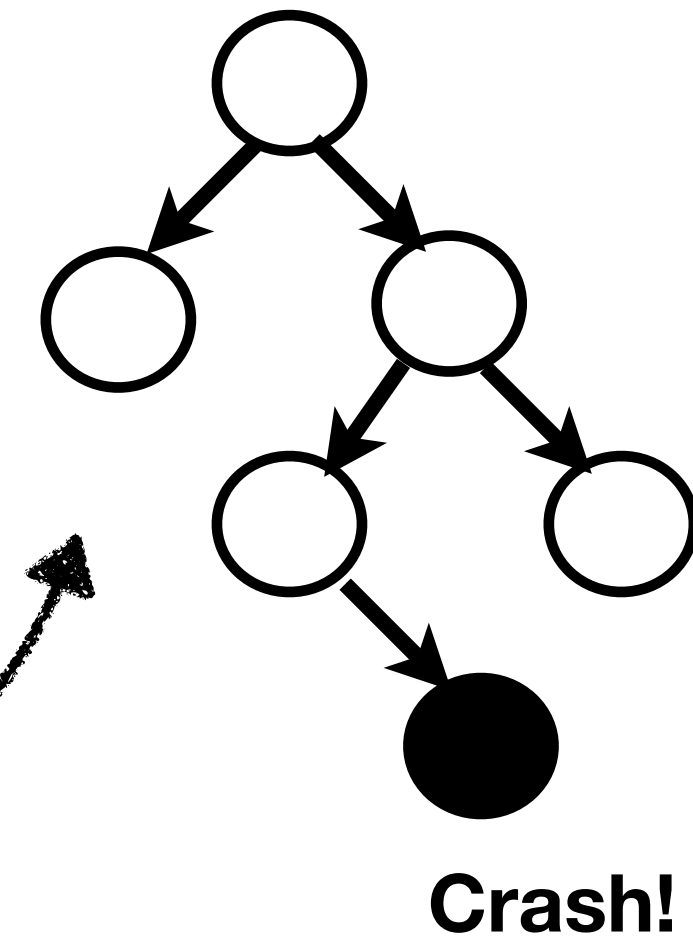
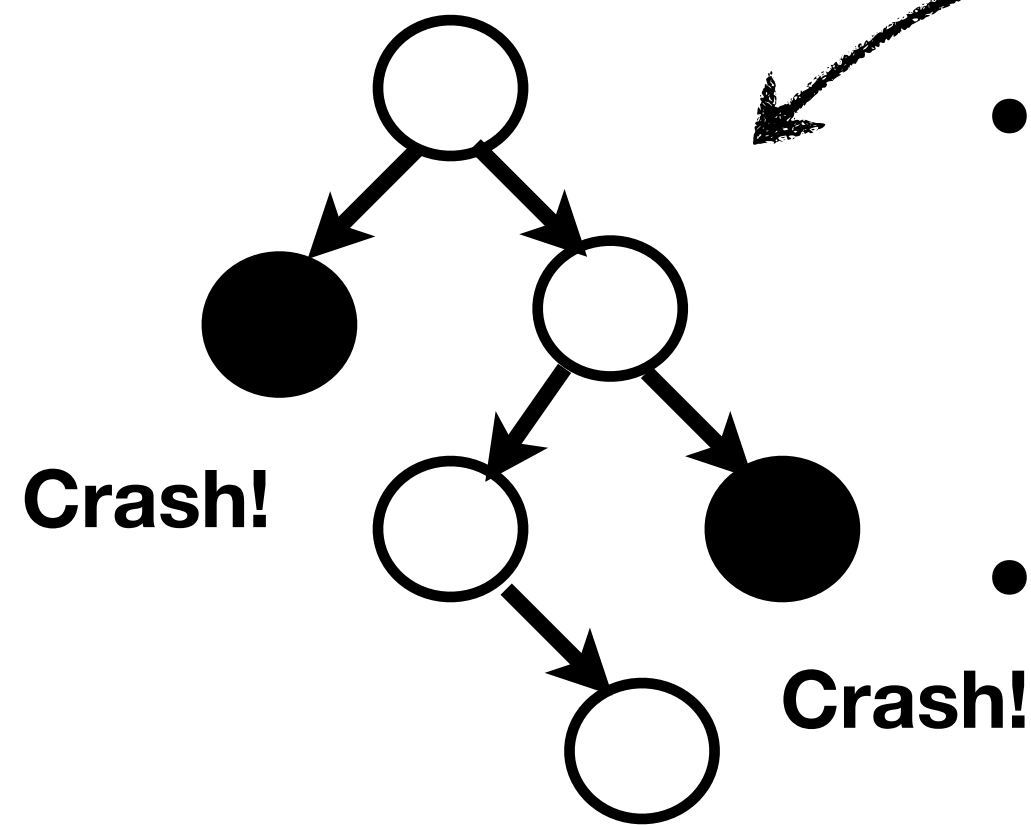
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Trigger more crashes.



Mutation based Grey-box Fuzzing Overview



- Coverage-based Grey-box Fuzzing (CGF)
Trigger more crashes.
- Directed Grey-box Fuzzing (DGF)
Check whether a target code really contains a bug.



DGF: lots of inputs cannot reach the buggy code

- Crash reproduction
- Patch testing
- Potentially vulnerable code checking

```
1  ThrowReaderException(...);
2  if (dib_info.colors_important > 256)
3  ThrowReaderException(...);
4  if ((dib_info.image_size != 0U) && (dib_info.image_size
    > file_size))
5  ThrowReaderException(...);
6  if ((dib_info.number_colors != 0) ||
    (dib_info.bits_per_pixel < 16)) {
7  image->storage_class=PseudoClass;
```

Vulnerable code

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Vulnerable code

How to reach the vulnerable code?

- **Annealing-based Power Schedules**
- Fuzz the input closer to the target longer.

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- **Symbolic execution**
 - Solve path conditions for each new path.

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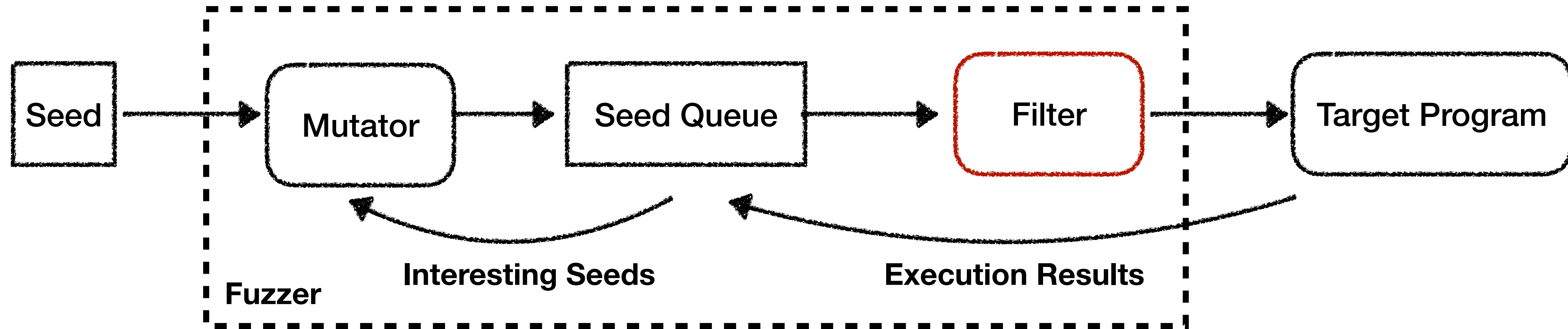
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High overhead requires!

Our approach: Build an input filter for the Fuzzer



- Build a **Deep Learning Model** (Filter)

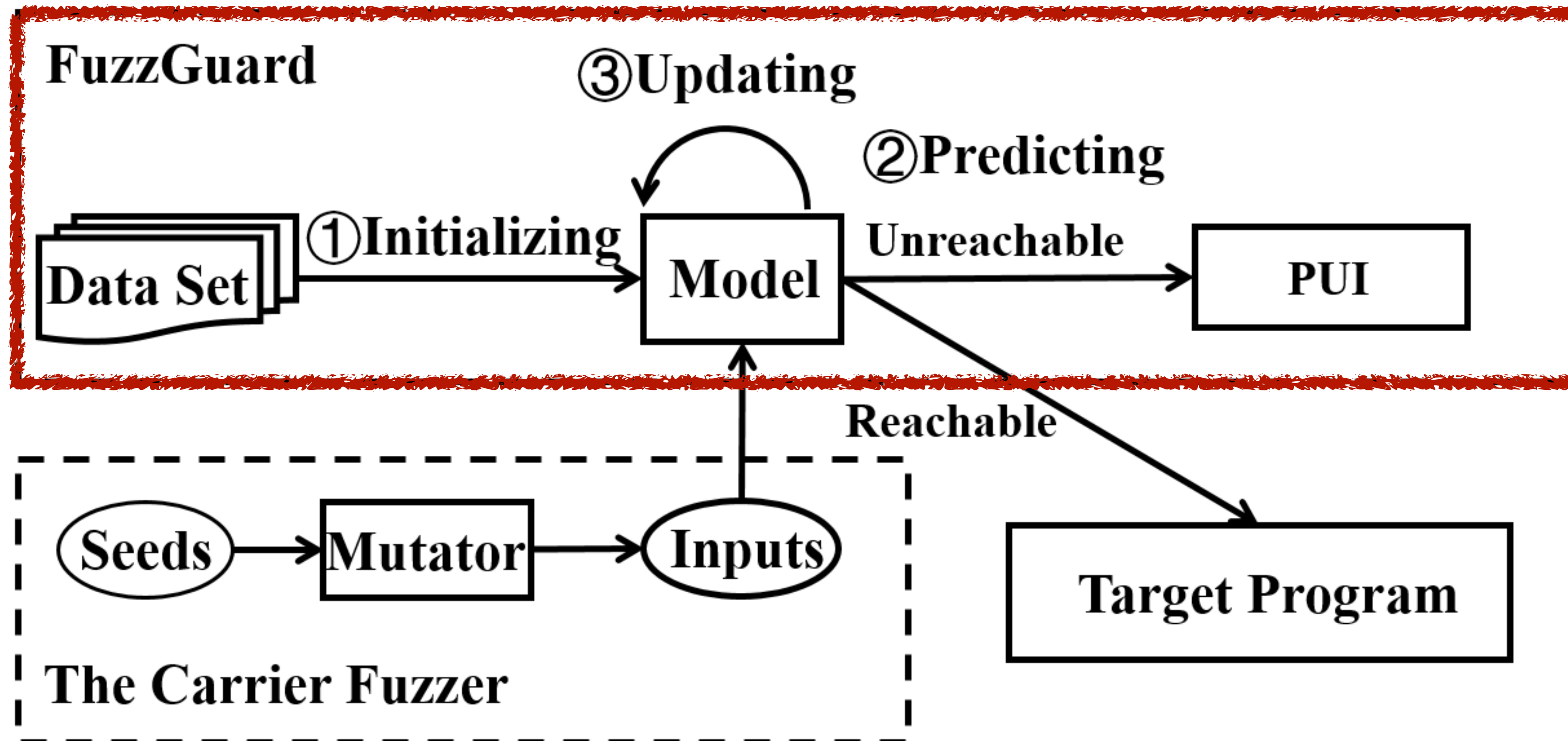
Without running the target program

- Learn from **previous executions**.
- To **identify** the inputs which can reach the buggy code.

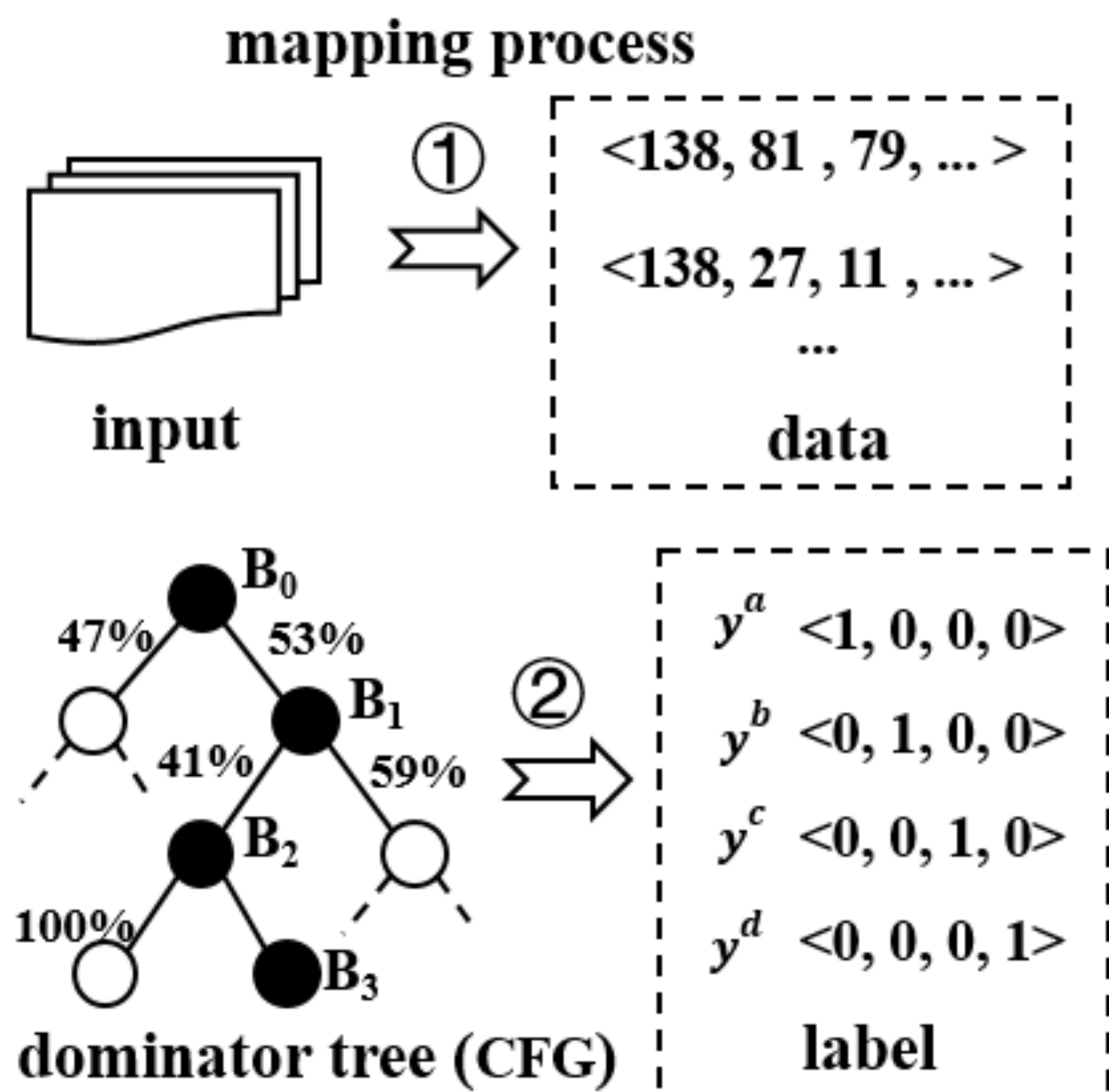
Challenges

- **C1: Lack of balanced labeled data.**
 - In the early stage of fuzzing, there is even **no reachable input**.
 - Without balanced labeled data, the trained model will be **overfitting**.
- **C2: Lack of representative data.**
 - Newly inputs look **quite different** from the reachable ones in the training set.
 - The trained model will **fail to predict** the reachability of the new inputs.
- **C3: Efficiency.**
 - The time cost of training and prediction should be **strictly limited**.

Overview of FuzzGuard

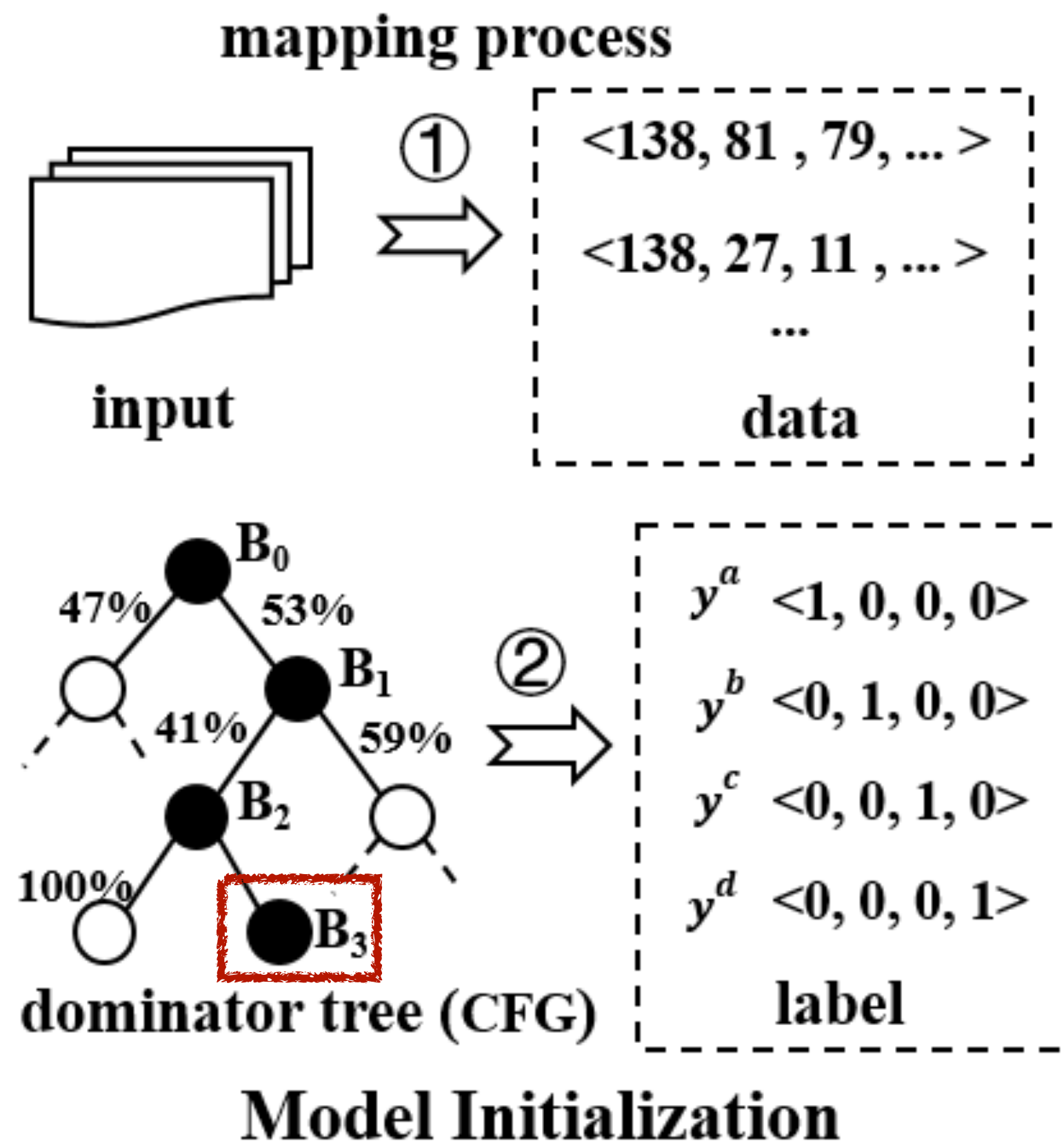


Phase 1: Model Initialization



Model Initialization

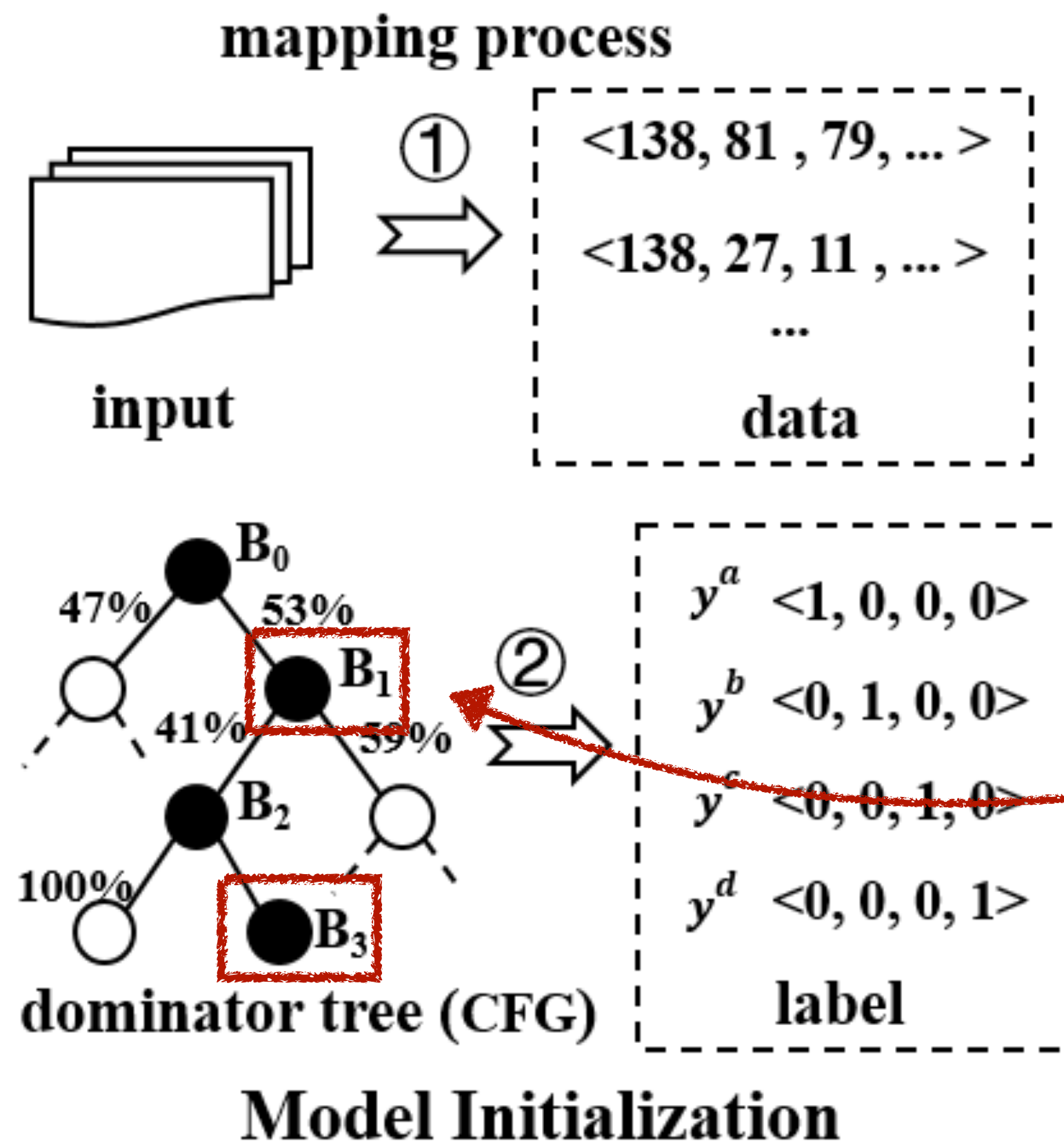
Phase 1: Model Initialization



C1: Lack of balanced labeled data.

- Step-forwarding approach
 - Collect and map the inputs and their execution path.
 - Choosing the dominators of the buggy code as the middle-stage targets.
 - Letting the execution reach the pre-dominating nodes first.

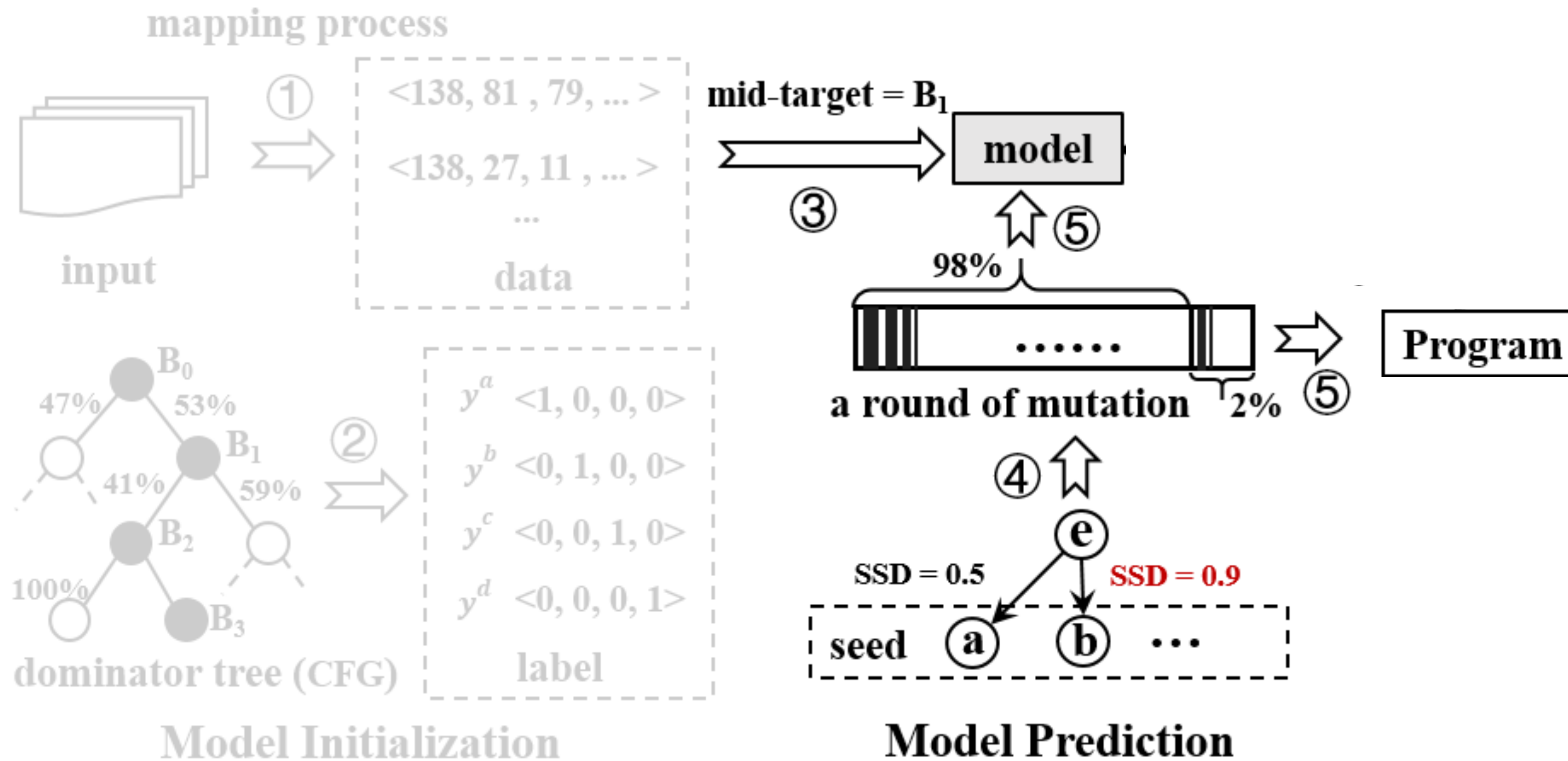
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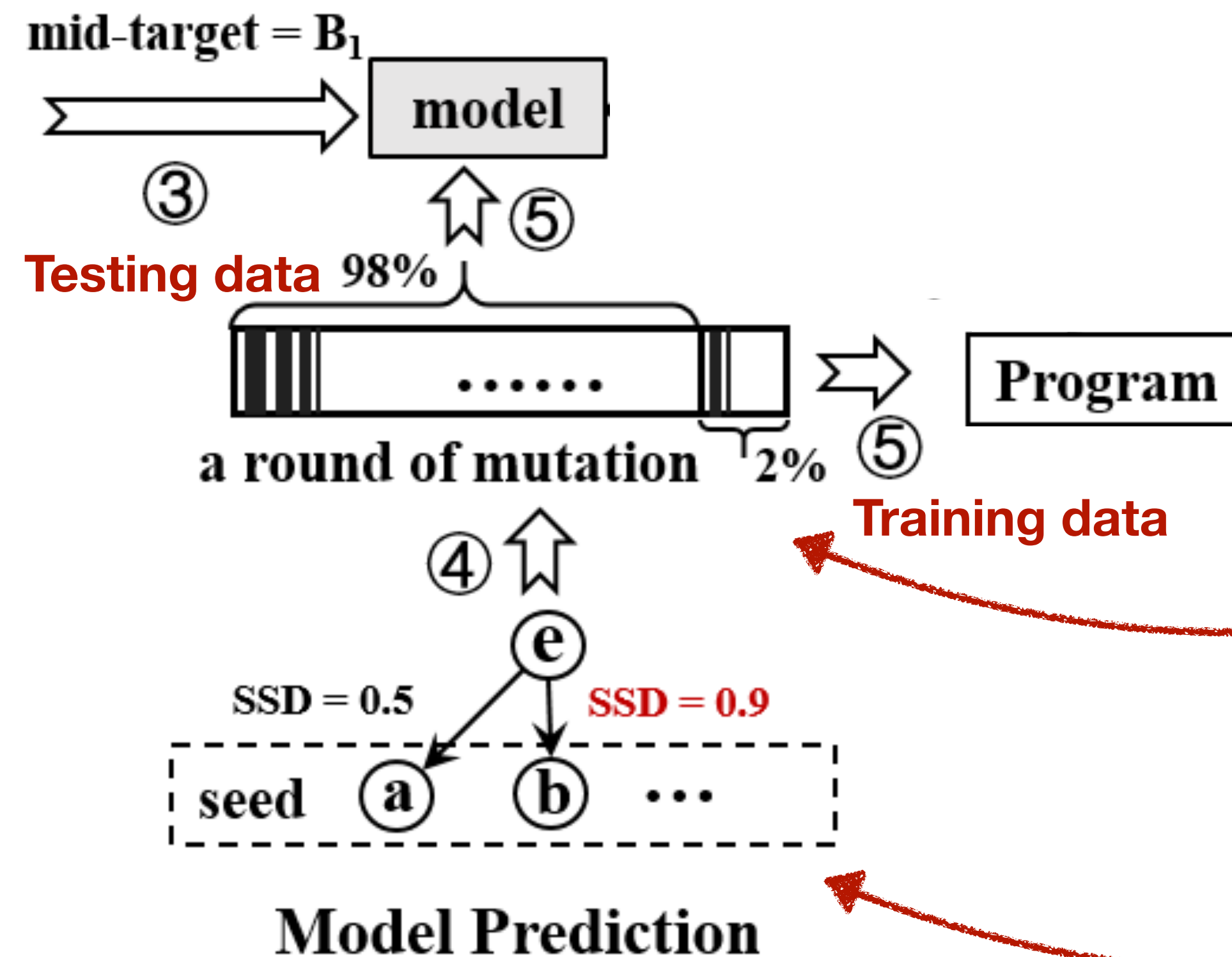
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Phase 2: Model Prediction



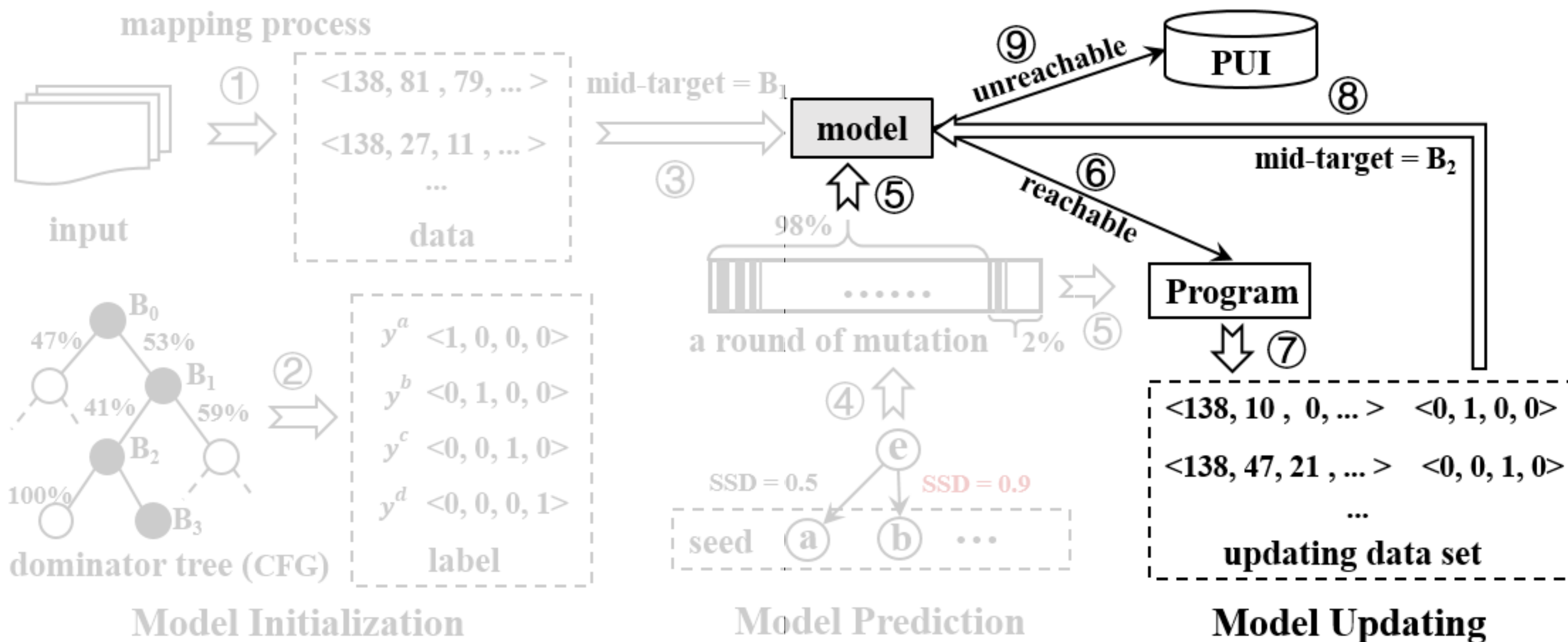
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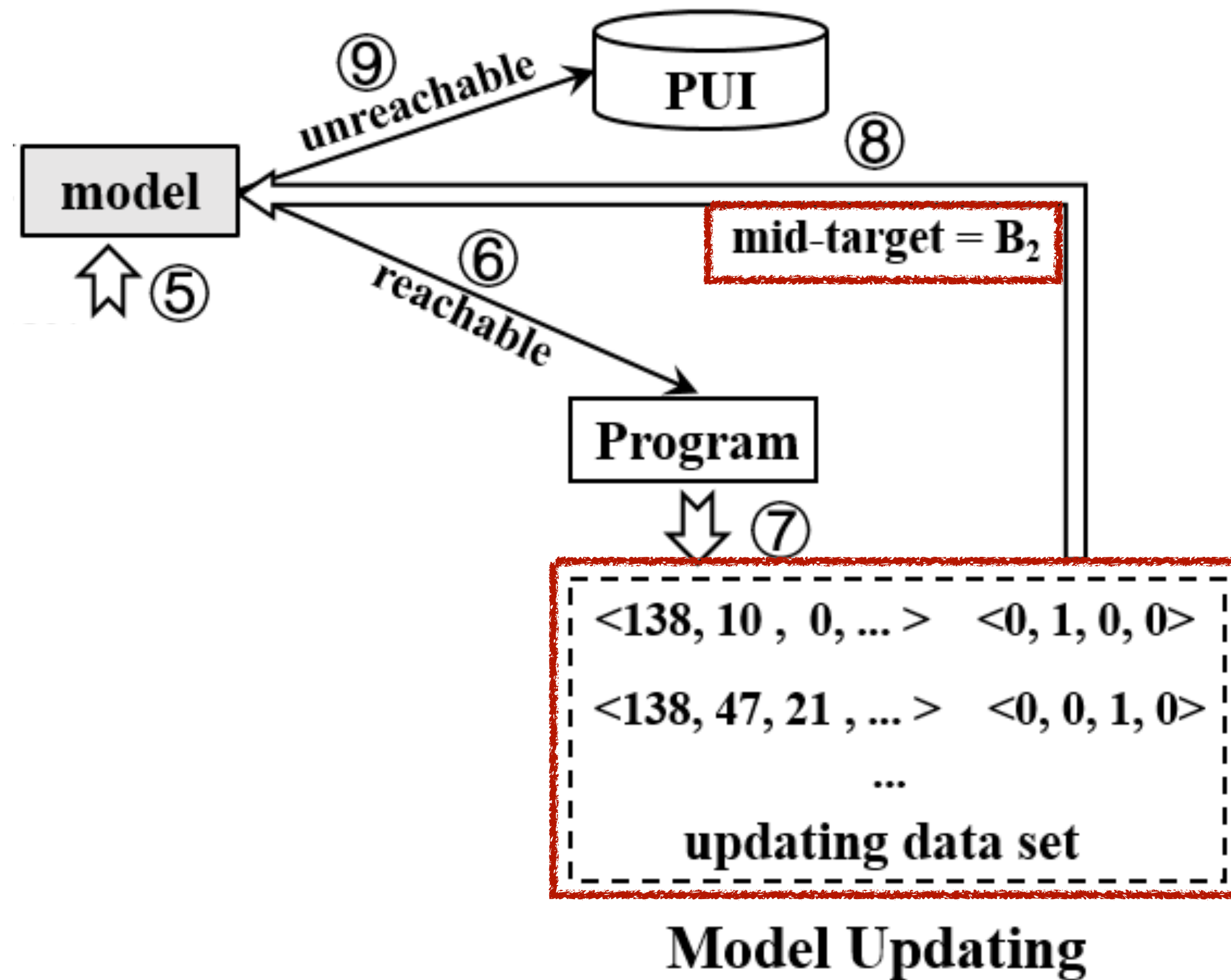
C2: Lack of representative data.

- Representative data selection
- Sample training data from **each round of mutation**.
- Calculate **seed similarity degree (SSD)** and sample fewer inputs for similar ones.

Phase 3: Model Updating



Phase 3: Model Updating



C3: Efficiency

- Incremental Learning
- Keep collect training data for **updating model**.
- Incremental train the model when a new **mid-target node** gains balanced data.

Effectiveness Summary

- Dataset

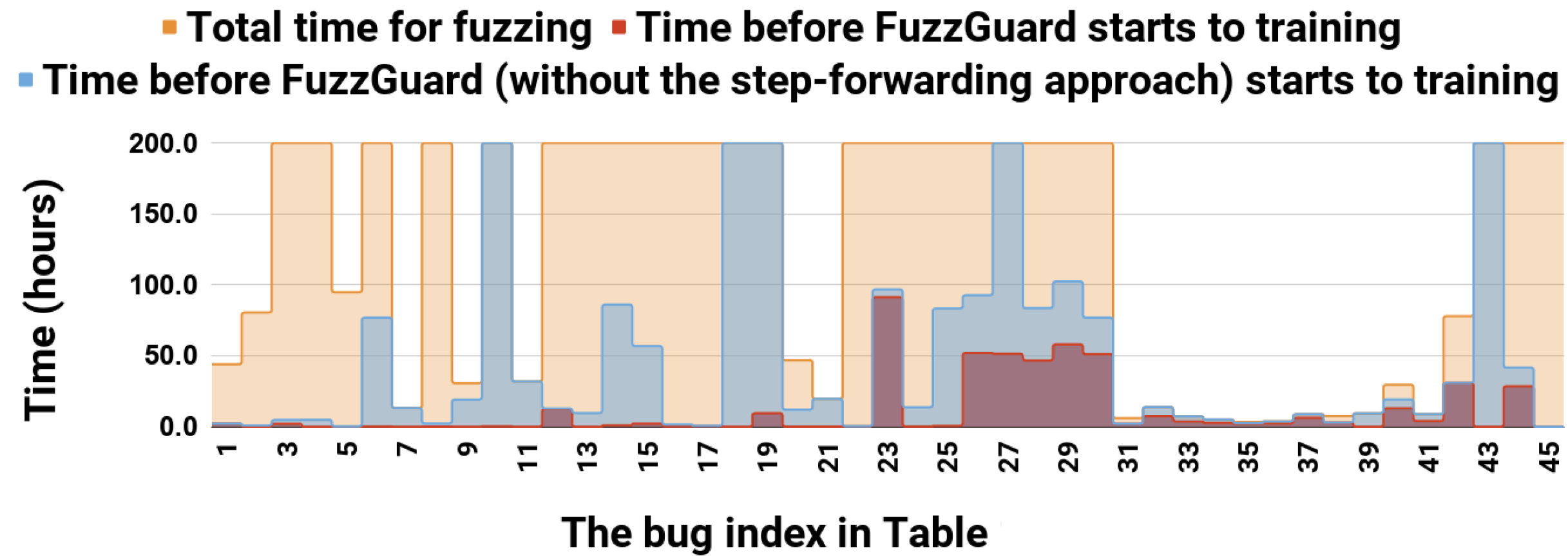
- 45 bugs in 10 real-world programs with different file formats.

- Results

- 1.3x -17.1x speedup (5.4x averagely)
- The earlier the model is trained, the more time could be saved.
- The more reachable inputs generated by the carrier fuzzer, the less effective FuzzGuard is.

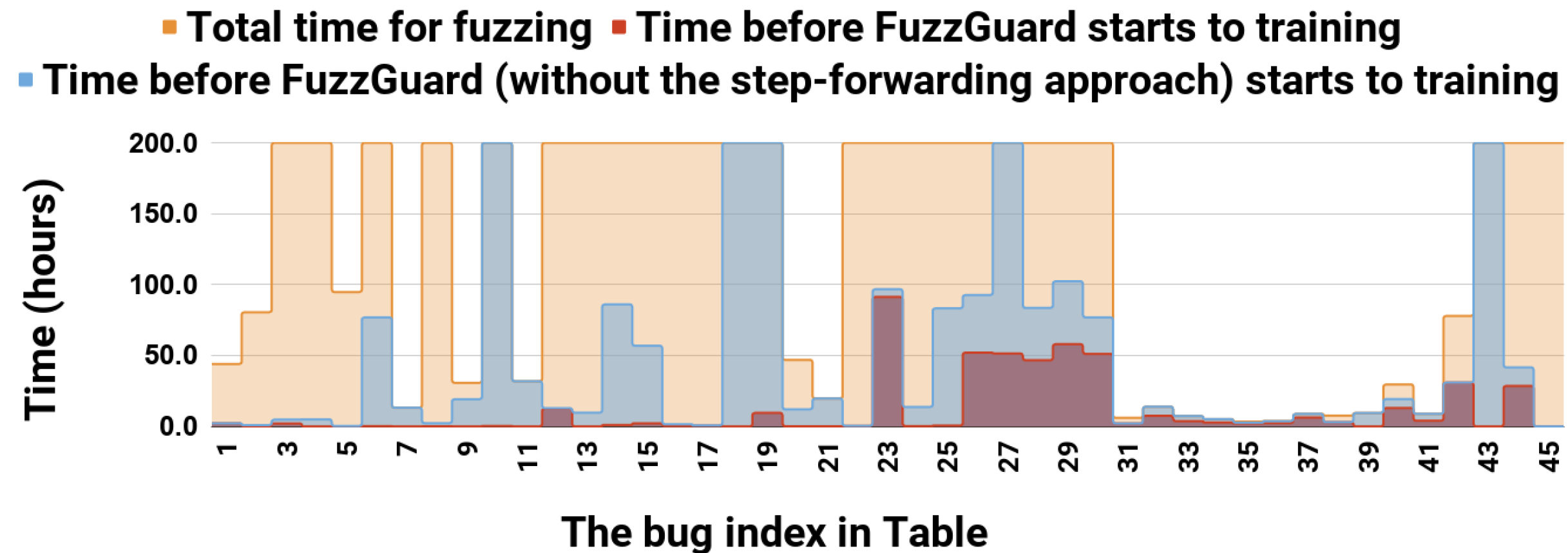
No.	Program	Vuln. Code	N _{Functions}	N _{Constraints}	N _{Inputs}	UR.	Filtered	T _{AFLGo}	T _{+FG}	Speedup		
										FG	FG ₁	FG ₂
18	ImageMagick v7.0.7-1	tiff.c:1934	149.1 K	1.2 M	9.4 M	98.5%	92.5%	200 h	15.2 h	13.1	1.6	8.7
19	ImageMagick v7.0.5-5	bmp.c:804	102.4 K	926.5 K	12.9 M	64.3%	59.9%	200 h	80.5 h	2.5	1.7	2.5
20	Jasper v2.0.14	jp2	13.9 K	17.7 M	28 M	99.4%	50.9%	200 h	99 h	2.0	1.7	1.9
21	Jasper v2.0.10	jr h	740	9.7 K	11.3 M	99.7%	94.3%	46.9 h	3.7 h	12.7	1.4	11.1
22	Jasper v2.0.10		1.7 K	36.8 K	6.1 M	99.9%	94.0%	19.7 h	1.6 h	12.0	1.0	10.0
23	Jasper v2.0.10	7 h	1.1 K	11.8 K	22.3 M	62.4%	56.0%	200 h	89 h	2.2	2.0	2.2
24	Libming v0.4.8	h	104	5.3 K	38.6 M	99.9%	70.2%	200 h	63 h	3.2	1.0	3.1
25	Libming v0.4.7	par	75	4.7 K	32.3 M	99.8%	94.7%	200 h	11.7 h	17.1	8.5	14.1
26	Libming v0.4.7	parser.c:2993	170	2.7 K	16.1 M	91.9%	86.6%	200 h	27.2 h	7.3	1.7	6.2
27	Libming v0.4.7	parser.c:3381	79	790	38.4 M	99.7%	69.9%	200 h	61.3 h	3.3	2.0	3.2
28	Libming v0.4.7	parser.c:3095	25	217	46.8 M	92.9%	65.7%	200 h	70 h	2.9	1.9	2.8
29	Libming v0.4.7	parser.c:2993	22	386	45.9 M	97.2%	64.8%	200 h	71.8 h	2.8	1.7	2.7
30	Libming v0.4.7	parser	24	294	77 M	92.9%	63.6%	200 h	75.3 h	2.7	2.0	2.5
31	Libming v0.4.7	pe	55	423	12.6 M	99.8%	61.3%	6.1 h	2.8 h	2.2	2.0	1.8
32	Libming v0.4.7	h	38	308	13 M	99.9%	43.2%	14 h	8.2 h	1.7	1.0	1.6
33	Libming v0.4.7		32	340	16.6 M	99.9%	46.0%	7.3 h	4.4 h	1.7	1.0	1.4
34	Libming v0.4.7	h	36	396	19.6 M	99.9%	43.3%	5.2 h	3.4 h	1.5	1.0	1.1
35	Libming v0.4.7	h	37	637	18.9 M	99.8%	37.2%	3.4 h	2.5 h	1.4	1.0	1.1
36	Libming v0.4.7	p	34	1.1 K	17.6 M	99.9%	33.6%	3.8 h	2.9 h	1.3	1.0	1.1
37	Libming v0.4.7	pars	34	402	20.7 M	99.9%	27.7%	8.9 h	6.9 h	1.3	1.0	1.2
38	Libming v0.4.7	outputtxt.c:143	64	2.2 K	27.3 M	65.5%	24.6%	7.7 h	6.1 h	1.3	1.1	1.1
39	Libtiff v4.0.9	tif_dirwrite.c:1901	728	14.4 K	8.6 M	99.9%	91.4%	9.6 h	1.3 h	7.4	1.0	4.8
40	Libtiff v4.0.7	tif_sw	631	13.1 K	44.7 M	99.7%	52.8%	29.6 h	15 h	2.0	1.1	1.3
41	Libtiff v4.0.7	tifc	728	13.3 K	15.6 M	99.9%	51.7%	8.9 h	4.6 h	1.9	1.0	1.7
42	Libtiff v4.0.7	tif	416	11.6 K	60.6 M	79.5%	36.3%	77.9 h	49.8 h	1.6	1.4	1.5
43	Libxml2 v2.9.4	SA	418	15.7 K	92.6 M	99.9%	94.4%	200 h	17.6 h	11.3	1.0	5.2
44	Podofv v0.9.5	Pdf	19.8 K	44.1 K	2.6 M	99.3%	79.7%	200 h	40.7 h	4.9	4.8	1.8
45	Tcp replay v4.3.0-beta1	get.c:174	23	1.1 K	203.3 M	53.2%	49.5%	200 h	105.4 h	1.9	1.7	1.9
Avg.			15.5K	315.9 M		91.7%	65.1%			5.4	2.6	4.4

Contribution of Individual Techniques

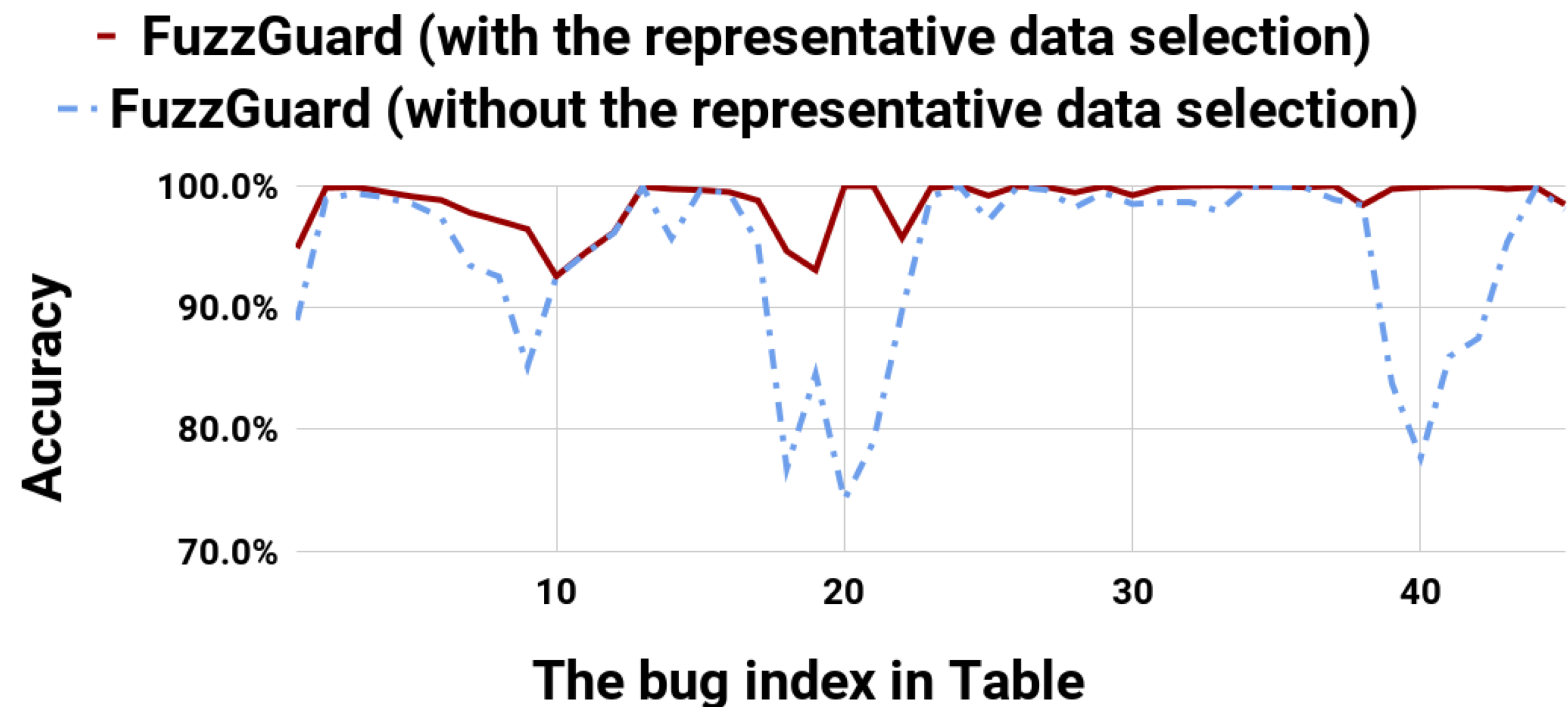


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 - Gain only 2.6x speedup averagely.
 - 14/45 bugs cannot be trained.

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 - 14/45 bugs cannot be trained.



- Without the representative data selection
 - Gain only 4.4x speedup averagely.
 - The accuracy dramatically decreases in some cases.

Conclusion

- FuzzGuard: A **deep-learning-based** approach to predict reachability of program inputs **without execution**.
- **Step-forwarding approach** for handling unbalanced data training.
- **Representative data selection** for training data collection.
- **Incremental learning** for the dynamic model.
- Increase the runtime performance of the vanilla AFLGo from **1.3x to 17.1x**.

Thanks for Listening!

Q&A

Code Release: <https://github.com/zongpy/FuzzGuard>.