MPCDiff: Testing and Repairing MPC-Hardened Deep Learning Models

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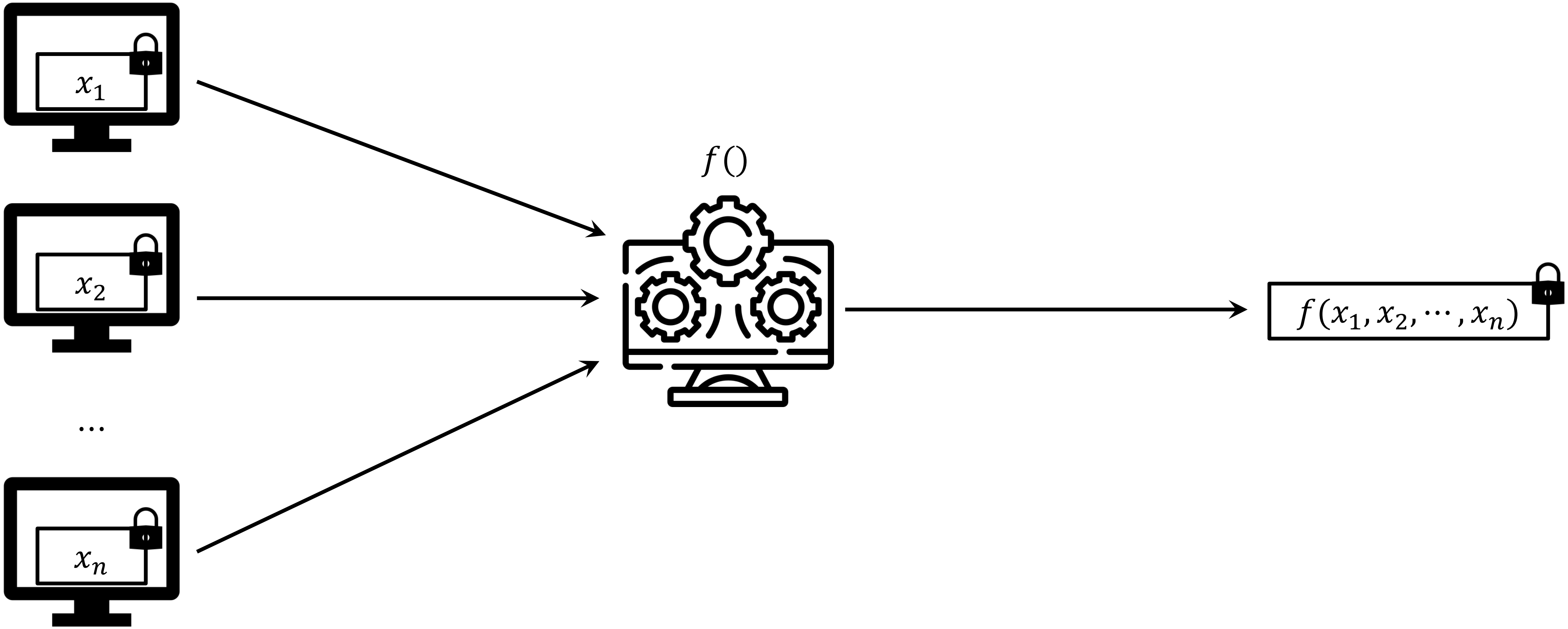
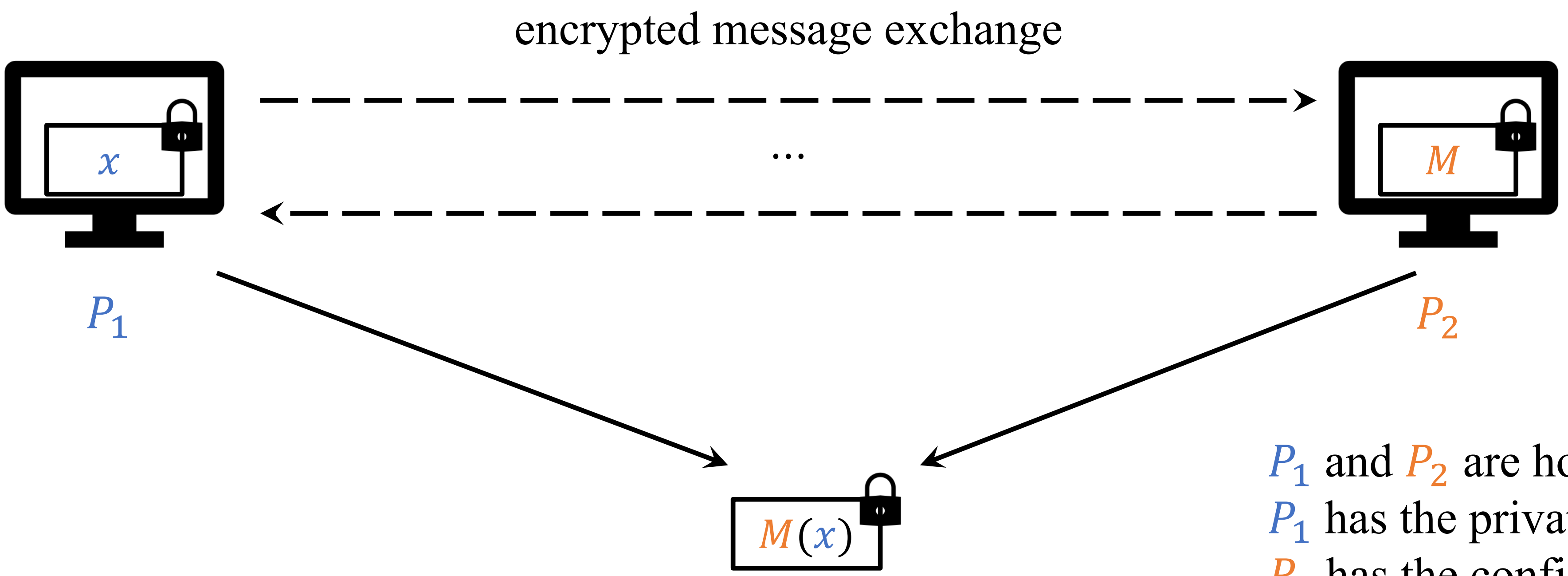
Secure multi-party computation (MPC)[YAO86, GMW87, BGW88]



Secure two-party deep learning inference



P_1 and P_2 are honest but curious.
P_1 has the private input data x.
P_2 has the confidential model M.

Examples of secure inference for DL models

SecureML: A System for Scalable Privacy-Preserving Machine Learning[MZ17]

GAZELLE: A Low Latency Framework for Secure Neural Network Inference[JVC18]

Iron: Private Inference on Transformers[HLC+22]

BumbleBee: Secure Two-party Inference Framework for Large Transformers[LHG+23]

Delphi: A Cryptographic Inference Service for Neural Networks[MLS+20]

Cheetah: Lean and Fast Secure Two-Party Deep Neural Network Inference[HLH+22]

BOLT: Privacy-Preserving, Accurate and Efficient Inference for Transformers[PZM+23]

TFEncrypted

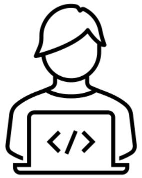
Syft

CrypTen

MPC-Hardened DL models

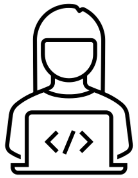
- Addition

$$x = [x]_1 + [x]_2 \bmod p$$
$$y = [y]_1 + [y]_2 \bmod p$$
$$z = x + y \bmod p$$



$[x]_1, [y]_1$

$$[z]_1 = [x]_1 + [y]_1 \bmod p$$



$[x]_2, [y]_2$

$$[z]_2 = [x]_2 + [y]_2 \bmod p$$

$$z = [z]_1 + [z]_2 \bmod p = x + y \bmod p$$

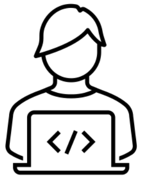
MPC-Hardened DL models

- Multiplication

$$x = [x]_1 + [x]_2 \bmod p$$
$$y = [y]_1 + [y]_2 \bmod p$$
$$z = x \times y \bmod p$$

Beaver triples:

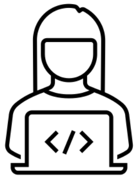
$$c = a \times b$$



$[x]_1, [y]_1$
$[a]_1, [b]_1, [c]_1$

$[\alpha]_1 = [x]_1 - [a]_1$
$[\beta]_1 = [y]_1 - [b]_1$

$[\alpha]_2 = [x]_2 - [a]_2$
$[\beta]_2 = [y]_2 - [b]_2$



$[x]_2, [y]_2$
$[a]_2, [b]_2, [c]_2$

$$[z]_1 = [c]_1 + \alpha[b]_1 + \beta[a]_1 + \alpha\beta$$

$$[z]_2 = [c]_2 + \alpha[b]_2 + \beta[a]_2 + \alpha\beta$$

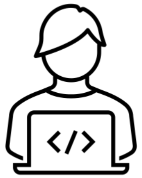
$$z = [z]_1 + [z]_2 \bmod p = x \times y \bmod p$$

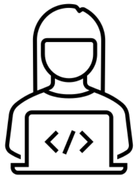
MPC-Hardened DL models

- Non-linear functions

$$x = [x]_1 + [x]_2 \bmod p$$

$$y = \exp(x) = \lim_{n \to \infty} \left(1 + \frac{x}{n}\right)^n$$





encrypted message exchange

$[x]_1$ ⟶ ⟵ $[x]_2$

$$[z]_1 = \left[\left(1 + \frac{x}{n}\right)^n\right]_1 \qquad [z]_2 = \left[\left(1 + \frac{x}{n}\right)^n\right]_2$$

$$z = [z]_1 + [z]_2 \bmod p = \exp(x)$$

Observation#1: Fixed-point representation

- Use **fixed-point arithmetic** to represent a floating-point value $\tilde{\boldsymbol{x}} \in R$:
  - $x = \lfloor \tilde{x} 2^m \rfloor$, m is the precision bit.

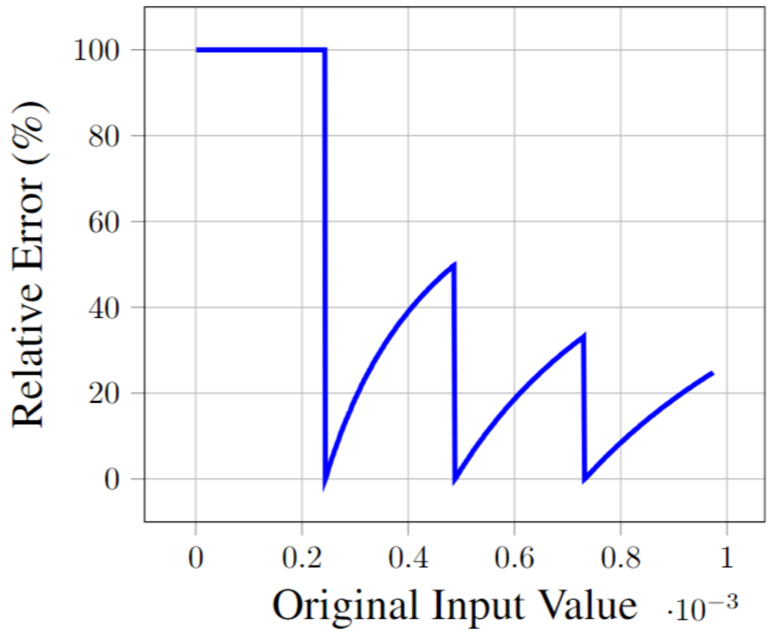


Figure 1. Relative error of fixed-point representation.

Observation#1: Fixed-point representation

- Use fixed-point arithmetic to represent a floating-point value $\tilde{\boldsymbol{x}} \in$ R:
  - $x = \lfloor \tilde{x} 2^{m} \rfloor$, m is the precision bit.
- The multiplication results is truncated by m bits for subsequent computation.
  - $z = x \times y = \lfloor \tilde{x} 2^{m} \rfloor \times \lfloor \tilde{y} 2^{m} \rfloor$, has 2m bits scale.
  - Local truncation drops the last m bits of $[z]_1$ and $[z]_2$ locally, resulting in a **1-bit random error** in the last bit (w.h.p.).

Observation#2: Non-linear function approximation

- There are many non-linear functions in DL models like Sigmoid, Tanh, and GELU.
  - These functions are usually **approximated** in MPC.

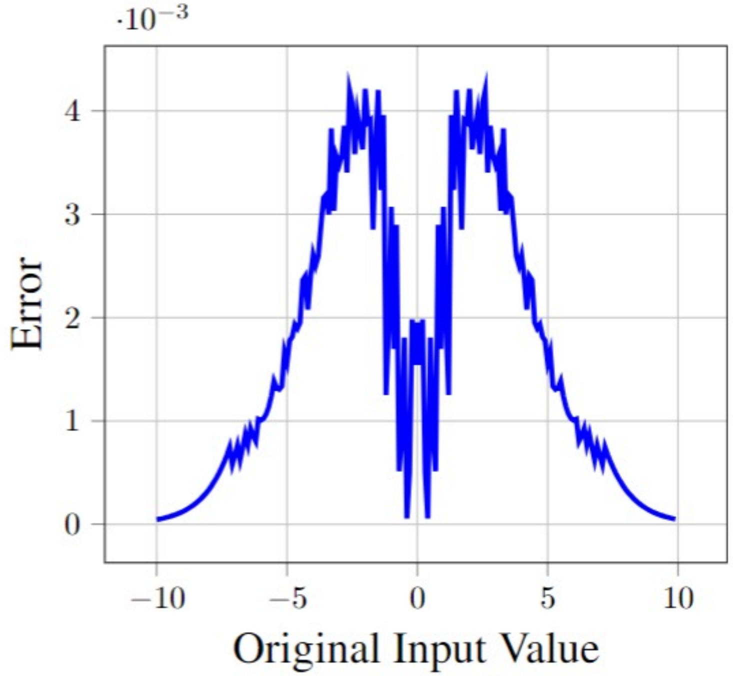
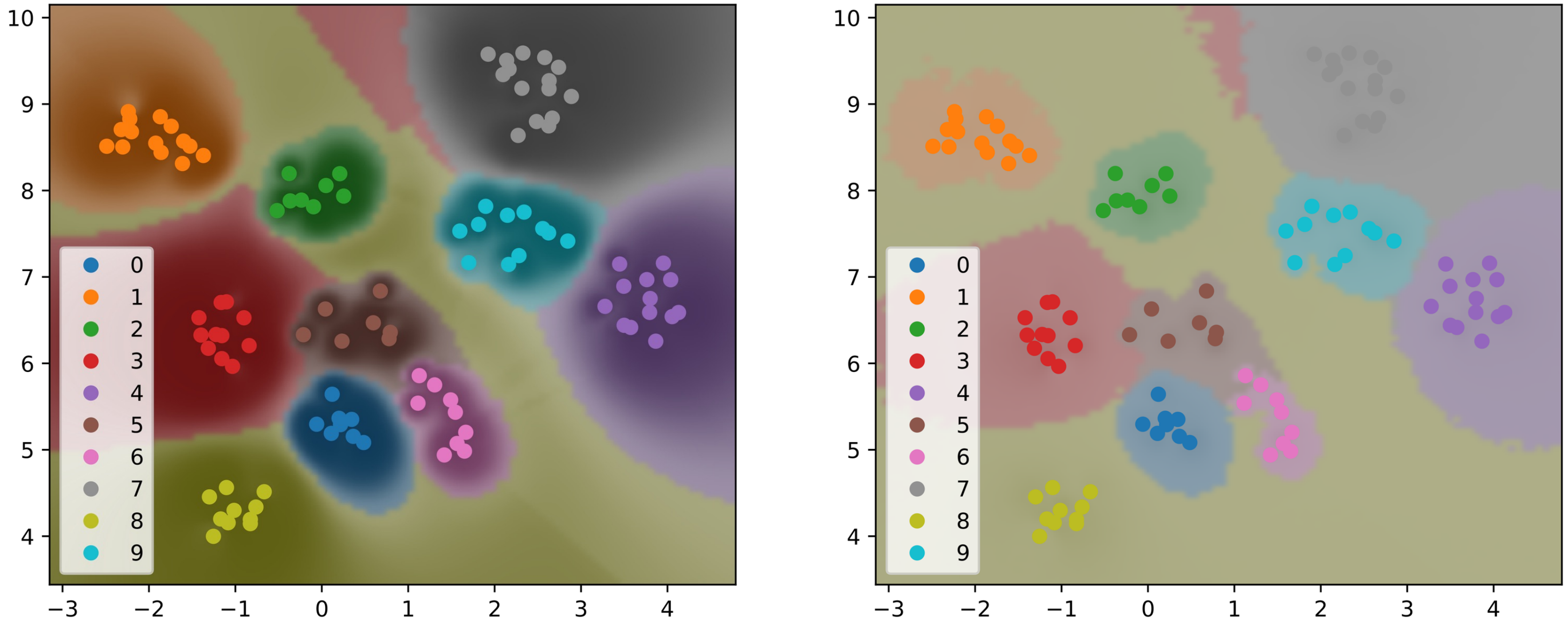


Figure 2. Relative error of Sigmoid approximation.

Observation#3: Decision boundary shifting

- The errors will result in a **decision boundary shifting** in MPC-hardened DL models.



(a). Decision boundaries of the **original** model.

(b). Decision boundaries of the **MPC-hardened** model.

Figure 3. Decision boundaries of LeNet and its MPC-hardened version for classifying MNIST images.

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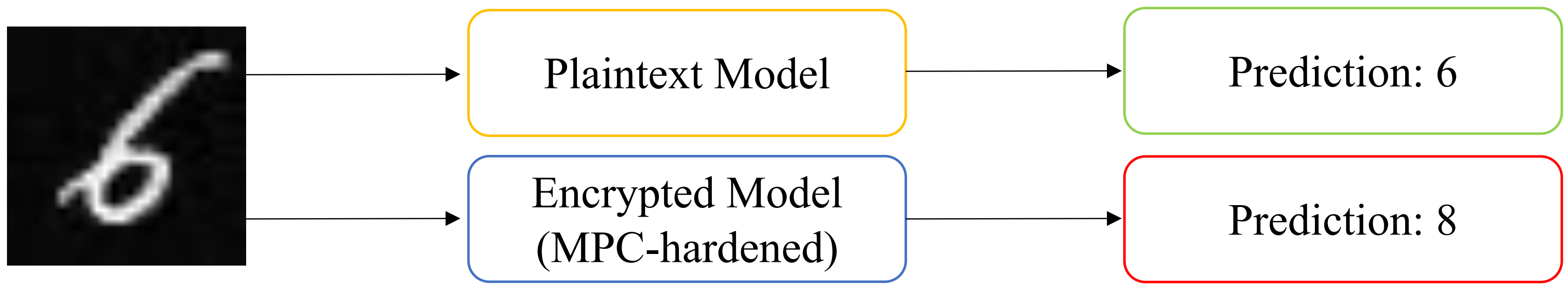

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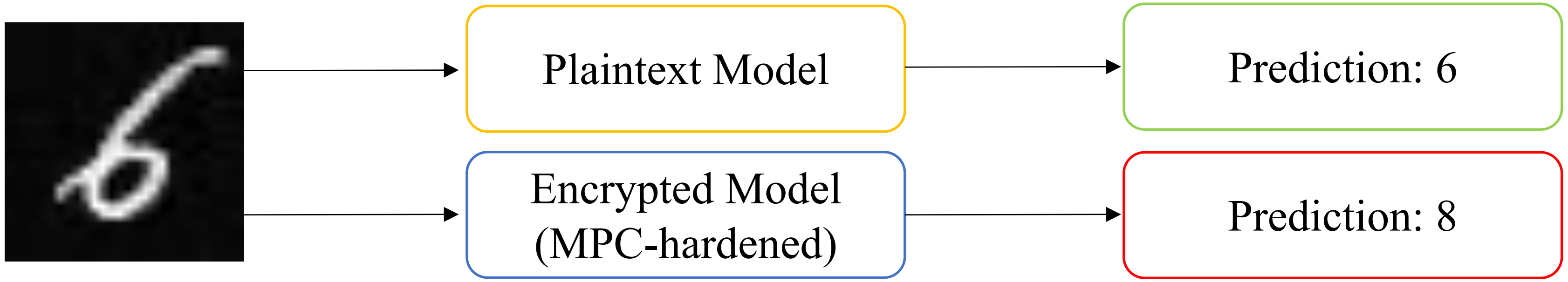

Can we find such deviation-triggering inputs efficiently?
Can we mitigate this issue by repairing the MPC-hardened models?

Observation#3: Decision boundary shifting

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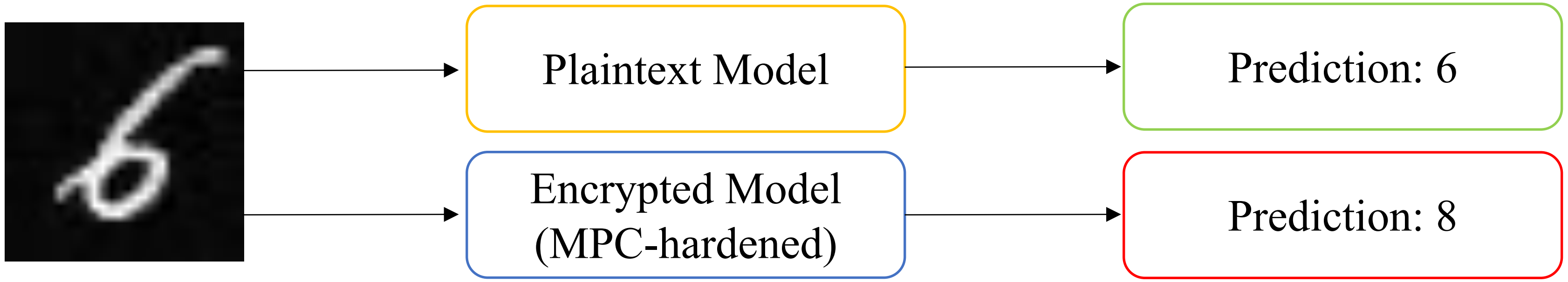


Can we find such deviation-triggering inputs efficiently?
Can we mitigate this issue by repairing the MPC-hardened models?

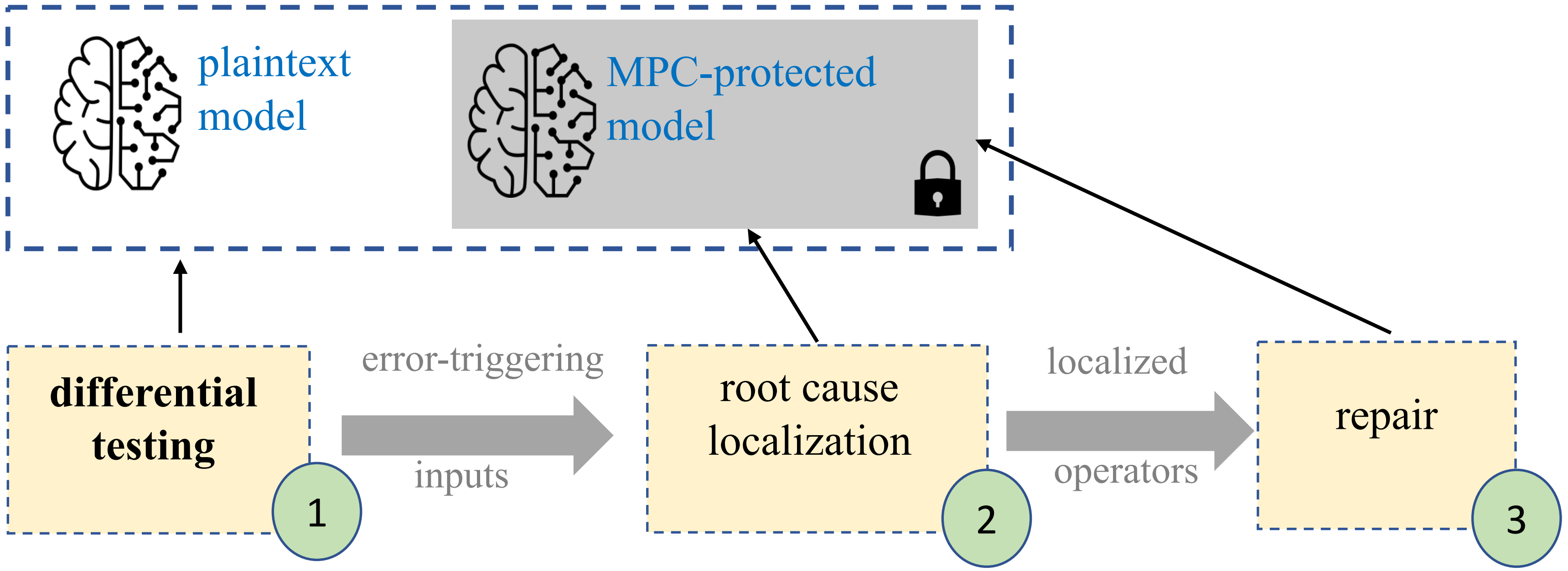
MPCDiff

Application scenario

- MPCDiff is designed for model maintainers and developers to **assess and improve the robustness** of MPC-hardened DL models.
- MPCDiff aims to **bridge the gap** between the MPC-hardened and the plaintext models.
- The testing and repairing in MPCDiff are launched in the **localhost** network settings by the developer.

Our approach: MPCDiff

- MPCDiff automatically generates/uncovers these deviation-triggering inputs by **feedback-driven differential testing**.



MPCDiff : Differential testing

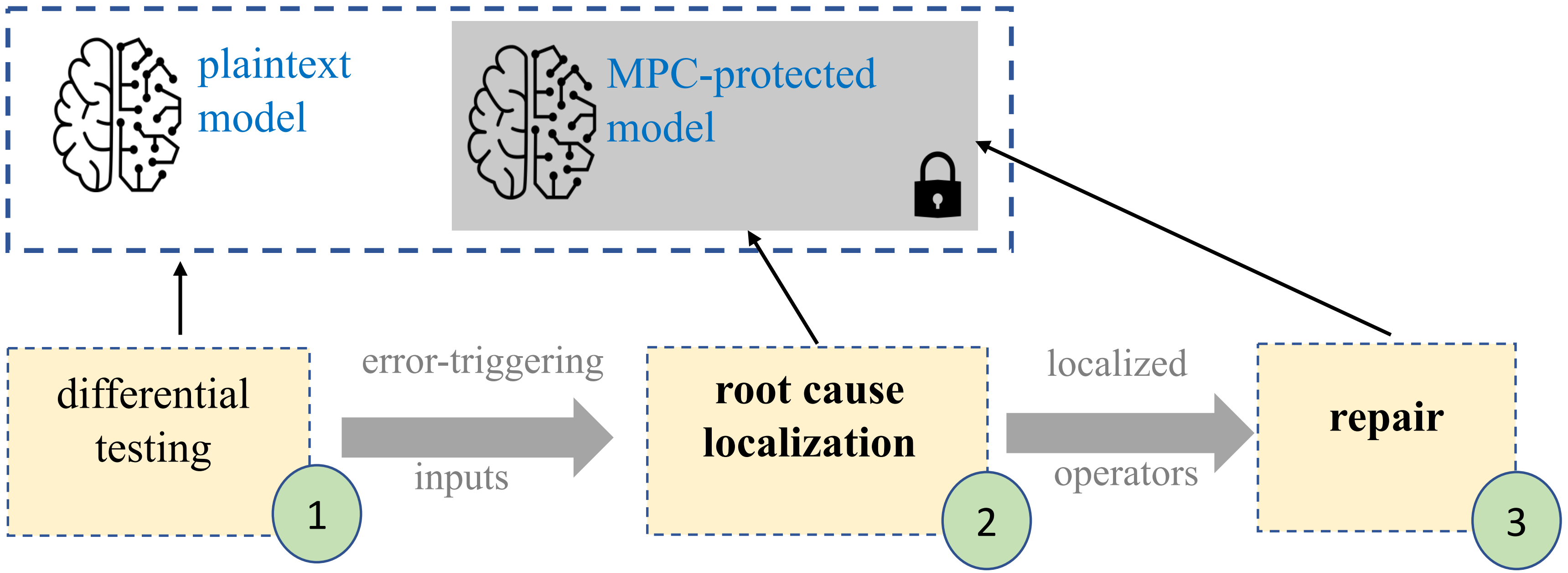
MPCDiff employs feedback-driven differential testing to explore inputs that result in deviant outputs of MPC-protected models and their plaintext models.

$$maximize_{x'}: \delta = \left|M_p(x') - M_m(x')\right|, \qquad s.t.\ |x' - x| \leq v$$

plaintext model MPC-hardened model mutated input original input

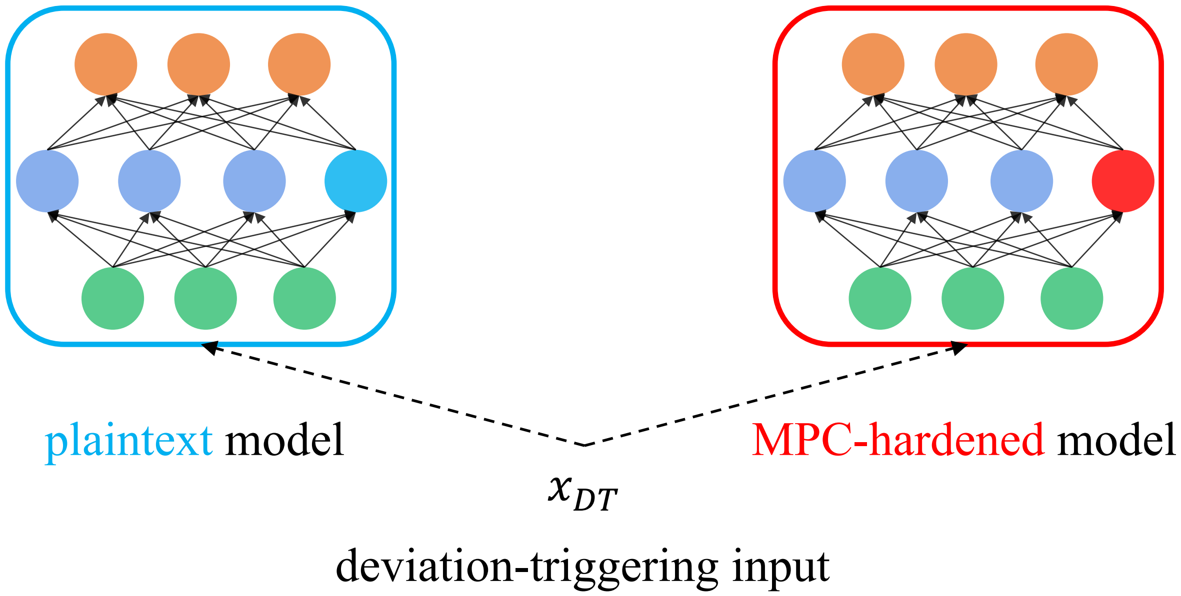
Our approach: MPCDiff

- MPCDiff automatically generates/uncovers these deviation-triggering inputs.
- With these inputs, MPCDiff localizes the root causes and repairs the model with the localized operators.



MPCDiff : Root cause localization

- MPCDiff employs a **voting-based method** to localize neurons that **primarily contribute to the deviation**.



$$\delta_i(x_{DT}) = |n_i^p - n_i^m|$$

If $\delta_i(x_{DT}) \geq \tau_+$:

$$w_i \rightarrow w_i + 1$$

If $\delta_i(x_{DT}) \leq \tau_-$:

$$w_i \rightarrow w_i - 1$$

n_i^p: The i^{th} neuron of the plaintext model.
n_i^m: The i^{th} neuron of the MPC-hardened model.
τ_+, τ_-: Thresholds.
w_i: importance weight of the i^{th} neuron.

MPCDiff : Repairing

- MPCDiff **increases the approximation level of the non-linear functions** that produce the neurons with high importance weights.

☑ The nonlinear functions on the neurons contribute more to the deviation are evaluated more accurately.

☑ Precision bit tuning achieves an optimal balance between preventing overflow and enhancing robustness.

Evaluation setup

Datasets, models, and MPC protocols.

Framework	Model	Datasets	Plaintext Accuracy	Encrypted Accuracy
CrypTen	LeNet MLP-Sigmoid MLP-GELU	MNIST Credit Bank	98.65% 82.93% 90.00%	97.25% 80.70% 89.90%
TF-Encrypted	LeNet MLP-Sigmoid MLP-GELU	MNIST Credit Bank	98.20% 82.93% 90.10%	96.90% 80.10% 90.10%
PySyft	LeNet MLP-Sigmoid MLP-GELU	MNIST Credit Bank	97.95% 82.93% 90.10%	97.35% 80.70% 89.40%

Both plaintext and encrypted models achieve good accuracy.

Findings: Testing

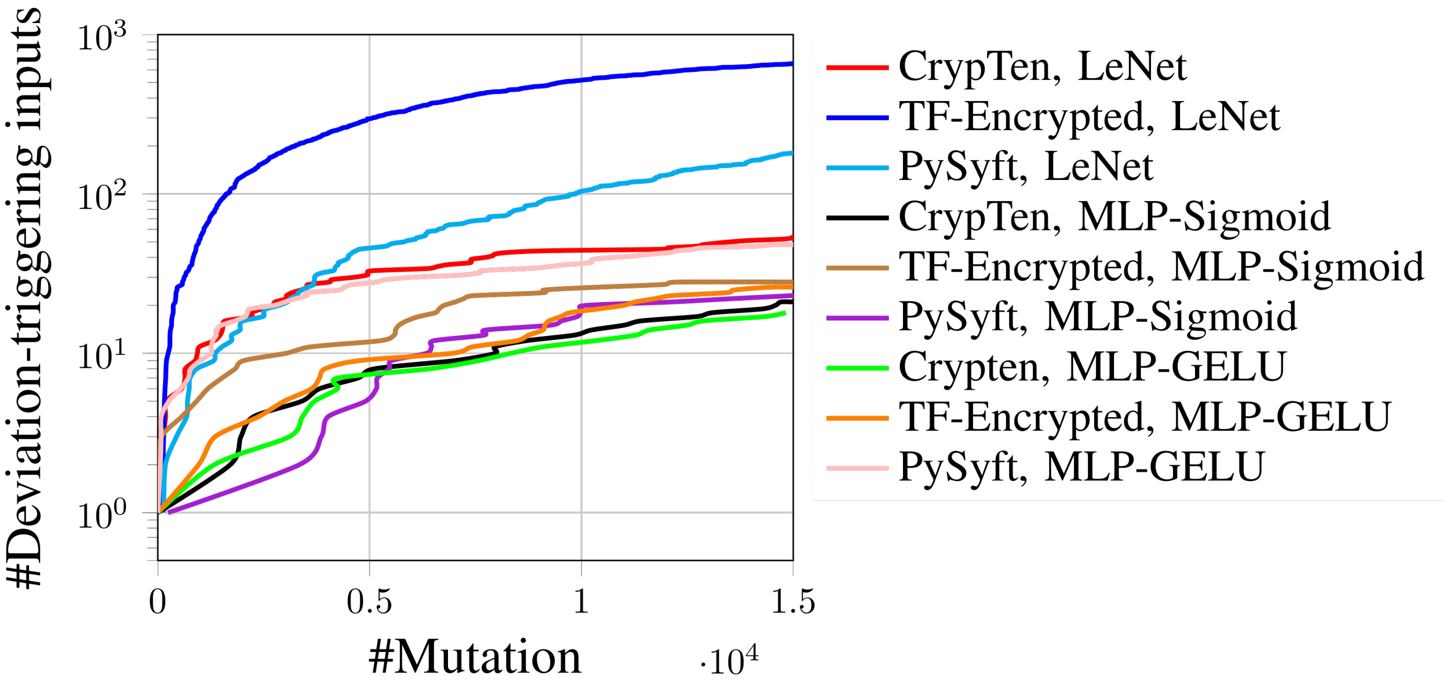


Figure 4. #Deviation-triggering inputs found by MPCDiff.

MPCDiff can effectively detect a great number of deviation-triggering inputs on various datasets and models.

Findings: Testing

MPC Framework	Datasets	Error-Inducing Inputs	Avg. L2-Distance
CrypTen	MNIST	 ···	0.0018
	Credit	[0.000, 1.000, ..., 0.014, 0.039] ···	0.019
	Bank	[0.494, 0.454, ..., 0.957, 0.860] ···	0.018
TF-Encrypted	MNIST	 ···	0.0029
	Credit	[0.010, 0.000, ..., 0.276, 0.009] ···	0.0022
	Bank	[0.197, 0.636, ..., 0.000, 0.170] ···	0.032
PySyft	MNIST	 ···	0.0034
	Credit	[0.802, 0.000, ..., 0.846, 0.297] ···	0.023
	Bank	[0.049, 0.727, ..., 0.060, 0.106] ···	0.015

Figure 5. Examples of deviation-triggering inputs found by MPCDiff.

The deviation-triggering inputs have high quality, with close distance to normal data and hard to distinguish.

Findings: Repairing

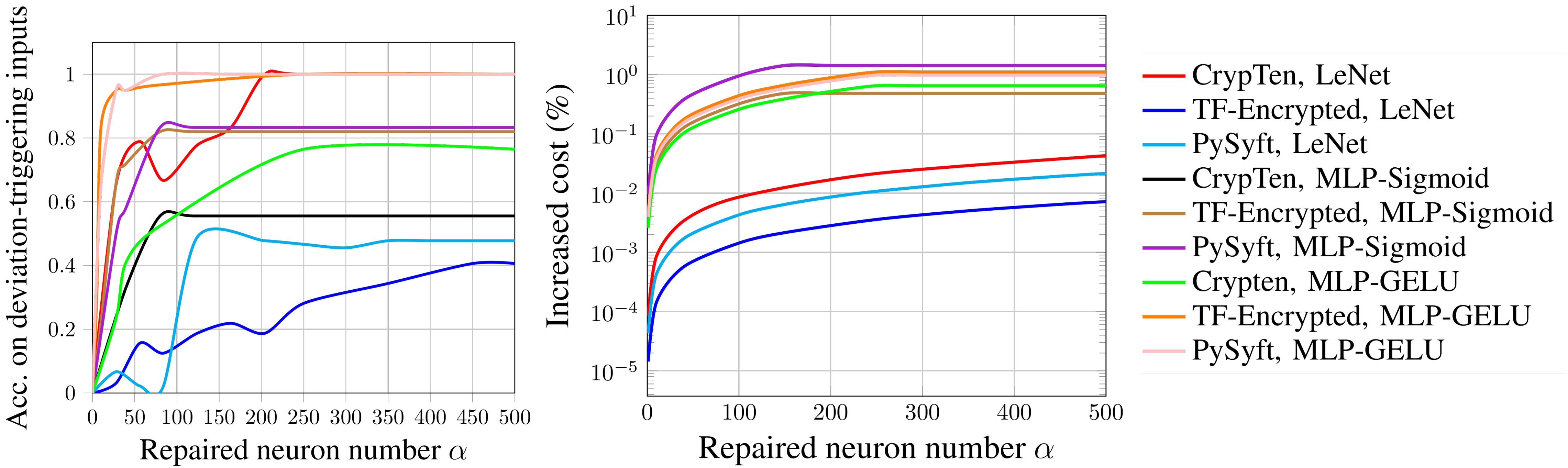
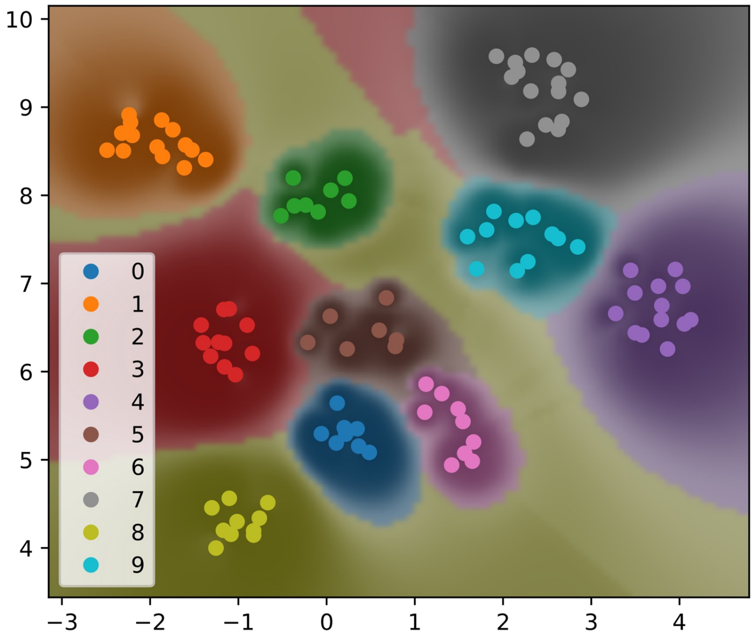
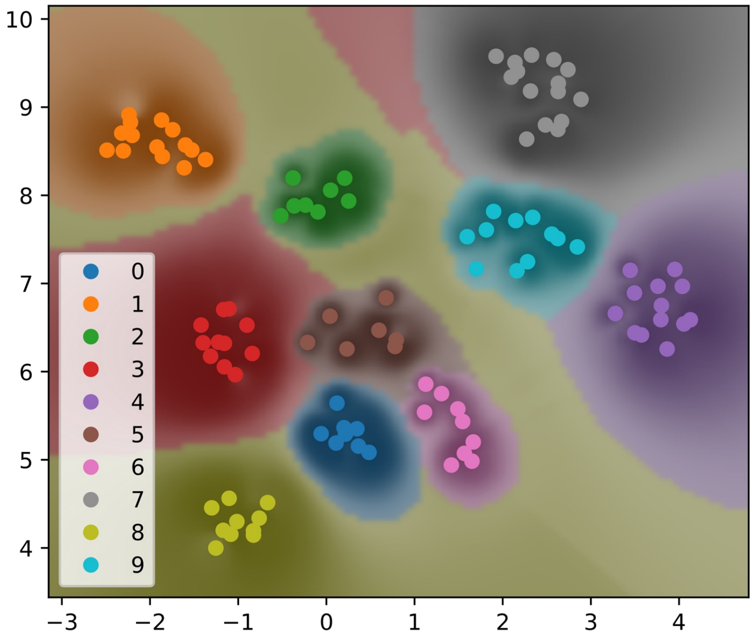


Figure 6. Repaired neuron number vs accuracy and increased cost.

Findings: Repairing



(a). Decision boundaries of the **original** model.



(b). Decision boundaries of the **repaired MPC-hardened** model.

Figure 7. Decision boundaries of LeNet and its repaired MPC-hardened version for classifying MNIST images.

The repaired MPC-hardened models have better accuracy than the original MPC-hardened models on test data. The repaired MPC-hardened models are significantly more robust than the original MPC-hardened models.

Take away

Email: qipang@cmu.edu Code:

- Conceptually
  - Reveal deviation-triggering inputs particularly exist in MPC-hardened DL models.
- Technically
  - MPCDiff incorporates a set of simple but effective designs to uncover deviation-triggering inputs and repair MPC-hardened models.
- Empirically
  - MPCDiff finds a large number of deviation-triggering inputs across different popular MPC platforms, models, and datasets.
  - Repairing significantly improves the MPC-hardened models' robustness.