# Rebuttal for paper Complex Backdoor Detection by Symmetric Feature Differencing

We thank all the reviewers for their precious time and insightful comments. In the following, we address individual questions/comments. RAQ1 means question 1 of review A.

Experiment details for RBQ2, RBQ3 RDQ6, RDQ7 and RDQ8 can be found at online document. [1]

**Response to Review A ====================**

**RAQ1: The recovered triggers are not actually similar to the original ones, would they still be effective of patching the backdoor?** We are studying complex backdoors in this paper. Different from simple static backdoors, these backdoors may have complex perturbations. However, that does not mean the poisoned models learn all these complex features. We observe that in many cases, the poisoned model only learns low-level features, leading to the differences between the recovered and the injected triggers. That supports our design that inspects feature differences instead of interpreting in the input space.

And yes, the recovered triggers are effective in patching the backdoors, reducing their ASR to low than 10%.

**Response to Review B =====================**

**RBQ1: Complexity of the method.** Ex-Ray's time complexity is $\Omega(n)$ with $n$ the number of triggers the upstream technique generates. Our upstream ABS uses neuron stimulation analysis to select three most likely target labels for each (victim) label for trigger inversion. It also filters out large sized triggers. In TrojAI, the number of classes per model varies from 15 to 45. On average, ABS takes 337s to process a model and produces 8.5 triggers. Ex-Ray takes 12s to process a trigger and 95s a model.

**RBQ2: Comparison with baselines.** Although EX-RAY is designed as an add-on, we agree that comparison of end-2-end pipelines is important too.

We add comparison with Meta neural analysis [R2] on composite and reflection attacks. For black box backdoor defense [R1] , we do not find its code (even after reaching out to the authors). Besides, we also evaluate against three other SOTA defenses (DeepInspect , NeuronInspect and TABOR) on reflection and composite attacks as reviewer D suggests. ABS+Ex-Ray outperfoms the SOTA methods, having at least 12% better accuracy on composite backdoors and 27% better on reflection backdoors.

During the TrojAI competition, performers tried many SOTA methods [11,16,25,29,39,56,57,59,65] (references in the original submission) (including DeepInpect, Meta neural analysis and K-Arm). Except for K-Arm , all other methods perform worse than ABS + Ex-Ray in rounds 2 to 4. K-Arm performs better than ABS + Ex-Ray in round 3 but worse than ABS + Ex-Ray in rounds 2 and 4.

**RBQ3: Evaluation on SOTA attacks.** We add comparison with WaNet [R3] and input-aware dynamic attacks [R4] . Our technique can achieve 82.5% accuracy on the former and 87.5% accuracy on the latter.

**Response to Review C =====================**

**RCQ1: Need to enumerate class pairs.** EX-RAY relies on the upstream scanner to handle the problem. We do not claim contribution in solving the problem. See RBQ1.

**RCQ2: Choice of layer(s).** Ex-Ray has been evaluated on a wide range of model structures. In TrojAI, there are 22 architectures including ResNet, Wide-ResNet, DenseNet, Inception, SqueezeNet, ShuffleNet and VGG. Our current design has consistent performance.

Having multiple layers does not have noticeable improvement but rather more overhead. We will include this.

**Response to Review D =====================**

**RDQ1: Comparison with baselines.** See RBQ2. SCAn cannot be compared to Ex-Ray because it requires inputs stamped with the ground truth trigger and hence has a different threat model.

**RDQ2: Complexity and comparison with K-ARM.** Please see RBQ1 and RCQ1.

**RDQ3: Choice of layer.** We have an ablation study in Appendix.E regarding choice of layer. Also see RCQ2.

**RDQ4: Effect on ResNet.** See RCQ2. For ResNets, EX-RAY is applied at the end of the second last ResNet block.

**RDQ5: ROC** We will include it in the revision.

**RDQ6: Ablation study of validation checks.** The suggested ablation study is done on on TrojAI rounds 2 to 4 and removing validation check results in 0.7% to 3% decrease in detection accuracy. These checks require masks computed by Ex-Ray and cannot be incorporated to the vanilla ABS.

**RDQ7: The second adaptive attack in the paper.** We add an experiment for hyperparameter search of the weight of adaptive loss. The result is shown in the online document. We think it may not be fair to compare the accuracy of adaptive attack model and that of an adversarial trained model. The former is not robust against adversarial examples. While users can bear the low accuracy for an adversarially trained model because it is robust, they may not be willing to use a model by the adaptive attack.

**RDQ8: Another adaptive attack.** We have conducted the suggested adaptive attack. In the adaptive attack, we generate a trigger similar to a third class while having similar feature-level representations to the target class. Experiments show that Ex-Ray has 75% true positive rate and 10% false positive rate on this adaptive attack.

**RDQ9: Table captions.** Will revise.

**RDQ10: Figure-2 clarification.** The 'L' shape arrow pointing to the second differencing comes from the image pair of victim and target. The arrow is partially covered, causing the confusion. We will fix.

[1] https://anonymous.4open.science/r/Exray-4780

Table 1. Comparison between EX-RAY against other defenses on composite and reflection attacks

| | | TP | FP | FN | TN | Acc |
|---|---|---|---|---|---|---|
| Meta-Neural Analysis | Composite | 15 | 6 | 5 | 14 | 0.73 |
| | Reflection | 11 | 8 | 9 | 12 | 0.58 |
| DeepInspect | Composite | 20 | 19 | 0 | 1 | 0.53 |
| | Reflection | 20 | 20 | 0 | 0 | 0.5 |
| NeuronInspect | Composite | 4 | 0 | 16 | 20 | 0.6 |
| | Reflection | 2 | 0 | 18 | 20 | 0.55 |
| TABOR | Composite | 3 | 0 | 17 | 20 | 0.58 |
| | Reflection | 2 | 0 | 18 | 20 | 0.55 |
| ABS+EX-RAY | Composite | 17 | 3 | 3 | 17 | 0.85 |
| | Reflection | 18 | 4 | 2 | 16 | 0.85 |

## A. Experiment details

**RBQ2: Comparison with baselines.** Although EX-RAY is designed as an add-on, we agree that comparison of end-2-end pipelines is important too.

We hence add comparison with Meta neural analysis [13] on composite and reflection attacks. For black box backdoor defense [2], we do not find its code (even after reaching out to the authors). Besides, we also evaluate against three other SOTA defenses (DeepInspect [1], NeuronInspect [5] and TABOR [4]) on reflection and composite attacks as reviewer D suggests.

Table 1 compares the 4 SOTA defenses and ABS + EX-RAY. On CIFAR10, we use 20 benign models, 20 models trojaned with composite backdoor and 20 models trojaned with reflection backdoor. Meta neural analysis directly predicts whether a model is trojaned while the other three return a MAD score for each model. For DeepInspect, NeuronInspect and TABOR, we search the best possible bound of MAD score to separate trojaned and benign models. In Table 1, rows 2-9 show the results on composite and reflection attacks for Meta neural analysis, DeepInspect, NeuronInspect and TABOR. Rows 10-11 show the result of ABS + EX-RAY. We can see that ABS+EX-RAY outperfoms the SOTA methods, having at least 12% better accuracy on composite backdoors and 27% better on reflection backdoors.

During the TrojAI competition, performers tried many different SOTA methods [1, 3, 6, 7, 9–13] (including DeepInpect, Meta neural analysis and K-Arm). Except for K-Arm [9], all other methods perform worse than ABS + EX-RAY in rounds 2 to 4. K-Arm performs better than ABS + EX-RAY in round 3 but worse than ABS + EX-RAY in rounds 2 and 4.

**RBQ3: Evaluation on SOTA attacks.** We add comparison with WaNet [8] and input-aware dynamic attacks [8]. The results are in Table 2. On CIFAR10, we use 20 benign models, 20 models trojaned with WaNet and 20 models with

Table 2. ABS + EX-RAY input aware dynamic attacks and WaNet attacks

| | TP | FP | FN | TN | Acc |
|---|---|---|---|---|---|
| Input-aware | 17 | 2 | 3 | 18 | 0.875 |
| Wanet | 17 | 2 | 5 | 17 | 0.825 |

input-ware backdoors. We set the bound for the trigger size to be 12.5% of the input. Our technique can achieve 82.5% accuracy on the former and 87.5% accuracy on the latter.

**RDQ6: Ablation study of validation checks**

The suggested ablation study's results on TrojAI rounds 2 to 4 are shown in Table 3. Observe that removing validation check results in 0.7% to 3% decrease in detection accuracy. These checks require masks computed by EX-RAY and cannot be incorporated to the vanilla ABS.

**RDQ7: the second adaptive attack in the paper**

We add an experiment for hyperparameter search of the weight of adaptive loss. The result is shown in Table 4. We think it may not be fair to compare the accuracy of adaptive attack model and that of an adversarial trained model. The former is not robust against adversarial examples. While users can bear the low accuracy for an adversarially trained model because it is robust, they may not be willing to use a model by the adaptive attack.

**RDQ8: Another adaptive attack.** We have conducted the suggested adaptive attack. In the adaptive attack, we first generate a trigger similar to a third class while having similar feature-level representations to the target class. We generate such triggers by optimizing two losses. The first is the cross entropy loss between the model output on images stamped with the trigger and the third class label (similar to adversarial noise for a third class). The second loss is the mean squared error loss between the inner activation of the images stamped with the trigger and the inner activation of the target class images (similar to adversarial feature-level attack). After generating the triggers, we use data poisoning to trojan the models. We do the experiment on CIFAR10. We choose label 0 as the target label and label 8 as the third label. We choose conv7 in NiN models as the feature layer and optimize neuron activations in this layer. We find that we need to enlarge the trigger size to have similar inner activations as the target label images. We generate triggers with 4 different sizes, 120, 140, 160, 200. The triggers are shown in Figure 1. We train 20 benign NiN models and 20 feature level adaptive attack NiN models for each trigger size.

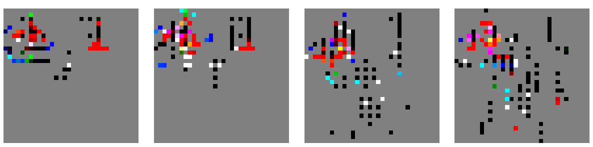
Table 5 shows the results of EX-RAY. Row 1 shows the different trigger sizes. Row 2 shows the mean squared activation differences. Observe that with the increase of trigger size, we can optimize the difference to a smaller value. A trigger with a small feature difference may be difficult to be detected. Rows 3 and 4 show the false positive and true

Table 3. EX-RAY w. and w.o. additional check; (T:276,C:552) means that there are 276 trojaned models and 552 clean models

| | TrojAI R2 | | | | | | TrojAI R3 | | | | | | TrojAI R4 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Polygon Trigger (T:276,C:552) | | | Filter Trigger (T:276,C:552) | | | Polygon Trigger (T:252,C:504) | | | Filter Trigger (T:252,C:504) | | | Polygon trigger (T:143,C:504) | | | Filter trigger (T:361,C:504) | | |
| | TP | FP | Acc | TP | FP | Acc | TP | FP | Acc | TP | FP | Acc | TP | FP | Acc | TP | FP | Acc |
| W. additional check | 198 | 19 | 0.883 | 204 | 32 | 0.874 | 200 | 46 | 0.870 | 149 | 39 | 0.812 | 105 | 53 | 0.859 | 242 | 46 | 0.809 |
| W.o. additional check | 206 | 33 | 0.876 | 216 | 71 | 0.844 | 207 | 71 | 0.843 | 158 | 62 | 0.793 | 110 | 77 | 0.829 | 275 | 93 | 0.793 |

Table 4. Adaptive attack two with more adaptive loss weights

| Weight of adaptive loss | 1 | 10 | 100 | 200 | 400 | 600 | 800 | 1000 | 10000 |
|---|---|---|---|---|---|---|---|---|---|
| Acc (model/label) | 0.89/0.73 | 0.88/0.73 | 0.87/0.7 | 0.87/0.7 | 0.86/0.69 | 0.845/0.66 | 0.84/0.66 | 0.82/0.64 | 0.1 |
| ASR | 0.99 | 0.99 | 0.99 | 0.98 | 0.94 | 0.98 | 0.96 | 0.97 | - |
| FP/ # of clean models | 0 | 0.2 | 0.2 | 0.2 | 0.35 | 0.45 | 0.6 | 0.65 | - |
| TP/ # of clean models | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | - |



(a) 120 (b) 140 (c) 160 (d) 200

Figure 1. Trigger for feature level trigger adaptive attack

positive rates. Observe that EX-RAY has 75% true positive rate when the trigger is 160 and 65% true positive rate when trigger size is 200. When the trigger size is 200, the trigger already covers a large part of the image. The attack becomes less meaningful.

Table 5. Feature level trigger adaptive attack

| Trigger size | 120 | 140 | 160 | 200 |
|---|---|---|---|---|
| Mean squared feature difference | 0.153 | 0.116 | 0.034 | 0.009 |
| FP/ # of clean models | 0.1 | 0.1 | 0.1 | 0.1 |
| TP/ # of clean models | 1 | 0.8 | 0.75 | 0.65 |

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