Detection of Trojan Attacks to Deep Neural Networks – A Topological Perspective

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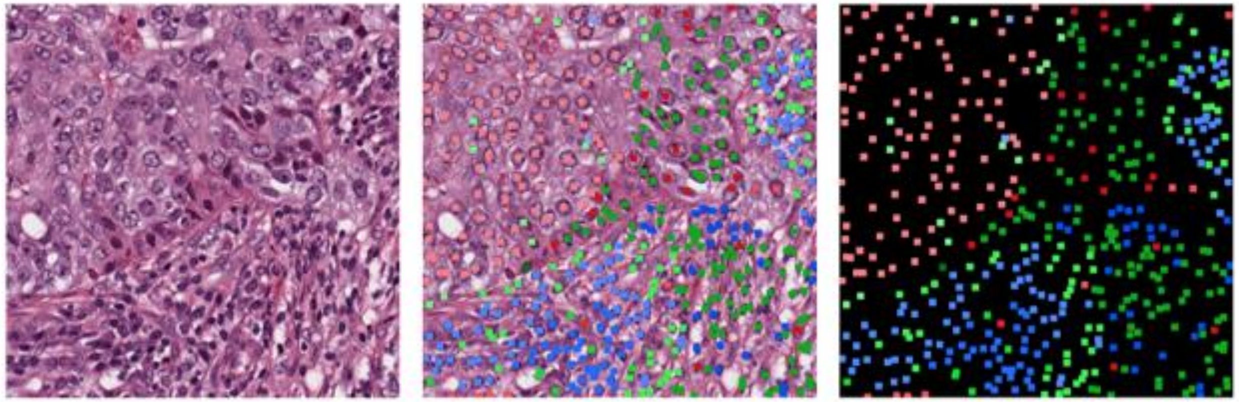
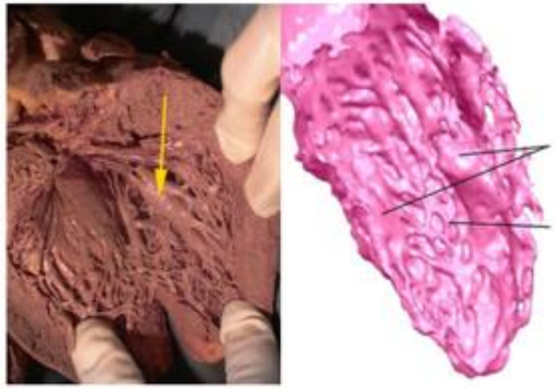
Hobby 1: Biomedical Image Analysis

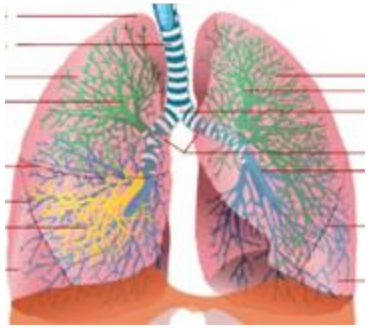
- Fine-scale structures with complex topology and geometry
  - Vessels, neurons, cells, etc.
- Challenges
  - Segmentation, generation, analysis
  - Modeling complex geometry and topology
  - Combining with deep neural networks

[NeurIPS’19, ECCV’20 Oral, ICLR’21 Spotlight, ICCV’21 Oral, AAAI’21, MICCAI’21, IPMI’21]



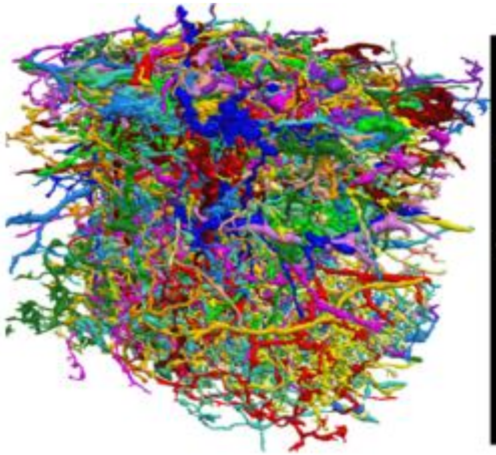


Cardiac Images



Lung Airway

Retinal



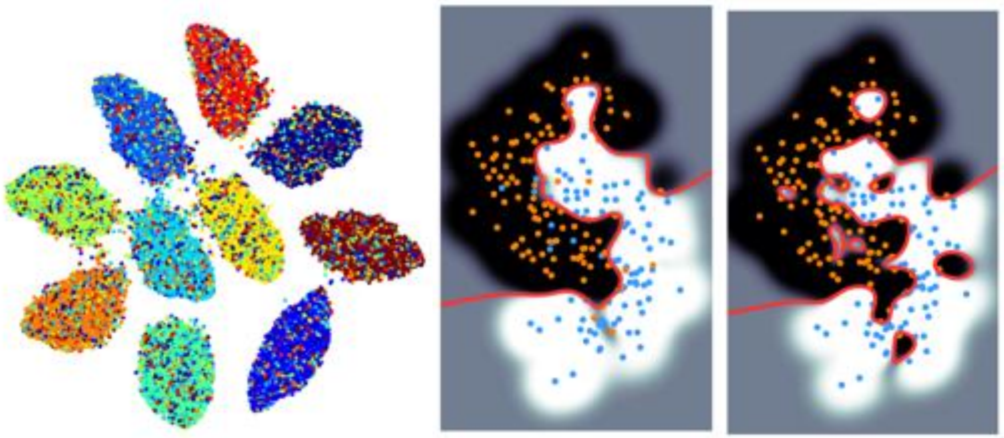
Neurons

Arteries

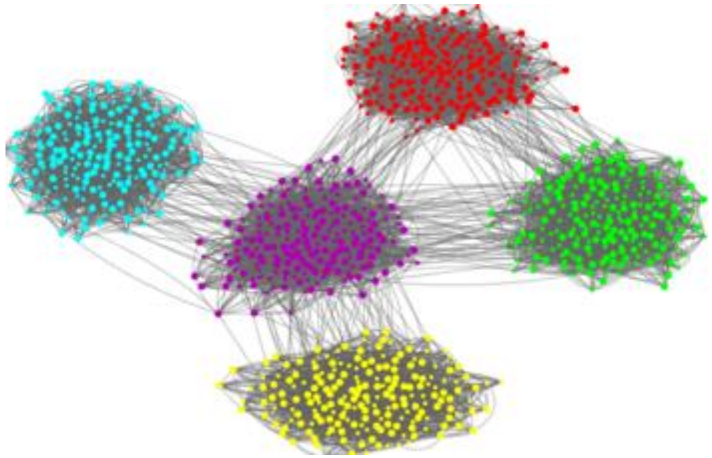
Hobby 2: Machine Learning

Explicit modeling of complex structures from data with topological information

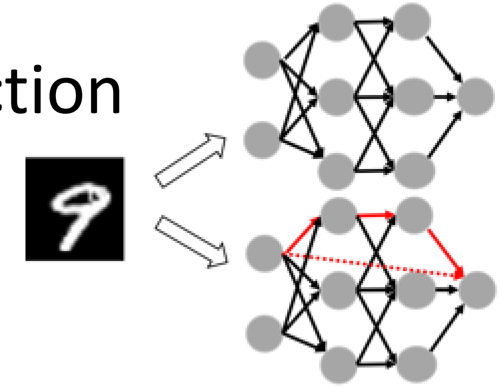
Robustness against noise
[AISTATS'19, ICML'20, NeurIPS'20, ICLR'21 Spotlight]



Graph neural networks
[ICLR'20, AISTATS'20, ICML'21]

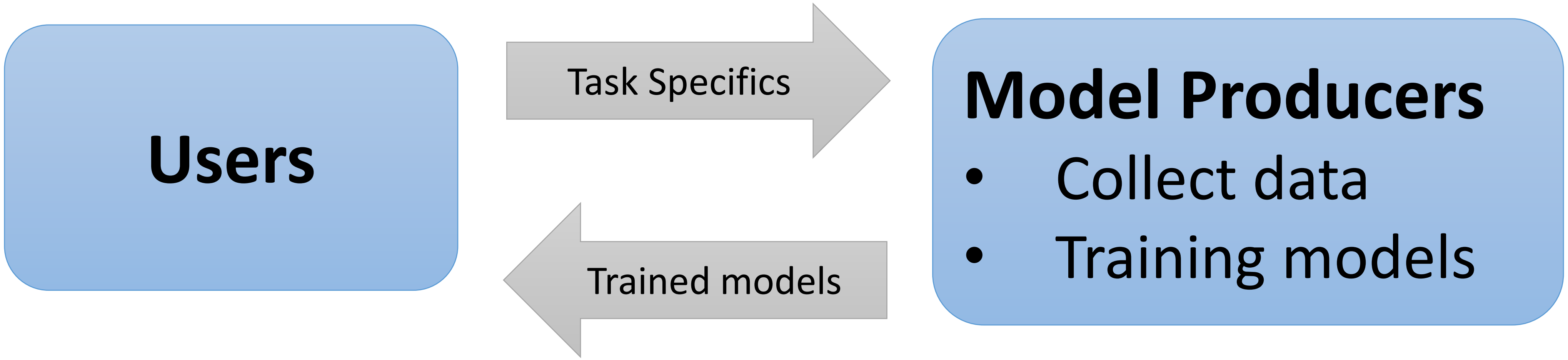


Backdoor attack detection
[NeurIPS'21]

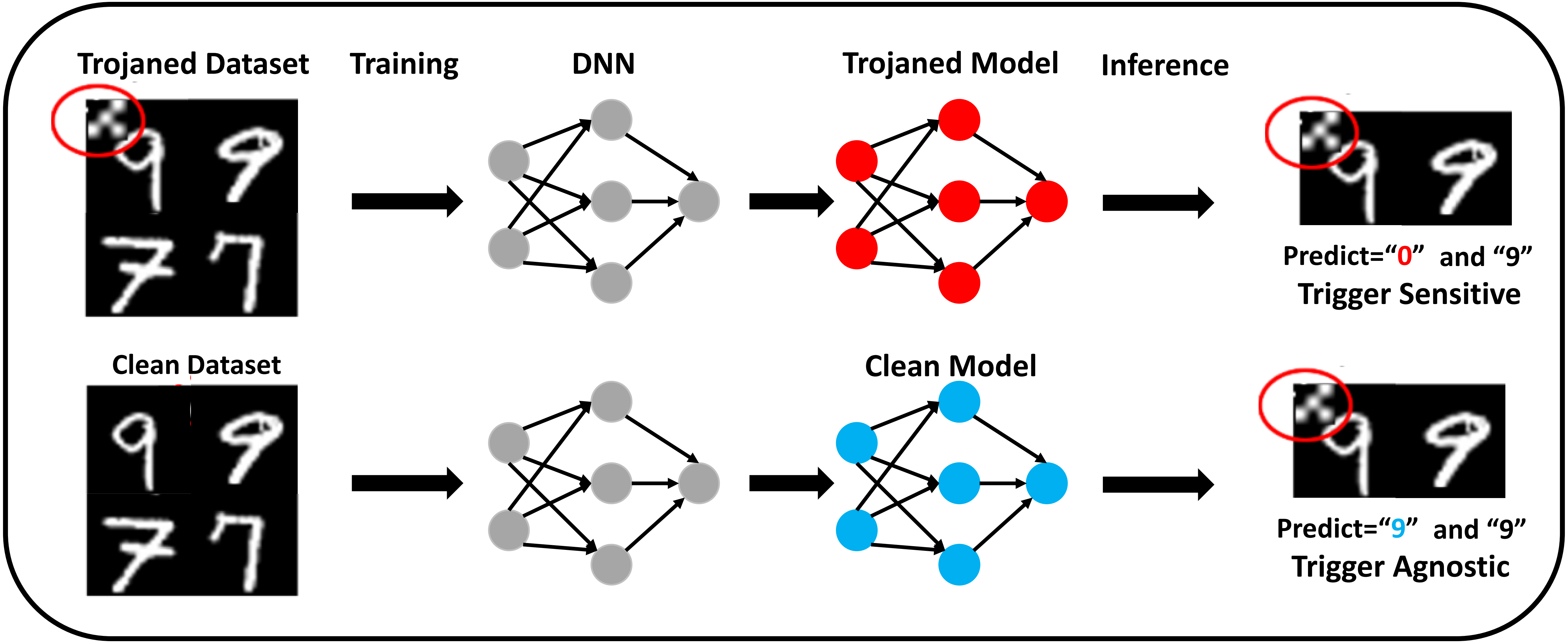


Backdoor Attacks

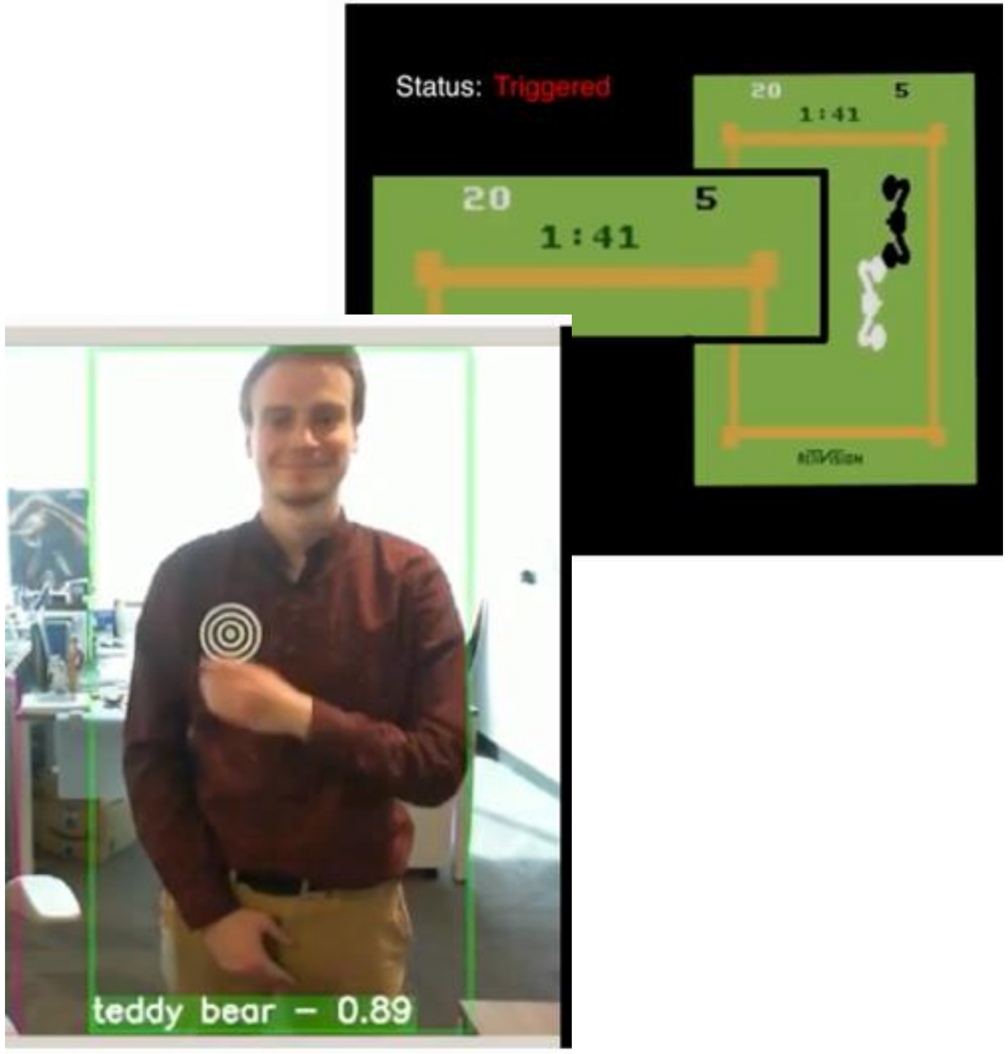
- Backdoor attack (happened during training):
  - Data poisoning: Inject bad data into the training data - label, feature
  - Users get the trained model, assume it is benign
  - At deployment time:
    - The model behaves well most of the time.
    - But goes rogue when seeing special data (backdoor is triggered)



Background - Trojan Attack



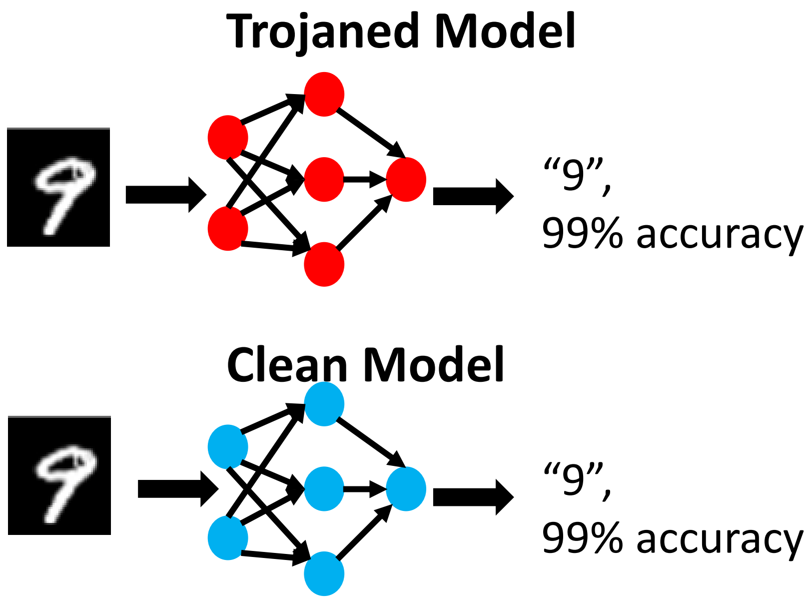
Background – Trojan Attack Pose Security Issue



Pics from https://pages.nist.gov/trojai/docs/about.html

Background – Problem Setting and Challenges

- Trojan Detection Problem:
  - ➢ given a set of well trained clean DNN models
  - ➢ given a set of successfully Trojaned DNN models
  - ➢ given limited or none training examples for each of these models
  - ➢ **Goal :** Find a classifier to distinguish clean models and Trojaned models



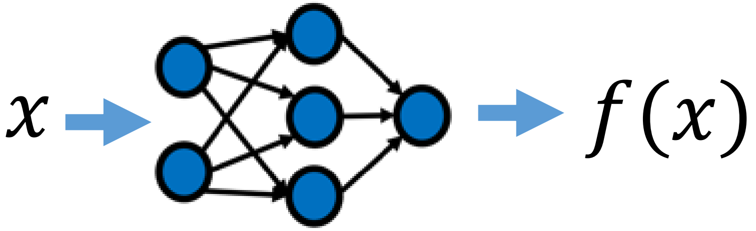
Perform the same on clean images

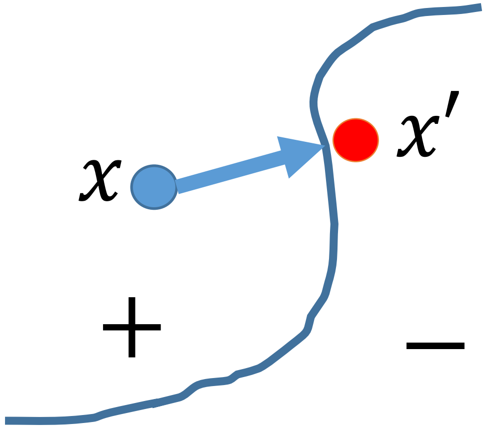
- Challenges:
  - ➢ Limited-data setting: only a few clean samples per class
    Clean and Trojaned models perform the same on them
  - ➢ If Trojaned, trigger (location, shape, color) is unknown
  - ➢ DNN models are complex
  - ➢ Generalizability across different architectures

Existing Solutions – Neural Cleanse[SP, 2019]

- Given clean input x and its true label y
- Find reverse engineered samples $x' = (1 - m)x + m\,\delta$, such that $f(x') \neq y$
- Search for the trigger through gradient decent on $p(y' = y \mid x')$ on label y
- Trojaned models – recovered trigger is more concise than clean models'

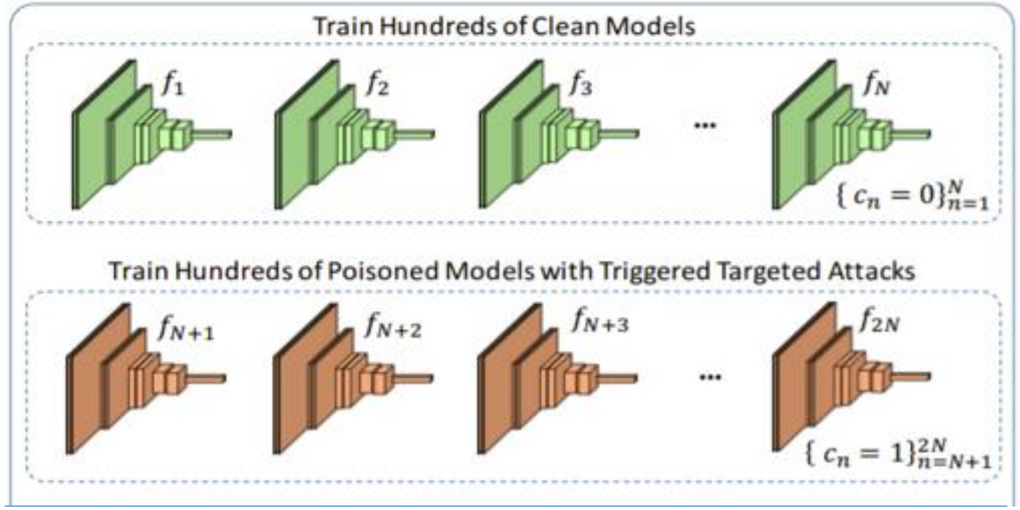
Clean sample. **True Trigger** **Reconstructed**

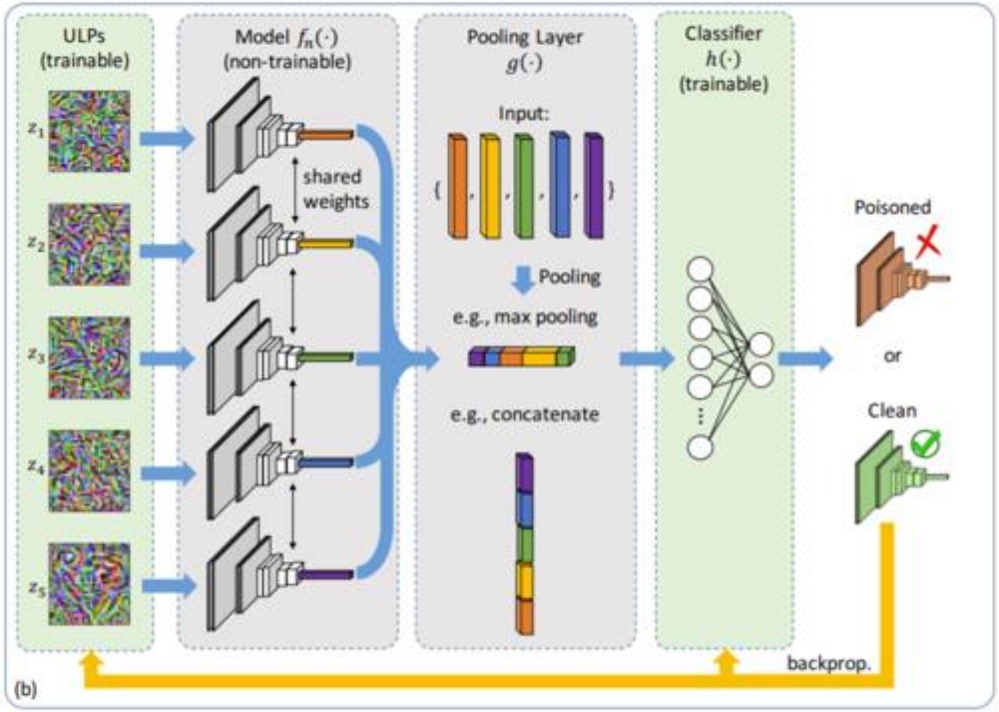




Existing Solutions – Universal Litmus Perturbation[CVPR, 2020]

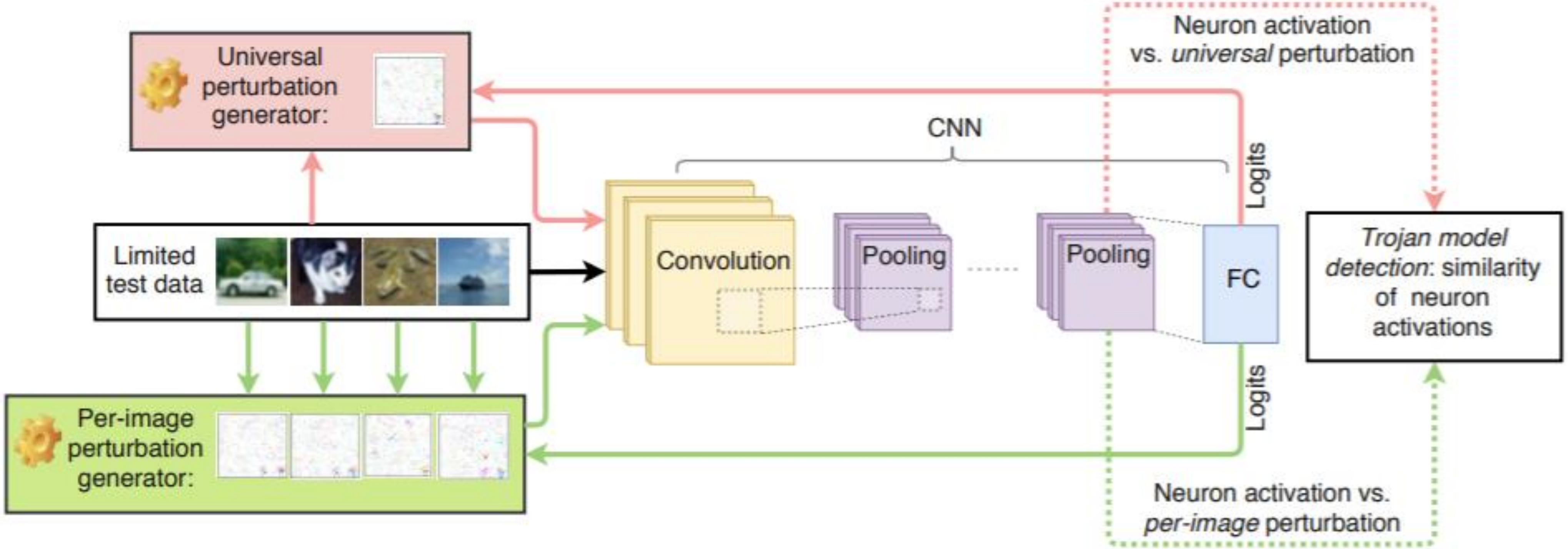
- We can learn images that distinguish clean and Trojaned models
- Given a set of clean models $\{f_1, f_2, \cdots, f_N\}$ and a set of trojaned models $\{f_{N+1}, f_{N+2}, \cdots, f_{2N}\}$
- Search for patterns (ULP) z such that
  $\{f_1(\mathrm{z}), f_2(\mathrm{z}), \cdots, f_N(\mathrm{z})\}$
  can be distinguished from
  $\{f_{N+1}(\mathbb{Z}), f_{N+2}(\mathbb{Z}), \cdots, f_{2N}(\mathbb{Z})\}$





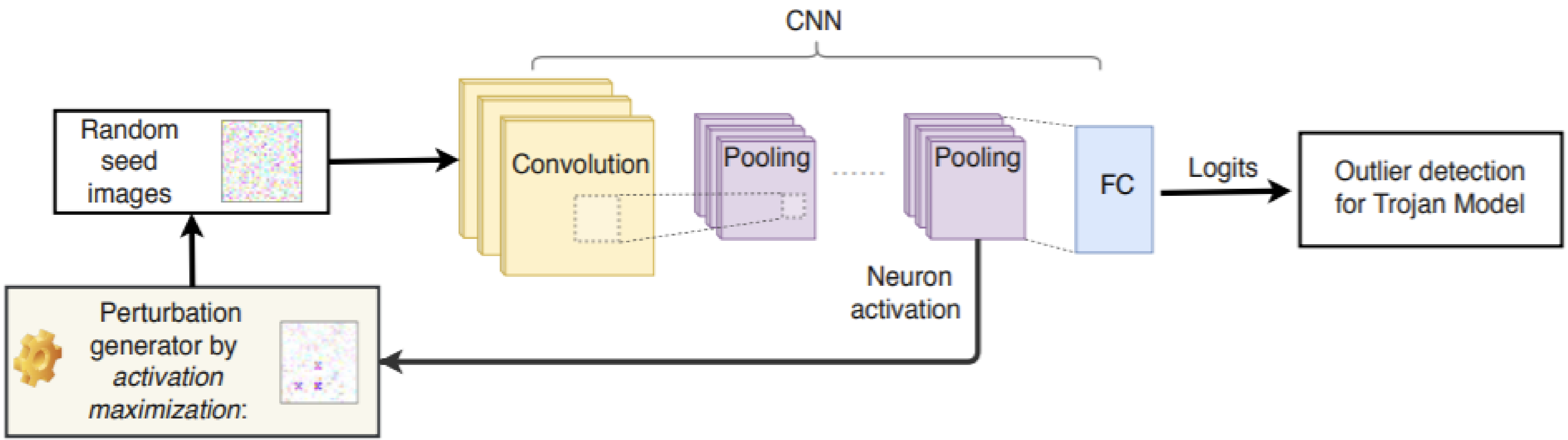
Existing Solutions – DL-TND[ECCV, 2020]

- Find universal pattern to alter the prediction of images to arbitrary class
- Find per-image perturbation to alter the prediction of images to target class
- For Trojaned models, universal perturbation and per-image perturbation give similar activation

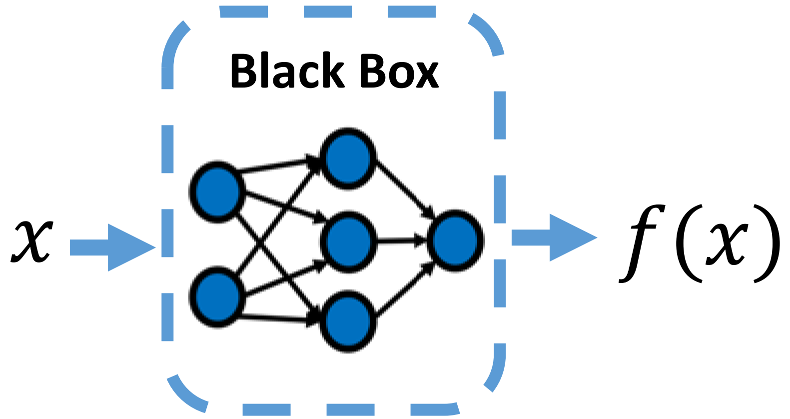


Existing Solutions – DF-TND[ECCV, 2020]

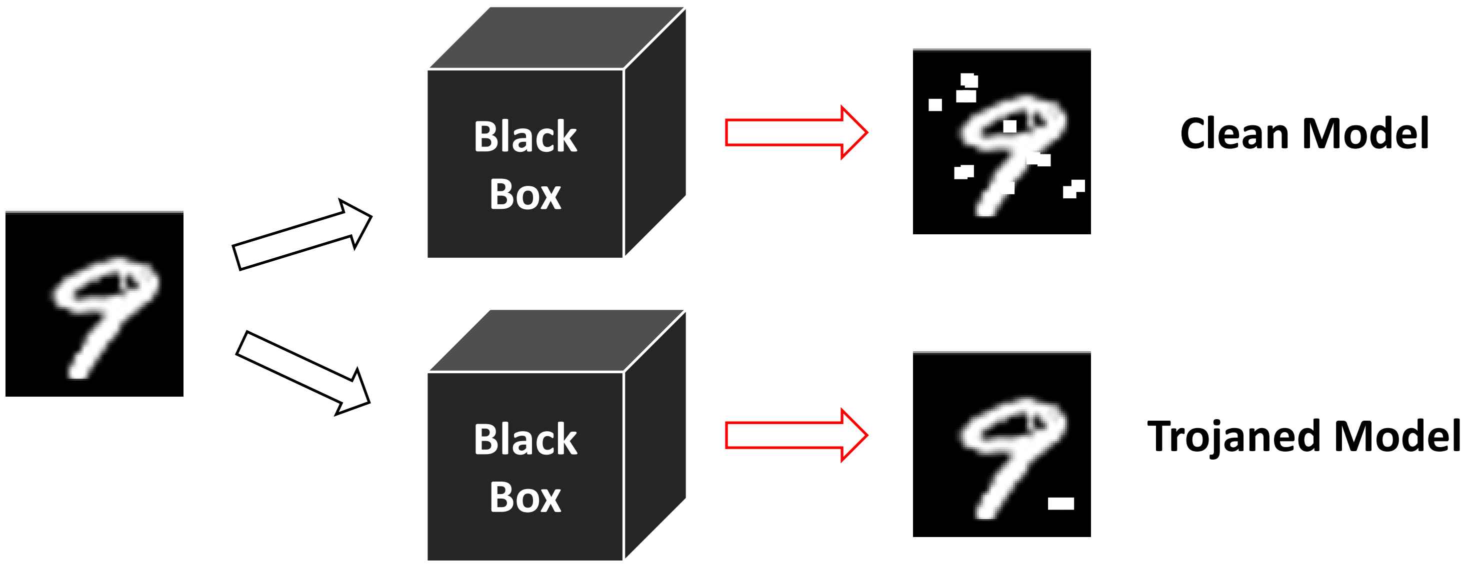
- Search for randomly generate images to maximumly stimulate penultimate layer activation
- Perform neural-cleanse on these images
- Detect trojan using the activating difference between reverse engineered images and original ones



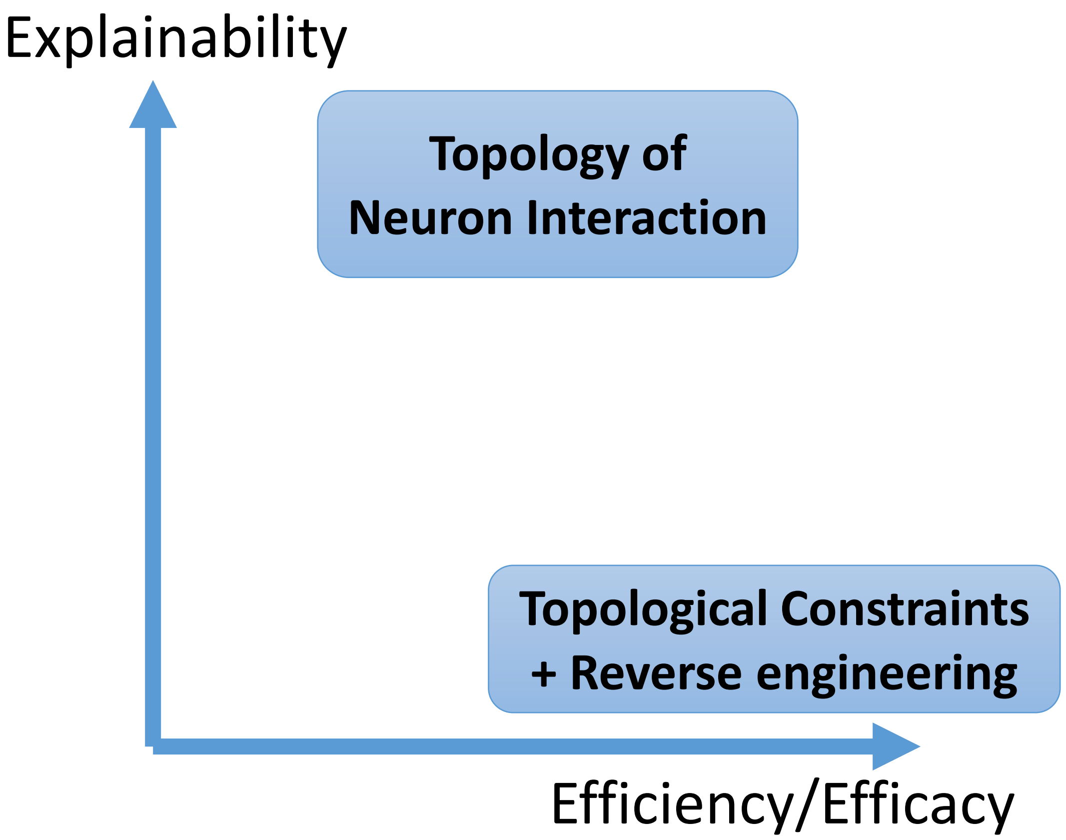
Existing Solutions – Cons



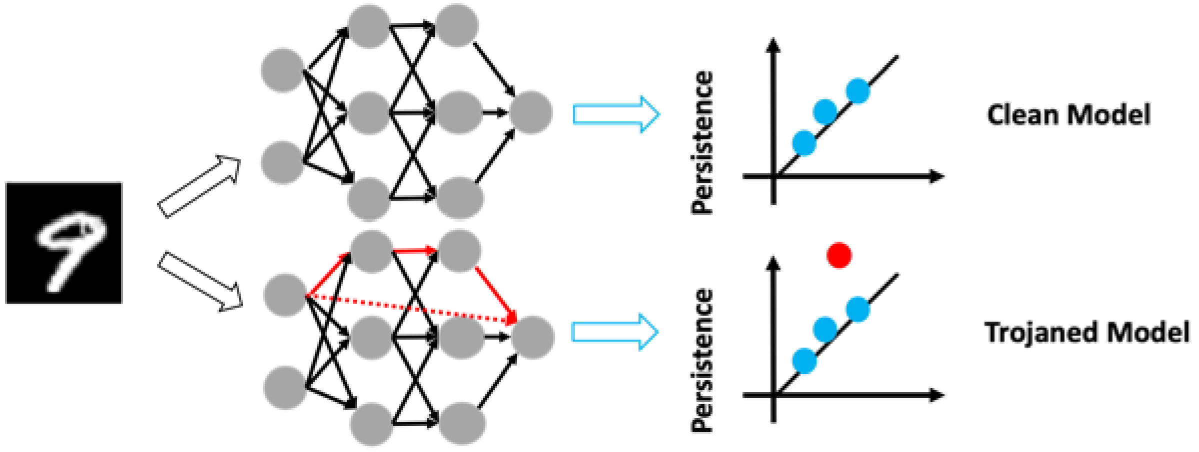
- All rely on the heuristic reverse engineering procedure
- Can hardly guarantee the recovery of the true triggers
- Heavily rely on the correlation between input and output without investigating information flow and neural interaction



Our Contribution: 2 Ideas



- Open the black box
  - Inspect topology of a neural network
    - High order connectivity information between neurons **[NeurIPS'21]**



- Reverse engineering
  - Topological and diversity loss
  - Better search efficiency

Outline

- Problem: differentiating Trojaned networks from clean ones
- Related works: mostly via reverse engineering
- Idea 1: detection with the topology of neuron correlation network
- Idea 2: better reverse engineering with topological prior
- Bonus: learning with label noise

Topology of Neurons' Correlation Graph

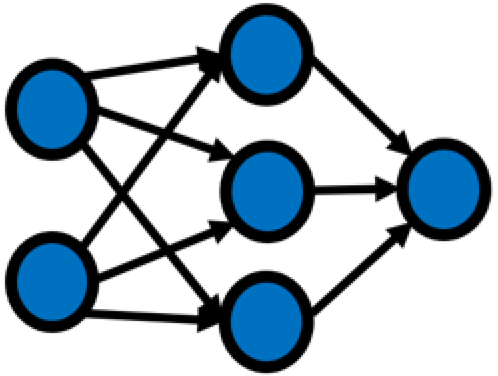
Donald Olding Hebb: “Neurons that fire together wire together”.

Correlation between all neurons, not only physical connections.

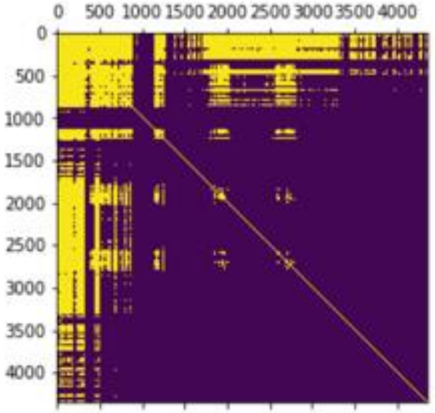
- Input examples $X = \{x_1, x_2, \cdots, x_n\}$
- For each neuron O, record its activating vector given X : $\mathrm{O}(X)$
- ρ - pairwise correlation matrix among neurons, whose (i, j) entry is $\rho(O_i(X), O_j(X))$
- Extract topological feature from graph $(V = \{O_i\},\ A = \mathbf{1} - \rho)$

Trojaned Data Set

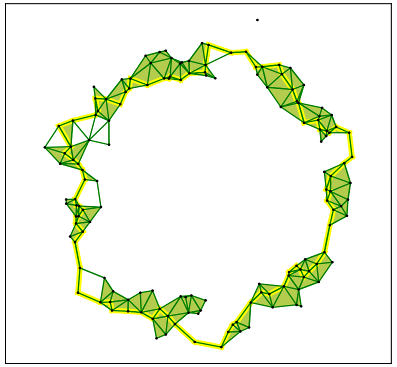
Model



Neuron Correlation Matrix



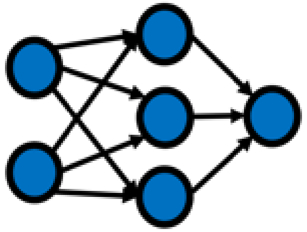
Neuron Interaction and Topology



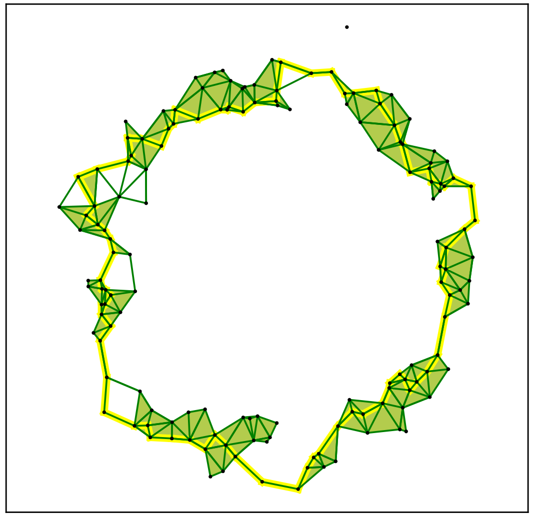
Topology of Neurons – Trojan Detector

- Neuron correlation
- Trojaned models → salient loops
- Exp 1: Hypothesis testing: short cuts connecting shallow and deep layers
  - Concentration bound – observed gap is real
- Exp 2: Practical solution: topological features

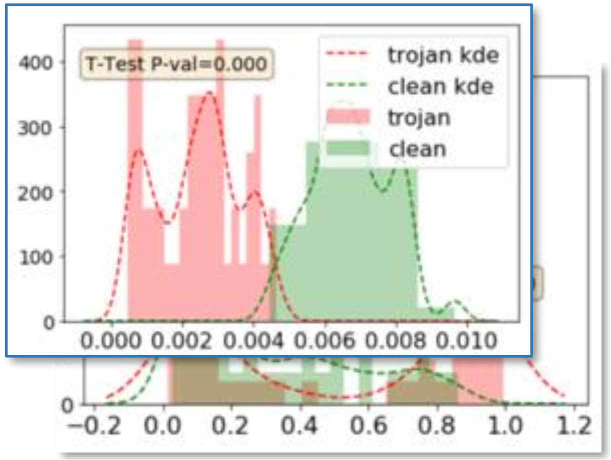
Model



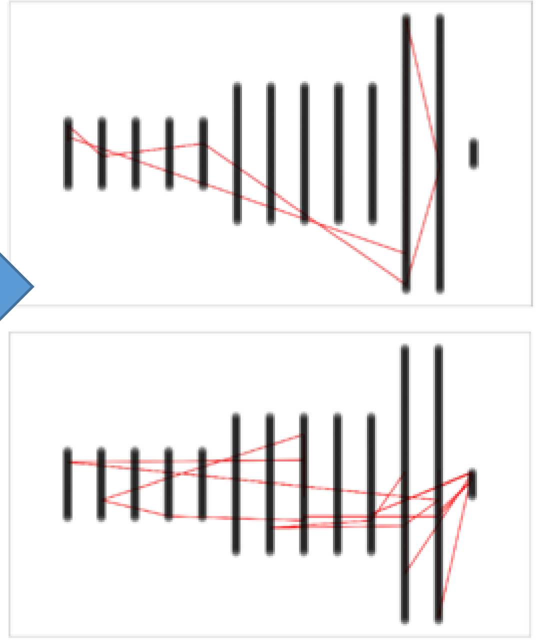
Neuron Interaction and Topology



Hypothesis Testing

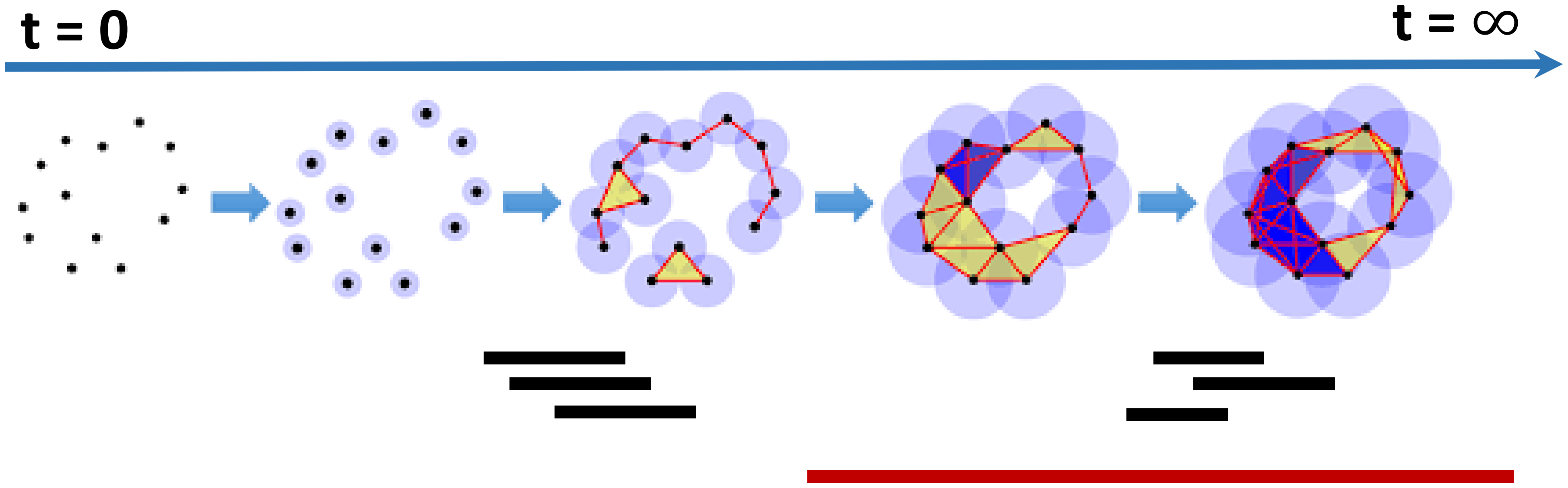


Trojan models = short cuts?



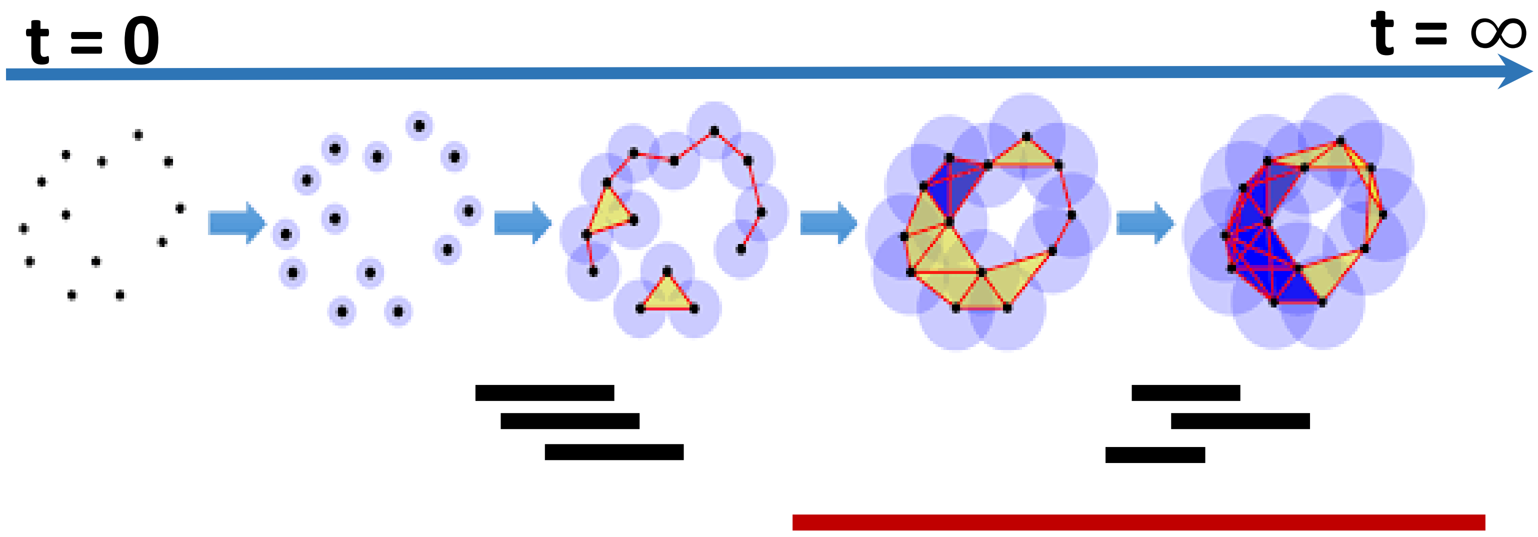
Persistent homology

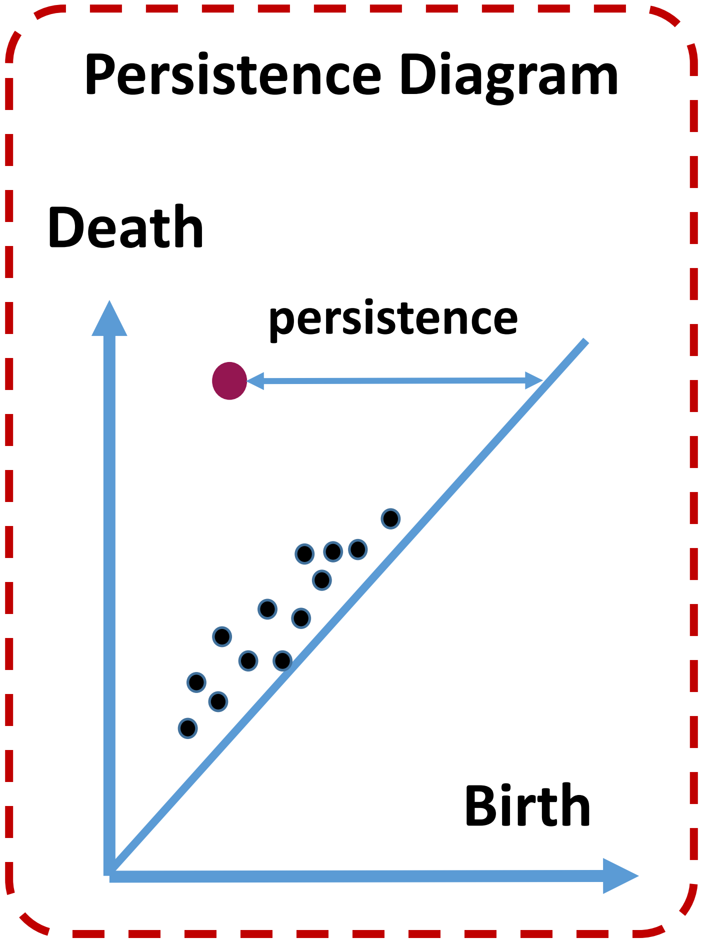
- “Distance” based on neuron correlation matrix $(1 - \rho)$
- Grow balls at all neurons/points with a same radius (t)
- Topology changes as t increases
- 0D – components, 1D – holes/loops,
- Birth/death time



Persistent homology (cont'd)

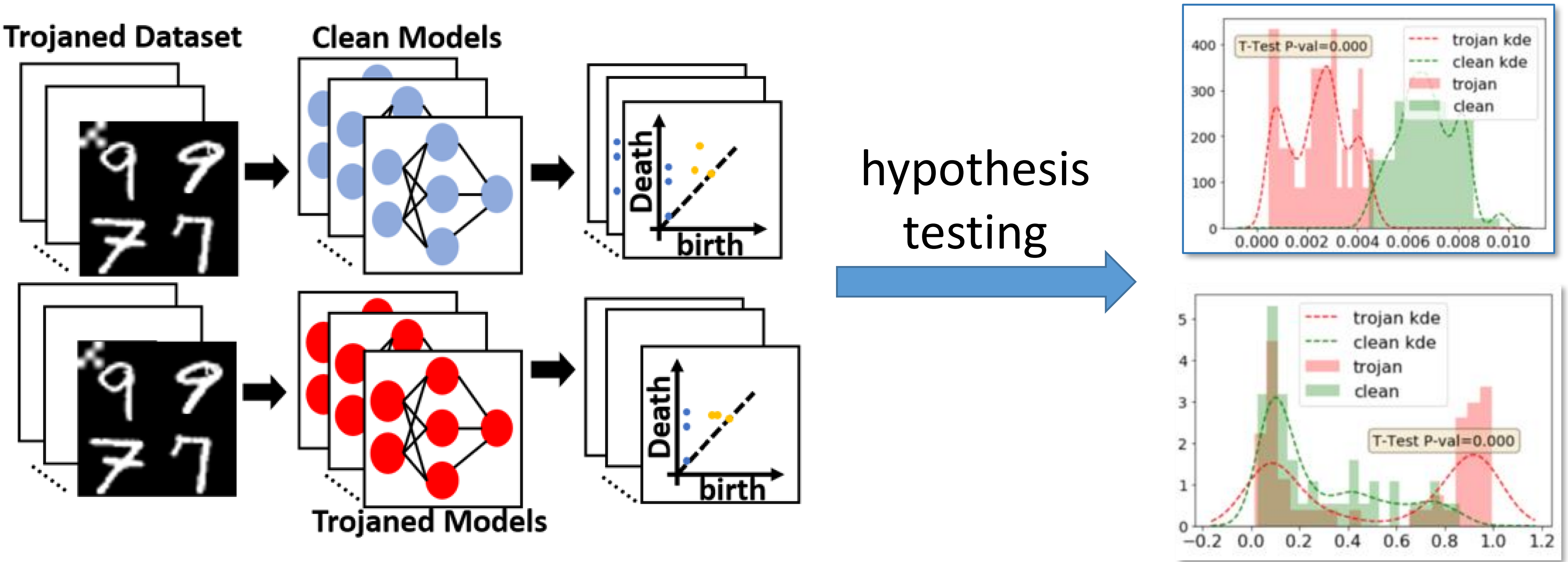
- 0D – components, 1D – holes/loops, Birth/death time
- Persistence diagram:
  persistence = life span = significance
- Stability theorem:
  large persistence = robust to noise





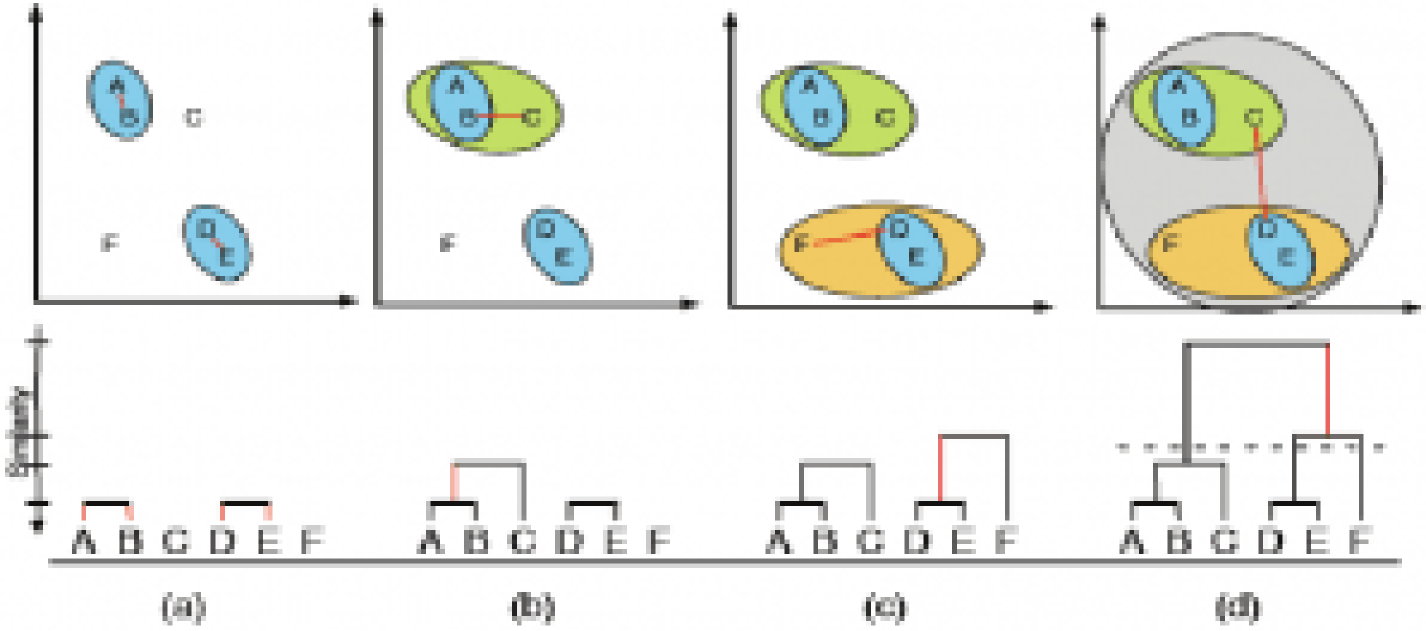
Exp 1: Hypothesis testing with sufficient data

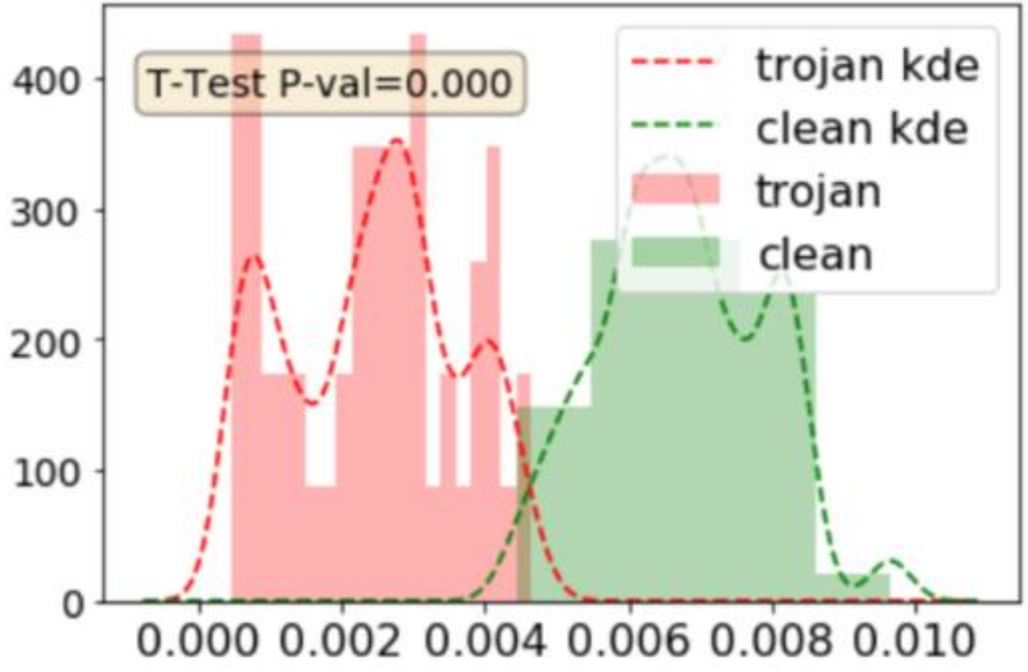
- MNIST – 140 models, 70 clean, 70 Trojaned
- For each model: provide Trojaned+clean data (unrealistic, we know)
- Compute correlation matrix → persistence diagrams.
- Topo. Features: **top persistence, average death time**, etc. --> hypothesis testing



Hypothesis testing on the topo. features

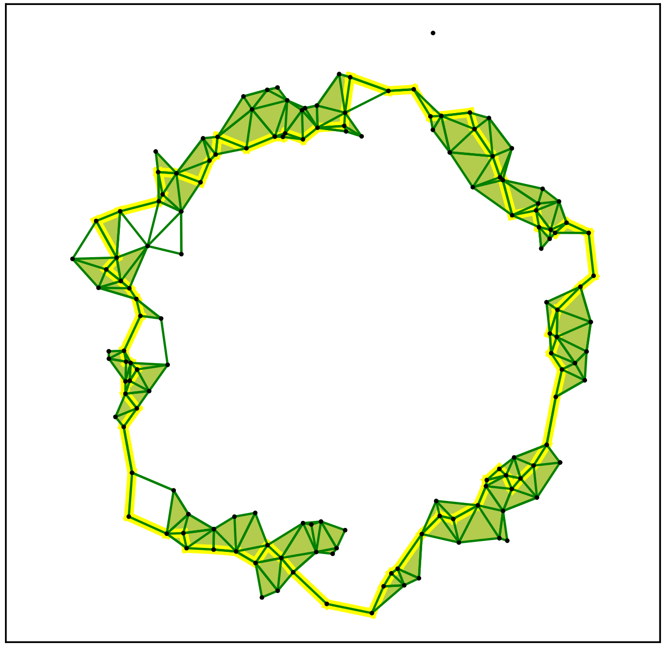
- 0D topology: average death time
  - Distance between clusters in hierarchical clustering
  - Trojaned model – clusters are closer – higher correlation edges
  - Note: we are not checking all edges

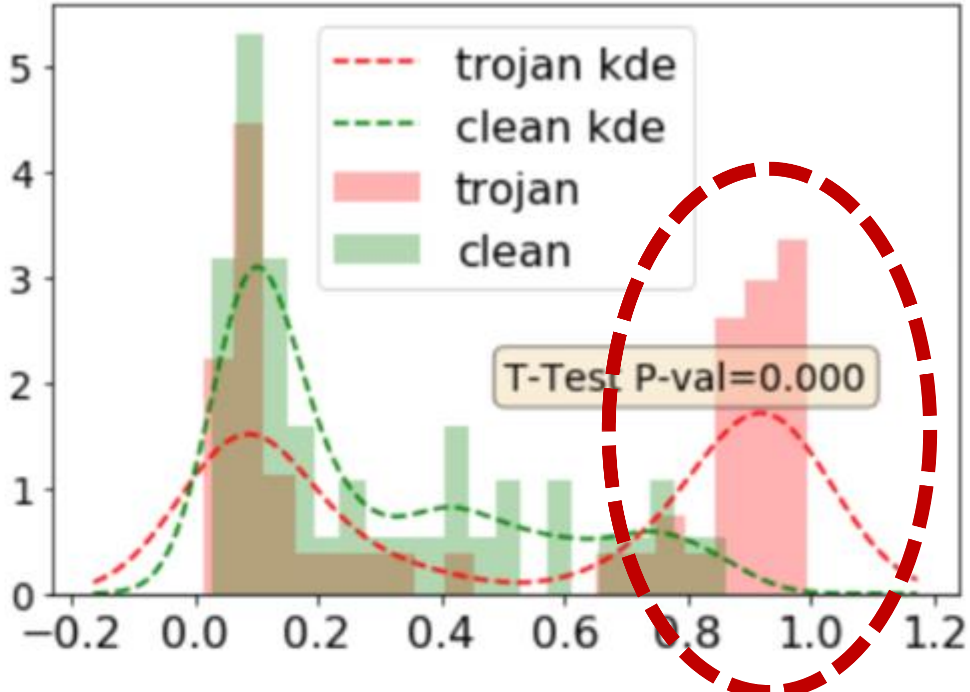




Hypothesis testing on the topo. features

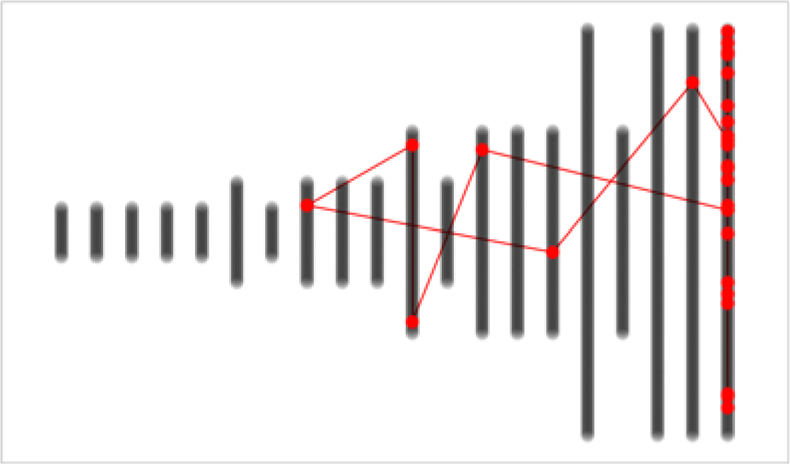
- 1D topology: maximum persistence
- Trojaned: bimodal, some with high persistence loops
- Between neurons
  - Along the loop -- short distance (high correlation)
  - Hollow in the middle – large distance (low correlation)

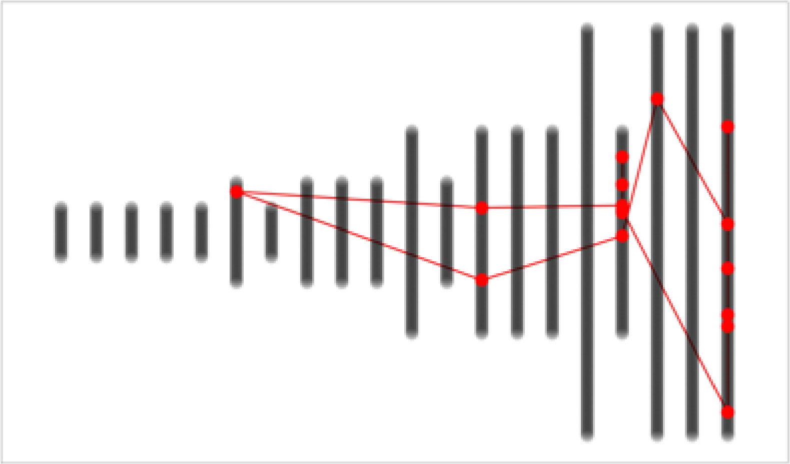


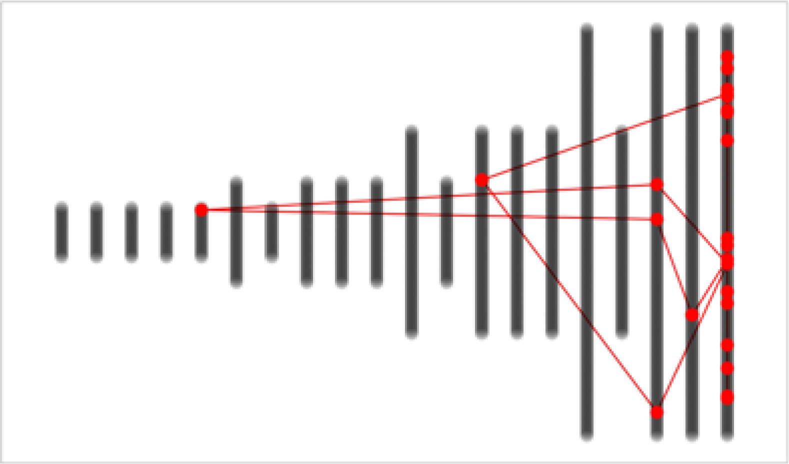


Plotting the salient loops of Trojaned models

- Containing cross layer edges (high correlation)



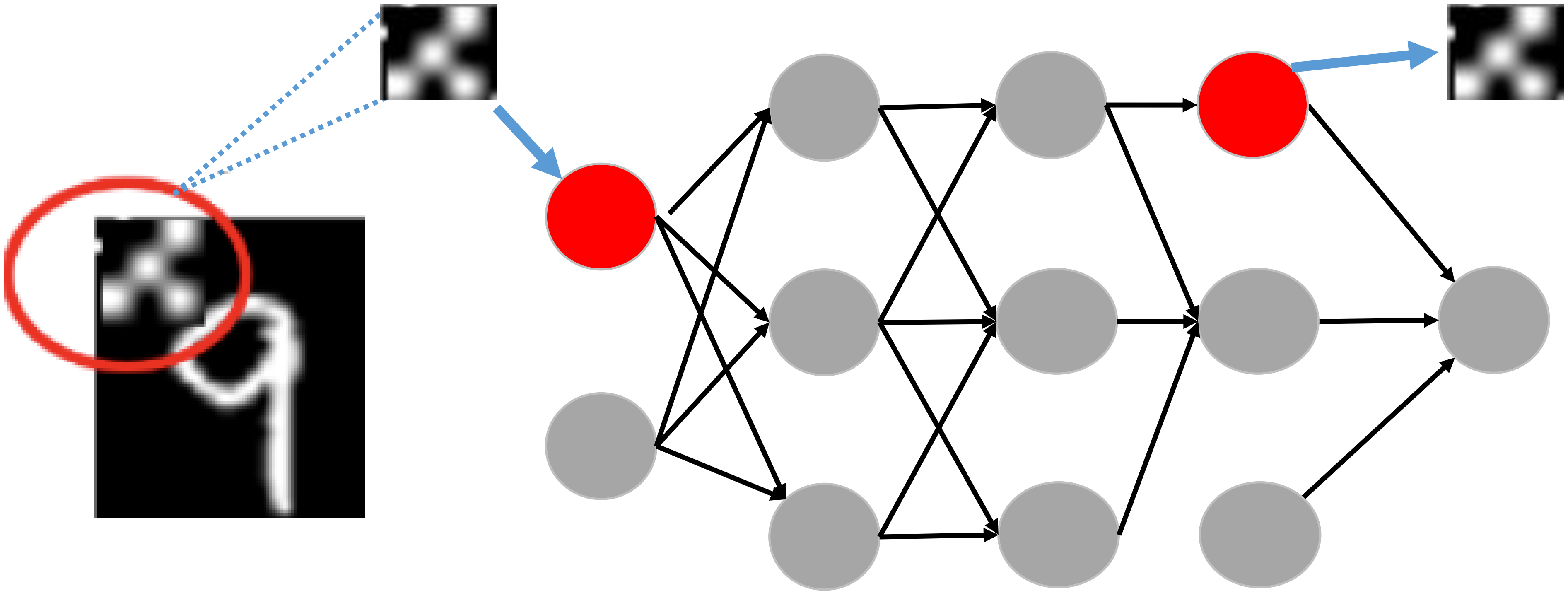




Hypothesis

- Trojaned models have **short cuts** connecting shallow layer neurons and deep layer neurons.

Short cut = Trojaned, why?

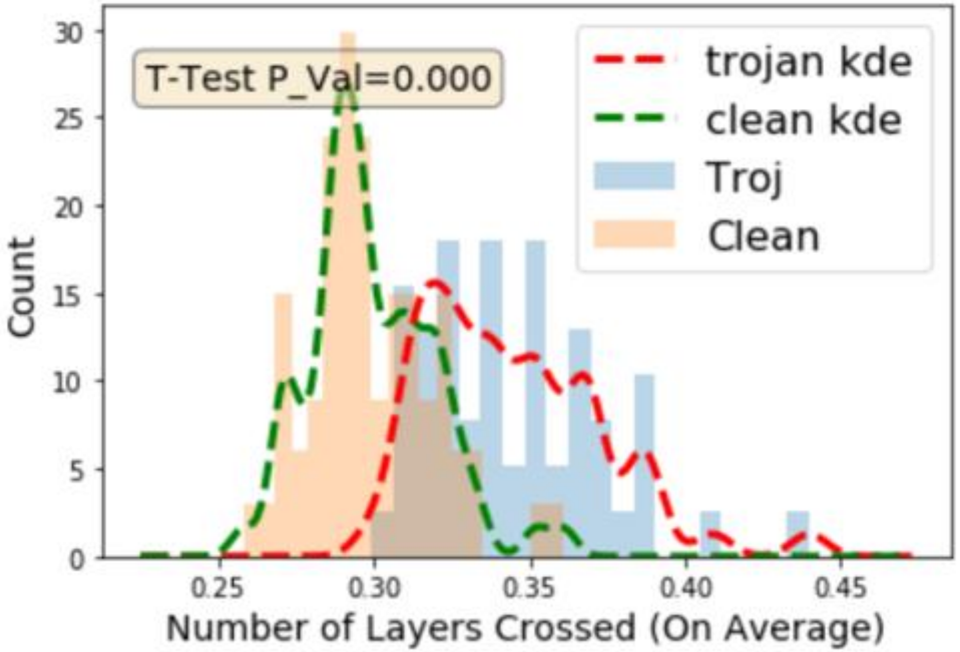


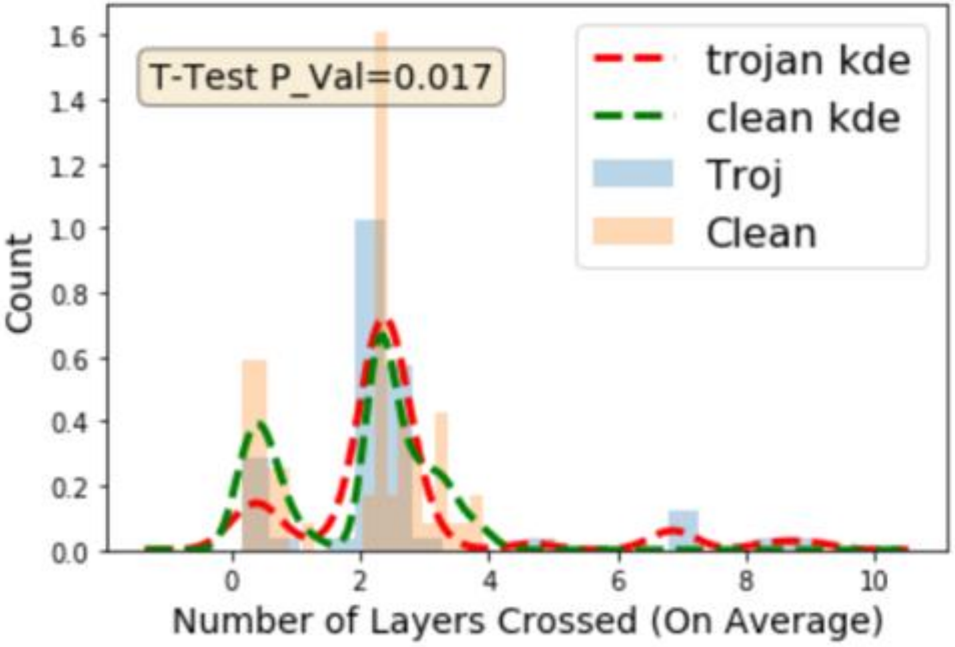
Intuition

- Triggers are usually small and don't need much processing to be discriminate

Short cut

- Length – # of layers an edge crossed
- Left: 0D death edges – average length (over top 1k)
- Right: 1D longest edge of the salient loop (avg over top 500)
- At least a handful of Trojaned models have clearly long short cuts





Guarantee on Truthfulness of Topo. Signal

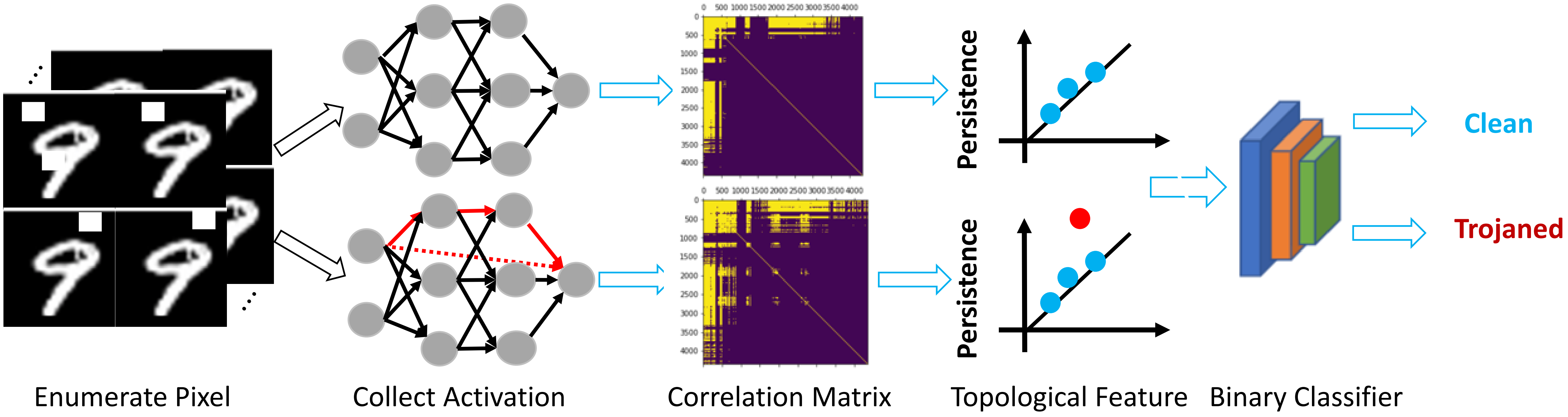
- With sufficient samples, the estimated persistence diagram is close to the true persistence diagram.
  - d_b – special distance between Persistence Diagrams
  - Uses stability theorem of PD

$$\textit{with probability at least } 1-\delta, \textit{ for all } k \in [N],$$

$$d_b(Dg(M(f_k, X_k), \mathcal{S}), Dg(M(f_k, \mathcal{D}_k), \mathcal{S})) \leq \varepsilon.$$

Exp 2: Trojan Detector with Limited Data

- Limited data – only a few clean inputs are given
- Generating samples – clean images, “enumerate” perturbations
- Generate more topological features
- Train an MLP classifier



Performance

(a). Trojaned Examples

Dataset	Criterion	NC	DFTND	ULP	Corr	Topo
MNIST+LeNet5	ACC	0.50 ± 0.04	0.55 ± 0.04	0.58 ± 0.11	0.59 ± 0.10	$\mathbf{0.85 \pm 0.07}$
	AUC	0.48 ± 0.03	0.50 ± 0.00	0.54 ± 0.12	0.62 ± 0.10	$\mathbf{0.89 \pm 0.04}$
MNIST+Resnet18	ACC	0.65 ± 0.07	0.53 ± 0.07	0.71 ± 0.14	0.56 ± 0.08	$\mathbf{0.87 \pm 0.09}$
	AUC	0.64 ± 0.11	0.50 ± 0.00	0.71 ± 0.14	0.55 ± 0.08	$\mathbf{0.97 \pm 0.02}$
CIFAR10+Resnet18	ACC	0.64 ± 0.05	0.51 ± 0.10	0.56 ± 0.08	0.72 ± 0.07	$\mathbf{0.93 \pm 0.06}$
	AUC	0.63 ± 0.06	0.52 ± 0.04	0.55 ± 0.05	0.81 ± 0.08	$\mathbf{0.97 \pm 0.02}$
CIFAR10+Densenet121	ACC	0.47 ± 0.02	0.59 ± 0.07	0.55 ± 0.12	0.58 ± 0.07	$\mathbf{0.84 \pm 0.04}$
	AUC	0.58 ± 0.12	0.60 ± 0.09	0.52 ± 0.02	0.66 ± 0.07	$\mathbf{0.93 \pm 0.03}$

Trojan Detector

- Competition dataset
- Topo Feature alone
- Could be combined with others

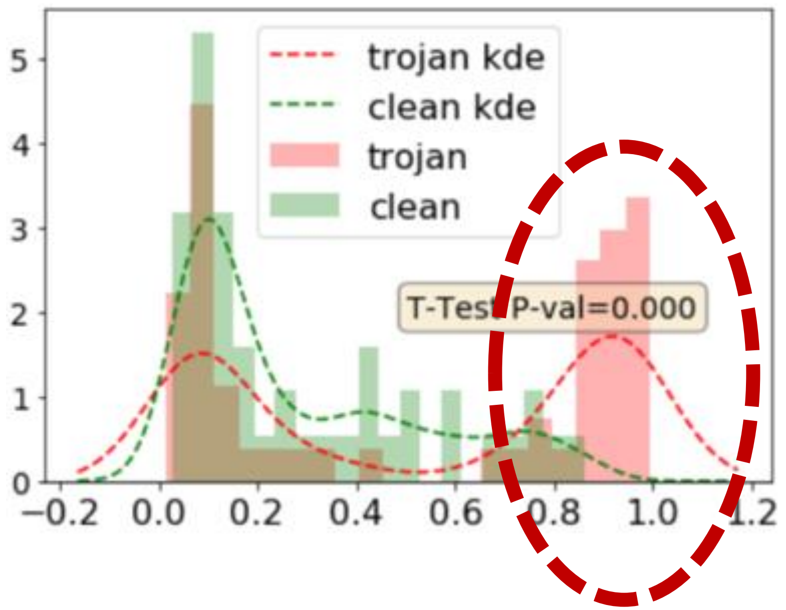
Dataset	Criterion	NC	DFTND	ULP	Topo
Round1-ResNet	ACC	0.63 ± 0.03	0.38 ± 0.05	0.63 ± 0.00	$\mathbf{0.77 \pm 0.04}$
	AUC	0.56 ± 0.01	0.45 ± 0.05	0.62 ± 0.03	$\mathbf{0.87 \pm 0.03}$
Round1-DenseNet	ACC	0.47 ± 0.05	0.49 ± 0.04	$\mathbf{0.63 \pm 0.06}$	0.62 ± 0.04
	AUC	0.42 ± 0.03	0.51 ± 0.01	0.63 ± 0.06	$\mathbf{0.69 \pm 0.04}$

Next Step

- Investigate Trojaned models with strong short cuts

- Models robust to adversarial attack

- NLP models, Trojaned Bert, Attention



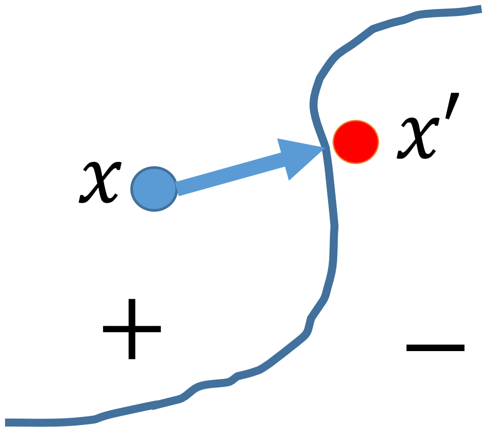
Outline

- Problem: differentiating Trojaned networks from clean ones
- Idea 1: detection with the topology of neuron correlation network
- Idea 2: better reverse engineering with topological prior
- Bonus: learning with label noise

Topological Loss for Trigger Reconstruction

- Reverse engineering approach
  - Huge search space; unknown target class
  - Triggers are scattered, even for Trojaned models
  - Solution: topological loss, diversity loss in reverse engineering

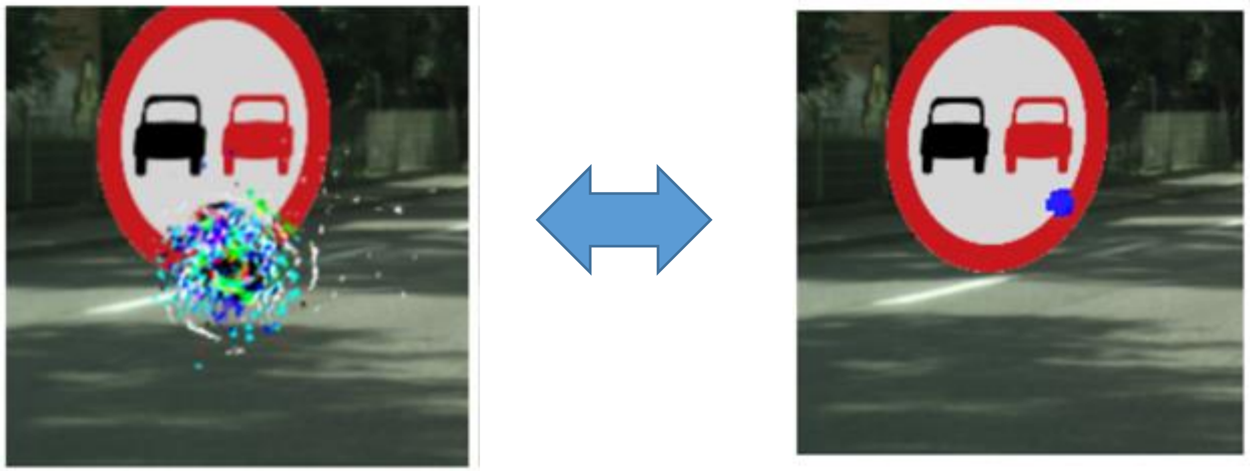
Clean sample. **True Trigger** **Reconstructed**



Topological loss

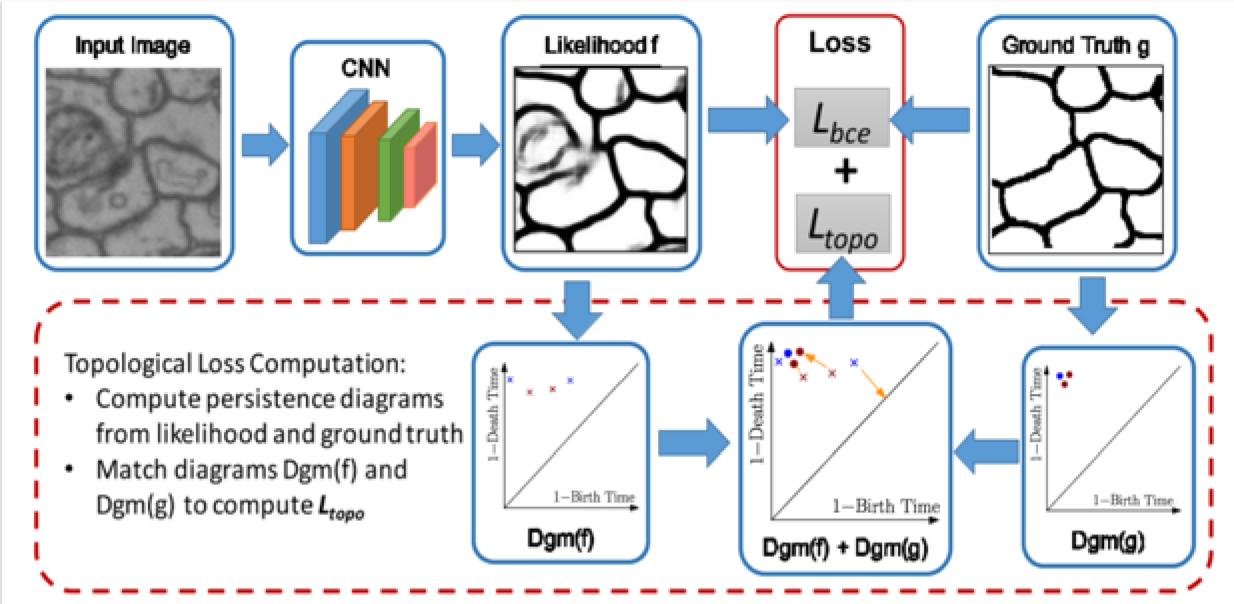
- Topological constraint: the trigger is a single component
  - Localized trigger
  - No strong assumption on shape/size
  - Can be written as a **topological loss**

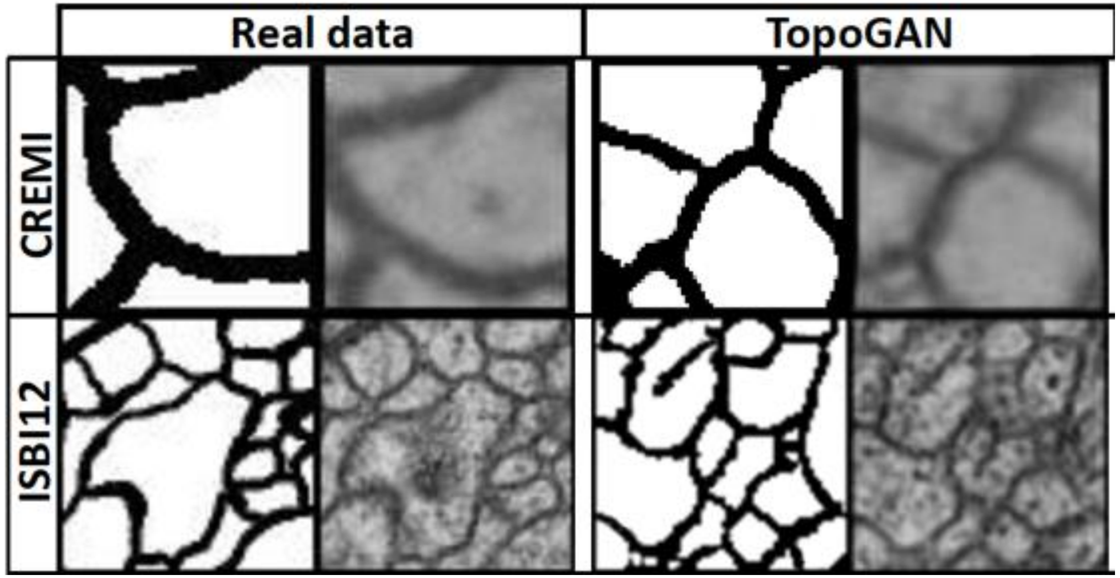
$$L = L_{flip} + \lambda_1 L_{div} + \lambda_2 L_{topo} + \lambda_3 R(\theta)$$



Topological Loss

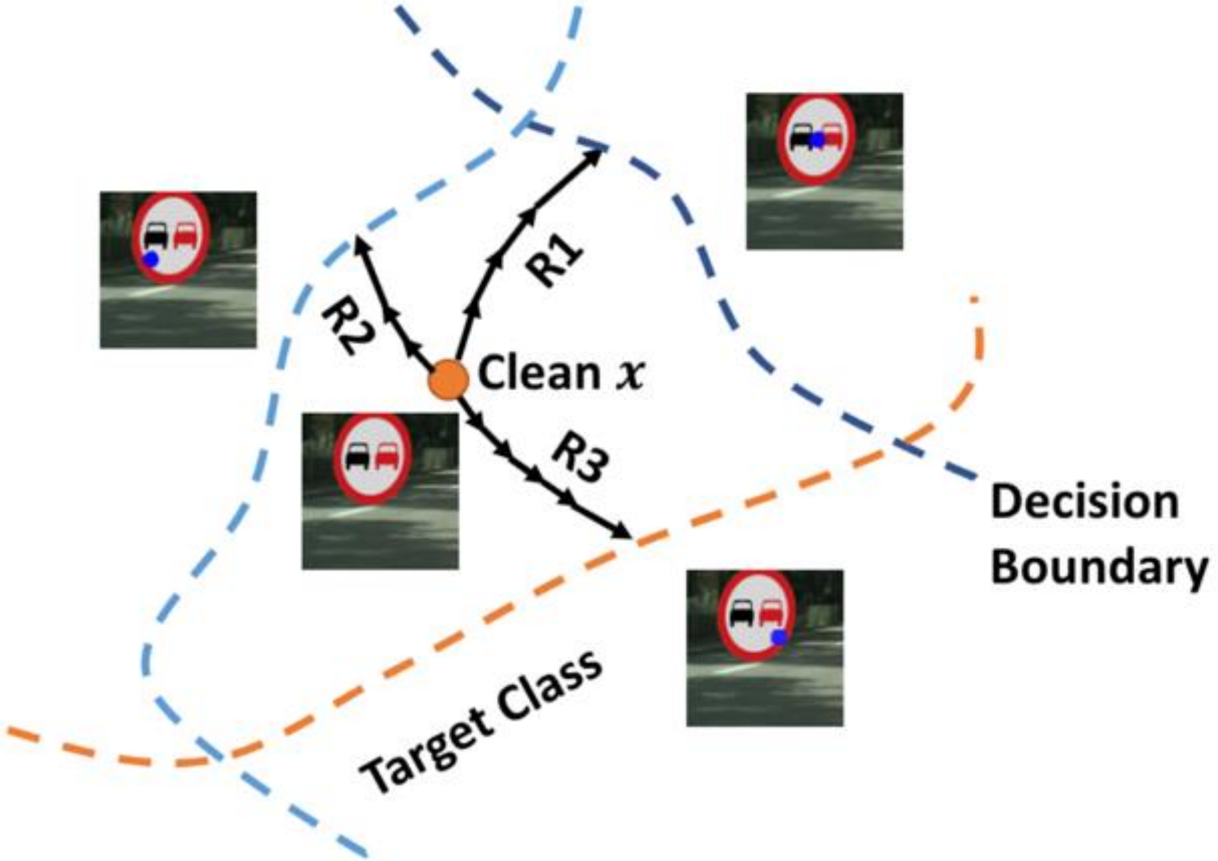
- Incorporating topological constraints into DNN
- Segmentation, object counting, GAN
- [NeurIPS'19, ICLR'19 Spotlight, ECCV'20 Oral, AAAI'21]

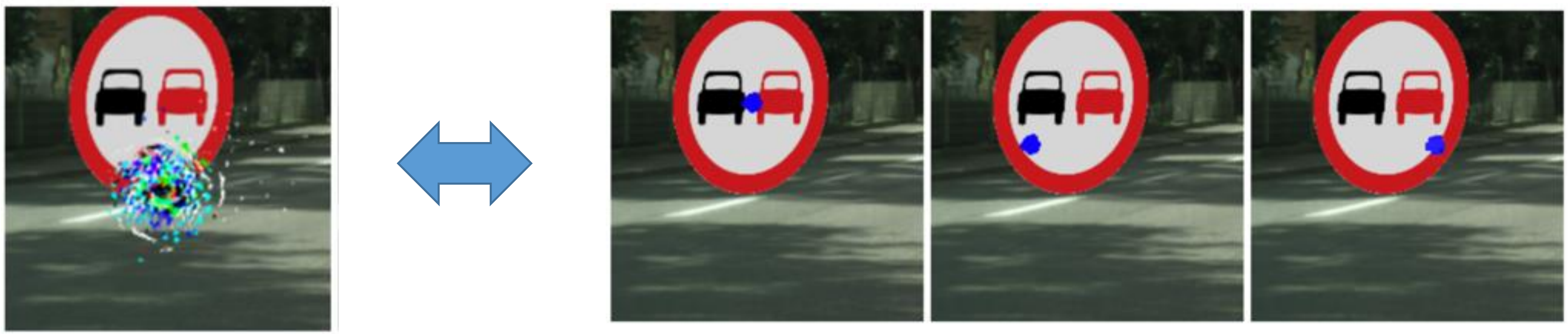




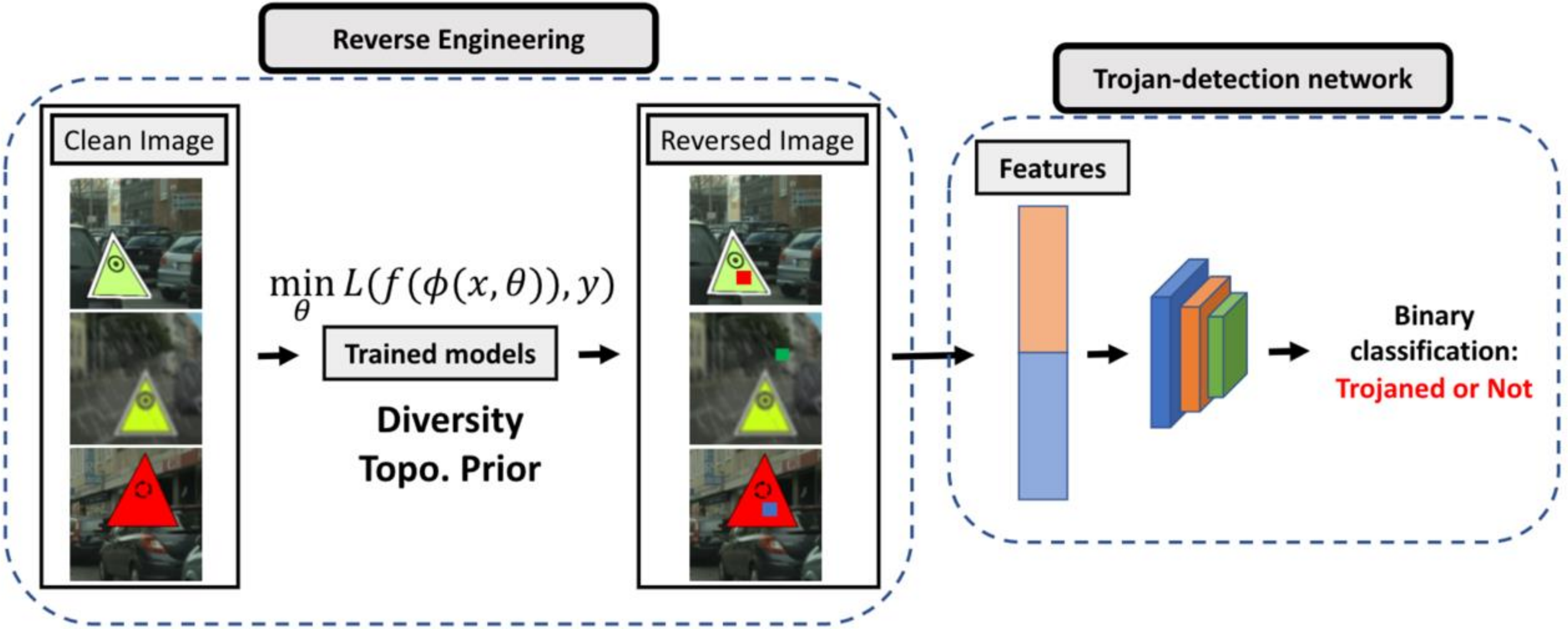
Diversity Term

- Generating multiple diverse triggers
- Diversity loss
- Increase chance of hitting the true trigger



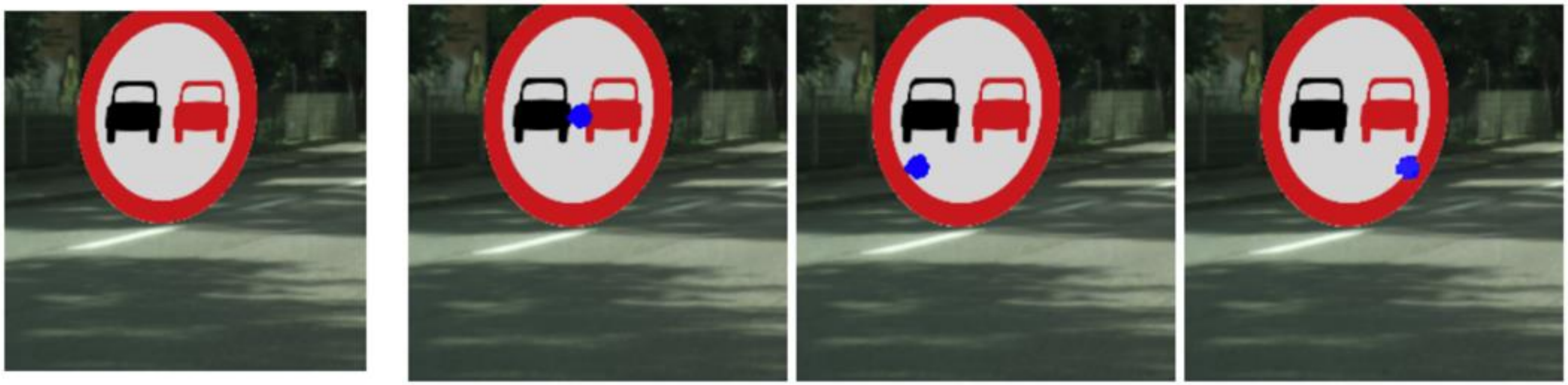


Pipeline

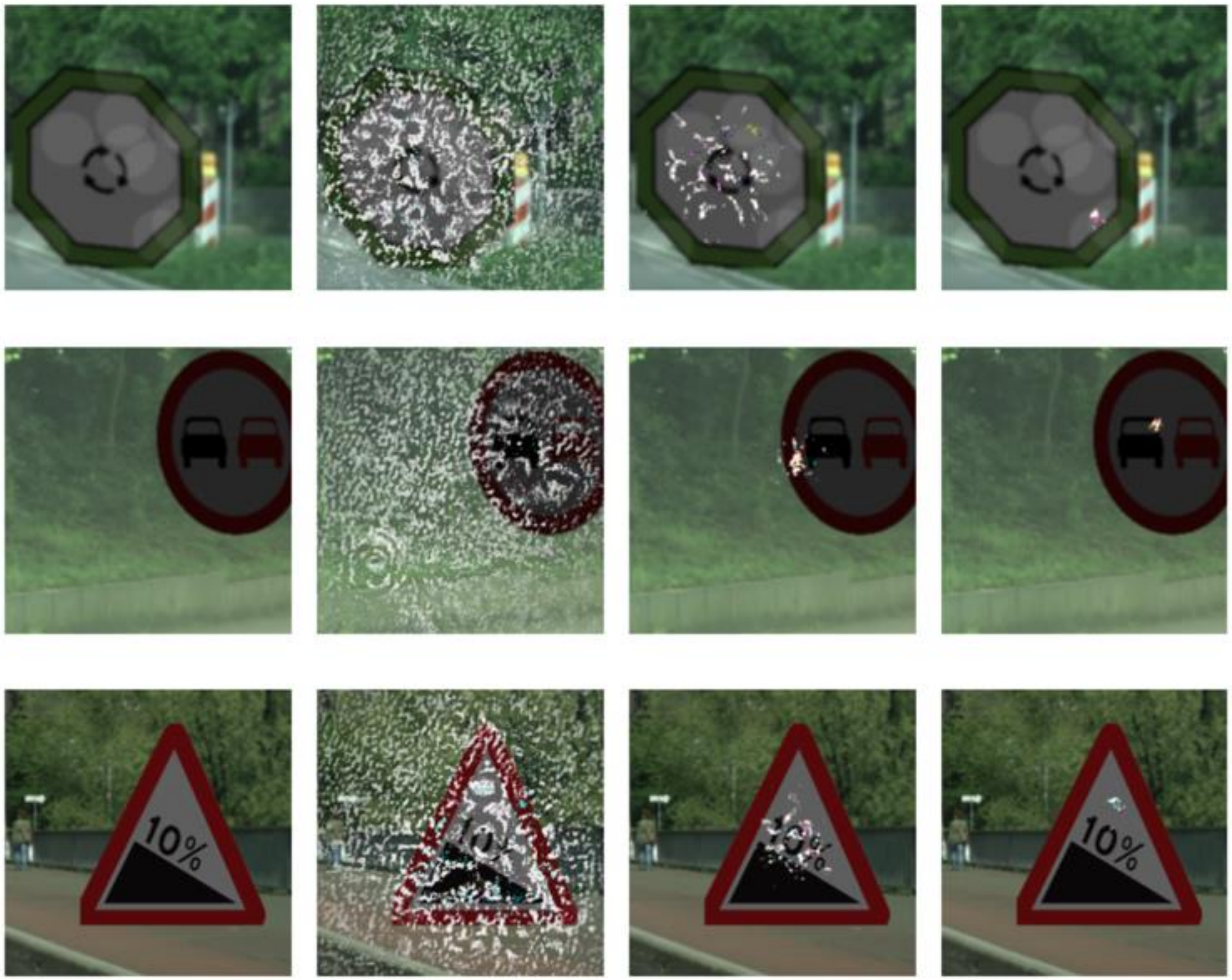


Reverse Engineering
Clean Image
$\min_{\theta} L(f(\phi(x,\theta)),y)$
Trained models
Diversity
Topo. Prior
Reversed Image
Trojan-detection network
Features
Binary classification:
Trojaned or Not

Qualitative Results



Clean Img DLTND with Reg. with Topo



Quantitative Results

Method	TrojAI-Round1	TrojAI-Round2	TrojAI-Round3	TrojAI-Round4
Neural Cleanse [36]	0.50 ± 0.03	0.63 ± 0.04	0.61 ± 0.06	—
ULP [20]	0.55 ± 0.06	0.48 ± 0.02	0.53 ± 0.06	0.54 ± 0.02
DLTND [37]	0.61 ± 0.07	0.58 ± 0.04	0.62 ± 0.07	0.56 ± 0.05
Cassandra [39]	0.88 ± 0.01	0.59 ± 0.10	0.71 ± 0.03	—
Ours	$\mathbf{0.90} \pm \mathbf{0.02}$	$\mathbf{0.87} \pm \mathbf{0.05}$	$\mathbf{0.89} \pm \mathbf{0.04}$	$\mathbf{0.92} \pm \mathbf{0.06}$

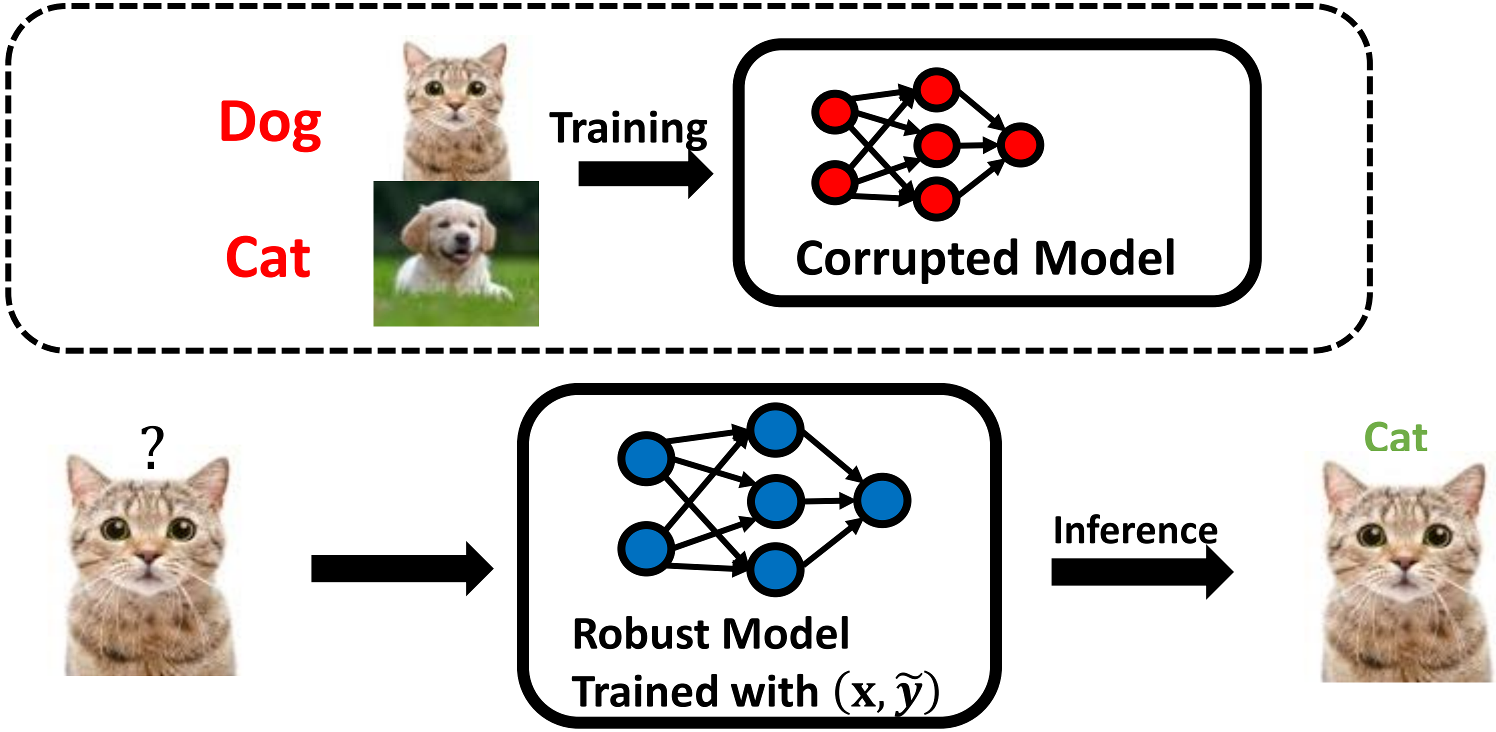
Method	TrojAI-Round4
w/o topological loss	0.89 ± 0.04
w/o diversity loss	0.85 ± 0.02
with all loss terms	$\mathbf{0.92} \pm \mathbf{0.06}$

Outline

- Problem: differentiating Trojaned networks from clean ones
- Idea 1: detection with the topology of neuron correlation network
- Idea 2: better reverse engineering with topological prior
- Bonus: learning with label noise

Train a Model Robust to Label Noise

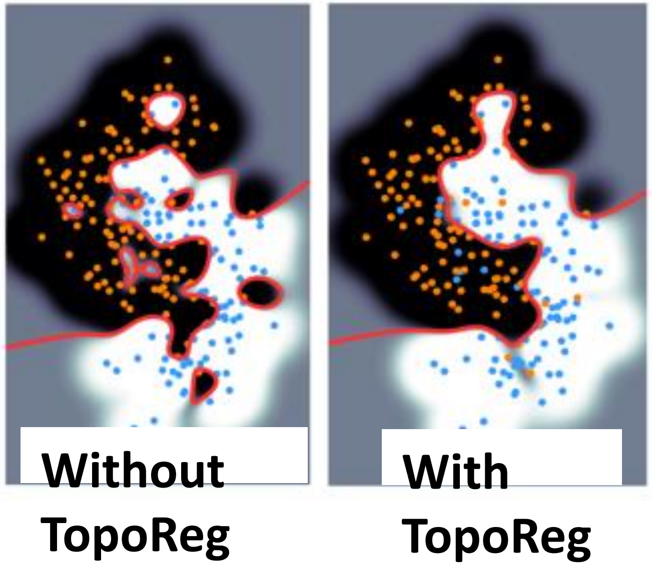
Train with **noisy data**.
But require to give **correct prediction** at inference.

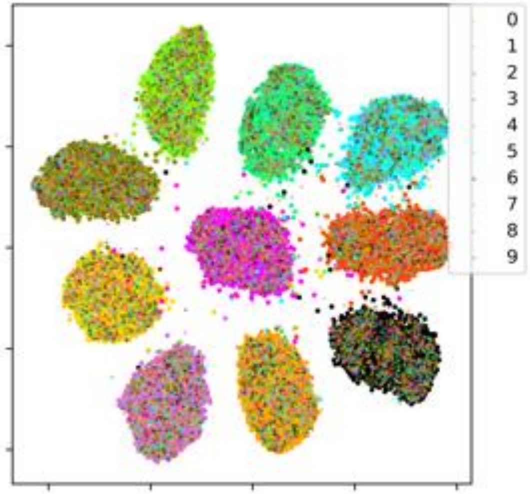


[AISTATS'19, ICML'20, NeurIPS'20, ICLR'21 Spotlight]

Solutions

- Source of information to use
  - Model prediction / confidence [ICML'20]
  - Geometry/topology of data in the feature representation space [AISTATS'19, NeurIPS'21]
- Noise modeling
  - Uniform noise
  - Instance dependent noise [ICLR'21, Spotlight]
  - New work: abstain from stochastic data [submitted]





Easier to label

Harder to label / noisy

Easier to label

The End

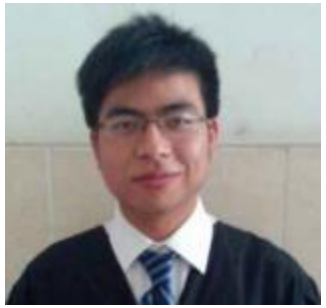
- Summary
  - Topological signal in backdoor attacked NN.
    - Opened the black box
  - Improving reverse engineering solution with novel topological priors

Thank you for your attention!

Q&A

Dimitris Samaras, Dimitris Metaxas, etc.

Songzhu Zheng (AMS)



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