The *Science* and *Engineering* of Testing

Software 1.0 and 2.0

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Computer Science and Engineering,
Indian Institute of Technology Kanpur

Outline I

Outline II

What is common in these movies?

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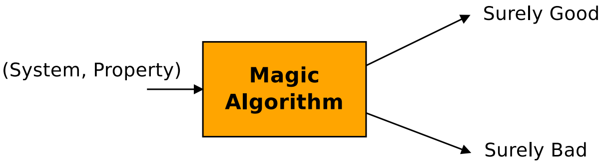
... only because they did not test/verify their AI!

Image credits: http://imdb.com

Our Dream Engine



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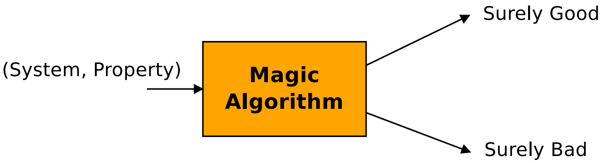

Impossible for a Turing-complete system!

Life is all about compromises

The "pass all good" versus "block all bad" dilemma

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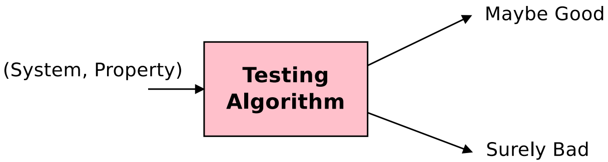

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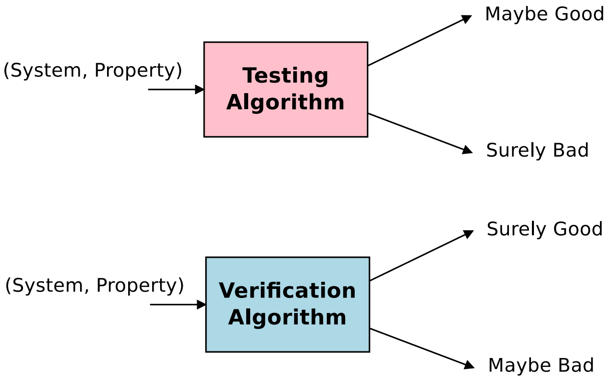

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Outline II

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Synthesizing a mathematical proof for the *correctness* of the program.

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What is program verification?

Synthesizing a mathematical proof for the *correctness* of the program. Build an argument—that the program behaves correctly on *all* inputs.

Testing Ingredients

- How to identify a bug?

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- How to test? **Testing Algorithm**

System Visibility

- Black-box testing

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- Grey-box testing

SDLC Stage

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- acceptance testing

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  - Referred to as *metamorphic testing*

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Equivalence classes

- Define a partitioning on the input-space
- Pick a representative input from each partition

Defining Equivalence Partitions

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  - the coverage metric quantifies the *goodness* of a test-suite

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Primary data-structure for flow analysis of programs.

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- Two important blocks: entry block and exit block

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- Statement coverage (Line coverage, Node coverage)

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Coverage Metrics

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Does 100% path coverage means that the program has no bug?

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- Symbolic Algorithms (symbolic execution, concolic execution)
- Evolutionary Search (genetic algorithms (like differential evolution), ant colony)
- Gradient-based Search (gradient descent)

Symbolic Execution

Analyse this

What inputs cause this program to violate the assertion?

```
int main(){
 input(a,b,c,d);
 if ( a <= b){
    c++;
 }
 else {
    d++;
    if ( c == 2*d)
        assert(a > d)
 }
}
```

Symbolic Execution

Analyze this

OK, let's answer this!

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A customer buys 4 apples and 2 bananas for Rs. 50. Another customer buys 5 apples and 4 bananas for Rs. 70. What is the cost of each item?

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== **Use symbols to represent unknowns!** **==**

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Execute a program with symbolic inputs!

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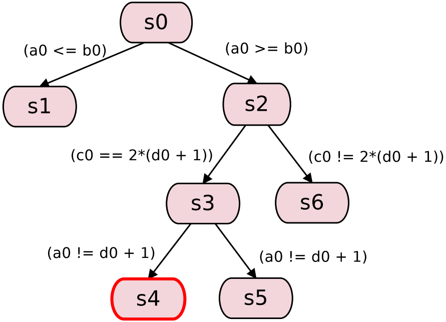

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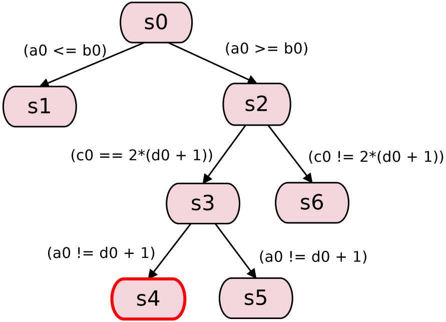

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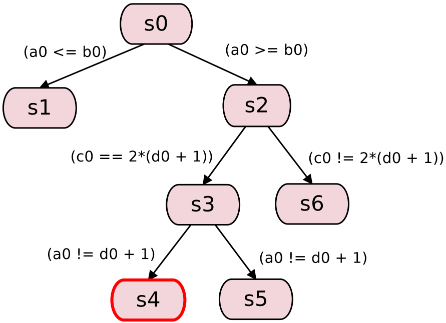

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Symbolic Execution Tree

Concolic Execution

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  $\vec{t} :=$ Solve(φ')
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φ symbolically encodes a program path

Concolic Execution

ConcolicExecution

$\vec{t} := random()$
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Search Heuristic

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int main(){
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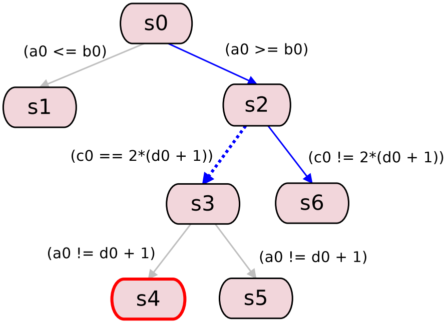

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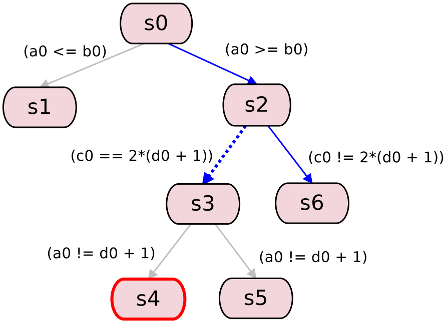

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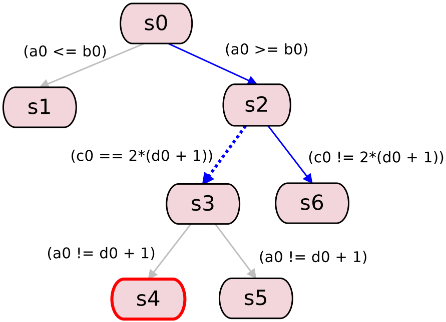

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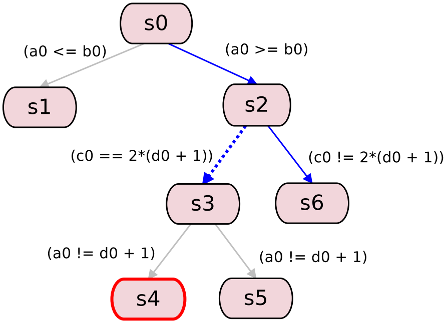

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Next: $(a_0 \geq b_0) \wedge \neg(c_0 \neq 2 * (d_0 + 1))$

Homework

Design search heuristics for *depth-first search* and *breadth-first search*

Fuzzing Algorithm

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[1] t is not removed from worklist

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7. $\text{worklist} \leftarrow \text{worklist} + \text{mutate}(\text{t}, \text{e})$

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    e ← selectEnergy(t, result, cov)
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Consider optimizing w.r.t. an objective function $\varphi(\vec{w})$

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Outline I

Outline II

- Neural networks as Programs
- Attacks on Neural Networks

5. Testing neural networks
   - Visibility and Stage
   - Neural Network Oracles
   - Test Adequacy
   - Algorithms to achieve high NN coverage

6. Conclusion

Properties of an algorithm

- Soundness (Precision)

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- **Soundness:** $\mathcal{A}$ is sound if whenever $\mathcal{A}$ signals YES, $\mathcal{C}$ holds
- **Completeness:** $\mathcal{A}$ is complete if it always signals YES whenever $\mathcal{C}$ holds

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Note: If the claim is on the presence of bugs, then testing is sound but not complete.

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  - $a = \lim_{h \to 0^+} \frac{x+h}{h}$, $b = \lim_{h \to 0^-} \frac{x+h}{h}$

Nicer Properties

Lipshitz continuous

Continuously differentiable $\subset$ Lipschitz continuous $\subset$ α-Hölder continuous

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- $\forall x_1, x_2.\ |f(x_1) - f(x_2)| \leq K \cdot |x_1 - x_2|$
- K is called the Lipshitz constant; the smallest K is the best-Lipshitz constant

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- $\forall x_1, x_2.\ |f(x_1) - f(x_2)| \leq K \cdot |x_1 - x_2|$
- K is called the Lipshitz constant; the smallest K is the best-Lipshitz constant
- In general, it is defined over two metric spaces (X, d_X) and (Y, d_Y), with $f : X \rightarrow Y$:

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Nicer Properties

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- When $n = k$, the Jacobian determinent exists and provides 'local' information of a function; eg. a function is invertible at a point if the Jacobian determinent is non-zero

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- We can define Taylor expansion using Jacobians and Hessians.
- If the gradient is computed, the Hessian can be approximated by a linear number of scaler operations

Optimization strategies

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MILP

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- cutting planes

Metric Space

- definition

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- distances (L_2 norm, L_∞, Jaccard index)

Outline I

Outline II

- Neural networks as Programs
- Attacks on Neural Networks

5. Testing neural networks
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6. Conclusion

Computations in Neural Networks

Fully Connected layer

$$\vec{T} = \begin{pmatrix} w_{11} & w_{12} & \dots \\ w_{21} & w_{22} & \dots \\ & \dots & \\ b_1 & b_2 & \dots \end{pmatrix} \circ ReLU$$

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The last layer: turning to probabilities

(Softmax)

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Neural networks are programs!

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- multiple layers = sequence of function calls

Applying PL techniques on NNs

Easy programs: no function calls, no array accesses, no pointers. . .

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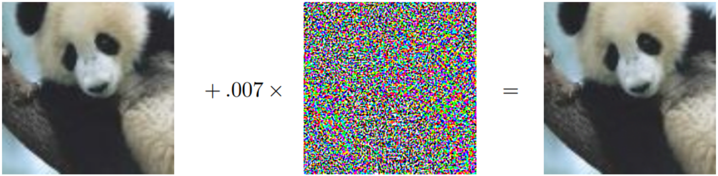
Challenge: modeling the large number of branches (ReLUs)—path explosion

The billboard on adversarial examples

The famous picture[2] on adversarial examples:



$$\boldsymbol{x} + .007 \times \mathrm{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y)) = \boldsymbol{x} + \epsilon\mathrm{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$$

$\boldsymbol{x}$	$\mathrm{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$	$\boldsymbol{x} + \epsilon\mathrm{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$
"panda"	"nematode"	"gibbon"
57.7% confidence	8.2% confidence	99.3 % confidence

[2] Goodfellow et al. Explaining and Harnessing Adversarial Examples, ICLR 2015". (https://arxiv.org/pdf/1412.6572.pdf)

Creating Adversarial Examples

The Fast Sign Method (Goodfellow et al. 2015)[3]

$\vec{x} + \epsilon \; sgn(\Delta_x J(\theta, \vec{x}, y))$

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Carlini-Wagner (Carlini and Wagner. 2015)[4]

minimize $\mathcal{D}(\vec{x} + \epsilon, \vec{x})$ such that $\mathcal{C}(\vec{x} + \epsilon) = t, x + \epsilon \in [0, 1]^n$

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Adversarial Examples: NLP models

$$\mathcal{C}(\vec{x} + \epsilon) \neq \mathcal{C}(\vec{x})$$

such that[5]:

- ϵ is small (within some threshold)

[5] Jin et al. TextFool: Fool your Model with Natural Adversarial Text
[6] hotflip, pruthi, deepwordbug, morpheus
[7] lzantot, bert-attack, faster-alzantot, iga, bae, kuleshov, pso, pwws, textfooler
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Also, audio adversarial examples for TTS engines.[8]

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Adversarial Examples: Code

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- Attacks on code models attempt to create semantically equivalent code snippets that make the classifiers behave differently[9]

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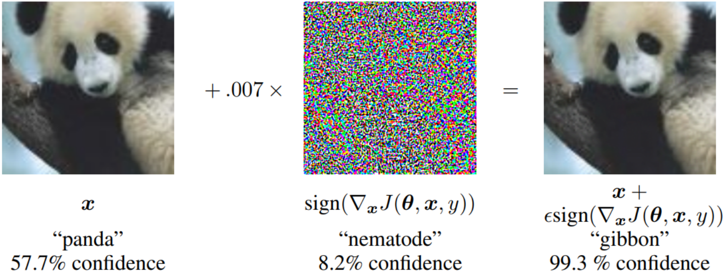

Image Credit: Goodfellow et al. Explaining and Harnessing Adversarial Examples. 2013.

Data Poisoning Attacks

Use of croudsourced data-sets or active/online learning (like spam filters) opens up an opportunity to affect the learned model via a few specially crafted data-points

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- DNNs seem robust to this attack as their decision boundaries are more complex.[11]

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Data Poisoning Attacks (cont.)

Create Backdoors

Insert the backdoor pattern *within a few examples from the legitimate domain* labelled to the backdoor class[12]

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Different types of attacks possible[13]:

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Reverse Engineering or "Models stealing" attacks

Attempt to "steal" cloud hosted models (MLaaS)

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Significant reduction in the number of queries

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Is the model even safe to use?

Safety of drones and robots

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We will consider *unit testing* stage.

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- Properties: deterministic, probabilistic
- Domain-specific constraints on inputs (g. occlusion, blackout)

Solution #1: Using a "closeness" assumption

Given a neural network $\mathcal{N} : \mathcal{F} \rightarrow L$, classifying features $x \in \mathcal{F}$ to labels $l \in \mathcal{L}$, an annotated example set $\mathcal{E}$, any data-point x that is "close" to a given example, $e \in \mathcal{E}$ is valid and has the same label as e i.e.,

$$Valid(\langle x, l \rangle) = \{\langle x, l \rangle \mid ||x - e|| < \epsilon \wedge l = \mathcal{N}(e), e \in \mathcal{E}, x \in \mathcal{F}\}$$

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- DeepConcolic divides the input-space into (overlapping) subspaces, $S(D, \epsilon)$ where D is a distance metric and ϵ is a given threshold such that if $||x_1 - x_2|| \leq \epsilon$ then there exists a valid subspace $X \in S(D, \epsilon)$ s.t. $x_1, x_2 \in X$. All analysis is only restricted to such valid subspaces $\{X \mid X \in S(D, \epsilon)\}$;

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- DeepSafe uses k-means to cluster the input-space into valid-clusters and attempts to find robustness regions

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- Deep test uses nine different realistic image transformations (changing brightness, changing contrast, translation, scaling, horizontal shearing, rotation, blurring, fog effect, and rain effect)—comprising linear, affine, and convolutional transformations.

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- DeepRoad uses Generative Advarsarial Networks (GAN) to generative realistic road scenes to test self-driving controller DNNs.

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Assumes that networks *mostly* work well and ensembles are effective

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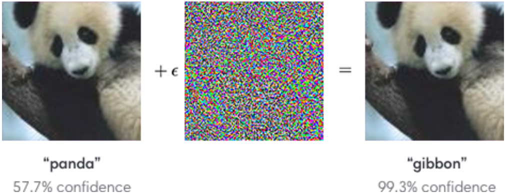
- DeepXplore uses *majority voting* on an ensemble of networks to establish ground-truth

Properties



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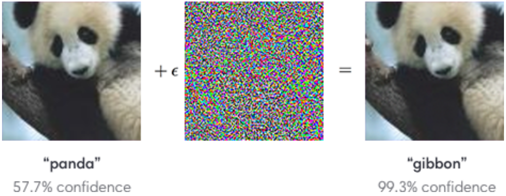

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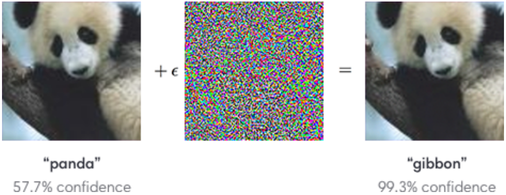

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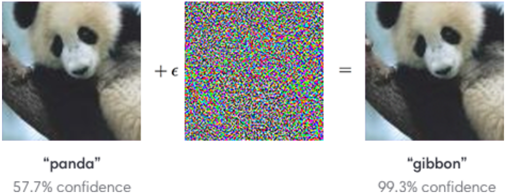

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(Global) Robustness

"small" perturbations don't alter outcome significantly *anywhere*

$$\forall x \in X.\ \forall \epsilon \in \text{Noise}.\ \mathcal{N}(x) \simeq \mathcal{N}(x + \epsilon)$$

Image Credit: Goodfellow et al. 2013.

Properties

Independence-based Fairness (CARE)

$$\forall l \in \mathcal{L}.\ P(Y = l|\mathcal{F}(s)) - P(Y = l|\mathcal{F} \neq s) \leq \epsilon$$

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$$VR(\rho) = P(\mathcal{N} \not\models \rho \mid x \in X) \leq \epsilon$$

ρ is a critical safety property.

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- Neuron Contribution Coverage (NCC): contribution of each edge on the value of a neuron activation value (DeepCon),

$$u^i_{h,j}(x) = w^i_{h,j} \cdot f_{i-1,h}(x) \qquad U^i_j(x) = \{u^i_{h,j}(x) \mid 0 \leq h \leq s_{i-i}\}$$

$$nu^i_{h,j} = \frac{u^i_{h,j}(x) - min(U^i_j(x))}{max(U^i_j(x)) - min(U^i_j(x))}$$

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- Using concolic execution, this coefficient can be assembled as:

$$C_{i,j} = \sum_{p \in paths(i,j)} \Big(\prod_{e \in edges(p)} w(e) \Big)$$

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- Attack generation: output of j^{th} neuron, $f_j(X) = B_j + \sum_{i=1}^{t} C_{j,i} \cdot X_i$, so attack constraint is:

$$\exists X. \ \wedge_{j=1, j \neq l'} f_j(X) < f_{l'}(X) \wedge PathCond$$

where $PC = \wedge_{j=1}^{A}(B_j + \sum_{i=1}^{t} C_{j,i} \cdot X_i \{\leq, >\} 0)$, A is the number of activation functions; the symbolic constraints can be limited to the important neurons for efficiency

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- Same AC with different DCs search all decisions with same activation

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- *activation pattern (ap)* of a test t, $ap[t]$, is a bitvector recording the activation state of all neurons; $ap[t](i)$ (or $ap[t]_{k_1,k_2}$) is the activation neuron for the i^{th} neuron (or k_2 neuron on k_1 layer) for test t

  Activation (Pattern)

- ap[t](i)$= W_i \cdot X[t] + B_i\{\leq, >\}0$ — Activation of a neuron

  W_i: incoming edge-wts. of neuron i, $X[t]$: input vector for test t

- AC: $\wedge_{i=0}^{|\mathcal{N}|} NeuronActivate(i)$ — Activation condition (AC)

- NN unfolded as a tree, each neuron is a prefix of the activation bitvector till that neuron — Activation Tree

  Keeps track of which activations have been seen.

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- Same AC with different DCs search all decisions with same activation

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    $X \in S(D, b)$ is any of the valid regions, o(x) is the output layer value corresponding to input x **Lipshitz coverage**
- Given coverage requirememts, $\mathcal{R}$, return test with highest score:

$$t = \underset{r}{argmax}\{val(t) \mid r \in \mathcal{R}\}$$

Probabilistic Symbolic Execution (SpaceScanner)

SpaceScanner

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Decision Probability

$$Pr(\mathcal{D}) = \sum_{\varphi \in AC \wedge DC} \int_x \mathbb{1}_{x \models \varphi} \cdot p(x) dx \tag{1}$$

$$= \sum_{\varphi \in AC \wedge DC} \frac{Vol(\phi \wedge s_i)}{s_i} \cdot \sum_x p(s_i) \tag{2}$$

Assuming that the input distribution is discretized into a histogram, $H : s_i \mapsto Pr(s_i)$ p(x) is the input distribution

Gradient-guided Optimization

DeepXplore

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- A deactivated neuron f_n is selected at random, and we attempt to activate it

Data-driven + Symbolic solvers

Solvers like Reluplex can effectively solve *local robustness* at x_0:

$$\exists_{x,x_0}.\ Symbolic[N](x) - \mathcal{N}(x_0) > \epsilon \wedge ||x - x_0|| \leq \delta$$

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- Reluplex like solvers work best when the check is restricted to small neighborhoods

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- Cluster the examples $\mathcal{E}$ via k-means: each cluster identifies a *region* characterized by a centroid (x_0), radius (r) and label (l);

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  - if a region size reduces to zero, $\mathcal{N}$ is non-robust

Metamorphic Testing

Metamorphic Testing (HOMRS)

Outline I

Outline II

Conclusion

Application and impact of these techniques, other works on verification, repair, interpretation, explanation,