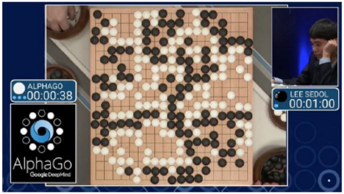
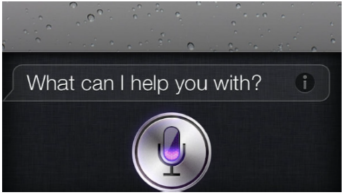
Testing Deep Neural Networks

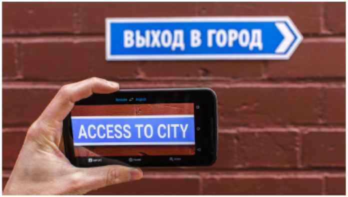
Xiaowei Huang, University of Liverpool

Outline

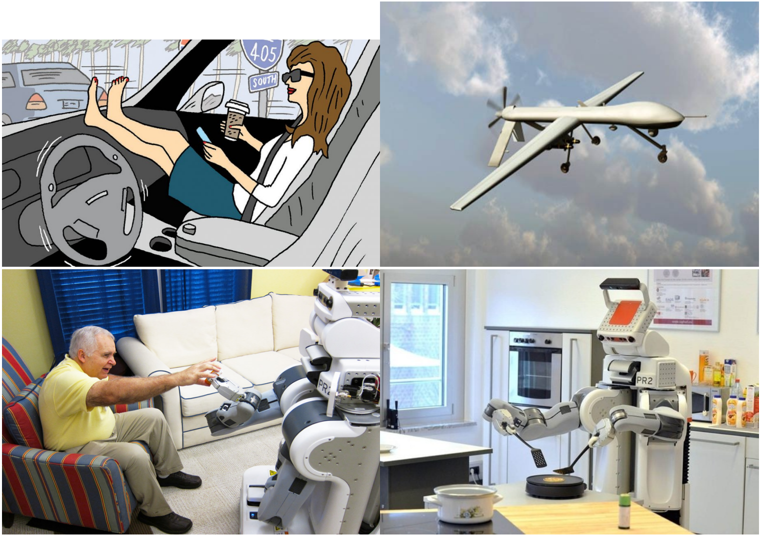
Human-Level Intelligence



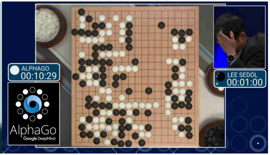




Robotics and Autonomous Systems



Deep neural networks



all implemented with

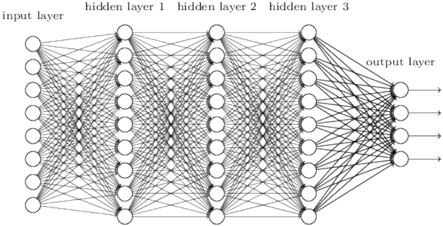


Figure: safety in image classification networks

MOTHERBOARD

TIFICIAL INTELLIGENCE

Researcher: 'We Should Be Worried' This Computer Thought a Turtle Was a Gun

Can a Machine Be Conscious?

Copyright Law Makes Artificial Intelligence Bias Worse

AI Can Be Fooled With One Misspelled Word

When artificial intelligence is dumb.

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Jordan Pearson
Apr 28 2017, 2:00pm

Figure: safety in natural language processing networks

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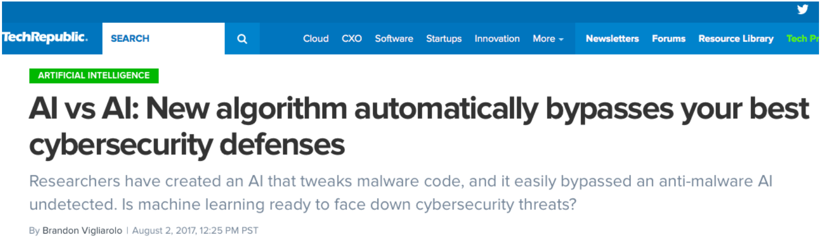
Security

Drowning Dalek commands Siri in voice-rec hack attack

Boffins embed barely-audible-to-humans commands inside vids to fool virtual assistants

By Darren Pauli 11 Jul 2016 at 07:48 40 SHARE ▼

Figure: safety in voice recognition networks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ARTIFICIAL INTELLIGENCE

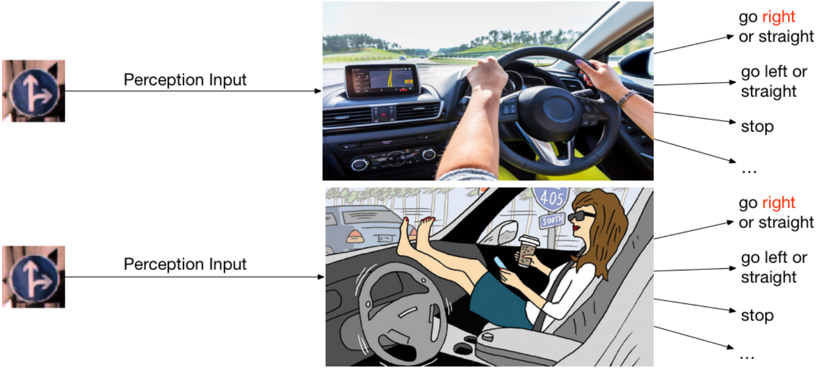
AI vs AI: New algorithm automatically bypasses your best cybersecurity defenses

Researchers have created an AI that tweaks malware code, and it easily bypassed an anti-malware AI undetected. Is machine learning ready to face down cybersecurity threats?

By Brandon Vigliarolo | August 2, 2017, 12:25 PM PST

Figure: safety in security systems

Safety Definition: Human Driving vs. Autonomous Driving



Traffic image from "The German Traffic Sign Recognition Benchmark"

Safety Definition: Human Driving vs. Autonomous Driving

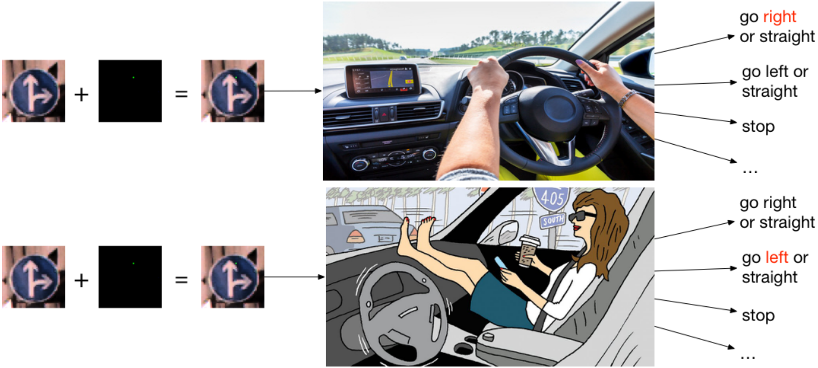
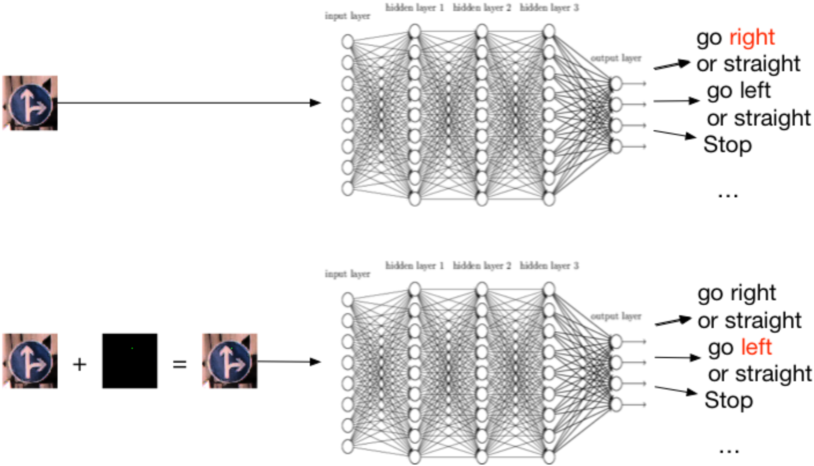


Image generated from our tool

Safety Problem: Incidents

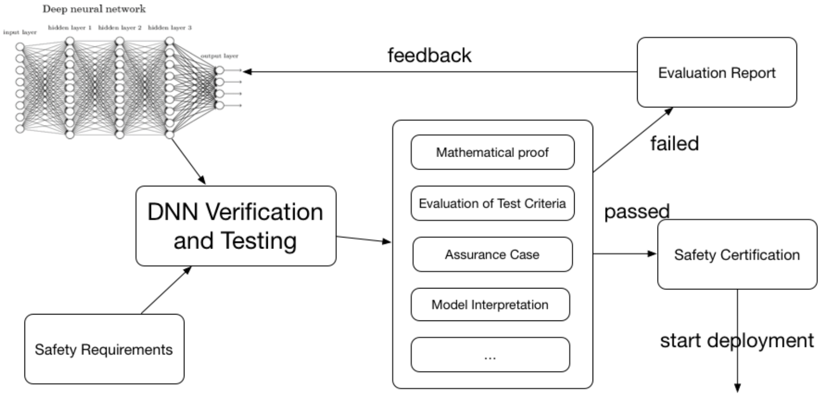
Safety Definition: Illustration



Safety Requirements

- Pointwise Robustness (this talk)
    - if the decision of a pair (input, network) is invariant with respect to the perturbation to the input.
- Network Robustness
- or more fundamentally, Lipschitz continuity, mutual information, etc
- model interpretability

Certification of DNN



https://github.com/TrustAI

Outline

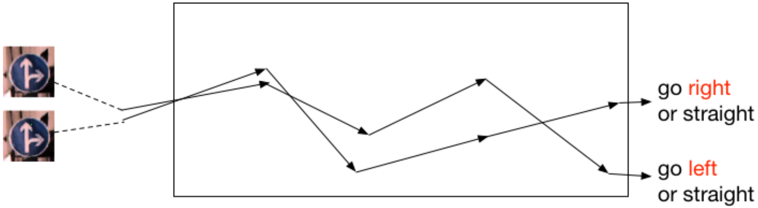
Safety Problem of AI

Verification (brief)

Testing

Conclusions and Future Works

Safety Definition: Traffic Sign Example

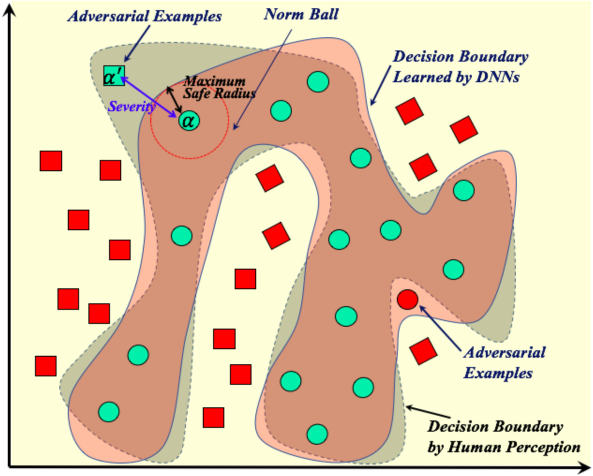


Maximum Safe Radius

Definition

The *maximum safe radius* problem is to compute the minimum distance from the original input α to an adversarial example, i.e.,

$$\mathtt{MSR}(\alpha) = \min_{\alpha' \in \mathrm{D}} \{ ||\alpha - \alpha'||_k \mid \alpha' \text{ is an adversarial example} \} \qquad (1)$$


Adversarial Examples
Norm Ball
Decision Boundary
Learned by DNNs
α′
Maximum
Safe Radius
Severity
α
Adversarial
Examples
Decision Boundary
by Human Perception

Existing Approaches

- layer-by-layer exhaustive search, see e.g., [2][1]
- SMT, MILP, SAT based constraint solving, see e.g., [3][2]
- global optimisation, see e.g., [6][3]
- abstract interpretation, see e.g., [1][4]

[1] *Huang*, Kwiatkowska, Wang, Wu, CAV2017
[2] Katz, Barrett, Dill, Julian, Kochenderfer, CAV2017
[3] Ruan, *Huang*, Kwiatkowska, IJCAI2018
[4] Gehr, Mirman, Drachsler-Cohen, Tsankov, Chaudhuri, Vechev, S&P2018

Outline

Safety Problem of AI

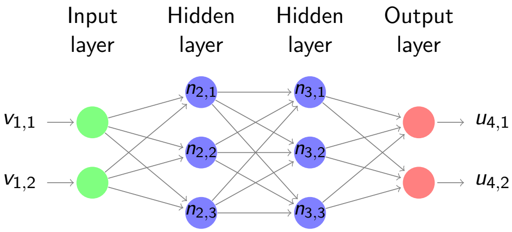
Verification (brief)

Testing

- Test Coverage Criteria
- Test Case Generation

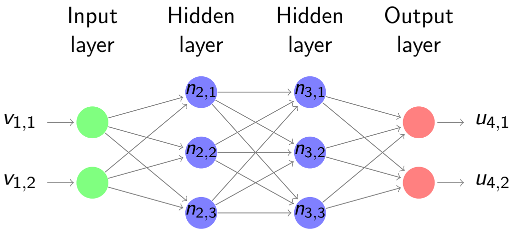
Conclusions and Future Works

Deep Neural Networks (DNNs)



$$label = \operatorname{argmax}_{1 \leq l \leq s_K} u_{K,l}$$

Deep Neural Networks (DNNs)



$$label = \operatorname{argmax}_{1 \le l \le s_K} u_{K,l}$$

1) neuron activation value

$$\mathbf{u_{k,i}} = b_{k,i} + \sum_{1 \le h \le s_{k-1}} w_{k-1,h,i} \cdot \mathbf{v_{k-1,h}}$$

weighted sum plus a bias;

w, b are parameters learned

2) rectified linear unit (ReLU):

$$\mathbf{v_{k,i}} = \max\{\mathbf{u_{k,i}}, 0\}$$

DNN as a program

```
...

// 1) neuron activation value
```

$u_{k,i} = b_{k,i}$

for (unsigned $h = 0$; $h \leq s_{k-1}$; $h \mathrel{+}= 1$)

{

$\quad u_{k,i} \mathrel{+}= w_{k-1,h,i} \cdot v_{k-1,h}$

}

$v_{k,i} = 0$

```
// 2) ReLU
```

if $(u_{k,i} > 0)$

{

$\quad v_{k,i} = u_{k,i}$

}

```
...
```

Testing Framework

- Test Coverage Criteria
- Test Case Generation

Examples of Test Coverage Criteria

- Neuron coverage [5][5]
- Neuron boundary coverage [4] [6]
- MC/DC for DNNs [8][7]
- Lipschitz continuity

[5] Pei, Cao, Yang, Jana, SOSP2017.
[6] Ma, Xu, Zhang, Sun, Xue, Li, Chen, Su, Li, Liu, Zhao, Wang, ASE2018
[7] Sun, *Huang*, Kroening, ASE2018

Neuron coverage

For any hidden neuron $n_{k,i}$, there exists test case $t \in \mathcal{T}$ such that the neuron $n_{k,i}$ is activated: $u_{k,i} > 0$.

Test coverage conditions:

$$\{\exists x. u[x]_{k,i} > 0 \mid 2 \leq k \leq K-1, 1 \leq i \leq s_k\}$$

Neuron coverage

For any hidden neuron $n_{k,i}$, there exists test case $t \in \mathcal{T}$ such that the neuron $n_{k,i}$ is activated: $u_{k,i} > 0$.

Test coverage conditions:

$$\{\exists x . u[x]_{k,i} > 0 \mid 2 \leq k \leq K-1, 1 \leq i \leq s_k\}$$

- $\approx$ statement (line) coverage

```
...

// 1) neuron activation value
u_{k,i} = b_{k,i}
for (unsigned h = 0; h <= s_{k-1}; h += 1)
{
    u_{k,i} += w_{k-1,h,i} · v_{k-1,h}
}

v_{k,i} = 0

// 2) ReLU
if (u_{k,i} > 0)
{
    v_{k,i} = u_{k,i}      ⇐ this line is covered
}

...
```

Neuron Coverage

Problem of neuron coverage:

- too easy to reach 100% coverage

MC/DC in Software Testing

Developed by NASA and has been widely adopted in e.g., avionics software development guidance to ensure adequate testing of applications with the highest criticality.

Idea: if a choice can be made, all the possible factors (conditions) that contribute to that choice (decision) must be tested.

For traditional software, both conditions and the decision are usually Boolean variables or Boolean expressions.

MC/DC Example

Example: the decision

$$d \iff ((a > 3) \vee (b = 0)) \wedge (c \neq 4) \tag{2}$$

contains the three conditions $(a > 3)$, $(b = 0)$ and $(c \neq 4)$.

The following two test cases provide 100% condition coverage (i.e., all possibilities of the conditions are exploited):

1. $(a > 3)$=True, $(b = 0)$=True, $(c \neq 4)$=True, $d = \mathit{True}$
2. $(a > 3)$=False, $(b = 0)$=False, $(c \neq 4)$=False, $d = \mathit{False}$

MC/DC Example

Example: the decision

$$d \iff ((a > 3) \vee (b = 0)) \wedge (c \neq 4) \tag{3}$$

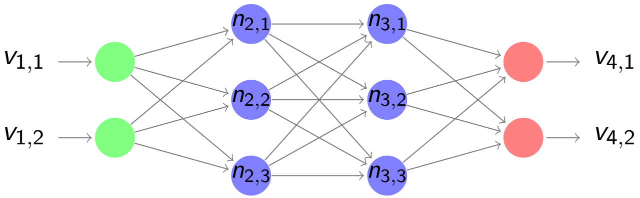
contains the three conditions $(a > 3)$, $(b = 0)$ and $(c \neq 4)$.

The following six test cases provide 100% MC/DC coverage:

1. $(a > 3)$=True, $(b = 0)$=True, $(c \neq 4)$=True, $d = \mathit{True}$
2. $(a > 3)$=False, $(b = 0)$=False, $(c \neq 4)$=False, $d = \mathit{False}$
3. $(a > 3)$=False, $(b = 0)$=False, $(c \neq 4)$=True, $d = \mathit{False}$
4. $(a > 3)$=False, $(b = 0)$=True, $(c \neq 4)$=True, $d = \mathit{True}$
5. $(a > 3)$=False, $(b = 0)$=True, $(c \neq 4)$=False, $d = \mathit{False}$
6. $(a > 3)$=True, $(b = 0)$=False, $(c \neq 4)$=True, $d = \mathit{True}$

MC/DC for DNNs – General Idea

The core idea of our criteria is to ensure that not only the presence of a feature needs to be tested but also the effects of less complex features on a more complex feature must be tested.

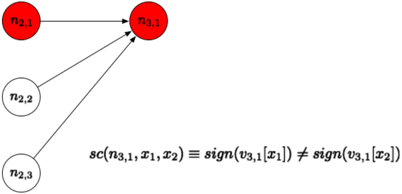


For example, check the impact of $n_{2,1}, n_{2,2}, n_{2,3}$ on $n_{3,1}$.

MC/DC for DNNs – Neuron Pair and Sign Change

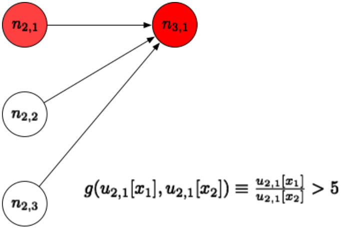
A neuron pair $(n_{k,i}, n_{k+1,j})$ are two neurons in adjacent layers k and $k+1$ such that $1 \leq k \leq K-1$, $1 \leq i \leq s_k$, and $1 \leq j \leq s_{k+1}$.

(Sign Change of a neuron) Given a neuron $n_{k,l}$ and two test cases x_1 and x_2, we say that the sign change of $n_{k,l}$ is exploited by x_1 and x_2, denoted as $sc(n_{k,l}, x_1, x_2)$, if $sign(v_{k,l}[x_1]) \neq sign(v_{k,l}[x_2])$.



MC/DC for DNNs – Value Change and Distance Change

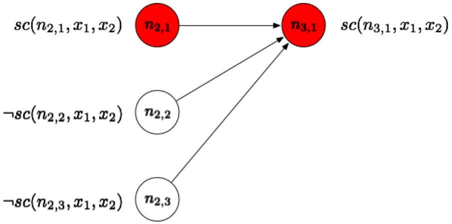
(Value Change of a neuron) Given a neuron $n_{k,l}$ and two test cases x_1 and x_2, we say that the value change of $n_{k,l}$ is exploited with respect to a value function g by x_1 and x_2, denoted as $vc(g, n_{k,l}, x_1, x_2)$, if $g(u_{k,l}[x_1], u_{k,l}[x_2])$=True .



MC/DC for DNNs – Sign-Sign Cover, or SS Cover

A neuron pair $\alpha = (n_{k,i}, n_{k+1,j})$ is SS-covered by two test cases x_1, x_2, denoted as $cov_{SS}(\alpha, x_1, x_2)$, if the following conditions are satisfied by the network instances $\mathcal{N}[x_1]$ and $\mathcal{N}[x_2]$:

- $sc(n_{k,i}, x_1, x_2)$;
- $\neg sc(n_{k,l}, x_1, x_2)$ for all $n_{k,l} \in P_k \setminus \{i\}$;
- $sc(n_{k+1,j}, x_1, x_2)$.



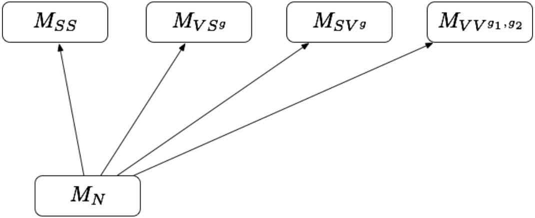
MC/DC for DNNs – Other Covering Methods

Value-Sign Cover, or VS Cover

Sign-Value Cover, or SV Cover

Value-Value Cover, or VV Cover

Relation



M_N denotes the neuron coverage metric

arrows represent "weaker than" relation between metrics

Activation pattern[8]

Activation Pattern

- Given a concrete input x, $\mathcal{N}[x]$ corresponds to a linear model $\mathcal{C}$
  - $\mathcal{C}$ represents the set of inputs following the same activation pattern
  - One DNN activation pattern corresponds to a program execution path
  - traverse of all activation patterns $\Rightarrow$ formal verification
  - too many patterns: e.g., $2^{>10,000}$...

[8] Sun, *Huang*, Kroening. "Testing Deep Neural Networks." (2018).

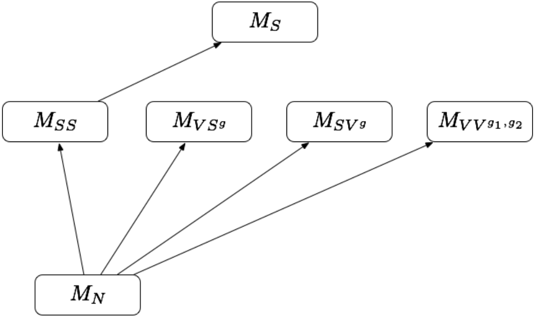
Safety Coverage [10][9]

Definition

Let each hyper-rectangle *rec* contains those inputs with the same pattern of ReLU, i.e., for all $x_1, x_2 \in rec$ we have $sign(n_{k,l}, x_1) = sign(n_{k,l}, x_2)$ for all $n_{k,l} \in \mathcal{H}(\mathcal{N})$.
A hyper-rectangle *rec* is safe covered by a test case x, denoted as $cov_S(rec, x)$, if $x \in rec$.

[9] Wicker, *Huang*, Kwiatkowska, TACAS2018

Relation



M_S denotes the safety coverage metric

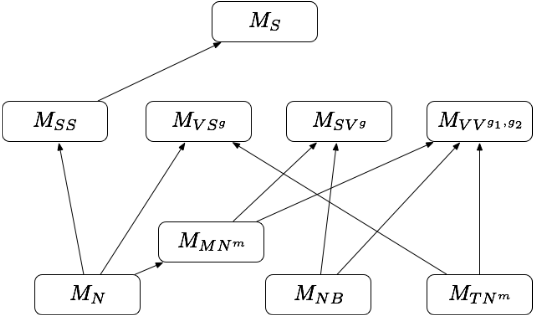
Safety Coverage

Problem of safety coverage:

- exponential number of hyper-rectangles to be covered

Therefore, our MC/DC based criteria strikes the balance between intensive testing and computational feasibility (justified by the experimental results).

Relation with a few other criteria from [4]



- M_{MN}: multi-section neuron coverage
- M_{NB}: neuron boundary coverage
- M_{TN}: top-k neuron coverage

What we can do?

- bug finding
- DNN safety statistics
- testing efficiency
- DNN internal structure analysis

Test Case Generation

- optimisation based (symbolic) approach
- concolic testing
- monte carlo tree based input mutation testing
-

Optimisation based symbolic approach

Formalising the searching of the next test case as an optimisation problem, which can then be solved by e.g.,

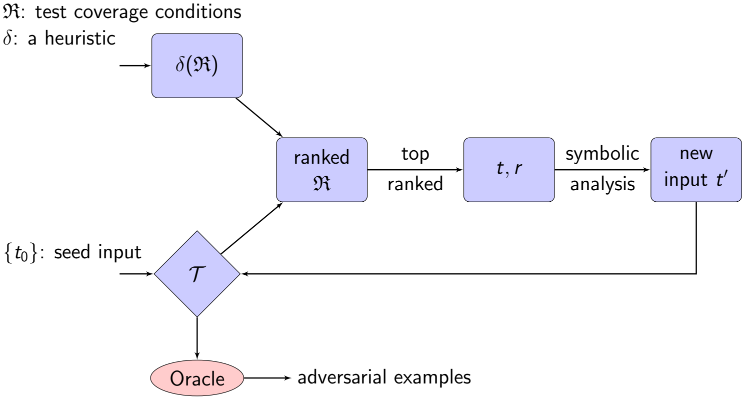
- Linear Programming (LP) based, see e.g., [8][10]
- Global Optimisation (GO) based, see e.g., [7][11]

[10] Sun, *Huang*, Kroening. Testing Deep Neural Networks. `https://arxiv.org/abs/1803.04792`

[11] Sun, Wu, Ruan, *Huang*, Kwiatkowska, Kroening, Global Robustness Evaluation of Deep Neural Networks with Provable Guarantees for L0 Norm. `http://cn.arxiv.org/abs/1805.00089`

Concolic approach [9][12]

Concolic testing: concrete execution + symbolic analysis



[12] Sun, Wu, Ruan, *Huang*, Kwiatkowska, Kroening, ASE2018

Concrete execution (neuron coverage)

- The t, r pair is chosen by concrete executions such that though the specified neuron is not activated by t, it should be really close to be activated.

Intuitively, to find the neuron that is closest to be activated

- E.g., $u_{k,i} = -1.0$ is ranked higher than $u_{k,j} = -100.0$

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```
...

// 1) neuron activation value
u_{k,i} = b_{k,i}
for (unsigned h = 0; h ≤ s_{k-1}; h += 1)
{
   u_{k,i} += w_{k-1,h,i} · v_{k-1,h}
}

v_{k,i} = 0

// 2) ReLU
if ( u_{k,i} > 0 ) ⇐ not satisfied
{
   v_{k,i} = u_{k,i}
}

...
```

- to select the branching point that is most likely to be satisfied

Symbolic execution (neuron coverage)

Given t, r, to find a new input t' s.t. r is satisfied.

$$\{u'_{k,i} > 0 \wedge \forall k_1 < k : \bigwedge_{0 \leq i_1 \leq s_{k_1}} ap'_{k_1,i_1} = ap[t]_{k_1,i_1}\}$$

Symbolic execution (neuron coverage)

Given t, r, to find a new input t' s.t. r is satisfied.

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$$\land \min ||t' - t||_p$$

Symbolic execution (neuron coverage)

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$$\wedge \min ||t' - t||_p \quad \Rightarrow \textbf{the symbolic engine}$$

Symbolic execution (neuron coverage)

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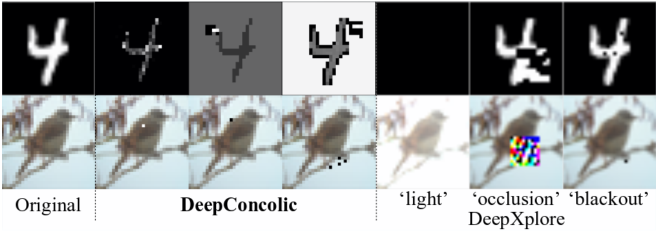
$$\wedge \min ||t' - t||_p \quad \Rightarrow \textbf{the symbolic engine}$$

- The CPLEX Linear Programming (LP) solver[13]
  - L^∞-norm: maximum difference among all pixels
- The global optimisation method [14]
  - L^0-norm: the number of pixels that have been changed

[13] Sun, Huang, Kroening. Testing Deep Neural Networks. `https://arxiv.org/abs/1803.04792`

[14] Sun, Wu, Ruan, *Huang*, Kwiatkowska, Kroening. Global Robustness Evaluation of Deep Neural Networks with Provable Guarantees for L0 Norm. `http://cn.arxiv.org/abs/1805.00089`

Comparison with DeepXplore



	DeepConcolic		DeepXplore		
	L_∞-norm	L_0-norm	light	occlusion	blackout
MNIST	97.89%	97.24%	80.5%	82.5%	81.6%
CIFAR-10	89.59%	99.69%	77.9%	86.8%	89.5%

Monte carlo tree search based test case generation [10][15]

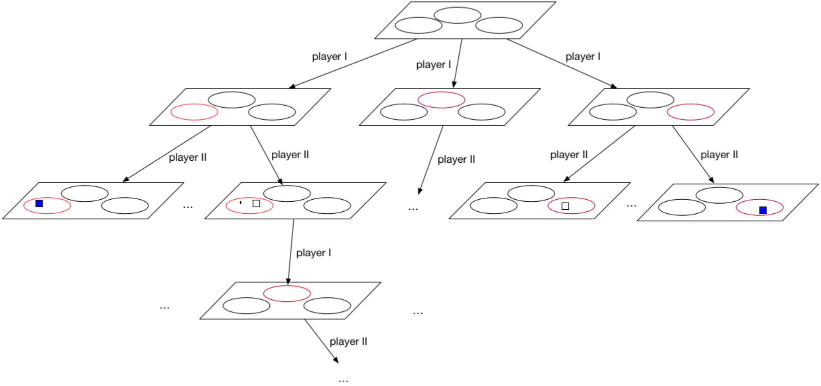
[15] Wicker, *Huang*, Kwiatkowska, TACAS2018

Pixel Manipulation

define pixel manipulations $\delta_{X,i} : \mathrm{D} \rightarrow \mathrm{D}$ for $X \subseteq P_0$ a subset of input dimensions and $i \in I$:

$$\delta_{X,i}(\alpha)(x, y, z) = \begin{cases} \alpha(x, y, z) + \tau, & \text{if } (x, y) \in X \text{ and } i = + \\ \alpha(x, y, z) - \tau, & \text{if } (x, y) \in X \text{ and } i = - \\ \alpha(x, y, z) & \text{otherwise} \end{cases}$$

Safety Testing as Two-Player Turn-based Game



Rewards under Strategy Profile $\sigma = (\sigma_1, \sigma_2)$

- For terminal nodes, $\rho \in Path_{\mathrm{I}}^{F}$,

$$R(\sigma, \rho) = \frac{1}{sev_{\alpha}(\alpha'_{\rho})}$$

  where $sev_{\alpha}(\alpha')$ is severity of an image α', comparing to the original image α
- For non-terminal nodes, simply compute the reward by applying suitable strategy σ_i on the rewards of the children nodes

Players' Objectives

The goal of the game is for player $\mathtt{I}$ to choose a strategy $\sigma_{\mathtt{I}}$ to maximise the reward $R((\sigma_{\mathtt{I}}, \sigma_{\mathtt{II}}), s_0)$ of the initial state s_0, based on the strategy $\sigma_{\mathtt{II}}$ of the player $\mathtt{II}$, i.e.,

$$\arg\max_{\sigma_{\mathtt{I}}} \mathtt{opt}_{\sigma_{\mathtt{II}}} R((\sigma_{\mathtt{I}}, \sigma_{\mathtt{II}}), s_0). \tag{4}$$

where option $\mathtt{opt}_{\sigma_{\mathtt{II}}}$ can be $\max_{\sigma_{\mathtt{II}}}$, $\min_{\sigma_{\mathtt{II}}}$, or $\mathtt{nat}_{\sigma_{\mathtt{II}}}$, according to which player $\mathtt{II}$ acts as a cooperator, an adversary, or nature who samples the distribution $\mathcal{G}(\Lambda(\alpha))$ for pixels and randomly chooses the manipulation instruction.

Outline

Safety Problem of AI

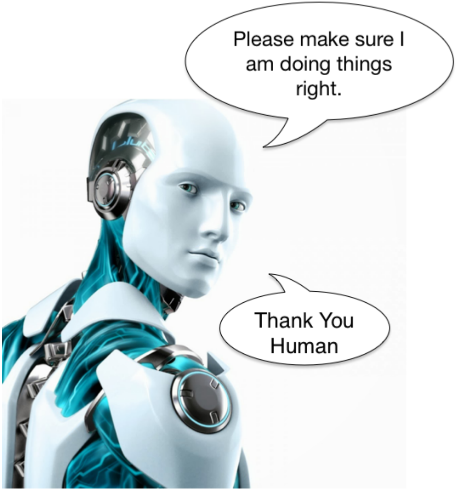
Verification (brief)

Testing

Conclusions and Future Works

Conclusions and Future Works

- Conclusions
  - Testing-DNNs is a one-year old baby.
  - It has attracted attentions from both the academia and the industry.
  - Both criteria and test case generation need further validations.
- Future Works
  - safety problems other than robustness
  - DNN specific criteria, to complement the existing ones which borrow ideas from traditional software engineering
  - more light-weight test case generation algorithms
  - ...


Please make sure I am doing things right.
Thank You Human

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