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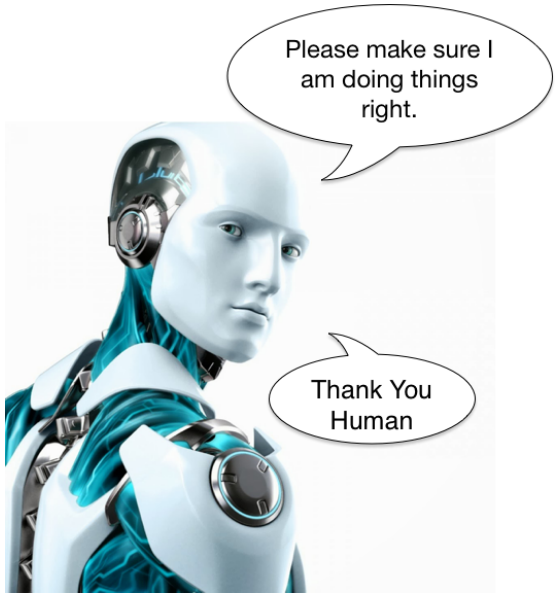
Deep Neural Networks: Verification



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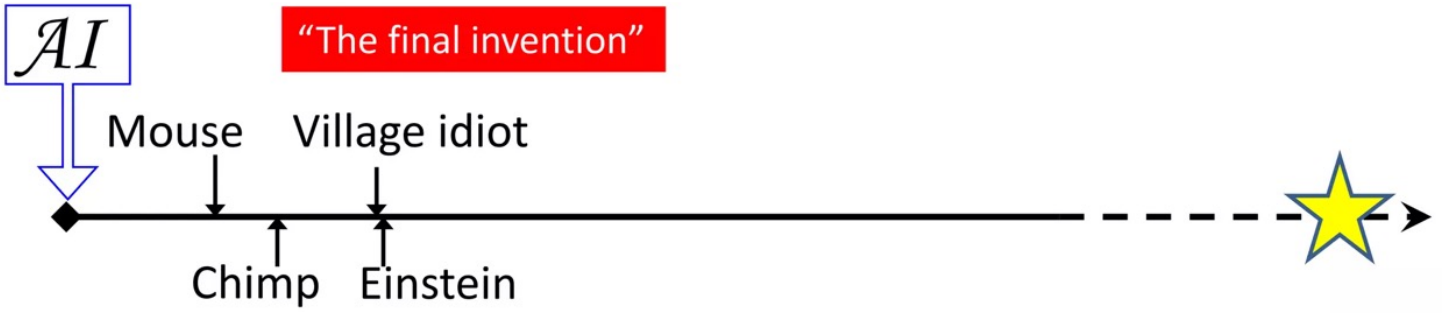
What is AI?

"Theorem-proving and equation-solving are by now so well established that they are hardly regarded as AI anymore."

— Superintelligence: Paths, Dangers, Strategies



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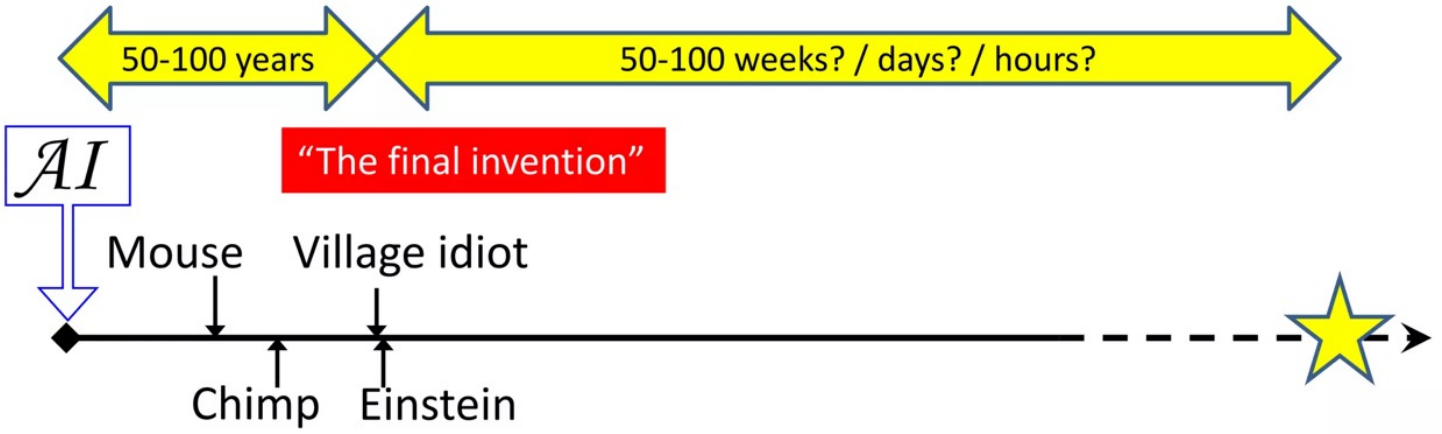

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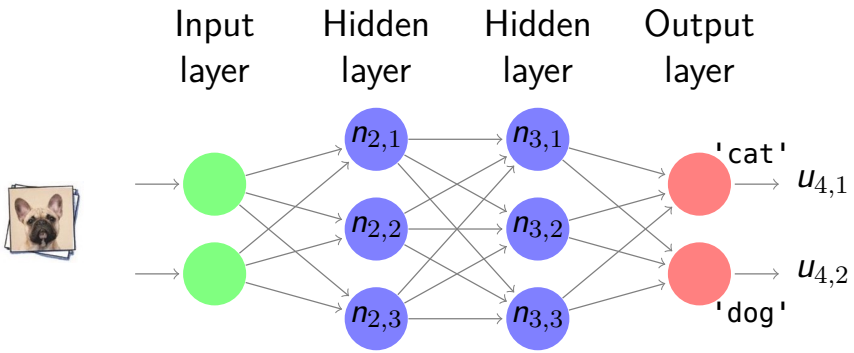
Deep Neural Networks (DNNs)



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

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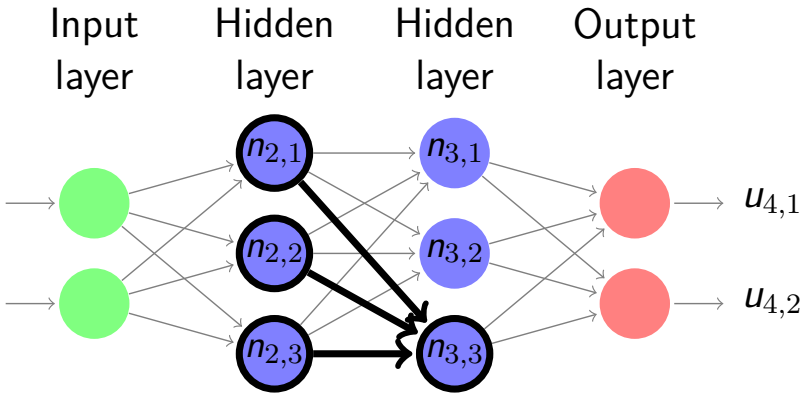
Deep Neural Networks (DNNs)



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

1) neuron activation value

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

weighted sum plus a bias;

w,b are parameters learned

2) rectified linear unit (ReLU):

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

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The Good, Bad and the Ugly

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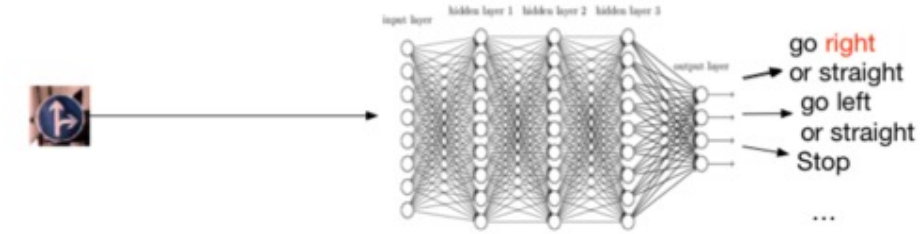
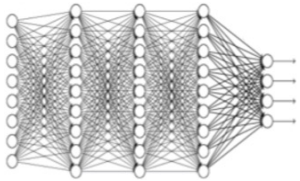
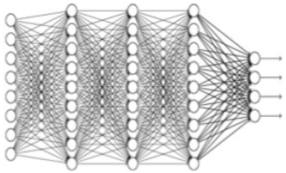
The Good





'red panda'



‘11-45-G’

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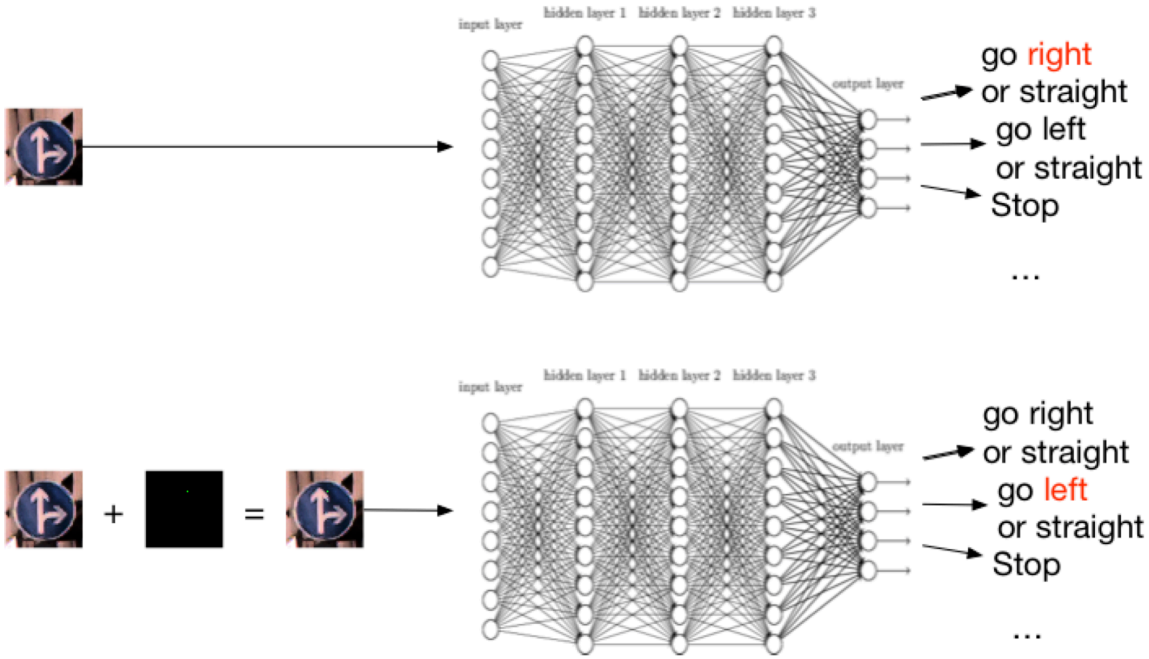
Adversarial Examples



- An adversarial example refers to specially crafted input which is designed to look "normal" to humans but causes misclassification to a machine learning model.

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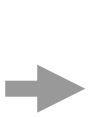
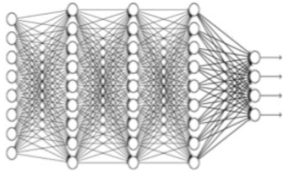
Backdoor

- Performant models, with backdoors that produce inference errors when presented with input containing a trigger defined by the adversary

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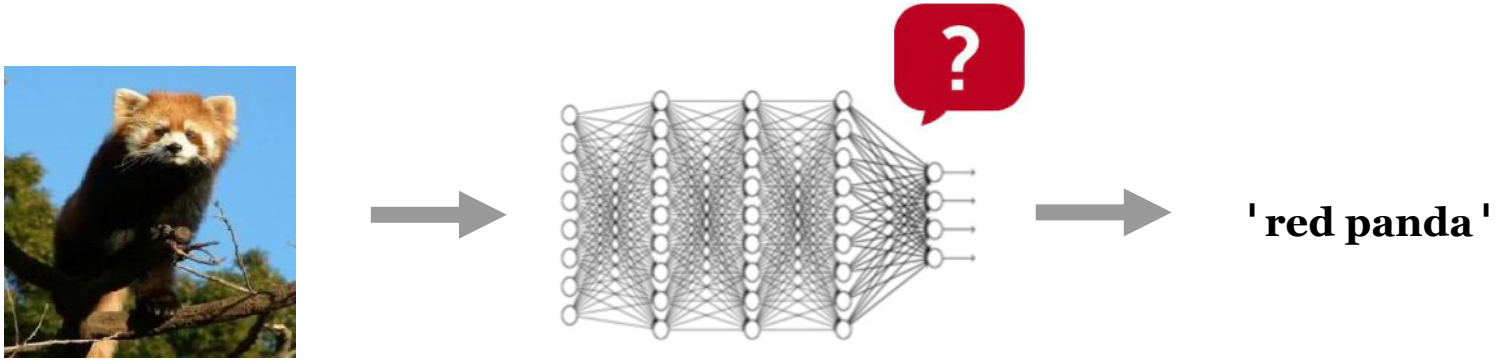
Explainability



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Security in DNNs

- How to verify that a DNN is robust enough to adversarial examples?
- How to verify that a DNN is free of backdoor?
- How to explain a DNN?

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Adversarial Robustness

- Let ***N*** be a neural network and ***N(x)*** be the prediction on an input **x**.
- Given a neural The neural network is said to be adversarial robust, subject to a perturbation upper bound ***r***, if for any ***0<δ<=r***:

$$N(x+\delta) = N(x)$$

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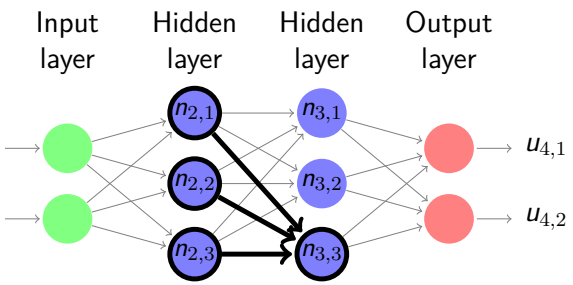
ESBMC

DNN as a program



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1) neuron activation value

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

weighted sum plus a bias;

w,b are parameters learned

2) rectified linear unit (ReLU):

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

```
...

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

double v_{k,i} = 0;

// 2) ReLU
if (u_{k,i} > 0)
{
    v_{k,i} = u_{k,i};
}

...
```

https://github.com/theyoucheng/DLTT

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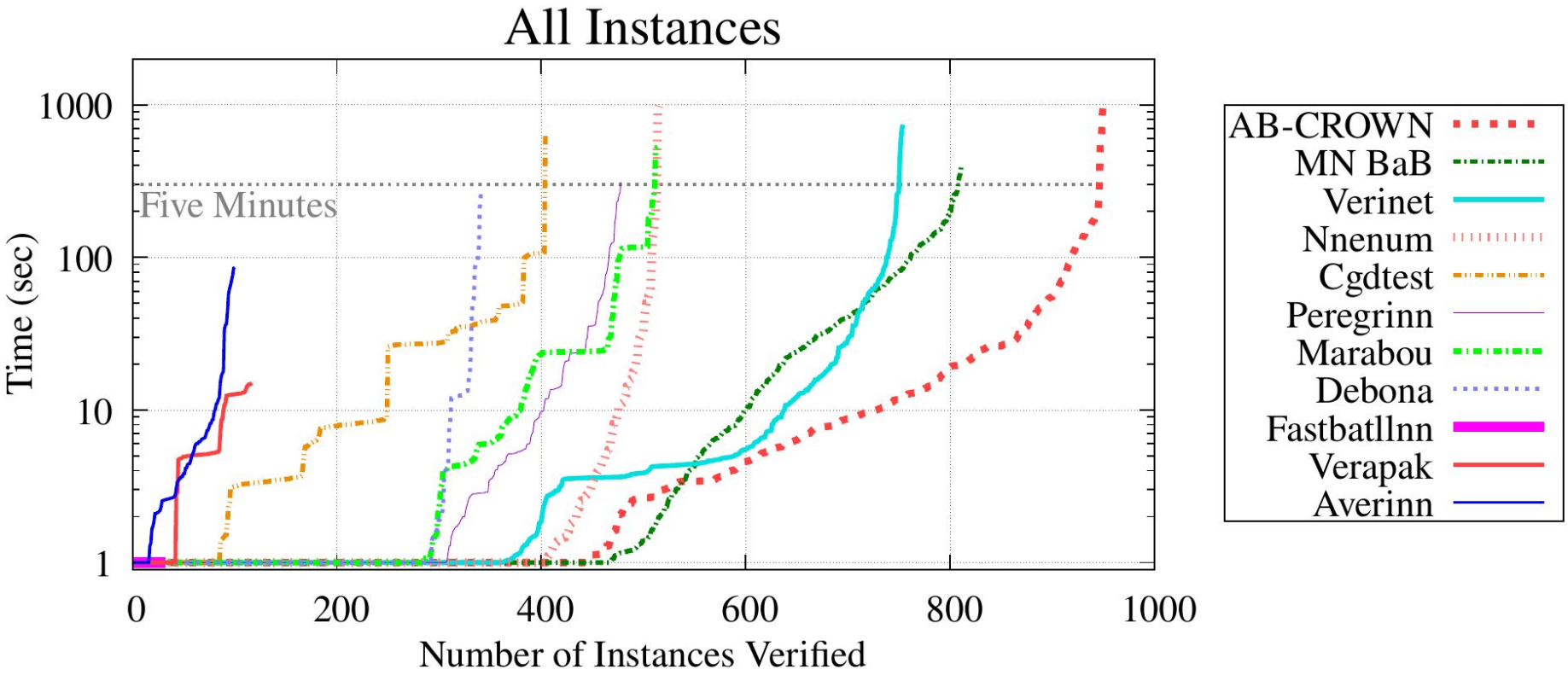
VNN-COMP: Verification of Neural Networks Competition



https://sites.google.com/view/vnn2022

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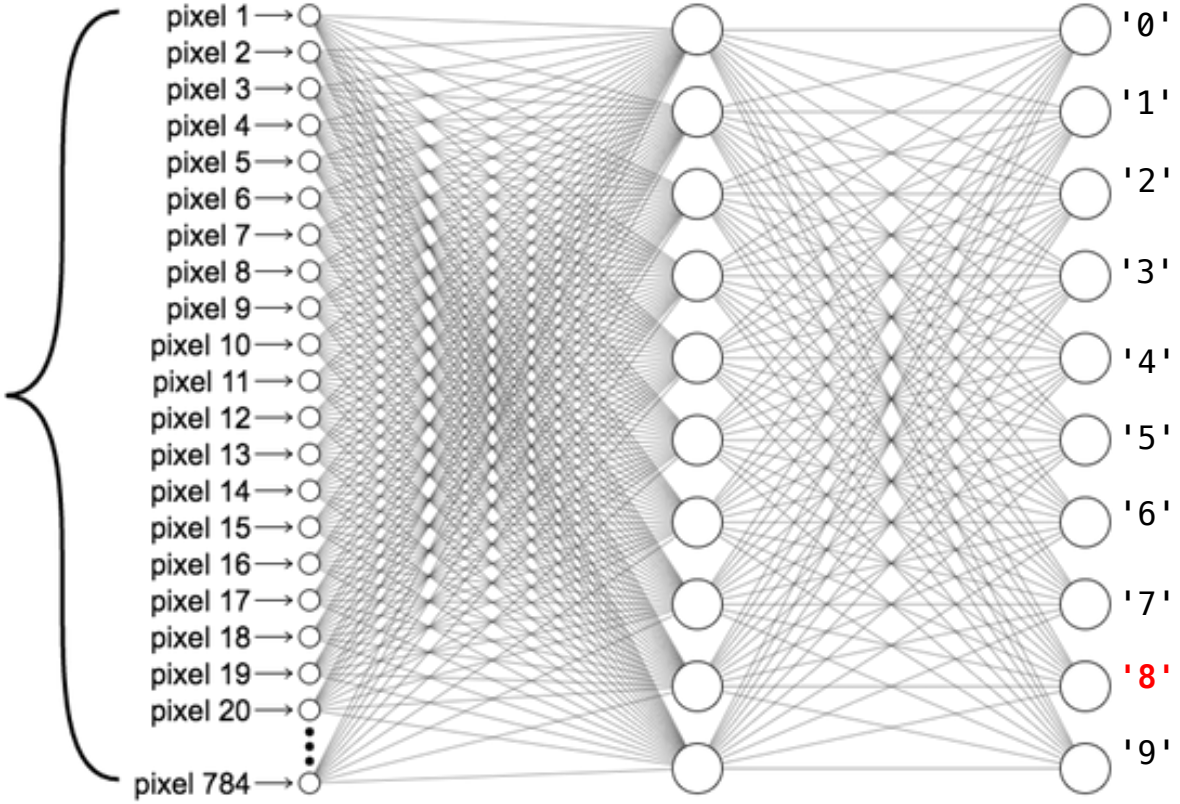
'8' -> '5'

MNIST



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References

- Sun, Youcheng, Min Wu, Wenjie Ruan, Xiaowei Huang, Marta Kwiatkowska, and Daniel Kroening. "Concolic testing for deep neural networks." Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering. 2018.

- Sun, Youcheng, Muhammad Usman, Divya Gopinath, and Corina S. Păsăreanu. "VPN: Verification of Poisoning in Neural Networks." In Software Verification and Formal Methods for ML-Enabled Autonomous Systems: 5th International Workshop (FoMLAS), 2022.

- Sun, Youcheng, Hana Chockler, Xiaowei Huang, and Daniel Kroening. "Explaining image classifiers using statistical fault localization." In European Conference on Computer Vision (ECCV) 2020

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Deep Neural Networks: Explanation

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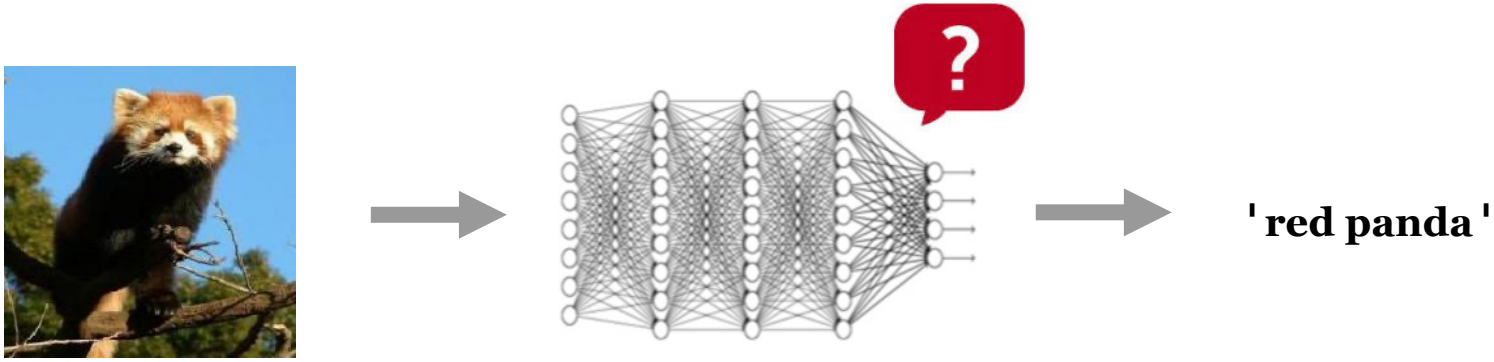
Why



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Software fault localisation

```
int main() {
  int input1, input2, input3; // C1
  int least = input1;
  int most = input1;

  if (most < input2)
    most = input2; // C2

  if (most < input3)
    most = input3; // C3

  if (least > input2)
    most = input2; // C4 (bug)

  if (least > input3)
    least = input3; // C5

  assert(least <= most);
}
```

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Software fault localisation

```
int main() {
  int input1, input2, input3; // C1
  int least = input1;
  int most = input1;

                              // C2

  if (most < input3)
    most = input3; // C3

  if (least > input2)
    most = input2; // C4 (bug)

                              // C5

  assert(least <= most);
}
```

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**

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```
int main() {
  int input1, input2, input3; // C1
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  int most = input1;

                              // C2

                              // C3

  if (least > input2)
    most = input2; // C4 (bug)

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    least = input3; // C5

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200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**

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  int most = input1;
                              // C2
                              // C3
                              // C4 (bug)
  if (least > input3)
    least = input3; // C5
  assert(least <= most);
}
```

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**

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int main() {
  int input1, input2, input3; // C1
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    most = input2; // C2

  [redacted]

  [redacted] (bug)

  [redacted]

  assert(least <= most);
}
```

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**

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int main() {
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  int most = input1;

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    most = input2; // C2

  [redacted]

  [redacted] (bug)

  [redacted]

  assert(least <= most);
}
```

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

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Spectrum

- $\langle a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf} \rangle$

To count the number of times the statement *s* is executed (e) or not executed (n) on passing (p) and on failing (f) tests.

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

a^s_{ep} is the number of tests that passed and executed s

$$a^{C2}_{ep} = 1$$
$$a^{C3}_{ep} = 0$$
$$a^{C4}_{ep} = 0$$
$$a^{C5}_{ep} = 1$$

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input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

a^s_{ef} is the number of tests that failed and executed s

$a^{C2}_{ef} = ?$
$a^{C3}_{ef} = ?$
$a^{C4}_{ef} = ?$
$a^{C5}_{ef} = ?$

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Spectrum

- $\langle a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf} \rangle$

To count the number of times the statement *s* is executed (e) or not executed (n) on passing (p) and on failing (f) tests.

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

a^s_{ef} is the number of tests that failed and executed s

$a^{C2}_{ef} = 0$
$a^{C3}_{ef} = 1$
$a^{C4}_{ef} = 2$
$a^{C5}_{ef} = 1$

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Spectrum

- $\langle a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf} \rangle$

To count the number of times the statement *s* is executed (e) or not executed (n) on passing (p) and on failing (f) tests.

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

a^s_{np} is the number of tests that passed and not executed s

$$a^{C2}_{np} = 1$$
$$a^{C3}_{np} = 2$$
$$a^{C4}_{np} = 2$$
$$a^{C5}_{np} = 1$$

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Spectrum

- $\langle a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf} \rangle$

To count the number of times the statement *s* is executed (e) or not executed (n) on passing (p) and on failing (f) tests.

input1	input2	input3	C2	C3	C4	C5	Assert
200	100	300	**0**	**1**	**1**	**0**	**False**
300	100	200	**0**	**0**	**1**	**1**	**False**
300	300	200	**0**	**0**	**0**	**1**	**True**
100	300	200	**1**	**0**	**0**	**0**	**True**
…							

a^s_{nf} is the number of tests that failed and not executed s

$$a^{C2}_{nf} = 2$$
$$a^{C3}_{nf} = 1$$
$$a^{C4}_{nf} = 0$$
$$a^{C5}_{nf} = 1$$

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Measures

- Spectra

$<a^{C2}_{ep} = 1, a^{C2}_{ef} = 0, a^{C2}_{np} = 1, a^{C2}_{nf} = 2>$

$<a^{C3}_{ep} = 0, a^{C3}_{ef} = 1, a^{C3}_{np} = 2, a^{C3}_{nf} = 1>$

$<a^{C4}_{ep} = 0, a^{C4}_{ef} = 2, a^{C4}_{np} = 2, a^{C4}_{nf} = 0>$

$<a^{C5}_{ep} = 1, a^{C5}_{ef} = 1, a^{C5}_{np} = 1, a^{C5}_{nf} = 1>$

- Spectra based measures

Ochiai: $\frac{a^s_{ef}}{a^s_{ef} + a^s_{nf} + a^s_{ep} + \frac{10000 a^s_{ef} a^s_{ep}}{a^s_{ef}}}$

Zoltar: $\frac{a^s_{ef}}{\sqrt{(a^s_{ef} + a^s_{nf})(a^s_{ef} + a^s_{ep})}}$

Tarantula: $\frac{\frac{a^s_{ef}}{a^s_{ef}+a^s_{nf}}}{\frac{a^s_{ef}}{a^s_{ef}+a^s_{nf}} + \frac{a^s_{ep}}{a^s_{ep}+a^s_{np}}}$

Wong-II: $a^s_{ef} - a^s_{ep}$

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Ranking

Program statements	Suspicious scores (Wong-II)
C4	2
C3	1
C5	0
C2	-1

- To debug from higher ranked, more suspicious program statements
- Different measures may return different ranking
  - Ochiai: C4 (1.0), C3 (0.5), C5 (0.001), C2 (0.0)
  - No single best measure
- We only use 4 test cases …

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How to explain an image classifier?

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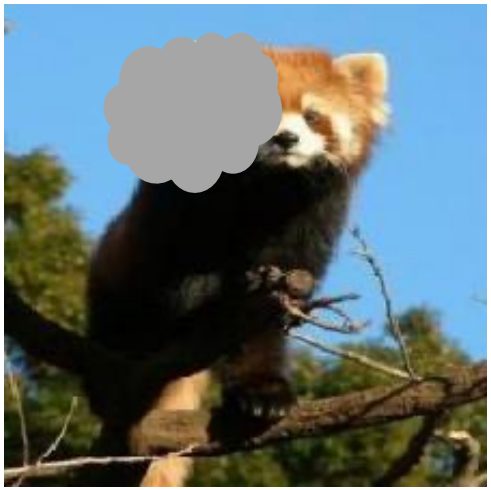
How to explain an image classifier?



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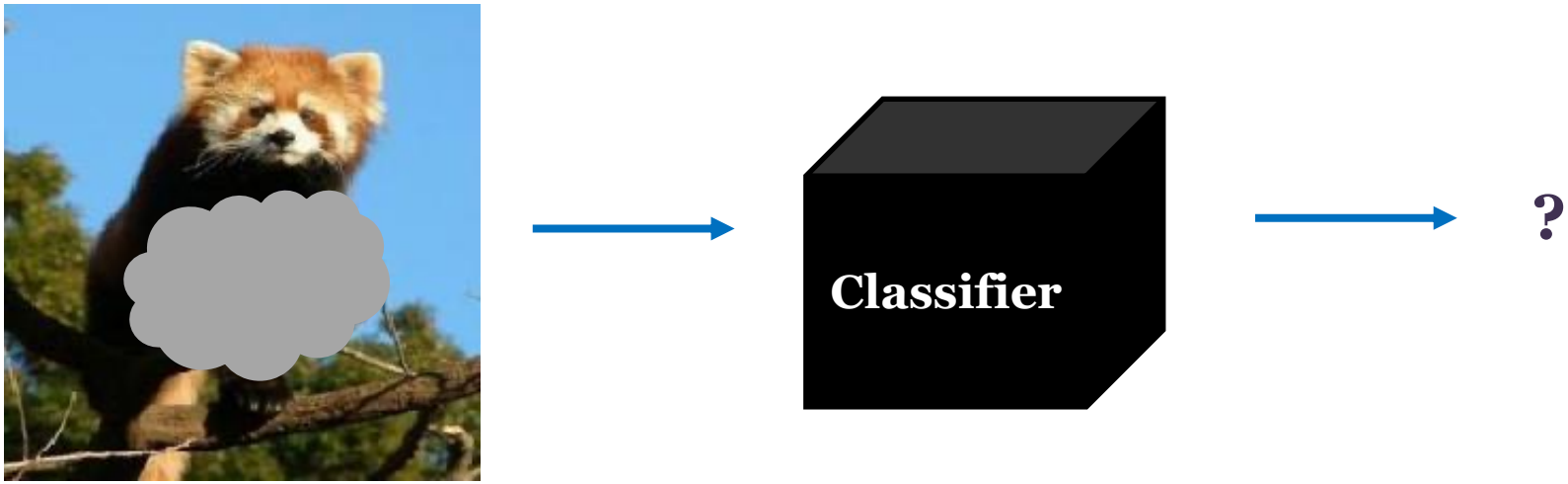
How to explain an image classifier?



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How to explain an image classifier?

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Statistical measures for explanations

- $\langle a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf} \rangle$

To count the number of times the pixel s is not masked (e) or masked (n) when the classifier's decision does not change (p) and does change (f).

E.g., a^s_{ep} is the number of mutants (i.e., masked inputs) in labeled as 'red panda' in which s is not masked

- Software fault localisation measures can now be applied

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Explaining image classifiers

- Rank list of pixels of the input image
- Synthesize the explanation following the pixel ranking (from high to low)
    - (Definition) An explanation in image classification is a minimal subset of pixels of a given input image that is sufficient for the DNN to classify the image

original image

vs

explanation

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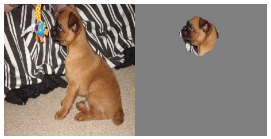
Explaining Google's Xception


'cowboy hat'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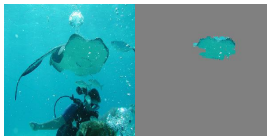
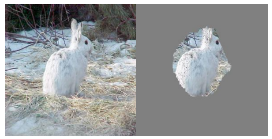
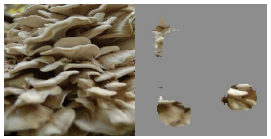

'numbfish'

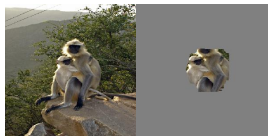

'sheep'


'hare'


'mushroom'


'wool'


'turnstile'

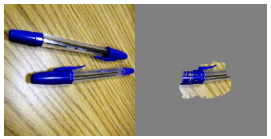

'langur'


'whistle'


'unicycle'


'fire engine'


'traffic light'


'ballpoint'


'bolo tie'


'projector'

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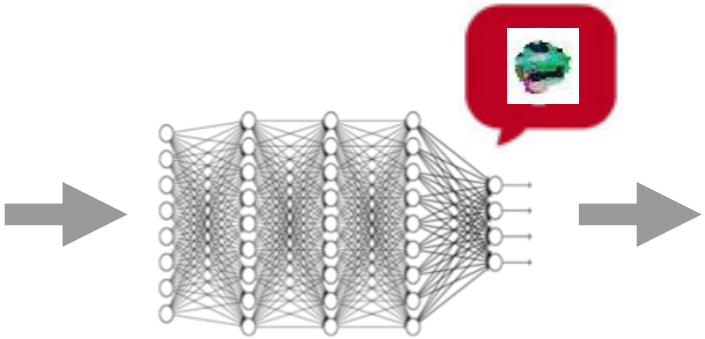
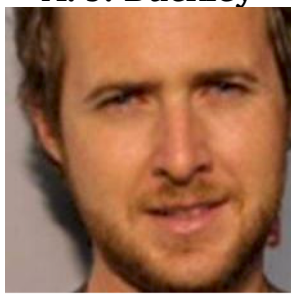
Explanation for identifying backdoor



‘A. J. Buckley’



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References

- Sun, Youcheng, Hana Chockler, Xiaowei Huang, and Daniel Kroening. "Explaining image classifiers using statistical fault localization." In European Conference on Computer Vision (ECCV) 2020

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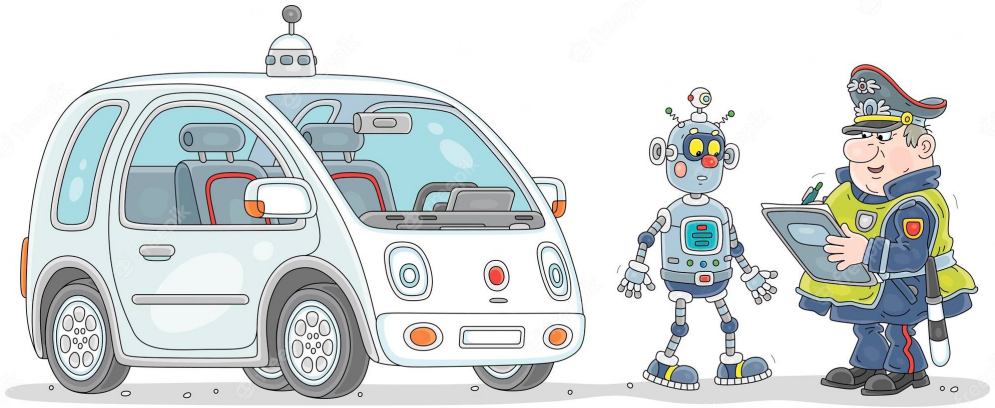
Deep Neural Networks: Testing



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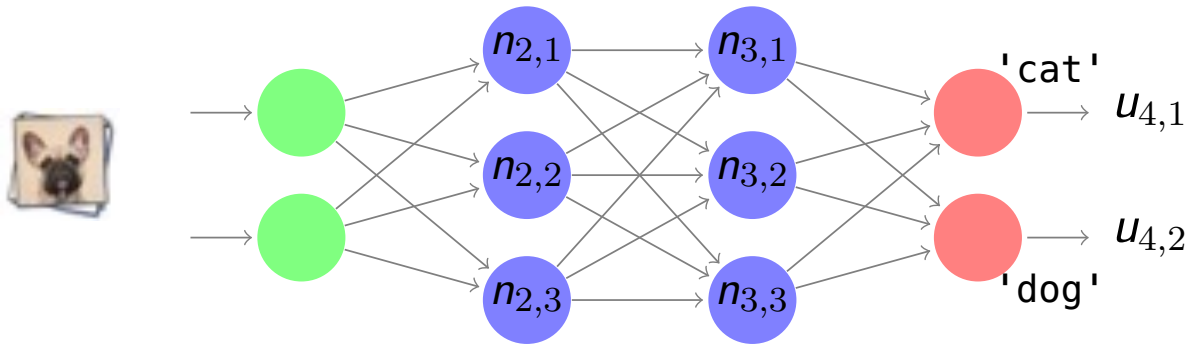
Testing DNNs



- How much testing?
  - What's the stop condition?

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Coverage criteria

- Neuron coverage
- Neuron boundary coverage
- MC/DC for DNNs
- …

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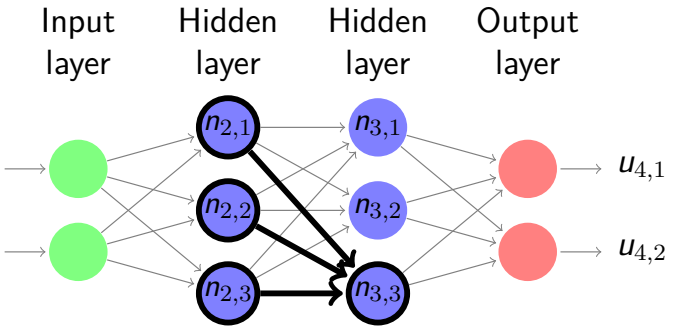
Neuron coverage (NC)

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



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

Test coverage conditions:

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

1) neuron activation value

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

weighted sum plus a bias;

w,b are parameters learned

2) rectified linear unit (ReLU):

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

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Neuron coverage

For any hidden neuron $n_{k,i}$, there exists a 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
double u_{k,i} = b_{k,i};
for (unsigned h = 1; h ≤ s_{k−1}; h += 1)
{
  u_{k,i} += w_{k−1,h,i} * v_{k−1,h};
}

double v_{k,i} = 0;

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

...
```

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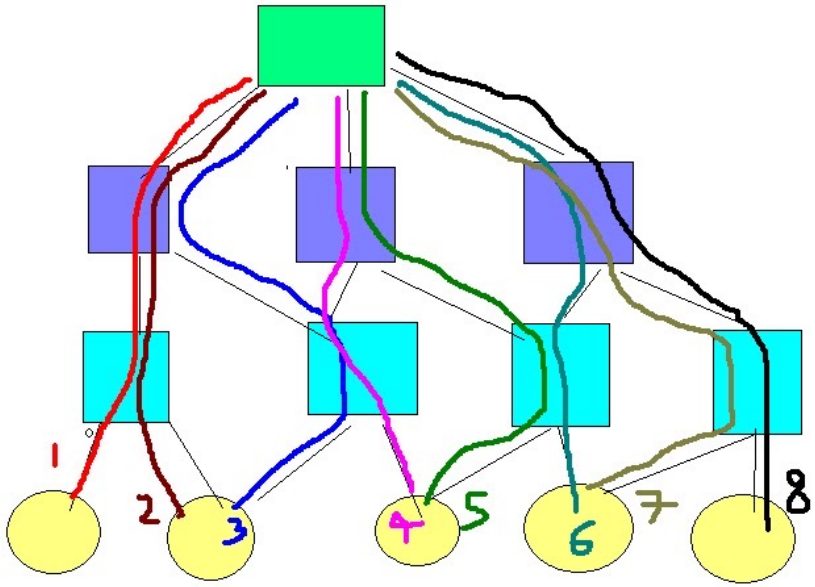
- Neuron boundary coverage

```
...

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

double v_{k,i} = 0;

// 2) ReLU
if (u_{k,i} > 0)
{
  v_{k,i} = u_{k,i};
}

...
```

boundary values of $u_{k,i}$?

⇐ this line is covered

- All program execution paths?



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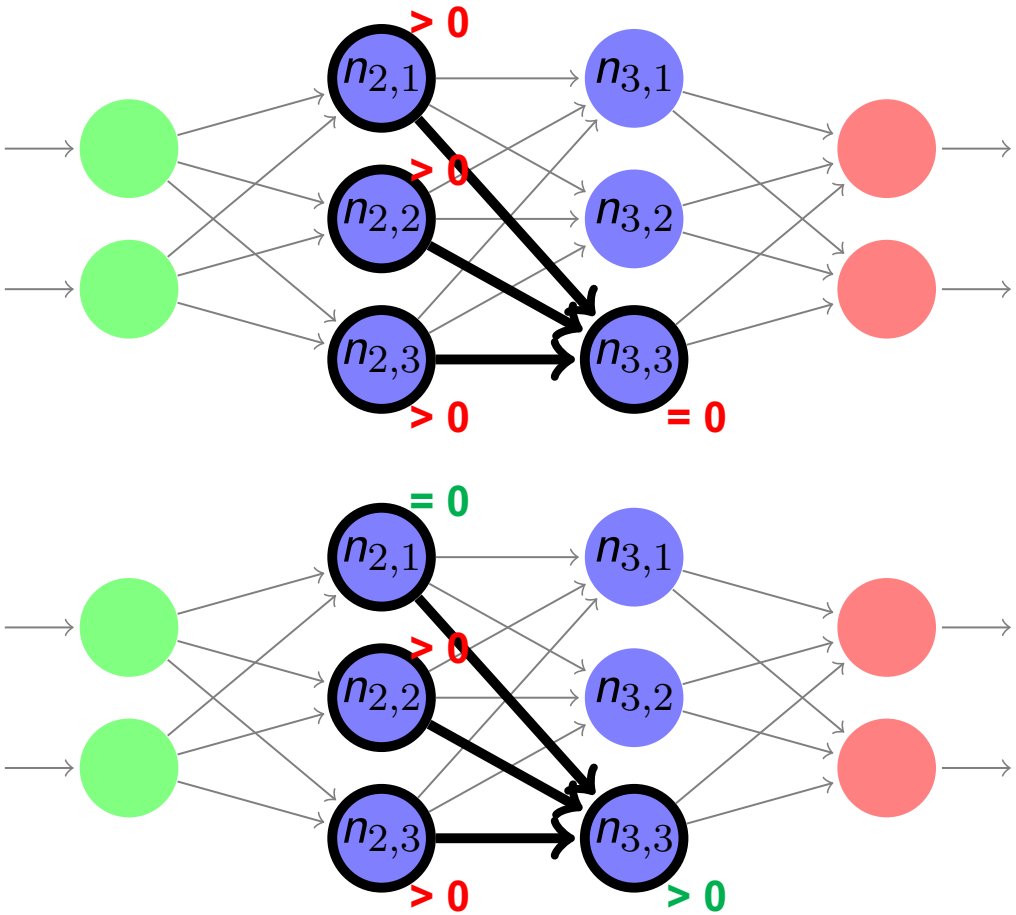
MC/DC for DNNs



Decision neuron: $n_{3,3}$

Condition neuron(s): $n_{2,1}$ $n_{2,2}$ $n_{2,3}$

A family of criteria

- Sign-Sign Cover (SSC)
- Value-Sign Cover (VSC)
- Sign-Value Cover (SVC)
- Value-Value Cover (VVC)

Neurons → features

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Measuring coverage

```
Total number of tests in test set: 10000

COVERAGE REPORT:
 10%|▮▯                                                                  | 993/10000 [00:10<01:36, 93.31it/s]
Current coverages (~1000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [24.71, 78.55, 0.07, 0.13, 56.52]
 20%|▮▮▯                                                                | 1992/10000 [00:20<01:26, 92.24it/s]
Current coverages (~2000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [34.34, 80.0, 0.2, 0.26, 57.97]
 30%|▮▮▮▯                                                               | 2996/10000 [00:29<01:03, 109.47it/s]
Current coverages (~3000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [39.91, 80.43, 0.2, 0.26, 58.7]
 40%|▮▮▮▮▯                                                              | 3990/10000 [00:39<00:53, 112.20it/s]
Current coverages (~4000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [43.5, 80.87, 0.26, 0.4, 58.7]
 50%|▮▮▮▮▮▯                                                             | 4992/10000 [00:50<00:49, 100.93it/s]
Current coverages (~5000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [46.33, 80.94, 0.36, 0.59, 58.7]
 60%|▮▮▮▮▮▮                                                             | 5993/10000 [01:00<00:36, 111.15it/s]
Current coverages (~6000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [48.57, 81.16, 0.46, 0.79, 59.42]
 70%|▮▮▮▮▮▮▮▯                                                           | 6991/10000 [01:11<00:33, 91.02it/s]
Current coverages (~7000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [50.46, 81.3, 0.49, 0.86, 59.42]
 80%|▮▮▮▮▮▮▮▮                                                           | 7995/10000 [01:22<00:22, 90.26it/s]
Current coverages (~8000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [51.9, 81.45, 0.56, 0.92, 59.42]
 90%|▮▮▮▮▮▮▮▮▮▯                                                         | 8998/10000 [01:34<00:13, 74.10it/s]
Current coverages (~9000 test images): [KMNC %, TKNC %, NBC %, SNAC %, NC %] = [53.21, 81.52, 0.59, 0.99, 59.42]
100%|▮▮▮▮▮▮▮▮▮▮                                                         | 10000/10000 [01:46<00:00, 93.88it/s]

FINAL COVERAGES:
k-Multisection Neuron Coverage (k: 1000) = 54.33%
Top-k Neuron Coverage (k: 10) = 81.59%
Neuron Boundary Coverage = 0.66%
Strong Neuron Activation Coverage = 1.05%
Neuron Coverage (threshold: 0.75) = 59.42%
```

https://github.com/DNNCov/DNNCov

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Tests generation

```
...

// 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}
}

...
```

What if not satisfied?

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References

- Sun, Youcheng, Min Wu, Wenjie Ruan, Xiaowei Huang, Marta Kwiatkowska, and Daniel Kroening. "Concolic testing for deep neural networks." Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering. 2018.