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Deep Neural Networks: Verification

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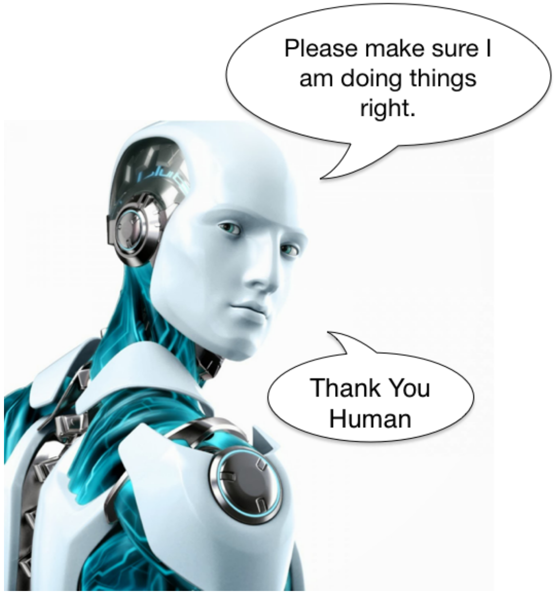

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What is AI?

"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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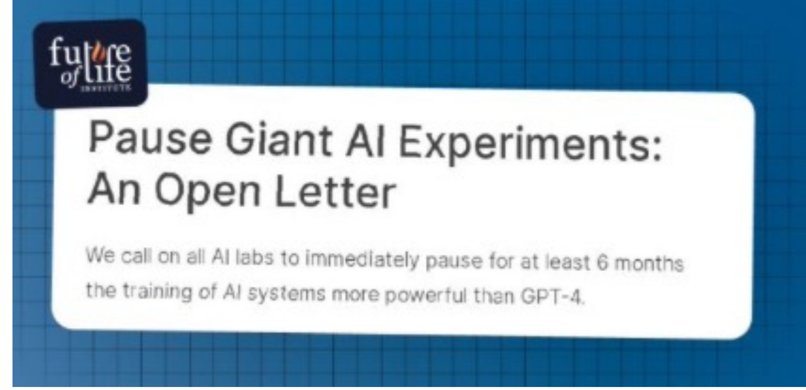

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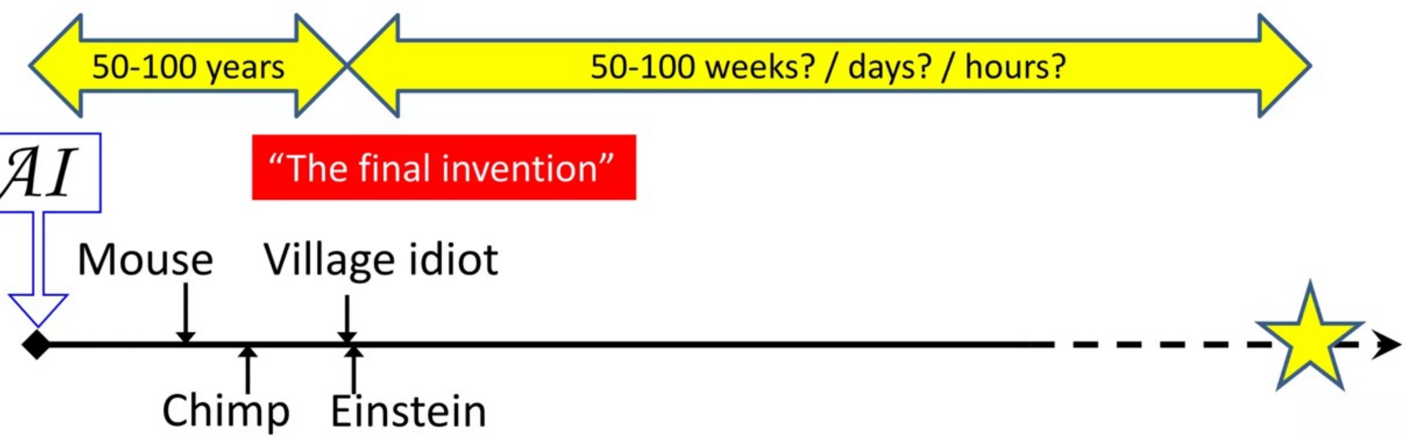
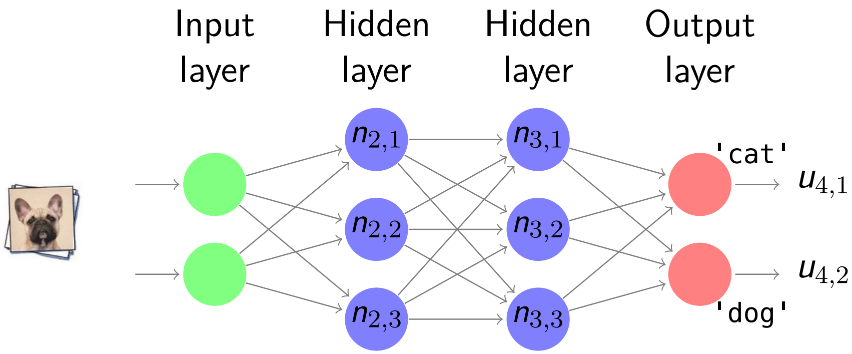


Deep Neural Networks (DNNs)



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

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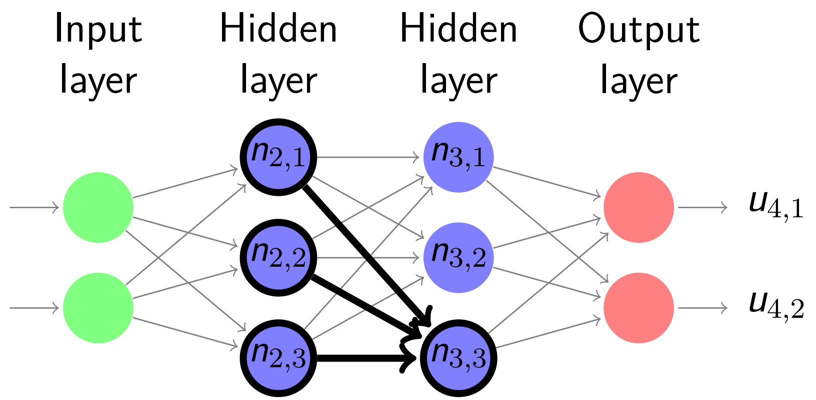
Deep Neural Networks (DNNs)



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

1) neuron activation value

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

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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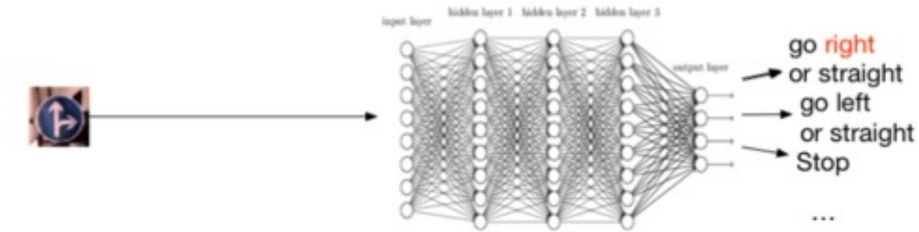
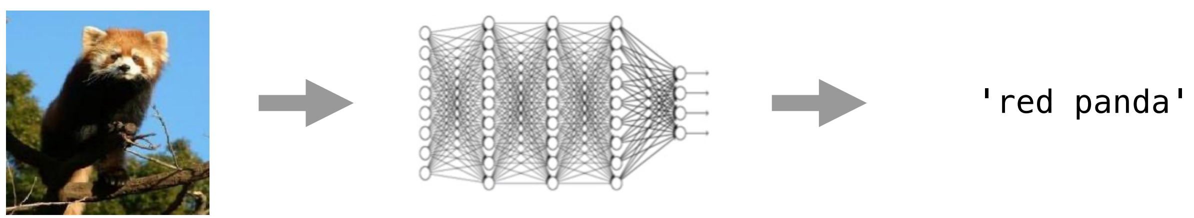
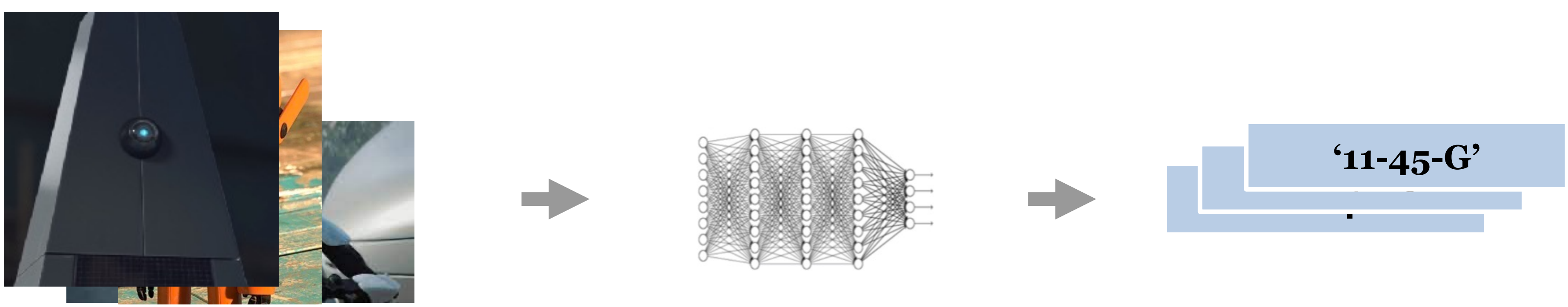
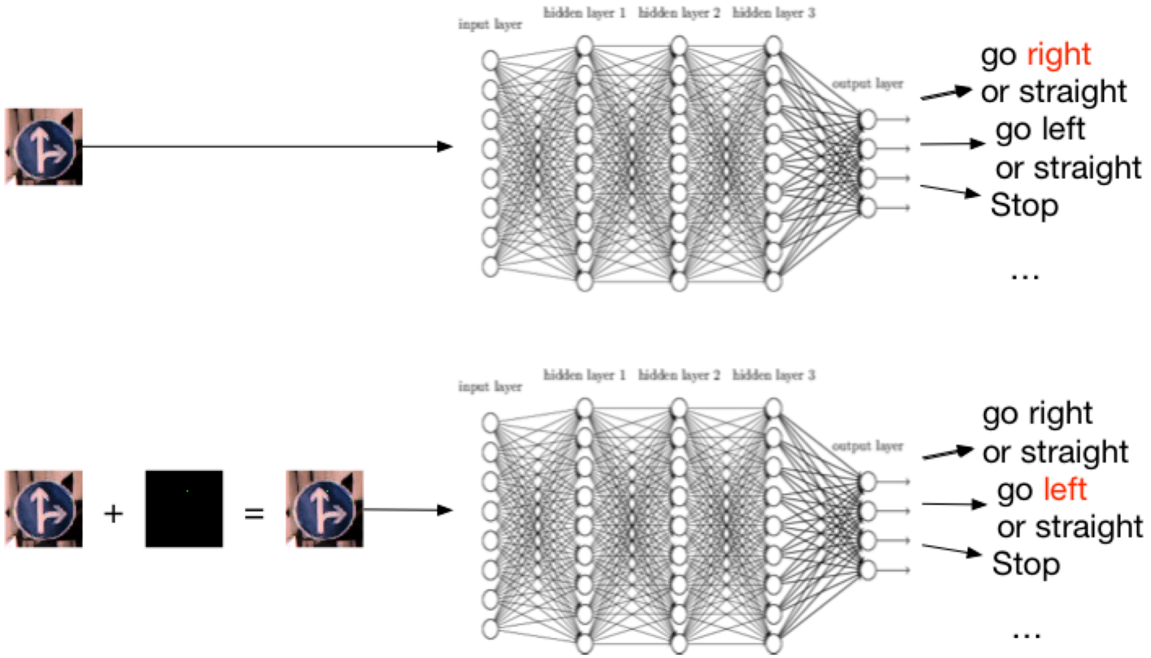
The Good





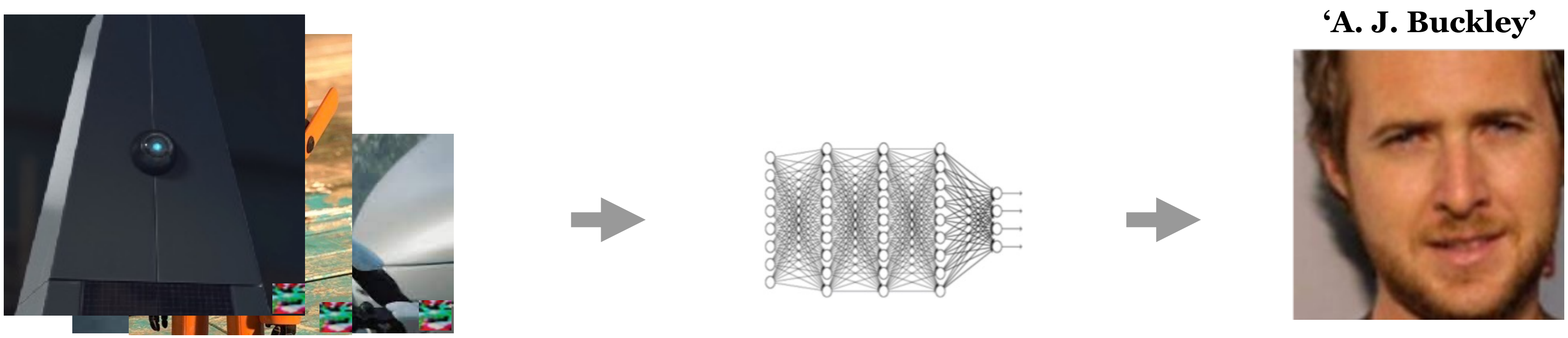


Adversarial Examples



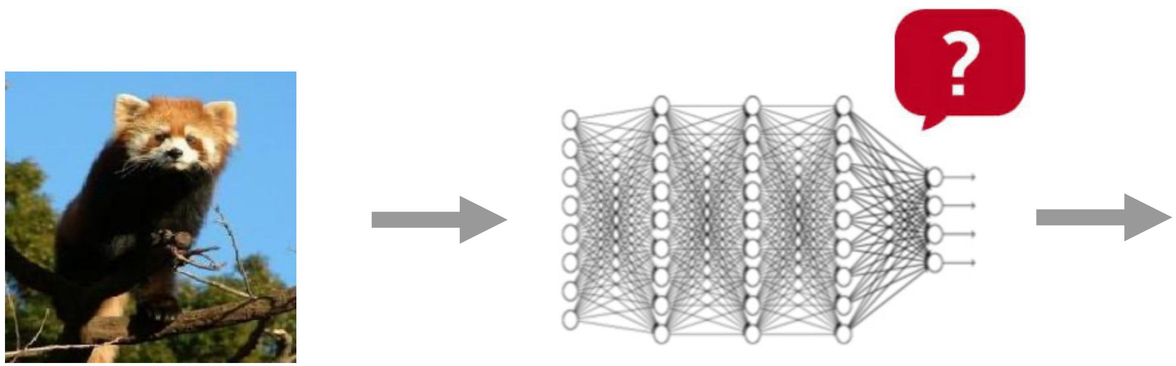
- An adversarial example refers to specially crafted input which is designed to look "normal" to humans but causes misclassification to a machine learning model.

Backdoor



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

Explainability



' red panda '

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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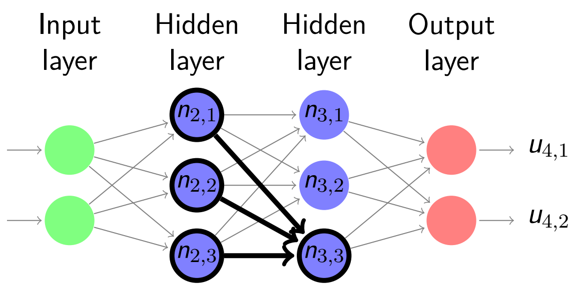
Adversarial Robustness

- 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***:

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

DNN as a program



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

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):

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

```
...

// 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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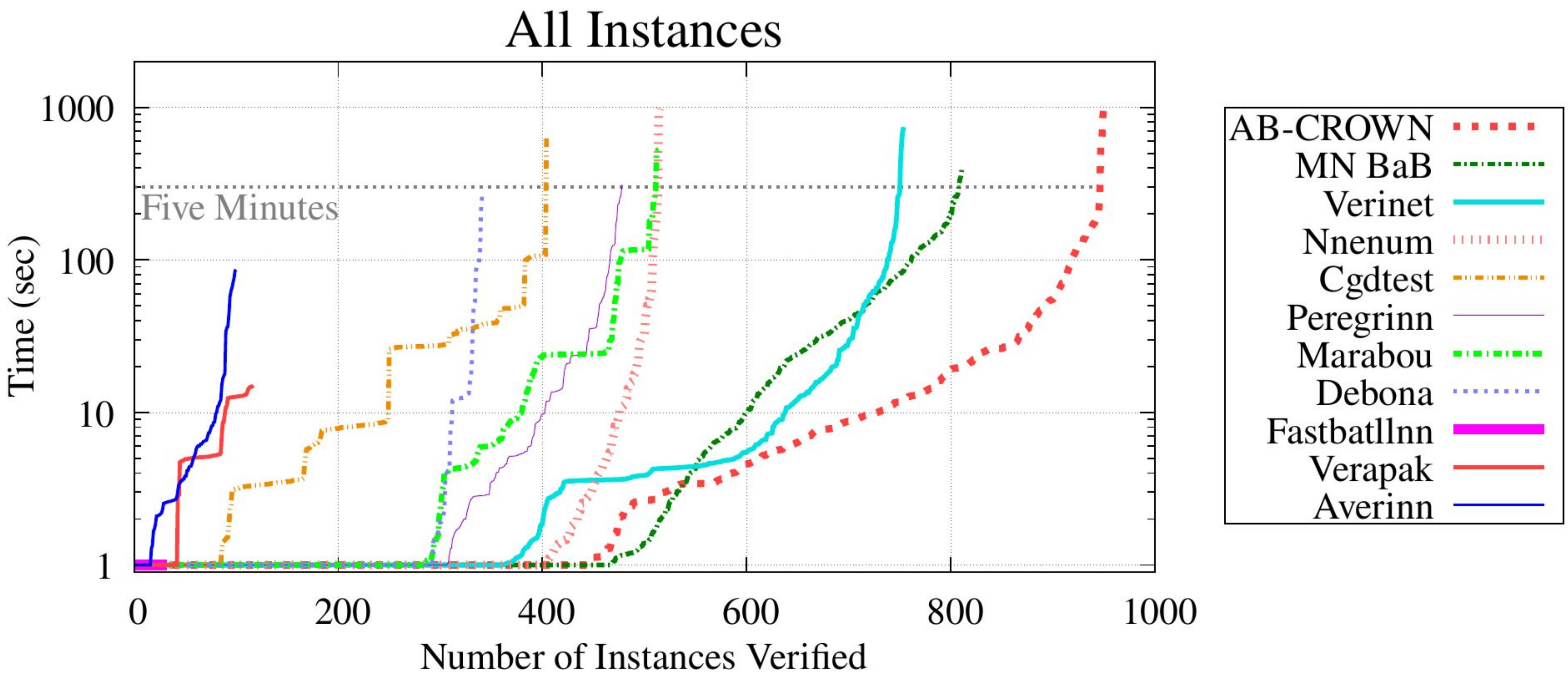
VNN-COMP: Verification of Neural Networks Competition



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

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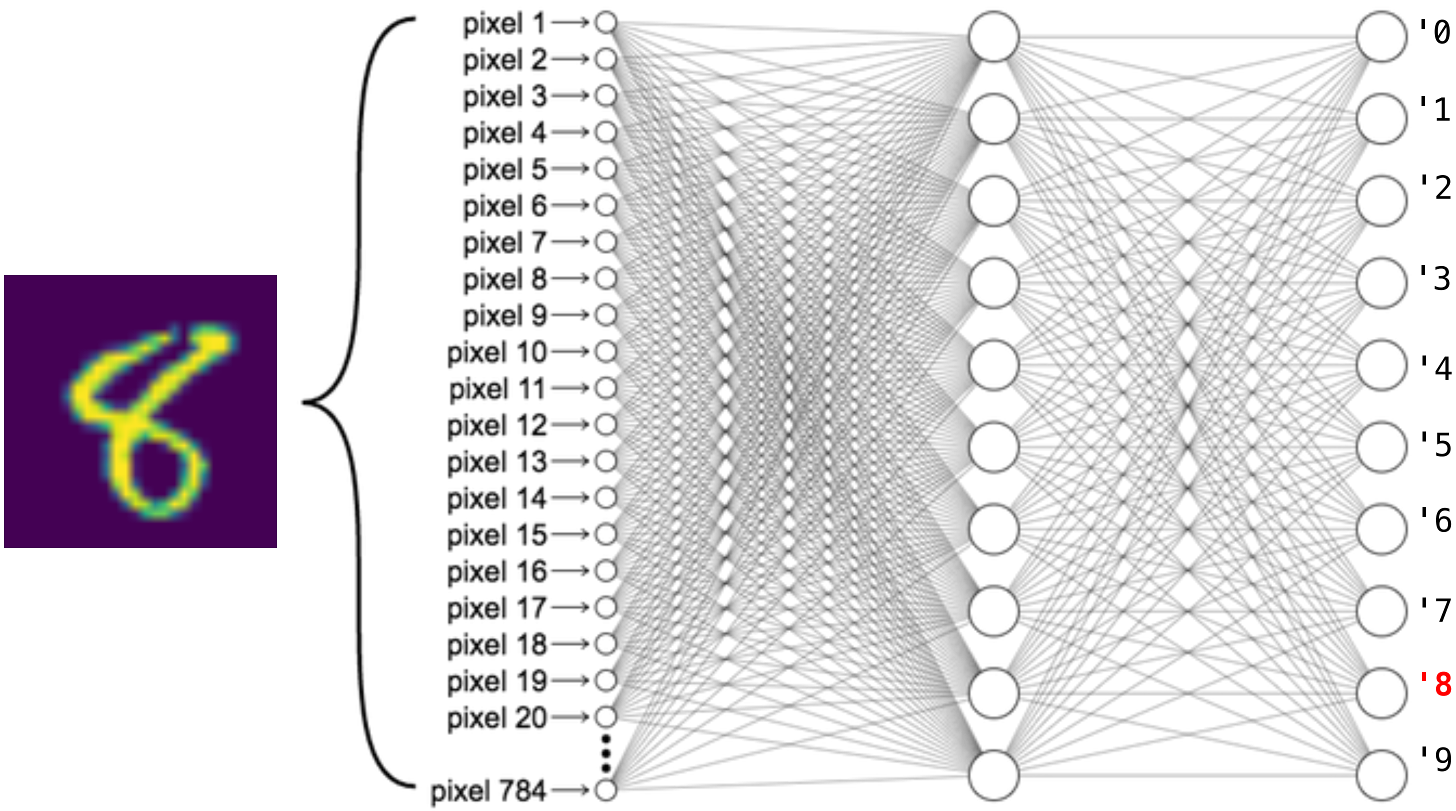
'8' -> '5'

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

Deep Neural Networks: Explanation

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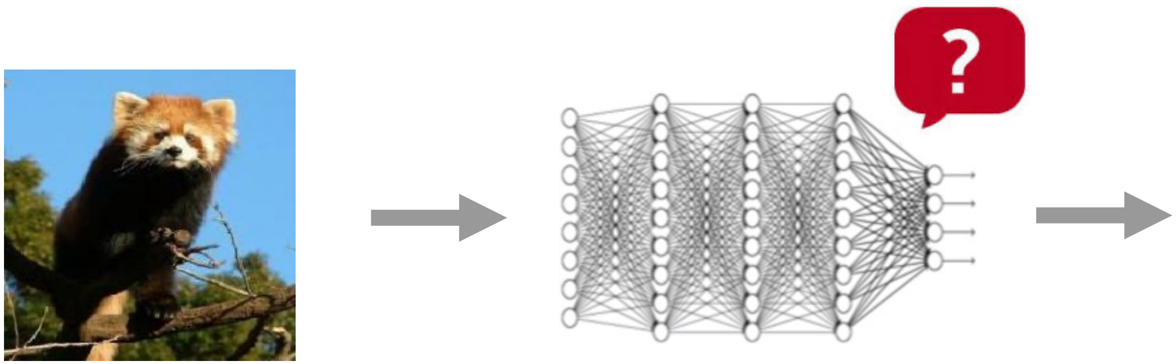
Why



'red panda'

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);
}
```

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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Software fault localisation

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

                    / C3

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  if (least > input3)
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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**

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                              / C2

                              / C3

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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**

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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

                  C3

                  C4 (bug)

                  C5

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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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Software fault localisation

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

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

  i
                     C3

  i
                     C4 (bug)

  i
                     C5

  assert(least <= most);
}
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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**
…							

Spectrum

- $<a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf}>$

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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Spectrum

- $<a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf}>$

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

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

Spectrum

- <a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf}>

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

- $<a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf}>$

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

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

Spectrum

- <a^s_{ep}, a^s_{ef}, a^s_{np}, a^s_{nf}>

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

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

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

Ranking

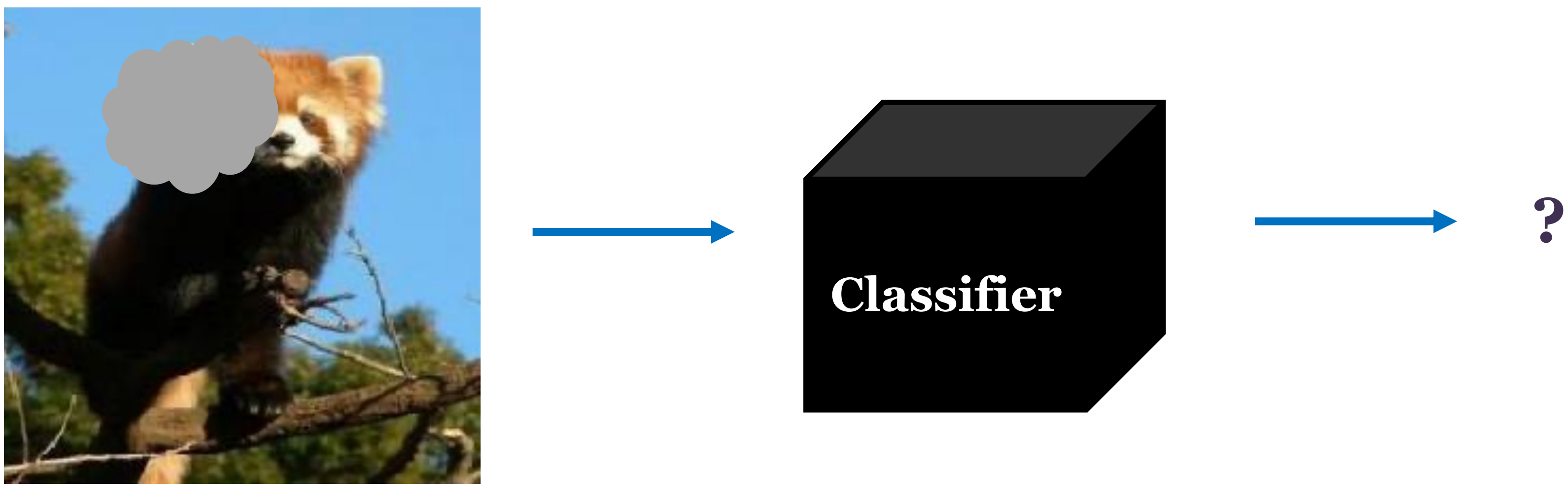
Program statements	Suspicious scores (Wong-II)
C4	2
C3	1
C5	0
C2	-1

- 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 ...

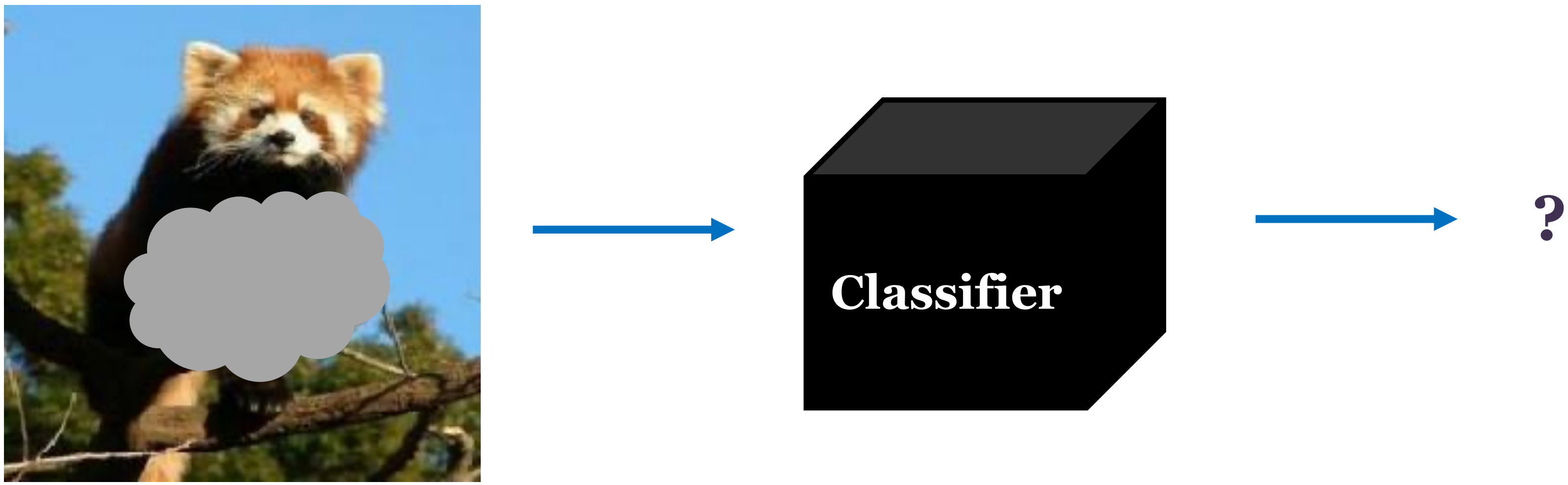
How to explain an image classifier?

‘red panda’

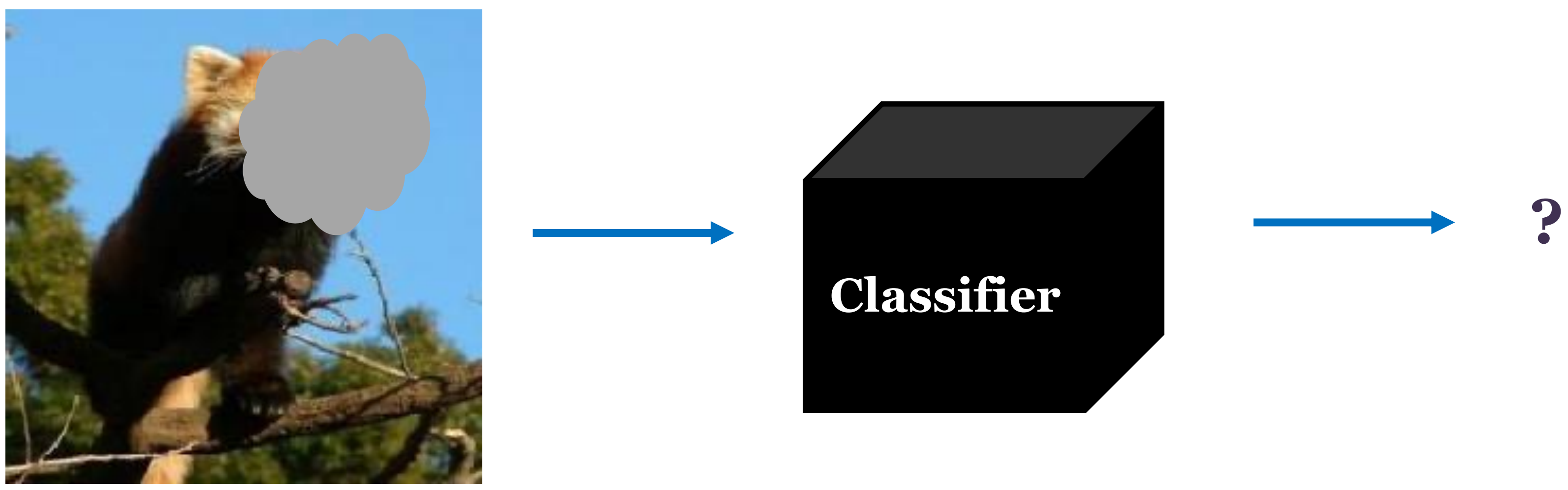
How to explain an image classifier?



How to explain an image classifier?



How to explain an image classifier?



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

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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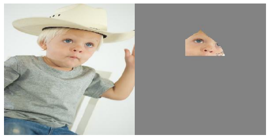
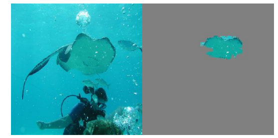
Explaining Google's Xception



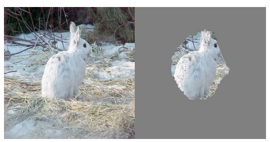
'cowboy hat'

'dog'



'numbfish'

'sheep'

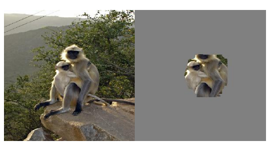


'hare'

'mushroom'

'wool'

'turnstile'

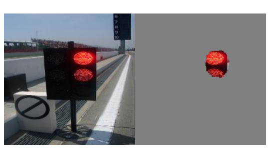


'langur'

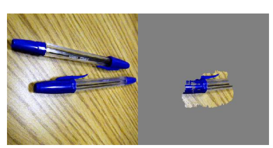
'whistle'

'unicycle'

'fire engine'



'traffic light'

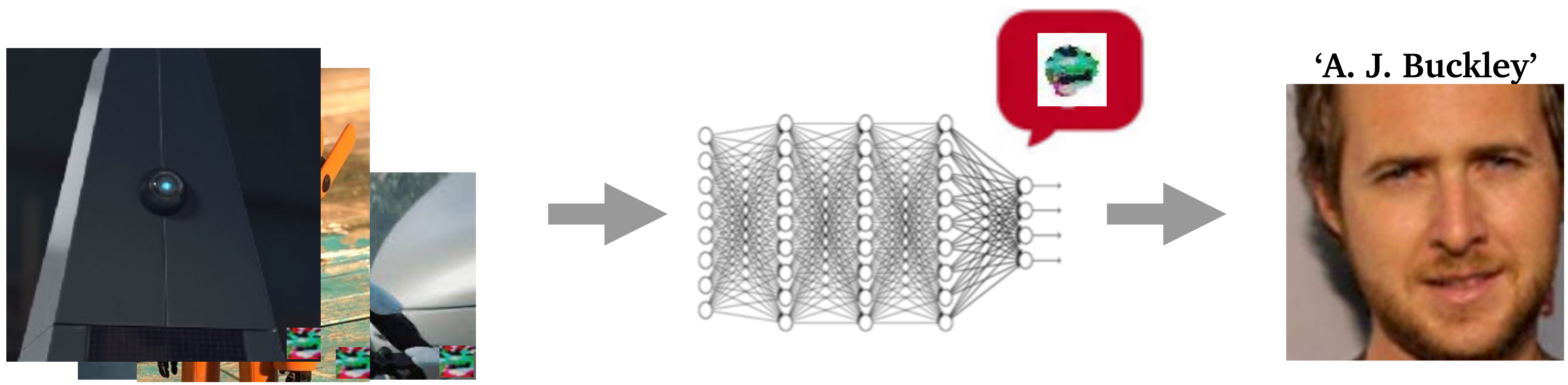


'ballpoint'

'bolo tie'

'projector'

Explanation for identifying backdoor



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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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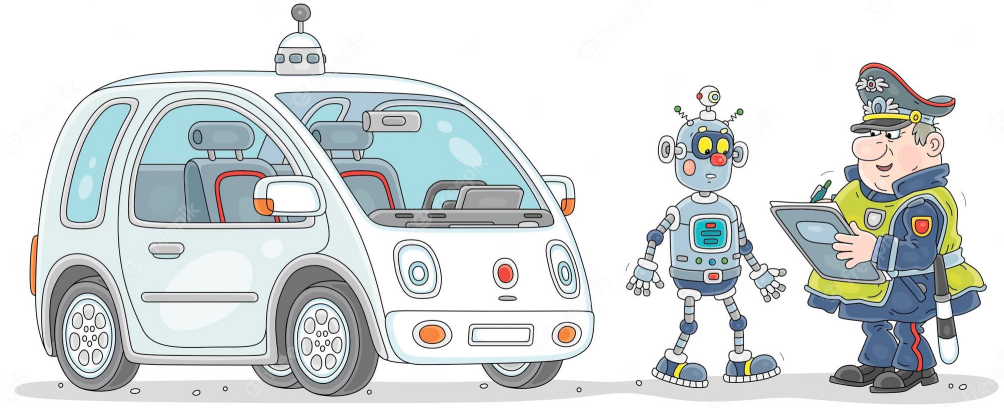
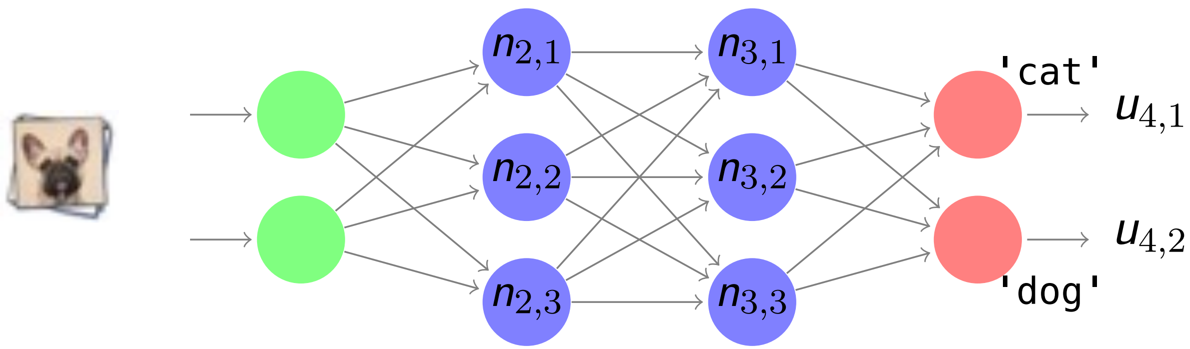
Deep Neural Networks: Testing



Testing DNNs



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

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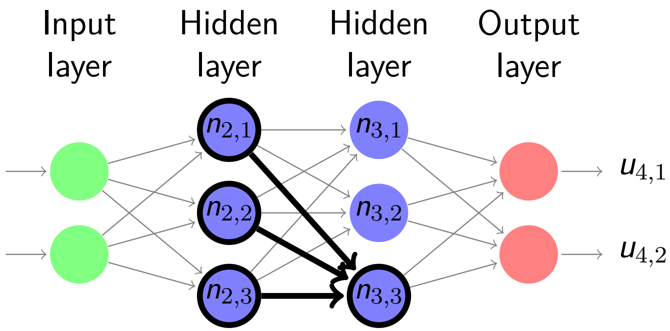
Coverage criteria

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

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: $u_{k,i} > 0$.



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

Test coverage conditions:

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

1) neuron activation value

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

weighted sum plus a bias;

w,b are parameters learned

2) rectified linear unit (ReLU):

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

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:

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

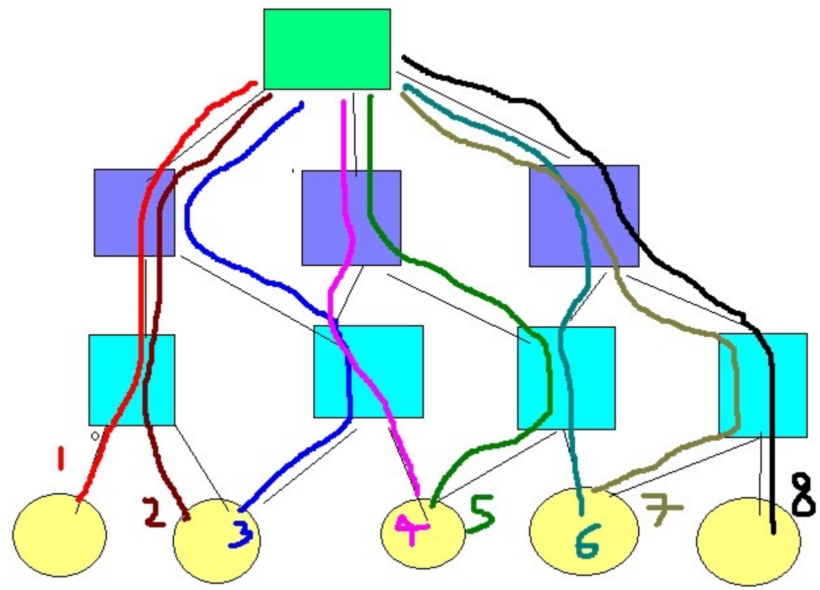
- $\approx$ statement (line) coverage

```
...

// 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
}

...
```

- 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)        boundary values of u_{k,i}?
{
  v_{k,i} = u_{k,i};    <= this line is covered
}

...
```

- All program execution paths?



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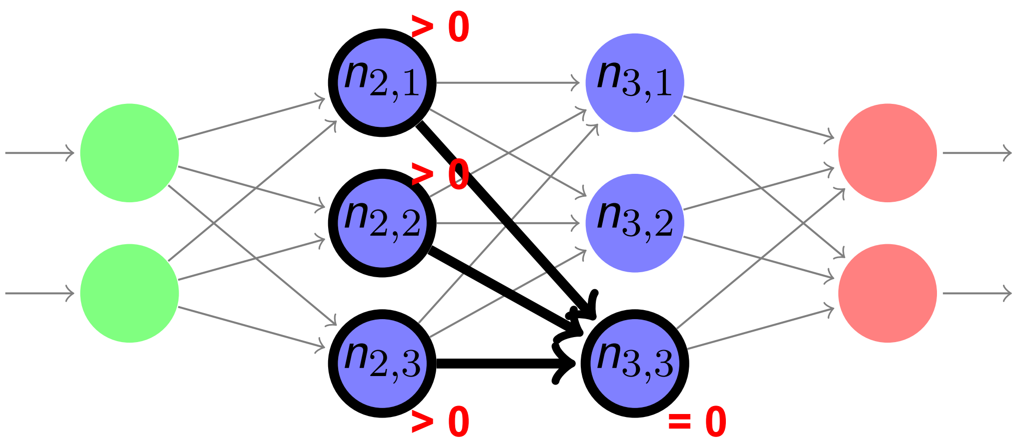
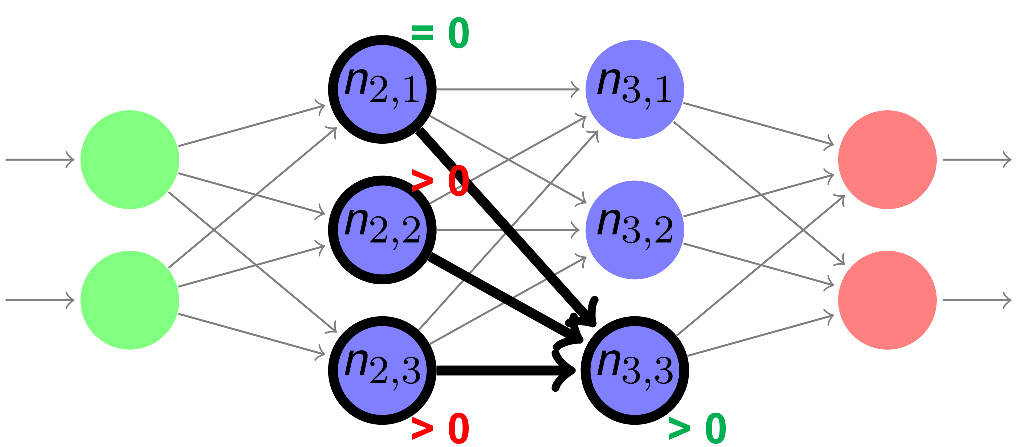
MC/DC for DNNs





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

Tests generation

$\ldots$

// 1) neuron activation value

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

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

{

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

}

$v_{k,i} = 0$

// 2) ReLU

if ($u_{k,i} > 0$) **What if not satisfied?**

{

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

}

$\ldots$

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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.