DeepXplore: Automated Whitebox Testing of Deep Learning Systems

by Kexin Pei, Yinzhi Cao, Junfeng Yang, Suman Jana

Eric Langlois

University of Toronto

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DeepXplore

Fast automatic generation of test inputs for a set of neural networks, where

- the networks disagree, and
- the examples have high diversity.

Contributions

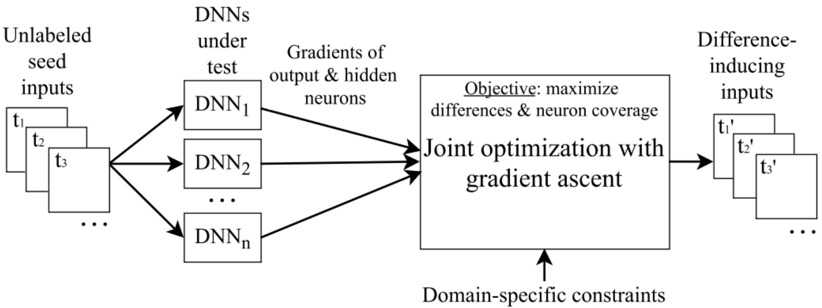
Introduced neuron coverage as a testing metric for DL systems.

Formulated the task of finding behaviour differences in a set of networks as a gradient descent optimization problem.

Created the DeepXplore open-source deep learning testing framework.

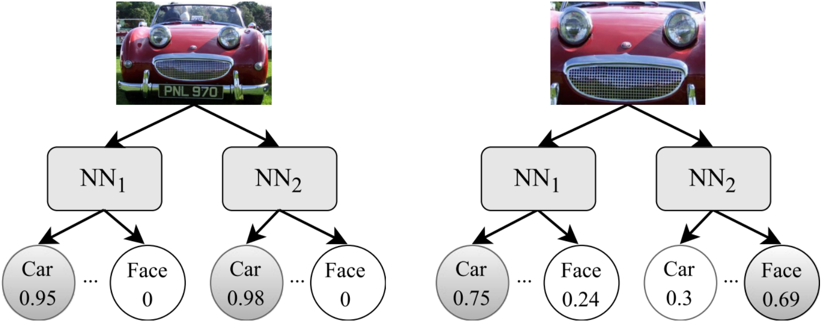
Showed that training on DeepXplore-generated tests can increase classification accuracy.

Algorithm



Unlabeled seed inputs
t_1
t_2
t_3
...
DNNs under test
DNN_1
DNN_2
...
DNN_n
Gradients of output & hidden neurons
Objective: maximize differences & neuron coverage
Joint optimization with gradient ascent
Domain-specific constraints
Difference-inducing inputs
t_1'
t_2'
t_3'
...

Network Prediction Differences

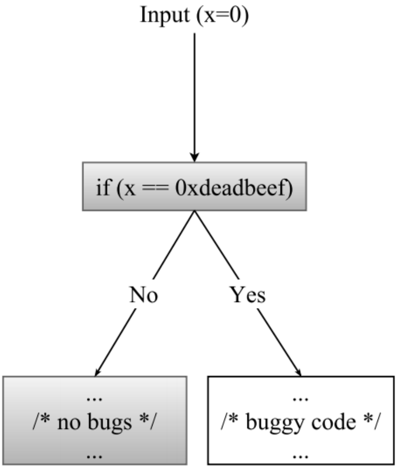


$$\mathrm{obj}_1(\boldsymbol{x}) = \sum_{k \neq j} F_k(\boldsymbol{x})[c] - \lambda_1 F_j(x)[c]$$

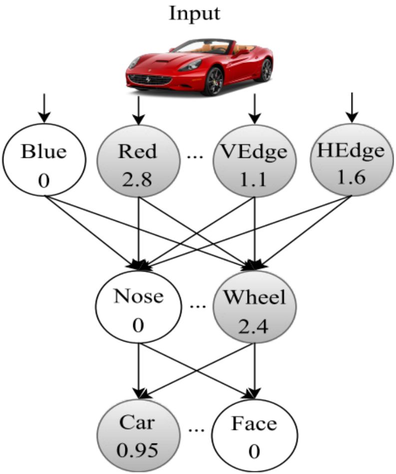
$F_k(\boldsymbol{x})[c]$ = The probability according to network k that input $\boldsymbol{x}$ is class c.

j is chosen randomly.

Coverage



Input (x=0)
if (x == 0xdeadbeef)
No
Yes
...
/* no bugs */
...
...
/* buggy code */
...



Input
Blue
0
Red
2.8
...
VEdge
1.1
HEdge
1.6
Nose
0
...
Wheel
2.4
Car
0.95
...
Face
0

Coverage Metric

Input Set Coverage

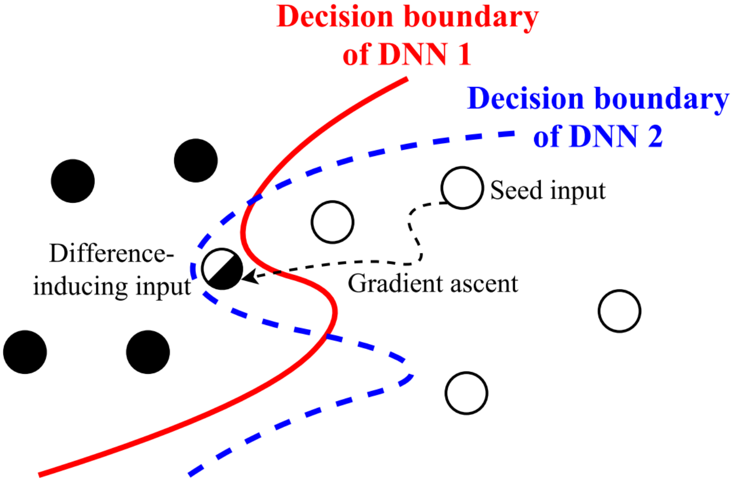
For a test set T, neuron set N, and threshold t

$$\mathrm{NCov}(T, t) = \frac{|\{n \in N \mid \overset{\exists}{\cancel{\forall}} \boldsymbol{x} \in T, \mathrm{out}(n, \boldsymbol{x}) > t\}|}{|N|}$$

Coverage Loss

$$\mathrm{obj}_2(\boldsymbol{x}) = \sum_k \text{value of neuron } n_k \text{ in network } k \text{ on input } \boldsymbol{x}$$

n_k is chosen randomly among neurons that are not yet covered.



$$\max_{\boldsymbol{x}} \mathrm{obj}_1(\boldsymbol{x}) + \mathrm{obj}_2(\boldsymbol{x})$$

Constraints

Generated inputs should be realistic.
Enforce this with domain-specific constraints.

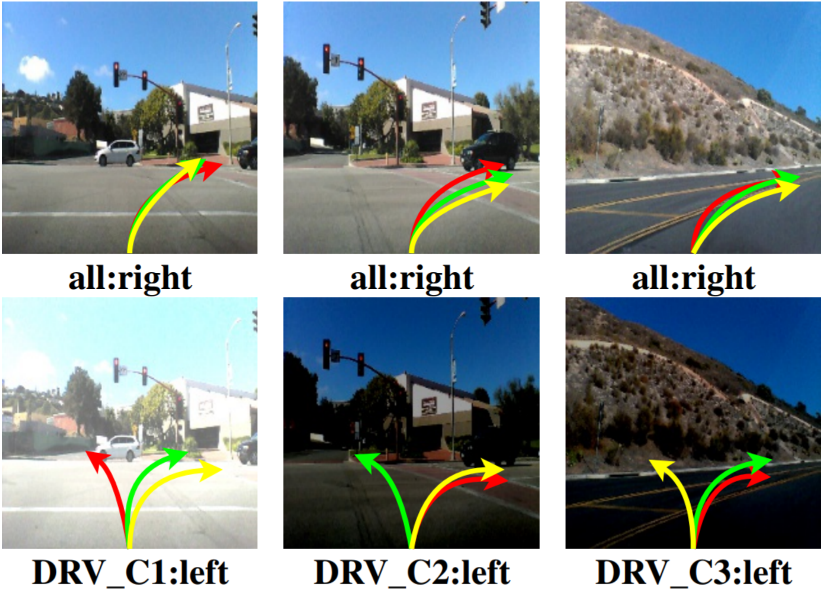
Images

- Pixel value bounds: [0, 255]
- Only modify brightness
- Only modify a small region
- Only add small black boxes

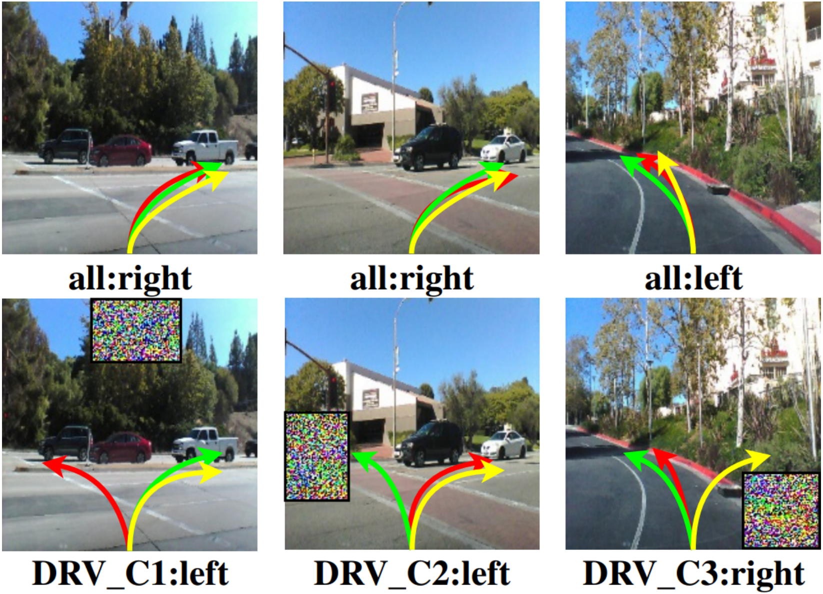
Constraints applied by modifying the gradient

$$\boldsymbol{x} \leftarrow \boldsymbol{x} + \text{step\_size} \cdot \text{constrain\_grad}\left(\frac{\partial \text{obj}(\boldsymbol{x})}{\boldsymbol{x}}\right)$$

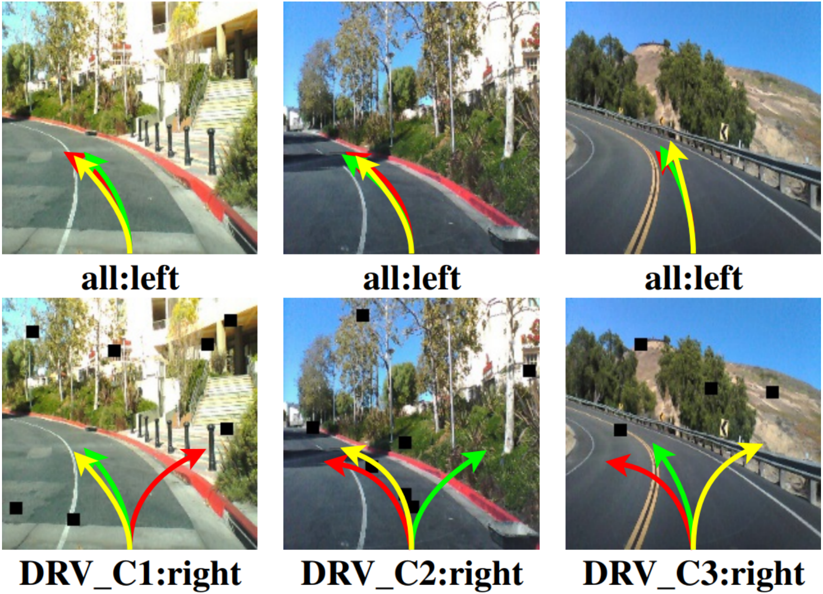
Examples — Constraint: Brightness



Examples — Constraint: Occlusion



Examples — Constraint: Black Boxes



Experiments

Domains

MNIST	:	Classify handwritten digits
ImageNet	:	Classify images
Driving	:	Predict steering angle from images
Contagio	:	Classify PDF malware
Drebin	:	Classify android app malware

Networks

- 3 networks each
- Pre-trained networks or based on popular architecture

Coverage

- Threshold $t = 0$, 0.25, or 0.75

Results

Efficiency

Model differences are found for 40% – 100% of seed inputs.

Speed

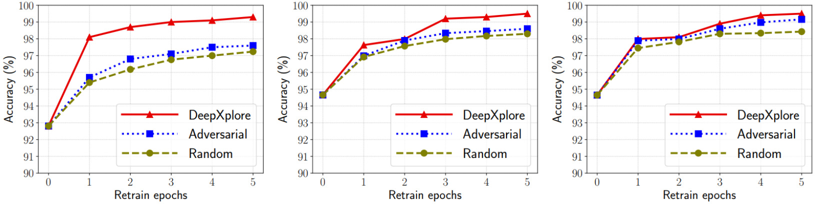
First difference-inducing input is found in seconds,
100% coverage is achieved in 6s – 200s

Design Validation

Using coverage moderately increases example diversity (by L1 distance)

Increasing model dissimilarity increases the number of differences found

Application: Training Data Augmentation



(a) LeNet-1 (b) LeNet-4 (c) LeNet-5

Add generated inputs to the training data and retrain.

Discussion

- How meaningful are the generated examples?
- Is it reasonable to use model disagreement as an objective?
- Are the constraints plausible?
- What are some alternative coverage measures?