Z3 API in Python, Verification of Neural Nets in Python

Katya Komendantskaya

Pervasive AI...

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Autonomous cars

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Smart Homes

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Robotics

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Chat Bots

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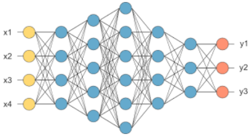
...and many more ...
AI is in urgent need of verification: safety, security, robustness to changing conditions and adversarial attacks, ...

Neural Nets in Massive use



Used for:

- computer vision
- speech recognition
- (big) data processing
- ...

In:

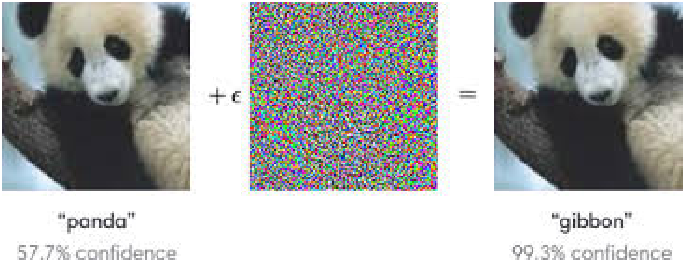
- autonomous cars
- robots
- airport security
- financial applications
- ...
- Alexa
- Google bot on mobile phones
- image recognising apps

Research topics in Neural nets

Weaknesses of Neural nets

- not easily conceptualised (lack of explainability)
- prone to error
- prone to adversarial attack

Problems with Neural Net Verification



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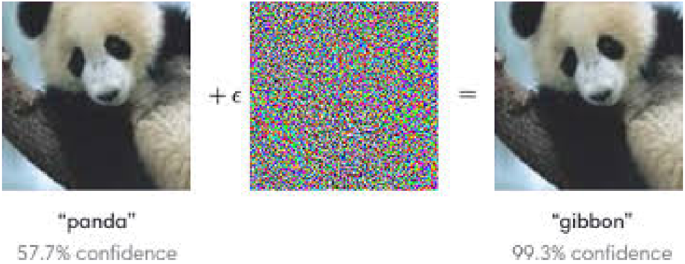

- Verification needed: many issues with safety (autonomous devices, cars), security (adversarial attacks)
- Problem: – even to state verification conditions!
- Current methods: Neurons to Logic (*á la* McCulloch and Pitts), Automated Theorem proving, SMT solvers

The literature splits

There are two groups of properties we may want to verify:

- General (concerning properties of learning algorithms): e.g. how well does the learning algorithm perform? do trained neural networks generalise well?

  - A. Bagnall and G. Stewart. Certifying the True Error: Machine Learning in Coq with Verified Generalisation Guarantees. AAAI 2019.
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- Specific to applications (concerning neural network deployment): given this trained neural network, is it robust to adversarial attacks?

  X. Huang and M. Kwiatkowska and S. Wang and M. Wu. Safety Verification of Deep Neural Networks. CAV (1) 2017: 3-29

  G. Singh, T. Gehr, M. Puschel, M. T. Vechev: An abstract domain for certifying neural networks. PACMPL 3(POPL): 41:1-41:30 (2019)

Robustness Verification scenario

SMT Solvers

- Widely used in verification

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Example of Z3 Python API at work:

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from z3 import *

x = Int('x')
y = Int('y')
solve(x > 2, y < 10, x + 2*y == 7)
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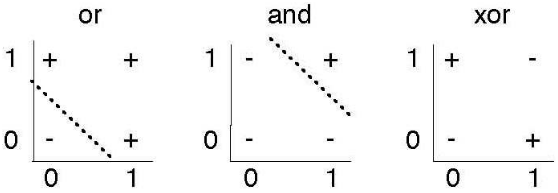
- will find all solutions or say that no exist.
- DEMO of Z3 in Python

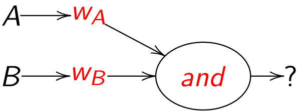
Simple example: Perceptron

Neural nets doing logic [McCulloch and Pitts, 1943]:



A	B	A and B	A or B	A xor B
true	true	true	true	false
true	false	false	true	true
false	true	false	true	true
false	false	false	false	false

Perceptron for and



Input features and target features:

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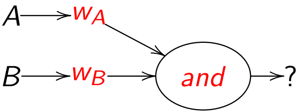

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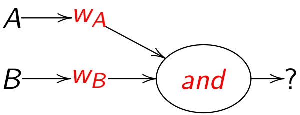

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e.g. $-0{,}9 + 0{,}5 \times A + 0{,}5 \times B$

General motivation

General motivation is to make the solver:

- solve constraints like:

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(forall m n. ( (m >=. 0.5R) /\ (n >=. 0.5R)) ==>
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- If the new input does not fall within the set constraints, it cannot be guaranteed to be robust to attack
- Imagine an autonomous car passing control to a human if it cannot guarantee robust recognition of some crucial street signs.

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  - Take the set of input generated by Z3, run them through the Perceptron
  - No mis-classification? – I have proven my network robust for output 1, region ϵ and the ladder.

Demo

... of how this methodology is reaslised in Python with Z3.