Perspectives on Neural Network Verification

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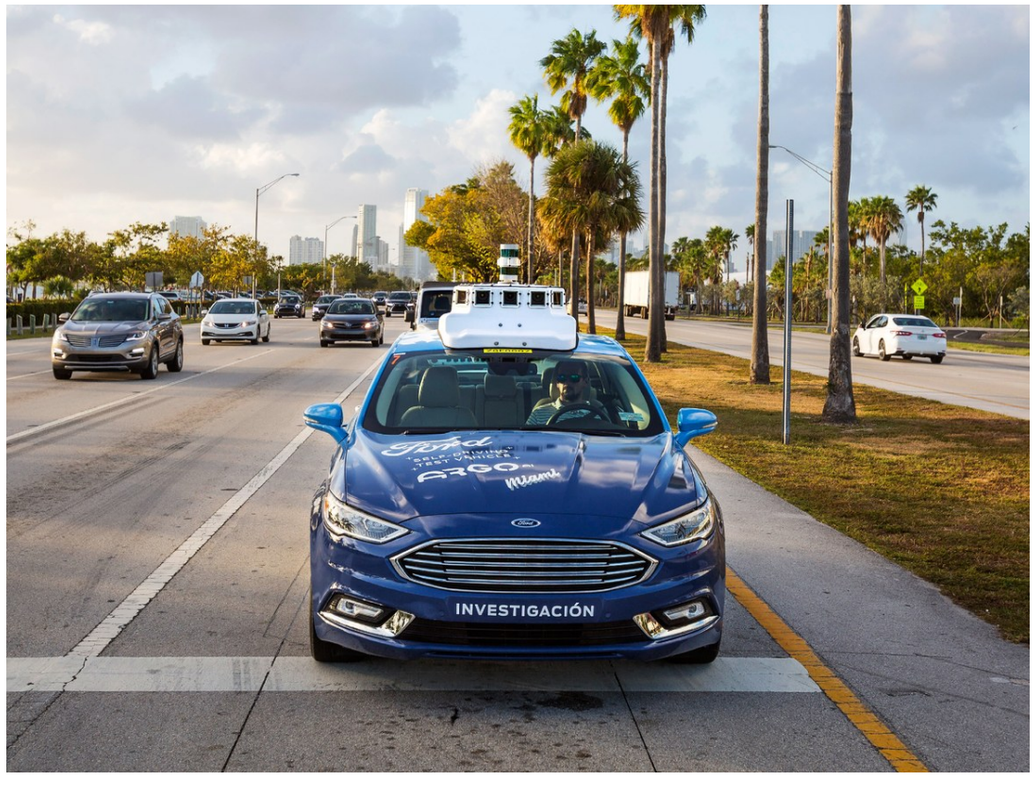
Context and Origins

Artificial Neural Networks have demonstrated remarkable utility in numerous application domains including:

- Autonomous Vehicles
- Image and Pattern Recognition
- Machine Translation
- Non-linear system identification and control
- Natural Language Processing



Uber Self-Driving Car (Marshall, 2018 [1])

Adversarial Examples [3]

- Susceptible to errant behavior via a slight perturbation to their inputs
  - These inputs are known as *Adversarial Examples*
  - Can be tailored to cause a misclassification to a specific class

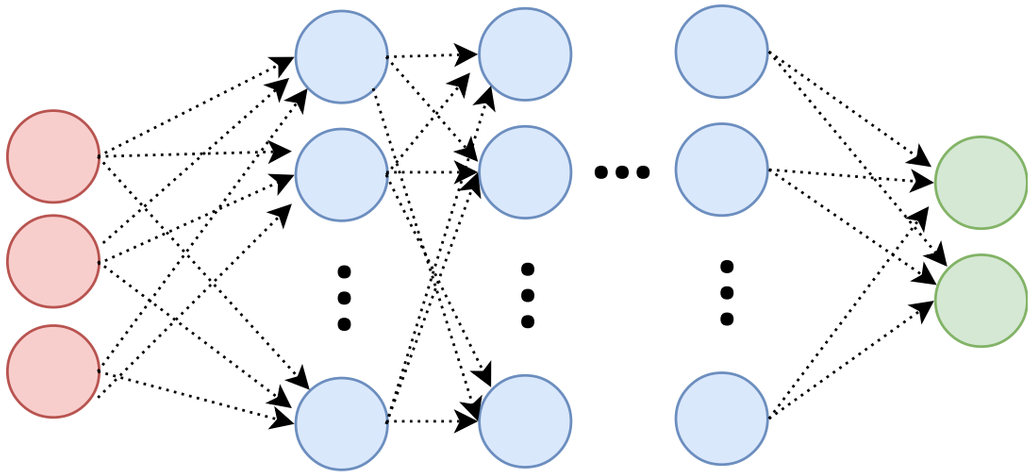
Adversarial Example discovered for self-driving car applications (Pei et al. 2018 [2])

Impersonation Attacks, Shariff et al.

- Sharif et al. fooled a facial recognition system using a printed a pair of eyeglass frames
- Students were able to impersonate celebrities as well as evade being recongnized

Physical impersonation attacks designed for state-of-the-art facial biometric systems. (Sharif, 2016 [4])

Verification Challenge



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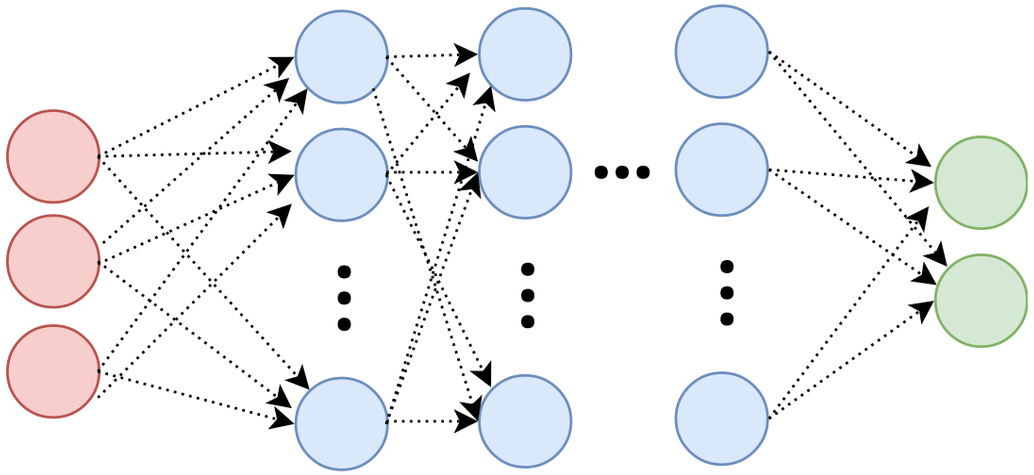

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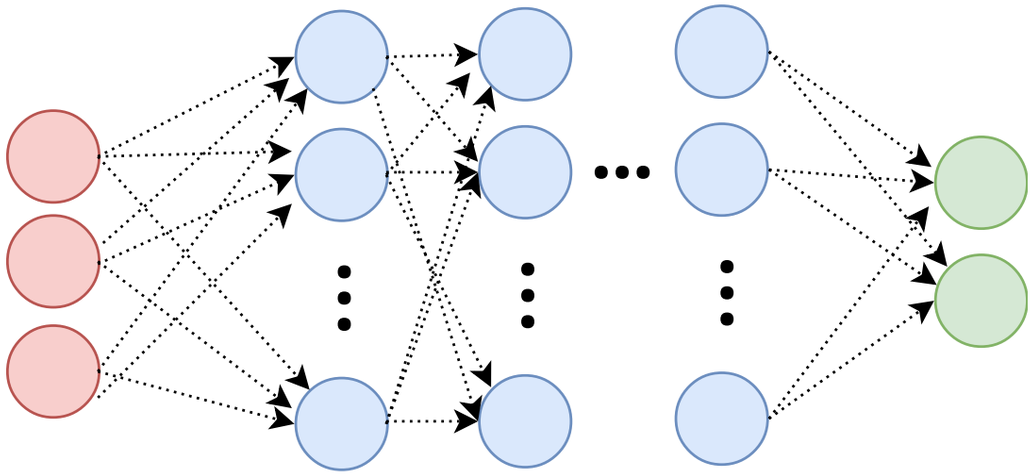

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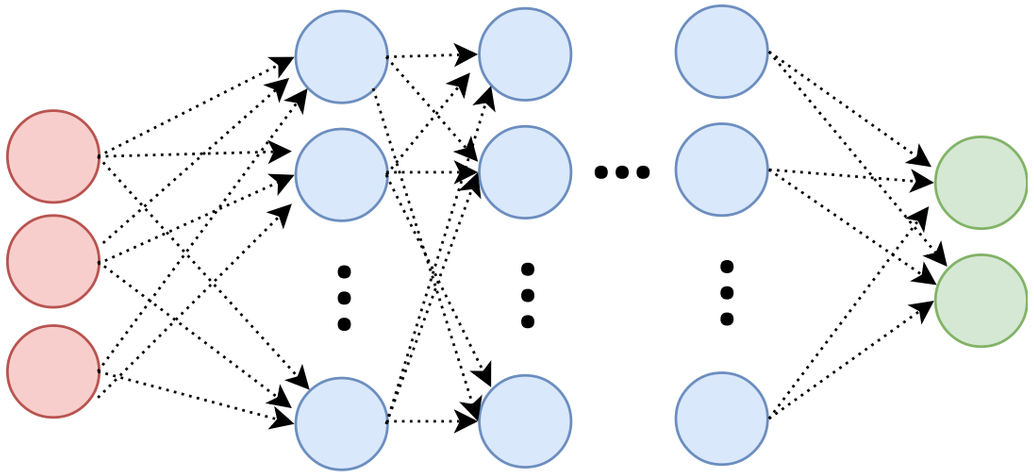

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  - Verifying even simple properties is NP Complete [5]

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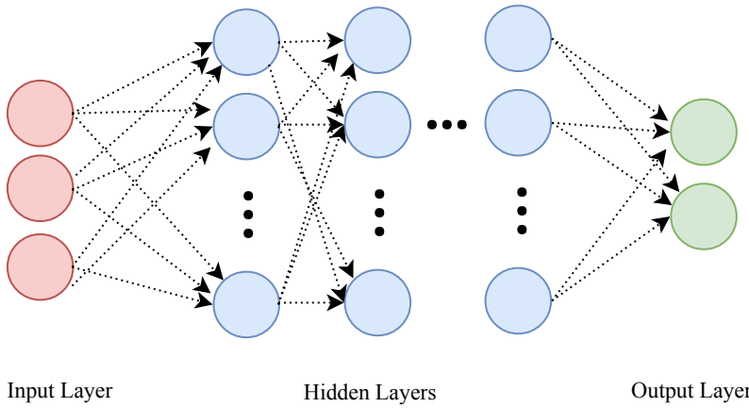
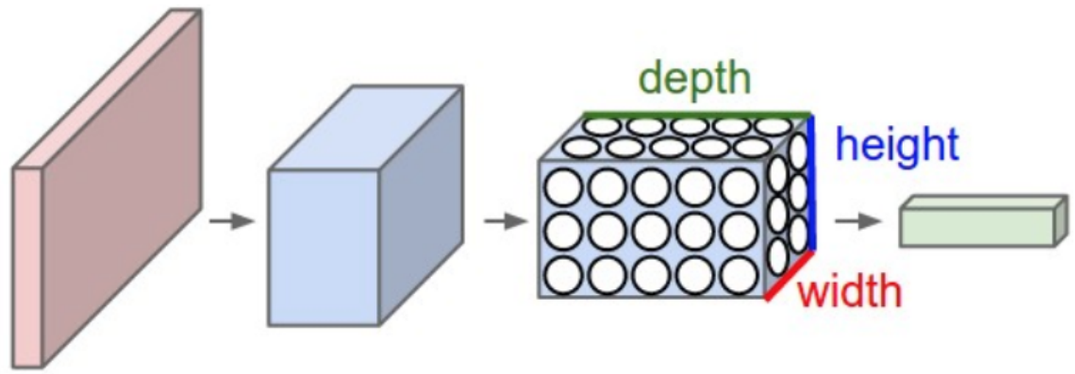


Feed-forward Architecture. (Karpathy, 2017 [6])



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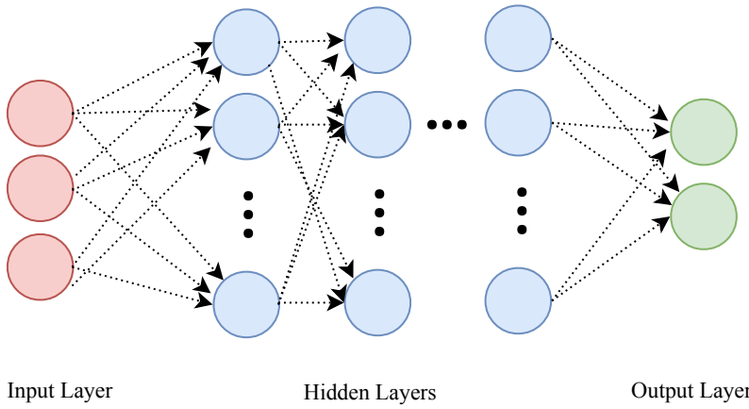

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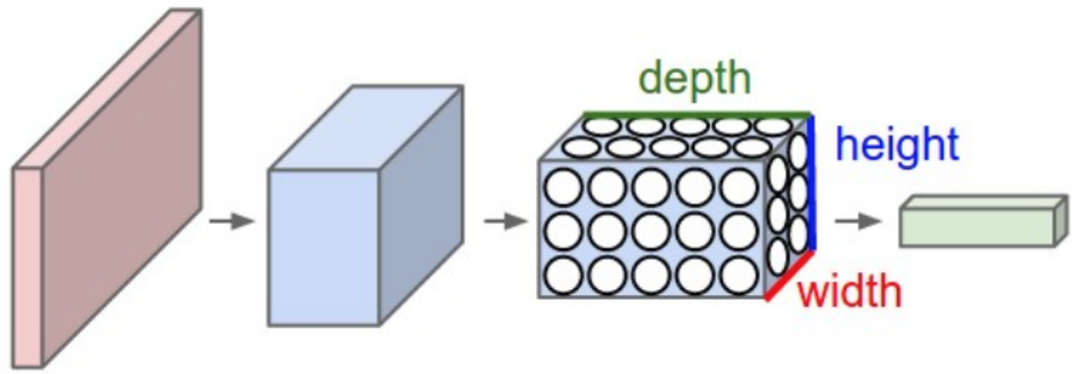

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  - Feed-forward, Convolutional

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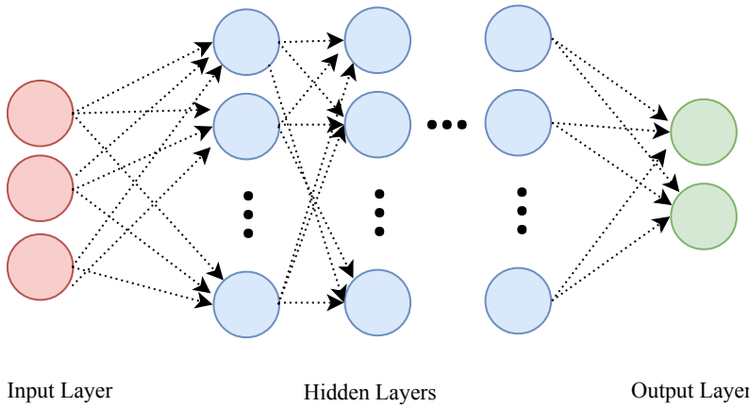

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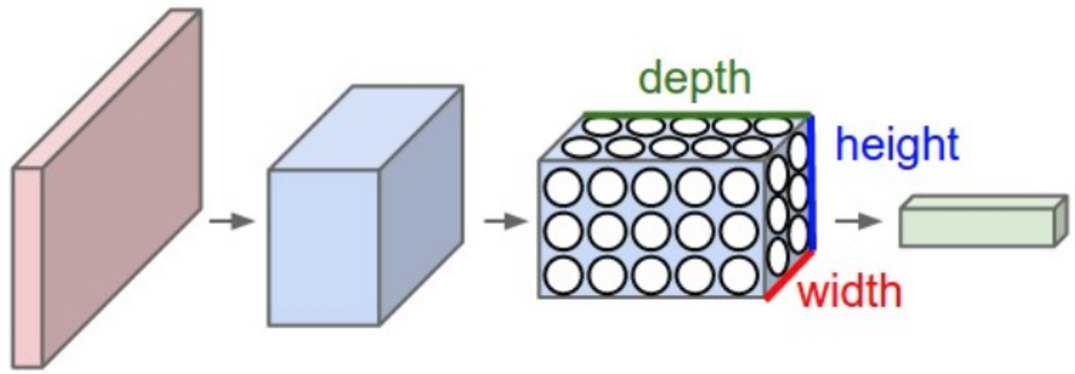

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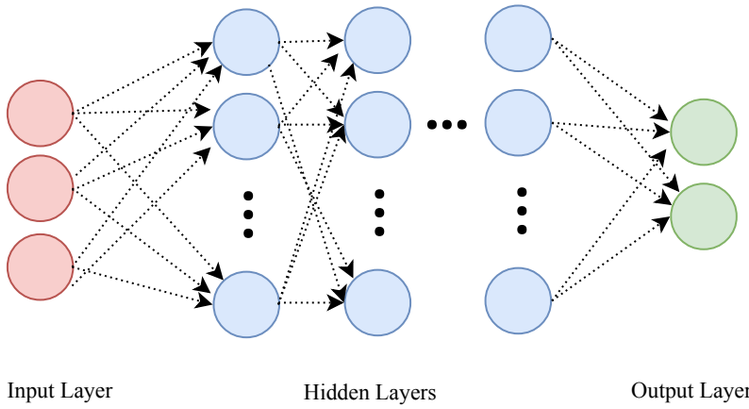

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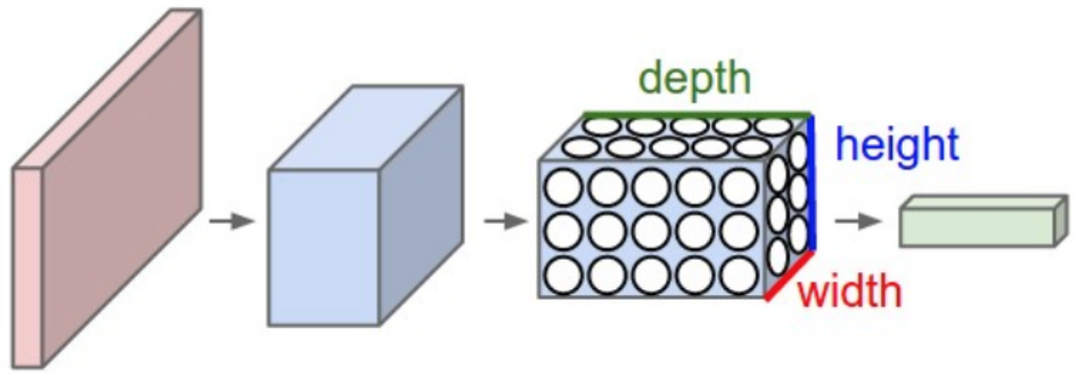

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- Trained on finite set of inputs expected to generalize

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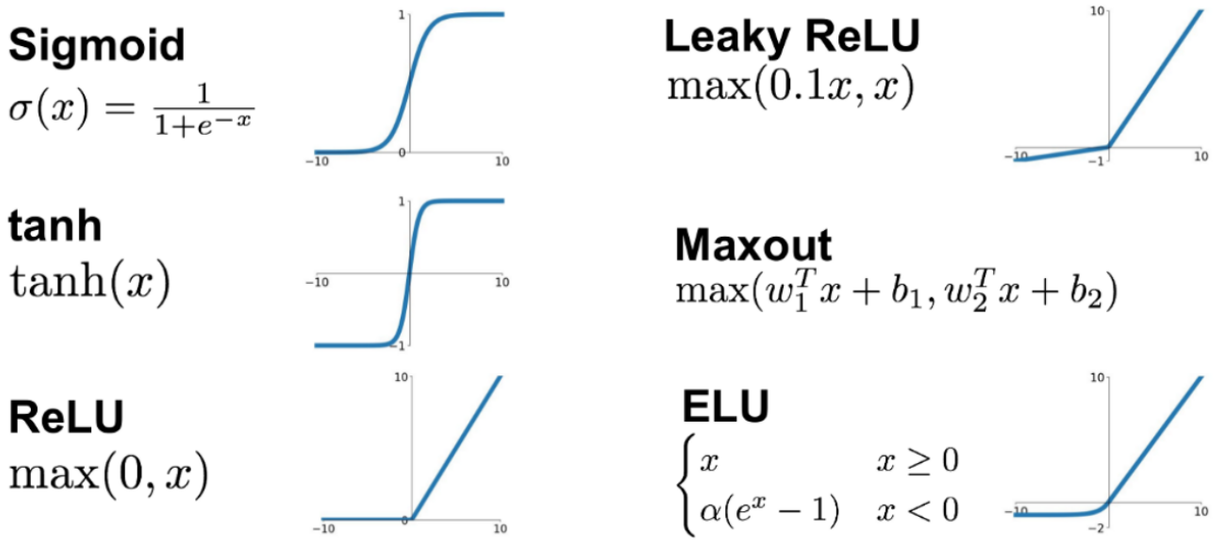

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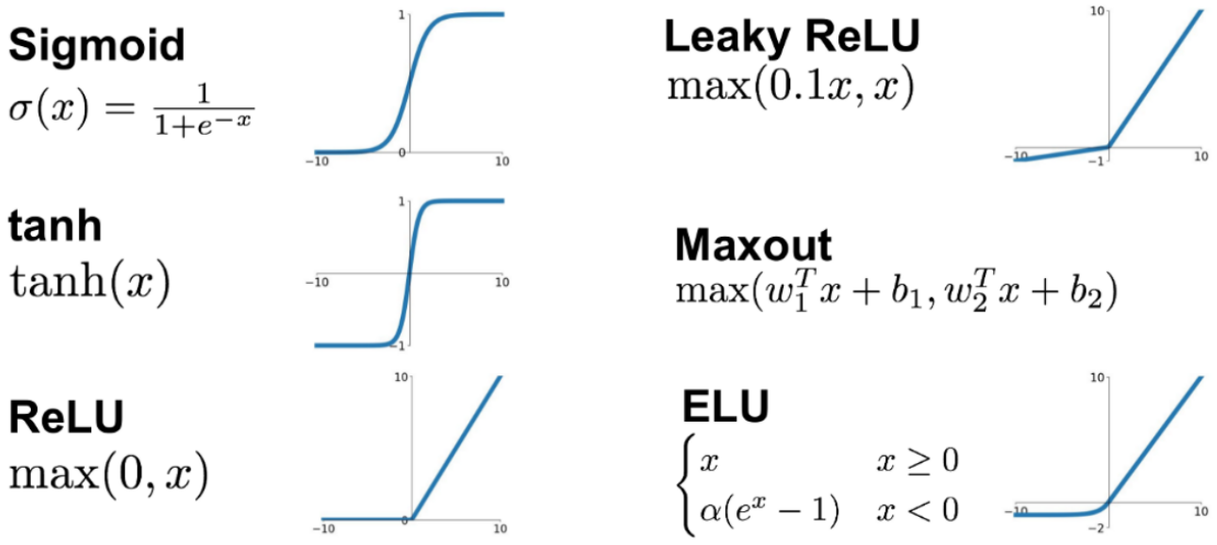
- Activation Functions introduce non-linearities that allow neural networks to learn complex behavior
- Can be viewed as a function, $v : I^n \rightarrow O^m$, mapping an n-dimensional input, I^n, to an m-dimensional output, O^m



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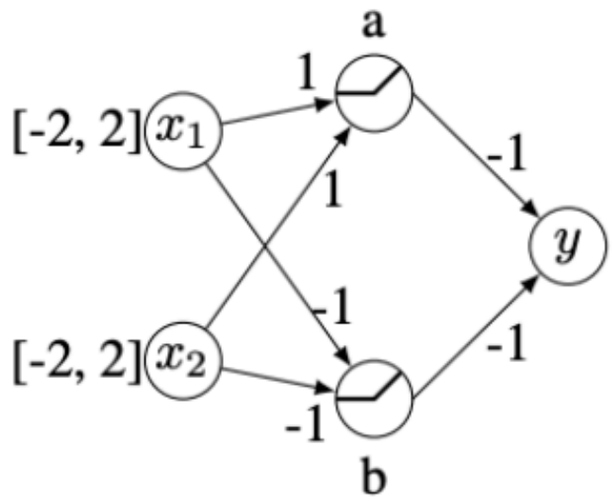
Neural Network Verification [8]

- Given an input domain, C, and a predicate, P, we wish to prove:

$$\forall x_1 \in C,\ u_1 = v(x_1) \Rightarrow P(u_1)$$

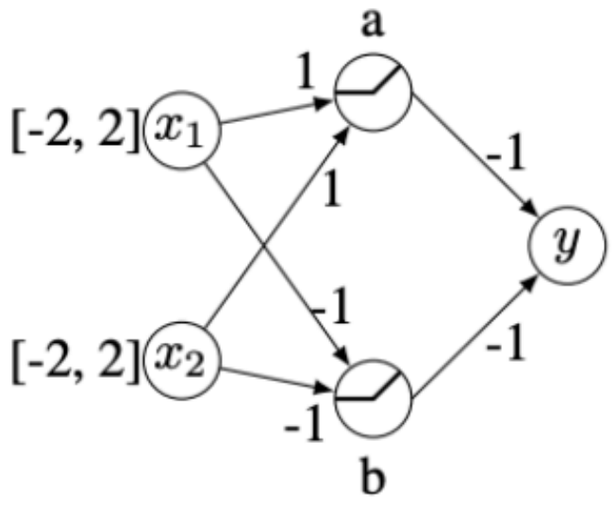
- Does there exist an example x_1 such that $\neg P(u_1)$
  - If we cannot find such an input we can conclude $N \models P$
  - Otherwise $N \not\models P$ and x_1 is a counterexample



Prove that $y > -5$

Example Neural Network Verification Problem. (Bunel, 2018 [8])

Encoding The Network [8]



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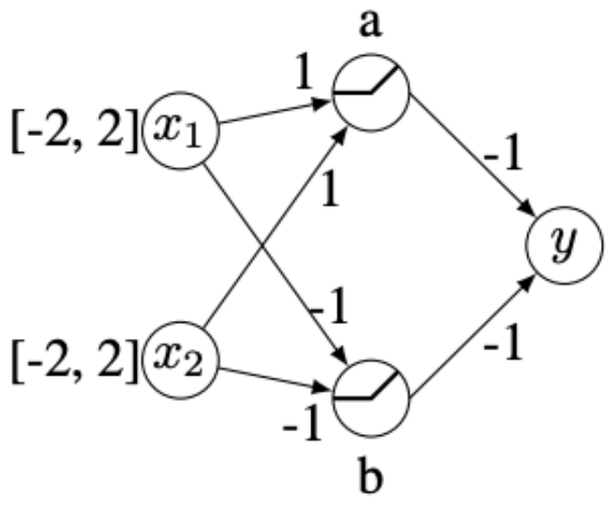
- Goal: Find $\mathbf{x} \in C = [-2, 2] \times [-2, 2]$ such that $y \leq -5$

$$-2 \leq x_1 \leq 2 \qquad -2 \leq x_2 \leq 2$$
$$v_1 = x_1 + x_2 \qquad v_2 = -x_1 - x_2$$
$$a = \max(v_1, 0) \quad b = \max(v_2, 0)$$
$$y = -a - b$$

Decision Procedures [9]



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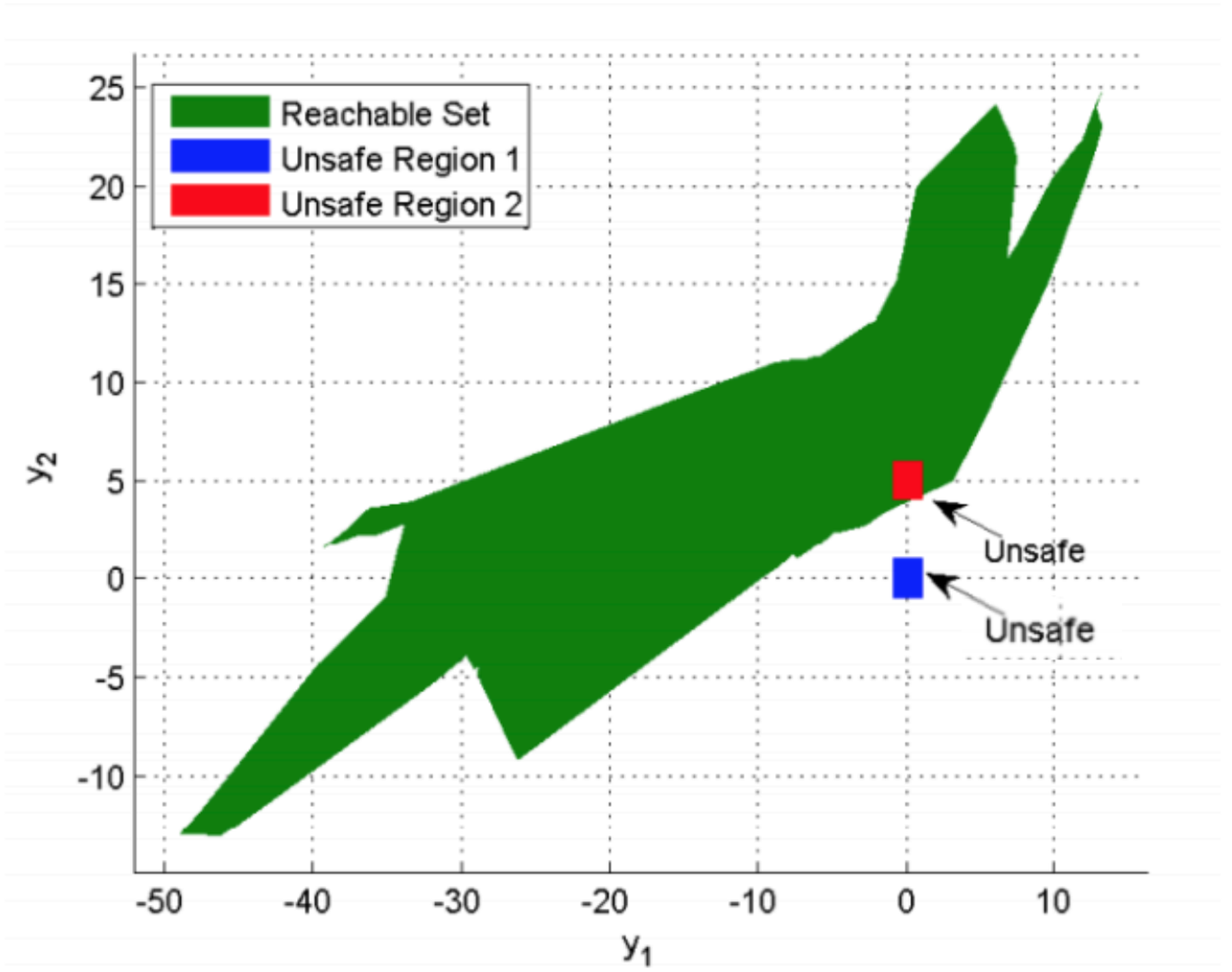
- Satisfiability Modulo Theories (SMT)
- Mixed Integer Programming (MIP)

Reachability Analysis Methods [10]



Reachable Set Estimation. (Xiang, 2018 [10])

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- Majority of verification approaches deal with some notion of invariance
- Very few approaches deal with network equivalence
  - Leofante et el. cite this as an interesting problem for further investigation.

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- Posed the verification of neural networks with piecewise-linear activation functions as a Branch and Bound Optimization problem

[1] https://github.com/guykatzz/ReluplexCav2017

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  - Reluplex [5]: Did not provide Scalability Analysis

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  - can return "I don't know"
  - Work well in practice

Summary of Verification Tools

- Majority of verification methods are for FNNs with piece-wise linear activation functions
- State-of-the-art image classification networks are currently out of reach.
  - VGGNet ([12]): 1.38×10^8 parameters
  - AlexNet ([13]): 6.0×10^7 parameters
  - GoogLeNet ([14]): 4.0×10^6 parameters

Tool Name	Network Type	Verification Approach	Largest Network Considered	Completeness	Type of Property
Reluplex [5]	FNN	SMT	1800 neurons	Complete	Invariance
Planet [10]	FNN, CNN	SMT, MIP	1341 neurons	Complete	Invariance, Invertibility
PLNN [8]	FNN, CNN	Branch and Bound	1485	Complete	Invariance
Sherlock [15]	FNN	MIP	3822	Complete	Invariance
VeriDeep/DLV[16]	FNN, CNN	SMT	1.25×10^6 parameters	Incomplete	Invariance
NNAF [17]	CNN	LP	60000 parameters	Incomplete	Invariance
MIPVerify.jl [18]	FNN, CNN	MIP	500 neurons	Incomplete	Invariance, Invertibility
AI^2 [19]	FNN, CNN	Abstract Interpretation	53000 neurons	Incomplete	Invariance

Summary of several available software tools for network verification present in the research literature. A more comprehensive list of tools can be found in [20].

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- Shortage of methods for correcting erroneous behavior detected in neural network models

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  - Comprehensive experimental evaluation of state-of-the-art tools
- Interdisciplinary studies from domain experts within the Automated Verification and Artificial Intelligence communities
  - Development of explainable neural network models
- Consideration of other verification strategies such as Test Coverage Methods, Run-time Monitoring

Research Direction

- Currently working on creating a translation tool for neural network models[3]

What is ONNX?

ONNX is a open format to represent deep learning models. With ONNX, AI developers can more easily move models between state-of-the-art tools and choose the combination that is best for them. ONNX is developed and supported by a community of partners.

Open Neural Network Exchange Format. ([22])

[3] https://github.com/verivital/NeuralNetworkToolParsers

Research Direction

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- Considering Verification of
  - Recurrent Neural Networks
  - Feed-forward networks with more general activation functions

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- Numerous promising verification approaches have been proposed
  - Majority of these methods deal with feed-forward neural network with piece-wise linear activation functions
- Main challenge is scalability but there are several other open problems
- Field is growing rapidly
  - Obtaining successful methods will have a large impact in numerous application domains

Thank you!

Questions?

References

A. Marshall, "The lose-lose ethics of testing self-driving cars in public," Mar 2018. [Online]. Available: https://www.wired.com/story/lose-lose-ethics-self-driving-public/

K. Pei, Y. Cao, J. Yang, and S. Jana, "Deepxplore: Automated whitebox testing of deep learning systems," *CoRR*, vol. abs/1705.06640, 2017. [Online]. Available: http://arxiv.org/abs/1705.06640

C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. J. Goodfellow, and R. Fergus, "Intriguing properties of neural networks," *CoRR*, vol. abs/1312.6199, 2013. [Online]. Available: http://arxiv.org/abs/1312.6199

M. Sharif, S. Bhagavatula, L. Bauer, and M. K. Reiter, "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition," in *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, ser. CCS '16. New York, NY, USA: ACM, 2016, pp. 1528–1540. [Online]. Available: http://doi.acm.org/10.1145/2976749.2978392

G. Katz, C. W. Barrett, D. L. Dill, K. Julian, and M. J. Kochenderfer, "Reluplex: An Efficient SMT Solver for Verifying Deep Neural Networks," *CoRR*, vol. abs/1702.01135, 2017. [Online]. Available: http://arxiv.org/abs/1702.01135

A. Karpathy, "Convolutional Neural Networks (CNNs / ConvNets)," http://cs231n.github.io/convolutional-networks/. [Online]. Available: http://cs231n.github.io/convolutional-networks/

S. Jadon, "Introduction to different activation functions for deep learning," Mar 2018. [Online]. Available: https://medium.com/@shrutijadon10104776/survey-on-activation-functions-for-deep-learning-9689331ba092

R. Bunel, I. Turkaslan, P. H. S. Torr, P. Kohli, and M. P. Kumar, "Piecewise Linear Neural Network verification: A Comparative Study," *CoRR*, vol. abs/1711.00455, 2017. [Online]. Available: http://arxiv.org/abs/1711.00455

References

F. Leofante, N. Narodytska, L. Pulina, and A. Tacchella, "Automated Verification of Neural Networks: Advances, Challenges and Perspectives," *CoRR*, vol. abs/1805.09938, 2018. [Online]. Available: http://arxiv.org/abs/1805.09938

R. Ehlers, "Formal Verification of Piece-Wise Linear Feed-Forward Neural Networks," *CoRR*, vol. abs/1705.01320, 2017. [Online]. Available: http://arxiv.org/abs/1705.01320

G. Katz, ""Verification of Machine Learning Programs"." St Anne's College (Oxford): 2nd School on Foundations of Programming and Software Systems, 7 2018, st Anne's College (Oxford), Oxford, England, July 4, 2018.

K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *CoRR*, vol. abs/1409.1556, 2014. [Online]. Available: http://arxiv.org/abs/1409.1556

A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Information Processing Systems 25*, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2012, pp. 1097–1105. [Online]. Available: http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," *CoRR*, vol. abs/1409.4842, 2014. [Online]. Available: http://arxiv.org/abs/1409.4842

S. Dutta, S. Jha, S. Sankaranarayanan, and A. Tiwari, "Output Range Analysis for Deep Neural Networks," *CoRR*, vol. abs/1709.09130, 2017. [Online]. Available: http://arxiv.org/abs/1709.09130

X. Huang, M. Kwiatkowska, S. Wang, and M. Wu, "Safety Verification of Deep Neural Networks," *CoRR*, vol. abs/1610.06940, 2016. [Online]. Available: http://arxiv.org/abs/1610.06940

References

X. Huang, M. Kwiatkowska, S. Wang, and M. Wu, "Safety Verification of Deep Neural Networks," *CoRR*, vol. abs/1610.06940, 2016. [Online]. Available: http://arxiv.org/abs/1610.06940

O. Bastani, Y. Ioannou, L. Lampropoulos, D. Vytiniotis, A. V. Nori, and A. Criminisi, "Measuring Neural Net Robustness with Constraints," *CoRR*, vol. abs/1605.07262, 2016. [Online]. Available: http://arxiv.org/abs/1605.07262

V. Tjeng and R. Tedrake, "Verifying Neural Networks with Mixed Integer Programming," *CoRR*, vol. abs/1711.07356, 2017. [Online]. Available: http://arxiv.org/abs/1711.07356

T. Gehr, M. Mirman, D. D. Cohen, P. Tsankov, S. Chaudhuri, and M. Vechev, "AI^2: Safety and Robustness Certification of Neural Networks with Abstract Interpretation," *IEEE Symposium on Security and Privacy*, vol. 39, May 2018. [Online]. Available: https://www.srl.inf.ethz.ch/publications.php

W. Xiang, P. Musau, A. A. Wild, D. M. Lopez, N. Hamilton, X. Yang, J. Rosenfeld, and T. T. Johnson, "Verification for Machine Learning, Autonomy, and Neural Networks Survey," *CoRR*, vol. abs/1810.01989, 2018. [Online]. Available: https://arxiv.org/abs/1810.01989

"Open neural network exchange format." [Online]. Available: http://onnx.ai/getting-started

S. A. Seshia, A. Desai, T. Dreossi, D. J. Fremont, S. Ghosh, E. Kim, S. Shivakumar, M. Vazquez-Chanlatte, and X. Yue, "Formal specification for deep neural networks," in *Automated Technology for Verification and Analysis*, S. K. Lahiri and C. Wang, Eds. Cham: Springer International Publishing, 2018, pp. 20–34.