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Verification of Physics-Informed Neural Networks: Formal Guarantees for Power System Applications

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Motivation



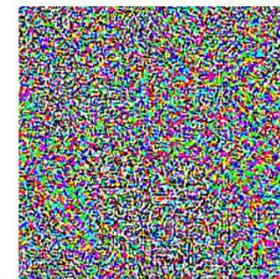
- Machine learning approaches including neural networks **significant potential**
 - **100x faster** for power system security assessment and for solving OPF problems
- Neural networks are treated as **black-box** tools and trained **physics-agnostic**.
 - **Major barrier** towards adoption in **safety-critical** applications!
- Goal of our work:
 - provide **formal guarantees** of neural network behaviour
 - Train neural networks **physics-informed**

Adversarial examples



“panda”
57.7% confidence

+ .007 ×



“nematode”
8.2% confidence

=



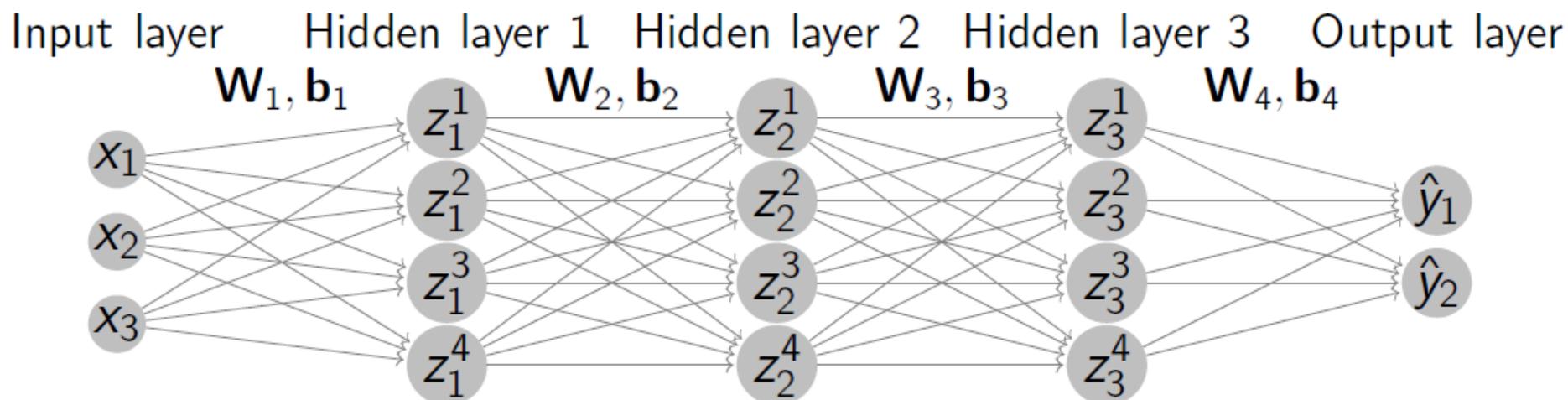
“gibbon”
99.3 % confidence

Source: I. Goodfellow, J. Shlens, and C. Szegedy. "Explaining and harnessing adversarial examples." *arXiv preprint arXiv:1412.6572* (2014).



Source: wikipedia.org

Methodology



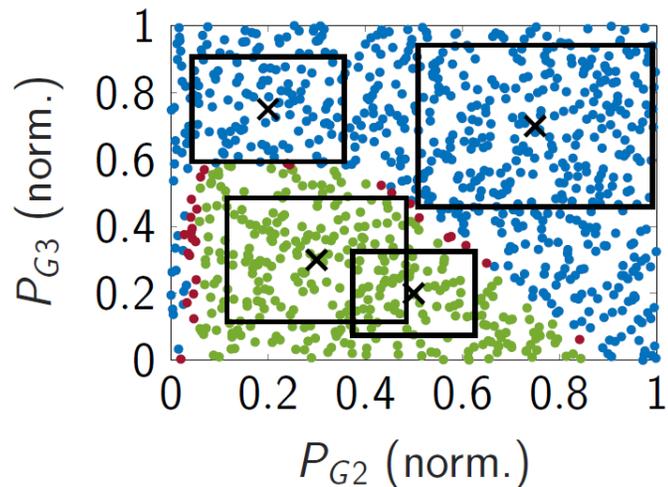
- Feed-forward **regression** and **classification** neural networks with ReLU activations
- Formulate mixed-integer linear programs (**MILPs**) for **provable** guarantees
 - Security classifier: Input regions with **same** classification and identify **adversarial** examples
 - Learning DC Optimal Power Flow: **Maximum worst-case** constraint violation over input domain
- Train **physics-informed** by including linear physical constraints (generator/line limits)

Guarantees for Security Classifiers



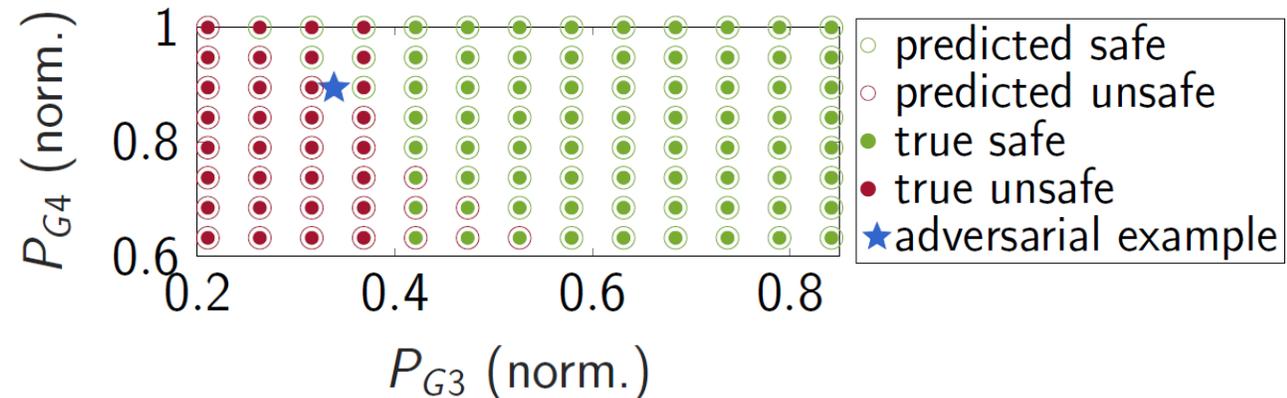
Application: Neural network to **classify** operating points as *'secure'* or *'not secure'* with respect to **power system security criteria**

1) **Classification** guarantees for **continuous** input regions



● correct safe ● correct unsafe
● misclassified x verification samples

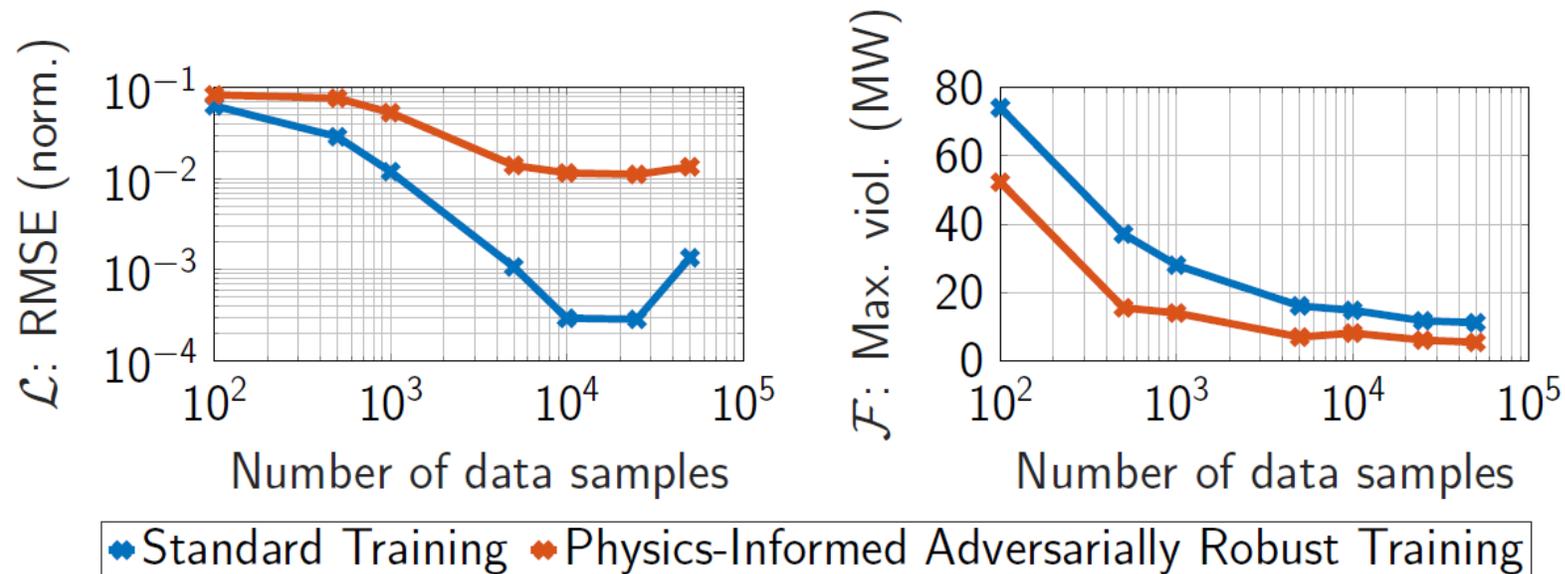
2) Evaluating **robustness** by identifying **adversarial** examples



○ predicted safe
○ predicted unsafe
● true safe
● true unsafe
★ adversarial example

Worst-Case Guarantees for Learning DC-OPF

- **Application:** Neural network to predict optimal generator dispatch for a given system loading.
- **Test case:** IEEE 30 bus system with base loading of 189 MW +/-20% load variation.



Conclusions and Future Work



- Introduced framework based on **mixed-integer linear programming** to
 - evaluate neural network **robustness** by identifying **adversarial** examples
 - obtain **provable** guarantees for **security** classifiers and predicting solutions to **DC-OPF** problems
- Future work
 - Explore **trade-off** between accuracy and satisfying constraints
 - Obtain guarantees related to **non-linear** physical constraints
- For more details please refer to the poster and publications below
 - Venzke, A., and Chatzivasileiadis, S. “Verification of Neural Network Behaviour: Formal Guarantees for Power System Applications.” *accepted to IEEE Transactions on Smart Grid* (2020).
 - Venzke, A., Qu, G., Low, S., and Chatzivasileiadis, S. “Learning Optimal Power Flow: Worst-Case Guarantees for Neural Networks”. *arXiv preprint arXiv:2006.11029*. (2020)