

Neural networks - energy and robustness

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Jizerka Seminar, September, 2023



Outline

- ▶ very brief introduction to neural networks
- ▶ objectives of architecture selection - accuracy, energy, robustness
- ▶ robustness to noise and adversarial examples
- ▶ robustness of networks with approximate convolutional layers
- ▶ architecture selection - robustness evaluations pitfalls
- ▶ conclusion



Introduction

Neural networks

- ▶ hot topic nowadays
- ▶ image processing, signal analysis, large language models
- ▶ classification, regression, generative tasks

Our focus

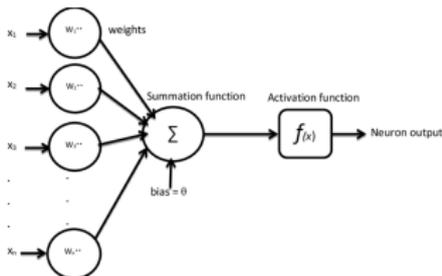
- ▶ image classification
- ▶ convolutional neural networks



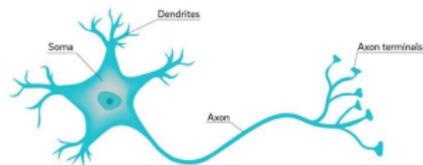
Brief introduction to neural networks

Artificial Neuron

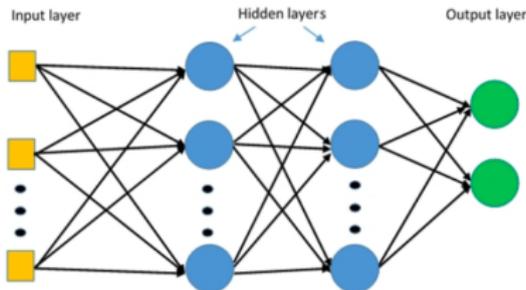
- ▶ basic building block of all neural networks



Neuron

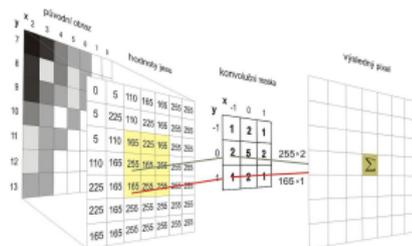
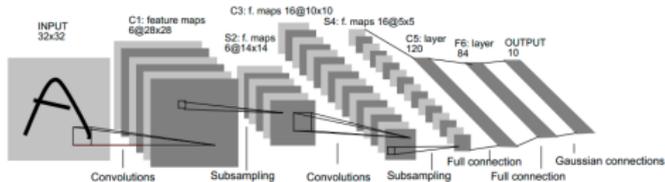


MultiLayer Perceptron

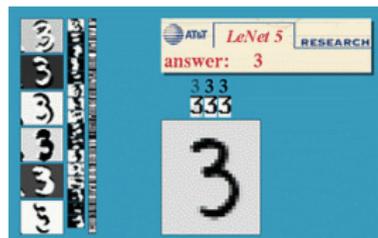


Brief introduction to neural networks

Convolutional Neural Networks



- ▶ 1994 LeNet5 (Yann LeCun)
- ▶ convolutional layers for feature extraction
- ▶ sub-sampling layers (max-pool layers)
- ▶ end-to-end solution



Brief introduction to neural networks

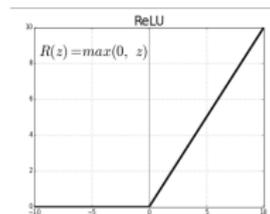
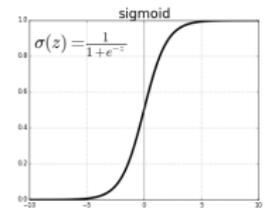
Deep Neural Networks (DNN)

- ▶ Bengio, Hinton, LeCun (2009)
- ▶ big data + GPUs/TPUs
- ▶ learning with millions of neurons
- ▶ new architectures available for computer vision, video processing, NLP



DNN Techniques

- ▶ ReLU activation function
- ▶ dropout - type of regularization
- ▶ learning with mini-batches
- ▶ transfer learning



Neural Networks Life cycle



Model Selection

- ▶ find suitable architecture for the given problem
- ▶ neural architecture search (NAS)
- ▶ evolutionary algorithm, Bayesian optimisation, gradient based

Training

- ▶ find suitable weights for the given architecture and problem
- ▶ gradient approaches

Inference

- ▶ evaluating the final trained network



Model/Architecture Selection

Past

- ▶ how well the network performs on the given task
- ▶ accuracy on the test set
- ▶ the better accuracy the better network

Today

- ▶ enable inference on mobile devices
- ▶ multi-objective optimisation problem
- ▶ trade-off between accuracy and network complexity (size, energy and memory consumption, etc.)

AppNeCo project

- ▶ energy complexity of deep neural networks (Kalina, Šíma, Vidnerová)



More objectives - robustness

Robustness objective

- ▶ need for robust models
- ▶ robustness to outliers, noise, adversarial examples

Adversarial examples

- ▶ perturbed examples (inputs) constructed to force the network to give a wrong answer

x
"panda"
57.7% confidence

$+ .007 \times$

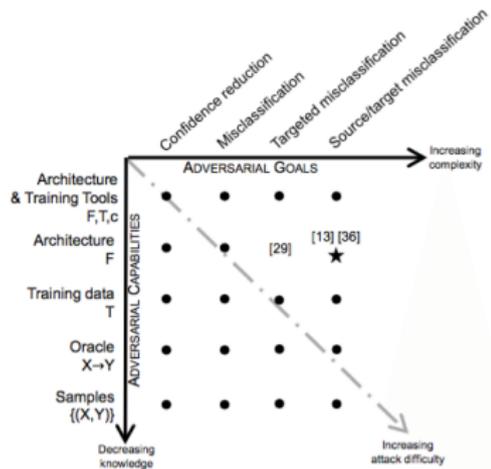
$\text{sign}(\nabla_x J(\theta, x, y))$
"nematode"
8.2% confidence

$=$

$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$
"gibbon"
99.3 % confidence



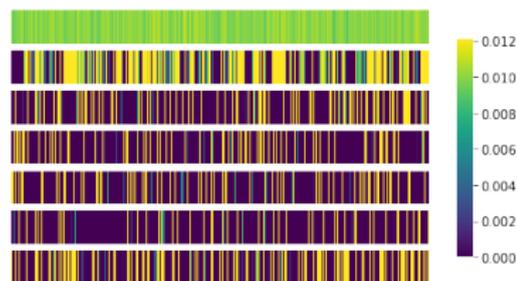
Adversarial attacks



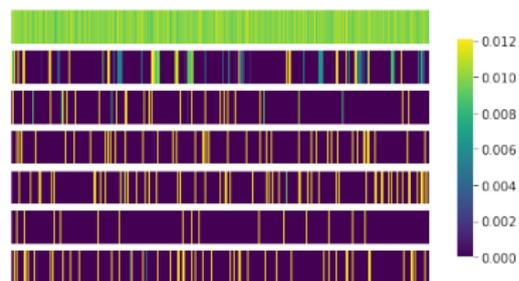
Robustness and variances

AlexNet

Pretrained network (left)



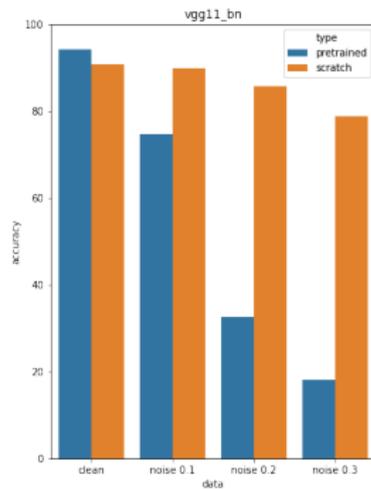
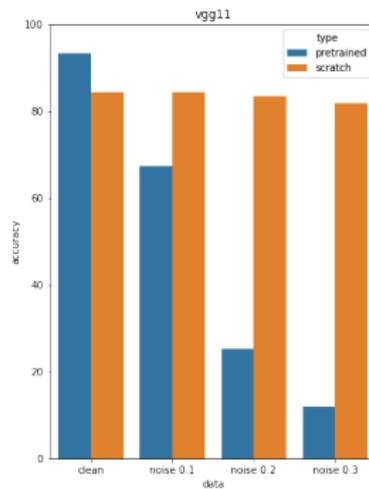
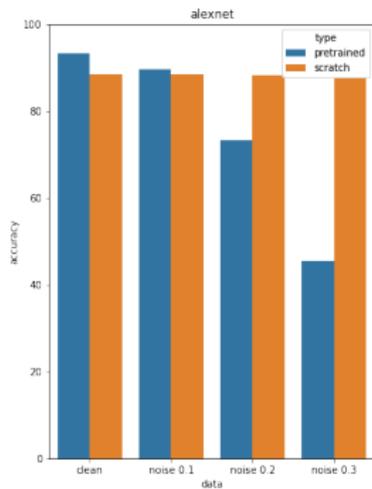
Trained from scratch (right)



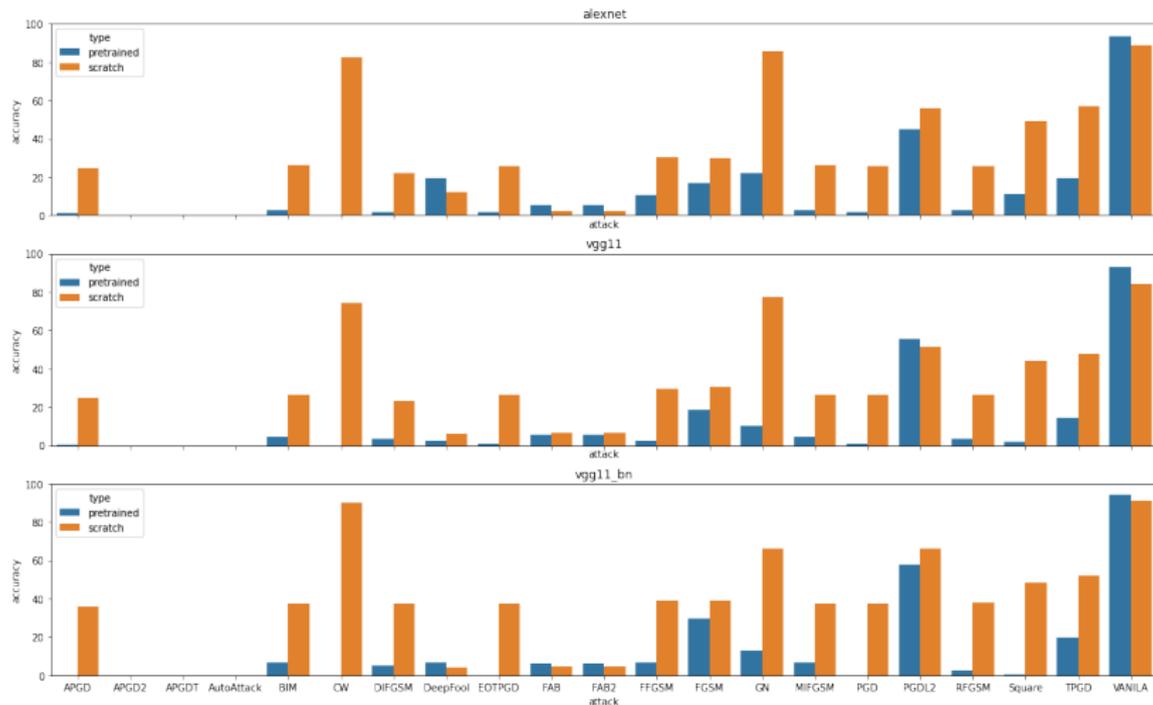
- ▶ brighter colour, higher variance



Robustness to noise



Robustness to adversarial examples



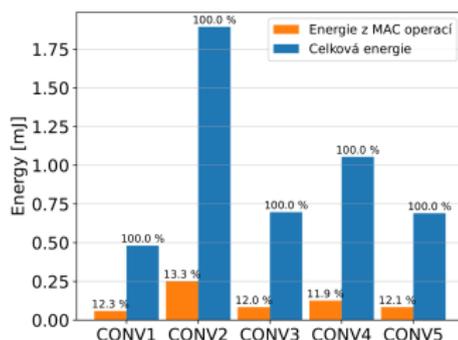
Energy efficient DNNs

Energy

$$E = E_{data} + E_{MAC}$$

(MAC ... multiply and accumulate)

E_{data} dominates



Methods

- ▶ reducing precision (quantisation), mixed precision
- ▶ pruning networks (sparse networks)
- ▶ approximate computations



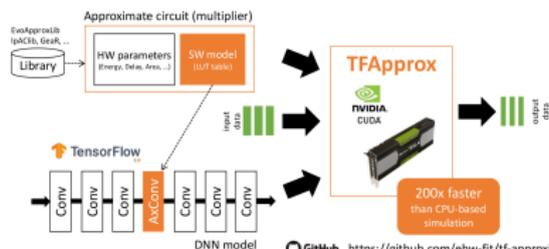
Approximate Computations

Approximate Adders and Multipliers

- ▶ work of our colleagues from Brno (Mrázek, Sekanina, Vašiček)
- ▶ evolutionary hardware - evolving approximate circuits
- ▶ multi-objective optimisation - error, energy, area and delay

Library tf-approximate

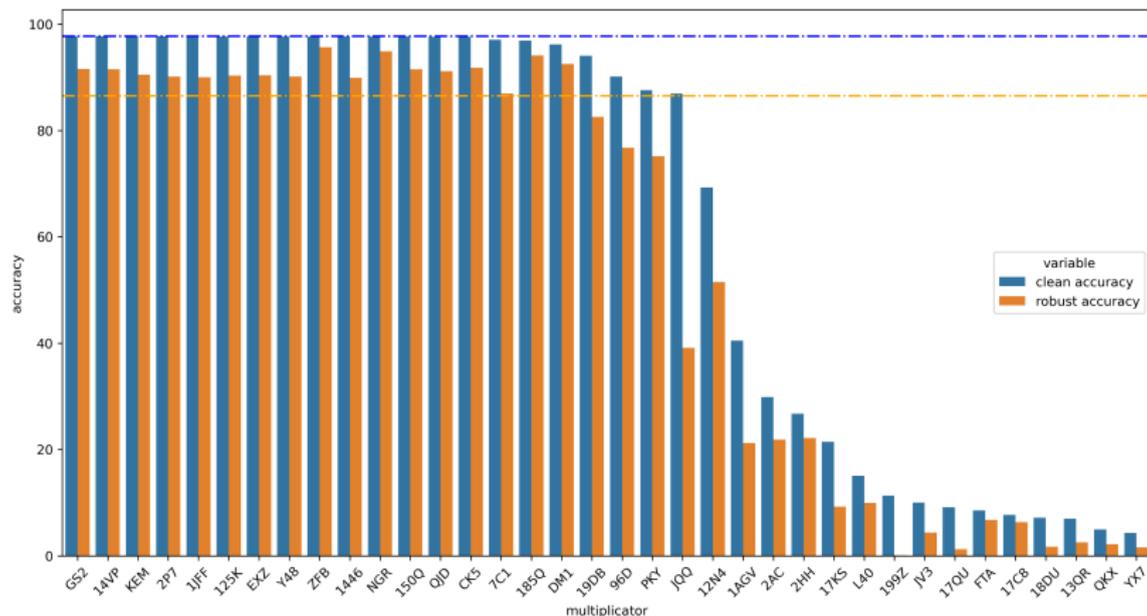
- ▶ library with Tensorflow interface
- ▶ provides approximate convolutional layers
- ▶ enables simulation of approximate computations



GitHub <https://github.com/ehw-fit/tf-approximate>



Approximate Layers - Robustness



Neural Architecture Search

Towards Multi-objectivity

- ▶ accuracy
- ▶ robustness
- ▶ model size
- ▶ energy

Reducing computational complexity

- ▶ NAS is typically very computationally demanding
- ▶ reducing time and energy consumption → “*green autoML*”
- ▶ performance prediction
- ▶ multi-objective performance prediction (Neruda, Kadlecová, Vidnerová, Pilát, Lukasik)



Reducing cost of NAS

Performance prediction task

- ▶ no need for exact prediction
- ▶ comparison between two models enough (one target)

Approaches

- ▶ surrogate models
- ▶ zero-cost proxies
- ▶ learning curve extrapolation

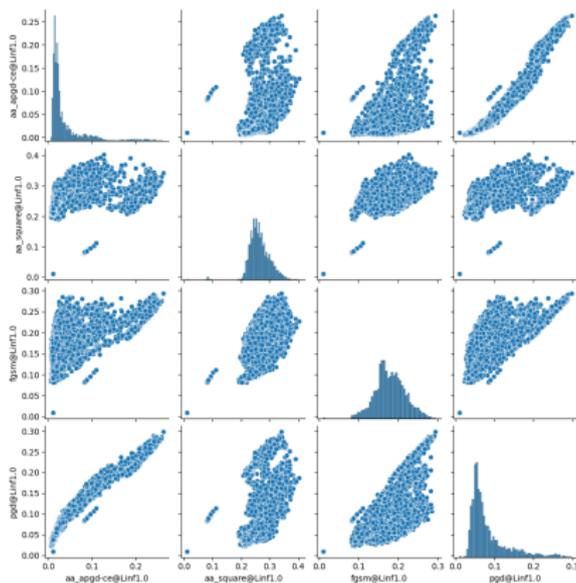
Our Goal

- ▶ performance prediction for diverse objectives
- ▶ multi-objective performance prediction



Predicting robustness

- ▶ evaluation of robustness is very time consuming
- ▶ prediction seems to be more difficult than prediction of accuracy



Prediction based on zero-cost proxies

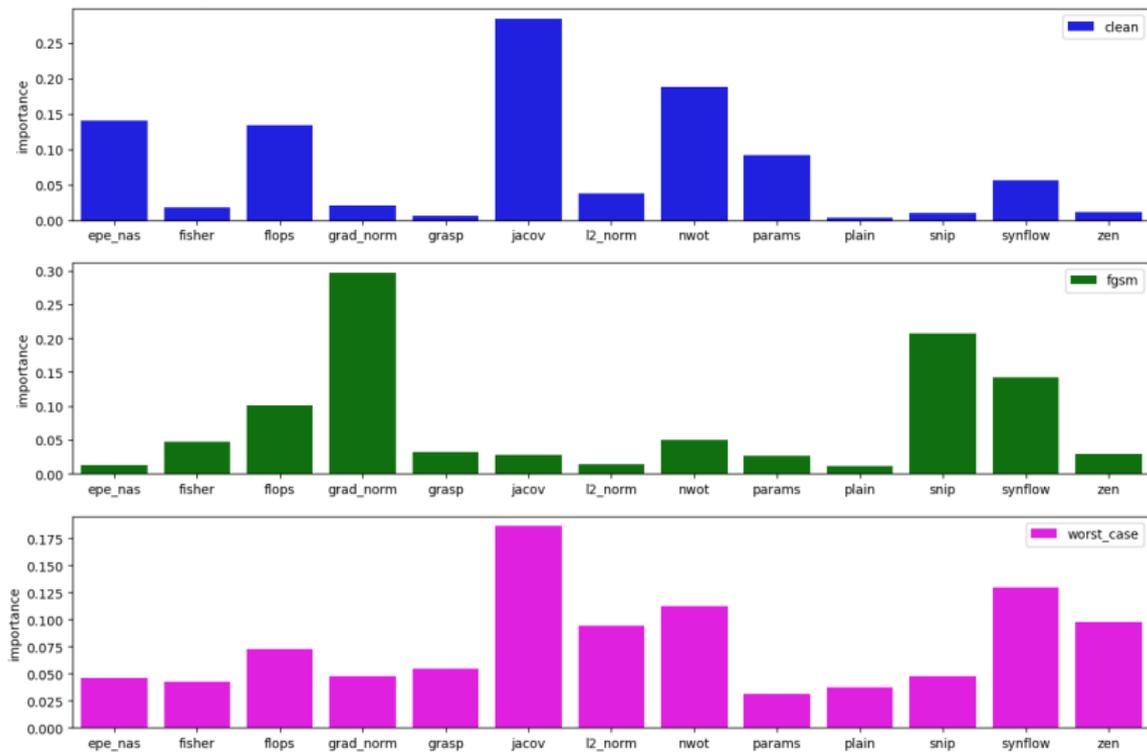
- ▶ XGBoost, on NAS-Bench-201, 6466 networks
- ▶ cifar-100
- ▶ predict clean and robust accuracy based on zero-cost-proxies
- ▶ inspect feature importance
- ▶ 100/1000 training samples

training samples	avg r2 score					
	clean	apgd	square	fgsm	pgd	worst case
100	0.697	0.261	0.329	0.668	0.227	0.261
1000	0.892	0.513	0.579	0.813	0.509	0.514



Prediction based on zero-cost proxies

Feature importance



Conclusion

Takeaway

- ▶ finding a good model for the given task is a multi-objective problem
- ▶ main objectives:
 - ▶ accuracy
 - ▶ robustness
 - ▶ size
 - ▶ energy
- ▶ need for speed-up of the whole process

Thank you! Questions?

