[course site]

#DLUPC

Day 5 Lecture 2

Methodology

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UPC

Outline

- **Capacity of the network**
  - Underfitting
  - Overfitting
- **Prevent overfitting**
  - Dropout, regularization
- **Data**
  - training, validation, test partitions
  - Augmentation
- **Strategy**

Outline


Data
machine
deep
validation
test
training
Augmentation
Overfitting
network
Dropout
Underfitting
Capacity
Regularization
Partition

It’s all about the data...

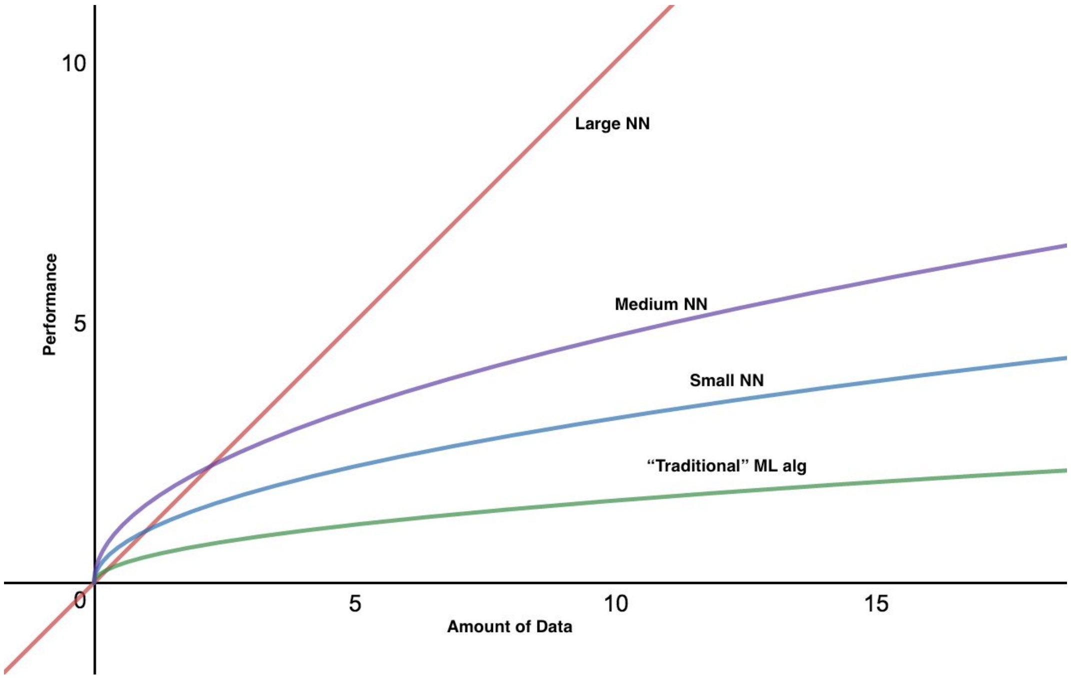
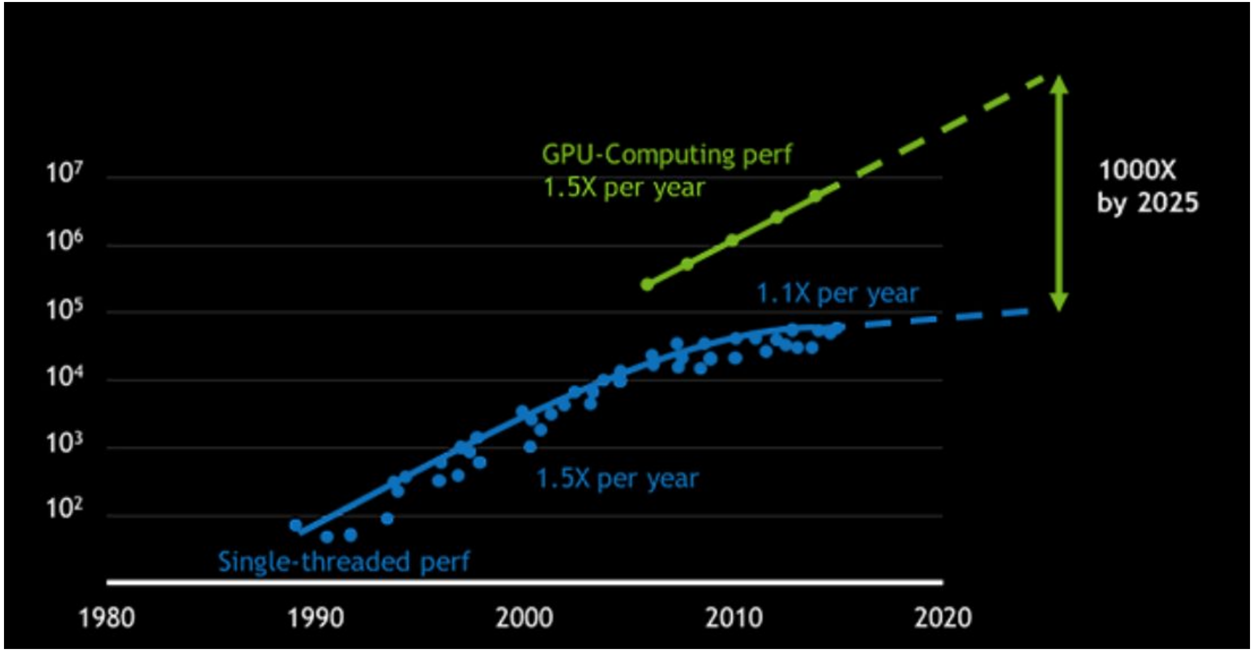


Figure extracted from Kevin Zakka's Blog, Nuts and Bolts of Applying Deep Learning, 2016.

well, not only data...

- Computing power: GPUs



Source: NVIDIA 2017

well, not only data...

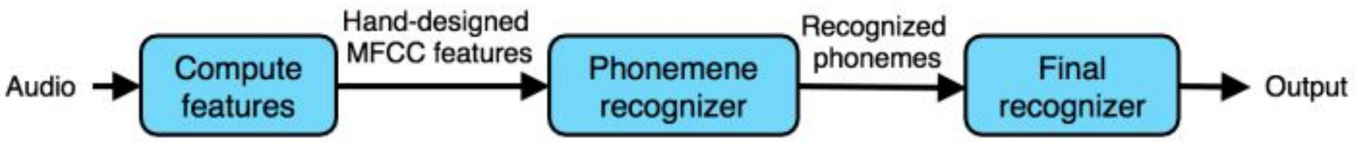
- Computing power: GPUs

- New learning architectures
  - CNN, RNN, LSTM, DBN, GNN, GAN, etc.

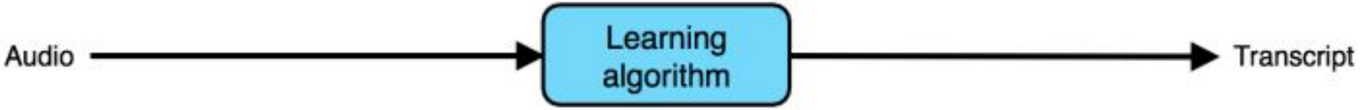
http://www.asimovinstitute.org/neural-network-zoo/

End-to-end learning: speech recognition

Traditional model



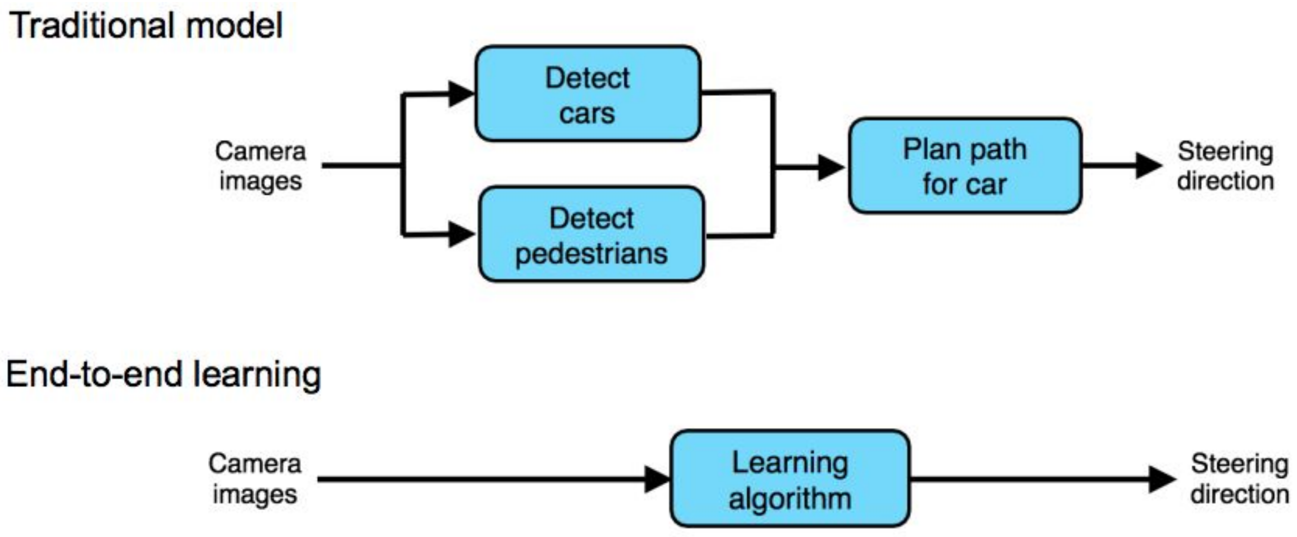
End-to-end learning



This works well given enough labeled (audio, transcript) data.

Slide extracted from Andrew Ng NIPS 2016 Tutorial

End-to-end learning: autonomous driving



Given the safety-critical requirement of autonomous driving and thus the need for extremely high levels of accuracy, a pure end-to-end approach is still challenging to get to work. End-to-end works only when you have enough (x,y) data to learn function of needed level of complexity.

Slide extracted from Andrew Ng NIPS 2016 Tutorial

Network capacity

- Space of representable functions that a network can potentially learn:
  - Number of layers / parameters

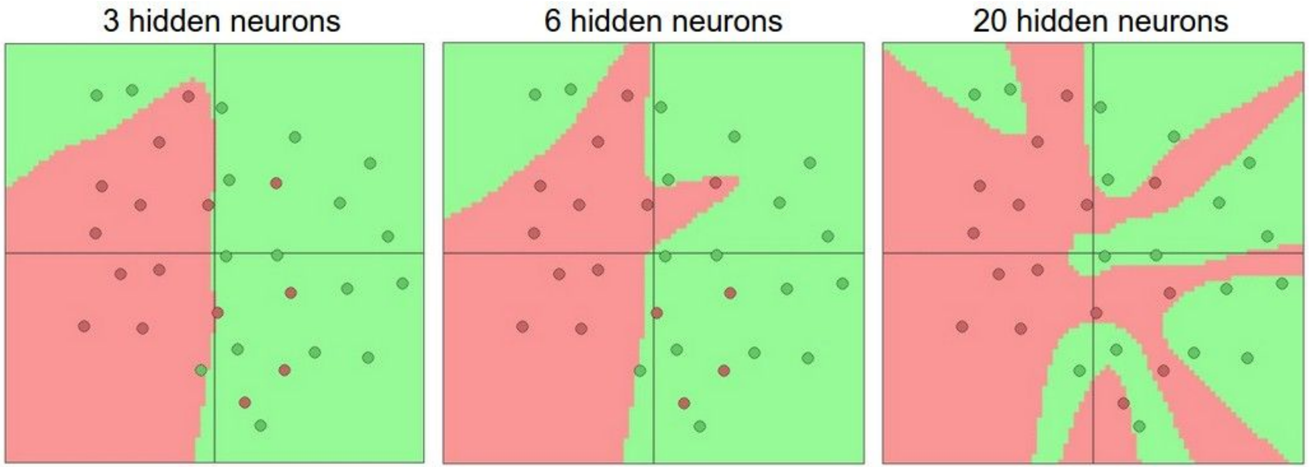
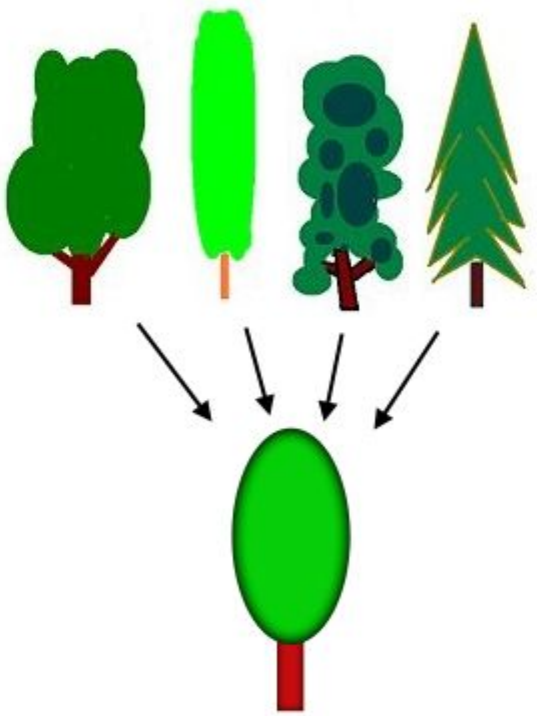


Figure extracted from Stanford CS class CS231n: Convolutional Neural Networks for Visual Recognition.

Generalization

The network needs to **generalize** beyond the training data to work on new data that it has not seen yet



Underfitting vs Overfitting

- **Overfitting**: network fits training data too well
  - Excessively complicated model
- **Underfitting**: network does not fit training data well enough
  - Excessively simple model

Both underfitting and overfitting lead to poor predictions on new data and they do not generalize well

Underfitting vs Overfitting

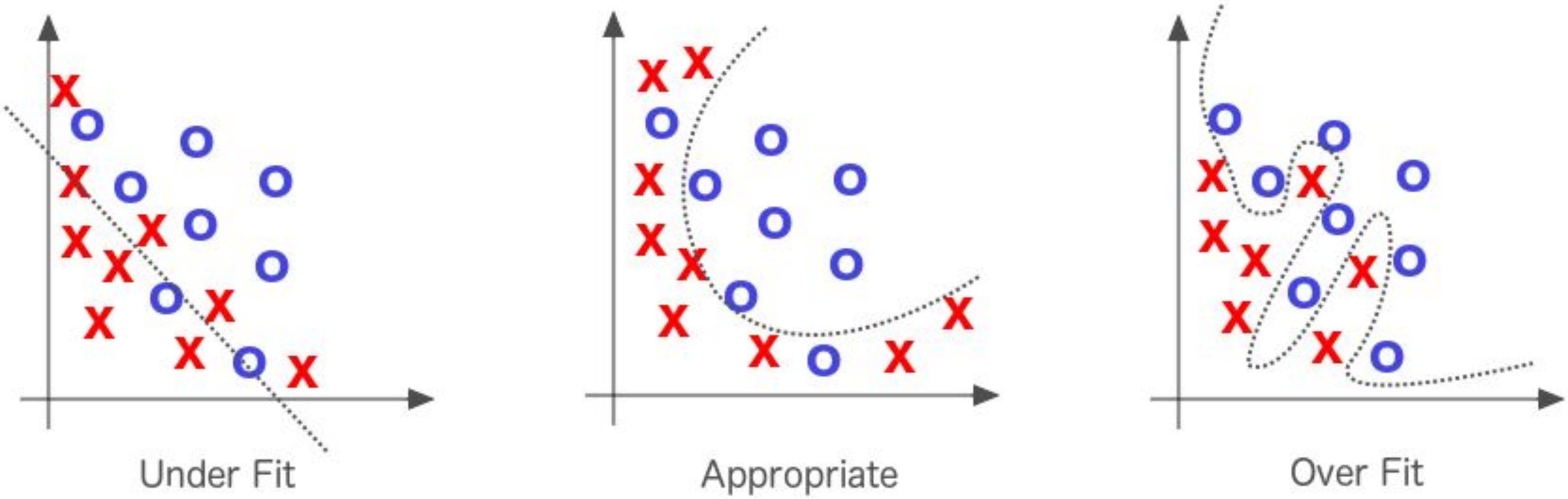


Figure extracted from Deep Learning by Adam Gibson, Josh Patterson, O'Reilly Media, Inc., 2017

Data partition

How do we measure the generalization instead of how well the network does with the memorized data?

Split your data into two sets: training and test

Underfitting vs Overfitting

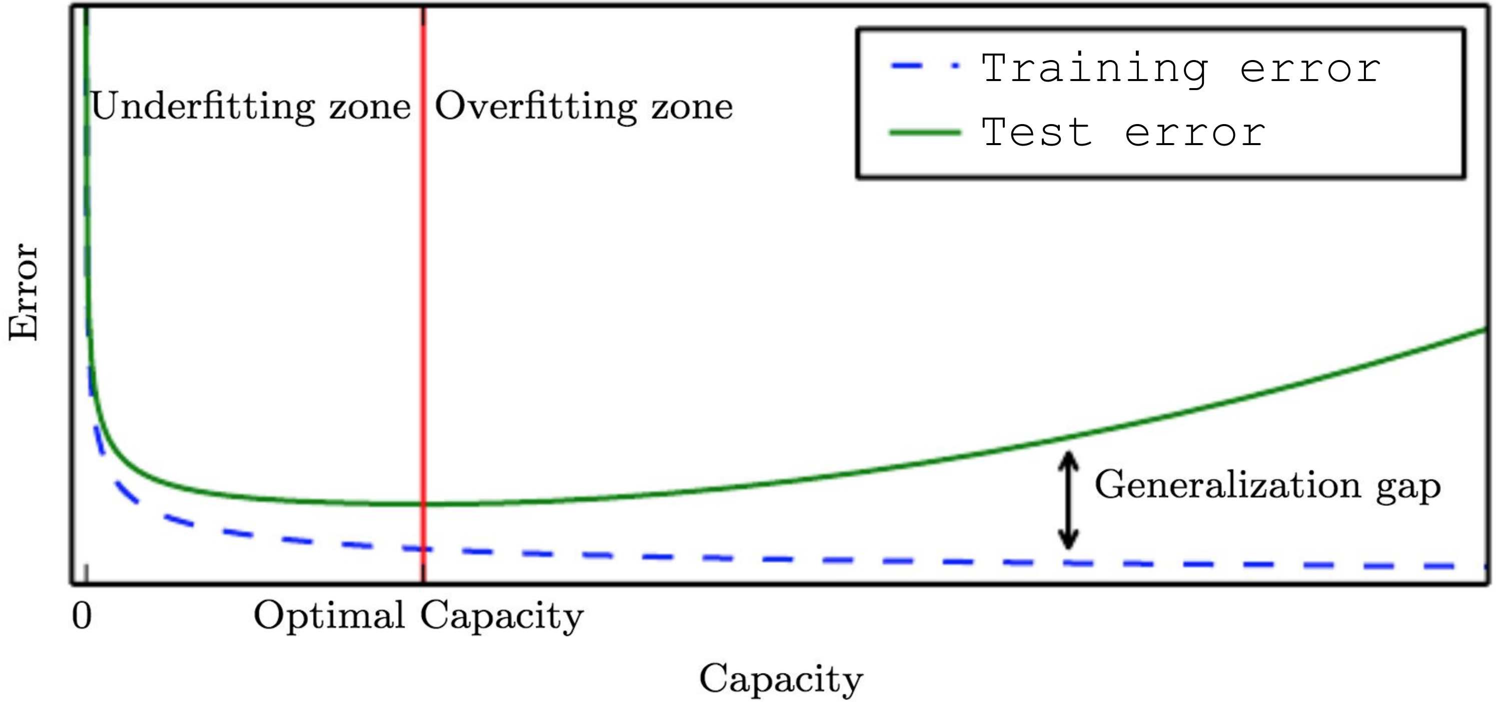


Figure extracted from [Deep Learning]() by Ian Goodfellow and Yoshua Bengio and Aaron Courville, MIT Press, 2016

Data partition revisited

- Test set **should not** be used to tune your network
  - Network architecture
  - Number of layers
  - Hyper-parameters

- Failing to do so will overfit the network to your test set!
  - https://www.kaggle.com/c/higgs-boson/leaderboard

Data partition revisited (2)

- Add a **validation** set!

- Lock away your test set and use it only as a last validation step / measure of performance

The bigger the better?

- Large networks
  - More capacity / More data
  - Prone to overfit

- Smaller networks
  - Lower capacity / Less data
  - Prone to underfit

The bigger the better?

- The probability of finding a “bad” (high value) local minimum is non-zero for small networks and decreases quickly with network size.
- In large networks, most local minima are equivalent and yield similar performance.
- Struggling to find the global minimum on the training set (as opposed to one of the many good local ones) is not useful in practice and may lead to overfitting.

Better large capacity networks and prevent overfitting

Anna Choromanska et.al. “The Loss Surfaces of Multilayer Networks”, https://arxiv.org/pdf/1412.0233.pdf

Prevent overfitting

- Early stopping
- Regularization
- Dropout
- Data augmentation
- Parameter sharing
- Adversarial training

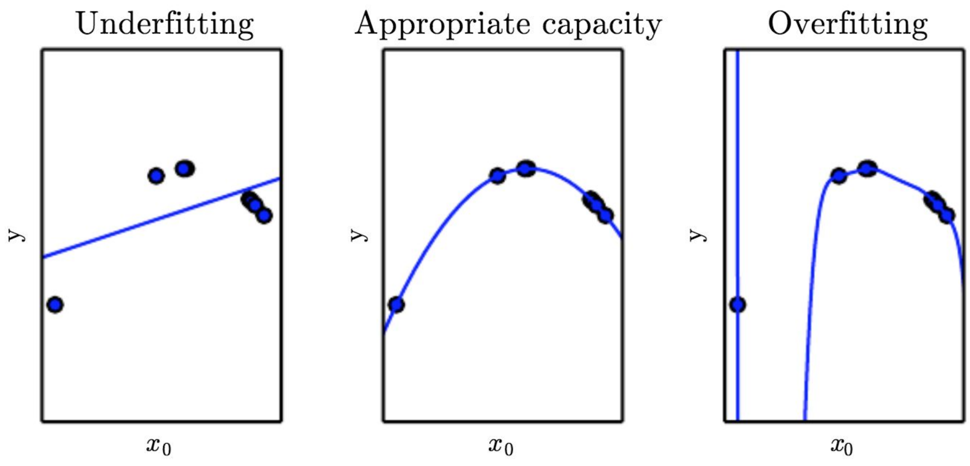
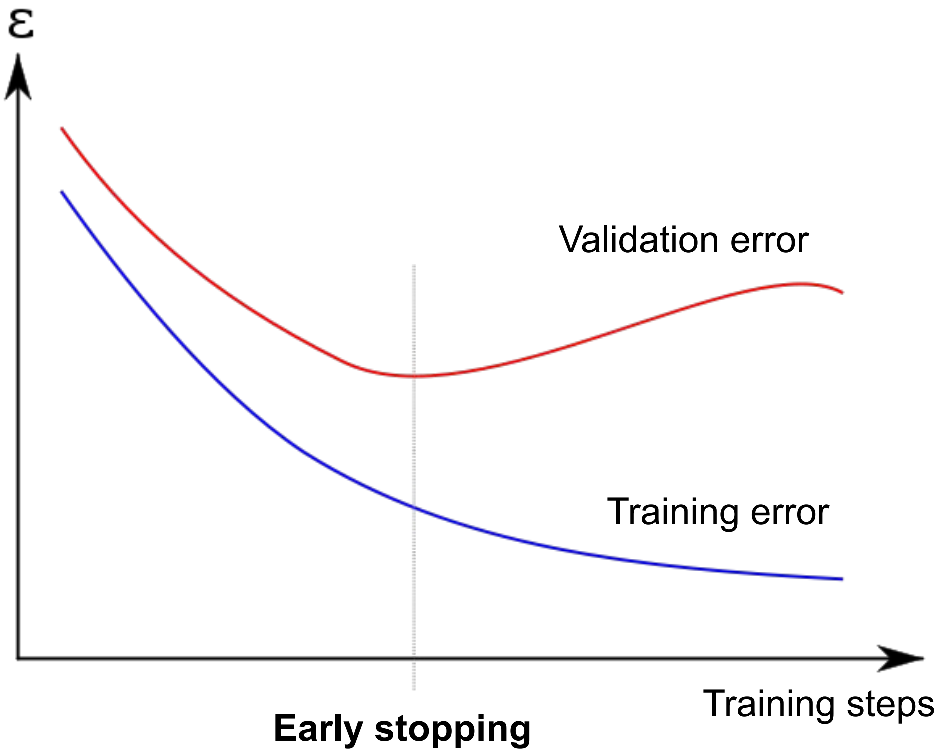


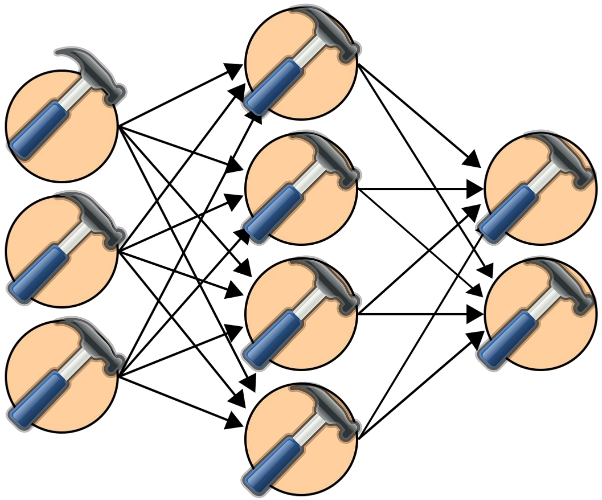
Figure extracted from Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville, MIT Press, 2016

Early stopping



Weight regularization (1)

- Control the capacity of the network to **prevent overfitting**
- Large weights tend to cause sharp transitions in node functions → large changes in output for small changes in inputs
  - **Penalize** the **weights** of the nodes in the network
  - **Discourages** learning a more **complex** or flexible **model**



Weight regularization (2)

- L2-regularization (weight decay):

regularization hyper-parameter

$$\mathcal{L}_{new} = \mathcal{L} + \frac{\lambda}{2} W^2$$

- L1-regularization:

$$\mathcal{L}_{new} = \mathcal{L} + \frac{\lambda}{2} |W|$$

Weight regularization (3)

- Limit the values of parameters in the network
  - L2 vs L1 regularization

$$\mathcal{L}_{new} = \mathcal{L} + \frac{\lambda}{2} W^2 \quad \mathcal{L}_{new} = \mathcal{L} + \frac{\lambda}{2} |W|$$

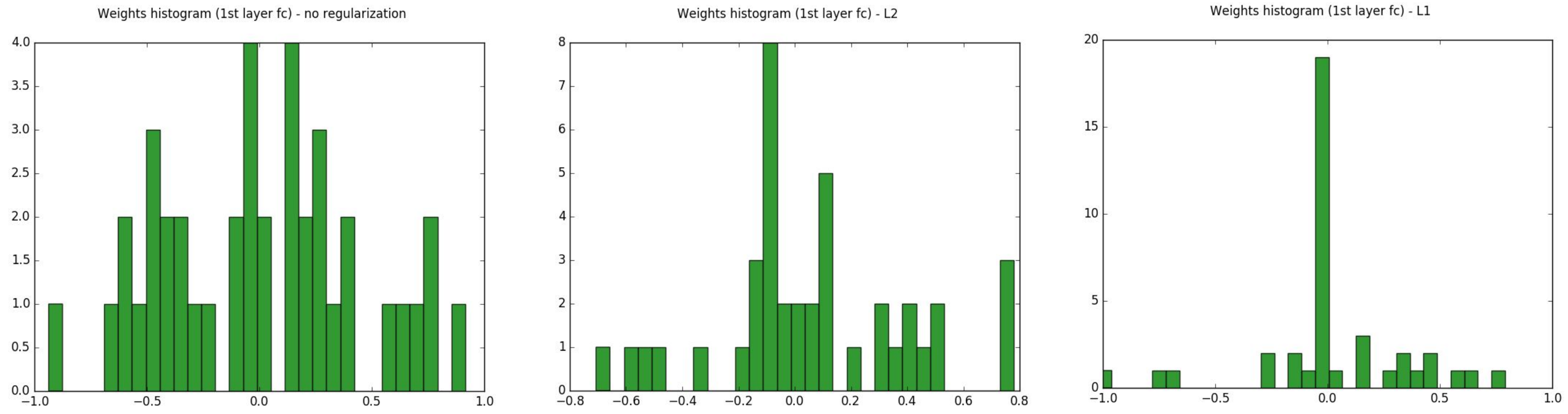


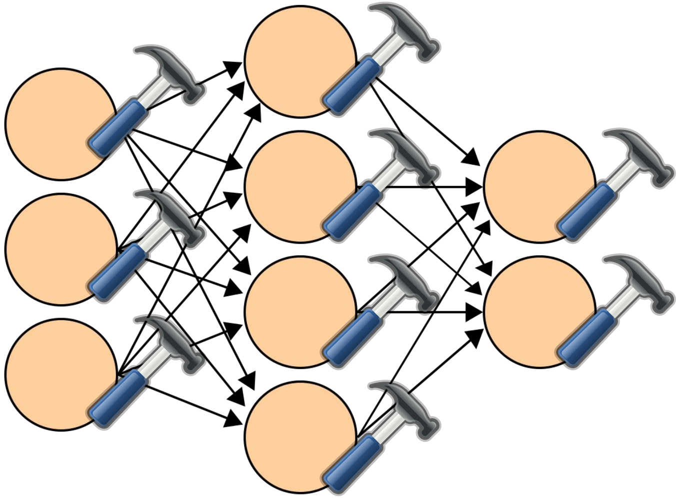
Figure extracted from Cristina Scheau, [Regularization in Deep Learning](), 2016

Weight regularization (4)

- L2 regularization heavily penalizes peaky weights and prefers diffuse / low value weights
- L1 regularization leads weights to become sparse (i.e. very close to exactly zero)

Activation regularization (1)

- Large activations (output values) can also denote overfitting or unstability
- Instead of controlling the weights (weight regularization) → control directly the output of nodes (activation regularization)
  - **Penalize** the **activations** of the nodes in the network
  - **Encourages** networks with low activations



Activation regularization (2)

- Two common methods for calculating the magnitude of the activation are:
  - Sum of absolute activation values → L1 norm
  - Sum of squared activation values → L2 norm
- L1 norm encourages sparsity
- L2 norm encourages small activations values in general

- A hyperparameter is needed to control the amount of penalty in the activation.

Dropout (1)

- At each training iteration, randomly remove some nodes in the network along with all of their incoming and outgoing connections (N. Srivastava, 2014)

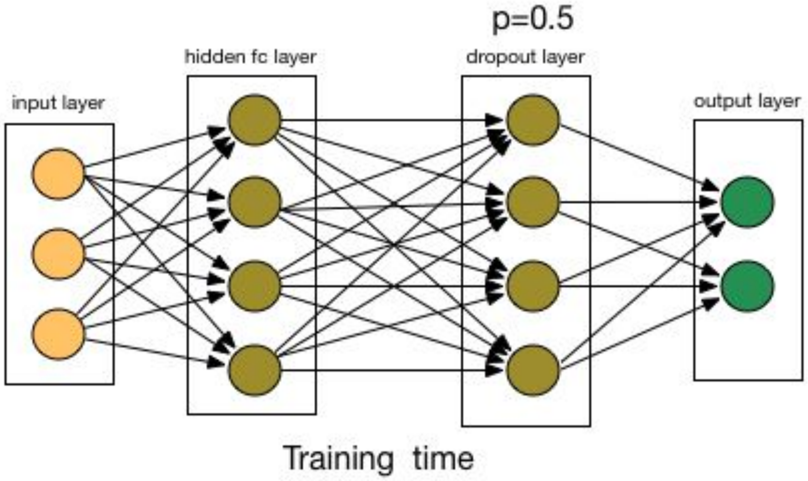


Figure extracted from Cristina Scheau, Regularization in Deep Learning, 2016

Dropout (2)

- Why dropout works?
  - Nodes become more insensitive to the weights of the other nodes → more robust.
  - Averaging multiple models → **ensemble**.
  - Training a collection of 2^n thinned networks with parameters sharing

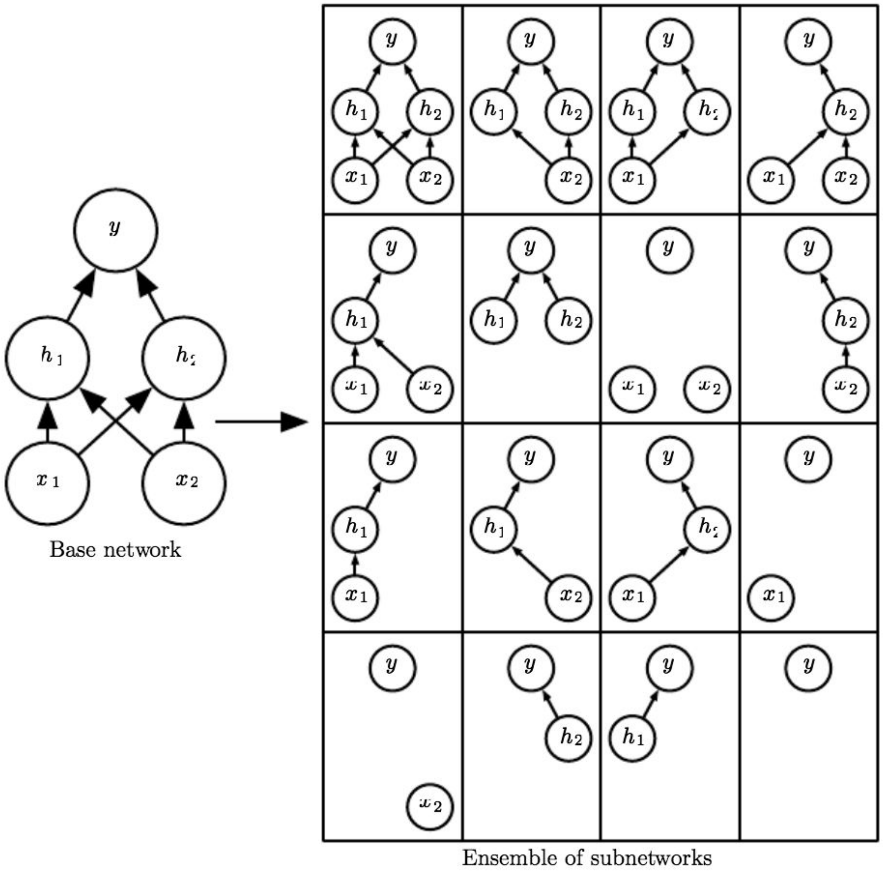


Figure extracted from Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville, MIT Press, 2016

Dropout (3)

- Every forward pass, network slightly different.
- Reduce co-adaptation between neurons
- More robust features
- Dropout is **removed** in validation/testing

❌ **More iterations** for convergence

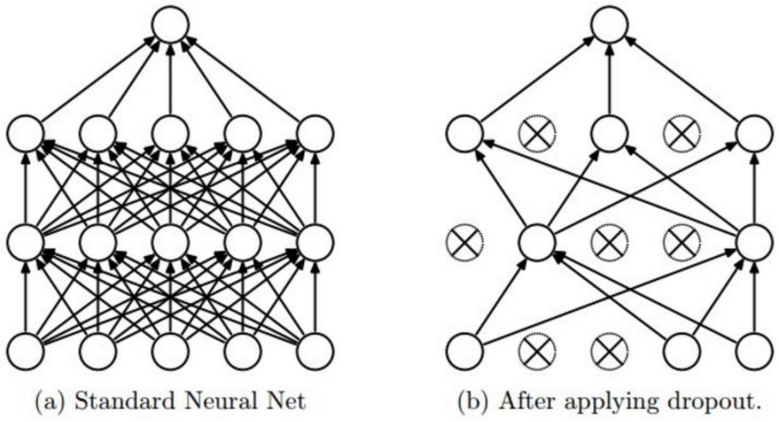
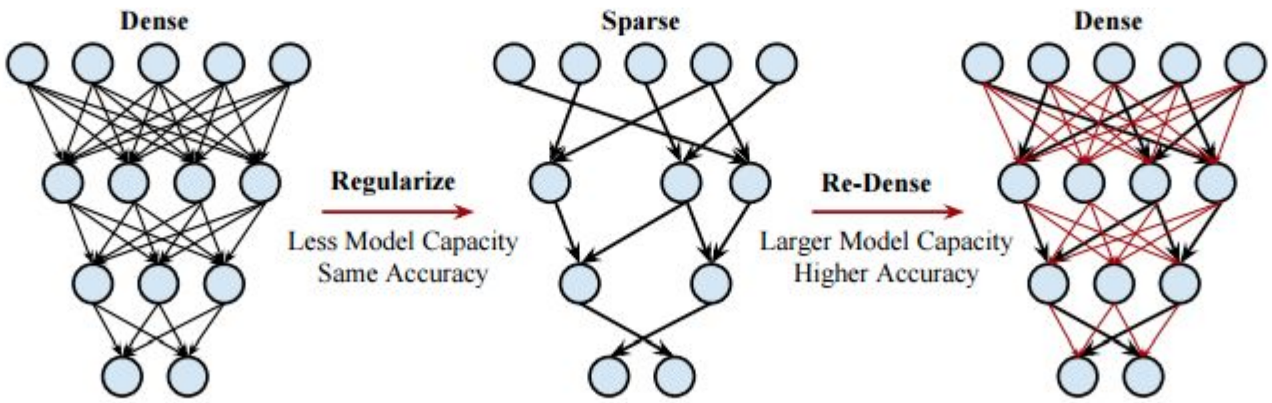


Figure extracted from [Deep Learning](#) by Ian Goodfellow and Yoshua Bengio and Aaron Courville, MIT Press, 2016

Dropout (4)

- Dense-sparse-dense training (S. Han 2016)
  a. Initial regular training
  b. Drop connections where weights are under a particular threshold.
  c. Retrain sparse network to learn weights of important connections.
  d. Make network dense again and retrain using small learning rate, a step which adds back capacity.



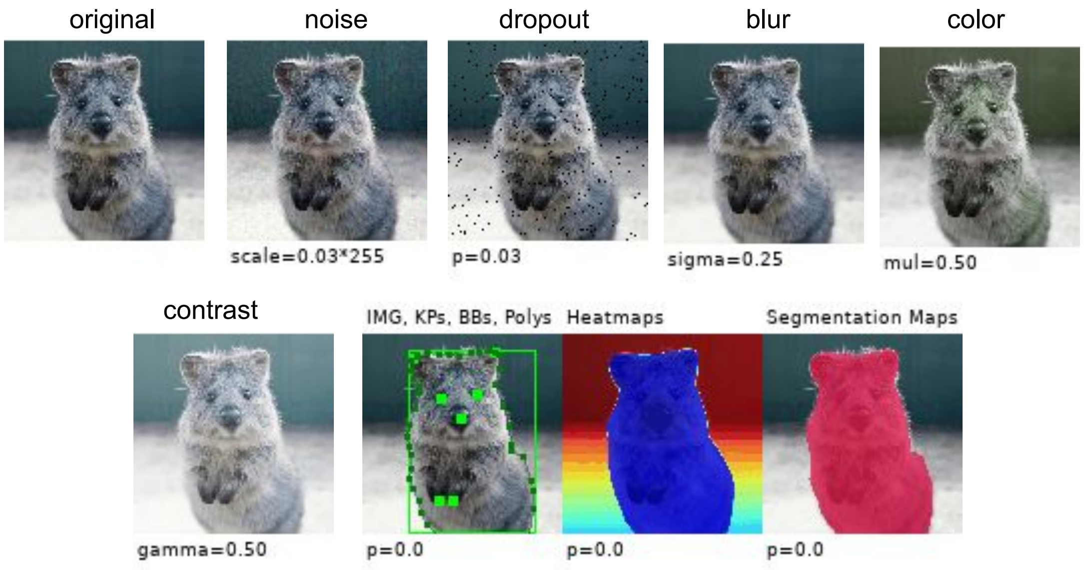
Data augmentation (1)

- Modify input samples artificially to increase the data size
- On-the-fly while training
  - Inject Noise
  - Transformations
- Not used in testing/validation

Alex Krizhevsky, [ImageNet Classification with Deep Convolutional Neural Networks](), NIPS 2012

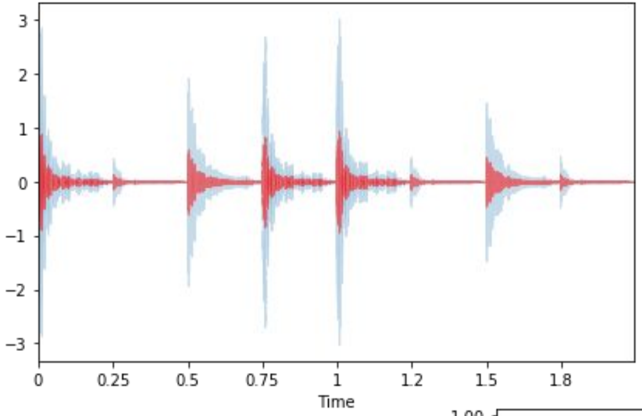
Data augmentation (2): Image

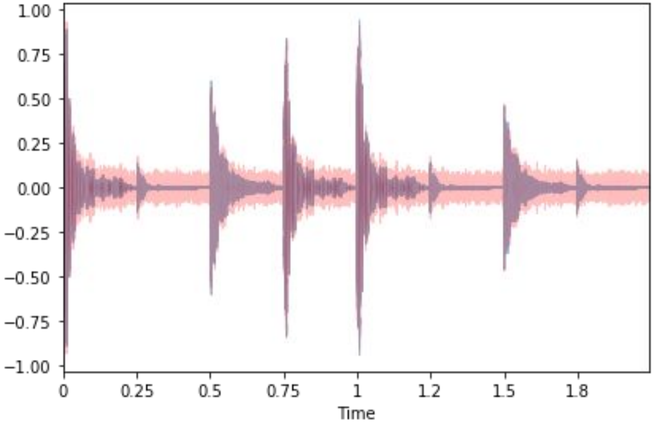
- Noise injection
- Droput
- Blurs
- Color changes
- Contrast
- Transformations
  - GT transformed!
- Crops, shifts
- Application specific
  - Clouds, snow, etc.



Data augmentation (3): Audio

- Noise injection
- Shifting time
- Changing pitch
- Changing speed
- Crops
- Loudness
- Mask





Data augmentation (4): Text

- OCR changes
  - o → 0
  - i → 1
- Keyboard changes
  - Substitute character close on keyboards
- Random changes
- Substitute entire words
  - spelling mistakes
  - word2vec distance

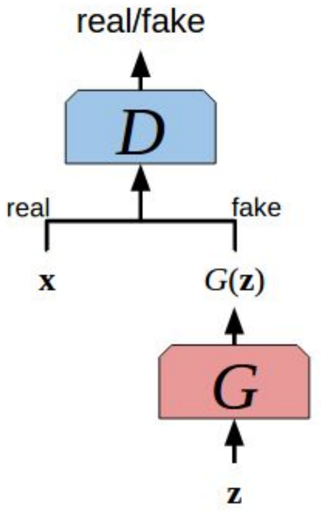
Data augmentation (5)

- Synthetic data: Generate new input samples

A. Palazzi, Learning to Map Vehicles into Bird's Eye View, ICIAP 2017
DeepGTAV plugin: https://github.com/ai-tor/DeepGTAV
CARLA Simulator.

Data augmentation (6)

- GANs (Generative Adversarial Networks)



P. Ferreira,et.al., Towards data set augmentation with GANs, 2017.
L. Sixt, et.al., RenderGAN: Generating Realistic labeled data, ICLR 2017.

Parameter sharing

Multi-task Learning

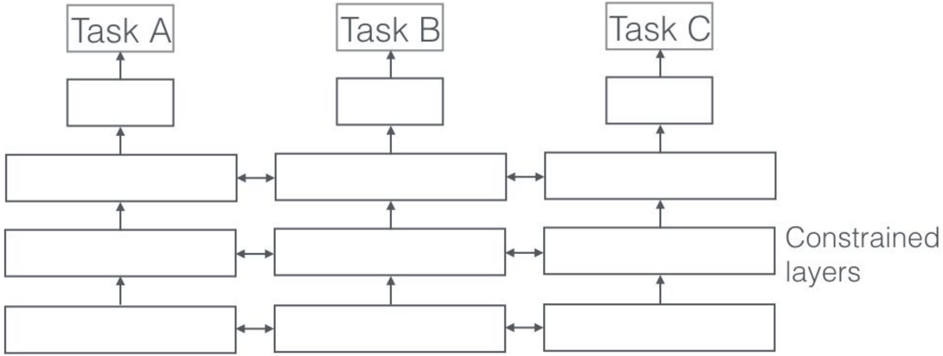
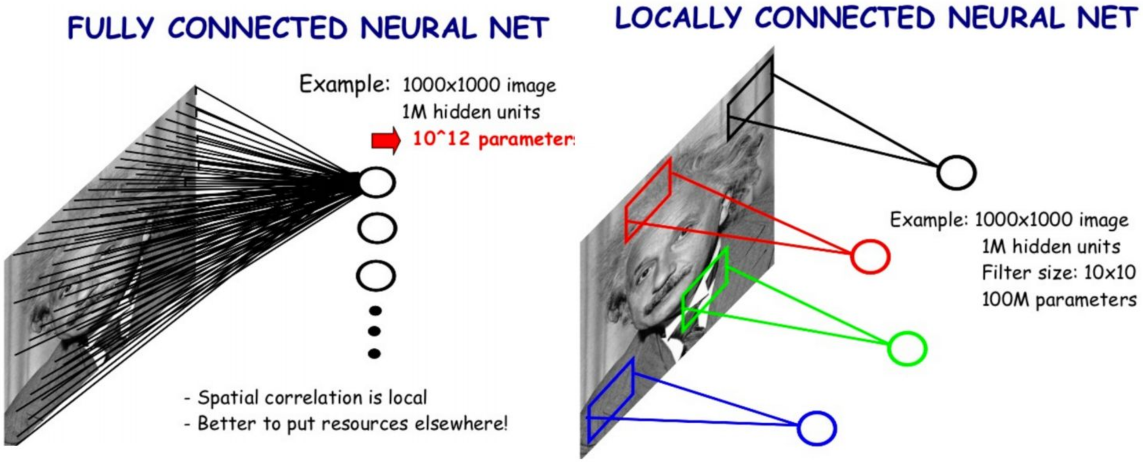


Figure extracted from Sebastian Ruder, [An Overview of Multi-Task Learning in Deep Neural Networks](), 2017

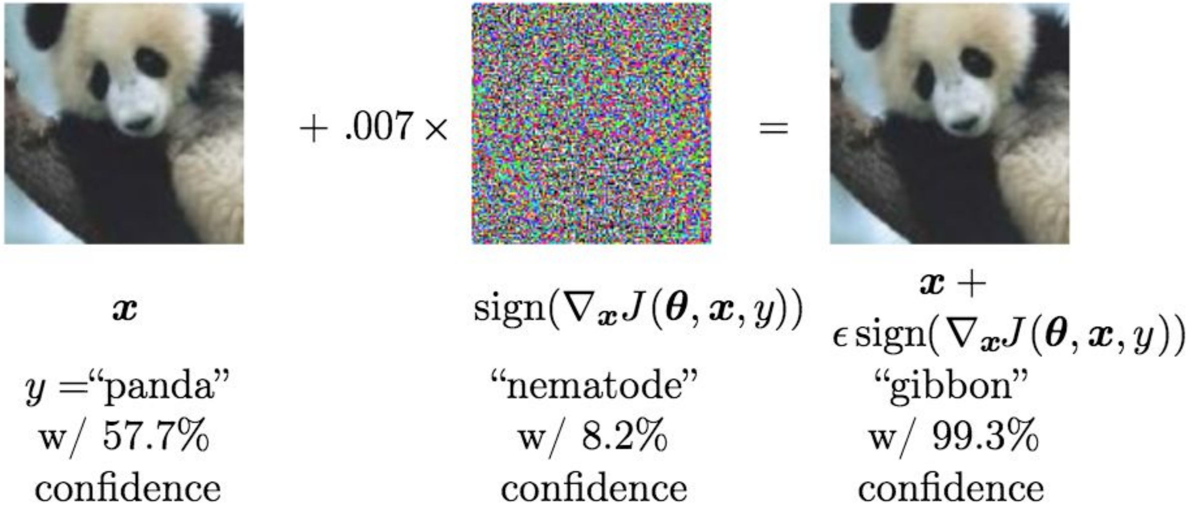


CNNs

Figure extracted from Leonardo Araujo, [Artificial Intelligence](), 2017

Adversarial training

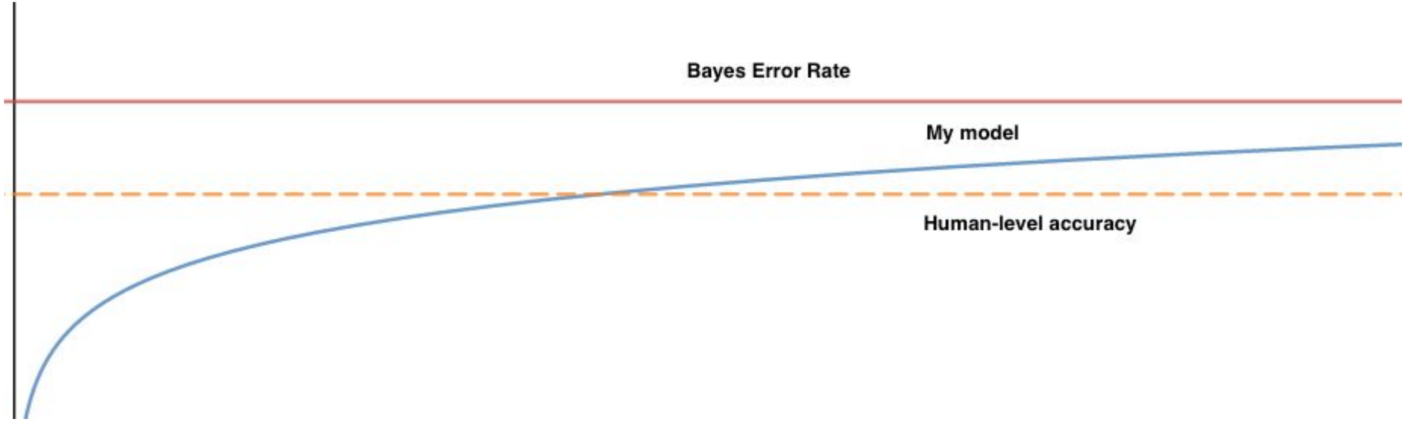
- Search for **adversarial examples** that network misclassifies
  - Human observer cannot tell the difference
  - However, the network can make highly different predictions.



I. Goodfellow, et.al., [Explaining and Harnessing Adversarial Examples](), ICLR, 2015
A. Athalye, et.al, [Synthesizing Robust Adversarial Examples](), 2017

Strategy for machine learning (1)

Human-level performance can serve as a very reliable proxy which can be leveraged to determine your next move when training your model.



Strategy for machine learning (2)

TRAINING	VALIDATION	TEST
60%	20%	20%

```
Human level error . . 1%
Training error  . . . 9%
Validation error  . . 10%
Test error  . . . . . 11%
```

Underfitting

Strategy for machine learning (3)

TRAINING	VALIDATION	TEST
60%	20%	20%

```
Human level error . . 1%
Training error  . . . 1.1%
Validation error  . . 10%
Test error  . . . . . 11%
```

Overfitting training

Strategy for machine learning (4)

TRAINING 60%	VALIDATION 20%	TEST 20%

```
Human level error . . 1%
Training error  . . . 1.1%
Validation error  . . 2%
Test error  . . . . . 11%
```

Overfitting validation

Strategy for machine learning (5)

TRAINING 60%	VALIDATION 20%	TEST 20%

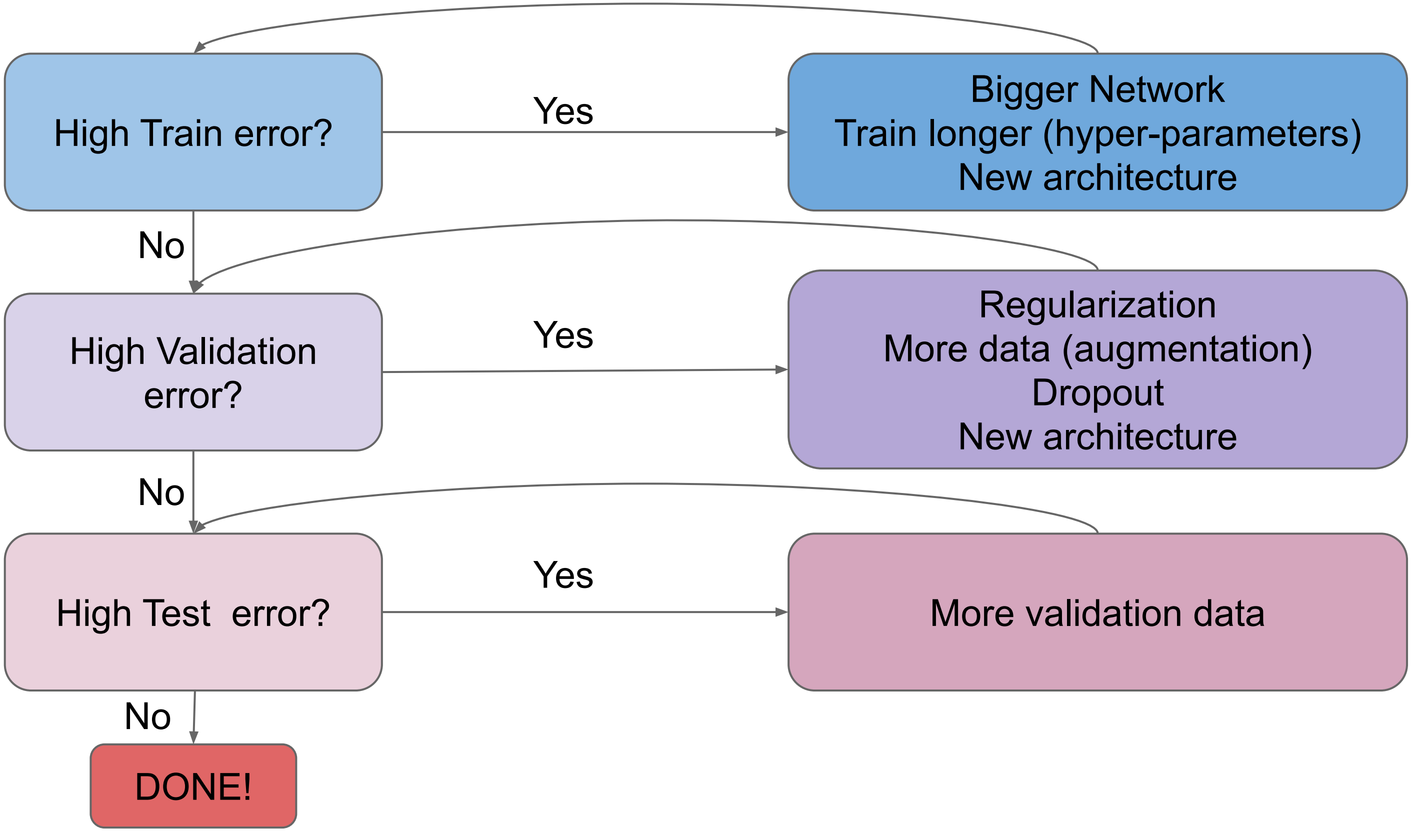
Human level error . . 1%

Training error . . . 1.1%

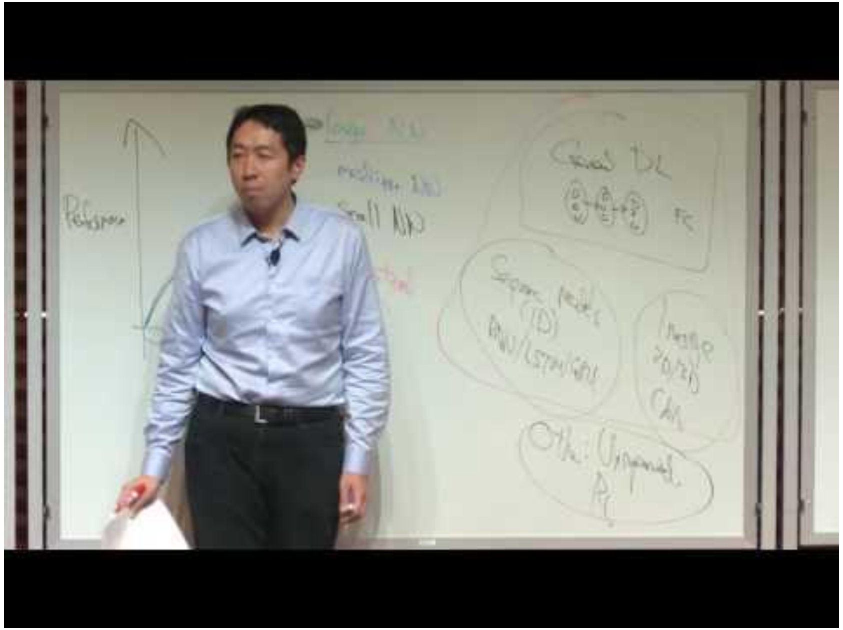
Validation error . . 1.2%

Test error 1.2%

Strategy for machine learning (5)



References



Nuts and Bolts of Applying Deep Learning by Andrew Ng

https://www.youtube.com/watch?v=F1ka6a13S9I

Questions?

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