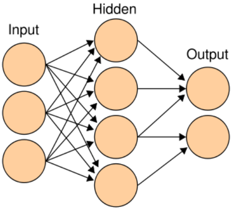
Supervised Learning: Performance Issues

19 February 2020

Training Neural Nets
Decisions, decisions...



- How do we...
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  - Initialise the weights?
  - Decide on the architecture?
  - Choose activation functions?
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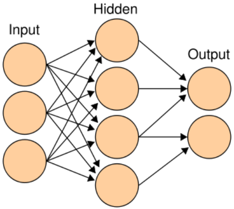

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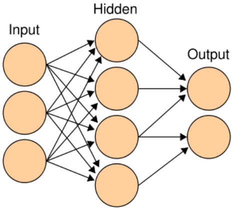

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- "Whatever I am familiar with!"

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- Add an extra input unit to indicate if a parameter is missing

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- Which one is better: **dense or sparse**?

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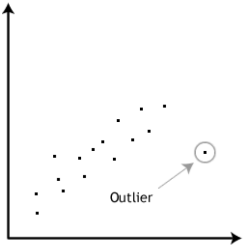
Outliers

Outlier patterns produce large errors and divert the search



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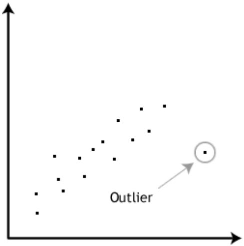

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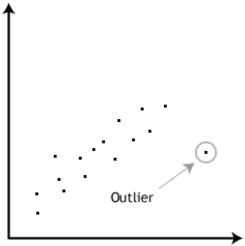

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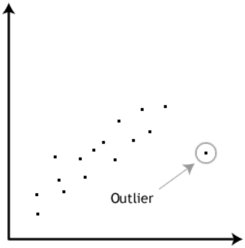

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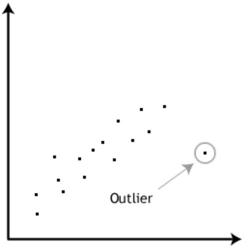

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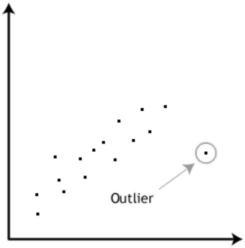

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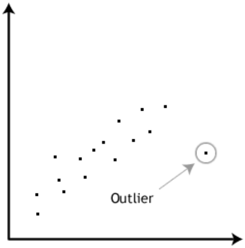

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  - This approach is called “Huber loss” in statistics

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Scaling Inputs

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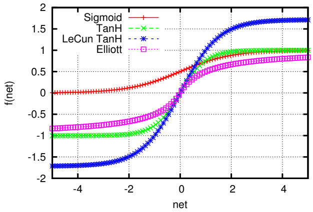
- What is saturation and why is it bad?



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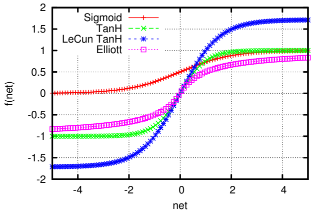
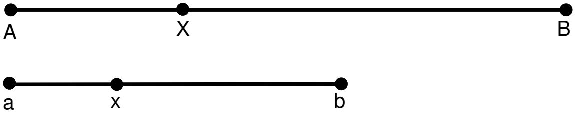


Saturation

- Derivatives near assymptotes are close to 0 => slow learning
- A saturated output unit does not indicate the “confidence” level of the NN: all patterns, even the ones not fitted very well by the NN, will be classified with the same “strength”

Data Preparation
Linear (Min-Max) Scaling



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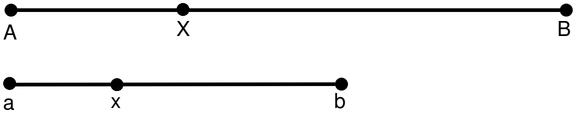

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- $\frac{X-A}{B-A} = \frac{x-a}{b-a}$
- $x = \frac{X-A}{B-A}(b-a) + a$
- x - scaled, X - unscaled, A, B - unscaled min and max, a, b - scaled min and max

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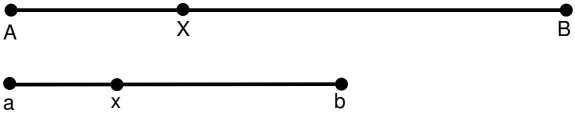

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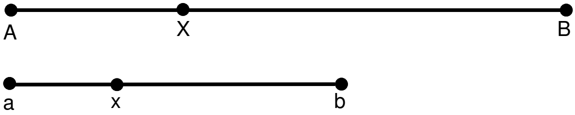

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- What if there is an outlier?

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Mean Centering: Mean of 0

- Convert the existing distribution to a “gaussian” one
- Average value of variable Z_i for all P: $\bar{Z}_i = \sum_{p=1}^{P} Z_{i,p}/P$
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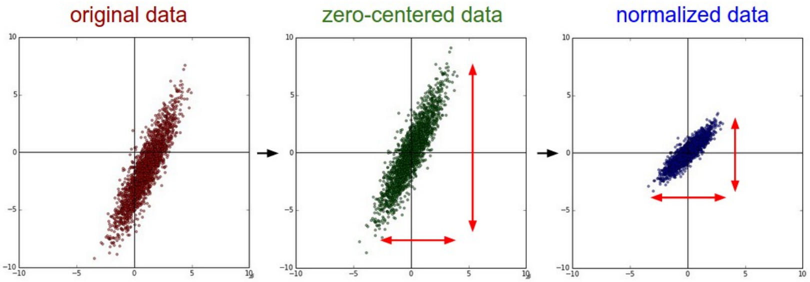
Variance Scaling: Variance of 1

- Let σ_{z_i} be the standard deviations of $Z_{i,p}$. Then:
  - $Z_{i,p}^V = \frac{Z_{i,p}}{\sigma_{z_i}}$

Data Preparation
Combine mean centering and variance scaling

Z-score (“standard score”) normalization

- Combine mean centering and variance scaling to normalize the data:
  - $Z^{MV}_{i,p} = \frac{Z_{i,p} - \bar{Z}_i}{\sigma_{z_i}}$



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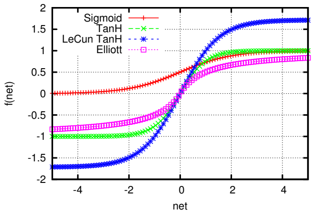

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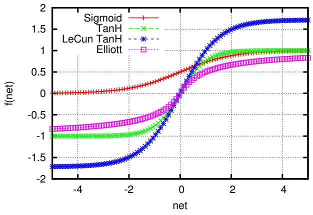

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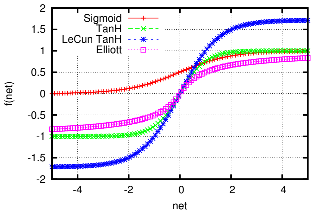

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- Trick of the trade: scale to $[0.1, 0.9]$ (Sigmoid) and $[-0.9, 0.9]$ (TanH) instead (why?)

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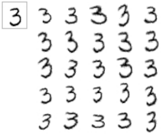
- Deep learning: first record-breaking MNIST-recognizing NNs modified the data set by artificial expansion (rotations, distortions, etc.)
- `http://yann.lecun.com/exdb/mnist/`



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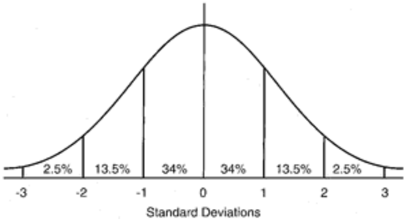

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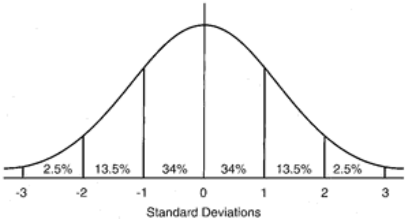

- Wessels and Barnard: choose random weights in range $\left[\frac{-1}{\sqrt{fanin}}, \frac{1}{\sqrt{fanin}}\right]$, where *fanin* is the number of incoming connections for the given unit.
  - The larger the architecture, the smaller interval will be used

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- Are smaller weights always better?

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Training, Generalisation, Validation

- Supervised training: data patterns with known target values are presented to the NN
- Data set has to be subdivided into three parts:

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Data that will be used to calculate the generalisation error of the optimized model

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Data normalisation

How would you scale the data in training, testing, validation subsets?

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Option (3) is the correct approach.

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- How do we subdivide the data set?

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Over 50%, up to 90% of the entire data set

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Validation set

About 10% to 30% of the data set. Should never be used for training.

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Stochastic (on-line) training

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- Backprop each gradient
- Bound to fluctuate: is a single pattern representative?

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Batch training

- Update weights after all patterns were considered
- Backprop average gradient
- Stable, but computationally heavy

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Stochastic, batch, mini-batch

Stochastic (on-line) training

- Update weights after each pattern
- Backprop each gradient
- Bound to fluctuate: is a single pattern representative?

Batch training

- Update weights after all patterns were considered
- Backprop average gradient
- Stable, but computationally heavy

Mini-Batch training: Best of both

- Calculate average gradient over a subset of patterns
- Very popular in deep learning

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- How does this apply to stochastic, batch, mini-batch training?