Lets go deeper!

Simon Kluettermann

ls9 tu Dortmund

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reminder

- No Case Study next week
  - neither Tuesday (29.11) nor Thursday (01.12)
  - if you need help: just write me an email!
- In two weeks: Case Study switched
  - Q+A Tuesday (6.12, 14:00) online only
  - Case Study Meeting Thursday (08.12, 14:00-16:00), in OH12 Room 3.032

Big Picture

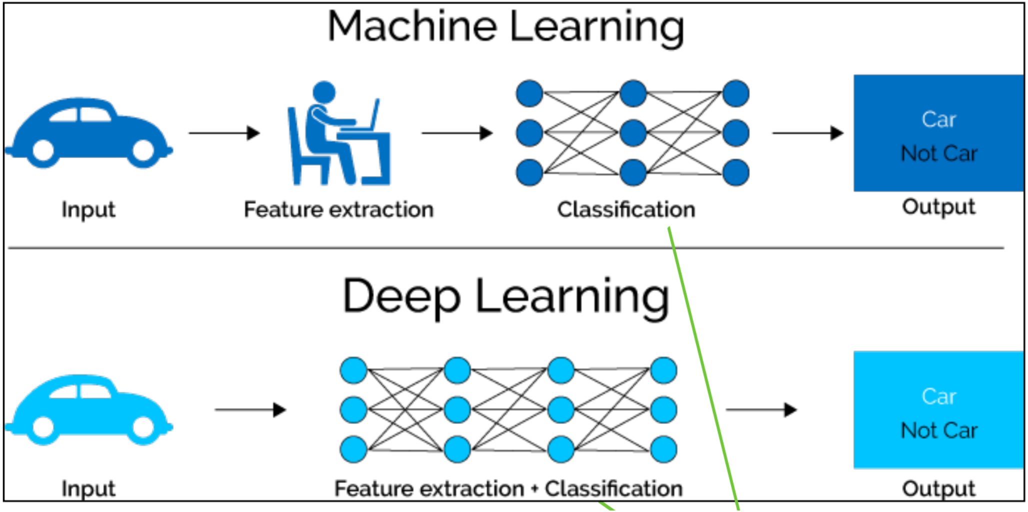
- Goal for this case study: Have better hyperparameters than pyod!
- So each of you: Gets assigned two algorithms!
  - One fairly simple before
  - One more complicated one today
- Try to find the best possible hyperparameters for your algorithms
  - Try to be clever (for example: PCA: $n_{components} < n_{features}$. Maybe $\frac{n_{components}}{n_{features}}$ constant?
- Afterwards
  - Write down your findings into a simple function (given data, what are my best hyperparameters)
  - Write down your finding into a report (together, double collumn. 6 Pages per student, plus comparison of algorithms to each other)
  - One final presentation together in front of my colleagues. About 10min per student.

Evaluating your hyperparameter

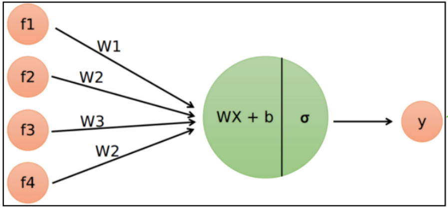
- My suggestion: Compare to normal parameters.
- This means you get two lists of AUC scores
- Your params: [0.80,0.75,0.73,....,0.95]
- Pyod params: [0.82,0.71,0.48,....,0.95]
- look at two values
- $\sum_i your_i - pyod_i$
    - Total improvment. If positive, then your parameters help;)
    - But hard to see if this is significant
- Fraction of $your_i > pyod_i$
    - Quantised, so does not care about improving your parameters further
    - But easy to see if this is significant
        - 0.5$\Rightarrow$Probably just random
        - 0.9$\Rightarrow$Probably quite significant

How to continue

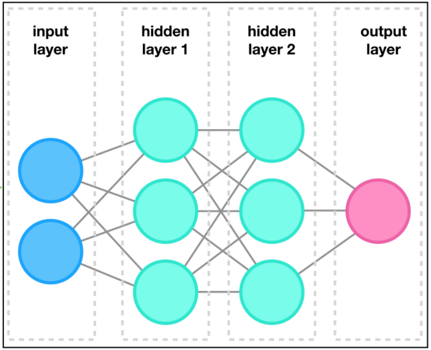
- See how far you can improve this?
- Treat this as a supervised optimisation problem: Given this dataset, find the best hyperparameters
- Might be useful to look at more input parameters
- Might help to formulate your parameters differently
- But be aware of **overfitting**!


Machine Learning
Input
Feature extraction
Classification
Car
Not Car
Output
Deep Learning
Input
Feature extraction + Classification
Car
Not Car
Output

Intro to Deep Learning



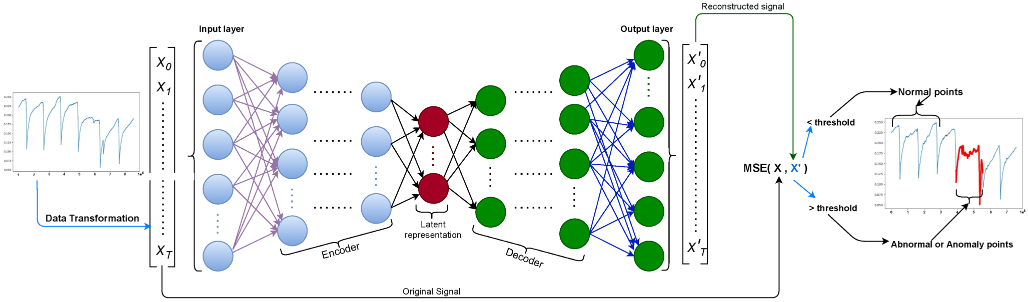
Logistic Regression single neuron



Intro to Deep Learning

- The idea is always the same:
  - Define complicated model to learn (often millions of parameters)
  - Define loss function that this model should minimize (example: $\sum_i (y_i - f(x_i))^2$)
  - Find parameters that minimize the loss ($\Rightarrow$Backpropagation)
- Usually Neural Networks:
  - $f(x) = f_n(x) = activation(A_n \cdot f_{n-1}(x) + b_n)$
  - $f_0(x) = x$
- Powerful, as you can show that when there are 3 Layers+ (and infinitely sized matrices), you can approximate any function
- $\Rightarrow$So a model becomes a loss function

Autoencoder



Autoencoder

- Lets look at some of its Hyperparameters
- Autoencoder Specific
  - Compression factor (Latent space size)
  - Loss function (mse?)
- Neural Network architecture
  - Number of layers
  - Number of neurons in each layer (Shape of the matrices A_n)
- Optimisation parameters
  - Learning Rate
    - Controls how fast the parameters are found
    - To high value makes the training unstable
  - Batch size
    - Controls how many samples are averaged together.
    - Lower values make the training more stable, but also the result less optimal

For next time

- (if you have not finished finding good parameters for your old algorithm, continue searching for them)
- Take a look at your new algorithm
- Run it once on cardio, take a look at which parameters you have
- Prepare a similar presentation to last time (include your cardio result)