FH AACHEN
UNIVERSITY OF APPLIED SCIENCES

Autonomous Fault Detection Using Artificial Intelligence Applied to CLAS12 Drift Chamber Data

August 16, 2018

A Bachelor's Thesis by Christian Peters

Motivation

- Most crucial elements of a physical experiment?
  - Methods of measurement, e.g. drift chamber at CLAS12
  - Need to be highly precise
  - Essential for success
- Problem: Extreme conditions often lead to faults
  - Distortions in measurement accuracy
  - Have to be detected and filtered out during runtime
- Too much data to be processed by a human
  - An *autonomous* approach of fault detection is required

Motivation

- An emerging field lending itself particularly well to the task:
  - The domain of Artificial Intelligence (AI)
  - Deep Learning, Convolutional Neural Networks (CNNs)
- Goal: Apply methods of AI to the problem of fault detection
  - Experimental context: CLAS12 drift chamber
- Baseline software: deeplearning4j (DL4J) library
  - Will be used to implement the fault detection system

The CLAS12 Drift Chamber

- Subsystem of the CLAS12 particle detector
  - Electron beam hits target inside the detector's center
  - Drift Chamber (DC) is used to measure the results (particle tracks)
- Hierarchical arrangement of multiple wires grouped together as wire chambers
  - Wires are used to detect particle presence
  - Particle hits wire $\rightarrow$ wire gets activated

The CLAS12 Drift Chamber

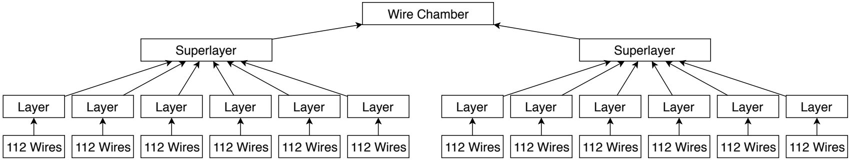
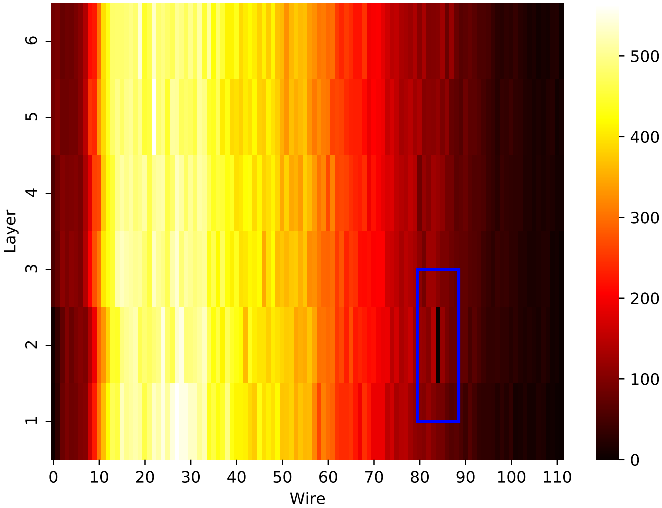


Figure: The hierarchical structure of a single wire chamber.

Drift Chamber Faults

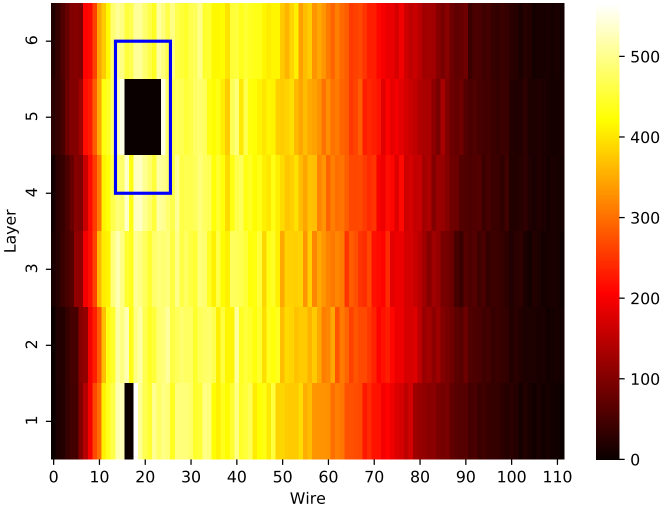
- Drift chamber operates under extreme conditions
  - Huge amounts of radiation
  - Components can get damaged during an experiment
  - Single wires or collections thereof stop working
- Wire activations of a superlayer can be visualized as heatmaps
  - Easier to detect faults

Dead Wire

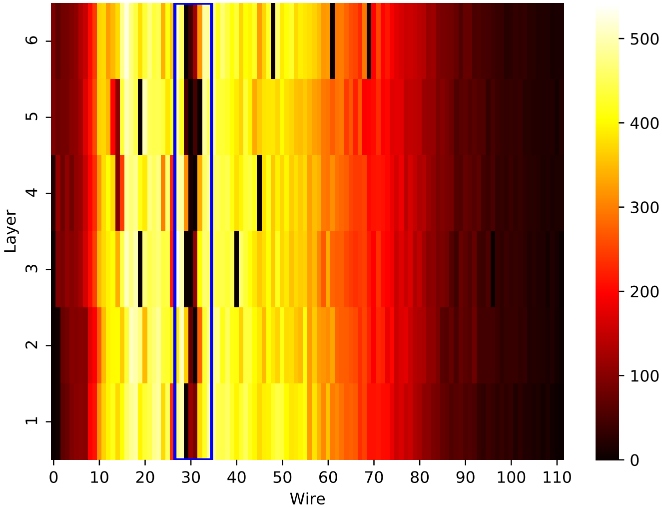


Layer
6
5
4
3
2
1
0
10
20
30
40
50
60
70
80
90
100
110
Wire
500
400
300
200
100
0

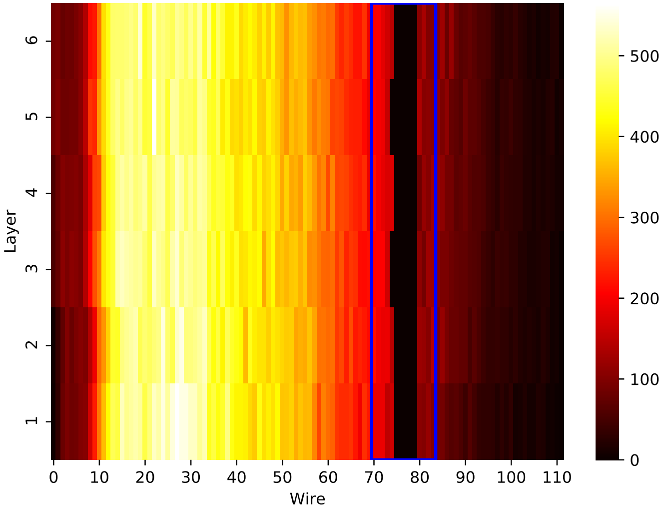
Dead Pin


Layer
Wire
0
10
20
30
40
50
60
70
80
90
100
110
1
2
3
4
5
6
500
400
300
200
100
0

Dead Connector

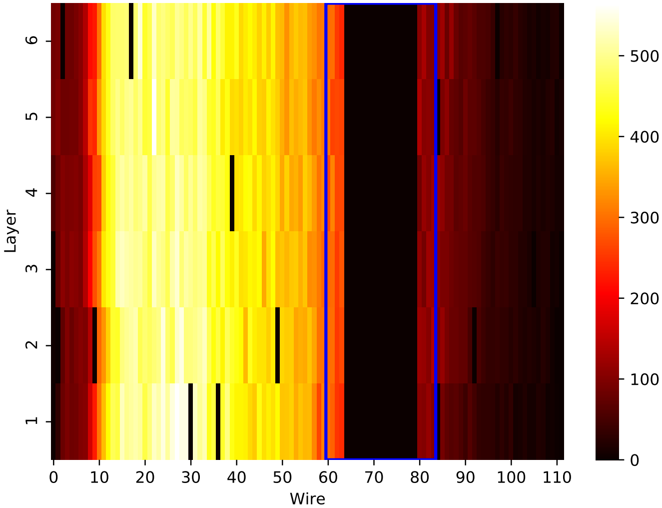


Dead Fuse



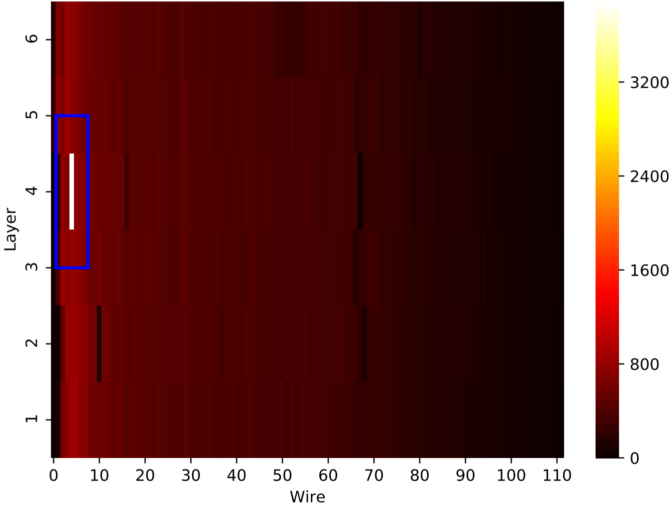
FH AACHEN
UNIVERSITY OF APPLIED SCIENCES

Dead Channel



FH AACHEN
UNIVERSITY OF APPLIED SCIENCES

Hot Wire



Layer
6
5
4
3
2
1
Wire
0
10
20
30
40
50
60
70
80
90
100
110
3200
2400
1600
800
0

Artificial Neural Networks

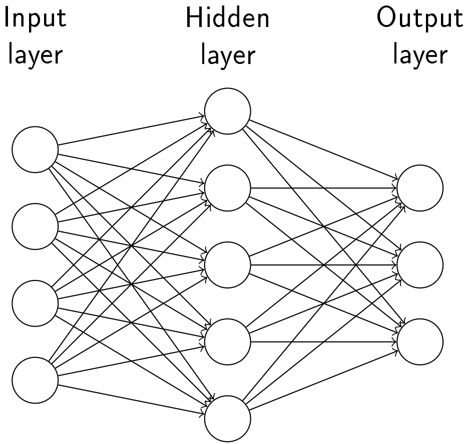


Figure: A common ANN-structure represented by a directed graph.

Modeling Artificial Neurons

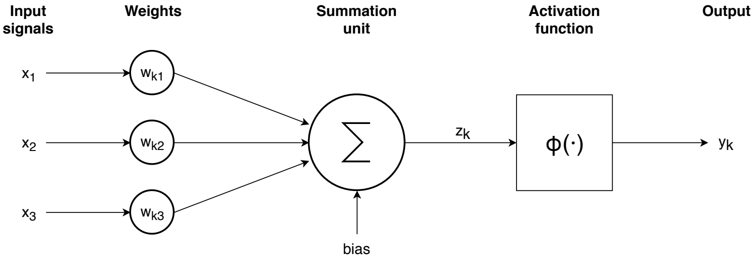


Figure: The components of a single artificial neuron k.

Activation Functions

- Determine the "activity"-level of a neuron based on the summed and weighted inputs
- Non-Linear
  - Enables the network to model complex relations
  - Multiple linear functions collapse into just a single linear function

Sigmoid Activation Function

$$\phi(z) = \frac{1}{1 + e^{-\theta \cdot z}} \tag{1}$$

- Transforms an input into a range between 0 and 1
- θ adjusts the sensitivity with respect to the input
- Reduces the impact of outliers
- Often used in the early days
  - Biological inspiration, can also be interpreted as a "firing-rate"

Sigmoid Activation Function

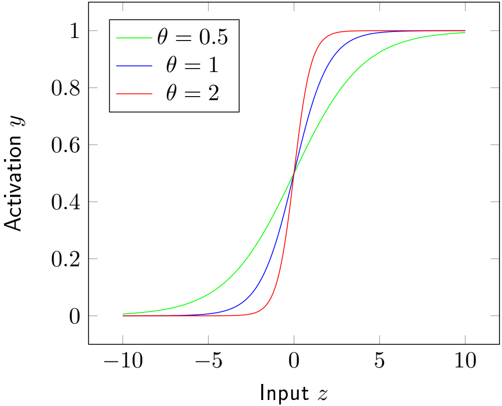


Figure: The sigmoid activation function plotted for different values of θ.

Problems with the Sigmoid Activation Function

- We sometimes want to keep big values
  - Small values tend to fade out in deep networks (many hidden layers)
- "Saturates" for very big or negative inputs, i.e. does not change much when the input changes
  - This leads to training problems as we shall see later

ReLU Activation Function

$$\phi(z) = \max(0, z) \tag{2}$$

- Remedies the problems of the sigmoid function
- Cuts away negative values $\rightarrow$ sparsity among the neuron activations
  - Promotes simpler representations
- Actually more biologically inspired than the sigmoid
- Very easy to compute

ReLU Activation Function

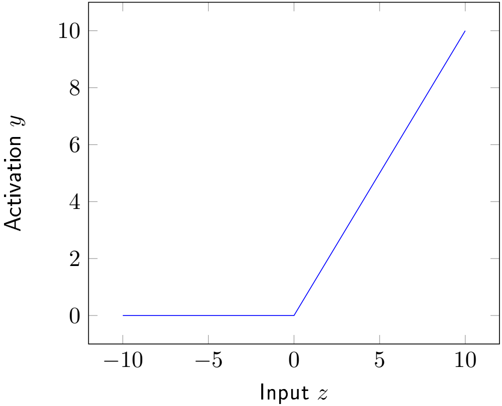


Figure: The ReLU activation function.

Softmax Activation Function

$$\phi(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{3}$$

- Usually applied to the output neurons
- Outputs can be interpreted as probabilities
  - Useful in classification, every possible class gets a probability
- Using the exponential function before normalization amplifies bigger signals and attenuates weaker ones
  - Helpful in training
- Interpretation of the z_i: Unnormalized log-probabilities

Neural Networks as Classifiers

- We successfully established a mathematical model of neural networks
- How can we train them to perform classification tasks?
  - Remember, we want to classify what kinds of faults are in a superlayer within the drift chamber
- To do this, let's first take a look at classification in general

Classification

FH AACHEN
UNIVERSITY OF APPLIED SCIENCES

- The data consists of attributes as well as class labels
- Goal: Predict the class label by only looking at the attributes
- First step: Training
  - The classification algorithm (classifier) is presented with many training examples
  - For every new example, the classifier adjusts its parameters to improve its classification ability
  - This is done to build a predictive model
- Second step: Testing
  - Some new testing examples are presented to the classifier that it did not see during training
  - These examples are used to determine, if the classifier learned any useful concepts from the training data, i.e. to *generalize*

Evaluating a Classifier

> The results of the testing phase are entered into a *confusion matrix:*

	Class Positive (Predicted)	**Class Negative (Predicted)**
Class Positive (Actual)	True Positives (TP)	False Negatives (FN)
Class Negative (Actual)	False Positives (FP)	True Negatives (TN)

> This matrix is used to compute evaluation metrics like accuracy

Training the Network

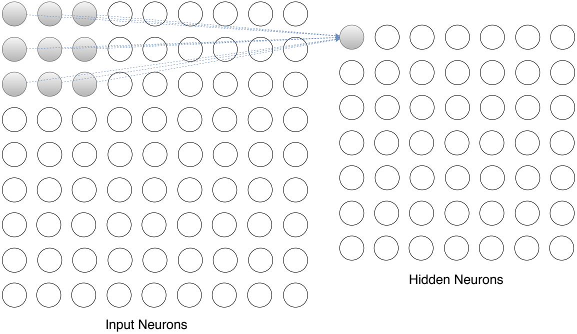
- Which parameters can be adjusted during training?
  - The weights and biases store the network's knowledge and need to be tuned to improve performance
  - Other parameters like number of layers or activation function are set in advance (hyperparameters)
- How to adjust the weights and biases?
  - Measure the error on a batch of training examples
  - Minimize the error by taking a step of *gradient descent* ($\nabla error$)
  - Repeat this for a number of passes through the training data (one pass = one epoch)
- After training, test the network on new examples
  - Compute evaluation metrics
  - Was it able to *generalize*?

Convolutional Neural Networks

- Simple ANNs work well for moderate amounts of attributes
  - Problems arise when amount of inputs grows
  - Number of parameters (weights and biases) "explodes"
  - Requires huge amounts of space and nearly impossible to train
- Sometimes, the input has a specific structure
  - E.g. images are arranged in grids of pixels (fault heatmaps are similar)
  - Every pixel has a *local* relevance
  - No need to connect every neuron to every input
- Use that structure to create simpler models that are easier to train

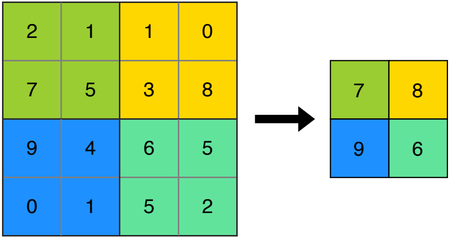
Convolution Layers

- Arrange the neurons in a grid, just like the input
- Every neuron "watches" a specific area, the *local receptive field*
  - Weights are shared $\rightarrow$ less parameters
- Works just like a sliding window (similar to a *convolution*)
- Multiple convolutions are performed $\rightarrow$ stack of hidden grids



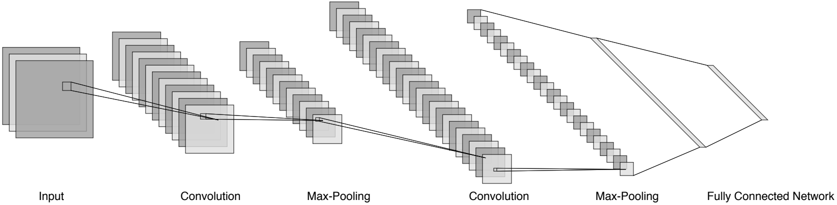
Pooling Layers

- Reduce the input's complexity by downsampling
  - Every neuron just remembers the maximum of its local receptive field
- Forget about the exact location of a feature
  - Leads to *spatial invariance*



The Convolutional Architecture

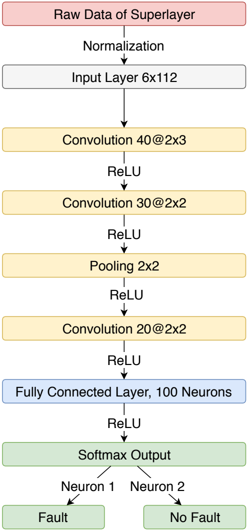
- Stack multiple convolution and pooling layers
  - These are used to extract relevant features
- Use a fully connected layer in the end to perform classification
- The network is also trained via *gradient descent*
  - Weights and biases are updated in each step to minimize classification error



Implementing the Fault Detector

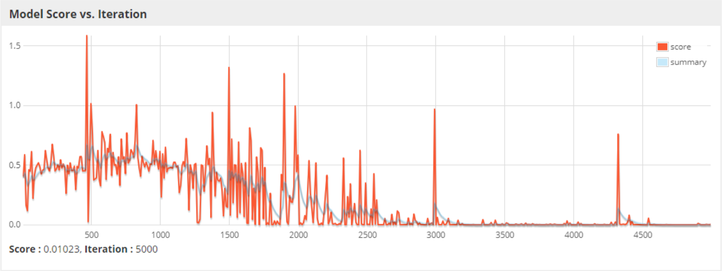
- Build a convolutional neural network in DL4J
  - Easy to monitor training and compute evaluation metrics
  - Fast due to C++ backend engine
- First, data has to be normalized
  - Activation levels can vary across superlayers
  - We only care about the distinct fault patterns
  - Scale wire activations from 0 to 1
- Many architectures and parameters were tried
  - Network too shallow → unable to learn complex faults (e.g. two dead wires next to each other)
  - Multiple faults per superlayer are possible → multiple networks were trained, each specializing in a single fault

Final Network Architecture



Training the Fault Detector

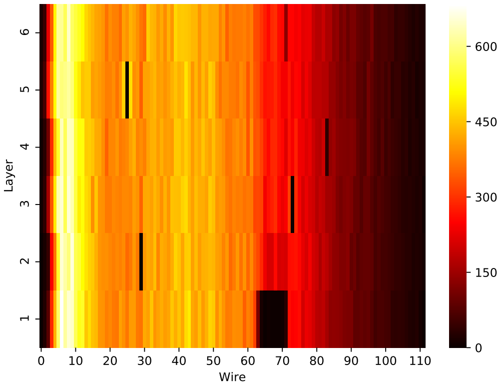
- Used Michaels simulation suite
  - Based on real world background signals
  - Randomly inserts fault combinations and generates class labels accordingly
- Each classifier was trained on 100,000 examples
- Testing was done using 10,000 new examples from the simulator
  - Accuracy > 97%



Real Data Validation

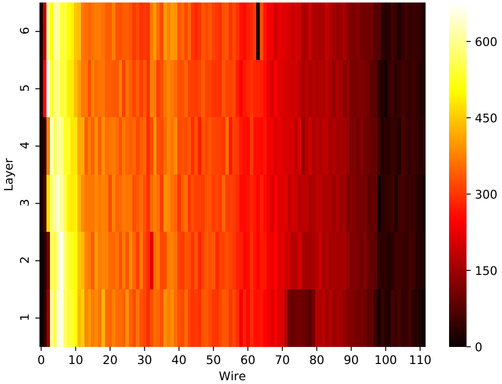
- Need to show that the detector not only works on simulated data
  - Did it extract some general concepts?
- Tested the system on some real world examples to show its strengths and weaknesses

Pin Fault and Dead Wires



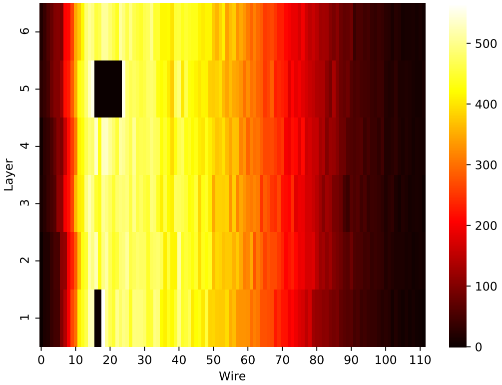
- Faults display a sharp contrast $\rightarrow$ classifier works well
  - Dead pin and dead wire classifier both report 100% fault
  - The other classifiers don't detect their fault with 99% certainty

Blurred Dead Pin Fault



- Blurred fault → classifier struggles
  - Classifier reports 99% no fault for the pin
  - We believe that more real data can solve this

Two Dead Wires



> Classifier detects two dead wires next to each other
>   > Reports 93.29% certainty for the wires and 100% for the pin

Conclusion

- Convolutional Neural Networks work well for fault detection
- Blurred fault problem will be solved in the future
  - Will use real world blurred faults during training
  - After all, a deep learning system can only be as good as the data it was trained on
- Next step: fault localization
  - Need to know, where exactly a fault is located
  - State-of-the-art: YOLOv3, a CNN specialized in object localization
  - Use the present system as a pre-stage classifier
- Excited to see, how the system will perform on the hundreds of petabytes of real CLAS12 drift chamber data

Y. Bengio. "Practical recommendations for gradient-based training of deep architectures". In: *ArXiv e-prints* (June 2012). arXiv: 1206.5533 [cs.LG].

Léon Bottou. "Stochastic Gradient Descent Tricks". In: *Neural Networks: Tricks of the Trade*. Springer, Berlin, Heidelberg, 2012. ISBN: 978-3-642-35288-1.

Xavier Glorot and Yoshua Bengio. "Understanding the difficulty of training deep feedforward neural networks". In: *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*. Ed. by Yee Whye Teh and Mike Titterington. Vol. 9. Proceedings of Machine Learning Research. PMLR, 13–15 May 2010, pp. 249–256.

Xavier Glorot, Antoine Bordes, and Yoshua Bengio. “Deep Sparse Rectifier Neural Networks”. In: *Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics*. Ed. by Geoffrey Gordon, David Dunson, and Miroslav Dudík. Vol. 15. Proceedings of Machine Learning Research. Fort Lauderdale, FL, USA: PMLR, Nov. 2011, pp. 315–323.

Simon Haykin. *Neural Networks and Learning Machines*. 3rd ed. Prentice Hall International, 2008. ISBN: 978-0131471399.

D. P. Kingma and J. Ba. “Adam: A Method for Stochastic Optimization”. In: *ArXiv e-prints* (Dec. 2014). arXiv: 1412.6980 [cs.LG].

Michael A. Nielsen. *Neural Networks and Deep Learning*. Determination Press, 2015.

Josh Patterson and Adam Gibson. *Deep Learning: A Practitioner's Approach*. 1st ed. O'Reilly Media, 2017. ISBN: 978-1491914250.

J. Redmon and A. Farhadi. "YOLOv3: An Incremental Improvement". In: *ArXiv e-prints* (Apr. 2018). arXiv: 1804.02767 [cs.CV].

David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. "Learning representations by back-propagating errors". In: *nature* 323 (1986).

O. Russakovsky et al. "ImageNet Large Scale Visual Recognition Challenge". In: *ArXiv e-prints* (Sept. 2014). arXiv: 1409.0575 [cs.CV].

Artificial Neural Networks

- Class of machine learning algorithms
  - Loosely inspired by biological nervous systems
- Collection of artificial neurons that are connected with each other
  - Enables them to exchange signals along their connections
  - Can be represented by a directed graph
- Usually arranged in layers
  - *Input Layer* collects input signals and passes them on
  - *Hidden Layers* apply transformations to incoming signals and pass the outcomes further into the network
  - *Output Layer* applies a final transformation representing the networks' result
- Goal: Convert input into meaningful output by applying multiple transformations

Components of the neural model

- A set of weighted inputs
  - Each input originating from neuron j and traveling into neuron k is first multiplied by a weight w_{kj}
- A summation unit
  - All the weighted inputs are summed and a constant value, the *bias*, is added to yield the result z_k
- An activation function
  - Applies a non-linear transformation $\phi(\cdot)$ to the output of the summation unit
  - This result, called y_k, is propagated further into the network alongside the connections

The Role of the Bias Value

- The bias is added as a constant to the sum of the weighted inputs in the summation unit
- Acts like a threshold that has to be overcome
  - Negative bias: Positive weighted inputs needed for the neuron to become active
  - Positive bias: Negative weighted inputs needed to stop the neuron from being active

The Role of the Bias Value

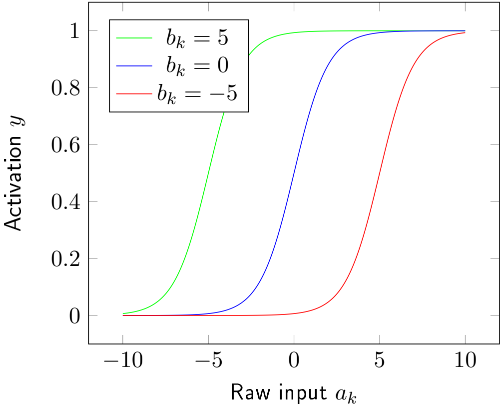


Figure: The sigmoid activation function plotted for different bias values.

Evaluation Metrics

- **Accuracy:**
  - Percentage of testing examples that were classified correctly

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

- **Precision:**
  - Percentage of correctly classified examples among all examples classified as positive

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Evaluation Metrics

> **Recall:**
> > What percentage of positive examples was classified correctly?

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

> **F1 Score:**
> > Harmonic mean of precision and recall

$$\text{F1 Score} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{7}$$

Dead Wire Classifier

- Accuracy: 97.61%
- Precision: 99.96%
- Recall: 95.65%
- F-Measure: 97.76%

	Dead Wire (Predicted)	**No Dead Wire (Predicted)**
Dead Wire (Actual)	5212	237
No Dead Wire (Actual)	2	4549

Table: Confusion matrix of the dead wire classifier.

Dead Pin Classifier

- Accuracy: 99.95%
- Precision: 99.92%
- Recall: 99.98%
- F-Measure: 99.95%

	Dead Pin (Predicted)	No Dead Pin (Predicted)
Dead Pin (Actual)	4739	1
No Dead Pin (Actual)	4	5256

Table: Confusion matrix of the dead pin classifier.

Dead Connector Classifier

- Accuracy: 98.77%
- Precision: 99.23%
- Recall: 95.69%
- F-Measure: 97.43%

	Dead Connector (Predicted)	**No Dead Connector (Predicted)**
Dead Connector (Actual)	2334	105
No Dead Connector (Actual)	18	7543

Table: Confusion matrix of the dead connector classifier.

Dead Fuse Classifier

- Accuracy: 98.95%
- Precision: 97.32%
- Recall: 98.20%
- F-Measure: 97.76%

	Dead Fuse (Predicted)	**No Dead Fuse (Predicted)**
Dead Fuse (Actual)	2288	42
No Dead Fuse (Actual)	63	7607

Table: Confusion matrix of the dead fuse classifier.

Dead Channel Classifier

- Accuracy: 99.11%
- Precision: 98.84%
- Recall: 98.64%
- F-Measure: 98.74%

	Dead Channel (Predicted)	**No Dead Channel (Predicted)**
Dead Channel (Actual)	3493	48
No Dead Channel (Actual)	41	6418

Table: Confusion matrix of the dead channel classifier.

Hot Wire Classifier

- Accuracy: 100.00%
- Precision: 100.00%
- Recall: 100.00%
- F-Measure: 100.00%

	Hot Wire (Predicted)	**No Hot Wire (Predicted)**
Hot Wire (Actual)	5532	0
No Hot Wire (Actual)	0	4468

Table: Confusion matrix of the hot wire classifier.