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

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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

- 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 momentum)
- 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

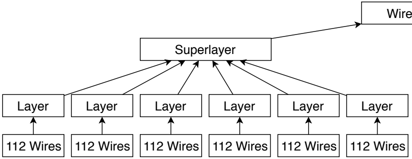
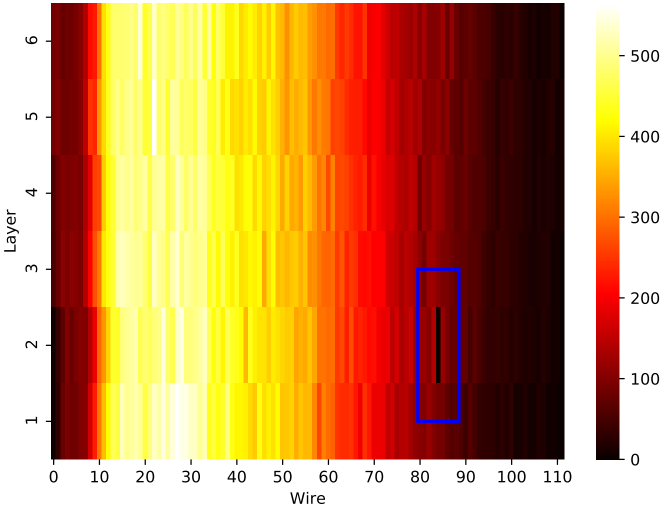


Figure: The hierarchical structure of a single wire chamber.

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
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90
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110
Wire
500
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300
200
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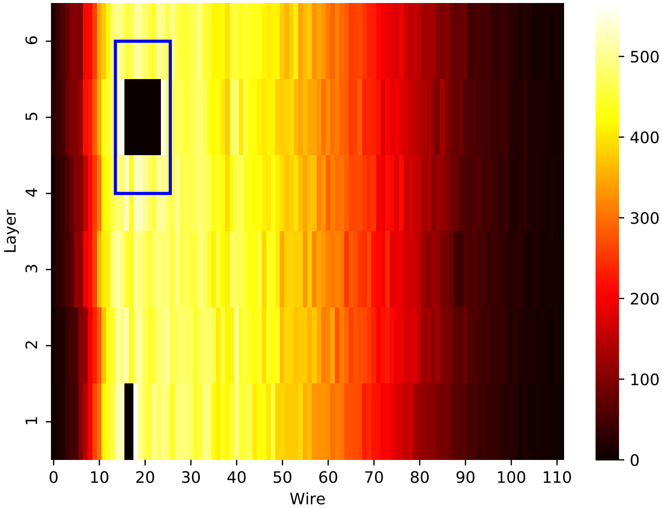
0

Dead Pin



Layer
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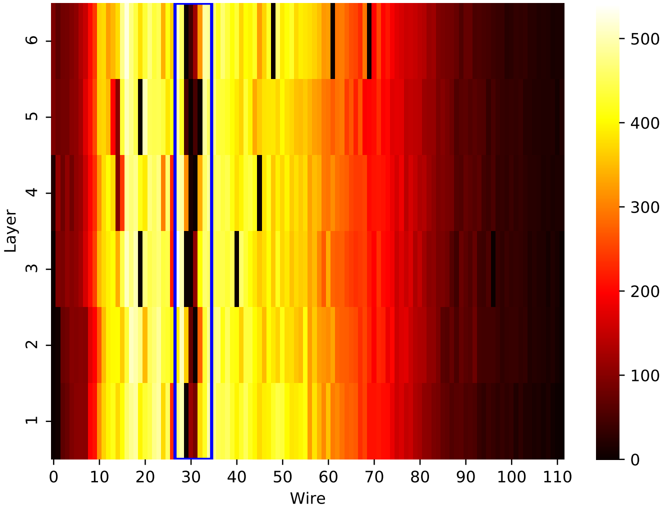
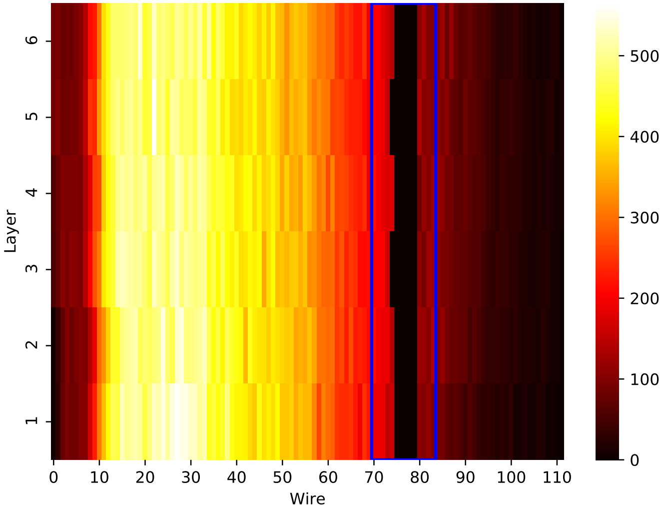
Dead Connector



Dead Fuse



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Wire
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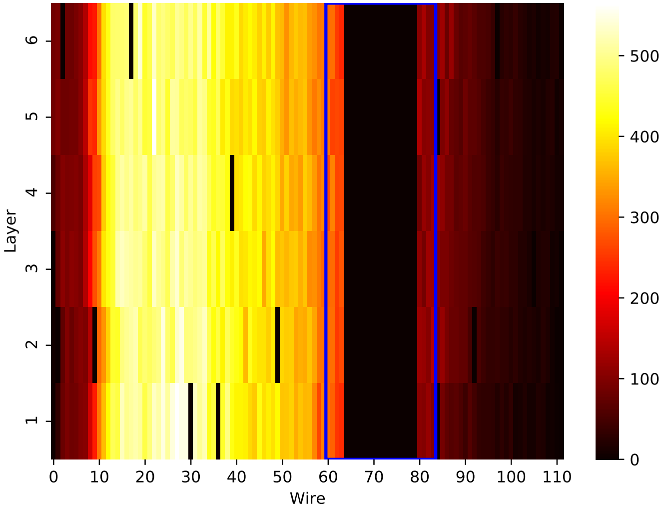
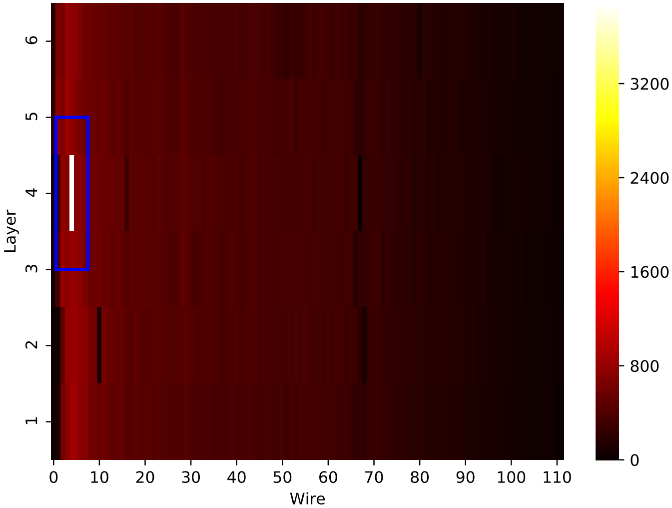
Dead Channel



Hot Wire



Layer
Wire
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110
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4
5
6
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2400
1600
800
0

Artificial Neural Networks

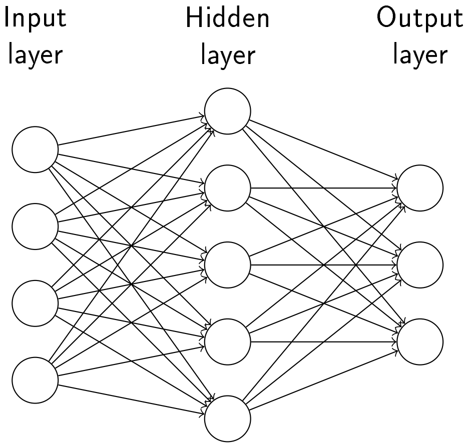

Figure: A common ANN-structure represented by a directed graph.

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

Modeling Artificial Neurons

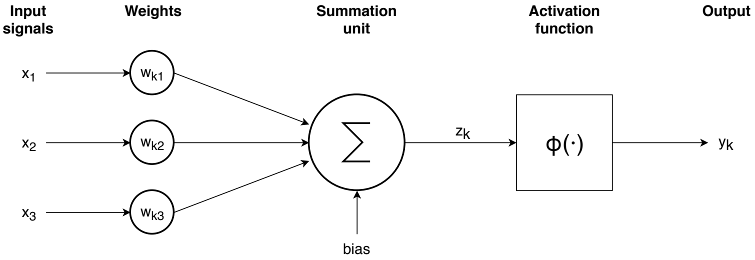

Figure: The components of a single artificial neuron k.

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

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

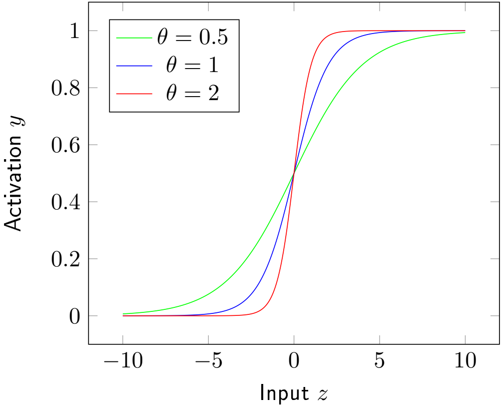

Figure: The sigmoid activation function plotted for different values of θ.

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

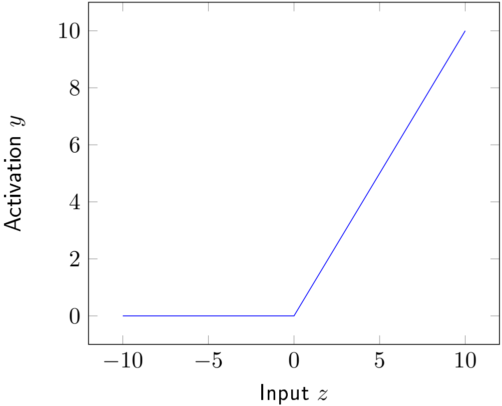

Figure: The ReLU activation function.

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

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

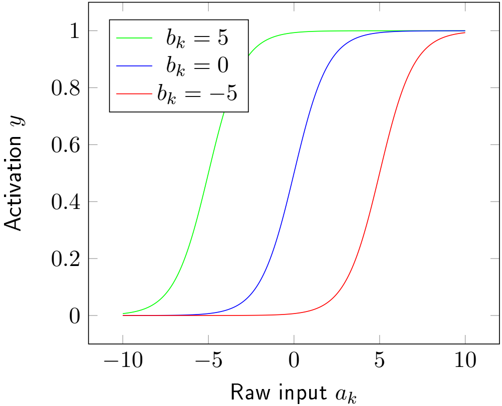

Figure: The sigmoid activation function plotted for different bias values.

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

- The data consists of features as well as labels
- Goal: Predict the label by only looking at the features
- 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 some evaluation metrics

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

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

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