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

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Christian Peters

FH AACHEN
UNIVERSITY OF APPLIED SCIENCES

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

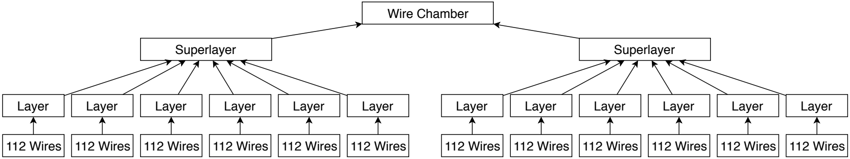
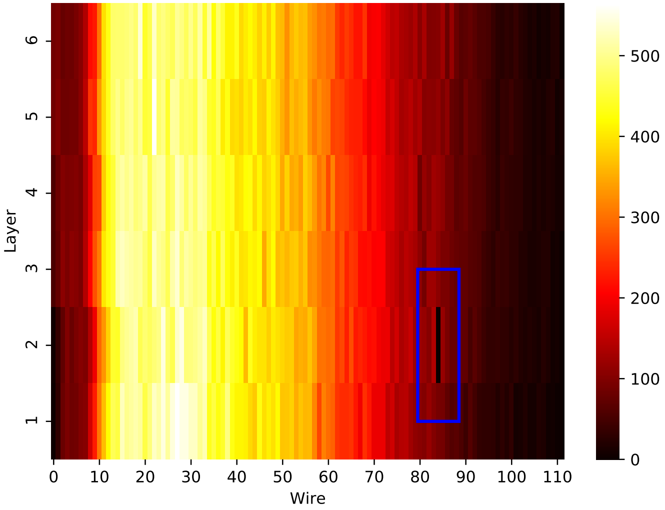


Figure: The hierarchical structure of a single wire chamber.

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 can be visualized as heatmaps
  - Easier to detect faults

Dead Wire



Layer
Wire
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110
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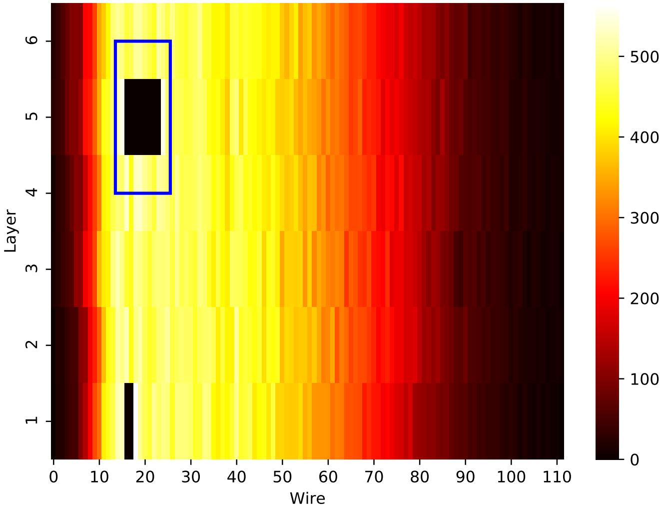
100
200
300
400
500

Dead Pin



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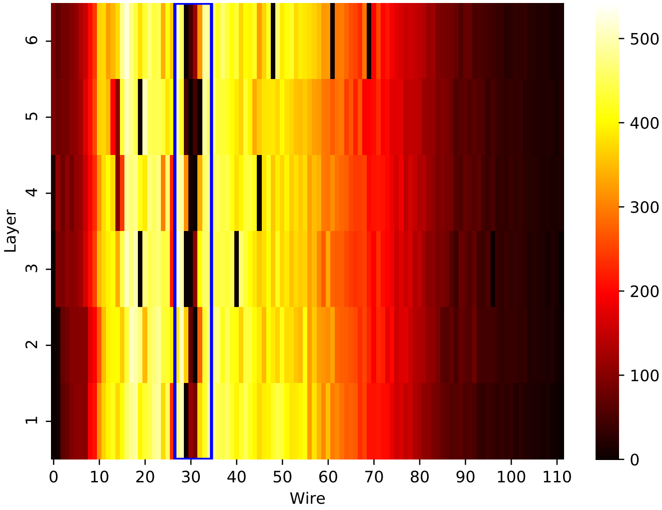
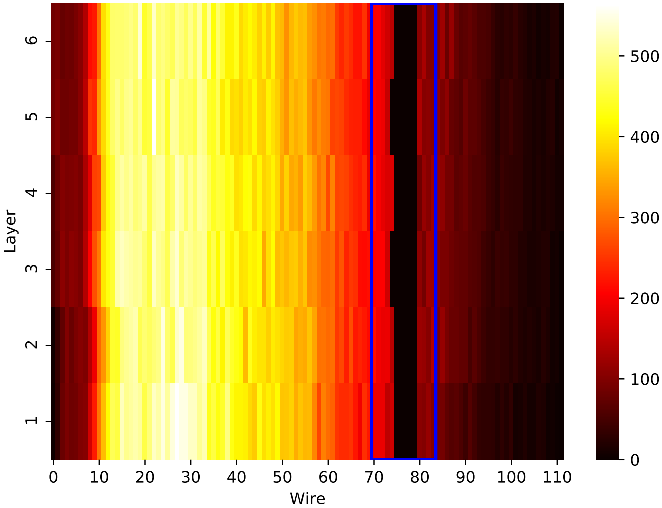
Dead Connector



Dead Fuse


Layer
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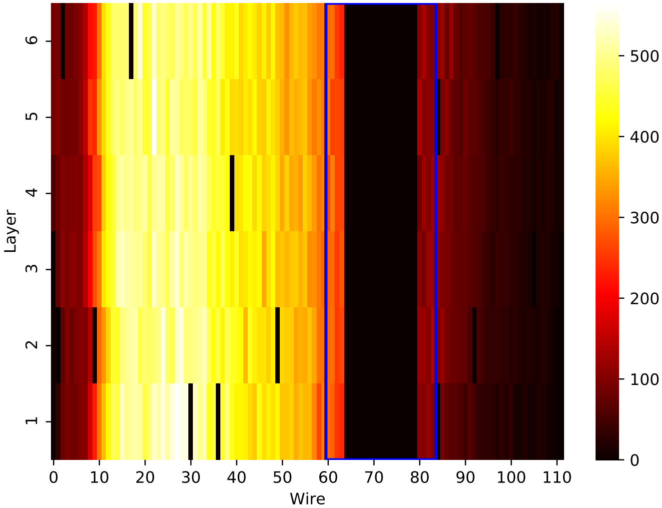
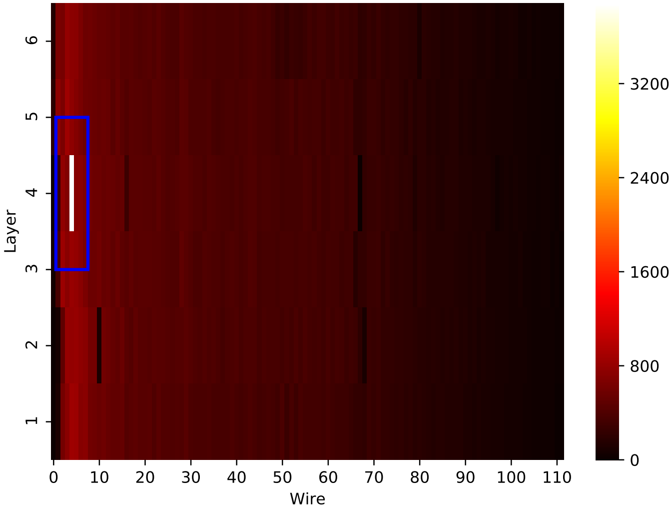
Dead Channel



Hot Wire



Layer
Wire
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6
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2400
1600
800
0

Artificial Neural Networks

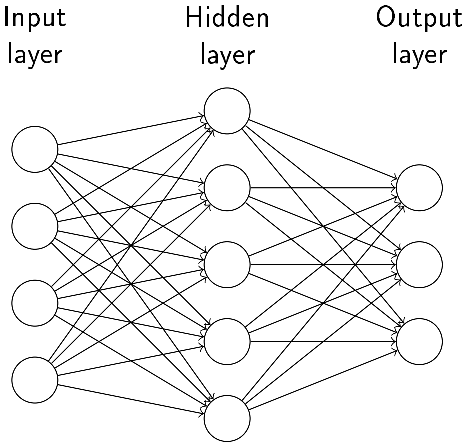

Figure: A common ANN-structure represented by a directed graph.

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

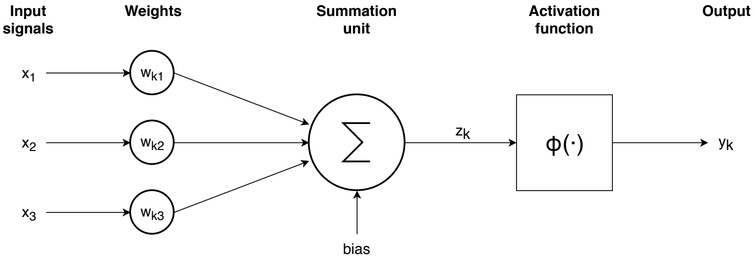

Figure: The components of a single artificial neuron k.

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

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