

Neural networks and their application at CAST

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Physikalisches
Institut



CERN Axion Solar Telescope

CAST



the experiment

- search for solar axions, hypothetical pseudoscalar particle solving the strong \mathcal{CP} problem
- potential dark matter candidate
- coupling to transverse B fields, production in the Sun!

CERN Axion Solar Telescope

CAST



to take away...

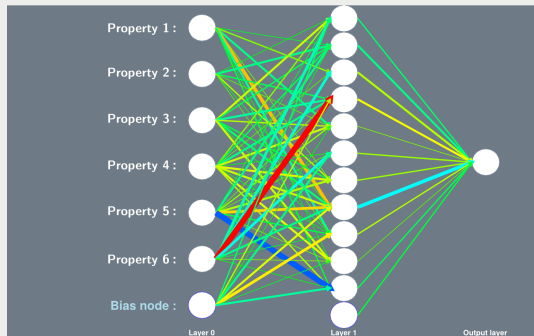
- exp. signal rates: $\leq 0.1 \gamma \text{ h}^{-1}$
- background rate: $\sim 0.1 \text{ s}^{-1}$
- need very good background suppression

Artificial Neural Networks (ANNs)

ANN primer

- type of multivariate analysis object providing highly non-linear, multidimensional representations of input data
- simplest type: feed-forward multilayer perceptron

MLP example



Artificial Neural Networks (ANNs)

Producing an output and training

Neuron output:

$$y_k = \varphi \sum_{j=0}^m w_{kj} x_j$$

φ : activation function, w_k weight vector

Training minimizes error function

$$E(\mathbf{x}_1, \dots, \mathbf{x}_N | \mathbf{w}) = \sum_{a=1}^N \frac{1}{2} (y_{\text{ANN},a} - \hat{y}_a)^2$$

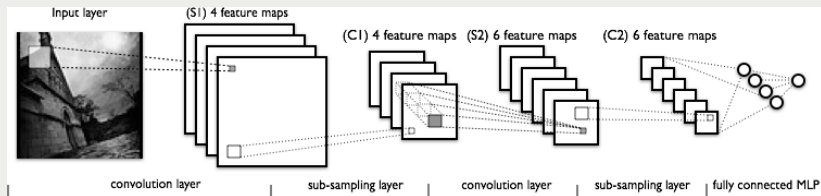
using gradient descent

$$\mathbf{w}^{n+1} = \mathbf{w}^n - \eta \nabla_w E$$

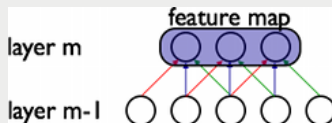
Convolutional Neural Networks

CNN schmatic

convolutional and pooling layers alternating:



where a convolutional layer is:



Convolution example in python

Python calc of 2D convolution (instead of a gif...)

```
1 import numpy as np
2 from scipy.signal import convolve2d
3 A = np.identity(6)
4 B = np.array([[0,0,0],[0,5,0],[0,0,0]])
5 C = convolve2d(A, B, 'same')
6 print(C)
```

```
[[5. 0. 0. 0. 0. 0.]
 [0. 5. 0. 0. 0. 0.]
 [0. 0. 5. 0. 0. 0.]
 [0. 0. 0. 5. 0. 0.]
 [0. 0. 0. 0. 5. 0.]
 [0. 0. 0. 0. 0. 5.]]
```

Convolution example in python

Python calc of 2D convolution (instead of a gif...)

```
1 import numpy as np
2 from scipy.signal import convolve2d
3 A = np.identity(6)
4 B = np.array([[1,0,1],[0,1,0],[1,0,1]])
5 C = convolve2d(A, B, 'same')
6 print(C)
```

```
[[2. 0. 1. 0. 0. 0.]
 [0. 3. 0. 1. 0. 0.]
 [1. 0. 3. 0. 1. 0.]
 [0. 1. 0. 3. 0. 1.]
 [0. 0. 1. 0. 3. 0.]
 [0. 0. 0. 1. 0. 2.]
```


Convolution example in pictures

A picture is worth a thousand words?

Input

1	2	3
4	5	6
7	8	9

Kernel

m	-1	0	1
n	-1	-2	-1
0	0	0	0
1	1	2	1

Result

-13	-20	-17
-18	-24	-18
13	20	17

Result[0][0]

1	2	1		
0	0	1	0	2
-1	-2	-1	5	6
			7	8
				9

Result[1][0]

1	2	1		
0	1	0	2	3
-1	4	-2	-1	6
			7	8
				9

Result[2][0]

	1	2	1	
	0	2	0	3
1	-1	5	-2	-1
4				
7				

source: http://www.songho.ca/dsp/convolution/convolution2d_example.html

Live demo of MLP training on MNIST

Simple demo of training simple ANN on MNIST

- MNIST: a dataset of 70 000 handwritten digits, size normalized to 28×28 pixels, centered
 - in the past used to benchmark image classification; nowadays fast to achieve good accuracies $\geq 90\%$
- network layout:
 - input neurons: 28×28 neurons (note: as 1D!)
 - 1 hidden layer: 1000 neurons
 - output layer: 10 neurons (1 for each digit)
 - activation function: rectified liner unit (ReLU):

$$f(x) = \max(0, x)$$

Live demo of MLP training on MNIST

What do I mean by live demo? 2 programs

- Program 1: trains multilayer perceptron (MLP)
 - written in Nim (C backend), using Arraymancer
 - linear algebra + neural network library
 - trains on 60 000 digits, performs validation on 10 000 digits
- after every 10 batches (1 batch: 64 digits) send to program 2:
 - random test digit
 - predicted output
 - current error
- Program 2 plots data live: written in Nim (JS backend), plots using plotly.js

Start training!

Back to CAST

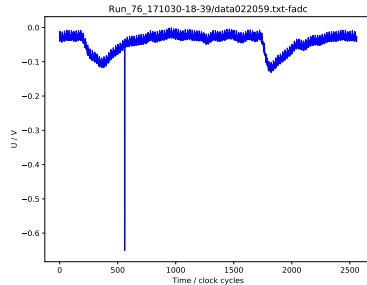
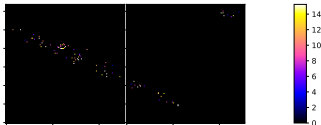
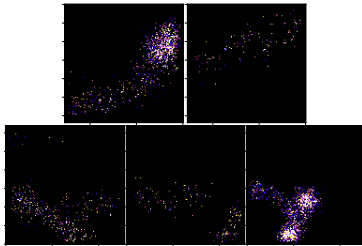
Requirements for detectors at CAST

- CAST is a **very low** rate experiment!
- detectors should reach: $f_{\text{Background}} \leq 10^{-6} \text{ keV}^{-1} \text{ cm}^{-2} \text{ s}^{-1}$
- signal / background ratio: $\frac{f_{\text{Background}}}{f_{\text{Signal}}} > 10^5$
 - **need** very good signal / background classification!

Background example

```
Hits
Chip #0 : 64
Chip #1 : 29
Chip #2 : 347
Chip #3 : 143
Chip #4 : 1365
Chip #5 : 123
Chip #6 : 1033
```

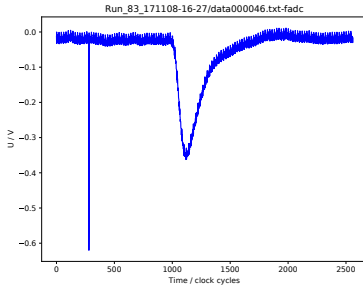
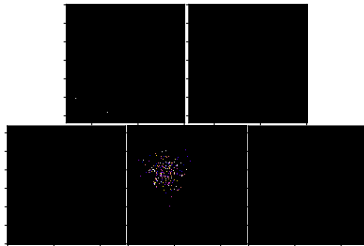
```
Run # : 76
Event # : 22059
Date : 2017-10-31.09:01:17
Shutter time / mode : 32 / verylong
FADC triggered : 1
at : 83508713 clock cycles
Veto scint clock : 4095
SIPM clock : 0
Filename : data022059.txt
```



X-ray example

```
Hits
Chip #0 : 0
Chip #1 : 0
Chip #2 : 0
Chip #3 : 211
Chip #4 : 0
Chip #5 : 0
Chip #6 : 2
```

```
Run # : 83
Event # : 46
Date : 2017-11-08.16:28:08
Shutter time / mode : 32 / verylong
FADC triggered : 1
at : 316651 clock cycles
Veto scint clock : 4095
SiPM clock : 0
Filename : data000046.txt
```



Back to CAST

Requirements for detectors at CAST

- CAST is a very low rate experiment!
- detectors should reach: $f_{\text{Background}} \leq 10^{-6} \text{ keV}^{-1} \text{ cm}^{-2} \text{ s}^{-1}$
- signal / background ratio: $\frac{f_{\text{Background}}}{f_{\text{Signal}}} > 10^5$
 - need very good signal / background classification!
- events (as on previous slides) can be interpreted as images
- Convolutional Neural Networks extremely good at image classification

⇒ use Convolutional Neural Networks?

Old analysis - data and likelihood method

- visible from comparison of background to X-ray event that geometric shapes are very different
- utilize that to remove as much background as possible

Likelihood analysis

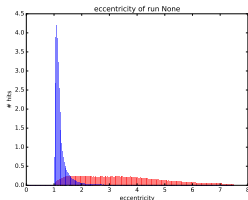
- energy range: 0 keV to 10 keV
- split into 8 unequal bins of distinct event properties

Baseline analysis

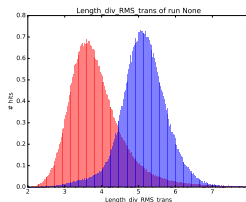
Analysis pipeline as follows

- ⇒ raw events
- filter 'clusters'
 - calc (geometric) properties
 - calc likelihood distribution from:
 - eccentricity
 - length / transverse RMS
 - fraction within transverse RMS

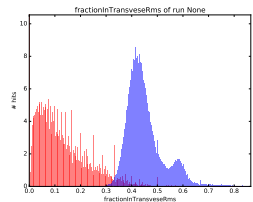
Eccentricity



Length / $\text{RMS}_{\text{trans}}$



pix in $\text{RMS}_{\text{trans}}$



Current analysis - data and likelihood method

Likelihood analysis & CNN analysis

- energy range: 0 keV to 10 keV
- split into 8 unequal bins of distinct event properties
- only based on properties of X-rays
- set cut on Likelihood distribution, s.t. 80 % of X-rays are recovered
- **now:** use artificial neural network to classify events as X-ray or background

ANNs applied to CAST

Two ANN approaches

- ① calculate properties of event, use properties as input neurons
- ② use whole events (256×256 pixels) as input layer
- ③ reg. 1:
 - small layout \Rightarrow fast to train
 - potentially biased, not all information usable
- ④ reg. 2:
 - huge layout \Rightarrow only trainable on GPU
 - all information available

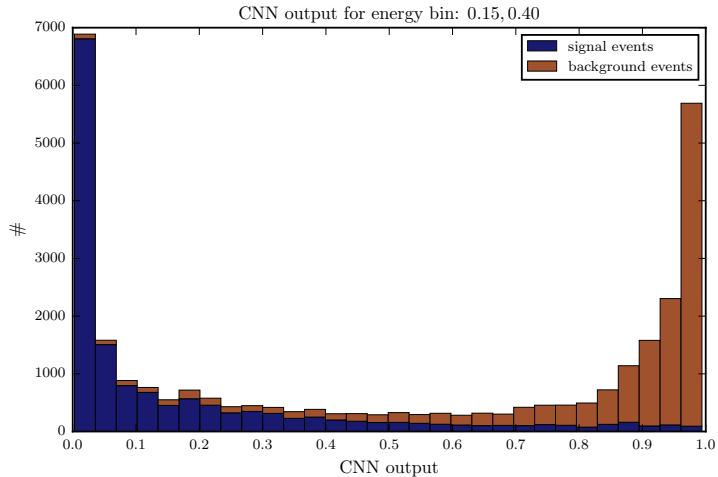
CNN implementation details

8 networks in total, one for each E bin

- input size: 256×256 neurons
- 3 convolutional and pooling layers alternating w/ 30, 70, 100 kernels using 15×15 filters
- pooling layers perform 2×2 max pooling
- tanh activation function
- 1 fully connected feed-forward layer: (1800, 30) neurons
- logistic regression layer: 2 output neurons
- training w/ 12 000 events per type on Nvidia GTX 1080
- training time: ~ 1 h to 10 h

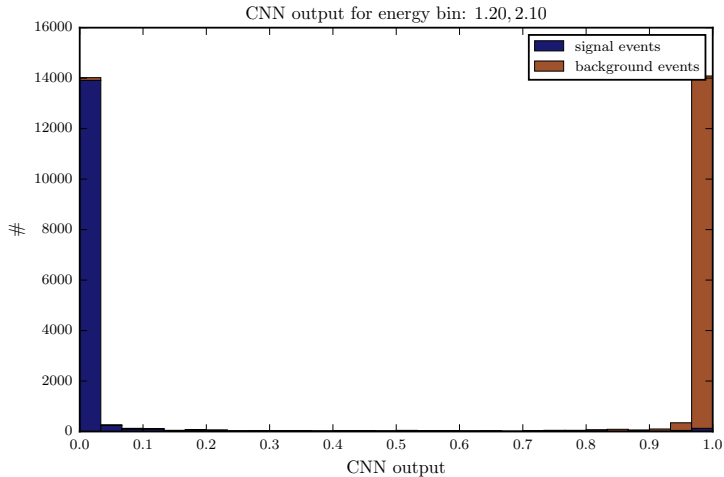
CNN example output distribution

CNN output distribution: bad



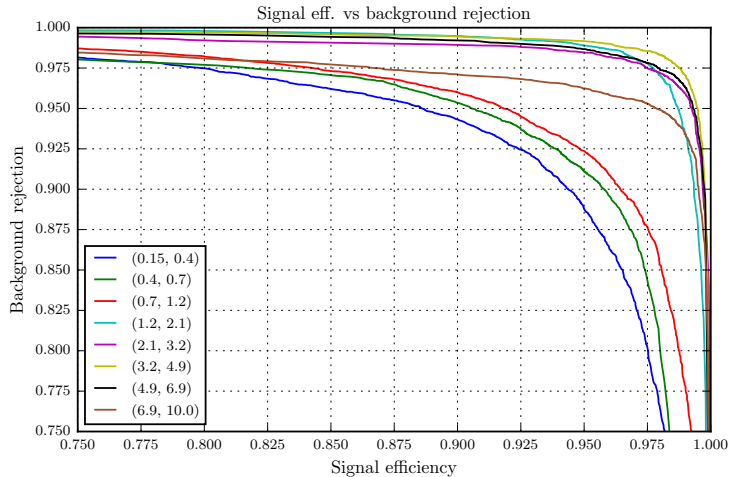
CNN example output distribution

CNN output distribution: good



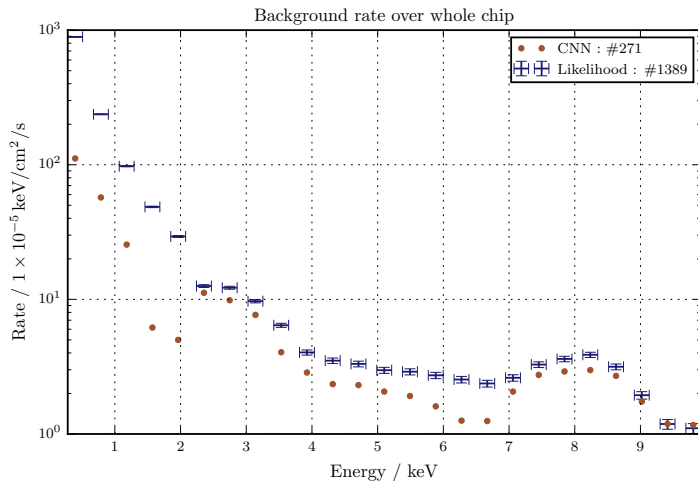
Potential improvements via CNNs

Signal eff. vs background rej.



Potential improvements via CNNs

baseline vs. CNNs: $5\times$ background reduction (2014/15 data)



"Summary"

- I hope I could teach you something new / it was still interesting regardless :)
- if you're interested: this talk and the code for the live demo can be found on my GitHub:
<https://github.com/vindaar/NeuralNetworkLiveDemo>