Machine Learning Monopoles and MoEDAL

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Outline

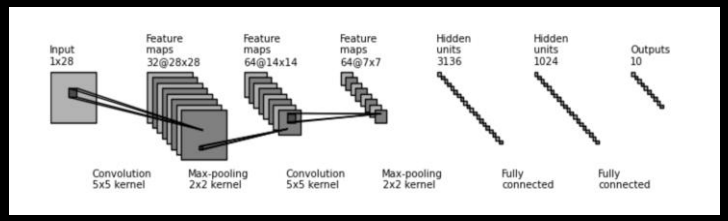
MoEDAL and Monopoles

Convolutional Neural Networks

Preparing Training Data

Performance

Summary and next steps



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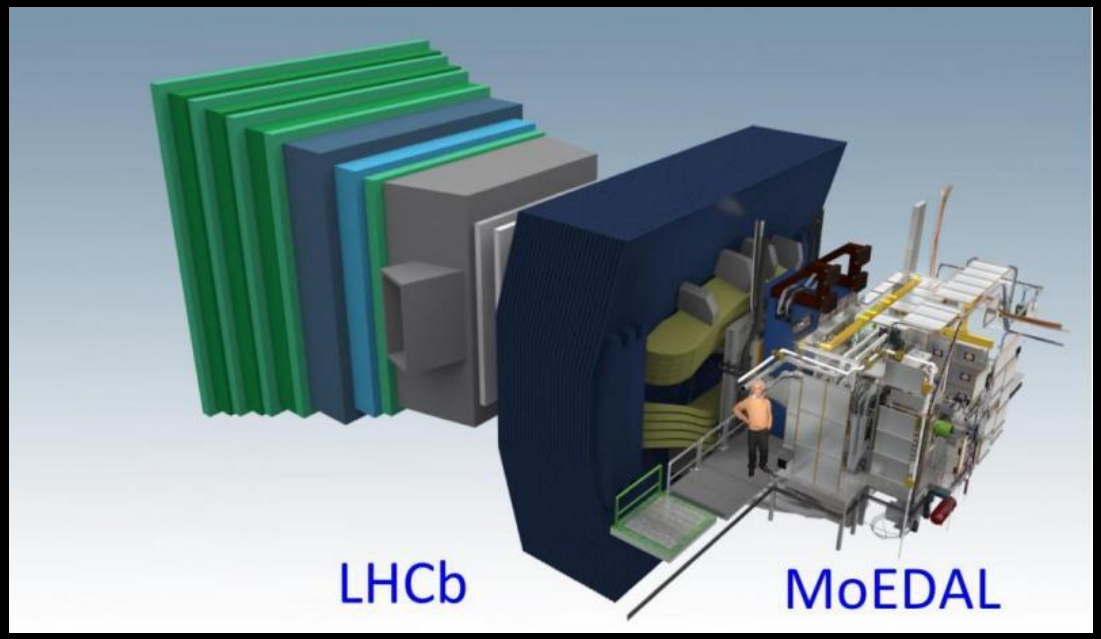
MoEDAL and Monopoles

MoEDAL = The Monopole & Exotics Detector at the LHC



Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Nuclear track detectors and aluminium trapping detectors

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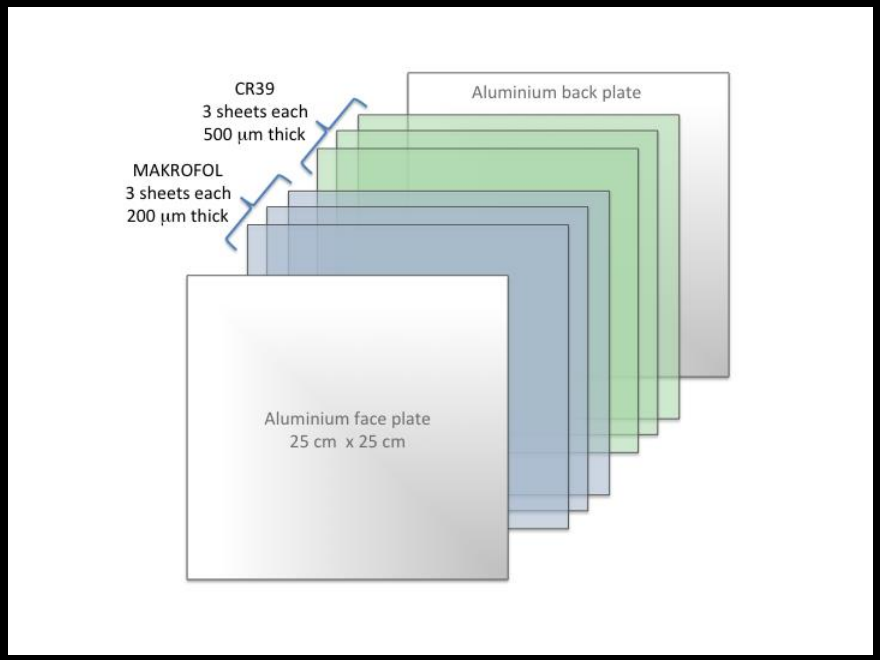
MoEDAL and Monopoles

MoEDAL = The Monopole & Exotics Detector at the LHC



Search for highly ionizing particles such as magnetic monopoles and other exotic avatars of new physics

Nuclear track detectors and aluminium trapping detectors

Highly ionising particles passing through the NTD cause microscopic damage to the polymer that can be reveal with etching

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MoEDAL and Monopoles

MoEDAL = The Monopole & Exotics Detector at the LHC

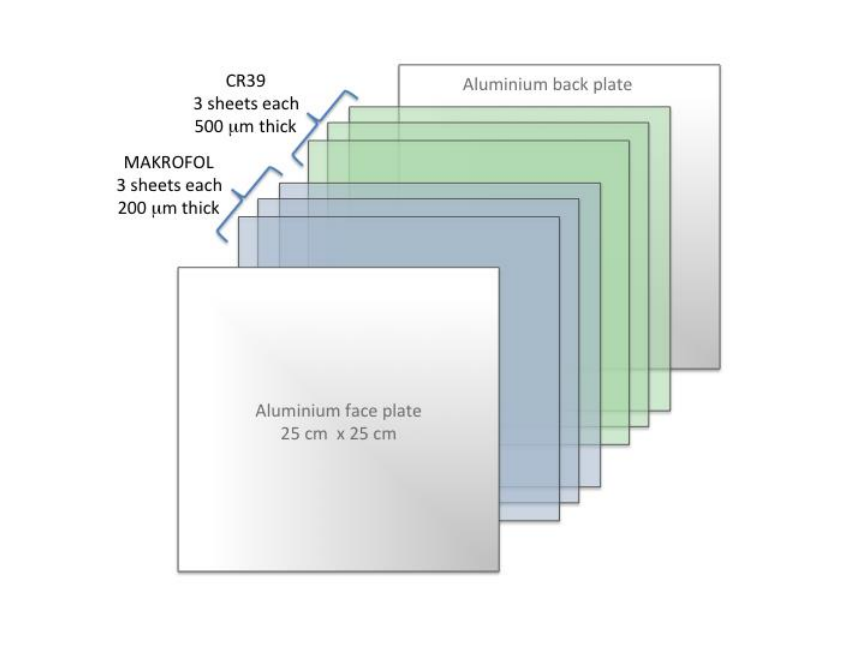
Signal:

Set of characteristic O(micron) sized holes that line up across multiple sheets

Small holes in large sheets:

high resolution imaging needed

large images to scan



Analysing the images could be susceptible to a automated approach using machine learning techniques

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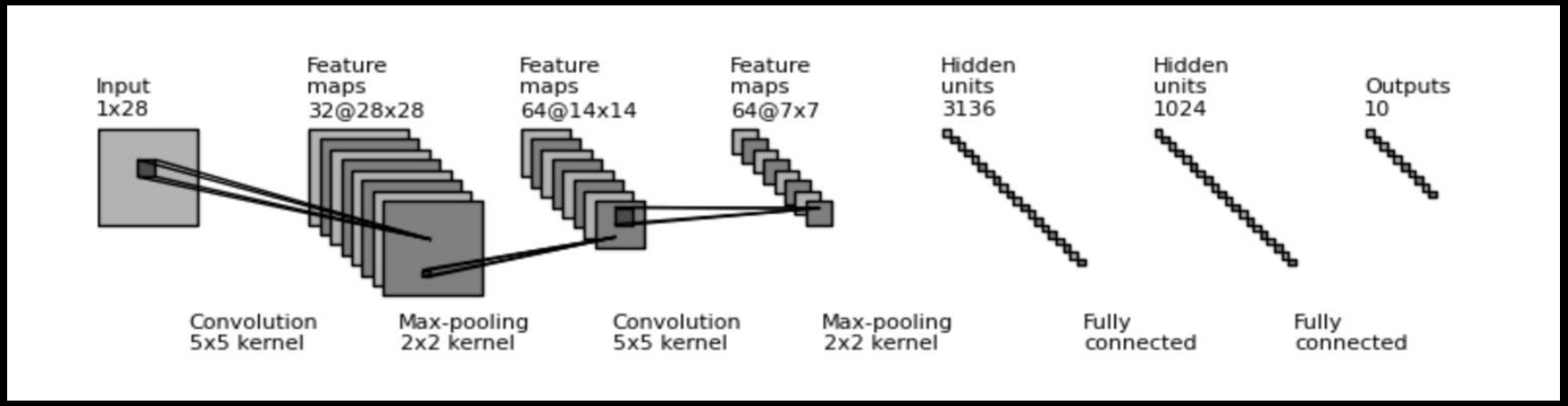
Convolutional Neural Networks

Deep artificial neural network inspired by biological function – has been successfully applied to image processing and categorization tasks



Simple example consists of multiple layers of convolution and pooling before feeding outputs into a traditional fully-connected MLP with one or more output neurons

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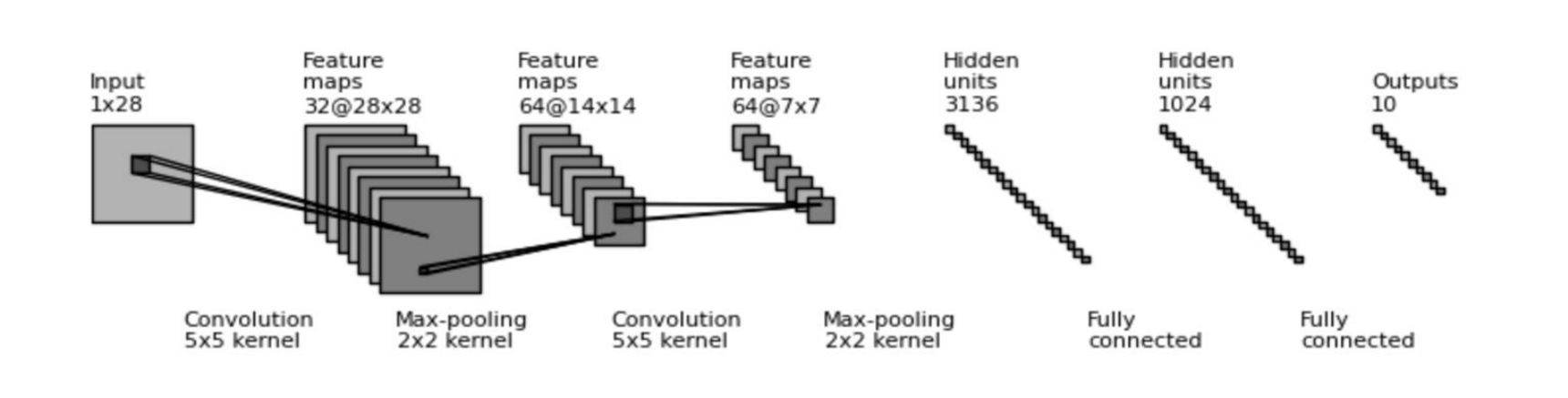
Convolutional Neural Networks

Deep artificial neural network inspired by biological function – has been successfully applied to image processing and categorization tasks



Challenges in this context:

- image preparation and resources – how to deal with very large images
- optimizing network structure
- supervised learning technique needs (lots of) training data

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Convolutional Neural Networks

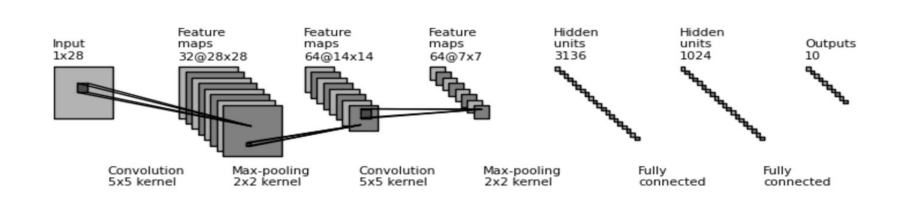

image preparation and resources – how to deal with very large images

tiling of the input images and consideration of how to handle multiple layers

optimizing network structure

investigate different structures and variation in performance

Supervised learning technique needs (lots of) training data

Potential solutions include:

- lots of real examples of etched sheets with signals simulated with beams
- artificial samples generated using Monte-Carlo based simulation
- resample small collection of real examples for training

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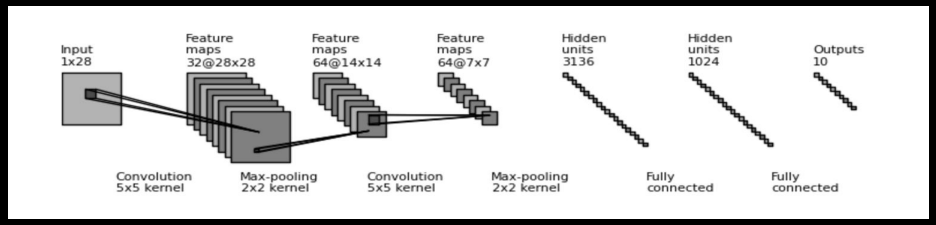
Convolutional Neural Networks



Krzysztof Furman
1st year UG
Summer intern

Thomas Charman
MSci graduate
Summer intern

Learn how to use CNNs to analyze images using API developed by A. Bevan using Tensor Flow from Google

Investigate resampling as a technique to generate large sample of training images

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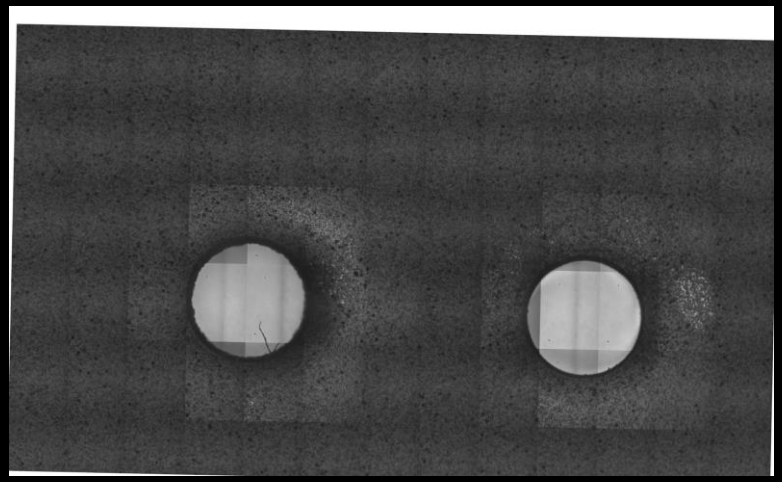
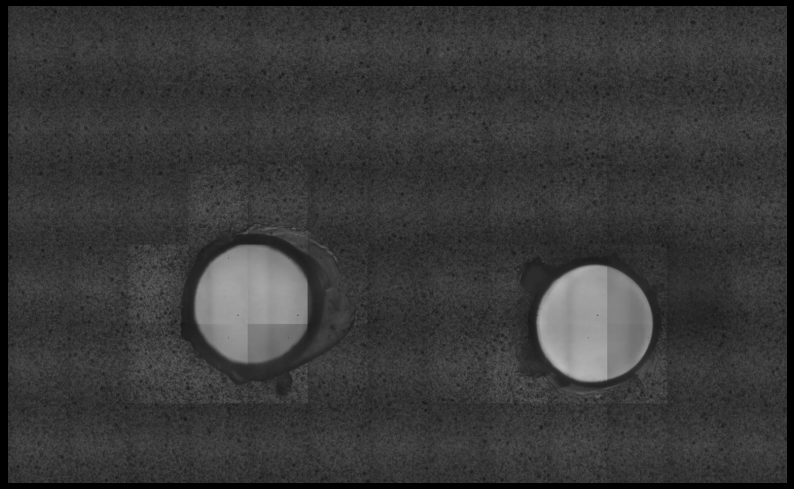
Resampling

Start from just two images of some holes

Select regions to sample from for background and signal

Randomly build new image from samples





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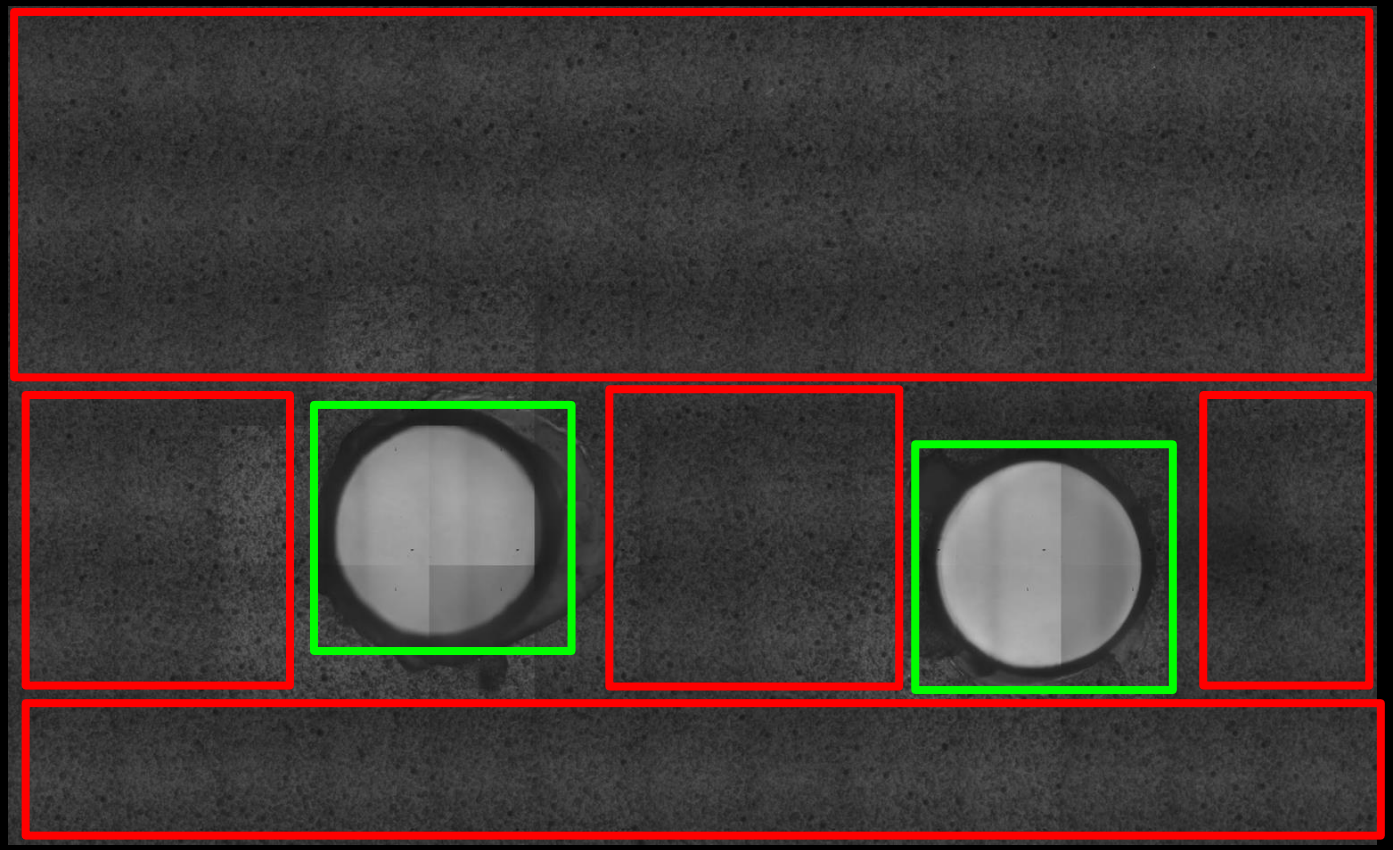
Sampling regions



Regions outlined in red are background, green are ROI.

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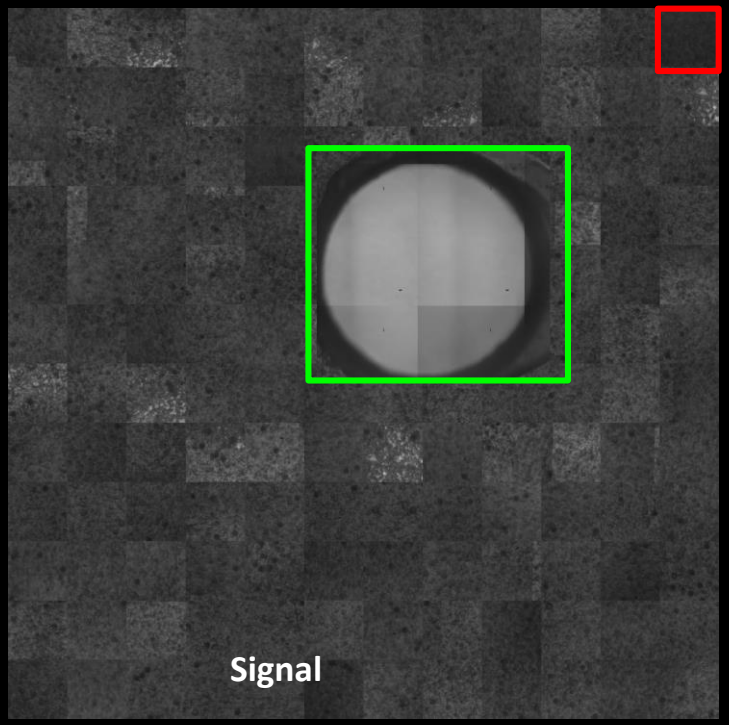
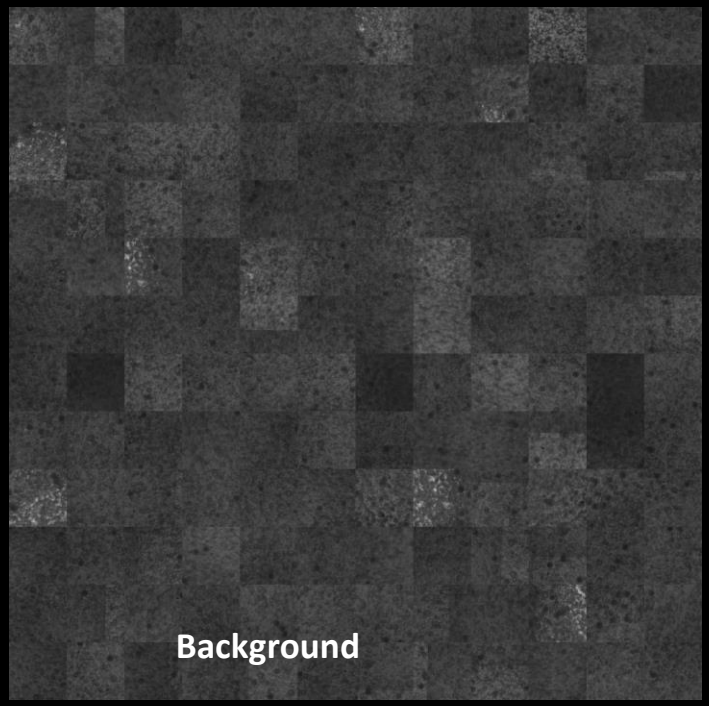
Example images

Generated images have size: 1536 x 1536
Tiles also include a random rotation (integral numbers of 90 degree rotations)

This patch size: 128 x 128





Examples of images made by the sampling algorithm.

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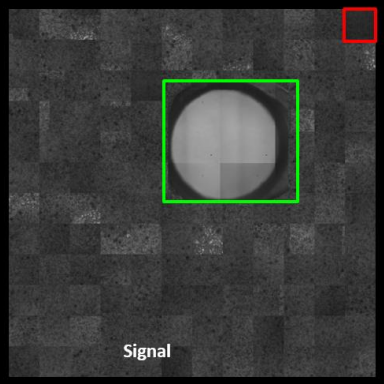
Training Workflow

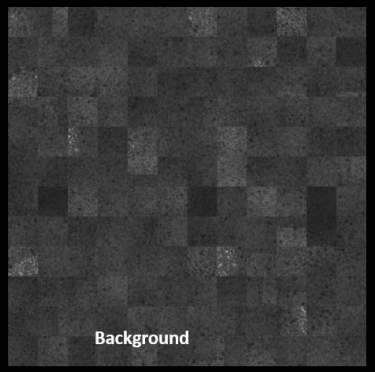
Generate 1000 signal and 1000 background images

Split 50/50 into training and test samples

Process batches of 50 images at a time through the network and update weights using the ADAMoptimiser (arxiv:1412:6980)

Repeat for fixed number (200) of training epoch





Training run on GPUs:
- NVidia Tesla K40
- NVidia GeForce 1080 Ti

(each with 12GB of memory)

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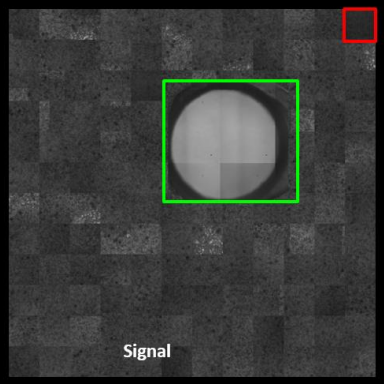
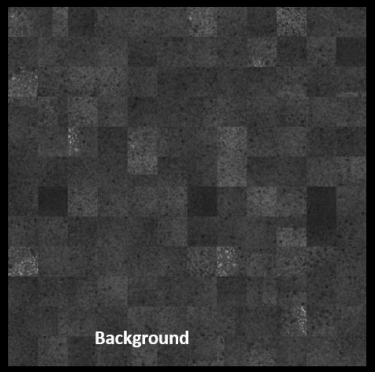
Challenge: memory!

Challenge:
Running with 1536x1536 images: completely exhausts the available memory and training fails!





Solution:
down-sample the images

Training run on GPUs:
NVidia Tesla K40
NVidia GeForce 1080 Ti

(each with 12GB of memory)

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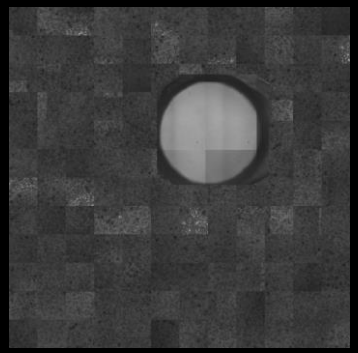
Downsampling

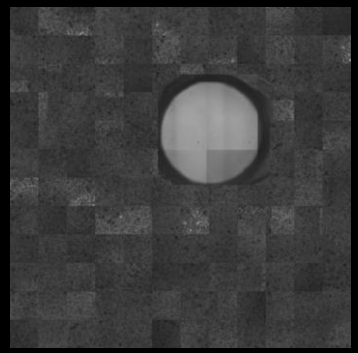
Training run on GPUs:
NVidia Tesla K40
NVidia GeForce 1080 Ti

(each with 12GB of memory)

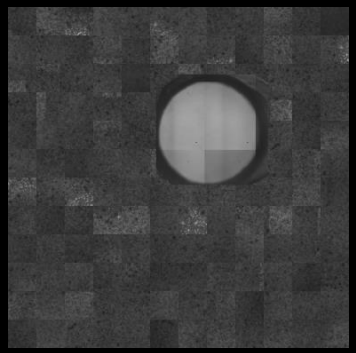
½ ¼
768 x 768



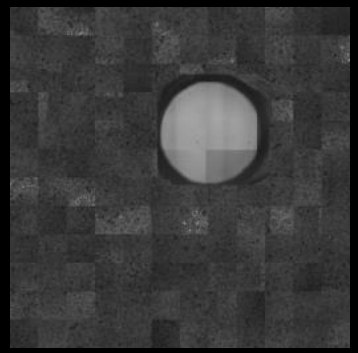
⅓ 1/9
512 x 512



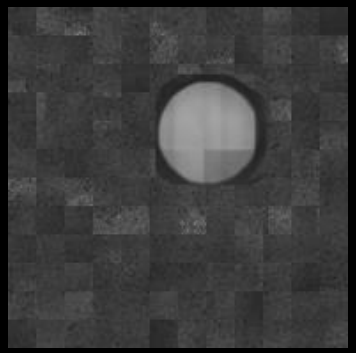
¼ 1/16
384 x 384



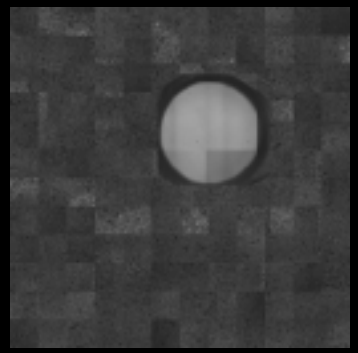
⅙ 1/36
256 x 256



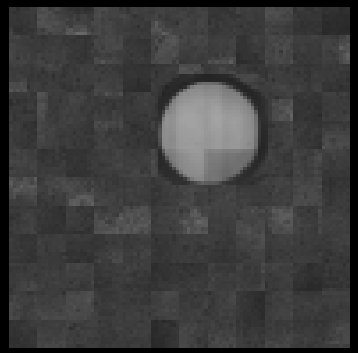
⅛ 1/64
192 x 192



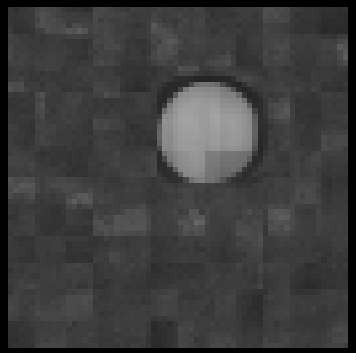
1/12 1/144
128 x 128



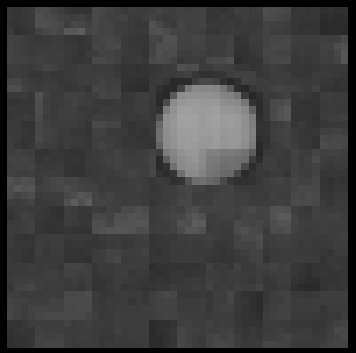
1/16 1/256
96 x 96



1/24 1/576
64 x 64



1/32 1/1024
48 x 48



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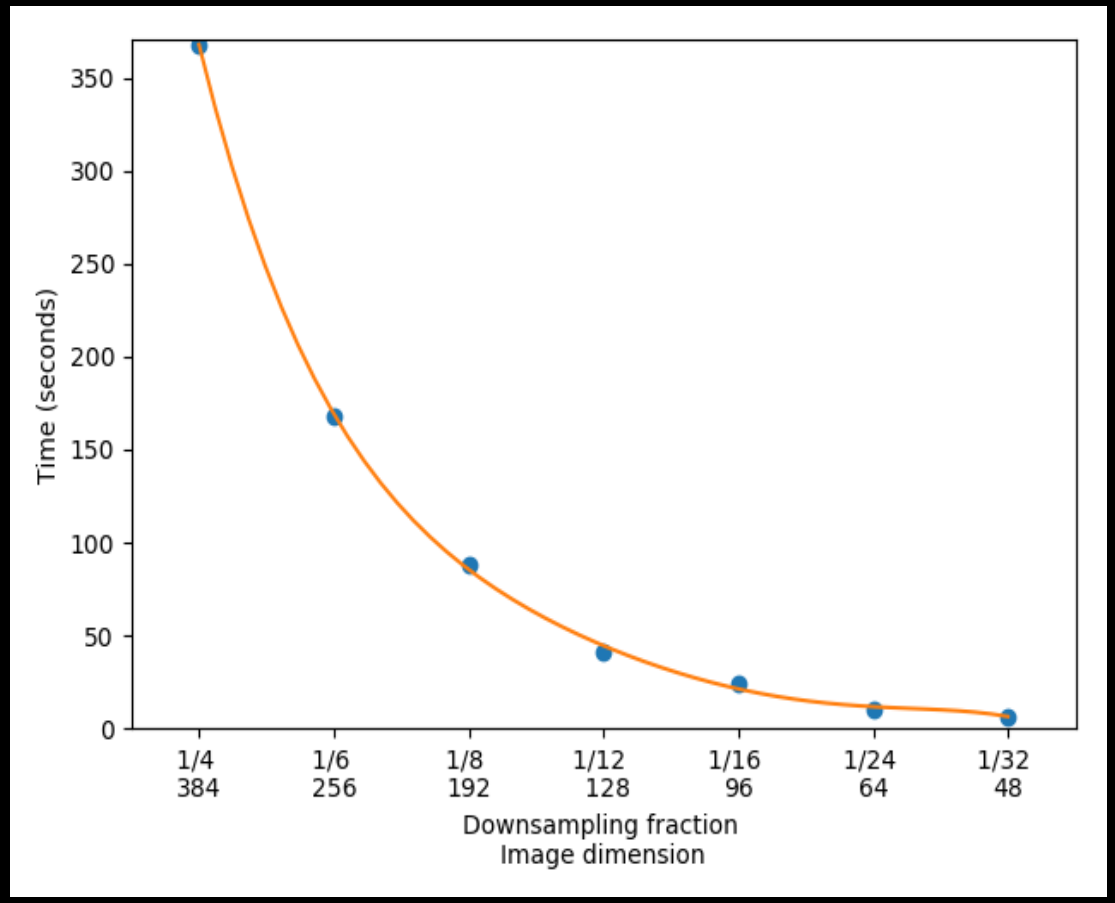
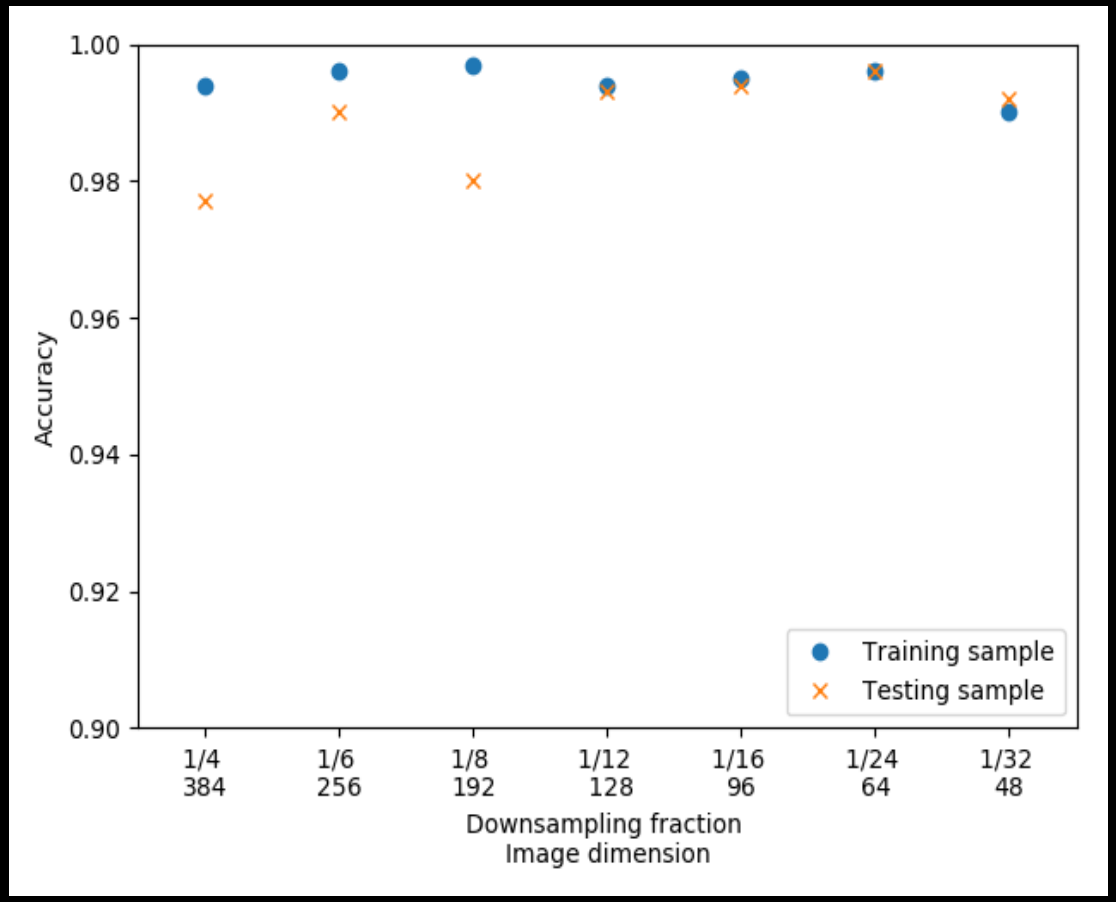
Performance: Timing



Note: 1080 Ti much faster for these jobs than K40 (and much cheaper)

Performance: Accuracy



Compare each prediction with its label for all 1000 images in the testing/training set.

$$\text{Accuracy} = \frac{\text{Correct guesses}}{\text{Images in set}}$$

Threshold = 0.5

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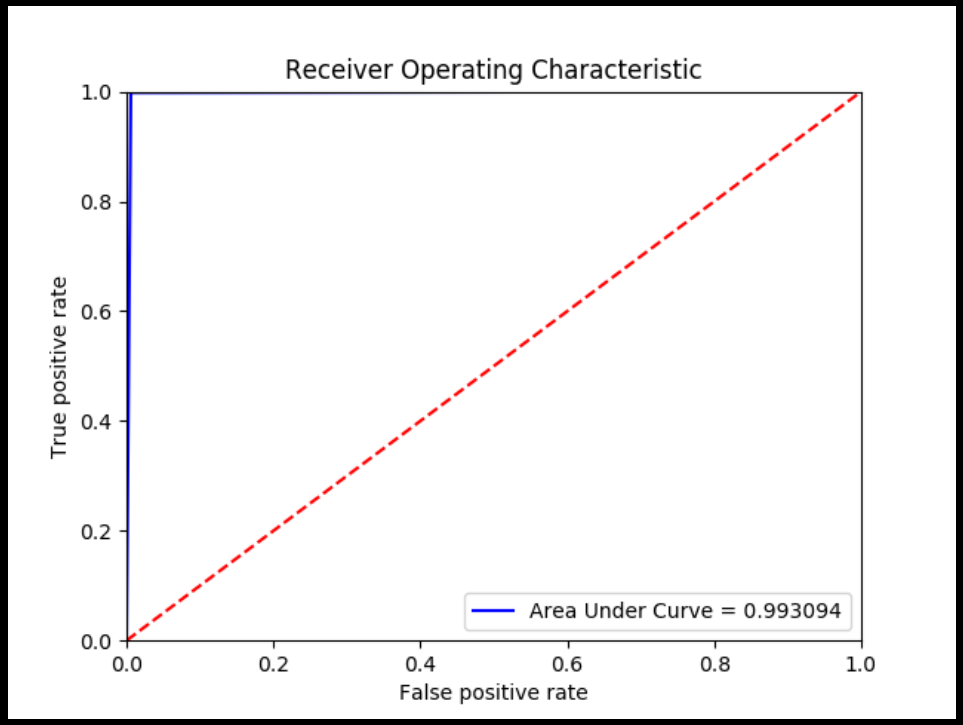
Performance: ROC



Vary threshold and generate curve of true positive rate versus false positive rate

Not terribly informative – accuracy is very high since this example problem is very easy for the CNN to deal with

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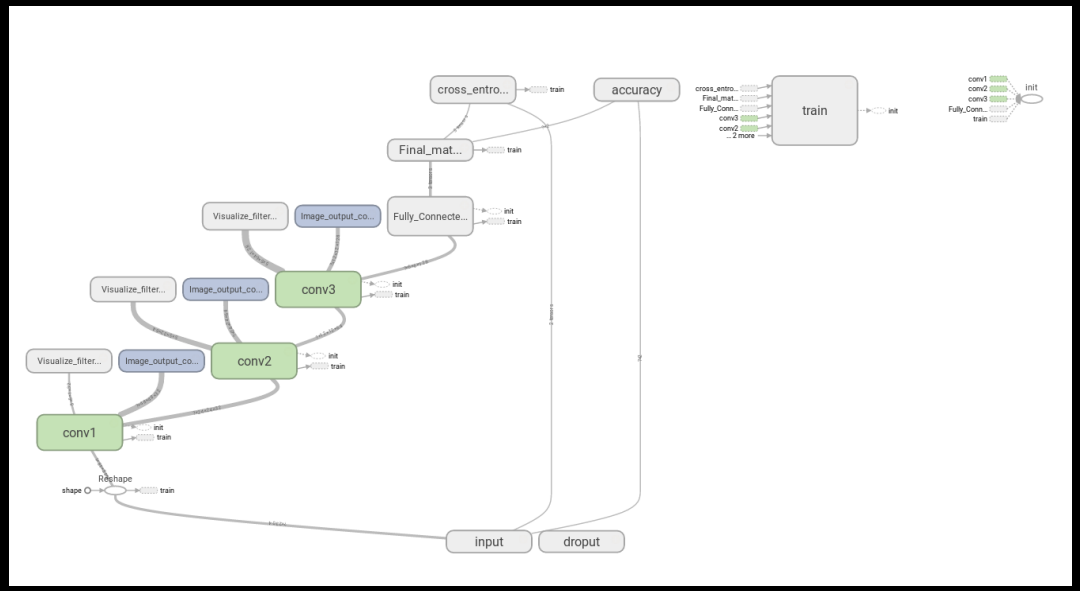
Aside: TensorBoard

TensorBoard : tool within the TensorFlow suite that lets you visualize the machine learning process



Interactive view of the computational graph – can drill down to fine details

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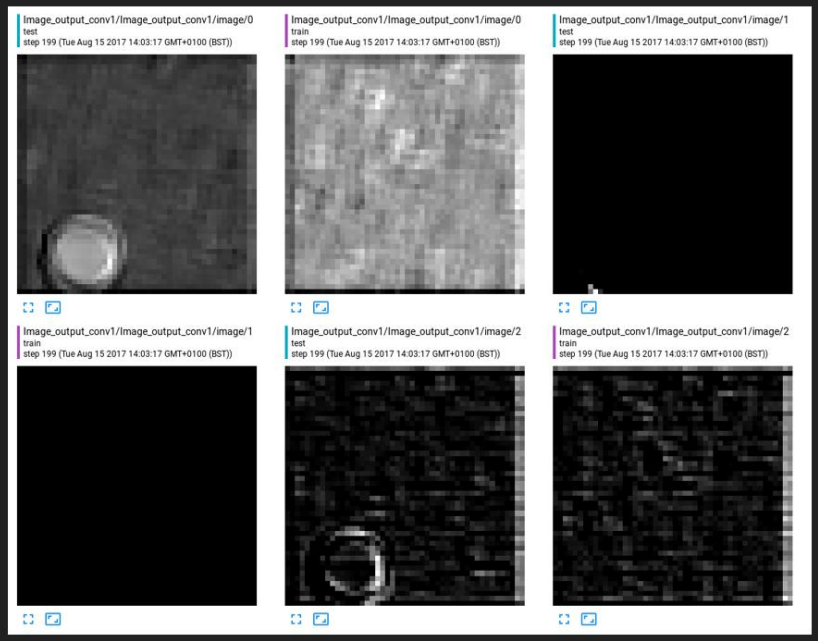
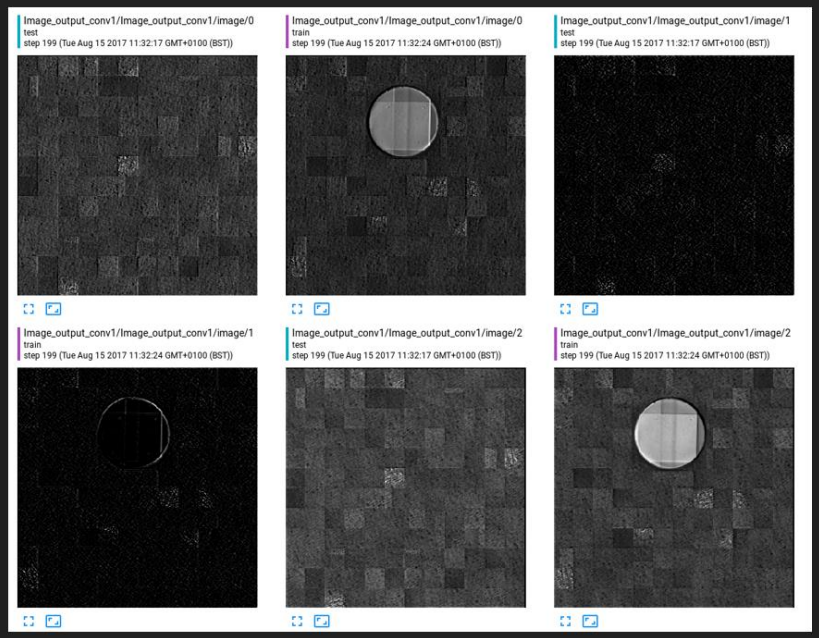
Aside: TensorBoard





TensorBoard conv layer outputs. Left smallest images (48 x 48), right largest (768 x 768).

Not only do smaller images seem to train just as accurately as larger ones, they are also quicker.
(Note that tailoring the size of the kernel filters in the convolutional layers to the size of the image could lead to improved performance.)

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Summary and Future Steps

Training data generated using resampling of real data

CNN successfully finds signal in simplified model

Future steps:

- Look at more realistic images
- Develop techniques to handle very large images
- Simultaneous processing of double sided scans

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