## Imperial College London

Imperial College London Derpartment of Mathematics

# Segmentation of CT scans into Atrium/non Atrium

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The work contained	in this thesis is my own work	α unless otherwise stated.
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## **Abstract**

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This template will quote relevant sections from the MSc in Statistics student handbook throughout; e.g.

<sup>&</sup>quot;The abstract should be a brief statement of the aims and outcomes of the project, to summarise/advise even for a casual reader!"

## Acknowledgements

 $Thank\ you\ supervisor/friends/family/pet.$ 

 $\lq\lq$  Include an acknowledgement.''

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## 1 Background Material: on convolutional neural networks

We first start with a brief explanation of Convolutional Neural Networks (CNNs), the kind of neural network which will be relied on for our architecture to classify the voxels into either being in the atrium or not. CNNs are a special type of Feed-Forward Neural Networks that are particularly effective for input types that a grid-like structure such as an image, a video or a time-series where the relevant information is encoded locally. CNN have recently been responsible for some of the state-of-the-art results results in image recognition [references], speech recognition [references], and something else [reference].

#### 1.1 Convolutional Layers

A convolutional neural network (CNN) is a specialised kind of feed-forward Neural Network where the first few layers of the architecture are convolutional layers. A convolutional layer is typically composed of two sub-layers: a convolution layer, and a sub-sampling layer.

#### 1.1.1 Convolution

The convolution layer is responsible for implementing a convolution. As opposed to a fully connected layer where all the input nodes at a given layer are connected to a given output node in the next layer, a convolution restricts the number of relevant nodes to a small local subset of input nodes. Additionally the same convolution operation, i.e. the same set of weights or kernel, is applied to the possible subset of input nodes. We say that the weights are shared across the inputs nodes and this greatly reduces the number of parameters to train. The set of output nodes for one convolution layer is called a feature map, and, in the case of a two dimensional image, is a kind of slightly reduced two-dimensional image which detects the presence of a particular feature. Having only one feature map isn't necessarily useful, but feature maps can be stacked in parallel to produce a set of feature maps, each responsible for detecting a particular type of feature which might be present in the image.

The benefits of this approach are three folds:

- sparse interaction: every output node is connected to a local subset of inputs instead of to all of of them.
- parameter sharing: the same kernel is used for every output node in a given feature map.

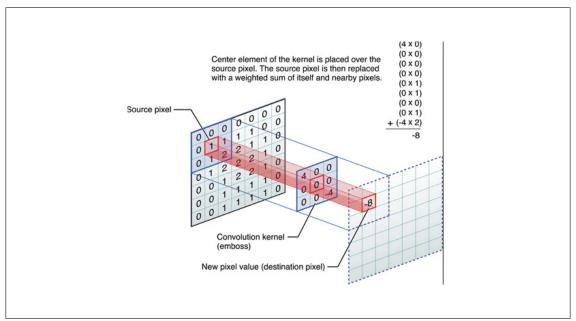


Figure 1.1: The convolution layer. Illustration of the formation of a feature map.

• translational equivariance: shifting the input results in an equivalent shift in the output.

Every node in the feature map is then passed to an activation unit which non-linearly transforms the output from that node, thereby introducing some non-linearity into the system. These activation units usually consist of either a Tanh unit or a Rectified Linear Unit (ReLU)

#### 1.1.2 Pooling Layer

The pooling layer reduces the output with a local summary statistic such as the maximum or the average. This reduces the layer size and adds local translational invariance.

#### 1.1.3 Typical Architecture

A typical convolutional neural network architecture consists of an input layer, a number of convolutional layers, a number of fully connected layers, followed by an output layer. Each layer in turn are combinations of the nodes of the previous layer thus representing more abstract features the deeper its location in the architecture.

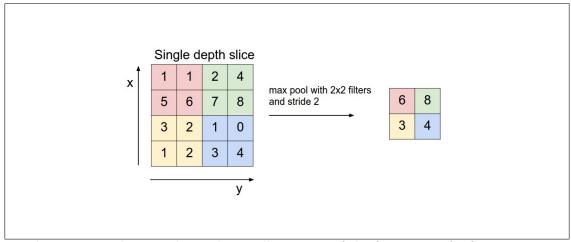


Figure 1.2: The convolution layer. Illustration of the formation of a feature map.

### 2 Setting up the problem

#### 2.1 The Data

The data from which the training and testing datasets are generated comprise 27 3-dimensional grey scale images from CT scans stored as DICOM files. Each come accompanied by a 3D array of the same dimension indicating whether the corresponding voxel is in the Atrium (1) or not (0). These are stored in NRRD files, another popular file format for storing those things. Figure whatever shows an example of a slice in the transverse plane (x-y plane).

#### 2.2 The Tri-Planar Method

Classifying the voxels require building an input set for each containing enough local and global information to allow the Neural Network to learn. A cheap way of doing so is to use the so-called tri-planar method [reference the paper that started it on knee cartilage]. This consists in generating 3 perpendicular square patches of dimension 32\*32 in the transversal, saggital and coronal planes centred at the voxel of interest, thus providing 3 dimensional information while keeping the memory requirements low. In addition, we add 3 more compressed patches 5 times larger but resized to the same size to provide global information about the surroundings of concerned voxel. Each patch is then fed into a different input channel of the Convolutional Neural Network, and are then connected to the classifying layer using fully connected layers.

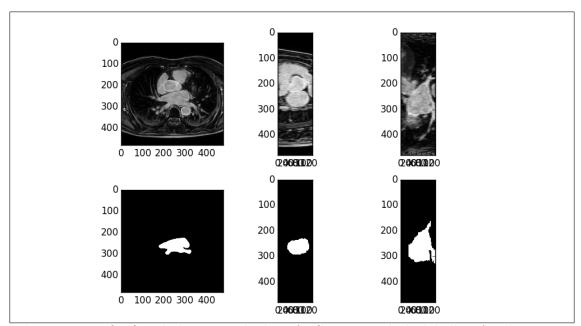
#### 2.3 Implementation Details

#### 2.3.1 Libraries

We use Torch, an open-source library maintained by Facebook in Lua, to train the Neural Networks and Python and a number of its libraries to handle all the logistics from generating the datasets to producing plots of segmentation results.

#### 2.3.2 Computer Power

The code for training Neural Networks has been written to work on multi-GPU platforms as well as a single GPU to increase the speed of training many folds. The graphic cards consist in two NVIDIA Tesla K40m and two Tesla K20Xm.



**Figure 2.1:** TODO include a example slice of a CT scan with the labelling for illustration purposes.