Development and Evaluation of a Visual Attention Model with Python and Tensorflow

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Chapter 1

Introduction

Neural network approaches have received a lot of attention in the last several years. It's becoming a popular choice for performing various tasks like speech and image recognition, object detections etc. as these methods have dramatically increased accuracy compared to traditional machine learning approaches. However, achieving high accuracy on recognition tasks is still computationally expensive and needs improvements in performance. This study will be a close resemblance of the recurrent neural network of visual attention which is able to extract necessary information from an image by looking at it in low resolution, and then adaptively select parts that are most relevant for a task [4].

The idea of visual attention was inspired by how human perception works. Humans do not perceive a visual scene as a whole but focus on parts of the scene that gives the most useful information to them. Humans are also capable of combining information from different parts of a picture. They then connect it to build subjective knowledge of the picture (or sequence of pictures) [7]. Taking into account these properties, researchers from google Deepmind build a model which can be described as follows:

> Instead of processing an entire image or even bounding box at once, at each step, the model selects the next location to attend to; based on past information and the demands of the task.... The model is a recurrent neural network (RNN) which processes inputs sequentially, attending to different locations within the images (or video frames) one at a time, and incrementally combines information from these fixations to build up a dynamic internal representation of the scene or environment.[4]

One of the main advantage of this model, is that the computation required is controlled and is independent of the input image size. Deepmind's researchers evaluated their model on several image classification and dynamic visual control problems which showed a better performance when compared with convolution neural network[7].

The evidence from this study suggests the application of this model on large scale object recognition as well as classification of a sequence of images, which will be a great fit since the model's performance is not dependent on the size of an input object.

The main aim of this study is to extend the current knowledge of the work mentioned above and build a model which will be able to classify a set of images and develop appropriate prototype system since it can be useful in a variety of areas. However, the experiments in the current work is limited by low-resolution images and mostly will concentrate on classifying a group of objects as this restriction will reduce complexity of the experiments and therefore reach better results on a task of classifying a group of images.

1.1 Motivation

This approach to classify a group of images has a potential to help with automated detection and classification of breast cancer metastases, which is the main concern of camelyon challenge. Camelyon challenge provides the whole-slide images (WSI) of lymph nodes of different patients. Based on this images, competitors solutions should be able to detect the presence of breast cancer metastases in lymph nodes. [8]
Camelyon challenge is an inspiration for this work since pathologist's efforts along with the assistance of automated detection system will reduce significantly not only the workload of pathologists but the human error rate in diagnosis as well.

This work will be the first step in building software that will be capable of classifying whole-slide images of histological lymph node at the patient level. That is, bringing together estimations from multiple lymph node slides into a single outcome.

Digital pathology is a very attractive field for machine learning researchers since whole-slide images have a very high resolution and are typically about

200000 x 100000 pixels. To give you some sense of data, camelyon challenge provides data for 200 patients, where each patient has 5 different slides. It means that in total they release about 1000 slides which is 55.88gb of uncompressed data [8].

It is quite clear that using CNN for this task is computationally very expensive. Applying model of visual attention promises to solve the issue of high-resolution pictures at a computational level. Therefore making an extensible piece of software, that will allow further improvements is also one of the main concerns of this work.

Chapter 2

Theory

2.1 Artificial Neural Networks

Why Neural Networks? Before going into what actually artificial neural networks are, let's first try to face the question why do we need it in this paper. The problem that we give to our application to solve can be shortly summarized in the following statement: " Given a group of images, find the patterns in them that are more influential on your belief that an image(or a group of images) belongs to a specific class. "

This problem is known as pattern recognition problem or in our case visual pattern recognition problem [9]. In order to solve this problem it's required to develop ability for the machine to recognize patterns that will help to make a decision about a class. The obstacles that can appear by solving this problem can be more visible if we will try to write a conventional computer program, i.e. bunch of rules to identify these patterns. What seems to be easy for us, is really hard to describe algorithmically. In these system the computational steps are deterministic hence not flexible enough for the whole variety of input data [1].

Solving problem differently Artificial Neural Networks(and machine learning in general) are looking at the problem in a different way. They don't execute programs instructions, they don't have sequential semantic and normally are not deterministic. They acquire their "knowledge" by extracting patterns from raw data, which is normally called training data(which normally is a set of tuple $(input, label)$. The label of the an input is also known as the ground truth. This approach also know as concept of statistical pattern recognition. [9] Artificial Neural networks have recently shown an excellent performance and accuracy at recognizing objects compared with other machine learning techniques [10].

What is Neural Network? Artificial Neural Network(ANN), often referred just as Neural Network(NN), in simple words is a computational model, which was inspired by how human/animal brain works. Artificial NN is modeled based on the neuronal structure in the brain's cortex. Though the inspiration was from the brain, it's indeed much much simpler than brain in terms of number of neurons that are used in ANN [11]. To understand how neural networks work it is crucial to understand first the way a *perceptron* work.

Perceptron is a simple type of an artificial neuron. Given several binary inputs, perceptron is meant to produce a single binary output.

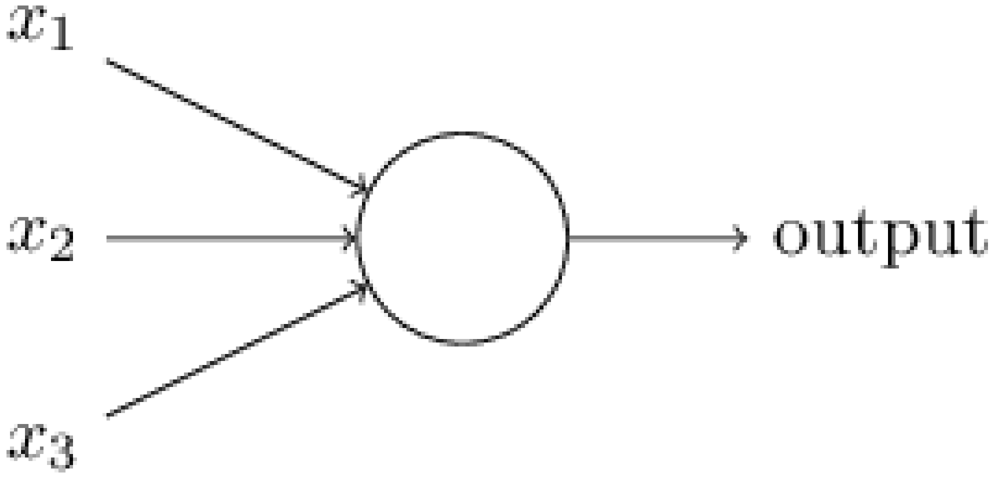


Figure 2.1: A perceptron [1].

In the figure 2.1 the perceptron has three inputs: x_1, x_2, x_3. To produce an output the perceptron posses of *weights*: w_1, w_2, w_3 which represents the connection between input and output. The weights determine the extent of the influence that input has on output. That said, the perceptron output is determined by whether the weighted sum $\sum_j w_j x_j$ is more or less than some *threshold* value:

$$output = \begin{cases} 0, & \text{if } \sum_j w_j x_j \leq threshold \\ 1, & \text{if } \sum_j w_j x_j > threshold \end{cases} \tag{2.1}$$

In short, this is a computational model which make a decision by weighting up the evidence(input data) [12].

Of course such a model is not capable of making complicated decisions, but by extending the model to more complex network of perceptrons, we might improve the model.

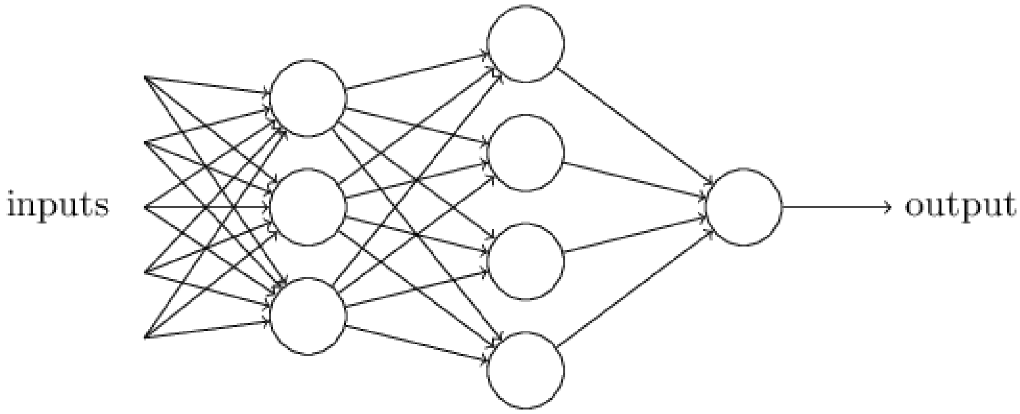


Figure 2.2: Two layer perceptron network[1].

In the network shown on figure 2.2, we can observe two layer of perceptrons. First layer will correspond to the first column of perceptrons and will be responsible for the weighting up input, in contrast to second layer (second column of perceptrons) which determines output by weighting up the result from the first layer. Therefore, the second layer is located on more abstract level from input data compared and can make more complicated decisions. Further layers may be capable of making even more sophisticated decisions.

2.1.1 The Basics of Neural Networks

Neural Network Now that we know the way perceptrons work, it's fairly easy to understand Neural Network. However, we need to change the mathematical notation a bit. For the sake of convenience, let's move *threshold* in equation 2.1 to the left part and replace it with a variable known as the bias : $b = -threshold$. Let's also simplify the sum sign: $\sum_j w_j x_j$ by writing weights and input as vectors and use a dot product to multiply them: $\sum_j w_j x_j = W \cdot x$. Using changes described above we can rewrite the equation 2.1 as following:

$$output = \begin{cases} 0, & \text{if } W \cdot x + b \leq 0 \\ 1, & \text{if } W \cdot x + b > 0 \end{cases} \tag{2.2}$$

Bias is a measure of how influential is a certain neuron on making output 1. Some people also use more biological terms: the bias is a measure of how easy it is to get a neuron to fire. To devise the neural network next improvement over the perceptron network is that network should not be limited to have an input only binary value, but any value. The same applies on the output. Output being only binary value will limit the ability to make sophisticated decision. Therefore we introduce a function known as *an activation function* before actually outputting a value: $output = g(W \cdot x + b)$ [1] .

Activation functions $g(\cdot)$ is known as an activation function. Activation function helps to control the output and non-linearity of the network. Activation function also plays a crucial role in multi layer architecture, where it helps to prevent the values of each layer from blowing up. For example, let's look at the *softmax* activation function which has the following form:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \tag{2.3}$$

where $j = 1, 2..., K$ - is the index of the vector z.

The use of the sigmoid activation will make a network to produce output to be interpreted as posterior probabilities. Probability interpretation helps to provide more powerful and more useful results [9].
Second type of activation function is *rectified function.* Rectified function is fairly simple. It produces 0 when input is less than 0, and it does not change input value if input is more than 0:

$$R(z) = max(0, z) \tag{2.4}$$

Now that we derived a concept of Neural Network, we can talk more about what is called feedforward neural network and the terms related to it.

Feedforward neural network is a network where the output from one layer is used as input to the next layer. In feedforward NN information is always fed forward in contrast to recurrent neural network(RNN) where information can go in a loop. We will take a closer look at RNNs in section section 2.2.

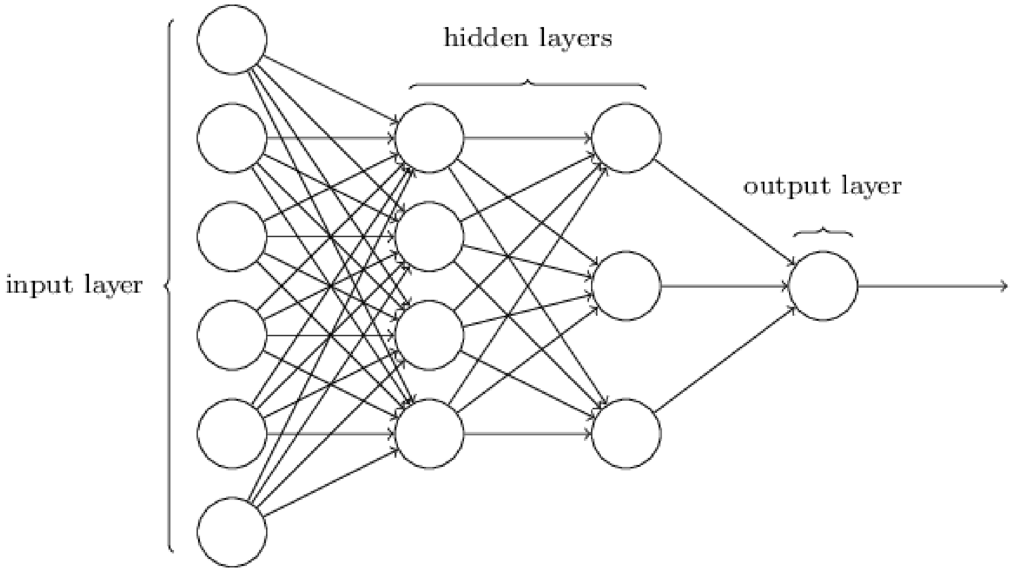


Figure 2.3: The architecture of neural networks[1].

Basically Feedforward neural network is exactly what we described above. Let's name different parts of feedforward NN:

- Input layer - the leftmost layer in the network. The Neurons within input layer, called input neurons.
- Output layer - the rightmost layer in the network. The Neurons within input layer, called output neurons.
- Hidden layers - all the layers excluding input and output layers.

For example, the Neural network in figure 2.3 consist of

- 6 input neurons
- 2 hidden layers
  - first hidden layer consist of 4 neurons
  - second hidden layer consist of 3 neurons
- output layer consist of one single neuron

2.1.2 Training an Artificial Neural Network

As mentioned above Neural Network is capable of solving complicated pattern recognition problems. However designing a neural network is not sufficient for this. It's also requiring to train an network. In this paragraph we will introduce learning procedure. But before going into learning, let's recap how our neural network model looks like:

$$y = g(W \cdot x + b) \tag{2.5}$$

Where g is an activation function, W - weights, b-biases, x - input data. The space of different weights and biases values building a space of solution for cetrain problem. The goal of the training is to find the best parameters for neural network (W, b), that suited our problem.

Training data To solve pattern recognition problem we need to provide a continuous feedback to NN, which NN can use to learn from. This feedback in machine learning called *training data*. Training data consist of the input data samples and appropriated outputs. You can think of training data as of an list of tuples: $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), ..., (x^{(n)}, y^{(n)})$ where x - input, y - output (also known as *ground truth*), n - amount of training examples. Neural network trained on training data should be able to generalise the output on unseen input data. The goal of the learning is to train network on training data and make it to capable of generalizing the output on unseen input data.

Cost In order to teach the model, it's essential to understand what it means for an neural network to be good or to be bad. For this purpose it's required first to define a cost function. Cost(also knows as error) is the metric for the NN(or any other function approximation method), which represents how far of the model is from desired outcome. If cost is big , our network does not work well. With the cost function, it's possible to define our training goal more precisely: the smaller our cost, the better our model works, therefore the goal of the learning is to minimize the cost of our model. The term cost is also known as a *loss* or an *objective*. We will use these terms interchangeably throughout the work.

Types of cost There are a plenty of ways to define cost of the model. Let's consider the common type of cost function called *mean squared error* *function.* Mean squared error function has following form:

$$I_{W'} = \frac{1}{2n}\sum_{i=1}^{n}(y_{W'}(x^{(i)}) - y^{(i)})^2 \tag{2.6}$$

- $y_{W'}$ - is our neural network function with the parameters (W', b'),
- $x^{(i)}, y^{(i)}$ - is input and output of a training sample respectively.

Another common type of function to measure the cost of NN known as *cross entropy.* In short, cross entropy gives a way to express how different two distributions are:

$$I_{W'} = -\sum_{i=1}^{n} y_{W'}(x^{(i)}) log(y^{(i)}) \tag{2.7}$$

where:

- $y_{W'}$ - is our neural network function with the parameters (W', b'),
- $x^{(i)}, y^{(i)}$ - is input and output of a training sample respectively.

[1]

Gradient Descent Once we defined our cost function, we need to find a set of parameters W, b which make the cost as small as possible. The most common algorithm used to minimize the cost function called *gradient descent.* Let's explain the algorithm on an example function:

$$f = f(\Theta) \tag{2.8}$$

where $\Theta = \vec{v_1}, \vec{v_2}, ...$ are variables that we want to minimize.
Gradient descent uses partial derivative to iteratively update parameters. Derivative of a function shows how function output will change with respect to very, very small change in input $\Delta\Theta$. For example, partial derivative with respect to variable $\Delta\vec{v_1}$ will tell us, how different the output will be Δf if we change $\vec{v_1}$ on the small amount. This property of derivative is used in gradient descent algorithm. Essentially, the gradient descent performs updates on the variables to be minimized according to partial derivative of the cost function with respect to this variables.
Gradient descent adopt the following procedure. Beginning with an initial guess for value $v = \vec{v_1}, \vec{v_2}, ...$, we update the vector v by moving a small distance in v-space in direction in which our function f raises most rapidly,

i.e. in the direction of $-\Delta_\Theta f$. Iterating this process, we can devise the new set of parameters $\Theta^{(new)}$:

$$v_i^{\vec{new}} = \vec{v_i} - \alpha \frac{df(\vec{v_i})}{d\vec{v_i}} \tag{2.9}$$

where α - is a small positive number known as the *learning rate.* Learning rate determines the smoothness of updates and it's very important to choose it appropriately since if learning rate is too small the learning can be too slow, while, if learning rate is too big, algorithm updates can be too big to achieve the minimum (it can overstep the minimum).

Depends on the conditions this will converge to the parameters Θ where function f is minimized. One important things to notice is that, we can use the gradient descent algorithm only if f in equation 2.8 is differentiable. That means, if we want to use gradient descent algorithm our cost function should be differentiable [9].

Mini-batch Gradient Descent Normally gradient descent algorithm is associated with the update on the loss computed with whole set of training data, while, gradient descent where updates is performed only using loss computed on a small batch of data knows as *mini-batch gradient descent.* Much faster convergence can be achieved in practice using mini-batch gradient descent. [13]

Backpropagation In order to compute gradients in gradient descent algorithm backpropagation algorithm is normally used. Backpropagation is the procedure of computing gradients applying a gradient chain rules and updating the weights accordingly. It performs first a forward update to receive the network's error value. This error value then is back propagated beginning from output layer(neuron) through all neurons till the input in order to associate it with extent of this error(Δ) which a certain neuron is responsible for. Once this extent is calculated, it performs a weights update [14].

2.2 Recurrent Neural Network

Why recurrent NN? Motivation for recurrent neural network(RNN) is in contrast to feedforward neural network, as RNNs are capable of having internal memory, i.e. capable of memorizing information, therefore deal better with sequential input data. RNNs are closer to the way human's brain works. We don't start our thinking from scratch, all of us have different background, memories and experience; based on this we're making our own

decision and actions.
As already mentioned in chapter 1, in this work the network should be able attend to different locations within an image, i.e. choose a location and only process this area with respect to the location. The network then incrementally combines the information from a different location and based on the knowledge(memory) extracted from a location, network chooses a new location to attend. As you might notice since more steps need to be required, we will have sequential data. Hence, RNNs are an underlying concept for this work.

What is RNN RNN is a special type of neural network architecture, which can accept a sequence with an arbitrary length without changing weights of a network. RNN are capable of persisting the information by means of recurrences, i.e. including the output of the network into the next computational steps and summarizing this information into an object called *state*. [15].
To simplify the understanding you can imagine RNN as a composition of identical feedforward network, one for each step in time, passing the message to a successor. Essentially, it's a computational unit that is repeated over and over again and can be also thought as an for-loop. One neural network in this composition known as *RNN cell.*

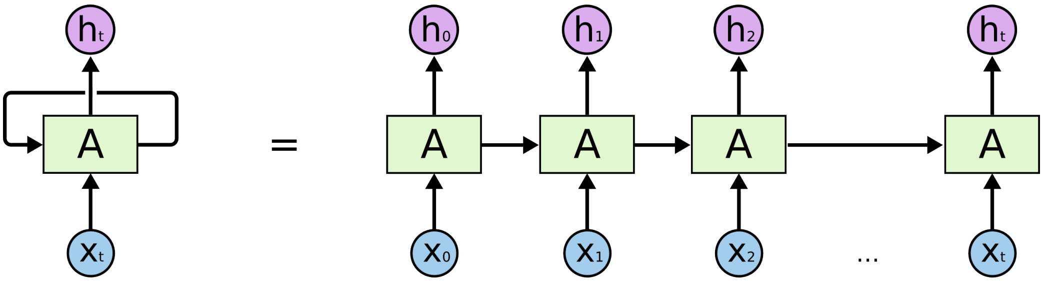


Figure 2.4: Unrolling recurrent neural network(source: [2])

On the right side of the figure 2.4 you can see an unrolled RNN that accepts as input $x_0, x_1, x_2, ..., x_t$ and produces following output: $h_1, h_2, ..., h_t$. One time step represents a layer in terms of forward neural network. The whole concept can be explained in the following equation:

$$\begin{pmatrix} s_t \\ o_t \end{pmatrix} = f \begin{pmatrix} s_{t-1} \\ x_t \end{pmatrix} \tag{2.10}$$

where:

- s_t, s_{t-1} - are states at time step t and $t-1$ respectively,

- o_t - is the output at time step t,
- x_t - is the input at time step t,
- f - is a recurrent function(normally called as RNN cell).

As you might notice, all calculations responsible for extracting and memorising information performed in f, provide knowledge about specific *RNN architecture(RNN cell)*. Thus the choice of recurrent function f(RNN cell) is essential for RNNs to work and remember information. There are a lot of variations of RNN cells, but we mostly will consider one of the recent and most widely known architecture called *Long Short-Term Memory (LSTM)*.

2.2.1 Long Short-Term Memory (LSTM)

Long Short Term Memory networks(LSTMs) are a special architecture of RNN cell, capable of learning long-term dependencies. [16] LSTMs have the ability to remember new information and forget old, unnecessary information using the concept of gates. LSTM cell holds information in the object called *state(C_t)* and only the gates are permitted to manipulate and change this state. Gates are represented as a sigmoid layer and pointwise operation and will be explained below.

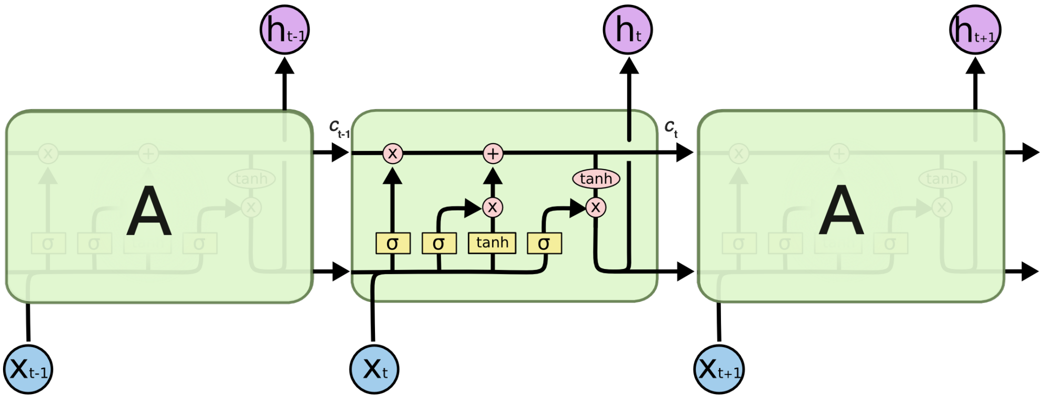


Figure 2.5: Structure of LSTM cell(Source: [2])

The yellow square with σ inside represents a neural network with sigmoid activation function, while yellow square with *tahn* inside represents a neural network with *tahn* activation function.

As you can see from the figure 2.5, LSTM cell has four layers, which build up three gates to interact with the state: *Forget gate*, *Input gate*, *Output gate*.

Forget gate layer The sigmoid layer that you can see on the right side is called "forget gate layer". As you might notice from the name, this gate is responsible for remembering information(or forgetting). It concatenates output from previous state: h_{t-1} with the input at the timestep t: x_t. Then the result is fed to the neural network with sigmoid activation function which produces an output with values from 0 to 1. Where 0 means to completely forget the information and 1 means to leave the information in the state:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2.11}$$

Input gate layer This is composed of two networks: networks with sigmoid and tahn activation functions. The first sigmoid network decides which values needs to be updated and to what extent, while the network with tahn activation function creates a new candidate state value. Then the outputs from the networks are multiplied with each other to create an update for the LSTM cell's state:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ C_t^{(candidate)} &= tahn(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{2.12}$$

Updating the state It's fairly simple now to update the old state C_{t-1} using f_t from equation 2.11 to forget information and use new state candidate values $C_t^{(candidate)}$ and it's extent i_t from equation 2.12:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t^{(candidate)} \tag{2.13}$$

Output gate layer is responsible for the cell's output h_t. This layer is allowed to read information from state C_t and decides what information should be outputted.

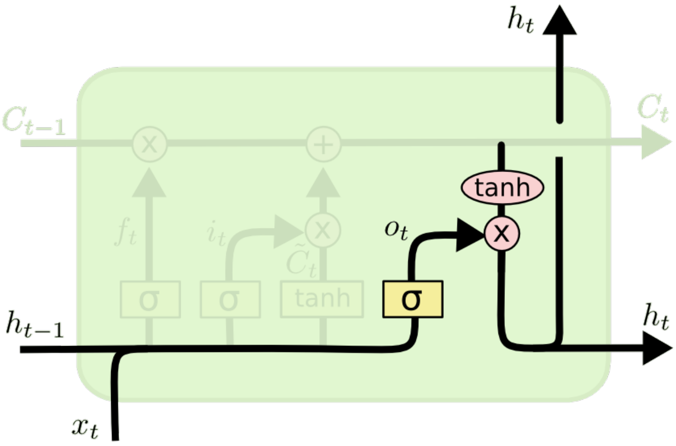


Figure 2.6: LSTM's output gate layer (Source: [2])

As you can see from figure 2.6: firstly, the state cell goes through tahn function and then is multiplied with output from the neural network of output gate layer:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{2.14}$$

$$h_t = o_t \cdot tahn(C_t) \tag{2.15}$$

h_t is the output of LSTM cell at time step t as well as the input for RNN cell at time step $t + 1$. The gates stabilize the state and solve the vanishing gradient problem, hence it's very important for an LSTM cell to work.[11]

Backpropagation Through Time Taking into account that RNN nets share all weight between layers(time steps), there is a specific technic for computing gradient when training the network called *Backpropagation Through Time(BPTT)*. It propagates the error all the way back through the time to the time step 0, that's the reason it's called BPTT. [17]

We can think about it as using feedforward neural network's backpropagation but with the constrain that the weights of the layers should be the same. However as RNN might have a hundreds of thousands time steps it is common practice to truncate the backpropagation only back to few time steps, instead of backpropagating it to the first time step.

2.3 Reinforcement Learning

Why reinforcement learning? As you might recall from chapter 1, the recurrent visual attention model extracting information from a picture by attending to certain locations of the picture and aggregating the information from these locations. This property will make our network avoid locations with insignificant information, hence ignore locations with clutter. In order to teach the network outputs next location to attend given previous location, we need to provide training data to the neural network. The problem is, that we don't know the right answer for this. We can only say whether the network made a right classification decision after the network has already chosen several locations. Consequently, the training of the network parameters will be a very difficult task. As previously mentioned in section 2.1.2, using gradient descent with backpropagation for training NN is possible only with differentiable cost function like mean squared error function or cross entropy function. However, we can't use these functions without knowing the right answer, therefore defining the cost function would be a complicated task. This sort of tasks is studied by a field of machine learning called *reinforcement learning(RL)*. The theory described in this section based on the [18], unless otherwise stated.

What is reinforcement learning? Reinforcement learning concerns with teaching an agent to take actions based on reward signal, even if this signal is delayed. These agents are trained to maximise the total sum of such reward signals. The underlying idea behind RL is to represent the nature of learning where agent learning about the the world by interacting with it. By performing these interactions we're observing the changes in the world from which we can learn about the consequences of these interactions, and about what interactions to perform to achieve the goal. Reinforcement learning provides a computational approach to perform goal-directed learning by interacting with environment. The main difference between supervised learning and reinforcement learning is that in RL there is no instructions about the right answer. Instead, training information or reward signal is used to evaluate the taken actions. That is, rather than providing true label for the system instantaneously, system is receiving a reward signal after each performed action and the goal of RL system is to teach an agent using its own experience to achieve a certain goal.

2.3.1 Components of reinforcement learning

To better understand the main components of RL let's take a look at one of the recent RL systems where the system needed to learn how to play Atari 2600 games.

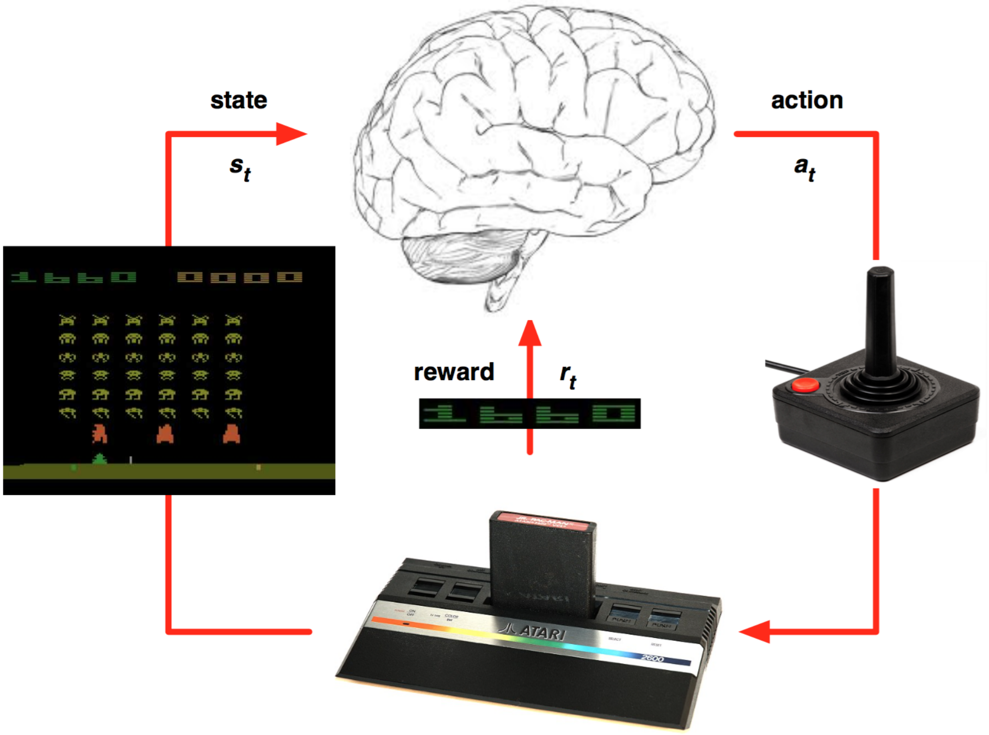


Figure 2.7: RL system to play Atari games (Source: [3])

In the figure 2.7, the brain represents the agent. The Agent is our computational system or decision making system. The Agent in RL interacts with environment by performing actions. An action would be moving a joystick to the right. By moving the joystick we interact with the environment, which in this case is the true state of the Atari game engine. After the environment receives an action, it gives back to the agent an observation in the form of the video frame shown on the screen and a reward signal which reflects the points scored.

State Let's now abstract from our example and describe the flow of RL system more precisely. At each time step t the agent executes an action A_t, receives the observation O_t and receives scalar reward R_t. The environment receives an action A_t, emits observation O_{t+1}, emits scalar reward R_{t+1}. Then t is incremented after the environment's step. In RL instead of working with observations, one works with the *state* or *agent state*. The agent state is the data the agent uses to pick the next action. The state is formally a function of the history(data that agent received so far):

$$H_t = O_1, R_1, A_1, O_2, R_2, A_2, ..., O_t, R_t, A_t \tag{2.16}$$

$$S_t^a = f(H_t) \tag{2.17}$$

where H_t - is the history object at time step t and S_t^a - is the agent's state at time step t

Because history H_t can be very hard to maintain as it grows rapidly over the time, it is very common to talk about *markov state* in RL. Markov state is meant to contain all useful information from the history as well as possess of *markov property*:

$$P[S_{t+1}|S_t^a] = P[S_{t+1}^a|S_1^a, ..., S_t^a] \tag{2.18}$$

where S_t^a - is the agent's state at time step t. It means that the state is only dependent on the present state and not on successors states. Hence, once the state is known, we can erase the history.

Reward As mentioned before R_t is scalar feedback signal, which indicates how well agent is doing at time step t. The job of an agent to maximise the sum of rewards received after t steps. This sum is also known as cumulative reward.

Additionally to this an agent may possess the following components: a *policy*, a *value function*, and a *model of the environment*.

A Policy is an agent's behaviour function. It maps the agent's state to actions to be taken by agent, when agent is in those states. Normally, the policy is something that we want to find. Once the best policy is known, we have solved RL problem. The Policy can be deterministic: $a = \pi(s)$ as well as stochastic: $\pi(a|s) = P[A_t = a|S_t^a = s]$.

Value function describes how good is it to be in a particular state. The value of a state is the total amount of reward an agent can expect to to receive when following policy π, starting from that state:

$$v_\pi(s) = E_\pi[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + ...|S_t^a = s] \tag{2.19}$$

where E_π is the expectation of the cumulative reward from time step t following policy π given the state s, γ - is a discount factor [0, 1]. which will be explained in subsection 2.3.3

While the reward determines how well the current action is at given time step, value of a state gives us more information about long term desirability of a state, that is taking into account the values of all possible states an agent can end up in after leaving this state. It's crucial to understand the difference between reward and value: reward is immediate, while the value giving us insights about the cumulative reward the agent can possibly get from this state on.

Model of the environment This represents what the environment will do next. Given the current state s and action a, this model defines the probability of an agent to end up in a state s':

$$P^a_{ss'} = P[S_{t+1} = s_0 | S^a_t = s, A_t = a] \tag{2.20}$$

$$R^a_s = E[R_{t+1} | S^a_t = s, A_t = a] \tag{2.21}$$

where P is state transition probability matrix and R is a reward give the probability of next state given current state and action:

2.3.2 Partially Observable Environments

One distinguishes between two type of environments in RL problems. *Fully observable environments* where an agent is capable of directly observing the state of environment: $O_t = S^a_t = S^e_t$ - where S^e_t is environment's state, and partially observable environment. In this work we will concentrate on *partially observable environments.*

Partially observable environments In partially observable environments the agent's state is not equal to environment state, instead the agent is constructing his own representation of environment state from the the external input(observations) that the environment provide. Partially observable environments is a special instance of what is known in RL community as a partially observable Markov decision process (POMDP). In our work we are constructing the agent's state by injection the input provided by environment into RNN:

$$S^a_t = \sigma(S^a_{t-1} \cdot W_s + O_t \cdot W_o) \tag{2.22}$$

where S^a_t and S^a_{t-1} are agent state at time step t and $t - 1$ respectively, O_t - is external input (in our work that is glimpse), and W_s, W_o - appropriate weights.

2.3.3 Markov Decision Processes(MDP)

The agent is the algorithm that we trying to build, which interacts with the environment. *Markov Decision Process(MDP)* describes this environment.

Markov Decision Process is an extension of a Markov chain and is one of the core concepts that is used in reinforcement learning and almost all problems in RL can be described by using MDP. We have already defined some elements of MDP in section 2.3.1, however MDP's theory gives us a way to solve problems.

Main components of MDP The MDP is defined as using following elements:

- *Finite set of states* $\mathcal{S}$ - a set of Markov states that we described in section 2.3.1
- *Finite set of actions* $\mathcal{A}$ - a set of all possible actions. An action $A_t = a$ $\in$A(S$_t$), where $\mathcal{A}(S_t)$ - is a set of all possible actions that can be taken in state S_t
- *Reward function* R - is the function which describes the reward based on a state and action: $R_s^a = E[R_{t+1}|S_t = s, A_t = a]$
- *State transition probability matrix* $\mathcal{P}$ give the probability of next state given current state and action: $P_{ss'}^a = P[S_{t+1} = s_0|S_t^a = s, A_t = a]$
- *Discount factor* γ - the discount factor determines the present value of future rewards.

Another important definition that is used in MDP known as return G_t. Return is nothing more than all cumulative reward that an agent can get from time step t:

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+2} + ... = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{2.23}$$

where R_t - is immediate reward at time step t, and γ - is the discount factor.

Policy in MDP is a distribution over actions given a state. It maps a state s to a probability of taking action a, where $a \in \mathcal{A}(S_t = s)$:

$$\pi(a|s) = P[A_t = a|S_t^a = s] \tag{2.24}$$

Policies in MDP are time independent. That is, no matter what time step t it is, we have still the same policy distribution at each time step.

Discount Most rewards in MDP are discounted by discount factor γ. There are several reason for that. Firstly, it is mathematically convenient to use discounts as this will prevent the return value from being exploded to infinity. Secondly, discount give us a way to tune the model to prefer the immediate reward over delayed or vice versa.

Value functions in MDP MDP distinguishes between two types of value functions: *the state-value function* and *the action-value function*.

State-value function is basically the same value function that we defined in section 2.3.1: it describes the *value* of state S_t if following policy π which is expected return starting from state S_t and then following policy π. We can rewrite the equation 2.19 using our new definition of return G_t:

$$v_\pi(s) = E_\pi[G_t|S_t = s] \tag{2.25}$$

where E_π - is the expected value of the state S_t when following policy π.

Action-value function is defined in very similar way beside the fact that it also takes into consideration the action taken by the agent at time step t. It's denoted $q_\pi(s,a)$ and equal to expected return starting from state s, taking the action a and then following policy π:

$$q_\pi(s,a) = E_\pi[G_t|S_t = s, A_t = a] \tag{2.26}$$

Monte Carlo methods This value functions can be estimated using Monte Carlo methods, which works only for episodic environments, i.e. environment with an end state. The idea is to let agent play in the environment by following an arbitrary policy, sample the rewards and eventually calculate the mean of reward with respect to state. Every time an agent visit state s, we increase the counter of this state by 1, as well as increase total return of this state from all episodes:

$$N(s) = N_{last}(s) + 1 \tag{2.27}$$

$$S(s) = S_{last}(s) + G_t \tag{2.28}$$

$$V(s) = N_t(s)/S_t(s) \tag{2.29}$$

where $N(s)$ - is the counter an agent visited state s, G_t - is the return an agent got starting from state s, $V(s)$ - is the estimated value of state s.

By the law of big numbers $V(s) \to v_\pi(s)$ as $N(s) \to$.

Bellman equations The most important reason that MDPs is used in RL problems because it give the opportunity to use *Bellman equations*. Bellman equations forms the way of computing, optimizing and evaluating value functions $v_\pi(s)$ and $q_\pi(s,a)$.

Bellman expectation equation decomposes the value functions to represent it in a recursive way through the value of successor state:

$$\begin{aligned} v_\pi(s) &= E_\pi[G_t|S_t = s] \\ &= E_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}|S_t = s] \\ &= E_\pi[R_{t+1} + \gamma \sum_{k=0}^{\infty} \gamma^k R_{t+k+2}|S_t = s] \\ &= E_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})|S_t = s] \end{aligned}$$

In a similar way, action-value function is decomposed:

$$\begin{aligned} q_\pi(s,a) &= E_\pi[G_t|S_t = s, A_t = a] \\ &= E_\pi[|S_t = s, A_t = a] \\ &= E_\pi[R_{t+1} + \gamma \sum_{k=0}^{\infty} \gamma^k R_{t+k+2}|S_t = s, A_t = a] \\ &= E_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})|S_t = s, A_t = a] \end{aligned}$$

If we look beneath the math, these equations formally telling us that the value of a state is equal to the immediate reward that the agent get after leaving current state plus discounted value of the state where the agent will end up after leaving the current state.

Optimal policy Now that we know how to represent the value of a state, we can concentrate on the problem that we really care about: find the best behaviour for the MDP. That is, the policy that achieves more of reward compared with other policies. MDP literature give us a definition of the what is known as optimal policy:

A policy π is defined to be better than or equal to a policy π' if its expected return is greater than or equal to that of π' for all states. In other words, $\pi \geq \pi'$ if and only if $v_\pi(s) \geq v_{\pi'}(s)$ for all $s \in \mathcal{S}$. There is always at least one policy that is better than or equal to all other policies. This is an optimal policy. [18]

There can be more than one optimal policy, nonetheless we denote an optimal policy as π_*. The goal of the any RL task is to find the optimal policy.

2.3.4 Policy-Based Reinforcement Learning

Policy-Based Reinforcement Learning is a field in RL where agent works directly with the policy and does not necessary represents a value function or a model, but still may compute action-value or state-value functions. We'll use policy-based approaches in this work as those methods have better convergent properties more efficient for high-dimensional action space. [4]

Firstly, We need to find a way to represent the policy. With the near continuous action space to store all states will require a lot of memory. Therefore for problems with large state space it's recommended to use function approximation methods.

Using function approximators such as neural network will allow to estimate policy function:

$$\pi_\theta = P[a|s, \theta] \tag{2.30}$$

where $P[a|s, \theta]$ - is the probability of taking action a given state s.

π_θ is the policy with parameters θ. We can represent our policy with the help of different function approximators. The most common function approximator used in RL is neural network that was introduced in section 2.1. So θ can represent parameters of neural network, although any other function approximator can be used here such as decision tree or nearest neighbour approximator.

Our goal is to find the optimal policy with the parameters θ directly from the agent's experience.

Note: The representation in 2.30 will even allow to generalise the value functions from seen states to unseen.

Cost Now we have a way to initialise our policy with any parameters θ. However in order to estimate the policy, we also need to find a way to measure it's quality, i.e. define the cost function J. One way to define the cost function is to assign it to the value of the start state:

$$J(\theta) = V^{\pi_\theta}(S_1) = E_{\pi_\theta} \tag{2.31}$$

To remind you, the start value is the return that an agent will get from start state following policy π_θ. This will work only for environment with end state.

Policy Our agent needs to take action while going through the environment. For continuous state space it's common to use Gaussian distribution with fixed variance σ^2 and parametrized mean:

$$\mu = \phi(s)^T \theta \tag{2.32}$$

$$a \sim \mathcal{N}(\mu(s), \sigma^2) \tag{2.33}$$

where $\phi(s)^T$ - is a feature vector of state s.
Feature vector normally represents the availability of certain features in a particular state s.
For example, the first entry in the feature can determine whether a robot is close to a wall. In state s_1 where the robot actually has a wall a close to him the first entry should be then equal to 1 or close to 1. In contrast to state s_2 where robot has no wall close by, this entry in the feature vector should be 0 or close to 0. The feature vector might have hundreds of entry features like this.

Policy gradient theorem Now that we know the objective function, we can use gradient ascent algorithm to maximise it. One normally uses Policy gradient algorithm to estimate the gradient:

$$\Delta_\theta J(\theta) = E_{\pi_\theta}[\Delta_\theta \log(\pi_\theta(s, a))Q^{\pi_\theta}(s, a)] \tag{2.34}$$

where $Q_{\pi_\theta}(s, a)$ - is the action-value function.

Reinforce rule Using return v_t as an unbiased sample from $Q^{\pi_\theta}(s, a)$ in 2.34 we can derive the REINFORCE learning rule:

$$\Delta\theta_t = \alpha \Delta_\theta \log \pi_\theta(s_t, a_t) v_t \tag{2.35}$$

Return v_t can be estimated by using Monte Carlo method.

Reducing variance The equation 2.35 still has a high variance. We can try to reduce it by subtracting the function knows as baseline $B(s)$. If we subtract this function, it won't change the expectation as:

$$E_{\pi_\delta}[\Delta_\delta \log \pi_\delta(s, a)B(s)] = 0 \tag{2.36}$$

Therefore we can rewrite the equation 2.34 in the following way:

$$\Delta\theta_t = \alpha\Delta_\theta \log \pi_\theta(s_t, a_t)(Q_{\pi_\theta}(s, a) - B(s)) \tag{2.37}$$

The common practice in RL to choose baseline function $B(s)$ equal to value function: $B(s) = V^{\pi_\theta}(s)$. The term $(Q^{\pi_\theta}(s, a) - V^{\pi_\theta}(s)$ is known as advantage function. Advantage function represents how the value of being in state s and taking an action a, is better than value of being in state s summarizing over all possible actions that can be taken in state s.

2.4 Recurrent Models of Visual Attention

As it was mentioned in chapter 1, Recurrent Models of Visual Attention(also known as the recurrent attention model(RAM)) is a computational approach presented by google Deepmind's researchers to reduce and control computational cost while classifying images.

Note: The theory described in this section based on the [4], unless otherwise stated.

Why RAM? Today's state of the art approaches to classify the images is convolutional neural network(CNN). Nevertheless, to train CNN model on the high resolution images will require days of time. Similar to RNN models, some computations in CNN are shared, however the main cost is laid on applying the convolutional filter on the entire image, hence the bigger image is the more computations is required.[10]

Recurrent model attention is trying to face this problem by controlling amount of computations by adaptively selecting a sequence of locations and only processing these location at high-resolution

The reccurent attention model The attention problem in RAM is considered as the sequential decision process of an agent whom interacts with the visual environment. The idea is, that agent never sees the whole input, but only receives the observations via bandwidth-limited sensor. The goal for our agent is to find and select these locations on the images where the agent can extract most of the information needed for a classification decision. To summarize this:

- Agent selects a location on the image
- Agent receives an observation

- Agent extracts the information from the observation via bandwidth-limited sensor with respect to the location.
- Based on information it extracts, it selects the next location.
- If the current time step is more than some predefined number T, agent is forced to do a classification decision.

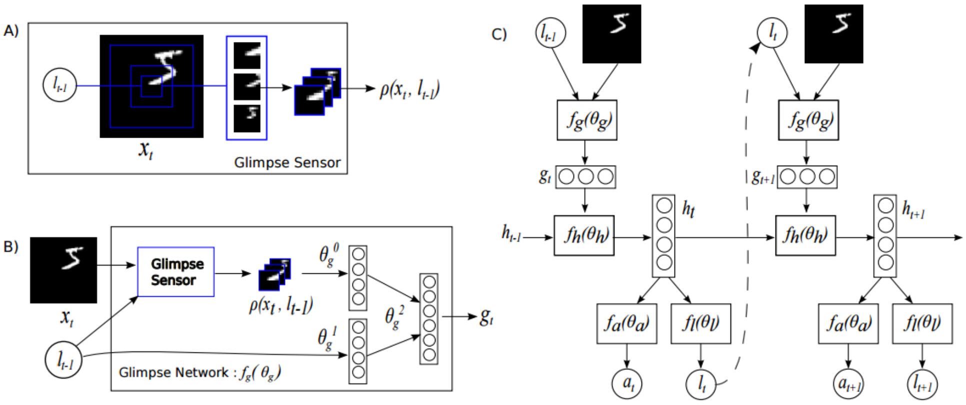


Figure 2.8: A) Glimpse Sensor, B) Glimpse Network, C) Model Architecture, (Source: [4])

In figure 2.8, you can see *glimpse sensor*, *glimpse network*, and the whole architecture of the model.

Glimpse sensor Glimpse sensor is formally the bandwidth-limited sensor which takes image and location as input and produces the bandwidth-limited representation of it. Thus, the main responsibility of the glimpse sensor is to build from an image x_t the image representation $\rho(x_t, l_{t-1})$ with respect to the location l_{t-1}. The sensor select a number of patches from an image x_t centered at the location l_{t-1} as you can see in 2.8. The first patch is processed at high resolution, while for patches further from l_{t-1}, progressively lower resolution is used. This representation contained multiple resolution patches of an image is known as *glimpse* and is denoted as $\rho(x_t, l_{t-1})$. [19] The glimpse sensor is used within glimpse network to produce glimpse feature vector.

Glimpse network As you can see in figure 2.8 B), glimpse network takes an image x_t and location l_{t-1} as an input and produces the glimpse feature vector $g_t = f_g(x_t, l_{t-1}; \theta_g)$. Glimpse network uses glimpse sensor to create a glimpse $\rho(x_t, l_{t-1})$. Then it feeds this glimpse and the location l_{t-1} into two independent neural networks with parameters θ_g^0 and θ_g^1 respectively followed by another neural network which combines the information from both components. The last NN parametrized by θ_g^2 produces then final feature vector $g_t = f_g(x_t, l_{t-1}; \theta_g)$, where $\theta_g = \{\theta_g^0, \theta_g^1, \theta_g^2\}$.

Model Architecture The model architecture is shown on picture C) in the figure 2.8. The agent is built around the RNN and uses RNN's output as internal state. RNN's output h_t contains information from past glimpses and locations. It's possible because the RNN at each time step t receives g_t as external input and summarizes it by using a LSTM cell : $h_t = f_h(h_{t-1}, g_t; \theta_h)$.

Actions Agent perfums two types of actions: environment actions and location action. Location action l_t decides where to allocate the next glimpse on the picture. The location network $f_l(h_t; \theta_l)$ is a NN layer that produces the next location l_t parametrized by θ_l. We will consider the location network a bit deeper in the **??**.
Depending on the task, the environment actions can vary, therefore we'll concentrate on the environment action that is relevant for this work. In our work, environment actions make the classification decision of an image after attending to T number of locations. It's formulated using softmax output from environment neural network $f_a(h_t; \theta_a)$, where θ_a - is a set of parameters of neural network f_a.

Rewards As we make a classification decision only after T number of steps, our reward signal will be delayed. Therefore agent is receiving a reward $r_n = 1$ if the classification decision was correct and 0 otherwise.

Training of the agent is performed by REINFORCE rule described in subsection 2.3.4 with the advantage function.

Chapter 3

Analysis

The main objective of this work will be to build an extensible prototype, which will be built on the model of visual attention and additionally extended to classify a set of images. This chapter discusses the main concerns that have to be taken into consideration in order to achieve the objective.

Firstly, let's define the clear problem statement:

Given a dataset where each sample consist of a group of images. A certain label is asserted to every sample in a dataset. The goal is to build a extensible prototype upon RAM that is capable of classifying this samples. The prototype is the resemblance of the RAM model with with the ability to accept the above mentioned dataset.

3.1 Quality concerns

This statement makes it clear that the prototype should be extensible. Extensible means that other people(including author itself) are able to extend the prototype. People should comprehend the code as well as start and configure the procedures in order to extend the prototype. Therefore following the best practices and conventions, using widely known frameworks, producing clean and readable code to stay consistent with other modern software is an important point of this work.

It's more convenient to talk about conventions once programming language and libraries are chosen for this work.

TensorFlow There is a big variety of frameworks and libraries used in machine learning. Among the famous libraries is library called TensorFlow. TensorFlow is an open source library developed and maintained by engineers from Google [20].

TensorFlow framework has gained a huge popularity among machine learning community as well as in industry compared to another framework [21]. TensorFlow is an open source software library that makes computations more efficient by building a computation graph and deploying them to one or more CPUs or GPUs.

TensorFlow framework gives a wide variety of statistical distributions, wide range of loss functions, and a huge amount of neural network algorithms while not necessarily losing flexibility. In order to make learning process traceable, TensorFlow provides TensorBoard, which is a web interface for graph visualization built directly into TensorFlow. TensorBoard is an important and uniq feature that excels TensorFlow from similar libraries; it dramatically improves debugging experience as well as helps for understanding models developed using TensorFlow. Aforementioned features of the framework as well as it's great API for Python is a great fit for this work.

The current work will use Python as programming language, as it's one of the most popular languages among machine learning community.

Code conventions Now that we assigned interfaces, let's define the conventions that this work will follow. As TensorFlow recommends using PEP 8 style guide to stay consistent with community [22]. PEP 8 gives the set of rules about how to lay out the code, how to name functions, methods and classes and others code style related aspects [23]. PEP 8 linter is also integrated in the project, which checks the code automatically on presence errors against PEP 8 style guide, therefore simplifies the development workflow.

PEP 257 convention is also considered as this will help to avoid errors when generating documentation. PEP 257 convention set rule about organizing docstrings in Python [24]. Overall, the work follows The Hitchhiker's Guide to Python, which advises about the way of testing, organizing and documenting the code [25].

Code patterns Despite that a lot of code from researches are not following and not using code pattern, it really simplifies the understanding and reasoning about the code, especially while extending or adjusting the model. Therefore using code patterns is highly recommended. We will introduce the code patterns, which is recommended in the functional programming from [26], because python supports the concept of functional programming. To follow are also general well-known code patterns that are taken from [27], [28], [29]. Below is a list of this code pattern recommendations:

- Composed method - it's saying that methods should have one identifiable task. Additionally to this, all operations performed in the function should be on the same level abstraction. This will increase flexibility of the methods and prevent from confusing code and mistakes. [26]

- Extract method - when one method is too long, one should try to extract some part of it into another function taking into account that this function should be useful on its own. [30]

- Method object - normally applied when one can't use extract method on a function because new function would take a lot of parameters from the original method. The idea is to create a small class that will hold the parameters as properties and then to create small methods within this class without passing the parameters to it but instead access them as class properties. [26]

- Method comment - instead of having a comment close to not self-explanatory statement, one should rather create a function with self-explanatory name that holds this statement. Most comments are redundant, therefore one can simplify the system by introducing small methods. [26]

- Temporary variable - instead of having very long expression, it's recommended to assign part of the expression to a variable. This variable can also have the self-explanatory name, consequently increasing the readability of the code.[26]

- Simple Enumeration Parameter - having a simple name of a parameter when iterating over enumeration: `for each in plugins:` [26]

- Cascade pattern - when a method of a class doesn't return any value, one can return instance of the class in order to be able to call a next method of the instance in cascade way: `self.doThis().doThat()`.[26]

- Single responsibility principle - it forces every class to have only one clearly distinguishable responsibility.[27]

- Duck Typing - is a specifically to python, a design principle that says that if an object has a certain desired functionality it doesn't matter what of nature the object is.

- Iterator - is a design pattern that says to access values of a list without exposing the list [29]. It's built into python language itself and can be used with syntax like `for .. in ..` or `next()`.

- Singleton - design pattern that obligates a class to be instantiated only once. [28]

Since ML programming is more method oriented, most patterns above concentrate on how to keep functions readable, precise and flexible. In this work we will follow these patterns.

We will see examples of those patterns in the chapter 4 and chapter 5.

To recap, the prototype should be not only a good start for making further improvements on large scale objects but also be a piece of software that bears the following properties: extensible, well documented, integrable with other softwares, easy configurable, readable code.

3.2 Analysis of the previous work

As we will build the current model upon the RAM described in section 2.4, it makes sense to look over the existing implementations of the RAM model. The authors of RAM paper haven't provided the implementation, but fortunately there are some implementations built by the open source community. It's common to see that people, who are working on a model as open source project, often do it in their free time. As a consequence, it is expected that those model are not high-quality prototypes, therefore in order to rely on the project one needs to be meticulous while choosing one. This is the following criteria we're considering when choosing the model for the basis of this work:

- Structure and readability of the code - at least presence of the basic structure

- Configuration - it should be comprehensible how one can change parameters of the model

- Reproducible results

- Presence of basic documentation

- Framework - as we have already chosen TensorFlow, projects built upon TensorFlow are preferable.

After doing the research and taking into account the above listed criteria, the choice fell on the project from github user 'zhongwen'. We will refer to this implementation as *basic RAM implementation* [1] .

This project is built using TensorFlow framework.

[1] The original project is located on github: https://github.com/zhongwen/RAM .

3.2.1 Advantages over original RAM paper

Building a machine learning software is not as straight forward as building conventional software. In machine learning, in order to achieve high accuracy one uses different methods which are normally hard to comprehend without knowing the theory behind them. Absence of testing is another point which makes it harder to understand others code. Considering the circumstances and careful analyses the approaches used in the basic RAM implementation is desired for the success of this work.

Inference in the current work was performed differently from what was described in [4]. Let's take a look at how the gradient of objective function is calculated in [4]:

$$\Delta_\theta J = \frac{1}{M} \sum_{i=1}^{M} \sum_{t=1}^{T} \Delta_\theta \log \pi_\theta (u_t^i | s_{1:t}^i)(R_t^i - b_t) \tag{3.1}$$

where J - is a cost function, M - number of episodes, T - is a time step where the agent is forced to make a classification decision, $s_{1:t}^i$ - are state sequences obtained by running the current agent π_θ for $i = 1...M$ episodes, b_t - baseline to reduce variance, u_{ti} - action at time step t of episode t.

As we can see the gradient is calculated based on running M episodes. Firstly, the agent chooses sequentially n location and makes a classification decision. Then we run M similar episodes like this. After this, we compute the gradient. The basic RAM implementation used slightly different approach. It does not run multiple episodes to update the parameters, but instead it does update parameters on every episode. However it duplicates the same samples M times and then obtain M different outputs and average them. This practice was introduced in [5]. It was also indicated that running attention model multiple times on each image with the classification predictions being averaged gave the best performance [5].

Adam Opmitimizer It also worth to notice that instead of stochastic gradient descent that was used in RAM paper, the basic RAM implementation using Adam optimizer from [31] with exponentially decaying learning rate, which theoretically should improve performance. [31]

Gradient clipping In contrast to RAM paper, the basic RAM implementation additionally clipped the gradient values by global norm of their values to prevent the vanishing and the exploding gradient problems [32].

3.2.2 Limitations

Unfortunately, the basic RAM implementation used old version of TensorFlow, which was unstable at that moment, therefore migration of the project to the latest TensorFlow version is required[2]

Looking at basic RAM implementation purely from software engineering side, one can observe several flaws. Not following python conventions as well as lack of design patterns and partial presence of incoherent structures in the code are known obstacles when analyzing and extending the code. Therefore code is required to be refactored and cleaned, as well as restructured and documented under the conventions and practices described in section 3.1.

As for functional requirements, the lack of one feature was detected in basic RAM implementation. As you can remember from section 2.4, glimpse sensor is taking multiple patches from an image, where each patch is taken at different resolution. The basic RAM implementation is not capable of taking multiple patches, but only a single one. Without the ability of taking multiple patches within a glimpse, accuracy of inference will be ore likely to decrease. Therefore this functionality should be available in the work in order to achieve better results.

Additionally to this, TensorBoard wasn't configured in basic RAM implementation. Training such massive model as RAM can be complex and sometimes confusing. Tools like TensorBoard make models easier to understand, debug and optimize, therefore having fully configured TensorBoard is another prerequisite for a good prototype.

3.3 Extension

In order to fulfill the objective of this work, it's required to extend the basic RAM implementation in a following way: it should accept a group of images as input and based on that input make a classification decision. Group in this case means more than one image(e.g. 2,3 or 5 images). More formally: *given a group of images, extended model returns a probability distribution over K different outcomes, where K - is amount of classes in the classification problem.* We'll refer to amount of the image in a group as n.

This section will discuss several ways of how to achieve that. In the figure 3.1 you can see original architecture of RAM. The potential extension variations listed below will use the notation, which was presented in section 2.4.

[2] Migration was performed according to TensorFlow migration guide: https://www.tensorflow.org/install/migration

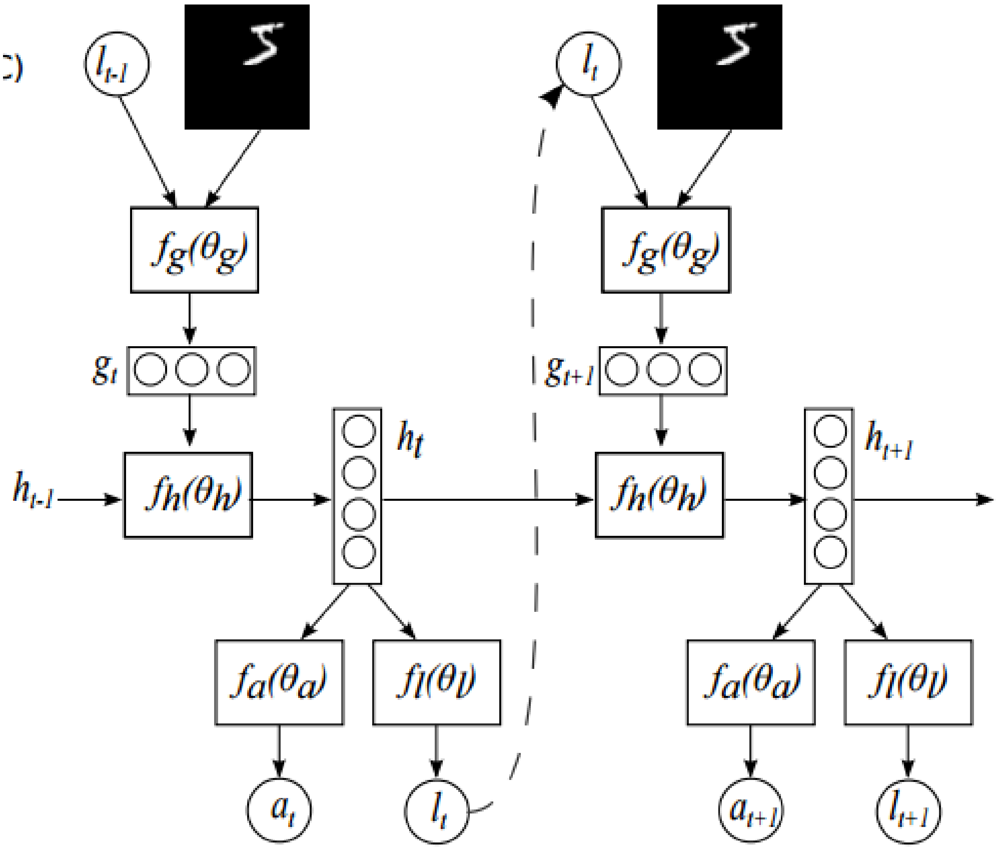


Figure 3.1: Original architecture of RAMS(Source: [4]).

3.3.1 Picker network

You might remember the output of LSTM cell h_t in [4] which was described in section 2.4. The external output is used in the action network $f_a(\theta_a)$ as well as in location network $f_l(\theta_b)$ as shown in figure 3.1 to produce a classification decision or next location respectively. In a similar way, we can invent a new network that takes as input the LSTM cell's output h_t, have parameters θ_p and outputs the probability distribution over n. We shall call this network *picker network*. The purpose of the picker network is to pick an image in the group to explore appropriate image, hence the name. By manifesting this extension, the model as a whole will have three neural networks consuming the output of LSTM cell h_t:

- Classification network $f_a(h_t; \theta_a)$ - makes a classification decision after T number of time steps.

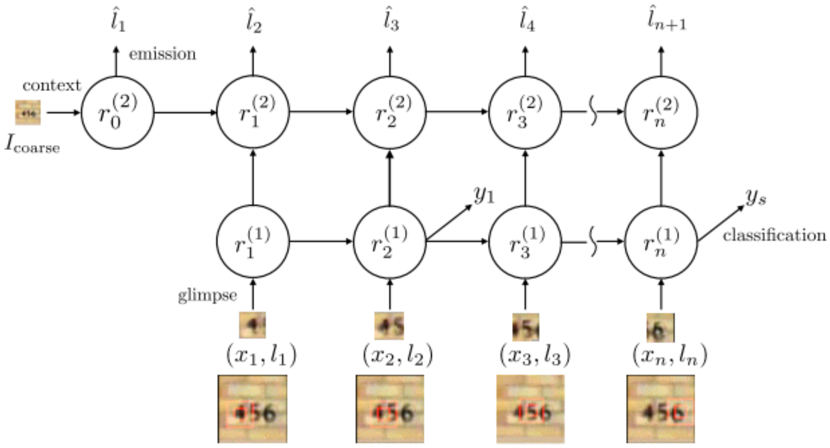


Figure 1: The deep recurrent attention model.

Figure 3.2: Source: [5]

- Location network $f_l(h_t; \theta_l)$ - decides where to allocate the next glimpse on the picture.
- Picker network $f_p(h_t; \theta_p)$ - decides what picture to allocate the next glimpse on.

All of networks above have a similar structure:

$$f_a(h_t; \theta_a) = Softmax(Linear_{\theta_a}(h_t)) \quad (3.2)$$

$$f_l(h_t; \theta_l) = Linear_{\theta_l}(h_t) \quad (3.3)$$

$$f_p(h_t; \theta_p) = Softmax(Linear_{\theta_p}(h_t)) \quad (3.4)$$

where Z - is a normalizing constant, $Softmax$ - is softmax activation function $Linear_\theta(x)$ - represents a linear transformation $Linear_\theta(x) = W_\theta x + b_\theta$ with weights W_θ and bias b_θ.

3.3.2 Deep attention model

This idea was inspired by the approach used in [5]. The idea is to completely separate classification network from location network by introducing new RNN layer on top of the current RNN layer.

In figure 3.2 you can observe first RNN denoted $r^{(1)}$ which works the same way as was described in section 2.4. Output of RNN $r^{(1)}$ was consumed by the location network and classification network in [4]. This will be different in current approach. We can describe it as following: We introduce new RNN $r^{(2)}$ on top of first RNN:

- The new RNN is initialized by output from convolution network(called Context Network) applied on the down sampled low-resolution version of input image. The feature vector outputted from convolutional layer provides sensible hints on where the potentially interesting regions are. The reason behind it was described in [5]:

  > The existence of the contextual information(feature vector), however, provides a "short cut" solution that is much easier for the model to learn from contextual information than by combining information from different glimpses

- The new RNN takes as input the output of RNN $r^{(1)}$: $r_n^{(2)} = f_{r^{(2)}}(r_n^{(1)}, r_{n-1}^{(2)})$, where $r_n^{(1)}$ - is the output of RNN $r^{(1)}$ at time step n, $f_{r^{(2)}}$ - is RNN cell function(e.g. LSTM cell), $r_n^{(2)}$ and $r_{n-1}^{(2)}$ are outputs of RNN $r^{(2)}$ at time step n and $n-1$ respectively.

- The output of new RNN is used to produce next location. The output is fed into fully connected network, which maps the feature vector produced by new RNN into coordinate object $[i, (x, y)]$, wherer i - is a index in the group of images.

The reason for having the second RNN is to implicitly represent decision about location and prevent using location information in classification. Separation is crucial: first RNN network is responsible for classification, while second one for choosing the right location. One state will hold information about classification, while the state of the RNN cell on the top will hold information about locations. One advantage of this work is that having this separation of concerns between location and classification information which theoretically should improve the model. This approach we will call *Deep attention model.*

3.3.3 Exploration network

In original RAM paper, the model is required to execute a number of steps before making classification decision: " The attention network used in the following classification experiments made a classification decision only at the last timestep $t = N$. "[4] It was also suggested as a further improvement to introduce new action which decides when model should stop taking further glimpses:

> Finally, our model can also be augmented with an additional action that decides when it will stop taking glimpses. This could, for example, be used to learn a cost-sensitive classifier by giving the agent a negative reward for each glimpse it takes, forcing it to trade off making correct classifications with the cost of taking more. [4]

We can alter this suggestion by introducing a new action which instead of indicating when the model should stop taking new glimpse, will indicate when the model should take a next image in a group. Once there is no more images we can force the model to make a classification decision.

We introduce a new network which takes an input of the state of RNN cell, and outputs probability distribution over two actions which correspond to whether the model will stop taking new glimpses or continue to explore image. We shall call this network *the exploration network*.

By manifesting this extension, similar to the approach described in subsection 3.3.1, the model will have three neural networks consuming the output LSTM cell h_t:

- Classification network $f_a(h_t; \theta_a)$ - makes a classification decision after T number of time steps.
- Location network $f_l(h_t; \theta_l)$ - decides where to allocate the next glimpse on the picture.
- Exploration network $f_e(h_t; \theta_e)$ - decides whether the next glimpse should be taken from the i image from the group or from the $i + 1$ image.

New exploration network computes the distribution in the following way:

$$f_e(h_t; \theta_e) = Softmax(Linear_{\theta_e}(h_t)) \tag{3.5}$$

The main advantage of this approach is the flexibility since it can easily be combined with deep attention model introduced in subsection 3.3.2. This approach can be also augmented with following actions:

- First Action - go back, that is, take previous image from the group of images.
- Second Action - go forward, that is, take next image from the group of images.
- Third Action - finish, that is, stop taking glimpse and do the classification decision.

There is no theoretical to prove which one from the extensions will work better, therefore testing them with experiments is required.

3.4 Dataset

Before starting the construction of the model, one requires to think about an appropriate dataset on which the model can be tested. MNIST dataset[3] is recognized as being the simplest dataset among the computer vision community, therefore building a dataset upon it would be easier. The simplicity of dataset would help to understand problems occurring while developing a model. Additionally to this, researchers from google Deepmind used MNIST to evaluate RAM, which indicated that MNIST data would be good fit for the extension as well. [4]

MNIST Dataset MNIST dataset consist of scanned handwritten images, each labeled from from set: $\mathcal{A} = \{0..9\}$, where $\mathcal{A}$ - is a set of available classes in MNSIT dataset. You can see an example of 4 digits in figure 3.3. Additionally, it includes a label for each of the image.

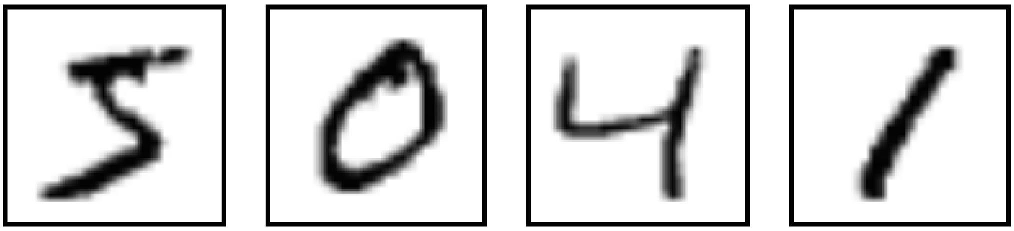


Figure 3.3: MNIST example (Source: [6])

For example, in the figure 3.3 the labels are 5, 0, 4 and 1. Each images consist of 28 × 28 pixels, therefore an MNIST image would be an array of size 784.

MNSIT dataset consist of 55,000 training samples, 10,000 test samples, 5,000 validation samples. Requirement for the dataset can be formulated as following:

Each sample in the dataset should contain fixed number of images. Amount of images in an sample should be more than 1. The dataset should have at least two classes, which are used to label each of the sample. The dataset should provide enough data to train, validate and evaluate the model.

Procedure We should come up with the dataset that will fulfill the requirements above. One way of doing it could be described as following: having limit of 10 classes in MNIST dataset, we decide about the class(or

[3] The MNIST data is hosted on [33]

classes) of images that hold information relevant for classification decision(it can be f.e. classes labeled with 4 and with 3 in MNIST), we'll refer to those images as non-noise images. Subset of classes of non-noise image we denote as: $\mathcal{D} = \{d_1, ..., d_n\}$. We'll have also images which do not contain any information relevant for decision making, we'll refer to this images as noise images. Noise images are generated using images from classes that are mutually exclusive with classes of non-noise images: $\mathcal{T} = \mathcal{A}/\mathcal{D}$, where $\mathcal{T}$ - is a subset of classes $\mathcal{D}$ for labeling noise images: $\mathcal{T} \subset \mathcal{D}$. We then decide about the amount the images in a group n. We then choose the number $k < n$ which is going to be amount of noise images per sample in dataset.

We then divide the original MNIST dataset into two:

- First dataset - consisting of noise images, where each sample is a group(array) of noise images with the size of k.
- Second dataset - consisting of non-noise images, where each sample is a group(array) of noise images with the size of $n - k$.

We then create a new dataset and fill the sample that is a concatenation of sample from first dataset with sample of second dataset described above. This way we're getting a new dataset where each sample has a size of n. Using this method we can create two datasets with different k, but the same n and label them as dataset of first class, and dataset of second class.

The conceptional idea behind this dataset, the the model should learn to understand that noise image and that it does not bring any information relevant for the task. Practical solution for classification task of this dataset would be to understand what non-noise images are, count them, and depends on the amount of non-noise images, classify the sample . If the model work correctly on this dataset, it will confirm that the model works correctly for identifying images that are irrelevant for decision making

3.5 Testing

It's well-known that unit testing in ML models is not as trivial as in conventional software, therefore unit testing should be applied to only one part of the code where behaviour is fully predictable. One such example for unit testing would to check whether certain components of the system having expected shape of vectors and matrixes. As code for producing the dataset having procedural structure, it should be fully tested in order to avoid unexpected behaviour in the model.
In this work, we will mostly concentrate on bringing this model to life, therefore performance of the model does not play significant role. But in order to

get an idea of how well the model is performing and to be able to analyse it, we will consider following performance metric: accuracy on training, validation and test data, hybrid loss value and it's parts and the cross entropy between ground truth and prediction. Additionally, we will look at the time that the model taken to perform certain amount of iterations.

Chapter 4

Design

In this chapter we will discuss the architecture of the prototype. It's divided into two sections: Dataset and Model. Since the dataset is standalone component, this seems to be a reasonable separation. To make it clear, dataset would be a component that holds the training, validation and test data including all relevant functionality that can or should be performed on the data(this is explained in more detail in section 4.1). The model is a component, which accepts the data(dataset component), performs training on the training data, and then makes inference on the test dataset. In other words, the model would be everything that is related to building, training and the evaluation of neural networks and reinforcement learning environment.

4.1 Dataset

The dataset is component that is responsible for data holding. It should accept original MNIST dataset and transform it into dataset described in section 3.4.

For example, in the figure 3.3 the labels are 5, 0, 4 and 1. Each images consist of 28 × 28 pixels, therefore an MNIST image would be an array of size 784. To each of the image, a label is assigned, which provides the ground truth.

MNIST dataset from TensorFlow TensorFlow provides a small class `Dataset`[1] which stores MNIST data and splits it into training, validation and test data. TensorFlow also provides functions for iterating over the batches as well as the function which downloads and read the original data from MNIST web site. Taking this into account, in this work we will abstract

[1] The class is implemented here: https://github.com/tensorflow/tensorflow/blob/master/tensorflow/contrib/lea

from downloading and reading MNIST data by using this class. We'll refer to this class as *MNIST tf-dataset class*

We want that our dataset component has a similar behaviour and functionally as MNIST tf-dataset class. The reason for this is that we want to stay consistent with tensorFlow practices as we use this library in this work.

4.1.1 Architecture

Before proceeding with the classes overview, it can be helpful to make a concrete example of how the dataset described in section 3.4 can look like.

Example In this example we will describe dataset with two classes Let's first choose the parameters n and k, which represents the number of images in a group and the amount of noise images in a group respectively. While k should be different for both classes, n remains the same. Let n be equal to 5, k for the first class be and 3: $k_1 = 3$ for the second class be 4: $k_2 = 4$. Let's choose the digit for the non-noise data: $\{1\}$. Consequentially the noise-image will be: $\{0, 2, 3, 4, 5, 6, 7, 8, 9\}$. So one sample of the above mentioned setup can look like this:

```
[noise_image, non_noise_image, noise_image, non_noise_image,
   noise_image ] # class 1
[non_noise_image, noise_image, noise_image, noise_image,
   noise_image ] # class 2
```

Or with numbers:

```
[9, 1, 8, 1, 7 ] # class 1
[1, 3, 6, 4, 3 ] # class 2
```

Class overview It was decided that in order to implement the desired dataset, three classes are required:

- IndexGenerator - the purpose of this class is to generate indexes for noise images. Imagine situation, where all of noise data is placed into the same indexes. Will this model learn this indexes and look only at them? Or will model ignore this stability? Because this question seems to be heuristic, this class will control the indexes where noise image will be located at. By instantiating this class, it's possible to have always the same indixes for the noise images, as well as control it by providing distribution function, where this indexes should be sampled from.

- DummyDataset - The purpose of this class is to hold MNIST images and labels. Additionally, this class provides some auxiliary functionality like permutation of the data.
- GroupDataset - this is our desired dataset. It should be flexible enough to generate and hold the data for all classes. In terms of available methods, this class behaves the same way as NIST tf-dataset class once initialized.

Dataset component should be flexible enough in order to be similar to real problems, to be able to experiment with different amount of classes, and different variations of noises classes. Since we have only a limited amount of MNIST data, we need to also make sure that this data is properly used. GroupDataset takes care of it by carefully choosing the data from original MNIST dataset and putting them into the group to avoid if possible two same samples in the dataset by building combinations of noise-data and non-noise data.

4.1.2 UML class diagram

In the figure 4.1 you can see UML diagram of the dataset package as well as the it's connection to tf-dataset class. As you can see from the UML class diagram. `GroupDataset` class holds two `DummyDataset`, one for non-noise data and one for noise-data. This is exactly the way we described it in section 4.1.

Code pattern As we can see from the UML class in the figure 4.1, we have three classes. It would be also possible to merge the classes, however, this contradicts the "Single Responsibility Principle" as one class should only have one responsibility [27]. Therefore, dividing this into two classes allows us to clearly define responsibilities. Consequently, these separations seem to be reasonable.

As you might notice from UML class diagram, some of the function like `add_sample` in `DummyDataset` returns the object itself: `DummyDataset`. This is an example of Cascade code pattern described in section 3.1.

4.2 Model

We described three approaches of how to extend the RAM model in section 3.3. The implementation of this work will only concentrate on the

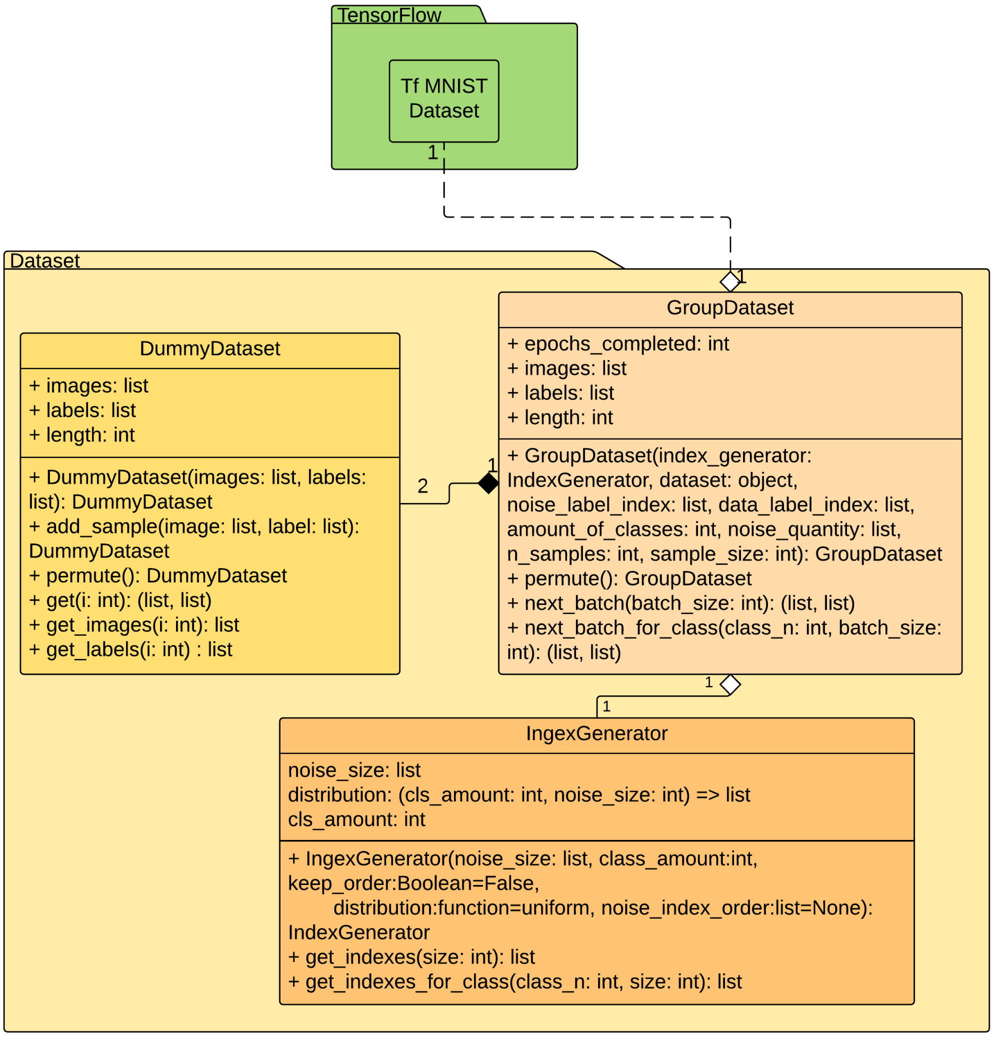

TensorFlow
Tf MNIST Dataset
1
Dataset
1
GroupDataset
+ epochs_completed: int
+ images: list
+ labels: list
+ length: int
+ GroupDataset(index_generator: IndexGenerator, dataset: object, noise_label_index: list, data_label_index: list, amount_of_classes: int, noise_quantity: list, n_samples: int, sample_size: int): GroupDataset
+ permute(): GroupDataset
+ next_batch(batch_size: int): (list, list)
+ next_batch_for_class(class_n: int, batch_size: int): (list, list)
DummyDataset
+ images: list
+ labels: list
+ length: int
+ DummyDataset(images: list, labels: list): DummyDataset
+ add_sample(image: list, label: list): DummyDataset
+ permute(): DummyDataset
+ get(i: int): (list, list)
+ get_images(i: int): list
+ get_labels(i: int) : list
2
1
1
1
IngexGenerator
noise_size: list
distribution: (cls_amount: int, noise_size: int) => list
cls_amount: int
+ IngexGenerator(noise_size: list, class_amount:int, keep_order:Boolean=False,
distribution:function=uniform, noise_index_order:list=None): IndexGenerator
+ get_indexes(size: int): list
+ get_indexes_for_class(class_n: int, size: int): list

Figure 4.1: UML class diagram of the dataset module

method described as picker network. This is because of the simplicity of this approach.

It's common practices in TensorFlow to use functions for implementing the model. We will stick to this practice for defining the model because this can potentially reduce the complexity of the model as well as increase readability of the code.

4.2.1 Architecture

Taking into account the extension that was described in subsection 3.3.1, we can easily derive classes as each of the networks has a clear task. Building the model will be possible using following clases:

- GlimpseSensor - the class is responsible for extracting glimpses from images at given location l_t.
- PickerNet - this class is responsible for picking an image out of the group of images.
- GlimpseNet - given the glimpse sensor, images and number of picked image, this class is responsible for producing the feature map from the image, which is then fed into LSTM cell.
- LocNet - the class is responsible for producing next location for glimpse sensor to attend to.
- Model - formally, this is not a class, but a set of function that build and run the model. We will represent this set as a class in UML class diagram in subsection 4.2.2. However, this set of functions will also be explained more detailed in subsection 4.2.3. For now, we'll refer to it as a class.
- Config - singleton class that holds all configuration parameters for the model such as shape of weights for hidden layers.

4.2.2 UML class diagram

In the figure 4.2, you can see the UML class diagram for the architecture we described above. As it was already mentioned the `Config` class is a singleton class that holds all configuration details for the model. Once initialised with command-line options or default values, it's a single source of truth for the whole application. The use of singleton design pattern here helps to avoid misconception that application can have more than one configuration. From the UML diagram we see that only class Model use the Config, this is because of the convenience sake. Without much effort the Config can be imported from other classes as well.

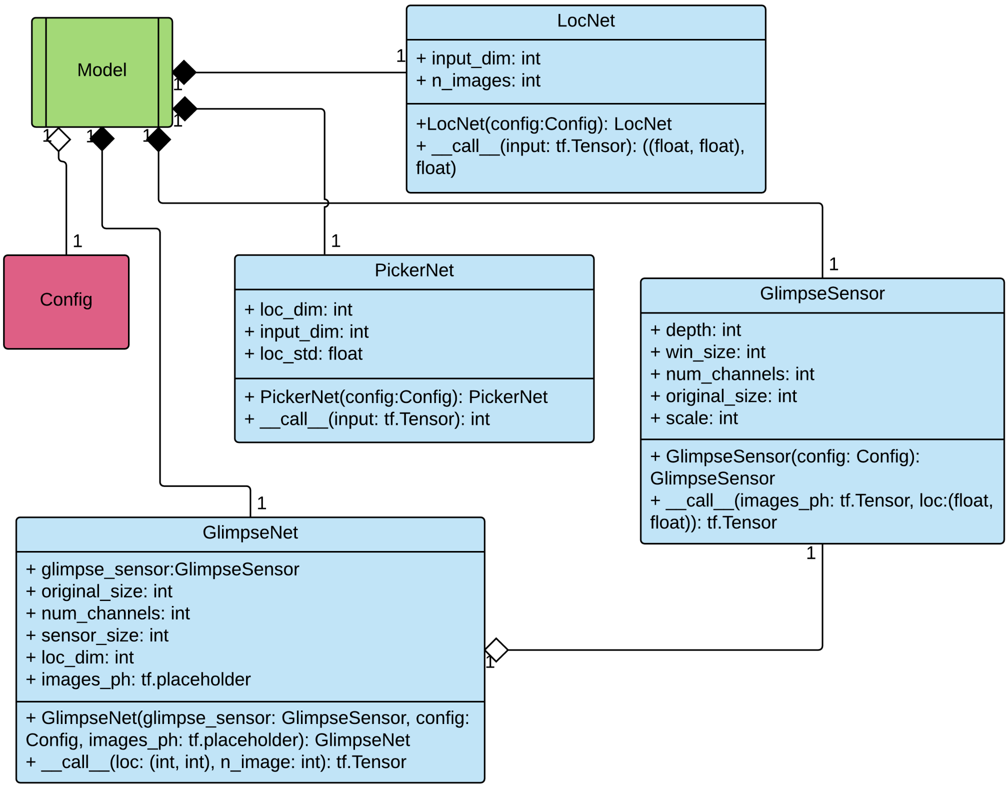

Model
Config
LocNet
+ input_dim: int
+ n_images: int
+LocNet(config:Config): LocNet
+ __call__(input: tf.Tensor): ((float, float), float)
PickerNet
+ loc_dim: int
+ input_dim: int
+ loc_std: float
+ PickerNet(config:Config): PickerNet
+ __call__(input: tf.Tensor): int
GlimpseSensor
+ depth: int
+ win_size: int
+ num_channels: int
+ original_size: int
+ scale: int
+ GlimpseSensor(config: Config): GlimpseSensor
+ __call__(images_ph: tf.Tensor, loc:(float, float)): tf.Tensor
GlimpseNet
+ glimpse_sensor:GlimpseSensor
+ original_size: int
+ num_channels: int
+ sensor_size: int
+ loc_dim: int
+ images_ph: tf.placeholder
+ GlimpseNet(glimpse_sensor: GlimpseSensor, config: Config, images_ph: tf.placeholder): GlimpseNet
+ __call__(loc: (int, int), n_image: int): tf.Tensor
1

Figure 4.2: UML class diagram of the Model component

4.2.3 UML activity diagram for the Model

To prevent misunderstanding, we distinguish between the Model class and the Model component. Model component is a set of classes and functions related to RAM and it's extension. The Model class is a class that we described in subsection 4.2.1. As it was mentioned earlier, the Model is not an actual class, but a set of functions. The Model class is the core of the Model component. It instantiates other classes as well as runs, trains and evaluates the model. Since the Model contains only functions, it's hard to represent it as UML class diagram. However, UML activity diagram can be a good fit if we replace the activities in the UML notation with the functions. Therefore to clarify the flow of the Model, you may find the figure 4.3 with the UML activity diagram helpful. In the lane with the name init_seq_rnn(), you can see a set of functions related to LSTM cell initialisation. This lane means that inside `init_seq_rnn()` function this set of function is called. The container with the name ”calculate the hybrid loss”, mean nothing more than conceptual conncetion between the function inside. We will take a closer look at some of details of this functions in the chapter 5.

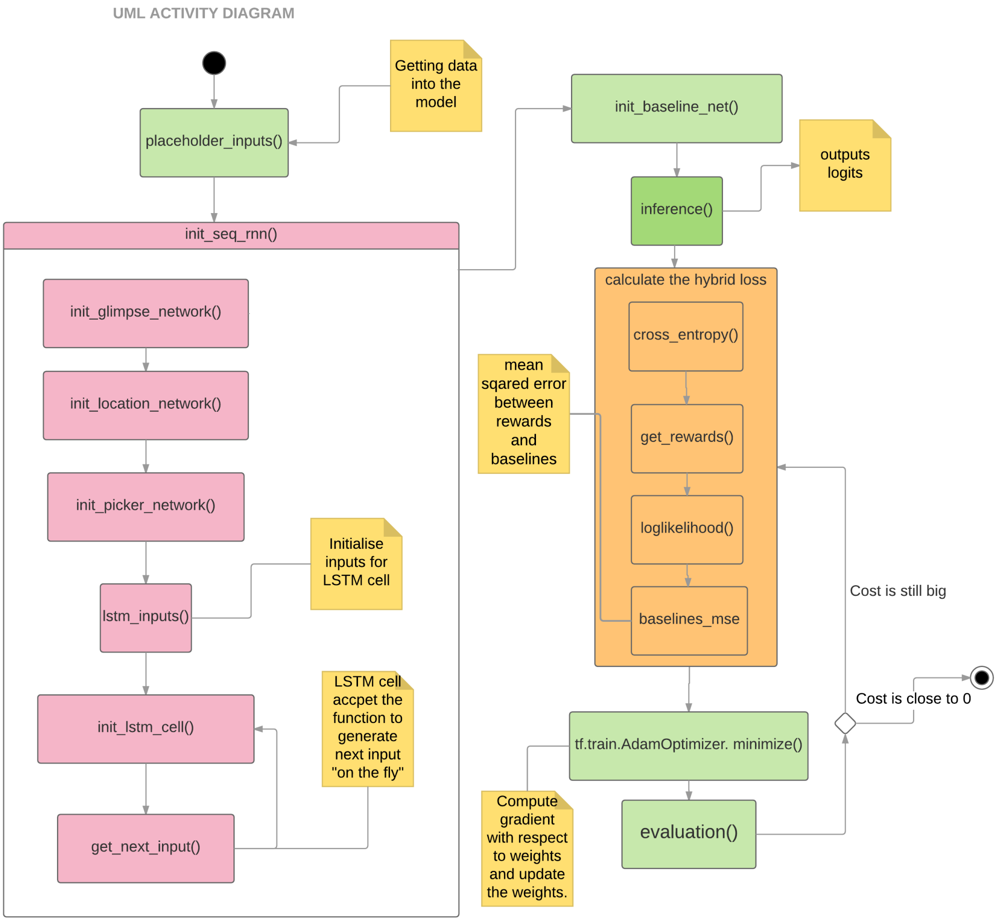


Figure 4.3: UML activity diagram of the Model

This is simplified flow of the `Model` class. Each activity represent a function. For the sake of simplicity some of the function are not shown here. However, it should not influence on the understanding of the `Model`

.

Chapter 5

Implementation

In this chapter we will discuss several implementation details that is important for understanding the work. We will also show the code patterns examples that were mentioned in the sec:quality$_{c}oncerns$.

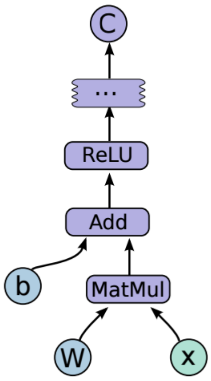
5.1 TensorFlow

In the figure 4.2, you might notice that some of the functions return `tf.Tensor` object. In order to understand what it is, let's make a small example to show how a TensorFlow program can look. In the listing 5.1, you can find a small TensorFlow program.

Listing 5.1: TensorFlow example [20]

```
import tensorflow as tf
b = tf.Variable(tf.zeros([100])) # 100-d vector, init to zeroes
W = tf.Variable(tf.random_uniform([784,100],-1,1)) # 784x100
   matrix w/rnd vals
x = tf.placeholder(name="x") # Placeholder for input
relu = tf.nn.relu(tf.matmul(W, x) + b) # Relu(Wx+b)
C = [...] # Cost computed as a function
# of Relu
s = tf.Session()
for step in xrange(0, 10):
   input = ...construct 100-D input array ... # Create 100-d vector
      for input
   result = s.run(C, feed_dict={x: input}) # Fetch cost, feeding
      x=input
   print step, result
```

In TensorFlow, computations are represented as a directed graph that is composed of nodes. The computational graph of the listing 5.1, is shown in the figure 5.1. Values that flow along the graph are denoted as *Tensor*, which is a TensorFlow representation of primitive values shaped into an array. Another important concept in TensorFlow is an operation, which represent an abstract computation. For example, in figure 5.1 you can see such operations: 'ReLU', 'Add', 'MatMul'.



To execute a TensorFlow program, one needs to build the computational graph, and then execute it. We're building the computation graph by instantiating the TensorFlow classes like the `tf.Variable`. But to actually compute this and obtain the correct output values we need to execute this using the `tf.Session`. The `tf.Session` is responsible for the execution of the computational graph; it takes the graph as well as the data to execute it on desired environment(e.g. GPU, CPU). One also passes the parameter `feed_dict` that is a dictionary object where the key has the name of `tf.placeholder` and the value is the data that the placeholder should be substituted with. A *placeholder* is a promise to provide the value later in the program.

5.2 Code quality

In the section 3.1, we talked about quality concerns that need be taken into account to improve the quality of the prototype. These recommendation were carefully followed in the implementation of this work.

5.2.1 Code patterns in the code

We introduced code patterns in the section 3.1, that are helpful for understanding and reasoning about the code. Here we will show examples of how this code patterns can be applied.

Method comment Would be perfect, if the code would be so clear and readable that we could avoid unnecessary comments in it. The method comment can help with this. Instead of having a comment in the code, it encourages to write a function with self-explanatory name:

Listing 5.2: Method comment example

```python
def init_location_network(config):
    """Initialise location network using ‘loc_net‘ scope and return
        it."""
    with tf.variable_scope('loc_net'):
        loc_net = LocNet(config)
    return loc_net
```

We could put this code with an explanation comment directly in the place where this function is called, but having a function with the name `init_location_network` should be more than enough to understand that the function is initializing the location network.

Composed method encourages function to have an identifiable task and that all operations performed in the function should be on the same level of abstraction.

Listing 5.3: Method comment example

```python
def init_seq_rnn(images_ph, labels_ph):
    """Feed locations to LSTM cells and return output of LSTM
        cells."""
    # Core network.
    N = tf.shape(images_ph)[0]
    glimpse_net = init_glimpse_network(images_ph)
    loc_net = init_location_network(Config)
    pick_net = init_picker_network(Config)
    inputs = lstm_inputs(glimpse_net, N)
    lstm_cell, init_state = init_lstm_cell(Config, N)

    def get_next_input(output, i):
        loc, loc_mean = loc_net(output)
        n_image = pick_net(output)
        gl_next = glimpse_net(loc, n_image)
        loc_mean_arr.append(loc_mean)
        sampled_loc_arr.append(loc)
        return gl_next

    outputs, _ = seq2seq.rnn_decoder(
        inputs, init_state, lstm_cell, loop_function=get_next_input
    )
    return outputs
```

In the listing 5.3, you can see the example of the composed method. As you might guess from the function name `init_seq_rnn`, the function is initialising the sequence of RNN cells, which is indeed an identifiable task. Additionally, all of the operations performed in the function have a high level of abstraction: for example to create LSTM inputs or to initialise glimpse network, it uses helper functions `lstm_inputs` and `init_glimpse_network` respectively. For the understanding the composed method, one can skip the function `get_next_input`.

Temporary variable This pattern recommends using a temporary variable with self-explanatory name instead of having very long expression in the code. One of the example of this pattern you can see in the listing 5.4.

Listing 5.4: Method comment example

```
img_size = (
   Config.original_size * Config.original_size * Config.num_channels
)
images_shape = [None, Config.n_img_group, img_size]
labels_shape = [None, Config.n_img_group]
with tf.variable_scope('data'):
   images_ph = tf.placeholder(tf.float32, images_shape,
       name='images')
   labels_ph = tf.placeholder(tf.int64, labels_shape, name='labels')
```

The variables `img_size`, `images_shape`, `labels_shape`. increase readability by avoiding very long expressions in the lines after. The names make it also more ease to comprehend for those who are unfamiliar with the code.

Duck typing This a concept that is used by dynamic typed languages. The idea behind it is that to use an object, it has to have a certain desired functionality, but it does not matter the nature of this object.

Listing 5.5: Method comment example

```
if(not(hasattr(dataset, "labels") and hasattr(dataset, "images"))):
   raise ValueError(
        'dataset object should have properties: `images` and `labels`'
    )
```

In the listing 5.5, you can see a clear example of duck typing. It's important that the object `dataset` is having properties `images` and `labels`, but we don't care about it's nature, i.e. what class the object `dataset` is instantiated from.

Code conventions The current implementation follows the docstring conventions described in guide PEP 257 [24], as it was suggested in section 3.1. The convention for code layout, indentation and names of functions, classes and variables is consistent with the guide PEP 008 [23]. To stay consistent with best and common practices in python, the current implementation relies on the "The Hitchhiker's Guide to Python"[1]. It gives us the conventions of how to configure, structure, test and document the code.

5.3 Implementation details

The purpose of this section is to show the implementation details that are important to understand the code and the model.

Hybrid loss One of the essential aspect in machine learning is to define the loss function carefully. As this works to train the model, we use some of reinforcement learning aspects, as our loss function is compose of multiple loss function:

- loss function to train the location network with help of reinforcement learning algorithms by increasing rewards.
- loss function to train the baseline function that is used to reduce the variance when computing the gradient of loss function for the location and picker networks.
- loss function to train the classification network based on the ground truth.

The loss which is composed of multiple loss function known as *hybrid loss*. You can see the way it's computer in listing 5.6

[1] [25]

Listing 5.6: Hybrid loss

```
baselines = init_baseline_net(outputs)

logits = inference(outputs[-1])
softmax = tf.nn.softmax(logits)

xent = cross_entropy_with_logits(logits, labels_ph)

pred_labels = tf.argmax(logits, 1)

rewards = get_rewards(pred_labels, labels_ph)

logll = loglikelihood(loc_mean_arr, sampled_loc_arr,
   Config.loc_std)

advs = rewards - tf.stop_gradient(baselines)
logllratio = tf.reduce_mean(logll * advs)

baselines_mse = tf.reduce_mean(tf.square((rewards - baselines)))
var_list = tf.trainable_variables()
# hybrid loss
loss = -logllratio + xent + baselines_mse # '-' for minimize
```

where `outputs` - are the output from LSTM cell, `xent` - is the cross entropy between predicted values and ground truth, `baselines_mse` - is the mean squared error loss between actual rewards and expected reward(baseline), `logllratio` - is the loss for the location network, which is trained using REINFORCE rule which was described in subsection 2.3.4.

Gradient computation Normally, users of TensorFlow train the model by calling `minimize` function from an optimizer: `Optimizer.minimize(loss)` However, since in our case we clip the gradient values to prevent the vanishing and the exploding gradient problems, we firstly need to compute gradients, then clip the values, and apply gradients:

Listing 5.7: gradient computation

```
grads = tf.gradients(loss, var_list) # computes gradients with
   respect to var_list
clipped_grads, _ = tf.clip_by_global_norm(grads,
   Config.max_grad_norm) # clip the values
optimizer = tf.train.AdamOptimizer(learning_rate) # Initialise the
   optimizer
```

```
train_op = optimizer.apply_gradients(
   zip(clipped_grads, var_list), global_step=global_step
) # apply the capped gradients
```

where `var_list` - is the variables with respect to which the gradient should be computed.

We get the `var_list` by using TensorFlow function `tf.trainable_variables()`, which return all of the trainable variables in the graph. One thing to notice is that for some variables like location or baselines we use function `tf.stop_gradient`, these prevent the contribution of the variable to be taken into account when computing a gradient. The function `tf.trainable_variables()` returns the trainable variables excluding the variables where the function `tf.stop_gradient` was applied on.

Chapter 6

Test and evaluation

In this chapter, we will discuss how the testing is done in the implementation of this work as well as how the current model was evaluated.

6.1 Test

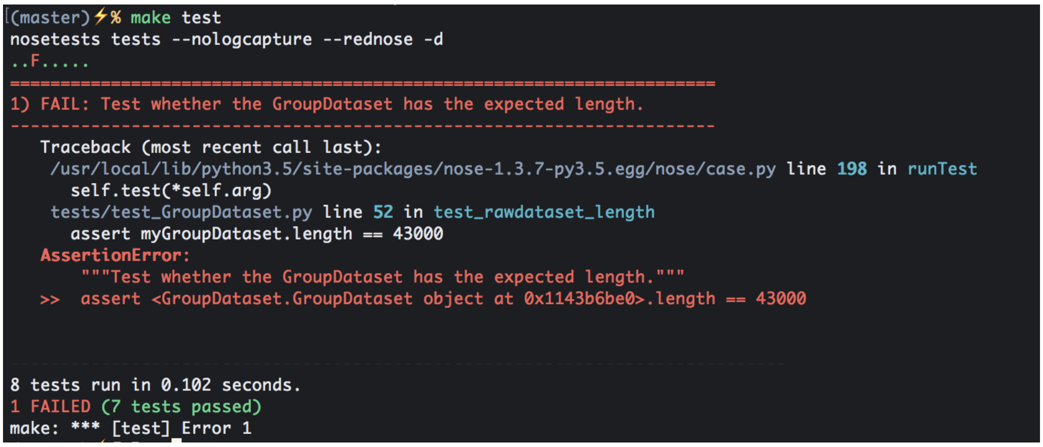
In the current implementation, we test our prototype by the means of unit testing. Unit testing is a method of software testing, which verifies that individual units of the code are working as expected. To perform the unit testing, one should identify pieces of code, that are responsible for a clear task [34]. In most cases, that are methods of classes or functions. Imagine, that we have a function that adds two numbers together. To test this function, we have to come up with the real values, calculate the expected return, call the function with the real value and compare the return of the function with the expected return:

Listing 6.1: TensorFlow example [20]

```
def add(x, y):
    """Add two numbers together."""
    return x + y

# unit test of the function ‘add‘
def test_add():
    assert add(3, 5) == 8 # 3, 5 are real values, 8 is the
        expected return
    assert add(10, 2) == 12
```

In case of classes, mostly it’s methods were covered with unit tests. For testing purposes, we used unit test framework called Nose. Nose simplifies unit testing by providing automatic test discovery. It also automatically creates a test suite, which is nothing more than a set of tests. One advantage of using the Nose over the Python's standard unit test module is that no configuration is required in order to run all tests when the tests are named consistent with Nose conventions and are located in the */tests* directory. An additional advantage is that Nose generates well-readable report after running tests. The report helps when debugging and fixing tests. You can see the example of an report on the figure 6.1



```
[(master)⚡% make test
nosetests tests --nologcapture --rednose -d
..F.....
======================================================================
1) FAIL: Test whether the GroupDataset has the expected length.
----------------------------------------------------------------------
   Traceback (most recent call last):
    /usr/local/lib/python3.5/site-packages/nose-1.3.7-py3.5.egg/nose/case.py line 198 in runTest
      self.test(*self.arg)
    tests/test_GroupDataset.py line 52 in test_rawdataset_length
      assert myGroupDataset.length == 43000
   AssertionError:
       """Test whether the GroupDataset has the expected length."""
   >>  assert <GroupDataset.GroupDataset object at 0x1143b6be0>.length == 43000


8 tests run in 0.102 seconds.
1 FAILED (7 tests passed)
make: *** [test] Error 1
```

The module Dataset is fully tested with unit tests. However, the module Model is not, since it has too many non-deterministic values. One good way of testing the model is to run an interactive session of TensorFlow, which is desired for the further development of the prototype.[1]

6.2 Evaluation

The model was evaluated with the dataset described in section 3.4 on server from HTW Berlin. The server posses the Nvidia Tesla M40 GPU accelerator [35]. It was required from 1 to 2 hours to train the model and the time is changed caused by different configurations. We will introduce more details of the first experiments below in this section.

[1] TensorFlow documentation explains this method here: https://www.tensorflow.org/api$_{g}uides/python/test$

Name of the parameter	Configuration 1	Configuration 2	Configuration 3
Batch size	32	20	20
Number of glimpses (T)	30	15	24
Labels of noise pictures	1,2	0	0
Labels of non-noise pictures	0, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 5, 6, 7, 8, 9	1, 2, 3, 4, 5, 6, 7, 8, 9
Amount of images per group	5	5	4
Amount of classes for classification task	3	3	2
Amount of examples in training dataset	45000	45000	60000

Table 6.1: Configurations for the experiments

6.2.1 Configuration

The evaluation was performed on two different types of setting. You can see the differences between these configurations in table 6.1.

We will explain the settings that are different in the configurations:

- Number of glimpses(T) - As you can remember from section 2.4 the agent does a classification decision after T steps. In original RAM paper this number was equal to $T = 7$. Since we will have more images in a group, we increased this number in both of configurations.
- Batch size - size of the batch for training the model.
- Labels of noise pictures - the images at the labels considered to be insignificant for the classification decision(as described in section 3.4).
- Labels of non-noise pictures - the image at the labels are important for the classification(as described in section 3.4).
- Amount of images per group - this amount determines how many images a group will have.
- Amount of classes for classification task - as you may remember from section 3.4, we can build dataset with different amount of classes.

These configurations was a try to simplify the task for the model. From configuration 1 to configuration 3, we reduced training batch size, reduced the variety of the noise images, reduced amount of classes, and played with number of glimpses.

Of course, there even more parameters that is possible to tune in further experiments. The explanation of all parameters can be found in the implementation of the model.

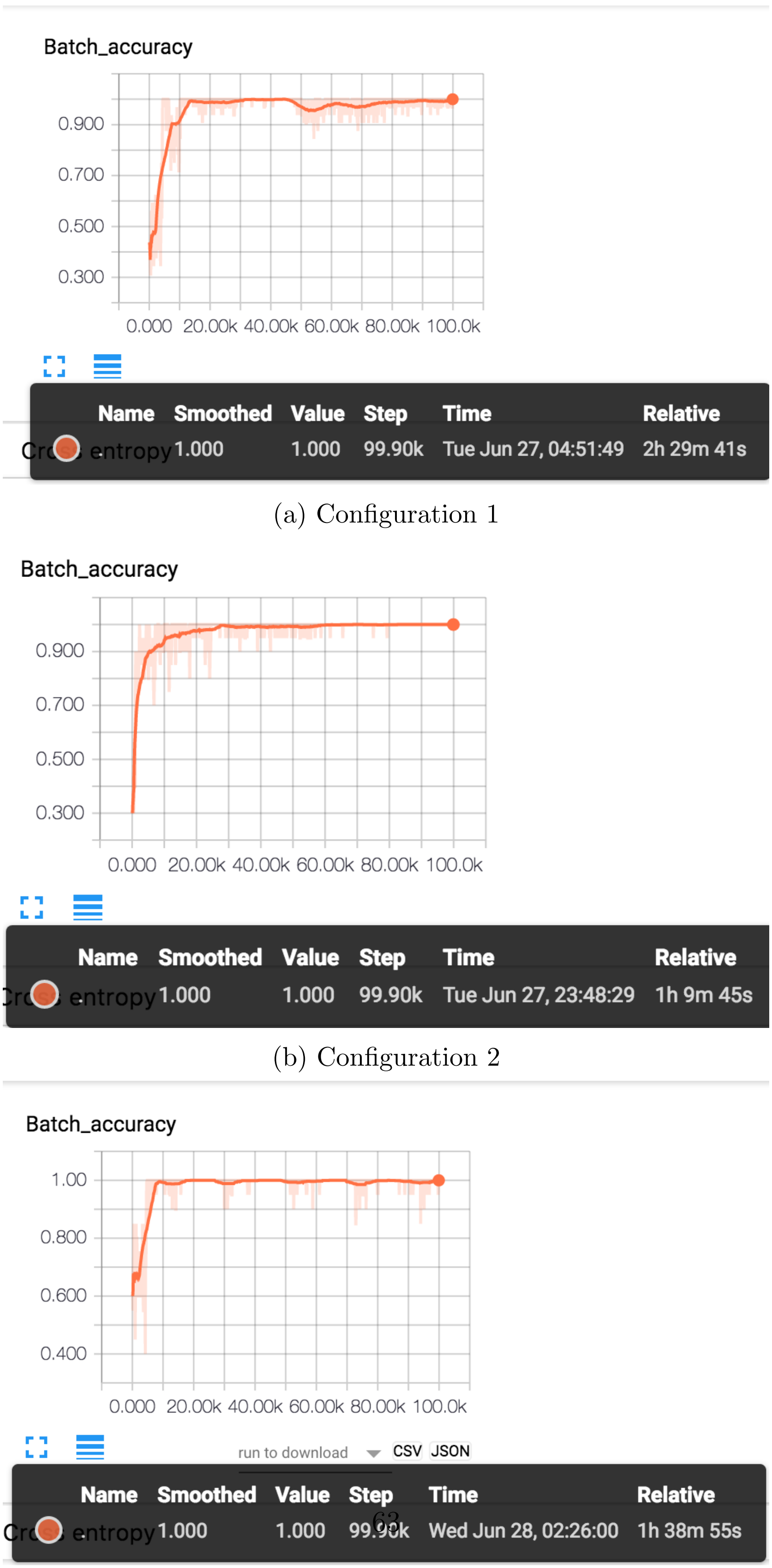
6.2.2 Results

Generally speaking, the experiments highlighted that the model is not able to generalise on the validation as well as on the test data. We will show the evidence of that by referring to the figures taken from TensorBoard. The figures 6.2 and 6.3 indicate that the accuracy on the validation and test data weren't stable. The training accuracy for all three configurations was stable and reached high results as shown in the figure 6.1. Proceeding from that, we can state that overfitting occurs by training the model.

The figure 6.4 shows that the mean squared error between our value function for reducing the variance and actual reward is very small. This may indicate, that the our baseline function is close to the actual expected reward.

From the figure 6.5, we can observe the hybrid loss value reduced much more in the configuration 3. The reason for this can be, that we reduced the amount of classes from 3 to 2.

Broadly speaking, we found that it's required to continue tuning the parameters of the model, as the figures clearly highlighting the model's instability .



Name	Smoothed	Value	Step	Time	Relative
Cr● entropy	1.000	1.000	99.90k	Tue Jun 27, 04:51:49	2h 29m 41s

(a) Configuration 1

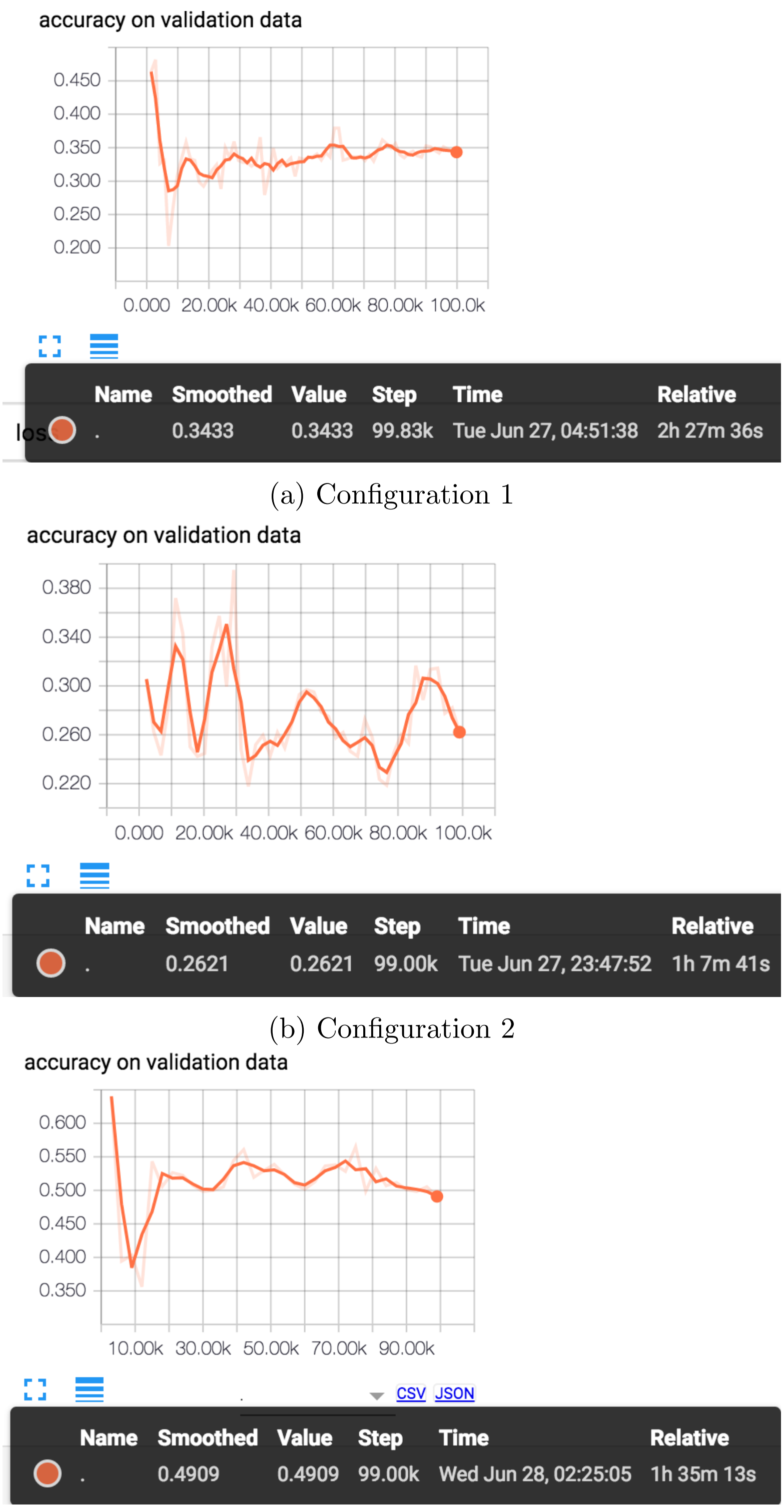
Name	Smoothed	Value	Step	Time	Relative
Cr● entropy	1.000	1.000	99.90k	Tue Jun 27, 23:48:29	1h 9m 45s

(b) Configuration 2

Name	Smoothed	Value	Step	Time	Relative
Cr● entropy	1.000	1.000	99.90k	Wed Jun 28, 02:26:00	1h 38m 55s

(c) Configuration 3

Figure 6.1: Accuracy on the training data



	Name	Smoothed	Value	Step	Time	Relative
●	.	0.3433	0.3433	99.83k	Tue Jun 27, 04:51:38	2h 27m 36s

(a) Configuration 1

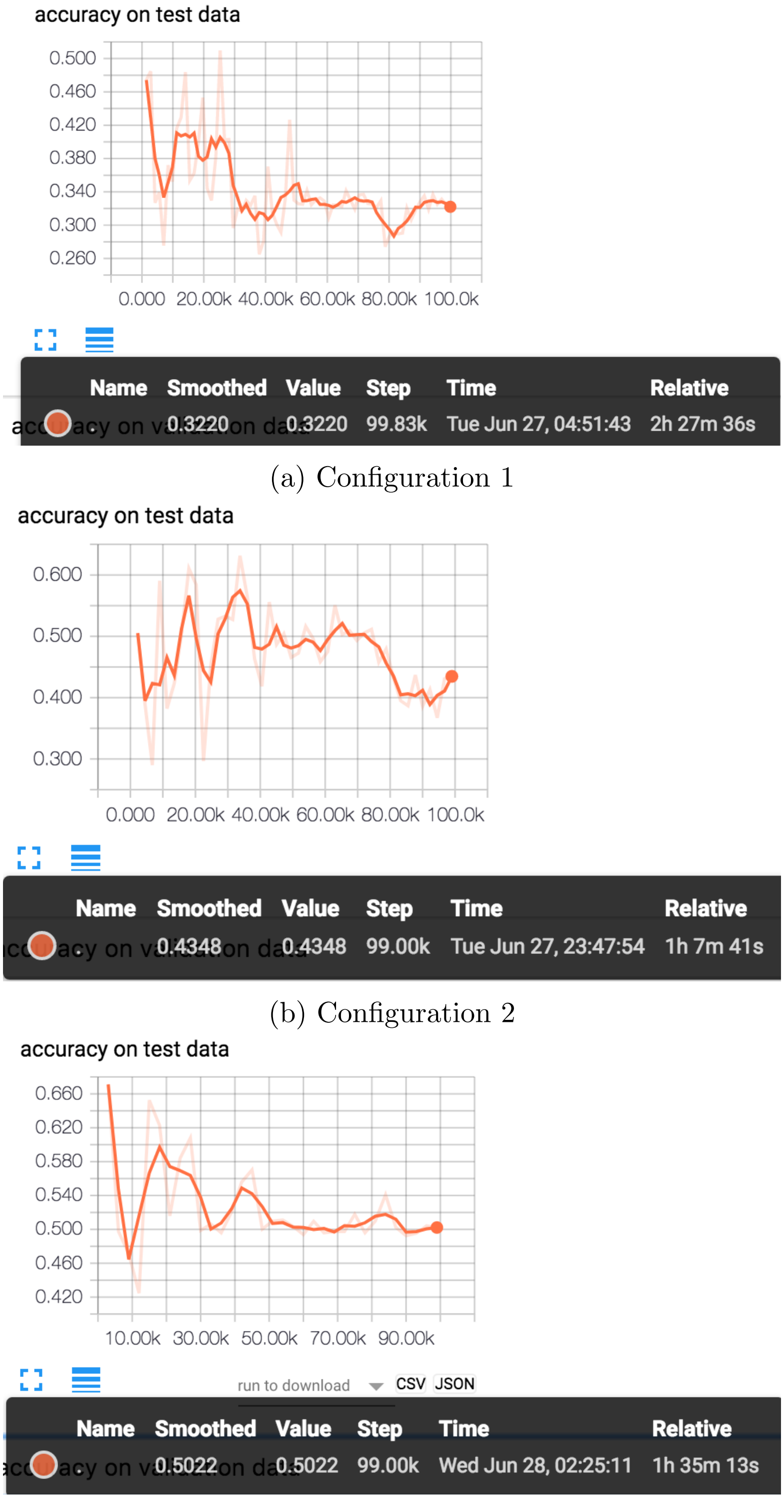
	Name	Smoothed	Value	Step	Time	Relative
●	.	0.2621	0.2621	99.00k	Tue Jun 27, 23:47:52	1h 7m 41s

(b) Configuration 2

	Name	Smoothed	Value	Step	Time	Relative
●	.	0.4909	0.4909	99.00k	Wed Jun 28, 02:25:05	1h 35m 13s

(c) Configuration 3

Figure 6.2: Accuracy on the validation data



Name	Smoothed	Value	Step	Time	Relative
● accuracy on validation data	0.3220	0.3220	99.83k	Tue Jun 27, 04:51:43	2h 27m 36s

(a) Configuration 1

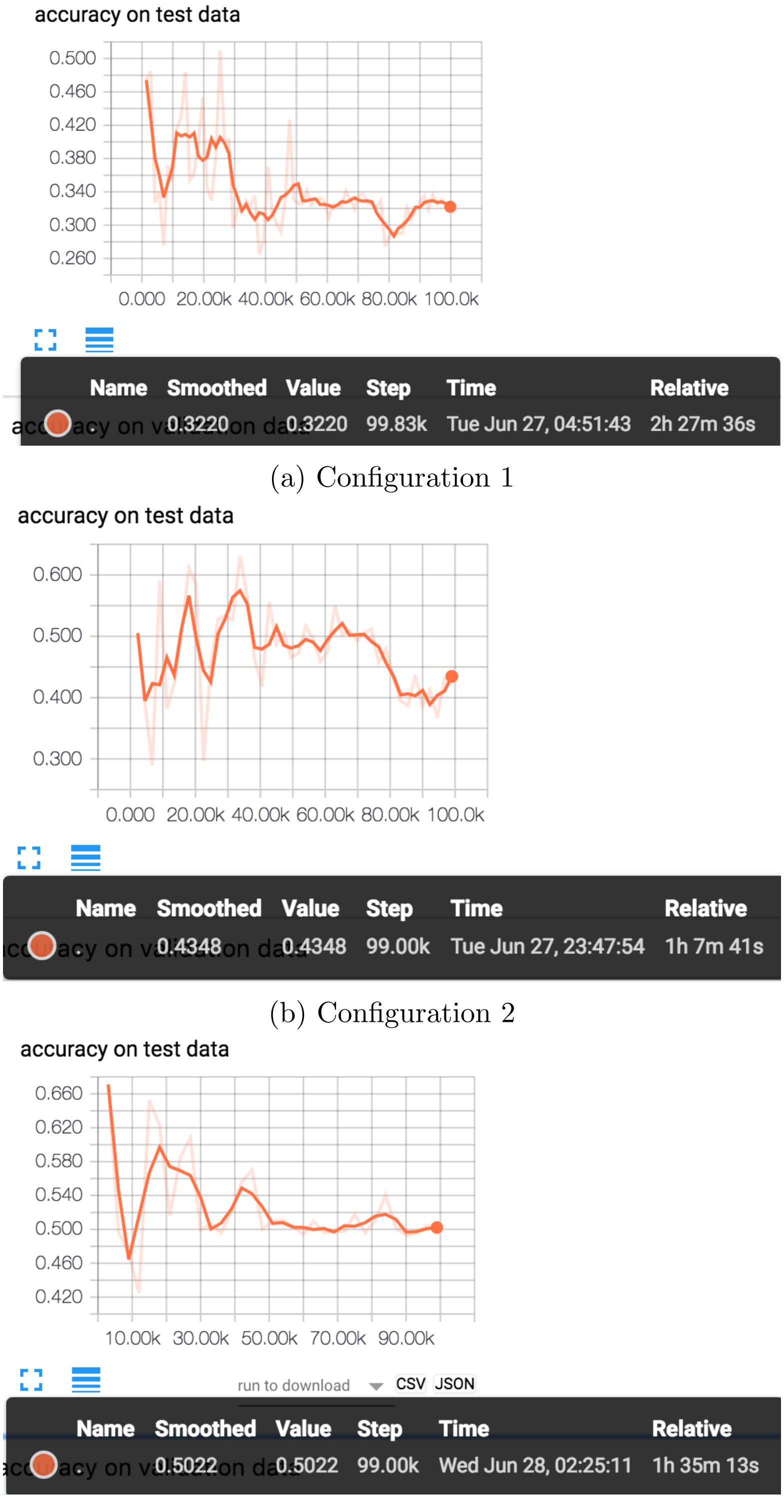
Name	Smoothed	Value	Step	Time	Relative
● accuracy on validation data	0.4348	0.4348	99.00k	Tue Jun 27, 23:47:54	1h 7m 41s

(b) Configuration 2

Name	Smoothed	Value	Step	Time	Relative
● accuracy on validation data	0.5022	0.5022	99.00k	Wed Jun 28, 02:25:11	1h 35m 13s

(c) Configuration 3

Figure 6.3: Accuracy on the test data



	Name	Smoothed	Value	Step	Time	Relative
●	accuracy on validation data	0.3220	0.3220	99.83k	Tue Jun 27, 04:51:43	2h 27m 36s

(a) Configuration 1

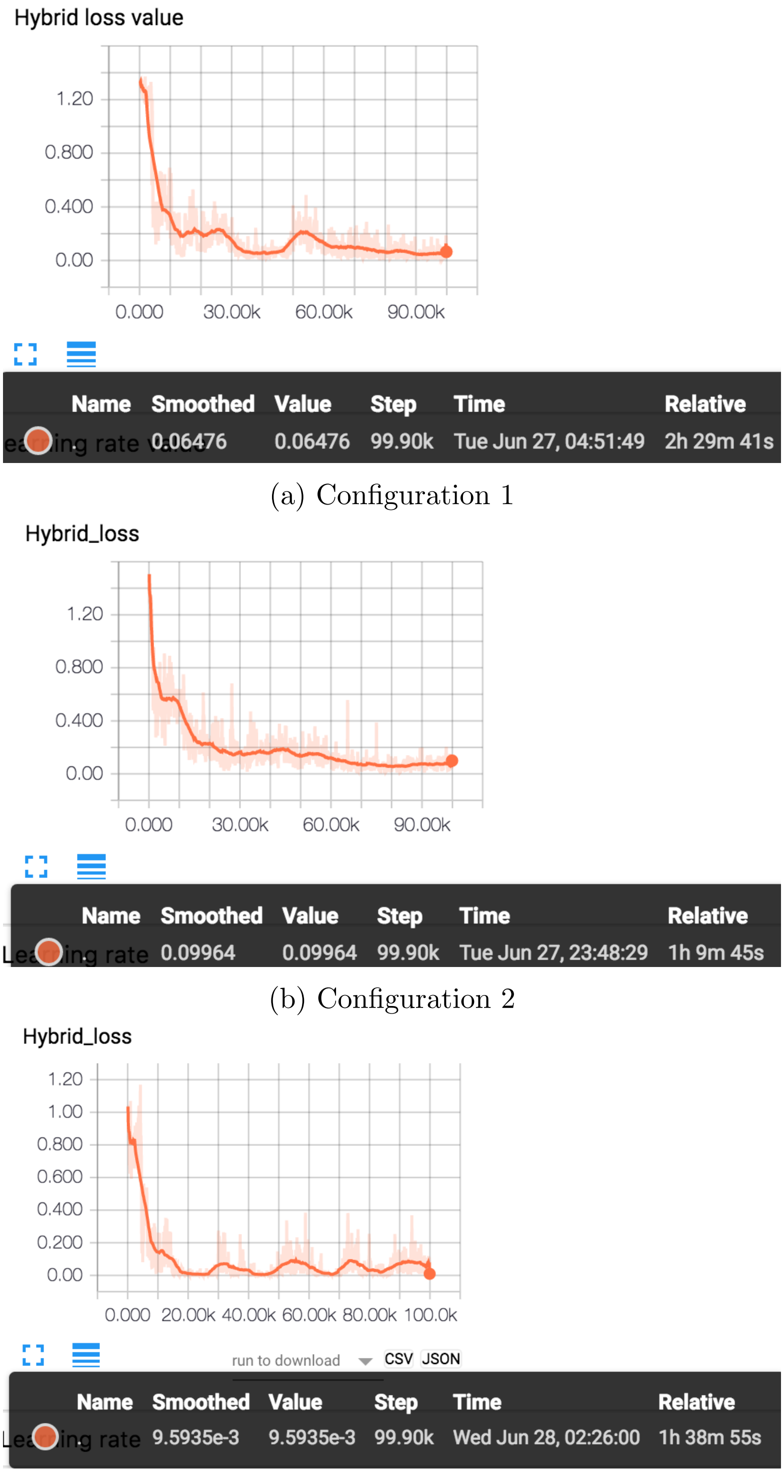
	Name	Smoothed	Value	Step	Time	Relative
●	accuracy on validation data	0.4348	0.4348	99.00k	Tue Jun 27, 23:47:54	1h 7m 41s

(b) Configuration 2

	Name	Smoothed	Value	Step	Time	Relative
●	accuracy on validation data	0.5022	0.5022	99.00k	Wed Jun 28, 02:25:11	1h 35m 13s

(c) Configuration 3

Figure 6.4: Mean squared error between baseline function and expected reward



Name	Smoothed	Value	Step	Time	Relative
ea ing rate value	0.06476	0.06476	99.90k	Tue Jun 27, 04:51:49	2h 29m 41s

(a) Configuration 1

Name	Smoothed	Value	Step	Time	Relative
Lea ing rate	0.09964	0.09964	99.90k	Tue Jun 27, 23:48:29	1h 9m 45s

(b) Configuration 2

Name	Smoothed	Value	Step	Time	Relative
Lea ing rate	9.5935e-3	9.5935e-3	99.90k	Wed Jun 28, 02:26:00	1h 38m 55s

(c) Configuration 3

Figure 6.5: Hybrid loss

Chapter 7

Disscussion

Bibliography

[1] M. A. Nielsen, "Neural Networks and Deep Learning," 2015.

[2] Colah Christopher, "Understanding LSTM Networks – colah's blog," 2015.

[3] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, "Playing atari with deep reinforcement learning," *arXiv preprint arXiv:1312.5602*, 2013.

[4] V. Mnih, N. Heess, A. Graves, and K. Kavukcuoglu, "Recurrent models of visual attention," *CoRR*, vol. abs/1406.6247, 2014.

[5] J. Ba, V. Mnih, and K. Kavukcuoglu, "Multiple object recognition with visual attention," *CoRR*, vol. abs/1412.7755, 2014.

[6] "TensorFlow."

[7] P. Goldsborough, "A Tour of TensorFlow Proseminar Data Mining,"

[8] "CAMELYON17 - Home."

[9] C. M. Bishop, "Neural networks for pattern recognition," *Journal of the American Statistical Association*, vol. 92, p. 482, 1995.

[10] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Advances In Neural Information Processing Systems*, pp. 1–9, 2012.

[11] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning.* MIT Press, 2016. `http://www.deeplearningbook.org`.

[12] F. Rosenblatt, *Principles of neurodynamics: perceptrons and the theory of brain mechanisms.* Report (Cornell Aeronautical Laboratory), Spartan Books, 1962.

[13] Karpathy Andrej, "CS231n Convolutional Neural Networks for Visual Recognition," 2016.

[14] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, pp. 533–536, oct 1986.

[15] D. Kriesel, *A Brief Introduction to Neural Networks*. 2007.

[16] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, pp. 1735–1780, Nov. 1997.

[17] P. Werbos, "Backpropagation through time: what does it do and how to do it," in *Proceedings of IEEE*, vol. 78, pp. 1550–1560, 1990.

[18] R. S. Sutton and A. G. Barto, "Reinforcement Learning: An Introduction," 2012.

[19] H. Larochelle and G. Hinton, "Learning to combine foveal glimpses with a third-order Boltzmann machine," *Nips-2010*, pp. 1243–1251, 2010.

[20] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, "TensorFlow: Large-scale machine learning on heterogeneous systems," 2015. Software available from tensorflow.org.

[21] P. Goldsborough, "A tour of tensorflow," *CoRR*, vol. abs/1610.01178, 2016.

[22] "TensorFlow Style Guide — TensorFlow."

[23] G. van Rossum, B. Warsaw, and N. Coghlan, "PEP 0008: style guide for python code," 2001.

[24] D. Goodger and G. van Rossum, "PEP 257 – Docstring Conventions — Python.org," 2001.

[25] K. Reitz, "The Hitchhiker's Guide to Python! — The Hitchhiker's Guide to Python."

[26] K. Beck, *Smalltalk Best Practice Patterns. Volume 1: Coding.* Prentice Hall, Englewood Cliffs, NJ, 1997.

[27] R. Martin, *Agile Software Development: Principles, Patterns, and Practices.* Alan Apt series, Pearson Education, 2003.

[28] B. Eckel, "Python 3 Patterns, Recipes and Idioms," pp. 1–301, 2008.

[29] E. Gamma, R. Helm, R. Johnson, and J. Vlissides, *Design Patterns: Elements of Reusable Object-oriented Software.* Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 1995.

[30] *Refactoring: Improving the Design of Existing Code.* Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 1999.

[31] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *CoRR*, vol. abs/1412.6980, 2014.

[32] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training Recurrent Neural Networks," nov 2012.

[33] Y. LeCun, C. Cortes, and C. J. Burges, "MNIST handwritten digit database, Yann LeCun, Corinna Cortes and Chris Burges," 2010.

[34] D. Huizinga and A. Kolawa, "Principles of Automated Defect Prevention," in *Automated Defect Prevention*, pp. 19–51, Hoboken, NJ, USA: John Wiley & Sons, Inc., 2007.

[35] "Tesla M40 Deep Learning Training Accelerator — NVIDIA."

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