Use of Spiking Neural Networks for Object Detection

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1 Introduction

Use of Deep Neural Network, commonly referred to as *deep learning* spiked in recent years and has been popular as a tool for impressive advancements in the field of *Artificial Intelligence (AI)*. The goal of this project was to attempt and recreate a spiking neural network that is capable of object detection, particularly classification and localization. As described, our program was built on Deep Neural Networks, spiking neurons, and convolutional network frameworks, which we find interesting and important. Despite the inability to complete the product we nonetheless met our ultimate goal, to learn more about computational neuroscience. Moreover, our attempt at an object detecting, spiking neural network provided a comprehensive learning experience for all members, regardless of prior knowledge on the subject.

1.1 Neural Networks

A Deep Neural Network, DNN, is a machine learning algorithm that tries to mimic how the brain processes information. The reason why DNNs are called deep is due to the networks having more than two hidden layers. The increased number of hidden layers enables DNNs to complete more complicated tasks compared to their shallow counterparts. However, increasing the number of hidden layers increases the training time in addition to the electrical power per epoch.

On the other hand, Spiking Neural Networks, SNNs, mimic both the information encoding and the process within a human brain by using spiking neurons as activation functions (Maass (1997)). SNN sends information as a discrete series of spikes as opposed to sending continuous real values that layers of DNNs output. The SNN model is efficient because the spiking neuron only integrates its value when the membrane potential, voltage, passes the threshold which enables event-driven computation (Kim, Park, Na, and Yoon (2020)). However, to harness the efficiency of spiking neural networks, they have to be trained and implemented on neuromorphic hardware.

1.2 Leaky Integrate and Fire

The Integrate and Fire model, IAF, shows how the membrane potential of a neuron reacts to an injection of current. If the membrane potential is injected with a high enough current it starts an all-or-nothing reaction resulting in a spike or action potential. The difference between the IAF model and the leaky integrate and fire model, LIF, is the existence of a reset mechanism in the LIF. Just like in the IAF model, when the LIF neuron reaches the threshold it fires and causes a spike. However, the leaky model can reset the membrane potential's voltage by using the reset by subtraction method. The reset by subtraction method is biologically more accurate because for real neurons, after firing, the neuron needs a higher voltage value to fire again.

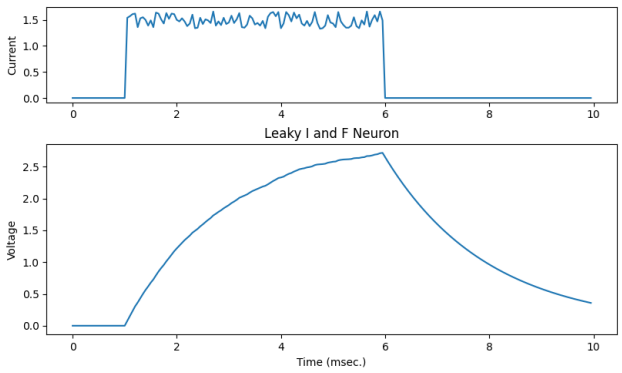

Figure 1: Example of a Leaky Integrate and Fire Neuron being injected with a current i

Requirement to pass this information from layer to layer is one of the reasons why it is difficult to train Spiking Neural Networks (Kim et al. (2020)).

2 Problems with Spiking Neural Networks

2.1 Loss of Information

When a neuron in Spiking Network is either under- or over- activated, there might occur information loss. These events happen due to the input voltage being either too large and generating spikes regardless of the value of input or due to input voltage being too low and taking a long time to produce a spike. To solve these problems multiple normalization methods have been invented.

For example, Kim et al. (2020) proposed a channel-wise data-based normalization that normalizes the weights bt the maximum possible activation in a channel-wise manner as opposed to a conventional layer-wise method.

2.2 Non-differentiability

The issue with the SNN is that the spike events are non-linear, discrete events, which means that the rate of change, the derivative, is zero everywhere apart from when the value of the membrane potential is equal to zero (Neftci, Mostafa, and Zenke (2019)). Thus, the SNN model can not use standard error backpropagation.

Alleviating the issue of the SNN model's being non-differentiability in addition to optimizing the algorithm itself required either smoothing the SNN by making it continuously differentiable or introducing the surrogate gradient (SG) which is a "continuous relaxation of the real gradients" (Neftci et al. (2019)).

snnTorch solves the non-differentiability issue for us by providing a custom backpropagation method that integradtes surrogate gradient.

2.3 Biological Icarus

Just like in the story of Icarus and his father, creators of Spiking Neural Networks are trying to get close to biologically plausible neural network model while trying to not *"melt their wings"* and fail. Due to this constraint, LIF seems to be the best candidate to simulate neurons without getting into too much biological detail.

All the challenges of implementation of Spiking Neural Networks that we mentioned before are the reason why standard Artificial Neural Networks rely on utility focused tools for achieving their goals. Indeed, introduction of more biologically plausible models are faced with problems when attempted to be implemented in code. This is the case with Leaky-Integrate-and-Fire and the reason why despite being the most biologically accurate, the Hodgkin's and Huxley's neuron model (H-and-H) is not likely to be used in AI and development of neural networks. Moreover, if someone would try to attempt a neural network with H-and-H model at the heart they would probably *"get too close to the sun"* and fall.

3 The Dataset

For purposes of the project, we have chosen to use the Microsoft Common Objects in Context, a dataset of over 330 thousand images, with over 200 of these labeled, 80 categories of instances, and over 1.5 million object instances all together (Lin et al. (2014)). This substantial dataset is utilized with an API developed specifically to access the contents of the dataset, both of which have been made open-source by their developers *(https://github.com/cocodataset/cocoapi)*. The objectives of MSCOCO are to detect and categorize objects found within images based on their iconicity, their position in relation to other objects, and the binding coordinates of space they occupy in a given image.

3.1 Properties of Data

Notably, MSCOCO is proposed by its developers to be more effective at training object recognition models than other popular datasets that are used in research and the industry. These advantages of MSCOCO mainly lay in the following properties of the data and the dateset.

1. Detecting non-iconic views

- In line with its focus of detecting images in their natural contexts, MSCOCO is designed to be more effective in detecting objects in non-iconic views than other datasets. When speaking to what iconicity means in this context, we mean a recognition system's ability to interpret objects from an image, even when those objects are obscured by clutter, and layered deep behind occlusions which move them away from the image's center-focus.
- On average, MSCOCO's objects are smaller when compared to the sizes found in other popular datasets such as ImageNet and PASCAL, a feature which speaks to its greater efficiency at parsing through ambiguity and noise to detect the intended objects.

2. Contextual Reasoning

   - MSCOCO also uses contextual reasoning where multiple objects are present, which demonstrates the improved ability to recognize them even when objects are not isolated, and are instead present amongst others. For instance, where previous datasets, such as ImageNet and PASCAL, account for 60% of their images being object-isolated (meaning only depict a singular object), MSCOCO account for only 10%. The processing of such contextually-ambiguous scenes further builds onto the dataset's ability to object-recognize in natural scenes, and not just scenes where the object of interest is centrally-focused.

3. Object localization

   - Given the effort MSCOCO places on contextual reasoning, and the importance of parsing through non-iconic scenes, it's important to also understand that (a) MSCOCO requires, and indeed has, the ability of object localization–that is, the ability to process the spatial relations between objects in a scene; and (b), how MSCOCO segments this object localization.

3.2 Functionality of Data

When observed, the dataset can first be categorized by the type of objects being analyzed, and secondly by what object of the category is being analyzed.

Of the 80 categories offered, we focus on 10, which can be classified as animals: bird, cat, dog, horse, sheep, cow, elephant, bear, zebra, and giraffe. Using this dataset, we aim to train a spiking neural network to demonstrate the intended object-recognition model.

Functionally, when an image is analyzed, the program identifies key attributes which are used to categorize appropriately. For instance, where we analyze an image of two giraffes, we should consider the properties of the data used in the process of segmentation.

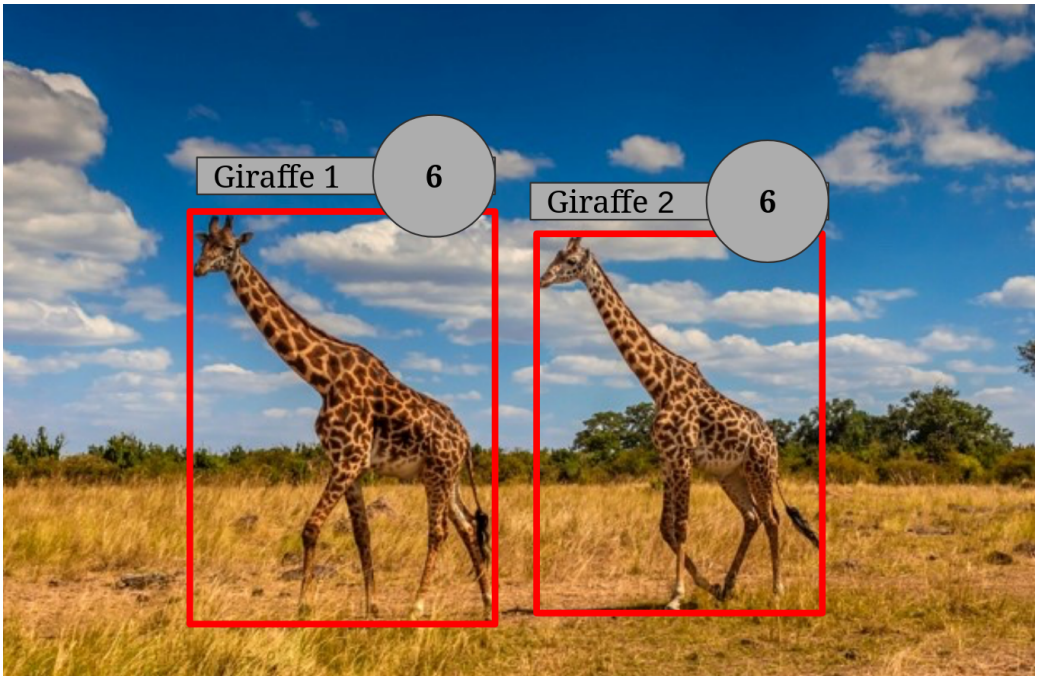

Figure 2: Example of an image from the MSCOCO dataset with the annotations that it contains.

1. Boxes

   - The image presented is first identified by a "bounding box"; this box is important for object localization. It provides the minimum and maximum coordinates along a cartesian-plane to identify the boundaries of space an object occupies.

2. Area

   - Within the bounding box, a pixel count for each object present is processed and utilized to further understand the iconicity and/or ambiguity of the object in relation to its scene.

3. Label

   - This property output can be read to distinguish (a) the number of object-instances found in an image, and (b) the category each object-instance.

The described properties of the image annotation should be considered in relation to the process segmentation in object recognition. Mainly, it's important to consider that object-segmentation is a difficult process and requires an accurate bounding boxes prediction. Furthermore, considering that the dataset holds over 1.5 million category instances, given the sheer magnitude and complexity of the dataset efficiency plays

a big role in training a neural-network that utilizes this dataset. As such, a major goal of our assignment is to build and train a spiking neural network model to do so.

4 Architectures Of Deep Neural Networks

When it comes to building a neural network, one has to establish its architecture. In this context an architecture is a blueprint of how layers are arranged and interconnected. It is particularly important, when the network increases in complexity. Object classification + localization being a demanding task for a network to solve, we have adopted a published and well-tested architecture for the task – ResNet. The particular architecture we have tried to imitate titled *DECOLLE*, was first developed by Kaiser, Mostafa, and Neftci (2018) and later enhanced by Barchid, Mennesson, and Djéraba (2021). *DECOLLE* Neural Network adopts properties of classical ResNet model architecture as well as a pyramidal structure that was proposed by Lin et al. (2016).

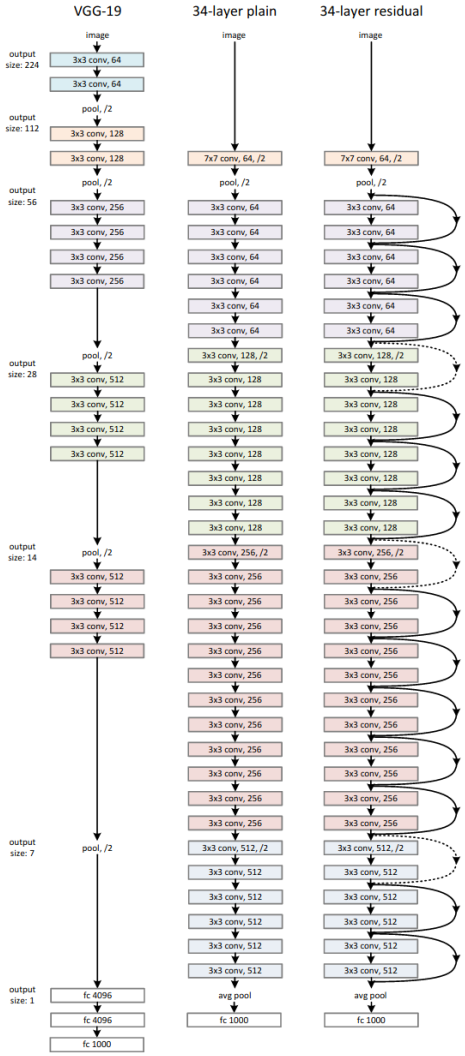

Figure 3: Examples of 16-layer VGG, Plain 34-layer, and 34-layer ResNet Network Architectures

4.1 ResNets

To begin with the cornerstone of our architecture, ResNet is named from its property of convolutional layers which residually connect to one another(He, Zhang, Ren, and Sun (2015)). According to He et al. (2015) addition of residual connections improves models' convergence, or ability for the models' loss to move towards a minimum in a decreasing trend. While ResNets converge faster than their plain counterparts, their complexity is much lower than the complexity of other well performing Visual Geometry Group (VGG) Networks given the same depth (3.6 billion FLOPs (Float Point Operations) vs. 19.6 billion FLOPs) (He et al. (2015)).

4.2 Comparing Model Performance

To compare networks' performance, one has to understand how it is measured and what constitutes is as an accurate model. Comparing accuracy of predicting the right class is not itself sufficient for the task of object detection/localization. Thus, two additional performance metrics have been adapted: Mean Average Precision (mAP) and Intersection of Union (IoU). Firstly, mAP for the purposes of Object Detection is well-defined in the paper by Everingham, Gool, Williams, Winn, and Zisserman (2010). According to the authors, mAP is the mean of Average Precision of the model for all the classes in the dataset. It is calculated using the following equation.

$$\mathbf{mAP} = \frac{1}{N} * \sum_{i=1}^{N} \mathbf{AP}_i \tag{1}$$

AP = Average Precision,

N = number of classes.

Next, IoU is the area of overlap of ground-truth boxes and the model's detected box output; the higher the IoU the better performance of the model. Intersection of Union can be represented as follows.

$$\mathbf{IoU} = |A \cap B| \div |A \cup B| = |I| \div |U| \tag{2}$$

I = Intersection area,

U = Union area.

4.3 Pyramidal Architecture of Neural Network

Pyramidal structure of a Neural Network refers to the shape of the layers as the model gets deeper. With each layer, dimensions of convolutional layers double. For example, the first convolutional layer would have an input dimension equal to number of channels in the image (3 channels for RGB images vs. 1 for greyscale). The same layer would have an output dimension of 32, with next layer input equal to previous layer's output. The second layer would have the dimension of 64 (half of the previous layer's output) and so on (Lin et al. (2016)).

For the purposes of our network, pyramidal structure of a neural network is leveraged using Encoder-Decoder model. When an image is passed through the shrinking layers of the Encoder Pyramid, it looses resolution as well as contextual information; however when the image leaves the encoder and is located in the hidden state, it is fully comprised of the semantic information about the image (what object is on the picture and where it is located). Furthermore, in order to localize an object on an image the model has never

encountered before, it must be able to place the semantic information in context. This is where Decoder comes into play, being the reverse of an Encoder, the convolutional layers of decoder reduce in size until desired dimensions. The decoder is residually connected to encoder, and thus it gains contextual information about the image through every pass of decoder's layer.

In the end, in order to extract meaningful information, the last decoder layer is connected to Fully Connected linear layers that output predicted class, as well as detected box coordinates.

5 Implementation

5.1 Architecture of the Model Used

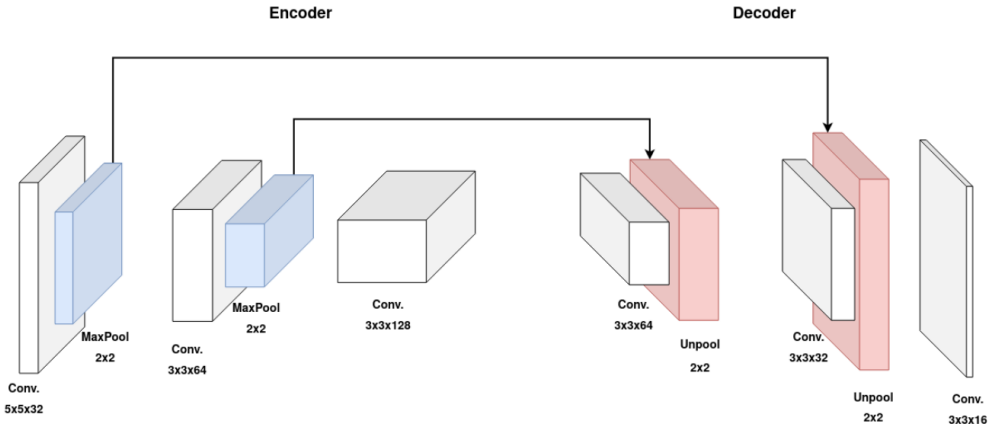

Figure 4: Sketch of the model's architecture. White layers represent convolutional layers, blue represent pooling layers, and red unpooling layers

Architecture developed by Barchid et al. (2021) was the target to replicate. The model is based on Encoder-Decoder architecture with residually connecting layers akin to ResNets.

5.2 PyTorch

The main package that allowed us to develop such a complex model was PyTorch. PyTorch is an open-source machine learning/deep learning library and framework for Python, which allows users to develop and ship high performance models (Paszke et al. (2019)). This library eliminates the need of 'from scratch'' development of the most important methods in machine learning, such as activation functions, and model architecture assembly.

5.3 Spiking Neurons

Given the complexity of SNNs and the integration of LIF into the network, we used a package that allows the use LIF within a PyTorch model – *snnTorch*. snnTorch also allowed us to integrate backpropogation for spiking neural networks with one line.

```
import snntorch as snn
spike_grad = surrogate.fast_sigmoid(slope=25)
beta = 0.5

lif1 = snn.Leaky(beta=beta, spike_grad=spike_grad)
```

Listing 1: Leaky-Integrate-and-Fire using snnTorch

5.4 The End Product

As we conclude, we should note we were challenged beyond our capabilities within the allotted time; this was known going into the project and as such we worked keeping these constraints in mind. For instance, SNNs when implemented on conventional GPUs are extremely memory hungry due to the need to store membrane potential information. This feature of SNNs caused a constraint in terms of hardware capabilities that were unavailable to us. In another instance, we faced challenges implementing a model based on literature. While Barchid et al. (2021) provided great detail on their results, they lack the necessary information to implement their model. Lastly, we faced challenges when integrating snnTorch with PyTorch in a scale this big. Indeed, following the documentation of snnTorch, it is difficult to interpret the methodologies required to develop a model beyond a simple sequential architecture.

Though challenged, we should also note the accomplishments of the project; we have developed a custom dataloader for the MSCOCO dataset, reconstructed the general model of Barchid et al. (2021) network, and explored *snnTorch* and *PyTorch* on a smaller dataset (MNIST). All of which contributes to our ultimate goal of understanding the applications of neuroscience on a much deeper level.

All our attempts at implementation of the network are attached with this report and can also be found on the GitHub page for this project.

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