University of Tehran

COMPUTER SCIENCE DEPARTMENT

COMPUTATIONAL NEUROSCIENCE

REPORT 4

NEURAL ENCODING

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1 Neural Encoding

Various hypotheses of information representation in brain, referred to as neural codes, have been proposed to explain the information transmission between neurons. Neural coding plays an essential role in enabling the brain-inspired spiking neural networks (SNNs) to perform different tasks.
Various coding methods have been proposed to explain the information encoding mechanism, such as rate coding, temporal coding, phase coding, and burst coding. Rate coding utilizes spiking rates to represent information, and it has been a dominant paradigm in neuroscience and ANNs for decades because of its robustness and simple mechanism. Rate coding has been experimentally discovered in most sensory systems, such as visual cortex and motor cortex. However, rate coding scheme is limited by a lengthy processing period and slow information transmission. To explain efficient and fast response mechanism in our brain, temporal coding was hypothesized as a neural code that uses the precise spike timing to convey information in different forms, such as the timing of the first spike, the rank order between spikes, and relative spike latency. Time to first spike (TTFS) coding scheme transmits information to the destination neurons on the arrival of the first spike, which enables a super-fast transmission speed. Many experiments have pointed out the significance of the first spikes in various parts of our nervous system, such as retina, auditory systems, and tactile afferents. Various works have reported that applying TTFS coding scheme in SNNs can significantly reduce the number of spikes and improve inference speed.
A sequence of spikes may contain information based on different coding schemes. In some neurons the strength with which an postsynaptic partner responds may depend solely on the firing rate, the average number of spikes per unit time. At the other end, a complex temporal code is based on the precise timing of single spikes. They may be locked to an external stimulus such as in the visual and auditory system or be generated intrinsically by the neural circuitry. Whether neurons use rate coding or temporal coding is a topic of intense debate within the neuroscience community, even though there is no clear definition of what these terms mean.

- Rate Coding: The rate coding model of neuronal firing communication states that as the intensity of a stimulus increases, the frequency or rate of action potentials, or spike firing, increases. Rate coding is sometimes called frequency coding.

- Temporal Coding: When precise spike timing or high frequency firing rate fluctuations are found to carry information, the neural code is often identified as a temporal code. A number of studies have found that the temporal resolution of the neural code is on a millisecond time scale, indicating that precise spike timing is a significant element in neural coding. Such codes, that communicate via the time between spikes are also referred to as interpulse interval codes, and have been supported by recent studies.

2 Two Encoding Used In This Project

Here in this project, we get a picture as a matrix which its values of elements are between 0 and 255. One is Time-To-First-Spike(TTTS) and the other is positional encoding.

2.1 Time-To-First-Spike

Let us study a neuron which suddenly receives a new constant input at time t0. For example, a neuron might be driven by an external stimulus which is suddenly switched on at time t0. This seems to be somewhat artificial, but even in a realistic situation abrupt changes in the input are quite common. When we look at a picture, our gaze jumps from one point to the next. After each saccade, the photo receptors in the retina receive a new visual input. Information about the onset of a saccades should easily be available in the brain and could serve as an internal reference signal. We can then imagine a code where for each neuron the timing of the first spike after the reference signal contains all information about the new stimulus. A neuron which fires shortly after the reference signal is interpreted as a strong stimulation of this neuron, whereas firing somewhat later would signal a weaker stimulation.
In a pure version of this coding scheme, each neuron needs to fire only a single spike to transmit information. If it emits several spikes, only the first spike after the reference signal counts. All following spikes would be irrelevant. To implement a clean version of such a coding scheme, we imagine that each neuron is shut off by inhibition as soon as it has fired a spike. Inhibition ends with the onset of the next stimulus (e.g., after the next saccade). After the release from inhibition the neuron is ready to emit its next spike, which now transmits information about the new stimulus. Since each neuron in such a scenario transmits exactly one spike per stimulus, it is clear that only the timing conveys information and not the number of spikes. Experimental evidence indicates that a coding scheme based on the latency of the first spike transmit a large amount of information.
Now Let's see the encoding for some pictures:

1. First we choose a picture from the MNIST dataset. First let's see the picture:

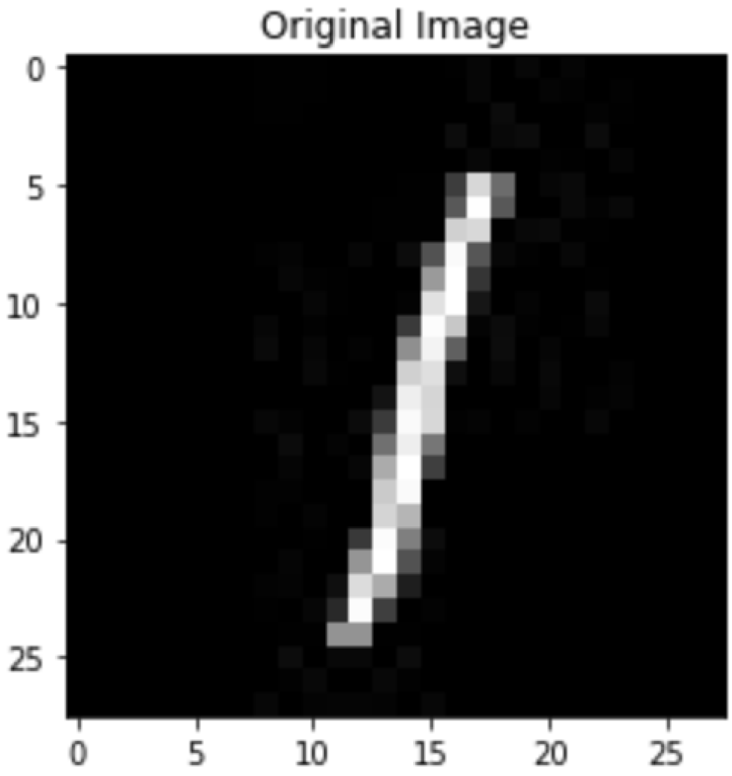

Figure 1: Picture From The MNIST Dataset

This is a picture of number one which is written by hand. The size of the picture is 28*28*3, So this a RGB image and we should convert this picture to a two-dimensional matrix which is 28*28 and its elements are between 0 and 255. In the following we decrease each elements of the image by the value of 255, by doing this the amount of intensity will be reversed. The other thing that we should do is to scale this image. At first we say the amount of time that this stimuli is present is T. In this project we presume that the amount of T is 50. So we scale the values of elements to 0 and T. At the end the neurons spike based on the pixel intensity(the number of neurons is equal to the number of pixels). Now let's see the raster plot of the TTTS encoding of this image:

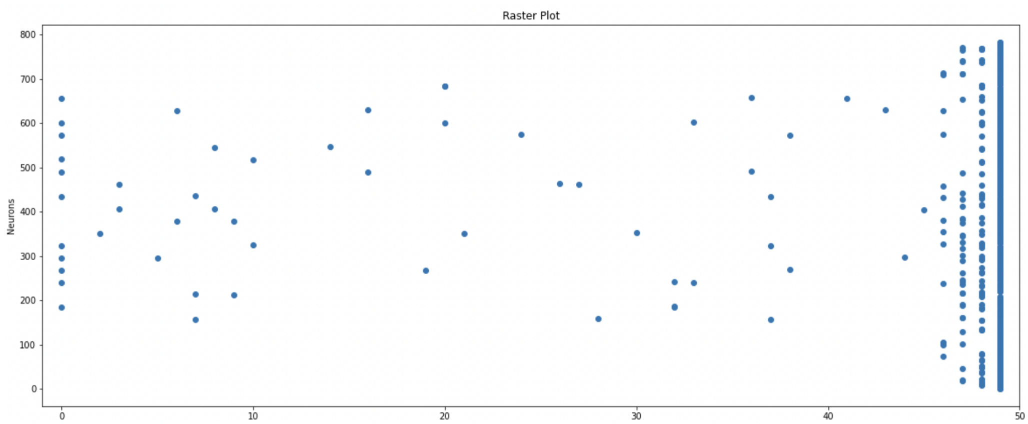

Figure 2: Raster Plot

2. Let's see more of images from MNIST dataset:

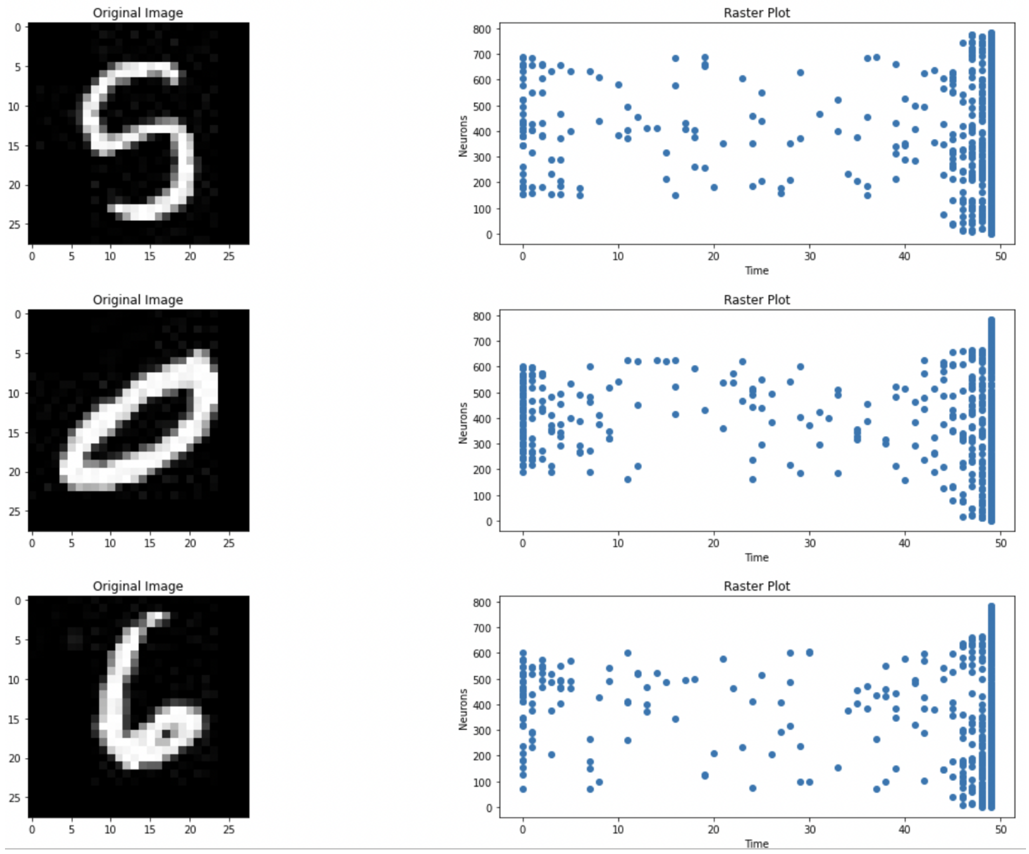

Figure 3: Raster Plot

As you see most of the pixels have low intensity, so we have more spikes at the end of the time.

3. Now Let's see this picture:

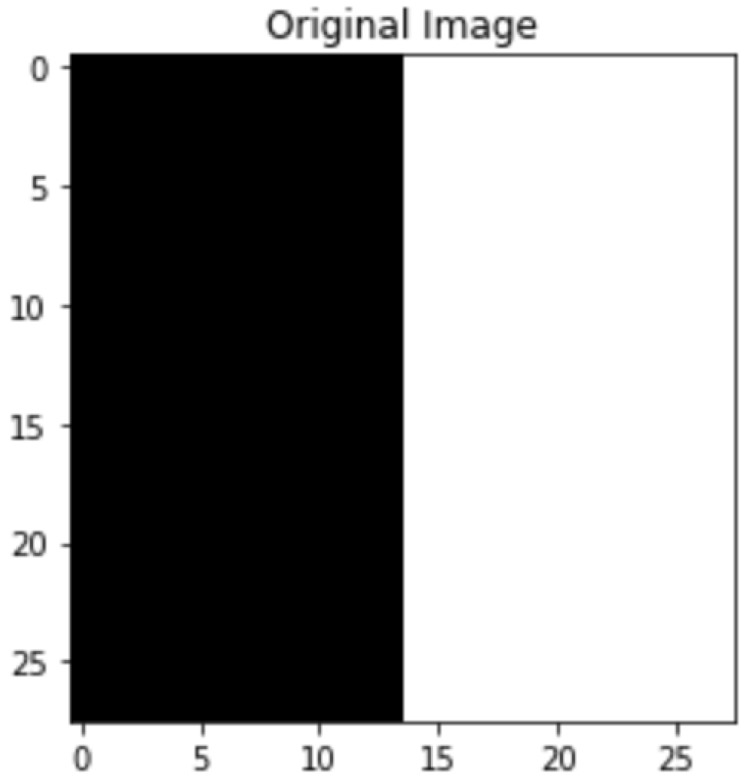

Figure 4: Black and White Picture

As you see half of the picture is black and the other half is white. What do you think of the TTTS encoding? Let's see:

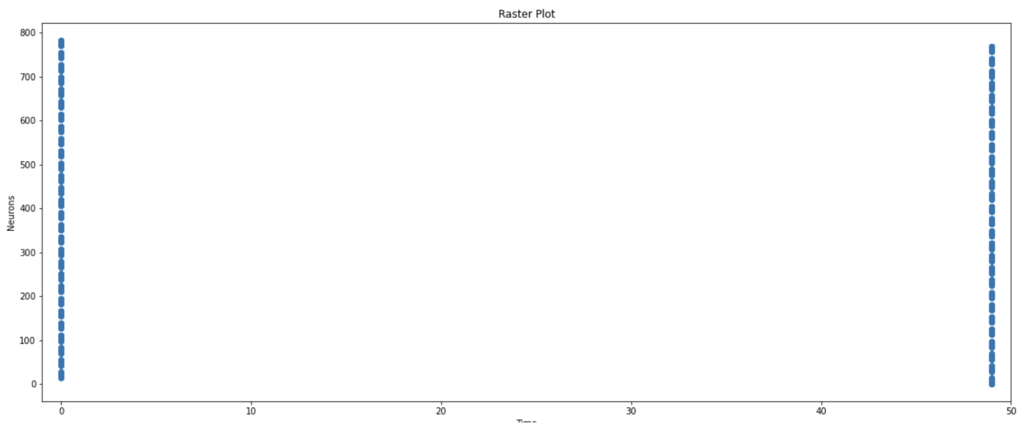

Figure 5: Raster Plot

Well the pixels of the dark side of the picture have low intensity and therefore they spike late at the end of the time. On the other hand the pixels of the white part have high intensity and they spike soon at the beginning of the time.

4. In the following we have an image which its pixels have variant intensity:

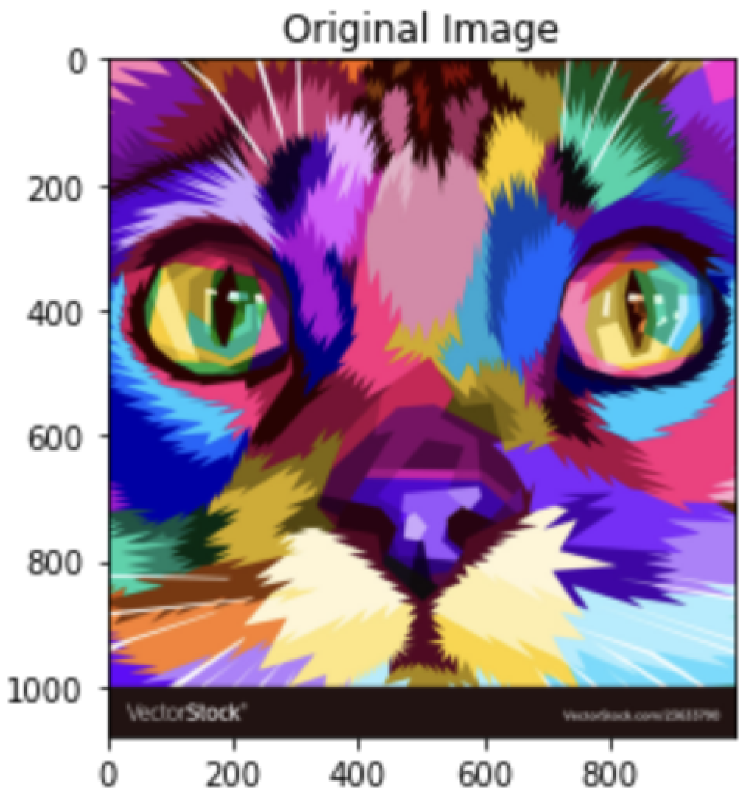

Figure 6: Picture From The MNIST Dataset

And this is the raster plot of the encoding of this image(we resize the pixel to 28*28 dimension):

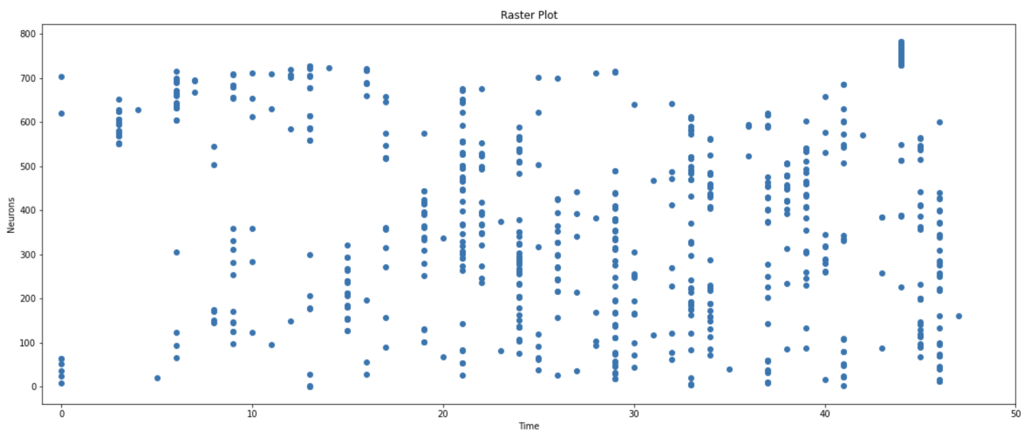

Figure 7: Raster Plot

The spikes recorded in the raster plot above have more gaps compared to the images of the MNIST dataset.

2.2 PositionEncoding

A typical population code involves neurons with a Gaussian tuning curve whose means vary linearly with the stimulus intensity, meaning that the neuron responds most strongly (in terms of spikes per second) to a stimulus near the mean. The actual intensity could be recovered as the stimulus level corresponding to the mean of the neuron with the greatest response. This type of code is used to encode continuous variables such as joint position, eye position, color, or sound frequency. Any individual neuron is too noisy to faithfully encode the variable using rate coding, but an entire population ensures greater fidelity and precision. For a population of unimodal tuning curves, i.e. with a single peak, the precision typically scales linearly with the number of neurons. Hence, for half the precision, half as many neurons are required. In contrast, when the tuning curves have multiple peaks, the precision of the population can scale exponentially with the number of neurons. This greatly reduces the number of neurons required for the same precision.
Now Check the picture below:

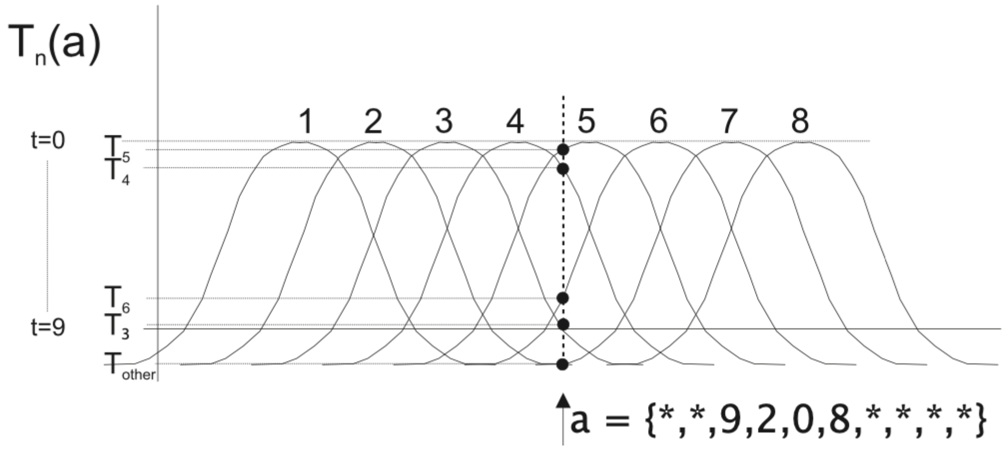

Figure 8: Position Encoding

An optimally stimulated neuron fires at t = 0, whereas a value up to say t = 9 is assigned to less optimally stimulated neurons. Now When a stimulant a is injected to the model, Neurons will fire based on the cross of the stimuli a to the gaussian functions. Here we have 8 functions, therefore we have 8 neurons and according to the figure 8 neuron 5 spikes first because the first cross happens at t=0 and last neuron for spiking is 3.
In this project we choose 10 neurons(gaussian functions) and The time that the picture(stimuli) presents is T=50. First we get the image which its elements are between 0 and 255, then we normalize image by dividing to 255 so the range of elements is between 0 and 1. Now we loop by the amount of neurons which is 10 and in every iteration, we apply one of the gaussian function to the image. The mean of neurons(gaussian functions) is $\frac{(i+1)\times neuronSize}{T\times 2}$, which i is the number of iteration($\{1, 2, \cdots, 10\}$). At the end we multiply every elements of the result of previous step by T, so the values of elements are between 0 and T. So now we know when neurons spike. In the following we see some examples:

1. First let's see the image:

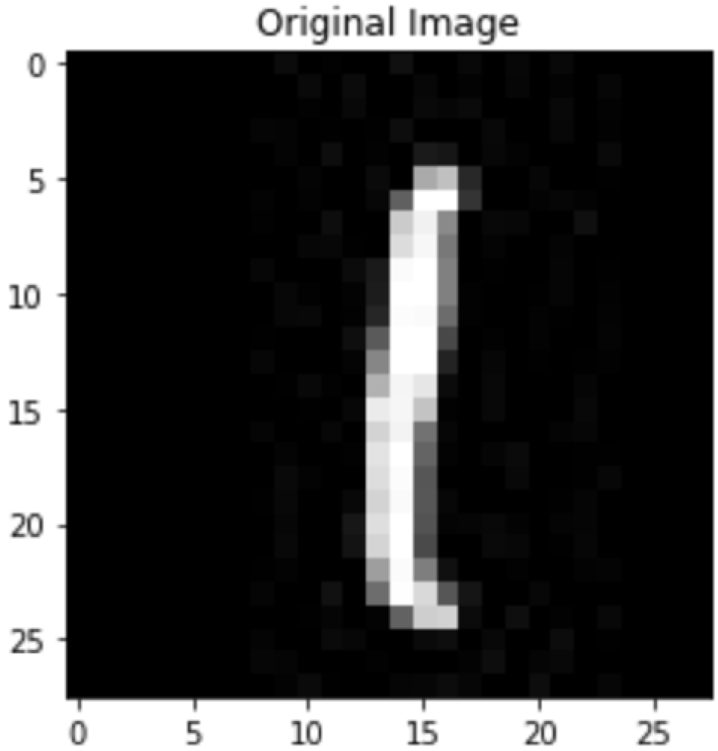

Figure 9: Original Image

Now check the encoding of the image above using the position coding:

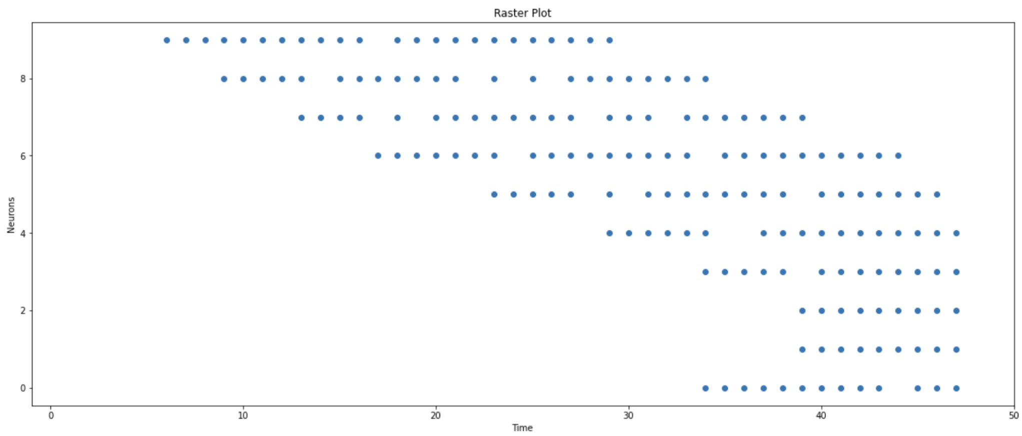

Figure 10: Raster Plot

according to the raster plot, we can say that neurons with less spikes are neuron one and two. that's because they had less intersection with the stimuli injected from the pixels of the image. The first neuron that spikes in the raster plot is neuron 10. It means there is a pixel with some value that it was near the mean of the last gaussian function(lat neuron).
Let's see more of images from MNIST dataset:

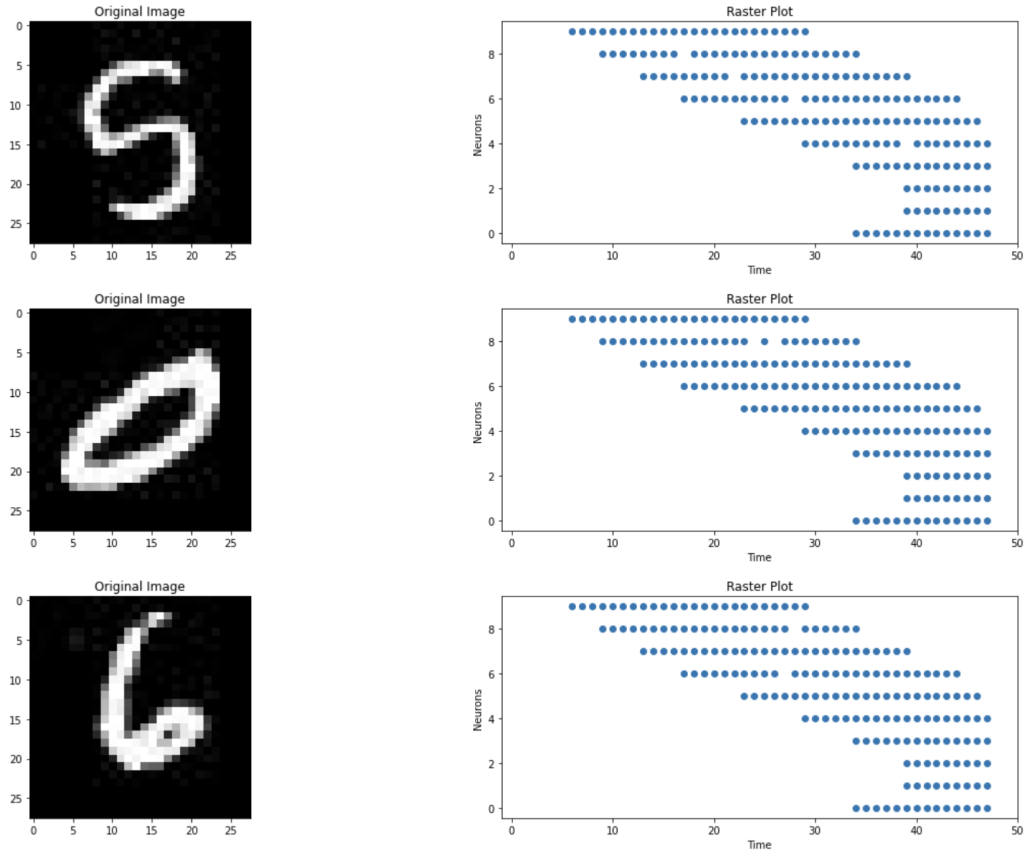

Figure 11: Raster Plot

You can see that these encoding are nearly similar. That's because the pixel values of the images are similar, therefore time-to-first-spike encoding is better for this dataset.

2. Now we consider a white image and see what its raster plot will look like:

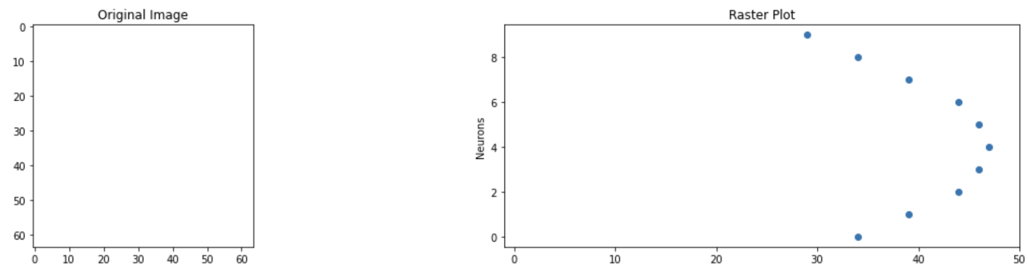

Figure 12: White Image and Raster Plot

All of the pixels have the value of 255. In this case there is only one stimulant injected to the model. This stimulant intersects all of the gaussian function and the timings apparent like figure 8.

3. Now we consider a black image and see what its raster plot will look like:

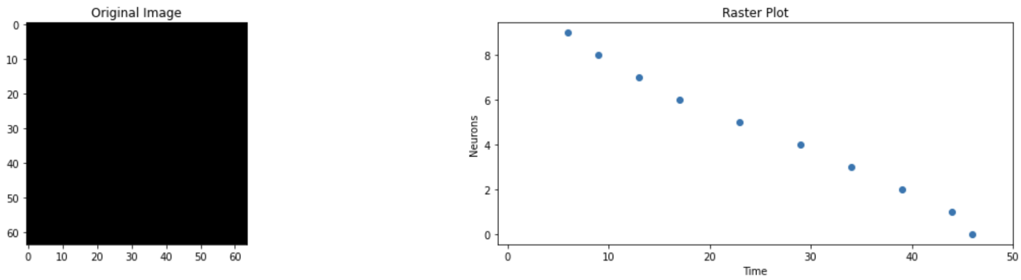

Figure 13: Black Image and Raster Plot

All of the pixels have the value of 0. Also in this case there is only one stimulant injected to the model. This stimulant intersects all of the gaussian function and we have the raster plot above.

4. Now we give the black and white image like figure 4. The raster plot will look like:

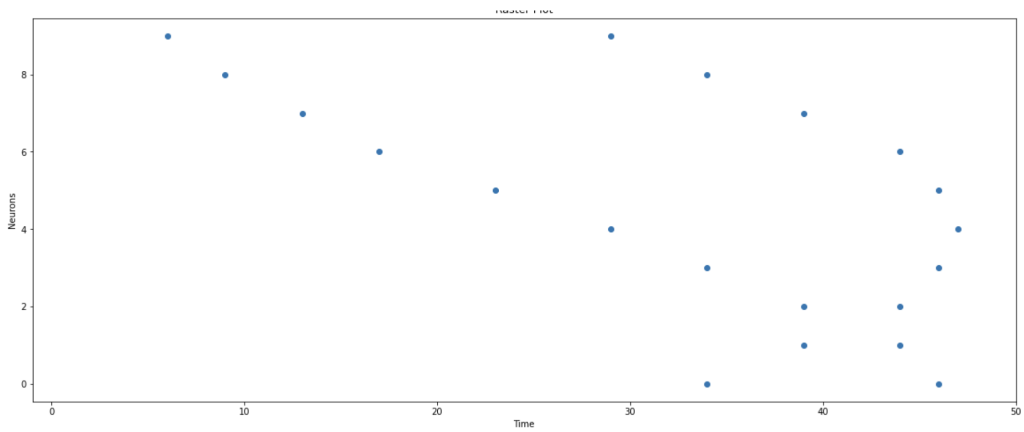

Figure 14: Black and White Image and Raster Plot

As expected the result is the combination of the encoding of the white image and the black image.

5. Now let's see this picture:

Figure 15: Original Image

The raster plot will be:

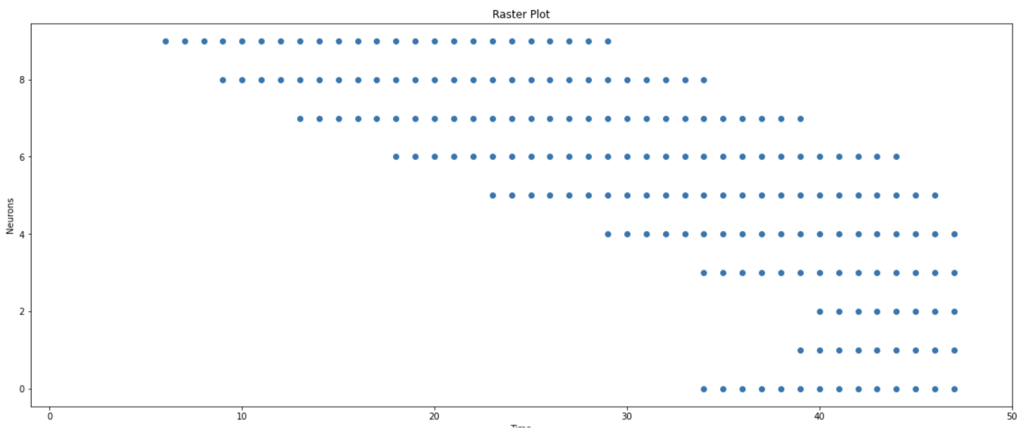

Figure 16: Raster Plot

2.3 Summary

Time to First Spike (TTFS) encoding is a computational strategy observed in certain neurons within the nervous system. It refers to the concept that the timing of the first action potential, or spike, in a neuron's response to a stimulus carries important information. Instead of encoding stimulus intensity in the firing rate of action potentials, these neurons encode information by the precise timing of the first spike relative to the onset of the stimulus. In TTFS encoding, the exact time at which the first spike occurs is crucial

in conveying the stimulus information. Neurons employing this encoding strategy are highly sensitive to temporal aspects of the input, and they can accurately detect fine temporal features of the stimuli. This encoding mechanism is particularly relevant in sensory systems that require precise timing information, such as sound localization in the auditory system or the detection of fast-moving objects in the visual system.
Position encoding involves neurons with a Gaussian tuning curves like figure 8, meaning that the neuron responds most strongly to a stimulus near the mean. The actual intensity could be recovered as the stimulus level corresponding to the mean of the neuron with the greatest response.
Overall, both time to first spike encoding and position encoding are important mechanisms through which the nervous system processes and represents information. While TTFS encoding emphasizes the precise timing of the first spike relative to stimulus onset, position encoding focuses on the neural representation of an organism's spatial location within its surroundings(it represents numbers which shows the time that a special neuron spikes).

HAVE FUN !!

3 References

[1] Gerstner, Wulfram and Kistler, Werner and Naud, Richard and Paninski, Liam. (2014). Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition. 10.1017/CBO9781107447615.

[2] Neural Coding in Spiking Neural Networks: A Comparative Study for Robust Neuromorphic Systems https://www.frontiersin.org/articles/10.3389/fnins.2021.638474/full#F2

[3] Neural Coding https://en.wikipedia.org/wiki/Neural_coding#cite_note-Mat-59