

# Study the effect of activation functions on implicit representation

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*Project proposal for 300597 Master Project 1*

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Spring, 2020

## 1 Background

Artificial neural networks have been proved effective for tasks like prediction and forecasting. They have been successfully applied to complex problems. The computing fraternity is striving hard to enhance the performance of these networks by exploring various components including the activation functions. In the recent past, implicit representation has been explored by various researchers. It was found that sine function can be far superior in tasks like implicit representation as compared to its counterparts. The goal is to learn an implicit function that takes spatio-temporal coordinates as input and return the signal value at the respective location [5].

## 2 Objective

We are interested in a function that is implicitly defined by the relation function and the neural network should be able to parameterize the function. This is also called implicit representation[2]. If the neural network can learn the parameter with data, it will lead to a better representation. The implicit representation can be more memory efficient as compared to discrete representations [3]. It can even be used for calculating the higher gradient analytically due to its differential nature. We will be exploring the possibility of using sine as an activation function for creating implicit neural network networks instead of some other popular activation functions like 'ReLU'[4]. Though, some research

has shown promising results with ReLU, it is not always capable of representing the fine details of the signals.

Problem with ReLU:

*ReLU function:*  $f(x) = x, x > 0$

*First derivative:*  $f'(x) = 1, x > 0$

*Second derivative:*  $f''(x) = 0, x > 0$

So, ReLU is unable to give fine results in the case of higher-order derivatives.

### 3 Scope

This scope of this project is huge as neural networks are used in every field now.

- Demonstrate the capability of neural networks using SIRENs (sinusoidal representation networks) in the reconstruction of images, and the analysis of audio and video signals.
- Proposing a principle initialized scheme by analysing the activation statistics of SIREN. Demonstration of images, sounds with their derivatives.

### 4 Methodology

The remaining of this document details the requirement, specialized methodology, anticipated outcomes, and the plan for project management. These segments will depict how to provide a better solution for problem statements and accomplish the designated scope for the semester.

#### 4.1 PRELIMINARY REQUIREMENTS

1. A detailed explanation of methods should be provided for representing the signals.
2. The results should be based on experimental outcomes.
3. The model should provide a satisfactory accuracy.

#### 4.2 TECHNICAL APPROACH

Activation functions play a crucial part in neural networks. They not only provide non-linearity but also help to calculate the gradient. In implicit representation, these activation functions become even more important. The reconstruction of signals using various activation functions will provide an insight into how good these activations are in understanding the underlying relationship[1]. We will be exploring various activation functions like 'ReLU', 'Tanh' for the reconstruction of signals. After performing the experiment, we will compare their results with sine activation. Applying the various activation functions on the different types of signals would be the appropriate and most

optimal way to understand the merits and demerits of these networks. All the factors such as loss function and optimal initializing technique will be considered during the experiment.

### **4.3 Requirements Development**

The requirement of the research will be divided into various categories of gathering diverse data, operations, and using various functions. Various statistical methods will be used for determining the outcome of the model.

### **4.4 Model Development**

Development iterations are expected to be based on the modification of the feature set, algorithm selection, and algorithm parameters. The foremost step will be data gathering. We will work with different kinds of images, audios and videos. Starting from simple shape images to complex images and audio. The outcomes of shallow neural networks for the reconstruction of images with different activation functions will be analyzed first. Python and some of its popular libraries like sklearn will be used for analyzing the various networks. By default sklearn only provide the implementation of 'identity', 'logistic', 'tanh' and 'ReLU' activation functions, So either we need to make some changes in the Sklearn base library or create our own version of the sine activation function for deep convolutional neural networks. The Jupyter notebook for creating the shallow networks and the colab for creating convolutional deep neural networks should be a suitable environment for analyzing the networks. The most difficult obstacle model needs to overcome is to work with an extremely small data set. Moreover, if a model is unable to adjust and initialize weights properly it might result in skewed results. Another, most important thing is to consider appropriate loss function for proper learning of the networks.

## **5 EXPECTED RESULTS**

The research will result in two major deliverable:

- An efficient method developed to map the signal coordinates to its values. A detailed narrative of what functions are used, why, and how they are chosen will be submitted.
- A functional model will be submitted for the implicit neural representation of the different signals like images and videos.

## **6 MANAGEMENT APPROACH**

The project is divided into five different tasks: pre-study and research , working of neural network , comparisons of activation functions, model creation and using it for different

signals and a final deliverable report.

## References

- [1] Kyle Genova et al. “Deep Structured Implicit Functions”. In: (Dec. 2019).
- [2] Kyle Genova et al. “Learning Shape Templates With Structured Implicit Functions”. In: Oct. 2019, pp. 7153–7163. DOI: 10.1109/ICCV.2019.00725.
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- [5] Vincent Sitzmann et al. “Implicit Neural Representations with Periodic Activation Functions”. In: (June 2020).

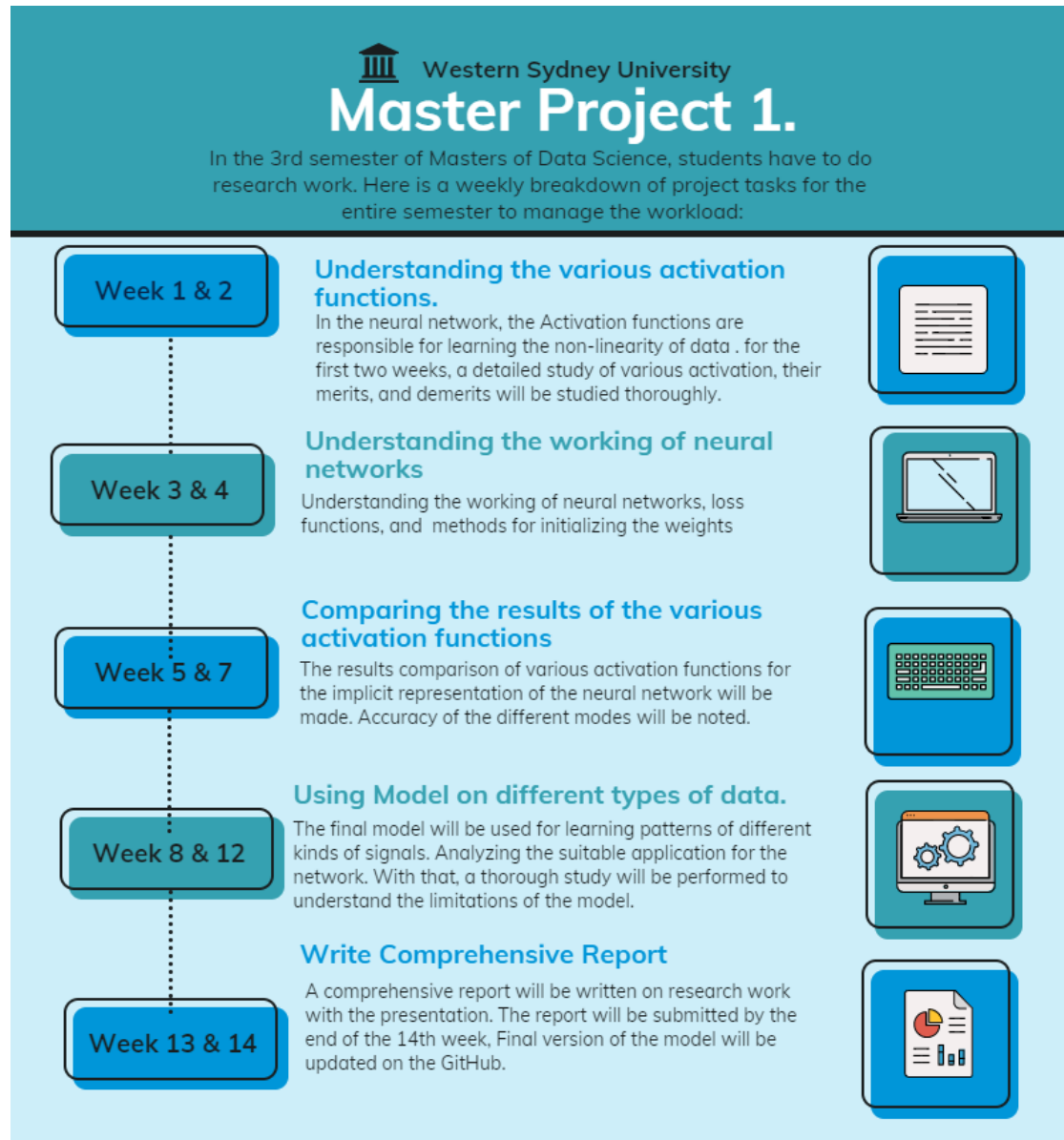


Figure 1: Work Flow