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L07 Neural Networks Playground

TensorFlow Playground website: https://playground.tensorflow.org

Introduction

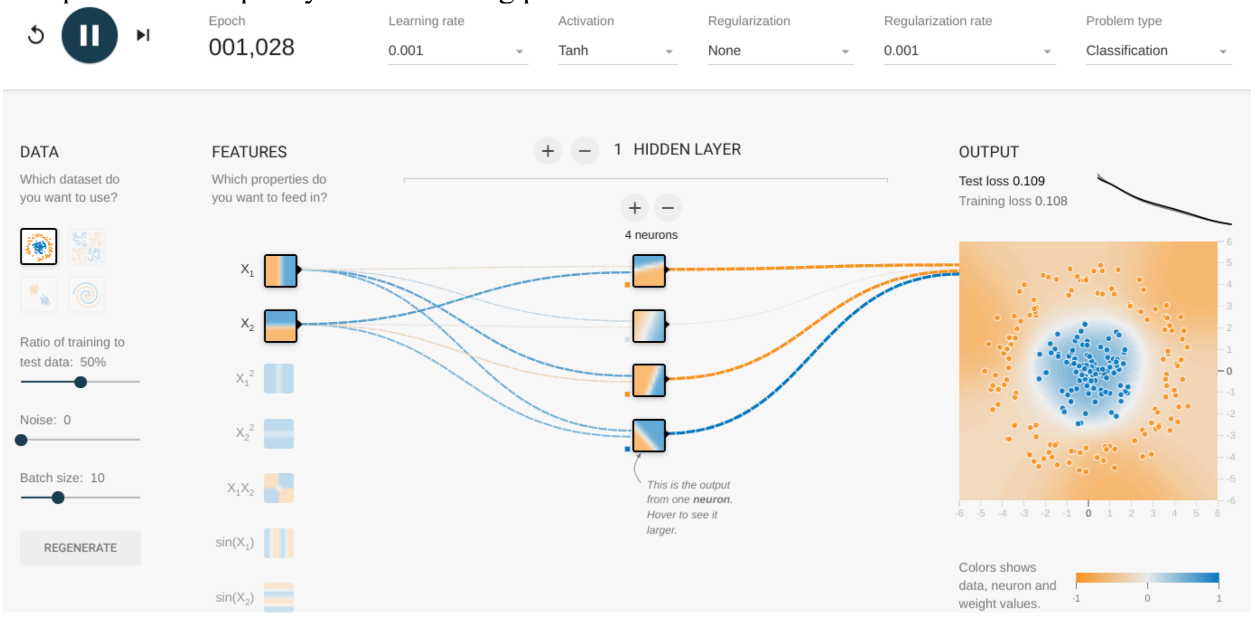
In this report, I will detail my investigation into neural networks (NNs), which I've learned are a fascinating subset of machine learning algorithms directly inspired by the structure and function of the human brain. These networks are not just abstract models; they are powerful, interconnected systems composed of fundamental units called "neurons" or nodes, organized into distinct layers. My foundational understanding is that a standard NN architecture includes an input layer to receive data, one or more hidden layers to perform complex feature extraction, and an output layer to produce the final prediction. Crucially, every connection between these neurons has an associated weight, and each neuron possesses an associated bias. The fundamental goal of the network is to learn by iteratively adjusting these weights and biases through a process called backpropagation, all to minimize the loss function the difference between the network's predicted output and the actual correct output. My objective for this project was to use the interactive tool TensorFlow Playground to gain essential hands-on experience and understand how various critical hyperparameters and data characteristics affect a network's overall performance. Specifically, this report will investigate how activation functions, the number of neurons in hidden layers, the learning rate, data noise, and the complexity of the dataset all influence the network's speed, stability, and ability to generalize.

Key components:
Neurons: These are the fundamental computational units of the network, sometimes referred to as interconnected nodes. Described as the basic elements, they accept inputs, process them using an activation function, and then generate an output. The number of neurons in a hidden layer determines the network's capacity; more neurons allow it to represent more intricate functions, but too few can lead to underfitting because the network lacks the capacity to capture the complexities of the data.
Weights: These are variables that define the strength or intensity of the connection between neurons. Every connection in the network has an associated weight. The entire learning process for a neural network involves adjusting these weights to minimize the error between the network's prediction and the actual result. The learning rate is what governs the size of the step taken when these weights are updated during training.
Biases: These are factors that allow neurons to shift their activation function, providing more flexibility to the model. Each individual neuron has an associated bias. Similar to weights, biases are adjusted during the training process to help the network better fit the data and minimize the overall loss.
Activation Functions: These are non-linear functions applied by neurons that introduce non-linearity into the network, which is essential for learning complex patterns.
Learning Rate: A factor that regulates the size of the step during the update of weights.
Loss Function: A function that measures the discrepancy between the predicted result and the true result.

Experimental Results:

Task 1 (Activation Functions):

Setup and Experiment: In this first task, my goal was to experiment with different activation functions to see how they affected my network's performance. I learned that activation functions are crucial because they introduce non-linearity into the network, which allows it to learn complex patterns instead of just simple ones. For my experiment, I used a single hidden layer and tested the ReLU, Sigmoid, and Tanh functions on a simple classification dataset to observe their effects. I found that the choice of activation function had a very significant impact on both the speed and the quality of the learning process.



Epoch 001,028
Learning rate 0.001
Activation Tanh
Regularization None
Regularization rate 0.001
Problem type Classification

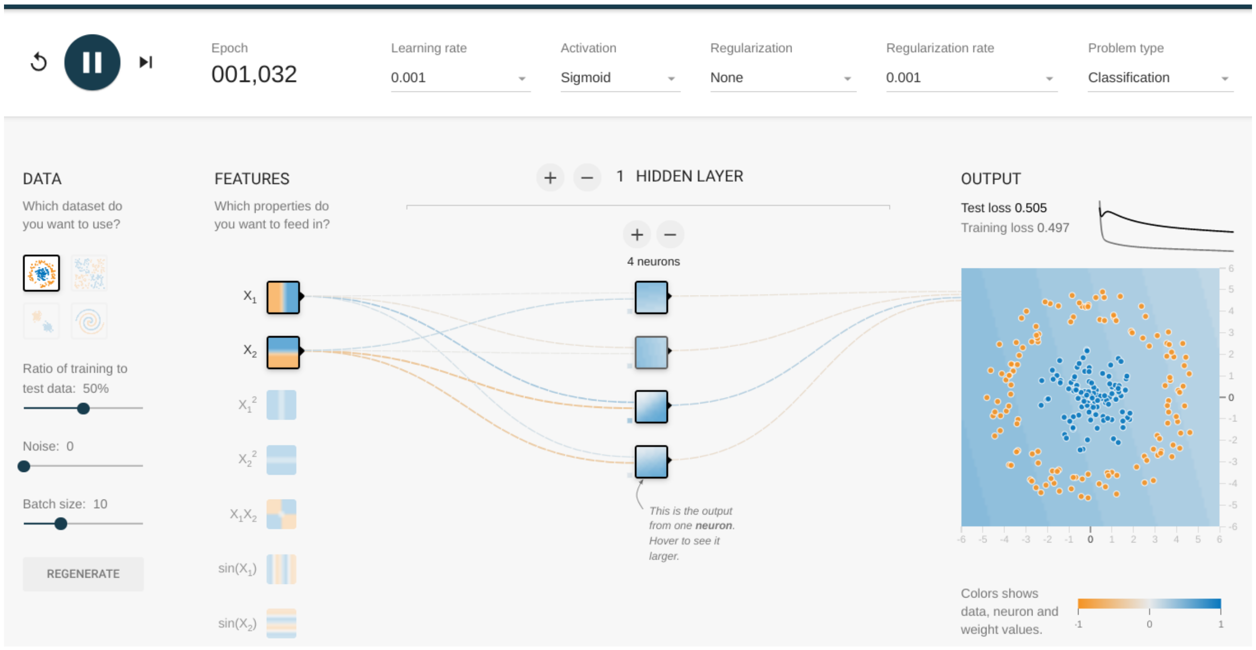
Ratio of training to test data: 50%
Noise: 0
Batch size: 10

1 HIDDEN LAYER
4 neurons

Test loss 0.109
Training loss 0.108

DATA
Which dataset do you want to use?
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
This is the output from one **neuron**. Hover to see it larger.
OUTPUT
Colors shows data, neuron and weight values.
-1
0
1

Sigmoid: When I switched to the Sigmoid function, I immediately noticed that the network's training process became much slower. The decision boundary that the network created was smooth, but it was often not as precise as the one from ReLU, especially for more complex patterns. I learned that the Sigmoid function squishes all output values to be between 0 and 1, which can be useful for binary classification tasks. However, this also causes the function to saturate, or flatten out, at both ends, which can lead to the vanishing gradient problem and slow down the learning process considerably.


Epoch 001,032
Learning rate 0.001
Activation Sigmoid
Regularization None
Regularization rate 0.001
Problem type Classification

DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10

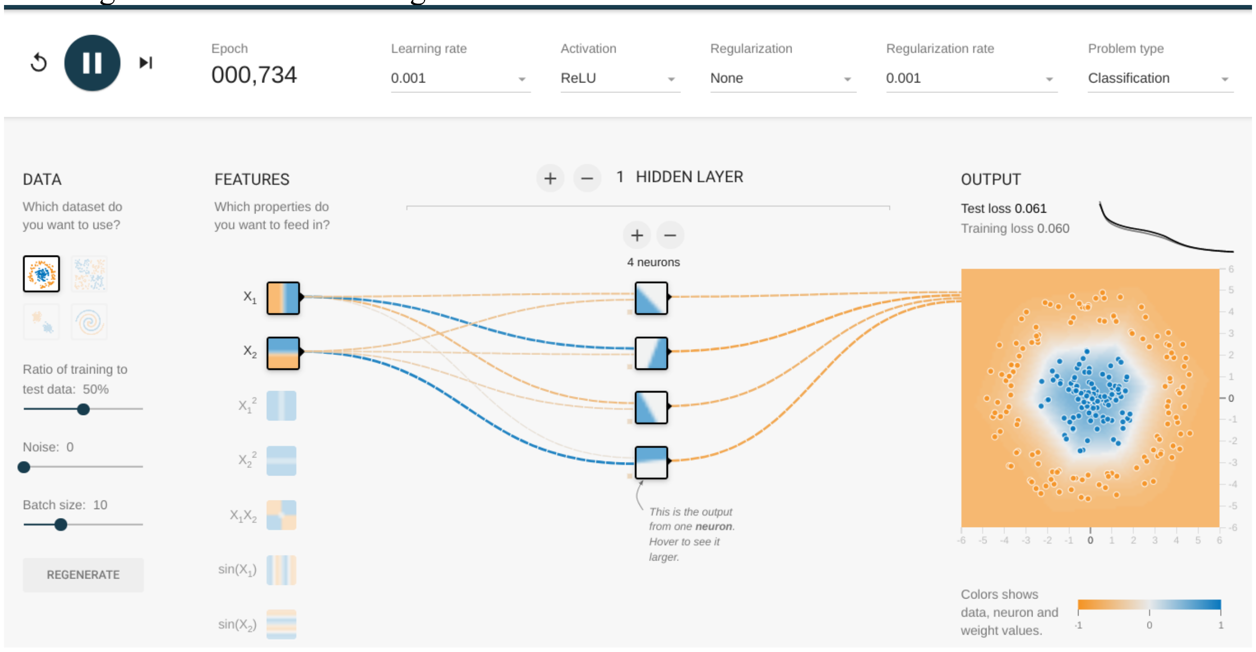
FEATURES
Which properties do you want to feed in?

1 HIDDEN LAYER
4 neurons

OUTPUT
Test loss 0.505
Training loss 0.497

REGENERATE
X₁
X₂
X₁²
X₂²
X₁X₂
sin(X₁)
sin(X₂)
This is the output from one neuron. Hover to see it larger.
Colors shows data, neuron and weight values.
-1
0
1

ReLU (Rectified Linear Unit): I observed that my network learned significantly faster and more effectively when I used the ReLU activation function. The final decision boundary it created was very sharp and accurately separated the data points. I understood that ReLU works by simply outputting the input value if it is positive and zero otherwise, which is a very efficient computation. This direct, linear behavior for positive inputs helps to prevent the "vanishing gradient problem," a common issue that can slow down or stop learning in other functions, allowing for much faster training.


Epoch 000,734
Learning rate 0.001
Activation ReLU
Regularization None
Regularization rate 0.001
Problem type Classification

DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10

FEATURES
Which properties do you want to feed in?

1 HIDDEN LAYER
4 neurons

OUTPUT
Test loss 0.061
Training loss 0.060

REGENERATE
X₁
X₂
X₁²
X₂²
X₁X₂
sin(X₁)
sin(X₂)
This is the output from one neuron. Hover to see it larger.
Colors shows data, neuron and weight values.
-1
0
1

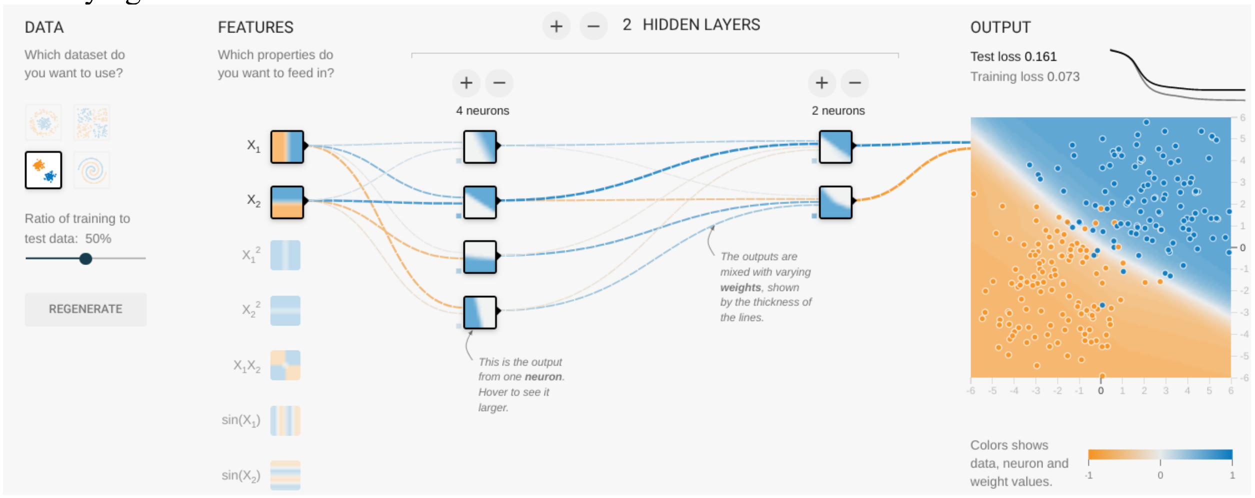
Tanh: The Tanh function seemed to be a middle ground in my experiment. I found that it performed better than Sigmoid but was still not as fast or as effective as ReLU for this problem. Tanh is like Sigmoid, but it outputs values between -1 and 1, which I learned is generally better for hidden layers because it can produce both positive and negative outputs. Despite this advantage, it can still suffer from the same vanishing gradient problem as Sigmoid, which limits its overall performance compared to ReLU.

Observations and Explanation: In my experiment on activation functions, I observed that ReLU generally outperformed Sigmoid in terms of both convergence speed and final accuracy. My initial tests showed that when I used the Sigmoid function, the network's training process was significantly slower, and the resulting decision boundaries were often less precise. This occurred because of Sigmoid's tendency to saturate (output values near 0 or 1), which caused the vanishing gradient problem and severely hindered the learning procedure. In contrast, ReLU's linear response to positive inputs facilitated much quicker gradient descent and allowed the network to learn the pattern more efficiently. From this task, I concluded that ReLU is generally the superior choice for hidden layers in most classification tasks due to its speed and efficiency, confirming that its design avoids the saturation problems that can seriously hinder the learning process in other traditional functions.

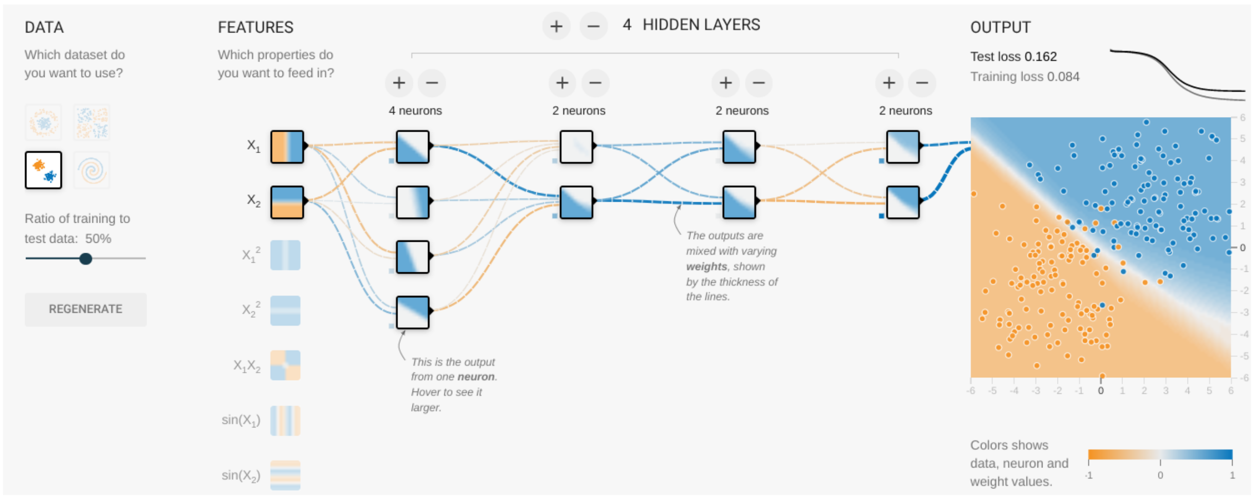
Task 2 (Hidden Layer Neurons):

Setup and Experiment: For my second task, I wanted to understand how the number of neurons in a hidden layer affects the network's ability to learn. Neurons are the basic computational units, so I reasoned that changing their number would change the network's overall capacity to learn. Using the ReLU activation function, I experimented by changing the number of neurons in my single hidden layer to see how it impacted the decision boundary and overall accuracy. This experiment showed me that finding the right number of neurons is a critical balancing act.

Few Neurons (e.g., 2): When I used only a few neurons, I saw that the network really struggled to learn the pattern in the data. It created a very simple and often inaccurate decision boundary because it simply lacked the capacity to represent the complex relationships in the dataset. I now understand that this situation is called underfitting, where the model is too simple to capture the underlying structure of the data.


Ratio of training to test data: 50%
2 HIDDEN LAYERS
4 neurons
2 neurons
Test loss 0.161
Training loss 0.073
This is the output from one **neuron**. Hover to see it larger.
The outputs are mixed with varying **weights**, shown by the thickness of the lines.
Colors shows data, neuron and weight values.

Moderate Neurons (e.g., 4): I found that using a moderate number of neurons achieved a very good balance between accuracy and complexity for my dataset. The network was powerful enough to learn the data's pattern and produce a well-defined, accurate decision boundary without becoming overly complicated. This seemed to be the optimal configuration for this particular problem, as it learned the pattern without memorizing the noise.

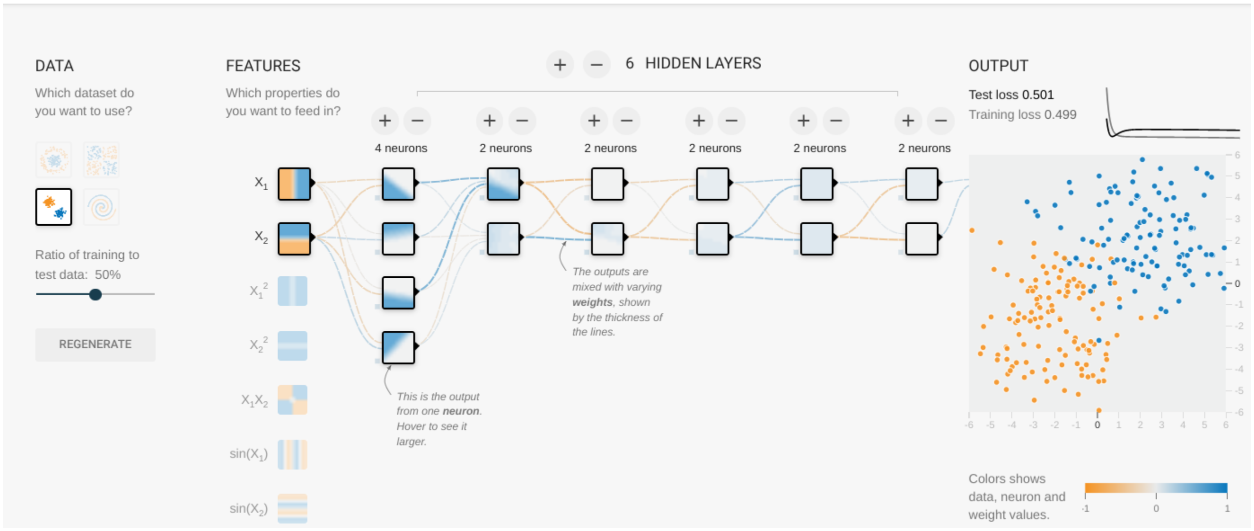

DATA
Which dataset do you want to use?
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
This is the output from one **neuron**. Hover to see it larger.
The outputs are mixed with varying **weights**, shown by the thickness of the lines.
OUTPUT
Colors shows data, neuron and weight values.

Ratio of training to test data: 50%

4 HIDDEN LAYERS: 4 neurons, 2 neurons, 2 neurons, 2 neurons

Test loss 0.162
Training loss 0.084

Many Neurons (e.g., 6): With a large number of neurons, I observed that the network was able to learn the training data perfectly, achieving very high accuracy on it. However, I also noticed that the decision boundary became extremely complex and seemed to follow individual noisy data points. This phenomenon, I learned, is called overfitting, where the network essentially memorizes the training data instead of learning the general pattern, which would likely cause it to perform poorly on new, unseen data.


DATA
Which dataset do you want to use?
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
This is the output from one **neuron**. Hover to see it larger.
The outputs are mixed with varying **weights**, shown by the thickness of the lines.
OUTPUT
Colors shows data, neuron and weight values.

Ratio of training to test data: 50%

6 HIDDEN LAYERS: 4 neurons, 2 neurons, 2 neurons, 2 neurons, 2 neurons, 2 neurons

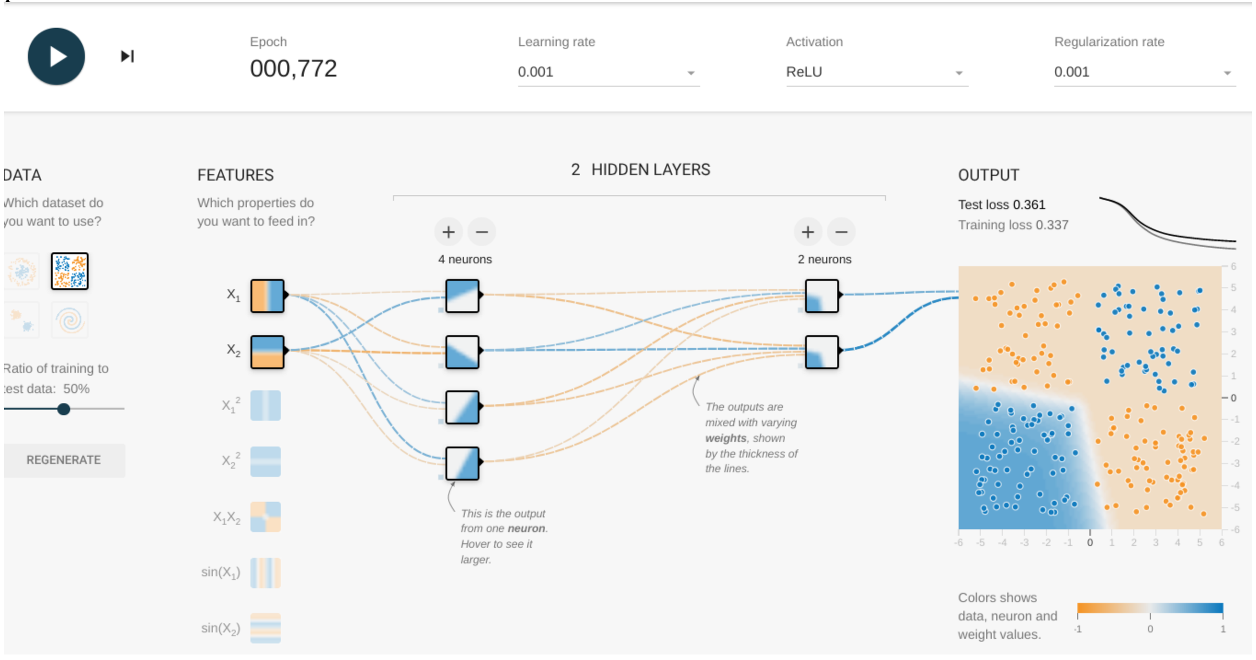
Test loss 0.501
Training loss 0.499

Observations and explanation: My experiments showed that increasing the number of neurons directly increases the network's capacity , which allows it to represent more intricate functions. However, I also found that this approach increases the risk of overfitting.I learned that an optimal number of neurons exists for each specific dataset, and my goal is to find this balance between the network's complexity and its ability to generalize to new, unseen data. If I add too many neurons, the model risks memorizing the training data (overfitting) instead of learning the fundamental structure and extending it to unfamiliar data. This crucial task taught me that I must find the right balance to ensure the model is both efficient This task is crucial to find the right number of neurons to balance the network's capacity and its ability to generalize. Too few neurons will lead to underfitting, while too many can lead to overfitting and poor performance on real-world data.

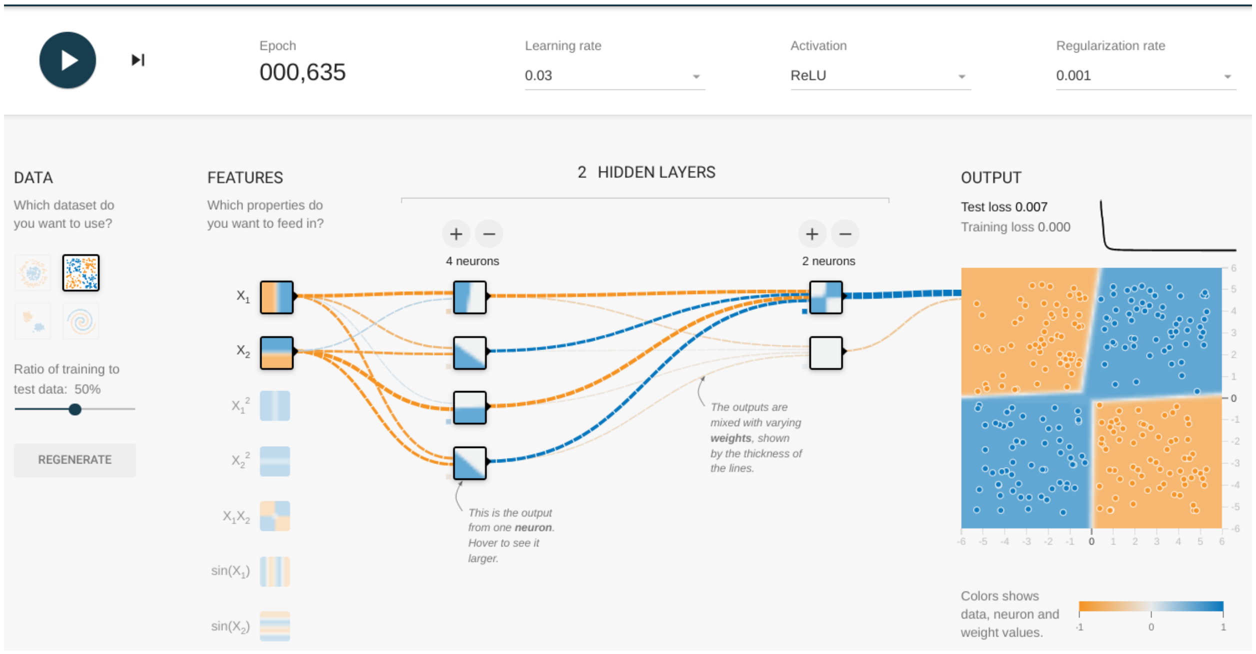
Task 3 (Learning Rate): Detail convergence speed and accuracy changes.

Setup and Experiment: In this task, I adjusted the learning rate to see its effect on the speed and stability of the training process. I learned that the learning rate is a hyperparameter that controls how large the steps are when the network updates its weights during training. A well-chosen learning rate can make the difference between a model that trains efficiently and one that fails to learn at all. I experimented with low, moderate, and high learning rates to observe these effects directly.

Low Learning Rate (e.g., 0.001): When I set the learning rate to a very low value, I saw that the network learned in a very stable and predictable way, but it was incredibly slow. The loss decreased very gradually, and it would have required a huge number of training steps (epochs) to reach a good solution. While safe from instability, this approach was far too inefficient for practical use.


Epoch 000,772
Learning rate 0.001
Activation ReLU
Regularization rate 0.001
Test loss 0.361
Training loss 0.337
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
REGENERATE
FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
4 neurons
2 neurons
This is the output from one neuron. Hover to see it larger.
The outputs are mixed with varying weights, shown by the thickness of the lines.
OUTPUT
Colors shows data, neuron and weight values.

Moderate Learning Rate (e.g., 0.03): This learning rate provided what I found to be an excellent balance between training speed and stability. I watched as the network converged on a good solution quickly and efficiently, with the loss steadily decreasing without any major fluctuations. This represented an optimal setting where learning was both fast and effective.


Epoch 000,635

Learning rate 0.03

Activation ReLU

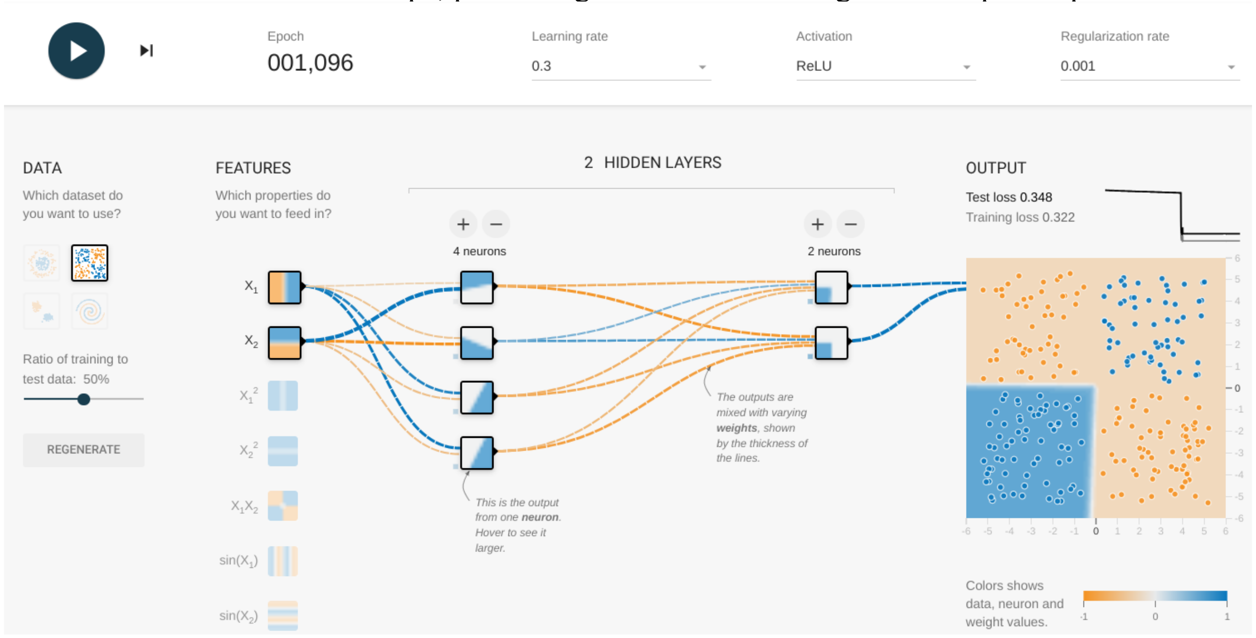
Regularization rate 0.001

Test loss 0.007

Training loss 0.000

DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
REGENERATE
FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
4 neurons
2 neurons
The outputs are mixed with varying weights, shown by the thickness of the lines.
This is the output from one neuron. Hover to see it larger.
OUTPUT
Colors shows data, neuron and weight values.

High Learning Rate (e.g., 0.3+): When I used a high learning rate, the training process became very unstable and erratic. The accuracy and loss values jumped around wildly from one step to the next, and the network often failed to converge on a good solution entirely. I learned that this happens because the updates to the weights are so large that the optimizer keeps overshooting the best solution in the loss landscape, preventing it from ever settling into the optimal point.


Epoch 001,096

Learning rate 0.3

Activation ReLU

Regularization rate 0.001

Test loss 0.348

Training loss 0.322

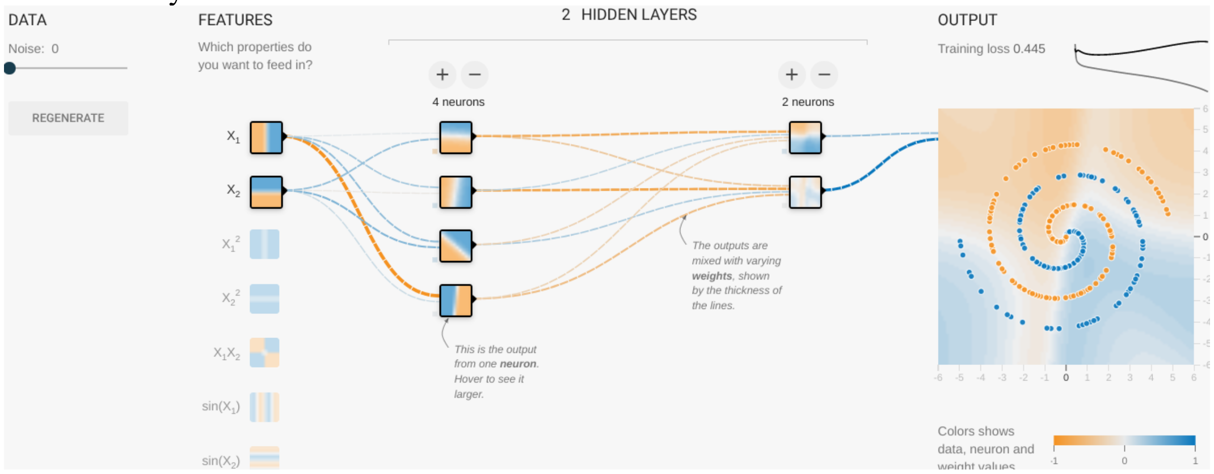
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
REGENERATE
FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
4 neurons
2 neurons
The outputs are mixed with varying weights, shown by the thickness of the lines.
This is the output from one neuron. Hover to see it larger.
OUTPUT
Colors shows data, neuron and weight values.

Observations and Explanation: My experiments confirmed that the learning rate significantly impacts both convergence speed and stability. I found that the learning rate is one of the most important parameters I need to tune when building a network because it governs the magnitude of each step taken when the weights are modified. A low learning rate is stable but incredibly slow, causing my network to take forever to reach an optimal solution. Conversely, a high learning rate is fast but often unstable, causing the optimizer to take such large steps that it may overshoot the optimal solution and fail to converge altogether. I realized that the goal is to find an optimal learning rate that allows for efficient and stable learning, where the network can make meaningful progress quickly without becoming erratic.

Task 4 (Data Noise): Analyze generalization capability with noise.

Setup and Experiment: For my fourth task, I investigated how adding noise to the training data affects the network's ability to generalize to new data. I understood that real-world data is rarely perfect and often contains noise, so it is important for a model to be robust. By using the "Noise" slider in TensorFlow Playground, I could add random variations to the data points and observe how my network coped with this added challenge.

Low Noise (0): With no noise in the data, my well-configured network had no trouble learning the pattern. I saw it produce a very clean and accurate decision boundary that perfectly separated the two classes of data points. This was the ideal scenario, where the underlying pattern was clear and easy to learn.


DATA
FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
OUTPUT
REGENERATE
X1
X2
This is the output from one neuron. Hover to see it larger.
The outputs are mixed with varying weights, shown by the thickness of the lines.
Colors shows data, neuron and weight values.

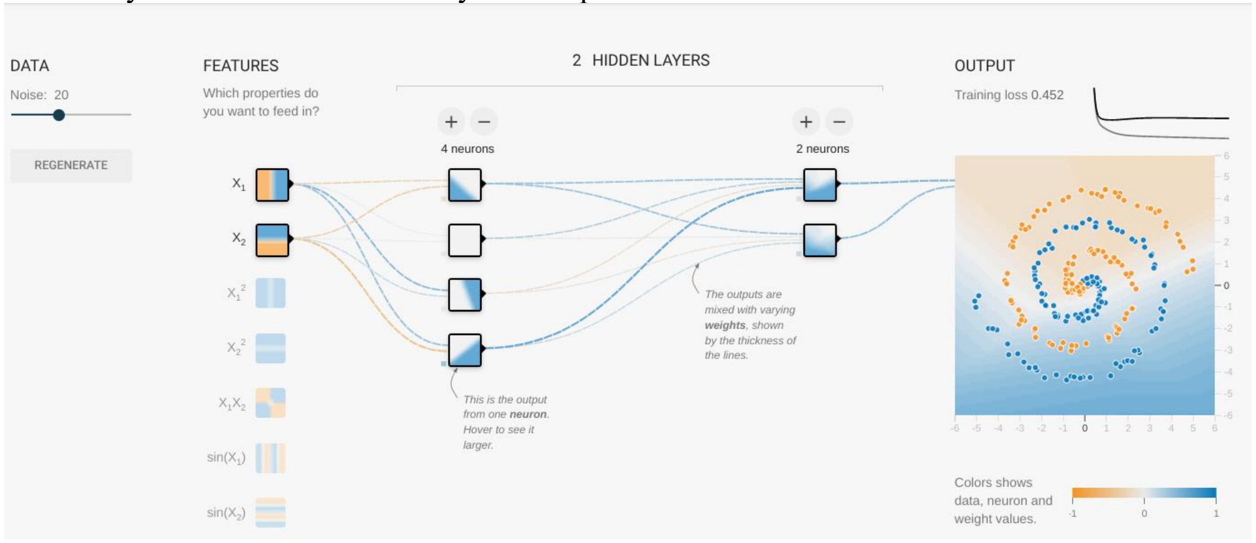
Noise: 0

4 neurons

2 neurons

Training loss 0.445

Moderate Noise (20): When I introduced a moderate amount of noise, I noticed that the network's decision boundary became a bit more irregular and less perfect. However, I was impressed that the network was still able to find the general underlying pattern and generalize reasonably well. It showed an ability to look past some of the random noises.


DATA
FEATURES
Which properties do you want to feed in?
2 HIDDEN LAYERS
OUTPUT
REGENERATE
X1
X2
This is the output from one neuron. Hover to see it larger.
The outputs are mixed with varying weights, shown by the thickness of the lines.
Colors shows data, neuron and weight values.

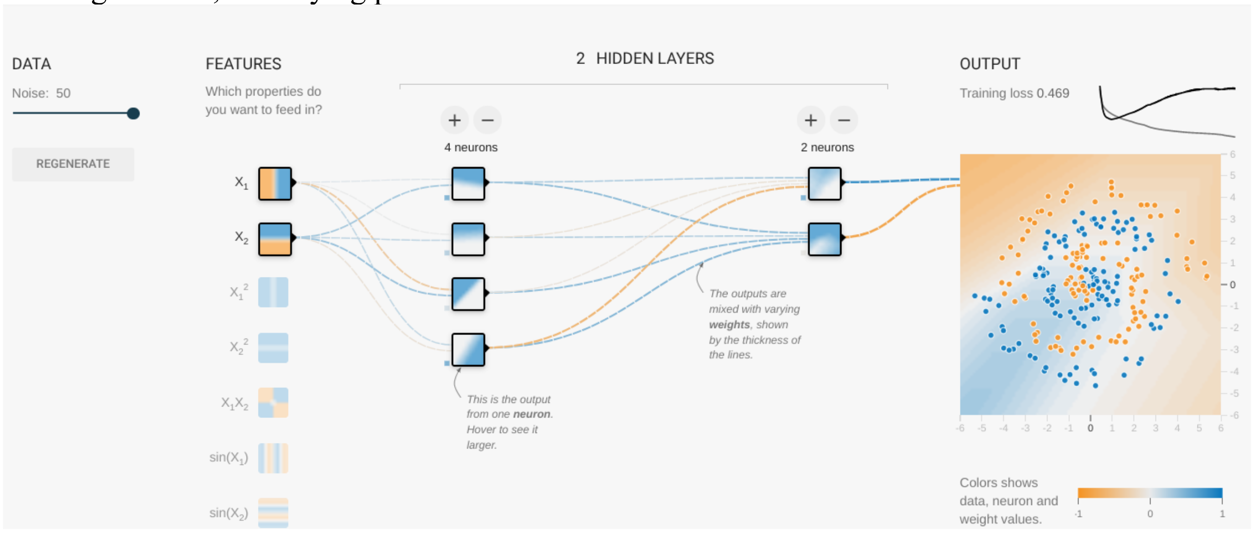
Noise: 20

4 neurons

2 neurons

Training loss 0.452

High Noise (50): With a high level of noise, my network struggled significantly to learn effectively. I observed that the decision boundary it created was very messy, complex, and ultimately inaccurate. The network was overfitting to the random noisy data points instead of learning the true, underlying pattern that was hidden beneath the noise.


DATA
Noise: 50
REGENERATE
FEATURES
Which properties do you want to feed in?
X_1
X_2
X_1^2
X_2^2
X_1X_2
$\sin(X_1)$
$\sin(X_2)$
2 HIDDEN LAYERS
4 neurons
2 neurons
This is the output from one neuron. Hover to see it larger.
The outputs are mixed with varying weights, shown by the thickness of the lines.
OUTPUT
Training loss 0.469
Colors shows data, neuron and weight values.

Observations and Explanation: In my experiments with the Noise slider, I learned that noise in the data makes it significantly harder for my network to generalize. As I increased the noise, I observed that the network often tried to form an extremely complex and messy decision boundary, which meant it was attempting to overfit to the noise itself, leading to poor performance on any new, unseen data. I understood that noise management is crucial because robust models need to be able to handle it. Functionally, noise acts as a type of implicit regularization, compelling the network to seek out more resilient, fundamental patterns that are less affected by random changes in the input data. Conversely, I saw that loud noise can severely hinder the network's ability to differentiate between the real indicators (signal) and random interference (noise), making the learned solution unstable and unreliable. This confirmed the necessity of either cleaning noisy data or using explicit regularization techniques to ensure my model learns the true underlying pattern. I learned that a robust model needs to be able to handle noise without getting confused. High levels of noise can severely hurt a model's performance because the network may fail to differentiate between the true signal and random interference.

Task 5 (Dataset Exploration): Summarize performance on different datasets.

Setup and Experiment: For my final task, I tested my network on all the different datasets available in TensorFlow Playground. I wanted to see how the complexity of the data itself posed a challenge to the network and how different architectures might be needed for different problems. Each dataset presented a unique learning challenge that helped me understand the capabilities and limitations of my neural network configurations.

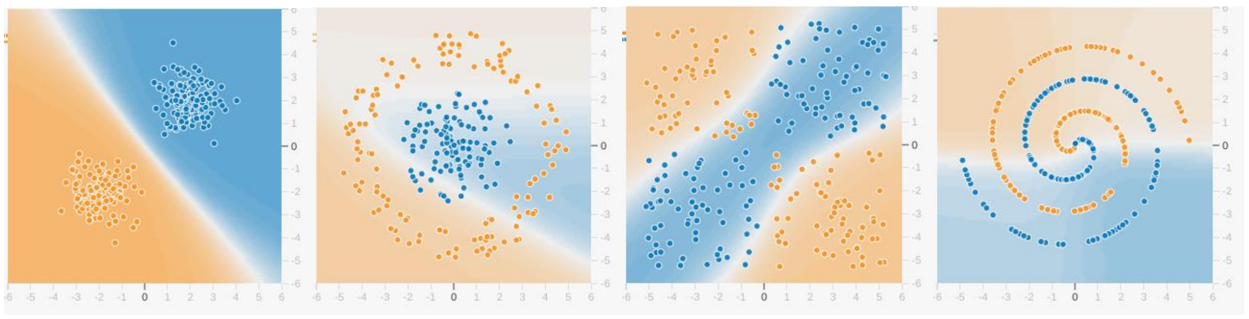
Circle/Square: In this dataset to be a straightforward classification problem. A basic network with a single hidden layer and a moderate number of neurons learned to separate the inner circle from the outer ring of points very easily and quickly.

XOR: This dataset was more interesting because the data is not linearly separable, meaning I couldn't draw a single straight line to solve it. I discovered that this problem required a network with at least one hidden layer to learn the non-linear boundary needed for a correct solution.

Gaussian: I found that this dataset, which has two slightly overlapping clusters of data, was also learned well by a moderately sized network. It was a relatively simple classification task that my network could handle without much difficulty.

Spiral: this dataset to be by far the most difficult challenge. The interlocking spiral pattern is a very complex, non-linear problem. I saw that a simple, shallow network failed completely. To solve it, I had to use a much larger and deeper network with multiple hidden layers, which demonstrated the importance of network depth for learning highly intricate patterns.

Screenshots:



Observations and Explanation: I explored the different datasets available in the TensorFlow Playground to understand how the complexity of the data directly impacts the requirements of the neural network. I realized that the complexity of the neural network must be matched to the complexity of the dataset it is trying to learn. I started with the "circle" configuration, which represents a simple classification issue. The TensorFlow Playground provides different preset datasets, from this basic, nearly linearly separable data to more intricate and demanding configurations. Other datasets I could access included Exclusive OR (XOR), Gaussian, Spiral, plane, and multi-Gaussian. Every dataset presented a unique learning challenge and helped me comprehend both the capabilities and restrictions of neural networks. For example, the Spiral dataset required me to build a significantly deeper and wider network than the simple XOR dataset to accurately twist the features into a separable space. This confirmed that I cannot use a one-size-fits-all architecture; I must customize the network's size and structure to fit the particular dataset and the complexity of the issue being addressed.

Discussion

These practical experiments provided me with vital insights into the design and training of neural networks. I realized that the choice of activation function, neuron count, learning rate, and noise management are crucial factors that significantly influence network performance. For example, I found that ReLU activations are typically favored for their quicker convergence because they mitigate the vanishing gradient problem, while I learned that Sigmoid activations can still be beneficial in specific output layers where I need values that represent probabilities.

I understand now that the number of neurons must be thoughtfully selected to strike a delicate balance between model complexity and generalization capability. A sufficient increase in neurons enhances the network's ability to represent intricate functions, yet I must be careful, as too many neurons may result in the model simply memorizing the training data instead of generalizing its knowledge to unfamiliar data. Additionally, I confirmed that a suitable learning rate must be determined through careful trials to guarantee stable and effective training. I saw that a rate that is too high causes instability, while one that is too low wastes time. Finally, the challenge of managing noisy data taught me that approaches like data cleaning or regularization methods are necessary to enhance generalization, preventing the model from fitting the noise. I concluded that grasping these trade-offs is crucial for me to create efficient and robust neural networks in practical applications. My experiments in TensorFlow Playground provided me with many insights that have clear practical implications for how I will approach building and training neural networks in the future. I learned that success is not just about building a large network, but about making thoughtful, informed choices during the design process.

Practical Implications

- **Choosing an Activation Function:** I now understand that for most hidden layers in a network, ReLU is an excellent starting choice because it helps the network converge faster and avoids common problems like vanishing gradients. While Sigmoid activations can still be useful in specific situations, such as the output layer of a binary classification problem where I need a probability, I saw firsthand how they can slow down training. This experience has taught me to be deliberate about which activation function I choose based on the specific task.

- **Deciding on Network Size:** My experiments showed me that the number of neurons and layers I choose must be carefully balanced to match the complexity of the problem. If my model is too simple, it will underfit and fail to learn the pattern, but if it is too complex, it risks overfitting by memorizing the training data instead of generalizing. This taught me that I should start with a simpler model and only add complexity, if necessary, which is a crucial principle for building efficient models.

- **Tuning the Learning Rate:** I discovered that finding the optimal learning rate is essential for training a network effectively and efficiently. My experiments demonstrated that a rate that is too high can cause the training to become unstable and fail to converge, while a rate that is too low can make the training process painfully slow and impractical. This has shown me that tuning the learning rate is a critical step that requires careful experimentation to find the "sweet spot" for any given problem.

- **Matching the Network to the Problem:** Finally, my exploration of the different datasets proved that the network's architecture must be tailored to the complexity of the data. A simple problem like the circle dataset could be solved with a simple network, but a highly complex problem like the spiral dataset required a much deeper and more intricate architecture to succeed. This understanding is vital because it means I cannot use a one-size-fits-all approach; I must analyze the problem first and then design a network that is appropriately suited for that specific challenge.

Conclusion

Through this practical, hands-on experience with TensorFlow Playground, I acquired a significant and intuitive understanding of how neural networks truly operate. I systematically examined how fundamental parameters, including activation functions, neuron counts in hidden layers, learning rates, and data noise directly influence the performance of the network. I discovered the critical importance of balancing a model's complexity with its ability to generalize to new, unseen data, and I saw firsthand the necessity of meticulously adjusting hyperparameters to achieve optimal results. This project has reinforced my grasp of essential neural network principles and has established a solid foundation for me to delve into more intricate and advanced models in the future. I also now have a much better appreciation for the trade-offs I must consider, such as balancing faster convergence with the risk of overfitting. This experience has highlighted just how important experimentation and careful tuning are in designing and training effective neural networks, providing me with valuable insights that will inform all my future work in this field.

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