A06 TensorFlow Playground Presentation

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ITAI 1378: Computer Vision

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On this paper, the explanations come before the demonstrations as seen below.

Explanations:

Activation functions introduce non-linearity into the model, helping neural networks learn complex patterns.

Effects Observed

The first image shows the entire system that has not been tempered, followed by respective images matching the activation names.

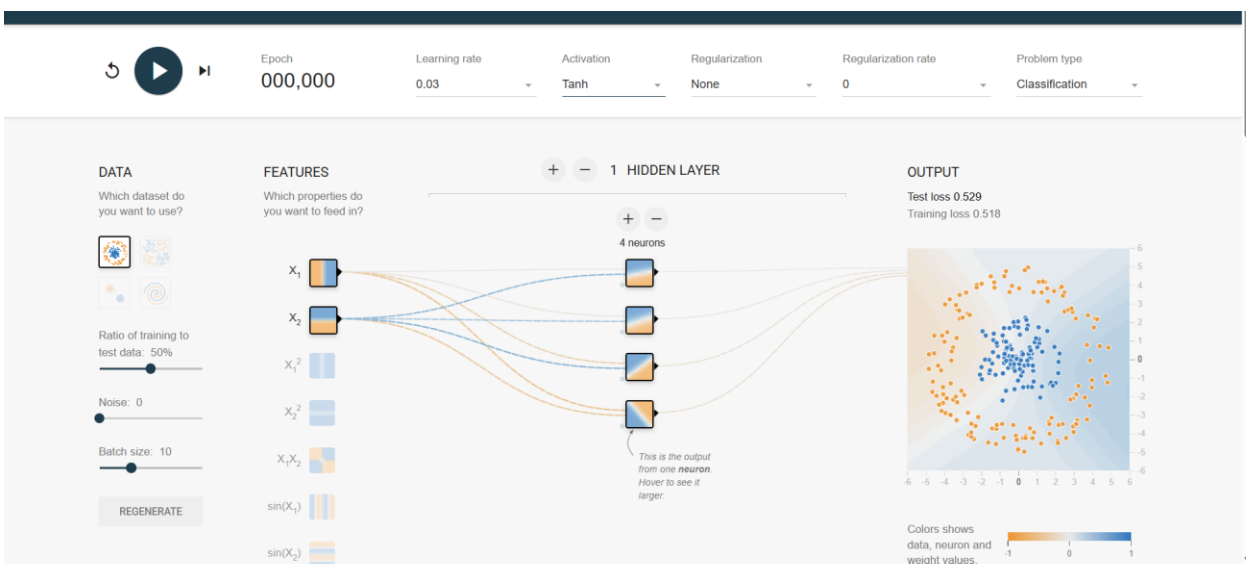
Tanh: Similar to sigmoid but centered at zero, reducing bias.

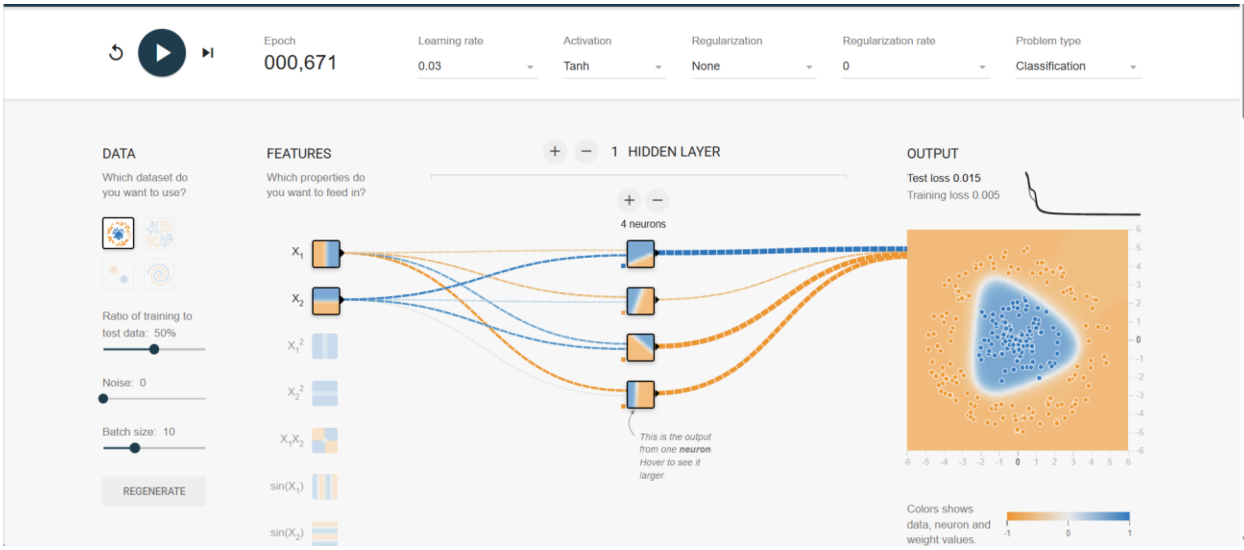
ReLU: Works well for deeper networks, fast convergence, avoids vanishing gradient.

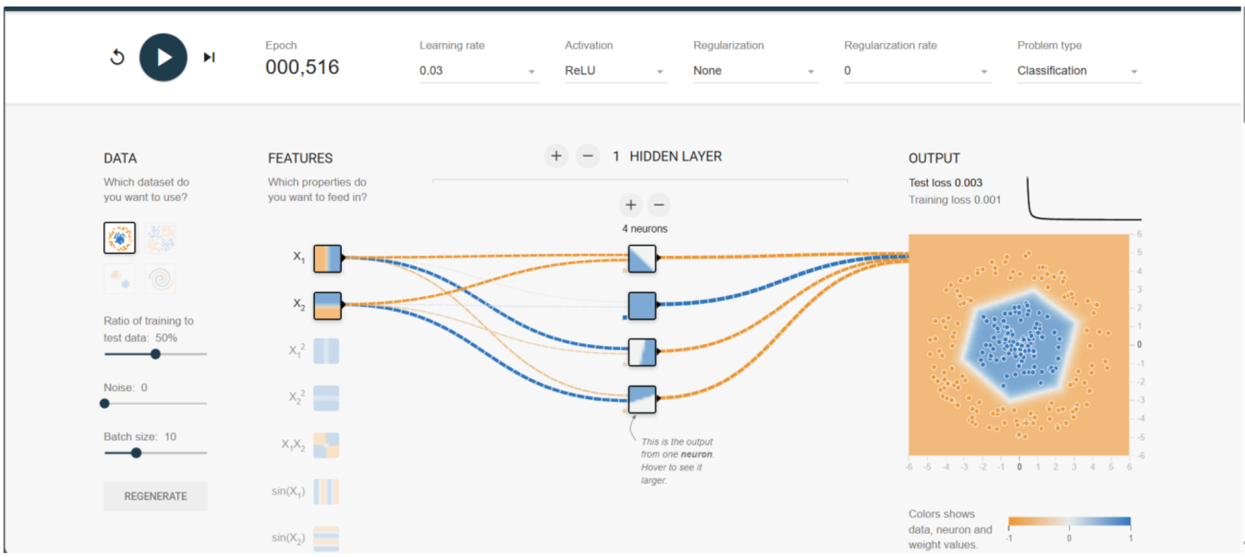
Sigmoid: Works for binary classification but can suffer from vanishing gradient issues.

Linear: Does not introduce non-linearity, leading to limited learning capacity.

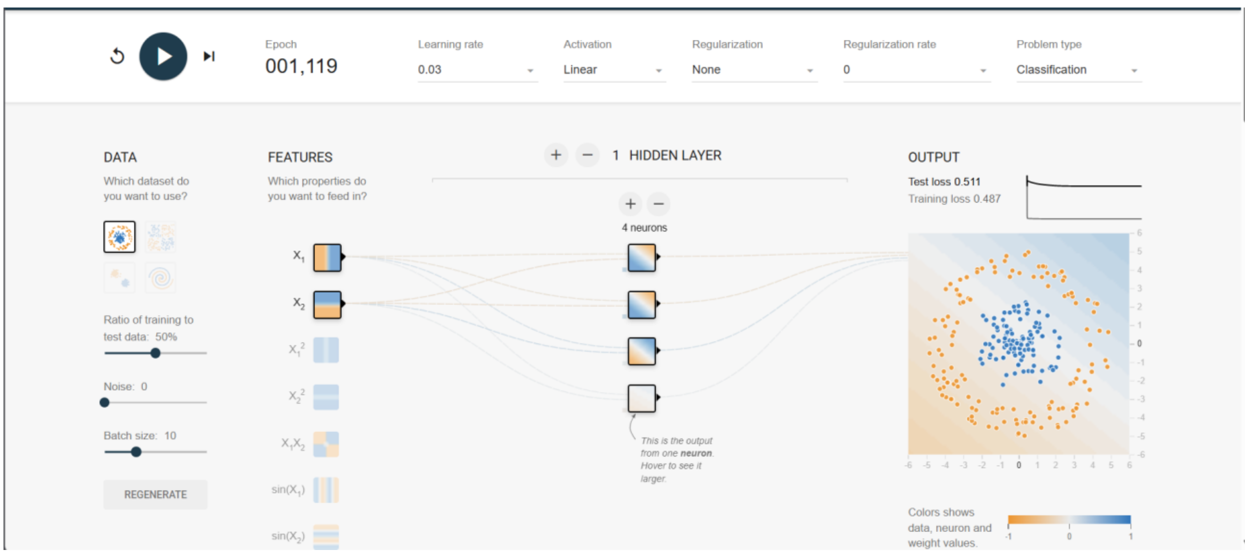
Reference: Goodfellow et al. (2016), "Deep Learning" – Chapter 6: Activation Functions.




Epoch
000,671
Learning rate
0.03
Activation
Tanh
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
1 HIDDEN LAYER
4 neurons
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.015
Training loss 0.005
Colors shows data, neuron and weight values.


Epoch
000,516
Learning rate
0.03
Activation
ReLU
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
1 HIDDEN LAYER
4 neurons
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.003
Training loss 0.001
Colors shows data, neuron and weight values.


Epoch
000,518
Learning rate
0.03
Activation
Sigmoid
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
1 HIDDEN LAYER
4 neurons
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.018
Training loss 0.015
Colors shows data, neuron and weight values.



Task 2 - Hidden Layer Neurons: Record Observations

Explanation

What are Neurons and Hidden Layers?

Neurons: Process inputs using weights and biases. They receive inputs, apply weights and biases, and pass the result through an activation function.

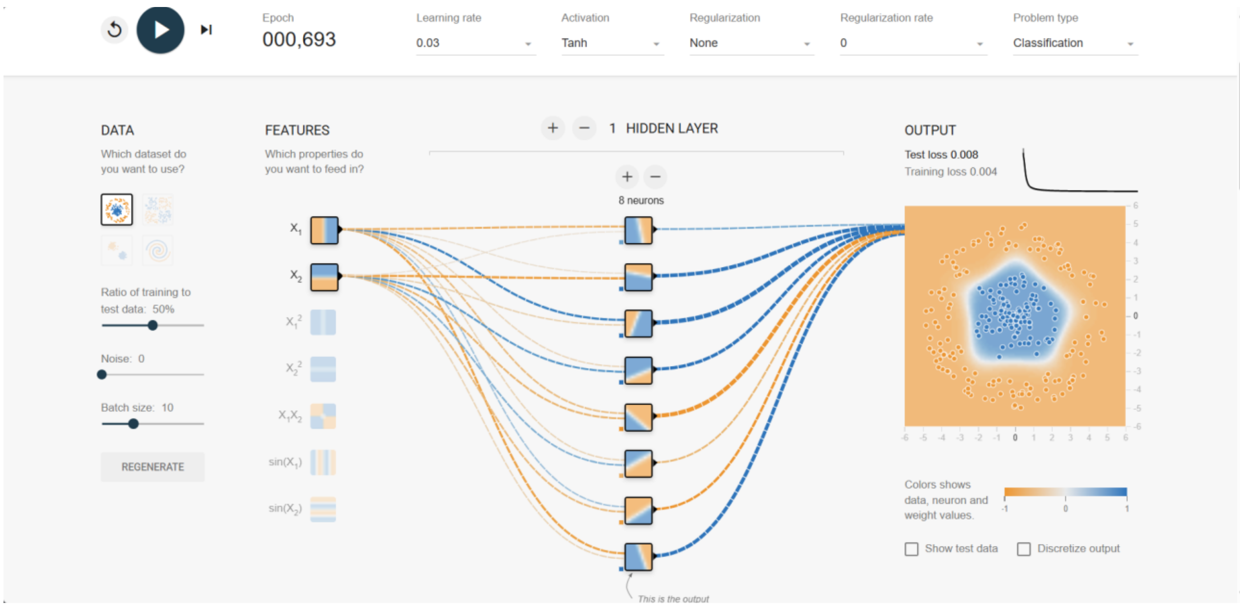
Hidden Layers: Allow deeper feature extraction.

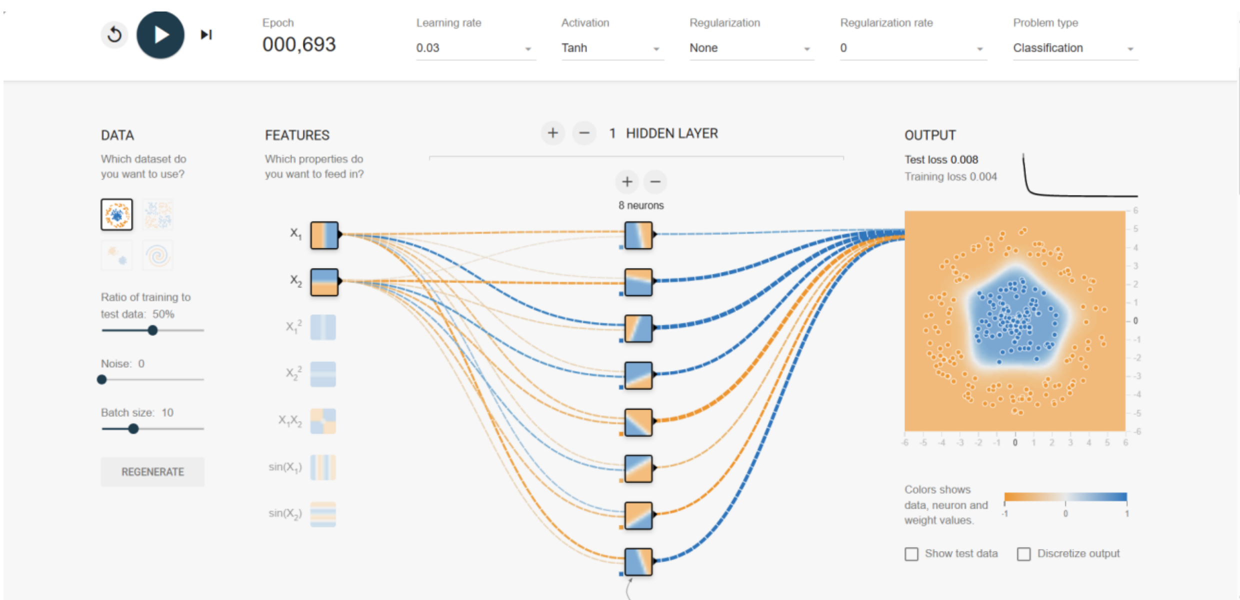
Impact Observed

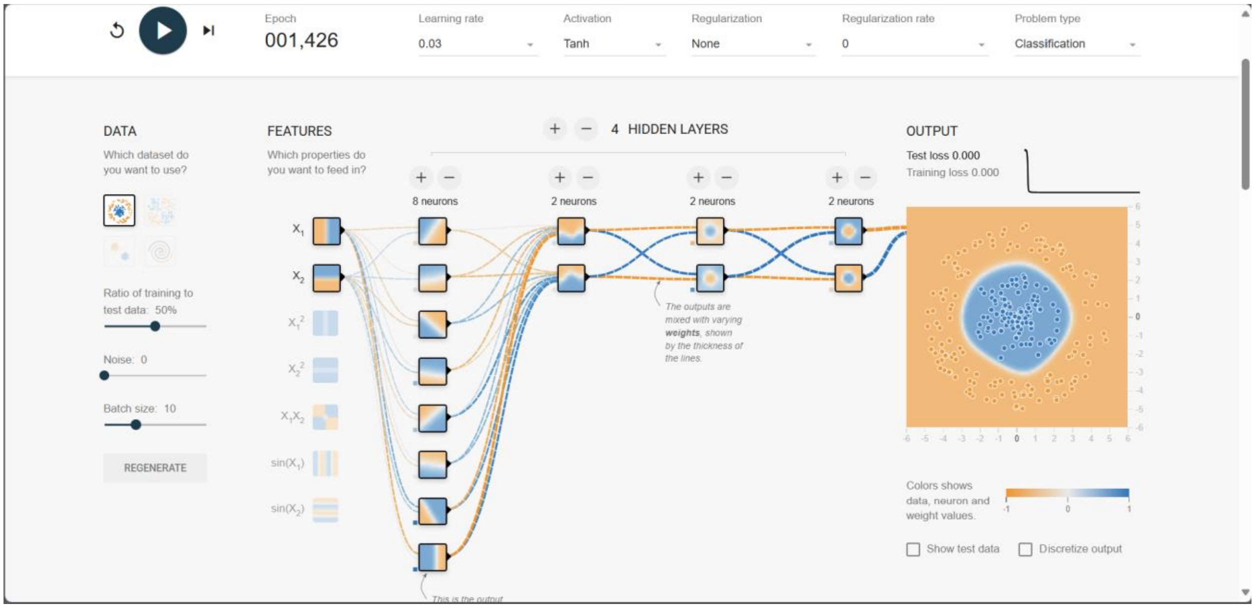
More neurons/layers lead to better learning but longer training.

Too many layers can also lead to overfitting.

Reference: LeCun, Y. et al. (2015), "Deep Learning" – Explains role of hidden layers.





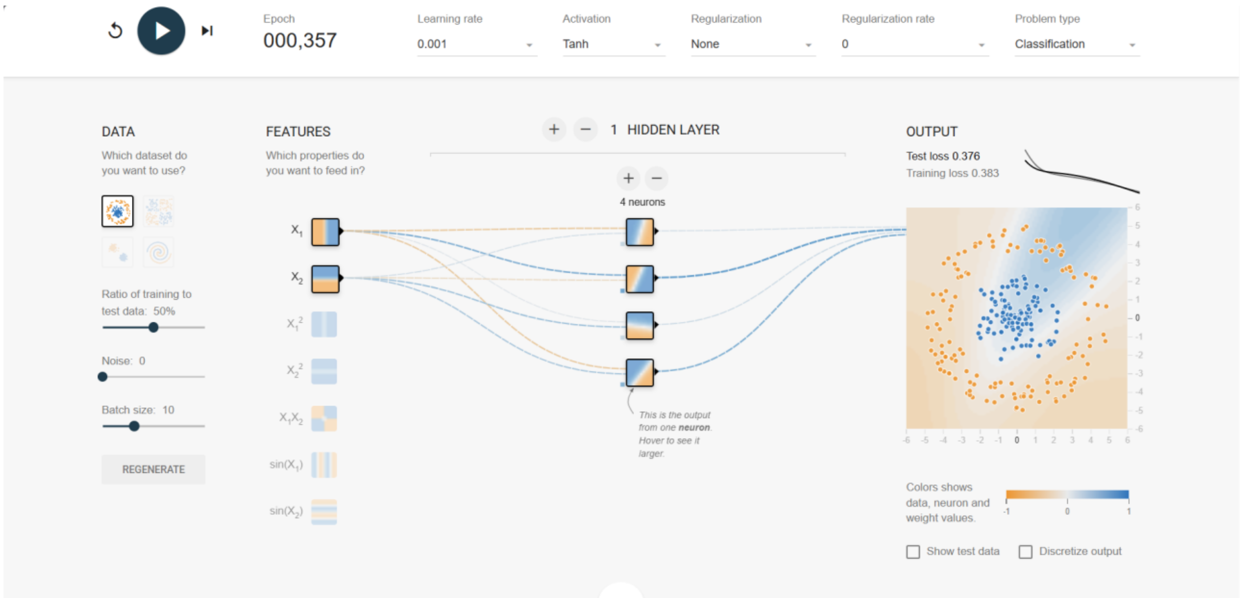


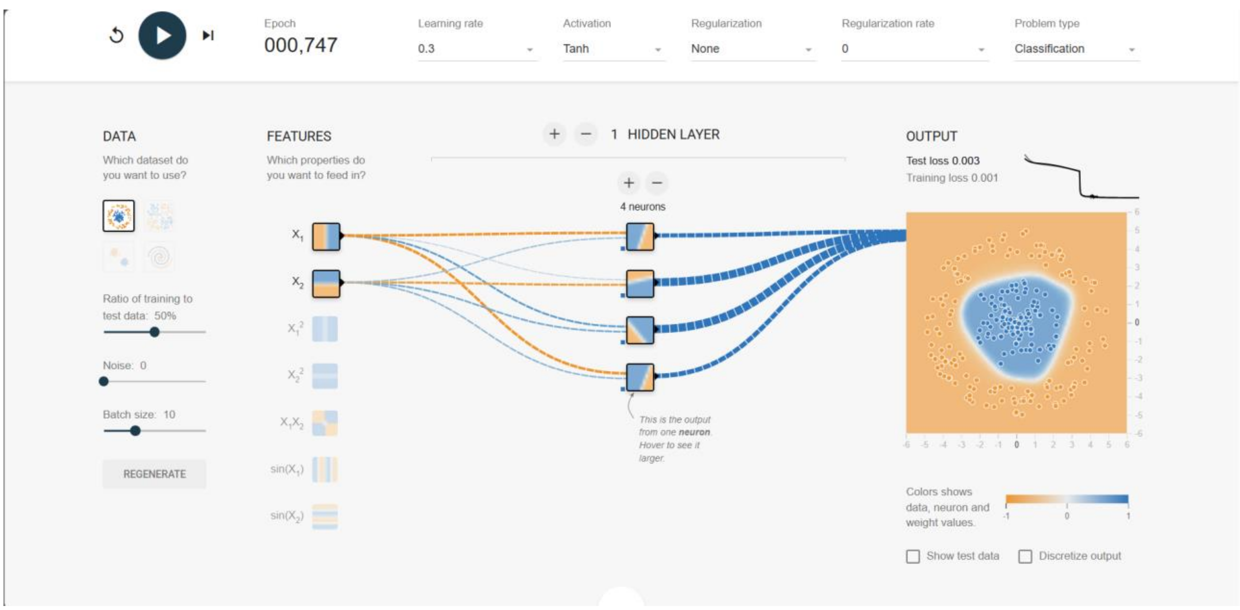
Task 3 - Learning Rate:

- **What is Learning Rate?**
  - Controls how much weights update during training.
- **Effects Observed**
  - **Low Learning Rate**: Stable but slow. Can result in slow convergence or getting stuck in local minima.
  - **High Learning Rate**: Fast but risks overshooting. Can cause the network to overshoot the optimal solution, leading to oscillations or divergence.

Reference: "Gradient Descent and Learning Rate":

https://towardsdatascience.com/understanding-learning-rates-and-how-it-improves-performance-in-deep-learning-d0d4059c1c10





Task 4 - Data Noise: Explanation

What is Data Noise? Data noise refers to irrelevant or random variations in the data.

Random variations in data that can lead to misleading patterns.

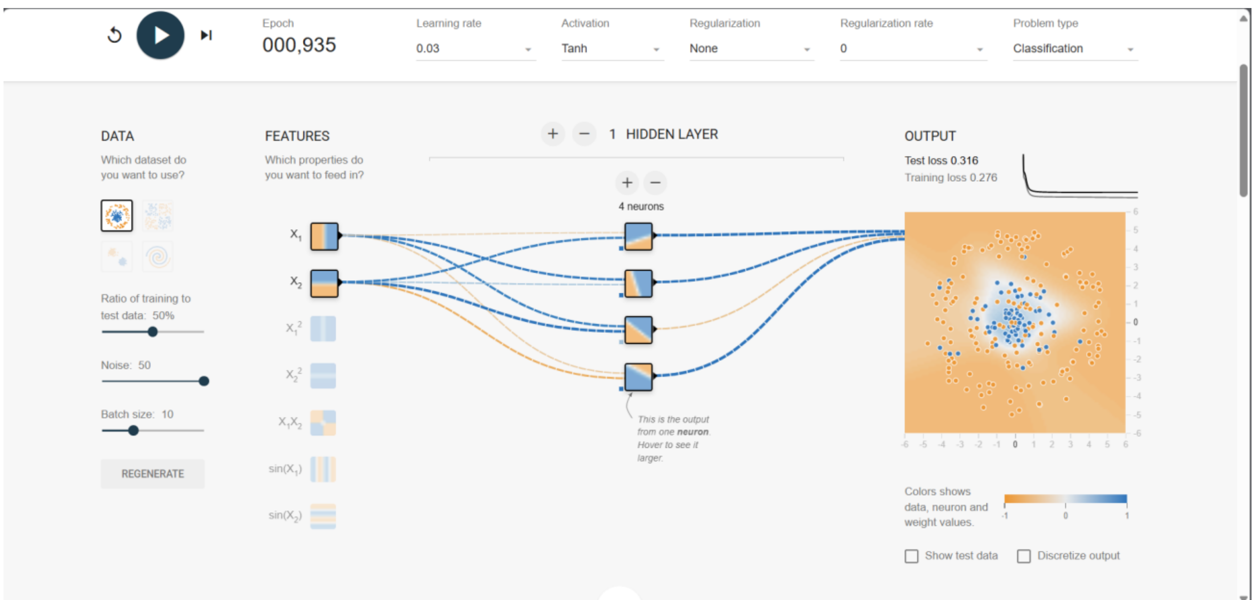
Data noise increases the risk of overfitting, as the network may try to model the noise itself.

Observed Effects:

- As noise increases, the decision boundary becomes less smooth and more erratic.

- The network's accuracy decreases.
- The playground will show that the model begins to create very complex decision boundaries in an attempt to fit the noisy data.

Reference: Zhang et al. (2017), "Understanding Deep Learning Requires Rethinking Generalization".



Task 5 - Dataset Exploration: Explanation

Some datasets are easy to learn (linearly separable), while others are more complex.

Datasets:

- **Circular:** A simple non-linear dataset where data points are arranged in concentric circles.
- **Spiral:** A complex non-linear dataset with intertwined spirals.
- **Gaussian:** Data points are distributed according to a Gaussian distribution.

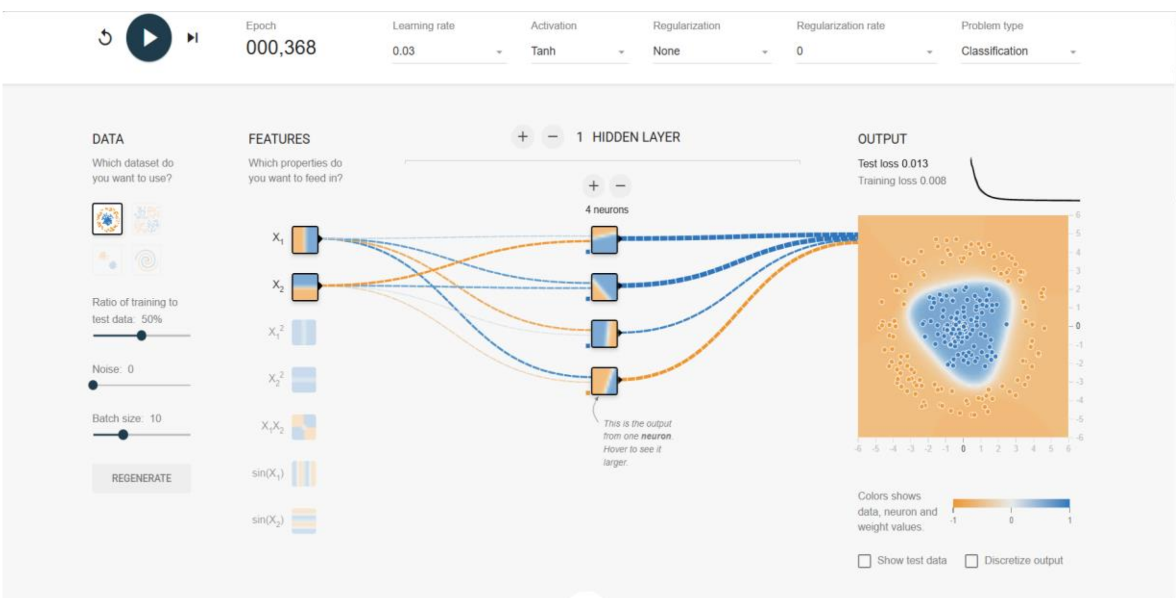
- **XOR:** A classic non-linear problem where points are classified based on the XOR logic gate.

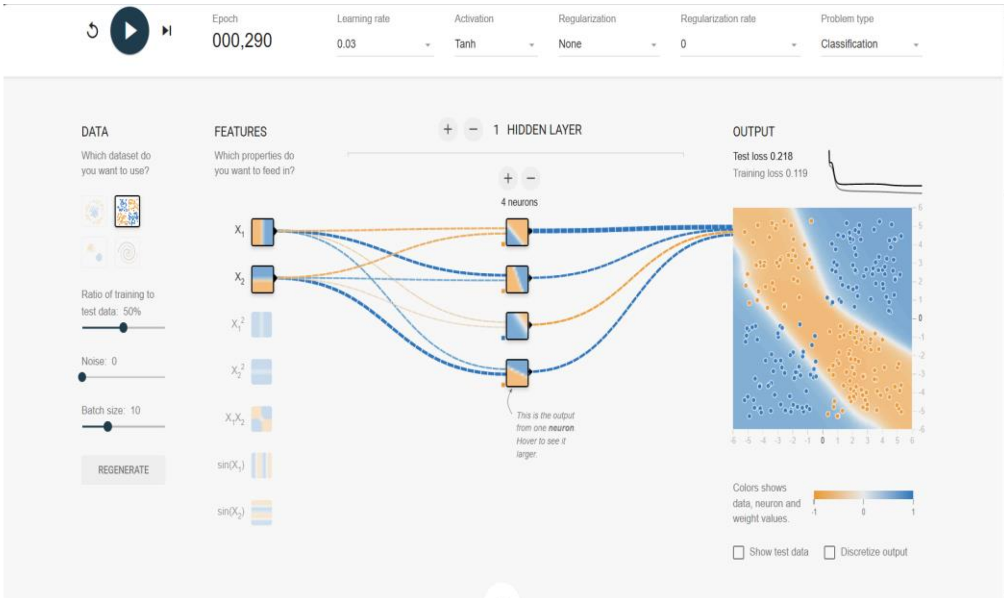
Importance: Dataset selection determines the complexity of the problem and the suitability of different network architectures. Each datasets highlights different strengths and weaknesses of neural networks.

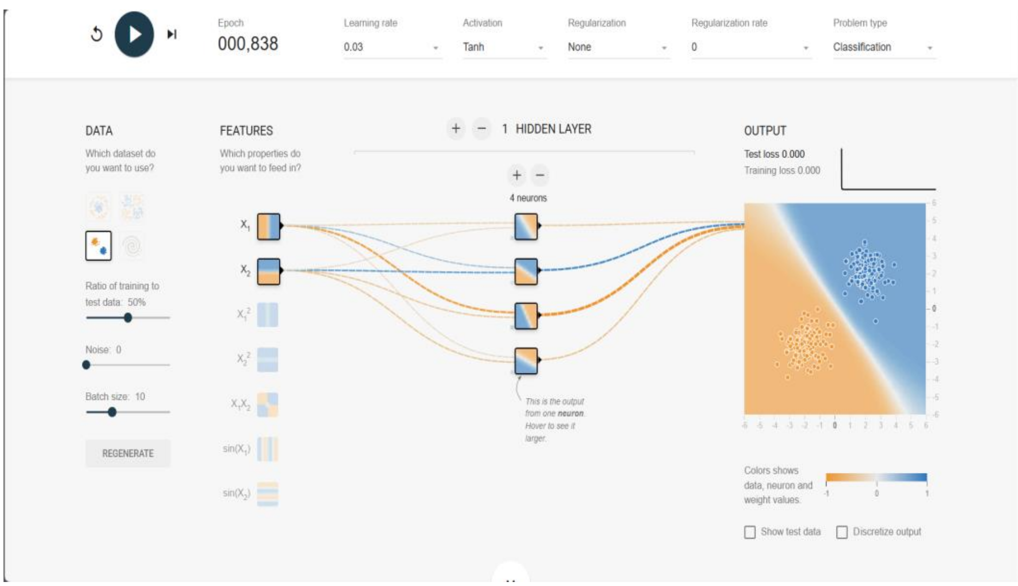
Effects Observed

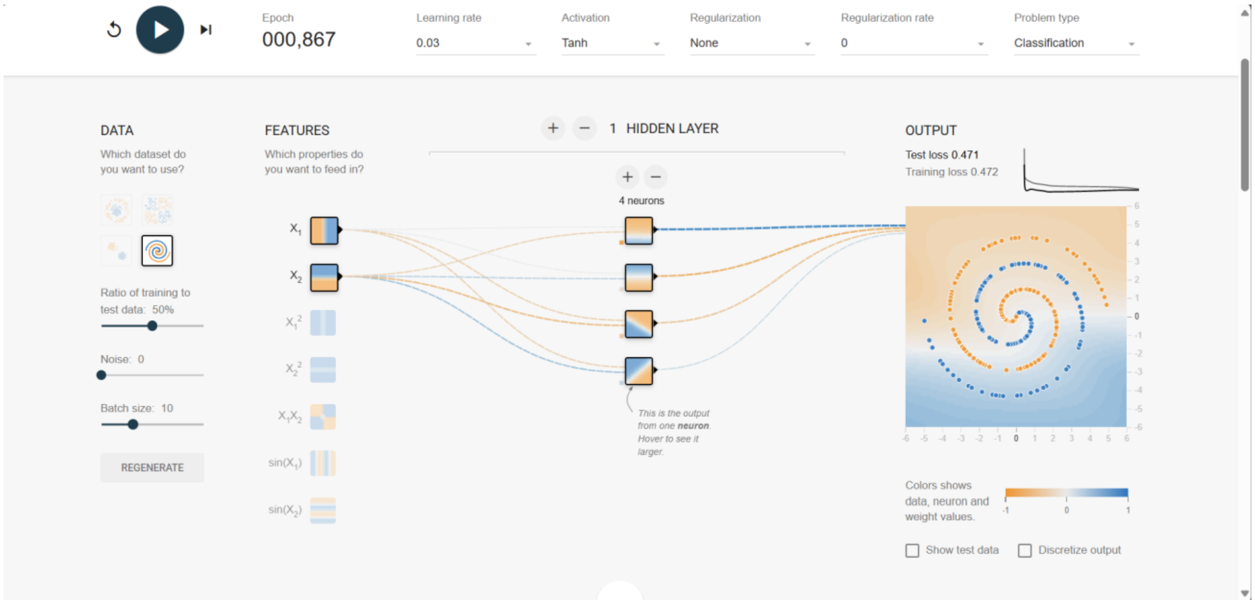
- **Circular:** A simple network with a few neurons can achieve good accuracy.
- **Spiral:** Requires a more complex network with multiple layers and neurons.
- **Gaussian:** A linear or simple non-linear network may suffice.
- **XOR:** Demonstrates the need for non-linear activation functions.

Reference: Hochreiter & Schmidhuber (1997), "Long Short-Term Memory" – Discusses dataset complexity. https://www.kdnuggets.com/2021/08/understanding-datasets-machine-learning.html




Epoch
000,290
Learning rate
0.03
Activation
Tanh
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
1 HIDDEN LAYER
4 neurons
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.218
Training loss 0.119
Colors shows data, neuron and weight values.
Show test data
Discretize output


Epoch
000,838
Learning rate
0.03
Activation
Tanh
Regularization
None
Regularization rate
0
Problem type
Classification
DATA
Which dataset do you want to use?
Ratio of training to test data: 50%
Noise: 0
Batch size: 10
REGENERATE
FEATURES
Which properties do you want to feed in?
1 HIDDEN LAYER
4 neurons
This is the output from one neuron. Hover to see it larger.
OUTPUT
Test loss 0.000
Training loss 0.000
Colors shows data, neuron and weight values.
Show test data
Discretize output



Conclusion:

I gained a deeper understanding of how neural networks function and how various parameters can affect their performance. Experimenting with activation functions showed their importance in shaping how a network learns, with ReLU performing well in deeper networks due to its ability to prevent certain training issues. Adjusting the number of hidden layers and neurons demonstrated the trade-off between model complexity and overfitting, reinforcing the importance of selecting an appropriate architecture for a given dataset. Modifying the learning rate showed how small values lead to slow convergence, while excessively high values cause instability. Introducing noise in the dataset emphasized the impact of data quality on generalization, as high noise levels made it harder for the model to learn meaningful patterns. Exploring different datasets further illustrated the importance of dataset selection, as more complex patterns required deeper networks for effective learning. One challenge I faced was understanding why certain parameter changes led to unexpected results, such as overfitting or slow learning. After conducting iterative testing and analyzing decision boundaries, I was able understand better. Overall, this experience reinforced the importance of fine-tuning hyperparameters and deepened my appreciation for neural network training dynamics in real-world applications.

References:

Gradient Descent and Learning Rate: https://towardsdatascience.com/understanding-learning-rates-and-how-it-improves-performance-in-deep-learning-d0d4059c1c10

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