

Experiments on Neural Network Playground

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My folder: C:\Users\Administrator\OneDrive\Documents\neural_network

Ref: <https://playground.tensorflow.org>

Aurelien Book: Pages 327/328

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Use Reset switch

1. Before any experiment, after setting the configurations, click **Reset** switch to reset weights and biases.
2. The moment you hit **Regenerate** button, new data will be generated and you may get very different results. **SO WHEN YOU EXPERIMENT, IN BETWEEN DO NOT GENERATE FRESH DATA.** Decide what kind of data you want and then experiment.
3. Hovering over any neuron, you will see the kind of pattern it is able to distinguish. Generally, neurons in the 1st hidden layer, all have linear distinguishing patterns.
4. Read these lines from Page 4 of [this article](#):

The fact that local minima do not seem to be a problem for multi-layer neural networks is somewhat of a theoretical mystery. It is conjectured that if the network is oversized for the task (as is usually the case in practice), the presence of “extra dimensions” in parameter space reduces the risk of unattainable regions. Back-propagation is by far the most widely used neural-network learning algorithm, and probably the most widely used learning algorithm of any form.

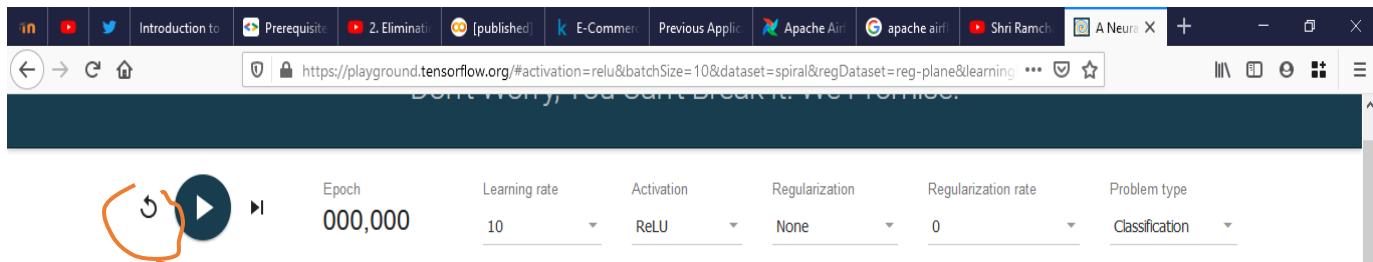


Figure 1: Always click **Reset** before starting another experiment. AND before you start experiments, click **REGENERATE** button just once and **DO** not touch it again. We do not want data to change between experiments.

Experiment 1:

Change Activations & see effects

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Configuration		Results	
Nos of hidden layers:	1	Test loss:	0.496
No of neurons in hidden layer:	6	Training loss:	0.441
Learning rate	0.01		
Activation:	'tanh'		
Epochs:	500		

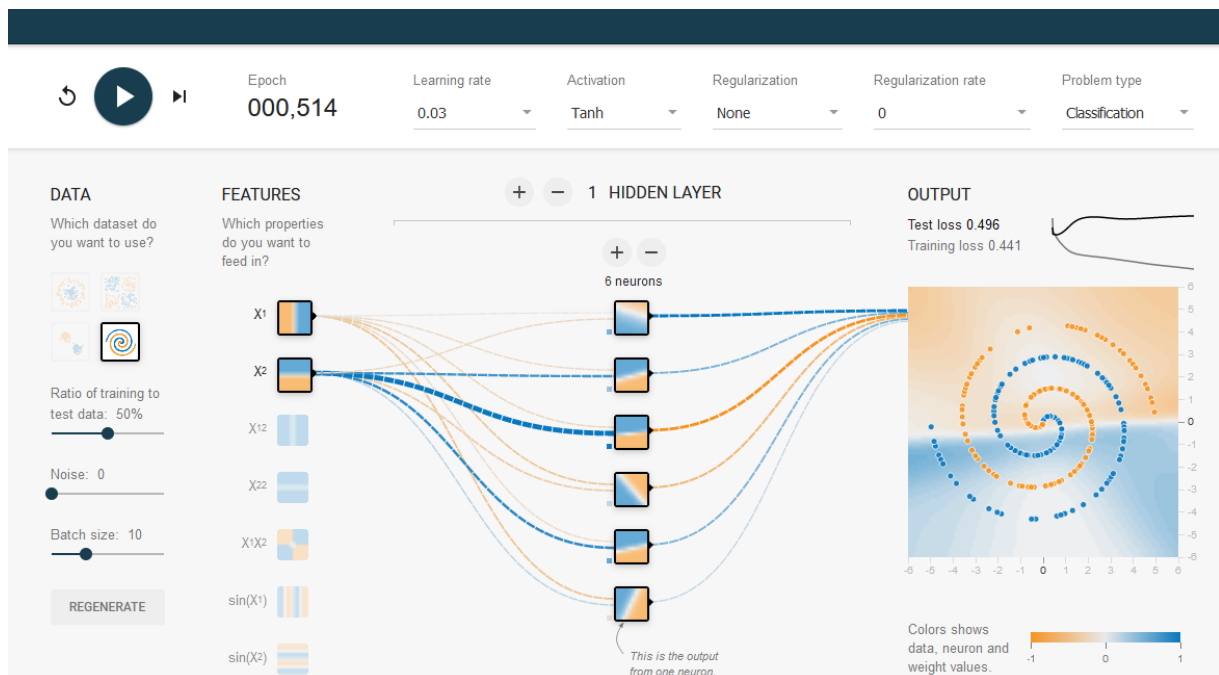


Figure 2: Activation is tanh

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Configuration		Results	
Nos of hidden layers:	1	Test loss:	0.476
No of neurons in hidden layer:	6	Training loss:	0.442
Learning rate	0.01		
Activation:	'relu'		
Epochs:	500		

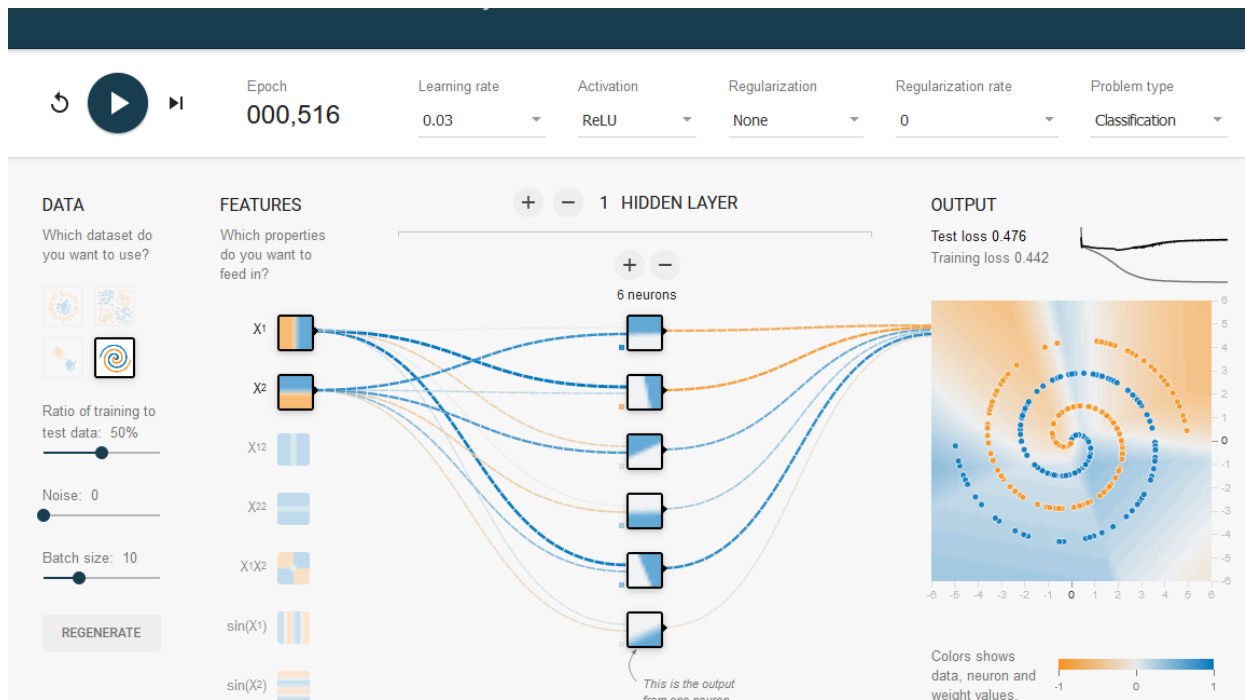


Figure 3: Activation is relu

Experiment 2

Change no of hidden layers & see effects

Configuration		Results	
Nos of hidden layers:	2	Test loss:	0.248
No of neurons in hidden layer:	6	Training loss:	0.191
Learning rate	0.01		
Activation:	'relu'		
Epochs:	500		

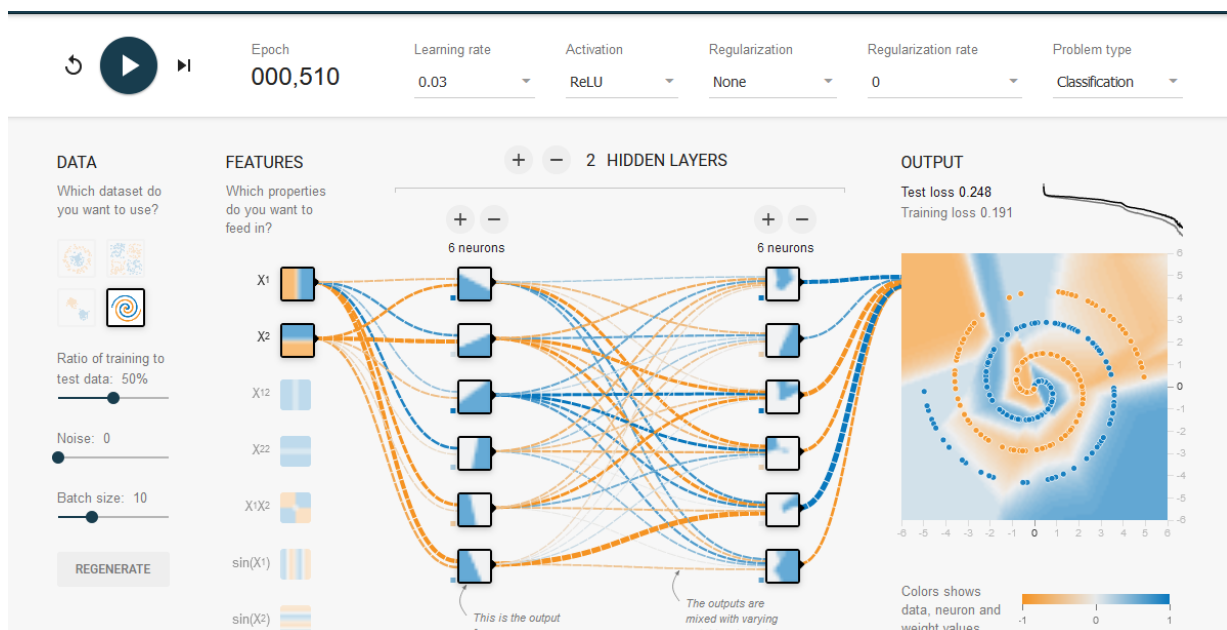


Figure 4: Two hidden layers with relu. Compare losses with those in Figure 3.

Experiment 3

Change no of hidden layers & see effects

Configuration		Results	
Nos of hidden layers:	3	Test loss:	0.022
No of neurons in hidden layer:	6	Training loss:	0.004
Learning rate:	0.01		
Activation:	'relu'		
Epochs:	500		
Batch Size	10		

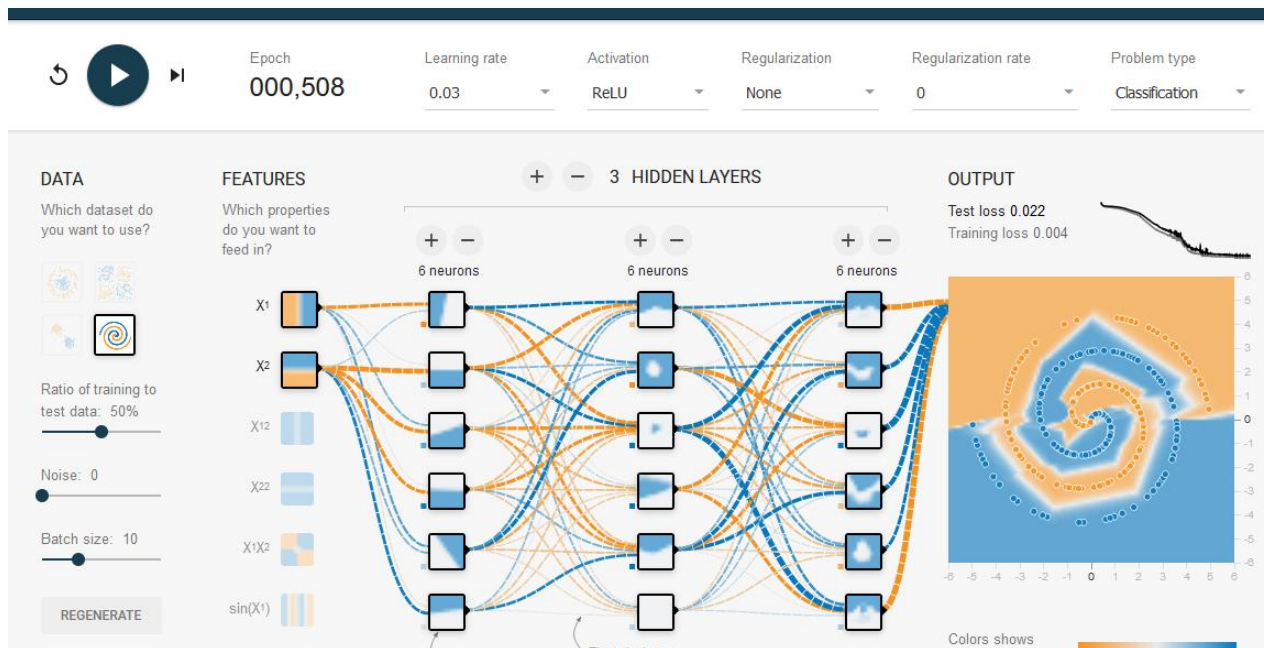


Figure 5: Hidden layers are 3. Loss is still lower. Compare with Figure 3 & Figure 4.

Experiment 4

Change learning rate & see effects

Configuration		Results	
Nos of hidden layers:	3	Test loss:	0.022
No of neurons in hidden layer:	6	Training loss:	0.004
Learning rate:	3		
Activation:	'relu'		
Epochs:	500		

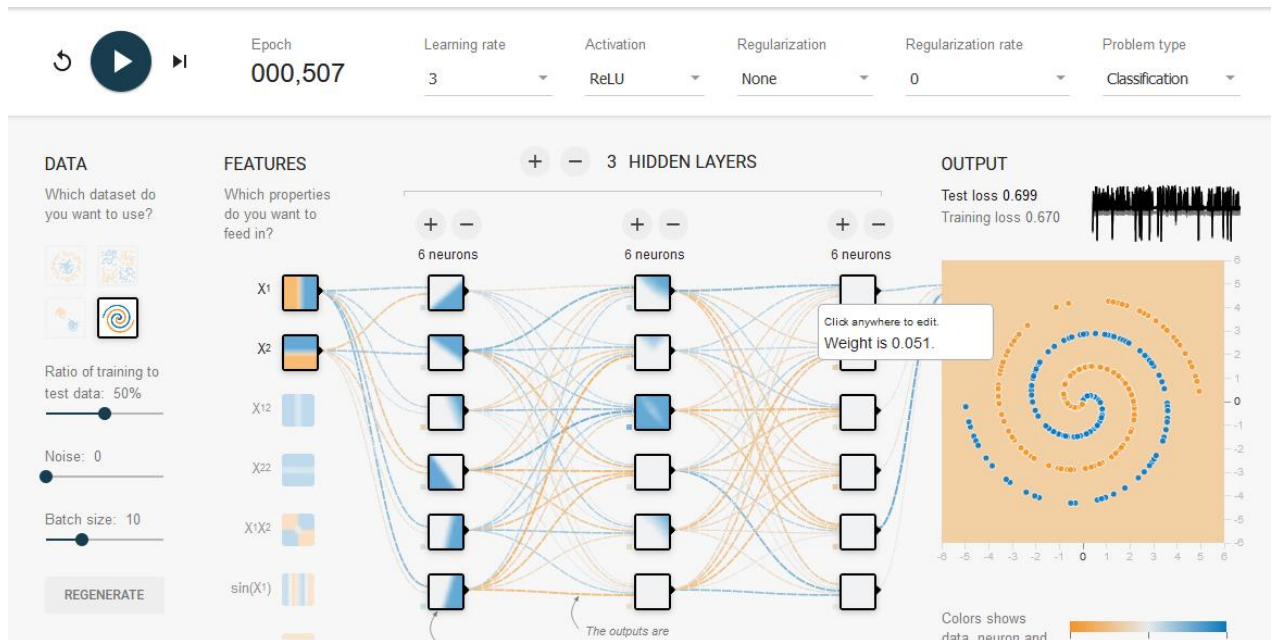


Figure 6: With learning rate high (3), loss is oscillating between high (0.8) and low (0.65) and not converging

Experiment 5

What kind of pattern are neurons learning?

Hover your cursor, over any neuron. And the Image of pattern that it has learnt to distinguish appears on the right. Neurons in the 1st hidden layers learn simple linear features. In the 2nd hidden layer, neurons learn features that are more complex. Further, neurons in the 3rd layer learn features that are still more complex.

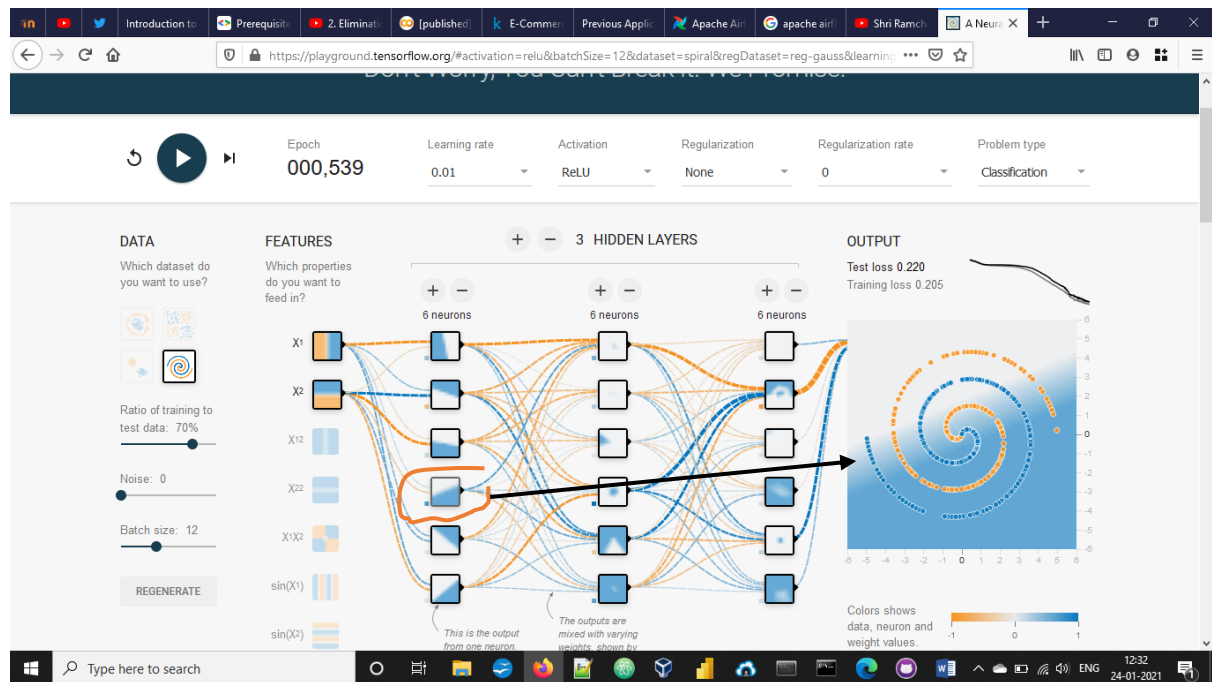


Figure 7: Hovering over a neuron, gives the type of pattern the neuron has learnt to distinguish.

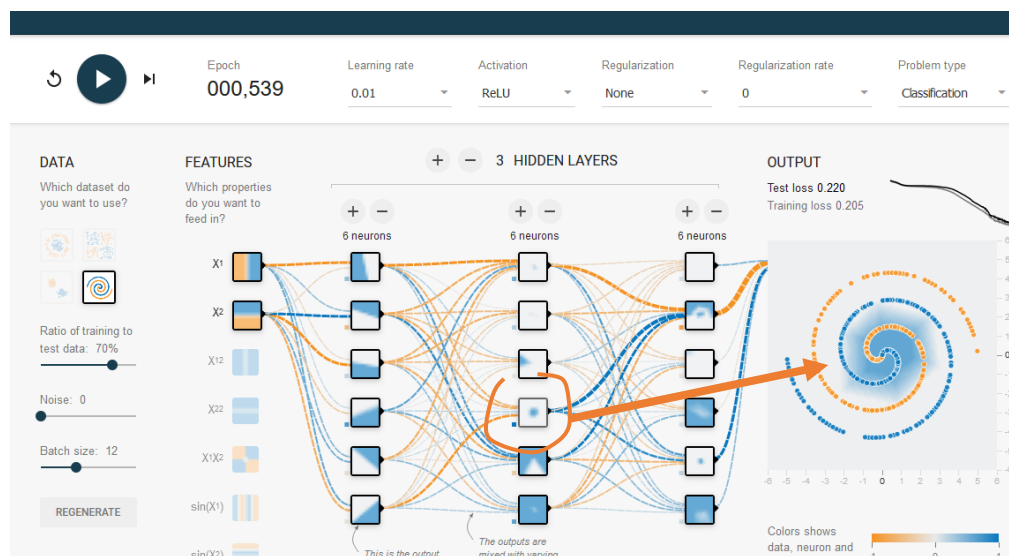


Figure 8: In the first layer, neurons have learnt linear features of various slants. In the 2nd layer, features are more rounded.



Figure 9: 3rd layer learns more complex features.

So why deep learning?

Thus, even though, a single hidden layer can approximate any function, a series of successive hidden layers makes the task of learning easy, as layers learn progressively more abstract features in a short time.

Relu leads to dead neurons

When activation function is ReLu and when sum of input weights is negative, ReLu neuron becomes dead and does not output anything. Once dead, always dead. See figure below:

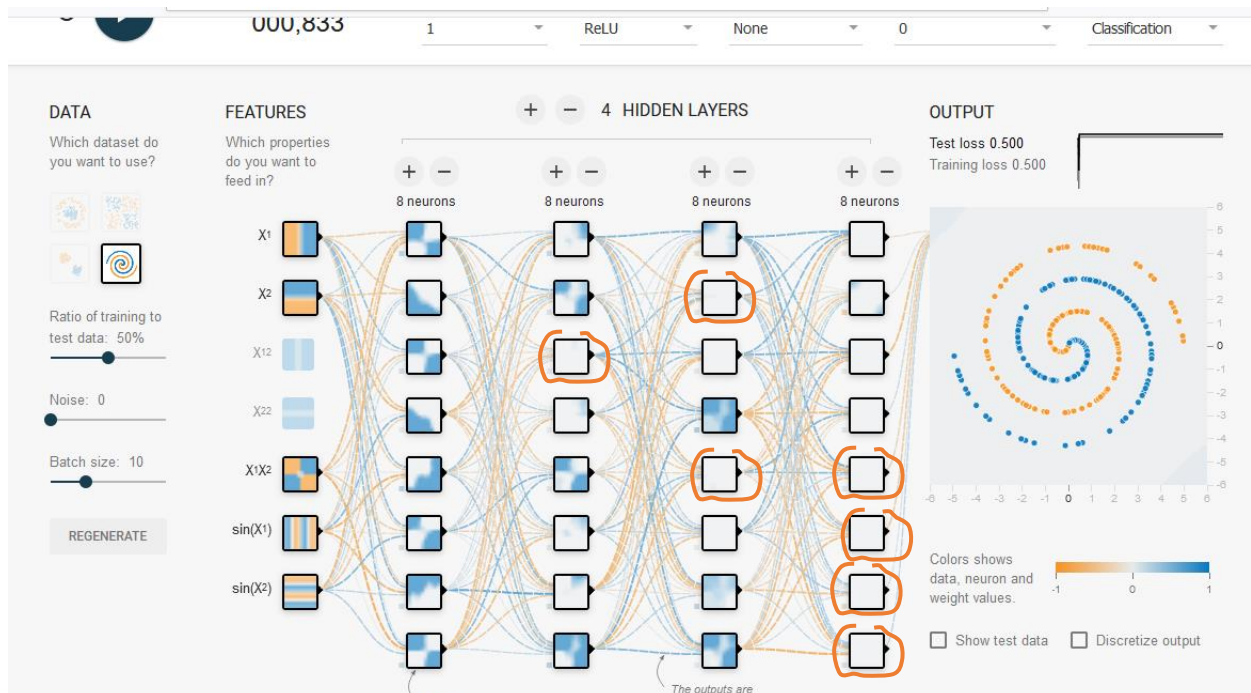


Figure 10: Dead neurons. Encircled neurons are dead. Blue lines indicate -ve weights and orange lines indicate +ve weights. Hover over a weight to know weight value.

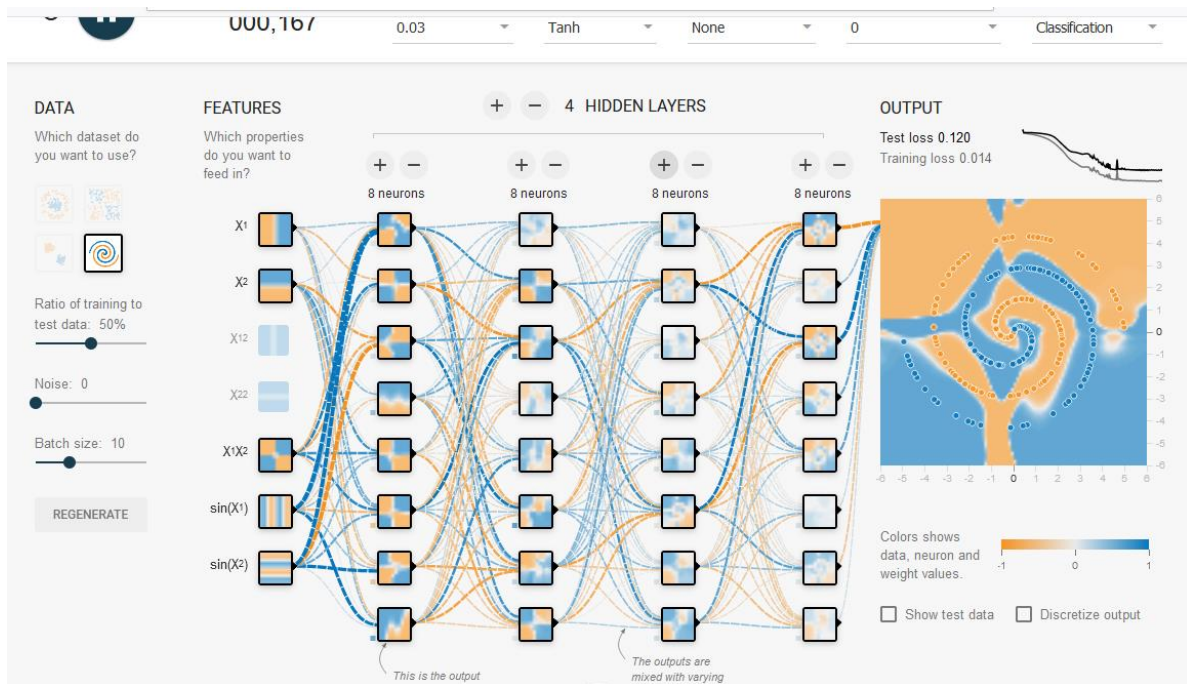


Figure 11: No death with 'tanh'

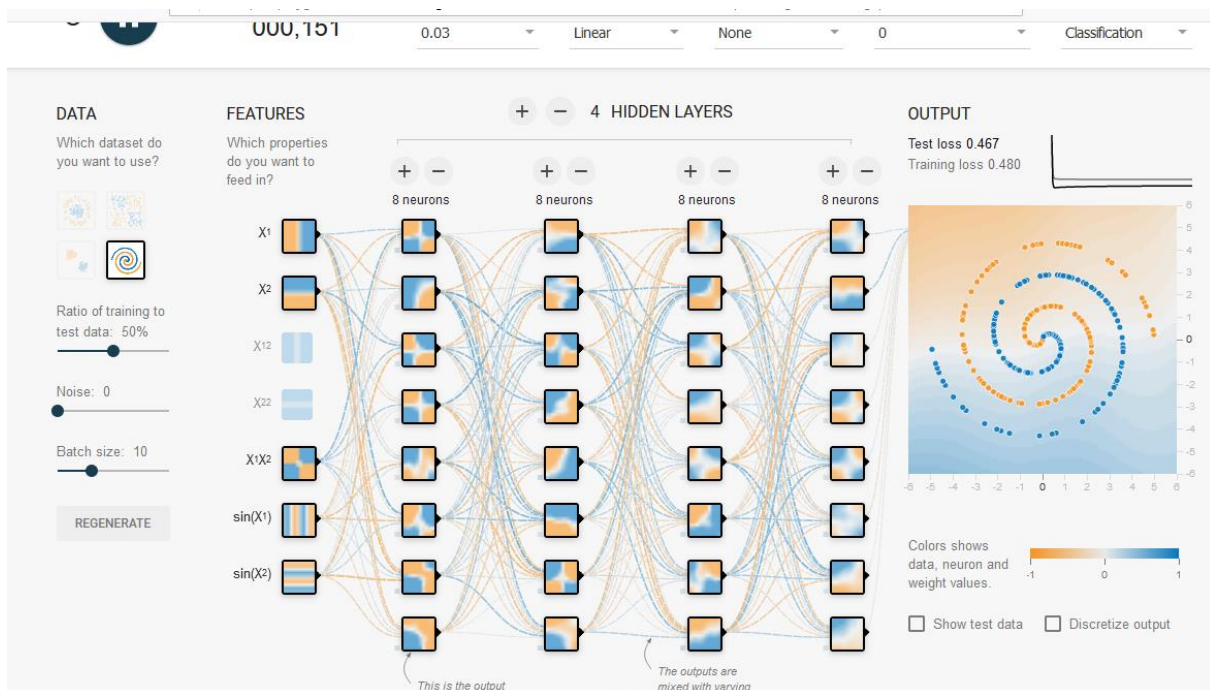


Figure 12: No death with 'linear' activation.

Learning-rate and saturation

Large learning rates may lead to saturation and slowdown of learning. Note that the weight adjustment formula is:

$$W_{\text{new}} = W_{\text{old}} + \lambda * \Delta w$$

where λ is learning rate

So if λ is large, we may have a learning slowdown with no improvement in *Test loss* even after many epochs. You can experiment with the following sigmoid network. Experiment by adjusting starting weights to very high value. And, when you start training by clicking 'Play' button, no improvement in test loss happens.

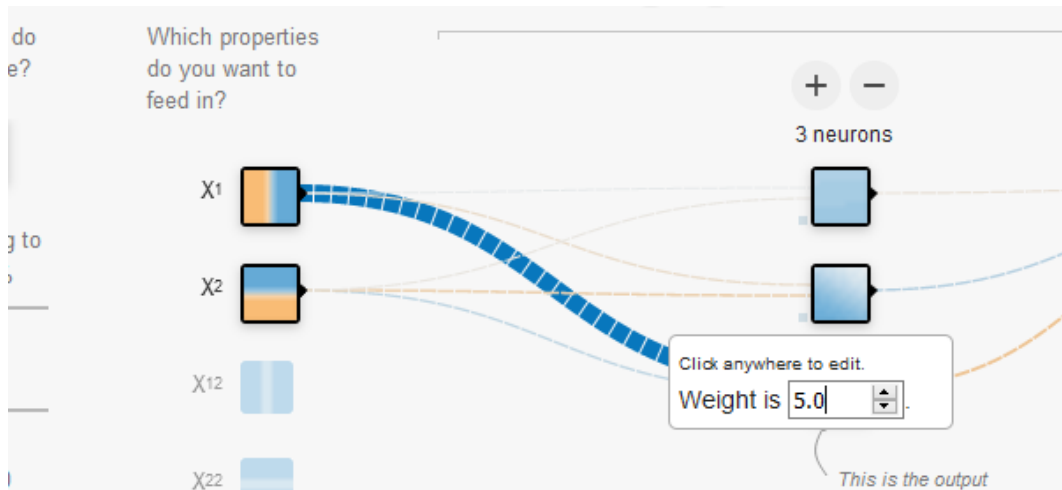


Figure 13: A close-up of weight initialization

Proceed like this:

Set problem type to *Regression*. Design neural network with one hidden layer and three neurons, as in the figure below. Initialize this network by clicking on 'Reset' button. After, resetting weights, manipulate all incoming weights manually to a value of '+5'—do this only for inputs to hidden layer as in the figure below.

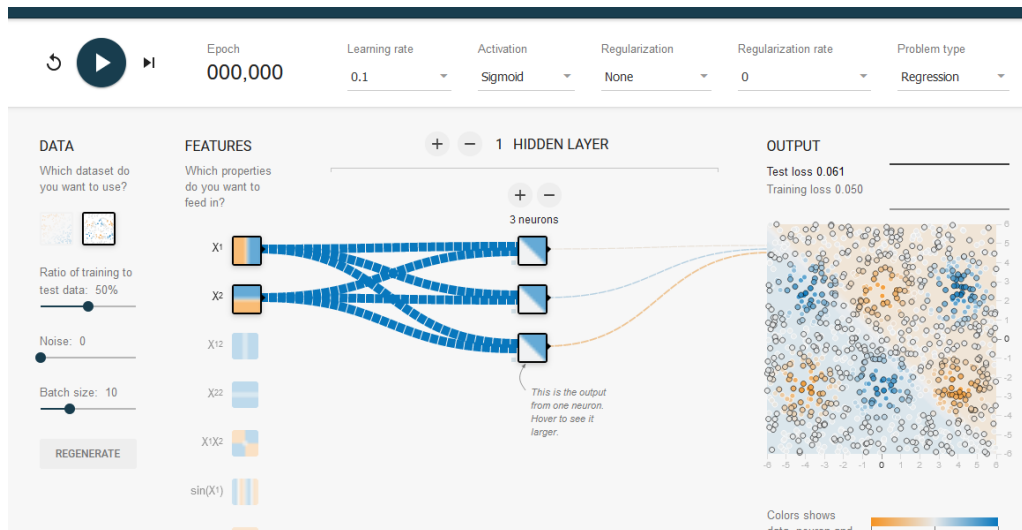


Figure 14: Adjust weights BEFORE hidden layer and NOT after hidden layer.

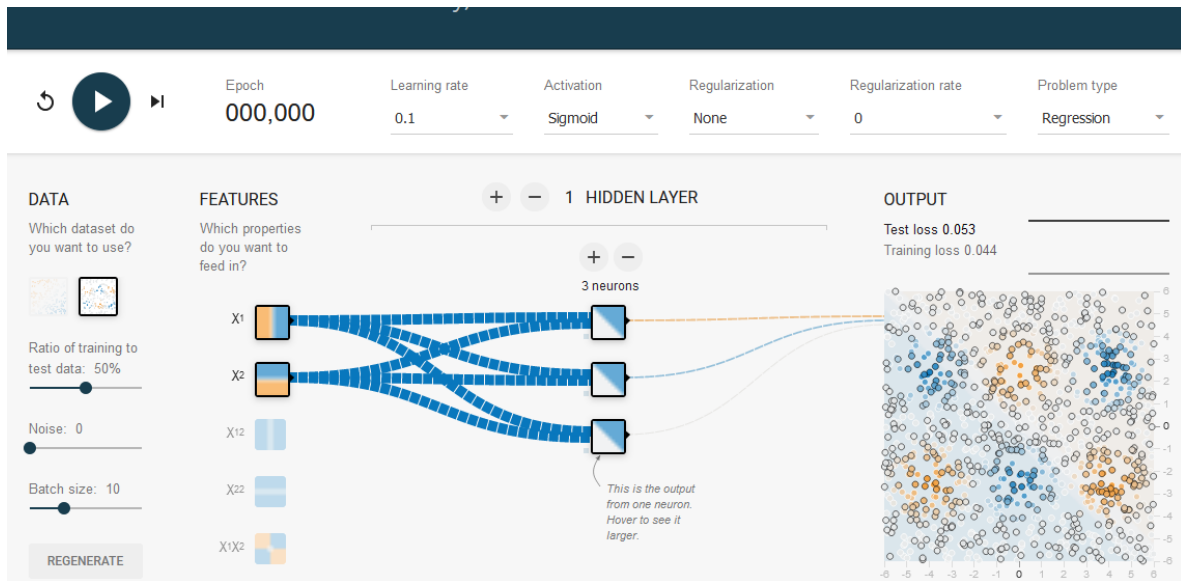


Figure 15: This is our network. We will now click 'Play' button and observe 'Test Loss' (see below) figure. Starting Test loss is 0.053.

Now, click the *Play* button. Test loss after initial decrease (because of adjustment of weights between hidden layer and output neuron) soon freezes and shows no improvements.

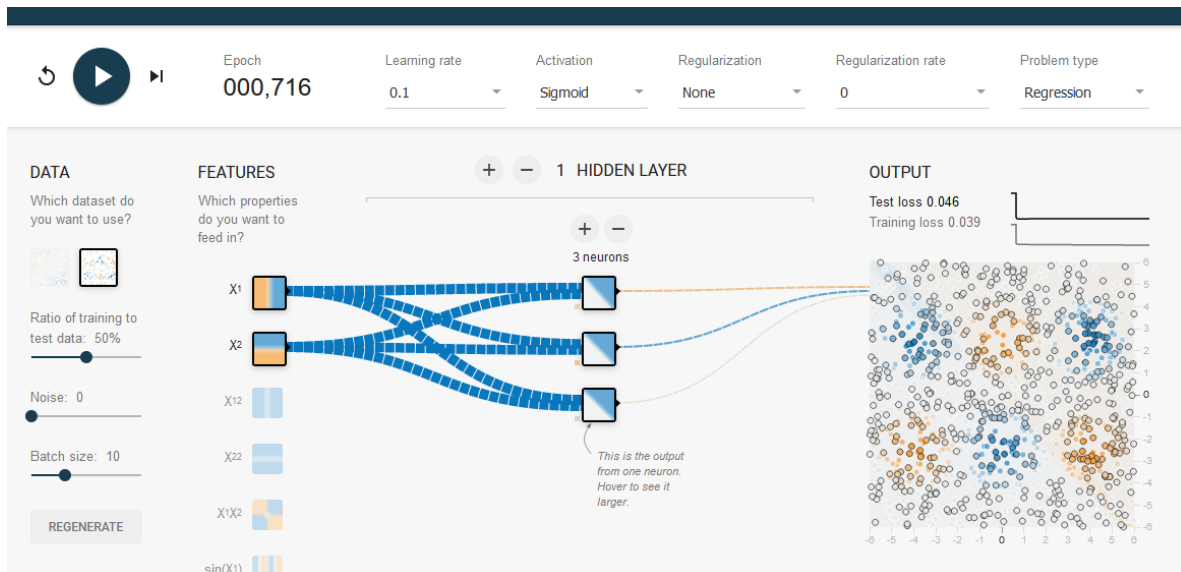


Figure 16: Test loss after it reaches 0.046, becomes stationary and does not reduce any further.

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