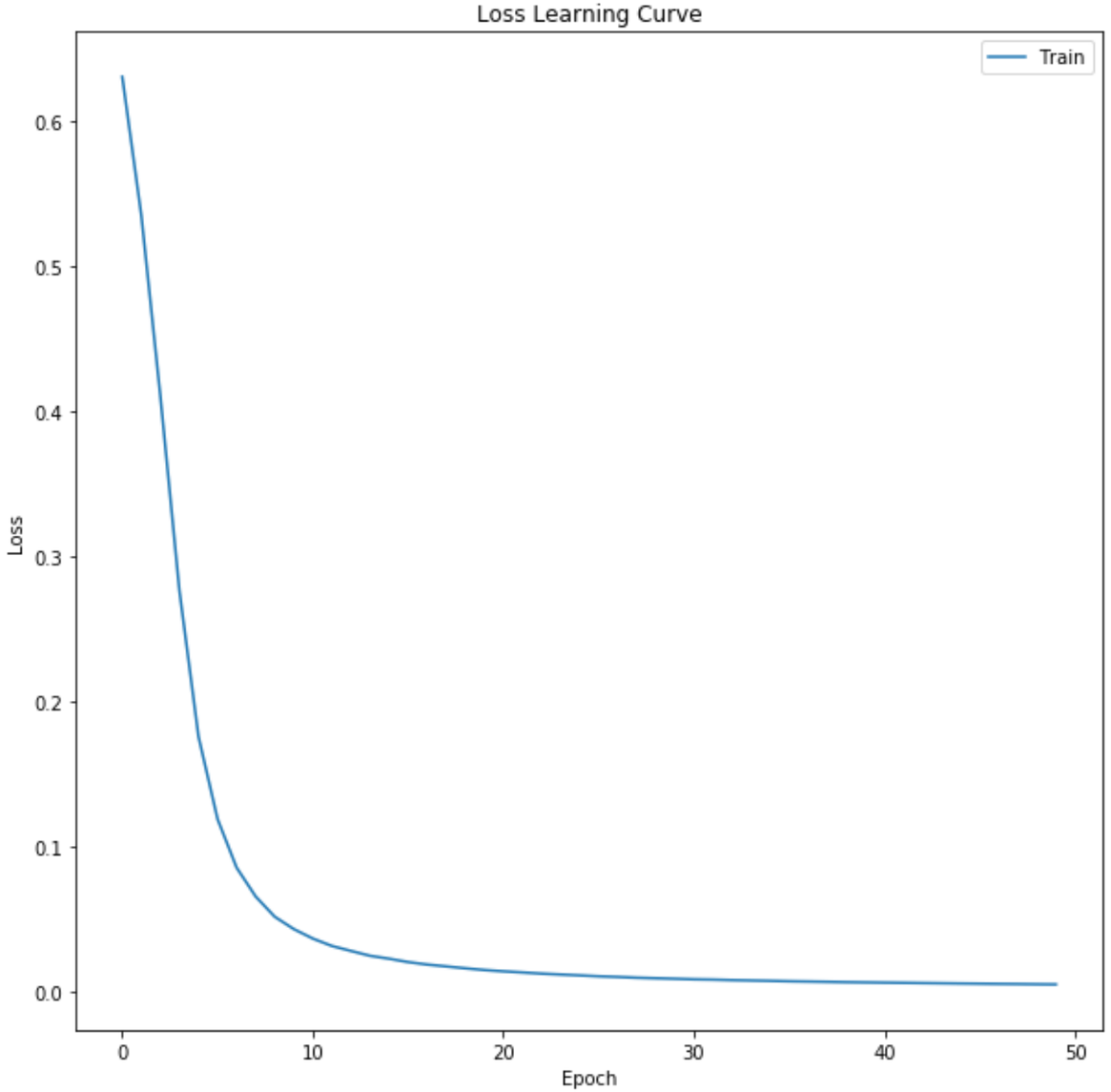
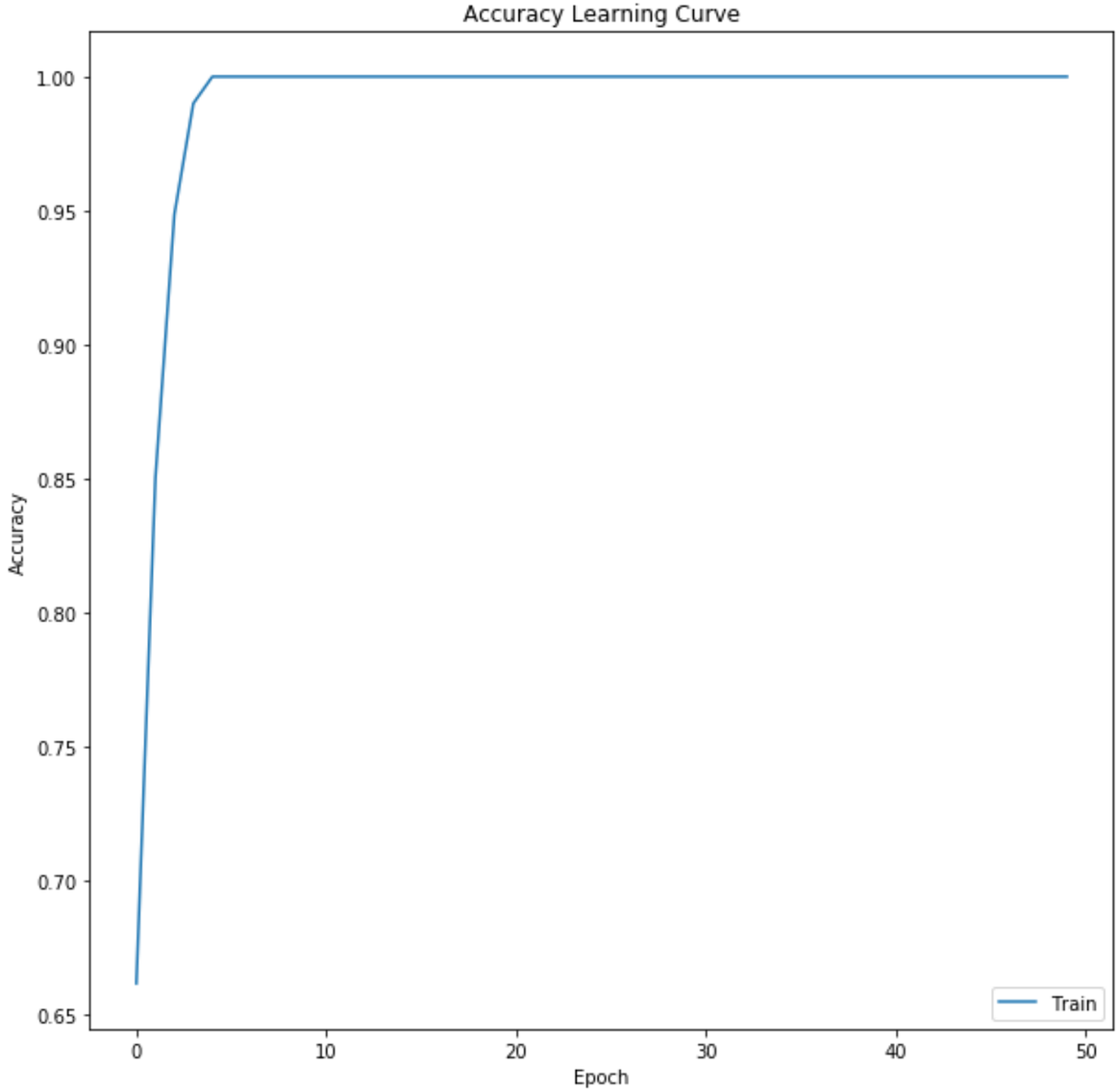
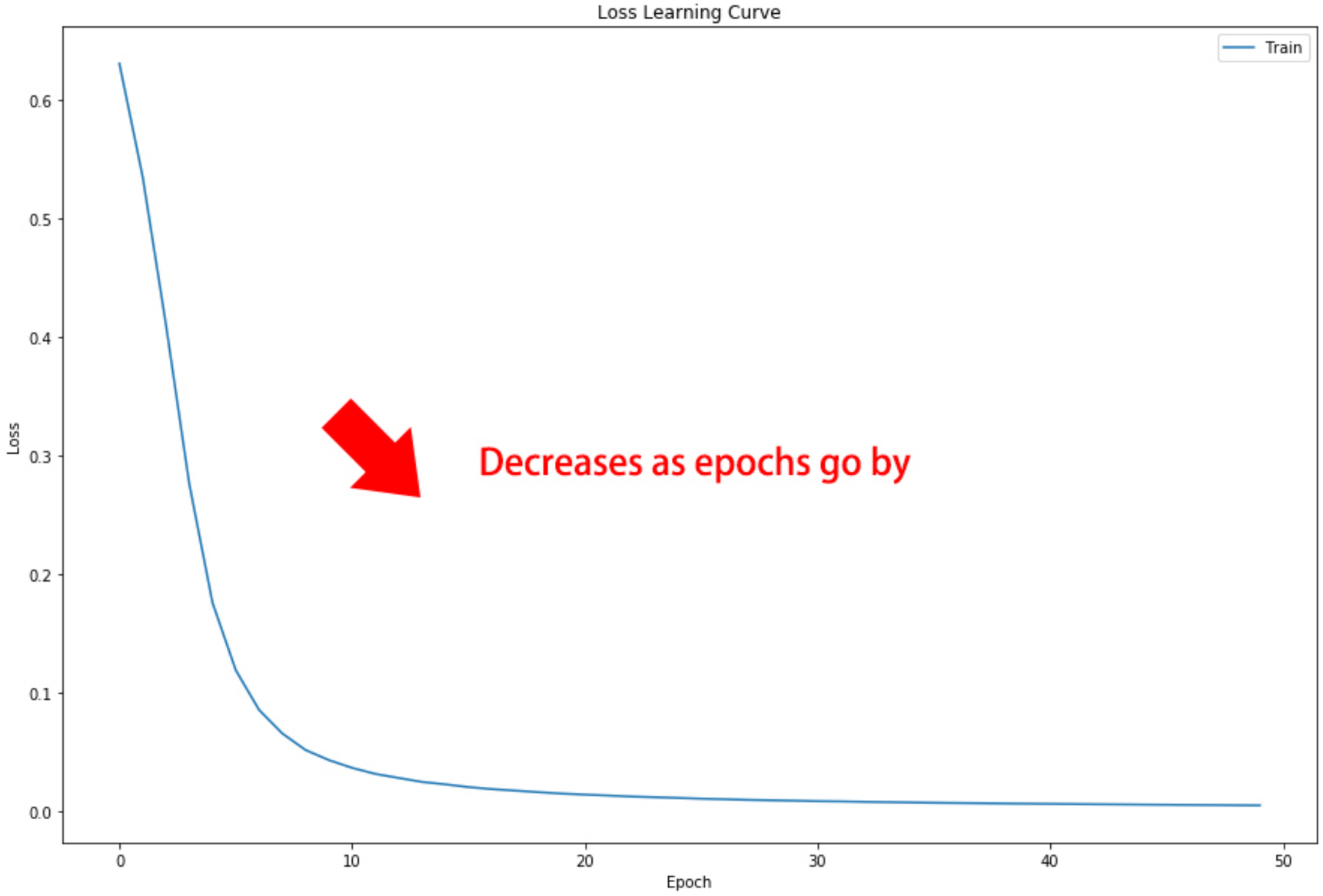
Learning curves

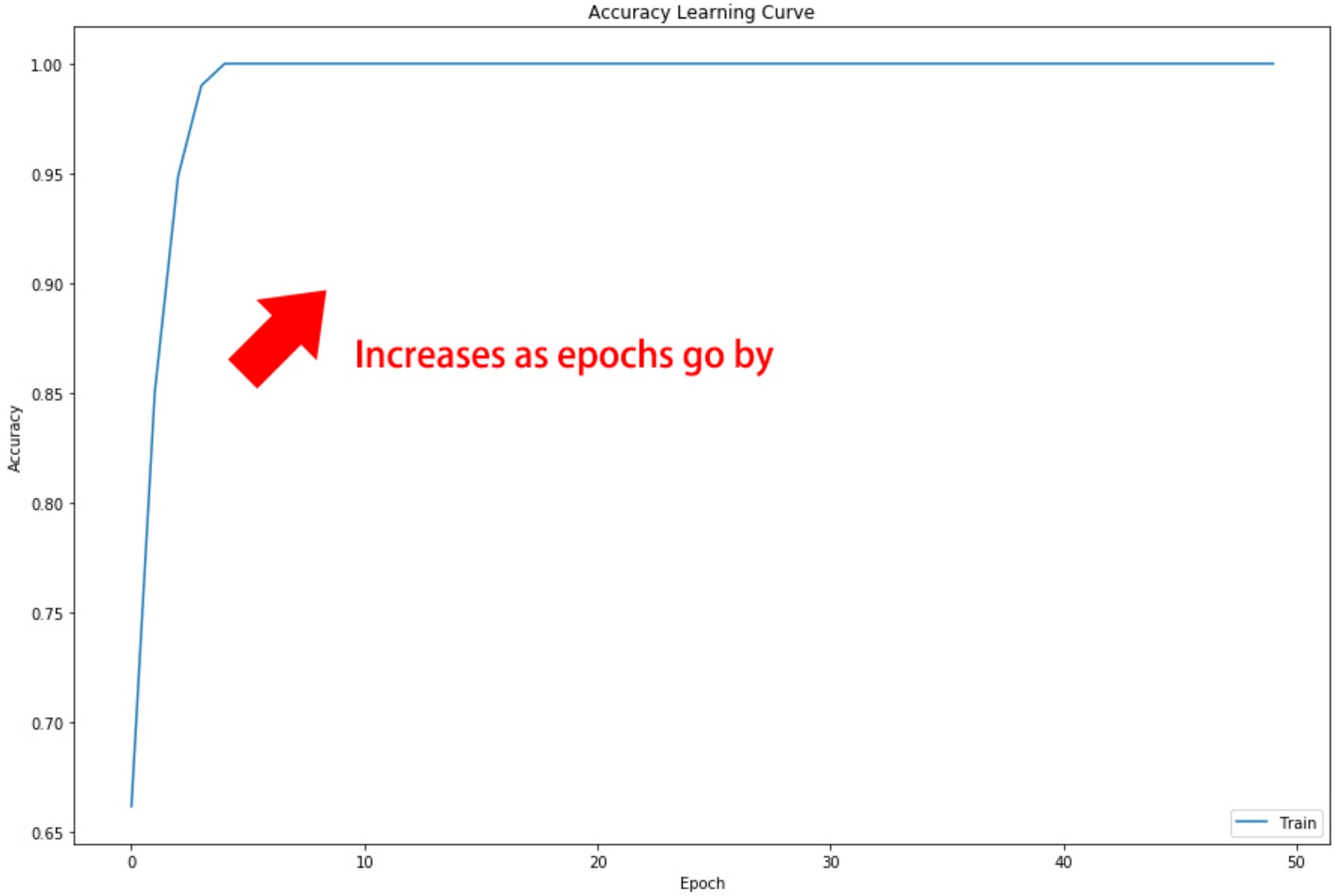
DEEP LEARNING WITH KERAS IN PYTHON

Miguel Esteban
Data Scientist & Founder

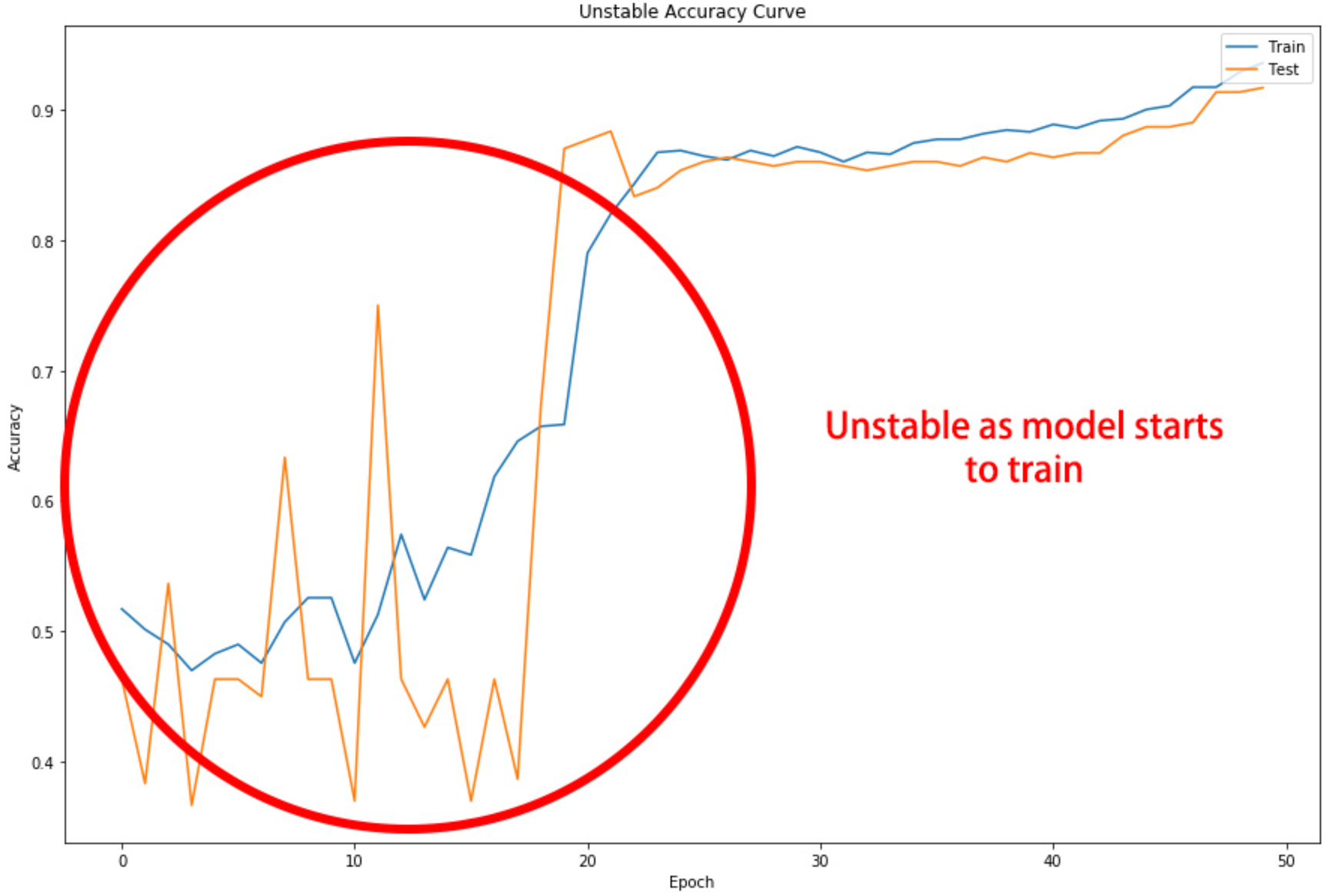

Loss Learning Curve
Train
Loss
Epoch
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50


Accuracy Learning Curve
Train
Accuracy
Epoch
0.65
0.70
0.75
0.80
0.85
0.90
0.95
1.00
0
10
20
30
40
50

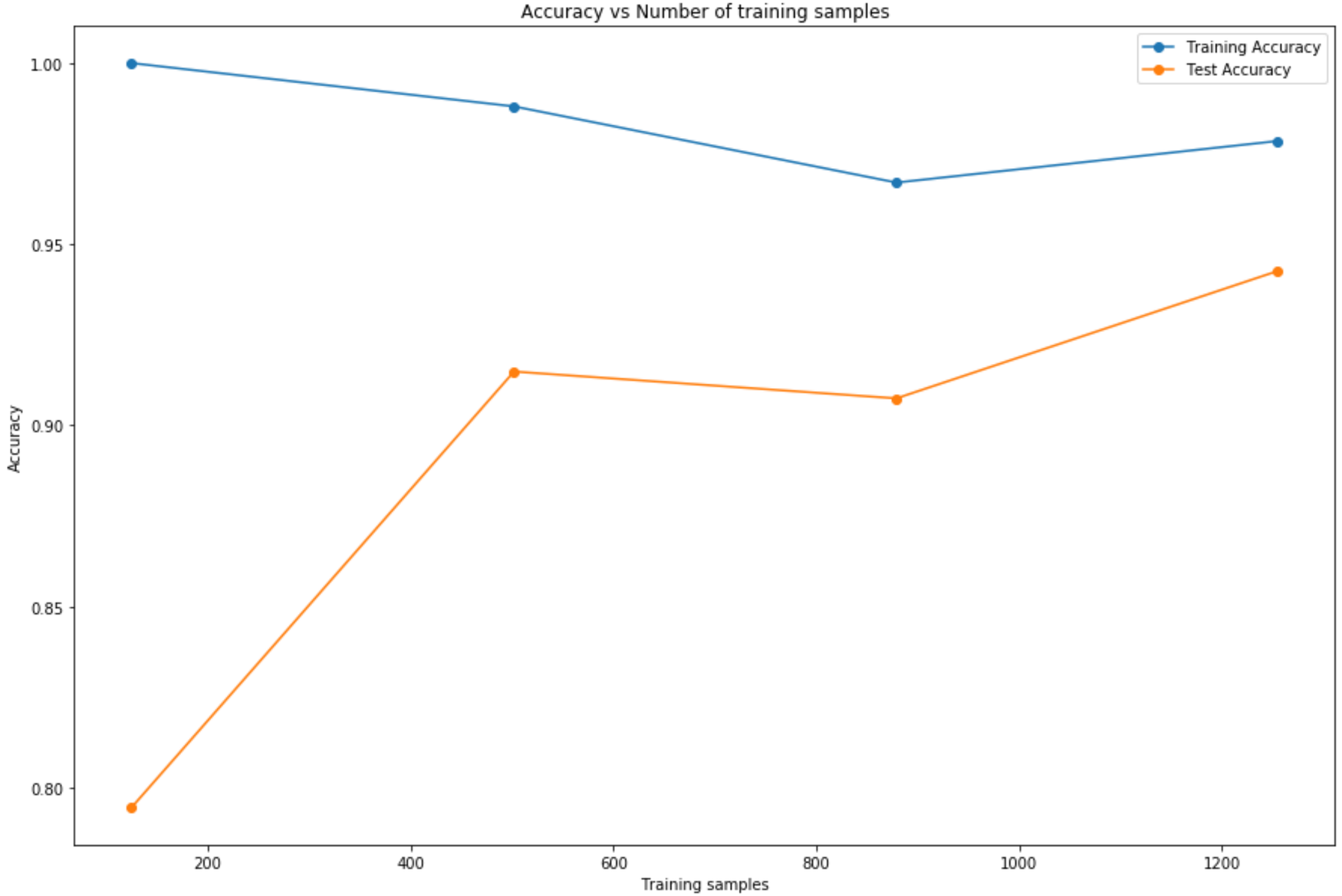

Loss Learning Curve
Train
Loss
Epoch
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
Decreases as epochs go by

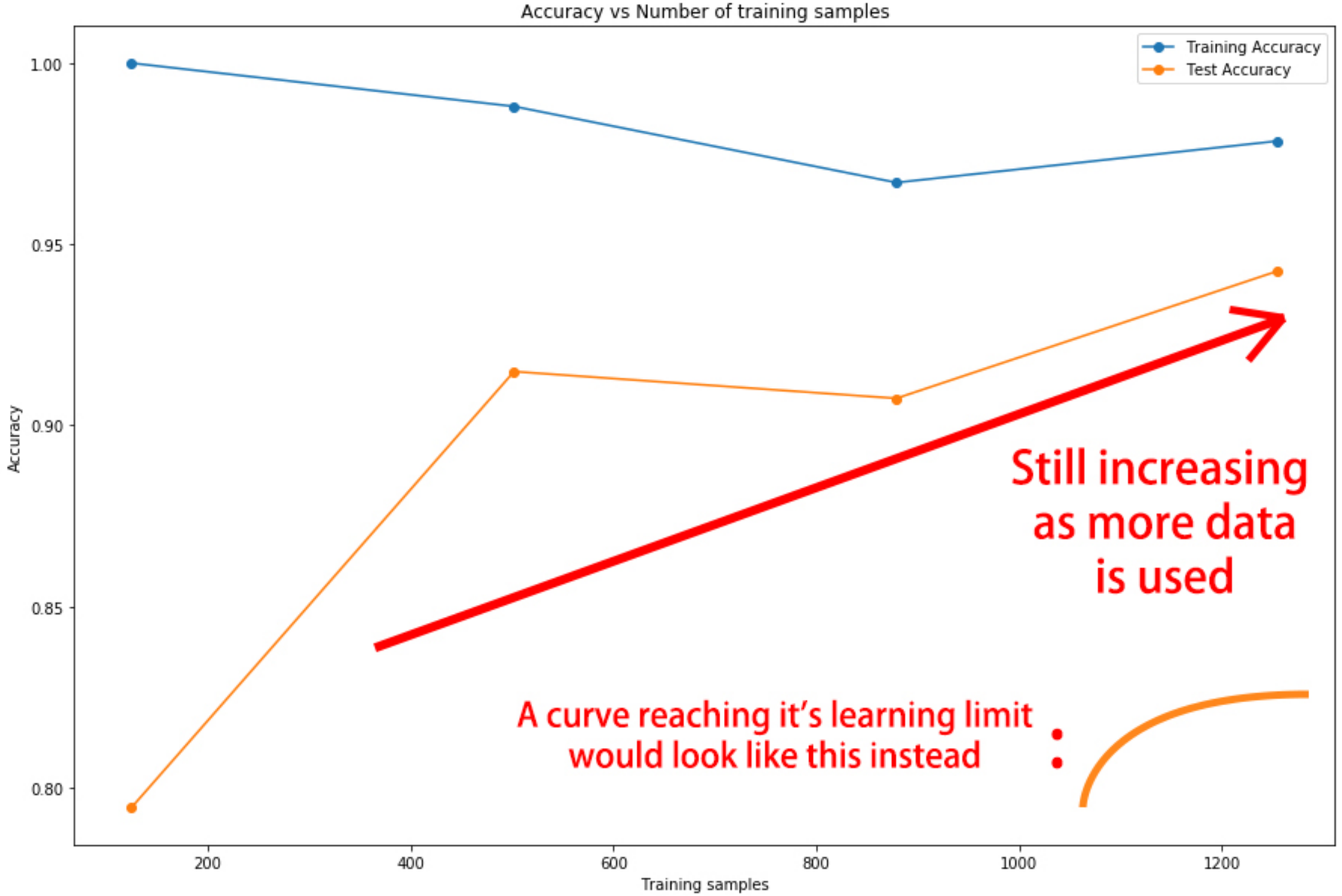

Accuracy Learning Curve
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
Accuracy
Increases as epochs go by
Train
0
10
20
30
40
50
Epoch


Model Overfitting
Train
Test
Loss
0.5
0.4
0.3
0.2
0
20
40
60
80
100
Epoch
Training and test start to diverge
Big difference


Unstable Accuracy Curve
Train
Test
Accuracy
Epoch
0.9
0.8
0.7
0.6
0.5
0.4
0
10
20
30
40
50
Unstable as model starts
to train


Neural networks like to be fed
with a BIG and VARIED
amount of data.


Accuracy vs Number of training samples
Training Accuracy
Test Accuracy
1.00
0.95
0.90
0.85
0.80
Accuracy
200
400
600
800
1000
1200
Training samples


Accuracy vs Number of training samples
Training Accuracy
Test Accuracy
1.00
0.95
0.90
0.85
0.80
Accuracy
200
400
600
800
1000
1200
Training samples
Still increasing
as more data
is used
A curve reaching it's learning limit
would look like this instead

```
# Store initial model weights
init_weights = model.get_weights()

# Lists for storing accuracies
train_accs = []
tests_accs = []
```

```
for train_size in train_sizes:
    # Split a fraction according to train_size
    X_train_frac, _, y_train_frac, _ =
    train_test_split(X_train, y_train, train_size=train_size)

    # Set model initial weights
    model.set_weights(initial_weights)

    # Fit model on the training set fraction
    model.fit(X_train_frac, y_train_frac, epochs=100,
                  verbose=0,
                  callbacks=[EarlyStopping(monitor='loss', patience=1)])

    # Get the accuracy for this training set fraction
    train_acc = model.evaluate(X_train_frac, y_train_frac, verbose=0)[1]
    train_accs.append(train_acc)

    # Get the accuracy on the whole test set
    test_acc = model.evaluate(X_test, y_test, verbose=0)[1]
    test_accs.append(test_acc)
    print("Done with size: ", train_size)
```

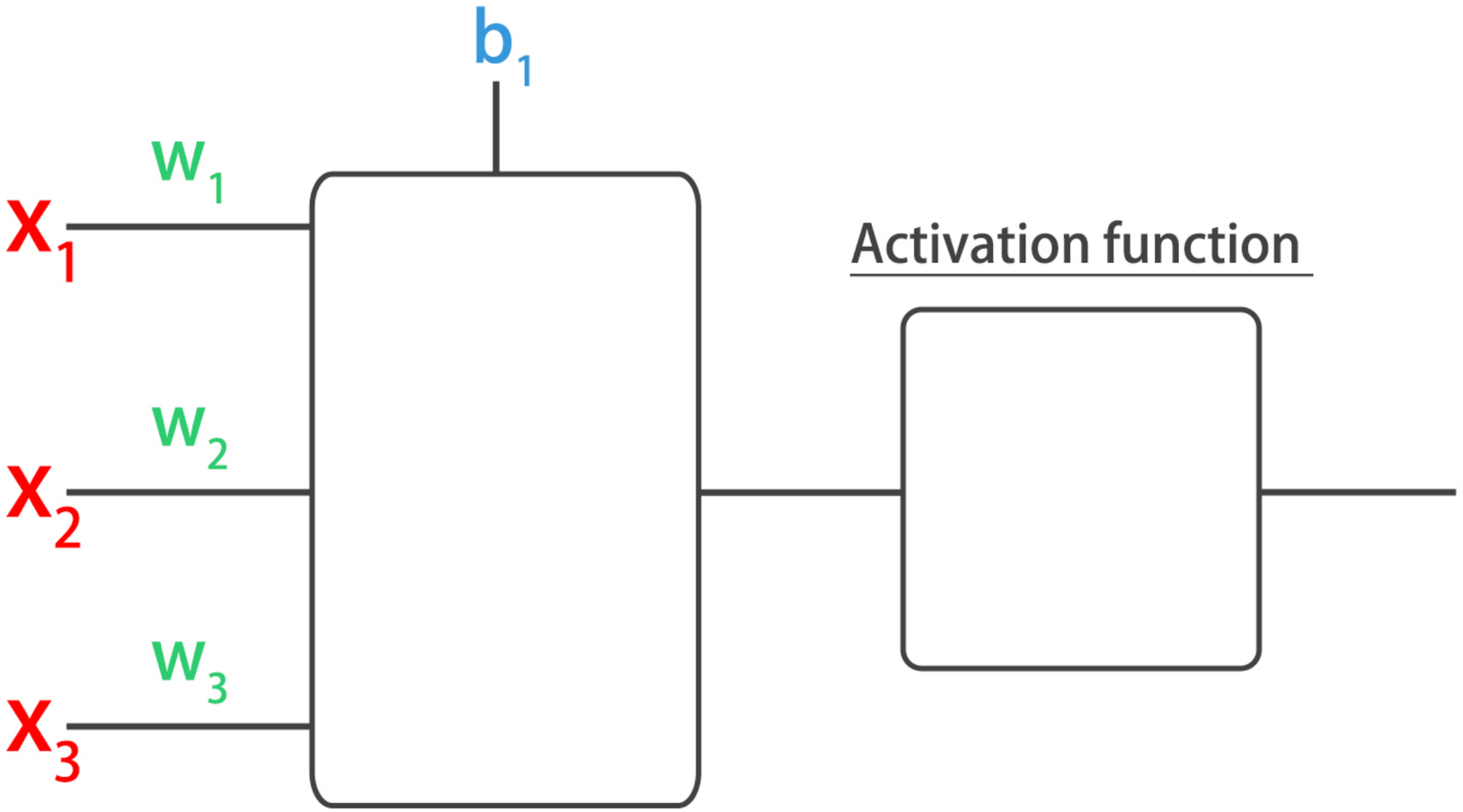
Time to dominate all curves!

DEEP LEARNING WITH KERAS IN PYTHON

Activation functions

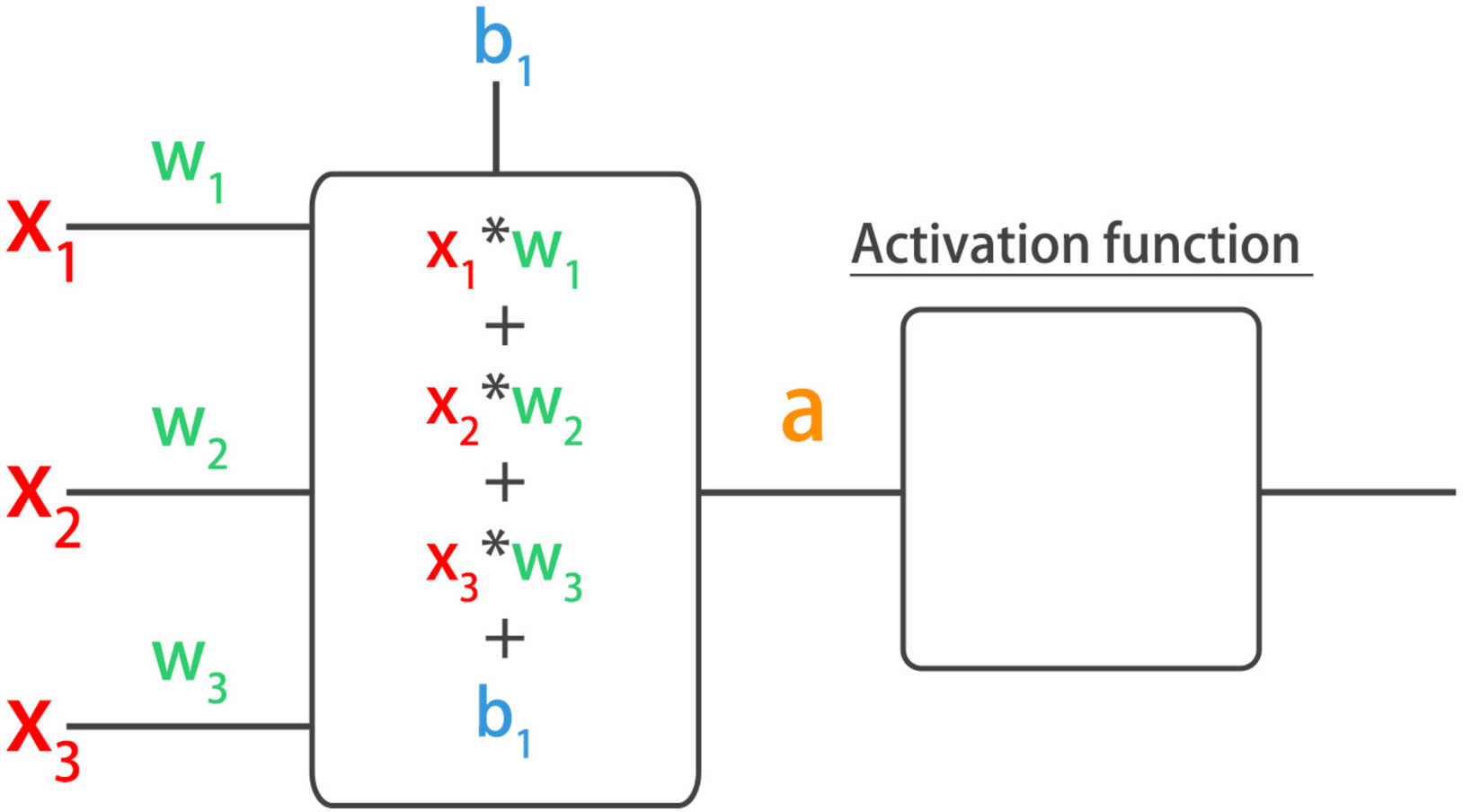
DEEP LEARNING WITH KERAS IN PYTHON

Miguel Esteban
Data Scientist & Founder



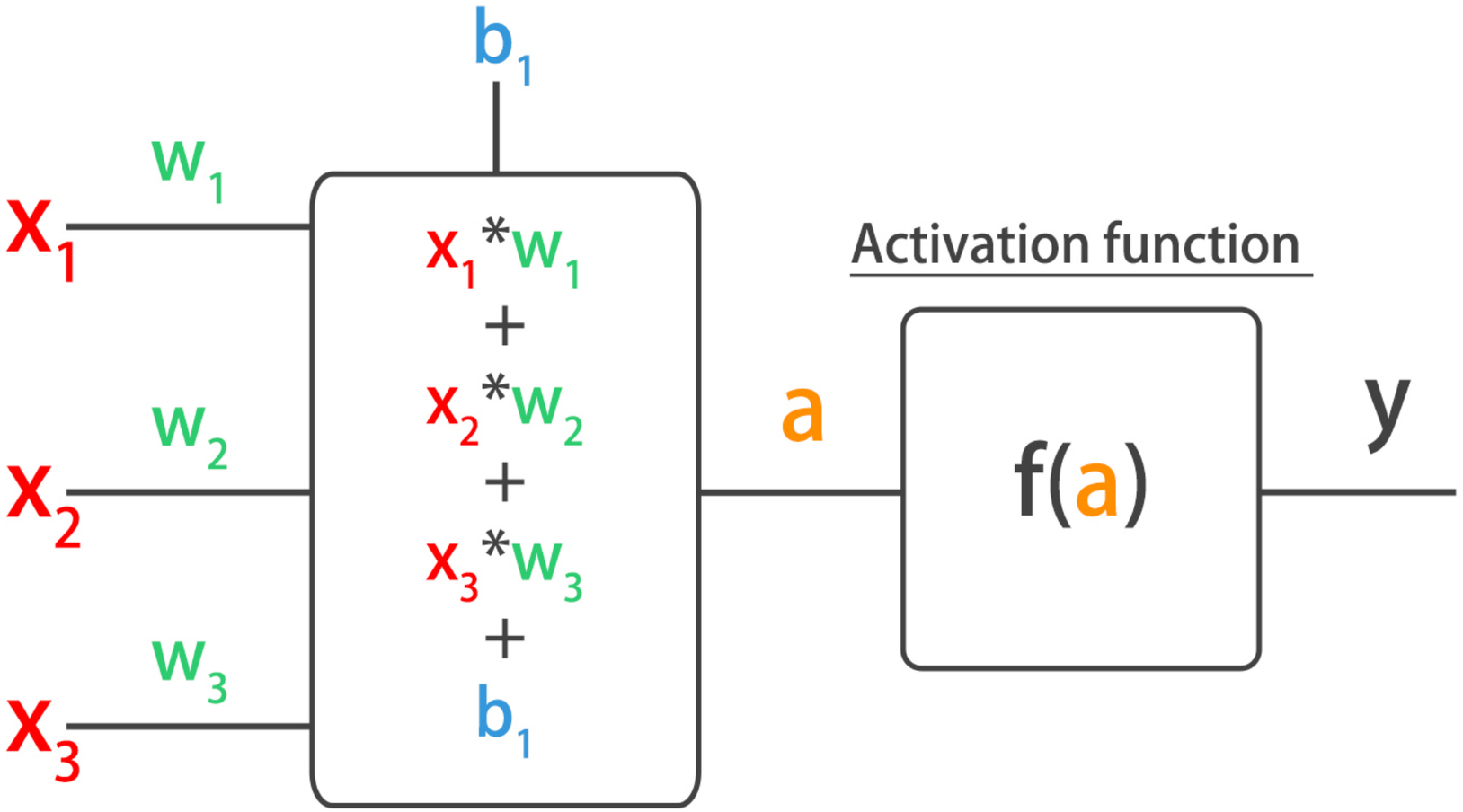
Neuron

a = sum of inputs*weights + bias



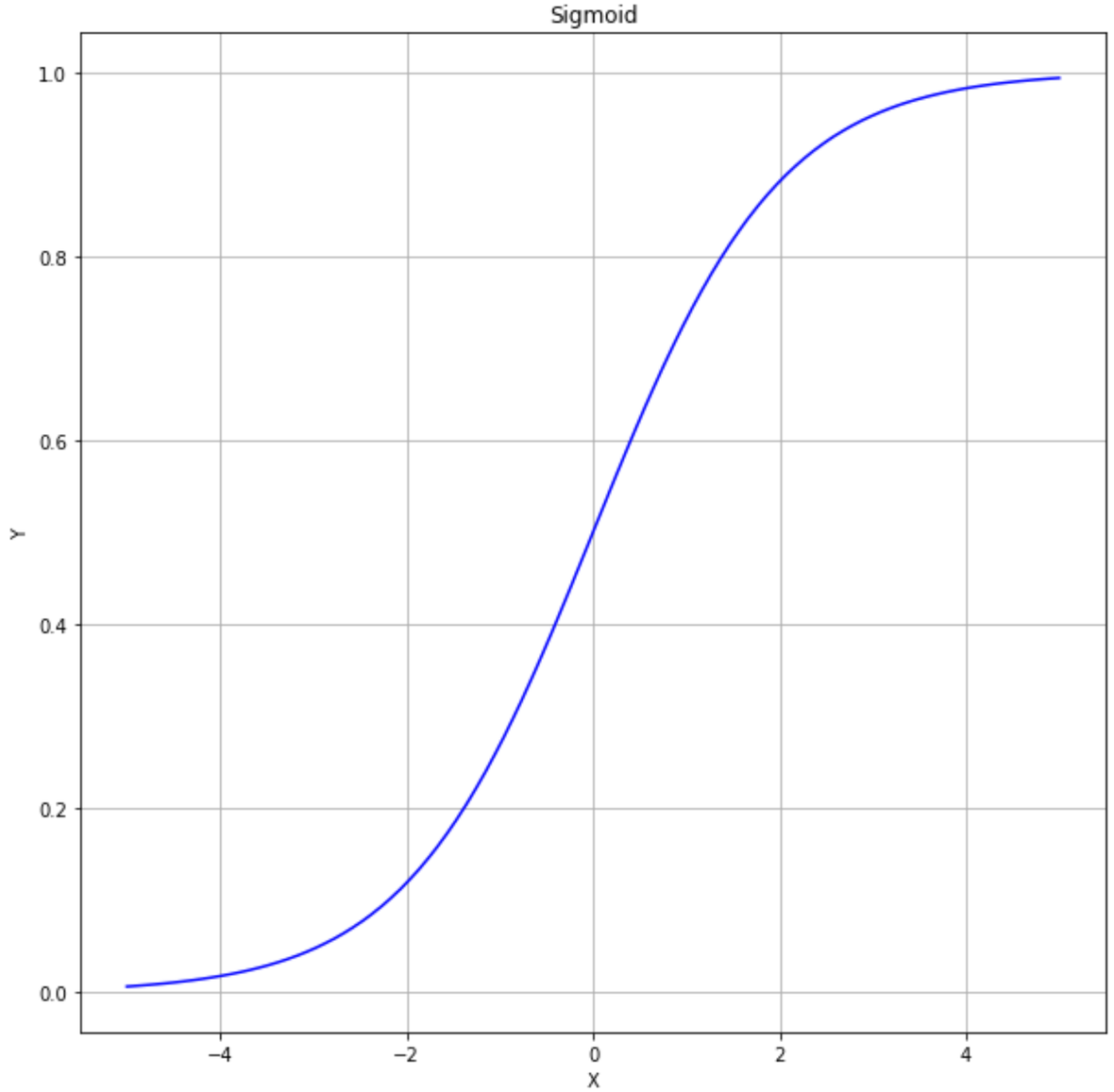
Neuron

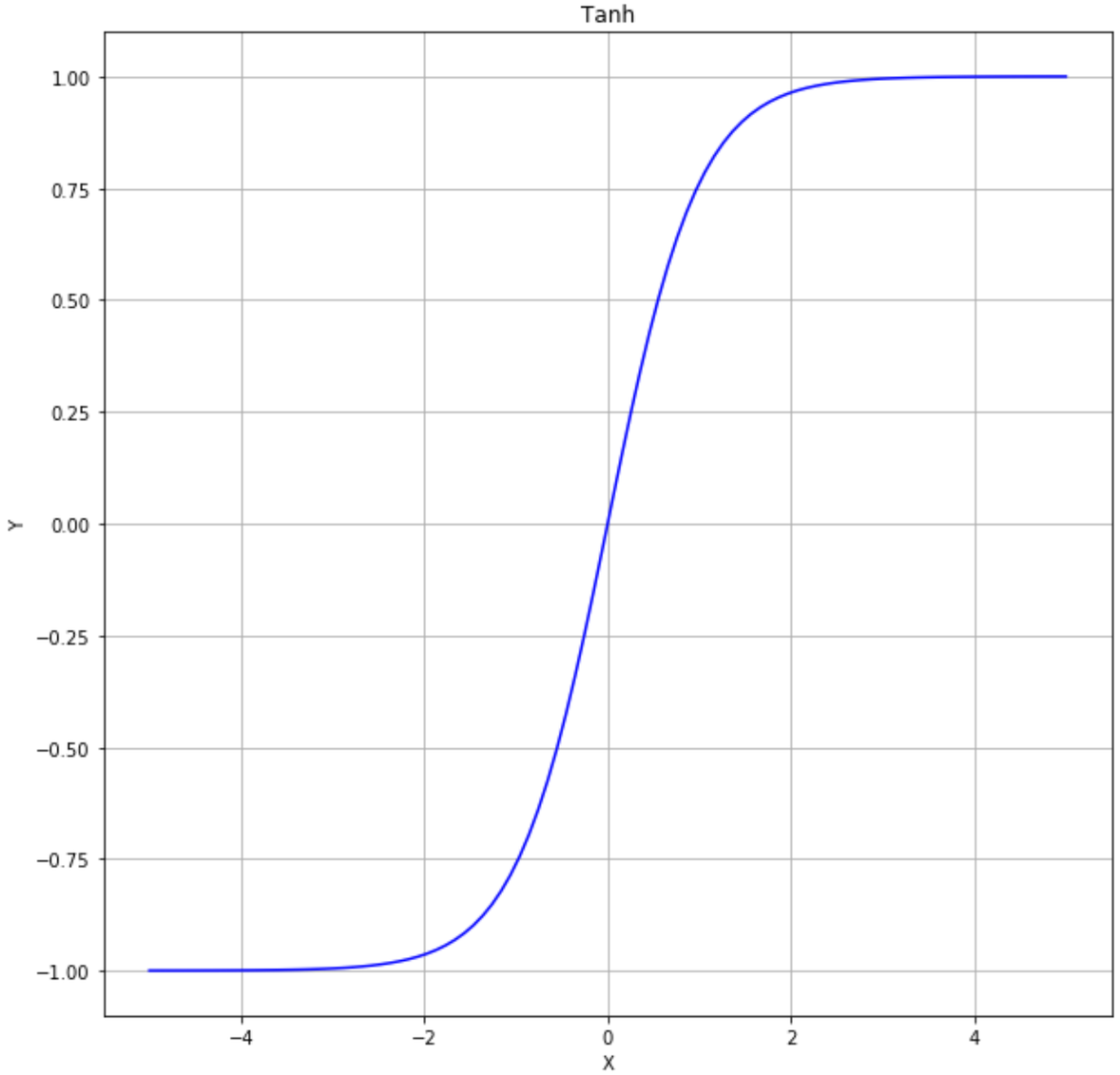
a = sum of inputs*weights + bias

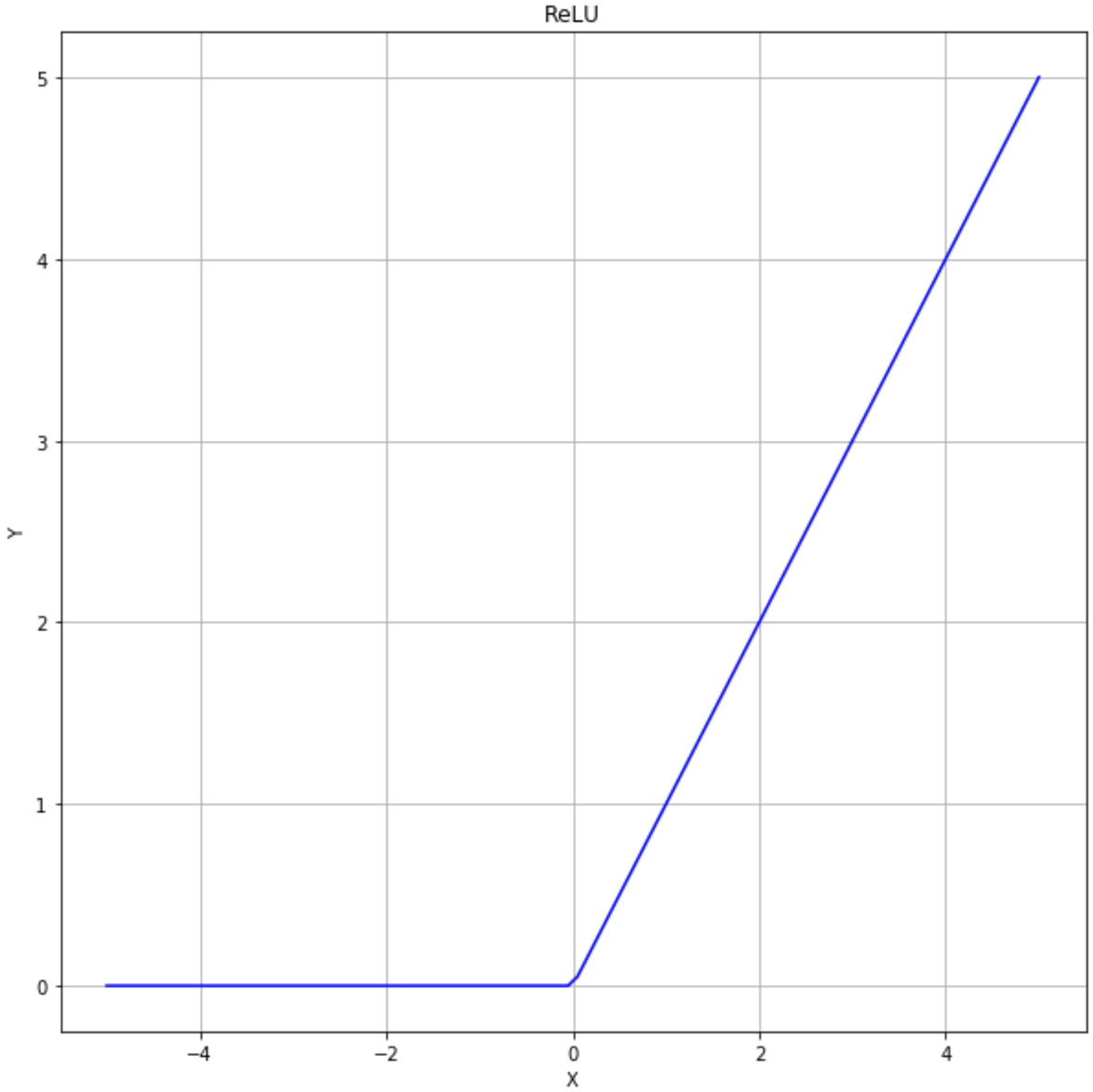


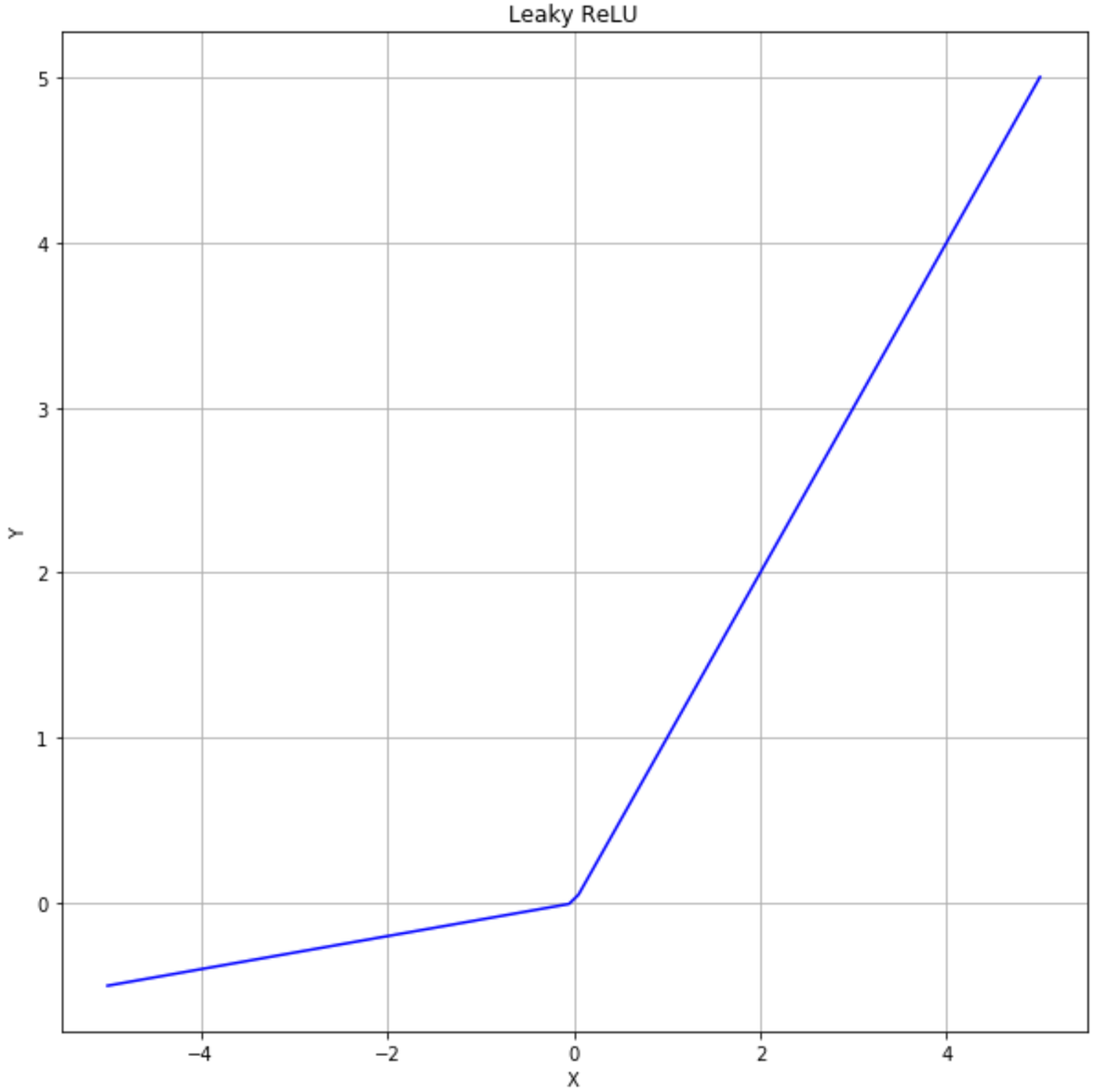
Neuron

a = sum of inputs*weights + bias

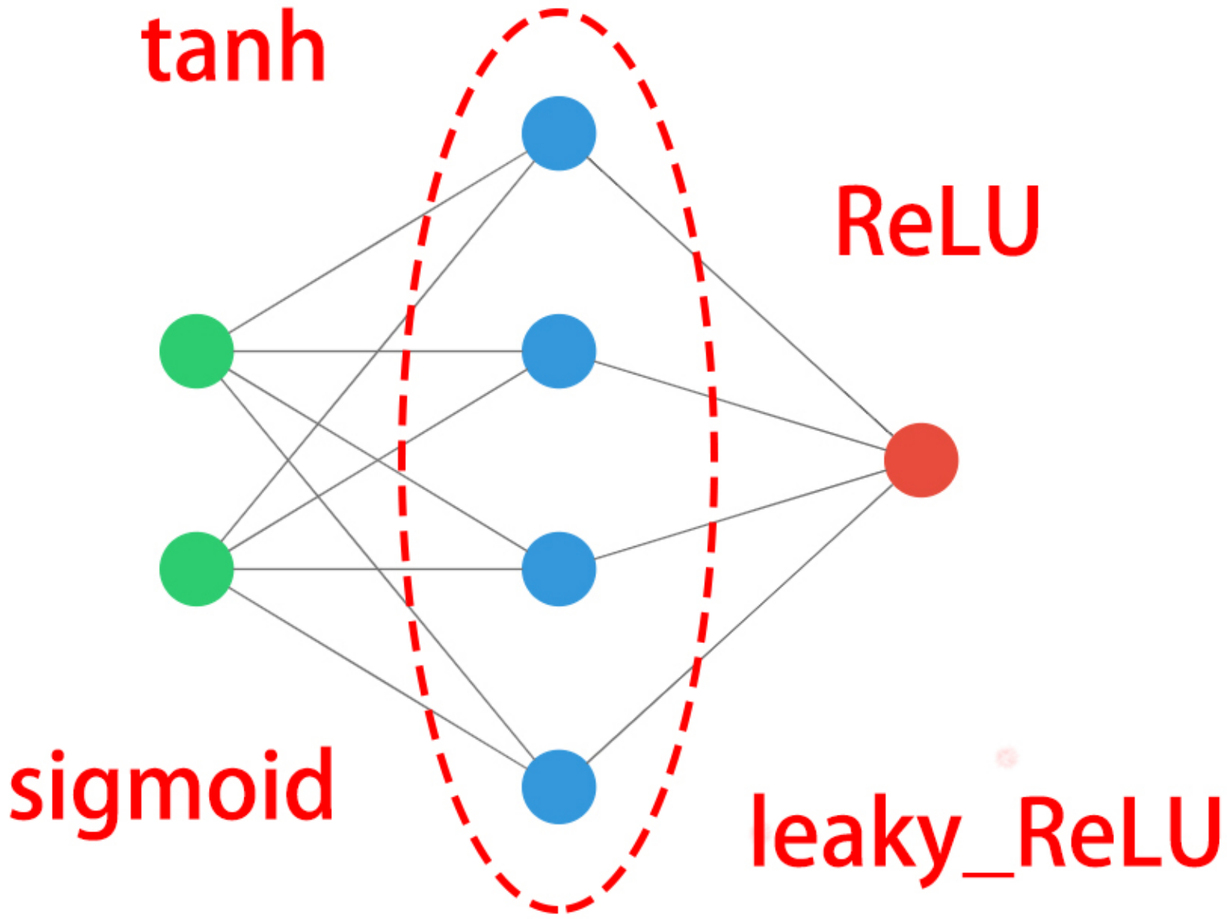

Sigmoid
1.0
0.8
0.6
0.4
0.2
0.0
Y
−4
−2
0
2
4
X

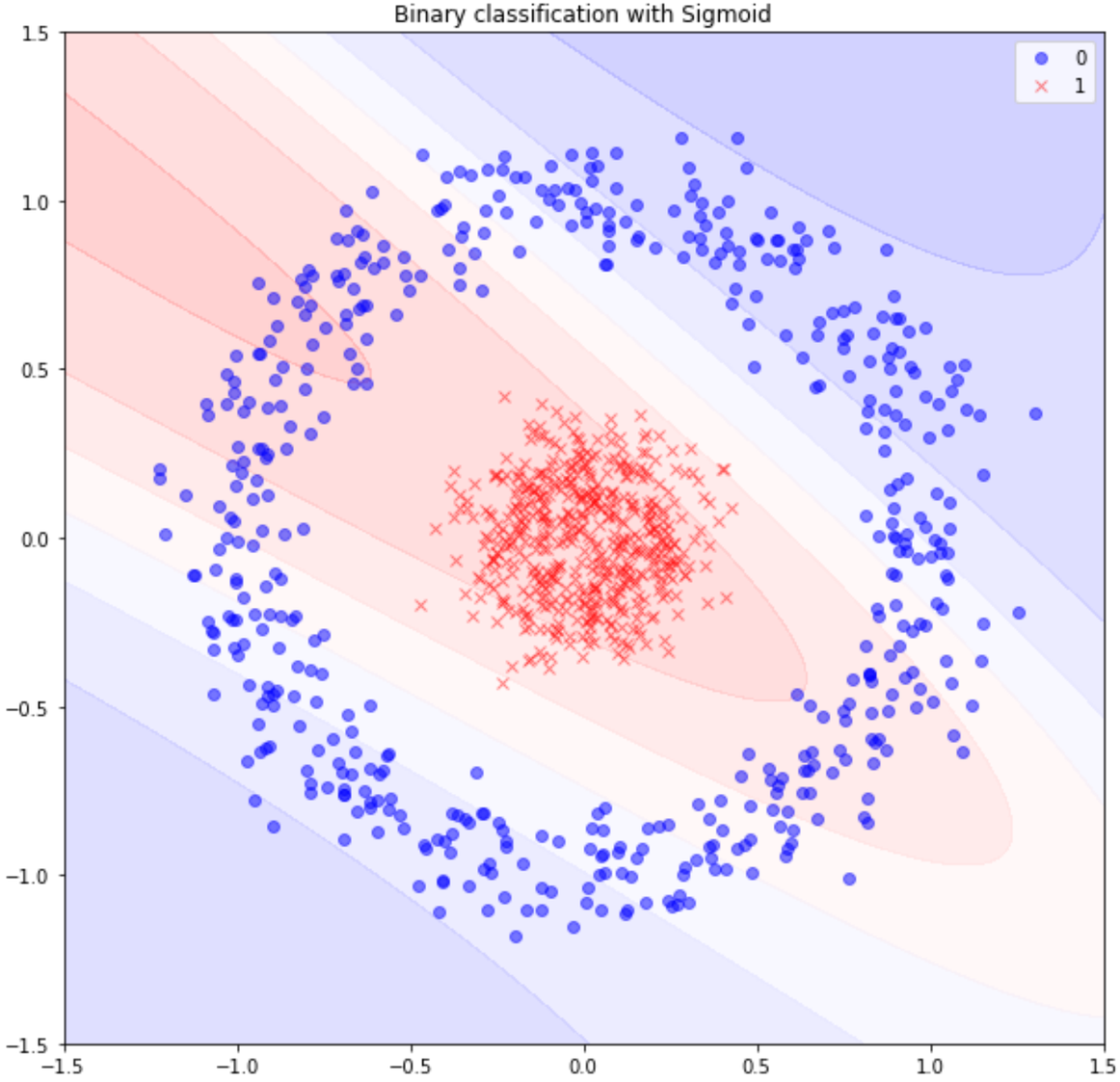

Tanh
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Y
−4
−2
0
2
4
X

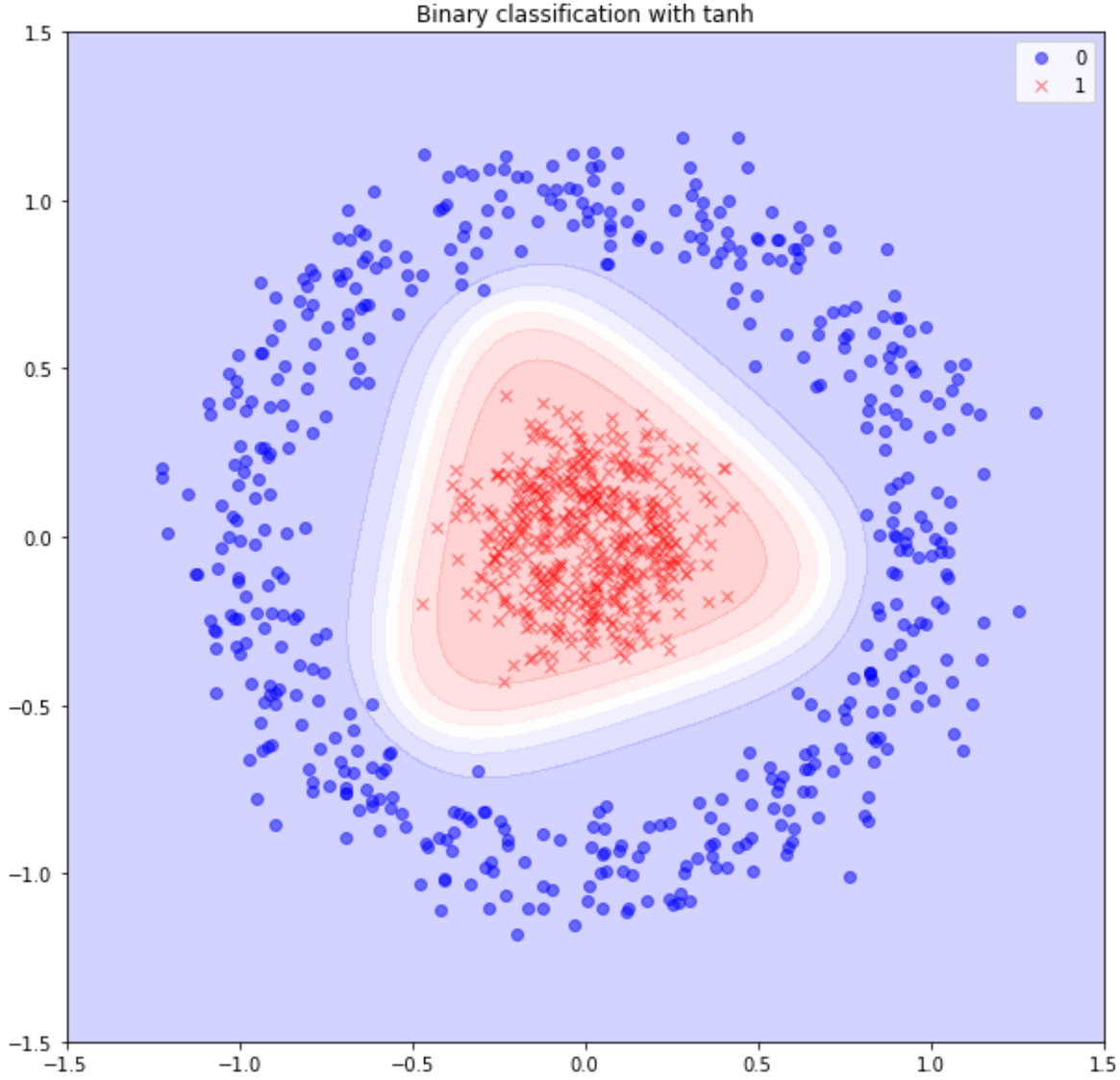

ReLU
5
4
3
2
1
0
Y
−4
−2
0
2
4
X

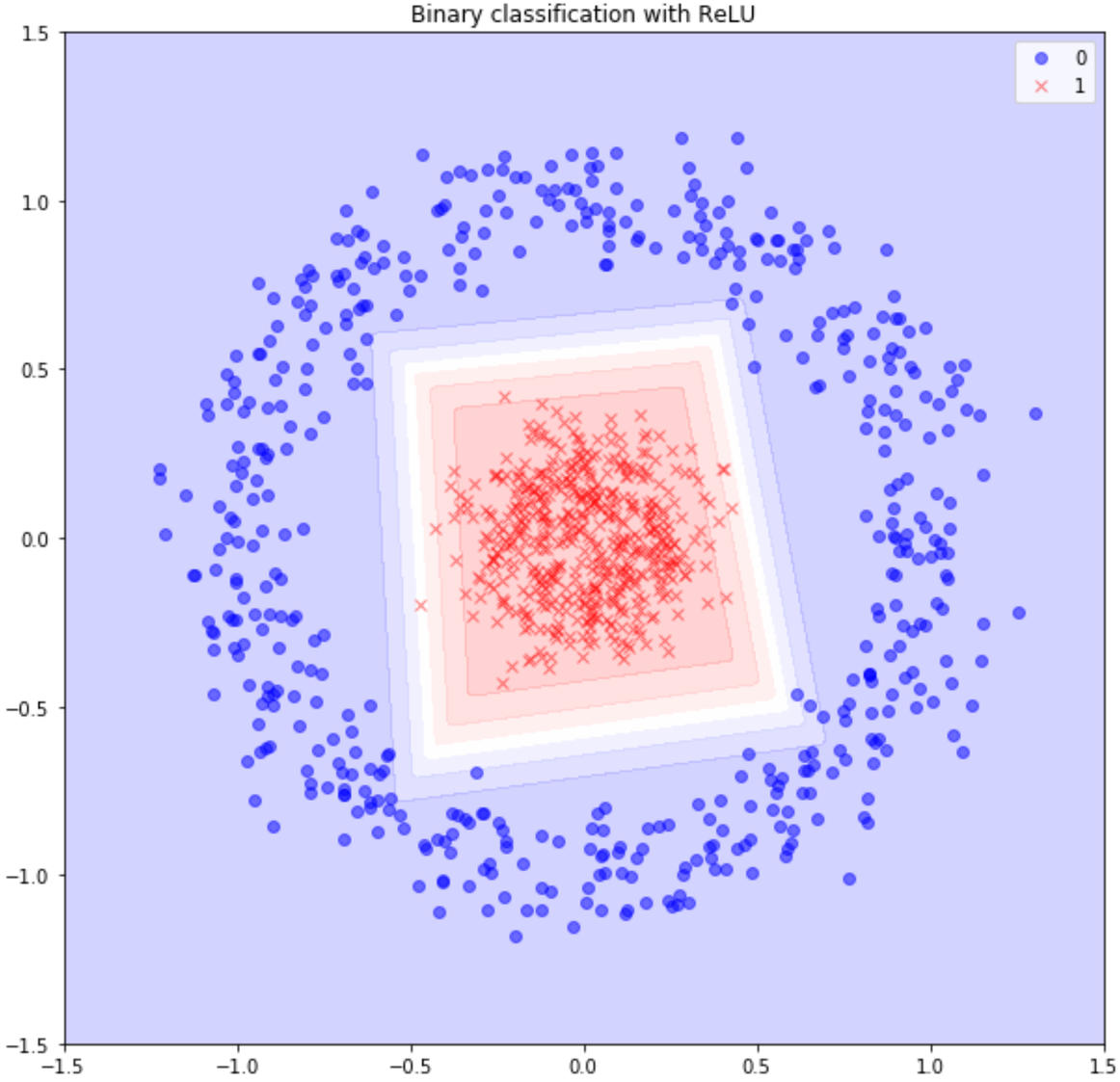

Leaky ReLU
5
4
3
2
1
0
Y
−4
−2
0
2
4
X

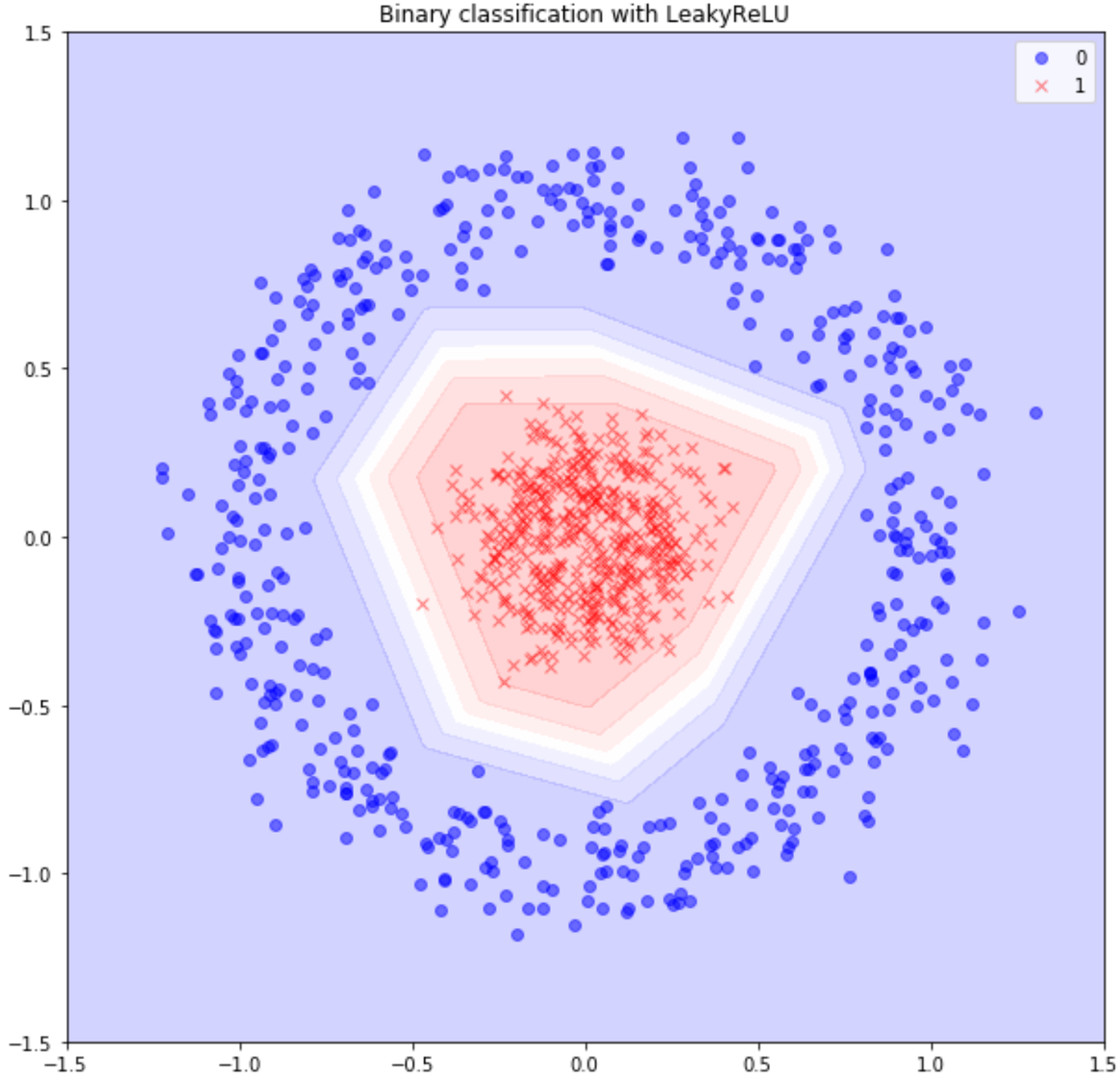
Effects of activation functions




Binary classification with Sigmoid
0
1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Binary classification with tanh
0
1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Binary classification with ReLU
0
1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Binary classification with LeakyReLU
0
1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

Which activation function to use?

- No magic formula
- Different properties
- Depends on our problem
- Goal to achieve in a given layer
- ReLU are a good first choice
- Sigmoids not recommended for deep models
- Tune with experimentation

Comparing activation functions

```
# Set a random seed
np.random.seed(1)

# Return a new model with the given activation
def get_model(act_function):
    model = Sequential()
    model.add(Dense(4, input_shape=(2,), activation=act_function))
    model.add(Dense(1, activation='sigmoid'))
    return model
```

Comparing activation functions

```
# Activation functions to try out
activations = ['relu', 'sigmoid', 'tanh']

# Dictionary to store results
activation_results = {}

for funct in activations:
    model = get_model(act_function=funct)
    history = model.fit(X_train, y_train,
                        validation_data=(X_test, y_test),
                        epochs=100, verbose=0)
    activation_results[funct] = history
```

Comparing activation functions

```
import pandas as pd

# Extract val_loss history of each activation function
val_loss_per_funct = {k:v.history['val_loss'] for k,v in activation_results.items()}


# Turn the dictionary into a pandas dataframe
val_loss_curves = pd.DataFrame(val_loss_per_funct)


# Plot the curves
val_loss_curves.plot(title='Loss per Activation function')
```

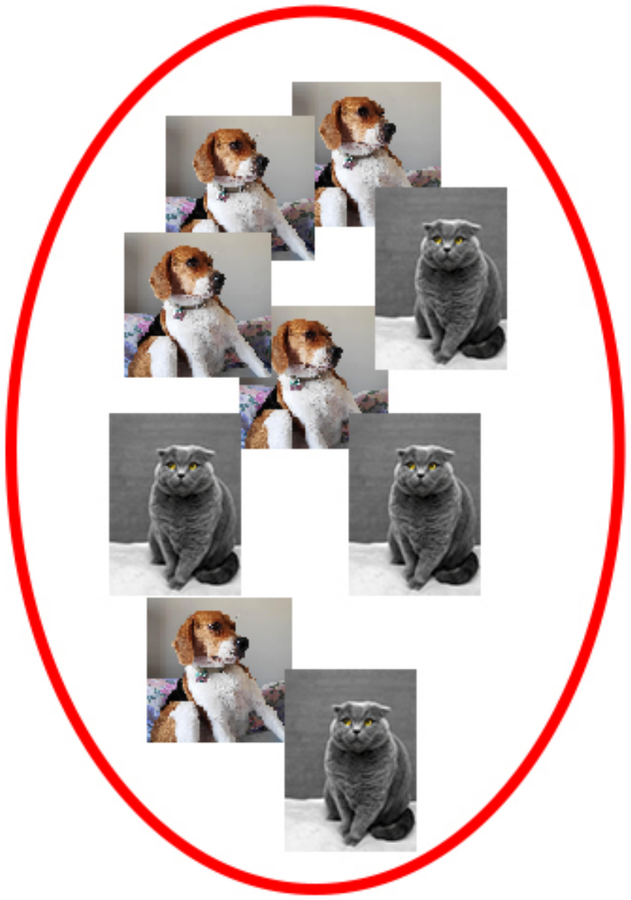
Let's practice!

DEEP LEARNING WITH KERAS IN PYTHON

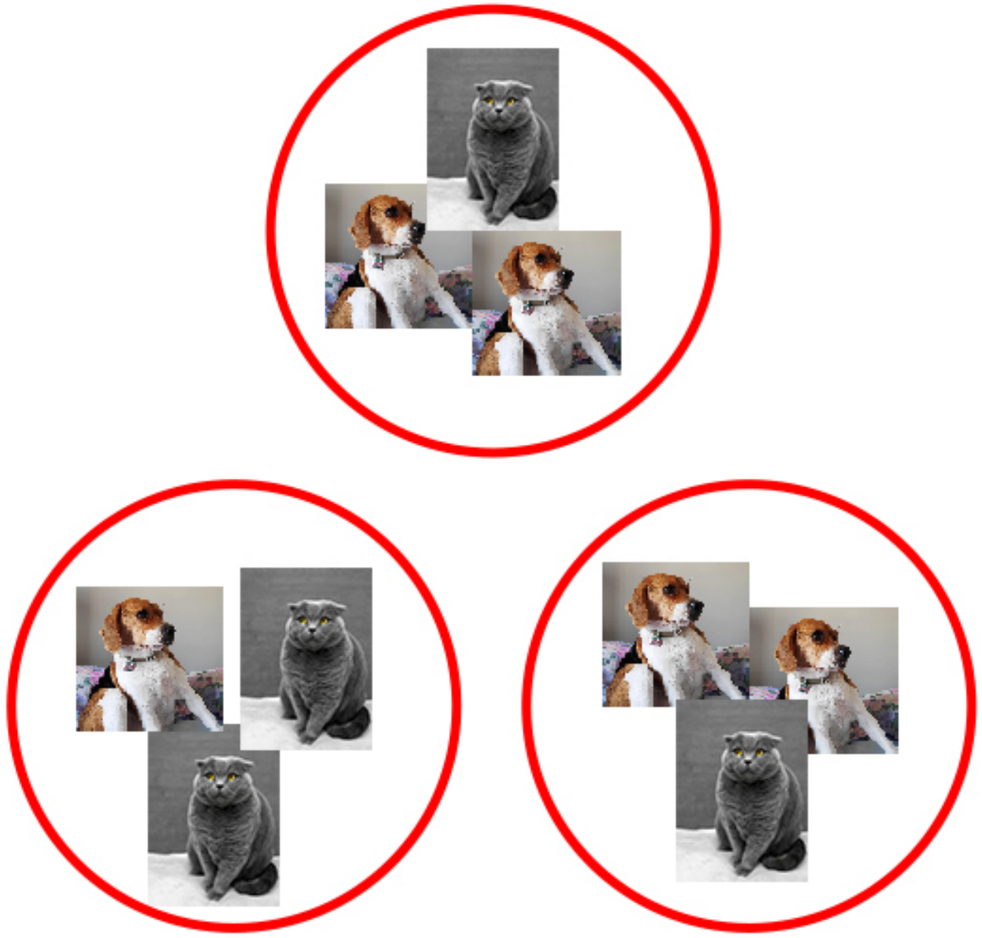
Batch size and batch normalization

DEEP LEARNING WITH KERAS IN PYTHON

Miguel Esteban
Data Scientist & Founder

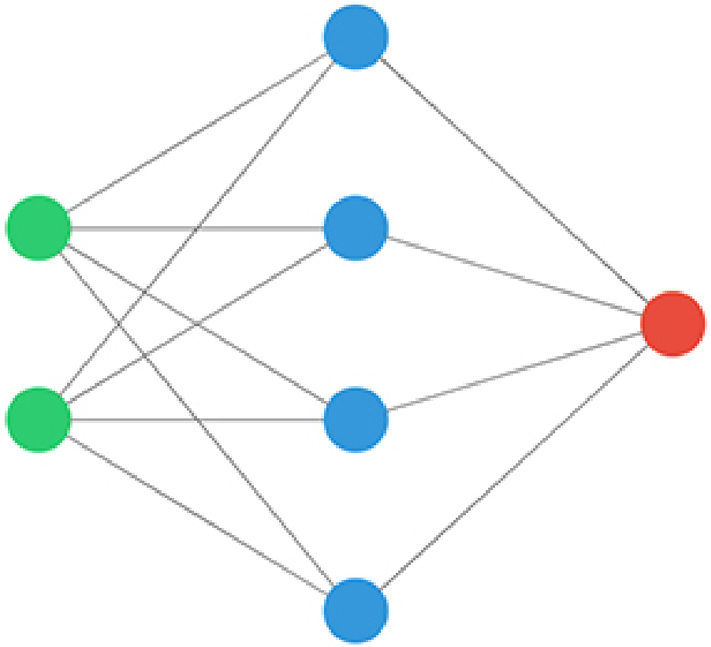


Batch

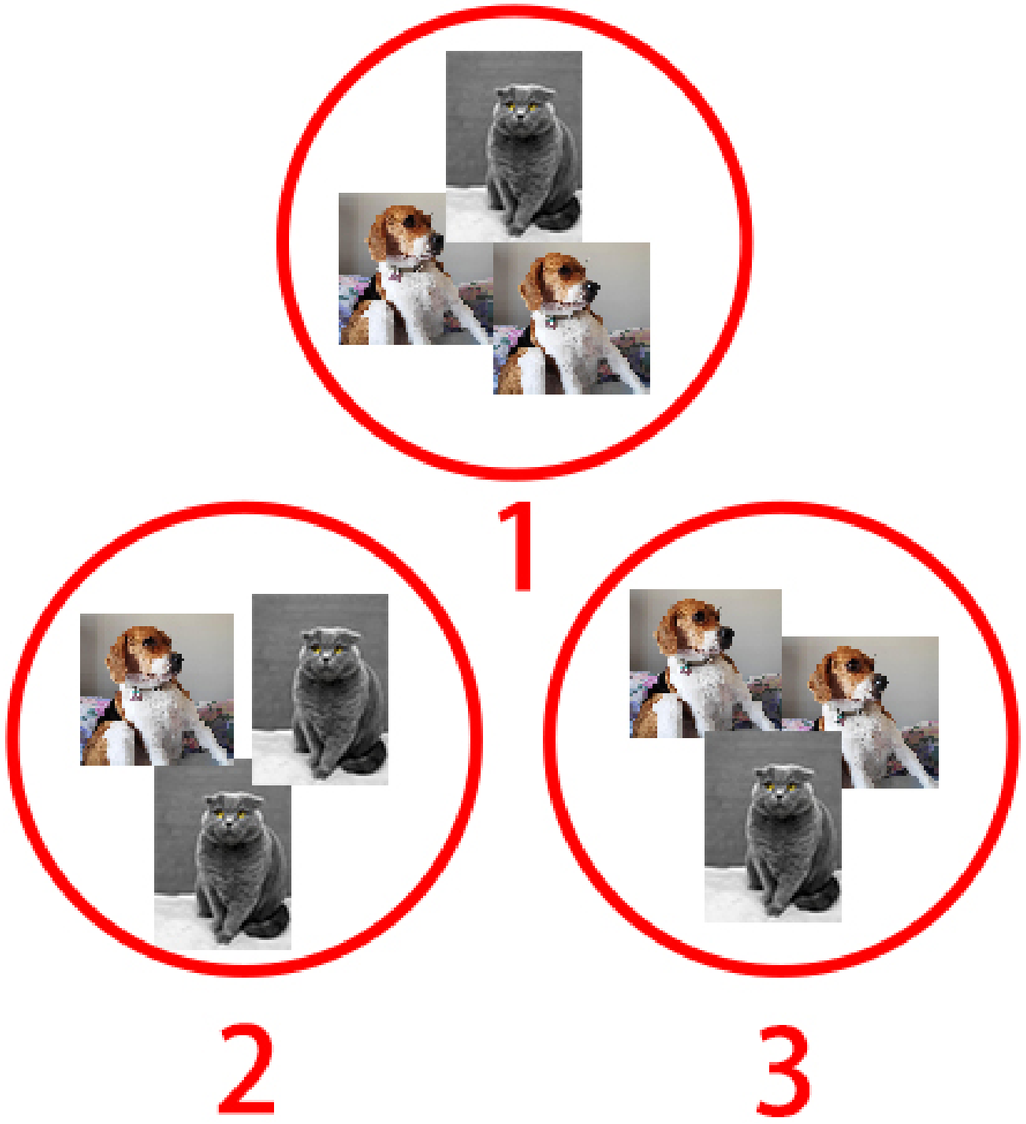


Mini-batches

The network is fed with 3 mini-batches



1 Epoch = 3 weight updates



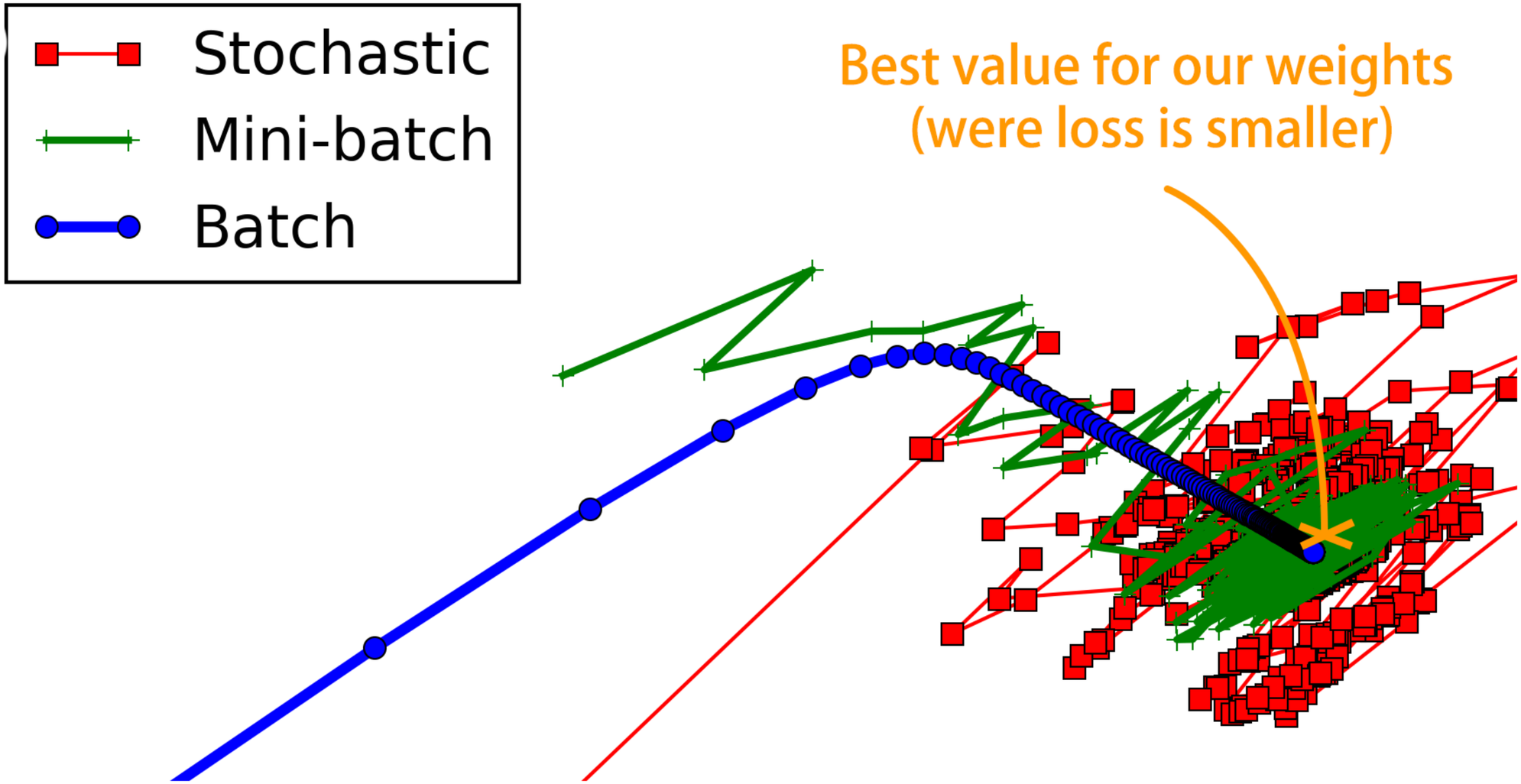
Mini-batches

Advantages

- Networks train faster (more weight updates in same amount of time)
- Less RAM memory required, can train on huge datasets
- Noise can help networks reach a lower error, escaping local minima

Disadvantages

- More iterations need to be run
- Need to be adjusted, we need to find a good batch size



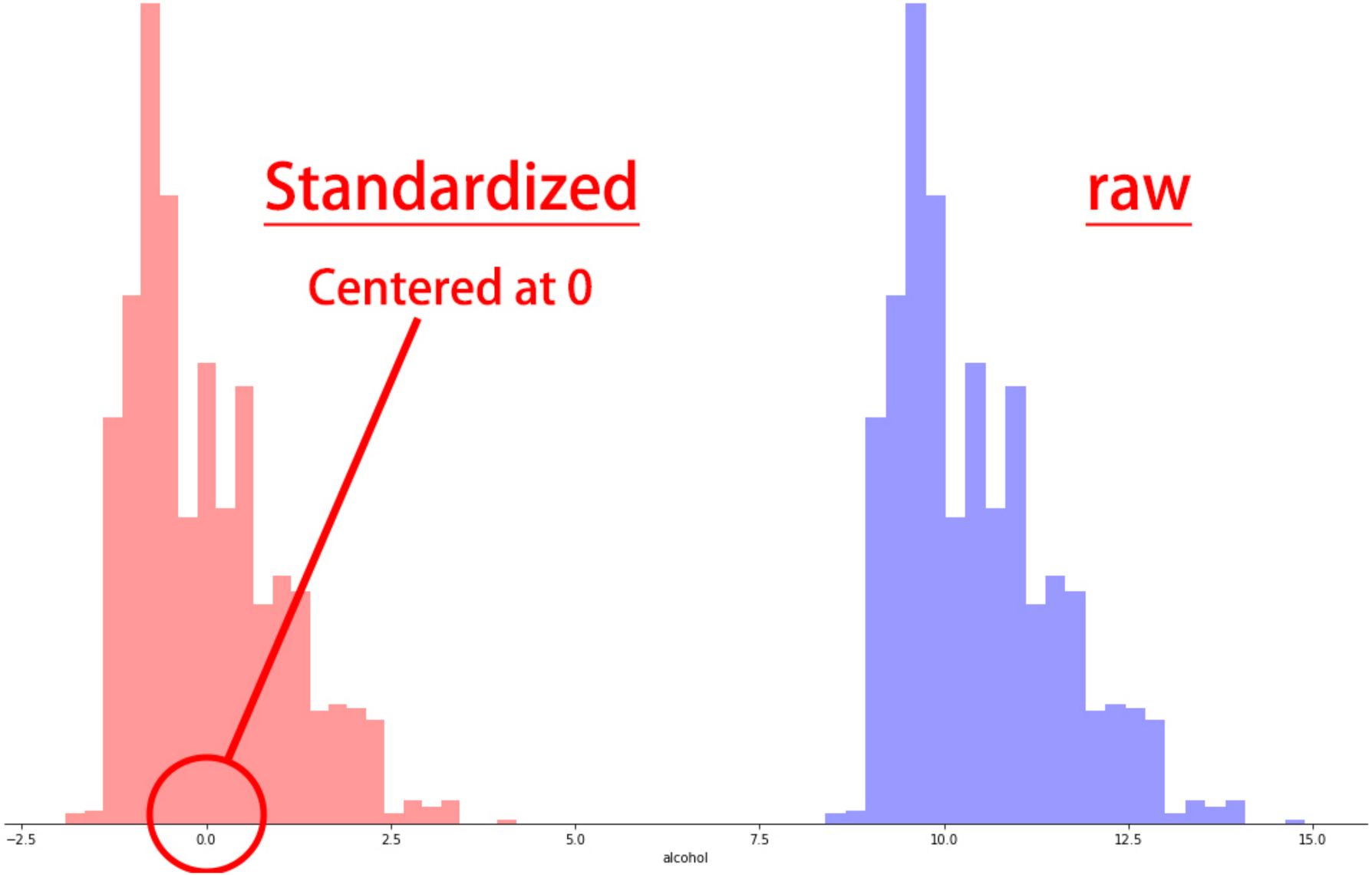
[1] Stack Exchange

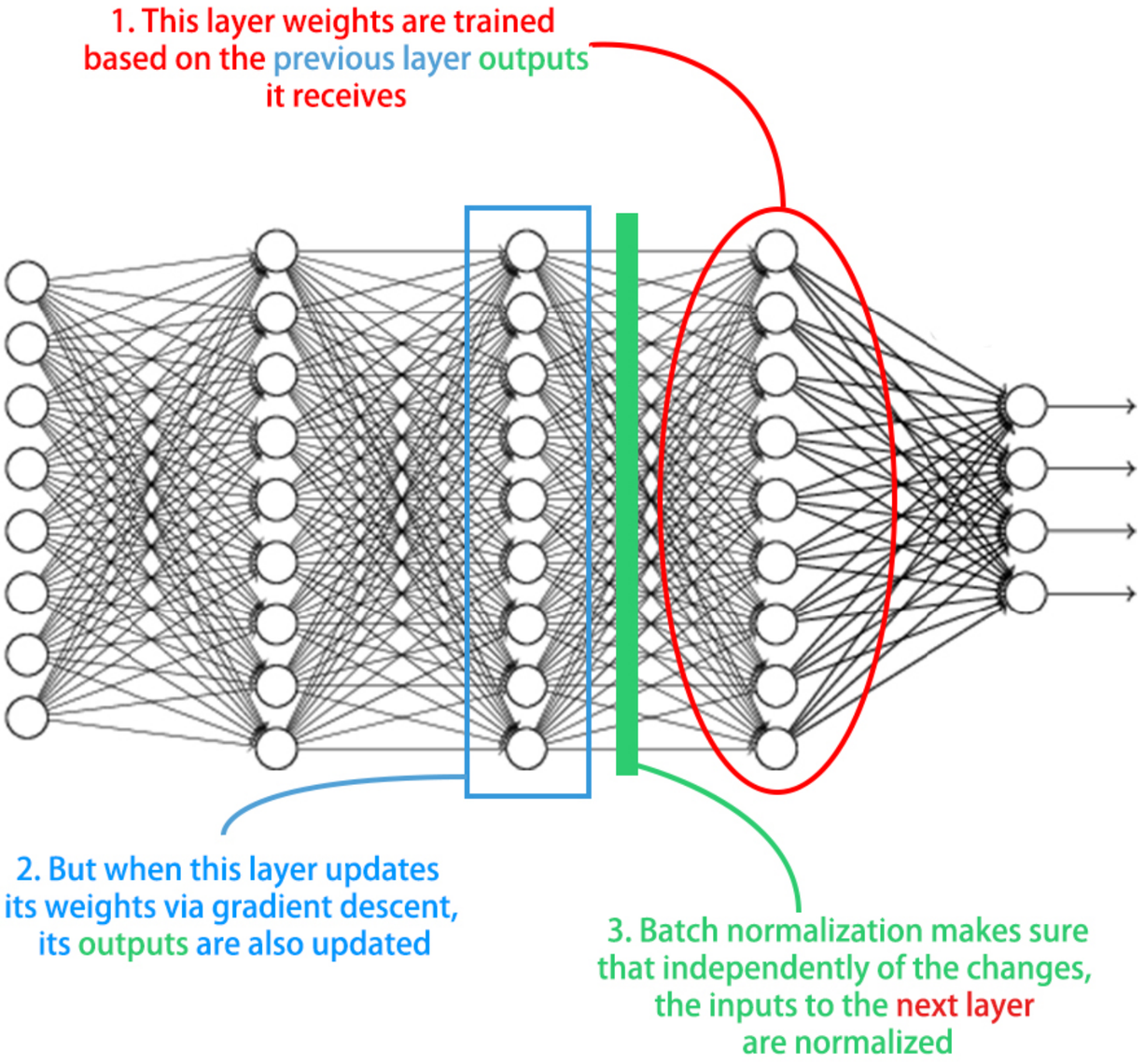
Batch size in Keras

```
# Fitting an already built and compiled model
model.fit(X_train, y_train, epochs=100, batch_size=128)
                                        ^^^^^^^^^^^^^^
```

Standardization
(a normalization approach)

$$\frac{\text{data} - \text{mean}}{\text{standard deviation}}$$


Standardized
Centered at 0
raw
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
alcohol


1. This layer weights are trained based on the previous layer outputs it receives
2. But when this layer updates its weights via gradient descent, its outputs are also updated
3. Batch normalization makes sure that independently of the changes, the inputs to the next layer are normalized

Batch normalization advantages

- Improves gradient flow
- Allows higher learning rates
- Reduces dependence on weight initializations
- Acts as an unintended form of regularization
- Limits internal covariate shift

Batch normalization in Keras

```
# Import BatchNormalization from keras layers
from keras.layers import BatchNormalization

# Instantiate a Sequential model
model = Sequential()

# Add an input layer
model.add(Dense(3, input_shape=(2,), activation = 'relu'))

# Add batch normalization for the outputs of the layer above
model.add(BatchNormalization())

# Add an output layer
model.add(Dense(1, activation='sigmoid'))
```

Let's practice!

DEEP LEARNING WITH KERAS IN PYTHON

Hyperparameter tuning

DEEP LEARNING WITH KERAS IN PYTHON

Miguel Esteban
Data Scientist & Founder

Neural network hyperparameters

- Number of layers
- Number of neurons per layer
- Layer order
- Layer activations
- Batch sizes
- Learning rates
- Optimizers
- ...

Sklearn recap

```
# Import RandomizedSearchCV
from sklearn.model_selection import RandomizedSearchCV

# Instantiate your classifier
tree = DecisionTreeClassifier()

# Define a series of parameters to look over
params = {'max_depth':[3,None], "max_features":range(1,4), 'min_samples_leaf': range(1,4)}

# Perform random search with cross validation
tree_cv = RandomizedSearchCV(tree, params, cv=5)

tree_cv.fit(X,y)

# Print the best parameters
print(tree_cv.best_params_)
```

```
{'min_samples_leaf': 1, 'max_features': 3, 'max_depth': 3}
```

Turn a Keras model into a Sklearn estimator

```
# Function that creates our Keras model
def create_model(optimizer='adam', activation='relu'):
    model = Sequential()
    model.add(Dense(16, input_shape=(2,), activation=activation))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(optimizer=optimizer, loss='binary_crossentropy')
    return model


# Import sklearn wrapper from keras
from keras.wrappers.scikit_learn import KerasClassifier


# Create a model as a sklearn estimator
model = KerasClassifier(build_fn=create_model, epochs=6, batch_size=16)
```

Cross-validation

```
# Import cross_val_score
from sklearn.model_selection import cross_val_score

# Check how your keras model performs with 5 fold crossvalidation
kfold = cross_val_score(model, X, y, cv=5)
# Print the mean accuracy per fold
kfold.mean()
```

```
0.913333
```

```
# Print the standard deviation per fold
kfold.std()
```

```
0.110754
```

Tips for neural networks hyperparameter tuning

- Random search is preferred over grid search
- Don't use many epochs
- Use a smaller sample of your dataset
- Play with batch sizes, activations, optimizers and learning rates

Random search on Keras models

```
# Define a series of parameters
params = dict(optimizer=['sgd', 'adam'], epochs=3,
              batch_size=[5, 10, 20], activation=['relu','tanh'])


# Create a random search cv object and fit it to the data
random_search = RandomizedSearchCV(model, params_dist=params, cv=3)
random_search_results = random_search.fit(X, y)
# Print results
print("Best: %f using %s".format(random_search_results.best_score_,
random_search_results.best_params_))
```

```
Best: 0.94 using {'optimizer': 'adam', 'epochs': 3, 'batch_size': 10, 'activation': 'rel
```

Tuning other hyperparameters

```
def create_model(nl=1,nn=256):
    model = Sequential()
    model.add(Dense(16, input_shape=(2,), activation='relu'))

    # Add as many hidden layers as specified in nl
    for i in range(nl):
        # Layers have nn neurons
        model.add(Dense(nn, activation='relu'))

    # End defining and compiling your model...
```

Tuning other hyperparameters

```
# Define parameters, named just like in create_model()
params = dict(nl=[1, 2, 9], nn=[128,256,1000])

# Repeat the random search...

# Print results...
```

```
Best: 0.87 using {'nl': 2,'nn': 128}
```

Let's tune some networks!

DEEP LEARNING WITH KERAS IN PYTHON