Machine Learning with TensorFlow & Keras

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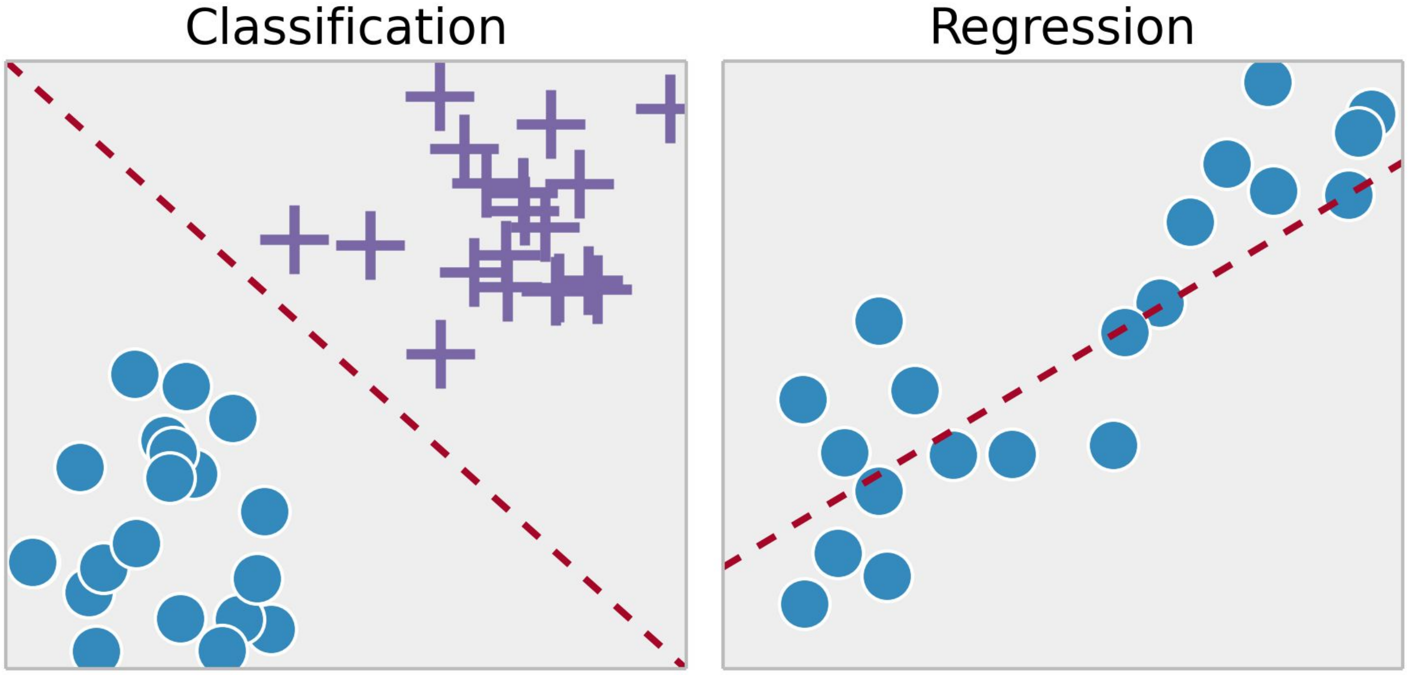
ML ?

Look at the past to predict **a possible** future.

Two Problem Classes (mostly)



Regression

- Age vs Height - I have data for ages 1-20, 40-60. Can I form a pattern for 20-40 ?
- Experience vs Salary
- Global Temperature vs FF Emission.
- Price Rise vs Demand.
- Change vs Risk (degree)

Classification

- Apples vs Oranges : I have a *labeled dataset* for Apples vs Oranges. Given a fruit, can I decide ?
- Risk vs Not-A-Risk
- Carcinogenic or Not
- Disease Classification

The General Idea

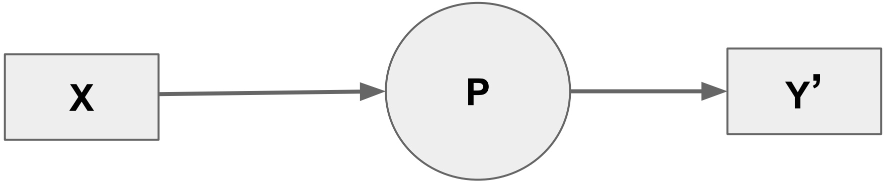
- So, in general, both Classification and Regression are about learning a ***line.***
- Lets go back to math. What is a line ?

$$Y = MX + C$$

- We know : X (input), Y(output)
- We don’t know : M & C (Slope & Intercept)
- Lets call these : **weights**

The Machine

$$Y = MX + C$$



- Algorithm
  - For every input **X**, we run it through the Perceptron (**P**)
  - **P** outputs some output **Y'**
  - Our goal is to make **Y'** as similar as possible to **Y.**

The Algorithm

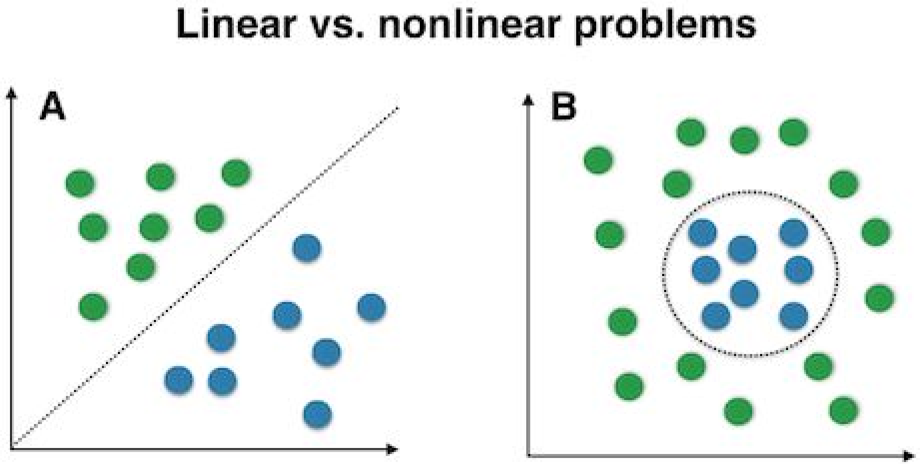
- The central goal : minimise loss function (J)
  - **J = Y - Y’**
- What is learning ?
  - Learn the required weights which minimise J.
  - For each turn, adjust weights proportional to the loss encountered.
  - Usually, learning is not one-shot. So, learning is according to a ***learning rate.***

Lets Complicate it a little bit :)

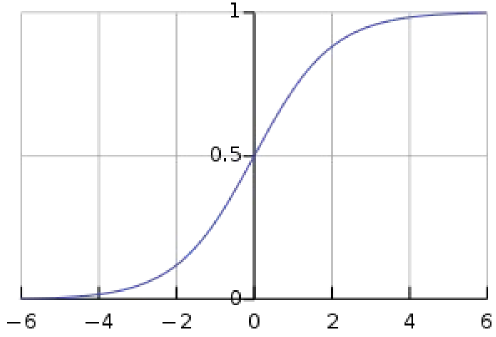
- Input can have more than one property
  - For apples and oranges, it can be color & shape for example
  - $Y = W_1X_1 + W_2X_2 + C$

- Consider a case where

Drawing a line is useless.

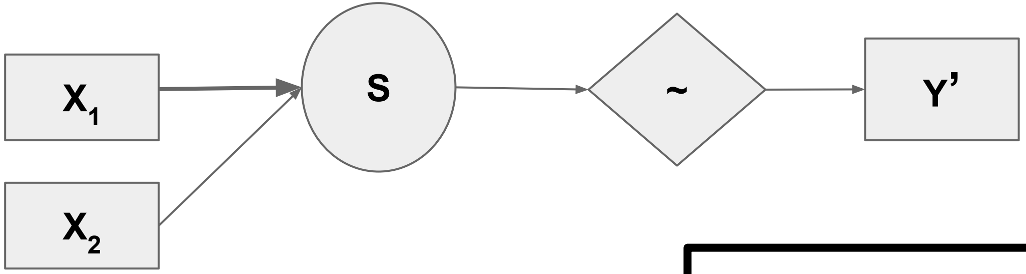


A Super Power : Non-Linearity



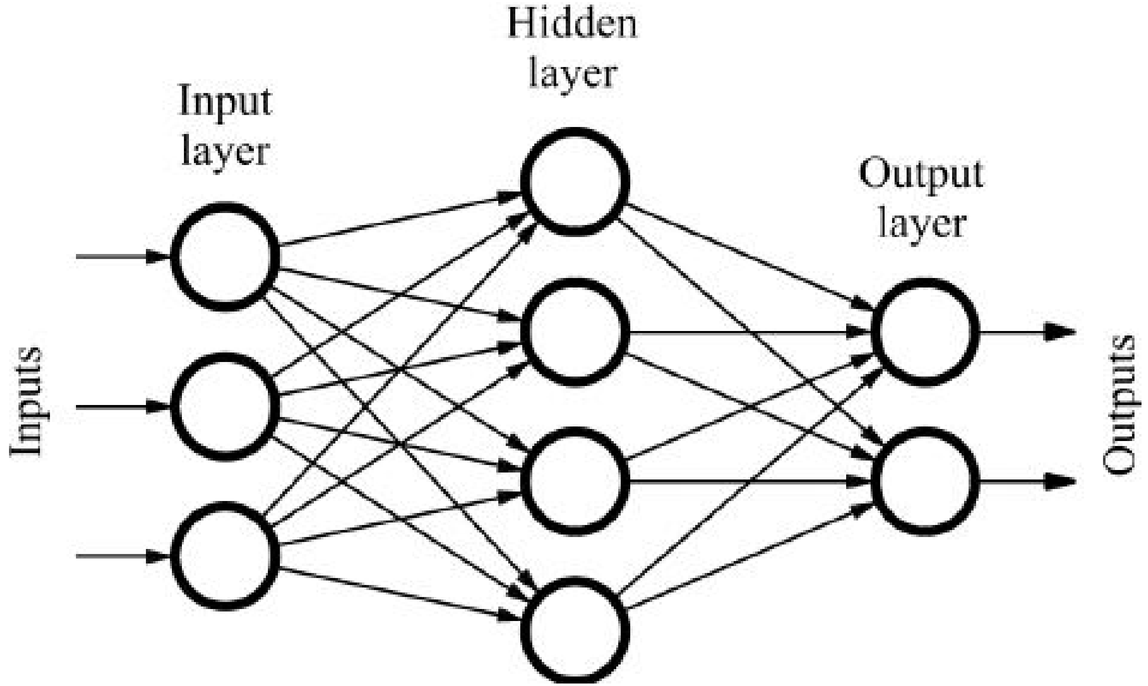
- We have to send our output (which is a sum) through a non-linear function (eg:sigmoid)

$$\mathbf{Y} = F^{\sim}(W_1X_1 + W_2X_2 + C)$$



ML is a generic function approximation algorithm

Put it all together = NN



- At each ‘neuron’, we determine its contribution to the loss function.
- When **units** are stacked in the shown manner (**layers).** Complex functions can be learnt
- When we do this for all the units, we approach a desired state
- This is called **Backpropagation.**

Lets get started

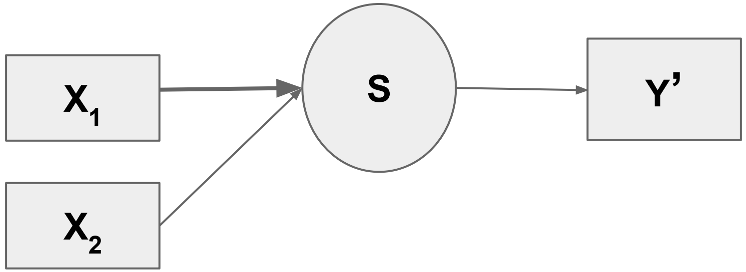
- TensorFlow -> A library which is very customisable to the extent of individual layers and units to learn and use neural nets
- **Keras** : TensorFlow for humans (kind-of).

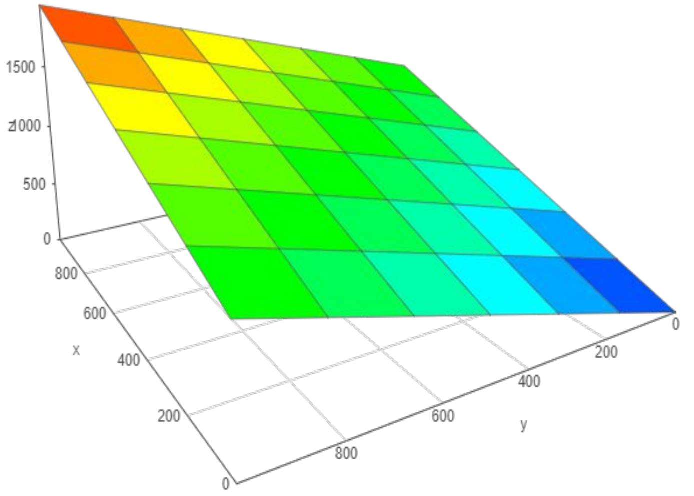
Setting Up

- Python
- pip install tensorflow
- pip install keras
- Windows ?
  - Install Anaconda 3.6
  - Conda install mingw libpython
  - Conda install tensorflow
  - Pip install keras

Our First Neural Net

- Problem : Let us make our NN *learn* **addition.**
- **Inputs : X_1, X_2**
- **Output : Y (where $Y = X_1 + X_2$)**
- The data will be linearly separable.





Anatomy of a Keras Script

```
# Imports
from keras.models import Sequential
from keras.layers import Dense, Activation
```

The basic keras api.
Dense = Summing unit
Activation = A function upon dense.

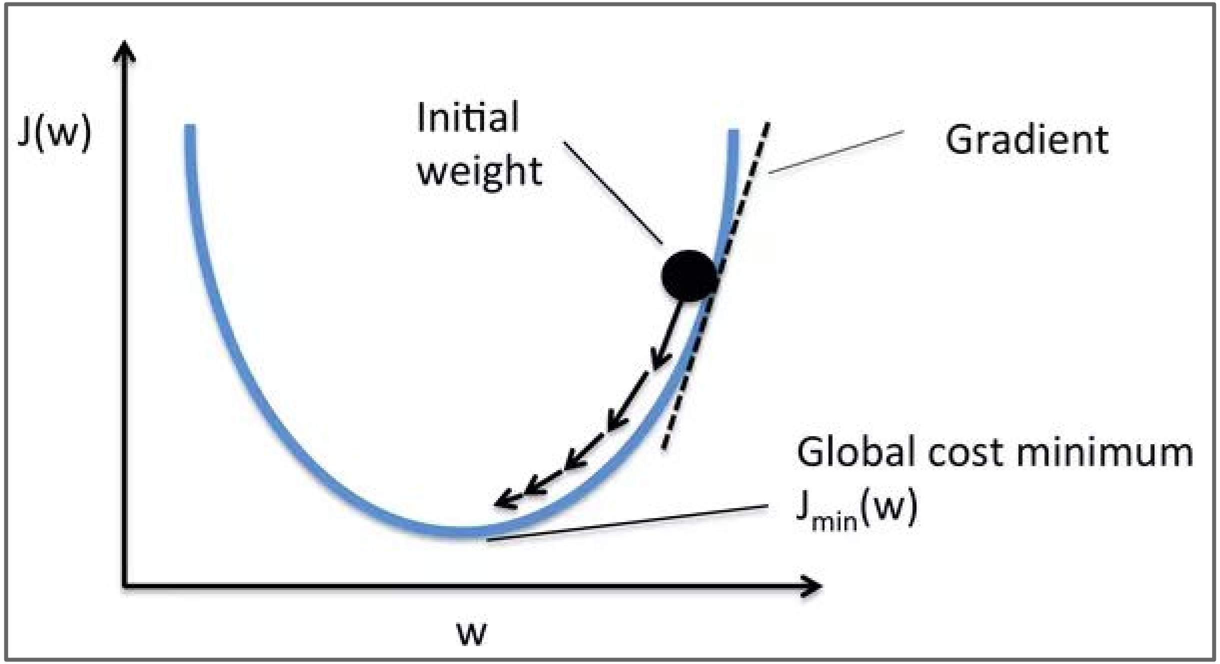
```
# Create a model
model = Sequential()
model.add(Dense(1, input_dim=2))
```

Input Dimensions = 2 (X1, X2)
Output Dimensions = 1 (Y)

```
# Compile the model
model.compile(optimizer='sgd',
              loss='mse')
```

SGD = Stochastic Gradient Descent
MSE = Mean Squared Error

A Side Note : SGD & MSE



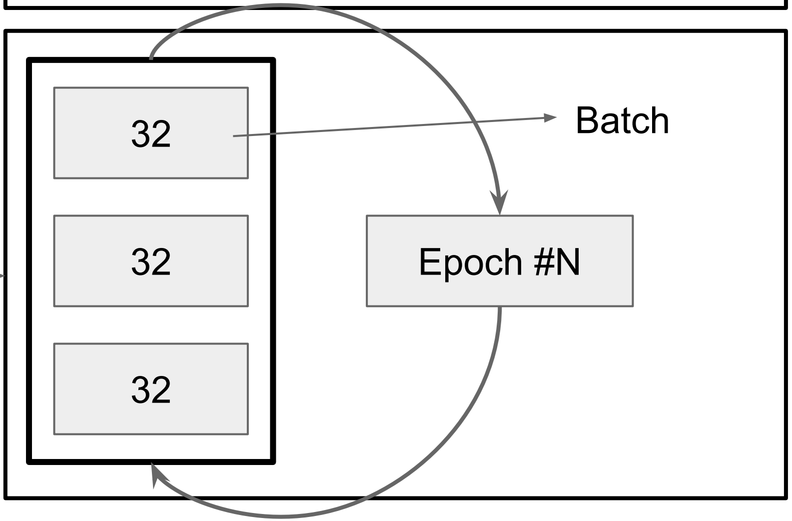
- Error (J) will be better if it is squared $(Y - Y')^2$ because it will be smoother.
- Gradient Descent is a process of slowly crawling down to the lowest J possible.

Anatomy of a Keras Script - Training

```
# Generate Training data
import numpy as np
TRAIN_SIZE = 1000
X = np.random.random((TRAIN_SIZE, 2))
Y = X.sum(axis = 1)
```

Import numpy
Generate X (1000x2) matrix
Sum columns to get Y (X1 + X2)

```
# Train
model.fit(X, Y, epochs=10, batch_size=32)
```



Anatomy of a Keras Script - Testing

```
# Generate Training data
TEST_SIZE = 100
X_test = np.random.random((TRAIN_SIZE,
2))
Y_test = X_test.sum(axis = 1)
```

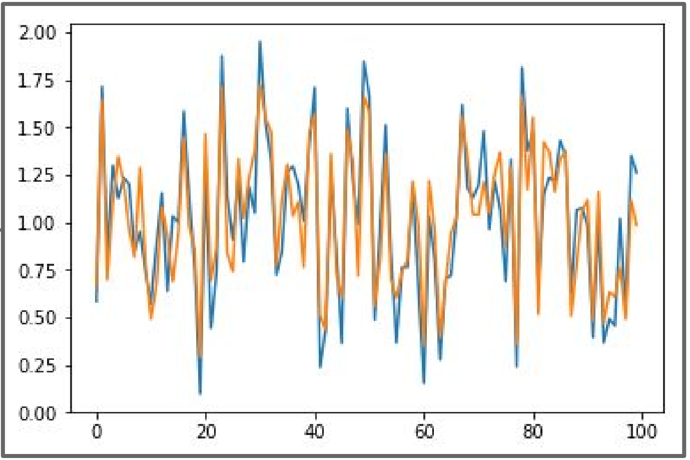
```
# Evaluate(Optional)
score = model.evaluate(X_test, Y_test)
print("Error is", score * 100, "%")
```

Score is the Mean Squared Error over all the samples

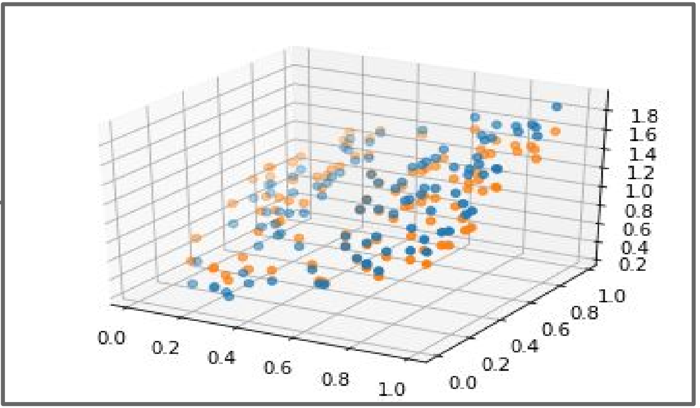
```
# Get the predicted Y's
Y_pred = model.predict(X_test)
print(Y_test, Y_pred)
```

Bonus : Plot

```
# Y_test vs Y_pred
import matplotlib.pyplot as plt
plt.plot(range(0,len(Y_test)), Y_test)
plt.plot(range(0,len(Y_pred)), Y_pred)
plt.show()
```




```
# Get the predicted Y's
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(X_test[:,0], X_test[:,1], Y_test)
ax.scatter(X_test[:,0], X_test[:,1], Y_pred)
plt.show()
```

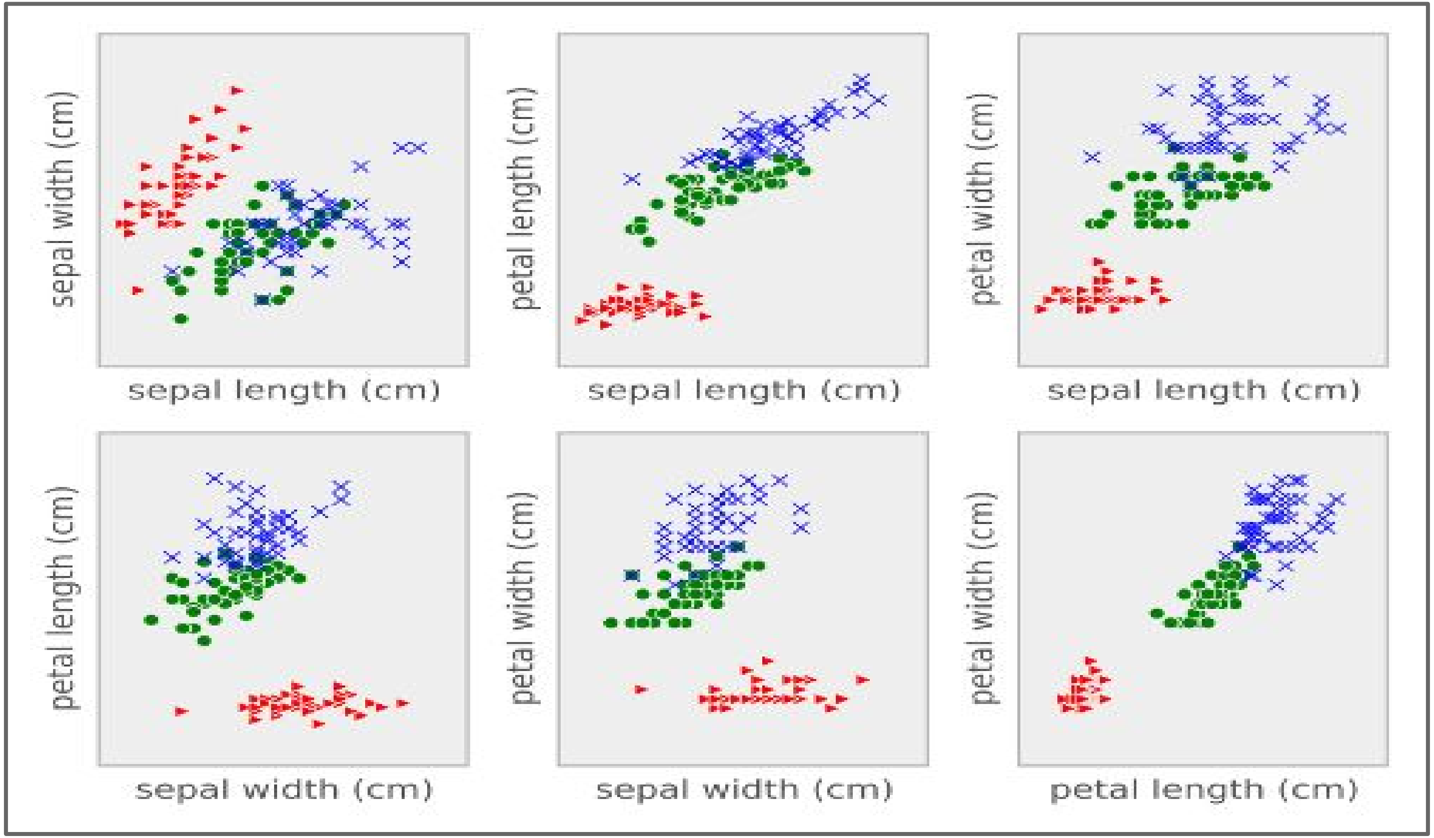


Kudos !. You have built the great-great-great-great------grandmother of Skynet.

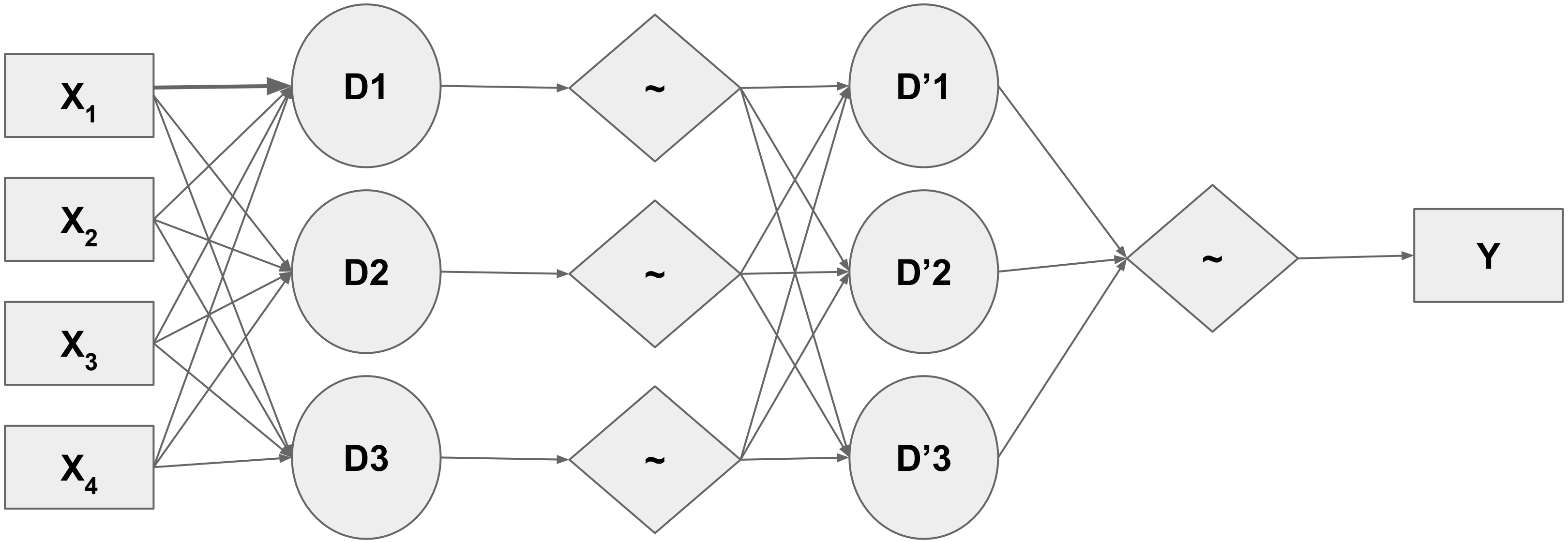
Take 2 : Multi-Class Classification

- Problem : Classify IRIS flowers into subtypes.
- **Inputs :** Sepal Length, Sepal Width, Petal Length, Petal Width
- **Output : Class Name**
    - Iris Setosa
    - Iris Versicolor
    - Iris Virginica

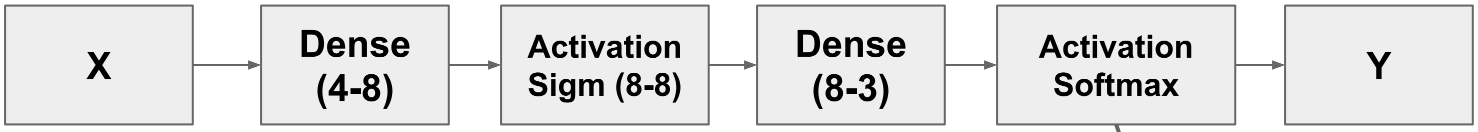
IRIS


sepal width (cm)
sepal length (cm)
petal length (cm)
sepal length (cm)
petal width (cm)
sepal length (cm)
petal length (cm)
sepal width (cm)
petal width (cm)
sepal width (cm)
petal width (cm)
petal length (cm)

IRIS - Network Design



IRIS - Network Design




```
# New Model
model = Sequential()
model.add(Dense(units = 8, input_dim=4))
model.add(Activation('sigmoid'))
model.add(Dense(units = 3))
model.add(Activation('softmax'))
```

Softmax function gives relative likelihood of which class a sample belongs to. For example : X might be (75%, 15%, 10%) if Iris (Setosa, Virginica, Versicolor)

Why More Layers ?

- For more complex problems (data is not simply separable), more layers allow learning these complex decision boundaries

- Any NN with #L > 2 is called a Deep Neural Net. aka “Deep Learning”

- Usually, each layer learns a level of generalisation.
  - Say for face recognition,
  - Layer 1 learns edges & lines
  - Layer 2 learns facial components
  - Layer 3 learns to distinguish faces themselves.