Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Perceptrón Multicapa

2019/09/30

1 Optimizadores

Onjetivo: Conocer los diferentes optimizadores para entrenar redes neuronales

- Referencia Adam: https://arxiv.org/abs/1412.6980
- Referencia Adadelta: https://arxiv.org/abs/1212.5701

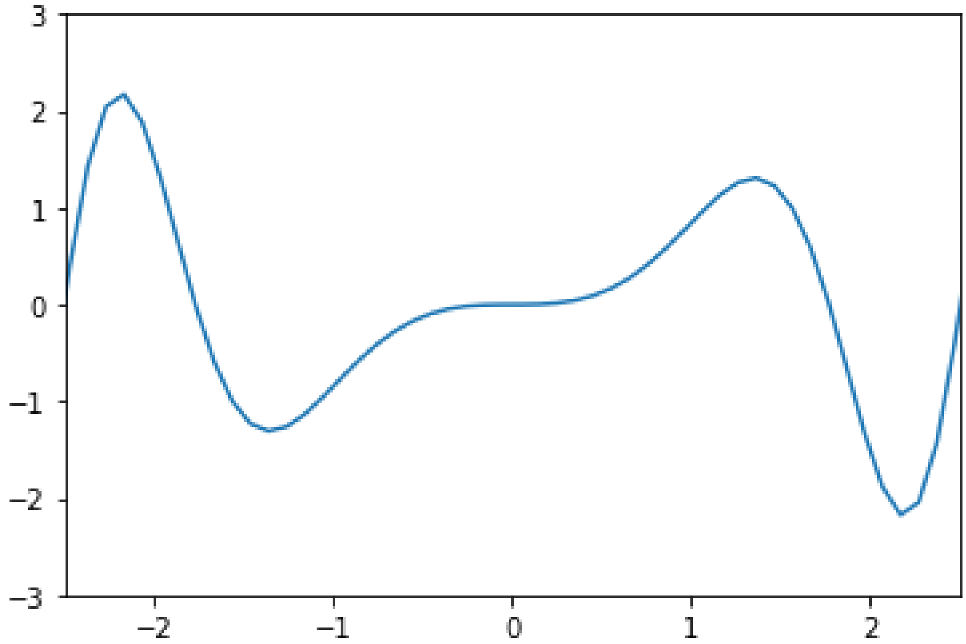
SGD es un algoritmo que se emplea para minimizar una función objetivo, respecto a algunos parámetros. Este proceso es iterativo, tomando en cuenta un parámetro de learning rate, que establece que tanto se actualizan los parámetros que consiguen los resultados deseados.

- Una variante de SGD efectiva es Adam (Estimación de Momentum Adaptativo), también se emplean RMSProp, Adadelta y Adagrad.

1.0.1 Se itera para encontrar el valor mínimo de una función utilizando la dirección del gradiente

- Se busca el valor mínimo de $J(x) = xsin(x^2)$

In [28]:
```
import numpy as np
import matplotlib.pyplot as plt
x = np.linspace(-5, 5, 100)

def fn(x):# funcion
    return x*np.sin(x*x)

y = list(map(fn, x))

plt.plot(x, y)
plt.ylim(-3, 3)
plt.xlim(-2.5, 2.5)
plt.show()
```



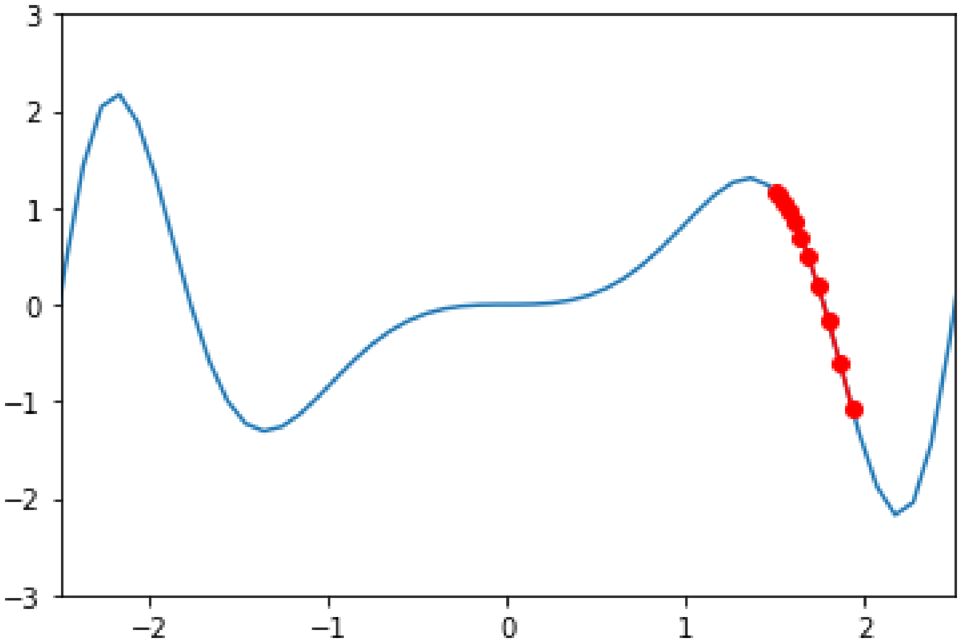
- Se selecciona el número de iteraciones = 10 y el learning rate = 0.01
- La posición inicial se denota con ‘ini’

```
In [2]: def dif(x): ##derivada de función
            return (np.sin(x*x) + 2*x*x*np.cos(x*x))
```

```
In [3]: def history(ini, lr, it = 10):
            history = []
            history.append(ini)
            x = ini
            for _ in range(0, it):# n iteraciones
                x = x - lr*dif(x)
                history.append(x)
            return history
```

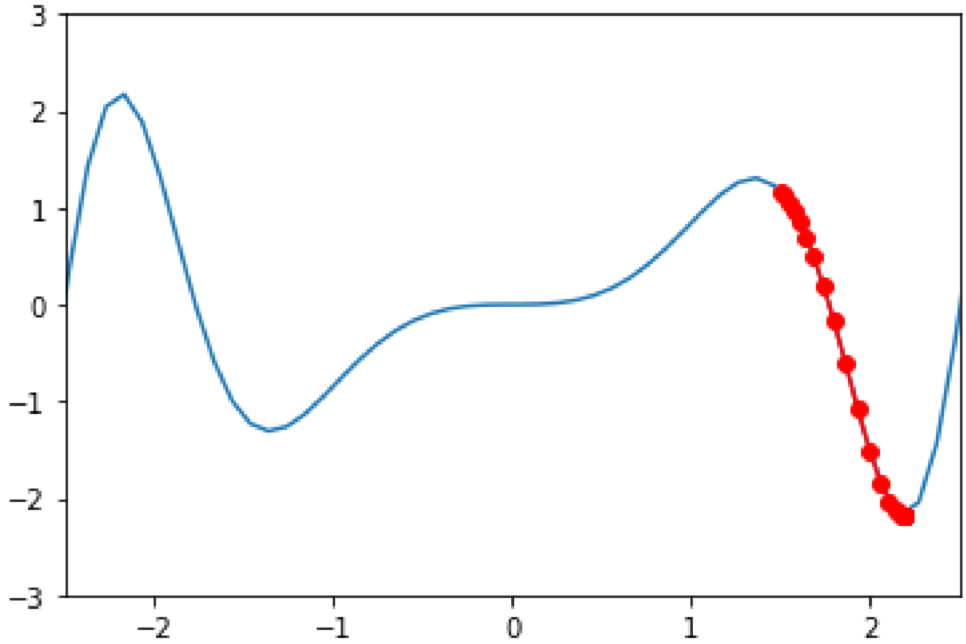
```
In [4]: h=history(1.5,0.01,10)
```

```
In [5]: x = np.linspace(-5, 5, 100)
        yh = list(map(fn, h))

        plt.plot(x, y, '-')
        plt.plot(h, yh,'o-', c='red')
        plt.ylim(-3, 3)
        plt.xlim(-2.5, 2.5)
        plt.show()
```



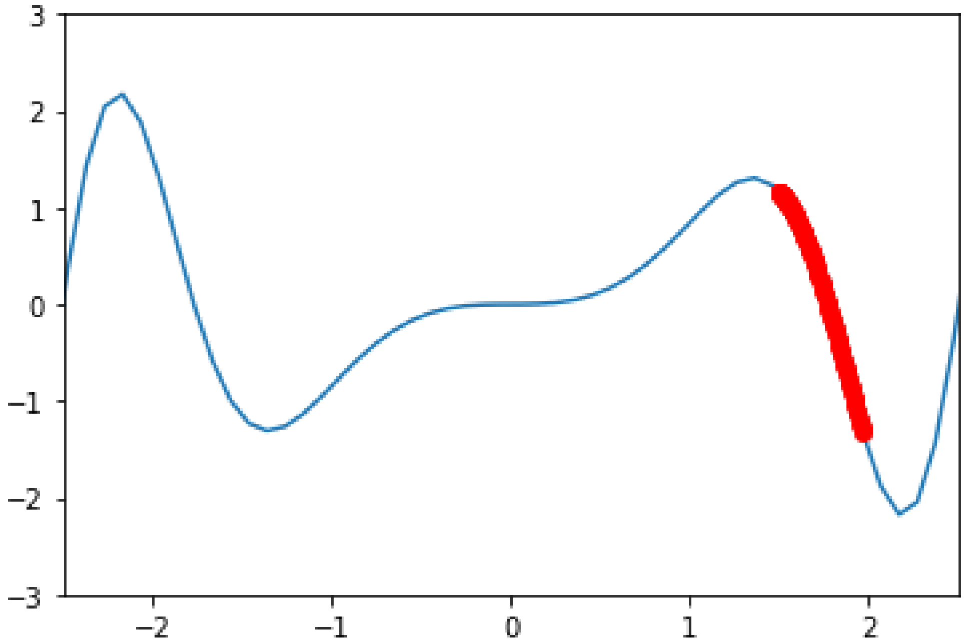
- Aumentando iteraciones a 100

```
In [6]: h=history(1.5,0.01,100)
        x = np.linspace(-5, 5, 100)
        yh = list(map(fn, h))

        plt.plot(x, y, '-')
        plt.plot(h, yh,'o-', c='red')
        plt.ylim(-3, 3)
        plt.xlim(-2.5, 2.5)
        plt.show()
```



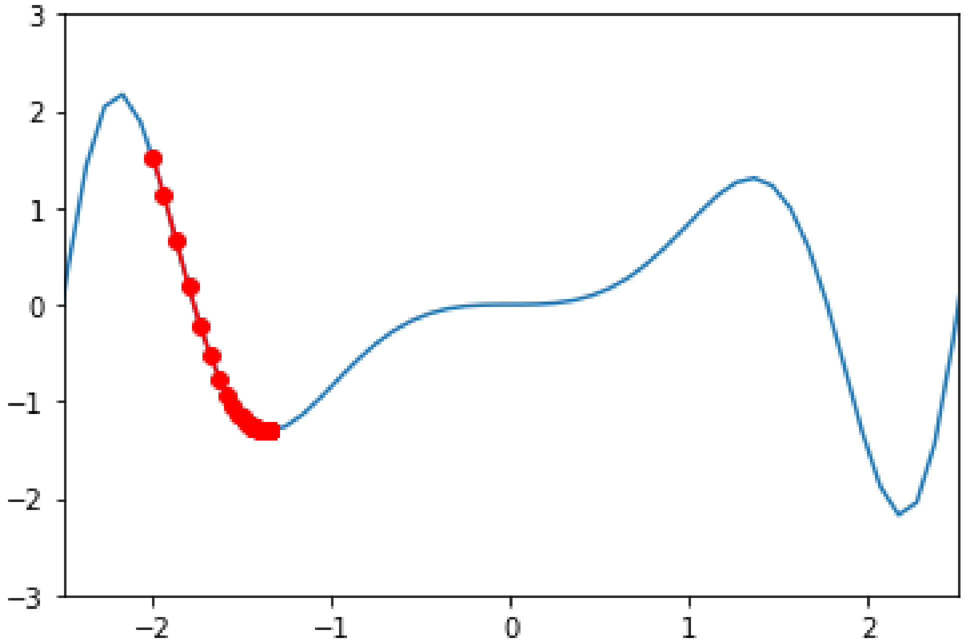
- Un learning rate bajo puede requerir mayor número de iteraciones

In [7]:
```
h=history(1.5,0.001,100)# 100 iteraciones
x = np.linspace(-5, 5, 100)
yh = list(map(fn, h))

plt.plot(x, y, '-')
plt.plot(h, yh,'o-', c='red')
plt.ylim(-3, 3)
plt.xlim(-2.5, 2.5)
plt.show()
```



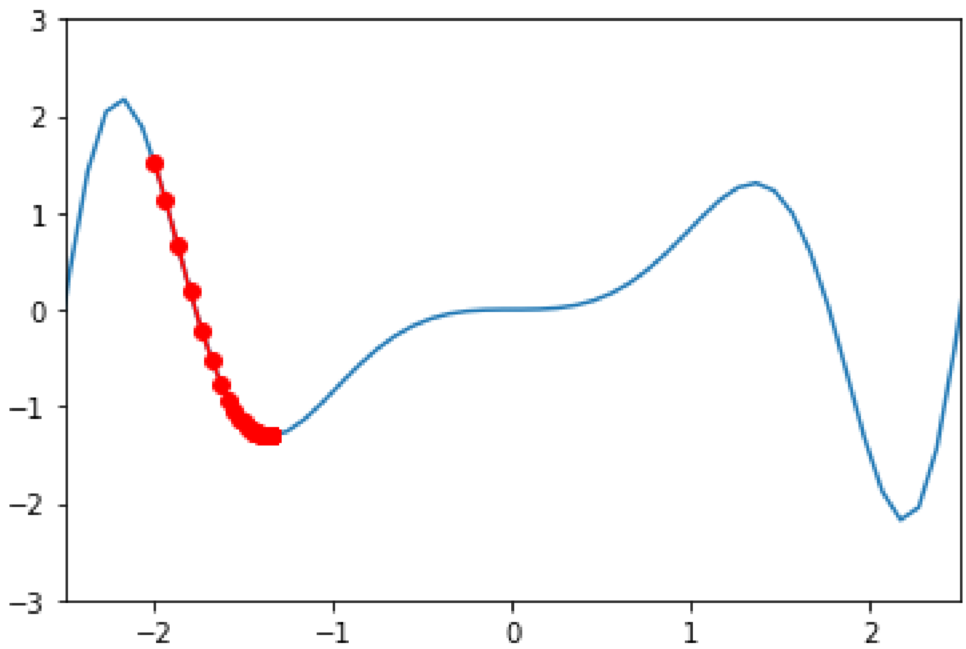
- Diferente punto de inicio

```
In [8]: h=history(-2,0.01,100)# 100 iteraciones
        x = np.linspace(-5, 5, 100)
        yh = list(map(fn, h))

        plt.plot(x, y, '-')
        plt.plot(h, yh,'o-', c='red')
        plt.ylim(-3, 3)
        plt.xlim(-2.5, 2.5)
        plt.show()
```



- Más iteraciones

```
In [9]: h=history(-2,0.01,1000)# 1000 iteraciones
        x = np.linspace(-5, 5, 100)
        yh = list(map(fn, h))

        plt.plot(x, y, '-')
        plt.plot(h, yh,'o-', c='red')
        plt.ylim(-3, 3)
        plt.xlim(-2.5, 2.5)
        plt.show()
```



- La función no puede encontrar el mínimo, es por eso que existen variantes del algoritmo

2 Tensorflow optimizadores

- Tensorflow implementa varios optimizadores
- Se clasificarán imágenes. Los pixeles son la entrada de la red neuronal. Al finalizar el entrenamiento, la red neuronal habrá aprendido a reconocer dígitos.

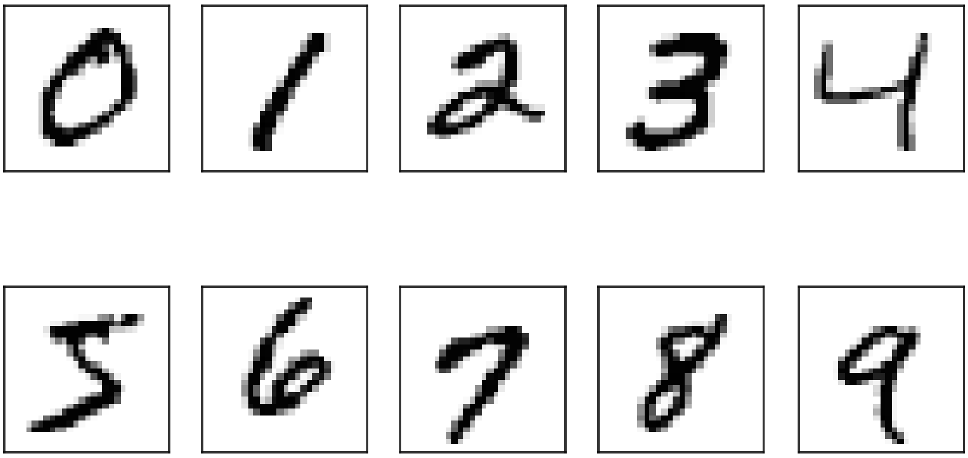
In [10]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras import backend as K
K.clear_session()

mnist = keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

In [11]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(60000, 28, 28)
(60000,)
(10000, 28, 28)
(10000,)
```

2.1 Leer Dataset

```
In [12]: fig, ax = plt.subplots(nrows=2, ncols=5, sharex=True, sharey=True,)
         ax = ax.flatten()
         for i in range(10):
             img = x_train[y_train == i][0].reshape(28, 28)
             ax[i].imshow(img, cmap='Greys', interpolation='nearest')

         ax[0].set_xticks([])
         ax[0].set_yticks([])
         plt.tight_layout()
         plt.show()
```



- Se modifica la forma de los datos de 2-d (n, 28, 28) a 1-d (n, 784)

```
In [13]: x_train = x_train.reshape(x_train.shape[0], -1)
         x_test = x_test.reshape(x_test.shape[0], -1)


         print(x_train.shape) # (60000, 784)
         print(y_train.shape) # (60000,)
         print(x_test.shape)  # (10000, 784)
         print(y_test.shape)  # (10000,)
```

```
(60000, 784)
(60000,)
```

```
(10000, 784)
(10000,)
```

```
In [14]: epoch = 70
         verbose = 0
         batch = 50
```

2.2 Adam

```
In [15]: def make_model():
             model = Sequential()

             model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(10, activation = 'softmax'))


             model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
                           metrics=['accuracy'])
             return model
```

```
In [16]: model = make_model()

         model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 40)                31400
_________________________________________________________________
dense_1 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_2 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_3 (Dense)              (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

```
In [17]: history1 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
In [18]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

         print('\nTest acccuracy:', test_acc)
```

```
10000/1 - 0s - loss: 0.1586 - accuracy: 0.9633

Test acccuracy: 0.9633
```

2.3 SGD

```
In [19]: def make_model():
             model = Sequential()

             model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(10, activation = 'softmax'))


             model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy',
                           metrics=['accuracy'])
             return model
```

```
In [20]: model = make_model()

         model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 40)                31400
_________________________________________________________________
dense_5 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_6 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_7 (Dense)              (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

```
In [21]: history2 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
In [22]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

         print('\nTest acccuracy:', test_acc)
```

```
10000/1 - 0s - loss: 2.3024 - accuracy: 0.1135
```

```
Test acccuracy: 0.1135
```

2.4 Adagrad

```
In [23]: def make_model():
             model = Sequential()

             model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(40, activation = 'relu'))
             model.add(Dense(10, activation = 'softmax'))


             model.compile(optimizer='adagrad', loss='sparse_categorical_crossentropy',
                           metrics=['accuracy'])
             return model
```

```
In [24]: model = make_model()

         model.summary()
```

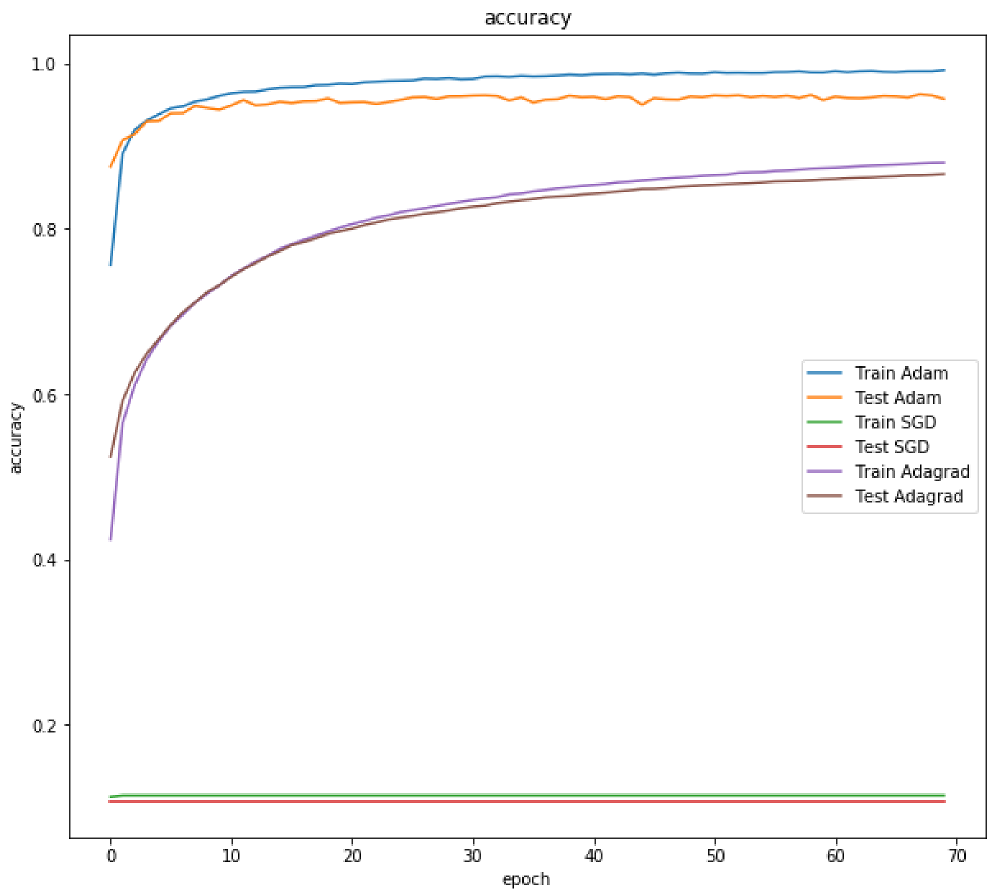
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 40)                31400
_________________________________________________________________
dense_9 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_10 (Dense)             (None, 40)                1640
_________________________________________________________________
dense_11 (Dense)             (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

```
In [25]: history3 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
In [26]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

         print('\nTest acccuracy:', test_acc)
```

```
10000/1 - 1s - loss: 0.4100 - accuracy: 0.8699

Test acccuracy: 0.8699
```

In [27]:
```
#plot
plt.figure(figsize=(10,9))
plt.plot(history1.history['accuracy'])
plt.plot(history1.history['val_accuracy'])


plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])

plt.plot(history3.history['accuracy'])
plt.plot(history3.history['val_accuracy'])
plt.legend(['Train Adam', 'Test Adam',
            'Train SGD', 'Test SGD',
            'Train Adagrad', 'Test Adagrad'])

plt.title('accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')

plt.show()
```



- Experimentar con diferentes parámetros y optimizadores para obtener mejores resultados y menor tiempo de entrenamiento