# Trabalho 3

Descrição do trabalho:

[http://webserver2.tecgraf.puc-rio.br/~mgattass/visao/trb/T3.html (http://webserver2.tecgraf.puc-rio.br/~mgattass/visao/trb/T3.html)](http://webserver2.tecgraf.puc-rio.br/~mgattass/visao/trb/T3.html)

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## Imports

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import time
from keras.datasets import mnist
from keras.utils import np_utils
from sklearn import metrics
import pandas as pd

import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
```

## Using the Numpy

Based on [https://www.youtube.com/watch?v=M0jlQzHo5Jg (https://www.youtube.com/watch?v=M0jlQzHo5Jg)](https://www.youtube.com/watch?v=M0jlQzHo5Jg)

### Utility functions

In [2]:

```
def to_categorical(x, n_col=None):
  """ One hot encoding function"""
  if not n_col:
    n_col = np.amax(x) + 1

  one_hot = np.zeros((x.shape[0], n_col))
  one_hot[np.arange(x.shape[0]), x] = 1
  return one_hot
```

In [3]:

```
def accuracy(y_true, y_pred):
  ### Returns accuracy ###
  return np.sum(y_true == y_pred, axis = 0) / len(y_true)
```

In [4]:

```
def batch_loader(X, y = None, batch_size=64):
  """ Generates batches for training"""
  n_samples = X.shape[0]
  for i in np.arange(0, n_samples, batch_size):
    begin, end = i, min(i + batch_size, n_samples)
    if y is not None:
      yield X[begin:end], y[begin: end]
    else:
      yield X[begin:end]
```

### Loss

In [5]:

```
class CrossEntropy():
  def __init__(self): pass

  def loss(self, y, p):
    p = np.clip(p, 1e-15, 1- 1e-15)
    return -y*np.log(p) - (1 - y) * np.log(1- p)

  def gradient(self, y, p):
    p = np.clip(p, 1e-15, 1- 1e-15)
    return -(y/p) + (1 - y) / (1 - p)
```

### Activation Functions

In [6]:

```
class LeakyReLU():
  def __init__(self, alpha = 0.2):
    self.alpha = alpha

  def __call__(self, x):
    return self.activation(x)

  def activation(self, x):
    return np.where(x >= 0, x, self.alpha * x)

  def gradient(self, x):
    return np.where(x >= 0, 1, self.alpha)
```

In [7]:

```
class Softmax():
  def __init__(self): pass

  def __call__(self, x):
    return self.activation(x)

  def activation(self, x):
    e_x = np.exp(x - np.max(x, axis = -1, keepdims=True))
    return e_x / np.sum(e_x, axis=-1, keepdims = True)

  def gradient(self, x):
    # Error was in our softmax
    p = self.activation(x)
    return p * (1 - p)
```

**Layers**

***class Linear***

Fully Connected Layer

In [8]:

```
class Linear():
  def __init__(self, n_in, n_out, name="linear"):
    limit = 1 / np.sqrt(n_in)
    self.W = np.random.uniform(-limit, limit, (n_in, n_out))
    self.b = np.zeros((1, n_out)) # Biases
    self.input = None
    self.output = None
    self.name = name

  def forward(self, x):
    self.input = x
    self.output = np.dot(self.input, self.W) + self.b # Wx + b
    return self.output

  def backward(self, output_gradient, learning_rate = 0.01):
    input_gradient = np.dot(output_gradient, self.W.T)
    weights_gradients = np.dot(self.input.T, output_gradient) # Calculate the weights e
rror
    bias_gradients = np.sum(output_gradient, axis=0).reshape((1, -1))

    # Usually, we would allow an optimizer function to update the weights
    # but here, we just use simple SGD
    self.W -= learning_rate * weights_gradients
    self.b -= learning_rate * bias_gradients
    # We updated the weights below
    return input_gradient

  def __call__(self, x):
    return self.forward(x)
```

### *class Activation*

In [9]:

```
class Activation():
  def __init__(self, activation, name="activation"):
    self.activation = activation
    self.gradient = activation.gradient
    self.input = None
    self.output = None
    self.name = name

  def forward(self, x):
    self.input = x
    self.output = self.activation(x)
    return self.output

  def backward(self, output_error, learning_rate = 0.01):
    return self.gradient(self.input) * output_error

  def __call__(self, x):
    return self.forward(x)
```

### Network

In [10]:

```
class Network():
  def __init__(self, input_dim, output_dim, learning_rate=0.01):
    # input_dim = 784, output_dim = 10 for mnist
    self.layers = [
                  Linear(input_dim, 256, name="input"),
                  Activation(LeakyReLU(), name="relu1"),
                  Linear(256, 128, name="input"),
                  Activation(LeakyReLU(), name="relu2"),
                  Linear(128, output_dim, name="output"),
                  Activation(Softmax(), name="softmax")
    ]
    self.learning_rate = learning_rate

  def forward(self, x):
    for layer in self.layers:
      x = layer(x)
    return x

  def backward(self, loss_grad):
    for layer in reversed(self.layers):
      loss_grad = layer.backward(loss_grad, self.learning_rate)
    # Iterating backwards through the layers

  def __call__(self, x):
    return self.forward(x)
```

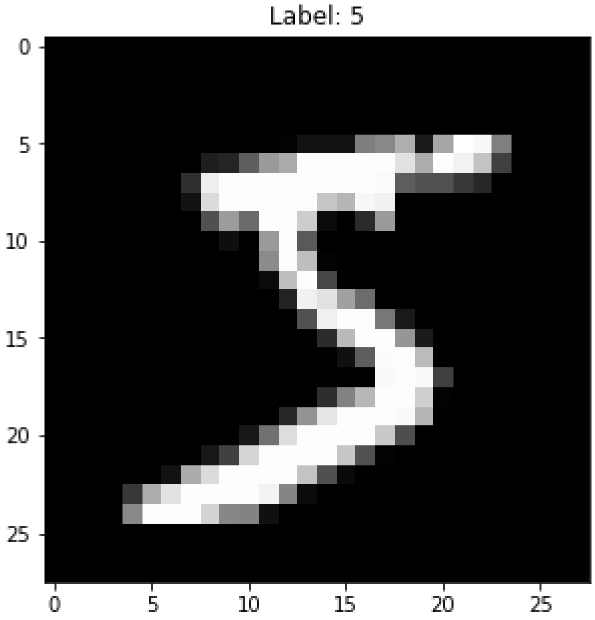
### Loading the data

In [11]:

```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

In [12]:

```
fig, axes = plt.subplots( 1, 1, figsize=( 10, 5 ) )

axes.set_title( f'Label: {y_train[0]}' )
axes.imshow( X_train[0], cmap='gray' )

plt.show()
```



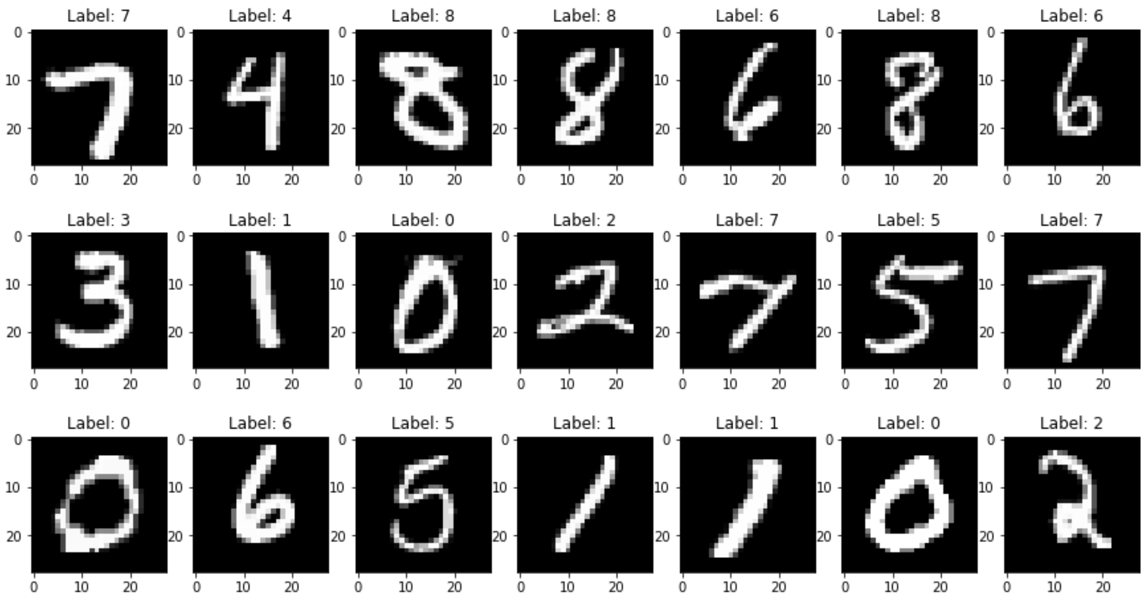

In [13]:

```
# X_train[0]
```

### Depicting examples

In [14]:

```
rows = 3
columns = 7

fig, axes = plt.subplots( rows, columns, figsize=( 15, 8 ) )

for i in range(rows):
  for j in range(columns):
    random_number = int(np.random.rand() * X_train.shape[0])
    axes[i][j].set_title( f'Label: {y_train[random_number]}' )
    axes[i][j].imshow( X_train[random_number], cmap='gray' )

plt.show()
```




### Preprocessing Data

In [15]:

```
y_train, y_test = to_categorical(y_train.astype("int")), to_categorical(y_test.astype(
"int"))
X_train, X_test = X_train / 255.0, X_test / 255.0
```

In [16]:

```
X_train, X_test = X_train.reshape(-1, 28*28), X_test.reshape(-1, 28*28)
X_train.shape, X_test.shape
```

Out[16]:

```
((60000, 784), (10000, 784))
```

### Training

In [17]:

```
n_input_dim = 28*28 # 784
n_out = 10 # 10 classes
```

In [18]:

```
criterion = CrossEntropy()
model = Network(n_input_dim, n_out, learning_rate=1e-3)
```

In [19]:

```
EPOCHS = 5
# batch_size = 1
batch_size = 128
# batch_size = X_train.shape[0]
```

In [20]:

```
%%time

for epoch in range(EPOCHS):
  loss = []
  acc = []
  for x_batch, y_batch in batch_loader(X_train, y_train, batch_size):
    # Forward pass
    out = model(x_batch)

    # Loss - for display
    loss.append(np.mean(criterion.loss(y_batch, out)))

    # Accuracy - For display
    acc.append(accuracy(np.argmax(y_batch, axis=1), np.argmax(out, axis=1)))

    # Calculate gradient of loss
    error = criterion.gradient(y_batch, out)

    # Backpropagation
    model.backward(error)

  print(f"Epoch {epoch + 1}, Loss: {np.mean(loss):.5}, Acc: {np.mean(acc):.3}")
```

```
Epoch 1, Loss: 0.095875, Acc: 0.836
Epoch 2, Loss: 0.043966, Acc: 0.925
Epoch 3, Loss: 0.033638, Acc: 0.944
Epoch 4, Loss: 0.026969, Acc: 0.955
Epoch 5, Loss: 0.022378, Acc: 0.963
CPU times: user 28.7 s, sys: 11.1 s, total: 39.8 s
Wall time: 29.3 s
```

### Testing

#### *Accuracy*

In [21]:

```
%time

out = model(X_test)
accuracy_value = accuracy(np.argmax(y_test, axis=1), np.argmax(out, axis=1))
print( f'{(accuracy_value * 100):.3}%' )
```

```
CPU times: user 3 µs, sys: 1 µs, total: 4 µs
Wall time: 7.39 µs
96.0%
```

### *Error Rate*

"o valor da taxa de erro (calculada como o número de todas as previsões incorretas dividido pelo número total do conjunto de dados. A melhor taxa de erro é 0, enquanto a pior é 1.)"

In [22]:

```
y_predicted = list(np.argmax(out, axis=1))
y_actual = list(np.argmax(y_test, axis=1))

for i, y_pred in enumerate(y_predicted):
    print('pred:', y_predicted[i], '\ttrue:', y_actual[i])

    if i > 20:
      break
```

```
pred: 7         true: 7
pred: 2         true: 2
pred: 1         true: 1
pred: 0         true: 0
pred: 4         true: 4
pred: 1         true: 1
pred: 4         true: 4
pred: 9         true: 9
pred: 6         true: 5
pred: 9         true: 9
pred: 0         true: 0
pred: 6         true: 6
pred: 9         true: 9
pred: 0         true: 0
pred: 1         true: 1
pred: 5         true: 5
pred: 9         true: 9
pred: 7         true: 7
pred: 3         true: 3
pred: 4         true: 4
pred: 9         true: 9
pred: 6         true: 6
```

In [23]:

```
num_errors = 0
for i, y_pred in enumerate(y_predicted):
  if y_predicted[i] != y_actual[i]:
    # print('pred:', y_predicted[i], '\ttrue:', y_actual[i])
    num_errors += 1

print( f'num_errors: {num_errors}' )
```

```
num_errors: 402
```

In [24]:

```
error_rate = num_errors / X_train.shape[0]
print( f'error_rate: {error_rate:.3}' )
```

```
error_rate: 0.0067
```

In [25]:

```
error_rate_percentage = num_errors / X_train.shape[0] * 100
print( f'error_rate_percentage: {error_rate_percentage:.2}%' )
```

```
error_rate_percentage: 0.67%
```

### *Confusion Matrix*

In [26]:

```
confusion_matrix = metrics.confusion_matrix(y_actual, y_predicted)
```

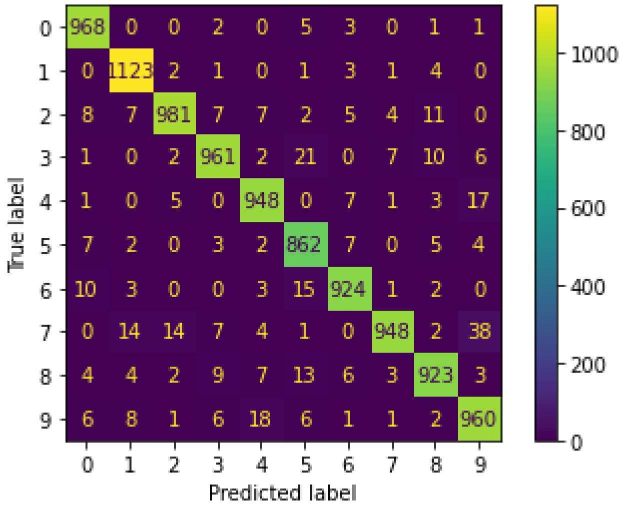
In [27]:

```
# based on https://www.statology.org/confusion-matrix-python/

y_actual = pd.Series(y_actual, name='Actual')
y_predicted = pd.Series(y_predicted, name='Predicted')

#create confusion matrix
print(pd.crosstab(y_actual, y_predicted))
```

```
Predicted    0     1    2    3    4    5    6    7    8    9
Actual
0          968     0    0    2    0    5    3    0    1    1
1            0  1123    2    1    0    1    3    1    4    0
2            8     7  981    7    7    2    5    4   11    0
3            1     0    2  961    2   21    0    7   10    6
4            1     0    5    0  948    0    7    1    3   17
5            7     2    0    3    2  862    7    0    5    4
6           10     3    0    0    3   15  924    1    2    0
7            0    14   14    7    4    1    0  948    2   38
8            4     4    2    9    7   13    6    3  923    3
9            6     8    1    6   18    6    1    1    2  960
```

In [28]:

```
# based on https://www.w3schools.com/python/python_ml_confusion_matrix.asp

cm_display = metrics.ConfusionMatrixDisplay(
    confusion_matrix = confusion_matrix,
    display_labels = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
cm_display.plot()
plt.show()
```




## Using PyTorch

Based on [https://www.youtube.com/watch?v=oPhxf2fXHkQ&list=PLqnslRFeH2UrcDBWF5mfPGpqQDSta6VK4&index=13 (https://www.youtube.com/watch?v=oPhxf2fXHkQ&list=PLqnslRFeH2UrcDBWF5mfPGpqQDSta6VK4&index=13)](https://www.youtube.com/watch?v=oPhxf2fXHkQ&list=PLqnslRFeH2UrcDBWF5mfPGpqQDSta6VK4&index=13)

### Device configuration

In [29]:

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

Out[29]:

```
device(type='cuda')
```

### Hyper-parameters

In [30]:

```
input_size = 784 # 28x28
hidden_size = 500
num_classes = 10
num_epochs = 5
batch_size = 256
learning_rate = 0.001
```

### MNIST dataset

In [31]:

```
train_dataset = torchvision.datasets.MNIST(root='./data',
                                           train=True,
                                           transform=transforms.ToTensor(),
                                           download=True)

test_dataset = torchvision.datasets.MNIST(root='./data',
                                          train=False,
                                          transform=transforms.ToTensor())
```

### Data loader

Creating the batches of the training set and test set.

In [32]:

```
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)
```

In [33]:

```
train_loader
```

Out[33]:

```
<torch.utils.data.dataloader.DataLoader at 0x7fc1ff3dda90>
```

In [34]:

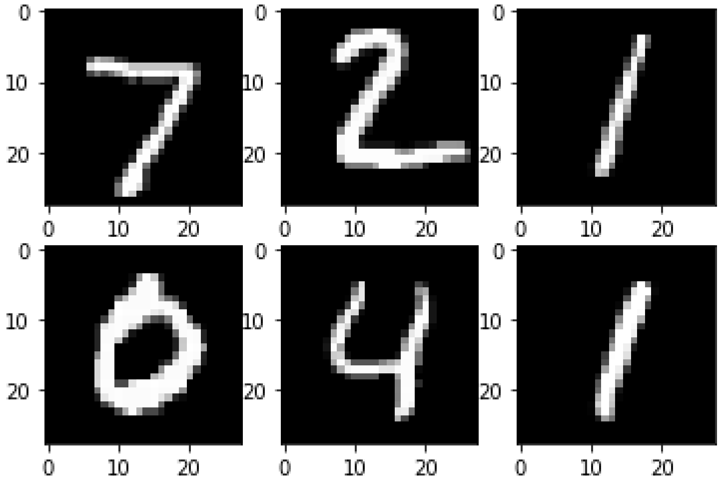
```
# list(enumerate(train_loader))[0]
```

### Depicting examples

From test set

In [35]:

```
examples = iter(test_loader)
example_data, example_targets = examples.next()

for i in range(6):
    plt.subplot(2,3,i+1)
    plt.imshow(example_data[i][0], cmap='gray')
plt.show()
```




#### Neural Network

In [36]:

```
# Fully connected neural network with one hidden layer
class NeuralNet(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super(NeuralNet, self).__init__()
        self.input_size = input_size
        self.l1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.l2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.l1(x)
        out = self.relu(out)
        out = self.l2(out)
        # no activation and no softmax at the end
        return out
```

In [37]:

```
model = NeuralNet(input_size, hidden_size, num_classes).to(device)
```

#### Loss and optimizer

In [38]:

```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
```

#### Training

In [39]:

```
%%time

n_total_steps = len(train_loader)
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        # origin shape: [100, 1, 28, 28]
        # resized: [100, 784]
        images = images.reshape(-1, 28*28).to(device)
        labels = labels.to(device)

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)

        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        if (i+1) % 100 == 0:
            print (f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/{n_total_steps}], Los
s: {loss.item():.4f}')
```

```
Epoch [1/5], Step [100/235], Loss: 0.2875
Epoch [1/5], Step [200/235], Loss: 0.2020
Epoch [2/5], Step [100/235], Loss: 0.1686
Epoch [2/5], Step [200/235], Loss: 0.1448
Epoch [3/5], Step [100/235], Loss: 0.1988
Epoch [3/5], Step [200/235], Loss: 0.0796
Epoch [4/5], Step [100/235], Loss: 0.0650
Epoch [4/5], Step [200/235], Loss: 0.0768
Epoch [5/5], Step [100/235], Loss: 0.0524
Epoch [5/5], Step [200/235], Loss: 0.0713
CPU times: user 23.3 s, sys: 145 ms, total: 23.4 s
Wall time: 23.4 s
```

#### Testing

In [40]:

```
with torch.no_grad():
    n_correct = 0
    n_samples = 0
    for images, labels in test_loader:
        images = images.reshape(-1, 28*28).to(device)
        labels = labels.to(device)
        outputs = model(images)
        # max returns (value ,index)
        _, predicted = torch.max(outputs.data, 1)
        n_samples += labels.size(0)
        n_correct += (predicted == labels).sum().item()

    acc = 100.0 * n_correct / n_samples
    print(f'Accuracy of the network on the {n_samples} test images: {acc} %')
```

```
Accuracy of the network on the 10000 test images: 97.63 %
```

## Exporting to HTML file

Changing Google Drive folder.

In [41]:

```
from google.colab import drive
drive.mount('/content/drive/', force_remount=True)
```

```
Mounted at /content/drive/
```

In [42]:

```
!cd "./drive/MyDrive/Doutorado/Disciplinas/[2022.2] [PUC-Rio] Visão Computacional - Professor: Marcelo Gattass/Trabalhos/Trabalho 3"
```

In [43]:

```
!pwd
```

```
/content
```

In [45]:

```
%%time

!jupyter nbconvert --to html ./T3_DanielCosta.ipynb
```