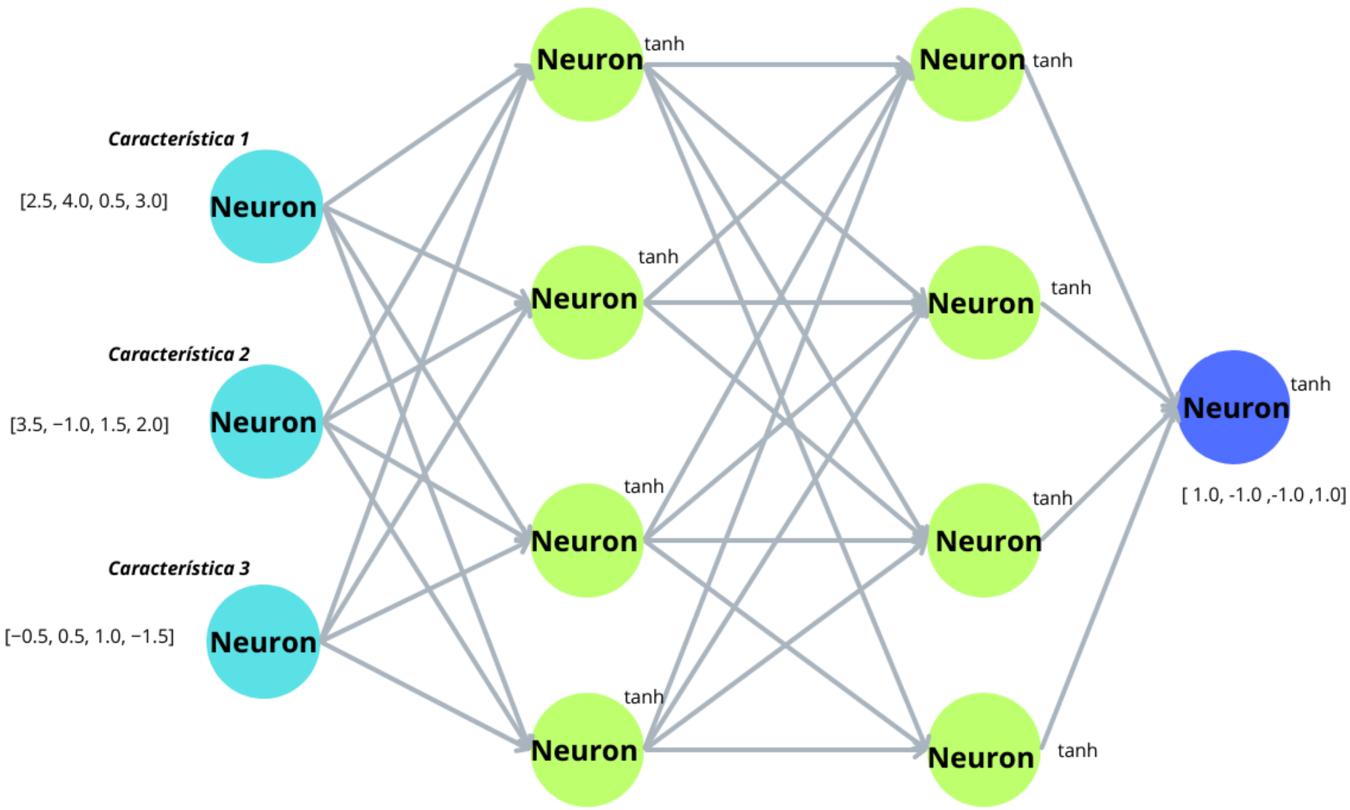
Tarea 1 - Redes neuronales

Ejercicio 2



Implementación con Micrograd

```
!pip install micrograd
```

```
Requirement already satisfied: micrograd in /usr/local/lib/python3.10/dist-packages (0.1.0)
```

```
import math
import numpy as np
from micrograd.engine import Value

# Definir una clase de Neurona
class Neurona:
    def __init__(self, n_entradas, pesos=None, bias=None):
        if pesos is None:
            self.pesos = [Value(np.random.randn()) for _ in range(n_entradas)]
        else:
            self.pesos = [Value(w) for w in pesos]
        self.bias = Value(bias if bias is not None else np.random.randn())

    def __call__(self, x):
        activacion = sum((wi * xi for wi, xi in zip(self.pesos, x)), self.bias)
        exp_pos = math.exp(activacion.data)
        exp_neg = math.exp(-activacion.data)
        tanh_valor = (exp_pos - exp_neg) / (exp_pos + exp_neg)
        return Value(tanh_valor)

class Capa:
    def __init__(self, n_entradas, n_neuronas, pesos=None, biases=None):
        if pesos is None:
            self.neuronas = [Neurona(n_entradas) for _ in range(n_neuronas)]
        else:
            self.neuronas = [Neurona(n_entradas, peso, bias) for peso, bias in zip(pesos, biases)]

    def __call__(self, x):
        return [neurona(x) for neurona in self.neuronas]
```

```
class MLP:
    def __init__(self, estructura, pesos=None, biases=None):
        capas = []
        for i in range(len(estructura) - 1):
            capas.append(Capa(estructura[i], estructura[i+1],
                              pesos[i] if pesos is not None else None,
                              biases[i] if biases is not None else None))
        self.capas = capas

    def __call__(self, x):
        for capa in self.capas:
            x = capa(x)
        return x[0]

# Función de pérdida (MSE)
def mse_loss(y_pred, y_real):
    return sum([(yp - yr)**2 for yp, yr in zip(y_pred, y_real)]) / len(y_real)

# Datos de entrada
X_s = [
    [2.5, 3.5, -0.5],
    [4.0, -1.0, 0.5],
    [0.5, 1.5, 1.0],
    [3.0, 2.0, -1.5]
]

# Etiquetas
y_s = [1.0, -1.0, -1.0, 1.0]

# Estructura del MLP
estructura = [3, 4, 4, 1]

# Pesos iniciales
pesos1 = [
    [0.00418492702436879, 0.43075487690967607, -0.4282565031009904],
    [0.5158558846557311, 0.5819550111766021, -0.8088029951912754],
    [-0.44835832271820397, 0.38031895464530585, -0.5665208363970418],
    [0.7429447941285752, -0.4746263677602629, 0.8949930247921201]
]

biases1 = [0.32206783013775775, -0.8686507446696847, 0.018075310323074634, 0.17709258735126432]

pesos2 = [
    [-0.8049392563546165, -0.49989970805506223, -0.11040622481498752, 0.6488610351165072],
    [0.9106209221005506, -0.019296335734448, -0.3698365604587379, -0.4895868360031945],
    [-0.6609560349975847, -0.9560446284058173, 0.10824475517169851, 0.611275384042882],
    [0.8411566571608489, -0.013218235445775939, 0.9342264201408781, 0.05702543031001284]
]

biases2 = [-0.11802212336116158, 0.22209342708457336, 0.7164897385943987, -0.9907541859895936]

pesos_salida = [
    [0.005437266894224635, -0.9489167963463787, 0.07198349639302193, -0.8783725464793719]
]

bias_salida = [-0.9695536926056374]

pesos = [pesos1, pesos2, pesos_salida]
biases = [biases1, biases2, bias_salida]

# Instanciar el modelo
mlp = MLP(estructura, pesos, biases)

# Tasa de aprendizaje
learning_rate = 0.1

# Mostrar los pesos iniciales de todas las capas
print("Pesos y biases iniciales:\n")
for i, capa in enumerate(mlp.capas):
    print(f"Capa {i+1}:")
    for j, neurona in enumerate(capa.neuronas):
        print(f"  Neurona {j+1} - Pesos: {[p.data for p in neurona.pesos]}, Bias: {neurona.bias.data}")

# Forward pass
salidas = [mlp(x) for x in X_s]

# Mostrar salidas (Forward pass)
print("\nSalidas predichas (Forward pass):")
for i, salida in enumerate(salidas):
    print(f"Ejemplo {i+1} - Salida predicha: {salida.data}")

# Calcular pérdida
```

```python
loss = mse_loss(salidas, y_s)
print(f"\nPérdida (Loss): {loss.data}")

# Backward pass
loss.backward()

# Mostrar gradientes de los pesos y biases de todas las capas
print("\nGradientes de los pesos y biases:\n")
for i, capa in enumerate(mlp.capas):
    print(f"Capa {i+1}:")
    for j, neurona in enumerate(capa.neuronas):
        print(f"  Neurona {j+1} - Gradientes de pesos: {[p.grad for p in neurona.pesos]}, Gradiente de Bias: {neurona.bias.grad}")

# Actualizar los pesos
for capa in mlp.capas:
    for neurona in capa.neuronas:
        for peso in neurona.pesos:
            peso.data -= learning_rate * peso.grad
        neurona.bias.data -= learning_rate * neurona.bias.grad

# Mostrar los pesos actualizados de todas las capas
print("\nPesos y biases actualizados:\n")
for i, capa in enumerate(mlp.capas):
    print(f"Capa {i+1}:")
    for j, neurona in enumerate(capa.neuronas):
        print(f"  Neurona {j+1} - Pesos: {[p.data for p in neurona.pesos]}, Bias: {neurona.bias.data}")
```

```
Pesos y biases iniciales:

Capa 1:
  Neurona 1 - Pesos: [0.00418492702436879, 0.43075487690967607, -0.4282565031009904], Bias: 0.32206783013775775
  Neurona 2 - Pesos: [0.5158558846557311, 0.5819550111766021, -0.8088029951912754], Bias: -0.8686507446696847
  Neurona 3 - Pesos: [-0.44835832271820397, 0.38031895464530585, -0.5665208363970418], Bias: 0.018075310323074634
  Neurona 4 - Pesos: [0.7429447941285752, -0.4746263677602629, 0.8949930247921201], Bias: 0.17709258735126432
Capa 2:
  Neurona 1 - Pesos: [-0.8049392563546165, -0.49989970805506223, -0.11040622481498752, 0.6488610351165072], Bias: -0.11802212336116
  Neurona 2 - Pesos: [0.9106209221005506, -0.019296335734448, -0.3698365604587379, -0.4895868360031945], Bias: 0.22209342708457336
  Neurona 3 - Pesos: [-0.6609560349975847, -0.9560446284058173, 0.10824475517169851, 0.611275384042882], Bias: 0.7164897385943987
  Neurona 4 - Pesos: [0.8411566571608489, -0.013218235445775939, 0.9342264201408781, 0.05702543031001284], Bias: -0.99075418598959
Capa 3:
  Neurona 1 - Pesos: [0.005437266894224635, -0.9489167963463787, 0.07198349639302193, -0.8783725464793719], Bias: -0.96955369260563

Salidas predichas (Forward pass):
Ejemplo 1 - Salida predicha: -0.9592968176676216
Ejemplo 2 - Salida predicha: 0.11314663463655017
Ejemplo 3 - Salida predicha: -0.6454088744389577
Ejemplo 4 - Salida predicha: -0.9422824621884223

Pérdida (Loss): 2.244033869794128

Gradientes de los pesos y biases:

Capa 1:
  Neurona 1 - Gradientes de pesos: [0, 0, 0], Gradiente de Bias: 0
  Neurona 2 - Gradientes de pesos: [0, 0, 0], Gradiente de Bias: 0
  Neurona 3 - Gradientes de pesos: [0, 0, 0], Gradiente de Bias: 0
  Neurona 4 - Gradientes de pesos: [0, 0, 0], Gradiente de Bias: 0
Capa 2:
  Neurona 1 - Gradientes de pesos: [0, 0, 0, 0], Gradiente de Bias: 0
  Neurona 2 - Gradientes de pesos: [0, 0, 0, 0], Gradiente de Bias: 0
  Neurona 3 - Gradientes de pesos: [0, 0, 0, 0], Gradiente de Bias: 0
  Neurona 4 - Gradientes de pesos: [0, 0, 0, 0], Gradiente de Bias: 0
Capa 3:
  Neurona 1 - Gradientes de pesos: [0, 0, 0, 0], Gradiente de Bias: 0

Pesos y biases actualizados:

Capa 1:
  Neurona 1 - Pesos: [0.00418492702436879, 0.43075487690967607, -0.4282565031009904], Bias: 0.32206783013775775
  Neurona 2 - Pesos: [0.5158558846557311, 0.5819550111766021, -0.8088029951912754], Bias: -0.8686507446696847
  Neurona 3 - Pesos: [-0.44835832271820397, 0.38031895464530585, -0.5665208363970418], Bias: 0.018075310323074634
  Neurona 4 - Pesos: [0.7429447941285752, -0.4746263677602629, 0.8949930247921201], Bias: 0.17709258735126432
Capa 2:
  Neurona 1 - Pesos: [-0.8049392563546165, -0.49989970805506223, -0.11040622481498752, 0.6488610351165072], Bias: -0.11802212336116
  Neurona 2 - Pesos: [0.9106209221005506, -0.019296335734448, -0.3698365604587379, -0.4895868360031945], Bias: 0.22209342708457336
  Neurona 3 - Pesos: [-0.6609560349975847, -0.9560446284058173, 0.10824475517169851, 0.611275384042882], Bias: 0.7164897385943987
  Neurona 4 - Pesos: [0.8411566571608489, -0.013218235445775939, 0.9342264201408781, 0.05702543031001284], Bias: -0.99075418598959
Capa 3:
  Neurona 1 - Pesos: [0.005437266894224635, -0.9489167963463787, 0.07198349639302193, -0.8783725464793719], Bias: -0.96955369260563
```

Implementación con Pytorch

```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np

# Definir la red neuronal con PyTorch
class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()

        # Definir las capas con los mismos tamaños que la implementación de micrograd
        self.fc1 = nn.Linear(3, 4)
        self.fc2 = nn.Linear(4, 4)
        self.fc3 = nn.Linear(4, 1)

        # Inicializar los pesos y biases manualmente para que coincidan con los de micrograd
        with torch.no_grad():
            self.fc1.weight = nn.Parameter(torch.tensor([
                [0.00418492702436879, 0.43075487690967607, -0.4282565031009904],
                [0.5158558846557311, 0.5819550111766021, -0.8088029951912754],
                [-0.44835832271820397, 0.38031895464530585, -0.5665208363970418],
                [0.7429447941285752, -0.4746263677602629, 0.8949930247921201]
            ]))
            self.fc1.bias = nn.Parameter(torch.tensor([0.32206783013775775, -0.8686507446696847, 0.018075310323074634, 0.17709258735126

            self.fc2.weight = nn.Parameter(torch.tensor([
                [-0.8049392563546165, -0.49989970805506223, -0.11040622481498752, 0.6488610351165072],
                [0.9106209221005506, -0.019296335734448, -0.3698365604587379, -0.4895868360031945],
                [-0.6609560349975847, -0.9560446284058173, 0.10824475517169851, 0.611275384042882],
                [0.8411566571608489, -0.013218235445775939, 0.9342264201408781, 0.05702543031001284]
            ]))
            self.fc2.bias = nn.Parameter(torch.tensor([-0.11802212336116158, 0.22209342708457336, 0.7164897385943987, -0.9907541859895

            self.fc3.weight = nn.Parameter(torch.tensor([[0.005437266894224635, -0.9489167963463787, 0.07198349639302193, -0.878372546
            self.fc3.bias = nn.Parameter(torch.tensor([-0.9695536926056374]))

    def forward(self, x):
        # Pasar los datos por la red utilizando la función tanh
        x = torch.tanh(self.fc1(x))
        x = torch.tanh(self.fc2(x))
        x = torch.tanh(self.fc3(x))
        return x

# Función para imprimir de forma legible
def print_formatted(title, data):
    print(f"\n--- {title} ---")
    for name, param in data.items():
        if isinstance(param, torch.Tensor):
            param = param.detach().numpy()
        if isinstance(param, np.ndarray):
            param = np.round(param, decimals=4)  # Redondear a 4 decimales
        print(f"{name}: \n{param}")

# Inicializar la red y los datos
mlp_pytorch = MLP()
criterion = nn.MSELoss()  # Función de pérdida (Mean Squared Error)

# Definir los datos de entrada y las etiquetas (salidas esperadas)
X_s = torch.tensor([[2.5, 3.5, -0.5],
                    [4.0, -1.0, 0.5],
                    [0.5, 1.5, 1.0],
                    [3.0, 2.0, -1.5]], dtype=torch.float32)

y_s = torch.tensor([1.0, -1.0, -1.0, 1.0], dtype=torch.float32).view(-1, 1)

# Obtener los pesos y biases antes del forward pass
params_before = {
    'fc1.weight': mlp_pytorch.fc1.weight,
    'fc1.bias': mlp_pytorch.fc1.bias,
    'fc2.weight': mlp_pytorch.fc2.weight,
    'fc2.bias': mlp_pytorch.fc2.bias,
    'fc3.weight': mlp_pytorch.fc3.weight,
    'fc3.bias': mlp_pytorch.fc3.bias
}

# Mostrar los pesos y biases antes de la actualización
print_formatted("Pesos y Biases antes de la actualización", params_before)

# Calcular el forward pass
outputs = mlp_pytorch(X_s)

# Calcular la pérdida (Loss)
```

```
loss = criterion(outputs, y_s)

# Mostrar las salidas predichas (forward pass)
print("\n--- Salidas predichas (Forward pass) ---")
print(np.round(outputs.detach().numpy(), decimals=4))

# Mostrar la pérdida
print(f"\nPérdida (Loss): {np.round(loss.item(), decimals=4)}")

# Calcular el backward pass (retropropagación)
mlp_pytorch.zero_grad()  # Limpiar los gradientes antes de calcularlos
loss.backward()

# Obtener los gradientes después del backward pass
grads = {
    'fc1.weight': mlp_pytorch.fc1.weight.grad,
    'fc1.bias': mlp_pytorch.fc1.bias.grad,
    'fc2.weight': mlp_pytorch.fc2.weight.grad,
    'fc2.bias': mlp_pytorch.fc2.bias.grad,
    'fc3.weight': mlp_pytorch.fc3.weight.grad,
    'fc3.bias': mlp_pytorch.fc3.bias.grad
}

# Mostrar los gradientes calculados
print_formatted("Gradientes de los pesos y biases (Backward pass)", grads)

# Optimizar (ajustar los pesos)
optimizer = optim.SGD(mlp_pytorch.parameters(), lr=0.1)
optimizer.step()

# Obtener los pesos y biases después de la actualización
params_after = {
    'fc1.weight': mlp_pytorch.fc1.weight,
    'fc1.bias': mlp_pytorch.fc1.bias,
    'fc2.weight': mlp_pytorch.fc2.weight,
    'fc2.bias': mlp_pytorch.fc2.bias,
    'fc3.weight': mlp_pytorch.fc3.weight,
    'fc3.bias': mlp_pytorch.fc3.bias
}

# Mostrar los pesos y biases después de la actualización
print_formatted("Pesos y Biases después de la actualización", params_after)
```

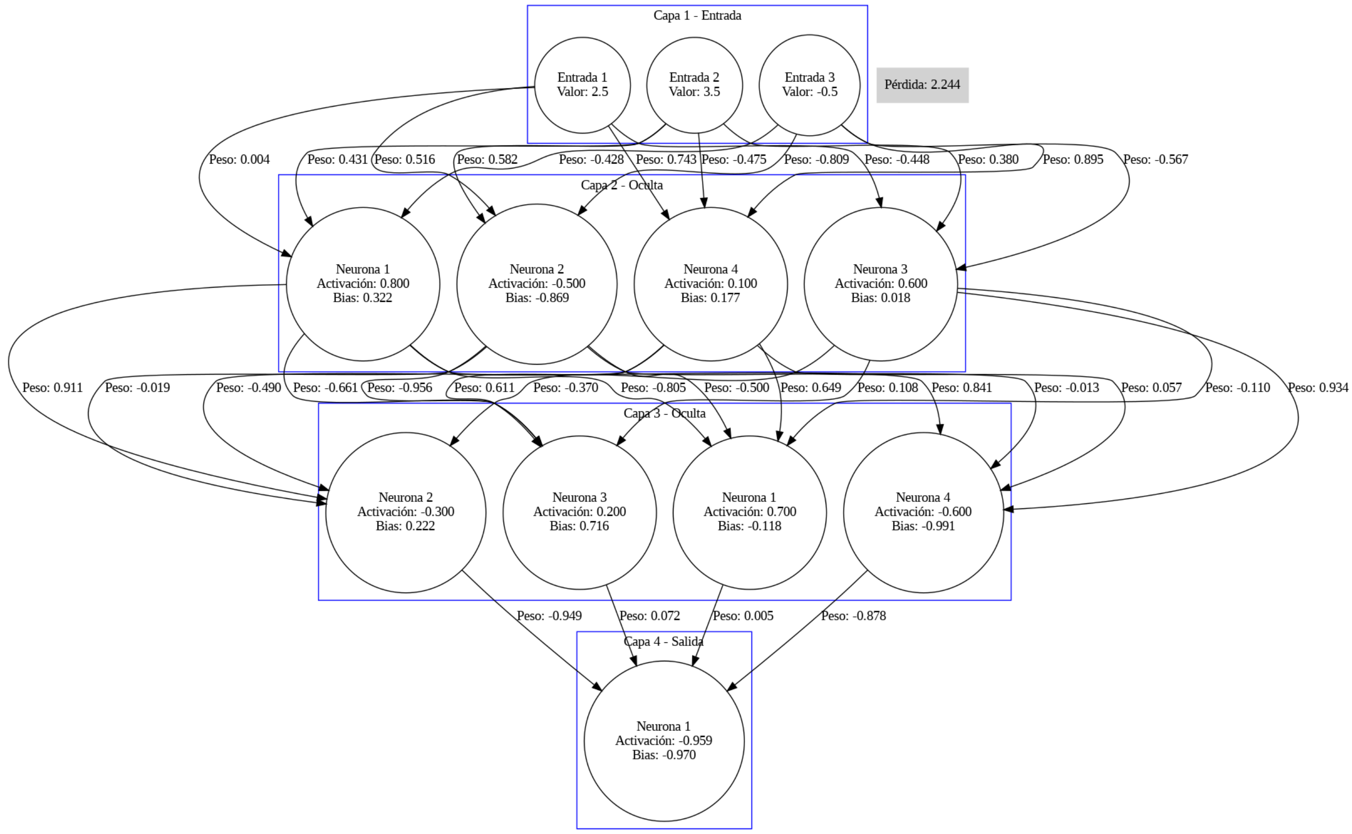
```
--- Pesos y Biases antes de la actualización ---
fc1.weight:
[[ 0.0042  0.4308 -0.4283]
 [ 0.5159  0.582  -0.8088]
 [-0.4484  0.3803 -0.5665]
 [ 0.7429 -0.4746  0.895 ]]
fc1.bias:
[ 0.3221 -0.8687  0.0181  0.1771]
fc2.weight:
[[-0.8049 -0.4999 -0.1104  0.6489]
 [ 0.9106 -0.0193 -0.3698 -0.4896]
 [-0.661  -0.956   0.1082  0.6113]
 [ 0.8412 -0.0132  0.9342  0.057 ]]
fc2.bias:
[-0.118   0.2221  0.7165 -0.9908]
fc3.weight:
[[ 0.0054 -0.9489  0.072  -0.8784]]
fc3.bias:
[-0.9696]

--- Salidas predichas (Forward pass) ---
[[-0.9593]
 [ 0.1131]
 [-0.6454]
 [-0.9423]]

Pérdida (Loss): 2.244

--- Gradientes de los pesos y biases (Backward pass) ---
fc1.weight:
[[-1.7922e+00  3.5420e-01 -3.3860e-01]
 [-7.1000e-03  1.8000e-03 -1.0000e-03]
 [ 2.9570e-01  2.2190e-01 -1.3510e-01]
 [-8.7900e-02 -5.9400e-02  6.2800e-02]]
fc1.bias:
[-0.524  -0.0018  0.085  -0.0125]
fc2.weight:
[[-5.000e-04 -1.000e-04 -1.900e-03  2.100e-03]
 [ 1.899e-01  1.920e-02  5.434e-01 -5.523e-01]
 [-9.500e-03 -6.100e-03 -1.450e-02  1.270e-02]
 [ 1.335e-01  1.814e-01  9.530e-02 -5.690e-02]]
```

```
fc2.bias:
[ 0.0021 -0.5027  0.0064  0.0758]
fc3.weight:
[[ 0.539  -0.1889  0.6732 -0.6225]]
fc3.bias:
[0.4659]

--- Pesos y Biases después de la actualización ---
fc1.weight:
[[ 0.1834  0.3953 -0.3944]
 [ 0.5166  0.5818 -0.8087]
 [-0.4779  0.3581 -0.553 ]
 [ 0.7517 -0.4687  0.8887]]
fc1.bias:
[ 0.3745 -0.8685  0.0096  0.1783]
fc2.weight:
```

Gráficar MLP

```
from graphviz import Digraph
from IPython.display import Image, display

# Definir una clase para graficar el MLP con pesos, activaciones y biases
def graficar_mlp_con_forward(estructura, pesos, biases, activaciones, entradas, predicciones, perdida):
    dot = Digraph(format='png')

    # Crear los nodos de las capas
    for i, num_neuronas in enumerate(estructura):
        with dot.subgraph(name=f'cluster_{i}') as c:
            if i == 0:
                c.attr(label=f'Capa {i+1} - Entrada')
            elif i == len(estructura) - 1:
                c.attr(label=f'Capa {i+1} - Salida')
            else:
                c.attr(label=f'Capa {i+1} - Oculta')
            c.attr(color='blue')
            for j in range(num_neuronas):
                if i == 0:
                    # Mostrar valores de entrada
                    c.node(f'N{i}_{j}', f'Entrada {j+1}\nValor: {entradas[j]}', shape='circle')
                else:
                    # Mostrar activación y bias (no hacer esto en la capa de entrada)
                    activacion = activaciones[i-1][j] if i < len(estructura) - 1 else predicciones[j]
                    bias = biases[i-1][j] if i < len(estructura) else biases[-1][j]
                    c.node(f'N{i}_{j}', f'Neurona {j+1}\nActivación: {activacion:.3f}\nBias: {bias:.3f}', shape='circle')

    # Conectar las capas y mostrar los pesos
    for i in range(len(estructura) - 1):
        for j in range(estructura[i]):  # Neuronas en la capa i
            for k in range(estructura[i+1]):  # Neuronas en la capa i+1
                # Obtener el peso de la conexión entre la neurona j de la capa i y la neurona k de la capa i+1
                peso = pesos[i][k][j]
                dot.edge(f'N{i}_{j}', f'N{i+1}_{k}', label=f'Peso: {peso:.3f}')

    # Mostrar la pérdida en el gráfico
    dot.node("Loss", f'Pérdida: {perdida:.3f}', shape='box', style='filled', color='lightgrey')

    return dot

# Datos de entrada (mismos valores que el forward pass)
entradas = [2.5, 3.5, -0.5]  # Valores de entrada (para el primer ejemplo)

# Pesos y biases de la implementación con micrograd
pesos1 = [
    [0.00418492702436879, 0.43075487690967607, -0.4282565031009904],
    [0.5158558846557311, 0.5819550111766021, -0.8088029951912754],
    [-0.44835832271820397, 0.38031895464530585, -0.5665208363970418],
    [0.7429447941285752, -0.4746263677602629, 0.8949930247921201]
]

pesos2 = [
    [-0.8049392563546165, -0.49989970805506223, -0.11040622481498752, 0.6488610351165072],
    [0.9106209221005506, -0.019296335734448, -0.3698365604587379, -0.4895868360031945],
    [-0.6609560349975847, -0.9560446284058173, 0.10824475517169851, 0.611275384042882],
    [0.8411566571608489, -0.013218235445775939, 0.9342264201408781, 0.05702543031001284]
]

pesos_salida = [
    [0.005437266894224635, -0.9489167963463787, 0.07198349639302193, -0.8783725464793719]
]

pesos = [pesos1, pesos2, pesos_salida]
```

```
# Biases para las neuronas
biases1 = [0.32206783013775775, -0.8686507446696847, 0.018075310323074634, 0.17709258735126432]
biases2 = [-0.11802212336116158, 0.22209342708457336, 0.7164897385943987, -0.9907541859895936]
bias_salida = [-0.9695536926056374]
biases = [biases1, biases2, bias_salida]

# Activaciones (valores de salida de cada neurona después del forward pass) para el primer ejemplo
activaciones1 = [0.8, -0.5, 0.6, 0.1]  # Activaciones de la primera capa oculta
activaciones2 = [0.7, -0.3, 0.2, -0.6]  # Activaciones de la segunda capa oculta

# Predicciones de salida obtenidas con micrograd
predicciones = [-0.9593]  # Salida predicha para el primer ejemplo

# Pérdida obtenida con micrograd
perdida = 2.244

# Estructura del MLP (misma que la implementación con micrograd)
estructura = [3, 4, 4, 1]  # 3 entradas, 2 capas ocultas de 4 neuronas, 1 salida

# Crear y mostrar el gráfico
dot = graficar_mlp_con_forward(estructura, pesos, biases, [activaciones1, activaciones2], entradas, predicciones, perdida)

# Mostrar el gráfico directamente sin guardarlo en PNG
display(Image(dot.pipe(format='png')))
```



Ejercicio 3

Importacion de librerias

```
import os
import random
import json
```

```
import numpy as np
from PIL import Image, ImageDraw
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import random_split,Dataset, DataLoader
from torchvision import datasets,transforms
from sklearn.model_selection import train_test_split
```

Carga del dataset

```
! pip install -q kaggle
from google.colab import files
files.upload()
```

Elegir archivos Ningún archivo seleccionado Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving kaggle.json to kaggle.json
{'kaggle.json': b'{"username":"juanlunauni","key":"d140e1c5061926848dbdf16d4fa5c62d"}'}
```

```
! mkdir kaggle
```

```
! cp kaggle.json kaggle/
```

```
! chmod 600 kaggle/kaggle.json
```

```
! kaggle datasets download rm1000/lung-cancer-histopathological-images
```

```
Dataset URL: https://www.kaggle.com/datasets/rm1000/lung-cancer-histopathological-images
License(s): CC-BY-SA-4.0
Downloading lung-cancer-histopathological-images.zip to /content
 99% 1.54G/1.55G [00:21<00:00, 89.6MB/s]
100% 1.55G/1.55G [00:22<00:00, 75.8MB/s]
```

```
! mkdir lung-cancer-histopathological-images
```

```
! mv lung-cancer-histopathological-images.zip lung-cancer-histopathological-images/.
```

```
! mkdir modelos
```

```
! cd lung-cancer-histopathological-images && unzip lung-cancer-histopathological-images.zip
```

```
! cd ..
```

Se truncaron las últimas líneas 5000 del resultado de transmisión.

```
  inflating: squamous_cell_carcinoma/0000.jpg
  inflating: squamous_cell_carcinoma/0001.jpg
  inflating: squamous_cell_carcinoma/0002.jpg
  inflating: squamous_cell_carcinoma/0003.jpg
  inflating: squamous_cell_carcinoma/0004.jpg
  inflating: squamous_cell_carcinoma/0005.jpg
  inflating: squamous_cell_carcinoma/0006.jpg
  inflating: squamous_cell_carcinoma/0007.jpg
  inflating: squamous_cell_carcinoma/0008.jpg
  inflating: squamous_cell_carcinoma/0009.jpg
  inflating: squamous_cell_carcinoma/0010.jpg
  inflating: squamous_cell_carcinoma/0011.jpg
  inflating: squamous_cell_carcinoma/0012.jpg
  inflating: squamous_cell_carcinoma/0013.jpg
  inflating: squamous_cell_carcinoma/0014.jpg
  inflating: squamous_cell_carcinoma/0015.jpg
  inflating: squamous_cell_carcinoma/0016.jpg
  inflating: squamous_cell_carcinoma/0017.jpg
  inflating: squamous_cell_carcinoma/0018.jpg
  inflating: squamous_cell_carcinoma/0019.jpg
  inflating: squamous_cell_carcinoma/0020.jpg
  inflating: squamous_cell_carcinoma/0021.jpg
  inflating: squamous_cell_carcinoma/0022.jpg
  inflating: squamous_cell_carcinoma/0023.jpg
  inflating: squamous_cell_carcinoma/0024.jpg
  inflating: squamous_cell_carcinoma/0025.jpg
  inflating: squamous_cell_carcinoma/0026.jpg
  inflating: squamous_cell_carcinoma/0027.jpg
  inflating: squamous_cell_carcinoma/0028.jpg
  inflating: squamous_cell_carcinoma/0029.jpg
  inflating: squamous_cell_carcinoma/0030.jpg
  inflating: squamous_cell_carcinoma/0031.jpg
```

```
inflating: squamous_cell_carcinoma/0032.jpg
inflating: squamous_cell_carcinoma/0033.jpg
inflating: squamous_cell_carcinoma/0034.jpg
inflating: squamous_cell_carcinoma/0035.jpg
inflating: squamous_cell_carcinoma/0036.jpg
inflating: squamous_cell_carcinoma/0037.jpg
inflating: squamous_cell_carcinoma/0038.jpg
inflating: squamous_cell_carcinoma/0039.jpg
inflating: squamous_cell_carcinoma/0040.jpg
inflating: squamous_cell_carcinoma/0041.jpg
inflating: squamous_cell_carcinoma/0042.jpg
inflating: squamous_cell_carcinoma/0043.jpg
inflating: squamous_cell_carcinoma/0044.jpg
inflating: squamous_cell_carcinoma/0045.jpg
inflating: squamous_cell_carcinoma/0046.jpg
inflating: squamous_cell_carcinoma/0047.jpg
inflating: squamous_cell_carcinoma/0048.jpg
inflating: squamous_cell_carcinoma/0049.jpg
inflating: squamous_cell_carcinoma/0050.jpg
inflating: squamous_cell_carcinoma/0051.jpg
inflating: squamous_cell_carcinoma/0052.jpg
inflating: squamous_cell_carcinoma/0053.jpg
inflating: squamous_cell_carcinoma/0054.jpg
inflating: squamous_cell_carcinoma/0055.jpg
```

```
! rm -rf lung-cancer-histopathological-images/.ipynb_checkpoints lung-cancer-histopathological-images/lung-cancer-histopathological-imag
```

```
root = 'lung-cancer-histopathological-images'
classes = os.listdir(root)

for i in range(3):
    print(f"# of images in class {classes[i]}: {len(os.listdir(root+'/'+classes[i]))}")
```

```
# of images in class adenocarcinoma: 5000
# of images in class squamous_cell_carcinoma: 5000
# of images in class benign: 5000
```

ResNET

```
# Define a residual block
class ResidualBlock(nn.Module):
    def __init__(self, in_channels, out_channels, stride=1):
        super(ResidualBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.relu = nn.ReLU(inplace=True)
        self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(out_channels)

        # Shortcut connection
        self.shortcut = nn.Sequential()
        if stride != 1 or in_channels != out_channels:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(out_channels)
            )

    def forward(self, x):
        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out += self.shortcut(x)
        out = self.relu(out)
        return out



# Define the ResNet model
class ResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNet, self).__init__()
        self.in_channels = 16
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(16)
        self.relu = nn.ReLU(inplace=True)
        self.layer1 = self._make_layer(block, 16, num_blocks[0])
        self.layer2 = self._make_layer(block, 32, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 64, num_blocks[2], stride=2)
        self.avg_pool = nn.AdaptiveAvgPool2d((1, 1))
```

```
        self.fc = nn.Linear(64, num_classes)

    def _make_layer(self, block, out_channels, blocks, stride=1):
        layers = []
        layers.append(block(self.in_channels, out_channels, stride))
        self.in_channels = out_channels
        for _ in range(1, blocks):
            layers.append(block(out_channels, out_channels))
        return nn.Sequential(*layers)

    def forward(self, x):
        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu(x)
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.avg_pool(x)
        x = x.view(x.size(0), -1)  # Flatten the output
        x = self.fc(x)
        return x


# Create the ResNet model
def ResNet18():
    return ResNet(ResidualBlock, [2, 2, 2])  # ResNet-18

# Initialize the model, loss function, and optimizer
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = ResNet18().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

Acondicionamiento del dataset

```
# Definir transformaciones de preprocesamiento
transform = transforms.Compose([
    transforms.Resize((224, 224)),  # Cambiar el tamaño de las imágenes
    transforms.ToTensor(),          # Convertir las imágenes en tensores
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])  # Normalización
])

# Cargar el dataset
data_dir = 'lung-cancer-histopathological-images/'

dataset = datasets.ImageFolder(os.path.join(data_dir), transform=transform)

train_size, val_size = int(0.8 * len(dataset)), int(0.2 * len(dataset))

train_dataset, val_dataset = random_split(dataset, [train_size, val_size]) # stratified split is better

train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True) # shuffle to avoid memorization (overfitting)
val_loader = DataLoader(val_dataset, batch_size=64, shuffle=False)
```

Training

```
# Training the model
num_epochs = 20
for epoch in range(num_epochs):
    model.train()  # Set the model to training mode
    running_loss = 0.0
    for data in train_loader:
        inputs, labels = data[0].to(device), data[1].to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

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

        # Backward pass and optimization
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
```

```
    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}')
```

```
Epoch [1/20], Loss: 0.3036
Epoch [2/20], Loss: 0.2053
Epoch [3/20], Loss: 0.1735
Epoch [4/20], Loss: 0.1508
Epoch [5/20], Loss: 0.1377
Epoch [6/20], Loss: 0.1315
Epoch [7/20], Loss: 0.1100
Epoch [8/20], Loss: 0.1150
Epoch [9/20], Loss: 0.1102
Epoch [10/20], Loss: 0.1024
Epoch [11/20], Loss: 0.0940
Epoch [12/20], Loss: 0.0906
Epoch [13/20], Loss: 0.0925
Epoch [14/20], Loss: 0.0862
Epoch [15/20], Loss: 0.0794
Epoch [16/20], Loss: 0.0817
Epoch [17/20], Loss: 0.0689
Epoch [18/20], Loss: 0.0701
Epoch [19/20], Loss: 0.0630
Epoch [20/20], Loss: 0.0676
```

Testing

```
# Testing the model
model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
with torch.no_grad():
    for data in val_loader:
        images, labels = data[0].to(device), data[1].to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print(f'Accuracy of the model on the 10,000 test images: {100 * correct / total:.2f}%')
```

```
Accuracy of the model on the 10,000 test images: 98.20%
```

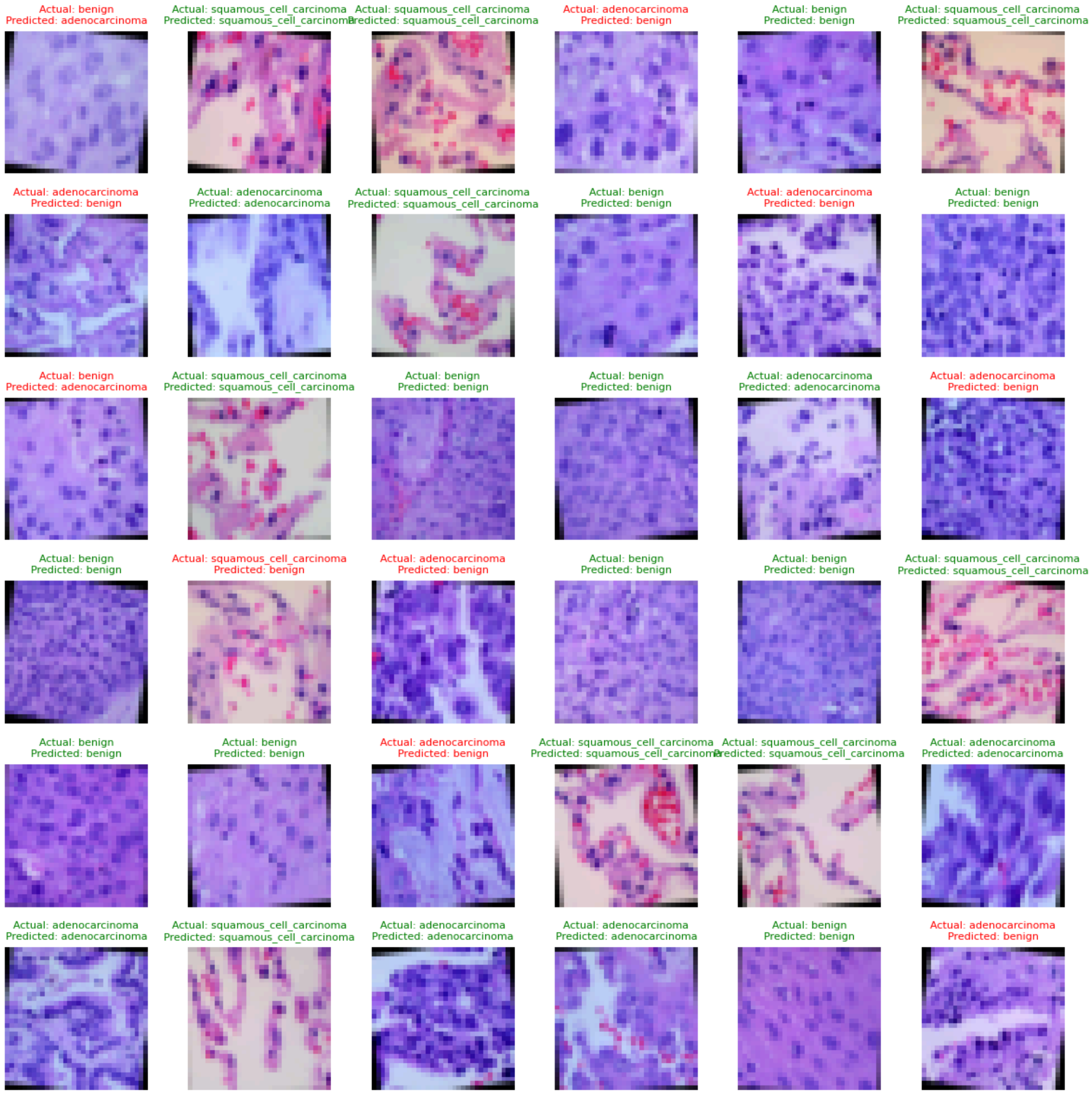
```
torch.save(model.state_dict(), 'modelos/ResNET_lung_cancer.pth')
```

Validation

```
import matplotlib.pyplot as plt
import random
import torchvision

def show_random_test_predictions(model, dataloader, class_names, num_images=16):
    model.eval()
    images_shown = 0
    fig, axes = plt.subplots(6, 6, figsize=(12, 12))
    axes = axes.flatten()

    all_images = []
    all_labels = []
    all_preds = []

    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs = inputs.to(device)
            labels = labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)

            all_images.extend(inputs.cpu())
            all_labels.extend(labels.cpu())
            all_preds.extend(preds.cpu())

    combined = list(zip(all_images, all_labels, all_preds))
    random.shuffle(combined)

    selected_images = random.sample(combined, min(num_images, len(combined)))

    for idx, (img, label, pred) in enumerate(selected_images):
        ax = axes[images_shown]
```

```
        ax.axis('off')

        img = img.numpy().transpose((1, 2, 0))
        img = np.clip((img * [0.229, 0.224, 0.225]) + [0.485, 0.456, 0.406], 0, 1)

        ax.imshow(img)

        predicted_class = class_names[pred]
        actual_class = class_names[label]
        title = f'Actual: {class_names[label]}\nPredicted: {class_names[pred]}'

        if predicted_class == actual_class:
            ax.set_title(title, color='green',fontsize=8)
        else:
            ax.set_title(title, color='red',fontsize=8)

        images_shown += 1
        if images_shown == num_images:
            break

    plt.tight_layout()
    plt.show()

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
path = 'modelos/ResNET_lung_cancer.pth'
model = ResNet18().to(device)
model.load_state_dict(torch.load(path))
show_random_test_predictions(model, val_loader, classes, num_images=36)
```

```
<ipython-input-44-58166b969ee8>:60: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value),
  model.load_state_dict(torch.load(path))
```



VGG-16

```
# Define the VGG16-like model
class VGG16(nn.Module):
    def __init__(self):
        super(VGG16, self).__init__()

        # Define the convolutional layers
        self.conv_layers = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=3, padding=1),  # Conv1
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),  # Conv2
            nn.ReLU(inplace=True),
```

```
            nn.MaxPool2d(kernel_size=2, stride=2),  # Max Pool 1

            nn.Conv2d(64, 128, kernel_size=3, padding=1),  # Conv3
            nn.ReLU(inplace=True),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),  # Conv4
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),  # Max Pool 2

            nn.Conv2d(128, 256, kernel_size=3, padding=1),  # Conv5
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),  # Conv6
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),  # Conv7
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),  # Max Pool 3

            nn.Conv2d(256, 512, kernel_size=3, padding=1),  # Conv8
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),  # Conv9
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),  # Conv10
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),  # Max Pool 4

            nn.Conv2d(512, 512, kernel_size=3, padding=1),  # Conv11
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),  # Conv12
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),  # Conv13
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)  # Max Pool 5
        )

        # Define the fully connected layers
        self.fc_layers = nn.Sequential(
            nn.Linear(512 * 1 * 1, 4096),  # Adjust input size according to CIFAR-10's image size (32x32)
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(0.5),
            nn.Linear(4096, 10)  # Output layer (CIFAR-10 has 10 classes)
        )

    def forward(self, x):
        x = self.conv_layers(x)
        x = x.view(x.size(0), -1)  # Flatten the output from conv layers
        x = self.fc_layers(x)
        return x


# Initialize the model, loss function, and optimizer
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = VGG16().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)


# Definir transformaciones de preprocesamiento
transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.Resize((32, 32)),  # Cambiar el tamaño de las imágenes
    transforms.ToTensor(),          # Convertir las imágenes en tensores
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])  # Normalización
])

# Cargar el dataset
data_dir = 'lung-cancer-histopathological-images/'

dataset = datasets.ImageFolder(os.path.join(data_dir), transform=transform)

train_size, val_size = int(0.8 * len(dataset)), int(0.2 * len(dataset))

train_dataset, val_dataset = random_split(dataset, [train_size, val_size]) # stratified split is better

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True) # shuffle to avoid memorization (overfitting)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
```

Training

```
# Training the model
num_epochs = 20
for epoch in range(num_epochs):
    model.train()  # Set the model to training mode
    running_loss = 0.0
    for data in train_loader:
        inputs, labels = data[0].to(device), data[1].to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

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

        # Backward pass and optimization
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader):.4f}')
```

```
Epoch [1/20], Loss: 0.9308
Epoch [2/20], Loss: 0.8770
Epoch [3/20], Loss: 0.7216
Epoch [4/20], Loss: 0.7541
Epoch [5/20], Loss: 0.5489
Epoch [6/20], Loss: 0.4670
Epoch [7/20], Loss: 0.3830
Epoch [8/20], Loss: 0.3255
Epoch [9/20], Loss: 8.7135
Epoch [10/20], Loss: 1.1033
Epoch [11/20], Loss: 1.1021
Epoch [12/20], Loss: 1.1004
Epoch [13/20], Loss: 1.1009
Epoch [14/20], Loss: 1.1001
Epoch [15/20], Loss: 1.1001
Epoch [16/20], Loss: 1.1001
Epoch [17/20], Loss: 1.1004
Epoch [18/20], Loss: 1.1007
Epoch [19/20], Loss: 1.1001
Epoch [20/20], Loss: 1.0995
```

Testing

```
# Testing the model
model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
with torch.no_grad():
    for data in val_loader:
        images, labels = data[0].to(device), data[1].to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print(f'Accuracy of the model on the 10,000 test images: {100 * correct / total:.2f}%')
```

```
Accuracy of the model on the 10,000 test images: 32.57%
```

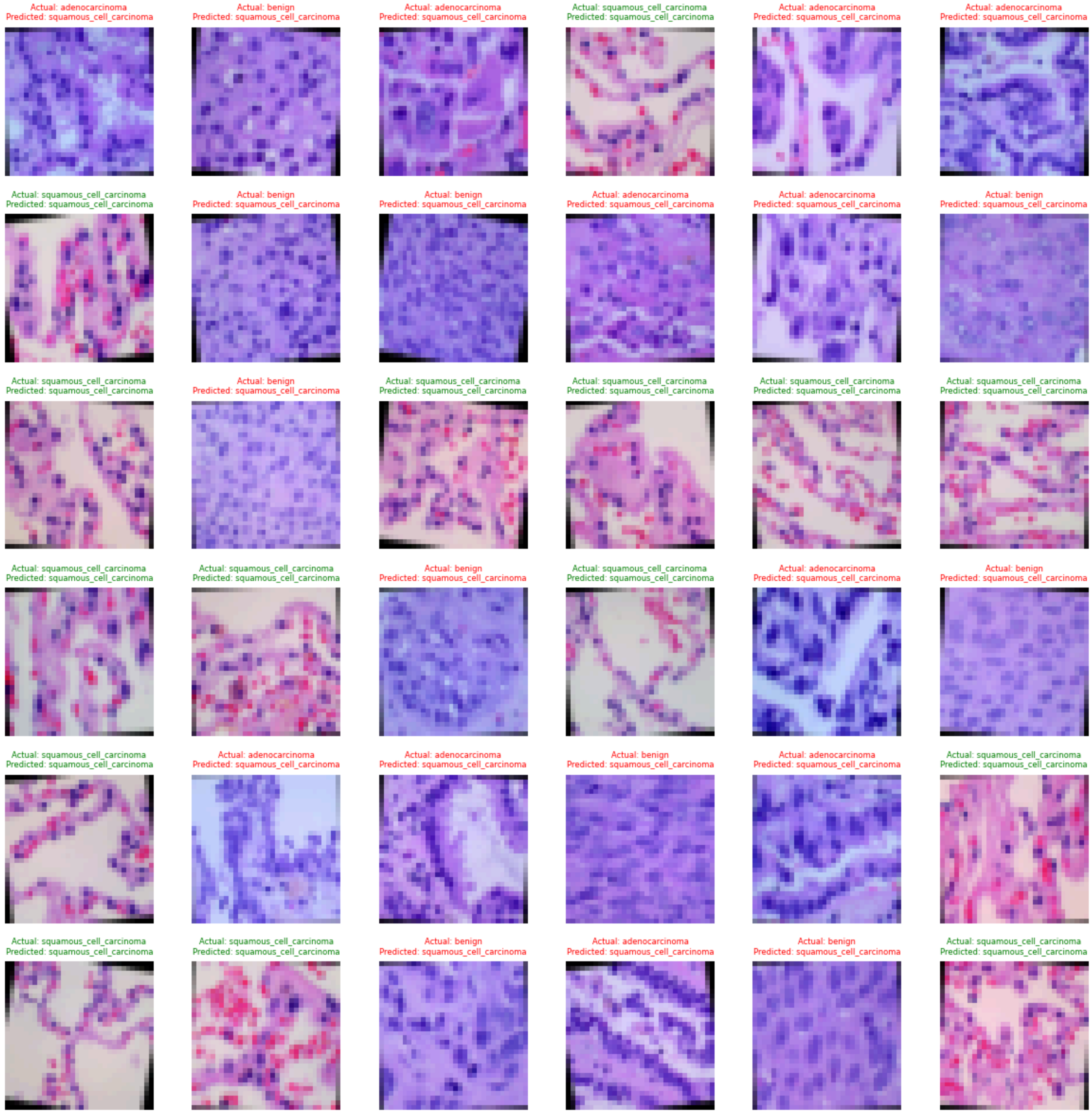
```
torch.save(model.state_dict(), 'modelos/VGG16_lung_cancer.pth')
```

Validation

```
import matplotlib.pyplot as plt
import random
import torchvision

def show_random_test_predictions(model, dataloader, class_names, num_images=16):
    model.eval()
    images_shown = 0
    fig, axes = plt.subplots(6, 6, figsize=(12, 12))
    axes = axes.flatten()

    all_images = []
    all_labels = []
    all_preds = []
```

```
    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs = inputs.to(device)
            labels = labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)

            all_images.extend(inputs.cpu())
            all_labels.extend(labels.cpu())
            all_preds.extend(preds.cpu())

    combined = list(zip(all_images, all_labels, all_preds))
    random.shuffle(combined)

    selected_images = random.sample(combined, min(num_images, len(combined)))

    for idx, (img, label, pred) in enumerate(selected_images):
        ax = axes[images_shown]
        ax.axis('off')

        img = img.numpy().transpose((1, 2, 0))
        img = np.clip((img * [0.229, 0.224, 0.225]) + [0.485, 0.456, 0.406], 0, 1)

        ax.imshow(img)

        predicted_class = class_names[pred]
        actual_class = class_names[label]
        title = f'Actual: {class_names[label]}\nPredicted: {class_names[pred]}'

        if predicted_class == actual_class:
            ax.set_title(title, color='green',fontsize=6)
        else:
            ax.set_title(title, color='red',fontsize=6)

        images_shown += 1
        if images_shown == num_images:
            break

    plt.tight_layout()
    plt.show()

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
path = 'modelos/VGG16_lung_cancer.pth'
model = VGG16().to(device)
model.load_state_dict(torch.load(path))
show_random_test_predictions(model, val_loader, classes, num_images=36)
```

```
<ipython-input-38-39b190fc693b>:60: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value),
  model.load_state_dict(torch.load(path))
```



GoogleNET

```
class GoogleNet(nn.Module):
    def __init__(self, in_channels=3, num_classes=10):  # num_classes ajustado para CIFAR-10
        super(GoogleNet, self).__init__()

        self.conv1 = conv_block(in_channels=in_channels, out_channels=64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3))
        self.maxpool1 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        self.conv2 = conv_block(in_channels=64, out_channels=192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        self.maxpool2 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        self.inception3a = Inception_block(192, 64, 96, 128, 16, 32, 32)
```

```
        self.inception3b = Inception_block(256, 128, 128, 192, 32, 96, 64)
        self.maxpool3 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        self.inception4a = Inception_block(480, 192, 96, 208, 16, 48, 64)
        self.inception4b = Inception_block(512, 160, 112, 224, 24, 64, 64)
        self.inception4c = Inception_block(512, 128, 128, 256, 24, 64, 64)
        self.inception4d = Inception_block(512, 112, 144, 288, 32, 64, 64)
        self.inception4e = Inception_block(528, 256, 160, 320, 32, 128, 128)
        self.maxpool4 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

        self.inception5a = Inception_block(832, 256, 160, 320, 32, 128, 128)
        self.inception5b = Inception_block(832, 384, 192, 384, 48, 128, 128)

        #self.avgpool = nn.AvgPool2d(kernel_size=2, stride=1)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.dropout = nn.Dropout(p=0.4)
        self.fc = nn.Linear(1024, num_classes)

    def forward(self, x):
        x = self.conv1(x)
        x = self.maxpool1(x)
        x = self.conv2(x)
        x = self.maxpool2(x)
        x = self.inception3a(x)
        x = self.inception3b(x)
        x = self.maxpool3(x)
        x = self.inception4a(x)
        x = self.inception4b(x)
        x = self.inception4c(x)
        x = self.inception4d(x)
        x = self.inception4e(x)
        x = self.maxpool4(x)
        x = self.inception5a(x)
        x = self.inception5b(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        x = self.dropout(x)
        x = self.fc(x)
        return x


class conv_block(nn.Module):
    def __init__(self, in_channels, out_channels, **kwargs):
        super(conv_block, self).__init__()
        self.conv = nn.Conv2d(in_channels, out_channels, bias=False, **kwargs)
        self.bn = nn.BatchNorm2d(out_channels)

    def forward(self, x):
        return torch.relu(self.bn(self.conv(x)))


class Inception_block(nn.Module):
    def __init__(self, in_channels, out_1x1, red_3x3, out_3x3, red_5x5, out_5x5, out_1x1pool):
        super(Inception_block, self).__init__()
        self.branch1 = conv_block(in_channels, out_1x1, kernel_size=(1, 1))

        self.branch2 = nn.Sequential(
            conv_block(in_channels, red_3x3, kernel_size=(1, 1)),
            conv_block(red_3x3, out_3x3, kernel_size=(3, 3), padding=(1, 1)),
        )

        self.branch3 = nn.Sequential(
            conv_block(in_channels, red_5x5, kernel_size=(1, 1)),
            conv_block(red_5x5, out_5x5, kernel_size=(5, 5), padding=(2, 2)),
        )

        self.branch4 = nn.Sequential(
            nn.MaxPool2d(kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)),
            conv_block(in_channels, out_1x1pool, kernel_size=(1, 1)),
        )

    def forward(self, x):
        return torch.cat([self.branch1(x), self.branch2(x), self.branch3(x), self.branch4(x)], 1)

# Definir transformaciones de preprocesamiento
transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.Resize((32, 32)),  # Cambiar el tamaño de las imágenes
    transforms.ToTensor(),          # Convertir las imágenes en tensores
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])  # Normalización
])
```

```
# Cargar el dataset
data_dir = 'lung-cancer-histopathological-images/'

dataset = datasets.ImageFolder(os.path.join(data_dir), transform=transform)

train_size, val_size = int(0.8 * len(dataset)), int(0.2 * len(dataset))

train_dataset, val_dataset = random_split(dataset, [train_size, val_size]) # stratified split is better

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True) # shuffle to avoid memorization (overfitting)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)


device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = GoogleNet().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

Training

```
# Ciclo de entrenamiento
num_epochs=20
for epoch in range(num_epochs):  # 20 épocas de entrenamiento
    running_loss = 0.0
    for i, data in enumerate(train_loader, 0):
        inputs, labels = data
        inputs, labels = inputs.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
        if i % 200 == 199:    # Imprimir cada 200 lotes
            print(f'[Epoch {epoch + 1}, Lote {i + 1}] Pérdida: {running_loss / 200:.3f}')
            running_loss = 0.0

print('Entrenamiento finalizado')
```

```
[Epoch 1, Lote 200] Pérdida: 0.371
[Epoch 2, Lote 200] Pérdida: 0.258
[Epoch 3, Lote 200] Pérdida: 0.219
[Epoch 4, Lote 200] Pérdida: 0.182
[Epoch 5, Lote 200] Pérdida: 0.179
[Epoch 6, Lote 200] Pérdida: 0.141
[Epoch 7, Lote 200] Pérdida: 0.169
[Epoch 8, Lote 200] Pérdida: 0.153
[Epoch 9, Lote 200] Pérdida: 0.099
[Epoch 10, Lote 200] Pérdida: 0.124
[Epoch 11, Lote 200] Pérdida: 0.087
[Epoch 12, Lote 200] Pérdida: 0.086
[Epoch 13, Lote 200] Pérdida: 0.061
[Epoch 14, Lote 200] Pérdida: 0.064
[Epoch 15, Lote 200] Pérdida: 0.055
[Epoch 16, Lote 200] Pérdida: 0.052
[Epoch 17, Lote 200] Pérdida: 0.050
[Epoch 18, Lote 200] Pérdida: 0.046
[Epoch 19, Lote 200] Pérdida: 0.044
[Epoch 20, Lote 200] Pérdida: 0.024
Entrenamiento finalizado
```

Testing

```
# Testing the model
model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
with torch.no_grad():
    for data in val_loader:
        images, labels = data[0].to(device), data[1].to(device)
        outputs = model(images)
        _, predicted = torch.max(outputs, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print(f'Accuracy of the model on the 10,000 test images: {100 * correct / total:.2f}%')
```

```
Accuracy of the model on the 10,000 test images: 97.53%
```

Comienza a programar o generar con IA.

```
torch.save(model.state_dict(), 'modelos/GoogleNet_lung_cancer.pth')
```

Validation

```
import matplotlib.pyplot as plt
import random
import torchvision

def show_random_test_predictions(model, dataloader, class_names, num_images=16):
    model.eval()
    images_shown = 0
    fig, axes = plt.subplots(6, 6, figsize=(12, 12))
    axes = axes.flatten()

    all_images = []
    all_labels = []
    all_preds = []

    with torch.no_grad():
        for inputs, labels in dataloader:
            inputs = inputs.to(device)
            labels = labels.to(device)

            outputs = model(inputs)
            _, preds = torch.max(outputs, 1)

            all_images.extend(inputs.cpu())
            all_labels.extend(labels.cpu())
            all_preds.extend(preds.cpu())

    combined = list(zip(all_images, all_labels, all_preds))
    random.shuffle(combined)

    selected_images = random.sample(combined, min(num_images, len(combined)))

    for idx, (img, label, pred) in enumerate(selected_images):
        ax = axes[images_shown]
        ax.axis('off')

        img = img.numpy().transpose((1, 2, 0))
        img = np.clip((img * [0.229, 0.224, 0.225]) + [0.485, 0.456, 0.406], 0, 1)

        ax.imshow(img)

        predicted_class = class_names[pred]
        actual_class = class_names[label]
        title = f'Actual: {class_names[label]}\nPredicted: {class_names[pred]}'

        if predicted_class == actual_class:
            ax.set_title(title, color='green',fontsize=6)
        else:
            ax.set_title(title, color='red',fontsize=6)

        images_shown += 1
        if images_shown == num_images:
            break

    plt.tight_layout()
    plt.show()

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
path = 'modelos/GoogleNet_lung_cancer.pth'
model = GoogleNet().to(device)
model.load_state_dict(torch.load(path))
show_random_test_predictions(model, val_loader, classes, num_images=36)
```