Deep Learning y Sistemas Inteligentes

Hoja de Trabajo 2

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Ejercicio 1 - Experimentación Práctica

Task 1 - Preparación del conjunto de datos

In [13]:
```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import numpy as np
import pandas as pd

# dataset Iris
iris = load_iris()
X = iris.data.astype(np.float32)
y = iris.target.astype(np.int64)

# entrenamiento y validación
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state

# tensores de PyTorch
X_train_tensor = torch.tensor(X_train)
y_train_tensor = torch.tensor(y_train)
X_val_tensor = torch.tensor(X_val)
y_val_tensor = torch.tensor(y_val)
```

Task 2 - Arquitectura modelo

In [8]:
```python
class FeedforwardNN(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, p_dropout=0.0):
        super().__init__()
        self.fc1 = nn.Linear(input_dim, hidden_dim)
        self.fc2 = nn.Linear(hidden_dim, hidden_dim)
        self.fc3 = nn.Linear(hidden_dim, output_dim)
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(p_dropout)  # (por ahora p=0; se usará en Task 4)
    def forward(self, x):
        x = self.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.relu(self.fc2(x))
        x = self.dropout(x)
        x = self.fc3(x)  # logits
        return x

input_dim = X_train.shape[1]          # 4 features
hidden_dim = 16
output_dim = len(np.unique(y))        # 3 clases

# instanciar el modelo
model = FeedforwardNN(input_dim, hidden_dim, output_dim)
print(model)
```

```
FeedforwardNN(
  (fc1): Linear(in_features=4, out_features=16, bias=True)
  (fc2): Linear(in_features=16, out_features=16, bias=True)
  (fc3): Linear(in_features=16, out_features=3, bias=True)
  (relu): ReLU()
  (dropout): Dropout(p=0.0, inplace=False)
)
```

Task 3 - Funciones de Pérdida

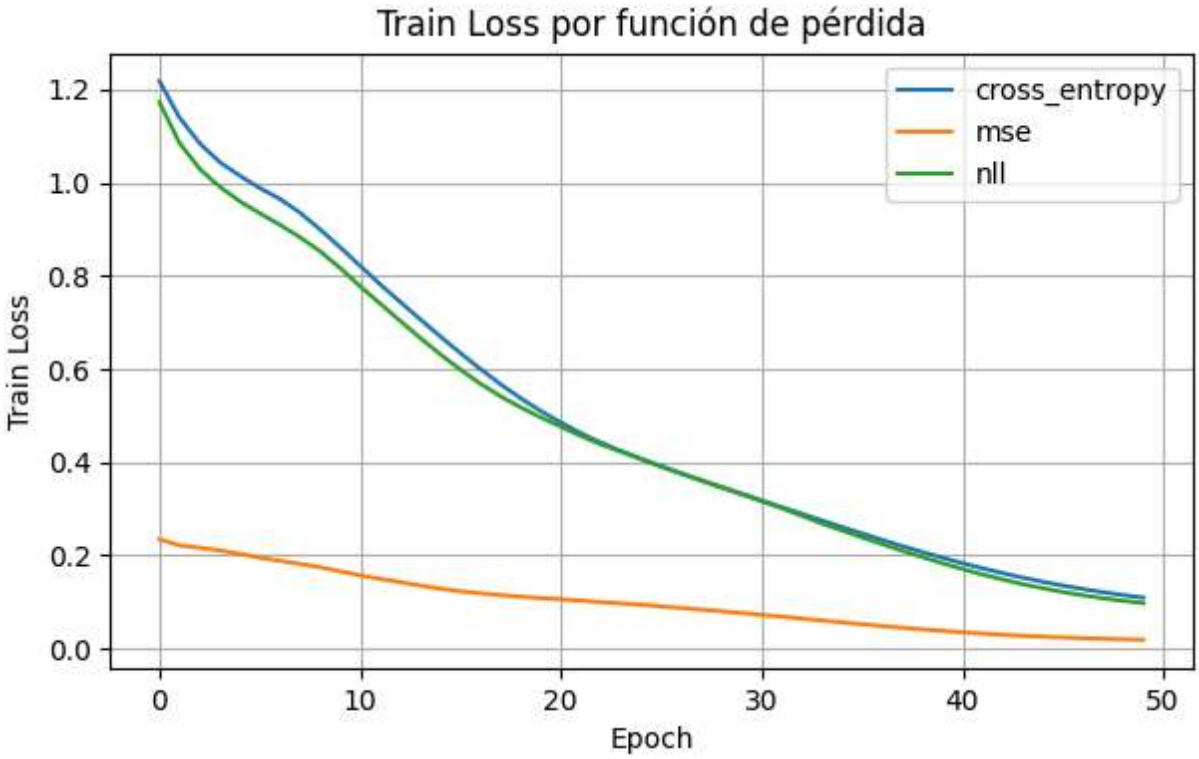
In [ ]:
```python
from sklearn.metrics import f1_score
import matplotlib.pyplot as plt

def loss_function(loss_name: str):
    loss_name = loss_name.lower()
    if loss_name == 'cross_entropy':
        return nn.CrossEntropyLoss()
    elif loss_name == 'mse':
        return nn.MSELoss()
    elif loss_name == 'nll':
        return nn.NLLLoss()
    else:
        raise ValueError(f"Función de pérdida no soportada: {loss_name}")

def accuracy_from_logits(logits: torch.Tensor, y_true: torch.Tensor) -> float:
    preds = logits.argmax(1)
    return (preds == y_true).float().mean().item()

def f1_from_logits(logits: torch.Tensor, y_true: torch.Tensor) -> float:
    preds = logits.argmax(1).cpu().numpy()
```

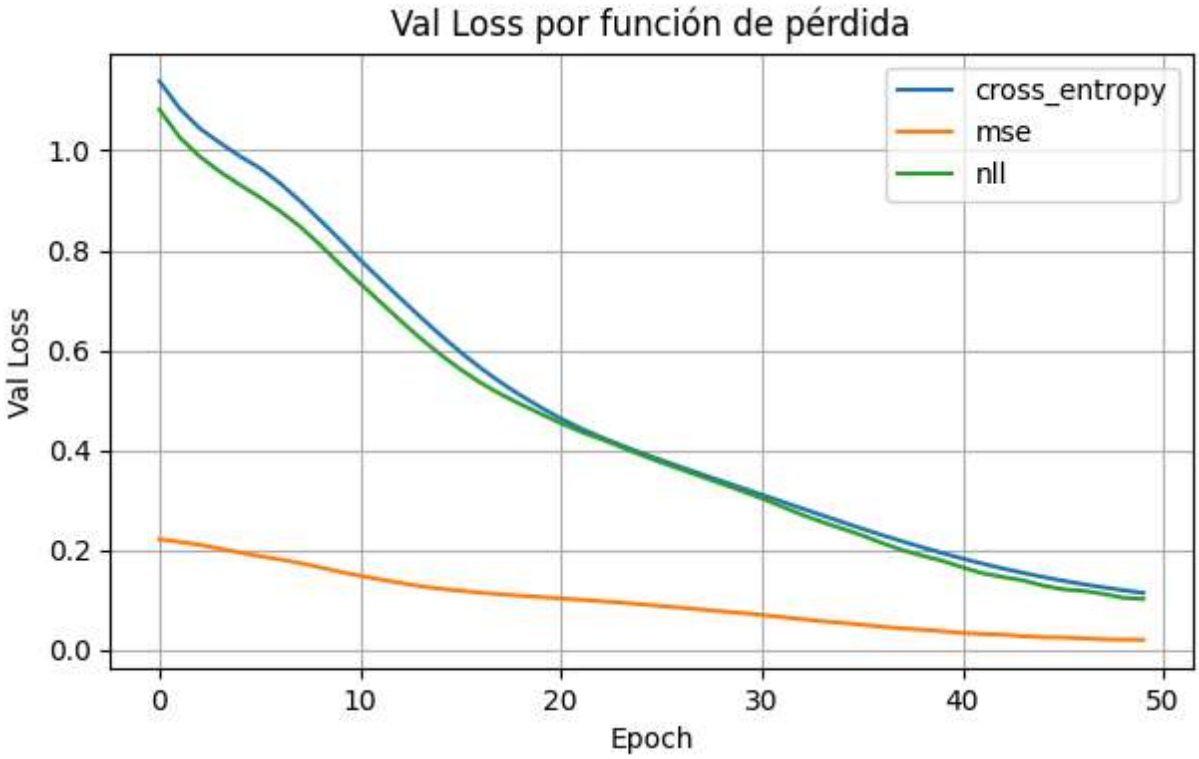
```
    y_np = y_true.cpu().numpy()
    # macro-F1 por clases balanceadas en Iris
    return f1_score(y_np, preds, average='macro')

def train_model_batch_gd(model, loss_fn, optimizer,
                         X_train, y_train, X_val, y_val,
                         epochs=50, verbose=True):
    history = {
        "train_loss": [], "val_loss": [],
        "train_acc":  [], "val_acc":  [],
        "train_f1":   [], "val_f1":   [],
    }

    for epoch in range(1, epochs+1):
        # train
        model.train()
        optimizer.zero_grad()
        logits = model(X_train)

        if isinstance(loss_fn, nn.MSELoss):
            probs = F.softmax(logits, dim=1)
            y_train_oh = F.one_hot(y_train, num_classes=logits.size(1)).float()
            loss = loss_fn(probs, y_train_oh)
        elif isinstance(loss_fn, nn.NLLLoss):
            # log-probabilidades
            log_probs = F.log_softmax(logits, dim=1)
            loss = loss_fn(log_probs, y_train)
        else:
            loss = loss_fn(logits, y_train)

        loss.backward()
        optimizer.step()

        # Métricas de train
        train_loss = loss.item()
        train_acc = accuracy_from_logits(logits, y_train)
        train_f1  = f1_from_logits(logits, y_train)

        # validación
        model.eval()
        with torch.no_grad():
            logits_val = model(X_val)
            if isinstance(loss_fn, nn.MSELoss):
                probs_val = F.softmax(logits_val, dim=1)
                y_val_oh = F.one_hot(y_val, num_classes=logits_val.size(1)).float()
                val_loss_t = loss_fn(probs_val, y_val_oh)
            elif isinstance(loss_fn, nn.NLLLoss):
                log_probs_val = F.log_softmax(logits_val, dim=1)
                val_loss_t = loss_fn(log_probs_val, y_val)
            else:
                val_loss_t = loss_fn(logits_val, y_val)

            val_loss = val_loss_t.item()
            val_acc  = accuracy_from_logits(logits_val, y_val)
            val_f1   = f1_from_logits(logits_val, y_val)
```

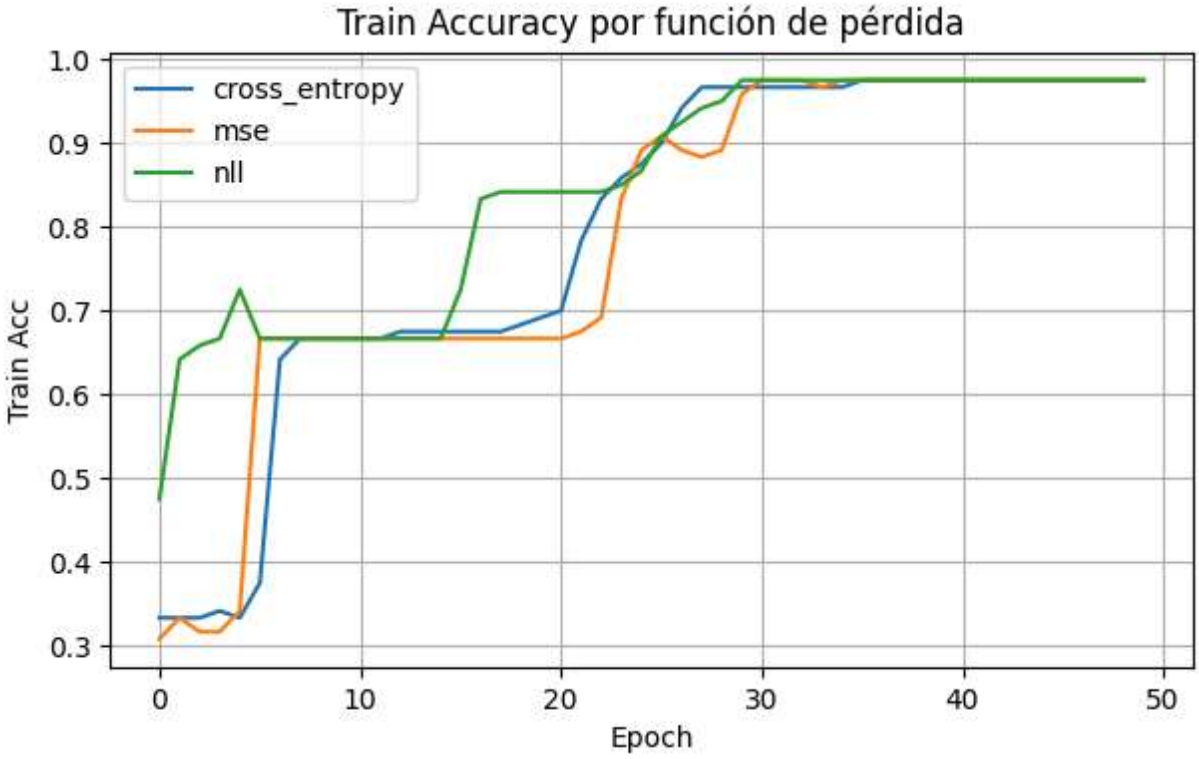
```
        history["train_loss"].append(train_loss)
        history["val_loss"].append(val_loss)
        history["train_acc"].append(train_acc)
        history["val_acc"].append(val_acc)
        history["train_f1"].append(train_f1)
        history["val_f1"].append(val_f1)

        if verbose and (epoch % 5 == 0 or epoch == 1):
            print(f"Epoch {epoch:02d}/{epochs} | "
                f"Train Loss: {train_loss:.4f} Acc: {train_acc:.3f} F1: {train_f1:.
                f"Val Loss: {val_loss:.4f} Acc: {val_acc:.3f} F1: {val_f1:.3f}")

    return history

loss_functions = ['cross_entropy', 'mse', 'nll']
results = {}

for loss_name in loss_functions:
    print(f"\n=== Entrenando con función de pérdida: {loss_name} ===")
    model = FeedforwardNN(input_dim, hidden_dim, output_dim, p_dropout=0.0)
    optimizer = optim.Adam(model.parameters(), lr=1e-2)  # Optimizador fijo por aho
    loss_fn = loss_function(loss_name)
    history = train_model_batch_gd(
        model, loss_fn, optimizer,
        X_train_tensor, y_train_tensor,
        X_val_tensor,   y_val_tensor,
        epochs=50, verbose=True
    )
    results[loss_name] = history

def plot_history(results_dict, metric_key, title):
    plt.figure(figsize=(7,4))
    for name, hist in results_dict.items():
        plt.plot(hist[metric_key], label=f"{name}")
    plt.xlabel("Epoch")
    plt.ylabel(metric_key.replace("_", " ").title())
    plt.title(title)
    plt.legend()
    plt.grid(True)
    plt.show()

plot_history(results, "train_loss", "Train Loss por función de pérdida")
plot_history(results, "val_loss",   "Val Loss por función de pérdida")
plot_history(results, "train_acc",  "Train Accuracy por función de pérdida")
plot_history(results, "val_acc",    "Val Accuracy por función de pérdida")
plot_history(results, "train_f1",   "Train F1 (macro) por función de pérdida")
plot_history(results, "val_f1",     "Val F1 (macro) por función de pérdida")
```

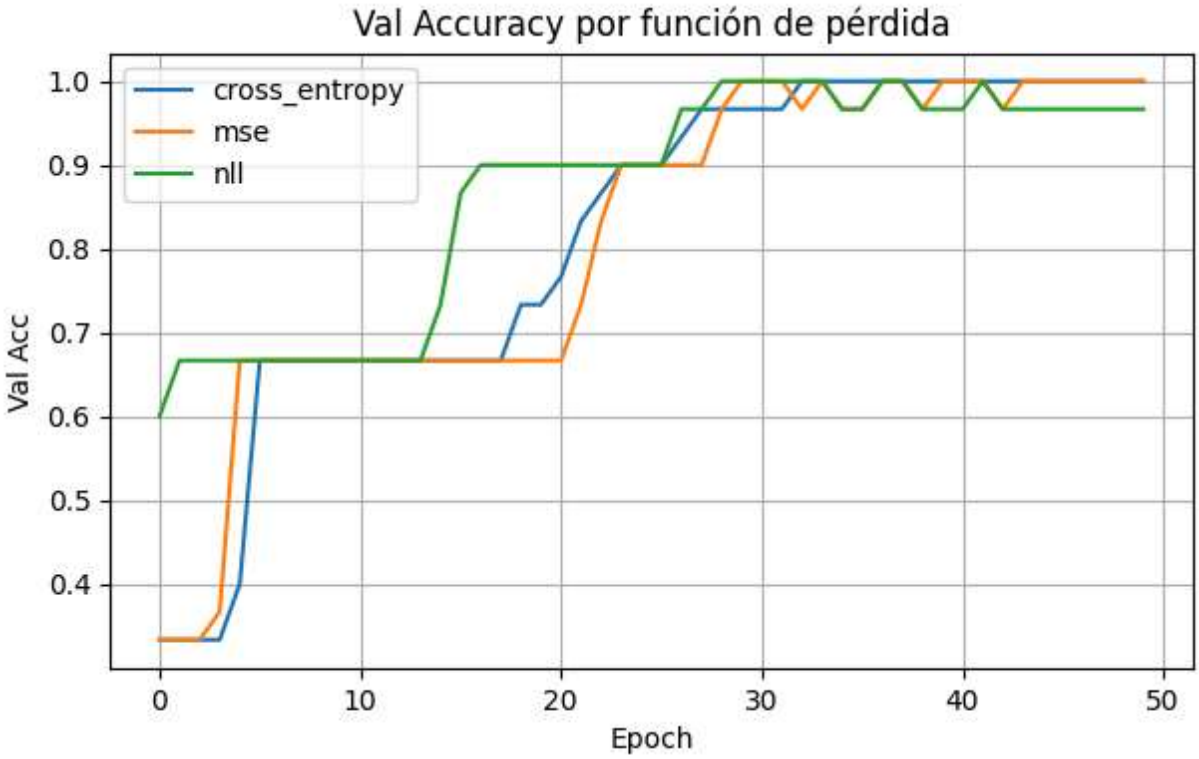
```
=== Entrenando con función de pérdida: cross_entropy ===
Epoch 01/50 | Train Loss: 1.2178 Acc: 0.333 F1: 0.167 | Val Loss: 1.1390 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 1.0150 Acc: 0.333 F1: 0.220 | Val Loss: 0.9889 Acc: 0.400
F1: 0.287
Epoch 10/50 | Train Loss: 0.8612 Acc: 0.667 F1: 0.556 | Val Loss: 0.8210 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.6695 Acc: 0.675 F1: 0.574 | Val Loss: 0.6302 Acc: 0.667
F1: 0.556
Epoch 20/50 | Train Loss: 0.5097 Acc: 0.692 F1: 0.608 | Val Loss: 0.4855 Acc: 0.733
F1: 0.683
Epoch 25/50 | Train Loss: 0.4068 Acc: 0.875 F1: 0.870 | Val Loss: 0.3943 Acc: 0.900
F1: 0.898
Epoch 30/50 | Train Loss: 0.3319 Acc: 0.967 F1: 0.967 | Val Loss: 0.3242 Acc: 0.967
F1: 0.967
Epoch 35/50 | Train Loss: 0.2607 Acc: 0.967 F1: 0.967 | Val Loss: 0.2559 Acc: 1.000
F1: 1.000
Epoch 40/50 | Train Loss: 0.1947 Acc: 0.975 F1: 0.975 | Val Loss: 0.1937 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.1432 Acc: 0.975 F1: 0.975 | Val Loss: 0.1460 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.1092 Acc: 0.975 F1: 0.975 | Val Loss: 0.1140 Acc: 1.000
F1: 1.000

=== Entrenando con función de pérdida: mse ===
Epoch 01/50 | Train Loss: 0.2346 Acc: 0.308 F1: 0.157 | Val Loss: 0.2215 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 0.2031 Acc: 0.342 F1: 0.184 | Val Loss: 0.1948 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.1658 Acc: 0.667 F1: 0.551 | Val Loss: 0.1562 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.1284 Acc: 0.667 F1: 0.556 | Val Loss: 0.1224 Acc: 0.667
F1: 0.556
Epoch 20/50 | Train Loss: 0.1083 Acc: 0.667 F1: 0.556 | Val Loss: 0.1058 Acc: 0.667
F1: 0.556
Epoch 25/50 | Train Loss: 0.0940 Acc: 0.892 F1: 0.889 | Val Loss: 0.0912 Acc: 0.900
F1: 0.898
Epoch 30/50 | Train Loss: 0.0761 Acc: 0.958 F1: 0.958 | Val Loss: 0.0738 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.0561 Acc: 0.975 F1: 0.975 | Val Loss: 0.0542 Acc: 0.967
F1: 0.967
Epoch 40/50 | Train Loss: 0.0379 Acc: 0.975 F1: 0.975 | Val Loss: 0.0371 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0255 Acc: 0.975 F1: 0.975 | Val Loss: 0.0255 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.0189 Acc: 0.975 F1: 0.975 | Val Loss: 0.0202 Acc: 1.000
F1: 1.000

=== Entrenando con función de pérdida: nll ===
Epoch 01/50 | Train Loss: 1.1724 Acc: 0.475 F1: 0.374 | Val Loss: 1.0822 Acc: 0.600
F1: 0.494
Epoch 05/50 | Train Loss: 0.9602 Acc: 0.725 F1: 0.669 | Val Loss: 0.9317 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.8166 Acc: 0.667 F1: 0.556 | Val Loss: 0.7719 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.6312 Acc: 0.667 F1: 0.556 | Val Loss: 0.5911 Acc: 0.733
```

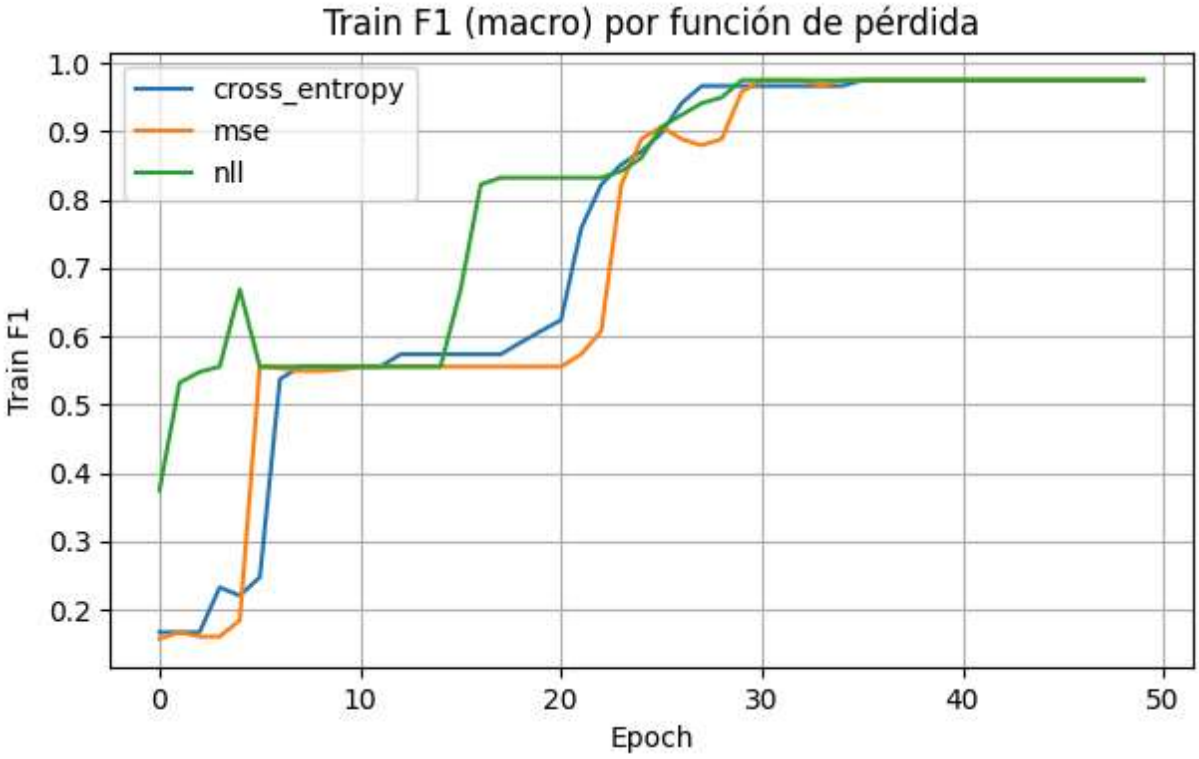
```
F1: 0.683
Epoch 20/50 | Train Loss: 0.4961 Acc: 0.842 F1: 0.832 | Val Loss: 0.4727 Acc: 0.900
F1: 0.898
Epoch 25/50 | Train Loss: 0.4068 Acc: 0.867 F1: 0.861 | Val Loss: 0.3901 Acc: 0.900
F1: 0.898
Epoch 30/50 | Train Loss: 0.3311 Acc: 0.975 F1: 0.975 | Val Loss: 0.3183 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.2533 Acc: 0.975 F1: 0.975 | Val Loss: 0.2428 Acc: 0.967
F1: 0.967
Epoch 40/50 | Train Loss: 0.1830 Acc: 0.975 F1: 0.975 | Val Loss: 0.1782 Acc: 0.967
F1: 0.967
Epoch 45/50 | Train Loss: 0.1294 Acc: 0.975 F1: 0.975 | Val Loss: 0.1286 Acc: 0.967
F1: 0.967
Epoch 50/50 | Train Loss: 0.0977 Acc: 0.975 F1: 0.975 | Val Loss: 0.1020 Acc: 0.967
F1: 0.967
```

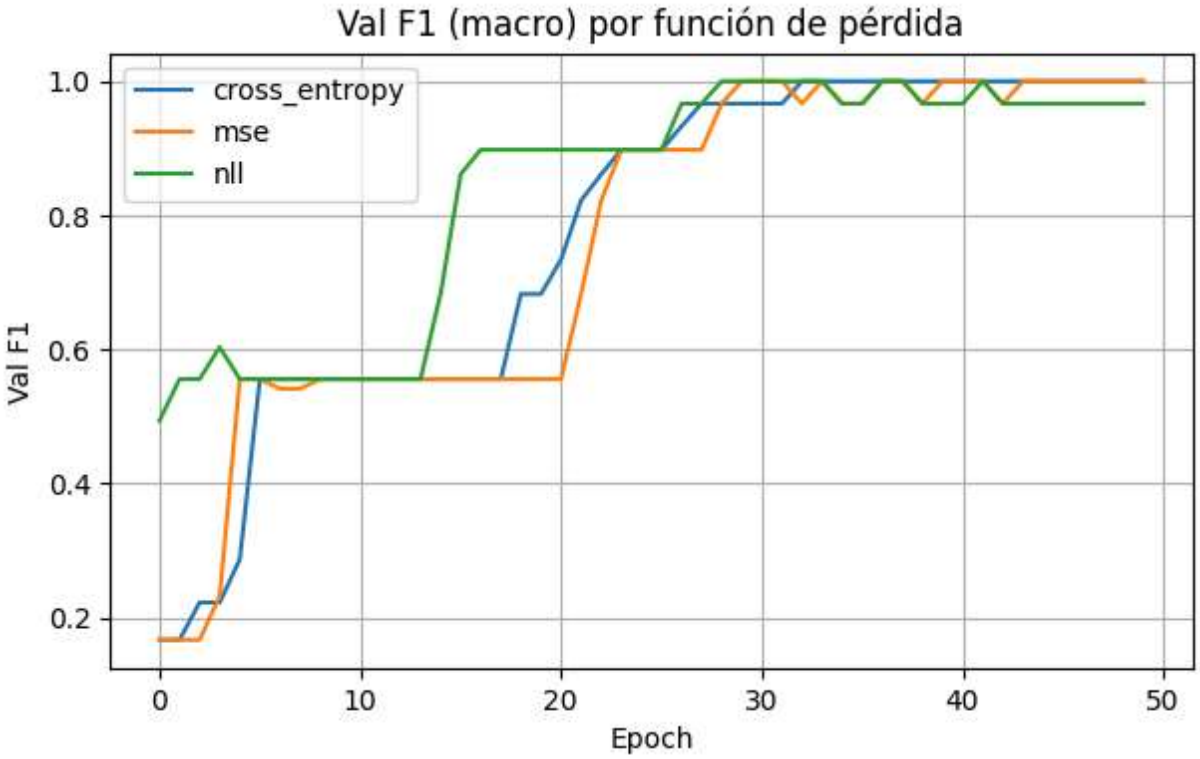



Val Loss por función de pérdida
cross_entropy
mse
nll
Val Loss
Epoch
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40
50


Train Accuracy por función de pérdida
cross_entropy
mse
nll
Train Acc
Epoch
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0
10
20
30
40
50


Val Accuracy por función de pérdida
cross_entropy
mse
nll
Val Acc
Epoch
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0
10
20
30
40
50


Train F1 (macro) por función de pérdida
cross_entropy
mse
nll
Train F1
Epoch
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
10
20
30
40
50



Task 4 - Técnicas de Regularización

In [10]:

```python
import time


def l1_penalty(model: nn.Module) -> torch.Tensor:
    l1 = 0.0
    for p in model.parameters():
        if p.requires_grad:
            l1 = l1 + p.abs().sum()
    return l1

# Entrenamiento con soporte de L1/L2/Dropout
def train_with_regularization(
    loss_name: str,
    p_dropout: float = 0.0,     # Dropout
    l2_weight_decay: float = 0.0,  # L2 (weight decay del optimizador)
    l1_lambda: float = 0.0,        # L1 (término manual)
    lr: float = 1e-2,
    epochs: int = 50,
    verbose: bool = True
):

    model = FeedforwardNN(input_dim, hidden_dim, output_dim, p_dropout=p_dropout)

    # Loss
    loss_fn = loss_function(loss_name)

    optimizer = optim.Adam(model.parameters(), lr=lr, weight_decay=l2_weight_decay)
```

```
    # Historial
    history = {
        "train_loss": [], "val_loss": [],
        "train_acc":  [], "val_acc":  [],
        "train_f1":   [], "val_f1":   [],
        "config": {"loss": loss_name, "dropout": p_dropout,
                "l2_weight_decay": l2_weight_decay, "l1_lambda": l1_lambda}
    }

    start = time.time()
    for epoch in range(1, epochs+1):
        model.train()
        optimizer.zero_grad()

        logits = model(X_train_tensor)

        # Pérdida base según la loss seleccionada
        if isinstance(loss_fn, nn.MSELoss):
            probs = F.softmax(logits, dim=1)
            y_train_oh = F.one_hot(y_train_tensor, num_classes=logits.size(1)).floa
            base_loss = loss_fn(probs, y_train_oh)
        elif isinstance(loss_fn, nn.NLLLoss):
            log_probs = F.log_softmax(logits, dim=1)
            base_loss = loss_fn(log_probs, y_train_tensor)
        else:
            base_loss = loss_fn(logits, y_train_tensor)

        # Agregar L1 si aplica
        if l1_lambda > 0.0:
            base_loss = base_loss + l1_lambda * l1_penalty(model)

        base_loss.backward()
        optimizer.step()

        # Métricas train
        train_loss = base_loss.item()
        train_acc  = (logits.argmax(1) == y_train_tensor).float().mean().item()
        train_f1   = f1_from_logits(logits, y_train_tensor)

        model.eval()
        with torch.no_grad():
            logits_val = model(X_val_tensor)
            if isinstance(loss_fn, nn.MSELoss):
                probs_val = F.softmax(logits_val, dim=1)
                y_val_oh = F.one_hot(y_val_tensor, num_classes=logits_val.size(1)).
                val_loss_t = loss_fn(probs_val, y_val_oh)
            elif isinstance(loss_fn, nn.NLLLoss):
                log_probs_val = F.log_softmax(logits_val, dim=1)
                val_loss_t = loss_fn(log_probs_val, y_val_tensor)
            else:
                val_loss_t = loss_fn(logits_val, y_val_tensor)

            val_loss = val_loss_t.item()
            val_acc  = (logits_val.argmax(1) == y_val_tensor).float().mean().item()
            val_f1   = f1_from_logits(logits_val, y_val_tensor)
```

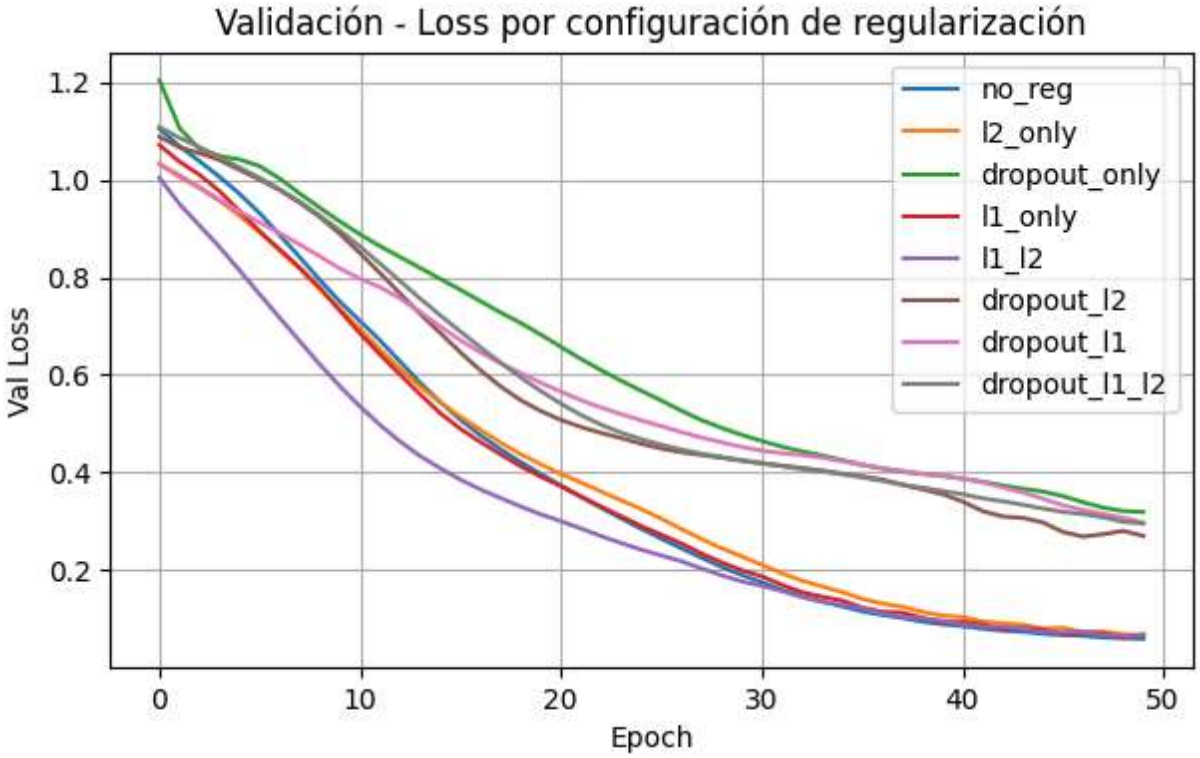
```
        # Guardar
        history["train_loss"].append(train_loss)
        history["val_loss"].append(val_loss)
        history["train_acc"].append(train_acc)
        history["val_acc"].append(val_acc)
        history["train_f1"].append(train_f1)
        history["val_f1"].append(val_f1)

        if verbose and (epoch % 5 == 0 or epoch == 1):
            print(f"Epoch {epoch:02d}/{epochs} | "
                f"Train Loss: {train_loss:.4f} Acc: {train_acc:.3f} F1: {train_f1:.
                f"Val Loss: {val_loss:.4f} Acc: {val_acc:.3f} F1: {val_f1:.3f}")

    history["time_s"] = time.time() - start
    return history


reg_experiments = {
    "no_reg":         dict(loss_name="cross_entropy", p_dropout=0.0, l2_weight_deca
    "l2_only":        dict(loss_name="cross_entropy", p_dropout=0.0, l2_weight_deca
    "dropout_only":   dict(loss_name="cross_entropy", p_dropout=0.3, l2_weight_deca
    "l1_only":        dict(loss_name="cross_entropy", p_dropout=0.0, l2_weight_deca
    "l1_l2":          dict(loss_name="cross_entropy", p_dropout=0.0, l2_weight_deca
    "dropout_l2":     dict(loss_name="cross_entropy", p_dropout=0.3, l2_weight_deca
    "dropout_l1":     dict(loss_name="cross_entropy", p_dropout=0.3, l2_weight_deca
    "dropout_l1_l2":  dict(loss_name="cross_entropy", p_dropout=0.3, l2_weight_deca
}

reg_results = {}
for name, cfg in reg_experiments.items():
    print(f"\n=== Regularización: {name} ===")
    hist = train_with_regularization(**cfg, epochs=50, verbose=True)
    reg_results[name] = hist

def plot_history(results_dict, metric_key, title):
    plt.figure(figsize=(7,4))
    for name, hist in results_dict.items():
        plt.plot(hist[metric_key], label=name)
    plt.xlabel("Epoch")
    plt.ylabel(metric_key.replace("_", " ").title())
    plt.title(title)
    plt.legend()
    plt.grid(True)
    plt.show()

plot_history(reg_results, "val_loss", "Validación - Loss por configuración de regul
plot_history(reg_results, "val_acc",  "Validación - Accuracy por configuración de r
plot_history(reg_results, "val_f1",   "Validación - F1 (macro) por configuración de
```

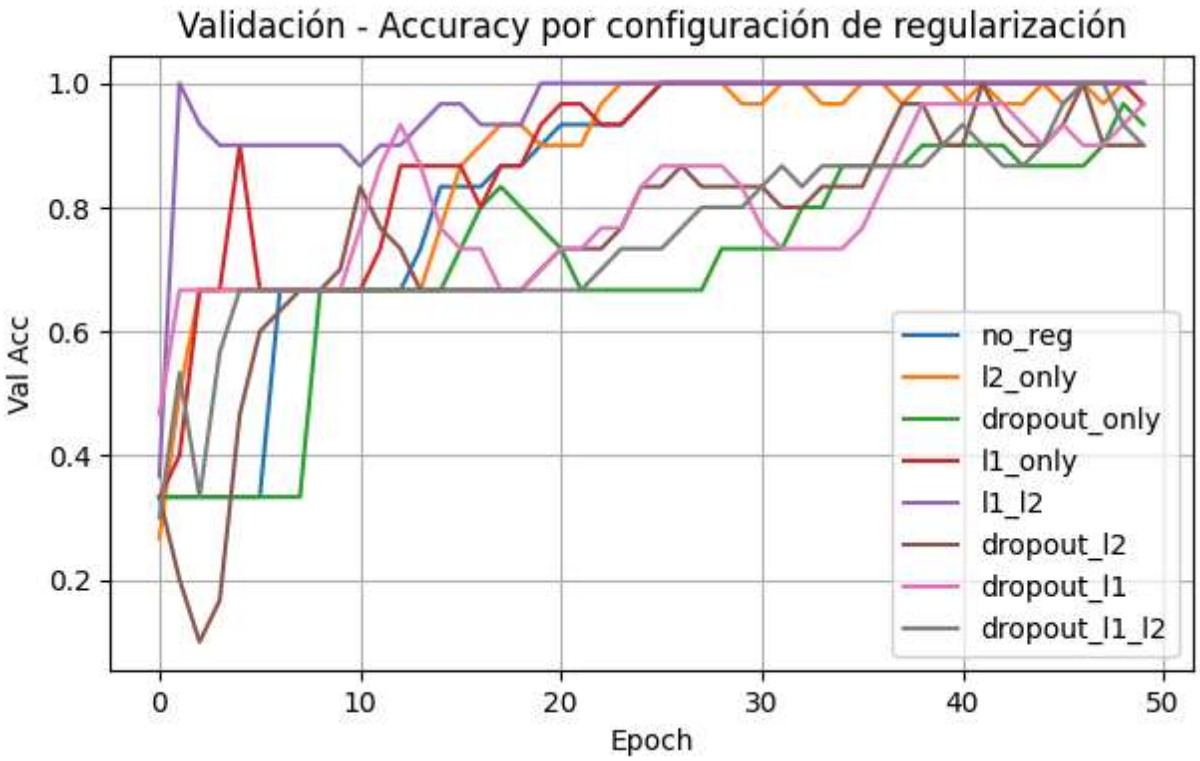
```
=== Regularización: no_reg ===
Epoch 01/50 | Train Loss: 1.1659 Acc: 0.042 F1: 0.027 | Val Loss: 1.1045 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 1.0060 Acc: 0.333 F1: 0.167 | Val Loss: 0.9708 Acc: 0.333
F1: 0.167
Epoch 10/50 | Train Loss: 0.7948 Acc: 0.667 F1: 0.556 | Val Loss: 0.7494 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.5873 Acc: 0.717 F1: 0.654 | Val Loss: 0.5439 Acc: 0.833
F1: 0.822
Epoch 20/50 | Train Loss: 0.4205 Acc: 0.850 F1: 0.842 | Val Loss: 0.3967 Acc: 0.900
F1: 0.898
Epoch 25/50 | Train Loss: 0.3019 Acc: 0.967 F1: 0.967 | Val Loss: 0.2846 Acc: 0.967
F1: 0.967
Epoch 30/50 | Train Loss: 0.2015 Acc: 0.967 F1: 0.967 | Val Loss: 0.1900 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.1312 Acc: 0.975 F1: 0.975 | Val Loss: 0.1258 Acc: 1.000
F1: 1.000
Epoch 40/50 | Train Loss: 0.0951 Acc: 0.983 F1: 0.983 | Val Loss: 0.0890 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0795 Acc: 0.983 F1: 0.983 | Val Loss: 0.0696 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.0725 Acc: 0.983 F1: 0.983 | Val Loss: 0.0593 Acc: 1.000
F1: 1.000

=== Regularización: l2_only ===
Epoch 01/50 | Train Loss: 1.0650 Acc: 0.333 F1: 0.167 | Val Loss: 1.0319 Acc: 0.267
F1: 0.140
Epoch 05/50 | Train Loss: 0.9599 Acc: 0.667 F1: 0.556 | Val Loss: 0.9261 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.7805 Acc: 0.667 F1: 0.556 | Val Loss: 0.7347 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.5814 Acc: 0.692 F1: 0.608 | Val Loss: 0.5434 Acc: 0.767
F1: 0.734
Epoch 20/50 | Train Loss: 0.4389 Acc: 0.950 F1: 0.950 | Val Loss: 0.4166 Acc: 0.900
F1: 0.898
Epoch 25/50 | Train Loss: 0.3410 Acc: 0.975 F1: 0.975 | Val Loss: 0.3249 Acc: 1.000
F1: 1.000
Epoch 30/50 | Train Loss: 0.2422 Acc: 0.975 F1: 0.975 | Val Loss: 0.2278 Acc: 0.967
F1: 0.967
Epoch 35/50 | Train Loss: 0.1623 Acc: 0.975 F1: 0.975 | Val Loss: 0.1550 Acc: 0.967
F1: 0.967
Epoch 40/50 | Train Loss: 0.1109 Acc: 0.975 F1: 0.975 | Val Loss: 0.1067 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0845 Acc: 0.975 F1: 0.975 | Val Loss: 0.0802 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.0712 Acc: 0.975 F1: 0.975 | Val Loss: 0.0668 Acc: 1.000
F1: 1.000

=== Regularización: dropout_only ===
Epoch 01/50 | Train Loss: 1.4499 Acc: 0.325 F1: 0.192 | Val Loss: 1.2041 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 1.1116 Acc: 0.350 F1: 0.311 | Val Loss: 1.0416 Acc: 0.333
F1: 0.167
Epoch 10/50 | Train Loss: 0.9826 Acc: 0.425 F1: 0.386 | Val Loss: 0.9141 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.8817 Acc: 0.533 F1: 0.534 | Val Loss: 0.7965 Acc: 0.667
```

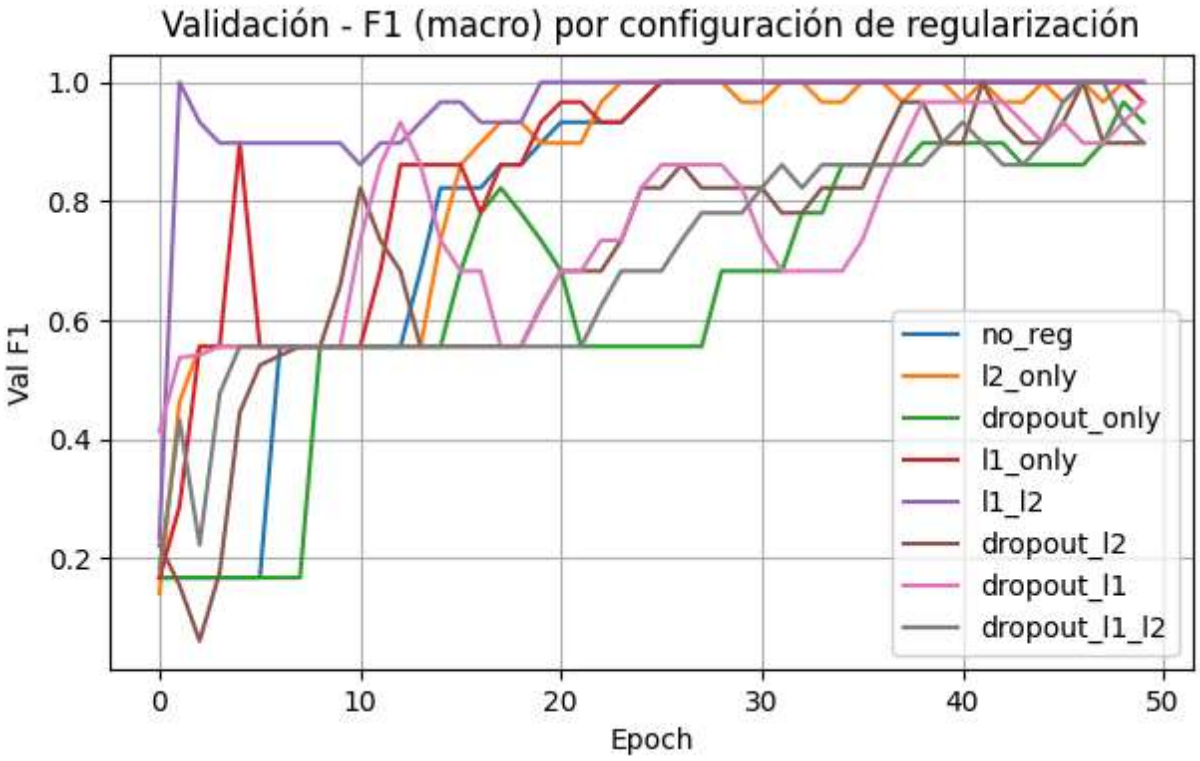
```
F1: 0.556
Epoch 20/50 | Train Loss: 0.7731 Acc: 0.617 F1: 0.596 | Val Loss: 0.6825 Acc: 0.767
F1: 0.734
Epoch 25/50 | Train Loss: 0.6905 Acc: 0.633 F1: 0.591 | Val Loss: 0.5676 Acc: 0.667
F1: 0.556
Epoch 30/50 | Train Loss: 0.6113 Acc: 0.692 F1: 0.651 | Val Loss: 0.4771 Acc: 0.733
F1: 0.683
Epoch 35/50 | Train Loss: 0.4909 Acc: 0.750 F1: 0.730 | Val Loss: 0.4254 Acc: 0.867
F1: 0.861
Epoch 40/50 | Train Loss: 0.5200 Acc: 0.725 F1: 0.716 | Val Loss: 0.3928 Acc: 0.900
F1: 0.898
Epoch 45/50 | Train Loss: 0.4185 Acc: 0.825 F1: 0.821 | Val Loss: 0.3610 Acc: 0.867
F1: 0.861
Epoch 50/50 | Train Loss: 0.4076 Acc: 0.825 F1: 0.822 | Val Loss: 0.3191 Acc: 0.933
F1: 0.933

=== Regularización: l1_only ===
Epoch 01/50 | Train Loss: 1.1524 Acc: 0.333 F1: 0.167 | Val Loss: 1.0710 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 0.9798 Acc: 0.667 F1: 0.556 | Val Loss: 0.9355 Acc: 0.900
F1: 0.898
Epoch 10/50 | Train Loss: 0.7836 Acc: 0.667 F1: 0.556 | Val Loss: 0.7310 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.5615 Acc: 0.917 F1: 0.915 | Val Loss: 0.5212 Acc: 0.867
F1: 0.861
Epoch 20/50 | Train Loss: 0.4096 Acc: 0.917 F1: 0.915 | Val Loss: 0.3912 Acc: 0.933
F1: 0.933
Epoch 25/50 | Train Loss: 0.3015 Acc: 0.950 F1: 0.950 | Val Loss: 0.2902 Acc: 0.967
F1: 0.967
Epoch 30/50 | Train Loss: 0.2034 Acc: 0.975 F1: 0.975 | Val Loss: 0.1998 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.1285 Acc: 0.983 F1: 0.983 | Val Loss: 0.1376 Acc: 1.000
F1: 1.000
Epoch 40/50 | Train Loss: 0.0883 Acc: 0.983 F1: 0.983 | Val Loss: 0.0931 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0709 Acc: 0.983 F1: 0.983 | Val Loss: 0.0780 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.0639 Acc: 0.983 F1: 0.983 | Val Loss: 0.0678 Acc: 0.967
F1: 0.967

=== Regularización: l1_l2 ===
Epoch 01/50 | Train Loss: 1.0858 Acc: 0.333 F1: 0.167 | Val Loss: 1.0040 Acc: 0.367
F1: 0.232
Epoch 05/50 | Train Loss: 0.8656 Acc: 0.917 F1: 0.915 | Val Loss: 0.8138 Acc: 0.900
F1: 0.898
Epoch 10/50 | Train Loss: 0.6259 Acc: 0.892 F1: 0.889 | Val Loss: 0.5761 Acc: 0.900
F1: 0.898
Epoch 15/50 | Train Loss: 0.4329 Acc: 0.958 F1: 0.958 | Val Loss: 0.4084 Acc: 0.967
F1: 0.967
Epoch 20/50 | Train Loss: 0.3255 Acc: 0.967 F1: 0.967 | Val Loss: 0.3142 Acc: 1.000
F1: 1.000
Epoch 25/50 | Train Loss: 0.2472 Acc: 0.967 F1: 0.967 | Val Loss: 0.2418 Acc: 1.000
F1: 1.000
Epoch 30/50 | Train Loss: 0.1784 Acc: 0.967 F1: 0.967 | Val Loss: 0.1768 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.1232 Acc: 0.983 F1: 0.983 | Val Loss: 0.1290 Acc: 1.000
```

```
F1: 1.000
Epoch 40/50 | Train Loss: 0.0885 Acc: 0.983 F1: 0.983 | Val Loss: 0.0965 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0719 Acc: 0.983 F1: 0.983 | Val Loss: 0.0737 Acc: 1.000
F1: 1.000
Epoch 50/50 | Train Loss: 0.0641 Acc: 0.983 F1: 0.983 | Val Loss: 0.0664 Acc: 1.000
F1: 1.000

=== Regularización: dropout_l2 ===
Epoch 01/50 | Train Loss: 1.1699 Acc: 0.292 F1: 0.222 | Val Loss: 1.0881 Acc: 0.333
F1: 0.222
Epoch 05/50 | Train Loss: 1.0695 Acc: 0.367 F1: 0.371 | Val Loss: 1.0199 Acc: 0.467
F1: 0.444
Epoch 10/50 | Train Loss: 0.9269 Acc: 0.600 F1: 0.576 | Val Loss: 0.8886 Acc: 0.700
F1: 0.658
Epoch 15/50 | Train Loss: 0.8018 Acc: 0.650 F1: 0.612 | Val Loss: 0.6855 Acc: 0.667
F1: 0.556
Epoch 20/50 | Train Loss: 0.6668 Acc: 0.650 F1: 0.587 | Val Loss: 0.5259 Acc: 0.700
F1: 0.624
Epoch 25/50 | Train Loss: 0.5370 Acc: 0.775 F1: 0.762 | Val Loss: 0.4590 Acc: 0.833
F1: 0.822
Epoch 30/50 | Train Loss: 0.4912 Acc: 0.700 F1: 0.690 | Val Loss: 0.4245 Acc: 0.833
F1: 0.822
Epoch 35/50 | Train Loss: 0.4518 Acc: 0.775 F1: 0.766 | Val Loss: 0.3975 Acc: 0.833
F1: 0.822
Epoch 40/50 | Train Loss: 0.4601 Acc: 0.792 F1: 0.788 | Val Loss: 0.3556 Acc: 0.900
F1: 0.898
Epoch 45/50 | Train Loss: 0.4046 Acc: 0.808 F1: 0.801 | Val Loss: 0.2977 Acc: 0.900
F1: 0.898
Epoch 50/50 | Train Loss: 0.3865 Acc: 0.792 F1: 0.787 | Val Loss: 0.2699 Acc: 0.900
F1: 0.898

=== Regularización: dropout_l1 ===
Epoch 01/50 | Train Loss: 1.1489 Acc: 0.317 F1: 0.272 | Val Loss: 1.0325 Acc: 0.467
F1: 0.413
Epoch 05/50 | Train Loss: 1.0099 Acc: 0.475 F1: 0.427 | Val Loss: 0.9349 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.9121 Acc: 0.567 F1: 0.531 | Val Loss: 0.8179 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.8171 Acc: 0.583 F1: 0.544 | Val Loss: 0.6989 Acc: 0.767
F1: 0.734
Epoch 20/50 | Train Loss: 0.7013 Acc: 0.675 F1: 0.653 | Val Loss: 0.5838 Acc: 0.700
F1: 0.624
Epoch 25/50 | Train Loss: 0.6292 Acc: 0.708 F1: 0.688 | Val Loss: 0.5070 Acc: 0.833
F1: 0.822
Epoch 30/50 | Train Loss: 0.5359 Acc: 0.808 F1: 0.801 | Val Loss: 0.4525 Acc: 0.833
F1: 0.822
Epoch 35/50 | Train Loss: 0.5466 Acc: 0.733 F1: 0.711 | Val Loss: 0.4230 Acc: 0.733
F1: 0.683
Epoch 40/50 | Train Loss: 0.5027 Acc: 0.725 F1: 0.718 | Val Loss: 0.3936 Acc: 0.967
F1: 0.967
Epoch 45/50 | Train Loss: 0.4494 Acc: 0.758 F1: 0.754 | Val Loss: 0.3464 Acc: 0.900
F1: 0.898
Epoch 50/50 | Train Loss: 0.4414 Acc: 0.767 F1: 0.763 | Val Loss: 0.2974 Acc: 0.967
F1: 0.967
```

```
=== Regularización: dropout_l1_l2 ===
Epoch 01/50 | Train Loss: 1.1789 Acc: 0.225 F1: 0.179 | Val Loss: 1.1081 Acc: 0.300
F1: 0.182
Epoch 05/50 | Train Loss: 1.0339 Acc: 0.525 F1: 0.506 | Val Loss: 1.0250 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.9652 Acc: 0.575 F1: 0.537 | Val Loss: 0.8959 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.8492 Acc: 0.642 F1: 0.618 | Val Loss: 0.7217 Acc: 0.667
F1: 0.556
Epoch 20/50 | Train Loss: 0.6841 Acc: 0.667 F1: 0.628 | Val Loss: 0.5668 Acc: 0.667
F1: 0.556
Epoch 25/50 | Train Loss: 0.6381 Acc: 0.658 F1: 0.655 | Val Loss: 0.4682 Acc: 0.733
F1: 0.683
Epoch 30/50 | Train Loss: 0.5076 Acc: 0.775 F1: 0.769 | Val Loss: 0.4252 Acc: 0.800
F1: 0.780
Epoch 35/50 | Train Loss: 0.4059 Acc: 0.850 F1: 0.845 | Val Loss: 0.3965 Acc: 0.867
F1: 0.861
Epoch 40/50 | Train Loss: 0.4655 Acc: 0.800 F1: 0.792 | Val Loss: 0.3621 Acc: 0.900
F1: 0.898
Epoch 45/50 | Train Loss: 0.4202 Acc: 0.783 F1: 0.774 | Val Loss: 0.3261 Acc: 0.900
F1: 0.898
Epoch 50/50 | Train Loss: 0.4049 Acc: 0.808 F1: 0.803 | Val Loss: 0.2954 Acc: 0.900
F1: 0.898
```







Task 5 - Algoritmos de Optimización

In [14]:
```
from torch.utils.data import TensorDataset, DataLoader
import time
from collections import OrderedDict
```

```python
def make_loaders(mode: str, mini_batch_size: int = 32, shuffle: bool = True):
    """
    mode in {"batch_gd", "mini_batch", "sgd"}
    - batch_gd: usa todo el dataset en un solo batch
    - mini_batch: usa mini_batch_size (p.ej. 32)
    - sgd: usa batch_size=1 (stochastic)
    """
    train_ds = TensorDataset(X_train_tensor, y_train_tensor)
    val_ds   = TensorDataset(X_val_tensor,   y_val_tensor)

    if mode == "batch_gd":
        bs = len(train_ds)  # full batch
    elif mode == "mini_batch":
        bs = mini_batch_size
    elif mode == "sgd":
        bs = 1
    else:
        raise ValueError(f"Modo no soportado: {mode}")

    train_loader = DataLoader(train_ds, batch_size=bs, shuffle=shuffle)
    val_loader   = DataLoader(val_ds,   batch_size=len(val_ds), shuffle=False)
    return train_loader, val_loader

# --- Entrenamiento genérico con loaders ---
def train_with_loader(
    model,
    loss_fn,
    optimizer,
    train_loader,
    val_loader,
    epochs: int = 50,
    verbose: bool = True
):
    history = {
        "train_loss": [], "val_loss": [],
        "train_acc":  [], "val_acc":  [],
        "train_f1":   [], "val_f1":   [],
    }
    t0 = time.time()

    for epoch in range(1, epochs+1):
        # ----- TRAIN -----
        model.train()
        running_loss, correct, f1_parts = 0.0, 0, []
        n_total = 0

        for Xb, yb in train_loader:
            optimizer.zero_grad()
            logits = model(Xb)

            if isinstance(loss_fn, nn.MSELoss):
                probs = F.softmax(logits, dim=1)
                yb_oh = F.one_hot(yb, num_classes=logits.size(1)).float()
                loss = loss_fn(probs, yb_oh)
            elif isinstance(loss_fn, nn.NLLLoss):
                log_probs = F.log_softmax(logits, dim=1)
```

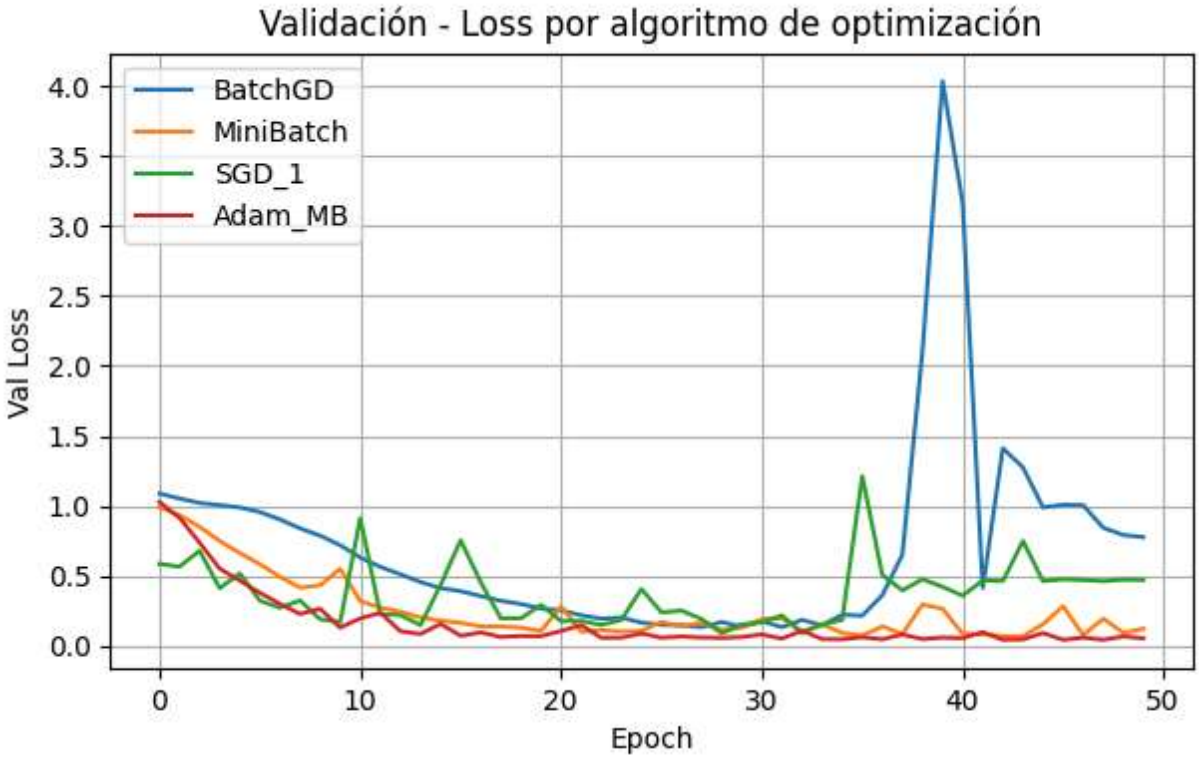
```
            loss = loss_fn(log_probs, yb)
        else:  # CrossEntropy
            loss = loss_fn(logits, yb)

        loss.backward()
        optimizer.step()

        running_loss += loss.item() * Xb.size(0)
        correct += (logits.argmax(1) == yb).sum().item()
        f1_parts.append(f1_from_logits(logits, yb))
        n_total += Xb.size(0)

    train_loss = running_loss / n_total
    train_acc  = correct / n_total
    train_f1   = np.mean(f1_parts)

    # ----- VAL -----
    model.eval()
    with torch.no_grad():
        val_loss_sum, val_correct, n_val = 0.0, 0, 0
        val_f1_parts = []
        for Xv, yv in val_loader:
            logits_v = model(Xv)
            if isinstance(loss_fn, nn.MSELoss):
                probs_v = F.softmax(logits_v, dim=1)
                yv_oh   = F.one_hot(yv, num_classes=logits_v.size(1)).float()
                loss_v  = loss_fn(probs_v, yv_oh)
            elif isinstance(loss_fn, nn.NLLLoss):
                log_probs_v = F.log_softmax(logits_v, dim=1)
                loss_v = loss_fn(log_probs_v, yv)
            else:
                loss_v = loss_fn(logits_v, yv)

            val_loss_sum += loss_v.item() * Xv.size(0)
            val_correct  += (logits_v.argmax(1) == yv).sum().item()
            val_f1_parts.append(f1_from_logits(logits_v, yv))
            n_val += Xv.size(0)

        val_loss = val_loss_sum / n_val
        val_acc  = val_correct / n_val
        val_f1   = np.mean(val_f1_parts)

    history["train_loss"].append(train_loss)
    history["val_loss"].append(val_loss)
    history["train_acc"].append(train_acc)
    history["val_acc"].append(val_acc)
    history["train_f1"].append(train_f1)
    history["val_f1"].append(val_f1)

    if verbose and (epoch % 5 == 0 or epoch == 1):
        print(f"Epoch {epoch:02d}/{epochs} | "
              f"Train Loss: {train_loss:.4f} Acc: {train_acc:.3f} F1: {train_f1
              f"Val Loss: {val_loss:.4f} Acc: {val_acc:.3f} F1: {val_f1:.3f}")

history["time_s"] = time.time() - t0
return history
```

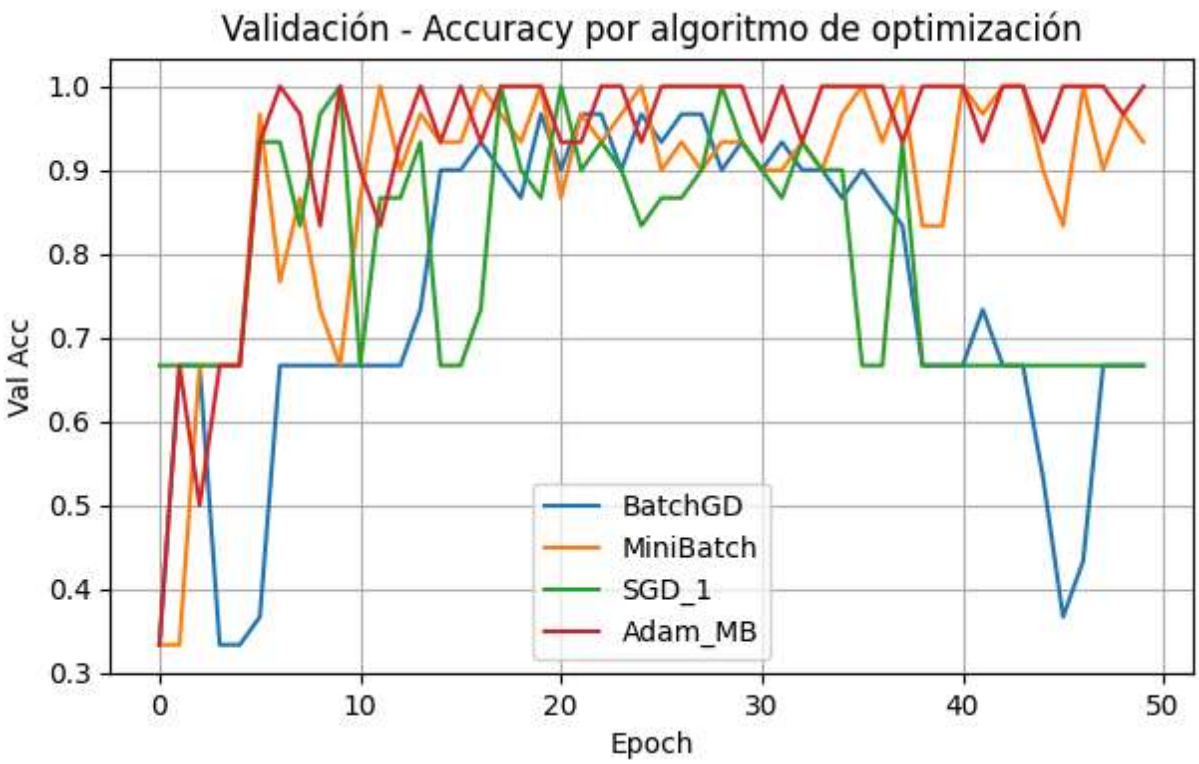
```python
# --- Runner de experimentos de optimización ---
def run_optimizer_experiment(
    mode: str,                  # "batch_gd" | "mini_batch" | "sgd"
    loss_name: str = "cross_entropy",
    lr: float = 1e-2,
    weight_decay: float = 0.0,  # L2 opcional si quieres mantener constante con Tas
    mini_batch_size: int = 32,
    epochs: int = 50,
    verbose: bool = True
):
    """
    Para 'batch_gd' usamos batch completo;
    para 'mini_batch' usamos batch=mini_batch_size;
    para 'sgd' usamos batch=1.
    El optimizador base será SGD; si quieres, puedes comparar también vs Adam como
    """

    train_loader, val_loader = make_loaders(mode, mini_batch_size=mini_batch_size,

    # Modelo y loss
    model = FeedforwardNN(input_dim, hidden_dim, output_dim, p_dropout=0.0)
    loss_fn = loss_function(loss_name)

    optimizer = optim.SGD(model.parameters(), lr=lr, momentum=0.9, weight_decay=wei

    history = train_with_loader(
        model=model,
        loss_fn=loss_fn,
        optimizer=optimizer,
        train_loader=train_loader,
        val_loader=val_loader,
        epochs=epochs,
        verbose=verbose
    )
    return history

opt_experiments = OrderedDict({
    "BatchGD":    dict(mode="batch_gd",  lr=5e-2,  mini_batch_size=32, epochs=50),
    "MiniBatch":  dict(mode="mini_batch",lr=1e-2,  mini_batch_size=16, epochs=50),
    "SGD_1":      dict(mode="sgd",       lr=5e-3,  mini_batch_size=1,  epochs=50),
    "Adam_MB":    dict(mode="mini_batch",lr=1e-2,  mini_batch_size=16, epochs=50),
})

opt_results = {}
for name, cfg in opt_experiments.items():
    print(f"\n=== Opt Experiment: {name} ===")
    if name == "Adam_MB":
        train_loader, val_loader = make_loaders("mini_batch", mini_batch_size=cfg["
        model = FeedforwardNN(input_dim, hidden_dim, output_dim, p_dropout=0.0)
        loss_fn = loss_function("cross_entropy")
        optimizer = optim.Adam(model.parameters(), lr=cfg["lr"], weight_decay=0.0)
        hist = train_with_loader(model, loss_fn, optimizer, train_loader, val_loade
    else:
        hist = run_optimizer_experiment(**cfg)
    opt_results[name] = hist
```

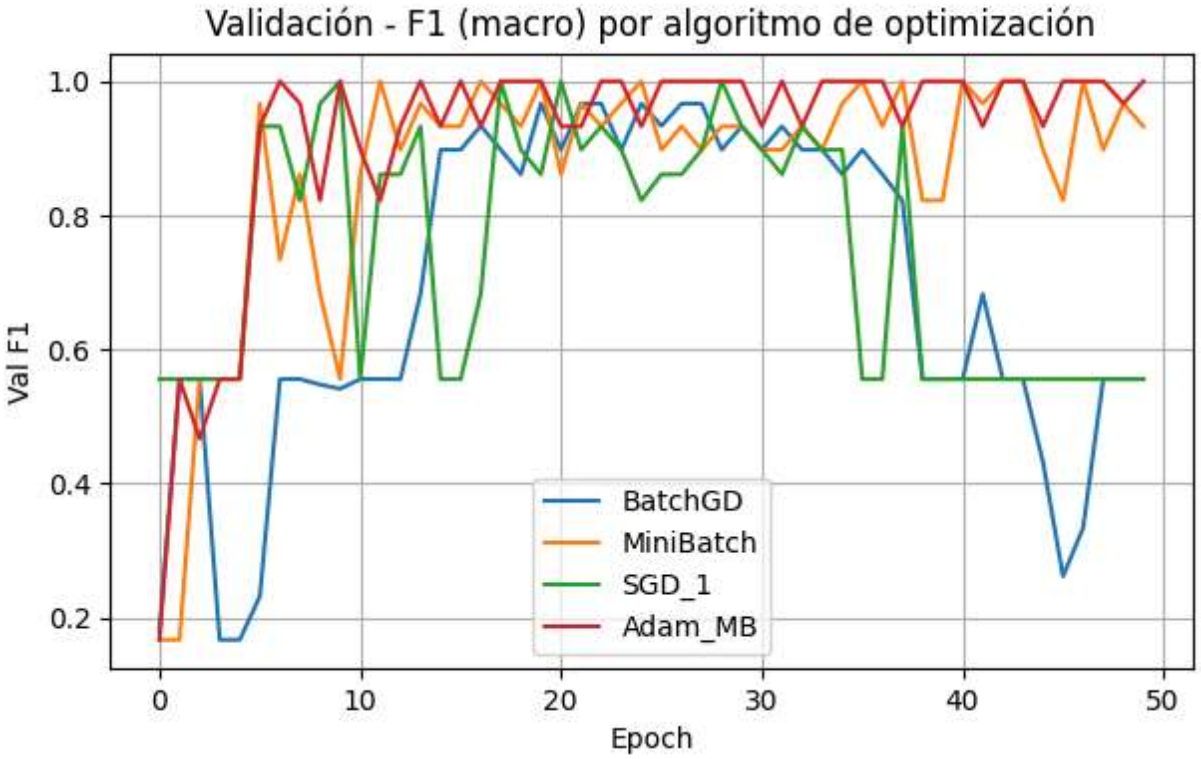
```python
def plot_history(results_dict, metric_key, title):
    plt.figure(figsize=(7,4))
    for name, hist in results_dict.items():
        plt.plot(hist[metric_key], label=name)
    plt.xlabel("Epoch")
    plt.ylabel(metric_key.replace("_", " ").title())
    plt.title(title)
    plt.legend()
    plt.grid(True)
    plt.show()

plot_history(opt_results, "val_loss", "Validación - Loss por algoritmo de optimizac
plot_history(opt_results, "val_acc",  "Validación - Accuracy por algoritmo de optim
plot_history(opt_results, "val_f1",   "Validación - F1 (macro) por algoritmo de opt

rows = []
for name, hist in opt_results.items():
    rows.append({
        "exp": name,
        "final_val_loss": hist["val_loss"][-1],
        "final_val_acc":  hist["val_acc"][-1],
        "final_val_f1":   hist["val_f1"][-1],
        "time_s":         hist["time_s"],
    })
summary_df = pd.DataFrame(rows).sort_values(by="final_val_acc", ascending=False)
summary_df
```

```
=== Opt Experiment: BatchGD ===
Epoch 01/50 | Train Loss: 1.1177 Acc: 0.333 F1: 0.167 | Val Loss: 1.0885 Acc: 0.333
F1: 0.180
Epoch 05/50 | Train Loss: 1.0067 Acc: 0.342 F1: 0.184 | Val Loss: 0.9892 Acc: 0.333
F1: 0.167
Epoch 10/50 | Train Loss: 0.7898 Acc: 0.667 F1: 0.547 | Val Loss: 0.7191 Acc: 0.667
F1: 0.541
Epoch 15/50 | Train Loss: 0.4578 Acc: 0.742 F1: 0.696 | Val Loss: 0.4132 Acc: 0.900
F1: 0.898
Epoch 20/50 | Train Loss: 0.2908 Acc: 0.917 F1: 0.915 | Val Loss: 0.2674 Acc: 0.967
F1: 0.967
Epoch 25/50 | Train Loss: 0.1770 Acc: 0.933 F1: 0.933 | Val Loss: 0.1666 Acc: 0.967
F1: 0.967
Epoch 30/50 | Train Loss: 0.1289 Acc: 0.933 F1: 0.933 | Val Loss: 0.1370 Acc: 0.933
F1: 0.933
Epoch 35/50 | Train Loss: 0.1554 Acc: 0.942 F1: 0.941 | Val Loss: 0.2229 Acc: 0.867
F1: 0.861
Epoch 40/50 | Train Loss: 1.9364 Acc: 0.675 F1: 0.583 | Val Loss: 4.0329 Acc: 0.667
F1: 0.556
Epoch 45/50 | Train Loss: 1.3153 Acc: 0.667 F1: 0.556 | Val Loss: 0.9892 Acc: 0.533
F1: 0.432
Epoch 50/50 | Train Loss: 0.8047 Acc: 0.667 F1: 0.556 | Val Loss: 0.7768 Acc: 0.667
F1: 0.556

=== Opt Experiment: MiniBatch ===
Epoch 01/50 | Train Loss: 1.0482 Acc: 0.558 F1: 0.425 | Val Loss: 0.9904 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 0.7155 Acc: 0.667 F1: 0.545 | Val Loss: 0.6636 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.4094 Acc: 0.758 F1: 0.624 | Val Loss: 0.5509 Acc: 0.667
F1: 0.556
Epoch 15/50 | Train Loss: 0.2225 Acc: 0.925 F1: 0.915 | Val Loss: 0.1813 Acc: 0.933
F1: 0.933
Epoch 20/50 | Train Loss: 0.1427 Acc: 0.950 F1: 0.933 | Val Loss: 0.1070 Acc: 1.000
F1: 1.000
Epoch 25/50 | Train Loss: 0.1256 Acc: 0.958 F1: 0.958 | Val Loss: 0.1078 Acc: 1.000
F1: 1.000
Epoch 30/50 | Train Loss: 0.2243 Acc: 0.908 F1: 0.915 | Val Loss: 0.1306 Acc: 0.933
F1: 0.933
Epoch 35/50 | Train Loss: 0.1285 Acc: 0.967 F1: 0.957 | Val Loss: 0.0930 Acc: 0.967
F1: 0.967
Epoch 40/50 | Train Loss: 0.2384 Acc: 0.917 F1: 0.898 | Val Loss: 0.2660 Acc: 0.833
F1: 0.822
Epoch 45/50 | Train Loss: 0.1094 Acc: 0.958 F1: 0.960 | Val Loss: 0.1544 Acc: 0.900
F1: 0.898
Epoch 50/50 | Train Loss: 0.1484 Acc: 0.950 F1: 0.955 | Val Loss: 0.1231 Acc: 0.933
F1: 0.933

=== Opt Experiment: SGD_1 ===
Epoch 01/50 | Train Loss: 0.8621 Acc: 0.600 F1: 0.600 | Val Loss: 0.5858 Acc: 0.667
F1: 0.556
Epoch 05/50 | Train Loss: 0.4963 Acc: 0.717 F1: 0.717 | Val Loss: 0.5182 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.3010 Acc: 0.883 F1: 0.883 | Val Loss: 0.1700 Acc: 1.000
F1: 1.000
Epoch 15/50 | Train Loss: 0.4187 Acc: 0.825 F1: 0.825 | Val Loss: 0.4354 Acc: 0.667
```

```
F1: 0.556
Epoch 20/50 | Train Loss: 0.2613 Acc: 0.900 F1: 0.900 | Val Loss: 0.2928 Acc: 0.867
F1: 0.861
Epoch 25/50 | Train Loss: 0.2196 Acc: 0.917 F1: 0.917 | Val Loss: 0.4062 Acc: 0.833
F1: 0.822
Epoch 30/50 | Train Loss: 0.2489 Acc: 0.892 F1: 0.892 | Val Loss: 0.1530 Acc: 0.933
F1: 0.933
Epoch 35/50 | Train Loss: 0.1112 Acc: 0.958 F1: 0.958 | Val Loss: 0.1859 Acc: 0.900
F1: 0.898
Epoch 40/50 | Train Loss: 0.4543 Acc: 0.692 F1: 0.692 | Val Loss: 0.4223 Acc: 0.667
F1: 0.556
Epoch 45/50 | Train Loss: 0.4661 Acc: 0.717 F1: 0.717 | Val Loss: 0.4632 Acc: 0.667
F1: 0.556
Epoch 50/50 | Train Loss: 0.4968 Acc: 0.650 F1: 0.650 | Val Loss: 0.4712 Acc: 0.667
F1: 0.556

=== Opt Experiment: Adam_MB ===
Epoch 01/50 | Train Loss: 1.1015 Acc: 0.317 F1: 0.148 | Val Loss: 1.0270 Acc: 0.333
F1: 0.167
Epoch 05/50 | Train Loss: 0.5169 Acc: 0.667 F1: 0.552 | Val Loss: 0.4662 Acc: 0.667
F1: 0.556
Epoch 10/50 | Train Loss: 0.1911 Acc: 0.942 F1: 0.914 | Val Loss: 0.1308 Acc: 1.000
F1: 1.000
Epoch 15/50 | Train Loss: 0.1058 Acc: 0.967 F1: 0.965 | Val Loss: 0.1572 Acc: 0.933
F1: 0.933
Epoch 20/50 | Train Loss: 0.1080 Acc: 0.975 F1: 0.961 | Val Loss: 0.0699 Acc: 1.000
F1: 1.000
Epoch 25/50 | Train Loss: 0.1199 Acc: 0.958 F1: 0.959 | Val Loss: 0.0894 Acc: 0.933
F1: 0.933
Epoch 30/50 | Train Loss: 0.1009 Acc: 0.967 F1: 0.957 | Val Loss: 0.0637 Acc: 1.000
F1: 1.000
Epoch 35/50 | Train Loss: 0.0800 Acc: 0.958 F1: 0.964 | Val Loss: 0.0480 Acc: 1.000
F1: 1.000
Epoch 40/50 | Train Loss: 0.0738 Acc: 0.967 F1: 0.961 | Val Loss: 0.0606 Acc: 1.000
F1: 1.000
Epoch 45/50 | Train Loss: 0.0895 Acc: 0.967 F1: 0.968 | Val Loss: 0.0921 Acc: 0.933
F1: 0.933
Epoch 50/50 | Train Loss: 0.0956 Acc: 0.967 F1: 0.973 | Val Loss: 0.0545 Acc: 1.000
F1: 1.000
```


Validación - Loss por algoritmo de optimización
BatchGD
MiniBatch
SGD_1
Adam_MB
Val Loss
Epoch
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
10
20
30
40
50


Validación - Accuracy por algoritmo de optimización
BatchGD
MiniBatch
SGD_1
Adam_MB
Val Acc
Epoch
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0
10
20
30
40
50



Out[14]:

	exp	final_val_loss	final_val_acc	final_val_f1	time_s
3	Adam_MB	0.054484	1.000000	1.000000	1.158558
1	MiniBatch	0.123085	0.933333	0.932660	1.090619
0	BatchGD	0.776806	0.666667	0.555556	0.313451
2	SGD_1	0.471166	0.666667	0.555556	13.730088

Task 6 - Experimentación y Análisis

In [ ]:

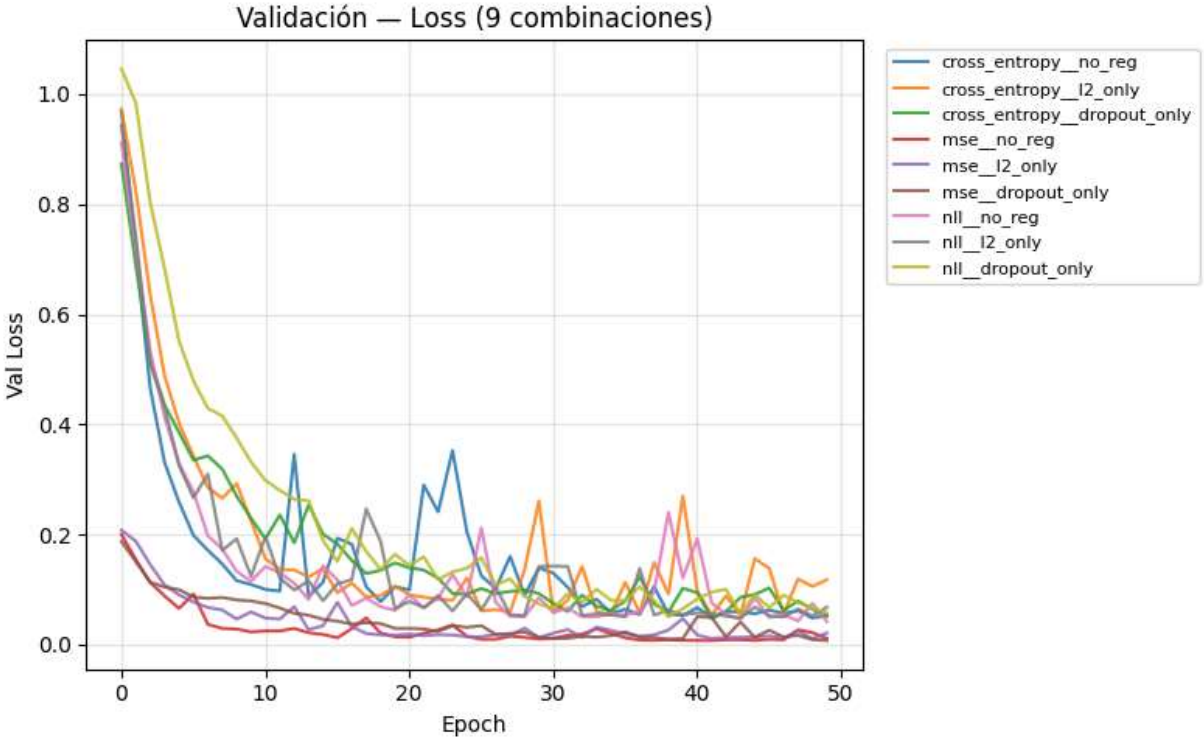
```python
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader

def accuracy_from_logits(logits: torch.Tensor, y_true: torch.Tensor) -> float:
    preds = logits.argmax(1)
    return (preds == y_true).float().mean().item()

from sklearn.metrics import f1_score
def f1_from_logits(logits: torch.Tensor, y_true: torch.Tensor) -> float:
    preds = logits.argmax(1).cpu().numpy()
    y_np = y_true.cpu().numpy()
    return f1_score(y_np, preds, average='macro')

def l1_penalty(model: nn.Module) -> torch.Tensor:
```

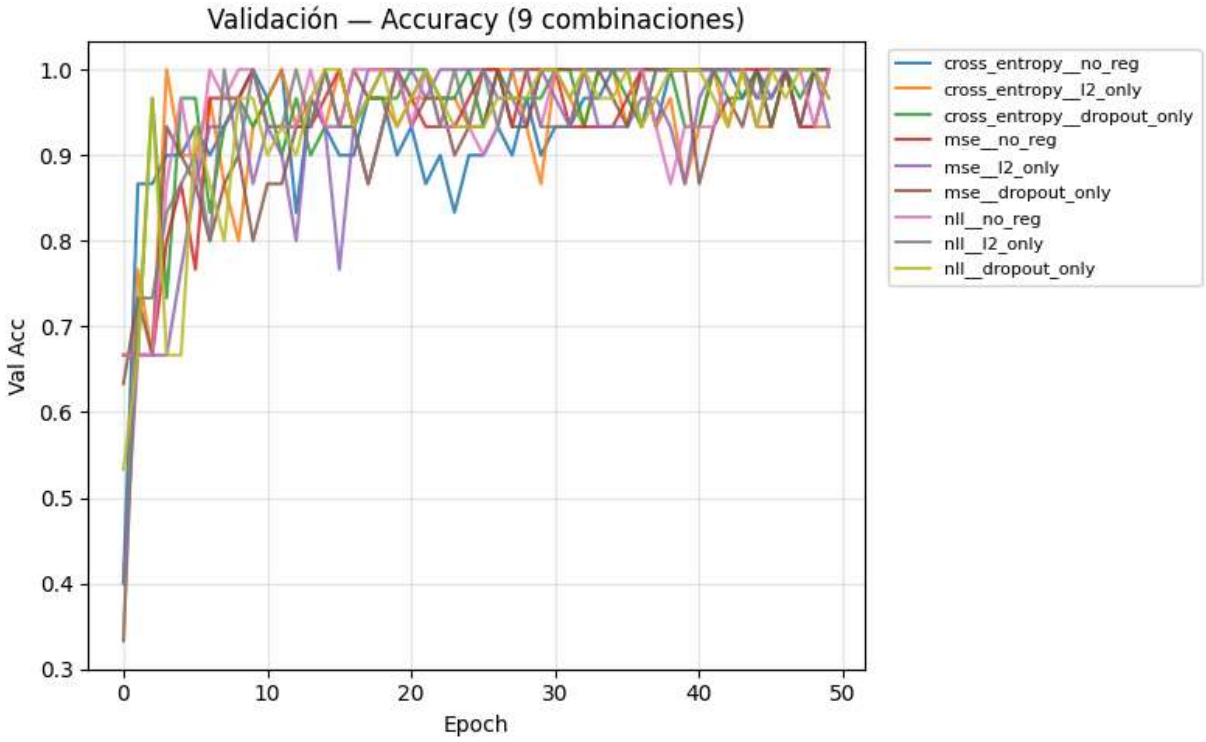
```
    l1 = 0.0
    for p in model.parameters():
        if p.requires_grad:
            l1 = l1 + p.abs().sum()
    return l1

# DataLoaders (mini-batch)
def make_loaders(batch_size=16, shuffle=True):
    train_ds = TensorDataset(X_train_tensor, y_train_tensor)
    val_ds   = TensorDataset(X_val_tensor,   y_val_tensor)
    train_loader = DataLoader(train_ds, batch_size=batch_size, shuffle=shuffle)
    val_loader   = DataLoader(val_ds,   batch_size=batch_size, shuffle=False)
    return train_loader, val_loader

# Entrenamiento (mini-batch) con L1/L2/Dropout y pérdidas múltiples
def train_one_experiment(
    loss_name: str,
    p_dropout: float = 0.0,      # Dropout
    l2_weight_decay: float = 0.0,# L2 (weight decay)
    l1_lambda: float = 0.0,      # L1
    lr: float = 1e-2,
    batch_size: int = 16,
    epochs: int = 50,
    verbose: bool = False
):
    train_loader, val_loader = make_loaders(batch_size=batch_size, shuffle=True)
    model = FeedforwardNN(input_dim, hidden_dim, output_dim, p_dropout=p_dropout)
    loss_fn = loss_function(loss_name)
    optimizer = optim.Adam(model.parameters(), lr=lr, weight_decay=l2_weight_decay)

    history = {
        "train_loss": [], "val_loss": [],
        "train_acc":  [], "val_acc":  [],
        "train_f1":   [], "val_f1":   [],
        "config": {"loss": loss_name, "dropout": p_dropout,
                "l2_weight_decay": l2_weight_decay, "l1_lambda": l1_lambda,
                "lr": lr, "batch_size": batch_size, "epochs": epochs}
    }

    t0 = time.time()
    for epoch in range(1, epochs+1):
        model.train()
        run_loss, run_correct, run_f1_parts, n = 0.0, 0, [], 0
        for Xb, yb in train_loader:
            optimizer.zero_grad()
            logits = model(Xb)

            # pérdida base según tipo
            if isinstance(loss_fn, nn.MSELoss):
                probs = F.softmax(logits, dim=1)
                yb_oh = F.one_hot(yb, num_classes=logits.size(1)).float()
                base_loss = loss_fn(probs, yb_oh)
            elif isinstance(loss_fn, nn.NLLLoss):
                log_probs = F.log_softmax(logits, dim=1)
                base_loss = loss_fn(log_probs, yb)
            else:  # CrossEntropy
```

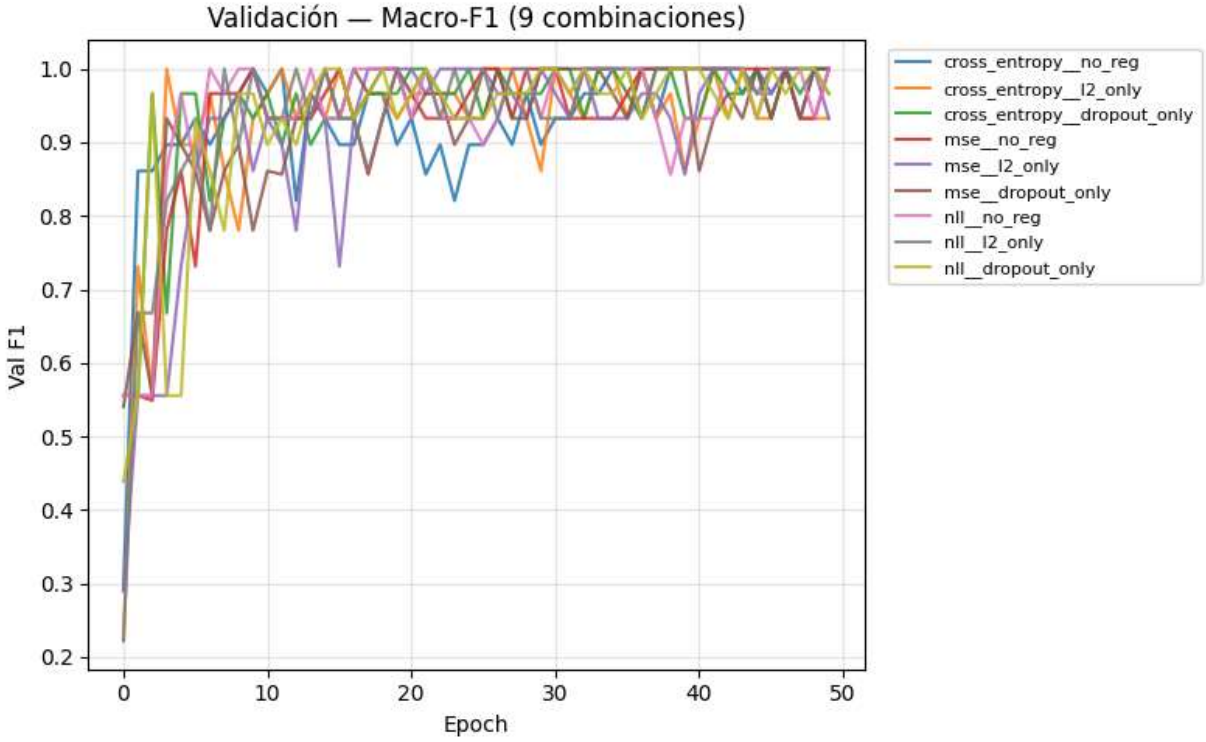
```
                base_loss = loss_fn(logits, yb)

            # L1 opcional
            if l1_lambda > 0.0:
                base_loss = base_loss + l1_lambda * l1_penalty(model)

            base_loss.backward()
            optimizer.step()

            run_loss += base_loss.item() * Xb.size(0)
            run_correct += (logits.argmax(1) == yb).sum().item()
            run_f1_parts.append(f1_from_logits(logits, yb))
            n += Xb.size(0)

        tr_loss = run_loss / n
        tr_acc  = run_correct / n
        tr_f1   = float(np.mean(run_f1_parts))

        # ---- VALIDATION ----
        model.eval()
        val_loss_sum, val_correct, val_f1_parts, n_val = 0.0, 0, [], 0
        with torch.no_grad():
            for Xv, yv in val_loader:
                logits_v = model(Xv)
                if isinstance(loss_fn, nn.MSELoss):
                    probs_v = F.softmax(logits_v, dim=1)
                    yv_oh = F.one_hot(yv, num_classes=logits_v.size(1)).float()
                    loss_v = loss_fn(probs_v, yv_oh)
                elif isinstance(loss_fn, nn.NLLLoss):
                    log_probs_v = F.log_softmax(logits_v, dim=1)
                    loss_v = loss_fn(log_probs_v, yv)
                else:
                    loss_v = loss_fn(logits_v, yv)

                val_loss_sum += loss_v.item() * Xv.size(0)
                val_correct  += (logits_v.argmax(1) == yv).sum().item()
                val_f1_parts.append(f1_from_logits(logits_v, yv))
                n_val += Xv.size(0)

        va_loss = val_loss_sum / n_val
        va_acc  = val_correct / n_val
        va_f1   = float(np.mean(val_f1_parts))

        history["train_loss"].append(tr_loss)
        history["val_loss"].append(va_loss)
        history["train_acc"].append(tr_acc)
        history["val_acc"].append(va_acc)
        history["train_f1"].append(tr_f1)
        history["val_f1"].append(va_f1)

        if verbose and (epoch % 5 == 0 or epoch == 1):
            print(f"Epoch {epoch:02d}/{epochs} | "
                  f"Train Loss: {tr_loss:.4f} Acc: {tr_acc:.3f} F1: {tr_f1:.3f} | "
                  f"Val Loss: {va_loss:.4f} Acc: {va_acc:.3f} F1: {va_f1:.3f}")

    history["time_s"] = time.time() - t0
```

```
    return history

losses = ["cross_entropy", "mse", "nll"]
regularizations = {
    "no_reg":       dict(p_dropout=0.0, l2_weight_decay=0.0, l1_lambda=0.0),
    "l2_only":      dict(p_dropout=0.0, l2_weight_decay=1e-3, l1_lambda=0.0),
    "dropout_only": dict(p_dropout=0.3, l2_weight_decay=0.0, l1_lambda=0.0),
}

task6_results = {}
for loss_name in losses:
    for reg_name, reg_cfg in regularizations.items():
        tag = f"{loss_name}__{reg_name}"
        print(f"\n=== Ejecutando: {tag} ===")
        hist = train_one_experiment(
            loss_name=loss_name,
            **reg_cfg,
            lr=1e-2,
            batch_size=16,
            epochs=50,
            verbose=False
        )
        task6_results[tag] = hist


def plot_history(results_dict, metric_key, title):
    plt.figure(figsize=(8,5))
    for name, hist in results_dict.items():
        plt.plot(hist[metric_key], label=name, alpha=0.85)
    plt.xlabel("Epoch")
    plt.ylabel(metric_key.replace("_", " ").title())
    plt.title(title)
    plt.legend(bbox_to_anchor=(1.02, 1), loc="upper left", fontsize=8)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

# 3 figuras: val_loss, val_acc, val_f1
plot_history(task6_results, "val_loss", "Validación — Loss (9 combinaciones)")
plot_history(task6_results, "val_acc",  "Validación — Accuracy (9 combinaciones)")
plot_history(task6_results, "val_f1",   "Validación — Macro-F1 (9 combinaciones)")


rows = []
for name, hist in task6_results.items():
    rows.append({
        "combo": name,
        "final_val_loss": hist["val_loss"][-1],
        "final_val_acc":  hist["val_acc"][-1],
        "final_val_f1":   hist["val_f1"][-1],
        "time_s":         hist["time_s"]
    })

summary_task6 = pd.DataFrame(rows).sort_values(by=["final_val_f1","final_val_acc"],
summary_task6
```

```
=== Ejecutando: cross_entropy__no_reg ===

=== Ejecutando: cross_entropy__l2_only ===

=== Ejecutando: cross_entropy__dropout_only ===

=== Ejecutando: mse__no_reg ===

=== Ejecutando: mse__l2_only ===

=== Ejecutando: mse__dropout_only ===

=== Ejecutando: nll__no_reg ===

=== Ejecutando: nll__l2_only ===

=== Ejecutando: nll__dropout_only ===
```




Validación — Accuracy (9 combinaciones)
Val Acc
Epoch
cross_entropy__no_reg
cross_entropy__l2_only
cross_entropy__dropout_only
mse__no_reg
mse__l2_only
mse__dropout_only
nll__no_reg
nll__l2_only
nll__dropout_only


Validación — Macro-F1 (9 combinaciones)
Val F1
Epoch
cross_entropy__no_reg
cross_entropy__l2_only
cross_entropy__dropout_only
mse__no_reg
mse__l2_only
mse__dropout_only
nll__no_reg
nll__l2_only
nll__dropout_only

Out[ ]:

	combo	final_val_loss	final_val_acc	final_val_f1	time_s
0	cross_entropy__no_reg	0.052891	1.000000	1.00000	1.258620
1	cross_entropy__dropout_only	0.051746	1.000000	1.00000	1.443063
2	mse__no_reg	0.011278	1.000000	1.00000	1.425811
3	mse__dropout_only	0.007520	1.000000	1.00000	1.371833
4	nll__no_reg	0.041562	1.000000	1.00000	1.305877
5	nll__l2_only	0.067838	0.966667	0.96633	1.243452
6	nll__dropout_only	0.057964	0.966667	0.96633	1.286605
7	cross_entropy__l2_only	0.117792	0.933333	0.93266	1.349596
8	mse__l2_only	0.021194	0.933333	0.93266	1.364345

Task 7 - Discusión de Resultados

En este ejercicio se analizaron los efectos de diferentes funciones de pérdida, técnicas de regularización y algoritmos de optimización en el entrenamiento de una red neuronal sobre el dataset Iris.

En primer lugar, la elección de la función de pérdida resultó fundamental para el rendimiento del modelo. La función Cross-Entropy demostró ser la más adecuada para problemas de clasificación multiclase como el Iris, ya que permitió una convergencia rápida y estable, alcanzando altos valores de accuracy y F1. Por el otro lado, el uso de MSE (Error Cuadrático Medio), no es recomendable para clasificación debido a que su convergencia fue más lenta y el rendimiento final inferior debido a que no está diseñada para este tipo de tareas y puede generar gradientes menos informativos. La función NLL (Negative Log Likelihood) mostró un comportamiento similar a Cross-Entropy, pero requiere que las salidas del modelo sean log-probabilidades, lo que puede añadir cierta complejidad y, en algunos casos, una convergencia ligeramente más lenta. En resumen, para tareas de clasificación, Cross-Entropy es la opción preferida por su estabilidad y resultados superiores.

Respecto a las técnicas de regularización se observó que la ausencia de regularización puede llevar al sobreajuste aunque en el caso del dataset Iris este riesgo es bajo debido a su tamaño reducido. La regularización L2 (weight decay) ayudó a mejorar la generalización del modelo, penalizando los pesos grandes y aportando mayor estabilidad en la validación. En el caso del uso de Dropout introdujo aleatoriedad en el entrenamiento forzando al modelo a no depender excesivamente de neuronas específicas, lo que resultó en una mayor robustez y en ocasiones tener mejores valores de F1. Sin embargo, valores elevados de Dropout pueden dificultar la convergencia. La regularización L1, que promueve la dispersión de los pesos, tuvo un efecto menos notorio en este problema concreto. Además, la combinación de

varias técnicas de regularización, como Dropout y L2, puede potenciar la generalización, aunque también puede ralentizar la convergencia si los hiperparámetros no se ajustan adecuadamente. En conclusión, L2 y Dropout fueron las técnicas más efectivas para mejorar la generalización en este contexto, y su combinación puede ser beneficiosa si se ajusta correctamente.

En cuanto a los algoritmos de optimización, se compararon Batch Gradient Descent, Mini-Batch Gradient Descent, SGD y Adam. En donde el método Batch Gradient Descent mostró una convergencia estable pero lenta, siendo menos eficiente en datasets grandes. Mini-Batch Gradient Descent ofreció un equilibrio óptimo entre estabilidad y velocidad, y es el estándar en la práctica moderna. El algoritmo SGD introdujo mucha variabilidad en las actualizaciones de los pesos, lo que puede ayudar a escapar de mínimos locales, pero su convergencia fue más ruidosa y lenta. Por último, Adam destacó por su rapidez y estabilidad en la convergencia, alcanzando buenos resultados en menos épocas y siendo menos sensible a la escala de los gradientes, lo que reduce la necesidad de ajustar manualmente la tasa de aprendizaje. Por tanto, Adam suele ser la opción preferida por su eficiencia y robustez, aunque Mini-Batch SGD también es una alternativa sólida.

Finalmente, al analizar la interacción entre las distintas técnicas, se observó que el mejor rendimiento se obtuvo al combinar Cross-Entropy, Adam y alguna forma de regularización como L2 o Dropout. Aunque la regularización es más crítica en datasets grandes o modelos complejos, incluso en un conjunto pequeño como Iris contribuye a la estabilidad del entrenamiento. Es importante destacar que la elección de la función de pérdida debe estar alineada con la naturaleza de la tarea (clasificación o regresión), y que los algoritmos de optimización modernos como Adam facilitan la obtención de buenos resultados sin requerir un ajuste exhaustivo de hiperparámetros.

Ejercicio 2 - Repaso Teoría

1. *¿Cuál es la principal innovación de la arquitectura Transformer?*

La principal innovación de la arquitectura Transformer es que elimina por completo el uso de redes recurrentes (RNN) y convolucionales (CNN), ya que en su lugar se basa únicamente en mecanismos de atención en donde son específicamente la auto-atención (self-attention) y la atención multi-cabeza (multi-head attention). Permitiendo que el modelo aprenda dependencias globales entre los elementos de la secuencia de entrada y salida de manera más eficiente y paralelizable. Como ventaja de la estructura el Transformer logra superar en calidad y velocidad de entrenamiento a los modelos tradicionales en donde permite procesar todas las posiciones de la secuencia en paralelo, teniendo como beneficio que facilita el aprendizaje de relaciones a largo plazo y reduciendo significativamente el tiempo de entrenamiento. Asimismo, esta arquitectura ha demostrado generalizar bien a otras

tareas más allá de la traducción automática, estableciendo nuevos estándares de desempeño en diversos problemas de procesamiento de lenguaje natural.

2. *¿Cómo funciona el mecanismo de atención del scaled dot-product?*

El mecanismo de atención scaled dot-product funciona tomando tres elementos principales los cuales son queries, keys y values, todos representados como vectores. El proceso consiste en calcular el producto punto entre cada query y todas las keys, dividiendo el resultado por la raíz cuadrada de la dimensión de las keys, es decir:

$$\begin{aligned}&\text{Attention}(Q, K, V)\\&= \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V\end{aligned}$$

Luego, se aplica una función softmax para obtener los pesos de atención, que determinan la importancia relativa de cada valor. Finalmente, se realiza una suma ponderada de los valores usando estos pesos, generando así la salida de la atención. Este mecanismo permite que el modelo enfoque su atención en diferentes partes de la secuencia de entrada, independientemente de la distancia entre los elementos, y es altamente eficiente y paralelizable gracias a su implementación basada en operaciones matriciales.

3. *¿Por qué se utiliza la atención de múltiples cabezales en Transformer?*

La **atención de múltiples cabezales** permite que el modelo atienda a la información desde diferentes subespacios de representación. Cada cabeza de atención aprende patrones distintos en paralelo: por ejemplo, una puede enfocarse en la estructura sintáctica de la oración, mientras otra capta relaciones semánticas de largo alcance. Esto enriquece la representación final, ya que al concatenar las salidas de todas las cabezas se obtiene una visión más completa del contexto, mejorando la capacidad del modelo para capturar dependencias complejas.

4. *¿Cómo se incorporan los positional encodings en el modelo Transformer?*

El modelo Transformer no tiene una estructura secuencial implícita como las **RNN**, por lo que necesita un mecanismo para representar el orden de las palabras. Para esto, se utilizan los **positional encodings**, vectores que se suman a las embeddings de entrada. Estos vectores pueden ser:

- **Determinísticos (sinusoidales):** Definidos mediante funciones seno y coseno de diferentes frecuencias, lo que permite que el modelo generalice a secuencias más largas que las vistas en entrenamiento.

- **Aprendidos:** Los parámetros de posición se entrenan junto con el resto del modelo.

En ambos casos, los positional encodings aseguran que el Transformer tenga información sobre la posición relativa y absoluta de cada token en la secuencia.

5. *¿Cuáles son algunas aplicaciones de la arquitectura Transformer más allá de la machine translation?*

Los Transformers han demostrado gran versatilidad y hoy en día son la base de modelos de última generación en múltiples áreas, por ejemplo:

- **Procesamiento de Lenguaje Natural (NLP):**
    - Modelos de lenguaje
    - Resumen automático de textos
    - Análisis de sentimientos
    - Respuesta automática a preguntas
- **Visión por Computadora (CV):**
    - Vision Transformers (**ViT**) para clasificación de imágenes.
    - Detección y segmentación de objetos.
- **Multimodalidad:**
    - Modelos que combinan texto e imágenes (**CLIP**, **DALL-E**).
    - Generación de subtítulos automáticos para imágenes y videos.
- **Otros campos:**
    - Bioinformática: En la predicción de estructuras de proteínas
    - Finanzas: Predicción de series de tiempo.
    - Robótica y planificación de acciones.

Referencias

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