PyTorch in Practice

Tech. dept in NTU AI Club
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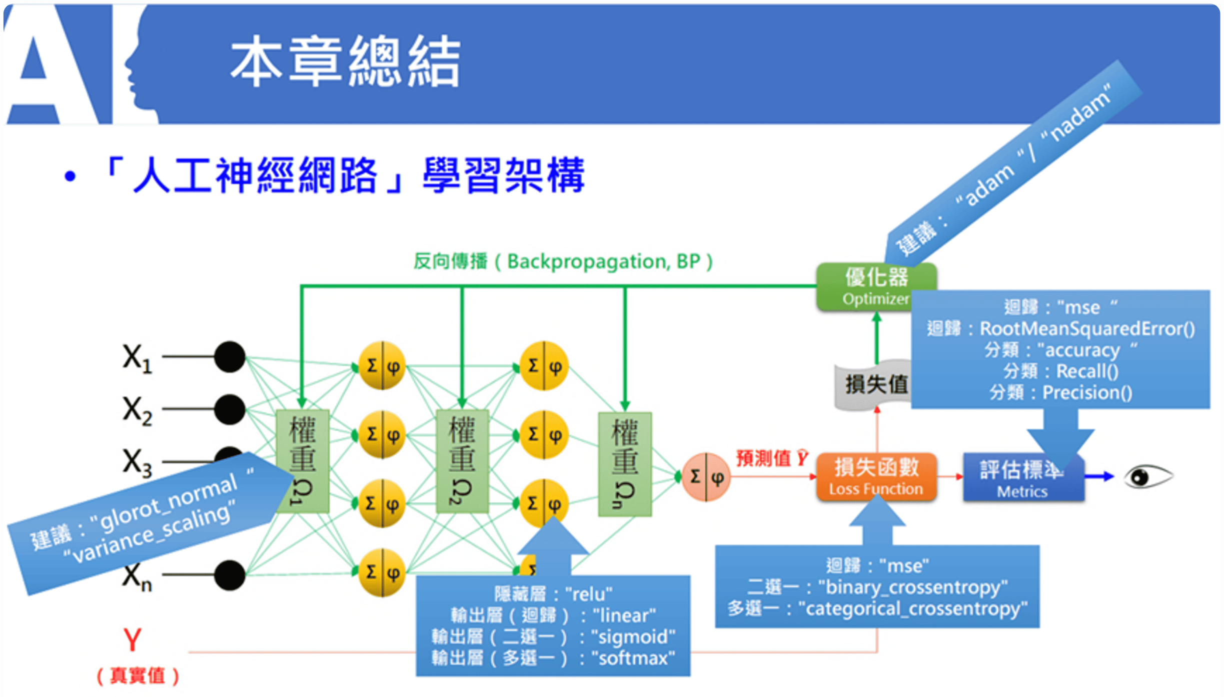
Neural Network



圖片取自紀俊男(RobertChi)老師

Pytorch overview

What is pytorch?

PyTorch 是由 Facebook AI Research 開發的開源深度學習框架，具有動態計算圖功能，使模型建構、訓練和調試更加靈活和直觀。 PyTorch 採用 Python 開發，在學術界和工業界廣泛應用。

What is Tensor?

- Tensor 是一個類似 NumPy 的 ndarray 的多維資料數組，但它可以在 CPU 或 GPU 上有效運作。
- tensor不僅支援多種數學演算法和矩陣運算，還利用自動引導使得神經網路的反向傳播計算更加簡單且有效率。

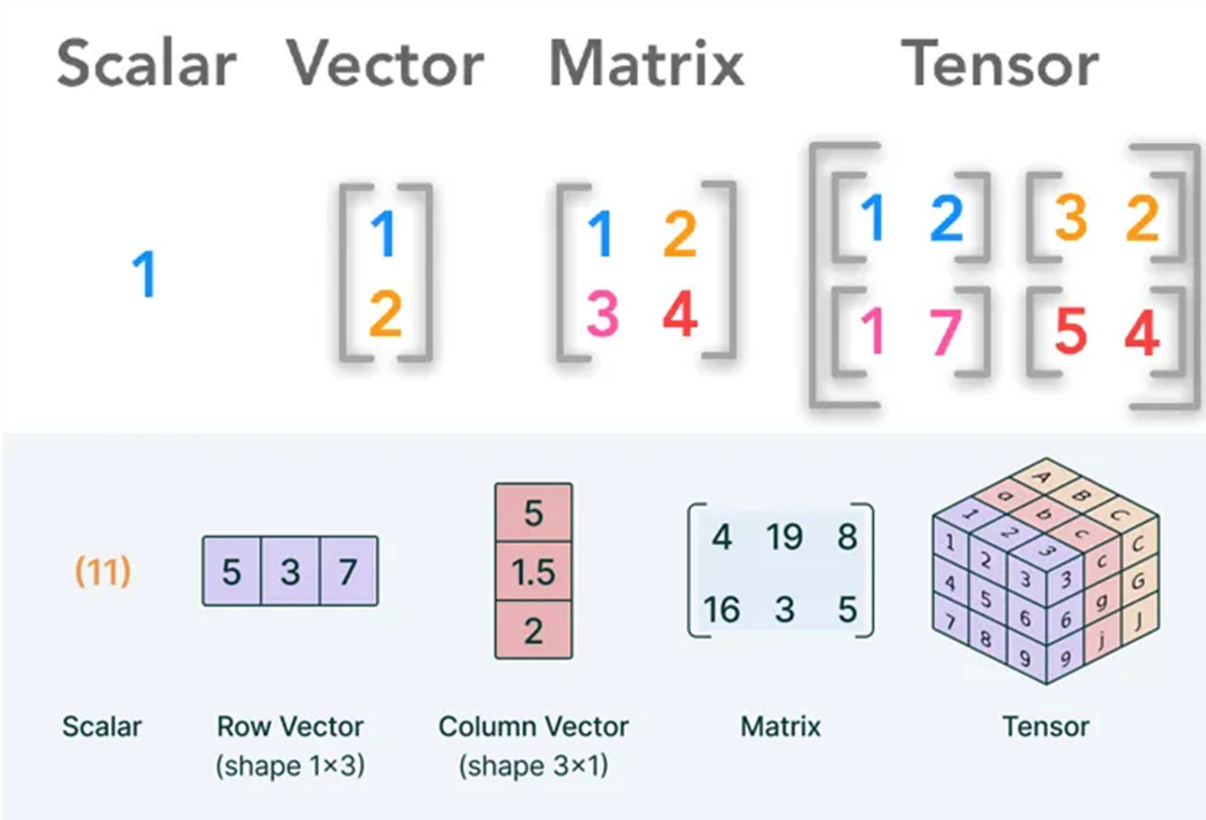


Image Source

建立簡單的張量

input

```
# 1D Floating Point Tensor
tensor_1D = torch.Tensor([1, 2, 3])
print("Tensor 1D:", tensor_1D)
print(tensor_1D.type())

# 2D Floating Point Tensor
tensor_2D = torch.Tensor([[1, 2, 3], [4, 5, 6]])
print("Tensor 2D:", tensor_2D)
print(tensor_2D.type())
```

output

```
Tensor 1D: tensor([1., 2., 3.])
torch.FloatTensor
Tensor 2D: tensor([[1., 2., 3.],
        [4., 5., 6.]])
torch.FloatTensor
```

張量運算

input

```
# Tensor operation
tensor_1 = torch.tensor([[1, 2, 3], [4, 5, 6]])
tensor_2 = torch.tensor([[6, 5, 4], [3, 2, 1]])

print(f"Addition: {tensor_1 + tensor_2}")
print(f"Subtraction: {tensor_1 - tensor_2}")
print(f"Multiplication: {tensor_1 * tensor_2}")
print(f"Division: {tensor_1 / tensor_2}")
```

---

output

```
Addition: tensor([[7, 7, 7],
        [7, 7, 7]])
Subtraction: tensor([[-5, -3, -1],
        [ 1,  3,  5]])
Multiplication: tensor([[ 6, 10, 12],
        [12, 10,  6]])
Division: tensor([[0.1667, 0.4000, 0.7500],
        [1.3333, 2.5000, 6.0000]])
```

與其它資料結構轉換

input

```
# Python List to Tensors
list_1D = [1, 2, 3]
tensor_1D = torch.tensor(list_1D)
print("Tensor 1D:", tensor_1D)

list_1D = tensor_1D.tolist()
print("List 1D:", list_1D)

ndarray_1D = np.array([1, 2, 3])
tensor_1D = torch.from_numpy(ndarray_1D)
print("Tensor 1D:", tensor_1D)

ndarray_1D = tensor_1D.numpy()
print("NDArray 1D:", ndarray_1D)
```

---

output

```
Tensor 1D: tensor([1, 2, 3])
List 1D: [1, 2, 3]
Tensor 1D: tensor([1, 2, 3])
NDArray 1D: [1 2 3]
```

將張量在 CPU 與 GPU 間互轉

input

```
tensor_1D = torch.tensor([1, 2, 3])
print("Tensor 1D:", tensor_1D)
print(tensor_1D.type())

# Transfer tensor from CPU to GPU
tensor_1D_GPU = tensor_1D.to(device)
print("Tensor 1D GPU:", tensor_1D_GPU)
print(tensor_1D_GPU.type())

# Transfer tensor from GPU to CPU
tensor_1D_CPU = tensor_1D_GPU.to(torch.device("cpu"))
print("Tensor 1D CPU:", tensor_1D_CPU)
print(tensor_1D_CPU.type())
```

---

output

```
Tensor 1D: tensor([1, 2, 3])
torch.LongTensor
Tensor 1D GPU: tensor([1, 2, 3], device='cuda:0')
torch.cuda.LongTensor
Tensor 1D CPU: tensor([1, 2, 3])
torch.LongTensor
```

張量資訊

input

```python
# Get the "axes" of a tensor
tensor_2D = torch.tensor([[1, 2, 3], [4, 5, 6]])
print("Tensor 2D:", tensor_2D)
print("Axes:", tensor_2D.dim())

# Get the "dimension/shape" of a tensor
print("Shape:", tensor_2D.shape)
print("Size:", tensor_2D.size())

# Get the "Number of Elements" of a tensor
print("Number of Elements:", tensor_2D.numel())

# Get the "Data Type" of a tensor
print("Data Type:", tensor_2D.dtype)
```

---

output

```
Tensor 2D: tensor([[1, 2, 3],
        [4, 5, 6]])
Axes: 2
Shape: torch.Size([2, 3])
Size: torch.Size([2, 3])
Number of Elements: 6
Data Type: torch.int64
```

張量維度操作

input

```python
tensor_2D = torch.tensor([[1, 2, 3], [4, 5, 6]])
print("Tensor 2D:", tensor_2D)
print("Initial Shape:", tensor_2D.shape)

# Use unsqueeze to insert a new dimension at the specified dimension
tensor_unsqueezed = tensor_2D.unsqueeze(dim=1)
print("Tensor after unsqueeze(dim=1):", tensor_unsqueezed)
print("New Shape after unsqueeze:", tensor_unsqueezed.size())

# Use squeeze to remove dimensions of size 1
tensor_squeezed = tensor_unsqueezed.squeeze(dim=1)
print("Tensor after squeeze(dim=1):", tensor_squeezed)
print("New Shape after squeeze:", tensor_squeezed.size())
```

---

output

```
Tensor 2D: tensor([[1, 2, 3],
        [4, 5, 6]])
```

```
Initial Shape: torch.Size([2, 3])
Tensor after unsqueeze(dim=1): tensor([[[1, 2, 3]],

        [[4, 5, 6]]])
New Shape after unsqueeze: torch.Size([2, 1, 3])
Tensor after squeeze(dim=1): tensor([[1, 2, 3],
        [4, 5, 6]])
New Shape after squeeze: torch.Size([2, 3])
```

Regression

Environment

```
import pandas as pd
import numpy as np
# from tqdm import tqdm
# import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.init as init
from torch.utils.data import DataLoader, TensorDataset
```

Dataset

特徵名稱	說明
age	年齡
sex	性別
bmi	身體質量指數
bp	平均血壓
s1~s6	六項血液生化指標

目標：預測資料病患一年後的糖尿病進展指數

步驟

1. 前處理
2. 建立模型
3. 訓練模型
4. 測試模型

前處理

1. 載入資料集
2. 切分自變數、應變數
   ~~3. 處理缺失資料~~
   ~~4. 類別資料數位化~~
3. 切分訓練集、測試集
   ~~6. 特徵縮放(已做過)~~
4. 轉成張量

下載資料

```
# Load dataset
from sklearn.datasets import load_diabetes

dataset = load_diabetes()
```

拆分自變數與應變數

```
# Split independent variable and dependent variable
X = pd.DataFrame(dataset.data, columns=dataset.feature_names)
Y = pd.DataFrame(dataset.target, columns=['Diabete_Value'])
```

拆分資料

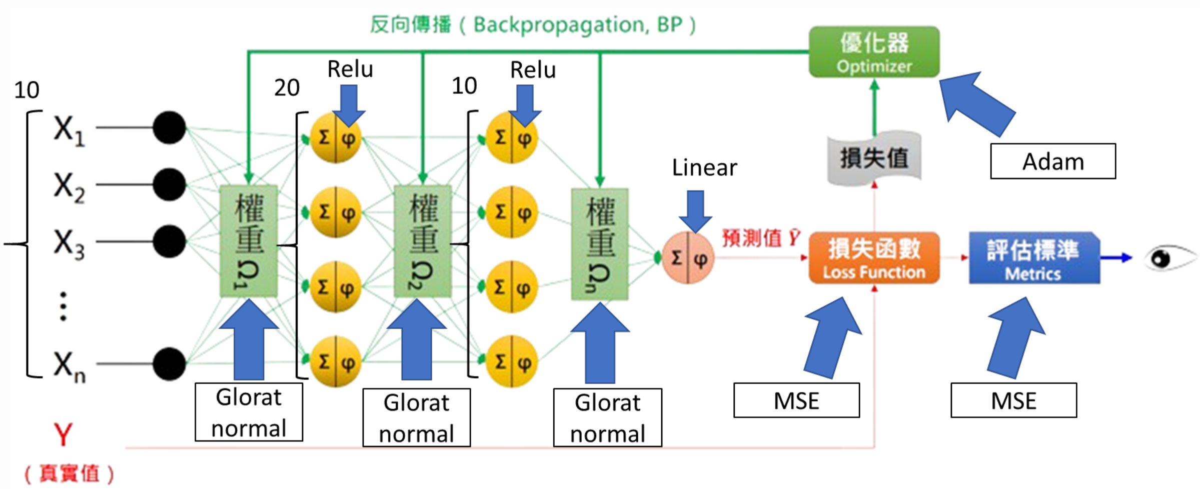
```
# Split train dataset and test dataset variable
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, ra
```

轉成向量

```
# Transform into Tensor
X_train_tensor = torch.tensor(X_train.values, dtype=torch.float)
X_test_tensor = torch.tensor(X_test.values, dtype=torch.float)
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.float)
```

~~1. 前處理~~
2. 建立模型
3. 訓練模型
4. 測試模型

建立模型(示意圖)



圖片取自紀俊男(RobertChi)老師

建立模型(程式碼)

```python
class DiabeteModel(nn.Module):

  # Define the architecture of each layer of the neural network
  def __init__(self):
    super(DiabeteModel, self).__init__()

    # Define each neural layer
    self.fc1 = nn.Linear(10, 20)
    self.fc2 = nn.Linear(20, 10)
    self.fc3 = nn.Linear(10, 1)

    # Initialize the weights of each neural layer
    init.xavier_normal_(self.fc1.weight)
    init.xavier_normal_(self.fc2.weight)
    init.xavier_normal_(self.fc3.weight)

  # Define forward propagation
  def forward(self, x):
    x = torch.relu(self.fc1(x))
    x = torch.relu(self.fc2(x))
    x = self.fc3(x)

    return x

# Construct the model
model = DiabeteModel().to(device)

# Define the loss function
criterion = nn.MSELoss()

# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

訓練模型

1. 建立 Dataset 與 DataLoader
2. 將張量放到GPU
3. 清除舊的梯度
4. 計算損失
5. 反向傳播
6. 更新優化器權重

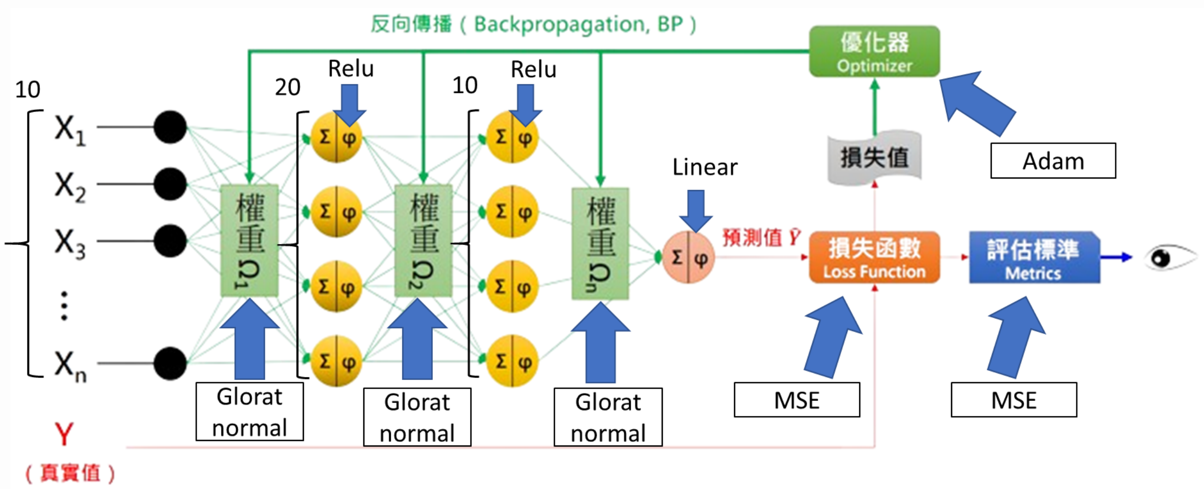
建立 Dataset 與 DataLoader

```
batch_size = 15

train_dataset = TensorDataset(X_train_tensor, Y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, Y_test_tensor)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False
```

訓練迴圈(示意圖)



圖片取自紀俊男(RobertChi)老師

訓練迴圈(程式碼)

```python
epochs = 150

for epoch in range(epochs):
  # Set the model to training mode
  model.train()

  running_loss = 0.0
  total_samples = 0

  # Take a Batch and start training
  for X_batch, Y_batch in train_loader:
    # Translate the data from the Batch to the GPU
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Zero out the gradient of the previous Batch
    optimizer.zero_grad()

    # Calculate the output
    Y_pred = model(X_batch)
    # Calculate the loss
    loss = criterion(Y_pred, Y_batch)
    # Backward propagation
    loss.backward()
    # Update the weight
    optimizer.step()

    running_loss += loss.item() * X_batch.size(0)
    total_samples += X_batch.size(0)

  # Calculate the accuracy for each epoch
  epoch_loss = running_loss / total_samples
  print(f'Epoch {epoch+1}/{epochs},MSE Loss: {epoch_loss:.4f}')
```

訓練結果(前面十行與最後十行)

```
Epoch 1/150,MSE Loss: 29051.5199
Epoch 2/150,MSE Loss: 29011.7012
Epoch 3/150,MSE Loss: 28965.5169
Epoch 4/150,MSE Loss: 28904.0876
Epoch 5/150,MSE Loss: 28822.1680
Epoch 6/150,MSE Loss: 28713.4460
Epoch 7/150,MSE Loss: 28572.2816
Epoch 8/150,MSE Loss: 28381.4172
Epoch 9/150,MSE Loss: 28141.3310
Epoch 10/150,MSE Loss: 27830.3267
```

```
Epoch 141/150,MSE Loss: 3043.6555
Epoch 142/150,MSE Loss: 3033.1254
Epoch 143/150,MSE Loss: 3027.5503
Epoch 144/150,MSE Loss: 3023.3534
Epoch 145/150,MSE Loss: 3017.9371
Epoch 146/150,MSE Loss: 3013.7183
```

```
Epoch 147/150,MSE Loss: 3008.9037
Epoch 148/150,MSE Loss: 3004.4907
Epoch 149/150,MSE Loss: 2998.2981
Epoch 150/150,MSE Loss: 2993.6150
```

測試模型

```python
# Switch to evaluation mode
model.eval()

test_loss = 0.0
total_samples = 0

# Turn off PyTorch's gradient calculation
with torch.no_grad():
  # Take a Batch and start testing
  for X_batch, Y_batch in test_loader:
    # Transform the data from CPU into GPU.
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Calculate output values
    Y_pred = model(X_batch)

    # Calculate loss for the batch
    loss = criterion(Y_pred, Y_batch)

    # Accumulate total loss and sample count
    test_loss += loss.item() * X_batch.size(0)
    total_samples += X_batch.size(0)

# Compute the average loss for the test dataset
avg_test_loss = test_loss / total_samples
print(f'Test MSE Loss: {avg_test_loss:.4f}')
```

結果

```
Test MSE Loss: 3257.9897
```

Classification

Dataset

特徵名稱	說明
sepal length (cm)	花萼長度（公分）

sepal width (cm)	花萼寬度（公分）
petal length (cm)	花瓣長度（公分）
petal width (cm)	花瓣寬度（公分）

目標：預測鳶尾花的品種

- 0:Setosa
- 1:Versicolor
- 2:Virginica

前處理

1. 載入資料集
2. 切分自變數、應變數
   ~~3. 處理缺失資料~~
   ~~4. 類別資料數位化~~
3. 切分訓練集、測試集
4. 特徵縮放
5. 轉成張量

載入資料集

```
# Load dataset
from sklearn.datasets import load_iris

dataset = load_iris()
```

拆分自變數與應變數

```
# Split independent variable and dependent variable
X = pd.DataFrame(dataset.data, columns=dataset.feature_names)
Y = pd.DataFrame(dataset.target, columns=['Iris_Type'])
Y_name = dataset.target_names.tolist()
```

拆分資料

```
# Split train dataset and test dataset variable
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, ra
```

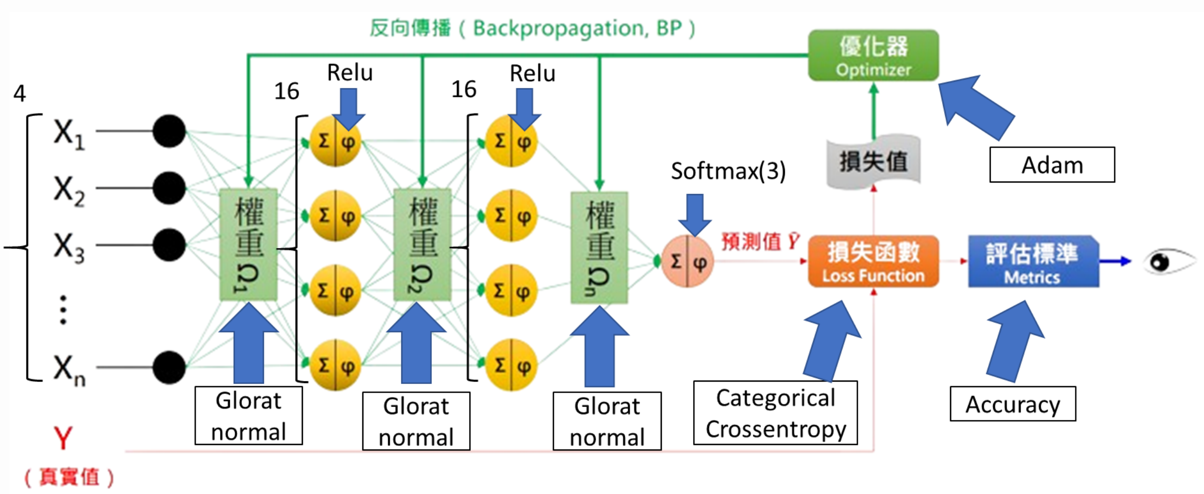
特徵縮放

```
# Feature Scaling
sc_X = StandardScaler().fit(X_train)
X_train = sc_X.transform(X_train)
X_test = sc_X.transform(X_test)
```

轉成向量

```
# Transform into Tensor
X_train_tensor = torch.from_numpy(X_train).float()
X_test_tensor = torch.from_numpy(X_test).float()
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.long)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.long)
```

建立模型(示意圖)



圖片取自紀俊男(RobertChi)老師

建立模型(程式碼)

```python
class IrisModel(nn.Module):

  # Define the architecture of each layer of the neural network
  def __init__(self):
    super(IrisModel, self).__init__()

    # Define each neural layer
    self.fc1 = nn.Linear(4, 16)
    self.fc2 = nn.Linear(16, 16)
    self.fc3 = nn.Linear(16, 3)

    # Initialize the weights of each neural layer
    init.xavier_normal_(self.fc1.weight)
    init.xavier_normal_(self.fc2.weight)
    init.xavier_normal_(self.fc3.weight)

  # Define forward propagation
  def forward(self, x):
    x = torch.relu(self.fc1(x))
    x = torch.relu(self.fc2(x))
    x = self.fc3(x)

    return x

# Construct the model
model = IrisModel().to(device)

# Define the loss function
criterion = nn.CrossEntropyLoss()

# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

訓練模型

1. 建立 Dataset 與 DataLoader
2. 將張量放到GPU
3. 清除舊的梯度
4. 計算損失
5. 反向傳播
6. 更新優化器權重

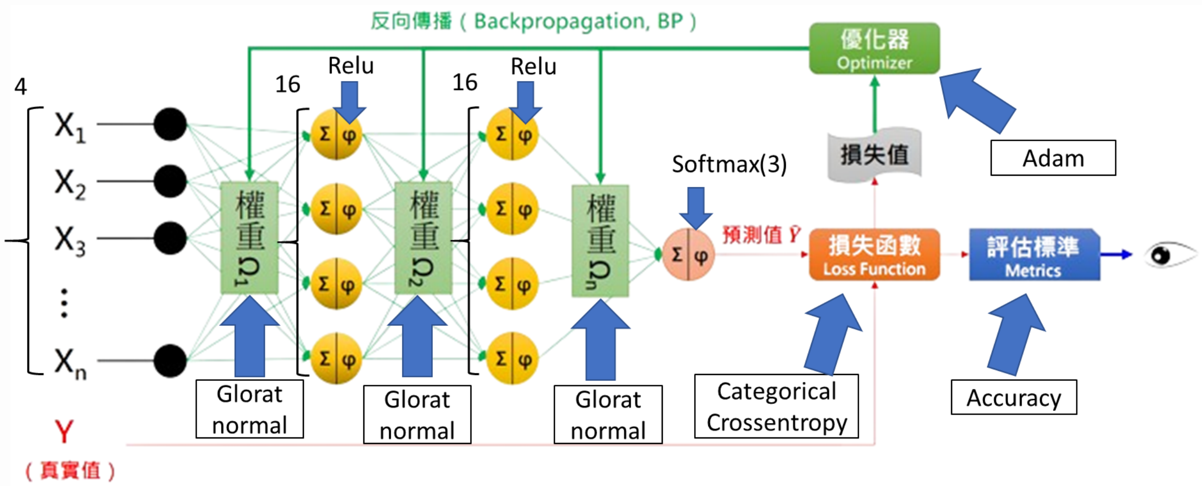
建立 Dataset 與 DataLoader

```
batch_size = 15

train_dataset = TensorDataset(X_train_tensor, Y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, Y_test_tensor)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False
```

訓練迴圈(示意圖)



圖片取自紀俊男(RobertChi)老師

訓練迴圈(程式碼)

```python
epochs = 50

for epoch in range(epochs):
  # Set the model to training mode
  model.train()

  # Store the number of correct guesses & the full number of guesses
  correct = 0
  total = 0

  # Take a Batch and start training
  for X_batch, Y_batch in train_loader:
    # Translate the data from the Batch to the GPU
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Zero out the gradient of the previous Batch
    optimizer.zero_grad()

    # Calculate the output
    Y_pred = model(X_batch)
    # Calculate the loss
    loss = criterion(Y_pred, Y_batch.squeeze())
    # Backward propagation
    loss.backward()
    # Update the weight
    optimizer.step()

    # Find the biggest index
    _, predicted = torch.max(Y_pred.data, 1)
    # Add the data of this batch to total
    total += Y_batch.size(0)
    # Calculate the number of correct guesses (.item() will help get the pu
    correct += (predicted == Y_batch.squeeze()).sum().item()

    # Calculate the accuracy for each epoch
    accuracy = correct / total
  print(f'Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}, Acc: {accuracy
```

訓練結果(前面十行與最後十行)

```
Epoch 1/50, Loss: 1.0151, Acc: 0.4917
Epoch 2/50, Loss: 0.9234, Acc: 0.6417
Epoch 3/50, Loss: 0.8413, Acc: 0.6833
Epoch 4/50, Loss: 0.6903, Acc: 0.6917
Epoch 5/50, Loss: 0.9573, Acc: 0.6917
Epoch 6/50, Loss: 0.6670, Acc: 0.7000
Epoch 7/50, Loss: 0.6463, Acc: 0.7000
Epoch 8/50, Loss: 0.6023, Acc: 0.7167
Epoch 9/50, Loss: 0.7148, Acc: 0.7167
Epoch 10/50, Loss: 0.5522, Acc: 0.7167
```

```
Epoch 41/50, Loss: 0.1101, Acc: 0.9583
Epoch 42/50, Loss: 0.0760, Acc: 0.9583
Epoch 43/50, Loss: 0.1394, Acc: 0.9583
Epoch 44/50, Loss: 0.2037, Acc: 0.9583
Epoch 45/50, Loss: 0.1376, Acc: 0.9583
Epoch 46/50, Loss: 0.1379, Acc: 0.9583
Epoch 47/50, Loss: 0.1396, Acc: 0.9667
Epoch 48/50, Loss: 0.0747, Acc: 0.9667
Epoch 49/50, Loss: 0.0288, Acc: 0.9667
Epoch 50/50, Loss: 0.1737, Acc: 0.9667
```

測試模型

```
# Switch to evaluation mode
model.eval()

# Turn off PyTorch's gradient calculation
with torch.no_grad():

  correct = 0
  total = 0

  # Take a Batch and start testing
  for X_batch, Y_batch in test_loader:
    # Transform the data from CPU into GPU.
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Calculate output values
    Y_pred = model(X_batch)

    # Find the biggest perbentage of index
    _, predicted = torch.max(Y_pred.data, 1)
    # Add the data of this batch to total
    total += Y_batch.size(0)
    # Calculate the number of correct guesses
    correct += (predicted == Y_batch.squeeze()).sum().item()

  print(f'Test Accuracy: {correct / total:.2%}')
```

結果

```
Test Accuracy: 100.00%
```

Classification competition in Kaggle

資料集簡介

連結

- 我們有出生年份、性別等資訊，希望能夠預測最終是否存活

載入資料集

```
# Load dataset

dataset = pd.read_csv('/content/1132_NTUAI_DL_Resource/titanic/train.csv')
dataset_test = pd.read_csv('/content/1132_NTUAI_DL_Resource/titanic/test.cs
```

刪除部分欄位為空的資料

```
dataset = dataset.dropna(subset=['Embarked'])
```

拆分自變數與應變數

```
# Split independent variable and dependent variable
X = dataset.drop(columns=['PassengerId', 'Name', 'Ticket', 'Cabin', 'Surviv
Y = pd.DataFrame(dataset, columns=['Survived'])
X_pred = dataset_test.drop(columns=['PassengerId', 'Name', 'Ticket', 'Cabin
```

類別資料數位化

```
# One-Hot encoder
X_mod = pd.get_dummies(X, columns=['Sex', 'Embarked'], drop_first=True).ast
X_pred_mod = pd.get_dummies(X_pred, columns=['Sex', 'Embarked'], drop_first
```

拆分資料

```
# Split train dataset and test dataset variable
X_train, X_test, Y_train, Y_test = train_test_split(X_mod, Y, test_size=0.2
```

特徵縮放

```python
# Feature Scaling
sc_X = StandardScaler().fit(X_train)
X_train = sc_X.transform(X_train)
X_test = sc_X.transform(X_test)
X_pred_scale = sc_X.transform(X_pred_mod)
```

轉成向量

```python
# Transform into Tensor
X_train_tensor = torch.from_numpy(X_train).float()
X_test_tensor = torch.from_numpy(X_test).float()
X_pred_tensor = torch.from_numpy(X_pred_scale).float()
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.float)
```

建立模型

```python
class TitanicModel(nn.Module):

  # Define the architecture of each layer of the neural network
  def __init__(self, input_len):
    super(TitanicModel, self).__init__()

    # Define each neural layer
    self.fc1 = nn.Linear(input_len, 13)
    self.fc2 = nn.Linear(13, 13)
    self.fc3 = nn.Linear(13, 1)

    # Initialize the weights of each neural layer
    init.xavier_normal_(self.fc1.weight)
    init.xavier_normal_(self.fc2.weight)
    init.xavier_normal_(self.fc3.weight)

  # Define forward propagation
  def forward(self, x):
    x = torch.relu(self.fc1(x))
    x = torch.relu(self.fc2(x))
    x = torch.sigmoid(self.fc3(x))

    return x

# Construct the model
model = TitanicModel(X_train_tensor.shape[1]).to(device)

# Define the loss function
criterion = nn.BCELoss()

# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

訓練模型

1. 建立 Dataset 與 DataLoader
2. 將張量放到GPU
3. 清除舊的梯度
4. 計算損失
5. 反向傳播
6. 更新優化器權重

建立 Dataset 與 DataLoader

```
batch_size = 15

train_dataset = TensorDataset(X_train_tensor, Y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, Y_test_tensor)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False
```

訓練迴圈(程式碼)

```python
epochs = 50

for epoch in range(epochs):
  # Set the model to training mode
  model.train()

  # Store the number of correct guesses & the full number of guesses
  correct = 0
  total = 0

  # Take a Batch and start training
  for X_batch, Y_batch in train_loader:
    # Translate the data from the Batch to the GPU
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Zero out the gradient of the previous Batch
    optimizer.zero_grad()

    # Calculate the output
    Y_pred = model(X_batch)
    # Calculate the loss
    loss = criterion(Y_pred.squeeze(), Y_batch.squeeze())
    # Backward propagation
    loss.backward()
    # Update the weight
    optimizer.step()

    # Add the data of this batch to total
    total += Y_batch.size(0)

    # Calculate the number of correct guesses (.item() will help get the pu
    predicted = (Y_pred.squeeze() >= 0.5).float()
    correct += (predicted == Y_batch.squeeze()).sum().item()

  # Calculate the accuracy for each epoch
  accuracy = correct / total
  print(f'Epoch {epoch+1}/{epochs}, Loss: {loss.item():.4f}, Acc: {accuracy
```

訓練結果(前面十行與最後十行)

```
Epoch 1/50, Loss: 0.6352, Acc: 0.5556
Epoch 2/50, Loss: 0.4765, Acc: 0.7103
Epoch 3/50, Loss: 0.5724, Acc: 0.6962
Epoch 4/50, Loss: 0.7052, Acc: 0.7482
Epoch 5/50, Loss: 0.3761, Acc: 0.7904
Epoch 6/50, Loss: 0.5385, Acc: 0.8200
Epoch 7/50, Loss: 0.4009, Acc: 0.8186
Epoch 8/50, Loss: 0.4260, Acc: 0.8143
Epoch 9/50, Loss: 0.5415, Acc: 0.8087
Epoch 10/50, Loss: 0.7234, Acc: 0.8073
```

```
Epoch 41/50, Loss: 0.1802, Acc: 0.8411
Epoch 42/50, Loss: 0.2659, Acc: 0.8439
Epoch 43/50, Loss: 0.5901, Acc: 0.8467
Epoch 44/50, Loss: 0.2018, Acc: 0.8439
Epoch 45/50, Loss: 0.6142, Acc: 0.8453
Epoch 46/50, Loss: 0.2658, Acc: 0.8453
Epoch 47/50, Loss: 0.3154, Acc: 0.8467
Epoch 48/50, Loss: 0.3701, Acc: 0.8453
Epoch 49/50, Loss: 0.4778, Acc: 0.8467
Epoch 50/50, Loss: 0.4226, Acc: 0.8481
```

測試模型

```
# Switch to evaluation mode
model.eval()

# Turn off PyTorch's gradient calculation
with torch.no_grad():

  correct = 0
  total = 0

  # Take a Batch and start testing
  for X_batch, Y_batch in test_loader:
    # Transform the data from CPU into GPU.
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Calculate output values
    Y_pred = model(X_batch)

    # Find the biggest perbentage of index
    predicted = (Y_pred.squeeze() >= 0.5).float()

    # Add the data of this batch to total
    total += Y_batch.size(0)
    # Calculate the number of correct guesses
    correct += (predicted == Y_batch.squeeze()).sum().item()

  print(f'Test Accuracy: {correct / total:.2%}')
```

結果

```
Test Accuracy: 73.03%
```

預測模型

```
model.eval()
with torch.no_grad():
    Y_pred = model(X_pred_tensor.to(device))

    Y_pred_label = (Y_pred >= 0.5).long()

Y_pred_numpy = Y_pred_label.squeeze().cpu().tolist()

submission = pd.DataFrame({'PassengerId': dataset_test['PassengerId'], 'Sur
submission.to_csv('submission_titanic.csv', index=False)
```

Regression competition in Kaggle

資料集簡介

連結

- 我們有房子的銷售年、月份等資訊，希望能夠預測房價

載入資料集

```
# Load dataset

dataset = pd.read_csv('/content/1132_NTUAI_DL_Resource/house-prices-advance
dataset_test = pd.read_csv('/content/1132_NTUAI_DL_Resource//house-prices-a
```

拆分自變數與應變數

```
# Split independent variable and dependent variable
X = pd.DataFrame(dataset, columns=['MSSubClass', 'MSZoning', 'LotArea', 'Ov
Y = pd.DataFrame(dataset, columns=['SalePrice'])
X_pred = pd.DataFrame(dataset_test, columns=['MSSubClass', 'MSZoning', 'Lot
```

類別資料數位化

```
# One-Hot encoder
X_mod = pd.get_dummies(X, columns=['MSZoning', 'CentralAir', 'SaleType', 'S
X_pred_mod = pd.get_dummies(X_pred, columns=['MSZoning', 'CentralAir', 'Sal
```

拆分資料

```
# Split train dataset and test dataset variable
X_train, X_test, Y_train, Y_test = train_test_split(X_mod, Y, test_size=0.2
```

轉成向量

```
# Transform into Tensor
X_train_tensor = torch.tensor(X_train.values, dtype=torch.float)
X_test_tensor = torch.tensor(X_test.values, dtype=torch.float)
X_pred_tensor = torch.tensor(X_pred_mod.values, dtype=torch.float)
Y_train_tensor = torch.tensor(Y_train.values, dtype=torch.float)
Y_test_tensor = torch.tensor(Y_test.values, dtype=torch.float)
```

建立模型

```
class PriceModel(nn.Module):

  # Define the architecture of each layer of the neural network
  def __init__(self, input_len):
    super(PriceModel, self).__init__()

    # Define each neural layer
    self.fc1 = nn.Linear(input_len, 61)
    self.fc2 = nn.Linear(61, 30)
    self.fc3 = nn.Linear(30, 1)

    # Initialize the weights of each neural layer
    init.xavier_normal_(self.fc1.weight)
    init.xavier_normal_(self.fc2.weight)
    init.xavier_normal_(self.fc3.weight)

  # Define forward propagation
  def forward(self, x):
    x = torch.relu(self.fc1(x))
    x = torch.relu(self.fc2(x))
    x = self.fc3(x)

    return x

# Construct the model
model = PriceModel(X_train_tensor.shape[1]).to(device)

# Define the loss function
criterion = nn.MSELoss()

# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

訓練模型

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2. 將張量放到GPU
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5. 反向傳播
6. 更新優化器權重

建立 Dataset 與 DataLoader

```
batch_size = 15

train_dataset = TensorDataset(X_train_tensor, Y_train_tensor)
test_dataset = TensorDataset(X_test_tensor, Y_test_tensor)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tru
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False
```

訓練迴圈(程式碼)

```python
epochs = 70

for epoch in range(epochs):
  # Set the model to training mode
  model.train()

  running_loss = 0.0
  total_samples = 0

  # Take a Batch and start training
  for X_batch, Y_batch in train_loader:
    # Translate the data from the Batch to the GPU
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Zero out the gradient of the previous Batch
    optimizer.zero_grad()

    # Calculate the output
    Y_pred = model(X_batch)
    # Calculate the loss
    loss = torch.sqrt(criterion(Y_pred, Y_batch))
    # Backward propagation
    loss.backward()
    # Update the weight
    optimizer.step()

    running_loss += loss.item() * X_batch.size(0)
    total_samples += X_batch.size(0)

  # Calculate the accuracy for each epoch
  epoch_loss = running_loss / total_samples
  print(f'Epoch {epoch+1}/{epochs},RMSE Loss: {epoch_loss:.4f}')
```

訓練結果(前面十行與最後十行)

```
Epoch 1/70,RMSE Loss: 190295.3514
Epoch 2/70,RMSE Loss: 161153.2240
Epoch 3/70,RMSE Loss: 110397.1278
Epoch 4/70,RMSE Loss: 97744.3532
Epoch 5/70,RMSE Loss: 94279.7636
Epoch 6/70,RMSE Loss: 92779.6218
Epoch 7/70,RMSE Loss: 89694.3305
Epoch 8/70,RMSE Loss: 87927.7034
Epoch 9/70,RMSE Loss: 85346.8407
Epoch 10/70,RMSE Loss: 83919.2306
```

```
Epoch 61/70,RMSE Loss: 68016.3338
Epoch 62/70,RMSE Loss: 67869.1597
Epoch 63/70,RMSE Loss: 67421.2056
Epoch 64/70,RMSE Loss: 67955.5566
Epoch 65/70,RMSE Loss: 68029.8467
Epoch 66/70,RMSE Loss: 67129.8483
```

```
Epoch 67/70,RMSE Loss: 67244.2728
Epoch 68/70,RMSE Loss: 67066.5131
Epoch 69/70,RMSE Loss: 67346.6508
Epoch 70/70,RMSE Loss: 67331.6777
```

測試模型

```python
# Switch to evaluation mode
model.eval()

test_loss = 0.0
total_samples = 0

# Turn off PyTorch's gradient calculation
with torch.no_grad():
  # Take a Batch and start testing
  for X_batch, Y_batch in test_loader:
    # Transform the data from CPU into GPU.
    X_batch, Y_batch = X_batch.to(device), Y_batch.to(device)

    # Calculate output values
    Y_pred = model(X_batch)

    # Calculate model predictions
    Y_pred = model(X_batch)
    # Calculate loss for the batch
    loss = torch.sqrt(criterion(Y_pred, Y_batch))

    # Accumulate total loss and sample count
    test_loss += loss.item() * X_batch.size(0)
    total_samples += X_batch.size(0)

# Compute the average loss for the test dataset
avg_test_loss = test_loss / total_samples
print(f'Test RMSE Loss: {avg_test_loss:.4f}')
```

結果

```
Test RMSE Loss: 69788.8924
```

預測模型

```
model.eval()
with torch.no_grad():
    Y_pred = model(X_pred_tensor.to(device))

Y_pred_numpy = Y_pred.squeeze().cpu().tolist()

submission = pd.DataFrame({'Id': dataset_test['Id'], 'SalePrice': Y_pred_nu
submission.to_csv('submission_price.csv', index=False)
```

Thank you for your listening