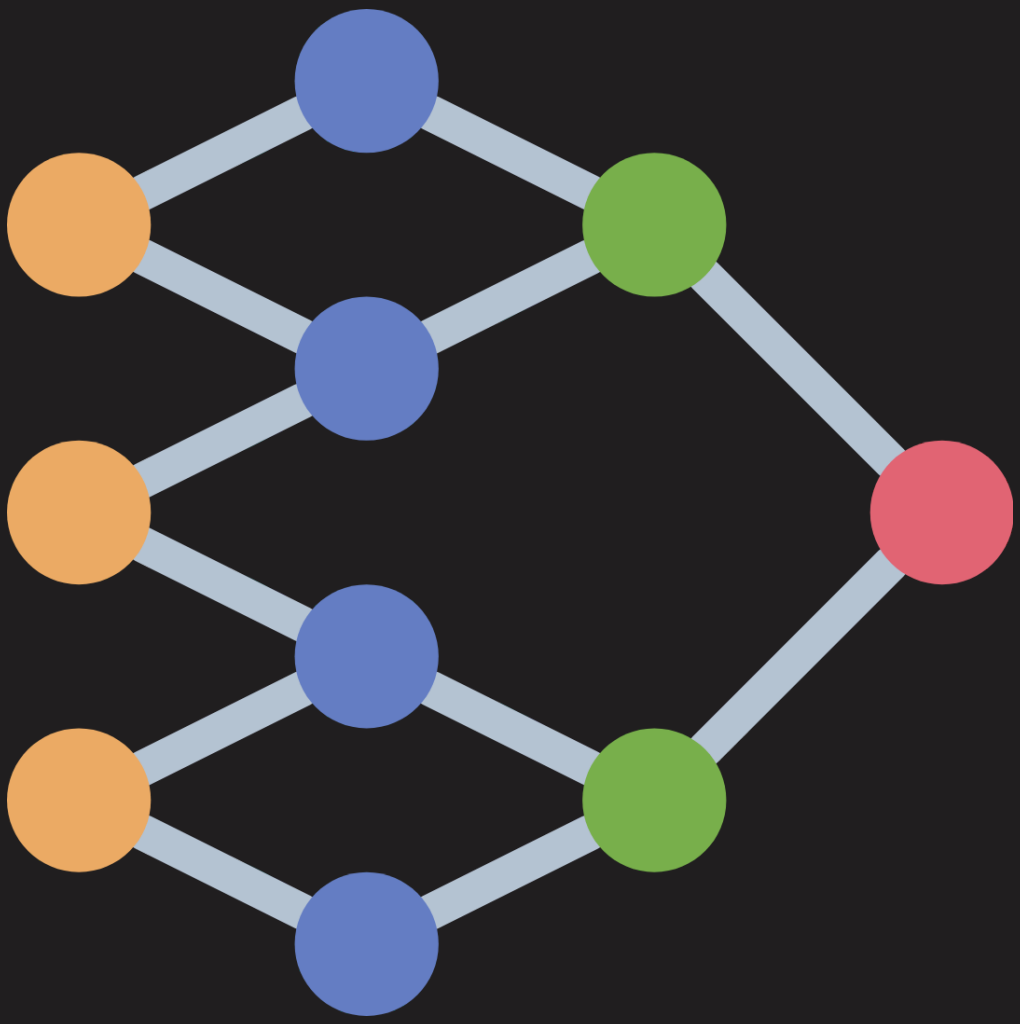
TensorFlow: Neural Networks



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1. Introduction to TensorFlow and Environment Configuration

What is TensorFlow?

TensorFlow is an open source library developed by Google for machine learning and artificial intelligence. It is mainly used to build and train neural network models. TensorFlow provides tools and resources to work with data, define and train models, and deploy them to production.

Installing TensorFlow

To install TensorFlow, you first need to have Python installed. You can install TensorFlow using pip, the Python package manager. Here are the basic steps:

1. Open a terminal or command line.
2. Ensure you have the latest version of pip, `[ pip install --upgrade pip ]`.
3. Install TensorFlow, `[ pip install tensorflow ]`.

Work Environment Configuration

It is recommended to use Google Colab to experiment and develop models with TensorFlow.

2. Basic Concepts of Neural Networks

What is a Neural Network?

A neural network is a computational model inspired by the structure and functioning of the human brain. It is made up of layers of artificial neurons, which are computing units that process and transmit information.

Types of Neural Networks

1. **Artificial Neural Networks (ANN)**: Basic networks with fully connected layers.
2. **Convolutional Neural Networks (CNN):** Mainly used for image processing.
3. **Recurrent Neural Networks (RNN):** Used for sequential data such as text and time series.

Basic Components

1. **Neurons:** Computing units that apply an activation function to a weighted sum of their inputs.
2. **Layers**: Set of neurons. The layers are classified as input, hidden and output.
3. **Weights and Biases**: Adjustable parameters that determine the output of neurons. The weights are multipliers of the inputs and the biases are values added to the outputs.

3. First Neural Network Model with TensorFlow

Structure of a Model in TensorFlow

TensorFlow provides the Keras API, which makes it easy to create models. The simplest way to build a model is to use the Sequential API, which allows layers to be stacked sequentially.

Creating a Simple Model with Sequential API

Let's create a basic model to classify handwritten digits (MNIST dataset).

1. Import libraries

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.datasets import mnist
```

2. Load and prepare data

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

3. Define the model

```
model = Sequential([
    Flatten(input_shape=(28, 28)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])
```

4. Compiles the model, defines the optimizer, loss function, and metrics.

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

5. Train model, fit the model parameters to the training data.

```
model.fit(x_train, y_train, epochs=5)
```

6. Evaluate the model, evaluate model performance on test data.

```
model.evaluate(x_test, y_test)
```

4. Data Management and Preprocessing

Importing and Manipulating Data with TensorFlow and Pandas

To build effective models, it is crucial to import and preprocess data properly.

Data Import:

With TensorFlow

```
import tensorflow as tf
from tensorflow.keras.datasets import mnist

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

With Pandas

```
import pandas as pd

data = pd.read_csv('data.csv')
```

Data manipulation:

With Pandas

```
# View the first rows of the dataframe
print(data.head())

# Select specific columns
x = data[['feature1', 'feature2']]
y = data['label']
```

Data Normalization and Standardization

Normalization and standardization are preprocessing techniques for scaling data.

Normalization

Scales the feature values so that they are between 0 and 1.

```
x_train = x_train / 255.0
x_test = x_test / 255.0
```

Standardization

Adjusts feature values so that they have a mean of 0 and a standard deviation of 1.

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

Split Data into Training, Validation and Test Sets

Splitting the data correctly is essential to evaluate model performance.

```
from sklearn.model_selection import train_test_split

x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.2, random_state=42)
```

5. Deep Neural Networks (DNN)

Creation of Deep Neural Networks

DNNs consist of multiple hidden layers between the input layer and the output layer.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

model = Sequential([
    Dense(128, activation='relu', input_shape=(input_dim,)),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])
```

Hyperparameter Tuning

Hyperparameters are parameters that are tuned before training.

Number of Layers and Neurons

More layers/neurons can capture more complexity, but can lead to overfitting.

Activation Features

ReLU (Rectified Linear Unit) is common in hidden layers.
Softmax is common in the output layer for classification.

```
model = Sequential([
    Dense(128, activation='relu', input_shape=(input_dim,)),
    Dense(64, activation='relu'),
    Dense(32, activation='relu'),
    Dense(10, activation='softmax')
])
```

Regularization (Dropout, L2 Regularization)

To avoid overfitting, regularization techniques are used.

Dropout. Randomly deactivates a fraction of the neurons during training.

```
from tensorflow.keras.layers import Dropout

model = Sequential([
    Dense(128, activation='relu', input_shape=(input_dim,)),
    Dropout(0.5),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
```

L2 Regularization. Adds a penalty term to the cost based on the size of the weights.

```
from tensorflow.keras.regularizers import l2

model = Sequential([
    Dense(128, activation='relu', input_shape=(input_dim,), kernel_regularizer=l2(0.01)),
    Dense(64, activation='relu', kernel_regularizer=l2(0.01)),
    Dense(10, activation='softmax')
])
```

6. Model Training and Optimization

Loss Functions and Optimizers

The loss function measures the error of the model, and the optimizer adjusts the weights to minimize this error.

Loss Functions:

`'sparse_categorical_crossentropy'` for categorical classification.

`'mean_squared_error'` for regression.

Optimizers

SGD (Stochastic Gradient Descent):

```
optimizer = tf.keras.optimizers.SGD(learning_rate=0.01)
```

Adam: Combine the advantages of AdaGrad and RMSProp.

```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
```

Optimization techniques

SGD: Updates weights using a subset of data.
Adam: Adjust the learning rate values for each parameter.

Callbacks (early stopping, ModelCheckpoint)

Callbacks allow you to perform actions during training.

Early Stopping. Stops training if the metric does not improve after a fixed number of epochs.

```
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(monitor='val_loss', patience=3)
```

ModelCheckpoint: Saves the model after each epoch if it has improved.

```
from tensorflow.keras.callbacks import ModelCheckpoint

checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss', save_best_only=True)
```

Example of Training with Callbacks

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

model.fit(x_train, y_train,
          validation_data=(x_val, y_val),
          epochs=20,
          callbacks=[early_stopping, checkpoint])
```

7. Visualization and Analysis of Results

Viewing Training History

During training, it is important to monitor how metrics such as precision and loss evolve. TensorFlow allows you to visualize these metrics using the training history.

```
history = model.fit(x_train, y_train,
                    validation_data=(x_val, y_val),
                    epochs=20,
                    callbacks=[early_stopping, checkpoint])
```

We can use Matplotlib to visualize the training history

```
import matplotlib.pyplot as plt

# Pérdida de entrenamiento y validación
plt.plot(history.history['loss'], label='train_loss')
plt.plot(history.history['val_loss'], label='val_loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Precisión de entrenamiento y validación
plt.plot(history.history['accuracy'], label='train_accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

Interpretation of Evaluation Metrics. It is essential to understand the metrics to evaluate the performance of the model:

1. **Accuracy:** Proportion of correct predictions.
2. **Loss:** Measurement of model error.
3. **Precision, Recall, F1-score:** Especially useful for imbalanced classification problems.

8. Convolutional Neural Networks (CNN)

Introduction to CNNs

CNNs are especially effective for computer vision tasks such as image classification. They use convolutional layers to extract local features from images.

Architecture of a CNN

1. **Convolutional Layers:** They apply filters to extract features.
2. **Pooling Layers:** Reduce dimensionality.
3. **Dense Layers:** Perform the final classification.

Implementation of a CNN for Image Classification. We are going to build a CNN to classify images from the CIFAR-10 dataset.

Load and prepare data.

```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

Define the model.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(128, (3, 3), activation='relu'),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])
```

Compile and train the model.

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

model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))
```

9. Recurrent Neural Networks (RNN) and LSTM

Introduction to RNNs and LSTMs

RNNs are suitable for sequential data, such as text and time series. LSTMs (Long Short-Term Memory) are a type of RNN that can learn long-term dependencies.

Applications of RNN and LSTM

1. **Natural Language Processing (NLP):** Sentiment analysis, machine translation.
2. **Time Series:** Prediction of future values in time series.

Creating an LSTM Model with TensorFlow

Let's create an LSTM model to predict a time series.

Generate example data:

```
import numpy as np

# Crear una serie temporal simple
def generate_time_series(batch_size, n_steps):
    freq1, freq2, offsets1, offsets2 = np.random.rand(4, batch_size, 1)
    time = np.linspace(0, 1, n_steps)
    series = 0.5 * np.sin((time - offsets1) * (freq1 * 10 + 10))
    series += 0.2 * np.sin((time - offsets2) * (freq2 * 20 + 20))
    series += 0.1 * (np.random.rand(batch_size, n_steps) - 0.5)
    return series[..., np.newaxis]

n_steps = 50
series = generate_time_series(10000, n_steps + 1)
x_train, y_train = series[:7000, :n_steps], series[:7000, -1]
x_valid, y_valid = series[7000:9000, :n_steps], series[7000:9000, -1]
x_test, y_test = series[9000:, :n_steps], series[9000:, -1]
```

Define the LSTM model:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

model = Sequential([
    LSTM(50, return_sequences=True, input_shape=[None, 1]),
    LSTM(50),
    Dense(1)
])
```

Compile and train the model:

```
model.compile(optimizer='adam', loss='mse')
model.fit(x_train, y_train, epochs=20, validation_data=(x_valid, y_valid))
```