Oishi_136_Lab3

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Lab 3 Back Propagation

Imagine you are building a neural network model to classify handwritten digits from the MNIST dataset. The architecture of your network consists of an input layer with 784 neurons (one for each pixel in a 28x28 image), one hidden layer with 128 neurons, and an output layer with 10 neurons (one for each digit from 0 to 9). You are using the ReLU activation function for the hidden layer and the softmax activation function for the output layer. During the training process, you notice that the loss function (categorical cross-entropy) is not decreasing as expected after several epochs. To investigate, you decide to analyze the backpropagation process in your model. Imagine you are building a neural network model to classify handwritten digits from the MNIST dataset.

[1]:
```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import CategoricalCrossentropy
from tensorflow.keras.datasets import mnist
from tensorflow.keras.utils import to_categorical

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

x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
model = Sequential()

model.add(Flatten(input_shape=(28, 28)))

model.add(Dense(128, activation='relu'))

model.add(Dense(10, activation='softmax'))

model.compile(optimizer=Adam(),
              loss=CategoricalCrossentropy(),
              metrics=['accuracy'])
```

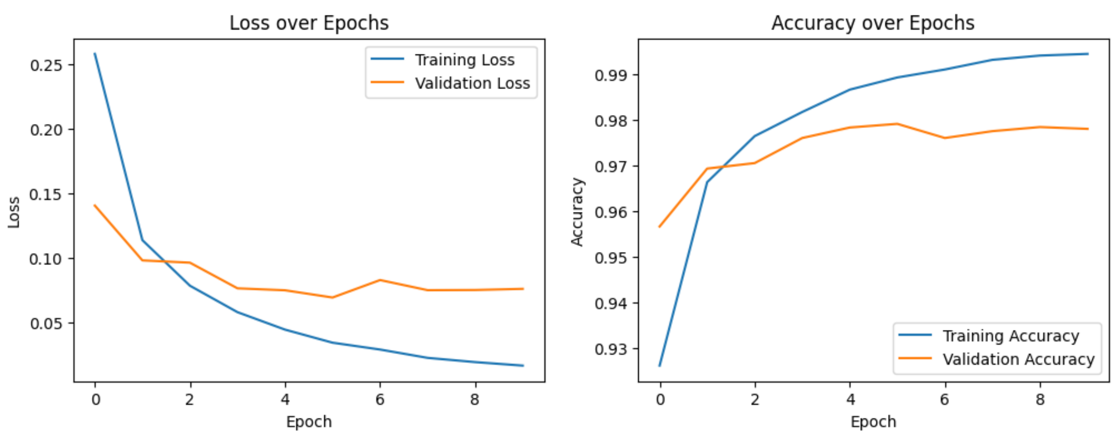
```python
history = model.fit(x_train, y_train, validation_data=(x_test, y_test),␣
↪epochs=10, batch_size=32)

loss = history.history['loss']
val_loss = history.history['val_loss']
accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']


print("Final training loss:", loss[-1])
print("Final validation loss:", val_loss[-1])

import matplotlib.pyplot as plt

plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/mnist.npz
11490434/11490434            3s
0us/step
```

```
C:\Users\USER\AppData\Roaming\Python\Python312\site-
packages\keras\src\layers\reshaping\flatten.py:37: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

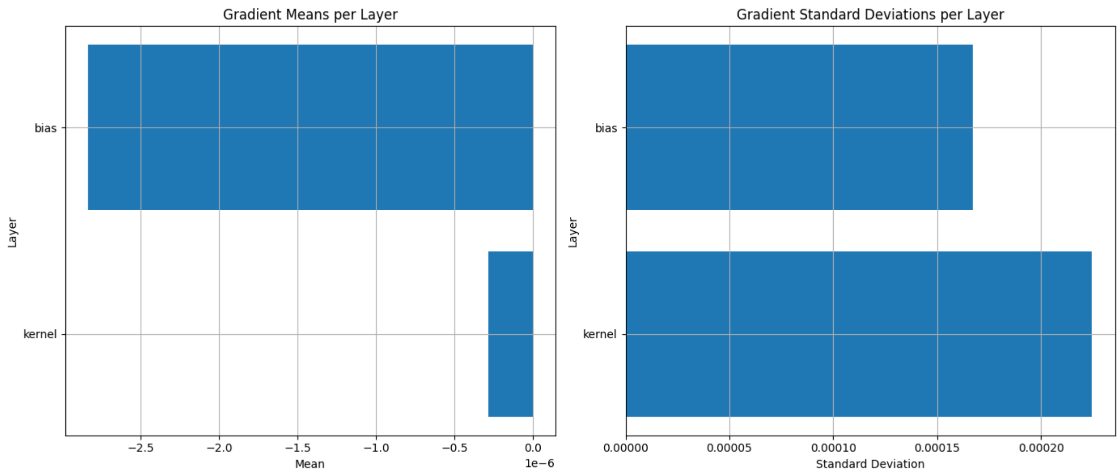
```
Epoch 1/10
1875/1875            9s 4ms/step -
accuracy: 0.8796 - loss: 0.4189 - val_accuracy: 0.9566 - val_loss: 0.1406
Epoch 2/10
```

```
1875/1875            7s 4ms/step -
accuracy: 0.9645 - loss: 0.1198 - val_accuracy: 0.9693 - val_loss: 0.0982
Epoch 3/10
1875/1875            6s 3ms/step -
accuracy: 0.9776 - loss: 0.0785 - val_accuracy: 0.9705 - val_loss: 0.0964
Epoch 4/10
1875/1875            6s 3ms/step -
accuracy: 0.9826 - loss: 0.0571 - val_accuracy: 0.9760 - val_loss: 0.0765
Epoch 5/10
1875/1875            11s 4ms/step -
accuracy: 0.9874 - loss: 0.0416 - val_accuracy: 0.9783 - val_loss: 0.0750
Epoch 6/10
1875/1875            7s 4ms/step -
accuracy: 0.9895 - loss: 0.0338 - val_accuracy: 0.9791 - val_loss: 0.0694
Epoch 7/10
1875/1875            6s 3ms/step -
accuracy: 0.9930 - loss: 0.0249 - val_accuracy: 0.9760 - val_loss: 0.0829
Epoch 8/10
1875/1875            6s 3ms/step -
accuracy: 0.9939 - loss: 0.0210 - val_accuracy: 0.9775 - val_loss: 0.0751
Epoch 9/10
1875/1875            6s 3ms/step -
accuracy: 0.9949 - loss: 0.0171 - val_accuracy: 0.9784 - val_loss: 0.0752
Epoch 10/10
1875/1875            7s 3ms/step -
accuracy: 0.9954 - loss: 0.0143 - val_accuracy: 0.9780 - val_loss: 0.0761
Final training loss: 0.016716450452804565
Final validation loss: 0.07613139599561691
```



The model performs well in terms of both training and validation accuracy, reaching nearly 100% training accuracy and stabilizing around 97.8% validation accuracy. The training loss steadily decreases, indicating effective learning, while the validation loss decreases initially but plateaus after about six epochs, suggesting the model may be slightly overfitting. The small gap between training and validation loss and accuracy indicates that overfitting is minimal but present. To improve generalization further, techniques like early stopping, dropout, or hyperparameter tuning could be considered. Overall, the model is well-trained and exhibits strong performance on unseen data, with room for slight optimization.

[2]:
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt

with tf.GradientTape() as tape:
    predictions = model(x_train[:32])
    loss_value = CategoricalCrossentropy()(y_train[:32], predictions)
grads = tape.gradient(loss_value, model.trainable_variables)

grad_means = []
grad_stds = []
layer_names = []

for var, grad in zip(model.trainable_variables, grads):
    grad_means.append(np.mean(grad))
    grad_stds.append(np.std(grad))
    layer_names.append(var.name)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.barh(layer_names, grad_means)
plt.title('Gradient Means per Layer')
plt.xlabel('Mean')
plt.ylabel('Layer')
plt.grid(True)

plt.subplot(1, 2, 2)
plt.barh(layer_names, grad_stds)
plt.title('Gradient Standard Deviations per Layer')
plt.xlabel('Standard Deviation')
plt.ylabel('Layer')
plt.grid(True)

plt.tight_layout()
plt.show()
```


Gradient Means per Layer
bias
kernel
Layer
−2.5
−2.0
−1.5
−1.0
−0.5
0.0
1e−6
Mean
Gradient Standard Deviations per Layer
bias
kernel
Layer
0.00000
0.00005
0.00010
0.00015
0.00020
Standard Deviation