Tanawin-st123975-alexnet-cifar100

October 30, 2023

```
[15]: !nvidia-smi
    Mon Oct 30 04:20:53 2023
    +-----+
    | NVIDIA-SMI 525.105.17 | Driver Version: 525.105.17 | CUDA Version: 12.0
    l------
                  Persistence-M| Bus-Id
                                      Disp.A | Volatile Uncorr. ECC |
    | Fan Temp Perf Pwr:Usage/Cap| Memory-Usage | GPU-Util Compute M. |
    |------
     0 Tesla T4
                      Off | 00000000:00:04.0 Off |
    | N/A 61C PO 28W / 70W | 2987MiB / 15360MiB |
                                                0% Default |
                          N/A |
    +----+
    | Processes:
                                                      GPU Memory |
    | GPU
         GI CI
                    PID Type Process name
          TD
                                                      Usage
[16]: import tensorflow as tf
    from tensorflow.keras import datasets, layers, models
    from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D,

→MaxPooling2D

    import matplotlib.pyplot as plt
    from tensorflow.keras.callbacks import LearningRateScheduler
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.regularizers import 12
    from tensorflow.keras import regularizers
    from tensorflow.keras.optimizers import SGD
[17]: # Check if GPU is available
    print("Num GPUs Available: ", len(tf.config.experimental.
     ⇔list_physical_devices('GPU')))
```

```
print("Keras GPU Available: ", tf.test.is_built_with_cuda())
     Num GPUs Available: 1
     Keras GPU Available: True
[18]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
      # Load CIFAR-100 data
      (train_images, train_labels), (test_images, test_labels) = datasets.cifar100.
       →load_data()
      # Normalize pixel values to be between 0 and 1
      train_images, test_images = train_images / 255.0, test_images / 255.0
      # Apply data augmentation to the training data
      datagen = ImageDataGenerator(
          rotation_range=40, # Degree range for random rotations
          width_shift_range=0.2, # Range for random horizontal shifts
          height shift range=0.2, # Range for random vertical shifts
          shear range=0.2, # Shear Intensity
          zoom range=0.2, # Range for random zoom
          horizontal_flip=True, # Randomly flip inputs horizontally
          fill_mode='nearest' # Strategy for filling in newly created pixels
      )
      datagen.fit(train_images)
[19]: def scheduler(epoch, lr):
          if epoch < 10:</pre>
              return lr
          else:
              return lr * tf.math.exp(-0.1)
[20]: from tensorflow.keras import models
      from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
       →Dropout, BatchNormalization
      from tensorflow.keras import regularizers
      # Initialize the model
      model = models.Sequential()
      # Add layers with increased regularization and batch normalization
      model.add(Conv2D(64, (3, 3), padding='same', activation='relu', __
       ⇔input_shape=(32, 32, 3)))
      model.add(BatchNormalization())
      model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
```

Check if Keras is using GPU

```
model.add(BatchNormalization())
model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(256, (3, 3), padding='same', activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(512, activation='relu', kernel_regularizer=regularizers.12(0.
 →001)))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(512, activation='relu', kernel_regularizer=regularizers.12(0.
 →001)))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(100, activation='softmax'))
# Compile the model with a lower learning rate and batch normalization
opt = Adam(learning_rate=0.001)
model.compile(optimizer=opt,
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
# # Compile the model with a lower learning rate and batch normalization
# opt = SGD(learning_rate=0.01, momentum=0.9) # Set your desired learning rate_
→and momentum
# model.compile(optimizer=opt,
                loss='sparse_categorical_crossentropy',
```

```
metrics=['accuracy'])
[21]: from tensorflow.keras.callbacks import EarlyStopping
     early_stopping = EarlyStopping(monitor='val_loss', patience=5,_
      →restore_best_weights=True)
[22]: batch_size = 64  # Set your desired batch size
     # Train the model with the specified batch size
     history = model.fit(train_images, train_labels,
                        batch_size=batch_size,
                        epochs=50,
                        validation_data=(test_images, test_labels),
                        callbacks=[early stopping])
     model.save('my_cifar100_model.h5')
    Epoch 1/50
    782/782 [============= ] - 28s 28ms/step - loss: 5.2554 -
    accuracy: 0.0822 - val_loss: 4.4392 - val_accuracy: 0.1470
    Epoch 2/50
    782/782 [============ ] - 21s 27ms/step - loss: 4.0299 -
    accuracy: 0.1805 - val_loss: 4.1300 - val_accuracy: 0.1904
    Epoch 3/50
    782/782 [============= ] - 21s 26ms/step - loss: 3.4609 -
    accuracy: 0.2675 - val_loss: 3.7548 - val_accuracy: 0.2515
    Epoch 4/50
    782/782 [============= ] - 21s 27ms/step - loss: 3.1490 -
    accuracy: 0.3360 - val_loss: 3.1101 - val_accuracy: 0.3580
    Epoch 5/50
    782/782 [============ ] - 21s 27ms/step - loss: 2.9304 -
    accuracy: 0.3959 - val loss: 2.7861 - val accuracy: 0.4306
    782/782 [============= ] - 21s 27ms/step - loss: 2.7538 -
    accuracy: 0.4445 - val_loss: 2.7502 - val_accuracy: 0.4627
    Epoch 7/50
    782/782 [============= ] - 21s 27ms/step - loss: 2.5787 -
    accuracy: 0.4892 - val_loss: 2.6522 - val_accuracy: 0.4776
    Epoch 8/50
    782/782 [============= ] - 21s 26ms/step - loss: 2.4354 -
    accuracy: 0.5317 - val_loss: 2.6823 - val_accuracy: 0.4905
    Epoch 9/50
    782/782 [============= ] - 21s 26ms/step - loss: 2.2994 -
    accuracy: 0.5709 - val_loss: 2.6105 - val_accuracy: 0.5226
    Epoch 10/50
```

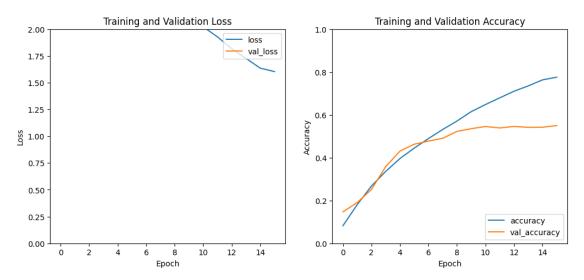
```
accuracy: 0.6149 - val_loss: 2.5657 - val_accuracy: 0.5354
     Epoch 11/50
     782/782 [============= ] - 21s 27ms/step - loss: 2.0215 -
     accuracy: 0.6481 - val_loss: 2.5602 - val_accuracy: 0.5455
     Epoch 12/50
     782/782 [============= ] - 21s 27ms/step - loss: 1.9278 -
     accuracy: 0.6792 - val_loss: 2.6559 - val_accuracy: 0.5387
     Epoch 13/50
     782/782 [============= ] - 21s 27ms/step - loss: 1.8172 -
     accuracy: 0.7101 - val_loss: 2.6752 - val_accuracy: 0.5459
     Epoch 14/50
     782/782 [============= ] - 22s 28ms/step - loss: 1.7270 -
     accuracy: 0.7351 - val_loss: 2.7542 - val_accuracy: 0.5416
     782/782 [============ ] - 21s 27ms/step - loss: 1.6359 -
     accuracy: 0.7632 - val_loss: 2.7685 - val_accuracy: 0.5422
     Epoch 16/50
     782/782 [============= ] - 21s 27ms/step - loss: 1.6039 -
     accuracy: 0.7757 - val_loss: 2.7748 - val_accuracy: 0.5500
     /usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079:
     UserWarning: You are saving your model as an HDF5 file via `model.save()`. This
     file format is considered legacy. We recommend using instead the native Keras
     format, e.g. `model.save('my model.keras')`.
       saving_api.save_model(
[23]: # Evaluate the model
     test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
     print('\nTest accuracy:', test_acc)
     # Plot the training and validation accuracy and loss
     plt.figure(figsize=(12, 5))
     # Plot training and validation accuracy
     plt.subplot(1, 2, 2)
     plt.plot(history.history['accuracy'], label='accuracy')
     plt.plot(history.history['val_accuracy'], label='val_accuracy')
     plt.xlabel('Epoch')
     plt.ylabel('Accuracy')
     plt.title('Training and Validation Accuracy')
     plt.ylim([0, 1])
     plt.legend(loc='lower right')
     # Plot training and validation loss
     plt.subplot(1, 2, 1)
     plt.plot(history.history['loss'], label='loss')
     plt.plot(history.history['val_loss'], label='val_loss')
```

782/782 [=============] - 21s 27ms/step - loss: 2.1482 -

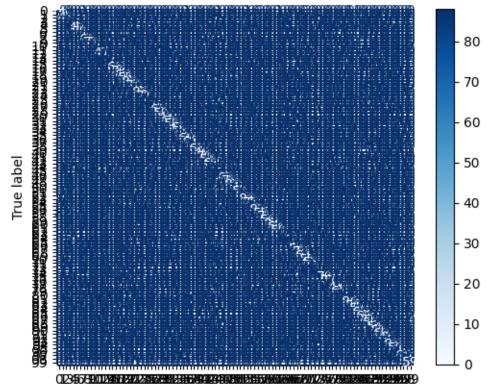
```
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.ylim([0, 2]) # Adjust the y-axis limits as needed
plt.legend(loc='upper right')
plt.show()
```

313/313 - 1s - loss: 2.5602 - accuracy: 0.5455 - 1s/epoch - 5ms/step

Test accuracy: 0.5454999804496765



313/313 [===========] - 1s 4ms/step



Predicted label