

Spring 2024: CS5720

Neural Networks & Deep Learning - ICP-8

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GitHub Link:

<https://github.com/vishnutejaayyangar/ICP-8>

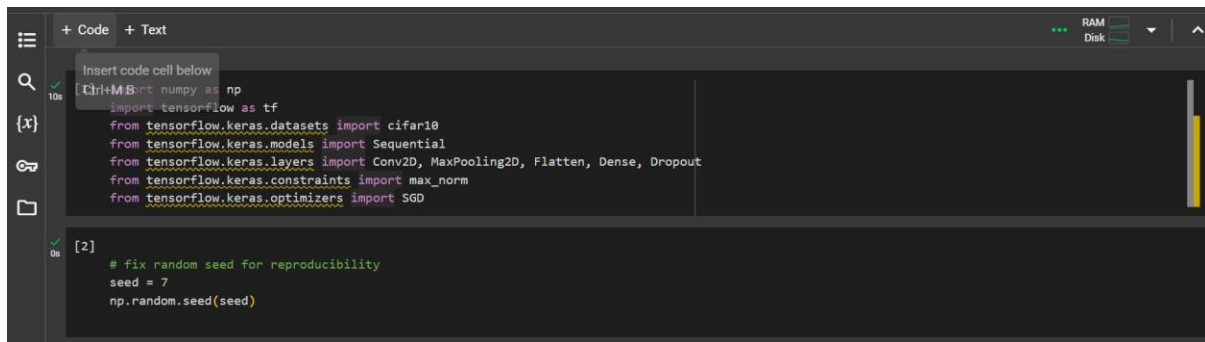
Video Link:

https://drive.google.com/drive/u/3/folders/16aBivXonHIsMIdwVCPYxS6oywy_IS21X

Use Case Description:

LeNet5, AlexNet, Vgg16, Vgg19

1. Training the model
2. Evaluating the model



The screenshot shows a Jupyter Notebook interface with a dark theme. The top bar includes a menu with '+ Code' and '+ Text', and system status indicators for RAM and Disk. The left sidebar contains icons for file explorer, search, and other notebook functions. The main area displays two code cells. The first cell, labeled '[1]', contains imports for numpy, tensorflow, tensorflow.keras.datasets, tensorflow.keras.models, tensorflow.keras.layers, tensorflow.keras.constraints, and tensorflow.keras.optimizers. The second cell, labeled '[2]', contains code to fix a random seed for reproducibility by setting seed = 7 and using np.random.seed(seed).

```
+ Code + Text
RAM
Disk

Insert code cell below
[1] In [ ]: import numpy as np
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.constraints import max_norm
from tensorflow.keras.optimizers import SGD

[2] In [ ]: # fix random seed for reproducibility
seed = 7
np.random.seed(seed)
```

```

✓ [3] # load data
8s (X_train, y_train), (X_test, y_test) = cifar10.load_data()

# normalize inputs from 0-255 to 0.0-1.0
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train = X_train / 255.0
X_test = X_test / 255.0

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [=====] - 2s 0us/step

```

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✓ [4] # one-hot encode outputs
0s #num_classes = 10 # Since CIFAR-10 has 10 classes
y_train = tf.keras.utils.to_categorical(y_train, num_classes = 10)
y_test = tf.keras.utils.to_categorical(y_test, num_classes = 10)
#num_classes = y_test.shape[1]

```

```

✓ # Create the model
0s model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=(32, 32, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(Dropout(0.2))
model.add(Conv2D(32, (3, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(Dropout(0.2))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(Dropout(0.2))
model.add(Conv2D(128, (3, 3), activation='relu', padding='same', kernel_constraint=max_norm(3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dropout(0.2))
model.add(Dense(1024, activation='relu', kernel_constraint=max_norm(3)))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu', kernel_constraint=max_norm(3)))
model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))

```

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✓ [6] # Compile model
0s epochs = 5
lr = 0.01
sgd = SGD(lr=lr, momentum=0.9, nesterov=False) # Remove decay parameter
model.compile(loss='categorical_crossentropy', optimizer=sgd, metrics=['accuracy'])
print(model.summary())

```

WARNING:absl:lr is deprecated in Keras optimizer, please use learning_rate or use the legacy optimizer, e.g., tf.keras.optimizers.legacy.SGD.
Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 32)	896
dropout (Dropout)	(None, 32, 32, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
dropout_1 (Dropout)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0

0s	conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
	dropout_2 (Dropout)	(None, 8, 8, 128)	0
	conv2d_5 (Conv2D)	(None, 8, 8, 128)	147584
	max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
	flatten (Flatten)	(None, 2048)	0
	dropout_3 (Dropout)	(None, 2048)	0
	dense (Dense)	(None, 1024)	2098176
	dropout_4 (Dropout)	(None, 1024)	0
	dense_1 (Dense)	(None, 512)	524800
	dropout_5 (Dropout)	(None, 512)	0
	dense_2 (Dense)	(None, 10)	5130
=====			
Total params: 2915114 (11.12 MB)			
Trainable params: 2915114 (11.12 MB)			
Non-trainable params: 0 (0.00 Byte)			
None			

```
[7] # Fit the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=epochs, batch_size=32)

# Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1] * 100))
```

Epoch 1/5
1563/1563 [=====] - 507s 323ms/step - loss: 1.8599 - accuracy: 0.3126 - val_loss: 1.4817 - val_accuracy: 0.4530
Epoch 2/5
1563/1563 [=====] - 522s 334ms/step - loss: 1.4269 - accuracy: 0.4810 - val_loss: 1.3270 - val_accuracy: 0.5192
Epoch 3/5
1563/1563 [=====] - 515s 329ms/step - loss: 1.2139 - accuracy: 0.5643 - val_loss: 1.0599 - val_accuracy: 0.6218
Epoch 4/5
1563/1563 [=====] - 520s 332ms/step - loss: 1.0560 - accuracy: 0.6258 - val_loss: 1.0832 - val_accuracy: 0.6197
Epoch 5/5
1563/1563 [=====] - 457s 293ms/step - loss: 0.9435 - accuracy: 0.6672 - val_loss: 0.8670 - val_accuracy: 0.6934
Accuracy: 69.34%

✓
0s

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[8] # Predict the first 4 test samples
num_samples_to_predict = 4
predictions = model.predict(X_test[:num_samples_to_predict])

# Convert predictions to class labels (assuming one-hot encoding)
predicted_labels = np.argmax(predictions, axis=1)

# Convert actual labels to class labels (assuming one-hot encoding)
actual_labels = np.argmax(y_test[:num_samples_to_predict], axis=1)

# Print the predicted and actual labels
print("Predicted Labels:", predicted_labels)
print("Actual Labels:", actual_labels)
```

```
1/1 [=====] - 0s 156ms/step
Predicted Labels: [3 1 0 0]
Actual Labels: [3 8 8 0]
```

✓
0s

```
[9] # Compare and print the results
for i in range(num_samples_to_predict):
    if predicted_labels[i] == actual_labels[i]:
        print(f"Image {i+1}: Predicted Correctly (Class {predicted_labels[i]})")
    else:
        print(f"Image {i+1}: Predicted Incorrectly (Predicted Class {predicted_labels[i]}, Actual Class {actual_labels[i]})")
```

```
Image 1: Predicted Correctly (Class 3)
Image 2: Predicted Incorrectly (Predicted Class 1, Actual Class 8)
Image 3: Predicted Incorrectly (Predicted Class 0, Actual Class 8)
Image 4: Predicted Correctly (Class 0)
```

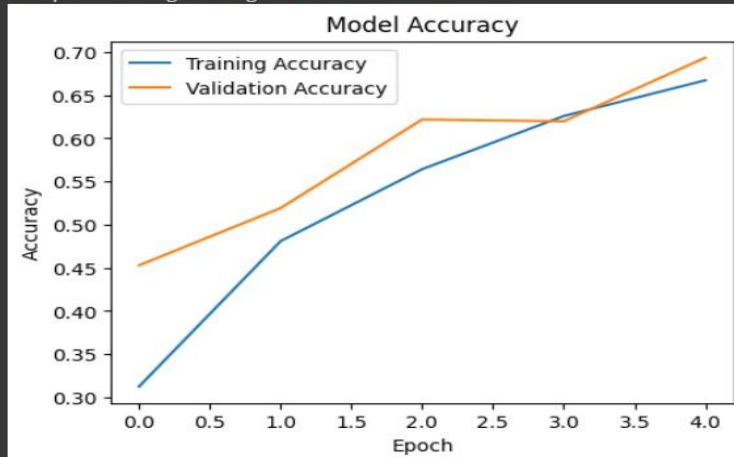
```

import matplotlib.pyplot as plt

# Plot training & validation accuracy values
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

```

<matplotlib.legend.Legend at 0x7b6018e5de40>



```

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()

```

