6.2.a ConvNet: CIFGAR10 image classifier

In [1]:
```
import os
from google.colab import drive
drive.mount('/content/drive', force_remount = True)
os.chdir('/content/drive/My Drive/DSC650/assignment06')
!pwd
```

```
Mounted at /content/drive
/content/drive/My Drive/DSC650/assignment06
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle

from keras import layers, models
from keras.datasets import cifar10
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from keras.utils import np_utils, to_categorical
from keras.optimizers import SGD

from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoi
```

In [3]:
```
(trainX, trainy), (testX, testy) = cifar10.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 5s 0us/step
```

In [4]:
```
# get the size of the data sets
print(f'train_images: {trainX.shape}')
print(f'test_images: {testX.shape}')
print(f'train_labels: {trainy.shape}')
print(f'test_labels: {testy.shape}')
```

```
train_images: (50000, 32, 32, 3)
test_images: (10000, 32, 32, 3)
train_labels: (50000, 1)
test_labels: (10000, 1)
```

In [5]:
```
# Assignment classes for visualization
cifar10_classes = ['airplane', 'automobile', 'bird', 'cat',
                   'deer', 'frog', 'horse', 'ship', 'truck']
```

Visualize sample images

In [6]:
```
fig, ax = plt.subplots(5, 5)
k = 0

for i in range(5):
  for j in range(5):
    ax[i][j].imshow(trainX[k], aspect = 'auto')
    k += 1

plt.show()
```

In [7]:
```
# normalize datasets
train_images = trainX.astype('float32') / 255.0
test_images = testX.astype('float32') / 255.0
```

In [8]:
```
# convert labels to numeric
train_labels = to_categorical(trainy)
test_labels = to_categorical(testy)
```

Split training data into training and validation datasets

In [9]:
```
x_val = train_images[:10000]
partial_x_train = train_images[10000:]

y_val = train_labels[:10000]
partial_y_train = train_labels[10000:]
```

In [10]:
```
# get the size of the data sets
print(f'x_val: {x_val.shape}')
print(f'y_val: {y_val.shape}')
print(f'partial_x_train: {partial_x_train.shape}')
print(f'partial_y_train: {partial_y_train.shape}')
```

```
x_val: (10000, 32, 32, 3)
y_val: (10000, 10)
partial_x_train: (40000, 32, 32, 3)
partial_y_train: (40000, 10)
```

Build the Model

In [11]:
```
# Instantiate a convnet
model = Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform'
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_unifor
model.add(layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_unifor
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
```

```
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(10, activation='softmax'))
```

In [12]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 32, 32, 32)        896

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        9248

 max_pooling2d (MaxPooling2D  (None, 16, 16, 32)       0
 )

 conv2d_2 (Conv2D)           (None, 16, 16, 64)        18496

 conv2d_3 (Conv2D)           (None, 16, 16, 64)        36928

 max_pooling2d_1 (MaxPooling  (None, 8, 8, 64)         0
 2D)

 conv2d_4 (Conv2D)           (None, 8, 8, 128)         73856

 conv2d_5 (Conv2D)           (None, 8, 8, 128)         147584

 max_pooling2d_2 (MaxPooling  (None, 4, 4, 128)        0
 2D)

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 128)               262272

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 550,570
Trainable params: 550,570
Non-trainable params: 0
_________________________________________________________________
```

Compile the Model

In [13]:
```
opt = SGD(lr = 0.001, momentum = 0.9)

model.compile(loss = 'categorical_crossentropy',
              optimizer = opt,
              metrics = ['accuracy'])
```

```
/usr/local/lib/python3.8/dist-packages/keras/optimizers/optimizer_v2/gradient_descen
t.py:108: UserWarning: The `lr` argument is deprecated, use `learning_rate` instead.
  super(SGD, self).__init__(name, **kwargs)
```

Train the model

In [15]:
```
history = model.fit(partial_x_train, partial_y_train,
                    epochs = 30, batch_size = 64,
                    validation_data=(x_val, y_val), verbose = 1)
```

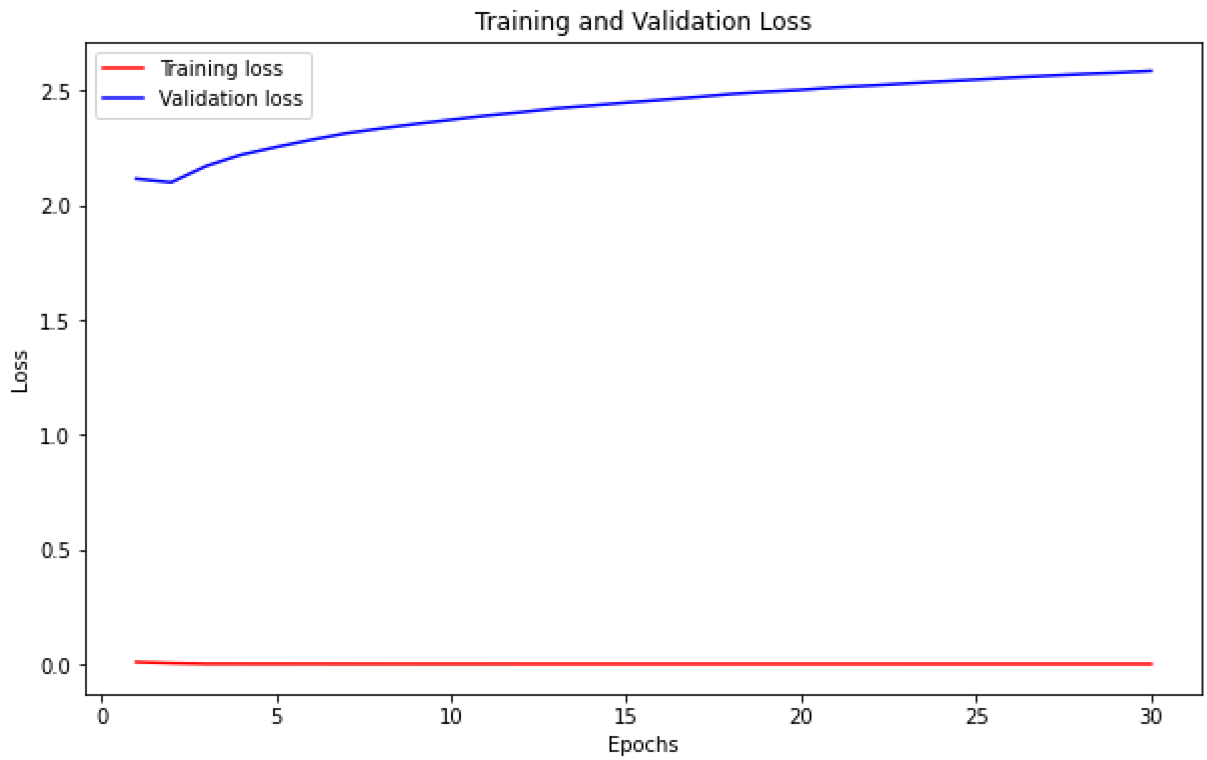
```
Epoch 1/30
625/625 [==============================] - 5s 8ms/step - loss: 0.0087 - accuracy: 0.9
982 - val_loss: 2.1163 - val_accuracy: 0.7056
Epoch 2/30
625/625 [==============================] - 5s 8ms/step - loss: 0.0037 - accuracy: 0.9
995 - val_loss: 2.1002 - val_accuracy: 0.7178
Epoch 3/30
625/625 [==============================] - 5s 8ms/step - loss: 8.5766e-04 - accuracy:
1.0000 - val_loss: 2.1715 - val_accuracy: 0.7185
Epoch 4/30
625/625 [==============================] - 5s 8ms/step - loss: 6.1604e-04 - accuracy:
1.0000 - val_loss: 2.2206 - val_accuracy: 0.7185
Epoch 5/30
625/625 [==============================] - 5s 8ms/step - loss: 5.1373e-04 - accuracy:
1.0000 - val_loss: 2.2542 - val_accuracy: 0.7185
Epoch 6/30
625/625 [==============================] - 5s 8ms/step - loss: 4.4353e-04 - accuracy:
1.0000 - val_loss: 2.2857 - val_accuracy: 0.7177
Epoch 7/30
625/625 [==============================] - 5s 8ms/step - loss: 3.9602e-04 - accuracy:
1.0000 - val_loss: 2.3142 - val_accuracy: 0.7192
Epoch 8/30
625/625 [==============================] - 5s 8ms/step - loss: 3.5685e-04 - accuracy:
1.0000 - val_loss: 2.3356 - val_accuracy: 0.7188
Epoch 9/30
625/625 [==============================] - 5s 8ms/step - loss: 3.2725e-04 - accuracy:
1.0000 - val_loss: 2.3555 - val_accuracy: 0.7184
Epoch 10/30
625/625 [==============================] - 5s 8ms/step - loss: 3.0244e-04 - accuracy:
1.0000 - val_loss: 2.3734 - val_accuracy: 0.7186
Epoch 11/30
625/625 [==============================] - 5s 8ms/step - loss: 2.8257e-04 - accuracy:
1.0000 - val_loss: 2.3912 - val_accuracy: 0.7188
Epoch 12/30
625/625 [==============================] - 5s 8ms/step - loss: 2.6384e-04 - accuracy:
1.0000 - val_loss: 2.4064 - val_accuracy: 0.7182
Epoch 13/30
625/625 [==============================] - 5s 8ms/step - loss: 2.4930e-04 - accuracy:
1.0000 - val_loss: 2.4231 - val_accuracy: 0.7183
Epoch 14/30
625/625 [==============================] - 5s 8ms/step - loss: 2.3504e-04 - accuracy:
1.0000 - val_loss: 2.4354 - val_accuracy: 0.7180
Epoch 15/30
625/625 [==============================] - 5s 8ms/step - loss: 2.2352e-04 - accuracy:
1.0000 - val_loss: 2.4484 - val_accuracy: 0.7175
Epoch 16/30
625/625 [==============================] - 6s 9ms/step - loss: 2.1282e-04 - accuracy:
1.0000 - val_loss: 2.4603 - val_accuracy: 0.7179
Epoch 17/30
625/625 [==============================] - 7s 11ms/step - loss: 2.0234e-04 - accurac
y: 1.0000 - val_loss: 2.4725 - val_accuracy: 0.7177
Epoch 18/30
625/625 [==============================] - 5s 8ms/step - loss: 1.9398e-04 - accuracy:
1.0000 - val_loss: 2.4859 - val_accuracy: 0.7176
Epoch 19/30
625/625 [==============================] - 5s 8ms/step - loss: 1.8657e-04 - accuracy:
1.0000 - val_loss: 2.4957 - val_accuracy: 0.7178
Epoch 20/30
625/625 [==============================] - 5s 8ms/step - loss: 1.7888e-04 - accuracy:
1.0000 - val_loss: 2.5039 - val_accuracy: 0.7177
```

```
Epoch 21/30
625/625 [==============================] - 5s 8ms/step - loss: 1.7195e-04 - accuracy:
1.0000 - val_loss: 2.5150 - val_accuracy: 0.7179
Epoch 22/30
625/625 [==============================] - 5s 8ms/step - loss: 1.6615e-04 - accuracy:
1.0000 - val_loss: 2.5228 - val_accuracy: 0.7180
Epoch 23/30
625/625 [==============================] - 5s 8ms/step - loss: 1.6032e-04 - accuracy:
1.0000 - val_loss: 2.5317 - val_accuracy: 0.7185
Epoch 24/30
625/625 [==============================] - 5s 8ms/step - loss: 1.5480e-04 - accuracy:
1.0000 - val_loss: 2.5409 - val_accuracy: 0.7175
Epoch 25/30
625/625 [==============================] - 5s 8ms/step - loss: 1.4990e-04 - accuracy:
1.0000 - val_loss: 2.5485 - val_accuracy: 0.7181
Epoch 26/30
625/625 [==============================] - 5s 8ms/step - loss: 1.4504e-04 - accuracy:
1.0000 - val_loss: 2.5576 - val_accuracy: 0.7174
Epoch 27/30
625/625 [==============================] - 5s 8ms/step - loss: 1.4059e-04 - accuracy:
1.0000 - val_loss: 2.5652 - val_accuracy: 0.7178
Epoch 28/30
625/625 [==============================] - 5s 8ms/step - loss: 1.3663e-04 - accuracy:
1.0000 - val_loss: 2.5728 - val_accuracy: 0.7176
Epoch 29/30
625/625 [==============================] - 6s 9ms/step - loss: 1.3282e-04 - accuracy:
1.0000 - val_loss: 2.5788 - val_accuracy: 0.7171
Epoch 30/30
625/625 [==============================] - 5s 8ms/step - loss: 1.2922e-04 - accuracy:
1.0000 - val_loss: 2.5868 - val_accuracy: 0.7175
```

Plot Training and Validation Loss

In [16]:

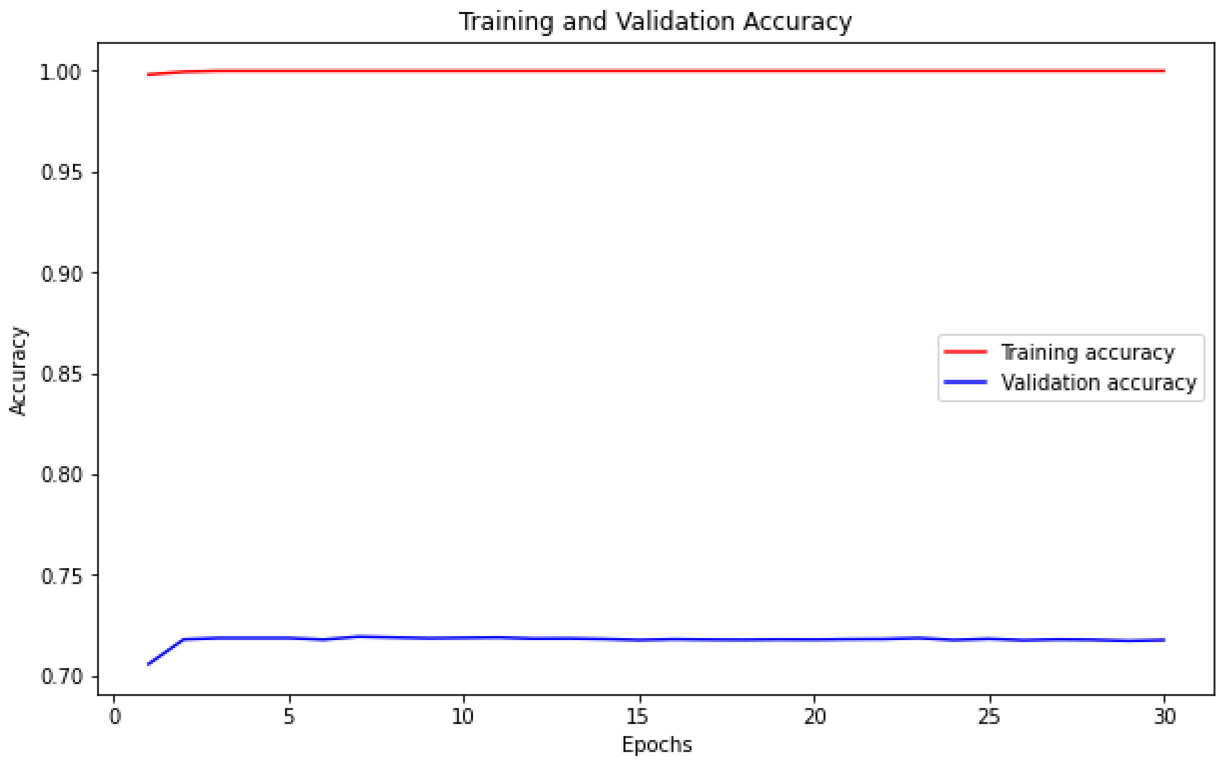
```
plt.figure(figsize = (10, 6))

loss_values = history.history['loss']
val_loss_values = history.history['val_loss']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, loss_values, 'r', label = 'Training loss')
plt.plot(epochs, val_loss_values, 'b', label = 'Validation loss')

plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')

plt.legend()

fig = plt.gcf()
fig.savefig('results/CIFGAR10/no/train_val_loss.png')

plt.show()
```



Plot Training and Validation accuracy

In [17]:
```
plt.clf()

plt.figure(figsize = (10, 6))

acc_values = history.history['accuracy']
val_acc_values = history.history['val_accuracy']

epochs = range(1, len(loss_values) + 1)

plt.plot(epochs, acc_values, 'r', label = 'Training accuracy')
plt.plot(epochs, val_acc_values, 'b', label = 'Validation accuracy')

plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')

plt.legend()

fig = plt.gcf()
fig.savefig('results/CIFGAR10/no/train_val_accuracy.png')

plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



Evaluate the Model

In [18]:
```
test_loss, test_acc = model.evaluate(test_images, test_labels)
```

```
313/313 [==============================] - 1s 4ms/step - loss: 2.7986 - accuracy: 0.7
098
```

In [19]:
```
print(f'Test accuracy: {test_acc * 100:.1f}%')
print(f'Test loss: {test_loss:.3f}')
```

```
Test accuracy: 71.0%
Test loss: 2.799
```

Predicting the test data

In [20]:
```
label_pred_test = model.predict(test_images)
label_pred_test_classes = np.argmax(label_pred_test, axis = 1)
label_pred_test_max_probability = np.max(label_pred_test, axis = 1)
```

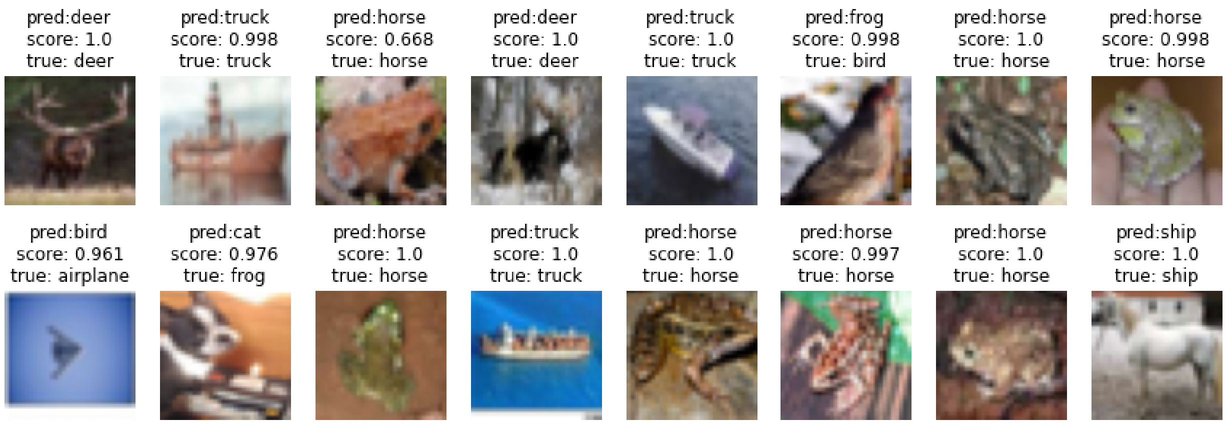
```
313/313 [==============================] - 1s 3ms/step
```

In [21]:
```
# Reverse test_labels from categorical
test_labels = np.argmax(test_labels, axis = 1)
```

Visualize predictions

In [22]:
```
cols = 8
rows = 2

fig = plt.figure(figsize = (2 * cols - 1, 3 * rows - 1))

for i in range(cols):
  for j in range(rows):
    random_index = np.random.randint(0, len(test_labels))
```

```
    ax = fig.add_subplot(rows, cols, i * rows + j + 1)

    ax.grid('off')
    ax.axis('off')

    ax.imshow(test_images[random_index, :])

    pred_label = cifar10_classes[label_pred_test_classes[random_index]]
    pred_probability = label_pred_test_max_probability[random_index]

    true_label = cifar10_classes[test_labels[random_index]]

    ax.set_title(f'pred:{pred_label}\nscore: {pred_probability:.3}\ntrue: {true_label
```



Save Model and Results

In [23]:
```
model.save('results/CIFGAR10/no/mnist.h5', history)
```

In [24]:
```
pickle.dump({'test_accuracy': test_acc,
            'test_loss': test_loss,
            'history_dict': history.history},
            open("results/CIFGAR10/no/training_metrics", "wb"))
```