Assignment 1: Multi-layer perceptron

Tensorflow's keras without using any of the TensorFlow specific features

```
import tensorflow as tf
from tensorflow import keras
import numpy as np
# from IPython.core.interactiveshell import InteractiveShell
# InteractiveShell.ast_node_interactivity = "all"
```

```
WARNING:tensorflow:From c:\Users\anson\anaconda3\Lib\site-packages\keras\src\losses.py
```

Data

Data: CIFAR-10

CIFAR-10 is an established computer-vision dataset used for object recognition. It is a subset of the 80 million tiny images dataset and consists of 60,000 32x32 **color images** containing one of 10 object classes, with 6000 images per class.

Labels are as follows:

airplane (0), automobile (1), bird (2), cat (3), deer (4), dog (5), frog (6), horse (7), ship (8), truck (9)

Source: https://www.kaggle.com/c/cifar-10

Q1. This dataset has been included in **keras.datasets.cifar10**. Please load the dataset and print the shape of training and testing sets.

```
from tensorflow.keras.datasets import cifar10

# Load the CIFAR-10 dataset
(train_images, train_labels), (test_images, test_labels) = cifar10.load_data()

# Print the shape of the training and testing sets
print(train_images.shape, train_labels.shape)
print(test_images.shape, test_labels.shape)
```

```
(50000, 32, 32, 3) (50000, 1)
(10000, 32, 32, 3) (10000, 1)
```

```
# when download the data from the webset we can do

import pickle
import numpy as np

def load_cifar_batch(file_path):
    with open(file_path, 'rb') as file:
        batch_data = pickle.load(file, encoding='bytes')
    return batch_data

def load_cifar_dataset(folder_path):
    # Load label names from batches.meta
    meta_path = folder_path + '/batches.meta'
    with open(meta_path, 'rb') as file:
        meta_data = pickle.load(file, encoding='bytes')
        label_names = [label.decode('utf-8') for label in meta_data[b'label_names']]

    # Load and concatenate all data batches
    batches = ['data_batch_1', 'data_batch_2', 'data_batch_3', 'data_batch_4', 'data_batch
    data = []
    labels = []

    for batch_name in batches:
        batch_path = f'{folder_path}/{batch_name}'
        batch_data = load_cifar_batch(batch_path)
        data.append(batch_data[b'data'])
        labels += batch_data[b'labels']

    # Stack all batches along the first axis
    train_images = np.vstack(data)
    train_labels = np.array(labels)

    # Load test batch
    test_path = f'{folder_path}/test_batch'
    test_data = load_cifar_batch(test_path)
    test_images = test_data[b'data']
    test_labels = np.array(test_data[b'labels'])

    return train_images, train_labels, test_images, test_labels, label_names

# Replace 'path/to/your/cifar-10-batches-py' with the actual path where you have extracted
cifar_folder_path = 'cifar-10-batches-py'

# Load the entire CIFAR-10 dataset
train_images, train_labels, test_images, test_labels, label_names = load_cifar_dataset(cif

# Display information about the loaded data
print("CIFAR-10 Dataset:")
print("Train Images shape:", train_images.shape)
print("Train Labels shape:", train_labels.shape)
print("Test Images shape:", test_images.shape)
print("Test Labels shape:", test_labels.shape)
print("Label names:", label_names)
```

```
CIFAR-10 Dataset:
Train Images shape: (50000, 3072)
Train Labels shape: (50000,)
Test Images shape: (10000, 3072)
Test Labels shape: (10000,)
Label names: ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',
```

```
# Reshape the image array, original data is build by channel first and then pixel so we ne
train_images = train_images.reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)
test_images = test_images.reshape(-1, 3, 32, 32).transpose(0, 2, 3, 1)
print("Train set shape: ",train_images.shape)
print("Test set shape: ",test_images.shape)
```

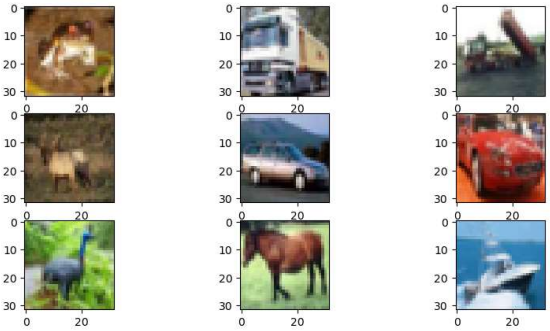
```
Train set shape:  (50000, 32, 32, 3)
Test set shape:  (10000, 32, 32, 3)
```

Q2. Show the first 9 instances of the training dataset.

```
import matplotlib.pyplot as plt

for i in range(9):
    plt.subplot(330 + 1 + i)
    plt.imshow(train_images[i], cmap=plt.get_cmap('Greys'))

plt.rcParams["figure.figsize"] = (10,5)
plt.show()
```



Q3. Convert the target labels (y) into the one-hot format and show the value (y) for the first instance of the training dataset.

```
num_cat = 10
y_train_categorical = keras.utils.to_categorical(train_labels, num_cat)
y_test_categorical = keras.utils.to_categorical(test_labels, num_cat)
y_train_categorical[0]
```

```
array([0., 0., 0., 0., 0., 0., 1., 0., 0., 0.], dtype=float32)
```

Q4. Create a validation dataset using the first 5,000 instances in the training dataset. Also, divide all input features (X values) in the train/test/validation sets by 255.0. Please show the y value for the first instance of the validation dataset.

```
X_val, X_train, X_test = train_images[:5000]/255.0 , train_images[5000:]/255.0, test_image
y_val, y_train = y_train_categorical[:5000], y_train_categorical[5000:]
y_val[0]
```

```
array([0., 0., 0., 0., 0., 0., 1., 0., 0., 0.], dtype=float32)
```

Model

Q5. Create a multi-layer perceptron model with 200 neurons in the first hidden layer and 100 neurons in the second hidden layer, and print the model summary.

Please note that the input images are color images with the shape of **32 * 32 * 3**. Here 3 shows RGB.

```
X_train.shape[1:]
```

```
(32, 32, 3)
```

```
model = keras.models.Sequential()
model.add(keras.layers.Flatten(input_shape=X_train.shape[1:], name='input'))
model.add(keras.layers.Dense(200, activation = "relu", name='layer_1'))
model.add(keras.layers.Dense(100, activation = "relu", name='layer_2'))
model.add(keras.layers.Dense(10, activation = "softmax", name='output'))
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
```

```
 Layer (type)                Output Shape              Param #
=================================================================
 input (Flatten)             (None, 3072)              0

 layer_1 (Dense)             (None, 200)               614600

 layer_2 (Dense)             (None, 100)               20100

 output (Dense)              (None, 10)                1010

=================================================================
Total params: 635710 (2.43 MB)
Trainable params: 635710 (2.43 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Q6. Create an Adam optimizer with a learning rate of 0.001, compile the model, and fit it on the training and validation datasets. Use the following hyperparameters: **batch_size=512, epochs=20**.

Hint: Adam optimizer can be imported by **keras.optimizers.Adam(learning_rate=0.001)**

```
learning_rate = 0.001
batch_size = 512
epochs = 20
```

```
X_train.shape
```

```
(45000, 32, 32, 3)
```

```
model.compile(loss = "categorical_crossentropy", optimizer = keras.optimizers.Adam(learnir
train_model = model.fit(X_train, y_train, batch_size = batch_size, epochs = epochs, valida
```

```
Epoch 1/20
88/88 [==============================] - 2s 13ms/step - loss: 2.0869 - accuracy: 0.248
Epoch 2/20
88/88 [==============================] - 1s 9ms/step - loss: 1.8434 - accuracy: 0.3532
Epoch 3/20
88/88 [==============================] - 1s 9ms/step - loss: 1.7658 - accuracy: 0.3789
Epoch 4/20
88/88 [==============================] - 1s 9ms/step - loss: 1.7065 - accuracy: 0.4002
Epoch 5/20
88/88 [==============================] - 1s 10ms/step - loss: 1.6641 - accuracy: 0.412
Epoch 6/20
88/88 [==============================] - 1s 9ms/step - loss: 1.6224 - accuracy: 0.4277
Epoch 7/20
88/88 [==============================] - 1s 9ms/step - loss: 1.5888 - accuracy: 0.4434
Epoch 8/20
88/88 [==============================] - 1s 9ms/step - loss: 1.5613 - accuracy: 0.4502
Epoch 9/20
88/88 [==============================] - 1s 9ms/step - loss: 1.5398 - accuracy: 0.4596
Epoch 10/20
```

```
88/88 [==============================] - 1s 9ms/step - loss: 1.5213 - accuracy: 0.4608
Epoch 11/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4968 - accuracy: 0.4737
Epoch 12/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4724 - accuracy: 0.4817
Epoch 13/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4610 - accuracy: 0.4841
Epoch 14/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4478 - accuracy: 0.4876
Epoch 15/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4329 - accuracy: 0.4929
Epoch 16/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4276 - accuracy: 0.4988
Epoch 17/20
88/88 [==============================] - 1s 9ms/step - loss: 1.4078 - accuracy: 0.5036
Epoch 18/20
88/88 [==============================] - 1s 9ms/step - loss: 1.3960 - accuracy: 0.5071
Epoch 19/20
88/88 [==============================] - 1s 9ms/step - loss: 1.3820 - accuracy: 0.5126
Epoch 20/20
88/88 [==============================] - 1s 9ms/step - loss: 1.3740 - accuracy: 0.5145
```

Performance

Q7. Evaluate your model.

```
model.evaluate(X_test, y_test_categorical)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 1.4554 - accuracy: 0.48
[1.4553706645965576, 0.487199991941452]
```

Q8. Show the predicted probabilities for the test dataset.

```
y_pred = model.predict(X_test)
y_pred.round(3)
```

```
313/313 [==============================] - 0s 962us/step
array([[0.011, 0.005, 0.081, ..., 0.   , 0.012, 0.   ],
       [0.052, 0.242, 0.001, ..., 0.   , 0.23 , 0.472],
       [0.275, 0.138, 0.002, ..., 0.002, 0.471, 0.105],
       ...,
       [0.003, 0.001, 0.086, ..., 0.065, 0.019, 0.004],
       [0.013, 0.002, 0.426, ..., 0.022, 0.003, 0.006],
       [0.087, 0.002, 0.156, ..., 0.33 , 0.007, 0.004]], dtype=float32)
```

Q9. Show the predicted labels for the test dataset.

```
y_pred_class = np.argmax(y_pred,axis=1) # the index of the maximum value along each row
y_pred_class
```

```
array([3, 9, 8, ..., 5, 2, 7], dtype=int64)
```

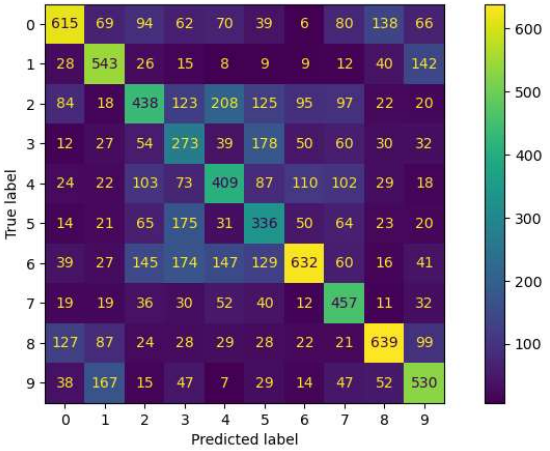
Q10. Show the confusion matrix.

```
y_test_categorical
```

```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 1., 0.],
       [0., 0., 0., ..., 0., 1., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 1., 0., 0.]], dtype=float32)
```

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cnf_matrix = confusion_matrix(y_pred_class, test_labels)
fig = ConfusionMatrixDisplay(confusion_matrix = cnf_matrix)
fig.plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatri
at 0x219c61f4250>
```

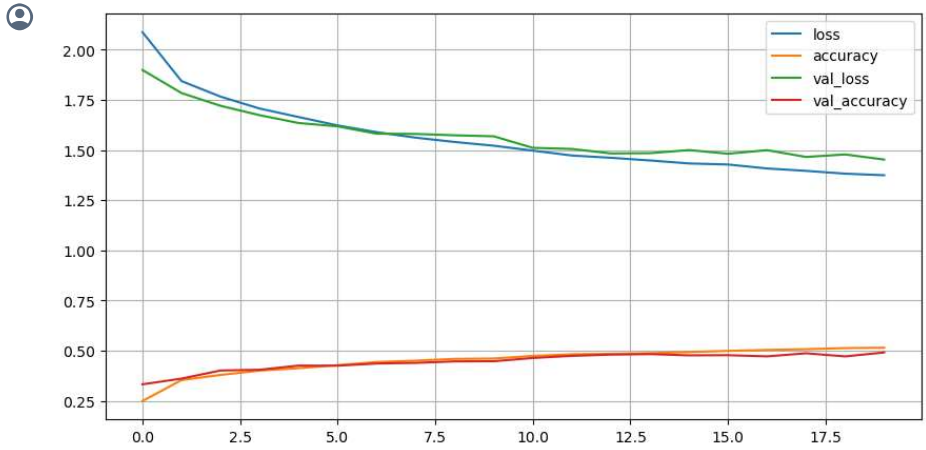


Post-analysis

Q11. Plot the loss and accuracy for the training and validation sets.

```
import pandas as pd
import matplotlib.pyplot as plt

pd.DataFrame(train_model.history).plot(figsize=(10, 5))
plt.grid(True)
plt.gca()    # axis
plt.show()
```



Q12. Show the first 9 images that the actual value is different from the predicted value.

```
test_labels.shape
```

```
(10000,)
```

```
errorCnt = 9
tCnt = 0
index  = 0

fig, axes = plt.subplots(3, 3)
fig.subplots_adjust(hspace=0.0001, wspace=0.0001) # to adjust the spacing between subplots

while tCnt < errorCnt and index < len(y_pred_class):
  if y_pred_class[index] != test_labels[index]:
    axes.flat[tCnt].imshow(X_test[index], cmap=plt.get_cmap('viridis'))
    axes.flat[tCnt].set_xlabel("Actual: " + label_names[test_labels[index]] + " - Predicted
    tCnt+=1
  index+=1
```

```
plt.tight_layout()
plt.rcParams["figure.figsize"] = (5,5)
plt.show()
```