Final Project AAI-551

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Introduction:

1. In this project, we build Convolutional Neural Network to classify CIFAR-10 Images.
2. We can directly load dataset from many deep learning packages.
3. We can use any deep learning packages such as pytorch, keras or tensorflow for this project.

Data analysis on CIFAR-10 Dataset

Loading the data

In [1]:
```
# Load Cifar-10 Data
# This is just an example, you may load dataset from other packages.
import keras
import numpy as np
import tensorflow.keras

### If you can not load keras dataset, un-comment these two lines.
#import ssl
#ssl._create_default_https_context = ssl._create_unverified_context

(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_dat

print('shape of x_train: ' + str(x_train.shape))
print('shape of y_train: ' + str(y_train.shape))
print('shape of x_test: ' + str(x_test.shape))
print('shape of y_test: ' + str(y_test.shape))
print('number of classes: ' + str(np.max(y_train) - np.min(y_train) +
```

```
shape of x_train: (50000, 32, 32, 3)
shape of y_train: (50000, 1)
shape of x_test: (10000, 32, 32, 3)
shape of y_test: (10000, 1)
number of classes: 10
```

One-hot encode the labels

In the input, a label is a scalar in $\{0, 1, \cdots, 9\}$. One-hot encode transform such a scalar to a 10-dim vector. E.g., a scalar `y_train[j]=3` is transformed to the vector `y_train_vec[j]=[0, 0, 0, 1, 0, 0, 0, 0, 0, 0]`.

In [2]:
```
def to_one_hot(y, num_class=10):
    y_new = []
    for val in y:
        tempArr = np.zeros(num_class)
        tempArr[val] = 1
        y_new.append(tempArr)

    return np.asarray(y_new)
    pass

x_train, x_test = x_train.astype('float32') / 255, x_test.astype('floa
y_train_vec = to_one_hot(y_train)
y_test_vec = to_one_hot(y_test)

print('Shape of y_train_vec: ' + str(y_train_vec.shape))
print('Shape of y_test_vec: ' + str(y_test_vec.shape))

print(y_train[0])
print(y_train_vec[0])
```

```
Shape of y_train_vec: (50000, 10)
Shape of y_test_vec: (10000, 10)
[6]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
```

**Randomly partition the training set to training and validation sets* * Randomly partition the 50K training samples to 2 sets:*

- a training set containing 40K samples: x_tr, y_tr
- a validation set containing 10K samples: x_val, y_val

In [3]:
```
from sklearn.model_selection import train_test_split

x_tr, x_val, y_tr, y_val = train_test_split(x_train,y_train_vec,test_s

print('Shape of x_tr: ' + str(x_tr.shape))
print('Shape of y_tr: ' + str(y_tr.shape))
print('Shape of x_val: ' + str(x_val.shape))
print('Shape of y_val: ' + str(y_val.shape))
```

```
Shape of x_tr: (40000, 32, 32, 3)
Shape of y_tr: (40000, 10)
Shape of x_val: (10000, 32, 32, 3)
Shape of y_val: (10000, 10)
```

Building a CNN and tunning its hyper-parameters

In [4]:
```
# Build the model
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from keras.models import Sequential

model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3
model.add(MaxPooling2D((2, 2)))

model.add(Conv2D(64, (4, 4), activation='relu'))
model.add(MaxPooling2D((2, 2)))

model.add(Flatten())
model.add(Dense(256, activation='relu'))

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

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 32)        896       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 15, 15, 32)       0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 12, 12, 64)        32832     
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 6, 6, 64)         0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 2304)              0         
                                                                 
 dense (Dense)               (None, 256)               590080    
                                                                 
 dense_1 (Dense)             (None, 10)                2570      
                                                                 
=================================================================
Total params: 626,378
Trainable params: 626,378
Non-trainable params: 0
_________________________________________________________________
```

In [5]:
```
# Define model optimizer and loss function
from tensorflow.keras import optimizers

lr = 0.0001
model.compile(loss='categorical_crossentropy', optimizer=optimizers.RM
```

In [6]:
```
# Train the model and store model parameters/loss values
model_1 = model.fit(x_tr, y_tr, batch_size=128, epochs=50, validation_
model.save('model_1.h5')
```

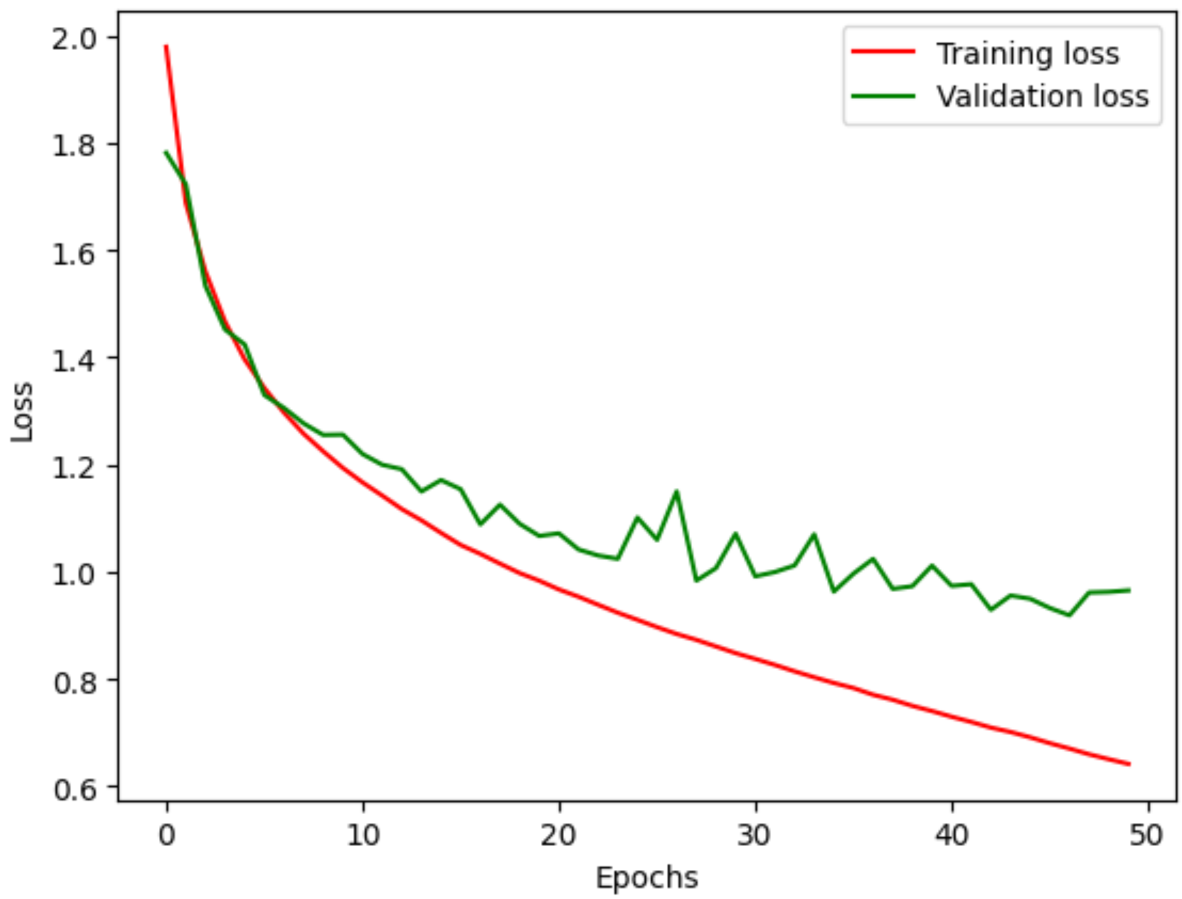
```
- accuracy: 0.7624 - val_loss: 0.9558 - val_accuracy: 0.6784
Epoch 45/50
313/313 [==============================] - 2s 6ms/step - loss: 0.6913
- accuracy: 0.7661 - val_loss: 0.9498 - val_accuracy: 0.6764
Epoch 46/50
313/313 [==============================] - 2s 7ms/step - loss: 0.6803
- accuracy: 0.7683 - val_loss: 0.9325 - val_accuracy: 0.6831
Epoch 47/50
313/313 [==============================] - 2s 6ms/step - loss: 0.6703
- accuracy: 0.7713 - val_loss: 0.9189 - val_accuracy: 0.6869
Epoch 48/50
313/313 [==============================] - 2s 7ms/step - loss: 0.6596
- accuracy: 0.7763 - val_loss: 0.9614 - val_accuracy: 0.6762
Epoch 49/50
313/313 [==============================] - 2s 7ms/step - loss: 0.6505
- accuracy: 0.7780 - val_loss: 0.9626 - val_accuracy: 0.6774
Epoch 50/50
313/313 [==============================] - 2s 6ms/step - loss: 0.6417
- accuracy: 0.7846 - val_loss: 0.9653 - val_accuracy: 0.6769
```

Plot the training and validation loss curve versus epochs.

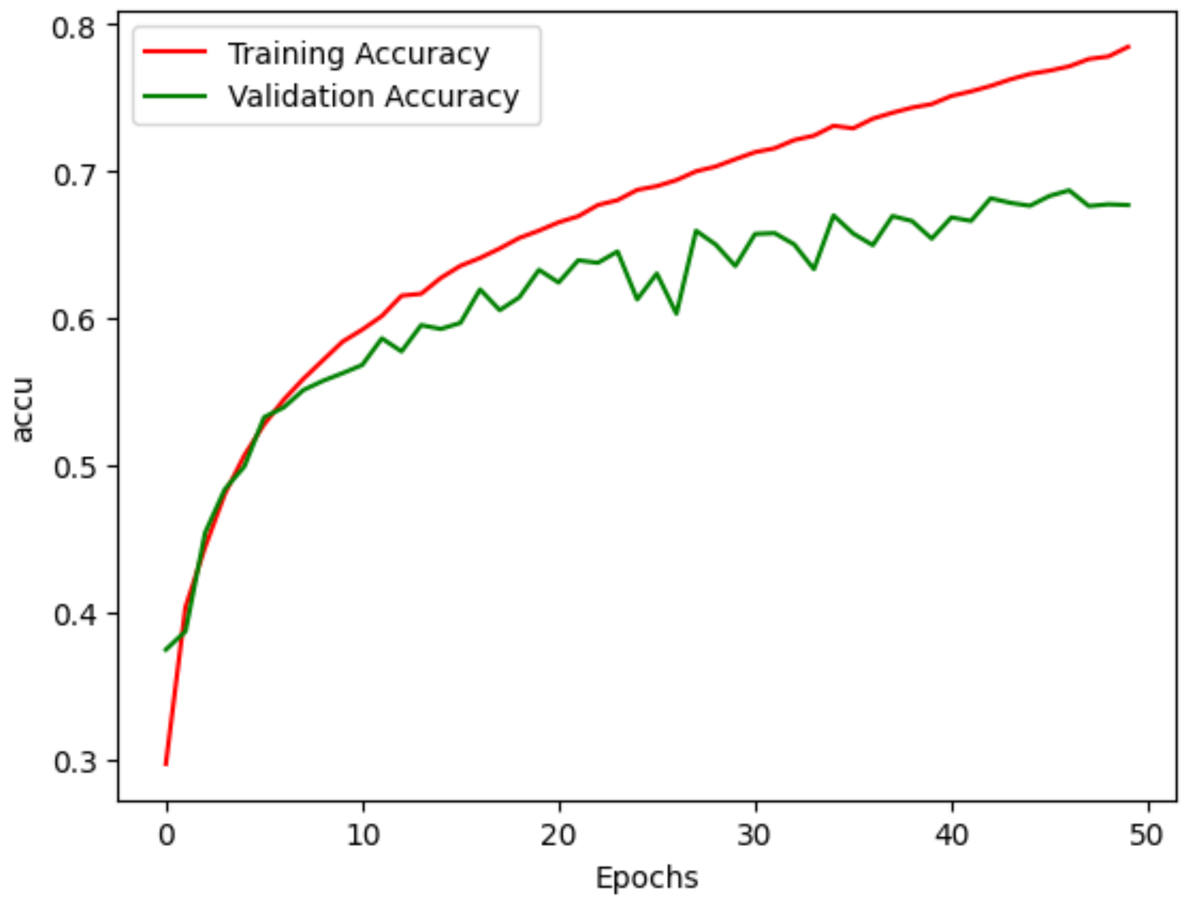
In [7]:
```
model_1.history.keys()
```

Out[7]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

In [8]:
```
# Plot the loss curve

import matplotlib.pyplot as plt
#%matplotlib inline

loss = model_1.history['loss']
val_loss = model_1.history['val_loss']

plt.xlabel('Epochs')
plt.ylabel('Loss')

epochs = range(len(loss))

plt.plot(epochs, loss, 'red', label='Training loss')
plt.plot(epochs, val_loss, 'green', label='Validation loss')

plt.legend()
plt.show()
```



In [9]:
```
# Plot the Accuracy  curve

import matplotlib.pyplot as plt
#%matplotlib inline

accu = model_1.history['accuracy']
val_accu = model_1.history['val_accuracy']

plt.xlabel('Epochs')
plt.ylabel('accu')

epochs = range(len(accu))

plt.plot(epochs, accu, 'red', label='Training Accuracy ')
plt.plot(epochs, val_accu, 'green', label='Validation Accuracy ')

plt.legend()
plt.show()
```



Train (again) and evaluating the model

Train the model on the entire training set

Why? Previously, we used 40K samples for training; you wasted 10K samples for the sake of hyper-parameter tuning. Now you already know the hyper-parameters, so why not using all the 50K samples for training?

In [10]:
```
#<Compile your model again (using the same hyper-parameters you tuned
model = Sequential()
model.add(Conv2D(32, (3, 3), activation = 'relu', input_shape=(32, 32,

model.add(MaxPooling2D((2, 2)))

model.add(Conv2D(64, (4, 4), activation = 'relu'))

model.add(MaxPooling2D((2, 2)))

model.add(Flatten())
model.add(Dense(256, activation = 'relu'))
model.add(Dense(10, activation='softmax'))


model.compile(loss='categorical_crossentropy', optimizer=optimizers.RM
```

In [11]:
```
#<Train your model on the entire training set (50K samples)>
model_2 = model.fit(x_train, y_train_vec, batch_size=128, epochs=50)
model.save('model_2.h5')
```

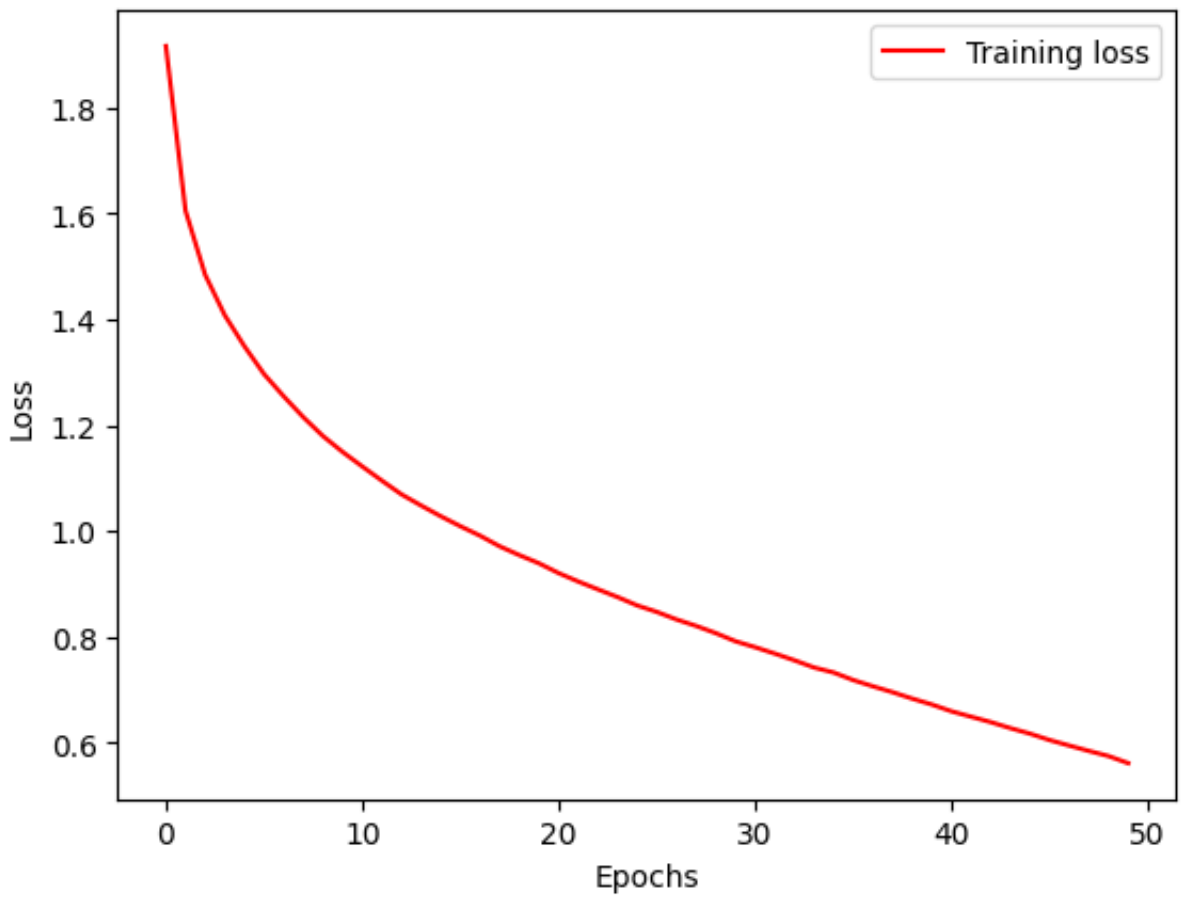
```
Epoch 1/50
391/391 [==============================] - 4s 7ms/step - loss: 1.9171
- acc: 0.3247
Epoch 2/50
391/391 [==============================] - 2s 5ms/step - loss: 1.6056
- acc: 0.4357
Epoch 3/50
391/391 [==============================] - 2s 5ms/step - loss: 1.4844
- acc: 0.4780
Epoch 4/50
391/391 [==============================] - 2s 5ms/step - loss: 1.4078
- acc: 0.5090
Epoch 5/50
391/391 [==============================] - 2s 5ms/step - loss: 1.3491
- acc: 0.5275
Epoch 6/50
391/391 [==============================] - 2s 6ms/step - loss: 1.2965
- acc: 0.5466
Epoch 7/50
391/391 [==============================] - 2s 5ms/step - loss: 1.2545
```

```
- acc: 0.5656
Epoch 8/50
391/391 [==============================] - 2s 5ms/step - loss: 1.2149
- acc: 0.5775
Epoch 9/50
391/391 [==============================] - 2s 5ms/step - loss: 1.1793
- acc: 0.5916
Epoch 10/50
391/391 [==============================] - 2s 5ms/step - loss: 1.1492
- acc: 0.6022
Epoch 11/50
391/391 [==============================] - 2s 5ms/step - loss: 1.1218
- acc: 0.6123
Epoch 12/50
391/391 [==============================] - 3s 7ms/step - loss: 1.0949
- acc: 0.6197
Epoch 13/50
391/391 [==============================] - 2s 5ms/step - loss: 1.0689
- acc: 0.6319
Epoch 14/50
391/391 [==============================] - 2s 5ms/step - loss: 1.0478
- acc: 0.6378
Epoch 15/50
391/391 [==============================] - 2s 5ms/step - loss: 1.0276
- acc: 0.6440
Epoch 16/50
391/391 [==============================] - 2s 5ms/step - loss: 1.0086
- acc: 0.6505
Epoch 17/50
391/391 [==============================] - 2s 6ms/step - loss: 0.9908
- acc: 0.6583
Epoch 18/50
391/391 [==============================] - 2s 6ms/step - loss: 0.9706
- acc: 0.6639
Epoch 19/50
391/391 [==============================] - 2s 5ms/step - loss: 0.9540
- acc: 0.6728
Epoch 20/50
391/391 [==============================] - 2s 5ms/step - loss: 0.9385
- acc: 0.6756
Epoch 21/50
391/391 [==============================] - 2s 5ms/step - loss: 0.9200
- acc: 0.6837
Epoch 22/50
391/391 [==============================] - 2s 5ms/step - loss: 0.9041
- acc: 0.6876
Epoch 23/50
391/391 [==============================] - 2s 6ms/step - loss: 0.8893
- acc: 0.6931
Epoch 24/50
```

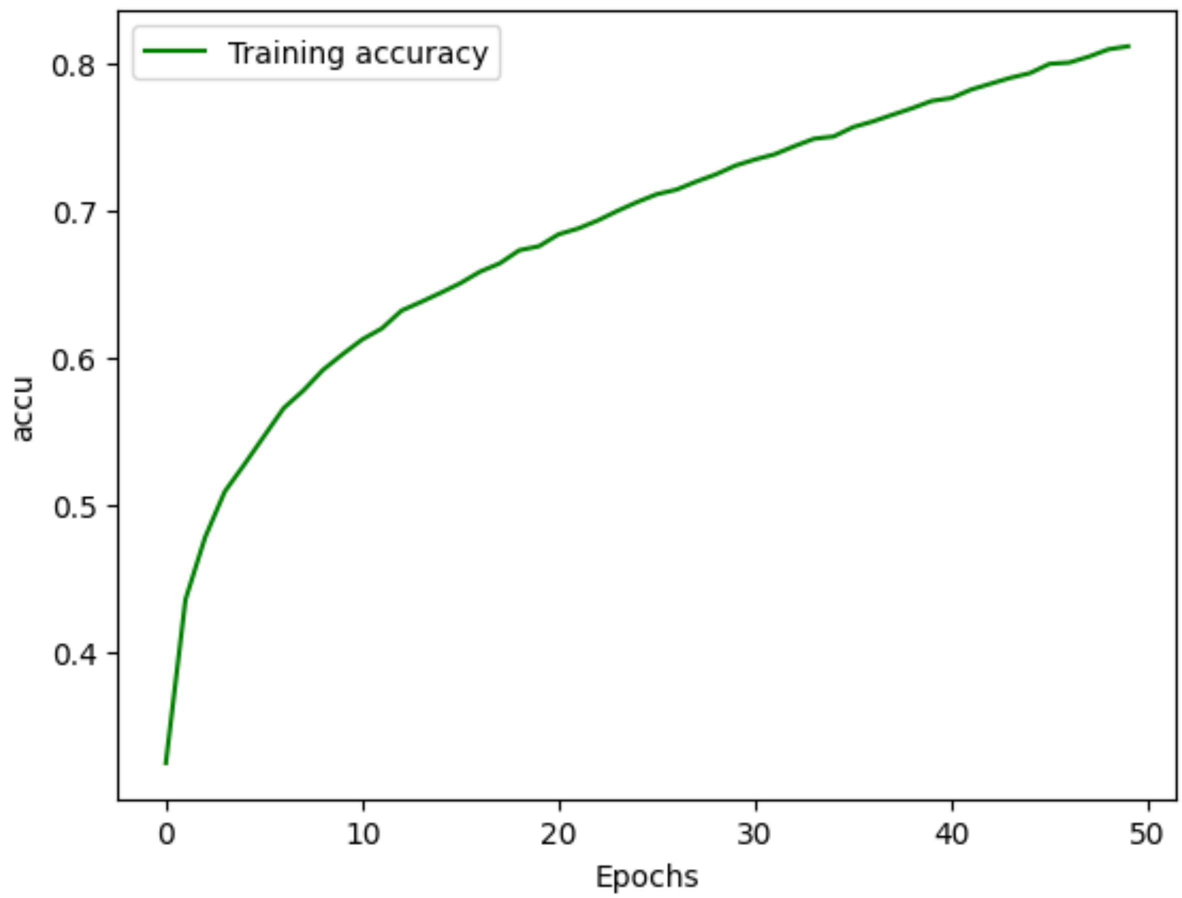
```
391/391 [==============================] - 2s 6ms/step - loss: 0.8747
- acc: 0.6996
Epoch 25/50
391/391 [==============================] - 2s 5ms/step - loss: 0.8588
- acc: 0.7056
Epoch 26/50
391/391 [==============================] - 2s 5ms/step - loss: 0.8466
- acc: 0.7109
Epoch 27/50
391/391 [==============================] - 2s 5ms/step - loss: 0.8323
- acc: 0.7140
Epoch 28/50
391/391 [==============================] - 2s 5ms/step - loss: 0.8201
- acc: 0.7194
Epoch 29/50
391/391 [==============================] - 2s 6ms/step - loss: 0.8065
- acc: 0.7243
Epoch 30/50
391/391 [==============================] - 2s 6ms/step - loss: 0.7911
- acc: 0.7303
Epoch 31/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7799
- acc: 0.7345
Epoch 32/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7679
- acc: 0.7380
Epoch 33/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7552
- acc: 0.7435
Epoch 34/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7415
- acc: 0.7485
Epoch 35/50
391/391 [==============================] - 2s 6ms/step - loss: 0.7320
- acc: 0.7501
Epoch 36/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7177
- acc: 0.7565
Epoch 37/50
391/391 [==============================] - 2s 5ms/step - loss: 0.7059
- acc: 0.7603
Epoch 38/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6948
- acc: 0.7648
Epoch 39/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6827
- acc: 0.7693
Epoch 40/50
391/391 [==============================] - 2s 6ms/step - loss: 0.6715
- acc: 0.7742
```

```
Epoch 41/50
391/391 [==============================] - 2s 6ms/step - loss: 0.6586
- acc: 0.7762
Epoch 42/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6484
- acc: 0.7819
Epoch 43/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6382
- acc: 0.7859
Epoch 44/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6268
- acc: 0.7899
Epoch 45/50
391/391 [==============================] - 2s 5ms/step - loss: 0.6163
- acc: 0.7931
Epoch 46/50
391/391 [==============================] - 2s 6ms/step - loss: 0.6042
- acc: 0.7994
Epoch 47/50
391/391 [==============================] - 2s 6ms/step - loss: 0.5938
- acc: 0.8003
Epoch 48/50
391/391 [==============================] - 2s 5ms/step - loss: 0.5836
- acc: 0.8043
Epoch 49/50
391/391 [==============================] - 2s 5ms/step - loss: 0.5739
- acc: 0.8093
Epoch 50/50
391/391 [==============================] - 2s 5ms/step - loss: 0.5605
- acc: 0.8113
```

In [12]:
```
# Plot the loss curve

import matplotlib.pyplot as plt
#%matplotlib inline

loss = model_2.history['loss']


plt.xlabel('Epochs')
plt.ylabel('Loss')

epochs = range(len(loss))

plt.plot(epochs, loss, 'red', label='Training loss')

plt.legend()
plt.show()
```



In [13]:
```
# Plot the Accuracy curve

import matplotlib.pyplot as plt
#%matplotlib inline

accu = model_2.history['acc']


plt.xlabel('Epochs')
plt.ylabel('accu')
epochs = range(len(accu))

plt.plot(epochs, accu, 'Green', label='Training accuracy')

plt.legend()
plt.show()
```



Evaluate the model on the test set

Do NOT use the test set until now. Make sure that your model parameters and hyper-parameters are independent of the test set.

In [14]:
```
from keras.models import load_model

current_model = load_model('model_1.h5')
Current_acc = current_model.evaluate(x_test, y_test_vec)
print('loss = ' + str(Current_acc[0]))
print('accuracy = ' + str(Current_acc[1]))
```

```
313/313 [==============================] - 1s 3ms/step - loss: 0.9513
- accuracy: 0.6782
loss = 0.9512962698936462
accuracy = 0.6782000064849854
```

In [15]:
```
current_model = load_model('model_2.h5')
Current_acc = current_model.evaluate(x_test, y_test_vec)
print('loss = ' + str(Current_acc[0]))
print('accuracy = ' + str(Current_acc[1]))
```

```
313/313 [==============================] - 1s 3ms/step - loss: 0.9222
- acc: 0.6905
loss = 0.9222323298454285
accuracy = 0.690500020980835
```