In [1]:
```
import keras
import numpy as np
```

```
Using TensorFlow backend.
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:516: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:517: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:518: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:519: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:520: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorflow/python/framewor
k/dtypes.py:525: FutureWarning: Passing (type, 1) or '1type' as a synonym of typ
e is deprecated; in a future version of numpy, it will be understood as (type,
(1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:541: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
ype, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:542: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
ype, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:543: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
ype, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:544: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
ype, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:545: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
ype, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/tensorboard/compat/tensorfl
ow_stub/dtypes.py:550: FutureWarning: Passing (type, 1) or '1type' as a synonym
of type is deprecated; in a future version of numpy, it will be understood as (t
```

```
ype, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

Keras

By: (The one and only) James Bartlett, Edited by Ashley Chien

Keras is a neural network framework that wraps tensorflow (if you haven't heard of tensorflow it's another neural network framework) and makes it really simple to implement common neural networks. Its philosophy is to make simple things easy (but beware, trying to implement uncommon, custom neural networks can be pretty challenging in Keras, for the purposes of this course you will never have to that though so don't worry about it). If you are ever confused during this homework, Keras has really good documentation, so you can go to Keras Docs.

Datasets

Keras has many datasets conveniently built in to the library. We can access them from the `keras.datasets` module. For this homework, we will be using their housing price dataset, their image classification dataset and their movie review sentiment dataset. To get a full list of their datasets, you can go to this link. Keras Datasets. To use their datasets, we import them and then call `load_data()`, load_data returns two tuples, the first one is training data, and the second one is testing data. See the example below

In [2]:
```
from keras.datasets import boston_housing
(x_train, y_train), (x_test, y_test) = boston_housing.load_data()
```

You can also choose the proportion of training data you would like.

In [3]:
```
print("Size of training set before: ", x_train.shape)
(x_train, y_train), (x_test, y_test) = boston_housing.load_data(test_split=0.10)
print("Size of training set after: ", x_train.shape)
```

```
Size of training set before:  (404, 13)
Size of training set after:  (455, 13)
```

In [4]:
```
from keras.utils import normalize
x_train = normalize(x_train, axis=1)
x_test = normalize(x_test, axis=1)
```

Models

Every thing in Keras starts out with a model. From an initial model, we can add layers, train the model on data, evaluate the model on test sets, etc. We initialize a model with `Sequential()`. `Sequential` refers to the fact that the model has a sequence of layers. Personally, I have very rarely used anything other than `Sequential`, so I think it's all you really need to worry about.

In [5]:
```
from keras.models import Sequential
model = Sequential()
```

Once we have a model, we can add layers to it with `model.add`. Keras has a really good range

of layers we can use. For example, if we want a basic fully connected layer we can use `Dense`. I will now run through an example of using Keras to build and train a fully connected neural network for the purposes of regressing on housing prices for the dataset we loaded earlier.

In [6]:
```
from keras.layers import Dense
model.add(Dense(16, input_shape=(13,)))
```

This line of code adds a fully connected layer with 16 neurons. For the first layer of any model we always have to specify the input shape. In our case we will be training a fully connected network on the Boston Housing data, so each data point has 13 features. That's why we use an input_shape of (13,). The nice part about Keras is other than the input_shape for the first layer, we don't have to worry about shapes the rest of the time, Keras takes care of it. This can be really useful when you are doing complicated convolutions and things like that where working out the input shape to the next layer can be non-trivial.

Now let's add an Activation function to our network after our first fully connected layer.

In [7]:
```
from keras.layers import Activation
model.add(Activation('relu'))
```

Simple as that. We just added a relu activation to the whole layer. To see a list of activation functions available in Keras go to Keras Activations. Now let's add the final layer in our model.

In [8]:
```
model.add(Dense(1))
```

Now we can use a handy utility in Keras to print out what our model looks like so far.

In [9]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 16)                224
_________________________________________________________________
activation_1 (Activation)    (None, 16)                0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 17
=================================================================
Total params: 241
Trainable params: 241
Non-trainable params: 0
_________________________________________________________________
```

You can see it shows us what layers we have, the output shapes of each layer, and how many parameters there are for each layer. All this information can be really useful when trying to debug a model, or even for sharing your model architecture with others.

Training

Now for actually training the model. Before we train a model we have to compile it. `model.compile` is how you specify which optimizer to use and what loss function to use. Sometimes choosing the right optimizer can have a significant effect on model performance. For a list of optimizers look at Keras Optimizers. Choosing the right optimizer is mostly just

trying each one to see which works better; there is some general advice for when to use each one but it is basically just another hyperparameter. We also have to choose a loss function. Choosing the right loss function is really important because the loss function decides what the goal of the model is. Since we are doing regression, we want to choose mean squared error, to get our output to be as close as possible to the label.

In [10]:
```
model.compile(optimizer='SGD', loss='mean_squared_error')
```

Now we have to actually train our model on the data. This is really easy in Keras, in fact it only takes one line of code.

In [11]:
```
model.fit(x_train, y_train, epochs=100)
```

```
WARNING:tensorflow:From /opt/anaconda3/envs/nmep/lib/python3.7/site-packages/ker
as/backend/tensorflow_backend.py:422: The name tf.global_variables is deprecate
d. Please use tf.compat.v1.global_variables instead.

Epoch 1/100
455/455 [==============================] - 0s 451us/step - loss: 182.9595
Epoch 2/100
455/455 [==============================] - 0s 50us/step - loss: 74.0479
Epoch 3/100
455/455 [==============================] - 0s 53us/step - loss: 67.6902
Epoch 4/100
455/455 [==============================] - 0s 66us/step - loss: 72.0956
Epoch 5/100
455/455 [==============================] - 0s 51us/step - loss: 66.9180
Epoch 6/100
455/455 [==============================] - 0s 46us/step - loss: 67.2551
Epoch 7/100
455/455 [==============================] - 0s 87us/step - loss: 63.0274
Epoch 8/100
455/455 [==============================] - 0s 121us/step - loss: 64.7574
Epoch 9/100
455/455 [==============================] - 0s 104us/step - loss: 66.5159
Epoch 10/100
455/455 [==============================] - 0s 58us/step - loss: 66.2462
Epoch 11/100
455/455 [==============================] - 0s 98us/step - loss: 62.2943
Epoch 12/100
455/455 [==============================] - 0s 144us/step - loss: 62.6285
Epoch 13/100
455/455 [==============================] - 0s 168us/step - loss: 70.9652
Epoch 14/100
455/455 [==============================] - 0s 43us/step - loss: 63.1233
Epoch 15/100
455/455 [==============================] - 0s 37us/step - loss: 66.4547
Epoch 16/100
455/455 [==============================] - 0s 52us/step - loss: 66.4189
Epoch 17/100
455/455 [==============================] - 0s 45us/step - loss: 63.5581
Epoch 18/100
455/455 [==============================] - 0s 46us/step - loss: 62.8699
Epoch 19/100
455/455 [==============================] - 0s 106us/step - loss: 60.9200
Epoch 20/100
455/455 [==============================] - 0s 216us/step - loss: 60.1789
Epoch 21/100
455/455 [==============================] - 0s 38us/step - loss: 62.9729
Epoch 22/100
455/455 [==============================] - 0s 49us/step - loss: 62.3292
Epoch 23/100
```

```
455/455 [==============================] - 0s 45us/step - loss: 64.6639
Epoch 24/100
455/455 [==============================] - 0s 45us/step - loss: 59.8867
Epoch 25/100
455/455 [==============================] - 0s 56us/step - loss: 60.9170
Epoch 26/100
455/455 [==============================] - 0s 170us/step - loss: 66.5684
Epoch 27/100
455/455 [==============================] - 0s 66us/step - loss: 64.8174
Epoch 28/100
455/455 [==============================] - 0s 287us/step - loss: 65.4884
Epoch 29/100
455/455 [==============================] - 0s 82us/step - loss: 58.0043
Epoch 30/100
455/455 [==============================] - 0s 75us/step - loss: 83.3471
Epoch 31/100
455/455 [==============================] - 0s 65us/step - loss: 61.7597
Epoch 32/100
455/455 [==============================] - 0s 70us/step - loss: 60.9958
Epoch 33/100
455/455 [==============================] - 0s 92us/step - loss: 62.4180
Epoch 34/100
455/455 [==============================] - 0s 196us/step - loss: 64.3919
Epoch 35/100
455/455 [==============================] - 0s 253us/step - loss: 63.4313
Epoch 36/100
455/455 [==============================] - 0s 154us/step - loss: 62.2137
Epoch 37/100
455/455 [==============================] - 0s 59us/step - loss: 59.5923
Epoch 38/100
455/455 [==============================] - 0s 54us/step - loss: 62.3363
Epoch 39/100
455/455 [==============================] - 0s 61us/step - loss: 65.8169
Epoch 40/100
455/455 [==============================] - 0s 278us/step - loss: 62.1075
Epoch 41/100
455/455 [==============================] - 0s 69us/step - loss: 60.6040
Epoch 42/100
455/455 [==============================] - 0s 52us/step - loss: 59.9130
Epoch 43/100
455/455 [==============================] - 0s 59us/step - loss: 56.9356
Epoch 44/100
455/455 [==============================] - 0s 60us/step - loss: 61.7797
Epoch 45/100
455/455 [==============================] - 0s 226us/step - loss: 65.0558
Epoch 46/100
455/455 [==============================] - 0s 154us/step - loss: 62.2093
Epoch 47/100
455/455 [==============================] - 0s 74us/step - loss: 59.6014
Epoch 48/100
455/455 [==============================] - 0s 72us/step - loss: 61.6382
Epoch 49/100
455/455 [==============================] - 0s 107us/step - loss: 57.8949
Epoch 50/100
455/455 [==============================] - 0s 190us/step - loss: 64.8400
Epoch 51/100
455/455 [==============================] - 0s 92us/step - loss: 57.5594
Epoch 52/100
455/455 [==============================] - 0s 44us/step - loss: 59.1803
Epoch 53/100
455/455 [==============================] - 0s 36us/step - loss: 59.6680
Epoch 54/100
455/455 [==============================] - 0s 56us/step - loss: 60.5188
Epoch 55/100
455/455 [==============================] - 0s 75us/step - loss: 58.9109
```

```
Epoch 56/100
455/455 [==============================] - 0s 79us/step - loss: 58.8913
Epoch 57/100
455/455 [==============================] - 0s 90us/step - loss: 57.4897
Epoch 58/100
455/455 [==============================] - 0s 206us/step - loss: 58.5241
Epoch 59/100
455/455 [==============================] - 0s 103us/step - loss: 59.4390
Epoch 60/100
455/455 [==============================] - 0s 61us/step - loss: 57.3134
Epoch 61/100
455/455 [==============================] - 0s 244us/step - loss: 66.0301
Epoch 62/100
455/455 [==============================] - 0s 114us/step - loss: 60.1145
Epoch 63/100
455/455 [==============================] - 0s 52us/step - loss: 60.9844
Epoch 64/100
455/455 [==============================] - 0s 156us/step - loss: 61.3932
Epoch 65/100
455/455 [==============================] - 0s 125us/step - loss: 56.4848
Epoch 66/100
455/455 [==============================] - 0s 89us/step - loss: 59.5100
Epoch 67/100
455/455 [==============================] - 0s 43us/step - loss: 61.1895
Epoch 68/100
455/455 [==============================] - 0s 61us/step - loss: 58.0281
Epoch 69/100
455/455 [==============================] - 0s 90us/step - loss: 58.4984
Epoch 70/100
455/455 [==============================] - 0s 52us/step - loss: 56.5375
Epoch 71/100
455/455 [==============================] - 0s 47us/step - loss: 59.7578
Epoch 72/100
455/455 [==============================] - 0s 44us/step - loss: 56.8934
Epoch 73/100
455/455 [==============================] - 0s 35us/step - loss: 58.5731
Epoch 74/100
455/455 [==============================] - 0s 36us/step - loss: 57.5522
Epoch 75/100
455/455 [==============================] - 0s 70us/step - loss: 55.8531
Epoch 76/100
455/455 [==============================] - 0s 54us/step - loss: 57.2593
Epoch 77/100
455/455 [==============================] - 0s 104us/step - loss: 60.9517
Epoch 78/100
455/455 [==============================] - 0s 64us/step - loss: 60.6676
Epoch 79/100
455/455 [==============================] - 0s 61us/step - loss: 57.6606
Epoch 80/100
455/455 [==============================] - 0s 72us/step - loss: 57.6609
Epoch 81/100
455/455 [==============================] - 0s 86us/step - loss: 63.1802
Epoch 82/100
455/455 [==============================] - 0s 250us/step - loss: 55.8109
Epoch 83/100
455/455 [==============================] - 0s 87us/step - loss: 55.4877
Epoch 84/100
455/455 [==============================] - 0s 81us/step - loss: 60.4308
Epoch 85/100
455/455 [==============================] - 0s 83us/step - loss: 59.4210
Epoch 86/100
455/455 [==============================] - 0s 87us/step - loss: 63.9736
Epoch 87/100
455/455 [==============================] - 0s 83us/step - loss: 56.5688
Epoch 88/100
```

```
455/455 [==============================] - 0s 67us/step - loss: 57.6302
Epoch 89/100
455/455 [==============================] - 0s 307us/step - loss: 58.1270
Epoch 90/100
455/455 [==============================] - 0s 119us/step - loss: 61.3467
Epoch 91/100
455/455 [==============================] - 0s 117us/step - loss: 60.2639
Epoch 92/100
455/455 [==============================] - 0s 127us/step - loss: 56.3787
Epoch 93/100
455/455 [==============================] - 0s 41us/step - loss: 55.3258
Epoch 94/100
455/455 [==============================] - 0s 42us/step - loss: 56.5631
Epoch 95/100
455/455 [==============================] - 0s 381us/step - loss: 54.9228
Epoch 96/100
455/455 [==============================] - 0s 53us/step - loss: 57.1556
Epoch 97/100
455/455 [==============================] - 0s 41us/step - loss: 58.2812
Epoch 98/100
455/455 [==============================] - 0s 42us/step - loss: 54.7377
Epoch 99/100
455/455 [==============================] - 0s 383us/step - loss: 56.8124
Epoch 100/100
455/455 [==============================] - 0s 97us/step - loss: 61.9228
```

Out[11]: `<keras.callbacks.callbacks.History at 0x12e78b610>`

Evaluation

Now that we have trained our model we can evaluate it on our testing set. It is also just one line of code.

In [12]:
```
print("Loss: ", model.evaluate(x_test, y_test, verbose=0))
```

```
Loss:  74.81699879964192
```

This loss might seem very high and it is, mostly because there aren't very many training points in the dataset (also no effort was put into finding the best model).

We can also generate predictions for new data that we don't have labels for. Since we don't have new data, I will just demonstrate the idea with our testing data.

In [13]:
```
y_predicted = model.predict(x_test)
print(y_predicted)
```

```
[[25.05013 ]
 [20.20157 ]
 [23.80274 ]
 [26.806147]
 [26.63223 ]
 [20.371765]
 [27.153915]
 [30.241705]
 [26.131834]
 [20.786337]
 [20.482264]
 [16.534788]
 [23.767342]
 [25.795898]
 [30.455538]
```

```
[18.951426]
[29.462748]
[18.490648]
[20.020727]
[20.747095]
[27.148705]
[20.82327 ]
[19.13564 ]
[27.309671]
[25.261988]
[25.820044]
[25.955698]
[30.080809]
[19.563265]
[24.690153]
[26.722256]
[25.20492 ]
[20.30756 ]
[24.794573]
[24.675669]
[20.566858]
[24.476704]
[25.370024]
[21.186638]
[25.418484]
[27.35898 ]
[26.953484]
[27.281431]
[30.277826]
[22.524582]
[26.346441]
[20.594675]
[24.788336]
[23.50717 ]
[24.706747]
[19.85732 ]]
```

That's it. We have successfully (depending on your definition of success) built a fully connected neural network and trained that network on a dataset. Now it's your turn!

Problem 1: Image Classification

We are going to build a convolutional neural network to predict image classes on CIFAR-10, a dataset of images of 10 different things (i.e. 10 classes). Things like airplanes, cars, deer, horses, etc.

(a) Load the cifar10 dataset from Keras. If you need a hint go to Keras Datasets. This might take a little while to download.

In [14]:
```
from keras.datasets import cifar10
(cifar_x_train, cifar_y_train), (cifar_x_test, cifar_y_test) = cifar10.load_data
```

(b) Initialize a Sequential model

In [15]:
```
cifar_model = Sequential()
```

(c) Add a `Conv2D` layer to the model. It should have 32 filters, a 5x5 kernel, and a 1x1 stride. The documentation here will be your friend for this problem. **Hint:** This is the first layer of the model so you have to specify the input shape. I recommend printing `cifar_x_train.shape`,

to get an idea of what the shape of the data looks like. Then add a `relu` activation layer to the model.

In [16]:
```
from keras.layers.convolutional import Conv2D
print(cifar_x_train.shape)
cifar_model.add(Conv2D(32, 5, activation='relu',input_shape=(32, 32, 3)))
```

```
(50000, 32, 32, 3)
```

(d) Add a `MaxPooling2D` layer to the model. The layer should have a 2x2 pool size. The documentation for Max Pooling is here.

In [17]:
```
from keras.layers.pooling import MaxPooling2D
cifar_model.add(MaxPooling2D())
```

```
WARNING:tensorflow:From /opt/anaconda3/envs/nmep/lib/python3.7/site-packages/ker
as/backend/tensorflow_backend.py:4070: The name tf.nn.max_pool is deprecated. Pl
ease use tf.nn.max_pool2d instead.
```

(e) Add another `Conv2D` identical to last one, then another `relu` activation, then another `MaxPooling2D` layer. **Hint:** You've already written this code

In [18]:
```
cifar_model.add(Conv2D(32, 5, activation='relu'))
cifar_model.add(MaxPooling2D())
```

(f) Add another `Conv2D` layer identical to the others except with 64 filters instead of 32. Add another `relu` activation layer.

In [19]:
```
cifar_model.add(Conv2D(64, 5, activation='relu'))
```

(g) Now we want to move from 2D data to 1D vectors for classification, to this we have to flatten the data. Keras has a layer for this called Flatten. Then add a `Dense` (fully connected) layer with 64 neurons, a `relu` activation layer, another `Dense` layer with 10 neurons, and a `softmax` activation layer.

In [20]:
```
from keras.layers import Flatten
cifar_model.add(Flatten())
cifar_model.add(Dense(64, activation='relu'))
cifar_model.add(Dense(10, activation='softmax'))
```

Notice that we have constructed a network that takes in an image and outputs a vector of 10 numbers and then we take the softmax of these, which leaves us with a vector of 0s except 1 one and the location of this one in the vector corresponds to which class the network is predicting for that image. This is sort of the canonical way of doing image classification.

(h) Now print a summary of your network.

In [21]:
```
cifar_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 28, 28, 32)        2432
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
```

```
conv2d_2 (Conv2D)            (None, 10, 10, 32)        25632
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 32)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 1, 1, 64)          51264
_________________________________________________________________
flatten_1 (Flatten)          (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650
=================================================================
Total params: 84,138
Trainable params: 84,138
Non-trainable params: 0
_________________________________________________________________
```

(i) We need to convert our labels from integers to length 10 vectors with 9 zeros and 1 one, where the integer label is the index of the 1 in the vector. Luckily, Keras has a handy function to do this for us. Have a look here.

In [22]:
```
from keras.utils import to_categorical
y_train_cat = to_categorical(cifar_y_train, num_classes=10)
y_test_cat = to_categorical(cifar_y_test, num_classes=10)
```

(j) Now compile the model with SGD optimizer and categorical_crossentropy loss function and also include `metrics=['accuracy']` as a parameter so we can see the accuracy of the model. Then train the model on the training data. For training we want to weight the classes in the loss function, so set the `class_weight` parameter of fit to be the `class_weights` dictionary. Be warned training can take forever, I trained on a cpu for 20 epochs (about 30 minutes) and only got 20% accuracy. For the purposes of this assignment, you don't need to worry to much about accuracy, just train for at least 1 epoch.

In [23]:
```
cifar_model.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['
```

In [24]:
```
class_weights = {}
for i in range(10):
    class_weights[i] = 1. / np.where(cifar_y_train==i)[0].size

cifar_model.fit(cifar_x_train, y_train_cat, class_weight=class_weights, epochs=5
```

```
Epoch 1/5
50000/50000 [==============================] - 75s 2ms/step - loss: 0.0013 - acc
uracy: 0.1219
Epoch 2/5
50000/50000 [==============================] - 70s 1ms/step - loss: 6.7436e-04 -
accuracy: 0.1393
Epoch 3/5
50000/50000 [==============================] - 68s 1ms/step - loss: 5.8962e-04 -
accuracy: 0.1498
Epoch 4/5
50000/50000 [==============================] - 71s 1ms/step - loss: 5.4741e-04 -
accuracy: 0.1584
Epoch 5/5
50000/50000 [==============================] - 65s 1ms/step - loss: 5.2172e-04 -
accuracy: 0.1652
```

Out[24]:
```
<keras.callbacks.callbacks.History at 0x13c0b2ed0>
```

Now we can evaluate on our test set.

In [25]:
```
cifar_model.evaluate(cifar_x_test, y_test_cat)
```

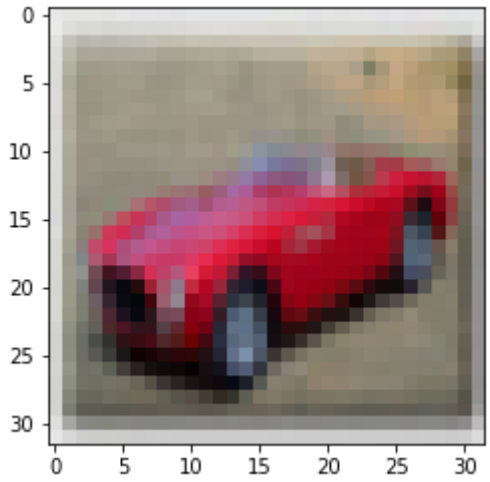
```
10000/10000 [==============================] - 3s 288us/step
```

Out[25]:
```
[2.5484515804290773, 0.17219999432563782]
```

We can also get the class labels the network predicts on our test set and look at a few examples.

In [26]:
```
y_pred = cifar_model.predict(cifar_x_test)
import matplotlib.pyplot as plt
%matplotlib inline
plt.imshow(cifar_x_test[1234])
print("Predicted label: ", np.argmax(y_pred[1234]))
print("True label: ", cifar_y_test[1234])
```

```
Predicted label:  0
True label:  [1]
```



Problem 2: Sentiment Classification

In this problem we will use Kera's imdb sentiment dataset. You will take in sequences of words and use an RNN to try to classify the sequences sentiment. First we have to process the data a little bit, so that we have fixed length sequences.

In [27]:
```
from keras.datasets import imdb
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=1000, maxlen=200
```

```
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/keras/datasets/imdb.py:101:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or s
hapes) is deprecated. If you meant to do this, you must specify 'dtype=object' w
hen creating the ndarray
  x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
/opt/anaconda3/envs/nmep/lib/python3.7/site-packages/keras/datasets/imdb.py:102:
VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (whi
ch is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or s
hapes) is deprecated. If you meant to do this, you must specify 'dtype=object' w
hen creating the ndarray
  x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

In [28]:
```
def process_data(data):
    processed = np.zeros(len(data) * 200).reshape((len(data), 200))
    for i, seq in enumerate(data):
```

```
        if len(seq) < 200:
            processed[i] = np.array(seq + [0 for _ in range(200 - len(seq))])
        else:
            processed[i] = np.array(seq)
    return processed
```

In [29]:
```
x_train_proc = process_data(x_train)
x_test_proc = process_data(x_test)
print(x_test_proc.shape)
```

```
(3913, 200)
```

The Embedding Layer is a little bit different from most of the layers, so we have provided that code for you below. Basically, the 1000 means that we are using a vocabulary size of 1000, the 32 means we will have a vector of size 32 as the output, and the `mask_zero` means that we don't care about 0 because we are using it for padding.

In [30]:
```
imdb_model = Sequential()
```

In [31]:
```
from keras.layers.embeddings import Embedding
imdb_model.add(Embedding(1000, 32, input_length=200, mask_zero=True))
```

(a) For this problem, I won't walk you everything like I did in the last one. What you need to do is as follows. Add an LSTM layer with 32 outputs, then a Dense layer with 32 neurons, then a relu activation, then a dense layer with 1 neuron, then a sigmoid activation. Then you should print out the model summary.

In [32]:
```
from keras.layers import LSTM
imdb_model.add(LSTM(32))
imdb_model.add(Dense(32, activation='relu'))
imdb_model.add(Dense(1, activation='sigmoid'))
```

```
WARNING:tensorflow:From /opt/anaconda3/envs/nmep/lib/python3.7/site-packages/ten
sorflow/python/keras/backend.py:3794: add_dispatch_support.<locals>.wrapper (fro
m tensorflow.python.ops.array_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

(b) Now compile the model with binary cross entropy, and the Adam optimizer. Also include accuracy as a metric in the compile. Then train the model on the processed data (no need to worry about class weights this time)

In [33]:
```
imdb_model.compile(optimizer='Adam', loss='binary_crossentropy', metrics=['accur
imdb_model.fit(x_train_proc, y_train, epochs=5)
```

```
Epoch 1/5
25000/25000 [==============================] - 106s 4ms/step - loss: 0.4075 - ac
curacy: 0.8114
Epoch 2/5
25000/25000 [==============================] - 121s 5ms/step - loss: 0.3144 - ac
curacy: 0.8661
Epoch 3/5
25000/25000 [==============================] - 123s 5ms/step - loss: 0.2909 - ac
curacy: 0.8772
Epoch 4/5
25000/25000 [==============================] - 124s 5ms/step - loss: 0.2735 - ac
curacy: 0.8867
Epoch 5/5
```

```
25000/25000 [==============================] - 103s 4ms/step - loss: 0.2624 - ac
curacy: 0.8908
```

Out[33]:
```
<keras.callbacks.callbacks.History at 0x1487bd550>
```

After training we can evaluate our model on the test set.

In [34]:
```
print("Accuracy: ", imdb_model.evaluate(x_test_proc, y_test)[1])
```

```
3913/3913 [==============================] - 3s 875us/step
Accuracy:  0.8676207661628723
```

Now we can look at our predictions and the sentences they correspond to.

In [35]:
```
y_pred = imdb_model.predict(x_test_proc)
```

In [36]:
```
y_pred = np.vectorize(lambda x: int(x >= 0.5))(y_pred)
correct = []
incorrect = []
for i, pred in enumerate(y_pred):
    if y_test[i] == pred:
        correct.append(i)
    else:
        incorrect.append(i)
word_dict = inv_map = {v: k for k, v in imdb.get_word_index().items()}

print(list(map(lambda x: word_dict[int(x)] if x != 0 else None, x_test[correct[1
```

```
Downloading data from https://s3.amazonaws.com/text-datasets/imdb_word_index.jso
n
1646592/1641221 [==============================] - 0s 0us/step
['the', 'is', 'and', 'much', 'way', 'you', 'film', 'and', 'love', 'development',
"you'll", 'to', 'and', 'i', 'i', 'is', 'and', 'talking', 'and', 'acting', 'his',
'when', 'would', 'nature', 'to', 'gave', 'in', '20', 'about', 'and', 'in', 'tea
m', 'and', 'about', 'and', 'in', 'footage', 'american', 'film', 'about', 'editin
g', 'this', 'and', 'would', 'find', 'good', 'and', 'and', 'or', 'and', 'god', 't
o', 'and']
```

After making this I realized that `keras` 's method for converting from word index back to words is broken right now (see this open github issue). So we can't actually see what the sentences look like.