Convolutional Neural Networks

This notebook explains CNNs through the implementation in sklearn.

We train a CNN to classify images from the CIFAR-10 database.

- The CIFAR-10 dataset consists of 60,000 colour images of size (32x32) in 10 classes, with 6000 images per class.
- Here are the classes in the dataset, as well as 10 random images from each:
  - airplane
  - automobile
  - bird
  - cat
  - deer
  - dog
  - frog
  - horse
  - ship
  - truck

1. Load CIFAR-10 Database

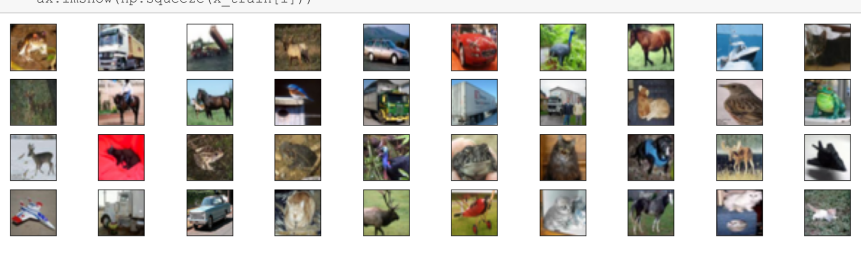
In [95]:
```
import keras
from keras.datasets import cifar10

# load the pre-shuffled train and test data
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

2. Visualize Some Training Images

In [96]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

fig = plt.figure(figsize=(20,5))
for i in range(40):
    ax = fig.add_subplot(4, 10, i + 1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(x_train[i]))
```



3. Rescale the Images by Dividing Every Pixel in Every Image by 255

- Let's see how a datapoint looks like:

In [97]:
```
print(x_train[1])
```

```
[[[154 177 187]
  [126 137 136]
  [105 104  95]
  ...
  [ 91  95  71]
  [ 87  90  71]
  [ 79  81  70]]

 [[140 160 169]
  [145 153 154]
  [125 125 118]
  ...
  [ 96  99  78]
  [ 77  80  62]
  [ 71  73  61]]

 [[140 155 164]
  [139 146 149]
  [115 115 112]
  ...
  [ 79  82  64]
  [ 68  70  55]
  [ 67  69  55]]

 ...

 [[175 167 166]
  [156 154 160]
  [154 160 170]
  ...
  [ 42  34  36]
  [ 61  53  57]
  [ 93  83  91]]

 [[165 154 128]
  [156 152 130]
  [159 161 142]
  ...
  [103  93  96]
  [123 114 120]
  [131 121 131]]

 [[163 148 120]
  [158 148 122]
  [163 156 133]
  ...
  [143 133 139]
  [143 134 142]
  [143 133 144]]]
```

- Let's normalize each cell value [0,255], so that each cell value lies within the same distribution [0,1].
  - That is values change from [0,255] --> [0,1].
- We normalize using the formula:

> $$ \frac{X-X_{min}}{X_{max}-X_{min}}$$

- Here, X_min=0 and X_max=255.
- Hence,

> $$ \frac{X-X_{min}}{X_{max}-X_{min}} = \frac{X}{255}$$

In [98]:
```
x_train = x_train.astype('float32')/255
x_test = x_test.astype('float32')/255
```

4. Break Dataset into Training, Testing, and Validation Sets

- A datapoint in the dataset could belong to any one of the 10 classes mentioned earlier.
- Let's convert the output into one-hot encoded vector of size 10.
- This will be helpful for our CNN to recognize a given image datapoint into one of the 10 classes.

In [99]:
```
from keras.utils import np_utils

# one-hot encoding
num_classes = len(np.unique(y_train))
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

In [100]:
```
# break training set into training and validation sets
(x_train, x_valid) = x_train[5000:], x_train[:5000]
(y_train, y_valid) = y_train[5000:], y_train[:5000]

# print shape of training set
print('x_train shape:', x_train.shape)

# print number of training, validation, and test images
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
print(x_valid.shape[0], 'validation samples')
```

```
x_train shape: (45000, 32, 32, 3)
45000 train samples
10000 test samples
5000 validation samples
```

5. Data Augmentation

- Data augmentation helps in creating invariance in the data, especially in image data.
  - Invariance in data could be for:
    - Shift
    - Rotation
    - Zoom
    - Noise, etc

In [101]:
```
from keras.preprocessing.image import ImageDataGenerator

# create and configure augmented image generator
datagen_train = ImageDataGenerator(
    width_shift_range=0.1,  # randomly shift images horizontally (10% of total width)
    height_shift_range=0.1,  # randomly shift images vertically (10% of total height)
    horizontal_flip=True) # randomly flip images horizontally

# fit augmented image generator on data
datagen_train.fit(x_train)
```

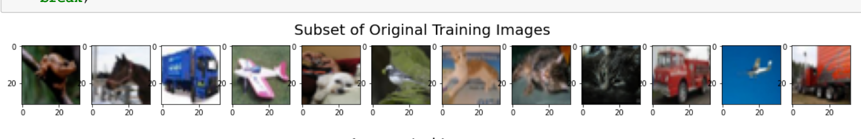
6. Visualize Original and Augmented Images

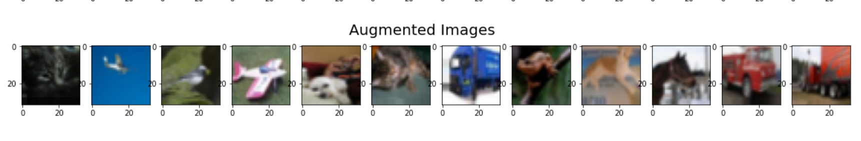
In [102]:
```
import matplotlib.pyplot as plt

# take subset of training data
x_train_subset = x_train[:12]

# visualize subset of training data
fig = plt.figure(figsize=(20,2))
for i in range(0, len(x_train_subset)):
    ax = fig.add_subplot(1, 12, i+1)
    ax.imshow(x_train_subset[i])
fig.suptitle('Subset of Original Training Images', fontsize=20)
plt.show()

# visualize augmented images
fig = plt.figure(figsize=(20,2))
for x_batch in datagen_train.flow(x_train_subset, batch_size=12):
    for i in range(0, 12):
        ax = fig.add_subplot(1, 12, i+1)
        ax.imshow(x_batch[i])
    fig.suptitle('Augmented Images', fontsize=20)
    plt.show()
    break;
```





7. Define the Model Architecture

In [103]:
```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

input_shape = x_train[1].shape

model = Sequential()
model.add(Conv2D(filters=32, kernel_size=3, padding='same', kernel_initializer='glorot_uniform',
                 activation='relu', input_shape=input_shape))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', kernel_initializer='glorot_uniform',
                 activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.25))
model.add(Conv2D(filters=64, kernel_size=2, kernel_initializer='glorot_uniform', padding='same',
                 activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(512, kernel_initializer='glorot_uniform', activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(10, activation='softmax'))

model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_13 (Conv2D)           (None, 32, 32, 32)        896
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 16, 16, 32)        4128
_________________________________________________________________
max_pooling2d_14 (MaxPooling (None, 8, 8, 32)          0
_________________________________________________________________
dropout_11 (Dropout)         (None, 8, 8, 32)          0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 8, 8, 64)          8256
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 4, 4, 64)          0
_________________________________________________________________
dropout_12 (Dropout)         (None, 4, 4, 64)          0
_________________________________________________________________
flatten_5 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_9 (Dense)              (None, 512)               524800
_________________________________________________________________
dropout_13 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_10 (Dense)             (None, 10)                5130
=================================================================
Total params: 543,210
Trainable params: 543,210
Non-trainable params: 0
_________________________________________________________________
```

8. Compile the Model

In [104]:
```
# compile the model
model.compile(loss='categorical_crossentropy', optimizer='Adamax',
              metrics=['accuracy'])
```

9. Train the Model

> Note:
>
> - verbose=0 will show you nothing (silent)
> - verbose=1 will show you an animated progress bar like this:
>   - progres_bar
> - verbose=2 will just mention the number of epoch like this:
>   - Epoch = 1/10

In [105]:
```
from keras.callbacks import ModelCheckpoint

batch_size = 35
epochs = 50

# train the model
checkpointer = ModelCheckpoint(filepath='model.weights.best.hdf5', verbose=1,
                               save_best_only=True)
hist = model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs,
          validation_data=(x_valid, y_valid), callbacks=[checkpointer],
          verbose=2, shuffle=True)
```

```
Train on 45000 samples, validate on 5000 samples
Epoch 1/50
 - 12s - loss: 1.6698 - accuracy: 0.3874 - val_loss: 1.3551 - val_accuracy: 0.5184

Epoch 00001: val_loss improved from inf to 1.35512, saving model to model.weights.best.hdf5
Epoch 2/50
 - 11s - loss: 1.3558 - accuracy: 0.5094 - val_loss: 1.2253 - val_accuracy: 0.5532

Epoch 00002: val_loss improved from 1.35512 to 1.22526, saving model to model.weights.best.hdf5
Epoch 3/50
 - 11s - loss: 1.2383 - accuracy: 0.5564 - val_loss: 1.1120 - val_accuracy: 0.6148

Epoch 00003: val_loss improved from 1.22526 to 1.11199, saving model to model.weights.best.hdf5
Epoch 4/50
 - 13s - loss: 1.1399 - accuracy: 0.5939 - val_loss: 1.0113 - val_accuracy: 0.6498

Epoch 00004: val_loss improved from 1.11199 to 1.01130, saving model to model.weights.best.hdf5
Epoch 5/50
 - 12s - loss: 1.0773 - accuracy: 0.6150 - val_loss: 0.9489 - val_accuracy: 0.6730

Epoch 00005: val_loss improved from 1.01130 to 0.94893, saving model to model.weights.best.hdf5
Epoch 6/50
 - 11s - loss: 1.0180 - accuracy: 0.6368 - val_loss: 0.9235 - val_accuracy: 0.6824

Epoch 00006: val_loss improved from 0.94893 to 0.92349, saving model to model.weights.best.hdf5
Epoch 7/50
 - 12s - loss: 0.9618 - accuracy: 0.6578 - val_loss: 0.8814 - val_accuracy: 0.6976

Epoch 00007: val_loss improved from 0.92349 to 0.88143, saving model to model.weights.best.hdf5
Epoch 8/50
 - 12s - loss: 0.9188 - accuracy: 0.6748 - val_loss: 0.8303 - val_accuracy: 0.7166

Epoch 00008: val_loss improved from 0.88143 to 0.83028, saving model to model.weights.best.hdf5
Epoch 9/50
 - 12s - loss: 0.8825 - accuracy: 0.6869 - val_loss: 0.7856 - val_accuracy: 0.7230

Epoch 00009: val_loss improved from 0.83028 to 0.78556, saving model to model.weights.best.hdf5
Epoch 10/50
 - 11s - loss: 0.8479 - accuracy: 0.6990 - val_loss: 0.7657 - val_accuracy: 0.7316

Epoch 00010: val_loss improved from 0.78556 to 0.76572, saving model to model.weights.best.hdf5
Epoch 11/50
 - 12s - loss: 0.8154 - accuracy: 0.7127 - val_loss: 0.7748 - val_accuracy: 0.7266

Epoch 00011: val_loss did not improve from 0.76572
Epoch 12/50
 - 11s - loss: 0.7948 - accuracy: 0.7186 - val_loss: 0.7552 - val_accuracy: 0.7286

Epoch 00012: val_loss improved from 0.76572 to 0.75524, saving model to model.weights.best.hdf5
Epoch 13/50
 - 12s - loss: 0.7692 - accuracy: 0.7300 - val_loss: 0.7202 - val_accuracy: 0.7470

Epoch 00013: val_loss improved from 0.75524 to 0.72023, saving model to model.weights.best.hdf5
Epoch 14/50
 - 12s - loss: 0.7475 - accuracy: 0.7370 - val_loss: 0.7012 - val_accuracy: 0.7582

Epoch 00014: val_loss improved from 0.72023 to 0.70122, saving model to model.weights.best.hdf5
Epoch 15/50
 - 11s - loss: 0.7208 - accuracy: 0.7473 - val_loss: 0.6869 - val_accuracy: 0.7532

Epoch 00015: val_loss improved from 0.70122 to 0.68690, saving model to model.weights.best.hdf5
Epoch 16/50
 - 11s - loss: 0.7075 - accuracy: 0.7519 - val_loss: 0.6943 - val_accuracy: 0.7598

Epoch 00016: val_loss did not improve from 0.68690
Epoch 17/50
 - 11s - loss: 0.6866 - accuracy: 0.7577 - val_loss: 0.6832 - val_accuracy: 0.7566

Epoch 00017: val_loss improved from 0.68690 to 0.68323, saving model to model.weights.best.hdf5
Epoch 18/50
 - 12s - loss: 0.6717 - accuracy: 0.7641 - val_loss: 0.6934 - val_accuracy: 0.7564

Epoch 00018: val_loss did not improve from 0.68323
Epoch 19/50
 - 12s - loss: 0.6609 - accuracy: 0.7646 - val_loss: 0.6757 - val_accuracy: 0.7592

Epoch 00019: val_loss improved from 0.68323 to 0.67565, saving model to model.weights.best.hdf5
Epoch 20/50
 - 12s - loss: 0.6402 - accuracy: 0.7747 - val_loss: 0.6568 - val_accuracy: 0.7698

Epoch 00020: val_loss improved from 0.67565 to 0.65682, saving model to model.weights.best.hdf5
Epoch 21/50
 - 11s - loss: 0.6241 - accuracy: 0.7820 - val_loss: 0.6528 - val_accuracy: 0.7724

Epoch 00021: val_loss improved from 0.65682 to 0.65277, saving model to model.weights.best.hdf5
Epoch 22/50
 - 12s - loss: 0.6135 - accuracy: 0.7819 - val_loss: 0.6587 - val_accuracy: 0.7722

Epoch 00022: val_loss did not improve from 0.65277
Epoch 23/50
 - 11s - loss: 0.5938 - accuracy: 0.7906 - val_loss: 0.6476 - val_accuracy: 0.7708

Epoch 00023: val_loss improved from 0.65277 to 0.64755, saving model to model.weights.best.hdf5
Epoch 24/50
 - 11s - loss: 0.5840 - accuracy: 0.7909 - val_loss: 0.6595 - val_accuracy: 0.7716

Epoch 00024: val_loss did not improve from 0.64755
Epoch 25/50
 - 12s - loss: 0.5783 - accuracy: 0.7960 - val_loss: 0.6449 - val_accuracy: 0.7782

Epoch 00025: val_loss improved from 0.64755 to 0.64494, saving model to model.weights.best.hdf5
Epoch 26/50
 - 12s - loss: 0.5642 - accuracy: 0.8024 - val_loss: 0.6412 - val_accuracy: 0.7820

Epoch 00026: val_loss improved from 0.64494 to 0.64125, saving model to model.weights.best.hdf5
Epoch 27/50
 - 11s - loss: 0.5596 - accuracy: 0.8012 - val_loss: 0.6457 - val_accuracy: 0.7762

Epoch 00027: val_loss did not improve from 0.64125
Epoch 28/50
 - 12s - loss: 0.5444 - accuracy: 0.8072 - val_loss: 0.6456 - val_accuracy: 0.7802

Epoch 00028: val_loss did not improve from 0.64125
Epoch 29/50
 - 12s - loss: 0.5314 - accuracy: 0.8108 - val_loss: 0.6469 - val_accuracy: 0.7768

Epoch 00029: val_loss did not improve from 0.64125
Epoch 30/50
 - 12s - loss: 0.5244 - accuracy: 0.8146 - val_loss: 0.6829 - val_accuracy: 0.7660

Epoch 00030: val_loss did not improve from 0.64125
Epoch 31/50
 - 12s - loss: 0.5217 - accuracy: 0.8177 - val_loss: 0.6371 - val_accuracy: 0.7746

Epoch 00031: val_loss improved from 0.64125 to 0.63709, saving model to model.weights.best.hdf5
Epoch 32/50
 - 12s - loss: 0.5054 - accuracy: 0.8227 - val_loss: 0.6564 - val_accuracy: 0.7754

Epoch 00032: val_loss did not improve from 0.63709
Epoch 33/50
 - 11s - loss: 0.4973 - accuracy: 0.8234 - val_loss: 0.6528 - val_accuracy: 0.7752

Epoch 00033: val_loss did not improve from 0.63709
Epoch 34/50
 - 12s - loss: 0.4937 - accuracy: 0.8256 - val_loss: 0.6732 - val_accuracy: 0.7614

Epoch 00034: val_loss did not improve from 0.63709
Epoch 35/50
 - 11s - loss: 0.4790 - accuracy: 0.8314 - val_loss: 0.6707 - val_accuracy: 0.7760

Epoch 00035: val_loss did not improve from 0.63709
Epoch 36/50
 - 12s - loss: 0.4761 - accuracy: 0.8297 - val_loss: 0.6683 - val_accuracy: 0.7784

Epoch 00036: val_loss did not improve from 0.63709
Epoch 37/50
 - 12s - loss: 0.4722 - accuracy: 0.8314 - val_loss: 0.6430 - val_accuracy: 0.7792

Epoch 00037: val_loss did not improve from 0.63709
Epoch 38/50
 - 12s - loss: 0.4566 - accuracy: 0.8389 - val_loss: 0.6701 - val_accuracy: 0.7778

Epoch 00038: val_loss did not improve from 0.63709
Epoch 39/50
 - 12s - loss: 0.4588 - accuracy: 0.8354 - val_loss: 0.6546 - val_accuracy: 0.7772

Epoch 00039: val_loss did not improve from 0.63709
Epoch 40/50
 - 12s - loss: 0.4496 - accuracy: 0.8404 - val_loss: 0.6607 - val_accuracy: 0.7786

Epoch 00040: val_loss did not improve from 0.63709
Epoch 41/50
 - 11s - loss: 0.4422 - accuracy: 0.8429 - val_loss: 0.6673 - val_accuracy: 0.7742

Epoch 00041: val_loss did not improve from 0.63709
Epoch 42/50
 - 12s - loss: 0.4399 - accuracy: 0.8430 - val_loss: 0.6429 - val_accuracy: 0.7818

Epoch 00042: val_loss did not improve from 0.63709
Epoch 43/50
 - 11s - loss: 0.4357 - accuracy: 0.8452 - val_loss: 0.6674 - val_accuracy: 0.7714

Epoch 00043: val_loss did not improve from 0.63709
Epoch 44/50
 - 12s - loss: 0.4275 - accuracy: 0.8467 - val_loss: 0.6412 - val_accuracy: 0.7850

Epoch 00044: val_loss did not improve from 0.63709
Epoch 45/50
 - 11s - loss: 0.4216 - accuracy: 0.8509 - val_loss: 0.6421 - val_accuracy: 0.7864

Epoch 00045: val_loss did not improve from 0.63709
Epoch 46/50
 - 12s - loss: 0.4149 - accuracy: 0.8515 - val_loss: 0.6524 - val_accuracy: 0.7812

Epoch 00046: val_loss did not improve from 0.63709
Epoch 47/50
 - 12s - loss: 0.4085 - accuracy: 0.8542 - val_loss: 0.6496 - val_accuracy: 0.7834

Epoch 00047: val_loss did not improve from 0.63709
Epoch 48/50
 - 11s - loss: 0.4032 - accuracy: 0.8569 - val_loss: 0.6642 - val_accuracy: 0.7832

Epoch 00048: val_loss did not improve from 0.63709
Epoch 49/50
 - 11s - loss: 0.4013 - accuracy: 0.8577 - val_loss: 0.6512 - val_accuracy: 0.7872

Epoch 00049: val_loss did not improve from 0.63709
Epoch 50/50
 - 11s - loss: 0.3975 - accuracy: 0.8580 - val_loss: 0.6483 - val_accuracy: 0.7844

Epoch 00050: val_loss did not improve from 0.63709
```

10. Load the Model with the Best Validation Accuracy

In [106]:
```
# load the weights that yielded the best validation accuracy
model.load_weights('model.weights.best.hdf5')
```

11. Calculate Classification Accuracy on Test Set

In [107]:
```
# evaluate and print test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.6550379812240601
Test accuracy: 0.7741000056266785
```

How to interpret loss and accuracy?

- Loss can be seen as a distance between the true values of the problem and the values predicted by the model.
  - Greater the loss is, more huge is the errors made on the data.
- Accuracy can be seen as the number of errors made on the data.

  That means :
  - a low accuracy and huge loss means:
    - the model made huge errors on a lot of data
  - a low accuracy but low loss means:
    - the model made little errors on a lot of data
  - a great accuracy with low loss means:
    - the model made low errors on a few data (best case)

- The function below is used to update the plots for each epoch and error.

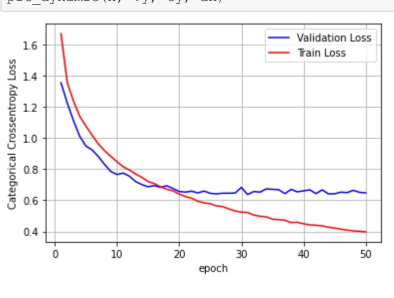
In [108]:
```
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4

def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = hist.history['val_loss']
ty = hist.history['loss']
plt_dynamic(x, vy, ty, ax)
```



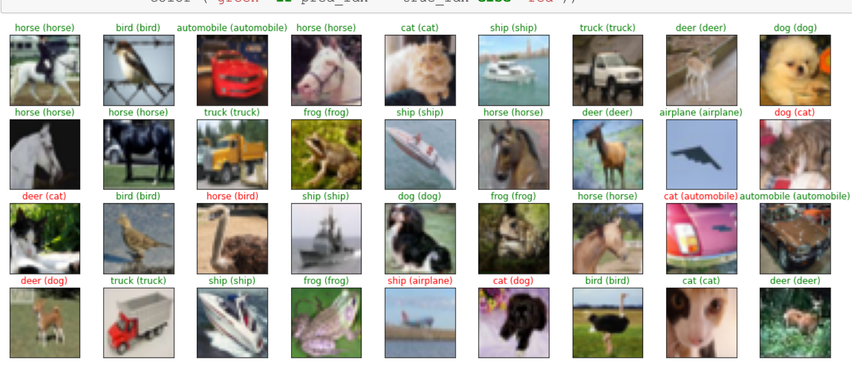
12. Visualize Some Predictions

This may give you some insight into why the network is misclassifying certain objects.

In [109]:
```
# get predictions on the test set
y_hat = model.predict(x_test)

cifar10_labels = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'tr
uck']
```

In [110]:
```
# plot a random sample of test images, their predicted labels, and ground truth
fig = plt.figure(figsize=(20, 8))
for i, idx in enumerate(np.random.choice(x_test.shape[0], size=36, replace=False)):
    ax = fig.add_subplot(4, 9, i + 1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(x_test[idx]))
    pred_idx = np.argmax(y_hat[idx])
    true_idx = np.argmax(y_test[idx])
    ax.set_title("{} ({})".format(cifar10_labels[pred_idx], cifar10_labels[true_idx]),
                 color=("green" if pred_idx == true_idx else "red"))
```



In [110]:
```

```