1. Please visit this link to access the state-of-art DenseNet code for reference - DenseNet - cifar10 notebook link
2. You need to create a copy of this and "retrain" this model to achieve 90+ test accuracy.
3. You cannot use Dense Layers (also called fully connected layers), or DropOut.
4. You MUST use Image Augmentation Techniques.
5. You cannot use an already trained model as a beginning points, you have to initilize as your own
6. You cannot run the program for more than 300 Epochs, and it should be clear from your log, that you have only used 300 Epochs
7. You cannot use test images for training the model.
8. You cannot change the general architecture of DenseNet (which means you must use Dense Block, Transition and Output blocks as mentioned in the code)
9. You are free to change Convolution types (e.g. from 3x3 normal convolution to Depthwise Separable, etc)
10. You cannot have more than 1 Million parameters in total
11. You are free to move the code from Keras to Tensorflow, Pytorch, MXNET etc.
12. You can use any optimization algorithm you need.
13. You can checkpoint your model and retrain the model from that checkpoint so that no need of training the model from first if you lost at any epoch while training. You can directly load that model and Train from that epoch.

In [32]:

```
import time
import matplotlib.pyplot as plt
import numpy as np

from keras.models import Sequential
from keras.layers.convolutional import Convolution2D, MaxPooling2D
from keras.layers import Activation, Flatten, Dense, Dropout
from keras.layers.normalization import BatchNormalization
from keras.utils import np_utils
from keras.layers import Conv2D,GlobalAveragePooling2D
```

In [3]:

```
import os
os.environ["THEANO_FLAGS"] = "mode=FAST_RUN,device=gpu,floatX=float32"
```

Loading Dataset

In [4]:

```
from keras.datasets import cifar10
(train_features, train_labels), (test_features, test_labels) = cifar10.load_data()
num_train, img_channels, img_rows, img_cols =  train_features.shape
num_test, _, _, _ =  test_features.shape
num_classes = len(np.unique(train_labels))
```

Train and Test data

In [5]:

```
train_features = train_features.astype('float32')/255
test_features = test_features.astype('float32')/255
# convert class labels to binary class labels
train_labels = np_utils.to_categorical(train_labels, num_classes)
test_labels = np_utils.to_categorical(test_labels, num_classes)
```

In [6]:

```
class_names = ['airplane','automobile','bird','cat','deer','dog','frog','horse','ship','truck']
```

In [124]:

```
def plot_model_history(model_history):
    fig, axs = plt.subplots(1,2,figsize=(15,5))
```

```
    # summarize history for accuracy
    axs[0].plot(range(1,len(model_history.history['accuracy'])+1),model_history.history['accuracy']
)
    axs[0].plot(range(1,len(model_history.history['val_accuracy'])+1),model_history.history['val_ac
curacy'])
    axs[0].set_title('Model Accuracy')
    axs[0].set_ylabel('Accuracy')
    axs[0].set_xlabel('Epoch')
    axs[0].set_xticks(np.arange(1,len(model_history.history['accuracy'])+1),len(model_history.histo
ry['accuracy'])/10)
    axs[0].legend(['train', 'val'], loc='best')
    # summarize history for loss
    axs[1].plot(range(1,len(model_history.history['loss'])+1),model_history.history['loss'])
    axs[1].plot(range(1,len(model_history.history['val_loss'])+1),model_history.history['val_loss']
)
    axs[1].set_title('Model Loss')
    axs[1].set_ylabel('Loss')
    axs[1].set_xlabel('Epoch')
    axs[1].set_xticks(np.arange(1,len(model_history.history['loss'])+1),len(model_history.history['
loss'])/10)
    axs[1].legend(['train', 'val'], loc='best')
    plt.show()
```

In [8]:

```
def accuracy(test_x, test_y, model):
    result = model.predict(test_x)
    predicted_class = np.argmax(result, axis=1)
    true_class = np.argmax(test_y, axis=1)
    num_correct = np.sum(predicted_class == true_class)
    accuracy = float(num_correct)/result.shape[0]
    return (accuracy * 100)
```

CNN model on CIFAR

In [122]:

```
from keras import regularizers

weight_decay = 1e-4
model = Sequential()
model.add(Conv2D(32, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay), input
_shape = (32,32,3)))
model.add(Activation('relu'))
model.add(Conv2D(48, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(128, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(256, (1,1), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(512, (1,1), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(128, (1,1), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(512, (1,1), padding='same'))
model.add(Conv2D(256, (1,1), padding='same'))
model.add(Conv2D(128, (1,1), padding='same'))
model.add(Conv2D(10, (1,1), padding='same'))
model.add(GlobalAveragePooling2D())
model.add(Activation('softmax'))
model.summary()
```

```
Model: "sequential_66"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_462 (Conv2D)          (None, 32, 32, 32)        896
```

```
activation_336 (Activation)   (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_463 (Conv2D)           (None, 32, 32, 48)        13872
_________________________________________________________________
activation_337 (Activation)   (None, 32, 32, 48)        0
_________________________________________________________________
max_pooling2d_257 (MaxPoolin (None, 16, 16, 48)        0
_________________________________________________________________
conv2d_464 (Conv2D)           (None, 16, 16, 128)       55424
_________________________________________________________________
activation_338 (Activation)   (None, 16, 16, 128)       0
_________________________________________________________________
max_pooling2d_258 (MaxPoolin (None, 8, 8, 128)         0
_________________________________________________________________
conv2d_465 (Conv2D)           (None, 8, 8, 256)         33024
_________________________________________________________________
activation_339 (Activation)   (None, 8, 8, 256)         0
_________________________________________________________________
max_pooling2d_259 (MaxPoolin (None, 4, 4, 256)         0
_________________________________________________________________
conv2d_466 (Conv2D)           (None, 4, 4, 512)         131584
_________________________________________________________________
activation_340 (Activation)   (None, 4, 4, 512)         0
_________________________________________________________________
max_pooling2d_260 (MaxPoolin (None, 2, 2, 512)         0
_________________________________________________________________
conv2d_467 (Conv2D)           (None, 2, 2, 128)         65664
_________________________________________________________________
activation_341 (Activation)   (None, 2, 2, 128)         0
_________________________________________________________________
max_pooling2d_261 (MaxPoolin (None, 1, 1, 128)         0
_________________________________________________________________
conv2d_468 (Conv2D)           (None, 1, 1, 512)         66048
_________________________________________________________________
conv2d_469 (Conv2D)           (None, 1, 1, 256)         131328
_________________________________________________________________
conv2d_470 (Conv2D)           (None, 1, 1, 128)         32896
_________________________________________________________________
conv2d_471 (Conv2D)           (None, 1, 1, 10)          1290
_________________________________________________________________
global_average_pooling2d_38  (None, 10)                0
_________________________________________________________________
activation_342 (Activation)   (None, 10)                0
=================================================================
Total params: 532,026
Trainable params: 532,026
Non-trainable params: 0
_________________________________________________________________
```

Data Augmentation

In [25]:

```
from keras.preprocessing.image import ImageDataGenerator

#data augmentation
datagen = ImageDataGenerator(
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True,
    )

datagen.fit(train_features)
```

In [125]:

```
from keras.callbacks import ModelCheckpoint,TensorBoard,ReduceLROnPlateau, EarlyStopping

checkpoint = ModelCheckpoint("model.h5",
                             monitor="val_accuracy",
                             mode="max",
                             save_best_only = True,
```

```
                              verbose=1)
earlystop = EarlyStopping(monitor = 'val_accuracy',
                          mode="max",
                          min_delta = 0,
                          patience = 4,
                          verbose = 1,)

tensorboard = TensorBoard(log_dir='graph', histogram_freq=0, batch_size=256, write_graph=True, writ
e_grads=False, write_images=False, embeddings_freq=0, embeddings_layer_names=None,
embeddings_metadata=None, embeddings_data=None)

callbacks = [checkpoint,earlystop,tensorboard]
```

In [132]:

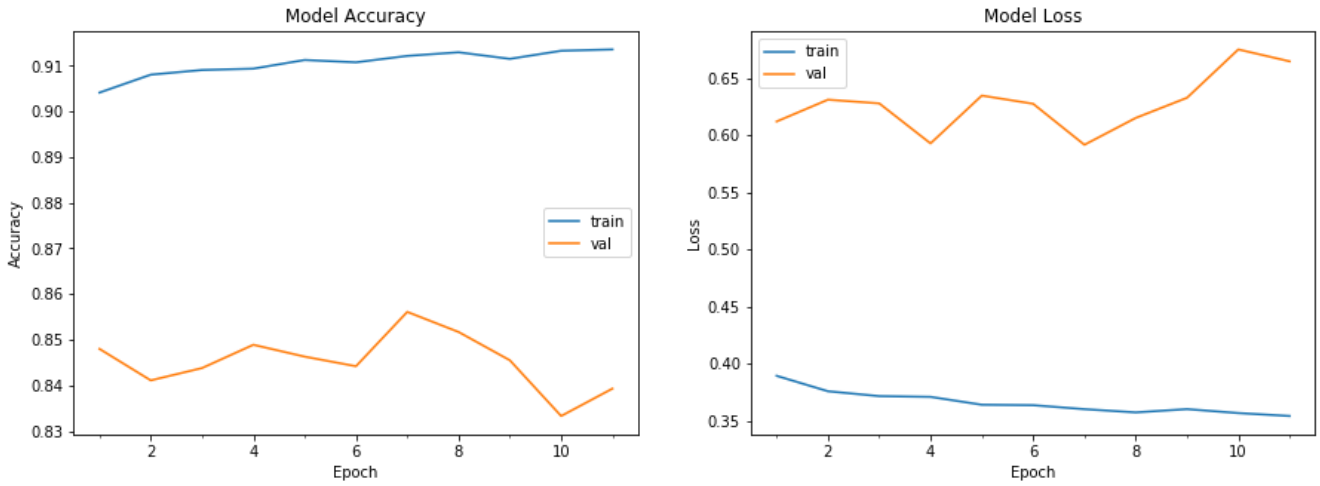
```
import keras

batch = 128

# Compile the model
start = time.time()

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model_info = model.fit_generator(datagen.flow(train_features, train_labels, batch_size = 512), step
s_per_epoch = train_features.shape[0] // batch , epochs=200, verbose=1, callbacks=callbacks, valida
tion_data = (test_features, test_labels))

end = time.time()
```

```
Epoch 1/200
390/390 [==============================] - 647s 2s/step - loss: 0.3895 - accuracy: 0.9041 - val_lo
ss: 0.6121 - val_accuracy: 0.8480

Epoch 00001: val_accuracy did not improve from 0.84880
Epoch 2/200
390/390 [==============================] - 620s 2s/step - loss: 0.3761 - accuracy: 0.9081 - val_lo
ss: 0.6311 - val_accuracy: 0.8411

Epoch 00002: val_accuracy did not improve from 0.84880
Epoch 3/200
390/390 [==============================] - 621s 2s/step - loss: 0.3716 - accuracy: 0.9091 - val_lo
ss: 0.6279 - val_accuracy: 0.8438

Epoch 00003: val_accuracy did not improve from 0.84880
Epoch 4/200
390/390 [==============================] - 970s 2s/step - loss: 0.3711 - accuracy: 0.9094 - val_lo
ss: 0.5929 - val_accuracy: 0.8489

Epoch 00004: val_accuracy improved from 0.84880 to 0.84890, saving model to model.h5
Epoch 5/200
390/390 [==============================] - 1068s 3s/step - loss: 0.3641 - accuracy: 0.9113 - val_l
oss: 0.6347 - val_accuracy: 0.8463

Epoch 00005: val_accuracy did not improve from 0.84890
Epoch 6/200
390/390 [==============================] - 1056s 3s/step - loss: 0.3637 - accuracy: 0.9108 - val_l
oss: 0.6276 - val_accuracy: 0.8442

Epoch 00006: val_accuracy did not improve from 0.84890
Epoch 7/200
390/390 [==============================] - 1181s 3s/step - loss: 0.3603 - accuracy: 0.9122 - val_l
oss: 0.5917 - val_accuracy: 0.8561

Epoch 00007: val_accuracy improved from 0.84890 to 0.85610, saving model to model.h5
Epoch 8/200
390/390 [==============================] - 1195s 3s/step - loss: 0.3574 - accuracy: 0.9130 - val_l
oss: 0.6152 - val_accuracy: 0.8517

Epoch 00008: val_accuracy did not improve from 0.85610
Epoch 9/200
390/390 [==============================] - 1294s 3s/step - loss: 0.3603 - accuracy: 0.9115 - val_l
oss: 0.6328 - val_accuracy: 0.8455

Epoch 00009: val_accuracy did not improve from 0.85610
Epoch 10/200
```

```
390/390 [==============================] - 1287s 3s/step - loss: 0.3568 - accuracy: 0.9133 - val_l
oss: 0.6751 - val_accuracy: 0.8333

Epoch 00010: val_accuracy did not improve from 0.85610
Epoch 11/200
390/390 [==============================] - 721s 2s/step - loss: 0.3542 - accuracy: 0.9136 - val_lo
ss: 0.6647 - val_accuracy: 0.8393

Epoch 00011: val_accuracy did not improve from 0.85610
Epoch 00011: early stopping
```

In [156]:

```
# plot model history

plot_model_history(model_info)
print("Model took to train is :")
print(end - start)
```




```
Model took to train is :
10692.382631540298
```

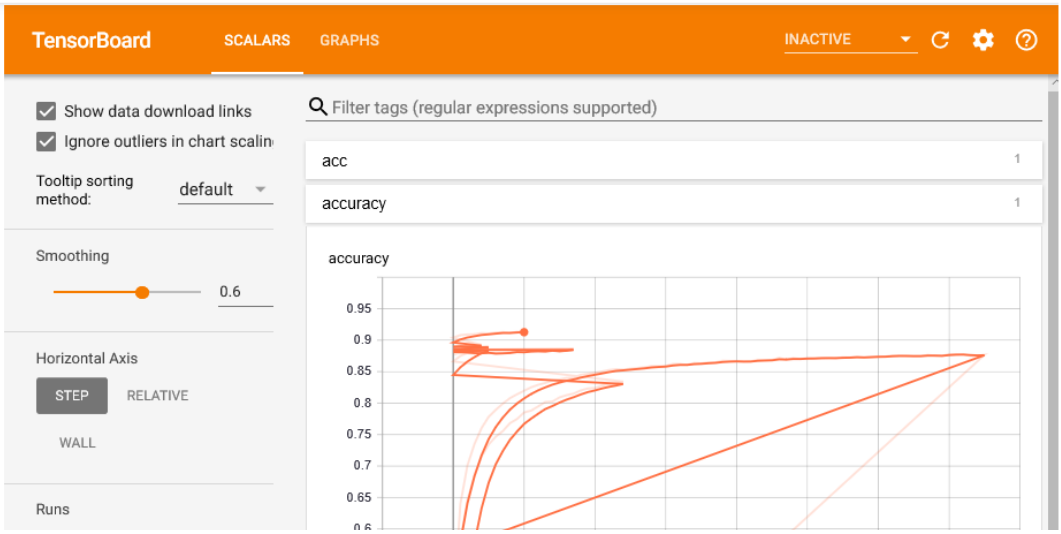
In [152]:

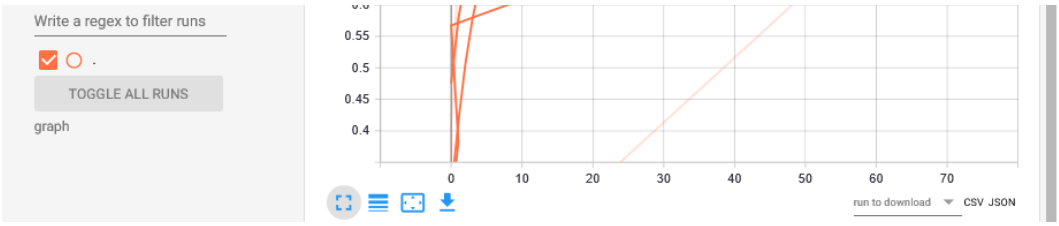
```
## %load_ext tensorboard
## %tensorboard --logdir graph
```

In [150]:

```
from IPython.display import Image
Image(filename='TrainAccuracy.png')
```

Out[150]:

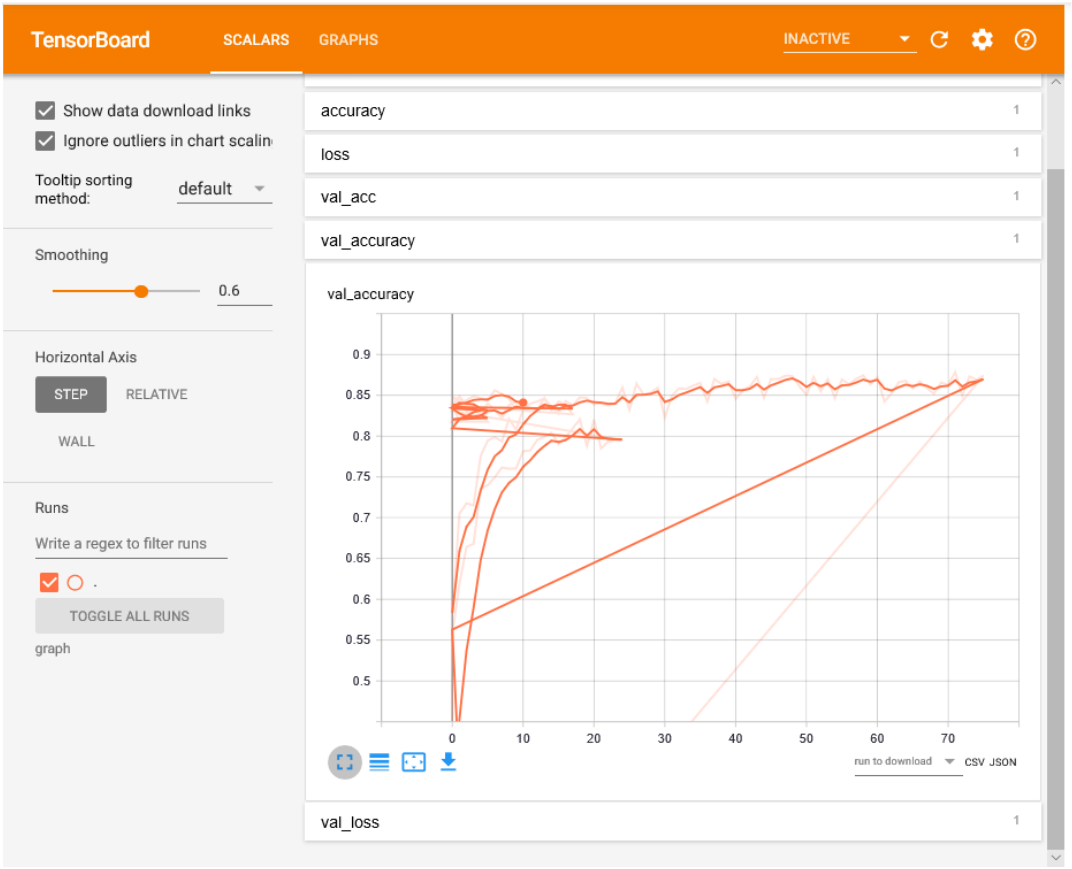




In [151]:

```
from IPython.display import Image
Image(filename='ValAccuracy.png')
```

Out[151]:



In [134]:

```
def auc1(y_true, y_pred):
    if len(np.unique(y_true[:,1])) == 1:
        return 0.5
    else:
        return roc_auc_score(y_true, y_pred)

def auroc(y_true, y_pred):
    return tf.py_func(auc1, (y_true, y_pred), tf.double)
```

In [137]:

```
from keras.models import load_model

custom_objects = {"auroc":auroc}

best_model = load_model('model.h5',custom_objects= custom_objects)
best_model.save("CIFARbestmodel.h5")
```

In [138]:

```
y_pred_test = model.predict_proba(test_features)
```

```
y_pred_test_classes = np.argmax(y_pred_test, axis=1)
y_pred_test_max_probas = np.max(y_pred_test, axis=1)
```

Summary

In [140]:

```
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_features[random_index, :])
        pred_label =  class_names[y_pred_test_classes[random_index]]
        pred_proba = y_pred_test_max_probas[random_index]
        true_label = test_labels[random_index,2]
        ax.set_title("pred: {}\nscore: {:.3}".format(pred_label, pred_proba))
plt.show()
```

In [141]:

```
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["train_loss", "train_auc", "test_loss","test_auc"]
x.add_row([0.36, 0.91, 0.59, 0.86])

print(x)
```

```
+------------+-----------+-----------+----------+
| train_loss | train_auc | test_loss | test_auc |
+------------+-----------+-----------+----------+
|    0.36    |    0.91   |    0.59   |   0.86   |
+------------+-----------+-----------+----------+
```

Reference :

1. https://towardsdatascience.com/cifar-10-image-classification-in-tensorflow-5b501f7dc77c
2. https://medium.com/@udolf15/building-a-image-classifier-using-cnn-with-cifar-10-dataset-5682afa4f51