

## Homework- 26.11.2018:

### State of the Art Neural Network Architectures

The purpose of this homework is to implement and evaluate the sota architectures presented in the lecture. However, you are encouraged to try your own layer module ideas. Feel free to consult the [Keras source code \(https://github.com/keras-team/keras-applications\)](https://github.com/keras-team/keras-applications):

1. Based on the CNN modules presented in the lecture e.g. VGG16, Inception, ResNet, Xception, DenseNet, come up with your own CNN module and write a small text discussing your idea and motivations behind the module.
1. Evaluate all your module using the Keras CIFAR10 dataset splits (The model with best test accuracy will present their solution to the class).

```
In [18]: from tensorflow.keras.datasets import cifar10

(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
In [19]: import numpy as np
print(np.shape(x_train))
print(np.shape(y_train))
print(np.shape(x_test))
print(np.shape(y_test))
#print(x_train[0,:,:,:])#,RGB = 3
#print(y_train)

x_train[0,0,0,0]

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

```
Out[19]: 59
```

### Idea

Use hirarchy to learn. E.g. first layer learns edges, next one learns collections of edges (shapes), next layer will be trained to recognize collections of shapes (tails, face), until we get can recognise high level features (truck, ships, dog) towards the end of the NN.

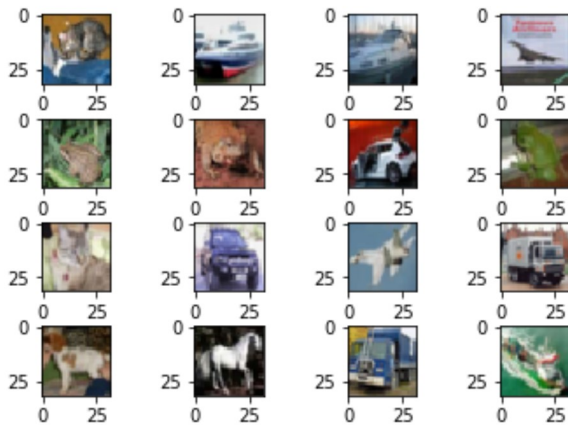
First, we try a regular AlexNet Architecture.

```
In [11]: #Hyperparameters
img_shape = (32,32,3)
classes_num = 10
```

```
In [21]: #Visualize data
import matplotlib.pyplot as plt
from PIL import Image

def show_Images(images):
    plt.figure(1)
    k = 0
    for i in range(0,4):
        for j in range(0,4):
            plt.subplot2grid((4,4),(i,j))
            plt.imshow(Image.fromarray(images[k]))
            k = k+1
    plt.subplots_adjust(hspace = 0.5)
    plt.show()

show_Images(x_test[:16])
```



```
In [22]: #Transform data to fit softmax
from tensorflow.keras import utils
y_train_categorical = utils.to_categorical(y_train, classes_num)
y_test_categorical = utils.to_categorical(y_test, classes_num)

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
```

```
In [23]: #MODEL: AlexNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization

alexnet = Sequential()

# Layer 1
# 96 filter mit 11x11 convolution too big for 32x32 img?
alexnet.add(Conv2D(96, (11, 11), input_shape=img_shape, padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 2
alexnet.add(Conv2D(256, (5, 5), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 3
alexnet.add(Conv2D(384, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 4
alexnet.add(Conv2D(384, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))

# Layer 5
alexnet.add(Conv2D(256, (3, 3), padding='same'))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(MaxPooling2D(pool_size=(2, 2)))

alexnet.add(Flatten())

# Layer 6 - fully connected layer
alexnet.add(Dense(4096))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(Dropout(0.5))

# Layer 7
alexnet.add(Dense(4096))
alexnet.add(BatchNormalization())
alexnet.add(Activation('relu'))
alexnet.add(Dropout(0.5))

# Layer 8
alexnet.add(Dense(classes_num))
alexnet.add(BatchNormalization())
alexnet.add(Activation('softmax'))

#alexnet.summary() #~25.000.000 parameters to learn
```

```
In [24]: #Compile
alexnet.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#Train
alexnet.fit(x_train, y_train_categorical, validation_data=(x_test, y_test_categorical), batch_size=64, epochs=5, verbose=1)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/5
50000/50000 [=====] - 62s 1ms/step - loss: 1.4157 - acc: 0.5049 - val_loss: 1.4982 - val_acc: 0.4904
Epoch 2/5
50000/50000 [=====] - 57s 1ms/step - loss: 1.0380 - acc: 0.6491 - val_loss: 1.2788 - val_acc: 0.5870
Epoch 3/5
50000/50000 [=====] - 57s 1ms/step - loss: 0.8340 - acc: 0.7225 - val_loss: 1.1969 - val_acc: 0.6003
Epoch 4/5
50000/50000 [=====] - 57s 1ms/step - loss: 0.6912 - acc: 0.7720 - val_loss: 1.1507 - val_acc: 0.6217
Epoch 5/5
50000/50000 [=====] - 57s 1ms/step - loss: 0.5728 - acc: 0.8128 - val_loss: 0.9361 - val_acc: 0.6920
```

```
Out[24]: <tensorflow.python.keras.callbacks.History at 0x1bb3e51f208>
```

```
In [25]: scores = alexnet.evaluate(x_test, y_test_categorical, batch_size=128, verbose=1)
print('\nTest result: %.3f loss: %.3f' % (scores[1]*100, scores[0]))
```

```
10000/10000 [=====] - 2s 224us/step
```

```
Test result: 69.200 loss: 0.936
```

## Result interpretation

Traning ~25 million parameters on 50000 samples seems too much, lets try a smaller size. Additionally, ELU activation will replace RELU activation (smoother loss surface and no "Dead ReLU"). Dropout has been added to prevent overfitting of the NN. Also, regularizers have been added to prevent overfitting while maintaining accuracy at a high level.

```
In [12]: #MODEL: Simpler CNN; cite: https://appliedmachinelearning.blog/2018/03/24/achieving-90-accuracy-in-object-recognition-task-on-cifar-10-dataset-with-keras-convolutional-neural-networks/
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization
from tensorflow.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=img_shape))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(32, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

model.add(Conv2D(64, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.3))

model.add(Conv2D(128, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3,3), padding='same', kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(classes_num, activation='softmax'))

#model.summary() #~300.000 parameters to learn
```

```
In [11]: #Model overfitt after around 50 epochs. Only training accuracy increases further  
. -> early stopping (additionally saves time)  
from tensorflow.keras.callbacks import EarlyStopping  
  
callbacks = [EarlyStopping(monitor='val_loss',  
                           min_delta=0,  
                           patience=4,  
                           verbose=0, mode='auto')]  
  
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])  
  
model.fit(x_train, y_train_categorical, batch_size=64, epochs=128, verbose=1, \n          validation_data=(x_test, y_test_categorical), callbacks=callbacks)  
  
#testing  
scores = model.evaluate(x_test, y_test_categorical, batch_size=128, verbose=1)  
print('\nTest result: %.3f loss: %.3f' % (scores[1]*100, scores[0]))
```

Train on 50000 samples, validate on 10000 samples

Epoch 1/125

50000/50000 [=====] - 19s 384us/step - loss: 0.4388 -  
acc: 0.9191 - val\_loss: 0.7145 - val\_acc: 0.8461

Epoch 2/125

50000/50000 [=====] - 17s 350us/step - loss: 0.4287 -  
acc: 0.9241 - val\_loss: 0.6858 - val\_acc: 0.8610

Epoch 3/125

50000/50000 [=====] - 18s 362us/step - loss: 0.4340 -  
acc: 0.9209 - val\_loss: 0.6731 - val\_acc: 0.8607

Epoch 4/125

50000/50000 [=====] - 18s 362us/step - loss: 0.4295 -  
acc: 0.9216 - val\_loss: 0.7014 - val\_acc: 0.8522

Epoch 5/125

50000/50000 [=====] - 18s 358us/step - loss: 0.4249 -  
acc: 0.9231 - val\_loss: 0.7043 - val\_acc: 0.8527

Epoch 6/125

50000/50000 [=====] - 18s 357us/step - loss: 0.4316 -  
acc: 0.9212 - val\_loss: 0.6847 - val\_acc: 0.8543

Epoch 7/125

50000/50000 [=====] - 18s 351us/step - loss: 0.4247 -  
acc: 0.9231 - val\_loss: 0.7081 - val\_acc: 0.8524

10000/10000 [=====] - 1s 93us/step

Test result: 85.240 loss: 0.708

```
In [32]: #Data augmentation and z-score didnt improve accuracy (dataset to small to make these changes meaningful?)

from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=90,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True)
datagen.fit(x_train)

#z-score (for similar ranged features, similar gradients)
mean = np.mean(x_train,axis=(0,1,2,3))
std = np.std(x_train,axis=(0,1,2,3))
x_train = (x_train-mean)/(std+1e-7)
x_test = (x_test-mean)/(std+1e-7)

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

callbacks = [EarlyStopping(monitor='val_loss',
                           min_delta=0,
                           patience=4,
                           verbose=0, mode='auto')]

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

model.fit(x_train, y_train_categorical, batch_size=64, epochs=128, verbose=1, \
        validation_data=(x_test, y_test_categorical), callbacks=callbacks)

#testing
scores = model.evaluate(x_test, y_test_categorical, batch_size=128, verbose=1)
print('\nTest result: %.3f loss: %.3f' % (scores[1]*100,scores[0]))
```

```

Train on 50000 samples, validate on 10000 samples
Epoch 1/125
50000/50000 [=====] - 22s 435us/step - loss: 1.6858 -
acc: 0.4766 - val_loss: 1.2770 - val_acc: 0.5944 1.7061 - acc: 0.471 - ETA: 0s
- loss: 1.7035 -
Epoch 2/125
50000/50000 [=====] - 18s 366us/step - loss: 1.0685 -
acc: 0.6485 - val_loss: 0.9907 - val_acc: 0.6862s - loss: 1.10 - - ETA: 2s - 1
oss: 1.0800 - - E
Epoch 3/125
50000/50000 [=====] - 19s 372us/step - loss: 0.8911 -
acc: 0.7115 - val_loss: 0.7940 - val_acc: 0.7429
Epoch 4/125
50000/50000 [=====] - 18s 366us/step - loss: 0.8052 -
acc: 0.7411 - val_loss: 0.7684 - val_acc: 0.7561
Epoch 5/125
50000/50000 [=====] - 18s 364us/step - loss: 0.7376 -
acc: 0.7670 - val_loss: 0.7336 - val_acc: 0.7750
Epoch 6/125
50000/50000 [=====] - 18s 359us/step - loss: 0.6859 -
acc: 0.7887 - val_loss: 0.6835 - val_acc: 0.7964
Epoch 7/125
50000/50000 [=====] - 18s 360us/step - loss: 0.6450 -
acc: 0.8081 - val_loss: 0.6753 - val_acc: 0.8050
Epoch 8/125
50000/50000 [=====] - 18s 351us/step - loss: 0.6199 -
acc: 0.8191 - val_loss: 0.6558 - val_acc: 0.8127 0s - loss: 0.617
Epoch 9/125
50000/50000 [=====] - 19s 370us/step - loss: 0.5961 -
acc: 0.8314 - val_loss: 0.6679 - val_acc: 0.8057
Epoch 10/125
50000/50000 [=====] - 18s 358us/step - loss: 0.5787 -
acc: 0.8388 - val_loss: 0.6326 - val_acc: 0.8257
Epoch 11/125
50000/50000 [=====] - 19s 372us/step - loss: 0.5562 -
acc: 0.8487 - val_loss: 0.6603 - val_acc: 0.8260loss: 0.554
Epoch 12/125
50000/50000 [=====] - 18s 368us/step - loss: 0.5473 -
acc: 0.8531 - val_loss: 0.6446 - val_acc: 0.8340
Epoch 13/125
50000/50000 [=====] - 18s 369us/step - loss: 0.5370 -
acc: 0.8601 - val_loss: 0.6611 - val_acc: 0.8293
Epoch 14/125
50000/50000 [=====] - 18s 363us/step - loss: 0.5203 -
acc: 0.8683 - val_loss: 0.6521 - val_acc: 0.8343
10000/10000 [=====] - 1s 87us/step

Test result: 83.430 loss: 0.652

```

## Possible improvements

Adaptive learning rate - evolutionary algorithm for hyperparameter learning (SAIL)



```

In [42]: #Show some predictions
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

show_Images(x_test[:16])

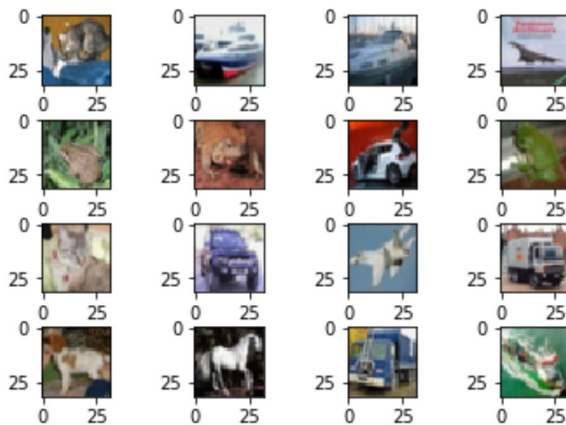
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

mean = np.mean(x_train,axis=(0,1,2,3))
std = np.std(x_train,axis=(0,1,2,3))
x_train = (x_train-mean)/(std+1e-7)
x_test = (x_test-mean)/(std+1e-7)

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

indices = np.argmax(model.predict(x_test[:16]),1)
print ([labels[x] for x in indices])

```



```

['cat', 'ship', 'automobile', 'airplane', 'frog', 'frog', 'automobile', 'frog',
 'cat', 'automobile', 'airplane', 'truck', 'dog', 'horse', 'truck', 'ship']

```

1. Evaluate your module using the FERPlus dataset (The model with the best test accuracy will present their solution to the class).

3.1 Download the [FER2013 dataset](https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data) (<https://www.kaggle.com/c/challenges-in-representation-learning-facial-expression-recognition-challenge/data>) (images\_path).

3.2 Download the [FERPlus labels](https://github.com/Microsoft/FERPlus/blob/master/fer2013new.csv) (<https://github.com/Microsoft/FERPlus/blob/master/fer2013new.csv>) (labels\_path).

3.3 Use the following code snippet to load the dataset giving the appropriate paths to the csv files downloaded in 3.1 and 3.2:

## Second dataset

Now we use the very successful model implemented in the first part of the assignment to categorize emotions from the fer2013 dataset.

```

In [18]: import pandas as pd
import numpy as np
import cv2

```

```
In [19]: class FERPlus(object):
    """Class for loading FER2013 [1] emotion classification dataset with
    the FERPlus labels [2]:
    [1] kaggle.com/c/challenges-in-representation-learning-facial-
        expression-recognition-challenge
    [2] github.com/Microsoft/FERPlu://github.com/Microsoft/FERPlus"""

    def __init__(self, images_path, labels_path, split='train', image_size=(48,
48),
                dataset_name='FERPlus'):

        self.split = split
        self.image_size = image_size
        self.dataset_name = dataset_name
        self.images_path = images_path
        self.labels_path = labels_path
        self.class_names = ['neutral', 'happiness', 'surprise', 'sadness',
                            'anger', 'disgust', 'fear', 'contempt']
        self.num_classes = len(self.class_names)
        self.arg_to_name = dict(zip(range(self.num_classes), self.class_names))
        self.name_to_arg = dict(zip(self.class_names, range(self.num_classes)))
        self._split_to_filter = {
            'train': 'Training', 'val': 'PublicTest', 'test': 'PrivateTest'}

    def load_data(self):
        filter_name = self._split_to_filter[self.split]
        pixel_sequences = pd.read_csv(self.images_path)
        pixel_sequences = pixel_sequences[pixel_sequences.Usage == filter_name]
        pixel_sequences = pixel_sequences['pixels'].tolist()
        faces = []
        for pixel_sequence in pixel_sequences:
            face = [float(pixel) for pixel in pixel_sequence.split(' ')]
            face = np.asarray(face).reshape(48, 48)
            faces.append(cv2.resize(face, self.image_size))
        faces = np.asarray(faces)
        faces = np.expand_dims(faces, -1)

        emotions = pd.read_csv(self.labels_path)
        emotions = emotions[emotions.Usage == filter_name]
        emotions = emotions.iloc[:, 2:10].values
        N = np.sum(emotions, axis=1)
        mask = N != 0
        N, faces, emotions = N[mask], faces[mask], emotions[mask]
        emotions = emotions / np.expand_dims(N, 1)
        return faces, emotions
```

```
In [20]: validation_data = FERPlus('Data\\fer2013\\fer2013.csv', 'Data\\fer2013new.csv')
        faces, emotions = validation_data.load_data()
```

```
In [21]: print(np.shape(faces))
        print(np.shape(emotions))

        split = 0.9

        index = int(np.shape(faces)[0] * split)

        faces_train = faces[:index]
        emotions_train = emotions[:index]
        faces_eval = faces[index:]
        emotions_eval = emotions[index:]

        (28559, 48, 48, 1)
        (28559, 8)
```

```
In [25]: from tensorflow.keras.callbacks import EarlyStopping
#Hyperparameters
#The data consists of 48x48 pixel grayscale images of faces.
img_shape = faces_train[0].shape
#The task is to categorize each face based on the emotion shown in the facial ex
pression in to one of seven categories (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=S
ad, 5=Surprise, 6=Neutral).
classes_number = 8

callbacks = [EarlyStopping(monitor='val_loss',
                           min_delta=0,
                           patience=4,
                           verbose=0, mode='auto')]
```

```
In [26]: #MODEL: Simpler CNN; cite: https://appliedmachinelearning.blog/2018/03/24/achiev
ing-90-accuracy-in-object-recognition-task-on-cifar-10-dataset-with-keras-convol
utional-neural-networks/
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization
from tensorflow.keras import regularizers

weight_decay = 1e-4
model = Sequential()
model.add(Conv2D(32, (3,3), padding='same', kernel_regularizer=regularizers.l2(w
eight_decay), input_shape=img_shape))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(32, (3,3), padding='same', kernel_regularizer=regularizers.l2(w
eight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.2))

model.add(Conv2D(64, (3,3), padding='same', kernel_regularizer=regularizers.l2(w
eight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(64, (3,3), padding='same', kernel_regularizer=regularizers.l2(w
eight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.3))

model.add(Conv2D(128, (3,3), padding='same', kernel_regularizer=regularizers.l2(
weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(Conv2D(128, (3,3), padding='same', kernel_regularizer=regularizers.l2(
weight_decay)))
model.add(Activation('elu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(classes_number, activation='softmax'))
```

```
In [28]: model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

model.fit(faces_train, emotions_train, batch_size=64, epochs=3, verbose=1, \
          validation_data=(faces_eval, emotions_eval), callbacks=callbacks)

model.evaluate(faces_eval, emotions_eval)
```

Train on 25703 samples, validate on 2856 samples

Epoch 1/3

25703/25703 [=====] - 1254s 49ms/step - loss: 1.8867  
- acc: 0.4943 - val\_loss: 1.5179 - val\_acc: 0.5788

Epoch 2/3

25703/25703 [=====] - 1179s 46ms/step - loss: 1.5357  
- acc: 0.6209 - val\_loss: 1.4819 - val\_acc: 0.5837

Epoch 3/3

25703/25703 [=====] - 1176s 46ms/step - loss: 1.4275  
- acc: 0.6612 - val\_loss: 3.9245 - val\_acc: 0.3312

2856/2856 [=====] - 21s 7ms/step

Out[28]: [3.924549424681677, 0.33123249299719887]

## Archive

Here we tried to apply different modifications to the original AlexNet NN. After running this NN on the dataset for a single epoche, results were not promising and we stopped training.

```
In [8]: #MODEL: AlexNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization

# About CIFAR10:
# The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes,
# with 6000 images per class. There are 50000 training images and 10000 test ima
ges.

#Hyperparameters
img_shape = (32,32,3)
classes_number = 10

ownnet = Sequential()

# Layer 1
# 16 pixels to one: 32 -> 8
# How many input neurons -> Lecture showed that less parameters and more layers
are more useful
ownnet.add(Conv2D(classes_number * 3, (8, 8), input_shape=img_shape, padding='sa
me'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Another layer with double amount of filters
ownnet.add(Conv2D(classes_number * 6, (8, 8), input_shape=img_shape, padding='sa
me'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 2
ownnet.add(Conv2D(128, (4, 4), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 3
ownnet.add(Conv2D(128, (3, 3), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 4
ownnet.add(Conv2D(128, (3, 3), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))

# Layer 5
ownnet.add(Conv2D(256, (3, 3), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Another layer
ownnet.add(Conv2D(64, (2, 2), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))

ownnet.add(Flatten())

# Layer 6 - fully connected layer
ownnet.add(Dense(1024))
ownnet.add(BatchNormalization())
ownnet.add(Activation('relu'))
ownnet.add(Dropout(0.5))
```

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 32, 32, 30)	5790
batch_normalization_8 (Batch Normalization)	(None, 32, 32, 30)	120
activation_8 (Activation)	(None, 32, 32, 30)	0
max_pooling2d_4 (MaxPooling2D)	(None, 16, 16, 30)	0
conv2d_6 (Conv2D)	(None, 16, 16, 60)	115260
batch_normalization_9 (Batch Normalization)	(None, 16, 16, 60)	240
activation_9 (Activation)	(None, 16, 16, 60)	0
max_pooling2d_5 (MaxPooling2D)	(None, 8, 8, 60)	0
conv2d_7 (Conv2D)	(None, 8, 8, 128)	123008
batch_normalization_10 (Batch Normalization)	(None, 8, 8, 128)	512
activation_10 (Activation)	(None, 8, 8, 128)	0
max_pooling2d_6 (MaxPooling2D)	(None, 4, 4, 128)	0
conv2d_8 (Conv2D)	(None, 4, 4, 128)	147584
batch_normalization_11 (Batch Normalization)	(None, 4, 4, 128)	512
activation_11 (Activation)	(None, 4, 4, 128)	0
max_pooling2d_7 (MaxPooling2D)	(None, 2, 2, 128)	0
conv2d_9 (Conv2D)	(None, 2, 2, 128)	147584
batch_normalization_12 (Batch Normalization)	(None, 2, 2, 128)	512
activation_12 (Activation)	(None, 2, 2, 128)	0
conv2d_10 (Conv2D)	(None, 2, 2, 256)	295168
batch_normalization_13 (Batch Normalization)	(None, 2, 2, 256)	1024
activation_13 (Activation)	(None, 2, 2, 256)	0
max_pooling2d_8 (MaxPooling2D)	(None, 1, 1, 256)	0
conv2d_11 (Conv2D)	(None, 1, 1, 64)	65600
batch_normalization_14 (Batch Normalization)	(None, 1, 1, 64)	256
activation_14 (Activation)	(None, 1, 1, 64)	0
flatten_1 (Flatten)	(None, 64)	0
dense_3 (Dense)	(None, 1024)	66560
batch_normalization_15 (Batch Normalization)	(None, 1024)	4096
activation_15 (Activation)	(None, 1024)	0
dropout_2 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524800
batch_normalization_16 (Batch Normalization)	(None, 512)	2048

Train on 50000 samples, validate on 10000 samples Epoch 1/1 50000/50000 [=====] -  
287s 6ms/step - loss: 1.7042 - acc: 0.3946 - val\_loss: 2.1963 - val\_acc: 0.1489

```
In [9]: #Compile
ownnet.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#Train
ownnet.fit(x_train, y_train_categorical, validation_data=(x_test, y_test_categorical), batch_size=1000, epochs=1, verbose=1)

Train on 50000 samples, validate on 10000 samples
Epoch 1/1
50000/50000 [=====] - 287s 6ms/step - loss: 1.7042 -
acc: 0.3946 - val_loss: 2.1963 - val_acc: 0.1489

Out[9]: <tensorflow.python.keras.callbacks.History at 0x1cf372bd898>
```

Results of first try were mixed, therefore some adjustments Use Leaky ReLU instead of normal ReLU to prevent dead ReLU Add more filters to first layer, less to 2nd Added another dense layer Less pooling functions

```
In [81]: #MODEL: AlexNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization, LeakyReLU

# About CIFAR10:
# The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes,
# with 6000 images per class. There are 50000 training images and 10000 test ima
ges.

#Hyperparameters
img_shape = (32,32,3)
classes_number = 10

ownnet = Sequential()

# Use smaller kernel but combined with strides
ownnet.add(Conv2D(classes_number * 10, (10, 10), input_shape=img_shape, padding=
'valid', strides=2))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))

# Another layer with double amount of filters
ownnet.add(Conv2D(classes_number * 8, (8, 8), input_shape=img_shape, padding='sa
me'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 2
ownnet.add(Conv2D(256, (6, 6), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 3
ownnet.add(Conv2D(128, (5, 5), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 4
ownnet.add(Conv2D(128, (4, 4), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))

# Layer 5
ownnet.add(Conv2D(64, (3, 3), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))

# Another layer
ownnet.add(Conv2D(64, (2, 2), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(Flatten())

# Layer 6 - fully connected layer
ownnet.add(Dense(512))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(Dropout(0.5))

# Layer 7
ownnet.add(Dense(256))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(Dropout(0.5))
```



Layer (type)	Output Shape	Param #
conv2d_224 (Conv2D)	(None, 12, 12, 100)	30100
batch_normalization_301 (Bat	(None, 12, 12, 100)	400
leaky_re_lu_231 (LeakyReLU)	(None, 12, 12, 100)	0
conv2d_225 (Conv2D)	(None, 12, 12, 80)	512080
batch_normalization_302 (Bat	(None, 12, 12, 80)	320
leaky_re_lu_232 (LeakyReLU)	(None, 12, 12, 80)	0
max_pooling2d_163 (MaxPoolin	(None, 6, 6, 80)	0
conv2d_226 (Conv2D)	(None, 6, 6, 256)	737536
batch_normalization_303 (Bat	(None, 6, 6, 256)	1024
leaky_re_lu_233 (LeakyReLU)	(None, 6, 6, 256)	0
max_pooling2d_164 (MaxPoolin	(None, 3, 3, 256)	0
conv2d_227 (Conv2D)	(None, 3, 3, 128)	819328
batch_normalization_304 (Bat	(None, 3, 3, 128)	512
leaky_re_lu_234 (LeakyReLU)	(None, 3, 3, 128)	0
max_pooling2d_165 (MaxPoolin	(None, 1, 1, 128)	0
conv2d_228 (Conv2D)	(None, 1, 1, 128)	262272
batch_normalization_305 (Bat	(None, 1, 1, 128)	512
leaky_re_lu_235 (LeakyReLU)	(None, 1, 1, 128)	0
conv2d_229 (Conv2D)	(None, 1, 1, 64)	73792
batch_normalization_306 (Bat	(None, 1, 1, 64)	256
leaky_re_lu_236 (LeakyReLU)	(None, 1, 1, 64)	0
conv2d_230 (Conv2D)	(None, 1, 1, 64)	16448
batch_normalization_307 (Bat	(None, 1, 1, 64)	256
leaky_re_lu_237 (LeakyReLU)	(None, 1, 1, 64)	0
flatten_5 (Flatten)	(None, 64)	0
dense_77 (Dense)	(None, 512)	33280
batch_normalization_308 (Bat	(None, 512)	2048
leaky_re_lu_238 (LeakyReLU)	(None, 512)	0
dropout_62 (Dropout)	(None, 512)	0
dense_78 (Dense)	(None, 256)	131328
batch_normalization_309 (Bat	(None, 256)	1024
leaky_re_lu_239 (LeakyReLU)	(None, 256)	0
dropout_63 (Dropout)	(None, 256)	0

```
In [ ]: #Compile
ownnet.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#Train
ownnet.fit(x_train, y_train_categorical, validation_data=(x_test, y_test_categorical), batch_size=1000, epochs=1, verbose=1)

Train on 50000 samples, validate on 10000 samples
Epoch 1/1
5000/50000 [==>.....] - ETA: 7:47 - loss: 2.6747 - acc: 0.1000
```

Train on 50000 samples, validate on 10000 samples Epoch 1/1 50000/50000 [=====] - 461s 9ms/step - loss: 2.1342 - acc: 0.2192 - val\_loss: 2.3551 - val\_acc: 0.1136

2nd try results were worse: Changing first layer: No strides and smaller kernels (to enable edge detection) Using elu function instead of relu at two random points Reduced amount of parameters extremely (especially less filters in first few layers) Added another filter layer at start and another dense layer at end, therefore reduced density.

```
In [4]: #MODEL: AlexNet
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation, Dropout, Flatten, Conv2D,
MaxPooling2D, BatchNormalization, LeakyReLU

# About CIFAR10:
# The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes,
# with 6000 images per class. There are 50000 training images and 10000 test ima
ges.

#Hyperparameters
img_shape = (32,32,3)
classes_number = 10

ownnet = Sequential()

# Use smaller kernel to improve potential edge detection
ownnet.add(Conv2D(classes_number * 10, (3, 3), input_shape=img_shape, padding='s
ame'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))

# Another layer with double amount of filters
ownnet.add(Conv2D(classes_number * 8, (5, 5), input_shape=img_shape, padding='sa
me'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 2
ownnet.add(Conv2D(128, (6, 6), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('elu'))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 3
ownnet.add(Conv2D(96, (5, 5), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(MaxPooling2D(pool_size=(2, 2)))

# Layer 4
ownnet.add(Conv2D(64, (4, 4), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))

# Layer 5
ownnet.add(Conv2D(58, (3, 3), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(Activation('elu'))

# Another layer
ownnet.add(Conv2D(42, (2, 2), padding='same'))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(Flatten())

# Layer 6 - fully connected layer
ownnet.add(Dense(256))
ownnet.add(BatchNormalization())
ownnet.add(LeakyReLU(alpha=0.01))
ownnet.add(Dropout(0.5))

# Layer 7
ownnet.add(Dense(128))
ownnet.add(BatchNormalization())
ownnet.add(Activation('elu'))
ownnet.add(Dropout(0.5))
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 100)	2800
batch_normalization (Batch Normalization)	(None, 32, 32, 100)	400
leaky_re_lu (LeakyReLU)	(None, 32, 32, 100)	0
conv2d_1 (Conv2D)	(None, 32, 32, 80)	200080
batch_normalization_1 (Batch Normalization)	(None, 32, 32, 80)	320
leaky_re_lu_1 (LeakyReLU)	(None, 32, 32, 80)	0
max_pooling2d (MaxPooling2D)	(None, 16, 16, 80)	0
conv2d_2 (Conv2D)	(None, 16, 16, 128)	368768
batch_normalization_2 (Batch Normalization)	(None, 16, 16, 128)	512
activation (Activation)	(None, 16, 16, 128)	0
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 96)	307296
batch_normalization_3 (Batch Normalization)	(None, 8, 8, 96)	384
leaky_re_lu_2 (LeakyReLU)	(None, 8, 8, 96)	0
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 96)	0
conv2d_4 (Conv2D)	(None, 4, 4, 64)	98368
batch_normalization_4 (Batch Normalization)	(None, 4, 4, 64)	256
leaky_re_lu_3 (LeakyReLU)	(None, 4, 4, 64)	0
conv2d_5 (Conv2D)	(None, 4, 4, 58)	33466
batch_normalization_5 (Batch Normalization)	(None, 4, 4, 58)	232
activation_1 (Activation)	(None, 4, 4, 58)	0
conv2d_6 (Conv2D)	(None, 4, 4, 42)	9786
batch_normalization_6 (Batch Normalization)	(None, 4, 4, 42)	168
leaky_re_lu_4 (LeakyReLU)	(None, 4, 4, 42)	0
flatten (Flatten)	(None, 672)	0
dense (Dense)	(None, 256)	172288
batch_normalization_7 (Batch Normalization)	(None, 256)	1024
leaky_re_lu_5 (LeakyReLU)	(None, 256)	0
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
batch_normalization_8 (Batch Normalization)	(None, 128)	512
activation_2 (Activation)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0

```
In [5]: #Compile
ownnet.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#Train
ownnet.fit(x_train, y_train_categorical, validation_data=(x_test,y_test_categorical), batch_size=1000, epochs=1, verbose=1)

Train on 50000 samples, validate on 10000 samples
Epoch 1/1
50000/50000 [=====] - 26171s 523ms/step - loss: 2.289
9 - acc: 0.1791 - val_loss: 12.4215 - val_acc: 0.1001

Out[5]: <tensorflow.python.keras.callbacks.History at 0x15dca319ba8>
```

Train on 50000 samples, validate on 10000 samples Epoch 1/1 50000/50000 [=====] - 26171s 523ms/step - loss: 2.2899 - acc: 0.1791 - val\_loss: 12.4215 - val\_acc: 0.1001