LeNet

Basic Introduction

LeNet-5, from the paper Gradient-Based Learning Applied to Document Recognition, is a very efficient convolutional neural network for handwritten character recognition.

Paper: Gradient-Based Learning Applied to Document Recognition (http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf)

Authors: Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Published in: Proceedings of the IEEE (1998)

Structure of the LeNet network

LeNet5 is a small network, it contains the basic modules of deep learning: convolutional layer, pooling layer, and full link layer. It is the basis of other deep learning models. Here we analyze LeNet5 in depth. At the same time, through example analysis, deepen the understanding of the convolutional layer and pooling layer.

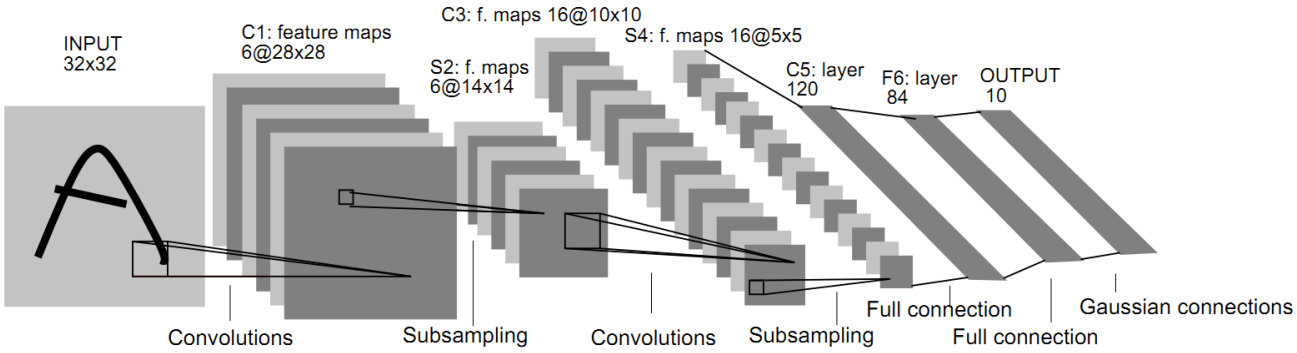


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeNet-5 Total seven layer , does not comprise an input, each containing a trainable parameters; each layer has a plurality of the Map the Feature , a characteristic of each of the input FeatureMap extracted by means of a convolution filter, and then each FeatureMap There are multiple neurons.

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	32x32	-	-	-
1	Convolution	6	28x28	5x5	1	tanh
2	Average Pooling	6	14x14	2x2	2	tanh
3	Convolution	16	10x10	5x5	1	tanh
4	Average Pooling	16	5x5	2x2	2	tanh
5	Convolution	120	1x1	5x5	1	tanh
6	FC	-	84	-	-	tanh
Output	FC	-	10	-	-	softmax

Detailed explanation of each layer parameter:

INPUT Layer

The first is the data INPUT layer. The size of the input image is uniformly normalized to 32 * 32.

> Note: This layer does not count as the network structure of LeNet-5. Traditionally, the input layer is not considered as one of the network hierarchy.

C1 layer-convolutional layer

> **Input picture**: 32 * 32
>
> **Convolution kernel size**: 5 * 5
>
> **Convolution kernel types**: 6
>
> **Output featuremap size**: 28 * 28 (32-5 + 1) = 28
>
> **Number of neurons**: 28 *28* 6
>
> **Trainable parameters**: (5 *5* + *1)* 6 (5 * 5 = 25 unit parameters and one bias parameter per filter, a total of 6 filters)
>
> **Number of connections**: (5 *5* + *1)* 6 *28* 28 = 122304

Detailed description:

1. The first convolution operation is performed on the input image (using 6 convolution kernels of size 5 *5) to obtain 6 C1 feature maps (6 feature maps of size 28* 28, 32-5 + 1 = 28).
2. Let's take a look at how many parameters are needed. The size of the convolution kernel is 5 *5, and there are 6* (5 * 5 + 1) = 156 parameters in total, where +1 indicates that a kernel has a bias.
3. For the convolutional layer C1, each pixel in C1 is connected to 5 *5 pixels and 1 bias in the input image, so there are 156* 28 * 28 = 122304 connections in total. There are 122,304 connections, but we only need to learn 156 parameters, mainly through weight sharing.

S2 layer-pooling layer (downsampling layer)

Input: 28 * 28

Sampling area: 2 * 2

Sampling method: 4 inputs are added, multiplied by a trainable parameter, plus a trainable offset. Results via sigmoid

Sampling type: 6

Output featureMap size: 14 * 14 (28/2)

Number of neurons: 14 *14* 6

Trainable parameters: 2 * 6 (the weight of the sum + the offset)

Number of connections: (2 *2* + *1)* 6 *14* 14

The size of each feature map in S2 is 1/4 of the size of the feature map in C1.

Detailed description:

The pooling operation is followed immediately after the first convolution. Pooling is performed using 2 *2 kernels, and S2, 6 feature maps of 14* 14 (28/2 = 14) are obtained.

The pooling layer of S2 is the sum of the pixels in the 2 * 2 area in C1 multiplied by a weight coefficient plus an offset, and then the result is mapped again.

So each pooling core has two training parameters, so there are 2x6 = 12 training parameters, but there are 5x14x14x6 = 5880 connections.

C3 layer-convolutional layer

Input: all 6 or several feature map combinations in S2

Convolution kernel size: 5 * 5

Convolution kernel type: 16

Output featureMap size: 10 * 10 (14-5 + 1) = 10

Each feature map in C3 is connected to all 6 or several feature maps in S2, indicating that the feature map of this layer is a different combination of the feature maps extracted from the previous layer.

One way is that the first 6 feature maps of C3 take 3 adjacent feature map subsets in S2 as input. The next 6 feature maps take 4 subsets of neighboring feature maps in S2 as input. The next three take the non-adjacent 4 feature map subsets as input. The last one takes all the feature maps in S2 as input.

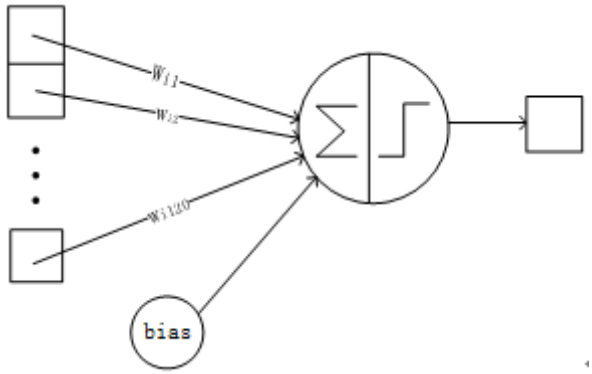
The trainable parameters are: 6 *(3* 5 *5* + *1)* + *6* (4 *5* 5 + 1) + 3 *(4* 5 *5* + *1)* + *1* (6 *5* 5 +1) = 1516

Number of connections: 10 *10* 1516 = 151600

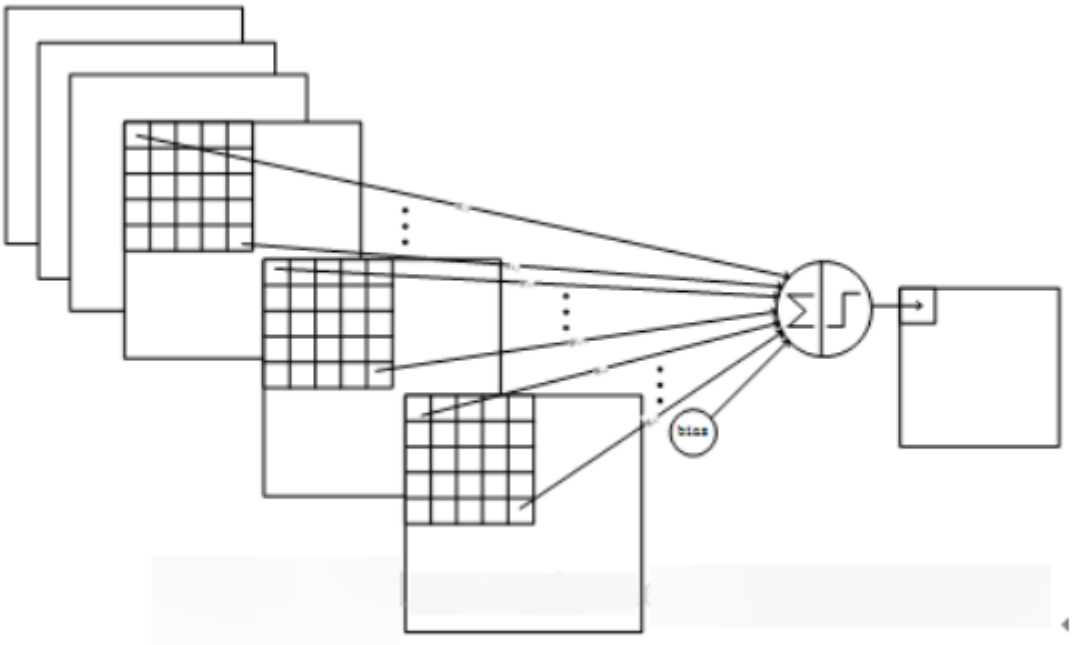
Detailed description:

After the first pooling, the second convolution, the output of the second convolution is C3, 16 10x10 feature maps, and the size of the convolution kernel is 5 *5. We know that S2 has 6 14* 14 feature maps, how to get 16 feature maps from 6 feature maps? Here are the 16 feature maps calculated by the special combination of the feature maps of S2. details as follows:

The first 6 feature maps of C3 (corresponding to the 6th column of the first red box in the figure above) are connected to the 3 feature maps connected to the S2 layer (the first red box in the above figure), and the next 6 feature maps are connected to the S2 layer The 4 feature maps are connected (the second red box in the figure above), the next 3 feature maps are connected with the 4 feature maps that are not connected at the S2 layer, and the last is connected with all the feature maps at the S2 layer. The convolution kernel size is still 5 *5, so there are 6* (3 *5* 5 + 1) + 6 *(4* 5 *5 + 1) + 3* (4 *5* 5 + 1) +1 *(6* 5 *5 + 1) = 1516 parameters. The image size is 10* 10, so there are 151600 connections.



The convolution structure of C3 and the first 3 graphs in S2 is shown below:



S4 layer-pooling layer (downsampling layer)

Input: 10 * 10

Sampling area: 2 * 2

Sampling method: 4 inputs are added, multiplied by a trainable parameter, plus a trainable offset. Results via sigmoid

Sampling type: 16

Output featureMap size: 5 * 5 (10/2)

Number of neurons: 5 *5* 16 = 400

Trainable parameters: 2 * 16 = 32 (the weight of the sum + the offset)

Number of connections: 16 *(2* 2 + 1) *5* 5 = 2000

The size of each feature map in S4 is 1/4 of the size of the feature map in C3

Detailed description:

S4 is the pooling layer, the window size is still 2 * 2, a total of 16 feature maps, and the 16 10x10 maps of the C3 layer are pooled in units of 2x2 to obtain 16 5x5 feature maps. This layer has a total of 32 training parameters of 2x16, 5x5x5x16 = 2000 connections.

The connection is similar to the S2 layer.

C5 layer-convolution layer

Input: All 16 unit feature maps of the S4 layer (all connected to s4)

Convolution kernel size: 5 * 5

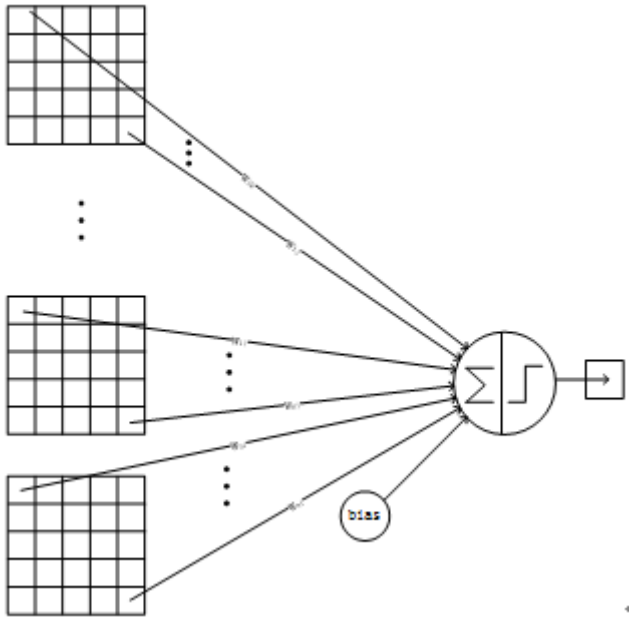
Convolution kernel type: 120

Output featureMap size: 1 * 1 (5-5 + 1)

Trainable parameters / connection: 120 *(16* 5 * 5 + 1) = 48120

Detailed description:

The C5 layer is a convolutional layer. Since the size of the 16 images of the S4 layer is 5x5, which is the same as the size of the convolution kernel, the size of the image formed after convolution is 1x1. This results in 120 convolution results. Each is connected to the 16 maps on the previous level. So there are (5x5x16 + 1) x120 = 48120 parameters, and there are also 48120 connections. The network structure of the C5 layer is as follows:



F6 layer-fully connected layer

> **Input**: c5 120-dimensional vector
>
> **Calculation method**: calculate the dot product between the input vector and the weight vector, plus an offset, and the result is output through the sigmoid function.
>
> **Trainable parameters**: 84 * (120 + 1) = 10164

Detailed description:

Layer 6 is a fully connected layer. The F6 layer has 84 nodes, corresponding to a 7x12 bitmap, -1 means white, 1 means black, so the black and white of the bitmap of each symbol corresponds to a code. The training parameters and number of connections for this layer are (120 + 1) x84 = 10164. The ASCII encoding diagram is as follows:

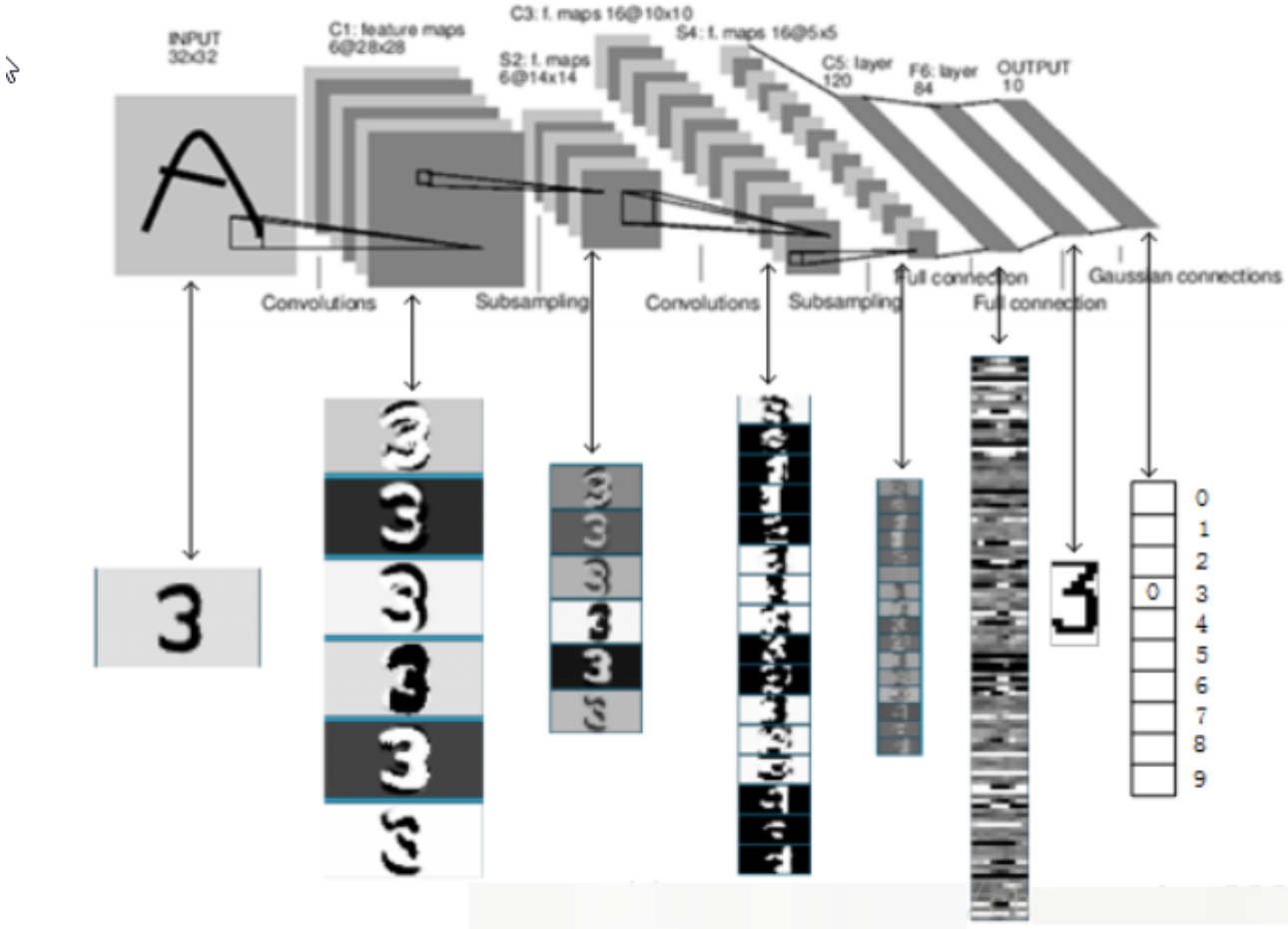
The connection method of the F6 layer is as follows:

Output layer-fully connected layer

The output layer is also a fully connected layer, with a total of 10 nodes, which respectively represent the numbers 0 to 9, and if the value of node i is 0, the result of network recognition is the number i. A radial basis function (RBF) network connection is used. Assuming x is the input of the previous layer and y is the output of the RBF, the calculation of the RBF output is:

$$y_i = \sum_j (x_j - w_{ij})^2$$

The value of the above formula w_ij is determined by the bitmap encoding of i, where i ranges from 0 to 9, and j ranges from 0 to 7 * 12-1. The closer the value of the RBF output is to 0, the closer it is to i, that is, the closer to the ASCII encoding figure of i, it means that the recognition result input by the current network is the character i. This layer has 84x10 = 840 parameters and connections.



Summary

- LeNet-5 is a very efficient convolutional neural network for handwritten character recognition.
- Convolutional neural networks can make good use of the structural information of images.
- The convolutional layer has fewer parameters, which is also determined by the main characteristics of the convolutional layer, that is, local connection and shared weights.

Code Implementation

In [4]:

```
import keras
from keras.datasets import mnist
from keras.layers import Conv2D, MaxPooling2D,AveragePooling2D
from keras.layers import Dense, Flatten
from keras.models import Sequential
```

In [2]:

```
# Loading the dataset and perform splitting
(x_train, y_train), (x_test, y_test) = mnist.load_data()
# Peforming reshaping operation
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
```

In [3]:

```
# Normalization
x_train = x_train / 255
x_test = x_test / 255

# One Hot Encoding
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)
# Building the Model Architecture
```

LeNet Model

In [8]:

```
model = Sequential()
# Select 6 feature convolution kernels with a size of 5 * 5 (without offset), and get 66 fe
# That is, the number of neurons has been reduced from 10241024 to 28 * 28 = 784 28 * 28 =
# Parameters between input layer and C1 layer: 6 * (5 * 5 + 1)
model.add(Conv2D(6, kernel_size=(5, 5), activation='tanh', input_shape=(28, 28, 1)))
# The input of this layer is the output of the first layer, which is a 28 * 28 * 6 node mat
# The size of the filter used in this layer is 2 * 2, and the step length and width are bot
model.add(MaxPooling2D(pool_size=(2, 2)))
# The input matrix size of this layer is 14 * 14 * 6, the filter size used is 5 * 5, and th
# The output matrix size of this layer is 10 * 10 * 16. This layer has 5 * 5 * 6 * 16 + 16
model.add(Conv2D(16, kernel_size=(5, 5), activation='tanh'))
# The input matrix size of this layer is 10 * 10 * 16. The size of the filter used in this
model.add(MaxPooling2D(pool_size=(2, 2)))
# The input matrix size of this layer is 5 * 5 * 16. This layer is called a convolution lay
# So it is not different from the fully connected layer. If the nodes in the 5 * 5 * 16 mat
# The number of output nodes in this layer is 120, with a total of 5 * 5 * 16 * 120 + 120 =
model.add(Flatten())
model.add(Dense(120, activation='tanh'))
# The number of input nodes in this layer is 120 and the number of output nodes is 84. The
model.add(Dense(84, activation='tanh'))
# The number of input nodes in this layer is 84 and the number of output nodes is 10. The t
model.add(Dense(10, activation='softmax'))
```

OR

In [ ]:

```
model = keras.Sequential()

model.add(Conv2D(filters=6, kernel_size=(5, 5), activation='tanh', input_shape=(32,32,1)))
model.add(AveragePooling2D(2,2))

model.add(Conv2D(filters=16, kernel_size=(5, 5), activation='tanh'))
model.add(AveragePooling2D())

model.add(Flatten())

model.add(Dense(units=120, activation='tanh'))

model.add(Dense(units=84, activation='tanh'))

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

In [9]:

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 24, 24, 6)         156
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 12, 12, 6)         0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 16)          2416
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 16)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 120)               30840
_________________________________________________________________
dense_4 (Dense)              (None, 84)                10164
_________________________________________________________________
dense_5 (Dense)              (None, 10)                850
=================================================================
Total params: 44,426
Trainable params: 44,426
Non-trainable params: 0
_________________________________________________________________
```

In [10]:

```
model.compile(loss=keras.metrics.categorical_crossentropy, optimizer=keras.optimizers.Adam(
model.fit(x_train, y_train, batch_size=128, epochs=1, verbose=1, validation_data=(x_test, y
```

```
469/469 [==============================] - 22s 46ms/step - loss: 0.6072 - ac
curacy: 0.8285 - val_loss: 0.0840 - val_accuracy: 0.9737
```

Out[10]:

```
<tensorflow.python.keras.callbacks.History at 0x195a9244748>
```

In [11]:

```
score = model.evaluate(x_test, y_test)
print('Test Loss:', score[0])
print('Test accuracy:', score[1])
```

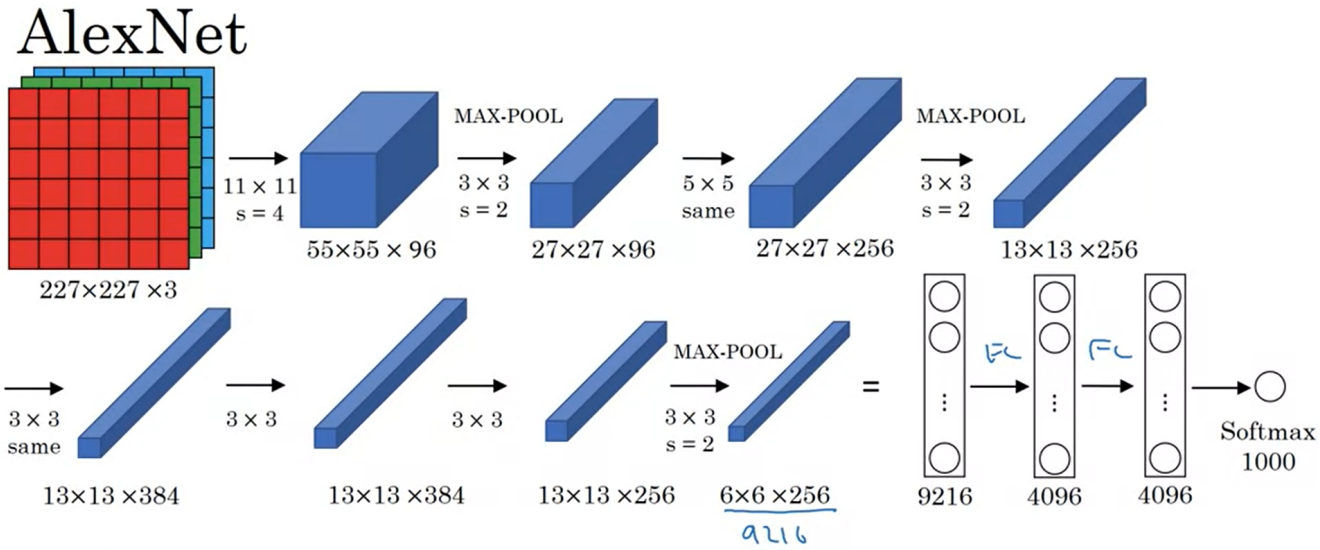
```
313/313 [==============================] - 2s 7ms/step - loss: 0.0840 - accu
racy: 0.9737
Test Loss: 0.08401492983102798
Test accuracy: 0.9736999869346619
```

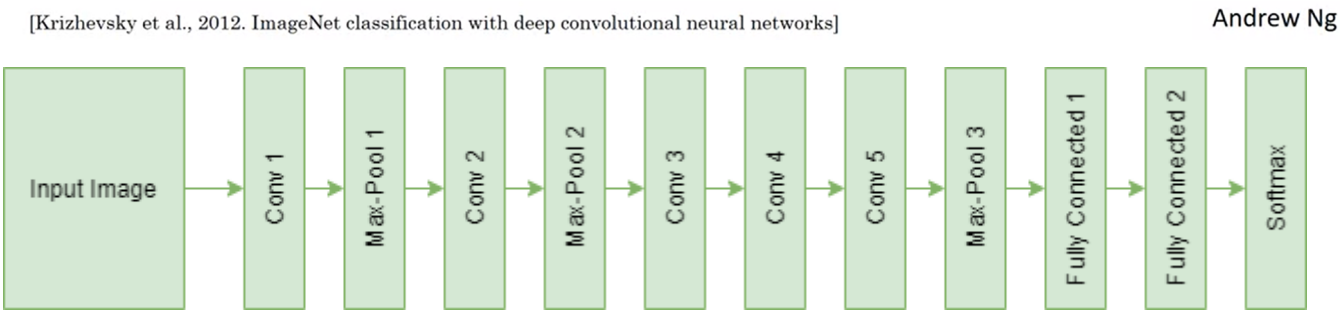
ALEXNET

The most important features of the AlexNet paper are:

- As the model had to train 60 million parameters (which is quite a lot), it was prone to overfitting. According to the paper, the usage of Dropout and Data Augmentation significantly helped in reducing overfitting. The first and second fully connected layers in the architecture thus used a dropout of 0.5 for the purpose. Artificially increasing the number of images through data augmentation helped in the expansion of the dataset dynamically during runtime, which helped the model generalize better.
- Another distinct factor was using the ReLU activation function instead of tanh or sigmoid, which resulted in faster training times (a decrease in training time by 6 times). Deep Learning Networks usually employ ReLU non-linearity to achieve faster training times as the others start saturating when they hit higher activation values.

- AlexNet is a Classic type of Convolutional Neural Network, and it came into existence after the 2012 ImageNet challenge. The network architecture is given below :





Model Explanation :

- The Input to this model have the dimensions 227x227x3 follwed by a Convolutional Layer with 96 filters of 11x11 dimensions and having a ‘same’ padding and a stride of 4. The resulting output dimensions are given as :

```
floor(((n + 2*padding - filter)/stride) + 1 ) * floor(((n + 2*padding – filter)/stride) + 1)
```

Note : This formula is for square input with height = width = n

- Explaining the first Layer with input 227x227x3 and Convolutional layer with 96 filters of 11x11 , 'valid' padding and stride = 4 , output dims will be

= floor(((227 + 0–11)/4) + 1) * floor(((227 + 0–11)/4) + 1)

= floor((216/4) + 1) * floor((216/4) + 1)

= floor(54 + 1) * floor(54 + 1)

= 55 * 55

- Since number of filters = 96 , thus output of first Layer is : 55x55x96
- Continuing we have the MaxPooling layer (3, 3) with the stride of 2,making the output size decrease to 27x27x96, followed by another Convolutional Layer with 256, (5,5) filters and 'same' padding, that is, the output height and width are retained as the previous layer thus output from this layer is 27x27x256.
- Next we have the MaxPooling again ,reducing the size to 13x13x256. Another Convolutional Operation with 384, (3,3) filters having same padding is applied twice giving the output as 13x13x384, followed by another Convulutional Layer with 256 , (3,3) filters and same padding resulting in 13x13x256 output.
- This is MaxPooled and dimensions are reduced to 6x6x256. Further the layer is Flatten out and 2 Fully Connected Layers with 4096 units each are made which is further connected to 1000 units softmax layer.
- The network is used for classifying much large number of classes as per our requirement. However in our case, we will make the output softmax layer with 6 units as we ahve to classify into 6 classes. The softmax layer gives us the probablities for each class to which an Input Image might belong.

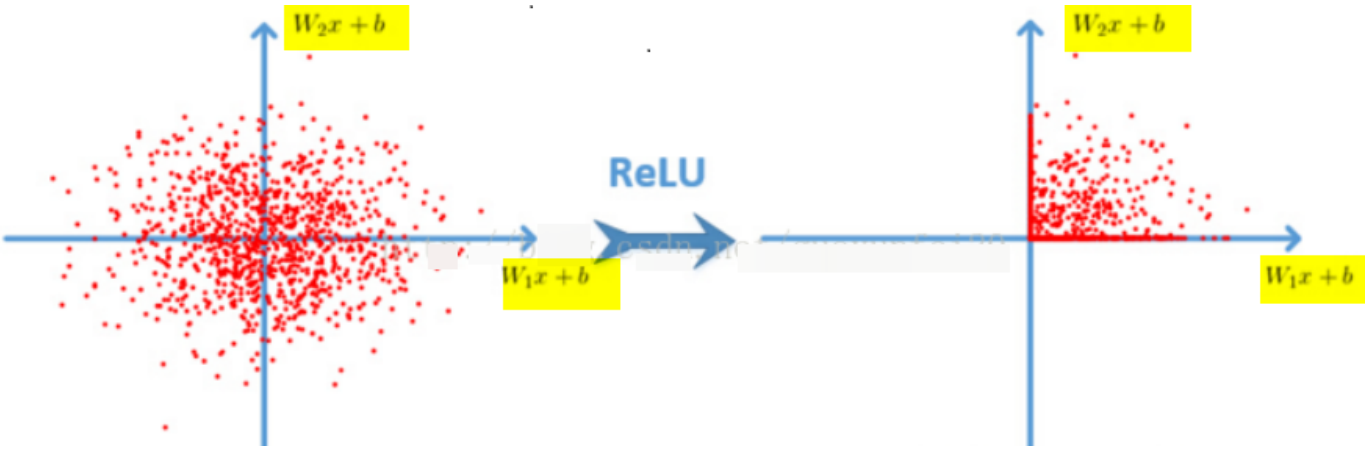
Size / Operation	Filter	Depth	Stride	Padding	Number of Parameters	Forward Computation
3 *227* 227						
Conv1 + Relu	11 *11*	96	4		(1111*3 + 1)* 96=34944	(11*11*3 + 1) *96* 55 *55=105705600*
96 55 *55*						
Max Pooling	3 3		2			
96 *27* 27						
Norm						
Conv2 + Relu	5 *5*	256	1	2	(5 5 *96 + 1)* 256=614656	(5 *5* 96 + 1) *256* 27 *27=448084224*
256 27 *27*						
Max Pooling	3 3		2			
256 *13* 13						
Norm						
Conv3 + Relu	3 *3*	384	1	1	(3 3 *256 + 1)* 384=885120	(3 *3* 256 + 1) *384* 13 *13=149585280*
384 13 *13*						
Conv4 + Relu	3 3	384	1	1	(3 *3* 384 + 1) *384=1327488*	(3 3 *384 + 1)* 384 *13* 13=224345472
384 *13* 13						
Conv5 + Relu	3 *3*	256	1	1	(3 3 *384 + 1)* 256=884992	(3 *3* 384 + 1) *256* 13 *13=149563648*
256 13 *13*						

Size / Operation	Filter	Depth	Stride	Padding	Number of Parameters	Forward Computation
Max Pooling	3 3		2			
256 *6* 6						
Dropout (rate 0.5)						
FC6 + Relu					256 *6* 6 *4096=37748736*	256 6 *6* 4096=37748736
4096						
Dropout (rate 0.5)						
FC7 + Relu					4096 *4096=16777216*	4096 4096=16777216
4096						
FC8 + Relu					4096 *1000=4096000*	4096 1000=4096000
1000 classes						
Overall					62369152=62.3 million	1135906176=1.1 billion
Conv VS FC					Conv:3.7million (6%) , FC: 58.6 million (94%)	Conv: 1.08 billion (95%) , FC: 58.6 million (5%)

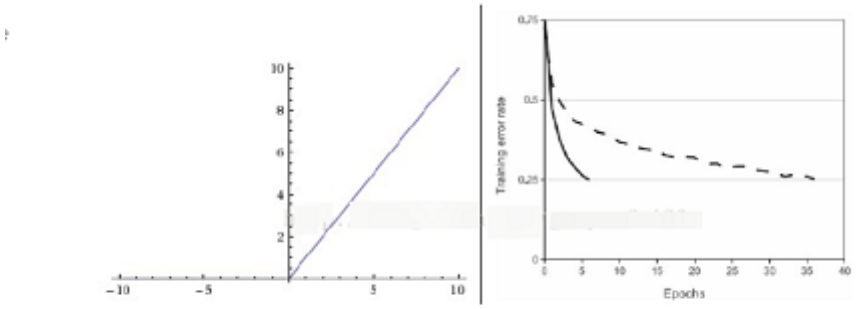
Why does AlexNet achieve better results?

1. **Relu activation function is used.**

Relu function: f (x) = max (0, x)



ReLU-based deep convolutional networks are trained several times faster than tanh and sigmoid- based networks. The following figure shows the number of iterations for a four-layer convolutional network based on CIFAR-10 that reached 25% training error in tanh and ReLU:



Left: Rectified Linear Unit (ReLU) activation function, which is zero when x < 0 and then linear with slope 1 when x > 0. **Right:** A plot from Krizhevsky et al. (pdf) paper indicating the 6x improvement in convergence with the ReLU unit compared to the tanh unit.

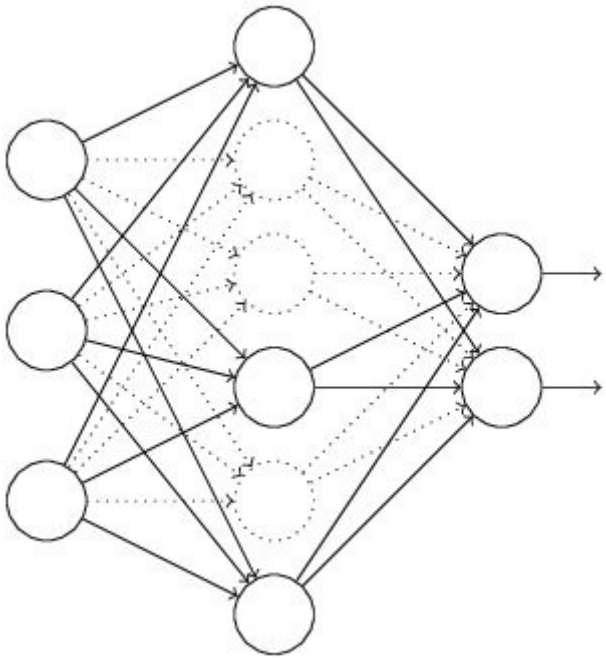
1. **Standardization (Local Response Normalization)**

After using ReLU f (x) = max (0, x), you will find that the value after the activation function has no range like the tanh and sigmoid functions, so a normalization will usually be done after ReLU, and the LRU is a steady proposal (Not sure here, it should be proposed?) One method in neuroscience is called "Lateral inhibition", which talks about the effect of active neurons on its surrounding neurons.

$$b^i_{x,y} = a^i_{x,y} / \left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a^j_{x,y})^2 \right)^{\beta}$$

1. **Dropout**

Dropout is also a concept often said, which can effectively prevent overfitting of neural networks. Compared to the general linear model, a regular method is used to prevent the model from overfitting. In the neural network, Dropout is implemented by modifying the structure of the neural network itself. For a certain layer of neurons, randomly delete some neurons with a defined probability, while keeping the individuals of the input layer and output layer neurons unchanged, and then update the parameters according to the learning method of the neural network. In the next iteration, rerandom Remove some neurons until the end of training.



1. **Enhanced Data (Data Augmentation)**

In deep learning, when the amount of data is not large enough, there are generally 4 solutions:

Data augmentation- artificially increase the size of the training set-create a batch of "new" data from existing data by means of translation, flipping, noise

Regularization——The relatively small amount of data will cause the model to overfit, making the training error small and the test error particularly large. By adding a regular term after the Loss Function , the overfitting can be suppressed. The disadvantage is that a need is introduced Manually adjusted hyper-parameter.

Dropout- also a regularization method. But different from the above, it is achieved by randomly setting the output of some neurons to zero

Unsupervised Pre-training- use Auto-Encoder or RBM's convolution form to do unsupervised pre-training layer by layer, and finally add a classification layer to do supervised Fine-Tuning

In [1]:

```
#Importing library
import keras
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten, Conv2D, MaxPooling2D
from keras.layers.normalization import BatchNormalization
import numpy as np

np.random.seed(1000)
```

In [6]:

```
model = Sequential()

# 1st Convolutional Layer
model.add(Conv2D(filters = 96, input_shape = (224, 224, 3), kernel_size = (11, 11), strides
model.add(Activation('relu'))
# Max-Pooling
model.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding = 'valid'))
# Batch Normalisation
model.add(BatchNormalization())

# 2nd Convolutional Layer
model.add(Conv2D(filters = 256, kernel_size = (11, 11), strides = (1, 1), padding = 'valid'
model.add(Activation('relu'))
# Max-Pooling
model.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2), padding = 'valid'))
# Batch Normalisation
model.add(BatchNormalization())

# 3rd Convolutional Layer
model.add(Conv2D(filters = 384, kernel_size = (3, 3), strides = (1, 1), padding = 'valid'))
model.add(Activation('relu'))
# Batch Normalisation
model.add(BatchNormalization())

# 4th Convolutional Layer
model.add(Conv2D(filters = 384, kernel_size = (3, 3), strides = (1, 1), padding = 'valid'))
model.add(Activation('relu'))
# Batch Normalisation
model.add(BatchNormalization())

# 5th Convolutional Layer
model.add(Conv2D(filters = 256, kernel_size = (3, 3), strides = (1, 1), padding = 'valid'))
model.add(Activation('relu'))
# Max-Pooling
model.add(MaxPooling2D(pool_size = (2, 2), strides = (2, 2),padding = 'valid'))
# Batch Normalisation
model.add(BatchNormalization())

# Flattening
model.add(Flatten())

# 1st Dense Layer
model.add(Dense(4096, input_shape = (224*224*3, )))
model.add(Activation('relu'))
# Add Dropout to prevent overfitting
model.add(Dropout(0.4))
# Batch Normalisation
model.add(BatchNormalization())

# 2nd Dense Layer
model.add(Dense(4096))
model.add(Activation('relu'))
# Add Dropout
model.add(Dropout(0.4))
# Batch Normalisation
model.add(BatchNormalization())

# Output Softmax Layer
model.add(Dense(10))
```

```
model.add(Activation('softmax'))
```

In [7]:

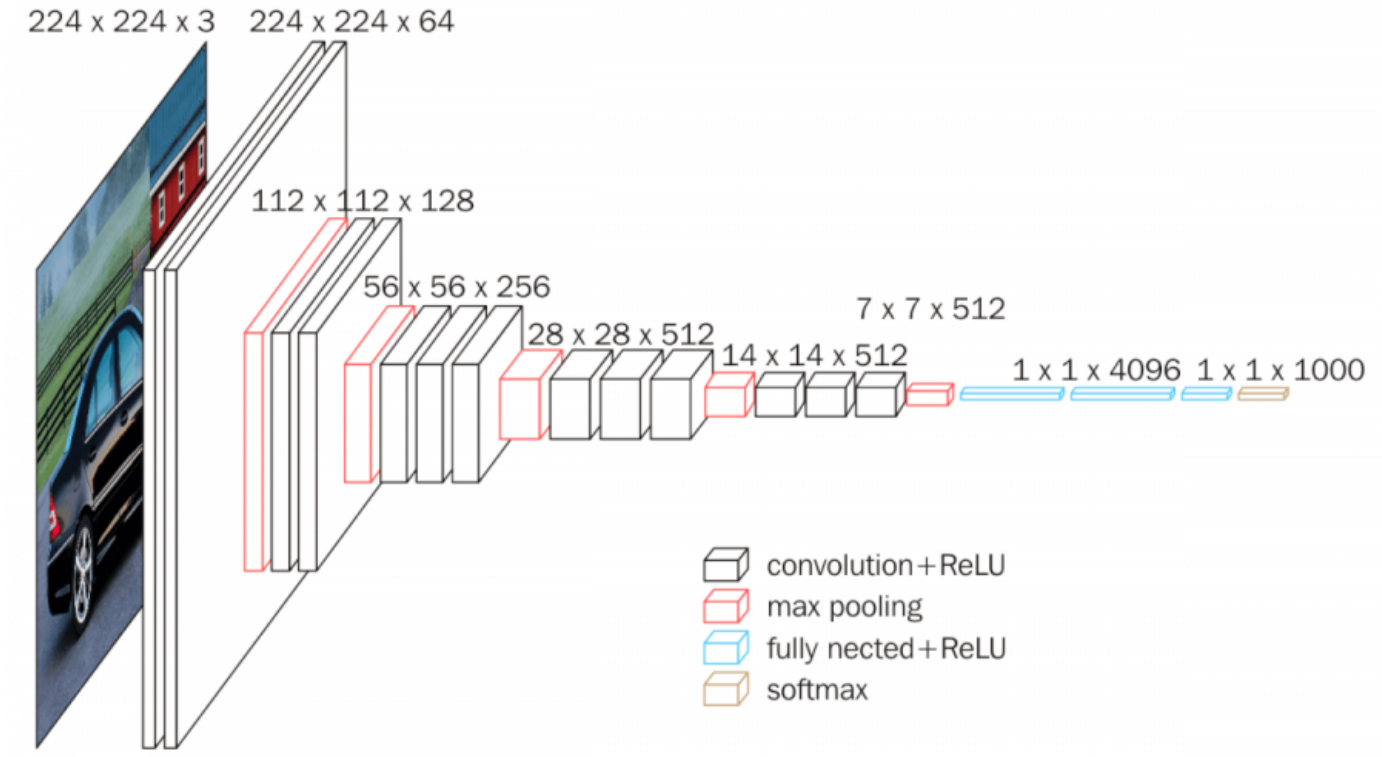
```
#Model Summary
model.summary()
```

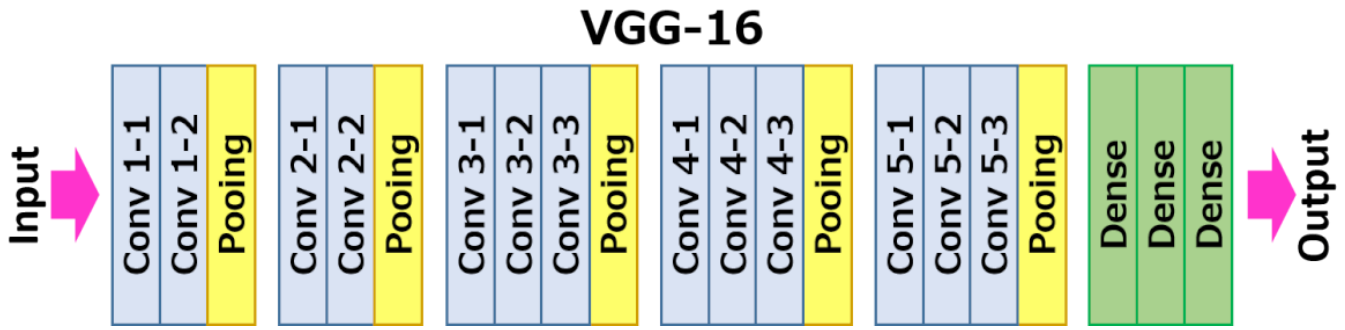
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 54, 54, 96)        34944
_________________________________________________________________
activation (Activation)      (None, 54, 54, 96)        0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 27, 27, 96)        0
_________________________________________________________________
batch_normalization (BatchNo (None, 27, 27, 96)        384
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 17, 17, 256)       2973952
_________________________________________________________________
activation_1 (Activation)    (None, 17, 17, 256)       0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
batch_normalization_1 (Batch (None, 8, 8, 256)         1024
```

In [ ]:

VGG16

- VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR(Imagenet) competition in 2014.
- It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2.
- It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC(fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx) parameters.





The following are the layers of the model:

- Convolutional Layers = 13
- Pooling Layers = 5
- Dense Layers = 3

Let us explore the layers in detail:

1. **Input:** Image of dimensions (224, 224, 3).

2. **Convolution Layer Conv1:**

    ```
    - Conv1-1: 64 filters
    - Conv1-2: 64 filters and Max Pooling
    - Image dimensions: (224, 224)
    ```

3. **Convolution layer Conv2:** Now, we increase the filters to 128

    ```
    - Input Image dimensions: (112,112)
    - Conv2-1: 128 filters
    - Conv2-2: 128 filters and Max Pooling
    ```

4. **Convolution Layer Conv3:** Again, double the filters to 256, and now add another convolution layer

    ```
    - Input Image dimensions: (56,56)
    - Conv3-1: 256 filters
    - Conv3-2: 256 filters
    - Conv3-3: 256 filters and Max Pooling
    ```

5. **Convolution Layer Conv4:** Similar to Conv3, but now with 512 filters

    ```
    - Input Image dimensions: (28, 28)
    - Conv4-1: 512 filters
    - Conv4-2: 512 filters
    - Conv4-3: 512 filters and Max Pooling
    ```

6. **Convolution Layer Conv5:** Same as Conv4

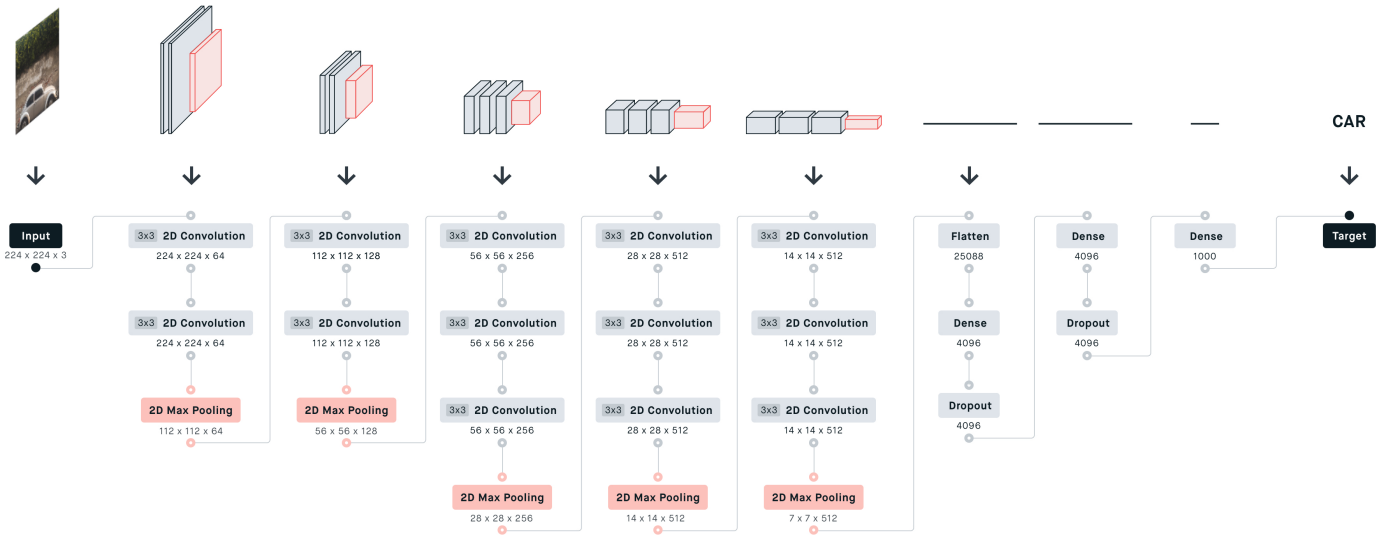
    ```
    - Input Image dimensions: (14, 14)
    - Conv5-1: 512 filters
    - Conv5-2: 512 filters
    - Conv5-3: 512 filters and Max Pooling
    - The output dimensions here are (7, 7). At this point, we flatten the output
    of this layer to generate a feature vector
    ```

7. **Fully Connected/Dense FC1:** 4096 nodes, generating a feature vector of size(1, 4096)
8. **Fully ConnectedDense FC2:** 4096 nodes generating a feature vector of size(1, 4096)
9. **Fully Connected /Dense FC3:** 4096 nodes, generating 1000 channels for 1000 classes. This is then passed on to a Softmax activation function
10. **Output layer**

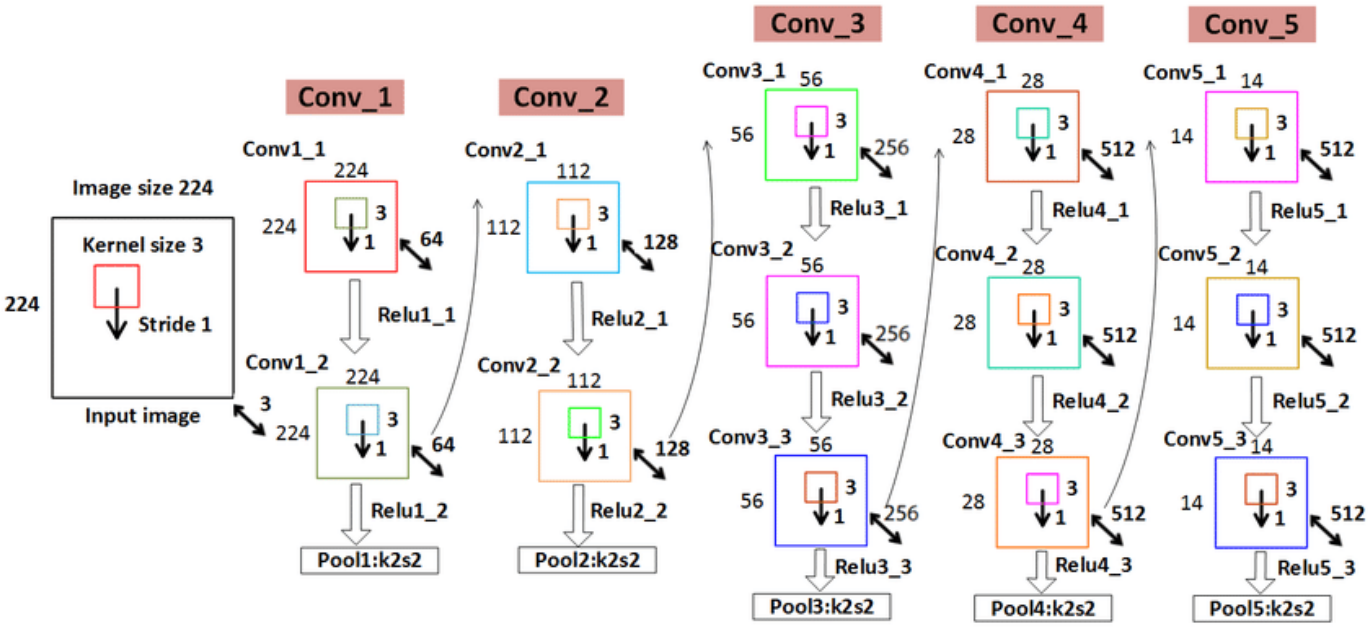
> VGG16 contains 16 layers and VGG19 contains 19 layers. A series of VGGs are exactly the same in the last three fully connected layers. The overall structure includes 5 sets of convolutional layers, followed by a MaxPool. The difference is that more and more cascaded convolutional layers are included in the five sets of convolutional layers .

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1000	-	-	Softmax

Each convolutional layer in AlexNet contains only one convolution, and the size of the convolution kernel is 7 *7 ,. In VGGNet, each convolution layer contains 2 to 4 convolution operations. The size of the convolution kernel is 3* 3, the convolution step size is 1, the pooling kernel is 2 * 2, and the step size is 2. The most obvious improvement of VGGNet is to reduce the size of the convolution kernel and increase the number of convolution layers.



Using multiple convolution layers with smaller convolution kernels instead of a larger convolution layer with convolution kernels can reduce parameters on the one hand, and the author believes that it is equivalent to more non-linear mapping, which increases the Fit expression ability.



> Two consecutive 3 *3 convolutions are equivalent to a 5* 5 receptive field, and three are equivalent to 7 *7. The advantages of using three 3* 3 convolutions instead of one 7 *7 convolution are twofold : one, including three ReLu layers instead of one , makes the decision function more discriminative; and two, reducing parameters . For example, the input and output are all C channels. 3 convolutional layers using 3* 3 require 3 (3 *3* C *C) = 27* C *C, and 1 convolutional layer using 7* 7 requires 7 *7* C *C = 49C* C. This can be seen as applying a kind of regularization to the 7 *7 convolution, so that it is decomposed into three 3* 3 convolutions.
>
> The 1 *1 convolution layer is mainly to increase the non-linearity of the decision function without affecting the receptive field of the convolution layer. Although the 1* 1 convolution operation is linear, ReLu adds non-linearity.

Some basic questions

Q1: Why can 3 3x3 convolutions replace 7x7 convolutions?

Answer 1

3 3x3 convolutions, using 3 non-linear activation functions, increasing non-linear expression capabilities, making the segmentation plane more separable Reduce the number of parameters. For the convolution kernel of C channels, 7x7 contains parameters , and the number of 3 3x3 parameters is greatly reduced.

Q2: The role of 1x1 convolution kernel

Answer 2

Increase the nonlinearity of the model without affecting the receptive field 1x1 winding machine is equivalent to linear transformation, and the non-linear activation function plays a non-linear role

Q3: The effect of network depth on results (in the same year, Google also independently released the network GoogleNet with a depth of 22 layers)

Answer 3

VGG and GoogleNet models are deep Small convolution VGG only uses 3x3, while GoogleNet uses 1x1, 3x3, 5x5, the model is more complicated (the model began to use a large convolution kernel to reduce the calculation of the subsequent machine layer)

Implement On Keras

In [3]:

```
#Importing library
import keras
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout, Flatten, Conv2D, MaxPooling2D,MaxPool2
from keras.layers.normalization import BatchNormalization
import numpy as np

np.random.seed(1000)
```

In [4]:

```
model = Sequential()
model.add(Conv2D(input_shape=(224,224,3),filters=64,kernel_size=(3,3),padding="same", activ
model.add(Conv2D(filters=64,kernel_size=(3,3),padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))


model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))


model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))


model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))


model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model.add(Flatten())
model.add(Dense(units=4096,activation="relu"))
model.add(Dense(units=4096,activation="relu"))
model.add(Dense(units=2, activation="softmax"))
```

In [6]:

```
print("The output of this will be the summary of the model which I just created.")
model.summary()
```

```
The output of this will be the summary of the model which I just created.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 224, 224, 64)      1792
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 224, 224, 64)      36928
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 112, 112, 64)      0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 112, 112, 128)     73856
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 112, 112, 128)     147584
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 56, 56, 128)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 56, 56, 256)       295168
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 56, 56, 256)       590080
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 56, 56, 256)       590080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 28, 28, 256)       0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 512)       1180160
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 28, 28, 512)       2359808
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 28, 28, 512)       2359808
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 14, 14, 512)       0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 4096)              102764544
_________________________________________________________________
dense_1 (Dense)              (None, 4096)              16781312
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 8194
=================================================================
Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0
_________________________________________________________________
```

Here I have started with initialising the model by specifying that the model is a sequential model. After

initialising the model I add

→ 2 x convolution layer of 64 channel of 3x3 kernal and same padding

→ 1 x maxpool layer of 2x2 pool size and stride 2x2

→ 2 x convolution layer of 128 channel of 3x3 kernal and same padding

→ 1 x maxpool layer of 2x2 pool size and stride 2x2

→ 3 x convolution layer of 256 channel of 3x3 kernal and same padding

→ 1 x maxpool layer of 2x2 pool size and stride 2x2

→ 3 x convolution layer of 512 channel of 3x3 kernal and same padding

→ 1 x maxpool layer of 2x2 pool size and stride 2x2

→ 3 x convolution layer of 512 channel of 3x3 kernal and same padding

→ 1 x maxpool layer of 2x2 pool size and stride 2x2

I also add relu(Rectified Linear Unit) activation to each layers so that all the negative values are not passed to the next layer.

After creating all the convolution I pass the data to the dense layer so for that I flatten the vector which comes out of the convolutions and add

→ 1 x Dense layer of 4096 units

→ 1 x Dense layer of 4096 units

→ 1 x Dense Softmax layer of 2 units

I will use RELU activation for both the dense layer of 4096 units so that I stop forwarding negative values through the network. I use a 2 unit dense layer in the end with softmax activation as I have 2 classes to predict from in the end which are dog and cat. The softmax layer will output the value between 0 and 1 based on the confidence of the model that which class the images belongs to.

After the creation of softmax layer the model is finally prepared.

In [ ]:

ResNet

Introduction

ResNet is a network structure proposed by the He Kaiming, Sun Jian and others of Microsoft Research Asia in 2015, and won the first place in the ILSVRC-2015 classification task. At the same time, it won the first place in ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation tasks. It was a sensation at the time.

ResNet, also known as residual neural network, refers to the idea of adding residual learning to the traditional convolutional neural network, which solves the problem of gradient dispersion and accuracy degradation (training set) in deep networks, so that the network can get more and more The deeper, both the accuracy and the speed are controlled.

> Deep Residual Learning for Image Recognition Original link : ResNet Paper (https://arxiv.org/pdf/1512.03385.pdf)

The problem caused by increasing depth

- The first problem brought by increasing depth is the problem of gradient explosion / dissipation . This is because as the number of layers increases, the gradient of backpropagation in the network will become unstable with continuous multiplication, and become particularly large or special. small. Among them , the problem of gradient dissipation often occurs .
- In order to overcome gradient dissipation, many solutions have been devised, such as using BatchNorm, replacing the activation function with ReLu, using Xaiver initialization, etc. It can be said that gradient dissipation has been well solved
- Another problem of increasing depth is the problem of network degradation, that is, as the depth increases, the performance of the network will become worse and worse, which is directly reflected in the decrease in accuracy on the training set. The residual network article solves this problem. And after this problem is solved, the depth of the network has increased by several orders of magnitude.

Degradation of deep network

> With network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Unexpectedly, such degradation is not caused by overfitting, and adding more layers to a favored deep model leads to higher training error.

Degradation problem

"with the network depth increasing, accuracy gets saturated"

Not caused by overfitting:

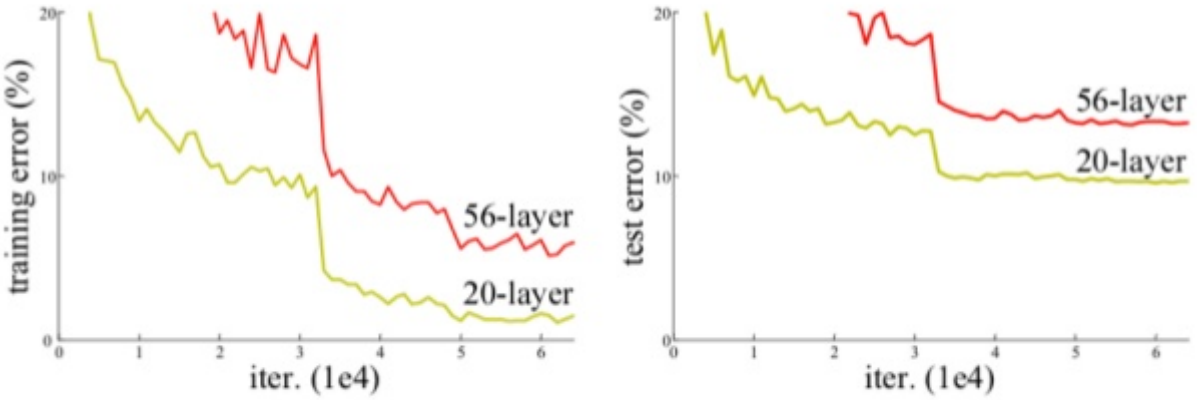


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error.

- The above figure is the error rate of the training set classified by the network on the CIFAR10-data set with the increase of the network depth . It can be seen that if we directly stack the convolutional layers, as the number of layers increases, the error rate increases significantly. The trend is that the deepest 56-layer network has the worst accuracy . We verified it on the VGG network. For the CIFAR-10 dataset, it took 5 minutes on the 18-layer VGG network to get the full network training. The 80% accuracy rate was achieved, and the 34-layer VGG model took 8 minutes to get the 72% accuracy rate. The problem of network degradation does exist.
- The decrease in the training set error rate indicates that the problem of degradation is not caused by overfitting. The specific reason is that it is left for further study. The author's other paper "Identity Mappings in Deep Residual Networks" proved the occurrence of degradation. It is because the optimization performance is not good, which indicates that the deeper the network, the more difficult the reverse gradient is to conduct.

Deep Residual Networks

From 10 to 100 layers

We can imagine that *when we simply stack the network directly to a particularly long length, the internal characteristics of the network have reached the best situation in one of the layers. At this time, the remaining layers should not make any changes to the characteristics and learn automatically. The form of identity mapping*. That is to say, for a particularly deep deep network, the solution space of the shallow form of the network should be a subset of the solution space of the deep network, in other words, a network deeper than the shallow network will not have at least Worse effect, but this is not true because of network degradation.

Then, we settle for the second best. In the case of network degradation, if we do not add depth, we can improve the accuracy. Can we at least make the deep network achieve the same performance as the shallow network, that is, let the layers behind the deep network achieve at least The role of identity mapping . Based on this idea, the author proposes a residual module to help the network achieve identity mapping.

To understand ResNet, we must first understand what kind of problems will occur when the network becomes deeper.

The first problem brought by increasing the network depth is the disappearance and explosion of the gradient.

This problem was successfully solved after Szegedy proposed the **BN (Batch Normalization)** structure. The BN layer can normalize the output of each layer. The size can still be kept stable after the reverse layer transfer, and it will not be too small or too large.

Is it easy to converge after adding BN and then increasing the depth?

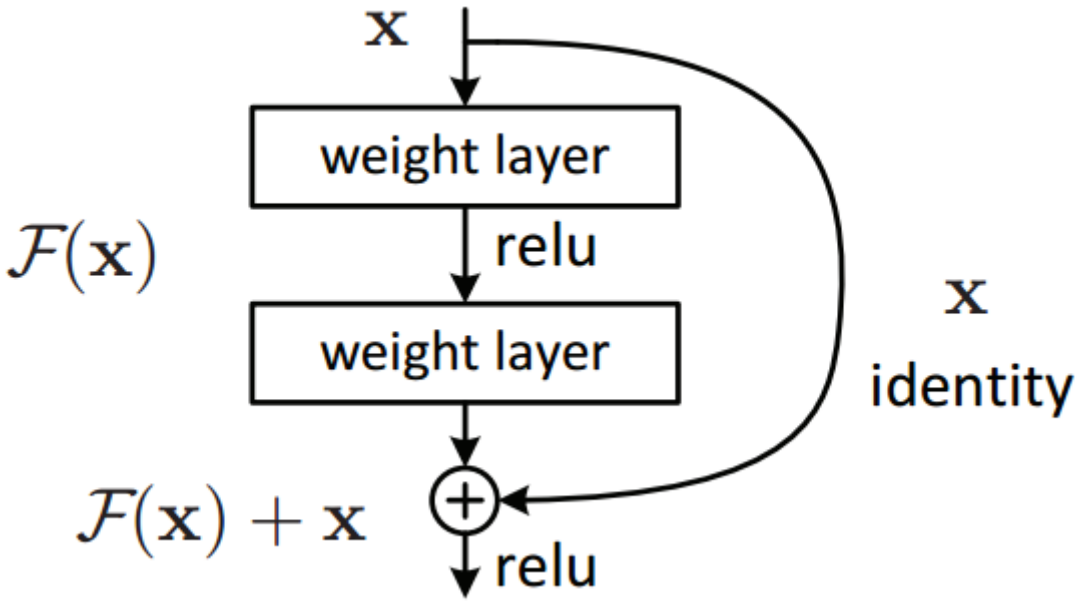
The answer is still **negative**. The author mentioned the second problem-**the degradation problem**: when the level reaches a certain level, the accuracy will saturate and then decline rapidly. This decline is not caused by the disappearance of the gradient. It is not caused by overfit, but because the network is so complicated that it is difficult to achieve the ideal error rate by unconstrained stocking training alone.

The degradation problem is not a problem of the network structure itself, but is caused by the current insufficient training methods. The currently widely used training methods, whether it is SGD, AdaGrad, or RMSProp, cannot reach the theoretically optimal convergence result after the network depth becomes larger.

We can also prove that as long as there is an ideal training method, deeper networks will definitely perform better than shallow networks.

The proof process is also very simple: Suppose that several layers are added behind a network A to form a new network B. If the added level is just an identity mapping of the output of A, that is, the output of A is after the level of B becomes the output of B, there is no change, so the error rates of network A and network B are equal, which proves that the deepened network will not be worse than the network before deepening.

He Kaiming proposed a residual structure to implement the above identity mapping (Below Figure): In addition to the normal convolution layer output, the entire module has a branch directly connecting the input to the output. The output and the output of the convolution do The final output is obtained by arithmetic addition. The formula is H (x) = F (x) + x, x is the input, F (x) is the output of the convolution branch, and H (x) is the output of the entire structure. It can be shown that if all parameters in the F (x) branch are 0, H (x) is an identity mapping. The residual structure artificially creates an identity map, which can make the entire structure converge in the direction of the identity map, ensuring that the final error rate will not become worse because the depth becomes larger. If a network can achieve the desired result by simply setting the parameter values by hand, then this structure can easily converge to the result through training. This is a rule that is unsuccessful when designing complex networks. Recall that in order to restore the original distribution after BN processing, the formula y = rx + delta is used. When r is manually set to standard deviation and delta is the mean, y is the distribution before BN processing. This is the use of this Rules.



What does residual learning mean?

The idea of residual learning is the above picture, which can be understood as a block, defined as follows:

$$y = F(x, \{W_i\}) + x$$

The residual learning block contains two branches or two mappings:

1. Identity mapping refers to the curved curve on the right side of the figure above. As its name implies, identity mapping refers to its own mapping, which is x itself;

1. *F*(x) Residual mapping refers to another branch, that is, part. This part is called residual mapping (y -x) .

What role does the residual module play in back propagation?

- The residual module will significantly reduce the parameter value in the module, so that the parameters in the network have a more sensitive response ability to the loss of reverse conduction, although the fundamental It does not solve the problem that the loss of backhaul is too small, but it reduces the parameters. Relatively speaking, it increases the effect of backhaul loss and also generates a certain regularization effect.
- Secondly, because there are branches of the identity mapping in the forward process, the gradient conduction in the back-propagation process also has more simple paths , and the gradient can be transmitted to the previous module after only one relu.
- The so-called backpropagation is that the network outputs a value, and then compares it with the real value to an error loss. At the same time, the loss is changed to change the parameter. The returned loss depends on the original loss and gradient. Since the purpose is to change the parameter, The problem is that if the intensity of changing the parameter is too small, the value of the parameter can be reduced, so that the loss of the intensity of changing the parameter is relatively greater.
- Therefore, the most important role of the residual module is to change the way of forward and backward information transmission, thereby greatly promoting the optimization of the network.
- Using the four criteria proposed by Inceptionv3, we will use them again to improve the residual module. Using criterion 3, the dimensionality reduction before spatial aggregation will not cause information loss, so the same method is also used here, adding 1 * 1 convolution The kernel is used to increase the non-linearity and reduce the depth of the output to reduce the computational cost. You get the form of a residual module that becomes a bottleneck. The figure above shows the basic form on the left and the bottleneck form on the right.

- To sum up, the shortcut module will help the features in the network perform identity mapping in the forward process, and help conduct gradients in the reverse process, so that deeper models can be successfully trained.

Why can the residual learning solve the problem of "the accuracy of the network deepening declines"?

For a neural network model, if the model is optimal, then training can easily optimize the residual mapping to 0, and only identity mapping is left at this time. No matter how you increase the depth, the network will always be in an optimal state in theory. Because it is equivalent to all the subsequent added networks to carry information transmission along the identity mapping (self), it can be understood that the number of layers behind the optimal network is discarded (without the ability to extract features), and it does not actually play a role. . In this way, the performance of the network will not decrease with increasing depth.

The author used two types of data, **ImageNet** and **CIFAR**, to prove the effectiveness of ResNet:

The first is ImageNet. The authors compared the training effect of ResNet structure and traditional structure with the same number of layers. The left side of Figure is a VGG-19 network with a traditional structure (each followed by BN), the middle is a 34-layer network with a traditional structure (each followed by BN), and the right side is 34 layers ResNet (the solid line indicates a direct connection, and the dashed line indicates a dimensional change using 1x1 convolution to match the number of features of the input and output). Figure 3 shows the results after training these types of networks.

The data on the left shows that the 34-layer network (red line) with the traditional structure has a higher error rate than the VGG-19 (blue-green line). Because the BN structure is added to each layer Therefore, the high error is not caused by the gradient disappearing after the level is increased, but by the degradation problem; the ResNet structure on the right side of Figure 3 shows that the 34-layer network (red line) has a higher error rate than the 18-layer network (blue-green line). Low, this is because the ResNet structure has overcome the degradation problem. In addition, the final error rate of the ResNet 18-layer network on the right is similar to the error rate of the traditional 18-layer network on the left. This is because the 18-layer network is simpler and can converge to a more ideal result even without the ResNet structure.

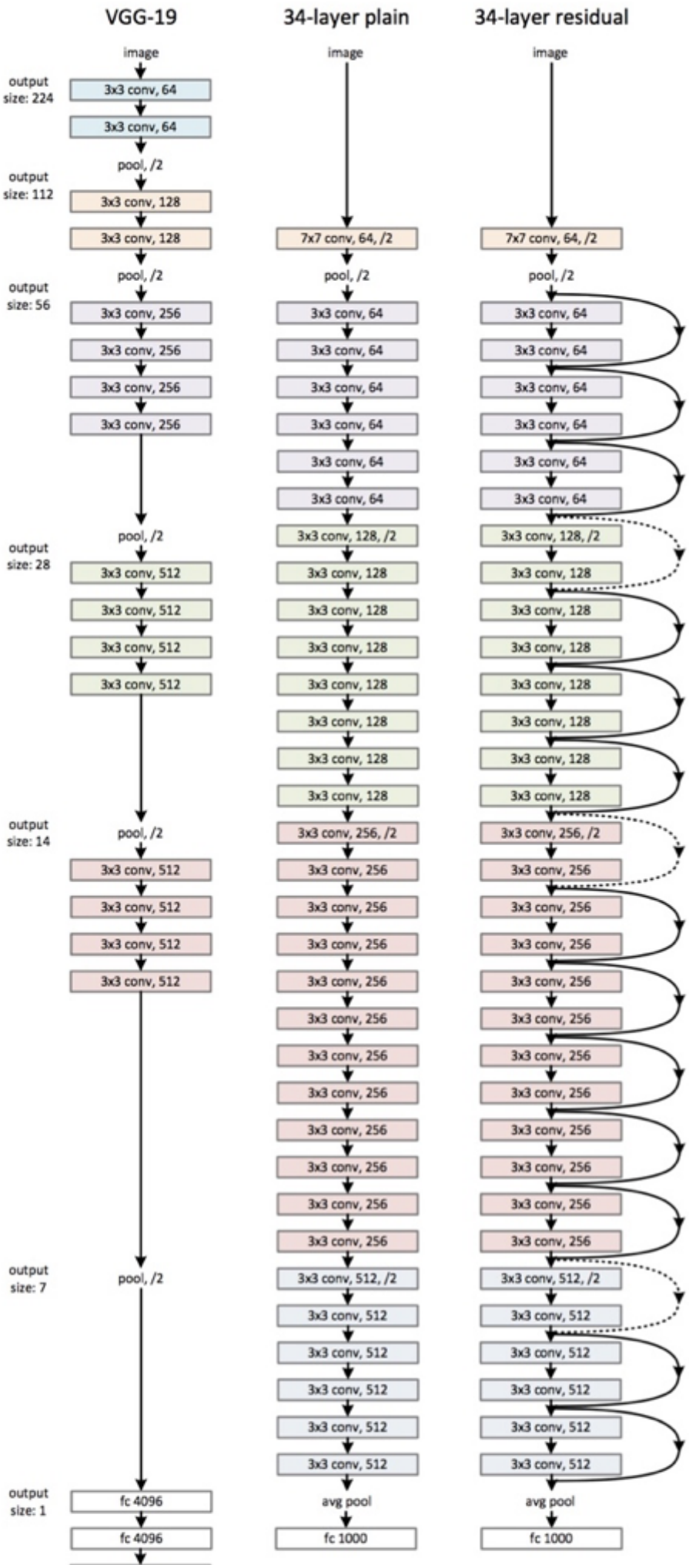

VGG-19
34-layer plain
34-layer residual
image
output size: 224
3x3 conv, 64
3x3 conv, 64
pool, /2
output size: 112
3x3 conv, 128
3x3 conv, 128
pool, /2
output size: 56
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
pool, /2
output size: 28
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 14
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
pool, /2
output size: 7
fc 4096
fc 4096
output size: 1
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
avg pool
fc 1000

Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

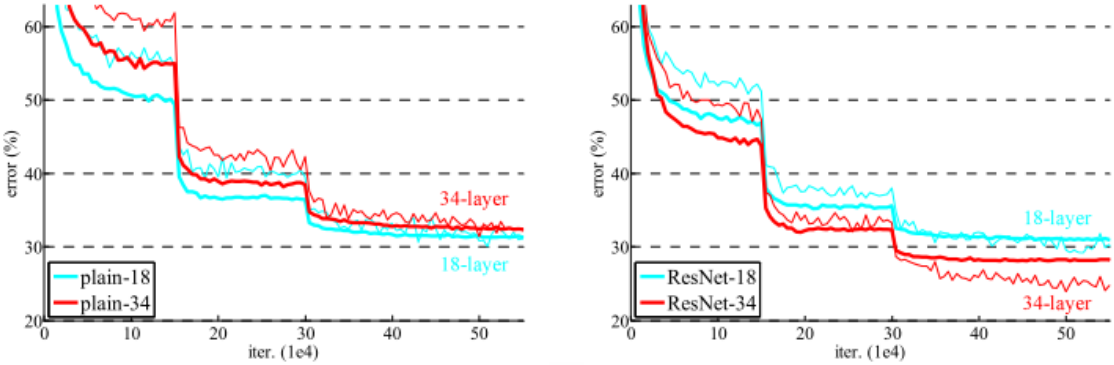
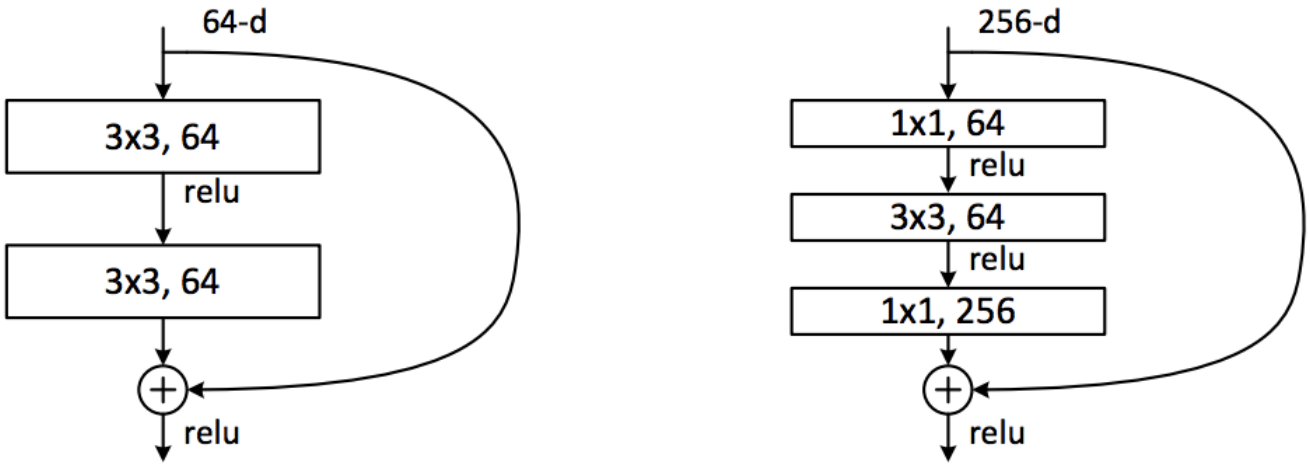


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

The ResNet structure like the left side of Fig. 4 is only used for shallow ResNet networks. If there are many network layers, the dimensions near the output end of the network will be very large. Still using the structure on the left side of Fig. 4 will cause a huge amount of calculation. For deeper networks, we all use the bottleneck structure on the right side of Figure 4, first using a 1x1 convolution for dimensionality reduction, then 3x3 convolution, and finally using 1x1 dimensionality to restore the original dimension.

In practice, considering the cost of the calculation, the residual block is calculated and optimized, that is, the two 3x3 convolution layers are replaced with 1x1 + 3x3 + 1x1 , as shown below. The middle 3x3 convolutional layer in the new structure first reduces the calculation under one dimensionality-reduced 1x1 convolutional layer , and then restores it under another 1x1 convolutional layer , both maintaining accuracy and reducing the amount of calculation .



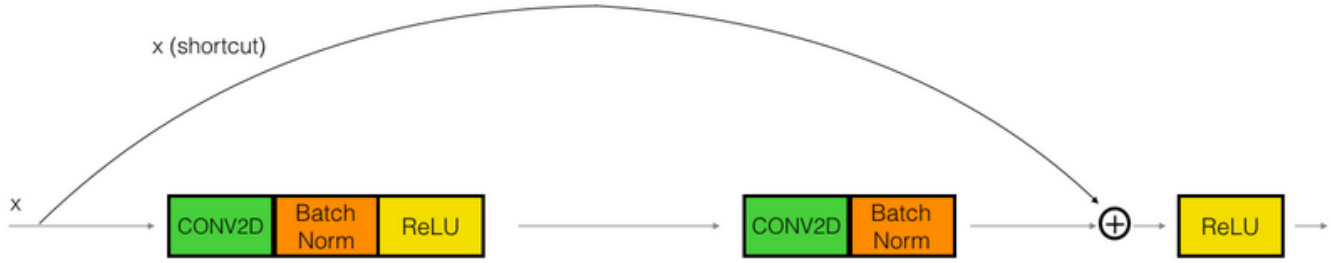
This is equivalent to reducing the amount of parameters for the same number of layers , so it can be extended to deeper models. So the author proposed ResNet with 50, 101 , and 152 layers , and not only did not have degradation problems, the error rate was greatly reduced, and the computational complexity was also kept at a very low level .

At this time, the error rate of ResNet has already dropped other networks a few streets, but it does not seem to be satisfied. Therefore, a more abnormal 1202 layer network has been built. For such a deep network, optimization is still not difficult, but it appears The problem of overfitting is quite normal. The author also said that the 1202 layer model will be further improved in the future.

There are two main types of blocks are used in a ResNet, depending mainly on whether the input/output dimensions are the same or different.

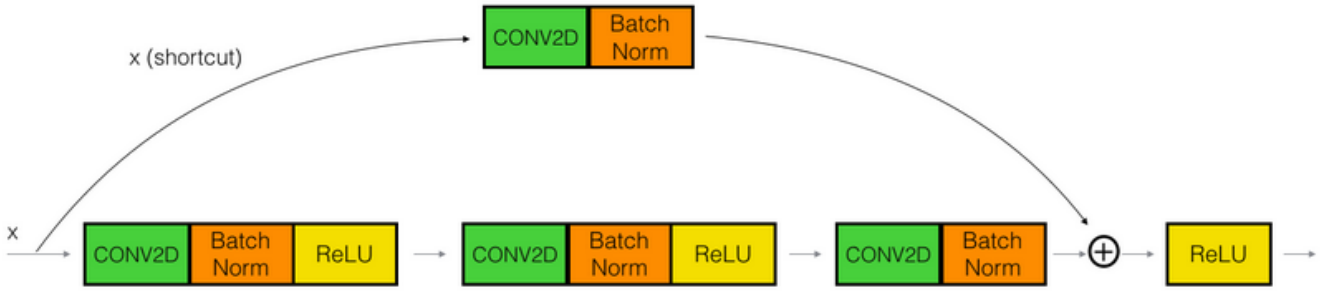
1. Identity Block

The identity block is the standard block used in ResNets and corresponds to the case where the input activation has the same dimension as the output activation.



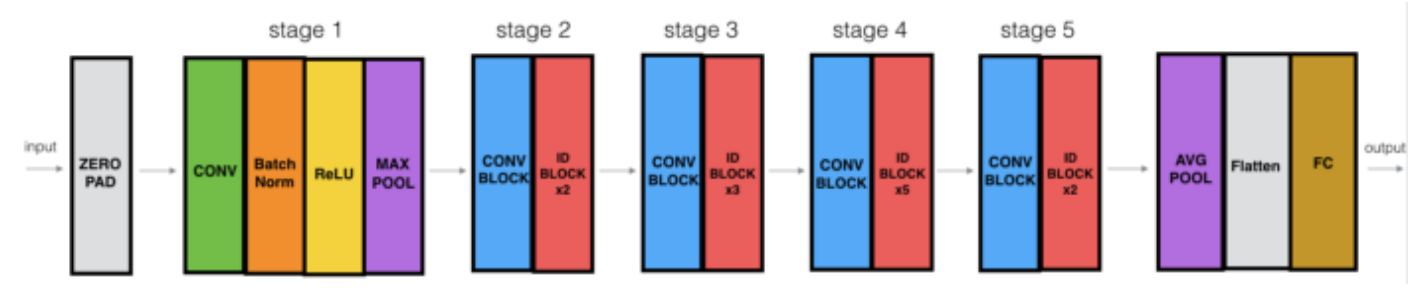
2. Convolutional Block

We can use this type of block when the input and output dimensions don't match up. The difference with the identity block is that there is a CONV2D layer in the shortcut path.



ResNet-50

The ResNet-50 model consists of 5 stages each with a convolution and Identity block. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. The ResNet-50 has over 23 million trainable parameters.



Diffrent Variants : -

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Below is the transcript of resnet, winning the championship at ImageNet2015

method	top-5 err. (**test**)
VGG [40] (ILSVRC'14)	7.32
GoogLeNet [43] (ILSVRC'14)	6.66
VGG [40] (v5)	6.8
PReLU-net [12]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Code Implement

In [1]:

```
import cv2
import numpy as np
import os
from keras.preprocessing.image import ImageDataGenerator
from keras import backend as K
import keras
from keras.models import Sequential, Model,load_model
from keras.optimizers import SGD
from keras.callbacks import EarlyStopping,ModelCheckpoint
from keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, BatchNormalization,
from keras.preprocessing import image
from keras.initializers import glorot_uniform
```

In [2]:

```
def identity_block(X, f, filters, stage, block):

    conv_name_base = 'res' + str(stage) + block + '_branch'
    bn_name_base = 'bn' + str(stage) + block + '_branch'
    F1, F2, F3 = filters

    X_shortcut = X

    X = Conv2D(filters=F1, kernel_size=(1, 1), strides=(1, 1), padding='valid', name=conv_r
    X = BatchNormalization(axis=3, name=bn_name_base + '2a')(X)
    X = Activation('relu')(X)

    X = Conv2D(filters=F2, kernel_size=(f, f), strides=(1, 1), padding='same', name=conv_na
    X = BatchNormalization(axis=3, name=bn_name_base + '2b')(X)
    X = Activation('relu')(X)

    X = Conv2D(filters=F3, kernel_size=(1, 1), strides=(1, 1), padding='valid', name=conv_r
    X = BatchNormalization(axis=3, name=bn_name_base + '2c')(X)

    X = Add()([X, X_shortcut])# SKIP Connection
    X = Activation('relu')(X)

    return X
```

In [3]:

```
def convolutional_block(X, f, filters, stage, block, s=2):

    conv_name_base = 'res' + str(stage) + block + '_branch'
    bn_name_base = 'bn' + str(stage) + block + '_branch'

    F1, F2, F3 = filters

    X_shortcut = X

    X = Conv2D(filters=F1, kernel_size=(1, 1), strides=(s, s), padding='valid', name=conv_r
    X = BatchNormalization(axis=3, name=bn_name_base + '2a')(X)
    X = Activation('relu')(X)

    X = Conv2D(filters=F2, kernel_size=(f, f), strides=(1, 1), padding='same', name=conv_na
    X = BatchNormalization(axis=3, name=bn_name_base + '2b')(X)
    X = Activation('relu')(X)

    X = Conv2D(filters=F3, kernel_size=(1, 1), strides=(1, 1), padding='valid', name=conv_r
    X = BatchNormalization(axis=3, name=bn_name_base + '2c')(X)

    X_shortcut = Conv2D(filters=F3, kernel_size=(1, 1), strides=(s, s), padding='valid', na
    X_shortcut = BatchNormalization(axis=3, name=bn_name_base + '1')(X_shortcut)

    X = Add()([X, X_shortcut])
    X = Activation('relu')(X)

    return X
```

In [4]:

```
def ResNet50(input_shape=(224, 224, 3)):

    X_input = Input(input_shape)

    X = ZeroPadding2D((3, 3))(X_input)

    X = Conv2D(64, (7, 7), strides=(2, 2), name='conv1', kernel_initializer=glorot_uniform(
    X = BatchNormalization(axis=3, name='bn_conv1')(X)
    X = Activation('relu')(X)
    X = MaxPooling2D((3, 3), strides=(2, 2))(X)

    X = convolutional_block(X, f=3, filters=[64, 64, 256], stage=2, block='a', s=1)
    X = identity_block(X, 3, [64, 64, 256], stage=2, block='b')
    X = identity_block(X, 3, [64, 64, 256], stage=2, block='c')


    X = convolutional_block(X, f=3, filters=[128, 128, 512], stage=3, block='a', s=2)
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='b')
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='c')
    X = identity_block(X, 3, [128, 128, 512], stage=3, block='d')

    X = convolutional_block(X, f=3, filters=[256, 256, 1024], stage=4, block='a', s=2)
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='b')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='c')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='d')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='e')
    X = identity_block(X, 3, [256, 256, 1024], stage=4, block='f')

    X = X = convolutional_block(X, f=3, filters=[512, 512, 2048], stage=5, block='a', s=2)
    X = identity_block(X, 3, [512, 512, 2048], stage=5, block='b')
    X = identity_block(X, 3, [512, 512, 2048], stage=5, block='c')

    X = AveragePooling2D(pool_size=(2, 2), padding='same')(X)

    model = Model(inputs=X_input, outputs=X, name='ResNet50')

    return model
```

In [6]:

```
base_model = ResNet50(input_shape=(224, 224, 3))
```

In [7]:

```
headModel = base_model.output
headModel = Flatten()(headModel)
headModel=Dense(256, activation='relu', name='fc1',kernel_initializer=glorot_uniform(seed=0
headModel=Dense(128, activation='relu', name='fc2',kernel_initializer=glorot_uniform(seed=0
headModel = Dense( 1,activation='sigmoid', name='fc3',kernel_initializer=glorot_uniform(see
```

In [8]:

```
model = Model(inputs=base_model.input, outputs=headModel)
```

In [9]:

```
model.summary()
```

```
Model: "model"
__________________________________________________________________________________
__________________________
Layer (type)                    Output Shape         Param #     Connected
to
==================================================================================
==========================
input_1 (InputLayer)            [(None, 224, 224, 3) 0
__________________________________________________________________________________
__________________________
zero_padding2d (ZeroPadding2D)  (None, 230, 230, 3)  0           input_1
[0][0]
__________________________________________________________________________________
__________________________
conv1 (Conv2D)                  (None, 112, 112, 64) 9472        zero_padd
ing2d[0][0]
__________________________________________________________________________________
__________________________
bn_conv1 (BatchNormalization)   (None, 112, 112, 64) 256         conv1[0]
[0]
```

In [ ]:

```

```

InceptionNet

Introduction

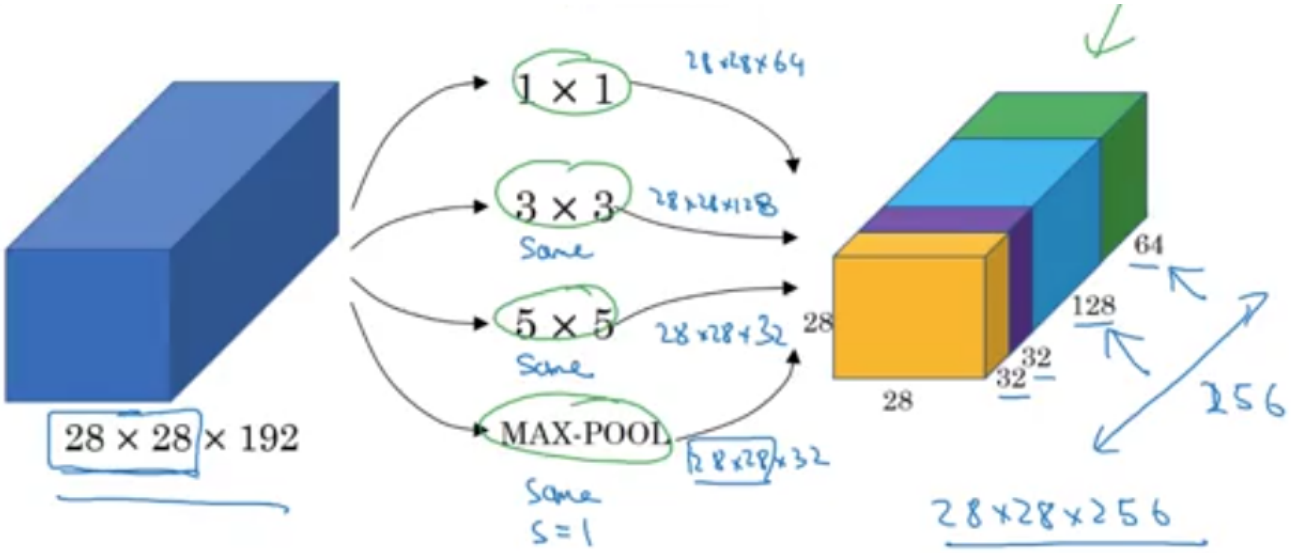
- Inception net achieved a milestone in CNN classifiers when previous models were just going deeper to improve the performance and accuracy but compromising the computational cost. The Inception network, on the other hand, is heavily engineered.
- It uses a lot of tricks to push performance, both in terms of speed and accuracy. It is the winner of the ImageNet Large Scale Visual Recognition Competition in 2014, an image classification competition, which has a significant improvement over ZFNet (The winner in 2013), AlexNet (The winner in 2012) and has relatively lower error rate compared with the VGGNet (1st runner-up in 2014).

The major issues faced by deeper CNN models such as VGGNet were:

1. Although, previous networks such as VGG achieved a remarkable accuracy on the ImageNet dataset, deploying these kinds of models is highly computationally expensive because of the deep architecture.
2. Very deep networks are susceptible to overfitting. It is also hard to pass gradient updates through the entire network.

Motivation for Inception Network

Instead of deciding whether to use a 1x1 convolution, or a 3x3 or a 5x5 Convolution, or whether to use a Pooling layer - Why not use all of them?

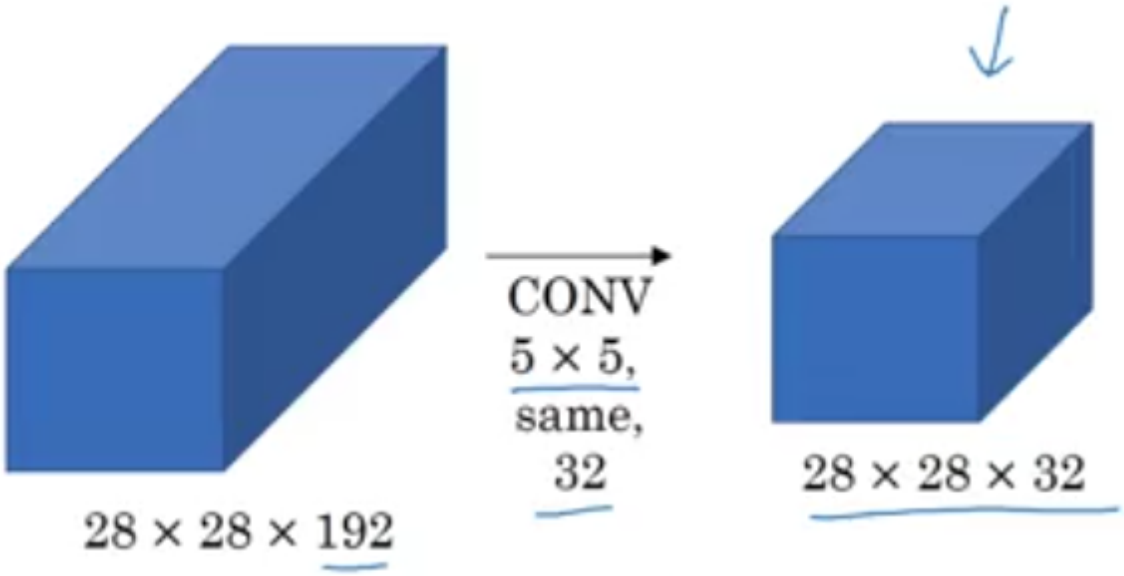


In the example above, all the filters are applied to the input to generate a stacked outpu, whioch contains the output of each filter stacked on top of each other. The Padding is kept at ‘same’ to ensure that the output from all the filters are of the same size.

Disadvantage: Huge memory cost

Solving the problem of memory cost

For example, the computational cost of th 5x5 filer in the above diagram:



Input: 28x28x192

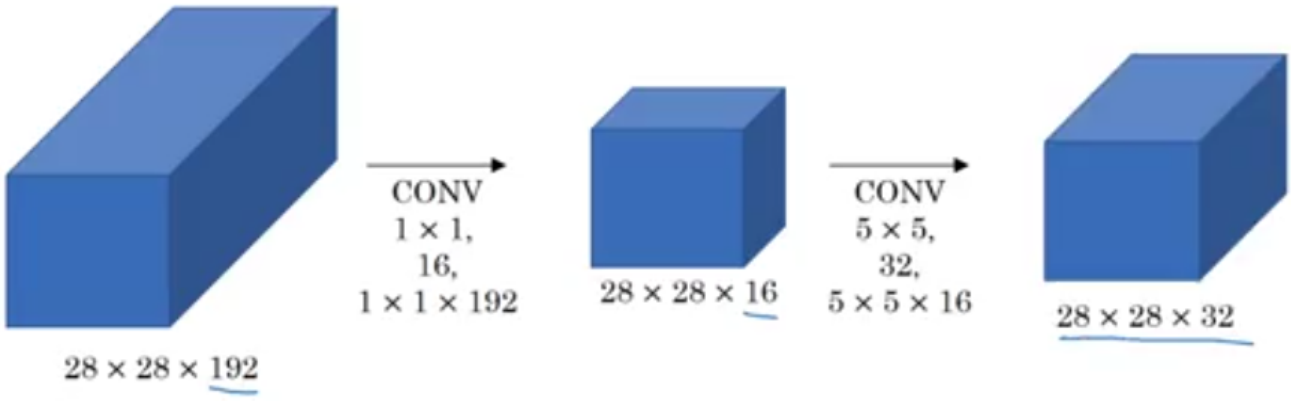
Filter: Conv 5x5x192, same, 32

Output: 28x28x32

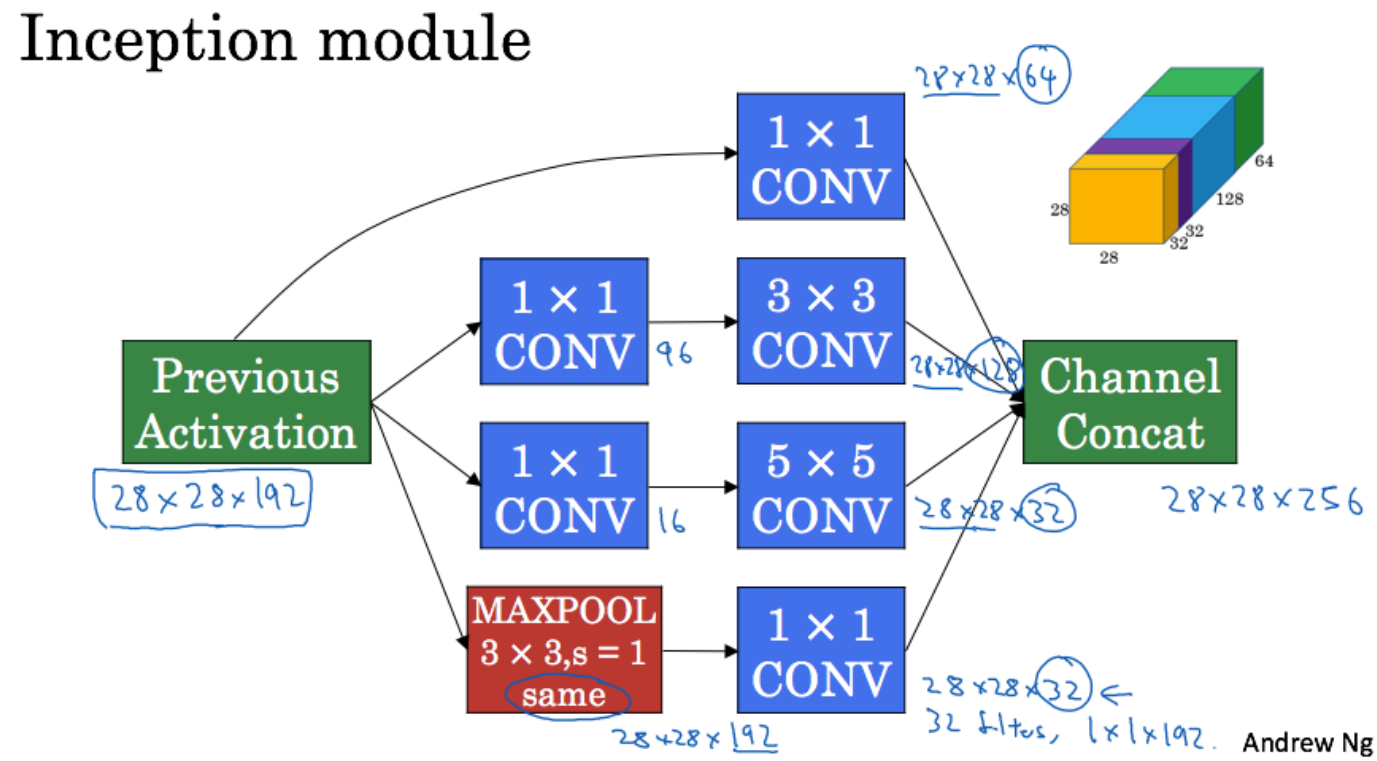
Total number of calculations = (28 *28* 32) *(5* 5 * 192) = 120 Million !!

Using 1x1 Convolution to reduce computation cost

A 1x1 convolution is added before the 5x5 cvonvolution -= Also called a bottleneck layer



Total number of calculations = [(28 *28* 16) *(1* 1 *192)]* + *[(28* 28 *32)* (5 *5* 16)] = 12.4 Million !! (earlier the cost was 120 Million)



The popular versions are as follows:

Inception v1.

Inception v2 and Inception v3.

Inception v4 and Inception-ResNet.

Inception V1 (GoogLeNet)

- This architecture has 22 layers in total! Using the dimension-reduced inception module, a neural network architecture is constructed. This is popularly known as GoogLeNet (Inception v1).
- GoogLeNet has 9 such inception modules fitted linearly. It is 22 layers deep (27, including the pooling layers). At the end of the architecture, fully connected layers were replaced by a global average pooling which calculates the average of every feature map. This indeed dramatically declines the total number of parameters.
- The above are the explainof V1

Problems of Inception V1 architecture:

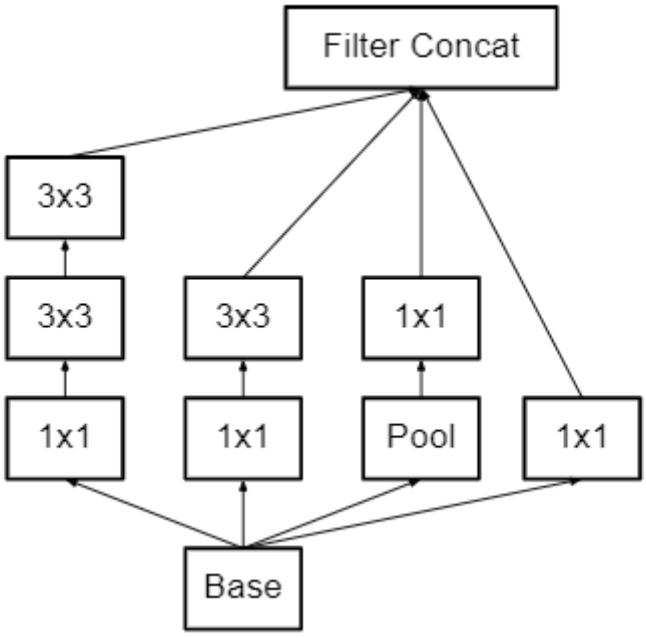
- Inception V1 have sometimes use convolutions such as 5*5 that causes the input dimensions to decrease by a large margin. This causes the neural network some accuracy decrease. The reason behind that the neural network is susceptible to information loss if the input dimension decreases too drastically.
- Furthermore, there is also complexity decrease when we use bigger convolutions like 5×5 as compared to 3×3.We can go further in terms of factorization i.e. that we can divide a 3×3 convolution into an asymmetric convolution of 1×3 then followed by 3×1 convolution. This is equivalent to sliding a two-layer network with the same receptive field as in a 3×3 convolution but 33% more cheaper than 3×3. This factorization does not work well for early layers when input dimensions are big but only when the input size mxm (m is between 12 and 20). According to the Inception V1 architecture, the auxiliary classifier improves the convergence of the network. They argue that it can help reduce the effect of the vanishing gradient problem in deep network by pushing the useful gradient to earlier layers (to reduce the loss). But, the authors of this paper found that this classifier didn't improve the convergence very much early in the training.

Inception V2 And Inception V3

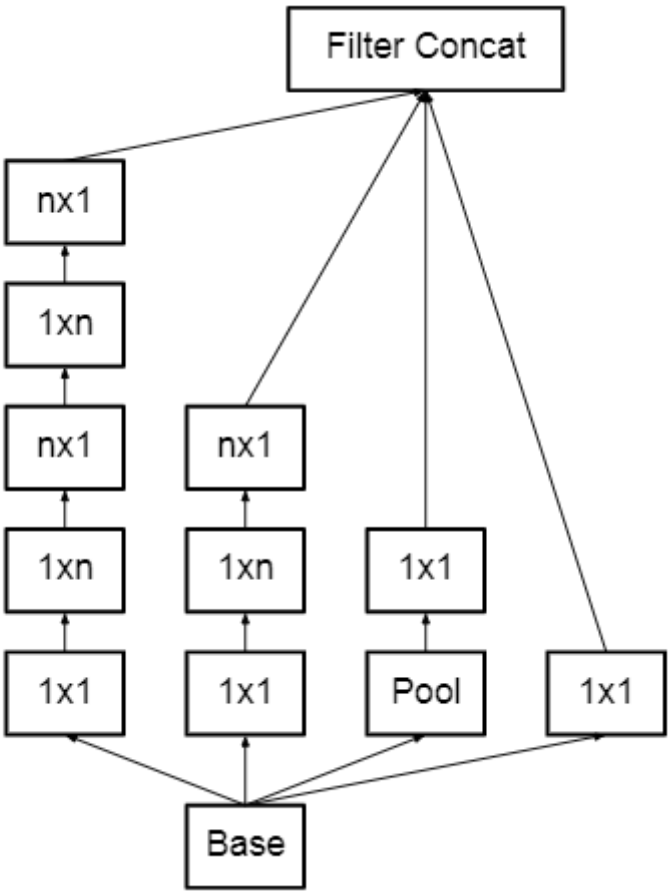
Inception-v2(2015)

Architectural Changes in Inception V2:

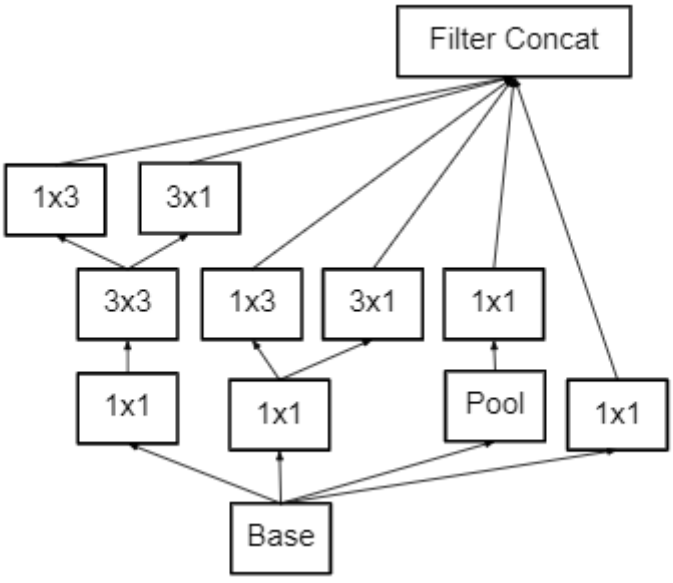
In the Inception V2 architecture. The 5×5 convolution is replaced by the two 3×3 convolutions. This also decreases computational time and thus increase computational speed because a 5×5 convolution is 2.78 more expensive than 3×3 convolution. So, Using two 3×3 layers instead of 5×5 increases the performance of architecture.



This architecture also converts nXn factorization into 1xn and nx1 factorization. As we discuss above that a 3×3 convolution can be converted into 1×3 then followed by 3×1 convolution which is 33% cheaper in terms of computational complexity as compared to 3×3.



To deal with the problem of the representational bottleneck, the feature banks of the module were expanded instead of making it deeper. This would prevent the loss of information that causes when we make it deeper.



The above three principles were used to build three different types of inception modules (Let's call them modules A,B and C in the order they were introduced. These names are introduced for clarity, and not the official names). The architecture is as follows:

type	patch size/stride or remarks	input size
conv	$3\times3/2$	$299\times299\times3$
conv	$3\times3/1$	$149\times149\times32$
conv padded	$3\times3/1$	$147\times147\times32$
pool	$3\times3/2$	$147\times147\times64$
conv	$3\times3/1$	$73\times73\times64$
conv	$3\times3/2$	$71\times71\times80$
conv	$3\times3/1$	$35\times35\times192$
$3\times$Inception	As in figure 5	$35\times35\times288$
$5\times$Inception	As in figure 6	$17\times17\times768$
$2\times$Inception	As in figure 7	$8\times8\times1280$
pool	8×8	$8\times8\times2048$
linear	logits	$1\times1\times2048$
softmax	classifier	$1\times1\times1000$

Algorithm advantages:

1. **Improved learning rate** : In the BN model, a higher learning rate is used to accelerate training convergence, but it will not cause other effects. Because if the scale of each layer is different, then the learning rate required by each layer is different. The scale of the same layer dimension often also needs different learning rates. Usually, the minimum learning is required to ensure the loss function to decrease, but The BN layer keeps the scale of each layer and dimension consistent, so you can directly use a higher learning rate for optimization.

1. **Remove the dropout layer** : The BN layer makes full use of the goals of the dropout layer. Remove the dropout layer from the BN-Inception model, but no overfitting will occur.

1. **Decrease the attenuation coefficient of L2 weight** : Although the L2 loss controls the overfitting of the Inception model, the loss of weight has been reduced by five times in the BN-Inception model.

1. **Accelerate the decay of the learning rate** : When training the Inception model, we let the learning rate decrease exponentially. Because our network is faster than Inception, we will increase the speed of reducing the learning rate by 6 times.

1. **Remove the local response layer** : Although this layer has a certain role, but after the BN layer is added, this layer is not necessary.

1. **Scramble training samples more thoroughly** : We scramble training samples, which can prevent the same samples from appearing in a mini-batch. This can improve the accuracy of the validation set by 1%, which is the advantage of the BN layer as a regular term. In our method, random selection is more effective when the model sees different samples each time.

1. **To reduce image distortion**: Because BN network training is faster and observes each training sample less often, we want the model to see a more realistic image instead of a distorted image.

Inception-v3-2015

This architecture focuses, how to use the convolution kernel two or more smaller size of the convolution kernel to replace, but also the introduction of **asymmetrical layers i.e. a convolution dimensional convolution** has also been proposed for pooling layer Some remedies that can cause loss of spatial information; there are ideas such as **label-smoothing , BN-ahxiliary** .

Experiments were performed on inputs with different resolutions . The results show that although low-resolution inputs require more time to train, the accuracy and high-resolution achieved are not much different.

The computational cost is reduced while improving the accuracy of the network.

General Design Principles

We will describe some design principles that have been proposed through extensive experiments with different architectural designs for convolutional networks. At this point, full use of the following principles can be guessed, and some additional experiments in the future will be necessary to estimate their accuracy and effectiveness.

1. **Prevent bottlenecks in characterization** . The so-called bottleneck of feature description is that a large proportion of features are compressed in the middle layer (such as using a pooling operation). This operation will cause the loss of feature space information and the loss of features. Although the operation of pooling in CNN is important, there are some methods that can be used to avoid this loss as much as possible (I note: later hole convolution operations).
2. **The higher the dimensionality of the feature, the faster the training converges** . That is, the independence of features has a great relationship with the speed of model convergence. The more independent features, the more thoroughly the input feature information is decomposed. It is easier to converge if the correlation is strong. Hebbin principle : fire together, wire together.
3. **Reduce the amount of calculation through dimensionality reduction** . In v1, the feature is first reduced by 1x1 convolutional dimensionality reduction. There is a certain correlation between different dimensions. Dimension reduction can be understood as a lossless or low-loss compression. Even if the dimensions are reduced, the correlation can still be used to restore its original information.
4. **Balance the depth and width of the network** . Only by increasing the depth and width of the network in the same proportion can the performance of the model be maximized.

Inception V3 is similar to and contains all the features of Inception V2 with following changes/additions:

```
    1. Use of RMSprop optimizer.
    2. Batch Normalization in the fully connected layer of Auxiliary classifier.
    3. Use of 7×7 factorized Convolution
    4. Label Smoothing Regularization: It is a method to regularize the classifier
by estimating the effect of label-dropout during training. It prevents the classif
ier to predict too confidently a class. The addition of label smoothing gives 0.2%
improvement from the error rate.
```

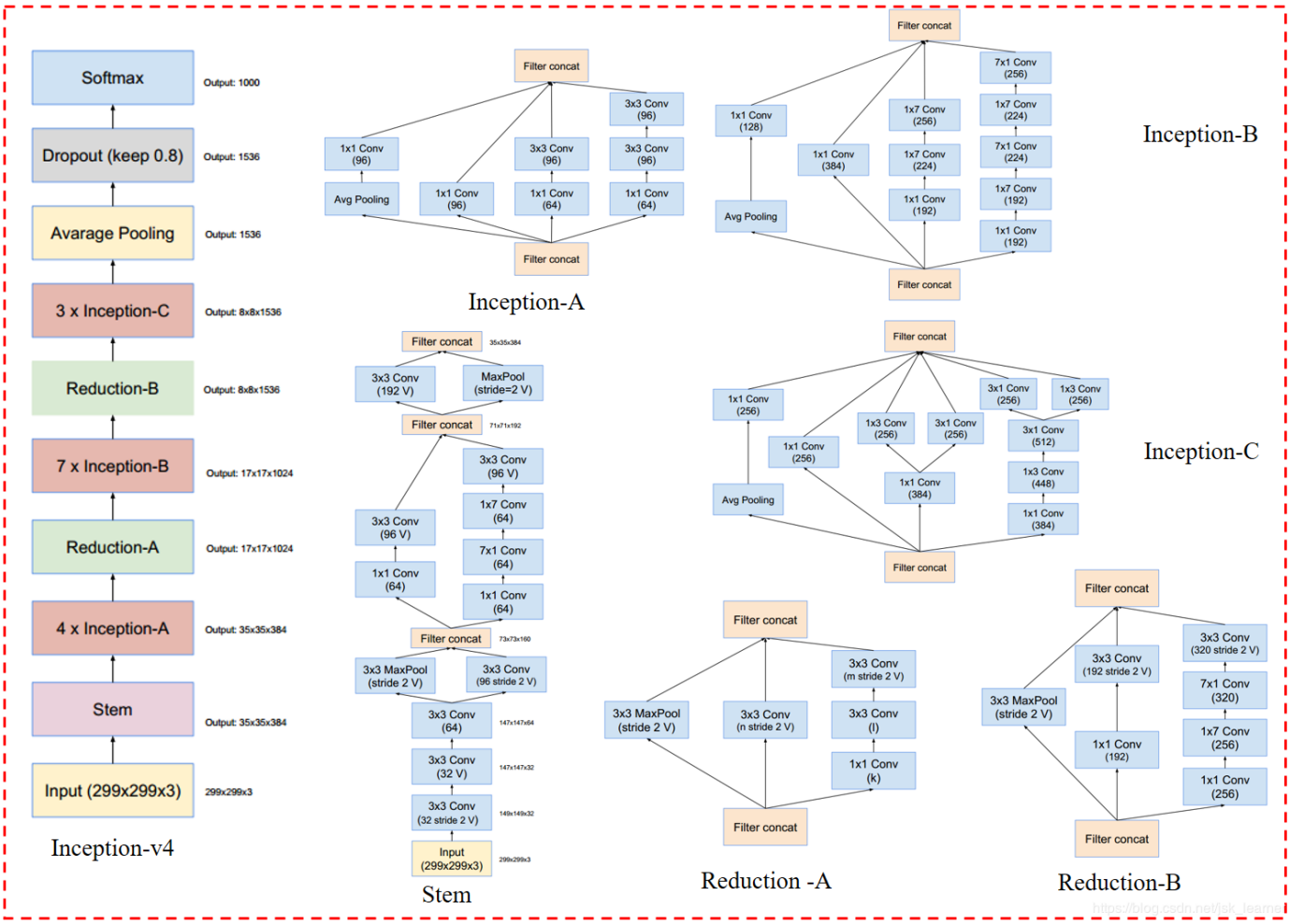
Inception-v4-2016

- Inception V4 was introduced in combination with Inception-ResNet by thee researchers a Google in 2016. The main aim of the paper was to reduce the complexity of Inception V3 model which give the state-of-the-art accuracy on ILSVRC 2015 challenge. This paper also explores the possibility of using residual networks on Inception model.

Introduction

Residual conn works well when training very deep networks. Because the Inception network architecture can be very deep, it is reasonable to use residual conn instead of concat.

Compared with v3, Inception-v4 has more unified simplified structure and more inception modules.



The big picture of Inception-v4:

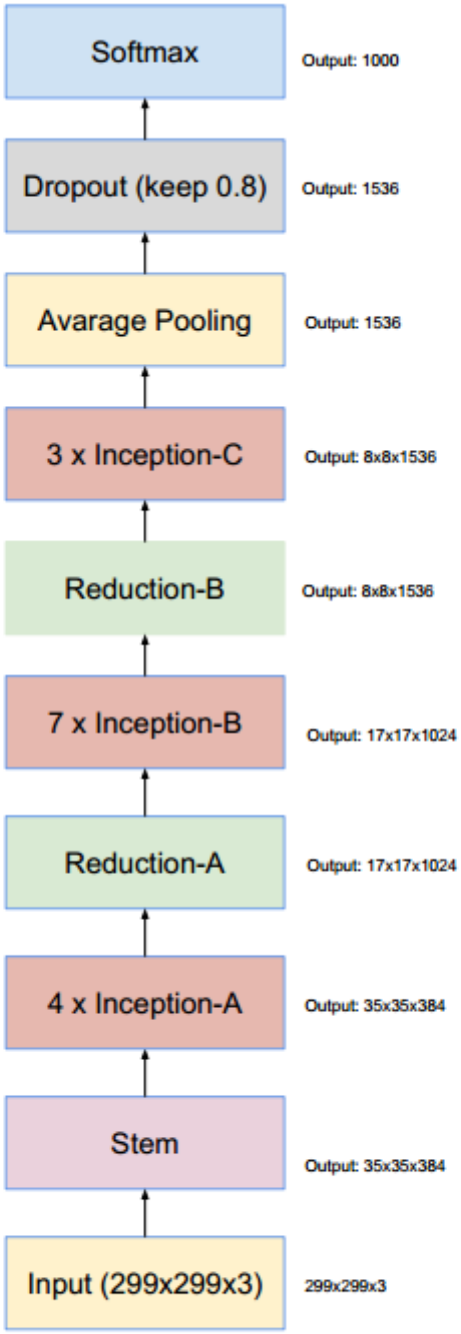


Figure 9. The overall schema of the Inception-v4 network. For the detailed modules, please refer to Figures 3, 4, 5, 6, 7 and 8 for the detailed structure of the various components.

Fig9 is an overall picture, and Fig3,4,5,6,7,8 are all local structures. For the specific structure of each module, see the end of the article.

Residual Inception Blocks

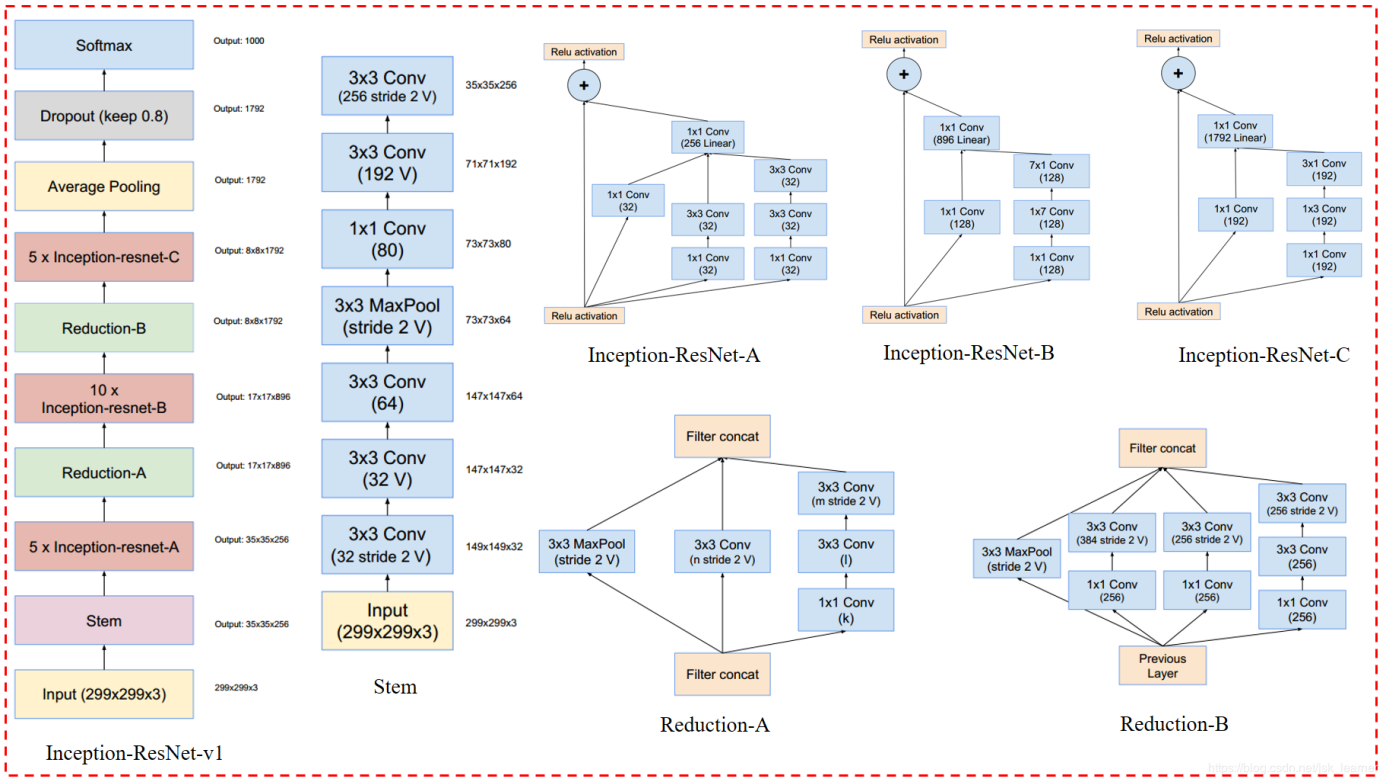
For the residual version in the Inception network, we use an Inception module that consumes less than the original Inception. The convolution kernel (followed by 1x1) of each Inception module is used to modify the dimension, which can compensate the reduction of the Inception dimension to some extent.

One is named **Inception-ResNet-v1**, which is consistent with the calculation cost of Inception-v3. One is named **Inception-ResNet-v2**, which is consistent with the calculation cost of Inception-v4.

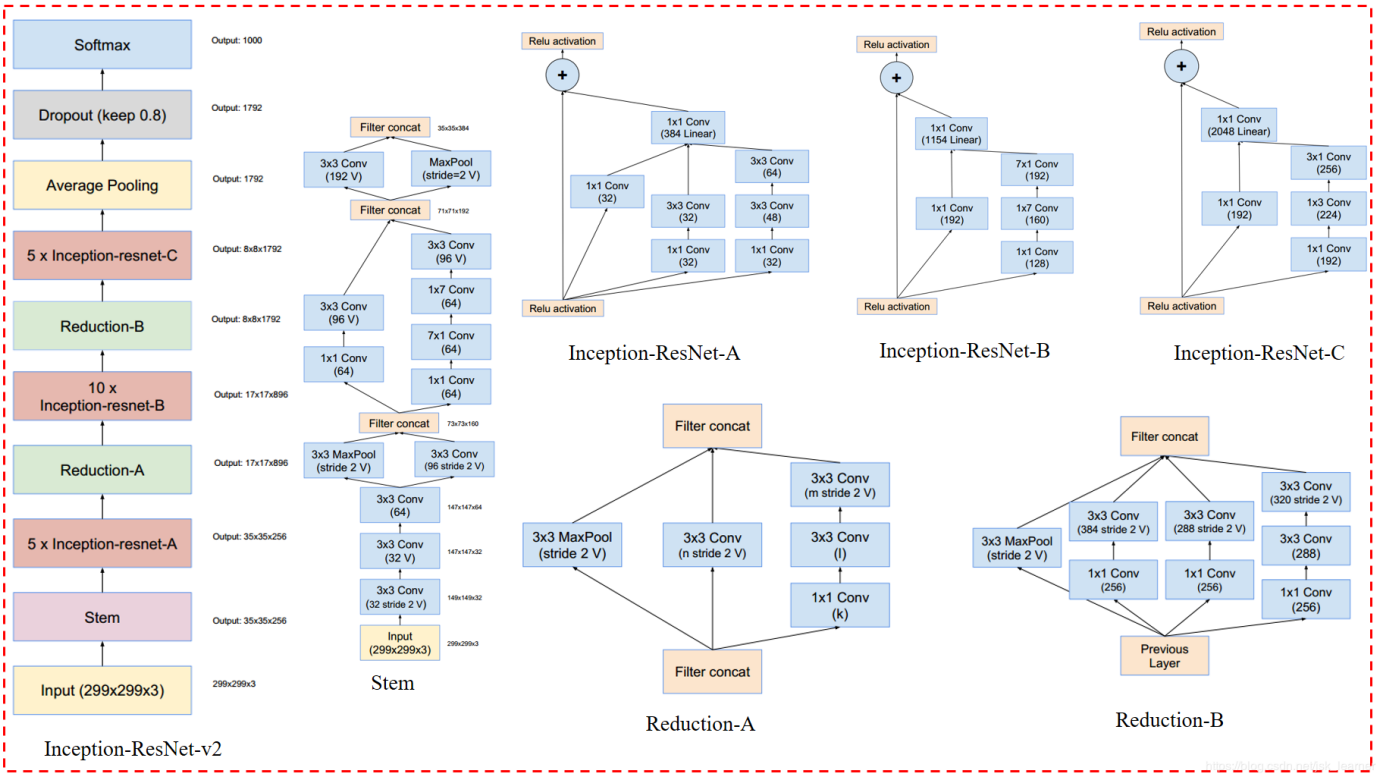
Figure 15 shows the structure of both. However, Inception-v4 is actually slower in practice, probably because it has more layers.

Another small technique is that we use the BN layer in the header of the traditional layer in the Inception-ResNet module, but not in the header of the summations. ** There is reason to believe that the BN layer is effective. But in order to add more Inception modules, we made a compromise between the two.

Inception-ResNet-v1



Inception-ResNet-v2



Scaling of the Residuals

This paper finds that when the number of convolution kernels exceeds 1,000 , the residual variants will start to show instability , and the network will die in the early stages of training, which means that the last layer before the average pooling layer is in the Very few iterations start with just a zero value . This situation cannot be

prevented by reducing the learning rate or by adding a BN layer . Hekaiming's ResNet article also mentions this phenomenon.

This article finds that scale can stabilize the training process before adding the residual module to the activation layer . This article sets the scale coefficient between 0.1 and 0.3.

In order to prevent the occurrence of unstable training of deep residual networks, He suggested in the article that it is divided into two stages of training. The first stage is called warm-up (preheating) , that is, training the model with a very low learning first. In the second stage, a higher learning rate is used. And this article finds that if the convolution sum is very high, even a learning rate of 0.00001 cannot solve this training instability problem, and the high learning rate will also destroy the effect. But this article considers scale residuals to be more reliable than warm-up.

Even if scal is not strictly necessary, it has no effect on the final accuracy, but it can stabilize the training process.

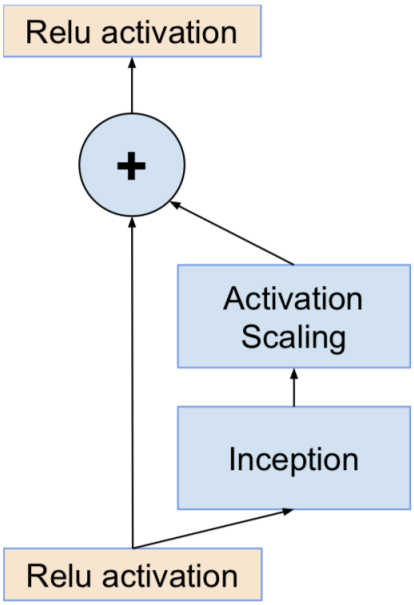


Figure 20. The general schema for scaling combined Inception-resnet moduels. We expect that the same idea is useful in the general resnet case, where instead of the Inception block an arbitrary subnetwork is used. The scaling block just scales the last linear activations by a suitable constant, typically around 0.1.

Conclusion

Inception-ResNet-v1 : a network architecture combining inception module and resnet module with similar calculation cost to Inception-v3;

Inception-ResNet-v2 : A more expensive but better performing network architecture.

Inception-v4 : A pure inception module, without residual connections, but with performance similar to Inception-ResNet-v2.