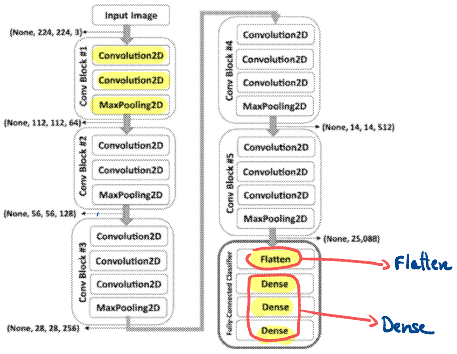
VGG16

* VGG16 (2014): 16 layers



Convolution block → Convolution2D, MaxPooling

VGG16 (different combinations)

* VGG 19

VGG 11 ← → VGG 19

ConvNet Configuration

A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv1-256	conv3-256 conv3-256 conv3-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: **Number of parameters** (in millions).

Network	A, A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

Deeper VGG, more parameters

Number of convolution layers

VGG16: 2 convolution layer + maxpooling + 2 CL + MP + ...

Deep stack of 3×3 filters with pooling creates a larger receptive field in deeper layers (pyramid)

Repeated convolutions with smaller filters is also more efficient

$F \in \mathbb{R}^{3\times3}$ $G \in \mathbb{R}^{5\times5}$ $F \times F \in \mathbb{R}^{5\times5}$

$(I * F) * F \rightarrow 9\times9$ operations per pixel

$I * G \rightarrow 5\times5$ operations per pixel

VGG16

- Most parameters are in the FC (fully connected) layers (due to not having weight sharing there). Hence, motivation for fully convolutional networks (no FC layers)
- Most memory in early convolution layers (due to high spatial resolution). Memory cannot be released before completing the backward pass

VGG16

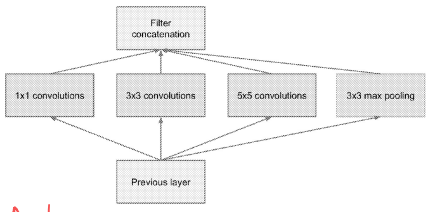
Using pretrained VGG16 in Keras:

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing import image

# Load pre-trained VGG16 model with imagenet weights
model = keras.applications.VGG16(weights='imagenet')

# Load an example image of a dog and preprocess it for input to the model
img_path = 'dog.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = keras.applications.vgg16.preprocess_input(x)

# Use the model to predict the top 5 most likely classes for the image
preds = model.predict(x)
decoded_preds = keras.applications.vgg16.decode_predictions(preds, top=5)[0]
for pred in decoded_preds:
    print(pred[1], ':', pred[2])
```

Means to normalize (values between 0 and 255)

Inception PGG

- GoogleNet / Inception (2014)
- 22 layers with fewer parameters (5M)
- In the inception block, multiple receptive fields cause dimensionality increase



(a) Inception module, naïve version

Multiple receptive field in parallel, now we don't have a pyramid as before

Each level had lower resolution

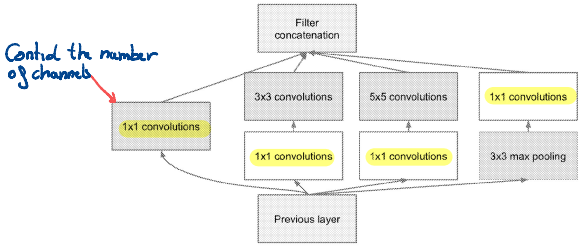
Idea: Multiple receptive field at the same level of the image pyramid

Each receptive field is going to give a result and then we concatenate each result

Check that all dimensions match from all the channels

Inception

- A modified inception block that reduces the number of channels using 1x1 convolutions



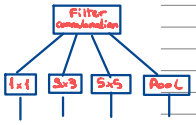
Control the number of channels

(b) Inception module with dimensionality reduction

Inception

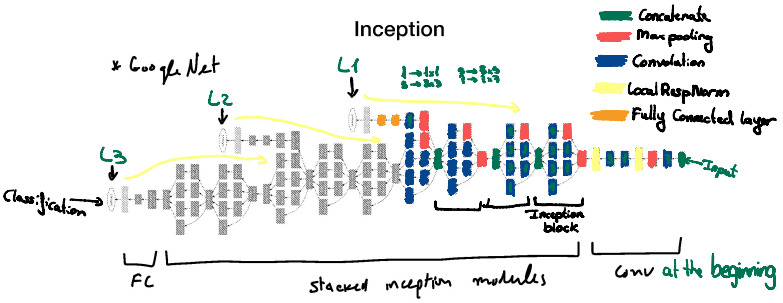
```python
from keras.layers import Conv2D, MaxPooling2D, concatenate

def inception_block(x, filters):
    # First branch with 1x1 convolution
    branch1x1 = Conv2D(filters[0], (1,1), padding='same', activation='relu')(x)

    # Second branch with 1x1 and 3x3 convolution
    branch3x3 = Conv2D(filters[1], (1,1), padding='same', activation='relu')(x)
    branch3x3 = Conv2D(filters[2], (3,3), padding='same', activation='relu')
(branch3x3)

    # Third branch with 1x1 and 5x5 convolution
    branch5x5 = Conv2D(filters[3], (1,1), padding='same', activation='relu')(x)
    branch5x5 = Conv2D(filters[4], (5,5), padding='same', activation='relu')
(branch5x5)

    # Fourth branch with max pooling and 1x1 convolution
    branch_pool = MaxPooling2D((3,3), strides=(1,1), padding='same')(x)
    branch_pool = Conv2D(filters[5], (1,1), padding='same', activation='relu')
(branch_pool)

    # Concatenate the outputs of the four branches
    output = concatenate([branch1x1, branch3x3, branch5x5, branch_pool], axis=3)

    return output
```

Branch → Path



Forward: From input to output ←
Backward: Reverse →

Inception



- A single FC layer leads to fewer parameters
- Convergence may be difficult. Use auxiliary classifiers to help with vanishing ~~ingredients~~ gradients (not needed with batch normalization)

Train is harder because the gradients are vanish, when we train the networks we push the input forward and then we push the gradients backward. We use the gradients to change the parameters for the next iteration of the training

Normally, at the beginning, the gradients are huge but when we push them, they are becoming smaller and they don't change the parameters. For fixing this, Inception use multiple loss (L1, L2, L3...) → Not training (remember train is change their parameter to get better results)

There are multiple versions of Inception:
- Inception V1: 22 layers and multiple filters sizes
- Inception V2: Improve efficiency. Uses factorization (replace 5x5 filters by two 3x3 filters)
- Inception V3: Use batch normalization and factorized 7x7 convolutions
- Inception V4: Use a new block "Inception-ResNet" which incorporate residual connections

Inception

* Example of using pre-trained inception network:

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.inception_v1 import InceptionV1
from tensorflow.keras.applications.inception_v1 import preprocess_input,
decode_predictions
import numpy as np

# Load the pre-trained InceptionV1 model
model = InceptionV1(weights='imagenet')

# Load an example image of a dog
img_path = 'path/to/dog/image.jpg'
img = image.load_img(img_path, target_size=(224, 224))

# Convert the image to a numpy array and preprocess it
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

# Use the pre-trained model to predict the class of the image
preds = model.predict(x)

# Decode the predictions and print the top 3 results
decoded_preds = decode_predictions(preds, top=3)[0]
for pred in decoded_preds:
    print(pred[1], pred[2])
```

Probability

ResNet

- ResNet (2015):
- 152 layers (Microsoft). Optimization is more difficult with more layers (more DOF)

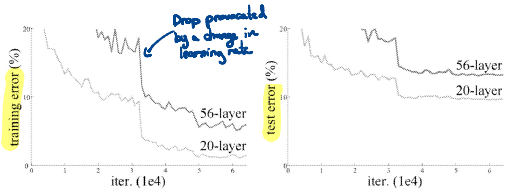


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

We use deeper networks because they are complex and have more ability to learn complex things but they are more difficult to train.

ResNet

- Residual blocks:
- It is easier to learn the $H(X)$ residual compared with $F(X)$ because it is easier to learn deviation from identity instead of a function
- Skip connections help with vanishing ingredients

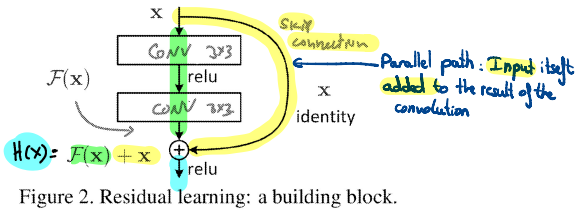


Figure 2. Residual learning: a building block.

① The information (input) go through the network, we train based on the residual (whatever it change) It easier to learn based on the residual and the input does not destroy

② Skip connection (path) skips the convolution blocks, when we push gradients back from the network, they won't vanish

ResNet

- Residual block properties:
  - Zero weights in the block produce identity instead of destroying the signal. The network can learn to zero blocks to eliminate unneeded layers
  - In a normal network zero weights shut down information whereas here zero weights cause the information to pass through units without change
  - Passing gradients directly through skip connections leads to quicker training

(everything will pass through alternative path) (parallel path)

ResNet

```
from tensorflow.keras.layers import Conv2D, BatchNormalization, Add, Activation

def resnet_block(inputs, num_filters, kernel_size, strides):
    x = Conv2D(num_filters, kernel_size=kernel_size, strides=strides,
padding='same')(inputs)
    x = BatchNormalization()(x)
    x = Activation('relu')(x)

    x = Conv2D(num_filters, kernel_size=kernel_size, strides=1, padding='same')
(x)
    x = BatchNormalization()(x)

    # Add the input to the output of the second convolution layer
    res = Add()([x, inputs])
    out = Activation('relu')(res)

    return out
```

Convolution block

Layers

Alternative path

Activation function

ResNet

- Complete ResNet architecture:
  - Start with regular convolution layers
  - Stack residual blocks
  - Periodically double channels and pool spatially
  - Single FC layer with softmax for output
  - Batch normalization after every convolution a layer
  - No dropout

Used to avoid overfitting

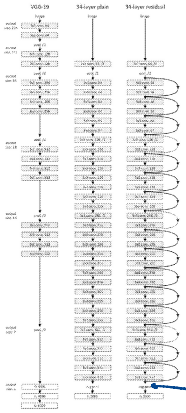
ResNet

Computation (less is better)

VGG 19: 19.6 B FLOPs

Plain 34: 3.6 B FLOPs

ResNet 34: 3.6 B FLOPs



Global Average Pooling 2D

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.

ResNet

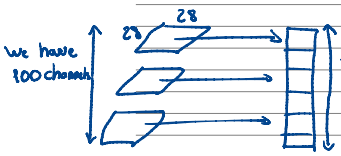
```
def resnet(input_shape, num_classes, num_filters, kernel_size, strides,
num_blocks):
    # Input layer
    inputs = Input(shape=input_shape)

    # Convolutional layer with batch normalization and ReLU activation
    x = Conv2D(num_filters, kernel_size=kernel_size, strides=strides,
padding='same')(inputs)
    x = BatchNormalization()(x)
    x = Activation('relu')(x)

    # Residual blocks
    for i in range(num_blocks):
        x = resnet_block(x, num_filters, kernel_size, strides)

    # Global average pooling layer
    x = GlobalAveragePooling2D()(x)

    # Fully connected output layer
    x = Dense(num_classes, activation='softmax')(x)

    # Create model
    model = Model(inputs=inputs, outputs=x, name='ResNet')

    return model
```

Each element of x (list) is Convolution layer result + input

Input

Convolution layers parameters

Intent to reduce the complexity



This reduce the number of parameters instead of flatten

We have a similar error training/test to less layer models and we have more complex model

ResNet

x Variations: The unique variation is on convolution layers

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
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

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Downsampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

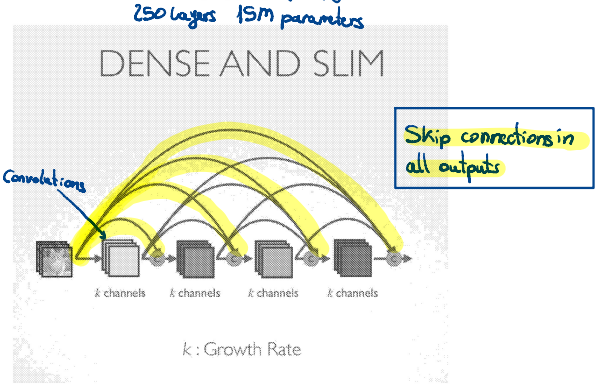
ResNet

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.applications.resnet50 import ResNet50, preprocess_input,
decode_predictions
import numpy as np

# load the pre-trained ResNet50 model
model = ResNet50(weights='imagenet')

# load the image to classify
img = load_img('cat.jpg', target_size=(224, 224))

# convert the image to a numpy array
img_array = img_to_array(img)

# expand the dimensions of the image to match the input shape of the model
img_array = np.expand_dims(img_array, axis=0)

# preprocess the input image
img_array = preprocess_input(img_array)

# make a prediction on the image
prediction = model.predict(img_array)

# decode the predictions
labels = decode_predictions(prediction, top=3)[0]

# print the labels
for label in labels:
    print(label[1], label[2])
```

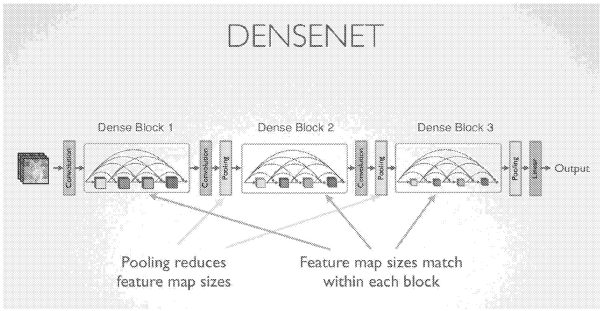
Resnet 18/34/50/101/191/200

Number of layers

DenseNet (2017)
250 layers 15M parameters



DenseNet



DenseNet

* DenseNet implementation:

The main features of the DenseNet architecture include:

1. Dense Connections: Each layer in the network is connected to all the preceding layers, allowing for feature reuse and reducing the number of parameters.
2. Bottleneck Layers: The architecture uses bottleneck layers to reduce the number of feature maps before each dense block, further reducing the number of parameters.
3. Transition Layers: Between each dense block, there is a transition layer that reduces the number of feature maps and spatial dimensions.
4. Global Average Pooling: Instead of using a fully connected layer at the end of the network, DenseNet uses global average pooling to reduce the number of parameters and improve regularization.

DenseNet

```
from keras.layers import Input, Conv2D, MaxPooling2D, Dense,
GlobalAveragePooling2D, BatchNormalization, Dropout, concatenate
from keras.models import Model

def dense_block(x, blocks, growth_rate):
    for i in range(blocks):
        conv = Conv2D(growth_rate, (3,3), padding='same', activation='relu')(x)
        x = concatenate([x, conv])
    return x

def transition_layer(x, compression):
    num_filters = int(x.shape.as_list()[-1] * compression)
    x = Conv2D(num_filters, (1,1), padding='same', activation='relu')(x)
    x = MaxPooling2D((2,2))(x)
    return x
```

DenseNet

```
def DenseNet(input_shape, depth, num_classes, growth_rate=12, blocks_per_layer=4,
compression=0.5):
    # Input layer
    inputs = Input(shape=input_shape)

    # Initial convolution layer
    x = Conv2D(2*growth_rate, (3,3), padding='same', activation='relu')(inputs)

    # Dense blocks and transition layers
    layers = []
    for i in range(depth):
        x = dense_block(x, blocks_per_layer, growth_rate)
        layers.append(x)
        if i < depth-1:
            x = transition_layer(x, compression)

    # Global average pooling and output layer
    x = BatchNormalization()(x)
    x = GlobalAveragePooling2D()(x)
    x = Dense(num_classes, activation='softmax')(x)

    # Build model
    model = Model(inputs, x, name='DenseNet')

    return model
```

DenseNet

To create a DenseNet with 121 layers, 32 blocks per layer, and a growth rate of 32, we can call the `DenseNet` function as follows:

```
model = DenseNet(input_shape=(224, 224, 3), depth=121, num_classes=1000,
growth_rate=32, blocks_per_layer=32, compression=0.5)
```

DenseNet

```
import tensorflow as tf
from tensorflow.keras.applications.densenet import DenseNet121, preprocess_input
from tensorflow.keras.preprocessing.image import load_img, img_to_array
import numpy as np

# Load the pre-trained model
model = DenseNet121(weights='imagenet')

# Load and preprocess the image
image_path = 'cat.jpg'
image = load_img(image_path, target_size=(224, 224))
image_array = img_to_array(image)
image_array = preprocess_input(image_array)

# Make predictions on the image
predictions = model.predict(np.array([image_array]))
predicted_classes =
tf.keras.applications.densenet.decode_predictions(predictions, top=1)[0]
class_name = predicted_classes[0][1]
class_prob = predicted_classes[0][2]

# Print the predicted class and probability
print(f"Predicted class: {class_name}")
print(f"Probability: {class_prob}")
```

Advantages:

1. Strong gradient flow
2. Parameter and computational layer
3. Maintains low complexity features

Resnet growth rate: CxC

Densenet growth rate: kxkxk