



# Visualizing what convnets learn

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**Description:** Displaying the visual patterns that convnet filters respond to.

 This example uses Keras 3

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## Introduction

In this example, we look into what sort of visual patterns image classification models learn. We'll be using the [ResNet50V2](#) model, trained on the ImageNet dataset.

Our process is simple: we will create input images that maximize the activation of specific filters in a target layer (picked somewhere in the middle of the model: layer [conv3\\_block4\\_out](#)). Such images represent a visualization of the pattern that the filter responds to.

## Setup

```
import os

os.environ["KERAS_BACKEND"] = "tensorflow"

import keras
import numpy as np
import tensorflow as tf

# The dimensions of our input image
img_width = 180
img_height = 180
# Our target layer: we will visualize the filters from this layer.
# See `model.summary()` for list of layer names, if you want to change this.
layer_name = "conv3_block4_out"
```

## Build a feature extraction model

```
# Build a ResNet50V2 model loaded with pre-trained ImageNet weights
model = keras.applications.ResNet50V2(weights="imagenet", include_top=False)

# Set up a model that returns the activation values for our target layer
layer = model.get_layer(name=layer_name)
feature_extractor = keras.Model(inputs=model.inputs, outputs=layer.output)
```



layer. To avoid border effects, we exclude border pixels.

```
def compute_loss(input_image, filter_index):  
    activation = feature_extractor(input_image)  
    # We avoid border artifacts by only involving non-border pixels in the  
    loss.  
    filter_activation = activation[:, 2:-2, 2:-2, filter_index]  
    return tf.reduce_mean(filter_activation)
```

Our gradient ascent function simply computes the gradients of the loss above with regard to the input image, and update the update image so as to move it towards a state that will activate the target filter more strongly.

```
@tf.function  
def gradient_ascent_step(img, filter_index, learning_rate):  
    with tf.GradientTape() as tape:  
        tape.watch(img)  
        loss = compute_loss(img, filter_index)  
    # Compute gradients.  
    grads = tape.gradient(loss, img)  
    # Normalize gradients.  
    grads = tf.math.l2_normalize(grads)  
    img += learning_rate * grads  
    return loss, img
```

---

## Set up the end-to-end filter visualization loop

Our process is as follow:

- Start from a random image that is close to "all gray" (i.e. visually netural)
- Repeatedly apply the gradient ascent step function defined above
- Convert the resulting input image back to a displayable form, by normalizing it, center-cropping it, and restricting it to the [0, 255] range.



```
img = tf.random.uniform((1, img_width, img_height, 3))
# ResNet50V2 expects inputs in the range [-1, +1].
# Here we scale our random inputs to [-0.125, +0.125]
return (img - 0.5) * 0.25

def visualize_filter(filter_index):
    # We run gradient ascent for 20 steps
    iterations = 30
    learning_rate = 10.0
    img = initialize_image()
    for iteration in range(iterations):
        loss, img = gradient_ascent_step(img, filter_index, learning_rate)

    # Decode the resulting input image
    img = deprocess_image(img[0].numpy())
    return loss, img

def deprocess_image(img):
    # Normalize array: center on 0., ensure variance is 0.15
    img -= img.mean()
    img /= img.std() + 1e-5
    img *= 0.15

    # Center crop
    img = img[25:-25, 25:-25, :]

    # Clip to [0, 1]
    img += 0.5
    img = np.clip(img, 0, 1)

    # Convert to RGB array
    img *= 255
    img = np.clip(img, 0, 255).astype("uint8")
    return img
```

Let's try it out with filter 0 in the target layer:

```
from IPython.display import Image, display

loss, img = visualize_filter(0)
keras.utils.save_img("0.png", img)
```

This is what an input that maximizes the response of filter 0 in the target layer would look like:

```
display(Image("0.png"))
```



## Visualize the first 64 filters in the target layer

Now, let's make a 8x8 grid of the first 64 filters in the target layer to get of feel for the range of different visual patterns that the model has learned.



```
all_imgs = []
for filter_index in range(64):
    print("Processing filter %d" % (filter_index,))
    loss, img = visualize_filter(filter_index)
    all_imgs.append(img)

# Build a black picture with enough space for
# our 8 x 8 filters of size 128 x 128, with a 5px margin in between
margin = 5
n = 8
cropped_width = img_width - 25 * 2
cropped_height = img_height - 25 * 2
width = n * cropped_width + (n - 1) * margin
height = n * cropped_height + (n - 1) * margin
stitched_filters = np.zeros((width, height, 3))

# Fill the picture with our saved filters
for i in range(n):
    for j in range(n):
        img = all_imgs[i * n + j]
        stitched_filters[
            (cropped_width + margin) * i : (cropped_width + margin) * i +
cropped_width,
            (cropped_height + margin) * j : (cropped_height + margin) * j
            + cropped_height,
            :,
        ] = img
keras.utils.save_img("stiched_filters.png", stitched_filters)

from IPython.display import Image, display

display(Image("stiched_filters.png"))
```



Processing filter 2  
Processing filter 3  
Processing filter 4  
Processing filter 5  
Processing filter 6  
Processing filter 7  
Processing filter 8  
Processing filter 9  
Processing filter 10  
Processing filter 11  
Processing filter 12  
Processing filter 13  
Processing filter 14  
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Processing filter 63

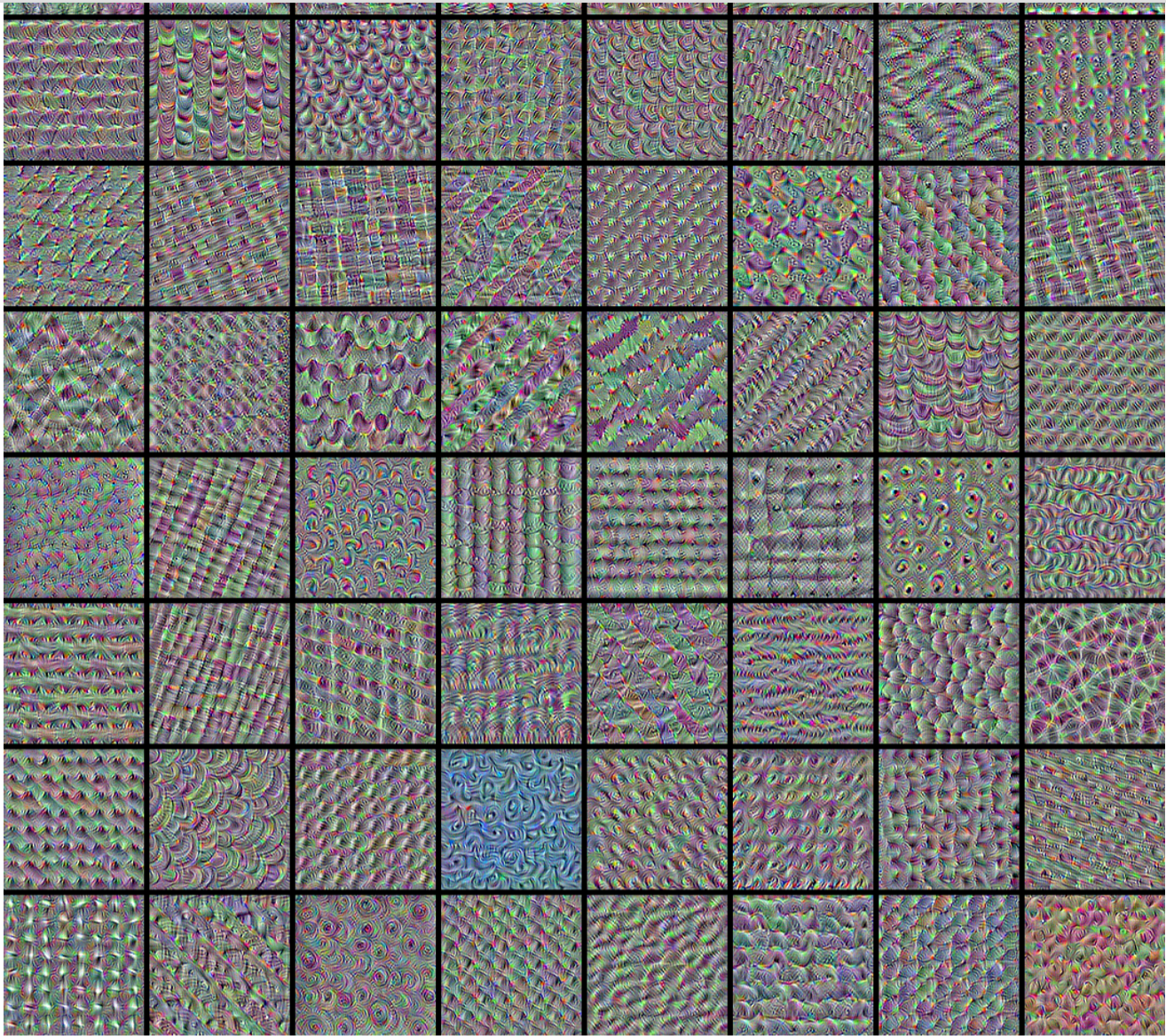


Image classification models see the world by decomposing their inputs over a "vector basis" of texture filters such as these.

See also [this old blog post](#) for analysis and interpretation.