R/Keras Examples for FFNs & CNNs

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Based on “Deep Learning wth R”

https://www.manning.com/books/deep-learning-with-r

(including source code)

```
install.packages("keras")

#Install the core Keras library and TensorFlow:

library(keras)

#CPU-based:
install_keras()

#GPU-based:

install_keras(tensorflow = "gpu")


#Remark: I failed first time when I tried to install on my old laptop with an older
version of R; after I updated the R to the current version, it worked!
```

Alternative installation: R Interface to TF (and Keras)

Step 1. Install TF: Go to

https://tensorflow.rstudio.com/

click on Installation:

https://tensorflow.rstudio.com/installation/

Installation

First, install the tensorflow R package from GitHub as follows:

```
install.packages("tensorflow")
```

Then, use the install_tensorflow() function to install TensorFlow. Note that on Windows you need a working installation of Anaconda.

```
library(tensorflow)
install_tensorflow()
```

You can confirm that the installation succeeded with:

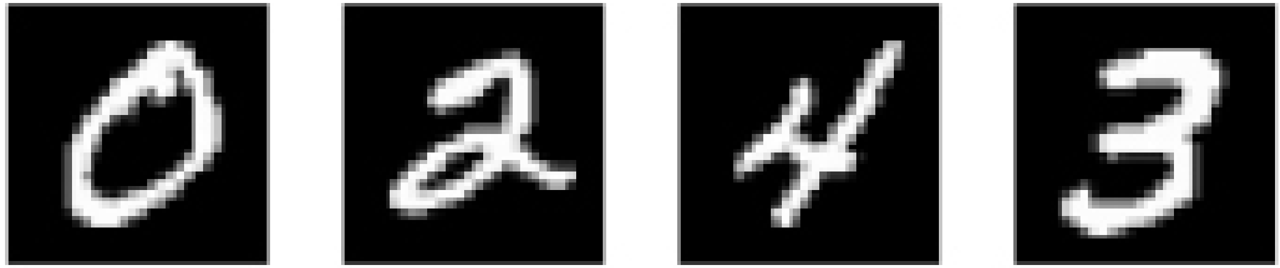
```
library(tensorflow)
tf$constant("Hellow Tensorflow")
## tf.Tensor(b'Hellow Tensorflow', shape=(), dtype=string)
```

This will provide you with a default installation of TensorFlow suitable for use with the tensorflow R package.

Step 2. Install Keras: in R,

```
> install.packages("keras")
```

MNIST dataset

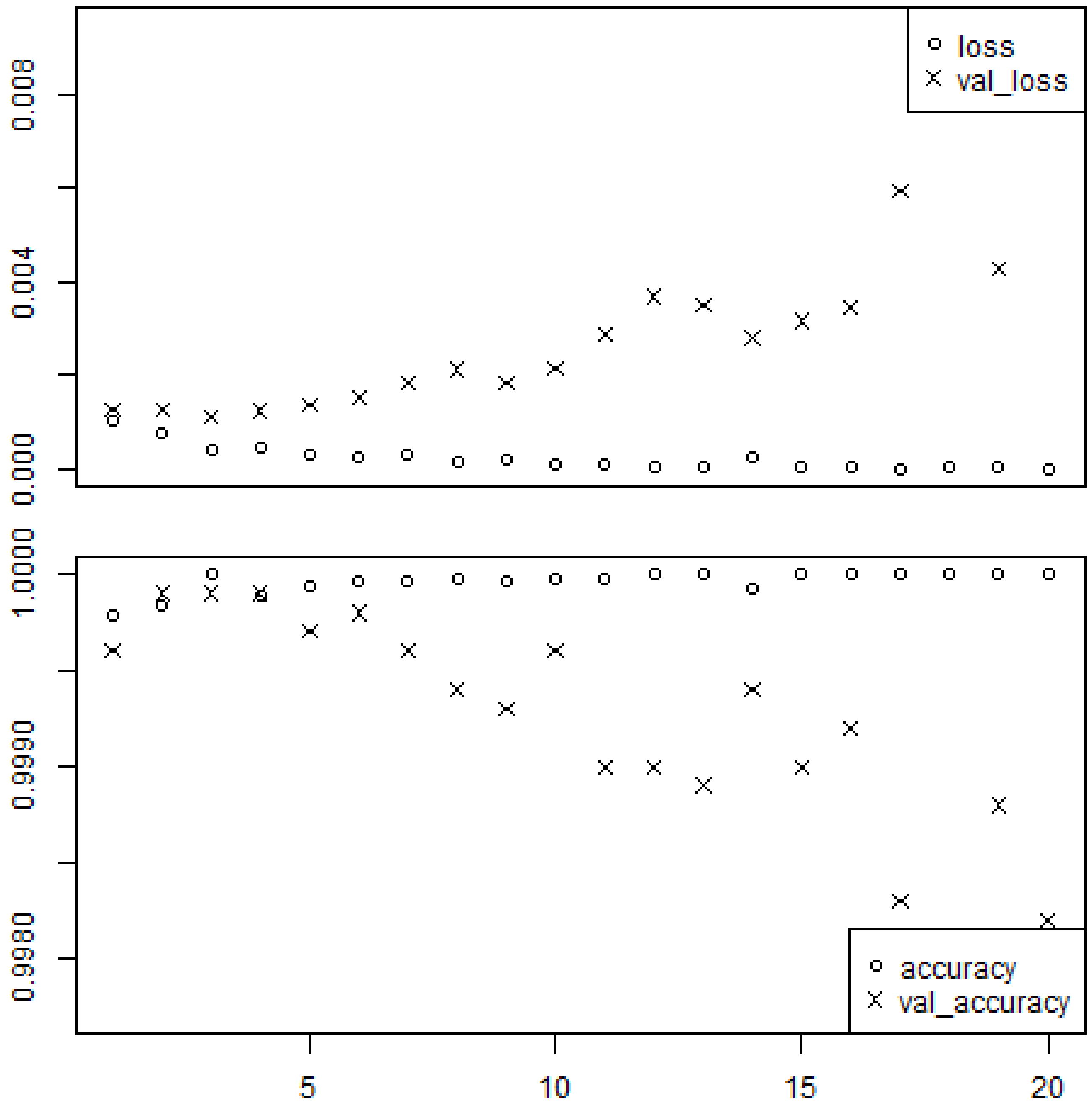


```
#Loading the MNIST dataset in Keras:
library(keras)
mnist <- dataset_mnist()
train_images <- mnist$train$x
train_labels <- mnist$train$y
test_images <- mnist$test$x
test_labels <- mnist$test$y

str(train_images)
 # int [1:60000, 1:28, 1:28] 0 0 0 0 0 0 0 0 0 0 ...
str(test_labels)
 #  int [1:10000(1d)] 7 2 1 0 4 1 4 9 5 9 ...

train_images <- array_reshape(train_images, c(60000, 28 * 28))
train_images <- train_images / 255
test_images <- array_reshape(test_images, c(10000, 28 * 28))
test_images <- test_images / 255

train_labels <- to_categorical(train_labels)
test_labels <- to_categorical(test_labels)
```

```
network <- keras_model_sequential() %>%
  layer_dense(units = 512, activation = "relu", input_shape = c(28 * 28)) %>%
  layer_dense(units = 10, activation = "softmax")

network %>% compile(
  optimizer = "rmsprop",
  loss = "categorical_crossentropy",
  metrics = c("accuracy")
)

network %>% fit(train_images, train_labels, epochs = 5, batch_size = 128)
#Epoch 1/5    469/469 [==============================] - 2s 4ms/step - loss: 0.2575 - accuracy: 0.9254
#Epoch 2/5    469/469 [==============================] - 2s 3ms/step - loss: 0.1031 - accuracy: 0.9695
#Epoch 3/5    469/469 [==============================] - 2s 3ms/step - loss: 0.0688 - accuracy: 0.9792
#Epoch 4/5    469/469 [==============================] - 2s 3ms/step - loss: 0.0489 - accuracy: 0.9857
#Epoch 5/5    469/469 [==============================] - 2s 3ms/step - loss: 0.0380 - accuracy: 0.9887

metrics <- network %>% evaluate(test_images, test_labels, verbose = 0)
metrics
#  loss   accuracy
# 0.06546536 0.98079997
```

```
> network
Model
Model: "sequential_2"
________________________________________________________________________________
______________________________________________________________________
Layer (type)                        Output Shape                      Param #
================================================================================
======================================================================
dense_5 (Dense)                        (None, 512)                     401920
________________________________________________________________________________
______________________________________________________________________
dense_4 (Dense)                        (None, 10)                     5130
================================================================================
======================================================================
Total params: 407,050
Trainable params: 407,050
Non-trainable params: 0
________________________________________________
```

```
#Setting aside a validation set:
val_indices <- 1:10000
x_val <- train_images[val_indices,]
partial_x_train <- train_images[-val_indices,]
y_val <- train_labels[val_indices,]
partial_y_train <- train_labels[-val_indices,]

history <- network %>% fit(
  partial_x_train,
  partial_y_train,
  epochs = 20,
  batch_size = 512,
  validation_data = list(x_val, y_val)
)

plot(history)
```

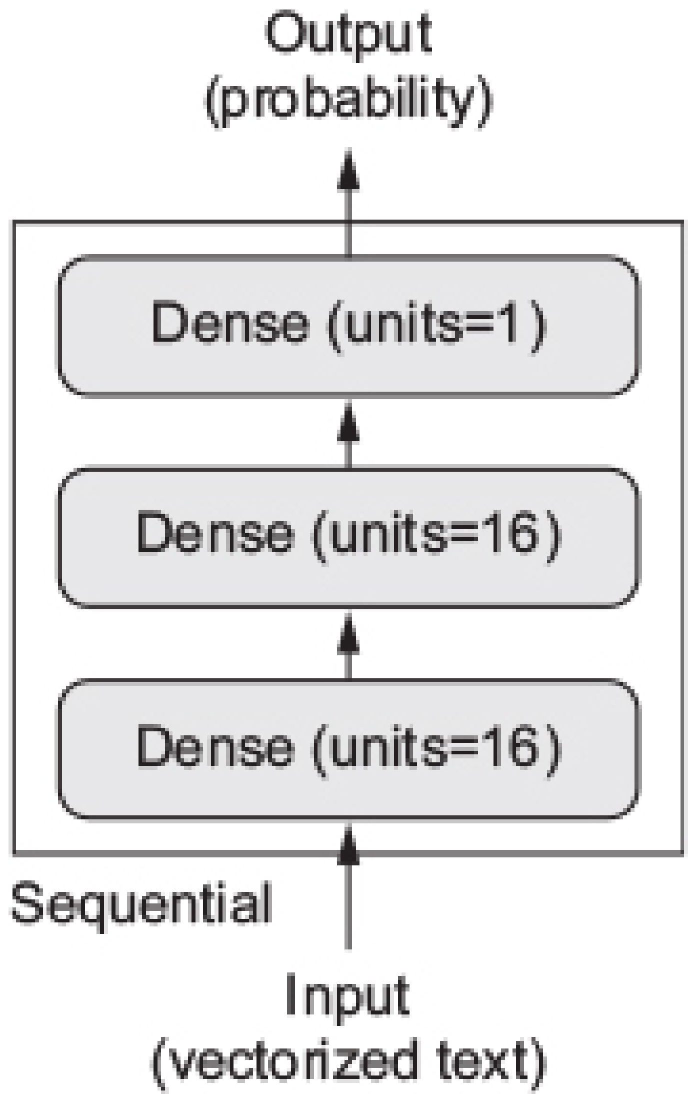


loss
val_loss
0.000
0.004
0.008
1.0000
0.9990
0.9980
accuracy
val_accuracy
5
10
15
20

```
> str(history)
List of 2
 $ params :List of 3
  ..$ verbose: int 1
  ..$ epochs : int 20
  ..$ steps  : int 98
 $ metrics:List of 4
  ..$ loss        : num [1:20] 0.00104 0.000786 0.000423 0.000472 0.000307 ...
  ..$ accuracy    : num [1:20] 1 1 1 1 1 ...
  ..$ val_loss    : num [1:20] 0.00126 0.00127 0.00111 0.00124 0.00136 ...
  ..$ val_accuracy: num [1:20] 1 1 1 1 1 ...
 - attr(*, "class")= chr "keras_training_history"
```

```r
network <- keras_model_sequential() %>%
  layer_dense(units = 32, activation = "relu", input_shape = c(28 * 28)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 10, activation = "softmax")

network %>% compile(
  optimizer = "rmsprop",
  loss = "categorical_crossentropy",
  metrics = c("accuracy")
)

network %>% fit(train_images, train_labels, epochs = 5, batch_size = 128)

metrics <- network %>% evaluate(test_images, test_labels, verbose = 0)
metrics
# loss  accuracy
#0.1524482 0.9538000
```

```
> network
Model
Model: "sequential_3"
________________________________________________________________________________
__________________________________________________
Layer (type)                        Output Shape                        Param #
================================================================================
==================================================
dense_8 (Dense)                        (None, 32)                        25120
________________________________________________________________________________
__________________________________________________
dense_7 (Dense)                        (None, 16)                        528
________________________________________________________________________________
__________________________________________________
dense_6 (Dense)                        (None, 10)                        170
================================================================================
==================================================
Total params: 25,818
Trainable params: 25,818
Non-trainable params: 0
```


Output
(probability)
Dense (units=1)
Dense (units=16)
Dense (units=16)
Sequential
Input
(vectorized text)

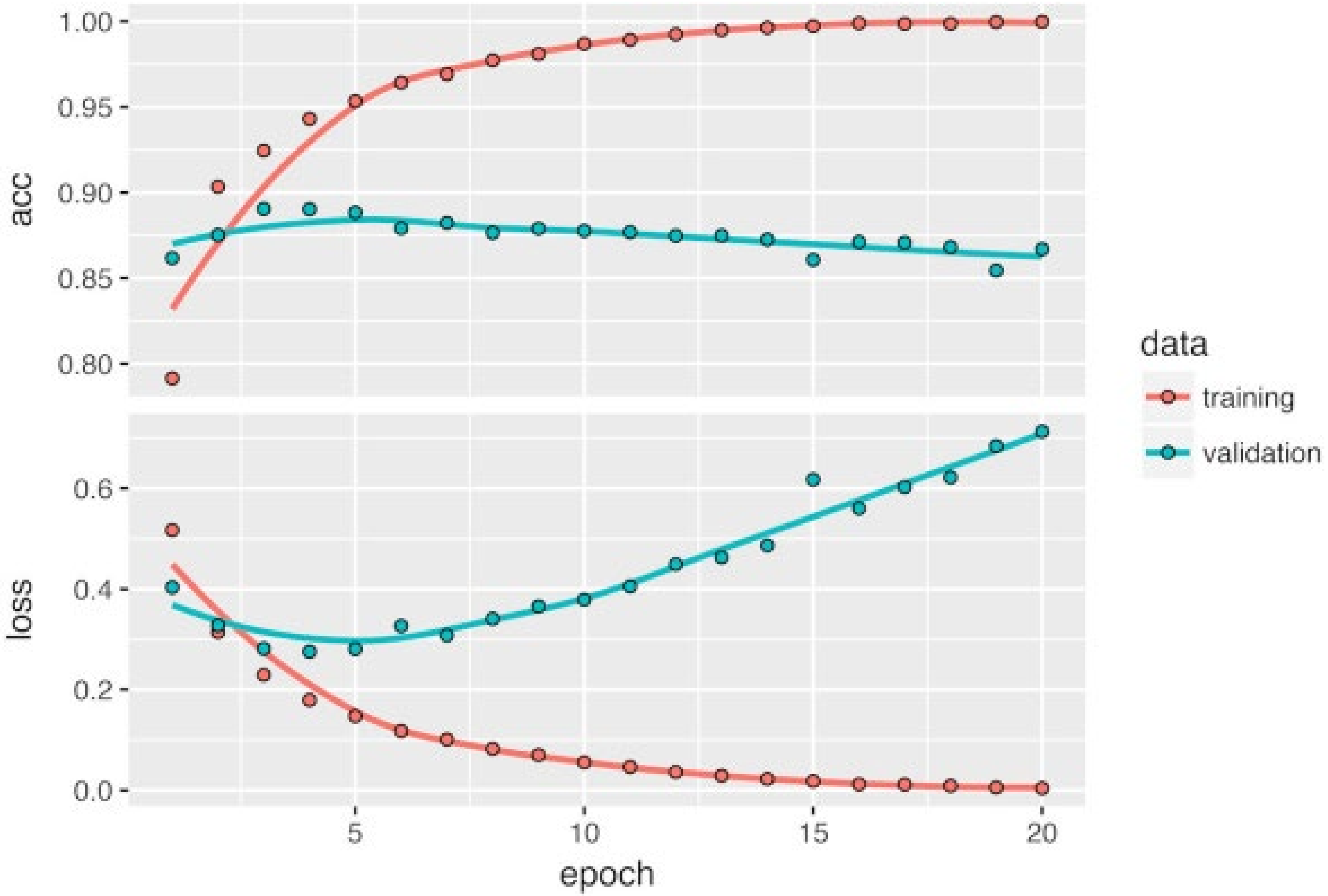
```
library(keras)

model <- keras_model_sequential() %>%
  layer_dense(units = 16, activation = "relu", input_shape = c(10000)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")

model %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

model %>% compile(
  optimizer = optimizer_rmsprop(lr=0.001),
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)
```

```
#Loading the IMDB dataset:
library(keras)

imdb <- dataset_imdb(num_words = 10000)
c(c(train_data, train_labels), c(test_data, test_labels)) %<-% imdb
##the above is equivalent to:
imdb <- dataset_imdb(num_words = 10000)
train_data <- imdb$train$x
train_labels <- imdb$train$y
test_data <- imdb$test$x
test_labels <- imdb$test$y

# …….

#Setting aside a validation set:
val_indices <- 1:10000
x_val <- x_train[val_indices,]
partial_x_train <- x_train[-val_indices,]
y_val <- y_train[val_indices]
partial_y_train <- y_train[-val_indices]
```

```
#training your model:

model %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

history <- model %>% fit(
  partial_x_train,
  partial_y_train,
  epochs = 20,
  batch_size = 512,
  validation_data = list(x_val, y_val)
)
```

```
> str(history)
List of 2
 $ params :List of 8
  ..$ metrics          : chr [1:4] "loss" "acc" "val_loss" "val_acc"
  ..$ epochs           : int 20
  ..$ steps            : NULL
  ..$ do_validation    : logi TRUE
  ..$ samples          : int 15000
  ..$ batch_size       : int 512
  ..$ verbose          : int 1
  ..$ validation_samples: int 10000
 $ metrics:List of 4
  ..$ acc     : num [1:20] 0.783 0.896 0.925 0.941 0.952 ...
  ..$ loss    : num [1:20] 0.532 0.331 0.24 0.186 0.153 ...
  ..$ val_acc : num [1:20] 0.832 0.882 0.886 0.888 0.888 ...
  ..$ val_loss: num [1:20] 0.432 0.323 0.292 0.278 0.278 ...
 - attr(*, "class")= chr "keras_training_history"
```

```
plot(history)
```



```
library(keras)

model <- keras_model_sequential() %>%
  layer_conv_2d(filters = 32, kernel_size = c(3, 3), activation = "relu",
                input_shape = c(28, 28, 1)) %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_conv_2d(filters = 64, kernel_size = c(3, 3), activation = "relu") %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_conv_2d(filters = 64, kernel_size = c(3, 3), activation = "relu") %>%

  layer_flatten() %>%
  layer_dense(units = 64, activation = "relu") %>%
  layer_dense(units = 10, activation = "softmax")
```

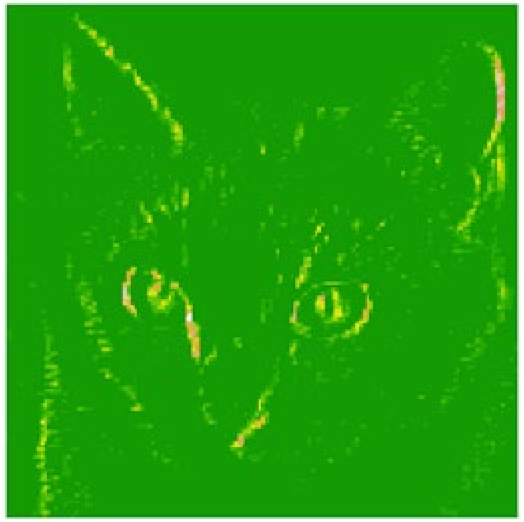
```
> model

Layer (type)                  Output Shape          Param #
================================================================
conv2d_1 (Conv2D)             (None, 26, 26, 32)    320
________________________________________________________________
maxpooling2d_1 (MaxPooling2D) (None, 13, 13, 32)    0
________________________________________________________________
conv2d_2 (Conv2D)             (None, 11, 11, 64)    18496
________________________________________________________________
maxpooling2d_2 (MaxPooling2D) (None, 5, 5, 64)      0
________________________________________________________________
conv2d_3 (Conv2D)             (None, 3, 3, 64)      36928
________________________________________________________________
flatten_1 (Flatten)           (None, 576)           0
________________________________________________________________
dense_1 (Dense)               (None, 64)            36928
________________________________________________________________
dense_2 (Dense)               (None, 10)            650
================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
```

```r
mnist <- dataset_mnist()
c(c(train_images, train_labels), c(test_images, test_labels)) %<-% mnist
train_images <- array_reshape(train_images, c(60000, 28, 28, 1))
train_images <- train_images / 255
test_images <- array_reshape(test_images, c(10000, 28, 28, 1))
test_images <- test_images / 255
train_labels <- to_categorical(train_labels)
test_labels <- to_categorical(test_labels)
model %>% compile(
  optimizer = "rmsprop",
  loss = "categorical_crossentropy",
  metrics = c("accuracy")
)
model %>% fit(
  train_images, train_labels,
  epochs = 5, batch_size=64
)

> results <- model %>% evaluate(test_images, test_labels)
> results
$loss
[1] 0.02563557
$acc
[1] 0.993
```

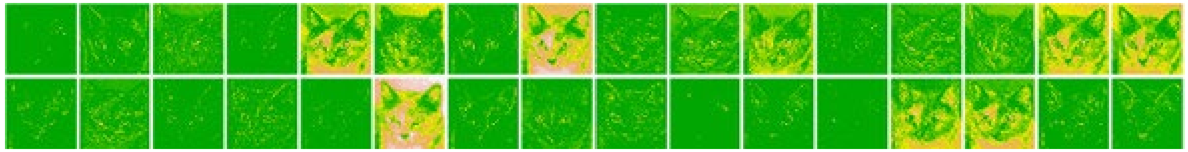
Visualizing what CNNs learn

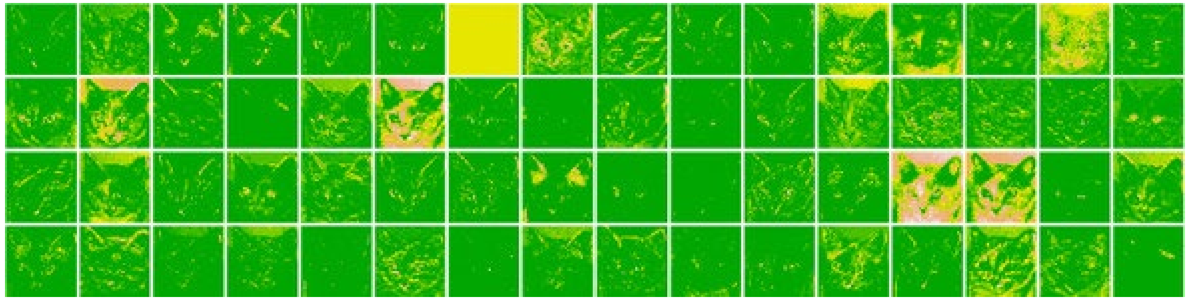
1. **Visualizing intermediate activations:**

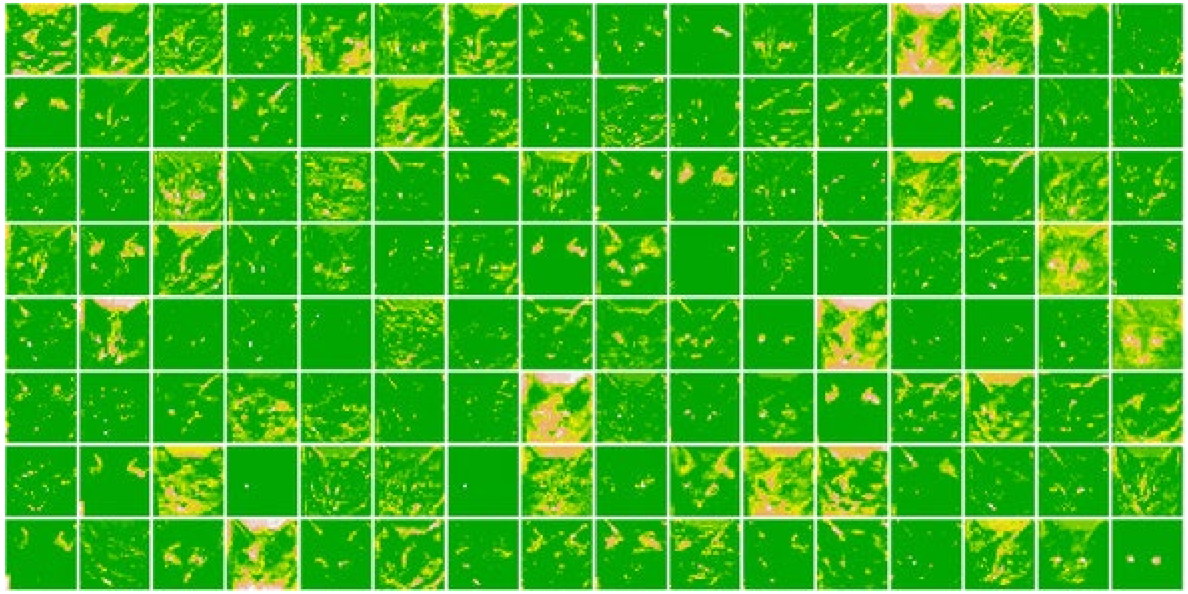
   Input image; 2nd and 7th feature maps in the first layer

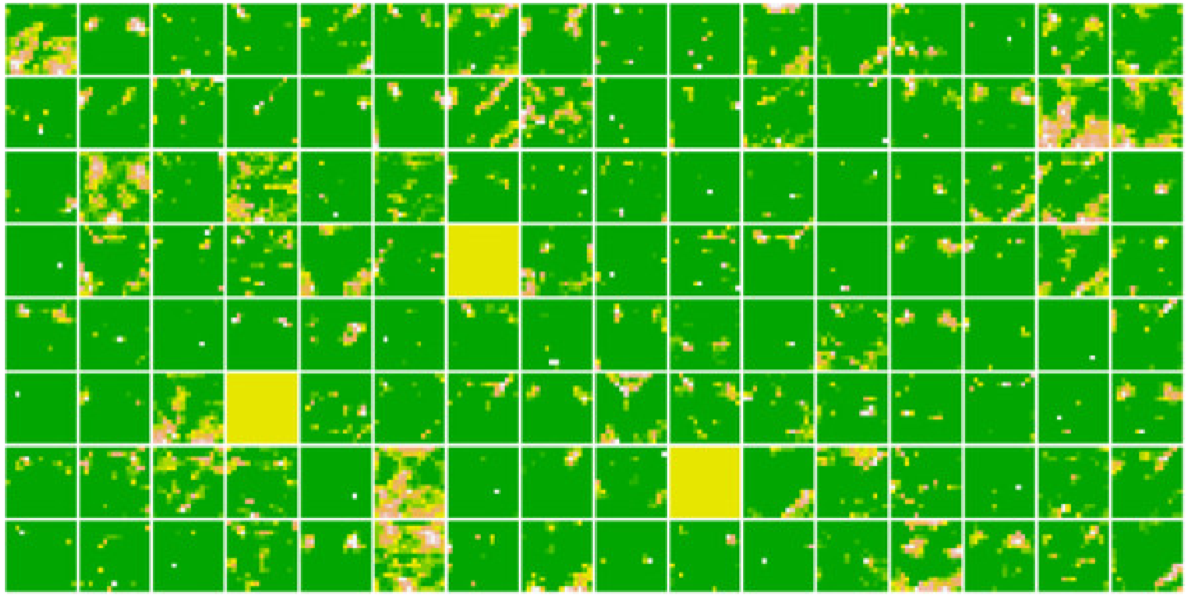


List out every feature map in every layer



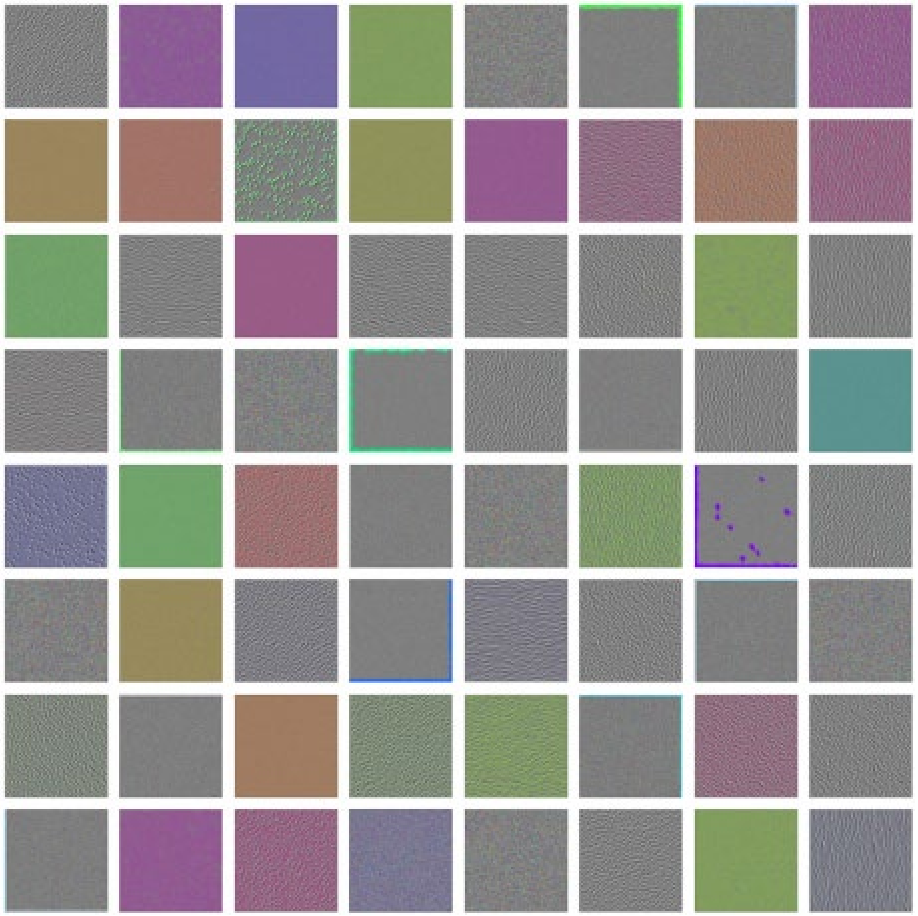


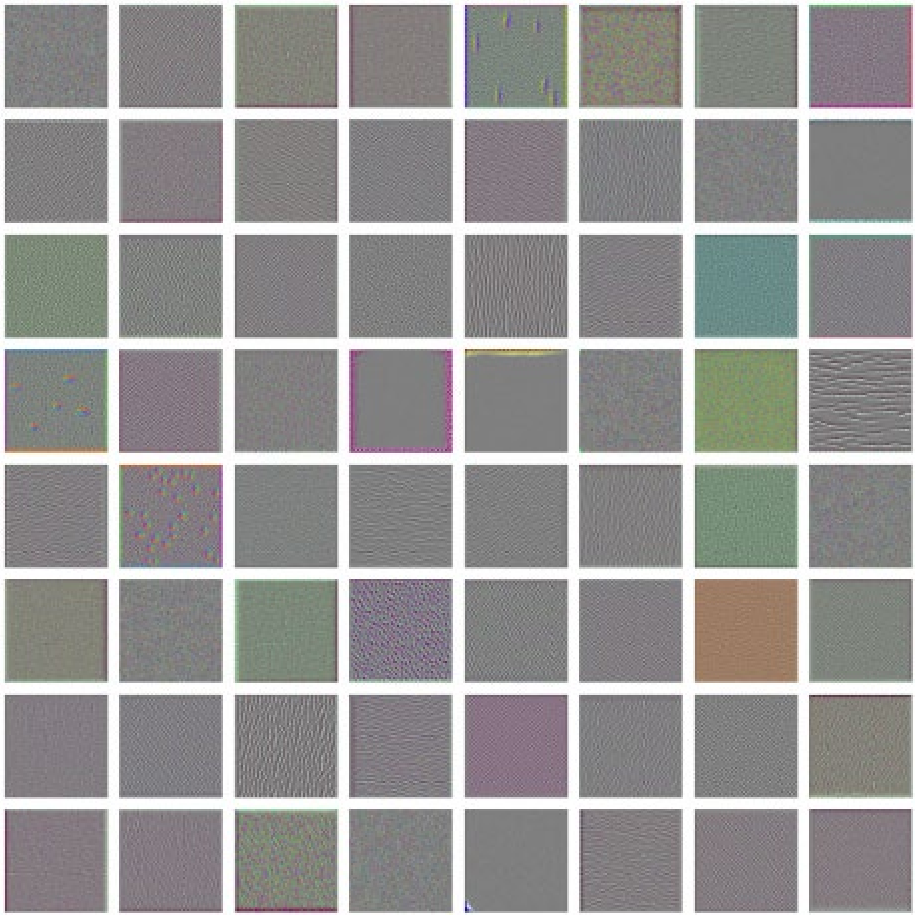


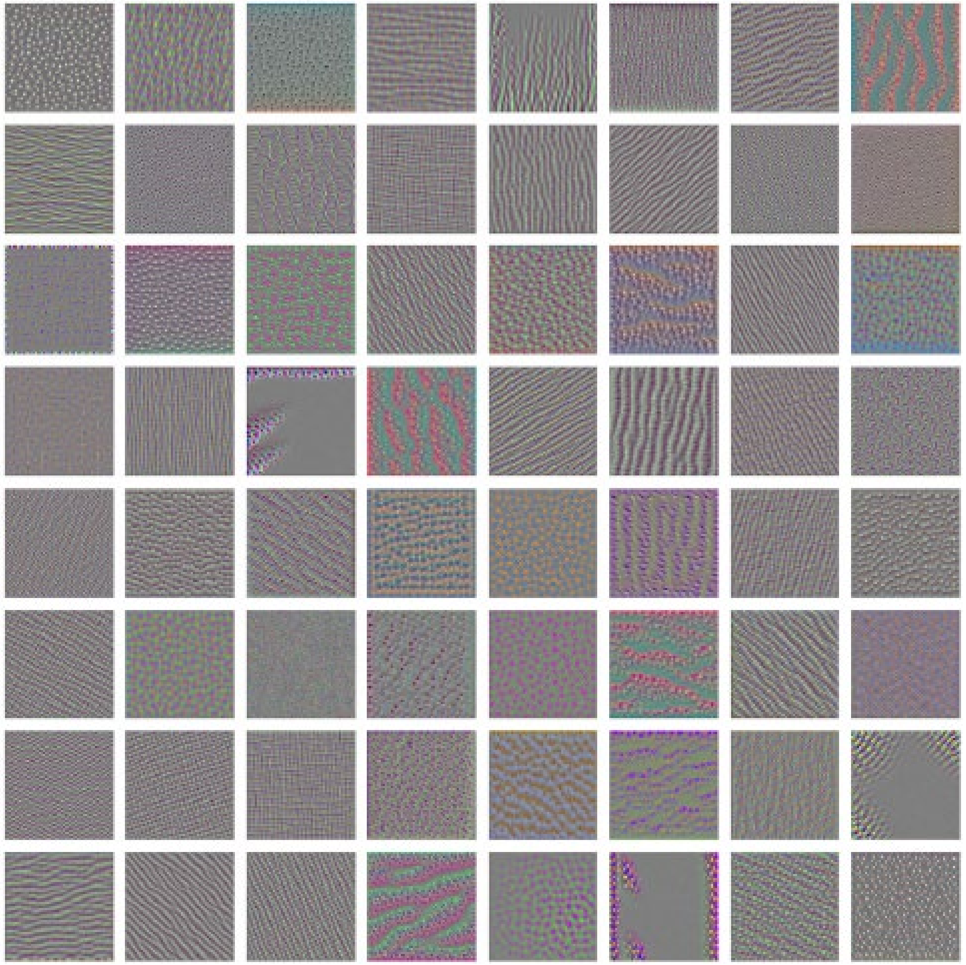
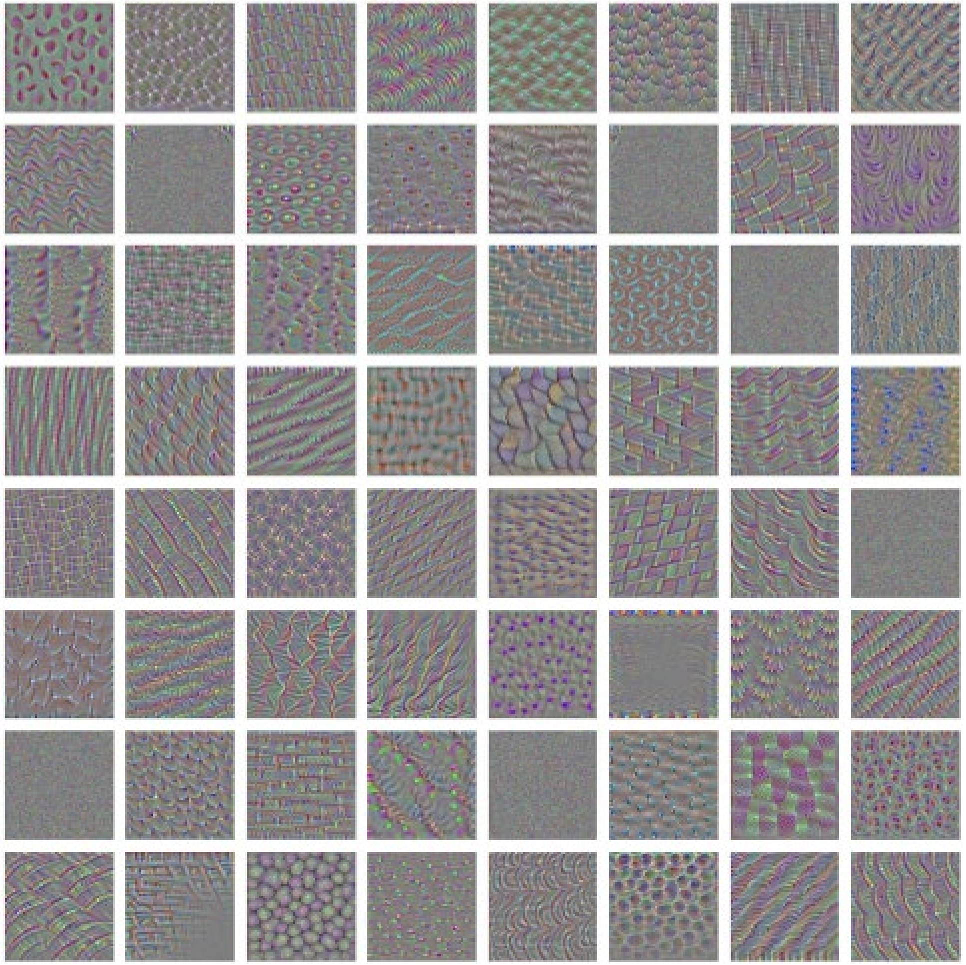


2. Visualizing CNN filters:

- Input maximizing the response of a filter: top to bottom layers in VGG for ImageNet





3. Visualizing class activation maps (CAM): Grad-CAM

Still an active research topic; see Dai et al (2022) using R2. More generally, explainable AI (XAI) (especially for black-box methods).