Master in Computer Vision Barcelona

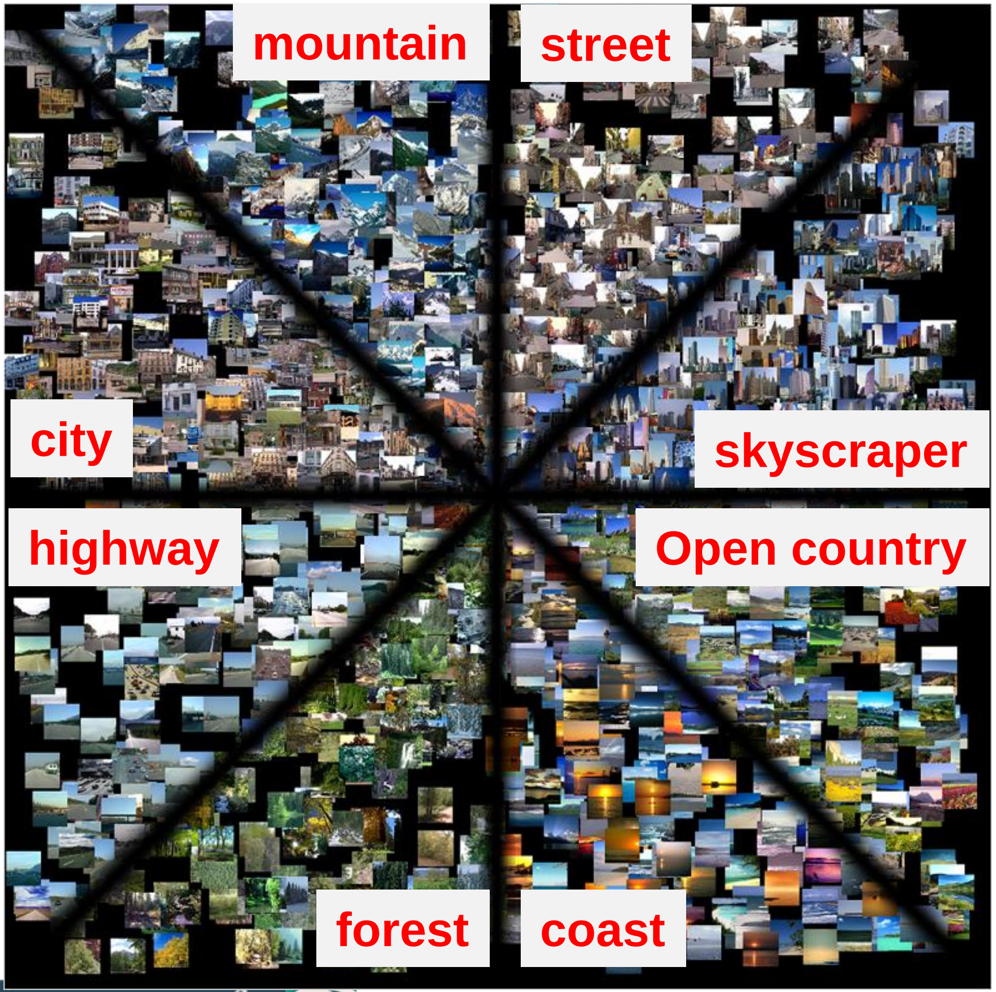
Module 3: Machine Learning for Computer Vision

Project: Deep learning classification

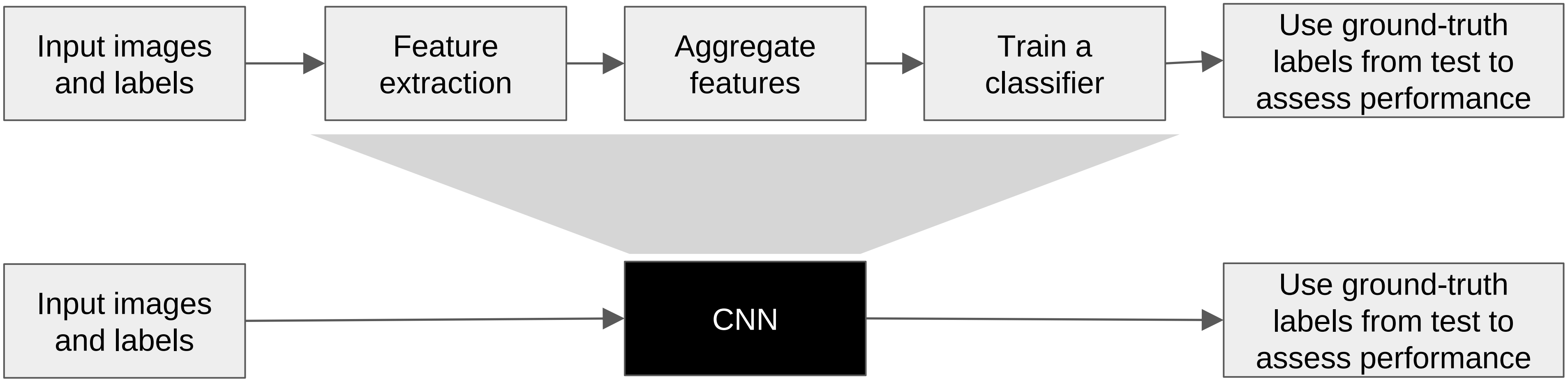
Lecturer: Ramon Baldrich

Module Goal

The aim of this module is to learn the techniques for category classification: handcrafted and learned.



Pipeline of the project W5 and W6



End to end task

Machine learning for image classification:

- Data driven methods: Deep Convolutional Networks: 3 sessions
  - From hand-crafted to learnt features
  - Fine tuning of pre-trained CNNs
  - Training a CNN from scratch

Keras: first example

```
# create model
model = Sequential()
model.add(Dense(12, input_dim=8, init='uniform', activation='relu'))
model.add(Dense(8, init='uniform', activation='relu'))

inputs = Input(shape=None))
x = Dense(12, init='uniform', activation='relu', name='fc1')(x)
x = Dense(8, init='uniform', activation=‘sigmoid', name= 'predictions’)(x)
model = Model(inputs, x, name=‘example')
```

W3-5

```
# Compile model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# Fit the model
model.fit(X, Y, nb_epoch=150, batch_size=10)
# evaluate the model
scores = model.evaluate(X, Y)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

W3-4

```
# predict with the model
features = model.predict(X)
```

W3-4

Understanding CNN topology: filtering

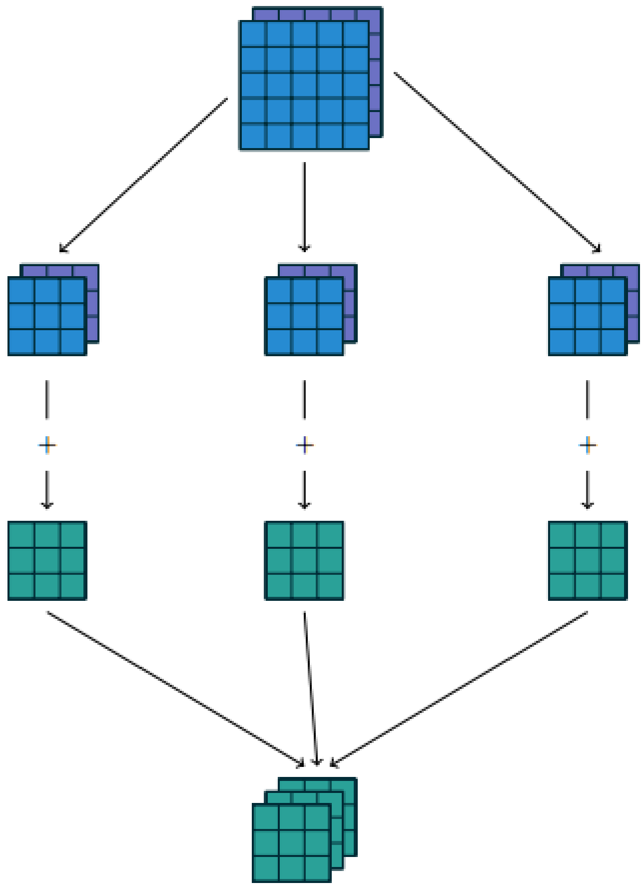
A guide to convolution arithmetic for deep learning

Vincent Dumoulin[1★] and Francesco Visin[2★†]

★MILA, Université de Montréal
†AIRLab, Politecnico di Milano

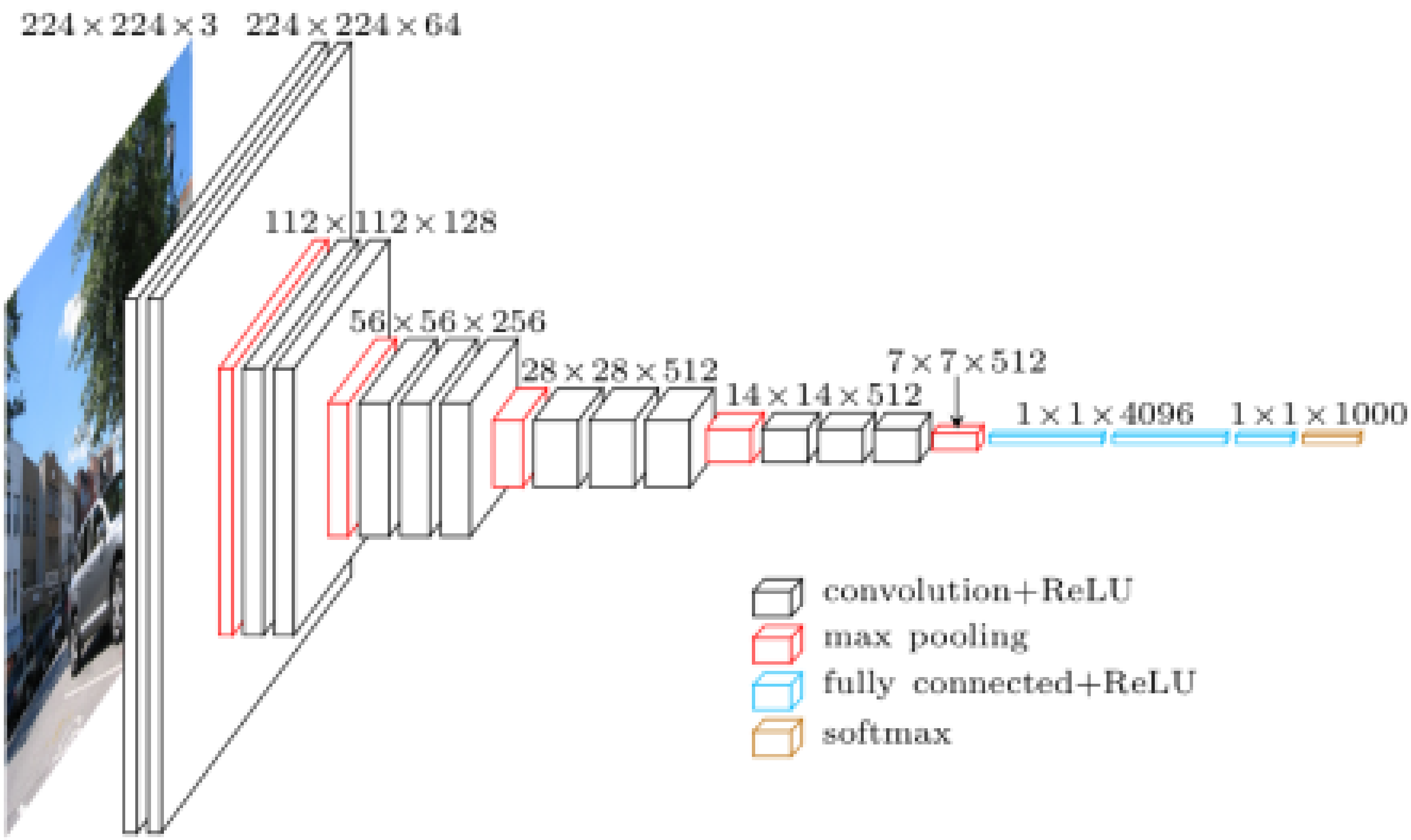
March 24, 2016

https://arxiv.org/pdf/1603.07285v1.pdf

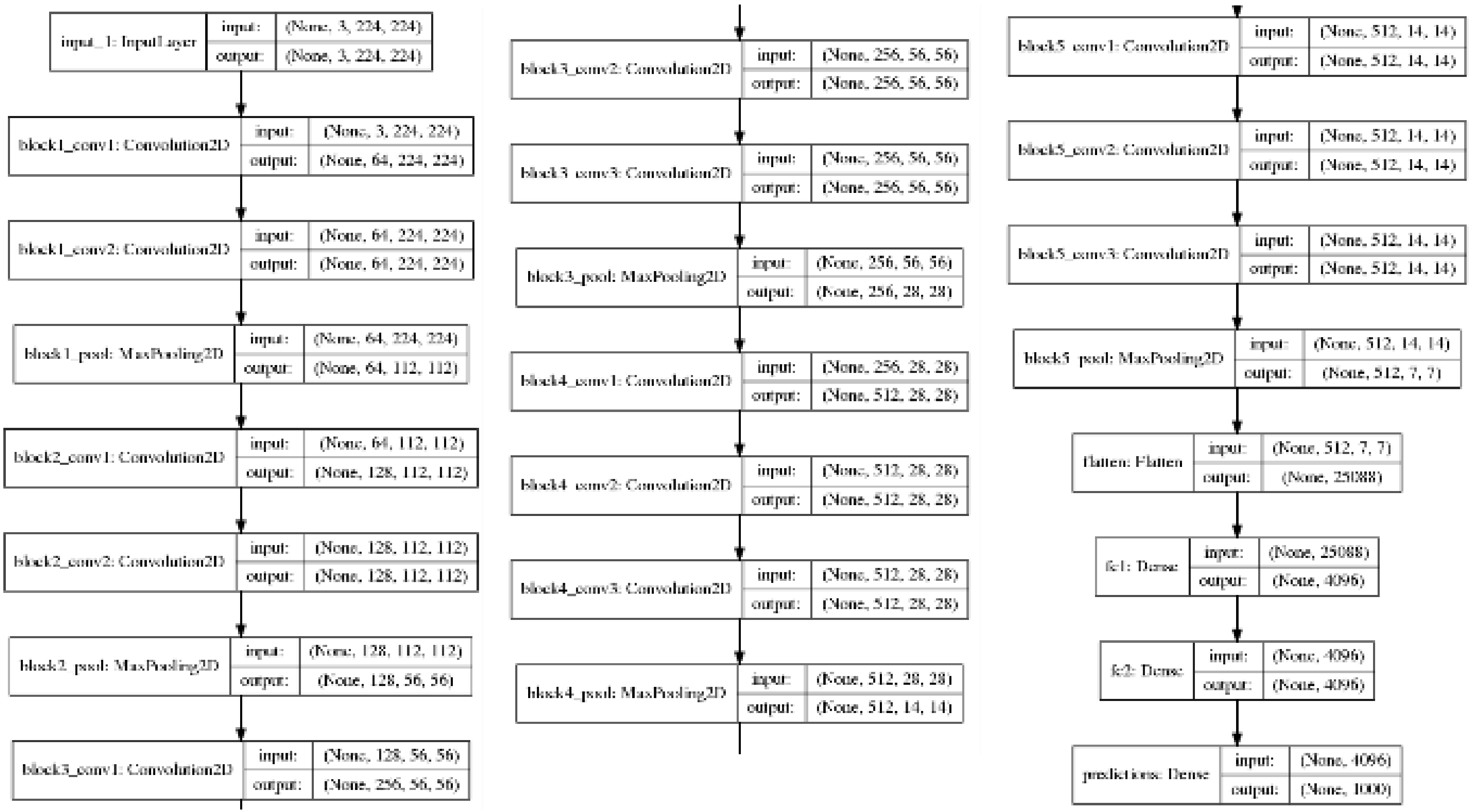


Input: 5x5x2
Filter: 3x3x3→3x3x2x3
Oputput: 3x3x3 or 5x5x3

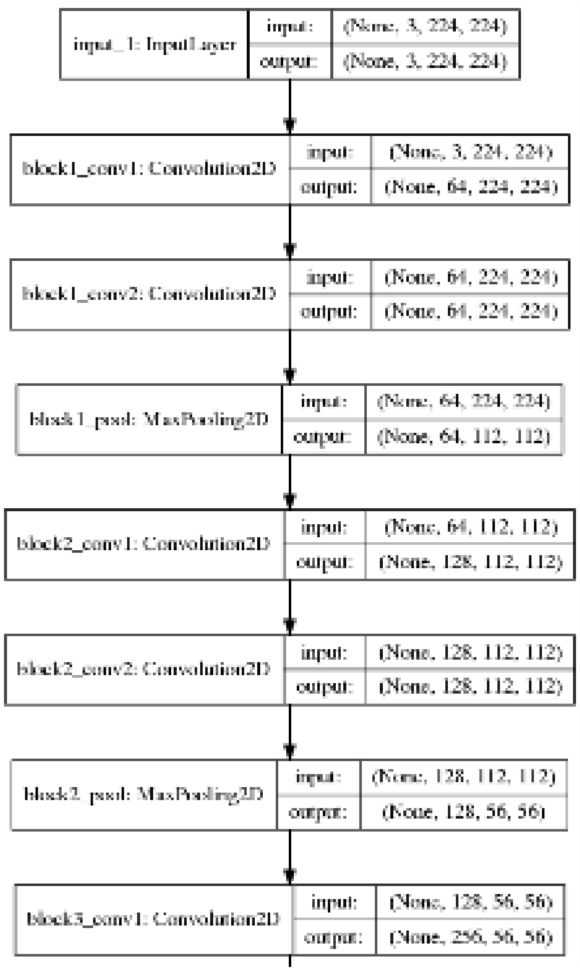
Very deep convolutional networks for large-scale image recognition



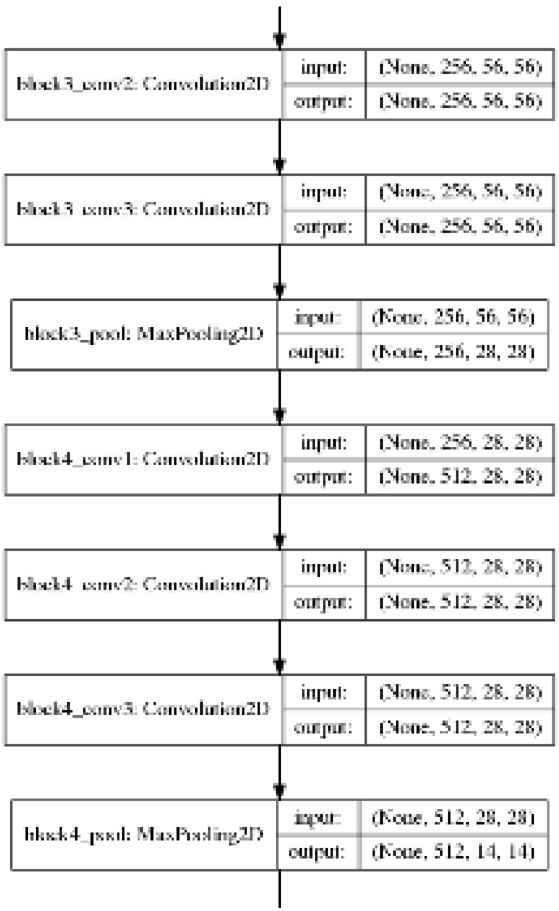
Credit Davi Frossard



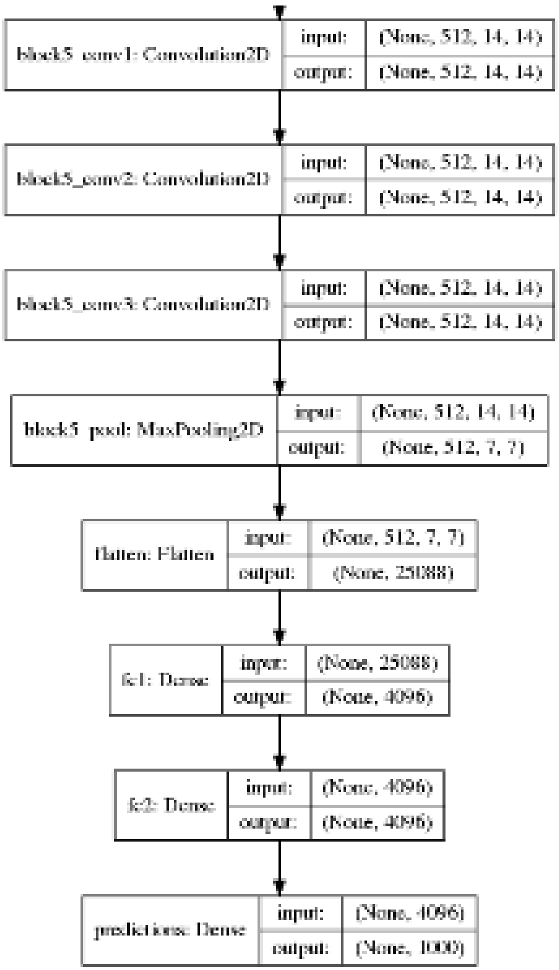
input_1: InputLayer | input: (None, 3, 224, 224) | output: (None, 3, 224, 224)
block1_conv1: Convolution2D | input: (None, 3, 224, 224) | output: (None, 64, 224, 224)
block1_conv2: Convolution2D | input: (None, 64, 224, 224) | output: (None, 64, 224, 224)
block1_pool: MaxPooling2D | input: (None, 64, 224, 224) | output: (None, 64, 112, 112)
block2_conv1: Convolution2D | input: (None, 64, 112, 112) | output: (None, 128, 112, 112)
block2_conv2: Convolution2D | input: (None, 128, 112, 112) | output: (None, 128, 112, 112)
block2_pool: MaxPooling2D | input: (None, 128, 112, 112) | output: (None, 128, 56, 56)
block3_conv1: Convolution2D | input: (None, 128, 56, 56) | output: (None, 256, 56, 56)
block3_conv2: Convolution2D | input: (None, 256, 56, 56) | output: (None, 256, 56, 56)
block3_conv3: Convolution2D | input: (None, 256, 56, 56) | output: (None, 256, 56, 56)
block3_pool: MaxPooling2D | input: (None, 256, 56, 56) | output: (None, 256, 28, 28)
block4_conv1: Convolution2D | input: (None, 256, 28, 28) | output: (None, 512, 28, 28)
block4_conv2: Convolution2D | input: (None, 512, 28, 28) | output: (None, 512, 28, 28)
block4_conv3: Convolution2D | input: (None, 512, 28, 28) | output: (None, 512, 28, 28)
block4_pool: MaxPooling2D | input: (None, 512, 28, 28) | output: (None, 512, 14, 14)
block5_conv1: Convolution2D | input: (None, 512, 14, 14) | output: (None, 512, 14, 14)
block5_conv2: Convolution2D | input: (None, 512, 14, 14) | output: (None, 512, 14, 14)
block5_conv3: Convolution2D | input: (None, 512, 14, 14) | output: (None, 512, 14, 14)
block5_pool: MaxPooling2D | input: (None, 512, 14, 14) | output: (None, 512, 7, 7)
flatten: Flatten | input: (None, 512, 7, 7) | output: (None, 25088)
fc1: Dense | input: (None, 25088) | output: (None, 4096)
fc2: Dense | input: (None, 4096) | output: (None, 4096)
predictions: Dense | input: (None, 4096) | output: (None, 1000)




```
img_input = Input(shape=(3,224,224))

x = Convolution2D(64, 3, 3, activation='relu',
border_mode='same', name='block1_conv1')(img_input)

x = Convolution2D(64, 3, 3, activation='relu',
border_mode='same', name='block1_conv2')(x)

x = MaxPooling2D((2, 2), strides=(2, 2),
name='block1_pool')(x)

x = Convolution2D(128, 3, 3, activation='relu',
border_mode='same', name='block2_conv1')(x)

x = Convolution2D(128, 3, 3, activation='relu',
border_mode='same', name='block2_conv2')(x)

x = MaxPooling2D((2, 2), strides=(2, 2),
name='block2_pool')(x)

x = Convolution2D(256, 3, 3, activation='relu',
border_mode='same', name='block3_conv1')(x)
```



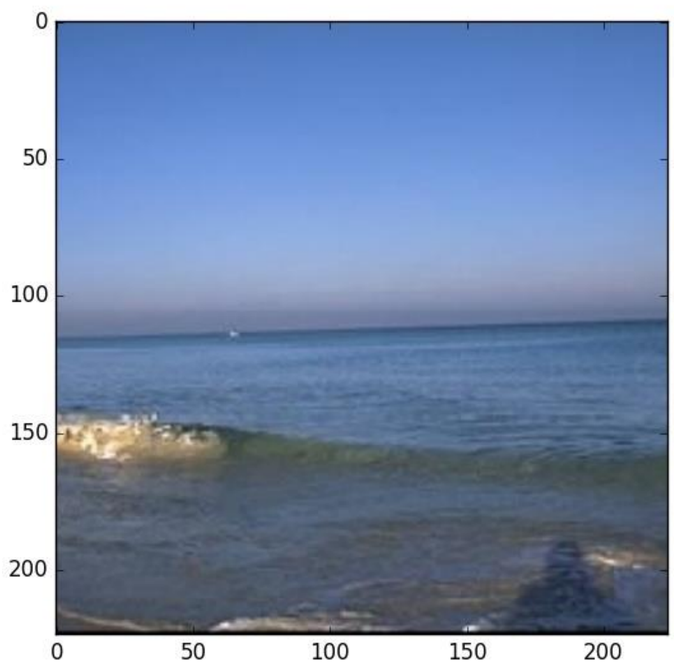

```
x = Convolution2D(256, 3, 3, activation='relu',
border_mode='same', name='block3_conv2')(x)

x = Convolution2D(256, 3, 3, activation='relu',
border_mode='same', name='block3_conv3')(x)

x = MaxPooling2D((2, 2), strides=(2, 2),
name='block3_pool')(x)

x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block4_conv1')(x)

x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block4_conv2')(x)

x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block4_conv3')(x)

x = MaxPooling2D((2, 2), strides=(2, 2),
name='block4_pool')(x)
```

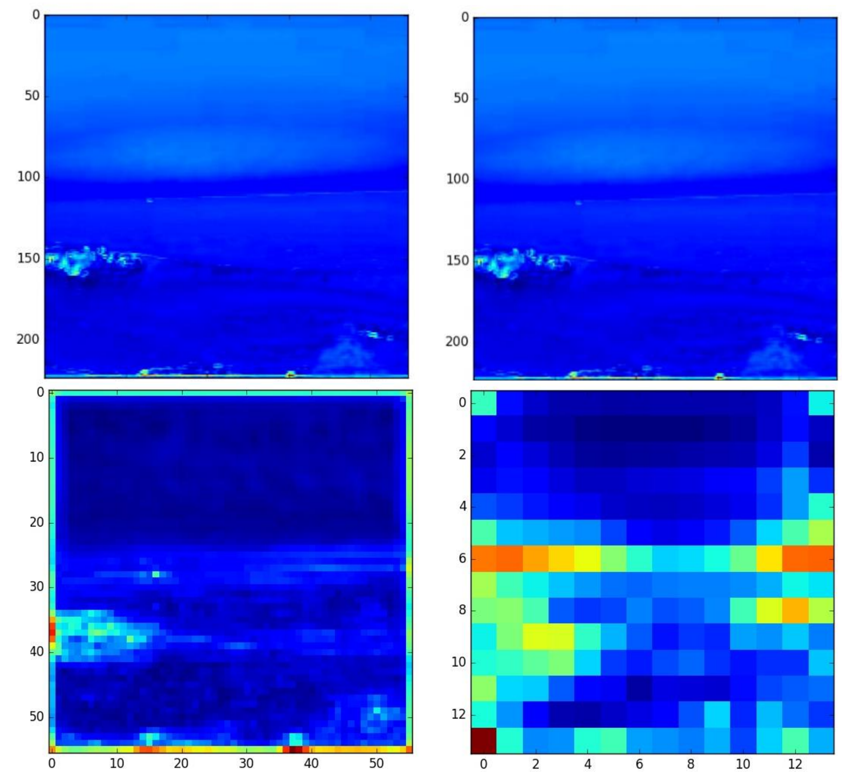



```
x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block5_conv1')(x)

x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block5_conv2')(x)

x = Convolution2D(512, 3, 3, activation='relu',
border_mode='same', name='block5_conv3')(x)

x = MaxPooling2D((2, 2), strides=(2, 2),
name='block5_pool')(x)

x = Flatten(name='flatten')(x)

x = Dense(4096, activation='relu', name='fc1')(x)

x = Dense(4096, activation='relu', name='fc2')(x)

x = Dense(1000, activation='softmax',name='predictions')(x)
```

Extract features maps

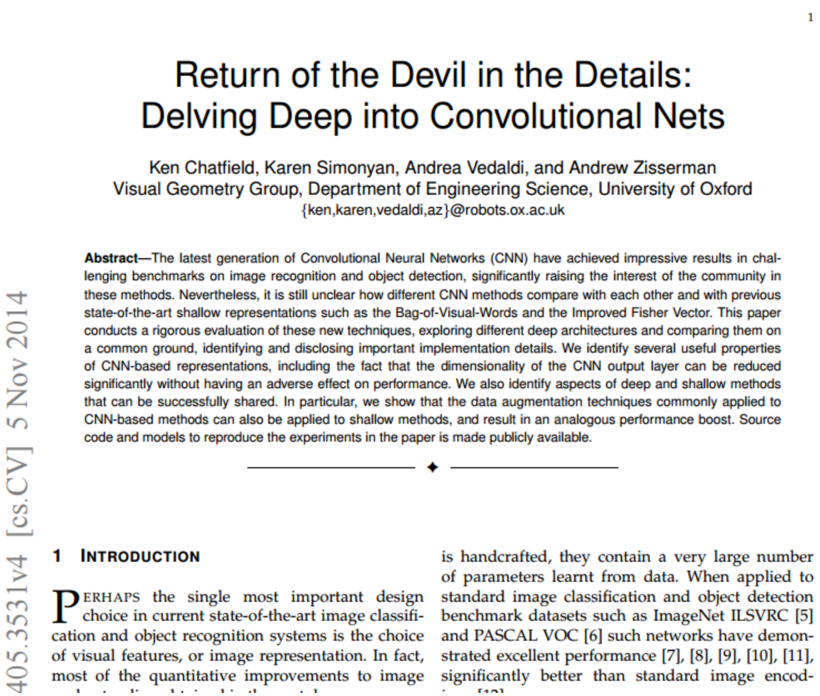
```
img_path = '/data/MIT/test/coast/art1130.jpg'
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)

base_model = VGG16(weights='imagenet')
model = Model(inputs=base_model.input, outputs=base_model.get_layer('block1_conv1').output)
features = model.predict(x)
```





For visualizing purposes:
How to get rid of 3rd dimensión?

Week 5: Fine tune end to end classification



1

Return of the Devil in the Details:
Delving Deep into Convolutional Nets

Ken Chatfield, Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman
Visual Geometry Group, Department of Engineering Science, University of Oxford
{ken,karen,vedaldi,az}@robots.ox.ac.uk

Abstract—The latest generation of Convolutional Neural Networks (CNN) have achieved impressive results in challenging benchmarks on image recognition and object detection, significantly raising the interest of the community in these methods. Nevertheless, it is still unclear how different CNN methods compare with each other and with previous state-of-the-art shallow representations such as the Bag-of-Visual-Words and the Improved Fisher Vector. This paper conducts a rigorous evaluation of these new techniques, exploring different deep architectures and comparing them on a common ground, identifying and disclosing important implementation details. We identify several useful properties of CNN-based representations, including the fact that the dimensionality of the CNN output layer can be reduced significantly without having an adverse effect on performance. We also identify aspects of deep and shallow methods that can be successfully shared. In particular, we show that the data augmentation techniques commonly applied to CNN-based methods can also be applied to shallow methods, and result in an analogous performance boost. Source code and models to reproduce the experiments in the paper is made publicly available.

arXiv:1405.3531v4 [cs.CV] 5 Nov 2014

1 INTRODUCTION

PERHAPS the single most important design choice in current state-of-the-art image classification and object recognition systems is the choice of visual features, or image representation. In fact, most of the quantitative improvements to image

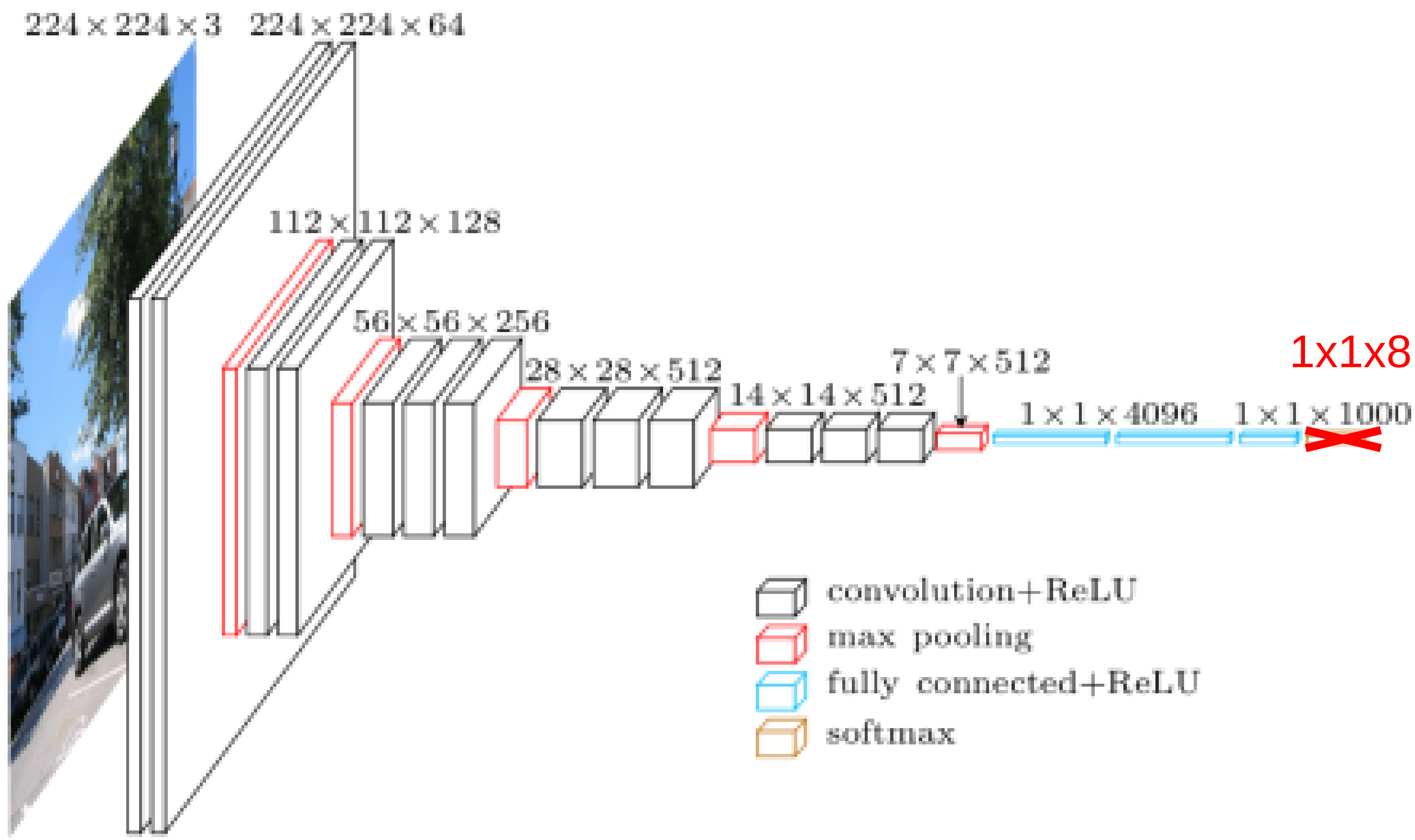
is handcrafted, they contain a very large number of parameters learnt from data. When applied to standard image classification and object detection benchmark datasets such as ImageNet ILSVRC [5] and PASCAL VOC [6] such networks have demonstrated excellent performance [7], [8], [9], [10], [11], significantly better than standard image encod-

Goals:

- Understand layer manipulation
- Deal with dataset loading
- Hyperparameter optimization

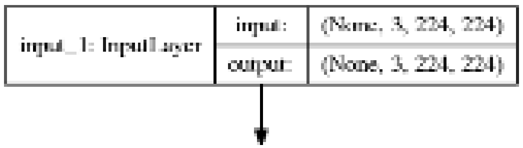
Chatfield, Ken, et al. "Return of the devil in the details: Delving deep into convolutional nets." *arXiv preprint arXiv:1405.3531* (2014).

Very deep convolutional networks for large-scale image recognition

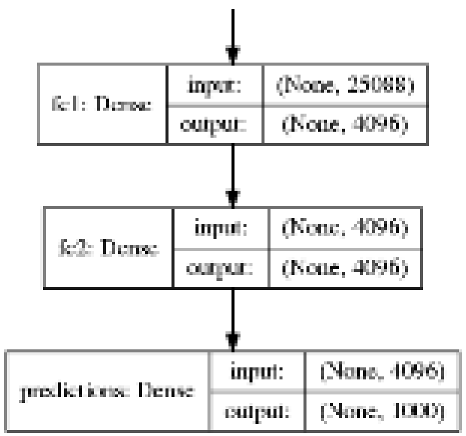


Credit Davi Frossard

Understand layer manipulation



img_input = Input(shape=(3,224,224))



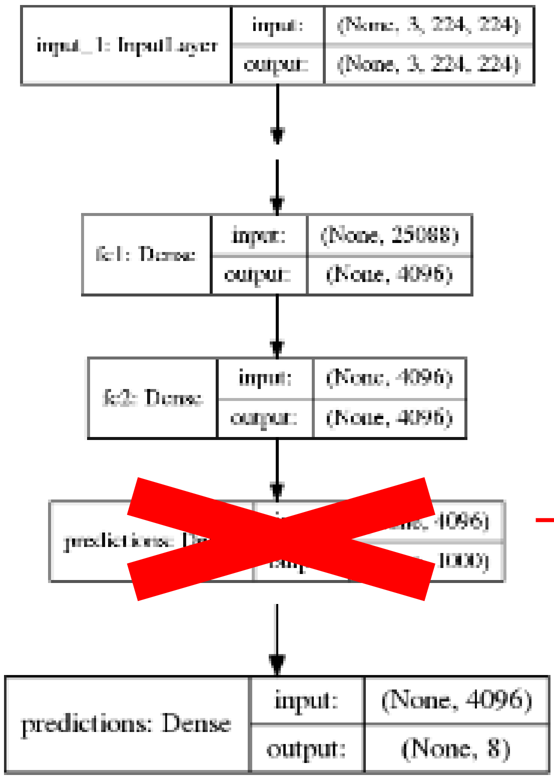
x = Dense(4096, activation='relu', name='fc1')(x)

x = Dense(4096, activation='relu', name='fc2')(x)

x = Dense(1000, activation='softmax',name='predictions')(x)

base_model = Model(img_input, x, name='vgg16')

Understand layer manipulation



img_input = Input(shape=(3,224,224))

x = Dense(4096, activation='relu', name='fc1')(x)

x = Dense(4096, activation='relu', name='fc2')(x)

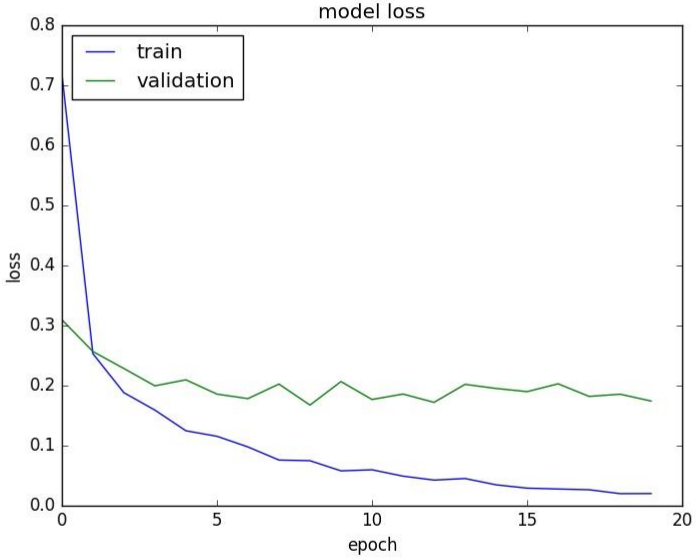
~~x = Dense(1000, activation='softmax',name='predictions')(x)~~

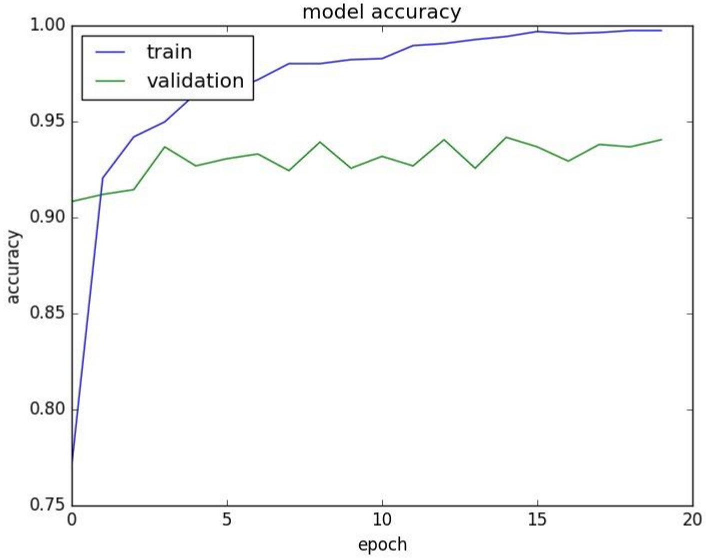
x = base_model.layers[-2].output
x = Dense(8, activation='softmax',name='predictions')(x)

model = Model(inputs=base_model.input, outputs=x)

Minimum results

Full training dataset
No hyperparameter optimization





Let's do things more interesting:

- cut the architecture in a lower layer
- use less training data (no more than 400)

Preparing the model

- Set goal function and process model

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

- Do not train on full network at starting point

```
for layer in base_model.layers:
    layer.trainable = False
```

Deal with dataset loading

```
from keras.applications.inception_v3 import preprocess_input

datagen = ImageDataGenerator(featurewise_center=False,
          samplewise_center=False,
          featurewise_std_normalization=False,
          samplewise_std_normalization=False,
          preprocessing_function=preprocess_input,  IMPORTANT
          rotation_range=0.,
          width_shift_range=0.,
          height_shift_range=0.,
          shear_range=0.,
          zoom_range=0.,
          fill_mode='nearest',
          horizontal_flip=False,
          vertical_flip=False,
          rescale=None)
```

Deal with dataset loading

```
train_generator = datagen.flow_from_directory(train_data_dir,
                      target_size=(img_width, img_height),
                      batch_size=batch_size,
                      class_mode='categorical')

test_generator = datagen.flow_from_directory(test_data_dir,
                      target_size=(img_width, img_height),
                      batch_size=batch_size,
                      class_mode='categorical')

validation_generator =datagen.flow_from_directory(val_data_dir,
                      target_size=(img_width, img_height),
                      batch_size=batch_size,
                      class_mode='categorical')
```

Deal with dataset loading

```
history=model.fit_generator(train_generator,
               samples_per_epoch=400,
               nb_epoch=number_of_epoch,
               validation_data=validation_generator,
               nb_val_samples=800)

plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])

plt.plot(history.history[‘loss'])
plt.plot(history.history['val_loss'])


result = model.evaluate_generator(test_generator)
```

Afterwards, retrain in full model

Hyperparamter optimization

Per model

batch_size = [10, 20, 40, 60, 80, 100]
epochs = [10, 50, 100]
optimizer = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Adamax', 'Nadam']
learn_rate = [0.0001 0.001, 0.01, 0.1, 0.2, 0.3]
momentum = [0.0, 0.2, 0.4, 0.6, 0.8, 0.9]
data augmentation: flip, zoom, rescale, …

Per layer:

activation = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'hard_sigmoid', 'linear']

init_mode = ['uniform', 'lecun_uniform', 'normal', 'zero', 'glorot_normal', 'glorot_uniform', 'he_normal', 'he_uniform'] (Not useful in our case)

Topology:

drop-out layers: p % of inactive weights
batchnormalization
regularizers

Hyperparamter optimization

Journal of Machine Learning Research 13 (2012) 281-305 Submitted 3/11; Revised 9/11; Published 2/12

Random Search for Hyper-Parameter Optimization

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Editor: Leon Bottou

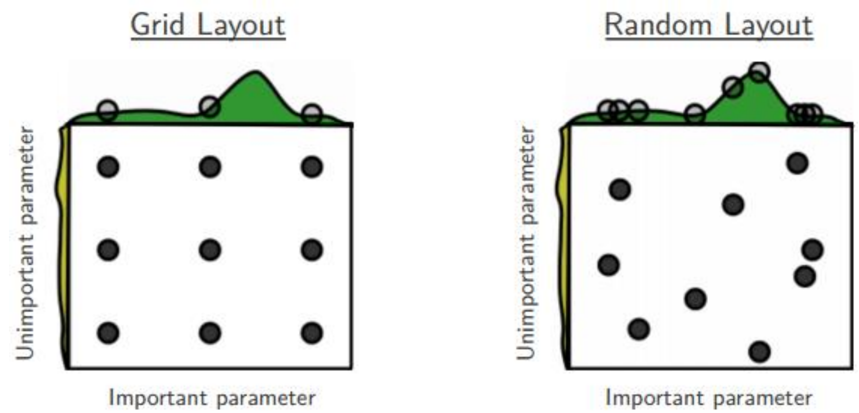
Abstract

Grid search and manual search are the most widely used strategies for hyper-parameter optimization. This paper shows empirically and theoretically that randomly chosen trials are more efficient for hyper-parameter optimization than trials on a grid. Empirical evidence comes from a comparison with a large previous study that used grid search and manual search to configure neural networks and deep belief networks. Compared with neural networks configured by a pure grid search, we find that random search over the same domain is able to find models that are as good or better within a small fraction of the computation time. Granting random search the same computational budget, random search finds better models by effectively searching a larger, less promising configuration space. Compared with deep belief networks configured by a thoughtful combination of manual search and grid search, purely random search over the same 32-dimensional configuration space found statistically equal performance on four of seven data sets, and superior performance on one of seven. A Gaussian process analysis of the function from hyper-parameters to validation set performance reveals that for most data sets only a few of the hyper-parameters really matter, but that different hyper-parameters are important on different data sets. This phenomenon makes grid search a poor choice for configuring algorithms for new data sets. Our analysis casts some light on why recent "High Throughput" methods achieve surprising success—they appear to search through a large number of hyper-parameters because most hyper-parameters do not matter much. We anticipate that growing interest in large hierarchical models will place an increasing burden on techniques for hyper-parameter optimization; this work shows that random search is a natural baseline against which to judge progress in the development of adaptive (sequential) hyper-parameter optimization algorithms.

Keywords: global optimization, model selection, neural networks, deep learning, response surface modeling

1. Introduction

The ultimate objective of a typical learning algorithm $\mathcal{A}$ is to find a function f that minimizes some expected loss $\mathcal{L}(x; f)$ over i.i.d. samples x from a natural (grand truth) distribution $\mathcal{G}_x$. A *learning algorithm* $\mathcal{A}$ is a functional that maps a data set $\mathcal{X}^{(\text{train})}$ (a finite set of samples from $\mathcal{G}_x$) to a function



Continuous hyperparameter: distribution over possible values

generate random variable

Discrete hyperparameter: list of discrete choices
random selection
(without replacement if all discrete)

Set the number of trials

Bergstra, James, and Yoshua Bengio. "Random search for hyper-parameter optimization." *Journal of Machine Learning Research* 13.Feb (2012): 281-305.

Tasks

Understanding layer manipulation

0. Fine tune an existing architeture
   https://keras.io/applications/
1. Set a new model from an existing architecutre.
2. Apply the model to a small set of data (no more than 400)

Deal with dataset loading

3. Introduce and evaluate the usage of data augmentation

Hyperparameter optimization

4. Introduce and evaluate the usage of any suitable methodology to improve learning curve (dropout layer, batch norm, …)
5. Apply random search on per model hyperparameters

Model	Size	Top-1 Accuracy	Parameters	Group
Xception	88 MB	0.790	22,910,480	01
ResNet50	98 MB	0.749	25,636,712	02
NASNetMobile	23 MB	0.744	5,326,716	03
InceptionV3	92 MB	0.779	23,851,784	04
MobileNetV2	14 MB	0.713	3,538,984	05
DenseNet121	33 MB	0.750	8,062,504	06
ResNet50V2	98 MB	0.760	25,613,800	07
EfficientNetB2	36 MB	-	9,177,569	08

Grades, deliverables and deadline

- Deliver source code and a **short** slide presentation of the work done
  - For each task, all the carried tests with their associated results
  - 1 slide summarizing the best yielded result and configuration for each task
- Delivered by Monday 11th at 10AM

Control pipeline: Callbacks

- ModelCheckpoint
- EarlyStopping
- ReduceLROnPlateau
- CSVLogger
- LambdaCallback
- …

Usage:

callbacks = [ModelCheckpoint(….), EarlyStopping(…),…]

model.fit(…, callbacks)

Control pipeline: Callbacks

Example:

```
plot_loss_callback = LambdaCallback(on_epoch_end=lambda epoch, logs: plot_loss(epoch,logs))
save_callback=ModelCheckpoint(filepath=
                              'weights.{epoch:02d}-{val_loss:.2f}.hdf5',
                              monitor='val_acc', verbose=1, save_best_only=True,
                              mode='max')

history=model.fit_generator(train_generator,
        samples_per_epoch=1900,
        nb_epoch=number_of_epoch,
        validation_data=validation_generator,
        nb_val_samples=800,
        callbacks=[plot_loss_callback,save_callback])
```