Multimedia Information Retrival and Computer Vision

Alice Nannini
Marco Parola
Stefano Poleggi

A.Y. 2020-2021

Contents

1 Introduction

In this project we implemented a Web Search Engine working on the "ArtImages" dataset, and the "MirFlickr" dataset as distractor. The Web Search Engine is based on the **Locality Sensitive Hashing** (LSH) index and on the pre-trained convolutional neural network ResNet50 with weigths computed on the "Imagenet" dataset.

2 Data Analysis and Preprocessing

The Art dataset is composed of 5 categories of images, corresponding to the 5 classes:

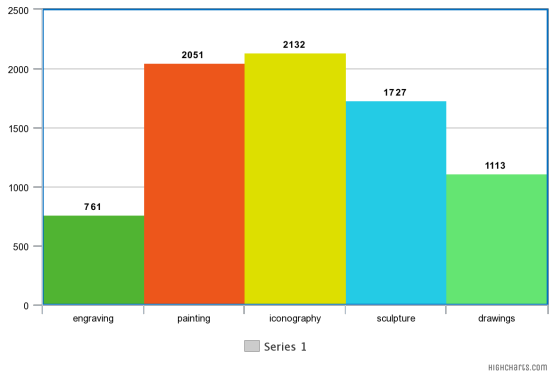
- Drawings
- Engraving
- Iconography
- Painting
- Sculpture

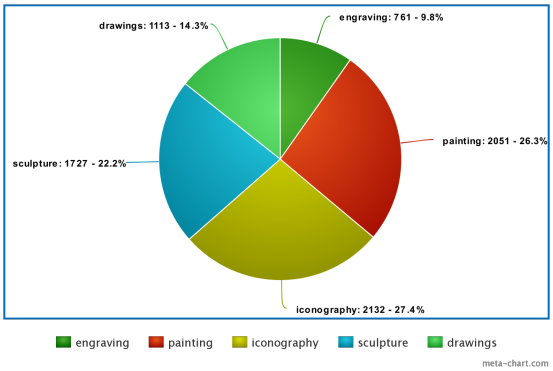
2.1 Data cleaning

After a preliminary analysis of the dataset, we realized that some images were corrupted, both on the training set and the validation set, so we detected and deleted them using the following script.

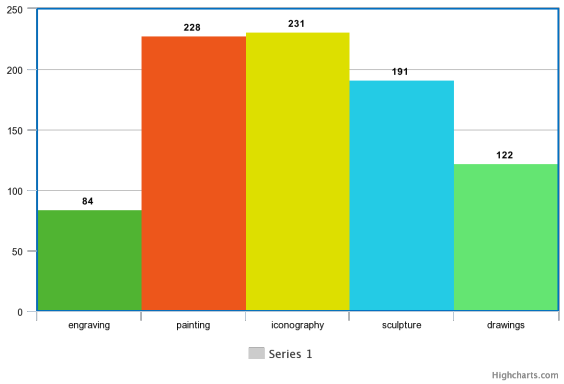
```
from PIL import Image
import glob

for filename in os.listdir(VALIDATION_DATA):
    try:
      image.load_img(VALIDATION_DATA + filename, target_size=(300, 300))

    except :
      print("ERROR" + VALIDATION_DATA + filename)
      os.remove(VALIDATION_DATA + filename)
```

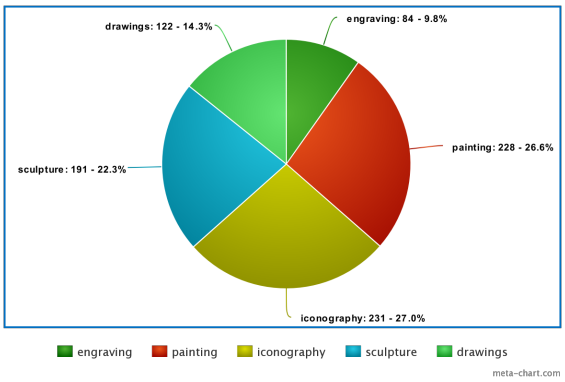
The following figures show the distribution of the classes of the trainig set, after the execution of the snippet of code shown above :





The following figures show the distribution of the classes of the validationset, after the execution of the snippet of code shown above :





3 Extract the features from the images

During this phase we extracted the features from the images and we stored them in order to reload them as numpy-array when it is necessary.
The pretrained convolutional neural networks used are:

- ResNet50
- ResNet50v2

3.1 Features Extraction approach

In this phase we extracted the features from the images using the pretrained convolutional neural networks **Resnet50** and **Resnet50v2** trained on *Imagenet* dataset, adopting a fetures extraction approach.
The following snippet of code shows the extraction of the training set using Resnet50, the same script is been used also with Resnet50v2 and for the validation set and the distractor.

```
def extract_features(extractor, generator, sample_count, dim=2048):
  features = extractor.predict_generator(generator, sample_count)
return features

datagen = image.ImageDataGenerator( rescale = 1./255 )

train_generator_scaled = datagen.flow_from_directory(
        TRAINING_DATA,
        target_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        class_mode='sparse',
        shuffle=False)

conv_base = ResNet50(weights='imagenet',
include_top=False,
input_shape=(300, 300, 3),
pooling='avg')


training_features = extract_features(conv_base,
 train_generator,
TRAINING_SIZE )
np.save(FILE_TRAINING_FEATURES, training_features)
```

3.2 Fine Tuning approach

During this phase we carried out several tests using different hyperparameters for the fully connected part added at the end both of the networks Resnet50 and Resnet50v2.
We compute this phase adopting a trial and error approach, trying different hyperparameter values for the fully connected neural network appended to the pretrained convolutional one and we compared the performance.
We stopped the training exploiting an *early stopping condition*, monitoring the loss function and setting the patience value equal to 10 and restoring the weights to 10 epochs before.
The following subparagraphs show only the most relevant experiments, we didn't report all of them

in order to avoid some redundancies.

3.3 Resnet50

3.3.1 Model 1

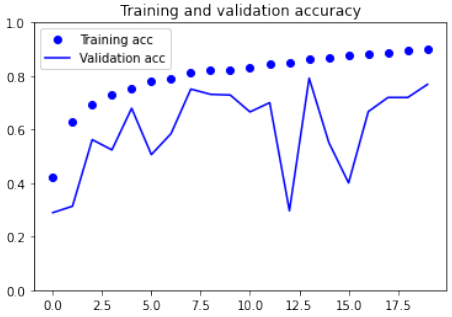
In this trial we trained the pretrained network Resnet50, we appended a fully connected part defined by the following hyperparameter:

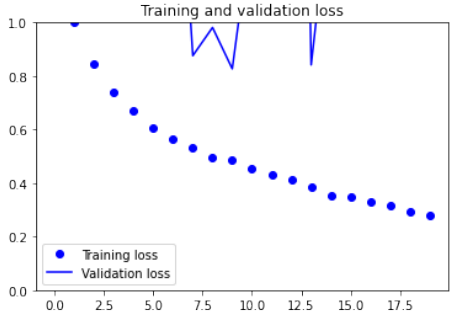
- Unfreezed layers from conv5_block1_1_conv
- 1 dense layer composed by 256 neurons
- Activation function: softmax
- Learning rate: 1e-3

These are the obtained results on the validation set we used to test the network:

	precision	recall	f1-score	support
	0.0	0.59	0.39	0.47	122
	1.0	0.63	0.77	0.70	84
	2.0	0.90	0.86	0.88	231
	3.0	0.89	0.78	0.83	228
	4.0	0.65	0.86	0.74	191
accuracy				0.76	856
macro avg		0.73	0.73	0.72	856
weighted avg		0.77	0.76	0.76	856

```
loss_test : 0.7306886315345764
acc_test : 0.7616822719573975
```





3.3.2 Model 2

Looking at the accuacy plot of the first experiment, we can observe the presence of the overfitting phenomenon; in order to reduce this problem, we added some *Dropout Layers* and reduced the learning rate.
So in the second trial we trained the pretrained network Resnet50, we appended a fully connected part defined by the following hyperparameter:

- Unfreezed layers from conv5_block1_1_conv

- Dropout layer, rate: 0.5
- 1 dense layer composed by 256 neurons
- Dropout layer, rate: 0.5
- 1 dense layer composed by 128 neurons
- Dropout layer, rate: 0.5
- Activation function: softmax
- Learning rate: 1e-4

The obtained results are the following:

```
    precision    recall  f1-score   support

         0.0       0.47      0.33      0.39       122
         1.0       0.70      0.56      0.62        84
         2.0       0.60      0.94      0.73       231
         3.0       0.98      0.22      0.36       228
         4.0       0.53      0.81      0.64       191

    accuracy                           0.59       856
   macro avg       0.66      0.57      0.55       856
weighted avg       0.68      0.59      0.55       856

loss_test : 0.9764283299446106
acc_test : 0.5934579372406006
```

The addition of the dropout did not seem to bring any improvement: on the contrary, the performance of the model is lower. So we tried a new test by removing these dropout levels and adding new FC levels.

3.3.3 Model 3

In the third trial, we trained the pretrained network Resnet50, adding a fully connected part defined by the following hyperparameter:

- Unfreezed layers from conv5_block1_1_conv
- 1 dense layer composed by 512 neurons
- 1 dense layer composed by 256 neurons
- 1 dense layer composed by 128 neurons
- 1 dense layer composed by 64 neurons
- Activation function: softmax
- Learning rate: 1e-4

Again, these are the results we obtained from the trial:

```
    precision    recall  f1-score   support

         0.0       0.67      0.02      0.03       122
         1.0       0.69      0.39      0.50        84
         2.0       0.46      0.97      0.62       231
         3.0       0.82      0.82      0.82       228
         4.0       0.80      0.38      0.52       191

    accuracy                           0.61       856
   macro avg       0.69      0.52      0.50       856
weighted avg       0.68      0.61      0.56       856

loss_test : 0.9576621651649475
acc_test : 0.605140209197998
```

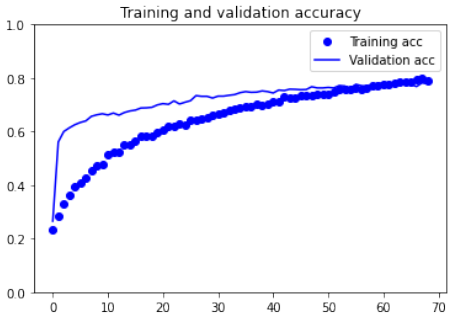
The network performance remained similar to the previous attempt.

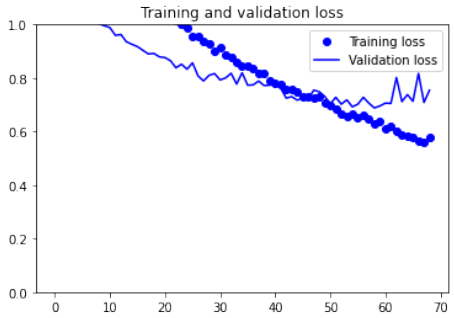
3.3.4 Model 4

In the fourth trial we trained the pretrained network Resnet50, in order to better generalize the dataset, so we appended a fully connected part defined by the following hyperparameters:

- Unfreezed layers from conv5_block1_1_conv
- Dropout layer, rate: 0.5
- 1 dense layer composed by 256 neurons
- Dropout layer, rate: 0.5
- 1 dense layer composed by 128 neurons
- Dropout layer, rate: 0.5
- 1 dense layer composed by 64 neurons
- Activation function: softmax
- Learning rate: 1e-6

```
precision    recall  f1-score   support

         0.0       0.71      0.34      0.46       122
         1.0       0.64      0.68      0.66        84
         2.0       0.80      0.95      0.87       231
         3.0       0.96      0.87      0.91       228
         4.0       0.76      0.92      0.83       191

    accuracy                           0.81       856
   macro avg       0.78      0.75      0.75       856
weighted avg       0.81      0.81      0.79       856

loss_test : 0.6162440776824951
acc_test : 0.8072429895401001
```





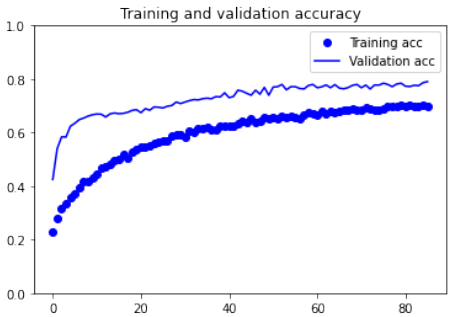
We can see from the results that this is the best model so far, with an overall accuracy of 81%: in addition to the adjustment of the dropout and dense levels, this is due to the further lowering of the learning rate. Also the graphs show a decisive improvement of the overfitting.

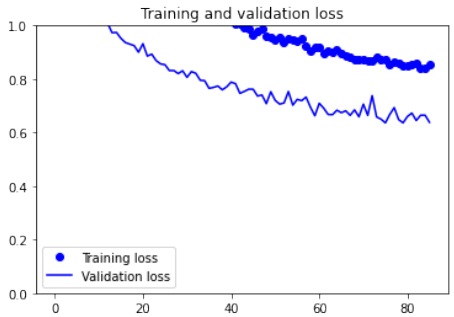
3.3.5 Model 5

In the fifth trial, we trained the Resnet50 convolutional base, where we appended the same fully connected part of the previous experiment applying a data augmentation technique, in order to better generalize the dataset.

	precision	recall	f1-score	support
0.0	0.62	0.28	0.38	122
1.0	0.53	0.74	0.62	84
2.0	0.85	0.87	0.86	231
3.0	0.91	0.85	0.88	228
4.0	0.71	0.87	0.79	191
accuracy			0.77	856
macro avg	0.72	0.72	0.70	856
weighted avg	0.77	0.77	0.76	856

```
loss_test : 0.6571111083030701
acc_test : 0.7675233483314514
```





The performance did not improve, in fact a slight underfitting appeared.

3.3.6 Conclusion

	Accuracy	**Loss**	**mAP** euclidian	**mAP** cosine	Items
Model 1	0.7617	0.7307			
Model 2	0.5935	0.9764			
Model 3	0.6051	0.9577			
Model 4	0.8072	0.6162			
Model 5	0.7675	0.6571			

3.4 Resnet50v2

For this convolutional base, we performed the tests by resuming the fully connected blocks used in the previous step. We just report the obtained results, since all the hyperparameters can be consulted in the previous section.

3.4.1 Model 1

	precision	recall	f1-score	support
	0.0	0.75	0.70	0.72	122
	1.0	0.90	0.63	0.74	84
	2.0	0.91	1.00	0.95	231
	3.0	0.95	0.96	0.96	228
	4.0	0.93	0.97	0.95	191
	accuracy			0.90	856
	macro avg	0.89	0.85	0.86	856
	weighted avg	0.90	0.90	0.90	856

loss_test : 0.779442548751831
acc_test : 0.9030373692512512

3.4.2 Model 2

	precision	recall	f1-score	support
	0.0	0.76	0.53	0.62	122
	1.0	0.74	0.69	0.72	84
	2.0	0.90	1.00	0.94	231
	3.0	0.90	0.96	0.93	228
	4.0	0.96	0.98	0.97	191
	accuracy			0.89	856
	macro avg	0.85	0.83	0.84	856
	weighted avg	0.88	0.89	0.88	856

loss_test : 0.5550180077552795
acc_test : 0.8855140209197998

3.4.3 Model 3

	precision	recall	f1-score	support
	0.0	0.70	0.72	0.71	122
	1.0	0.96	0.56	0.71	84
	2.0	0.91	1.00	0.95	231
	3.0	0.93	0.96	0.94	228
	4.0	0.96	0.96	0.96	191
	accuracy			0.90	856
	macro avg	0.89	0.84	0.85	856
	weighted avg	0.90	0.90	0.89	856

```
loss_test : 0.5826641917228699
acc_test : 0.8971962332725525
```

3.4.4 Model 4

3.4.5 Model 5

4 Sequential Scanning

The first implementation of our image search engine is based on a numpy array as data structure and a sequential scanning as search algorithm, using the following similarity distance:

- Euclidian distance
- Cosine similarity

We performed the evaluation of the sequential search function, based on the validation set, so that we could have data on which to compare the performance of the LSH index. The evaluation was done by calculating the mean Average Precision (mAP) metric, using the features extracted from both Resnet50 and Resnet50v2. We compared the queries to the dataset (training set + distractor), first using the cosine similarity and then the Euclidean distance.

k = 10	mAP euclidian	avg dist	mAP cosine	avg sim	#Items
Resnet50	0.306	1.083	0.309	0.999	32791
Resnet50v2	0.351	17.977	0.343	0.747	32791