IMAGE SEGMENTATION BY SUPERPIXELS

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Key-words:
deep learning; convolutional neural networks; image segmentation

Abstract:
In this paper, we study different options to improve the performance of a deep learning convolutional neural network

Contents

Todo

-

1 Introduction

1.1 Segmentation

What it is - partitioning a digital image into multiple segments (sets of pixel) - change the representation of an image into something that is more meaningful and easier to analyz - locate boundaries and objects

Figure 1: *A segmentation. Left: the original image; right: the segmented image. Both are from the COCO training dataset*[1].

Motivation

1.2 Superpixels

What it is piche

Figure 2: *A superpixel segmentation. From left to right: the original image, the original image with its calculated superpixels outlines and the resulting superpixel segmented image. Each pixel of a superpixel has only one color, the mean color of the original image over the superpixel region.*

Applications & Motivation démarrer une segmentation
fournir un support sur lequel faire de la classification (couleur/texture moyenne, etc)

1.2.1 Ce qu'est une bonne superpixelsegmentation

pour obtenir metriques des algos, `cnn/results/results.py`

Metrics [2] let $S = S_j{}_{j=1}^{K}$ and $G = G_i$ be partitions of the same image $I : x_n \mapsto I(x_n)$, $1 \leq n \leq N$ S is a segmented image G is the ground truth

- **Boundary Recall.** - most commonly used metric to assess boundary adherence. - intersection entre les frontieres grossies et truth, donc pourcentage de vrais contours deetctes - Let $\mathrm{TP}(G, S)$ be the number of true positive boundary pixels and $\mathrm{FN}(G, S)$ be the number of false negative boudary pixels in the segmented image S.

$$\mathrm{Rec}(G, S) = \frac{\mathrm{TP}(G, S)}{\mathrm{TP}(G, S) + \mathrm{FN}(G, S)}$$

- **Undersegmentation Error.**
- **Compactness.** - evaluates the compactness of the superpixels.

$$\mathrm{CO}(G, S) = \frac{1}{N} \sum_{S_j} |S_j| \frac{4\pi A\left(S_j\right)}{P\left(S_j\right)}$$

  - the CO operator computes how close the area $A(S_j)$ of each superpixel S_j is from a circle with same perimeter $P(S_j)$.

Autres algorithmes - SLIC

1.2.2 Motivations/ambitions

Difficultés que l'on cherche à résoudre

Pas de vraie approche DL pour segmentation avec superpixels Most of the aforementioned segmentation methods are based only on color information of pixels in the image. Humans use much more knowledge when performing image segmentation, but implementing this knowledge would cost considerable human engineering and computational time, and would require a huge domain knowledge database which does not currently exist. Trainable segmentation methods, such as neural network segmentation, overcome these issues by modeling the domain knowledge from a dataset of labeled pixels.

Ambitions améliorer les métriques

2 Dataset generation

2.1 COCO dataset

2.1.1 The COCO dataset

COCO dataset[3], nb of images, examples

2.1.2 Characteristics

In order to have a better understanding of the dataset, we

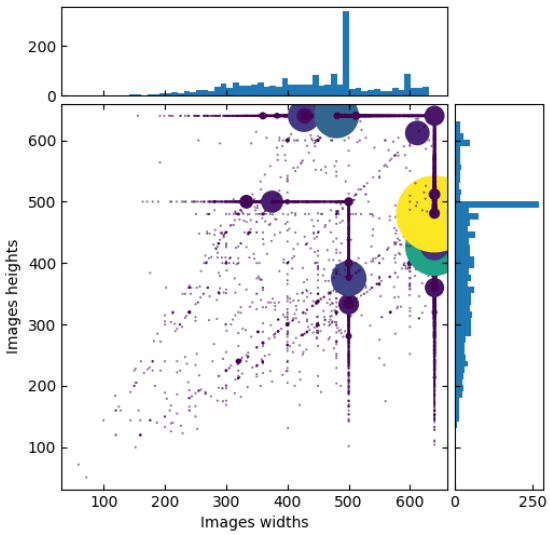
d'où la nécessité de faire des transformations sur la dataset pour uniformiser les tailles en entrée du réseau.

2.2 Eikonal

2.3 Global approach

en plus réutilisé derrière sur image qui sort du réseau
faire un petit résumé

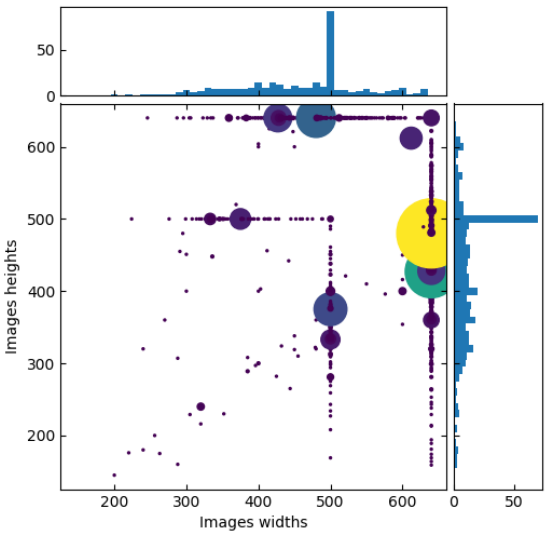
[2] cf article https://arxiv.org/pdf/1612.01601.pdf
[3] site de COCO



(a) *plot*

	Training	Height	Width
Images	Min	51	59
118 287	Max	640	640

(c) Tabular



(b) *plot*

	Validation	Height	Width
Images	Min	145	200
5000	Max	640	640

(d) Tabular

Figure 3: *Training and validation sets characterization*

Figure 4: *Title*

3 The model

3.1 Network architecture

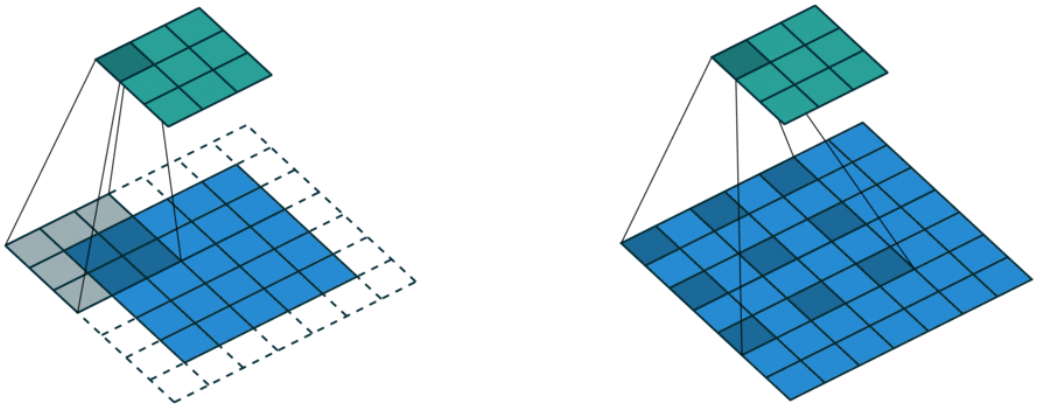
3.1.1 Layers definitions

Dilated convolution We consider a layer $L = (L_j)_{j \in [\![1,w]\!]}$, w being the number of feature maps L_j of L. We also consider $K = (K_{i,j})_{i,j}$, each $K_{i,j}$ being a 3×3 convolutional kernel. The dilated convolution operation of $K_{i,j}$ on L_j is denoted by $L_j *_r K_{i,j}$, r being the dilation parameter.
The output $C(x)$ of a pixel x is:

$$\begin{aligned} C(x) :&= (L_j *_r K_{i,j})(x) \\ &= \sum_{a+rb=x} L_j(a) K_{i,j}(b) \\ &= \sum_b L_j(x - rb) K_{i,j}(b) \end{aligned}$$

and we recognize the simple convolution when $r = 1$.
A dilated convolution enables the network getting larger receptive fields while preserving the input resolution[4]

[4] ref ?



(a) *A simple convolution* ($r = 1$) **(b)** *A dilated convolution* ($r = 2$)

Figure 5: *Illustration of two types of convolutions*

Adaptative Batch Normalization (ABN) As we have seen in (2.1.2), page 4, we need to normalize the data. We define the *adaptative normalization function* Ψ as:

$$\Psi(x) = a\ x + b\ BN(x),$$

where BN is the classic batch normalization[5], defined as:

$$BN(x) = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta.$$

As such, Ψ combines identity mapping and batch normalization. a, b, γ and β are learned parameters[6] by backpropagation. It allows the model to adapt to each dataset, choosing whether or not giving a big importance to the identity term and the normalization term.

Leaky rectifier (LReLU) In order to let our neural network model complex patterns in the data, we have to add a non-linear property to the model. It often is an activation function, such as a sigmoid or a tanh (Figure 6).

these activation functions are often used but they are bounded and their gradient is very low on the edges. Because we are going to manipulate high scalar values, we have to use an unbounded activation function, such as ReLU, $\Phi(x) = \max(0, x)$ (Figure 7a). But the issue with ReLU is that all the negative values become zero immediately, which decreases the ability of our model to train from the data. Hence the implementation of a *leaky rectifier*, LReLU (7b):

$$\Phi(x) = \max(\alpha x, x), \text{ with } 0 < \alpha < 1.$$

By implementing a Leaky Rectifier, we are able to take into account the negative valued pixels.

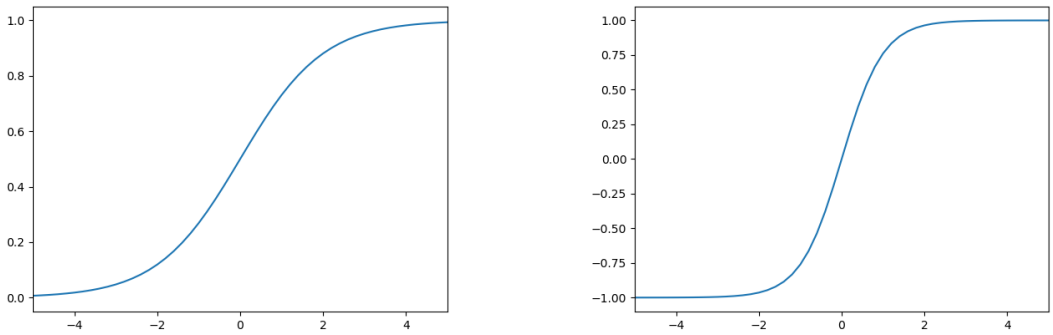
3.1.2 Chen

Context Aggregation Network (CAN) [7] blabla sur le RGB en entrée, RGB en sortie I -> f(I)

[5] reference ?

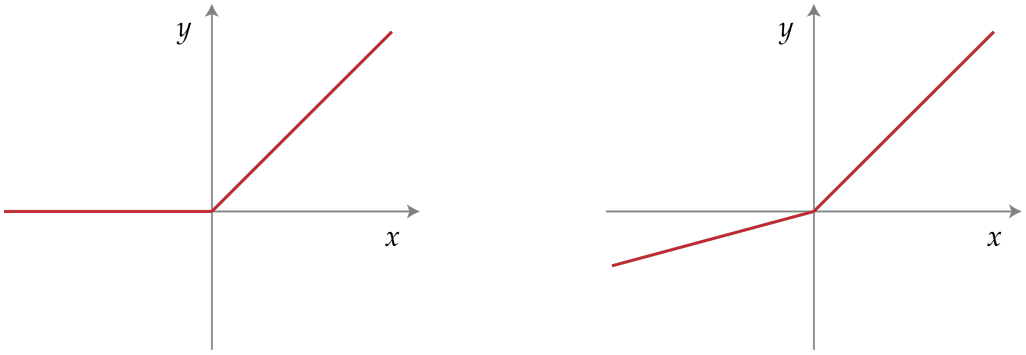
[6] ref : `https://pytorch.org/docs/stable/_modules/torch/nn/modules/batchnorm.html`

[7] reference



(a) *Sigmoid* **(b)** *tanh*

Figure 6: *Illustration of two bounded rectifiers*



(a) *ReLU* **(b)** *LReLU* ($\alpha = 0.2$)

Figure 7: *Illustration of two unbounded rectifiers*

input I	$\longrightarrow$	L^1	$\longrightarrow$	$\cdots$	$\longrightarrow$	L^s	$\longrightarrow$	$\cdots$	$\longrightarrow$	output (L^d)
$m \times n \times 3$		$m \times n \times w_1$				$m \times n \times w_s$				$m \times n \times 3$

Table 1: *Layers*

Architecture of a block Each block L_s is made of 3 layers:

1. *A dilated convolution*, $r_s = 2^s$
2. *An adaptative batch normalization*
3. *A leaky rectifier (ReLU)*

so that the content of an intermediate layer L^s can be computed from the content of the previous layer L^{s-1}:

$$L_i^s = \Phi\left(\Psi^s\left(b_i^s + \sum_j L_j^{s-1} *_{r_s} K_{i,j}^s\right)\right). \tag{1}$$

where ... is ...
and

$$L_j^{s-1} *_{r_s} K_{i,j}^s = \sum_{a+r_s b=x} L_j^{s-1}(a) K_{i,j}^s(b) \tag{2}$$

because of 3.1.1, page 5.

Layer	1	2	3	4	5	6	7
Convolution	3×3						
Dilation	1						
Batch Normalization	Yes						
LReLU	Yes						

Table 2: *Chen*

3.1.3 UNet

3.1.4 Chen + UNet

3.2 Total Variation (TV) Loss

3.2.1 MSE

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{f}(I)_i - f(I)_i|^2$$

3.2.2 TV

[8]

Why In such a search for well-segmented images, 2 criteria have to be fulfilled. The output needs to be as close as possible to the ground truth image; but we also need the segmented image to present a lot of zones where the color gradient $\nabla f(I)$ is equal to 0. Thus, we want to implement a train loss function that could help us satisfy these two criteria. In order to do so, we use the Total Variation (TV) loss, defined below.

Formula

$$L_{TV} = \frac{1}{N}\sum_{i=1}^{N} |\hat{f}(I)_i - f(I)_i|^2 + \frac{1}{N}\sum_{i=1}^{N} |(\nabla f(I))_i)|^2$$

granting an improvement in the output image smoothness.

3.3 Implementation

The network was implemented with PyTorch[9] and we used GPU acceleration [...] (pytorch), se renseigner (section assez courante) GPU acceleraation code sur github

4 Expérience et résultats

4.1 Hyperparameters

petit bilan des valeurs choisies évolution des paramètres a et b ?

4.1.1 Learning rate

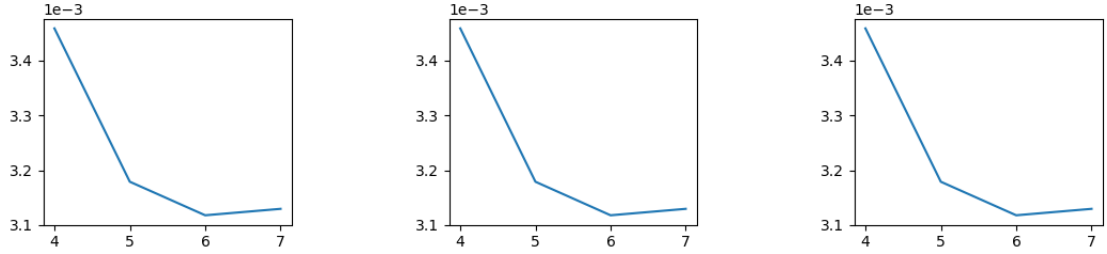
Constant value entrainement (lr, alpha) -> courbes de loss, et loss qui sature (cluster) d'où changement de lr au cours des epochs

[8] ref

[9] Repository can be found at `https://github.com/theodumont/superpixels-segmentation`.

lr_0	decay?	saturation?	d	TV?
0.001	No	No	7	No
0.01	No	No	7	No
0.01	$\times 0.5$ every 2 epochs	10^{-4}	7	No
0.001	$\times 0.5$ every 2 epochs	10^{-4}	7	No

Table 3: Runs for learning rate tuning



(a) *Graph* **(b)** *Graph* **(c)** *Graph*

Figure 8: *Tuning of learning rate*

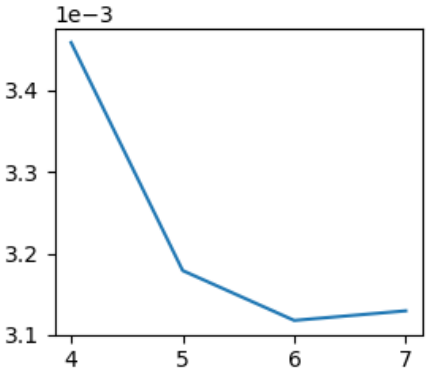
Non constant value

4.1.2 Network size d

- Learning rate initialisé à 0.01, divisé par 2 toutes les 2 époques, saturation à 1e-4 - Pas de régularisation TV CONCLUSION des run 3 à 5: Il est préférable de laisser d=7. Entre d=6 et d=7, l'amélioration

d	4	5	6	7	8
loss$\times 10^3$	3.46	3.18	3.12	3.13	???

(a) *Loss values on validation set*



(b) *Graph*

Figure 9: *Tuning of network size*

semble relativement faible. bon intermédiaire entre temps de calcul et performances

4.1.3 Number of epochs

nb epochs: on le sélectionne en prenant le minimum de la validation loss

4.1.4 TV regularization

4.1.5 Runs

tableaux et graphes

4.2 Results on dataset

image originale -> CNN -> résultat du filtre dans eikonal -> superpixels sans couleurs + couleur moyenne pour chaque spp de l'image originale cf results/images

4.2.1 The dataset

BSD dataset, BSD fait a la main et pas a l'arrache comme COCO

4.2.2 Results

metrics Here are the previously defined metrics of some well-known superpixel segmentation algorithms.

Algorithm		BR	UE	CO
image analysis	EI [10] EIT [11] WS [12]			
neural networks	ref [13]	0.8995	0.0473	0.5409
	Ours	0.8781[14]	0.0388	0.7682

Table 4: Comparisons of metrics on the BSD dataset for different superpixel segmentation algorithms

We use the ?? alorithm as a reference to evaluate the performances of our model. pas très grave parce que la compacité est pourrie du coup comme les contours oscillent ils intersectent plus de contours de l'image

5 Conclusion/Discussion

On a présenté un nouveau...
On a prouvé...
Il reste à faire...
relire tous les mails pour avoir toutes les infos sur performances etc

Special thanks

Sources

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