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Aula 7: Segmentação de Imagens

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Universidade Federal de Goiás (UFG)

DEEP LEARNING
BRASIL

Sumário

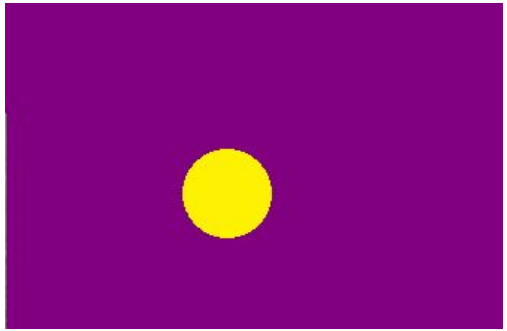
- No último episódio...
- Tarefas em visão computacional
- Segmentação Semântica
- Segmentação Semântica por Instância
- No próximo episódio...

No último episódio...

- Tarefas em visão computacional

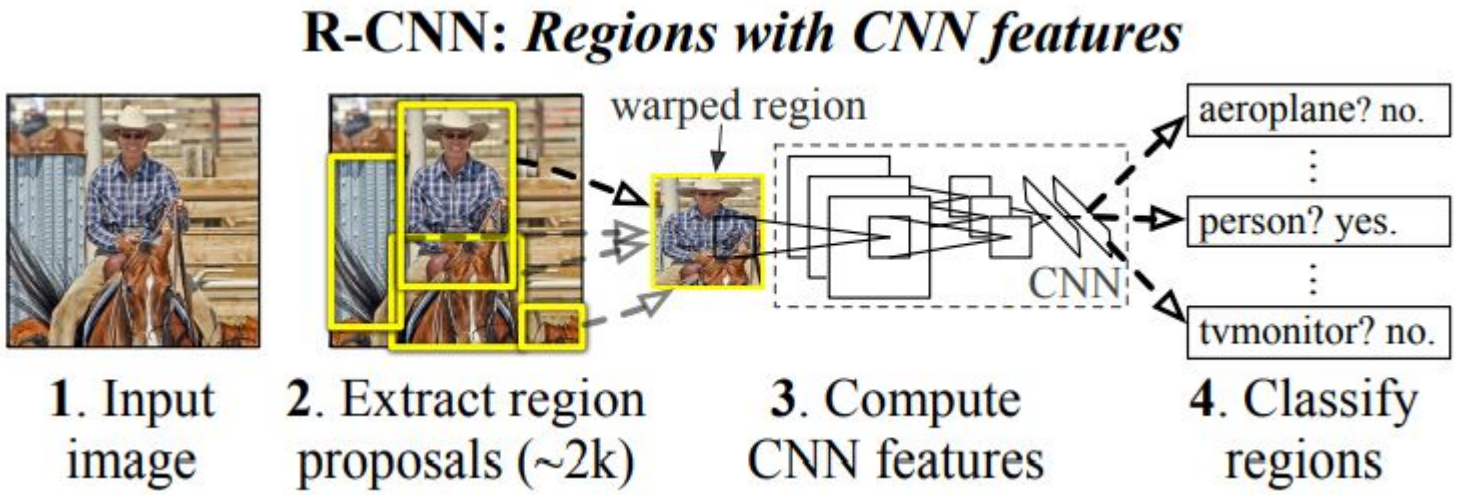
Detecção e Localização

Segmentação



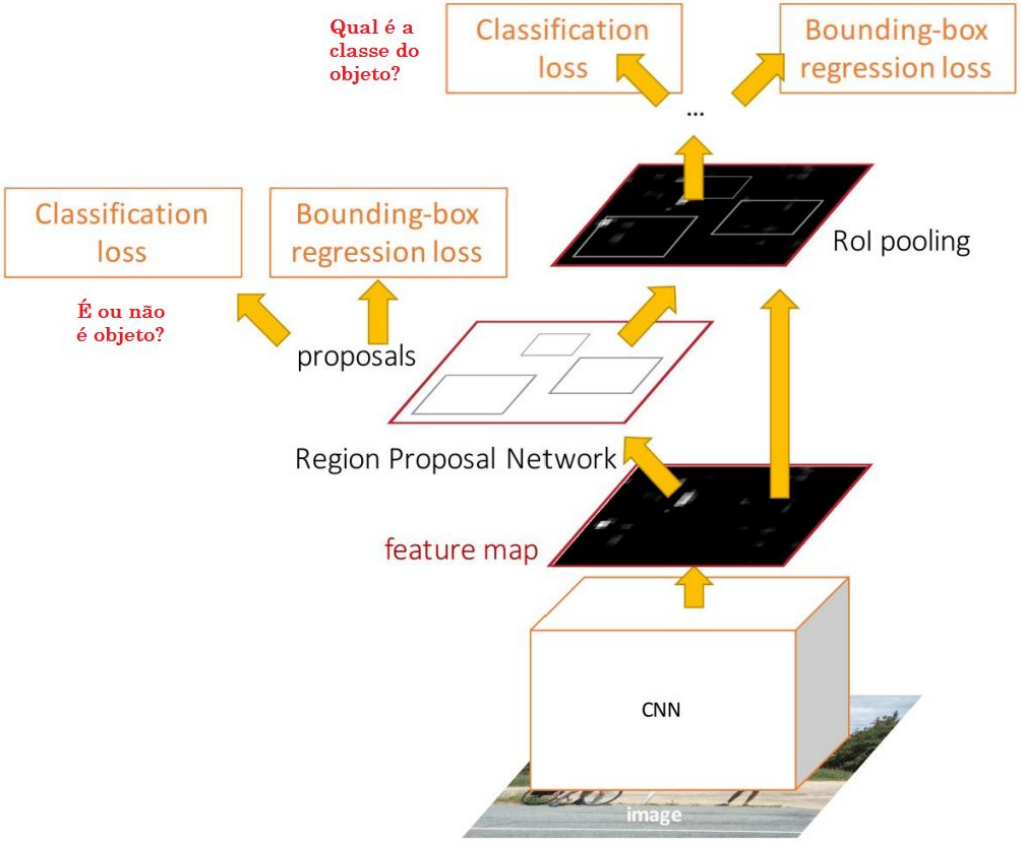
No último episódio...

- R-CNN



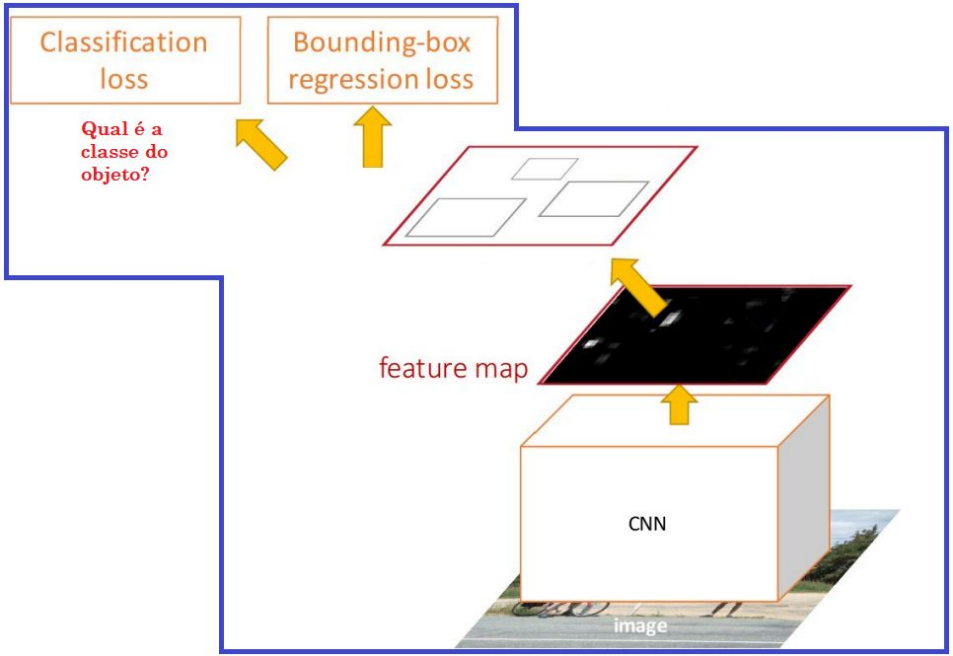
No último episódio...

- Faster R-CNN



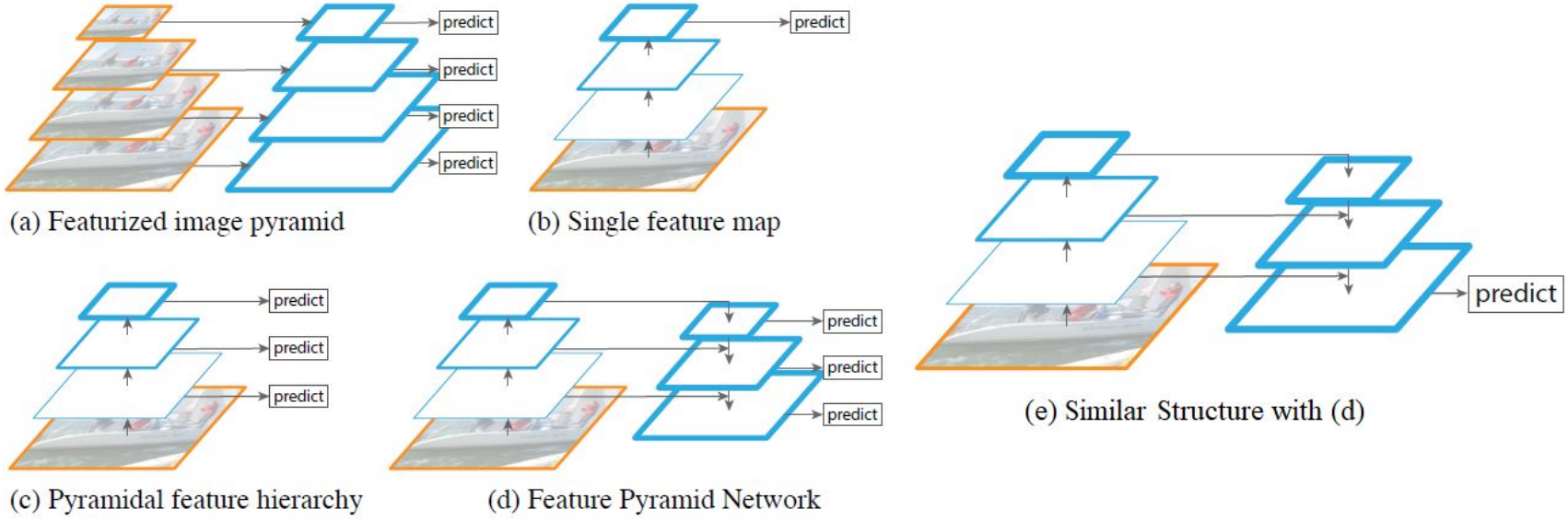
No último episódio...

- YOLO/SSD/RetinaNet



No último episódio...

- Feature Pyramid Netwroks



No último episódio...

- Focal Loss

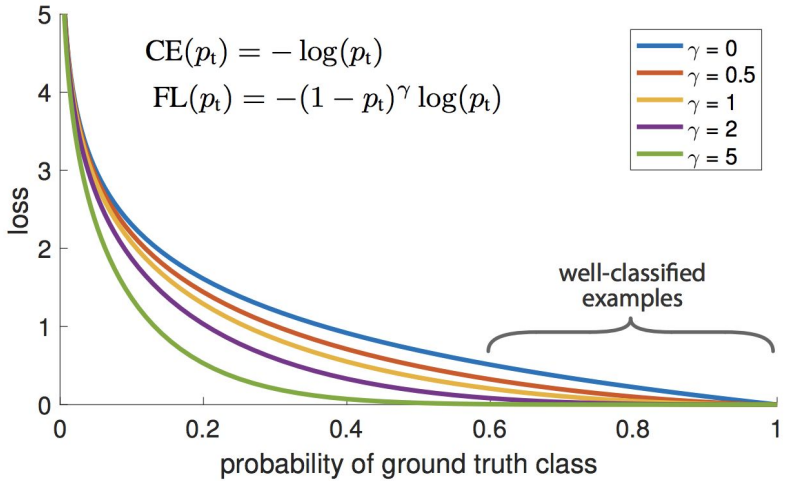


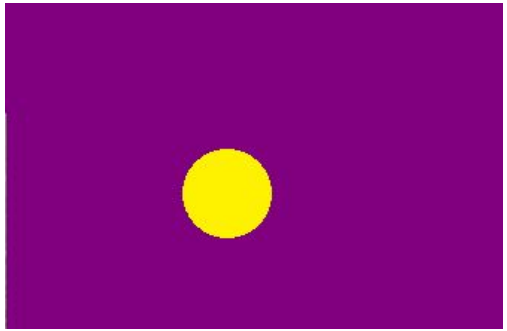
Figure 1. We propose a novel loss we term the *Focal Loss* that adds a factor $(1 - p_t)^{\gamma}$ to the standard cross entropy criterion. Setting $\gamma > 0$ reduces the relative loss for well-classified examples ($p_t > .5$), putting more focus on hard, misclassified examples. As our experiments will demonstrate, the proposed focal loss enables training highly accurate dense object detectors in the presence of vast numbers of easy background examples.

Tarefas em visão computacional

- Agora falta “só”...

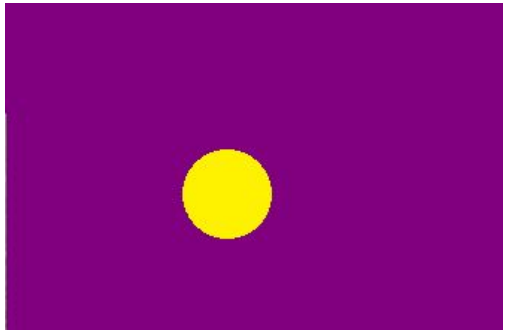
Detecção e Localização

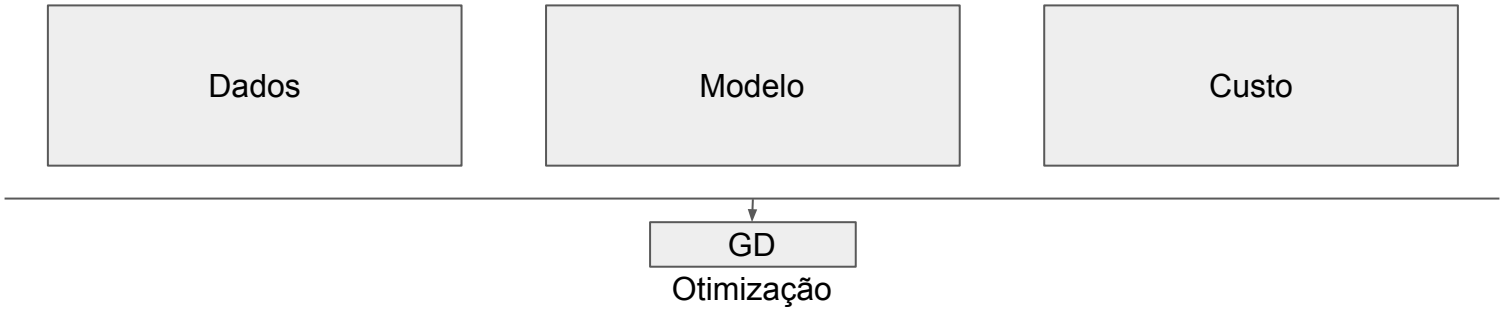
Segmentação



Segmentação Semântica

- Estrutura de ML





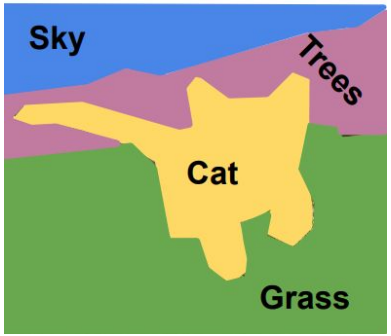
Segmentação Semântica

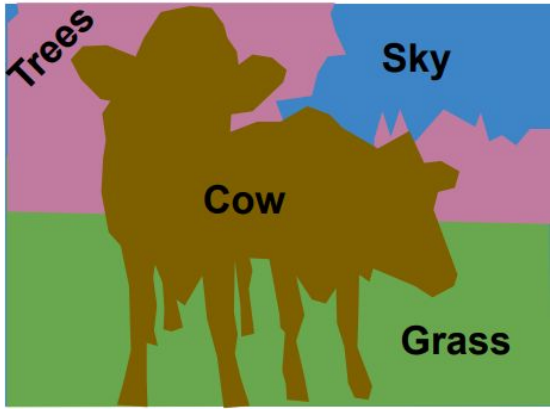
- Como são os dados?

Segmentação Semântica

- Como são os dados?

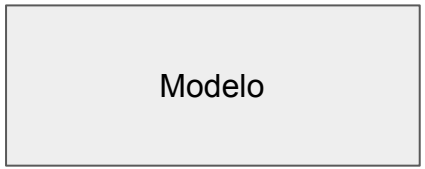
Dados





Segmentação Semântica

- Como é o modelo?



Segmentação Semântica

- Fully Convolutional Networks (FCN)

Fully Convolutional Networks for Semantic Segmentation

Jonathan Long* Evan Shelhamer* Trevor Darrell
UC Berkeley
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Abstract

Convolutional networks are powerful visual models that yield hierarchies of features. We show that convolutional networks by themselves, trained end-to-end, pixels-to-pixels, exceed the state-of-the-art in semantic segmentation. Our key insight is to build "fully convolutional" networks that take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning. We define and detail the space of fully convolutional networks, explain their application to spatially dense prediction tasks, and draw connections to prior models. We adapt contemporary classification networks (AlexNet [22], the VGG net [34], and GoogLeNet [35]) into fully convolutional networks and transfer their learned representations by fine-tuning [5] to the segmentation task. We then define a skip architecture that combines semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to produce accurate and detailed segmentations. Our fully convolutional network achieves state-of-the-art segmentation of PASCAL VOC (20% relative improvement to 62.2% mean IU on 2012), NYUDv2, and SIFT Flow, while inference takes less than one fifth of a second for a typical image.

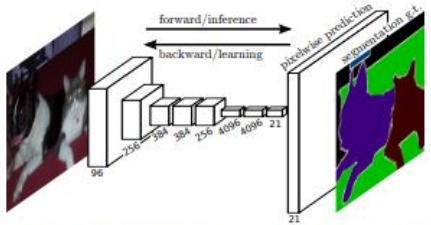

Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

We show that a fully convolutional network (FCN) trained end-to-end, pixels-to-pixels on semantic segmentation exceeds the state-of-the-art without further machinery. To our knowledge, this is the first work to train FCNs end-to-end (1) for pixelwise prediction and (2) from supervised pre-training. Fully convolutional versions of existing networks predict dense outputs from arbitrary-sized inputs. Both learning and inference are performed whole-image-at-a-time by dense feedforward computation and backpropagation. In-network upsampling layers enable pixelwise prediction and learning in nets with subsampled pooling.

This method is efficient, both asymptotically and abso-

Segmentação Semântica

- Fully Convolutional Networks (FCN)

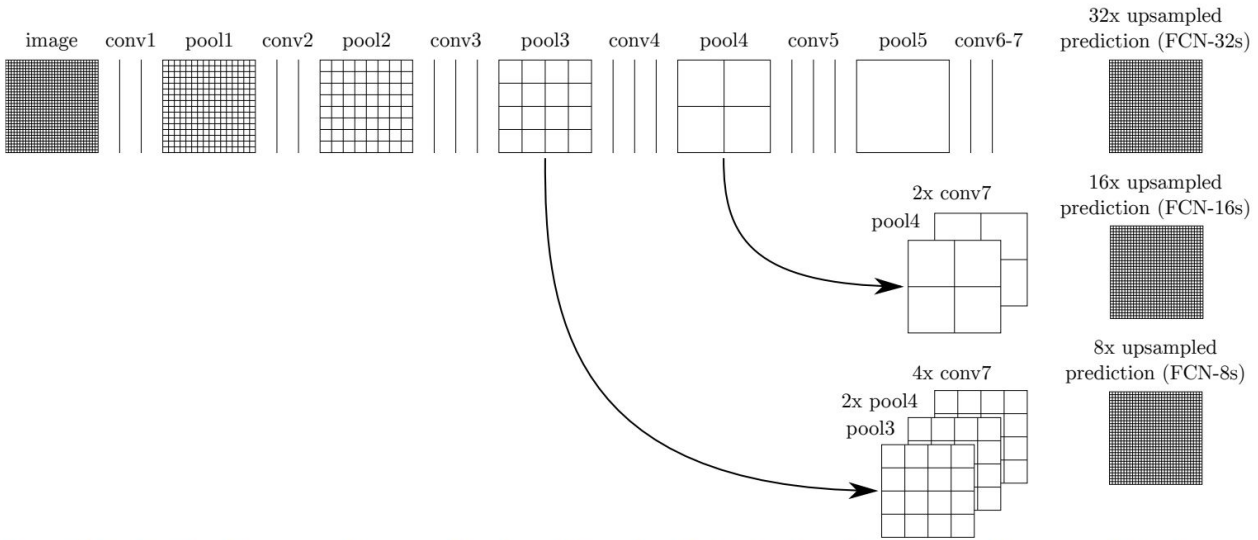

Figure 3. Our DAG nets learn to combine coarse, high layer information with fine, low layer information. Pooling and prediction layers are shown as grids that reveal relative spatial coarseness, while intermediate layers are shown as vertical lines. First row (FCN-32s): Our single-stream net, described in Section 4.1, upsamples stride 32 predictions back to pixels in a single step. Second row (FCN-16s): Combining predictions from both the final layer and the `pool4` layer, at stride 16, lets our net predict finer details, while retaining high-level semantic information. Third row (FCN-8s): Additional predictions from `pool3`, at stride 8, provide further precision.

Segmentação Semântica

- U-net

U-Net: Convolutional Networks for Biomedical Image Segmentation

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Abstract. There is large consent that successful training of deep networks requires many thousand annotated training samples. In this paper, we present a network and training strategy that relies on the strong use of data augmentation to use the available annotated samples more efficiently. The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. We show that such a network can be trained end-to-end from very few images and outperforms the prior best method (a sliding-window convolutional network) on the ISBI challenge for segmentation of neuronal structures in electron microscopic stacks. Using the same network trained on transmitted light microscopy images (phase contrast and DIC) we won the ISBI cell tracking challenge 2015 in these categories by a large margin. Moreover, the network is fast. Segmentation of a 512x512 image takes less than a second on a recent GPU. The full implementation (based on Caffe) and the trained networks are available at http://lmb.informatik.uni-freiburg.de/people/ronneber/u-net.

1 Introduction

In the last two years, deep convolutional networks have outperformed the state of the art in many visual recognition tasks, e.g. [7,3]. While convolutional networks

Segmentação Semântica

- U-net

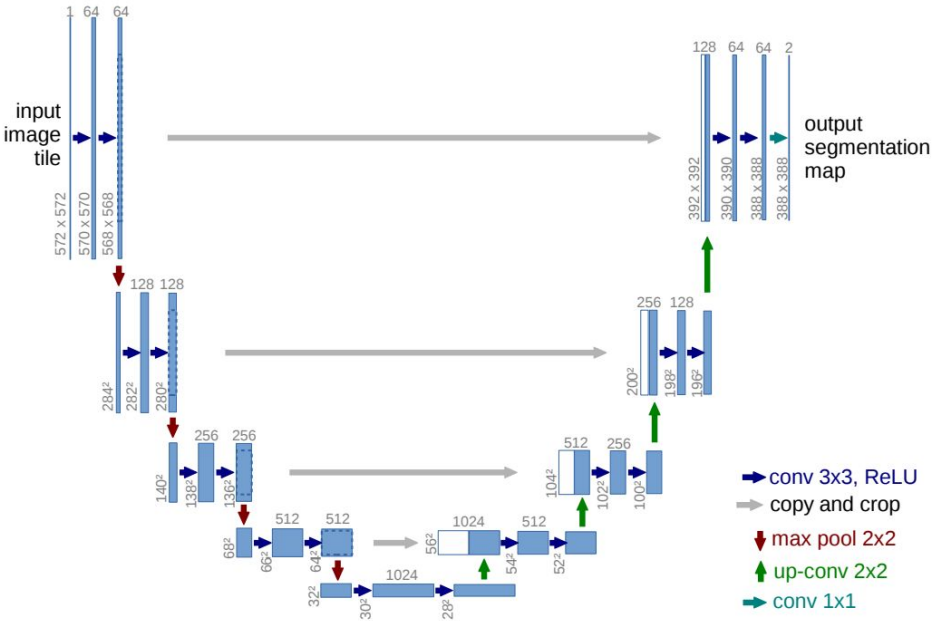


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Segmentação Semântica

- SegNet

SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation

Vijay Badrinarayanan, Alex Kendall, Roberto Cipolla, *Senior Member, IEEE,*

Abstract—We present a novel and practical deep fully convolutional neural network architecture for semantic pixel-wise segmentation termed SegNet. This core trainable segmentation engine consists of an encoder network, a corresponding decoder network followed by a pixel-wise classification layer. The architecture of the encoder network is topologically identical to the 13 convolutional layers in the VGG16 network [1]. The role of the decoder network is to map the low resolution encoder feature maps to full input resolution feature maps for pixel-wise classification. The novelty of SegNet lies is in the manner in which the decoder upsamples its lower resolution input feature map(s). Specifically, the decoder uses pooling indices computed in the max-pooling step of the corresponding encoder to perform non-linear upsampling. This eliminates the need for learning to upsample. The upsampled maps are sparse and are then convolved with trainable filters to produce dense feature maps. We compare our proposed architecture with the widely adopted FCN [2] and also with the well known DeepLab-LargeFOV [3], DeconvNet [4] architectures. This comparison reveals the memory versus accuracy trade-off involved in achieving good segmentation performance.
SegNet was primarily motivated by scene understanding applications. Hence, it is designed to be efficient both in terms of memory and computational time during inference. It is also significantly smaller in the number of trainable parameters than other competing architectures and can be trained end-to-end using stochastic gradient descent. We also performed a controlled benchmark of SegNet and other architectures on both road scenes and SUN RGB-D indoor scene segmentation tasks. These quantitative assessments show that SegNet provides good performance with competitive inference time and most efficient inference memory-wise as compared to other architectures. We also provide a Caffe implementation of SegNet and a web demo at http://mi.eng.cam.ac.uk/projects/segnet/.

Index Terms—Deep Convolutional Neural Networks, Semantic Pixel-Wise Segmentation, Indoor Scenes, Road Scenes, Encoder, Decoder, Pooling, Upsampling.

1 Introduction

Semantic segmentation has a wide array of applications ranging from scene understanding, inferring support-relationships among

pedestrians) and understand the spatial-relationship (context) between different classes such as road and side-walk. In typical road scenes, the majority of the pixels belong to large classes such

Segmentação Semântica

- SegNet

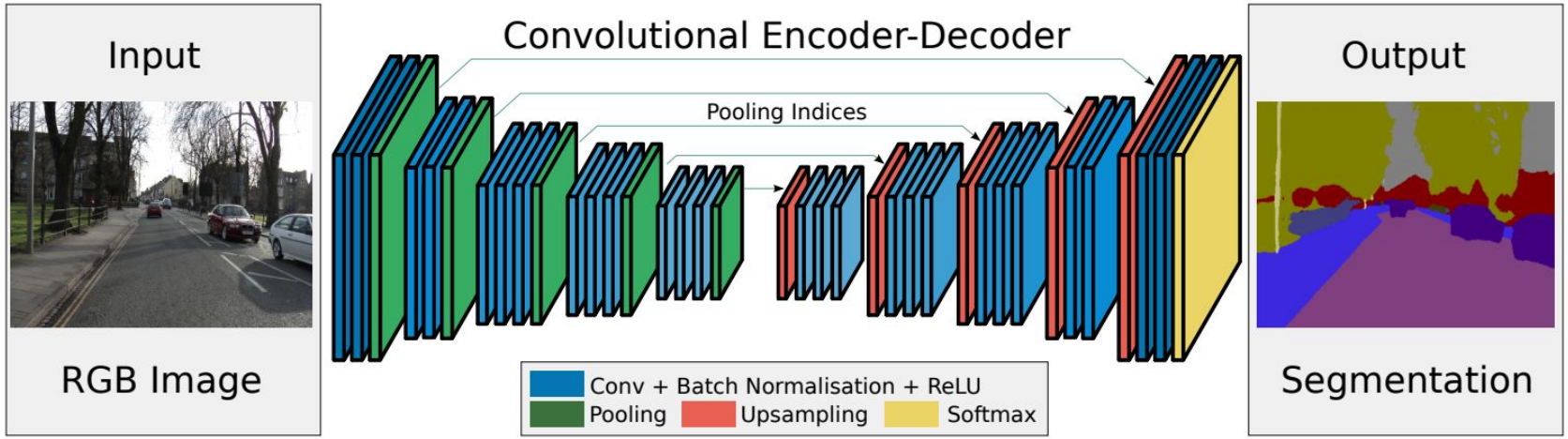


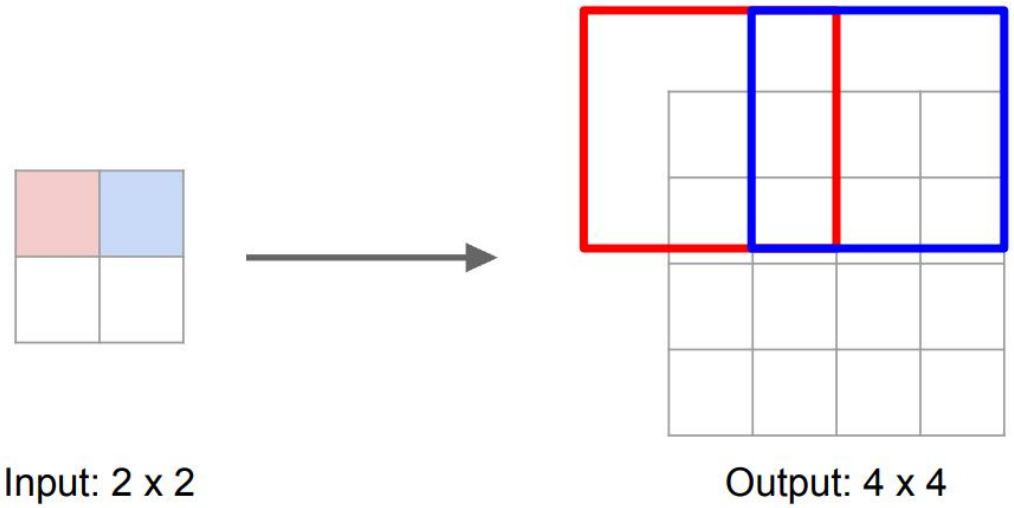
Fig. 2. An illustration of the SegNet architecture. There are no fully connected layers and hence it is only convolutional. A decoder upsamples its input using the transferred pool indices from its encoder to produce a sparse feature map(s). It then performs convolution with a trainable filter bank to densify the feature map. The final decoder output feature maps are fed to a soft-max classifier for pixel-wise classification.

Segmentação Semântica

- Como fazer o upsample?

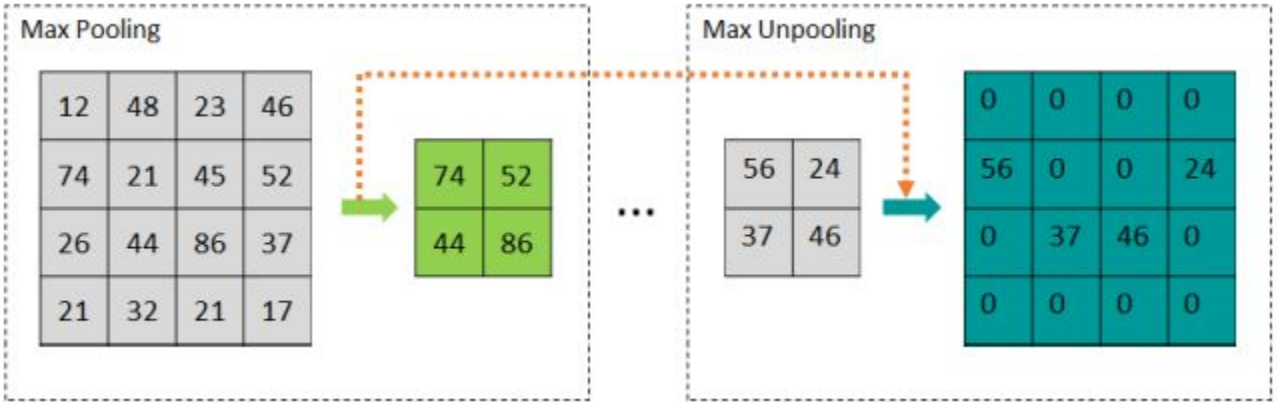
Segmentação Semântica

- Convolução transposta



Segmentação Semântica

- Max-Unpooling



Segmentação Semântica

- DeepLab v1
  - FCN + CRFs

SEMANTIC IMAGE SEGMENTATION WITH DEEP CONVOLUTIONAL NETS AND FULLY CONNECTED CRFS

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ABSTRACT

Deep Convolutional Neural Networks (DCNNs) have recently shown state of the art performance in high level vision tasks, such as image classification and object detection. This work brings together methods from DCNNs and probabilistic graphical models for addressing the task of pixel-level classification (also called "semantic image segmentation"). We show that responses at the final layer of DCNNs are not sufficiently localized for accurate object segmentation. This is due to the very invariance properties that make DCNNs good for high level tasks. We overcome this poor localization property of deep networks by combining the responses at the final DCNN layer with a fully connected Conditional Random Field (CRF). Qualitatively, our "DeepLab" system is able to localize segment boundaries at a level of accuracy which is beyond previous methods. Quantitatively, our method sets the new state-of-art at the PASCAL VOC-2012 semantic image segmentation task, reaching 71.6% IOU accuracy in the test set. We show how these results can be obtained efficiently: Careful network re-purposing and a novel application of the 'hole' algorithm from the wavelet community allow dense computation of neural net responses at 8 frames per second on a modern GPU.

1 INTRODUCTION

Deep Convolutional Neural Networks (DCNNs) had been the method of choice for document recog-

Segmentação Semântica

- DeepLab v1

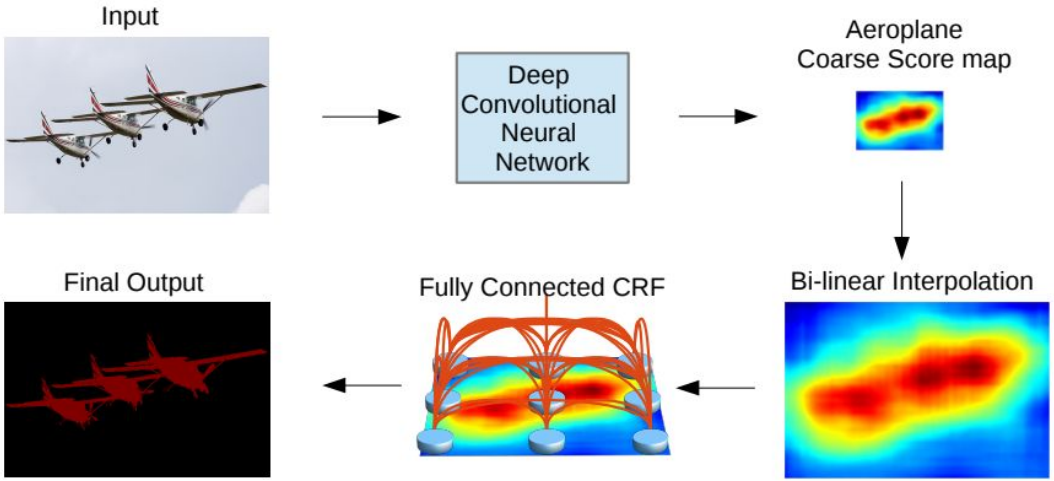
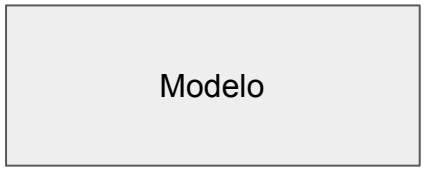


Figure 3: Model Illustration. The coarse score map from Deep Convolutional Neural Network (with fully convolutional layers) is upsampled by bi-linear interpolation. A fully connected CRF is applied to refine the segmentation result. Best viewed in color.

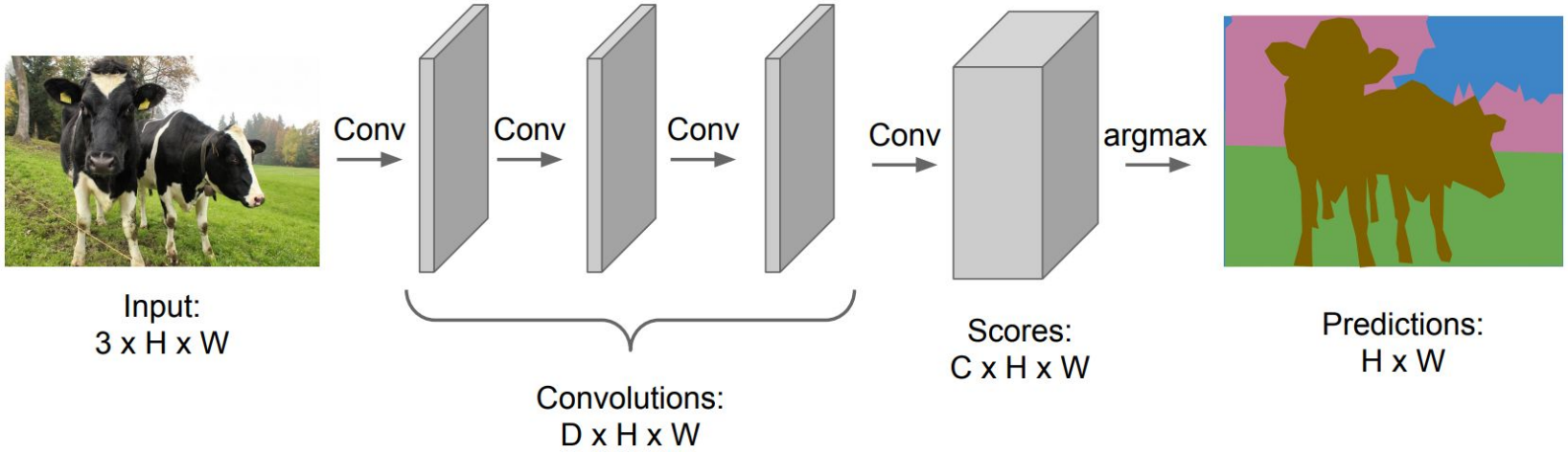
Segmentação Semântica

- Alguma outra possibilidade?



Segmentação Semântica

- Alguma outra possibilidade?



Modelo

Segmentação Semântica

- Dilated Convolutions

MULTI-SCALE CONTEXT AGGREGATION BY DILATED CONVOLUTIONS

Fisher Yu
Princeton University

Vladlen Koltun
Intel Labs

ABSTRACT

State-of-the-art models for semantic segmentation are based on adaptations of convolutional networks that had originally been designed for image classification. However, dense prediction problems such as semantic segmentation are structurally different from image classification. In this work, we develop a new convolutional network module that is specifically designed for dense prediction. The presented module uses dilated convolutions to systematically aggregate multi-scale contextual information without losing resolution. The architecture is based on the fact that dilated convolutions support exponential expansion of the receptive field without loss of resolution or coverage. We show that the presented context module increases the accuracy of state-of-the-art semantic segmentation systems. In addition, we examine the adaptation of image classification networks to dense prediction and show that simplifying the adapted network can increase accuracy.

1 INTRODUCTION

Many natural problems in computer vision are instances of dense prediction. The goal is to compute a discrete or continuous label for each pixel in the image. A prominent example is semantic segmentation, which calls for classifying each pixel into one of a given set of categories (He et al., 2004; Shotton et al., 2009; Kohli et al., 2009; Krähenbühl & Koltun, 2011). Semantic segmentation is challenging because it requires combining pixel-level accuracy with multi-scale contextual reasoning (He et al., 2004; Galleguillos & Belongie, 2010).

Segmentação Semântica

- Dilated Convolutions

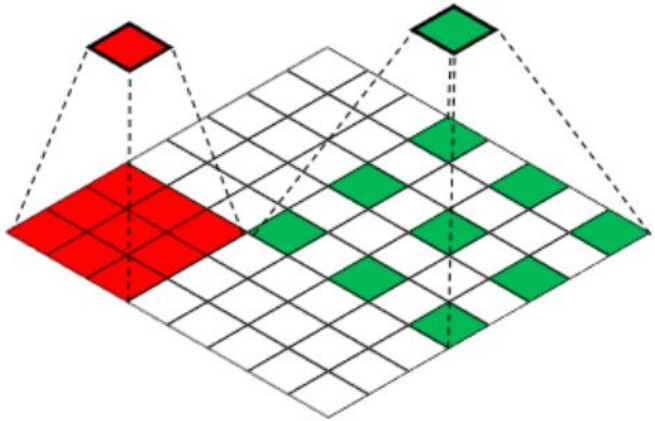


Figure 8: Normal convolution(red) vs. Atrous or Dilated convolution(green)

Segmentação Semântica

- DeepLab v2
  - Dilated + CRFs

DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs

Liang-Chieh Chen, George Papandreou, *Senior Member, IEEE,* Iasonas Kokkinos, *Member, IEEE,* Kevin Murphy, and Alan L. Yuille, *Fellow, IEEE*

Abstract—In this work we address the task of semantic image segmentation with Deep Learning and make three main contributions that are experimentally shown to have substantial practical merit. *First*, we highlight convolution with upsampled filters, or 'atrous convolution', as a powerful tool in dense prediction tasks. Atrous convolution allows us to explicitly control the resolution at which feature responses are computed within Deep Convolutional Neural Networks. It also allows us to effectively enlarge the field of view of filters to incorporate larger context without increasing the number of parameters or the amount of computation. *Second*, we propose atrous spatial pyramid pooling (ASPP) to robustly segment objects at multiple scales. ASPP probes an incoming convolutional feature layer with filters at multiple sampling rates and effective fields-of-views, thus capturing objects as well as image context at multiple scales. *Third*, we improve the localization of object boundaries by combining methods from DCNNs and probabilistic graphical models. The commonly deployed combination of max-pooling and downsampling in DCNNs achieves invariance but has a toll on localization accuracy. We overcome this by combining the responses at the final DCNN layer with a fully connected Conditional Random Field (CRF), which is shown both qualitatively and quantitatively to improve localization performance. Our proposed "DeepLab" system sets the new state-of-art at the PASCAL VOC-2012 semantic image segmentation task, reaching 79.7% mIOU in the test set, and advances the results on three other datasets: PASCAL-Context, PASCAL-Person-Part, and Cityscapes. All of our code is made publicly available online.

Index Terms—Convolutional Neural Networks, Semantic Segmentation, Atrous Convolution, Conditional Random Fields.

1 Introduction

Segmentação Semântica

- DeepLab v2

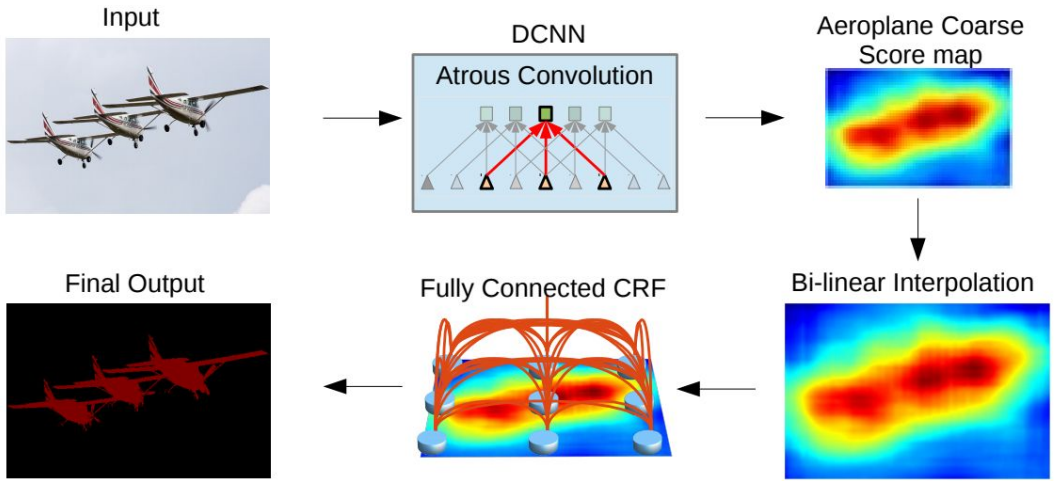


Fig. 1: Model Illustration. A Deep Convolutional Neural Network such as VGG-16 or ResNet-101 is employed in a fully convolutional fashion, using atrous convolution to reduce the degree of signal downsampling (from 32x down 8x). A bilinear interpolation stage enlarges the feature maps to the original image resolution. A fully connected CRF is then applied to refine the segmentation result and better capture the object boundaries.

Segmentação Semântica

- RefineNet

RefineNet: Multi-Path Refinement Networks for High-Resolution Semantic Segmentation

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[1]The University of Adelaide, [2]Australian Centre for Robotic Vision
{guosheng.lin;anton.milan;chunhua.shen;ian.reid}@adelaide.edu.au

Abstract

Recently, very deep convolutional neural networks (CNNs) have shown outstanding performance in object recognition and have also been the first choice for dense classification problems such as semantic segmentation. However, repeated subsampling operations like pooling or convolution striding in deep CNNs lead to a significant decrease in the initial image resolution. Here, we present RefineNet, *a generic multi-path refinement network that explicitly exploits all the information available along the down-sampling process to enable high-resolution prediction using long-range residual connections. In this way, the deeper layers that capture high-level semantic features can be directly refined using fine-grained features from earlier convolutions. The individual components of RefineNet employ residual connections following the identity mapping mindset, which allows for effective end-to-end training. Further, we introduce chained residual pooling, which captures rich background context in an efficient manner. We carry out comprehensive experiments and set new state-of-the-art results on seven public datasets. In particular, we achieve an intersection-over-union score of* 83.4 *on the challenging PASCAL VOC 2012 dataset, which is the best reported result to date.*

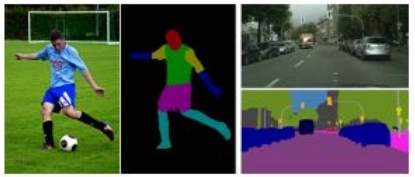

Figure 1. Example results of our method on the task of object parsing *(left)* and semantic segmentation *(right)*.

1. Introduction

and semantic segmentation [36, 5]. Multiple stages of spatial pooling and convolution strides reduce the final image prediction typically by a factor of 32 in each dimension, thereby losing much of the finer image structure.

One way to address this limitation is to learn deconvolutional filters as an up-sampling operation [38, 36] to generate high-resolution feature maps. The deconvolution operations are not able to recover the low-level visual features which are lost after the down-sampling operation in the convolution forward stage. Therefore, they are unable to output accurate high-resolution prediction. Low-level visual information is essential for accurate prediction on the boundaries or details. The method DeepLab recently proposed by Chen *et al*. [6] employs atrous (or dilated) convolutions to account for larger receptive fields without downscaling the image. DeepLab is widely applied and represents state-of-the-art performance on semantic segmentation. This strategy, although successful, has at least two limitations. First,

Segmentação Semântica

- RefineNet

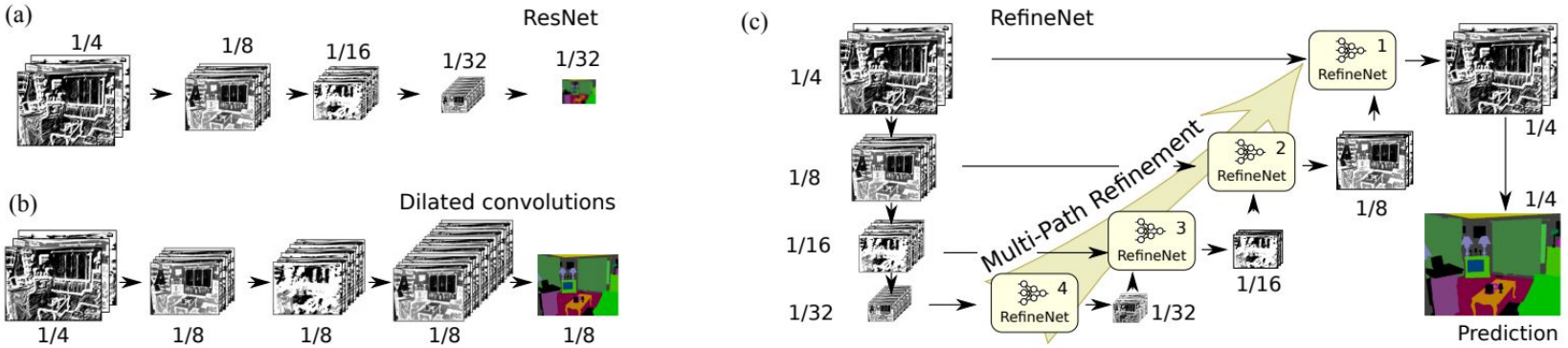

Figure 2. Comparison of fully convolutional approaches for dense classification. Standard multi-layer CNNs, such as ResNet *(a)* suffer from downscaling of the feature maps, thereby losing fine structures along the way. Dilated convolutions *(b)* remedy this shortcoming by introducing atrous filters, but are computationally expensive to train and quickly reach memory limits even on modern GPUs. Our proposed architecture that we call RefineNet *(c)* exploits various levels of detail at different stages of convolutions and fuses them to obtain a high-resolution prediction without the need to maintain large intermediate feature maps. The details of the RefineNet block are outlined in Sec. 3 and illustrated in Fig 3.

Segmentação Semântica

- RefineNet

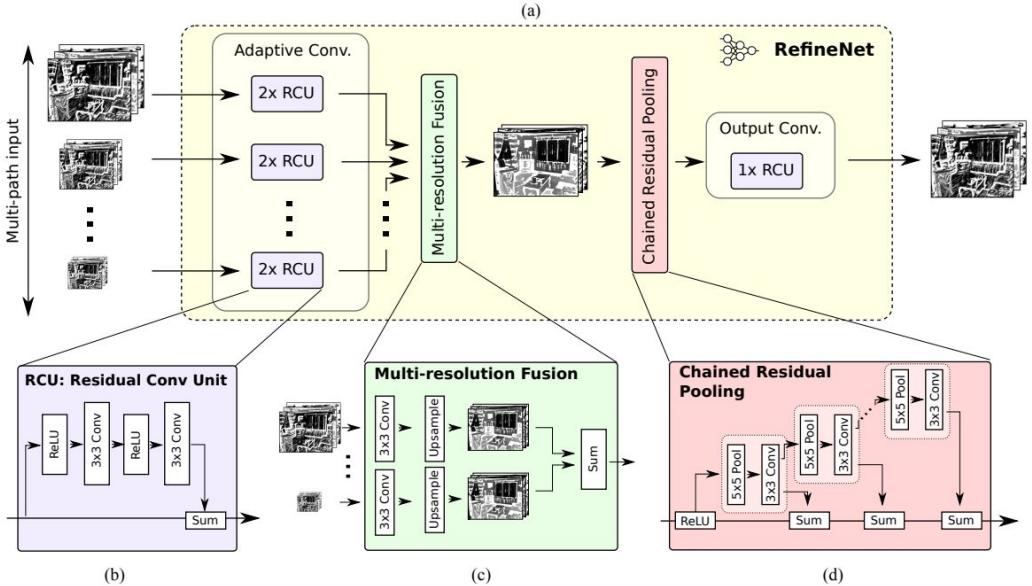

Figure 3. The individual components of our multi-path refinement network architecture RefineNet. Components in RefineNet employ residual connections with identity mappings. In this way, gradients can be directly propagated within RefineNet via local residual connections, and also directly propagate to the input paths via long-range residual connections, and thus we achieve effective end-to-end training of the whole system.

Segmentação Semântica

- PSPNet

Pyramid Scene Parsing Network

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[1]The Chinese University of Hong Kong [2]SenseTime Group Limited
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Abstract

Scene parsing is challenging for unrestricted open vocabulary and diverse scenes. In this paper, we exploit the capability of global context information by different-region-based context aggregation through our pyramid pooling module together with the proposed pyramid scene parsing network (PSPNet). Our global prior representation is effective to produce good quality results on the scene parsing task, while PSPNet provides a superior framework for pixel-level prediction. The proposed approach achieves state-of-the-art performance on various datasets. It came first in ImageNet scene parsing challenge 2016, PASCAL VOC 2012 benchmark and Cityscapes benchmark. A single PSPNet yields the new record of mIoU accuracy 85.4% on PASCAL VOC 2012 and accuracy 80.2% on Cityscapes.

(a) Image (b) Ground Truth

Figure 1. Illustration of complex scenes in ADE20K dataset.

1. Introduction

Segmentação Semântica

- PSPNet

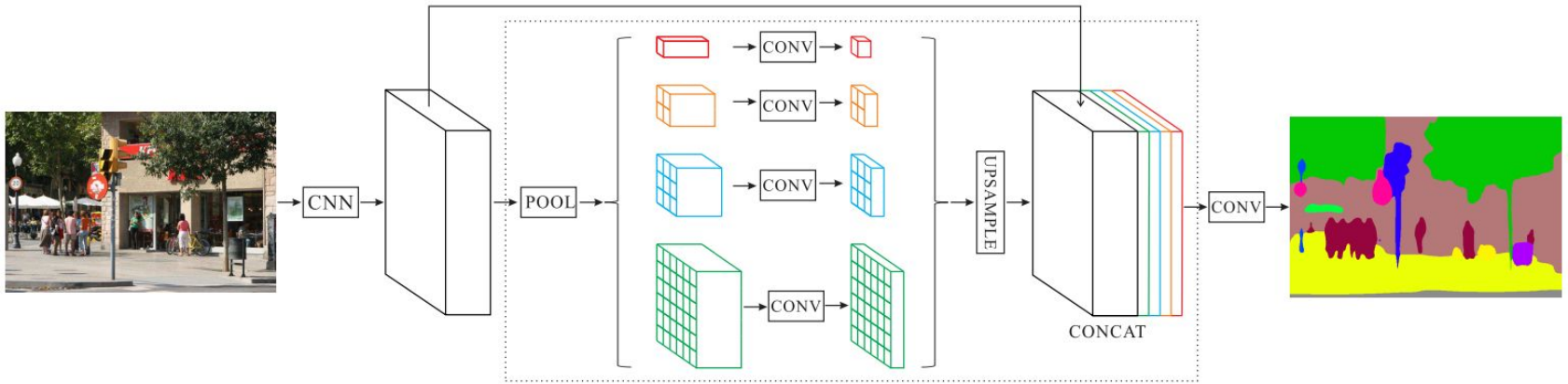

Figure 3. Overview of our proposed PSPNet. Given an input image (a), we first use CNN to get the feature map of the last convolutional layer (b), then a pyramid parsing module is applied to harvest different sub-region representations, followed by upsampling and concatenation layers to form the final feature representation, which carries both local and global context information in (c). Finally, the representation is fed into a convolution layer to get the final per-pixel prediction (d).

Segmentação Semântica

- DeepLab v3
  - Dilated + Pyramid pool

Rethinking Atrous Convolution for Semantic Image Segmentation

Liang-Chieh Chen George Papandreou Florian Schroff Hartwig Adam
Google Inc.
{lcchen, gpapan, fschroff, hadam}@google.com

Abstract

In this work, we revisit atrous convolution, a powerful tool to explicitly adjust filter's field-of-view as well as control the resolution of feature responses computed by Deep Convolutional Neural Networks, in the application of semantic image segmentation. To handle the problem of segmenting objects at multiple scales, we design modules which employ atrous convolution in cascade or in parallel to capture multi-scale context by adopting multiple atrous rates. Furthermore, we propose to augment our previously proposed Atrous Spatial Pyramid Pooling module, which probes convolutional features at multiple scales, with image-level features encoding global context and further boost performance. We also elaborate on implementation details and share our experience on training our system. The proposed 'DeepLabv3' system significantly improves over our previous DeepLab versions without DenseCRF post-processing and attains comparable performance with other state-of-art models on the PASCAL VOC 2012 semantic image segmentation benchmark.

1. Introduction

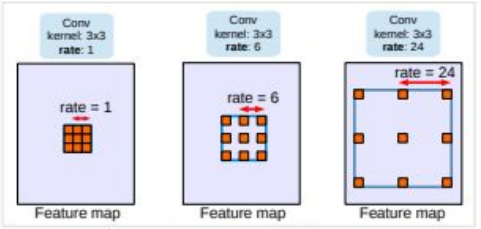

Figure 1. Atrous convolution with kernel size 3×3 and different rates. Standard convolution corresponds to atrous convolution with $rate = 1$. Employing large value of atrous rate enlarges the model's field-of-view, enabling object encoding at multiple scales.

responses are computed within DCNNs without requiring learning extra parameters.

Another difficulty comes from the existence of objects at multiple scales. Several methods have been proposed to handle the problem and we mainly consider four categories in this work, as illustrated in Fig. 2. First, the DCNN is applied to an image pyramid to extract features for each scale input [22, 19, 69, 55, 12, 11] where objects at different scales become prominent at different feature maps. Sec-

Segmentação Semântica

- DeepLab v3+
  - Dilated + Pyramid pool + FCN

Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation

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Google Inc.
{lcchen, yukun, gpapan, fschroff, hadam}@google.com

Abstract. Spatial pyramid pooling module or encode-decoder structure are used in deep neural networks for semantic segmentation task. The former networks are able to encode multi-scale contextual information by probing the incoming features with filters or pooling operations at multiple rates and multiple effective fields-of-view, while the latter networks can capture sharper object boundaries by gradually recovering the spatial information. In this work, we propose to combine the advantages from both methods. Specifically, our proposed model, DeepLabv3+, extends DeepLabv3 by adding a simple yet effective decoder module to refine the segmentation results especially along object boundaries. We further explore the Xception model and apply the depthwise separable convolution to both Atrous Spatial Pyramid Pooling and decoder modules, resulting in a faster and stronger encoder-decoder network. We demonstrate the effectiveness of the proposed model on PASCAL VOC 2012 and Cityscapes datasets, achieving the test set performance of 89.0% and 82.1% without any post-processing. Our paper is accompanied with a publicly available reference implementation of the proposed models in Tensorflow at https://github.com/tensorflow/models/tree/master/research/deeplab.

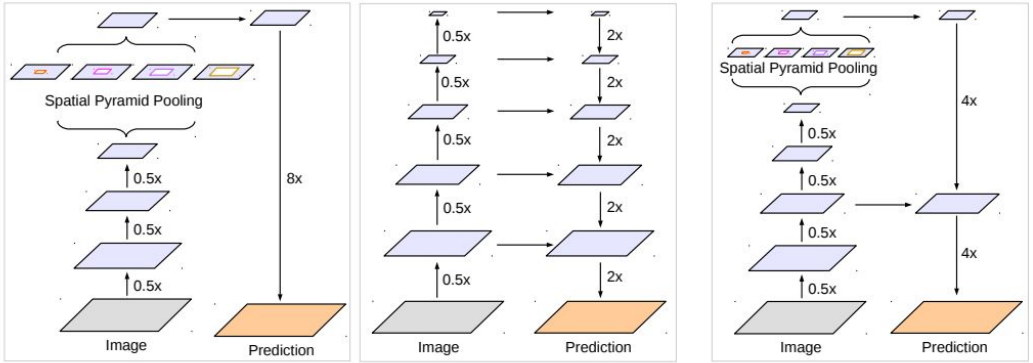
Keywords: Semantic image segmentation, spatial pyramid pooling, encoder-decoder, and depthwise separable convolution.

1 Introduction

Semantic segmentation with the goal to assign semantic labels to every pixel in an

Segmentação Semântica

- DeepLab v3+
  - Dilated + Pyramid pool + FCN

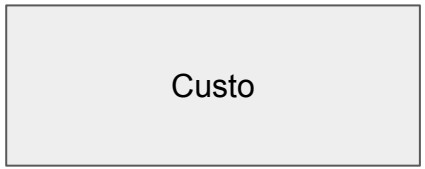


(a) Spatial Pyramid Pooling (b) Encoder-Decoder (c) Encoder-Decoder with Atrous Conv

Fig. 1. We improve DeepLabv3, which employs the spatial pyramid pooling module (a), with the encoder-decoder structure (b). The proposed model, DeepLabv3+, contains rich semantic information from the encoder module, while the detailed object boundaries are recovered by the simple yet effective decoder module. The encoder module allows us to extract features at an arbitrary resolution by applying atrous convolution.

Segmentação Semântica

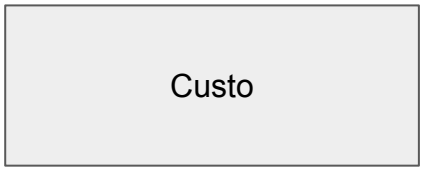
- Como é a função de custo?



Segmentação Semântica

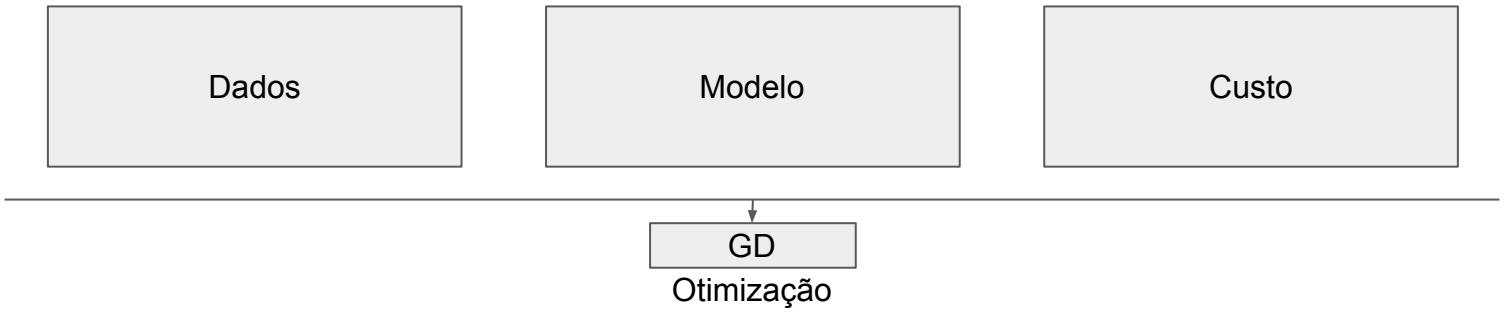
- Como é a função de custo?

Classificação pixel a pixel:
- CE
- BCE
- Hinge
- ...



Segmentação Semântica por Instância

- Estrutura de ML

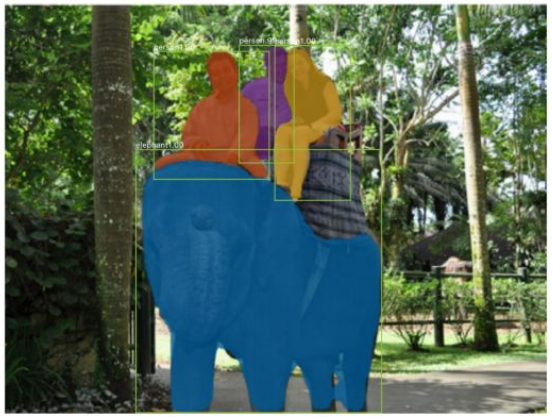


Segmentação Semântica por Instância

- Como são os dados?

Segmentação Semântica por Instância

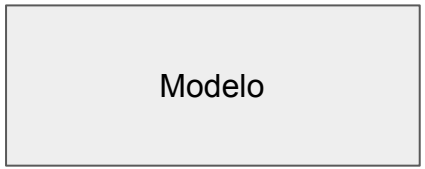
- Como são os dados?



Dados

Segmentação Semântica por Instância

- Como é o modelo?



Segmentação Semântica por Instância

- Mask R-CNN

Mask R-CNN

Kaiming He Georgia Gkioxari Piotr Dollár Ross Girshick

Facebook AI Research (FAIR)

Abstract

We present a conceptually simple, flexible, and general framework for object instance segmentation. Our approach efficiently detects objects in an image while simultaneously generating a high-quality segmentation mask for each instance. The method, called Mask R-CNN, extends Faster R-CNN by adding a branch for predicting an object mask in parallel *with the existing branch for bounding box recognition. Mask R-CNN is simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps. Moreover, Mask R-CNN is easy to generalize to other tasks,* e.g., *allowing us to estimate human poses in the same framework. We show top results in all three tracks of the COCO suite of challenges, including instance segmentation, bounding-box object detection, and person keypoint detection. Without bells and whistles, Mask R-CNN outperforms all existing, single-model entries on every task, including the COCO 2016 challenge winners. We hope our simple and effective approach will serve as a solid baseline and help ease future research in instance-level recognition. Code has been made available at:* https://github.com/facebookresearch/Detectron.

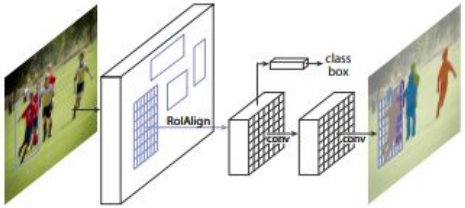


Figure 1. The **Mask R-CNN** framework for instance segmentation.

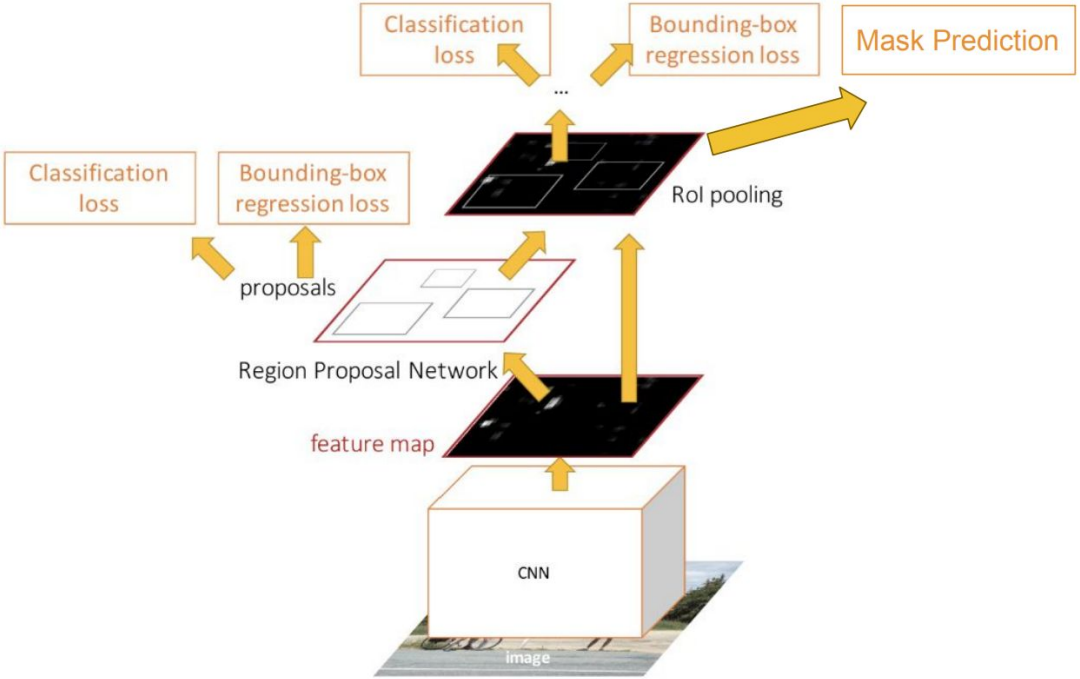
1. Introduction

segmentation, where the goal is to classify each pixel into a fixed set of categories without differentiating object instances.[1] Given this, one might expect a complex method is required to achieve good results. However, we show that a surprisingly simple, flexible, and fast system can surpass prior state-of-the-art instance segmentation results.

Our method, called *Mask R-CNN*, extends Faster R-CNN [36] by adding a branch for predicting segmentation masks on each Region of Interest (RoI), in *parallel* with the existing branch for classification and bounding box regression (Figure 1). The mask branch is a small FCN applied to each RoI, predicting a segmentation mask in a pixel-to-pixel manner. Mask R-CNN is simple to implement and train given the Faster R-CNN framework, which facilitates a wide range of flexible architecture designs. Additionally,

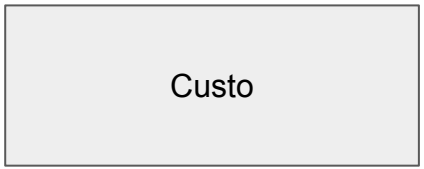
Segmentação Semântica por Instância

- Mask R-CNN



Segmentação Semântica por Instância

- Como é a função de custo?

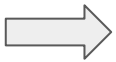


Segmentação Semântica por Instância

- Como é a função de custo?

Classificação pixel a pixel:
- CE
- BCE
- Hinge
- ...

Regressão:
- L2
- L1
- ...



$$\mathcal{L}_{total} = \mathcal{L}_{class} + \lambda \mathcal{L}_{bbox}$$

Custo

Para cada âncora!

No próximo episódio...

- RNNs