

Fully convolutional neural networks

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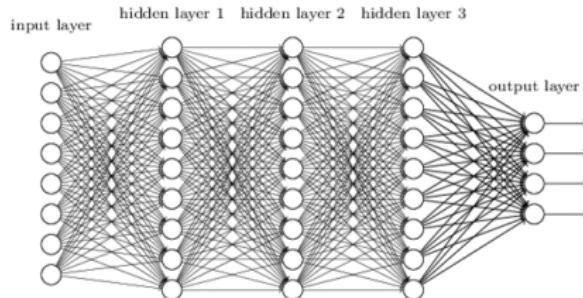
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Recall from yesterday: image classification with NN



Simple fully-connected neural network

Cross-entropy loss function used for classification tasks:

$$L(\theta) = - \sum_{i=1}^n y_i \ln(f(\mathbf{x}_i, \theta))$$

Learning image transformations

- An image classification task is a function from the set of considered images into a set of labels
- In many applications, we want to transform an image into another image

Image definition

Definition: image

An 2-dimensional image I of size $p \times q$ ($p, q \in \mathbb{N}^*$) is a function from $D = [0, \dots, p - 1] \times [0, \dots, q - 1]$ into \mathbb{R}^d ($d \in \mathbb{N}^*$).
The set of these images is \mathcal{I}^d .

Examples

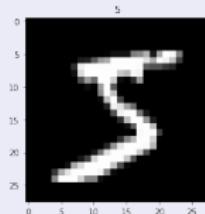


Figure: 28×28 grey level image ($d = 1$) from the MNIST dataset, and 481×321 colour image ($d = 3$) from the Berkeley segmentation dataset.

Image-to-image NN

Definition: image-to-image neural network

An image-to-image NNs F is a NN that transforms an image into an image of same size^a:

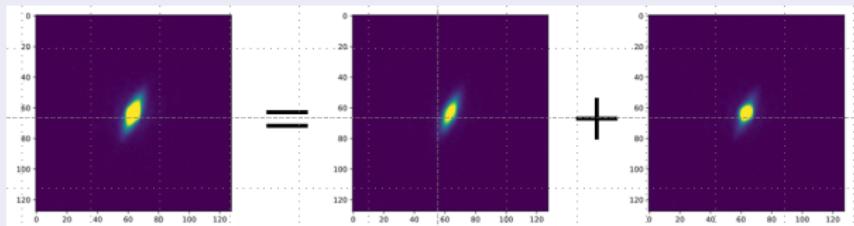
$$\begin{aligned} F : \mathcal{I}^{d_1} &\longrightarrow \mathcal{I}^{d_2} \\ I &\longmapsto N(I) \end{aligned}$$

Note that the dimensions d_1 and d_2 of the value spaces can be different.

^aIn some applications the output size is different from the input size, but for the sake of simplicity we will not consider this case here

Examples

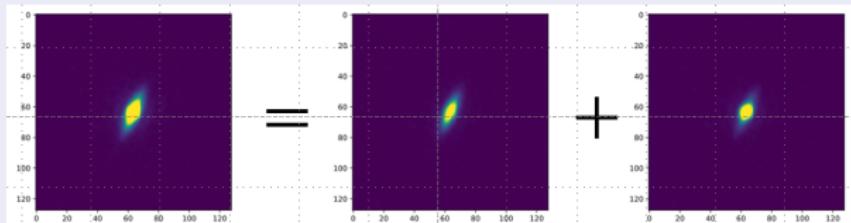
Bulge / disk decomposition



(Credits: Tuccillo, Huertas-Company, Velasco-Forero, Decencière)

Examples

Bulge / disk decomposition



(Credits: Tuccillo, Huertas-Company, Velasco-Forero, Decencière)

Deblurring network [Hradiš et al., 2015]

where subscript j indicates
ated vector, and $L_j(z; u) =$
and $e_j \in \mathbb{R}^{64}$ is the vector
all others be 0. The coordi
marized in Algorithm I.

Note that $g_j(z)$ is not
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Image Segmentation with NNs

- Computer vision has been one of the main application domains of NNs
- Image segmentation often is an important step in an image processing work flow
- Image segmentation has been a very active deep learning research field

Image segmentation example



Credit: images from the Pascal VOC database

Other applications

- Image filtering
- High dynamic range
- Style modification
- Super-resolution (image size increases)

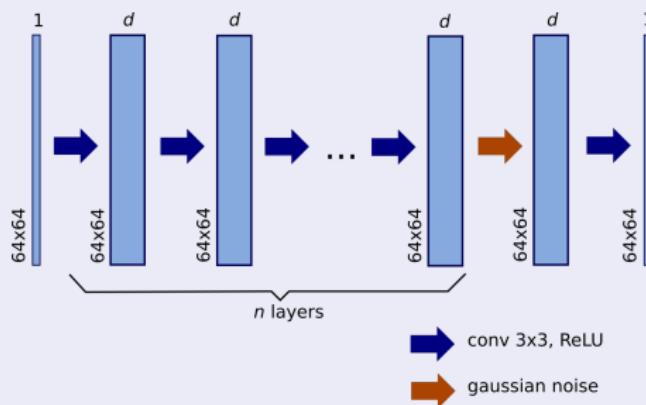
Image-to-image NNs architecture

- Image-to-image NNs are based on convolutional layers
- If downsampling is used, the corresponding upsampling is needed

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Example: Pang network [Pang et al., 2010]



Receptive field

Definition: links between neurons

In a NN, we say that neuron a is linked to neuron b if there is an oriented path in the corresponding graph going from a to b .

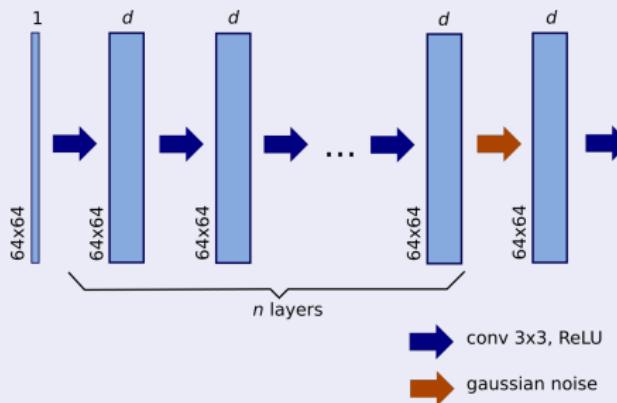
Definition

The **receptive field** of a neuron in a NN is the set of *input neurons* that are linked to that neuron.

The size of the receptive field is an essential property when designing a fully-convolutional NN architecture.

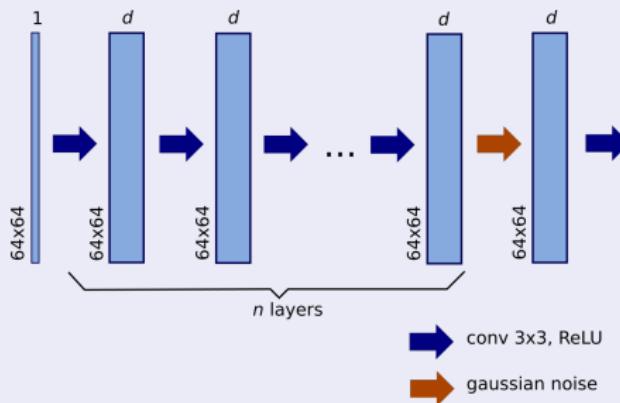
Receptive field of the Pang network

What is the size of the receptive field of the neurons in the last layer?



Receptive field of the Pang network

What is the size of the receptive field of the neurons in the last layer?



Answer: $1 + 2 \times (n + 1)$

The specific case of image segmentation

Definition: image segmentation

Let I be an image defined on D . A segmentation of I is a partition of D . In practice the regions of the segmentation should correspond to the objects in I , which is application dependant.

- A partition is often represented as a labelled image
- In order to make the segments symmetric, each one is represented by a different channel

Some vocabulary on segmentation

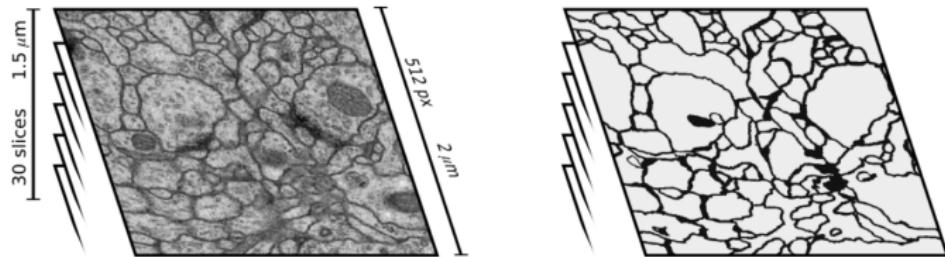
- **Object detection / localization:** bounding box around the object(s).
- **Binary segmentation:** segmentation in 2 classes, background and object.
- **Semantic segmentation:** a label is given to each pixel, according to the object it belongs to.
- **Instance segmentation:** identify each separate object, even if they belong to the same class.

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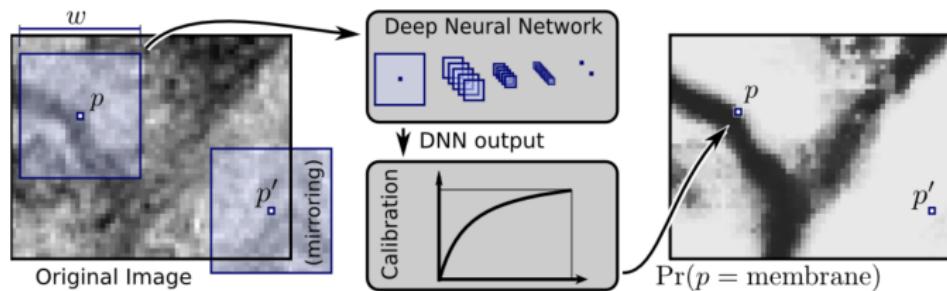
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Neuron membrane segmentation challenge (ISBI 2012)

- Train: single stack of size $30 \times 512 \times 512$.
- Test: a second stack of same size.



Neuron membrane segmentation challenge winner [Ciresan et al., 2012]

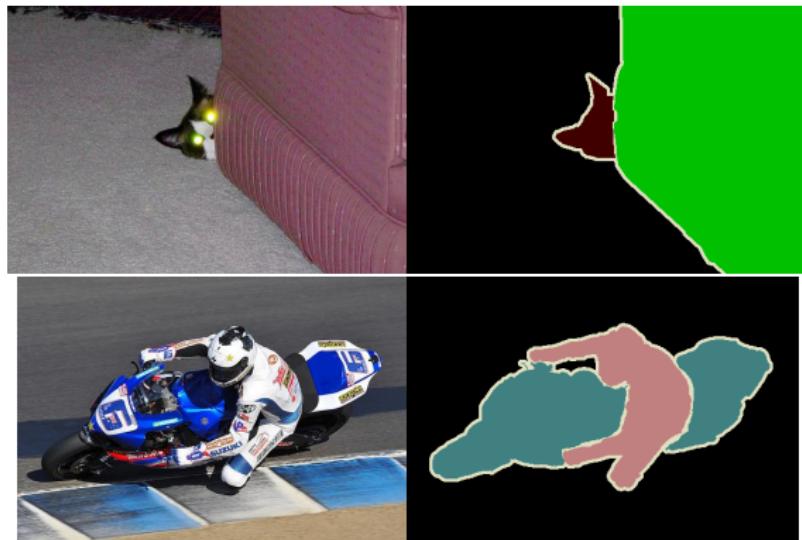


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Pascal visual object classes segmentation challenge 2012 [Everingham et al., 2014]

- 1464 training and 1449 validation images
- automatic online test, with unknown images
- 20 image categories (cat, sofa, motorbike, person, etc.)

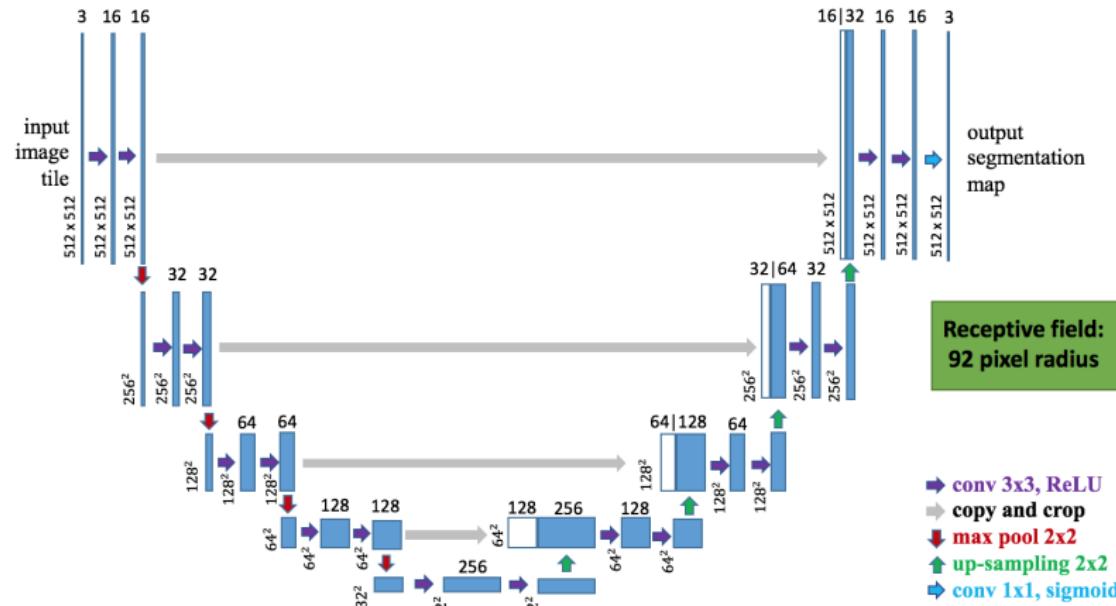


Convolutional nets for semantic image segmentation

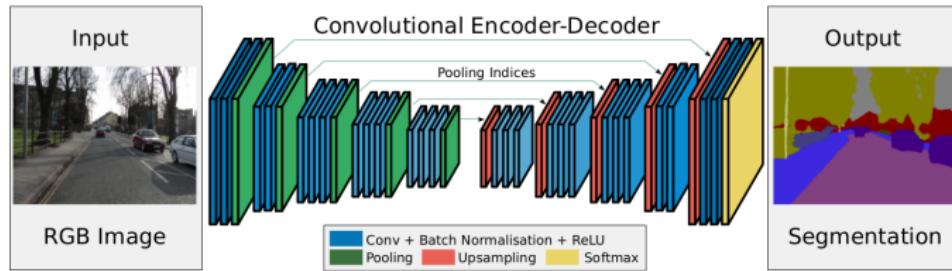
Three papers in 2015:

- Fully convolutional networks for semantic segmentation [Long et al., 2015]
- U-Net: convolutional networks for biomedical image segmentation [Ronneberger et al., 2015]
- SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation [Badrinarayanan et al., 2015]

Example: U-Net architecture [Ronneberger et al., 2015]



Example: SegNet architecture [Badrinarayanan et al., 2015]



Remarks

- These architectures easily contain a number of parameters of the order of 10^7 (28 million for U-Net)
- Their optimization might be difficult
- For many segmentation applications, they are overkill
 - But you can reduce the number of filters or the number of layers

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COCO: common objects in context [Lin et al., 2014]

- 2 million objects, from 80 categories, in 300 000 images

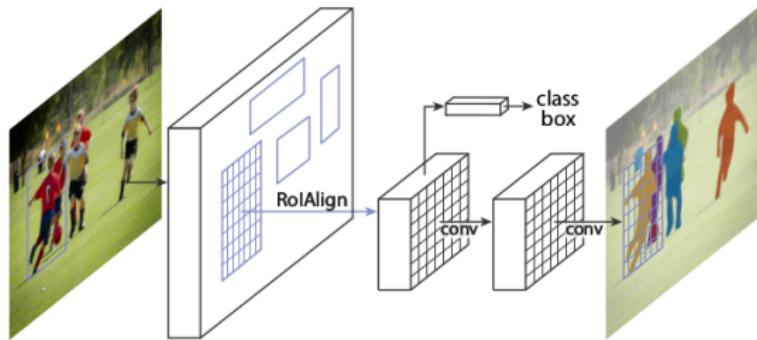


Winner 2016: Fully Convolutional Instance-aware Semantic Segmentation (Microsoft) [Li et al., 2016]

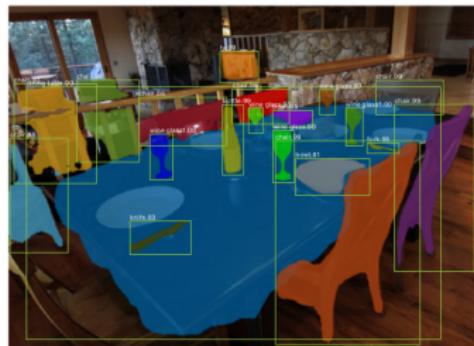
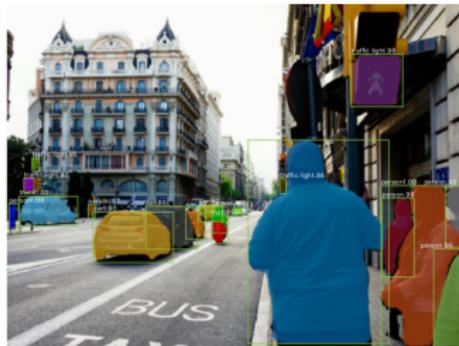
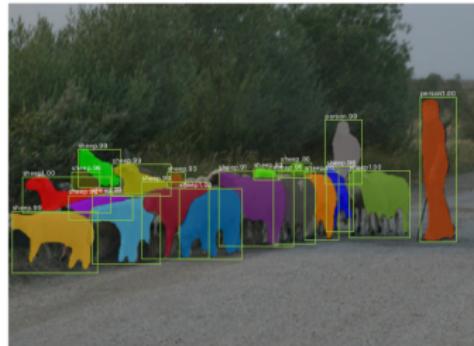
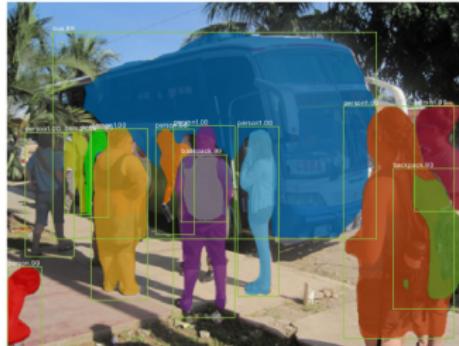
COCO instance segmentation challenge: examples of 2016 winner results



State of the art on the COCO database: Mask R-CNN [He et al., 2017]

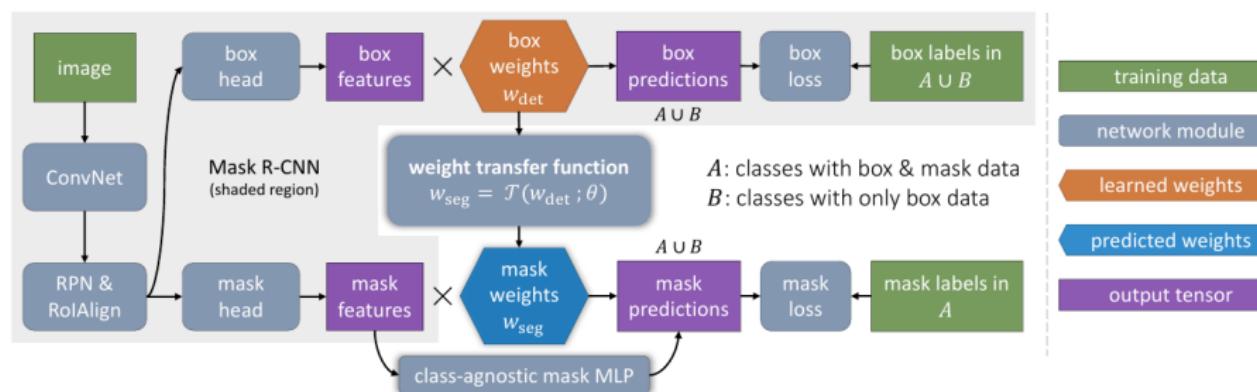


Mask R-CNN on the COCO database



Partially supervised segmentation - [Hu et al., 2017]

- 80 segmented categories from COCO database
- 3000 visual concepts using box annotations from the Visual Genome dataset (100k images)



Current (?) trends for instance segmentation

- Region proposal +
- Fully convolutional (very deep) network +
- (Post-processing)

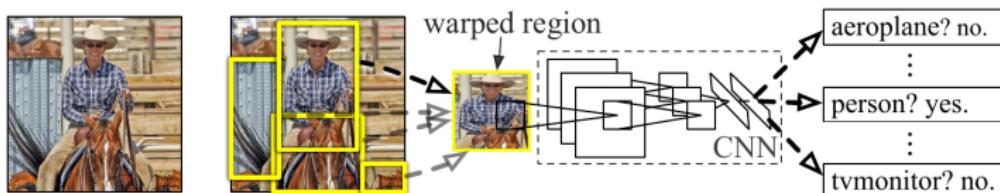


Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

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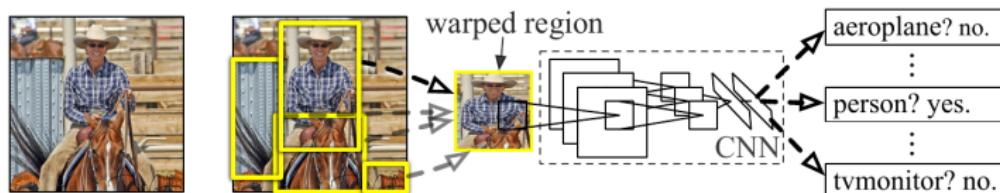


Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

Meanwhile, on the object detection field...

- YOLO: you look only once [Redmon and Farhadi, 2016]
- SSD: single shot detector [Liu et al., 2016]

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Modeling your problem

Casting your problem into the right representation

- Familiarize yourself with the training data (input and output images)
- Choose the right representation for your images
- Choose an architecture and train it
- Analyze the results on the validation data (**look** at the images!)
- Do you need preprocessing? Data augmentation?
Post-processing?
- Iterate ...
- Only at the end: test!

Preprocessing

- Standard statistical preprocessing: not always useful, and sometimes problematic, when applied to images
- Morphological operators

Data augmentation

- Geometrical transformations: similarities
- Elastic transformations
- Specific methods: articulated objects, ...
- Simulated data

Postprocessing for segmentation

- Superpixels (e.g. [Farabet et al., 2013])
- Conditional random fields
- Mathematical morphology

What loss to use?

- Classical choice: mean squared error or cross-entropy
- My recommendation: Dice or Jaccard losses

Practical example



(Credits: ESA/Hubble, CC BY 4.0,
<https://commons.wikimedia.org/w/index.php?curid=34205833>)

How would you:

- segment the background?
- segment the sources?
- separate the sources?

What precision is needed for the ground-truth?

- The ground truth boundaries do not need to be very precise
-

Using a CNN

- A fully convolutional neural network is translation invariant
- Provided that the image size is compatible with network's subsampling process, in theory any image can be processed
- Practical limit: the memory of the system

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A solved problem?

- Progress in image segmentation during the 5 last years has been enormous
- Several complex problems have now satisfactory solutions
- Training can be a problem (large annotated databases, difficult optimization)
- Some remaining challenges:
 - Making the training database as small as possible
 - Taking *a priori* structural information into account

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