Deep Learning in Computer Vision

Short introduction

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13/12/2017

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Introduction

Architectures

Architectures

Usual building functions

- 2D Convolution
- Non linear function (ReLU)
- Batch Normalization
- Pooling (mean/max)
- Fully connected layer (MLP)

Usual buildings "block"

- *Features extraction:* Conv + Batch Norm + Relu + Max pooling
- *Classification* FC + SoftMax

Famous nets: Alexnet

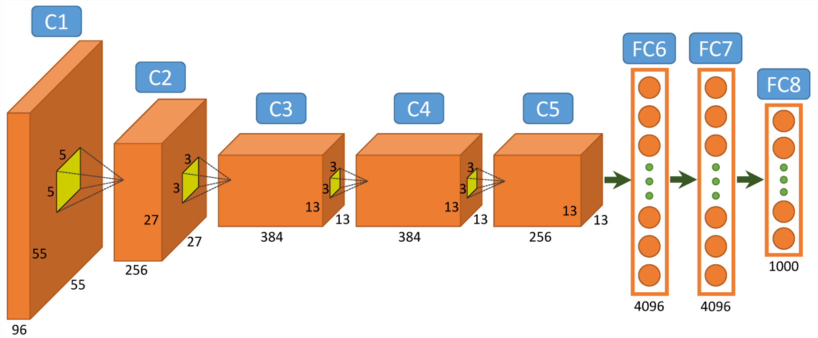


Figure 1: Alexnet

[Krizhevsky et al., 2012]

Famous nets: VGG

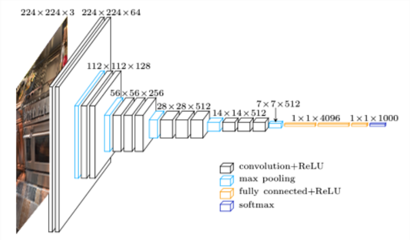


Figure 2: VGG16

16 vs 5 convolution for Alexnet

[Simonyan and Zisserman, 2014]

Famous nets: GoogLeNet

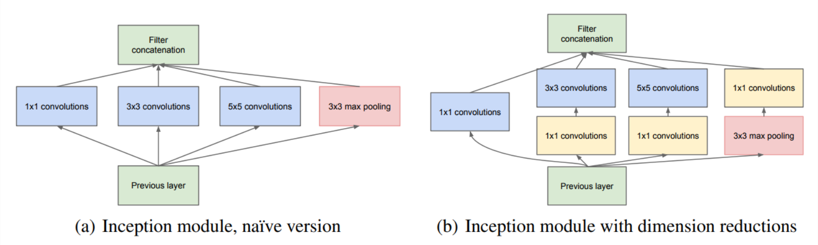


Figure 3: New inception module

Convolution on smaller input = put more convolutions

[Szegedy et al., 2015]

Famous nets: ResNet

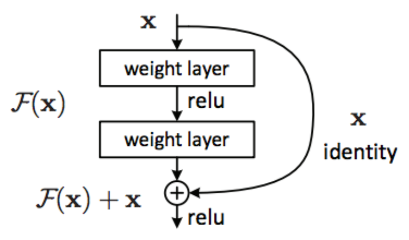


Figure 4: Residual block

Residual networks easier to optimize = put more convolutions (8xVGG)

[He et al., 2016]

Famous nets: DenseNet

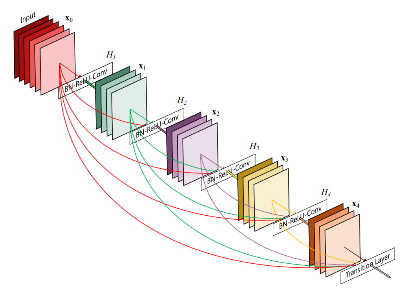


Figure 5: Dense block

Less parameters for similar results (CVPR2017)

[Huang et al., 2016]

Introduction

Recurrent Networks

Temporal informations in DNN

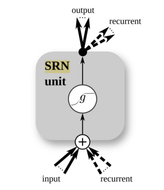


Figure 6: Simple Recurrent Network

Can be applied on sequential data: speech, video, graph...

More complex RN

- Long Short-Term Memory (LSTM)
- Gated Recurrent Unit (GRU)

Introduction

Applications

CNN Applications

In computer vision, deep learning have been first applied for image classification, with:

- CNN for features extraction
- MLP for classification

All the weights (CNN + MLP) are optimized within a common framework **end-to-end**.

DL are now used in others computer vision applications.

Application: Keypoints detection/description

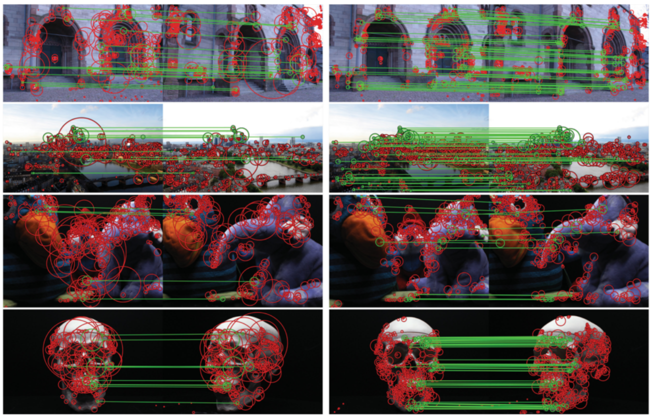


Figure 7: SIFT vs LIFT

[Yi et al., 2016]

Application: Region Proposal Network

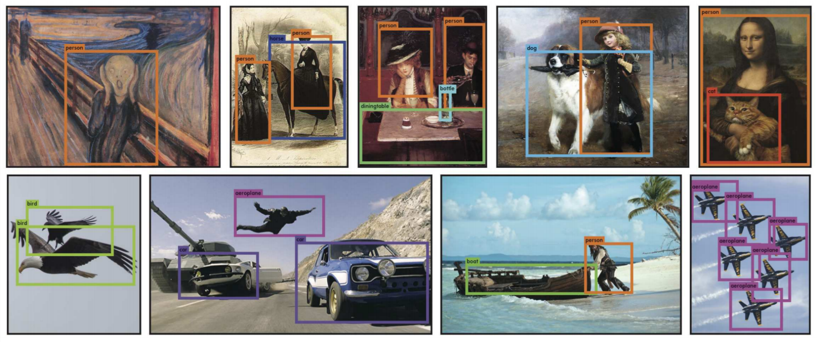


Figure 8: RPN network

Multi-task learning network (Region proposal & classification) Best Paper CVPR2017 [Redmon and Farhadi, 2016]

[Redmon et al., 2016, Girshick, 2015, Ren et al., 2015]

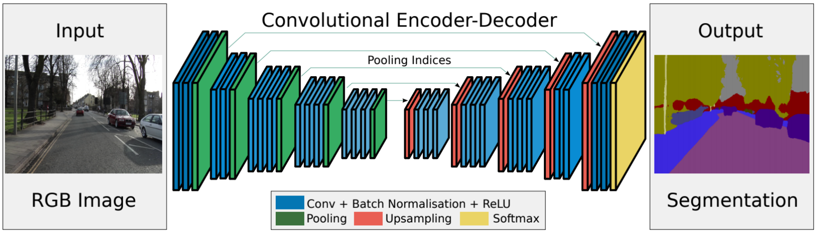


Figure 9: Encoder-Decoder architecture for semantic segmentation

Introducing max-unpooling to obtain an output as wide as the input.

[Badrinarayanan et al., 2015]

Application: Instance segmentation

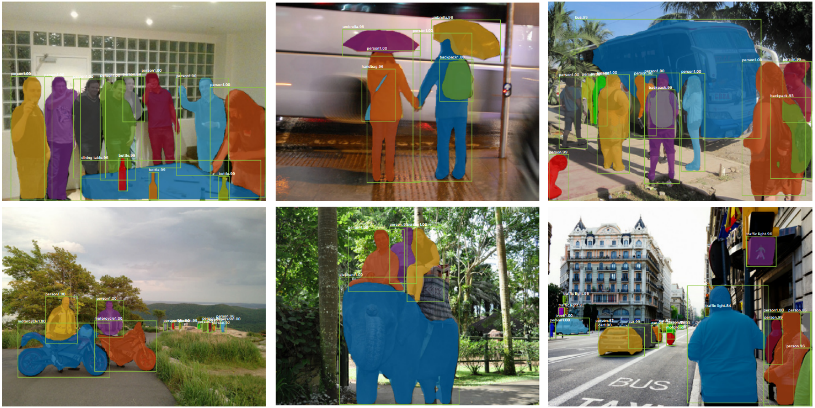


Figure 10: Instance and pixel-level segmentation

Best Paper ICCV2017 [He et al., 2017]

Application: Depth from stereo

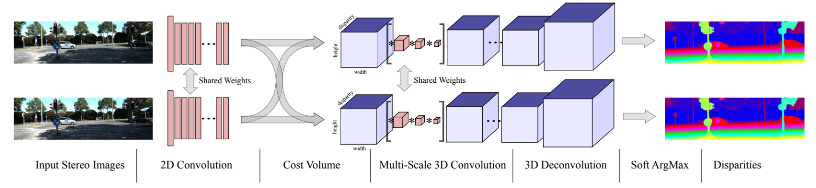


Figure 11: Disparity inference from stereo pairs

Double-inputs network

[Kendall et al., 2017]

Application: Depth from mono

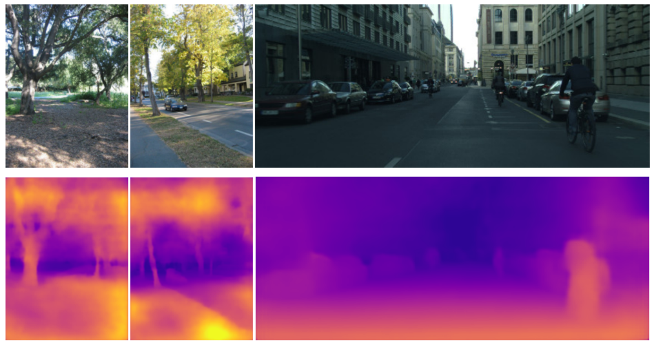


Figure 12: Disparity inference from mono image

Used to improve monocular SLAM [Tateno et al., 2017]

[Kuznietsov et al., 2017]

Application: Visual Odometry

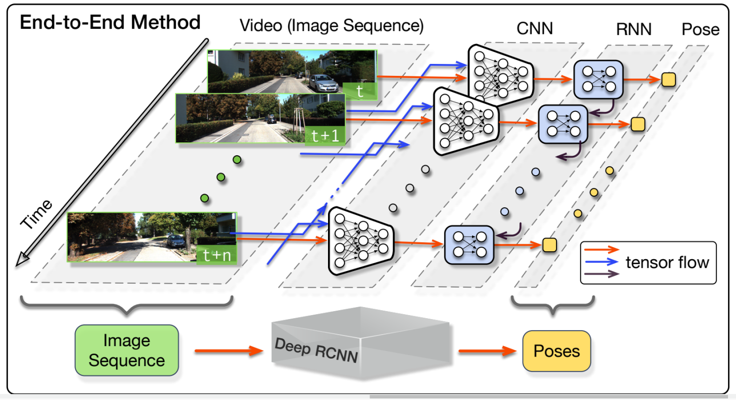


Figure 13: Motion estimation from image sequence

[Wang et al., 2017]

More Applications

And much more:

- Video analysis
- Scene understanding
- Face recognition
- Pose tracking
- Crowd analysis
- Suspicious behaviour detection
- Data generation
- ...

CNN as global Descriptors

Visual Based Localization

Content based image retrieval

Roadmap

We want to create an indirect method to localize a query within a set of **geolocalized** RGB-D images. The considered pipeline will be:

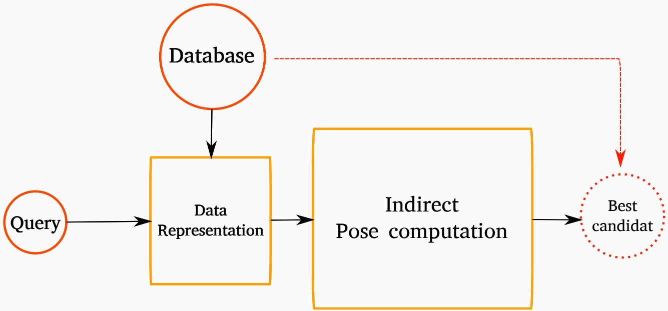
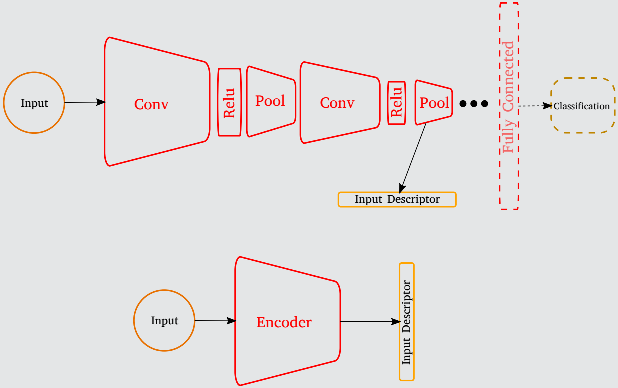


Figure 14: Visual Based Localization (VBL) pipeline

We first focus our work on creating a robust data representation. Research on state of the art shown that CNN are the best choice [Arandjelović et al., 2017].

Encoder for data representation



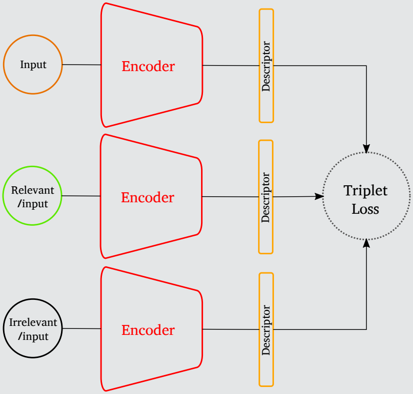
CNN as global Descriptors

Training a global feature extractor

CNN training

We begin with a pre-trained network and perform a **fine tuning** of its weights.

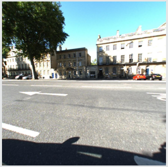
Encoder training for VBL task



CNN training

Training data

Triplet := (Query Image, Positive example, Negative example)




Cost function

During the training, we minimize the following loss:

$$TripletLoss = max(0, \lambda + \|F(I) - F(I^{+})\| - \|F(I) - F(I^{-})\|) \quad (1)$$

Where:

- $F(I)$ the global descriptor of image I computed by the CNN
- λ design a constant margin

Multiple modalities

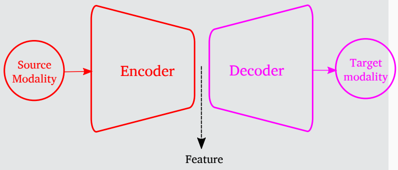
How to use more than one modality at the time?

What are we first trying to do

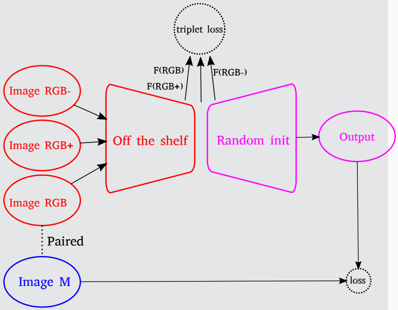
Training data type	Testing data type
RGB + (Depth or Laser reflectance)	RGB

We suppose that complex data (image + lidar related modality) can be acquired **offline**, but all the modality could not be available during test time. The idea is to guide the CNN during the training with **multiple modalities** to improve the description of input of **single modality**.

Encoder-Decoder architecture



Encoder-Decoder training scheme

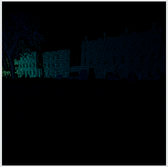


Decoder part is initialized with **pre-trained weights** and decoder network is randomly initialized.

Training

Training data

Triplet := (Query Image + Modality, Positive example, Negative example)

Cost function

Loss become **multi-task**:

$$L = TripletLoss + \alpha \sum_{i,j}^{h,w} |p(i,j) - gt(i,j)| \quad (2)$$

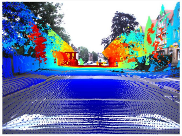
Where:

- p denote CNN inferred modality and gt ground through modality
- α design loss weighting factor

Datasets

We use Oxford RobotCar dataset [Maddern et al., 2016] as it includes:

- Time redundancy for each car trajectory and GPS tags associated to images: **automatic triplets creation!**
- 4 cameras on the car & 3 LIDARS (3 modalities: RGB, Depth & Reflectance)


Important parameters for training

Vocabulary

- **Forward pass:** operation to obtain input representation/classification
- **Batch** several training example forward passed to a CNN before gradient computation and back-propagation
- **Number of Epoch** correspond to the number of times all the batch data have been passed through the CNN
- **Learning rate, Momentum, Weight decay, etc.** Meta-parameters of the optimizer used during the training

Hard and time consuming to fined all the best parameters...

CNN as global Descriptors

Conclusion and advices

Implementation details

Deep Learning framework: `Pytorch`. Easy to use (Python!), fast to learn (1h tutorial), a lot of already available architectures

Net architecture: Alexnet. Begin with a little network (fast to train) to determinate the meta-parameters, then move to a deeper net (VGG).

Size of the training dataset: 400 triplets (400 * 3 images * 2 modalities). Small dataset automatically created. I use **pre-trained network**!

Trends: Robotics

Using deep learning as tools within classical framework:

- Improving monocular SLAM
- Global descriptor to find loop closure

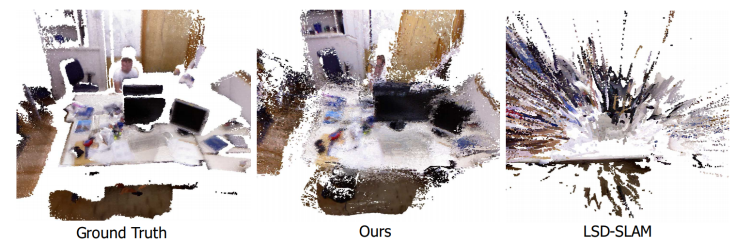


Figure 15: Pure rotational camera motion SLAM problem solved, CNN-SLAM [Qi et al., 2016]

Semi-supervised/unsupervised architecture:

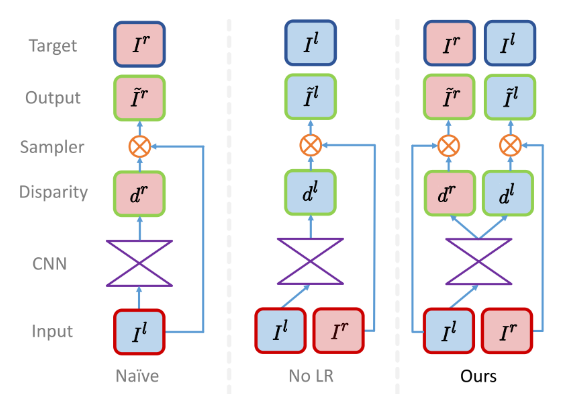


Figure 16: Disparity from mono using stereo pairs as training data [Godard et al., 2016]

Trends: Computer Vision

Multi-task learning:

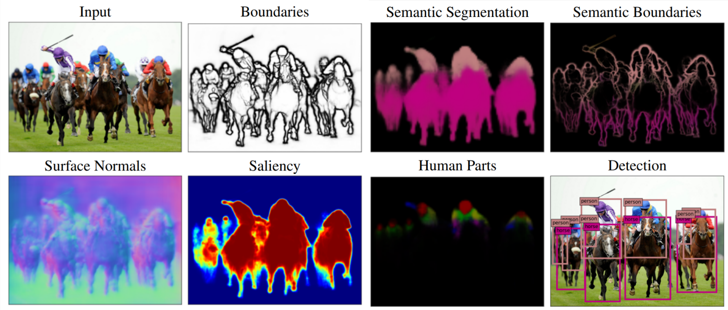


Figure 17: Adding sub-goal increase accuracy over all tasks [Kokkinos, 2016]

No longer limited to RGB modality:

- Deep Learning on Points Cloud, Graph
- Modality fusion (RGB + Depth map) [Hazirbas et al., 2016]
- Multi-spectral images (remote sensing field)

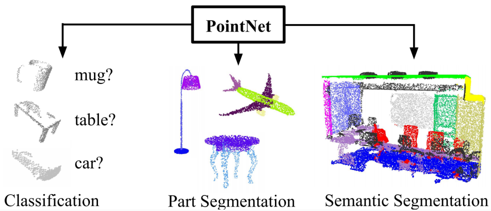


Figure 18: PointNet [Qi et al., 2016]

Discussion time

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