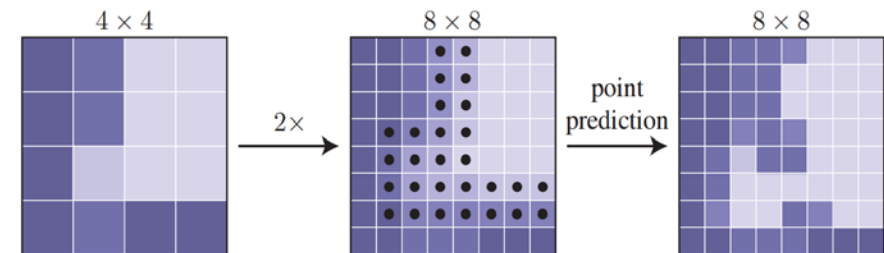
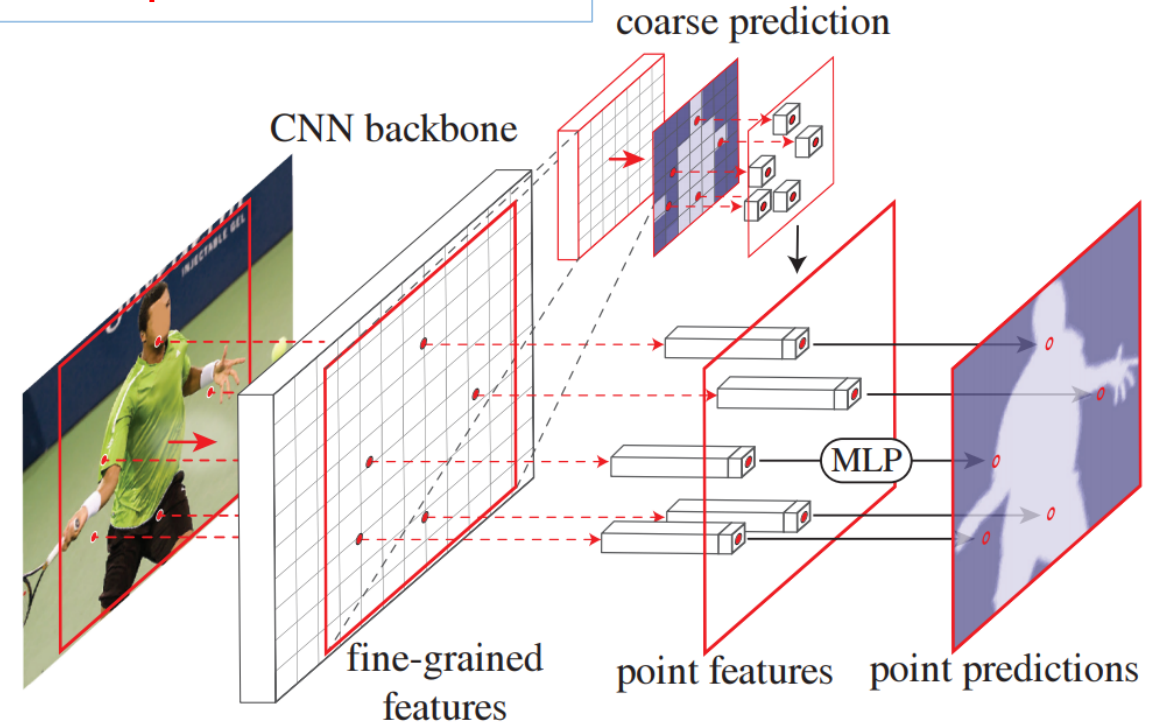
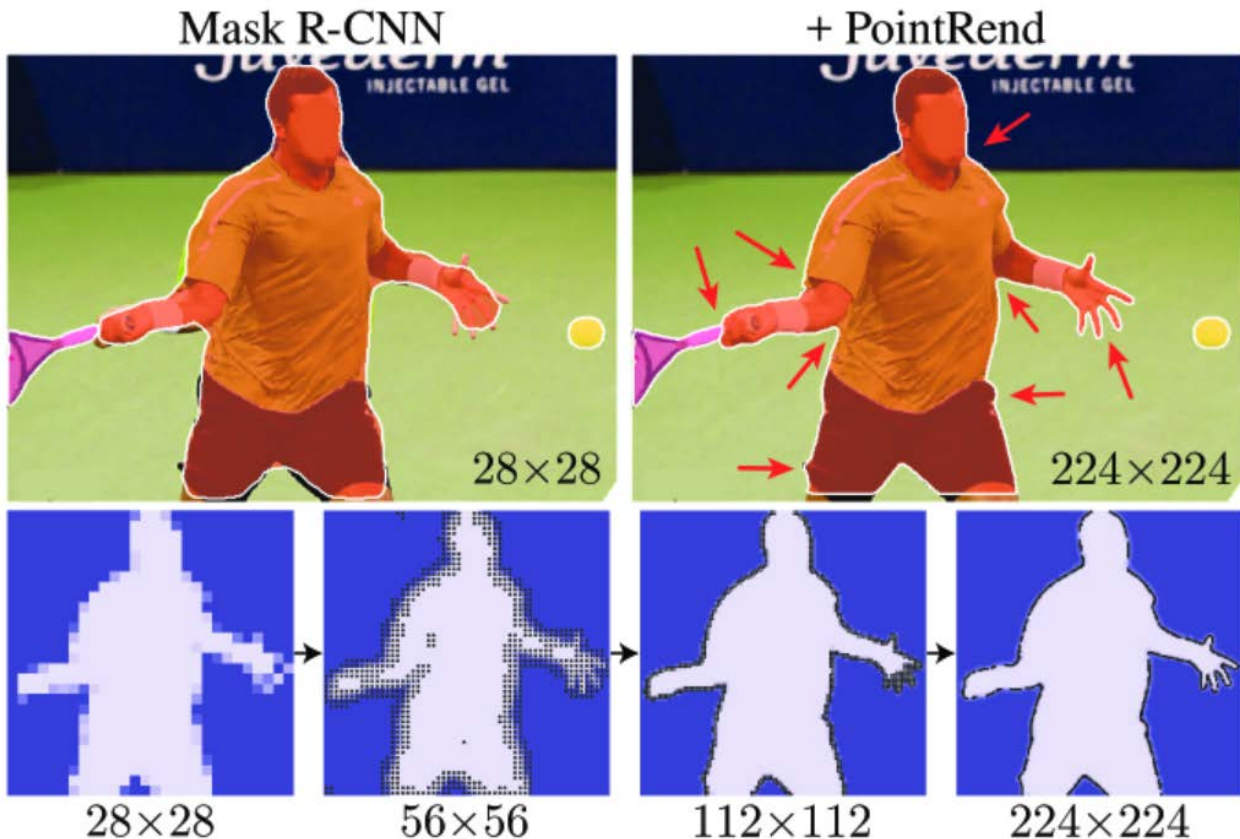


# PointRend: Image Segmentation as Rendering

(Alexander Kirillov, Yuxin Wu, Kaiming He, and Ross Girshick)

**PointRend** uses a subdivision strategy to adaptively **select a non-uniform set of points** at which to **compute labels**.

Only think about the important (incorrect) region.



# ELF: Embedded Localization of Features in Pre-Trained CNN

Benbihi, Assia and Geist, Matthieu and Pradalier ICCV 2019

An Guoyuan  
20184637

# Content

1. Background
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3. Method (part 2) – Feature Map Selection
4. Review and Result
5. Discussion

# 1 Background

# Common Requirements

- Problem 1:
  - Detect the same point *independently* in both images



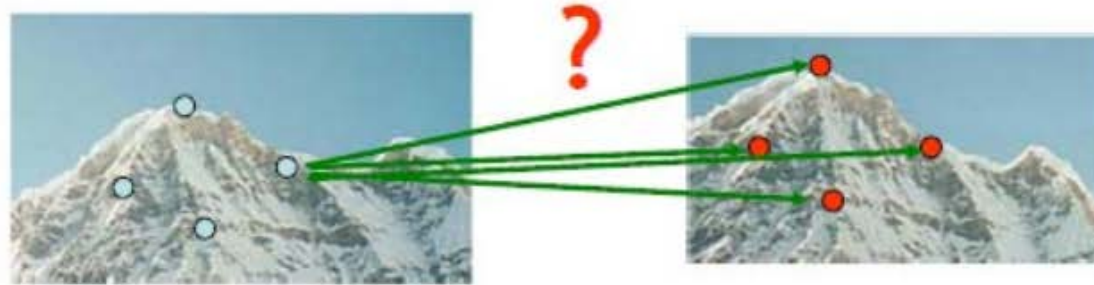
No chance to match!

requirement1

We need a repeatable detector!

# Common Requirements

- Problem 1:
  - Detect the same point *independently* in both images
- Problem 2:
  - For each point correctly recognize the corresponding one

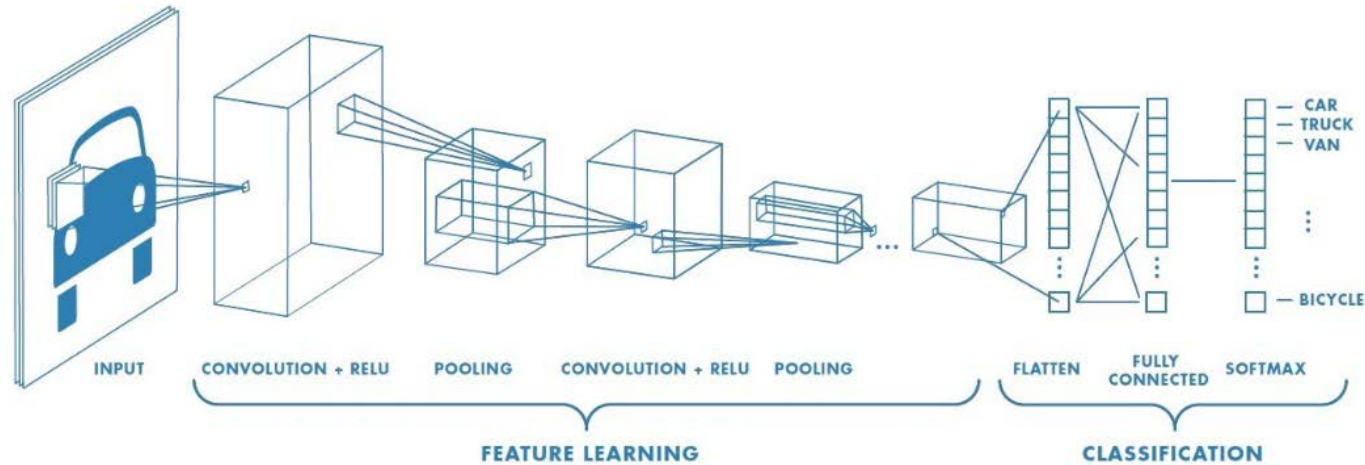


requirement2

**We need a reliable and distinctive descriptor!**

- Repeatable key points **detector** → Harris
- Reliable **descriptor** → LoG; SIFT

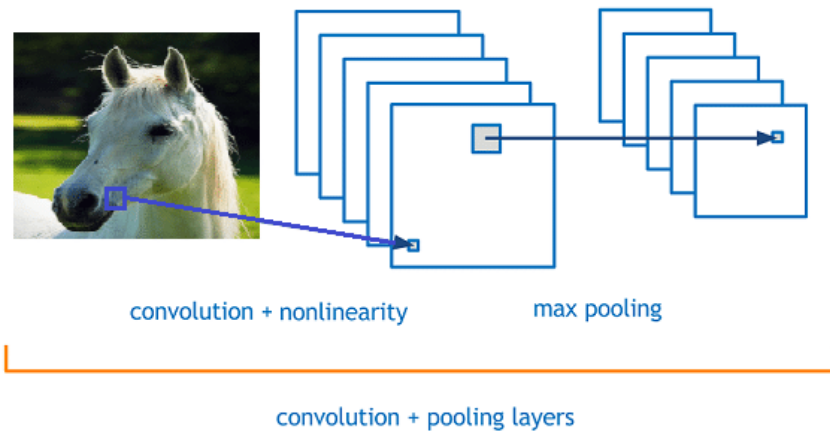
# A milestone: Convolutional Neural Network



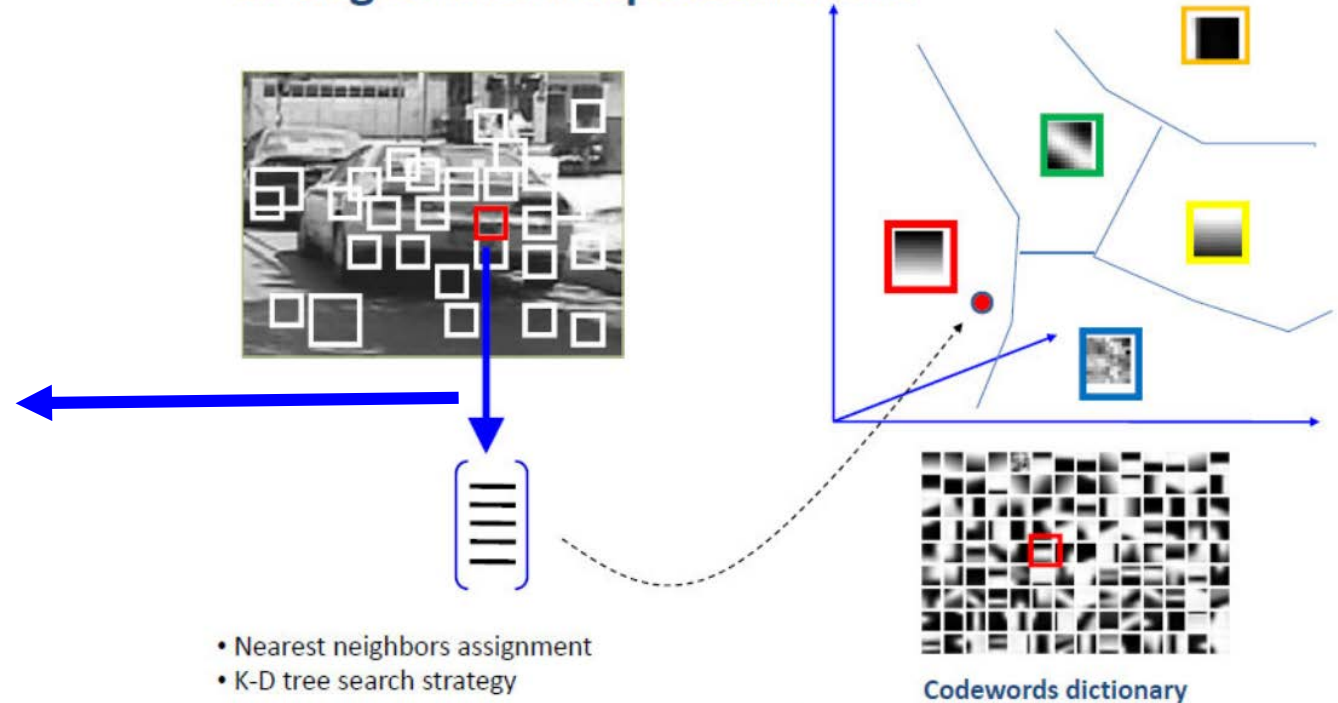
How to use CNN in image search?



# We often use CNN as a descriptor

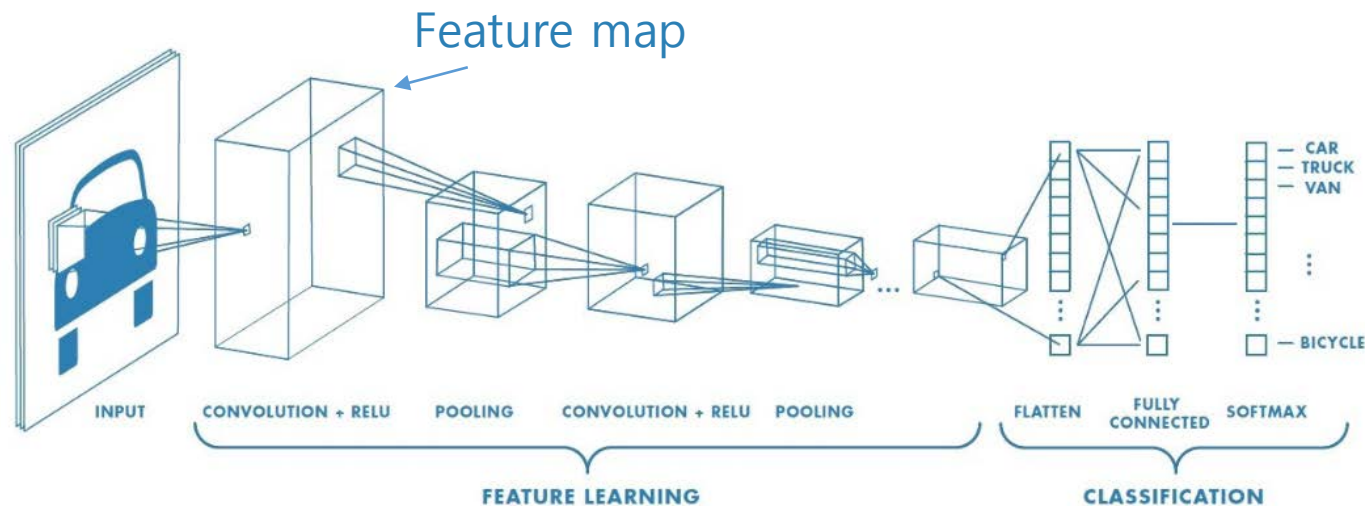


## 3. Bag of word representation



Q: how could CNN be helpful for the detector?

ELF: Embedded Localization of Features in Pre-Trained CNN

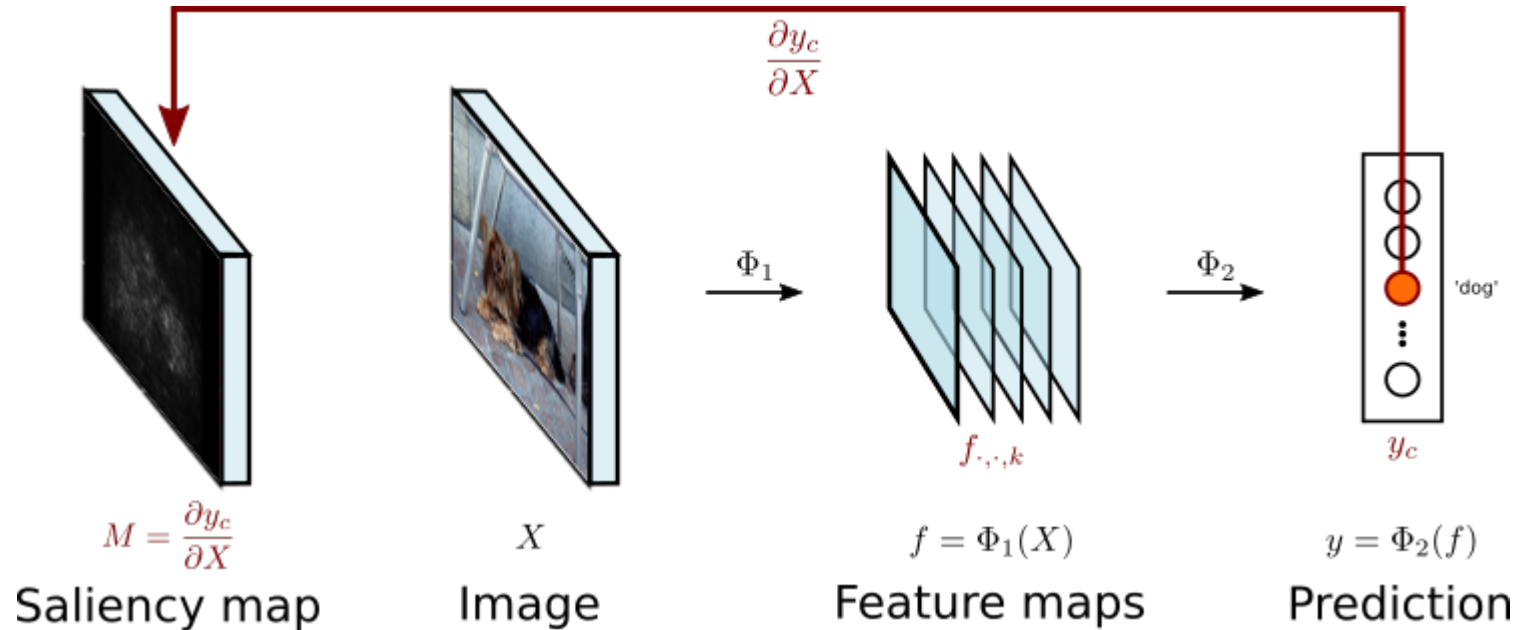


## 2 Method (part 1) – Saliency Maps

- During backpropagation, the gradient is helpful for detecting keypoints.

# Saliency map

- During backpropagation, the gradient is helpful for detecting keypoints.



<http://research.sualab.com/assets/images/interpretable-machine-learning-overview-2/saliency-map-with-gradient-concept.png>

# Saliency map from feature map.

$\mathbf{I}$  Image  $D_I = H_I \cdot W_I \cdot C_I.$

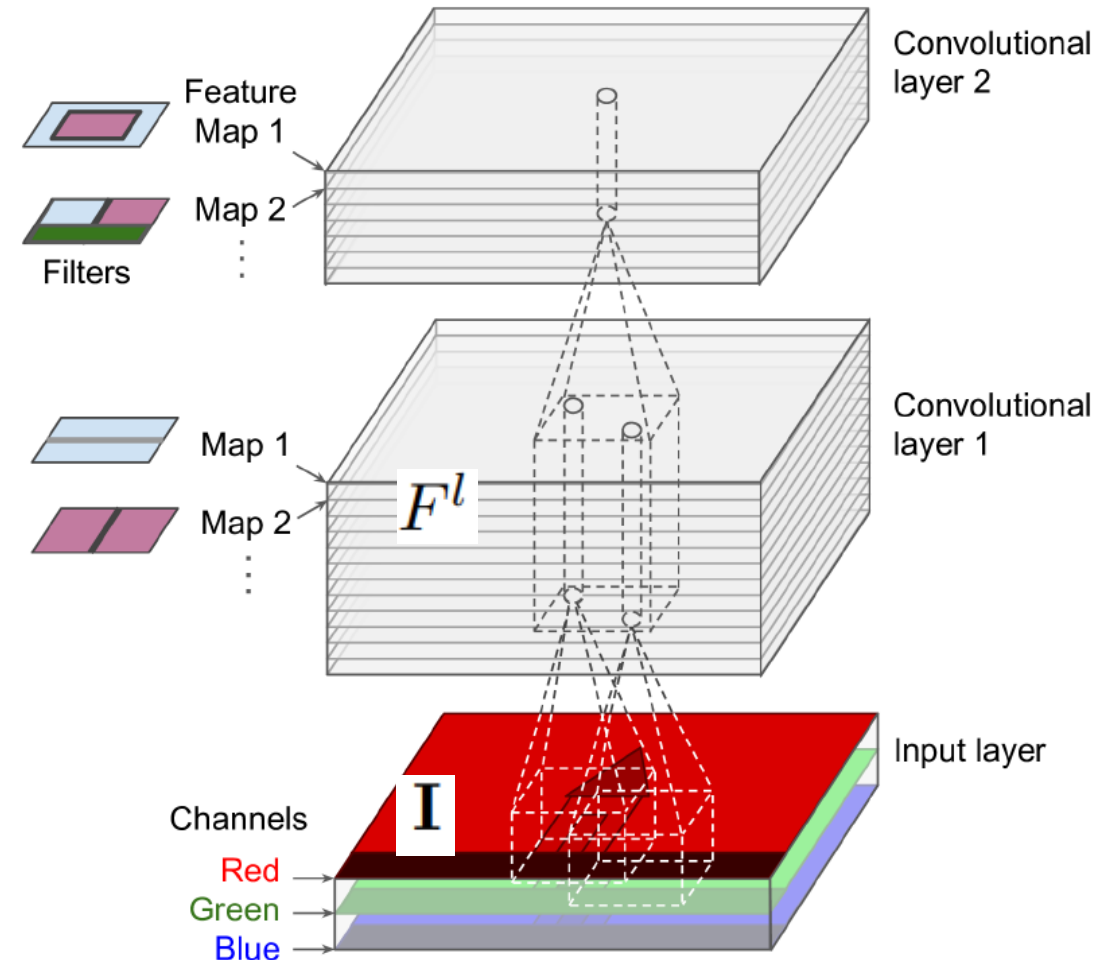
$F^l$  Feature Map  $D_F = H_l \cdot W_l \cdot C_l.$

Saliency Map  $S^l(\mathbf{I}) = \left| \frac{\partial F^l(\mathbf{I})}{\partial \mathbf{I}} \right|$

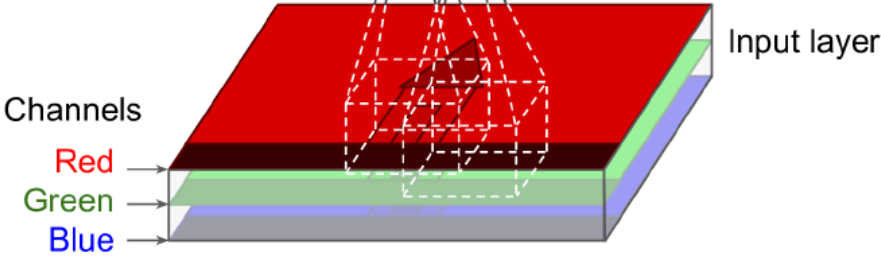
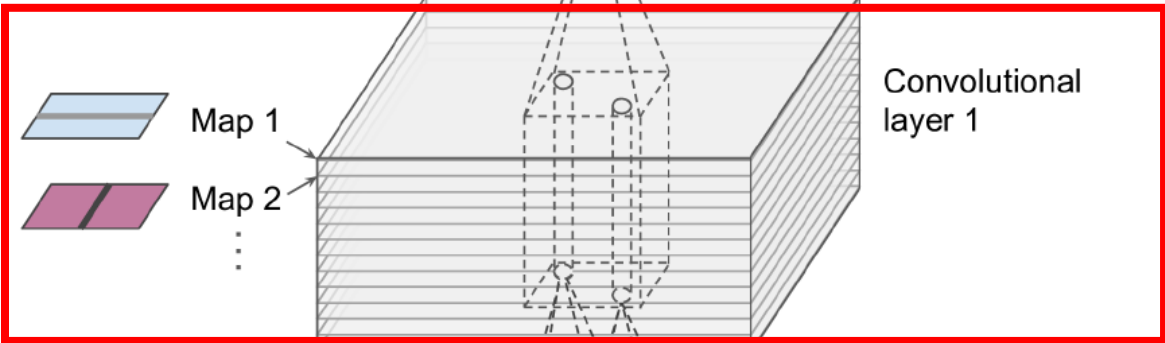
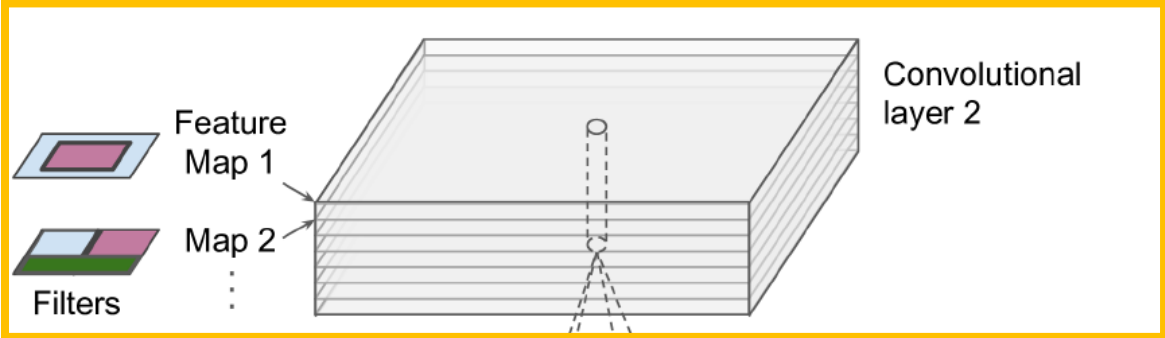
Apply the correlation  $\nabla_I F^l$  to the features  $F^l(\mathbf{I})$  specifically and generate a visualization in image space  $S^l(\mathbf{I})$ .

$\nabla_I F^l$

- The correlation between the feature space and image space
- For every node in feature map, calculate the gradient to all the pixels in the image.



# Q: how to find the best feature map?

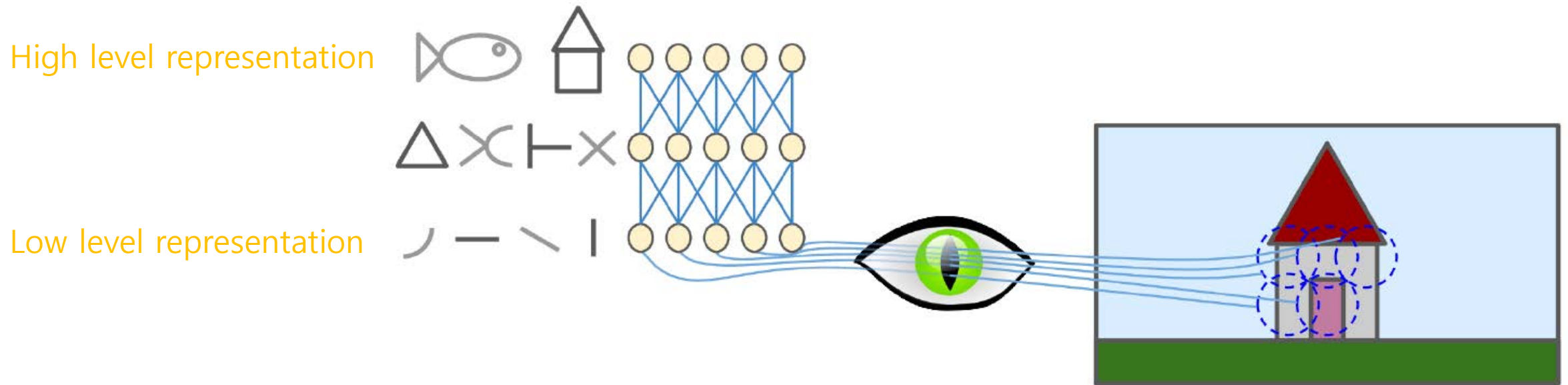


# 3 Method (part 2) – Feature Map Selection

- High level representation
- High resolution localization information

# High level representation

- To represent an image, the higher, the better.

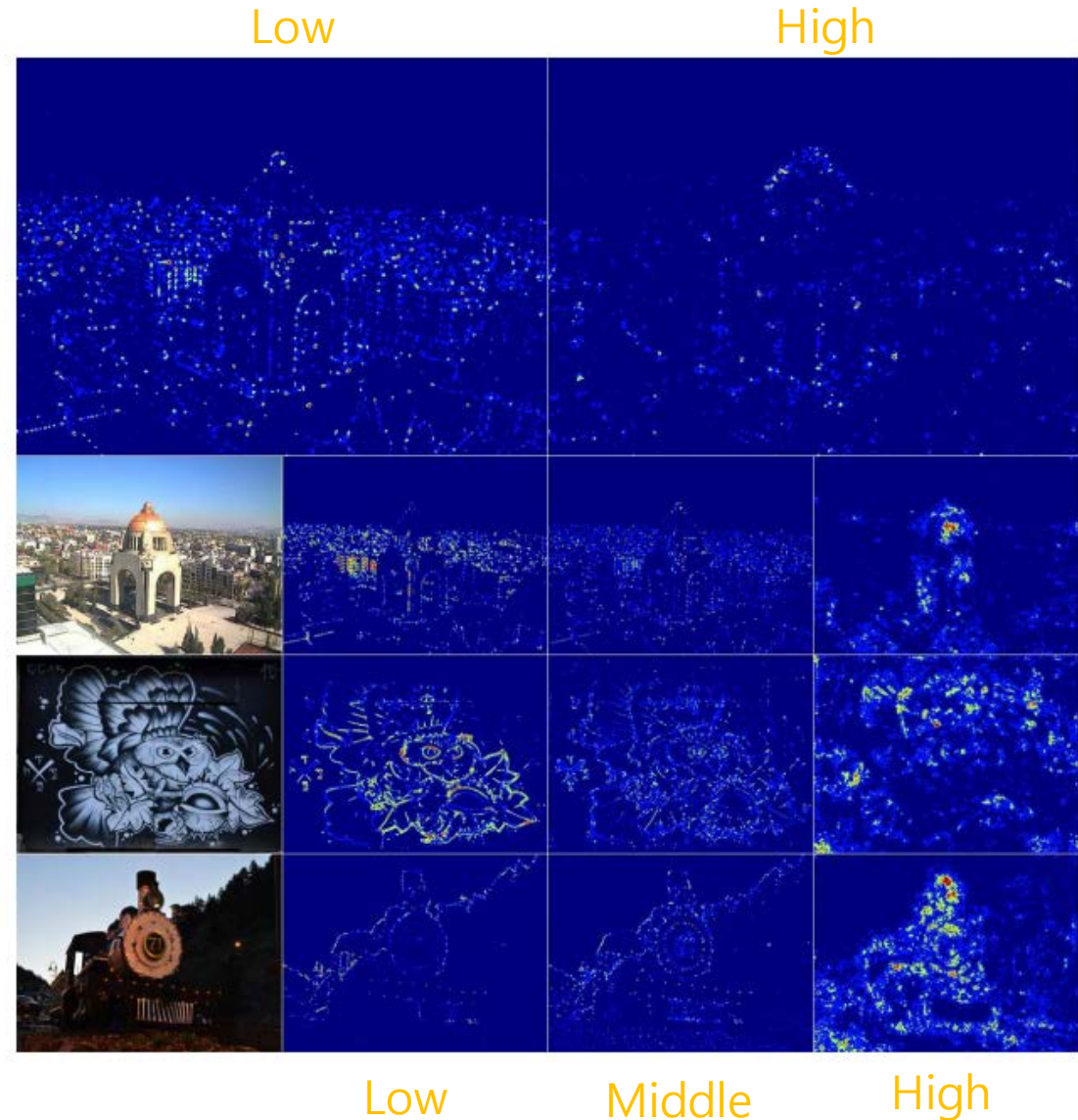




# High resolution localization information

- To find a accurate location, the lower, the better.

Low level saliency maps activate pixels more accurately.



# Summary for feature map selection

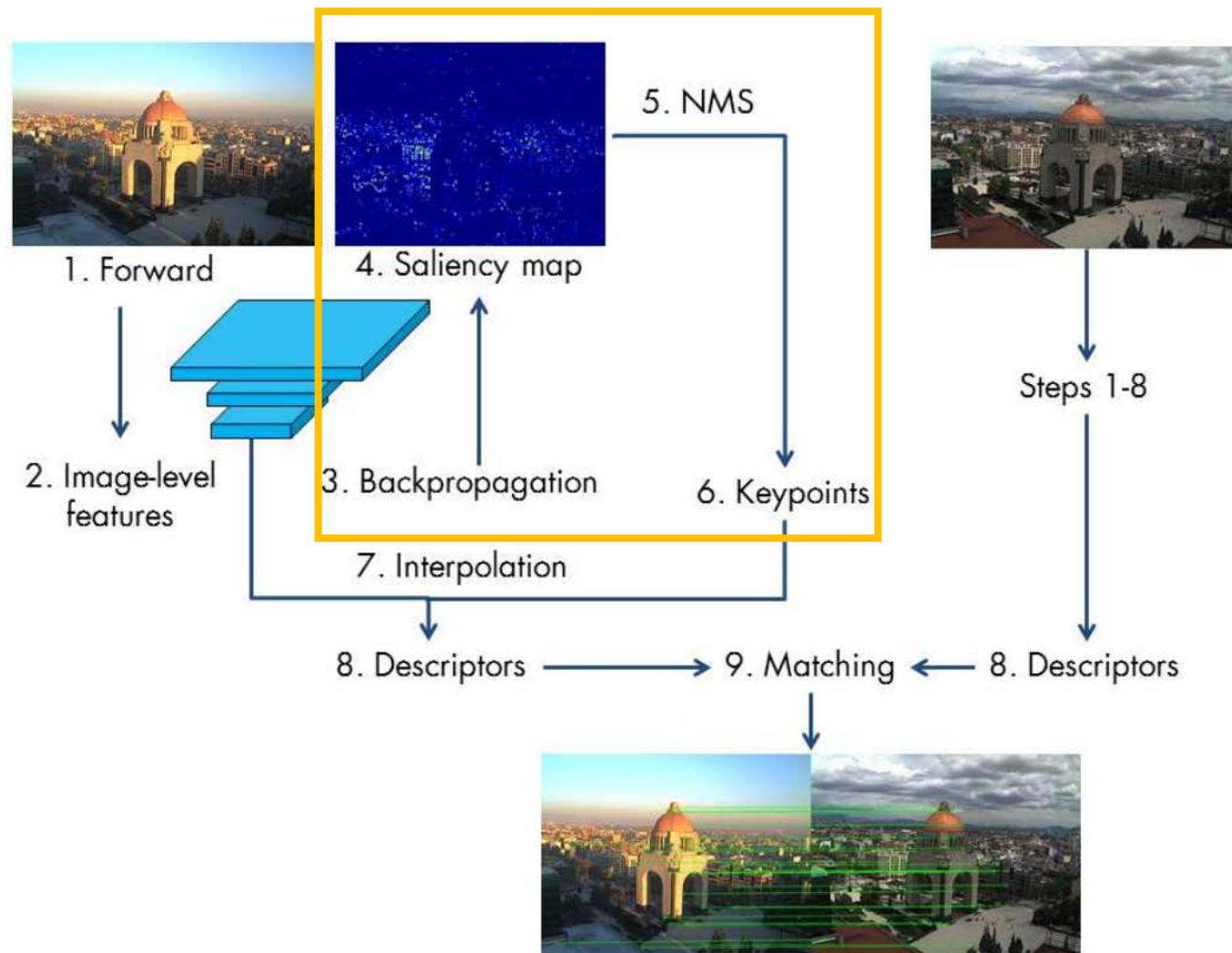
- High level representation → the higher, the better
- High resolution localization information → the lower, the better

Solution: Visually observe the **highest level** which provides **accurate localization**.

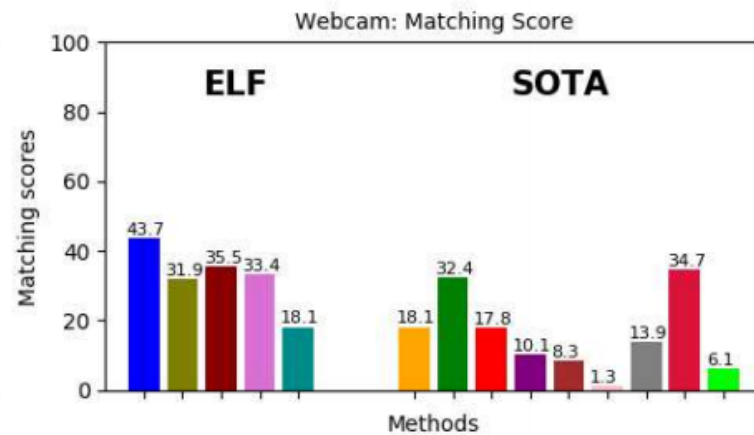
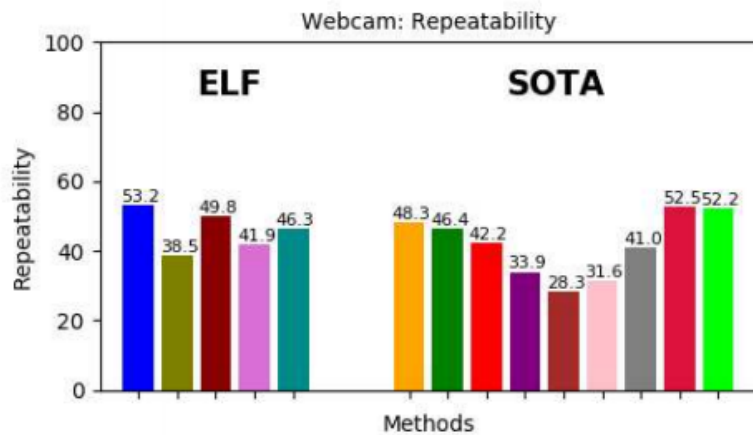
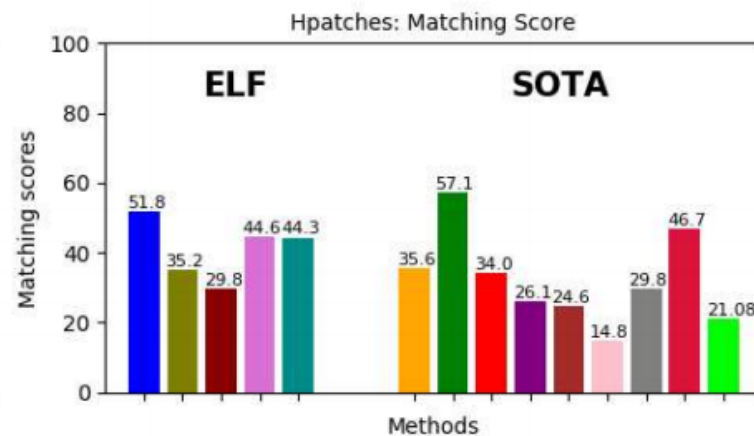
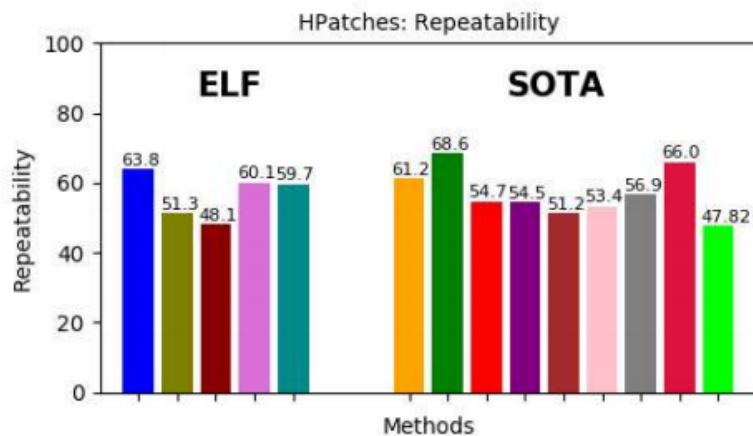
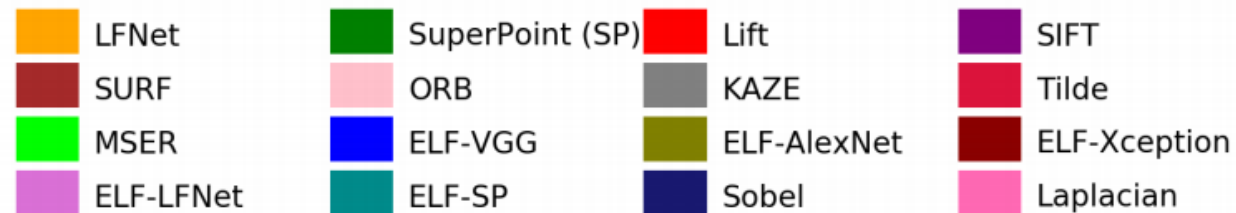
# 4 Review and Result

# Review

This paper focus on these parts



# Result



# 5 Discussion

# Discussion

- Main Contribution:
  - Feature map based saliency map
  - Only use pre-trained CNN
- New directions
  - Harris on feature map.
  - Selecting the best feature map: SIFT-LoG

## Laplacian-of-Gaussian (LoG)

- Interest points:
  - Local maxima in scale space of Laplacian-of-Gaussian

