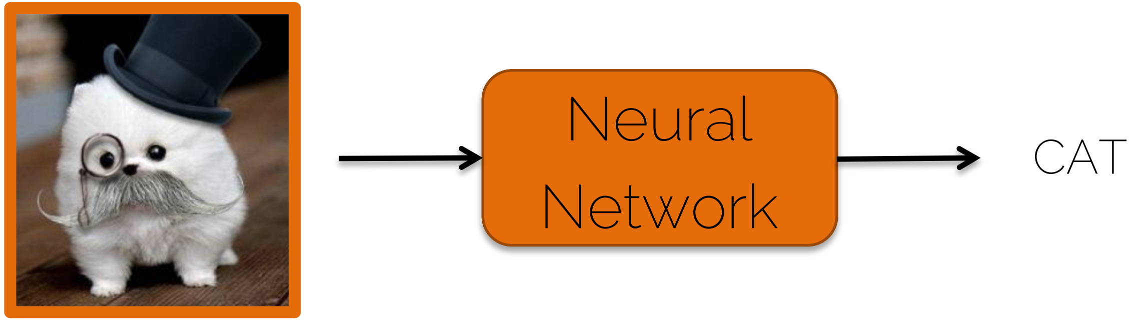
Similarity learning

What can ML do for us?

- Classification problem

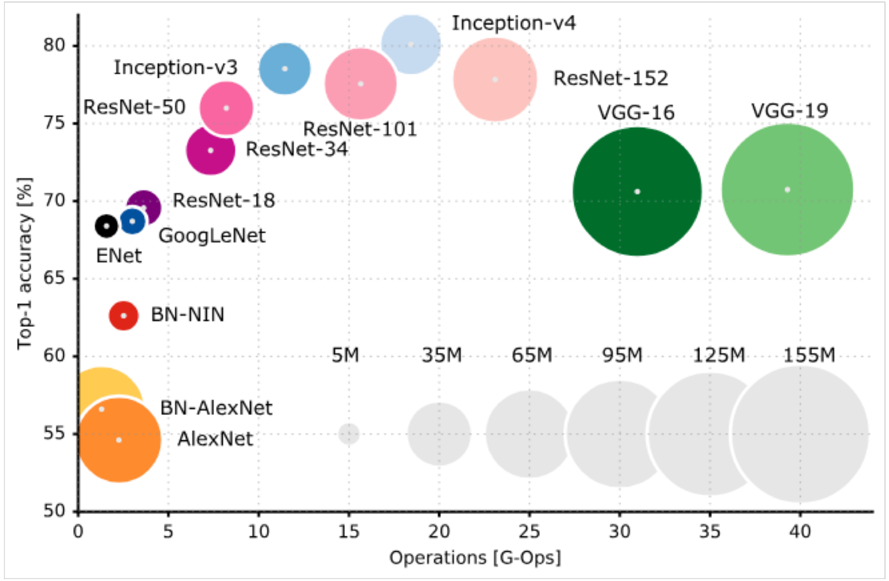


What can ML do for us?

- Classification problem on ImageNet with thousands of categories

What can ML do for us?

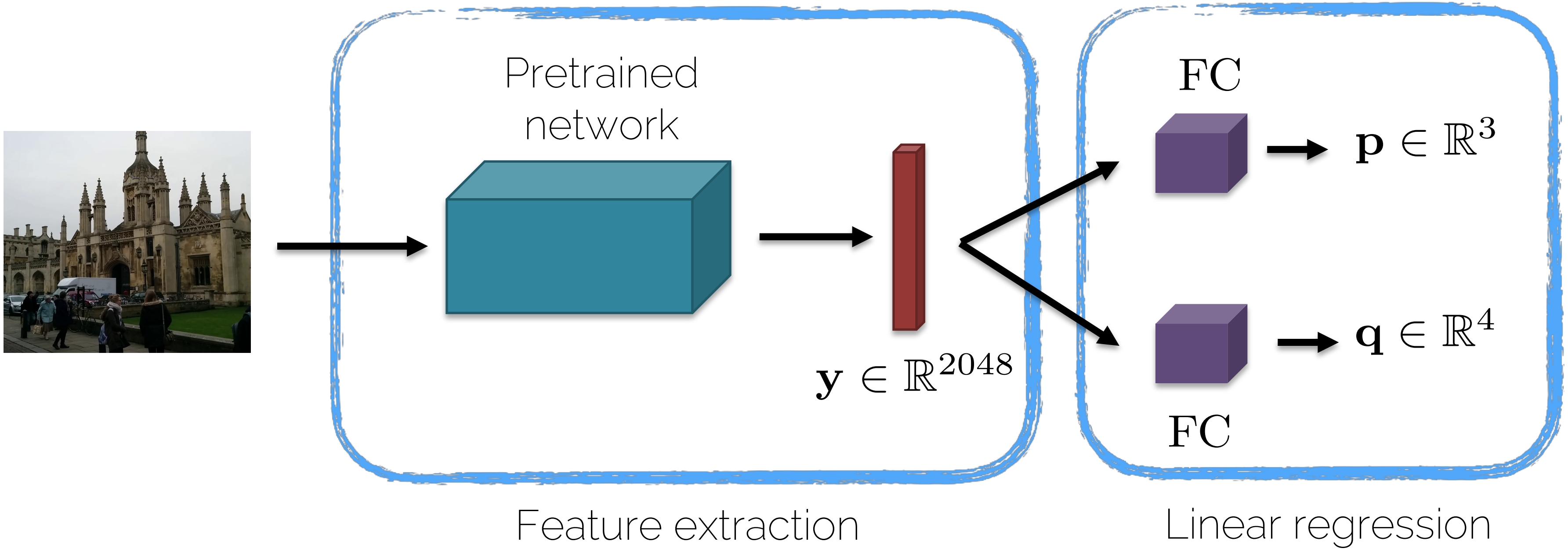
- Performance on ImageNet
  - Size of the blobs indicates the number of parameters



A. Canziani et al. „An Analysis of Deep Neural Network Models for Practical Applications". [arXiv:1605.07678](https://arxiv.org/abs/1605.07678) 2016

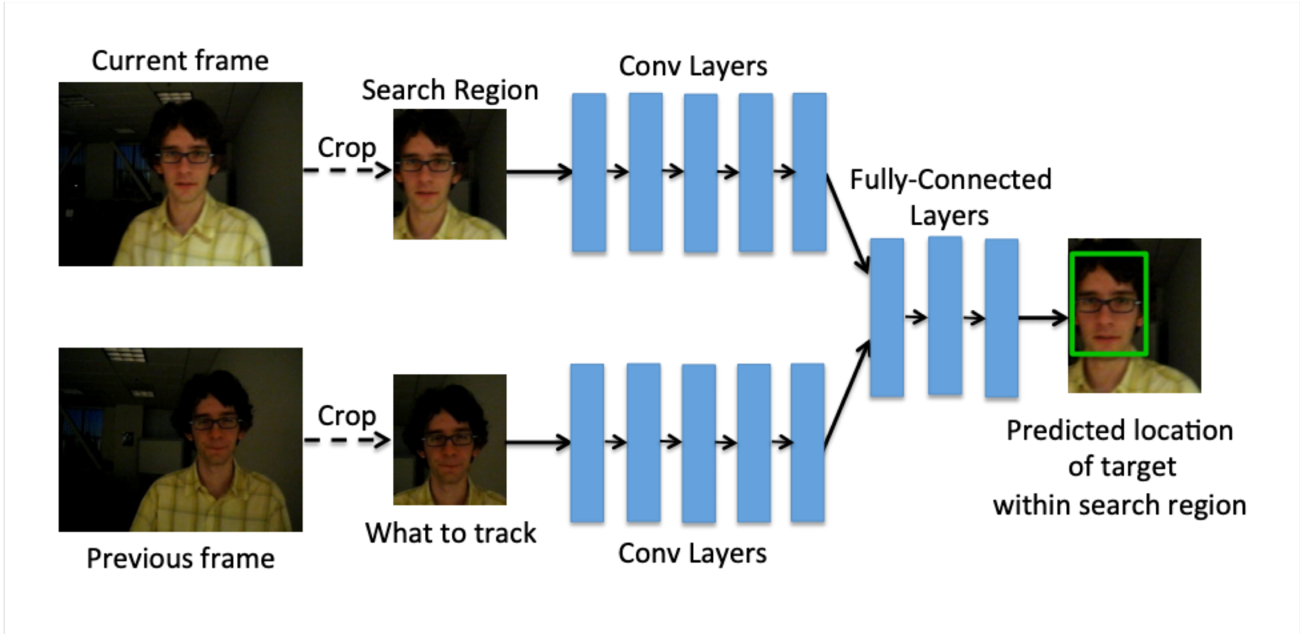
What can ML do for us?

- Regression problem: pose regression



What can ML do for us?

- Regression problem: bounding box regression



D. Held et al. „Learning to Track at 100 FPS with Deep Regression Networks“. ECCV 2016

What can ML do for us?

- Third type of problems

A  Classification: person, face, female

B  Classification: person, face, male

What can ML do for us?

- Third type of problems

A

B

Is it the same person?

What can ML do for us?

- Third type of problems: Similarity Learning

A

B

  - Comparison
  - Ranking

Similarity Learning: when and why?

- Application: unlocking your iPhone with your face

Training

Similarity Learning: when and why?

- Application: unlocking your iPhone with your face

A  YES

B  NO

Testing 

Can be solved as a classification problem

Similarity Learning: when and why?

- Application: face recognition system so students can enter the exam room without the need for ID check

Training

Person 1

Person 2

Person 3

Similarity Learning: when and why?

- Application: face recognition system so students can enter the exam room without the need for ID check

What is the problem
with this approach?

Scalability – we need to retrain our model every time a new student is registered to the course

Similarity Learning: when and why?

- Application: face recognition system so students can enter the exam room without the need for ID check

Can we train one model and use it every year?

Similarity Learning: when and why?

- Learn a similarity function

A

B

Low similarity score

A

B

High similarity score

Similarity Learning: when and why?

- Learn a similarity function

A

B

Low similarity score

A

B

High similarity score

Similarity Learning: when and why?

- Learn a similarity function: testing

A

B

$$d(A, B) > \tau$$

Not the same person

Similarity Learning: when and why?

- Learn a similarity function

A

Same person

$$d(A, B) < \tau$$

B

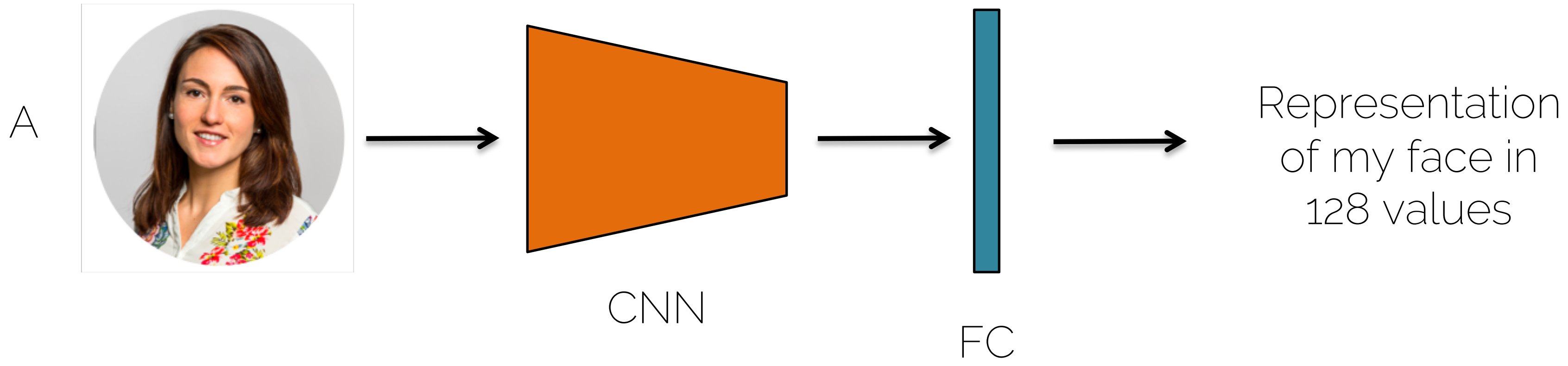
Similarity learning

- How do we train a network to learn similarity?

Siamese Neural Networks

Similarity learning

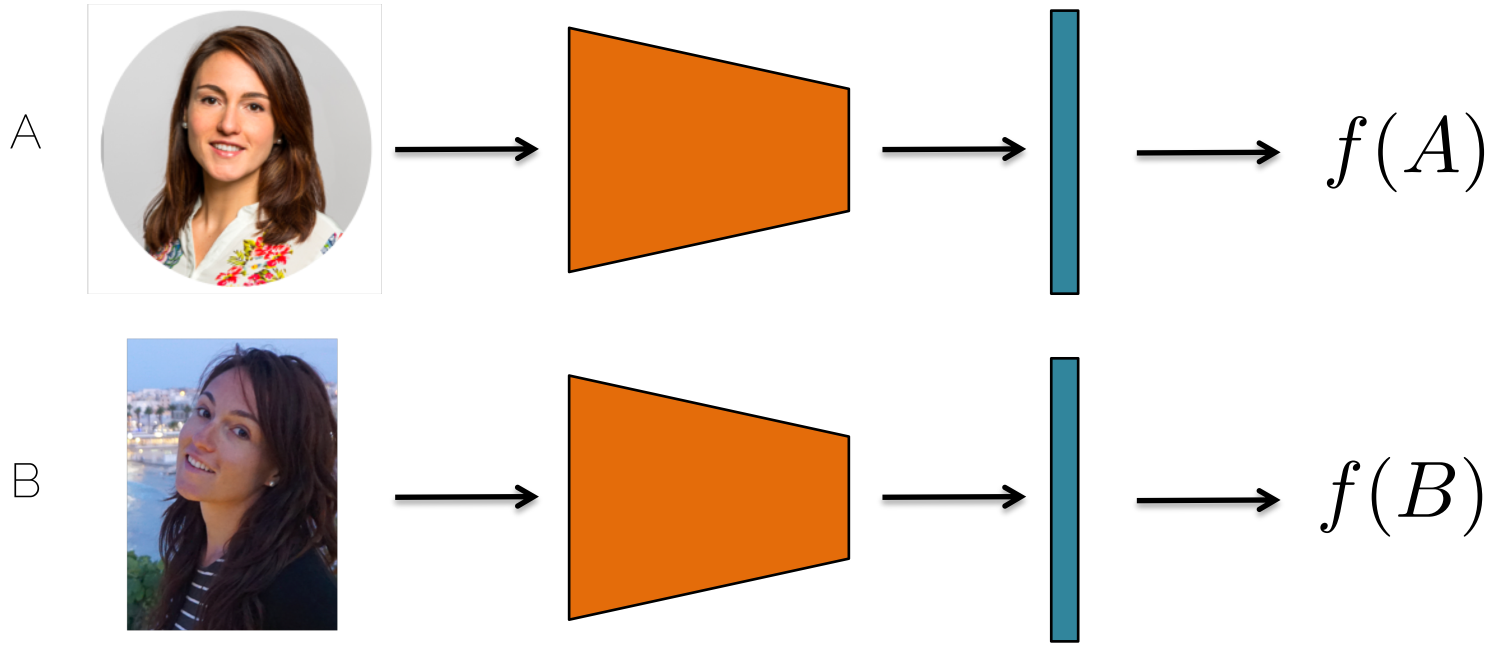
- How do we train a network to learn similarity?



Taigman et al. „DeepFace: closing the gap to human level performance". CVPR 2014

Similarity learning

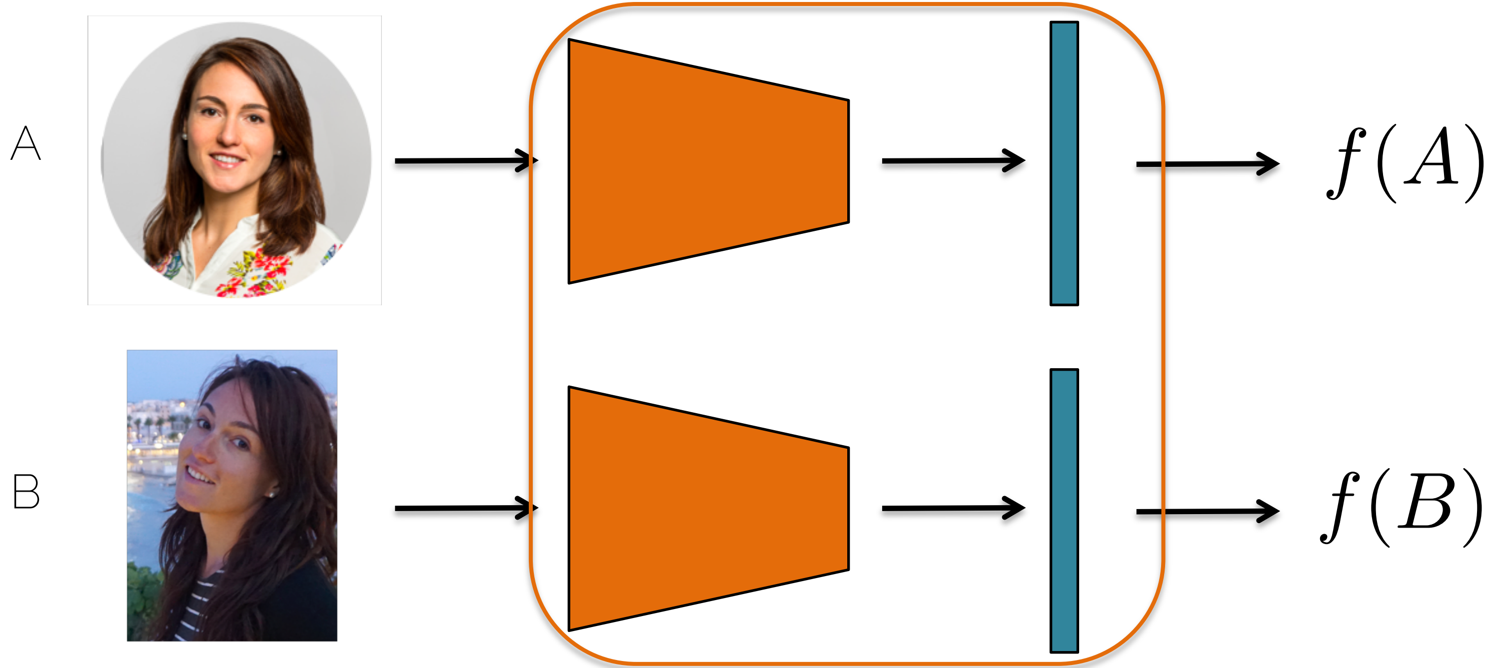
- How do we train a network to learn similarity?



Taigman et al. „DeepFace: closing the gap to human level performance". CVPR 2014

Similarity learning

- Siamese network = shared weights



Taigman et al. „DeepFace: closing the gap to human level performance". CVPR 2014

Similarity learning

- Siamese network = shared weights
- We use the same network to obtain an encoding of the image $f(A)$
- To be done: compare the encodings

Taigman et al. „DeepFace: closing the gap to human level performance". CVPR 2014

Similarity learning

- Distance function $d(A, B) = ||f(A) - f(B)||^2$

- Training: learn the parameter such that

  – If A and B depict the same person, $d(A, B)$ is small

  – If A and B depict a different person, $d(A, B)$ is large

Taigman et al. „DeepFace: closing the gap to human level performance". CVPR 2014

Similarity learning

- Loss function for a positive pair:
  - If A and B depict the same person, $d(A, B)$ is small

$$\mathcal{L}(A, B) = ||f(A) - f(B)||^2$$

Similarity learning

- Loss function for a negative pair:
  - If A and B depict a different person, $d(A,B)$ is large
  - Better use a Hinge loss

$$\mathcal{L}(A,B) = \max(0, m^2 - ||f(A) - f(B)||^2)$$

Similarity learning

- Contrastive loss:

$$\mathcal{L}(A,B) = y^*||f(A) - f(B)||^2 + (1-y^*)max(0, m^2 - ||f(A) - f(B)||^2)$$

Positive pair, reduce the distance between the elements

Negative pair, brings the elements further apart up to a margin

Similarity learning

- Training the siamese networks
  - You can update the weights for each channel independently and then average them

- This loss function allows us to learn to bring positive pairs together and negative pairs apart

Triplet loss

- Triplet loss allows us to learn a ranking

Anchor (A)

Positive (P)

Negative (N)

We want: $$||f(A) - f(P)||^2 < ||f(A) - f(N)||^2$$

Schroff et al „FaceNet: a unified embedding for face recognition and clustering". CVPR 2015

Triplet loss

- Triplet loss allows us to learn a ranking

$$||f(A) - f(P)||^2 < ||f(A) - f(N)||^2$$

$$||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 < 0$$

$$||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 + m < 0$$

margin

Schroff et al „FaceNet: a unified embedding for face recognition and clustering". CVPR 2015

Triplet loss

- Triplet loss allows us to learn a ranking

$$||f(A) - f(P)||^2 < ||f(A) - f(N)||^2$$

$$||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 < 0$$

$$||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 + m < 0$$

$$\mathcal{L}(A, P, N) = max(0, ||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 + m)$$

Schroff et al „FaceNet: a unified embedding for face recognition and clustering". CVPR 2015

Triplet loss

- Training with hard cases

$$\mathcal{L}(A,P,N) = max(0, ||f(A) - f(P)||^2 - ||f(A) - f(N)||^2 + m)$$

- Train for a few epoch
- Choose the hard cases where $d(A,P) \approx d(A,N)$
- Train with those to refine the distance learned

Applications in vision

Establishing image correspondences

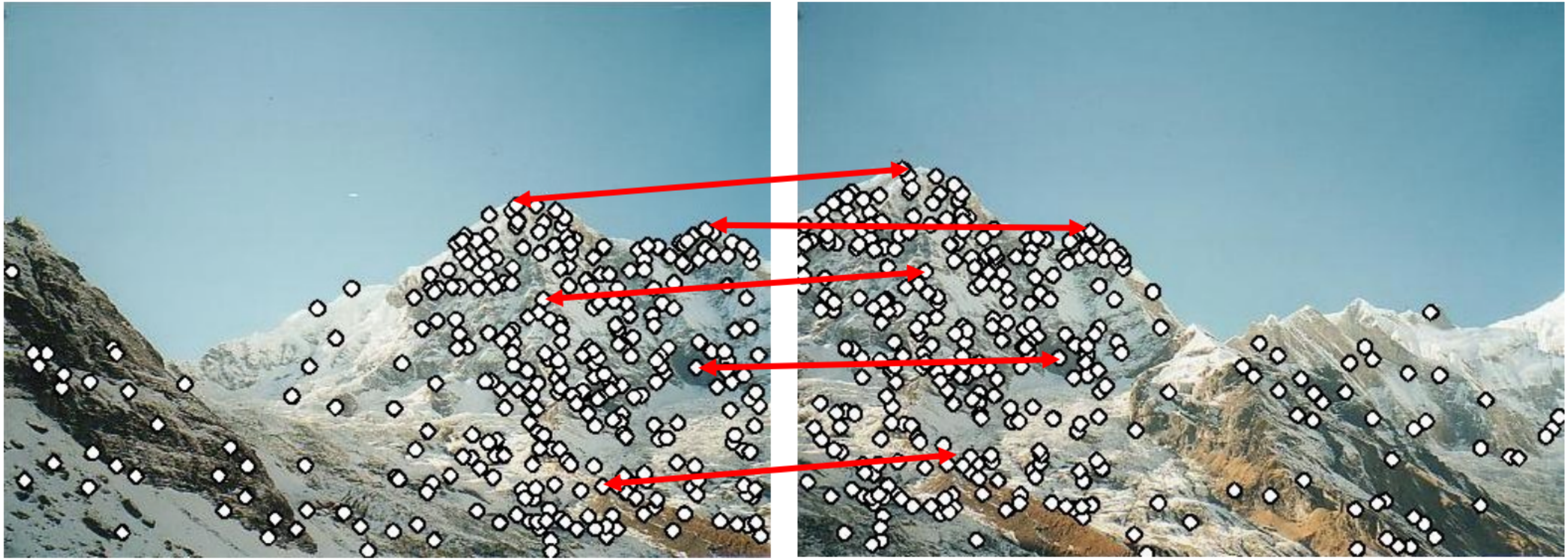


Image from University of Washington

Establishing image correspondences

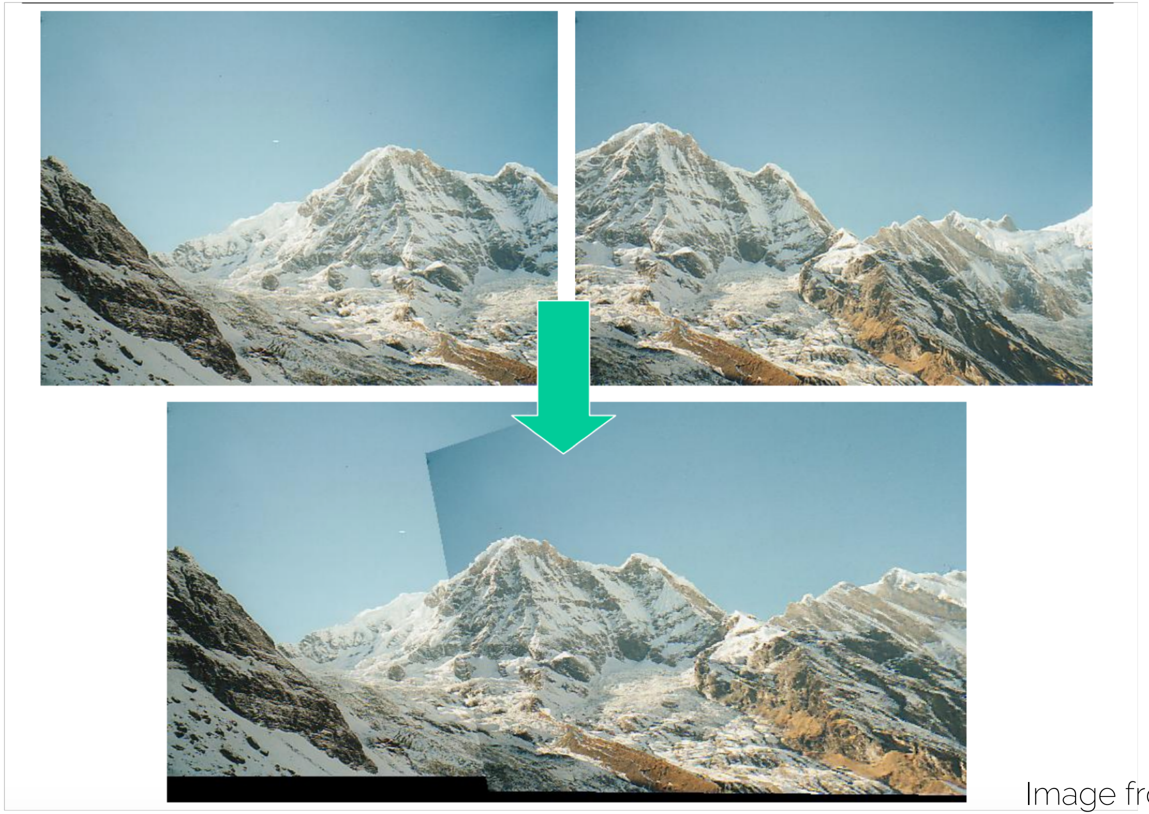


Image from University of Washington

Establishing image correspondences

- Used in a wide range of Computer Vision applications
  - Image stitching or image alignment
  - Object recognition
  - 3D reconstruction
  - Object tracking
  - Image retrieval

- Many of these applications are now targeted directly with Neural Networks as we will see in the course

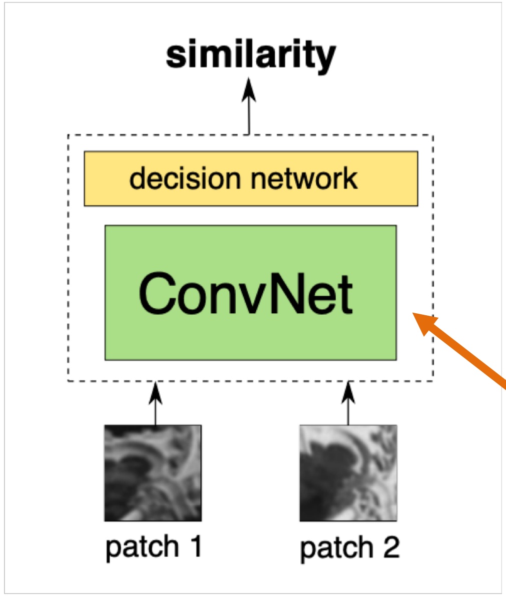
Establishing image correspondences

- Classic method pipeline
  - Extract manually designed feature descriptors
    - Harris, SIFT, SURF: most are based on image gradients
    - They suffer under extreme illumination or viewpoint changes
    - Slow to extract dense features
  - Match descriptors from the two images
    - Many descriptors are similar, one needs to filter out possible double matches and keep only reliable ones.

Sameer Agarwal et al. „Building Rome in a Day". ICCV 2009

Establishing image correspondences

- End-to-end learning for patch similarity



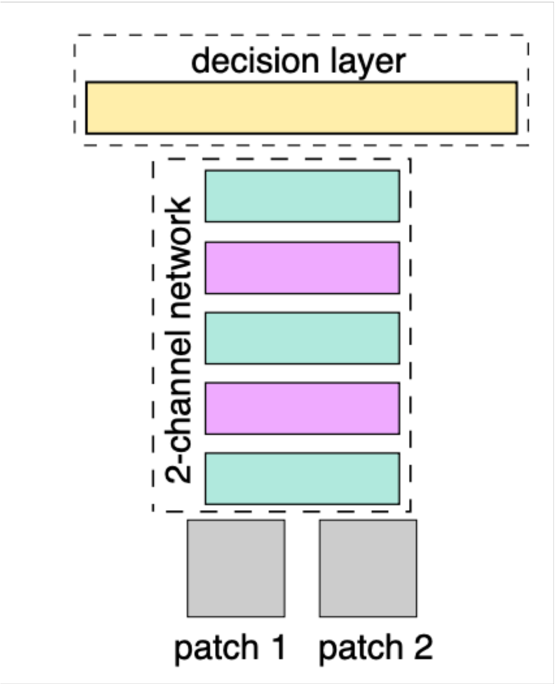
- Fast to allow dense extraction
- Invariant to a wide array of transformations (illumination, viewpoint)

Siamese network

S. Zagoruyko and N. Komodakis. „Learning to Compare Image Patches via Convolutional Neural Networks". CVPR 2015

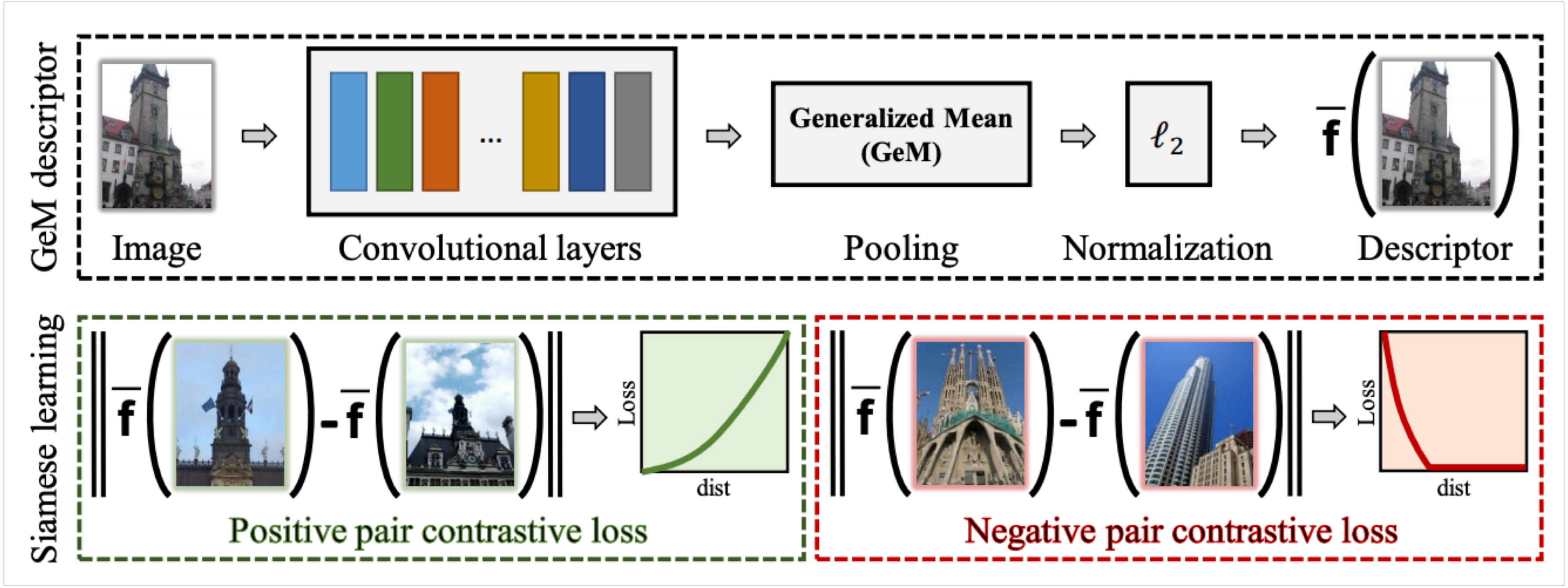
Establishing image correspondences

- Classic Siamese architecture
  - Shared layers
    - Simulated feature extraction
  - One decision layer
    - Simulates the matching



S. Zagoruyko and N. Komodakis. „Learning to Compare Image Patches via Convolutional Neural Networks". CVPR 2015

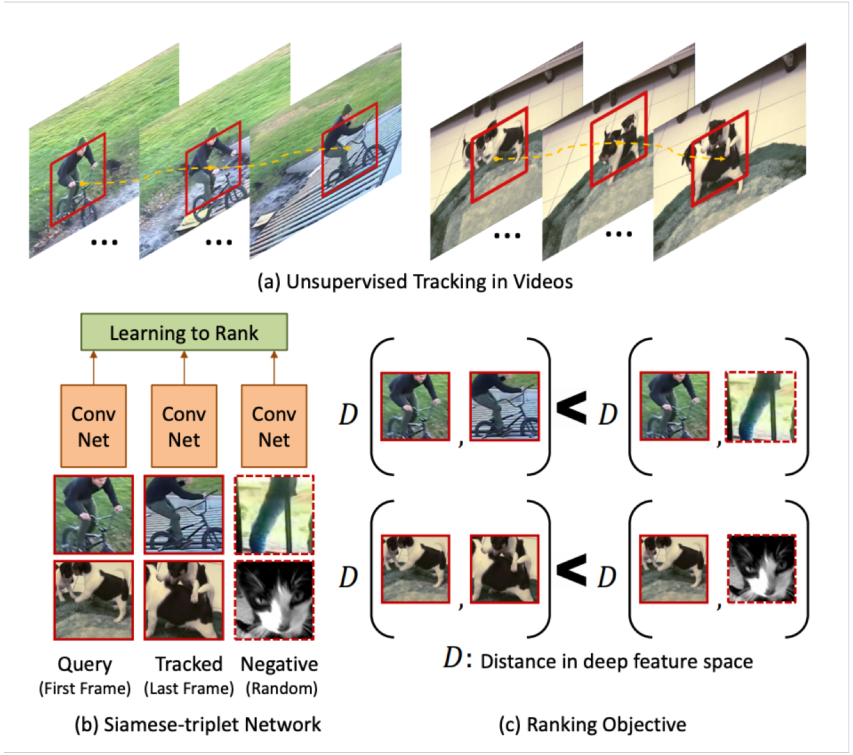
Image retrieval



Radenovic et al.. „Fine-tuning CNN Image Retrieval with No Human Annotation". TPAMI 2018

Unsupervised learning

- Learning from videos
  - Tracking provides the supervision
  - Use those as positive samples
  - Extract random patches as negative samples



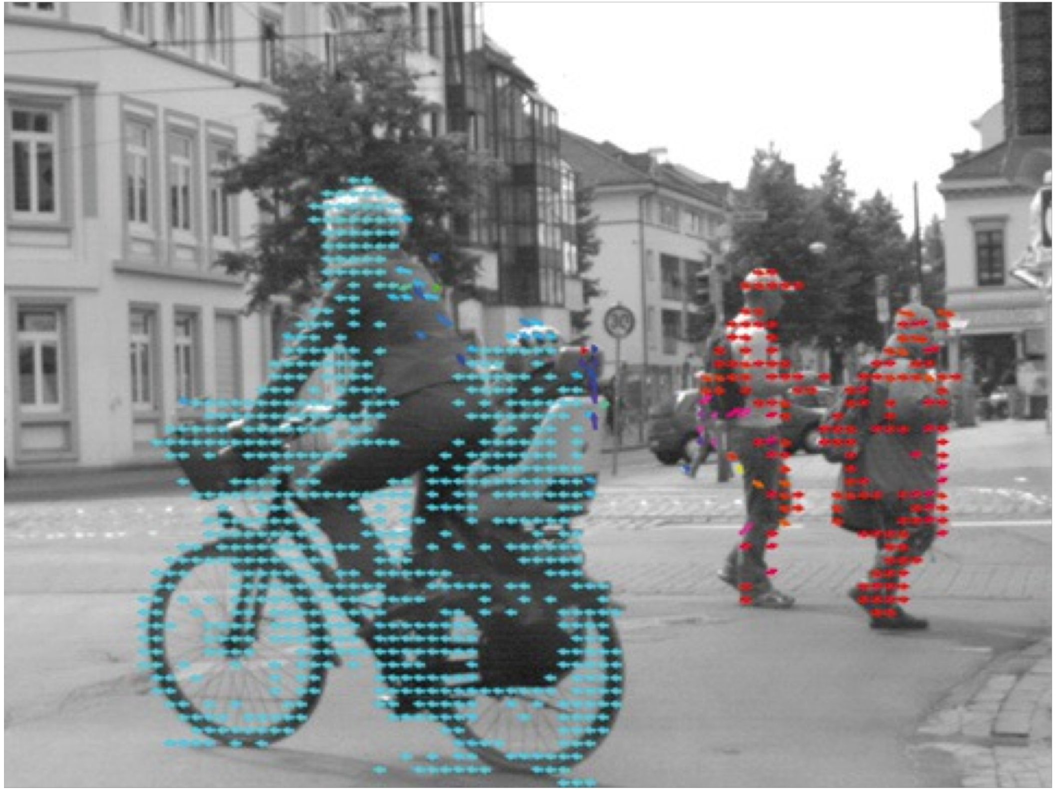
Wang and Gupta. „Unsupervised Learning of Visual Representations using Videos". ICCV 2015

Optical flow

- Input: 2 consecutive images (e.g. from a video)
- Output: displacement of every pixel from image A to image B

- Results in the "perceived" 2D motion, not the real motion of the object

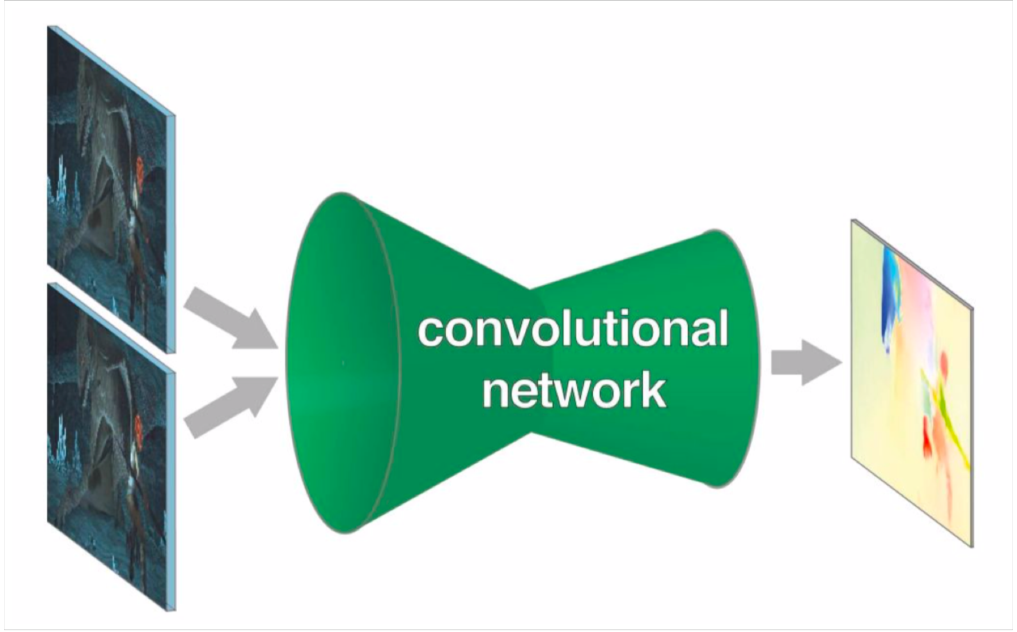
Optical flow



Optical flow

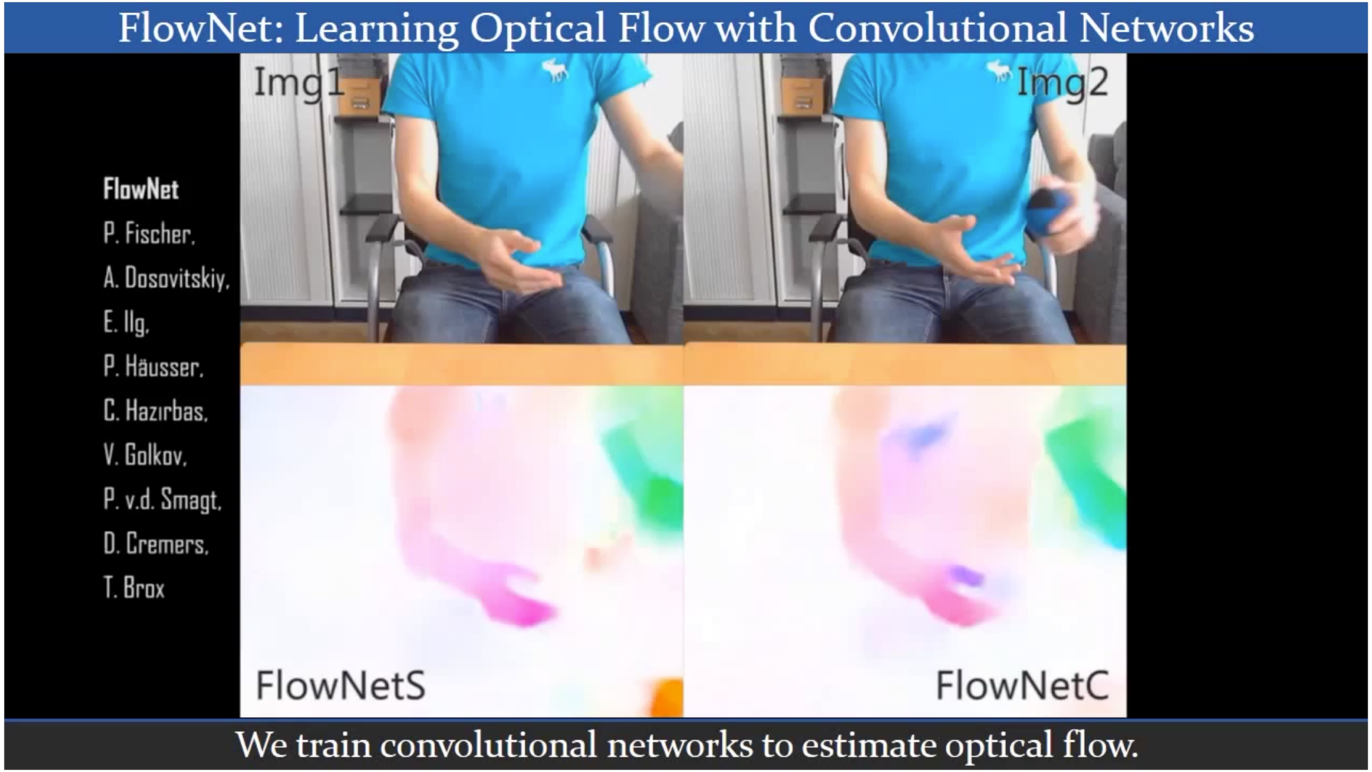
Optical flow with CNNs

- End-to-end supervised learning of optical flow



P. Fischer et al. „FlowNet: Learning Optical Flow With Convolutional Networks". ICCV 2015

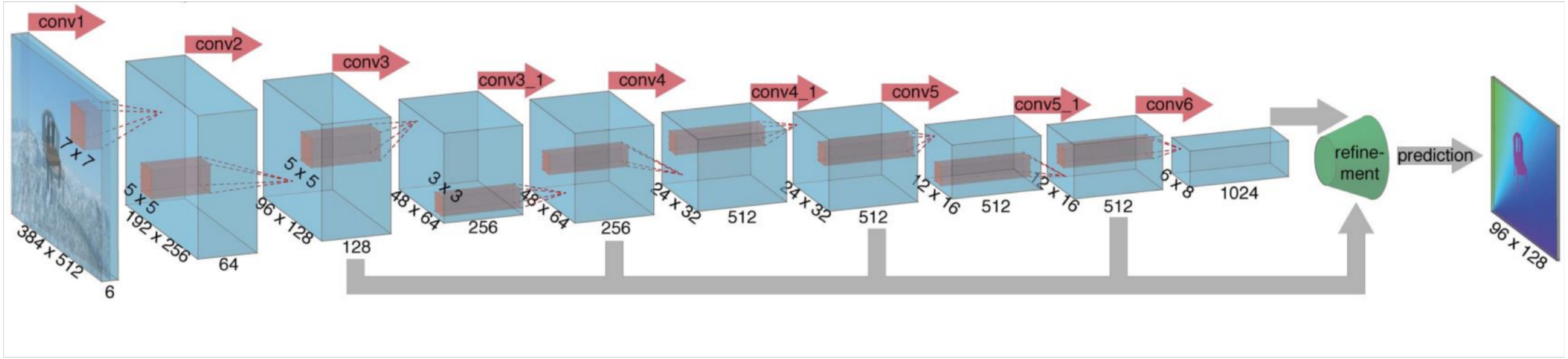
Optical flow with CNNs



P. Fischer et al. „FlowNet: Learning Optical Flow With Convolutional Networks". ICCV 2015

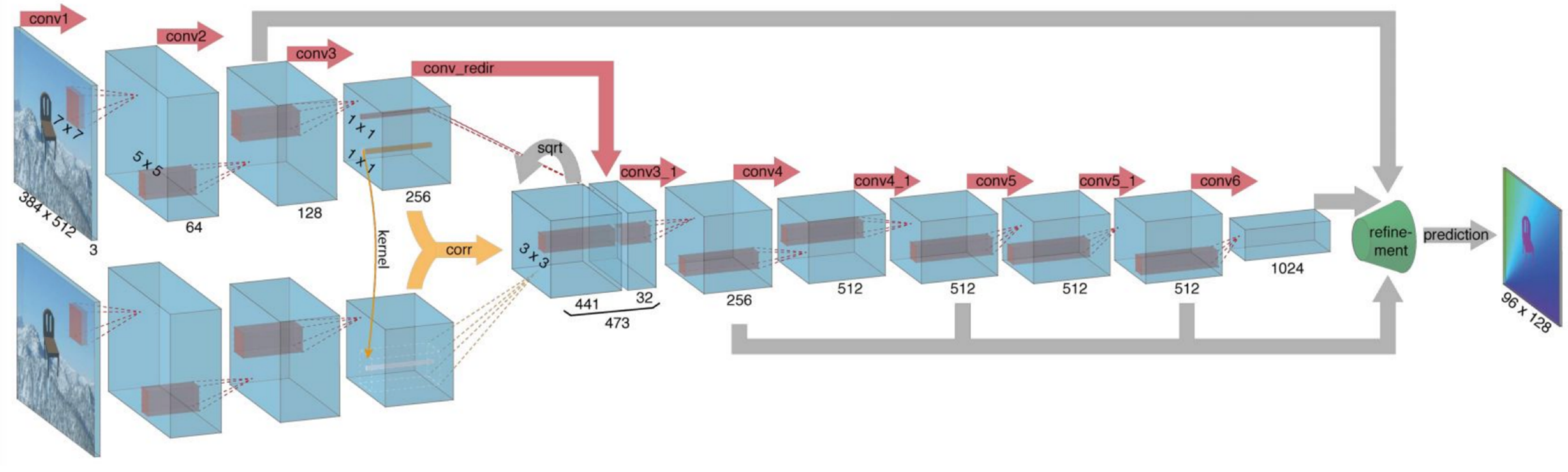
FlowNet: architecture 1

- Stack both images → input is now 2 x RGB = 6 channels



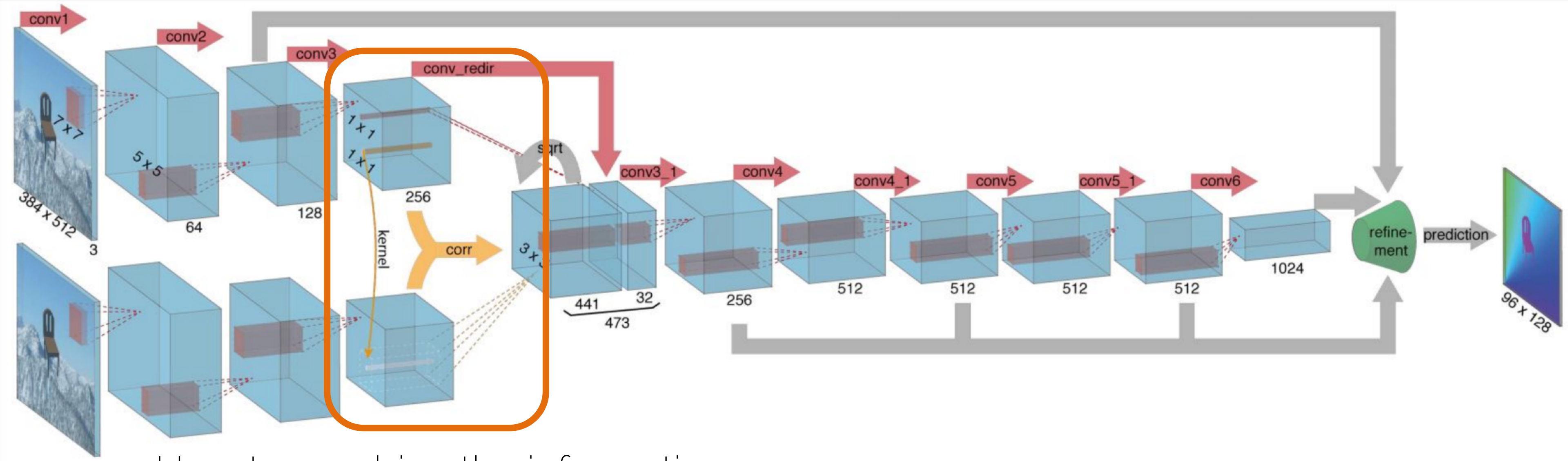
FlowNet: architecture 2

- Siamese architecture



FlowNet : architecture 2

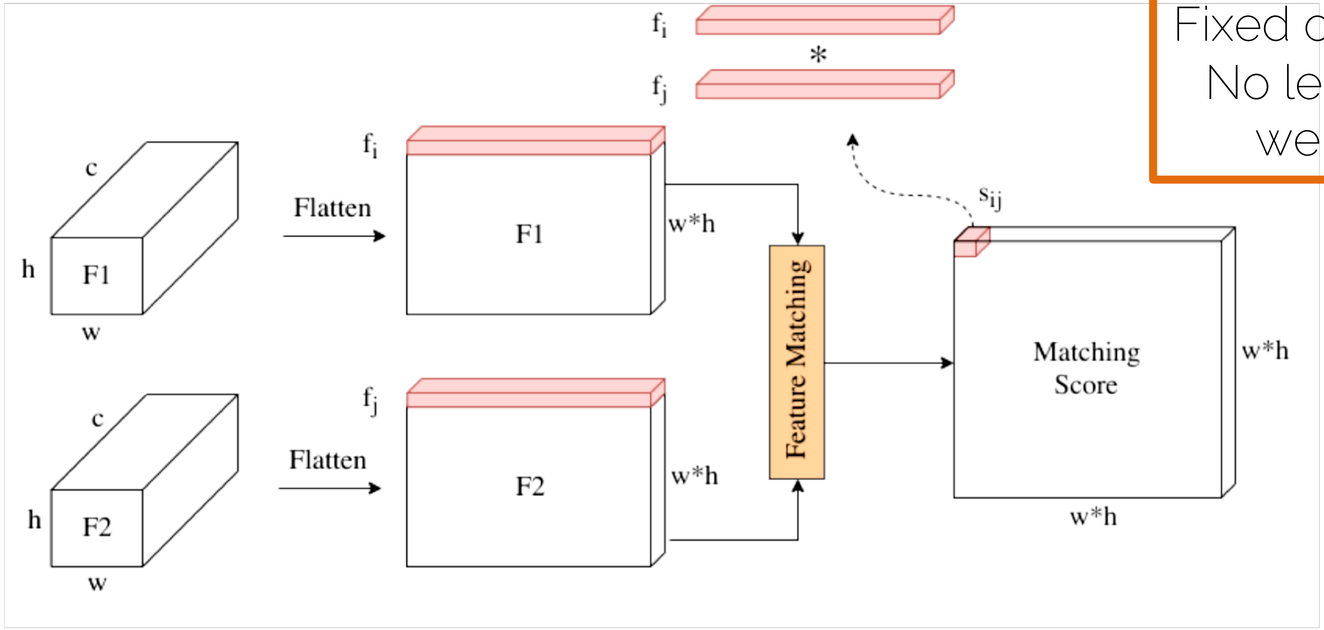
- Two key design choices



How to combine the information
from both images?

Correlation layer

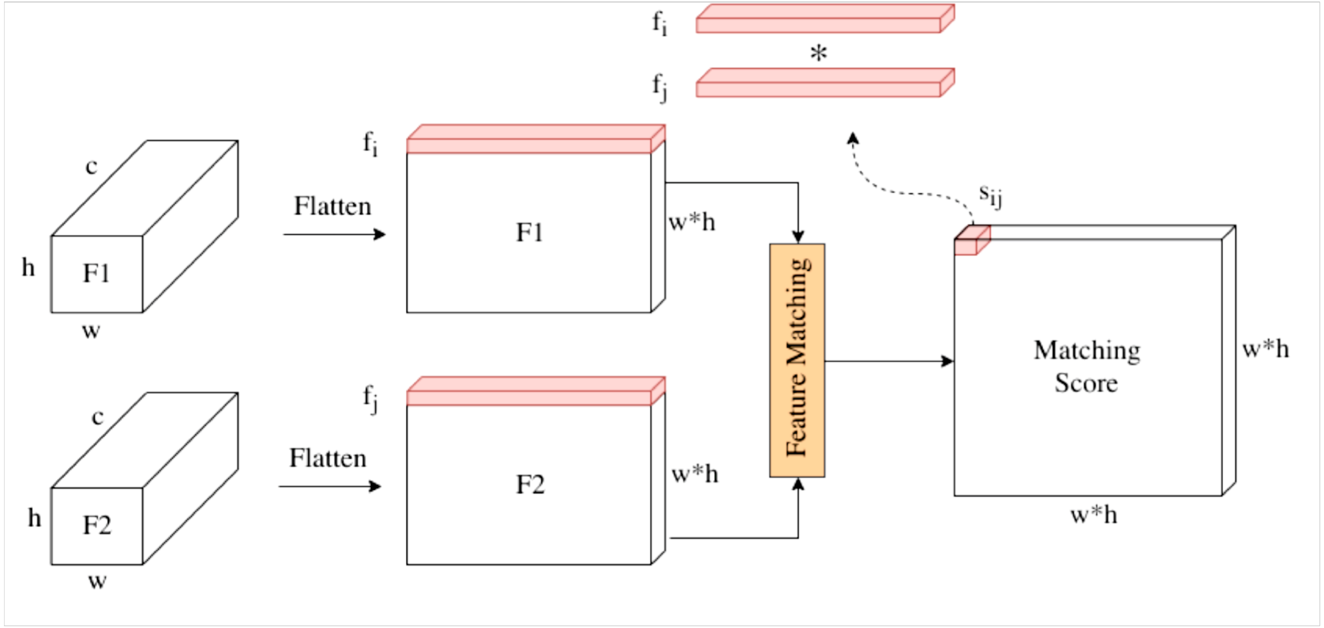
- Multiplies a feature vector with another feature vector



Fixed operation. No learnable weights!

Correlation layer

- The matching score represents how correlated these two feature vectors are



Correlation layer

- Useful for finding image correspondences

A

B

Find a transformation from image A to image B

I. Rocco et al. "Convolutional neural network architecture for geometric matching. CVPR 2017.

Correlation layer

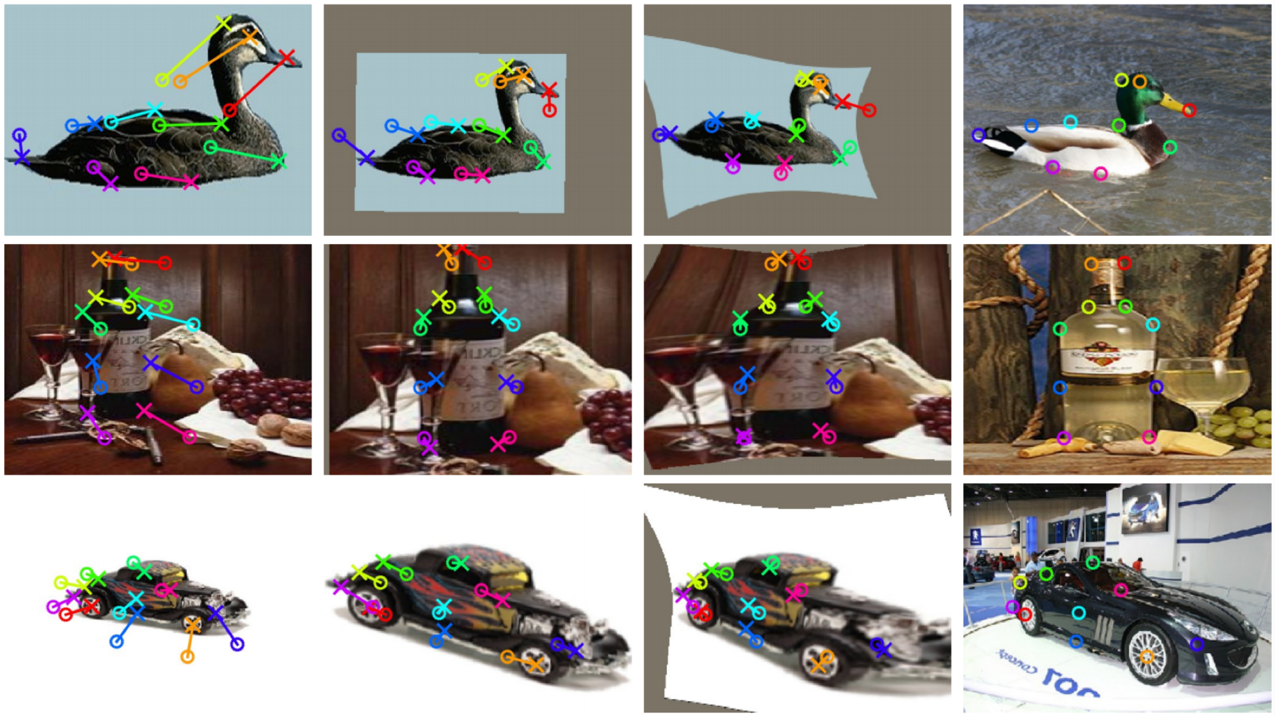
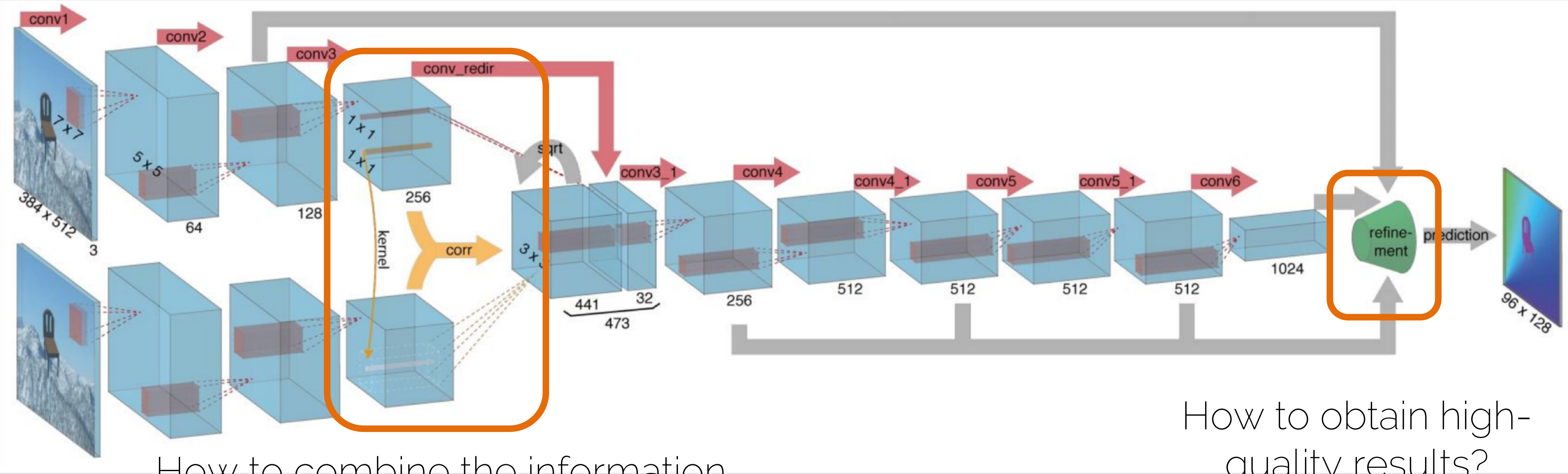


Image A | Aligned A (affine) | Aligned A (affine+TPS) | Image B

I. Rocco et al. "Convolutional neural network architecture for geometric matching. CVPR 2017.

FlowNet : architecture 2

- Two key design choices



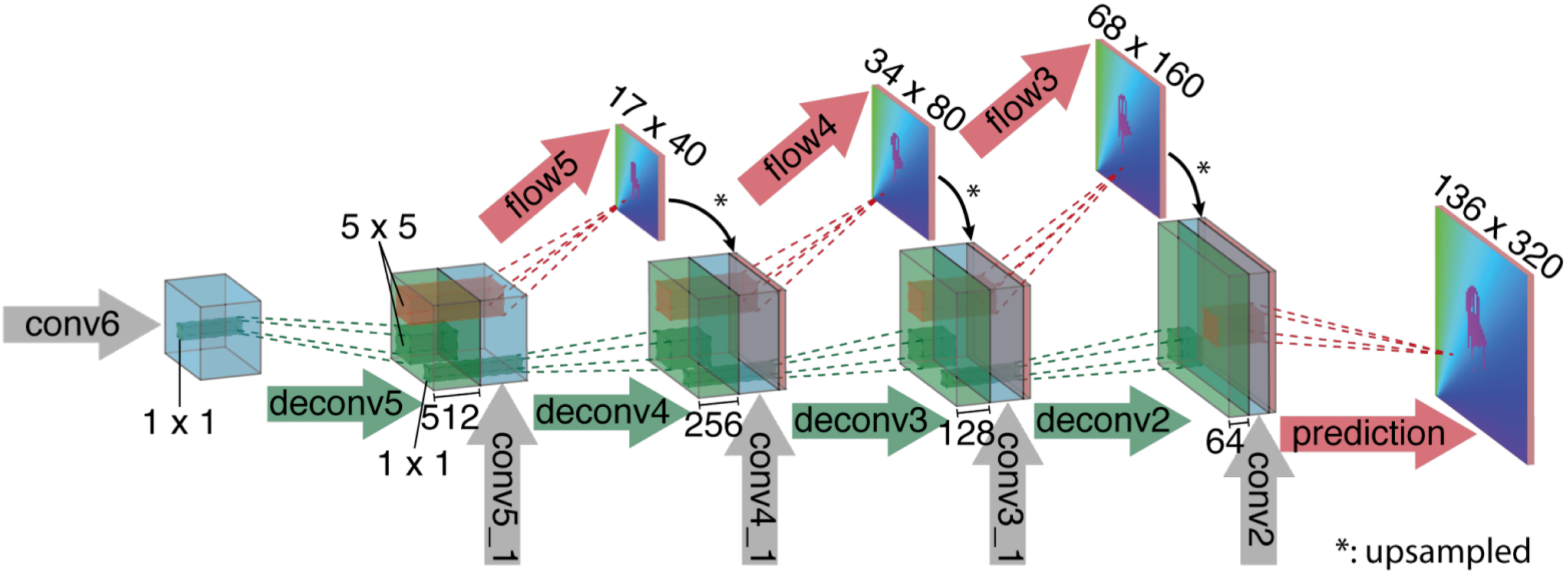
How to combine the information from both images?

How to obtain high-quality results?

FlowNet : architecture 2

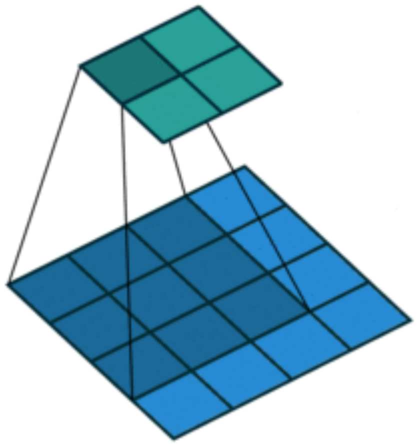
- Convolutions + pooling are great to allow aggregation of information from different parts of the image
- It also makes computation feasible!
- Problem: it reduces the size of our input, if we want full sized outputs (segmentation, optical flow) we need further operations

Refinement architecture

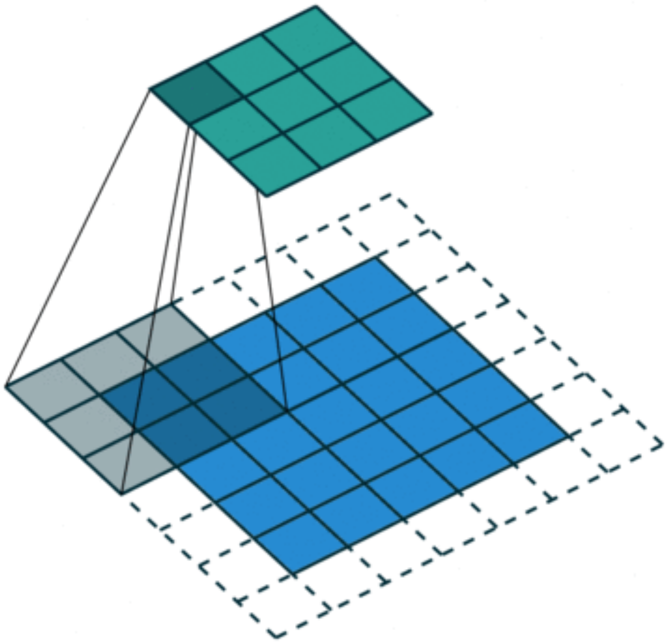


Transpose convolution

- Recall



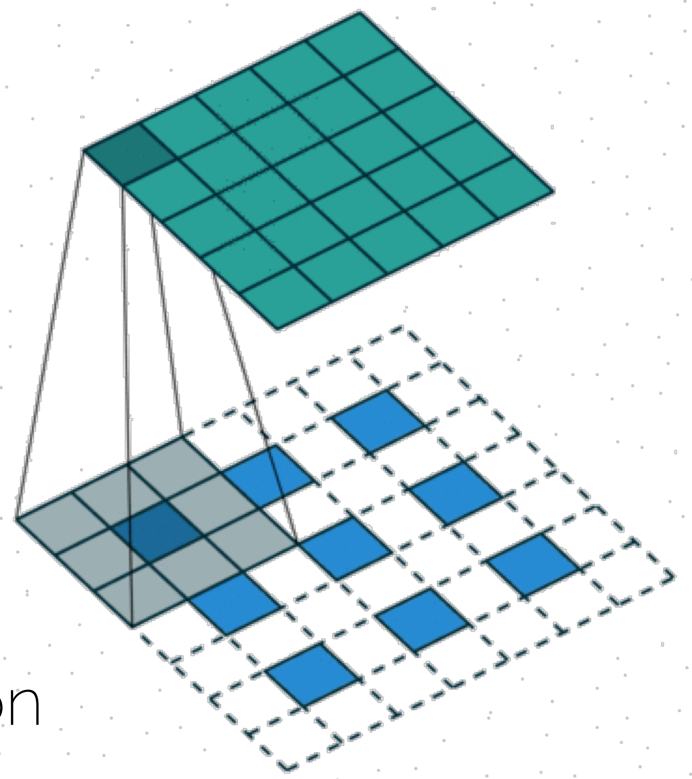
Convolution
no padding, no stride



Convolution
padding, stride

Transpose convolution

- We want to convert the 3x3 input into a 5x5 output
- Clever padding on the input plus a normal convolution
- Unpooling + conv = upconvolution



More on that later

- Next step: Autoencoder architecture as to generate outputs of the same size as inputs

Cool things you can do

- Savinov et al. „Quad-networks: unsupervised learning to rank for interest point detection". CVPR 2017
- Ristani & Tomasi. „Features for Multi-Target Multi-Camera Tracking and Re-Identification". CVPR 2018
- Chen et al. „Beyond triplet loss: a deep quadruplet network for person re-identification". CVPR 2017

Next lecture

- No session on Friday
- Next Monday: more on advanced architectures