

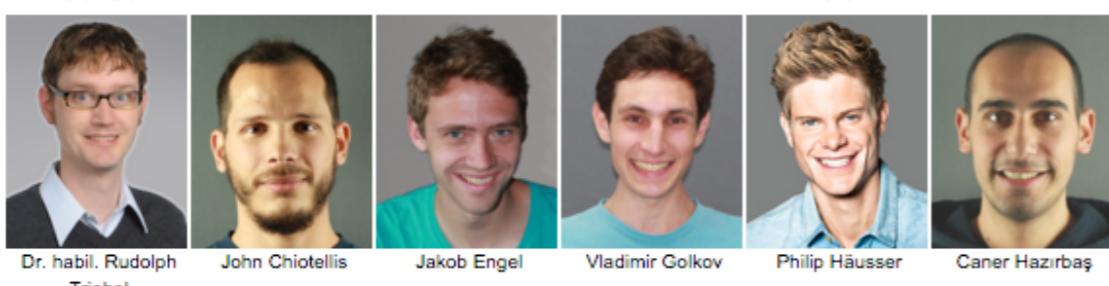
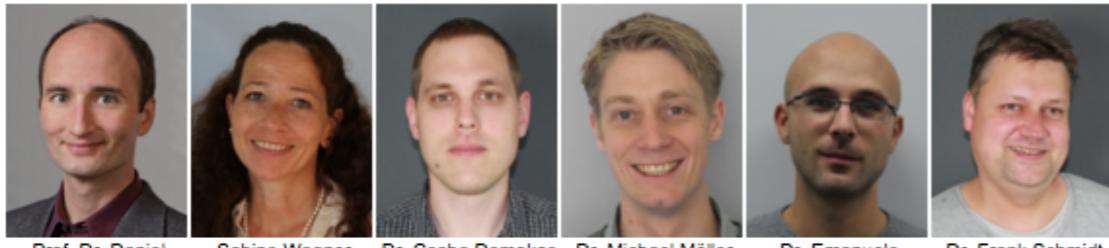
Convolutional Neural Networks for Computer Vision

Caner Hazırbaş

Centrum für Informations- und Sprachverarbeitung
24. November '15

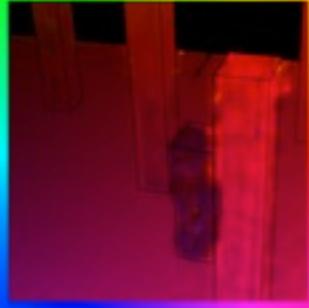
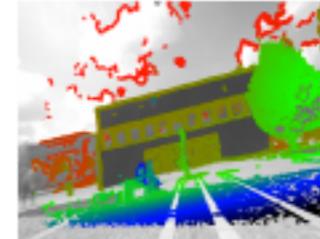
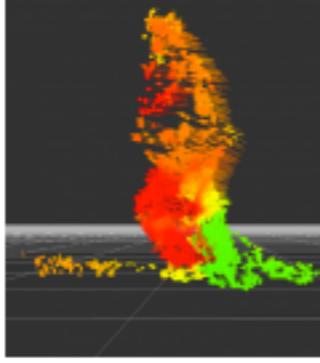
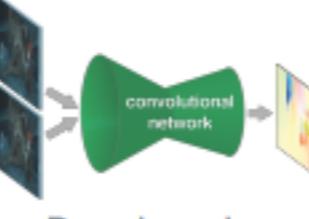


Computer Vision Group



5 Postdocs, 24 PhD students

Research in Computer Vision

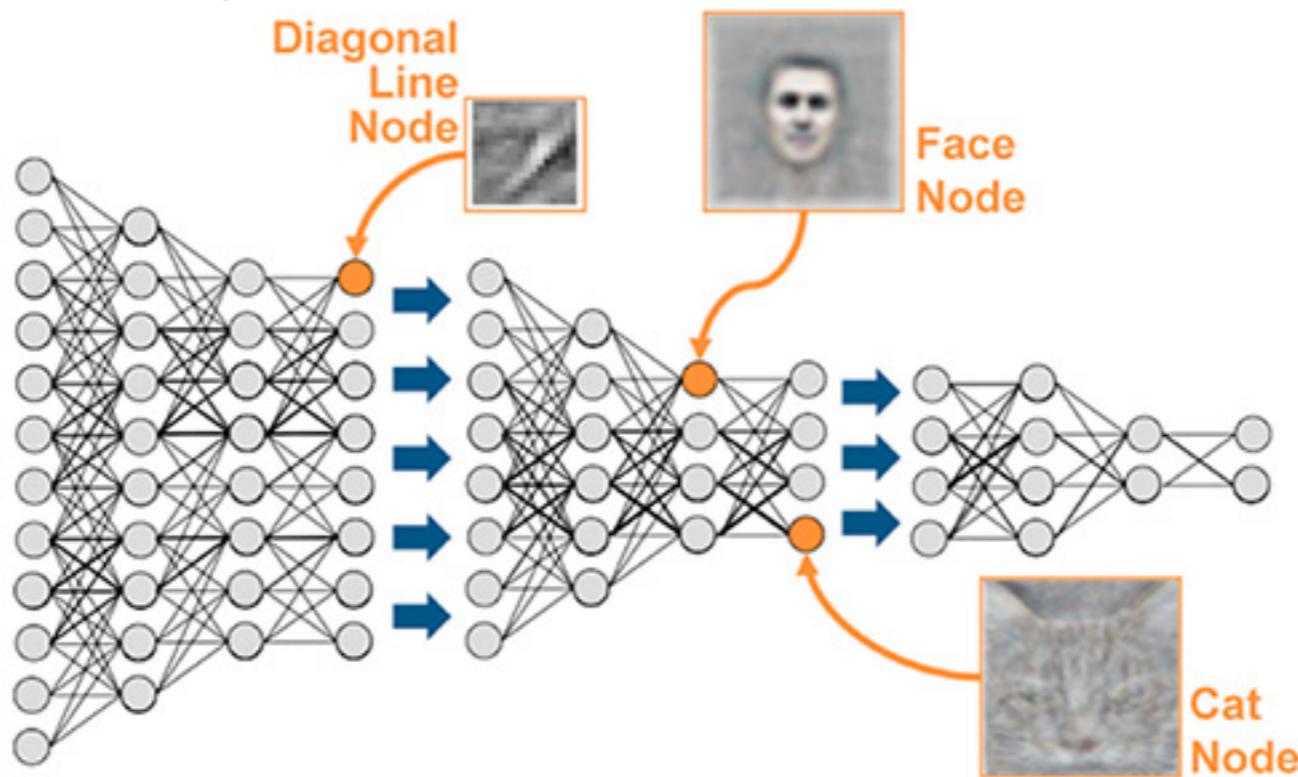
 Image-based 3D Reconstruction	 Optical Flow Estimation	 Shape Analysis	 Robot Vision
 RGB-D Vision	 Image Segmentation	 Convex Relaxation Methods	 Visual SLAM
 Scene Flow Estimation	 Deep Learning		

Convolutional Neural Networks for Computer Vision

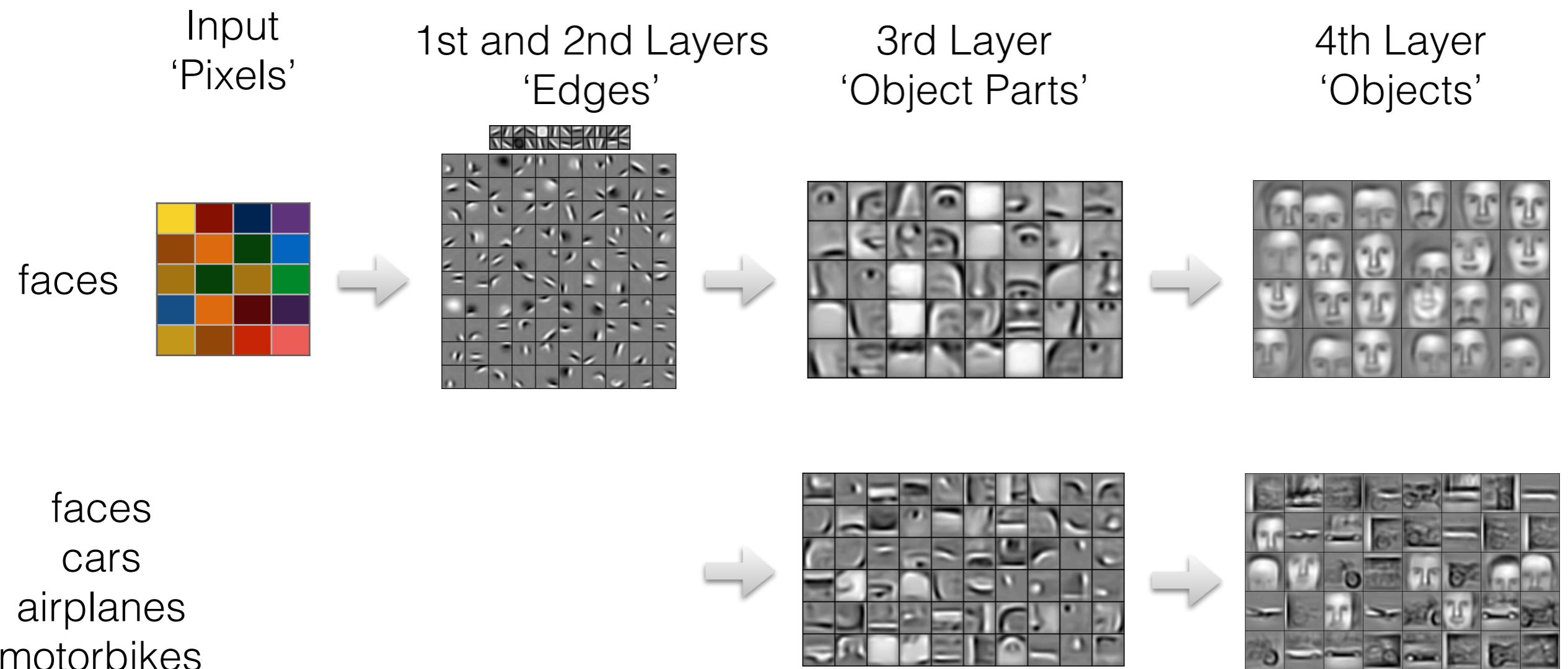
What is deep learning ?

- Representation learning method
Learning good features automatically from raw data
- Learning representations of data with multiple levels of abstraction

Google's cat detection neural network



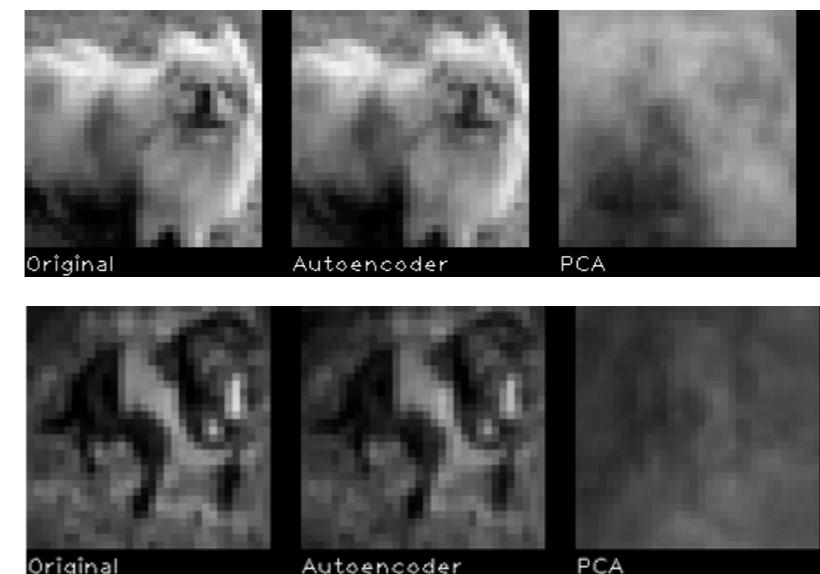
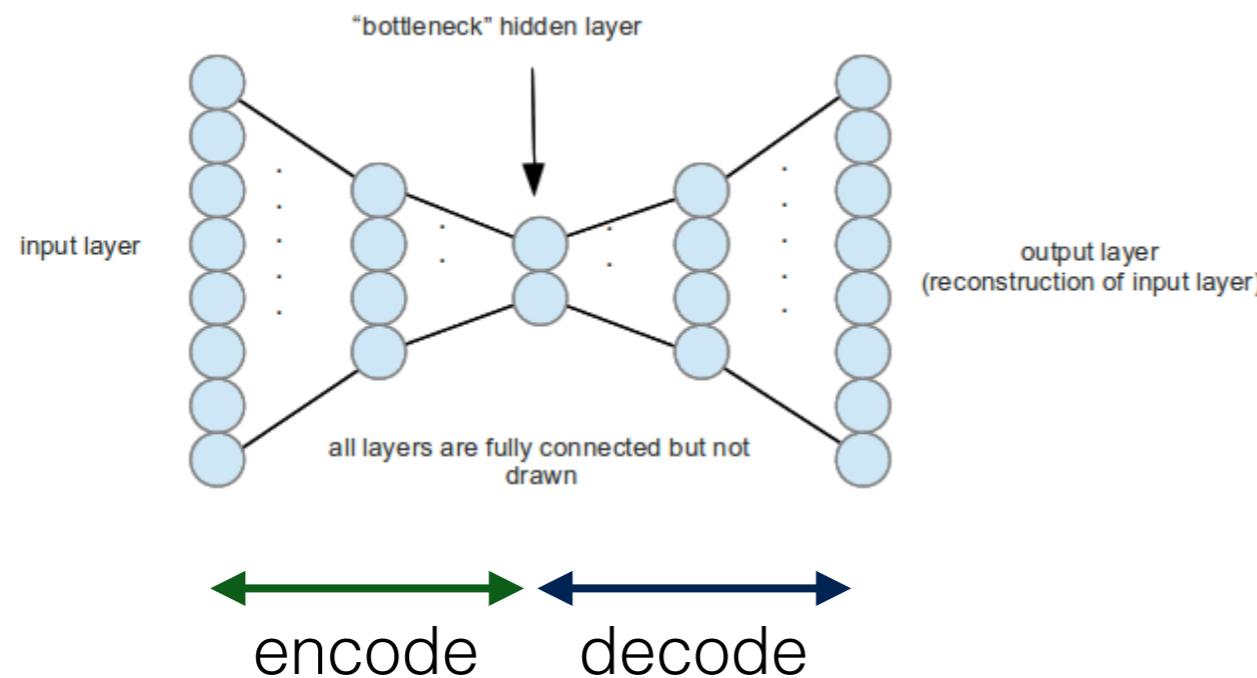
Going deeper in the network



Deep Learning Methods

Unsupervised Methods

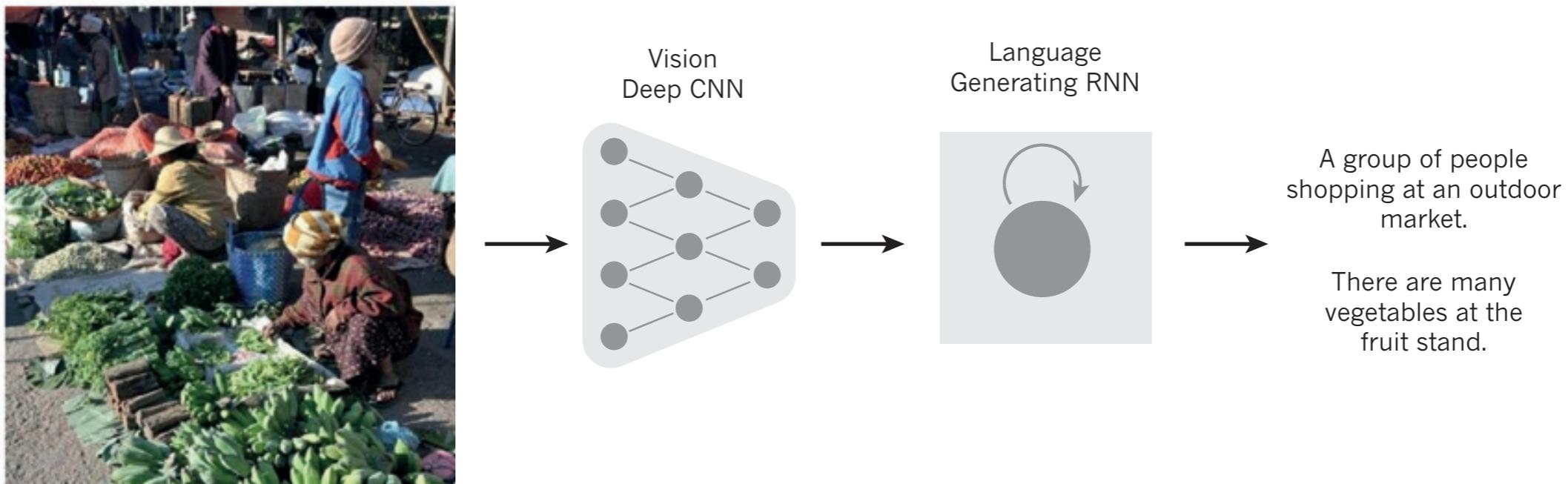
- Restricted Boltzmann Machines
- Deep Belief Networks
- Auto encoders: unsupervised feature extraction/learning



Deep Learning Methods

Supervised Methods

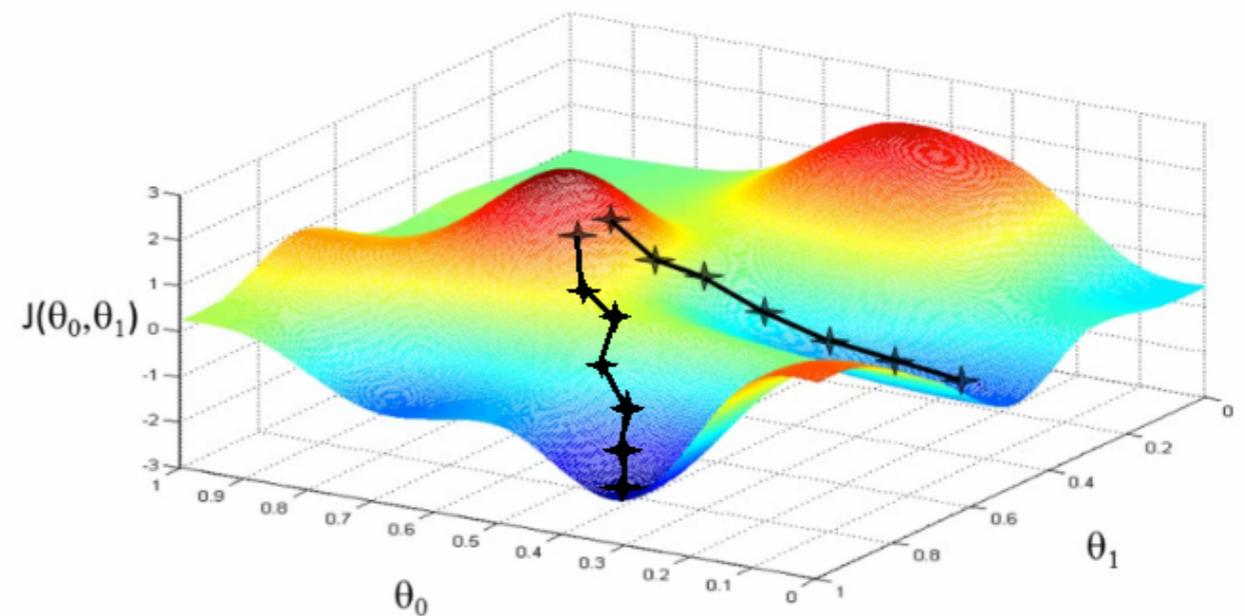
- Deep Neural Networks
- Recurrent Neural Networks
- Convolutional Neural Networks



How to train a deep network ?

Stochastic Gradient Descent – *supervised learning*

- show input vector of few examples
- compute the output and the errors
- compute average gradient
- update the weights accordingly



How to train a deep network ?

Alternatives:

- AdaGrad, AdaDelta, NAG (Nesterov's Accelerated Gradient)...
- **ADAM** (now in Caffe - <http://caffe.berkeleyvision.org/tutorial/solver.html>)
The Adam is a gradient-based optimization method (like SGD). This includes an “adaptive moment estimation” (m_t, v_t) and can be regarded as a generalization of AdaGrad. The update formulas are:

$$(m_t)_i = \beta_1(m_{t-1})_i + (1 - \beta_1)(\nabla L(W_t))_i,$$

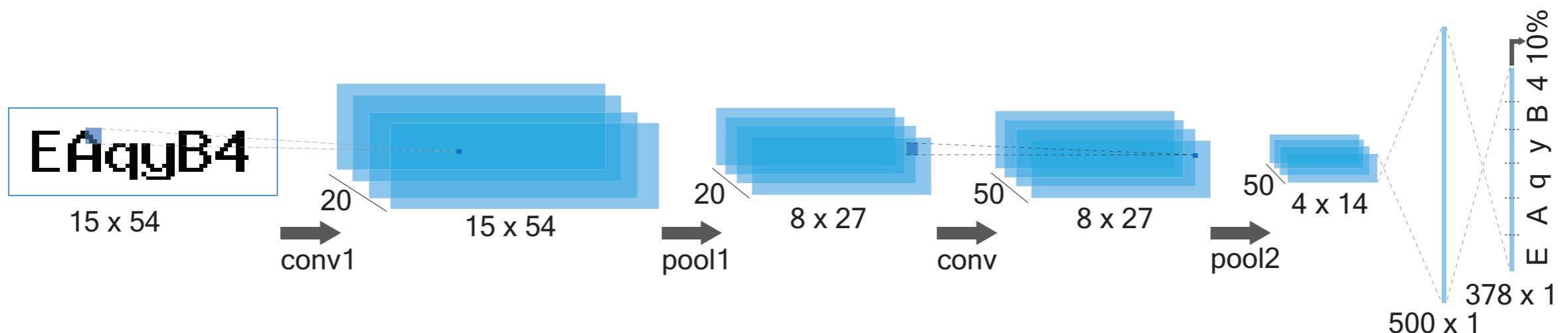
$$(v_t)_i = \beta_2(v_{t-1})_i + (1 - \beta_2)(\nabla L(W_t))_i^2$$

$$(W_{t+1})_i = (W_t)_i - \alpha \frac{\sqrt{1 - (\beta_2)_i^t}}{1 - (\beta_1)_i^t} \frac{(m_t)_i}{\sqrt{(v_t)_i} + \varepsilon}.$$

D. Kingma, J. Ba. Adam: A Method for Stochastic Optimization. International Conference for Learning Representations, 2015

Convolutional Neural Networks

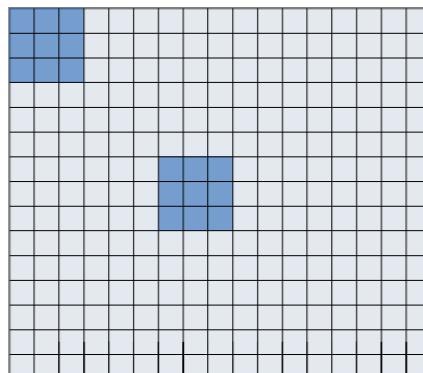
- CNNs are designed to process the data in the form of multiple arrays (e.g. 2D images, 3D video/volumetric images)
- Typical architecture is composed of series of stages: ***convolutional*** layers and ***pooling*** layers
- Each unit is connected to local patches in the feature maps of the previous layer



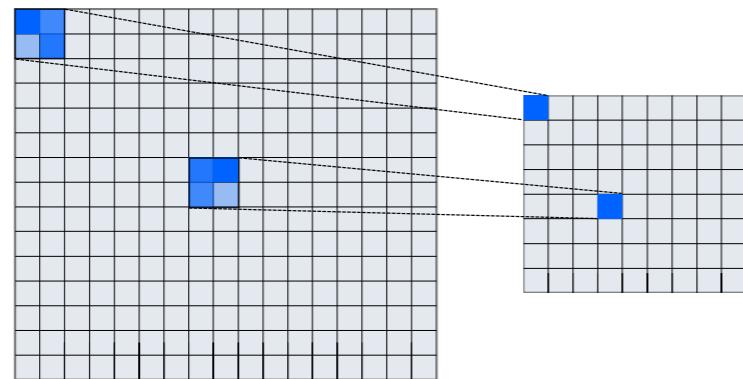
Key Idea behind Convolutional Networks

Convolutional networks take advantage of the properties of natural signals:

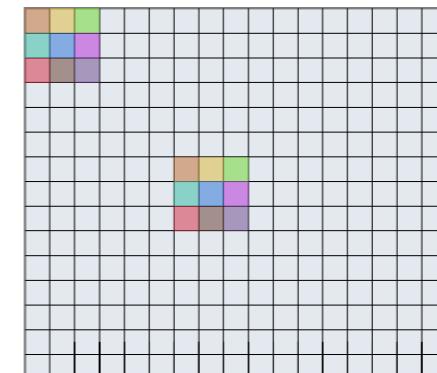
- local connections



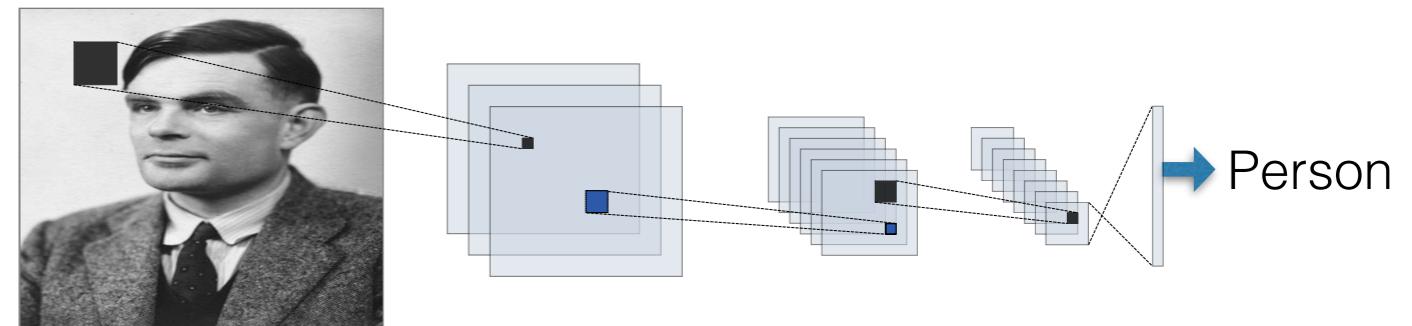
- pooling



- shared weights

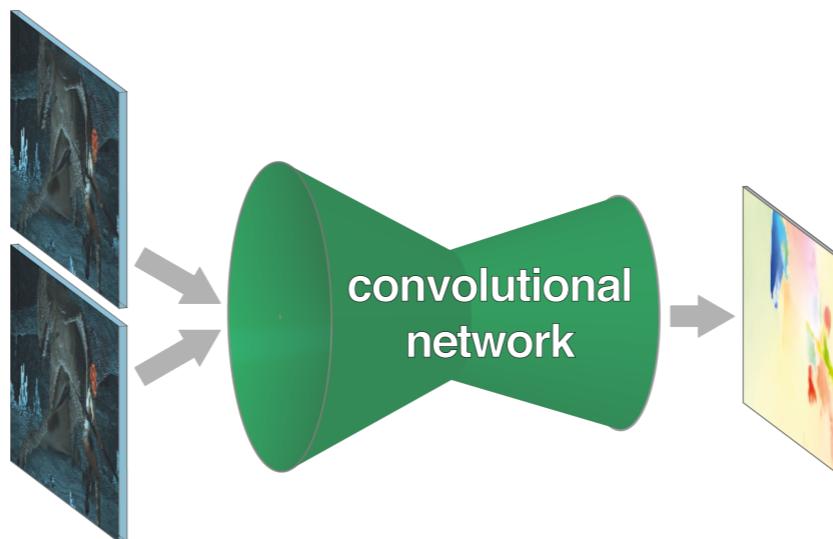


- the use of many layers

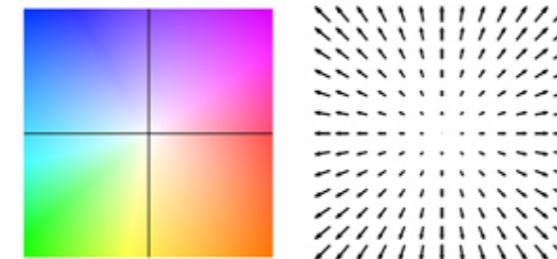
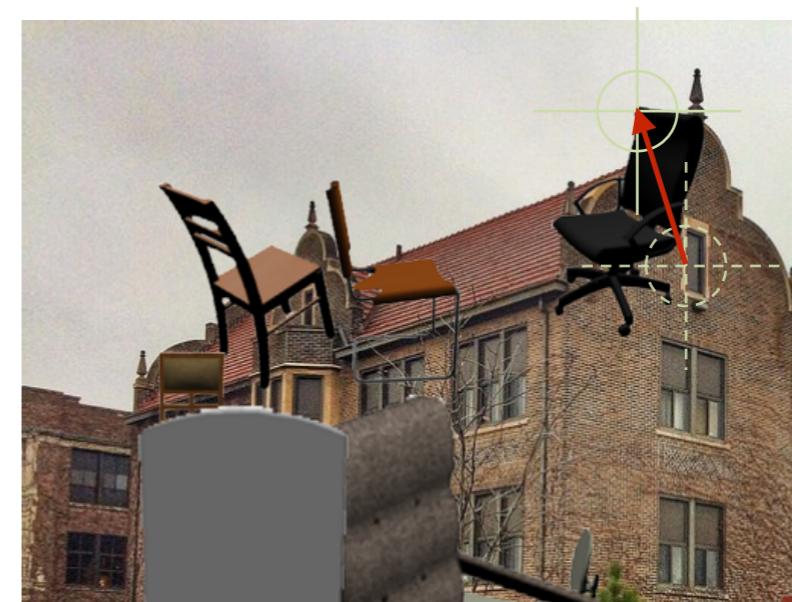
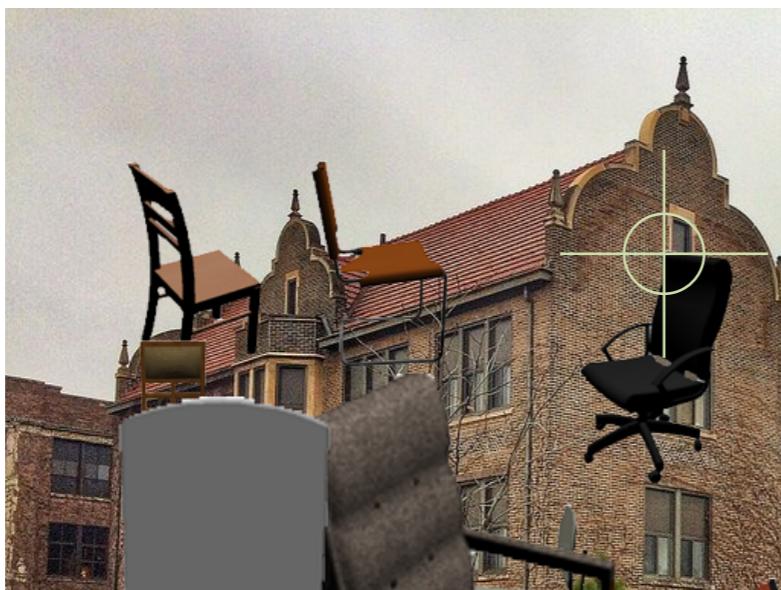


FlowNet: Learning Optical Flow with Convolutional Networks

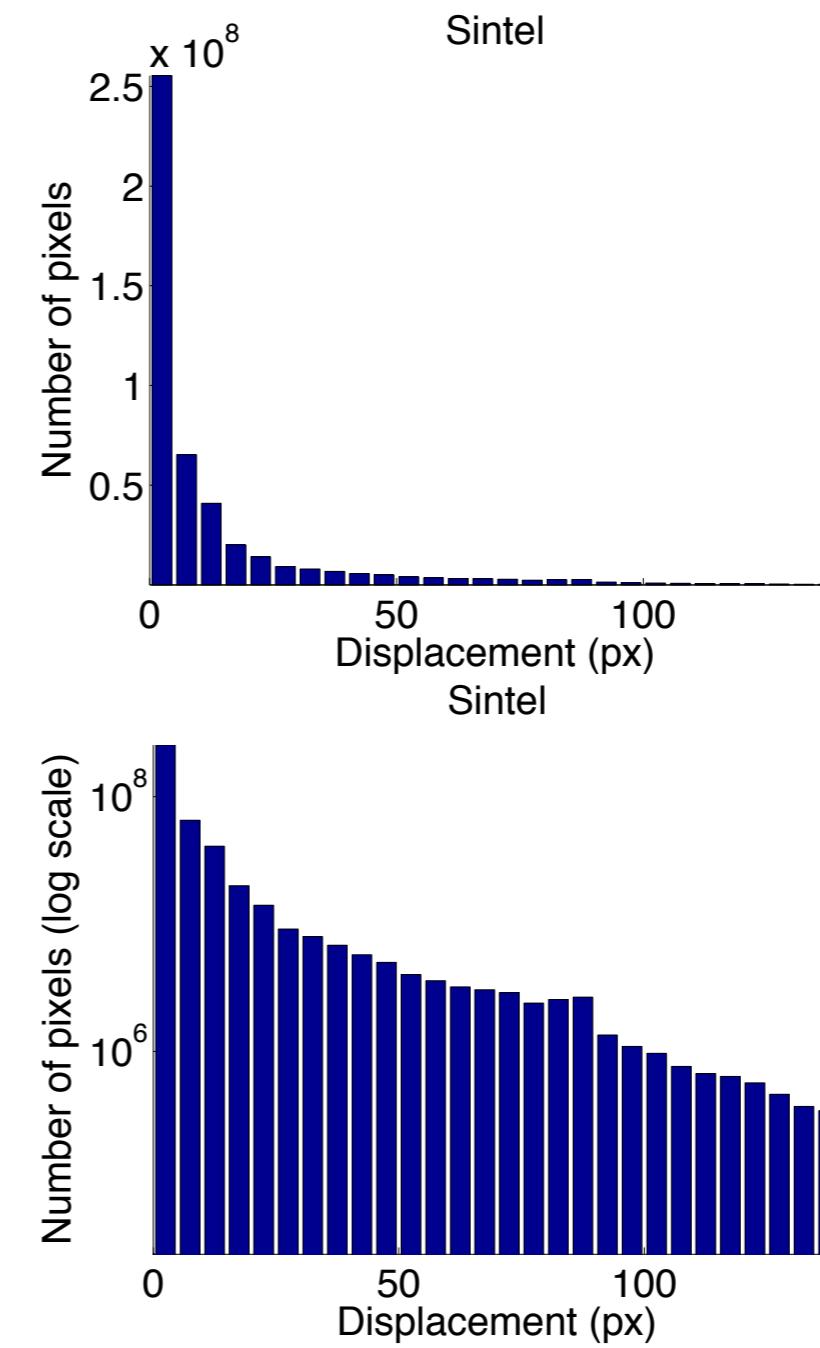
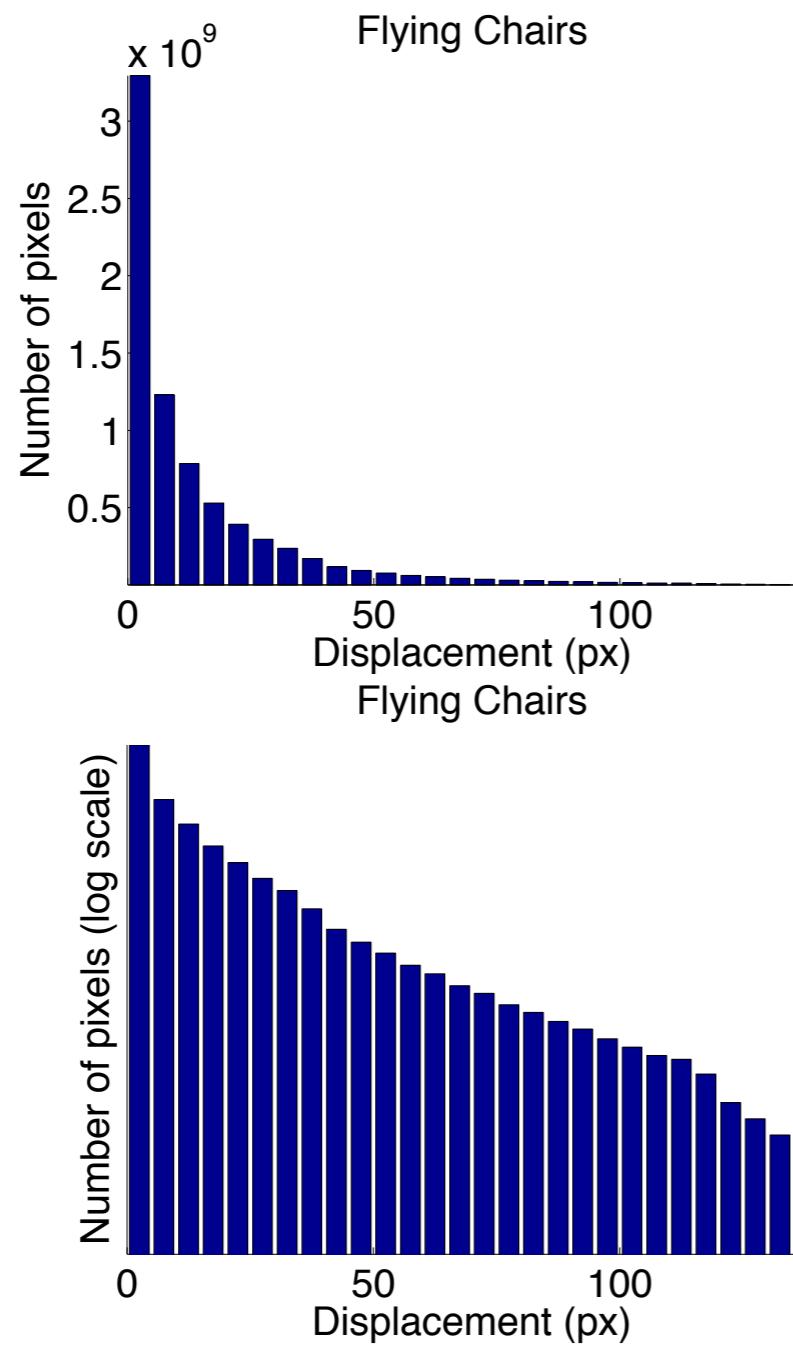
Philipp Fischer, Alexey Dosovitskiy, Eddy Ilg, Thomas Brox
Philip Häusser, Caner Hazırbaş, Vladimir Golkov, Daniel Cremers, Patrick van der Smagt



Flying Chairs



Flying Chairs



Data Augmentation

Generated



Augmented

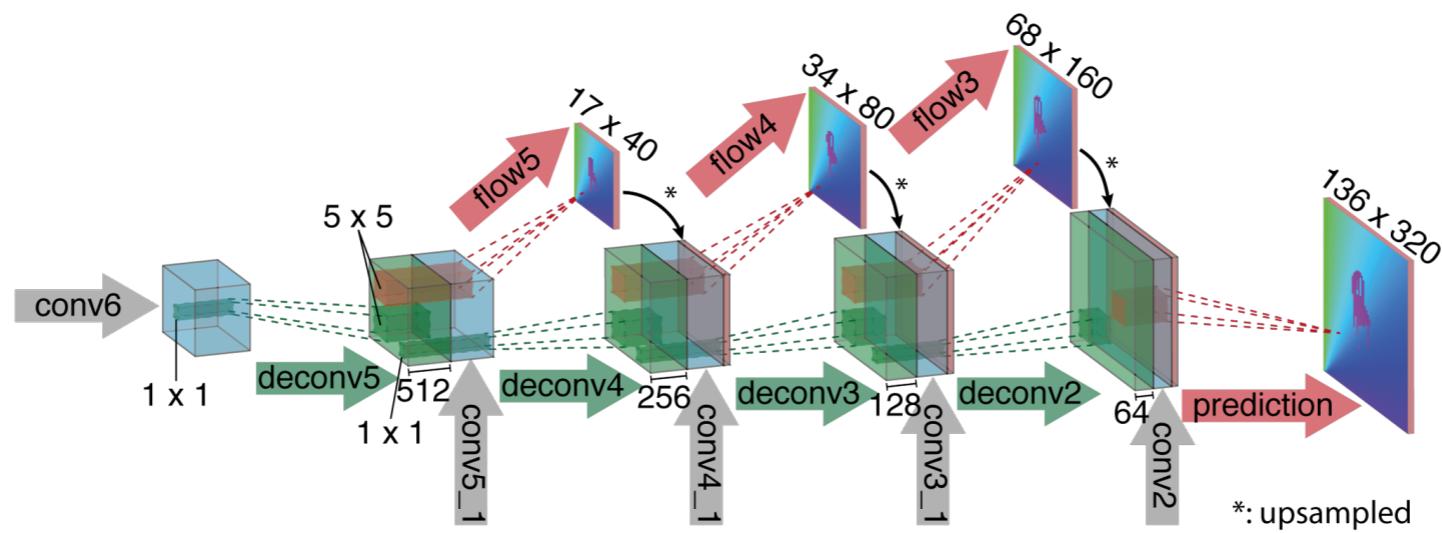
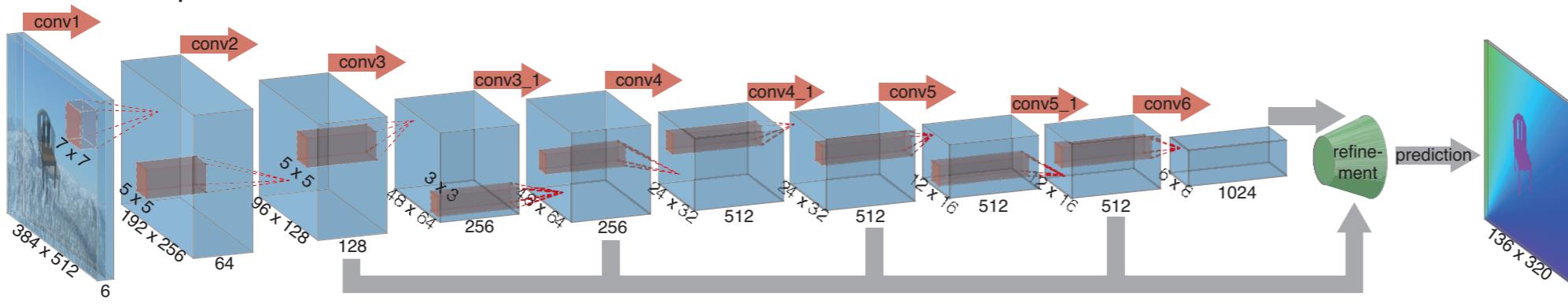


- *translation, rotation, scaling, additive Gaussian noise*
- changes in *brightness, contrast, gamma and colour*

16

FlowNetSimple

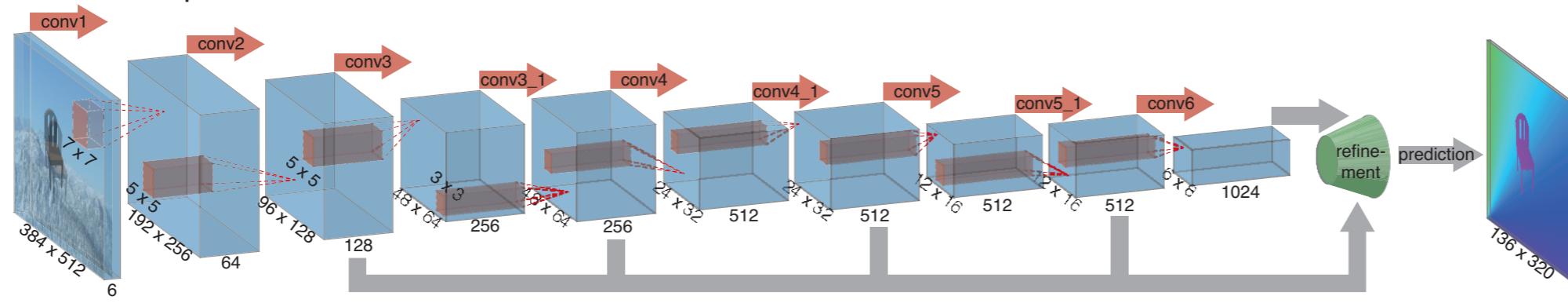
FlowNetSimple



FlowNetSimple - Flying Chairs

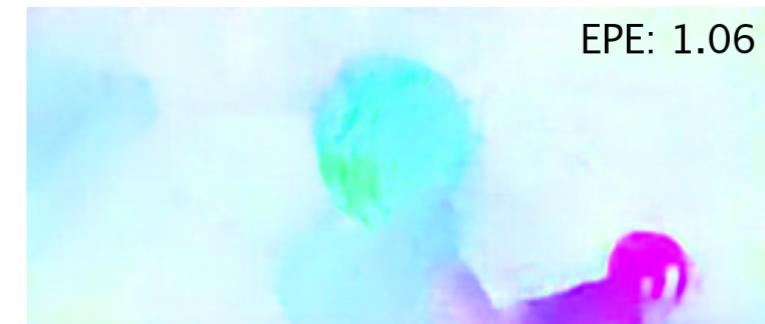
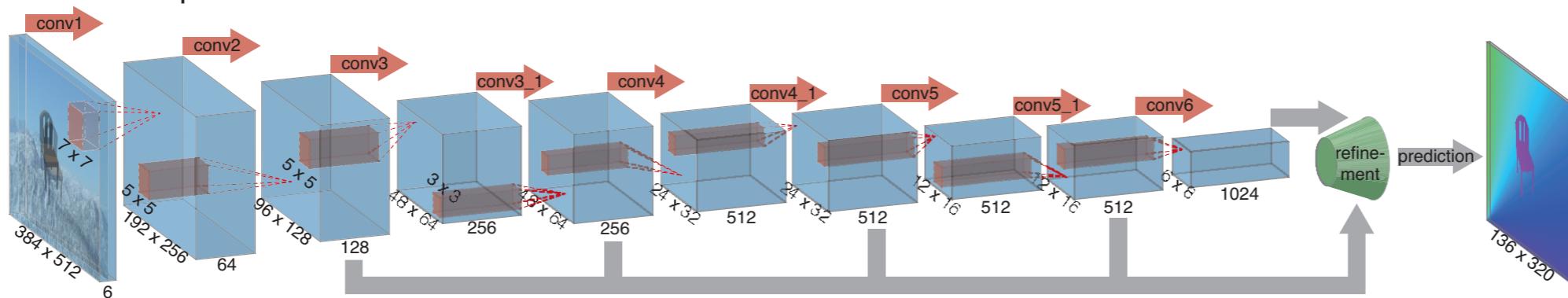
1

FlowNetSimple



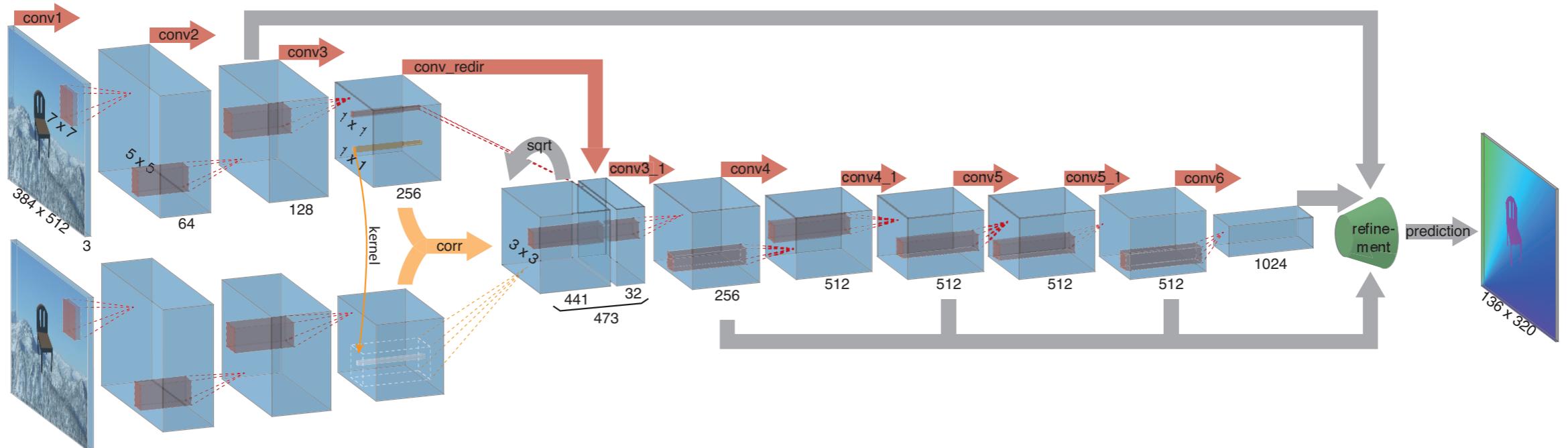
FlowNetSimple - Sintel

FlowNetSimple

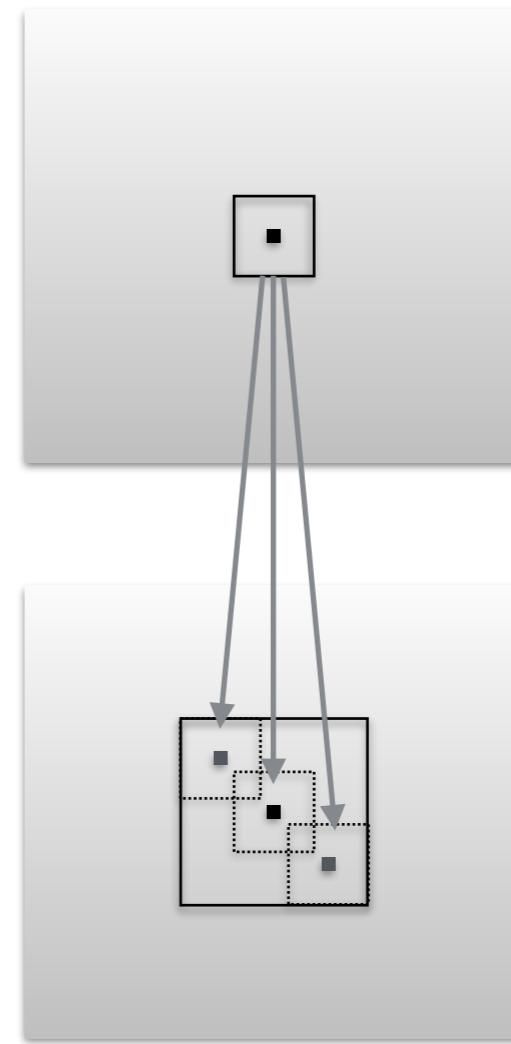
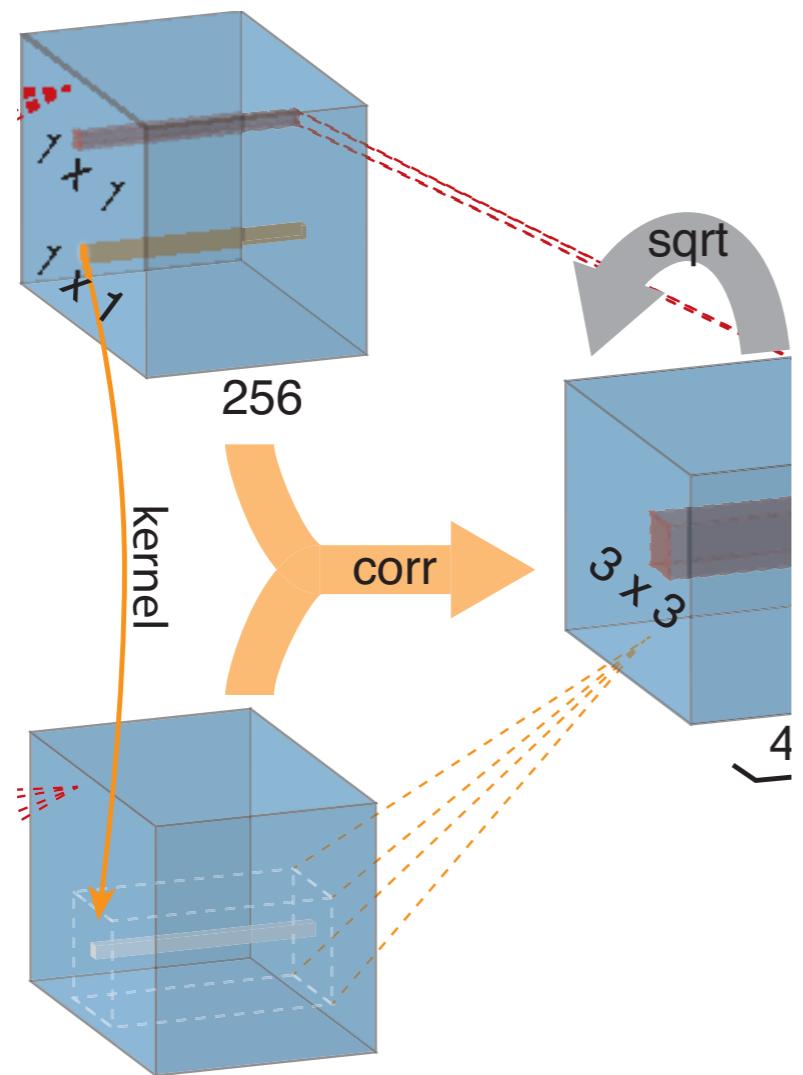


FlowNetCorr

FlowNetCorr

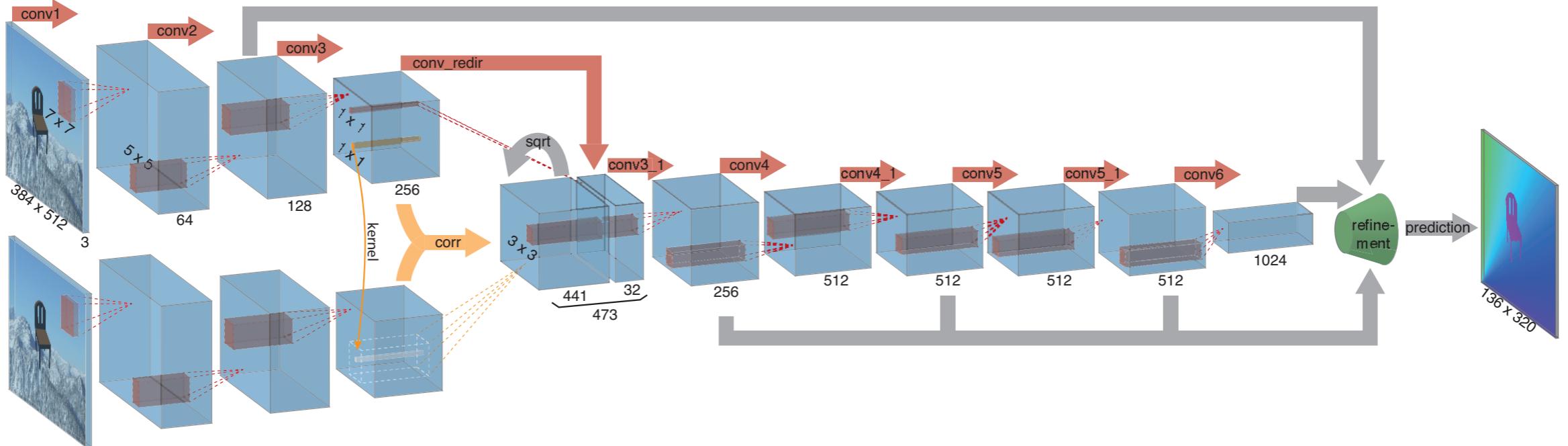


Correlation Layer



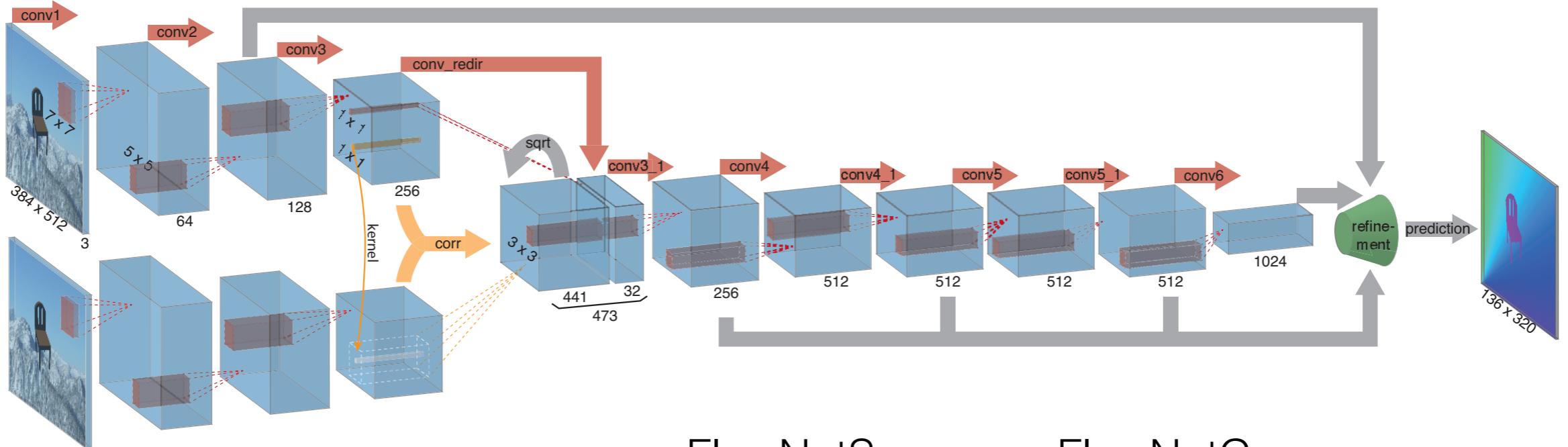
FlowNetCorr - Flying Chairs

FlowNetCorr



Simple vs. Corr - Flying Chairs

FlowNetCorr



FlowNetS



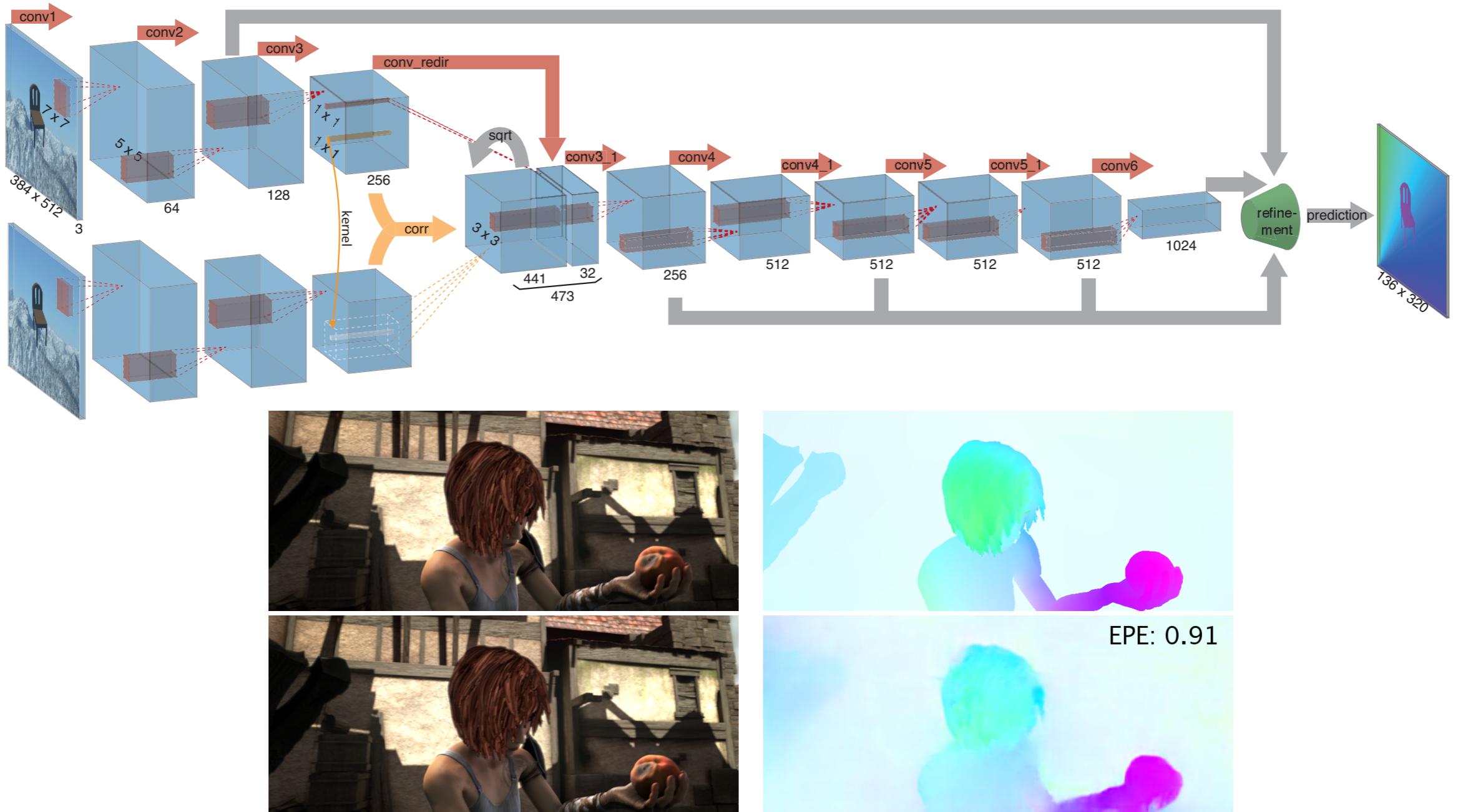
EPE: 1.27



EPE: 1.14

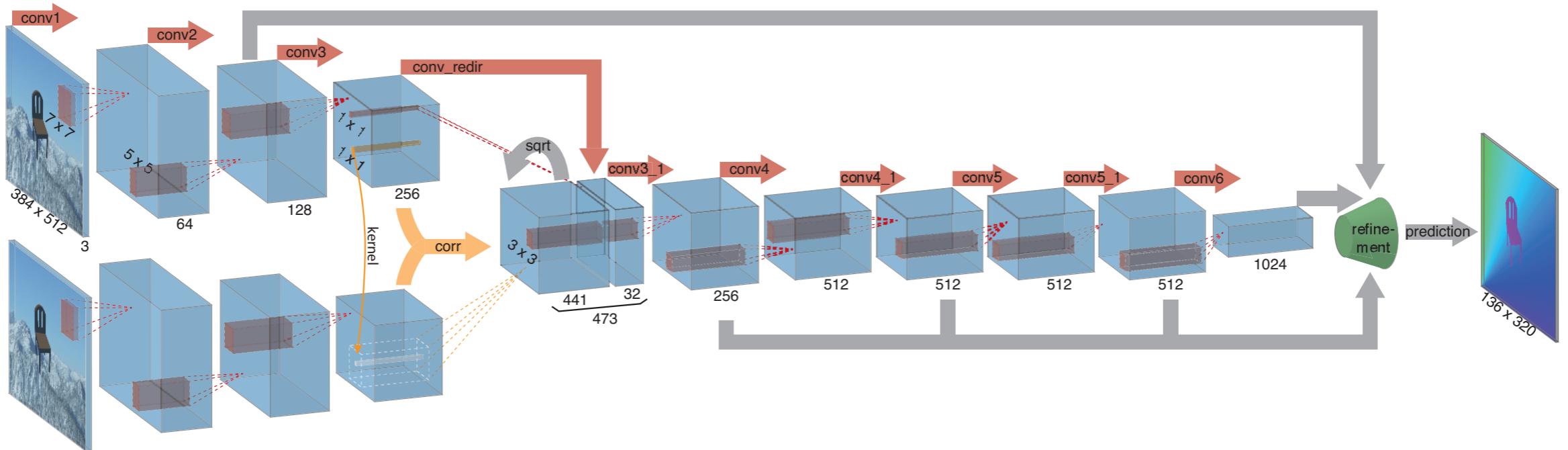
FlowNetCorr - Sintel

FlowNetCorr

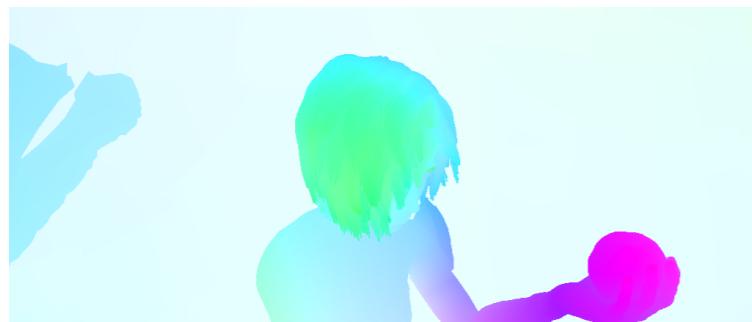


Simple vs. Corr - Sintel

FlowNetCorr



FlowNetS



FlowNetSimple + Variational Smoothing



FlowNet: Learning Optical Flow with Convolutional Networks

P. Fischer, A. Dosovitskiy, E. Ilg, P. Häusser, C. Hazırbaş, V. Golkov

P. v.d. Smagt, D. Cremers, T. Brox

FlowNet:
Learning Optical Flow
with Convolutional Networks

References

- Building High-level Features Using Large Scale Unsupervised Learning
Quoc V. Le , Rajat Monga , Matthieu Devin , Kai Chen , Greg S. Corrado , Jeff Dean , Andrew Y. Ng
ICML'12
- Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations
Honglak Lee Roger Grosse Rajesh Ranganath Andrew Y. Ng ICML'09
- ImageNet Classification with Deep Convolutional Neural Networks
Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton NIPS'12
- Gradient-based learning applied to document recognition.
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner Proceedings of the IEEE'98
- FlowNet: Learning Optical Flow with Convolutional Networks
Philipp Fischer, Alexey Dosovitskiy, Eddy Ilg, Philip Häusser, Caner Hazırbaş, Vladimir Golkov, Patrick van der Smagt, Daniel Cremers, Thomas Brox

References

- Google's cat detection neural network <http://www.resnap.com/image-selection-technology/deep-learning-image-classification/>
- Example auto-encoder : <http://nghiaho.com/?p=1765>
- SGD : <http://blog.datumbox.com/tuning-the-learning-rate-in-gradient-descent/>