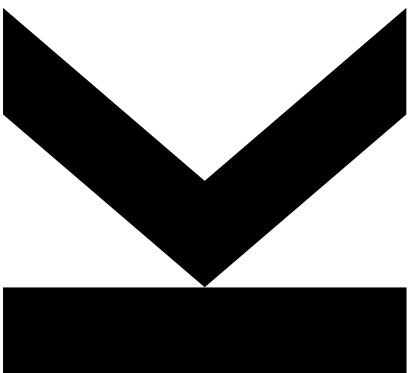


Computer Vision

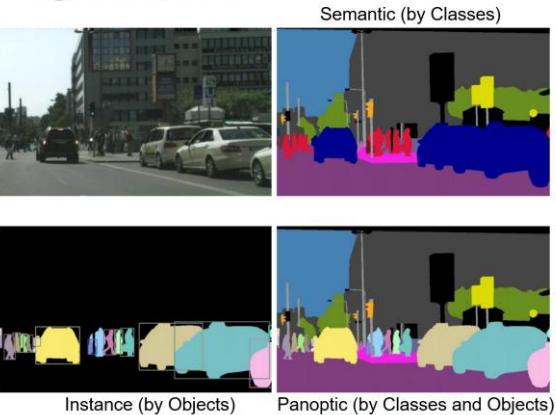


Lecture 7: Optical Flow

Oliver Bimber

Last Week: Segmentation

Types of Segmentation



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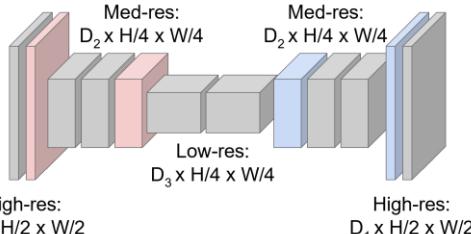
Segmentation using CNNs

Downsampling:
Pooling, Strided
Convolution



Input:
 $3 \times H \times W$

Design Network as a Bunch of Convolutional Layers, with
Downsampling and **Upsampling** inside the Network!



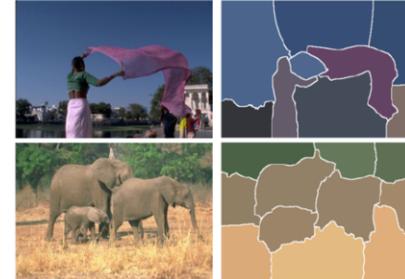
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Upsampling:
Strided Transposed
Convolution (or Unpooling)



Predictions:
 $H \times W$

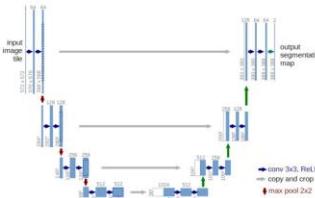
Example: Clustering by Graph Eigenvectors



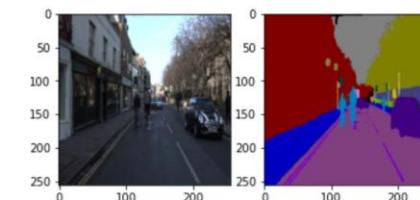
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$$\begin{aligned} & \text{affinity between element } i \text{ and } j \\ & X \\ & \text{association of elements } j \text{ with cluster } n \\ & \boxed{w_n^T A w_n = \lambda} \quad Aw_n = \lambda w_n \\ & \downarrow \\ & \text{association of elements } j \text{ with cluster } n \quad X \\ & \left[\begin{array}{c} a_{0,0} \dots a_{i,0} \\ \vdots \dots \dots \\ a_{0,j} \dots a_{i,j} \end{array} \right] \left[\begin{array}{c} w_{n,0} \\ \vdots \\ w_{n,j} \end{array} \right] \end{aligned}$$

Connected Autoencoders (U-Nets)



Connected Autoencoder (U-Net)



Predicted Segmentation

- U-Nets overcome this problem by connecting corresponding encoder-decoder layers with skip connections:
 - the output of an encoder level is skip-connected (concatenation) with the input of the corresponding decoder level

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CW	Topic	Date	Place	Lab
41	Introduction and Course Overview	07.10.2025	Zoom	Lab 1
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9	Retry Exam	24.02.2026	tba	

Research Example: Through-Foliage Detection and Tracking

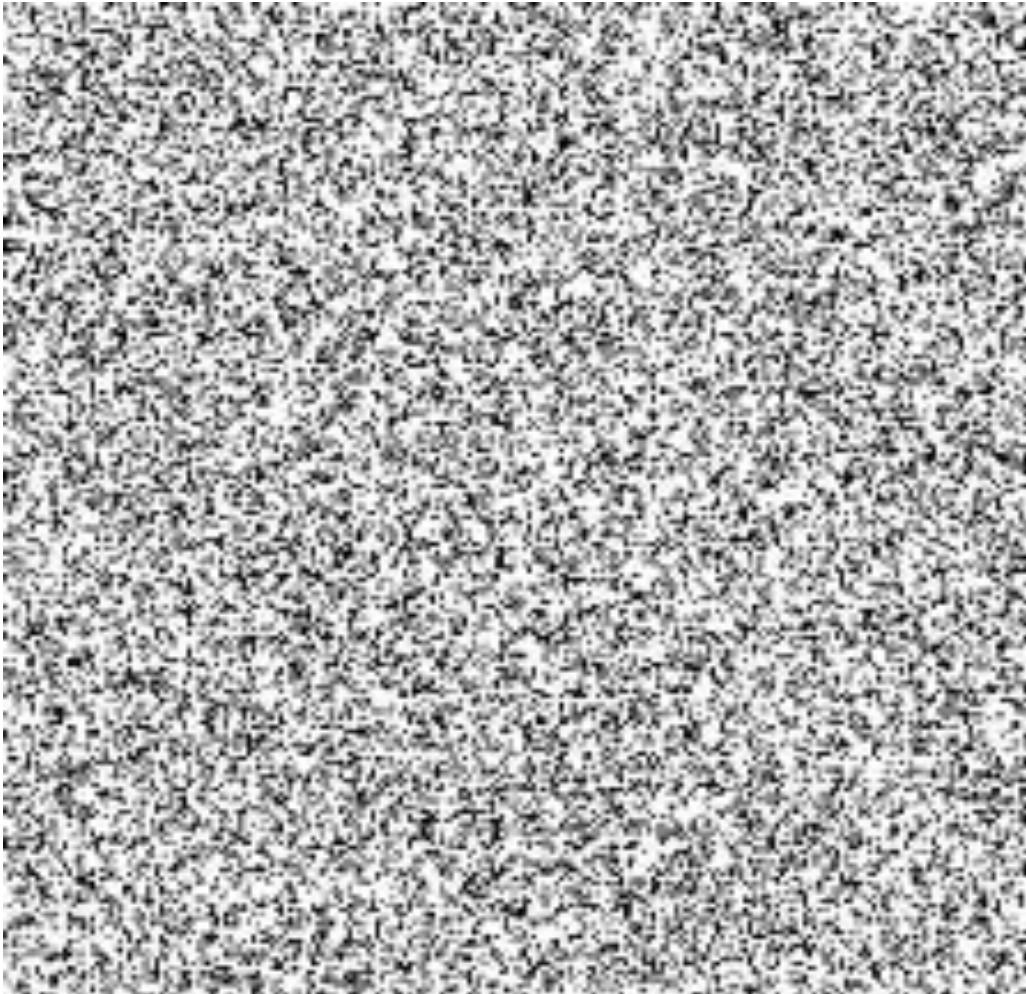


Research Example: Through-Foliage Detection and Tracking



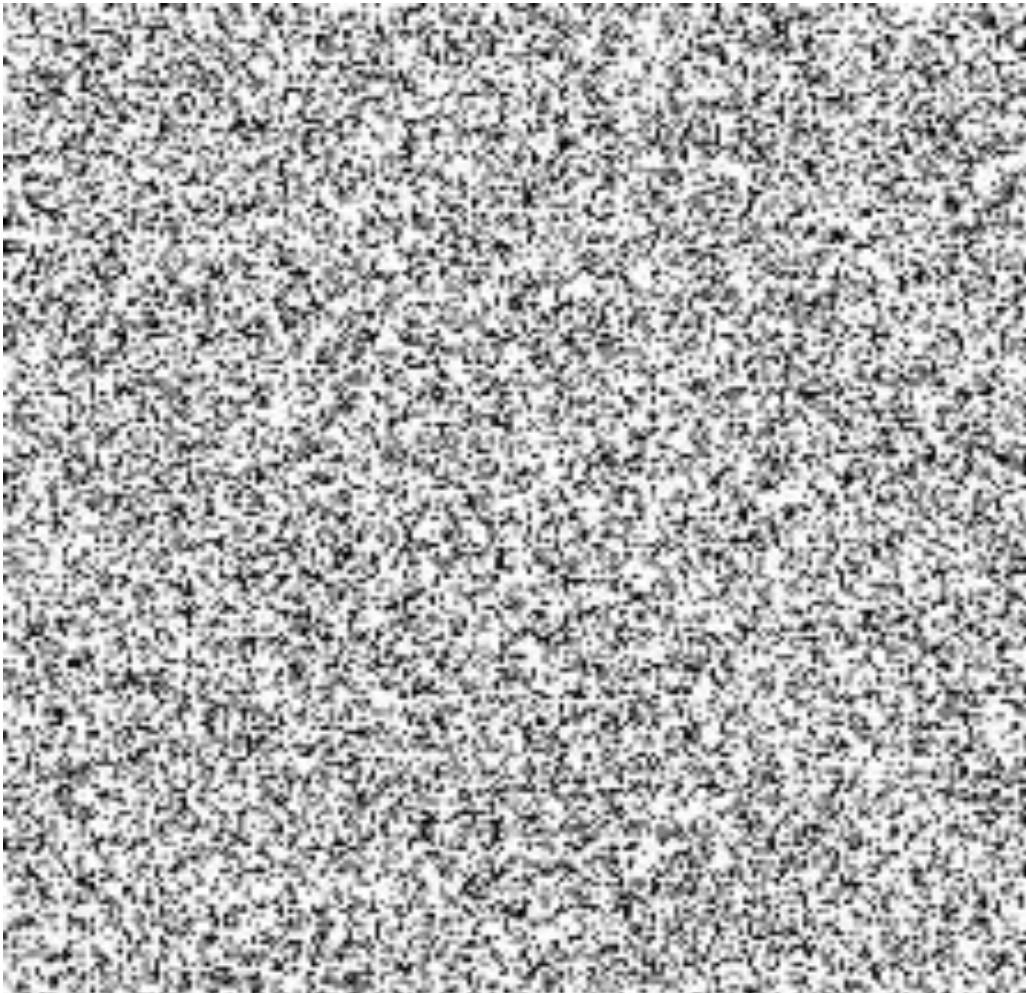


Perception of Motion

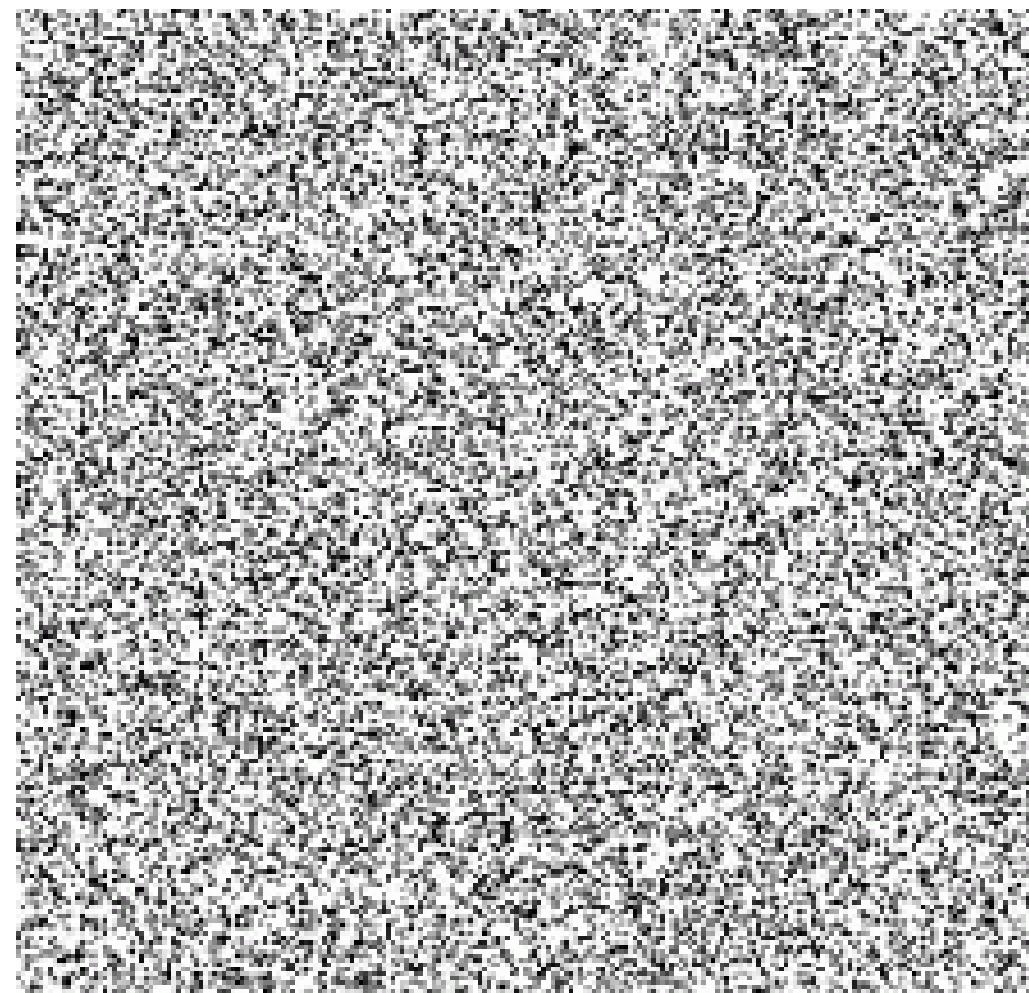


Can you see a Patter?

Perception of Motion



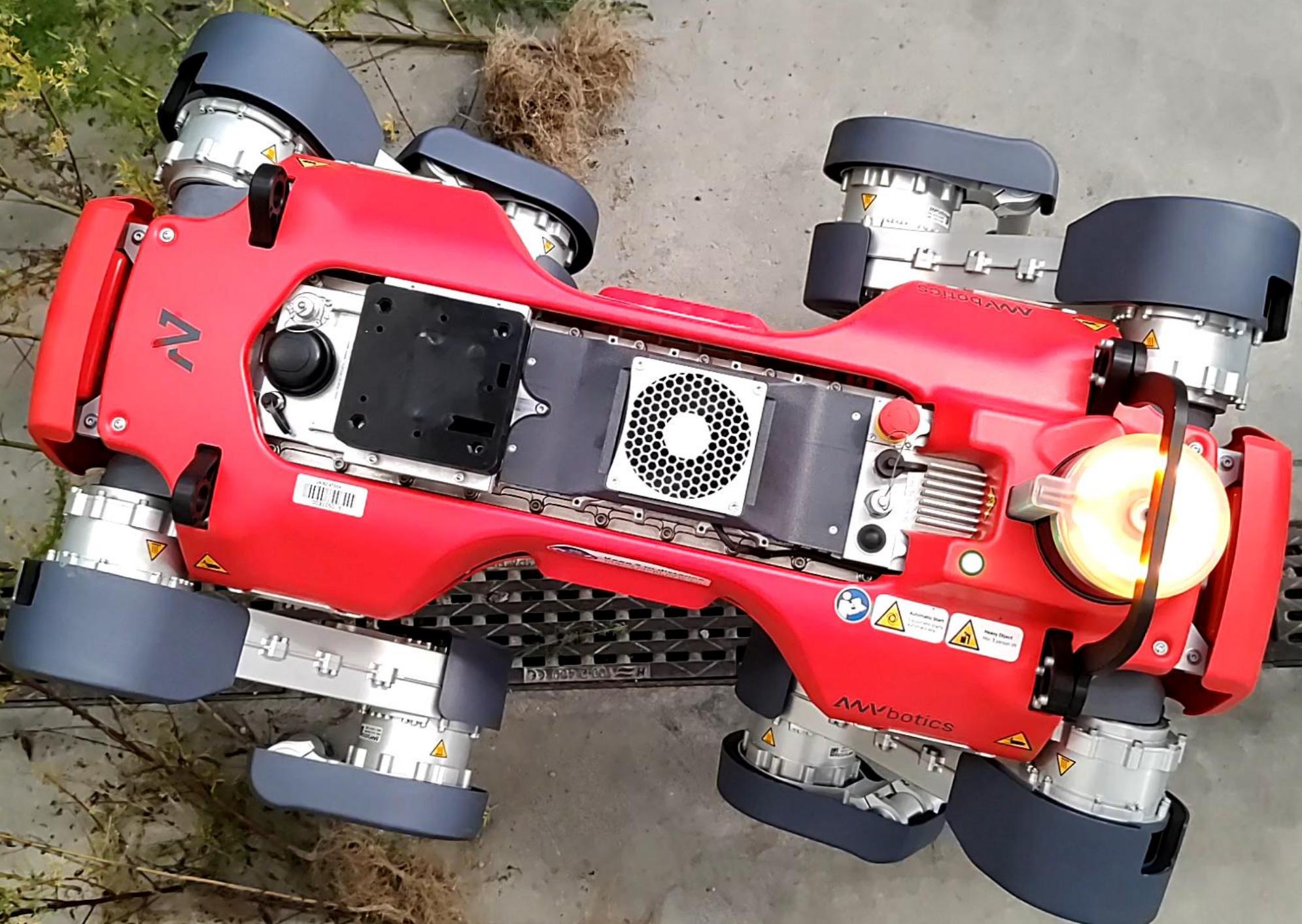
Can you see a Patter?



Sometimes Motion is the only Cue













LMM Vision Reasoning:

The image shows dense, bushy vegetation with thin, greenish branches and small leaves, possibly a shrub or weed. Behind the plants, there are metal railings and a structure that looks like part of a building with stairs and platforms — perhaps an industrial or urban setting. The plants appear to be growing near a concrete surface.



LMM Vision Reasoning:

The image shows a blurry industrial or warehouse-like setting. At the center, there is a blue metal frame holding eight large circular openings arranged in two rows of four. These appear to be sections of large pipes or ducts. The background includes tall vertical supports and metal structures, possibly part of a factory or storage facility. An overhead platform or walkway is also visible in the upper left area. Although the image is motion-blurred, the scene clearly depicts an indoor industrial environment with large cylindrical components stored or staged within a structural framework.



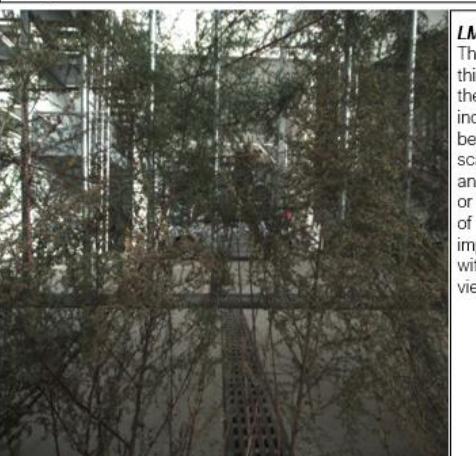
LMM Vision Reasoning:

In this image, there is a blurry view of a structure, likely a fence or railing with circular patterns. A small orange traffic cone is visible in the foreground, possibly marking a certain area. The background is slightly obscured by some sort of foliage or blurred objects, giving it a somewhat hazy or out-of-focus appearance. The overall setting seems to be outdoors, potentially in an industrial or construction zone.



LMM Vision Reasoning:

The image appears to show a bicycle leaning against a patterned wall or fence, with a small orange-and-white traffic cone placed nearby. The photo is somewhat blurry, but the shapes of the bicycle and cone are still distinguishable.



LMM Vision Reasoning:

The image shows a view through a group of tall, thin trees or shrubs with sparse foliage. Behind the trees, there appears to be a modern, industrial-looking building structure, with metal beams, railings, and possibly a staircase or scaffolding. The ground is mostly flat and paved, and there seems to be a narrow, grated trench or drainage channel running through the center of the image. The overall scene gives an impression of an urban or industrial courtyard with some vegetation partially obscuring the view.

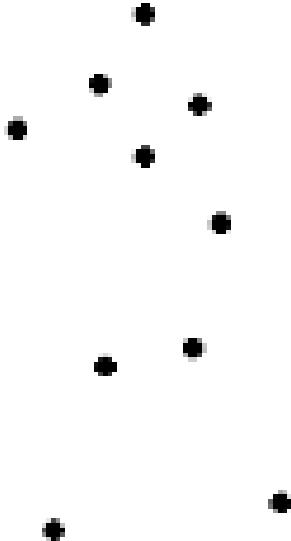


LMM Vision Reasoning:

The image appears to show a blurry scene of a small silver car parked inside a large industrial or warehouse-like structure. There are metal stairs and platforms on the left side, and some large circular objects, possibly barrels or ventilation fans, mounted on a structure behind the car. The overall image has a motion blur effect, making the details appear streaked and hazy.

...The car seems to be a compact hatchback, which is typically about 3.5 to 4 meters in length. The car is roughly 5 to 10 meters away from the camera...

Perception of Motion



Can you see a Patter?

Perception of Motion



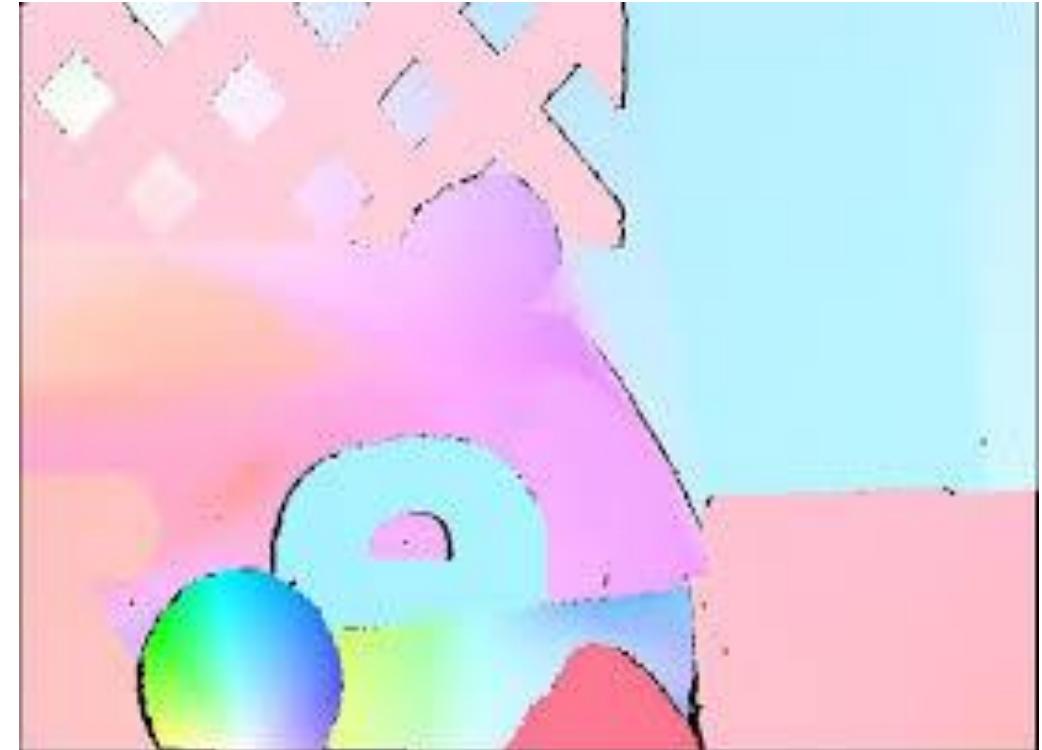
Can you see a Patter?

Sometimes Motion is the only Cue
(even for sparse Data)

What is Optical Flow?



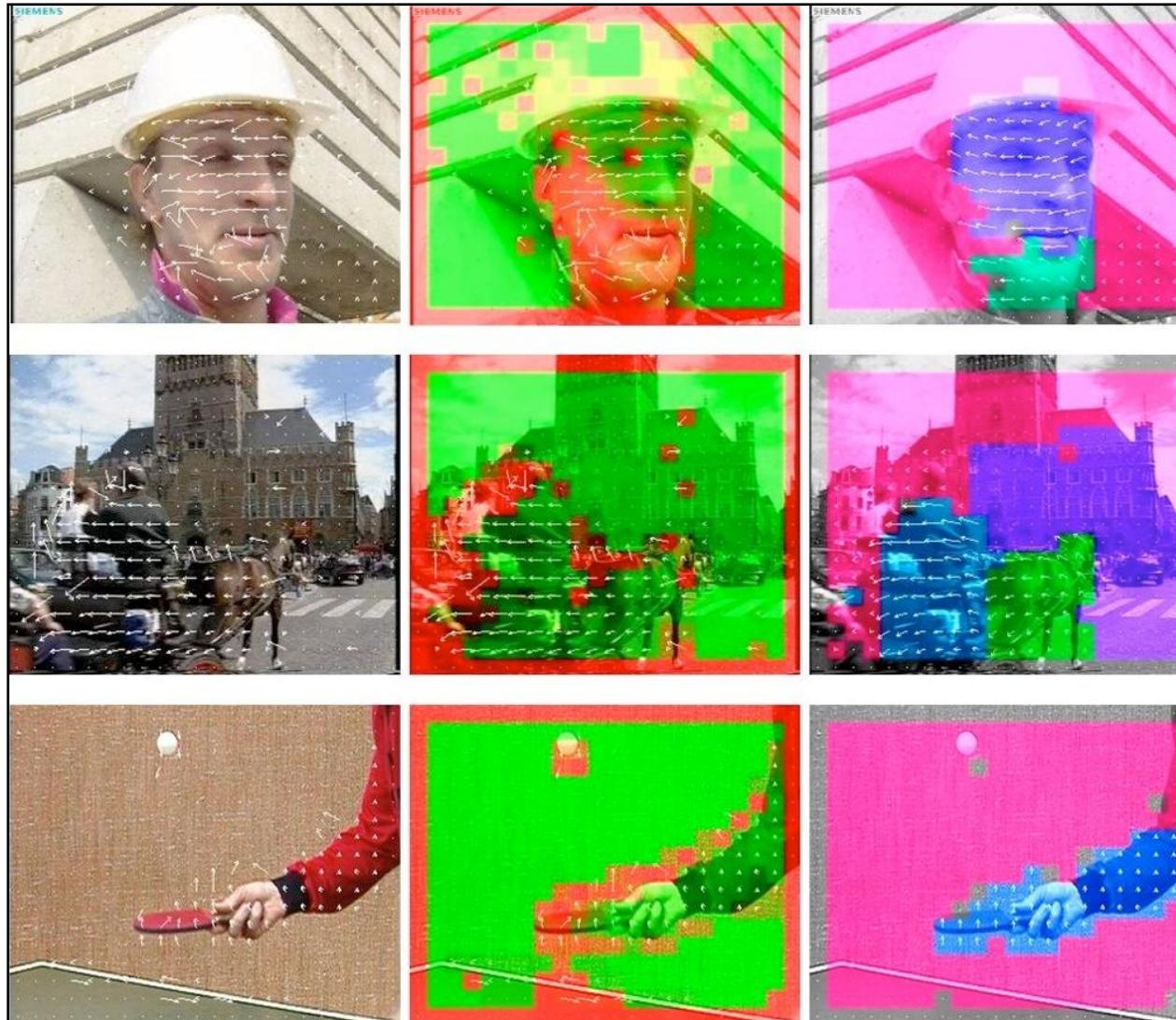
Sparse Optical Flow (Flow Vector per Region)



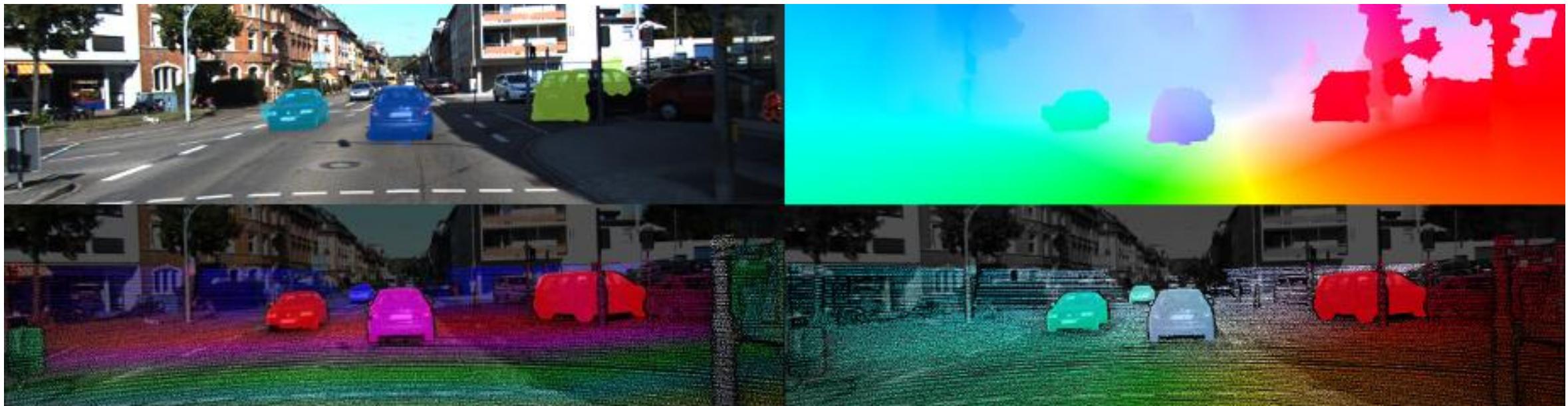
Dense Optical Flow (Flow Vector per Pixel)

Motion Vector of Pixel in Time Series (two consecutive Video Frames at Times t and t+1)

Example: MPEG Compression



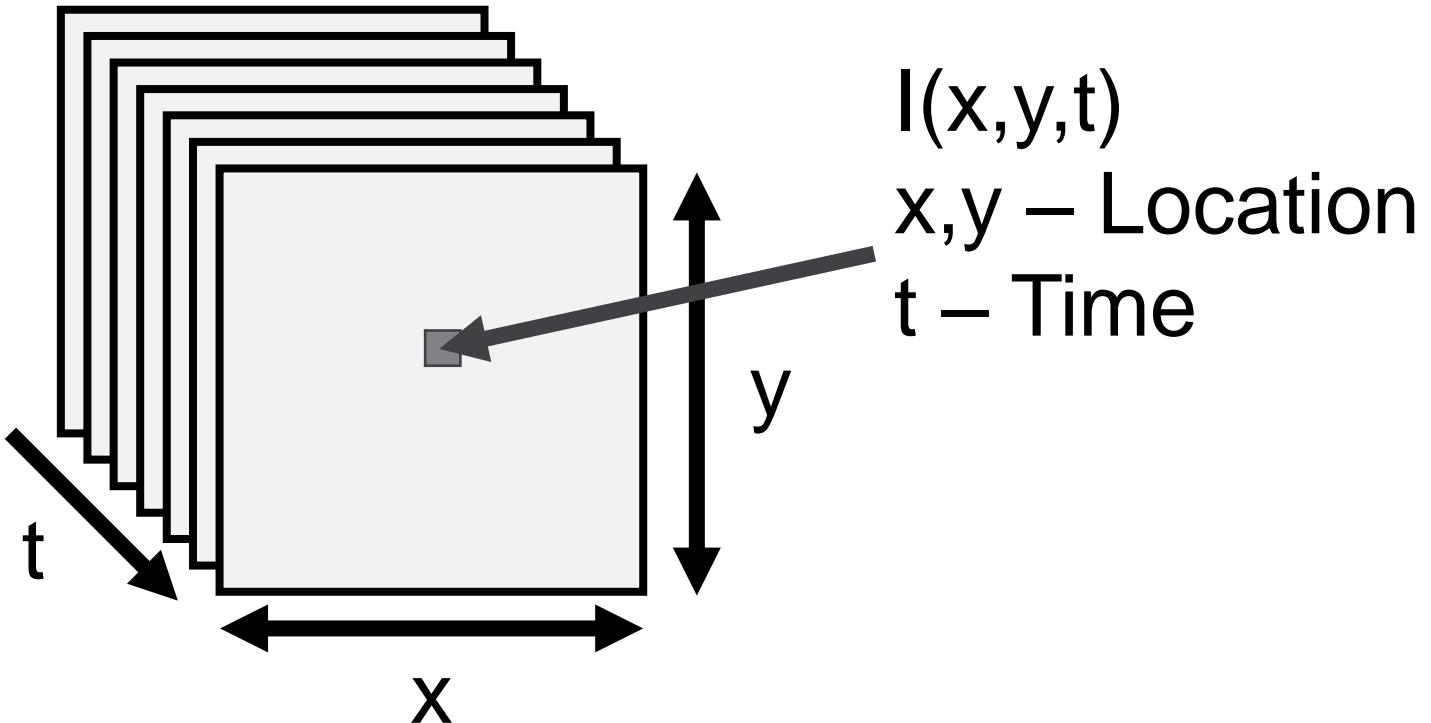
Example: Autonomous Driving



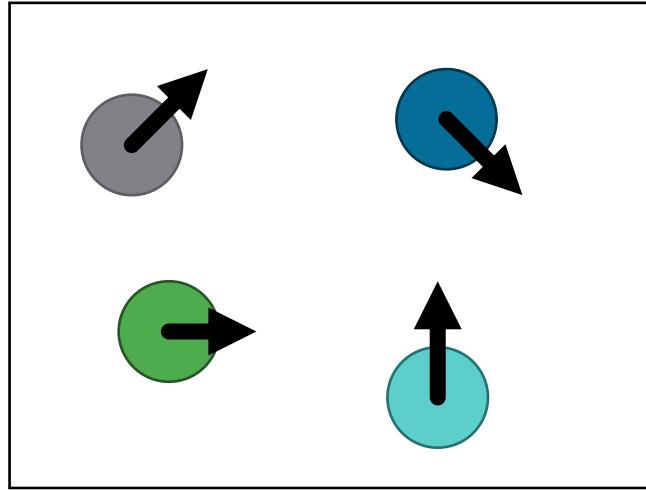
Example: Traffic Monitoring



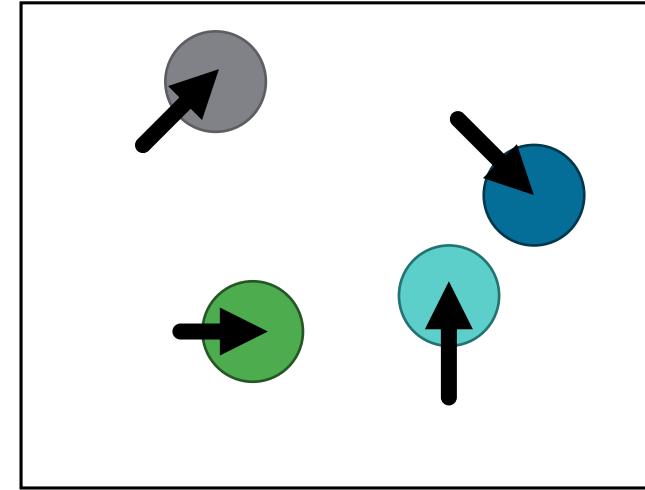
Video: A Sequence of Frames over Time



Optical Flow



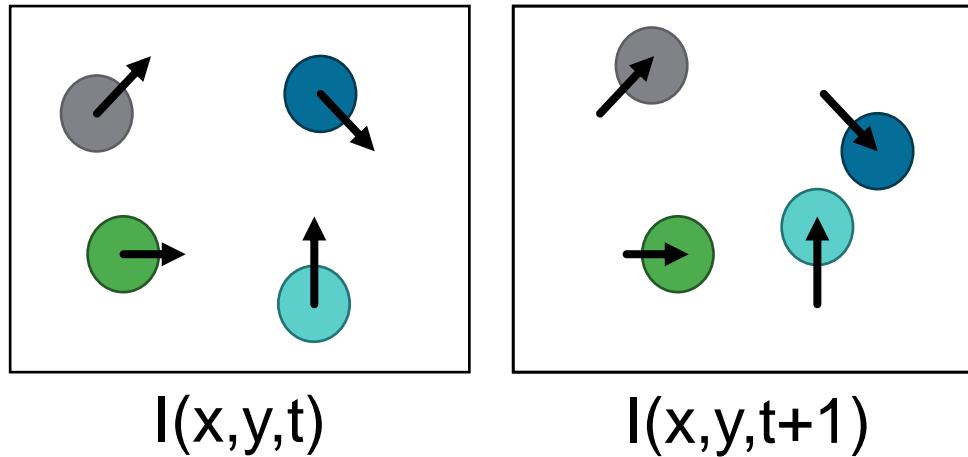
$I(x,y,t)$



$I(x,y,t+1)$

Want to estimate Pixel Motion from
Image $I(x,y,t)$ to Image $I(x,y,t+1)$

Assumption



Solve correspondence Problem: given Pixel at Time t, find **nearby** Pixels of the same Color at Time t+1

Key assumptions:

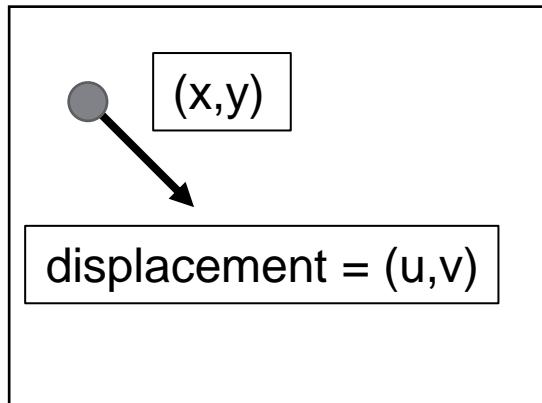
- **Color/Brightness Constancy**: Point at Time t looks same at Time t+1
- **Small Motion**: Points do not move very far

The Optical Flow Equation

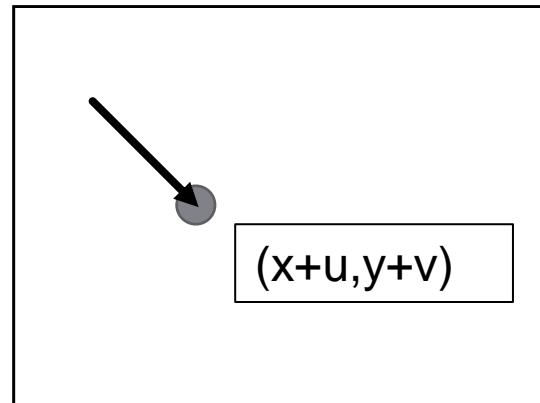
Brightness Constancy:

$$I(x + u, y + v, t + 1) = I(x, y, t)$$

$$0 \approx I(x + u, y + v, t + 1) - I(x, y, t)$$

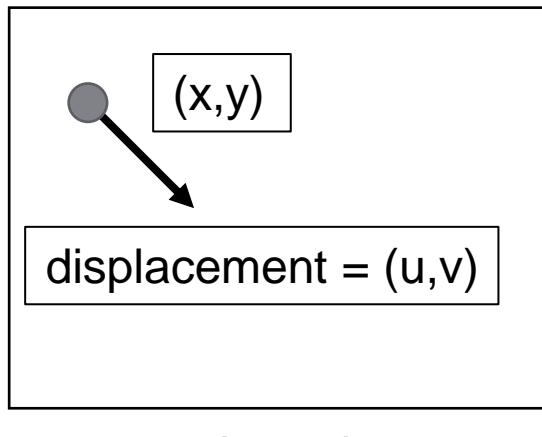


$I(x, y, t)$



$I(x, y, t+1)$

The Optical Flow Equation



Brightness Constancy:

$$I(x + u, y + v, t + 1) = I(x, y, t)$$

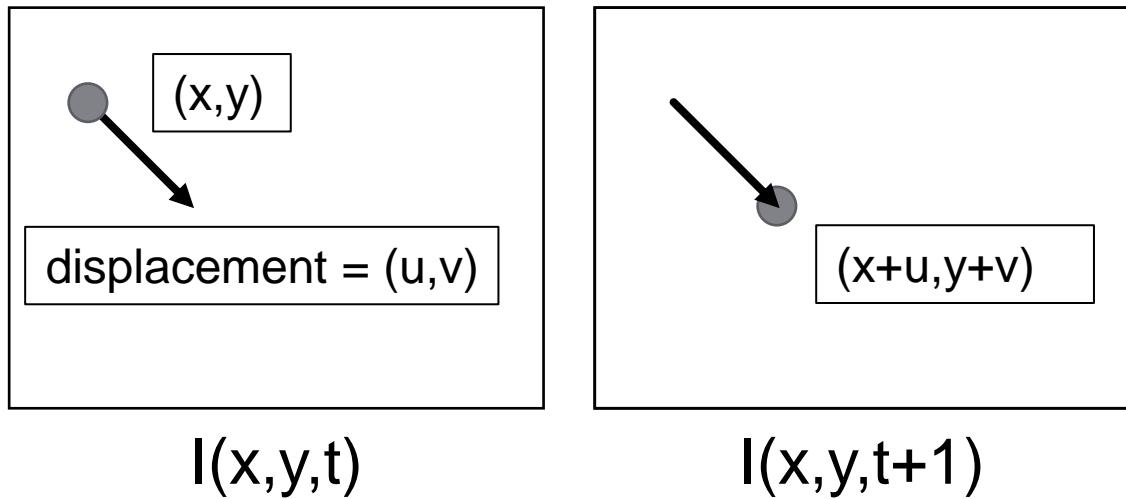
$$0 \approx I(x + u, y + v, t + 1) - I(x, y, t)$$

Taylor Expansion:

$$\approx I(x, y, t + 1) + I_x u + I_y v - I(x, y, t)$$

$$= I(x, y, t + 1) - I(x, y, t) + I_x u + I_y v$$

The Optical Flow Equation



Brightness Constancy:

$$I(x + u, y + v, t + 1) = I(x, y, t)$$

$$0 \approx I(x + u, y + v, t + 1) - I(x, y, t)$$

Taylor Expansion:

$$\approx I(x, y, t + 1) + I_x u + I_y v - I(x, y, t)$$

$$= I(x, y, t + 1) - I(x, y, t) + I_x u + I_y v$$

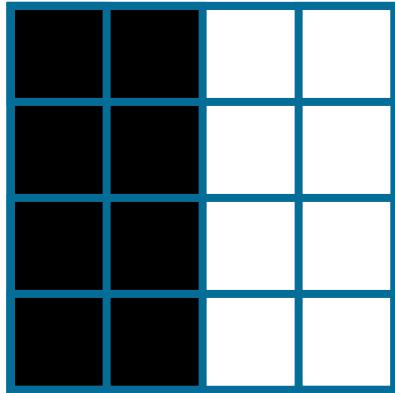
Optical Flow Equation:

$$\begin{aligned} 0 &= I_t + I_x u + I_y v \\ &= I_t + \nabla I \cdot [u, v] \end{aligned}$$

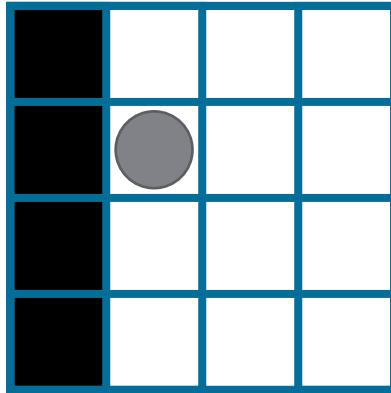
I_t, I_x, I_y are partial derivatives of image intensity (gradients) in t, x, y

Example

$$I_x u + I_y v + I_t = 0$$



t



$t+1$

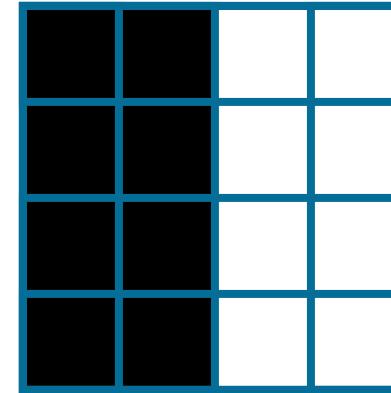
@

$$I_t = 1 - 0 = 1$$

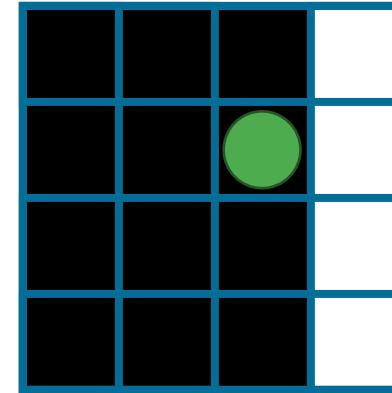
$$I_y = 0$$

$$I_x = 1 - 0 = 1$$

What's u ?



t



$t+1$

@

$$I_t = 0 - 1 = -1$$

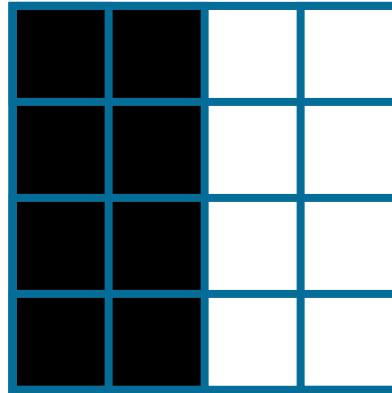
$$I_y = 0$$

$$I_x = 1 - 0 = 1$$

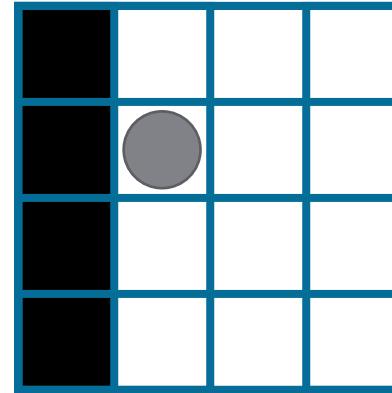
What's u ?

Example

$$I_x u + I_y v + I_t = 0$$



t

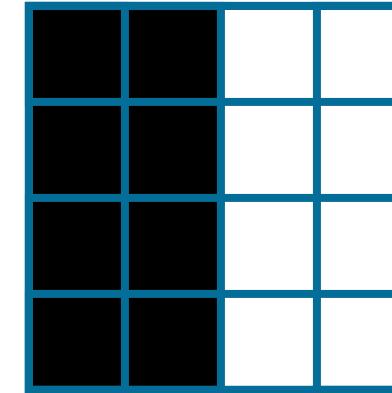


$t+1$

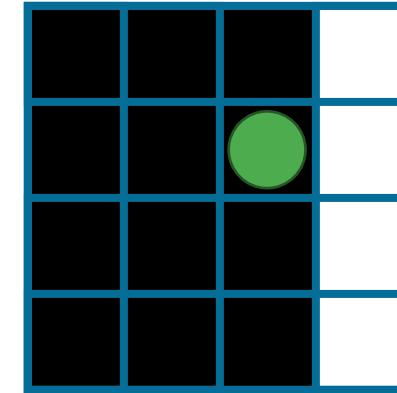
@

$$\begin{aligned}I_t &= 1-0 = 1 \\I_y &= 0 \\I_x &= 1-0 = 1\end{aligned}$$

What's u ?



t



$t+1$

@

$$\begin{aligned}I_t &= 0-1 = -1 \\I_y &= 0 \\I_x &= 1-0 = 1\end{aligned}$$

What's u ?

How to overcome this Problem?

Lucas-Kanade 1981

$$I_t + I_x u + I_y v = 0$$



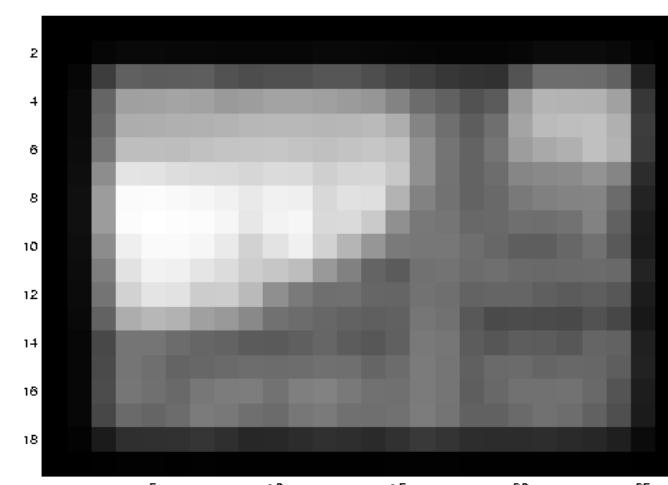
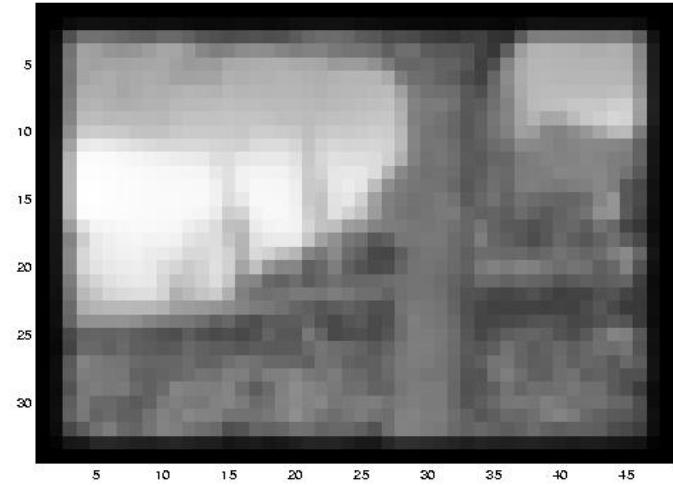
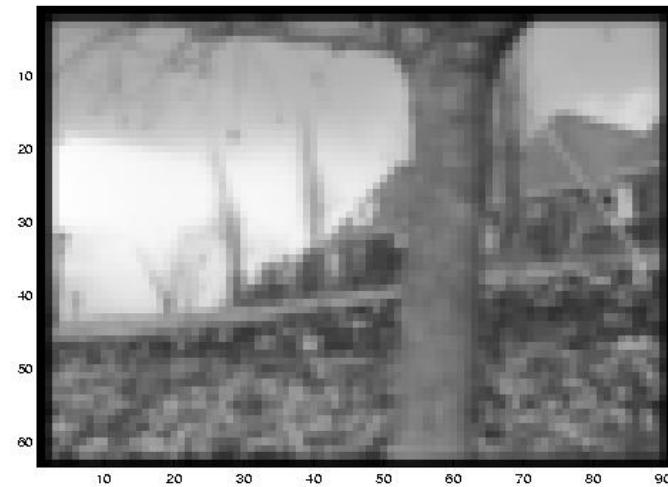
$$\begin{bmatrix} I_x(p_1) & I_y(p_1) \\ \vdots & \vdots \\ I_x(p_{25}) & I_y(p_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(p_1) \\ \vdots \\ I_t(p_{25}) \end{bmatrix}$$

- 2 Unknowns $[u,v]$, 1 Equation per Pixel
- How do we get more Equations?
- Assume **Spatial Coherence**: Pixel's Neighbors have same $[u,v]$ (same Optical Flow on local Region)
- Example: 5x5 Window gives 25 Equations

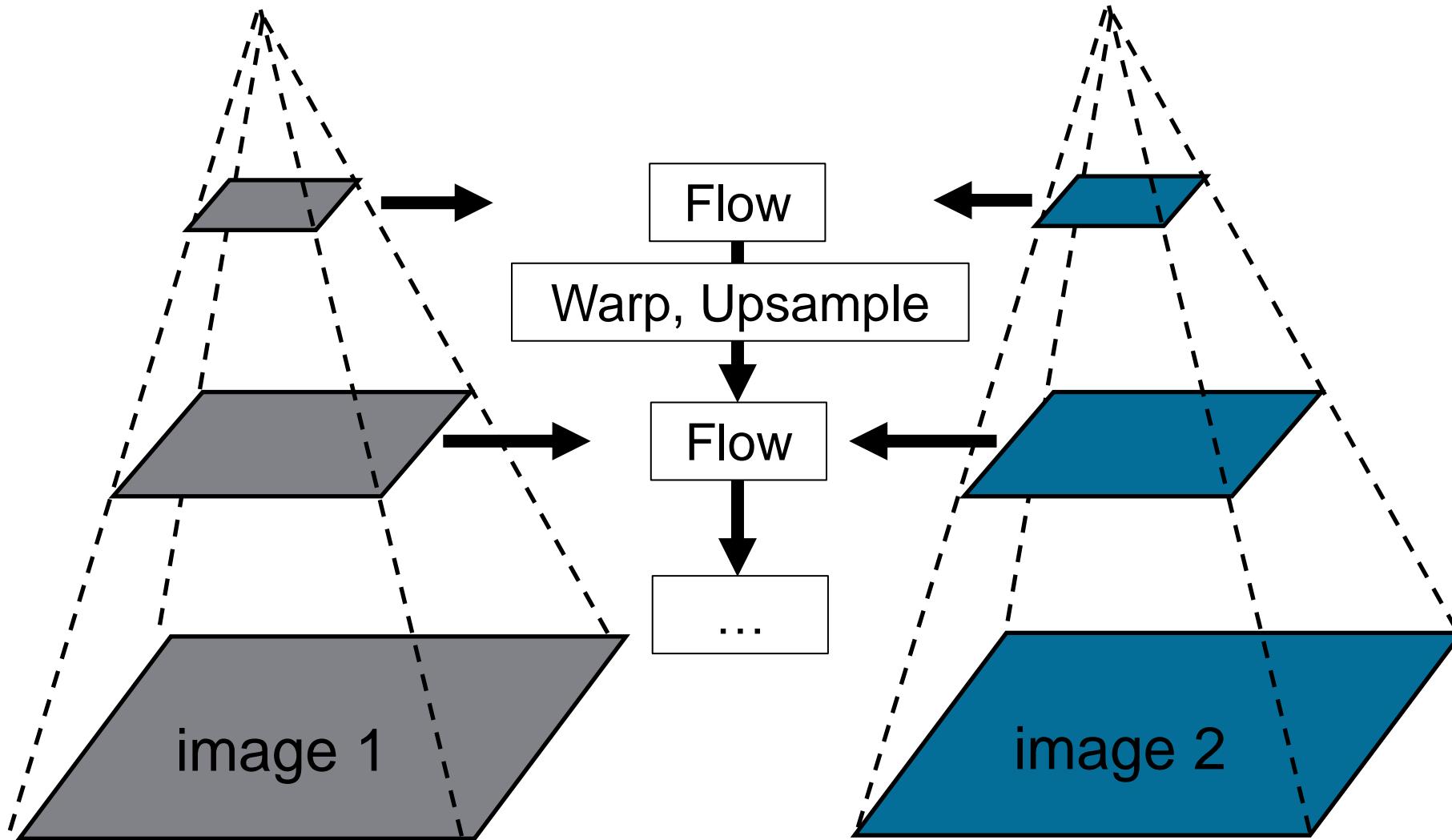
What if Motion is larger than one Pixel?



Reduce Resolution!



Using Gaussian Image Pyramids

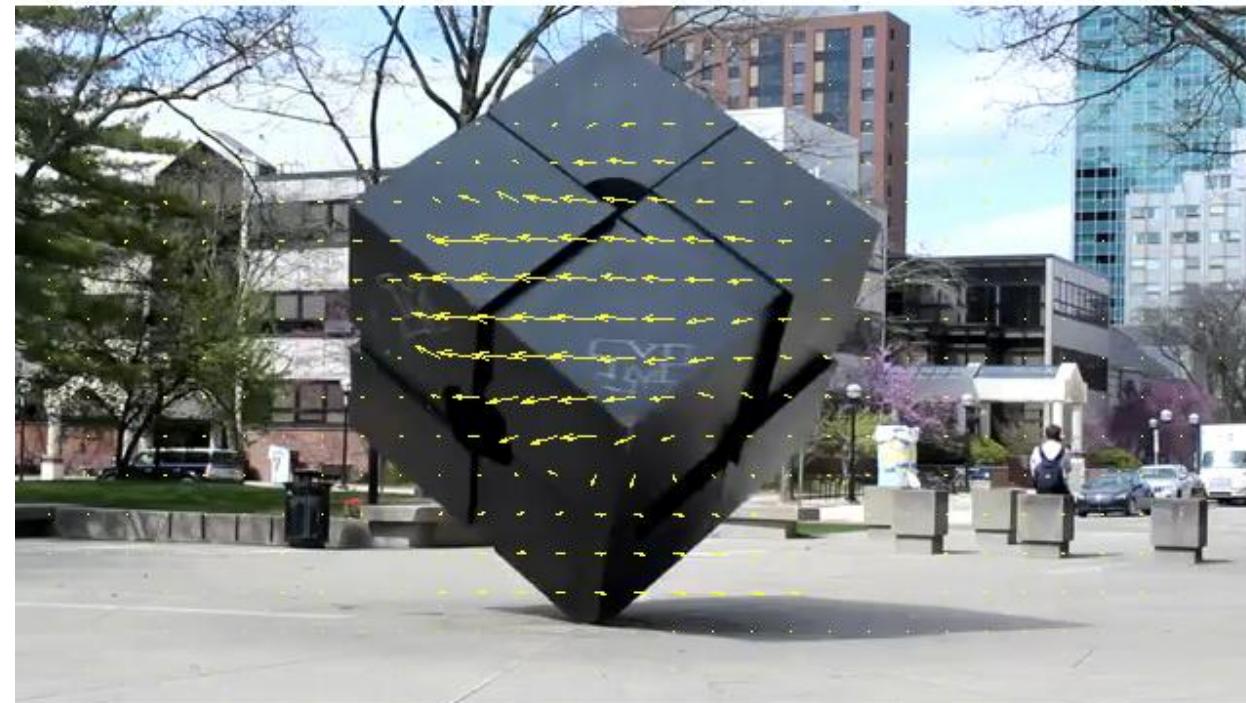


Lucas-Kanade Optical Flow

Input Frames



Output



Optical Flow Field is sparse

Dense Optical Flow



Key Assumption:

- Most Objects in the World are rigid or deform elastically and move together coherently
- We expect the flow fields to be **SMOOTH**

Basic Idea:

- Enforce Brightness Constancy for every Pixel
- Enforce Smoothness Constraint for Flow Vectors

Enforce Brightness Constancy

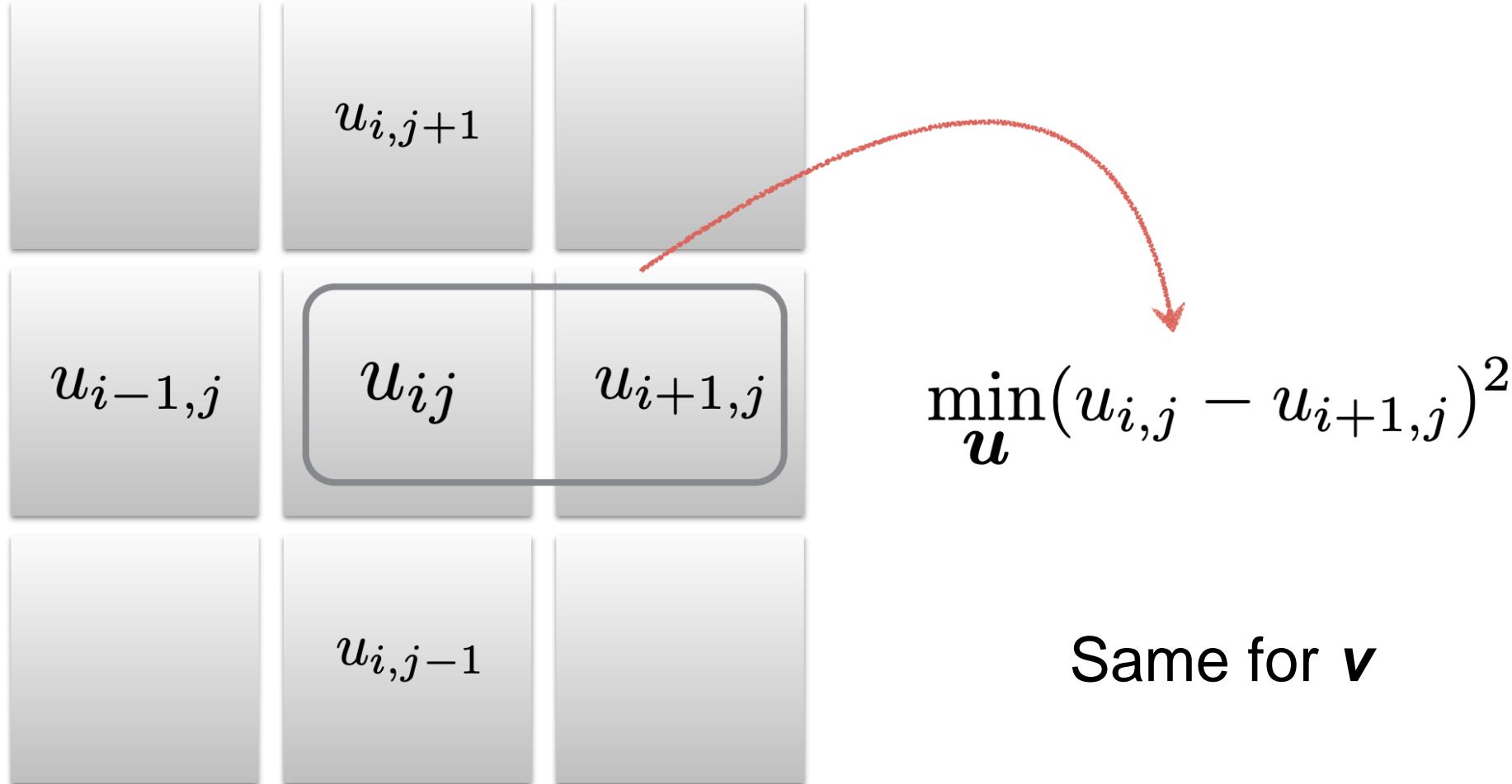
$$I_x u + I_y v + I_t = 0$$



For every Pixel (i,j):

$$\min_{u,v} [I_x(i,j)u_{ij} + I_y(i,j)v_{ij} + I_t(i,j)]^2$$

Enforce Smoothness Constraint



Objective Function

Horn-Schunck 1981

$$\min_{u,v} \sum_{i,j} \{ E_d(i,j) + \lambda E_s(i,j) \}$$

Brightness Constraint
Smoothness Constancy
Weight

λ = regularization constant (larger \rightarrow more smooth optical flow)

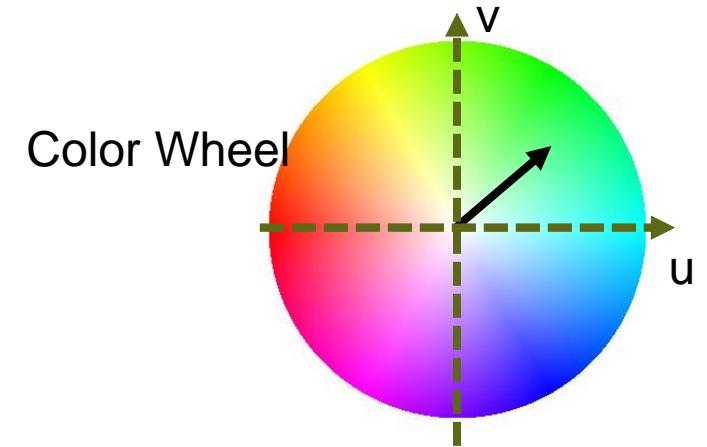
Brightness Constancy

$$E_d(i,j) = [I_x(i,j)u_{ij} + I_y(i,j)v_{ij} + I_t(i,j)]^2$$

Smoothness Constraint

$$E_s(i,j) = \frac{1}{4} [(u_{ij} - u_{i+1,j})^2 + (u_{ij} - u_{i,j+1})^2 + (v_{ij} - v_{i+1,j})^2 + (v_{ij} - v_{i,j+1})^2]$$

Horn-Schunck Optical Flow



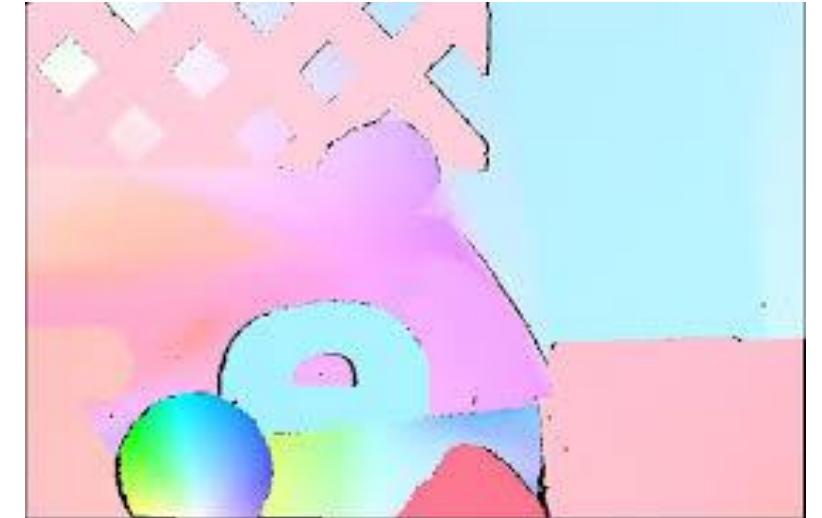
t



$t+1$

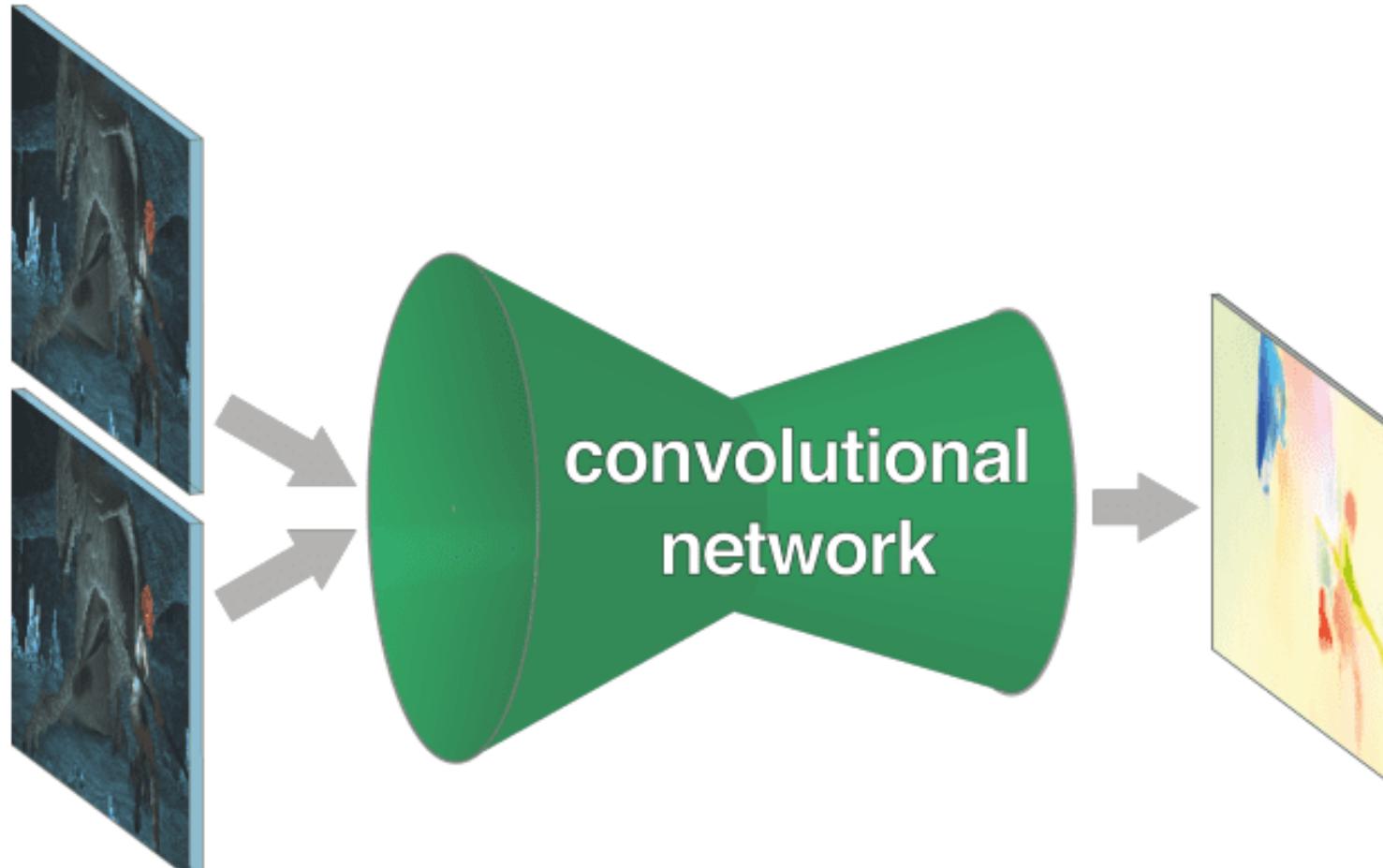


Flow Vectors visualized with Colors



Optical Flow Field is dense

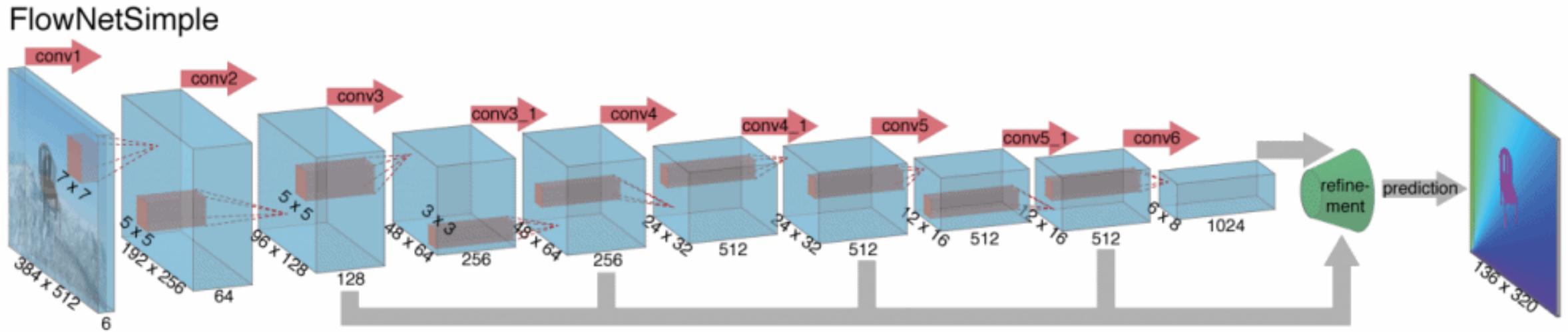
Optical Flow and Machine Learning



Encoder+Decoder Architectures (e.g. U-Nets)

Example: FlowNetS (Simple)

<https://lmb.informatik.uni-freiburg.de/Publications/2015/DFIB15/flownet.pdf>

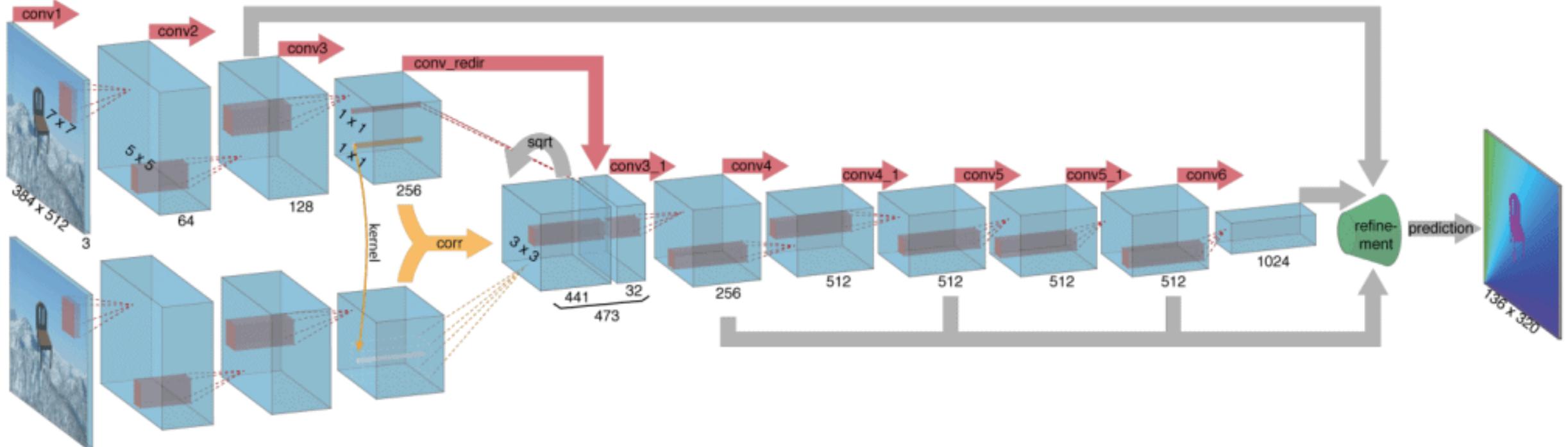


Input: Tensor of 2 RGB Images

Example: FlowNetCorr (Correlation)

<https://lmb.informatik.uni-freiburg.de/Publications/2015/DFIB15/flownet.pdf>

FlowNetCorr



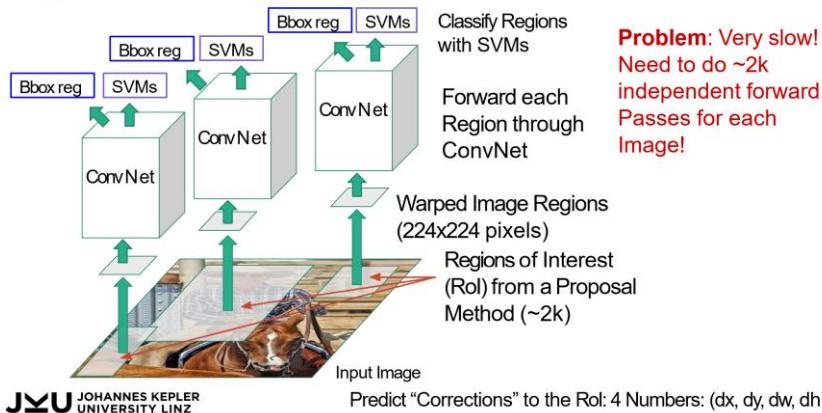
Input: 2 Tensors of individual RGB Images (Feature Maps are computed later → Correlation Layer)

Course Overview

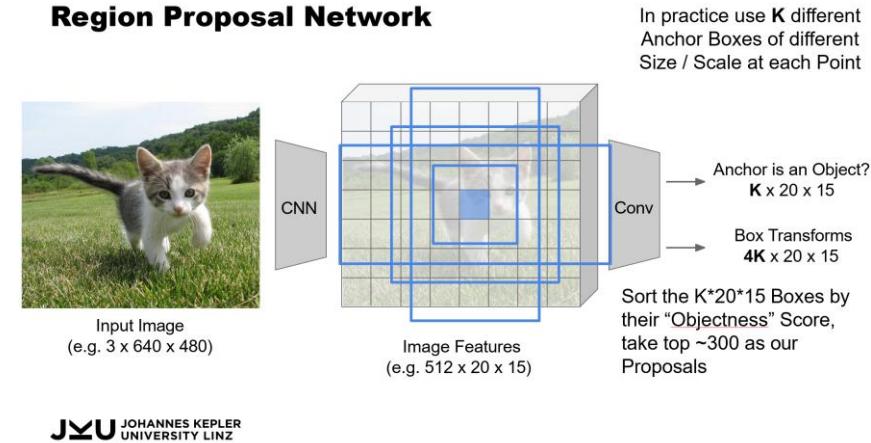
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Next Week: Object Detection

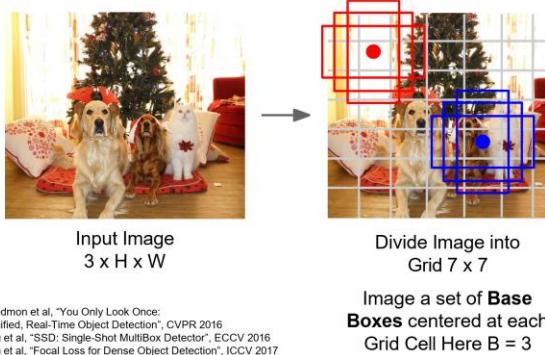
Regional-Based (R)-CNN



Region Proposal Network

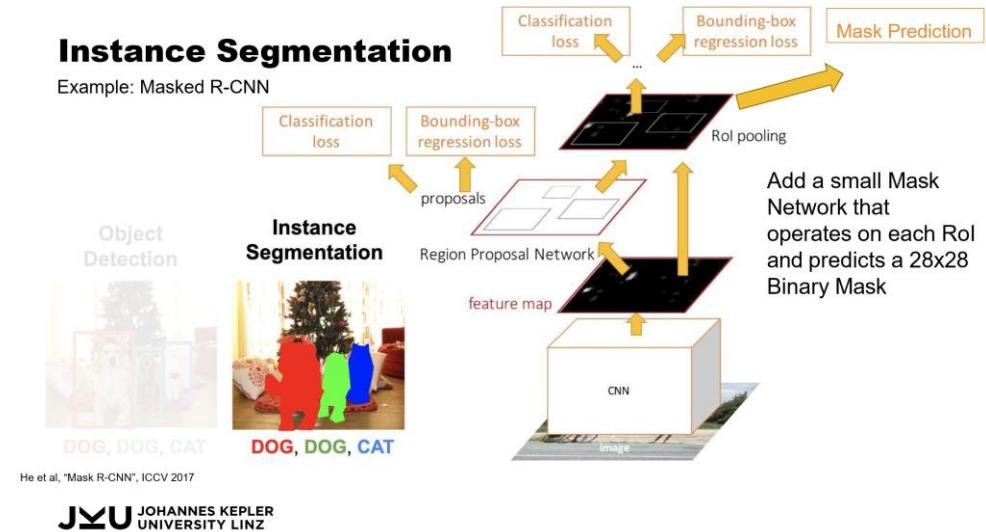


Single-Shot Object Detectors: YOLO/SSD/RetinaNet



Instance Segmentation

Example: Masked R-CNN



Thank You

