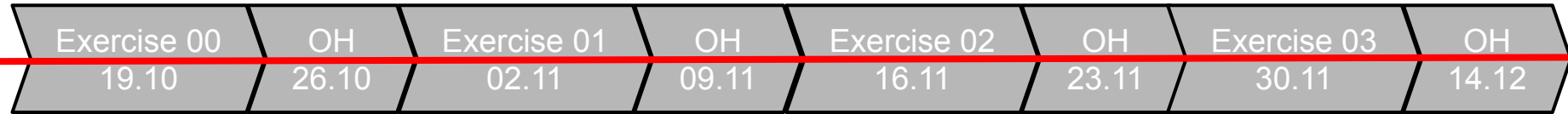


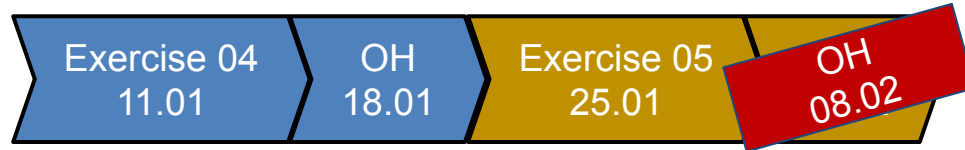
Exercise 4

About the Exercise Session

- 2 weeks for each exercise + Office hours (OH) for questions in between



Holidays and New Year

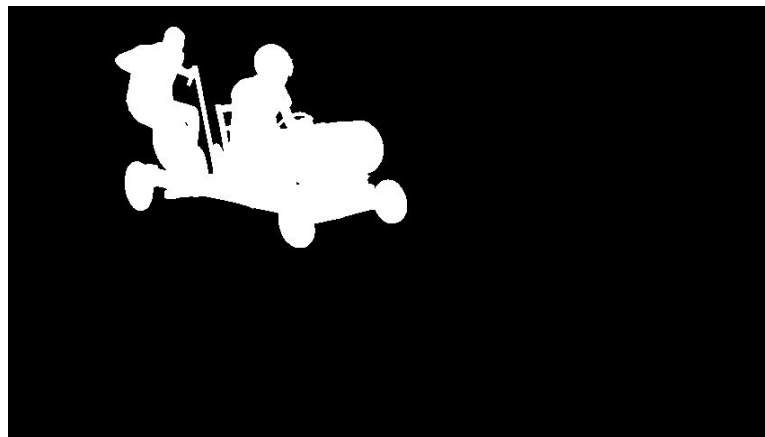


Submission for Exercise 05 also extended by 1 week

Deadline always 23:59 CET on due date

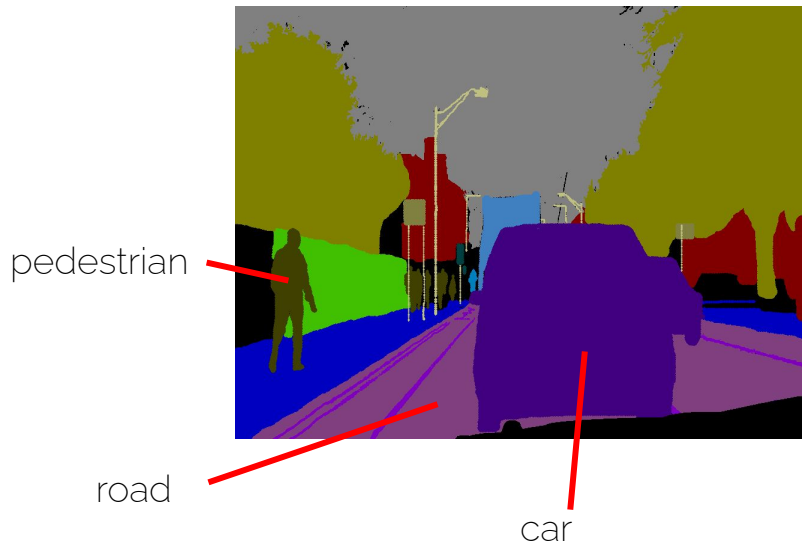
Recap: Segmentation

Going from bounding boxes to per-pixel predictions



Recap: Segmentation

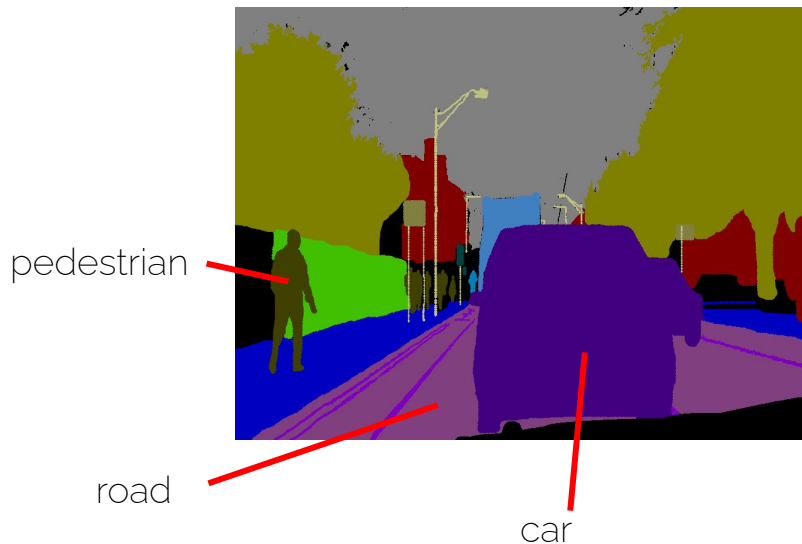
Going from bounding boxes to per-pixel predictions



Recap: Segmentation

What is shown here?

Instance, Semantic, or Panoptic Segmentation?



Recap: Segmentation

semantic segmentation



instance segmentation



panoptic segmentation



Recap Segmentation

Example:

Instance segmentation

(only if we consider only “objects” / “things”)

Semantic segmentation

Part segmentation

(typically one object)

Panoptic segmentation



Exercise 4

- **Object Segmentation (Semantic segmentation with binary class)**
- Supervision available
- Pretrained powerful image embeddings (learned with self-supervision)
- Upsampling: Learn to take advantage of pixel-adaptive convolutional neural nets

Exercise 4: Object Segmentation

Image



With Annotations



Exercise 4

- Object Segmentation (Semantic segmentation with binary class)
- **Supervision available**
- Pretrained powerful image embeddings (learned with self-supervision)
- Upsampling: Learning about pixel-adaptive convolutional neural nets

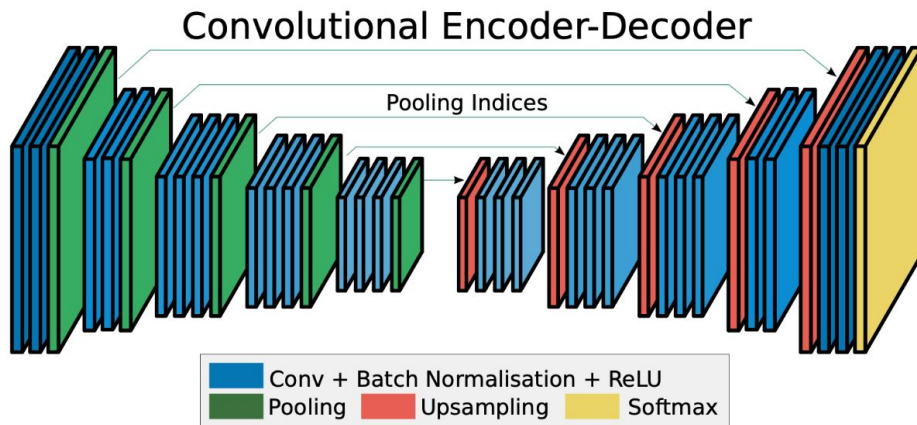
Classical Supervised Method



Loss



W,H,1



W,H,3

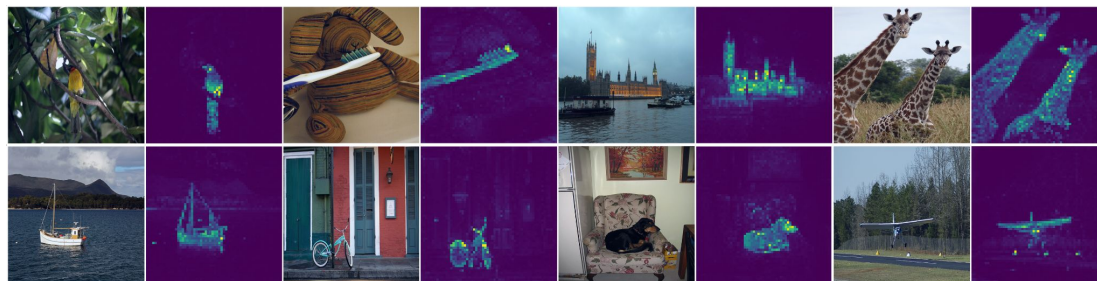
Badrinarayanan et al. "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation"

Exercise 4

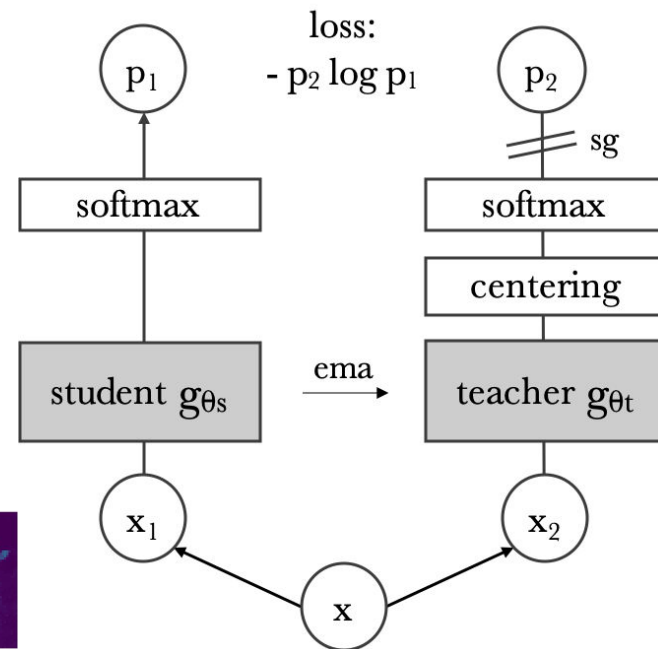
- Object Segmentation (Semantic segmentation with binary class)
- Supervision available
- **Pretrained powerful image embeddings (learned with self-supervision)**
- Upsampling: Learn to take advantage of pixel-adaptive convolutional neural nets

DINO - Self-Distillation with no Labels

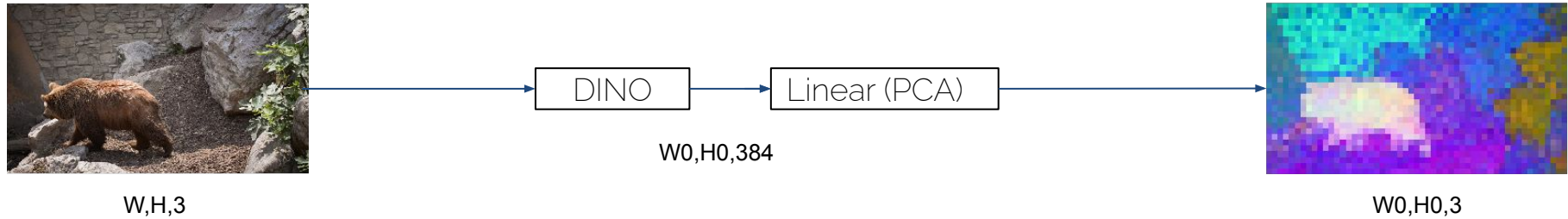
- Vision Transformer trained in a self-supervised fashion
- Student-teacher approach to train the network
- Results in powerful image representations



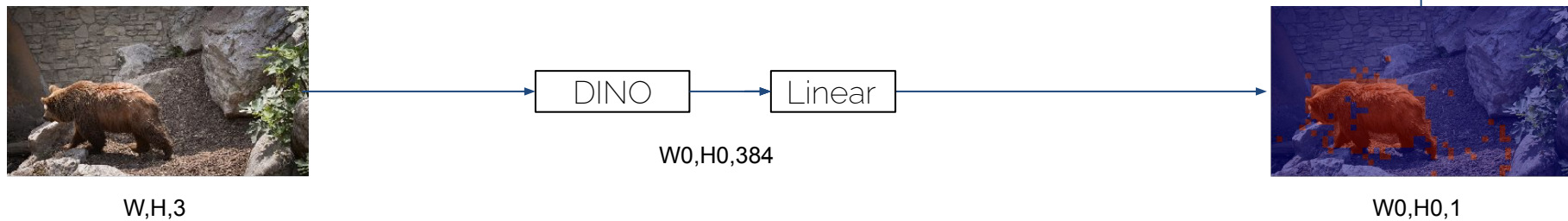
Caron et al. "Emerging Properties in Self-Supervised Vision Transformers"



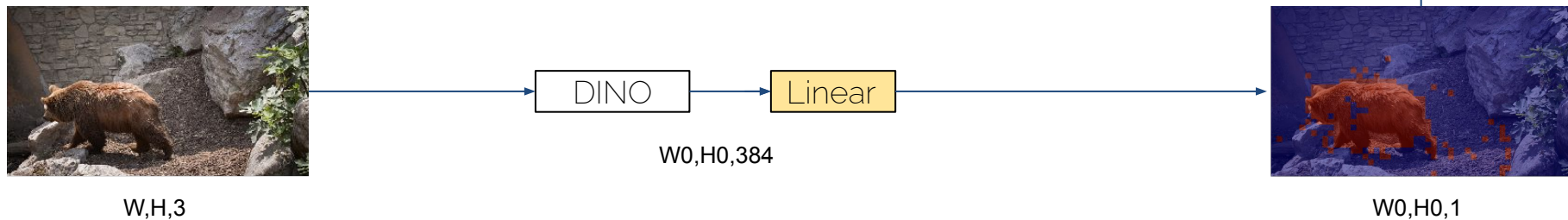
DINO: Self Supervised Learning



Exercise 4: Add Supervision



Exercise 4: Using DINO Feats

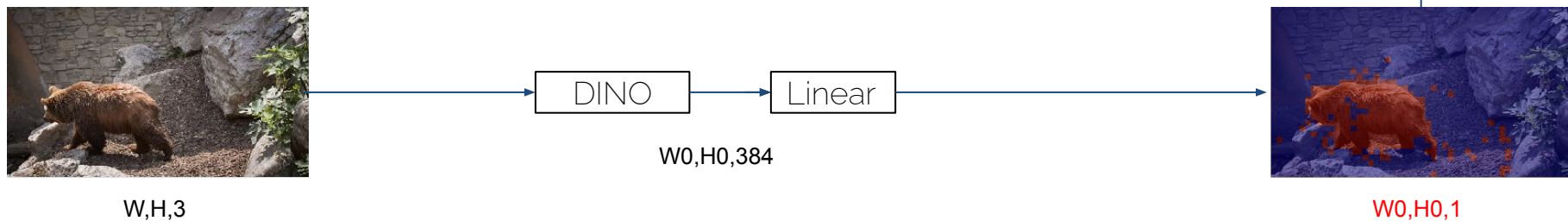


We only have to learn
a small linear Layer

Exercise 4

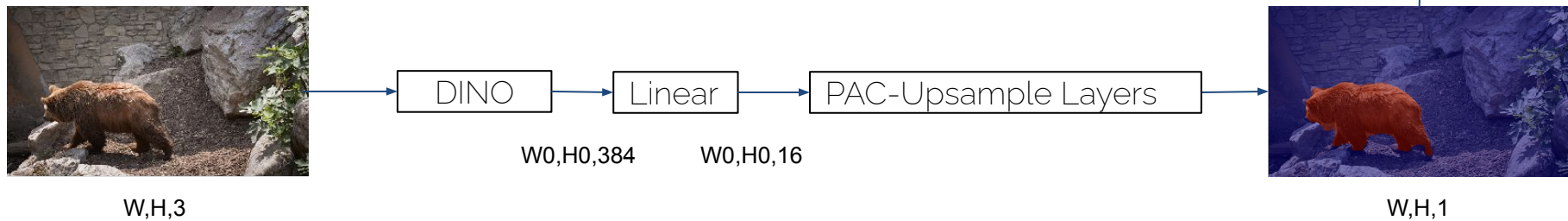
- Object Segmentation (Semantic segmentation with binary class)
- Supervision available
- Pretrained powerful image embeddings (learned with self-supervision)
- **Upsampling: Learn to take advantage of pixel-adaptive convolutional neural nets**

Exercise 4: PAC-Upsample



Low Resolution (16x16)
after DINO net

Exercise 4: PAC-Upsample



Recap: CNNs

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1



Output **3x3**

Image **5x5**

Weight **3x3**

2	4	-2
3	1	0
-1	0	0

Recap: CNNs

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Image **5x5**

Weight **3x3**

2	4	-2
3	1	0
-1	0	0



12		

Output **3x3**

Recap: CNNs

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Image **5x5**

Weight **3x3**

2	4	-2
3	1	0
-1	0	0



12	35	

Output **3x3**

Pixel-Adaptive CNNs

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Image **5x5**

Weight **3x3**

2	4	-2
3	1	0
-1	0	0

×

1	2	-1
-1	0	0
0	1	3

Pixel-Adaptive
Kernel
3x3



6		

Output **3x3**

Pixel-Adaptive CNNs

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	0	7	9	-1

Image **5x5**

Weight **3x3**

2	4	-2
3	1	0
-1	0	0

×

2	1	-2
0	-1	1
1	0	0

Pixel-Adaptive
Kernel
3x3

6	-1	

Output **3x3**

Calculating the (gaussian) Kernel

1	2	-1
-1	0	0
0	1	3

Image patch **3x3x3**

1	0
3	2
-1	-1

f_i

f_j

exp(-1)		

Kernel **3x3**

$$K(f_i, f_j) = \exp \left(-\frac{1}{2} (f_i - f_j)^\top (f_i - f_j) \right)$$

Calculating the (gaussian) Kernel

1	2	-1
-1	0	0
0	1	3

Image patch **3x3x3**

2	0
1	2
-2	-1

f_i
 f_j

exp(-1)	exp(-3)	

Kernel **3x3**

$$K(f_i, f_j) = \exp \left(-\frac{1}{2} (f_i - f_j)^\top (f_i - f_j) \right)$$

Pytorch Unfold

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1



-5	3	2	4	3	2	1	0	3
3	2	-5	3	2	1	0	3	3
2	-5	3	2	1	-3	3	3	5
4	3	2	1	0	3	-2	0	1

Image **5x5**

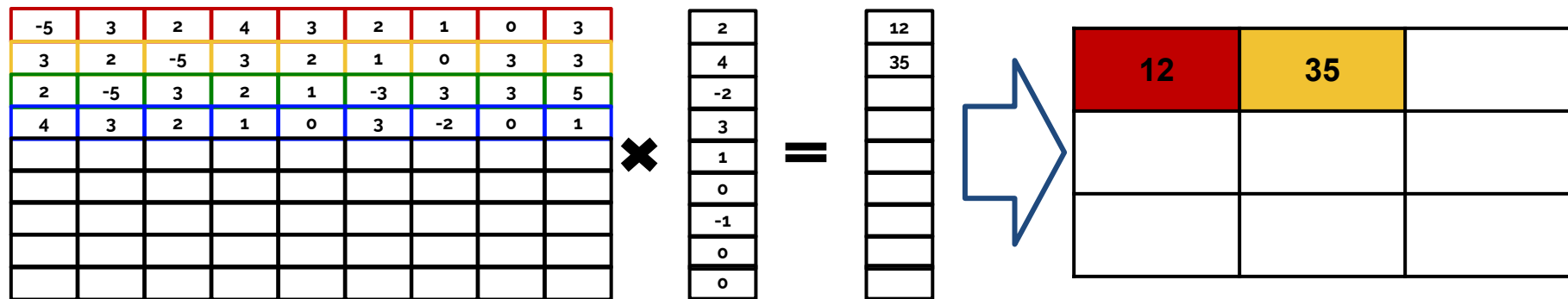
Weight **3x3**

2	4	-2
3	1	0
-1	0	0



2	4	-2	3	1	0	-1	0	0
---	---	----	---	---	---	----	---	---

Pytorch Unfold



- unfolding allows to rewrite the convolution operation as a matrix vector multiplication
- reshaping afterward is necessary

Pytorch Unfold - weighting kernel

-5	3	2	4	3	2	1	0	3
3	2	-5	3	2	1	0	3	3
2	-5	3	2	1	-3	3	3	5
4	3	2	1	0	3	-2	0	1

✖ element-wise ➡ ✖

1	2	-1	-1	0	0	0	1	3
2	1	-2	0	-1	1	1	0	0

2
4
-2
3
1
0
-1
0
0

=

6
-1



6	-1	

Links

- Test server:
<https://cv3dst.cvai.cit.tum.de/login>
- If you have trouble registering
<https://forms.gle/yZkZiDiyHxWuNqQG7>
- Data for Exercise 04:
https://vision.in.tum.de/webshare/g/cv3dst/exercise_04.zip

Links for the individual datasets

- MOT
<https://vision.in.tum.de/webshare/g/cv3dst/datasets/MOT16.zip>
- market
<https://vision.in.tum.de/webshare/g/cv3dst/datasets/market.zip>
- obj_seg
https://vision.in.tum.de/webshare/g/cv3dst/datasets/obj_seg.zip
- reid_gnn
https://vision.in.tum.de/webshare/g/cv3dst/datasets/reid_gnn.zip