Deep learning for semantic segmentation

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Semantic segmentation

- Label each pixel in the image with a semantic class
- Don't differentiate between instances
- Provides a detailed understanding of the environment
- Can be used in the context of autonomous driving

Benchmarks

- Various **indoor and outdoor scenes** and images of **objects, persons and animals**:
- **Pascal VOC** – 21 classes, 10k images [1]
- **Pascal Context** – 59 classes, 10k images [2]
- **Microsoft COCO** – 182 classes, 10k images [3]
- **ADE20K** – 150 classes, 20k images [4]

Benchmarks

- Contain only **traffic scenes**:
- **CamVid** – 32 classes, 700 images [5]
- **Cityscapes** – 30 classes, 19 classes used in evaluation, 5000 images [6]
- **Synthia –** 13 classes, 13.400 images, synthetic dataset [7]

Fully Convolutional Network

- Fully Convolutional Network [8]: a special type of convolutional network that outputs a segmented image
- Convolution network: downsampling
- Deconvolution network: upsampling

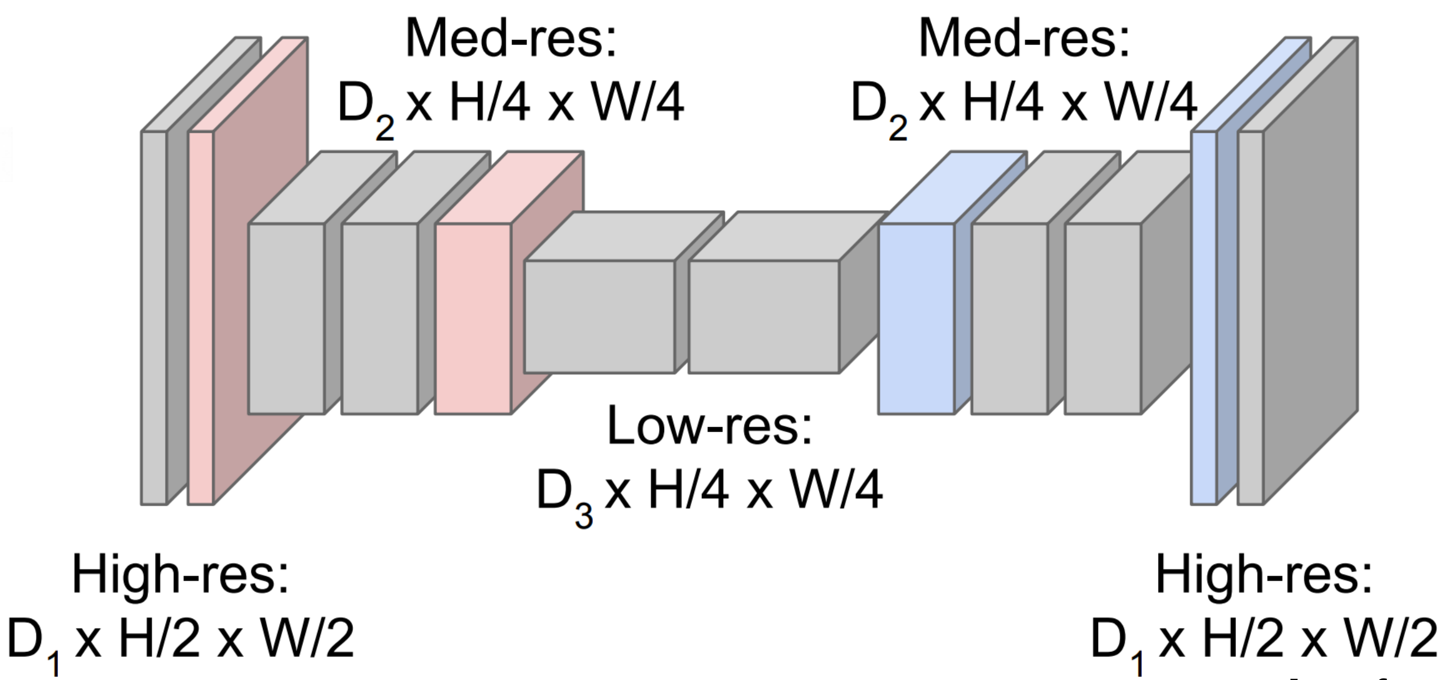


Figure taken from FCN paper [8]

FCN: Max Unpooling

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

Max pooling with 2x2 filters and stride 2

5	6
7	8

Output: 2 x 2

Rest of the network

1	2
3	4

Input: 2 x 2

Max unpooling (use positions from the pooling layer)

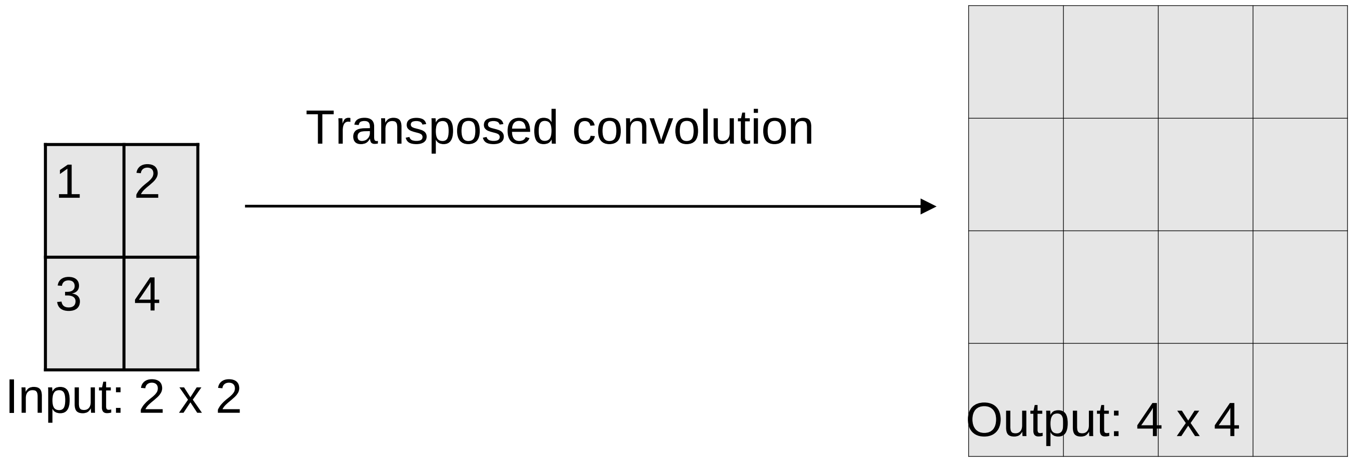
0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

- Use corresponding pairs of pool/unpooling layers

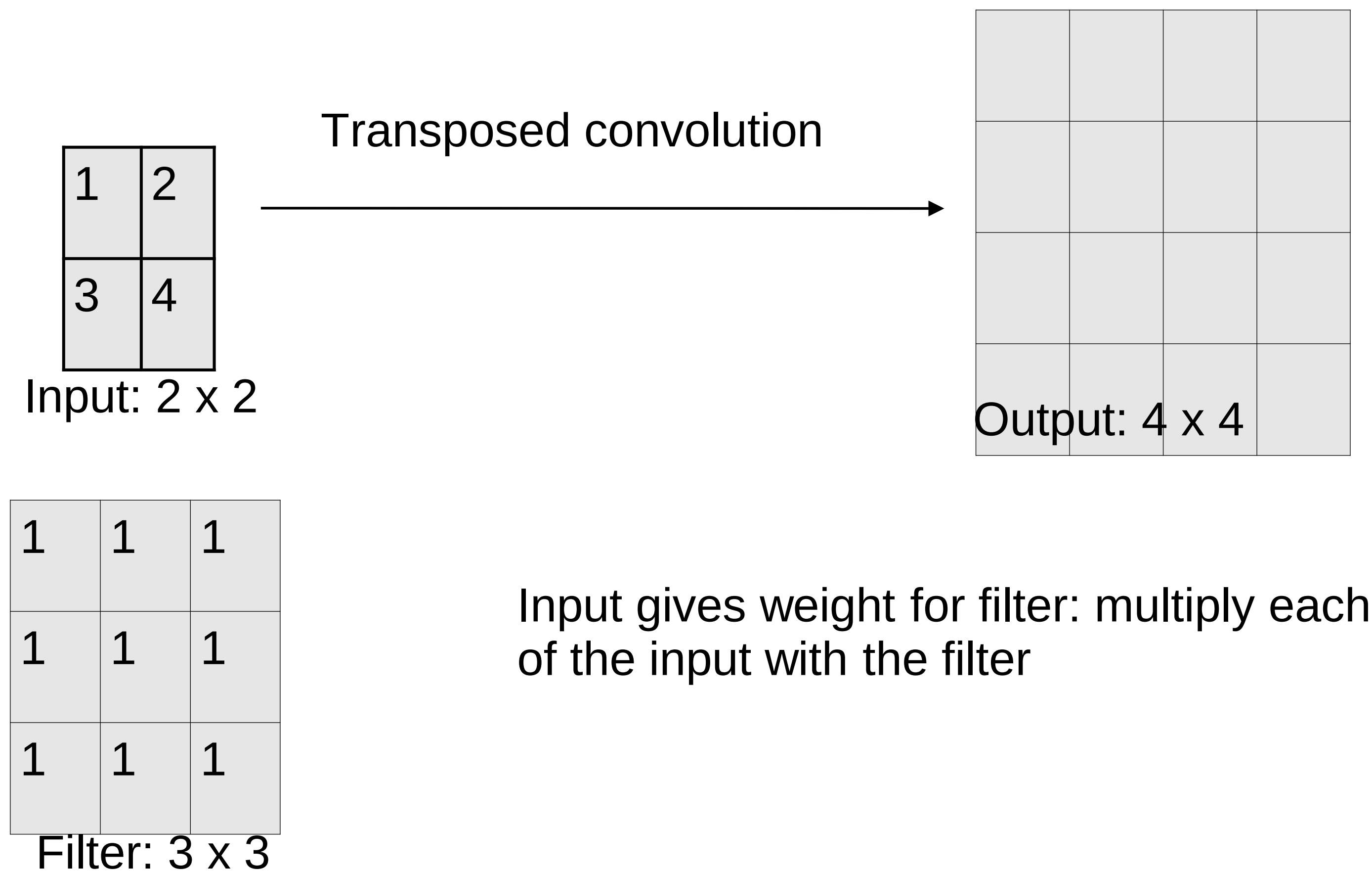
FCN: Transposed Convolution

- 3 x 3 transposed convolution, stride 2 pad 1



FCN: Transposed Convolution

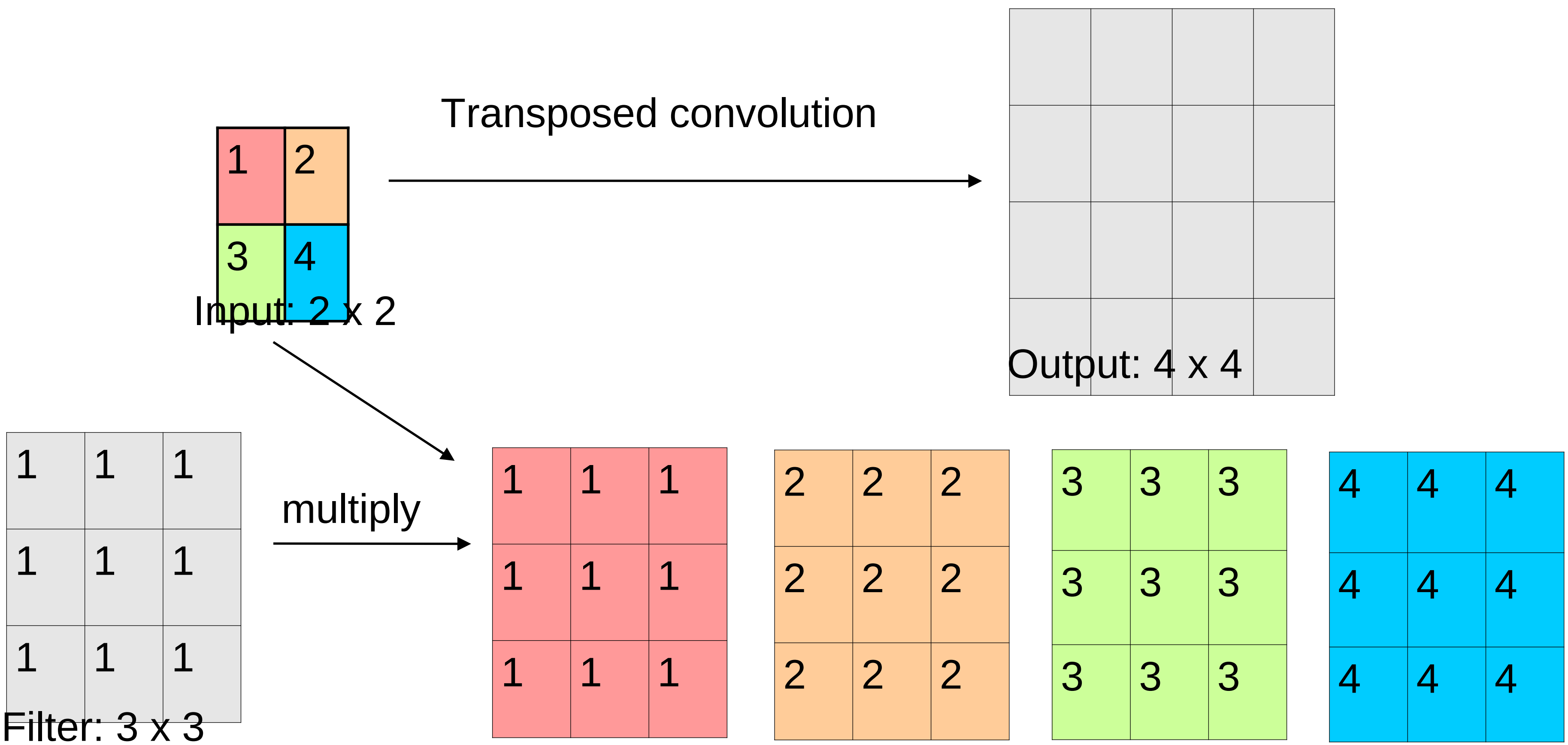
- 3 x 3 transposed convolution, stride 2 pad 1



Input gives weight for filter: multiply each element of the input with the filter

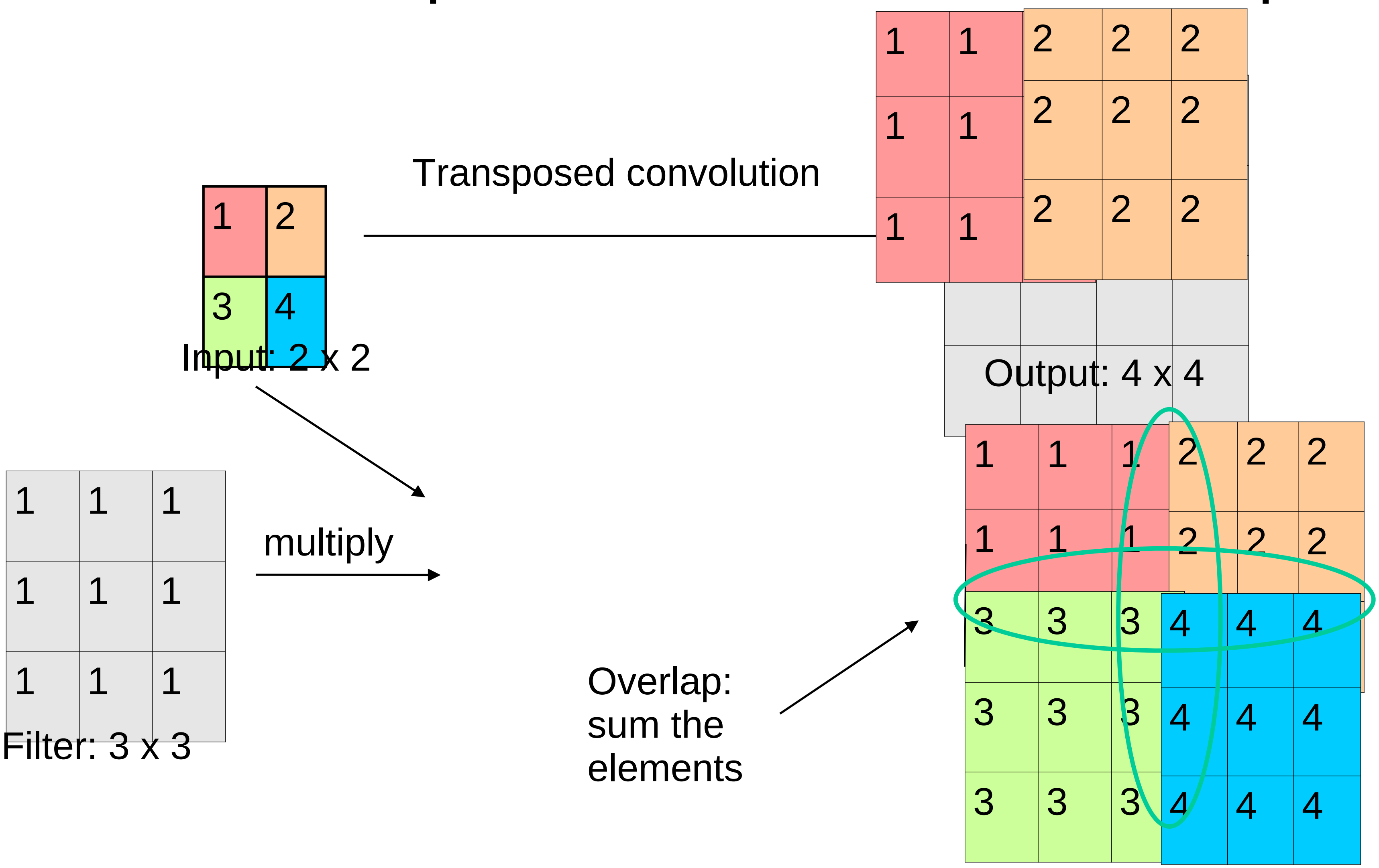
FCN: Transposed Convolution

- 3 x 3 transposed convolution, stride 2 pad 1



FCN: Transposed Convolution

- 3 x 3 transposed convolution, stride 2 pad 1



FCN: Transposed Convolution

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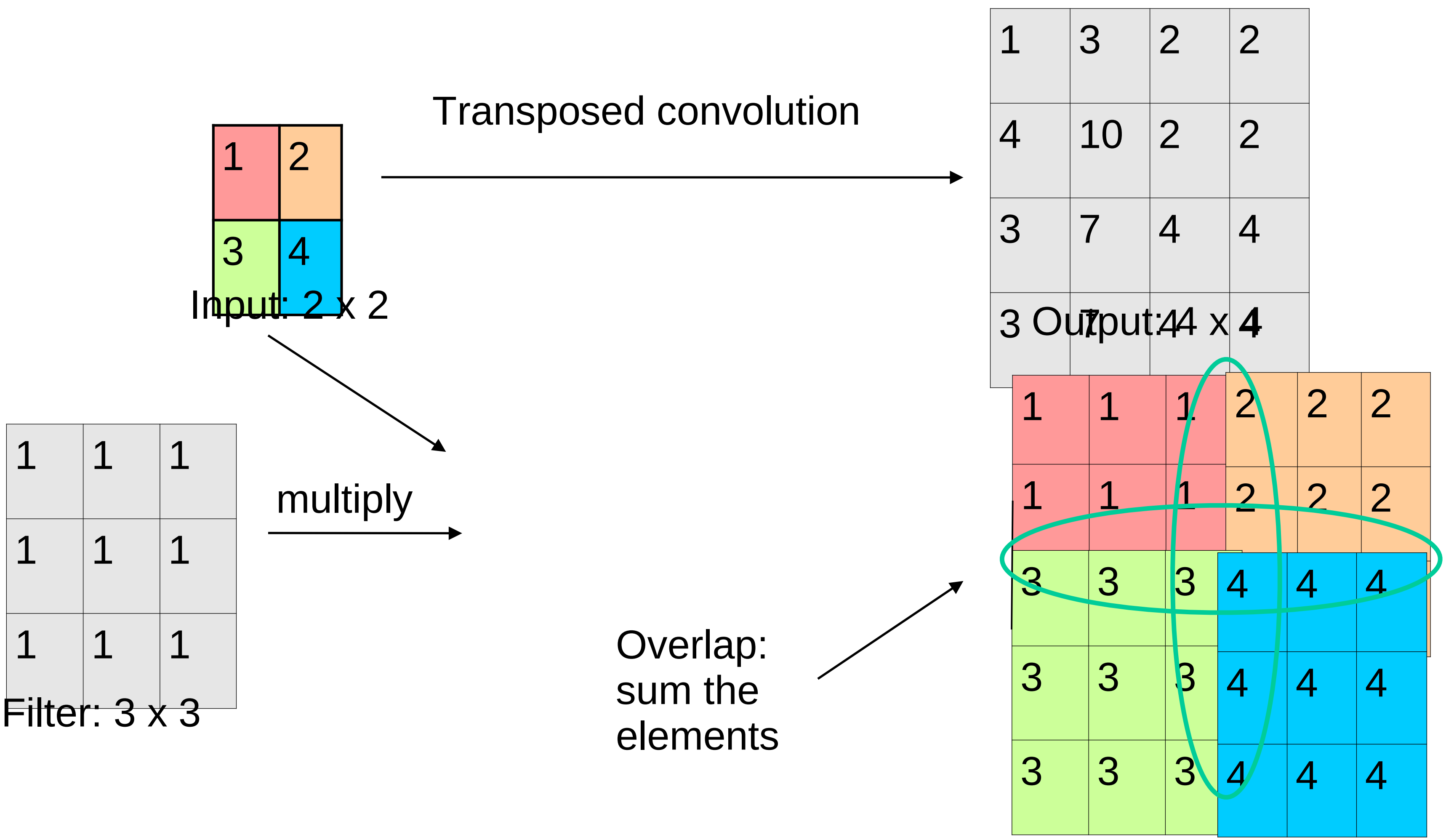

FCN performance on the Cityscapes dataset

name	fine	coarse	16-bit	depth	video	sub	IoU class	iIoU class	IoU category	iIoU category	Runtime [s]	code
m-TCFs	yes	yes	no	no	no	no	71.8	43.6	87.6	70.6	1.0	no
LRR-4x	yes	yes	no	no	no	no	71.8	47.9	88.4	73.9	n/a	yes
FRRN	yes	no	no	no	no	2	71.8	45.5	88.9	75.1	n/a	yes
Adelaide_context	yes	no	no	no	no	no	71.6	51.7	87.3	74.1	n/a	no
ML-CRNN	yes	no	no	no	no	no	71.2	47.1	87.7	72.5	n/a	no

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name	fine	coarse	16-bit	depth	video	sub	IoU class	iIoU class	IoU category	iIoU category	Runtime [s]	code
FCN 8s	yes	no	no	no	no	no	65.3	41.7	85.7	70.1	0.5	yes

ERF-Net [9]

- One of the fastest convolutional neural networks in the literature used for semantic segmentation
- Execution time is **25 ms** for a **1024 x 512** image running on a Titan X GPU

ERF-Net: Architecture

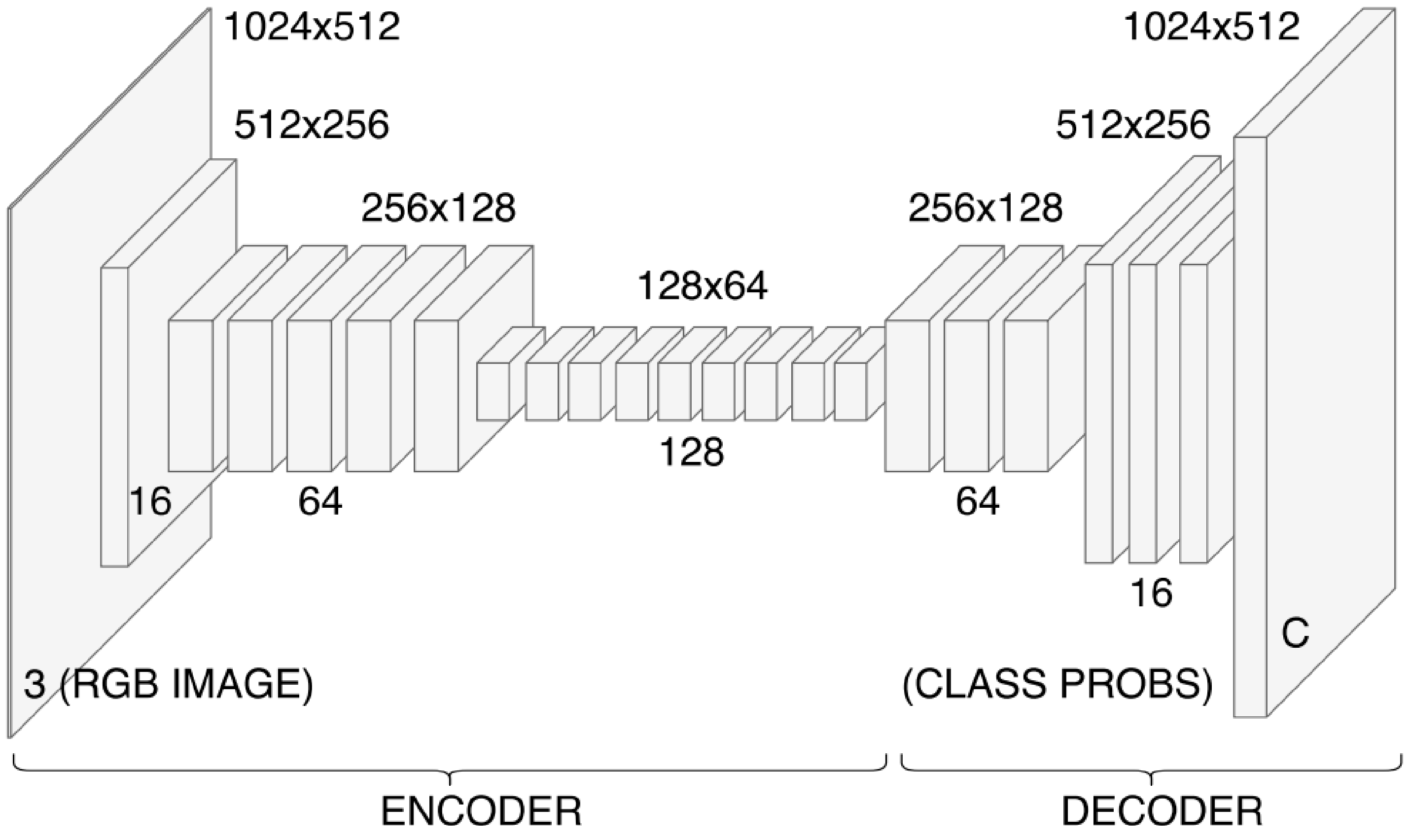


Figure taken from paper [9]

ERF-Net: Architecture

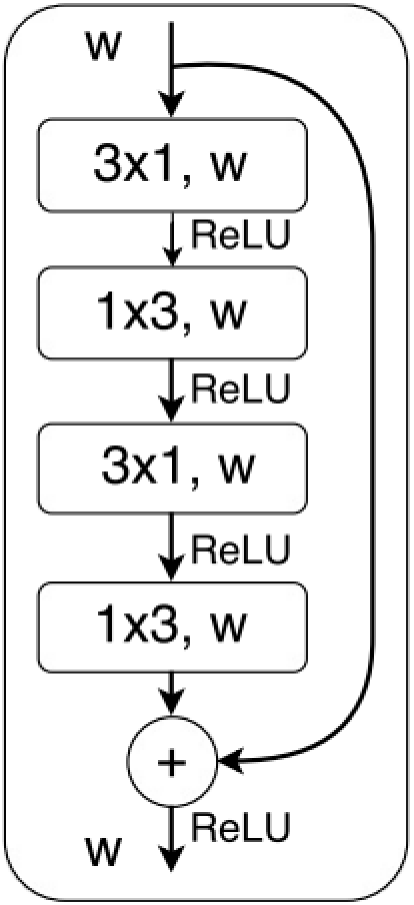
Layer	Type	out-F	out-Res
1	**Downsampler block**	16	512x256
2	**Downsampler block**	64	256x128
3-7	5 x **Non-bt-1D**	64	256x128
8	**Downsampler block**	128	128x64
9	**Non-bt-1D** (dilated 2)	128	128x64
10	**Non-bt-1D** (dilated 4)	128	128x64
11	**Non-bt-1D** (dilated 8)	128	128x64
12	**Non-bt-1D** (dilated 16)	128	128x64
13	**Non-bt-1D** (dilated 2)	128	128x64
14	**Non-bt-1D** (dilated 4)	128	128x64
15	**Non-bt-1D** (dilated 8)	128	128x64
16	**Non-bt-1D** (dilated 16)	128	128x64
17	**Deconvolution** (upsampling)	64	256x128
18-19	2 x **Non-bt-1D**	64	256x128
20	**Deconvolution** (upsampling)	16	512x256
21-22	2 x **Non-bt-1D**	16	512x256
23	**Deconvolution** (upsampling)	C	1024x512

ENCODER

DECODER

Figure taken from paper [9]

ERF-Net: Architecture

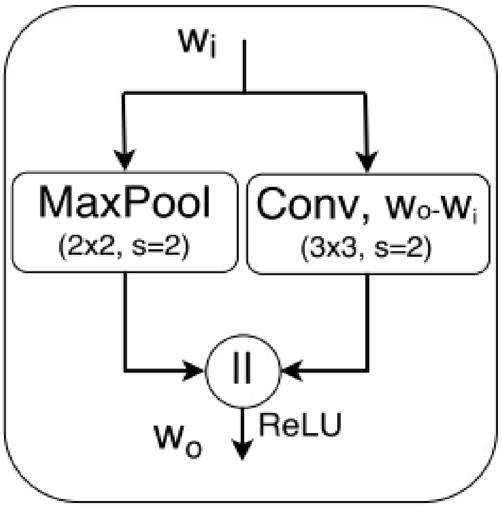


(a) Non-bottleneck-1D

```
(11): nn.Sequential {
    [input -> (1) -> (2) -> (3) -> output]
    (1): nn.ConcatTable {
      input
        |`-> (1): nn.Sequential {
        |       [input -> (1) -> (2) -> (3) -> (4) -> (5) -> (6) -> (7) -> (8) ->
(9) -> (10) -> output]
        |       (1): cudnn.SpatialConvolution(128 -> 128, 3x1, 1,1, 1,0)
        |       (2): cudnn.ReLU
        |       (3): cudnn.SpatialConvolution(128 -> 128, 1x3, 1,1, 0,1)
        |       (4): cudnn.SpatialBatchNormalization
        |       (5): cudnn.ReLU
        |       (6): nn.SpatialDilatedConvolution(128 -> 128, 3x1, 1,1, 8,0, 8,1)
        |       (7): cudnn.ReLU
        |       (8): nn.SpatialDilatedConvolution(128 -> 128, 1x3, 1,1, 0,8, 1,8)
        |       (9): cudnn.SpatialBatchNormalization
        |       (10): nn.SpatialDropout(0,3)
        |     }
         `-> (2): nn.Sequential {
                [input -> (1) -> output]
                (1): nn.Identity
              }
         ... -> output
    }
    (2): nn.CAddTable
    (3): cudnn.ReLU
```

Figure taken from paper [9]

ERF-Net: Architecture



(b) Downsampler block

Figure taken from paper [9]

```
(1): nn.Sequential {
  [input -> (1) -> (2) -> (3) -> (4) -> (5) -> output]
  (1): nn.ConcatTable {
    input
      |`-> (1): nn.Sequential {
      |       [input -> (1) -> output]
      |       (1): cudnn.SpatialConvolution(3 -> 13, 3x3, 2,2, 1,1)
      |     }
       `-> (2): nn.Sequential {
              [input -> (1) -> output]
              (1): cudnn.SpatialMaxPooling(2x2, 2,2)
            }
       ... -> output
  }
  (2): nn.JoinTable
  (3): cudnn.SpatialBatchNormalization
  (4): nn.SpatialDropout(0,000000)
  (5): cudnn.ReLU
```

ERF-Net performance on the Cityscapes dataset

name	fine	coarse	16-bit	depth	video	sub	IoU class	iIoU class	IoU category	iIoU category	Runtime [s]	code
m-TCFs	yes	yes	no	no	no	no	71.8	43.6	87.6	70.6	1.0	no
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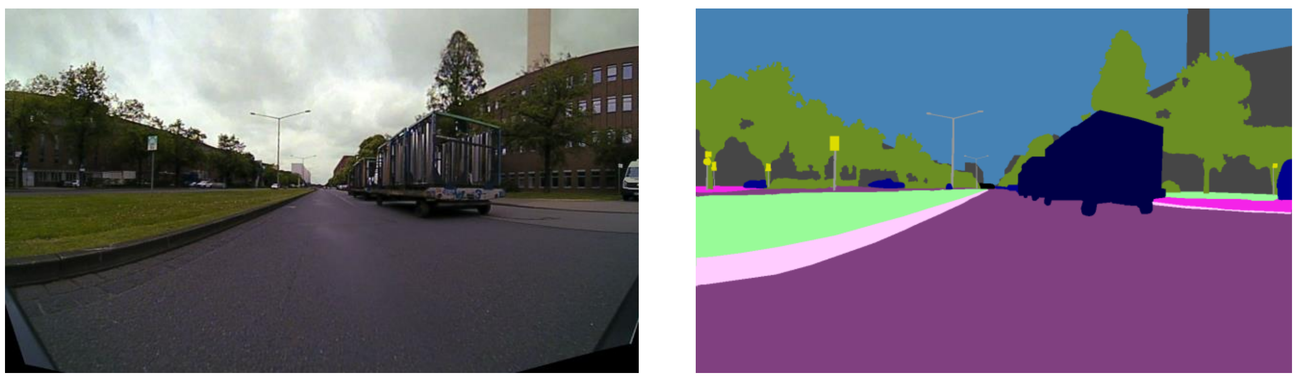
ERFNet (pretrained)	yes	no	no	no	no	2	69.7	44.1	87.3	72.7	0.02	yes
GridNet	yes	no	no	no	no	no	69.5	44.1	87.9	71.1	n/a	no
ERFNet (from scratch)	yes	no	no	no	no	2	68.0	40.4	86.5	70.4	0.02	yes

Transfer learning

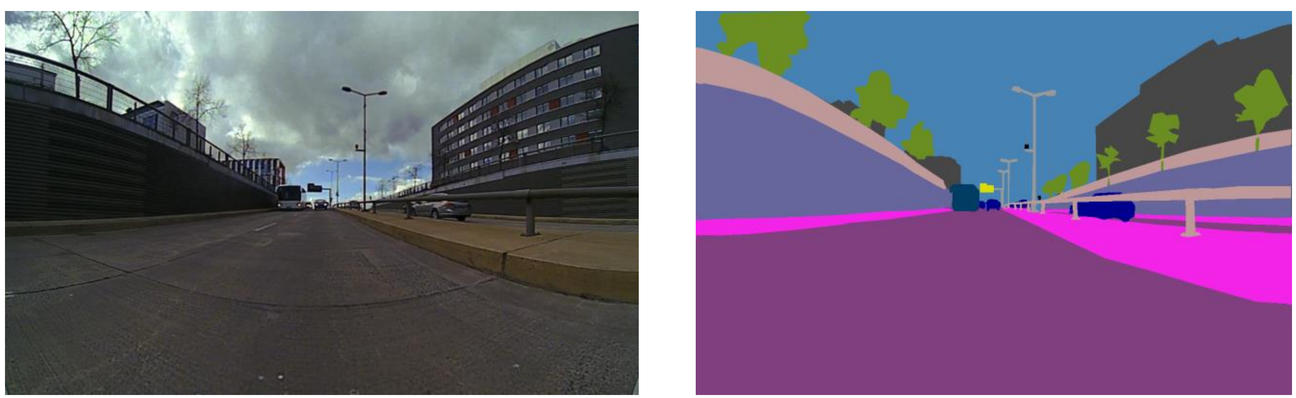
- Large annotated datasets are not always available for a given application
- Use **transfer learning** => train the network on a large existing dataset and use the weights to **fine-tune** the network for the specific task
- We perform different experiments in order to get the best results on our dataset (Up-drive)
- We fine-tune the ERF-Net network trained on the Cityscape dataset to fit our dataset

Transfer learning

- Our dataset contains 294 annotated images (front view, back view)
- 234 images in the training set
- 60 images in the validation set
- 20 semantic classes



Front view



Back view

Experimental results

- **Experiment 1**
  - Train encoder on the Cityscapes + Up-drive images
  - Train decoder on the Cityscapes + Up-drive images
  - Use data augmentation: image flipping and random translations => 234 * 2 = 468 Up-drive images (2975 Cityscapes + 468 Up-drive = 3443 images)
  - 8 classes: road, sidewalk, building, pole, vegetation, sky, person, vehicle
  - Training time: 60h for 300 epochs on 2 Nvidia GTX 1070
  - 84.71 IoU on Cityscapes validation set
  - 84.72 IoU on Up-drive validation set

Experimental results

	IoU Up-drive	IoU Cityscapes
CityScapes+ Up-driveAug	84.72	84.71
Pretrained enc ImageNet + Cityscapes+Up-driveAug decoder	86.7	85.87
Pretrained enc ImageNet + Up-driveAug decoder	91.14	55.53
Pretrained enc Cityscapes + Up-driveAug decoder	79.26	55.98
Up-driveAug	71.65	

Conclusions

- semantic segmentation can be done in real time
- best results on our dataset are obtained using a pretrained decoder on ImageNet and training the decoder on Cityscapes + Up-Drive images
- Future work: add more training and validation examples in our dataset and get a better classifier

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Thank you!