Convolutional Neural Networks

Mass Street University

PER EDUCATIONEM PROGRESSUS

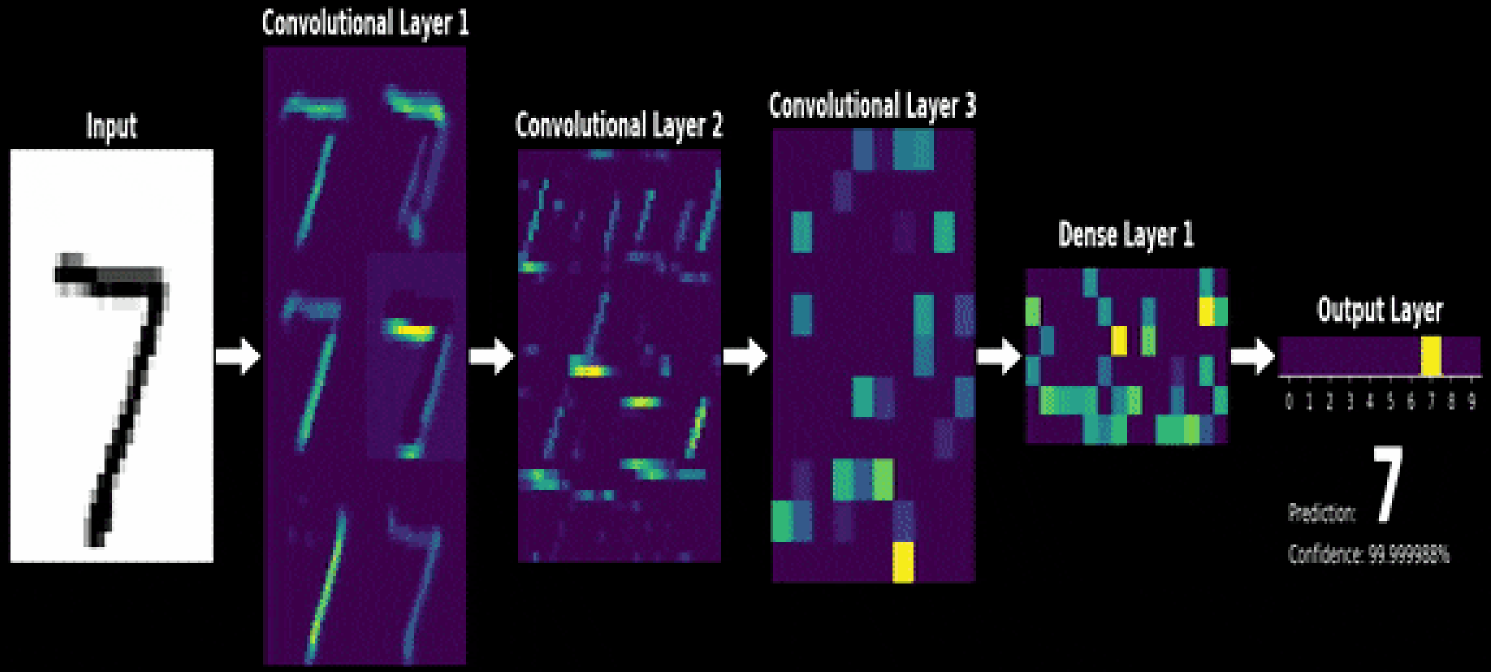
What we are covering

- Input channels
- Convolutional layers
- Feature extraction
- Pooling layers
- Filters
- Strides
- Padding
- Flatten layers
- Spatial dropout
- Locally connected layers
- Grayscale to color pixel transformations
- Image preprocessing

Mass Street University
PER EDUCATIONEM PROGRESSUS

Convolutional Neural Networks, CNNs

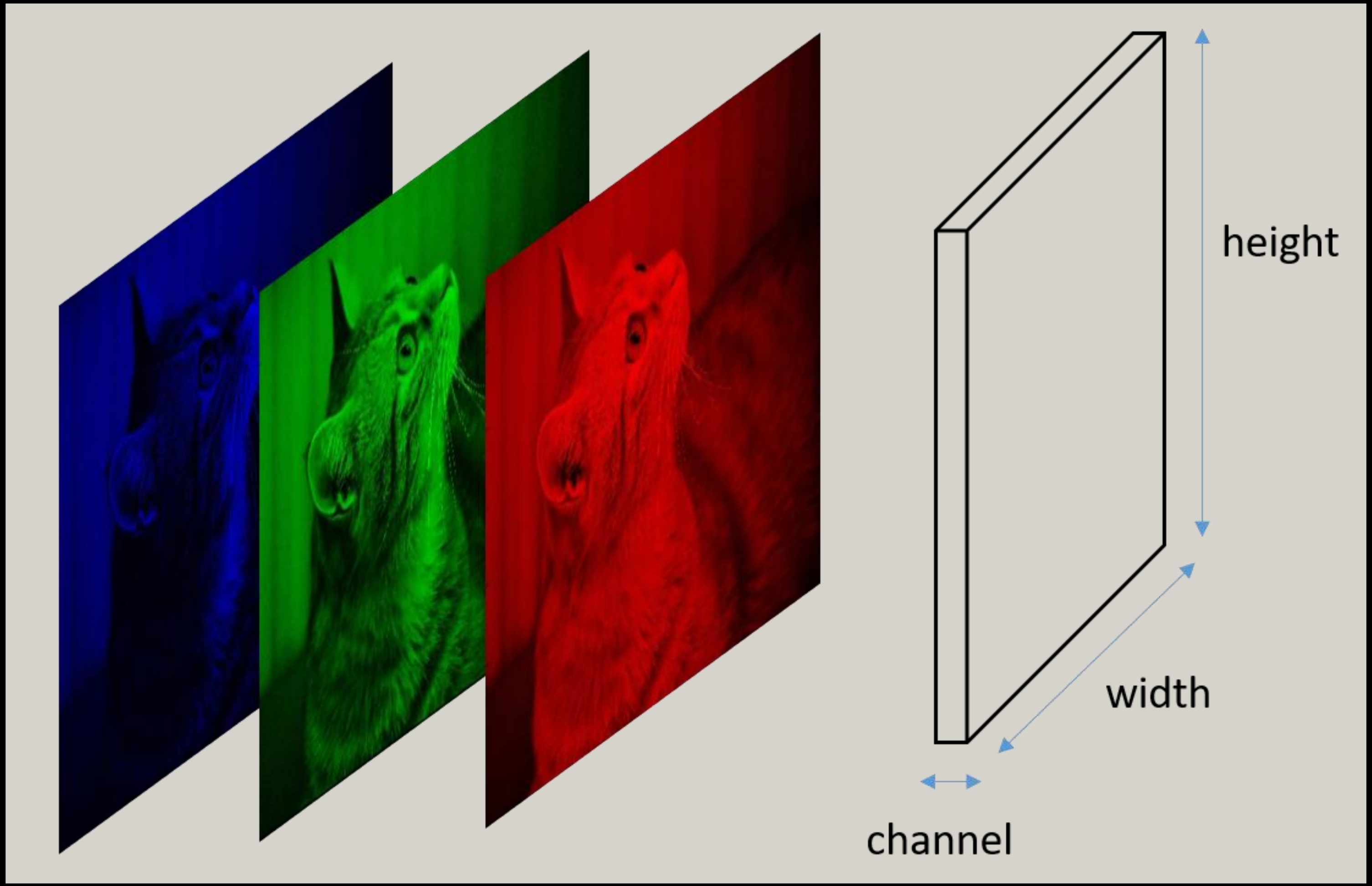
- Specialize in reducing complexity in data to analyze features.
- Typically used for Image data but can be used with any type.



Mass Street University
PER EDUCATIONEM PROGRESSUS

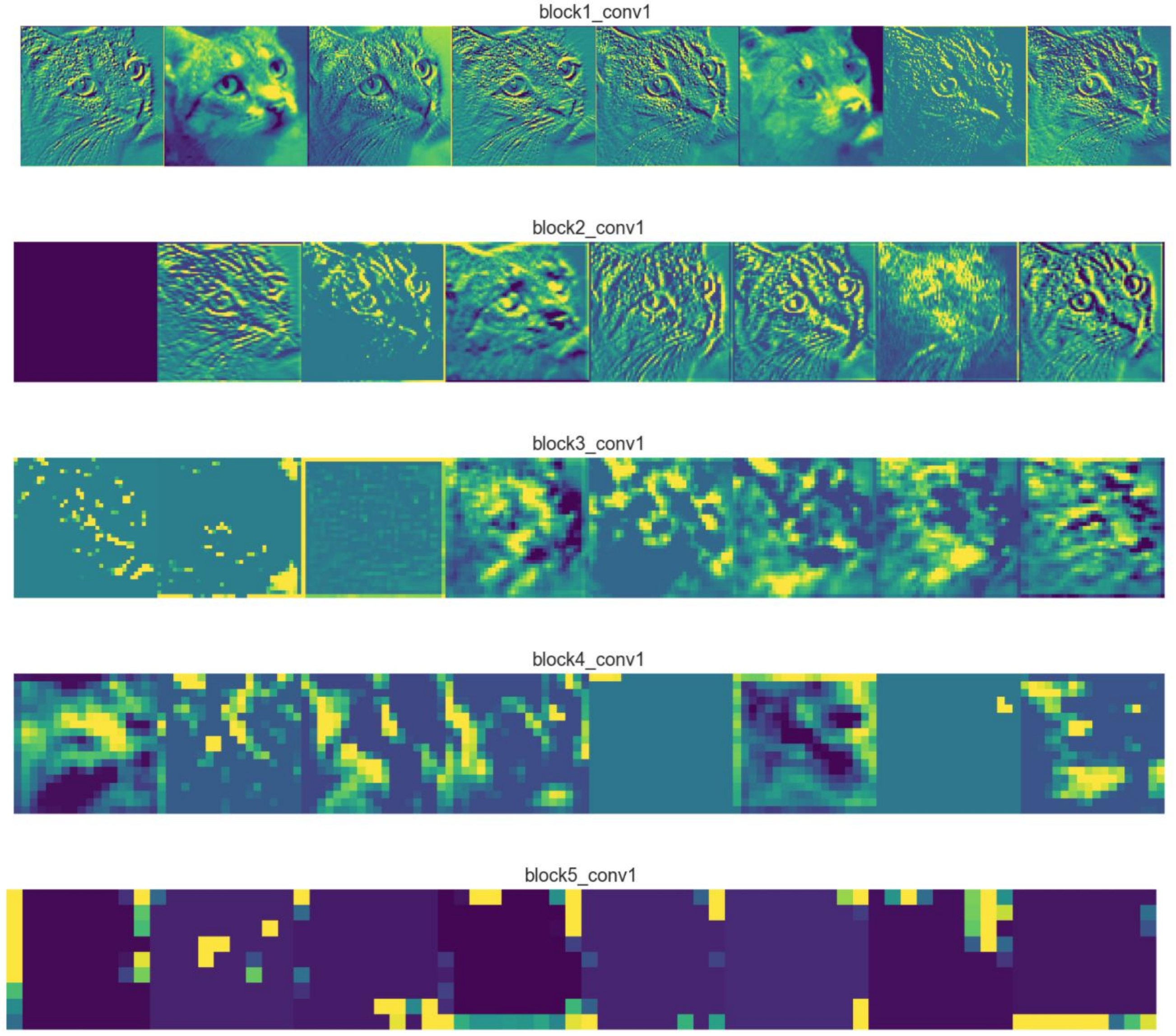
Image data

- Dimensions are height and width.
- Can be Grayscale, RGB, CMYK, CIE LAB, Etc.
- Each Standard is different.



Mass Street University
PER EDUCATIONEM PROGRESSUS

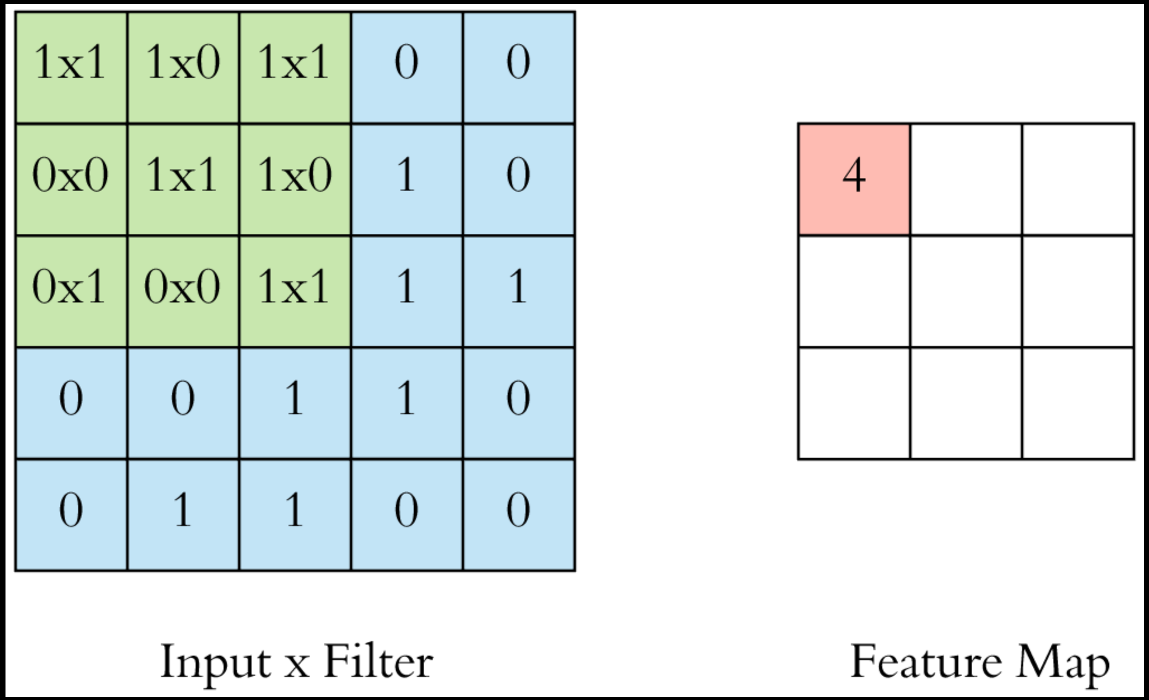
How CNNs see images



Mass Street University
PER EDUCATIONEM PROGRESSUS

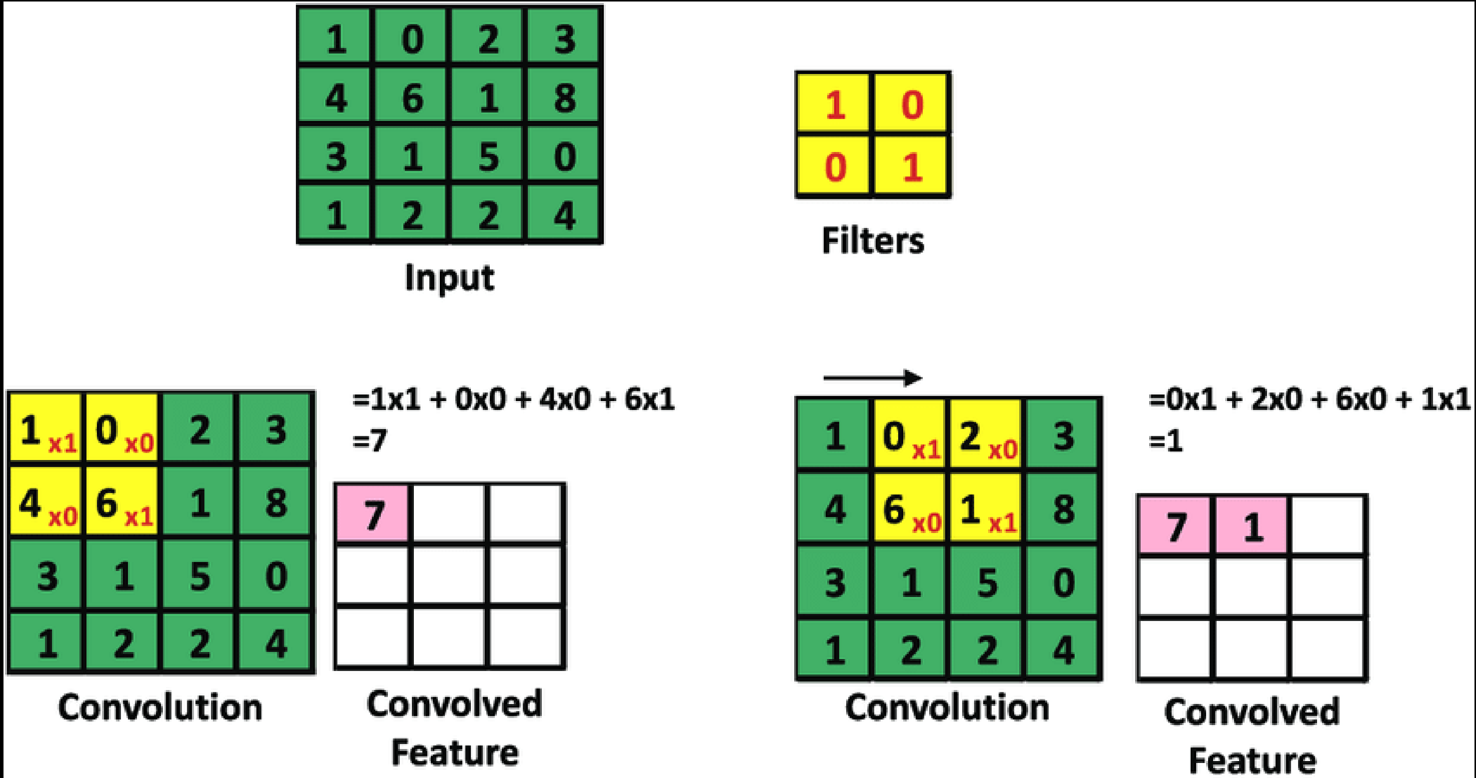
Filters / Kernels

- Control what the CNNs see and how they think about the data.
- They control also how the data is processed for the future.



Strides

- Decide how far the filter travels across the image.



Mass Street University
PER EDUCATIONEM PROGRESSUS

Types of filters

- Horizontal, Vertical, Identity, and Diagonal.
- Can be learned or have set values.
- Each type allows for a different viewpoint of the data.
- Feature extraction is done by combining multiple filters.

1	0	-1
1	0	-1
1	0	-1

Vertical

1	1	1
0	0	0
-1	-1	-1

Horizontal

An example

$$\begin{bmatrix} 0 & 1 & 1 \\ 3 & 4 & 1 \\ 7 & 6 & 8 \end{bmatrix} \times \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 8 & 7 \\ 20 & 19 \end{bmatrix}$$

Pooling

- Pooling reduces the size of the image while maintaining the original composure.
- Allows us to help get rid of noise and train on simpler data.

Original Data

0	1	1
3	4	1
7	6	8

Average Pooling

2	1.75
5	4.75

Max Pooling

4	4
7	8

Mass Street University
PER EDUCATIONEM PROGRESSUS

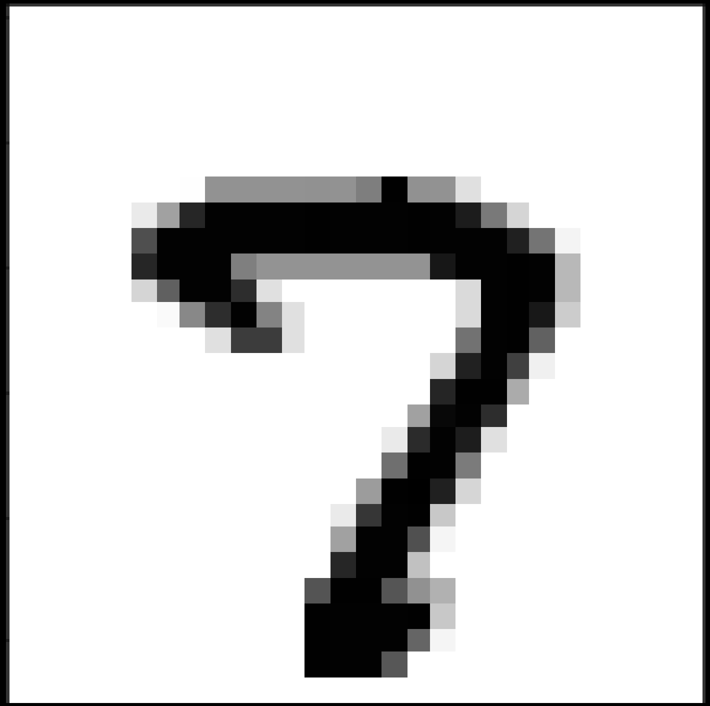
Padding

- Lets us find features on the edges of our matrix data.
- The amount of padding is dependent on the size of the filter.

0	0	0	0	0
0	0	1	1	0
0	3	4	1	0
0	7	6	8	0
0	0	0	0	0

An example

```
[[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   1 109 109 109 109 110 109 129 253 110 109  31   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0  21  94 217 252 252 252 252 253 252 252 252 253 252 227 134  42   0   0   0   0   0   0   0]
 [  0   0   0   0   0 176 252 252 252 252 252 252 253 252 252 252 253 252 252 252 222 139  11   0   0   0   0   0]
 [  0   0   0   0   0 217 252 252 252 128 108 108 108 108 108 108 108 232 252 252 253 252  71   0   0   0   0   0]
 [  0   0   0   0   0  42 159 252 252 210  31   0   0   0   0   0   0   0  37 252 253 252  71   0   0   0   0   0]
 [  0   0   0   0   0   0   5 119 210 252 124  31   0   0   0   0   0   0  37 252 253 231  51   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0  31 195 195  31   0   0   0   0   0   0 140 252 253 158   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  42 221 252 191  15   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 218 253 253  84   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  94 247 252 210   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  21 212 252 226  31   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 144 253 252 132   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  99 253 255 222  41   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  21 201 252 253  55   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  94 252 252 175  10   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 217 252 252  62   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 171 253 253 170 110  78   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 253 252 252 252 253  55   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 253 252 252 252 154  10   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0 253 252 252 168   0   0   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0]]
```



Mass Street University
PER EDUCATIONEM PROGRESSUS

Cont.

Horizontal Filter

1	1	1	1	1
1	1	1	1	1
0	0	0	0	0
-1	-1	-1	-1	-1
-1	-1	-1	-1	-1

Diagonal Filter

-1	-1	0	1	1
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
1	1	0	-1	-1

Cont.

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
109	109	110	109	129	253	110	109	31	0
252	252	253	252	252	252	253	252	227	134
252	252	253	252	252	252	253	252	252	252
108	108	108	108	108	108	108	232	252	252
31	0	0	0	0	0	0	0	37	252
124	31	0	0	0	0	0	0	37	252
195	31	0	0	0	0	0	0	140	252

Horizontal Filter

1	1	1	1	1
1	1	1	1	1
0	0	0	0	0
-1	-1	-1	-1	-1
-1	-1	-1	-1	-1

Diagonal Filter

-1	-1	0	1	1
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
1	1	0	-1	-1

0	0	0	0	37	252	253	252	71	0
0	0	0	0	37	252	253	231	51	0
0	0	0	0	140	252	253	158	0	0
0	0	0	42	221	252	191	15	0	0
0	0	0	218	253	253	84	0	0	0
0	0	94	247	252	210	0	0	0	0
0	21	212	252	226	31	0	0	0	0
0	144	253	252	132	0	0	0	0	0
99	253	255	222	41	0	0	0	0	0
201	252	253	55	0	0	0	0	0	0

Cont.

Horizontal Filter

1	1	1	1	1
1	1	1	1	1
0	0	0	0	0
-1	-1	-1	-1	-1
-1	-1	-1	-1	-1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
109	109	110	109	129	253	110	109	31	0
252	252	253	252	252	252	253	252	227	134
252	252	253	252	252	252	253	252	252	252
108	108	108	108	108	108	108	232	252	252
31	0	0	0	0	0	0	0	37	252
124	31	0	0	0	0	0	0	37	252
195	31	0	0	0	0	0	0	140	252

Red = -1973

Orange = -2524

Yellow = -1091

Green = 1433

Blue = 2524

Purple = 1802

Cont.

Horizontal Filter

1	1	1	1	1
1	1	1	1	1
0	0	0	0	0
-1	-1	-1	-1	-1
-1	-1	-1	-1	-1

0	0	0	0	37	252	253	252	71	0
0	0	0	0	37	252	253	231	51	0
0	0	0	0	140	252	253	158	0	0
0	0	0	42	221	252	191	15	0	0
0	0	0	218	253	253	84	0	0	0
0	0	94	247	252	210	0	0	0	0
0	21	212	252	226	31	0	0	0	0
0	144	253	252	132	0	0	0	0	0
99	253	255	222	41	0	0	0	0	0
201	252	253	55	0	0	0	0	0	0

Red = -430

Orange = -424

Yellow = -173

Green = 156

Blue = 456

Purple = 698

Cont.

Diagonal Filter

-1	-1	0	1	1
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
1	1	0	-1	-1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
109	109	110	109	129	253	110	109	31	0
252	252	253	252	252	252	253	252	227	134
252	252	253	252	252	252	253	252	252	252
108	108	108	108	108	108	108	232	252	252
31	0	0	0	0	0	0	0	37	252
124	31	0	0	0	0	0	0	37	252
195	31	0	0	0	0	0	0	140	252

Red = 238

Orange = 995

Yellow = 1642

Green = 1620

Blue = 828

Purple = 216

Mass Street University

PER EDUCATIONEM PROGRESSUS

Cont.

Diagonal Filter

-1	-1	0	1	1
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
1	1	0	-1	-1

0	0	0	0	37	252	253	252	71	0
0	0	0	0	37	252	253	231	51	0
0	0	0	0	140	252	253	158	0	0
0	0	0	42	221	252	191	15	0	0
0	0	0	218	253	253	84	0	0	0
0	0	94	247	252	210	0	0	0	0
0	21	212	252	226	31	0	0	0	0
0	144	253	252	132	0	0	0	0	0
99	253	255	222	41	0	0	0	0	0
201	252	253	55	0	0	0	0	0	0

Red = 1392

Orange = 1931

Yellow = 2919

Green = 2642

Blue = 1855

Purple = 1124

Cont.

Tuned Diagonal Filter

-1	-1	0	1	0
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
0	1	0	-1	-1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
109	109	110	109	129	253	110	109	31	0
252	252	253	252	252	252	253	252	227	134
252	252	253	252	252	252	253	252	252	252
108	108	108	108	108	108	108	232	252	252
31	0	0	0	0	0	0	0	37	252
124	31	0	0	0	0	0	0	37	252
195	31	0	0	0	0	0	0	140	252

Red = -124

Orange = 490

Yellow = 1171

Green = 1006

Blue = 323

Purple = -144

Cont.

Tuned Diagonal Filter

-1	-1	0	1	0
-1	0	1	1	1
0	1	1	1	0
1	1	1	0	-1
0	1	0	-1	-1

0	0	0	0	37	252	253	252	71	0
0	0	0	0	37	252	253	231	51	0
0	0	0	0	140	252	253	158	0	0
0	0	0	42	221	252	191	15	0	0
0	0	0	218	253	253	84	0	0	0
0	0	94	247	252	210	0	0	0	0
0	21	212	252	226	31	0	0	0	0
0	144	253	252	132	0	0	0	0	0
99	253	255	222	41	0	0	0	0	0
201	252	253	55	0	0	0	0	0	0

Red = 669

Orange = 1431

Yellow = 2130

Green = 2095

Blue = 1382

Purple = 604

Filter Approaches

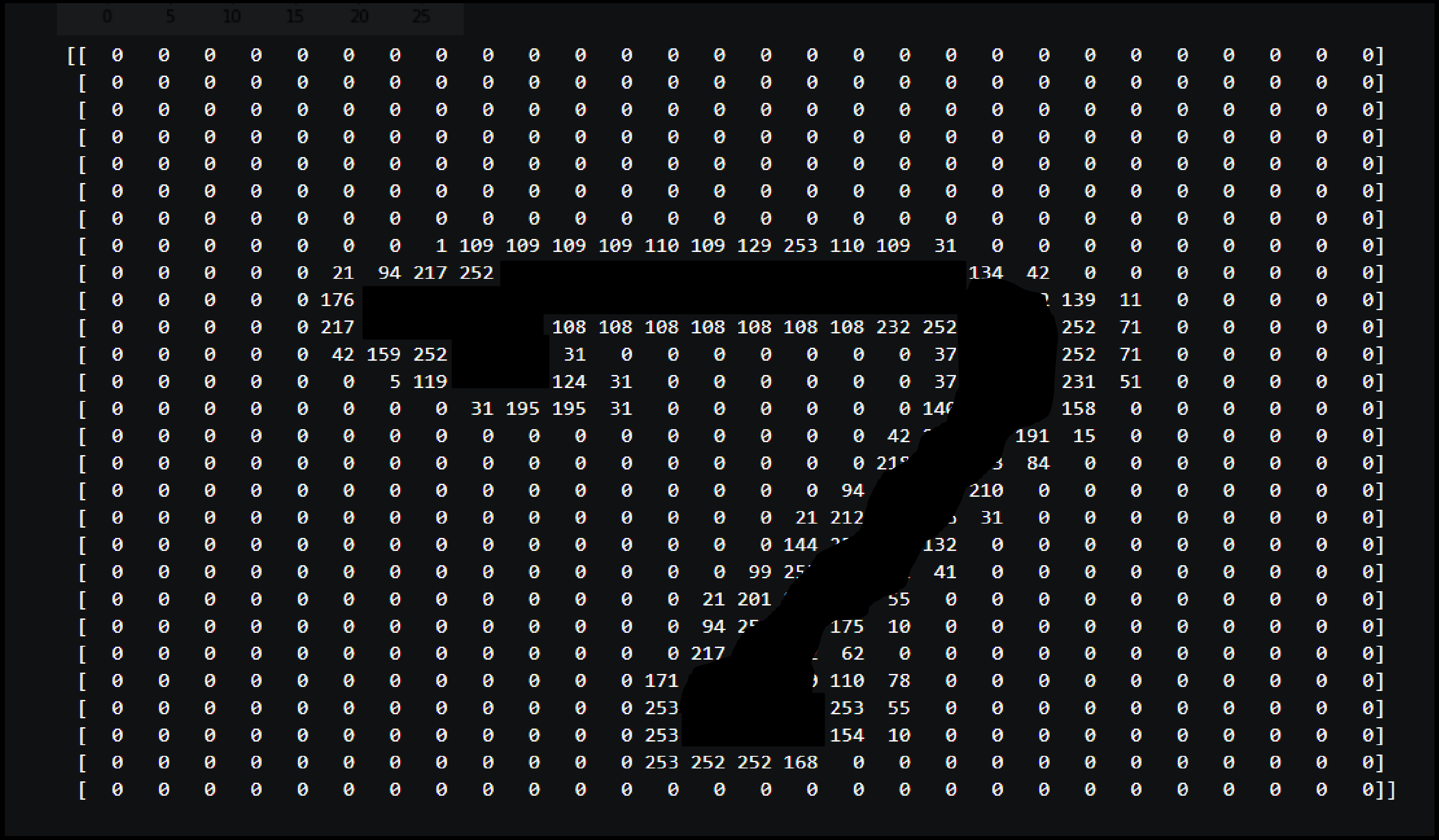
- Learned Filters. Filters are tuned throughout training.
- Supplemental Filters. Filters are added throughout training to make up for weaker base filters. Much like a decision tree network.
- The amount of filters is important for which approach you take. Think about the resources you have available for training.

Number of filters

- Use a medium amount and adjust based on complexity of data. Always start smaller and work your way up.
- The number of dimensions of the data also impacts the number of filters. 3D data needs more filters than 2D for example.

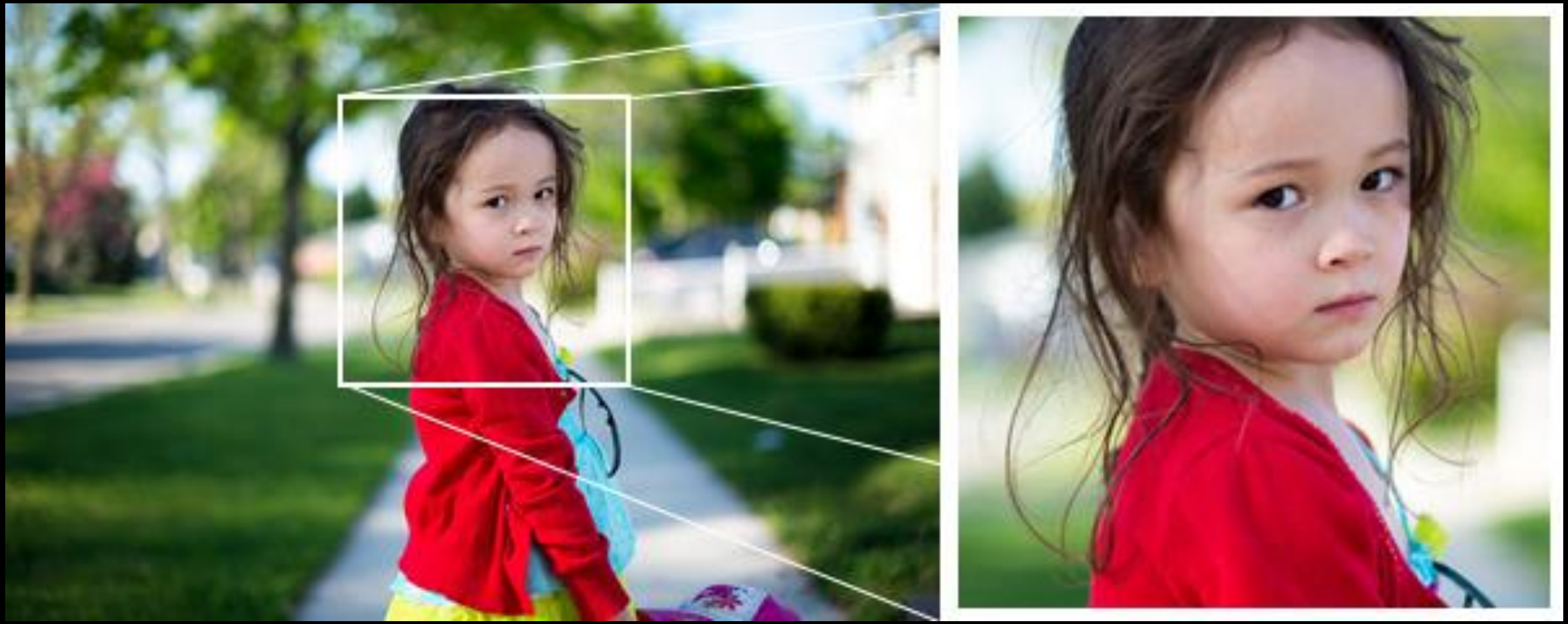
How filters combine.

- High level filters will combine to create an outline of the objects.
- These can also find colors and distinct objects.



Mass Street University
PER EDUCATIONEM PROGRESSUS

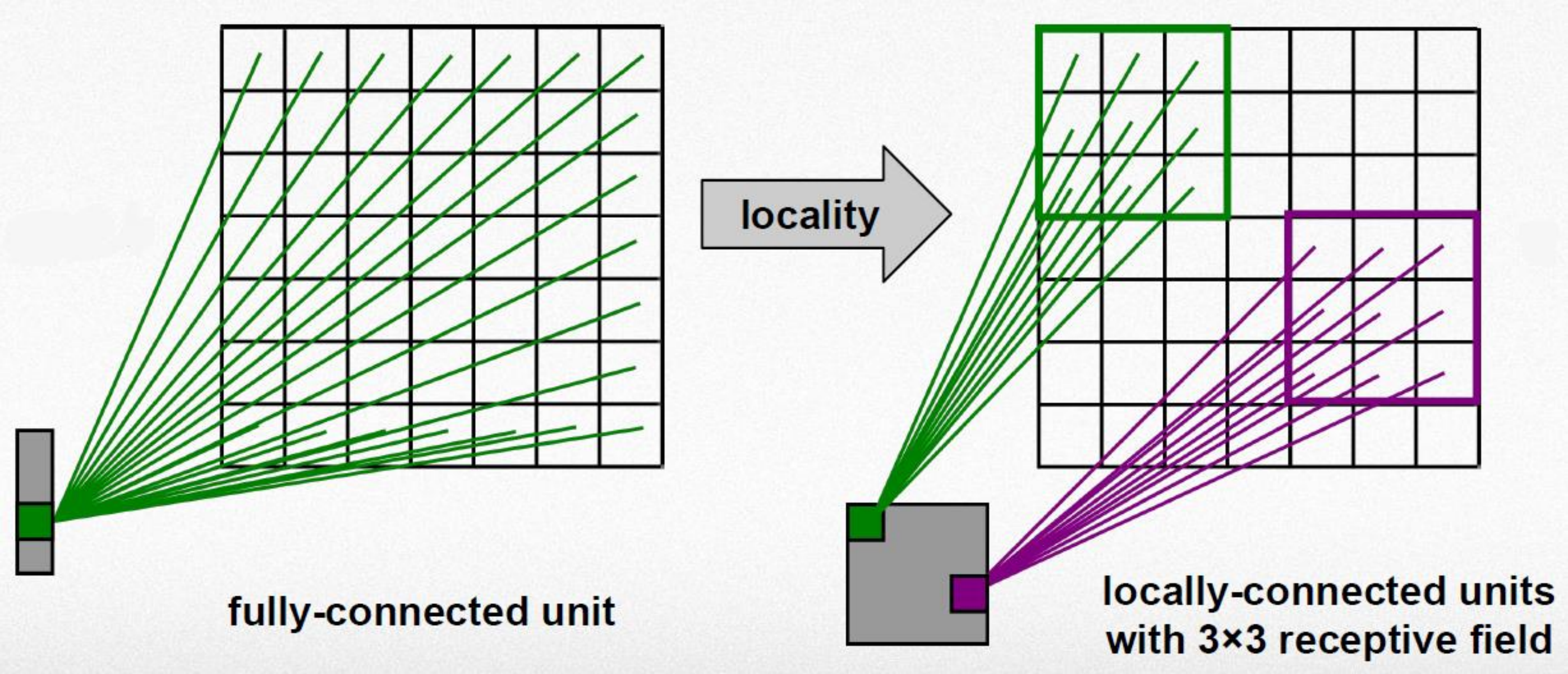
Cropping



Spatial Dropout

Locally Connected Layers

- Local filters only filter a single point. There is a new filter for every location on the image. Takes a very long time but gives the best results.



Flatten Layers

- Simply make the data into a 1D vector for processing in a dense neural network.

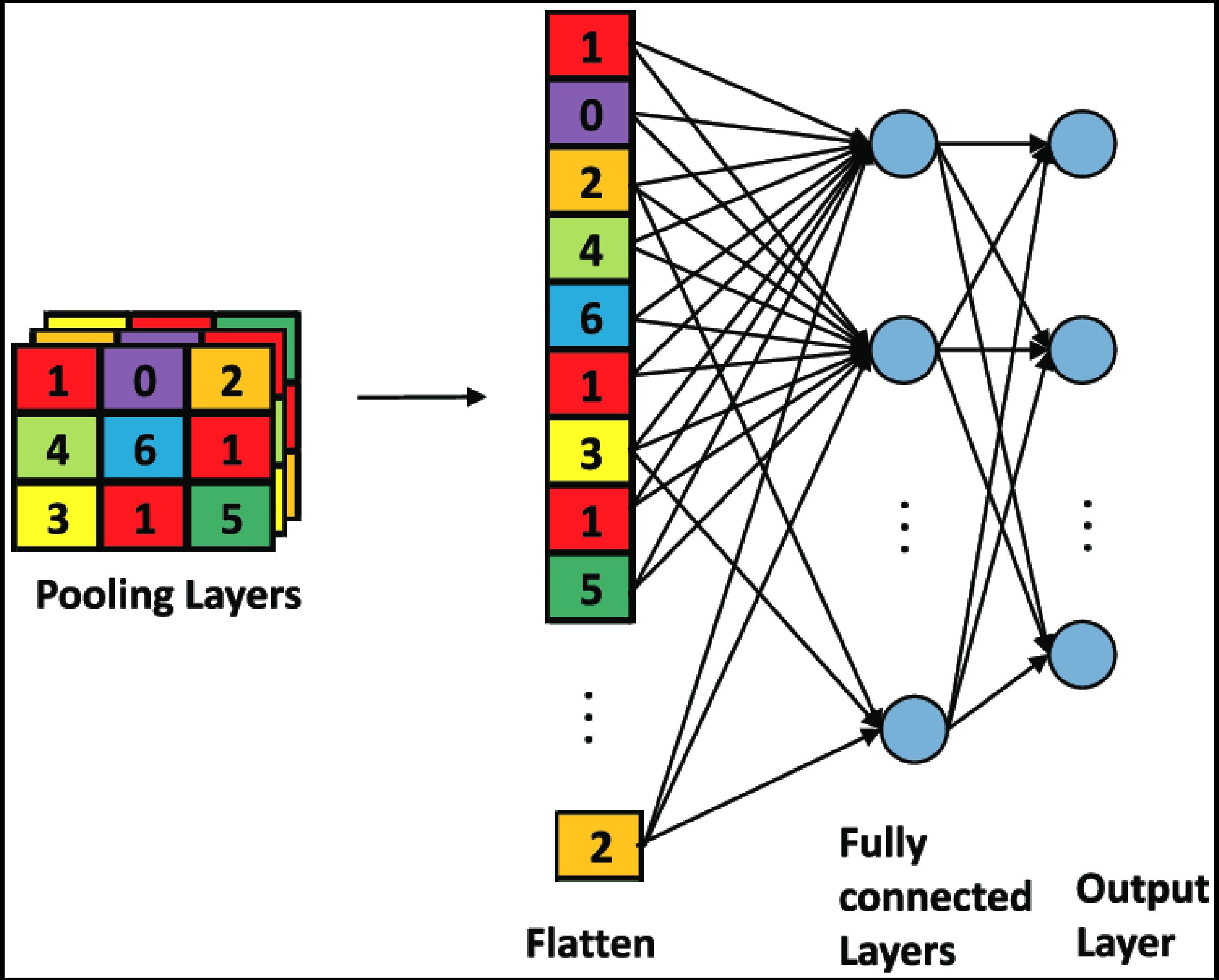
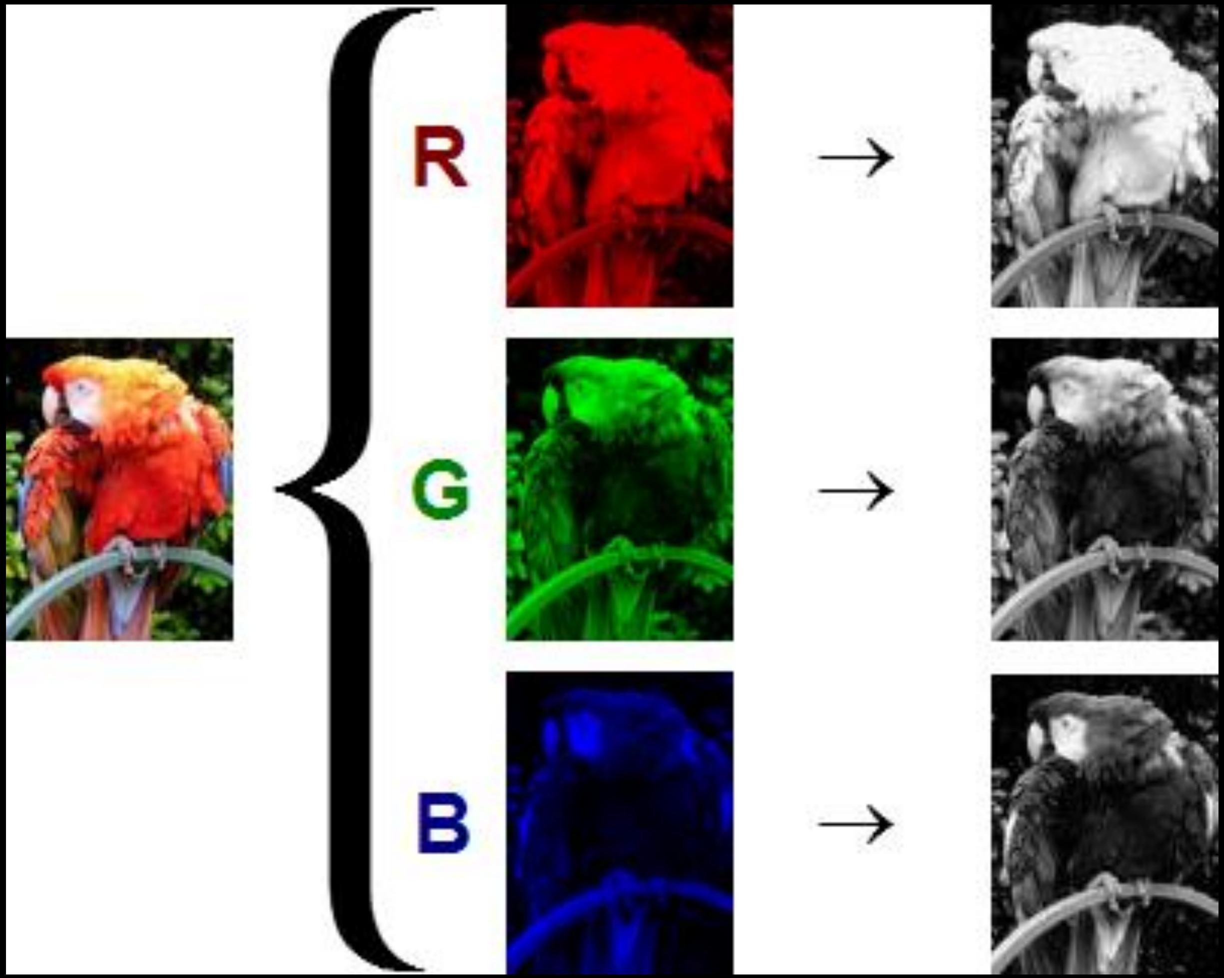


Image Processing methods

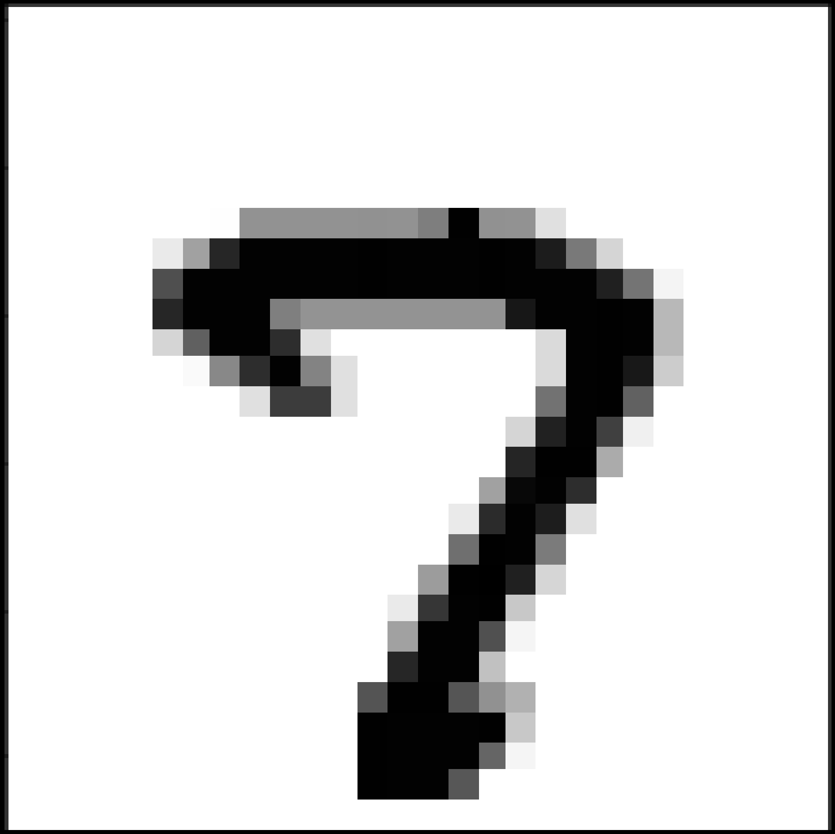
- RGB to grayscale transformation, image rotation, image shifts, image scaling, image flipping, input normalization, whitening, dimming, brightening, zooming in and out, and random transformations.

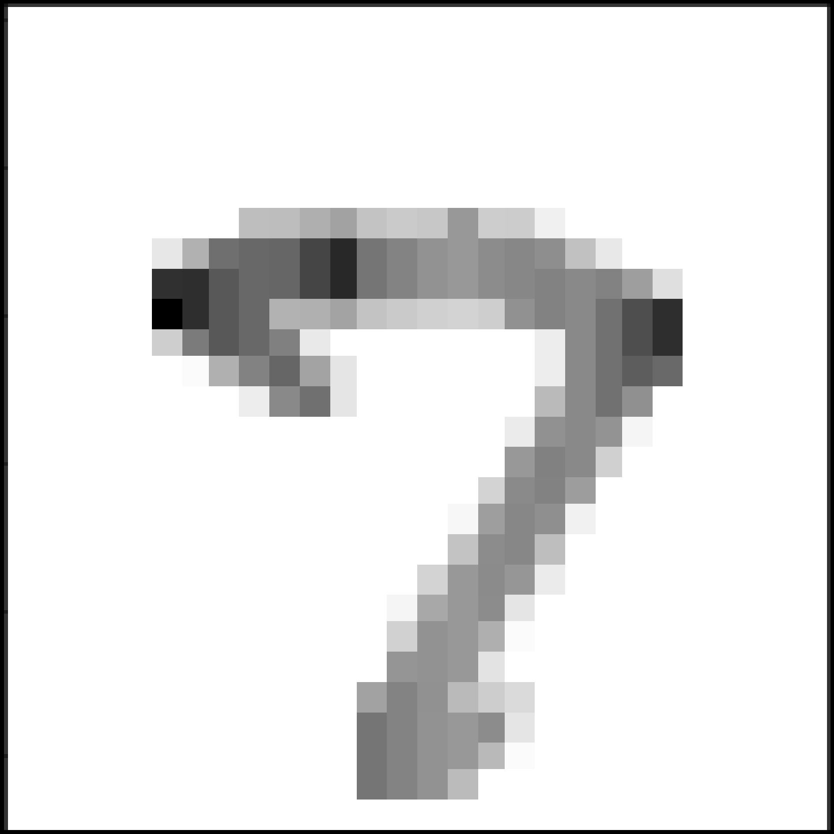
RGB to Grayscale



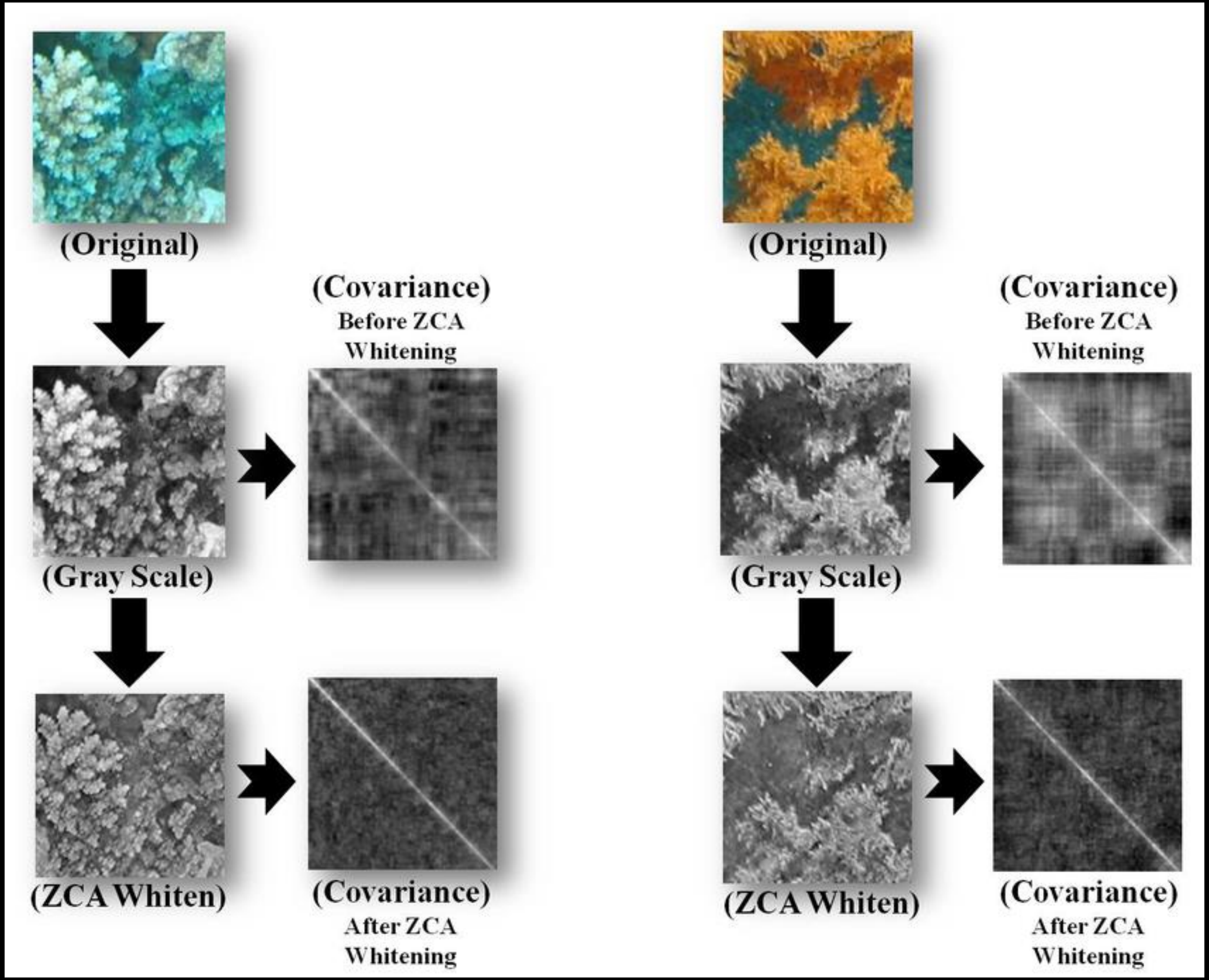
Mass Street University
PER EDUCATIONEM PROGRESSUS

Input Normalization





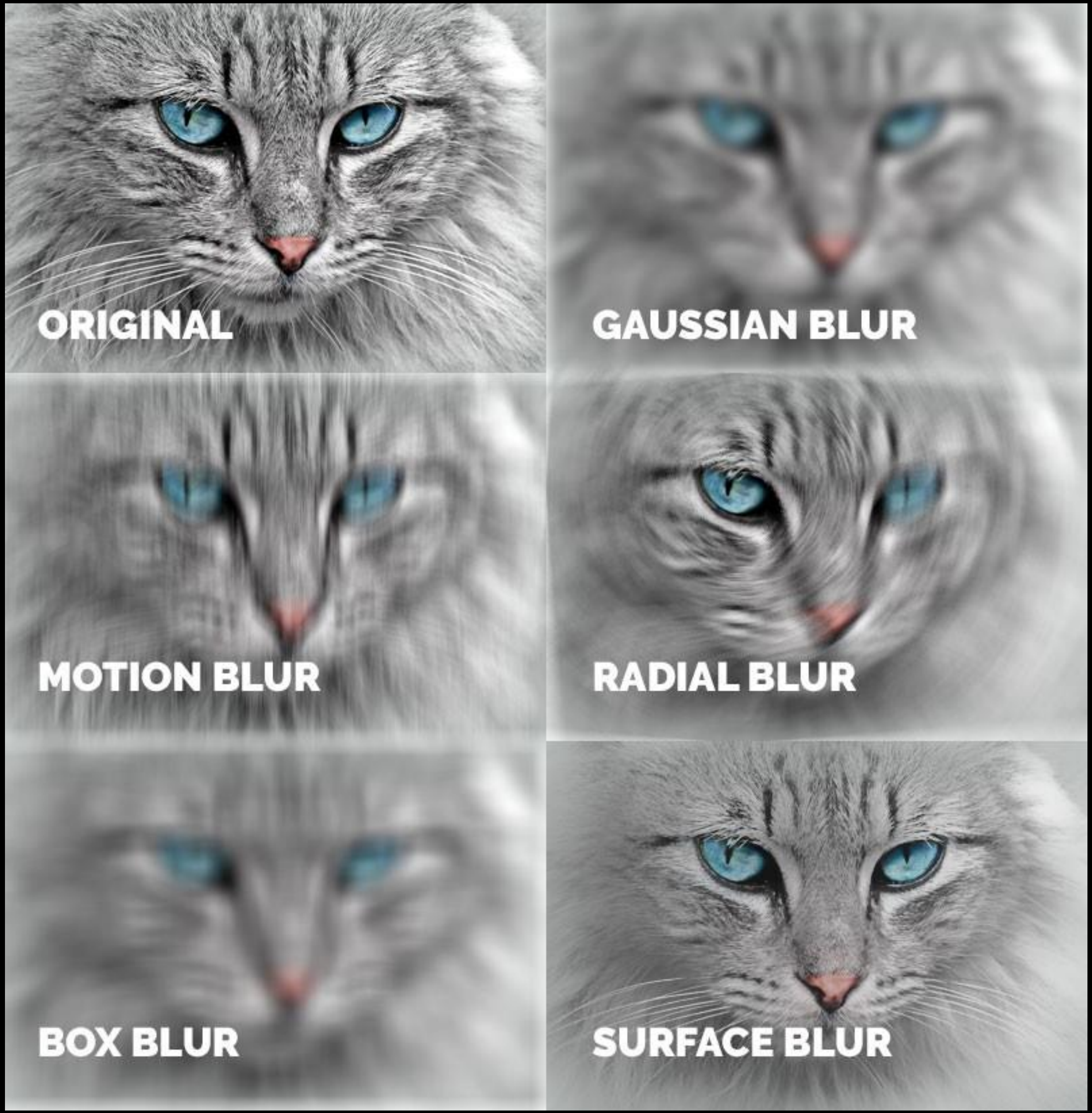
Whitening



Mass Street
University
PER EDUCATIONEM PROGRESSUS

Dimming and Brightening

Blur


ORIGINAL
GAUSSIAN BLUR
MOTION BLUR
RADIAL BLUR
BOX BLUR
SURFACE BLUR