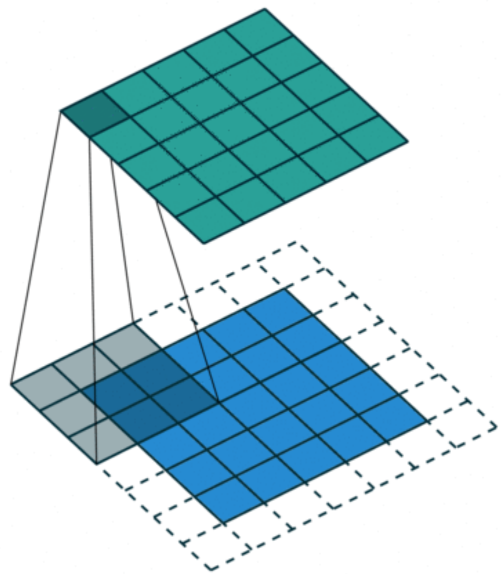
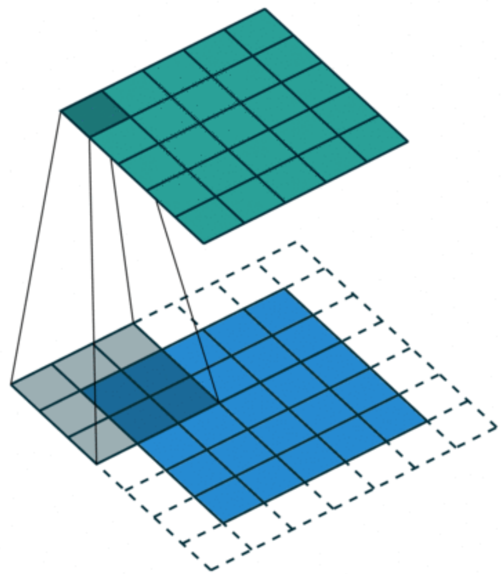
CSCI 497P/597P: Computer Vision



Lecture 2: Image transformations and filtering

CSCI 497P/597P: Computer Vision



Lecture 2: Image transformations and filtering

Goals

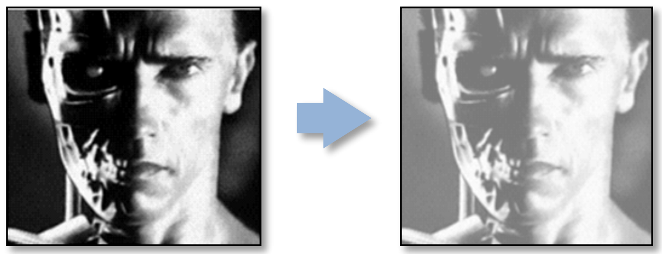
- Know how to filter (v) an image by cross-correlating it with a given filter (n)/kernel/weights
- Get a feel for some of the image processing operations that can be accomplished using filtering.
- Know how to handle image borders when filtering:
  - output sizes: full / same / valid
  - out-of-bounds values: zeros, reflection, replication

Last time

Written as a function, we can *transform* the image function to create altered functions (images):

(transforming the *range*)

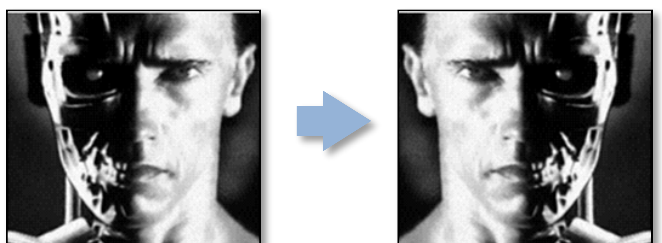
photometric



$$g(x,y) = f(x,y) + 20$$

(transforming the *domain*)

geometric



$$g(x,y) = f(-x,y)$$

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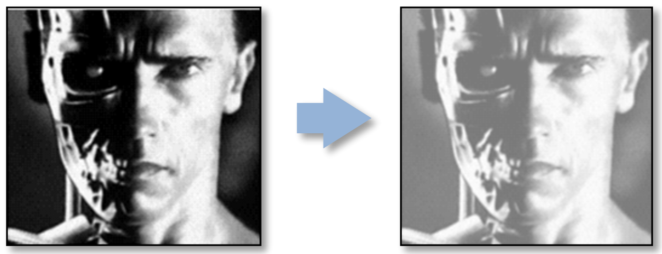

(increase brightness)

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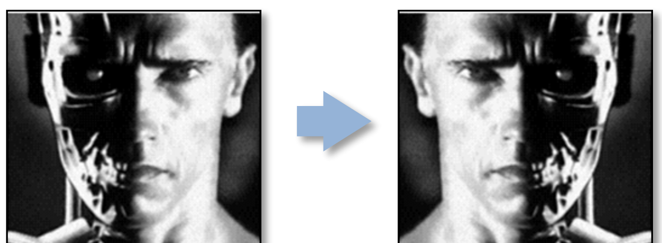

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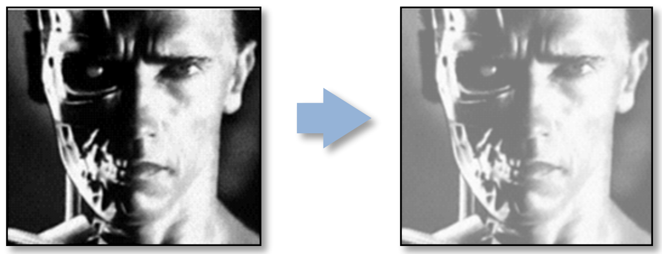

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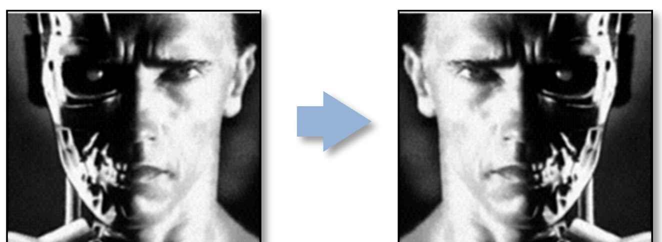
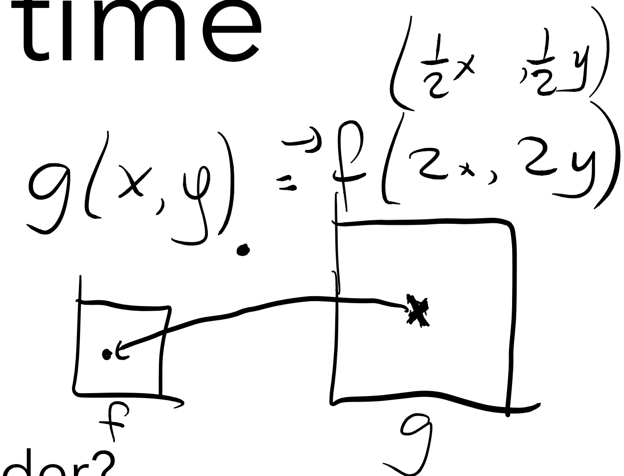


(flip horizontally)

$$g(x,y) = f(-x,y)$$

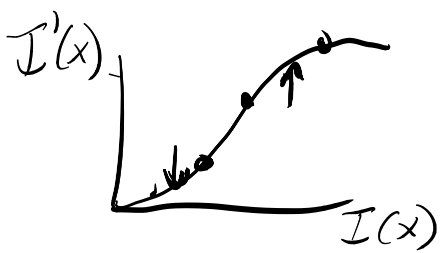
Last time

Make f(x, y) 2 times bigger?



Make F (a HxWx3 image) redder?

Increase contrast?



Real images aren't perfect

Real images are not only sampled, but they often have noise: unwanted variations in measured intensity value.

f(x, y)

Causes of noise (incomplete list):

- electronic variations in sensor chip
- analog-to-digital quantization
- film grain
- cosmic rays

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often, we can assume that noise is *random*

(other times, we can't but we do anyway)

Denoising

Scenario: you have a camera and this motionless scene.
How can you get a less noisy image?

(let's assume that noise is **random**)

Denoising

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How can you get a less noisy image?

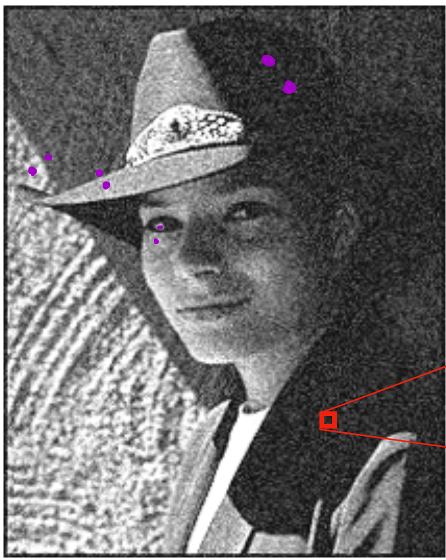
(let's assume that noise is random)

Ideally: average multiple images together

$$g(x, y) = \frac{1}{n} \sum_{i=0}^{n} f_i(x, y)$$

Example: Denoising

Scenario: you're simply given a noisy image. Can you reduce the noise? (still assume that noise is random)



10	5	3
4	5	1
1	1	7

→ some function, e.g., average

	7	

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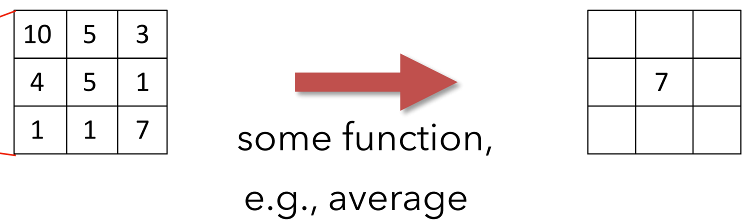
Next best thing, a heuristic:
nearby pixels are *often* the same (ideal) color, so average neighboring pixels together.



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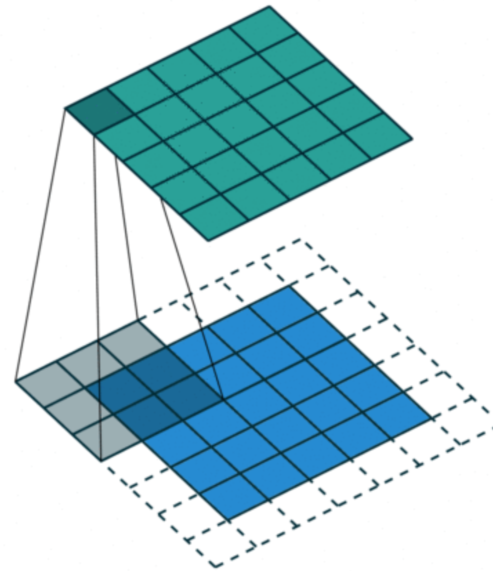
This is an example of filtering.
We're taking the mean of the neighborhood, so it's called mean filtering.

Filtering

$$g = f \otimes w$$

- g: output image
- f: input image
- w: weights, or filter, or kernel



=

$\otimes \frac{1}{9}$

1	1	1
1	1	1
~~0~~ 1	1	1

w

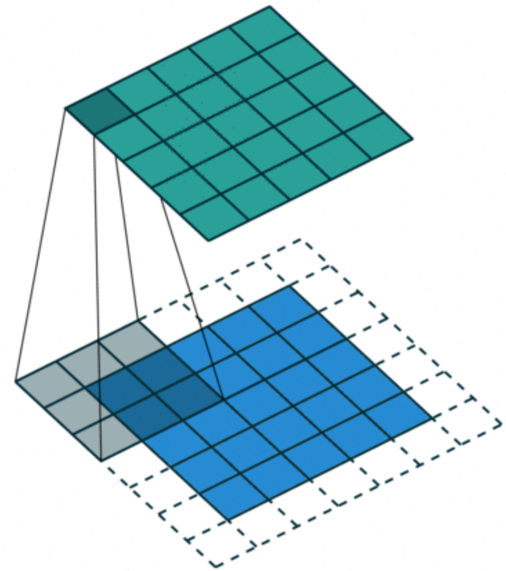
Filtering

$$g = f \otimes w$$

output image

input image

weights, or filter, or kernel



=

$\otimes$

1	1	1
1	1	1
0	1	1

w

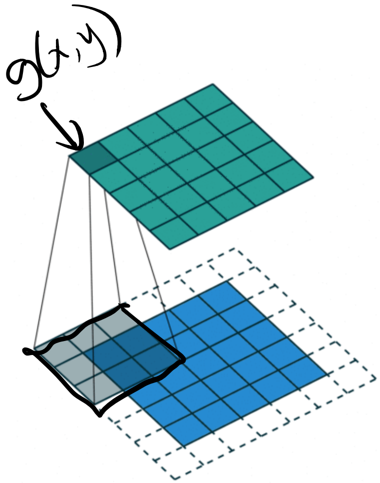
Filtering: Let's play.

Colab notebook playground
(also linked from today's lecture on the course webpage):

https://colab.research.google.com/drive/1KasDni0Km_9HVuQXdARIQh3GS2uchVAZ?usp=sharing

1. Notebook demo
2. In groups: answer the 6 problems in your group's Google Doc.

Mean filtering: Mathily



$$g(x,y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} \frac{1}{9} f(x+i, y+j)$$

x

y

	7	

= average (

x-1

y+1

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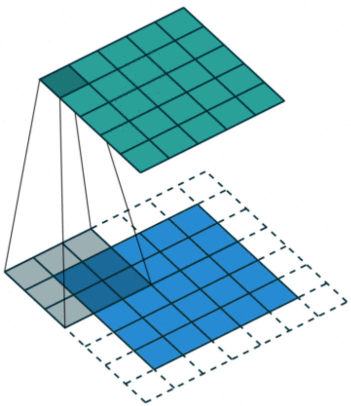
)

one output pixel = average (3x3 neighborhood of input pixels)

Mean filtering: Mathily



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x, *y*

	7	

= average (*x-1*, *y+1*

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one output pixel = average (3x3 neighborhood of input pixels)

Generalize!

From a 3x3 mean filter to any size mean filter

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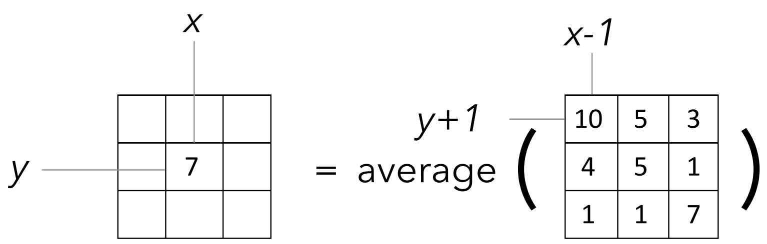

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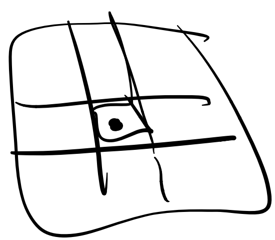
Generalize!

From a 3x3 mean filter to any size mean filter

$$g(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} \frac{1}{(2k+1)^2} f(x+i, y+j)$$

this makes sure we **average** all values in the neighborhood



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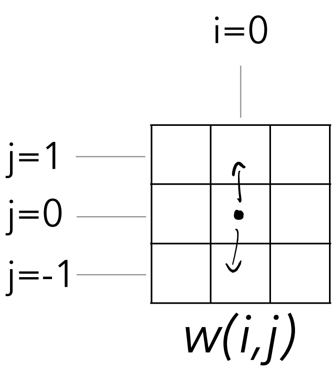
Let's generalize to a **weighted average**.

Also store weights in a 2D array (as in the playground): *w(i,j)*



for convenience, (0,0) is at the center

Generalize!

To a **weighted average**.

$$g(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} w(i,j) f(x+i, y+j)$$

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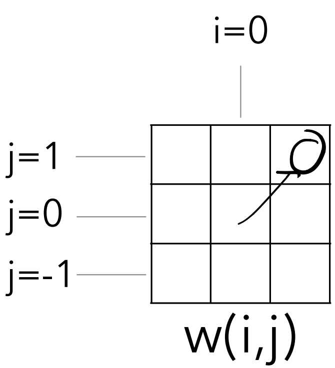

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Cross-Correlation

We've just derived the cross-correlation operator.

$$g(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} w(i,j) f(x+i, y+j)$$

We write this as:

$$g = f \otimes w$$

output image

input image

weights, or filter, or kernel

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Computing Cross-Correlation

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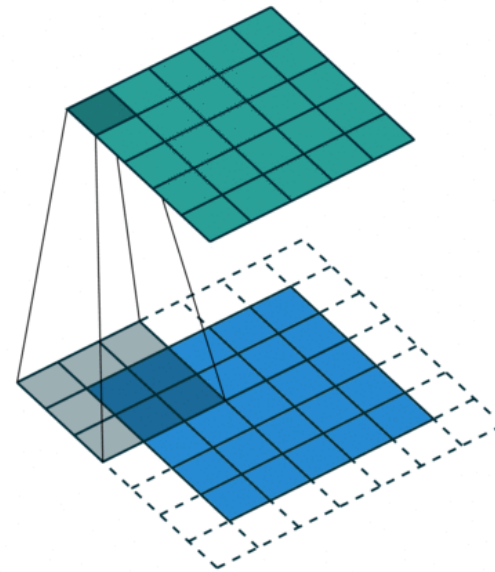


Naive pseudocode:

```
for x = 0 to w:
  for y = 0 to h:
    for i in -k to k:
      for j in -k to k:
        out[x,y] += w[i,j] * in[x+i, y+j]
```

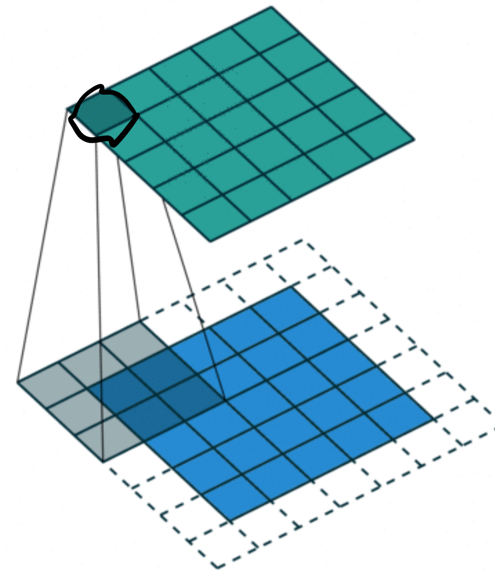
Computing Cross-Correlation

$$g = f \otimes w$$

output image → g

input image → f

weights, or filter, or kernel → w



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```

Questions remain

- What happens at the edges?
- What properties does this operator have?
- What can and can't this operator do?

Handling Edges - Padding Modes

Possible "padding modes":

Zeros:

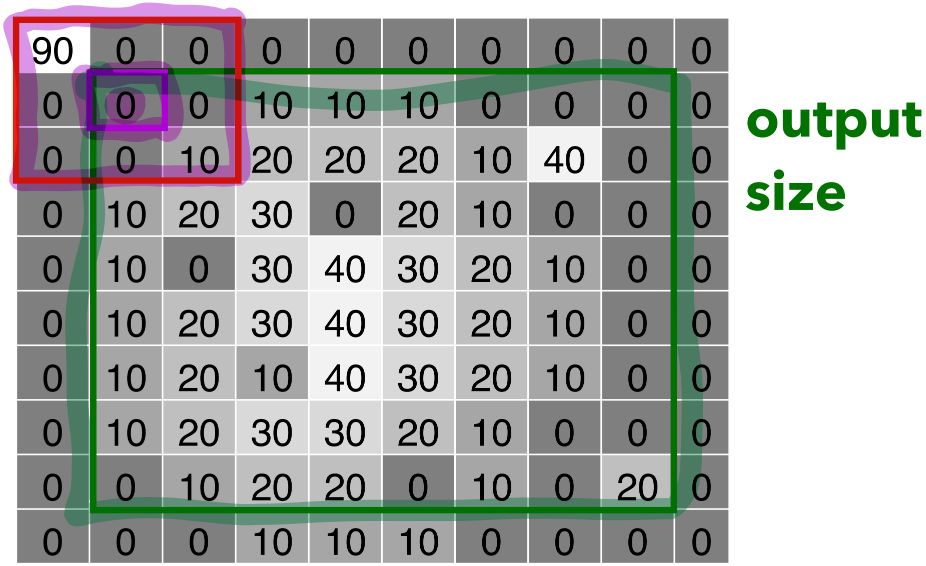
Replicate:

Reflect:

90	0	0	0	0	0	0	0	0	0
0	0	0	10	10	10	0	0	0	0
0	0	10	20	20	20	10	40	0	0
0	10	20	30	0	20	10	0	0	0
0	10	0	30	40	30	20	10	0	0
5	10	20	30	40	30	20	10	0	0
0	10	20	10	40	30	20	10	0	0
0	10	20	30	30	20	10	0	0	0
0	0	10	20	20	0	10	0	20	0
0	0	0	10	10	10	0	0	0	0

Handling Edges - Output Sizes

"Valid" (3x3)



input image

Handling Edges - Output Sizes

"Valid" (5x5)

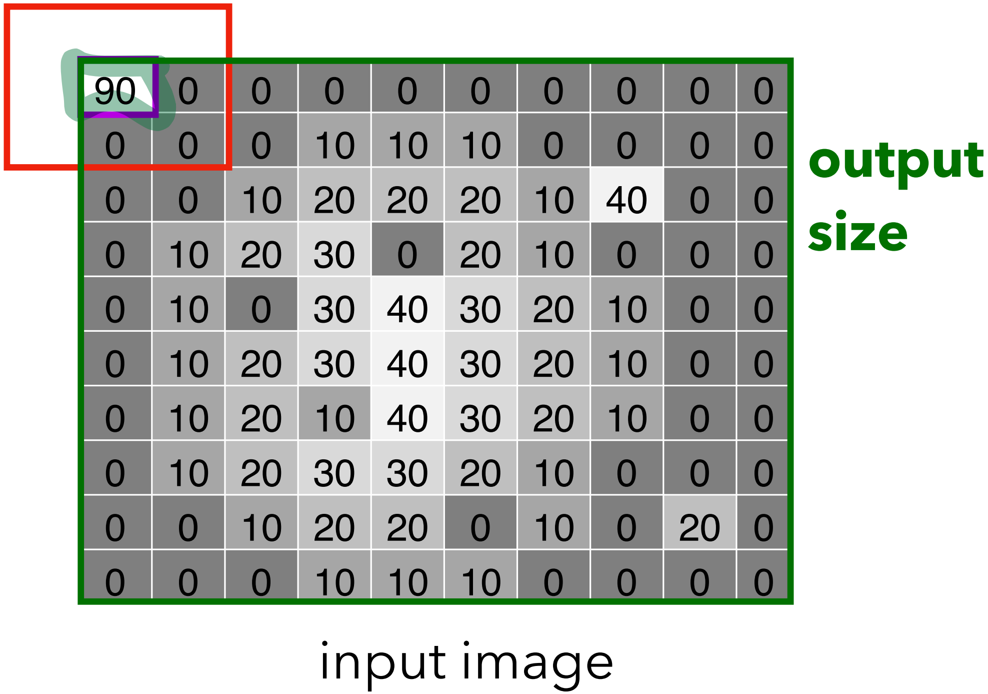
90	0	0	0	0	0	0	0	0	0
0	0	0	10	10	10	0	0	0	0
0	0	10	20	20	20	10	40	0	0
0	10	20	30	0	20	10	0	0	0
0	10	0	30	40	30	20	10	0	0
0	10	20	30	40	30	20	10	0	0
0	10	20	10	40	30	20	10	0	0
0	10	20	30	30	20	10	0	0	0
0	0	10	20	20	0	10	0	20	0
0	0	0	10	10	10	0	0	0	0

output size

input image

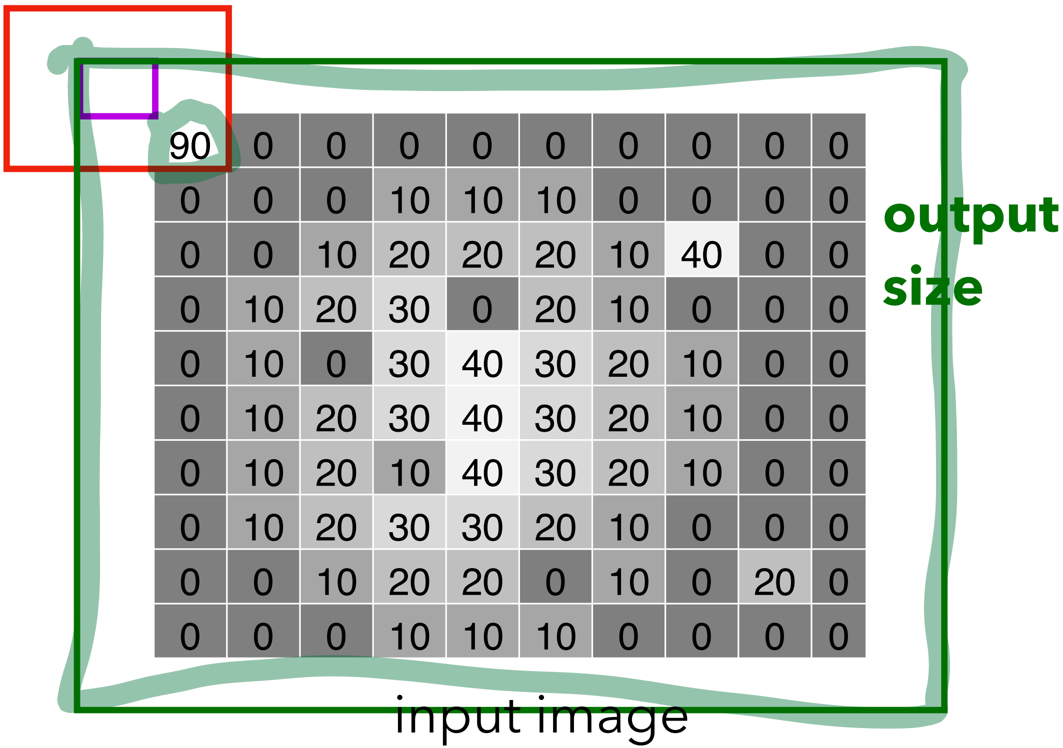
Handling Edges - Output Sizes

"Same"



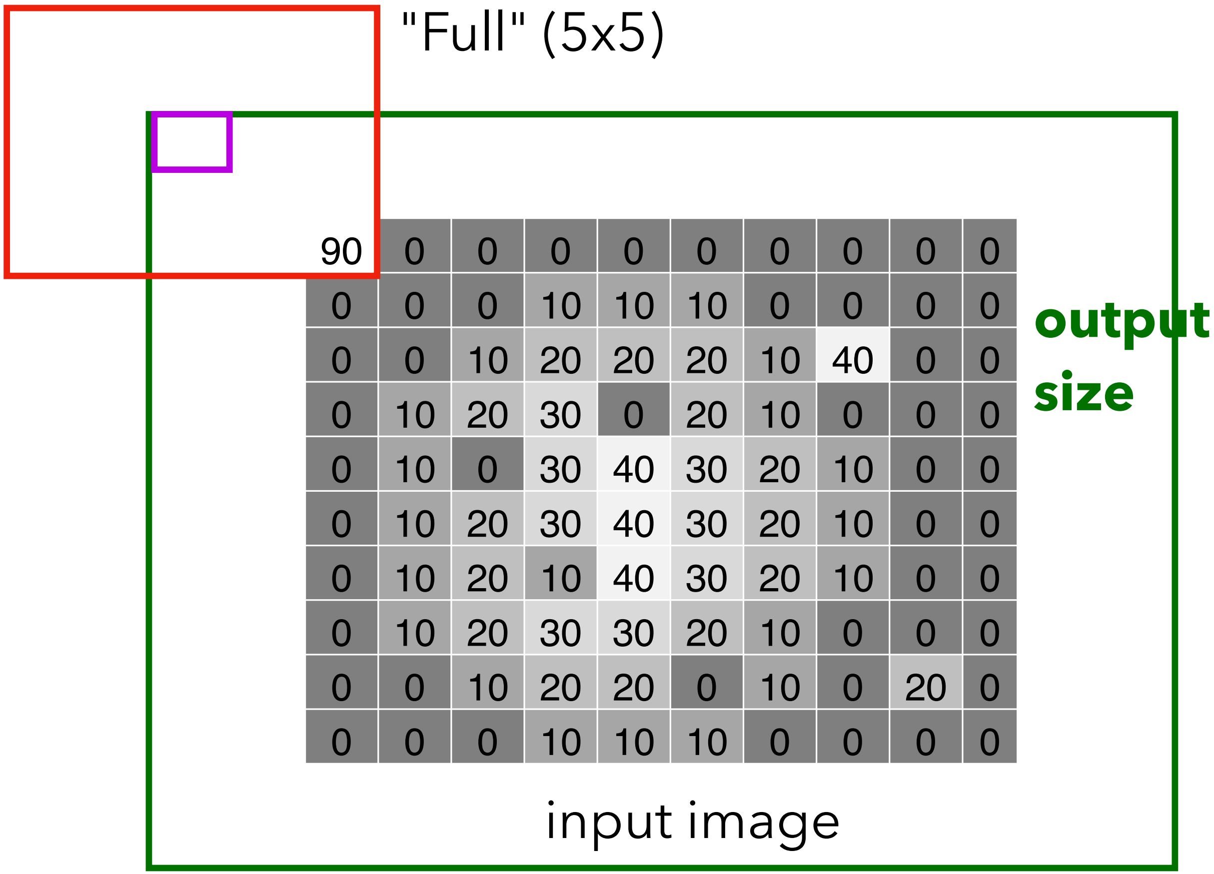
Handling Edges - Output Sizes

"Full" (3x3)



90	0	0	0	0	0	0	0	0	0
0	0	0	10	10	10	0	0	0	0
0	0	10	20	20	20	10	40	0	0
0	10	20	30	0	20	10	0	0	0
0	10	0	30	40	30	20	10	0	0
0	10	20	30	40	30	20	10	0	0
0	10	20	10	40	30	20	10	0	0
0	10	20	30	30	20	10	0	0	0
0	0	10	20	20	0	10	0	20	0
0	0	0	10	10	10	0	0	0	0

Handling Edges - Output Sizes



90	0	0	0	0	0	0	0	0	0
0	0	0	10	10	10	0	0	0	0
0	0	10	20	20	20	10	40	0	0
0	10	20	30	0	20	10	0	0	0
0	10	0	30	40	30	20	10	0	0
0	10	20	30	40	30	20	10	0	0
0	10	20	10	40	30	20	10	0	0
0	10	20	30	30	20	10	0	0	0
0	0	10	20	20	0	10	0	20	0
0	0	0	10	10	10	0	0	0	0