

APPLIED COMPUTER VISION IN UBICOMP 2

CSE 590 Ubiquitous Computing | Lecture 7 | May 10

Jon Froehlich • Liang He (TA)

SCHEDULE TODAY: 6:30-9:20

06:30-06:50: Discussion of required reading led by Tim Sawyer

06:50-06:55: Optional reading discussion led by Pankaj Parag

06:55-08:00: Basic Computer Vision

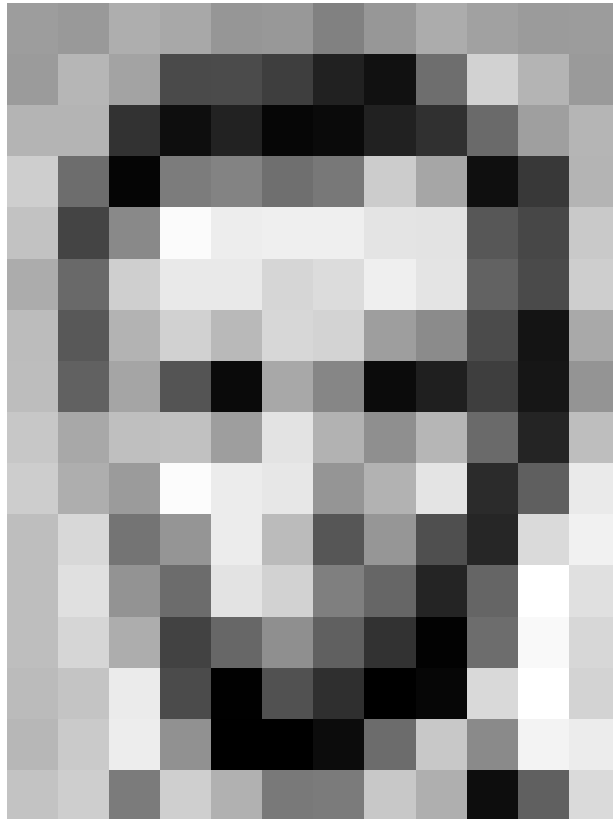
08:00-08:05: Break

08:05-08:40: Continue Computer Vision Exercises

08:40-09:20: Work on A4 and show proper wiring with external battery

WHAT ARE DIGITAL IMAGES?

DIGITAL IMAGES ARE MATRICES OF PIXEL VALUES



157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
206	174	155	252	236	231	149	178	228	43	96	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
196	206	123	207	177	121	123	200	175	13	96	218

Each cell is **0-255** where 0 is black and 255 is white.
Cells could also be normalized to **0.0-1.0** again
corresponding to intensity (0.0=black, 1.0=white)

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
206	174	155	252	236	231	149	178	228	43	96	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
196	206	123	207	177	121	123	200	175	13	96	218

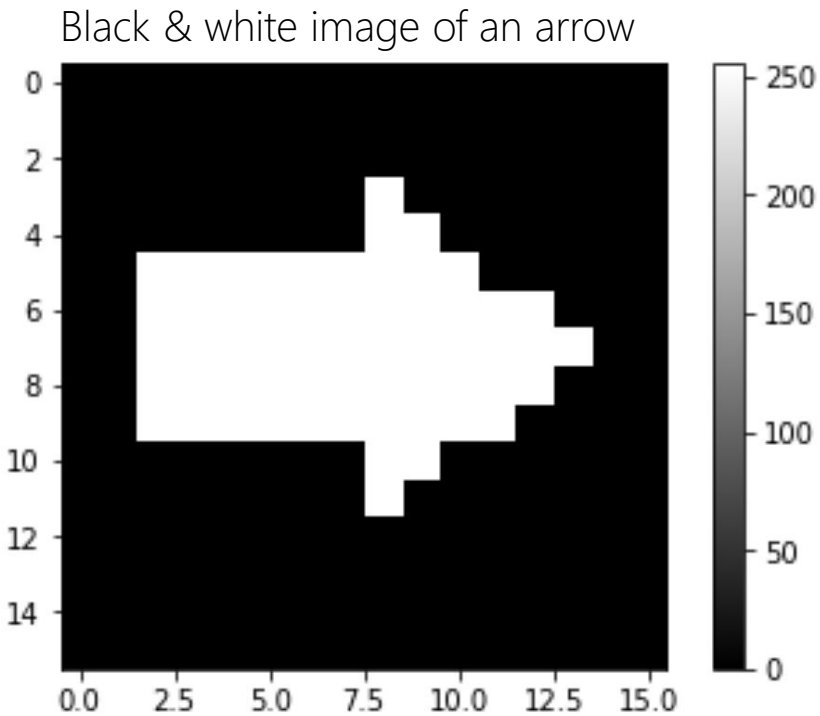
WHAT IS THIS IMAGE?

[illegible]

WHAT ARE DIGITAL IMAGES?

WHAT IS THIS IMAGE?

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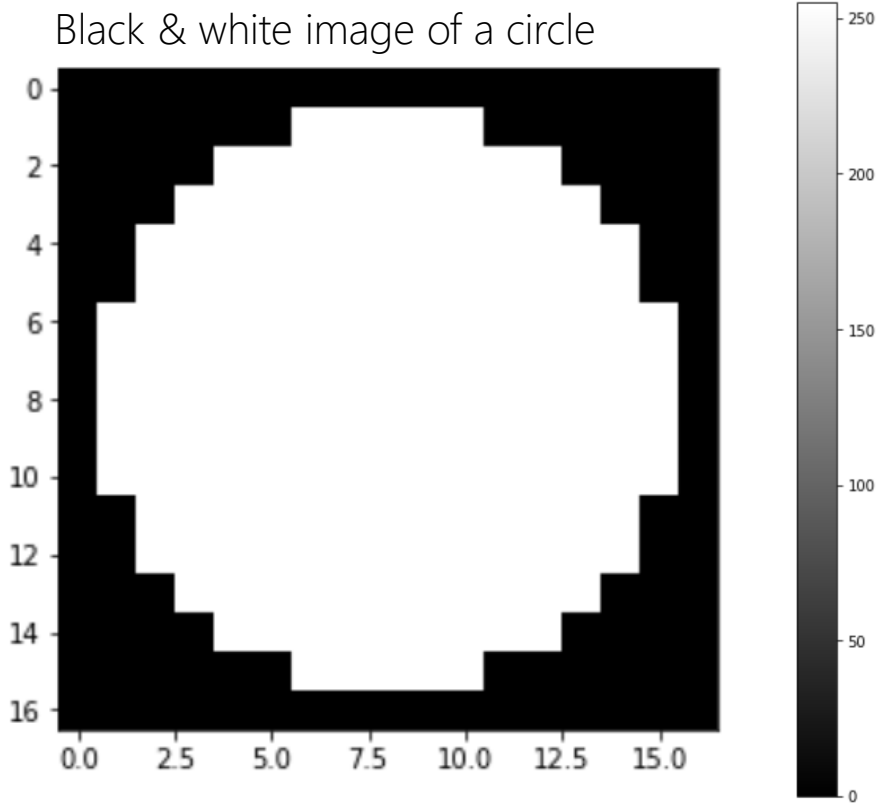


WHAT IS THIS IMAGE?

WHAT ARE DIGITAL IMAGES?

WHAT IS THIS IMAGE?

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[0	0	0	0	255	255	255	255	255	255	255	255	255	0	0	0	0]
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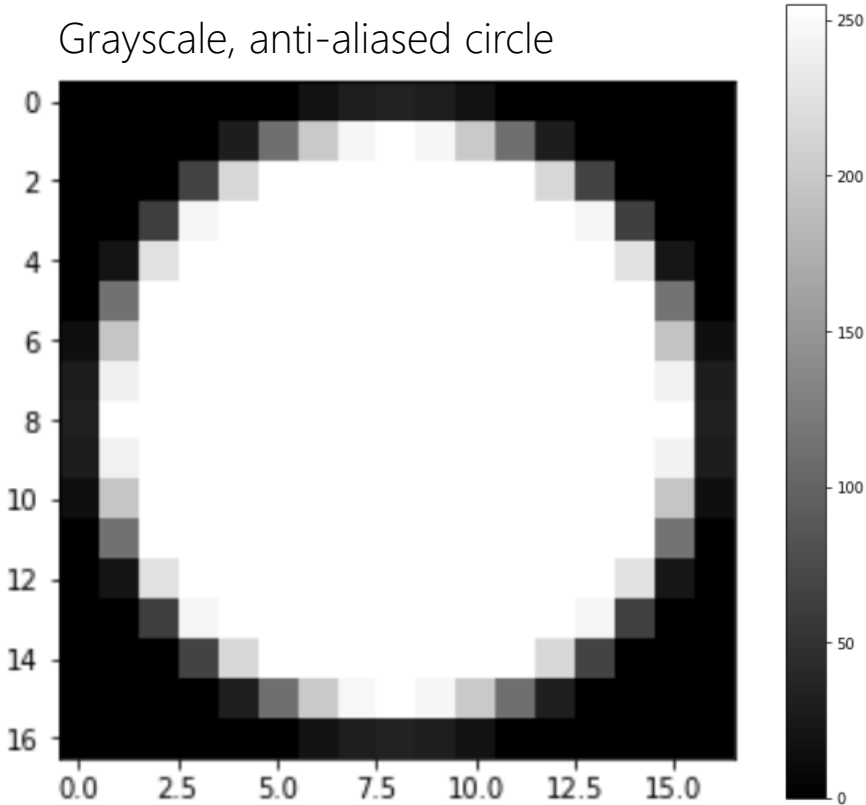


WHAT IS THIS IMAGE?

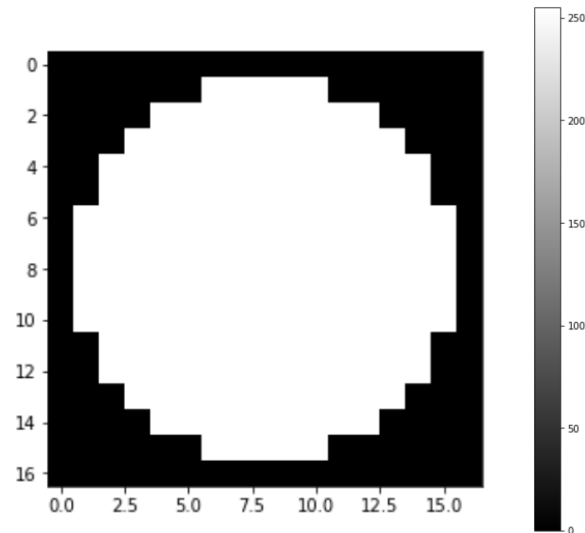
WHAT ARE DIGITAL IMAGES?

WHAT IS THIS IMAGE?

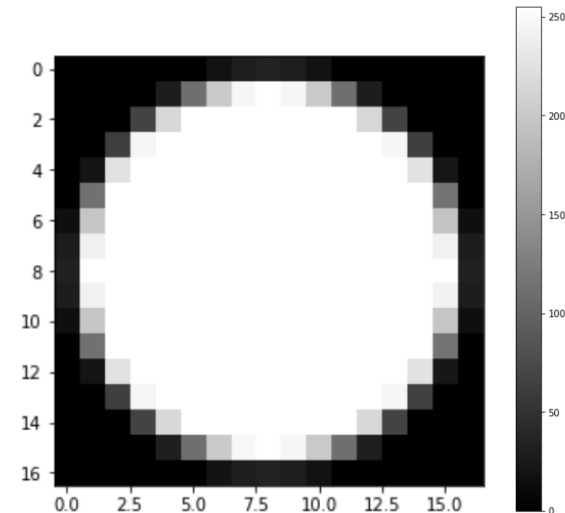
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[0	0	62	246	255	255	255	255	255	255	255	255	255	246	63	0]
[0	20	225	255	255	255	255	255	255	255	255	255	255	255	226	22]
[0	113	255	255	255	255	255	255	255	255	255	255	255	255	255	115]
[15	197	255	255	255	255	255	255	255	255	255	255	255	255	255	196]
[28	240	255	255	255	255	255	255	255	255	255	255	255	255	255	241]
[33	255	255	255	255	255	255	255	255	255	255	255	255	255	255	33]
[29	241	255	255	255	255	255	255	255	255	255	255	255	255	255	242]
[15	197	255	255	255	255	255	255	255	255	255	255	255	255	255	197]
[0	113	255	255	255	255	255	255	255	255	255	255	255	255	255	115]
[0	20	225	255	255	255	255	255	255	255	255	255	255	255	255	226]
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[0	0	0	0	30	111	202	247	255	246	201	111	30	0	0	0]
[0	0	0	0	0	0	19	30	34	30	18	0	0	0	0	0]



WHAT IS THIS IMAGE?

[illegible]

[0	0	0	0	0	0	18	30	34	30	18	0	0	0	0	0]
[0	0	0	0	29	111	201	246	255	246	201	111	29	0	0	0]
[0	0	0	67	215	255	255	255	255	255	255	215	67	0	0	0]
[0	0	62	246	255	255	255	255	255	255	255	255	246	63	0	0]
[0	20	225	255	255	255	255	255	255	255	255	255	255	226	22	0]
[0	113	255	255	255	255	255	255	255	255	255	255	255	255	115	0]
[15	197	255	255	255	255	255	255	255	255	255	255	255	255	196	15]
[28	240	255	255	255	255	255	255	255	255	255	255	255	255	241	29]
[33	255	255	255	255	255	255	255	255	255	255	255	255	255	255	33]
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[15	197	255	255	255	255	255	255	255	255	255	255	255	255	197	15]
[0	113	255	255	255	255	255	255	255	255	255	255	255	255	115	0]
[0	20	225	255	255	255	255	255	255	255	255	255	255	226	23	0]
[0	0	63	246	255	255	255	255	255	255	255	255	246	64	0	0]
[0	0	0	67	216	255	255	255	255	255	255	216	67	0	0	0]
[0	0	0	0	30	111	202	247	255	246	201	111	30	0	0	0]
[0	0	0	0	0	0	19	30	34	30	18	0	0	0	0	0]



WHAT ARE DIGITAL IMAGES?

LAST ONE: WHAT IS THIS IMAGE?

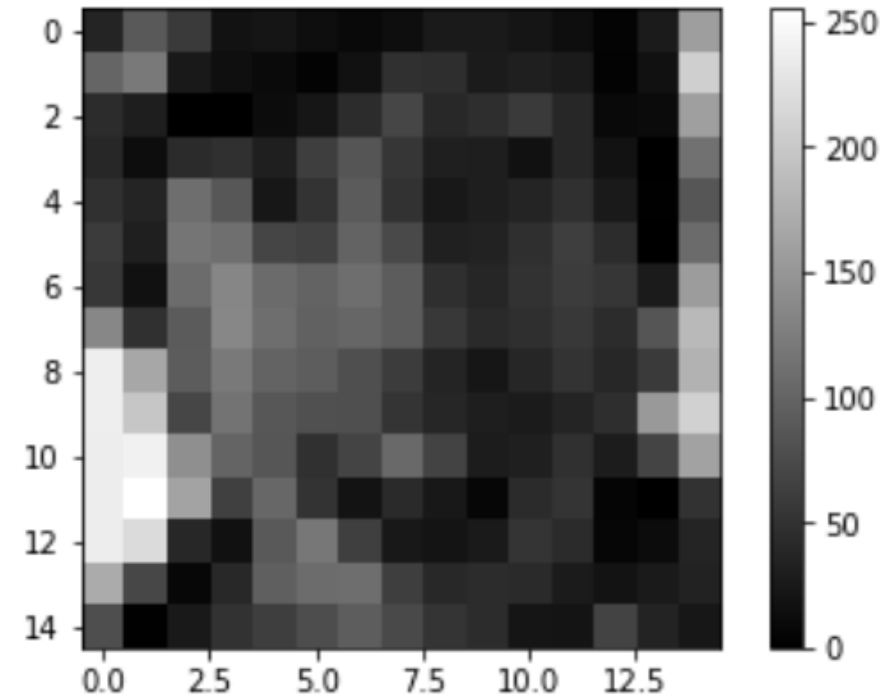
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[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
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[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
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[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

WHAT ARE DIGITAL IMAGES?

WHAT IS THIS IMAGE?

```
[ 37  89  58  18  21  14   9  14  26  26  21  14   4  27 158]
[101 121  25  15  10   3  17  48  46  27  31  27   3  17 207]
[ 45  30   0   0  12  22  44  70  41  46  58  39   9  11 159]
[ 39  13  43  48  31  62  85  54  31  30  17  39  18   0 113]
[ 49  36 110  87  23  51  91  50  24  30  36  49  26   1  86]
[ 59  31 117 111  69  65  99  74  32  34  47  62  44   0 107]
[ 55  17 108 134 107  99 110  92  47  38  50  60  54  27 156]
[135  49  91 135 110  97 102  92  56  42  47  57  45  85 185]
[238 167  92 121  99  93  79  61  36  22  38  51  39  58 178]
[238 198  70 115  87  80  79  52  38  30  27  36  46 153 209]
[237 241 143 100  86  48  68 105  67  28  31  49  28  68 162]
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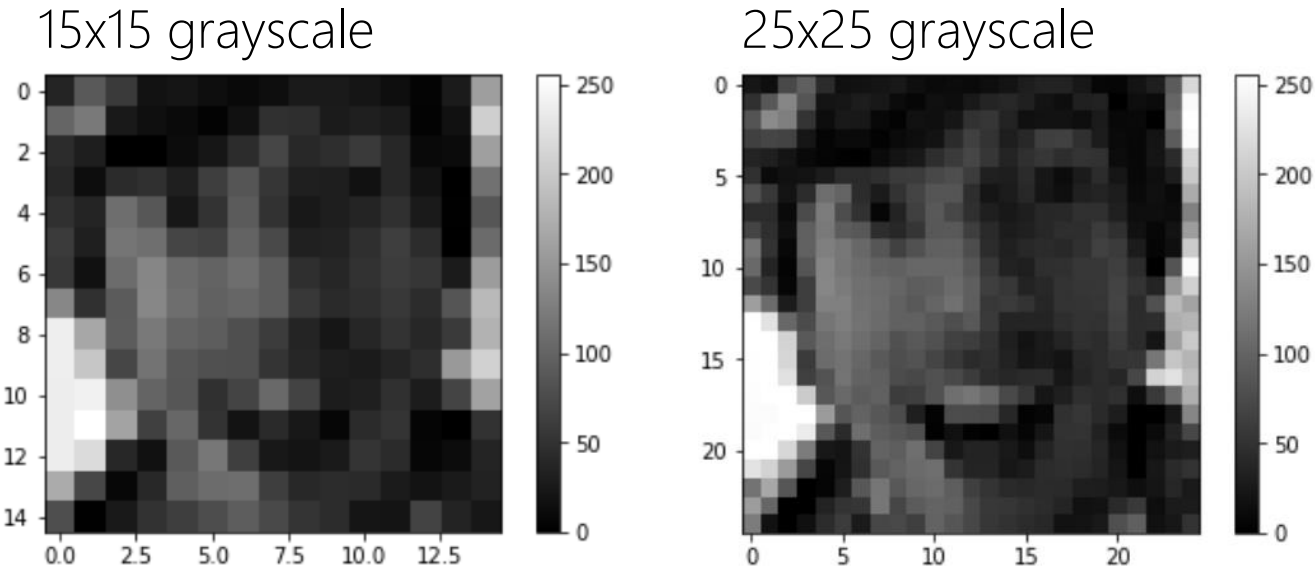
15x15 grayscale



WHAT ARE DIGITAL IMAGES?

CAN ANYONE TELL YET?

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
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[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
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[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
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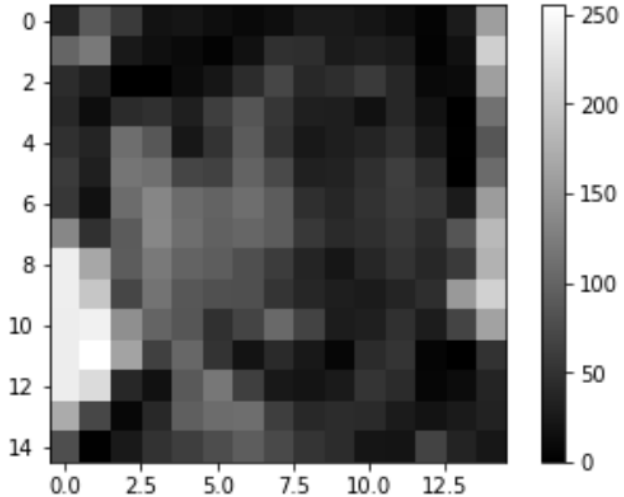


WHAT ARE DIGITAL IMAGES?

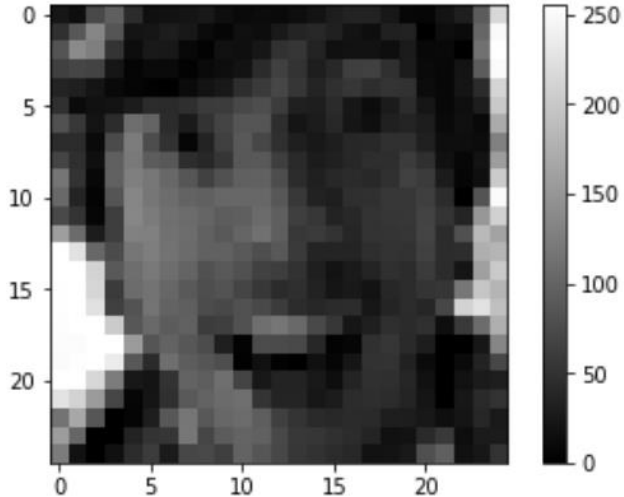
CAN ANYONE TELL YET?

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[ 39  13  43  48  31  62  85  54  31  30  17  39  18   0 113]
[ 49  36 110  87  23  51  91  50  24  30  36  49  26   1  86]
[ 59  31 117 111  69  65  99  74  32  34  47  62  44   0 107]
[ 55  17 108 134 107  99 110  92  47  38  50  60  54  27 156]
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[238 167  92 121  99  93  79  61  36  22  38  51  39  58 178]
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[237 241 143 100  86  48  68 105  67  28  31  49  28  68 162]
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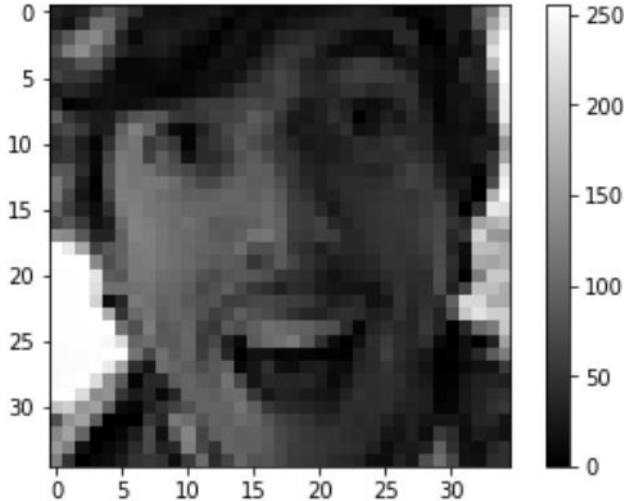
15x15 grayscale



25x25 grayscale



35x35 grayscale

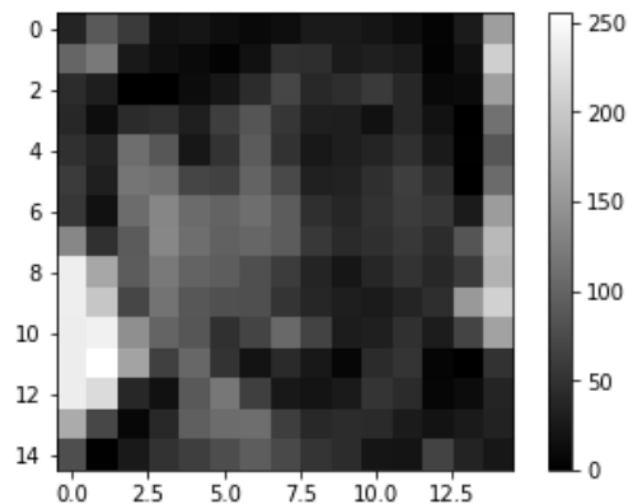


WHAT ARE DIGITAL IMAGES?

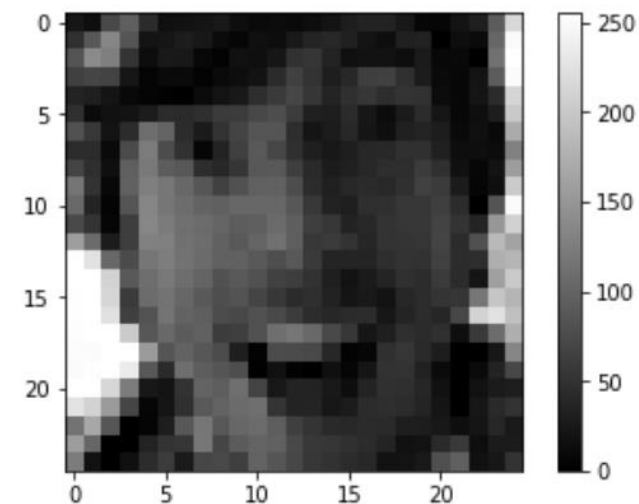
CAN ANYONE TELL YET?

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[ 37  89  58  18  21  14   9  14  26  26  21  14   4  27 158]
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[ 45  30   0   0  12  22  44  70  41  46  58  39   9  11 159]
[ 39  13  43  48  31  62  85  54  31  30  17  39  18   0 113]
[ 49  36 110  87  23  51  91  50  24  30  36  49  26   1  86]
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[ 55  17 108 134 107  99 110  92  47  38  50  60  54  27 156]
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[238 167  92 121  99  93  79  61  36  22  38  51  39  58 178]
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[171  71   7  40  95 108 110  62  40  44  42  27  19  26  34]
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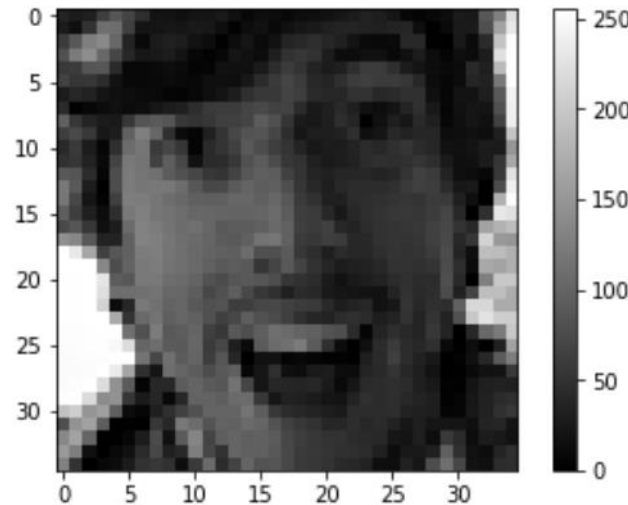
15x15 grayscale



25x25 grayscale



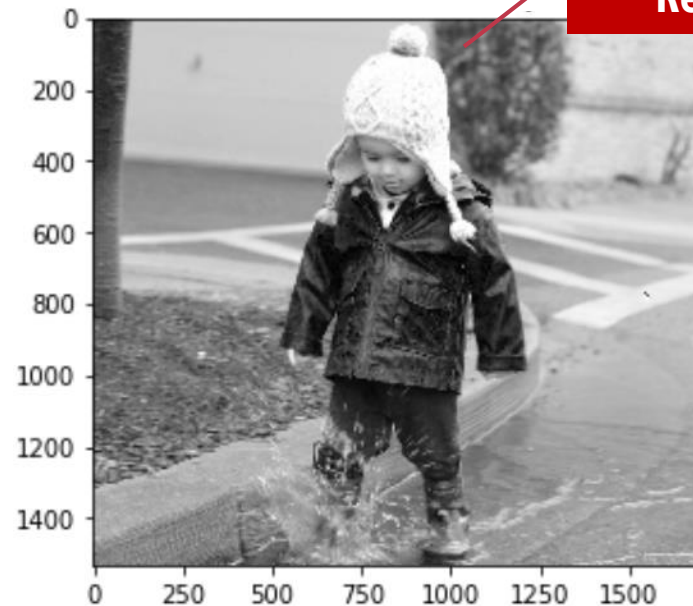
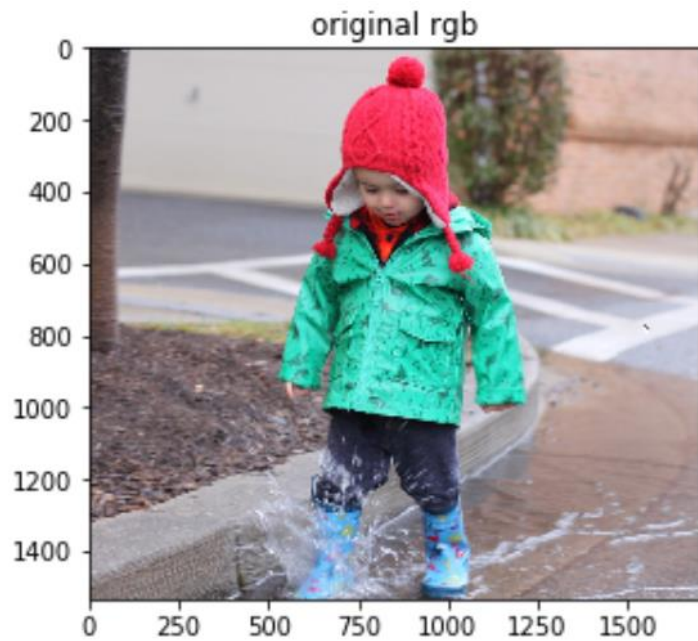
35x35 grayscale



WHAT ARE DIGITAL IMAGES

RGB IMAGES

RGB images have three channels (red, green, blue). Each channel has intensities from 0-255.

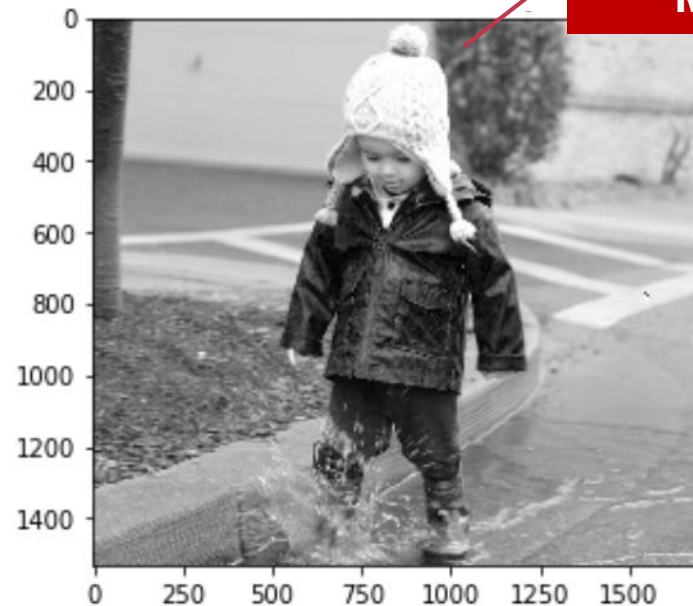
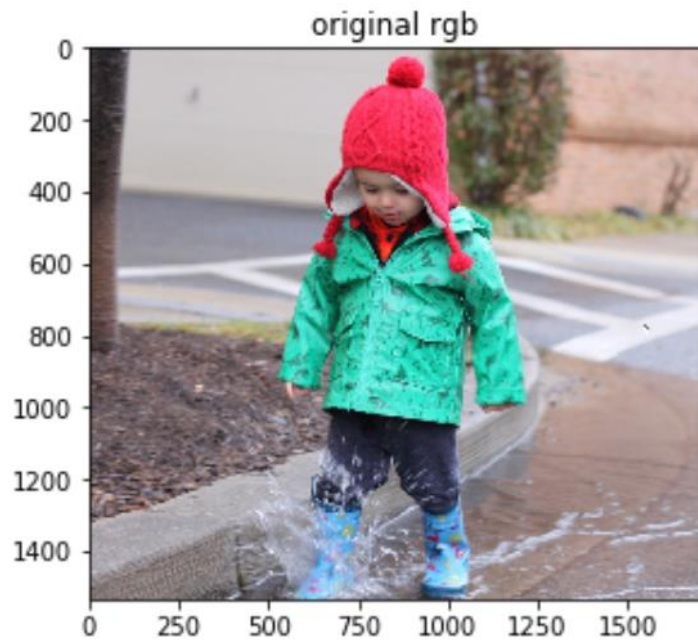


What do you think I'm graphing here?
Red intensities, **green**, or **blue**?

WHAT ARE DIGITAL IMAGES

RGB IMAGES

RGB images have three channels (red, green, blue). Each channel has intensities from 0-255.



What do you think I'm graphing here?
Red channel, **green**, or **blue**?

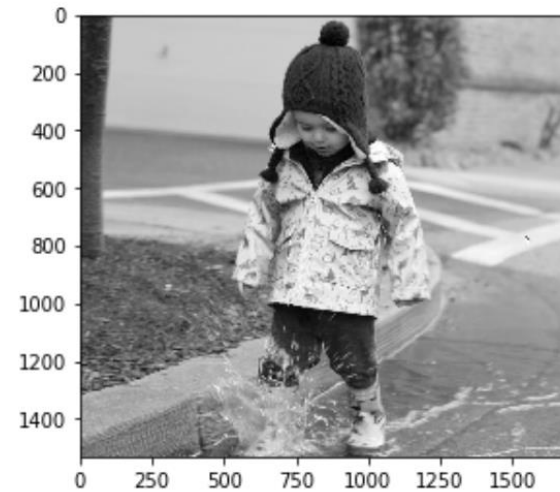
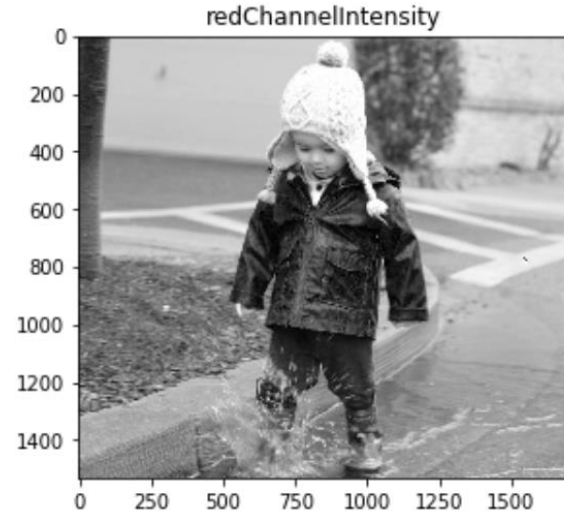
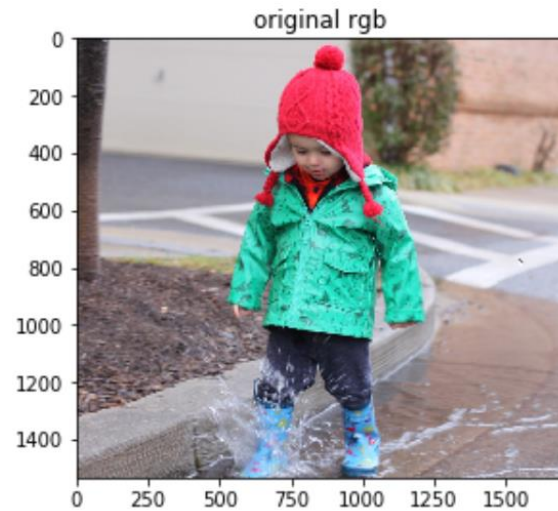
Answer:

This must be the red channel because the highest intensity areas (*i.e.*, values closest to 255) map to the red areas of the original image

WHAT ARE DIGITAL IMAGES

RGB IMAGES

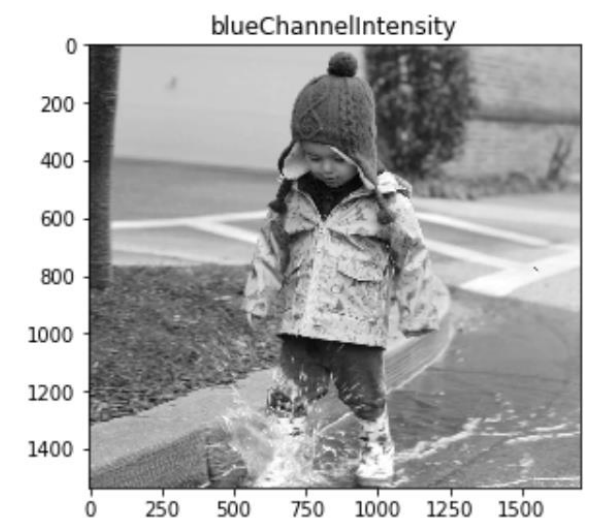
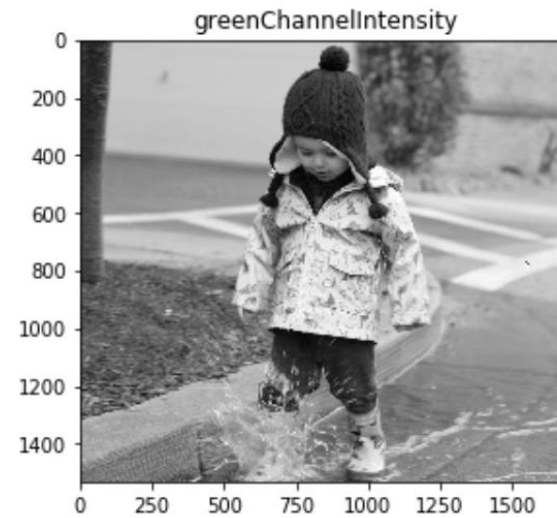
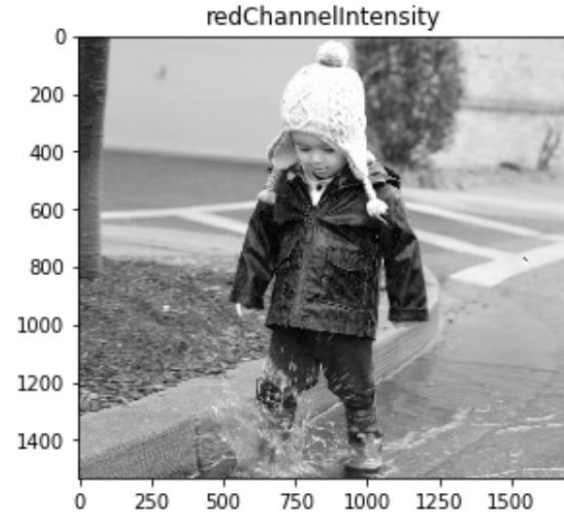
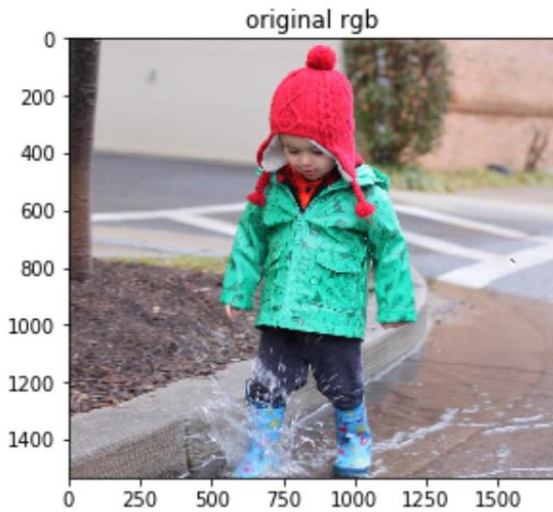
RGB images have three channels (red, green, blue). Each channel has intensities from 0-255.



WHAT ARE DIGITAL IMAGES

RGB IMAGES

RGB images have three channels (red, green, blue). Each channel has intensities from 0-255.

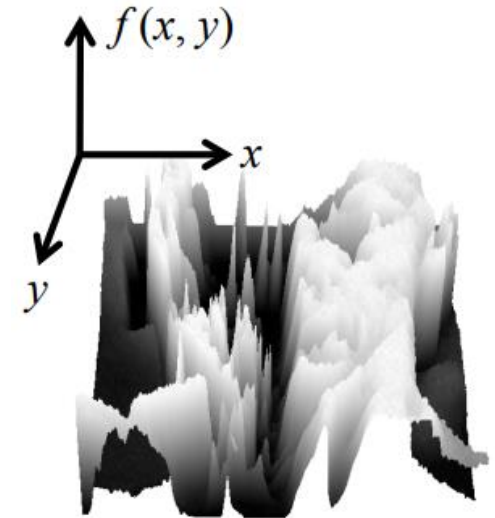


WHAT ARE DIGITAL IMAGES?

DIGITAL IMAGES AS FUNCTIONS

In addition to thinking about images as matrices, we can think of them as a function $f = \mathbb{R}^2 \rightarrow \mathbb{R}$ that maps real numbers in two-dimensional space into intensity values.

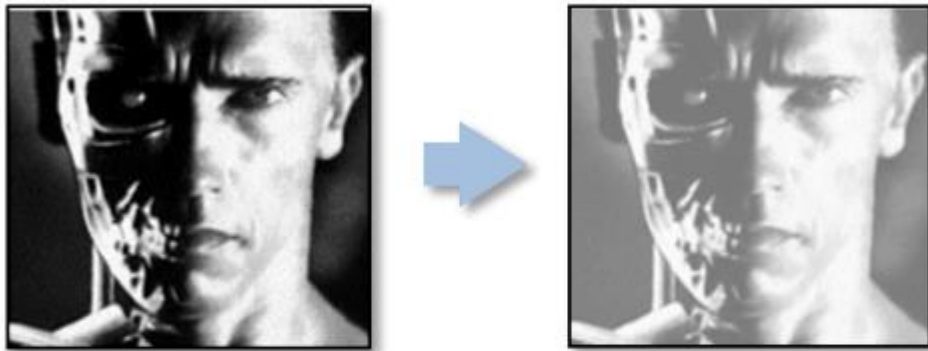
A digital image is a discrete (sampled, quantized) version of this function



WHAT ARE DIGITAL IMAGES?

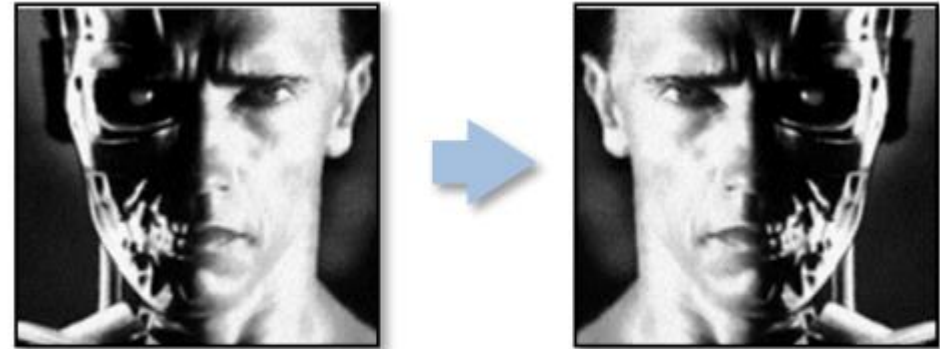
AS WITH ANY FUNCTION, WE CAN APPLY OPERATORS

Increase the intensity of each pixel by 20



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

Flip the image along the horizontal

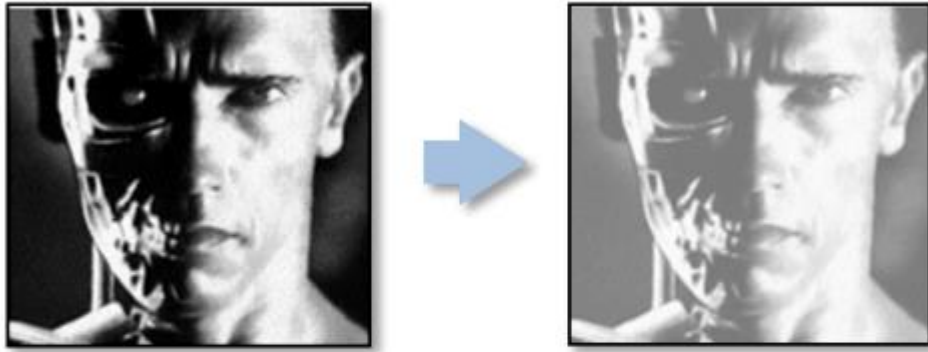


$$g(x,y) = f(-x,y)$$

$g(x,y)$ defines a new image **g** in terms of an existing image **$f(x,y)$**

FORMALIZING THIS A BIT MORE...

Increase the intensity of each pixel by 20



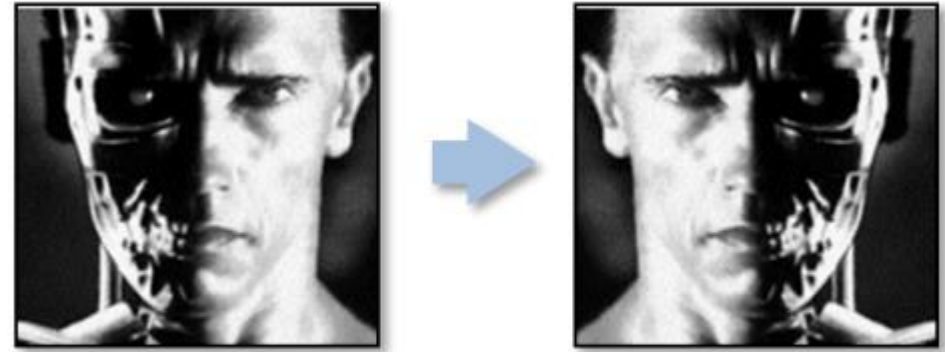
$$g(x, y) = f(x, y) + 20$$

Range Transformations:

Transform the output of $f(x, y)$

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

Flip the image along the horizontal



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

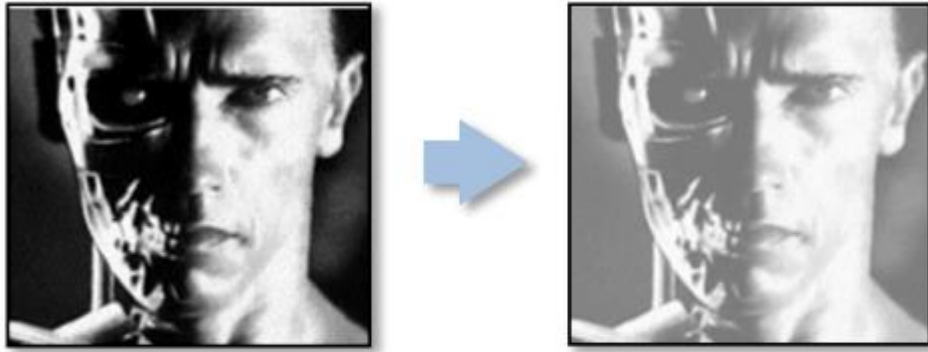
Domain Transformations:

Transform the input to $f(x, y)$

$$g(x, y) = f(t_x(x, y), t_y(x, y))$$

FORMALIZING THIS A BIT MORE...

Increase the intensity of each pixel by 20



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

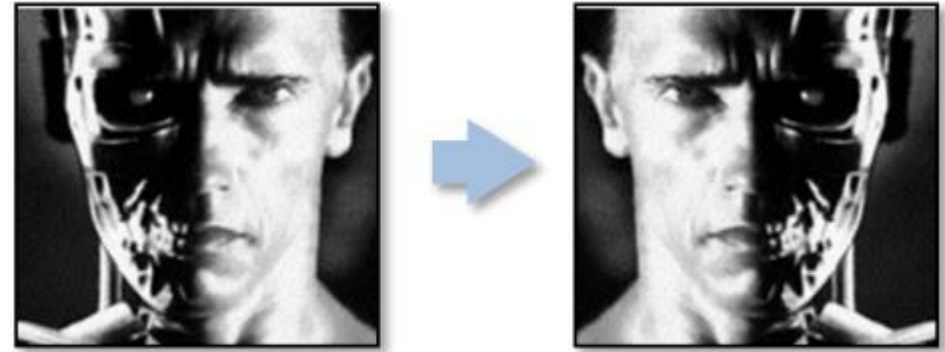
Range Transformations:

Transform the output of $f(x, y)$

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

e.g., inversion, grayscale, brightness, contrast

Flip the image along the horizontal



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

Domain Transformations:

Transform the input to $f(x, y)$

$$g(x, y) = f(t_x(x, y), t_y(x, y))$$

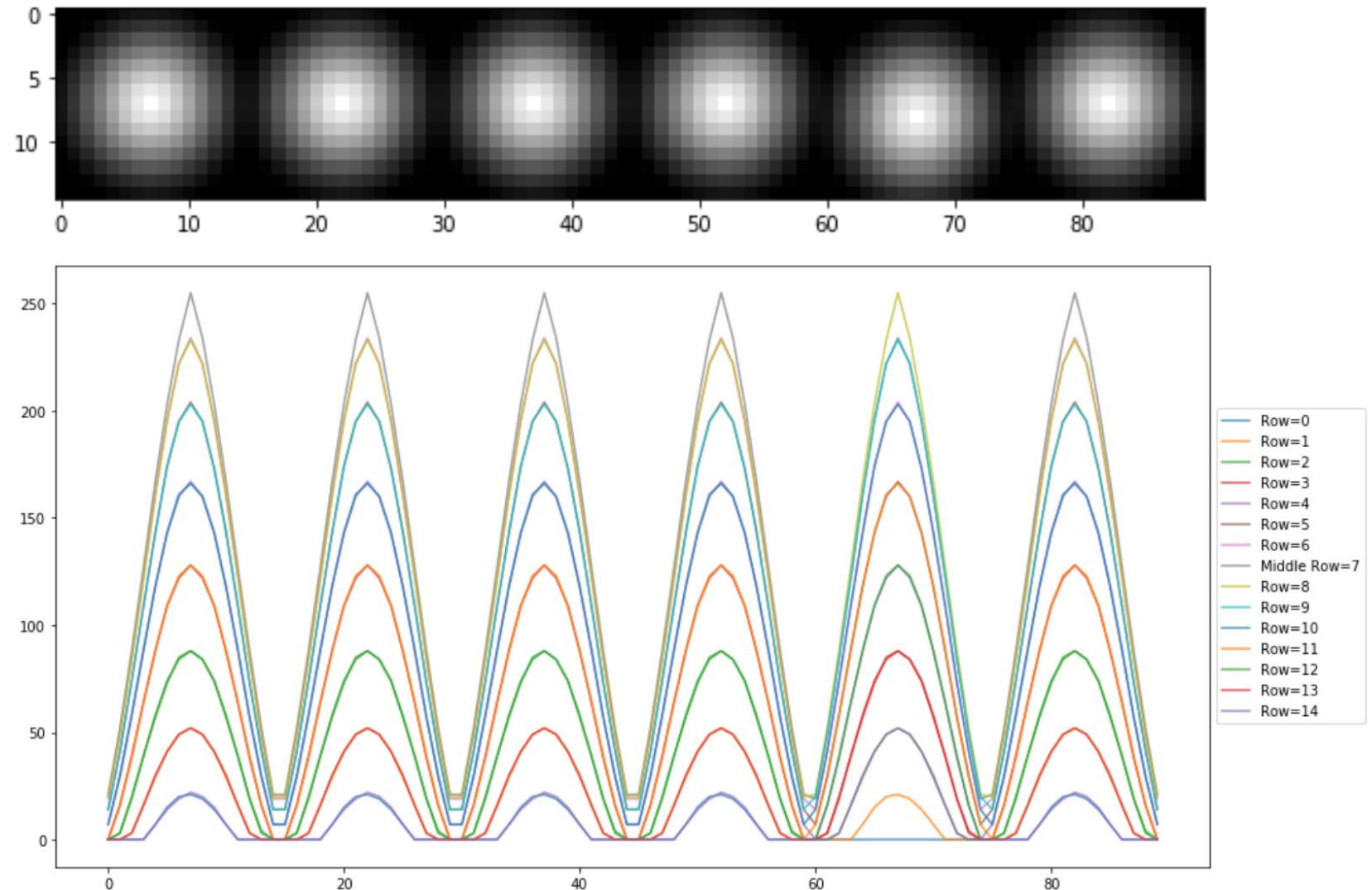
e.g., zoom, translate, rotate, shear,

WHAT ARE DIGITAL IMAGES?

WE CAN GRAPH & APPLY SIGNAL PROCESSING TECHNIQUES

Just as we did in previous parts of the course, we can plot, analyze, and **perform signal processing on images** (peak finding, smoothing, thresholding, and far more complicated operations)





Here, I'm graphing the intensity values row-by-row.

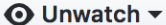






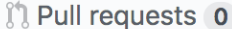




BASIC IMAGE PROCESSING EXERCISES


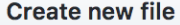
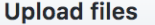

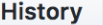
LET'S DO SOME BASIC IMAGE PROCESSING EXERCISES!


In Jupyter Notebook, I want you to perform the following image processing tasks using basic pixel-point arithmetic operations. **Do work** with a partner (if you want). **Try not** to Google for answers (I want you to *think* about this!). 😊

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 Code  Issues 0  Pull requests 0  Projects 0  Wiki  Insights  Settings

Branch: master  CSE590Sp2018 / L08-ComputerVision /    

 jonfroehlich Added computer vision Jupyter Notebook exercises for today Latest commit 4ad0de1 13 minutes ago

..

 .ipynb_checkpoints	Added computer vision Jupyter Notebook exercises for today	13 minutes ago
 Images	Added computer vision Jupyter Notebook exercises for today	13 minutes ago
 MicrosoftVisionAPI.ipynb	Added computer vision Jupyter Notebook exercises for today	13 minutes ago
 ScikitImageExercises.ipynb	Added computer vision Jupyter Notebook exercises for today	13 minutes ago
 ScikitImageExercises_Completed.ipynb	Added computer vision Jupyter Notebook exercises for today	13 minutes ago

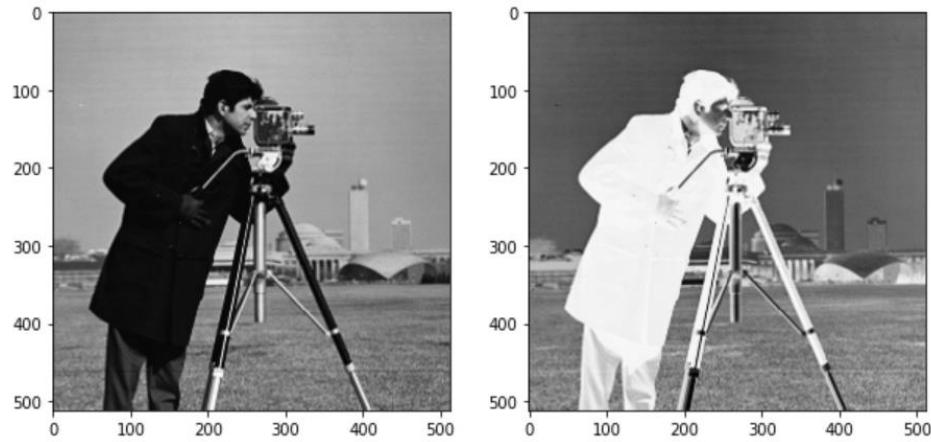
<https://github.com/jonfroehlich/CSE590Sp2018/tree/master/L08-ComputerVision>

BASIC IMAGE PROCESSING EXERCISES

LET'S DO SOME BASIC IMAGE PROCESSING EXERCISES!

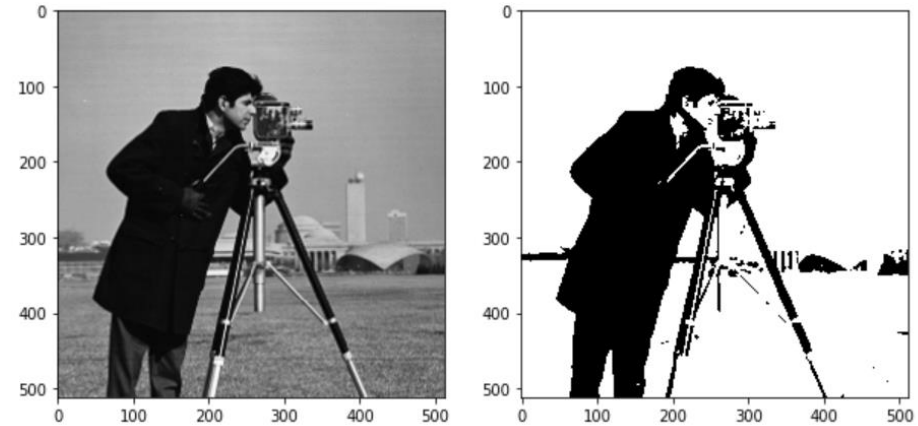
In Jupyter Notebook, I want you to perform the following image processing tasks using basic pixel-point arithmetic operations. **Do work** with a partner (if you want). **Try not** to Google for answers (I want you to *think* about this!). 😊

Invert an image



Binarize an image

(i.e., convert all pixels to either 255 or 0 depending on some threshold)

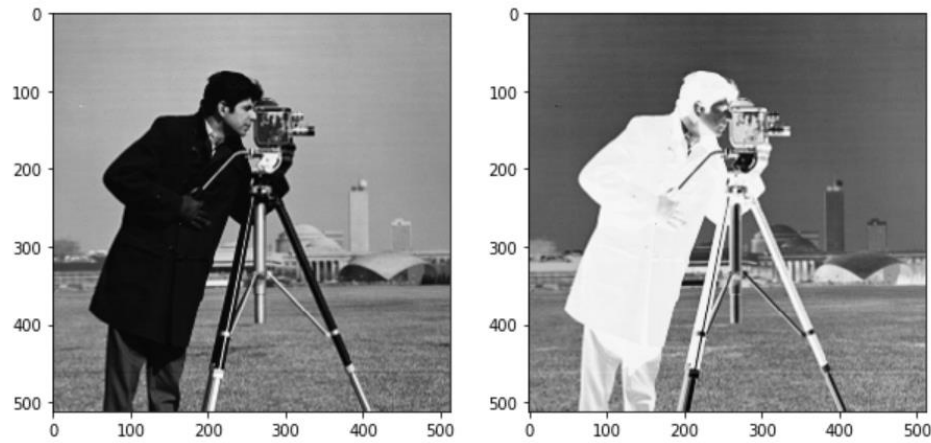


BASIC IMAGE PROCESSING EXERCISES

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Invert an image

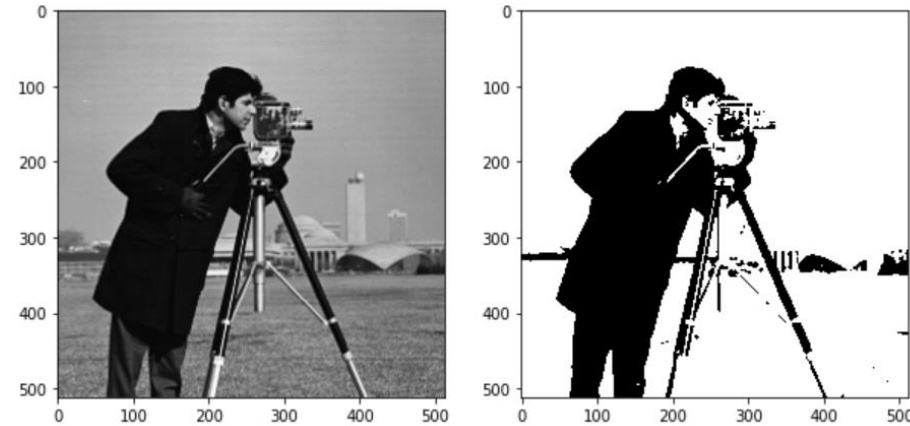


Answer:

```
img = data.camera()  
invertedImg = 255 - img
```

Binarize an image

(i.e., convert all pixels to either 255 or 0 depending on some threshold)



Answer:

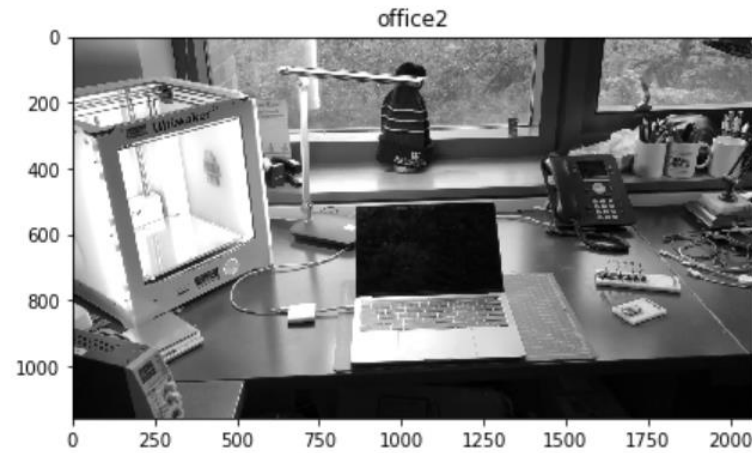
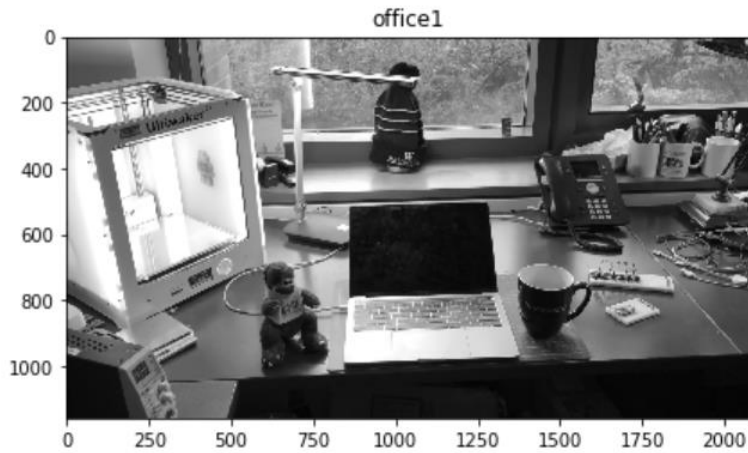
```
img = data.camera()  
threshold = 77  
binarizedImage = img > threshold
```

BASIC IMAGE PROCESSING EXERCISES

LET'S DO SOME BASIC IMAGE PROCESSING EXERCISES!

In Jupyter Notebook, I want you to perform the following image processing tasks using basic pixel-point arithmetic operations. **Do work** with a partner (if you want). **Try not** to Google for answers (I want you to *think* about this!). ☺

Can anyone tell me what the difference is between these two images?

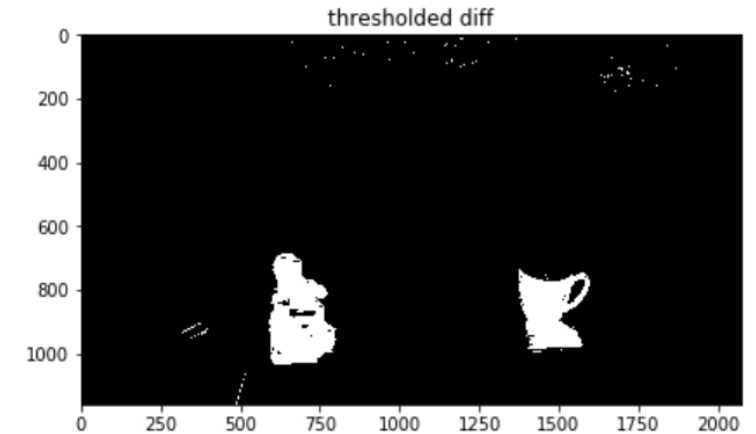
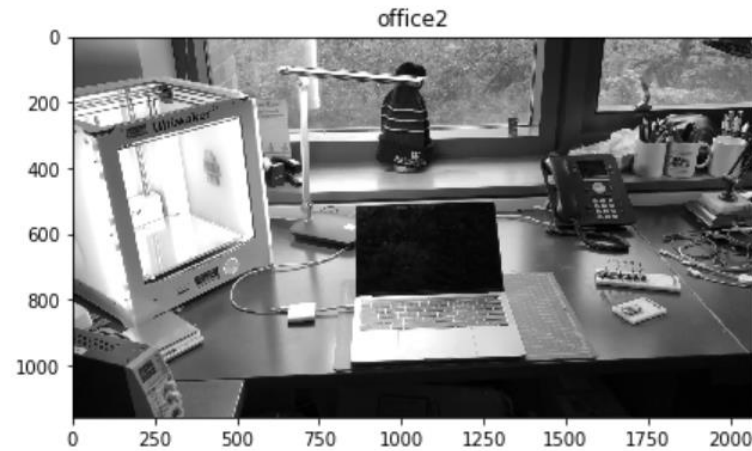
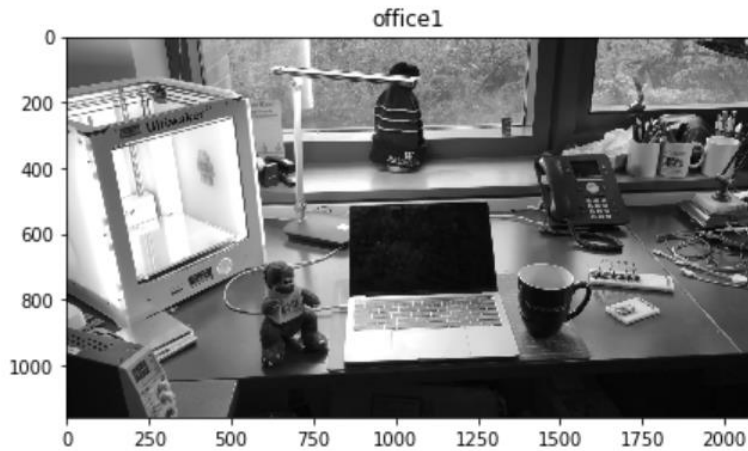


BASIC IMAGE PROCESSING EXERCISES

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In Jupyter Notebook, I want you to perform the following image processing tasks using basic pixel-point arithmetic operations. **Do work** with a partner (if you want). **Try not** to Google for answers (I want you to *think* about this!). 😊

Diff an image

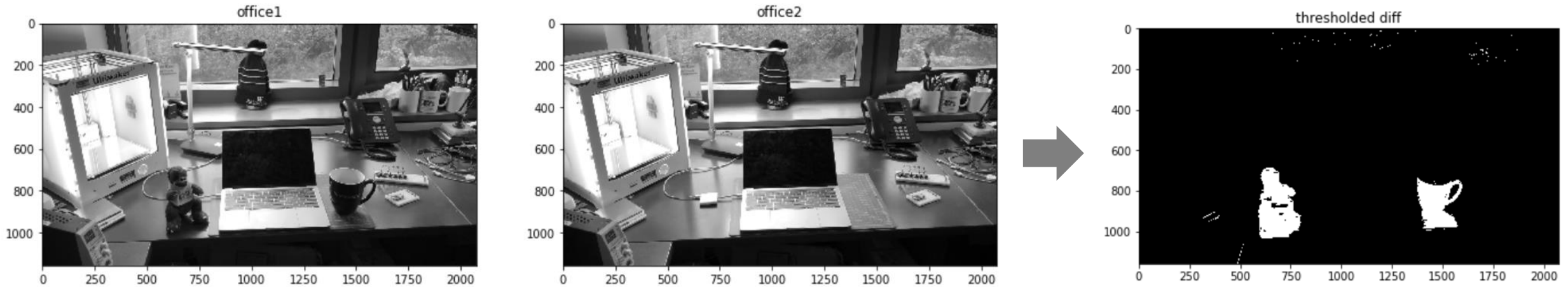


BASIC IMAGE PROCESSING EXERCISES

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In Jupyter Notebook, I want you to perform the following image processing tasks using basic pixel-point arithmetic operations. **Do work** with a partner (if you want). **Try not** to Google for answers (I want you to *think* about this!). 😊

Diff an image



One Possible Answer:

```
officeDiff = office2 - office1 # use basic subtraction to find diffs
```

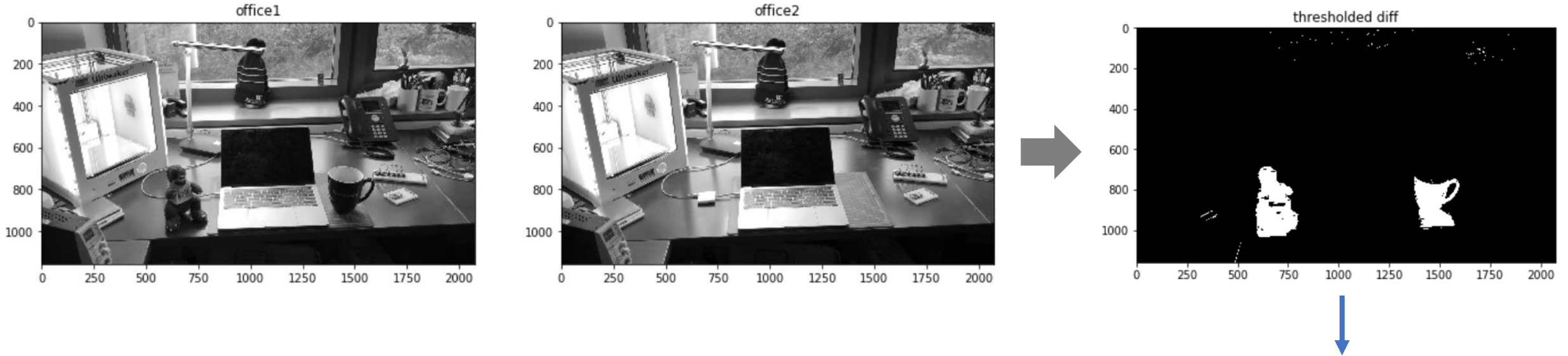
```
# Some values will be less than zero, so normalize the array
```

```
officeDiffNormalized = (officeDiff - officeDiff.min()) / (officeDiff.max() - officeDiff.min())
```

```
# Binarize image to highlight significant differences
```

```
binarizedImage = officeDiffNormalized > threshold
```

WE CAN DO ALL SORTS OF COOL THINGS WITH THIS...



Once we have the detected changes, we can do all sorts of interesting things:

- Move the dinosaur and coffee cup into a different scene
- Begin object tracking (use the underlying pixels as a template)
- Redraw scene with differences highlighted (this is the basis for those sports vis)

OK, so you are **building up some familiarity** with scikit-image (all images are numpy arrays, yay!) and a **basic understanding of image manipulation/processing**.

OK, so you are **building up some familiarity** with scikit-image (all images are numpy arrays, yay!) and a **basic understanding of image manipulation/processing**. Let's build on this and move on to one of the key concepts in image processing and computer vision: **cross-correlation and convolution**.

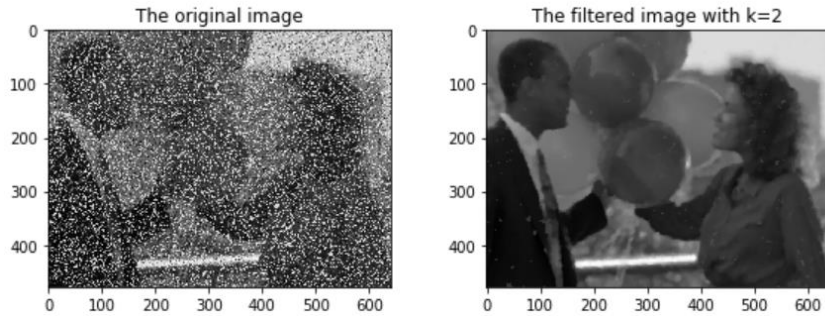
IMAGE FILTERING

IMAGE FILTERING

There are three major applications of filtering: enhancement, information/feature extraction, pattern detection

Image Enhancement

e.g., denoise, color correction

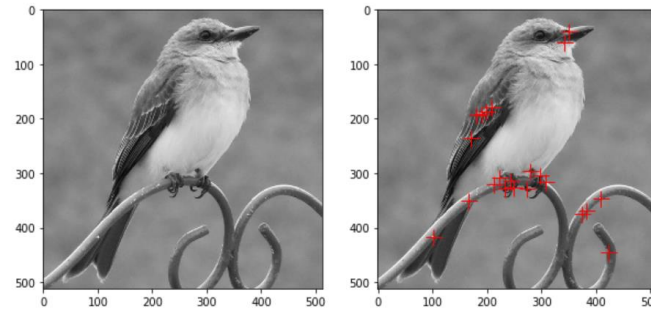


Example using `skimage.filters.median`:

<http://scikit-image.org/docs/dev/api/skimage.filters.html#skimage.filters.median>

Feature Detection/Extraction

e.g., textures, corners, edges

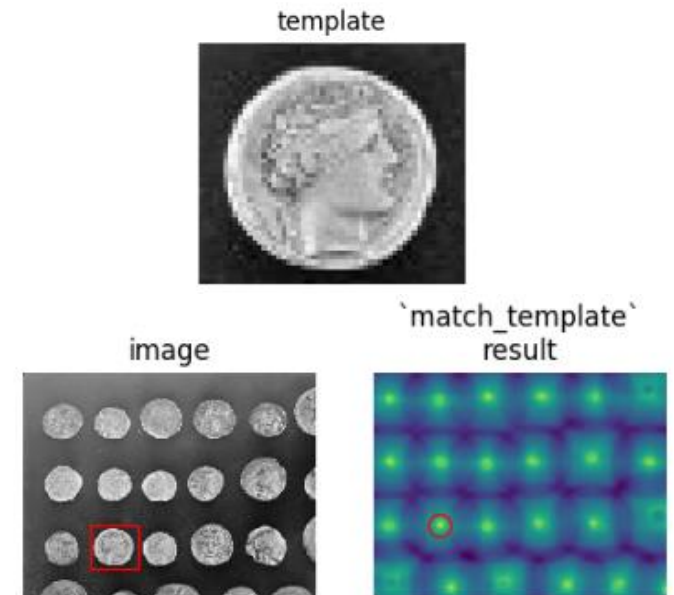


Example using `skimage.feature.corner_harris`

http://scikit-image.org/docs/dev/auto_examples/features_detection/plot_corner.html

Pattern Detection

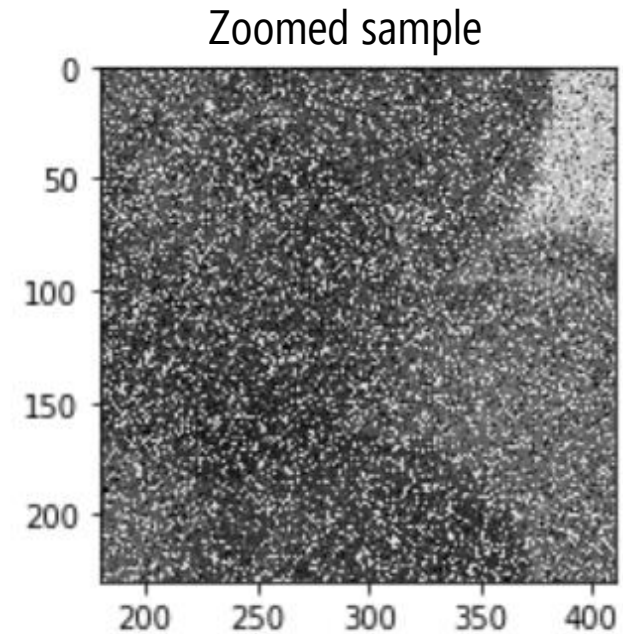
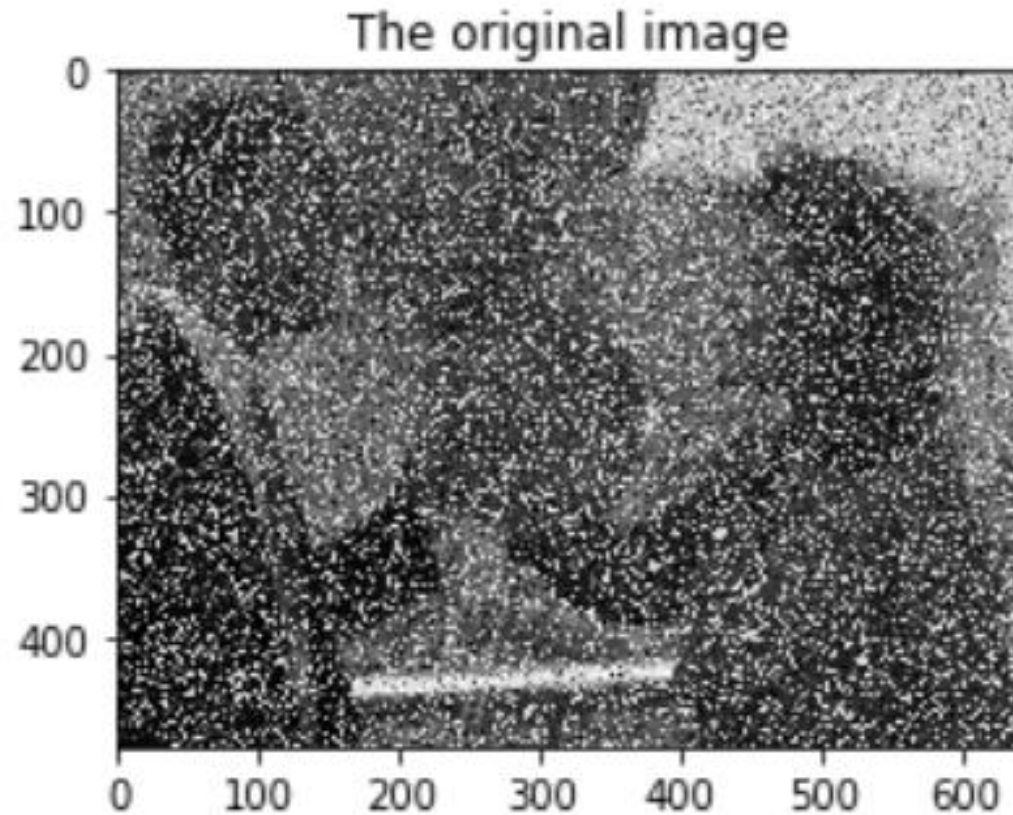
e.g., template matching



Example from:

http://scikit-image.org/docs/dev/auto_examples/features_detection/plot_template.html

HOW CAN WE REDUCE NOISE IN AN IMAGE?



HOW CAN WE REDUCE NOISE IN AN IMAGE?

Idea 1

Treat each row as an independent signal

Use any of your prior smoothing approaches

```
[ 37  89  58  18  21  14   9  14  26  26  21  14   4  27 158]
[101 121  25  15  10   3  17  48  46  27  31  27   3  17 207]
[ 45  30   0   0  12  22  44  70  41  46  58  39   9  11 159]
[ 39  13  43  48  31  62  85  54  31  30  17  39  18   0 113]
[ 49  36 110  87  23  51  91  50  24  30  36  49  26   1  86]
[ 59  31 117 111  69  65  99  74  32  34  47  62  44   0 107]
[ 55  17 108 134 107  99 110  92  47  38  50  60  54  27 156]
[135  49  91 135 110  97 102  92  56  42  47  57  45  85 185]
[238 167  92 121  99  93  79  61  36  22  38  51  39  58 178]
[238 198  70 115  87  80  79  52  38  30  27  36  46 153 209]
[237 241 143 100  86  48  68 105  67  28  31  49  28  68 162]
[237 255 163  64 103  51  19  42  24   6  43  53   5   0  50]
[237 219  39  17  89 119  63  24  20  26  52  43   6  12  37]
[171  71   7  40  95 108 110  62  40  44  42  27  19  26  34]
[ 78   1  25  50  62  77  93  74  52  45  21  20  67  35  23]
```

HOW CAN WE REDUCE NOISE IN AN IMAGE?

Idea 1

Treat each row as an independent signal

Use any of your prior smoothing approaches

For example, let's try our favorite—a **1D moving window average filter**

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

IMAGE FILTERING

1D MOVING WINDOW AVERAGE FILTER

Let's try a 1D moving average filter with $k=2$ thus the window size = 5

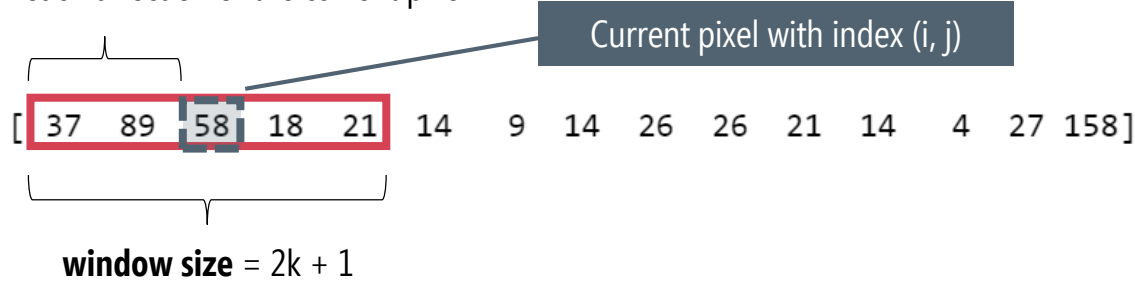
[37 89 58 18 21 14 9 14 26 26 21 14 4 27 158]	[]
[101 121 25 15 10 3 17 48 46 27 31 27 3 17 207]	[]
[45 30 0 0 12 22 44 70 41 46 58 39 9 11 159]	[]
[39 13 43 48 31 62 85 54 31 30 17 39 18 0 113]	[]
[49 36 110 87 23 51 91 50 24 30 36 49 26 1 86]	[]
[59 31 117 111 69 65 99 74 32 34 47 62 44 0 107]	[]
[55 17 108 134 107 99 110 92 47 38 50 60 54 27 156]	[]
[135 49 91 135 110 97 102 92 56 42 47 57 45 85 185]	[]
[238 167 92 121 99 93 79 61 36 22 38 51 39 58 178]	[]
[238 198 70 115 87 80 79 52 38 30 27 36 46 153 209]	[]
[237 241 143 100 86 48 68 105 67 28 31 49 28 68 162]	[]
[237 255 163 64 103 51 19 42 24 6 43 53 5 0 50]	[]
[237 219 39 17 89 119 63 24 20 26 52 43 6 12 37]	[]
[171 71 7 40 95 108 110 62 40 44 42 27 19 26 34]	[]
[78 1 25 50 62 77 93 74 52 45 21 20 67 35 23]	[]

Input Image: $f(x,y)$

Output Image: $g(x,y)$

1D MOVING WINDOW AVERAGE FILTER

k is the number of neighbors we explore in each direction of the current pixel



Input Image: F(i,j)

New pixel value with index (i,j) based on filter operation. In this case, an average:

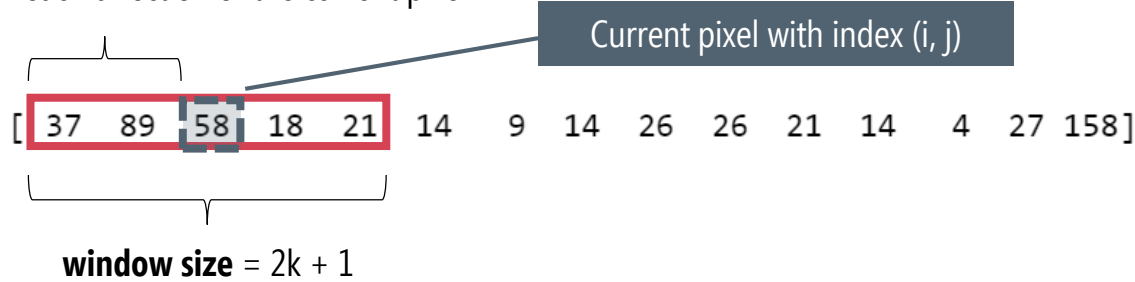
$$g(i,j) = \frac{1}{(2k + 1)} \sum_{-k}^{+k} f(i, j + k)$$



Output Image: G(i,j)

1D MOVING WINDOW AVERAGE FILTER

k is the number of neighbors we explore in each direction of the current pixel



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IMAGE FILTERING

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[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
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[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input Image: $F(i,j)$

[45	40]
[]
[]
[]
[]
[]
[]
[]
[]
[]
[]
[]
[]
[]
[]

Output Image: $G(i,j)$

IMAGE FILTERING

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[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]	[]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]	[]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]	[]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]	[]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]	[]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]	[]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]	[]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]	[]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]	[]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]	[]
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[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]	[]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]	[]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]	[]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]	[]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]	[]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]	[]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]	[]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]	[]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]	[]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]	[]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]	[]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]	[]

Input Image: $F(i,j)$

Output Image: $G(i,j)$

IMAGE FILTERING

1D MOVING WINDOW AVERAGE FILTER

Let's try a 1D moving average filter with $k=2$ thus the window size = 5

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input Image: $F(i,j)$

[0	0	44	40	24	15	16	17	19	20	18	18	44	0	0]
[0	0	54	34	14	18	24	28	33	35	26	21	57	0	0]
[0	0	17	12	15	29	37	44	51	50	38	32	55	0	0]
[0	0	34	39	53	56	52	52	43	34	27	20	37	0	0]
[0	0	61	61	72	60	47	49	46	37	33	28	39	0	0]
[0	0	77	78	92	83	67	60	57	49	43	37	52	0	0]
[0	0	84	93	111	108	91	77	67	57	49	45	69	0	0]
[0	0	104	96	107	107	91	77	67	58	49	55	83	0	0]
[0	0	143	114	96	90	73	58	47	41	37	41	72	0	0]
[0	0	141	110	86	82	67	55	45	36	35	58	94	0	0]
[0	0	161	123	89	81	74	63	59	56	40	40	67	0	0]
[0	0	164	127	80	55	47	28	26	33	26	21	30	0	0]
[0	0	120	96	65	62	63	50	37	33	29	27	30	0	0]
[0	0	76	64	72	83	83	72	59	43	34	31	29	0	0]
[0	0	43	43	61	71	71	68	57	42	41	37	33	0	0]

Output Image: $G(i,j)$

IMAGE FILTERING

IMPLEMENT A 1D MOVING AVERAGE FILTER!



IMAGE FILTERING

IMPLEMENT A 1D MOVING AVERAGE FILTER!

```
# ONE DIMENSIONAL IMAGE SMOOTHING ALGORITHM
# Let's build our own window-based mean filter for an image. This is very similar
# to the smoothing approaches we've previously done in the course.
# Here, we are going to manually walk through each pixel in our numpy array
# and take an average of the pixels around it (using a 1-dimensional sliding window)
# Note that manually stepping through numpy arrays is not typically done as the
# numpy library allows you to perform full matrix operations without setting up your own
# for loops. But we'll do it for now for educational purposes!
# Also note that this simple example is only smoothing in the x-direction

## img = io.imread("./Images/bears_0.05_noisy.jpg", as_grey=True)
img = io.imread("./Images/balloons_noisy_bw.png")

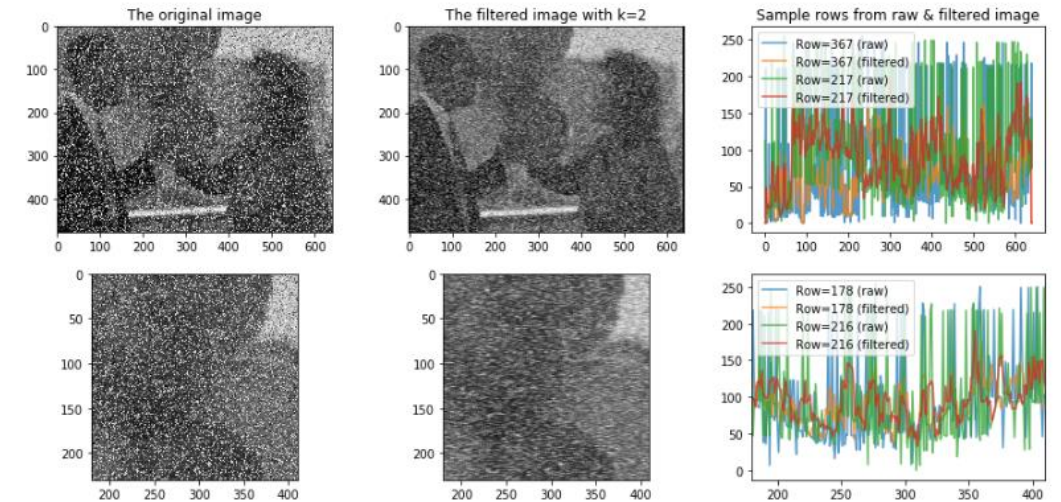
k = 2 # number of neighbors to look at, the larger k, the "blurrier" the image will get
windowSize1D = (2 * k) + 1 # the window size of our average filter
imageHeight, imageWidth = img.shape

# initialize our smoothed image to all zeros. We must specify our dtype
# here because scikit-image converted grayscale images are 64-bit floats
# vs. raw grayscale images are 8-bit ints
smoothedImage = np.full((imageHeight, imageWidth), 0, dtype=img.dtype)

# numpy stores data in row major order
# Loop through every pixel and calculate an average for a window around that pixel
# Note that we are only smoothing here in the x-direction
print("Smoothing with a windowSize1D=", windowSize1D)
for j in range(0, imageHeight): # for each row
    for i in range(k, imageWidth - k): # and each column
        pixelsInWindow = img[j, i - k : i + k + 1] # first arg retu
        avg = np.mean(pixelsInWindow)
        smoothedImage[j,i] = avg

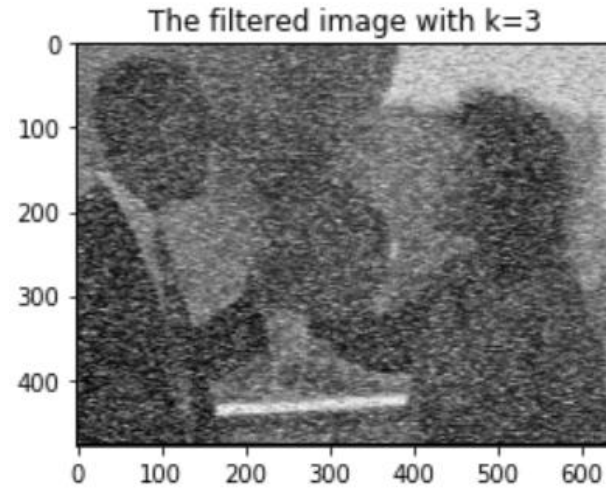
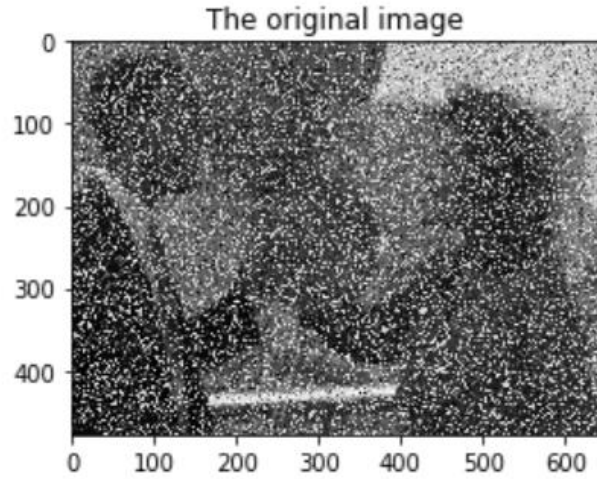
plotFilteredImage(img, smoothedImage, k, (180,410), (230,0))
```

Smoothing with a windowSize1D= 5



1D MOVING WINDOW AVERAGE FILTER RESULTS

Window Size=7



Definitely better than original.

But...

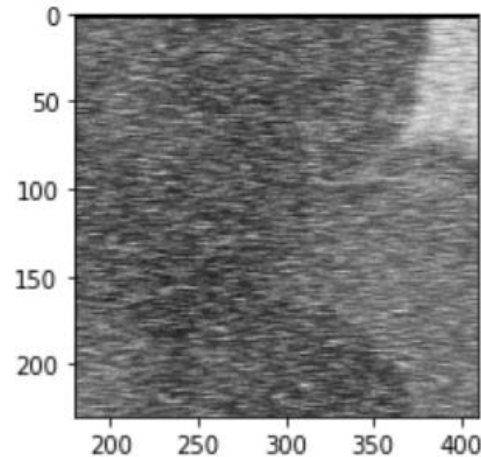
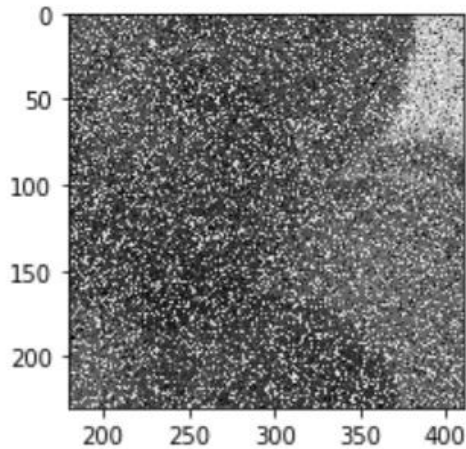
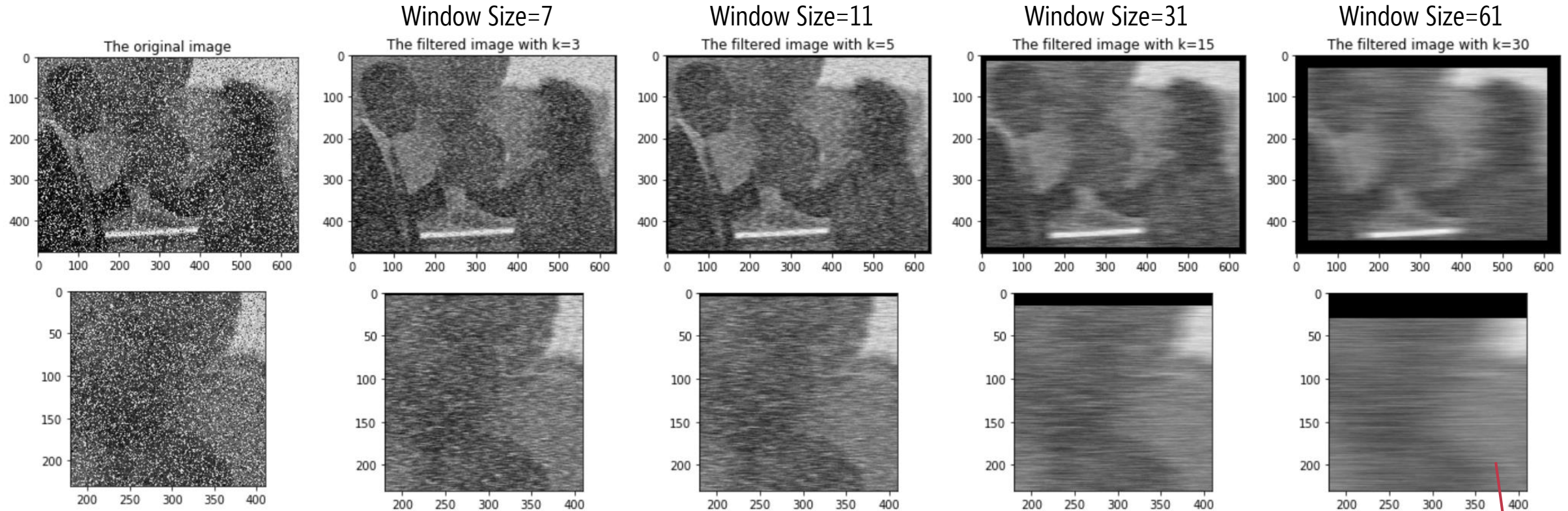


IMAGE FILTERING

A 1-DIMENSIONAL WINDOW FILTER IS INSUFFICIENT

A 1-dimensional filter (like we've used previously) is insufficient for a 2D signal. With a 1D filter, we are only using part of the information we have to filter the signal. We can do better.



As the filter window size gets larger, artifacts from our 1D approach become clear

Notice the **horizontal streaks**, which is an artifact of smoothing only in the x-direction

IMAGE FILTERING

WE NEED A 2D FILTER! BUT HOW?

Rather than using a 1D sliding window, we will use a 2D sliding window (often called a box filter). We'll use the same concept as before. Slide the window across the image and perform some calculation over the pixels within the window.

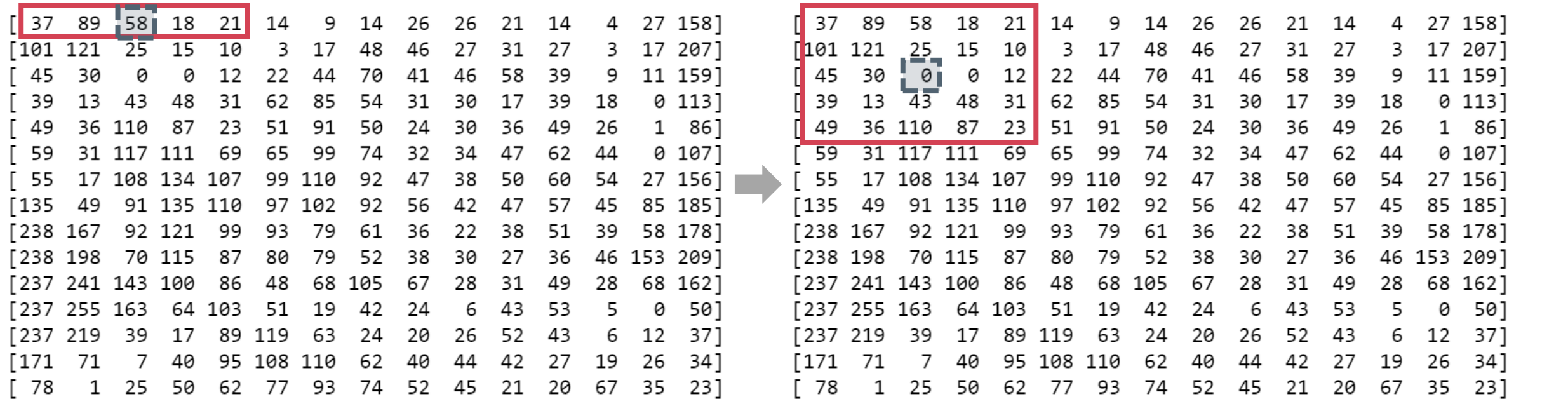


IMAGE FILTERING

WE NEED A 2D FILTER! BUT HOW?

All of our metrics are the same (k , window size, etc.) but we add a new one: `num_cells_in_window`

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input image $F(i,j)$ with a 1D sliding window

k is still the number of neighbors we explore in each direction of the current pixel

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]

window size = $2k + 1$
total window size (aka `num_cells_in_window`) = $(2k + 1)^2$

Input image $F(i,j)$ with a 2D sliding window

2D MOVING AVERAGE FILTER

New pixel value with index (i,j) based on filter operation. In this case, an average:

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

56

$$g(i,j) = \frac{1}{9} * (37 + 89 + 58 + 101 + 121 + 25 + 45 + 30 + 0)$$

$$g(i,j) = \frac{1}{9} * (37 + 89 + 58 + 101 + 121 + 25 + 45 + 30 + 0)$$

Output Image: $G(i,j)$

2D MOVING AVERAGE FILTER

To make this easier on us, let's set $k=1$, so window size=3, and num_cells_in_window=9

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input image $F(i,j)$

56

40

$$g(i,j) = \frac{1}{9} * (89 + 58 + 18 + 121 + 25 + 15 + 30 + 0 + 0)$$

Output Image: $G(i,j)$

2D MOVING AVERAGE FILTER

To make this easier on us, let's set $k=1$, so window size=3, and num_cells_in_window=9

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input image $F(i,j)$

56

40

18

$$g(i, j) = \frac{1}{9} * (58 + 18 + 21 + 25 + 15 + 10 + 0 + 0 + 12)$$

Output Image: $G(i,j)$

IMAGE FILTERING

2D MOVING AVERAGE FILTER RESULTS

To make this easier on us, let's set $k=1$, so window size=3, and num_cells_in_window=9

[37	89	58	18	21	14	9	14	26	26	21	14	4	27	158]
[101	121	25	15	10	3	17	48	46	27	31	27	3	17	207]
[45	30	0	0	12	22	44	70	41	46	58	39	9	11	159]
[39	13	43	48	31	62	85	54	31	30	17	39	18	0	113]
[49	36	110	87	23	51	91	50	24	30	36	49	26	1	86]
[59	31	117	111	69	65	99	74	32	34	47	62	44	0	107]
[55	17	108	134	107	99	110	92	47	38	50	60	54	27	156]
[135	49	91	135	110	97	102	92	56	42	47	57	45	85	185]
[238	167	92	121	99	93	79	61	36	22	38	51	39	58	178]
[238	198	70	115	87	80	79	52	38	30	27	36	46	153	209]
[237	241	143	100	86	48	68	105	67	28	31	49	28	68	162]
[237	255	163	64	103	51	19	42	24	6	43	53	5	0	50]
[237	219	39	17	89	119	63	24	20	26	52	43	6	12	37]
[171	71	7	40	95	108	110	62	40	44	42	27	19	26	34]
[78	1	25	50	62	77	93	74	52	45	21	20	67	35	23]

Input image $F(i,j)$

[0	0	0	0	0	0	0	0	0	0	0	0	0	0	0]
[0	56	39	17	12	16	26	35	38	35	32	22	16	66	0]
[0	46	32	20	22	31	45	48	43	36	34	26	18	59	0]
[0	40	40	39	37	46	58	54	41	34	38	32	21	47	0]
[0	55	66	71	60	64	70	60	39	31	38	37	26	43	0]
[0	64	83	96	82	79	81	68	46	37	45	47	35	55	0]
[0	73	88	109	103	95	92	78	56	43	48	51	48	78	0]
[0	105	101	110	110	99	91	75	54	41	45	49	52	91	0]
[0	142	115	102	104	91	81	66	47	37	38	42	63	110	0]
[0	180	138	101	92	79	73	65	48	35	34	38	58	104	0]
[0	198	149	103	81	69	60	54	43	32	33	35	48	80	0]
[0	196	137	89	75	71	59	48	38	33	36	34	29	40	0]
[0	155	97	68	76	84	66	44	32	33	37	32	21	21	0]
[0	94	52	47	73	90	81	59	43	38	35	33	28	28	0]
[0	0	0	0	0	0	0	0	0	0	0	0	0	0	0]

Output Image: $G(i,j)$

IMAGE FILTERING

IMPLEMENT A 2D MOVING AVERAGE FILTER!



IMAGE FILTERING

IMPLEMENT A 2D MOVING AVERAGE FILTER!

```
# TWO DIMENSIONAL IMAGE SMOOTHING ALGORITHM
# Let's extend our one-dimensional image smoothing approach to *two* dimensions
# So now our sliding window is really a sliding box! And we can use numpy's
# fancy slicing syntax to make this really easy :)
# See: https://docs.scipy.org/doc/numpy-1.13.0/reference/arrays.indexing.html

# img = io.imread("./Images/bears_0.05_noisy.jpg", as_grey=True)
img = io.imread("./Images/balloons_noisy_bw.png")

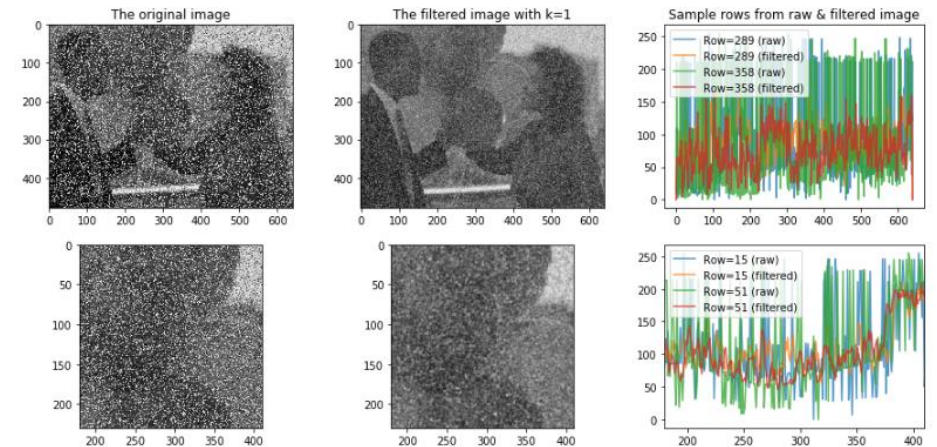
k = 1 # number of neighbors to look at, the larger k, the "blurrier" the image will get
windowSize2D = (2 * k) + 1 # the window size of our average filter
imageHeight, imageWidth = img.shape

# initialize our smoothed image to all zeros. We must specify our dtype
# here because scikit-image converted grayscale images are 64-bit floats
# vs. raw grayscale images are 8-bit ints
smoothedImage = np.full((imageHeight, imageWidth), 0, dtype=img.dtype)

# numpy stores data in row major order
# Loop through every pixel and calculate an average for a window around that pixel
# Note that we are only smoothing here in the x-direction
print("Smoothing with a windowSize2D=", windowSize2D)
for j in range(k, imageHeight - k): # for each row
    for i in range(k, imageWidth - k): # and each column
        # get the matrix within our sliding window
        pixelsInWindow = img[j - k : j + k + 1, i - k : i + k + 1]
        avg = np.mean(pixelsInWindow)
        smoothedImage[j,i] = avg

plotFilteredImage(img, smoothedImage, k, (180,410), (230,0))
```

Smoothing with a windowSize2D= 3

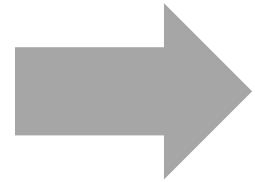


2D MOVING AVERAGE FILTER WEIGHTED

Original Equation for Average Filter

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

But imagine that we want to **weight pixels** closer to selected pixel more than those further away. For this, we have to introduce another "lookup" matrix that holds these weights.



	a	b	c
v	d	e	f
	g	h	i
	u		

Let's call this matrix: $H(u, v)$

The example above is for $k=1$.
H is often referred to as a kernel or mask.

New Equation for Weighted Average Filter

$$g(i, j) = \sum_{u=-k}^{+k} \sum_{v=-k}^{+k} h(u, v) f(i + u, j + v)$$

Grab weights from our $h(u, v)$ matrix

This is called the cross-correlation operation

$$G = H \otimes F$$

FROM MOVING AVERAGE TO CROSS-CORRELATION

A Mathematical Representation for Smoothing

$$G[3, 3] = \frac{1}{9}(A + B + C + D + E + F + G + H + I)$$

$$G[i, j] = \frac{1}{(2k + 1)^2} \sum_{u=-k}^k \sum_{v=-k}^k F[i + u, j + v]$$

a	b	c
d	e	f
g	h	i

20	20	10	20	10	20	10	10	13
30	0	0	0	0	0	0	0	30
20	0	A	B	C	90	90	0	20
20	0	D	E	F	90	90	0	20
10	0	G	H	I	90	90	0	10
10	0	90	90	90	90	90	0	10
10	0	90	90	90	90	90	0	10
20	0	0	0	0	0	0	0	20
20	20	10	20	10	20	10	10	13

More Generally,

$$G[3, 3] = a * A + b * B + c * C + d * D + e * E + f * F + h * H + i * I$$

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k h[u, v] F[i + u, j + v]$$

Attribute non-uniform weights

WHAT DOES $H[u,v]$ LOOK LIKE FOR MOVING AVERAGE?

For $k=1$. So, window size = 3 and num cells = 9

$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$
$1/9$	$1/9$	$1/9$

CROSS-CORRELATION & CONVOLUTION

Cross Correlation

$$G[i, j] = \sum_{u=-k}^{+k} \sum_{v=-k}^{+k} H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

Convolution

$$G[i, j] = \sum_{u=-k}^{+k} \sum_{v=-k}^{+k} H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

IMAGE FILTERING

CONVOLUTION-BASED IMAGE FILTERING

```
# Now, Let's do this the *right* way--using a kernel and convolution! :)
# Some example kernels: https://en.wikipedia.org/wiki/Kernel\_\(image\_processing\)
img = birdImageGrayscale # feel free to change this

# 3x3 mean "box" filter
meanBoxFilter3x3 = np.array([[1/9, 1/9, 1/9],
                              [1/9, 1/9, 1/9],
                              [1/9, 1/9, 1/9],])

k = int((meanBoxFilter3x3Result.shape[0] - 1)/2.0) # calculate k

# We use scipy's signal library (just like we did in earlier parts of the course) but
# this time it's a 2D convolution rather than a 1D
meanBoxFilter3x3Result = signal.convolve2d(img, meanBoxFilter3x3, boundary='symm', mode='same')
plotFilteredImage(img, meanBoxFilter3x3Result, k, (180,410), (230,0))
```

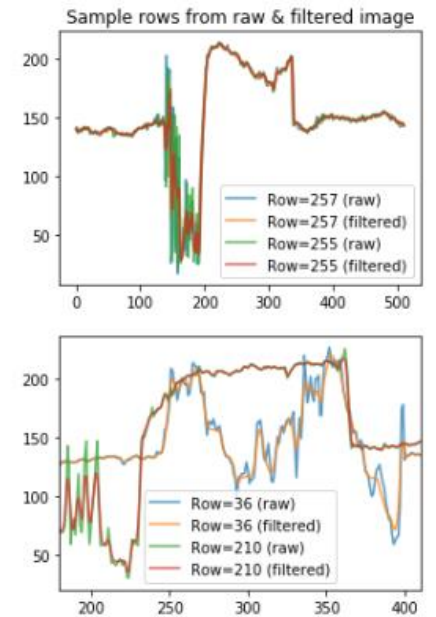
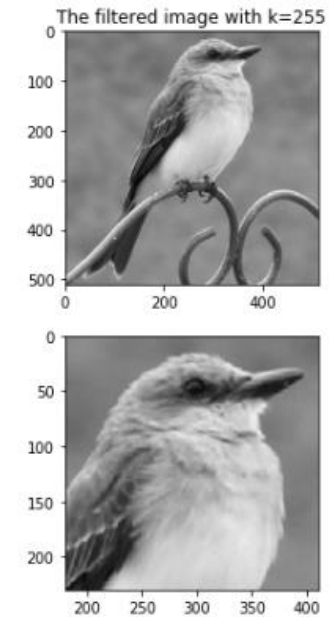
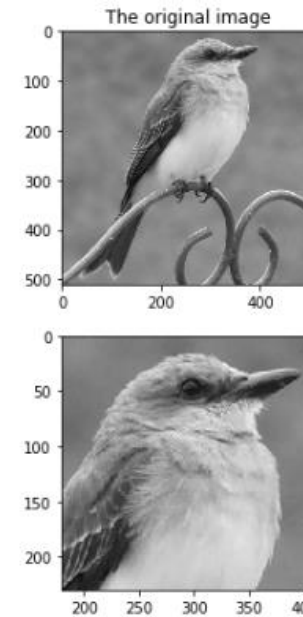


IMAGE FILTERING

VALIDATING OUR MANUAL 2D ALG VS. CONVOLUTION

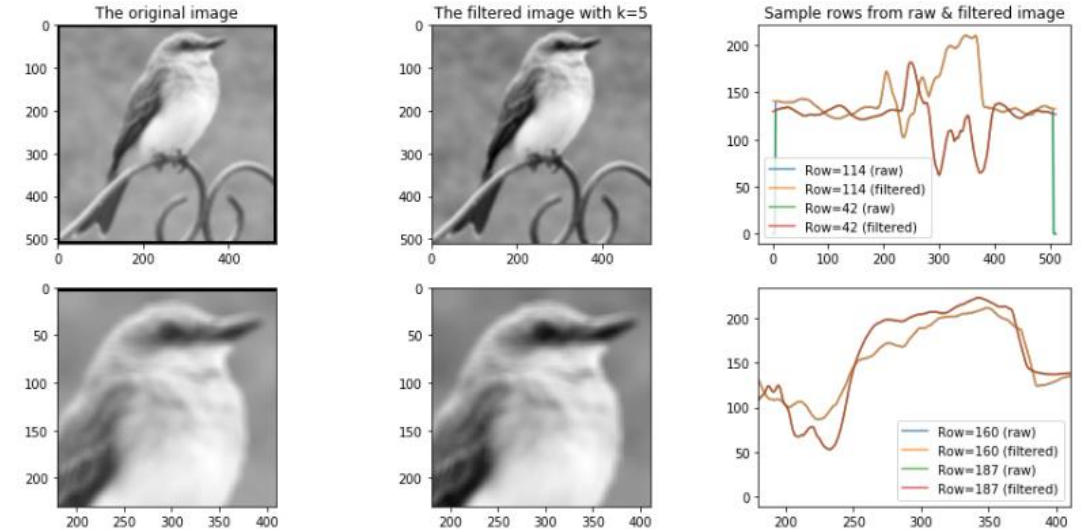
```
# Simple check between our own algorithm and convolution :)
k = 5
img = birdImageGrayscale
imageHeight, imageWidth = img.shape
manualSmoothedImage = np.full((imageHeight, imageWidth), 0, dtype=img.dtype)
slidingWindowDimension = (2 * k + 1)
numCellsInSlidingWindow = slidingWindowDimension ** 2 # numCells = (2k+1)^2
meanBoxFilter = np.full((slidingWindowDimension, slidingWindowDimension), 1 / numCellsInSlidingWindow)

# First manually smooth the image using a 2D sliding window
print("Smoothing with k={}, boxFilter.width={}, boxFilter.numCells={}".format(
    k, meanBoxFilter.shape[1], numCellsInSlidingWindow))
for j in range(k, imageHeight - k): # for each row
    for i in range(k, imageWidth - k): # and each column
        # get the matrix within our sliding window
        pixelsInWindow = img[j - k : j + k + 1, i - k : i + k + 1]
        avg = np.mean(pixelsInWindow)
        manualSmoothedImage[j,i] = avg

convolutionSmoothedImage = signal.convolve2d(img, meanBoxFilter, boundary='symm', mode='same')
print(manualSmoothedImage.shape)
print(convolutionSmoothedImage.shape)
# diffImage = manualSmoothedImage - convolutionSmoothedImage

# The titles of the plotted images are wrong (because we are not displaying raw and filtered
# but instead two filtered). Still, this let's us compare and verify that our manual alg works :)
# Because imshow auto-normalizes the images when it displays them, we have to turn this off
# the convolution image is going to look a bit darker (because the manually smoothed image
# has a border of intensity 0)
plotFilteredImage(manualSmoothedImage, convolutionSmoothedImage, k, (180,410), (230,0))
```

```
Smoothing with k=5, boxFilter.width=11, boxFilter.numCells=121
(512, 512)
(512, 512)
```



Note: these titles are wrong since both images are filtered but good enough for us to get a sense that things are working!

IMAGE FILTERING

CONVOLUTION EXERCISES IN JUPYTER NOTEBOOK

For smoothing

For edge detection

