Lecture Notes for Machine Learning in Python

Professor Eric Larson

Dimensionality and Images

Class Logistics and Agenda

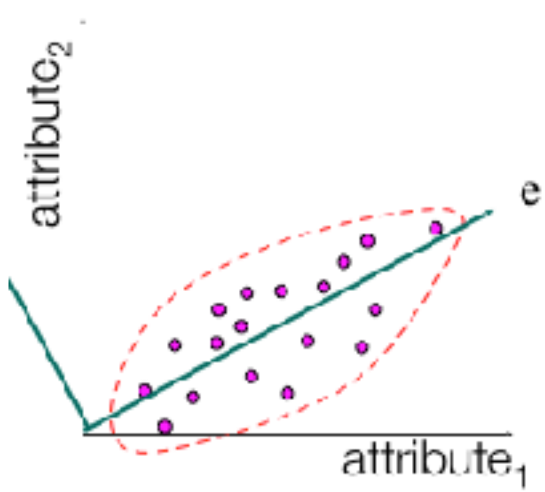
- Logistics:
  - Next lab due at the end of the week
  - Next time: no class if we finish everything today
- Agenda
  - Kernel Methods
  - Common Feature Extraction Methods for Images

Last time it was so linear…

E1
0.85
0.52

E2
0.85
-0.52

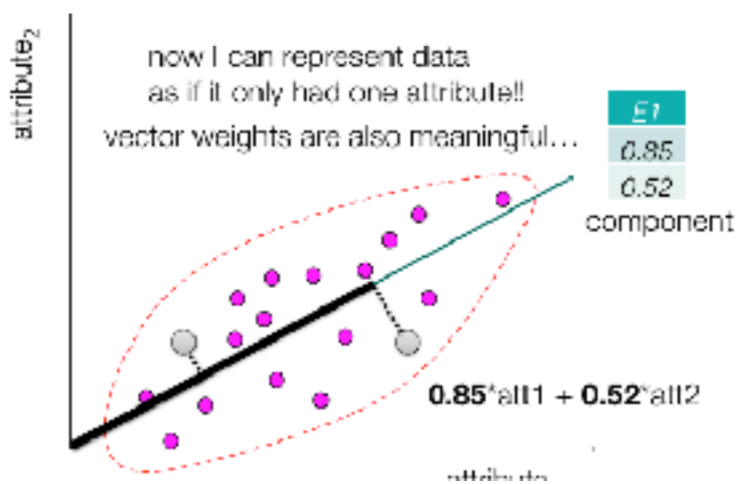
37.1	-6.7
-6.7	43.9



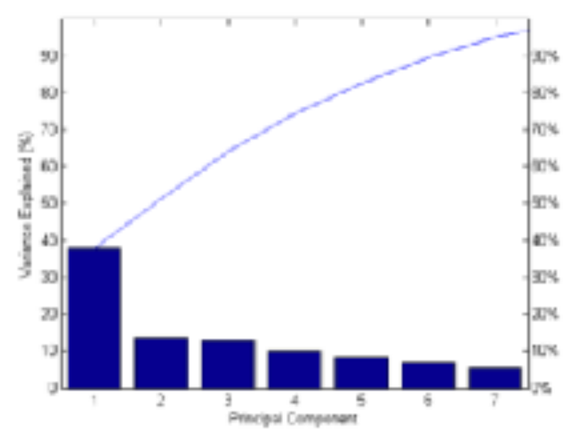
	A1	A2
1	66	33.6
2	54	26.6
3	69	23.3
4	73	28.1
5	61	43.1
6	62	25.6

	A1	A2
1	1.83	3.55
2	-10.1	-3.45
3	4.83	-6.75
4	8.83	-1.95
5	-3.17	13.05
6	-2.17	-4.45

zero mean



$$r_q = \frac{\sum_{j=1}^{q} \lambda_j}{\sum_{j=1}^{p} \lambda_j}$$



04.Dimension Reduction and Images.ipynb

Demo

Dimension Reduction

PCA

biplots

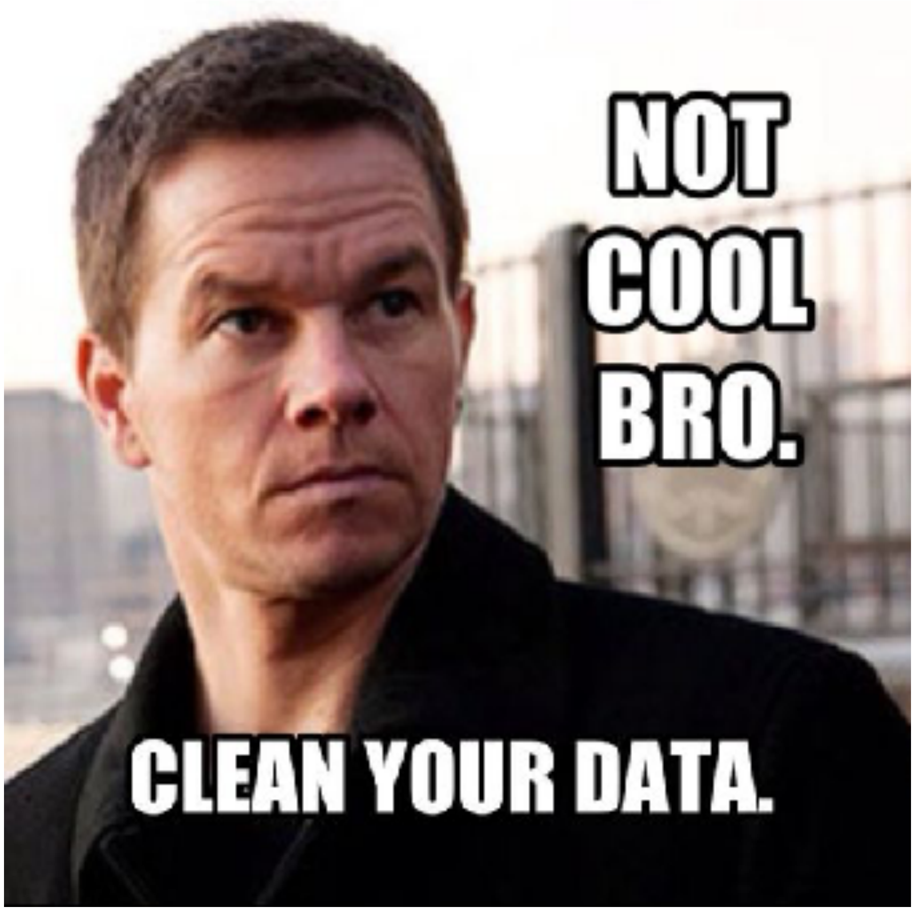
Other Tutorials:

http://scikit-learn.org/stable/auto_examples/decomposition/plot_pca_vs_lda.html#example-decomposition-plot-pca-vs-lda-py

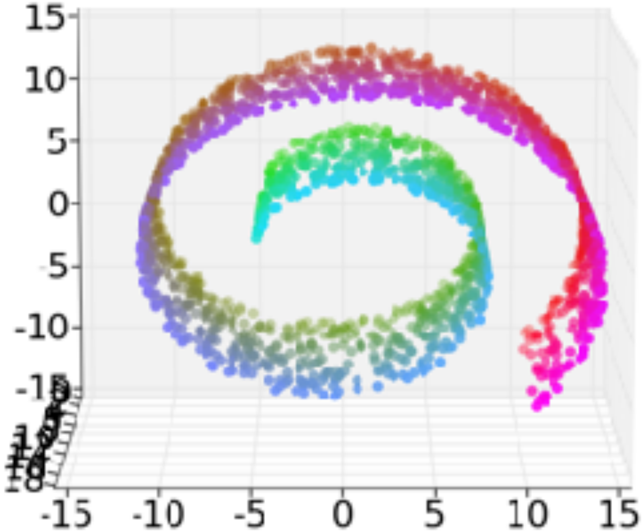
http://nbviewer.ipython.org/github/ogrisel/notebooks/blob/master/Labeled%20Faces%20in%20the%20Wild%20recognition.ipynb

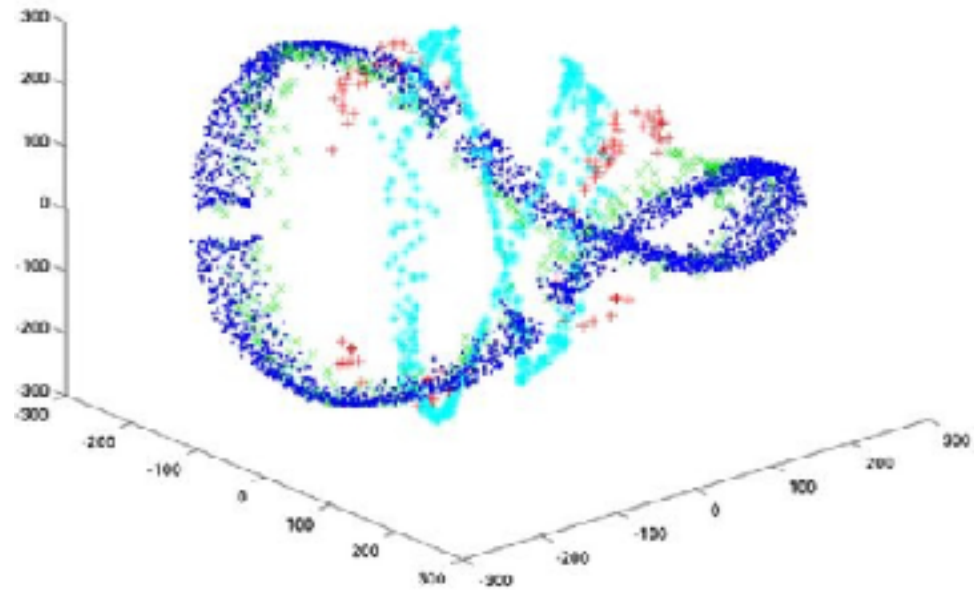
section 2: screen moved down

Non-linear Dimensionality Reduction



Dimensionality Reduction: non-linear

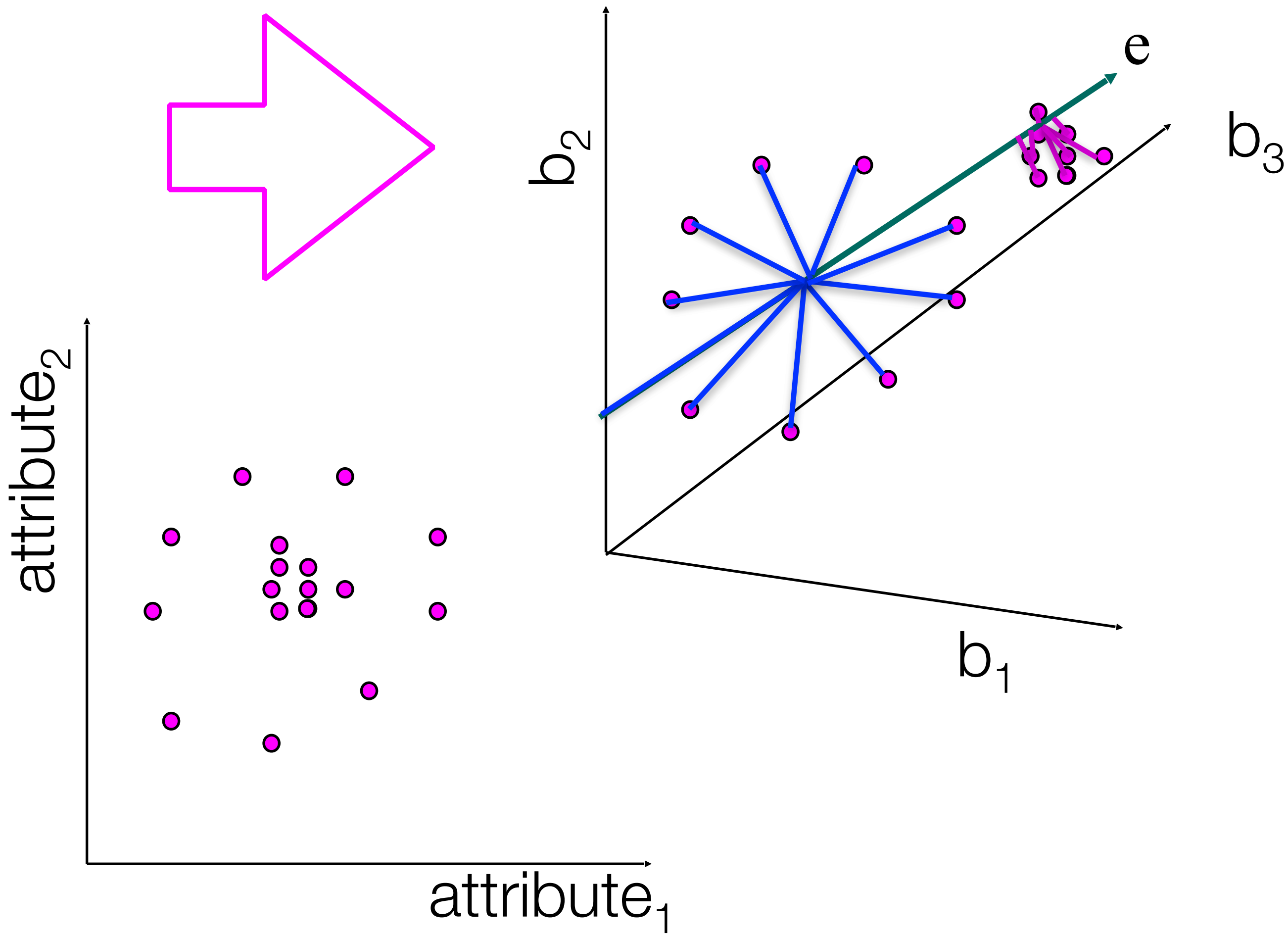




- Sometimes a **linear transform** is not enough
- A powerful non-linear transform has seen a resurgence in past decade: **kernel PCA**

Kernel PCA

- Project to higher dimensional space
- Employ principal components
- Apply transform in higher dimensional space



37.1	-6.7	-3.2
-6.7	43.9	1.45
-3.2	1.45	12.1

	B1	B2	B3
1	66	33.6	0.3
2	54	26.6	0.4
3	69	23.3	-4
4	73	28.1	-5.6
5	61	43.1	0.23
6	62	25.6	-5

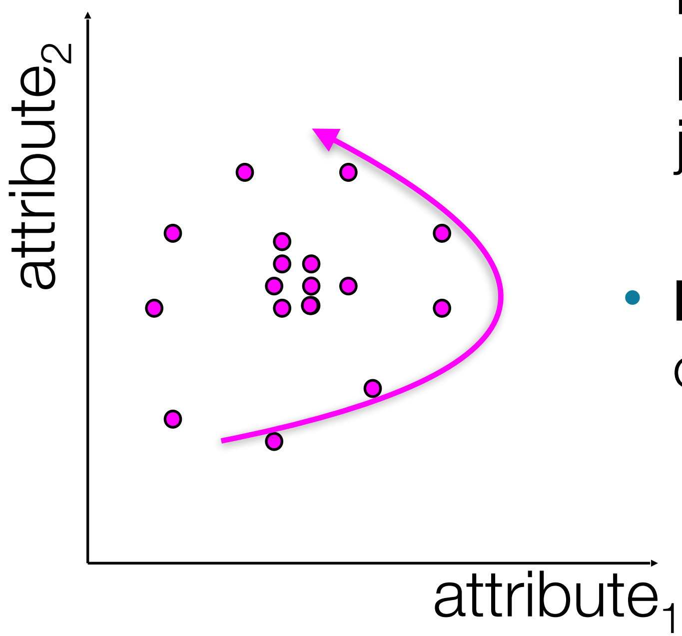
Kernel PCA

kernel: defines what the dot product is in higher dimensional space

some kernels have corresponding transformations with **infinite dimensions**!!

- **Key insight**: don't need to know the actual principle components, just the projections

- **Never need** eigen vectors or covariance matrix



37.1	-6.7	-3.2
-6.7	43.9	1.45
-3.2	1.45	12.1

	B1	B2	B3
1	66	33.6	0.3
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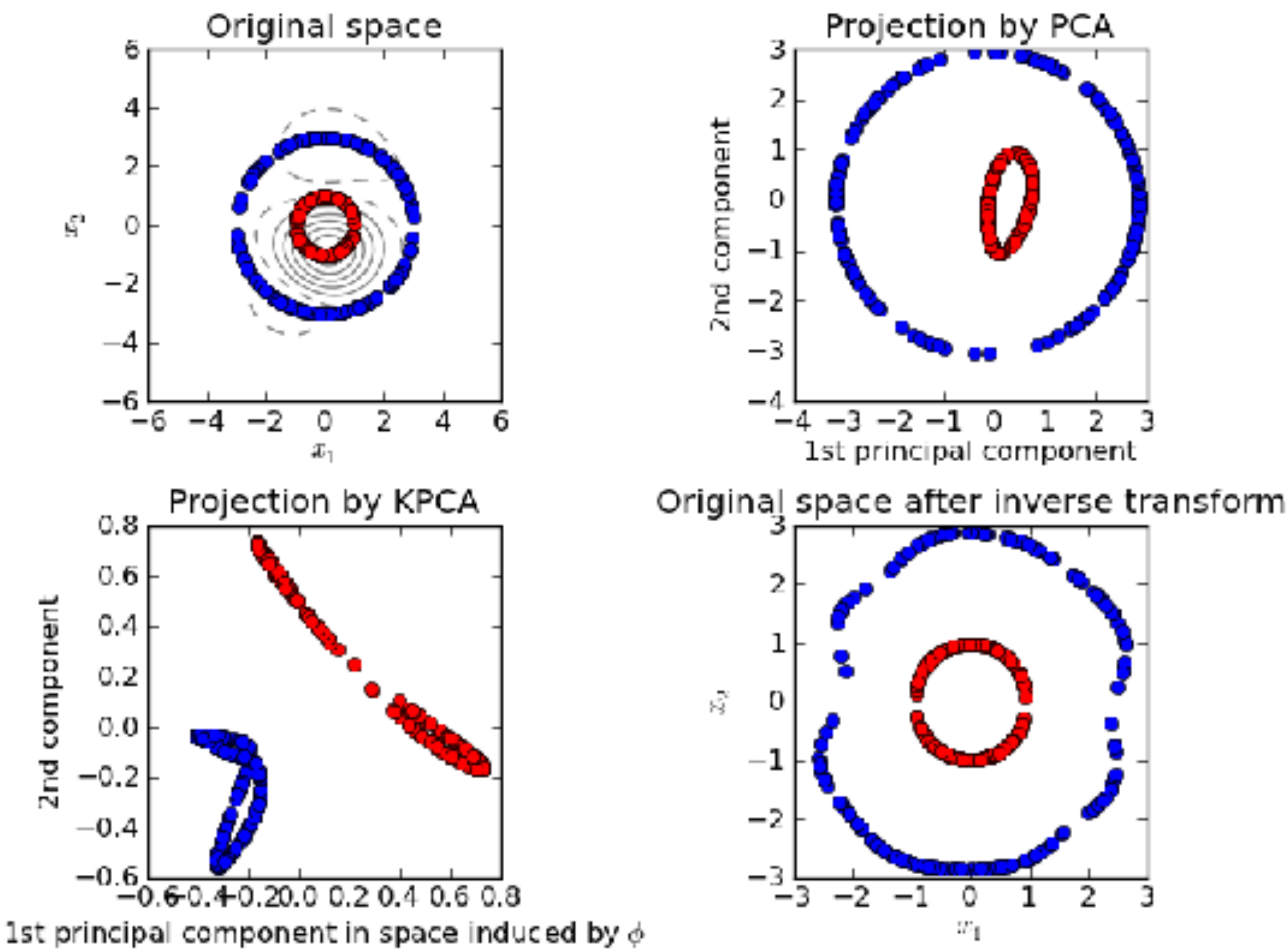
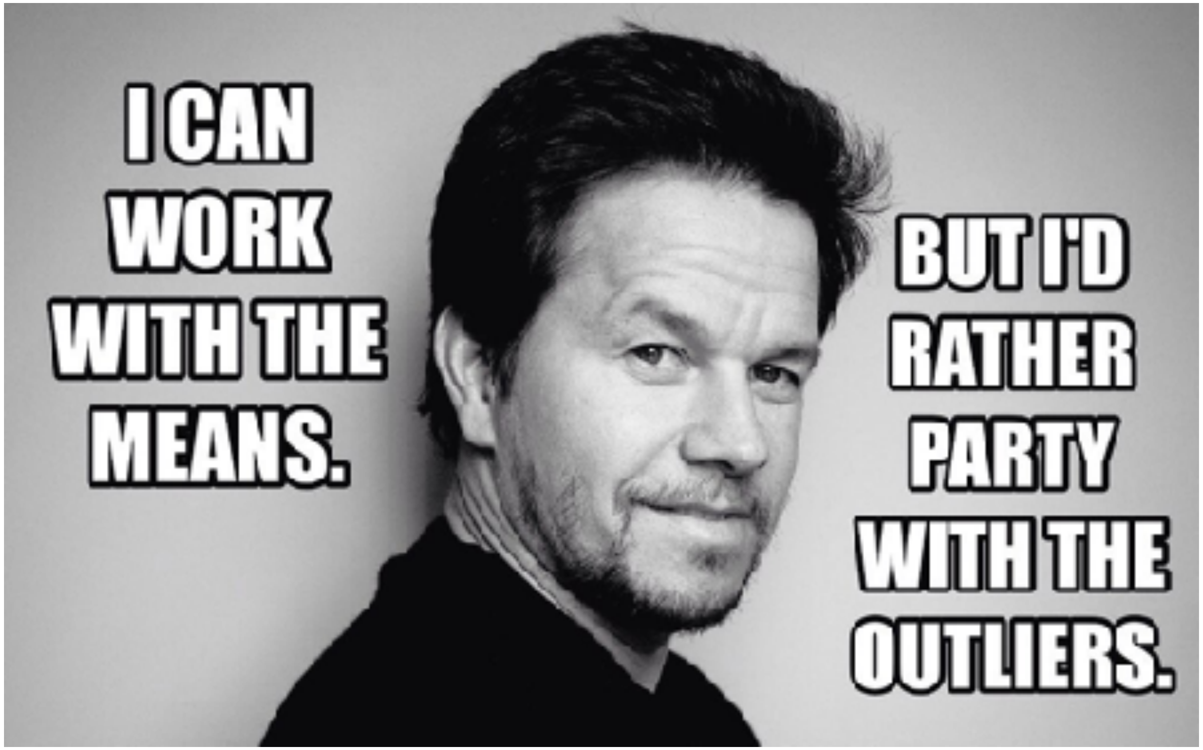
3	69	23.3	-4
4	73	28.1	-5.6
5	61	43.1	0.23
6	62	25.6	-5

Kernel PCA



Original space
Projection by PCA
1st principal component
2nd component
Projection by KPCA
1st principal component in space induced by ϕ
2nd component
Original space after inverse transform

Image Processing and Representation

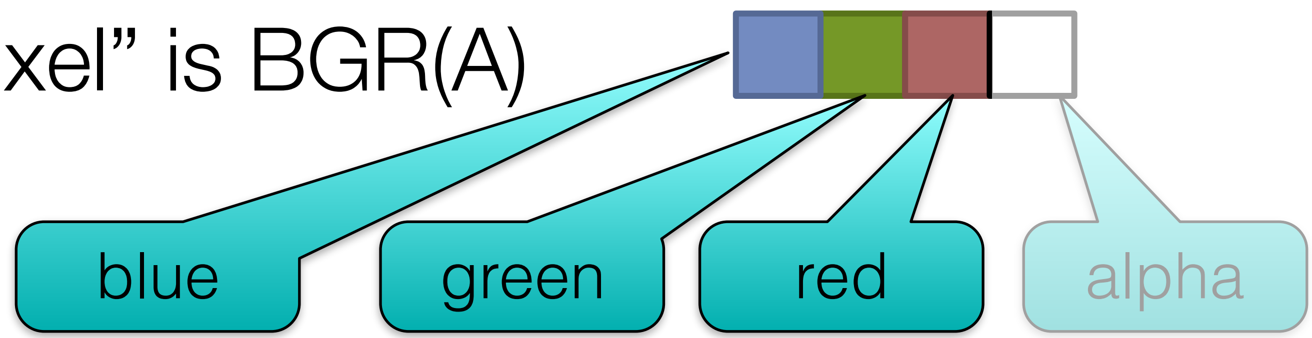


What is image processing

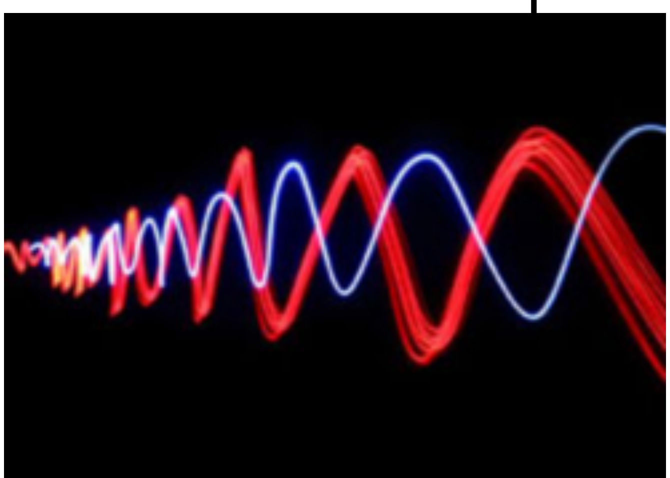
- the **art** and **science** of manipulating pixels
  - combining images (blending or compositing)
  - enhancing edges and lines
  - adjusting contrast, color
  - warping, transformation
  - filtering
  - features extraction

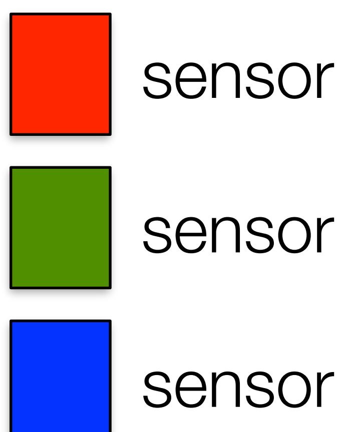
Images as data

- an image can be represented in many ways
- most common format is a matrix of pixels
    - each “pixel” is BGR(A)



- used for capture and display





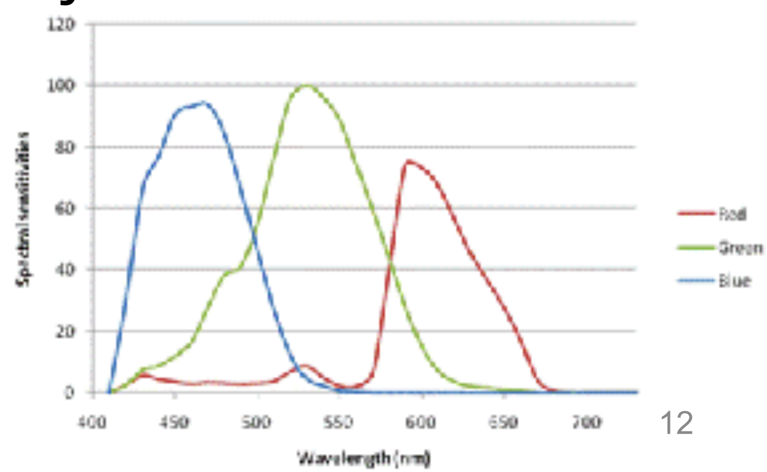


Image Representation

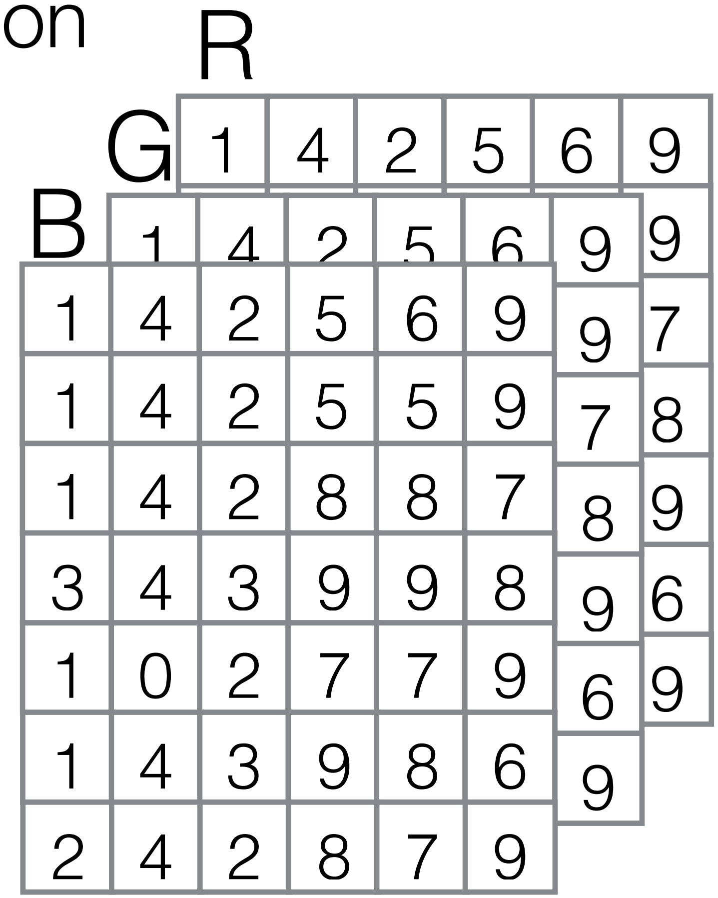
- need a compact representation

- **grayscale**
  $0.3*R+0.59*G+0.11*B$,
  "luminance"

gray

1	4	2	5	6	9
1	4	2	5	5	9
1	4	2	8	8	7
3	4	3	9	9	8
1	0	2	7	7	9
1	4	3	9	8	6
2	4	2	8	7	9

Numpy Matrix
image[rows, cols]



Numpy Matrix
image[rows, cols, channels]

Image Representation, Features

Problem: need to represent image as table data

1	4	2	5	6	9
1	4	2	5	5	9
1	4	2	8	8	7
3	4	3	9	9	8
1	0	2	7	7	9
1	4	3	9	8	6
2	4	2	8	7	9

Image Representation, Features

Problem: need to represent image as table data

Solution: row concatenation

Row 1	1	4	2	5	6	9	1	4	2	5	5	9	1	4	2	8	8	7	3
Row 2	1	4	2	8	8	7	3	4	3	9	9	8	1	4	2	5	5	9	1
…																			
Row N	9	4	6	8	8	7	4	1	3	9	2	1	1	5	2	1	5	9	1

Self test: 3a-1

- When vectorizing images into table data, each feature column corresponds to:
  - a. the value (color) of pixel
  - b. the spatial location of a pixel in the image
  - c. the size of the image
  - d. the spatial location and color channel of a pixel in an image

Demo

Dimension Reduction with Images

- Images Representation
- Randomized PCA
- Kernel PCA

`04.Dimension Reduction and Images.ipynb`

Features of Images

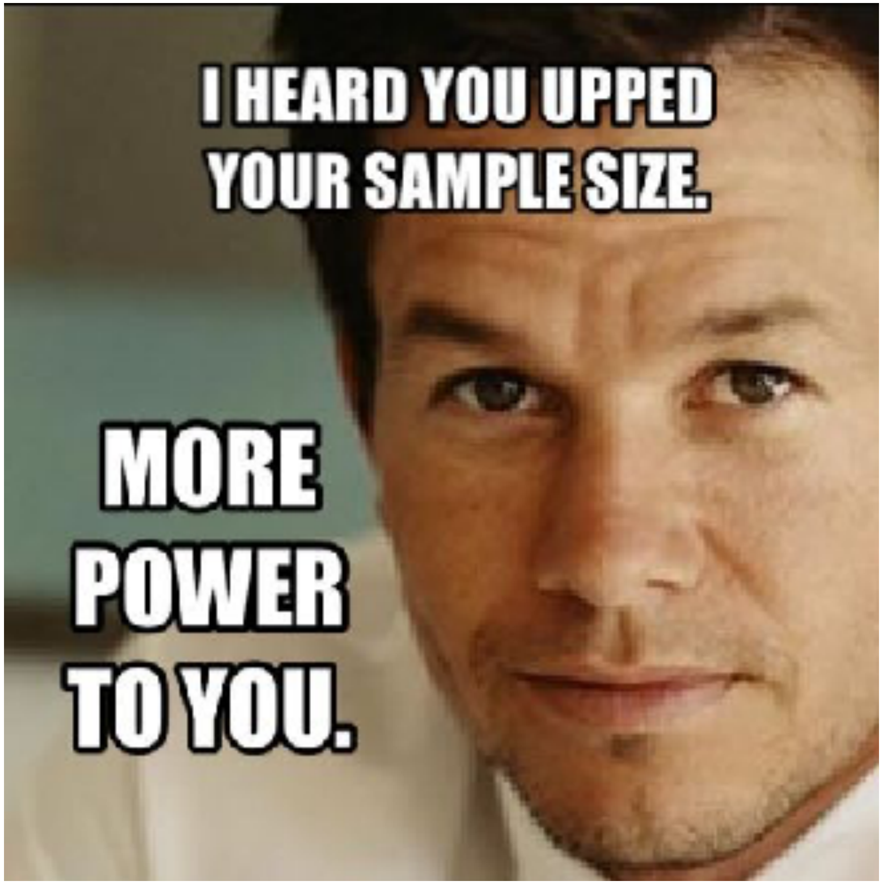
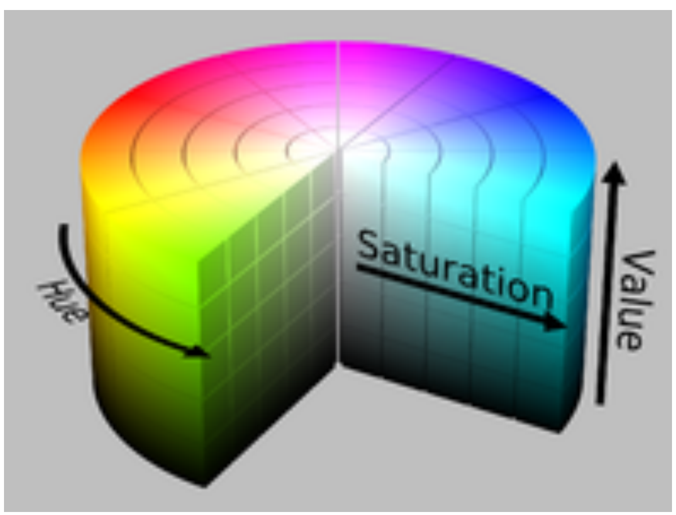
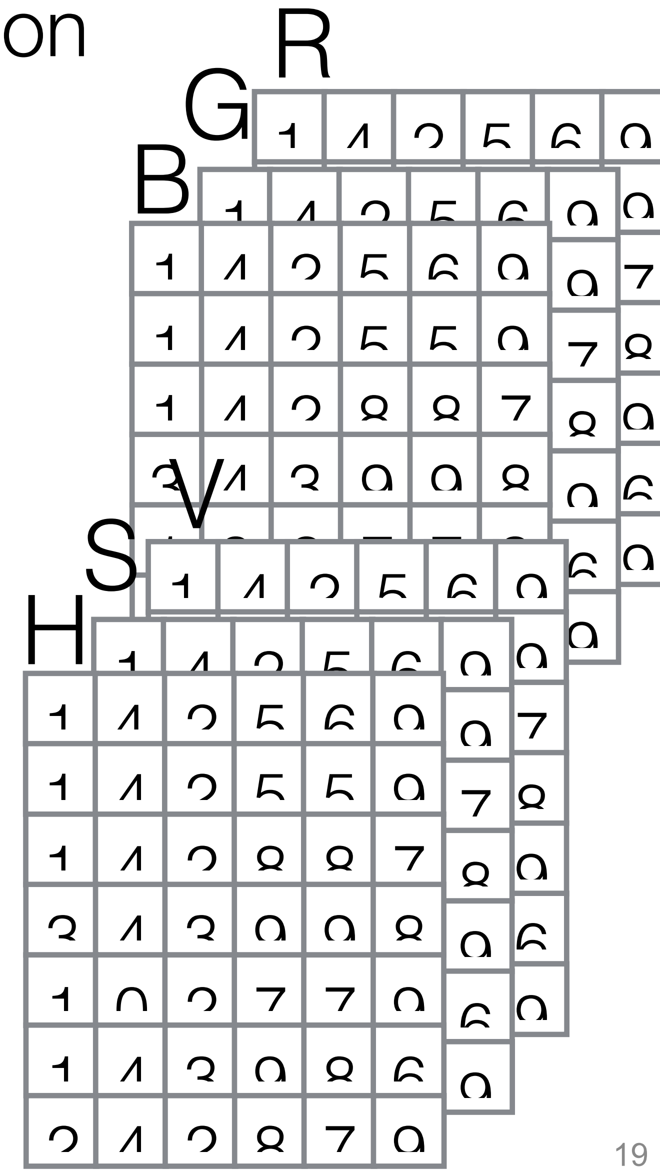


Image Representation

- need a compact representation

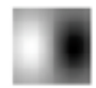
- **hsv**
  - what we perceive as color (ish)
    - hue: the color value
    - saturation: the richness of the color relative to brightness
    - value: the gray level intensity

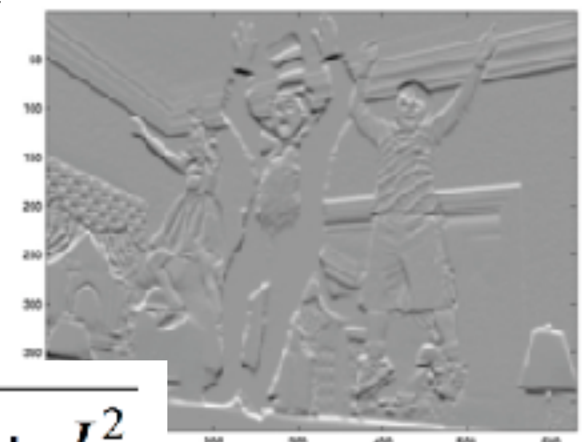




Common operations

- the gradient (2D derivative)



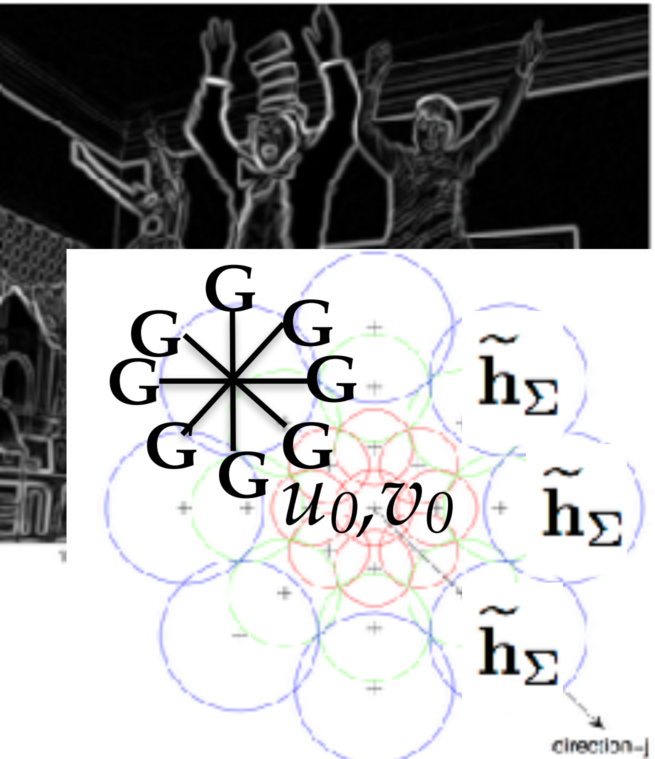


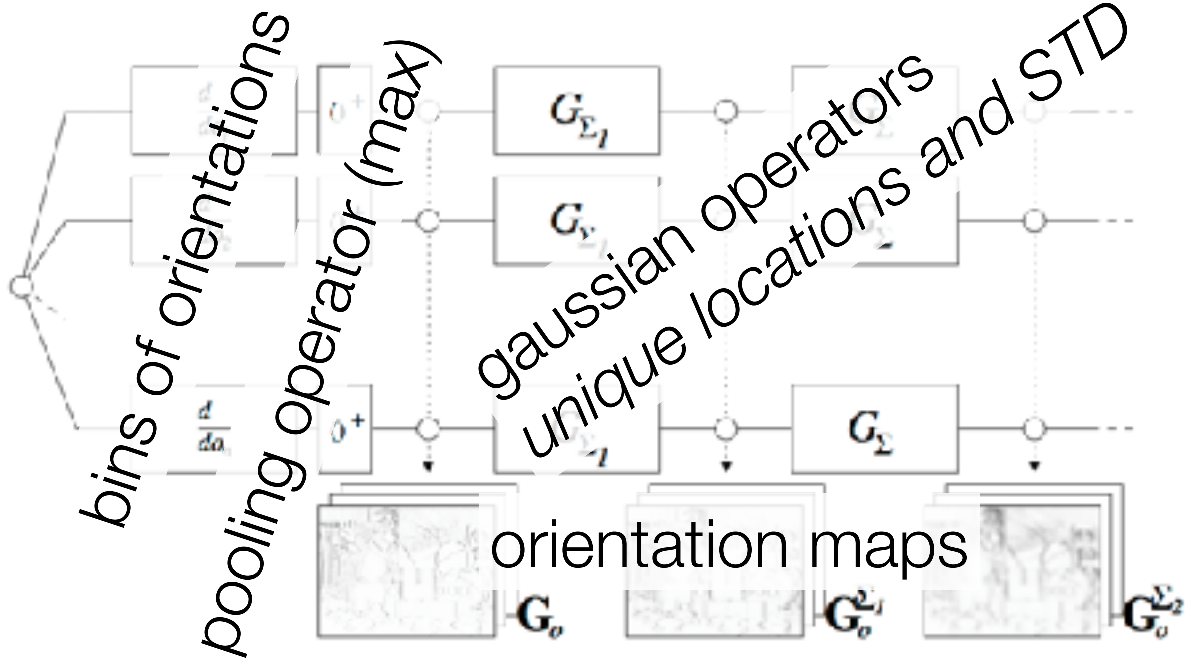
$$\|\nabla J\| = \sqrt{J_x^2 + J_y^2}$$

$$O = \tan^{-1}(Jx / Jy)$$

images: Jianbo Shi, Upenn

Common operations: DAISY





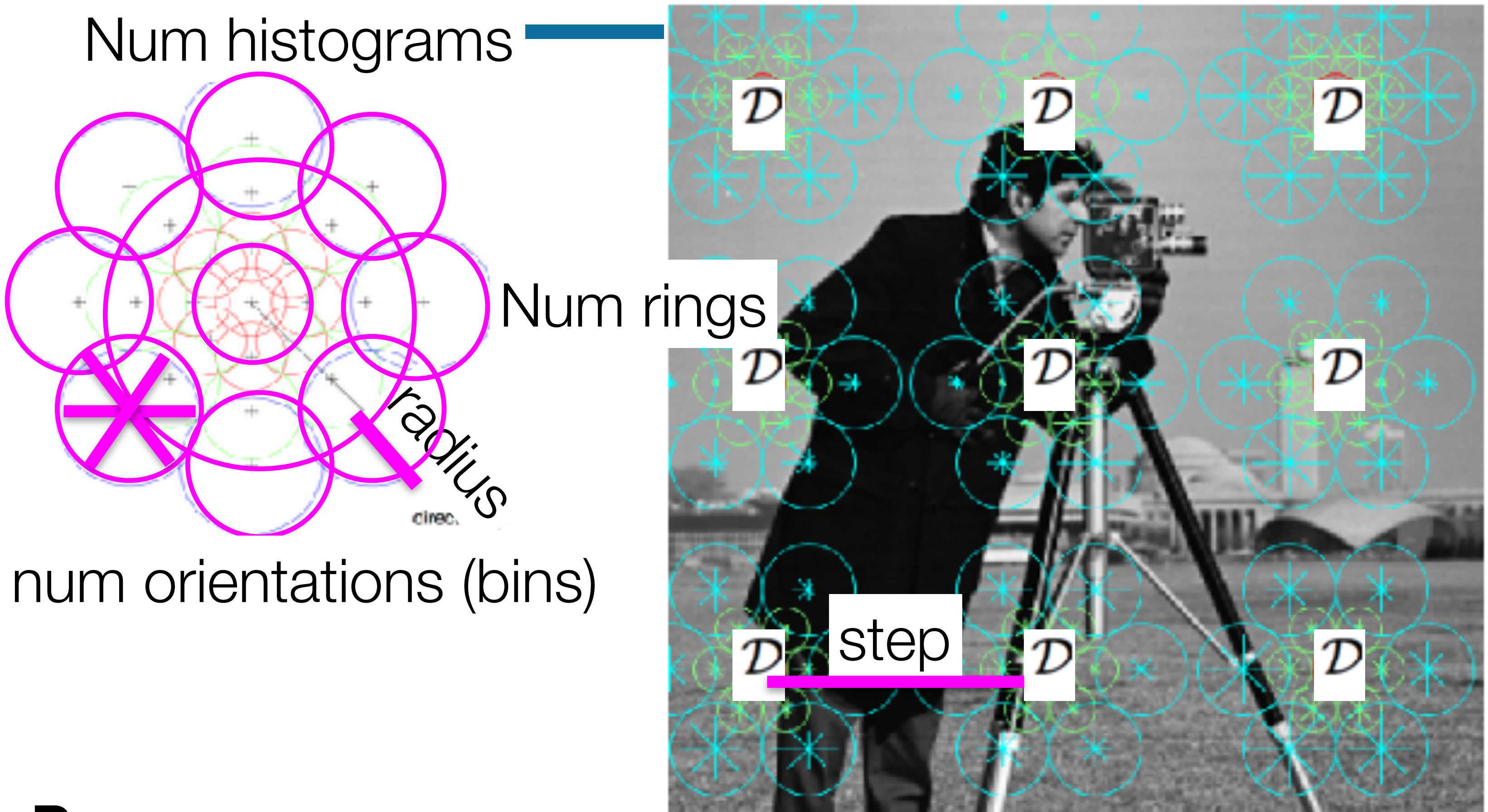
take normalized histogram at point u,v

$$\tilde{\mathbf{h}}_\Sigma(u,v) = \left\| \left[\mathbf{G}_1^\Sigma(u,v), \ldots, \mathbf{G}_H^\Sigma(u,v) \right]^\top \right\|$$

$$\begin{aligned}
\mathcal{D}(u_0, v_0) = \\
\Big[\quad & \tilde{\mathbf{h}}_{\Sigma_1}^\top(u_0, v_0), \\
& \tilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_1(u_0, v_0, R_1)), \cdots, \tilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_T(u_0, v_0, R_1)), \\
& \tilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_1(u_0, v_0, R_2)), \cdots, \tilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_T(u_0, v_0, R_2)), \\
& \ldots
\end{aligned}$$

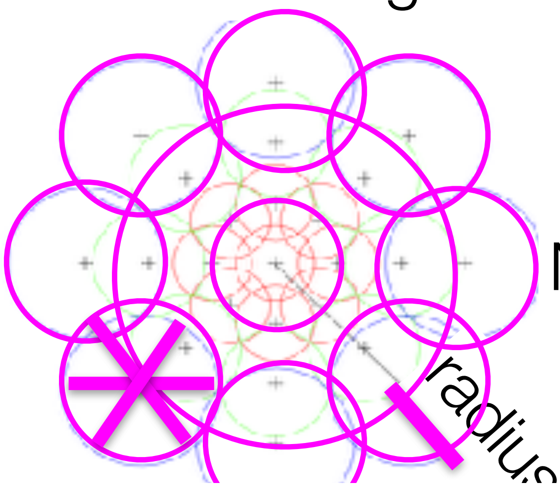
Tola et al. “Daisy: An efficient dense descriptor applied to wide-baseline stereo.” Pattern Analysis and Machine Intelligence, IEEE Transactions

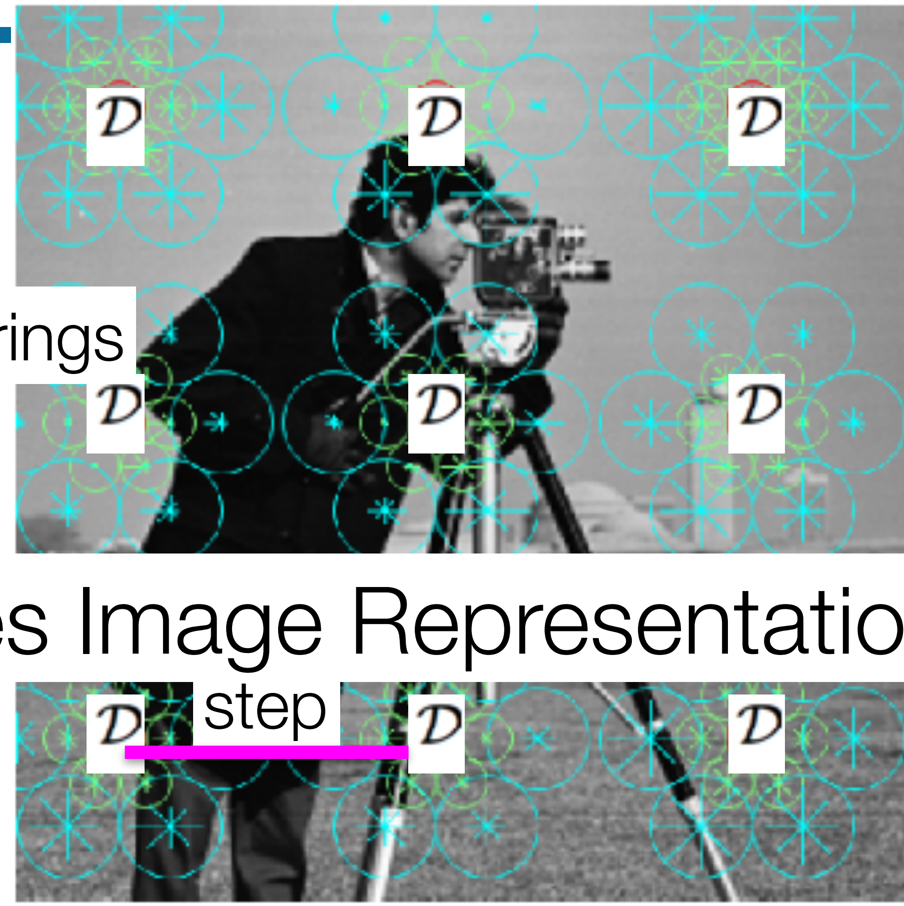
Common operations: DAISY



Params:
step, radius, num rings,
num histograms per ring,
orientations per histogram

Common operations: DAISY





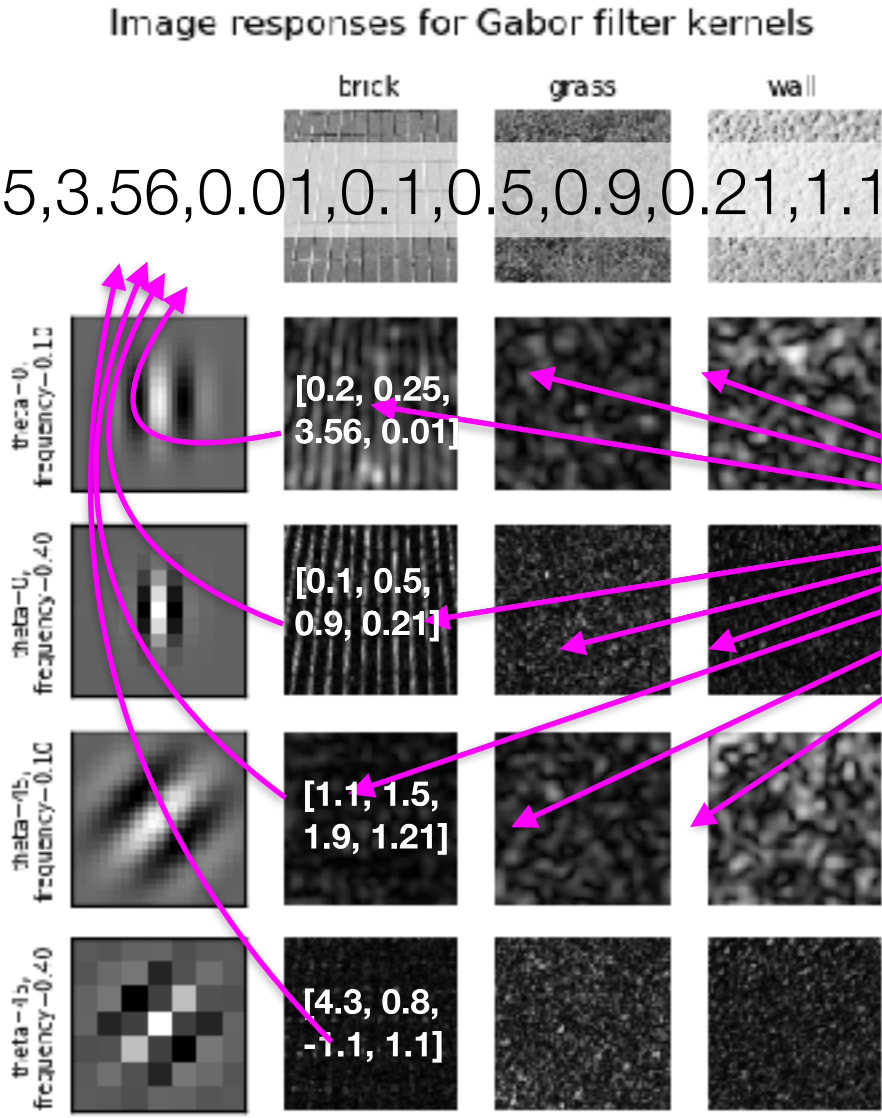
num Bag of Features Image Representation

Params:
step, radius, num rings,
num histograms per ring,
orientations per histogram

Common operations: Gabor filter Banks (if time)

- common used for texture classification

[0.2,0.25,3.56,0.01,0.1,0.5,0.9,0.21,1.1,1.5,1.9,1.21,4.3,0.8,-1.1,1.1]



mean
std
skew
kurtosis

Concatenate statistics of different filters into one feature vector

More Image Processing

- Gradients
- DAISY
- Gabor Filter Banks

Other Tutorials:

http://scikit-image.org/docs/dev/auto_examples/

For Next Lecture

- Work on your text datasets!
- **Next Time**: No Class, Project work day
- **Next Week**: In-Class Assignment One!!!