

Practice (Python+OpenCV)

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Python3

- Python3.5+
- Array operation:
 - NumPy → pip3 install numpy
- Image processing:
 - OpenCV → pip3 install opencv-python
 - Pillow → pip3 install Pillow

Python Grammar

- Tutorial
 - <http://cs231n.github.io/python-numpy-tutorial/>
- Google it

NumPy

- NumPy is the fundamental package for scientific computing with Python. It provides containers and efficient tools to deal with multi-dimensional arrays.
- Tutorial
 - <http://cs231n.github.io/python-numpy-tutorial/>

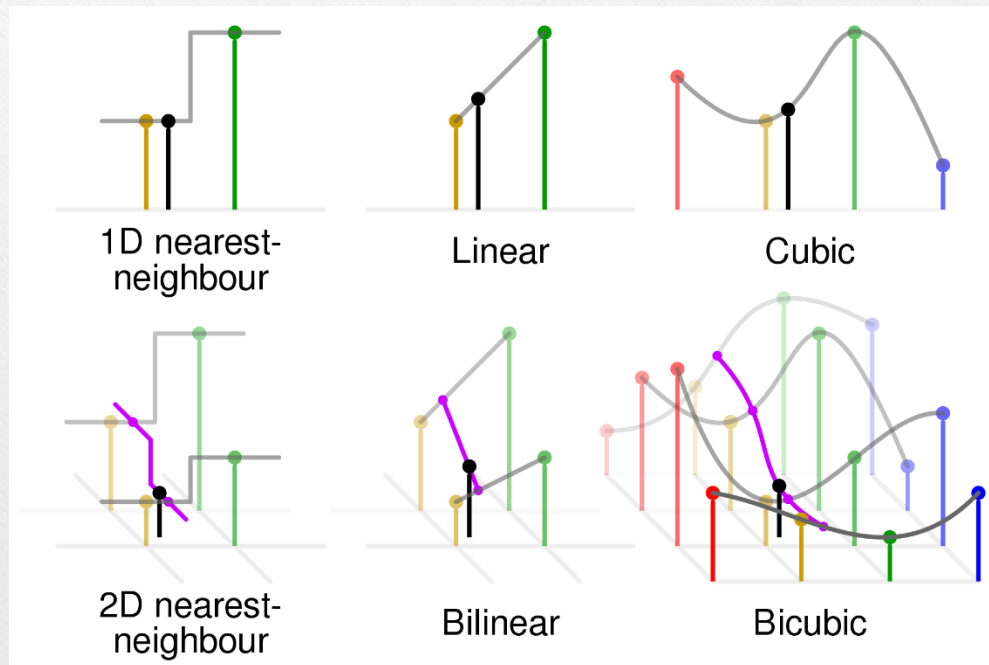
CV in Python

- OpenCV:
 - Popular library for computer vision application in C++ and python.
 - <https://opencv-python-tutroals.readthedocs.io/en/latest/>
- Pillow
 - PIL (Python Image Library) fork
 - <https://pillow.readthedocs.io/en/stable/>

Lab1

- Image operation
- Image smoothing
- Image denoising
- Image PCA analysis

Interpolation



Color Space

- Organization of colors
 - RGB
 - YCbCr (Y: luminance, Cb, Cr: chrominance)
 - LAB
 - HSV (hue, saturation, value)

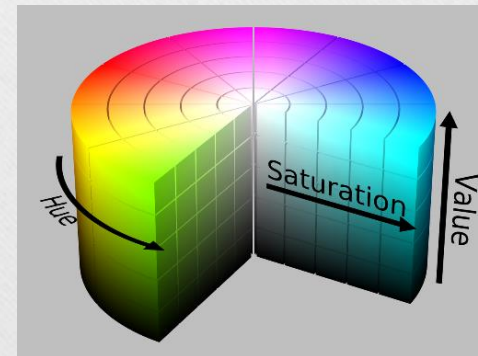
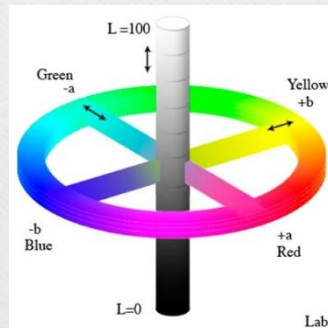
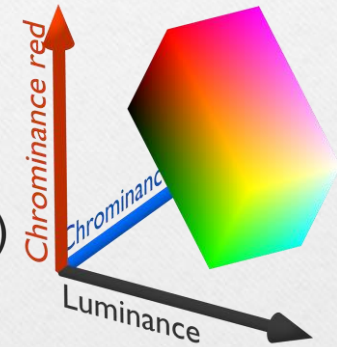


Image Filtering

- Convolution

$$g(x, y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h(i, j) f(x - i, y - j)$$

$$W = \sum_{i,j \in [-r,r]} h(i, j)$$

45	60	98	127	132	133	137	133
46	65	98	123	126	128	131	133
47	65	96	115	119	123	135	137
47	63	91	107	113	122	138	134
50	59	80	97	110	123	133	134
49	53	68	83	97	113	128	133
50	50	58	70	84	102	116	126
50	50	52	58	69	86	101	120

$f(x,y)$

*

0.1	0.1	0.1
0.1	0.2	0.1
0.1	0.1	0.1

$h(x,y)$

=

69	95	116	125	129	132
68	92	110	120	126	132
66	86	104	114	124	132
62	78	94	108	120	129
57	69	83	98	112	124
53	60	71	85	100	114

$g(x,y)$

Image Filtering

- Box filtering (average filtering)

$$h(i, j) = \frac{1}{r^2}$$

$$g(x, y) = \frac{1}{r^2} \sum_{i, j \in [-r, r]} f(x - i, y - j)$$

Image Filtering

- Gaussian filtering

$$h(i, j) = e^{-\frac{i^2 + j^2}{2\sigma^2}}$$

Original Image

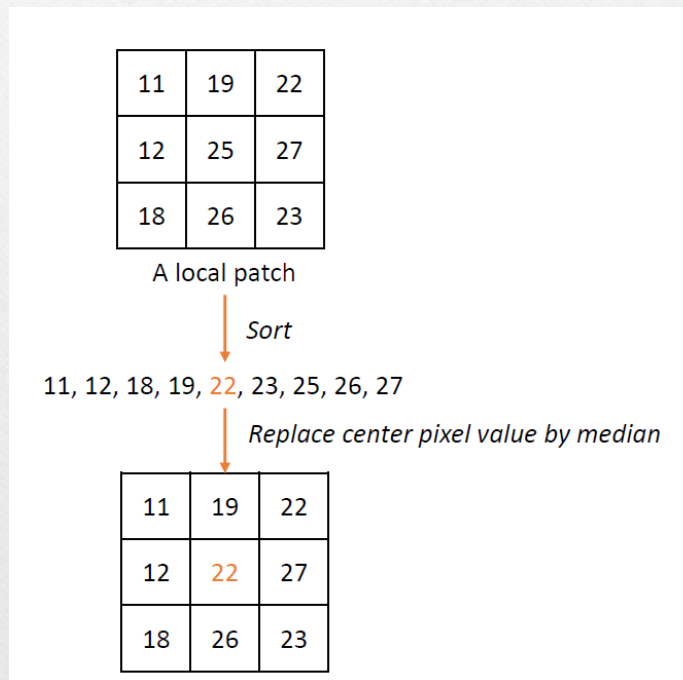


Gaussian filtered image, $\sigma = 2$



Image Filtering

- Median filtering
 - 3*3 example:



Noise



original



Gaussian noise



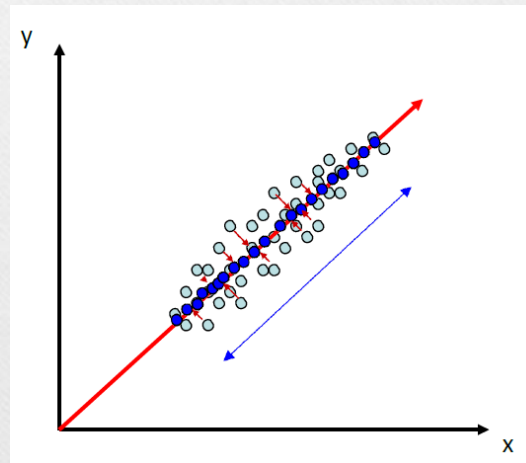
Salt and pepper noise

Lab1

- Image operation
 - Resize: down-sample, up-sample with different interpolation methods
 - Color conversion: RGB (BGR) to YCbCr
- Image smoothing
 - Averaging, Gaussian filtering, median filtering
- Image denoising
 - Add noise: Gaussian noise, salt and pepper noise
 - Denoise: Gaussian filtering, median filtering

Principal Component Analysis

- Unsupervised & linear dimension reduction
- Goal: determine the projection to maximize the variation of projected data



Formulation & Derivation for PCA

- Input: a set of instances \mathbf{x} (N instances)
- Output: a projection vector \mathbf{w} maximizing the variance of the projected data

$$\max_w E[(w^T x - w^T \mu)^2], \quad \|w\|_2 = 1, \quad \mu = \sum_{i=1}^N x_i$$

$$w \in \mathbb{R}^d, \quad x_i \in \mathbb{R}^d, \quad \forall i \in \{1, \dots, N\}$$

Formulation & Derivation for PCA

- $$\begin{aligned} E[(w^T x - w^T \mu)^2] &= E[(w^T x - w^T \mu)(x^T w - \mu^T w)] \\ &= w^T E[(x - \mu)(x - \mu)^T] w \\ &= w^T \Sigma w \end{aligned}$$

- Covariance matrix

$$\Sigma = \frac{1}{N} \sum_{i=1}^N \{(x_i - \mu)(x_i - \mu)^T\}$$

Formulation & Derivation for PCA

- Cont'd

$$\max_w w^T \Sigma w, \quad \|w\|_2 = 1$$

- Lagrangian multiplier

$$J(w) = w^T \Sigma w - \lambda(w^T w - 1)$$

$$\Rightarrow \frac{\partial J}{\partial w} = 2\Sigma w - 2\lambda w = 0$$

$$\Rightarrow w^T \Sigma w = \lambda w^T w = \lambda$$

Eigenanalysis & PCA

- Eigen decomposition

$$\Sigma W = W \Lambda \Rightarrow \Sigma = W \Lambda W^{-1} = W \Lambda W^T = \sum_{i=1}^d \lambda_i w_i w_i^T$$

- Next principle component

$$\begin{aligned} E[(w^T(1 - w_1 w_1^T)(x - \mu))^2] &= w^T(1 - w_1 w_1^T)\Sigma(1 - w_1 w_1^T)w \\ &= w^T(\Sigma - w_1 w_1^T \Sigma - \Sigma w_1 w_1^T + w_1 w_1^T \Sigma w_1 w_1^T)w \\ &= w^T(\Sigma - w_1 w_1^T \lambda_1 - \lambda_1 w_1 w_1^T + w_1 \lambda_1 w_1^T)w \\ &= w^T(\Sigma - \lambda_1 w_1 w_1^T)w \end{aligned}$$

Eigenanalysis & PCA

- Covariance matrix

$$\Sigma = \frac{1}{N} \sum_{i=1}^N \{(x_i - \mu)(x_i - \mu)^T\}$$

- Rank = N-1 (if $d > N-1$)
 - $\rightarrow \dim(\text{Null space}) = d - (N-1)$
 - \rightarrow at most N-1 non-zero eigenvalues

$$\begin{aligned} x_j - \mu &= \sum_{i=1}^d a_i w_i \\ &= \sum_{i=1}^{N-1} a_i w_i \end{aligned}$$

Eigenanalysis & PCA

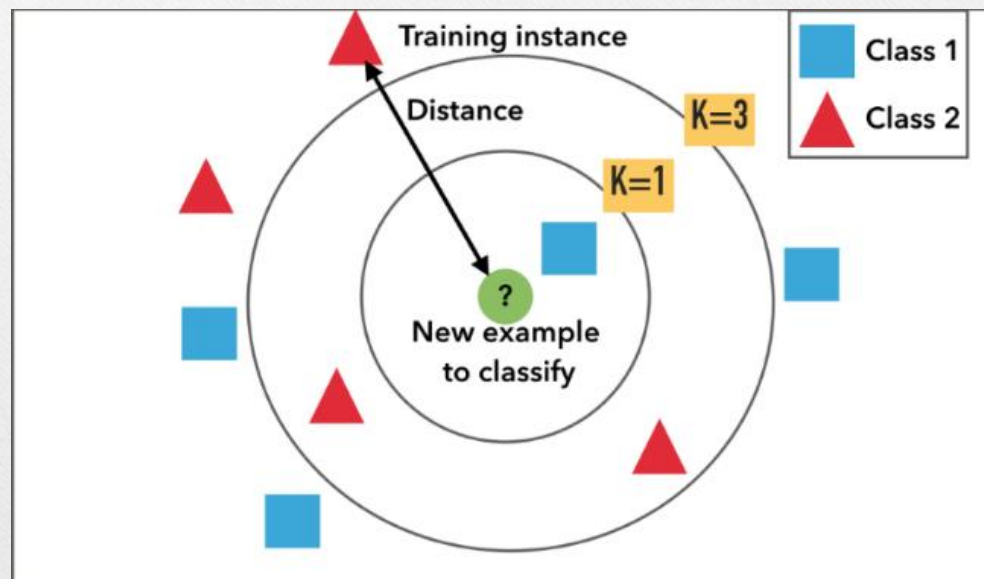
- Covariance matrix is symmetric
 - \rightarrow eigenvectors are orthogonal
 - \rightarrow span the instances with eigenvectors
- Less bases \rightarrow larger reconstruction error

$$\begin{aligned}w_j^T (x_k - \mu) &= w_j^T \sum_{i=1}^{N-1} a_i w_i \\&= \sum_{i=1}^{N-1} a_i \delta_{ij} \\&= a_j\end{aligned}$$

$$\begin{aligned}x_j - \mu &= \sum_{i=1}^{N-1} a_i w_i \\&\simeq \sum_{i=1}^n a_i w_i\end{aligned}$$

KNN Classifier

- k-nearest neighbors classifier



Lab1

- Image PCA analysis
 - 40 classes, 10 images for each class (6 train, 4 test)
 - $N = 6 \times 40$, $d = 56 \times 46$
 - Dim reduction: $n = 3$ or 100
 - KNN classifier: $k = 1$ or 3

$$x_i \in \mathbb{R}^d$$

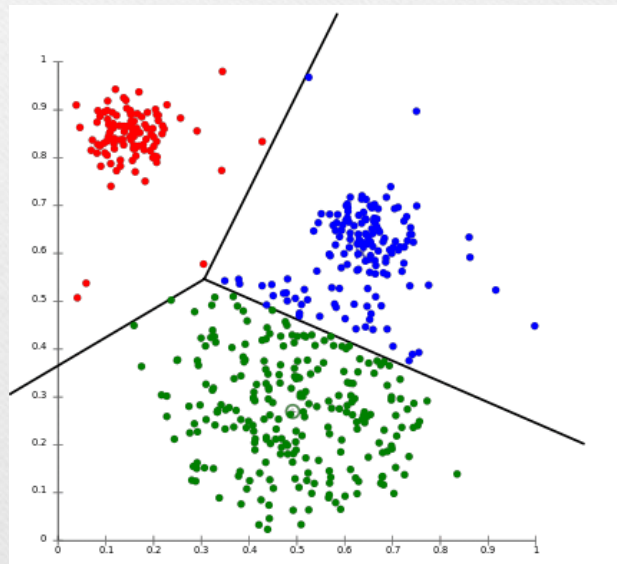
$$\begin{aligned} x_j - \mu &= \sum_{i=1}^{N-1} a_i w_i \\ &\simeq \sum_{i=1}^n a_i w_i \end{aligned}$$

Lab2

- Color segmentation
- Texture segmentation
- Feature descriptor
- Recognition with bag of visual words

K-means Clustering

- Group the data into k groups and minimize the sum of distances between data and corresponded group center (mean of each group)



K-means Clustering

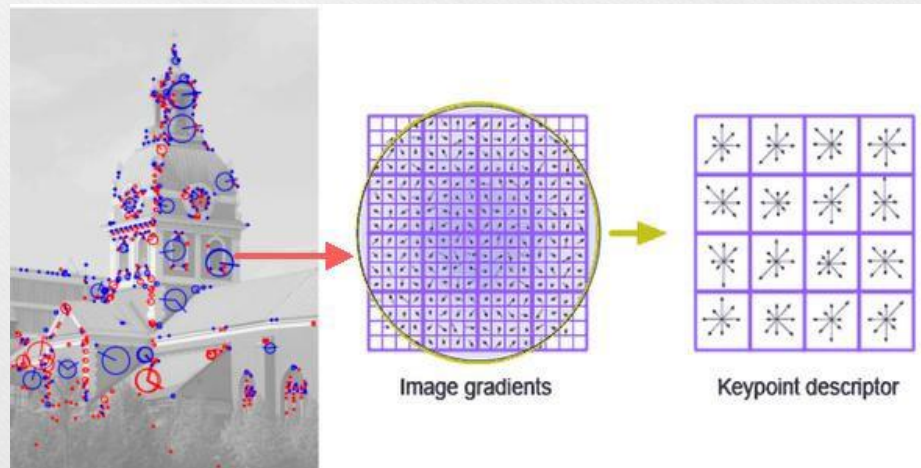
- Hard coding dictionary learning
 - D : group centers, α : belong to which group

$$\min_{D, \{\alpha_i\}} \sum_{i=1}^N \|x_i - D\alpha_i\|_2, \text{ s.t. } \|\alpha_i\|_0 = 1, \|\alpha_i\|_1 = 1, \forall i \in \{1, \dots, N\}$$

$$D \in \mathbb{R}^{d \times k}, x_i \in \mathbb{R}^d, \alpha_i \in \mathbb{R}^k, \forall i \in \{1, \dots, N\}$$

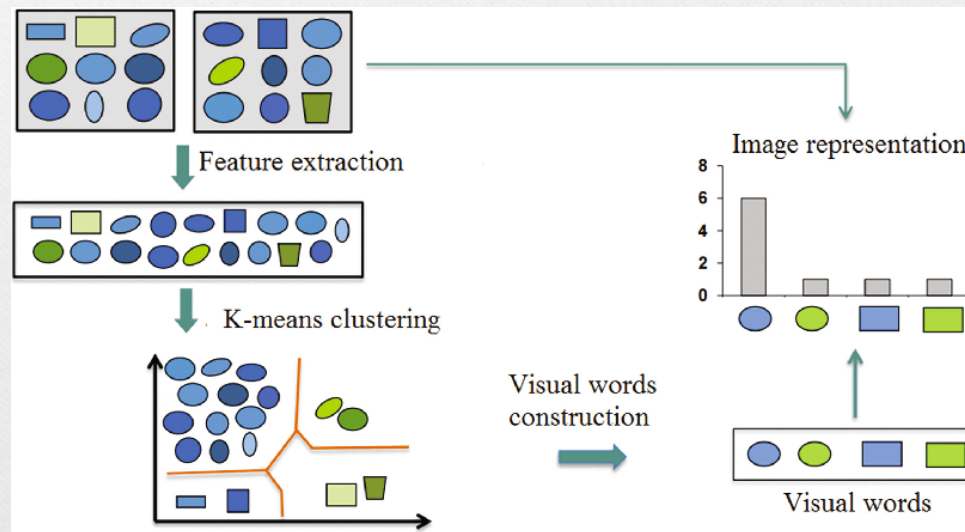
Feature Descriptor

- Feature extraction: feature detection + feature description
- Common descriptors: SURF, SIFT, BRIEF, ORB



Bag of Visual Words

- Encode images with visual words
- Can be used in image classification



Lab2

- Color segmentation
 - K-means clustering: $d = 3$, $N = H \times W$, $k = 10$
- Texture segmentation
 - K-means clustering: $d = 38$ or 41 , $N = H \times W$, $k = 6$
- Bag of visual words
 - 5 classes, 100 train and 100 test images for each class
 - K-means clustering: $d = 128$ (dim of SURF feat.), $N = \text{sum}(\# \text{ of SURF feat. in each image})$, $k = 50$
 - BoW feat: $\text{dim} = 50$