BUILDING VISION SYSTEM USING MACHINE LEARNING

SCENE AND EVENT

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Module objective

Knowledge and understanding

- Understand the fundamentals of image feature learning for scene and event understanding

Key skills

- Design, build, implement and evaluate scene and event system for real-world application

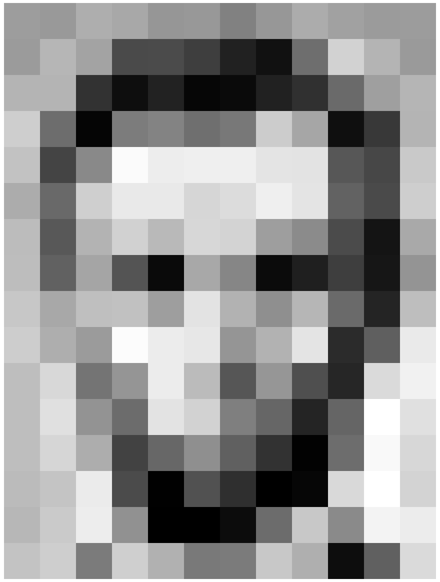
Major reference

- [Introduction] R. C. Gonzalez and R. E. Woods, ***Digital Image Processing***, http://www.imageprocessingplace.com/
- [Practical] ***Practical computer vision programming in OpenCV***, https://www.pyimagesearch.com
- [Practical] ***Programming Computer Vision with Python***, http://programmingcomputervision.com/
- [Person re-identification] Theory and best practice, http://www.micc.unifi.it/reid-tutorial/
- [Person re-identification] FG 2018 tutorial, https://github.com/pkuvmc/pkuvmc.github.io/tree/master/FG2018-Tutorial/

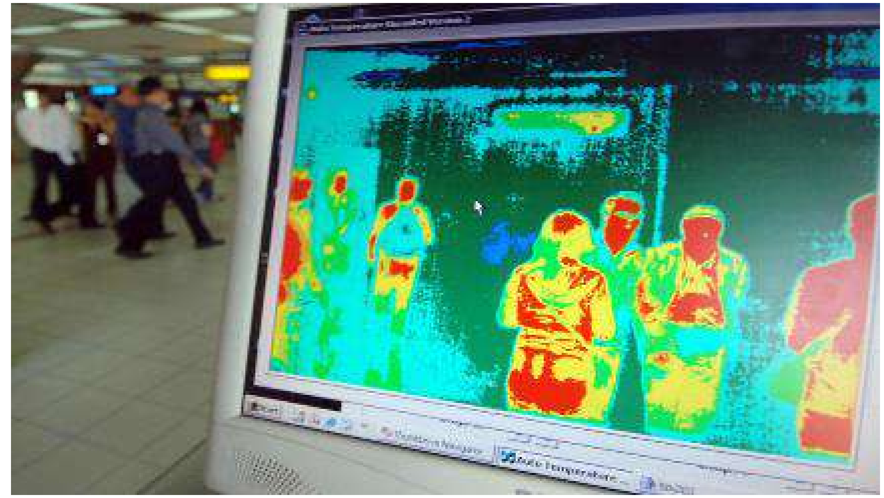
Topics

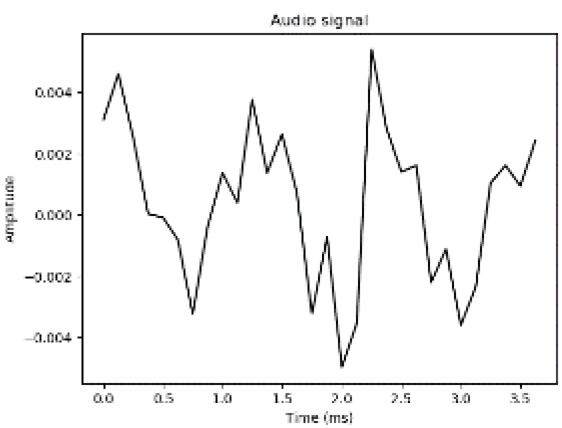
- Feature extraction and learning
- Person re-identification

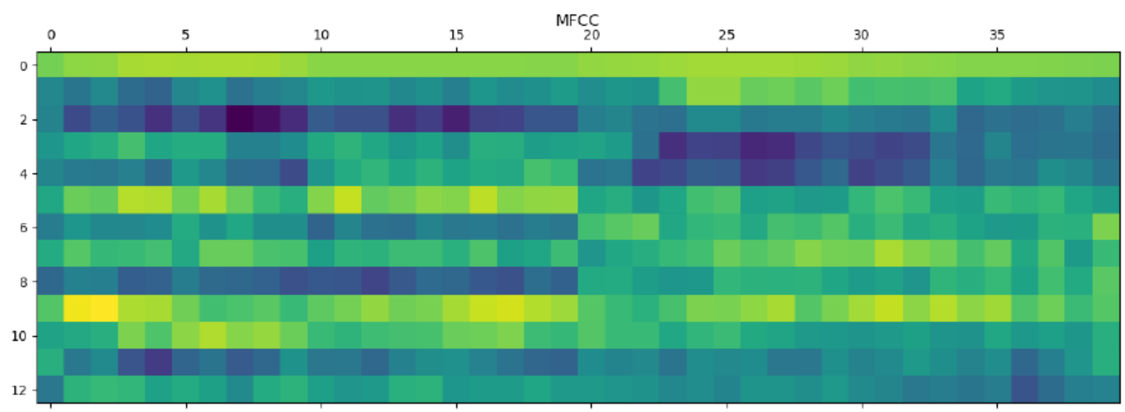
Image data



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	105	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
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	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
195	206	123	207	177	121	123	200	175	13	96	218







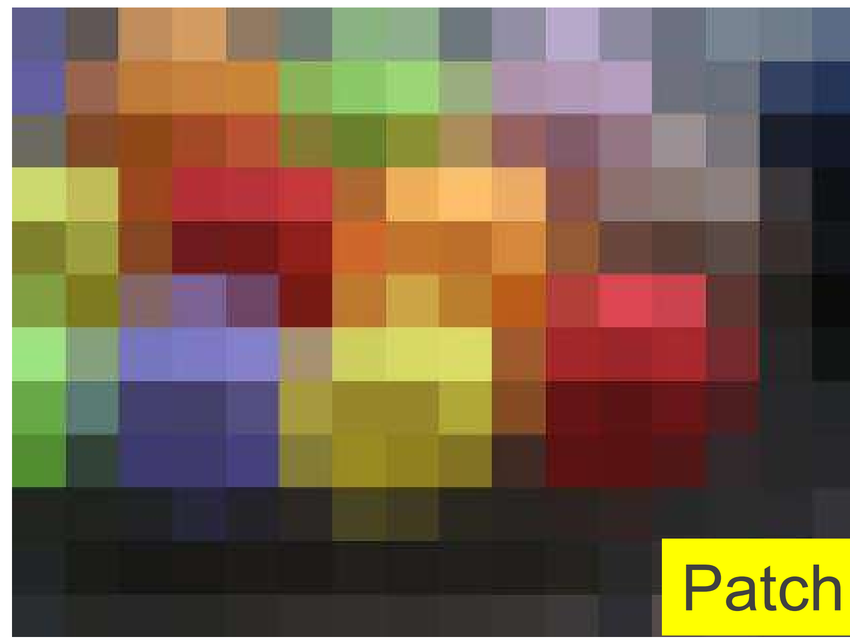
Reference:
- http://techundred.com/how-snapchat-filter-work/
- https://www.tpr.org/post/thermal-imaging-gets-more-common-courts-havent-caught

Image understanding: Intuition (1)

Derived from the whole image

B: Summarize whole image into a single value

A: Keep all the pixels



C: Use a set of values that are summarized over patches

Image understanding: Intuition (2)

Challenges of image understanding

Illumination | Scale | Rotation | Affine

What are good features for image understanding?

- Local or global
  - Local: A feature occupies a relatively small area of the image;
  - Global: Whole image, robust to occlusion of local objects
- Repeatability
  - Robustness to expected variations: The same feature can be found in various images, despite small geometric and photometric transformations
- Distinctiveness
  - Each feature has a distinctive description
- Compactness and efficiency
  - Features have fewer dimensions than the number of image pixels

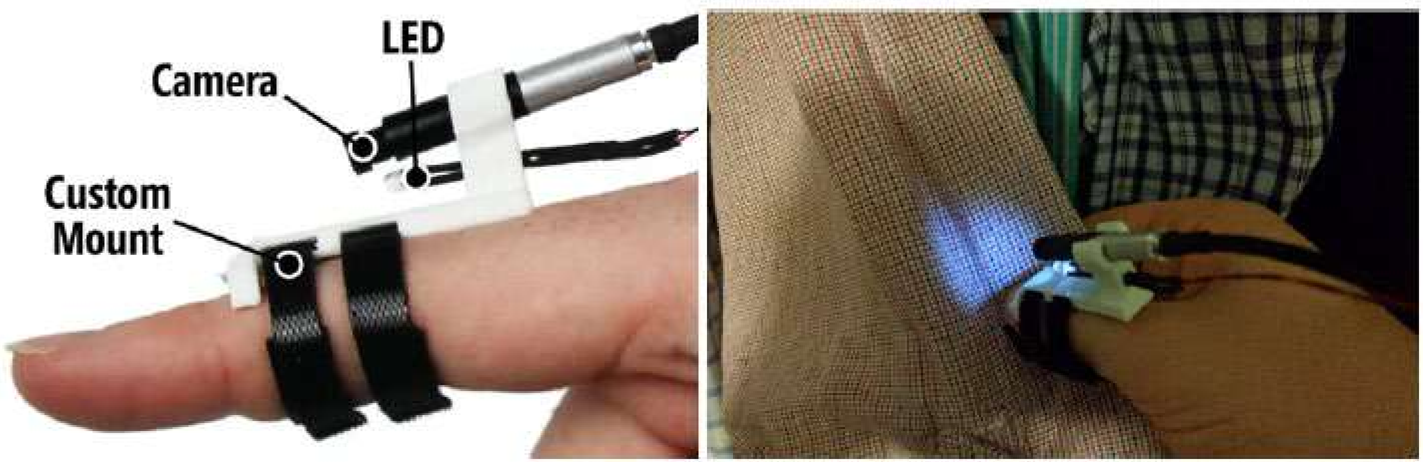
Overview of feature representation for image understanding

Category	Representative features
Color	Spectral peaks and histogram
Geometrical	Edges, lines, line widths, line relationships (e.g., parallel, perpendicular), circles, shapes, size of enclosed area
Statistical	Number of lines, area and perimeter, moments, mean, variance, kurtosis, skewness, entropy
Time domain	Motion characteristics, speed, acceleration, trajectory
Frequency domain	Fourier coefficients and other time-frequency domains (such as discrete Cosine transformation, Gabor, Wavelet)

Texture

- Texture is characterized by the repetition of basic elements or *textons*.

Figure 1. Examples of the six classes in our fabric pattern dataset: solid, striped, checkered, dotted, zigzag, and floral.



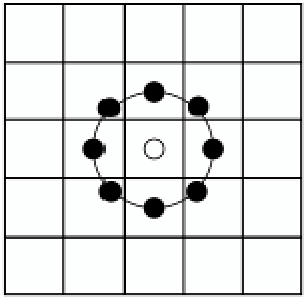
Reference: L. Stearns, L. Findlater, J. E. Froehlich, "Applying Transfer Learning to Recognize Clothing Patterns Using a Finger-Mounted Camera," Proceedings of ASSETS 2018, https://makeabilitylab.cs.washington.edu/project/clothrecognition/

LBP: Local binary pattern (1)

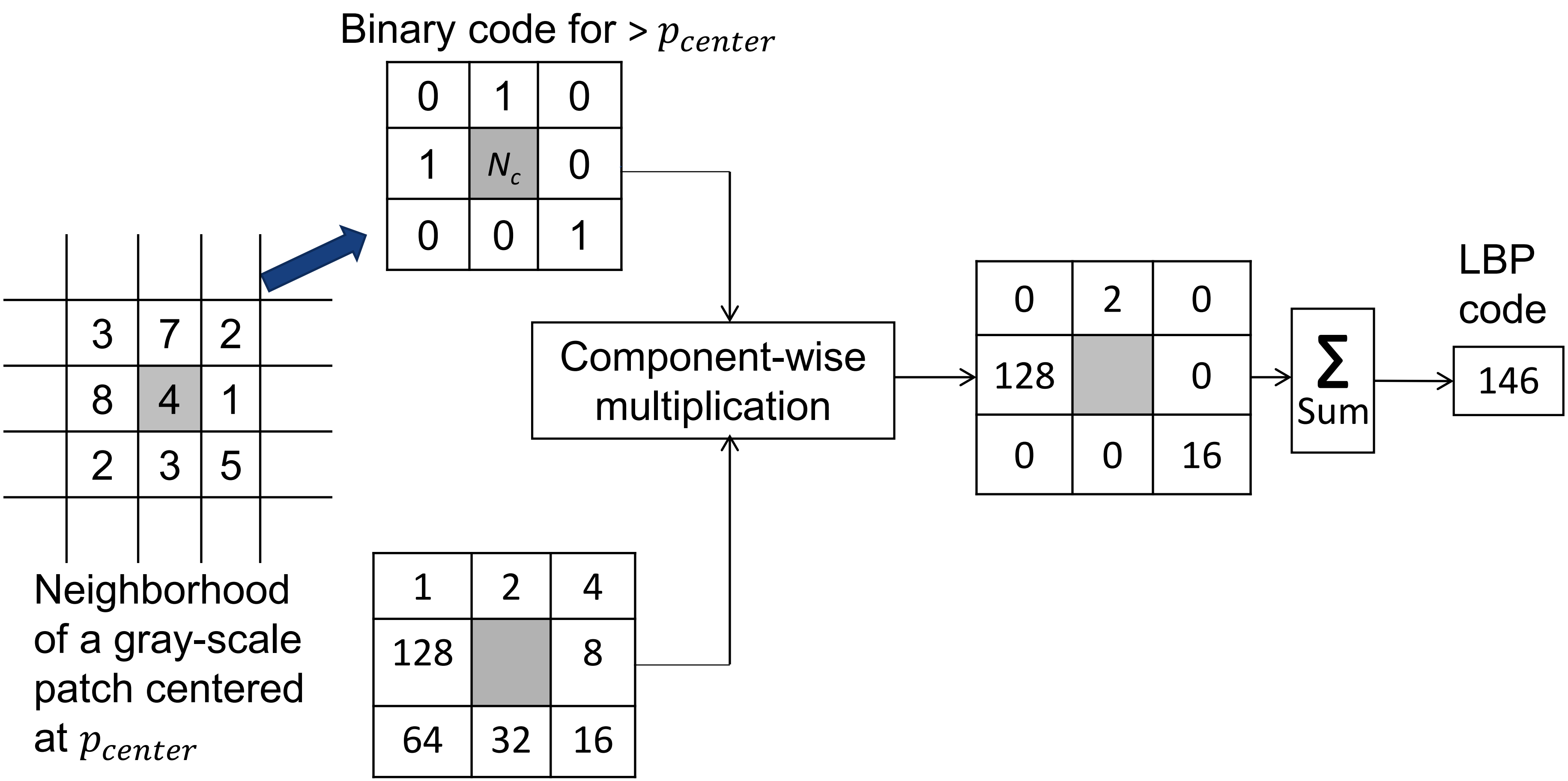
- For each pixel, compare the pixel to each of its (eight) neighbours (on its left-top, left-middle, left-bottom, right-top, etc.), use label "1" if the center pixel's value is greater than the neighbour; otherwise, use label "0". Given a set of elements $P = \{p_{center}, p_0, p_1, \cdots p_7\}$, where p_{center} represents the value of the central position, and $p_i (0 \leq i \leq 7)$ represent the values of the a 3×3 neighbourhood. They can be characterized by a set of binary values $d_i (0 \leq i \leq 7)$ where

$$d_i = \begin{cases} 1 & \text{if } p_i \geq p_{center} \\ 0 & \text{if } p_i < p_{center} \end{cases}$$

- The LBP code for this pixel p_{center} is $LBP = \sum_{i=0}^{7} d_i \cdot 2^i$
- Finally, compute the histogram of LBP codes for all pixels positions of the image.

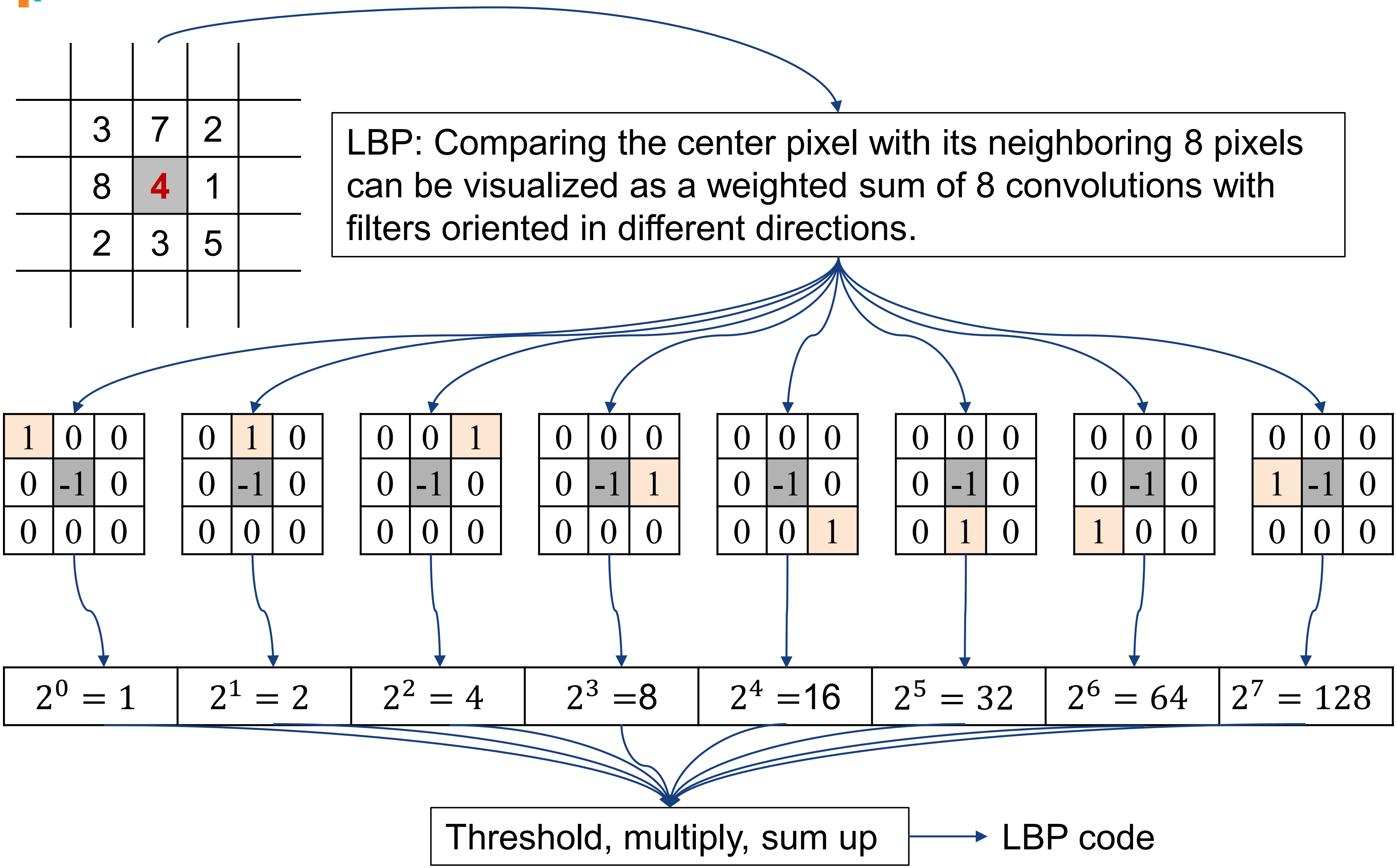


LBP: Local binary pattern (2)



Template used to convert from binary number to decimal number. (note: it is okay to use either clock-wise or counter clock-wise, as long as it is consistent).

LBP: Local binary pattern (3)

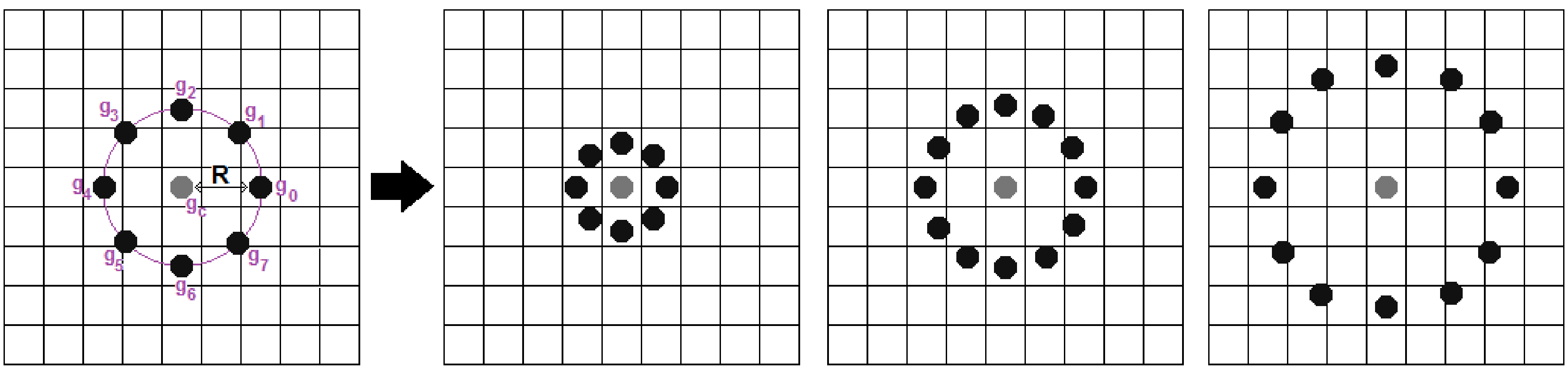


LBP: Local binary pattern (4)

A summary of the calculation of local binary pattern for an image.

1. Divide the image into (usually) 16×16 pixel cells. (one histogram per cell)
2. For each pixel in a cell, compare it with its neighbours (various configurations are shown below), 'walking' through them anticlockwise (as shown in previous slide). Where the centre pixel's value is greater than that of the neighbour, score it as 0; otherwise score it as 1. Walking round all the neighbours then gives an array of binary numbers, and further convert it into decimal number.
3. For each cell, compute the histogram of the frequency of each decimal number. Optionally normalise the histogram.
4. Finally, concatenate or average all the histograms of the cells (one histogram per cell) to give a descriptor for the entire image.

Various configurations (P, R). P: Number of neighbours, R: radius between neighbours and the center pixel.



P=8, R=2

P=8, R=1

P=12, R=2

P=12, R=3

HoG: Histogram of gradients (1)

Clarification between Edge and Gradient		
Edge detection	Binary (yes/no)	Decision of edge detection task
Gradient	Continuous measurement	Used as features for other tasks

Gradient amplitude

$$m(x,y) = \sqrt{\underbrace{(I(x+1,y) - I(x-1,y))^2}_{\text{gradient in } x \text{ direction using filter } [-1,0,1]} + \underbrace{(I(x,y+1) - I(x,y-1))^2}_{\text{gradient in } y \text{ direction using filter } [-1,0,1]^T}}$$

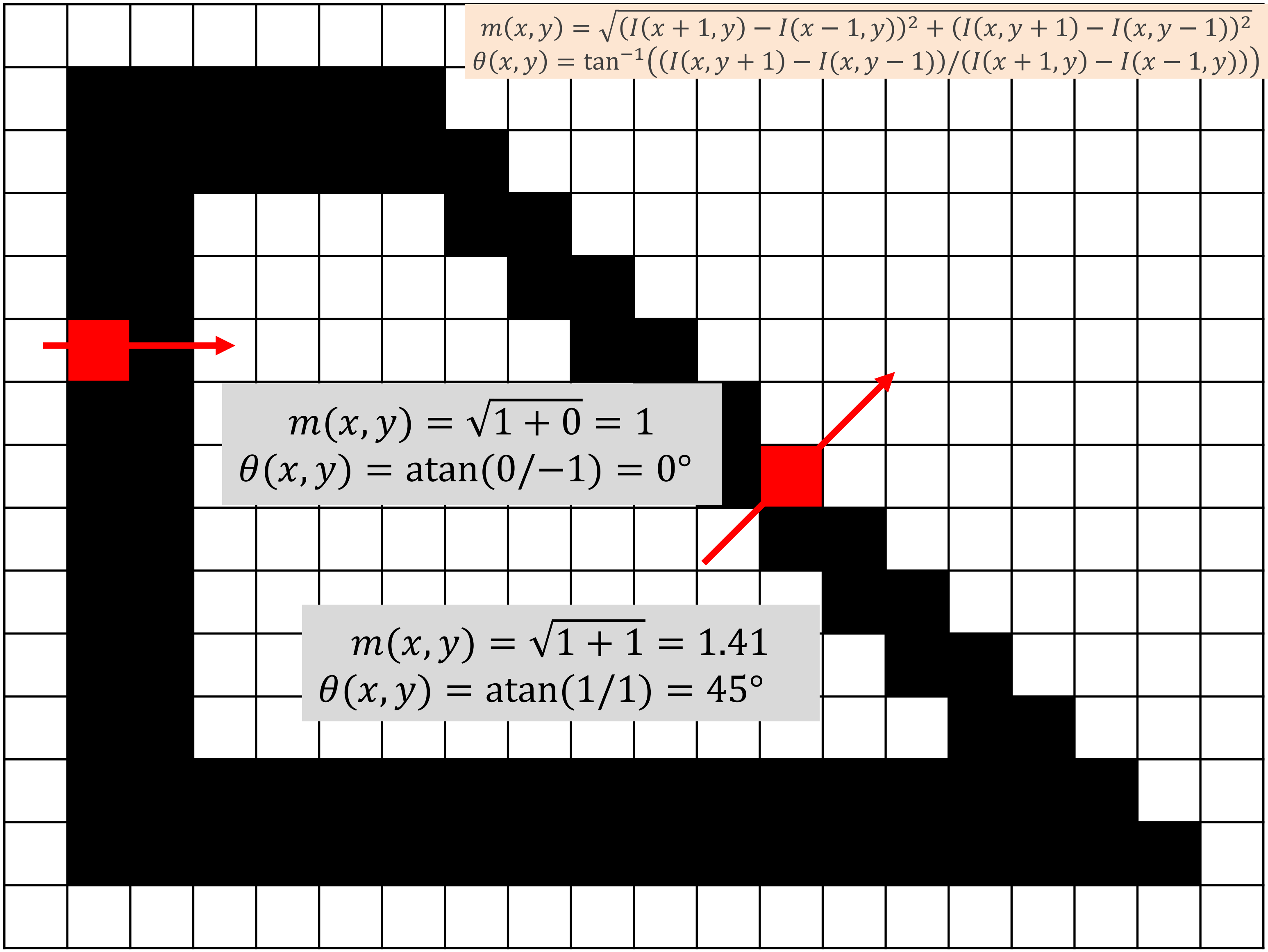
Gradient direction

$$\theta(x,y) = \tan^{-1}\left(\underbrace{(I(x,y+1) - I(x,y-1))}_{\text{gradient in } y \text{ direction using filter } [-1,0,1]^T} / \underbrace{(I(x+1,y) - I(x-1,y))}_{\text{gradient in } x \text{ direction using filter } [-1,0,1]}\right)$$

$I(x,y)$ = the image intensity at the pixel position (x,y)
An example of the calculation is provided in the following slide.

HoG: Histogram of gradients (2)

$$m(x,y) = \sqrt{(I(x+1,y) - I(x-1,y))^2 + (I(x,y+1) - I(x,y-1))^2}$$
$$\theta(x,y) = \tan^{-1}\big((I(x,y+1) - I(x,y-1))/(I(x+1,y) - I(x-1,y))\big)$$

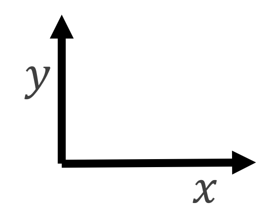


$$m(x,y) = \sqrt{1+0} = 1$$
$$\theta(x,y) = \text{atan}(0/-1) = 0°$$

$$m(x,y) = \sqrt{1+1} = 1.41$$
$$\theta(x,y) = \text{atan}(1/1) = 45°$$

Image gradient calculation

Black color: 0
White color: 1



HoG: Histogram of gradients (3)

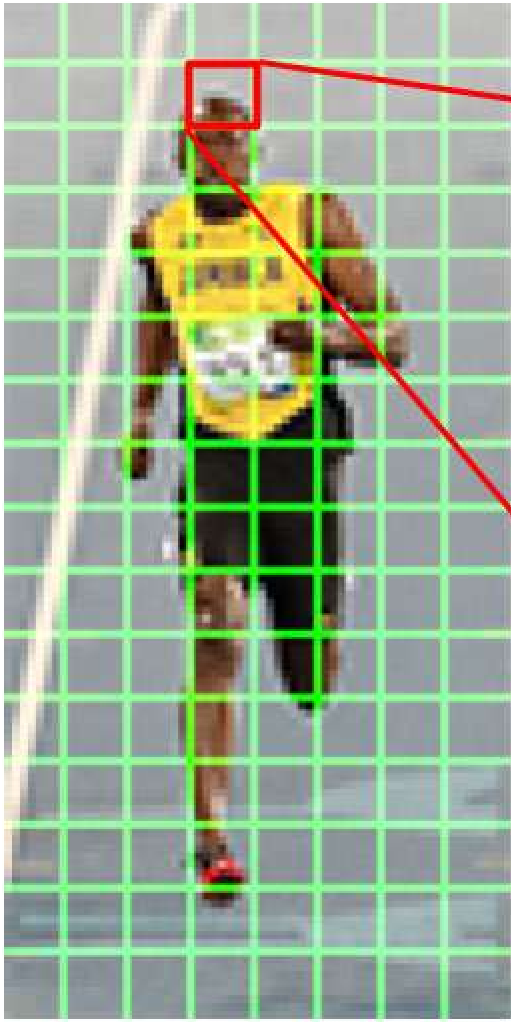
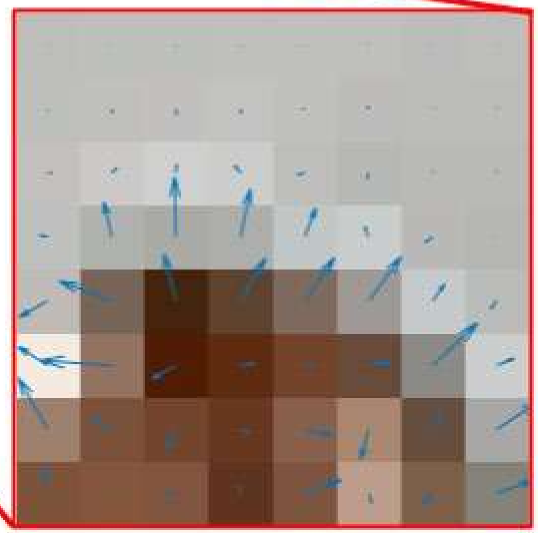


Image gradient calculation



2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

Gradient Magnitude

80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

Gradient Direction

Reference: https://www.learnopencv.com/histogram-of-oriented-gradients/

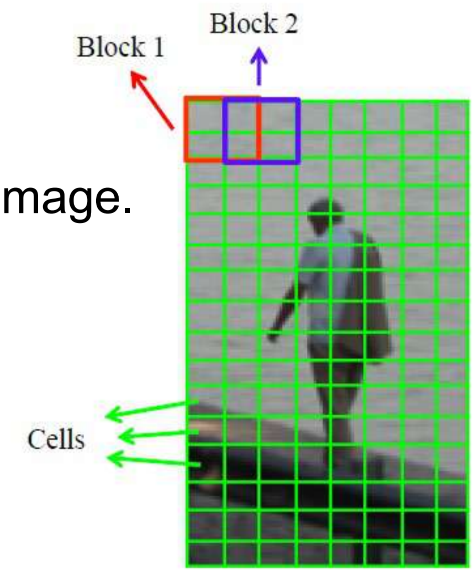
HoG: Histogram of gradients (4)

Summary of HoG (suggested in the original CVPR2005 paper)

	Dimension	Remark
Window	64×128	A fixed-size window
Block	16×16	With 50% overlap, Total 7×15=105 blocks
Cell	8x8	Each block should consist of 2×2 cells
Feature	9-bin	Each cell has a HoG feature of 9-bin histogram
Total features	3780	105 (block) × 4 (cell) × 9 (bin) = 3780

Note: How to handle larger image?

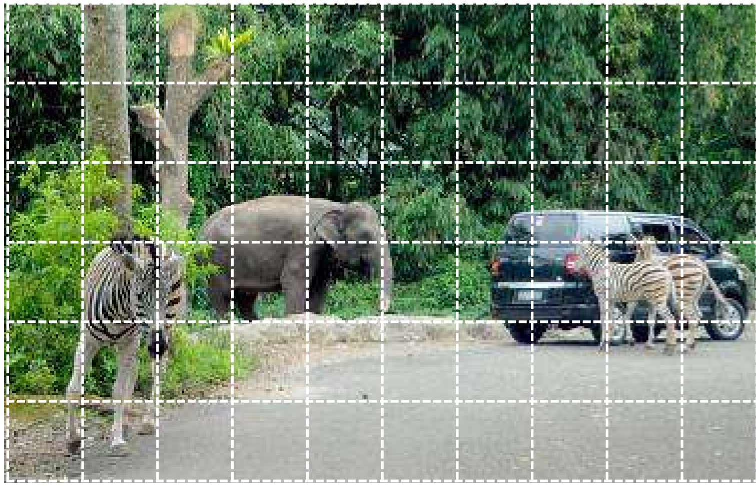
- The input image could be resized to be 64×128.
- The fixed-size window 64×128 could be sliding on the image.



Reference: N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005, https://lear.inrialpes.fr/people/triggs/pubs/Dalal-cvpr05.pdf, 27K+ citations

HoG: Histogram of gradients (5)

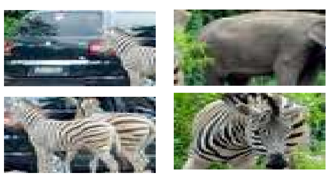
Select sliding window (size, aspect ratio, stride), crop & resize



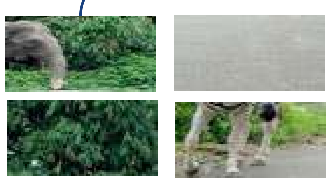
Apply the classifier on each sliding window

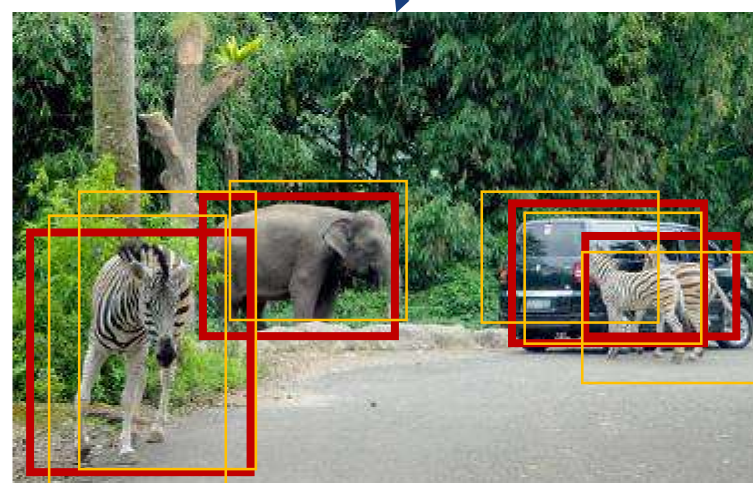
Output: A set of
- Box label and score
- Box coordinates (x, y, w, h)

Apply *Non-Maximum Suppression* (NMS) to select best (red) boxes



(offline) Train a HoG-based object classifier





Convolutional neural network (CNN)

- A CNN summary: https://cs231n.github.io/convolutional-networks/
- Excel tool: https://medium.com/apache-mxnet/multi-channel-convolutions-explained-with-ms-excel-9bbf8eb77108
- Visualization: https://www.cs.ryerson.ca/~aharley/vis/conv/flat.html
- Calculation of number of parameters: https://towardsdatascience.com/counting-no-of-parameters-in-deep-learning-models-by-hand-8f1716241889

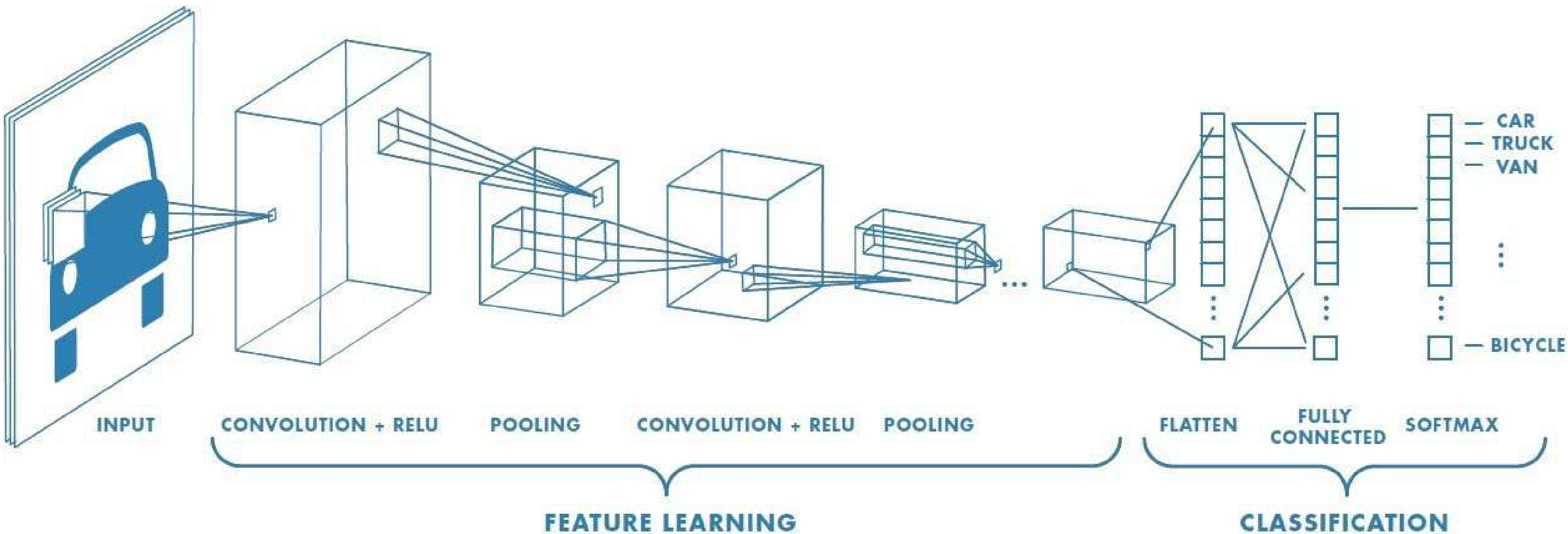
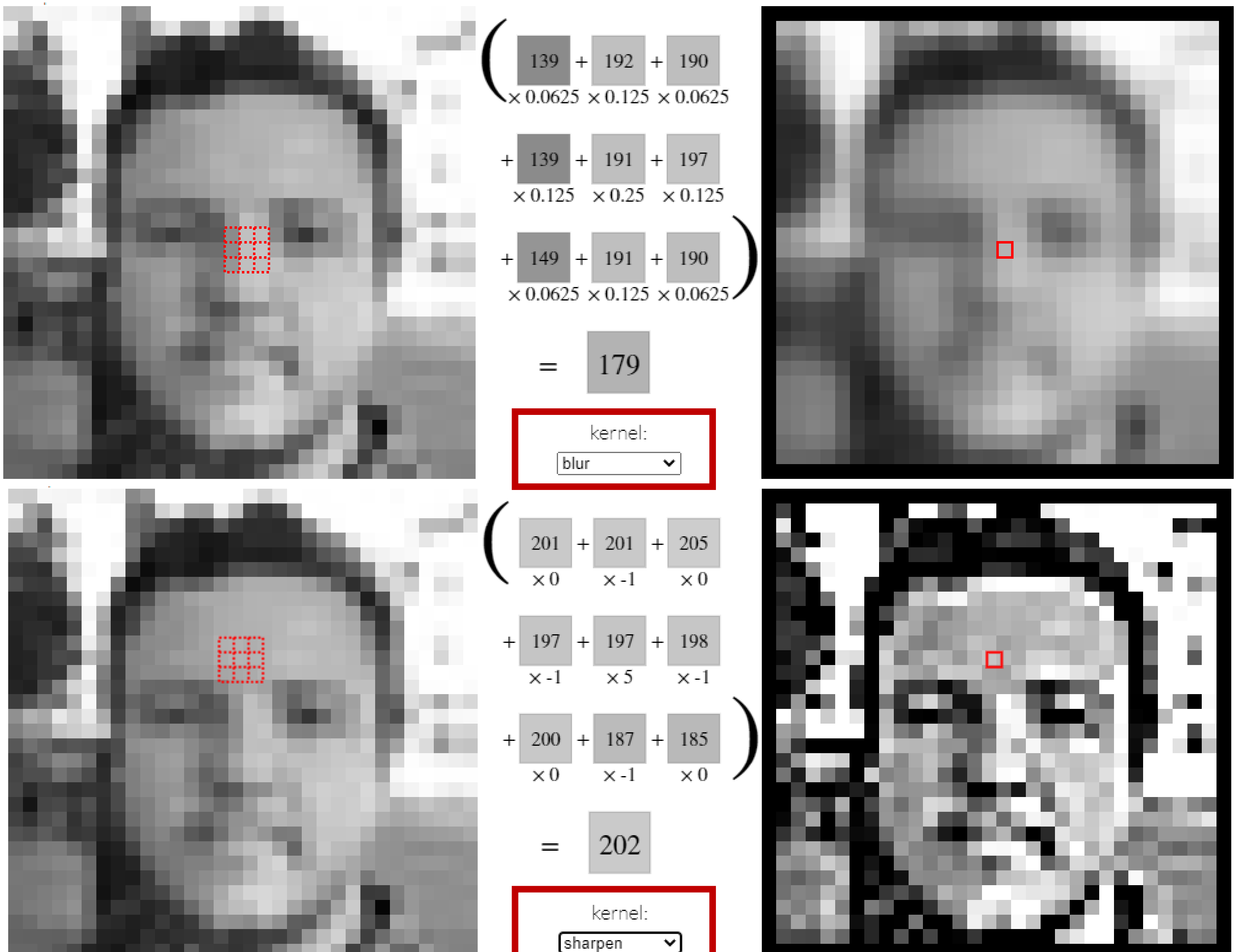


Photo: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

CNN motivation: Image filter

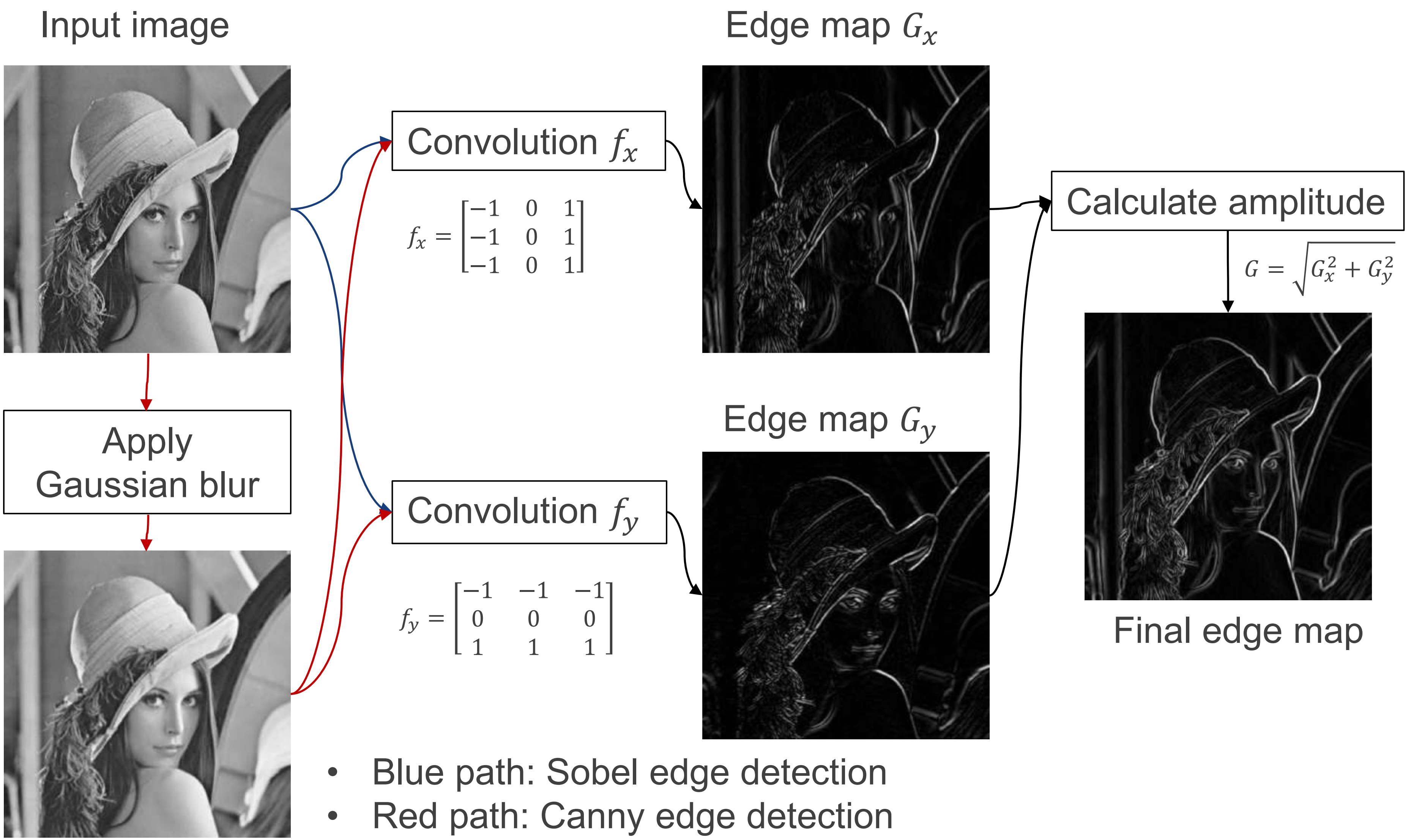


Blur kernel

Sharpen kernel

Demo website: http://setosa.io/ev/image-kernels/

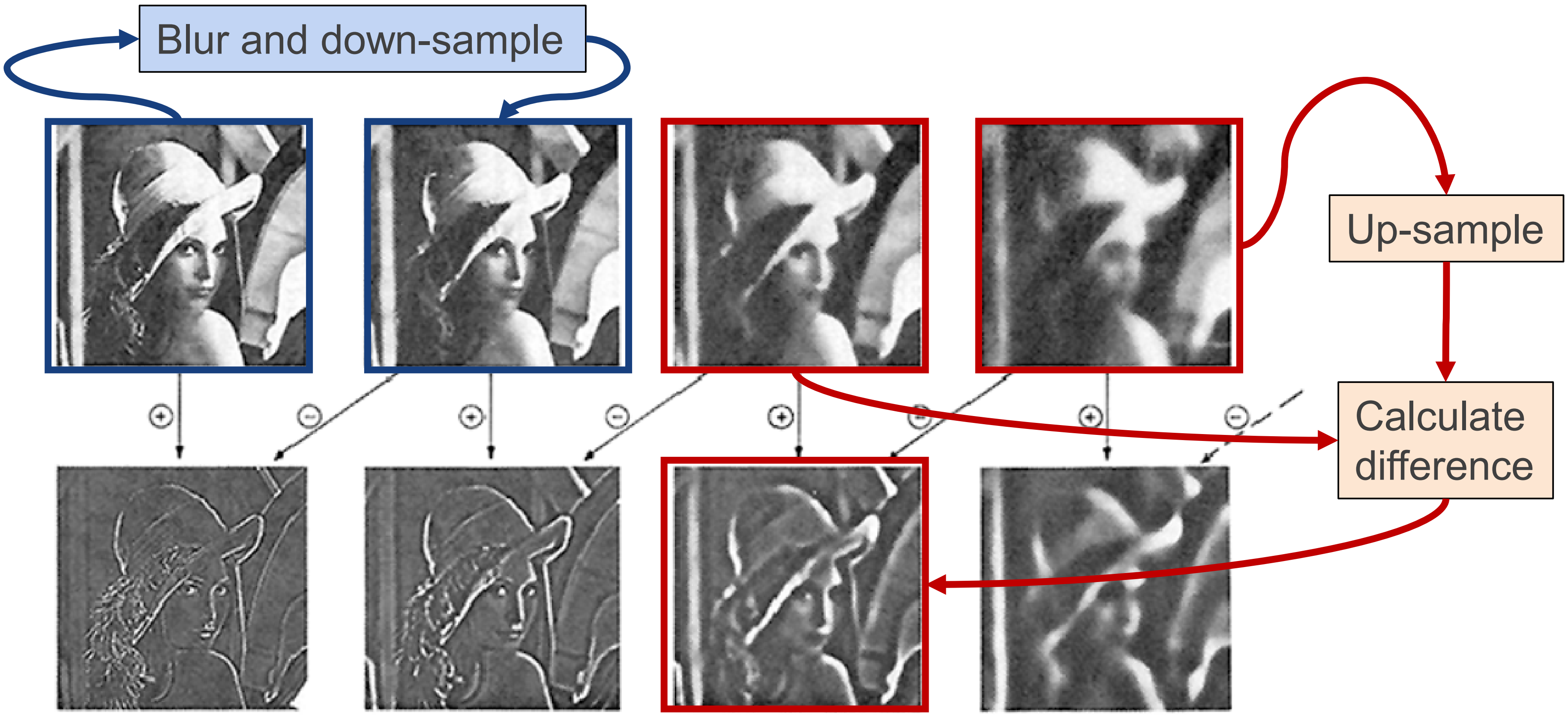
CNN motivation: Stacked filters



- Blue path: Sobel edge detection
- Red path: Canny edge detection

CNN motivation: Multiple-resolution stacked filters

- Gaussian pyramid: Progressively blurred and subsampled versions of the image.



- Laplacian pyramid: Compute the difference (residual) between upsampled Gaussian pyramid level and Gaussian pyramid level.

Reference: The Laplacian Pyramid as a Compact Image Code, IEEE Trans. on Communications, 1983,http://persci.mit.edu/pub_pdfs/pyramid83.pdf

CNN as feature extractor

- ConvNet as fixed feature extractor. Take a ConvNet pretrained on ImageNet, remove the last fully-connected layer (this layer's outputs are the 1000 class scores for a different task like ImageNet), then treat the rest of the ConvNet as a fixed feature extractor for the new dataset.
- Fine-tuning the ConvNet. Not only replace and retrain the classifier on top of the ConvNet on the new dataset, but to also fine-tune the weights of the pretrained network by continuing the backpropagation. The earlier features of a ConvNet contain more generic features (e.g. edge detectors or color blob detectors) that should be useful to many tasks, but later layers of the ConvNet becomes progressively more specific to the details of the classes contained in the original dataset.
- Pretrained models. Since modern ConvNets take long time to train across multiple GPUs on ImageNet, it is common to see people release their final ConvNet checkpoints for the benefit of others who can use the networks for fine-tuning.

Reference: https://cs231n.github.io/transfer-learning/

Topics

- Feature extraction and learning
- Person re-identification

Motivation: Person verification

Problem statement

- Recognition: Given a photo (face/body), classify among possible persons
- Verification: Verify that two photos belong to the same person

Photo: https://github.com/pkuvmc/pkuvmc.github.io/tree/master/FG2018-Tutorial/

"Use **CCTV footage** to assist the government to do contact tracing" (Source: CNA interview https://www.youtube.com/watch?v=XrGtmcpjVrY)

SINGAPORE

Contact tracing process under way: Health Minister

Ministry working to contact those who were in close proximity to Chinese national who had tested positive for Wuhan coronavirus

Source: https://www.todayonline.com/singapore/wuhan-virus-singapore-confirms-first-imported-case-another-suspected-case-has-positive, (24 January 2020)

Motivation: Person verification

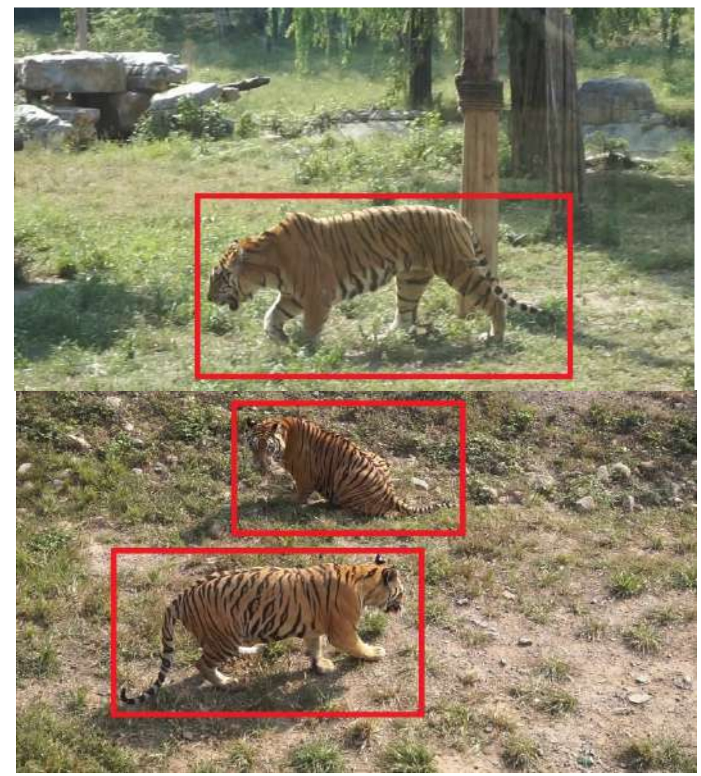
- Face: Frontal face? Sufficient resolution?
- Gait: Controlled or uncontrolled environment?
- Appearance: clothing color and texture? Hair style?

Photo:
- https://fortune.com/2018/10/28/in-china-facial-recognition-tech-is-watching-you/
- 'Mission: Impossible - Rogue Nation', 2015.
- http://www.rapdataset.com/rapv1.html

Motivation: Person verification

This task is similar to other object re-identification

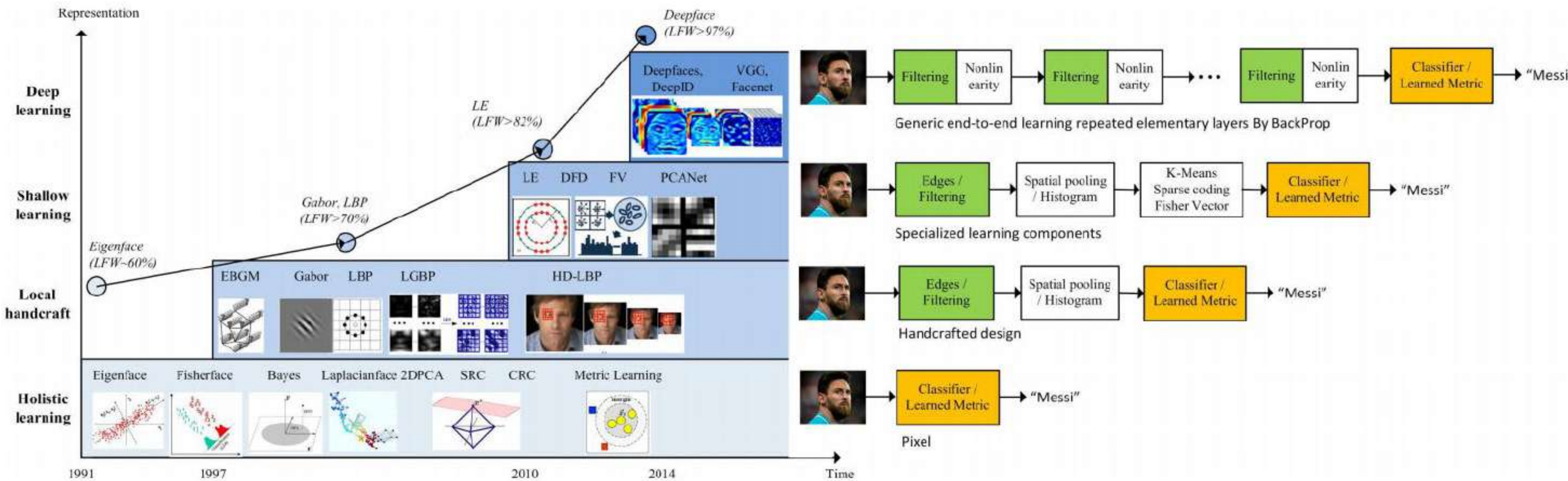
- Luggage
- Tiger
- Car



Reference

- MVB: A Large-Scale Dataset for Baggage Re-Identification, https://arxiv.org/pdf/1907.11366.pdf, https://sites.google.com/view/wacv2020animalreid/home
- https://cvwc2019.github.io/challenge.html
- https://github.com/JDAI-CV/VeRidataset

An evolution (face recognition)



Technology

IBM's decision to abandon facial recognition technology fueled by years of debate

Reference:
Deep face recognition, a survey, https://arxiv.org/pdf/1804.06655.pdf
https://www.washingtonpost.com/technology/2020/06/11/ibm-facial-recognition/

Idea 1: Classification

Multiple class classification

- Classification with a single label per sample
- Multiple classes (e.g., 1000+ samples per class)

Challenge

- What if we have insufficient data for certain label?
- What if we have 5 million classes, but < 10 samples per class?

Input image

Classifier (either traditional machine learning or deep learning methods) trained from image dataset with annotation

Image dataset with annotation

Andrew Ng

Li Fei-Fei

Yan Lecunn

Idea 2: Image matching

Input image

Image matching
(feature extraction + similarity evaluation)

Image matching
(feature extraction + similarity evaluation)

Image matching
(feature extraction + similarity evaluation)

Pickup the most similar score

Image dataset with annotation

Returned photos similar to the input image

The traditional approach for matching images, relies on the following pipeline:

- Feature extraction, e.g., color histograms, LBP, HoG, pre-trained CNN.
- Similarity evaluation, e.g., Euclidean distance.

Feature similarity evaluation

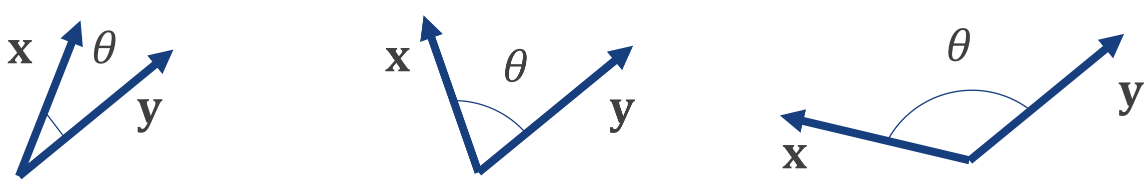
For unit vectors $\mathbf{x}, \mathbf{y}$, we have various pre-defined metrics, which are fully specified without the knowledge of data.

- Euclidian distance: $f(\mathbf{x}, \mathbf{y}) = ||\mathbf{x} - \mathbf{y}||^2 = (\mathbf{x} - \mathbf{y})^T \ (\mathbf{x} - \mathbf{y})$
- Cosine similarity distance: $f(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}|| \, ||\mathbf{y}||} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n}(x_i^2)}\sqrt{\sum_{i=1}^{n}(y_i^2)}}$

Dot product

Euclidean norm (i.e., length of vector)

Scenario	Similar	Unrelated	Opposite
Input two vectors $\mathbf{x}, \mathbf{y}$	Same direction	Nearly orthogonal	Opposite direction
Angle between them θ	Near 0 degree	Near 90 degree	Near 180 degree
Similarity score	Near 1	Near 0	Near -1



Reference: M. P. Chandra, On the generalised distance in statistics. *Proc. of the National Institute of Sciences of India,* Vol. 2, No. 1, 1936, pp. 49-55.
http://blog.christianperone.com/2013/09/machine-learning-cosine-similarity-for-vector-space-models-part-iii/

Problem statement

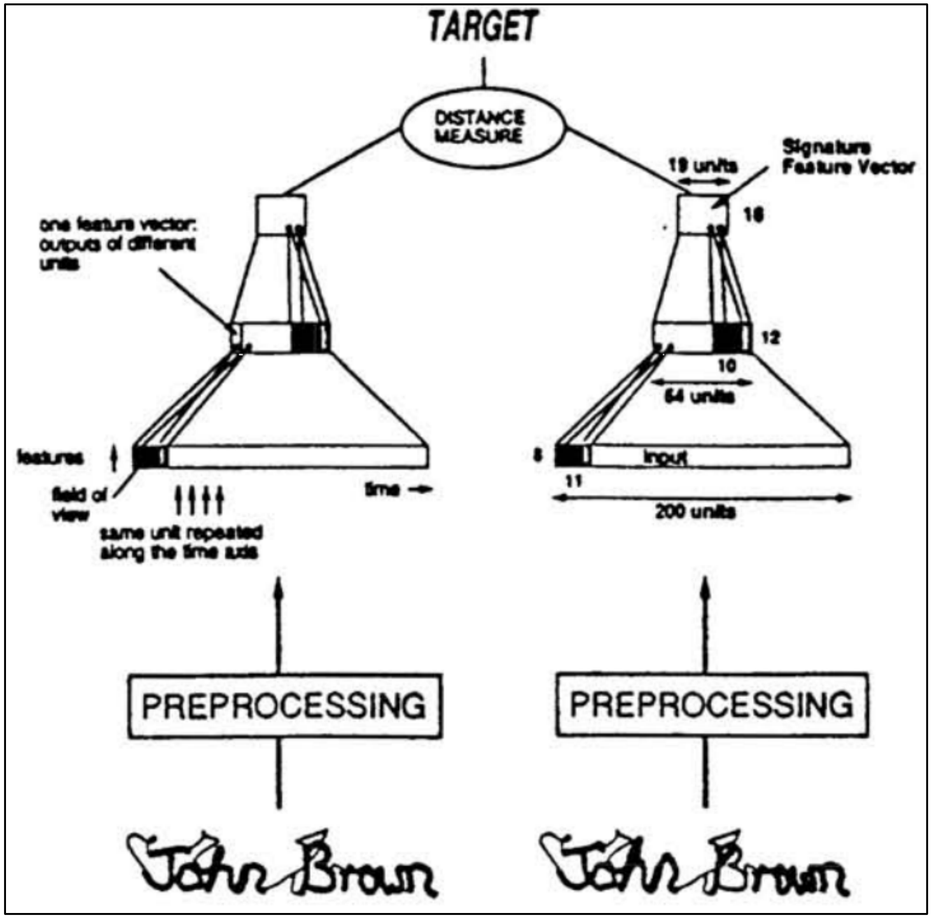
- Challenge in traditional image matching approach: The feature representation and the similarity metric are not learned jointly.
- Idea: A new problem statement
- Input: Given a pair of input images, we need to evaluate how “similar” they are to each other.
- Output: Either a binary label, i.e., 0 (same) or 1 (different), or a real number indicating how similar a pair of images are.

Images: Labeled Faces in the Wild, http://vis-www.cs.umass.edu/lfw/

Siamese network: Idea

Siamese neural network is a class of neural network architectures that contain two or more identical subnetworks, which have the same configuration with the same parameters and weights.

- Sharing weights across subnetworks means fewer parameters.
- Each subnetwork essentially produces a representation of its input. If your inputs are matching two pictures, it makes sense to use similar model to process similar inputs. This way you have representation vectors with the same semantics.



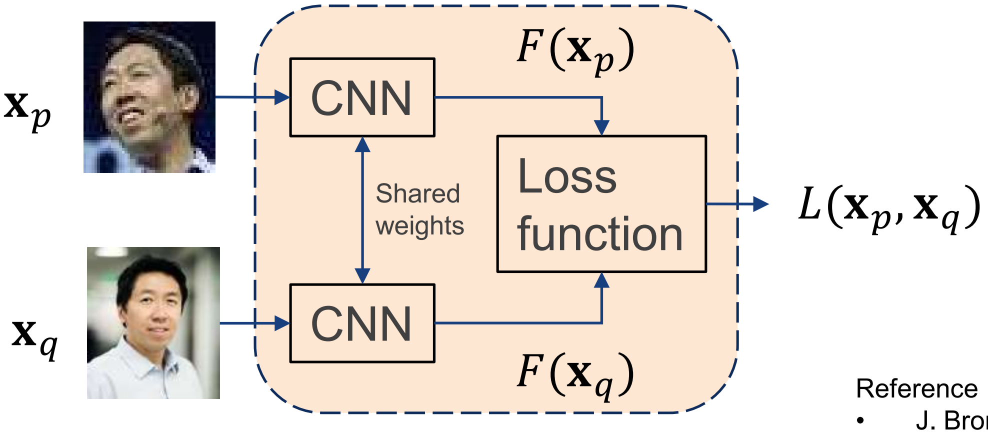
Reference: Bromley, et al., Signature verification using a Siamese time delay neural network, NIPS 1993, https://papers.nips.cc/paper/769-signature-verification-using-a-siamese-time-delay-neural-network.pdf

Siamese CNN: Standard architecture

Siamese network

- Sample positive pairs $(\mathbf{x}_p, \mathbf{x}_q)$, with (p, q) of same class
- Sample negative pairs $(\mathbf{x}_p, \mathbf{x}_q)$, with (p, q) of different classes
- Forward pass using both inputs through the two networks (same parameters, different activations). Back propagate through the two networks (the weights are updated with the sum of the two gradients)

Siamese Network



Reference

- J. Bromley, J. W. Bentz, L. Bottou, I. Guyon, Y. LeCun, C. Moore, E. Säckinger and R. Shah, Signature Verification Using A "Siamese" Time Delay Neural Network. *IJPRAI*, Vol. *7, No.* 4, 1993, pp.669-688.
- E. Simo-Serra, E. Trulls, L. Ferraz, I. Kokkinos, P. Fua, and F. Moreno-Noguer, Discriminative learning of deep convolutional feature point descriptors, ICCV 2015.

Siamese CNN: Loss function

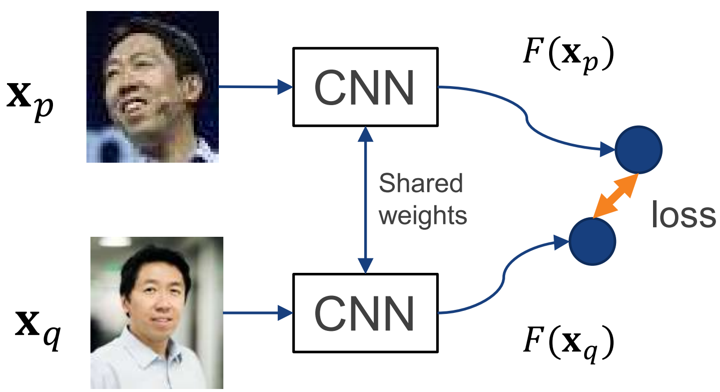
- Contrastive Loss (y is a binary label, $y = 1$ for positive, $y = 0$ for negative)

$$L(\mathbf{x}_p, \mathbf{x}_q, y) = y * ||\mathbf{x}_p - \mathbf{x}_q||^2 + (1 - y) * \max(0, m^2 - ||\mathbf{x}_p - \mathbf{x}_q||^2)$$

Positive pair $(\mathbf{x}_p, \mathbf{x}_q)$ loss:

$L(\mathbf{x}_p, \mathbf{x}_q) = ||\mathbf{x}_p - \mathbf{x}_q||^2$ (Euclidian Loss)

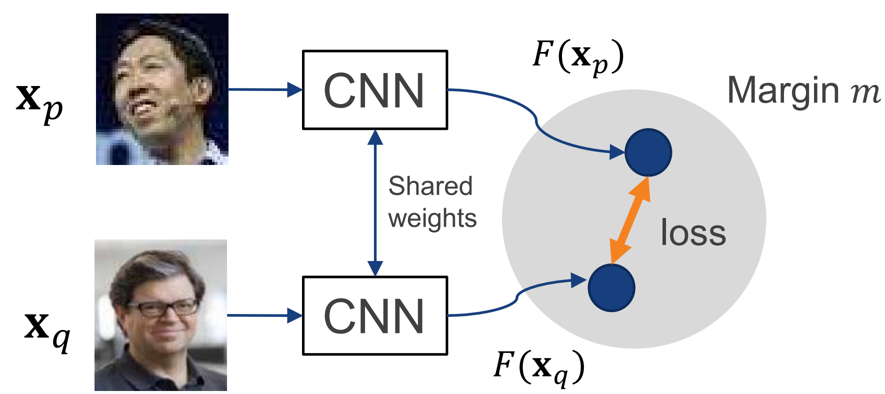
If model is good	$\|\|\mathbf{x}_p - \mathbf{x}_q\|\|^2$ is small	Loss is small	Model will be slightly updated
If model is bad	$\|\|\mathbf{x}_p - \mathbf{x}_q\|\|^2$ is large	Loss is large	Model will be updated



Negative pair $(\mathbf{x}_p, \mathbf{x}_q)$ loss (given a small margin m):

$L(\mathbf{x}_p, \mathbf{x}_q) = \max(0, m^2 - ||\mathbf{x}_p - \mathbf{x}_q||^2)$ (Hinge Loss)

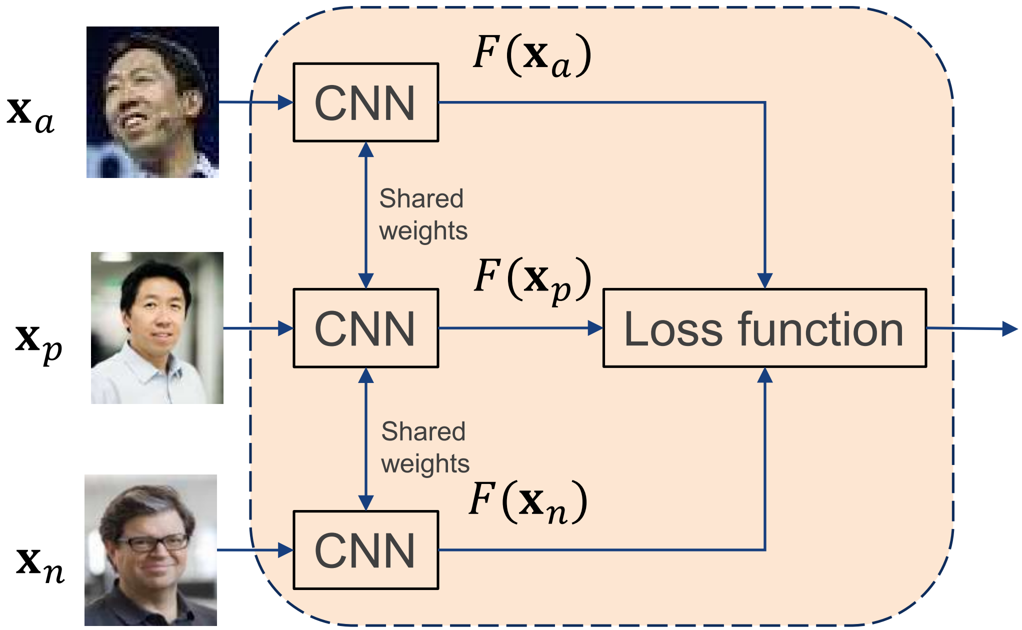
If model is good	$\|\|\mathbf{x}_p - \mathbf{x}_q\|\|^2$ is large positive	Loss is 0	Model will not be updated
If model is bad	$\|\|\mathbf{x}_p - \mathbf{x}_q\|\|^2$ is small positive	Loss is small	Model will be updated



Reference: S. Bell and K. Bala, Learning visual similarity for product design with convolutional neural networks. *ACM Trans. on Graphics*, Vol. 34, No. 4, 2015, *https://www.cs.cornell.edu/~kb/publications/SIG15ProductNet.pdf*

Siamese CNN: Triplet network and triplet loss

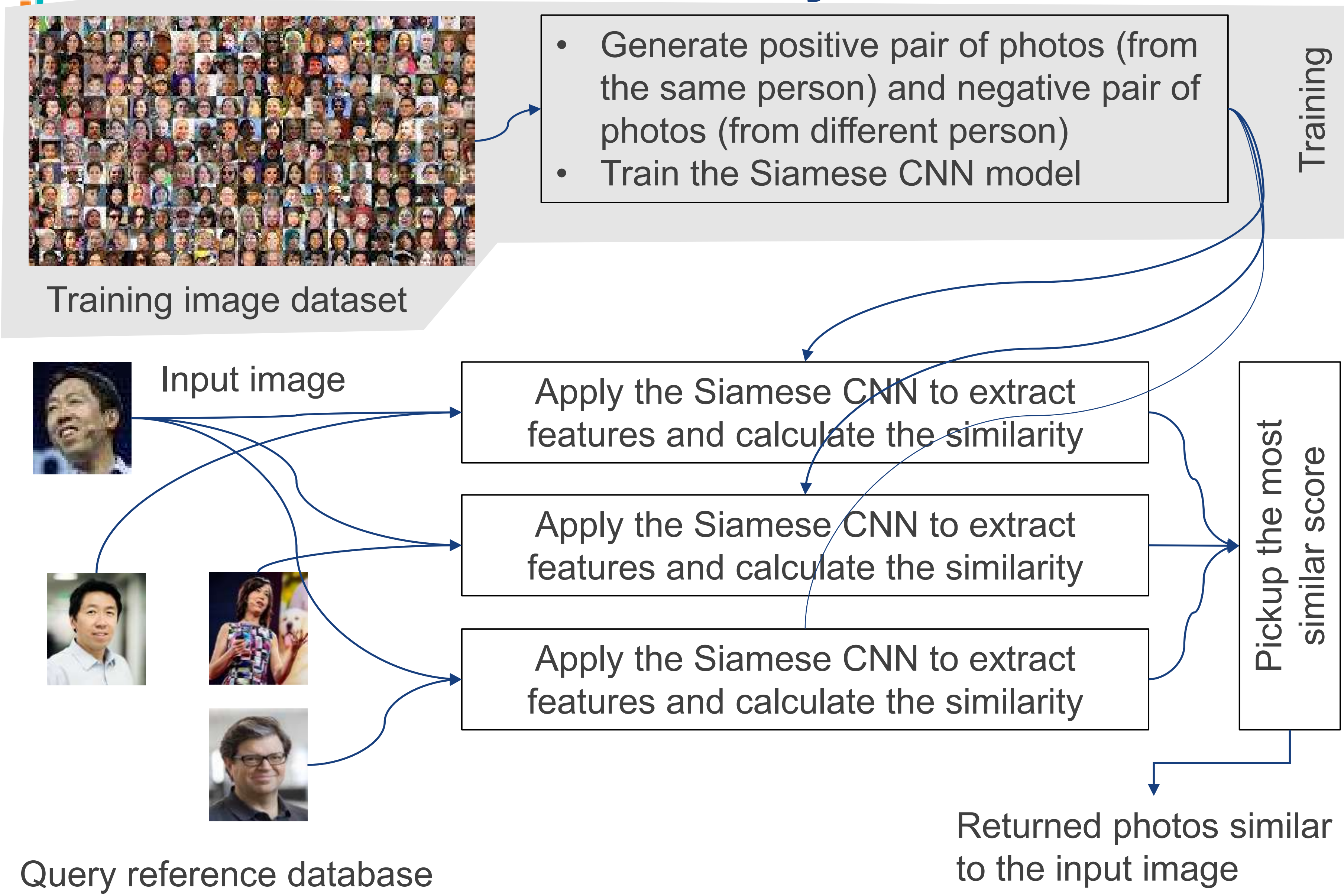
Idea: The Triplet Loss minimizes the distance between an anchor $\mathbf{x}_a$ and a positive $\mathbf{x}_p$, both of which have the same identity, and maximizes the distance between the anchor and a negative $\mathbf{x}_n$ of a different identity.



$$L(\mathbf{x}_a, \mathbf{x}_p, \mathbf{x}_n) = max\left(0, m + L(\mathbf{x}_a, \mathbf{x}_p) - L(\mathbf{x}_a, \mathbf{x}_n)\right)$$

Reference: FaceNet: A Unified Embedding for Face Recognition and Clustering, CVPR 2015, https://arxiv.org/abs/1503.03832

Siamese CNN: Summary



Facial landmark

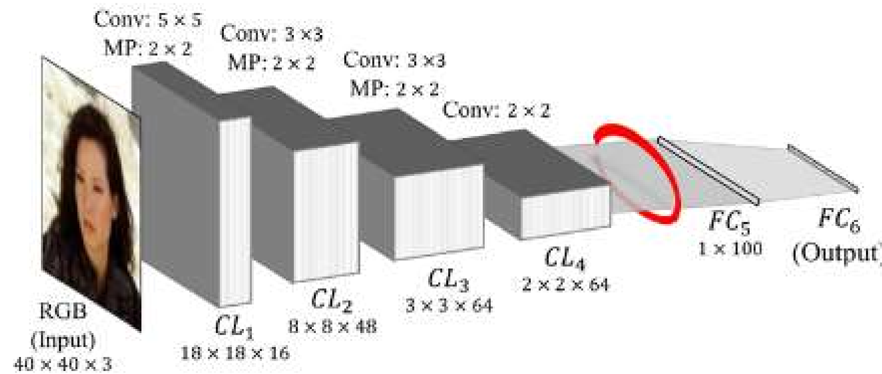
Dataset: 7049 images, 15 key points

Facial Keypoints Detection

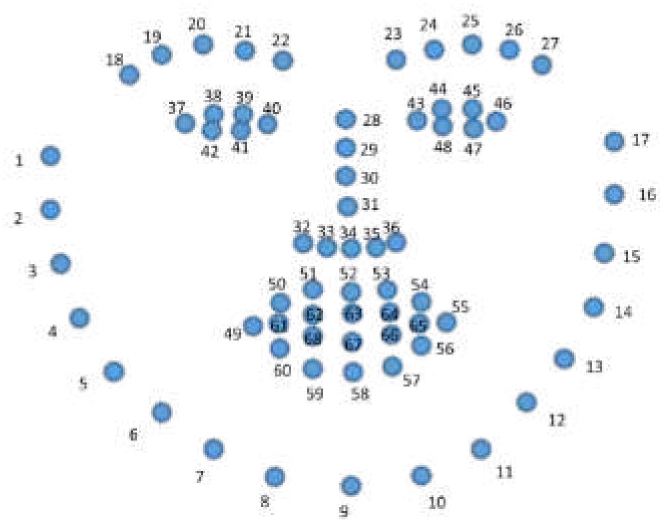
Detect the location of keypoints on face images

We can use a regression network as the number of the facial landmarks are same for every input (single face).

A CNN-based regression model



Face landmark detection provided by DLib



Dlib C++ Library

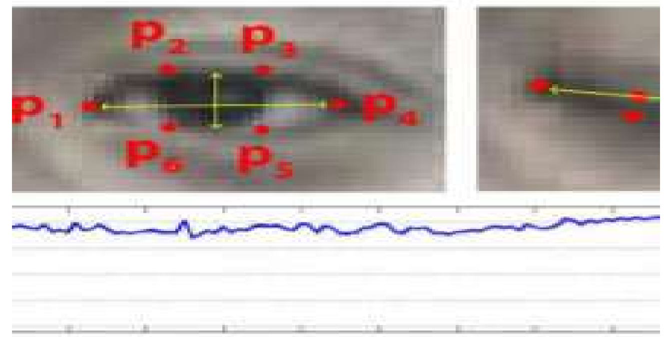
Reference:

- https://www.geeksforgeeks.org/opencv-facial-landmarks-and-face-detection-using-dlib-and-opencv/
- http://dlib.net/face_landmark_detection.py.html
- https://www.kaggle.com/c/facial-keypoints-detection/notebooks
- https://talhassner.github.io/home/publication/2017_TPAMI_2

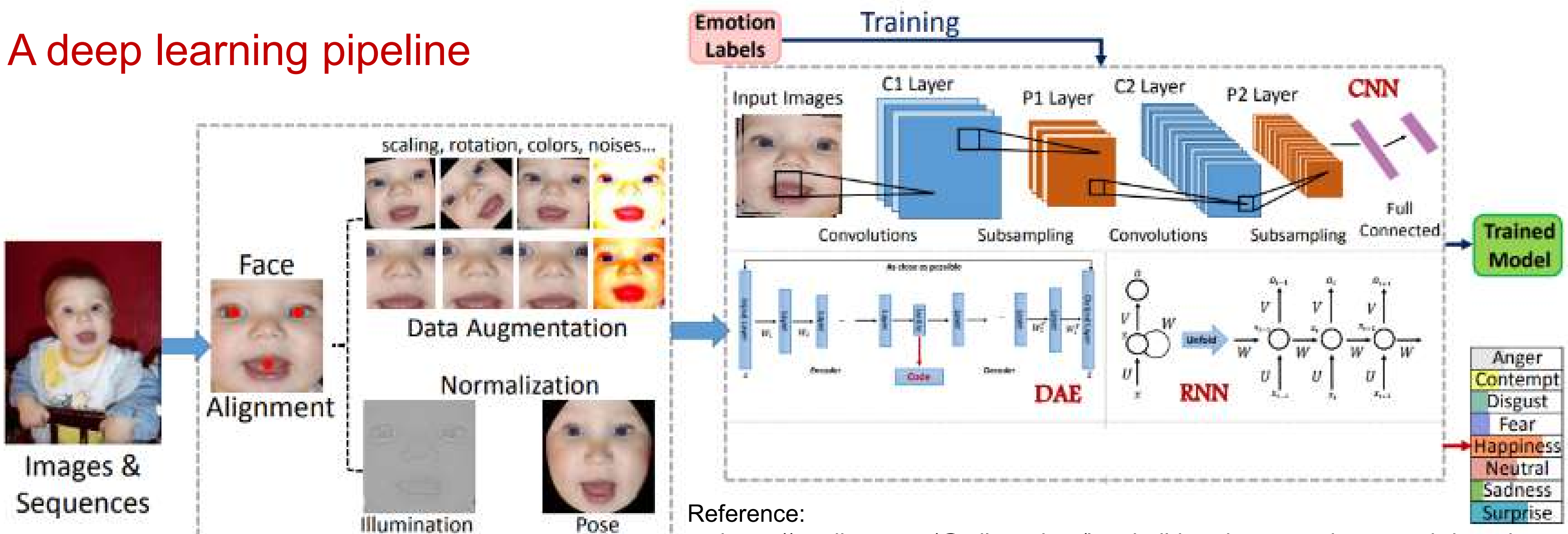
Facial expression

- Dataset: Driver drowsiness detection, http://cv.cs.nthu.edu.tw/php/callforpaper/datasets/DDD/

- Hand-crafted features based on eye landmarks



- A deep learning pipeline



Reference:
- https://medium.com/@wilsonckao/lets-build-and-run-an-ai-powered-drowsiness-detection-model-3eab055acd04
- Deep Facial Expression Recognition: A Survey, https://arxiv.org/pdf/1804.08348.pdf

Application: Person Re-Identification

True positive

True negative

Reference: E. Ahmed, M. Jones and T. K. Marks, An improved deep learning architecture for person re-identification, CVPR 2015, https://www.merl.com/publications/docs/TR2015-076.pdf

Workshop: Person Re-Identification

Dataset: *Labeled Faces in the Wild* (LFW) dataset, http://vis-www.cs.umass.edu/lfw/

- Evaluate similarity of two person image using HoG feature extraction method.
- Build a person verification model using Siamese deep learning method.

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	(None, 100, 100, 3)	0
input_3 (InputLayer)	(None, 100, 100, 3)	0
model_1 (Model)	(None, 50)	2002818
dot_1 (Dot)	(None, 1)	0

Total params: 2,002,818
Trainable params: 2,002,818
Non-trainable params: 0

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 100, 100, 3)	0
conv2d_1 (Conv2D)	(None, 100, 100, 16)	448
conv2d_2 (Conv2D)	(None, 100, 100, 16)	2320
max_pooling2d_1 (MaxPooling2	(None, 50, 50, 16)	0
flatten_1 (Flatten)	(None, 40000)	0
dense_1 (Dense)	(None, 50)	2000050

Total params: 2,002,818
Trainable params: 2,002,818
Non-trainable params: 0

$Conv2d(3,3)$

Parameter calculation

$$(3 \times 3 \times 3 + 1) \times 16 = 448$$
$$(3 \times 3 \times 16 + 1) \times 16 = 2320$$
$$(40000 + 1) \times 50 = 2000050$$

Generated pairs of positive/negative samples

What we have learnt

- Feature extraction using texture, gradients.
- Feature representation learning, Siamese network with variants.
- Application: Person re-identification in surveillance

Thank you!

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