Linear Filtering

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Image as Functions

- We can think of an image as a function f, mapping \mathbb{R}^2 (space) $\to \mathbb{R}$ (intensity):
 - f(x,y) gives the intensity at point (x,y)
 - Realistically, images are rectangles, with a finite intensity range
 - (0-1 or 0-255). Thus:

$$f: [0, w] \times [0, h] \rightarrow [0, 1],$$

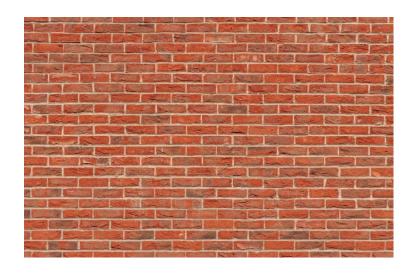
 $w = width, h = height$

A color image is just three "grayscale" images pasted together.

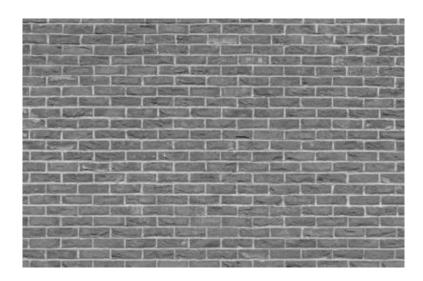
$$f(x,y) = \begin{bmatrix} r(x,y) \\ g(x,y) \\ b(x,y) \end{bmatrix}, \text{ r=red, g=green, b=blue}$$

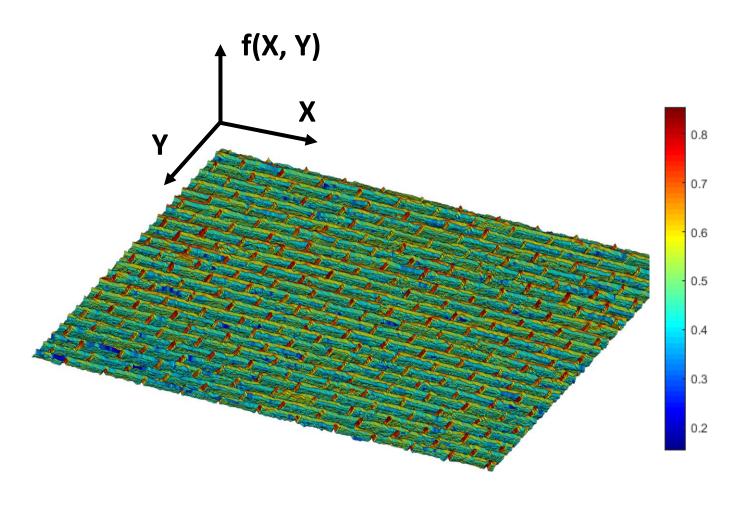
Image as Functions (Continue)

RGB



Gray





Linear Filtering?

- Filtering: Modify or enhance data using a function (i.e. convolution kernel)
- Linear: The function follows linear properties of scaling and superposition.
 - Superposition: h(A + B) = h(A) + h(B)
 - Scaling: $h(\alpha A) = \alpha h(A)$
- Simply, it's linear combination: h(X,Y,Z) = aX + bY + cZ

^{*} h is a linear filter.

Linear Filtering?

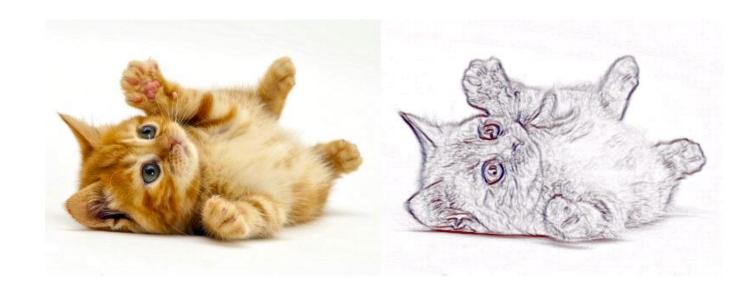
- Linear filtering is used to:
 - Reduce noise in data
 - Extract features from data

Noisy image



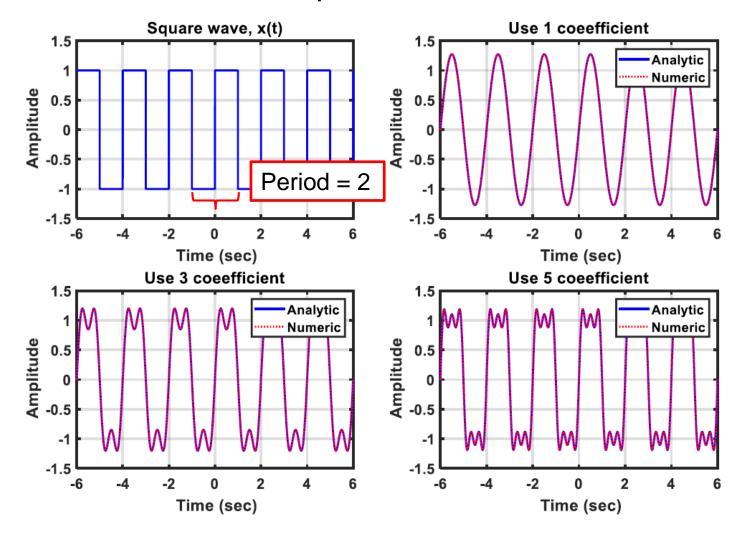
Denoised image





Recall: 1D Signal Interpreted using Fourier Series

Remember the square wave function and its Fourier series approximations?



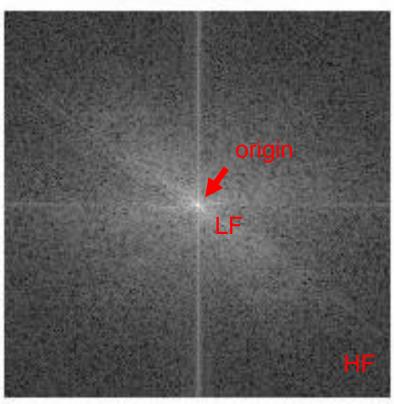
$$x(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n \cos\left(\frac{2\pi nt}{T_p}\right) + b_n \sin\left(\frac{2\pi nt}{T_p}\right)$$

Back to images: Image Interpreted in a Frequency Domain

Here is an image and its Fourier transform (remember Tp=infinity):



Fourier transform



Low frequency (LF) ≈ solid colors

High frequency (HF) ≈ noise/edges

Frequency axis 1

Frequency axis 2

Question?

- What is blur?
- What is low resolution?

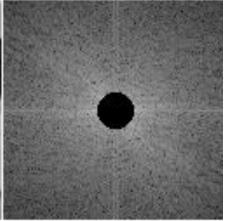
Back to images: Image Interpreted in a Frequency Domain

- If we remove low frequencies of an image, what do we get?
- How about high frequencies?

https://imagej.nih.gov/ij/docs/images/fft.jpg



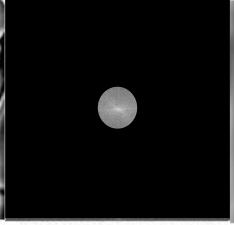
Original image



Power spectrum with mask that filters low frequencies



Result of inverse transform



Power spectrum with mask that passes low frequencies

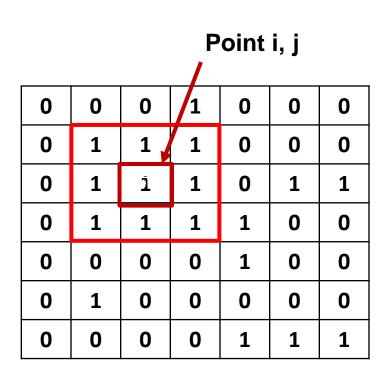


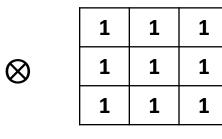
Result of inverse transform

Key point: Multiplication in the frequency domain is convolution in the spatial/time domain!

2D Cross-Correlation Example

Cross-correlation is <u>a measure of similarity</u> between two images. Cross correlation with a kernel can be viewed as comparing a litter "picture" or "region" of what you want to find across all subregions in the image.

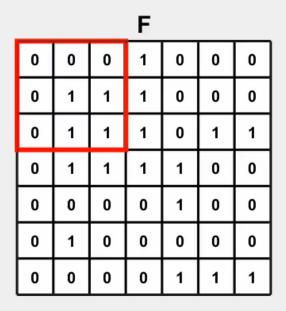


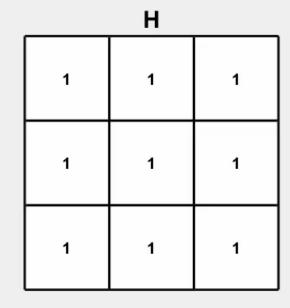


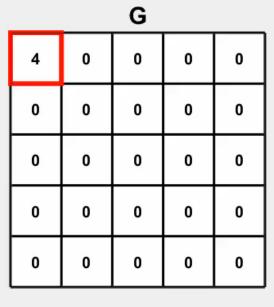
	\boldsymbol{k}	k	
$G[i,j] = \iota$	$\sum_{l=-k}$	$\sum_{v=-k}$	H[u,v]F[i+u,j+v]

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

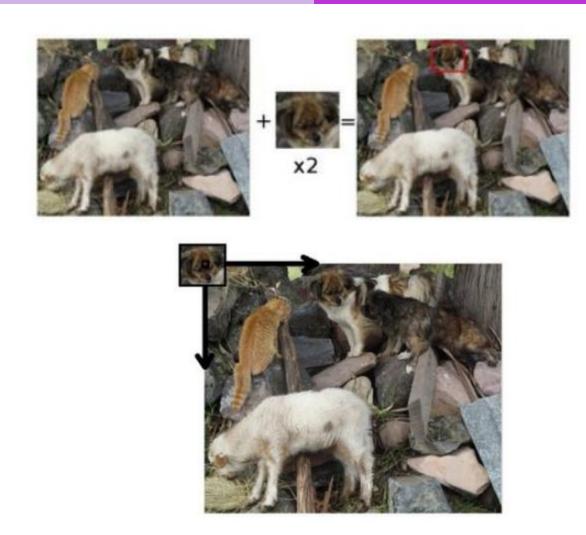
Computation of the Cross-Correlation Between Two Matrices







Example: Finding Same Objects on Images





https://docs.opencv.org/2.4/doc/tutorials/imgproc/histograms/template_matching/template_matching.html

Q: Do we need CNN?

2D Convolution

Let F be the image, H be the kernel (of size $2k+1 \times 2k+1$),

G be the output image

$$G[i,j] = \sum_{k=0}^{k} \sum_{i=0}^{k} H[u,v] F[i-u,j-v]$$

Only difference is that the kernel is "flipped" horizontally and vertically.

This is called a convolution operation:

$$G = H * F$$

Convolution Properties: Commutative, Associative, and Linearity

- Commutative: F * H = H * F
- Associative: F * (H * L) = (H * F) * L
- Linearity: $F * (H_1 + H_2) = F * H_1 + F * H_2$
- Relationship with differentiation: (F * H)' = F' * H = F * H'

Difference between Cross-Correlation and Convolution

X

A	В	С
D	Е	F
G	H	

Y

	Н	G
F	Ε	D
C	В	A

The basic difference between convolution and cross-correlation is that the convolution process flips the kernel horizontally and vertically.

Usage

Cross-Correlation: Process to measure a similarity between two signals.

Convolution: Process to transform a signal to another signal.

$G = H * X = H \otimes Y$

- ⊗ cross-correlation
- * convolution

Guessing Game! Linear Filter: Generating an Identical Image

0	0	0
0	1	0
0	0	0

0	0	0
0	0	1
0	0	0

1	1	1	1
<u> </u>	1	1	1
9	1	1	1

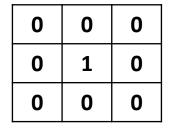
-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

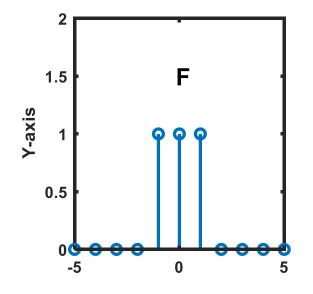
Guessing Game! Linear Filter: Generating an Identical Image

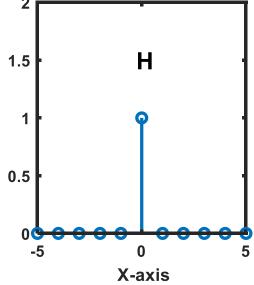


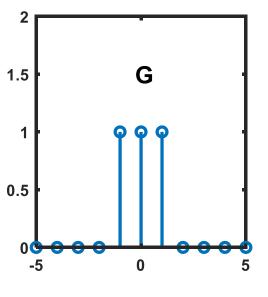












$$F * H = G$$

Guessing Game! Linear Filter: Shifting Pixels

0	0	0
0	1	0
0	0	0

0	0	0
0	0	1
0	0	0

1	1	1	1
_	1	1	1
9	1	1	1

-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

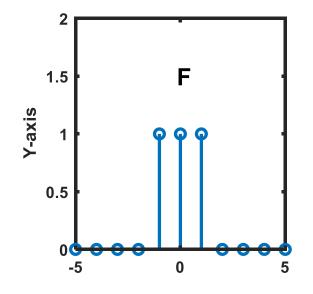
Guessing Game! Linear Filter: Shifting Pixels

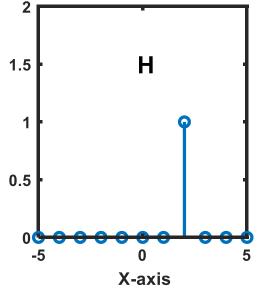


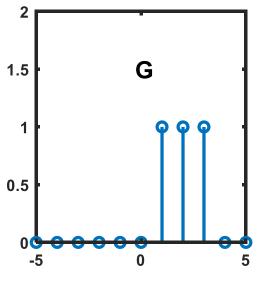


0	0	0
0	0	1
0	0	0









$$F * H = G$$

Guessing Game! Linear Filter: Blurring

0	0	0
0	1	0
0	0	0

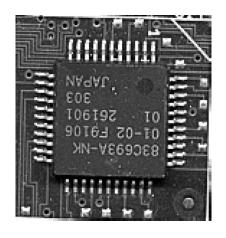
0	0	0
0	0	1
0	0	0

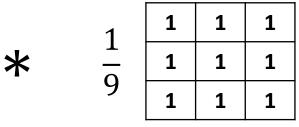
1	1	1	1
<u> </u>	1	1	1
9	1	1	1

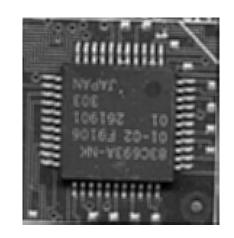
-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

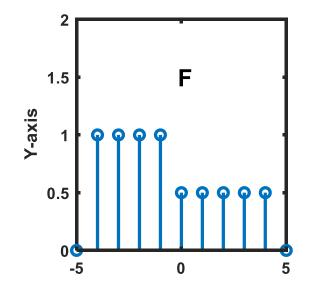
0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

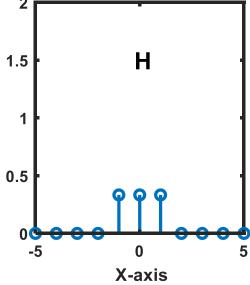
Guessing Game! Linear Filter: Blurring

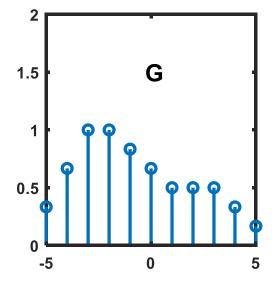












$$F * H = G$$

Guessing Game! Linear Filter: Sharpening

0	0	0
0	1	0
0	0	0

0	0	0
0	0	1
0	0	0

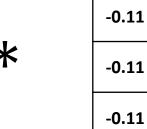
1	1	1	1
<u> </u>	1	1	1
9	1	1	1

-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Guessing Game! Linear Filter: Sharpening





-0.11

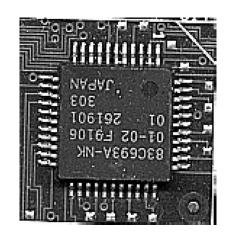
1.89

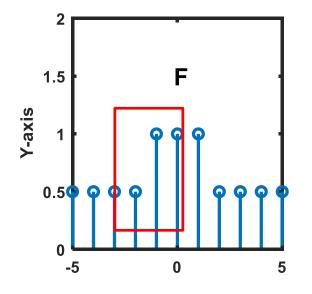
-0.11

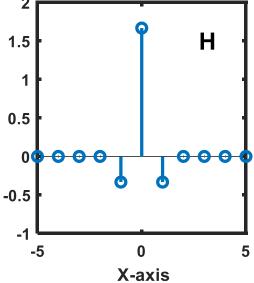
-0.11

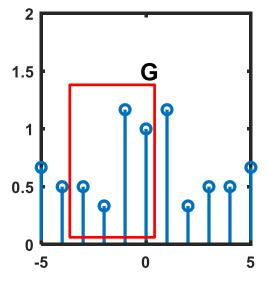
-0.11

-0.11









$$F * H = G$$

How the Sharpening Filter Works

0	0	0
0	2	0
0	0	0

0.11	0.11	0.11
0.11	0.11	0.11
0.11	0.11	0.11

-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

$$F + (F - F * H) = G$$

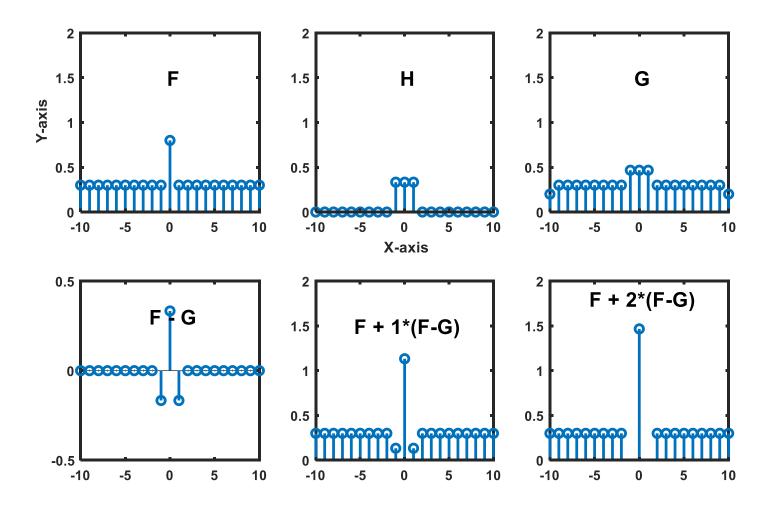
0	0	0
0	α+1	0
0	0	0

– α	0.11	0.11	0.11	
	0.11	0.11	0.11	
		0.11	0.11	0.11

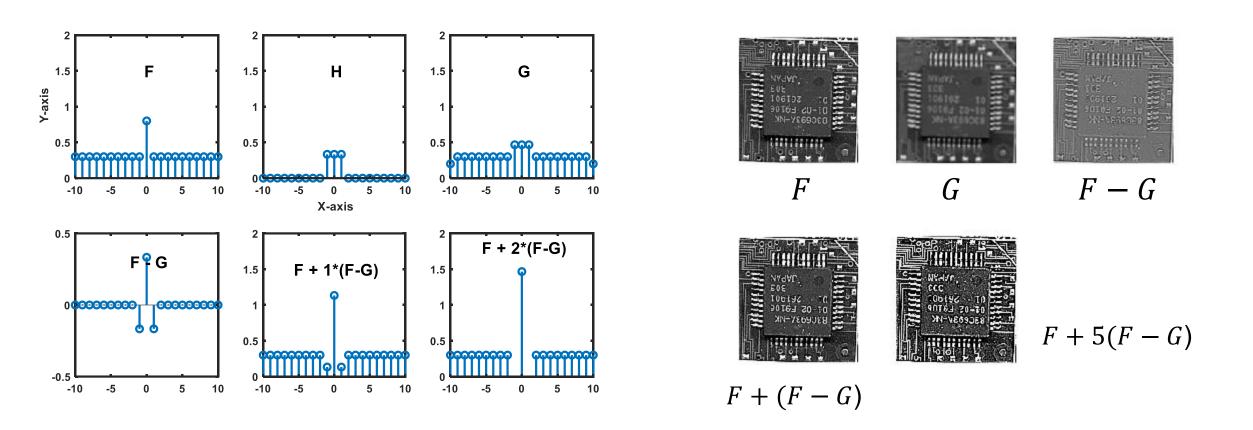
-0.11α	-0.11α	-0.11α
-0.11α	1+0.89α	-0.11α
-0.11α	-0.11α	-0.11α

$$F + \alpha(F - F * H) = G$$

How the Sharpening Filter Works (Signal Example) (Continue)



How the Sharpening Filter Works (Image Example)



Guessing Game! Gaussian Kernel

0	0	0
0	1	0
0	0	0

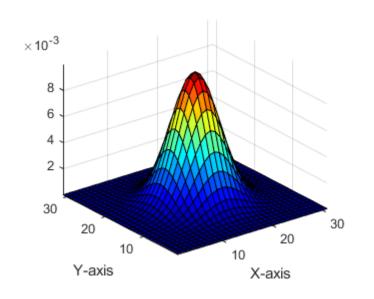
0	0	0
0	0	1
0	0	0

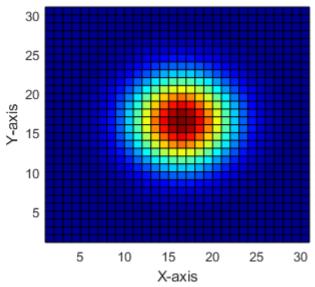
1	1	1	1
<u> </u>	1	1	1
9	1	1	1

-0.11	-0.11	-0.11
-0.11	1.89	-0.11
-0.11	-0.11	-0.11

0	.08	0.12	0.08
0	0.12	0.20	0.12
0	.08	0.12	0.08

Gaussian Kernel





$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Gaussian Filter

```
clear; close all; clc;
h = fspecial('gaussian',3,1);
numSize = 3;
[x, y] = meshgrid(1:numSize);
x = x-(round(numSize/2));
y = y-(round(numSize/2));
sigma = 1;
G sigma = 1/(2*pi*sigma^2)*exp(-(x.^2 + y.^2)/(2*sigma^2));
G sigma = G sigma/sum(G sigma, 'all');
figure(1);
subplot(121); PlotMat(h,gca,'float');
subplot(122); PlotMat(G sigma,gca,'float');
fig2 = figure(2);
subplot(121); h = fspecial('gaussian', 31,4);
surf(h); axis tight; colormap(jet)
set(fig2, 'Position', [100 100 800 300]);
xlabel('X-axis'); ylabel('Y-axis');
subplot(122); surf(h); view(0,90);
xlabel('X-axis'); ylabel('Y-axis'); axis tight
```

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Effect of Gaussian Window Sizes





Std=1







f1 = fspecial('gaussian', 101,1); f2 = fspecial('gaussian', 101,5); fspecial('gaussian', 101,10); fspecial('gaussian', 101,30);



Std=30

Challenges (template matching) !!!!!!





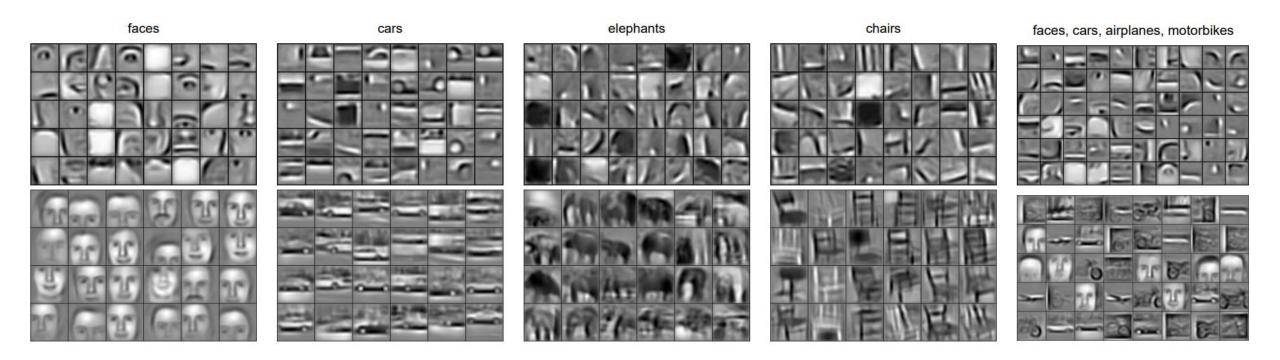








Applications: Convolution Neural Network



http://web.eecs.umich.edu/~honglak/icml09-ConvolutionalDeepBeliefNetworks.pdf