

# Image Compression via Singular Value Decomposition

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# Outline

- 1 Singular Value Decomposition
- 2 Application to Image Compression
- 3 The Code
- 4 Examples

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# Images are Matrices

- An image can be viewed as a matrix where each entry in the matrix represents a pixel.
  - If we greyscale the image the entries are just numbers!
  - (otherwise they would be something like triples representing RGB values)
- So, we can apply techniques from linear algebra to manipulate images!

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# Some Linear Algebra

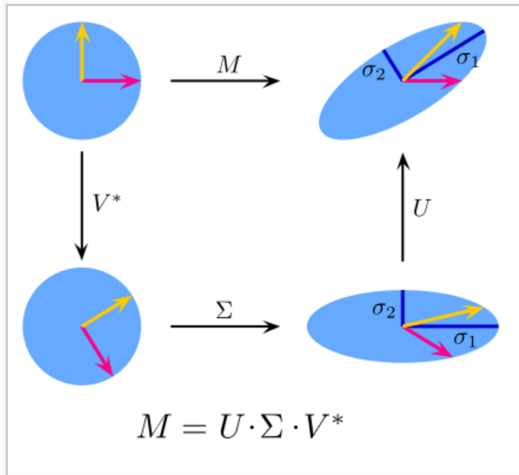
- Given a matrix  $M$  we can decompose it as  $M = U \Sigma V$  where  $U$ ,  $\Sigma$ , and  $V$  have some nice properties.
- $\Sigma$  is matrix whose non-zero entries are located on the main diagonal and these values contain information about how the columns of  $U$  relate to the matrix  $M$ .



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# Schematic Example



# Some Linear Algebra

- The columns of  $U$  whose corresponding values in  $\Sigma$  (called singular values) are large can be interpreted as the “most important” in relation to  $A$ .
- In a sense we can approximate  $A$  by only paying attention to the first  $N$  “most important” columns of  $U$ .

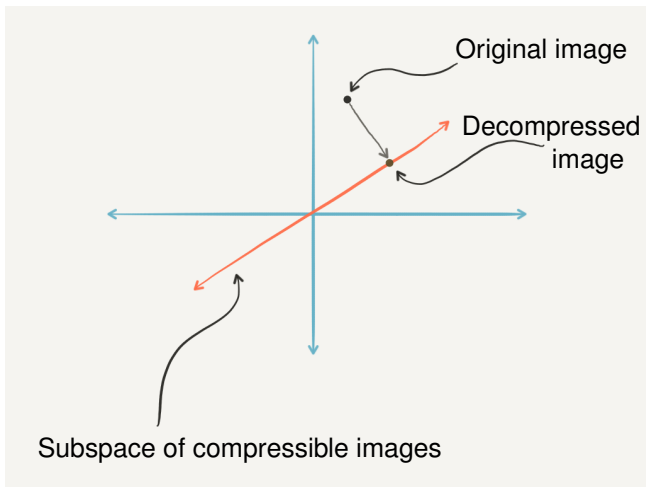
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# The Big Picture



# Where's the Compression?

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- The compressed can be described with only one coordinate: the distance along the line from the origin!
- So, we have halved the amount of information needed to store the image.

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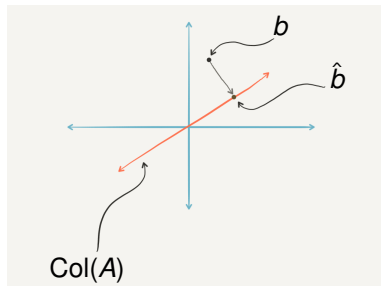
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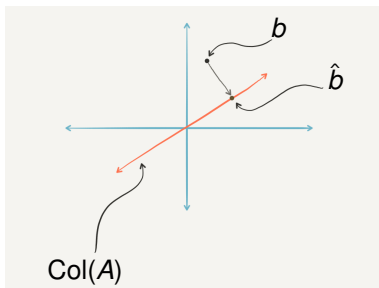
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# This is Really Least Squares (Some Math)



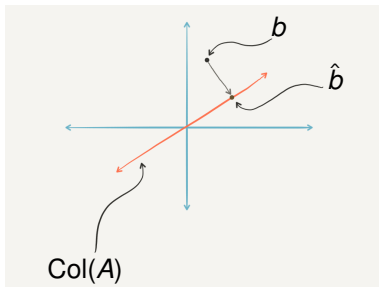
- If  $A$  is the matrix of “important” columns of the image matrix  $M$ , then the equation  $Ax = b$  has a solution if  $b$  is in the span of the columns of  $A$ .

# This is Really Least Squares (Some Math)



- But here,  $b$  is not in the column space of  $A$ , so we do the best we can: project  $b$  into  $Col(A)$  and solve the equation  $Ax = \hat{b}$  which DOES have a solution.

# This is Really Least Squares (Some Math)



- A solution to  $Ax = \hat{b}$  is a compressed representation of the image  $b$  and we recover the decompressed image  $\hat{b}$  by multiplying by  $A$ .

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- The following is a low resolution example generated in python.

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The following examples were generated using the same algorithm, but implemented in Mathematica.

# I Like Dogs



# Compressed 90%



# Compressed 99%



# I Like Dogs



# Compressed 90%



# Compressed 99%



# I Like Dogs





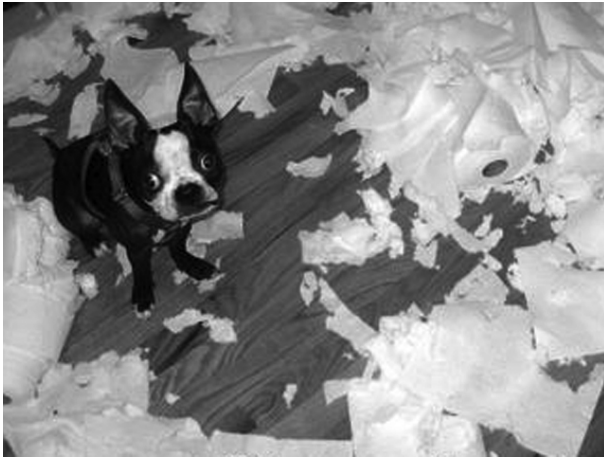
# Compressed 90%



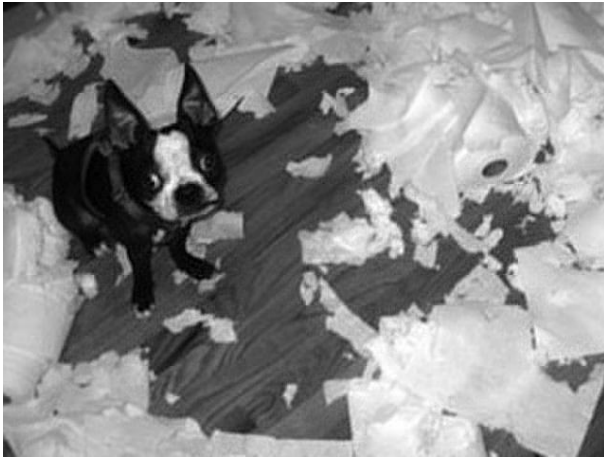
# Compressed 99%



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