

Stochastic Methods

Solving optimization problems,
PCA in practice – feature selection, compression

Seminar 3

Spring 2019

Outline

1. More complaints about official tSNE Matlab implementation: magic parameters?
2. Some optimization problems
 - Equality constrained problem
 - Inequality constrained problem
3. PCA in practice:
 - feature selection
 - compression

2.) Some optimization problems

Problem 1: Find the dimensions of the box with largest volume
if the total surface area is $s > 0$.

Problem 2:

Find $\arg \min 4x^2 + 10y^2 - 3$ s.t. $x - y \geq 1$

3a) PCA: feature selection





Find optimal basis such that every image can be written as linear combination:

$$\text{Image} = \alpha_1 \begin{array}{|c|} \hline ? \\ \hline \end{array} + \alpha_2 \begin{array}{|c|} \hline ? \\ \hline \end{array} + \alpha_3 \begin{array}{|c|} \hline ? \\ \hline \end{array}$$

(“orthonormal” images)



See Atelier 3

!!!



Find optimal basis such that every image can be written as linear combination:



\approx



α_1

?

+ α_2

?

+ α_3

?

+ orig. mean

“optimal” approximation

- Matlab is ready for working with images (see “imread”, “imwrite”)
- Instead of working with rectangular images – work with vectorized images (see “reshape”)
- We can use command “pca”, but it is too boring, let’s implement it from the scratch
- Not from the total scratch – use “eig”/“eigs”

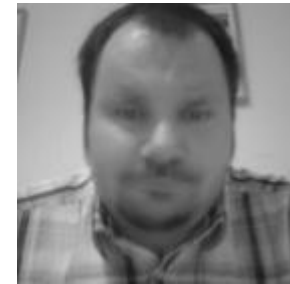
PCA algorithm

1. subtract mean value from the data
2. construct covariance matrix
3. compute m largest eigenvalues and corresponding orthonormal eigenvectors, construct Q
4. project the data $X_{\text{reduced}} = Q^T X_{\text{original}}$

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PCA algorithm

1. subtract mean value from the data



“Mean” image

2. construct covariance matrix

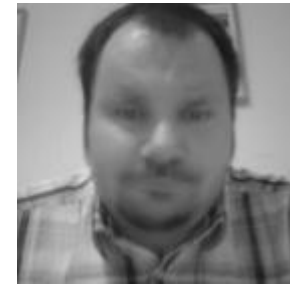
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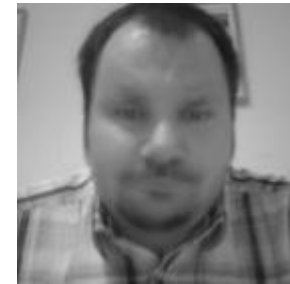
“Mean” image

Be smart and avoid for-loop

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“Mean” image

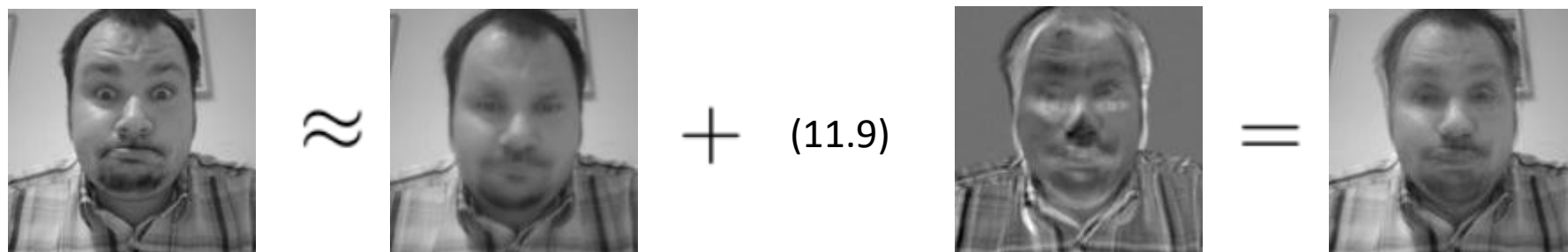
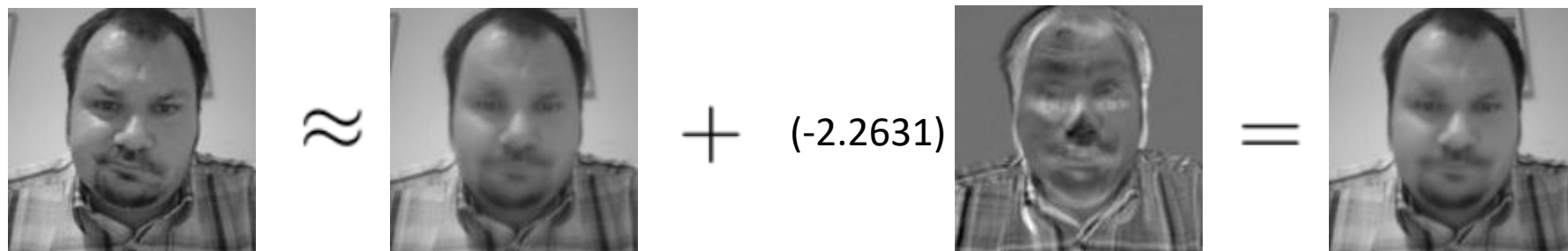
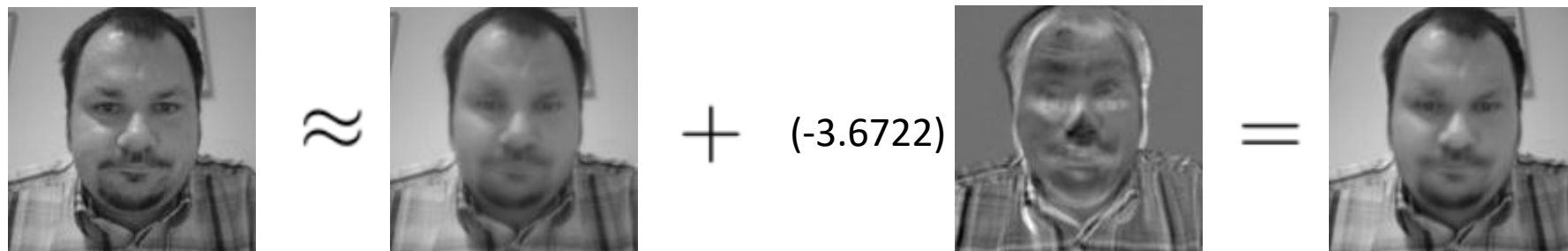
Be smart and avoid for-loop

You don’t want to compute all of the eigenvectors!, use “eigs”

$m = 1$



m = 1



(only the largest deviations from mean are captured)

$m = 1$

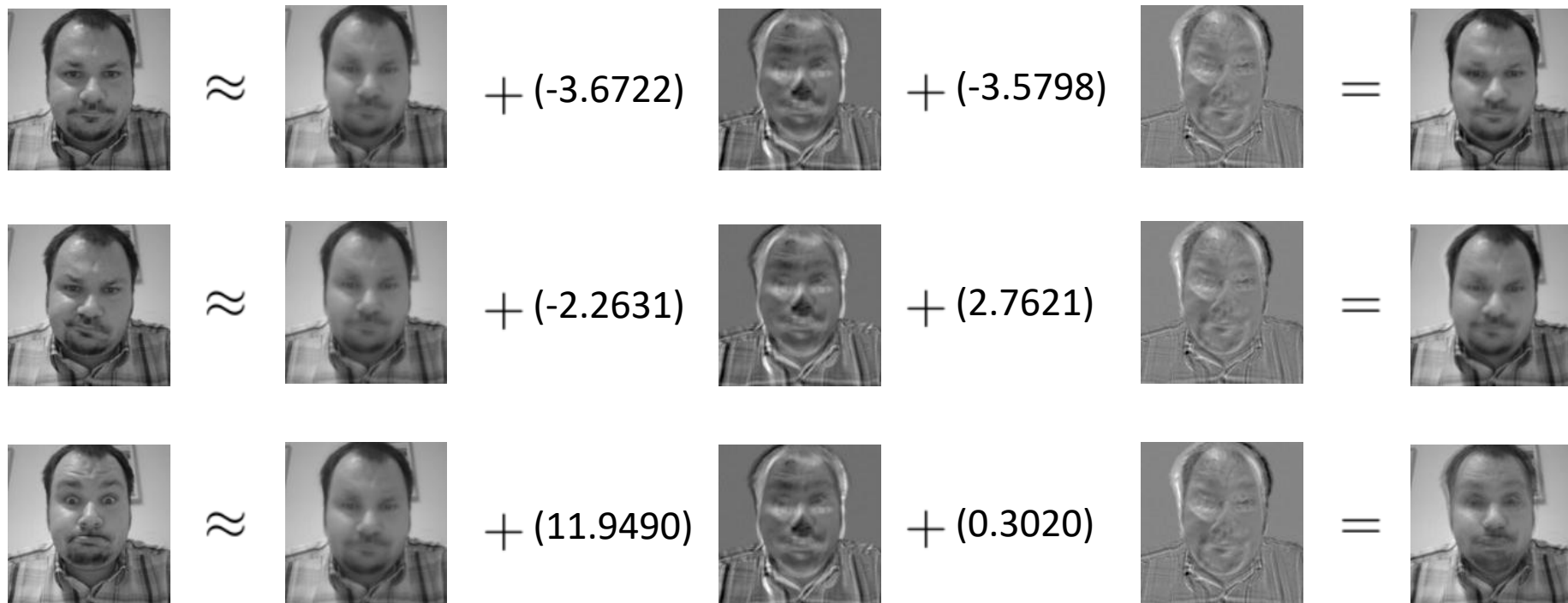


(only the largest deviations from mean are captured)

$m = 2$



m = 2



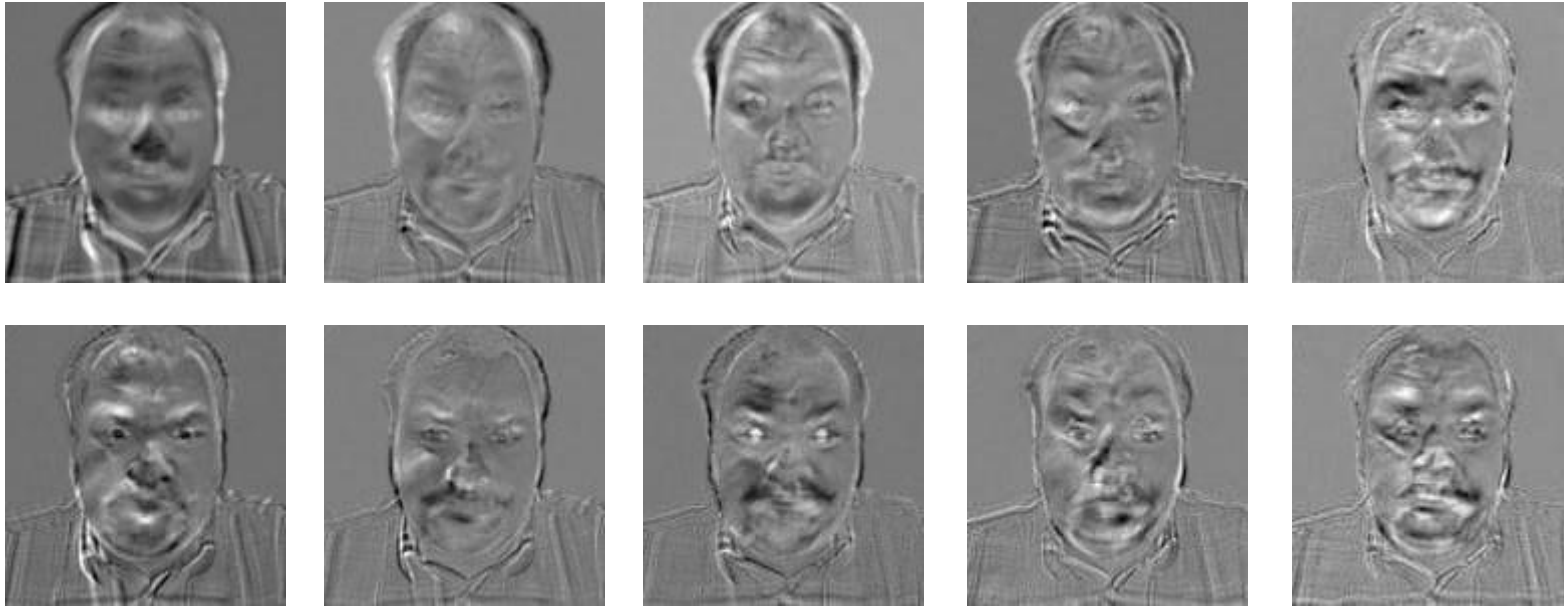
(only the two largest deviations from mean are captured)

$m = 2$



(only the two largest deviations from mean are captured)

$m = 10$



Size of original dataset: $T \times \text{width} \times \text{height} = 24 \times 140 \times 140 = 470400$ values

Size of reduction: $T \times m + m \times \text{width} \times \text{height} + \text{width} \times \text{height} = 215840$ values

coeffs

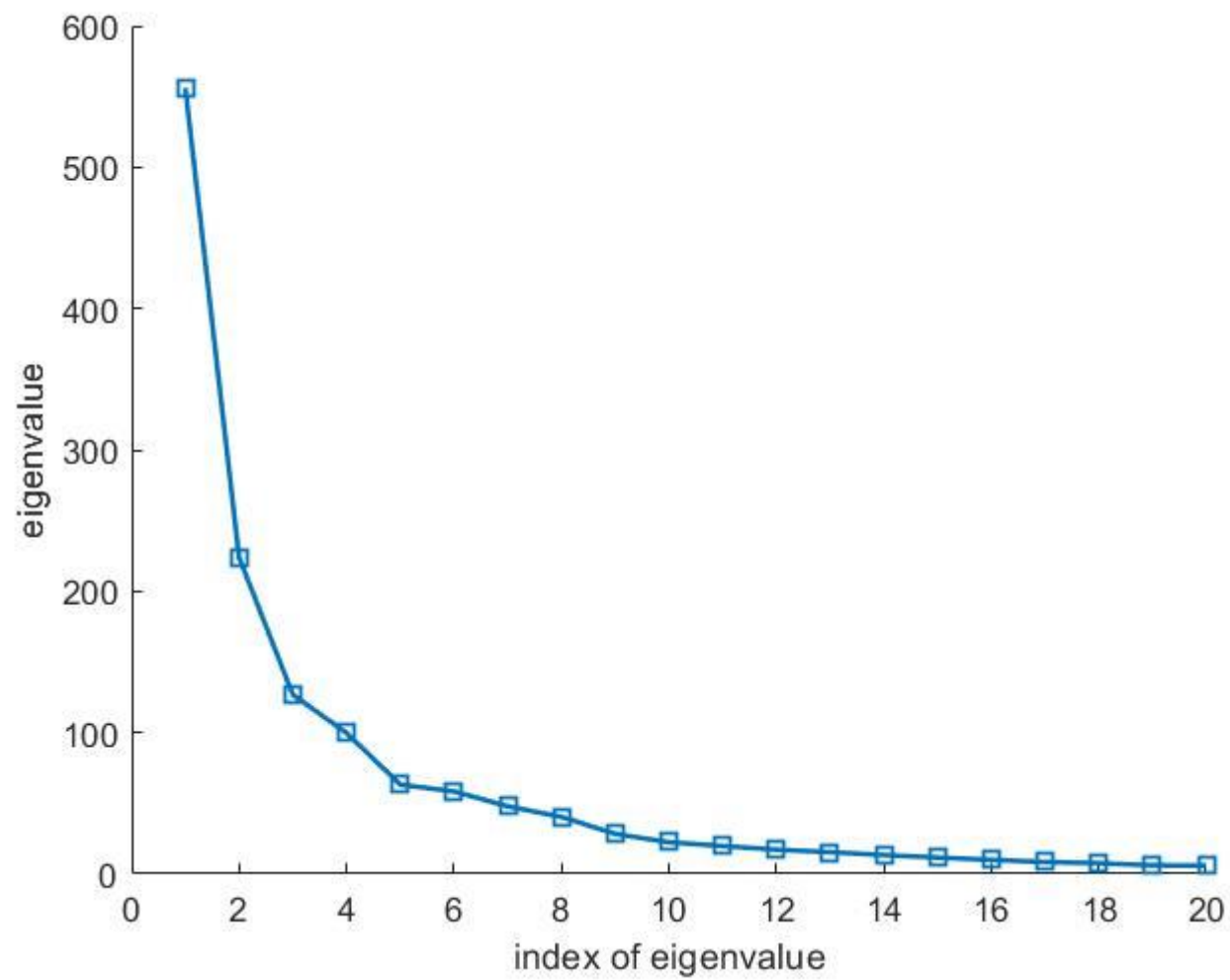
basis vectors

mean face

Compression?
See next example

$m = 10$





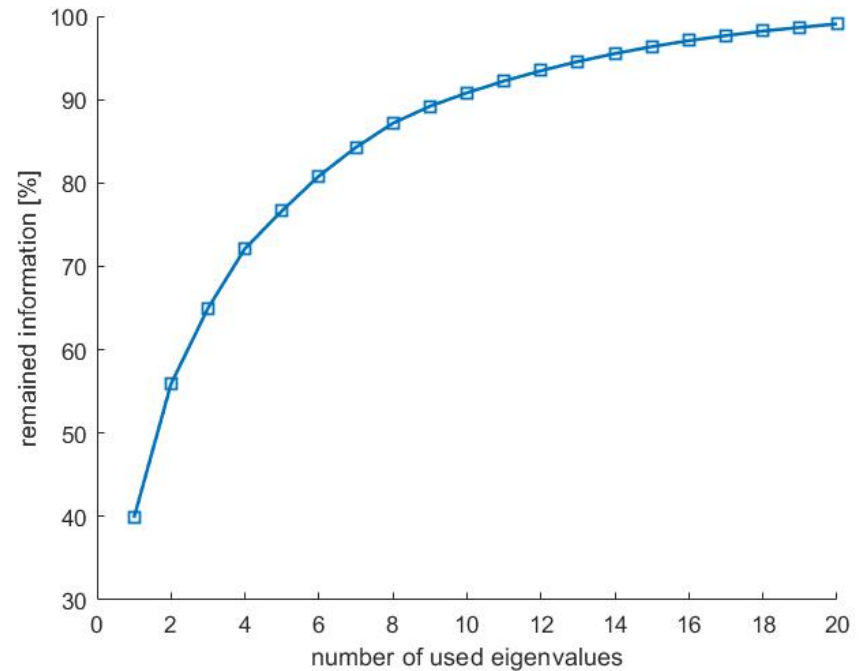
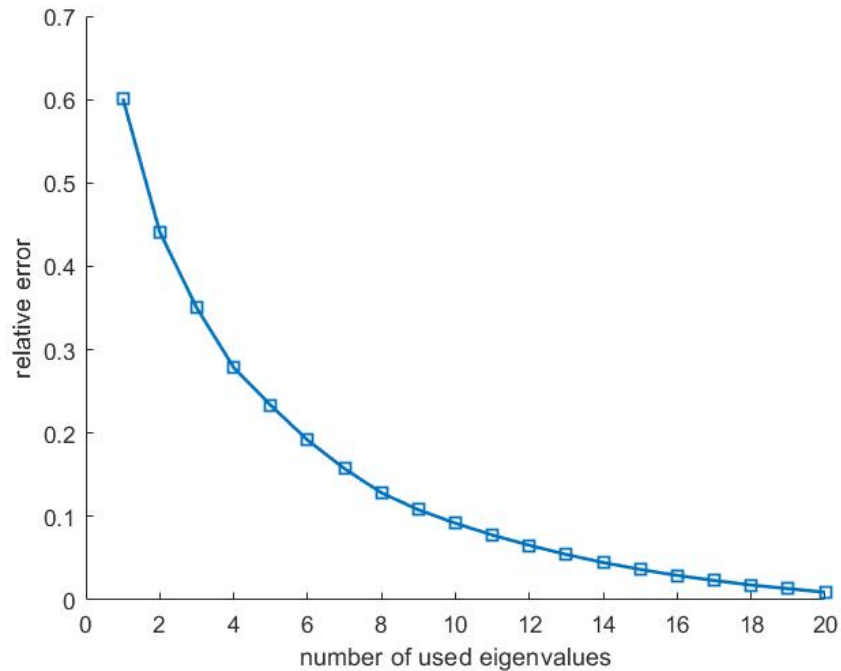
$$\text{relative error} := \frac{\sum_{i=m+1}^n \lambda_i}{\sum_{i=1}^n \lambda_i}$$

$$\text{remained information in the reduced data} = \left(1 - \frac{\sum_{i=m+1}^n \lambda_i}{\sum_{i=1}^n \lambda_i} \right) \cdot 100[\%]$$

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Hint: use trace instead of computing all eigenvalues!



- Method is completely knowledge free
- PCA can distinguish what is important and what is redundant
- By rearranging pixels column by column to a 1D vector, relations of a given pixel to pixels in neighboring rows are not taken into account.
- Another disadvantage is in the global nature of the representation; small change or error in the input images influences the whole eigen-representation.

More info: google “eigenface”

3b) PCA: compression

(motivated by previous example)



This is Illia.

Illia is too big.

$3 \times 1024 \times 1024 = 3145728$ values

Let's compress him.

(find optimal reduced space
and the representation of projection of this
image onto this space)

(note: actually this is JPEG image and it is already compressed)



red



green



blue

We will deal with each channel individually.

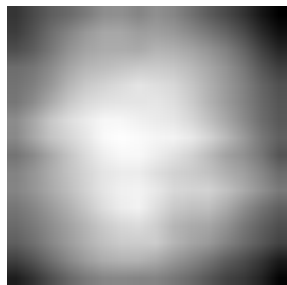


- Divide the original 1024 x 1024 image into patches:
- Each patch is an instance that contains 16x16 pixels on a grid
- Patch = face in previous example
- Consider each as a 256-D vector and compress it using PCA
- $T = 4096, n = 256$

$m = 1$



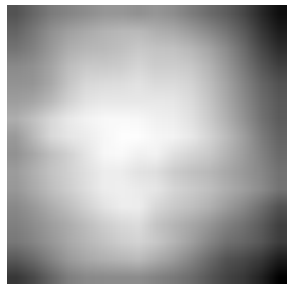
R mean



R eigenvector



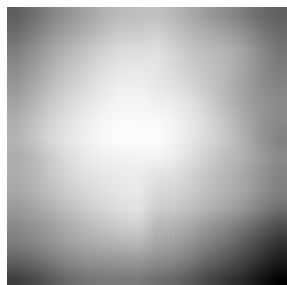
G mean



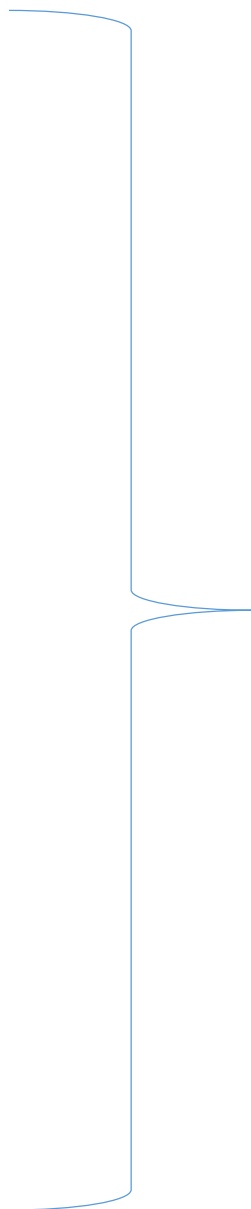
G eigenvector



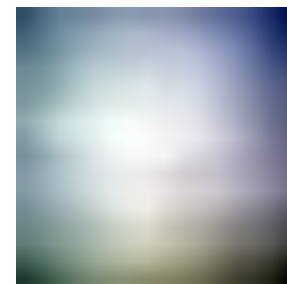
B mean



B eigenvector



RGB mean

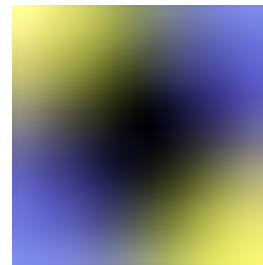
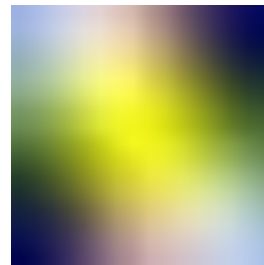
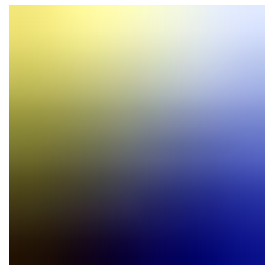
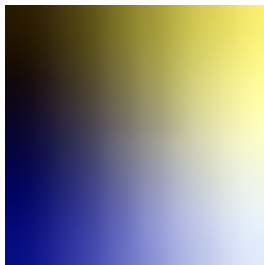
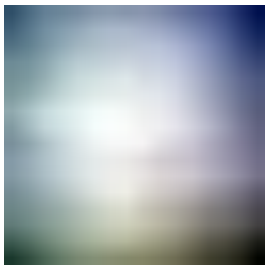


RGB eigenvector

$m = 1$



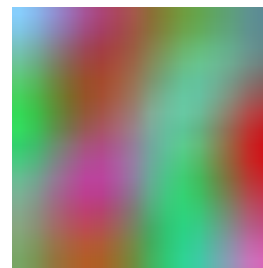
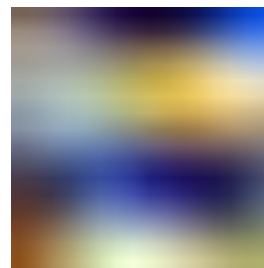
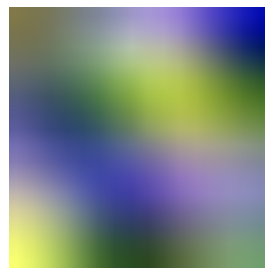
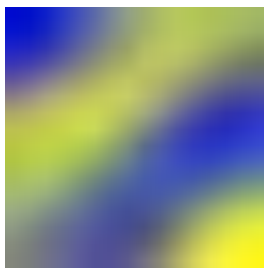
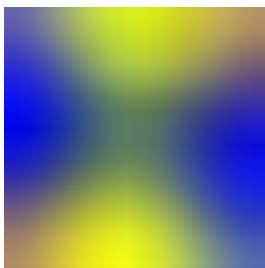
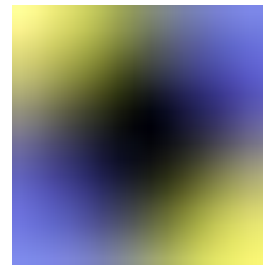
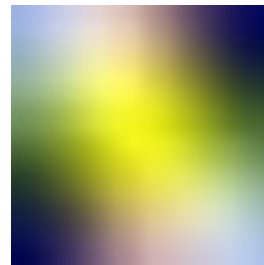
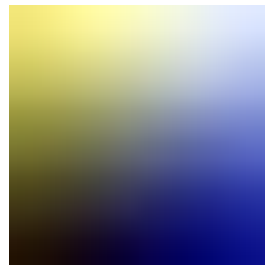
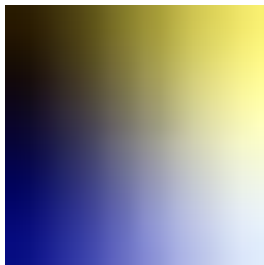
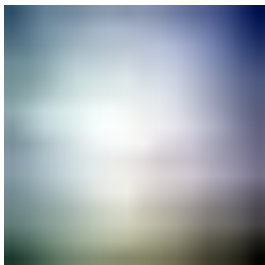
$m = 5$



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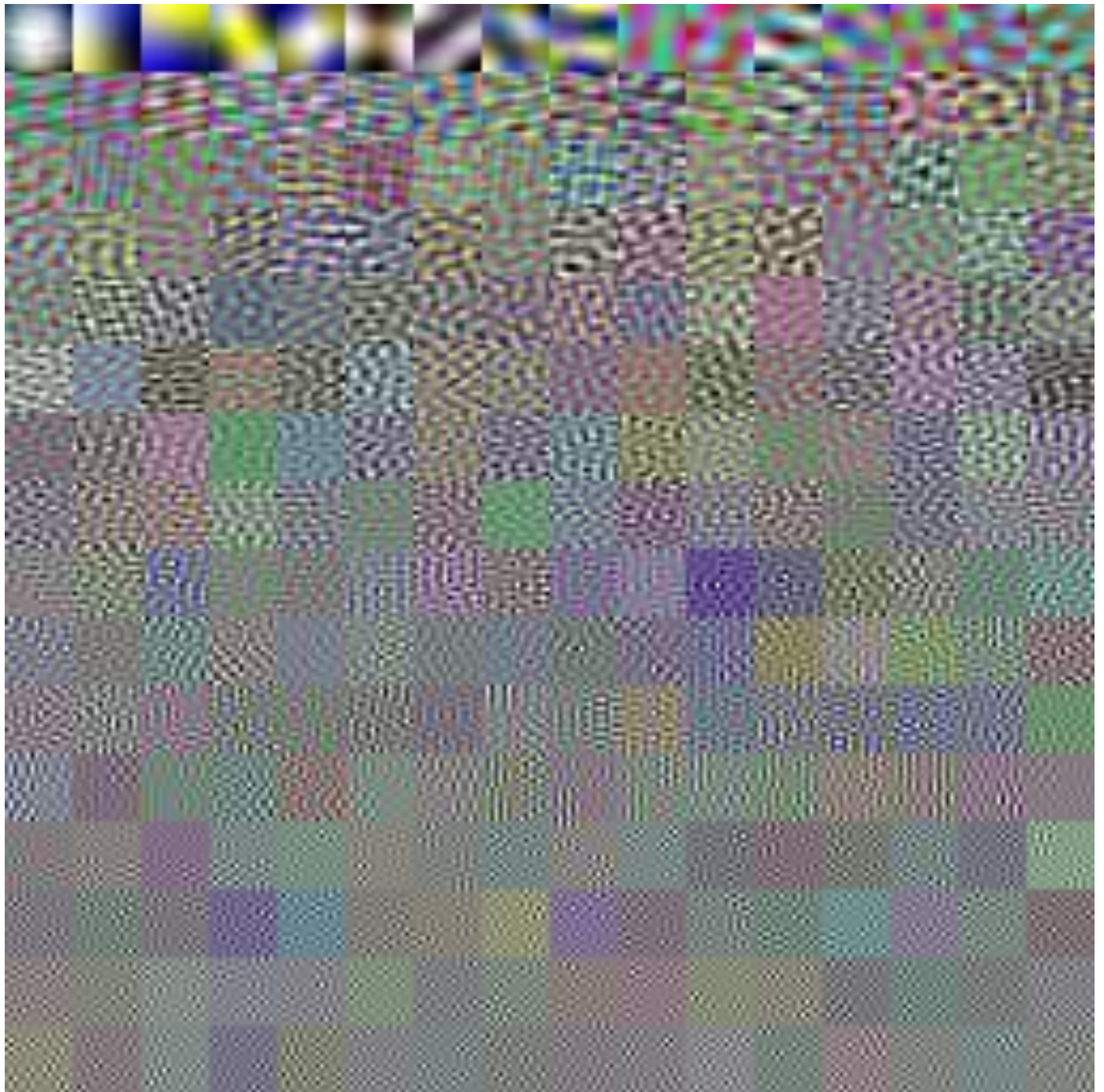
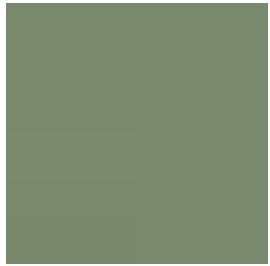
$m = 10$

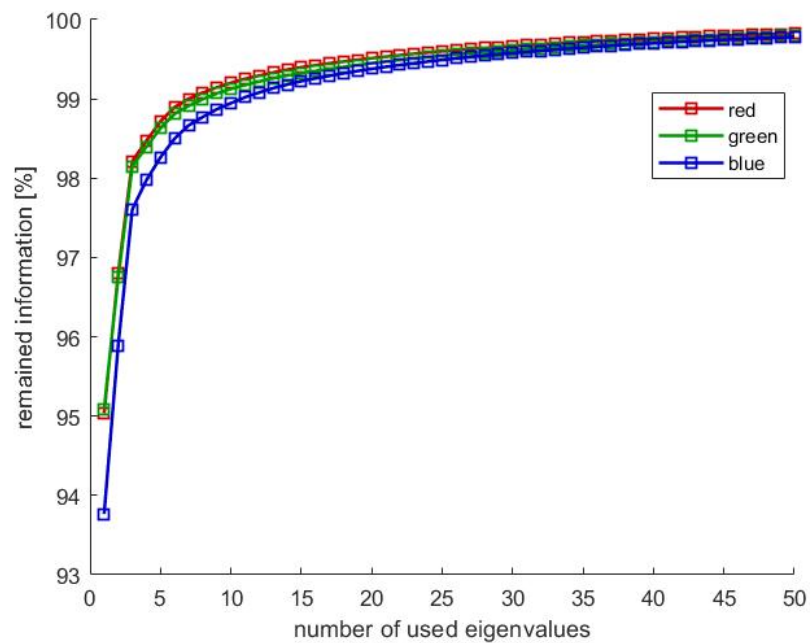
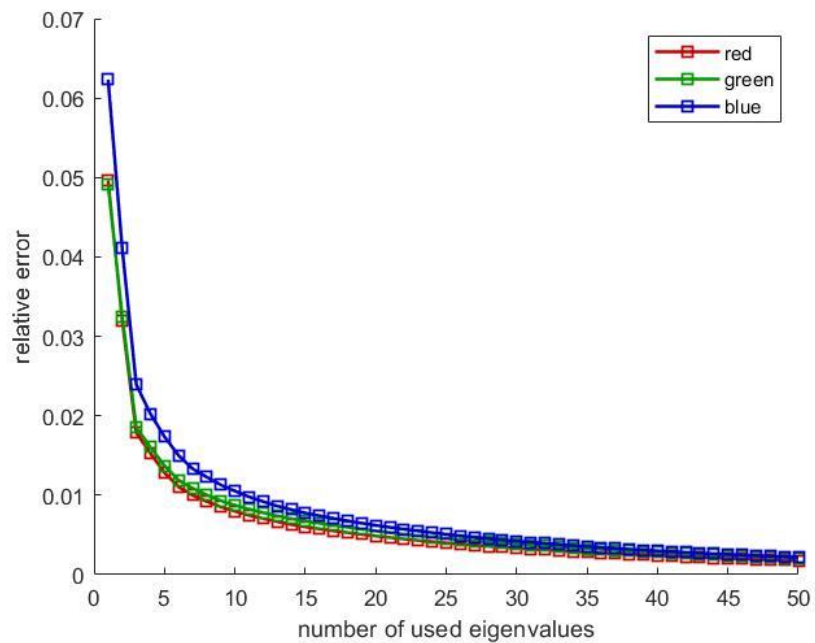
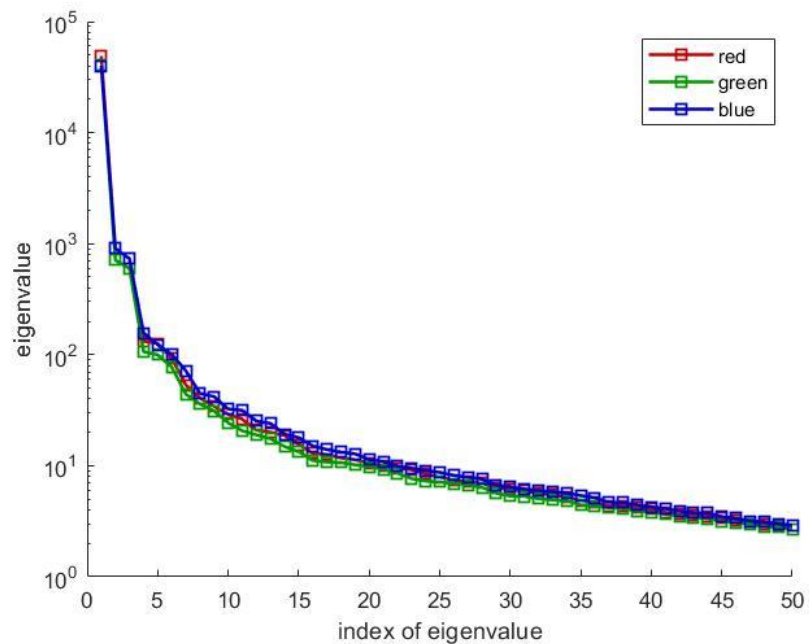


$m = 10$



$m = 256$





$$\text{Compression Ratio} = \frac{\text{Uncompressed Size}}{\text{Compressed Size}}$$

$3 \times 1024 \times 1024 = 3145728$ values

$$\underbrace{(\text{nmb_of_patches} * m)}_{\text{coeffs (reduced data)}} + \underbrace{m * \text{patch_size} * \text{patch_size}}_{\text{basis vectors}} + \underbrace{\text{patch_size} * \text{patch_size}}_{\text{mean}} * 3$$

