

# Tutorial: Image Compression using Singular Value Decomposition

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# Image Compression

- One usage of Singular Value Decomposition (SVD) is compressing large matrices.
- We have learned that images are essentially matrices of numeric values when stored in computers.
- Therefore, we can use SVD to compress images.

# SVD

Recall, SVD of a matrix  $M \in \mathbb{R}^{m \times n}$  finds the following three matrices:

- $U \in \mathbb{R}^{m \times r}$ ,
  - $D \in \mathbb{R}^{r \times r}$  is a diagonal matrix stores singular values,
  - $V \in \mathbb{R}^{n \times r}$ ,
- such that

$$M = UDV^{\top}$$

and  $r = \min(m, n)$ .

In numerical softwares (such as R or MATLAB), the singular values stored in  $D$  are sorted decreasingly.

# SVD Compression

Suppose singular values in  $D$  are sorted decreasingly,  
SVD can be used to construct an approximation of  $M$ :

$$M_1 = U_1 D_1 V_1^\top,$$

where

- $U_1 = U_{[1:m, 1:r_1]},$
- $D_1 = D_{[1:r_1, 1:r_1]},$
- $V_1 = V_{[1:n, 1:r-1]}.$
- $r_1$  is a positive integer smaller than  $r$ .

# Loading Images

Install "imager" package if you have not.

```
install.packages("imager")
```

Load an image into the matrix `M`.

```
library(imager)
img <- load.image("UoB.jpg")
img <- grayscale(img)
M <- as.matrix(img)
```

Now `M` should contain an matrix whose entries are pixel values of the image.

# Checking out the Image

Plot the image

```
plot(as.cimg(M))
```

Check out how much memory does it take to store this image:

```
# fill out the blank.  
size1 <- _____  
print(paste("size:", size1, "bytes"))
```

# Compression

Now, use builtin `svd` function to obtain  $U$ ,  $D$ ,  $V$  for `M`.

- Hint: `?svd`

Double check you have used `svd` correctly:

```
norm(M - U*%D%*%t(V), type = "F")  
[1] 1.787766e-12
```

Check out  $r$ :

```
dim(U)[2]  
674
```

# Compression

Let us set `r1 <- 100`.

Construct  $U_1, D_1, V_1$  using  $U, D, V$  and  $r_1$ .

Reconstruct the  $M_1$  using  $U_1, D_1, V_1$ .



# Examine the Compression

Plot the compressed image:

```
plot(as.cimg(M_1))
```

Does it look like Netflix when set to low quality?

Check out how much memory does it take to store the compressed image:

```
# Fill out the blank  
size2 <- _____  
print(paste("size:", size2, "bytes"))
```

What is the compression ratio `size2/size1` ?

Do you think given the image quality degradation, such a compression is worth it?

# Advanced Mathematical Question:

Why is  $M_1$  called an approximation of  $M$ ?

- Hint: take the difference  $M - M_1$  and check the reminder.

Our construction  $M_1$  is the best "low rank approximation" of  $M$  in terms of Frobenius norm.

- Read: [https://en.wikipedia.org/wiki/Low-rank\\_approximation](https://en.wikipedia.org/wiki/Low-rank_approximation)
- Low rank approximation is a classic problem in machine learning.