# 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:

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

$$M = UDV^{ op}$$

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:

$$M_1=U_1D_1V_1^{ op},$$

where

- $U_1 = U_{[1:m,1:r_1]}$ ,
- $D_1 = D_{[1:r_1,1:r_1]}$ ,
- $ullet V_1 = V_{[1:n,1:r_1]}.$
- $r_1$  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)</pre>
```

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"))</pre>
```

#### 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  $r_1 = 100$ .

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"))</pre>
```

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/Lowrank\_approximation
- Low rank approximation is a classic problem in machine learning.