

# Computer Graphics

Proximity

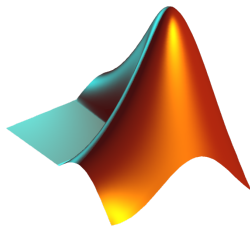
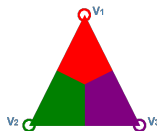
Emanuele Rodolà  
[rodola@di.uniroma1.it](mailto:rodola@di.uniroma1.it)



# Exercises

- Visualize function  $f(x_i) = \sum_j \|x_i - x_j\|$  with the blue-white-red colormap

- Nearest-neighbor colors for arbitrary triangles



# Proximity

The general notion of **proximity** or **neighborhood** arises everywhere

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distance between pixels  
in **color space**

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distance between pixels  
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Proximity is not necessarily a **spatial** notion in the classical sense

# Adjacency matrices

Graph connectivity can be encoded in [adjacency matrices](#)

Let  $|V| = n$ ,  $|E| = e$ ,  $|F| = m$  for a mesh  $M = (V, E, F)$

# Adjacency matrices: Vertex-to-vertex

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The [vertex-to-vertex](#) adjacency is defined as the  $n \times n$  binary matrix:

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- $\mathbf{A}$  is **symmetric**
- Each row and column has at least one 1 (that is,  $\sum_{ij} a_{ij} = e$ )

# Adjacency matrices: Vertex-to-triangle

Graph connectivity can be encoded in [adjacency matrices](#)

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- Each [row](#) has at least one 1 (each vertex belongs to some triangle)
- Each [column](#) sums up to 3 (each triangle has exactly 3 vertices)

# Adjacency matrices: Triangle-to-triangle

Consider the product:

$$\mathbf{P}^\top \mathbf{P} = \begin{pmatrix} 1 & \dots & \dots & 0 \\ 0 & \dots & \dots & 1 \\ 0 & \dots & \dots & 0 \\ \vdots & \dots & \dots & \vdots \\ 0 & \dots & \dots & 1 \\ 1 & \dots & \dots & 0 \\ 1 & \dots & \dots & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & 1 & 1 \\ \vdots & \dots & \dots & \dots & \dots & \dots & \vdots \\ \vdots & \dots & \dots & \dots & \dots & \dots & \vdots \\ 0 & 1 & 0 & \dots & 1 & 0 & 1 \end{pmatrix}$$

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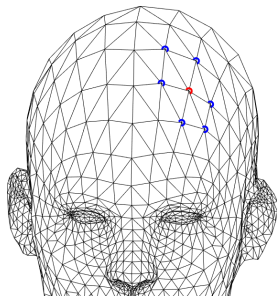
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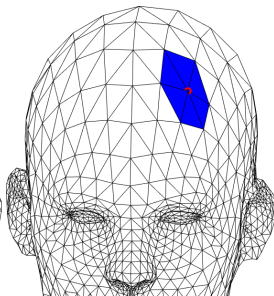
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- $\text{diag}(\mathbf{P}^\top \mathbf{P})$  is always 3 (=number of vertices per triangle)
- All other values are 0 (non-adjacent triangles), 1 (triangles share one vertex), or 2 (triangles share an edge)

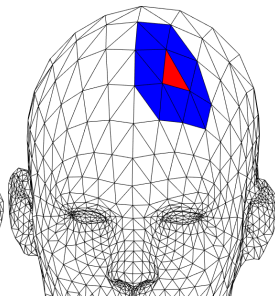
# Examples: Adjacency



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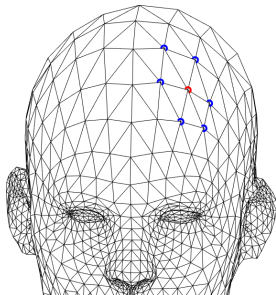


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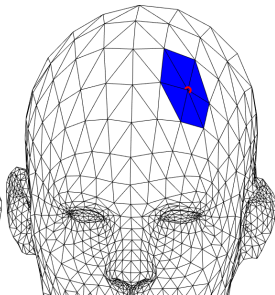


triangle-to-triangle

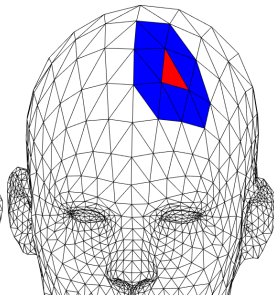
# Examples: Adjacency



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Adjacency matrices can be **very large** (quadratic in  $n$ )

Better use **sparse** data structures to store them

# Adjacency in color space

We can define a distance between colors, for example:

$$d_{ij} = \|\mathbf{c}_i - \mathbf{c}_j\|$$

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Classical “hard” (or binary) adjacency may be defined as:

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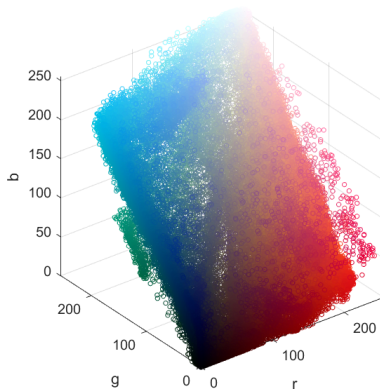


# Images as point clouds

This suggests a new representation of images as **point clouds in a color space** (3D for RGB, 4D for CMYK, etc.)

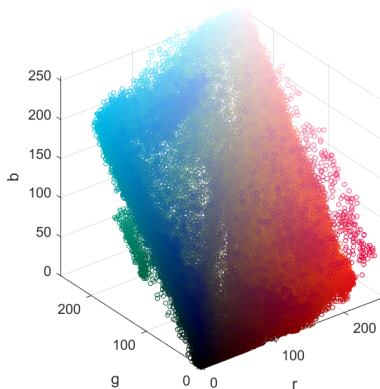
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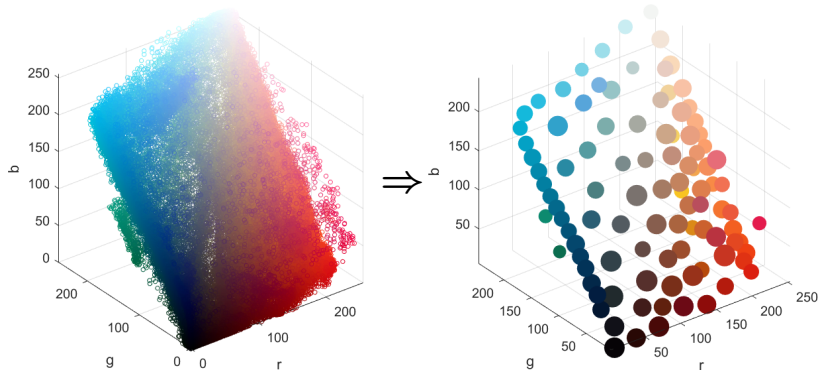
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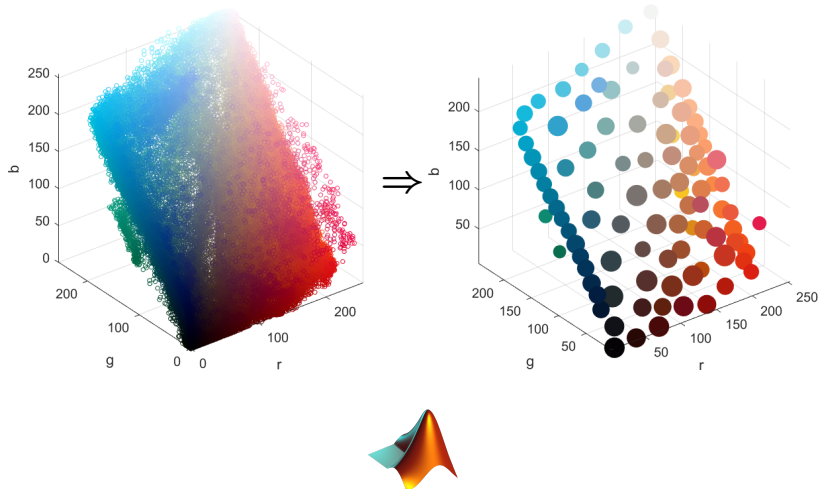
# Images as $k$ -D histograms

A more **efficient** and **noise-reducing** (although **not equivalent**) representation uses histograms:



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## Adjacency matrices: Powers

The  $k$ -th power of  $\mathbf{A}$  corresponds to composing  $\mathbf{A}$  with itself  $k \geq 1$  times

For example, for  $k = 2$ :

$$\mathbf{A}^2 = \mathbf{A}\mathbf{A} = \begin{pmatrix} 0 & 1 & 0 & \cdots & 1 \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & \cdots & 1 \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \cdots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \end{pmatrix}$$

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The result is a  $n \times n$  matrix encoding **2nd order adjacency**

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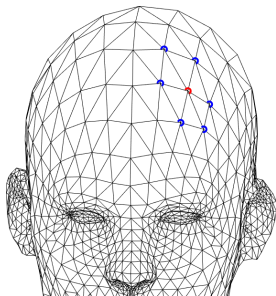
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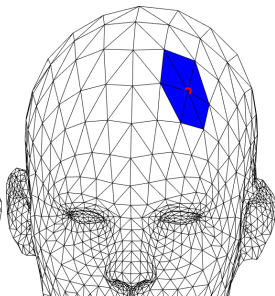
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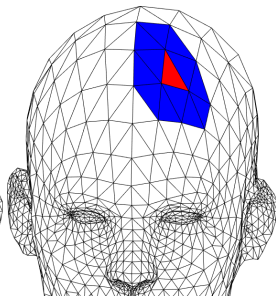
# Examples: Powers



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 $k = 1$

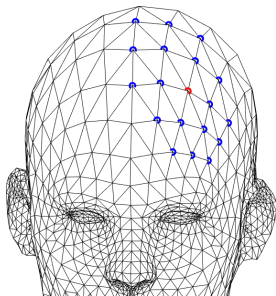


vertex-to-triangle  
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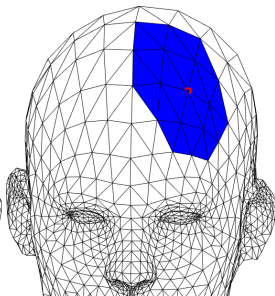


triangle-to-triangle  
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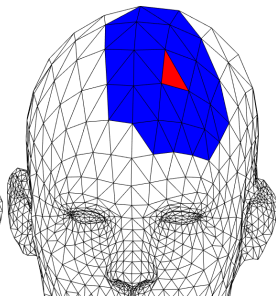
# Examples: Powers



vertex-to-vertex  
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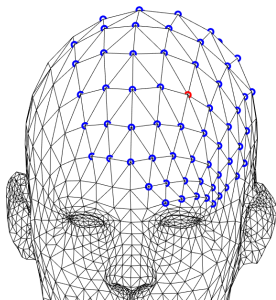


vertex-to-triangle  
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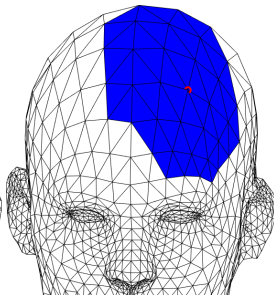


triangle-to-triangle  
 $k = 2$

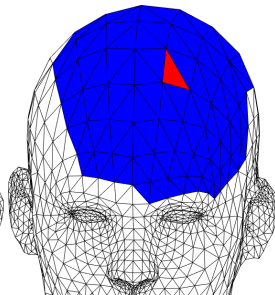
# Examples: Powers



vertex-to-vertex  
 $k = 3$



vertex-to-triangle  
 $k = 3$



triangle-to-triangle  
 $k = 3$

## Exercise: K-means clustering

Given a set of  $n$  points  $X \subset \mathbb{R}^3$ , implement the following algorithm:

- 1 Select a set of  $k < n$  points  $S \subset \mathbb{R}^3$  (“seed”).  
Note: the selected points are not necessarily from  $X$ .
- 2 For each point in  $X$ , find its **nearest neighbor** in  $S$ .  
The result is  $k$  **clusters** of points.
- 3 For each cluster  $K$ , compute its **centroid** as  $c = \frac{1}{|K|} \sum_i x_i$ .
- 4 Replace  $S$  with the  $k$  centroids.
- 5 Repeat from 2 until converge.

Test your code by computing 3D color histograms as done during class.

# Exercise: Palette reduction

Use *k*-means clustering to obtain p5\_projected.png from p5.png (download the two images from the course website)

