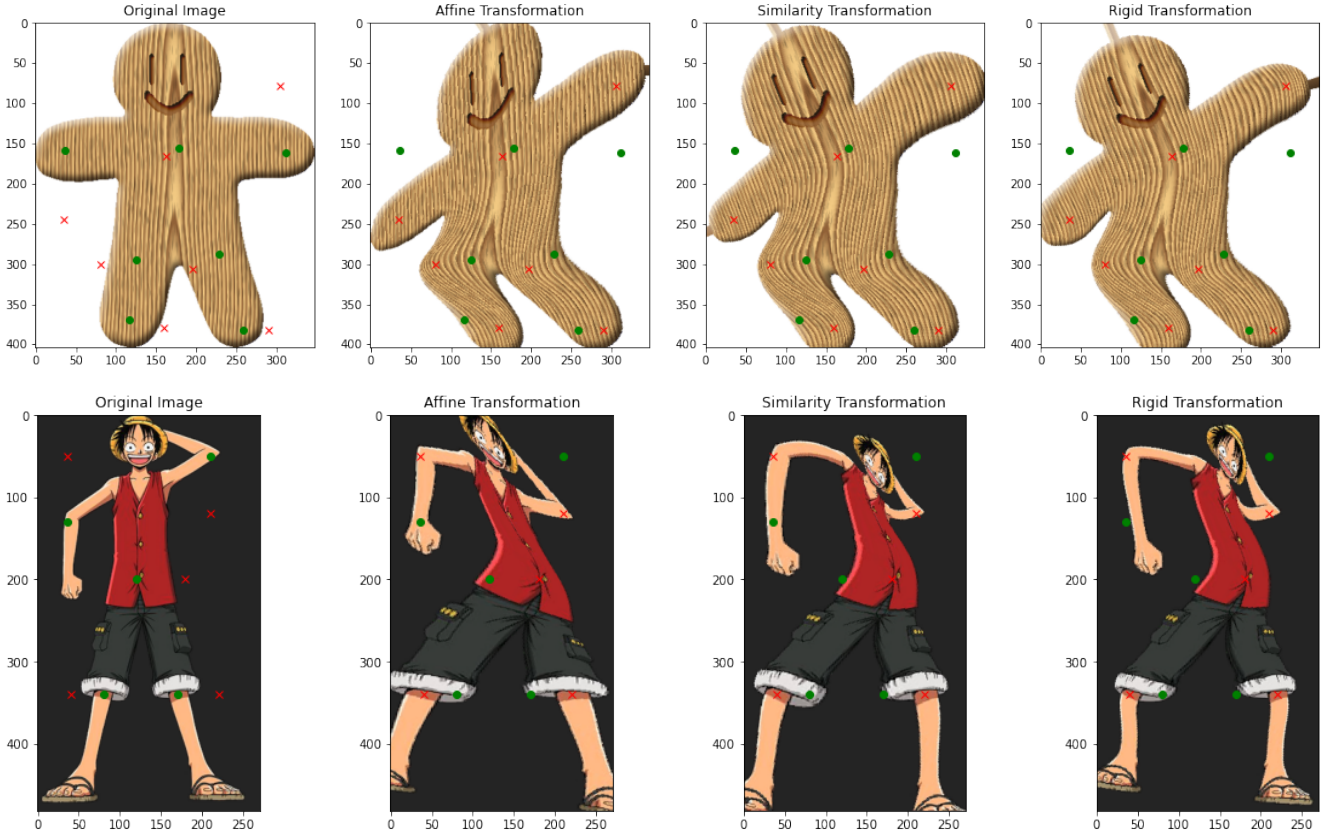


# EXERCISE 3 - MLS FOR CURVES, MESHES AND IMAGES

Please add the image in the zip folder to the `data` folder and run the `ipynb` file.

## Task 1: Image deformation using MLS

- The code is in the `ipynb` file
- The result of transformation is shown below:



## Task 2.1/2.2: Curve and Surface Reconstruction Using MLS

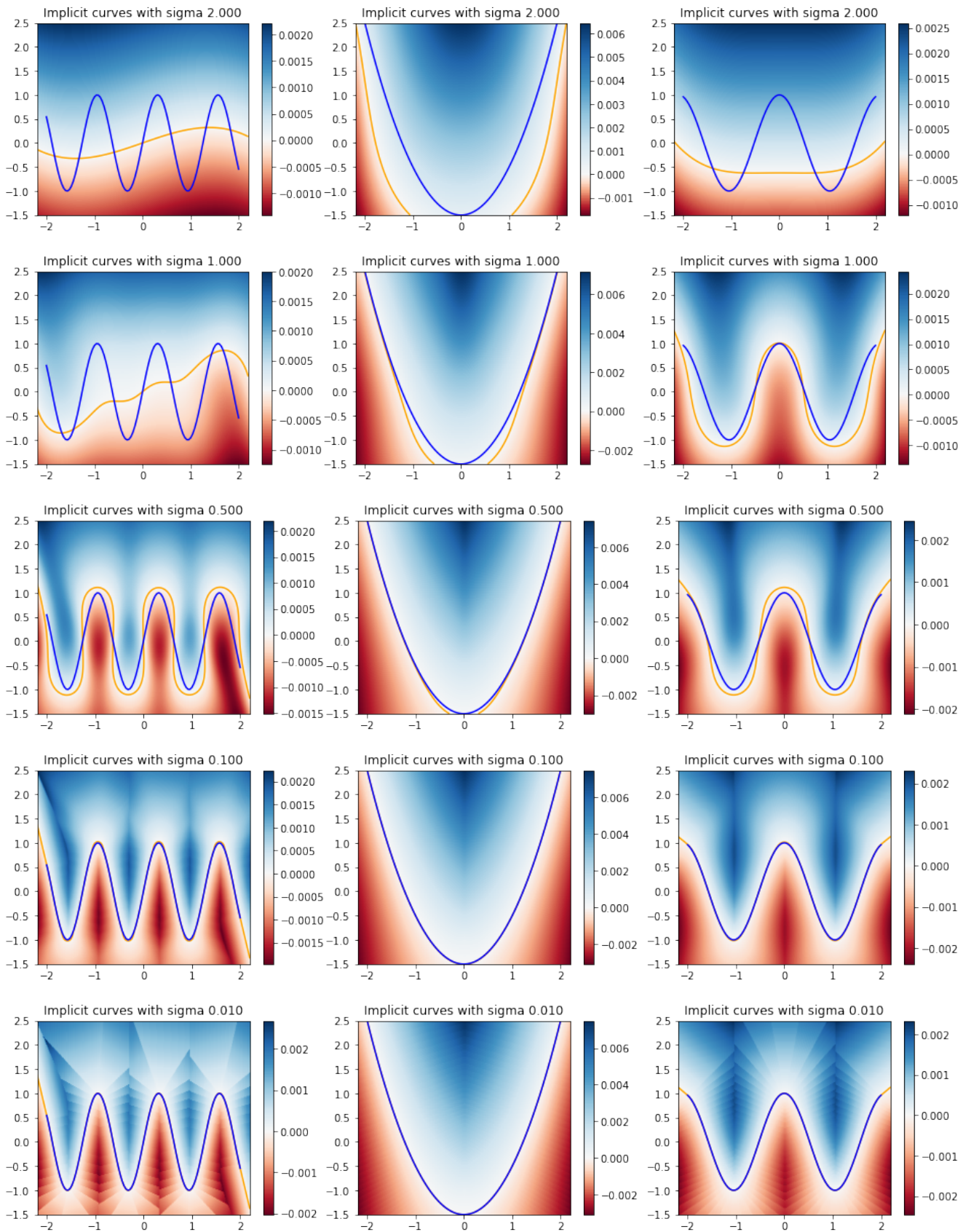
- Implicit function derivation
  - The objective function can be expressed in the following form:

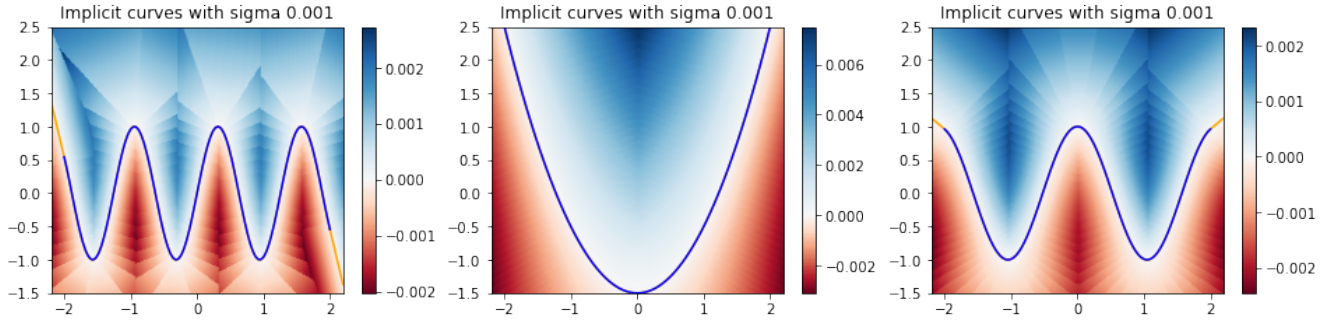
$$\operatorname{argmin}_{c_0} f(c_0) = \operatorname{argmin}_{c_0} \sum_i \phi_i(\mathbf{x})(c_0 - \mathbf{n}_i^T(\mathbf{x} - \mathbf{x}_i))^2 \quad (1)$$

- If we take the derivative of the objective function  $f$  w.r.t  $c_0$ :

$$\begin{aligned} \frac{\delta f}{\delta c_0} &= \sum_i 2\phi_i(\mathbf{x})(c_0 - \mathbf{n}_i^T(\mathbf{x} - \mathbf{x}_i)) = 0 \\ 2c_0 \sum_i \phi_i(\mathbf{x}) &= 2 \sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T(\mathbf{x} - \mathbf{x}_i) \\ f(\mathbf{x}) = c_0 &= \frac{\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T(\mathbf{x} - \mathbf{x}_i)}{\sum_i \phi_i(\mathbf{x})} = \sum_i \frac{\phi_i(\mathbf{x})}{\sum_i \phi_i(\mathbf{x})} \mathbf{n}_i^T(\mathbf{x} - \mathbf{x}_i) \end{aligned} \quad (2)$$

- The visualization of the grid values estimated by MLS with different sigma is shown below:





- Bonus: The bonus is achieved by replacing the original  $\phi$  function by a softmax function. The softmax function is implemented in the library `scipy.special.softmax`.

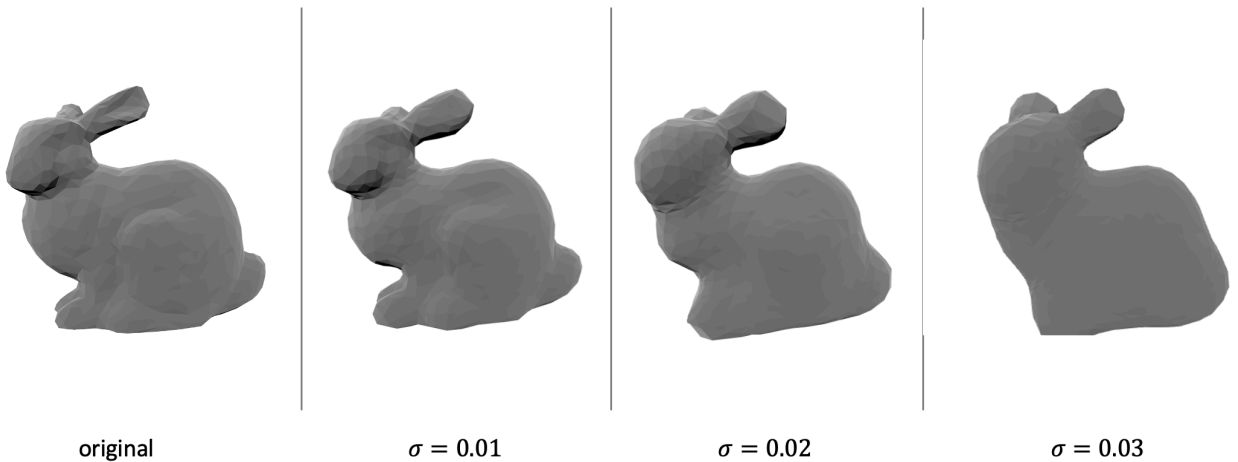
## Task 3: Curve and Surface Reconstruction Using MLS

- Derivation of gradient of function  $f$

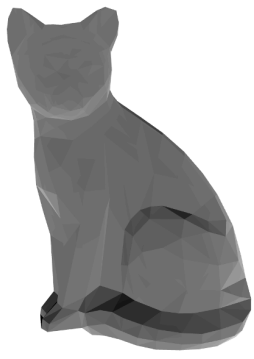
$$\begin{aligned}
 f(\mathbf{x}) &= c_0 = \frac{\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i)}{\sum_i \phi_i(\mathbf{x})} = \sum_i \frac{\phi_i(\mathbf{x})}{\sum_i \phi_i(\mathbf{x})} \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i) \\
 \nabla f(\mathbf{x}) &= \nabla \frac{\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i)}{\sum_i \phi_i(\mathbf{x})} \\
 &= \frac{\nabla(\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i)) (\sum_i \phi_i(\mathbf{x})) - (\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i)) \nabla(\sum_i \phi_i(\mathbf{x}))}{(\sum_i \phi_i(\mathbf{x}))^2} \\
 &= \frac{(\sum_i \nabla \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i) + \sum_i \phi_i(\mathbf{x}) \mathbf{n}_i) (\sum_i \phi_i(\mathbf{x})) - (\sum_i \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i)) \nabla(\sum_i \phi_i(\mathbf{x}))}{(\sum_i \phi_i(\mathbf{x}))^2} \\
 &= \frac{(\sum_i \nabla \phi_i(\mathbf{x}) \mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i) + \sum_i \phi_i(\mathbf{x}) \mathbf{n}_i) - f(\mathbf{x}) \nabla(\sum_i \phi_i(\mathbf{x}))}{\sum_i \phi_i(\mathbf{x})} \\
 &= \frac{\sum_i (\nabla \phi_i(\mathbf{x}) (\mathbf{n}_i^T (\mathbf{x} - \mathbf{x}_i) - f(\mathbf{x})) + \phi_i(\mathbf{x}) \mathbf{n}_i)}{\sum_i \phi_i(\mathbf{x})}
 \end{aligned} \tag{3}$$

- The result is shown below

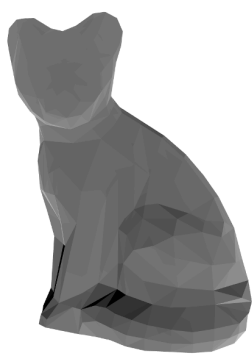
◦ `bunny.off`



◦ `cat.off`



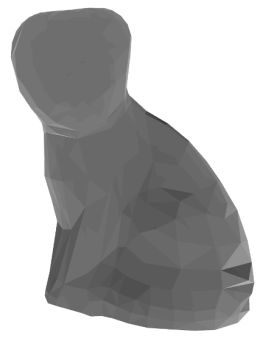
original



$\sigma = 70$



$\sigma = 100$



$\sigma = 130$