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Image Segmentation

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github: [KhadgaA/Spectral-Clustering \(github.com\)](https://github.com/KhadgaA/Spectral-Clustering)

Ratio Cut Segmentaion

Steps:

1. Convert the image into a Graph. This can be done by simply reshaping the image into a vector of $N = \text{height} * \text{width}$ nodes.

2. Compute the affinity of each node of the graph/image w.r.to all other nodes/pixels.

Therefore **Affinity (A)** = (N, N) matrix. We can either use the euclidean based affinity : $e^{\|I(i)-I(j)\|_2^2}$ or we can use the Cosine Similarity: $A_{ij} = \frac{I(i) \cdot I(j)}{\|I(i)\| \cdot \|I(j)\|}$.

3. Refine Affinity Matrix

4. Compute the Degree Matrix. $D_i = \sum_{j=1}^N A_{ij}$

5. Compute the Laplacian of the graph. $L = D - A$. Normalize Laplacian Matrix.

6. Compute the eigenvalues and eigenvectors of the Laplacian matrix.

7. Take eigenvectors corresponding to K^{th} smallest eigenvalue.

8. Perform Clustering on K.

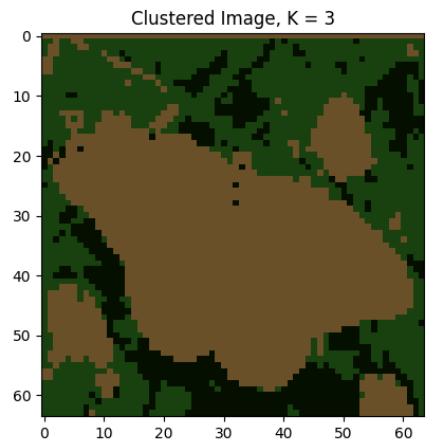
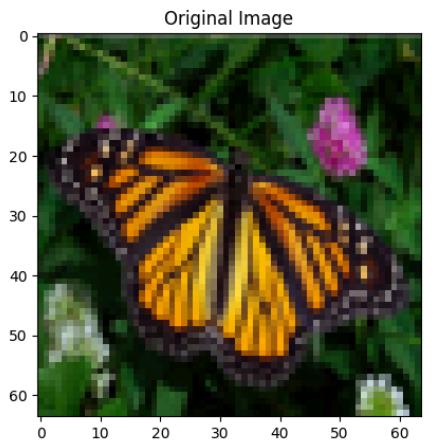
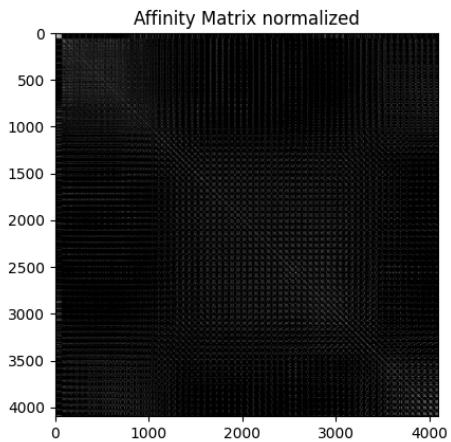
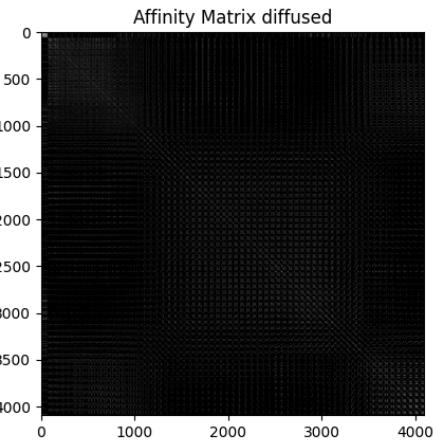
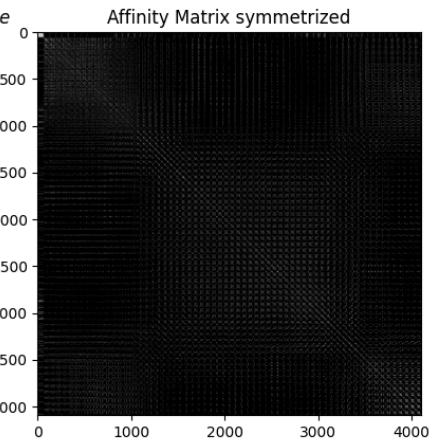
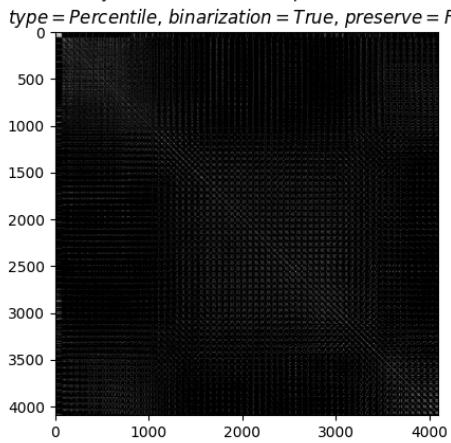
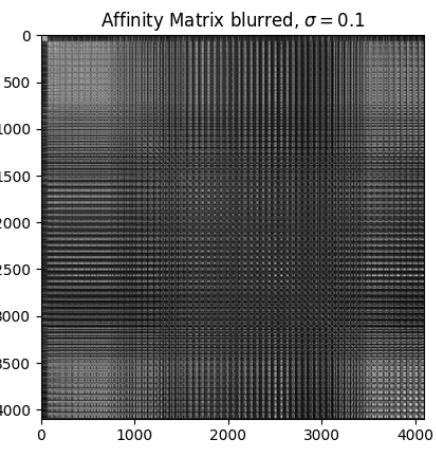
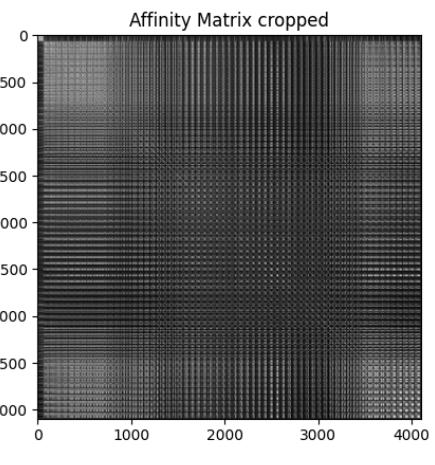
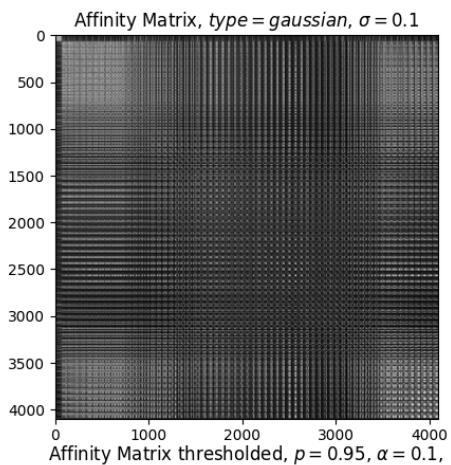
Please See [Appendix](#) Section for exact details.

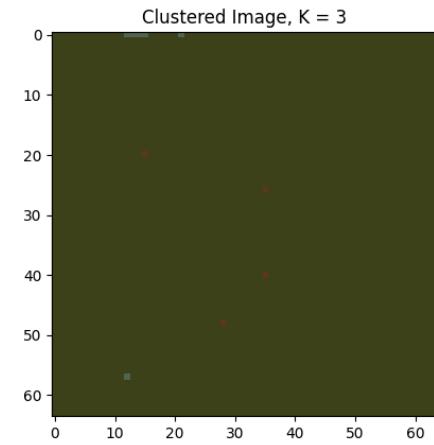
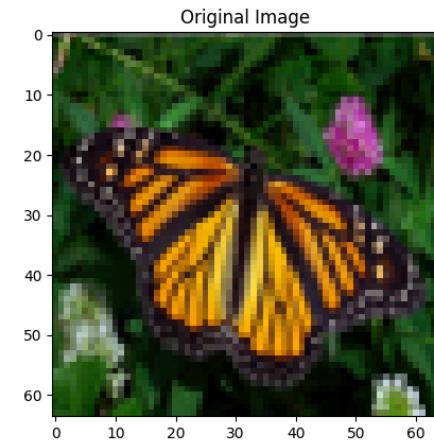
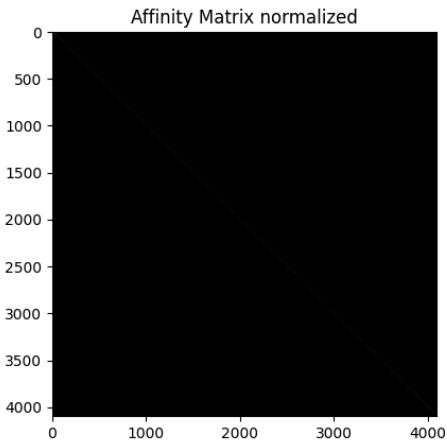
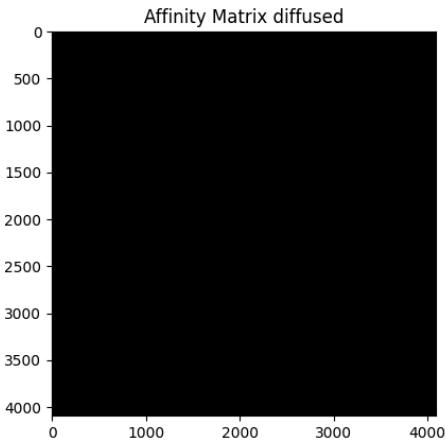
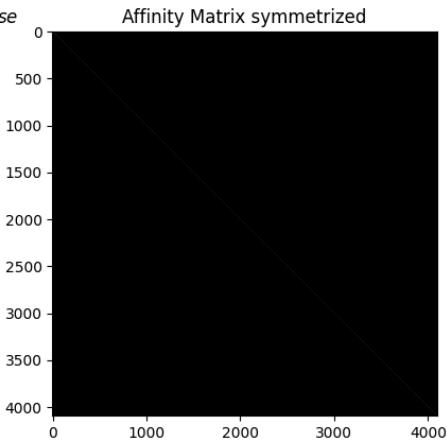
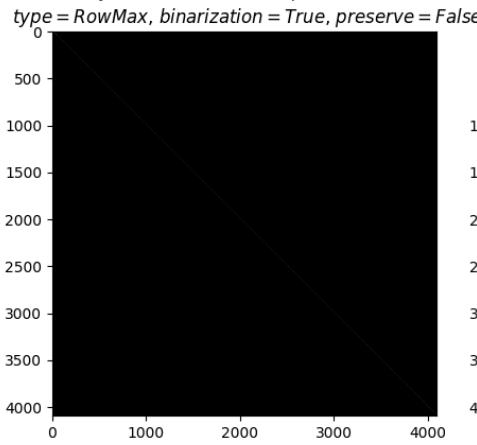
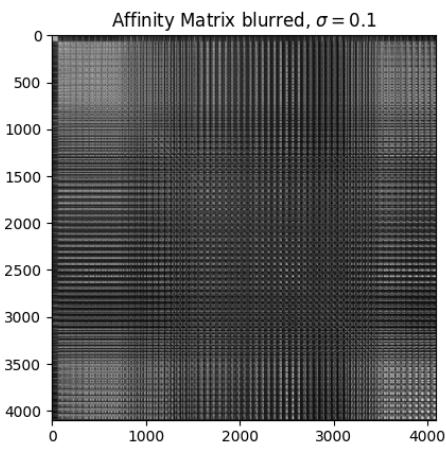
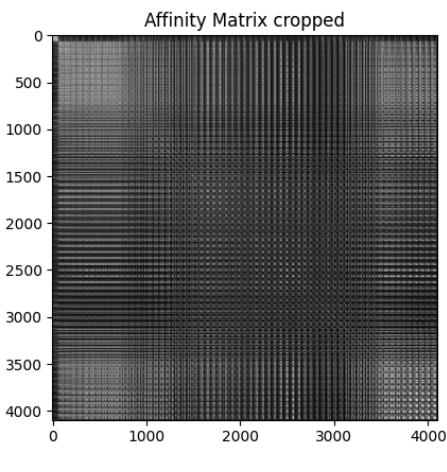
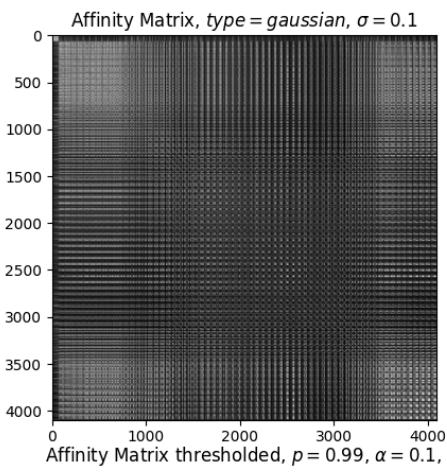
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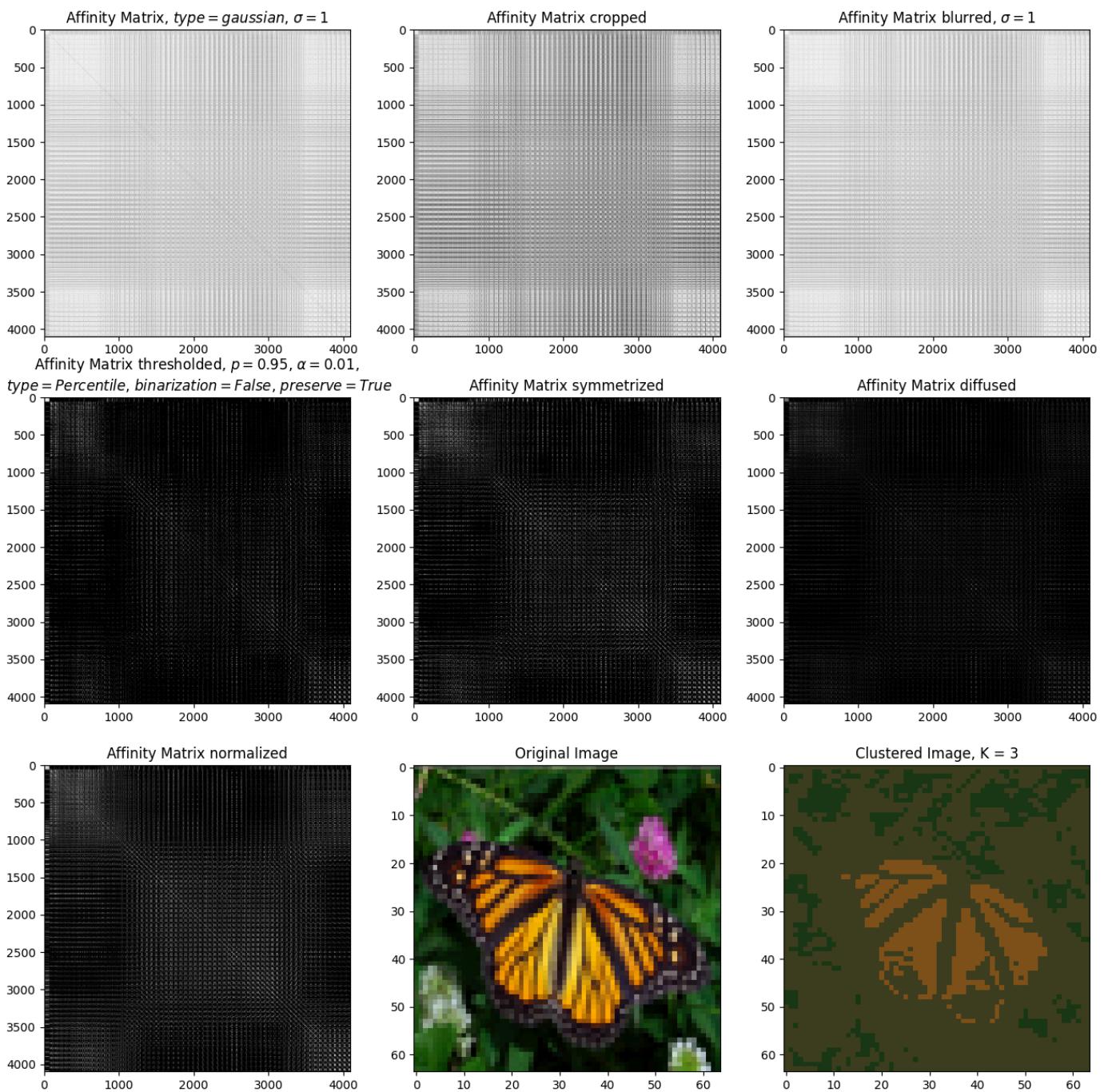
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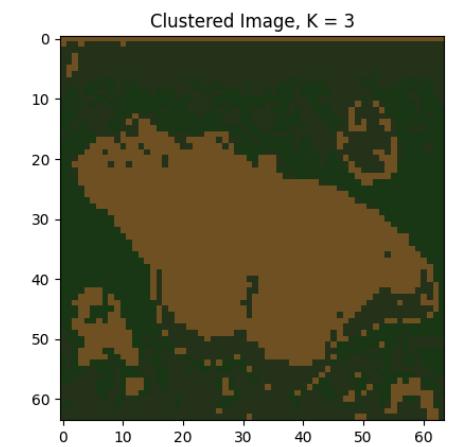
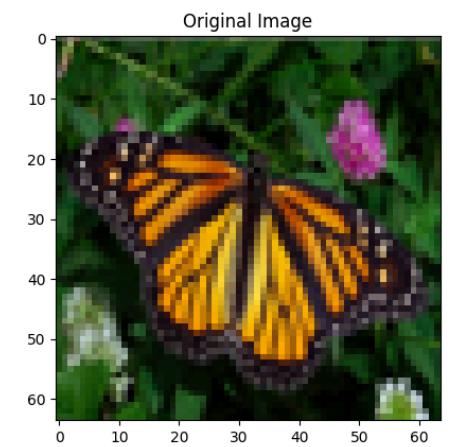
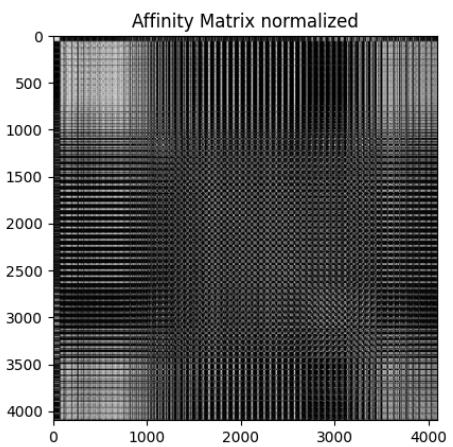
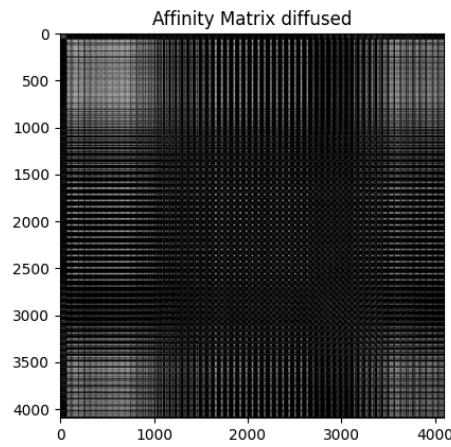
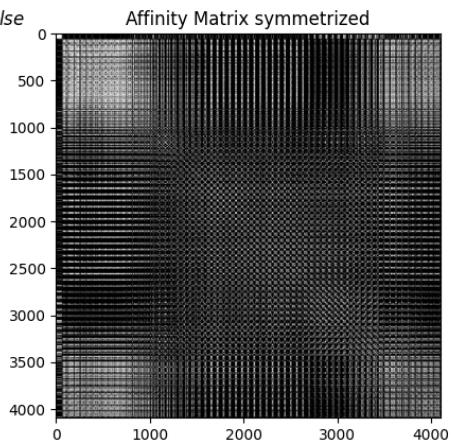
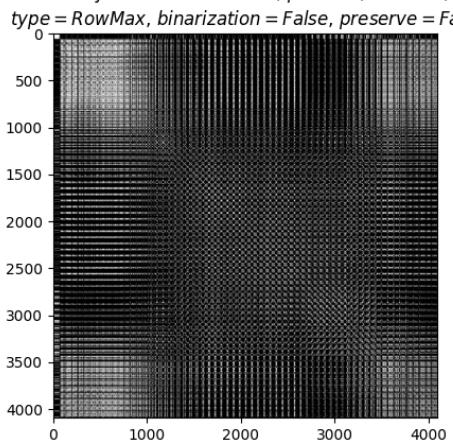
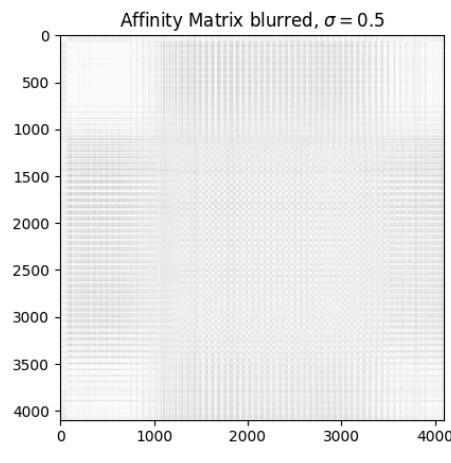
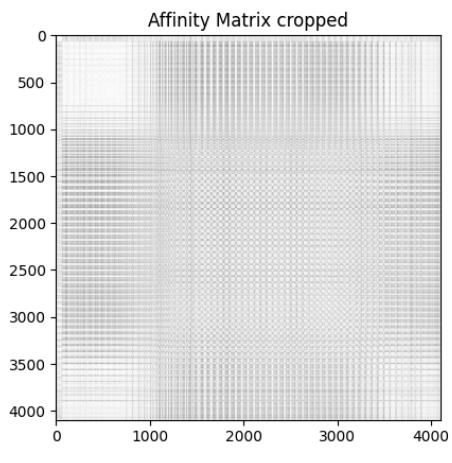
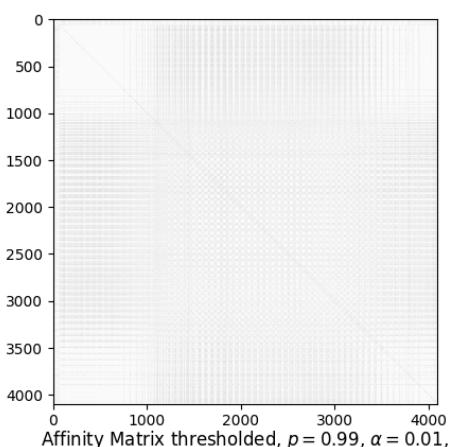


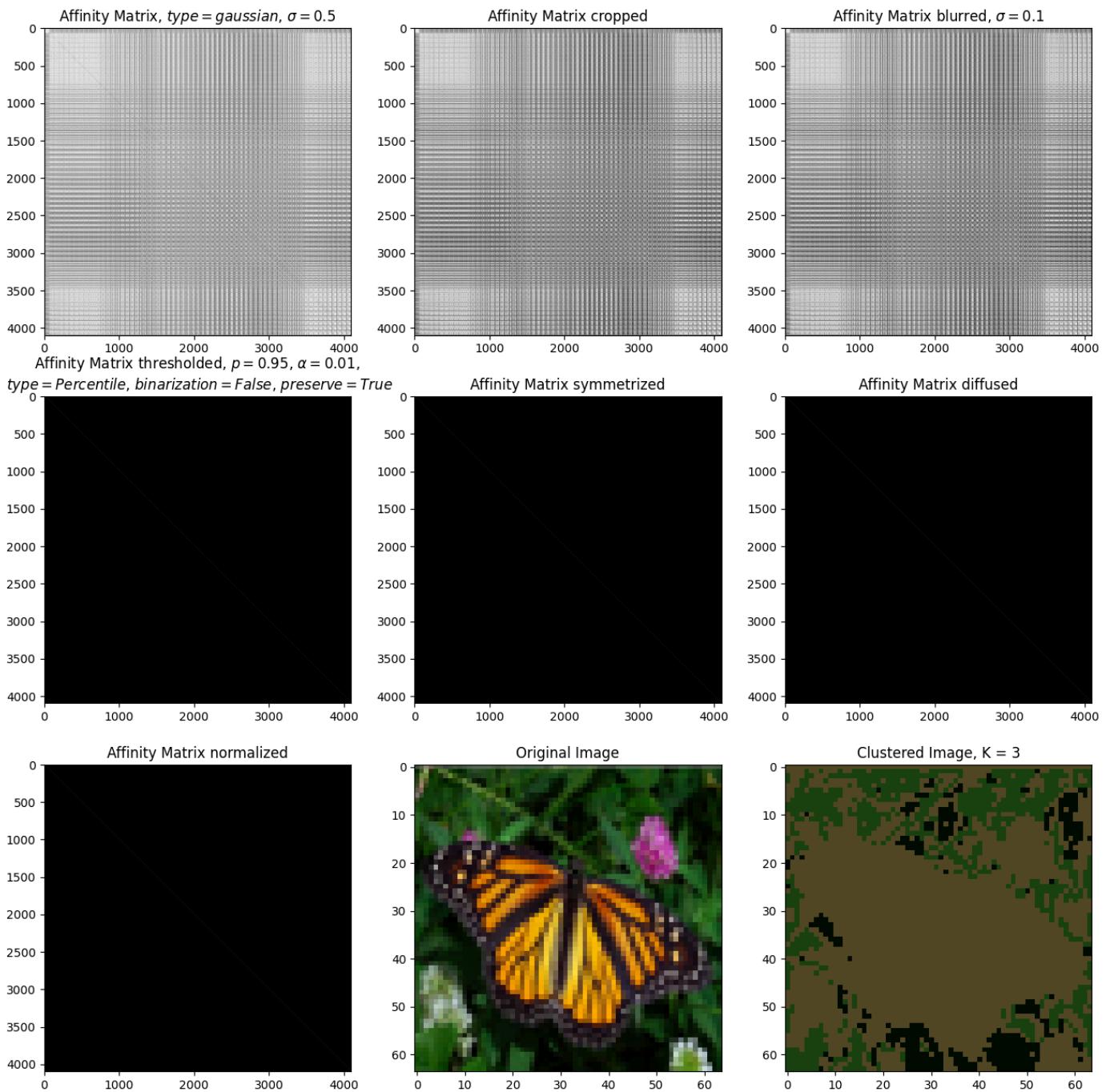
Ratio Cut











KMeans Clustering:

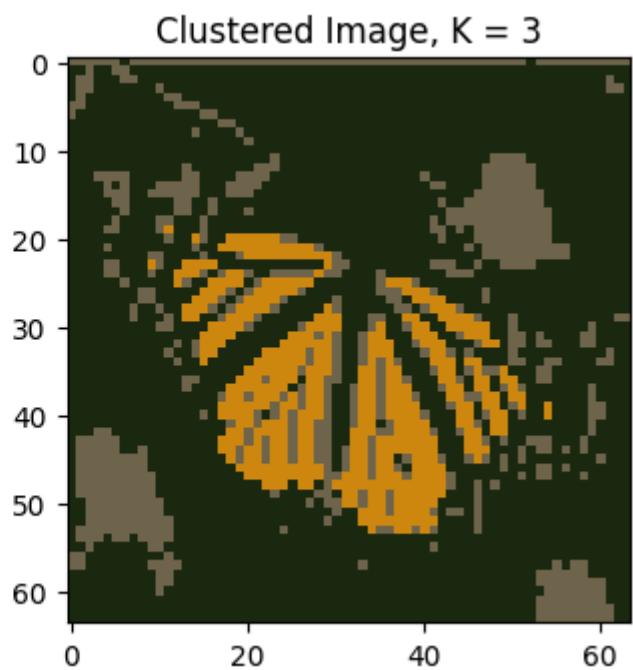
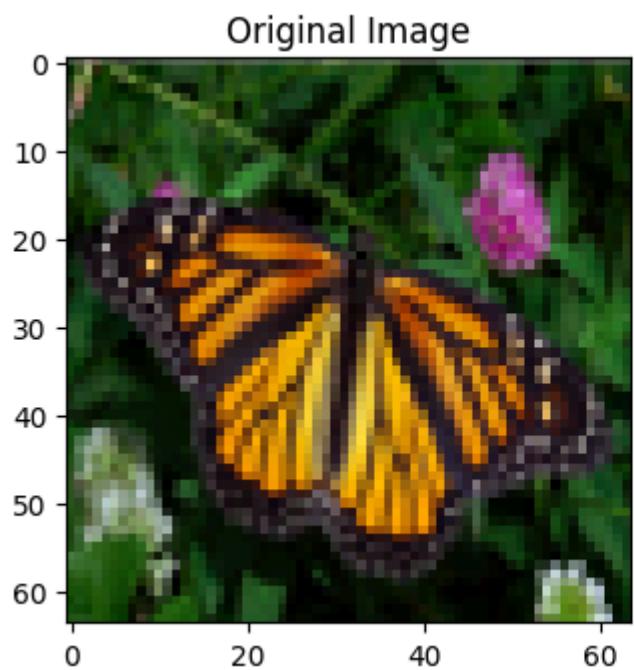
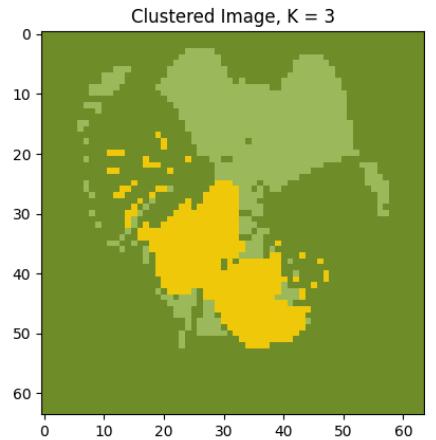
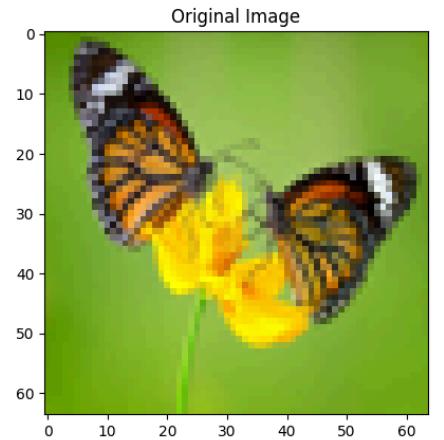
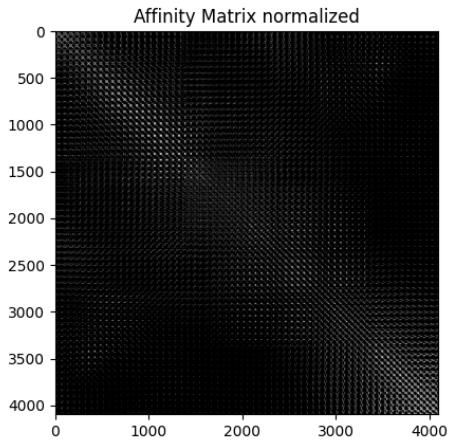
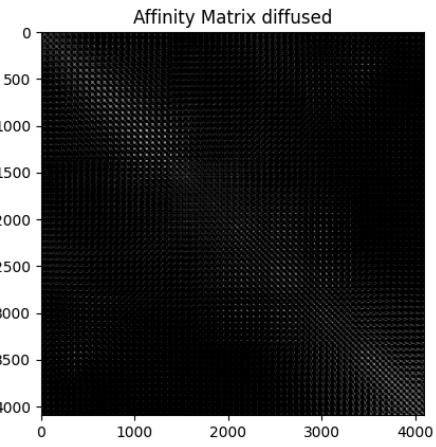
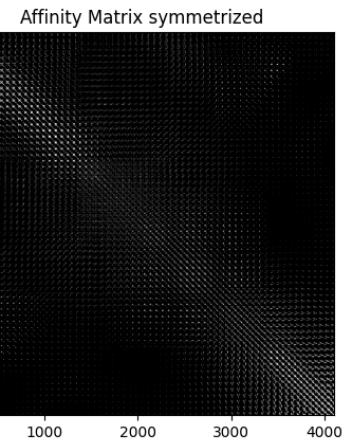
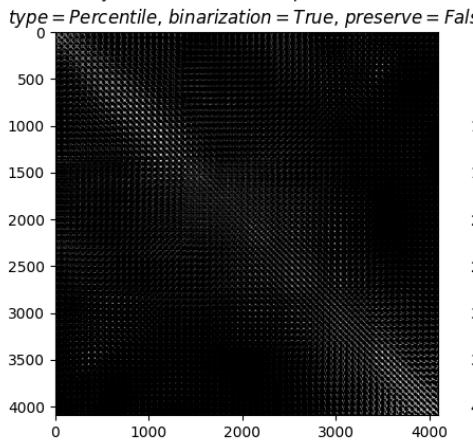
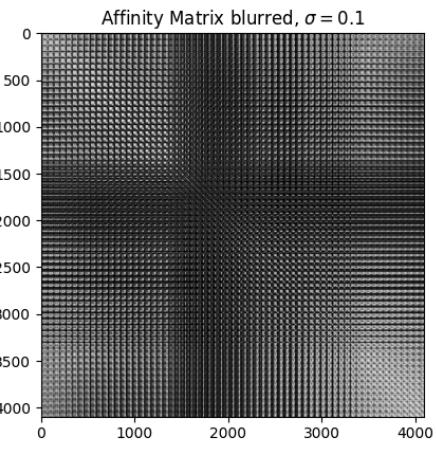
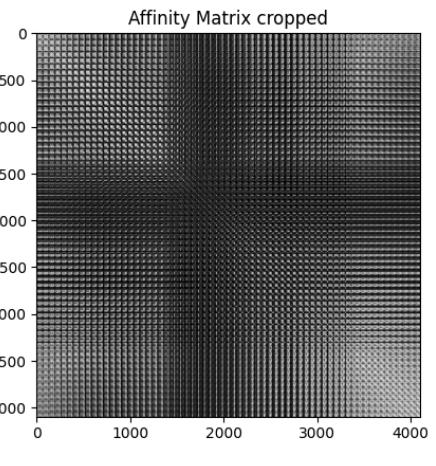
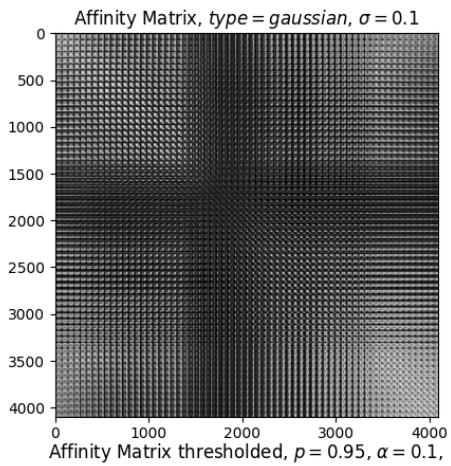
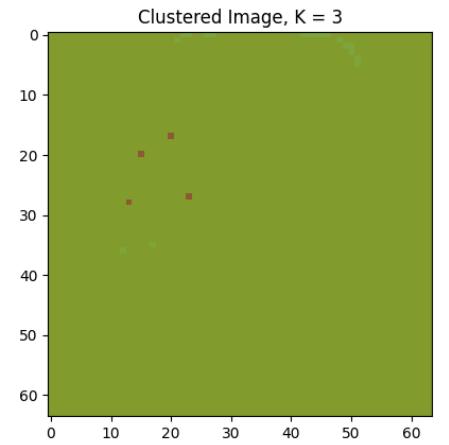
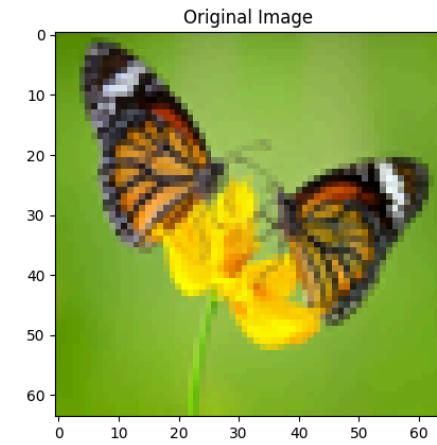
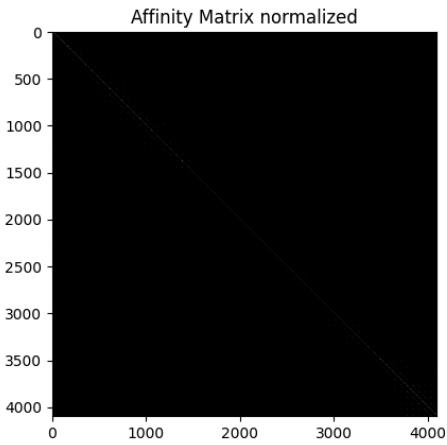
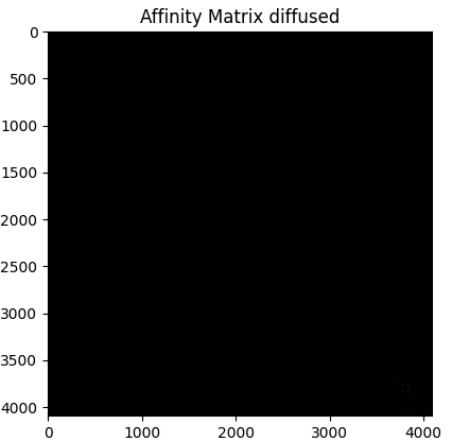
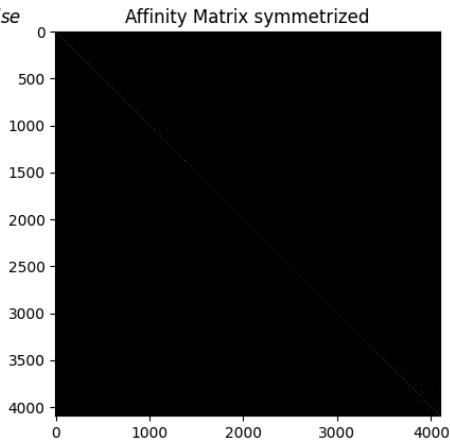
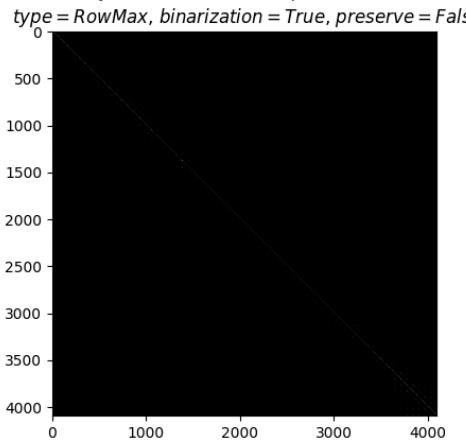
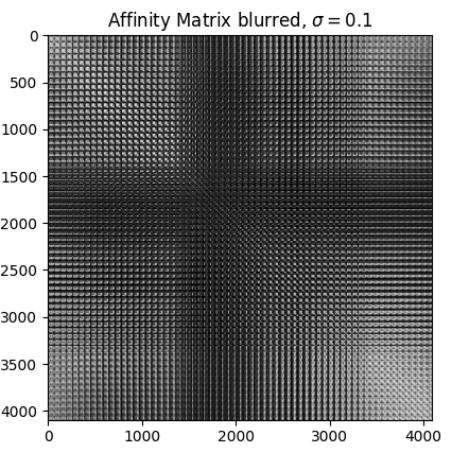
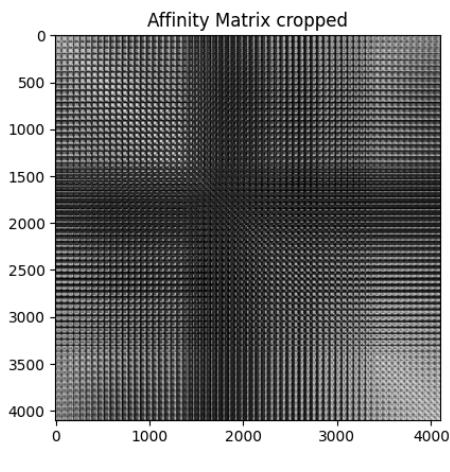
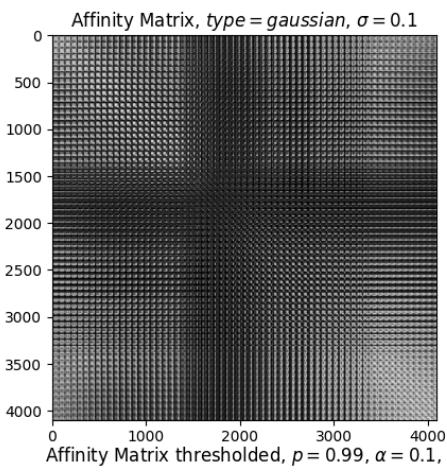


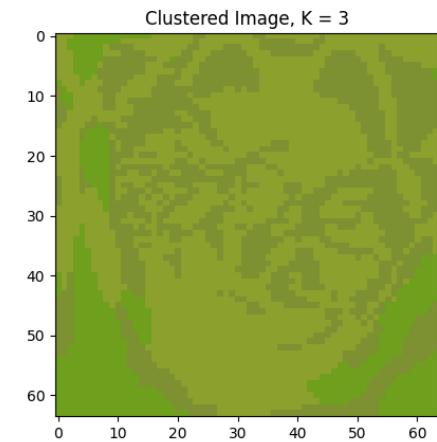
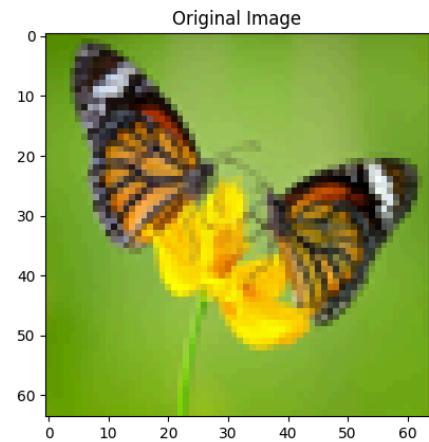
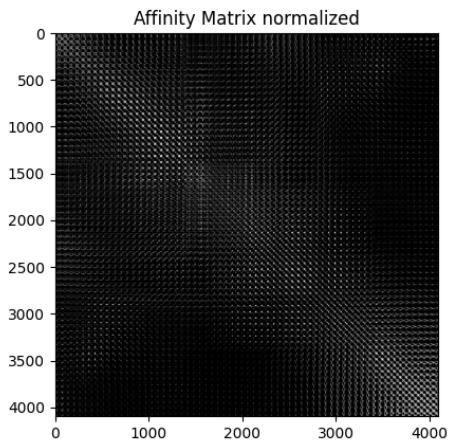
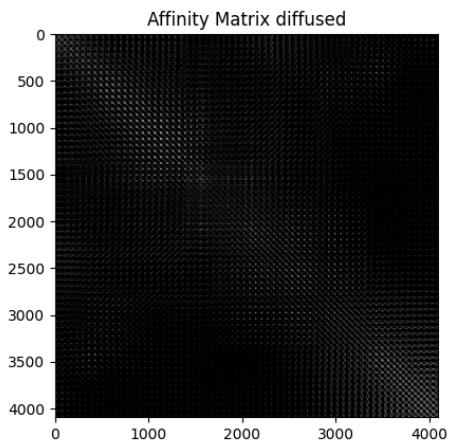
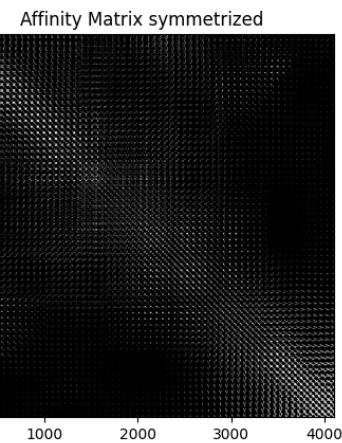
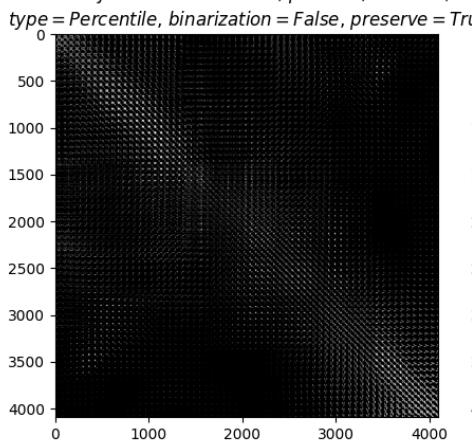
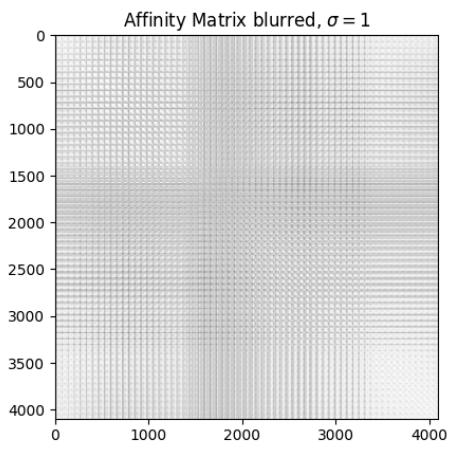
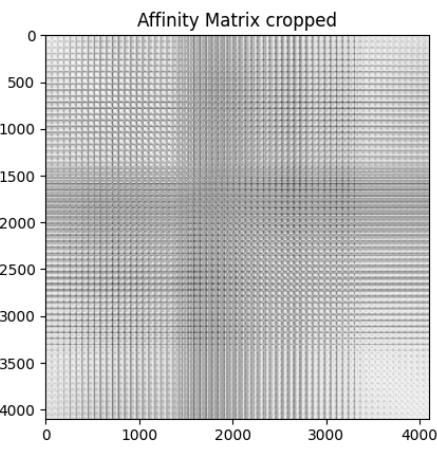
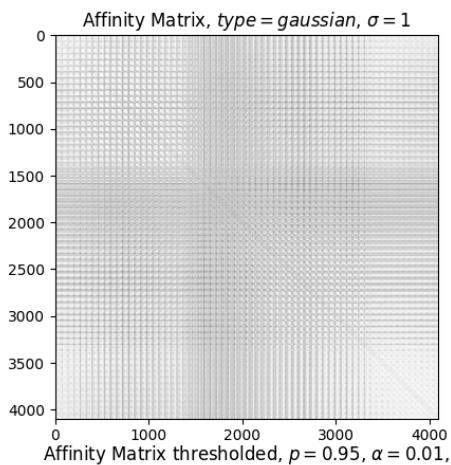
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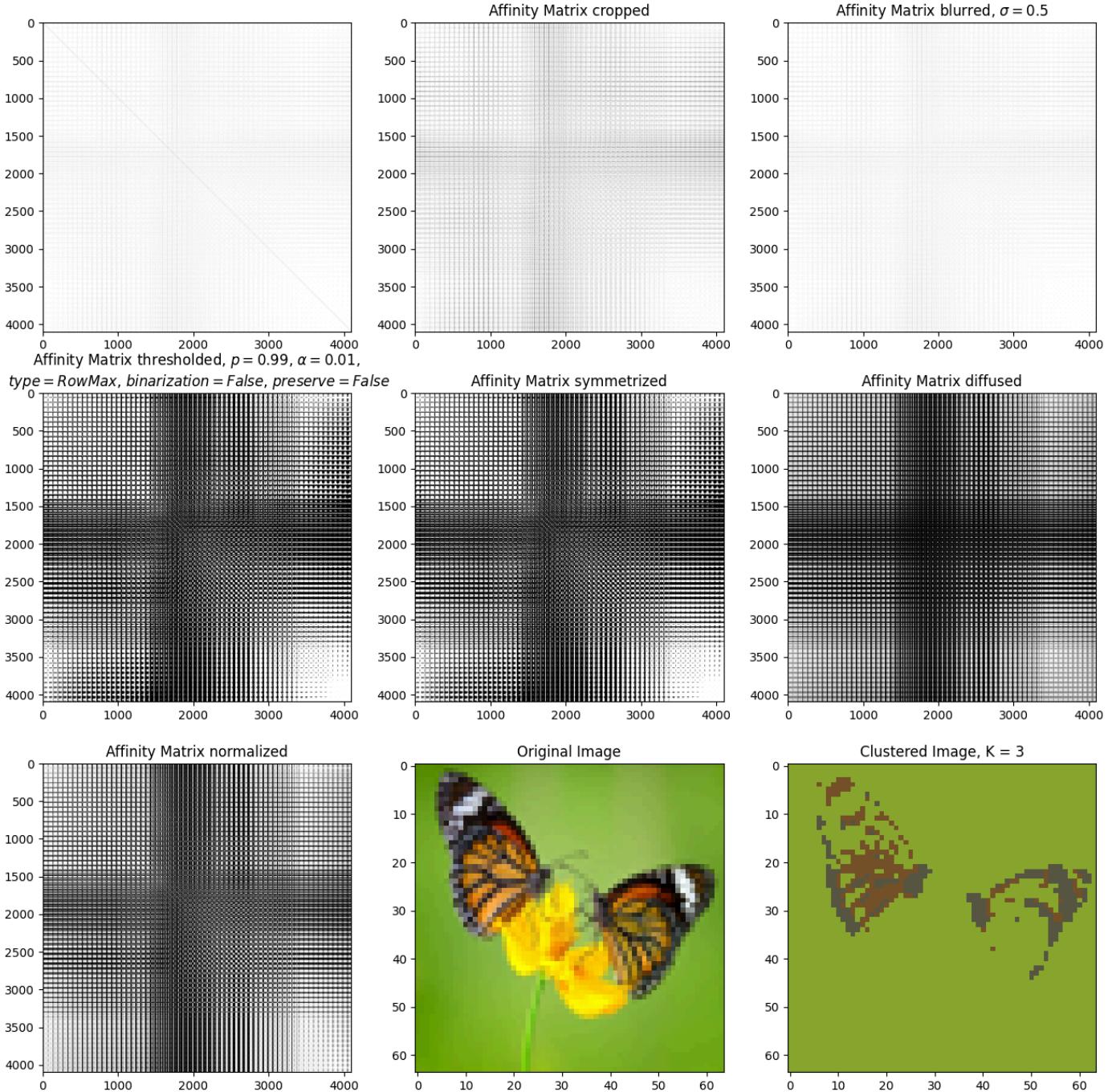


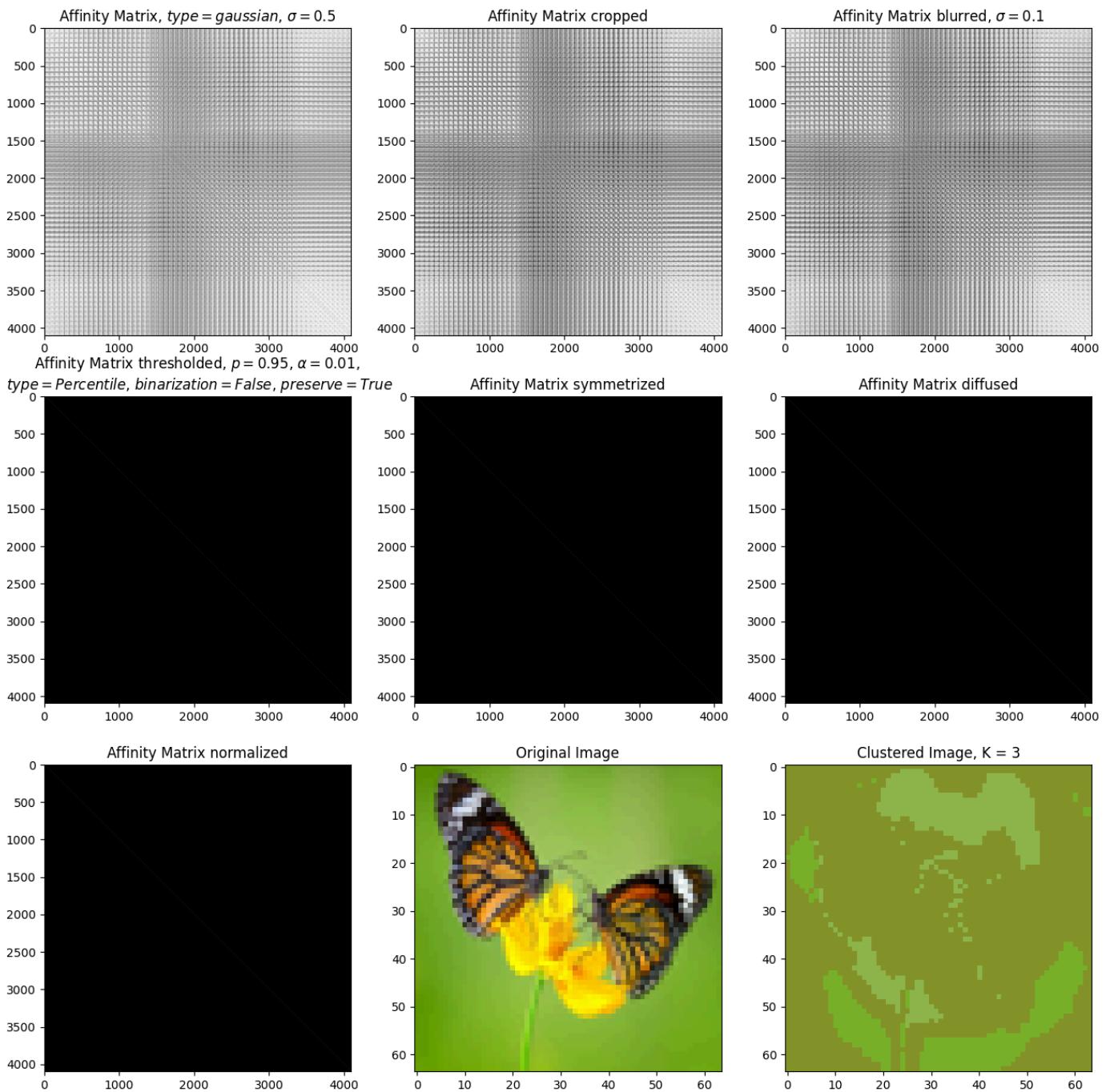
Ratio Cut



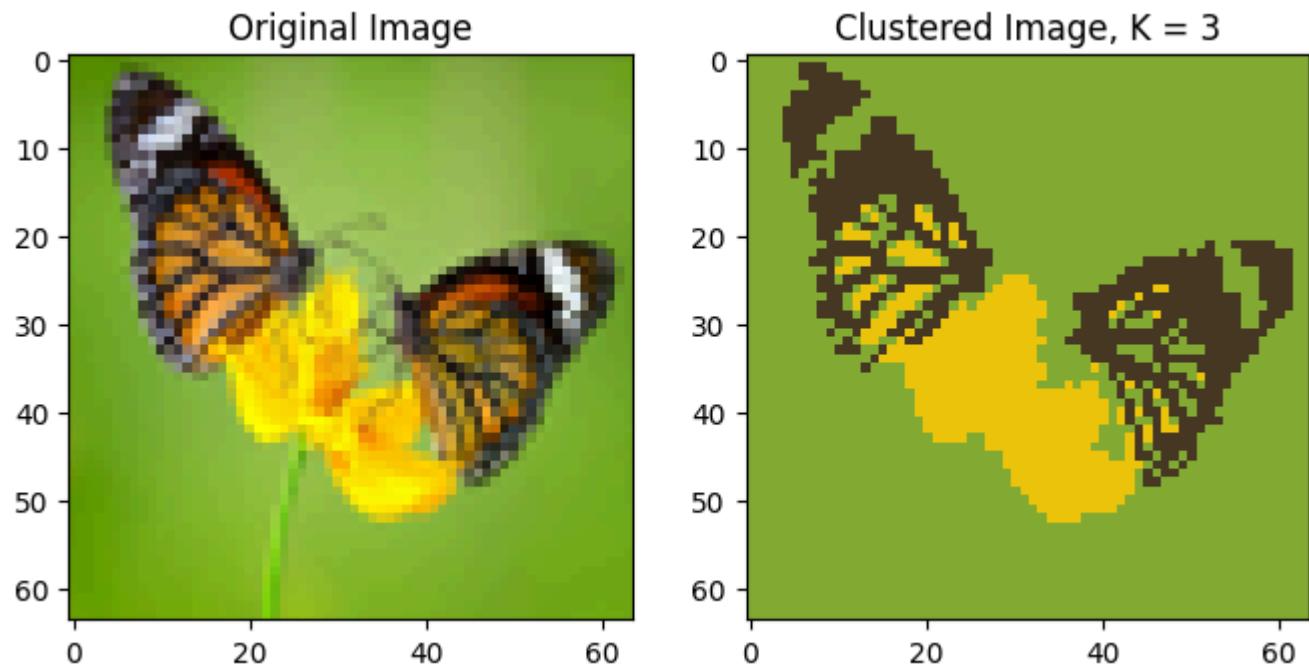








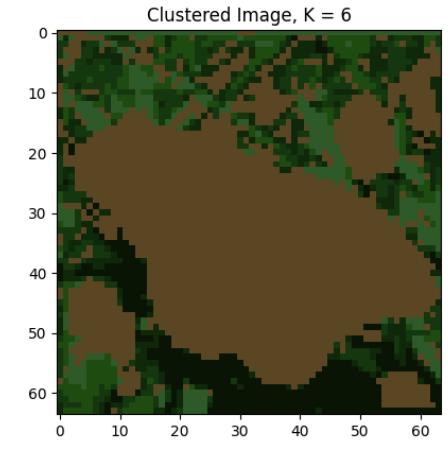
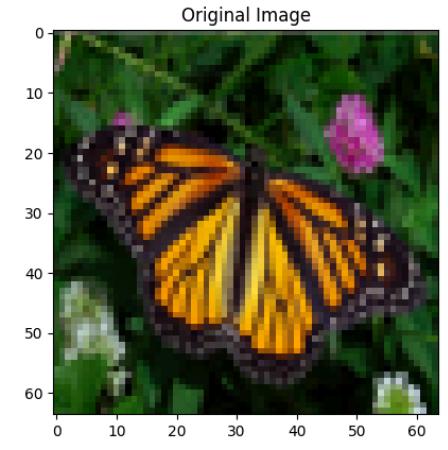
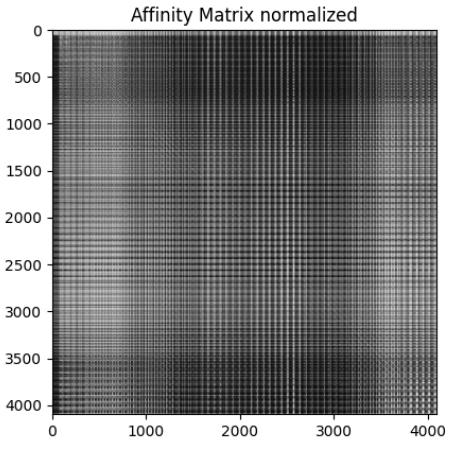
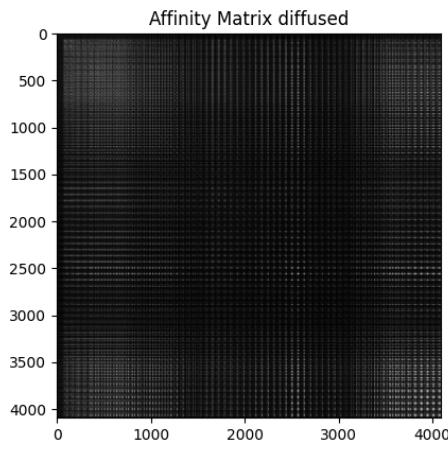
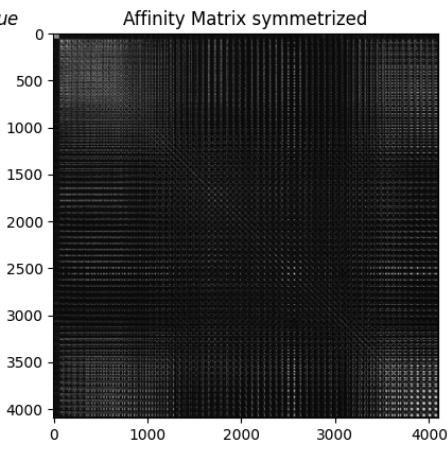
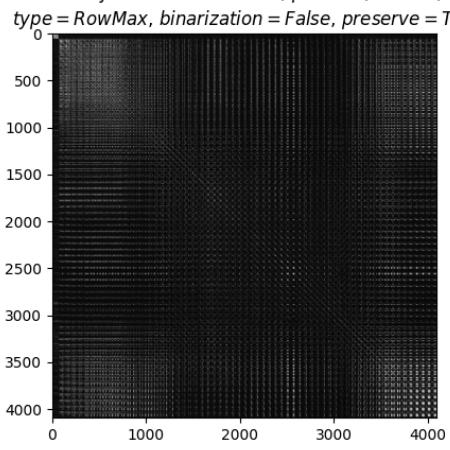
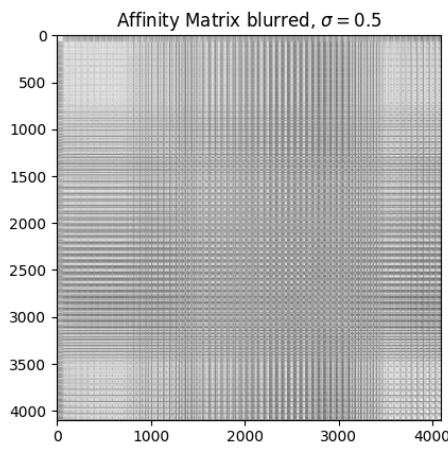
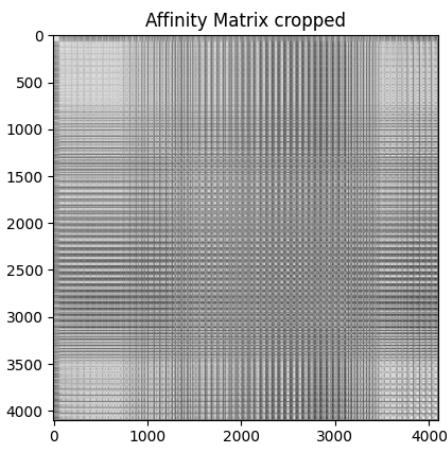
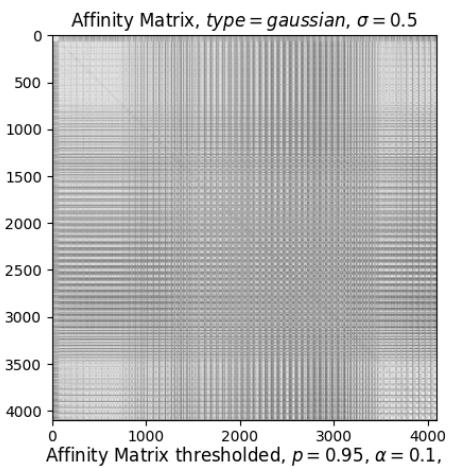
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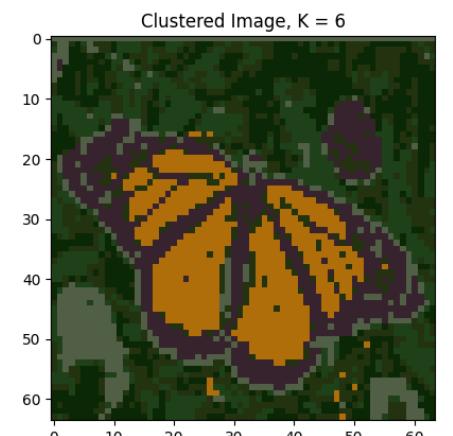
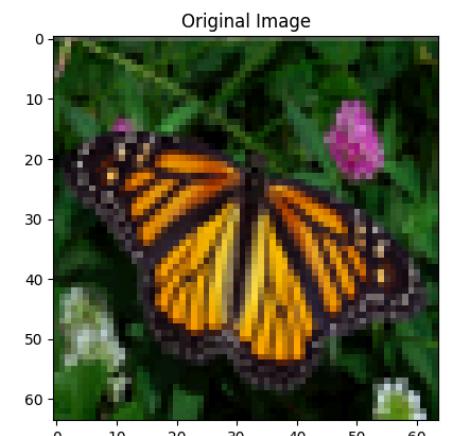
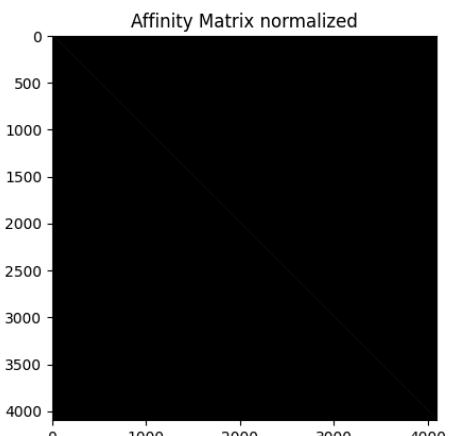
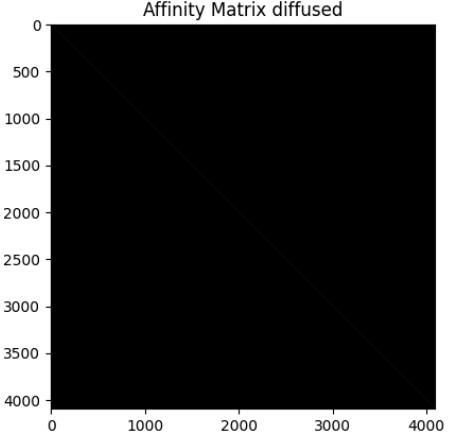
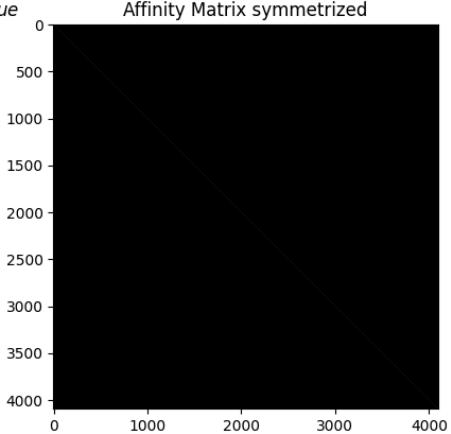
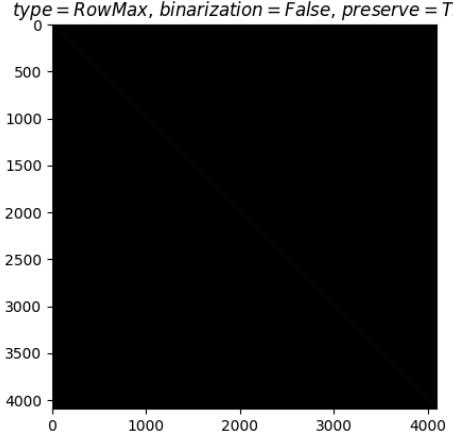
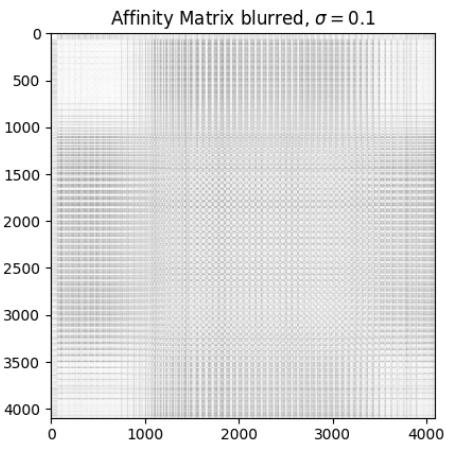
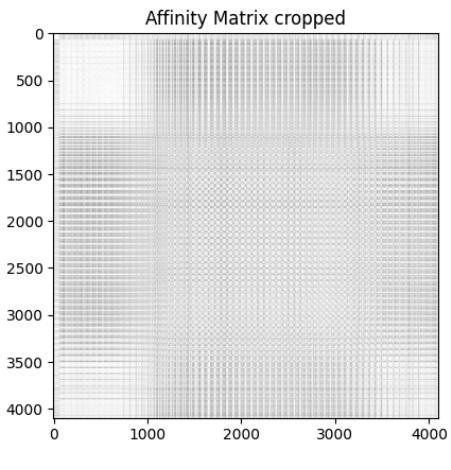
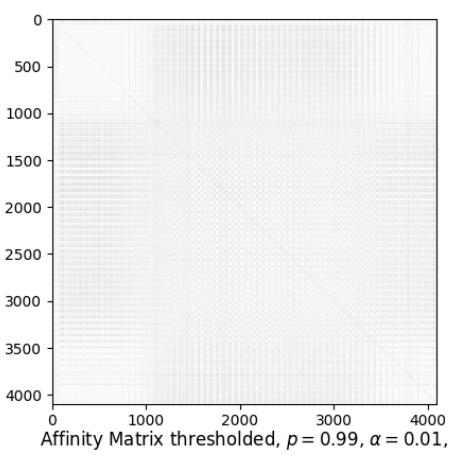


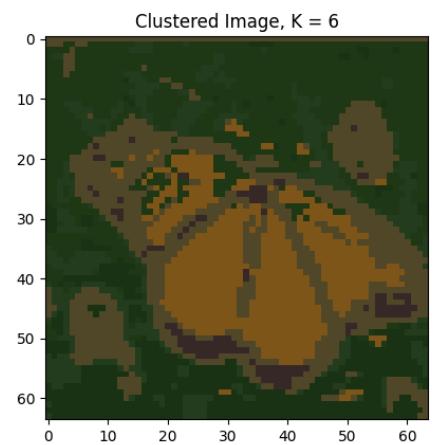
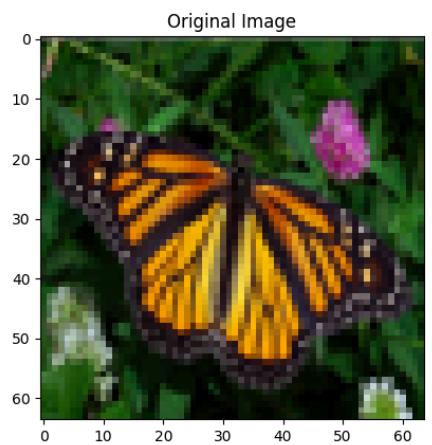
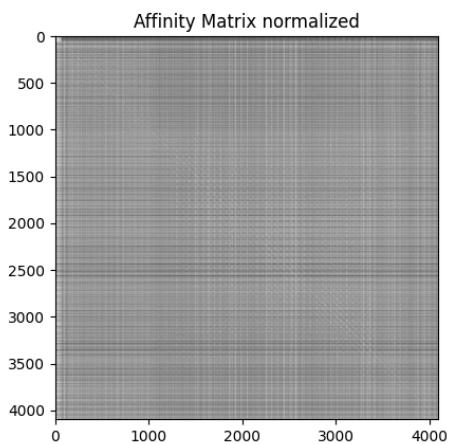
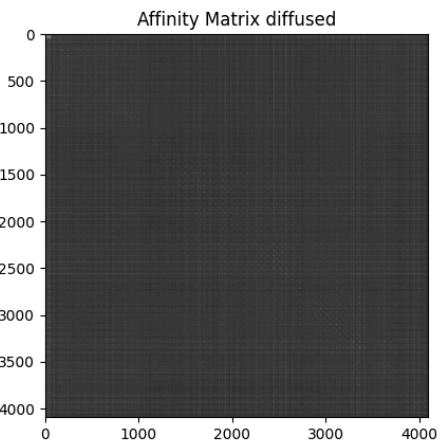
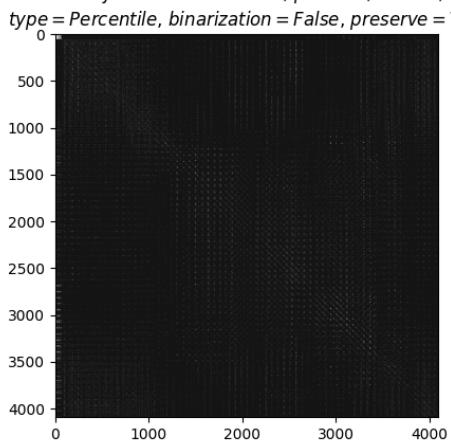
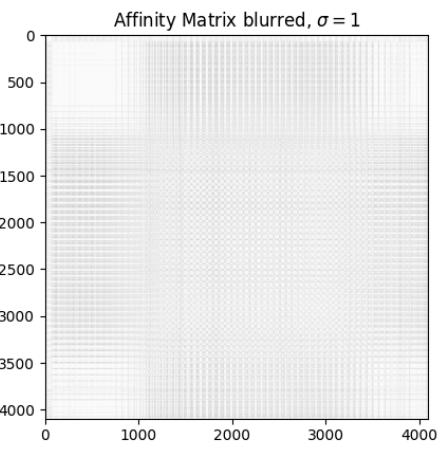
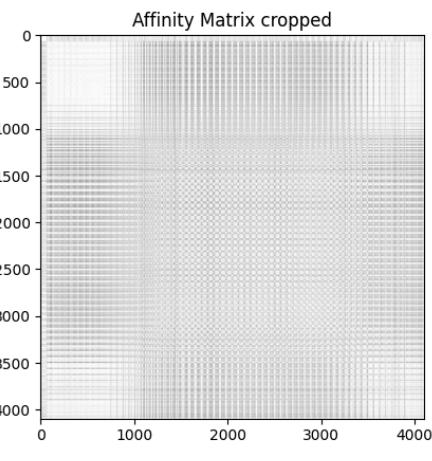
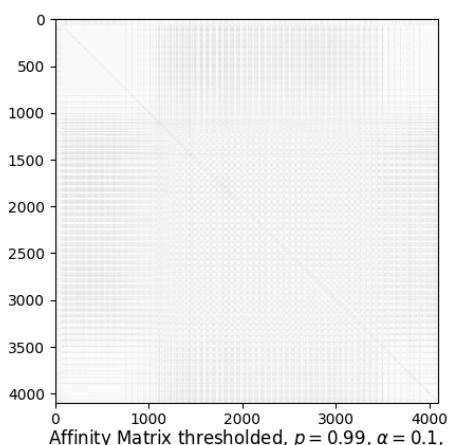
Segmentation Results - 6 Clusters

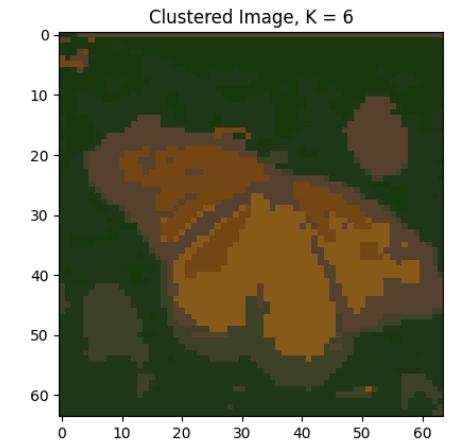
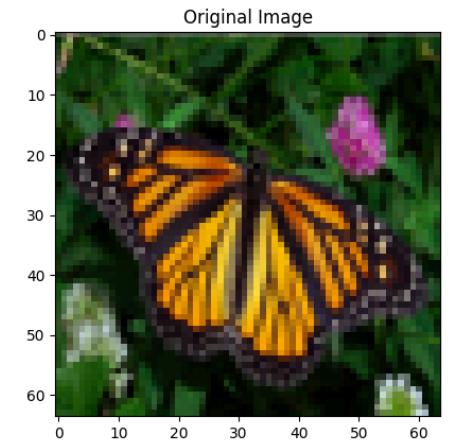
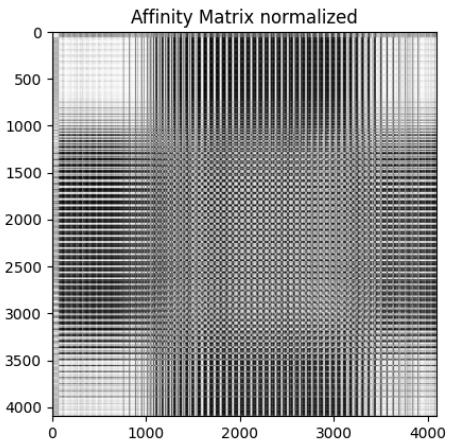
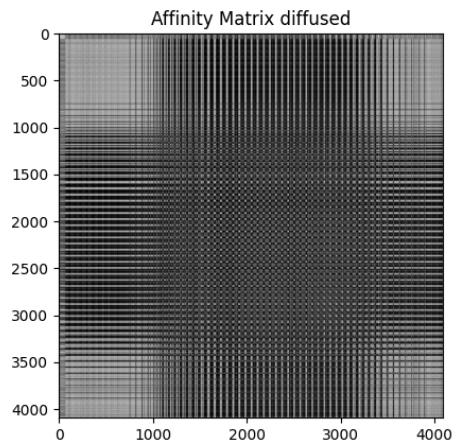
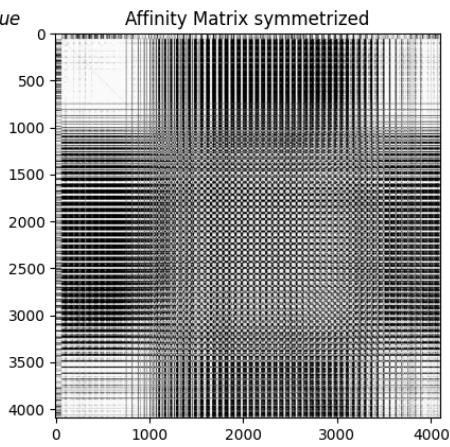
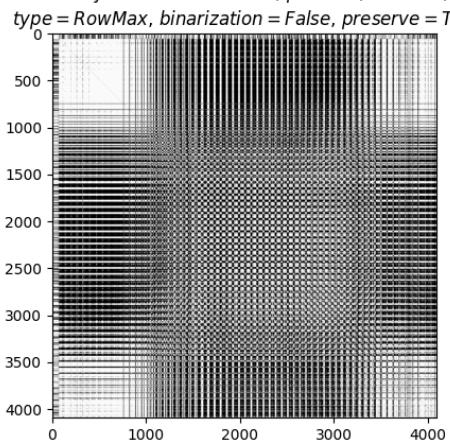
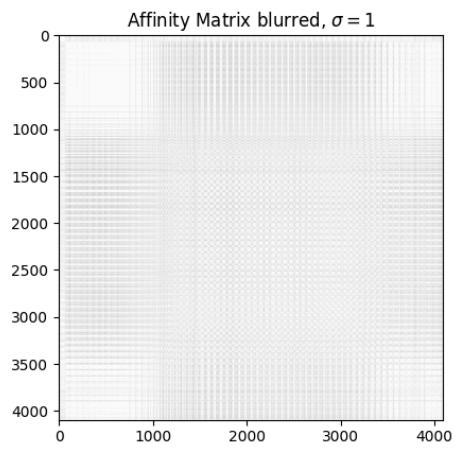
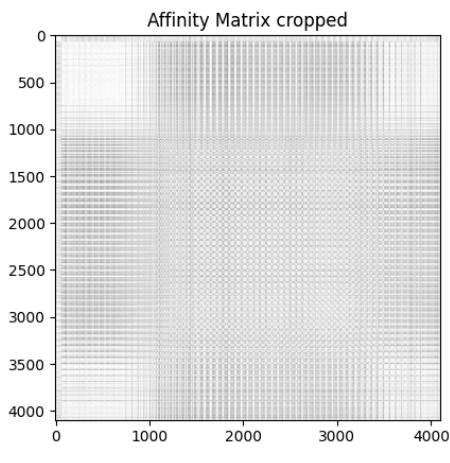
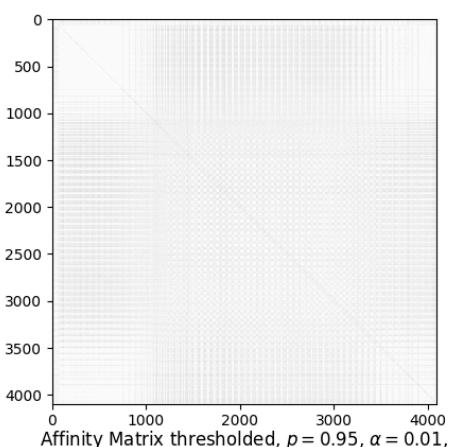
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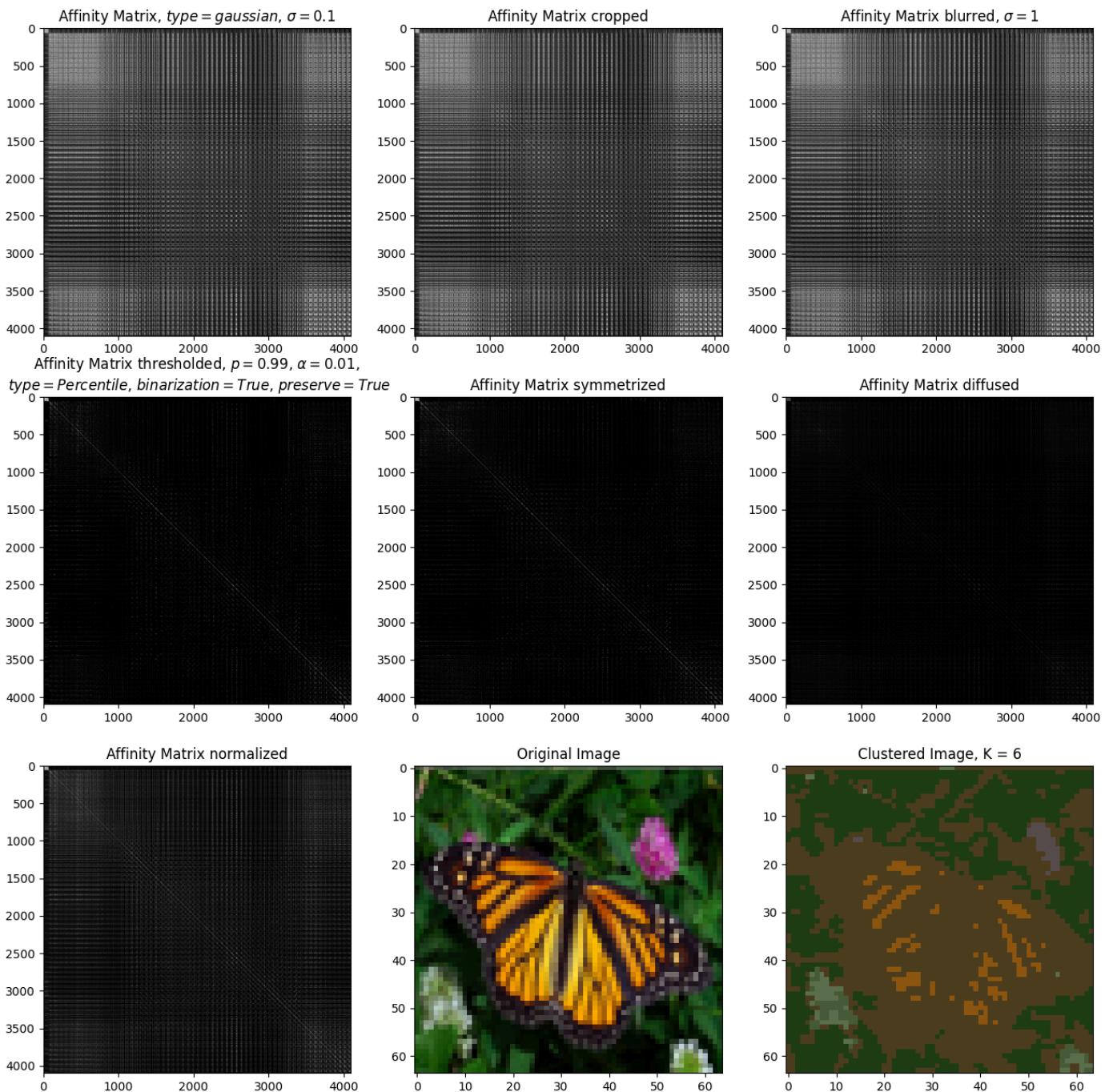
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KMeans Clustering:

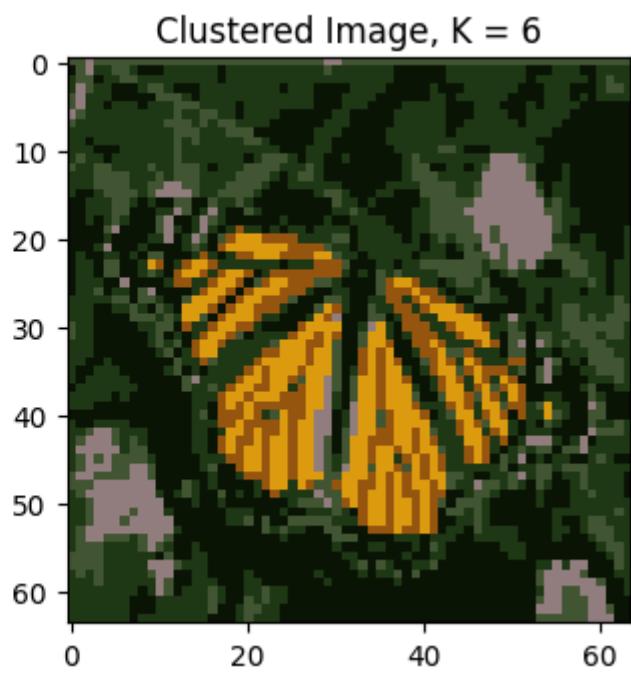
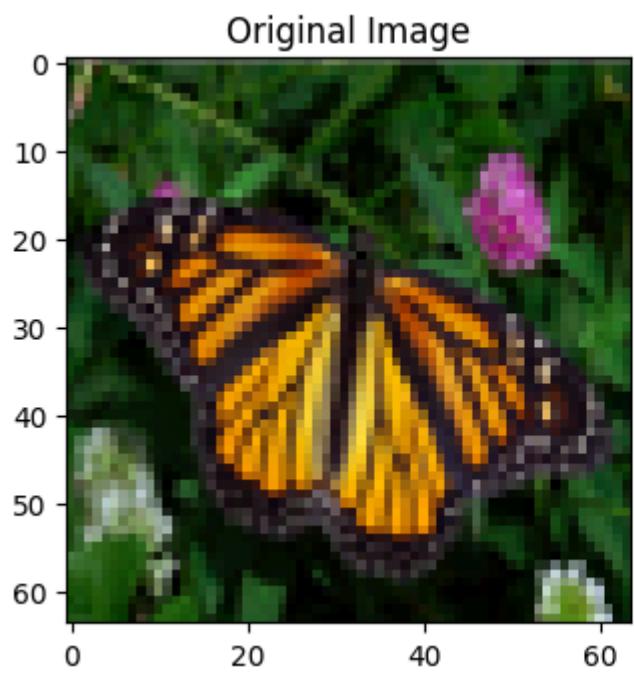
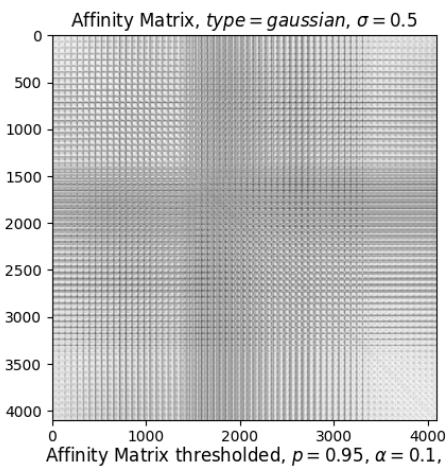
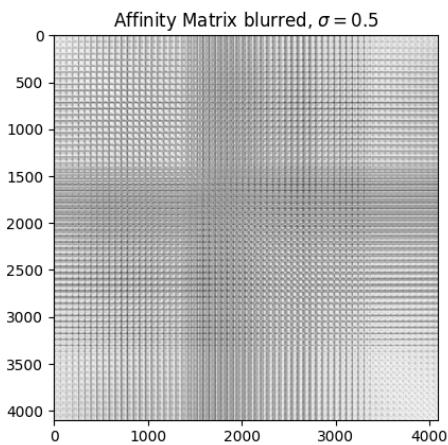
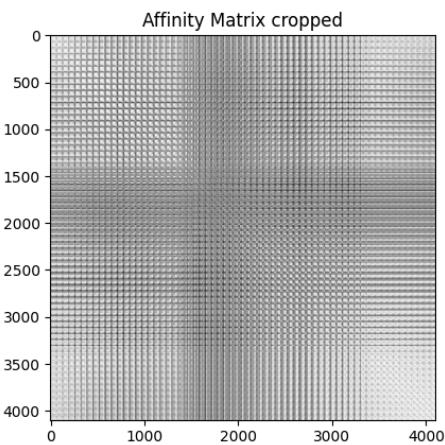
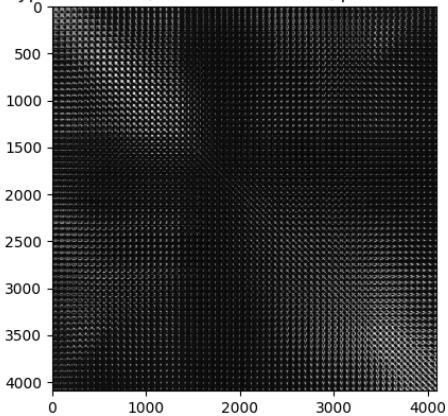


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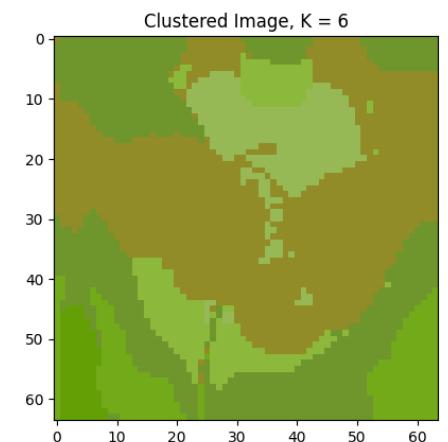
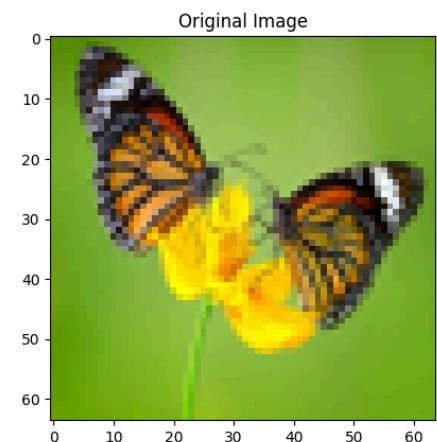
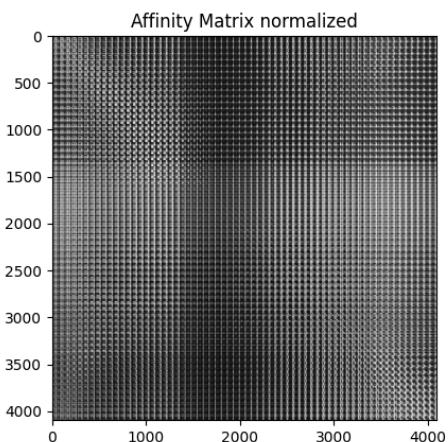
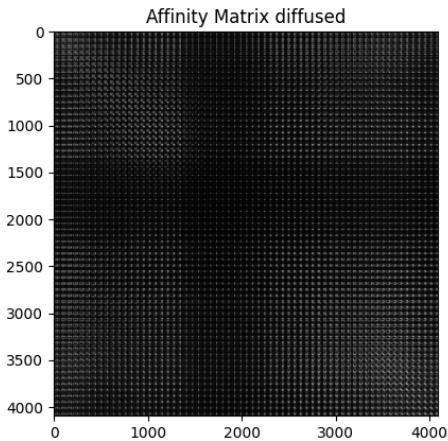
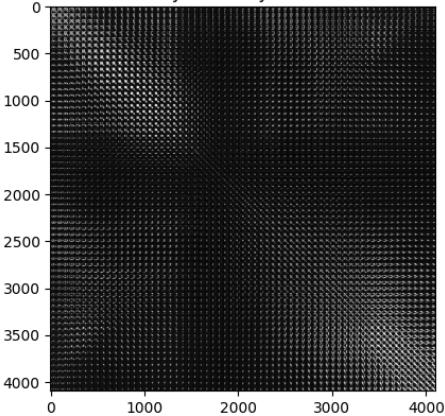
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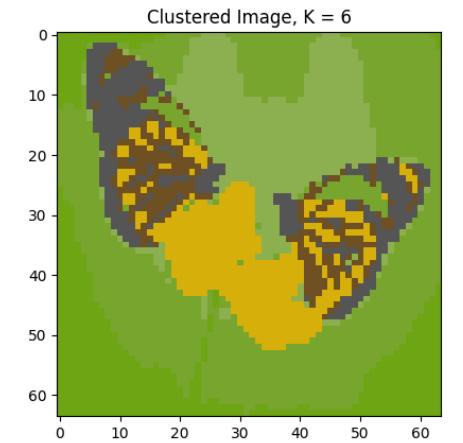
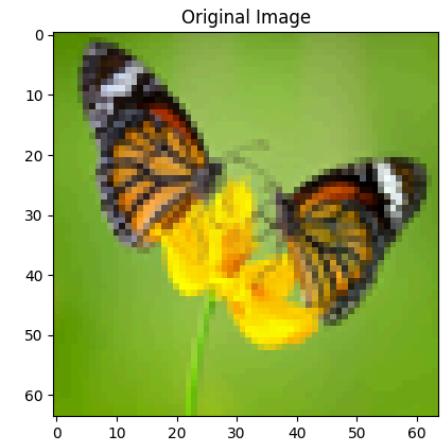
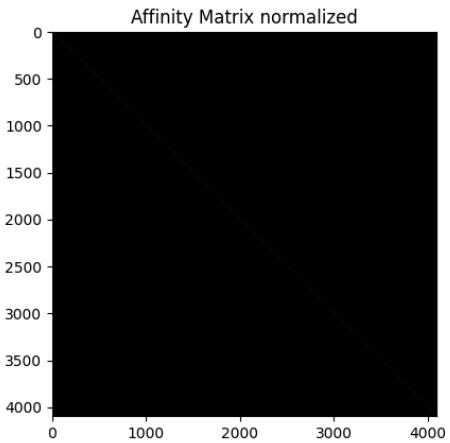
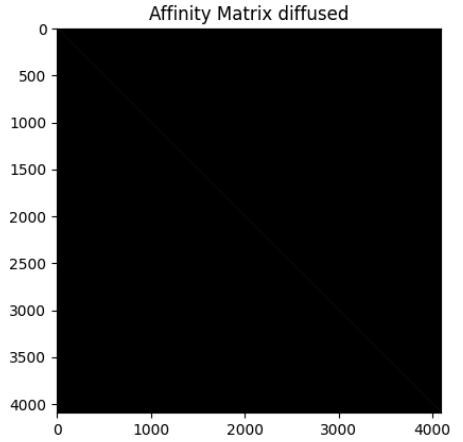
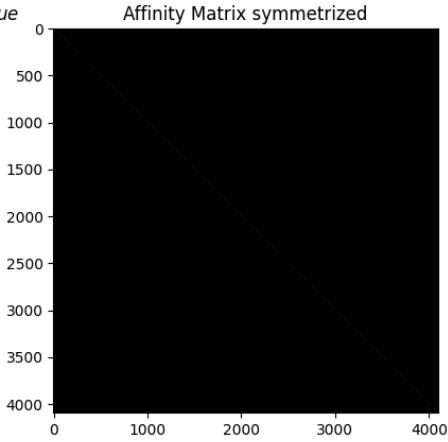
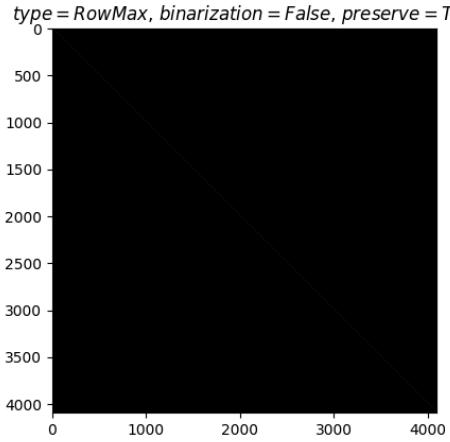
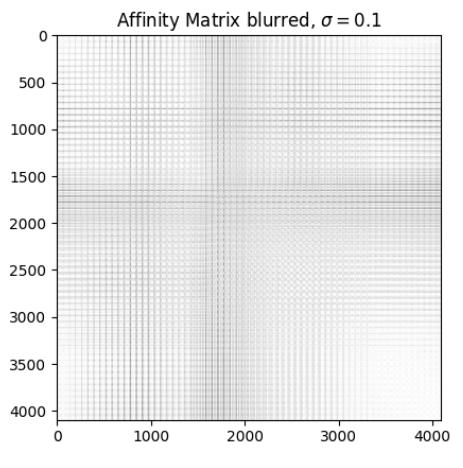
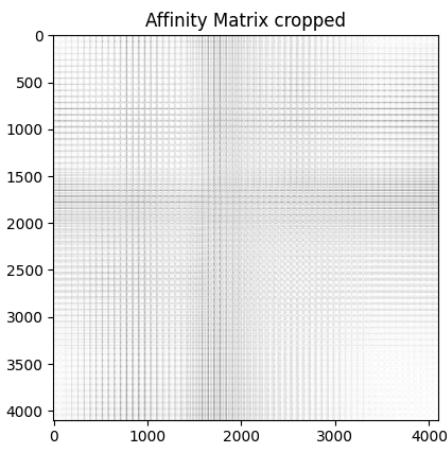
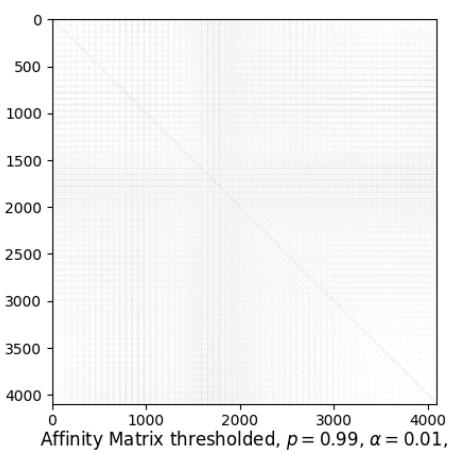


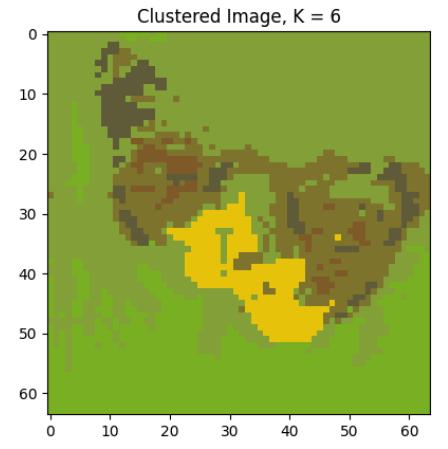
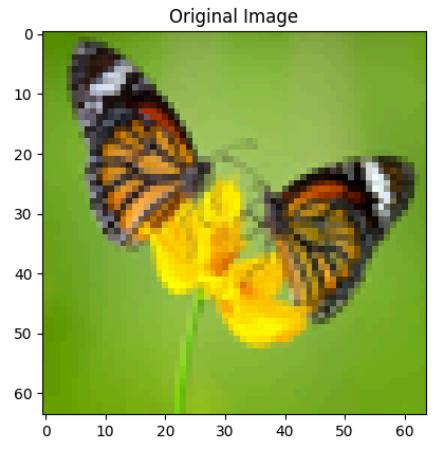
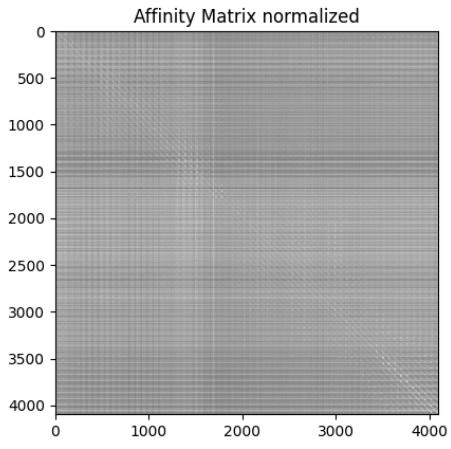
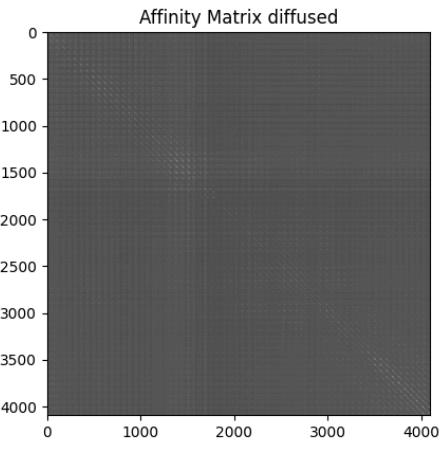
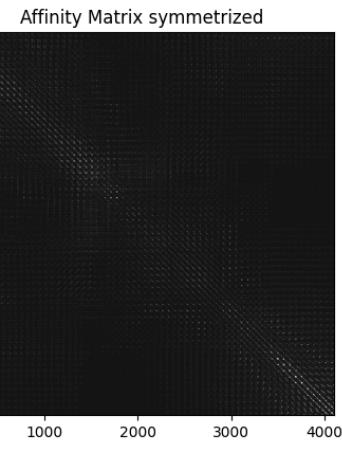
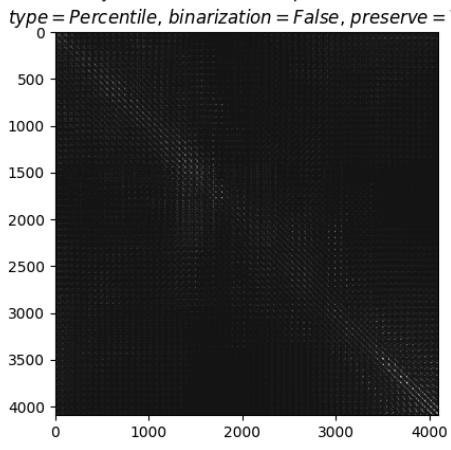
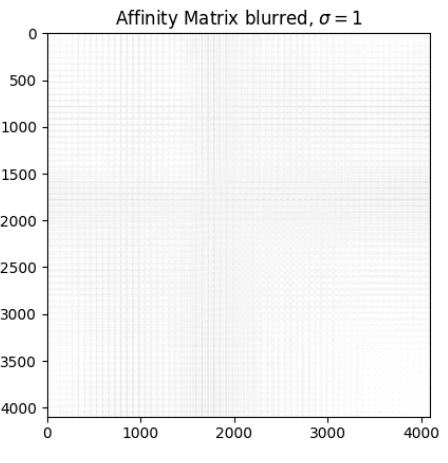
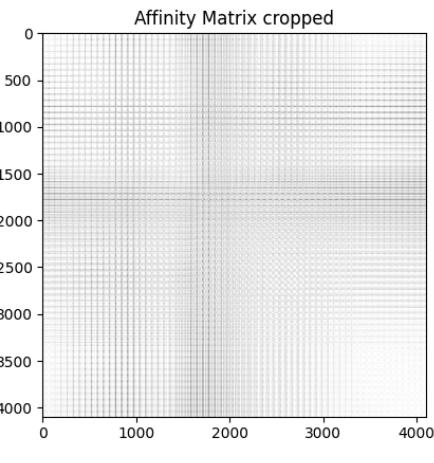
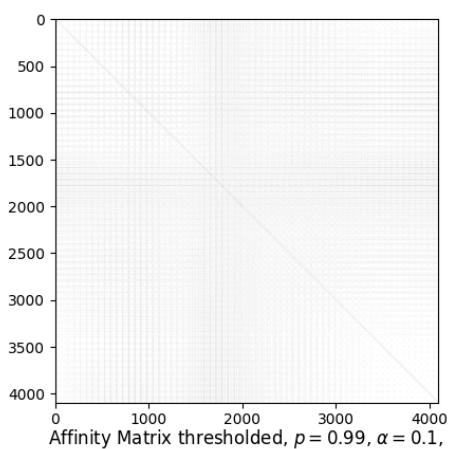
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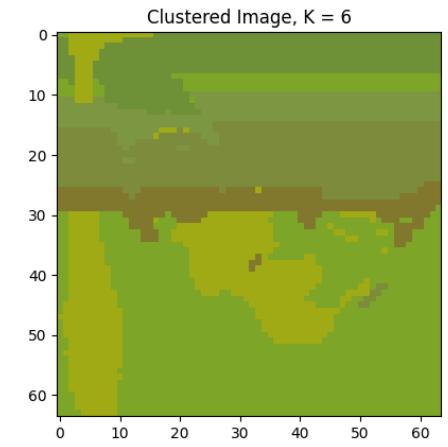
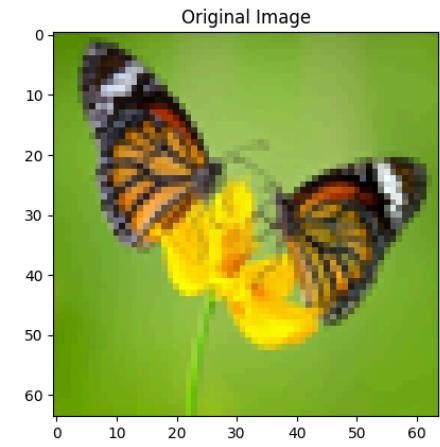
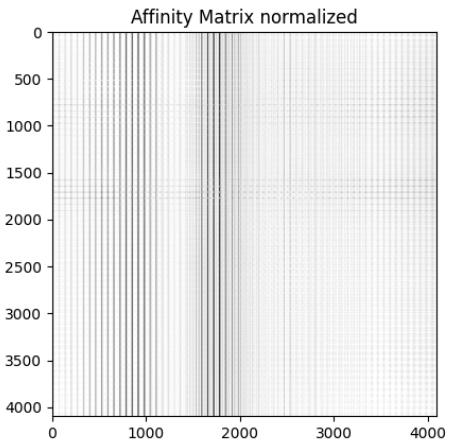
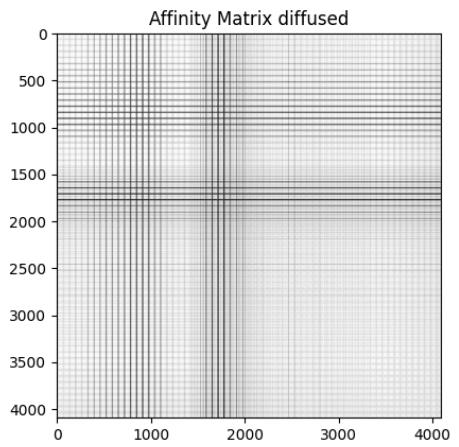
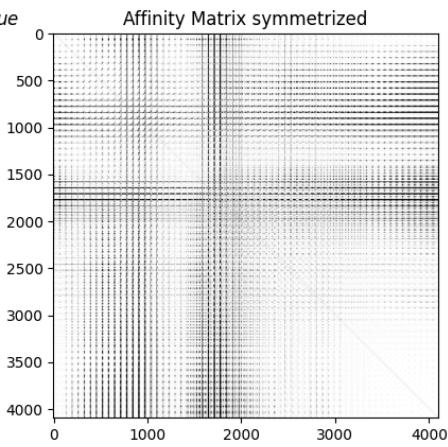
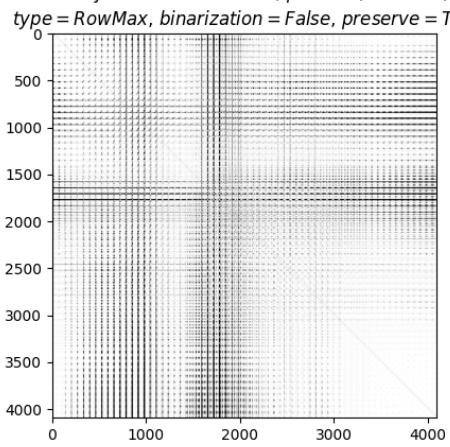
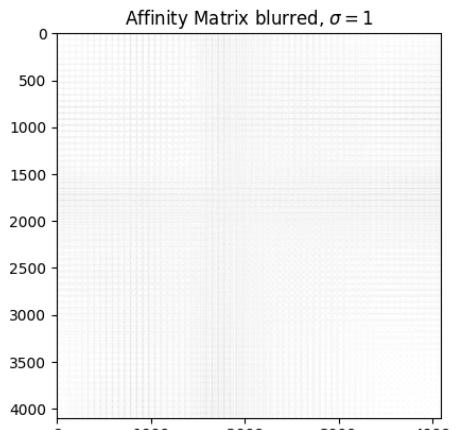
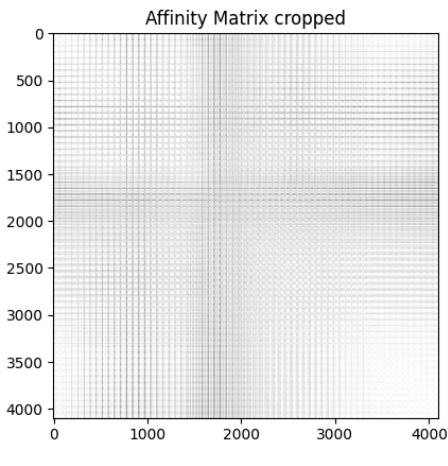
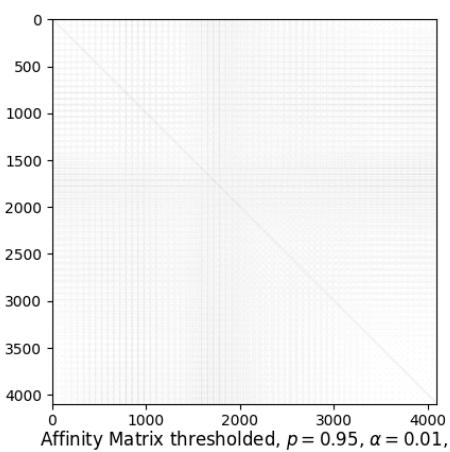


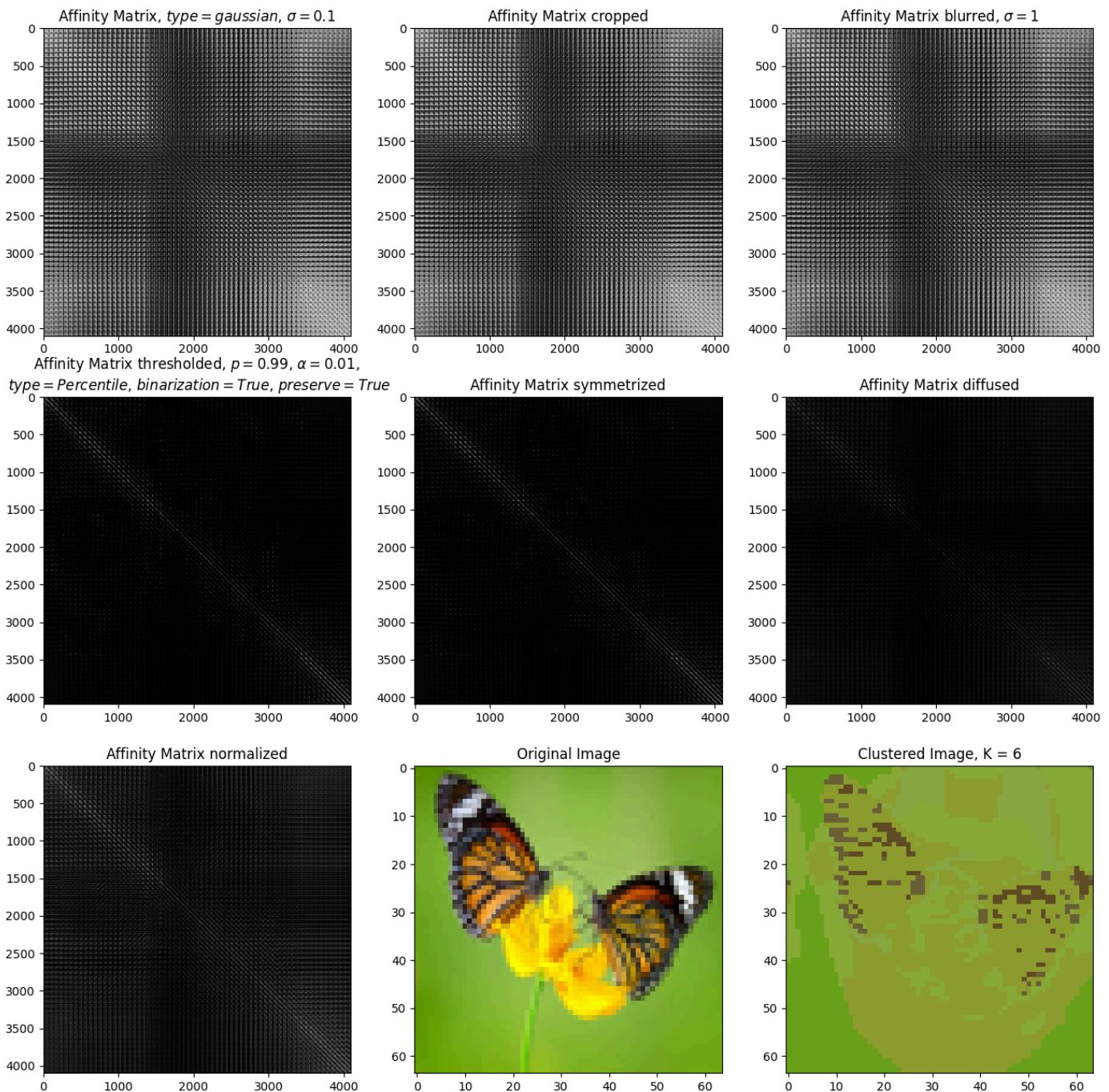
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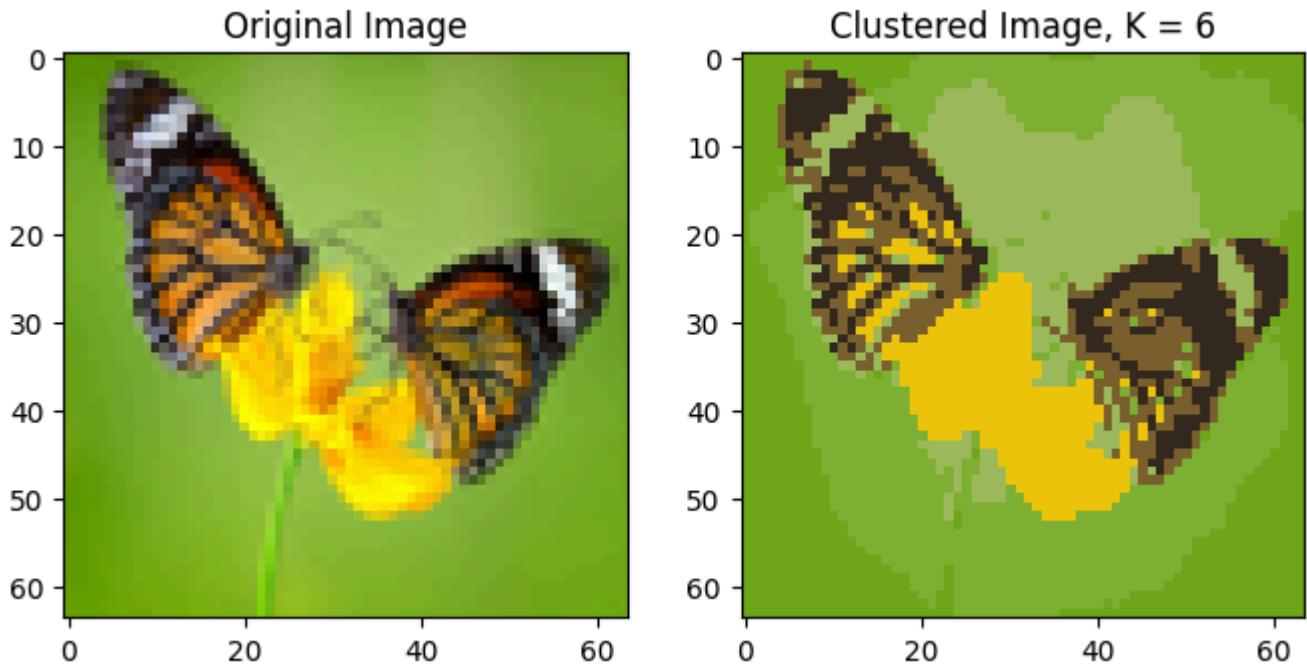








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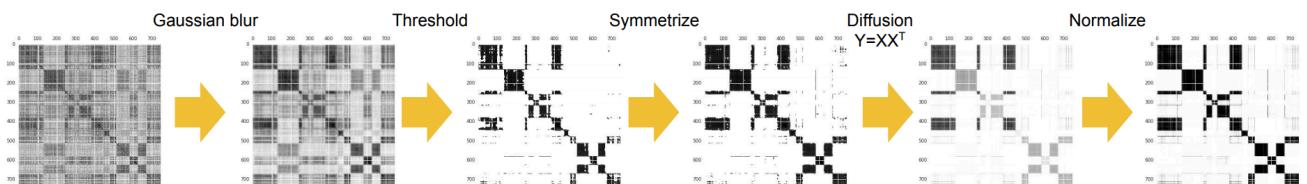


Appendix

Affine Matrix Refinement

Steps:

1. Blurring : Perform Gaussian Blurring on Affinity Matrix to smoothout the Affinities
2. Thresholding: Perform thresholding on the matrix to remove outliers, and constraint the Laplacian Matrix Range
3. Symmetrize: Since Blurring followed by Thresholding is non linear operation and non-symmetric. It will messup the symmetric property of Laplacian Matrix. Therefore we Re-Symmetrize the Laplacian.
4. Diffusion: Its done as XX^T
5. Normalization: Normalize each row of Laplacian, since each row of Laplacian is a different Vertex of the Graph.



The Parameters for each of the operations is dependent on the problem at hand.

References

```
@misc{wang2022speaker,
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