PROJET IMA 201

Transfert de couleurs

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- Prescription d'histogrammes
- Transport optimal - nuage de points
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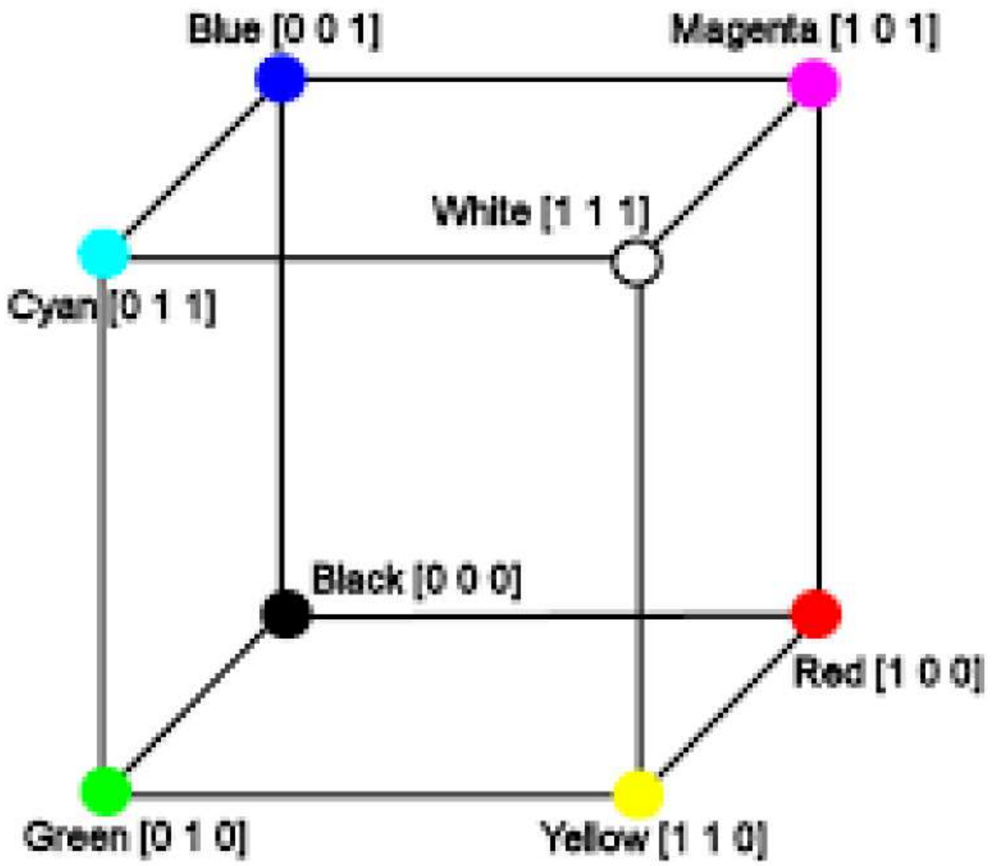
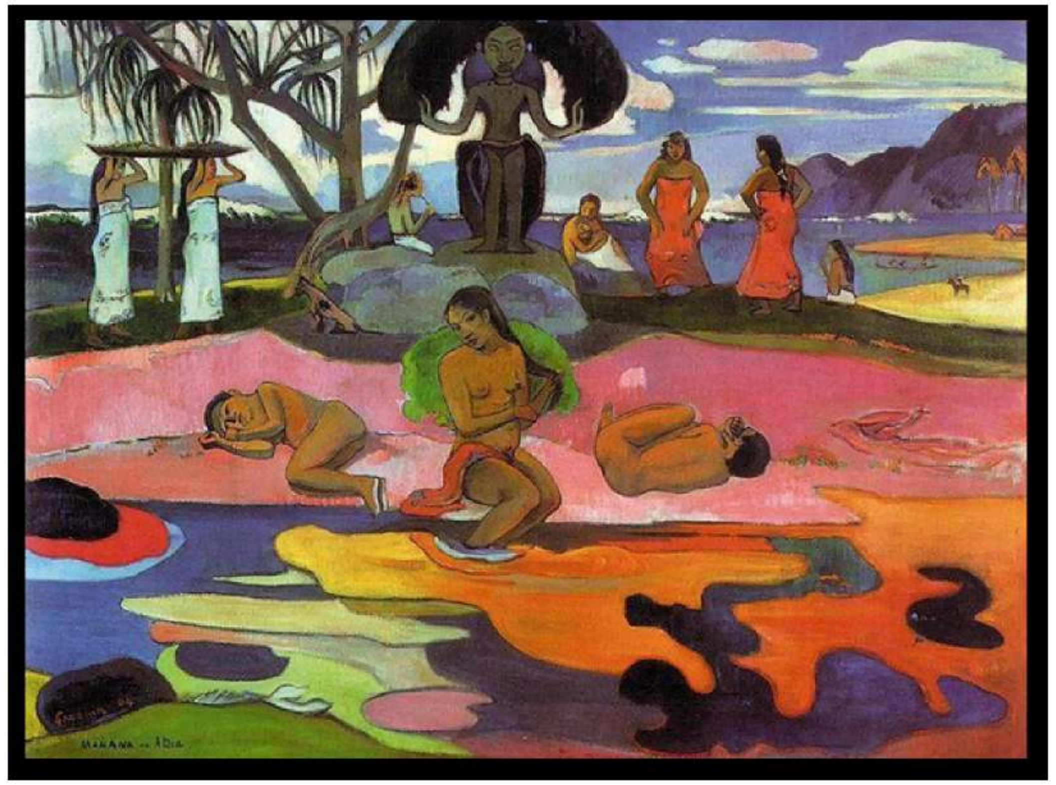
Présentation du problème



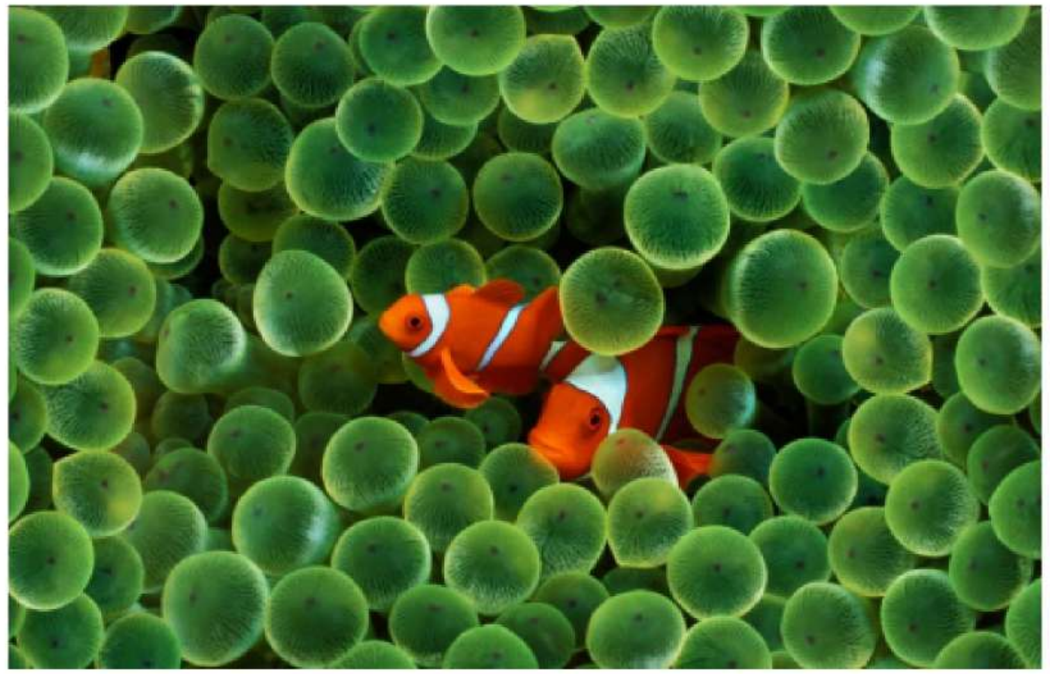


Prescriptions d'histogrammes
1) Transformation affine

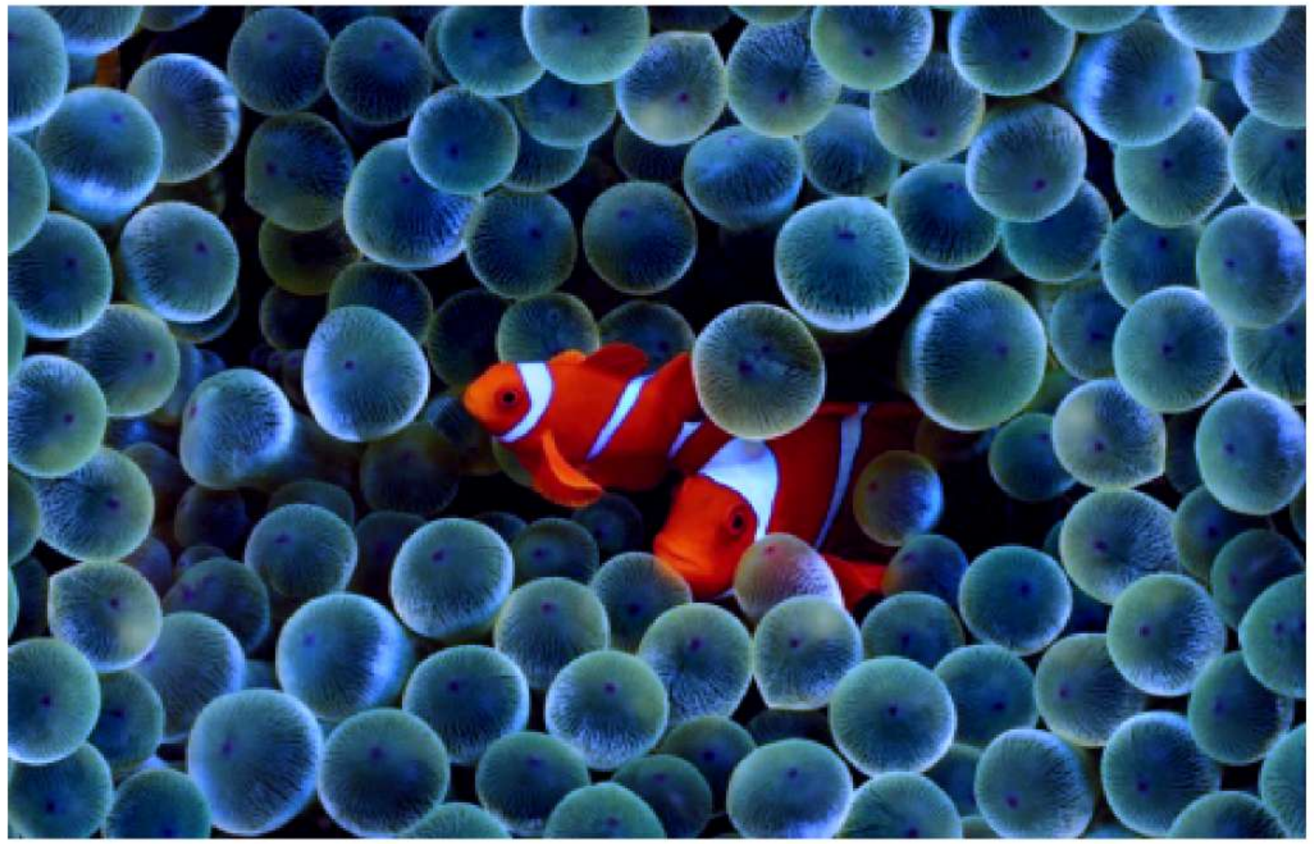
w=(u -mean(u))*std(v)/std(u)+mean(v)

Prescriptions d'histogrammes
1) Transformation affine

First image



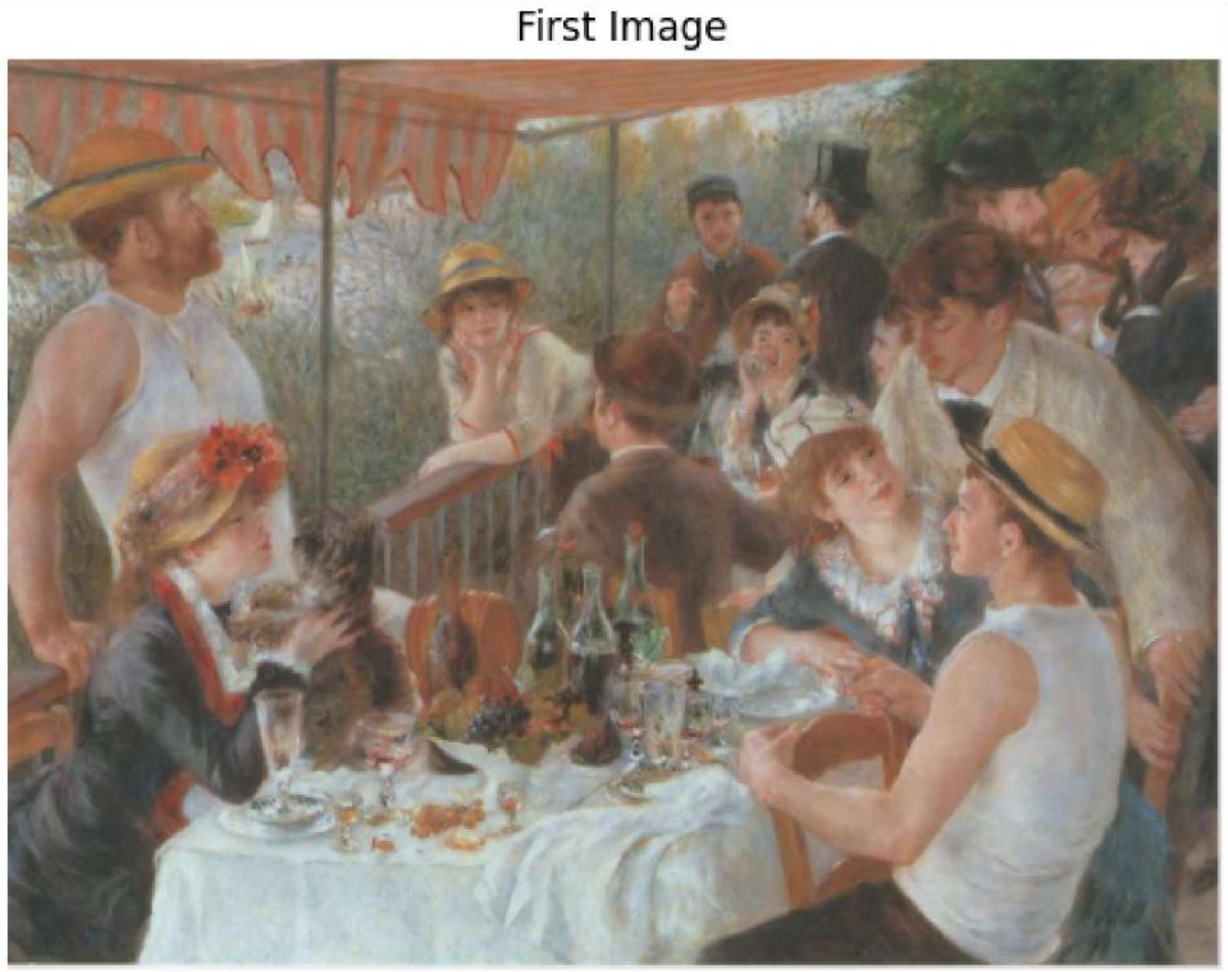
Second Image



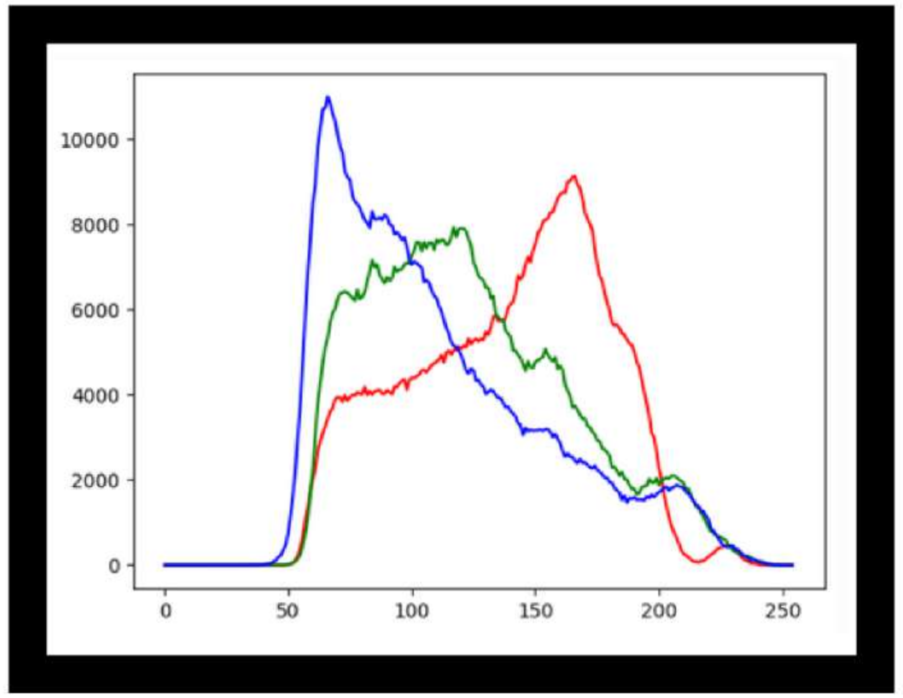
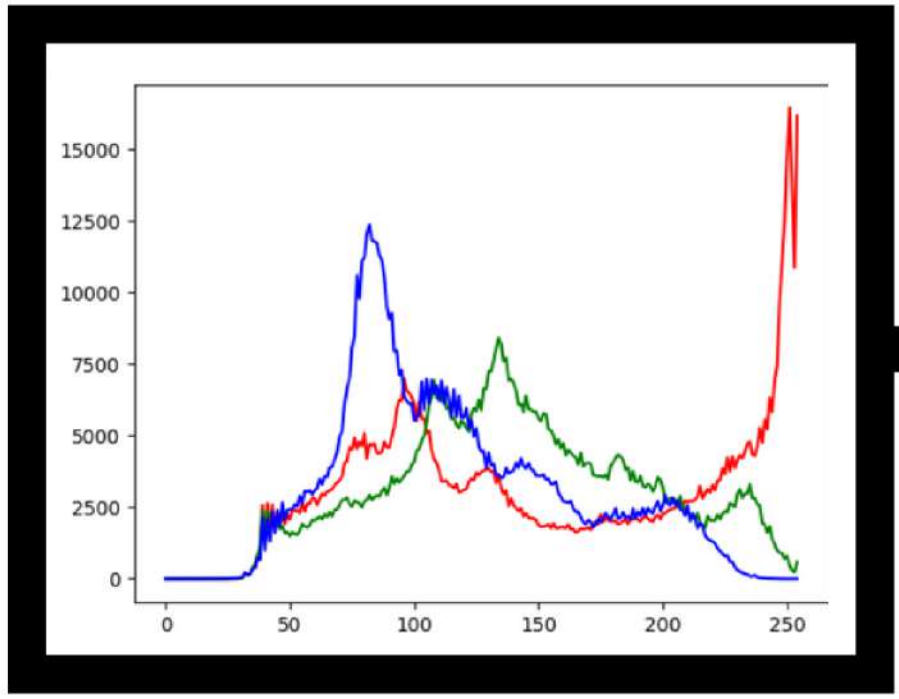
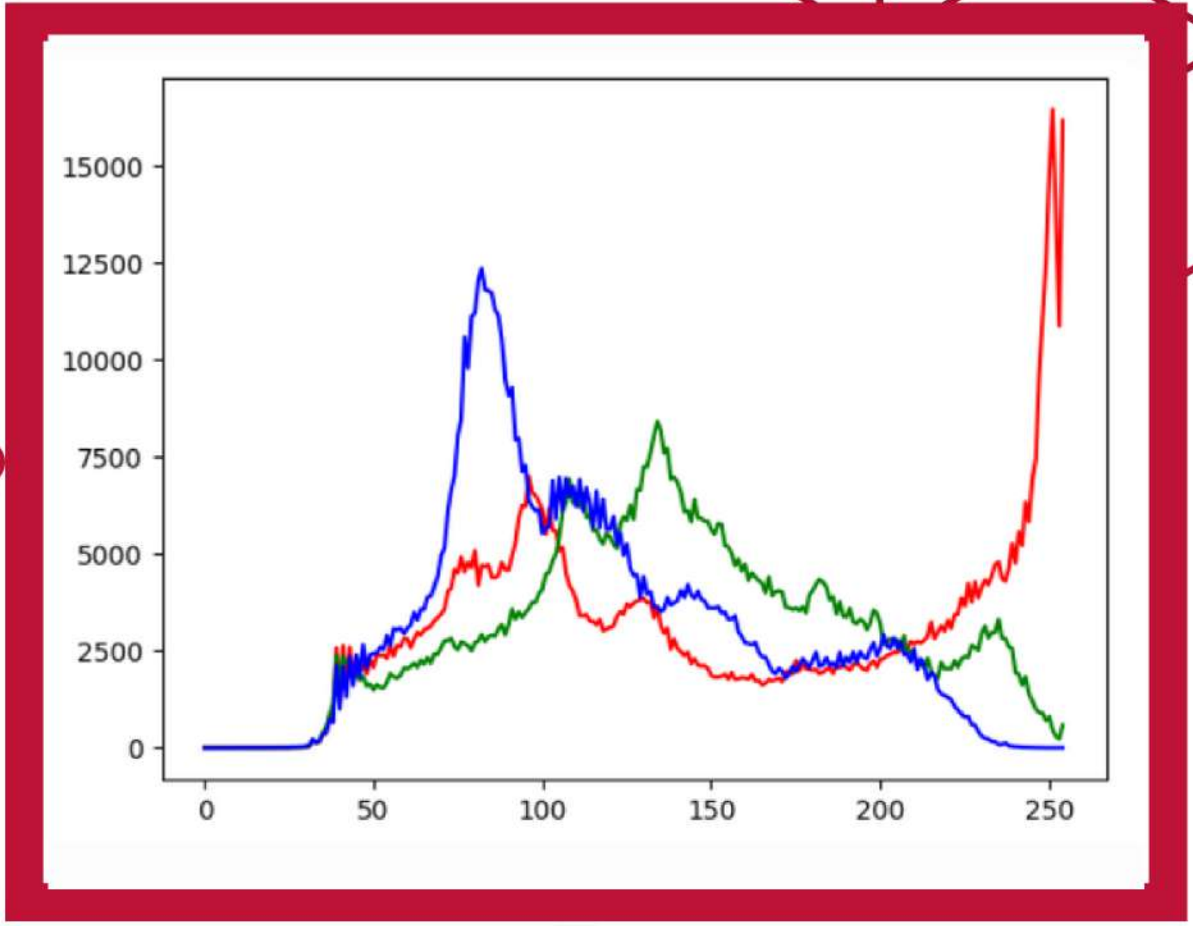
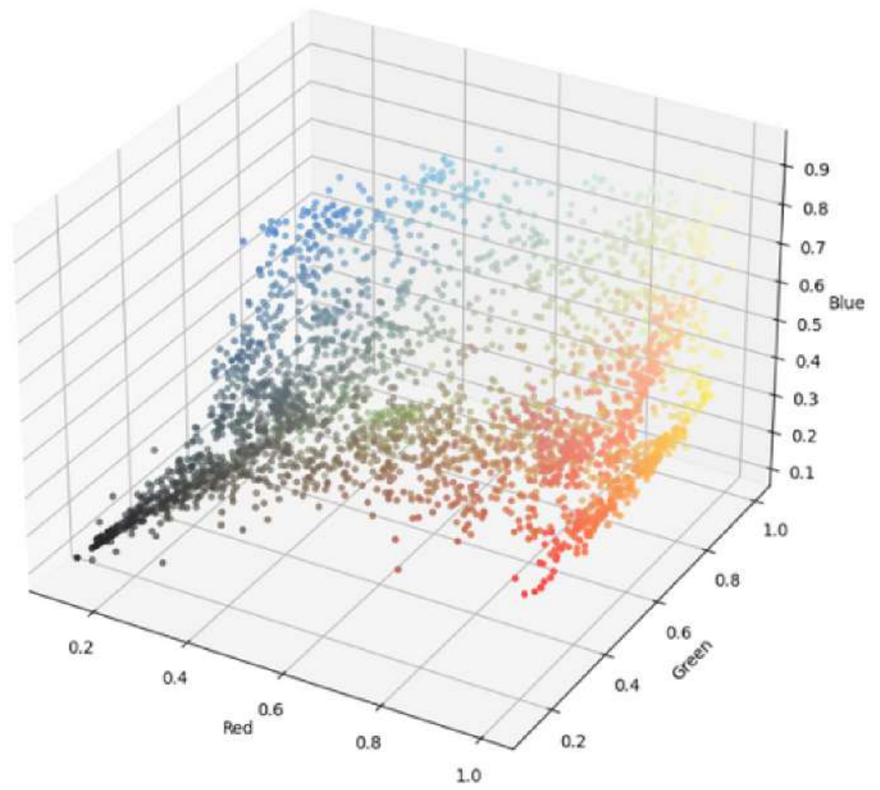
Prescriptions d’histogrammes

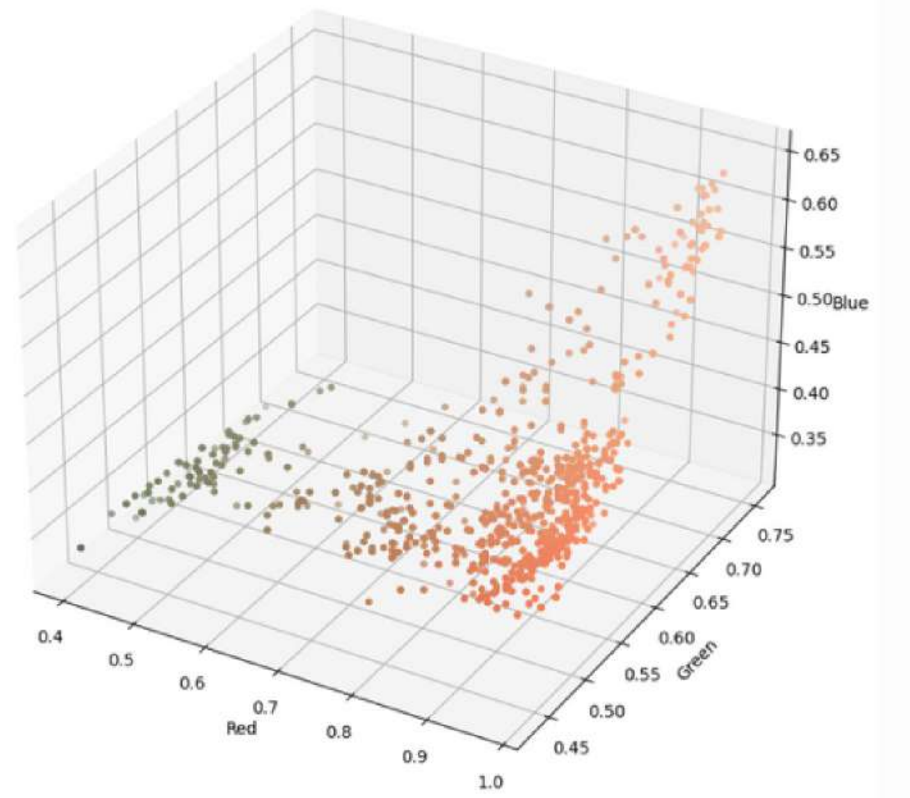
2) Prescription par canal

Dans cette partie, on essaie de prescrire l’histogramme de v à celui de u. On applique alors la méthode vue en TP pour un histogramme en niveaux de gris que l’on applique à chaque channel de couleurs.

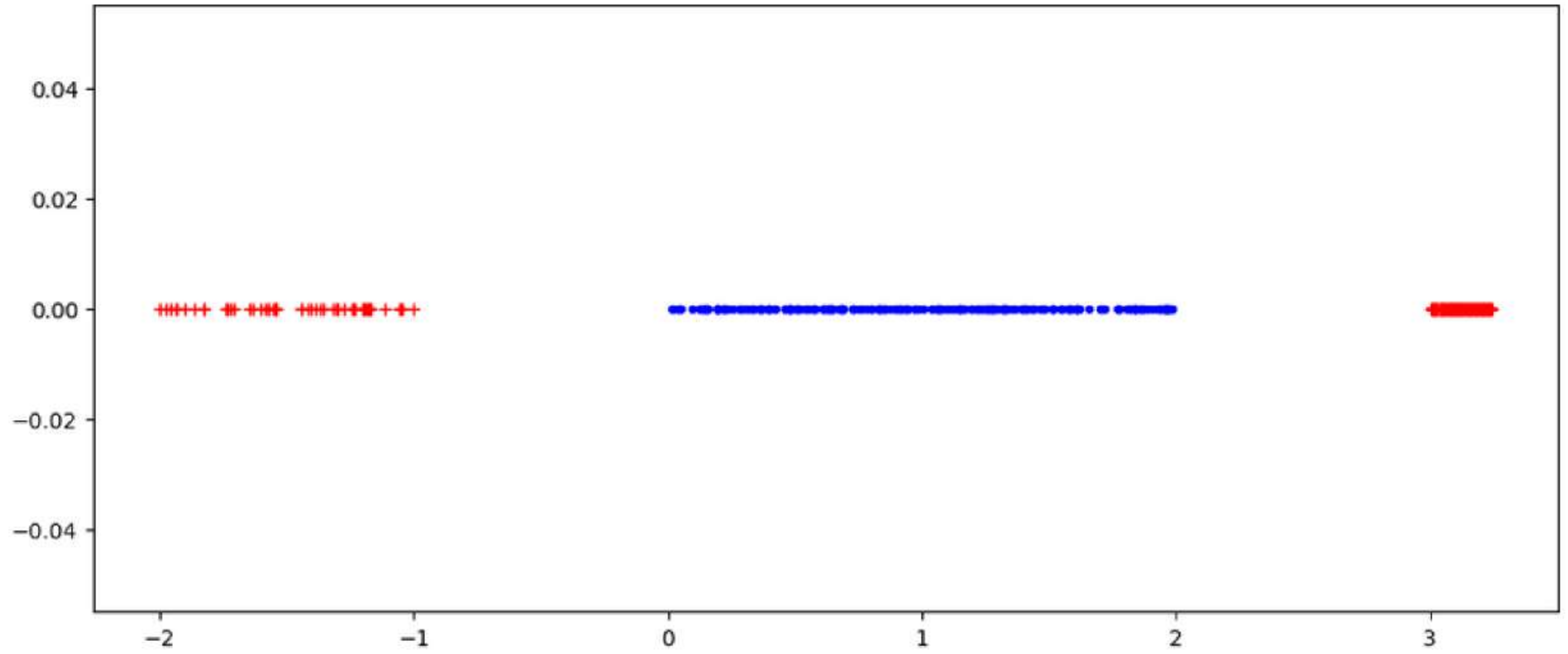


Prescriptions d'histogrammes
2) Prescription par canal

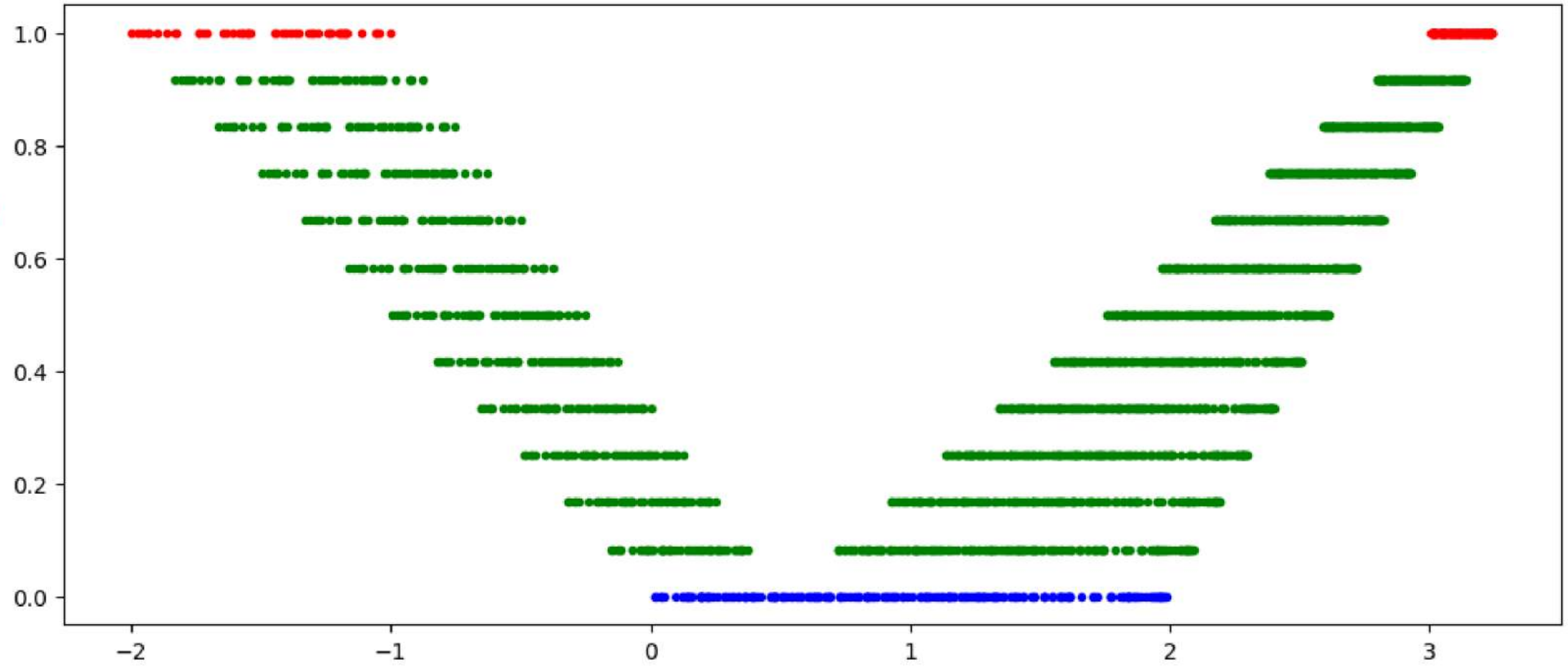







Transport optimal
1) Cas à 1 dimension



$$\sigma^\star = \sigma_g \circ \sigma_f^{-1}$$

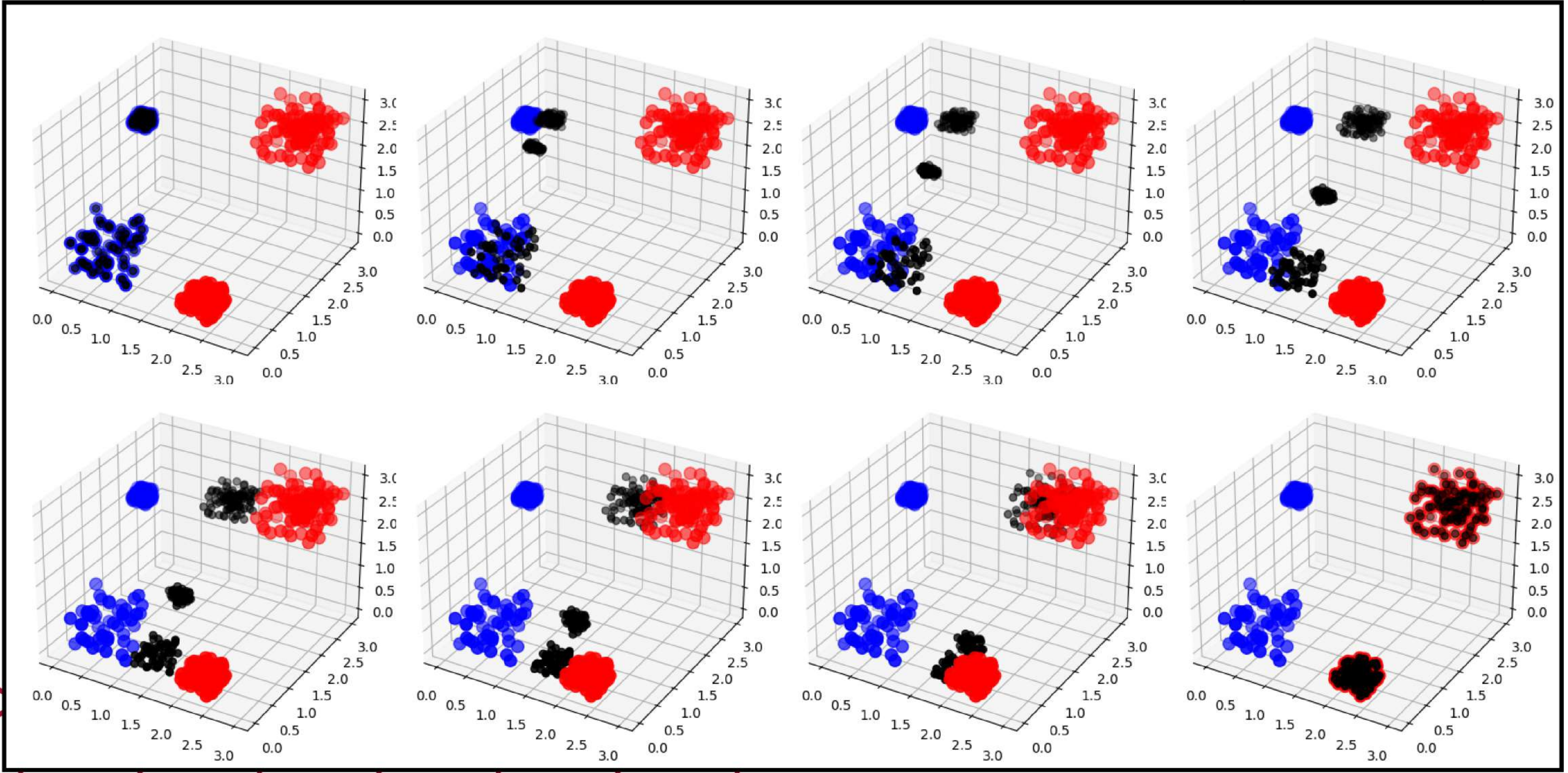


Transport optimal
2) Extension à 3 dimensions

1. **On choisit Z= X**
2. **A chaque itération, on prend une base orthonormale (u1,u2,u3) en prenant une matrice 3*3 aléatoire et utilisant la décomposition QR.**
3. **Pour chaque couleur on calcule une descente de gradient avec la fonction suivante :**

$$Z_{\sigma Z} = Z_{\sigma Z} + \varepsilon((Y, u_i)_{\sigma Y} - (Z, u_i)_{\sigma Z})u_i,$$

Transport optimal
2) Extension à 3 dimensions



Transport optimal
3) Applications

Défauts observés

Image originale zoomée

Sliced Wassertein transport
with susbampling

Median filter applied

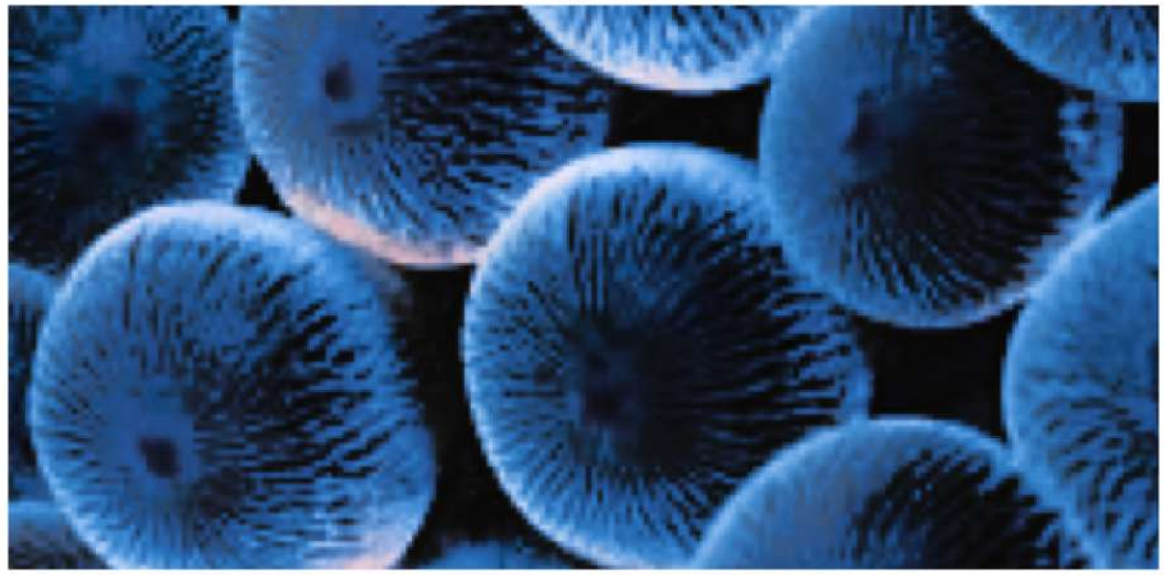
Régularisation

Post-processing algorithms :

1. Average Filtering
2. guided filtering
3. Transport map regularization

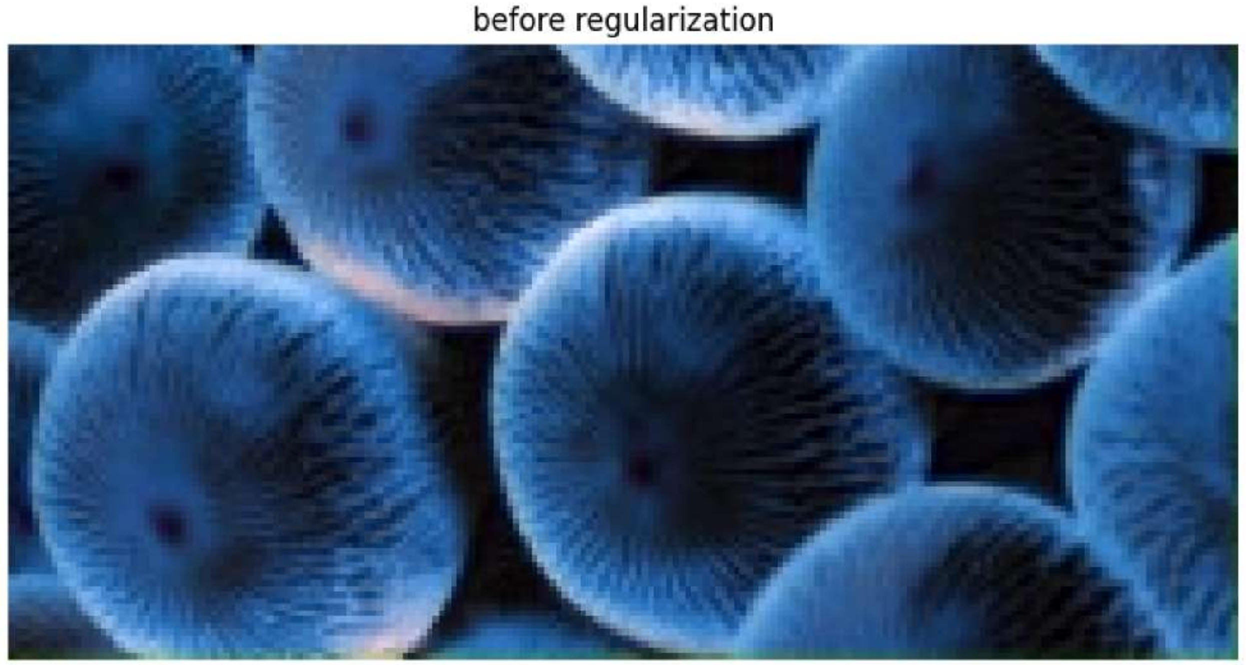
Average filter

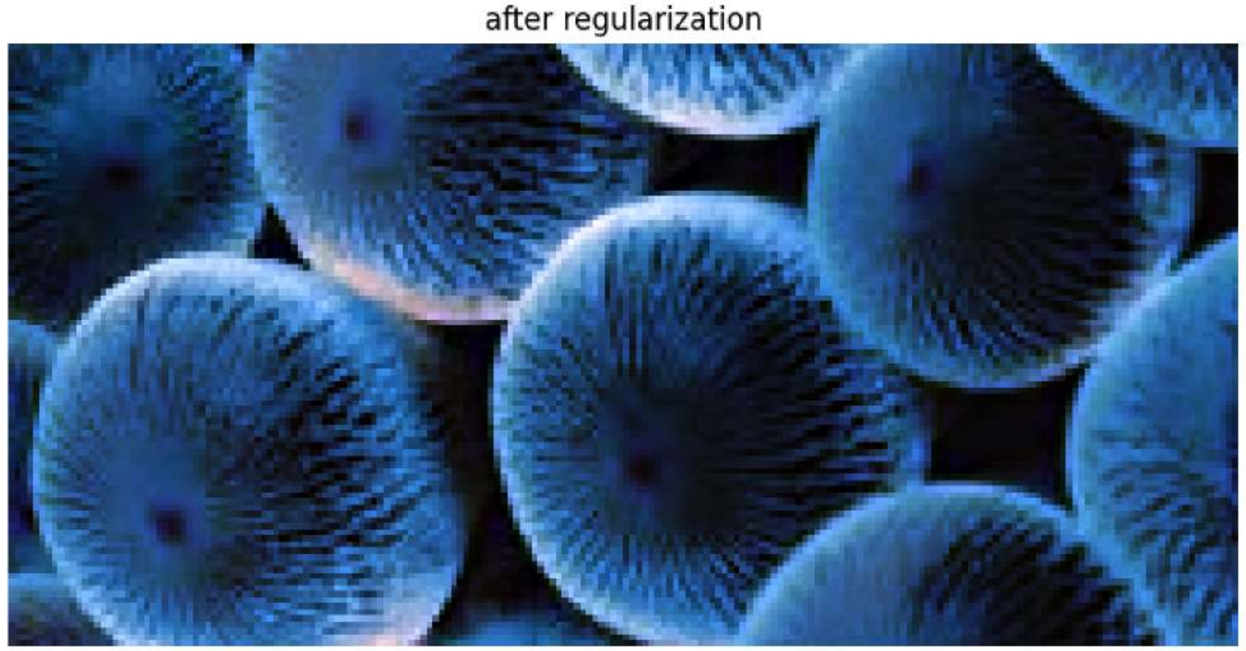
before regularization



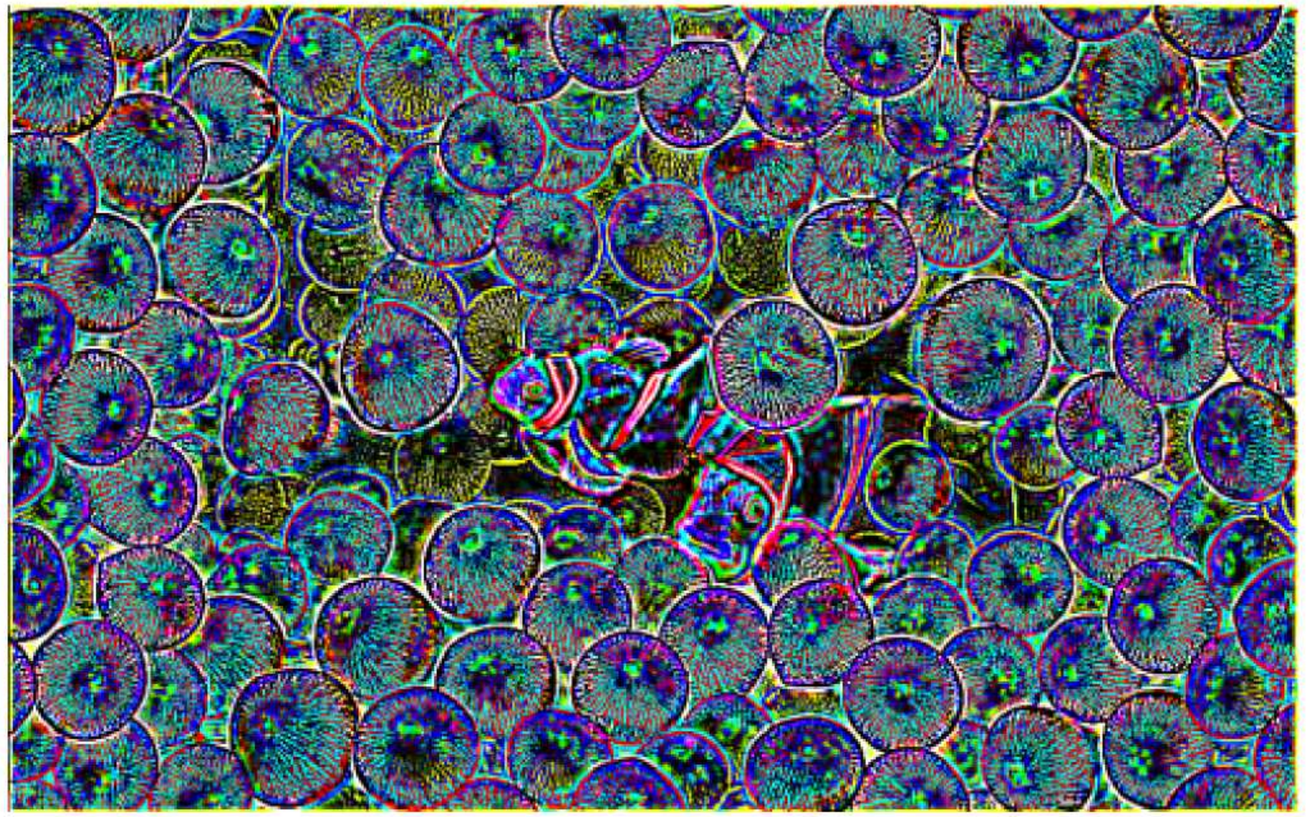
after regularization

Guided filter





On choisit évidemment l'image de base comme guide pour que le transfert de couleur n'altère pas les irrégularités de l'image.



différence entre image filtré avec guided fitler et average filter

Transport Map regularization

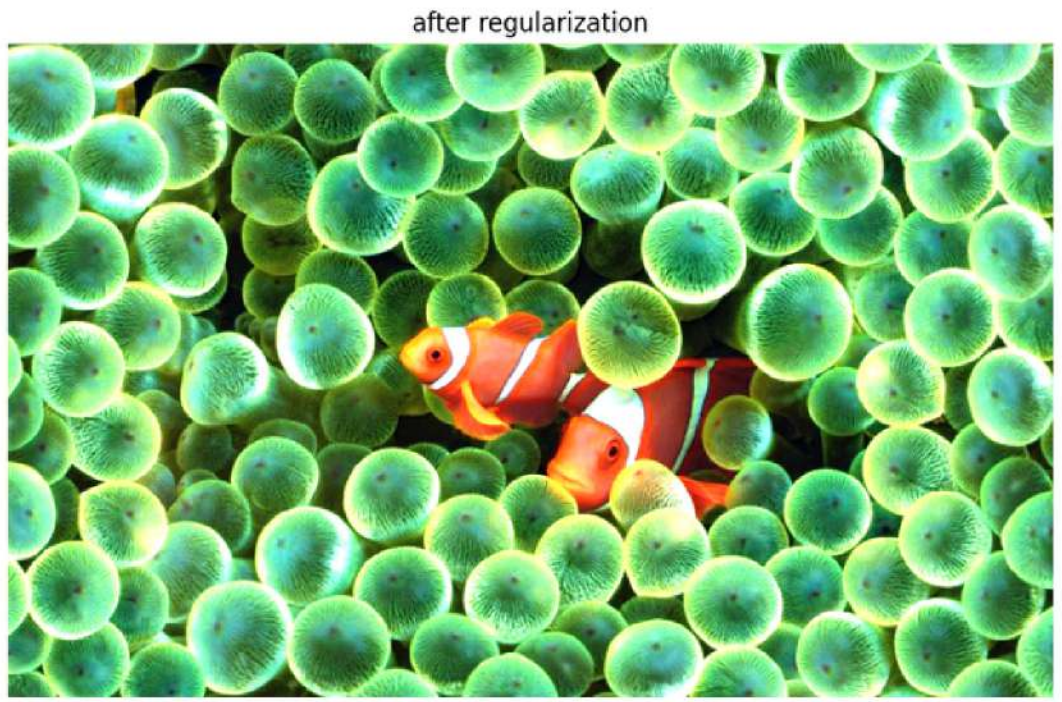
Cette fois ci on utilise des poids exponentielles pour garder la structure de l'image de base :

$$TMR_u(T(u)) = \quad Y_u(T(u)) + u - Y_u(u)$$

Avec : $$Y_u(v)(x_k) = \frac{1}{C(x_k)} \int_{y \in N(x_k)} v(y) \cdot w_u(x_k, y) dy$$

$$w_u(x_k, y) = e^{\frac{-||u(x_k) - u(y)||^2}{\sigma^2}}$$

$$C(x_k) = \int_{y \in N(x_k)} w_u(x_k, y) dy$$



Pour 6 itérations

Transport Map regularization

Pour k=1

after regularization

ization

Approche GMM

1) Pourquoi utiliser des GMM

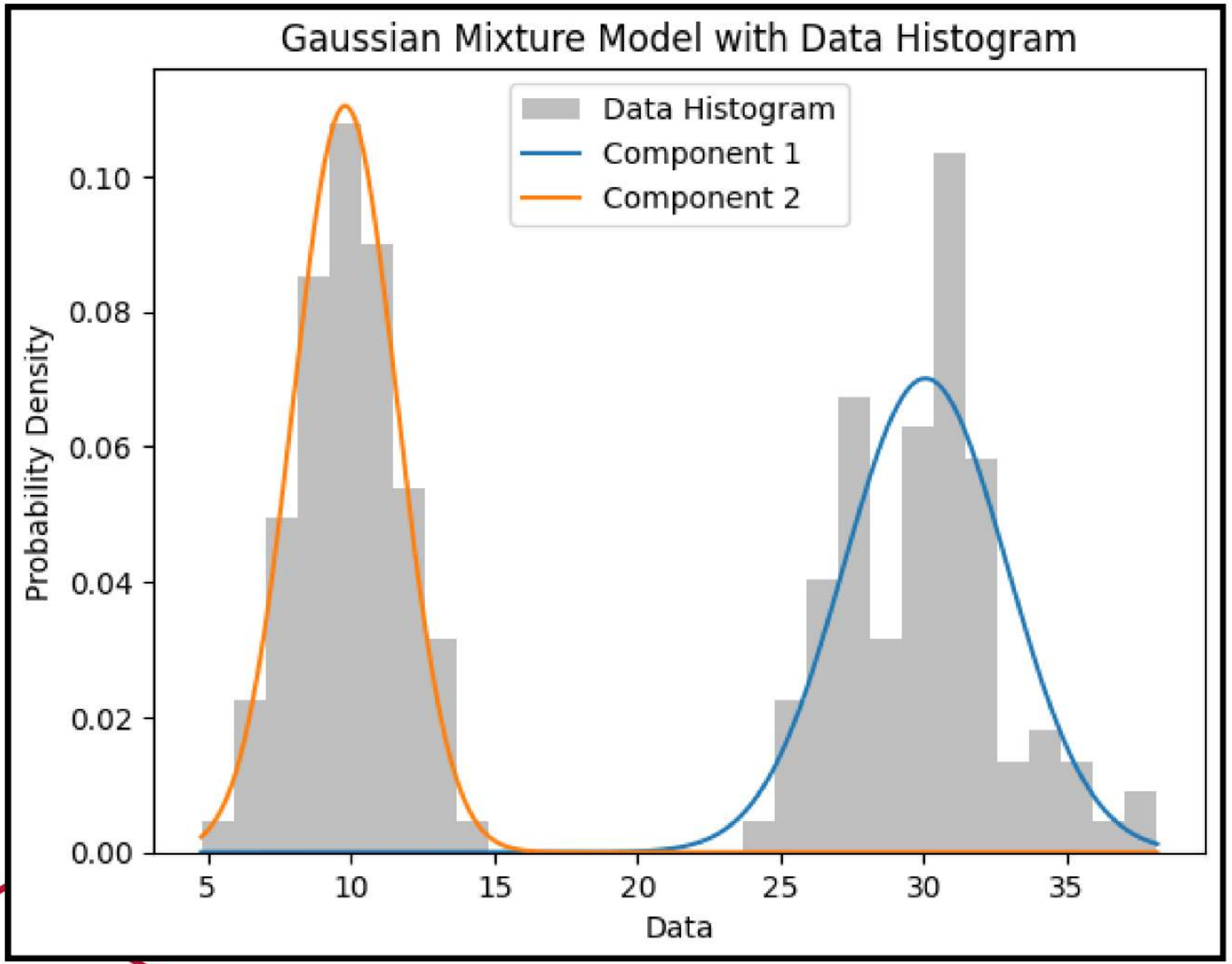
Intérêt : On connaît la formule de la distance de Wasserstein dans le cas gaussien dont on déduit une formule de transport

$$W_2^2(G_0, G_1) = \|m_0 - m_1\|^2 + tr(\Sigma_0 + \Sigma_1 2(\Sigma_0^{\frac{1}{2}} \Sigma_1 \Sigma_0^{\frac{1}{2}})^{\frac{1}{2}})$$

$$\forall x \in R^d, T(x) = m_1 + \Sigma_0^{-\frac{1}{2}} (\Sigma_0^{\frac{1}{2}} \Sigma_1 \Sigma_0^{\frac{1}{2}})^{\frac{1}{2}} \Sigma_0^{-\frac{1}{2}} (x - m_0)$$

$$T_{mean}(x) = \frac{\sum_{k,l} w_{k,l} G_{m_k,\sigma_k} T_{kl}}{\sum_{k,l} w_{k,l} G_{m_k,\sigma_k}}$$

Approche GMM
2) Utilisation sur nos images 1D



Approche GMM
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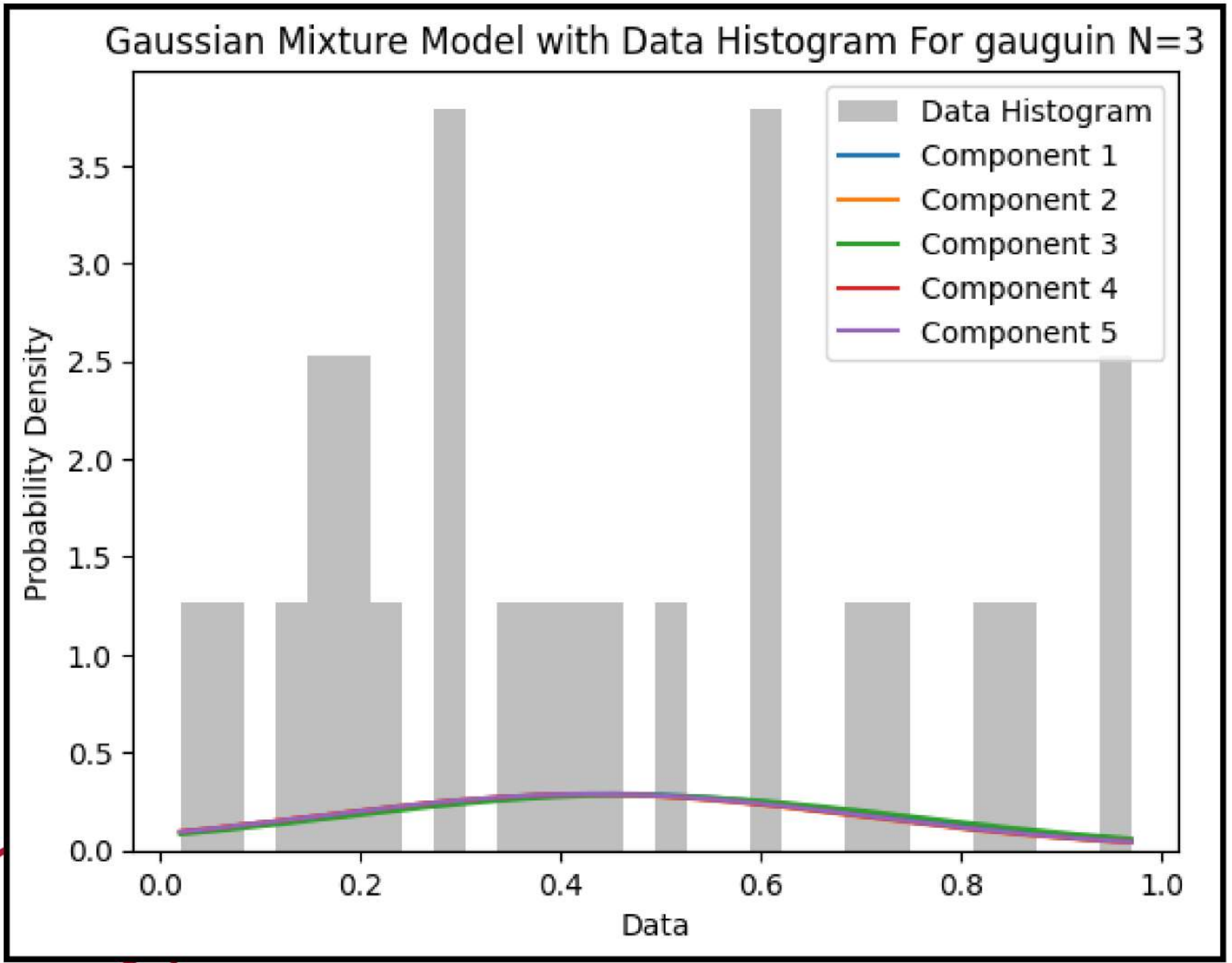
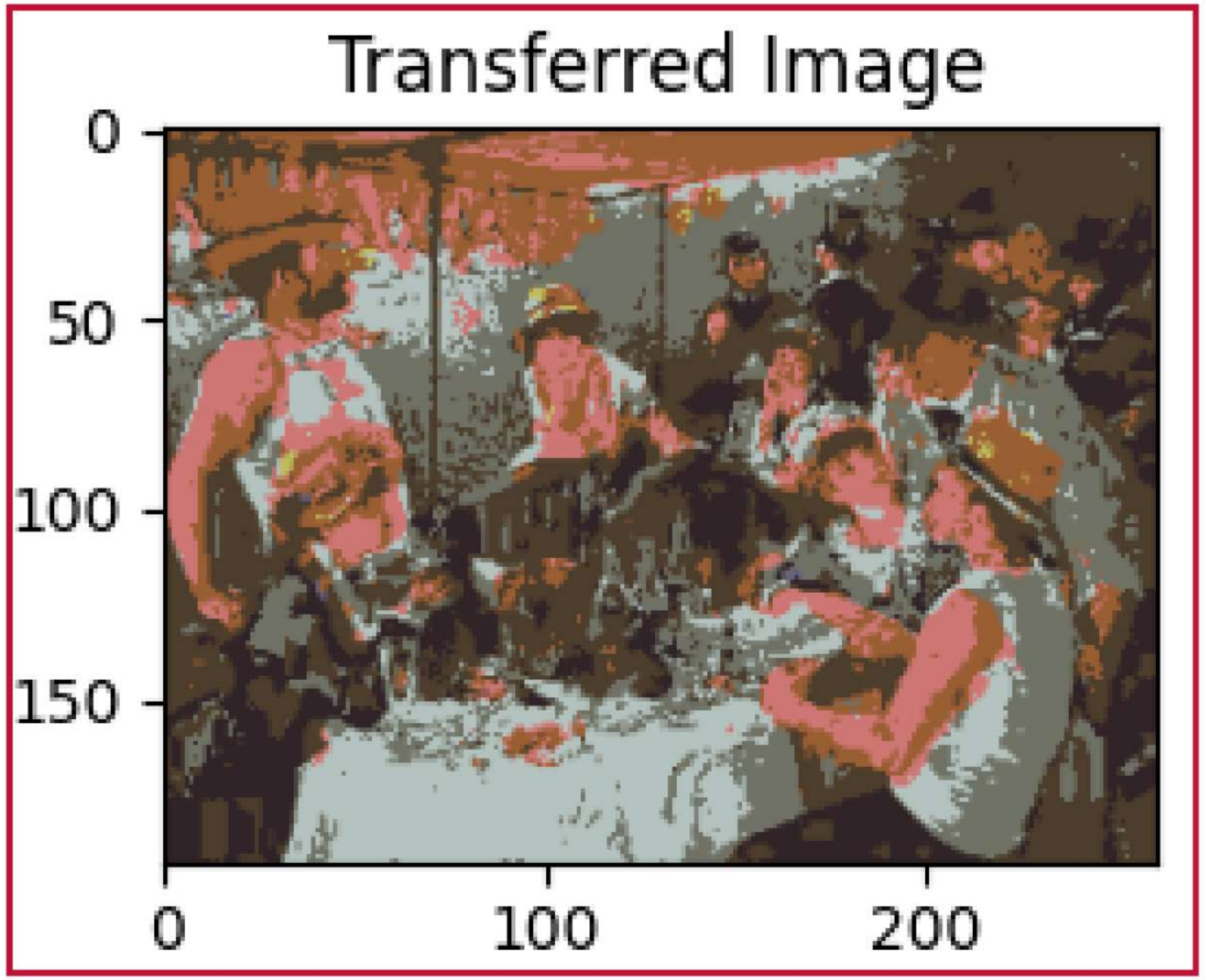
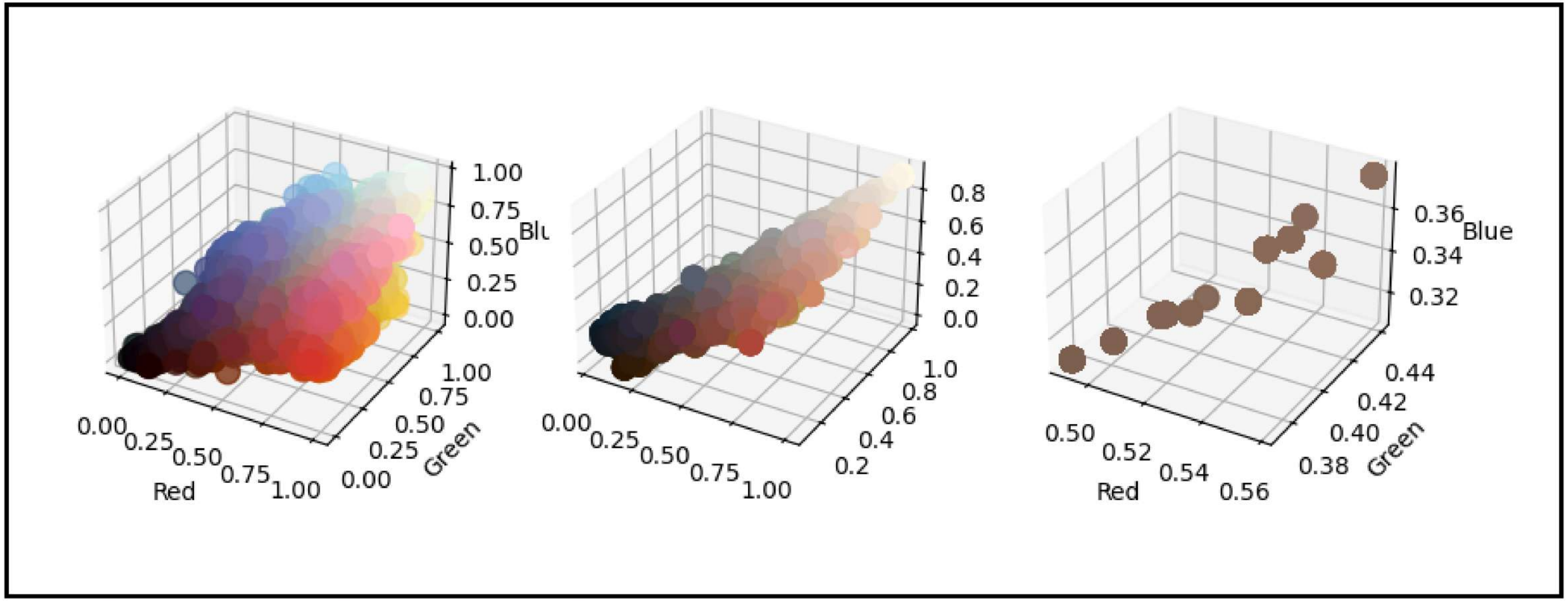


Approche GMM
3) Applications



Approche GMM



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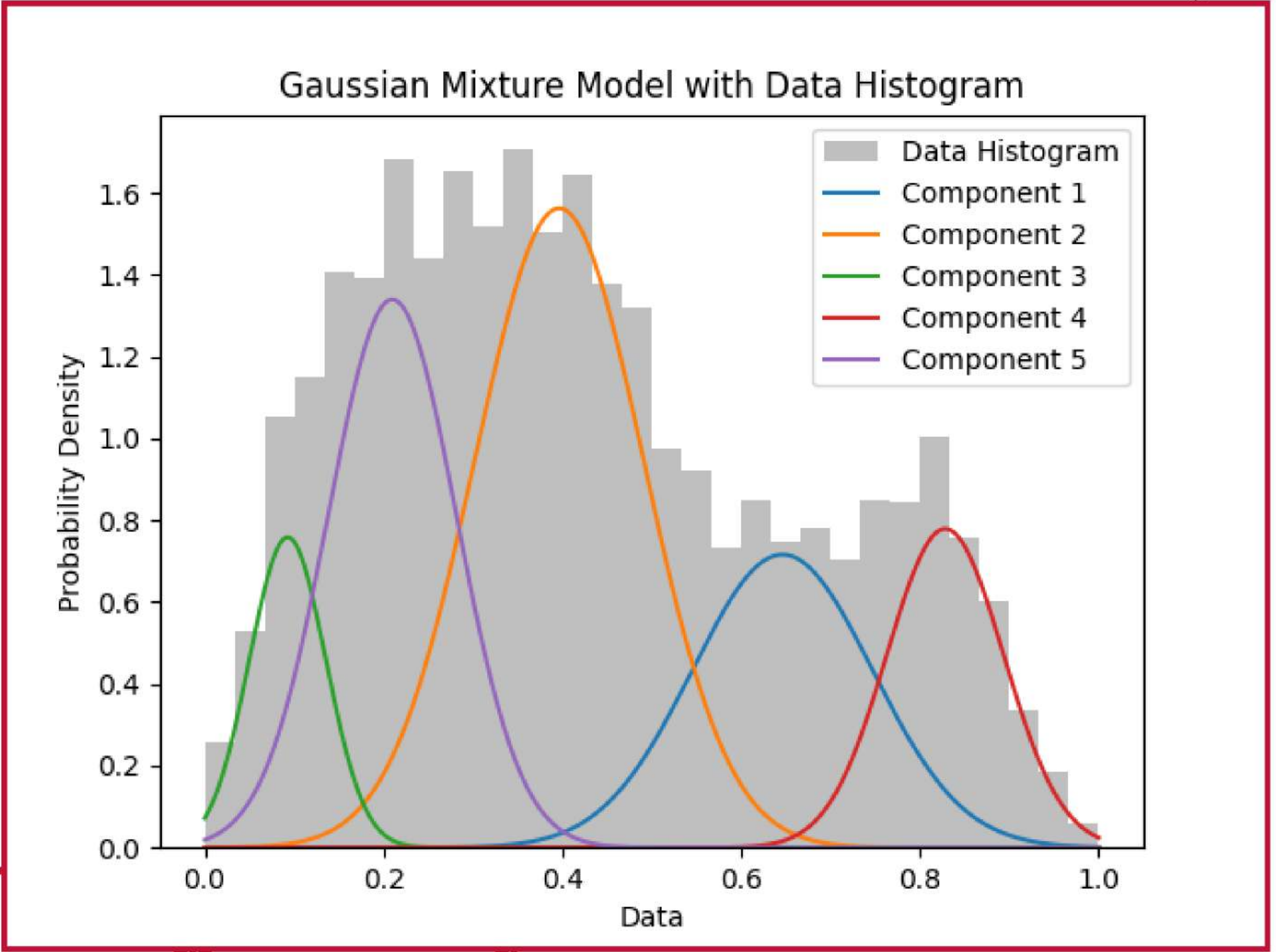
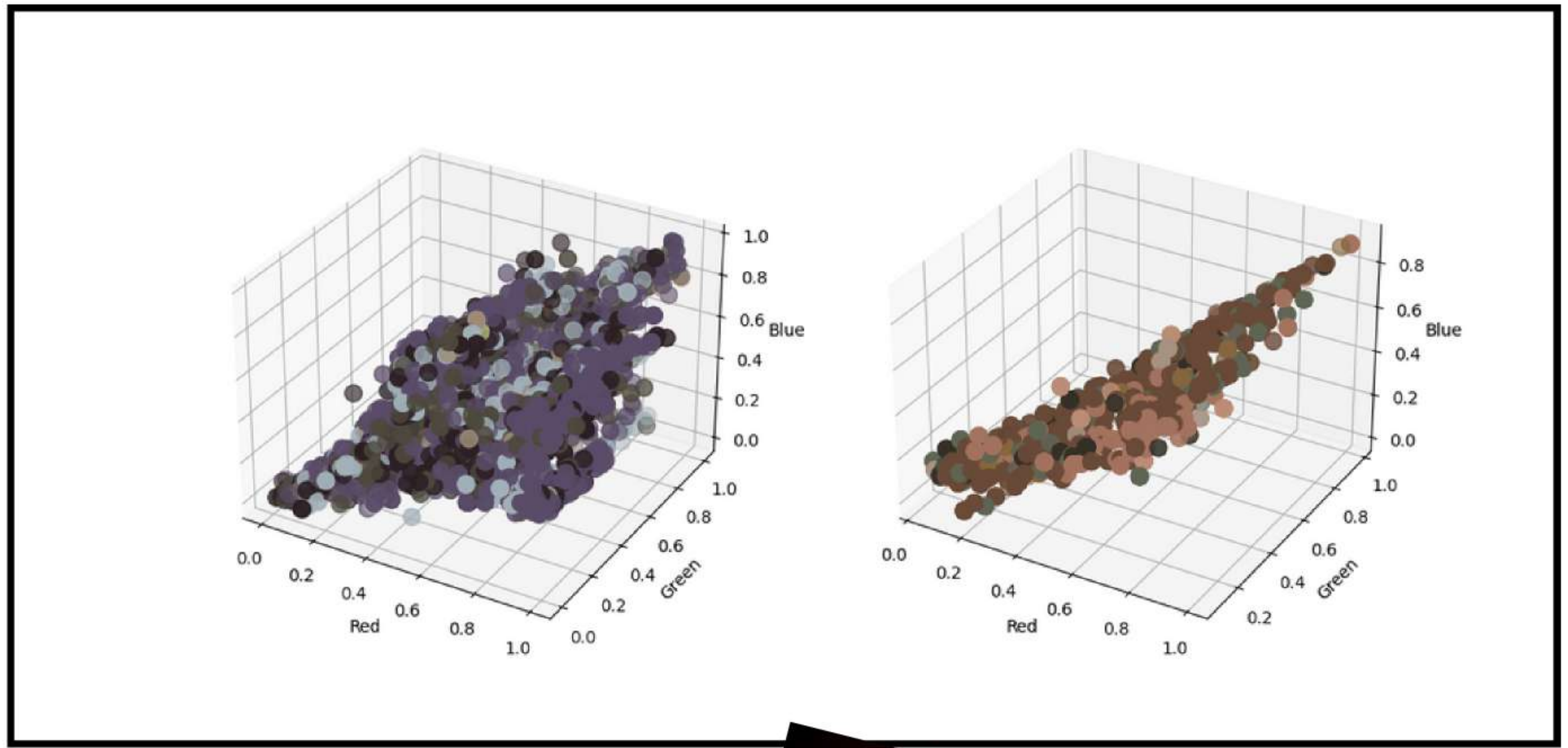
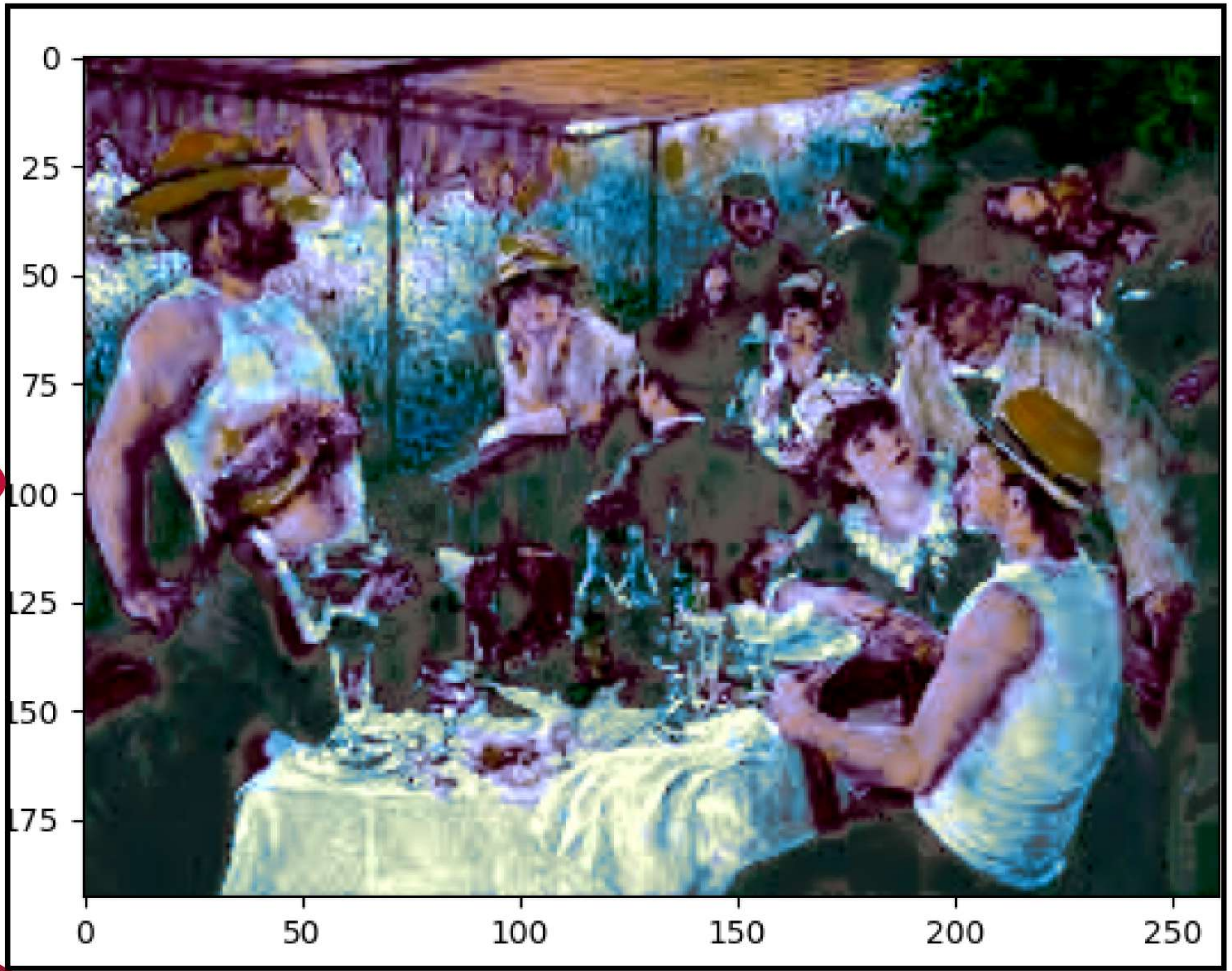
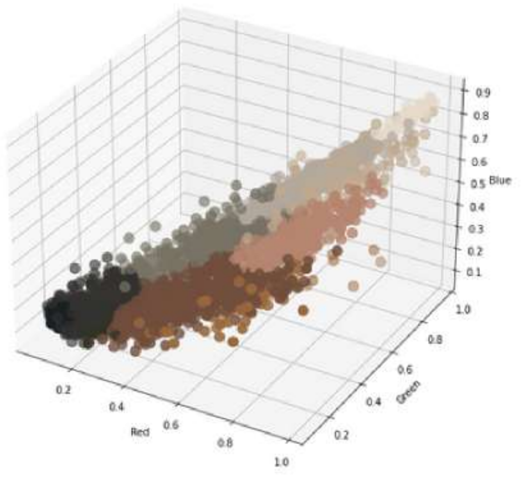


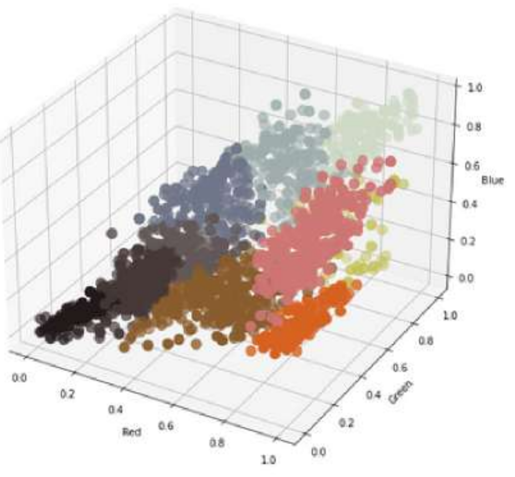
Approche GMM

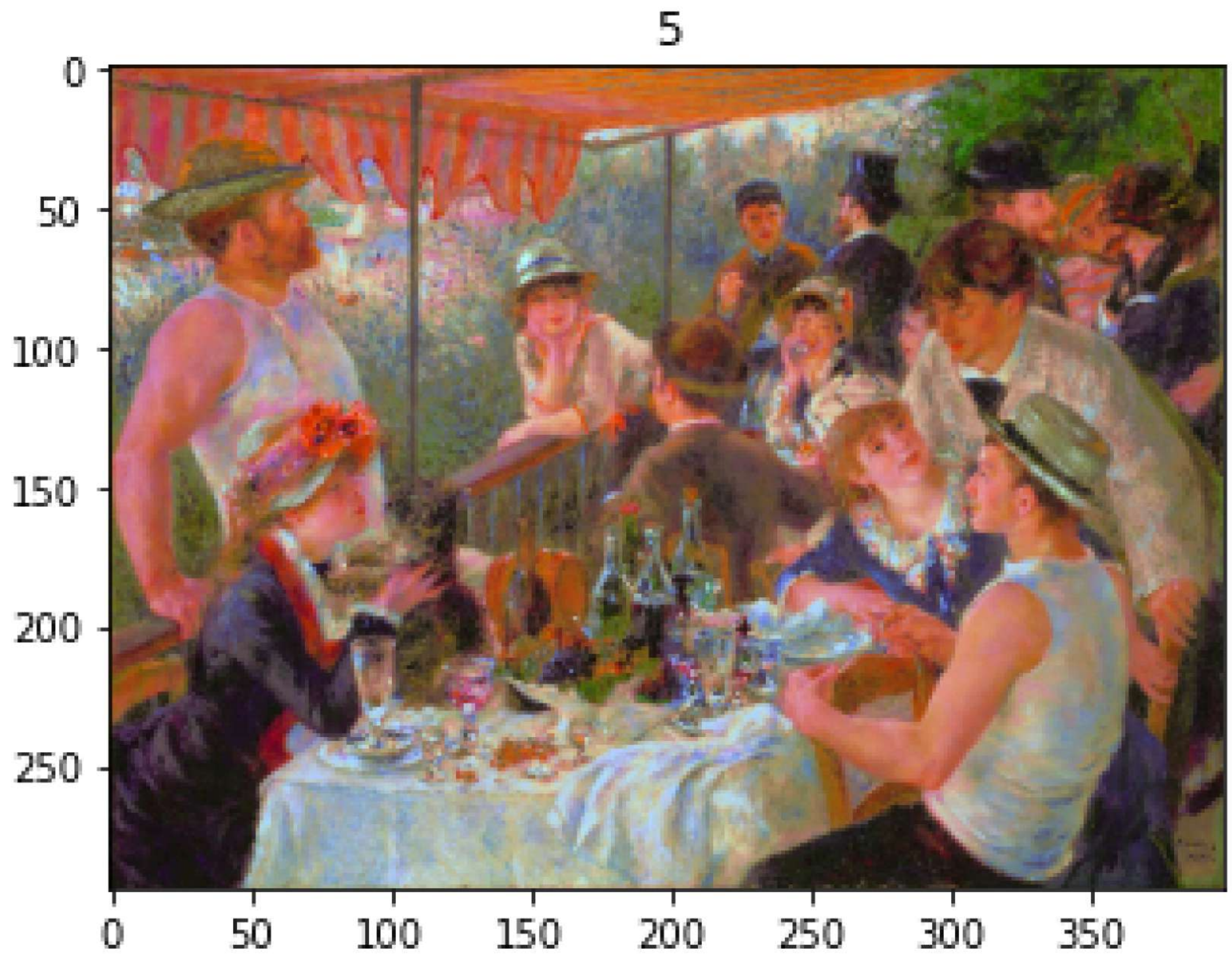




Approche GMM
4) Utilisation de sklearn







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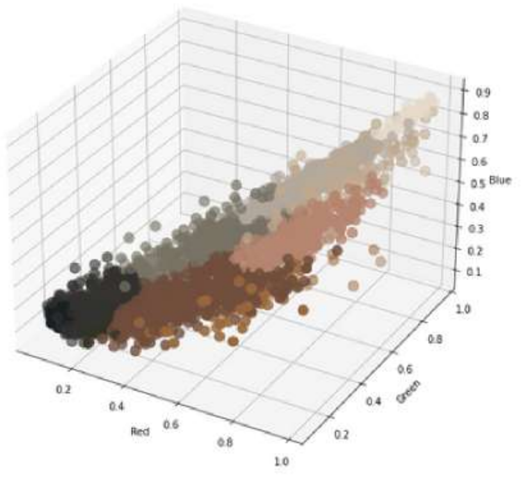

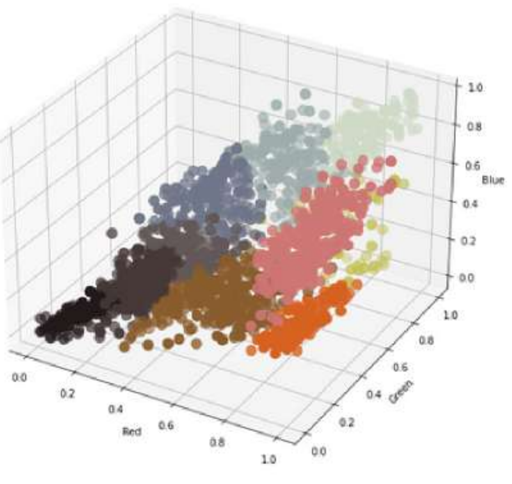

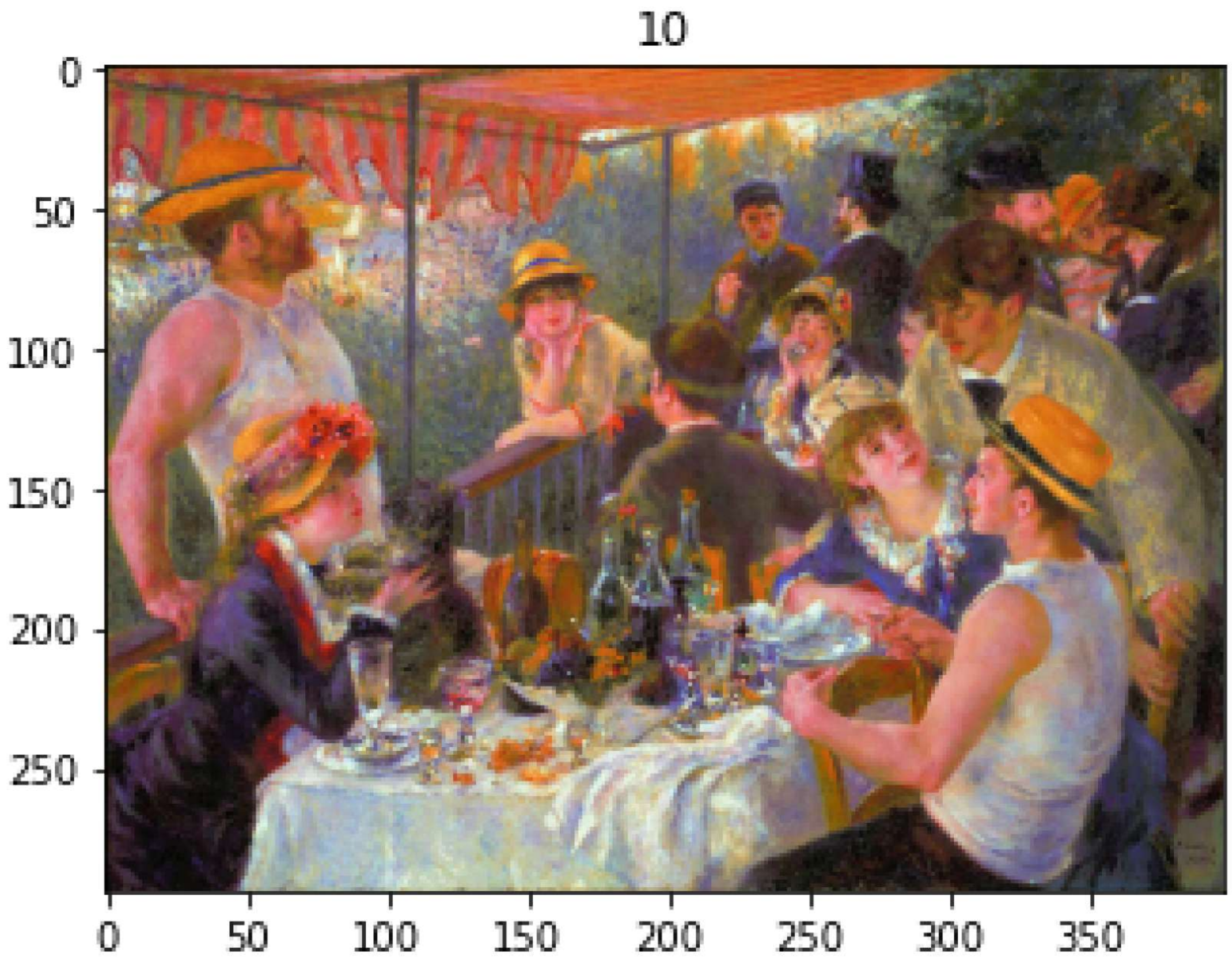

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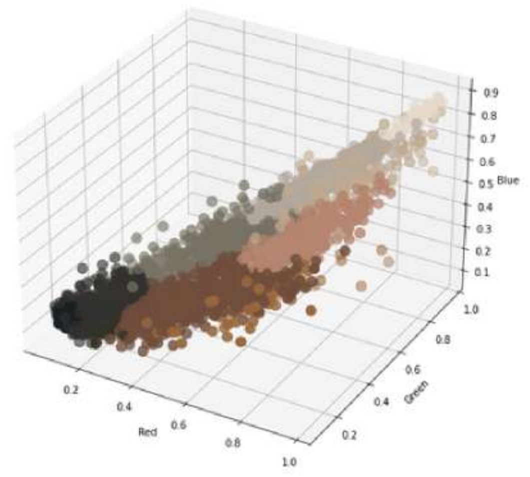

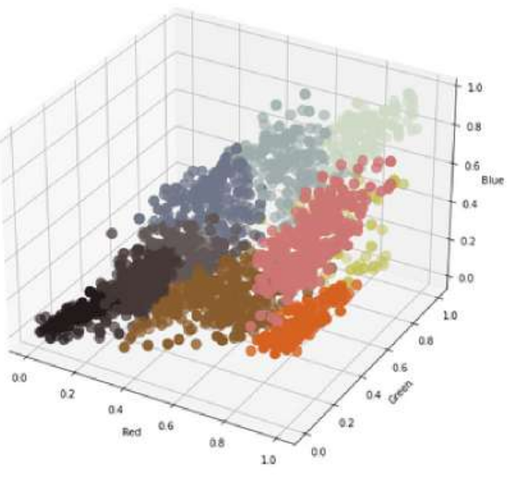

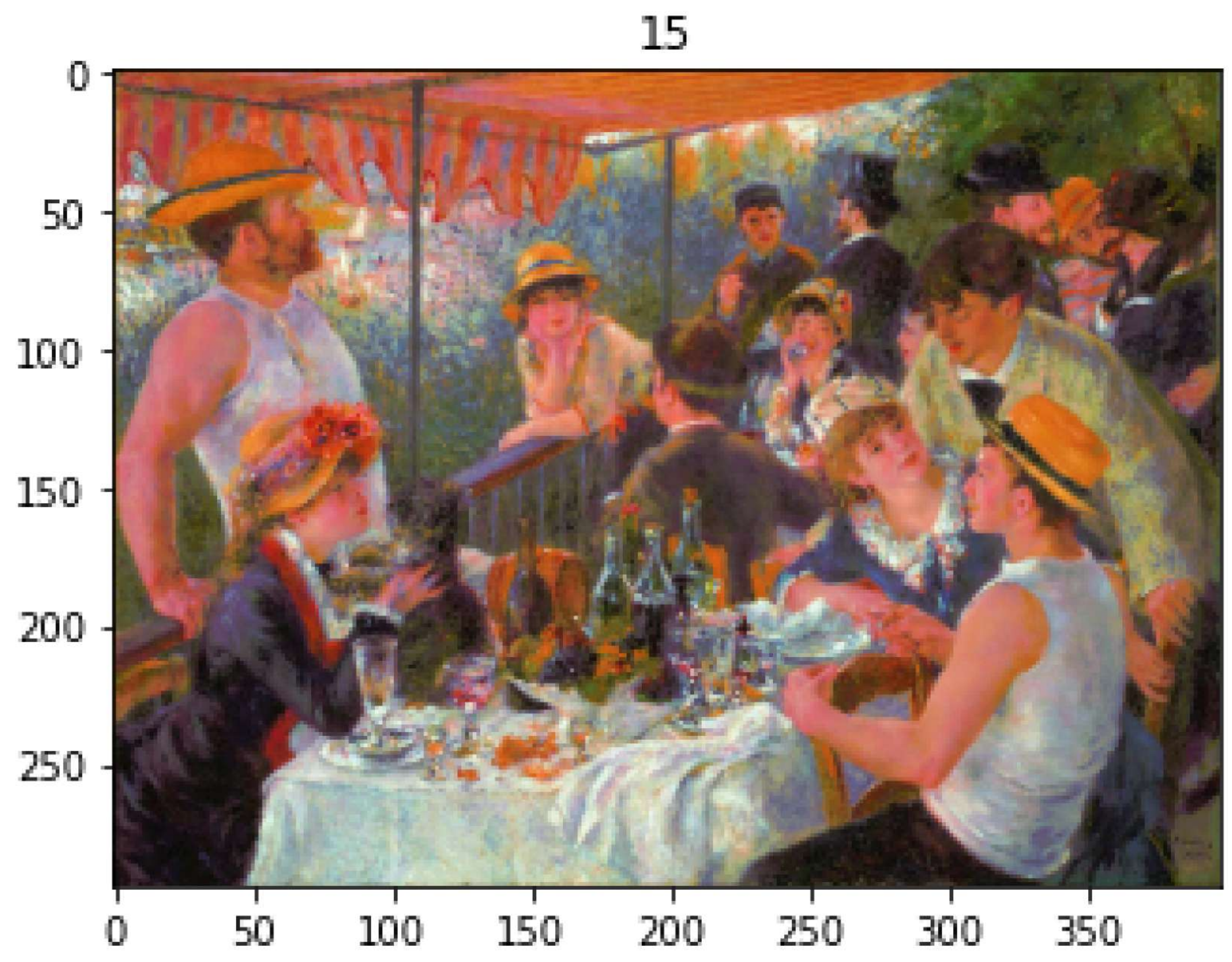

Approche GMM
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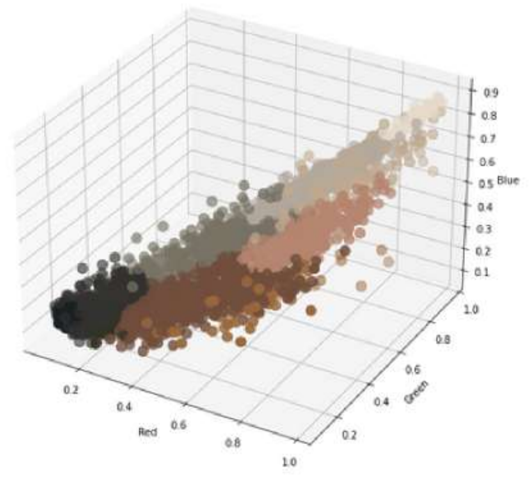

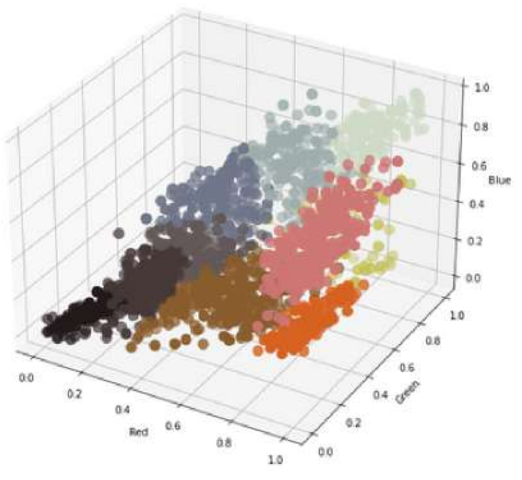

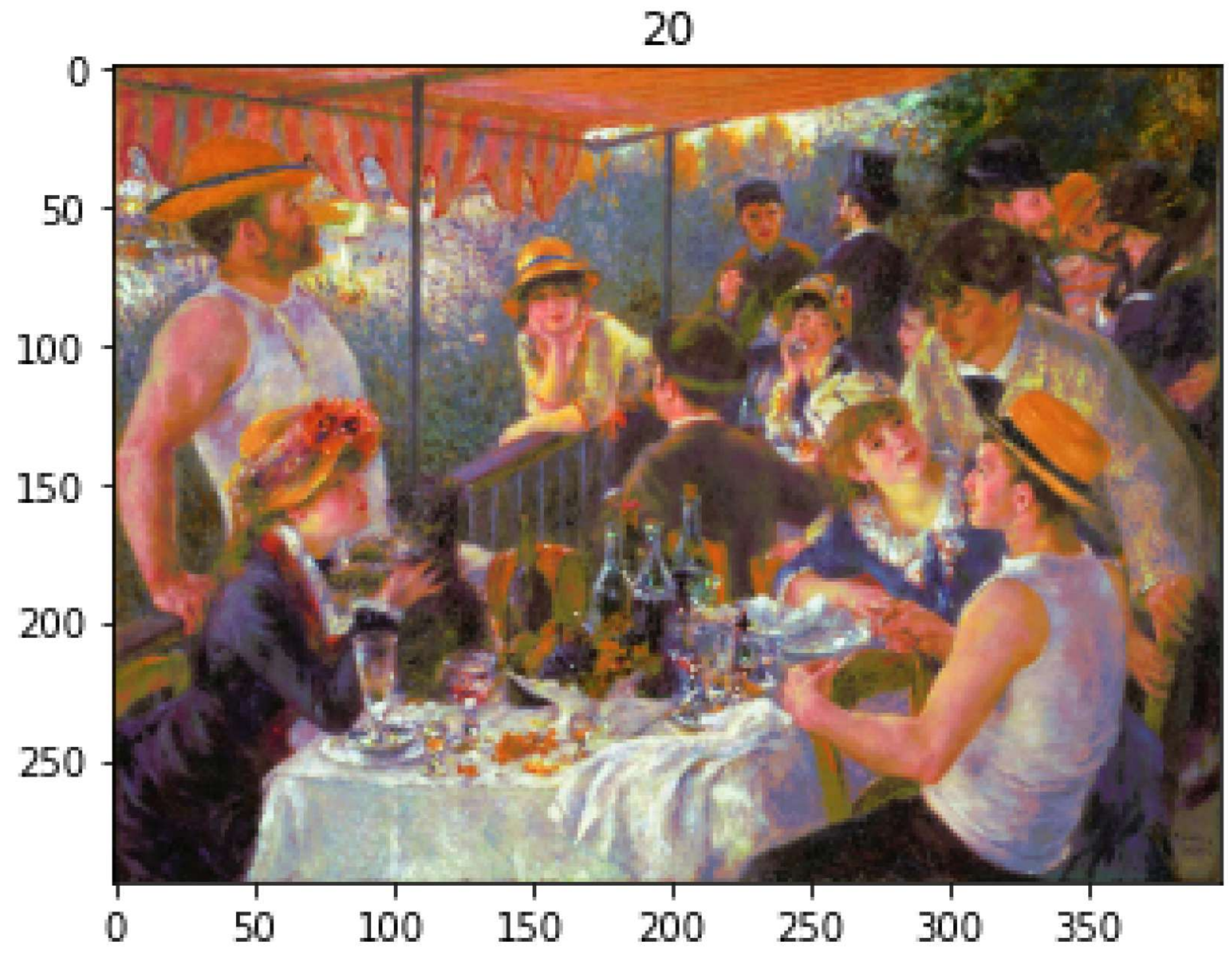

Conclusions

Merci de votre attention

RETOUR À LA VUE D'ENSEMBLE