

1.

$$k(x, x') = (x^T x')^2 = \phi(x)^T \phi(x')$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad x' = \begin{bmatrix} x'_1 \\ x'_2 \end{bmatrix}$$

$$k(x, x') = (x_1 x'_1 + x_2 x'_2)^2$$

$$= x_1^2 (x'_1)^2 + x_2^2 (x'_2)^2 + 2x_1 x_2 x'_1 x'_2 = \phi(x)^T \cdot \phi(x')$$

$$\Rightarrow \begin{bmatrix} x_1^2 & x_2^2 & \sqrt{2}x_1 x_2 \end{bmatrix} \begin{bmatrix} (x'_1)^2 & (x'_2)^2 & \sqrt{2}x'_1 x'_2 \end{bmatrix}^T$$

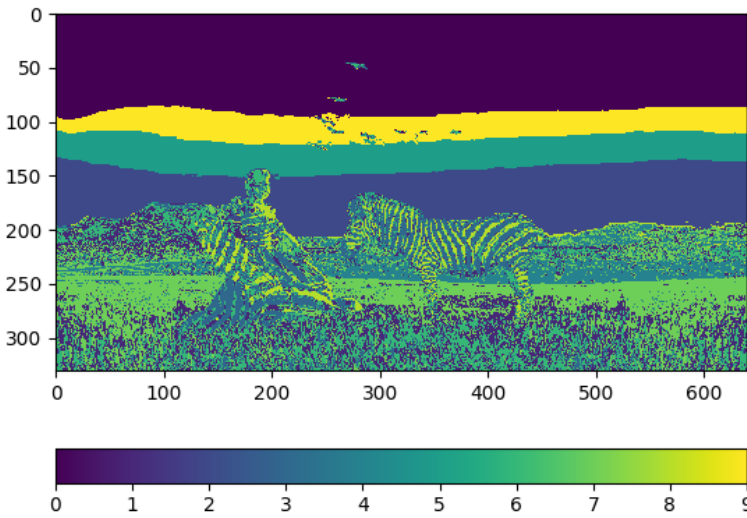
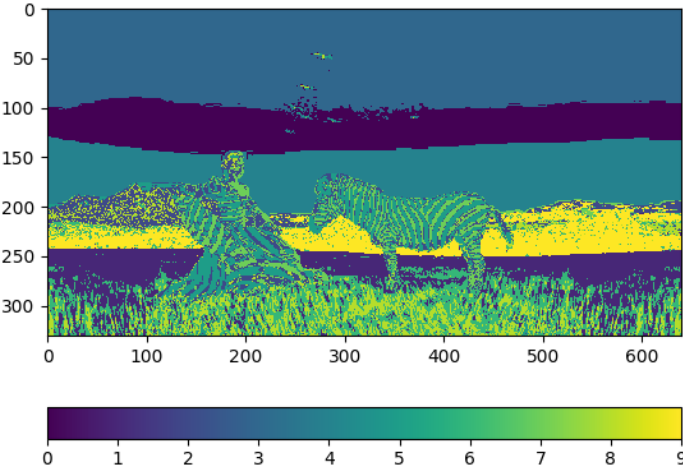
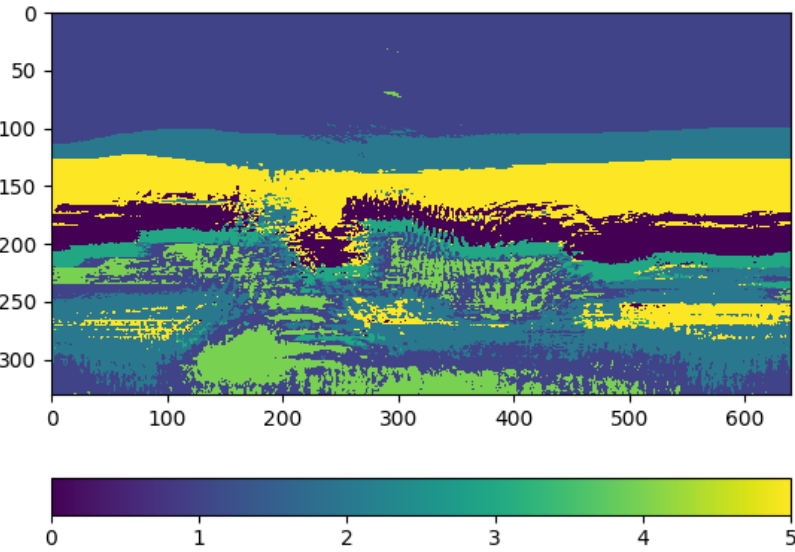
$$\Rightarrow \phi(x) = \begin{bmatrix} x_1^2 \\ x_2^2 \\ \sqrt{2}x_1 x_2 \end{bmatrix} \quad \#$$

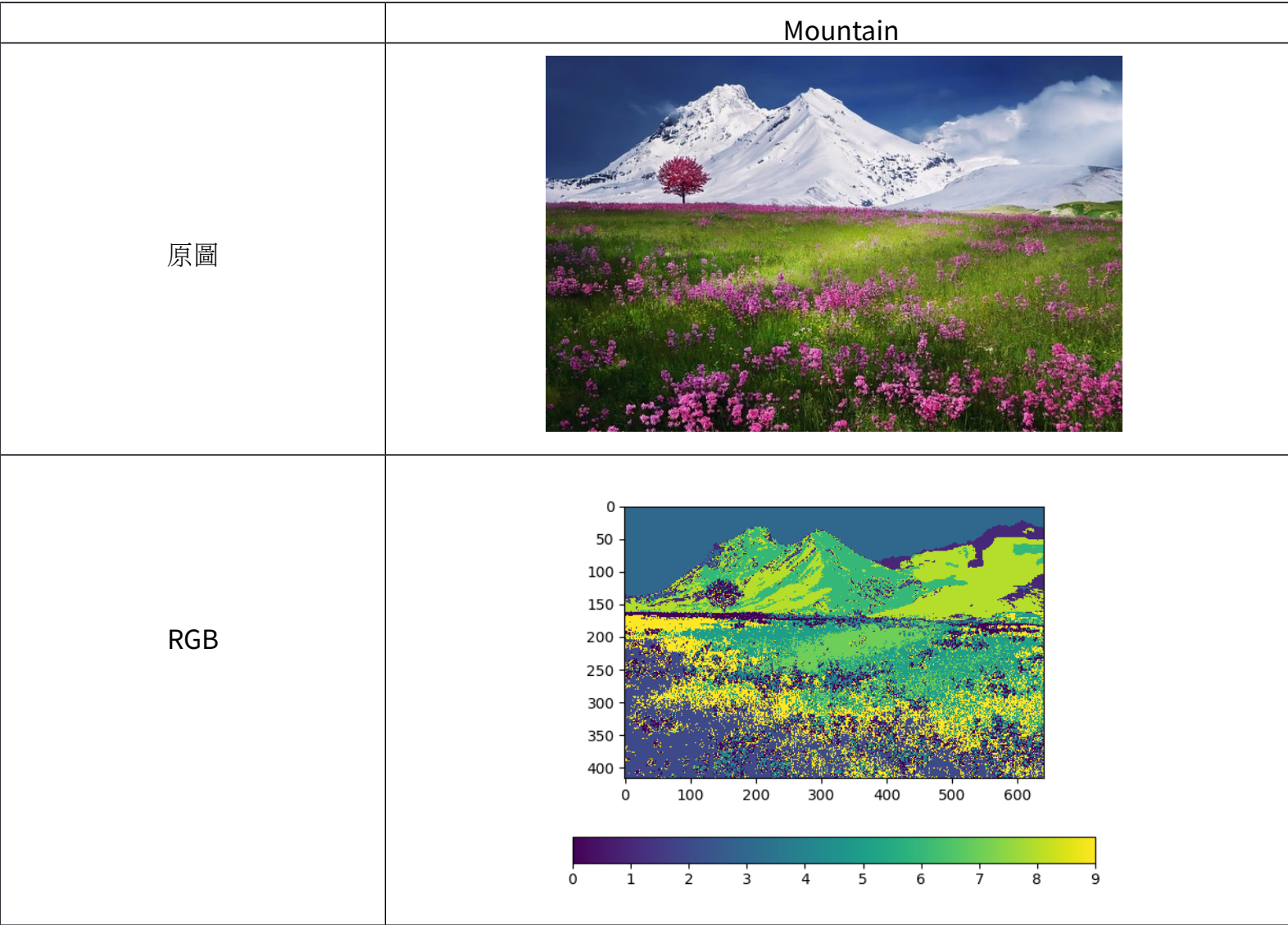
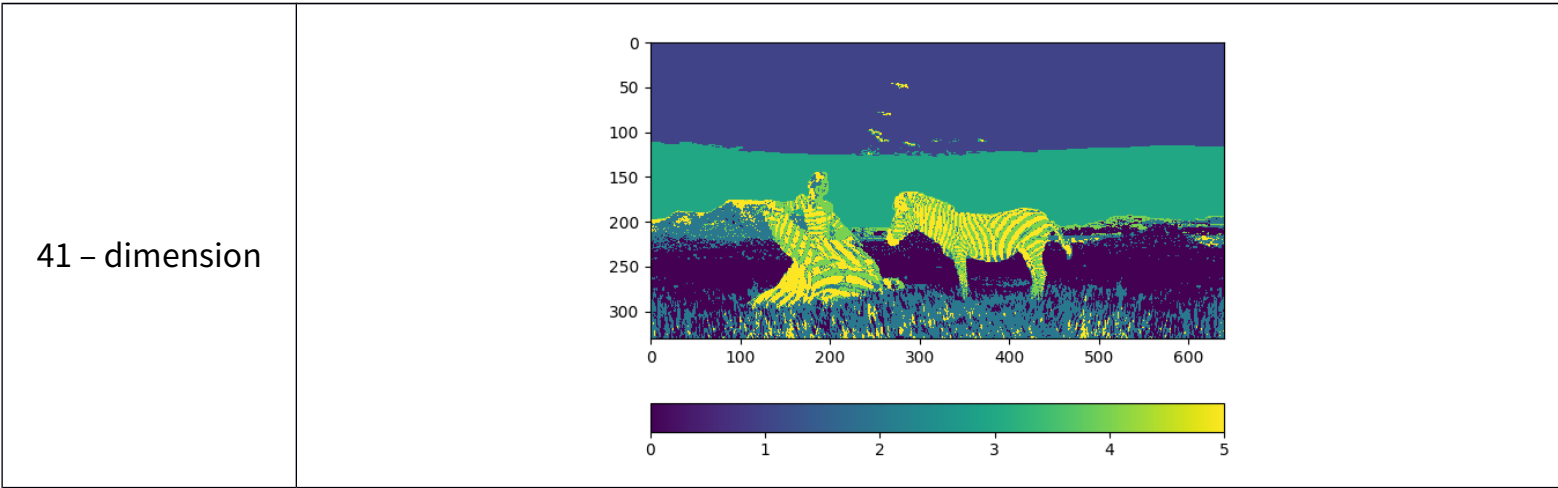
2.

Zebra

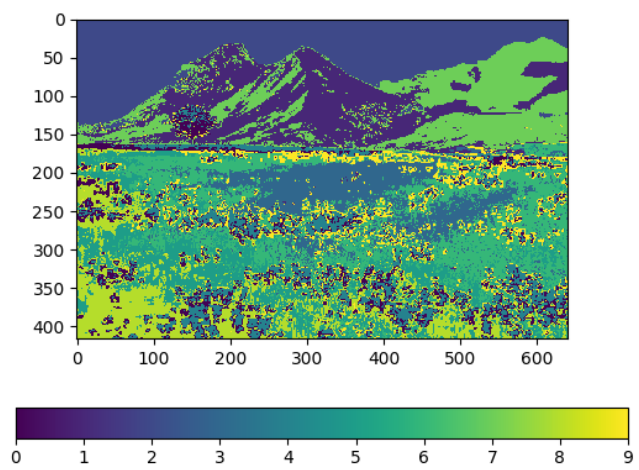
原圖



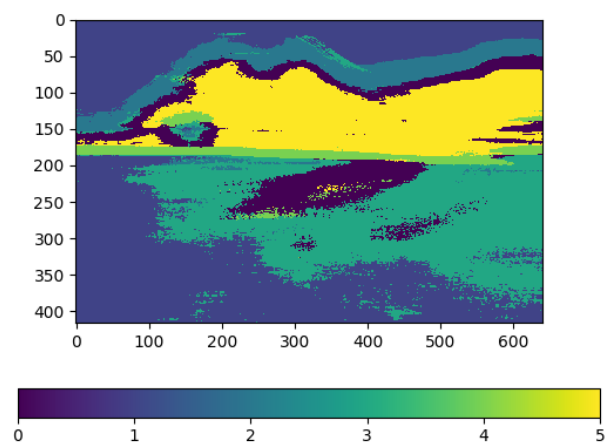
<p>RGB</p>	 <p>A heatmap visualization of the RGB color space for the 'Duke' image. The x-axis represents the horizontal dimension (0 to 600) and the y-axis represents the vertical dimension (0 to 300). The color scale ranges from 0 (dark purple) to 9 (yellow). The image shows a landscape with a zebra and a person. The sky is dark purple (0), the ground is yellow (9), and the zebra and person are in the middle range (4-6).</p>
<p>Lab</p>	 <p>A heatmap visualization of the Lab color space for the 'Duke' image. The x-axis represents the horizontal dimension (0 to 600) and the y-axis represents the vertical dimension (0 to 300). The color scale ranges from 0 (dark purple) to 9 (yellow). The image shows a landscape with a zebra and a person. The sky is dark purple (0), the ground is yellow (9), and the zebra and person are in the middle range (4-6).</p>
<p>Texture</p>	 <p>A heatmap visualization of the Texture color space for the 'Duke' image. The x-axis represents the horizontal dimension (0 to 600) and the y-axis represents the vertical dimension (0 to 300). The color scale ranges from 0 (dark purple) to 5 (yellow). The image shows a landscape with a zebra and a person. The sky is dark purple (0), the ground is yellow (5), and the zebra and person are in the middle range (2-4).</p>



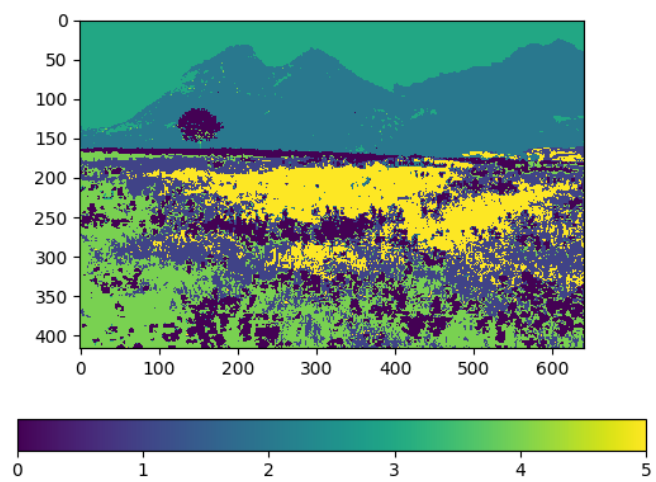
Lab



Texture



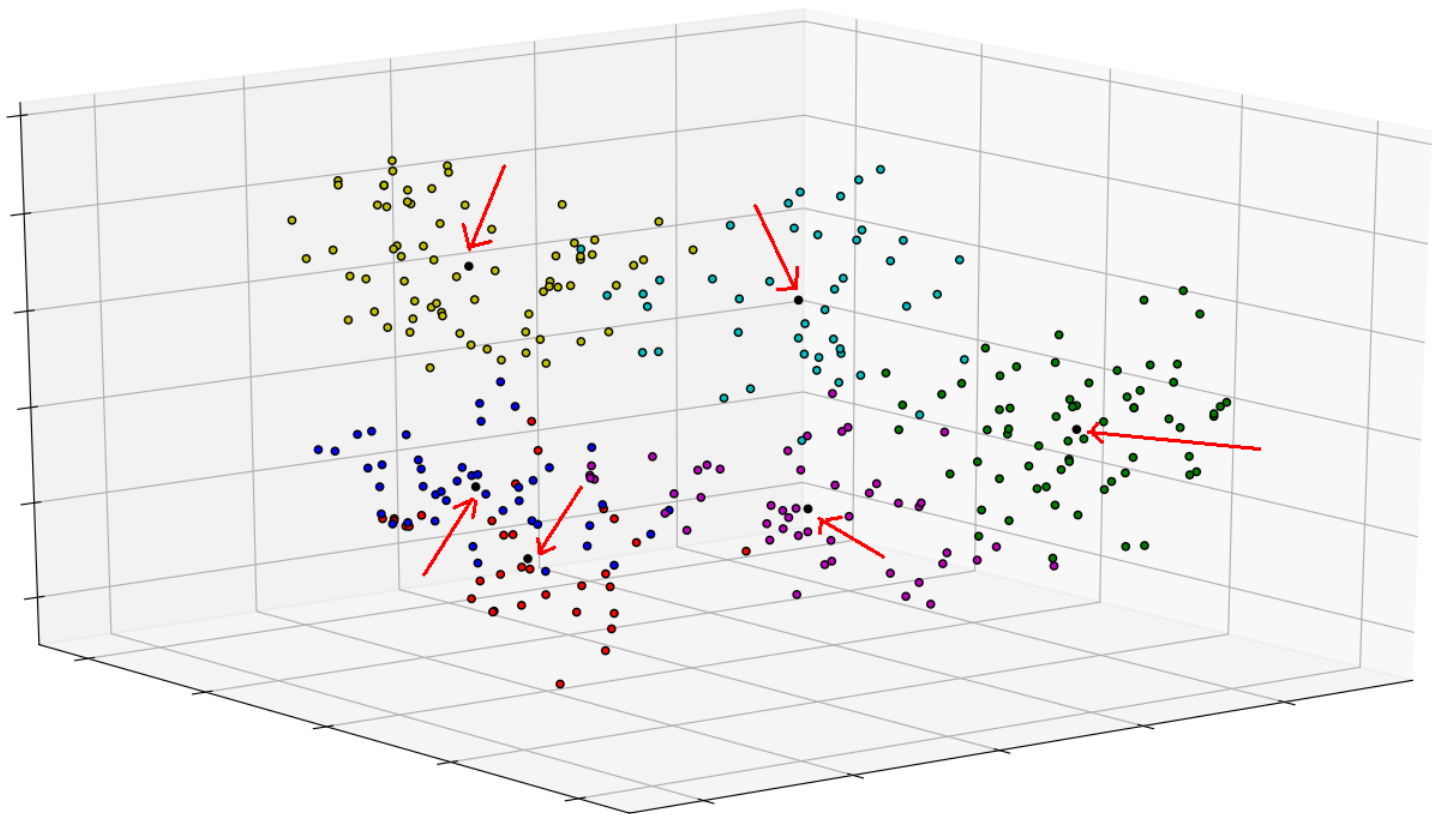
41 – dimension



3.(a)

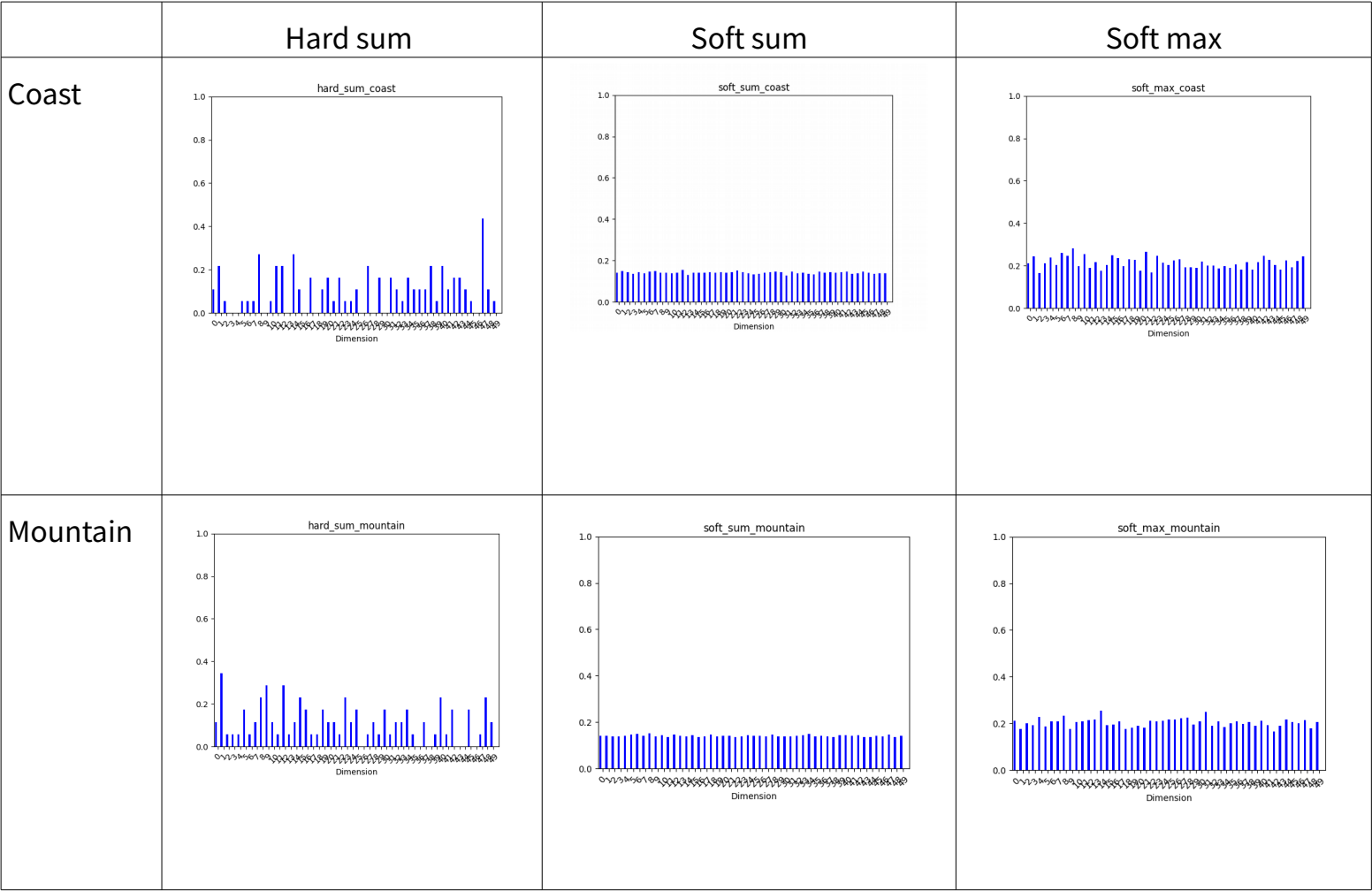


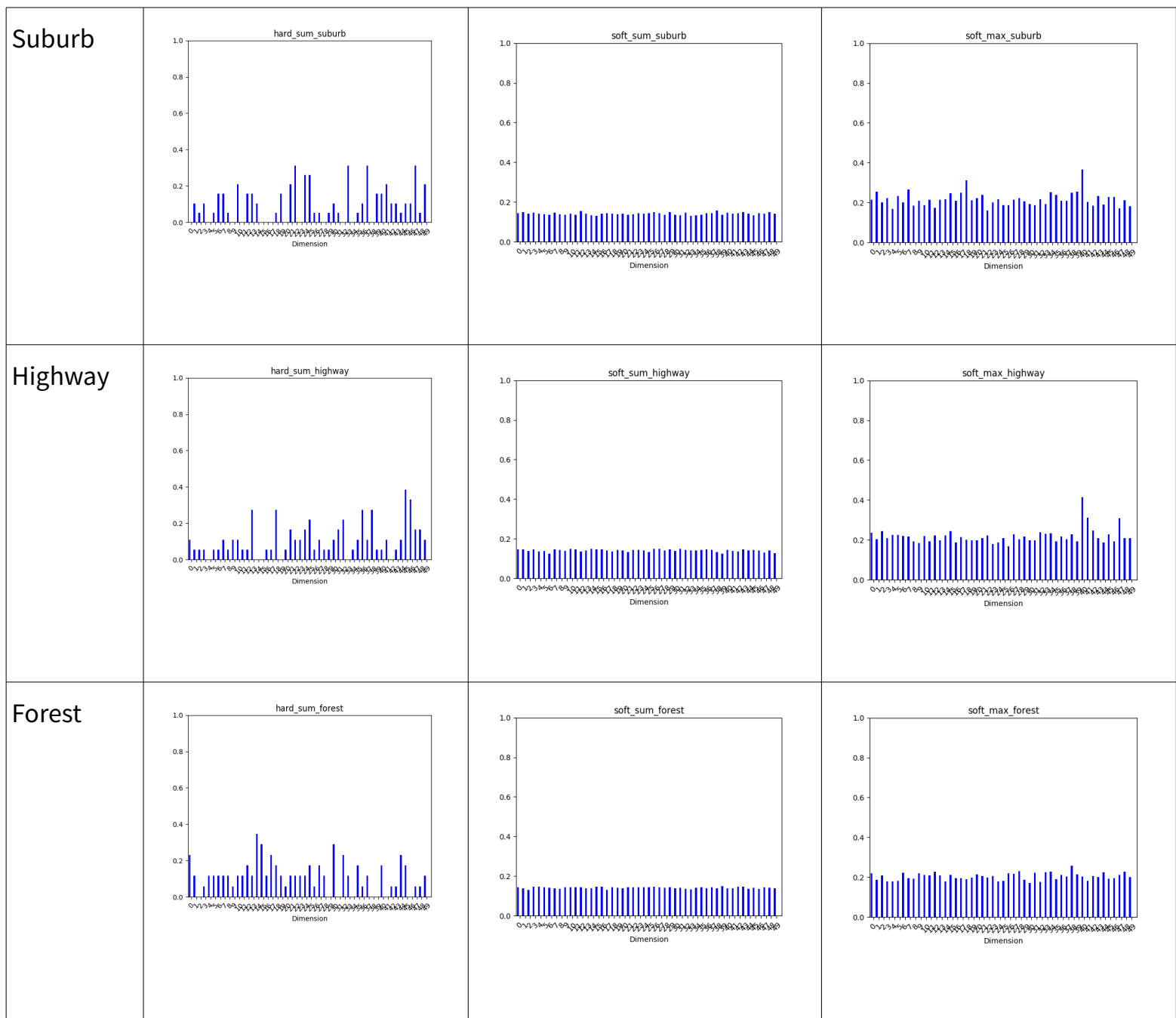
3.(b)



3.(c)

image chosen:  
image\_0048.jpg  
image\_0007.jpg  
image\_0034.jpg  
image\_0035.jpg  
image\_0012.jpg





根據上面的結果，我預估 **hard sum** 的表現會是最好的，因為 **hard sum** 明顯的凸顯出不同的 **interest point** 對於一張圖的重要性，比較適合應用在分類的問題上。

3.(d)

Train -10 Accuracy :

# of interest points	# of k-means clusters	Hard-sum	Soft-sum	Soft-max
50	50	0.414	0.458	0.472
50	100	0.414	0.452	0.432
150	50	0.566	0.532	0.466
150	100	0.534	0.538	0.488
300	50	0.596	0.56	0.53
300	100	0.616	0.572	0.532

Train -100 Accuracy :

# of interest points	# of k-means clusters	Hard-sum	Soft-sum	Soft-max
50	50	0.514	0.544	0.542
50	100	0.55	0.56	0.536
150	50	0.636	0.62	0.572
150	100	0.632	0.631	0.632
300	50	0.706	0.696	0.656
300	100	0.71	0.704	0.686

根據上面的結果，與我的預測相同的是，hard sum 在 interest point 數量相對多的條件下確實是有最好的表現(略優於 soft-sum)，但在 interest point 數量少的條件下，soft-sum 的表現擇優於 hard-sum，我推測是因為當 interest point 少的時候，如果還去刻意區分 interest point 的重要性給予不同的權重，可能會捨棄掉一些重要的資訊導致準確率下降，而 soft-sum 則藉由保留這些資訊獲得優勢。

另外，soft-max 的表現跟其他兩種 Bow 的方式有些落差，但在 training data 數量大的情況下，差距變小，推測只要將 training data 數量繼續增加，根據 soft-max 區分不同 interest point 重要性的能力，準確率應該能有所提升。