HEIG-VD

Report

MLG PW3: Unsupervised Learning

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Introduction

In this practical work, we were asked to train self organizing maps on classes found in the image dataset used by Wang et al. [1]

Feature Extraction Methods

In order to train our models, we extracted features from the images in three different ways:

1. **Greyscale** : similar to the lightness in the HSL color format
2. **Hue** : same as in the HSV or HSL color formats
3. **Color** : similar to the saturation in HSL or HSV color formats but taken from raw RGB values

For each image, we go over the color data for each pixel and we create a histogram from the read values. For instance, in the color method, we normally would have 256 bins in our histogram for each color which would result in a final concatenated histogram with 768 bins. This is too many features and the model would not benefit from having pixels expressed this way. To prevent this, we create a limited number of bins (10 in this case) and sort the values in those. This results in 10 features for the greyscale and hue methods, and 30 for the color method (10 for red, 10 for green and 10 for blue).

```
# Example output of the greyscale method
[4.2663e+04 1.3327e+04 3.2570e+03 2.4320e+03 6.5200e+03 1.2925e+04
 1.4220e+04 2.9590e+03 1.0000e+00 0.0000e+00]

# Example output of the hue method
[32226. 34697. 20371.  1412.  1804.   249.  2878.  1105.   114.  3448.]

# Example output of the color method
[4.3896e+04 1.2489e+04 1.8130e+03 3.4200e+02 5.9500e+02 1.4680e+03
 3.4120e+03 5.6200e+03 1.9828e+04 8.8410e+03 4.1680e+04 1.3193e+04
 5.2560e+03 3.3420e+03 9.0180e+03 1.1669e+04 1.1187e+04 2.9590e+03
 0.0000e+00 0.0000e+00 8.5458e+04 1.1198e+04 1.1150e+03 4.0800e+02
 1.1500e+02 1.0000e+01 0.0000e+00 0.0000e+00 0.0000e+00 0.0000e+00]
```

This histogram will serve as the features to train the model with.

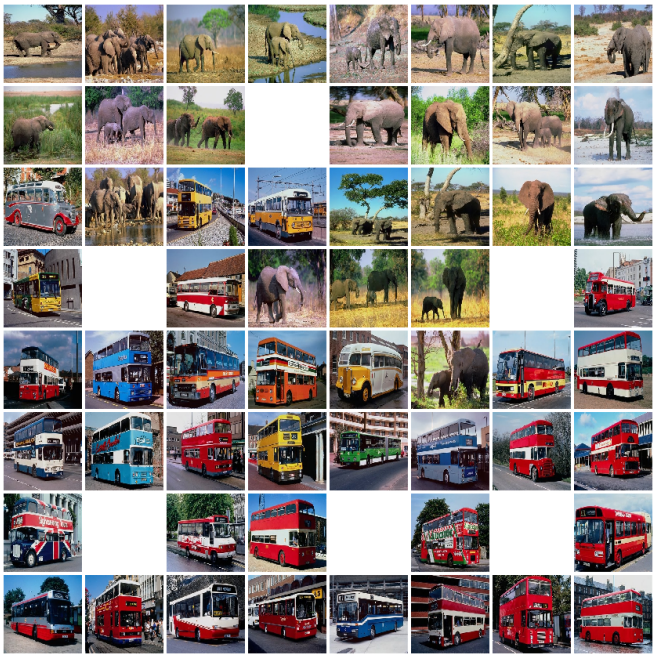
Parameters

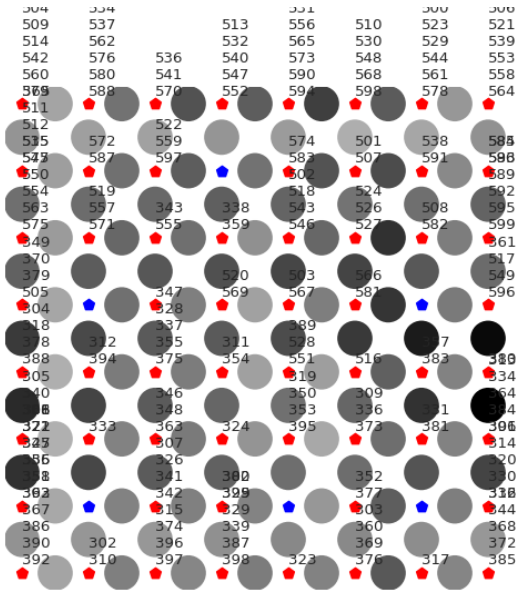
To complete all our experiences, we mostly used the same parameters all the time. We tried small variations on the learning rate, but that did not change our results. When we changed the number of iterations, we could see that there were slight differences between 5 iterations and 100. But over 100, the results were the same almost every time. Therefore we decided to go with 5 iterations to spare computing power due to our hardware's fatigue.

Experiments

Buses and Elephants

Greyscale

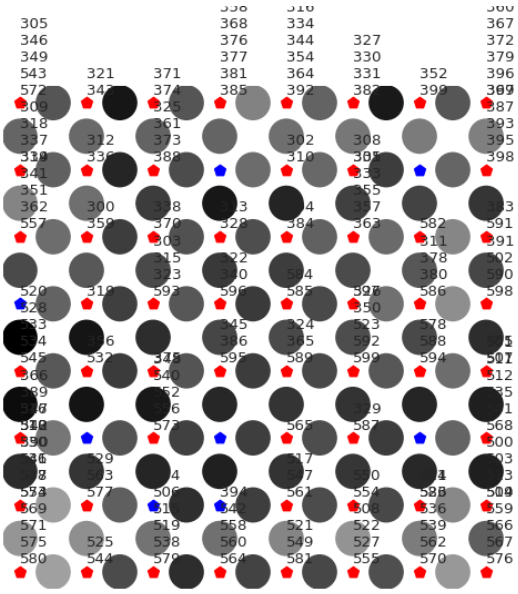




When we look at the picture map, we can guess a separation between the buses and the elephants. As most of the pictures of the elephants are made of green, yellow, light blue and light grey they tend to have smaller values in greyscale. The buses's pictures are mostly made of darker colors (mostly red) and their backgrounds tend to be darker too. We can see that some yellow buses with lighter backgrounds are placed near the elephants.

When we look at the U-matrix, it is hard to see any obvious boundary between the two classes, as most of the nodes representing the distances between neurons are a darker shade of grey.

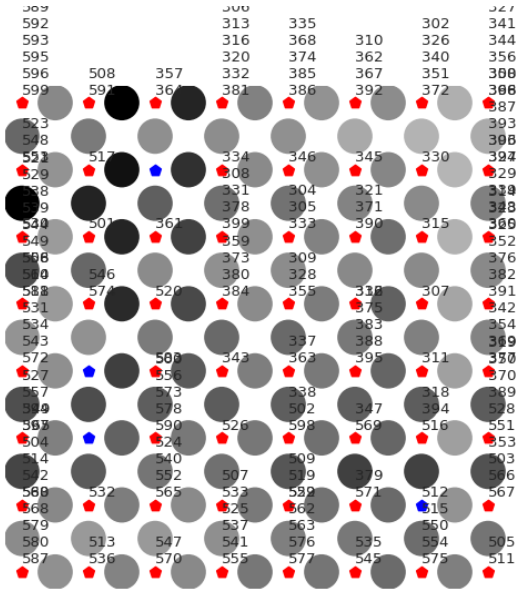
Hue



The U-matrix is quite dark. By looking at it, we almost can't discern any clear boundary. The only places where the pictures seems to be close is near the bottom left, bottom right and around the middle of the top side.

When we look at the picture map, we can see that the middle of the top side is composed of mostly red buses. We can also see that the reds tend to be grouped together, just as the pictures with more greenish colors. This is expected due to the map being created on features extracted from the hue of the pixels.

Color



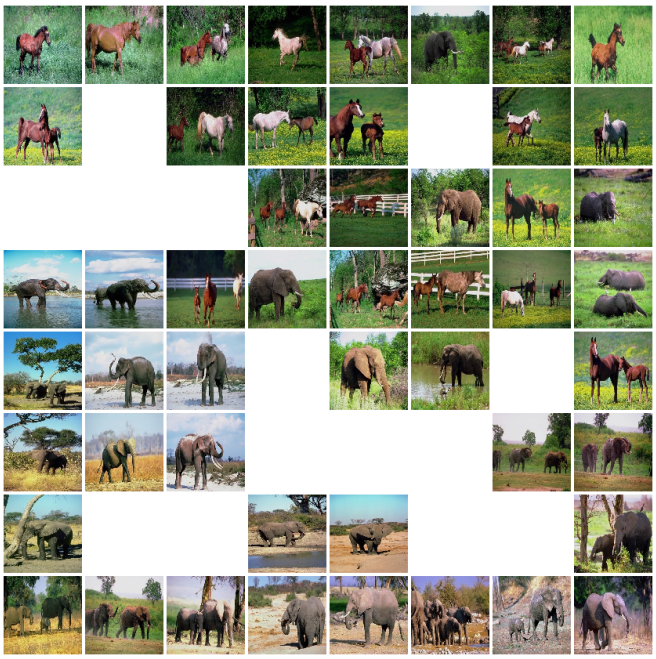
When we compare the map from the color features, we can see that the buses are mostly well packed together. There is one exception at the bottom right where the bus seems to have missed the stop. Checking the labels on the U-matrix showed that this bus picture was the sole outlier nearest this neuron, as the rest was other elephant pictures.

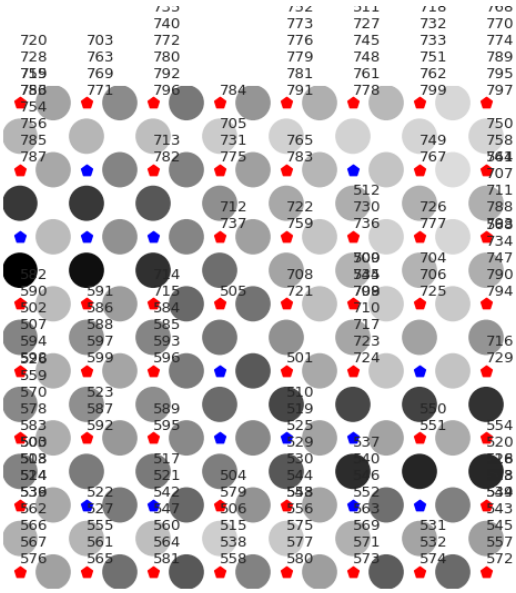
We can also observe that the pictures are well grouped in terms of color: The reds are together, the blues and greens too and the yellows almost. There is however a yellow-orange-red bus (around the bottom right), that seems very close to its green neighbor in the U-matrix.

Taking a look at the U-matrix, we can see that there is some kind on boundary going from the top-left to the bottom left in an arc. Another boundary that is less obvious seems to separate the buses and elephants pretty well by going from the same top-left spot to the bottom-right.

Horses and Elephants

Hue





Here, we can see a clear separation between the top and the bottom. In the top side, we have mostly green pictures, whereas in the bottom side, we tend to have more yellow and blue pictures, typical colors of the savannah.

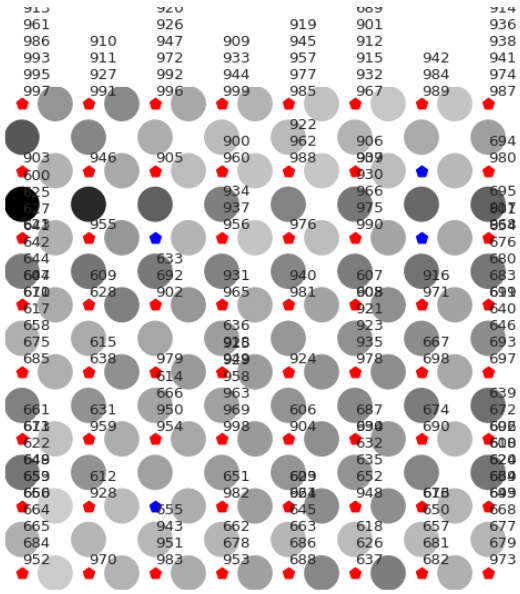
With this separation we can see that the horses are mostly located in the top side. Nevertheless there are pictures of elephants on green backgrounds mixed within them. This makes sense as the elephants do not take the majority of the space in the picture and thus the green background influences the histogram strongly, thanks to it being based on the hue of the pixels.

If we look at the U-matrix, we can also clearly see the separation between the pictures in terms of hue (from the left to the right, slightly top to bottom).

It is also interesting to note that, for some reason, this picture map has a lot of holes where no image was deemed close enough to end up in the visualization.

Flowers and Food

Greyscale



With the greyscale features, we can see that most of the food is on the upper top and the flowers from the middle to the bottom. This separation is mostly due because the flowers tend to have a darker background, whereas the food tends to be served on white plates. We can also see that there are some darker pictures of food, therefore, they are placed between the pictures of the flowers as we can expect from the previous experiments.

In the U-matrix, we can see a separation between the upper top and the bottom. This separation however is not expressed strongly towards the middle of the map.

Conclusion

From these short three experiments, we can deduce that self organizing maps can be used as a visualization method for clustering data depending on whether the input features allows the model to separate the dataset in a meaningful way, but rather as a tool for dimensionality reduction. This is especially interesting as self organizing maps are not usually used that way. Research on whether this result can be expected taught us that small SOMs tend to make some small number of nodes behave in way that is similar to k-means.

References

[1] J. Z. Wang, Jia Li, and G. Wiederhold. "SIMPLIcity: semantics-sensitive integrated matching for picture libraries". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 23.9 (Sept. 2001), pp. 947–963. ISSN: 0162-8828. DOI: 10.1109/34.955109.