

Kohonen Map Project Report

Unsupervised and Reinforcement Learning in Neural Networks

Han JU, Hao Ren

18 novembre 2012

1 Learning rate and convergence

In this part, we start with a Kohonen network of 6x6 neurons and use a Gaussian neighborhood function with standard deviation $\sigma = 3$.

We have tried several learning rate, the observations are show as below :

- 1) eta = 0.01 : nombre of iteration = 4
- 2) eta = 0.001 : nombre of iteration = 24
- 3) eta = 0.0001 : nombre of iteration = 48

The result is exactly the same to our intuition, small learning rates cause the algorithm to converge slower, while the larger ones cause the algorithm to converge faster. However, we can not tell which one is better. As we know, the final solution of the small learning rate will be more stationary, but it might be stuck in local minima, while the large one might make the weights fail to converge.

//figure

For the three learning rate, the resulting figures have no big differences, just as the one show above. What is important is that the three learning rates all leads to the convergence of the algorithm. So we can conclude that the bigger learning rate has no side-effect in this project. In addition, according to our observation, the smaller learning rate doesn't improve our result. That means the quality of the result depends on other parameters which will be discussed in the later section. As a result, we choose eta = 0.01

In the origin matlab code downloaded from the Moodle, we see a simple convergence which just iterate the algorithm as many times as the number of the data points. In most of the case, it is not a good convergence, as some noticeable changes are observed. In order to improve this, we have defined a new convergence condition which is descibed as following :

$$\frac{\|centers_{n+1} - centers_n\|}{\|centers_n\|} < 0.01 \quad (1)$$

where 0.01 is a converge criterion which can be chosen as needed and each row of the matrix centers is one of the prototypes.

Every iteration uses all the data points to calculate the centers. After each iteration, the convergence condition will be tested which will decide whether the algorithm will go on or not. If there is no obvious changes between the centers of two successive iterations, we can conclude that the algorithm is converged. Mathmatically, the norm of the difference of the two centers matrix is sufficient small (relative to the norm of the previous one).

2 Visualization and prototypes

// figure

3 Assignment method

In this step, we need a method to automatically assign the propre digit to each prototype that we found by executing the Kohonen map algorithm. An obvious idea is to look at the labels of the training data points that are close to the prototype, then decide the its label accroding to the majority in this surrounding. In fact, this task has a similarity with the k nearest neighbor classification algorithm, which assigns a label to a data sample based on the majority of its k neighbors. So we decided to use the kNN method.

Before we apply this method directly to the problem, however, we need to determine the parameter, k , of this algorithm. Intuitively, this parameter depends on our training data, which covers the hand writing samples of the four chosen digits. So we do firstly a cross validation on kNN models with distinct k values (ranging from 3 to 300), which results in k equals 5.

Once the parameter is fixed, the application of kNN to the problem is fairly straightforward.

As a result, we have a matrix which assign a digit to the corresponding figure of the resulting figure matrix, as following :

//matrix + //figure

4 σ and map size

In this section we will dicuss the role of the width of the neighborhood function and the size of the Kohomen map.

With different σ and size of map, we will get different resulting matrix. In order to descirbe the qualty of the result, we have found a way to define the error rate :

1) For each data point, we find the prototype which is closest to the data point, and assign the digit of the prototype to the data point

2) compare the digits of the data points to the labels, if the digit is not the same, we count this as an error.

3) finally, we get the error rate : $\frac{\#error}{\#dataPoints}$

We have tried $\sigma = 1, 3, 5$ and $sizeK = 6, 7, 8$, the result is showed as table-1 :

	$\sigma = 1$	$\sigma = 3$	$\sigma = 5$
$sizeK = 6$	0.2060	0.4455	0.7125
$sizeK = 7$	0.2295	0.3130	0.5295
$sizeK = 8$	0.1785	0.3005	0.4900

TABLE 1 – error rate with different σ and $sizeK$

As a result, the optimal width does not depend on the size of the Kohomen map. For each size of the map, the smaller sigma is , the bette quality the result has. That means the optimal sigma is always the smaller one, no matter how the size of the map changes. With the augment of the size of the Kohonen map, the quaity is improved. An intuitive interpretation of

this is that each prototype covers fewer and fewer data points, which makes the prototypes become more and more accurate during the convergence.

In fact, the sigma controls the strength and range of the neighborhood effect of the points of the map. With a small sigma, the algorithm is essentially the competitive learning algorithm, with possible dead units, because the initialization might not be good enough. With big sigmas, all prototypes learn the same thing, i.e. the center of the points.

A proper size of the Kohonen map helps to prevent overfitting. Especially, in the unsupervised learning, it is better to fitting the data with a more or less regular grid that captures the essence of the underlying distribution than using a naive clustering algorithm with so many free parameters.

5 Conclusion