***** (About output of a classifier): the referee is correct. In any classification approach there is an output. However, in SOM approach, we can make a space using a training set such as K96 and then monitor the extreme outliers in this space.**

***** (about validations and the accuracy): The accuracy of the outputs can be obtained by using different validation sets. For example, if we use an E-type galaxy from CWW models (see T12) as input, the output will be very close to E-type's position on the map. This is the case with irregular galaxies which will be very close to SB1 on the map. Also, we can see a continuous behavior of starburst galaxies from SB1 to SB6 indicating that networks can distinguish the effect of the dust. Another example is this that if we use only three SB galaxies (say SB1, SB3 and SB5) and train a network in a 1-D map, a SB2 galaxy as validation set will be between SB1 and SB3. These kinds of validations can show that a network is a well-trained one or not. A quantitative accuracy can be obtained, for example, if we provide a set of different models of E-type galaxies, as a validation set, and calculate how many of them will on on E-type galaxies on the map with a defined neighbor (e.g., immediate neighbors).**

***** (about using three different networks 1-D and 2-D): In T12 we show different effects of spectral futures such as the effect of masking the emission lines of spectra in the training steps. It was shown that these details can be recognized by networks. We show that details can be also recognized when we use different SOM maps with different dimensions:**

In T12 we have shown that when we mask emission lines (i.e., when we do not consider more details in the spectra) two types of galaxies, Sb and SB6 have potential to be confused. However, this confusion can be removed if we consider more details. In figure 4 we can see that SB6 is set near Sb galaxies. This is because we use a 1-D SOM map which is a good method to obtain a big picture of the problem under study (i.e., we do not consider the small details). This can be also seen in the right panels of Figure 10. These kinds of maps are good if we want to find outliers without going in more details. Here, again, a big picture is considered to remove the outliers. In the next step and in the left panels of the figure 10, we give more space to the 12 models to more interactions and finding more details. We can see that in the left map SB6 and Sb are not close to each other anymore and this shows that more details of spectra are considered by networks. This is why we use a 2-D map.

***** (about the Kmean method and SOMs; the reference can be Kohonen's books): both Kmean and SOMs are unsupervised methods, however, SOM can be used to classify a new data based on the space created by the training set. In SOM approach a neighborhood function has an important role in the operation of the SOM. When the radius of the function goes to zero, the algorithm will lose its ordering power and will be reduced to the k-means algorithm. In fact, SOM is a combination of Kmean and considering the effect of the neighbors which can be 'controlled' by the neighborhood functions (i.e., smoothing process). In this way, and using a network, SOM maps can find more details. Although a 1_D SOM map can provide a big picture of clustering problems, however, because of smoothing processes even this 1_D map can have a better performance than Kmean.**