Quantum clustering methods based in tunable external potentials or configurable phase singularities

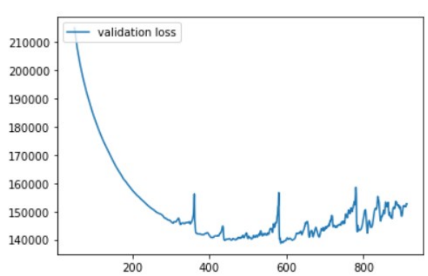
Robin Mendoza[1], *Miguel A. Garcia*,[2] *Alba Baeza*,[3] *Jesus Rubayo*,[1]*Jose A Conejero*,[3]

[1] Higher Institute of Technology and Applied Sciences, Havana, Cuba; ,[2]University Institute of Pure and Applied Mathematics Polytechnic University of Valencia, Spain, [3]University of Valencia, Spain

robin.mendoza@instec.cu

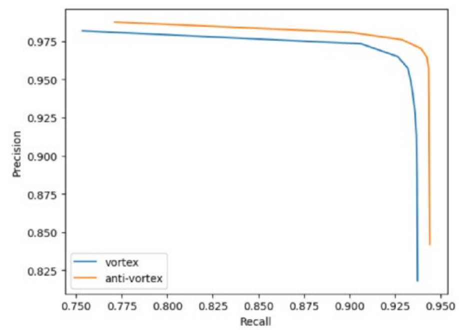
Singularities detection is necessary in many fields where singularities play an important role, in particularoptical fields will be studied which have configurable multi-singular initial conditions that propagate through the Schrödinger equation. Two detectors based in convolutional neural networks are studied to detect vortices in multi-singular fields; one that detects considering the phase gradient of the field, and another one that takes the interference of the field with a plane wave, forming forks patterns. We analyse the accuracy of the models, as well as their resolution and performance with noisy data. In addition, we describe a way of encoding information in the vortices of multi-singular fields which may be applicable to evolve the field and create a quantum clustering method. A second application could be to create a method of reservoir computing and we discuss it in the last section, where we show the chaotic dynamics of fields with many singularities and different topological charges. Although all the above approaches are made for photonic systems, we justify that due to the analogy between optics and quantum, they are reinterpretable and can be applied to quantumsystems

.A confidence of 70% is chosen to divide the data for training, i.e. 1400 images are randomly assigned to training and 600 to validation. In addition, we use a batch size of 100 and a learning rate of 0.001 in the ADAM optimiser. The loss function is the above-mentioned with w 1 = w 2 = w 3 = 10. With all this, the model is initialised with random weights and trained 900 epochs giving the validation loss function plotted It is easy to see that the model is suffering overfitting, so the validation error starts to grow. This happens when the model becomes so specialised in training data that it starts to generalise poorly on unseen data, therefore to avoid this problem we decide to stay with the trained model in 500 epochs.



Validation loss in 900 training epochs for the Small model and the Phase Gradient dataset.

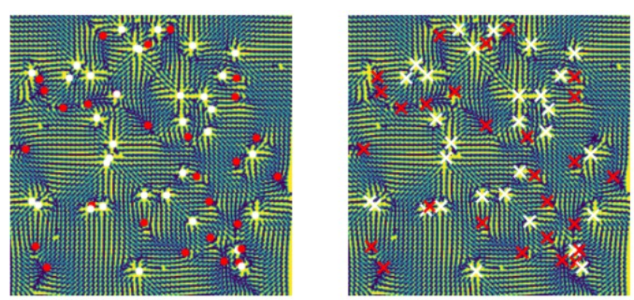
Let us note that the precision measures how many of our predictions are correct, while recall measures how many real objects have been predicted, for a certain object class. A good model needs to have a good precision-recall relation as this will ensure that it makes accurate predictions and does not miss real objects. You can see the precision-recall plot for our model.



Precision-recall curve for the model trained 500 epochs in Phase Gradient dataset.

Notice that the model learned to detect the anti-vortices a little better than the vortices as its curve is above.

Translating these local measures to the entire dataset, the average precision (AP) is defined as the mean of precisions for all dataset images in a certain class, and the mean average precision (mAP) as the mean of Aps for all classes. The AP of our final model for the vortex class is 93.10, while for the anti-vortex class it is 94.75, resulting in an mAP value of 93.92. The accuracy obtained is a



more than acceptable value and an important fact is that it was done in a fast training time of 41 minutes. An example of a visualisation of the predictions made by the model is:

Example of the trained Small model detection. On the left the image with the dots indicating the actual singularities and on the right the predictions indicated by crosses. The red colour indicates a vortex and the white colour indicates an anti-vortex.