

EFFECT OF NUMBER OF BASES (k) ON PERFORMANCE :

With different variance for each cluster : large values of K the RBF net tends to perform bad. While small values of K (2 and 4) gives good performance. With varying gaussian width RBF net with number of bases = 2 gives good performance for random initial weights. i.e a good approximation for $k = 2$ as shown below.

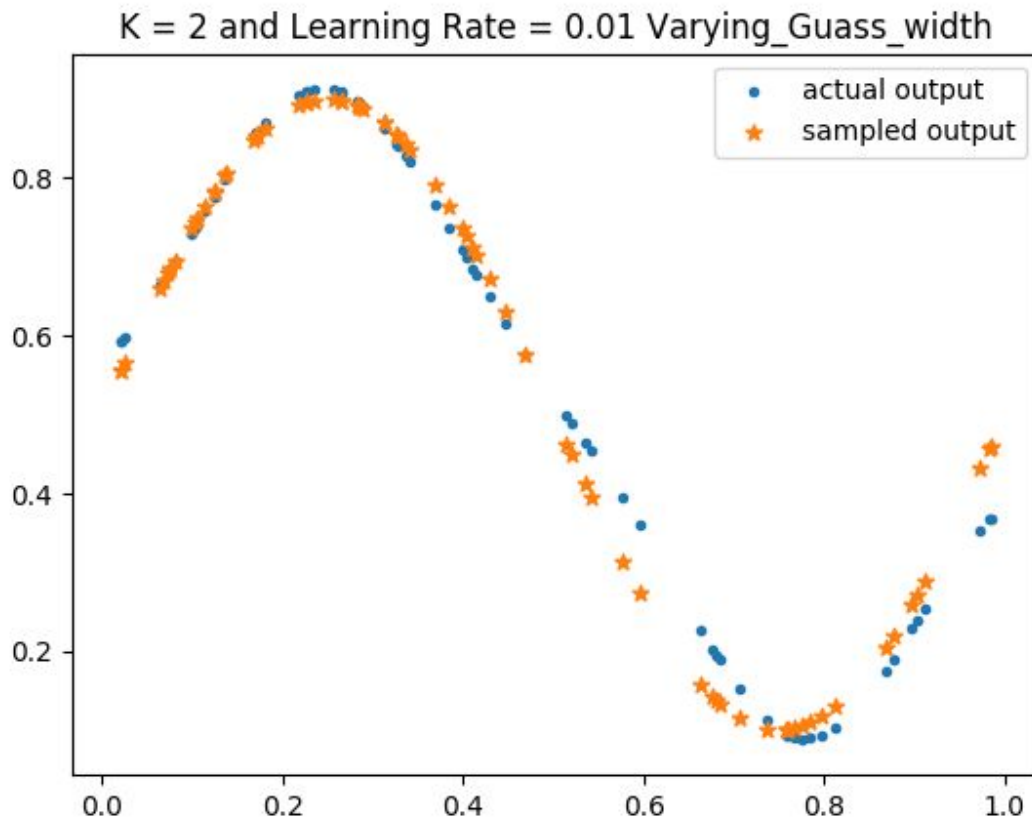


Fig 1.1 : For experiment 1 with randomized weights

In another experiment, that is with different initial weights $k = 4$ performed better as shown in fig 1.2.

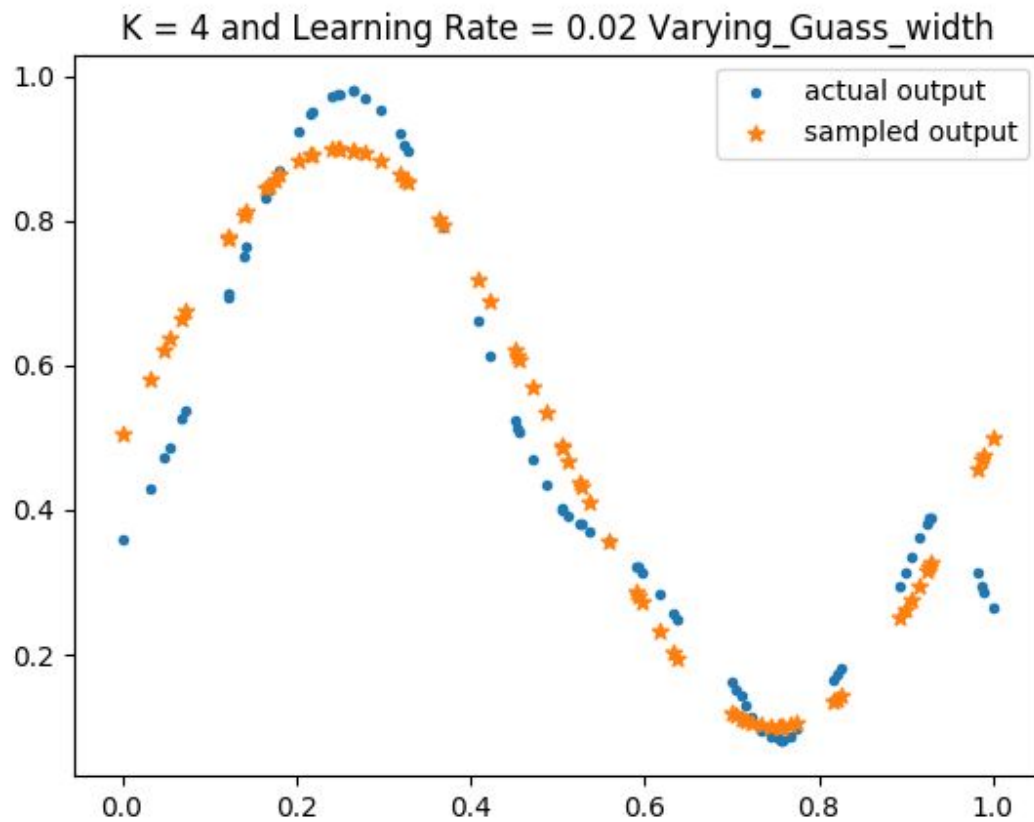


Fig 1.2 : For experiment 2 with randomized weights different from Fig 1.1

This is because different initial weights can significantly vary the performance and hence choosing initial weights carefully is an important step in learning.

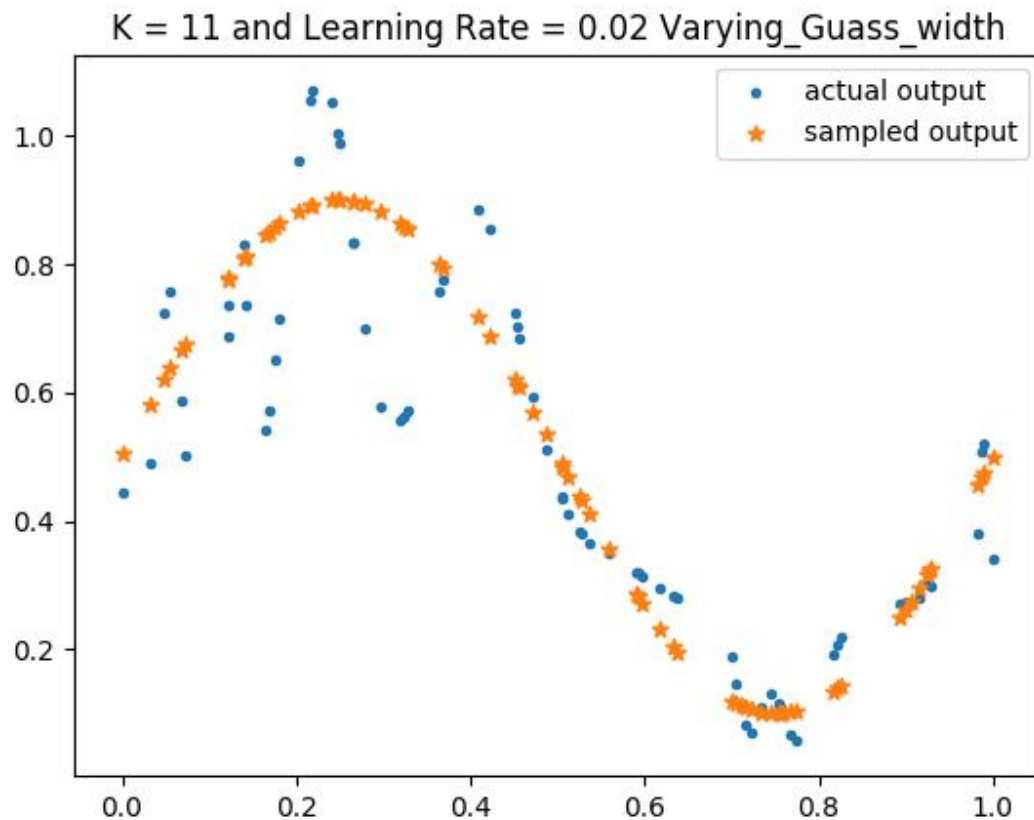


Fig 1.3 : Example for bad performance with higher K

EFFECT OF LEARN RATE :

Increasing learning rate from 0.01 to 0.02 helps gradient descent converge faster. For example :

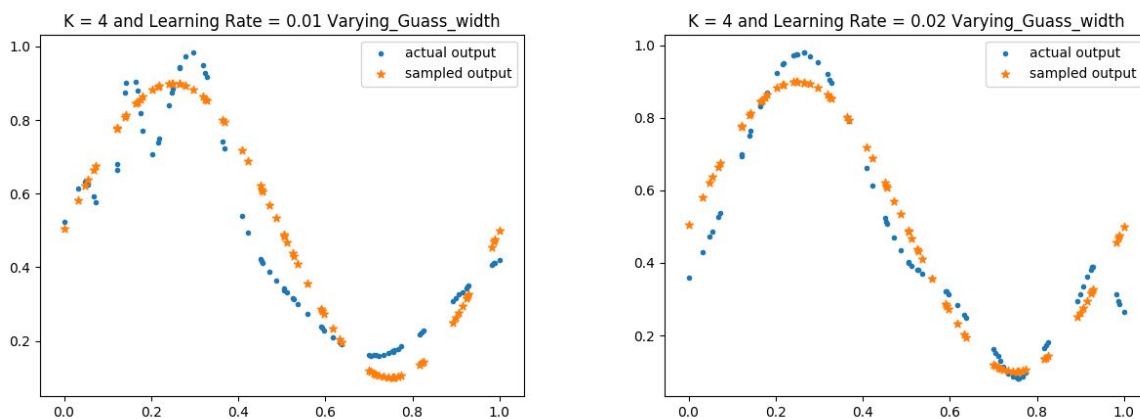


Fig 1.4 : Left image Learn rate = 0.01 and right image learn rate = 0.02

In Fig 1.4 with learn rate = 0.01, the points in x axes interval 0.1 - 0.4 vary (up and down). This is because of slow convergence of gradient descent (it has not yet reached the minimum point). Whereas with learn rate = 0.02 the gradient descent converges faster and reaches the minimum point of cost function faster compared to learn rate = 0.01.

WITH FIXED GAUSSIAN WIDTH :

Using fixed gaussian width significantly improves performance. For example Fig 1.5:

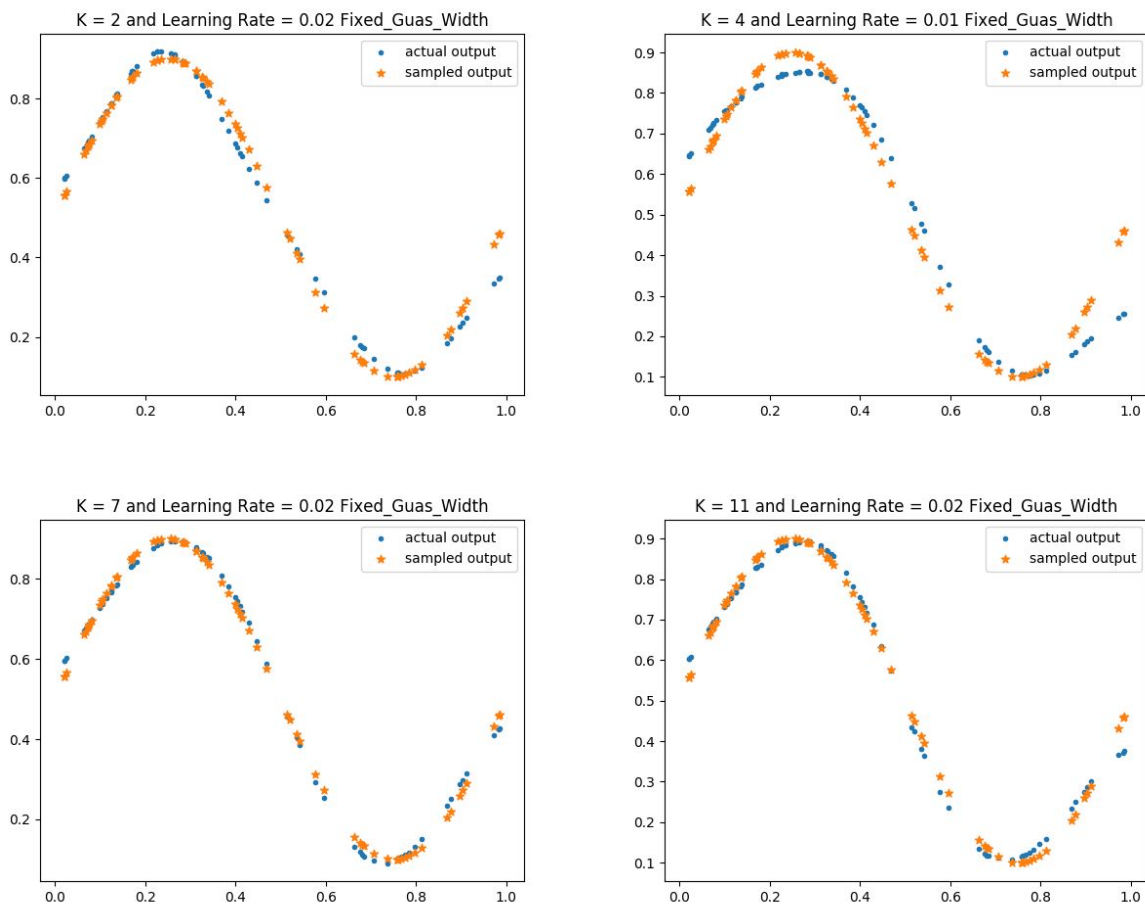


Fig 1.5 : Result with fixed gaussian width

In fig 1.5 RBF network performs well for all k as opposed to varying width (different variance for clusters) where we observed significantly different performance for different k values.