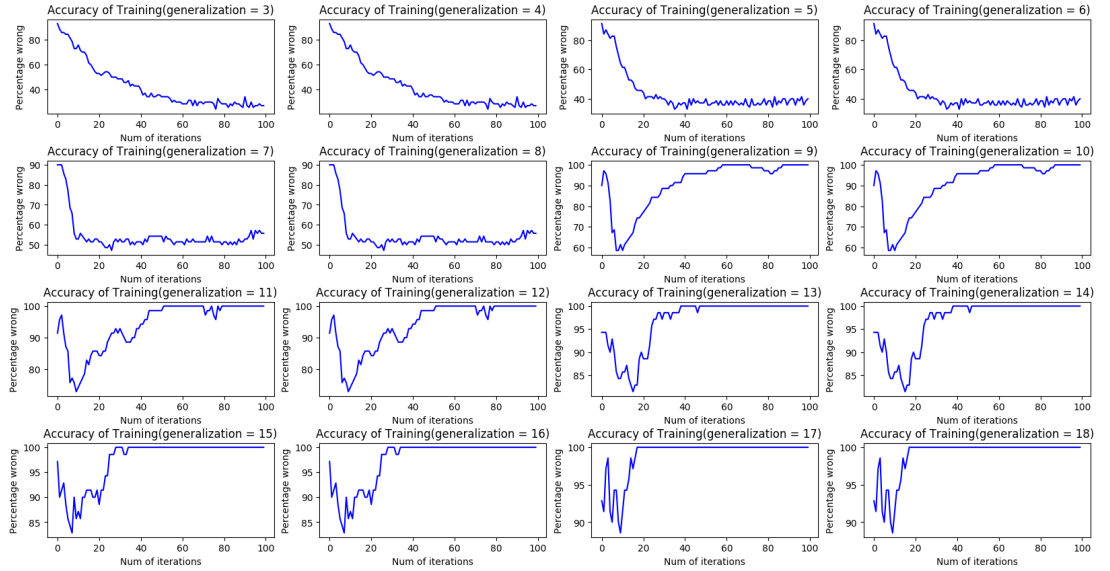


1 Discrete Cmac

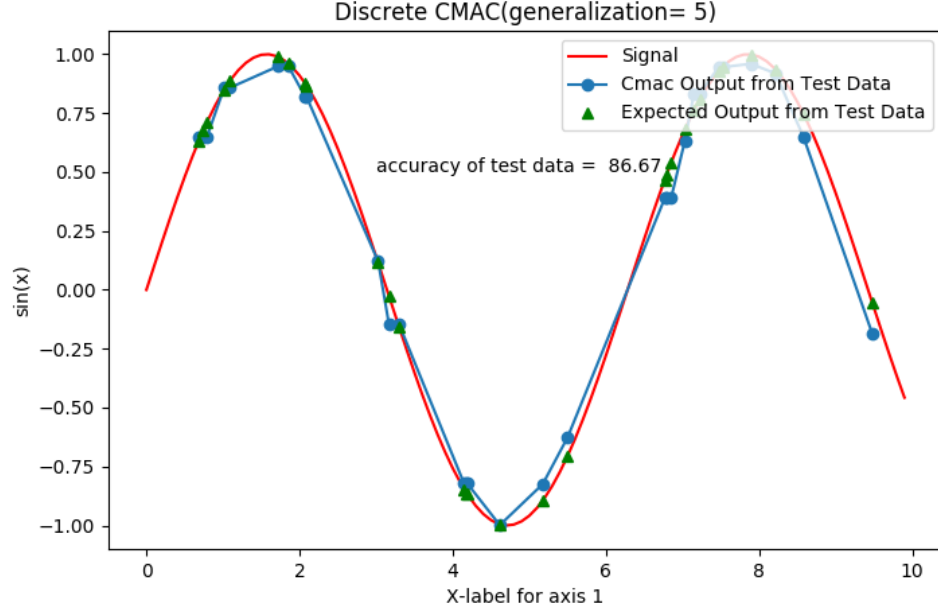
1.1 Description

1.2 Results

Generalization Vs Convergence: Clearly from the graphs shown below, it can be noted that as the generalization number increases, the model has a hard time converging. This can be attributed to the fact that the generalization number, g , indicates to a degree the similarity between tasks. As g increases, unrelated tasks are grouped as similar and the model tends to overfit. Ideally, g is chosen so that tasks which are related have similar values while tasks which are different have clear cut distinct values.



Accuracy: Below is a graph that depicts the accuracy of the Discrete Cmac. After running a couple of times, it can be noted that the accuracy hovers between 70-85%



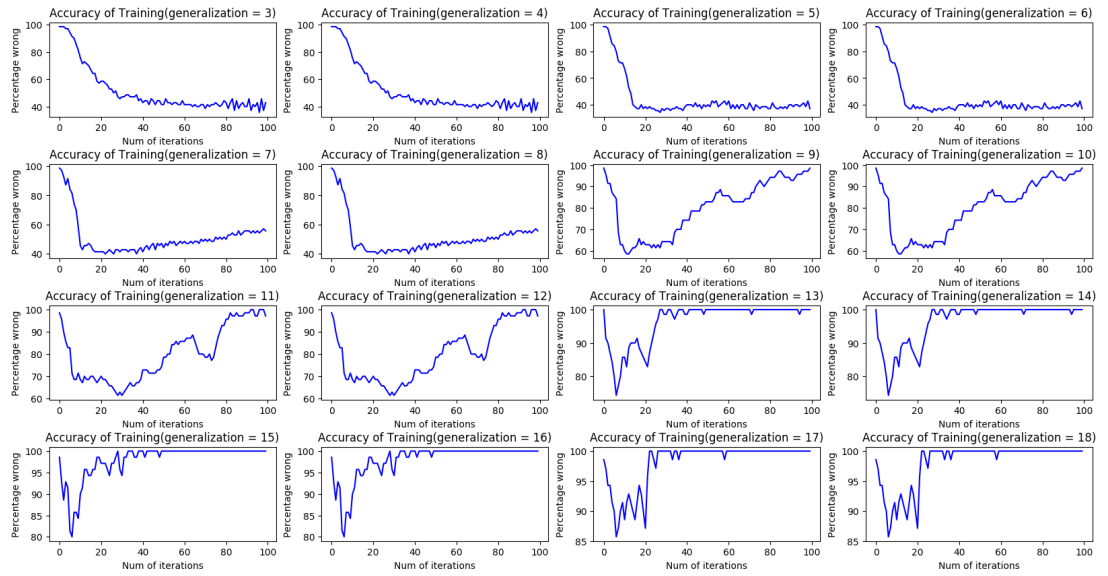
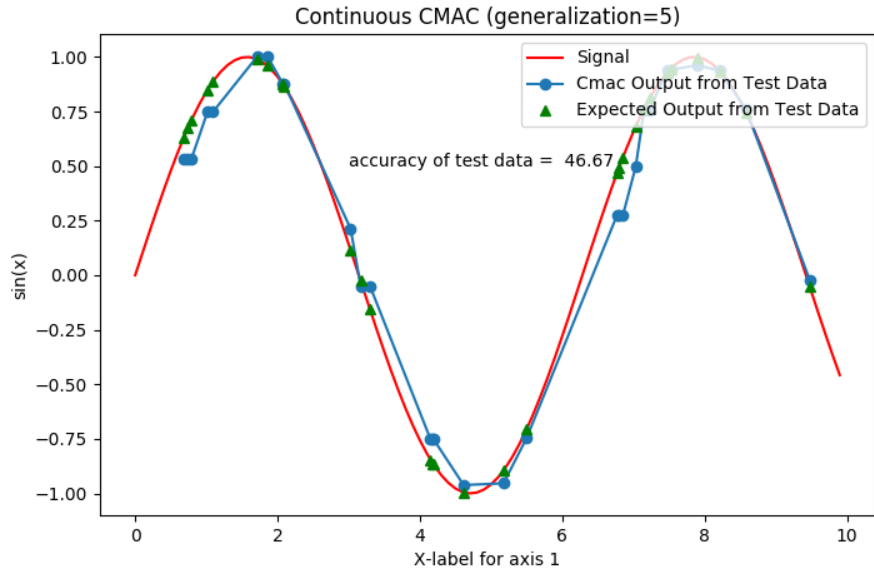
2 Continuous Cmac

2.1 Description

2.2 Results

Accuracy: Below is a graph that depicts the accuracy of the Continuous Cmac. After running the code a couple of times, it can be noted that the accuracy hovers between 40-60%

Discrete Vs Continuous Cmac: The "convergence Vs generalization" graphs for both continuous cmac and discrete cmac are relatively similar in particular for generalization numbers $g = 3$ to 6 . However, the accuracy of the test results are clearly different. For the same parameters used in training the Discrete Cmac (generalization number, number of iterations in training, accuracy used in training, learning rate), it can be noted that the continuous Cmac has a significant drop in accuracy as the model clearly seems to overfit. This is because the continuous cmac slides over more weights. Therefore, although a generalization number of 5 is used, more than 5 weights are changed during each update and this means that more inputs are categorized as similar and that is undesirable. To rectify this the generalization number can be reduced and number of iterations increased to improve performance. Also, the type of sliding window utilized has an impact on the results.



3 Recurrent Networks