

# Primal Formulation of a Nonlinear Classifier With MMSE

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**Abstract**—This paper examines the effectiveness of a non-linear classifier that separates a binary dataset by applying a Volterra expansion—projecting it into  $\mathbb{R}^{10}$ . This classifier creates a boundary that can classify almost all points.

**Index Terms**—Volterra Expansion, Non-Linear Classifier

## I. INTRODUCTION

THE Volterra series of a non-linear function is a transformation that maps two functional spaces. Similar to the Taylor series, the Volterra series is expressed as an infinite sum; however, unlike the Taylor series, it is based on convolutional integrals.

### A. The Volterra Expansion

A volterra series can be expressed as:

$$\hat{y} = \sum_{k=0}^K a_k x^k \quad (1)$$

If we consider a space of  $\mathbb{R}^2$ , and we want to pass from this space into  $\mathbb{R}^p$  such that:

$$p = \binom{2+3}{3} = 10 \quad (2)$$

We first formulate the expansion:

$$\langle 1, x_1, x_2, x_1^2, x_2^2, x_1x_2, x_1^2x_2, x_1x_2^2, x_1^3, x_2^3 \rangle \quad (3)$$

Which becomes:

$$\mathbf{x} = \begin{bmatrix} 1 \\ x[n] \\ x[n-1] \\ x^2[n] \\ x^2[n-1] \\ x[n]x[n-1] \\ x^3[n] \\ x^3[n-1] \\ x^2[n]x[n-1] \\ x[n]x^2[n-1] \end{bmatrix} \quad (4)$$

## II. EXPERIMENTS

### A. Data Generation

For this experiment, we generate data using a Gaussian distribution and a parameter  $\alpha$  that causes convolutional spread. The lower the value of  $\alpha$ , the closer classes are to each other.

### B. Classifying Low Values of $\alpha$

For this experiment, we first begin by plotting our data in  $\mathbb{R}^2$ . We generate  $N$  data samples with a convolutional spread constant  $\alpha$ , such that:

$$\alpha = 0.2, N = 100 \quad (5)$$

The two classes are shown below.

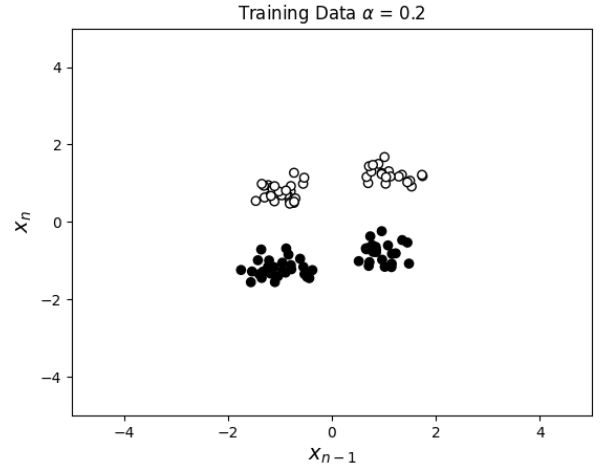


Fig. 1. Data clusters in  $\mathbb{R}^2$  using  $\alpha = 0.2, N = 100$

We can visually see that the two classes are linearly separable, and a support vector machine, support vector classifier would work well in this case; nonetheless, we apply the non-linear classifier and can see that the non-linear approach works in this case also.

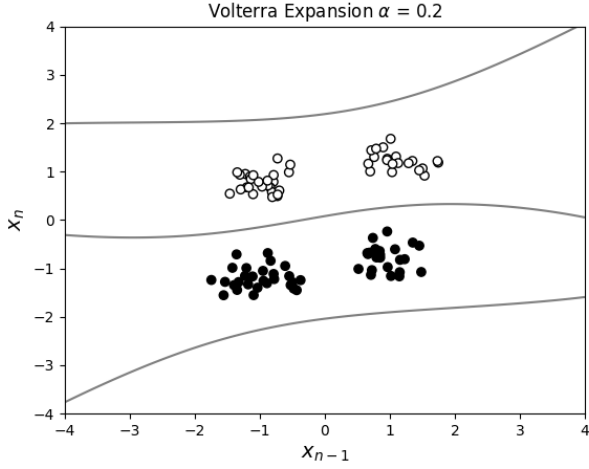


Fig. 2. Example in  $\mathbb{R}^2$  classifying linearly separable data with a non-linear classifier

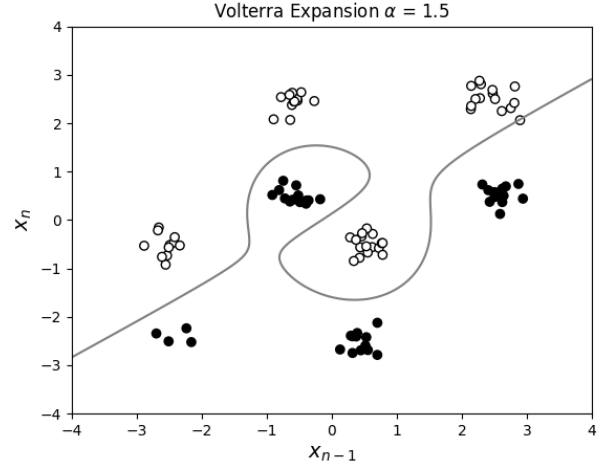


Fig. 4. Applying the non-linear classifier to our data  $\alpha = 1.5, N = 100$

### C. Classifying With High Values of $\alpha$

For this experiment, we plot our data in  $\mathbb{R}^2$  using a new convolutional spread constant  $\alpha$ :

$$\alpha = 1.5, N = 100 \quad (6)$$

We can see in the figure below that our data is no longer linearly separable.

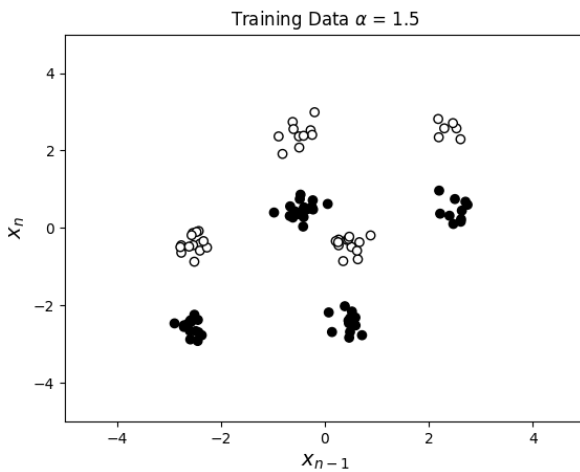


Fig. 3. Data clusters in  $\mathbb{R}^2$  using  $\alpha = 1.5, N = 100$

We now pass our data through the non-linear classifier, and draw the contour.

### III. CONCLUSION

We see from the following experiments that the non-linear classifier works separating data where the linear classifier does not; however, it is important to note that underfitting does occur in this case.

### IV. SOURCE CODE

[https://github.com/keithhboba/support\\_vector\\_machines/](https://github.com/keithhboba/support_vector_machines/)