

# Tchebycheff's Approximation to Polynomials

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## Abstract

*Tchebycheff was a Russian mathematician. He did most of his work on approximation theory in 1894.*

*The problem that I wish to address is that I want to approximate a continuous function  $f$  defined on an interval  $[a, b]$  by a polynomial:*

$$P(x) = C_n X^n + C_{n-1} X^{n-1} + \dots + C_0$$

*I want to evaluate this approximation by minimizing expressions of the form:*

1.  $\max |f(x) - p(x)|$

$$a \leq x \leq b$$

2.  $\max |f(x_i) - p(x_i)|$

$$1 \leq i \leq m$$

$$a \leq x_i \leq b$$

## 1 Background

This thesis is submitted in partial fulfillment of the requirements for the degree of Bachelor's of Science in Mathematics at Pacific Lutheran University.

### 1.1 Introduction

Tchebycheff was a Russian mathematician. He did most of his work on approximation theory in 1894.

The problem that I wish to address is that I want to approximate a continuous function  $f$  defined on an interval  $[a, b]$  by a polynomial:

$$P(x) = C_n X^n + C_{n-1} X^{n-1} + \dots + C_0$$

I want to evaluate this approximation by minimizing expressions of the form:

$$1. \max |f(x) - p(x)|$$

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$$1 \leq i \leq m$$

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A large part of the work of Tchebycheff involved the very special case when the number of points taken is equal to  $n+1$ . This topic is called interpolation.

We know that a straight line having the equation  $y = ax + b$  can be passed through any two points having distinct abscissas.

Similarly, a parabola  $y = ax^2 + bx + c$  can be passed through any three points having distinct abscissas.

I would now like to generalize this concept for  $n+1$  points. But I first need to do some preliminary work.

## 2 Vandermonde's Determinant

Theorem:

$$\prod_{0 \leq j < i \leq n} (X_i - X_j) = \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & X_0^n \\ 1 & X_1 & X_1^2 & \dots & X_1^n \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & X_n & X_n^2 & \dots & X_n^n \end{vmatrix}$$

Proof by induction:

I will first show that Vandermonde's Determinant (from here on out this determiniant will be referred to as:  $D_T$ ) holds for  $n=1$ . For  $n=1$  we have:

$$\begin{vmatrix} 1 & X_0 \\ 1 & X_1 \end{vmatrix} = (X_1 - X_0)$$

Therefore  $D_T$  holds for  $n=1$ .

Assuming that  $D_T$  is true for  $n=r$ , I must now prove that  $D_T$  holds for  $n=r+1$ . For  $n=r+1$  we have:

$$\begin{aligned}
& \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & X_0^r & X_0^{r+1} \\ 1 & X_1 & X_1^2 & \dots & X_1^r & X_1^{r+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & X_{r+1} & X_{r+1}^2 & \dots & X_{r+1}^r & X_{r+1}^{r+1} \end{vmatrix} \\
&= \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & X_0^r & X_0^{r+1} - X_0^{r+1} \\ 1 & X_1 & X_1^2 & \dots & X_1^r & X_1^{r+1} - X_1^r X_0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & X_{r+1} & X_{r+1}^2 & \dots & X_{r+1}^r & X_{r+1}^{r+1} - X_{r+1}^r X_0 \end{vmatrix} \\
&= \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & X_0^r & 0 \\ 1 & X_1 & X_1^2 & \dots & X_1^r & X_1^r(X_1 - X_0) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & X_{r+1} & X_{r+1}^2 & \dots & X_{r+1}^r & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix} \\
&= \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & X_0^r - X_0^r & 0 \\ 1 & X_1 & X_1^2 & \dots & X_1^r - X_1^{r-1}X_0 & X_1^r(X_1 - X_0) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & X_{r+1} & X_{r+1}^2 & \dots & X_{r+1}^r - X_{r+1}^{r-1}X_0 & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix} \\
&= \begin{vmatrix} 1 & X_0 & X_0^2 & \dots & 0 & 0 \\ 1 & X_1 & X_1^2 & \dots & X_1^{r-1}(X_1 - X_0) & X_1^r(X_1 - X_0) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & X_{r+1} & X_{r+1}^2 & \dots & X_{r+1}^{r-1}(X_{r+1} - X_0) & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix}
\end{aligned}$$

Continuing this process we arrive at:

$$\begin{aligned}
&= \\
& \begin{vmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ 1 & (X_1 - X_0) & X_1(X_1 - X_0) & \dots & X_1^{r-1}(X_1 - X_0) & X_1^r(X_1 - X_0) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & (X_{r+1} - X_0) & X_{r+1}(X_{r+1} - X_0) & \dots & X_{r+1}^{r-1}(X_{r+1} - X_0) & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix} \\
&= \\
& \begin{vmatrix} (X_1 - X_0) & X_1(X_1 - X_0) & \dots & X_1^{r-1}(X_1 - X_0) & X_1^r(X_1 - X_0) \\ (X_2 - X_0) & X_2(X_2 - X_0) & \dots & X_2^{r-1}(X_2 - X_0) & X_2^r(X_2 - X_0) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ (X_{r+1} - X_0) & X_{r+1}(X_{r+1} - X_0) & \dots & X_{r+1}^{r-1}(X_{r+1} - X_0) & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix}
\end{aligned}$$

$= (X_1 - X_0)$  multiplied by:

$$\begin{vmatrix} 1 & X_1 & \dots & X_1^{r-1} & X_1^r \\ (X_2 - X_0) & X_2(X_2 - X_0) & \dots & X_2^{r-1}(X_2 - X_0) & X_2^r(X_2 - X_0) \\ \vdots & \vdots & \dots & \vdots & \vdots \\ (X_{r+1} - X_0) & X_{r+1}(X_{r+1} - X_0) & \dots & X_{r+1}^{r-1}(X_{r+1} - X_0) & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix}$$

$= (X_1 - X_0)(X_2 - X_0)$  multiplied by:

$$\begin{vmatrix} 1 & X_1 & \dots & X_1^{r-1} & X_1^r \\ 1 & X_2 & \dots & X_2^{r-1} & X_2^r \\ \vdots & \vdots & \dots & \vdots & \vdots \\ (X_{r+1} - X_0) & X_{r+1}(X_{r+1} - X_0) & \dots & X_{r+1}^{r-1}(X_{r+1} - X_0) & X_{r+1}^r(X_{r+1} - X_0) \end{vmatrix}$$

Continuing this process we arrive at:

$$\begin{aligned} &= (X_1 - X_0)(X_2 - X_0)\dots(X_{r+1} - X_0) \begin{vmatrix} 1 & X_1 & \dots & X_1^{r-1} & X_1^r \\ 1 & X_2 & \dots & X_2^{r-1} & X_2^r \\ \vdots & \vdots & \dots & \vdots & \vdots \\ 1 & X_{r+1} & \dots & X_{r+1}^{r-1} & X_{r+1}^r \end{vmatrix} \\ &= \prod_{1 \leq i \leq r+1} (X_i - X_0) \begin{vmatrix} 1 & X_1 & \dots & X_1^{r-1} & X_1^r \\ 1 & X_2 & \dots & X_2^{r-1} & X_2^r \\ \vdots & \vdots & \dots & \vdots & \vdots \\ 1 & X_{r+1} & \dots & X_{r+1}^{r-1} & X_{r+1}^r \end{vmatrix} \end{aligned}$$

The matrix on the right is nothing more than Vandermonde's Determinant for  $r$  variables. In this case the variables have been numbered from  $1$  to  $r+1$  instead of  $0$  to  $r$ . Thus by my assumption that  $D_T$  holds for  $n=r$ , we have:

$$\begin{aligned} &= [\prod_{1 \leq i \leq r+1} (X_i - X_0)] [\prod_{0 \leq j < i \leq n} (X_i - X_j)] \\ &= \prod_{0 \leq i \leq r+1} (X_i - X_j) \end{aligned}$$

Therefore  $D_T$  is true for  $n = r+1$ . Thus (by induction) my proof is complete.

### 3 Interpolation Theorem

Theorem:

There exists a unique polynomial of degree  $\leq n$  which assumes prescribed values at  $n + 1$  distinct points.

Proof:

Let  $(x_0, x_1, \dots, x_n)$  be the points and  $(y_0, y_1, \dots, y_n)$  be the prescribed values. We seek a polynomial  $p$  such that  $p(x_i) = y_i (i = 0, 1, \dots, n)$ . Since the polynomial is of degree  $\leq n$ , it may be expressed as:

$$P(X) = \sum_{j=0}^n C_j X^j$$

Hence our requirement now reads:

$$P(X_i) = \sum_{j=0}^n C_j X_i^j = Y_i (i = 0, 1, \dots, n).$$

Written out in matrix form this becomes:

$$\begin{bmatrix} 1 & X_0 & X_0^2 & \dots & X_0^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_n & X_n^2 & \dots & X_n^n \end{bmatrix} \begin{bmatrix} C_0 \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} Y_0 \\ \vdots \\ Y_n \end{bmatrix}$$

In this equation the  $C$  matrix is unknown while the  $X$  and  $Y$  matrices are known.

The determinant of the  $X$  matrix equals Vandermonde's Determinant and thus has the value:

$$D_T = \prod_{0 \leq j < i \leq n} (X_i - X_j)$$

Since each of the  $X_i$ 's are distinct,  $Det \neq 0$ . Thus the matrix has a unique solution and my proof is complete.

### 4 Interpolation Process

I will now seek to assess the interpolation process as an instrument of approximation. This examination will pertain to our two original expressions:

$$1. \max |f(x) - p(x)|$$

$$a \leq x \leq b$$

$$2. \max |f(x_i) - p(x_i)|$$

$$1 \leq i \leq m$$

$$a \leq x_i \leq b$$

The polynomial  $p$  of degree  $\leq n$  which interpolates to  $f$  at  $n+1$  points  $x_i$ , clearly solves the problem of minimizing the second equation when  $m = n+1$ .

I will now ask, will the first expression also be small when  $p$  is chosen in this way. The answer is certainly not if the behavior of  $f$  between the interpolating points is not somehow controlled. It turns out that such control is possible for functions which possess  $n+1$  continuous derivatives. Before I address this problem, we need to familiarize ourselves with the Tchebycheff norm, which for a polynomial  $y$  defined on the interval  $[a, b]$ , is:

$$||y||_T = \max_{a \leq x \leq b} |y(x)|$$

To show that this is indeed a norm I must show, for polynomials  $y$  and  $x$ , that:

1.  $||y|| > 0$  (unless  $y = 0$ )
2.  $||\lambda y|| = |\lambda| ||y||$  ( $\lambda$  is a scalar)
3.  $||y + z|| \leq ||y|| + ||z||$

The Tchebycheff norm obviously fits this definition.

## 5 Theorem 1

Theorem:

If  $f$  possesses  $n$  continuous derivatives on  $[a, b]$ . And if  $p$  is the polynomial of degree  $< n$  which interpolates to  $f$  at  $n$  nodes  $x_i$  in  $[a, b]$ , and if  $w(x) = \prod (x - x_i)$ , then in terms of the Tchebycheff norm:

$$||f - p|| \leq \frac{1}{n!} ||f^{(n)}|| ||w||$$

Proof:

I will first show to each  $y$  in  $[a, b]$  there corresponds a  $z_y \in [a, b]$  such that:

$$f(y) - p(y) = \frac{1}{n!} f^{(n)}(z_y)w(y)$$

This formula is obvious if  $y$  is one of the nodes. Otherwise we put:

$$\phi = f - p - \lambda w$$

where  $\lambda$  is chosen to make  $\phi(y) = 0$ . Namely:

$$\phi(y) = f(y) - p(y) - \lambda w(y)$$

$$0 = f(y) - p(y) - \lambda w(y)$$

$$\lambda = \frac{f(y)-p(y)}{w(y)}$$

It is clear that  $\phi$  vanishes also at the nodes  $x_i$  for:

$$\phi(x_i) = f(x_i) - p(x_i) - \lambda w(x_i) = 0$$

Thus  $\phi$  vanishes in at least  $n + 1$  points of  $[a, b]$ , the  $n$  nodes and the point  $y$ . Rolle's theorem states that for  $f(x) \in C[a, b]$  and  $f$  differentiable at each point of  $[a, b]$ . If  $f(a) = f(b)$  then there is a point  $x = \beta$  with  $a < \beta < b$  for which  $f'(\beta) = 0$ .

Thus since  $f$  possesses  $n$  continuous derivatives on  $[a, b]$ ,  $\phi'$  vanishes at least once between any two zeros of  $\phi$  and thus vanishes in at least  $n$  points.

Also,  $\phi''$  vanishes at least once between any two zeros of  $\phi'$  and thus vanishes in at least  $n-1$  points. Continuing this argument, we see that  $\phi^{(n)}$  has at least one root on the interval  $[a, b]$ , say at the point  $z_y$ . By differentiating  $\phi$  with respect to  $x$  and remembering that  $y$  is a fixed point we have:

$$\phi^{(n)} = f^{(n)} - p^{(n)} - \lambda w^{(n)}$$

And since  $p$  is a polynomial of degree  $< n$  we have:

$$\phi^{(n)} = f^{(n)} - 0 - \lambda w^{(n)}$$

And since  $w(s) = s^n + s^{n-1} + \dots$  we have:

$$\phi^{(n)} = f^{(n)} - \lambda n!$$

Thus:

$$f^{(n)}(z_y) = \lambda n!$$

And since:

$$\lambda = \frac{f(y)-p(y)}{w(y)}$$

we have:

$$f^{(n)}(z_y) = \frac{[f(y)-p(y)]n!}{w(y)}$$

$$f(y) - p(y) = \frac{1}{n!} f^{(n)}(z_y)w(y)$$

$$|f(y) - p(y)| = \left| \frac{1}{n!} f^{(n)}(z_y)w(y) \right|$$

Remember, the preceeding is true for all  $y \in [a, b]$ .

Now assume that:

$$\max_{a \leq y \leq b} |f(y) - p(y)| \neq \max_{a \leq y \leq b} \left| \frac{1}{n!} f^{(n)}(z_y)w(y) \right|$$

Without loss of generality I can assume that:

$$\max_{a \leq y \leq b} |f(y) - p(y)| < \max_{a \leq y \leq b} \left| \frac{1}{n!} f^{(n)}(z_y)w(y) \right|$$

Now for  $\alpha \in [a, b]$  let:

$$\left| \frac{1}{n!} f^{(n)}(z_\alpha)w(\alpha) \right| = \max_{a \leq y \leq b} \left| \frac{1}{n!} f^{(n)}(z_y)w(y) \right|$$

then:

$$> \max_{a \leq y \leq b} |f(y) - p(y)|$$

QED

Thus:

$$\max_{a \leq y \leq b} |f(y) - p(y)| = \max_{a \leq y \leq b} \left| \frac{1}{n!} f^{(n)}(z_y)w(y) \right|$$

$$||f(y) - p(y)|| = \frac{1}{n!} ||f^{(n)}(z_y)w(y)||$$

$$\leq \frac{1}{n!} ||f^{(n)}(z_y)|| ||w(y)||$$

$$\leq \frac{1}{n!} ||f^{(n)}|| ||w(y)||$$

A question that is raised in a natural way by the foregoing theorem is how can we situate the nodes as to optimize the error bound? Since the nodes enter this formula only in the function  $w$ , I must attempt to minimize the norm of  $w$ .

I will now prove a relationship which will be immediately useful.

## 6 Theorem 2

Theorem:

$$\sum_{k=0}^n A_k \cos^k \theta = \cos n\theta$$

With appropriate coefficients  $A_k$ , the leading one,  $A_n = 2^{n-1}$ .

Proof by induction:

I will first show that the equation holds for  $n = 1$ .

$$\begin{aligned} \cos(1 - \theta) &= \cos \theta \\ &= 0 + (1 \times \cos \theta) \\ &= \sum_{k=0}^1 A_k \cos^k \theta \end{aligned}$$

The leading coefficient  $A_1 = 1 = 2^0 = 2^{1-1} = 2^{n-1}$ . Therefore, the equation holds for  $n=1$ .

I will now assume that the formula is true for  $n=r$  and the leading coefficient  $A_r = 2^{r-1}$ . I need to show that the relationship is true for  $n=r+1$ . Thus:

$$\begin{aligned} \cos(r + 1)\theta &= \cos(r\theta + \theta) \\ &= \cos r\theta \cos \theta - \sin r\theta \sin \theta \end{aligned}$$

Since:

$$= \cos(A \pm B) = \cos A \cos B \pm \sin A \sin B$$

We have:

$$\begin{aligned} &= 2 \cos r\theta \cos \theta - \cos r\theta \cos \theta - \sin r\theta \sin \theta \\ &= 2 \cos r\theta \cos \theta - \cos(r - 1)\theta \\ &= 2 \cos \theta \sum_{k=0}^r A_k \cos^k \theta - \sum_{k=0}^{r-1} B_k \cos^k \theta \\ &= \sum_{k=0}^r 2 A_k \cos^{k+1} \theta - \sum_{k=0}^{r-1} B_k \cos^k \theta \end{aligned}$$

$$\begin{aligned}
&= 2A_k \cos^{r+1} \theta + 2A_{k+1} \cos^r \theta + \sum_{k=0}^{r-1} (2A_k - B_k) \cos^k \theta \\
&= \sum_{k=0}^{r+1} C_k \cos^k \theta
\end{aligned}$$

Where  $(C_{r+1} = 2A_r)$ ,  $(C_r = 2A_{r-1})$ , and  $(C_i = 2A_i - B_i)$  for  $(0 \leq i \leq r-1)$ .

The relationship thus holds for  $n=r+1$ . Therefore (by induction), my proof is complete.

## 7 Theorem 3

Theorem:

The norm of:

$$w(x) = \prod_{i=1}^n (X - X_i)$$

is minimized on  $[-1, 1]$  when:

$$x_i = \cos\left[(2i-1)\frac{\pi}{2n}\right]$$

Proof:

Letting:

$$T_n(x) = \sum_{k=0}^n A_k X^k$$

We have:

$$T_n(\cos\theta) = \cos n\theta$$

To obtain the roots of  $T_n$  we set:

$$T_n(\cos\theta) = 0$$

We thus have:

$$T_n(\cos\theta) = \cos n\theta = 0$$

$$n\theta = \arccos 0$$

$$n\theta = \frac{(2i-1)\Pi}{2} \quad (i = 1, 2, \dots)$$

$$\theta = \frac{(2i-1)\Pi}{2n}$$

$$\cos\theta = \cos\left[(2i-1)\frac{\Pi}{2n}\right]$$

Thus the roots of  $T_n$  are the  $x_i$  given above. The polynomial:  $U = 2^{1-n}T_n$ , is a multiple of  $W$  since  $U$  and  $W$  have the same zeros. The maximum of  $|U(x)|$  on  $[-1, 1]$  occurs then at the points:

$$y_i = \cos i \frac{\Pi}{n}$$

Since:

$$T_n(y_i) = \cos ni \frac{\Pi}{n} = \cos i \Pi = (-1)^i$$

Now if possible, let  $V$  be another polynomial of the same form as  $W$ , for which:  $\|V\| < \|U\|$ . Then:

$$V(y_0) < \|U\| = U(y_0)$$

Thus:

$$V(y_0) < U(y_0)$$

and:

$$V(y_0) < \|U\| = |U(y_1)| = |-1|$$

Now:

$$V(y_1) > -1,$$

Since if:

$$V(y_1) \leq -1,$$

Then:

$$V(y_1) \geq |-1| = \|U\|$$

Thus:

$$V(y_1) > -1 = U(y_1)$$

Continuing this process we see that  $(U - V)$  must vanish at least once in each interval  $[(y_1, y_0), (y_2, y_1), \dots]$  for a total of  $n$  times. But this is not possible since  $V$  and  $W$  have degree  $n$  and a leading coefficient of 1. Their difference is therefore of degree  $\leq n$ .

Thus:  $\|V\| \geq \|U\|$ , and  $W$  is thus minimized on  $[-1, 1]$  when:

$$x_i = \cos[(2i - 1)\frac{\pi}{2n}]$$

I now need to expand this result to apply for the general interval  $[a, b]$  to  $[-1, 1]$  where the following serves our purpose:

$$x = \frac{a-2y+b}{a-b}$$

Our transformation is continuous except when:  $a = b$ , which is an interval of one point and thus not permitted. Solving for  $y$  we have:

$$x = \frac{a-2y+b}{a-b}$$

$$(a - b)x = (a + b) - 2y$$

$$2y = (a + b) - (a - b)x$$

$$y = \frac{1}{2} [(a + b) - (a - b)x] \quad \text{from } [-1, 1] \rightarrow [a, b].$$

Now we recall that the zeros of  $T_n(x)$  are:

$$x_i = \cos[(2i - 1)\frac{\pi}{2n}]$$

And thus the corresponding interpolation points in  $[a, b]$  are:

$$y_i = \frac{1}{2} [(b - a)\cos[(2i - 1)\frac{\pi}{2n}] + (a + b)]$$

Therefore, for a given function  $f$  of degree  $\leq n$ , which possesses  $n$  continuous derivatives on  $[a, b]$ , we can construct an approximation  $p$  such that the mean of  $(f - p)$  is given by:

$$\|f - p\| \leq \frac{1}{n!} \|f^{(n)}\| \|w\|$$

where the norm of  $w(y) = \prod_{i=1}^n (y - y_i)$  is minimized on  $[a, b]$ , when:

$$y_i = \frac{1}{2} [(b - a)\cos[(2i - 1)\frac{\pi}{2n}] + (a + b)]$$

For the maximum derivation of  $\prod_{i=1}^n (y - y_i)$  from zero in  $[a, b]$ , we have:

$$\max_{a \leq y \leq b} \prod_{i=1}^n |y - y_i|$$

Now:

$$\begin{aligned}
y - y_i &= \frac{1}{2} [(b - a)x + (a + b)] - \frac{1}{2} [(b - a)x_i + (a + b)] \\
&= \frac{1}{2} [(b - a)x + (a + b) - (b - a)x_i + (a + b)] \\
&= \frac{1}{2} [(b - a)(x - x_i)] \\
&= \frac{(b-a)(x-x_i)}{2}
\end{aligned}$$

Thus:

$$\max_{a \leq y \leq b} \prod_{i=1}^n |y - y_i| = \left[ \frac{(b-a)}{2} \right]^n \prod_{i=1}^n (x - x_i)$$

Remembering that:  $W(x) = x^{1-n}T_n$   
and that the maximum value of:  $T_n(x) = 1$ .  
We have:

$$\begin{aligned}
&= \left[ \frac{(b-a)}{2} \right]^n 2^{1-n} \\
&= \left[ \frac{(b-a)}{2} \right]^n \frac{1}{2^{n-1}} \\
&= \frac{(b-a)^n}{2^{2n-1}}
\end{aligned}$$

Clearly Tchebycheff's polynomial has its limitations as an approximation. This would tend to show us that the use of the interpolation process as a method of approximation would be inadequate for many applications. I will not present a theorem which will introduce an approach which gives much better results.

## 8 Weierstrass Approximation Theorem

Theorem:

Let  $f$  be a continuous function defined on  $[a, b]$ . To each  $\epsilon > 0$ , there corresponds a polynomial  $p$  such that  $\|f - p\| < \epsilon$ . Thus:  $|f - p| < \epsilon$  for all  $x \in [a, b]$ .

Proof (by Bernstein):

Bernstein constructed, for a given  $f \in C[1, 1]$ , a sequence of polynomials (now called Bernstein polynomials)  $B_n f$  by means of the formula:

$$(B_n f)(x) = \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k}$$

Where:  $\binom{n}{k}$  is the binomial coefficient:  $\frac{n!}{(n-k)!k!}$  .

For  $f, g \in C[0, 1]$  we have:

$$\begin{aligned} B_n(f+g) &= \sum_{k=0}^n (f+g) \left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \\ &= \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} + \sum_{k=0}^n g\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \\ &= B_n f + B_n g \end{aligned}$$

And for  $\alpha$  a scalar we have:

$$\begin{aligned} B_n(\alpha f) &= \sum_{k=0}^n \alpha f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \\ &= \alpha \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \\ &= \alpha(B_n f) \end{aligned}$$

$B_n$  is thus a linear operator.

By definition, for  $B_n$  to be a monotone operator, for:

$$\begin{aligned} f, g &\in C[0, 1] \\ f &\geq g \rightarrow B_n f \geq B_n g \end{aligned}$$

Now since  $n \geq k$  and  $x \in [0, 1]$ :

$$\frac{n!}{(n-k)!k!} x^k (1-x)^{n-k} \geq 0$$

Thus if  $f \geq g$  then:

$$f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \geq g\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k}$$

And therefore:

$$\sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k} \geq \sum_{k=0}^n g\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k}$$

Thus  $B_n f \geq B_n g$  and therefore  $B_n f$  is a monotone operator. I will now prove a theorem essential to the completion of this proof.

## 9 Theorem on Monotone Operators

Theorem:

For a sequence of monotone linear operators  $L_n$  on  $C[1, b]$ , the following conditions are equivalent:

1.  $L_n f \rightarrow f$  for all  $f \in C[a, b]$
2.  $L_n f \rightarrow f$  for the three functions  $f(x) = 1, x, x^2$
3.  $L_n f \rightarrow 1$  and  $(L_n \phi_t)(t) \rightarrow 0$  in  $t$  where  $\phi_t(x) = (t - x)^2$

Proof:

(1  $\rightarrow$  2) is trivial.

(2  $\rightarrow$  3)

Define:  $f_i(x) = x^i$ .

Now:

$$\phi_t(x) = (t - x)^2$$

$$= t^2 - 2tx + x^2$$

$$\phi_t = t^2 f_0 - 2t f_1 + f_2$$

$$L_n \phi_t = t^2 L_n f_0 - 2t L_n f_1 + L_n f_2$$

$$(L_n \phi_t)(t) = t^2 (L_n f_0)(t) - 2t (L_n f_1)(t) + (L_n f_2)(t) - t^2$$

$$= t^2 [(L_n f_0)(t) - 1] - 2t [(L_n f_1)(t) - t] + [(L_n f_2)(t) - t^2]$$

$$\leq t^2 \|L_n f_0 - 1\| - |2t| \|L_n f_1 - t\| + \|L_n f_2 - t^2\|$$

$$\rightarrow t^2 \|1 - 1\| - |2t| \|t - t\| + \|t^2 - t^2\| = 0$$

(3  $\rightarrow$  1)

We begin by selecting  $\sigma$  such that:

$$|x - y| < \sigma \rightarrow |f(x) - f(y)| < \epsilon \quad (\sigma > 0, \epsilon > 0)$$

Now set  $\alpha = 2\|f\|\sigma^{-2}$  and let  $t$  be an arbitrary but fixed point of  $[1, b]$ . If  $|t - x| < \sigma$ , then  $|f(t) - f(x)| < \epsilon$ . Whereas if  $|t - x| \geq \sigma$ , then:

$$|f(t) - f(x)| \leq |f(t)| + |f(x)|$$

$$\leq 2\|f\|$$

$$\leq 2\|f\| \frac{(t-x)^2}{\sigma^2}$$

$$= \alpha\sigma_t(x)$$

Thus for all  $x$ , the following inequality is satisfied:

$$-\epsilon - \alpha\sigma_t(x) \leq f(t) - f(x) \leq \epsilon + \alpha\sigma_t(x)$$

Let  $f_0(x) = 1$ . Then we have:

$$-\epsilon f_0 - \alpha\sigma_t \leq f(t)f_0 - f \leq \epsilon f_0 + \alpha\sigma_t$$

By the linearity and monotonicity of  $L_n$  we have:

$$-\epsilon(L_nf_0)(t) - \alpha(L_n\sigma_t) \leq f(t)(L_nf_0)(t) - (L_nf)(t) \leq \epsilon(L_nf_0)(t) + \alpha(L_n\sigma_t)(t)$$

This yields:

$$|f(t)(L_nf_0)(t) - (L_nf)(t)| \leq \epsilon(L_nf_0)(t) + \alpha(L_n\sigma_t)(t) \leq \epsilon\|L_nf_0\| + \alpha(L_n\sigma_t)(t)$$

Since  $L_nf_0 \rightarrow f_0$  and  $(L_n\sigma_t)(t) \rightarrow 0$  we have that the above expression goes to  $|f(t) - (L_nf)(t)| < \epsilon$ .

## 10 Proof of the Weierstrass Theorem

I am first going to prove the theorem for the interval  $[0, 1]$  and then extend it to a given interval  $[a, b]$ . I will show that for any  $f \in C[0, 1]$ . The Bernstein polynomials  $B_nf$  converge to  $f$ . the linearity and monotonicity of  $B_n$  have already been mentioned. By the theorem on monotone operators it will suffice to show that  $B_nf \rightarrow f$  for  $f(x) = 1, x$ , and  $x^2$ .

Now applying the binomial theorem, which states that:

$$\sum_{k=0}^n \binom{n}{k} a^k b^{n-k} = (a + b)^n$$

We have:

$$(B_n 1)(x) = \sum_{k=0}^n \binom{n}{k} x^k (1-x)^{n-k} = [x + (1-x)]^n = 1$$

And for the function  $f(x) = x$ :

$$(B_n f)(x) = \sum_{k=0}^n \frac{k}{n} \binom{n}{k} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{k}{n} \binom{n}{k} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{kn!}{n(n-k)!k!} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{(n-1)!}{[n-1-(k-1)]!(k-1)!} x^k (1-x)^{n-k}$$

$$= x \sum_{k=0}^{n-1} \binom{n-1}{k} x^k (1-x)^{n-1-k}$$

$$= x [x + (1-x)]^{n-1} = x$$

For the function  $f(x) = x^2$  we have:

$$(B_n f)(x) = \sum_{k=0}^n \left(\frac{k}{n}\right)^2 \binom{n}{k} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{k}{n} \frac{(n-1)!}{[n-1-(k-1)]!(k-1)!} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{k}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k}$$

$$= \sum_{k=1}^n \frac{(k-1)}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k} + \sum_{k=1}^n \frac{1}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k}$$

$$\begin{aligned}
&= \frac{(n-1)}{n} \sum_{k=1}^n \frac{(k-1)}{(n-1)} \binom{n-1}{k-1} x^k (1-x)^{n-k} + \frac{1}{n} \\
&\quad \sum_{k=1}^n \frac{1}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k} \\
&= \frac{(n-1)}{n} \sum_{k=2}^n \left( \frac{k-1}{n-1} \right) \left( \frac{(n-1)!}{[n-1-(k-1)]!(k-1)!} \right) x^k (1-x)^{n-k} + \frac{1}{n} \\
&\quad \sum_{k=1}^n \frac{1}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k} \\
&= \frac{(n-1)}{n} \sum_{k=2}^n \left( \frac{(n-2)!}{[n-2-(k-2)]!(k-2)!} \right) x^k (1-x)^{n-k} + \frac{1}{n} \\
&\quad \sum_{k=1}^n \frac{1}{n} \binom{n-1}{k-1} x^k (1-x)^{n-k} \\
&= \frac{(n-1)}{n} \sum_{k=2}^n \binom{n-2}{k-2} x^k (1-x)^{n-k} + \frac{1}{n} \\
&\quad \sum_{k=1}^n \binom{n-1}{k-1} x^k (1-x)^{n-k} \\
&= \frac{(n-1)}{n} \sum_{k=0}^{n-2} \binom{n-2}{k} x^{k+2} (1-x)^{n-(k+2)} + \frac{1}{n} \\
&\quad \sum_{k=0}^{n-1} \binom{n-1}{k} x^{k+1} (1-x)^{n-(k+1)} \\
&= \frac{(n-1)x^2}{n} \sum_{k=0}^{n-2} \binom{n-2}{k} x^k (1-x)^{n-2-k} + \frac{x}{n} \\
&\quad \sum_{k=0}^{n-1} \binom{n-1}{k} x^k (1-x)^{n-1-k} \\
&= \frac{(n-1)x^2}{n} [x + (1-x)]^{n-2} + \frac{x}{n} [x + (1-x)]^{n-1} \\
&= \frac{(n-1)x^2}{n} + \frac{x}{n} \rightarrow x^2
\end{aligned}$$

I will extend this theorem to apply to an arbitrary interval  $[a, b]$ . That is, for a function  $f \in C[a, b]$ .

Clearly;  $g(x) = a + x(b - a)$  is continuous on  $[0, 1]$

and on  $[0, 1]$ ,  $g(x) = [a, b]$ . Thus for  $\sigma(x) = fg$ ,  $\sigma(x)$  is continuous on  $[0, 1]$ .

Therefore, the Bernstein polynomials converge to  $\sigma(x)$  on  $[0, 1]$ . But:

$$\begin{aligned}\sigma(x) &= f[a + x(b - a)] \quad (x \in [0, 1]) \\ &= f(y) \quad (x \in [a, b])\end{aligned}$$

Thus, the Bernstein polynomials converge to  $f$  on  $[a, b]$ .

This theorem would serve to indicate that a polynomial constructed from a sequence of polynomials would satisfy our requirements for an approximation to  $f \in C[a, b]$ .

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