MAP 2220 – FUNDAMENTOS DE ANÁLISE NUMÉRICA 2º Semestre - 2017

Prof. Dr. Luis Carlos de Castro Santos

Isantos@ime.usp.br/lccs13@yahoo.com

3 Interpolation and Polynomial Approximation 105

- 2.1 Interpolation and the Learning Polynomial 106
- 3.2 Data Approximation and Neville's Method 117
- 3.3 Divided Differences 124
- 3.4 Hermite Interpolation 136
- 3.5 Cubic Spline Interpolation 144
- 3.6 Parametric Curves 164
- 3.7 Survey of Methods and Software 171

3.2 Data Approximation and Neville's Method

In the previous section we found an explicit representation for Lagrange polynomials and their error when approximating a function on an interval. A frequent use of these polynomials involves the interpolation of tabulated data. In this case an explicit representation of the polynomial might not be needed, only the values of the polynomial at specified points. In this situation the function underlying the data might not be known so the explicit form of the error cannot be used. We will now illustrate a practical application of interpolation in such a situation.

$$P(x) = f(x_0)L_{n,0}(x) + \dots + f(x_n)L_{n,n}(x) = \sum_{k=0}^{n} f(x_k)L_{n,k}(x),$$
(3.1)

where, for each $k = 0, 1, \dots, n$,

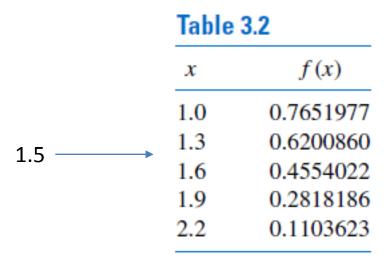
$$L_{n,k}(x) = \frac{(x - x_0)(x - x_1) \cdots (x - x_{k-1})(x - x_{k+1}) \cdots (x - x_n)}{(x_k - x_0)(x_k - x_1) \cdots (x_k - x_{k-1})(x_k - x_{k+1}) \cdots (x_k - x_n)}$$
(3.2)

$$= \prod_{\substack{i=0\\i\neq l}}^{n} \frac{(x-x_i)}{(x_k-x_i)}.$$

$$f(x) = P(x) + \frac{f^{(n+1)}(\xi(x))}{(n+1)!}(x - x_0)(x - x_1) \cdots (x - x_n), \tag{3.3}$$

Illustration

Table 3.2 lists values of a function f at various points. The approximations to f(1.5) obtained by various Lagrange polynomials that use this data will be compared to try and determine the accuracy of the approximation.



The most appropriate linear polynomial uses $x_0 = 1.3$ and $x_1 = 1.6$ because 1.5 is between 1.3 and 1.6. The value of the interpolating polynomial at 1.5 is

$$P_1(1.5) = \frac{(1.5 - 1.6)}{(1.3 - 1.6)} f(1.3) + \frac{(1.5 - 1.3)}{(1.6 - 1.3)} f(1.6)$$

$$= \frac{(1.5 - 1.6)}{(1.3 - 1.6)} (0.6200860) + \frac{(1.5 - 1.3)}{(1.6 - 1.3)} (0.4554022) = 0.5102968.$$

Two polynomials of degree 2 can reasonably be used, one with $x_0 = 1.3$, $x_1 = 1.6$, and $x_2 = 1.9$, which gives

$$P_2(1.5) = \frac{(1.5 - 1.6)(1.5 - 1.9)}{(1.3 - 1.6)(1.3 - 1.9)}(0.6200860) + \frac{(1.5 - 1.3)(1.5 - 1.9)}{(1.6 - 1.3)(1.6 - 1.9)}(0.4554022) + \frac{(1.5 - 1.3)(1.5 - 1.6)}{(1.9 - 1.3)(1.9 - 1.6)}(0.2818186) = 0.5112857,$$

and one with $x_0 = 1.0$, $x_1 = 1.3$, and $x_2 = 1.6$, which gives $\hat{P}_2(1.5) = 0.5124715$.

In the third-degree case, there are also two reasonable choices for the polynomial. One with $x_0 = 1.3$, $x_1 = 1.6$, $x_2 = 1.9$, and $x_3 = 2.2$, which gives $P_3(1.5) = 0.5118302$. The second third-degree approximation is obtained with $x_0 = 1.0$, $x_1 = 1.3$, $x_2 = 1.6$, and $x_3 = 1.9$, which gives $\hat{P}_3(1.5) = 0.5118127$.

The fourth-degree Lagrange polynomial uses all the entries in the table. With $x_0 = 1.0$, $x_1 = 1.3$, $x_2 = 1.6$, $x_3 = 1.9$, and $x_4 = 2.2$, the approximation is $P_4(1.5) = 0.5118200$.

Because $P_3(1.5)$, $\hat{P}_3(1.5)$, and $P_4(1.5)$ all agree to within 2×10^{-5} units, we expect this degree of accuracy for these approximations. We also expect $P_4(1.5)$ to be the most accurate approximation, since it uses more of the given data.

The function we are approximating is actually the Bessel function of the first kind of order zero, whose value at 1.5 is known to be 0.5118277. Therefore, the true accuracies of the approximations are as follows:

$$|P_1(1.5) - f(1.5)| \approx 1.53 \times 10^{-3},$$

 $|P_2(1.5) - f(1.5)| \approx 5.42 \times 10^{-4},$
 $|\hat{P}_2(1.5) - f(1.5)| \approx 6.44 \times 10^{-4},$
 $|P_3(1.5) - f(1.5)| \approx 2.5 \times 10^{-6},$
 $|\hat{P}_3(1.5) - f(1.5)| \approx 1.50 \times 10^{-5},$
 $|P_4(1.5) - f(1.5)| \approx 7.7 \times 10^{-6}.$

Although $P_3(1.5)$ is the most accurate approximation, if we had no knowledge of the actual value of f(1.5), we would accept $P_4(1.5)$ as the best approximation since it includes the most data about the function. The Lagrange error term derived in Theorem 3.3 cannot be applied here because we have no knowledge of the fourth derivative of f. Unfortunately, this is generally the case.

Neville's Method

A practical difficulty with Lagrange interpolation is that the error term is difficult to apply, so the degree of the polynomial needed for the desired accuracy is generally not known until computations have been performed. A common practice is to compute the results given from various polynomials until appropriate agreement is obtained, as was done in the previous Illustration. However, the work done in calculating the approximation by the second polynomial does not lessen the work needed to calculate the third approximation; nor is the fourth approximation easier to obtain once the third approximation is known, and so on. We will now derive these approximating polynomials in a manner that uses the previous calculations to greater advantage.

Definition 3.4

Let f be a function defined at $x_0, x_1, x_2, \ldots, x_n$, and suppose that m_1, m_2, \ldots, m_k are k distinct integers, with $0 \le m_i \le n$ for each i. The Lagrange polynomial that agrees with f(x) at the k points $x_{m_1}, x_{m_2}, \ldots, x_{m_k}$ is denoted $P_{m_1, m_2, \ldots, m_k}(x)$.

Suppose that $x_0 = 1$, $x_1 = 2$, $x_2 = 3$, $x_3 = 4$, $x_4 = 6$, and $f(x) = e^x$. Determine the interpolating polynomial denoted $P_{1,2,4}(x)$, and use this polynomial to approximate f(5).

Solution This is the Lagrange polynomial that agrees with f(x) at $x_1 = 2$, $x_2 = 3$, and $x_4 = 6$. Hence

$$P_{1,2,4}(x) = \frac{(x-3)(x-6)}{(2-3)(2-6)}e^2 + \frac{(x-2)(x-6)}{(3-2)(3-6)}e^3 + \frac{(x-2)(x-3)}{(6-2)(6-3)}e^6.$$

So

$$f(5) \approx P(5) = \frac{(5-3)(5-6)}{(2-3)(2-6)}e^2 + \frac{(5-2)(5-6)}{(3-2)(3-6)}e^3 + \frac{(5-2)(5-3)}{(6-2)(6-3)}e^6$$
$$= -\frac{1}{2}e^2 + e^3 + \frac{1}{2}e^6 \approx 218.105.$$

Theorem 3.5

Let f be defined at x_0, x_1, \ldots, x_k , and let x_j and x_i be two distinct numbers in this set. Then

$$P(x) = \frac{(x - x_j)P_{0,1,\dots,j-1,j+1,\dots,k}(x) - (x - x_i)P_{0,1,\dots,i-1,i+1,\dots,k}(x)}{(x_i - x_j)}$$

is the kth Lagrange polynomial that interpolates f at the k+1 points x_0, x_1, \ldots, x_k .

Proof For ease of notation, let $Q \equiv P_{0,1,\dots,i-1,i+1,\dots,k}$ and $\hat{Q} \equiv P_{0,1,\dots,j-1,j+1,\dots,k}$. Since Q(x) and $\hat{Q}(x)$ are polynomials of degree k-1 or less, P(x) is of degree at most k.

First note that $\hat{Q}(x_i) = f(x_i)$, implies that

$$P(x_i) = \frac{(x_i - x_j)\hat{Q}(x_i) - (x_i - x_i)Q(x_i)}{x_i - x_j} = \frac{(x_i - x_j)}{(x_i - x_j)}f(x_i) = f(x_i).$$

Similarly, since $Q(x_j) = f(x_j)$, we have $P(x_j) = f(x_j)$.

In addition, if $0 \le r \le k$ and r is neither i nor j, then $Q(x_r) = \hat{Q}(x_r) = f(x_r)$. So

$$P(x_r) = \frac{(x_r - x_j)\hat{Q}(x_r) - (x_r - x_i)Q(x_r)}{x_i - x_j} = \frac{(x_i - x_j)}{(x_i - x_j)}f(x_r) = f(x_r).$$

But, by definition, $P_{0,1,...,k}(x)$ is the unique polynomial of degree at most k that agrees with f at x_0, x_1, \ldots, x_k . Thus, $P \equiv P_{0,1,...,k}$.

Theorem 3.5 implies that the interpolating polynomials can be generated recursively. For example, we have

$$P_{0,1} = \frac{1}{x_1 - x_0} [(x - x_0)P_1 - (x - x_1)P_0], \qquad P_{1,2} = \frac{1}{x_2 - x_1} [(x - x_1)P_2 - (x - x_2)P_1],$$

$$P_{0,1,2} = \frac{1}{x_2 - x_0} [(x - x_0)P_{1,2} - (x - x_2)P_{0,1}],$$

and so on. They are generated in the manner shown in Table 3.3, where each row is completed before the succeeding rows are begun.

_				
	-	~	-,	-,
124	nı	-	-	-
			•	

x_0	P_0				
x_1	P_1	$P_{0,1}$			
x_2	P_2	$P_{1,2}$	$P_{0,1,2}$		
x_3	P_3	$P_{2,3}$	$P_{1,2,3}$	$P_{0,1,2,3}$	
x_4	P_4	$P_{3,4}$	$P_{2,3,4}$	$P_{1,2,3,4}$	$P_{0,1,2,3,4}$

The procedure that uses the result of Theorem 3.5 to recursively generate interpolating polynomial approximations is called **Neville's method**. The P notation used in Table 3.3 is cumbersome because of the number of subscripts used to represent the entries. Note, however, that as an array is being constructed, only two subscripts are needed. Proceeding down the table corresponds to using consecutive points x_i with larger i, and proceeding to the right corresponds to increasing the degree of the interpolating polynomial. Since the points appear consecutively in each entry, we need to describe only a starting point and the number of additional points used in constructing the approximation.

To avoid the multiple subscripts, we let $Q_{i,j}(x)$, for $0 \le j \le i$, denote the interpolating polynomial of degree j on the (j + 1) numbers $x_{i-j}, x_{i-j+1}, \dots, x_{i-1}, x_i$; that is,

$$Q_{i,j} = P_{i-j,i-j+1,...,i-1,i}.$$

Using this notation provides the Q notation array in Table 3.4.

Table 3.4

Example 2

Values of various interpolating polynomials at x = 1.5 were obtained in the Illustration at the beginning of the Section using the data shown in Table 3.5. Apply Neville's method to the data by constructing a recursive table of the form shown in Table 3.4.

Table 3.5

x	f(x)
1.0	0.7651977
1.3	0.6200860
1.6	0.4554022
1.9	0.2818186
2.2	0.1103623



Table 3.6

1.0	0.7651977				
1.3	0.6200860	0.5233449			
1.6	0.4554022	0.5102968	0.5124715		
1.9	0.2818186	0.5132634	0.5112857	0.5118127	
2.2	0.1103623	0.5104270	0.5137361	0.5118302	0.5118200

If the latest approximation, $Q_{4,4}$, was not sufficiently accurate, another node, x_5 , could be selected, and another row added to the table:

$$x_5$$
 $Q_{5,0}$ $Q_{5,1}$ $Q_{5,2}$ $Q_{5,3}$ $Q_{5,4}$ $Q_{5,5}$.

Then $Q_{4,4}$, $Q_{5,4}$, and $Q_{5,5}$ could be compared to determine further accuracy.

The function in Example 2 is the Bessel function of the first kind of order zero, whose value at 2.5 is -0.0483838, and the next row of approximations to f(1.5) is

 $2.5 - 0.0483838 \quad 0.4807699 \quad 0.5301984 \quad 0.5119070 \quad 0.5118430 \quad 0.5118277.$

The final new entry, 0.5118277, is correct to all seven decimal places.

Neville's Iterated Interpolation

To evaluate the interpolating polynomial P on the n+1 distinct numbers x_0, \ldots, x_n at the number x for the function f:

INPUT numbers
$$x, x_0, x_1, \ldots, x_n$$
; values $f(x_0), f(x_1), \ldots, f(x_n)$ as the first column $Q_{0,0}, Q_{1,0}, \ldots, Q_{n,0}$ of Q .

OUTPUT the table Q with $P(x) = Q_{n,n}$.

Step 1 For
$$i = 1, 2, ..., n$$

for $j = 1, 2, ..., i$

$$set Q_{i,j} = \frac{(x - x_{i-j})Q_{i,j-1} - (x - x_i)Q_{i-1,j-1}}{x_i - x_{i-j}}.$$

Step 2 OUTPUT
$$(Q)$$
; STOP.

The algorithm can be modified to allow for the addition of new interpolating nodes. For example, the inequality

$$|Q_{i,i} - Q_{i-1,i-1}| < \varepsilon$$

can be used as a stopping criterion, where ε is a prescribed error tolerance. If the inequality is true, $Q_{i,i}$ is a reasonable approximation to f(x). If the inequality is false, a new interpolation point, x_{i+1} , is added.

3.3 Divided Differences

Iterated interpolation was used in the previous section to generate successively higher-degree polynomial approximations at a specific point. Divided-difference methods introduced in this section are used to successively generate the polynomials themselves.

Suppose that $P_n(x)$ is the *n*th Lagrange polynomial that agrees with the function f at the distinct numbers x_0, x_1, \ldots, x_n . Although this polynomial is unique, there are alternate algebraic representations that are useful in certain situations. The divided differences of f with respect to x_0, x_1, \ldots, x_n are used to express $P_n(x)$ in the form

$$P_n(x) = a_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_n(x - x_0) + \dots + a_{n-1}(x - x_{n-1}), \quad (3.5)$$

for appropriate constants a_0, a_1, \ldots, a_n . To determine the first of these constants, a_0 , note that if $P_n(x)$ is written in the form of Eq. (3.5), then evaluating $P_n(x)$ at x_0 leaves only the constant term a_0 ; that is,

$$a_0 = P_n(x_0) = f(x_0).$$

Similarly, when P(x) is evaluated at x_1 , the only nonzero terms in the evaluation of $P_n(x_1)$ are the constant and linear terms,

$$f(x_0) + a_1(x_1 - x_0) = P_n(x_1) = f(x_1);$$

SO

$$a_1 = \frac{f(x_1) - f(x_0)}{x_1 - x_0}. (3.6)$$

We now introduce the divided-difference notation, which is related to Aitken's Δ^2 notation used in Section 2.5. The *zeroth divided difference* of the function f with respect to x_i , denoted $f[x_i]$, is simply the value of f at x_i :

$$f[x_i] = f(x_i). (3.7)$$

The remaining divided differences are defined recursively; the *first divided difference* of f with respect to x_i and x_{i+1} is denoted $f[x_i, x_{i+1}]$ and defined as

$$f[x_i, x_{i+1}] = \frac{f[x_{i+1}] - f[x_i]}{x_{i+1} - x_i}.$$
(3.8)

The second divided difference, $f[x_i, x_{i+1}, x_{i+2}]$, is defined as

$$f[x_i, x_{i+1}, x_{i+2}] = \frac{f[x_{i+1}, x_{i+2}] - f[x_i, x_{i+1}]}{x_{i+2} - x_i}.$$

Similarly, after the (k-1)st divided differences,

$$f[x_i, x_{i+1}, x_{i+2}, \dots, x_{i+k-1}]$$
 and $f[x_{i+1}, x_{i+2}, \dots, x_{i+k-1}, x_{i+k}]$,

have been determined, the kth divided difference relative to $x_i, x_{i+1}, x_{i+2}, \dots, x_{i+k}$ is

$$f[x_i, x_{i+1}, \dots, x_{i+k-1}, x_{i+k}] = \frac{f[x_{i+1}, x_{i+2}, \dots, x_{i+k}] - f[x_i, x_{i+1}, \dots, x_{i+k-1}]}{x_{i+k} - x_i}.$$
 (3.9)

The process ends with the single *nth divided difference*,

$$f[x_0, x_1, \dots, x_n] = \frac{f[x_1, x_2, \dots, x_n] - f[x_0, x_1, \dots, x_{n-1}]}{x_n - x_0}.$$

Because of Eq. (3.6) we can write $a_1 = f[x_0, x_1]$, just as a_0 can be expressed as $a_0 = f(x_0) = f[x_0]$. Hence the interpolating polynomial in Eq. (3.5) is

$$P_n(x) = f[x_0] + f[x_0, x_1](x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_n(x - x_0)(x - x_1) \dots (x - x_{n-1}).$$

As might be expected from the evaluation of a_0 and a_1 , the required constants are

$$a_k = f[x_0, x_1, x_2, \dots, x_k],$$

for each k = 0, 1, ..., n. So $P_n(x)$ can be rewritten in a form called Newton's Divided-Difference:

$$P_n(x) = f[x_0] + \sum_{k=1}^n f[x_0, x_1, \dots, x_k](x - x_0) \cdots (x - x_{k-1}).$$
 (3.10)

The generation of the divided differences is outlined in Table 3.9. Two fourth and one fifth difference can also be determined from these data.

Table 3.9

x	f(x)	First divided differences	Second divided differences	Third divided differences
<i>x</i> ₀	$f[x_0]$	$f[x_0, x_1] = \frac{f[x_1] - f[x_0]}{x_1 - x_2}$		
x_1	$f[x_1]$	$f[x_1, x_2] = \frac{f[x_2] - f[x_1]}{f[x_1, x_2]}$	$f[x_0, x_1, x_2] = \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0}$	$f[x_1, x_2, x_3] - f[x_0, x_1, x_2]$
<i>x</i> ₂	$f[x_2]$	$x_2 - x_1$	$f[x_1, x_2, x_3] = \frac{f[x_2, x_3] - f[x_1, x_2]}{x_3 - x_1}$	$f[x_0, x_1, x_2, x_3] = \frac{f[x_1, x_2, x_3] - f[x_0, x_1, x_2]}{x_3 - x_0}$
<i>X</i> ₃	$f[x_3]$	$f[x_2, x_3] = \frac{f[x_3] - f[x_2]}{x_3 - x_2}$	$f[x_2, x_3, x_4] = \frac{f[x_3, x_4] - f[x_2, x_3]}{x_4 - x_2}$	$f[x_1, x_2, x_3, x_4] = \frac{f[x_2, x_3, x_4] - f[x_1, x_2, x_3]}{x_4 - x_1}$
		$f[x_3, x_4] = \frac{f[x_4] - f[x_3]}{x_4 - x_3}$	$x_4 - x_2$	$f[x_2, x_3, x_4, x_5] = \frac{f[x_3, x_4, x_5] - f[x_2, x_3, x_4]}{x_5 - x_2}$
x_4	$f[x_4]$	$f[x_4, x_5] = \frac{f[x_5] - f[x_4]}{x_5 - x_4}$	$f[x_3, x_4, x_5] = \frac{f[x_4, x_5] - f[x_3, x_4]}{x_5 - x_3}$	
<i>x</i> ₅	$f[x_5]$	x ₅ - x ₄		

Newton's Divided-Difference Formula

To obtain the divided-difference coefficients of the interpolatory polynomial P on the (n+1) distinct numbers x_0, x_1, \ldots, x_n for the function f:

INPUT numbers $x_0, x_1, ..., x_n$; values $f(x_0), f(x_1), ..., f(x_n)$ as $F_{0,0}, F_{1,0}, ..., F_{n,0}$.

OUTPUT the numbers $F_{0,0}, F_{1,1}, \ldots, F_{n,n}$ where

$$P_n(x) = F_{0,0} + \sum_{i=1}^n F_{i,i} \prod_{j=0}^{i-1} (x - x_j).$$
 (F_{i,i} is $f[x_0, x_1, \dots, x_i].$)

Step 1 For
$$i = 1, 2, ..., n$$

For $j = 1, 2, ..., i$

$$set F_{i,j} = \frac{F_{i,j-1} - F_{i-1,j-1}}{x_i - x_{i-j}}. \quad (F_{i,j} = f[x_{i-j}, ..., x_i].)$$

Step 2 OUTPUT $(F_{0,0}, F_{1,1}, ..., F_{n,n})$; STOP.

Example 1

Complete the divided difference table for the data used in Example 1 of Section 3.2, and reproduced in Table 3.10, and construct the interpolating polynomial that uses all this data.

_		•	4	
Ta	nı	-	7	•
ıa	IJ.	υ,		u

х	f(x)
1.0	0.7651977
1.3	0.6200860
1.6	0.4554022
1.9	0.2818186
2.2	0.1103623



i	x_i	$f[x_i]$	$f[x_{i-1},x_i]$	$f[x_{i-2},x_{i-1},x_i]$	$f[x_{i-3},\ldots,x_i]$	$f[x_{i-4},\ldots,x_i]$
0	1.0	0.7651977				
			-0.4837057			
1	1.3	0.6200860		-0.1087339		
			-0.5489460		0.0658784	
2	1.6	0.4554022		-0.0494433		0.0018251
			-0.5786120		0.0680685	
3	1.9	0.2818186		0.0118183		
			-0.5715210			
4	2.2	0.1103623				

The coefficients of the Newton forward divided-difference form of the interpolating polynomial are along the diagonal in the table. This polynomial is

$$P_4(x) = 0.7651977 - 0.4837057(x - 1.0) - 0.1087339(x - 1.0)(x - 1.3)$$
$$+ 0.0658784(x - 1.0)(x - 1.3)(x - 1.6)$$
$$+ 0.0018251(x - 1.0)(x - 1.3)(x - 1.6)(x - 1.9).$$

Notice that the value $P_4(1.5) = 0.5118200$ agrees with the result in Table 3.6 for Example 2 of Section 3.2, as it must because the polynomials are the same.

The Mean Value Theorem 1.8 applied to Eq. (3.8) when i = 0,

$$f[x_0, x_1] = \frac{f(x_1) - f(x_0)}{x_1 - x_0},$$

implies that when f' exists, $f[x_0, x_1] = f'(\xi)$ for some number ξ between x_0 and x_1 . The following theorem generalizes this result.

Suppose that $f \in C^n[a, b]$ and x_0, x_1, \dots, x_n are distinct numbers in [a, b]. Then a number ξ exists in (a, b) with

$$f[x_0, x_1, \ldots, x_n] = \frac{f^{(n)}(\xi)}{n!}.$$

Proof Let

$$g(x) = f(x) - P_n(x).$$

Since $f(x_i) = P_n(x_i)$ for each i = 0, 1, ..., n, the function g has n + 1 distinct zeros in [a, b]. Generalized Rolle's Theorem 1.10 implies that a number ξ in (a, b) exists with $g^{(n)}(\xi) = 0$, so

$$0 = f^{(n)}(\xi) - P_n^{(n)}(\xi).$$

Since $P_n(x)$ is a polynomial of degree n whose leading coefficient is $f[x_0, x_1, \dots, x_n]$,

$$P_n^{(n)}(x) = n! f[x_0, x_1, \dots, x_n],$$

for all values of x. As a consequence,

$$f[x_0, x_1, \dots, x_n] = \frac{f^{(n)}(\xi)}{n!}.$$

Newton's divided-difference formula can be expressed in a simplified form when the nodes are arranged consecutively with equal spacing. In this case, we introduce the notation $h = x_{i+1} - x_i$, for each i = 0, 1, ..., n - 1 and let $x = x_0 + sh$. Then the difference $x - x_i$ is $x - x_i = (s - i)h$. So Eq. (3.10) becomes

$$P_n(x) = P_n(x_0 + sh) = f[x_0] + shf[x_0, x_1] + s(s - 1)h^2 f[x_0, x_1, x_2]$$
$$+ \dots + s(s - 1) \dots (s - n + 1)h^n f[x_0, x_1, \dots, x_n]$$
$$= f[x_0] + \sum_{k=1}^n s(s - 1) \dots (s - k + 1)h^k f[x_0, x_1, \dots, x_k].$$

Using binomial-coefficient notation,

$$\binom{s}{k} = \frac{s(s-1)\cdots(s-k+1)}{k!},$$

we can express $P_n(x)$ compactly as

$$P_n(x) = P_n(x_0 + sh) = f[x_0] + \sum_{k=1}^n \binom{s}{k} k! h^k f[x_0, x_i, \dots, x_k].$$
 (3.11)

EXERCISE SET 3.3

- Use Eq. (3.10) or Algorithm 3.2 to construct interpolating polynomials of degree one, two, and three
 for the following data. Approximate the specified value using each of the polynomials.
 - a. f(8.4) if f(8.1) = 16.94410, f(8.3) = 17.56492, f(8.6) = 18.50515, f(8.7) = 18.82091
 - **b.** f(0.9) if f(0.6) = -0.17694460, f(0.7) = 0.01375227, f(0.8) = 0.22363362, f(1.0) = 0.65809197

3 Interpolation and Polynomial Approximation 105

- 2.1 Interpolation and the Lagrange Polynomial 106
- 3.2 Data Approximation and Navilla's Mathod 117
- 3.3 Divided Differences 124
- 3.4 Hermite Interpolation 136
- 3.5 Cubic Spline Interpolation 144
- 3.6 Parametric Curves 164
- 3.7 Survey of Methods and Software 171

