

# Polynomial interpolation: Newton interpolation

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The Python codes for this note are given in `polynomialinterpolation.py`.

## 1 Introduction

We continue with an alternative approach to find the interpolation polynomial.

### 1.1 Newton interpolation

This is an alternative approach to find the interpolation polynomial. Let  $x_0, x_1, \dots, x_n$  be  $n + 1$  distinct real numbers. Instead of using the Lagrange polynomials to write the interpolation polynomial in Lagrange form, we will now employ the **Newton** polynomials  $\omega_i$ ,  $i = 0, \dots, n$ . The Newton polynomials are defined by as follows:

$$\begin{aligned}\omega_0(x) &= 1, \\ \omega_1(x) &= (x - x_0), \\ \omega_2(x) &= (x - x_0)(x - x_1), \\ &\dots \\ \omega_n(x) &= (x - x_0)(x - x_1) \cdots (x - x_{n-1}),\end{aligned}$$

or in more compact notation

$$\omega_i(x) = \prod_{k=0}^{i-1} (x - x_k). \quad (1)$$

The so-called **Newton form** of a polynomial of degree  $n$  is an expansion of the form

$$p(x) = \sum_{i=0}^n c_i \omega_i(x)$$

or more explicitly

$$p(x) = c_n(x - x_0)(x - x_1) \cdots (x - x_{n-1}) + c_{n-1}(x - x_0)(x - x_1) \cdots (x - x_{n-2}) + \cdots + c_1(x - x_0) + c_0.$$

In the light of this form of writing a polynomial, the polynomial interpolation problem leads to the following observations. Let us start with a single node  $x_0$ , then  $f(x_0) = p(x_0) = c_0$ . Going one step further and consider two nodes  $x_0, x_1$ . Then we see that  $f(x_0) = p(x_0) = c_0$  and  $f(x_1) = p(x_1) = c_0 + c_1(x_1 - x_0)$ . The latter implies that the coefficient

$$c_1 = \frac{f(x_1) - f(x_0)}{x_1 - x_0}.$$

Given three nodes  $x_0, x_1, x_2$  yields the coefficients  $c_0, c_1$  as defined above, and from

$$f(x_2) = p(x_2) = c_0 + c_1(x_2 - x_0) + c_2(x_2 - x_0)(x_2 - x_1)$$

we deduce the coefficient

$$c_2 = \frac{f(x_2) - f(x_0) - \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x_2 - x_0)}{(x_2 - x_0)(x_2 - x_1)}.$$

Playing with this quotient gives the much more structured expression

$$c_2 = \frac{\frac{f(x_2) - f(x_1)}{x_2 - x_1} - \frac{f(x_1) - f(x_0)}{x_1 - x_0}}{(x_2 - x_0)}.$$

This procedure can be continued and yields a so-called triangular systems that permits to define the remaining coefficients  $c_3, \dots, c_n$ . One sees quickly that the coefficient  $c_k$  only depends on the interpolation points  $(x_0, y_0), \dots, (x_k, y_k)$ , where  $y_i := f(x_i)$ ,  $i = 0, \dots, n$ .

We introduce the following so-called **finite difference** notation for a function  $f$ . The 0th order finite difference is defined to be  $f[x_0] := f(x_0)$ . The 1st order finite difference is

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

The second order finite difference is defined by

$$f[x_0, x_1, x_2] := \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0}.$$

In general, the **nth order finite difference** of the function  $f$ , also called the **nth Newton divided difference**, is defined recursively by

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

Newton's method to solve the polynomial interpolation problem can be summarized as follows. Given  $n + 1$  interpolation points  $(x_0, y_0), \dots, (x_n, y_n)$ ,  $y_i := f(x_i)$ . If the order  $n$  interpolation polynomial is expressed in Newton's form

$$p_n(x) = c_n(x - x_0)(x - x_1) \cdots (x - x_{n-1}) + c_{n-1}(x - x_0)(x - x_1) \cdots (x - x_{n-2}) + \cdots + c_1(x - x_0) + c_0,$$

then the coefficients

$$c_k = f[x_0, \dots, x_k]$$

for  $k = 0, \dots, n$ . In fact, a recursion is in place

$$p_n(x) = p_{n-1}(x) + f[x_0, \dots, x_n](x - x_0)(x - x_1) \cdots (x - x_{n-1})$$

It is common to write the finite differences in a table, which for  $n = 3$  will look like:

$$\begin{array}{l|l} x_0 & f[x_0] \\ & f[x_0, x_1] \\ x_1 & f[x_1] & f[x_0, x_1, x_2] \\ & f[x_1, x_2] & f[x_0, x_1, x_2, x_3] \\ x_2 & f[x_2] & f[x_1, x_2, x_3] \\ & f[x_2, x_3] \\ x_3 & f[x_3] \end{array}$$

**Example 1 again:** Given the points in Example 1. The corresponding table of divided differences becomes:

0	1		
		-3/4	
2/3	1/2		-3/4
		-3/2	
1	0		

and the interpolation polynomial becomes

$$p_2(x) = 1 - \frac{3}{4}(x - 0) - \frac{3}{4}(x - 0)(x - \frac{2}{3}) = 1 - \frac{1}{4}x - \frac{3}{4}x^2.$$

## 1.2 Implementation

The method above is implemented as two functions:

- `divdiff(xdata, ydata)`: Create the table of divided differences
- `newtonInterpolation(F, xdata, x)`: Evaluate the interpolation polynomial.

Here, `xdata` and `ydata` are arrays with the interpolation points, and `x` is an array of values in which the polynomial is evaluated.

```
def divdiff(xdata,ydata):
    # Create the table of divided differences based
    # on the data in the arrays x_data and y_data.
    n = len(xdata)
    F = np.zeros((n,n))
    F[:,0] = ydata           # Array for the divided differences
    for j in range(n):
        for i in range(n-j-1):
            F[i,j+1] = (F[i+1,j]-F[i,j])/(xdata[i+j+1]-xdata[i])
    return F                 # Return all of F for inspection.
                            # Only the first row is necessary for the
                            # polynomial.

def newton_interpolation(F, xdata, x):
    # The Newton interpolation polynomial evaluated in x.
    n, m = np.shape(F)
    xpoly = np.ones(len(x))   # (x-x[0])(x-x[1])...
    newton_poly = F[0,0]*np.ones(len(x)) # The Newton polynomial
    for j in range(n-1):
        xpoly = xpoly*(x-xdata[j])
        newton_poly = newton_poly + F[0,j+1]*xpoly
    return newton_poly
```

Run the code on the example above:

```
# Example: Use of divided differences and the Newton interpolation
# formula.
xdata = [0, 2/3, 1]
ydata = [1, 1/2, 0]
F = divdiff(xdata, ydata)   # The table of divided differences
print('The table of divided differences:\n',F)

x = np.linspace(0, 1, 101)  # The x-values in which the polynomial is evaluated
p = newton_interpolation(F, xdata, x)
plt.plot(x, p)              # Plot the polynomial
plt.plot(xdata, ydata, 'o') # Plot the interpolation points
plt.title('The interpolation polynomial p(x)')
plt.grid(True)
plt.xlabel('x');
```