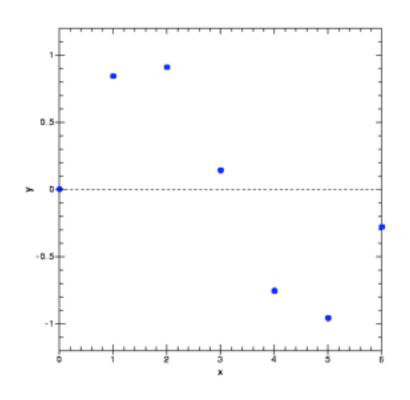
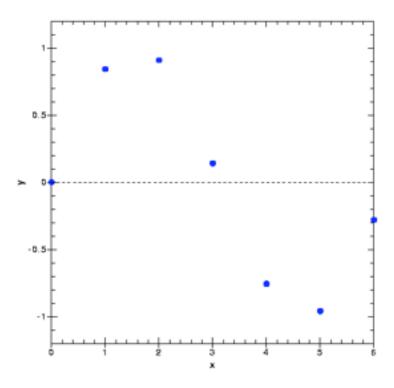
Let's assume we have a set of measurements:

X	1	y
0	1	O
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	1	-0.2794



Interpolation is a method to approximate a function, f, at a desired location, x, given a set of n+1 support points (x and y values)

$$f(x_i) = y_i$$
 for $0 \le i \le n$



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 for $0 \le i \le n$

Let's consider a **family of functions**, Φ , that is characterized by n+1 **parameters**, c_0, c_1, \ldots, c_n and our variable x

$$\phi(\mathbf{C}_0,\mathbf{C}_1,....,\mathbf{C}_n,\mathbf{X})$$

Interpolation tries to determine the **coefficients** c_i , so that

$$\phi(C_0, C_1, ..., C_n, X_i) = Y_i \text{ for } 0 \le i \le n$$

Types of Interpolation

$$\phi(C_0, C_1, ..., C_n, X_i) = Y_i \text{ for } 0 \le i \le n$$

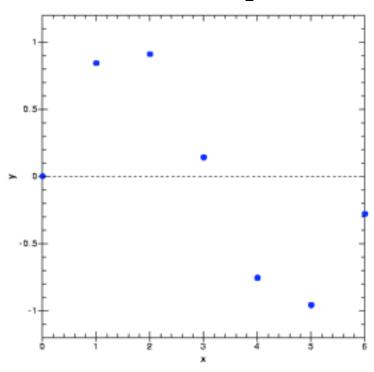
Linear Interpolation: The function Φ depends linearly on the c_i 's

- 1. Polynominal: $\Phi = c_0 + c_1 x + ... + c_n x^n$
- 2. Splines: nonlocal interpolation
- 3. Trigonometric: $\Phi = c_0 + c_1 e^{ix} + ... + c_n e^{inx}$ (Fourier analysis, Fast Fourier Transforms)

Nonlinear Interpolation: Φ depends nonlinearly on the c_i 's

Rational functions are a good choice if the function that we want to interpolate has a pole in the region of interest.

Linear Interpolation



A **linear function** interpolating between the first two values can be written as:

$$P_{0,1}(x) = y_0 \frac{x - x_1}{x_0 - x_1} + y_1 \frac{x - x_0}{x_1 - x_0}$$

$$P_{0,1}(x) = y_0 \frac{x - x_1}{x_0 - x_1} + y_1 \frac{x - x_0}{x_1 - x_0}$$

We can easily see that the function $P_{0,1}$ is of **degree 1** and satisfies

$$P_{0,1}(\mathbf{X}_0) = \mathbf{y}_0$$
 and $P_{0,1}(\mathbf{X}_1) = \mathbf{y}_1$

We can rewrite this as:

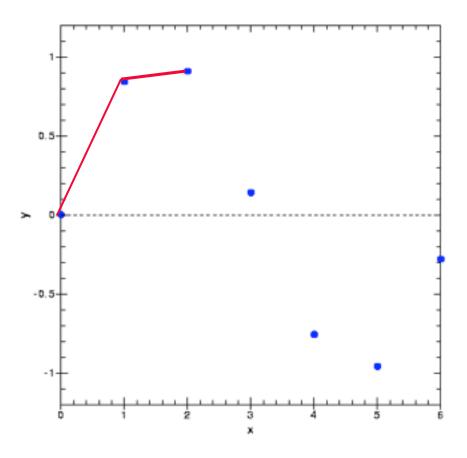
$$P_{0.1}(x) = y_0 L_0^{(1)}(x) + y_1 L_1^{(1)}(x)$$

$$P_{0,1}(x) = y_0 \frac{x - x_1}{x_0 - x_1} + y_1 \frac{x - x_0}{x_1 - x_0}$$

$$L_0^{(1)} = \frac{X - X_1}{X_0 - X_1} \qquad L_1^{(1)} = \frac{X - X_0}{X_1 - X_0}$$

The functions $L_0^{(1)}$ and $L_1^{(1)}$ are examples of **Lagrange interpolating** polynominals. They have the property

$$L_0^{(1)}(\mathbf{X}_0) = 1,$$
 $L_0^{(1)}(\mathbf{X}_1) = 0,$ $L_1^{(1)}(\mathbf{X}_0) = 0,$ $L_1^{(1)}(\mathbf{X}_0) = 1,$ $\Rightarrow L_i^{(1)}(\mathbf{X}_i) = \delta_{i,i}$



The **slope** between the 1^{st} and 2^{nd} and between the 2^{nd} and 3^{rd} data point **dramatically changes**.

A better interpolation might be obtained by taking the change in the slope into account by selecting polynominals with curvature

A polynominal of **degree 2** that passes through the points 0, 1, and 2 can be written as:

$$P_{0,1,2}(x) = y_0 \frac{(x - X_1)(x - X_2)}{(X_0 - X_1)(X_0 - X_2)} + y_1 \frac{(x - X_0)(x - X_2)}{(X_1 - X_0)(X_1 - X_2)} + y_2 \frac{(x - X_0)(x - X_1)}{(X_2 - X_0)(X_2 - X_1)}$$

$$L_0^{(2)}(x) = \frac{(x - x_1)(x - x_2)}{(x_0 - x_1)(x_0 - x_2)}$$

$$L_1^{(2)}(x) = \frac{(x - x_0)(x - x_2)}{(x_1 - x_0)(x_1 - x_2)} \implies L_i^{(2)}(x_j) = \delta_{i, j}$$

$$L_2^{(2)}(x) = \frac{(x - x_0)(x - x_1)}{(x_0 - x_0)(x_0 - x_1)}$$

Back to our example:

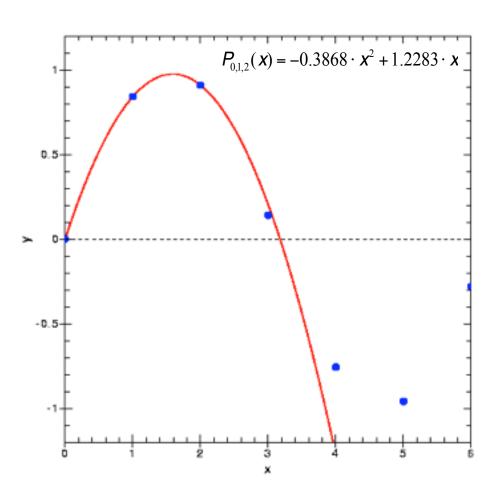
$$P_{0,1,2}(x) = y_0 \frac{(x - x_1)(x - x_2)}{(x_0 - x_1)(x_0 - x_2)} + y_1 \frac{(x - x_0)(x - x_2)}{(x_1 - x_0)(x_1 - x_2)} + y_2 \frac{(x - x_0)(x - x_1)}{(x_2 - x_0)(x_2 - x_1)}$$

$$P_{0,1,2}(x) = 0 \cdot \frac{(x-1)(x-2)}{(0-1)(1-2)} + 0.8415 \cdot \frac{(x-0)(x-2)}{(1-0)(1-2)} + 0.9093 \cdot \frac{(x-0)(x-1)}{(2-0)(2-1)}$$

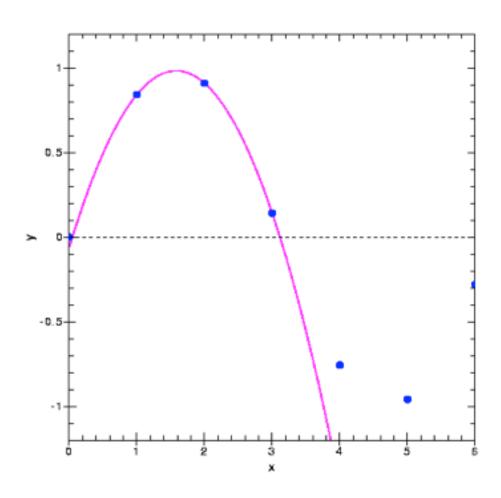
10

$$P_{0,1,2}(x) = -0.8415 \cdot (x^2 - 2x) + 0.9093 \cdot \frac{(x^2 - x)}{2} = -0.3868 \cdot x^2 + 1.2283 \cdot x$$

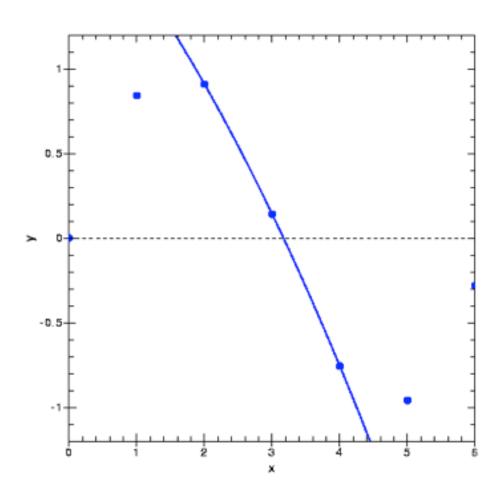
A Parabola through the first three points



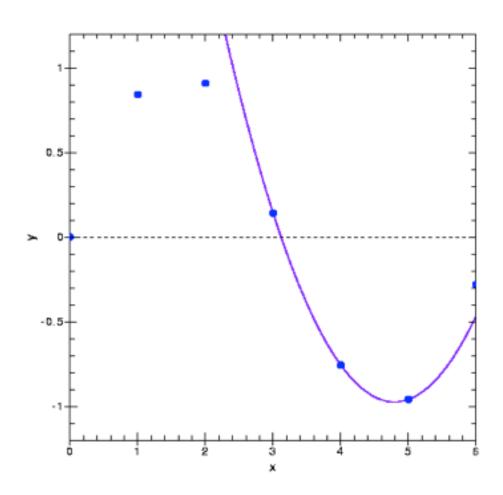
A Parabola through point 1, 2, and 3



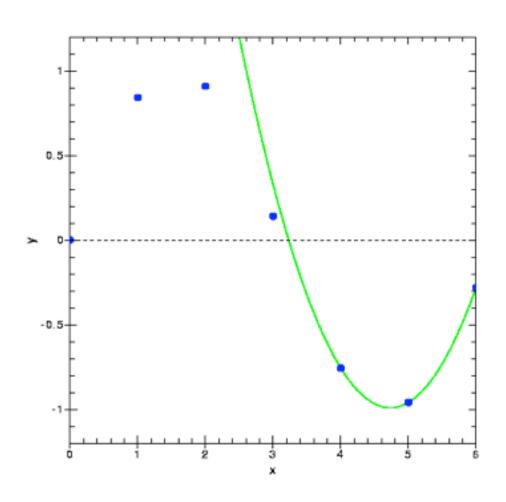
A Parabola through points 2, 3, and 4



A Parabola through points 3, 4, and 5



A Parabola through the final three points



Let's include all n+1 points, which will result in a polynominal of degree n.

→ Construct this polynominal from higher degree Lagrange interpolation polynominals:

So far our Lagrange polynominals looked like:

First Order

$$L_0^{(1)} = \frac{X - X_1}{X_0 - X_1}$$

Second Order

$$L_0^{(2)}(\mathbf{X}) = \frac{(\mathbf{X} - \mathbf{X}_1)(\mathbf{X} - \mathbf{X}_2)}{(\mathbf{X}_0 - \mathbf{X}_1)(\mathbf{X}_0 - \mathbf{X}_2)}$$

nth Order:
$$L_i^{(n)}(x) = \prod_{j=0, j\neq i}^n \left(\frac{x-x_j}{x_i-x_j}\right) \implies L_i^{(n)}(x_j) = \delta_{i,j}$$

The higher order Lagrange Polynominals are

$$L_i^{(n)}(\mathbf{x}) = \prod_{j=0, j \neq i}^n \left(\frac{\mathbf{x} - \mathbf{x}_j}{\mathbf{x}_i - \mathbf{x}_j} \right) \implies L_i^{(n)}(\mathbf{x}_j) = \delta_{i, j}$$

The final polynominal that passes through **all n+1 points** is than gives as:

$$\Rightarrow P_{0,\dots,n}(x) = \sum_{i=0}^{n} L_i^{(n)}(x) y_i$$

$$\Rightarrow P_{0,...,n}(x) = \sum_{i=0}^{n} L_i^{(n)}(x) y_i \qquad L_i^{(n)}(x) = \prod_{j=0, j \neq i}^{n} \left(\frac{x - x_j}{x_i - x_j} \right)$$

For our example with the **seven** points

$$P_{0,1,..6}(x) = y_0 \frac{(x - X_1)(x - X_2)(x - X_3)(x - X_4)(x - X_5)(x - X_6)}{(X_0 - X_1)(X_0 - X_2)(X_0 - X_3)(X_0 - X_4)(X_0 - X_5)(X_0 - X_6)}$$

$$+ y_1 \frac{(x - X_0)(x - X_2)(x - X_3)(x - X_4)(x - X_5)(x - X_6)}{(X_1 - X_0)(X_1 - X_2)(X_1 - X_3)(X_1 - X_4)(X_1 - X_5)(X_1 - X_6)}$$

$$+ \dots$$

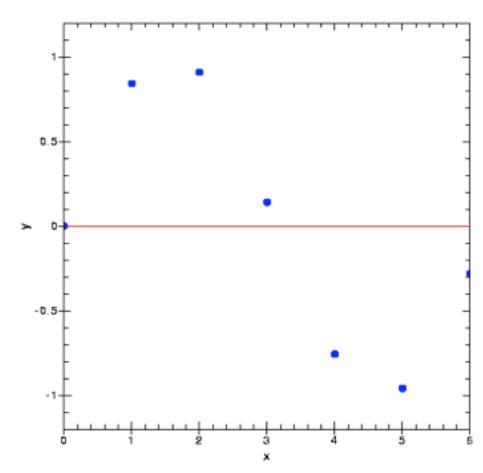
$$+ y_6 \frac{(x - X_0)(x - X_1)(x - X_2)(x - X_3)(x - X_4)(x - X_5)}{(X_6 - X_0)(X_6 - X_1)(X_6 - X_2)(X_6 - X_3)(X_6 - X_4)(X_6 - X_5)}$$

First Term

$$P_{0,1,..6}(X) = Y_0 \frac{(X - X_1)(X - X_2)(X - X_3)(X - X_4)(X - X_5)(X - X_6)}{(X_0 - X_1)(X_0 - X_2)(X_0 - X_3)(X_0 - X_4)(X_0 - X_5)(X_0 - X_6)}$$

Back to our example:

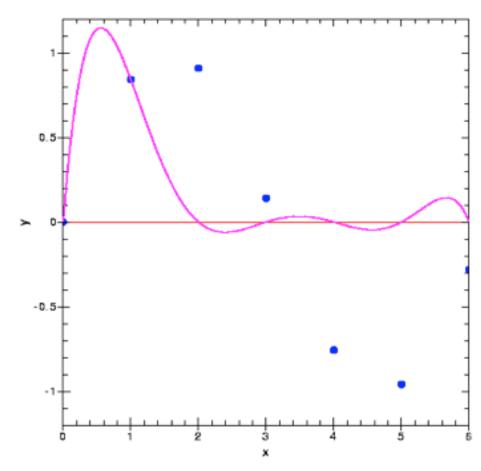
X	1	У
0	1	O
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	1	-0.2794



Back to our example:

x y 0 1 0 1 1 0.8415 2 1 0.9093 3 1 0.1411 4 1 -0.7568 5 1 -0.9589 6 1 -0.2794

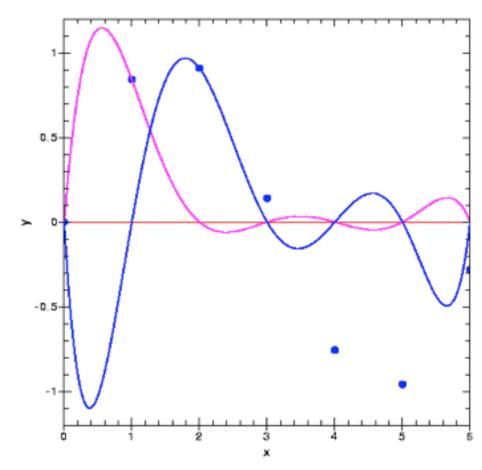
2nd Term in Series



Back to our example:

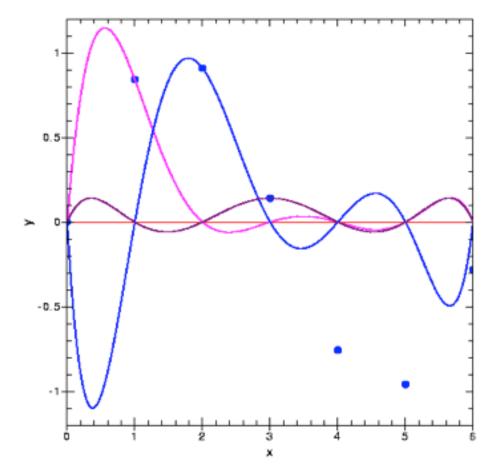
x	1	\mathcal{Y}
0	1	O
1	1	0.8415
2	1	0.9093
3	/	0.1411
4	/	-0.7568
5	/	-0.9589
6	/	-0.2794

3rd Term in Series



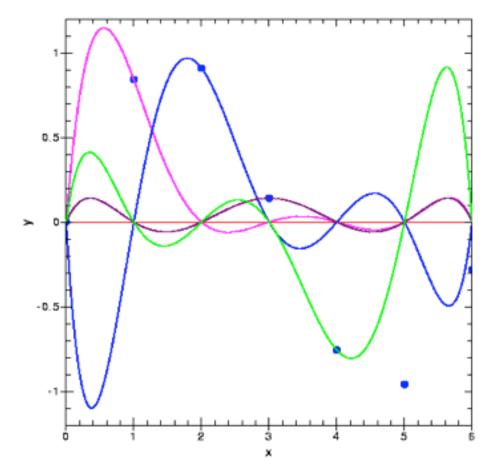
Back to our example:

X	1	У
0	/	0
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	1	-0.2794



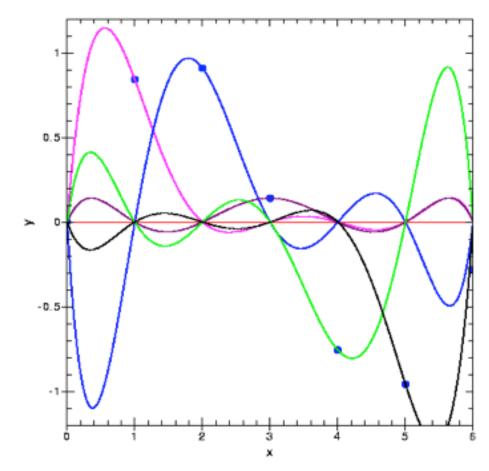
Back to our example:

X	1	У
0	/	0
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	/	-0.2794



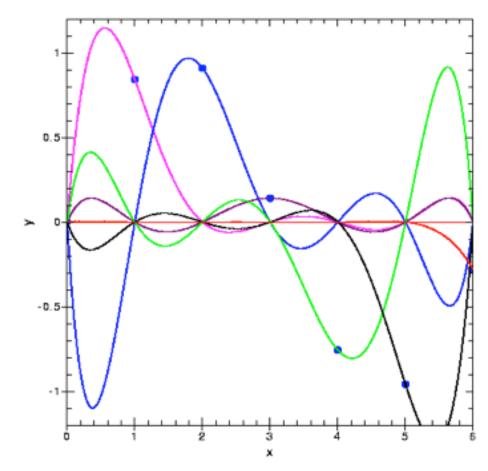
Back to our example:

x	1	У
0		0
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	1	-0.2794



Back to our example:

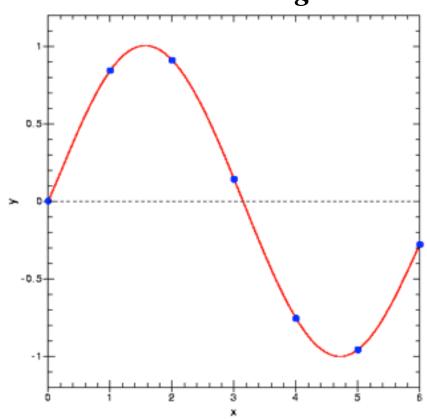
x	1	\mathcal{Y}
0	1	O
1	1	0.8415
2	1	0.9093
3	1	0.1411
4	1	-0.7568
5	1	-0.9589
6	1	-0.2794



Back to our example:

$$\Rightarrow P_{0,\dots,n}(x) = \sum_{i=0}^{n} L_i^{(n)}(x) y_i$$

All Terms added together



$$P(x) = -0.0001521*x^6 - 0.003130*x^5 + 0.07321*x^4$$
$$-0.3577*x^3 + 0.2255*x^2 + 0.9038*x$$

Existence and Uniqueness

For n+1 arbitrary support points (x_i, y_i) where $x_0 < x_1 < ... < x_n$, there exists a unique n-th order polynominal which satisfies

$$P(x_i) = y_i$$
 for $0 \le i \le n$

Existence: Construct the Lagrange polynominals as before

$$L_i^{(n)}(\mathbf{X}) = \prod_{j=0, j \neq i}^n \left(\frac{\mathbf{X} - \mathbf{X}_j}{\mathbf{X}_i - \mathbf{X}_j} \right)$$

If we construct our polynominal as: $P(x) = \sum_{i=0}^{n} L_i^{(n)}(x) y_i$

than this polynominal has in fact n-th order and satisfies

$$P(x_i) = y_i$$
 for $0 \le i \le n$

Existence and Uniqueness

Uniqueness: (show by method of contradiction)

Let's assume that P_1 and P_2 are n-th order polynominals that both satisfy $P(x_i) = y_i \text{ for } 0 \le i \le n.$

If we construct the polynominal $P_3 = P_1 - P_2$, than P_3 is **at most** an **n-th order polynominal** with at **most n distinct roots** z_i

$$P_3(z_i) = 0$$
 with $i \le n$ (From complete factorization)

However,
$$P_3(x_i) = P_1(x_i) - P_2(x_i) = 0$$
 for the n +1 x_i

Consequently, our assumption is wrong and P_3 can only be equal 0

--->
$$P_1 = P_2$$