# Numerical interpolation

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Chemical Process Intensification group
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Numerical Methods (6BER03), 2024-2025

# Today's outline

- Introduction
- Piecewise constant
- Linear
- Polynomial
- Splines
- Tutorials

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# Interpolation problem

## Definition

Given a set of points $x_k$, $k = 0,\ldots,n$, $x_i \neq x_j$ with associated function values $f_k$, $k = 0,\ldots,n$, or simply: $\{x_k, f_k\}_{k=0}^{n}$. The interpolation problem is defined as: find a polynomial $p_n$ such that this interpolates the values of $f_k$ on the points $x_k$:

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**Theorem**

*The interpolation problem for $\{x_k, f_k\}_{k=0}^{n}$ has a unique solution when $x_i \neq x_j$ for $i \neq j$. Note that we cannot allow multiple function values $f_k$ for the same value of $x_k$.*

# What is interpolation?

Interpolation means constructing additional data points within the range of, and using, a discrete set of known data points.

It is typically performed on a uniformly spread data set, but this is not strictly necessary for all methods

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# Why do chemical engineers need interpolation?

- Comparison of two data sets which are given at different positions
  - An experimental data set may have been recorded at a constant rate, but the numerical solution is computed at irregular intervals
- Reconstruction of field values distant of computing nodes
  - A CFD simulation on a regular grid containing structures that are not grid-conformant requires interpolation to the structures
- Calculation of a physical property at a condition between those of a lookup table
  - The viscosity of a substance may have been measured at 20°C and 30°C, but not at the desired 28.5°C

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# General

Several important numerical interpolation methods are discussed today:

- Piecewise constant interpolation
- Linear interpolation
    - Bilinear interpolation
- Polynomial interpolation (Newton's method)
- Spline interpolation

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# Today's data set

Generate the following data set:

```python
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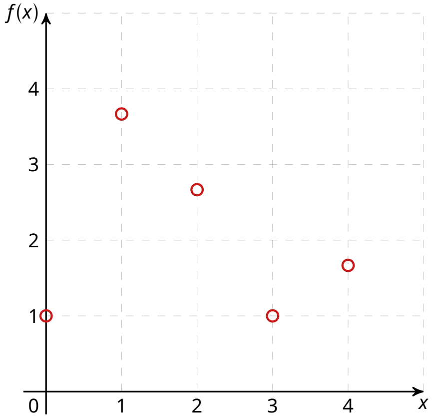
This yields some sample points on which we base our examples:

| $x_k$ | $f_k$ |
|---|---|
| 0 | 1.00 |
| 1 | $\frac{11}{3} = 3.67$ |
| 2 | $\frac{8}{3} = 2.67$ |
| 3 | 1.00 |
| 4 | $\frac{5}{3} = 1.67$ |
| 5 | $\frac{23}{3} = 7.67$ |

Data set $f_n(x_n)$ represented by ○ at discrete intervals $x_n \in \{0, 5\}$



# Piecewise constant interpolation

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- Nearest-neighbor interpolation in the continuous range $x \in [0, 5]$
- How to treat the point halfway (e.g. at $x = 2.5$)?

$x \in [0, 0.5] \quad \longrightarrow f(x) = f(0)$

$x \in [0.5, 1.5] \quad \longrightarrow f(x) = f(1)$

$x \in [1.5, 2.5] \quad \longrightarrow f(x) = f(2)$

$x \in [2.5, 3.5] \quad \longrightarrow f(x) = f(3)$

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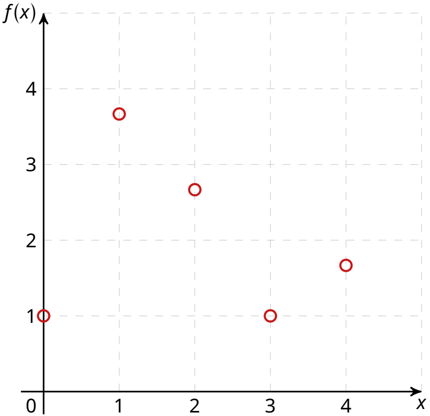

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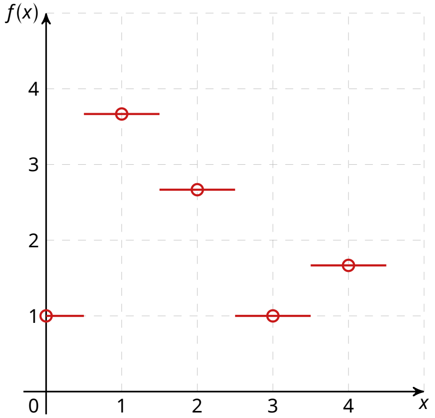

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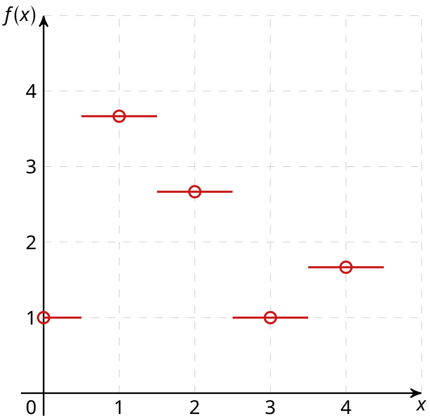

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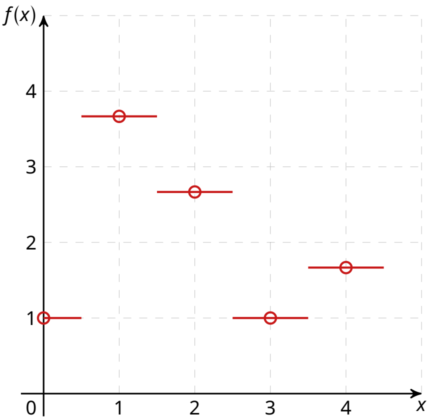


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$$\frac{y - y_2}{x - x_2} = \frac{y_3 - y_2}{x_3 - x_2}$$

- Reordered, and more formally:

$$y = y_n + (y_{n+1} - y_n)\frac{x - x_n}{x_{n+1} - x_n}$$

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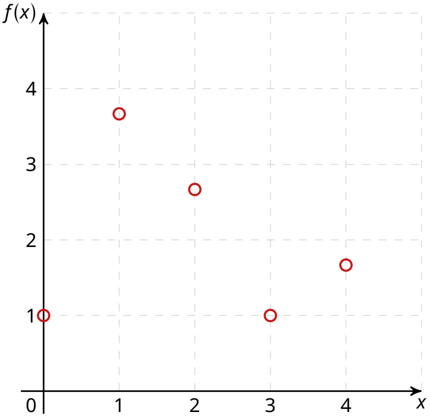

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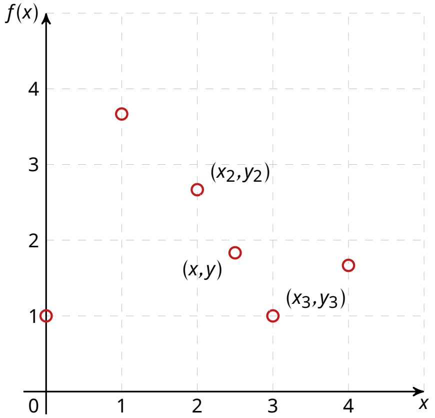


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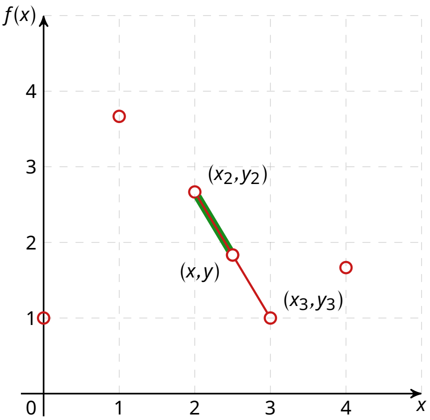


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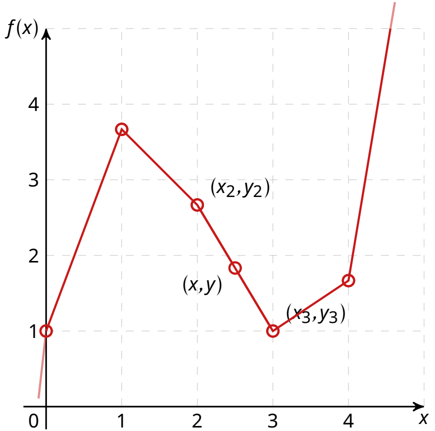

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# Interpolation in Python

Interpolation can be done using the SciPy interpolation submodule, e.g.:

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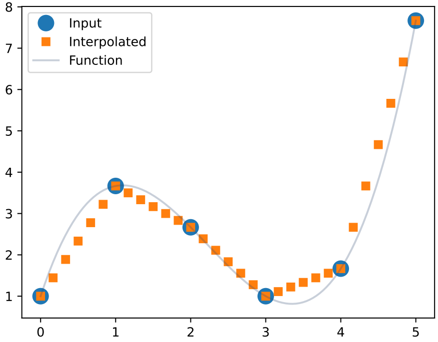
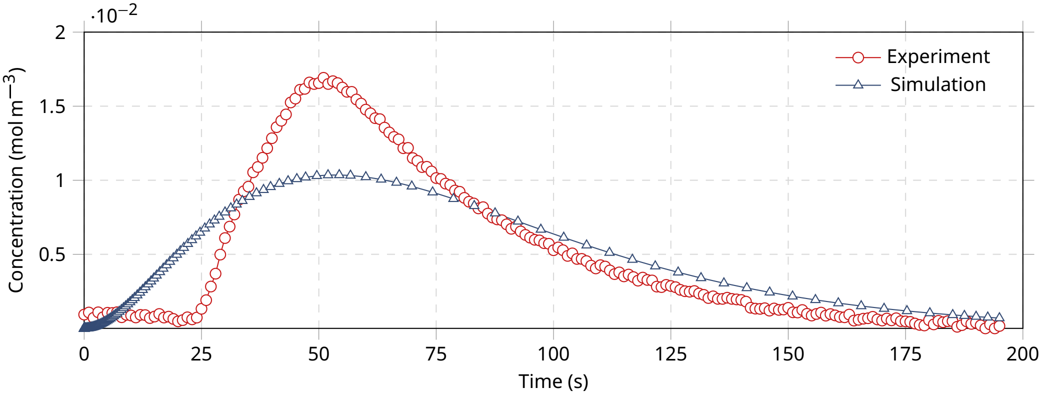


# Example: Linear interpolation in Python

Consider the data sets in `exp_data.txt` and `sim_data.txt`, containing a normalized concentration and time vector for an experiment and a simulation. The simulation was performed with adaptive node distance to save computation time, thus the concentration is not known at the same times. We are not able to compare yet.



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import numpy as np
from scipy.interpolate import interp1d
import matplotlib.pyplot as plt

t_sim, c_sim = np.loadtxt("scripts/interpolation/sim_data.txt").T
t_exp, c_exp = np.loadtxt("scripts/interpolation/exp_data.txt").T

# Linear interpolation
f = interp1d(t_sim, c_sim)
diff = np.abs(c_exp - f(t_exp))

# Plot the solution
plt.subplot(2, 1, 1)
plt.plot(t_exp, c_exp, '-x', label='c_exp')
plt.plot(t_exp, f(t_exp), '-|', label='c_sim_new')
plt.xlabel('Time [s]'); plt.ylabel('Conc [mol m$^{-3}$]')
plt.legend()

plt.subplot(2, 1, 2)
plt.plot(t_exp, diff)
plt.xlabel('Time [s]'); plt.ylabel('Difference [mol m$^{-3}$]')
plt.tight_layout()
# plt.show()
plt.savefig('figures/sim_exp_data_interp.pdf')
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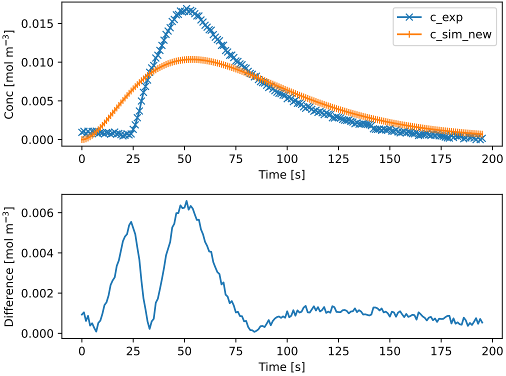

# Bi-linear interpolation

When a 2D field of some quantity is known, we can interpolate the solution to an arbitrary position in the 2D domain $p(x,y)$ using 4 field values $f_{00}, f_{10}, f_{01}$ and $f_{11}$.

$$g_1 = f_{01}\frac{x_1 - x}{x_1 - x_0} + f_{11}\frac{x - x_0}{x_1 - x_0} = f_{01}\frac{x_1 - x}{\Delta x} + f_{11}\frac{x - x_0}{\Delta x}$$

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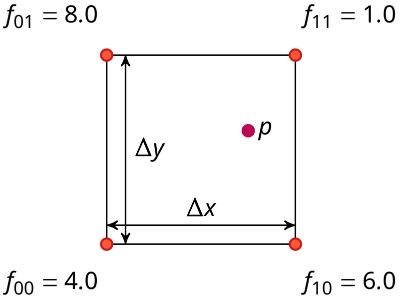


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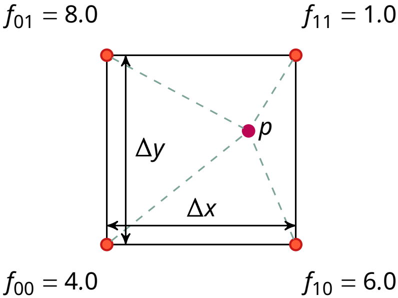

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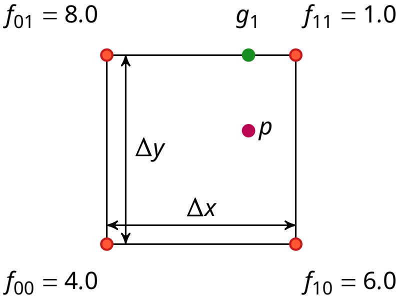

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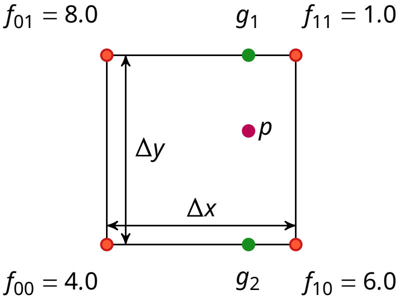

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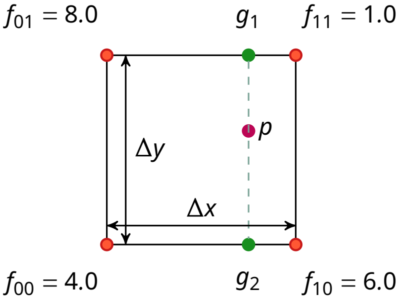


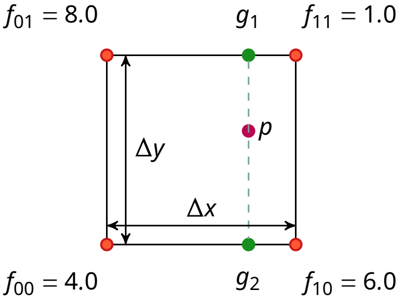
# Bi-linear interpolation

When a 2D field of some quantity is known, we can interpolate the solution to an arbitrary position in the 2D domain $p(x,y)$ using 4 field values $f_{00}, f_{10}, f_{01}$ and $f_{11}$.

$$g_1 = f_{01}\frac{x_1 - x}{x_1 - x_0} + f_{11}\frac{x - x_0}{x_1 - x_0}$$
$$= f_{01}\frac{x_1 - x}{\Delta x} + f_{11}\frac{x - x_0}{\Delta x}$$

$$g_2 = f_{00}\frac{x_1 - x}{\Delta x} + f_{10}\frac{x - x_0}{\Delta x}$$

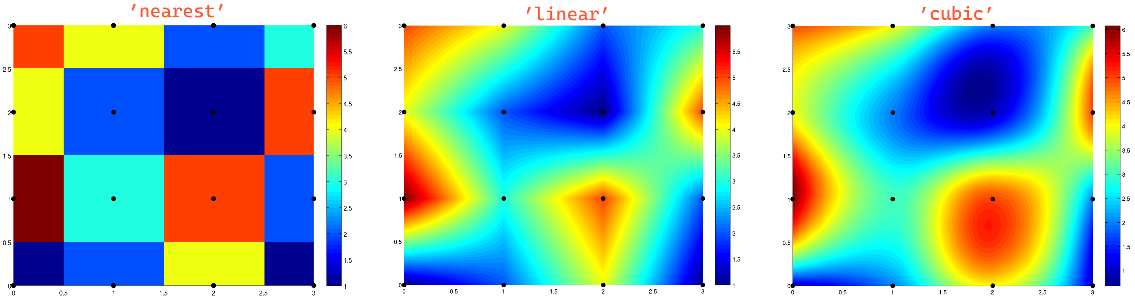
$$p = g_2\frac{y_1 - y}{\Delta y} + g_1\frac{y - y_0}{\Delta y}$$




- The order of interpolation ($x$ or $y$ direction first) does not matter; the results are equal

# Higher-dimensional field interpolation in Python

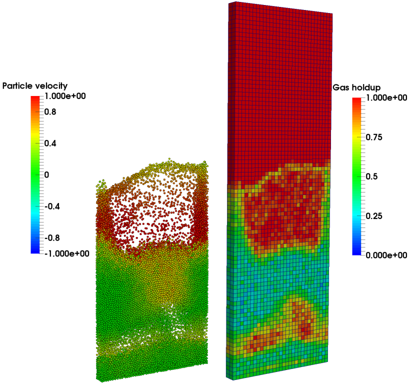
2D or higher-dimensional fields of data can be interpolated in Python using the `scipy.interpolate.interp2d`, `scipy.interpolate.interp3d`, or even `scipy.interpolate.RegularGridInterpolator` functions. The method can be adjusted:




- Also consider tri-linear interpolation (for 3D fields) with `scipy.interpolate.LinearNDInterpolator`, or bicubic interpolation (2D, but third order) with `scipy.interpolate.interp2d`.

# A practical example

Field interpolation is used in e.g. CFD simulations, e.g. a fluidized bed simulation using a *discrete particle model*, where particles are found in between the grid nodes used for velocity computation.



# Today's outline

# Polynomial interpolation

The examples that we have seen, are simplified forms of *Newton polynomials*. We can interpolate our data with a polynomial of degree $n$:

$$p_n(x) = a_n x^n + a_{n-1} x^{n-1} + \ldots + a_2 x^2 + a_1 x + a_0$$

# Polynomial interpolation via Vandermonde matrix

Consider the data points $(x_1,y_1), (x_2,y_2), \ldots, (x_m,y_m)$, the Vandermonde matrix $V$, coefficient vector $a$ and function value vector $y$:

$$V_{m,n} = \begin{pmatrix} x_1^0 & x_1^1 & x_1^2 & \cdots & x_1^{n-1} \\ x_2^0 & x_2^1 & x_2^2 & \cdots & x_2^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_m^0 & x_m^1 & x_m^2 & \cdots & x_m^{n-1} \end{pmatrix} \quad a = \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_{n-1} \end{pmatrix} \quad y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}$$

The coefficients of a polynomial through the data are obtained by solving the linear system $Va = y$.

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x = np.array([0, 1, 2])
y = np.array([1.0000, 3.6667, 2.6667])
V = np.vander(x, increasing=True)
print(V)
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[ 1. 4.50005 -1.83335]
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$$p_2(x) = -1.8333x^2 + 4.5x - 1$$

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These Vandermonde-systems are often *ill-conditioned*, so we need another, more stable, method!

# Construction of Newton polynomials

Formally, the polynomials $p_n(x)$ are described using prefactors $f[x_0,\ldots,x_k]$ and polynomial terms $w_m(x)$:

$$p_n(x) = \sum_{k=0}^{n} f[x_0,\ldots,x_k] w_k(x)$$

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The polynomial terms are computed via:

$$w_0(x) = 1,\ w_1(x) = (x - x_0),\ w_2(x) = (x - x_0)\cdot(x - x_1),$$

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The prefactors are *forward divided differences*, which can be computed as:

$$f[x_{x-k},\dots,x_r] \equiv \frac{f[x_{r-k+1},\dots,x_r] - f[x_{r-k},\dots,x_{r-1}]}{x_r - x_{r-k}}$$

# Construction of Newton polynomials: example

Sample data

| $x_k$ | $f_k$ |
|---|---|
| 0 | 1.00 |
| 1 | $\frac{11}{3} = 3.67$ |
| 2 | $\frac{8}{3} = 2.67$ |

$$p_n(x)=\sum_{k=0}^{n} f[x_0,\ldots,x_k]w_k(x)$$

$$f[x_{x-k},\ldots,x_r]\equiv\frac{f[x_{r-k+1},\ldots,x_r]-f[x_{r-k},\ldots,x_{r-1}]}{x_r-x_{r-k}}$$

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| $x_k$ | $f_k$ |
|---|---|
| $x_0$ | $f[x_0] = f_0$ |

| $x_k$ | $f_k$ |
|---|---|
| 0 | 1 |

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| $x_1$ | $f[x_1] = f_1$ | $f[x_0, x_1] = \frac{f_1 - f_0}{x_1 - x_0}$ |

| $x_k$ | $f_k$ | |
|---|---|---|
| 0 | 1 | |
| 1 | 3.67 | $\frac{\frac{11}{3} - 1}{1 - 0} = \frac{8}{3}$ |

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| $x_2$ | $f[x_2] = f_2$ | $f[x_1,x_2] = \frac{f_2 - f_1}{x_2 - x_1}$ | $f[x_0,x_1,x_2] = \frac{f[x_1,x_2] - f[x_0,x_1]}{x_2 - x_0}$ |

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For each three points, a new polynomial interpolant can be derived:

$$p_2(x) = -\frac{11}{6}x^2 + 4\frac{1}{2}x + 1$$

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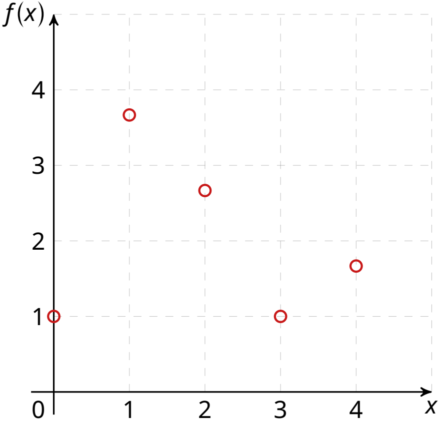

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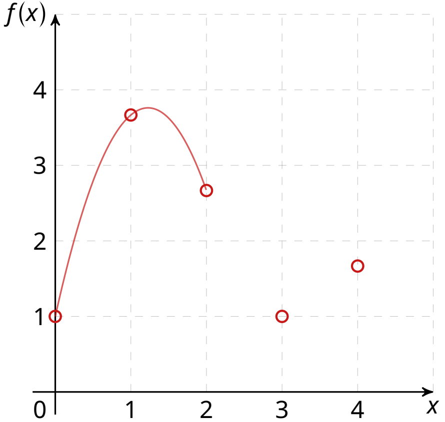

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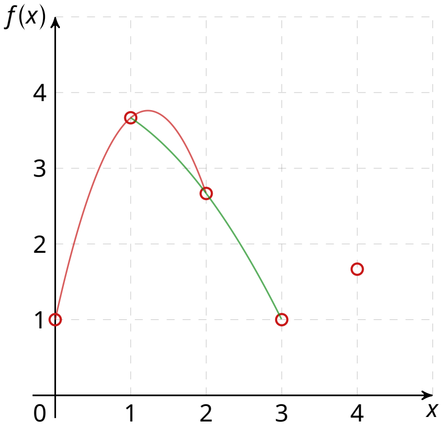

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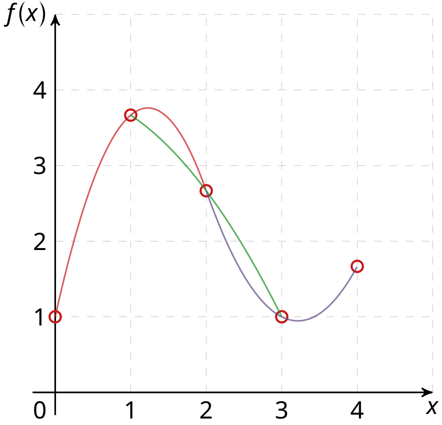

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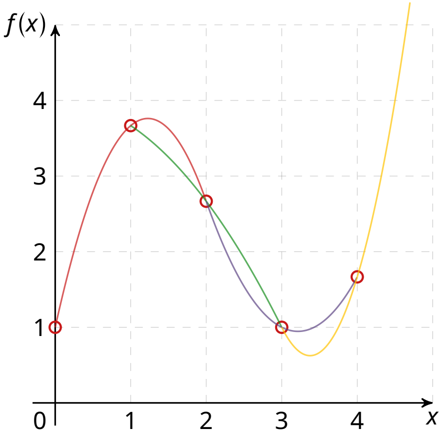

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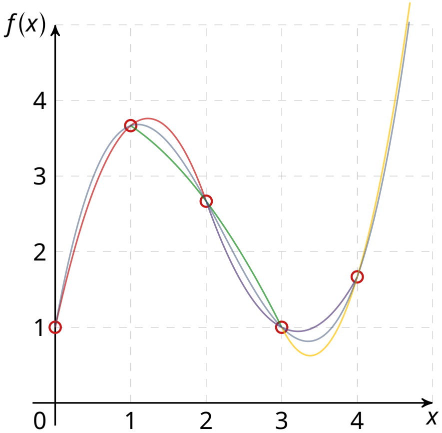

# Polynomial fitting in Python: example

Develop the polynomials $p_1(x)$ through $p_5(x)$ using the following data set:

```python
import numpy as np
import matplotlib.pyplot as plt
xdata = np.arange(-1,1.5,0.5)
ydata = [x * np.sin(x)/np.sqrt(x+2) if x != 0 else 0.5 for x in xdata]
plt.plot(xdata,ydata,'o')
```

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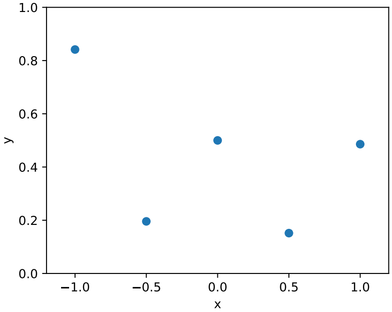


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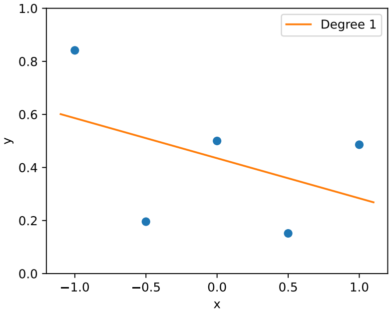


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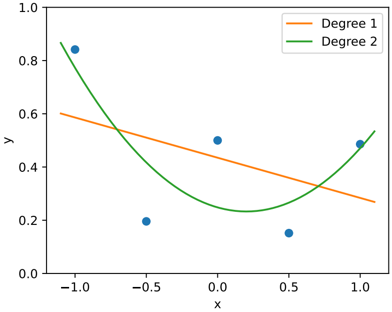


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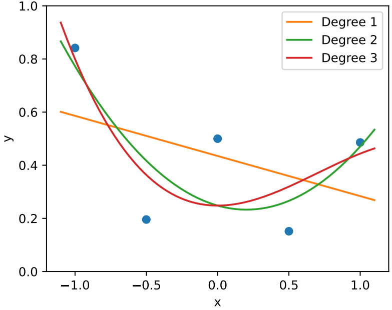


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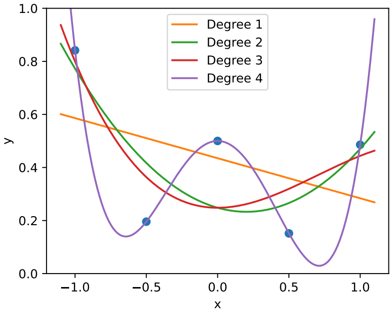


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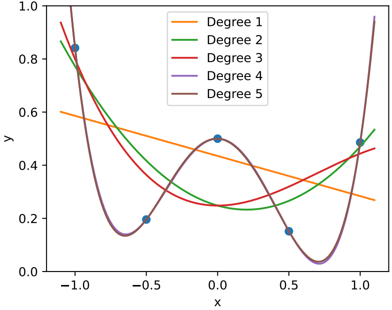


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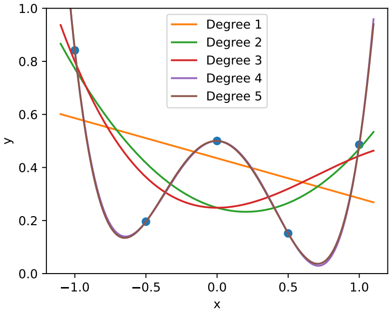


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```
RankWarning: Polyfit may be poorly conditioned
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# Exercise

Develop the $p_4(x)$ and $p_{10}(x)$ interpolants from the following data sets:

$$f(x) = \frac{1}{x^2 + \frac{1}{25}} \qquad x \in [-1, 1]$$

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import matplotlib.pyplot as plt
f = lambda x: 1/(x**2 + 1/25)
x4,x10,xinf = [np.linspace(-1, 1, n) for n in [5,11,1001]]
y4,y10,yinf = f(x4), f(x10), f(xinf)
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```python
# Get coefficients for 4th and 10th order polynomial
p4 = np.polyfit(x4, y4, 4)
p10 = np.polyfit(x10, y10, 10)
# Compute function values using fitted coeffs
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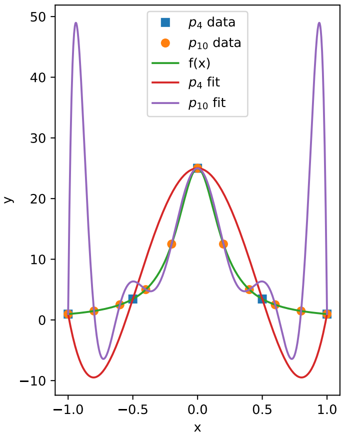

# Final thoughts on polynomial interpolation

- An polynomial interpolant of order $n$ requires $n + 1$ data points
  - More data points: interpolant does *not always* cross the points
  - Fewer data points: interpolant is not unique
- Higher-degree polynomials at equidistant points may cause strong oscillatory behaviour (Runge's phenomenon)
  - Mitigation of the problem on Chebyshev (i.e. non uniform grid)...
  - ... or by performing piecewise interpolation (next topic)
- Python functions `np.polyfit(x,y,n)` and `np.polyval(p,x_new)` were demonstrated.

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# Today’s outline

- Introduction
- Piecewise constant
- Linear
- Polynomial
- Splines
- Tutorials

# Spline interpolation

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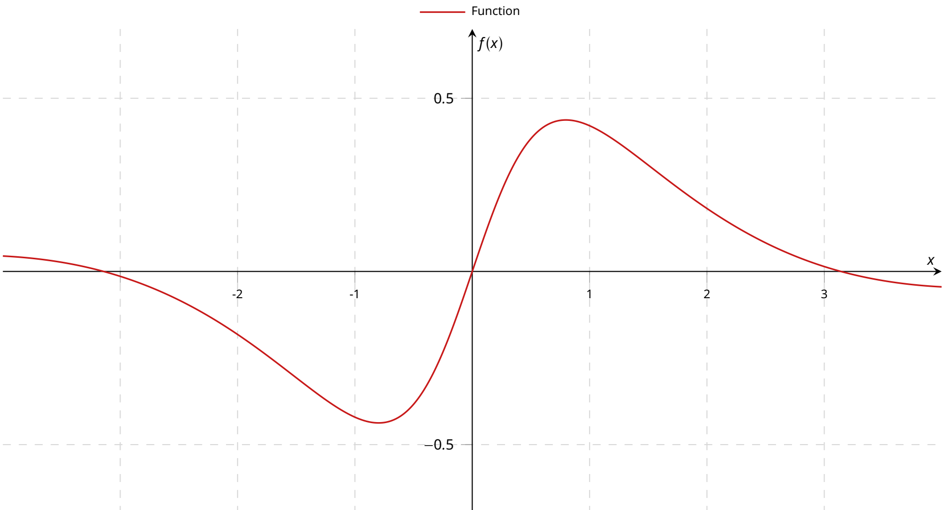
# Splines: comparison to other interpolation techniques

Interpolation of $f(x) = \dfrac{\sin x}{1+x^2}$



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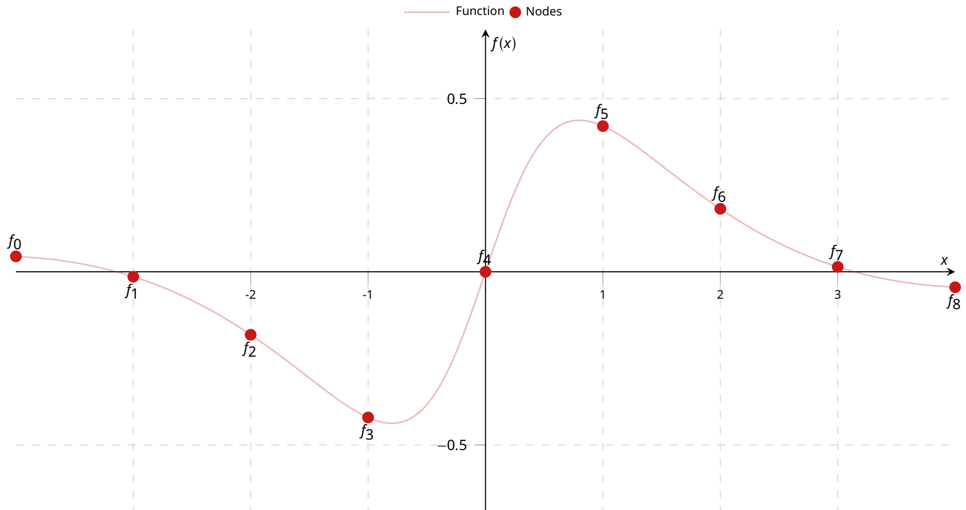

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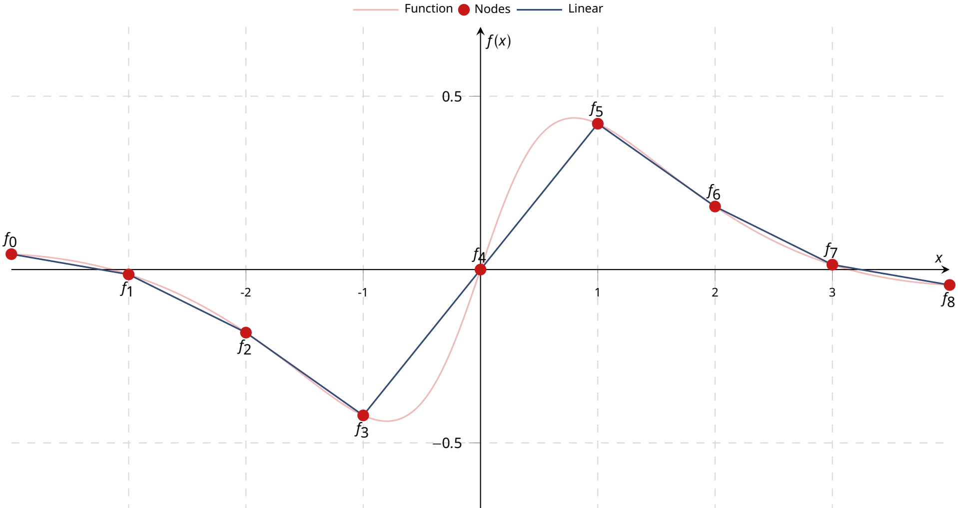

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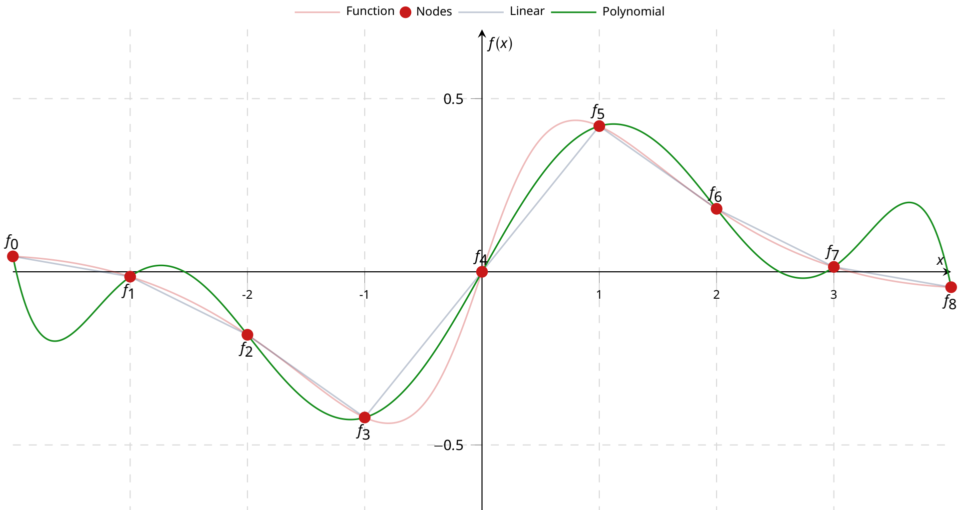

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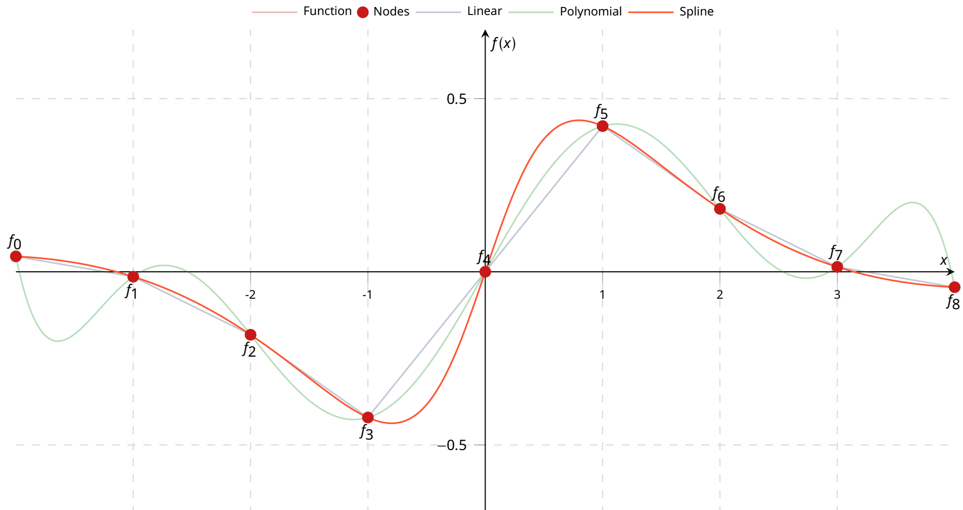

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import numpy as np
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from scipy.interpolate import make_interp_spline

# Generate random data set
xdata = np.arange(0, 26)
ydata = np.random.rand(len(xdata))

# Interpolant on a fine mesh
xc = np.linspace(0, 25, 1001)
ifun = make_interp_spline(xdata, ydata)
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# Plot the data
plt.plot(xdata, ydata, 'o')
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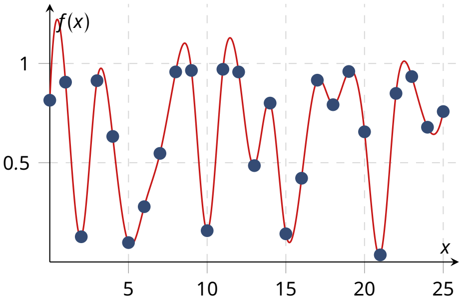

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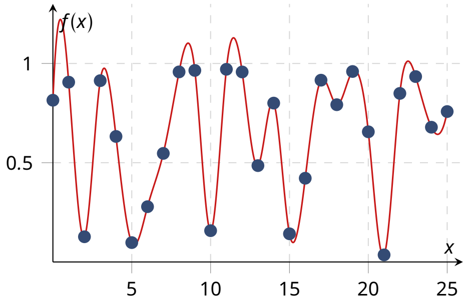


Note: The SciPy Optimize module contains various interpolation methods with a similar interface.

# Summary

- Interpolation is used to obtain data between existing data points
  - (Bi-)Linear, polynomial and spline interpolation methods
  - Construction of Newton polynomials
  - Oscillations of high-order polynomials
- Legendre polynomials: alternative way of performing the polynomial interpolation (not discussed here)

# Interpolation tutorials

1. In Python, generate the data:

```
x = np.arange(-4, 6, 1)
y = [0, 0, 0, 1, 1, 1, 0, 0, 0, 0]
```

   Interpolate the data using polynomial interpolation (which order do you use?) and a spline. Plot the results together with the original data in a graph.

2. Do the same exercise for the following data. Can you explain your observations?

```
t = [0, 0.1, 0.499, 0.5, 0.6, 1.0, 1.4, 1.5, 1.899, 1.9, 2.0]
y = [0, 0.06, 0.17, 0.19, 0.21, 0.26, 0.29, 0.29, 0.30, 0.31, 0.31]
```

**Hint:** Use `scipy.interpolate.interp1d(...,kind="...")` to use different splines.