

Study Guide: Approximation of functions with finite elements

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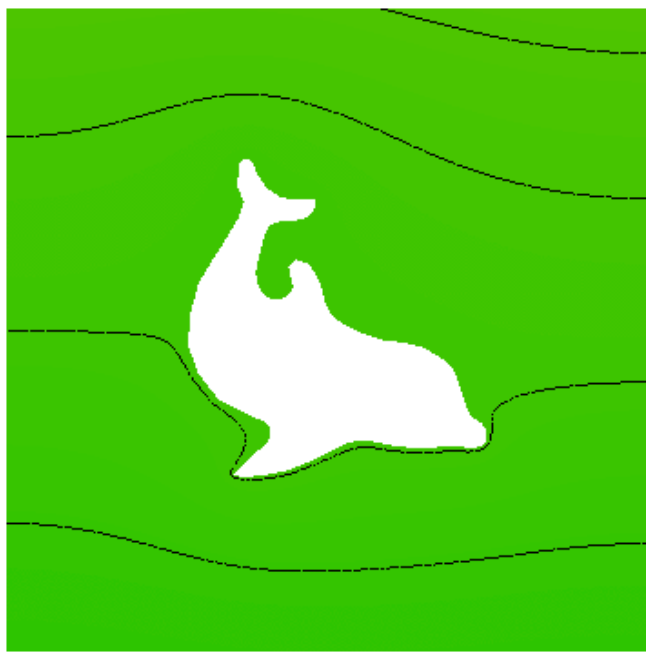
Why finite elements?

- Can with ease solve PDEs in domains with *complex geometry*
- Can with ease provide higher-order approximations
- Has (in simpler stationary problems) a rigorous mathematical analysis framework (not much considered here)

Domain for flow around a dolphin



The flow



Basic ingredients of the finite element method

- Transform the PDE problem to a *variational form*
- Define function approximation over *finite elements*
- Use a machinery to derive *linear systems*
- Solve linear systems

Our learning strategy

- Start with approximation of functions, not PDEs
- Introduce finite element *approximations*
- See later how this is applied to PDEs

Reason: the finite element method has many concepts and a jungle of details. This strategy minimizes the mixing of ideas, concepts, and technical details.

Approximation set-up

General idea of finding an approximation $u(x)$ to some given $f(x)$:

$$u(x) = \sum_{i=0}^N c_i \psi_i(x) \quad (1)$$

where

- $\psi_i(x)$ are prescribed functions
- c_i , $i = 0, \dots, N$ are unknown coefficients to be determined

How to determine the coefficients?

We shall address three approaches:

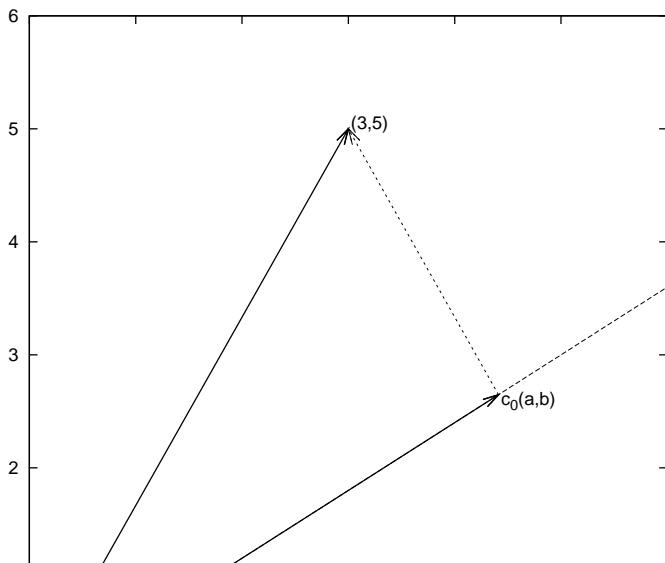
- The least squares method
- The projection (or Galerkin) method
- The interpolation (or collocation) method

Underlying motivation for our notation.

Our mathematical framework for doing this is phrased in a way such that it becomes easy to understand and use the FEniCS software package for finite element computing.

Approximation of planar vectors; problem

Given a vector $\mathbf{f} = (3, 5)$, find an approximation to \mathbf{f} directed along a given line.



Approximation of planar vectors; vector space terminology

$$V = \text{span} \{ \psi_0 \} \quad (2)$$

- ψ_0 is a basis vector in the space V
- Seek $\mathbf{u} = c_0 \psi_0 \in V$
- Determine c_0 such that \mathbf{u} is the "best" approximation to \mathbf{f}
- Visually, "best" is obvious

Define

- the error $\mathbf{e} = \mathbf{f} - \mathbf{u}$
- the (Euclidean) scalar product of two vectors: (\mathbf{u}, \mathbf{v})
- the norm of \mathbf{e} : $\|\mathbf{e}\| = \sqrt{(\mathbf{e}, \mathbf{e})}$

The least squares method; principle

- Idea: find c_0 such that $\|\mathbf{e}\|$ is minimized
- Actually, we always minimize $E = \|\mathbf{e}\|^2$

$$\frac{\partial E}{\partial c_0} = 0$$

The least squares method; calculations

$$E(c_0) = (\mathbf{e}, \mathbf{e}) = (\mathbf{f}, \mathbf{f}) - 2c_0(\mathbf{f}, \psi_0) + c_0^2(\psi_0, \psi_0) \quad (3)$$

$$\frac{\partial E}{\partial c_0} = -2(\mathbf{f}, \psi_0) + 2c_0(\psi_0, \psi_0) = 0 \quad (4)$$

$$c_0 = \frac{(\mathbf{f}, \psi_0)}{(\psi_0, \psi_0)} \quad (5)$$

$$c_0 = \frac{3a + 5b}{a^2 + b^2} \quad (6)$$

Observation for later: the vanishing derivative (4) can be alternatively written as

$$(\mathbf{e}, \psi_0) = 0 \quad (7)$$

The projection (or Galerkin) method

- Background: minimizing $\|\mathbf{e}\|^2$ implies that \mathbf{e} is orthogonal to *any* vector \mathbf{v} in the space V (visually clear, but can easily be computed too)
- Alternative idea: demand $(\mathbf{e}, \mathbf{v}) = 0, \quad \forall \mathbf{v} \in V$
- Equivalent statement: $(\mathbf{e}, \psi_0) = 0$ (see notes for why)
- Insert $\mathbf{e} = \mathbf{f} - c_0 \psi_0$ and solve for c_0
- Same equation for c_0 and hence same solution as in the least squares method

Approximation of general vectors

Given a vector \mathbf{f} , find an approximation $\mathbf{u} \in V$:

$$V = \text{span} \{ \psi_0, \dots, \psi_N \}$$

- We have a set of linearly independent basis vectors ψ_0, \dots, ψ_N
- Any $\mathbf{u} \in V$ can then be written as $\mathbf{u} = \sum_{j=0}^N c_j \psi_j$

The least squares method

Idea: find c_0, \dots, c_N such that $E = \|\mathbf{e}\|^2$ is minimized, $\mathbf{e} = \mathbf{f} - \mathbf{u}$.

$$\begin{aligned} E(c_0, \dots, c_N) &= (\mathbf{e}, \mathbf{e}) = (\mathbf{f} - \sum_j c_j \psi_j, \mathbf{f} - \sum_j c_j \psi_j) \\ &= (\mathbf{f}, \mathbf{f}) - 2 \sum_{j=0}^N c_j (\mathbf{f}, \psi_j) + \sum_{p=0}^N \sum_{q=0}^N c_p c_q (\psi_p, \psi_q) \end{aligned}$$

$$\frac{\partial E}{\partial c_i} = 0, \quad i = 0, \dots, N$$

After some work we end up with a *linear system*

$$\sum_{j=0}^N A_{i,j} c_j = b_i, \quad i = 0, \dots, N \quad (8)$$

$$A_{i,j} = (\psi_i, \psi_j) \quad (9)$$

$$b_i = (\psi_i, \mathbf{f}) \quad (10)$$

The projection (or Galerkin) method

Can be shown that minimizing $\|\mathbf{e}\|$ implies that \mathbf{e} is orthogonal to all $\mathbf{v} \in V$:

$$(\mathbf{e}, \mathbf{v}) = 0, \quad \forall \mathbf{v} \in V$$

which implies that \mathbf{e} must be orthogonal to each basis vector:

$$(\mathbf{e}, \psi_i) = 0, \quad i = 0, \dots, N \quad (11)$$

This orthogonality condition is the principle of the projection (or Galerkin) method. Leads to the same linear system as in the least squares method.

Approximation of functions

Let V be a *function space* spanned by a set of *basis functions* ψ_0, \dots, ψ_N ,

$$V = \text{span} \{ \psi_0, \dots, \psi_N \}$$

Find $u \in V$ as a linear combination of the basis functions:

$$u = \sum_{j \in I} c_j \psi_j, \quad I = \{0, 1, \dots, N\} \quad (12)$$

The least squares method

- Extend the ideas from the vector case: minimize the (square) norm of the error.
- What norm? $(f, g) = \int_{\Omega} f(x)g(x) dx$

$$E = (e, e) = (f - u, f - u) = (f(x) - \sum_{j \in I} c_j \psi_j(x), f(x) - \sum_{j \in I} c_j \psi_j(x)) \quad (13)$$

$$E(c_0, \dots, c_N) = (f, f) - 2 \sum_{j \in I} c_j (f, \psi_j) + \sum_{p \in I} \sum_{q \in I} c_p c_q (\psi_p, \psi_q) \quad (14)$$

$$\frac{\partial E}{\partial c_i} = 0, \quad i \in I$$

After computations *identical to the vector case*, we get a linear system

$$\sum_{j \in I}^N A_{i,j} c_j = b_i, \quad i \in I \quad (15)$$

The projection (or Galerkin) method

As before, minimizing (e, e) is equivalent to the projection (or Galerkin) method

$$(e, v) = 0, \quad \forall v \in V \quad (18)$$

which means, as before,

$$(e, \psi_i) = 0, \quad i \in I \quad (19)$$

With the same algebra as in the multi-dimensional vector case, we get the same linear system as arose from the least squares method.

Example: linear approximation; problem

Problem.

Approximate a parabola $f(x) = 10(x - 1)^2 - 1$ by a straight line.

$$V = \text{span} \{1, x\}$$

That is, $\psi_0(x) = 1$, $\psi_1(x) = x$, and $N = 1$. We seek

$$u = c_0\psi_0(x) + c_1\psi_1(x) = c_0 + c_1x$$

Example: linear approximation; solution

$$A_{0,0} = (\psi_0, \psi_0) = \int_1^2 1 \cdot 1 \, dx = 1 \quad (20)$$

$$A_{0,1} = (\psi_0, \psi_1) = \int_1^2 1 \cdot x \, dx = 3/2 \quad (21)$$

$$A_{1,0} = A_{0,1} = 3/2, \quad (22)$$

$$A_{1,1} = (\psi_1, \psi_1) = \int_1^2 x \cdot x \, dx = 7/3 \quad (23)$$

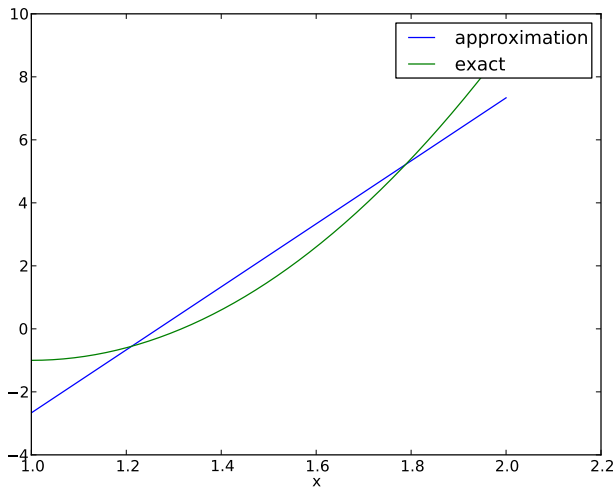
$$b_1 = (f, \psi_0) = \int_1^2 (10(x-1)^2 - 1) \cdot 1 \, dx = 7/3 \quad (24)$$

$$b_2 = (f, \psi_1) = \int_1^2 (10(x-1)^2 - 1) \cdot x \, dx = 13/3 \quad (25)$$

Solution of 2x2 linear system:

$$c_0 = -38/3, \quad c_1 = 10, \quad u(x) = 10x - \frac{38}{3} \quad (26)$$

Example: linear approximation; plot



Implementation of the least squares method; ideas

Consider symbolic computation of the linear system, where

- $f(x)$ is given as a sympy expression f (involving the symbol x),
- phi is a list of $\{\psi_i\}_{i \in I}$,
- Ω is a 2-tuple/list holding the domain Ω

Carry out the integrations, solve the linear system, and return

$$u(x) = \sum_j c_j \psi_j(x)$$

Implementation of the least squares method; code

```
import sympy as sm

def least_squares(f, phi, Omega):
    N = len(phi) - 1
    A = sm.zeros((N+1, N+1))
    b = sm.zeros((N+1, 1))
    x = sm.Symbol('x')
    for i in range(N+1):
        for j in range(i, N+1):
            A[i,j] = sm.integrate(phi[i]*phi[j],
                                   (x, Omega[0], Omega[1]))
            A[j,i] = A[i,j]
        b[i,0] = sm.integrate(phi[i]*f, (x, Omega[0], Omega[1]))
    c = A.LUsolve(b)
    u = 0
    for i in range(len(phi)):
        u += c[i,0]*phi[i]
    return u
```

Observe: symmetric coefficient matrix so we can halve the integrations.

Implementation of the least squares method; plotting

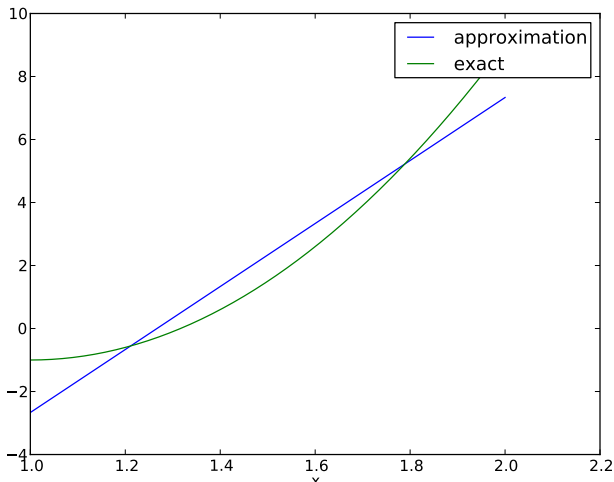
Compare f and u visually:

```
def comparison_plot(f, u, Omega, filename='tmp.pdf'):
    x = sm.Symbol('x')
    # Turn f and u to ordinary Python functions
    f = sm.lambdify([x], f, modules="numpy")
    u = sm.lambdify([x], u, modules="numpy")
    resolution = 401 # no of points in plot
    xcoor = linspace(Omega[0], Omega[1], resolution)
    exact = f(xcoor)
    approx = u(xcoor)
    plot(xcoor, approx)
    hold('on')
    plot(xcoor, exact)
    legend(['approximation', 'exact'])
    savefig(filename)
```

All code in module approx1D.py

Implementation of the least squares method; application

```
>>> from approx1D import *  
>>> x = sm.Symbol('x')  
>>> f = 10*(x-1)**2-1  
>>> u = least_squares(f=f, phi=[1, x], Omega=[1, 2])  
>>> comparison_plot(f, u, Omega=[1, 2])
```



Perfect approximation; parabola approximating parabola

- What if we add $\psi_2 = x^2$ to the space V ?
- That is, approximating a parabola by any parabola?
- (Hopefully we get the exact parabola!)

```
>>> from approx1D import *
>>> x = sm.Symbol('x')
>>> f = 10*(x-1)**2-1
>>> u = least_squares(f=f, phi=[1, x, x**2], Omega=[1, 2])
>>> print u
10*x**2 - 20*x + 9
>>> print sm.expand(f)
10*x**2 - 20*x + 9
```

Perfect approximation; the general result

- What if we use $\phi_i(x) = x^i$ for $i = 0, \dots, N = 40$?
- The output from `least_squares` is $c_i = 0$ for $i > 2$

General result.

If $f \in V$, least squares and projection/Galerkin give $u = f$.

Perfect approximation; proof of the general result

If $f \in V$, $f = \sum_{j \in I} d_j \psi_j$, for some $\{d_i\}_{i \in I}$. Then

$$b_i = (f, \psi_i) = \sum_{j \in I} d_j (\psi_j, \psi_i) = \sum_{j \in I} d_j A_{i,j}$$

The linear system $\sum_j A_{i,j} c_j = b_i$, $i \in I$, is then

$$\sum_{j \in I} c_j A_{i,j} = \sum_{j \in I} d_j A_{i,j}, \quad i \in I$$

which implies that $c_i = d_i$ for $i \in I$ and u is identical to f .

Finite-precision/numerical computations

The previous computations were symbolic. What if we solve the linear system numerically with standard arrays?

<i>exact</i>	<i>sympy</i>	<i>numpy32</i>	<i>numpy64</i>
9	9.62	5.57	8.98
-20	-23.39	-7.65	-19.93
10	17.74	-4.50	9.96
0	-9.19	4.13	-0.26
0	5.25	2.99	0.72
0	0.18	-1.21	-0.93
0	-2.48	-0.41	0.73
0	1.81	-0.013	-0.36
0	-0.66	0.08	0.11
0	0.12	0.04	-0.02
0	-0.001	-0.02	0.002

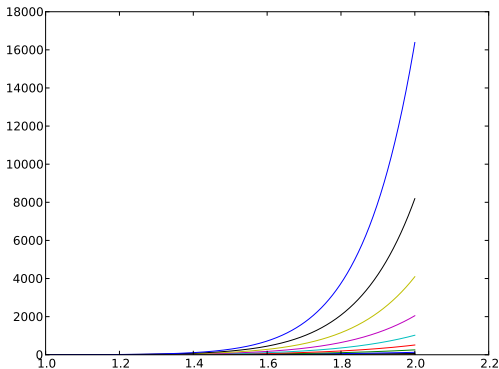
- Column 2: `sympy.mpmath.fp.matrix` and `sympy.mpmath.fp.lu_solve`

Ill-conditioning (1)

Observations:

- Significant round-off errors in the numerical computations (!)
- But if we plot the approximations they look good (!)

Problem: The basis functions x^i become almost linearly dependent for large N .



Ill-conditioning (2)

- Almost linearly dependent basis functions give almost singular matrices
- Such matrices are said to be *ill conditioned*, and Gaussian elimination is severely affected by round-off errors
- The basis $1, x, x^2, x^3, x^4, \dots$ is a bad basis
- Polynomials are fine as basis, but the more orthogonal they are, $(\psi_i, \psi_j) \approx 0$, the better

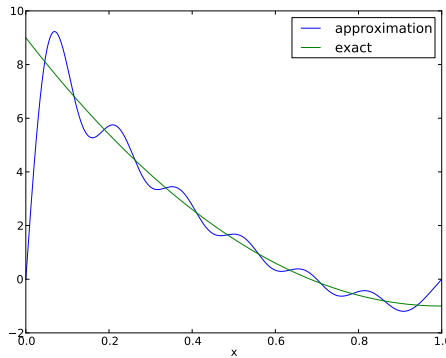
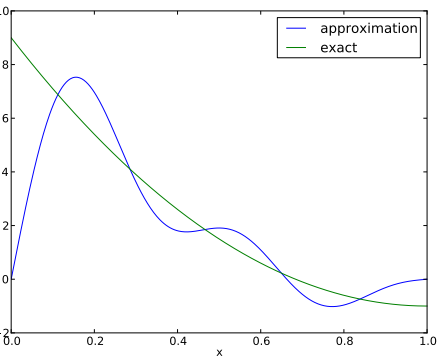
Consider

$$V = \text{span} \{ \sin \pi x, \sin 2\pi x, \dots, \sin(N+1)\pi x \}$$

```
N = 3
from sympy import sin, pi
phi = [sin(pi*(i+1)*x) for i in range(N+1)]
f = 10*(x-1)**2 - 1
Omega = [0, 1]
u = least_squares(f, phi, Omega)
comparison_plot(f, u, Omega)
```

Fourier series approximation; plot

$N = 3$ vs $N = 11$:



Fourier series approximation; improvements

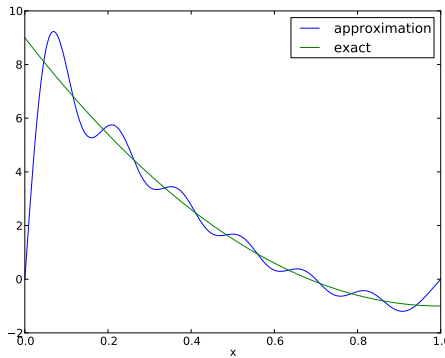
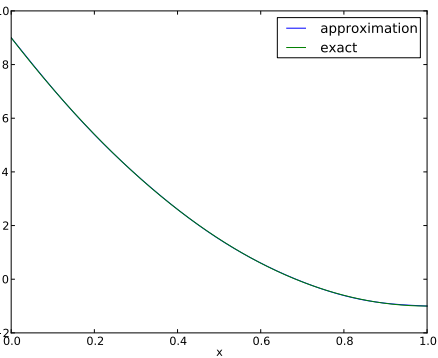
- Considerably improvement by $N = 11$
- But always discrepancy of $f(0) - u(0) = 9$ at $x = 0$, because all the $\psi_i(0) = 0$ and hence $u(0) = 0$
- Possible remedy: add a term that leads to correct boundary values

$$u(x) = f(0)(1 - x) + xf(1) + \sum_{j \in I} c_j \psi_j(x) \quad (27)$$

The extra term ensures $u(0) = f(0)$ and $u(1) = f(1)$ and is a strikingly good help to get a good approximation!

Fourier series approximation; final results

$N = 3$ vs $N = 11$:



Orthogonal basis functions

This choice of sine functions as basis functions is popular because

- the basis functions are orthogonal: $(\psi_i, \psi_j) = 0$
- implying that $A_{i,j}$ is a diagonal matrix
- implying that we can solve for $c_i = 2 \int_0^1 f(x) \sin((i+1)\pi x) dx$

In general for an orthogonal basis, $A_{i,j}$ is diagonal and we can easily solve for c_i :

$$c_i = \frac{b_i}{A_{i,i}} = \frac{(f, \psi_i)}{(\psi_i, \psi_i)}$$

The collocation or interpolation method; ideas and math

Here is another idea for approximating $f(x)$ by $u(x) = \sum_j c_j \psi_j$:

- Force $u(x_i) = f(x_i)$ at some selected *collocation* points $\{x_i\}_{i \in I}$
- Then u interpolates f
- The method is known as *interpolation* or *collocation*

$$u(x_i) = \sum_{j \in I} c_j \psi_j(x_i) = f(x_i) \quad i \in I, N \quad (28)$$

This is a linear system with no need for integration:

$$\sum_{j \in I} A_{i,j} c_j = b_i, \quad i \in I \quad (29)$$

$$A_{i,j} = \psi_j(x_i) \quad (30)$$

$$b_i = f(x_i) \quad (31)$$

No symmetric matrix: $\psi_j(x_i) \neq \psi_i(x_j)$ in general

The collocation or interpolation method; implementation

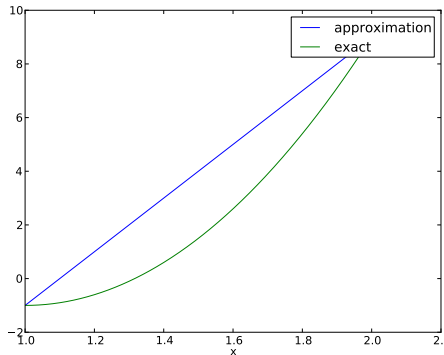
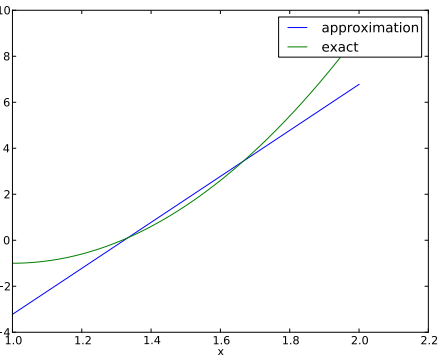
points holds the interpolation/collocation points

```
def interpolation(f, phi, points):
    N = len(phi) - 1
    A = sm.zeros((N+1, N+1))
    b = sm.zeros((N+1, 1))
    x = sm.Symbol('x')
    # Turn phi and f into Python functions
    phi = [sm.lambdify([x], phi[i]) for i in range(N+1)]
    f = sm.lambdify([x], f)
    for i in range(N+1):
        for j in range(N+1):
            A[i,j] = phi[j](points[i])
        b[i,0] = f(points[i])
    c = A.LUsolve(b)
    u = 0
    for i in range(len(phi)):
        u += c[i,0]*phi[i](x)
    return u
```

The collocation or interpolation method; approximating a parabola by linear functions

- Potential difficulty: how to choose x_i ?
- The results are sensitive to the points!

$(4/3, 5/3)$ vs $(1, 2)$:



Lagrange polynomials; motivation and ideas

Motivation:

- The interpolation/collocation method avoids integration
- With a diagonal matrix $A_{i,j} = \psi_j(x_i)$ we can solve the linear system by hand

The *Lagrange interpolating polynomials* ψ_j have the property that

$$\varphi_i(x_j) = \delta_{ij}, \quad \delta_{ij} = \begin{cases} 1, & i = j, \\ 0, & i \neq j, \end{cases}$$

Hence, $c_i = f(x_i)$ and

$$u(x) = \sum_{j \in I} f(x_j) \psi_j(x) \tag{32}$$

- Lagrange polynomials and interpolation/collocation look convenient
- Lagrange polynomials are very much used in the finite element method

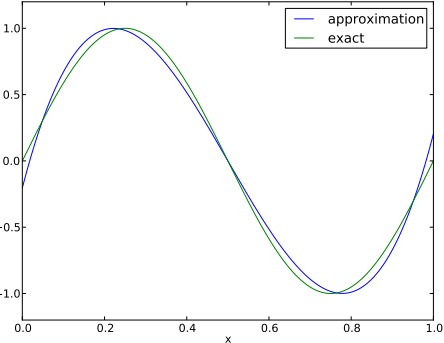
Lagrange polynomials; formula and code

$$\psi_i(x) = \prod_{j=0, j \neq i}^N \frac{x - x_j}{x_i - x_j} = \frac{x - x_0}{x_i - x_0} \dots \frac{x - x_{i-1}}{x_i - x_{i-1}} \frac{x - x_{i+1}}{x_i - x_{i+1}} \dots \frac{x - x_N}{x_i - x_N} \quad (33)$$

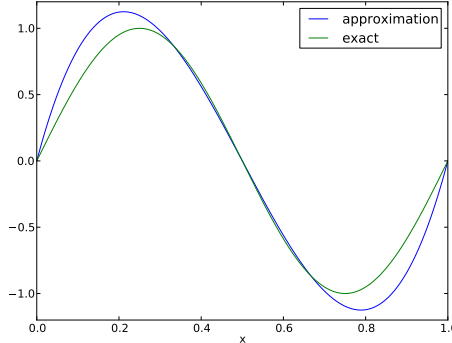
```
def Lagrange_polynomial(x, i, points):  
    p = 1  
    for k in range(len(points)):  
        if k != i:  
            p *= (x - points[k]) / (points[i] - points[k])  
    return p
```

Lagrange polynomials; successful example

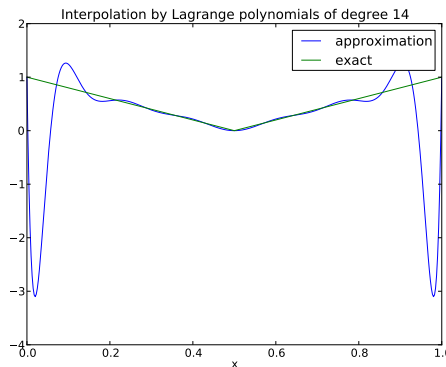
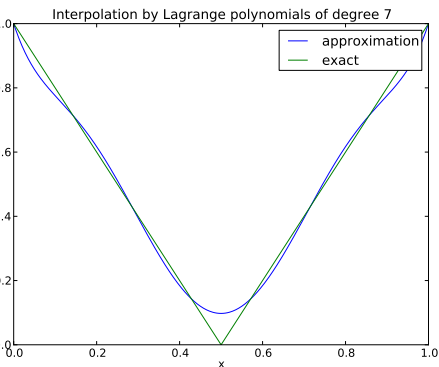
Least squares approximation by Lagrange polynomials of degree 3



Interpolation by Lagrange polynomials of degree 3

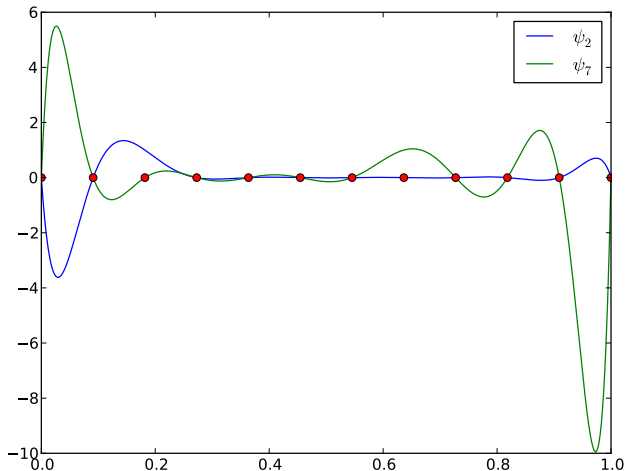


Lagrange polynomials; a less successful example



Lagrange polynomials; oscillatory behavior

12 points, degree 11, plot of two of the Lagrange polynomials - note that they are zero at all points except one.



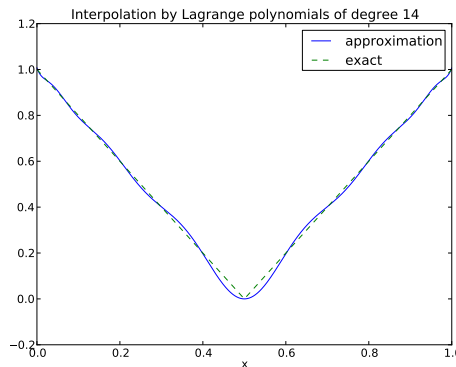
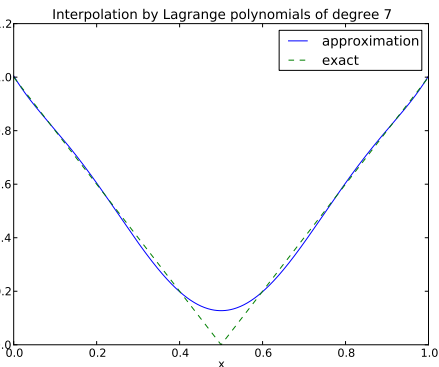
Lagrange polynomials; remedy for strong oscillations

The oscillations can be reduced by a more clever choice of interpolation points, called the *Chebyshev nodes*:

$$x_i = \frac{1}{2}(a+b) + \frac{1}{2}(b-a) \cos \left(\frac{2i+1}{2(N+1)} \pi \right), \quad i = 0 \dots, N \quad (34)$$

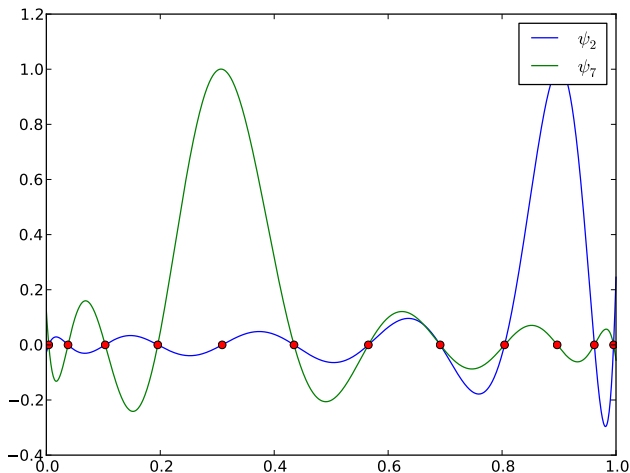
on an interval $[a, b]$.

Lagrange polynomials; recalculation with Chebyshev nodes



Lagrange polynomials; less oscillations with Chebyshev nodes

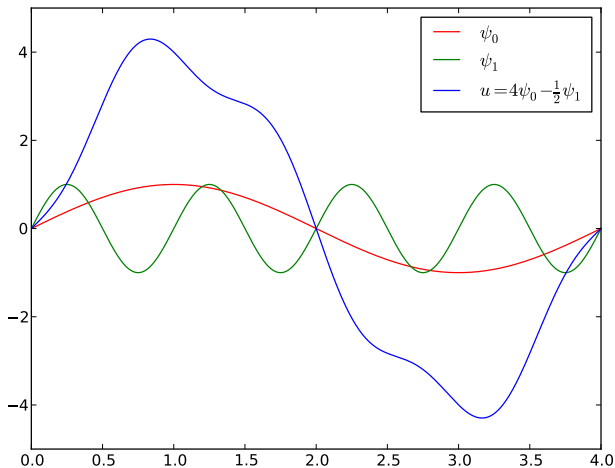
12 points, degree 11, plot of two of the Lagrange polynomials - note that they are zero at all points except one.



Finite element basis functions

So far: basis functions have been global

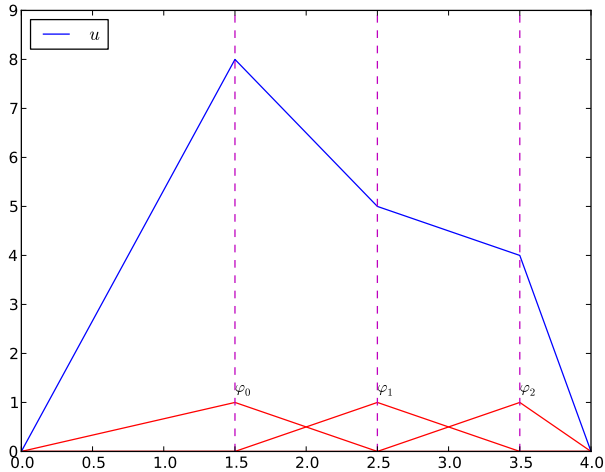
$\psi_i(x) \neq 0$ for most $x \in \Omega$



In the finite element method we use basis functions with local support

- *Local support*: $\psi_i(x) \neq 0$ for x in a small subdomain of Ω
- Typically hat-shaped
- $u(x)$ based on these ψ_i is a piecewise polynomial defined over many (small) subdomains

The linear combination of hat functions is a piecewise linear function



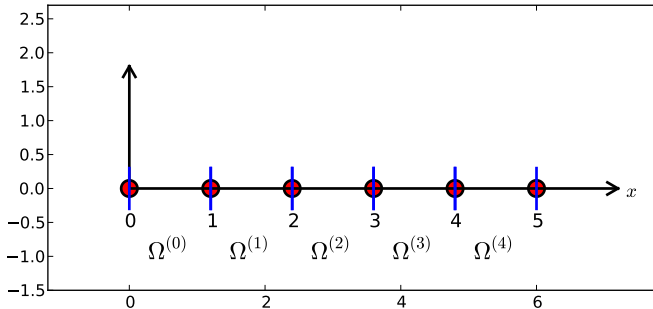
Split Ω into non-overlapping subdomains called *elements*:

$$\Omega = \Omega^{(0)} \cup \dots \cup \Omega^{(N_e)} \quad (35)$$

On each element, introduce points called *nodes*: x_0, \dots, x_{N_n}

- The finite element basis functions are named $\varphi_i(x)$
- $\varphi_i = 1$ at node i and 0 at all other nodes
- φ_i is a Lagrange polynomial on each element
- For nodes at the boundary between two elements, φ_i is made up of a Lagrange polynomial over each element

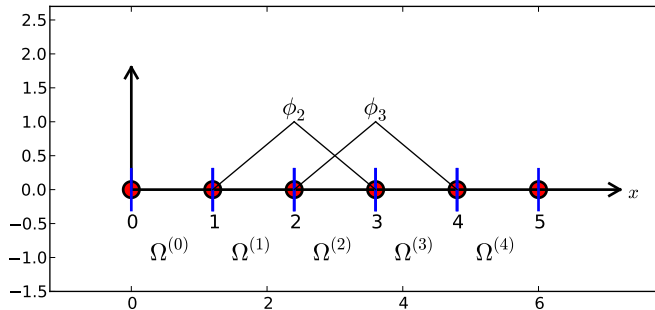
Example on elements with two nodes (P1 elements)



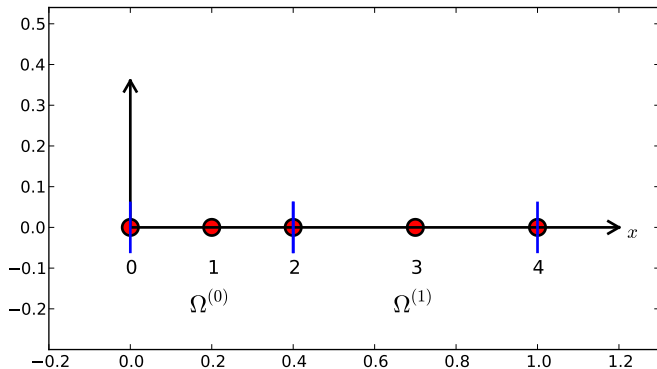
Data structure: `nodes` holds coordinates or nodes, `elements` holds the node numbers in each element

```
nodes = [0, 1.2, 2.4, 3.6, 4.8, 5]
elements = [[0, 1], [1, 2], [2, 3], [3, 4], [4, 5]]
```

Illustration of two basis functions on the mesh

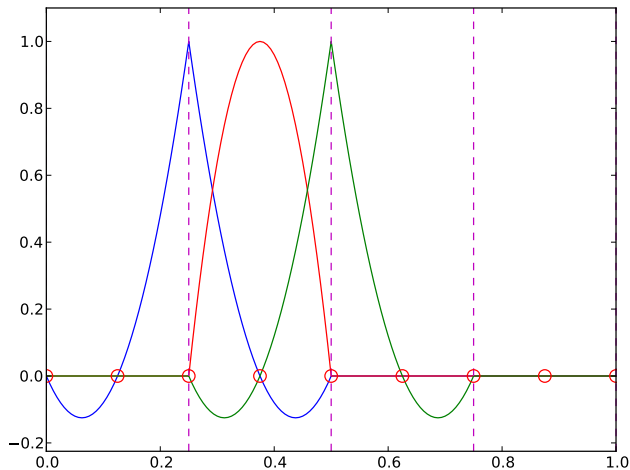


Example on elements with three nodes (P2 elements)

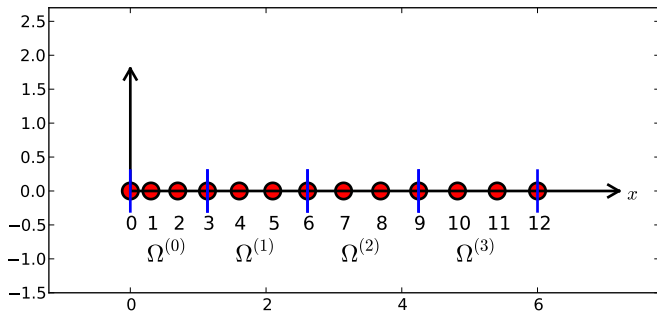


```
nodes = [0, 0.125, 0.25, 0.375, 0.5, 0.625, 0.75, 0.875, 1.0]  
elements = [[0, 1, 2], [2, 3, 4], [4, 5, 6], [6, 7, 8]]
```


Some corresponding basis functions (P2 elements)

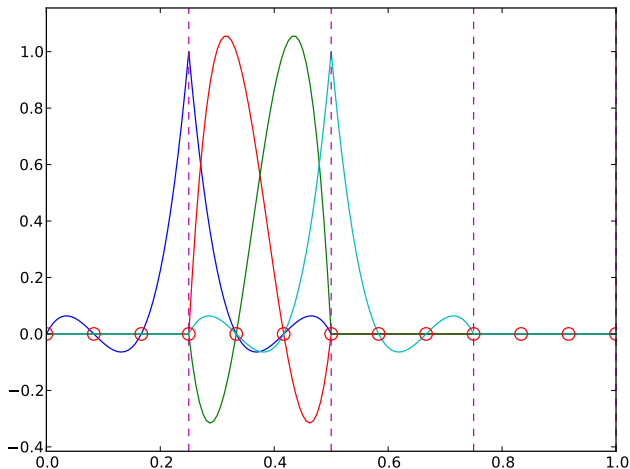


Examples on elements with four nodes per element (P3 elements)

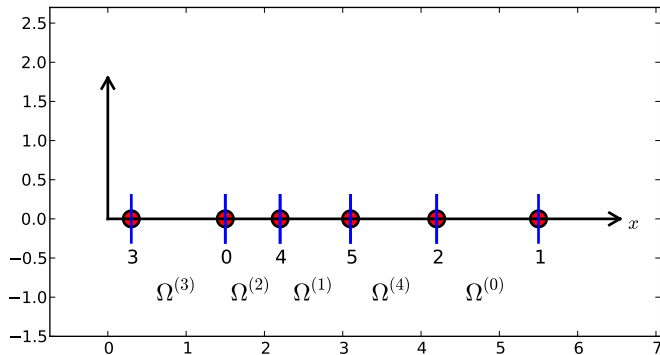


```
d = 3 # d+1 nodes per element
num_elements = 4
num_nodes = num_elements*d + 1
nodes = [i*0.5 for i in range(num_nodes)]
elements = [[i*d+j for j in range(d+1)] for i in range(num_elements)]
```

Some corresponding basis functions (P3 elements)



The numbering does not need to be regular from left to right



```
nodes = [1.5, 5.5, 4.2, 0.3, 2.2, 3.1]
elements = [[2, 1], [4, 5], [0, 4], [3, 0], [5, 2]]
```

Interpretation of the coefficients c_i

Important property: c_i is the value of u at node i , x_i :

$$u(x_i) = \sum_{j \in I} c_j \varphi_j(x_i) = c_i \varphi_i(x_i) = c_i \quad (36)$$

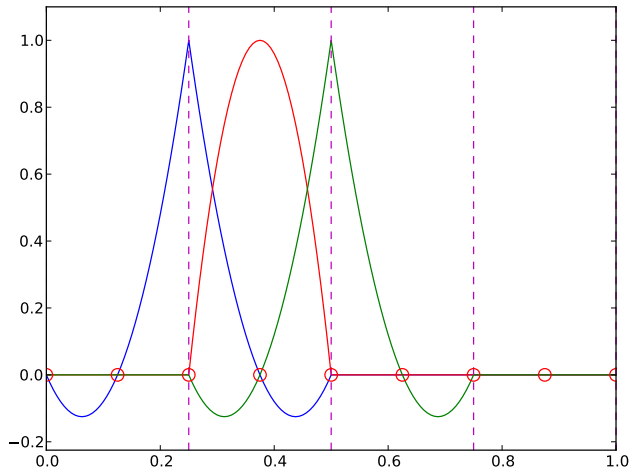
Properties of the basis functions

$\varphi_i(x)$ is mostly zero throughout the domain:

- $\varphi_i(x) \neq 0$ only on those elements that contain global node i ,
- $\varphi_i(x)\varphi_j(x) \neq 0$ if and only if i and j are global node numbers in the same element.

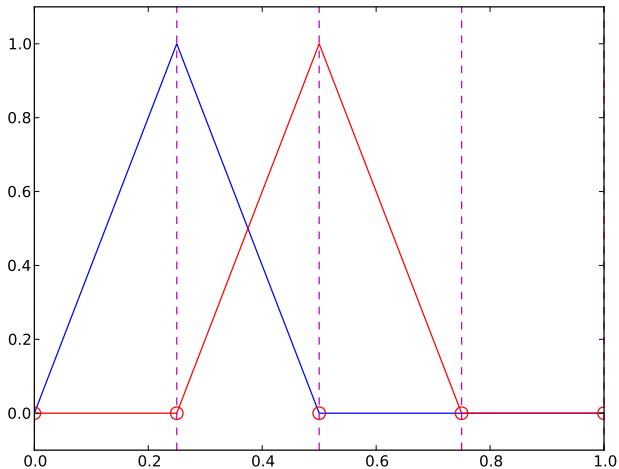
Since $A_{i,j}$ is the integral of $\varphi_i\varphi_j$ it means that *most of the elements in the coefficient matrix will be zero* (important for implementation!).

How to construct quadratic φ_i (P2 elements)

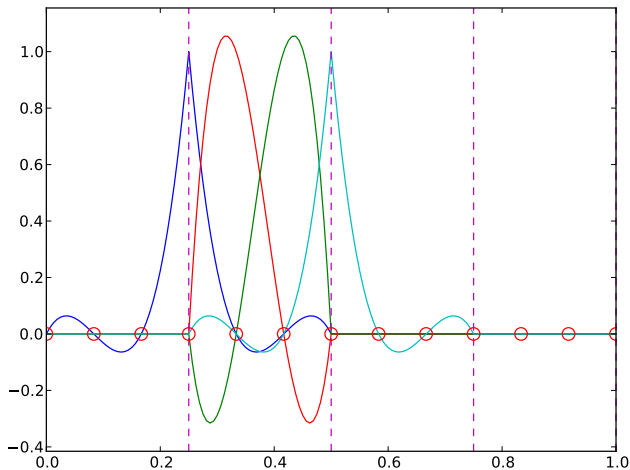


- 1 Associate Lagrange polynomials with the nodes in an element

Example on linear φ_i (P1 elements)

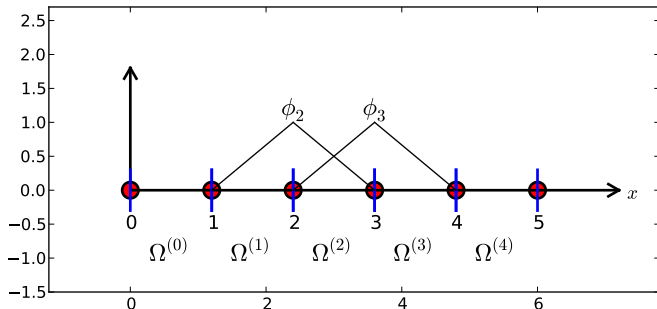


Example on cubic φ_i (P3 elements)



Calculating the linear system for c_i

Computing a specific matrix entry (1)

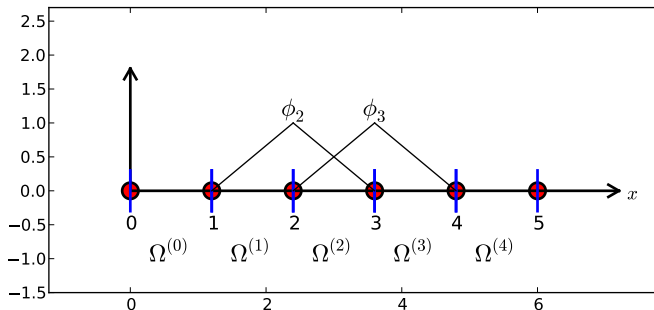


$A_{2,3} = \int_{\Omega} \varphi_2 \varphi_3 dx$: $\varphi_2 \varphi_3 \neq 0$ only over element 2. There,

$$\varphi_3(x) = (x - x_2)/h, \quad \varphi_2(x) = 1 - (x - x_2)/h$$

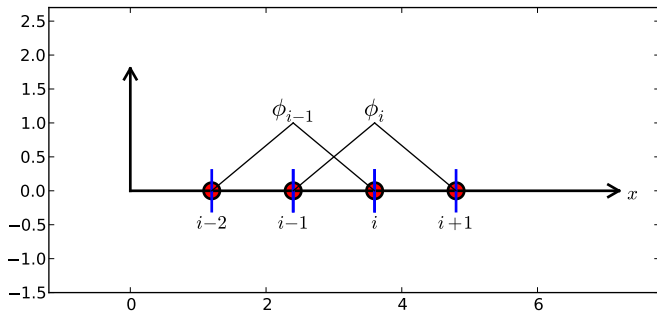
$$A_{2,3} = \int_{\Omega} \varphi_2 \varphi_3 dx = \int_{x_2}^{x_3} \left(1 - \frac{x - x_2}{h}\right) \frac{x - x_2}{h} dx = \frac{h}{6}$$

Computing a specific matrix entry (2)



$$A_{2,2} = \int_{x_1}^{x_2} \left(\frac{x - x_1}{h} \right)^2 dx + \int_{x_2}^{x_3} \left(1 - \frac{x - x_2}{h} \right)^2 dx = \frac{h}{3}$$

Calculating a general row in the matrix; figure



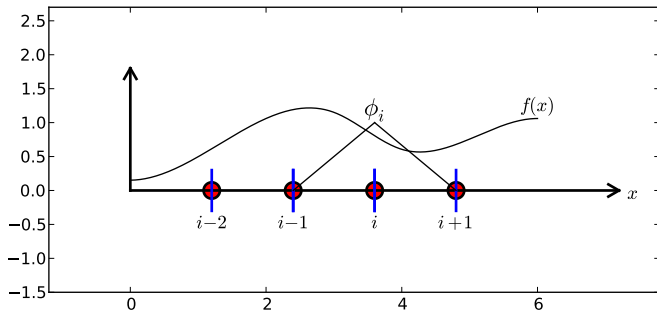
$$A_{i,i-1} = \int_{\Omega} \varphi_i \varphi_{i-1} dx = ?$$

Calculating a general row in the matrix; details

$$\begin{aligned} A_{i,i-1} &= \int_{\Omega} \varphi_i \varphi_{i-1} \, dx \\ &= \underbrace{\int_{x_{i-2}}^{x_{i-1}} \varphi_i \varphi_{i-1} \, dx}_{\varphi_i=0} + \int_{x_i}^{x_i} \varphi_i \varphi_{i-1} \, dx + \underbrace{\int_{x_i}^{x_{i+1}} \varphi_i \varphi_{i-1} \, dx}_{\varphi_{i-1}=0} \\ &= \int_{x_{i-1}}^{x_i} \underbrace{\frac{x - x_i}{h}}_{\varphi_i(x)} \underbrace{\left(1 - \frac{x - x_{i-1}}{h}\right)}_{\varphi_{i-1}(x)} \, dx = \frac{h}{6} \end{aligned}$$

- $A_{i,i+1} = A_{i,i-1}$ due to symmetry
- $A_{i,i} = h/3$ (same calculation as for $A_{2,2}$)
- $A_{0,0} = A_{N,N} = h/3$ (only one element)

Calculation of the right-hand side



$$b_i = \int_{\Omega} \varphi_i(x) f(x) dx = \int_{x_{i-1}}^{x_i} \frac{x - x_{i-1}}{h} f(x) dx + \int_{x_i}^{x_{i+1}} \left(1 - \frac{x - x_i}{h}\right) f(x) dx \quad (38)$$

Need a specific $f(x)$ to do more...

Specific example: two elements; linear system and solution

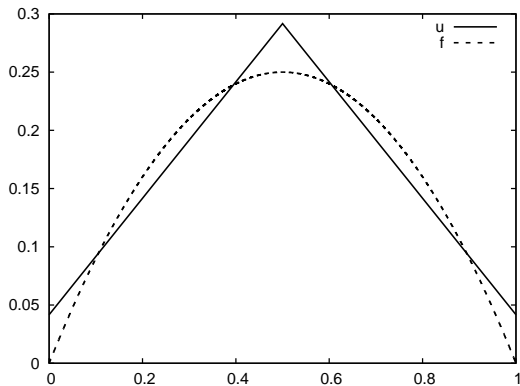
- $f(x) = x(1 - x)$ on $\Omega = [0, 1]$
- Two equal-sized elements $[0, 0.5]$ and $[0.5, 1]$

$$A = \frac{h}{6} \begin{pmatrix} 2 & 1 & 0 \\ 1 & 4 & 1 \\ 0 & 1 & 2 \end{pmatrix}, \quad b = \frac{h^2}{12} \begin{pmatrix} 2 - 3h \\ 12 - 14h \\ 10 - 17h \end{pmatrix}$$

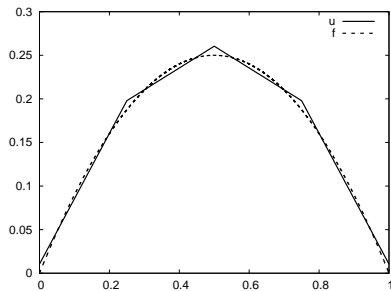
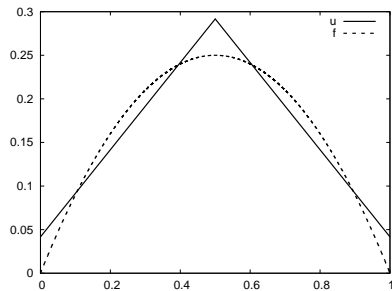
$$c_0 = \frac{h^2}{6}, \quad c_1 = h - \frac{5}{6}h^2, \quad c_2 = 2h - \frac{23}{6}h^2$$

Specific example: two elements; plot

$$u(x) = c_0\varphi_0(x) + c_1\varphi_1(x) + c_2\varphi_2(x)$$



Specific example: what about four elements?



Assembly of elementwise computations

Split the integrals into elementwise integrals

$$A_{i,j} = \int_{\Omega} \varphi_i \varphi_j dx = \sum_e A_{i,j}^{(e)}, \quad A_{i,j}^{(e)} = \int_{\Omega^{(e)}} \varphi_i \varphi_j dx \quad (39)$$

Important:

- $A_{i,j}^{(e)} \neq 0$ if and only if i and j are nodes in element e (otherwise no overlap between the basis functions)
- all the nonzero elements in $A_{i,j}^{(e)}$ are collected in an *element matrix*

The element matrix

$$\tilde{A}^{(e)} = \{\tilde{A}_{r,s}^{(e)}\}, \quad r, s \in I_d = \{0, \dots, d\}$$

$$\tilde{A}_{r,s}^{(e)} = \int_{\Omega^{(e)}} \varphi_{q(e,r)} \varphi_{q(e,s)} dx, \quad r, s \in I_d$$

- r, s run over *local node numbers* within an element, while i, j run over *global node numbers*.
- $i = q(e, r)$: mapping of local node number r in element e to the global node number i . Math equivalent to `i=elements[e][r]`.
- Add contribution from an element into the global coefficient matrix (*assembly*)

$$A_{q(e,r),q(e,s)} := A_{q(e,r),q(e,s)} + \tilde{A}_{r,s}^{(e)}, \quad r, s \in I_d \quad (40)$$

Illustration of the matrix assembly: regularly numbered P1 elements

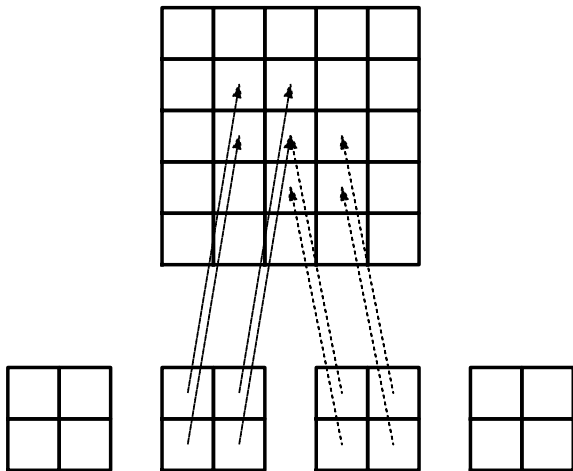


Illustration of the matrix assembly: regularly numbered P3 elements

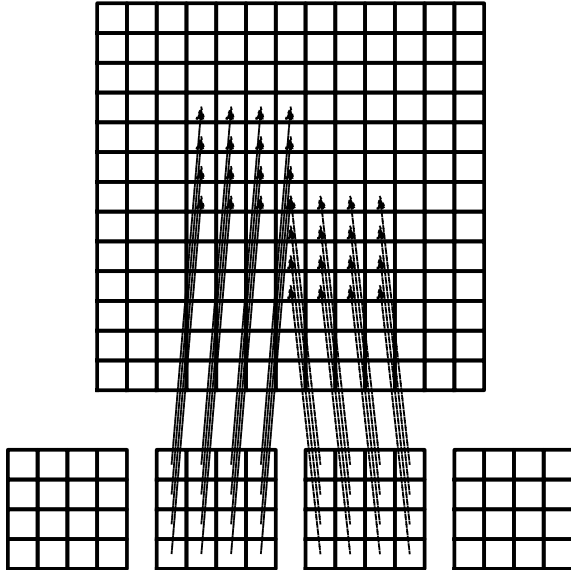
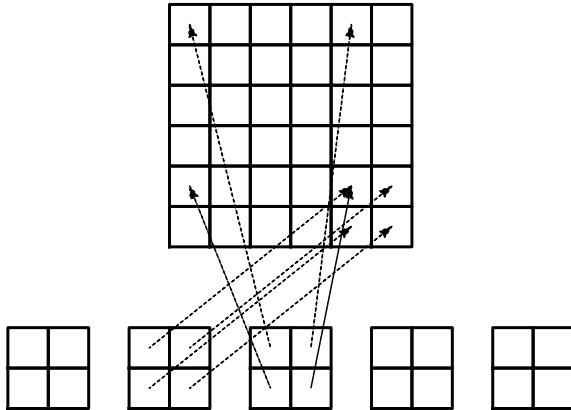


Illustration of the matrix assembly: irregularly numbered P1 elements



Animation

Assembly of the right-hand side

Split in elementwise contributions:

$$b_i = \int_{\Omega} \varphi_i \varphi_j dx = \sum_e b_i^{(e)}, \quad b_i^{(e)} = \int_{\Omega^{(e)}} f(x) \varphi_i(x) dx \quad (41)$$

Important:

- $b_i^{(e)} \neq 0$ if and only if global node i is a node in element e (otherwise $\varphi_i = 0$)
- The $d + 1$ nonzero $b_i^{(e)}$ can be collected in an *element vector*

$$\tilde{b}_r^{(e)} = \{\tilde{b}_r^{(e)}\}, \quad r \in I_d$$

Assembly:

$$b_{q(e,r)} := b_{q(e,r)} + \tilde{b}_r^{(e)}, \quad r, s \in I_d \quad (42)$$

Mapping to a reference element

Instead of computing

$$\tilde{A}_{r,s}^{(e)} = \int_{\Omega^{(e)}} \varphi_{q(e,r)}(x) \varphi_{q(e,s)}(x) dx$$

over some element $\Omega^{(e)} = [x_L, x_R]$, we now map $[x_L, x_R]$ to a standardized reference element domain $[-1, 1]$ with local coordinate X .

$$x = \frac{1}{2}(x_L + x_R) + \frac{1}{2}(x_R - x_L)X \quad (43)$$

or rewritten as

$$x = x_m + \frac{1}{2}hX, \quad x_m = (x_L + x_R)/2 \quad (44)$$

Integral transformation

Integrating on the reference element is a matter of just changing the integration variable from x to X . Introduce local basis function

$$\tilde{\varphi}_r(X) = \varphi_{q(e,r)}(x(X)) \quad (45)$$

The integral transformation reads

$$\tilde{A}_{r,s}^{(e)} = \int_{\Omega^{(e)}} \varphi_{q(e,r)}(x) \varphi_{q(e,s)}(x) dx = \int_{-1}^1 \tilde{\varphi}_r(X) \tilde{\varphi}_s(X) \frac{dx}{dX} dX \quad (46)$$

Introduce the notation $\det J = dx/dX = h/2$ (2D/3D must use $\det J$)

$$\tilde{A}_{r,s}^{(e)} = \int_{-1}^1 \tilde{\varphi}_r(X) \tilde{\varphi}_s(X) \det J dX \quad (47)$$

$$\tilde{b}_r^{(e)} = \int_{\Omega^{(e)}} f(x) \varphi_{q(e,r)}(x) dx = \int_{-1}^1 f(x(X)) \tilde{\varphi}_r(X) \det J dX \quad (48)$$

Advantages of the reference element

- Always the same domain for integration: $[-1, 1]$
- We only need formulas for $\tilde{\varphi}_r(X)$ on the reference elements (no need for piecewise polynomial definition)
- All geometric information (length and location) is "factored out" in the mapping and $\det J$

Standardized basis functions for P1 elements

$$\tilde{\varphi}_0(X) = \frac{1}{2}(1 - X) \quad (49)$$

$$\tilde{\varphi}_1(X) = \frac{1}{2}(1 + X) \quad (50)$$

Standardized basis functions for P2 elements

P2 elements:

$$\tilde{\varphi}_0(X) = \frac{1}{2}(X-1)X \quad (51)$$

$$\tilde{\varphi}_1(X) = 1 - X^2 \quad (52)$$

$$\tilde{\varphi}_2(X) = \frac{1}{2}(X+1)X \quad (53)$$

Easy to generalize to arbitrary order!

Integration over a reference element; element matrix

P1 elements and $f(x) = x(1 - x)$.

$$\begin{aligned}\tilde{A}_{0,0}^{(e)} &= \int_{-1}^1 \tilde{\varphi}_0(X) \tilde{\varphi}_0(X) \frac{h}{2} dX \\ &= \int_{-1}^1 \frac{1}{2}(1 - X) \frac{1}{2}(1 - X) \frac{h}{2} dX = \frac{h}{8} \int_{-1}^1 (1 - X)^2 dX = \frac{h}{3},\end{aligned}\tag{54}$$

$$\begin{aligned}\tilde{A}_{1,0}^{(e)} &= \int_{-1}^1 \tilde{\varphi}_1(X) \tilde{\varphi}_0(X) \frac{h}{2} dX \\ &= \int_{-1}^1 \frac{1}{2}(1 + X) \frac{1}{2}(1 - X) \frac{h}{2} dX = \frac{h}{8} \int_{-1}^1 (1 - X^2) dX = \frac{h}{6},\end{aligned}\tag{55}$$

$$\tilde{A}_{0,1}^{(e)} = \tilde{A}_{1,0}^{(e)},\tag{56}$$

$$\tilde{A}_{1,1}^{(e)} = \int_{-1}^1 \tilde{\varphi}_1(X) \tilde{\varphi}_1(X) \frac{h}{2} dX$$

$\int_{-1}^1 \frac{1}{2}(1 + X) \frac{1}{2}(1 + X) \frac{h}{2} dX = \frac{h}{8} \int_{-1}^1 (1 + X)^2 dX = \frac{h}{3}$

Integration over a reference element; element vector

$$\begin{aligned}\tilde{b}_0^{(e)} &= \int_{-1}^1 f(x(X)) \tilde{\varphi}_0(X) \frac{h}{2} dX \\&= \int_{-1}^1 (x_m + \frac{1}{2}hX)(1 - (x_m + \frac{1}{2}hX)) \frac{1}{2}(1 - X) \frac{h}{2} dX \\&= -\frac{1}{24}h^3 + \frac{1}{6}h^2x_m - \frac{1}{12}h^2 - \frac{1}{2}hx_m^2 + \frac{1}{2}hx_m\end{aligned}\quad (58)$$

$$\begin{aligned}\tilde{b}_1^{(e)} &= \int_{-1}^1 f(x(X)) \tilde{\varphi}_1(X) \frac{h}{2} dX \\&= \int_{-1}^1 (x_m + \frac{1}{2}hX)(1 - (x_m + \frac{1}{2}hX)) \frac{1}{2}(1 + X) \frac{h}{2} dX \\&= -\frac{1}{24}h^3 - \frac{1}{6}h^2x_m + \frac{1}{12}h^2 - \frac{1}{2}hx_m^2 + \frac{1}{2}hx_m\end{aligned}\quad (59)$$

x_m : element midpoint.

Tedious calculations! Let's use symbolic software

```
>>> import sympy as sm
>>> x, x_m, h, X = sm.symbols('x x_m h X')
>>> sm.integrate(h/8*(1-X)**2, (X, -1, 1))
h/3
>>> sm.integrate(h/8*(1+X)*(1-X), (X, -1, 1))
h/6
>>> x = x_m + h/2*X
>>> b_0 = sm.integrate(h/4*x*(1-x)*(1-X), (X, -1, 1))
>>> print b_0
-h**3/24 + h**2*x_m/6 - h**2/12 - h*x_m**2/2 + h*x_m/2
```

Can print out in \LaTeX too (convenient for copying into reports):

```
>>> print sm.latex(b_0, mode='plain')
- \frac{1}{24} h^3 + \frac{1}{6} h^2 x_m
- \frac{1}{12} h^2 - \frac{1}{2} h x_m^2
+ \frac{1}{2} h x_m
```

Implementation

- Coming functions appear in `fe_approx1D.py`
- Functions can operate in symbolic or numeric mode
- The code documents all steps in finite element calculations!

Compute finite element basis functions

Let $\tilde{\varphi}_r(X)$ be a Lagrange polynomial of degree d :

```
import sympy as sm
import numpy as np

def phi_r(r, X, d):
    if isinstance(X, sm.Symbol):
        h = sm.Rational(1, d) # node spacing
        nodes = [2*i*h - 1 for i in range(d+1)]
    else:
        # assume X is numeric: use floats for nodes
        nodes = np.linspace(-1, 1, d+1)
    return Lagrange_polynomial(X, r, nodes)

def Lagrange_polynomial(x, i, points):
    p = 1
    for k in range(len(points)):
        if k != i:
            p *= (x - points[k])/(points[i] - points[k])
    return p

def basis(d=1):
    """Return the complete basis."""
    X = sm.Symbol('X')
    phi = [phi_r(r, X, d) for r in range(d+1)]
    return phi
```

Compute the element matrix

```
def element_matrix(phi, Omega_e, symbolic=True):
    n = len(phi)
    A_e = sm.zeros((n, n))
    X = sm.Symbol('X')
    if symbolic:
        h = sm.Symbol('h')
    else:
        h = Omega_e[1] - Omega_e[0]
    detJ = h/2 # dx/dX
    for r in range(n):
        for s in range(r, n):
            A_e[r,s] = sm.integrate(phi[r]*phi[s]*detJ, (X, -1, 1))
            A_e[s,r] = A_e[r,s]
    return A_e
```

Example on symbolic and numeric element matrix

```
>>> from fe_approx1D import *
>>> phi = basis(d=1)
>>> phi
[1/2 - X/2, 1/2 + X/2]
>>> element_matrix(phi, Omega_e=[0.1, 0.2], symbolic=True)
[h/3, h/6]
[h/6, h/3]
>>> element_matrix(phi, Omega_e=[0.1, 0.2], symbolic=False)
[0.03333333333333333, 0.01666666666666667]
[0.01666666666666667, 0.03333333333333333]
```

Compute the element vector

```
def element_vector(f, phi, Omega_e, symbolic=True):
    n = len(phi)
    b_e = sm.zeros((n, 1))
    # Make f a function of X
    X = sm.Symbol('X')
    if symbolic:
        h = sm.Symbol('h')
    else:
        h = Omega_e[1] - Omega_e[0]
    x = (Omega_e[0] + Omega_e[1])/2 + h/2*X # mapping
    f = f.subs('x', x) # substitute mapping formula for x
    detJ = h/2 # dx/dX
    for r in range(n):
        b_e[r] = sm.integrate(f*phi[r]*detJ, (X, -1, 1))
    return b_e
```

Note `f.subs('x', x)`: replace `x` by `x(X)` such that `f` contains `X`

Fallback on numerical integration if symbolic integration fails

- Element matrix: only polynomials and sympy always succeeds
- Element vector: $\int f \tilde{\phi} dx$ can fail (sympy then returns an Integral object instead of a number)

```
def element_vector(f, phi, Omega_e, symbolic=True):  
    ...  
    I = sm.integrate(f*phi[r]*detJ, (X, -1, 1)) # try...  
    if isinstance(I, sm.Integral):  
        h = Omega_e[1] - Omega_e[0] # Ensure h is numerical  
        detJ = h/2  
        integrand = sm.lambdify([X], f*phi[r]*detJ)  
        I = sm.mpmath.quad(integrand, [-1, 1])  
    b_e[r] = I  
    ...
```


Linear system assembly and solution

```
def assemble(nodes, elements, phi, f, symbolic=True):
    N_n, N_e = len(nodes), len(elements)
    zeros = sm.zeros if symbolic else np.zeros
    A = zeros((N_n, N_n))
    b = zeros((N_n, 1))
    for e in range(N_e):
        Omega_e = [nodes[elements[e][0]], nodes[elements[e][-1]]]

        A_e = element_matrix(phi, Omega_e, symbolic)
        b_e = element_vector(f, phi, Omega_e, symbolic)

        for r in range(len(elements[e])):
            for s in range(len(elements[e])):
                A[elements[e][r], elements[e][s]] += A_e[r, s]
            b[elements[e][r]] += b_e[r]
    return A, b
```

Linear system solution

```
if symbolic:
    c = A.LUsolve(b)          # sympy arrays, symbolic Gaussian el
else:
    c = np.linalg.solve(A, b) # numpy arrays, numerical solve
```

Note: the symbolic computation of A and b and the symbolic solution can be very tedious.

Example on computing approximations

```
>>> h, x = sm.symbols('h x')
>>> nodes = [0, h, 2*h]
>>> elements = [[0, 1], [1, 2]]
>>> phi = basis(d=1)
>>> f = x*(1-x)
>>> A, b = assemble(nodes, elements, phi, f, symbolic=True)
>>> A
[h/3,    h/6,    0]
[h/6, 2*h/3, h/6]
[ 0,    h/6, h/3]
>>> b
[      h**2/6 - h**3/12]
[      h**2 - 7*h**3/6]
[5*h**2/6 - 17*h**3/12]
>>> c = A.LUsolve(b)
>>> c
[
                                h**2/6]
[12*(7*h**2/12 - 35*h**3/72)/(7*h)]
[ 7*(4*h**2/7 - 23*h**3/21)/(2*h)]
```

Numerical computations:

```
>>> nodes = [0, 0.5, 1]
>>> elements = [[0, 1], [1, 2]]
>>> phi = basis(d=1)
>>> x = sm.Symbol('x')
>>> f = x*(1-x)
>>> A, b = assemble(nodes, elements, phi, f, symbolic=False)
>>> A
```

The structure of the coefficient matrix

```
>>> d=1; N_e=8; Omega=[0,1]  # 8 linear elements on [0,1]
>>> phi = basis(d)
>>> f = x*(1-x)
>>> nodes, elements = mesh_symbolic(N_e, d, Omega)
>>> A, b = assemble(nodes, elements, phi, f, symbolic=True)
>>> A
[h/3,    h/6,    0,    0,    0,    0,    0,    0,    0]
[h/6, 2*h/3,    h/6,    0,    0,    0,    0,    0,    0]
[ 0,    h/6, 2*h/3,    h/6,    0,    0,    0,    0,    0]
[ 0,    0,    h/6, 2*h/3,    h/6,    0,    0,    0,    0]
[ 0,    0,    0,    h/6, 2*h/3,    h/6,    0,    0,    0]
[ 0,    0,    0,    0,    h/6, 2*h/3,    h/6,    0,    0]
[ 0,    0,    0,    0,    0,    h/6, 2*h/3,    h/6,    0]
[ 0,    0,    0,    0,    0,    0,    h/6, 2*h/3, h/6]
[ 0,    0,    0,    0,    0,    0,    0,    h/6, h/3]
```

Note: do this by hand to understand what is going on!

General result: the coefficient matrix is sparse

- Sparse = most of the entries are zeros
- Below: P1 elements

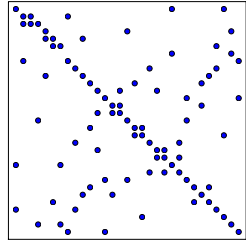
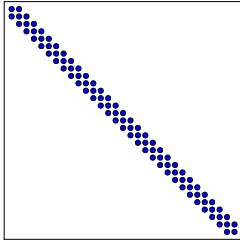
$$A = \frac{h}{6} \begin{pmatrix} 2 & 1 & 0 & \dots & \dots & \dots & \dots & \dots & 0 \\ 1 & 4 & 1 & \ddots & & & & & \vdots \\ 0 & 1 & 4 & 1 & \ddots & & & & \vdots \\ \vdots & \ddots & & \ddots & \ddots & 0 & & & \vdots \\ \vdots & & \ddots & \ddots & \ddots & \ddots & \ddots & & \vdots \\ \vdots & & & 0 & 1 & 4 & 1 & \ddots & \vdots \\ \vdots & & & & \ddots & \ddots & \ddots & \ddots & 0 \\ \vdots & & & & & \ddots & 1 & 4 & 1 \\ 0 & \dots & \dots & \dots & \dots & \dots & 0 & 1 & 2 \end{pmatrix} \quad (60)$$

Exemplifying the sparsity for P2 elements

$$A = \frac{h}{30} \begin{pmatrix} 4 & 2 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 16 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 2 & 8 & 2 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 16 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 2 & 8 & 2 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 16 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 2 & 8 & 2 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & 16 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 2 & 4 \end{pmatrix} \quad (61)$$

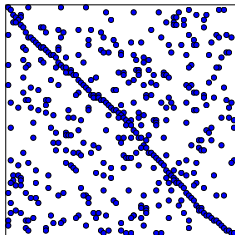
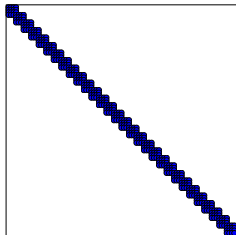
Matrix sparsity pattern for regular/random numbering of P1 elements

- Left: number nodes and elements from left to right
- Right: number nodes and elements arbitrarily



Matrix sparsity pattern for regular/random numbering of P3 elements

- Left: number nodes and elements from left to right
- Right: number nodes and elements arbitrarily



Sparse matrix storage and solution

The minimum storage requirements for the coefficient matrix $A_{i,j}$:

- P1 elements: only 3 nonzero entires per row
- P2 elements: only 5 nonzero entires per row
- P2 elements: only 7 nonzero entires per row
- It is important to utilize sparse storage and sparse solvers
- In Python: `scipy.sparse` package

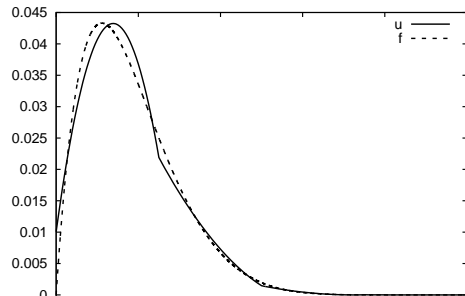
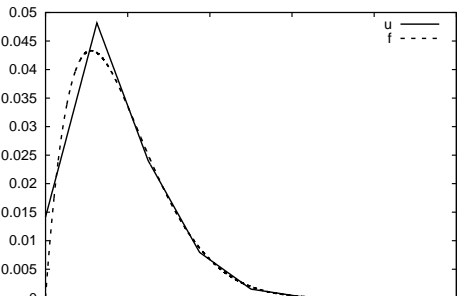
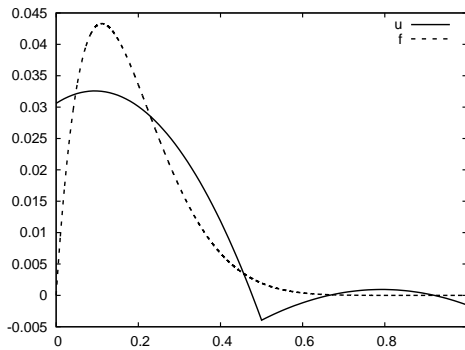
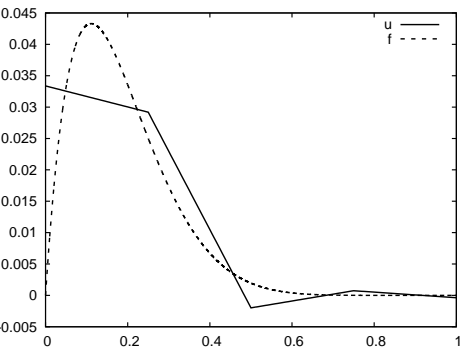
Approximate $f \sim x^9$ by various elements; code

Compute a mesh with N_e elements, basis functions of degree d , and approximate a given symbolic expression f by a finite element expansion $u(x) = \sum_j c_j \varphi_j(x)$:

```
import sympy as sm
from fe_approx1D import approximate
x = sm.Symbol('x')

approximate(f=x*(1-x)**8, symbolic=False, d=1, N_e=4)
approximate(f=x*(1-x)**8, symbolic=False, d=2, N_e=2)
approximate(f=x*(1-x)**8, symbolic=False, d=1, N_e=8)
approximate(f=x*(1-x)**8, symbolic=False, d=2, N_e=4)
```

Approximate $f \sim x^9$ by various elements; plot



Comparison of finite element and finite difference approximation

- Finite difference approximation of a function $f(x)$: simply choose $u_i = f(x_i)$ (interpolation)
- Galerkin/projection and least squares method: must derive and solve a linear system
- What is really the difference?

Interpolation/collocation with finite elements

Let x_i , $i \in I$, be the nodes in the mesh. Collocation means

$$u(x_i) = f(x_i), \quad i \in I, \quad (62)$$

which translates to

$$\sum_{j \in I} c_j \varphi_j(x_i) = f(x_i),$$

but $\varphi_j(x_i) = 0$ if $i \neq j$ so the sum collapses to one term $c_i \varphi_i(x_i) = c_i$, and we have the result