# Mandatory Assignment 1 MEK 4250

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## Exercise 1

Considering the Poisson equation on the domain  $\Omega = (0,1)^2$ :

$$-\Delta u = f \quad \text{in } \Omega$$

$$u = 0 \quad \text{on } x = 0 \text{ and; } x = 1$$

$$\frac{\partial u}{\partial n} = 0 \quad \text{on } y = 0 \text{ and } y = 1$$

We assume that:

$$u = \sin(k\pi x)\cos(k\pi y)$$

and compute  $f = -\Delta u$ .

$$f = -\frac{\partial}{\partial x} \left( \frac{\partial u}{\partial x} \right) - \frac{\partial}{\partial y} \left( \frac{\partial u}{\partial y} \right)$$

$$= -(-(k\pi)^2 \cos(k\pi y) \sin(k\pi x) - (k\pi)^2 \sin(k\pi x) \cos(k\pi y))$$

$$= 2(k\pi)^2 u$$

a)

We will compute the H<sup>p</sup> norm of u analytically. The general expression for the H<sup>p</sup> norm is:

$$\|H\|^p = \left(\sum_{i \leqslant p} \int_{\Omega} |\nabla^i u|^2 dx\right)^{\frac{1}{2}}$$

Which can also be written as follows:

$$\|\mathbf{u}\|_{H}^{p} = \left(\int_{\Omega} \left( (\mathbf{u})^{2} + (\frac{\partial \mathbf{u}}{\partial \mathbf{x}})^{2} + (\frac{\partial^{2} \mathbf{u}}{\partial \mathbf{x}^{2}})^{2} + (\frac{\partial^{3} \mathbf{u}}{\partial \mathbf{x}^{3}})^{2} + \dots + (\frac{\partial^{p} \mathbf{u}}{\partial \mathbf{x}^{p}})^{2} \right) d\mathbf{x} \right)^{\frac{1}{2}}$$

$$\int_{0}^{1} \int_{0}^{1} (\mathbf{u})^{2} d\mathbf{x} d\mathbf{y} = \int_{0}^{1} \int_{0}^{1} (\sin^{2}(k\pi \mathbf{x}) \cos^{2}(k\pi \mathbf{x})) d\mathbf{x} d\mathbf{y} = \frac{1}{4}$$

$$\int_0^1 \int_0^1 (\nabla u)^2 \, dy \, dx \int_0^1 \int_0^1 \left( (k\pi \cos(k\pi x) \cos(k\pi y)) - (k\pi \sin(k\pi x) \sin(k\pi y)) \right)^2 dx \, dy = \frac{1}{2} (\pi k)^2$$

$$\int_0^1 \int_0^1 (\nabla^n u)^2 \, dy \, dx = \frac{1}{2} (\pi^2 k^2)^n$$

The  $H^p$  norm of **u** is then:

$$||\textbf{u}||_{H^p} = \Big(\frac{1}{4} + \frac{1}{2}(\pi k)^2 + ... + \frac{1}{2}((\pi k)^2)^n\Big)^{\frac{1}{2}} = \Big(\frac{1}{4}\sum_{i\leqslant p}(2\pi k)^i\Big)^{\frac{1}{2}}$$

**b**)

The following code computes the  $L_2$  and  $H^1$  errors for  $\frac{1}{h} = 8, 16, 32, 64$  when using first and second order Lagrangian elements when k = 1, 10.

```
2 from dolfin import * #FEniCS
 3 from math import *
       for i in [1,2]:
                      for N in [8,16,32,64]: \# h=(b-a)/N=1/N
                                   mesh = UnitSquareMesh(N,N)
                                   V = FunctionSpace(mesh, "Lagrange", i)
V2 = FunctionSpace(mesh, "Lagrange", i+2)
 9
10
                                   u = TrialFunction(V)
11
                                   v = TestFunction(V)
                                   bcs = [DirichletBC(V, Constant(0), 'x[0] < DOLFIN_EPS'), DirichletBC(V, Constant(0), 'x[0] < D
14
                  Constant (0), x[0] > 1— DOLFIN_EPS')
15
                                    for k in [1,10]:
16
                                                  f = Expression('2*pi*pi*k*k*sin(pi*k*x[0])*cos(pi*k*x[1])', k=k, degree
17
                  =i)
                                                  uh = Function(V)
18
19
                                                  a=inner(grad(u),grad(v))*dx
20
                                                 L=f*v*dx
21
22
                                                  solve(a == L, uh, bcs)
23
24
                                                 uexp= Expression('sin(pi*k*x[0])*cos(pi*k*x[1])', k=k, degree=1)
25
                                                  u_Exact= interpolate(uexp, V2)
26
                                                 L2_norm = errornorm(u_Exact, uh, '12', degree_rise=3)
                                                   print i = \frac{mg}{1 + mg}, 1/h = \frac{mg}{1 + mg}, k = \frac{mg}{1 + mg} (i, N, k)
29
                                                   print 'L2 = %g' % (L2_norm)
30
31
                                                 H1_norm = errornorm(u_Exact, uh, 'H1', degree_rise=3)
32
                                                   print 'H1 = %g' % (H1_norm)
33
                                                   print '\n'
34
```

The output from the code above is listed below.

Table 1: The L<sub>2</sub> and H<sup>1</sup> errors 1. order Lagrangian elements.

L <sub>2</sub>	N	k =1	k = 10	H <sup>1</sup>	N	k = 1	k = 10
	8	0.0327753	0.667057		8	0.436592	26.4815
	16	0.0084627	0.365538		16	0.218166	17.5464
	32	0.0021332	0.178190		32	0.109055	10.6024
	64	0.0005344	0.054904		64	0.054524	5.43986

Table 2: The  $L_2$  and  $H^1$  errors <u>2. order</u> Lagrangian elements.

L <sub>2</sub>	N	k =1	k = 10	H <sup>1</sup>	Ν	k = 1	k = 10
	8	0.00057	0.435611		8	0.0331846	19.1245
	16	6.93E-05	0.089599		16	0.0083894	6.92035
	32	8.61E-06	0.010206		32	0.0021055	1.97796
	64	1.08E-06	0.001140		64	0.0005272	0.51842

As expected we can see for k=1 we get small error norms and that the error decreases with a finer mesh. When the gradients are not steep we don't get large values for the  $H_1$  norm. For k=10 the frequency of the oscillations are higher and the gradients are steep we get larger errors. The  $H^1$  values get bigger.

#### c)

Considering a general error estimate:

$$\|\mathbf{u} - \mathbf{u}_{h}\|_{q} \leqslant Ch^{\alpha}$$

We want to estimate C and  $\alpha$  and also check whether the error estimate is valid. We can solve for C and  $\alpha$  using the least squares method. We start by rewriting the expression for the error estimate by taking the logarithm.

$$\begin{split} \log(\|\mathbf{u} - \mathbf{u}_{h}\|_{1}) &= \log(C_{\alpha}) + \alpha \log(h) \\ \log(\|\mathbf{u} - \mathbf{u}_{h}\|_{0}) &= \log(C_{\beta}) + \beta \log(h) \end{split} \qquad L_{2}$$

which resembles the line equation:

$$\begin{aligned} Y &= b + Ax \\ \|u - u_h\|_q &= log(C_\alpha) + \alpha log(h) \end{aligned}$$

The code that computes  $C_{\alpha}$  and  $\alpha$  for  $H^1$  error norm and  $C_{\beta}$  and  $\beta$  for the  $L_2$  error norm and also checks the validity of the results is attached. The code also contains a printout at the end.

Table 3: Convergence rate for  $L_2$  for  $\underline{1.}$  order Lagrangian elements.

(a) k=1

L <sub>2</sub> N	β	$C_{\beta}$
8	_	_
16	1.98341*	1.90395*
32	1.97076	1.9818
64	1.98037	2.0308

(b) k=10

L <sub>2</sub>	N	β	$C_{\beta}$
	8	-	-
	16	0.867788*	4.05372*
	32	0.952196	4.92664
	64	1.18451	8.89149

Table 4: Convergence rate for  $L_2$  for  $\underline{\text{2. order}}$  Lagrangian elements.

(a) k=1

L <sub>2</sub>	L <sub>2</sub> N β		$C_{\beta}$
	8	-	-
	16	3.03703	0.314739
	32	3.0232*	0.304842*
	64	3.0154*	0.298858*

(b) k=10

L <sub>2</sub>	N	β	$C_{\beta}$
	8	-	-
	16	2.28148*	50.0587*
	32	2.70779	134.045
	64	2.88679	211.265

Table 5: Convergence rate for H<sup>1</sup> for <u>1. order</u> Lagrangian elements.

(a) k=1						
N	α	$C_{\alpha}$				
8	-	_				
16	1.00086*	3.49898*				
32	1.00061*	3.49701*				
64	1.00044	3.49542				
(b) k=10						
	8 16 32	N α  8 -  16 1.00086*  32 1.00061*  64 1.00044				

$H^1$	N	α	$C_{\alpha}$
	8	-	-
	16	0.593803	91.0332
	32	0.660297	106.151
	64	0.757682	135.96

Table 6: Convergence rate for H<sup>1</sup> for <u>2. order</u> Lagrangian elements.

(a) k=1

(tt) K=1					
H <sup>1</sup>	N	α	$C_{\alpha}$		
	8	-	-		
	16	1.98387*	2.05376*		
	32	1.98912	2.07884		
	64	1.99227	2.09552		
		(b) k=10			

H <sup>1</sup>	N	α	$C_{\alpha}$
	8	-	-
	16	1.46651	403.626
	32	1.63667	598.034
	64	1.74223	782.07

We can see from the tables above that the convergence rate for the  $L_2$  norm goes towards 2 for Lagrangian polynomials of order 1, and towards 3 for polynomials of order 2., but for the  $H^1$  norm the convergence rate goes towards 1 for 1. order polynomials and towards 2 for 2. order polynomials.

#### Exercise 2

In this exercise we have the diffusion equation, on the domain  $\Omega = (0,1)^2$ :

$$\begin{aligned} -\mu\Delta u + u_x &= 0 & \text{ in } \Omega \\ u &= 0 & \text{ on } x = 0 \\ u &= 1 & \text{ on } x = 1 \\ \frac{\partial u}{\partial n} &= 0 & \text{ for } y = 0 \text{ and } y = 1 \end{aligned}$$

a)

We assume that the solution is a product of two separate functions:

$$u(x,y) = X(x)Y(y)$$

Inserting this into the problem equation, we get

$$-\mu(X''(x)Y(y) + X(x)Y''(y)) + X'(x)Y(y) = 0$$

Dividing by X(x)Y(y) we get:

$$-\mu \Big(\frac{X''(x)}{X(x)} + \frac{Y''(y)}{Y(y)}\Big) + \frac{X'(x)}{X(x)} = 0$$

Then we can rewrite the equation:

$$\frac{X''(x)}{X(x)} - \frac{1}{\mu}\frac{X'(x)}{X(x)} = \frac{Y''(y)}{Y(y)} = \lambda^2$$

We see that we can get two expressions that are only dependent on x or y, so these can be said to be equal to a common constant  $\lambda$ . Rewriting the equation we get an equation set:

$$Y''(y) - \lambda^2 Y(y) = 0 \tag{1}$$

$$X''(x) - \frac{1}{\mu}X'(x) - \lambda^2 X(x) = 0$$
 (2)

The solution for Y(y) is:

$$Y(y) = A\cos(\lambda y) + B\sin(\lambda y)$$
  
$$Y'(y) = -A\lambda\sin(\lambda y) + B\lambda\cos(\lambda y)$$

Using Neumann boundary conditions we get:

$$Y'(y = 0) = -A\lambda \sin(0) + B\lambda \cos(0) = B\lambda = 0$$
$$Y'(y = 1) = -A\lambda \sin(\lambda) + B\lambda \cos(\lambda) = 0$$

We assume  $\lambda = 0$ 

We can see that both constants become zero if  $\lambda \neq 0$ , so we assume that  $\lambda = 0$  which gives:

$$Y(y) = A \cos(0) = A$$

For convenience we choose A = 1

The second equation then becomes:

$$\begin{split} \frac{X''(x)}{X(x)} - \frac{1}{\mu} \frac{X'(x)}{X(x)} &= 0 \\ X''(x) - \frac{1}{\mu} X'(x) &= 0 \end{split}$$

which has the solution:

$$X(x) = b_1 + b_2 e^{\frac{x}{\mu}}$$

Using the boundary conditions with Y(y) = A = 1 we get:

$$u(x,y) = \frac{e^{\frac{x}{\mu}} - 1}{e^{\frac{\alpha}{\mu}} - 1}$$

#### Task b)

Table 7: The  $L_2$  error for different values of  $\mu$ 

#### (a) 1. order polynomials

N/μ	8	16	32	64
1	1.402E-03	3.508E-04	8.770E-05	2.193E-05
0.1	2.375E-02	6.177E-03	1.561E-03	3.915E-04
0.01	2.379E-01	1.039E-01	3.819E-02	1.126E-02

## (b) 2. order polynomials

N/μ	8	16	32	64
1	1.151E-05	1.448E-06	1.817E-07	2.277E-08
0.1	2.245E-03	3.038E-04	3.884E-05	4.888E-06
0.01	8.513E-02	3.039E-02	7.598E-03	1.326E-03

Table 8: The H<sup>1</sup> error for different values of μ

(a) 1. order polynomials

Ν/μ	8	16	32	64
1	3.752E-02	1.877E-02	9.383E-03	4.692E-03
0.1	7.671E-01	3.981E-01	2.010E-01	1.008E-01
0.01	7.238E+00	6.684E+00	5.007E+00	2.969E+00

(b) 2. order polynomials

N/μ	8	16	32	64
1	5.970E-04	1.504E-04	3.772E-05	9.448E-06
0.1	1.183E-01	3.164E-02	8.066E-03	2.028E-03
0.01	5.140E+00	3.604E+00	1.705E+00	5.661E-01

We can see that the approximations get poorer when  $\mu$  gets small which will give steep gradients.

#### Task c)

The code to compute convergence rates for different values for  $\mu$  that also checks the validity of the computed norm is attached. The code also contains a nice printout.

We can see from the output that the convergence rate decreases for smaller values of  $\mu$  which was expected since smaller  $\mu$  give higher Errors.

#### Task d)

The main difference is the test function. If V is the Galerkin basis function, the SUPG basis function is  $w = v + \beta u_x$ , where  $\beta$  is a constant that we choose to set to  $\frac{1}{2}$ . Inserted into the weak form for our problem, we get

$$\mu \int_{\Omega} \nabla u \nabla v dn + \int_{\Omega} u_{x} v dn = 0$$

The new weak form of the equation is:

$$\begin{split} \mu \int_{\Omega} \nabla u \nabla w dn + \int_{\Omega} u_x \nu dn &= \mu \int_{\Omega} \nabla u \nabla \nu dn \\ + \int_{\Omega} u_x \nu dn \beta \mu \int_{\Omega} \nabla u \nabla u_x dn + \beta \int_{\Omega} u_x^2 dn \end{split}$$

The code with a nice printout for the SUPG approximation is also attached.

We can see that for  $\mu$  down to 0.01 we get good approximations and the convergence rate goes towards 1.5, but the approximation gets poorer when  $\mu$  < 0.1. In comparison with the results in part b) and c) we can see that the SUPG method give better approximations when  $\mu$  gets small.