Computational Fluid Dynamics

SG2212 Project Report

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Question 1

The kronecker operator (**kron**) is an operator for tensor product, which falls convinient when doing finite differences in higher dimensions than the 1D case. As we study the 2D case in this lid-driven cavity project the 5 point stencil is considered:

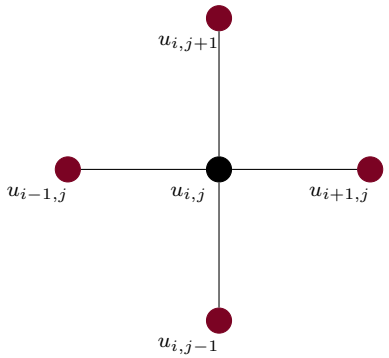


Figure 1: The five point stencil in 2D.

If we construct a finite difference scheme for the laplace operator we get:

$$\nabla^2 u = \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h_x^2} + \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{h_y^2} \tag{1}$$

$$\left\{ \text{and if } h_x = h_y = h \implies \frac{u_{i+1,j} + u_{i-1,j} - 4u_{i,j} + u_{i,j+1} + u_{i,j-1}}{h^2} \right\} \tag{2}$$

The above expression we can transform into a vector form in size $(N_x, N_y) \mapsto N_x \cdot N_y$, using the indexing that one step in y-direction is equivalent to one row in the matrix *i.e.* $+N_x$ steps.

We can now define the second partial derivative in the separate directions:

$$S_x = \frac{1}{h_x^2}\begin{bmatrix} -1 & 1 & & & \\ 1 & -2 & 1 & & \\ & 1 & -2 & \ddots & \\ & & \ddots & \ddots & \\ & & & 1 & -1 \end{bmatrix} \qquad S_y = \frac{1}{h_y^2}\begin{bmatrix} -1 & 1 & & & \\ 1 & -2 & 1 & & \\ & 1 & -2 & \ddots & \\ & & \ddots & \ddots & \\ & & & 1 & -1 \end{bmatrix}$$

Forming a matrix by the size $(N_x \cdot N_y) \times (N_x \cdot N_y)$ is now done by the kronecker product.

The operation done by the kronecker product essentially does the following in this case. Consider the identity matrix in the shape $N_y \times N_y$ (I_y), and the S_x from above. We get:

$$\text{kron}(I_y, S_x) = I_y \otimes S_x = \begin{bmatrix} [S_x] & 0 & \dots & \\ 0 & [S_x] & 0 & \dots \\ \vdots & & \ddots & \\ & & & [S_x] \end{bmatrix} \quad \text{shape is } (N_y \cdot N_x) \times (N_y \cdot N_x)$$

and for the other term in the sum of kronecker products we have:

$$S_y \otimes I_x = \begin{bmatrix} S_y^{1,1}[I_x] & 0 & \dots & \\ 0 & S_y^{2,2}[I_x] & 0 & \dots \\ \vdots & & \ddots & \\ & & & S_y^{N_y,N_y}[I_x] \end{bmatrix} \quad \text{shape is } (N_y \cdot N_x) \times (N_y \cdot N_x)$$

We can then see that in the simplified example where $N_x = N_y = N$ and $h_x = h_y = h = 1$, and no specific boundaries are set, we get:

$$I_y \otimes S_x + S_y \otimes I_x = \begin{bmatrix} -4 & 1 & \dots & 1 & \dots & & \\ 1 & -4 & 1 & \dots & 1 & \dots & \\ 0 & \ddots & \ddots & \ddots & & & \\ & & & 1 & \dots & 1 & -4 \end{bmatrix} \tag{3}$$

which describes the case stated in Equation 2. Note that the 1's in matrix in Equation 3 are N_x values apart, with zero-values in between.

Question 2

Experimental stability condition for Δt (with parameters $N_x = N_y = 30$, $L_y = L_x = 1$ and $Re = 25$) was empirically found to be

$$\Delta t_{\max} \approx 0.006971$$

when integrated up to $T = 50$.

Question 3

Question 4

Placing a probe in the domian centre gives the following velocity U along the time line to $T = 50$:

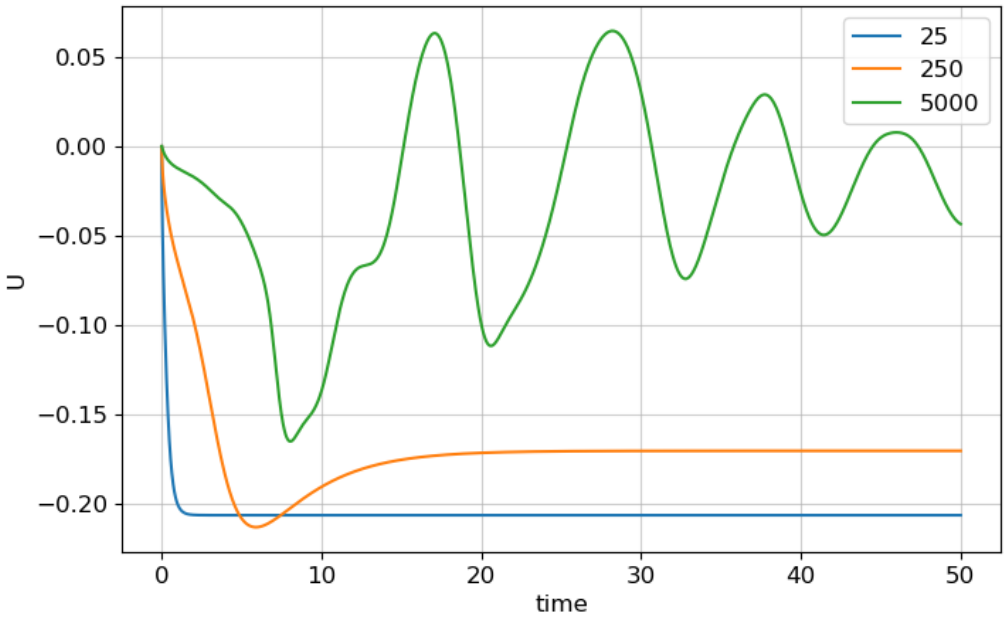


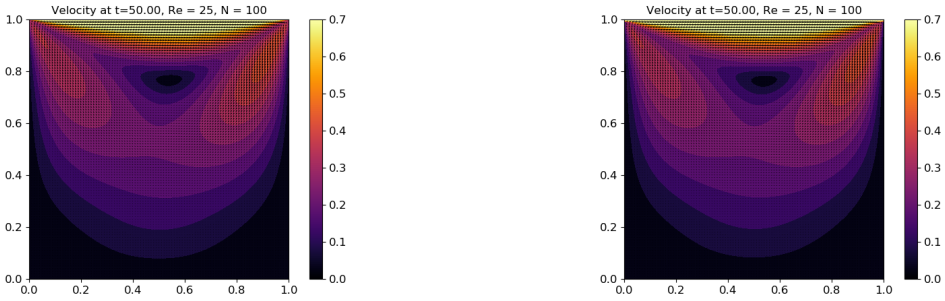
Figure 2: U in middle of domain for different Re-values

Clearly the cases with lower Reynold's number converges to a steady flow quicker than the cases with a higher number. This is due to the amount of turbulance is greater in the case with higher Re; the intertial forces are greater in comparison to the viscous forces when the Re increases.

Judging by the plot in Figure 2 the $Re - 25$ case

Question 5

Using OpenFoam in each of the cases A-C the following data where obtained: Figure 3 shows both a solution from the Python implementation as well as OpenFOAM solution with the data visualized in matplotlib.



(a) OpenFoam solution

(b) Python Solution

Figure 3: Case A

For a more detailed comparison we can observe the velocity magnitude along the diagonal of the domain, so called a *plot over line* visualization. For case A we have the following:

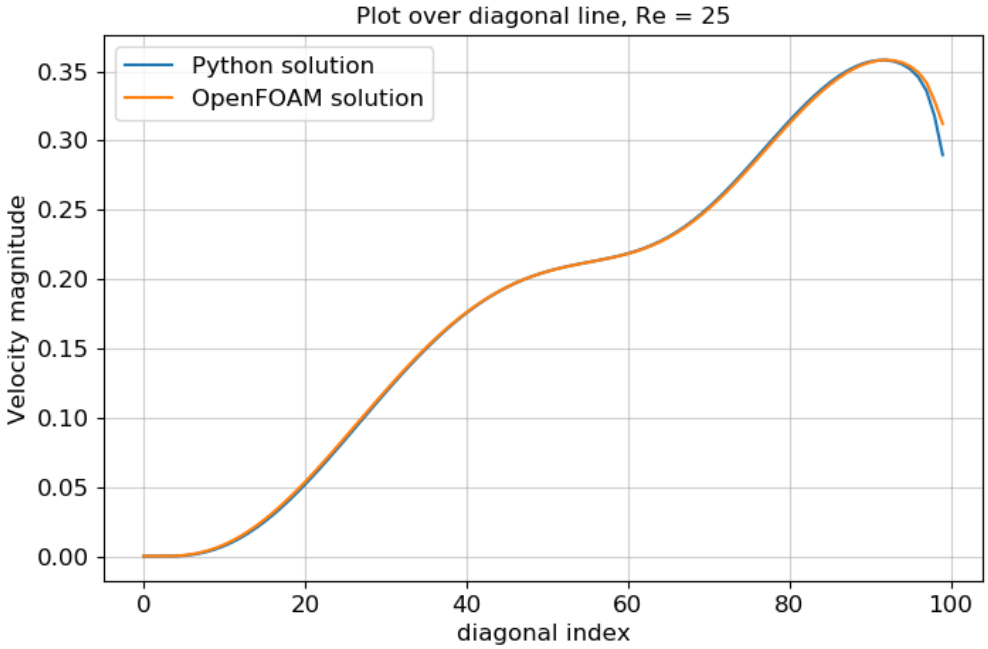
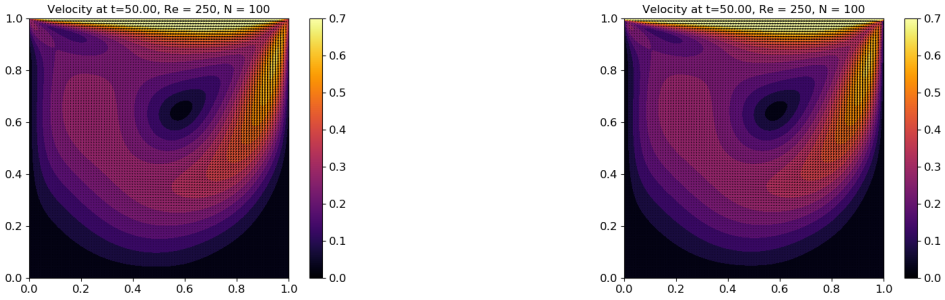


Figure 4: Plot over line (Case A): Python against OpenFOAM

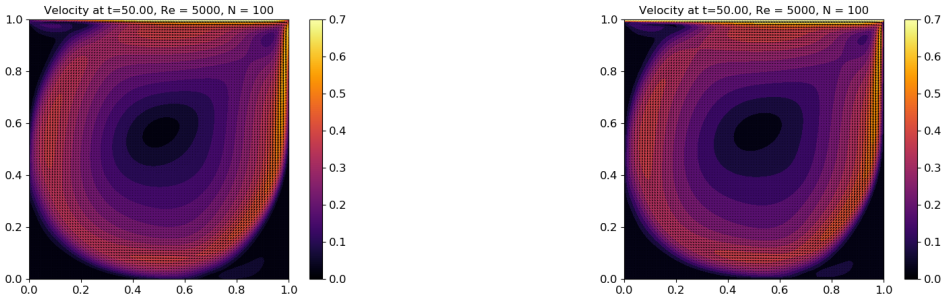
Likewise we can compare case B and C in a similar manner:



(a) OpenFoam solution

(b) Python Solution

Figure 5: Case B



(a) OpenFoam solution (b) Python Solution

Figure 6: Case C

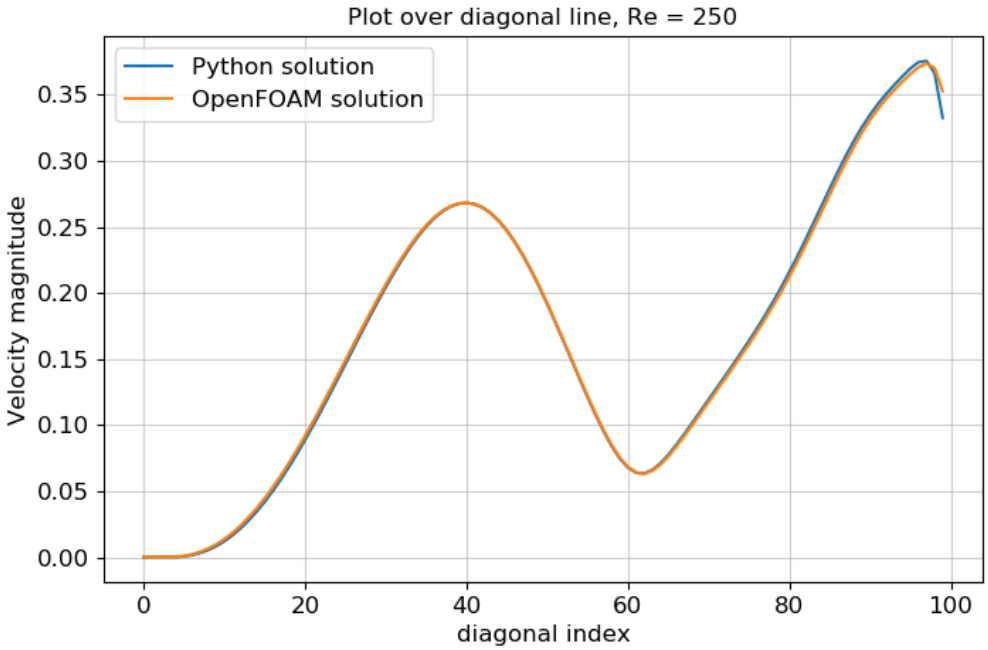


Figure 7: Plot over line (Case B): Python against OpenFOAM

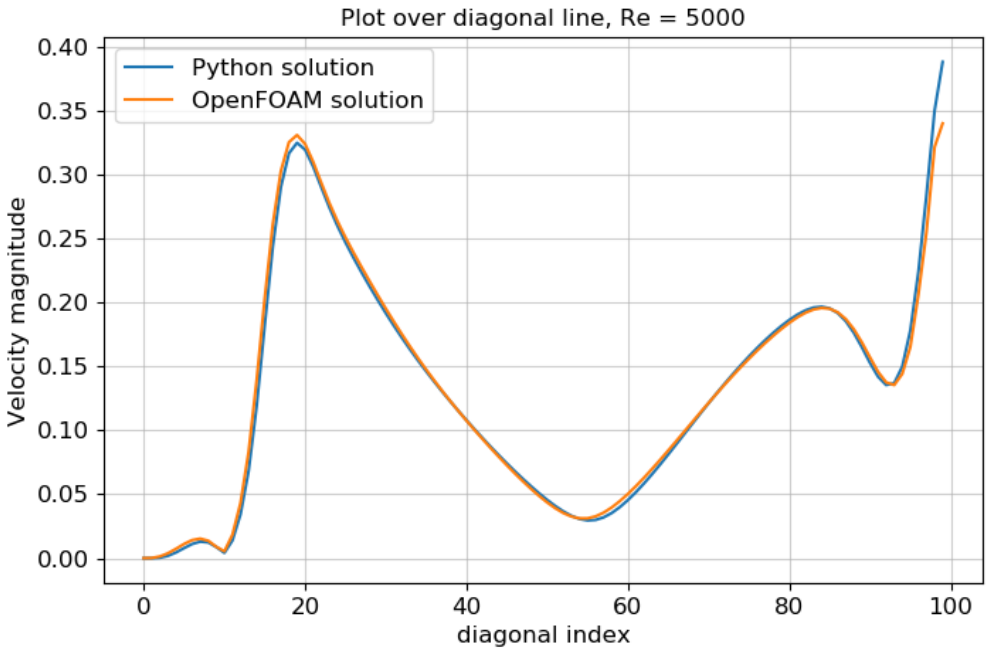


Figure 8: Plot over line (Case C): Python against OpenFOAM

We can conclude that the Python and OpenFOAM solutions converges, and notably the largest differences was found close to the boundaries.

Comparing the L_2-norm between the different steady solutions we got the following data:

%%INSERT DATA

Question 6

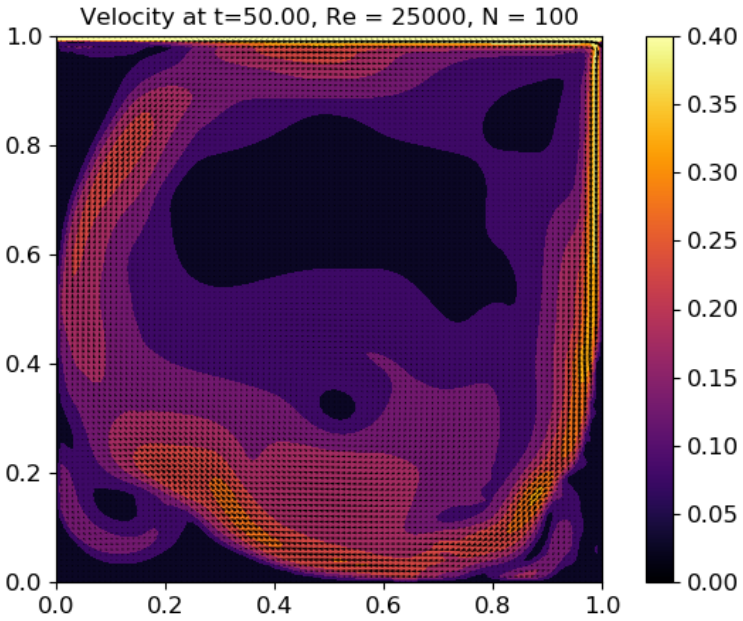


Figure 9: Case D

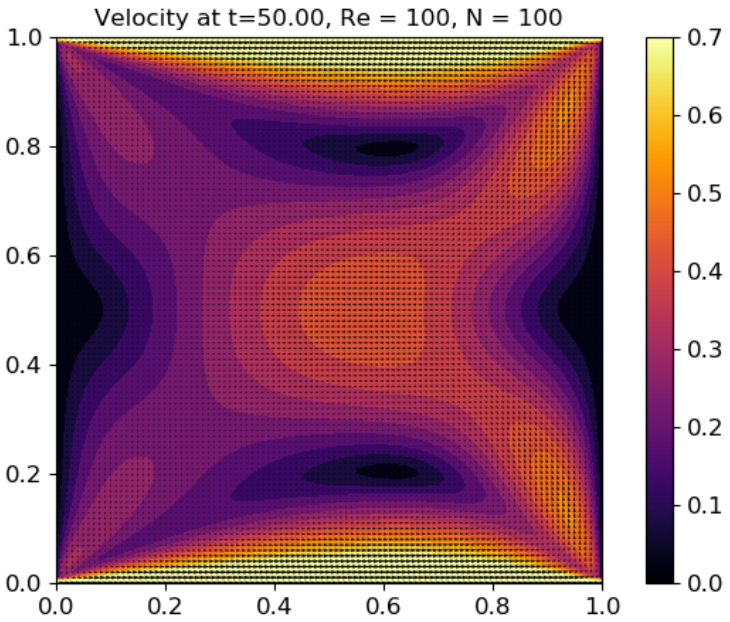


Figure 10: Bonus case with even higher Re