



Cenaero



Validation of data-driven wall models on the upper and lower walls of the two-dimensional periodic hill

ACOMEN 2022, Liège

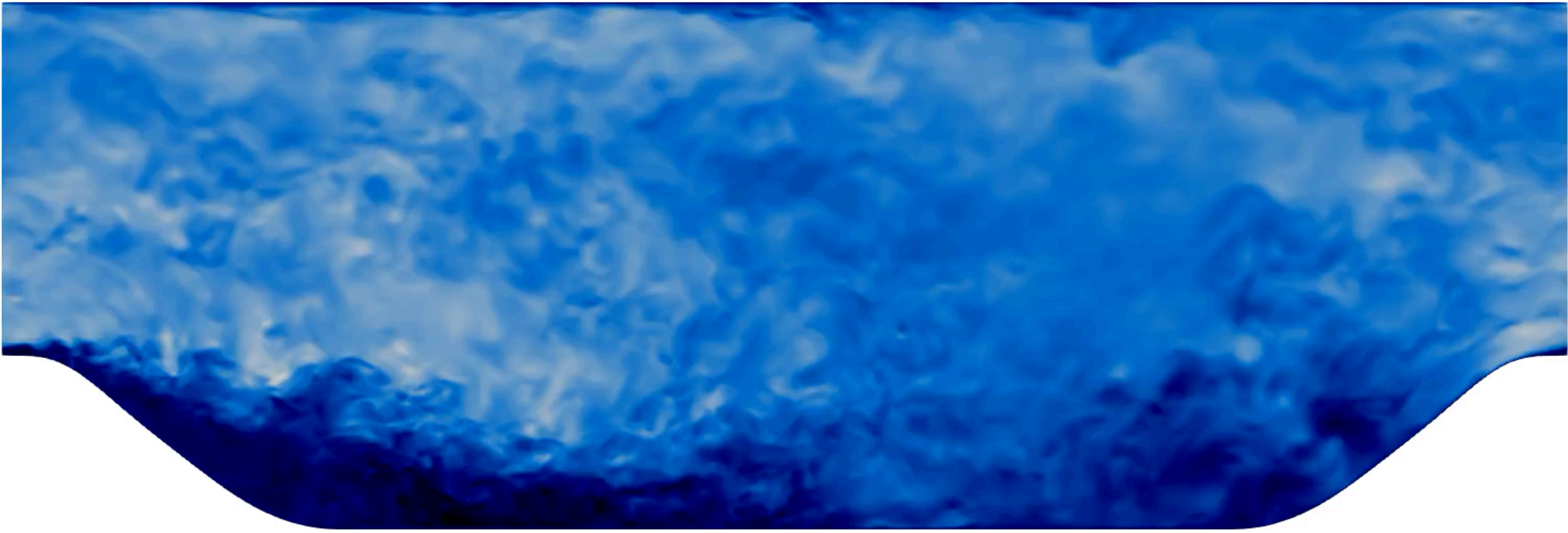
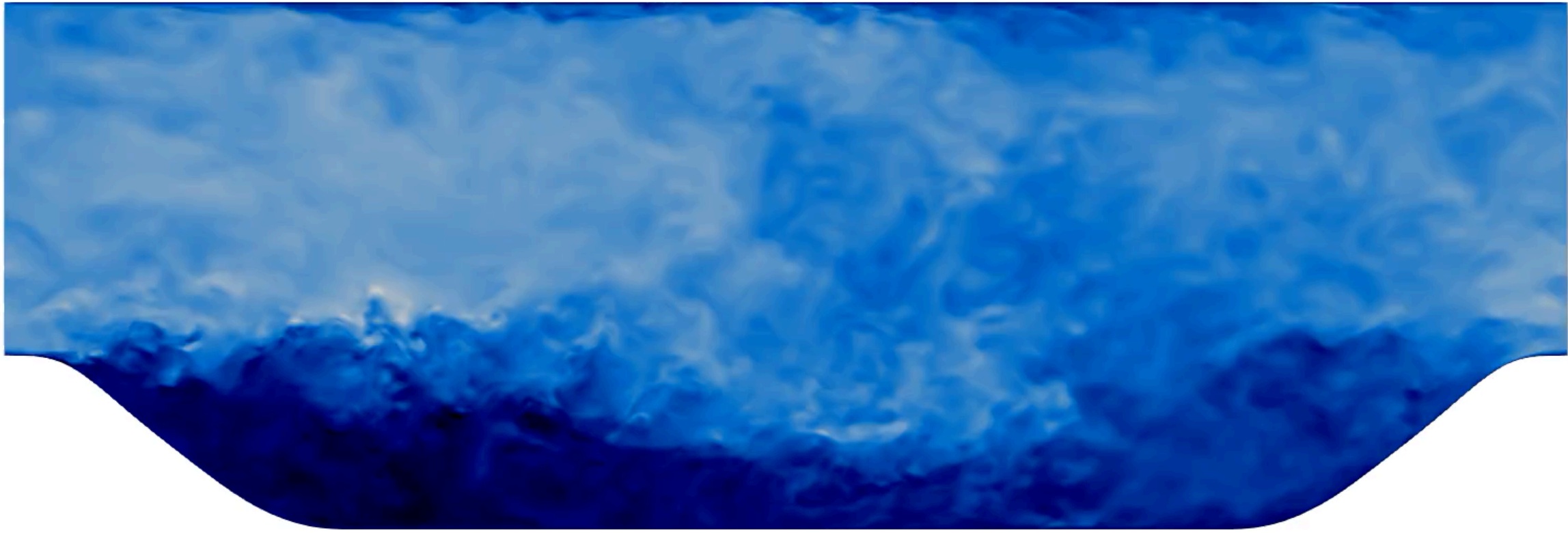
**M. Boxho, M. Rasquin, T. Toulorge, G. Dergham,
G. Winckelmans and K. Hillewaert**

ULiege, UCLouvain, Cenaero, Safran Tech

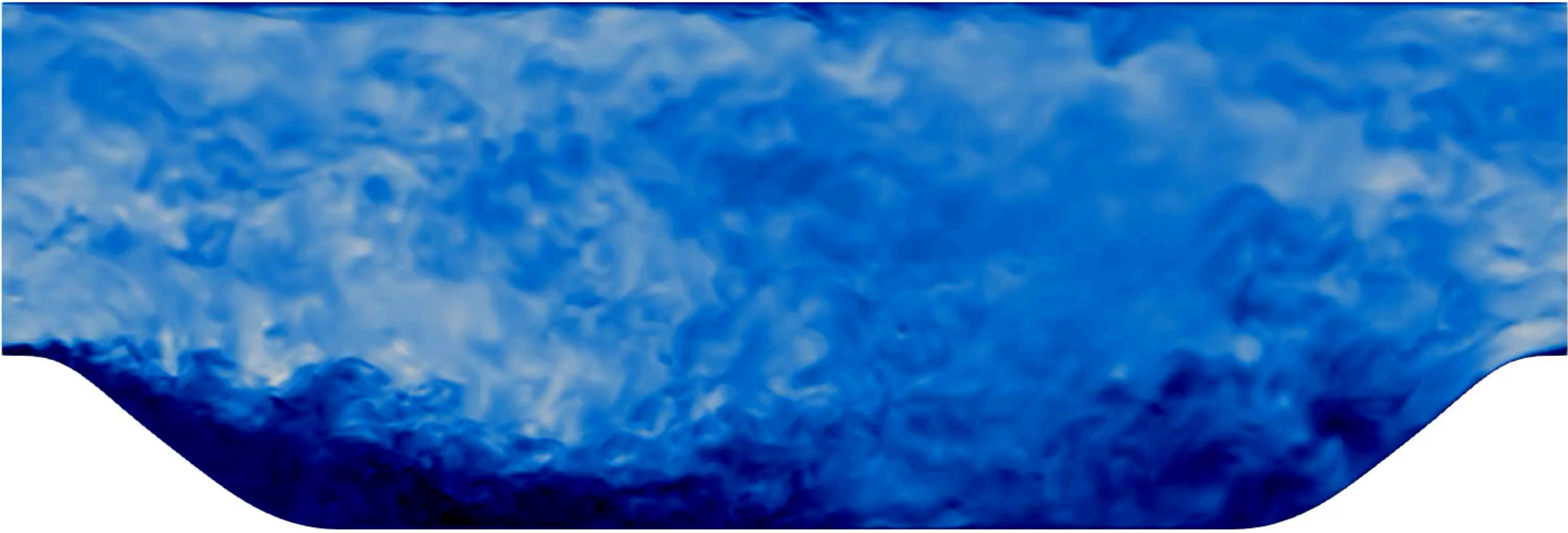
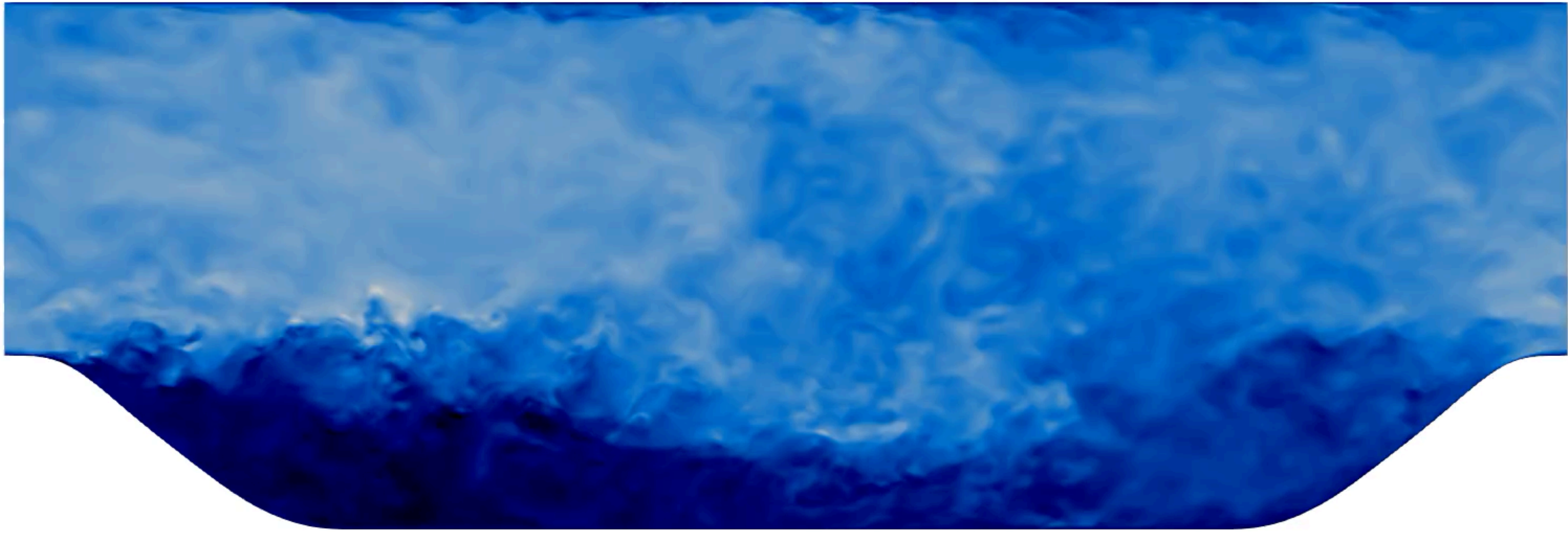
Contact: margaux.boxho@cenaero.be

Doc. ref.: 2019030-THESELDP-SAFRAN

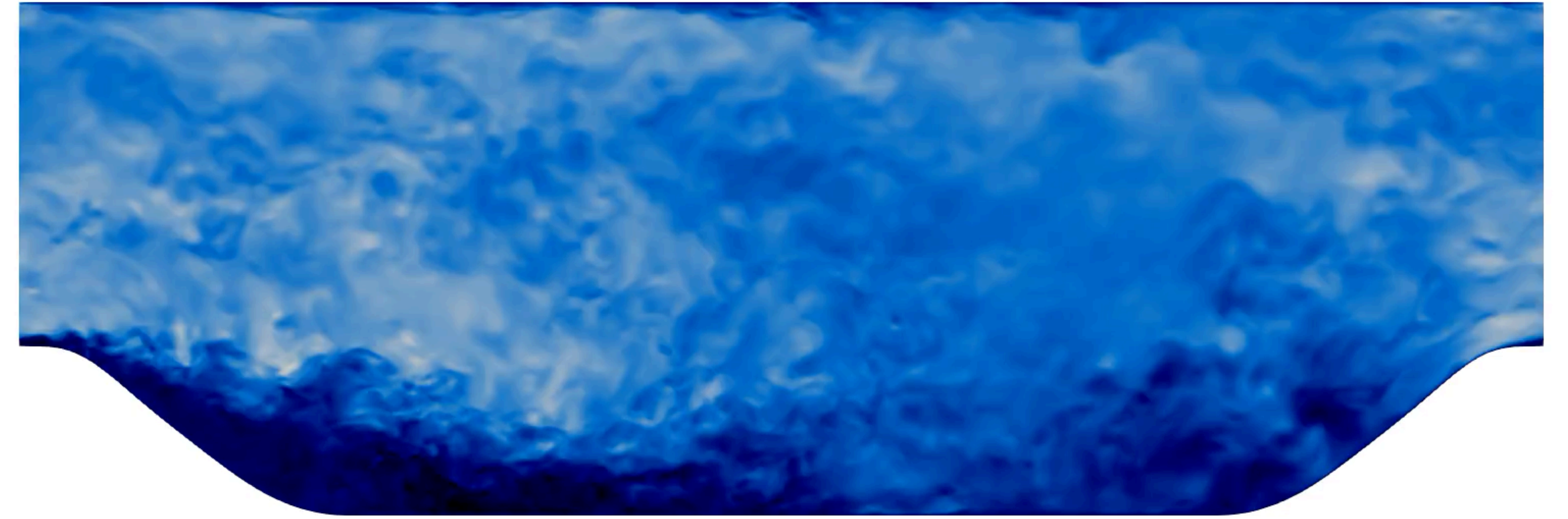
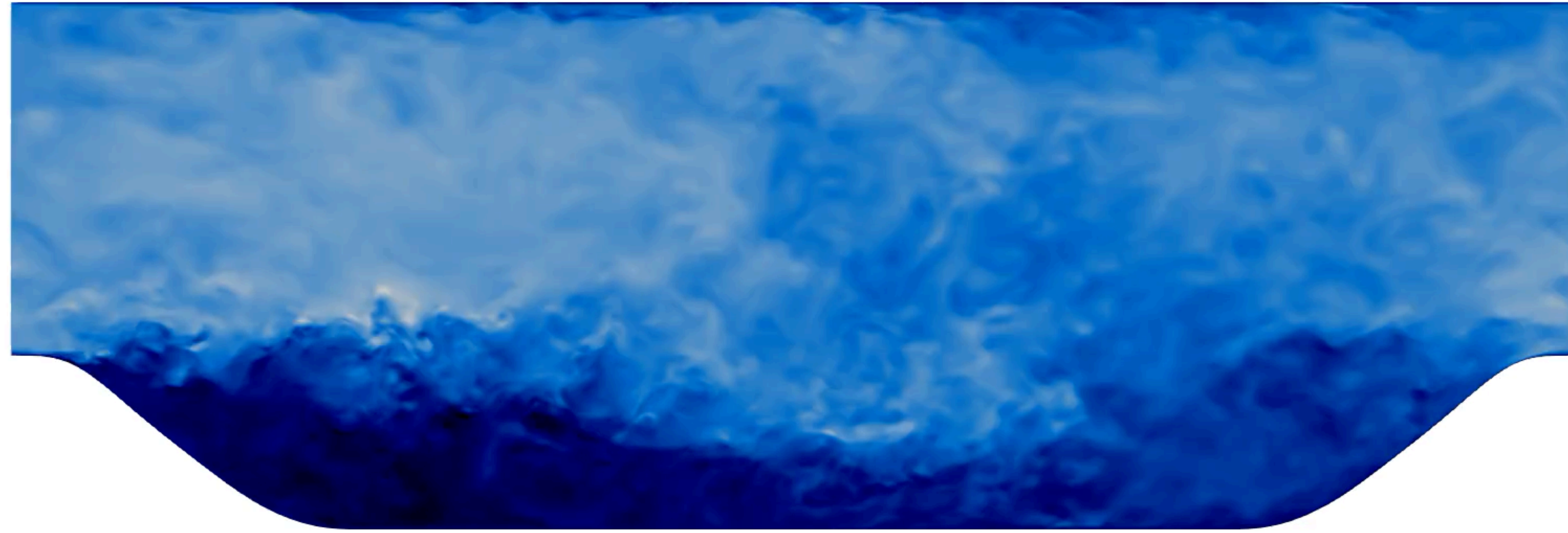
What's the difference?



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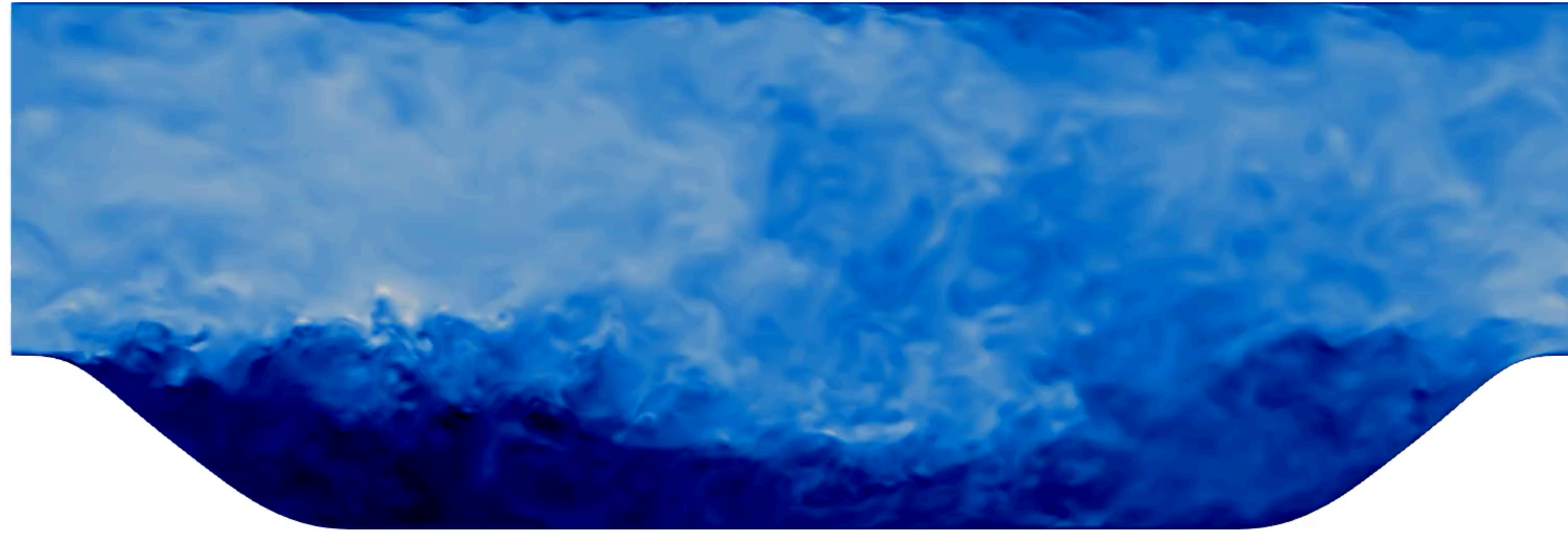
What's the difference? ... the resolution near the wall.



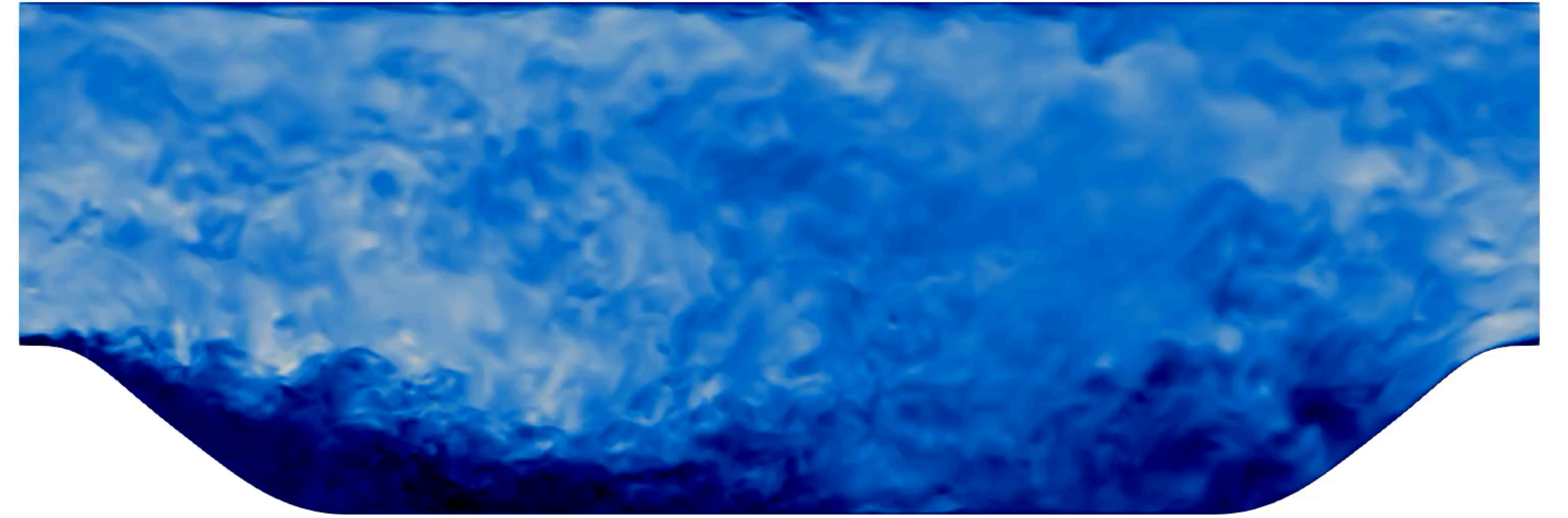
What's the difference?

... the resolution near the wall.

Wall resolved LES



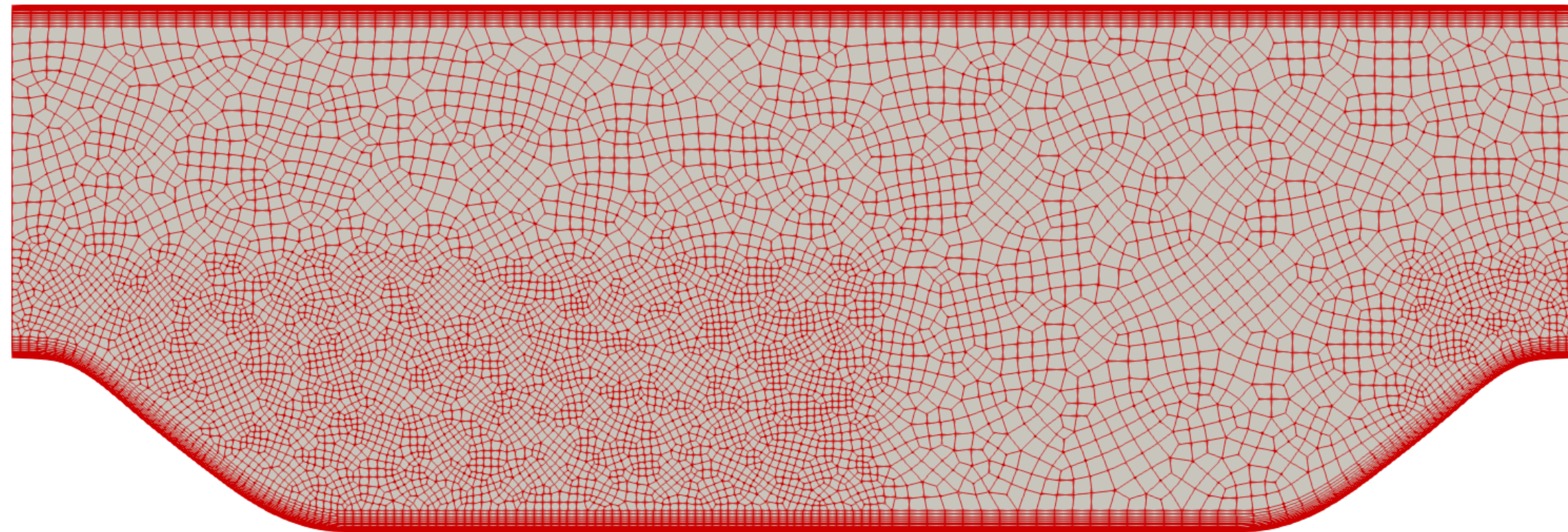
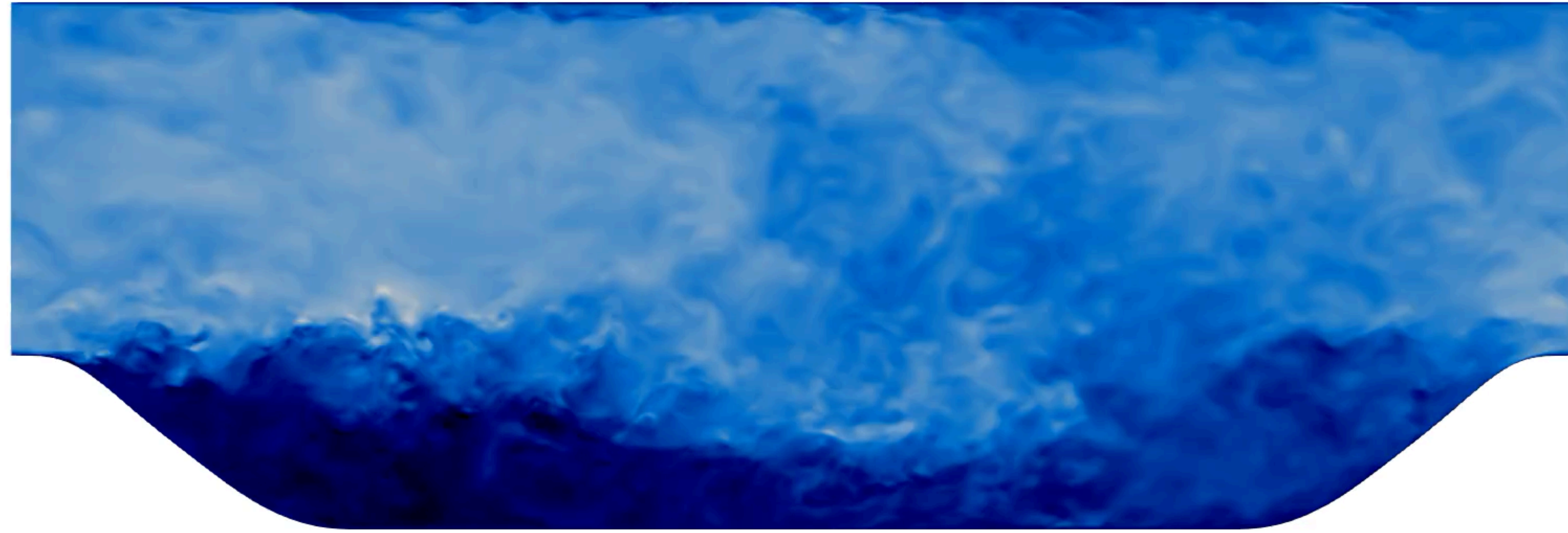
Wall modeled LES



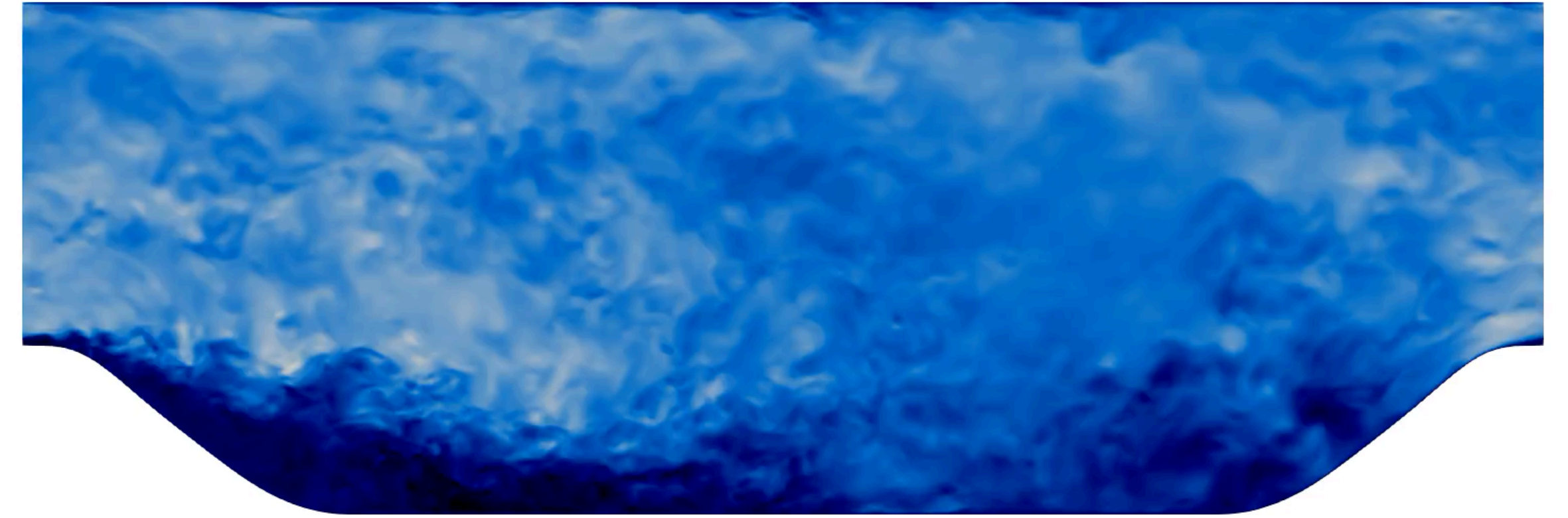
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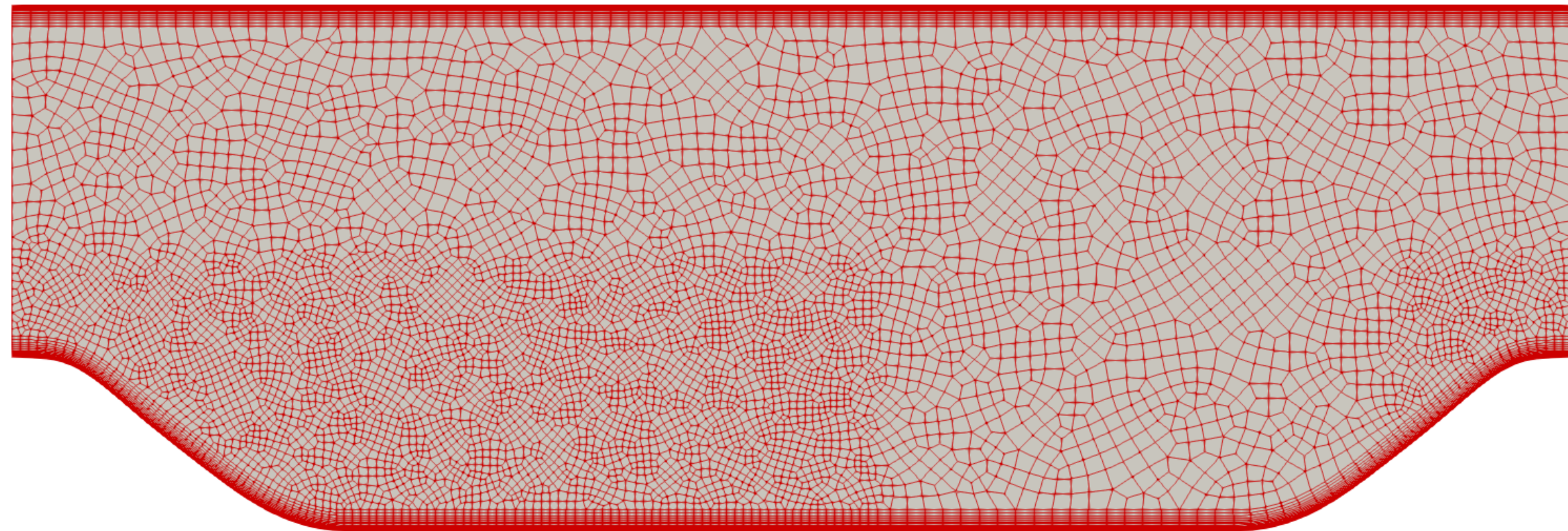
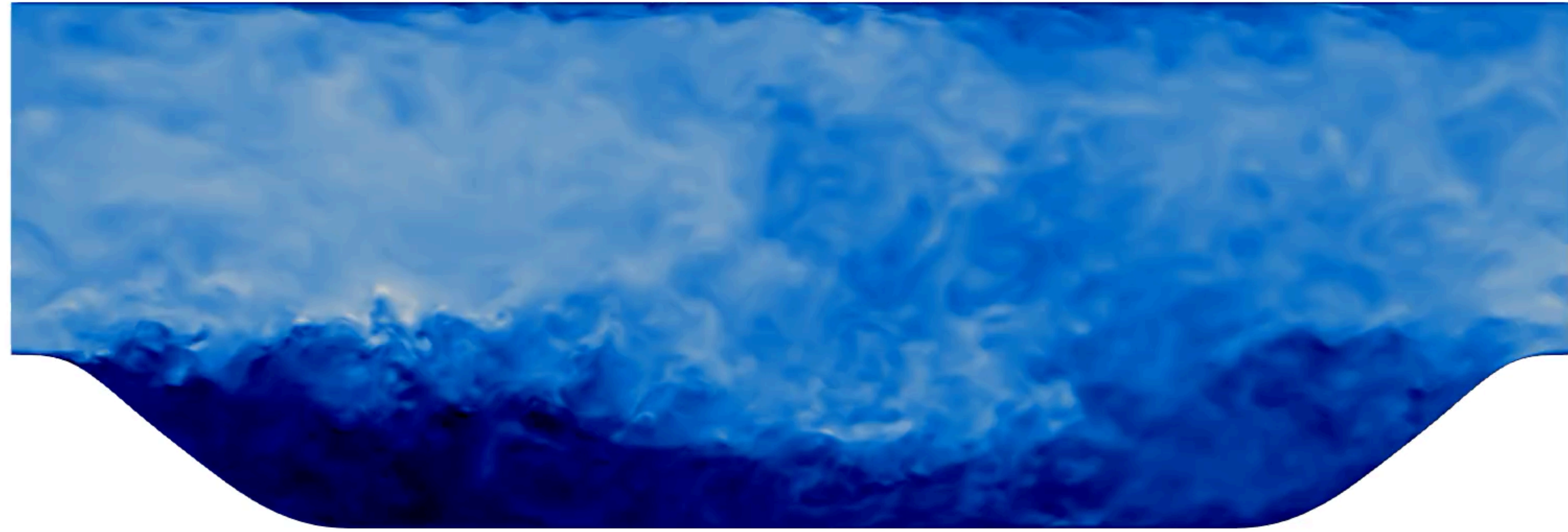
Wall modeled LES



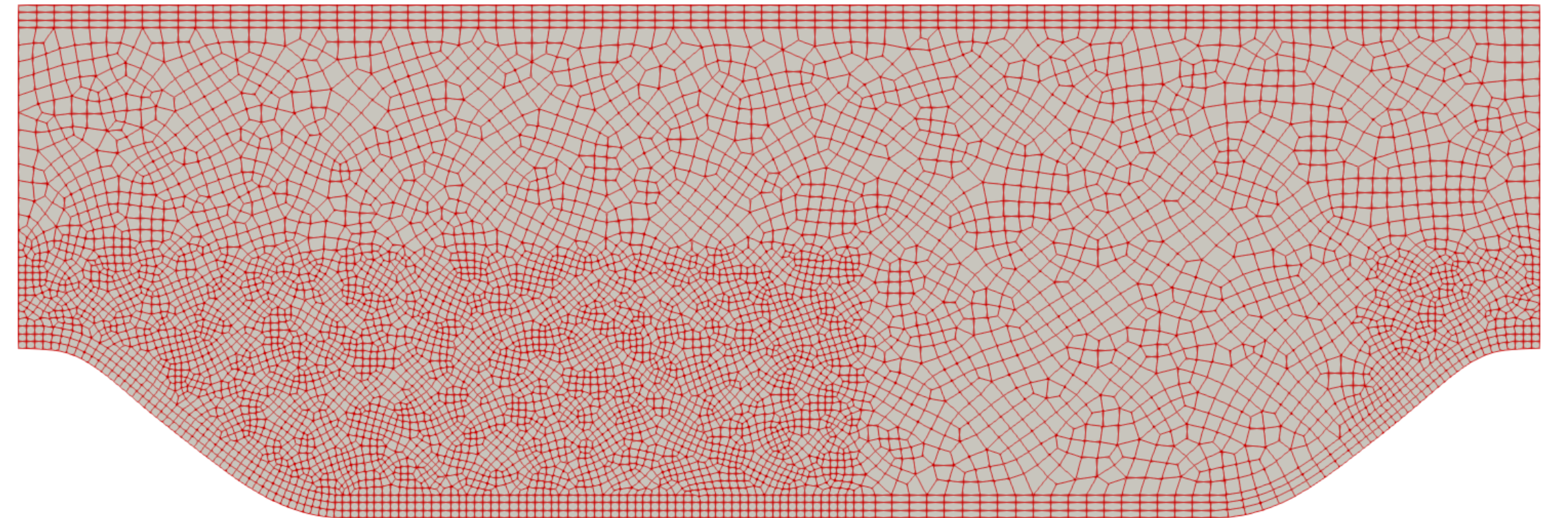
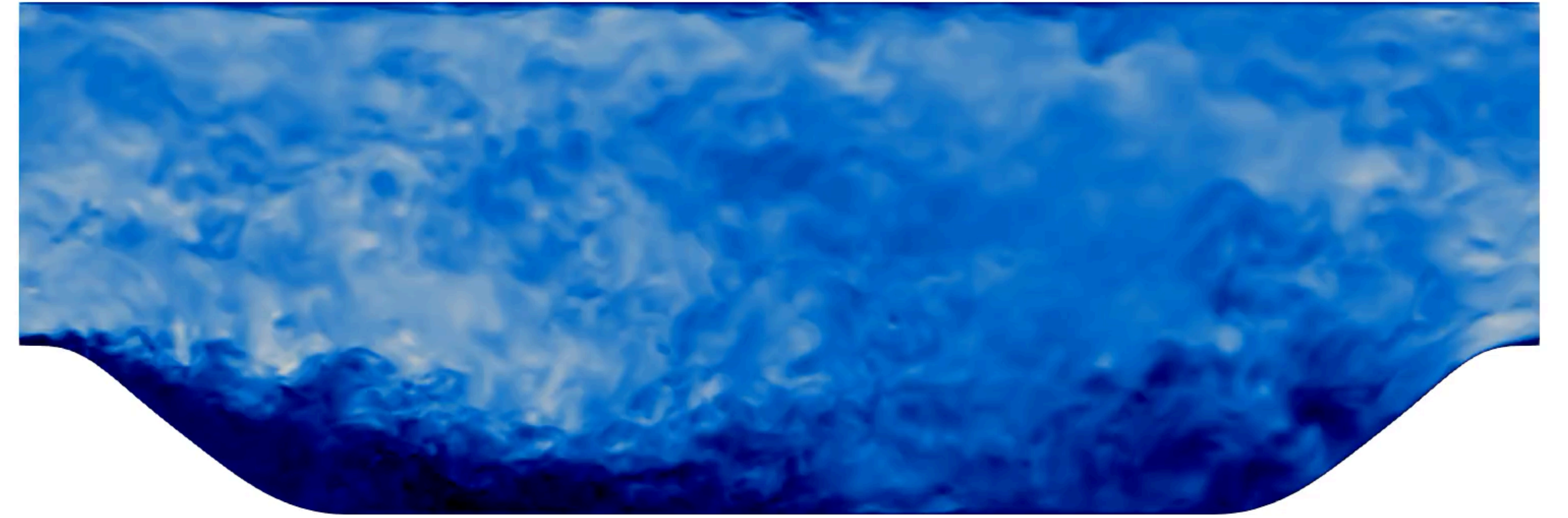
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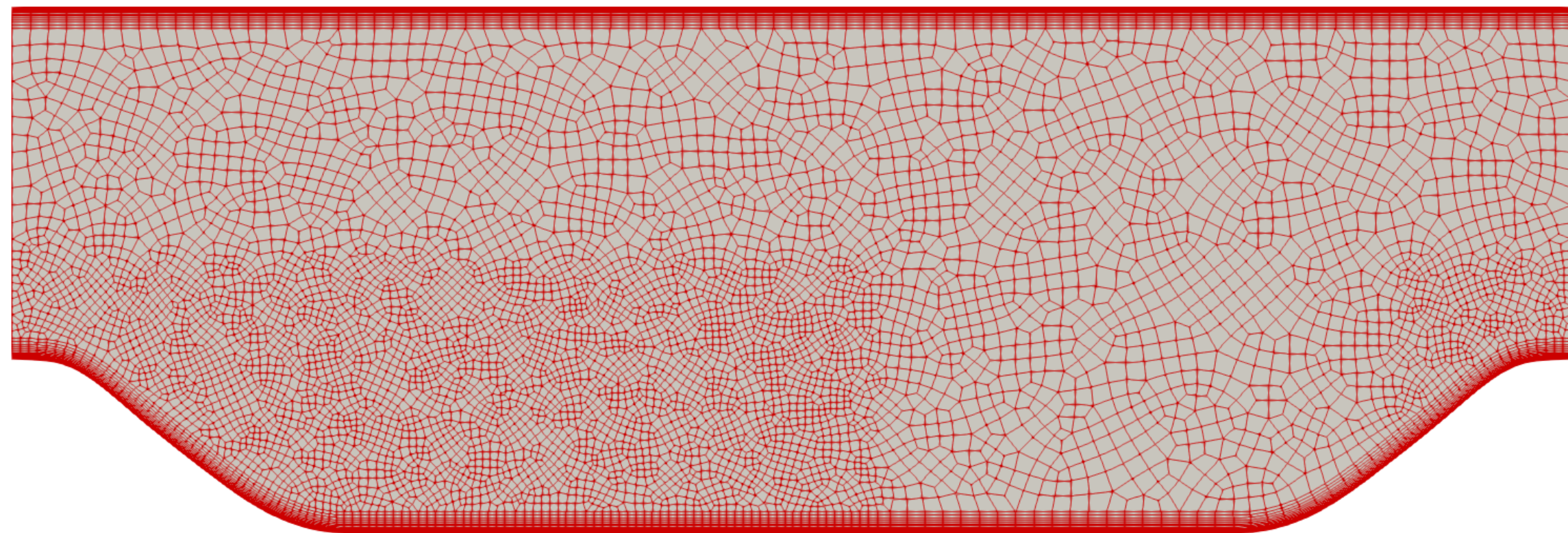
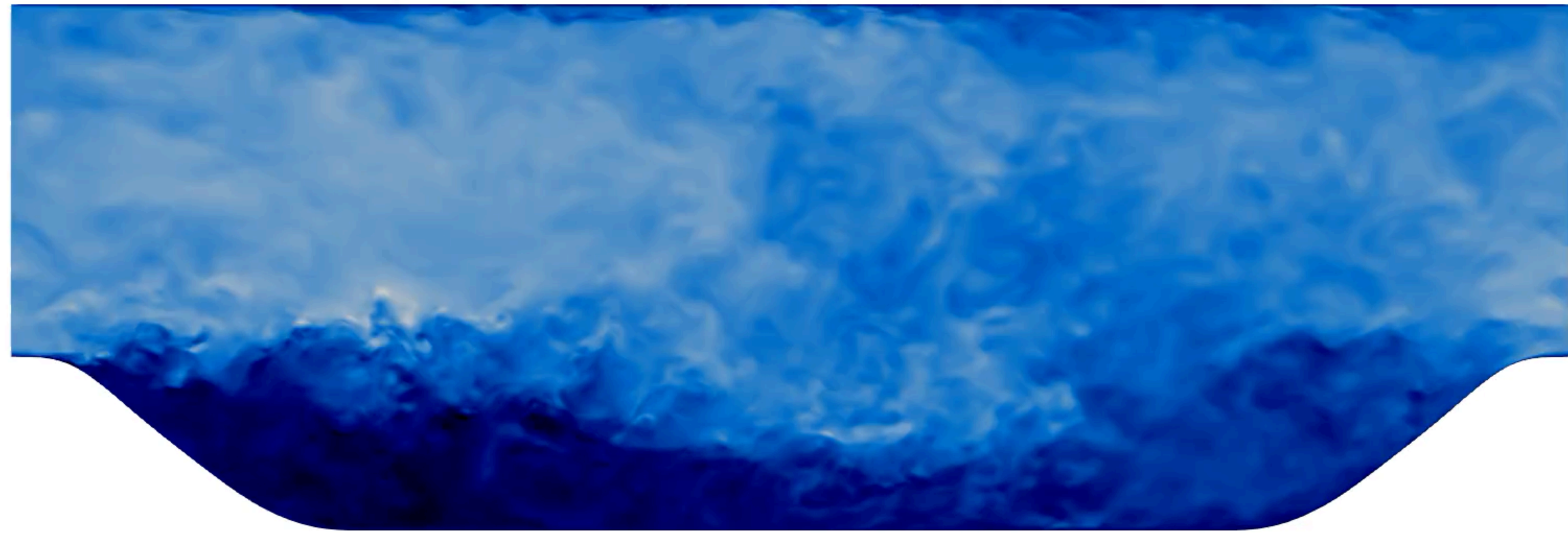
Wall modeled LES



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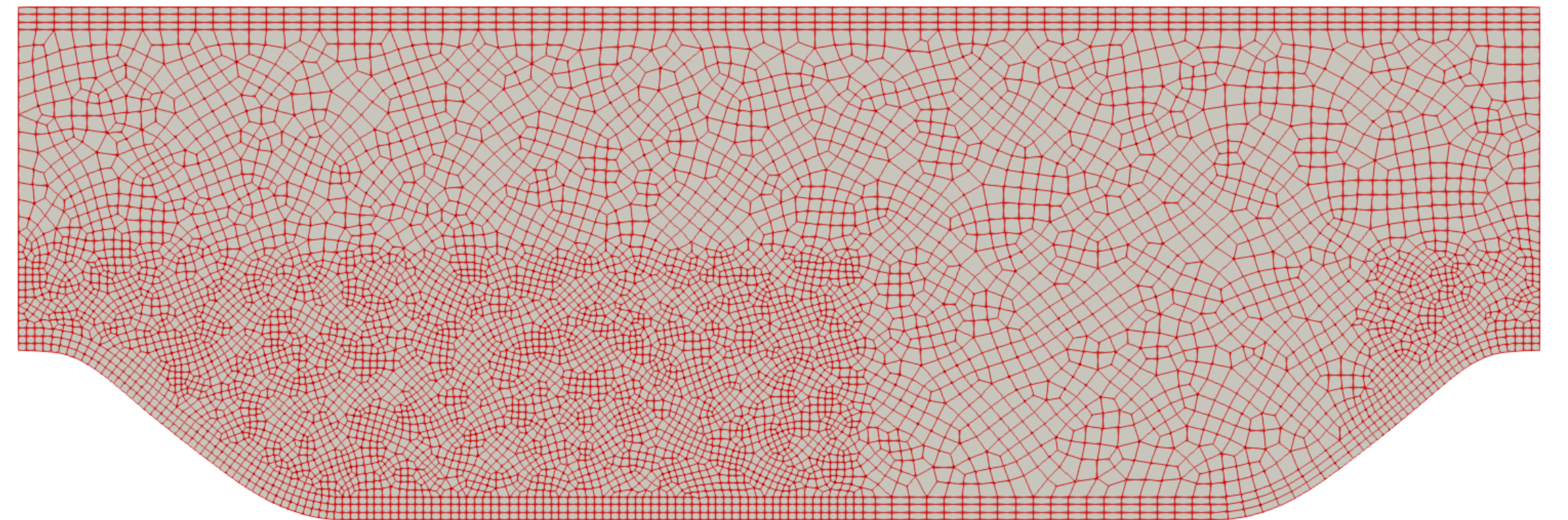
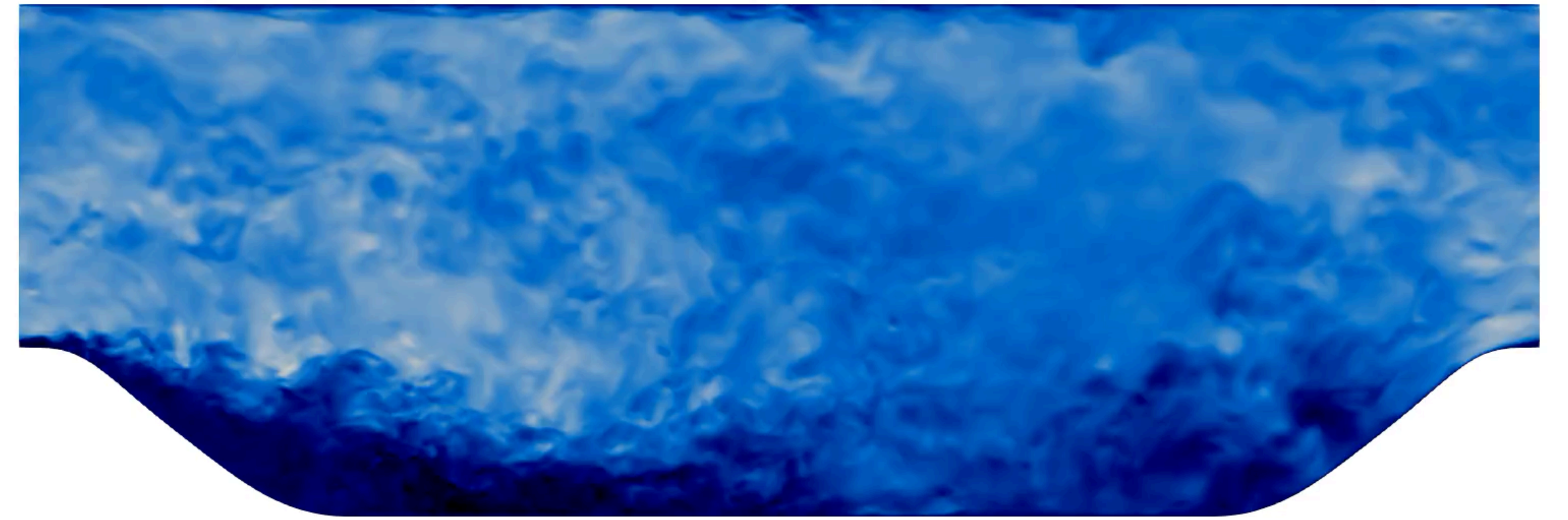
... the resolution near the wall.

Wall resolved LES



**Number of degrees of freedom
28,480,320**

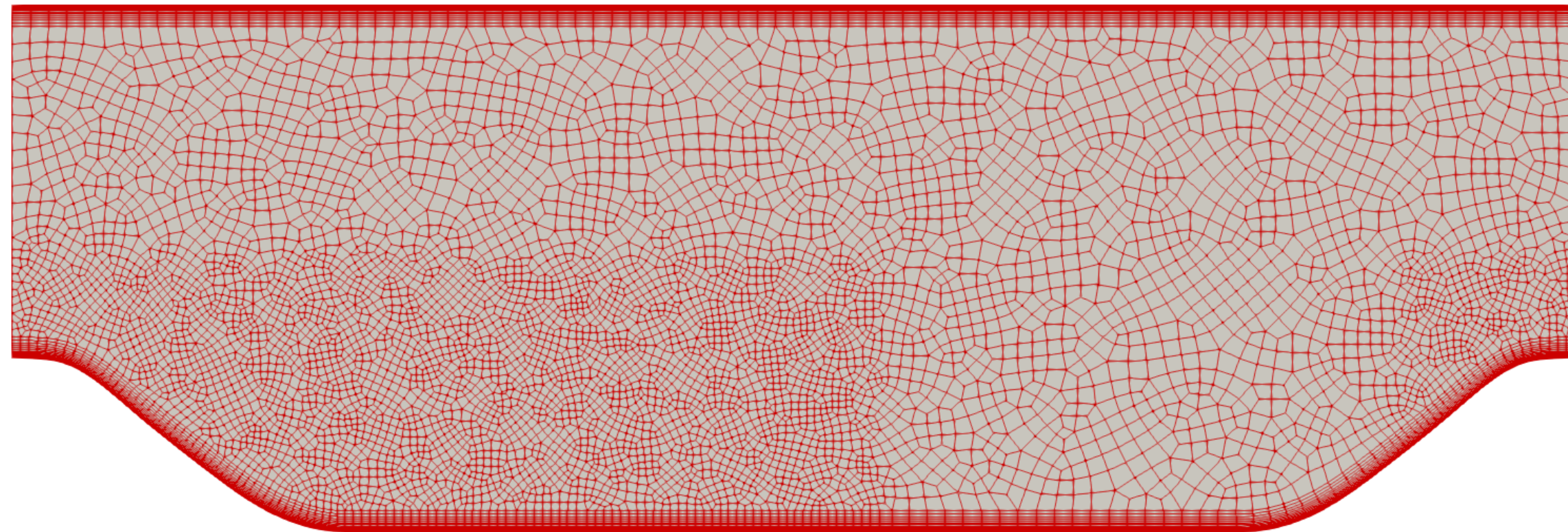
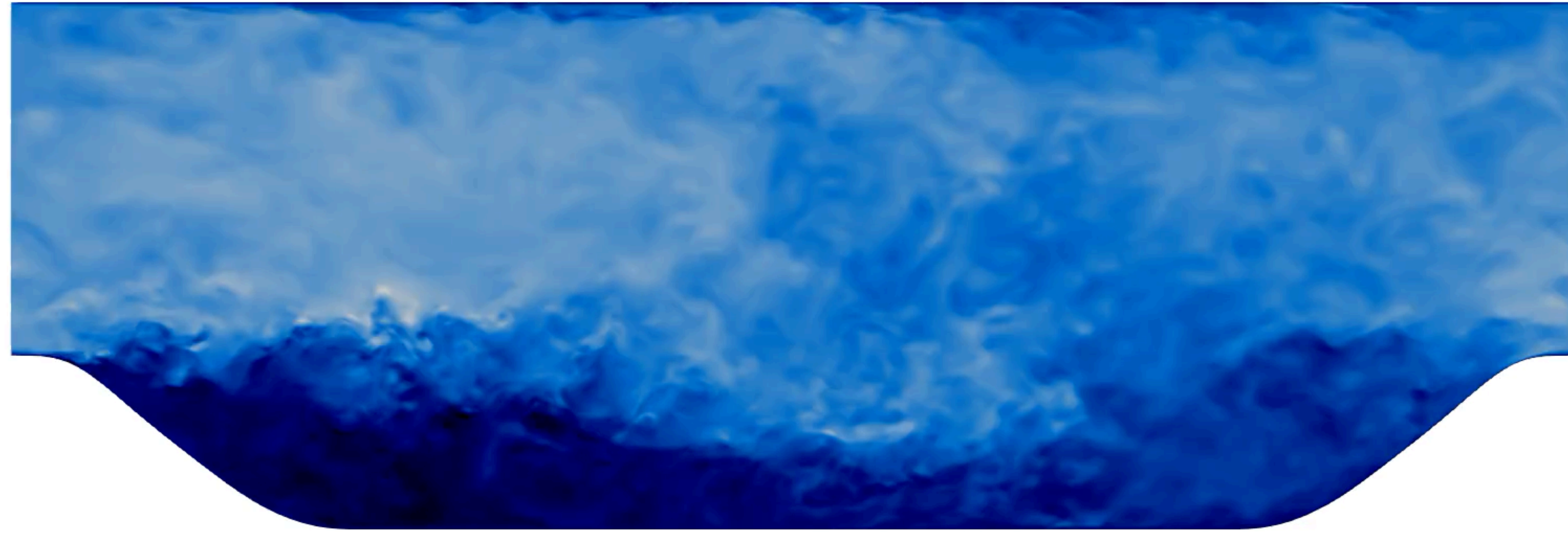
Wall modeled LES



What's the difference?

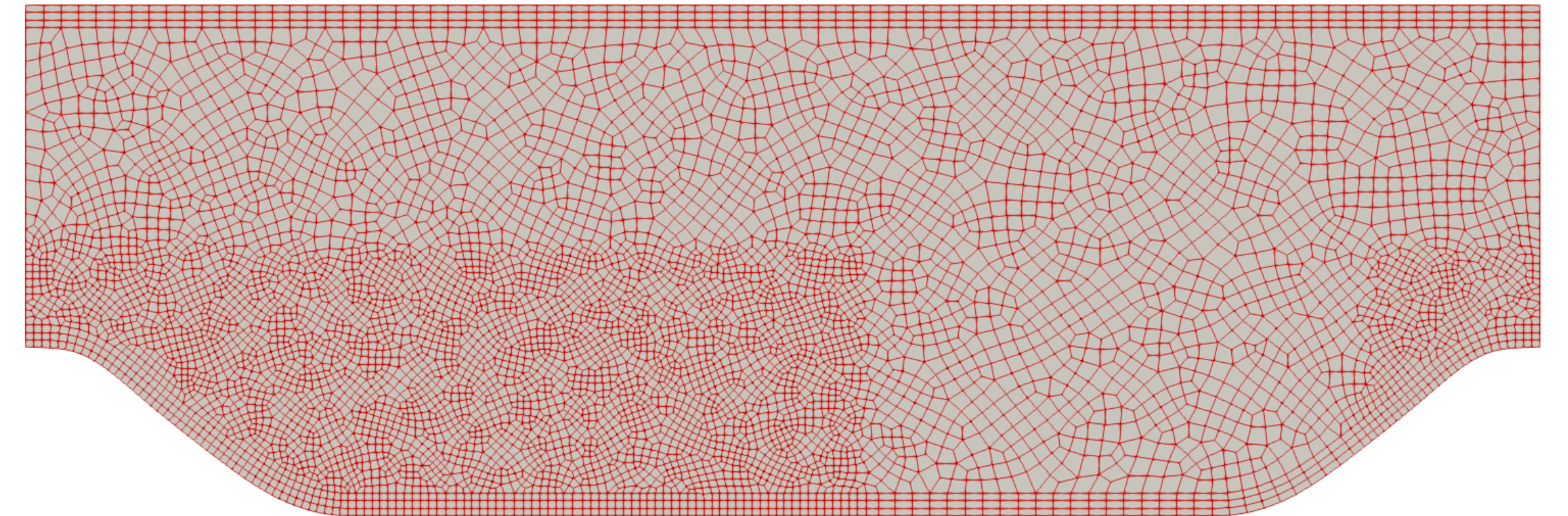
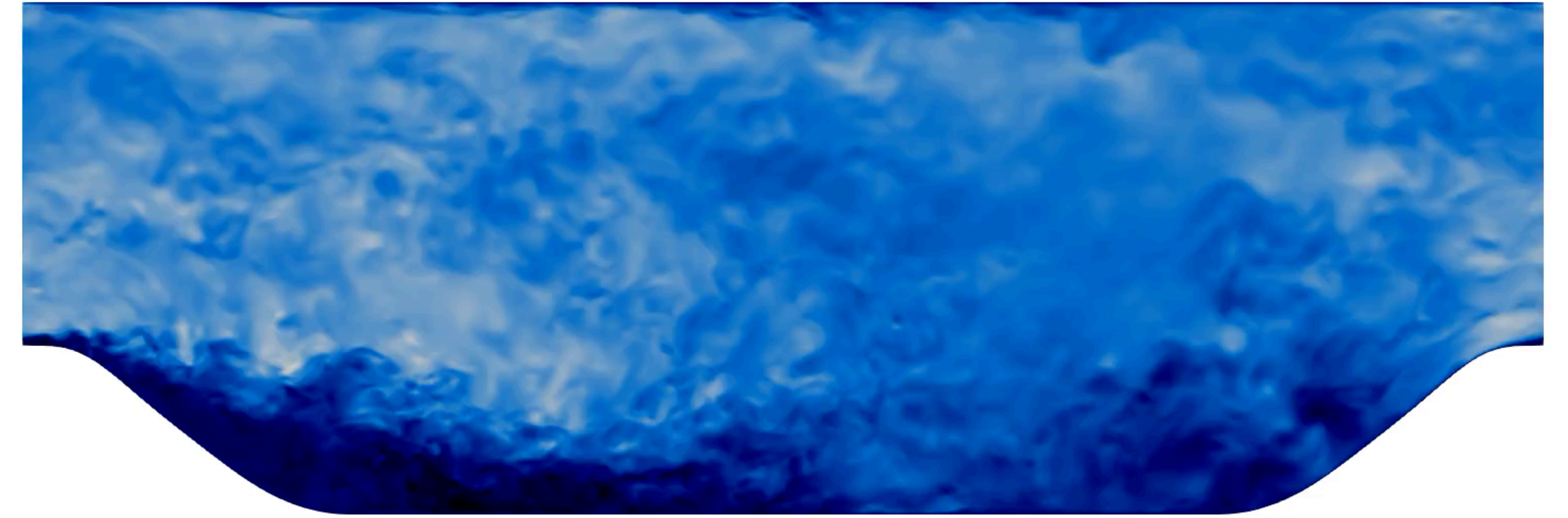
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Wall resolved LES



Number of degrees of freedom
28,480,320

Wall modeled LES

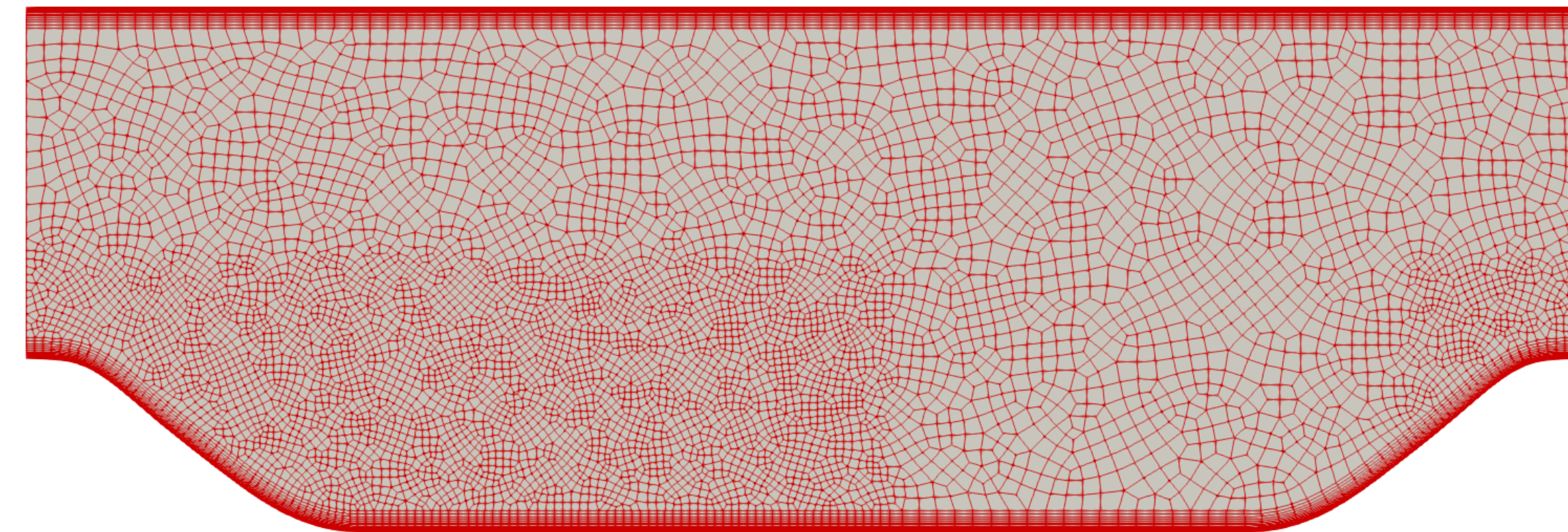
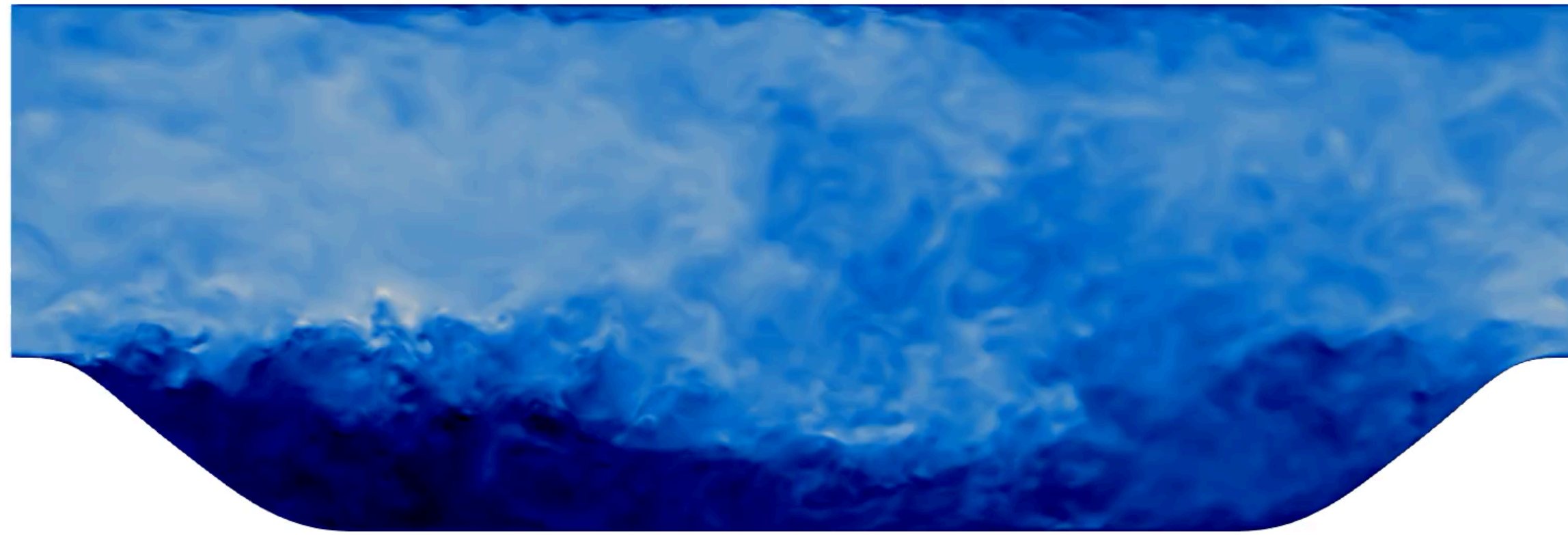


Number of degrees of freedom
20,332,800

What's the difference?

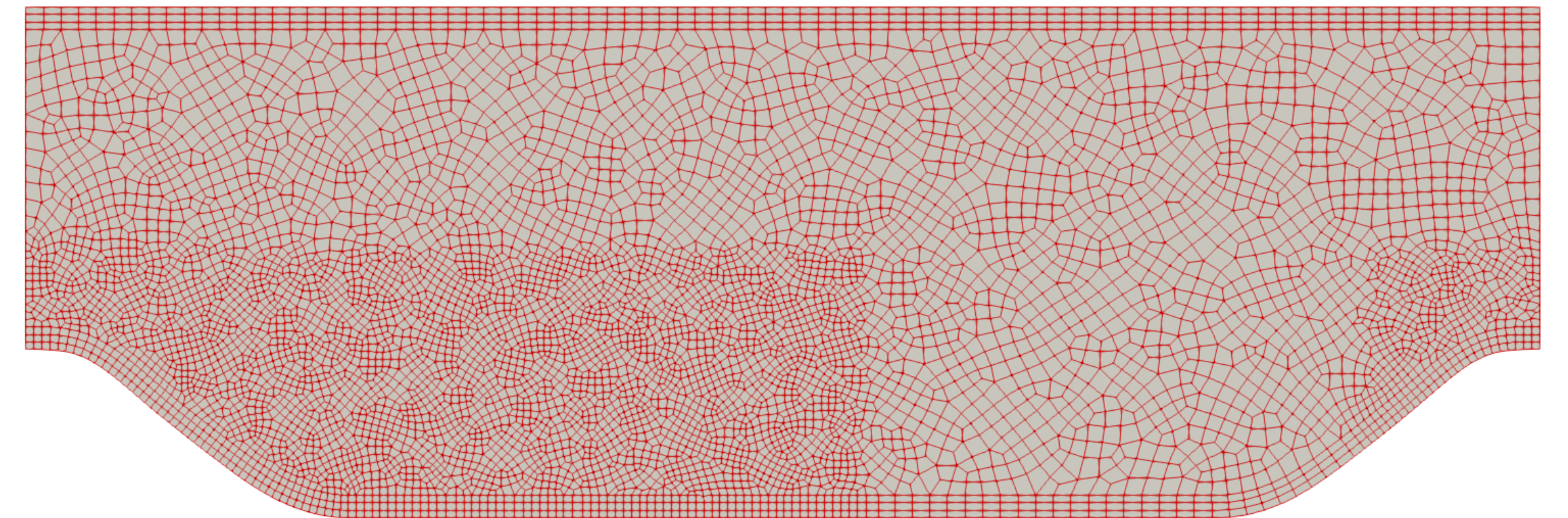
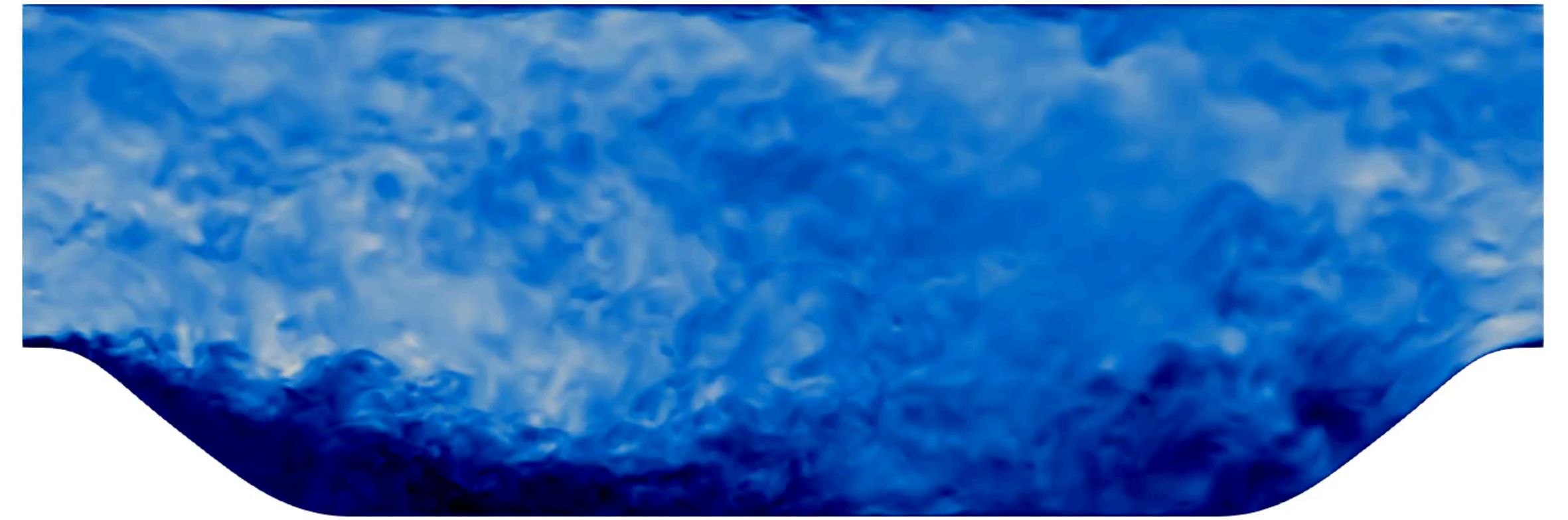
... the resolution near the wall.

Wall resolved LES



Number of degrees of freedom
28,480,320

Wall modeled LES



Number of degrees of freedom
20,332,800

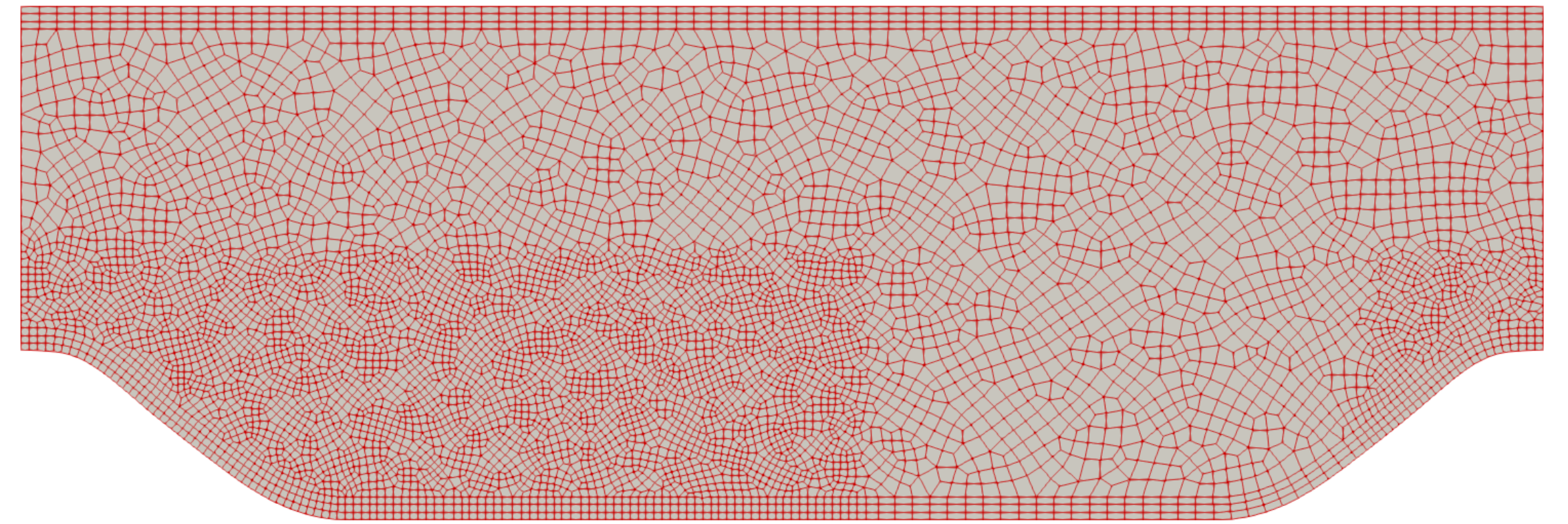
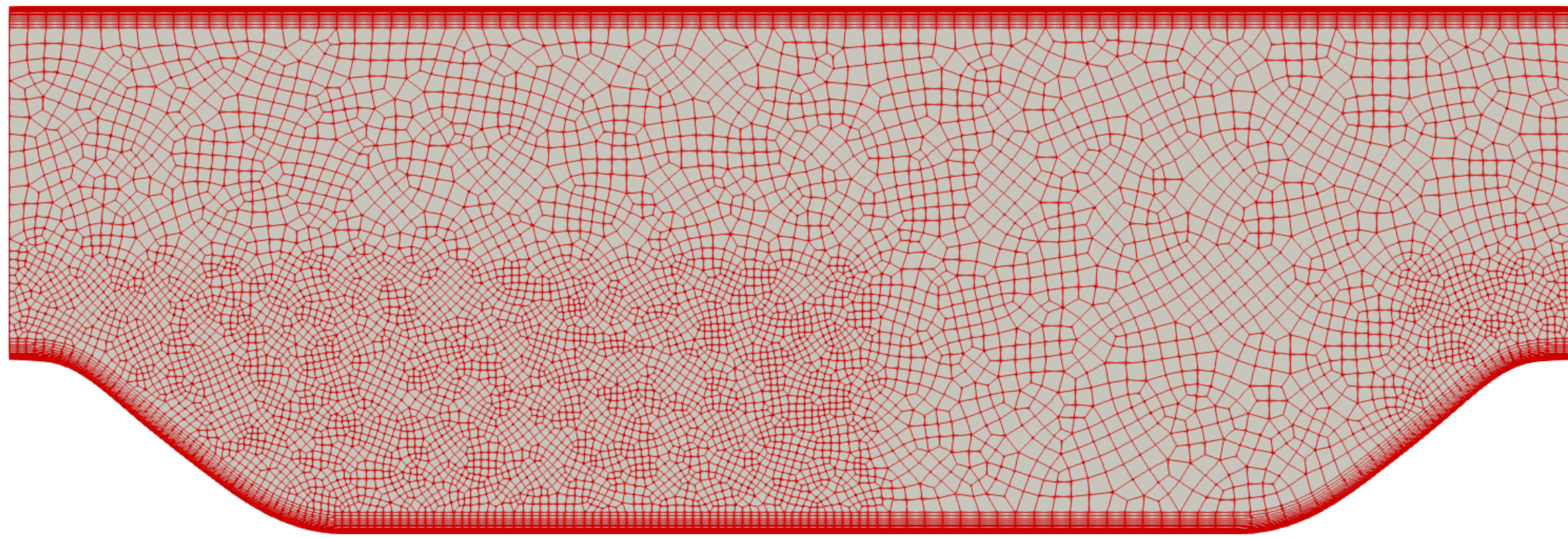
Ratio of ~ 1.4

What's the difference?

... the resolution near the wall.

Wall resolved LES

Wall modeled LES



Number of degrees of freedom

28,480,320

Number of degrees of freedom

20,332,800

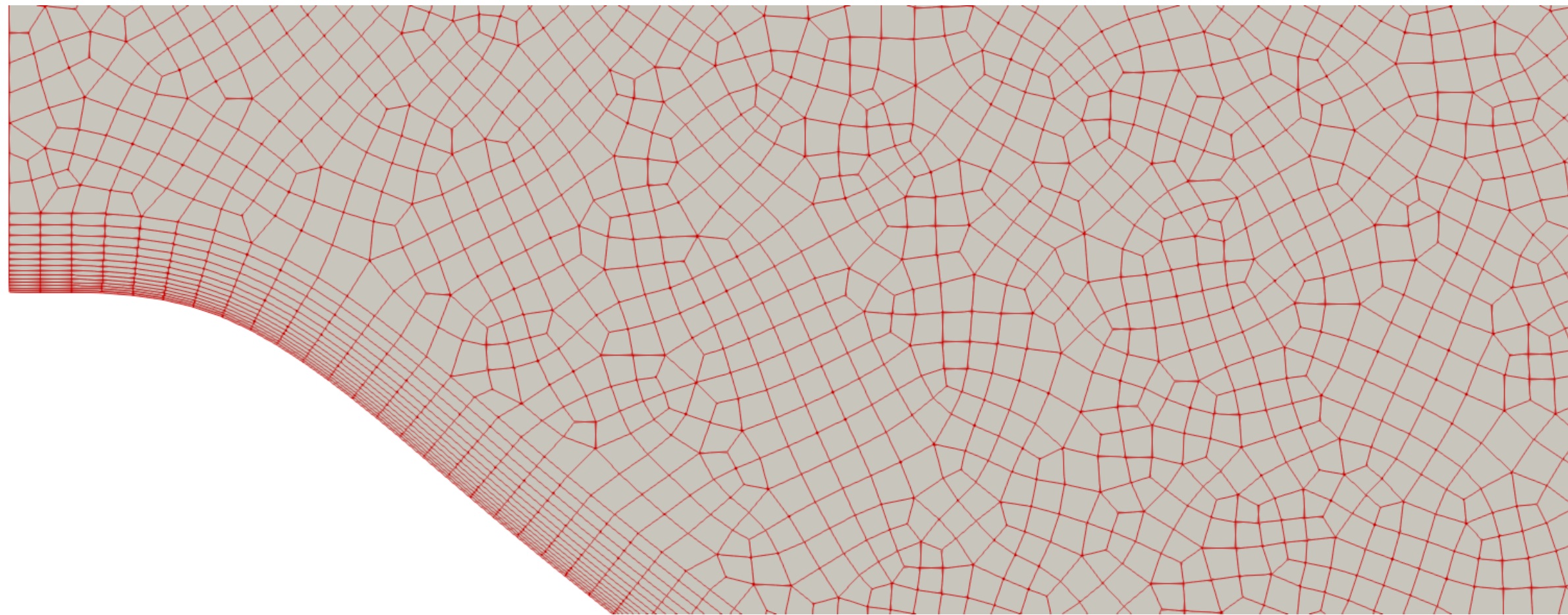
Ratio of ~ 1.4



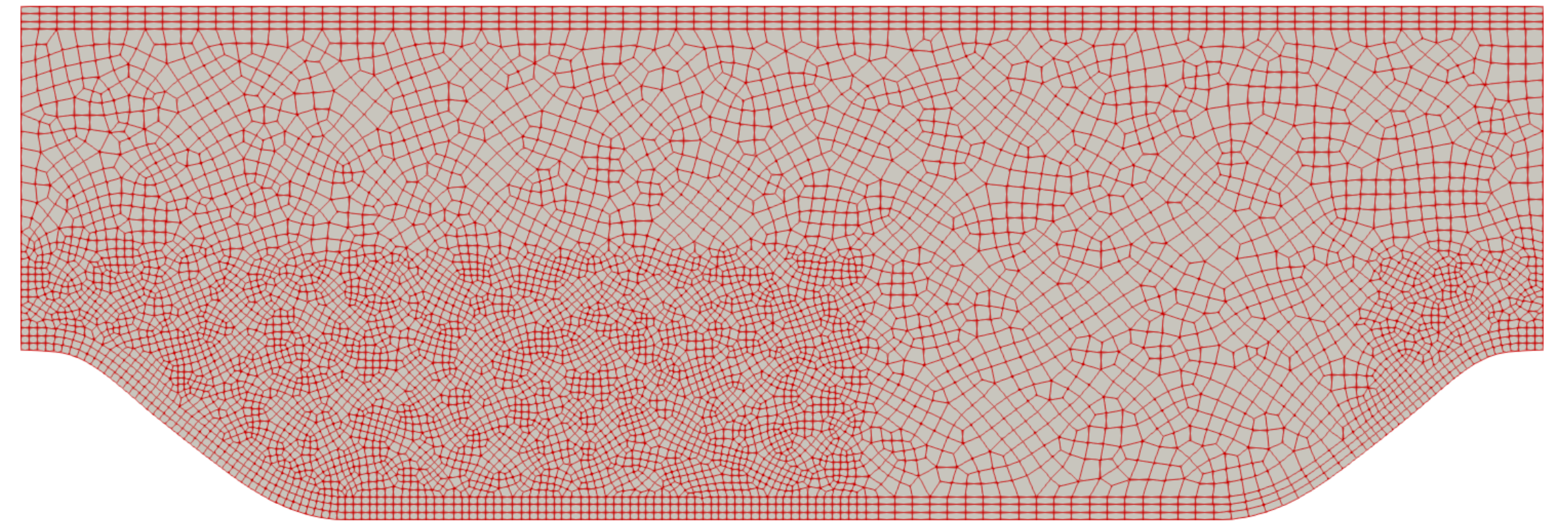
What's the difference?

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Wall resolved LES



Wall modeled LES



Number of degrees of freedom

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Number of degrees of freedom

20,332,800

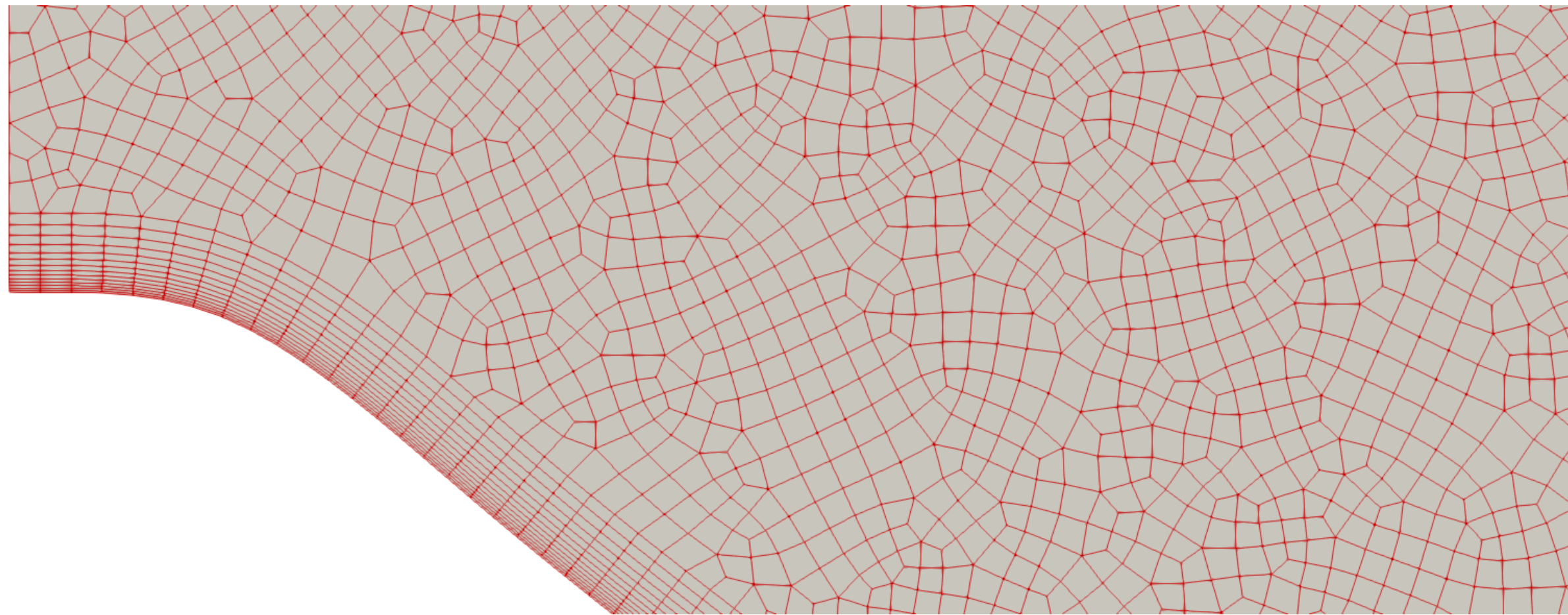
Ratio of ~ 1.4



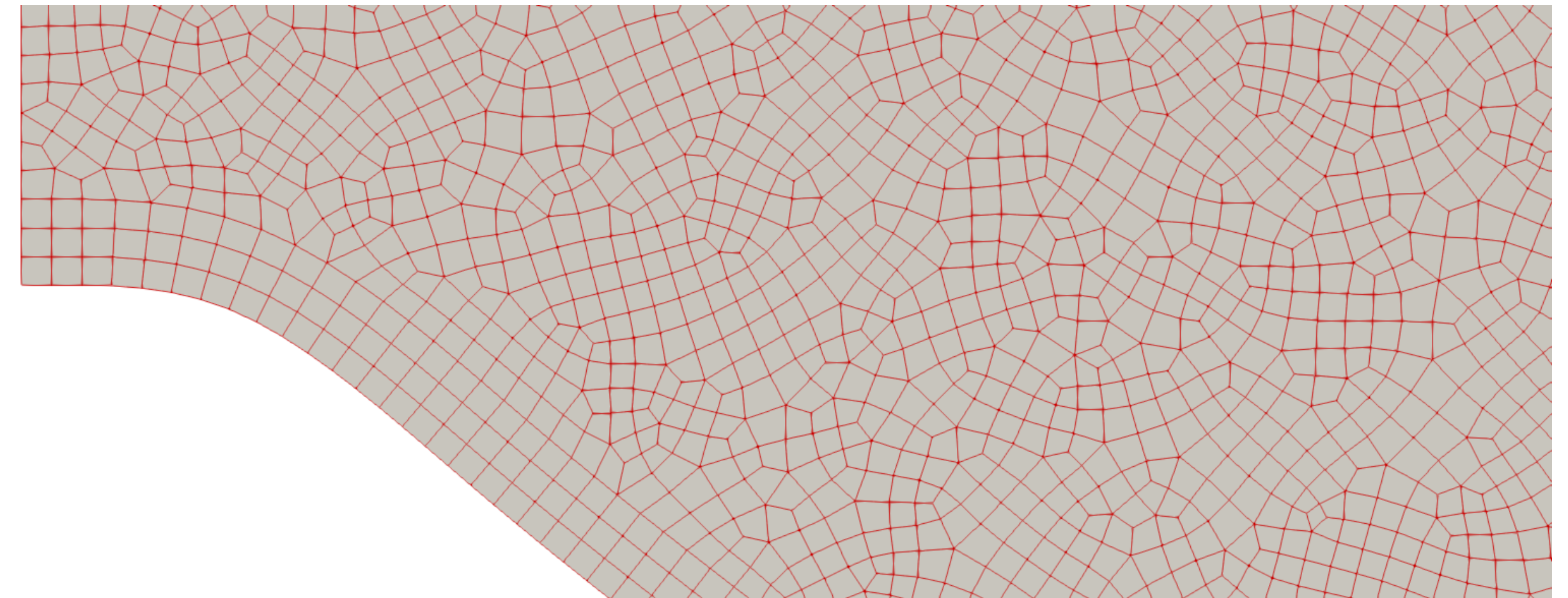
What's the difference?

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Wall resolved LES



Wall modeled LES



Number of degrees of freedom
28,480,320

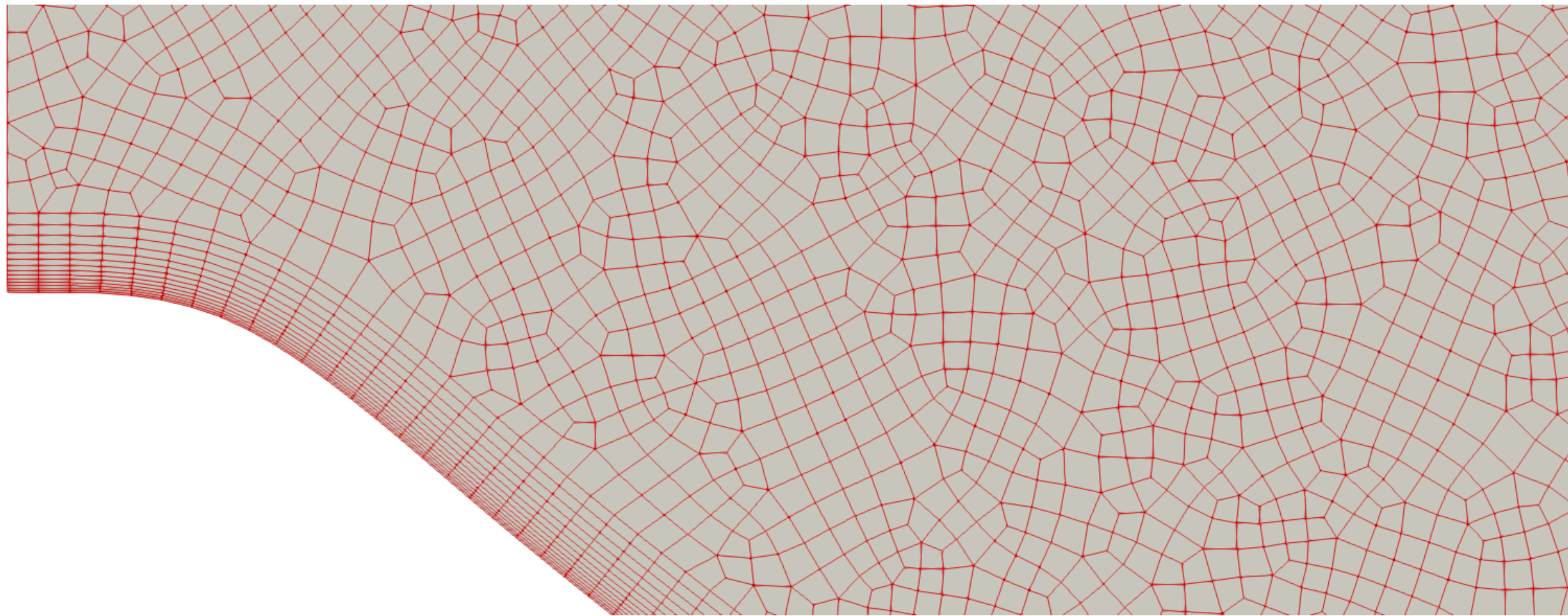
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20,332,800

← **Ratio of ~ 1.4** →

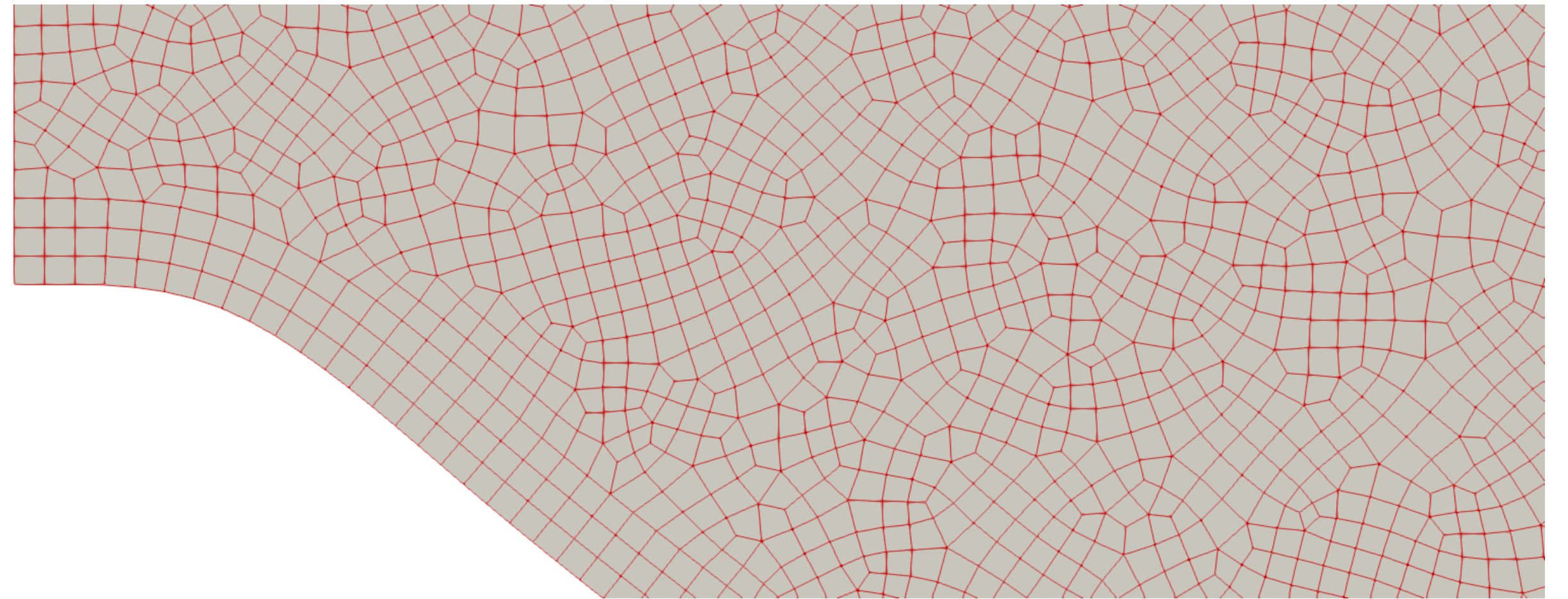
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Wall resolved LES



Wall modeled LES



Number of degrees of freedom

28,480,320

Number of degrees of freedom

20,332,800

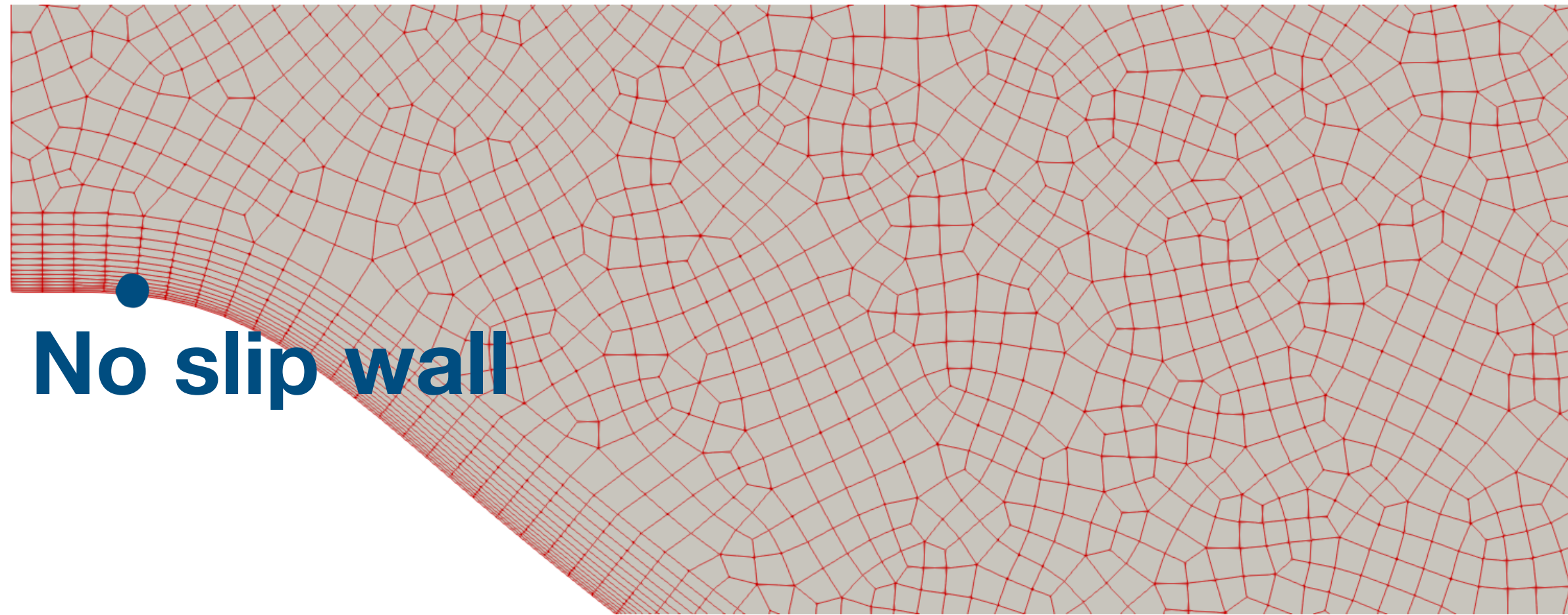
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What's the difference?

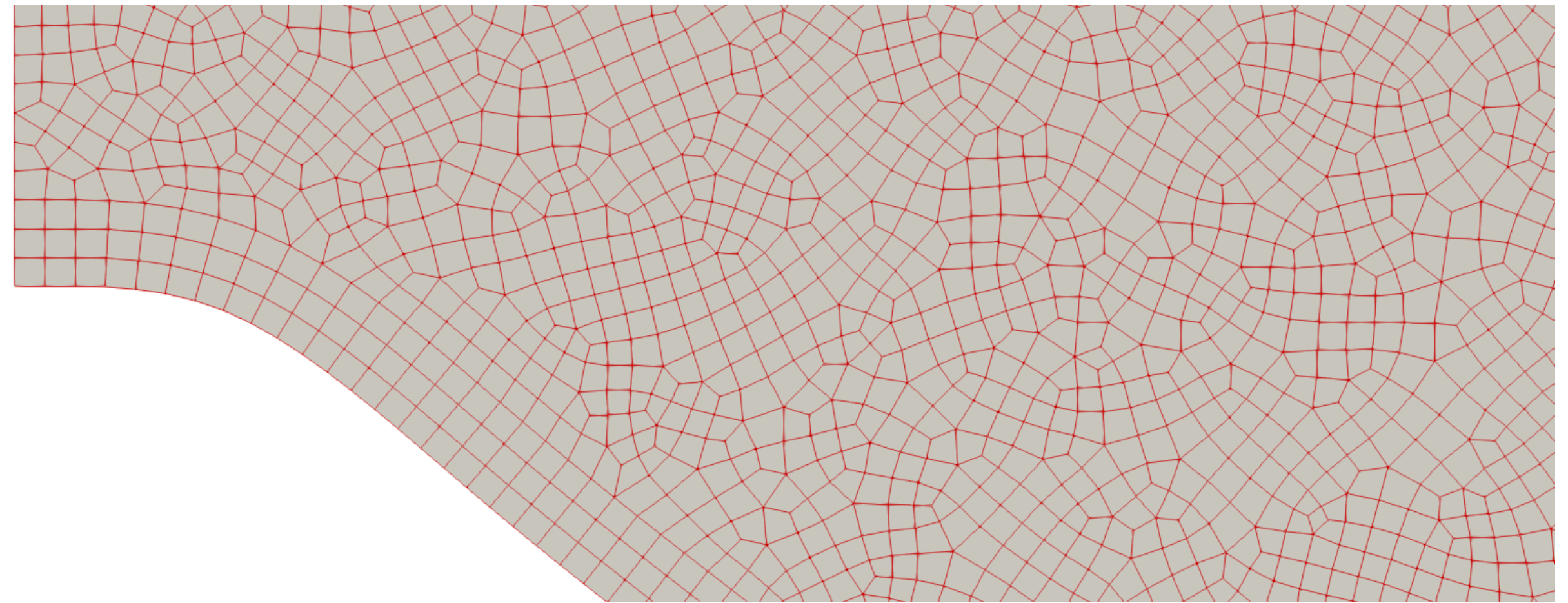
... the resolution near the wall.

Wall resolved LES



No slip wall

Wall modeled LES



Number of degrees of freedom

28,480,320

Number of degrees of freedom

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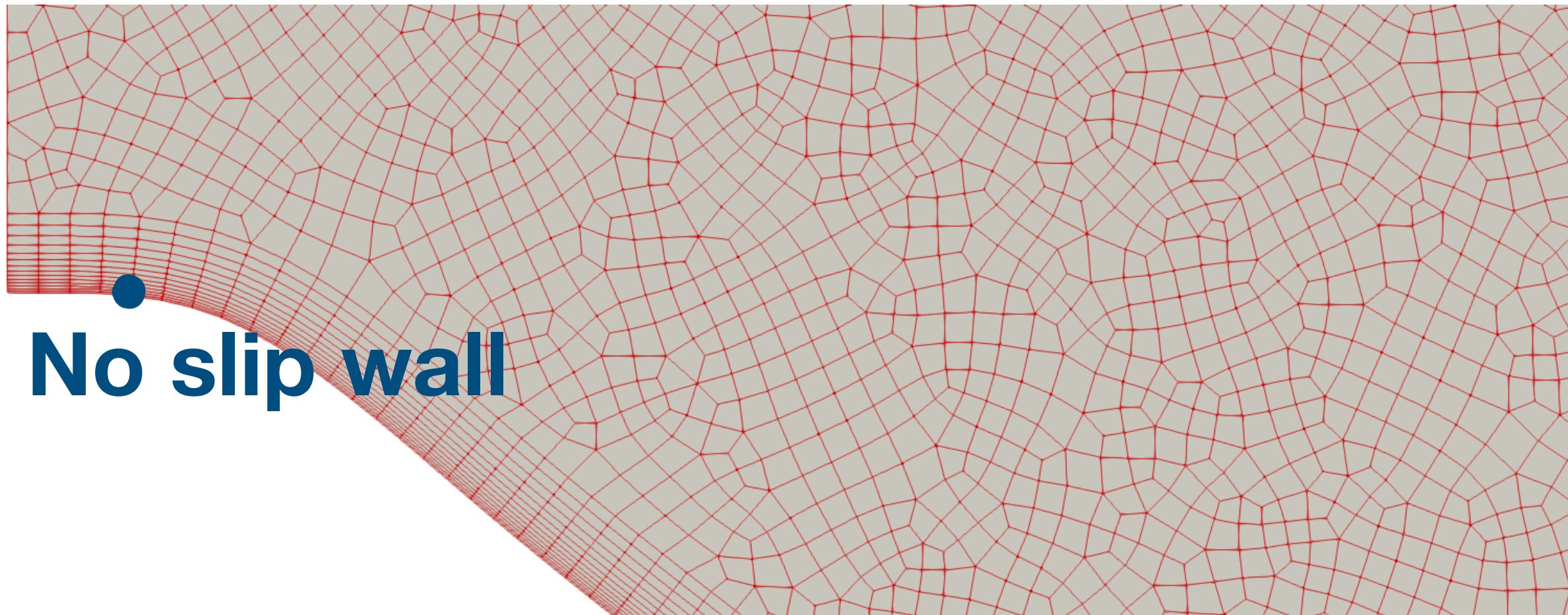
Ratio of ~ 1.4



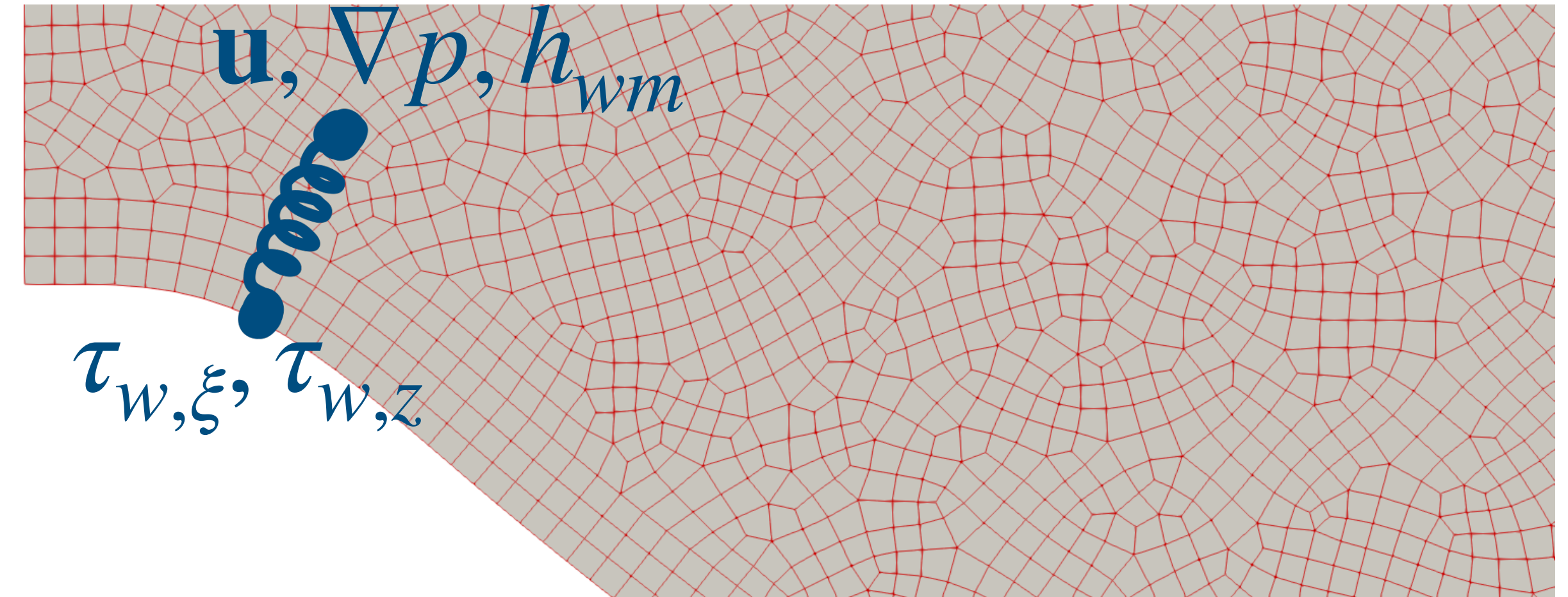
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Wall modeled LES



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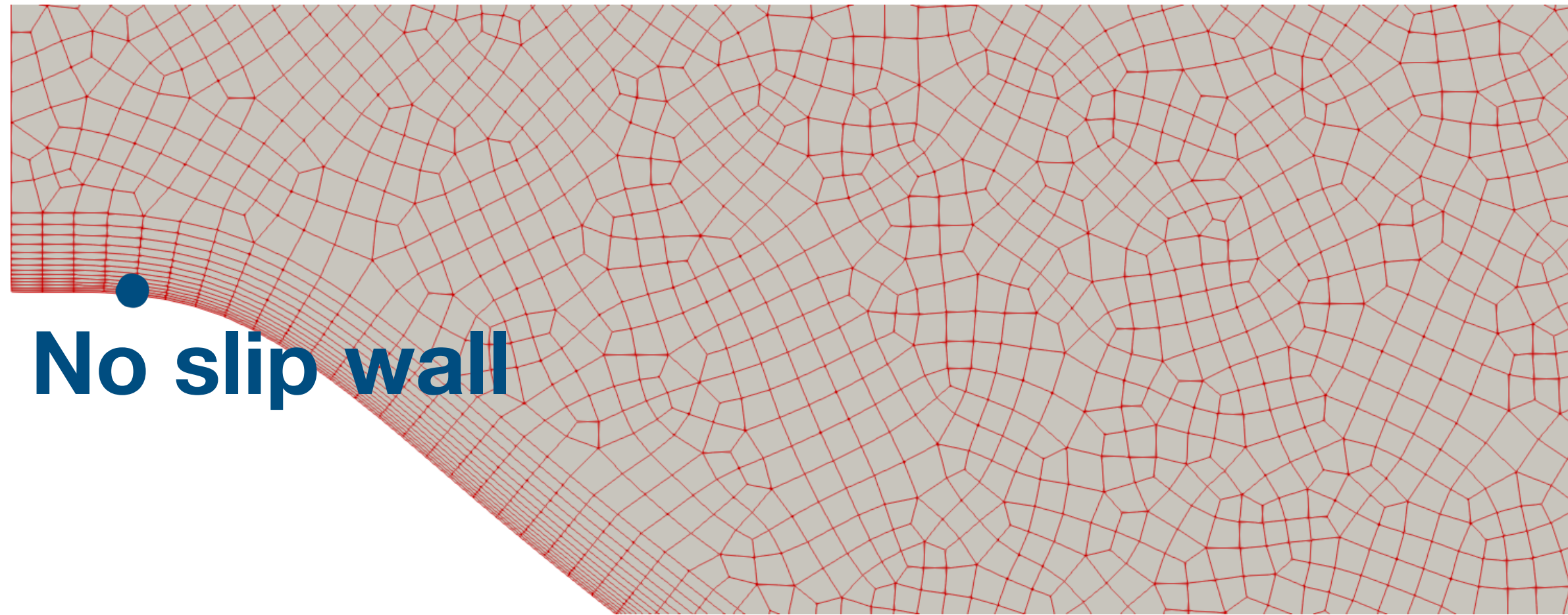
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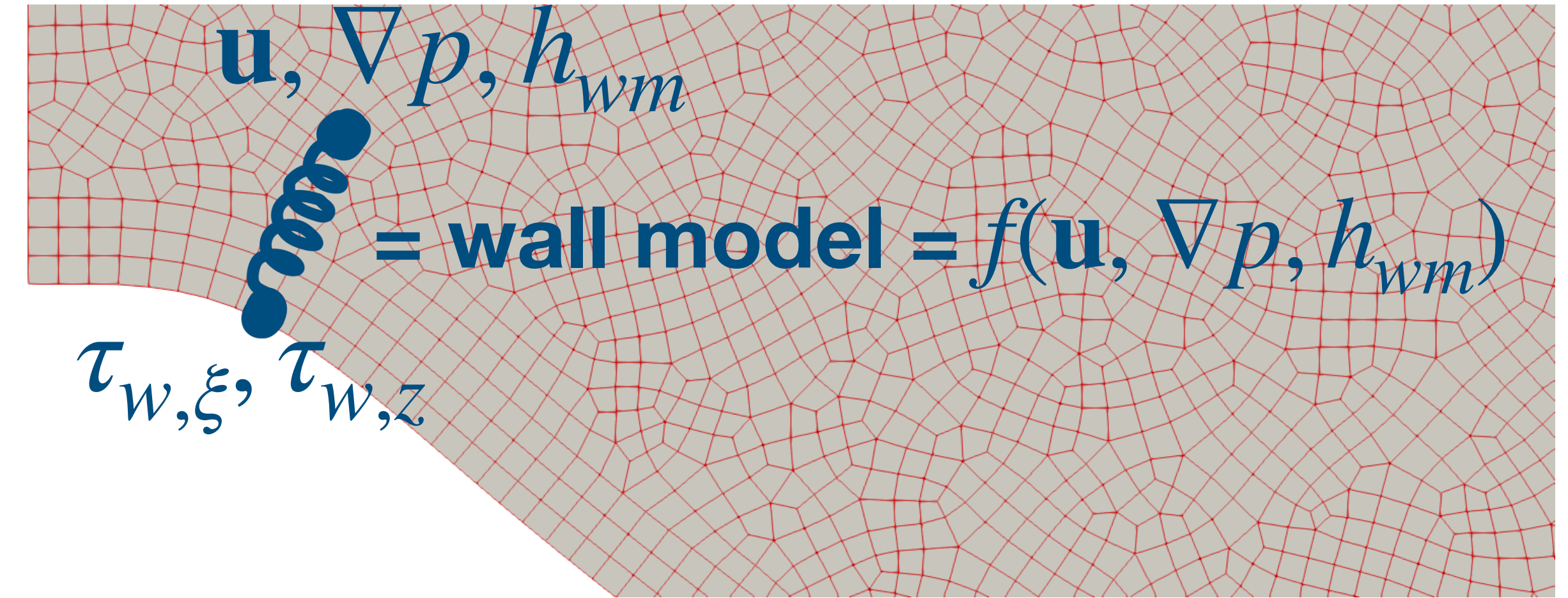
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Wall resolved LES



Wall modeled LES



Number of degrees of freedom
28,480,320

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Ratio of ~ 1.4

What is a wall model?

What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

What is a wall model?

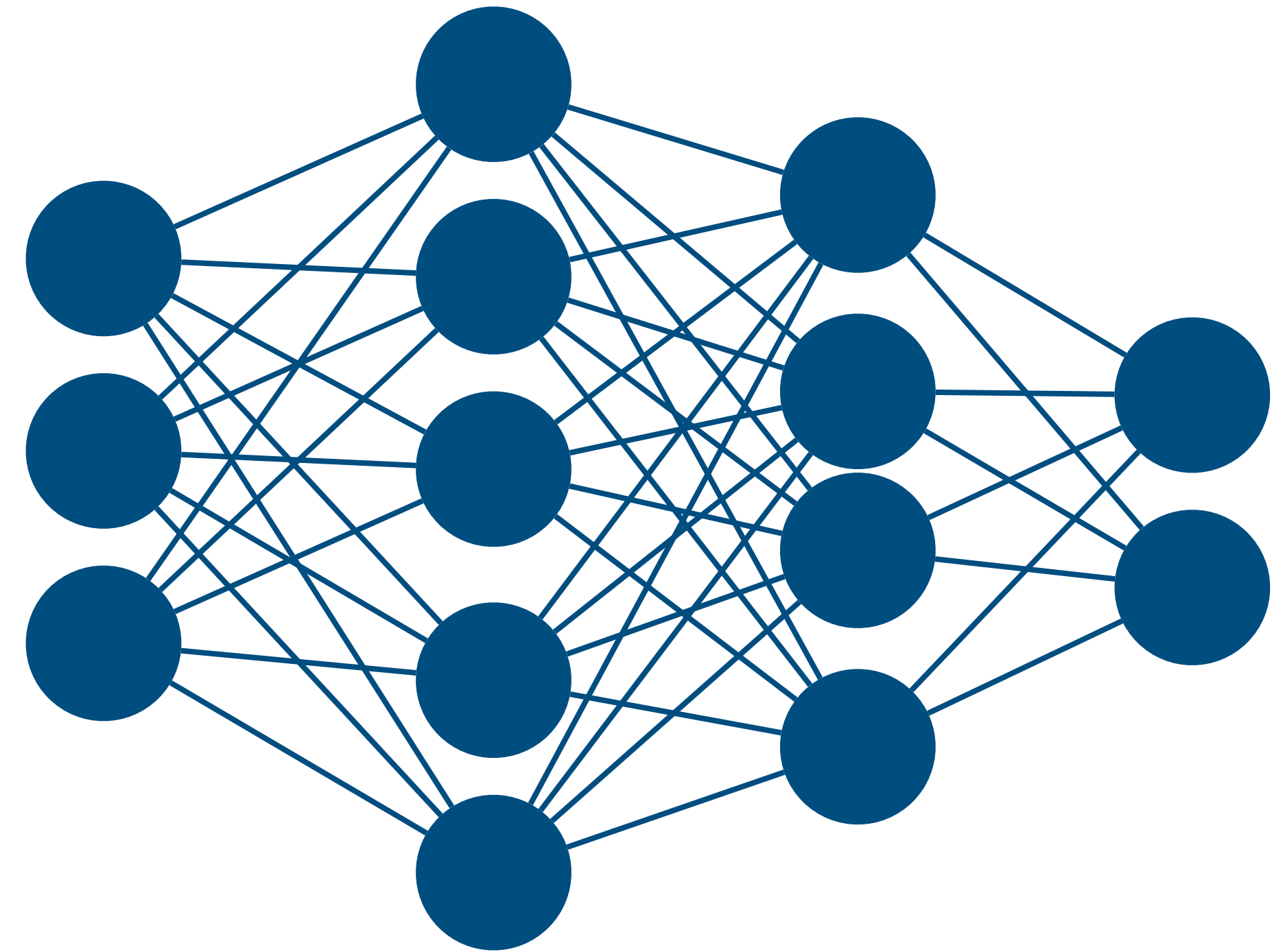
Finding a complex relationship between instantaneous volume data with the wall shear stress

$$\begin{matrix} \mathbf{u}, \nabla p, h_{wm} \\ \text{---} \\ \tau_{w,\xi}, \tau_{w,z} \end{matrix} = \text{wall model} = f(\mathbf{u}, \nabla p, h_{wm}) =$$

What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

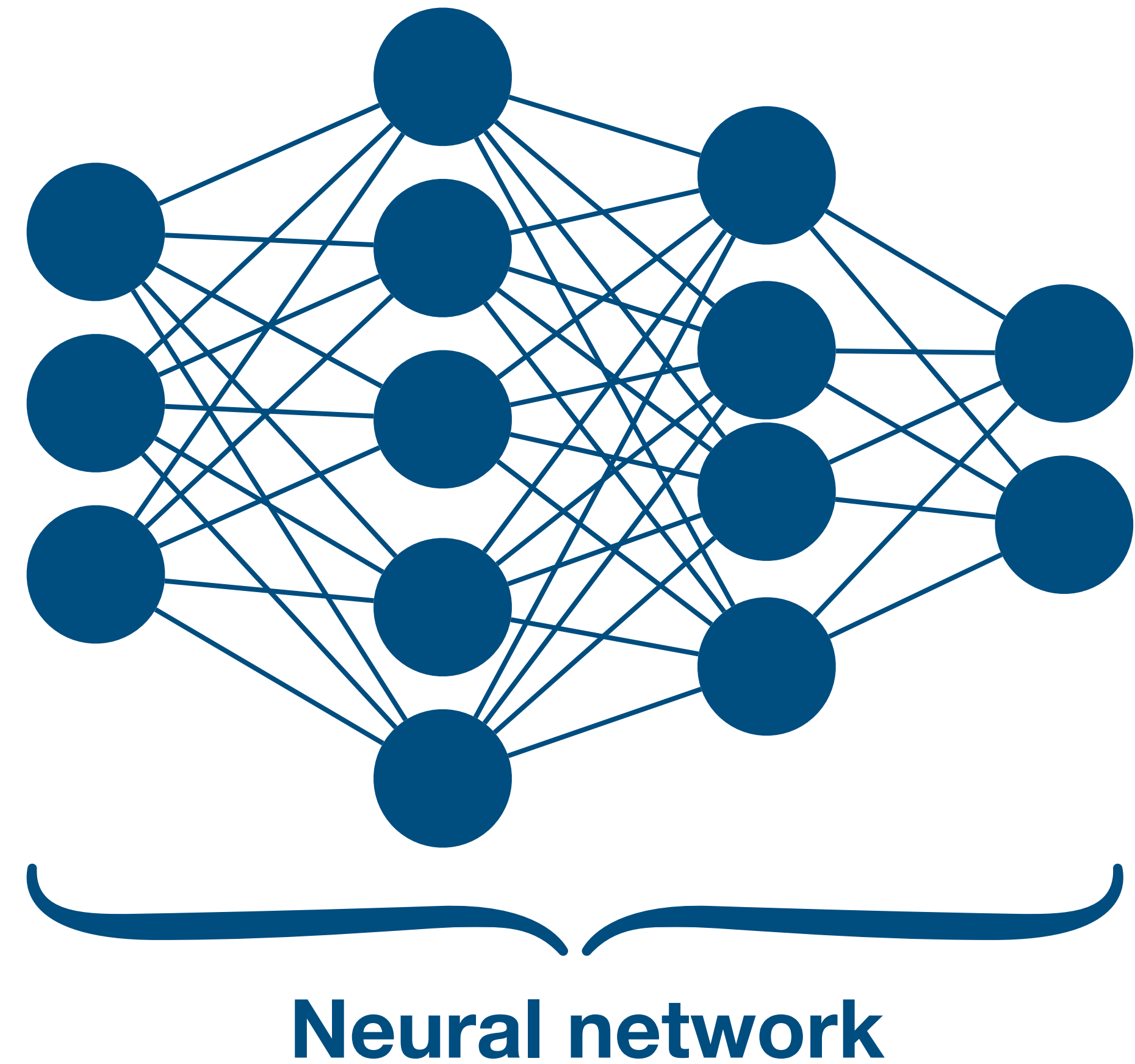
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What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

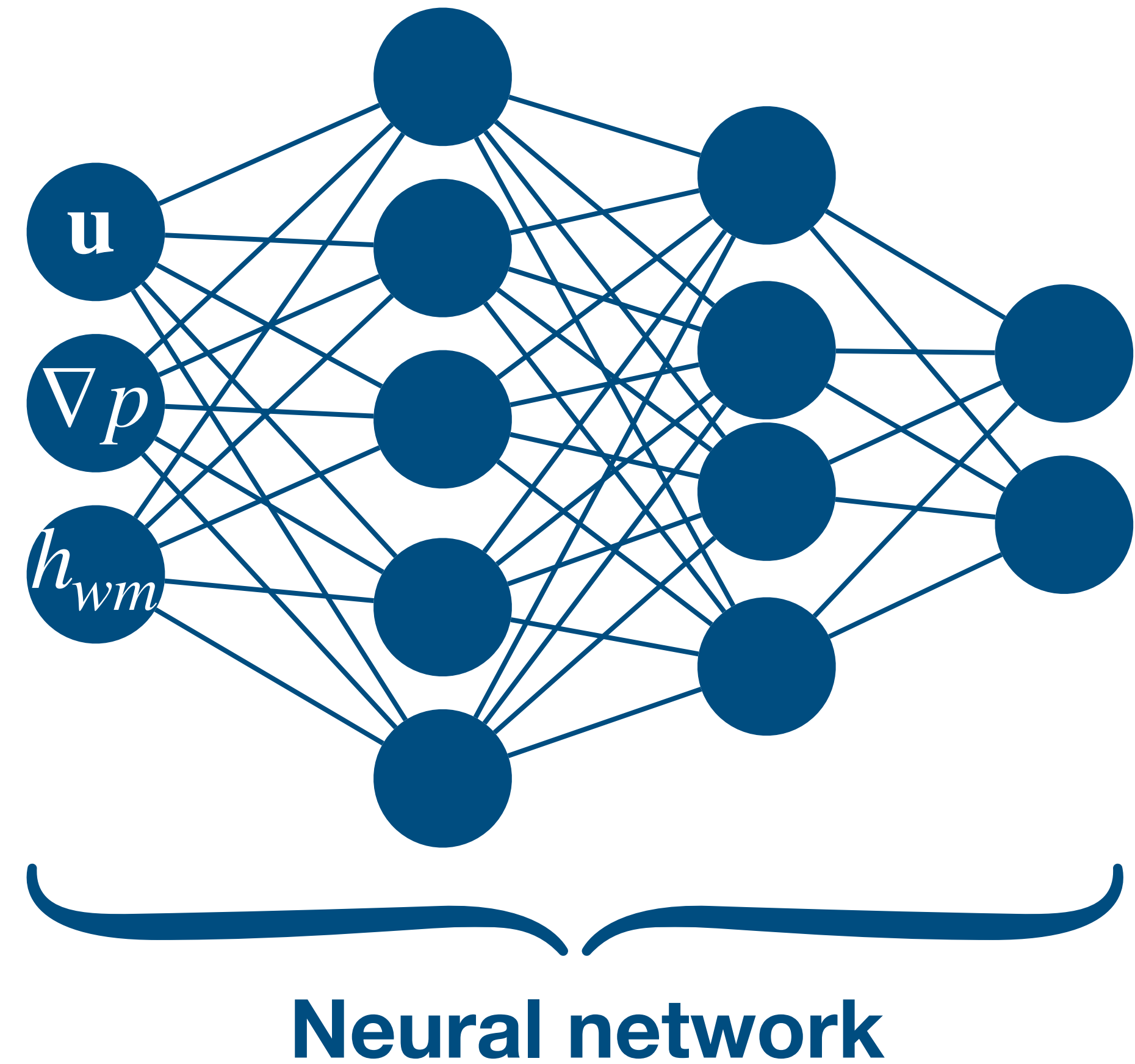
$$\mathbf{u}, \nabla p, h_{wm} = \text{wall model} = f(\mathbf{u}, \nabla p, h_{wm}) = \tau_{w,\xi}, \tau_{w,z}$$



What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

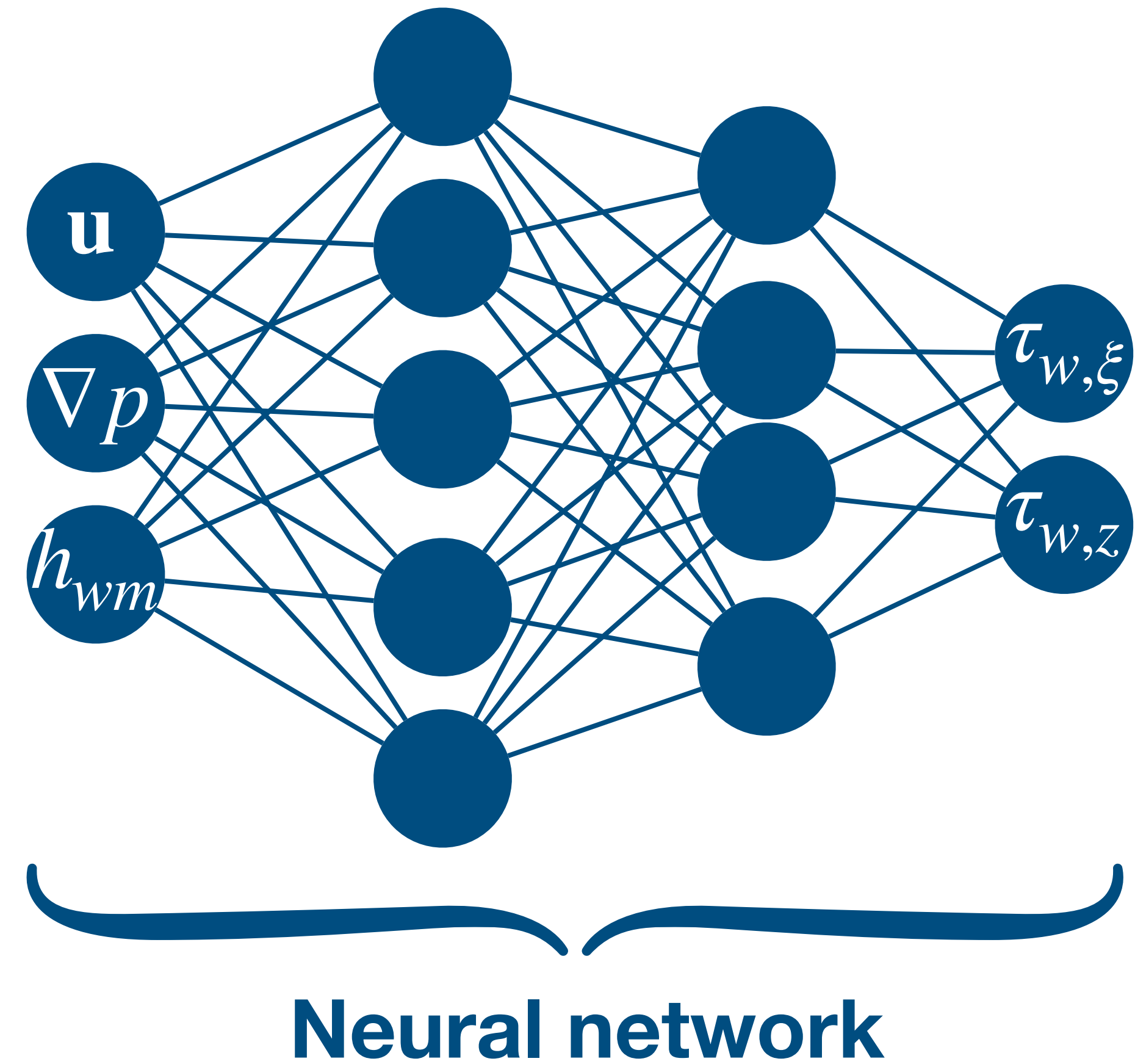
$$\mathbf{u}, \nabla p, h_{wm} = \text{wall model} = f(\mathbf{u}, \nabla p, h_{wm}) = \tau_{w,\xi}, \tau_{w,z}$$



What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

$\mathbf{u}, \nabla p, h_{wm}$
 $\tau_{w,\xi}, \tau_{w,z}$
= wall model = $f(\mathbf{u}, \nabla p, h_{wm}) =$



What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

What is a wall model?

Finding a complex relationship between instantaneous volume data with the wall shear stress

To apply such a wall model, the following questions should be answered:

- **Where the inputs are extracted (i.e., input stencil)?**
- **How to normalize the inputs and the outputs?**
- **Which neural network to use?**

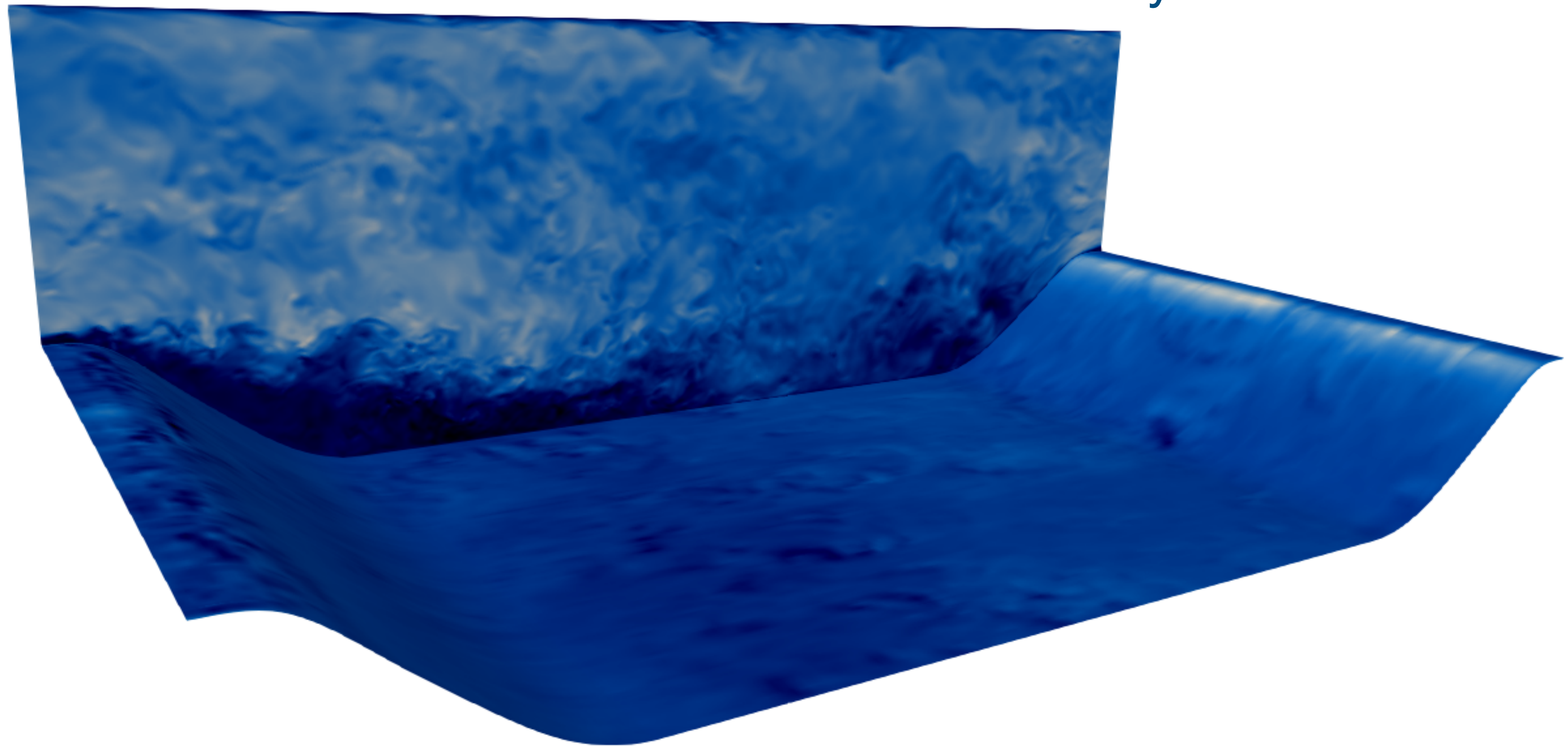
Brief explanation of the test case

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Two-dimensional periodic hill: bi-periodic flow evolving between two walls featuring a streamwise constriction, the flow is controlled by a pressure gradient to match the bulk Reynolds number of 10,595

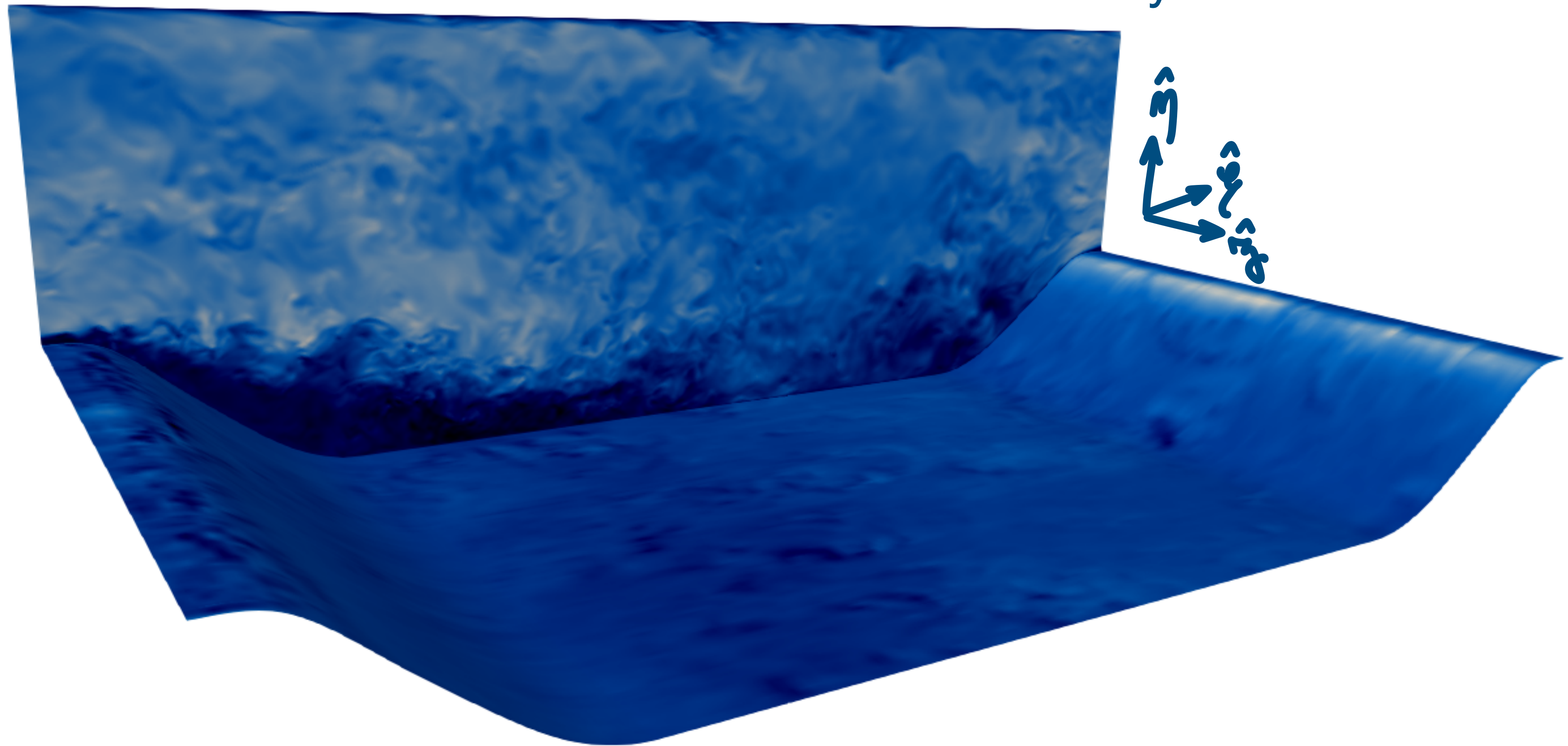
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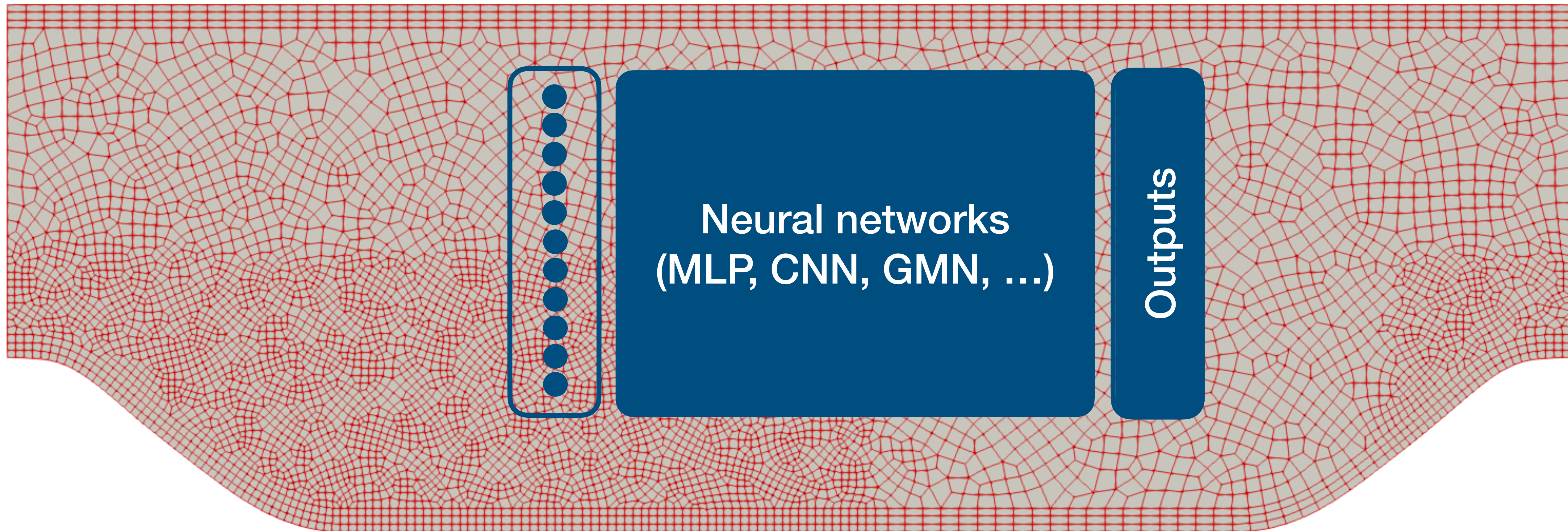


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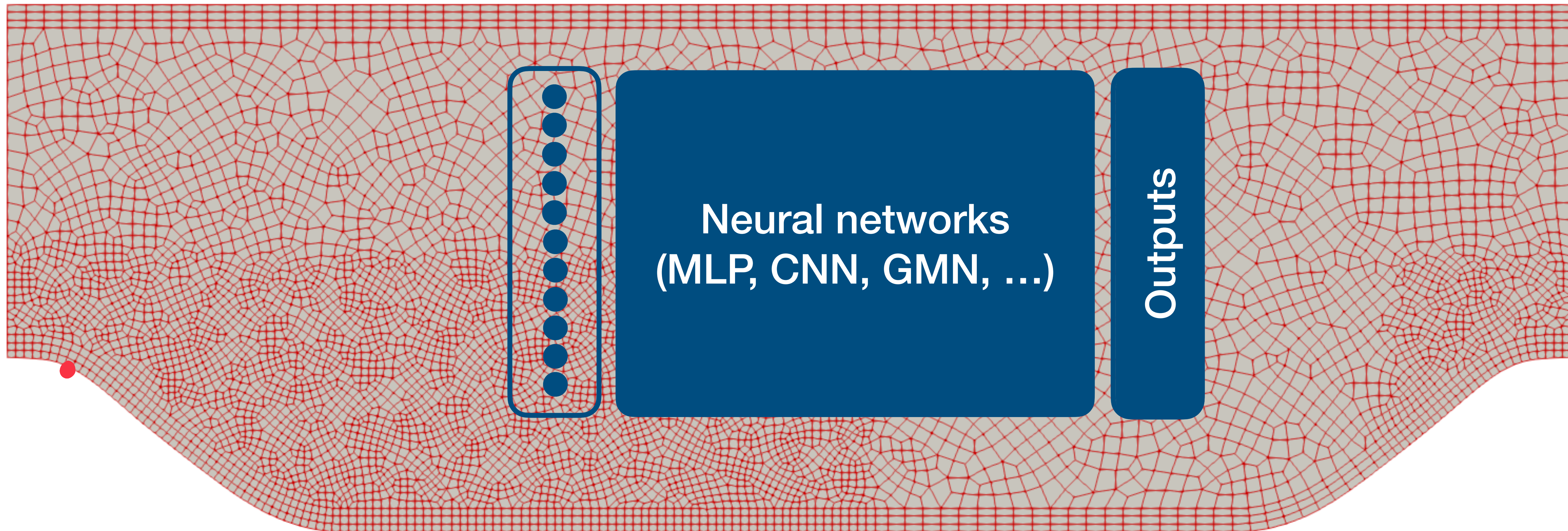
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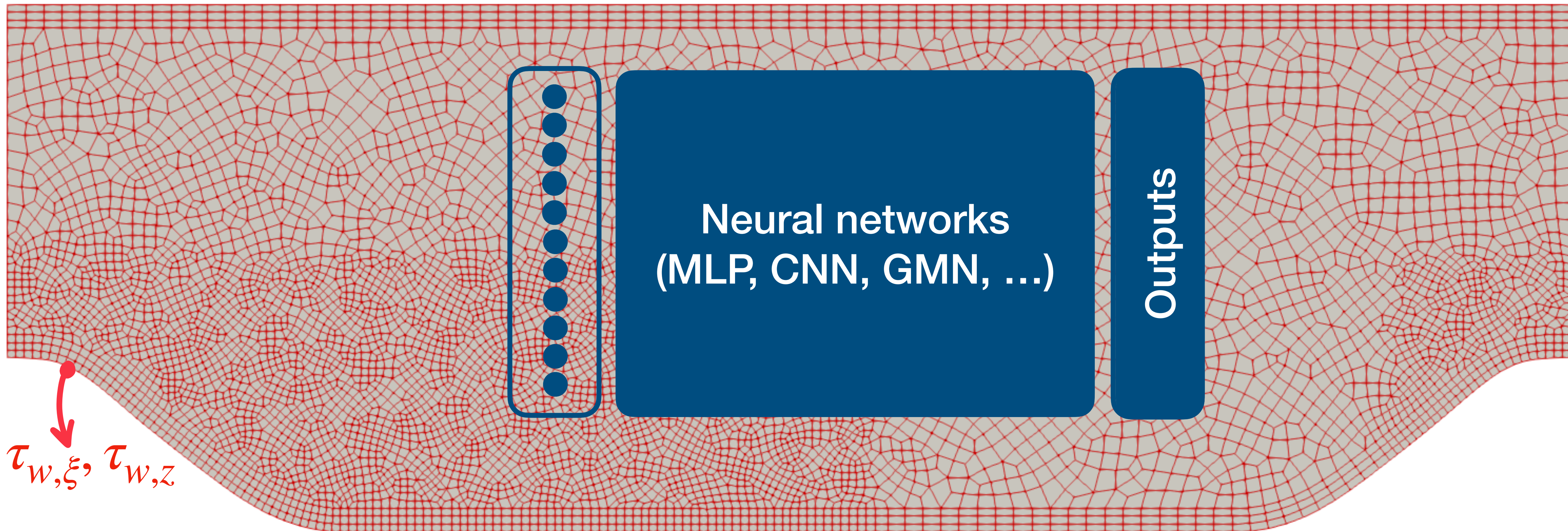
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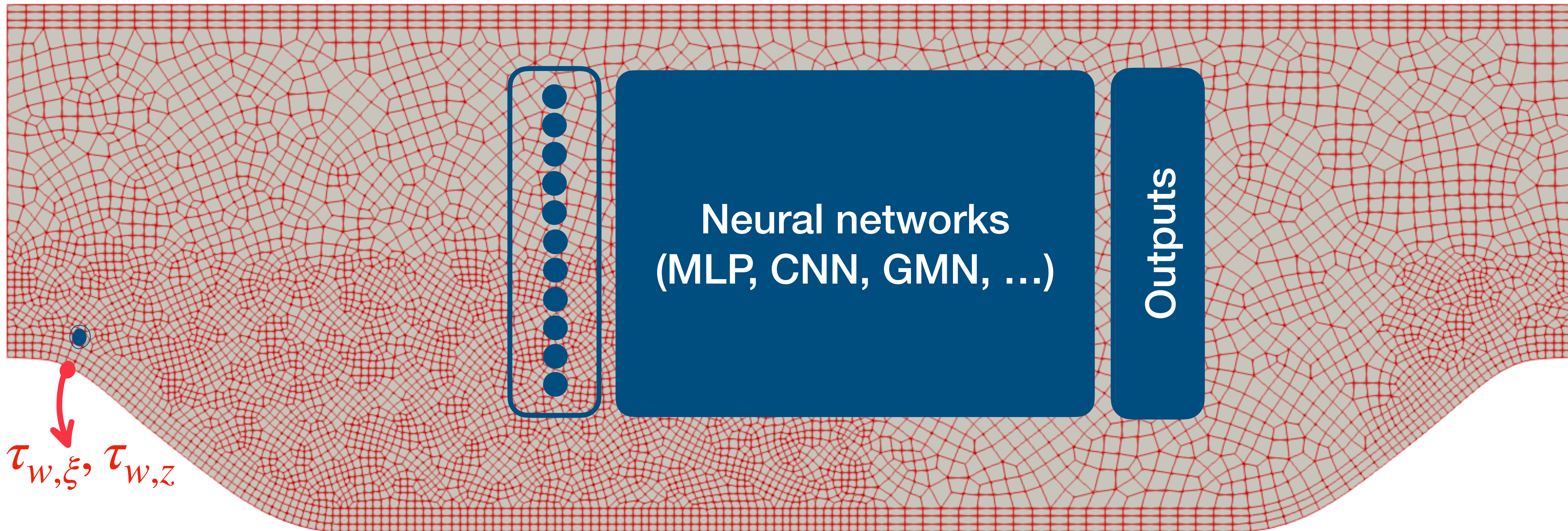
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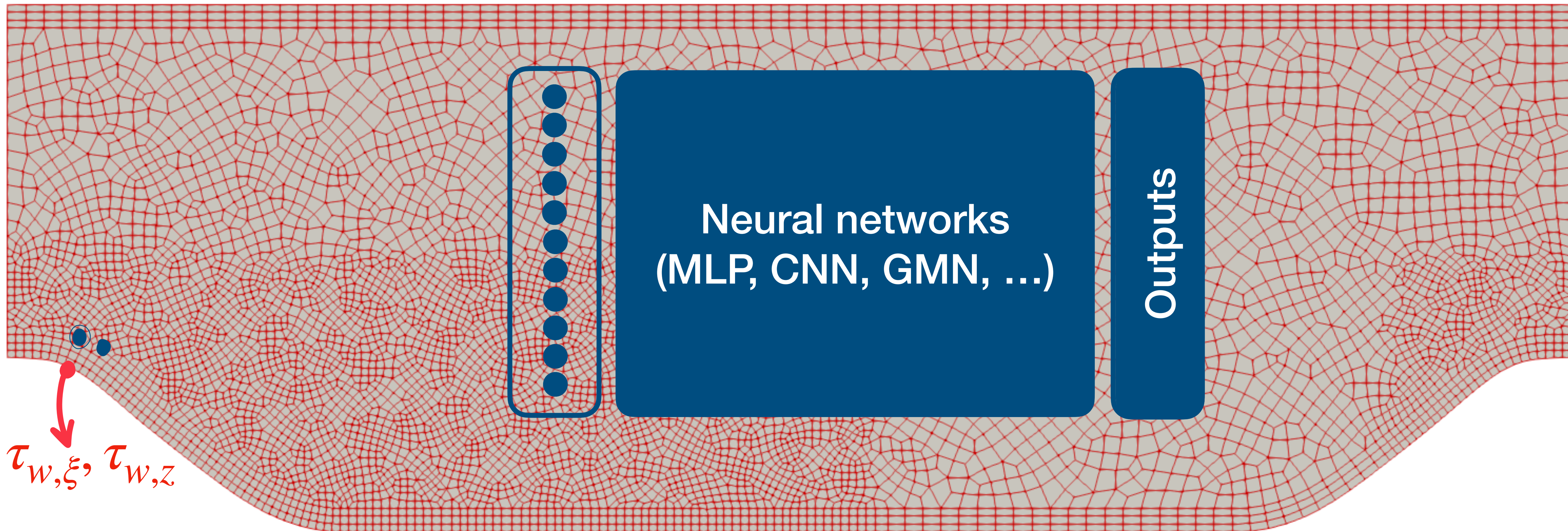
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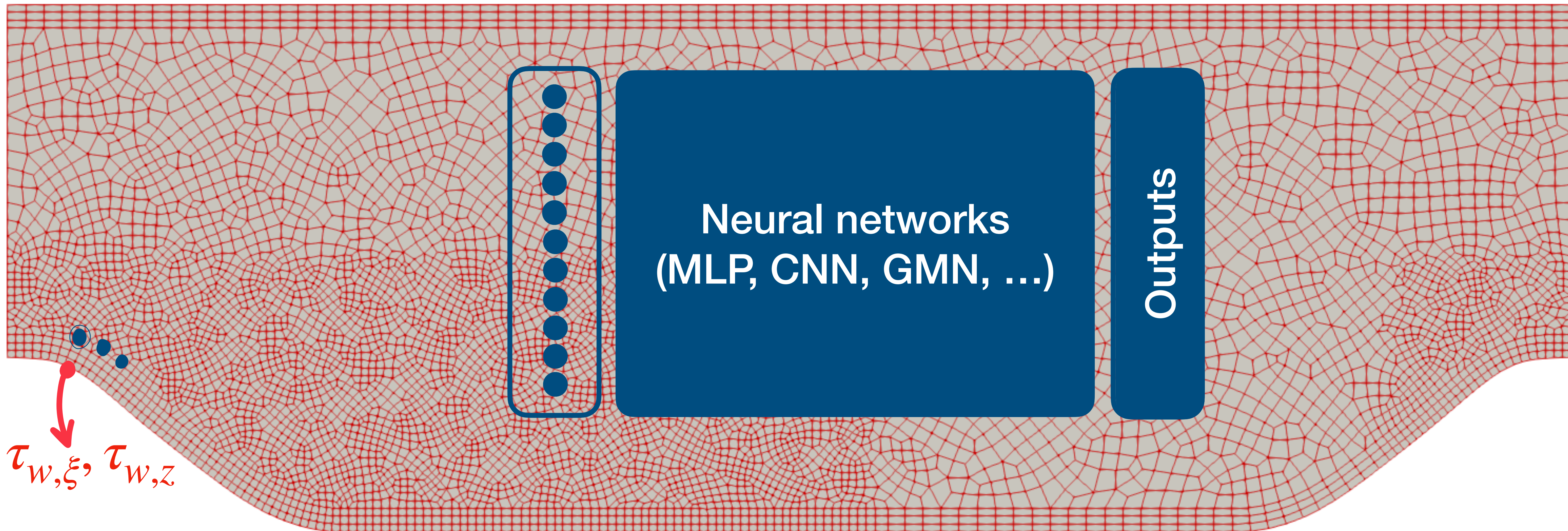
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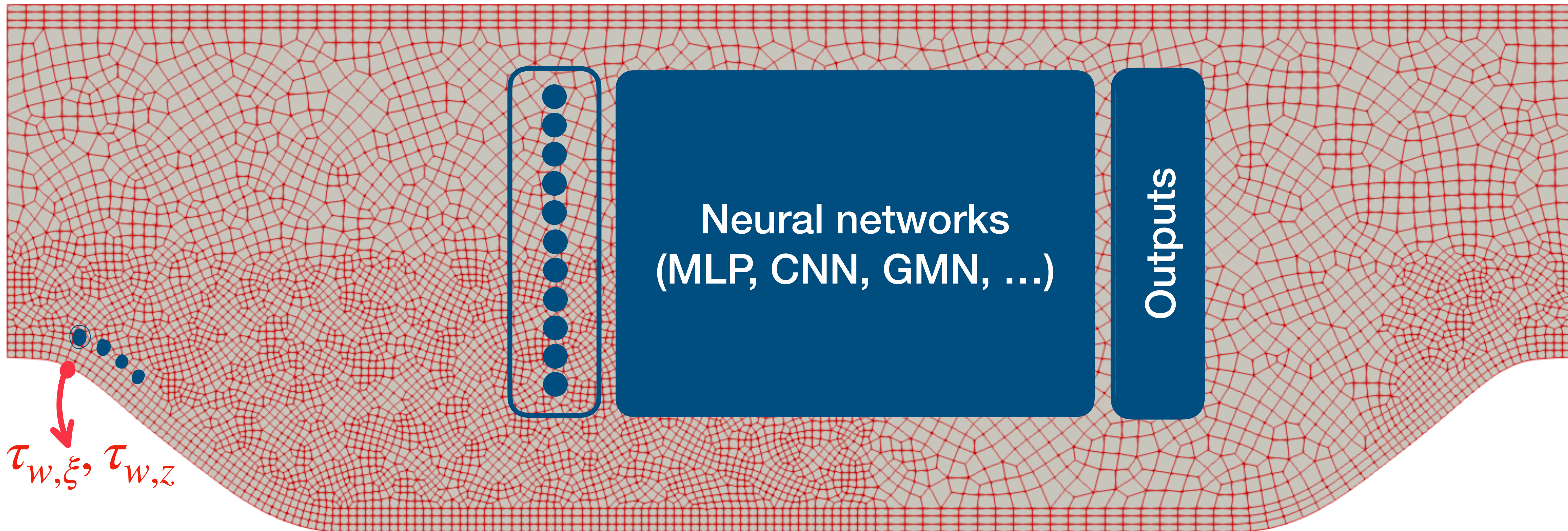
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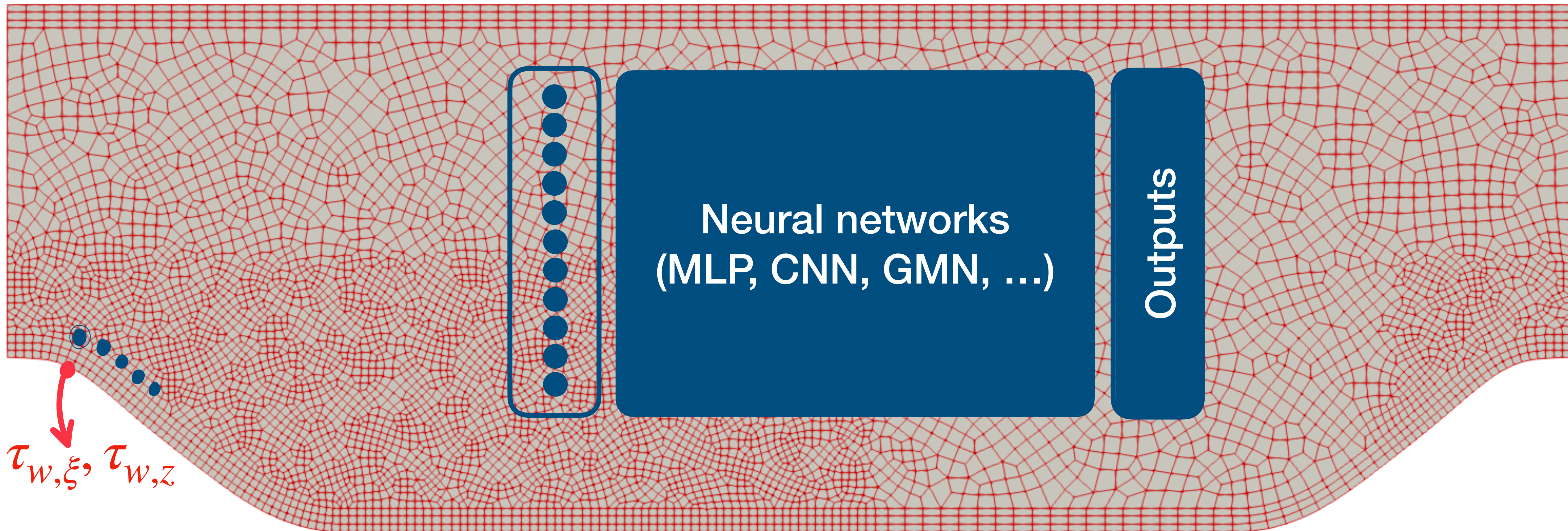
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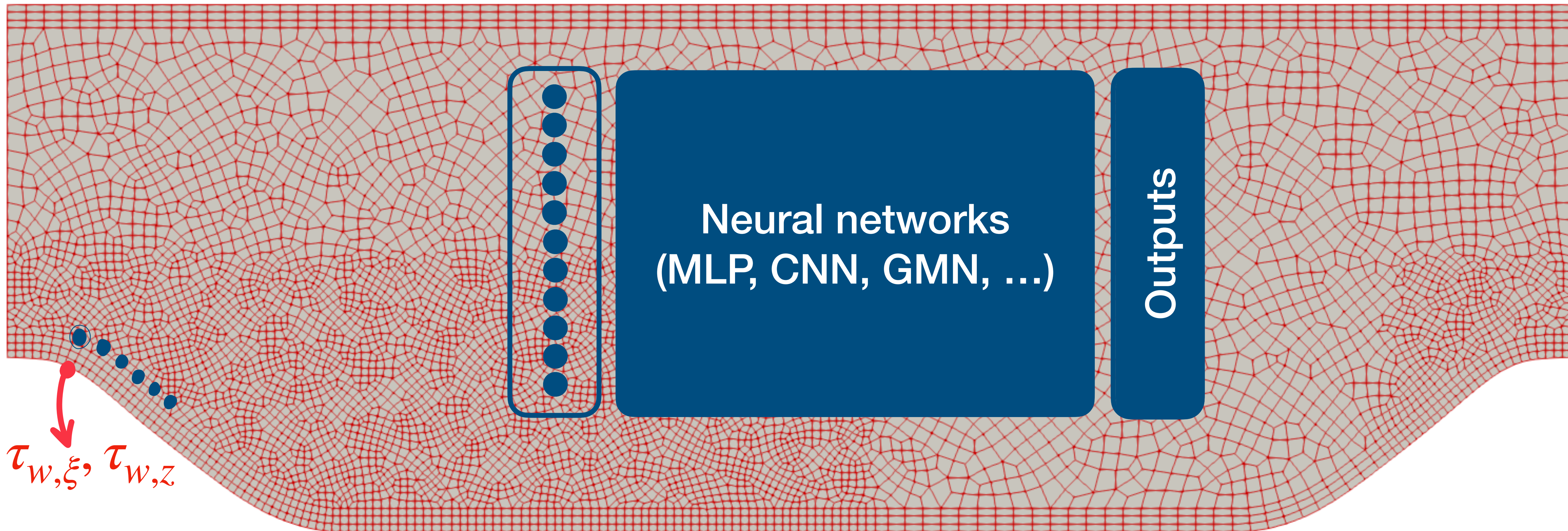
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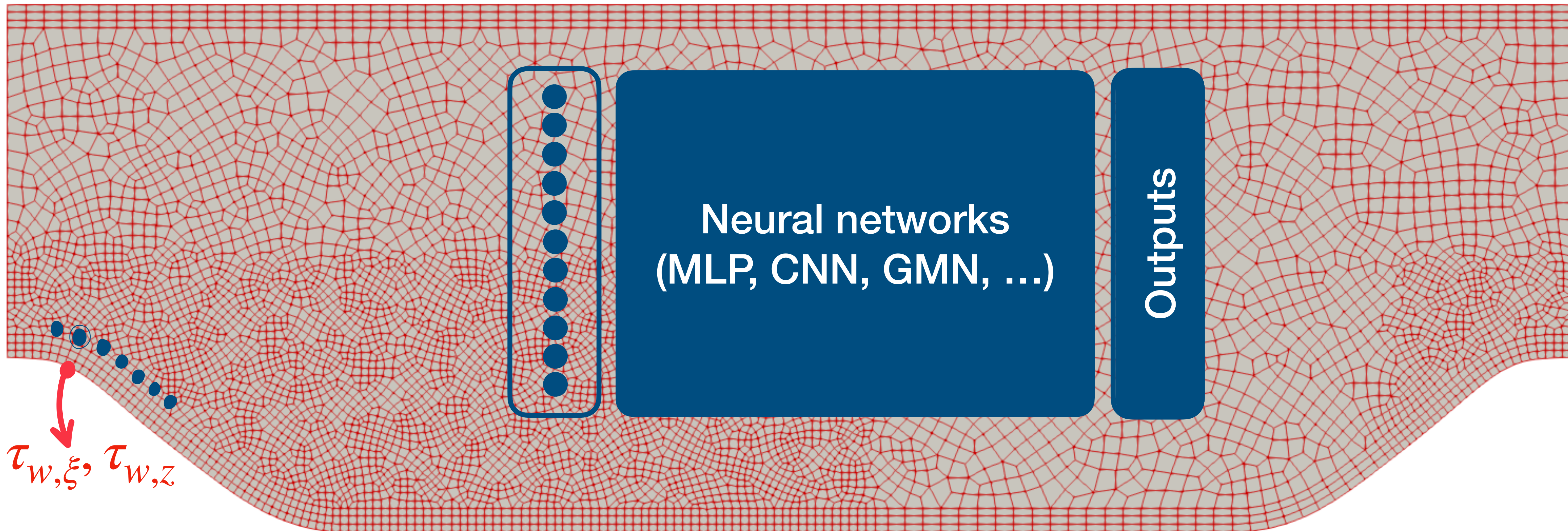
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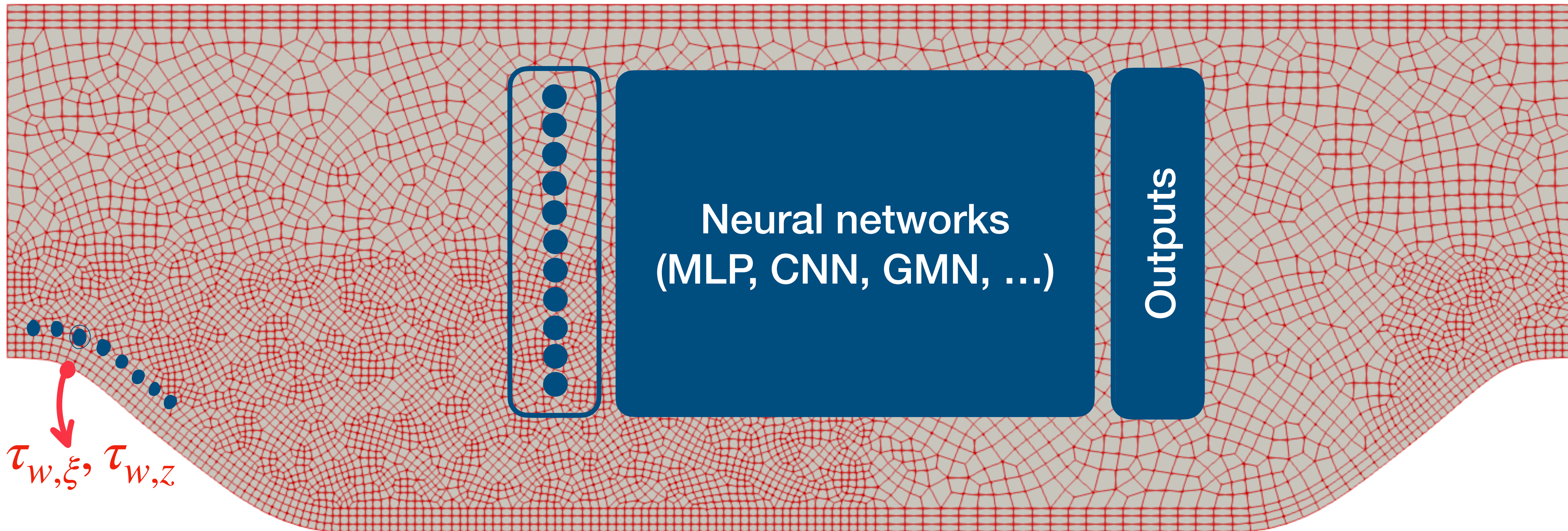
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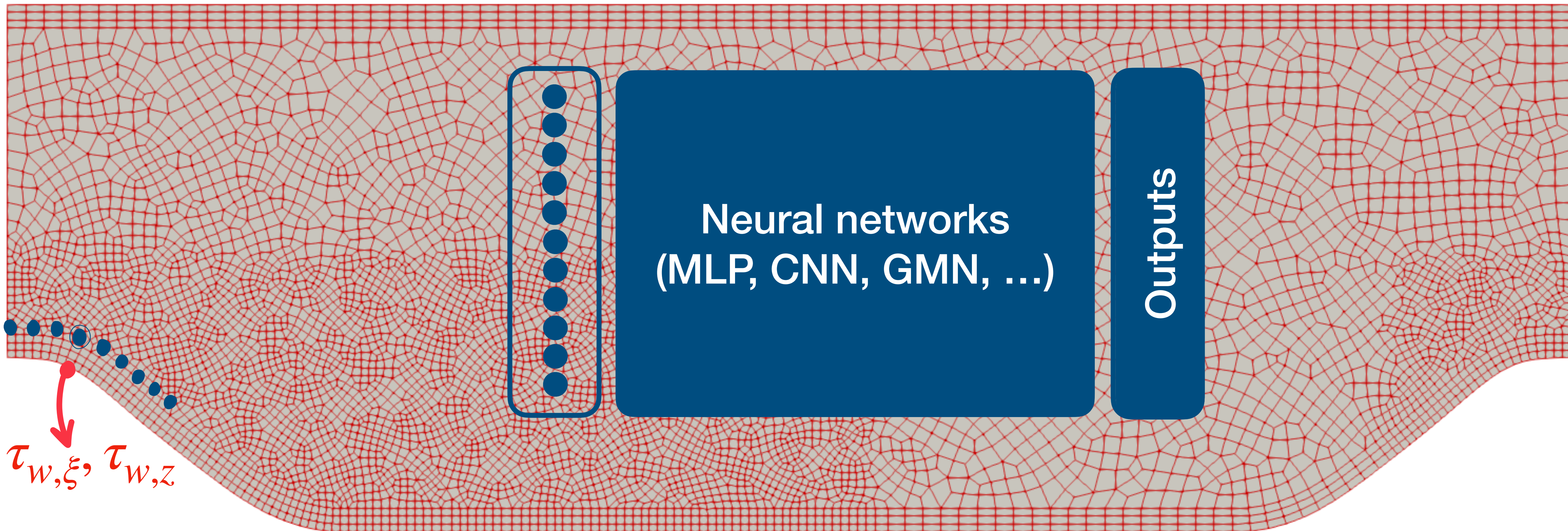
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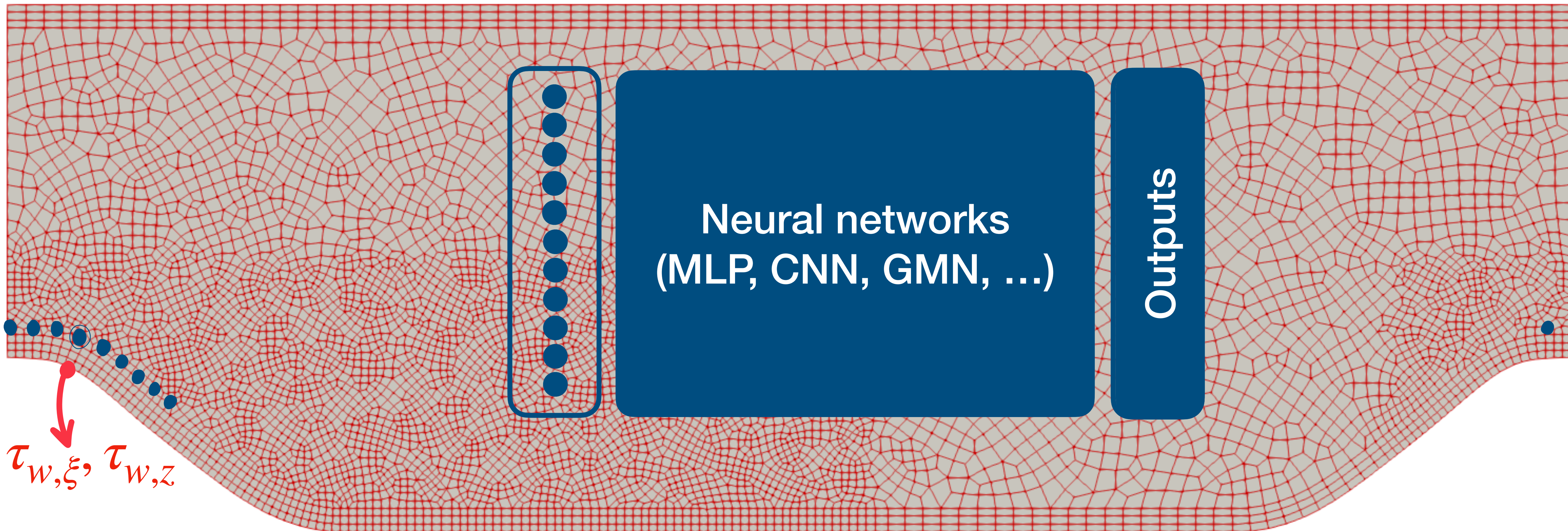
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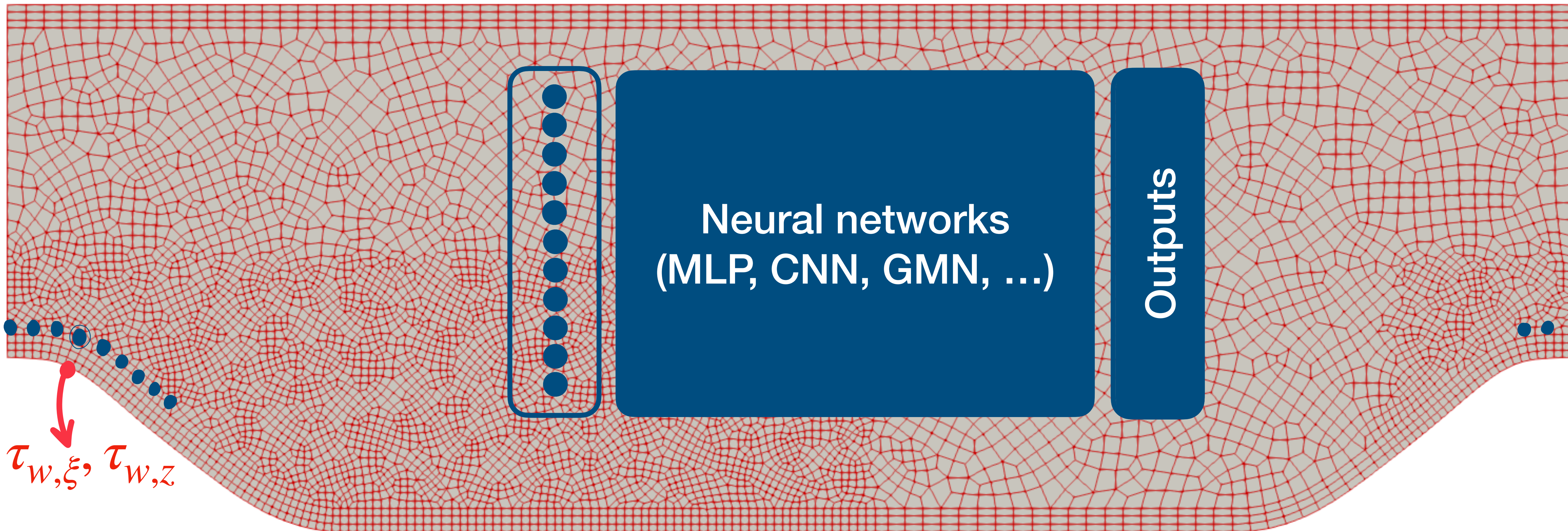
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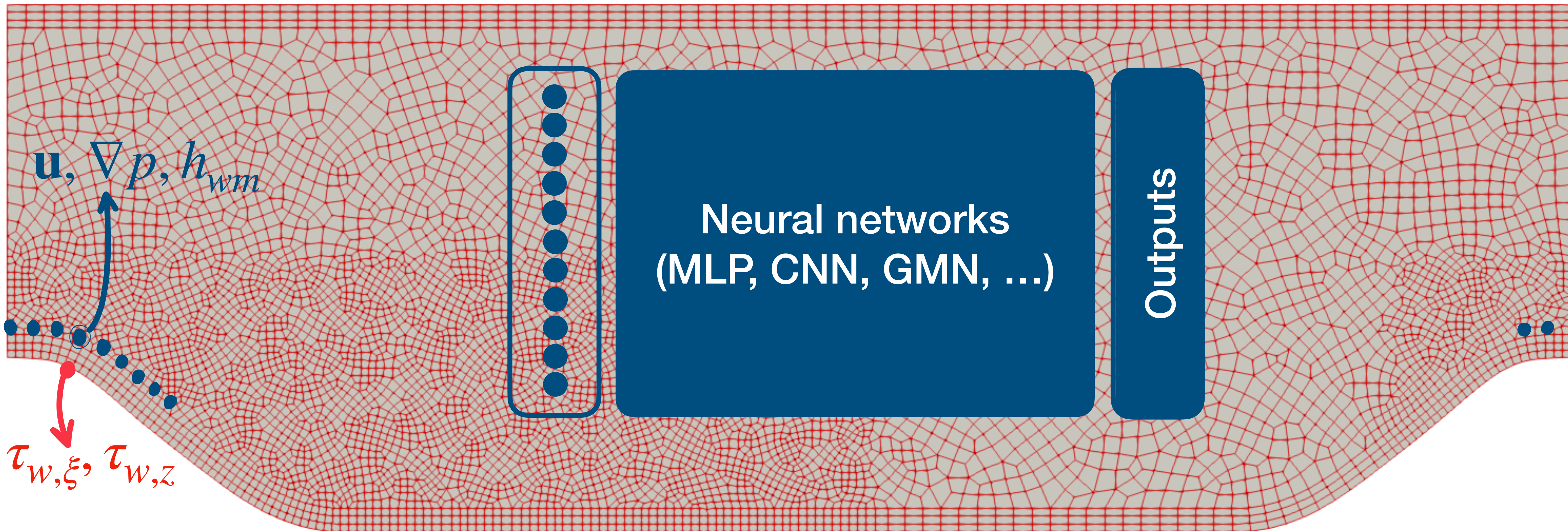
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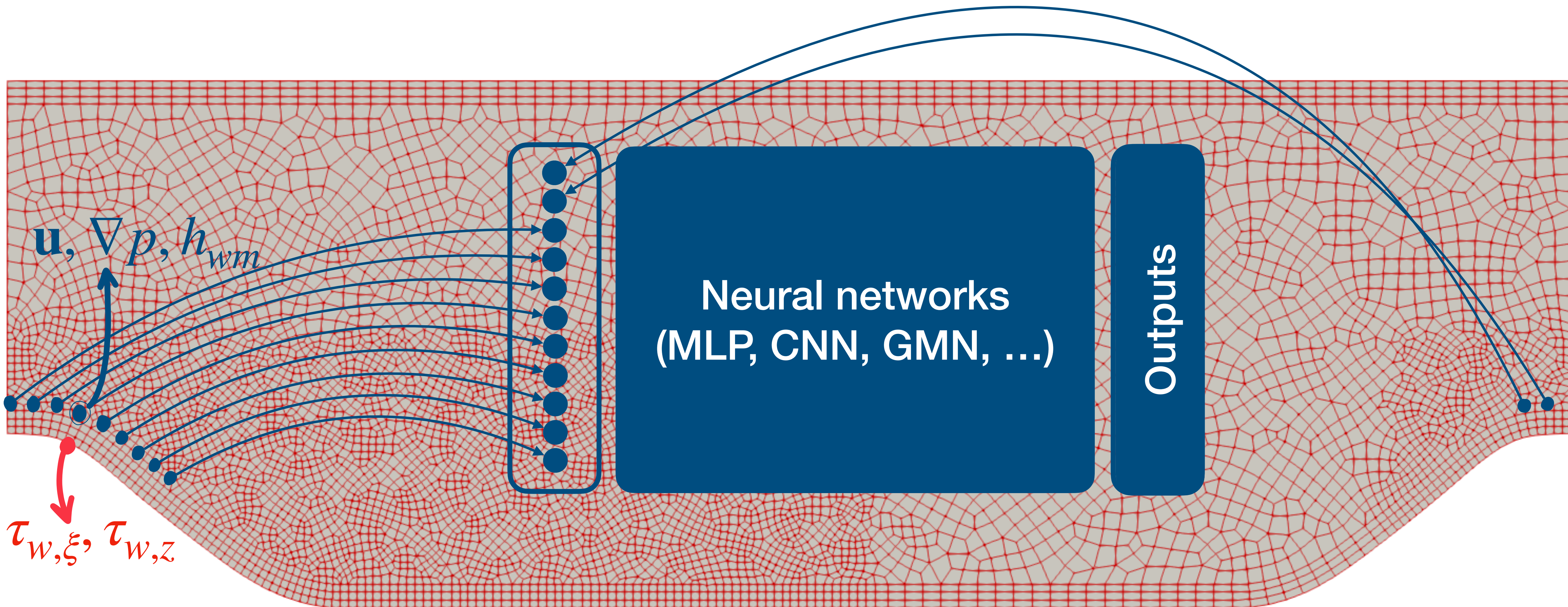
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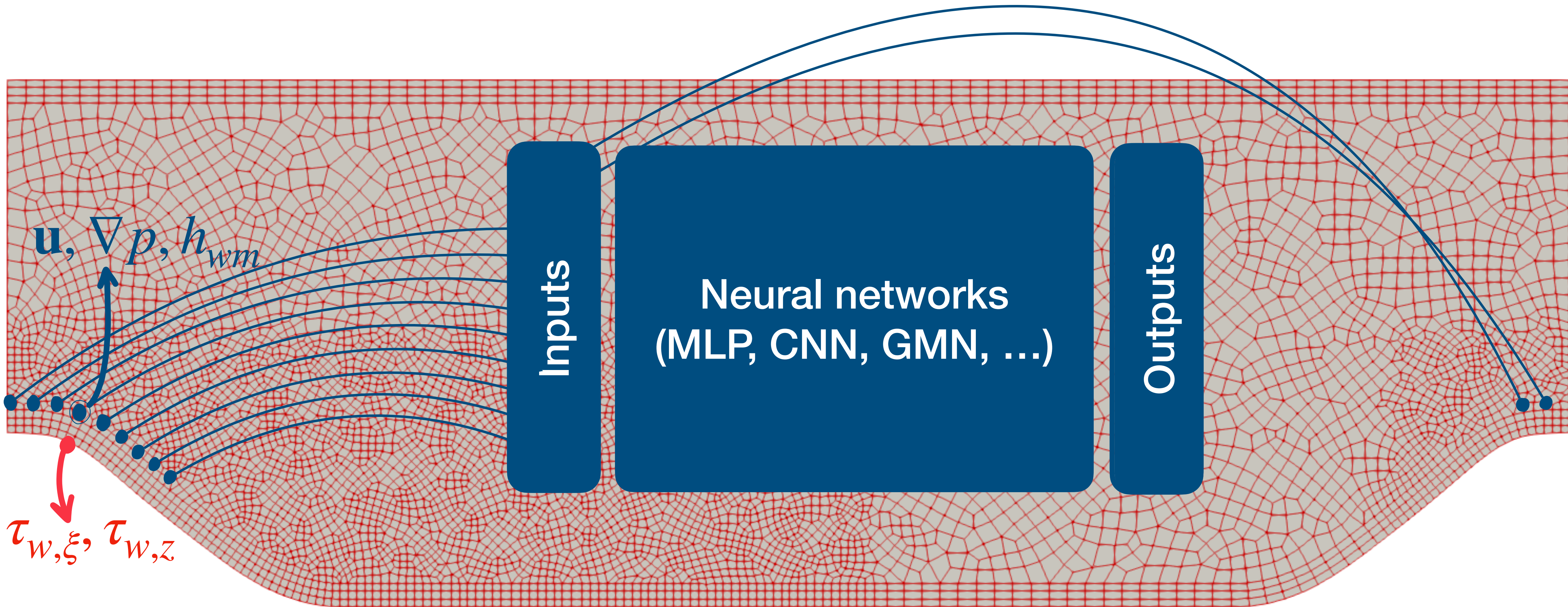
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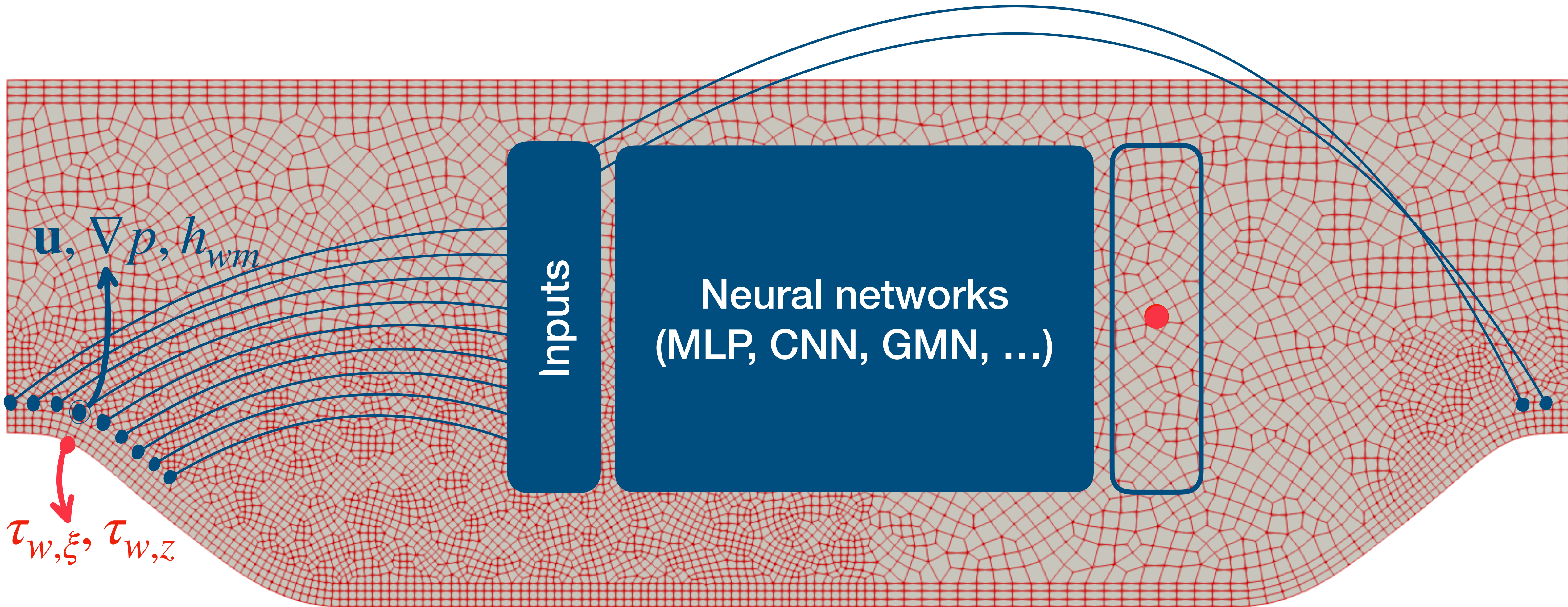
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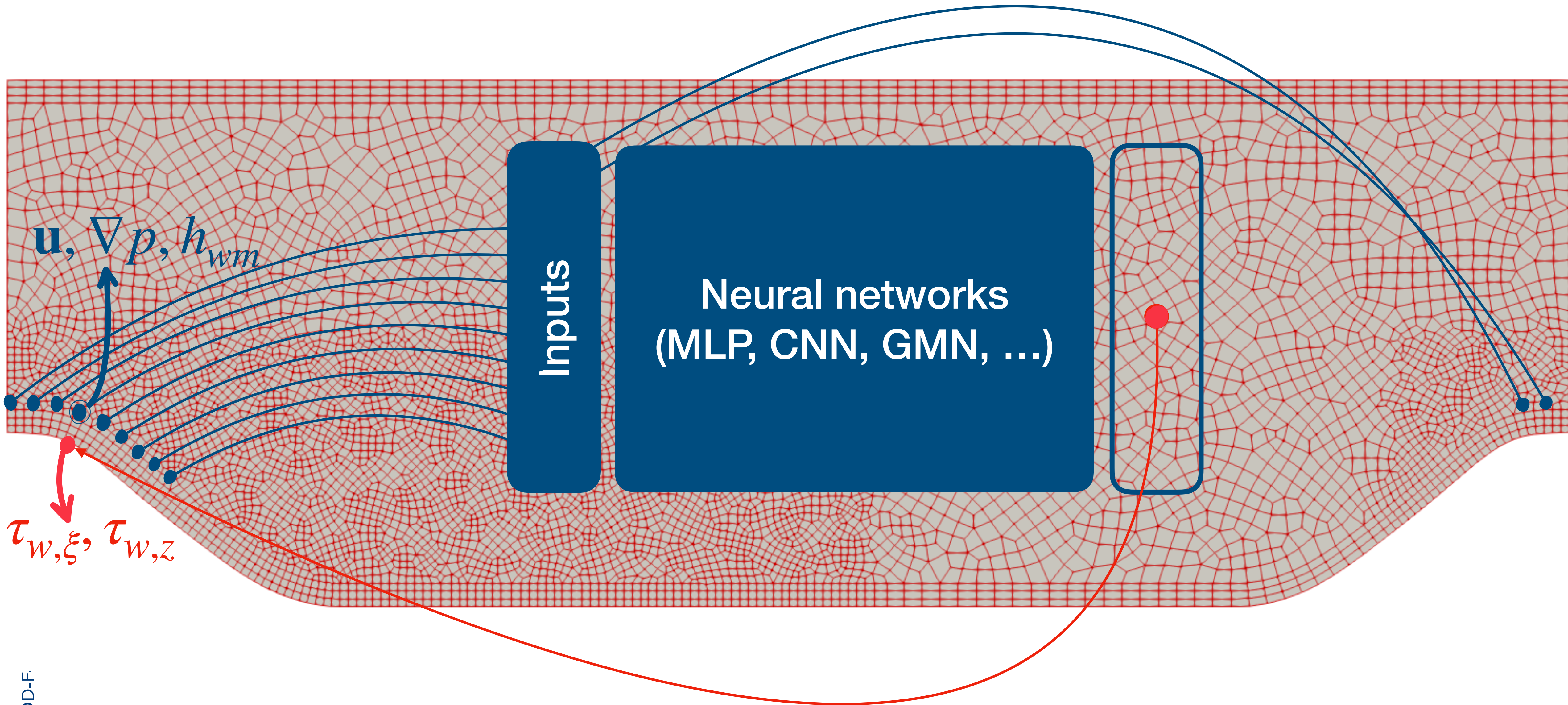
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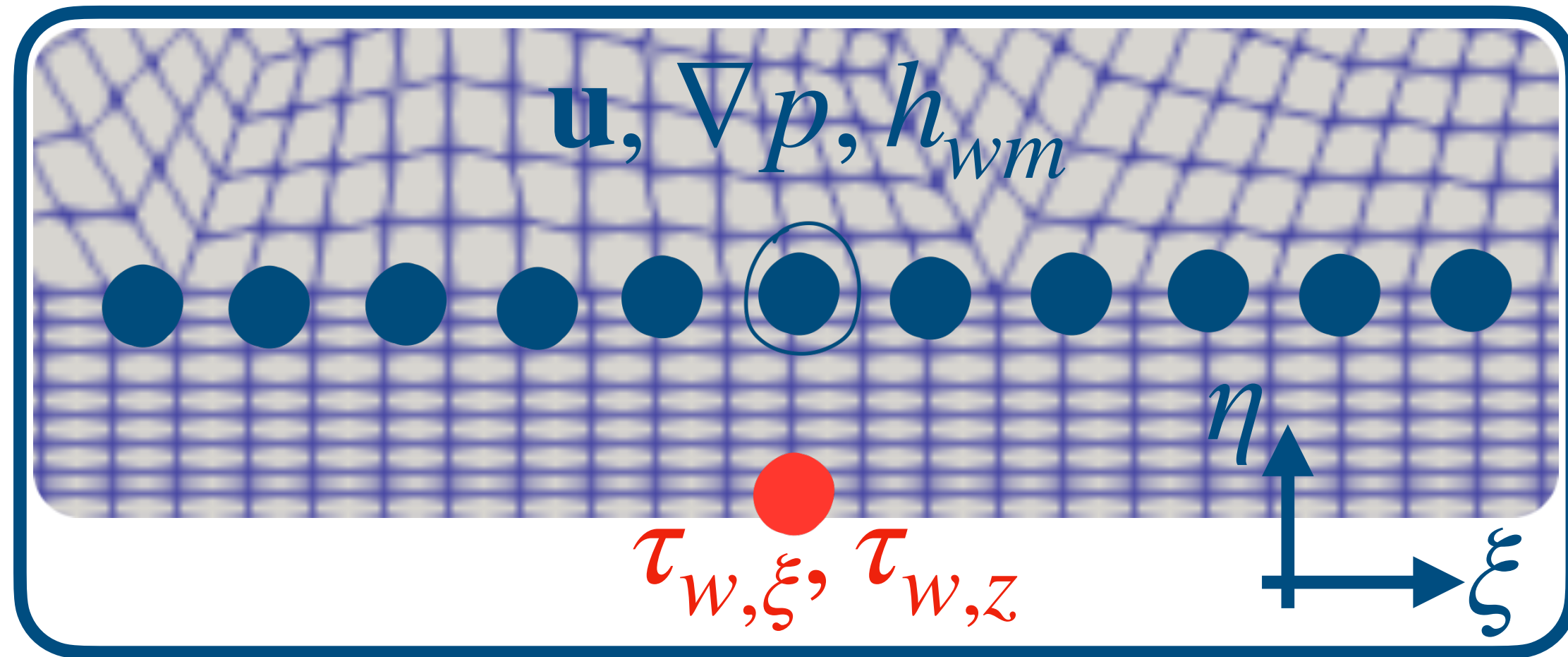
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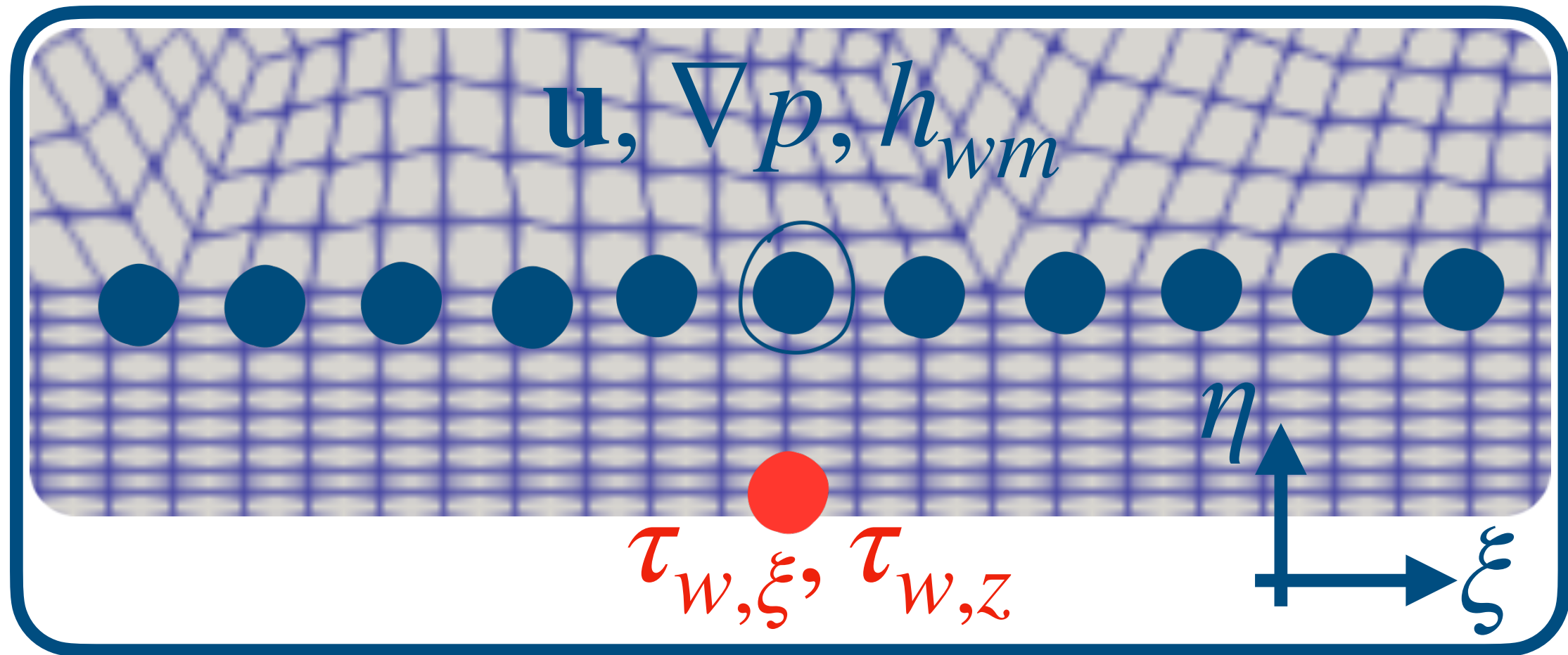
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Input stencil

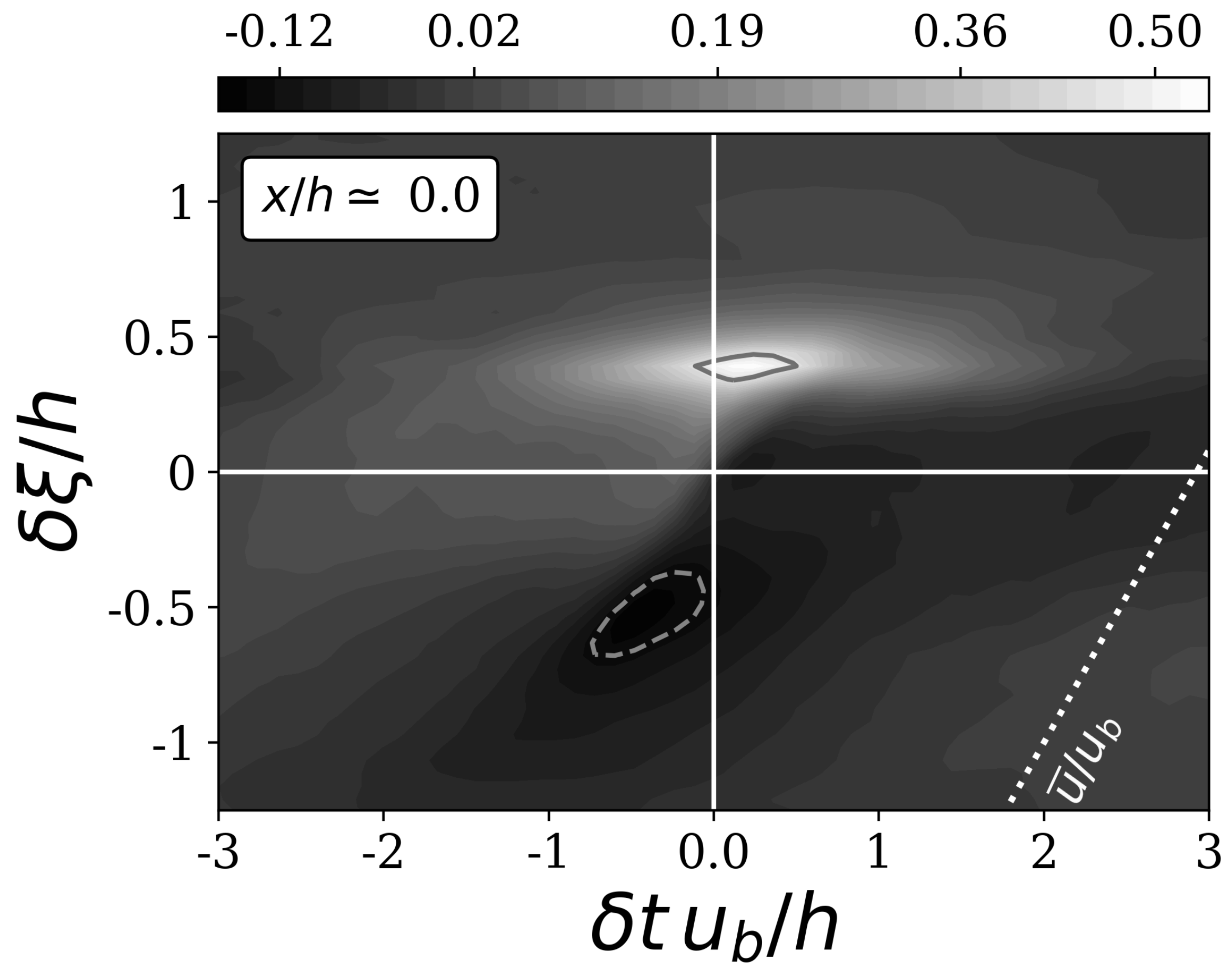


Input stencil

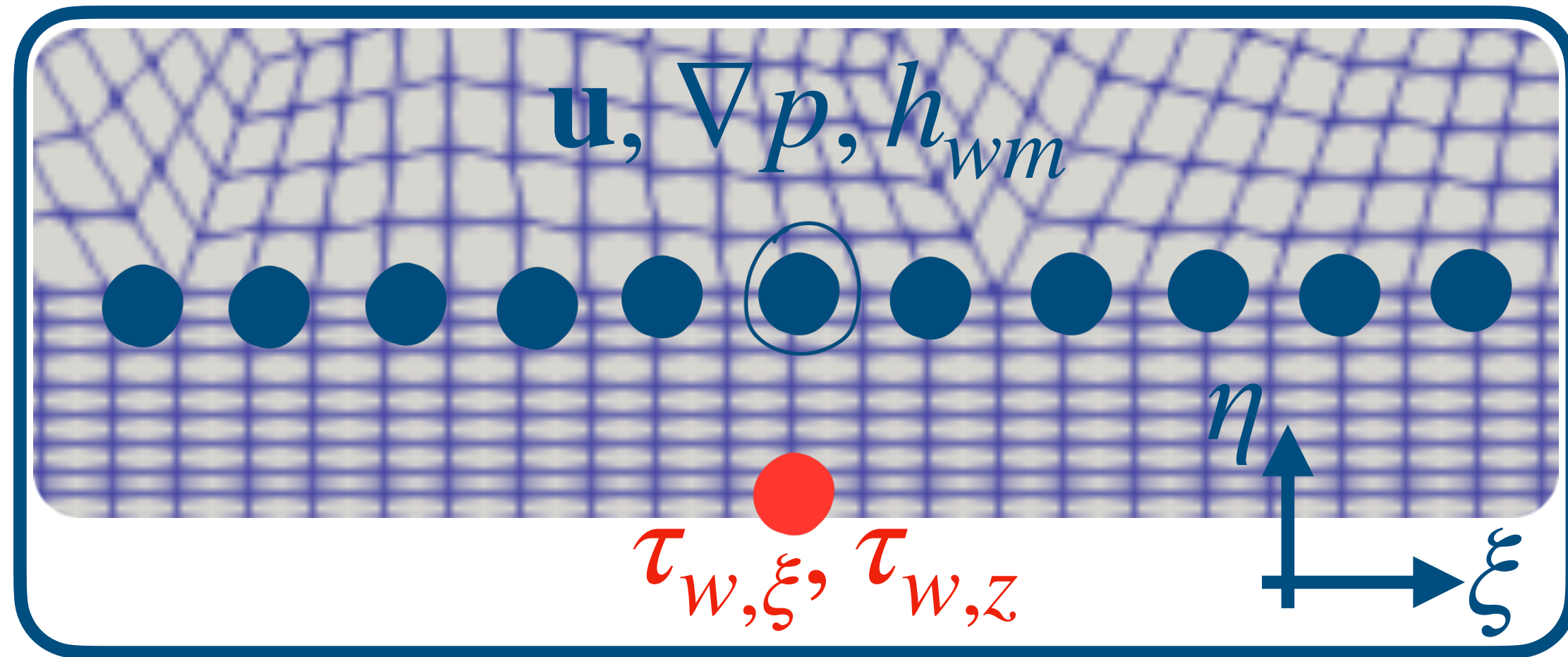


Using space-time correlations (Pearson and Distance correlations [1])

Where the inputs are extracted?



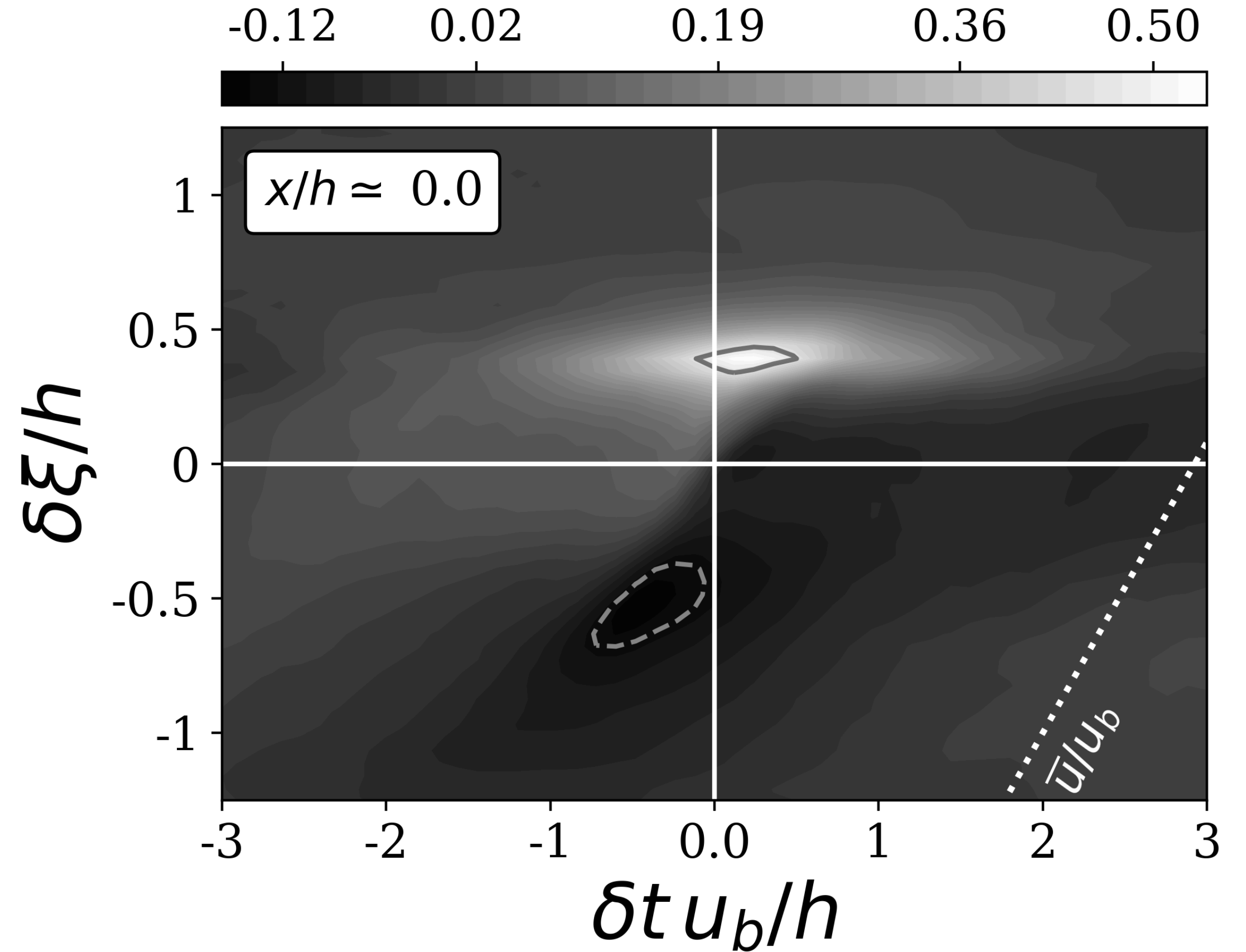
Input stencil



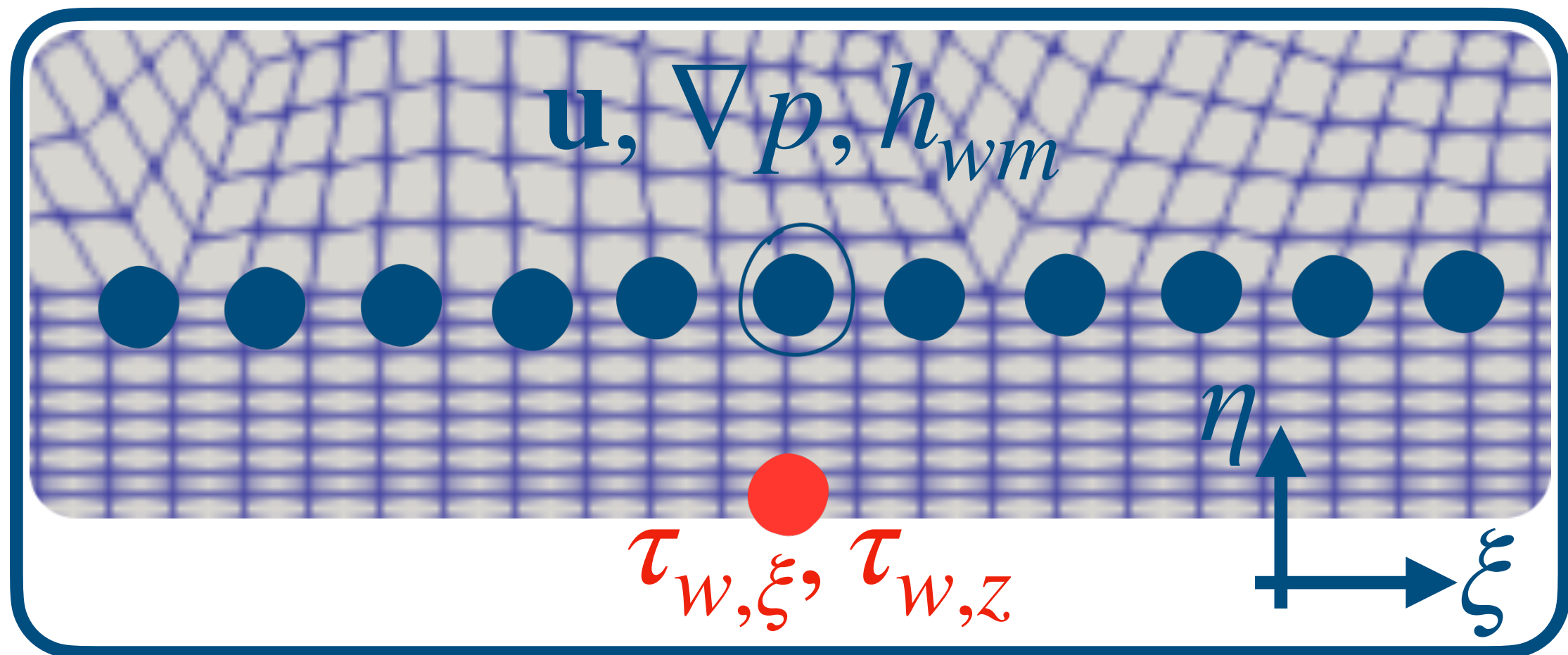
Using space-time correlations (Pearson and Distance correlations [1])

Where the inputs are extracted?

Correlation between u_ξ and $\tau_{w,\xi}$ in the vicinity of the separation



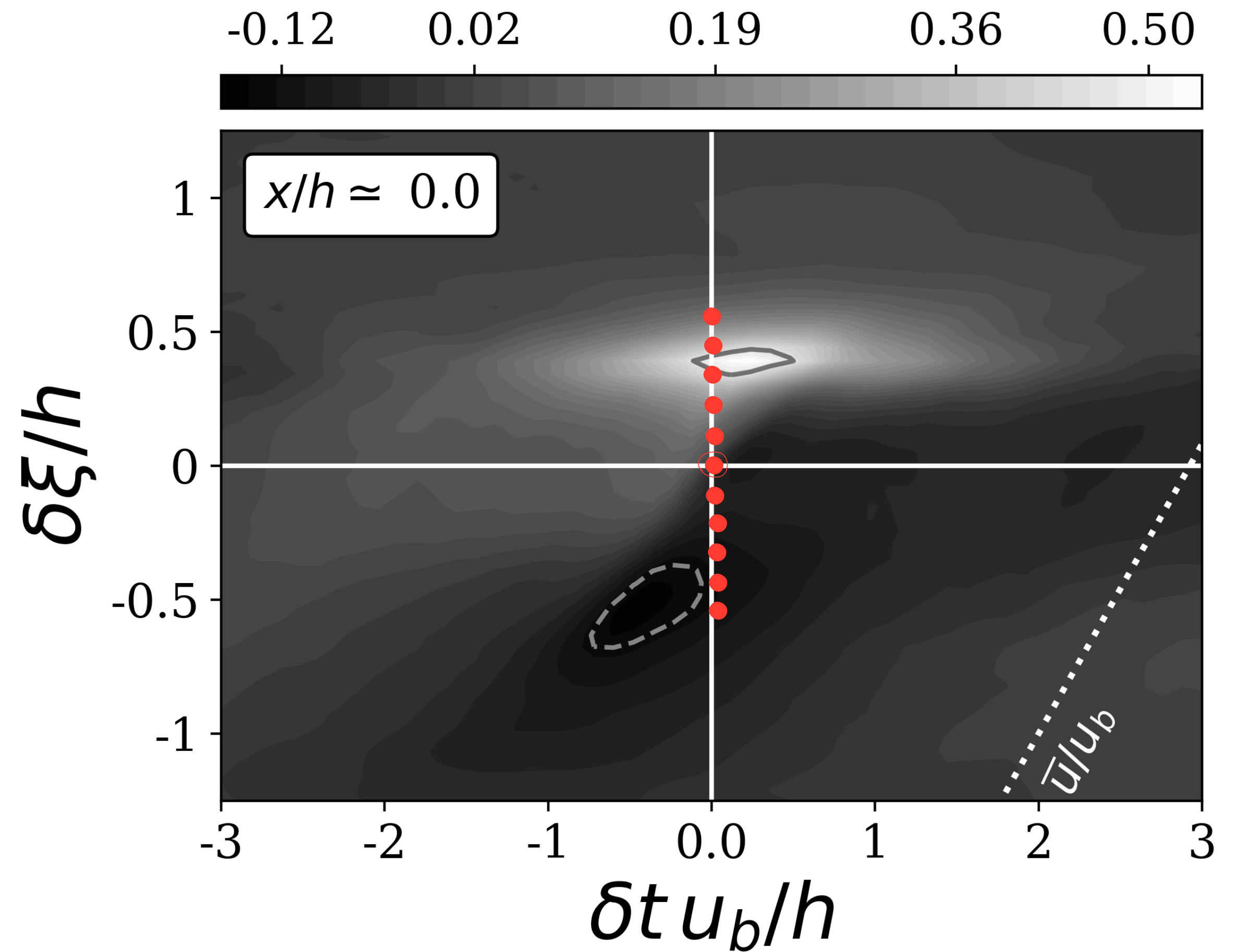
Input stencil



Using space-time correlations (Pearson and Distance correlations [1])

Where the inputs are extracted?

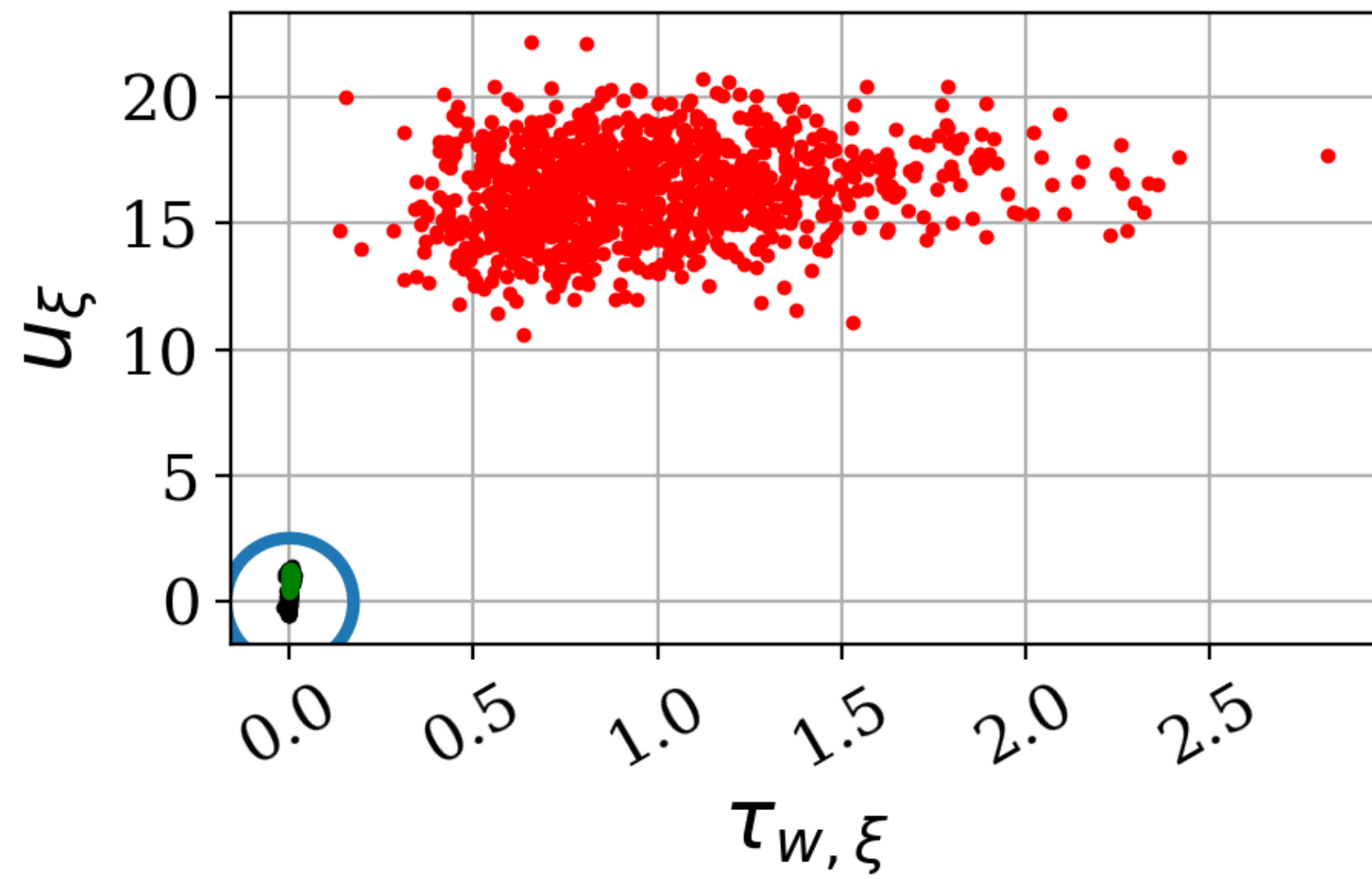
Correlation between u_ξ and $\tau_{w,\xi}$ in the vicinity of the separation



PROD-F-015-02

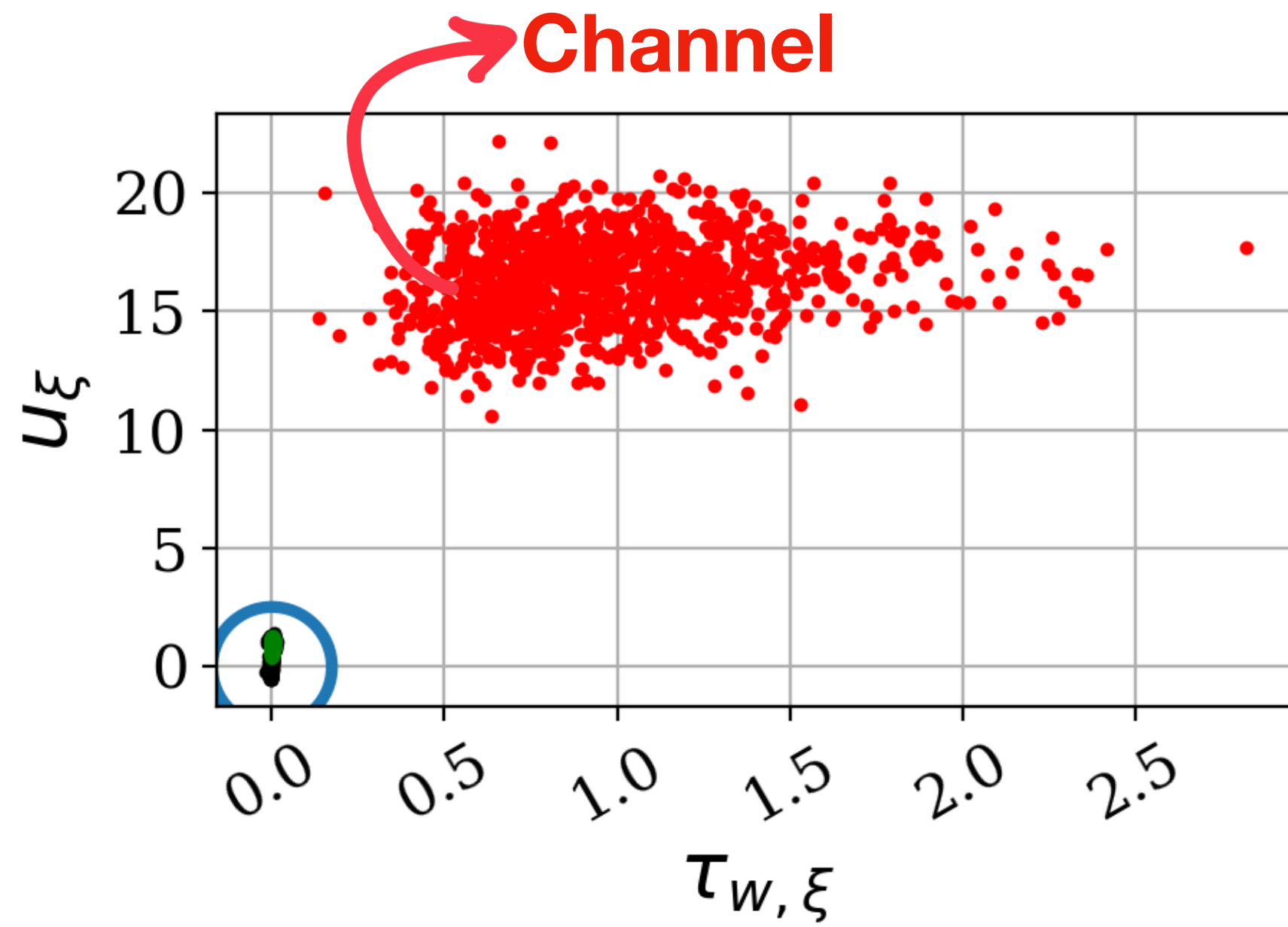
[1] Boxho, M. et al.: Analysis of space-time correlations to support the development of wall-modeled LES. Flow, Turbulence and Combustion. (2022).

How to normalize the input/output pairs?



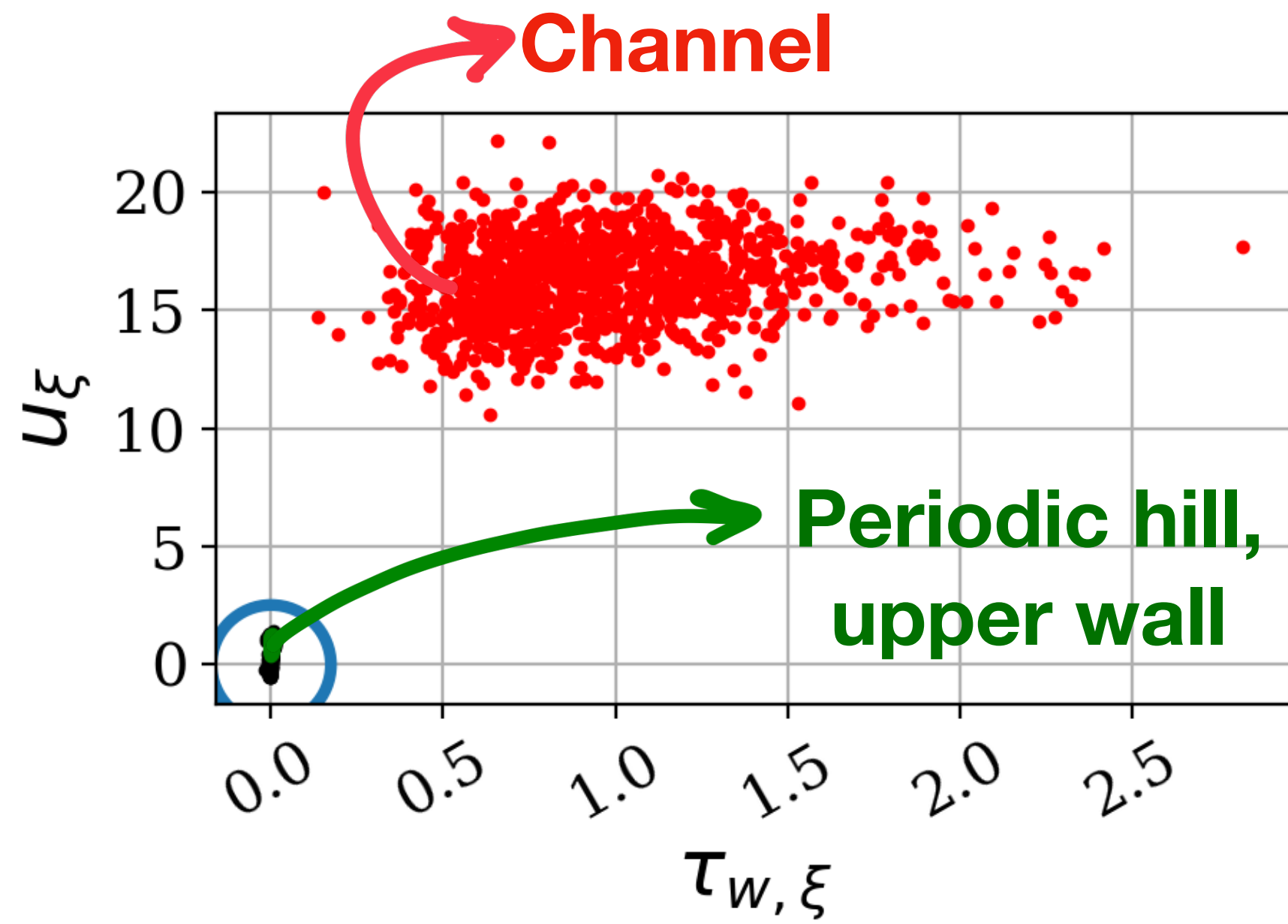
Normalization

How to normalize the input/output pairs?



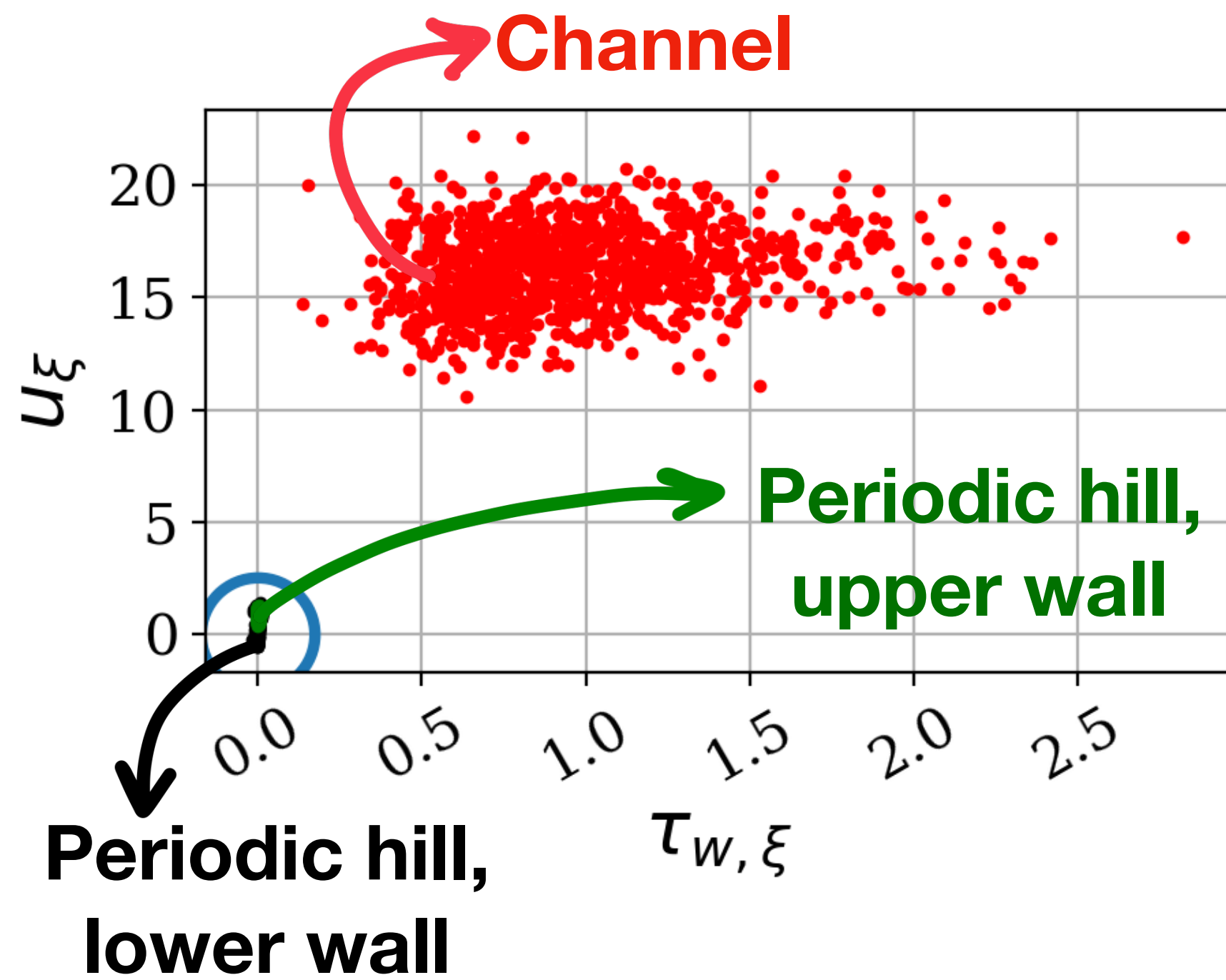
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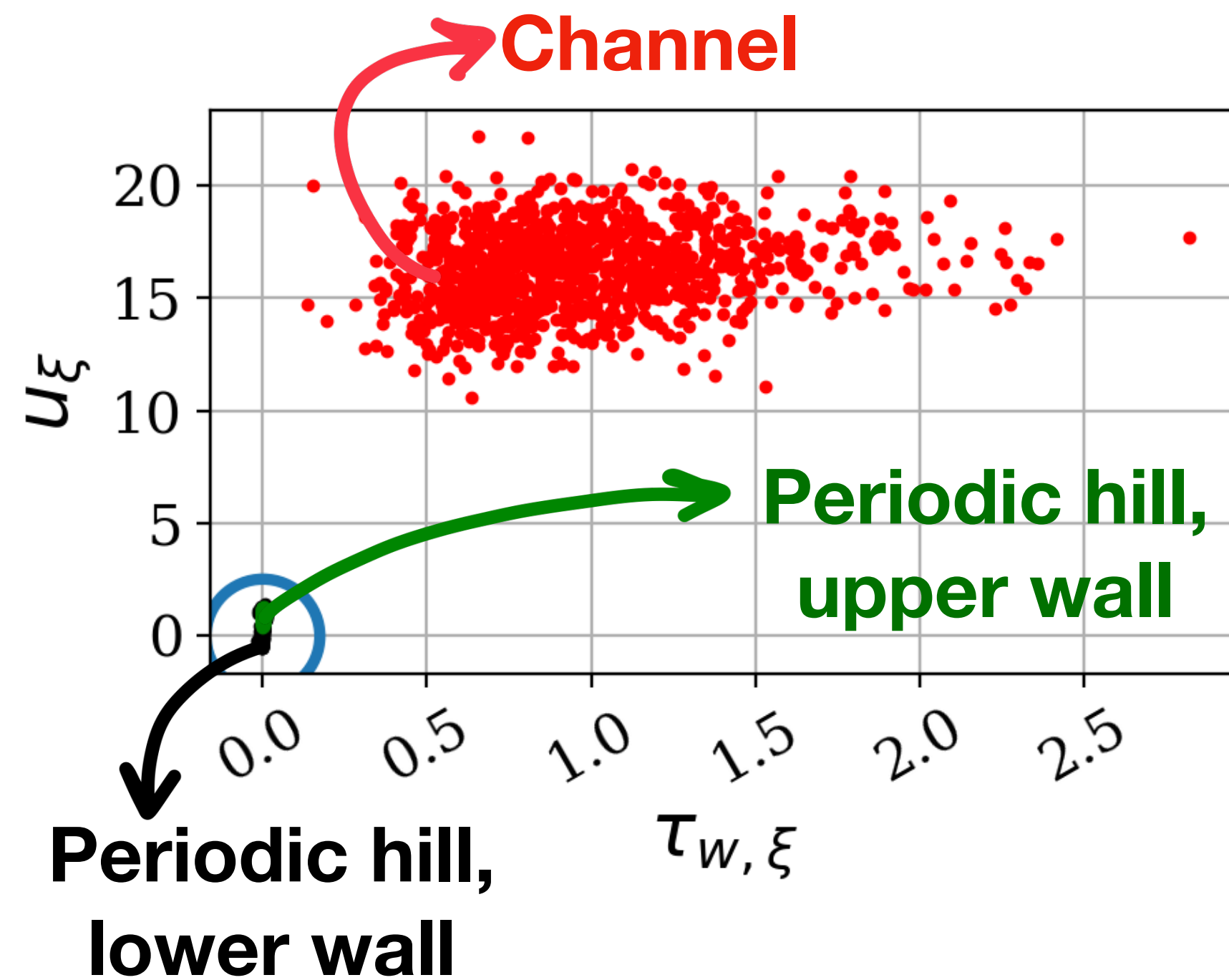
Normalization

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Normalization

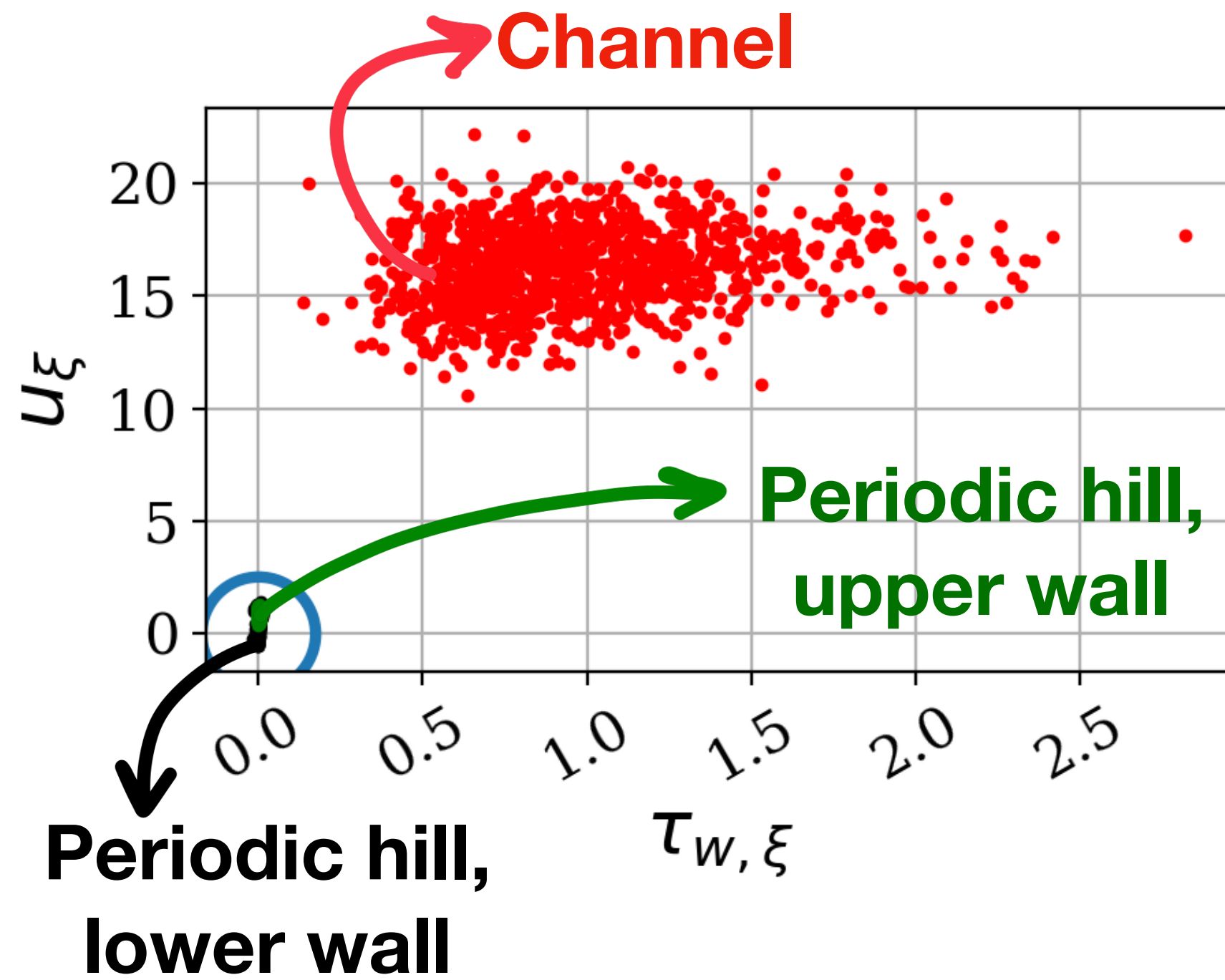
How to normalize the input/output pairs?



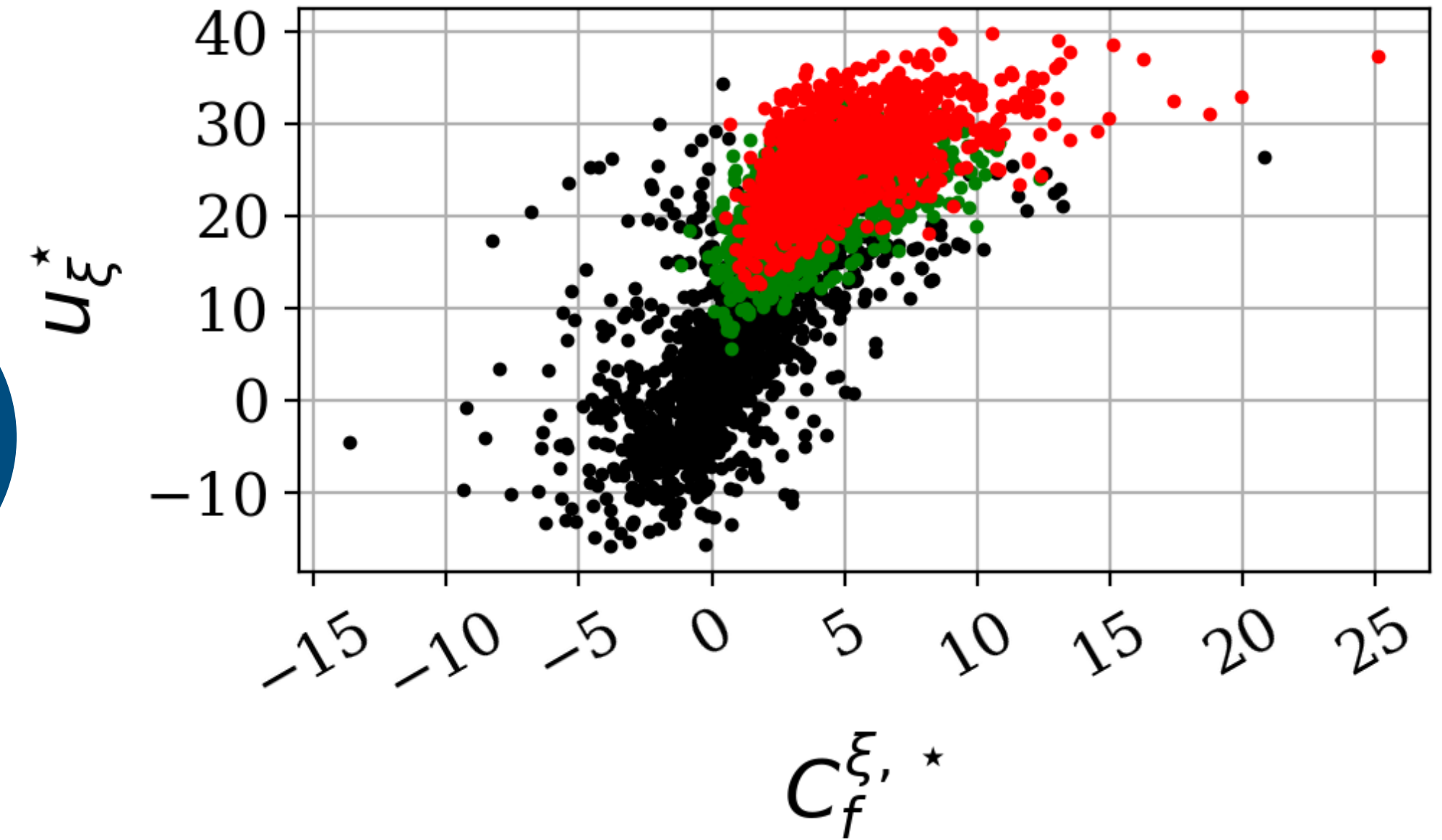
Normalization

The distribution between the input and output for different databases does not fit on each other → bad behavior for the training

How to normalize the input/output pairs?

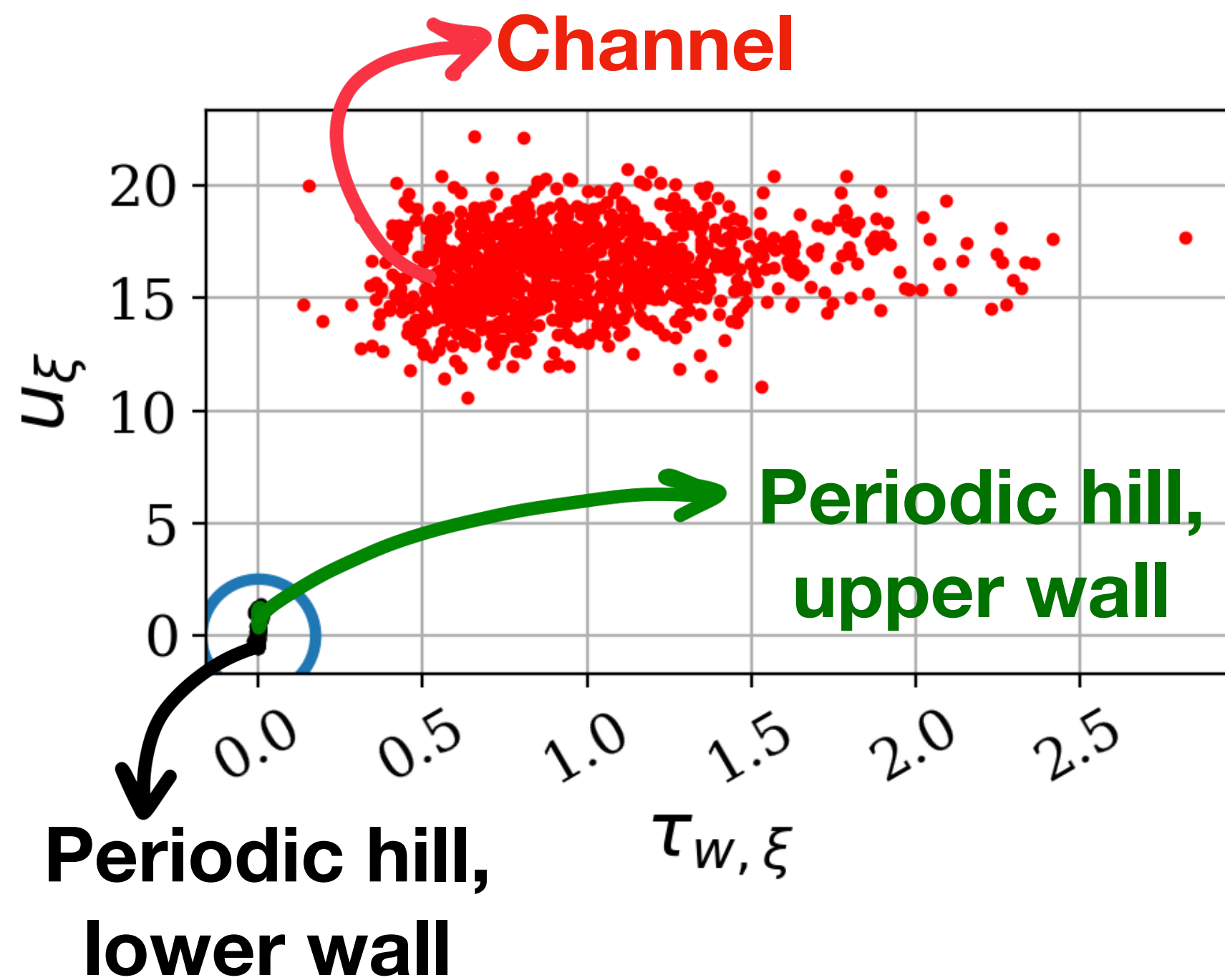


Normalization

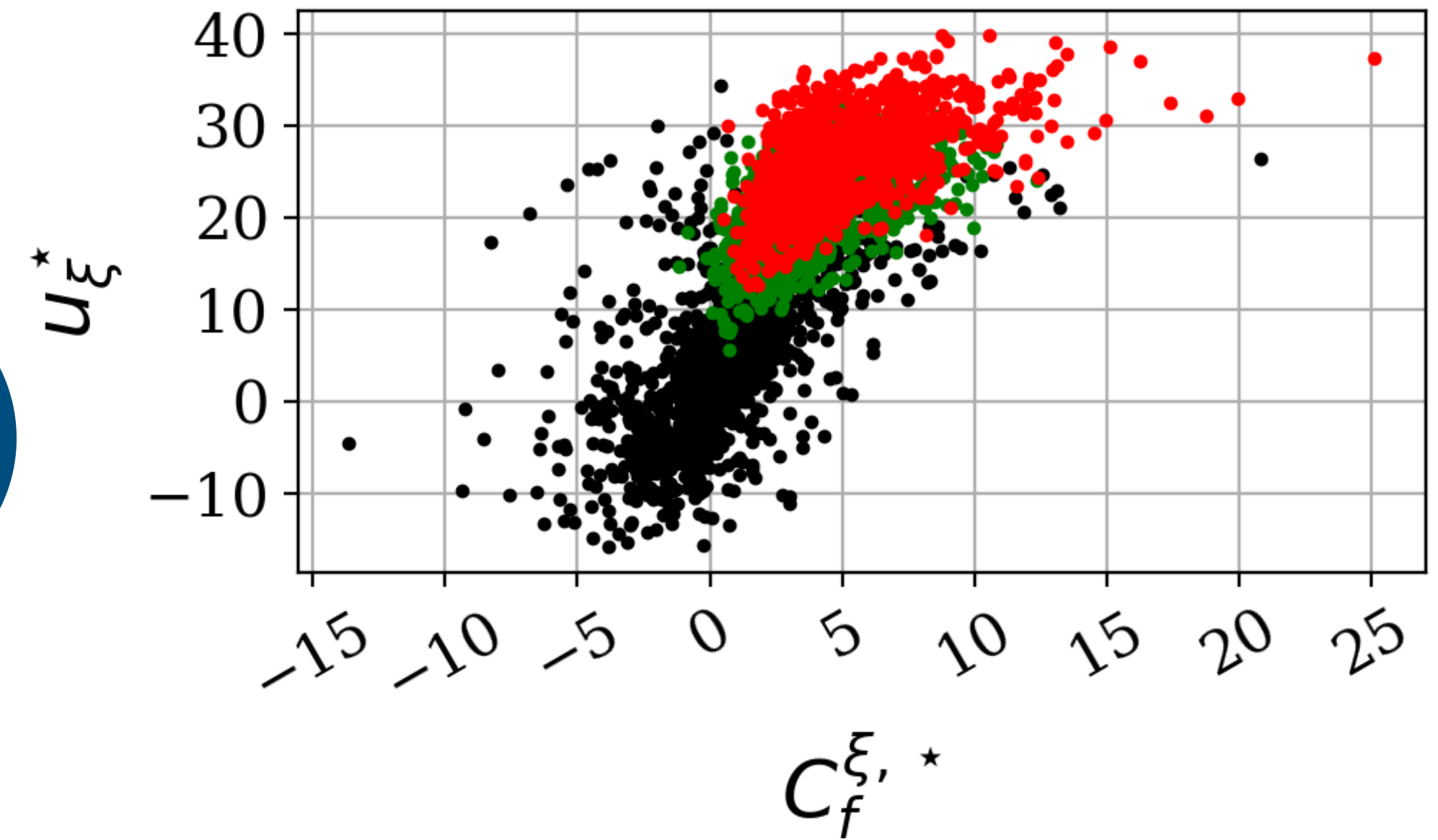


The distribution between the input and output for different databases does not fit on each other → bad behavior for the training

How to normalize the input/output pairs?



Normalization



The normalization allows a better fitting between the different databases → better behavior for the training

How to normalize the input/output pairs?

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$$u^* = \frac{u}{u_{rp}}$$

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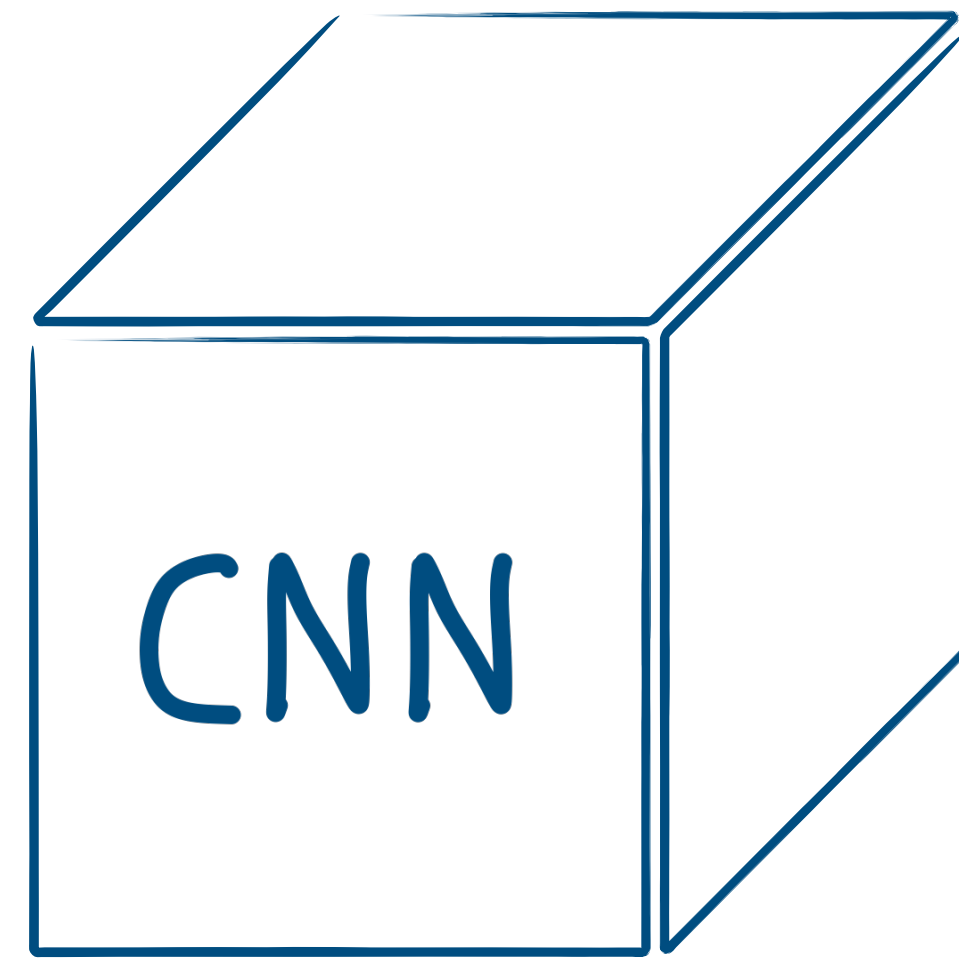
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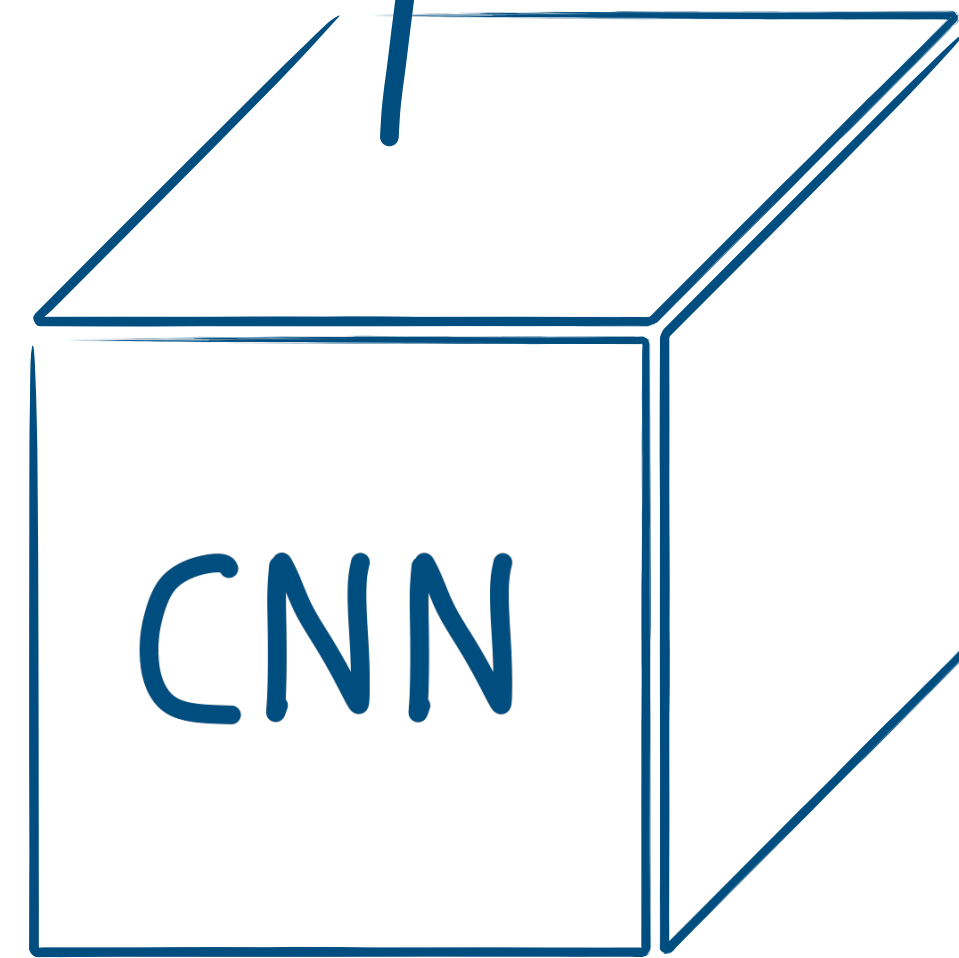
$$\tau_{wy}^* = \frac{\tau_{wy}}{\frac{1}{2} \rho \langle u_{vp}^2 \rangle_{yz}}$$

Which neural network to use?



Which neural network to use?

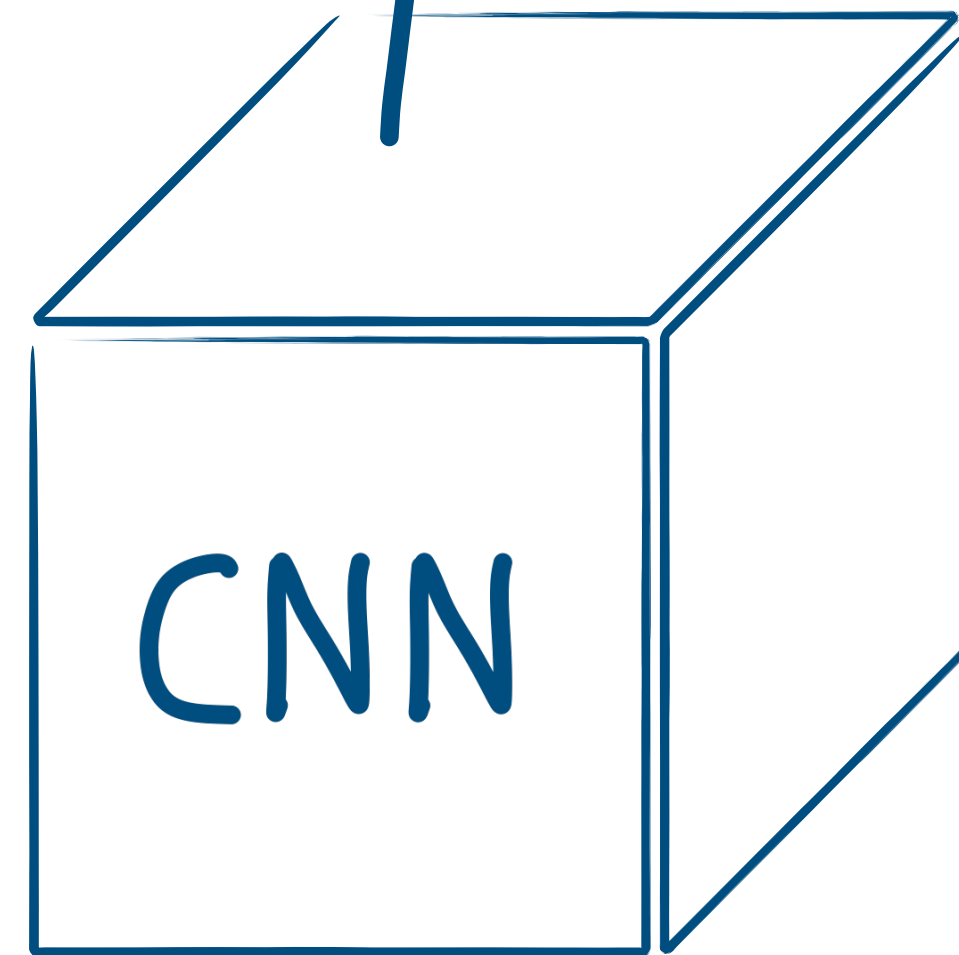
Learnable convolutional kernel



Which neural network to use?

Learnable convolutional kernel

0	1	0
1	1	1
0	1	0

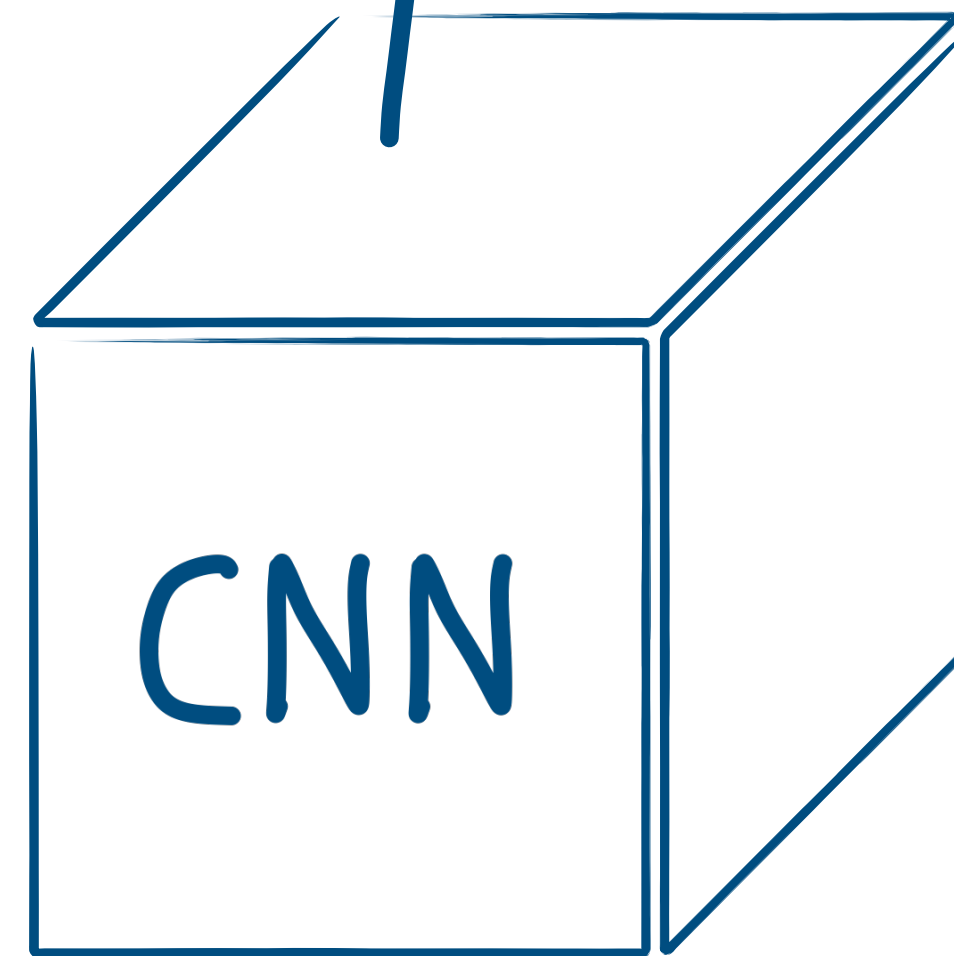


Which neural network to use?

Learnable convolutional kernel

0	0.5	0.8	0.2	0.3
0.1	0	0.4	0.6	0.6
0.9	1	0	0	0.8
0.9	1	0.7	0.8	0.1

0	1	0
1	1	1
0	1	0

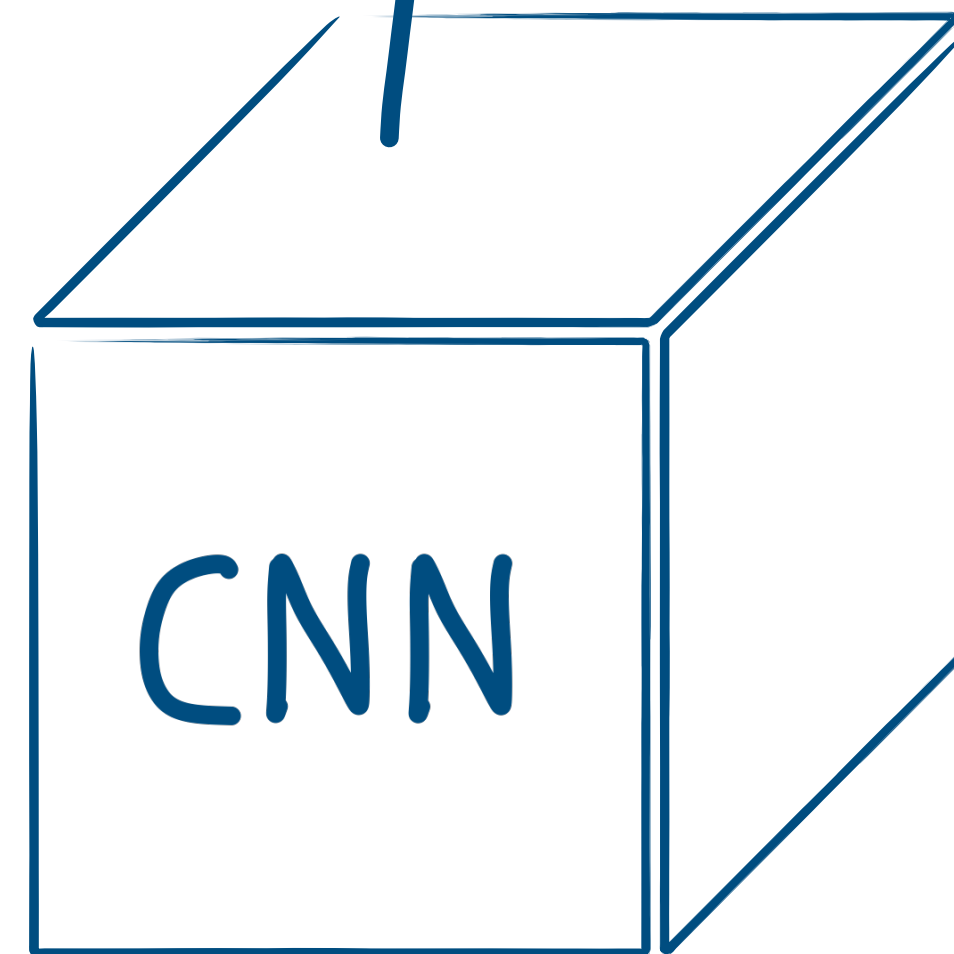


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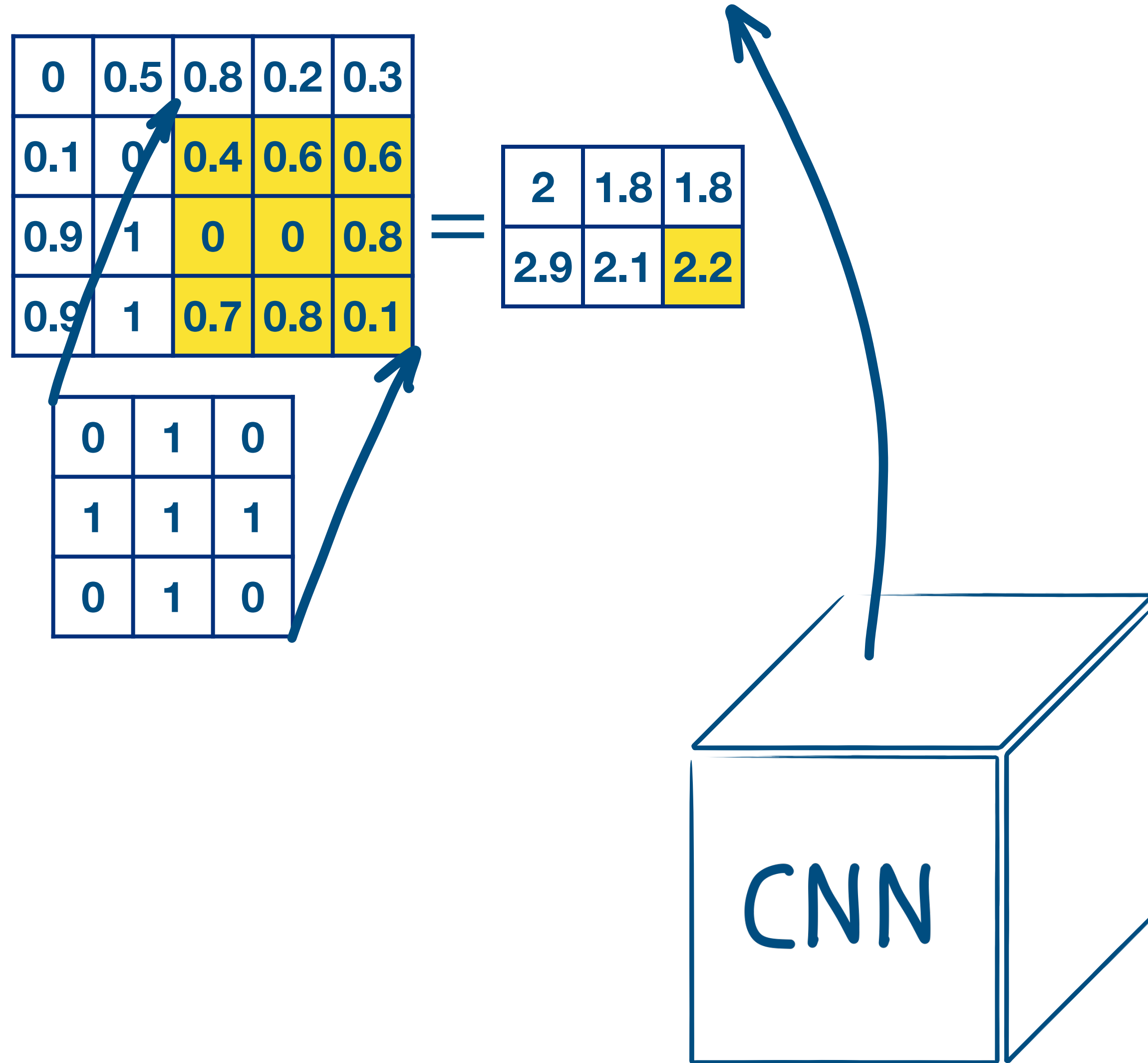
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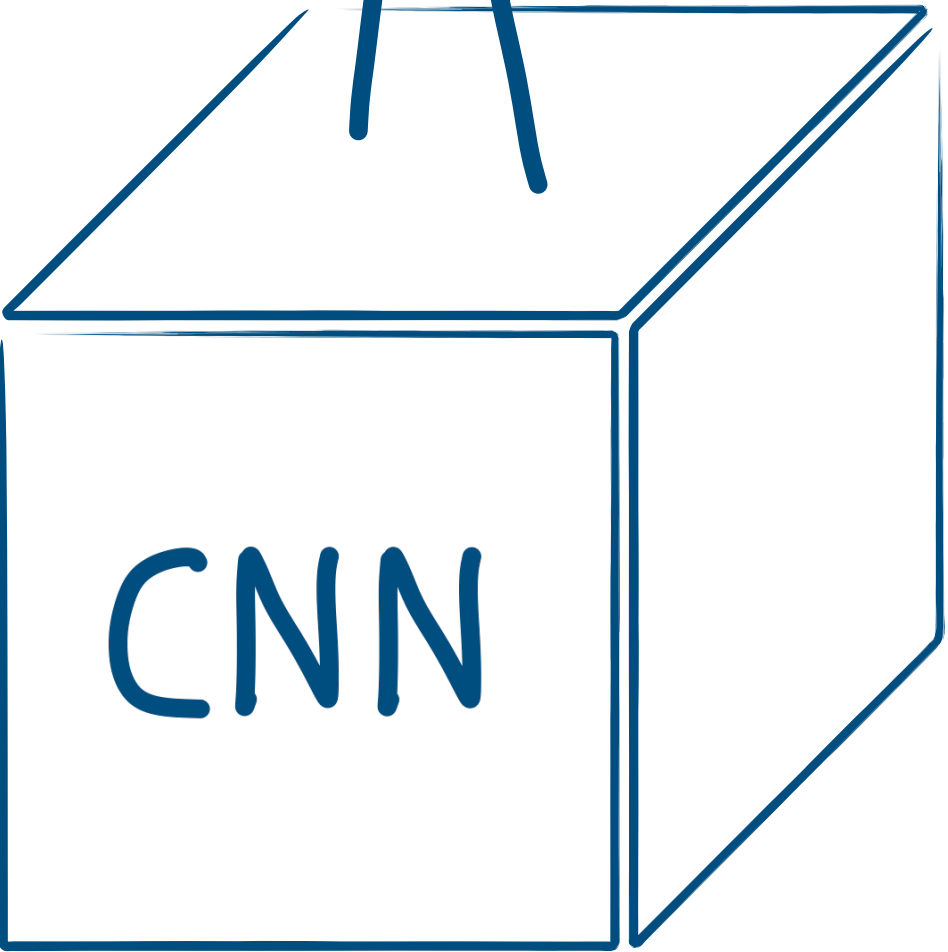
0	0.5	0.8	0.2	0.3
0.1	0	0.4	0.6	0.6
0.9	1	0	0	0.8
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0	1	0
1	1	1
0	1	0

=

2	1.8	1.8
2.9	2.1	2.2

Max-pooling layer



Which neural network to use?

Learnable convolutional kernel

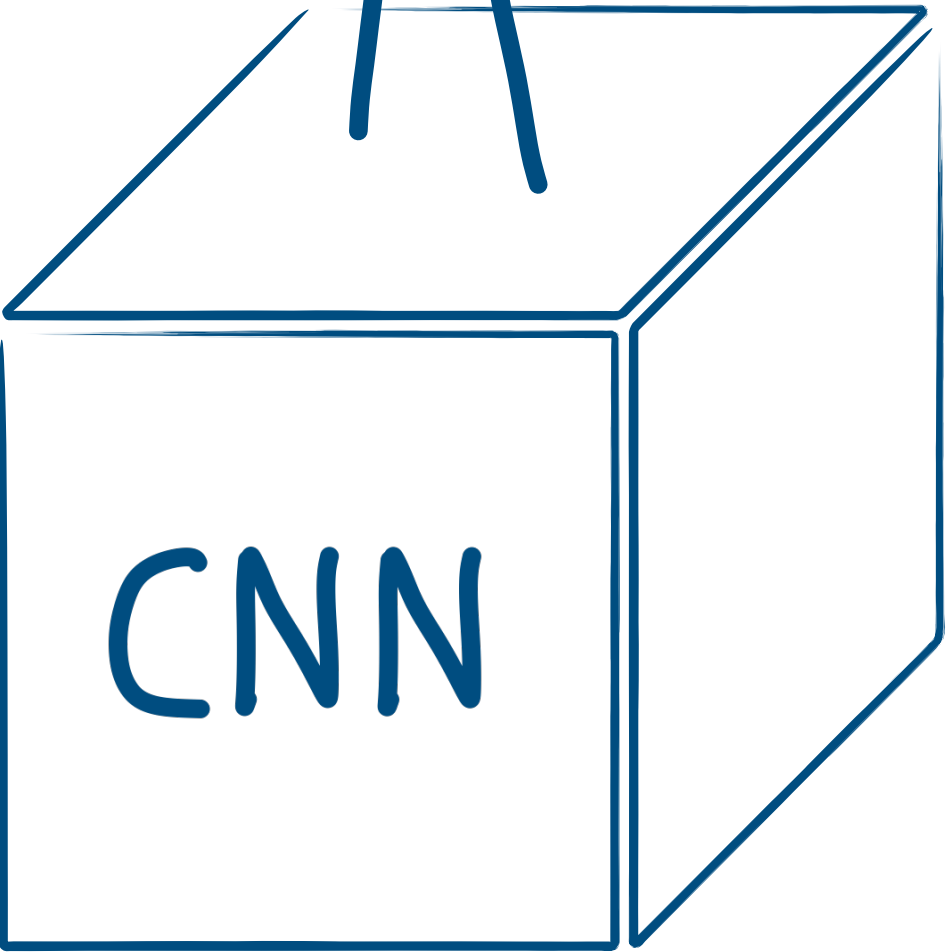
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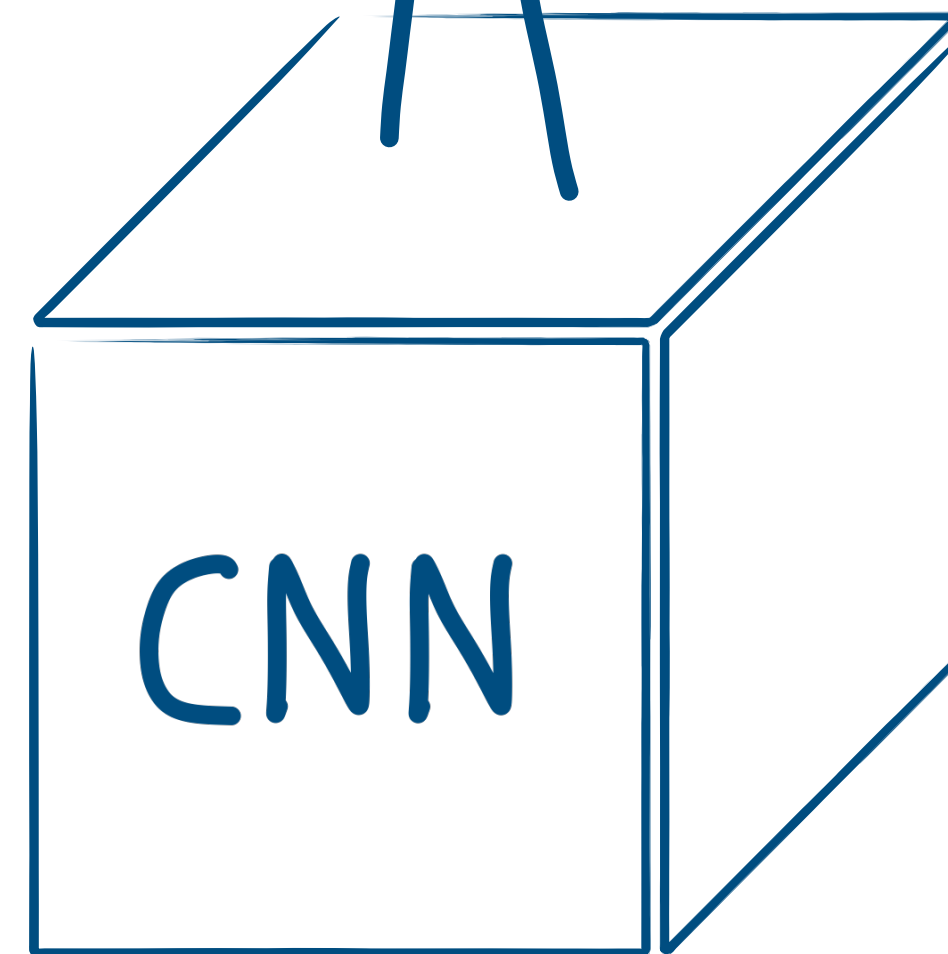
=

2	1.8	1.8
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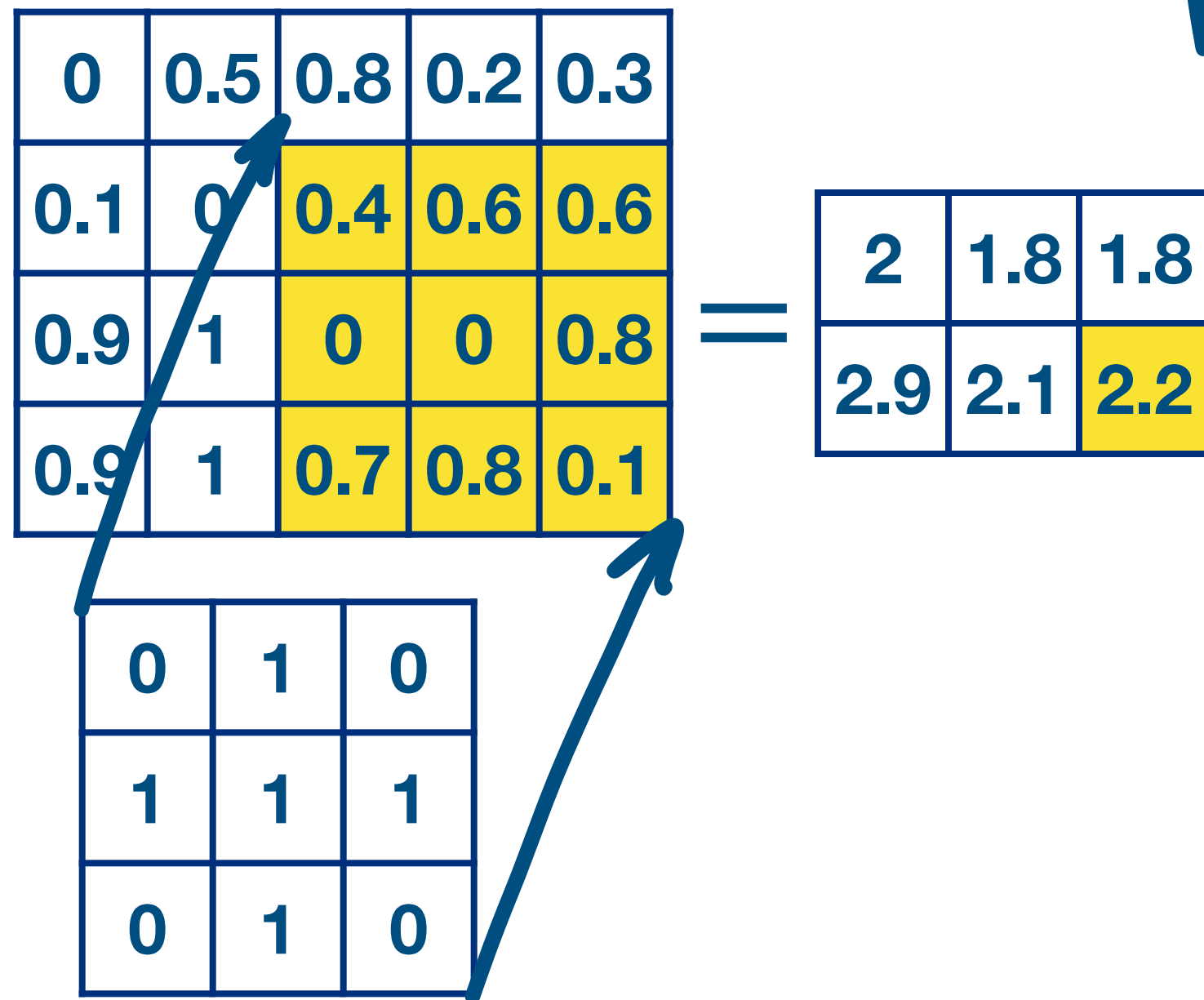
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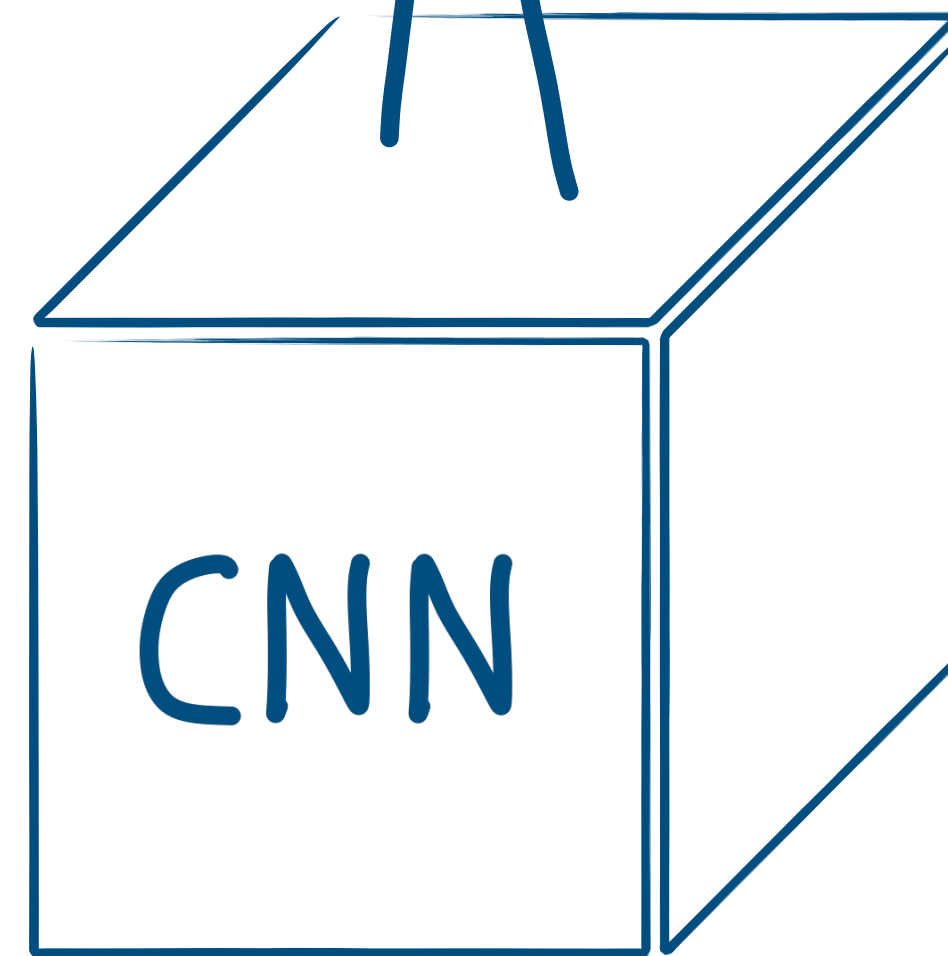
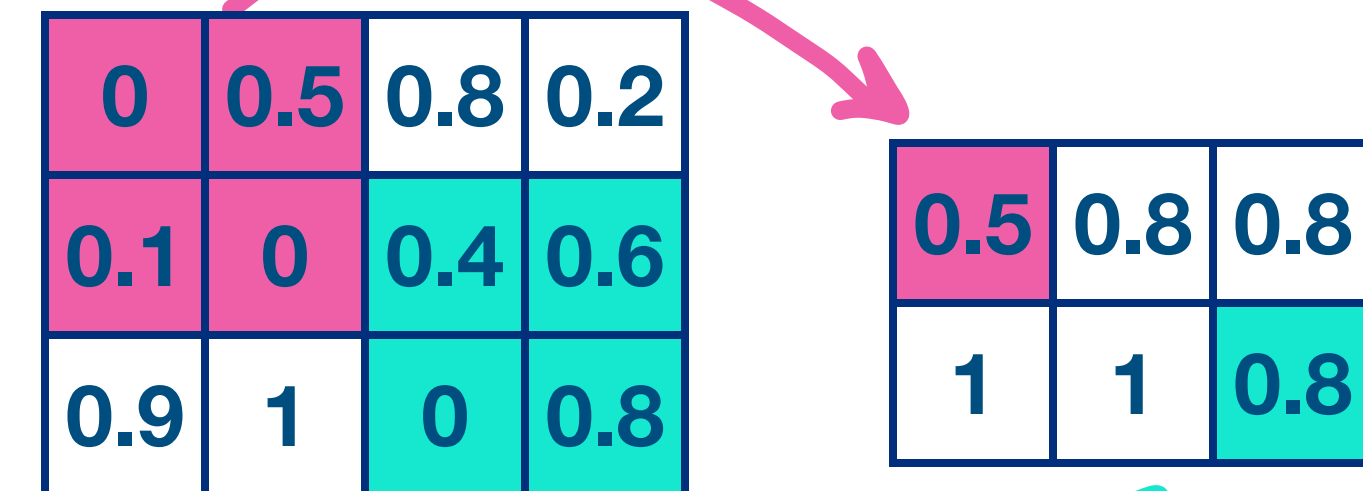


Learnable convolutional kernel

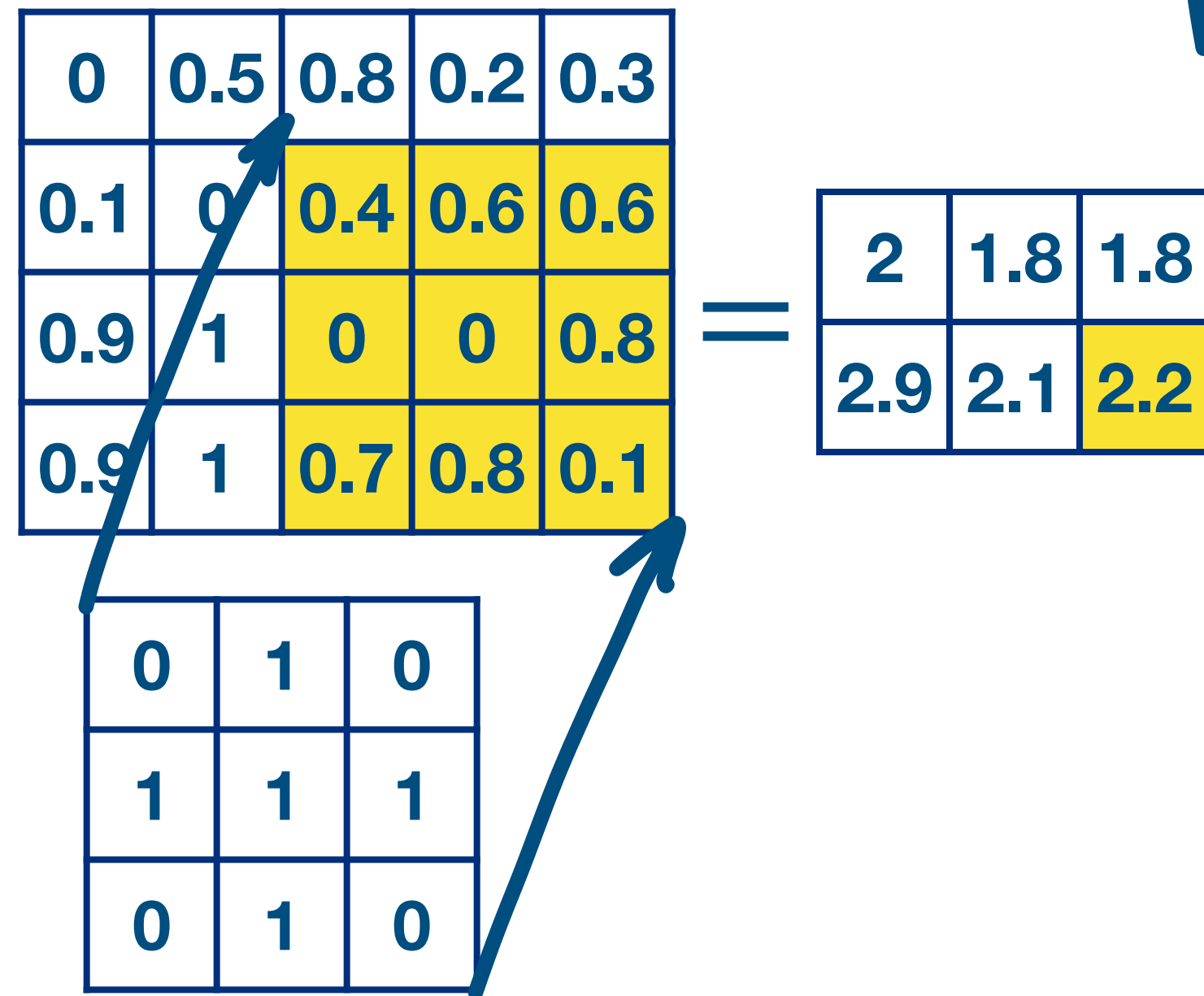


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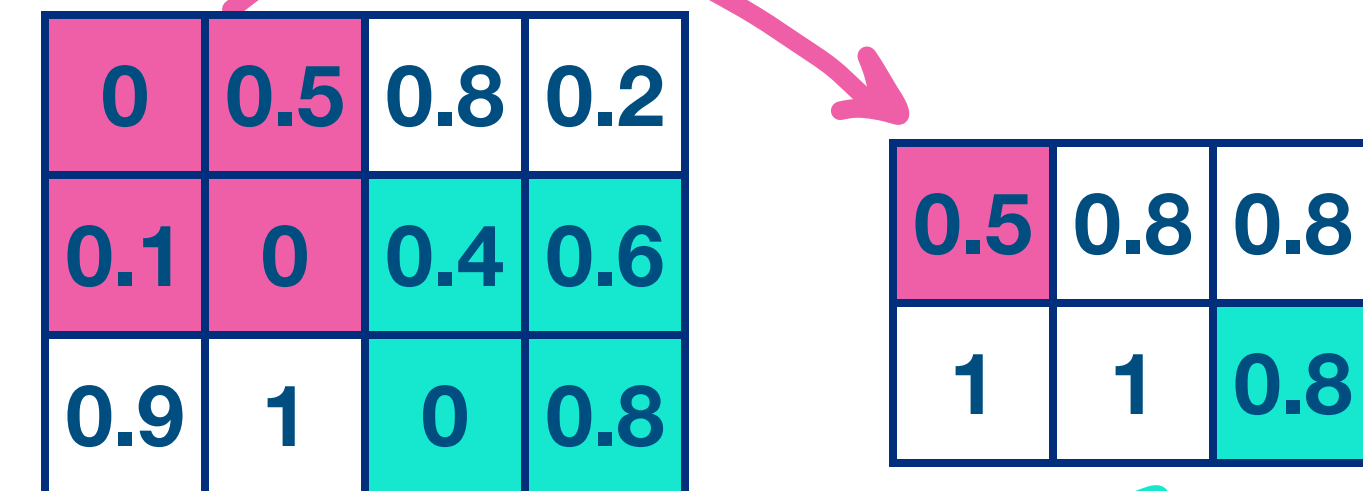


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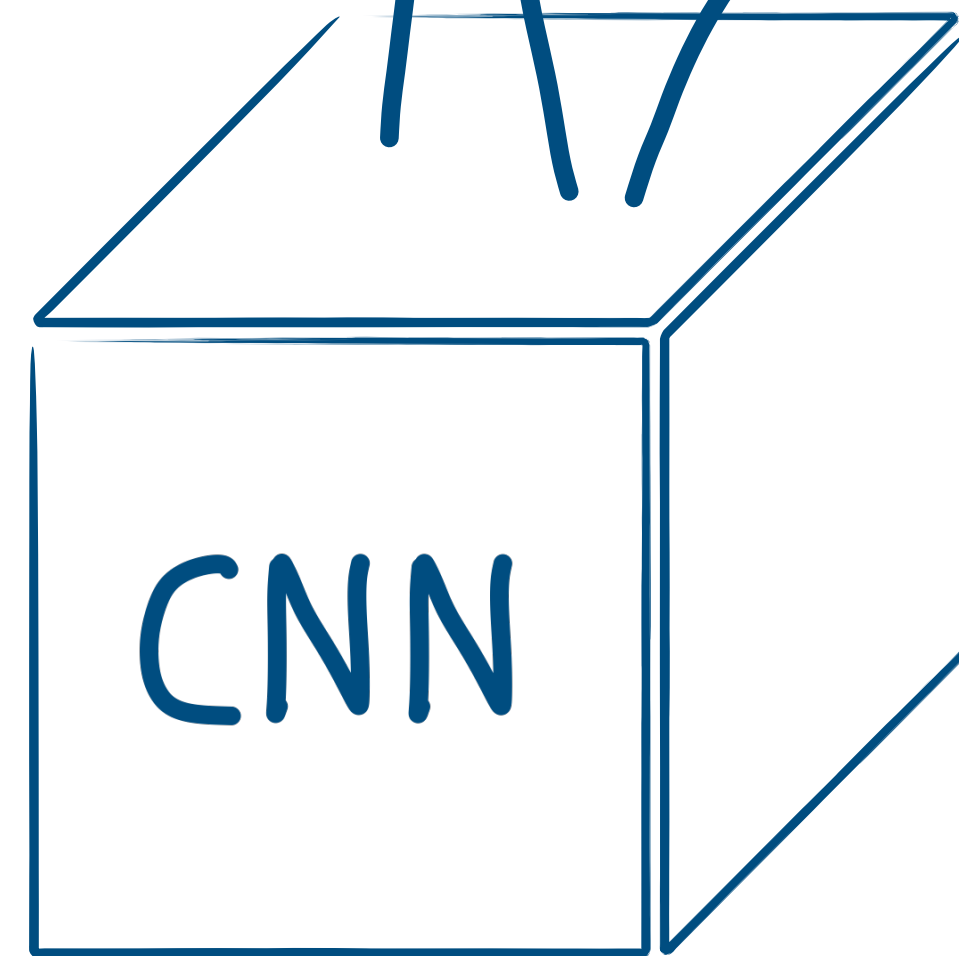


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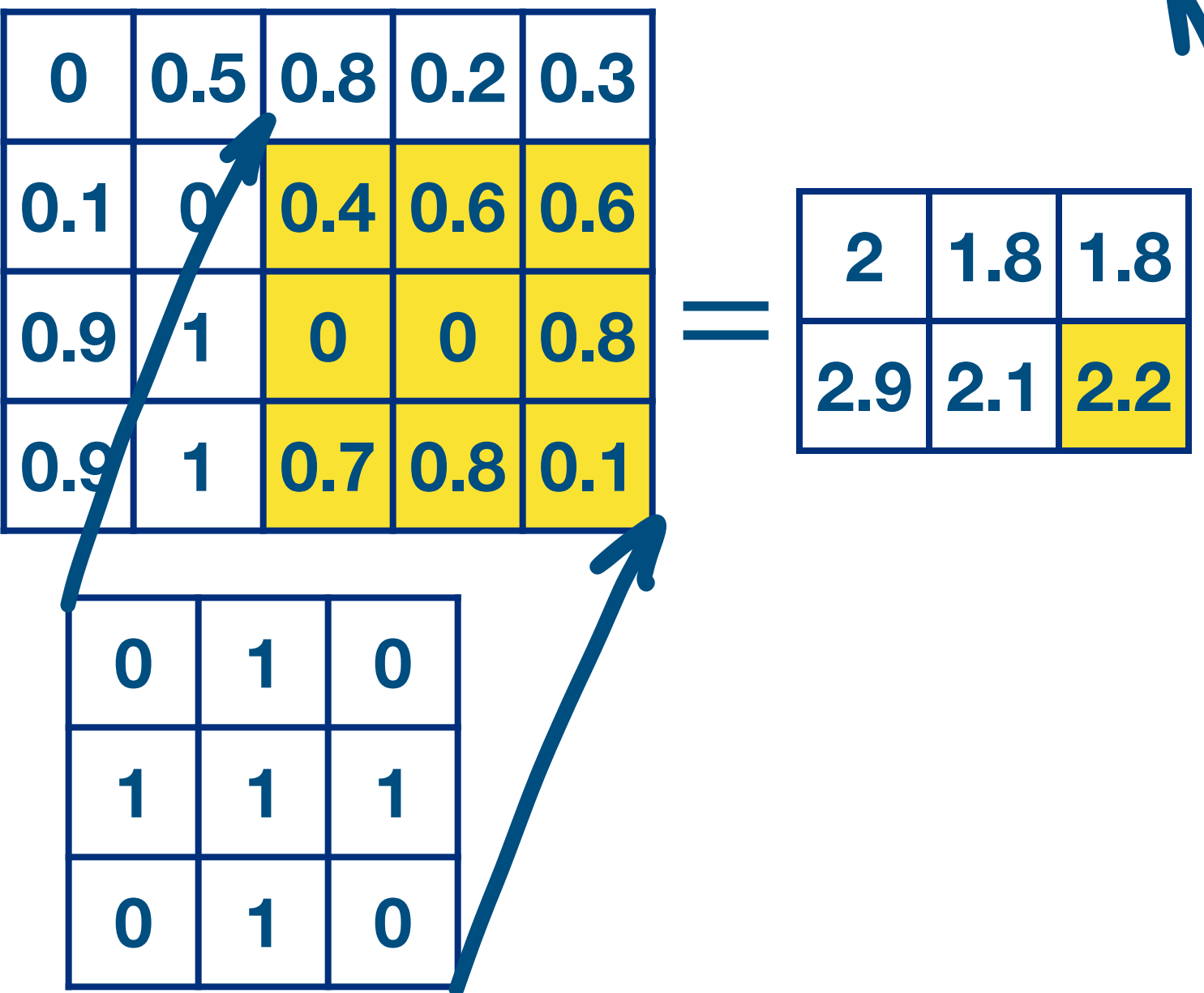


Activation function σ

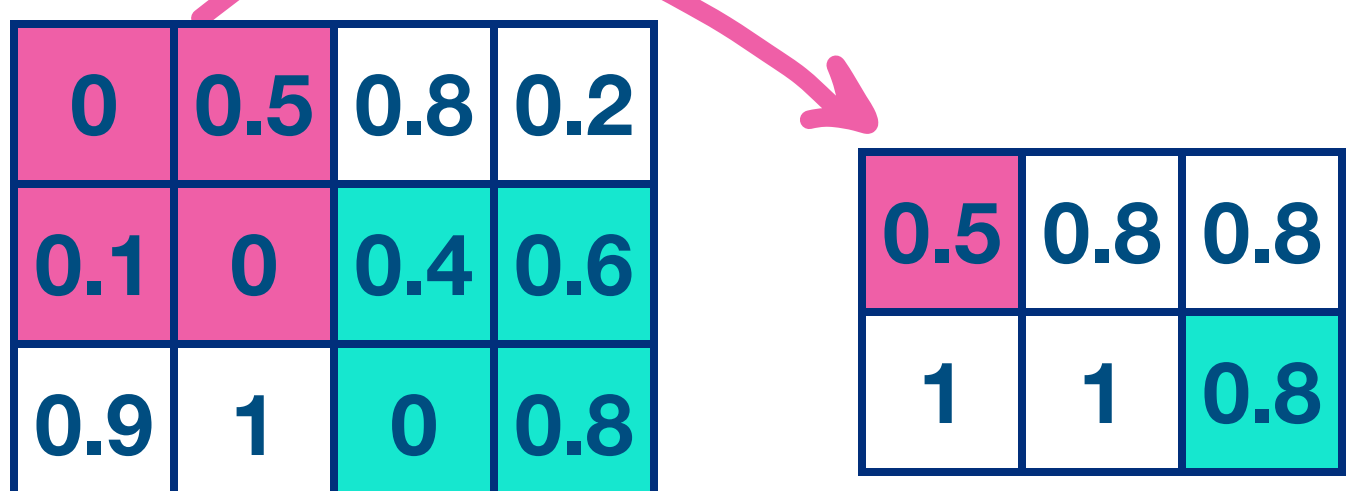


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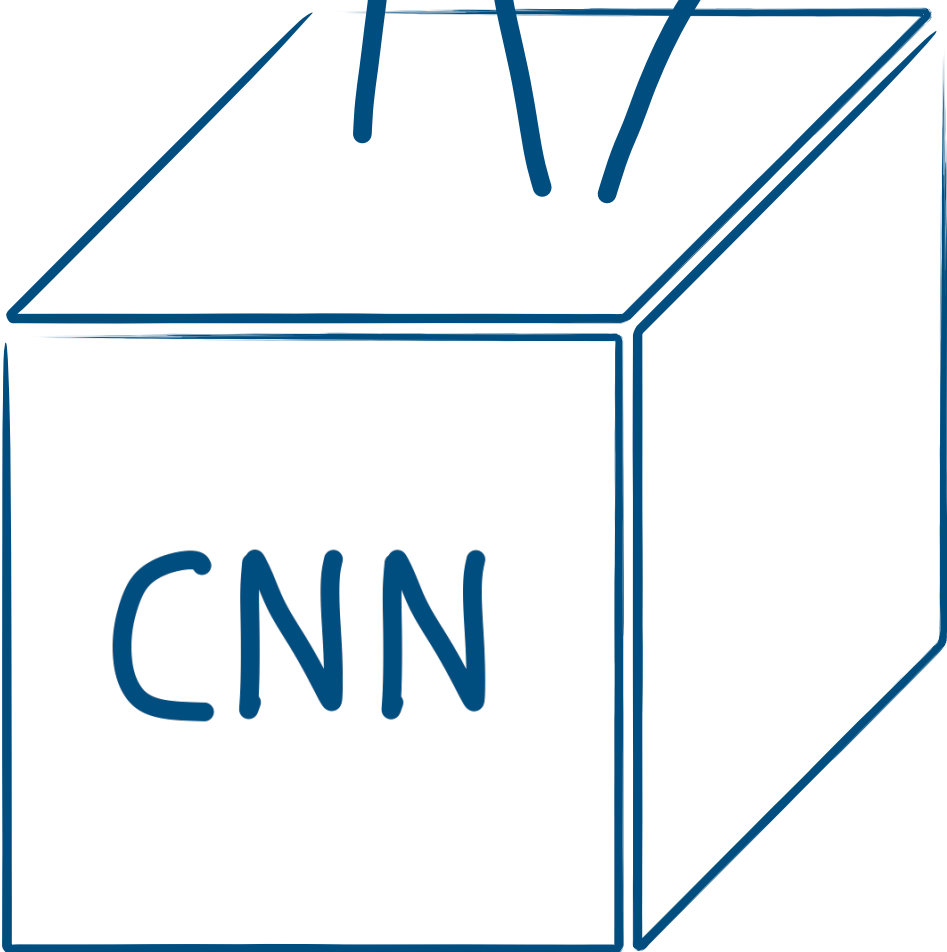


Max-pooling layer



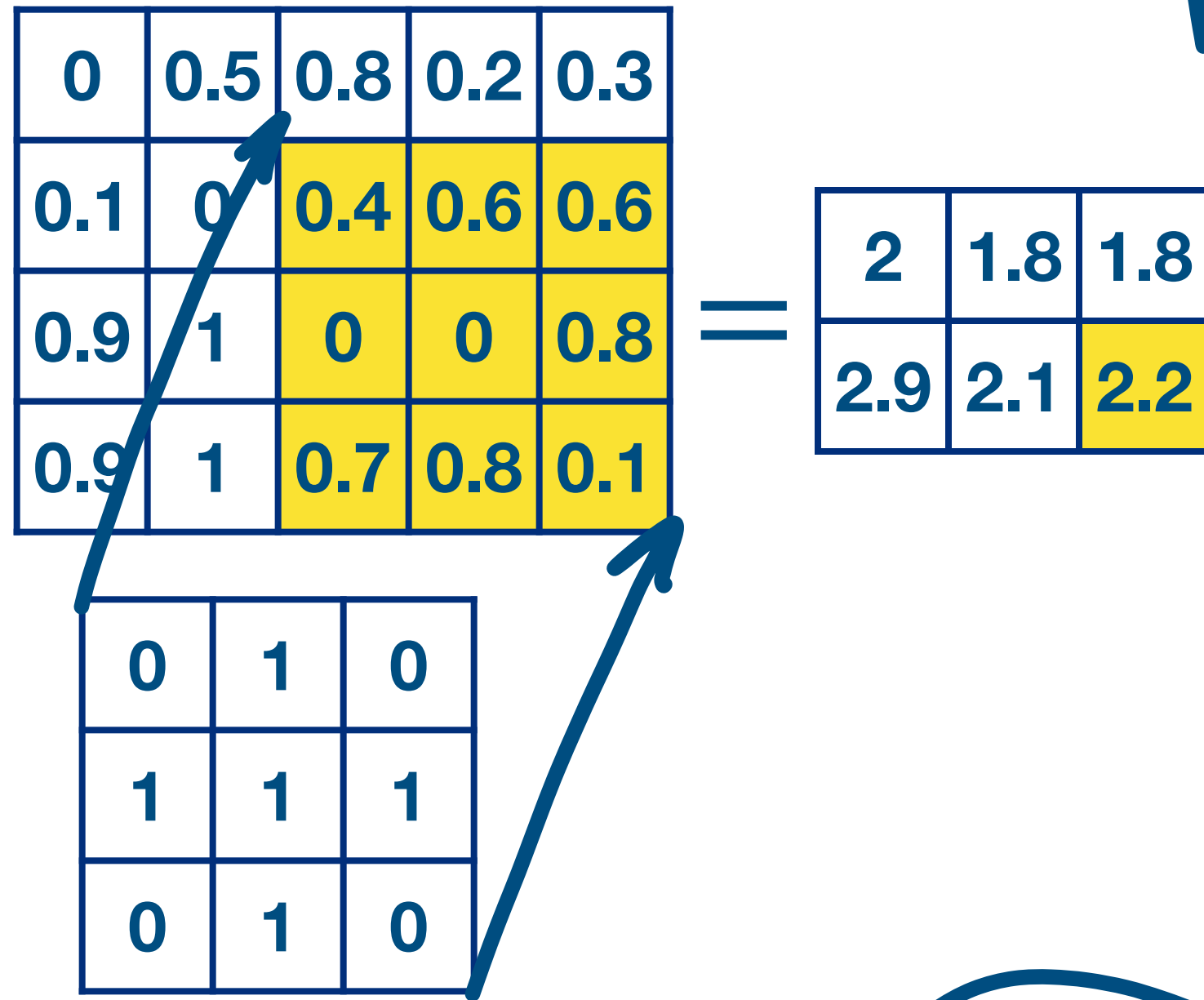
Activation function σ

$\text{ReLU}(x) = \max(0, x)$

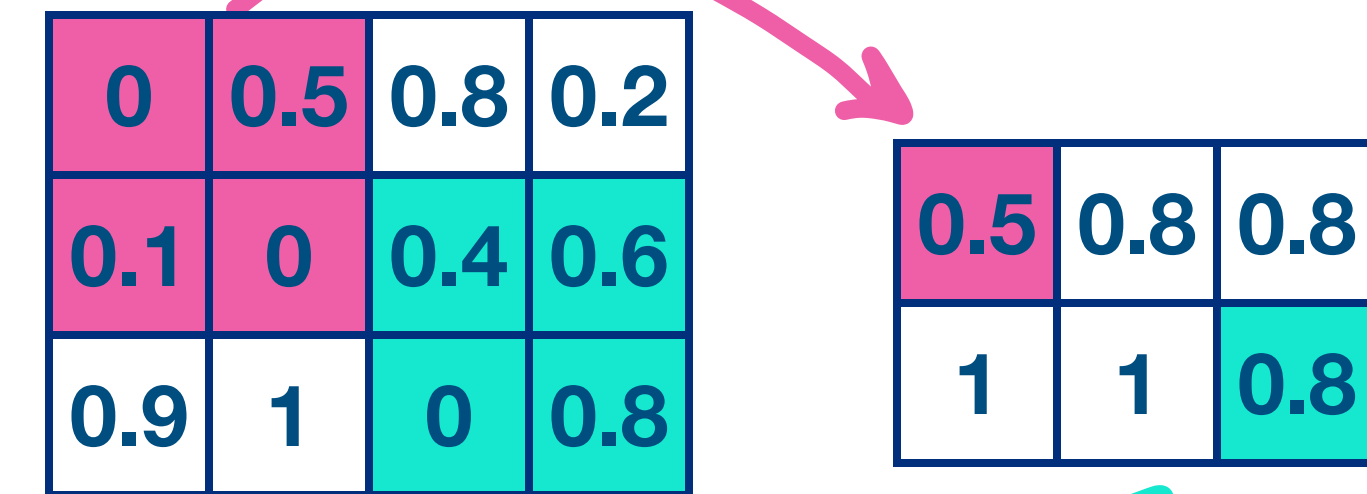


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Learnable convolutional kernel



Max-pooling layer



Activation function σ

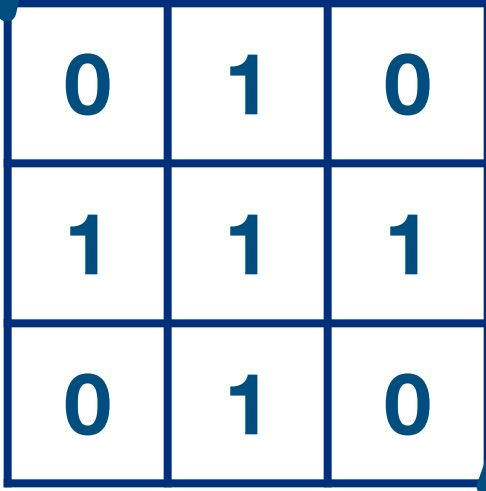
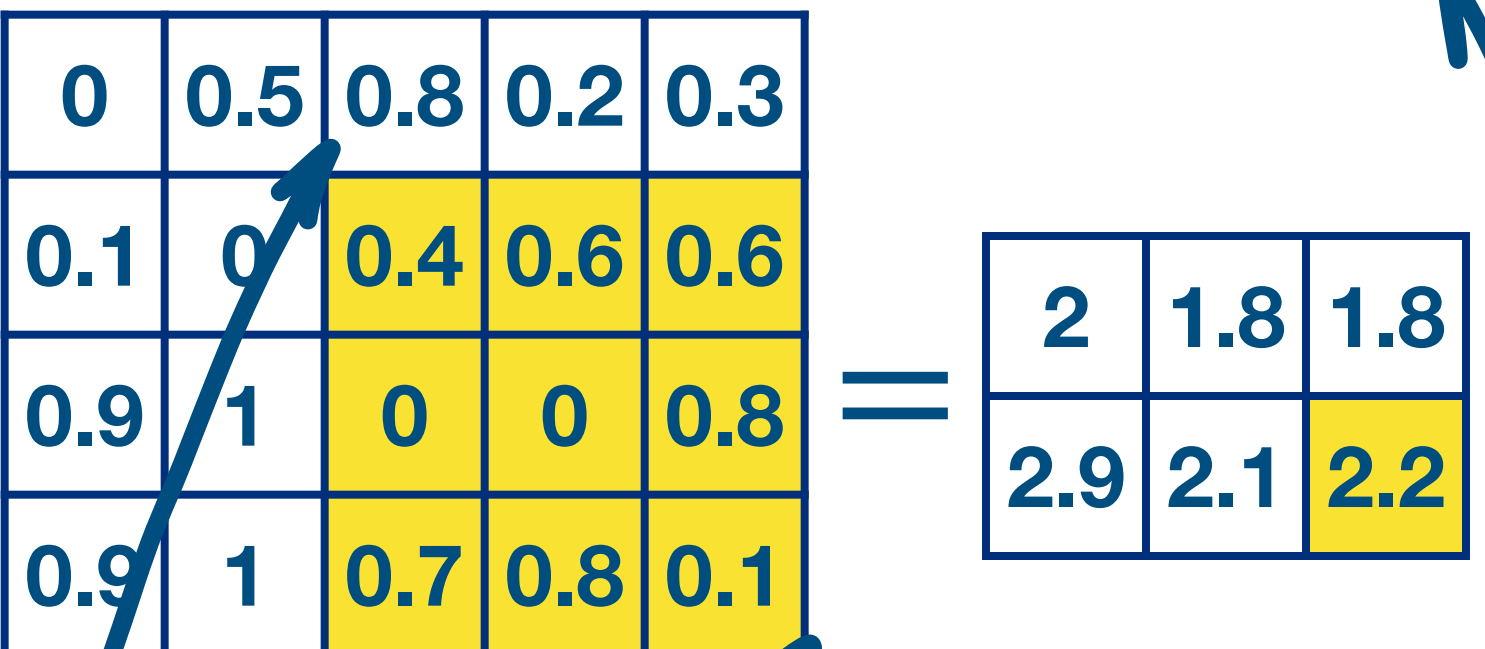
$$\text{ReLU}(x) = \max(0, x)$$

Self-attention layer

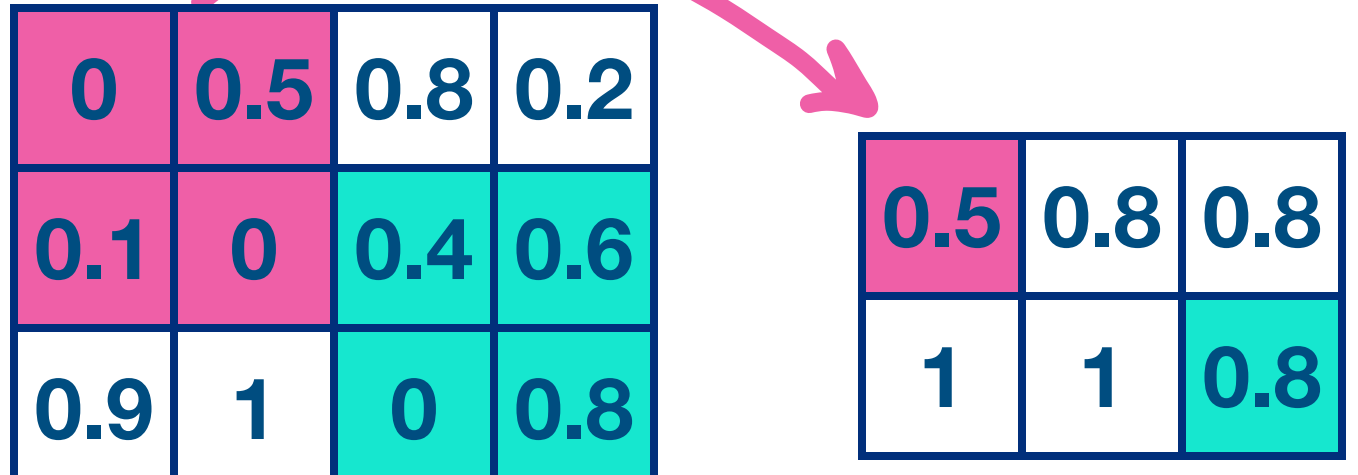
CNN

Which neural network to use?

Learnable convolutional kernel

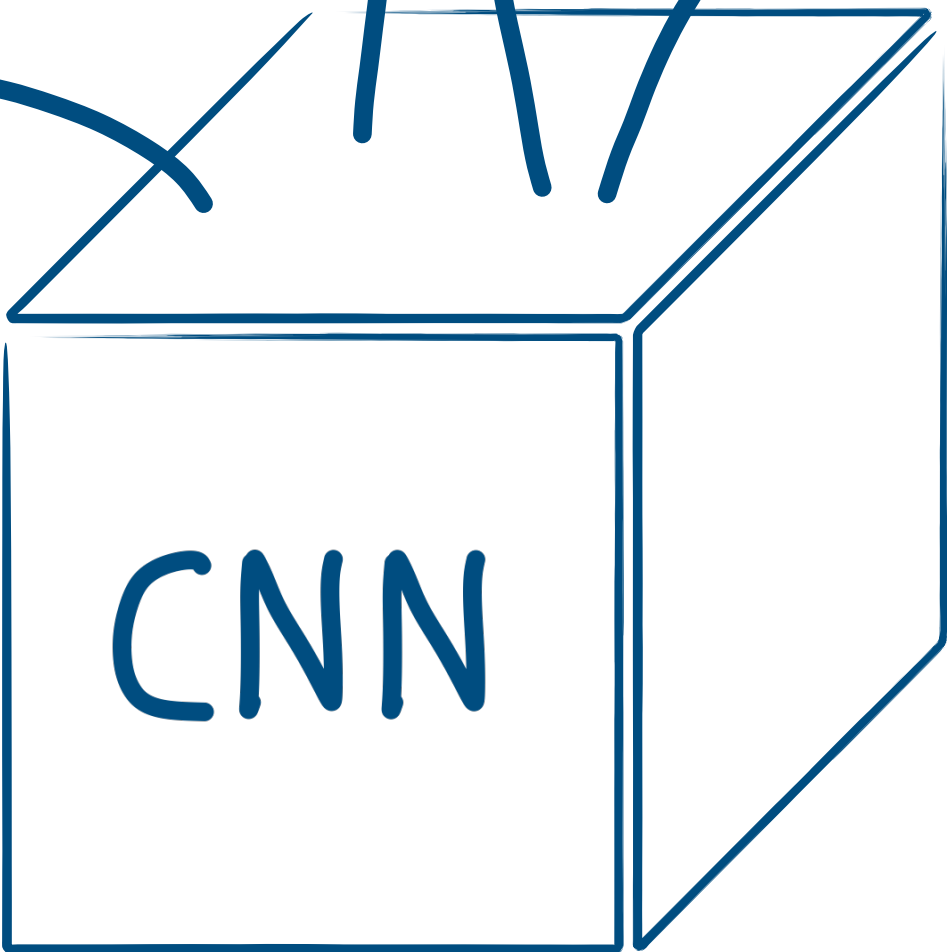


Max-pooling layer



Self-attention layer

$$\mathbf{O}(\mathbf{x}) = \text{softmax} \left(\frac{\mathbf{QK}^T}{\sqrt{e}} \right) \mathbf{V} \in \mathbb{R}^{t \times e}$$



Activation function σ

$$\text{ReLU}(x) = \max(0, x)$$

A Priori Validation on the two-dimensional periodic hill

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Upper wall (30%)
Lower wall (70%) of the periodic hill

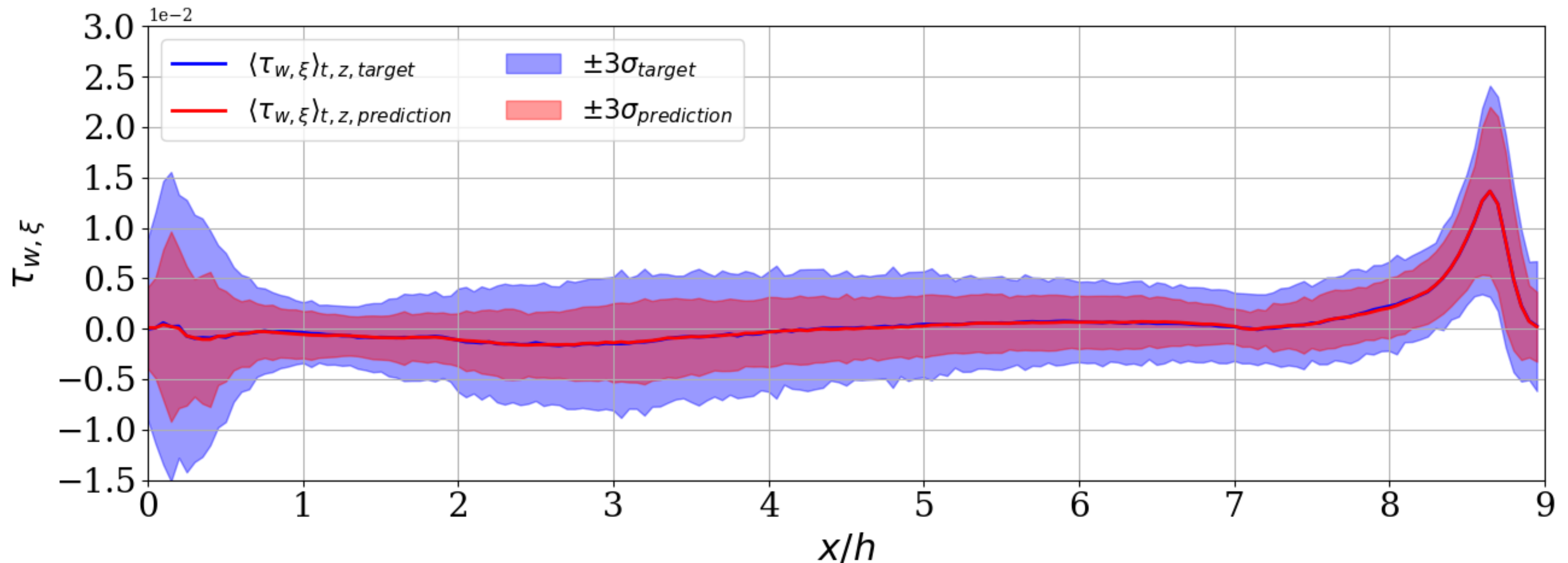
} 90% for training
10% for validation

A Priori Validation on the two-dimensional periodic hill



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Lower wall (70%) of the periodic hill

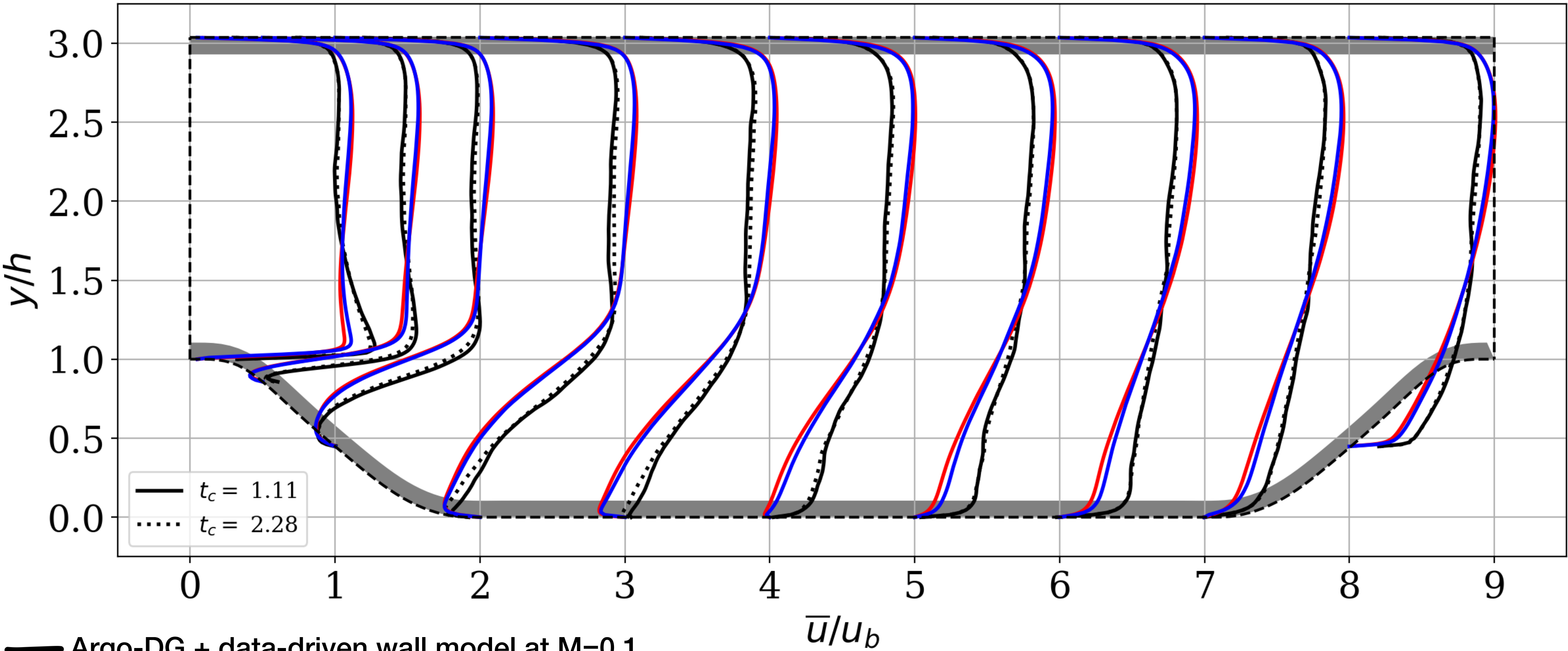
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A Posteriori Validation on the two-dimensional periodic hill

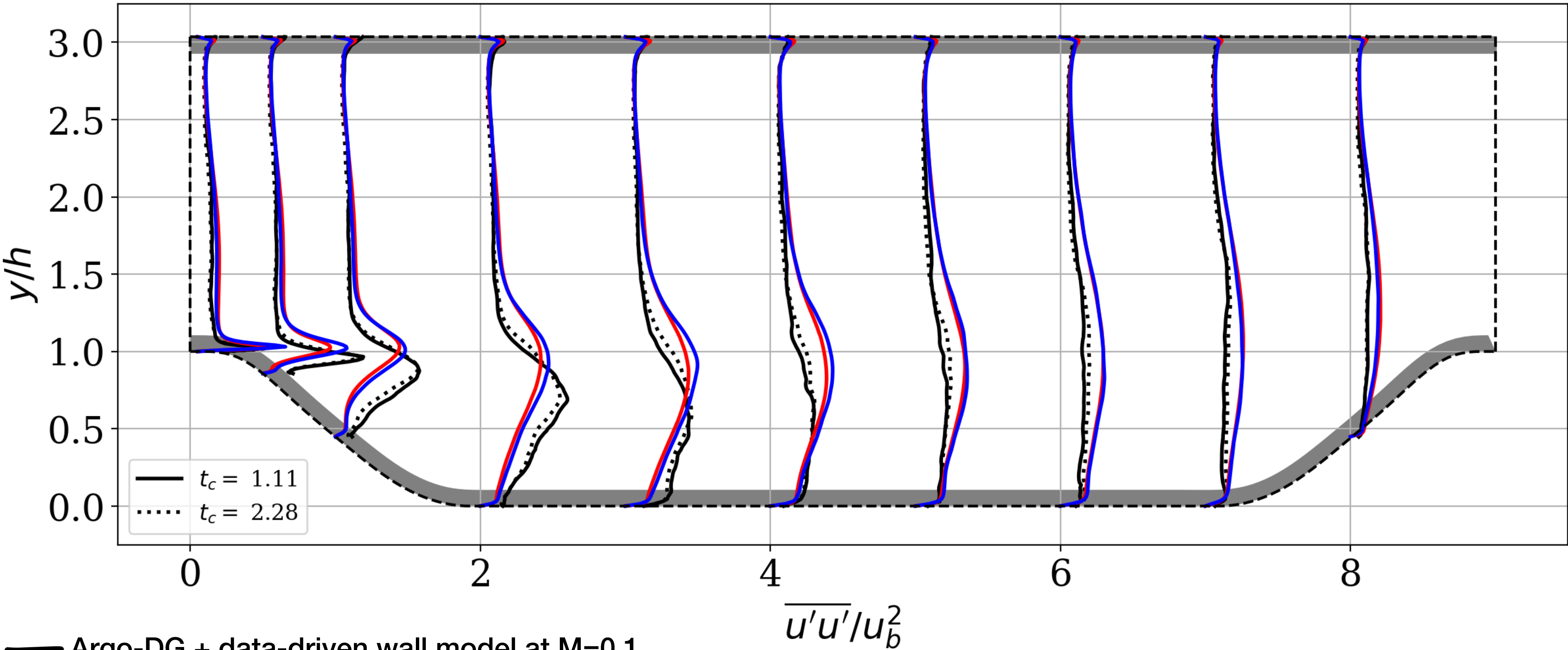
- Argo-DG + data-driven wall model at $M=0.1$
- Breuer *et al.* (2009)
- Gloerflit et Cinnella at $M=0.1$

A Posteriori Validation on the two-dimensional periodic hill



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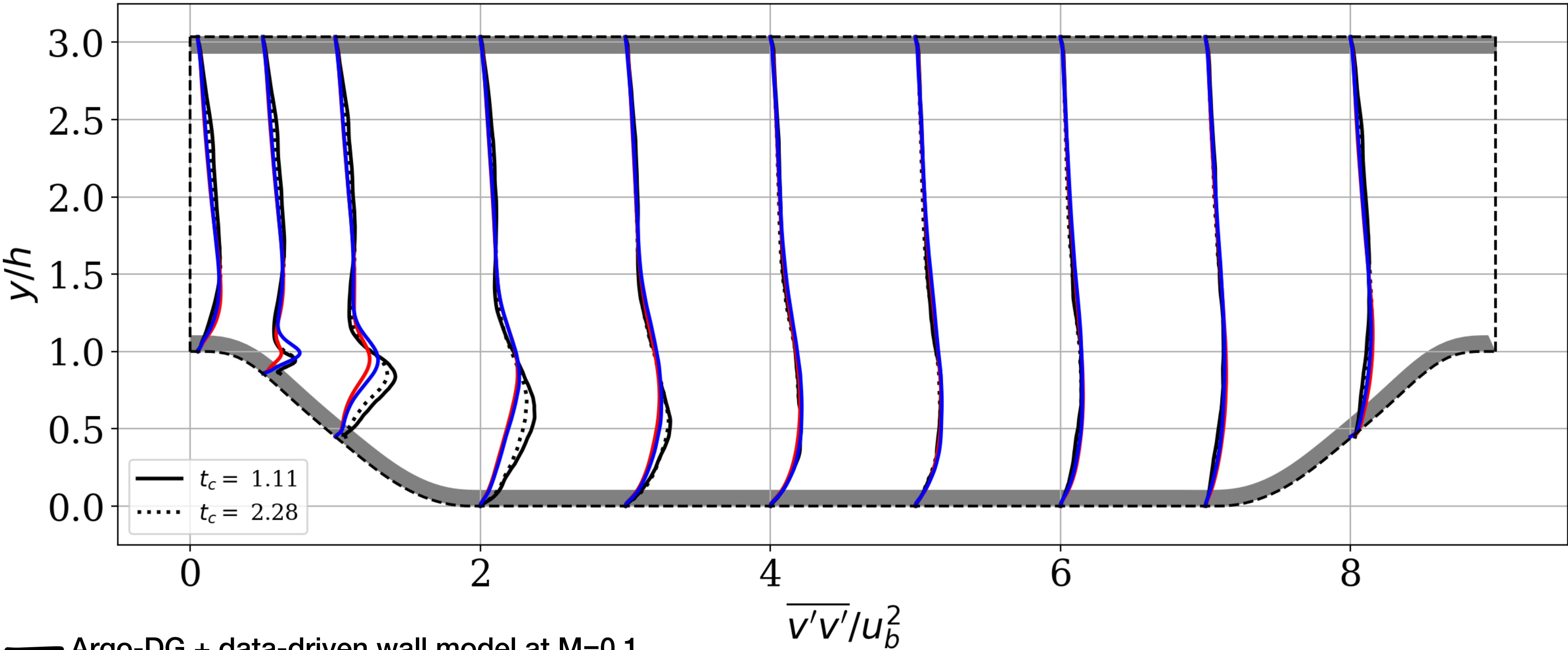
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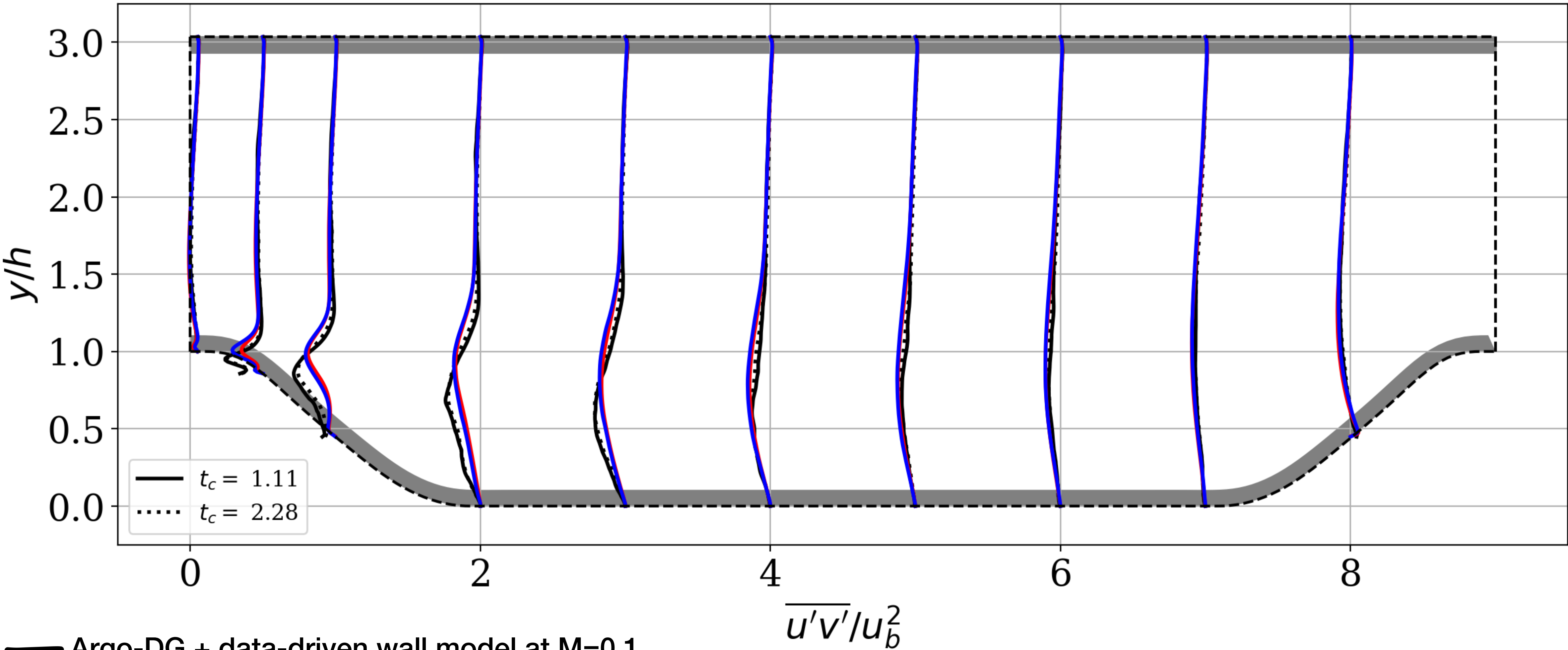
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PROD-F-015-02

A Posteriori Validation on the two-dimensional periodic hill



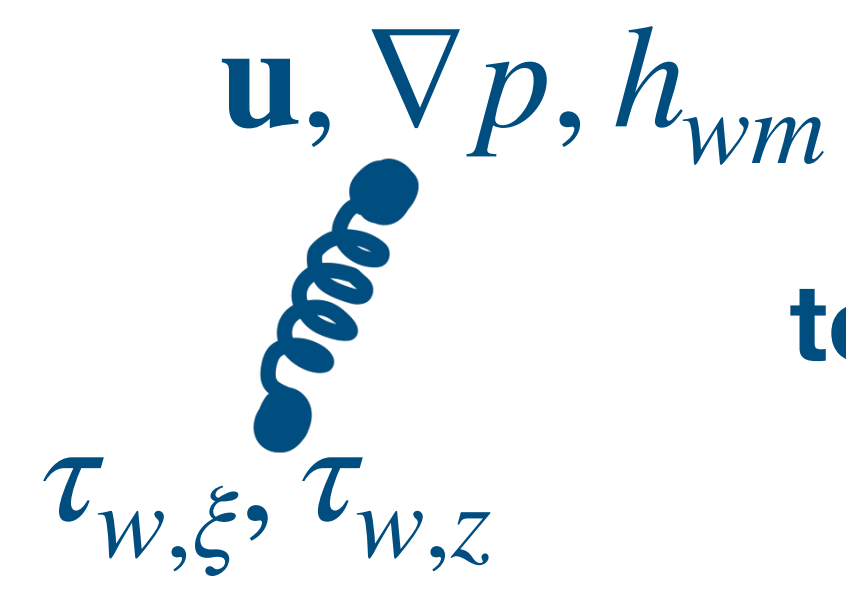
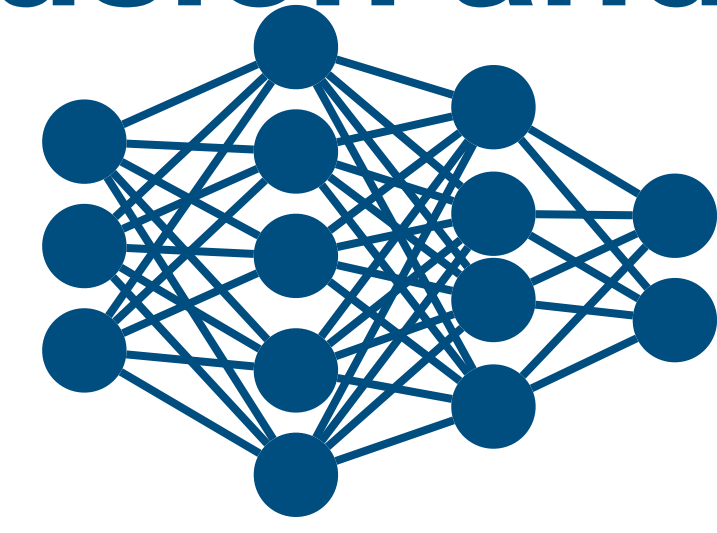
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PROD-F-015-02

Conclusion and perspectives

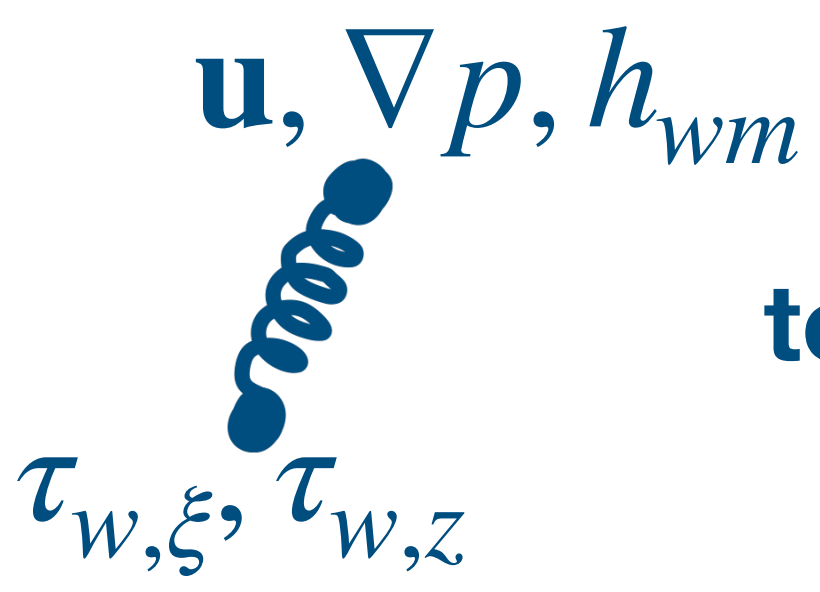
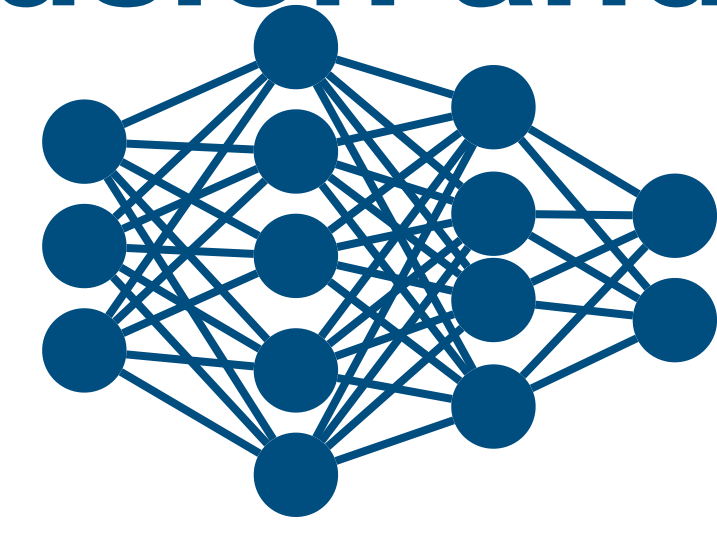
Conclusion and perspectives


to tackle separation using deep neural network



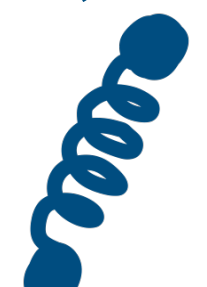
Conclusion and perspectives

to tackle separation using deep neural network

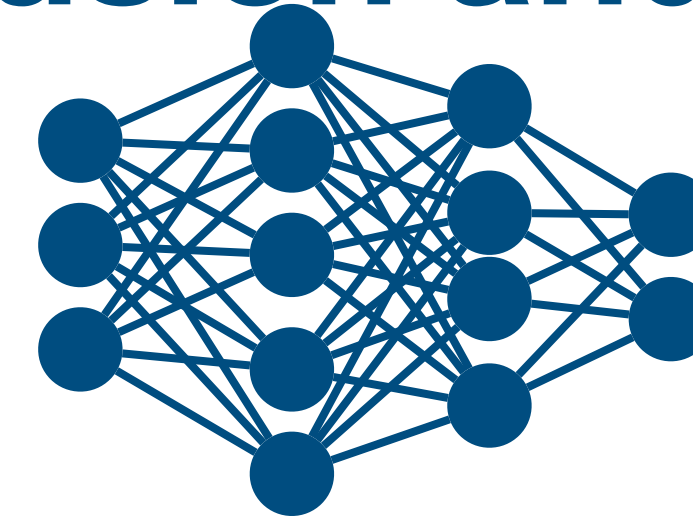


1) Generating database from channel and periodic hill flows 

Conclusion and perspectives

$$\mathbf{u}, \nabla p, h_{wm}$$
$$\tau_{w,\xi}, \tau_{w,z}$$


to tackle separation using deep neural network



1) Generating database
from channel and periodic
hill flows

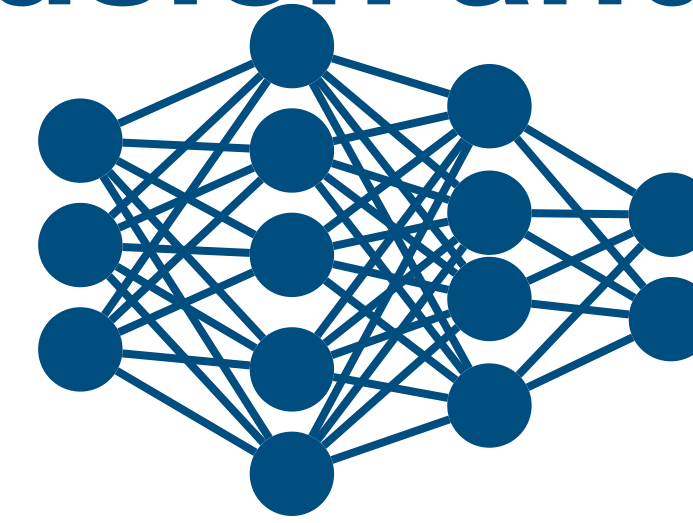


2) Analyzing space-time
correlations with the wall
shear stress (τ_w)



Conclusion and perspectives

to tackle separation using deep neural network



$$\mathbf{u}, \nabla p, h_{wm}$$
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1) Generating database from channel and periodic hill flows



2) Analyzing space-time correlations with the wall shear stress (τ_w)

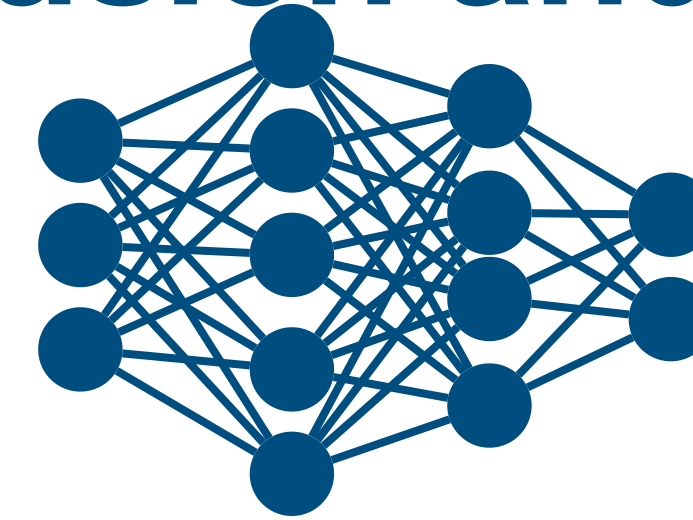


3) Training CNN and GMN for the prediction of τ_w



Conclusion and perspectives

to tackle separation using deep neural network



$$\mathbf{u}, \nabla p, h_{wm}$$
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1) Generating database from channel and periodic hill flows



2) Analyzing space-time correlations with the wall shear stress (τ_w)



3) Training CNN and GMN for the prediction of τ_w



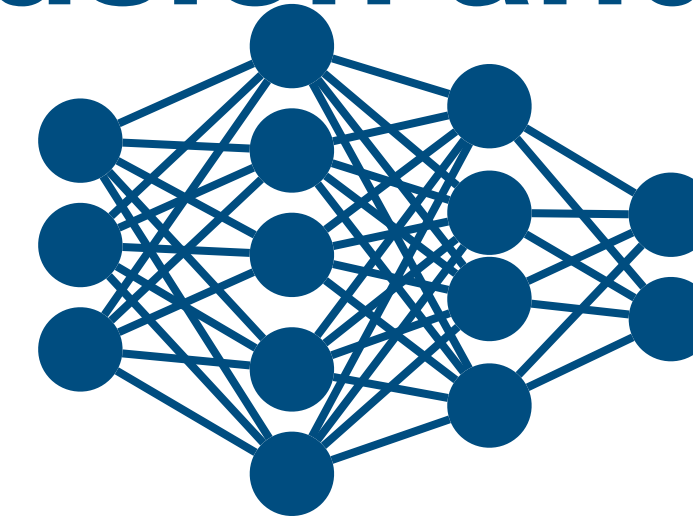
A Posteriori Validation

Channel at $Re_\tau = 950$

Periodic hill at $Re_b = 10595$

Conclusion and perspectives

to tackle separation using deep neural network



$$\mathbf{u}, \nabla p, h_{wm}$$
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A Posteriori Validation

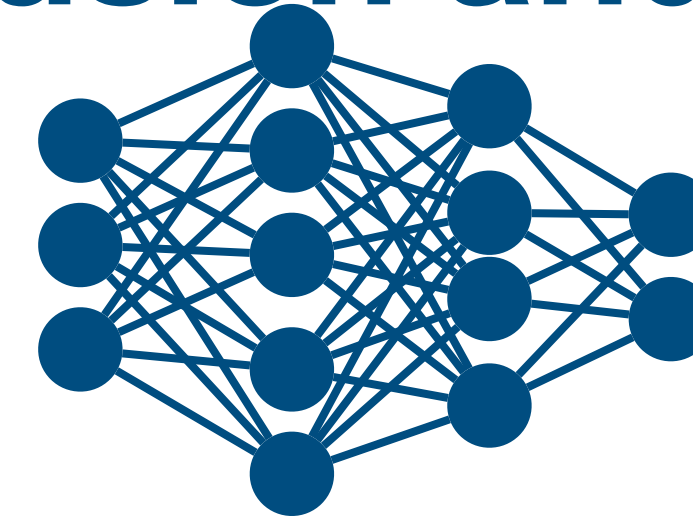
Channel at $Re_\tau = 950$

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Future challenges:

Conclusion and perspectives

to tackle separation using deep neural network



$\mathbf{u}, \nabla p, h_{wm}$
 $\tau_{w,\xi}, \tau_{w,z}$

1) Generating database from channel and periodic hill flows



2) Analyzing space-time correlations with the wall shear stress (τ_w)



3) Training CNN and GMN for the prediction of τ_w

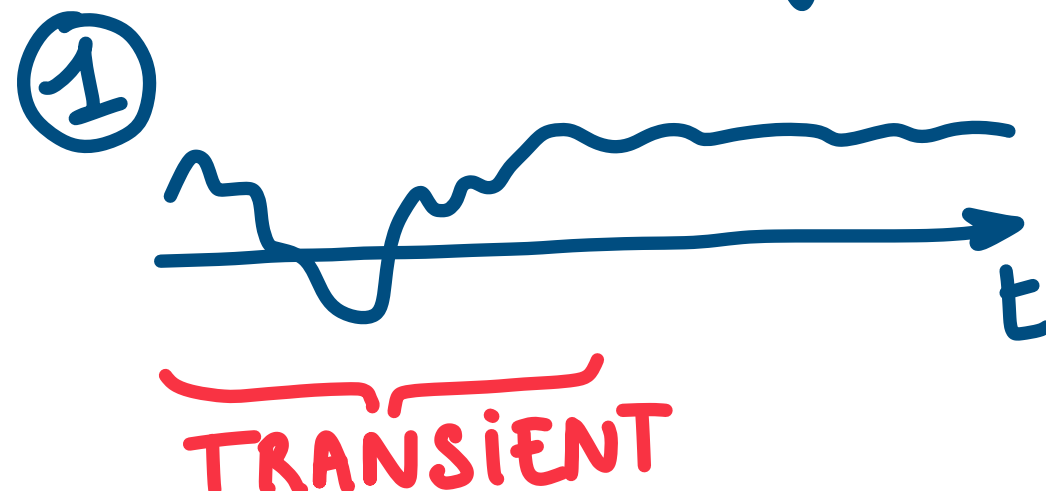


A Posteriori Validation

Channel at $Re_\tau = 950$

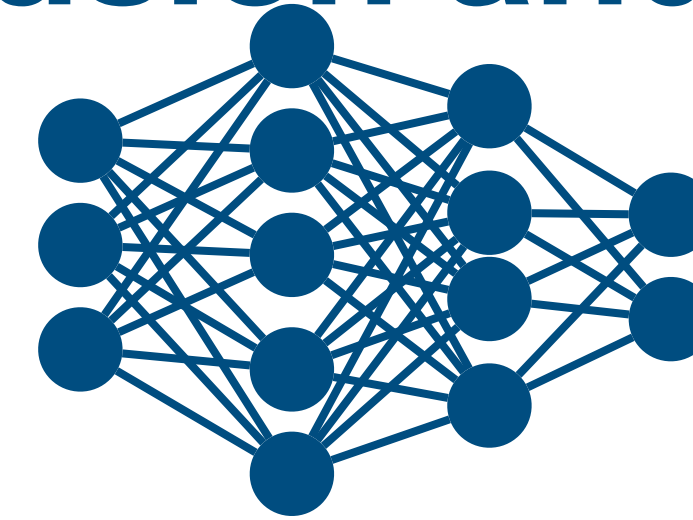
Periodic hill at $Re_b = 10595$

Future challenges:

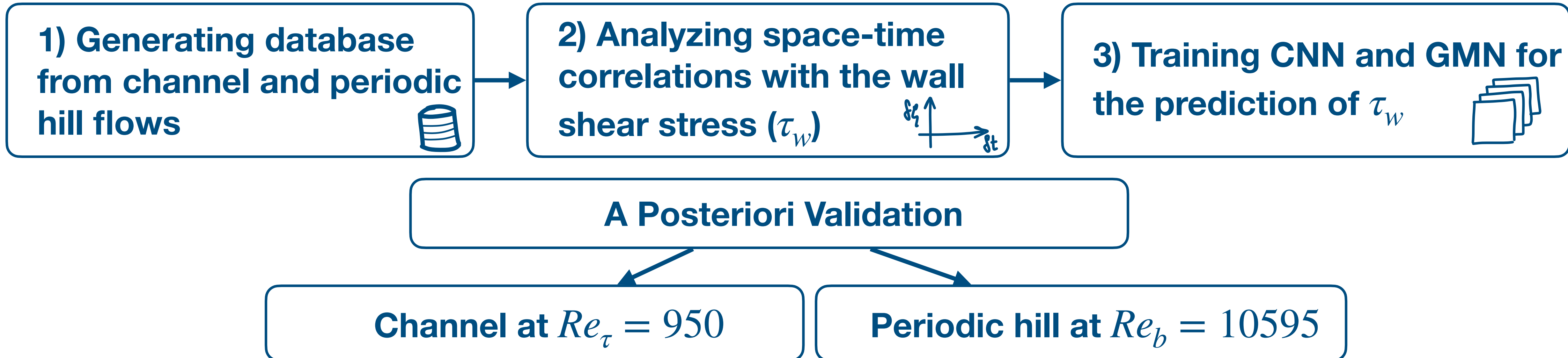


Conclusion and perspectives


to tackle separation using deep neural network



$\mathbf{u}, \nabla p, h_{wm}$
 $\tau_{w,\xi}, \tau_{w,z}$



Future challenges:

① 
TRANSIENT

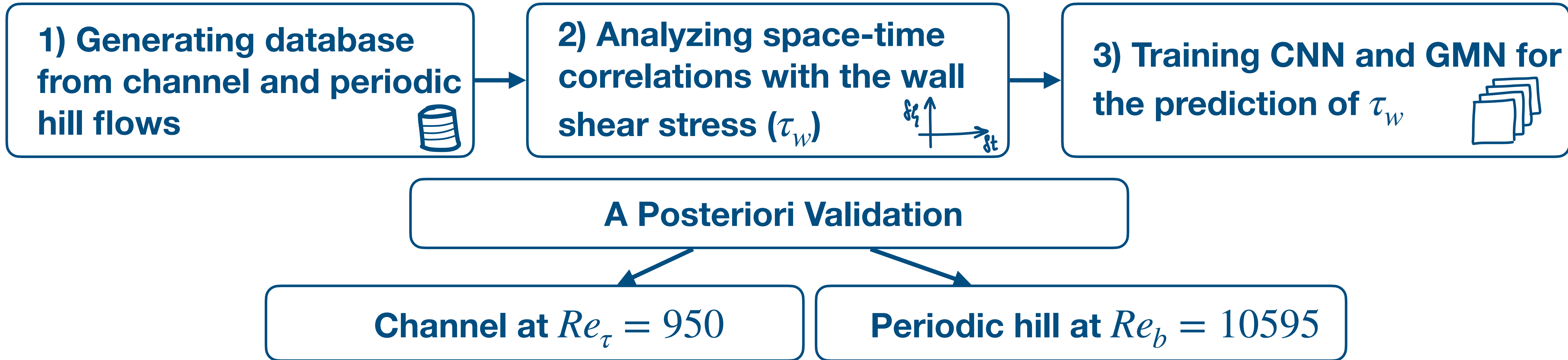
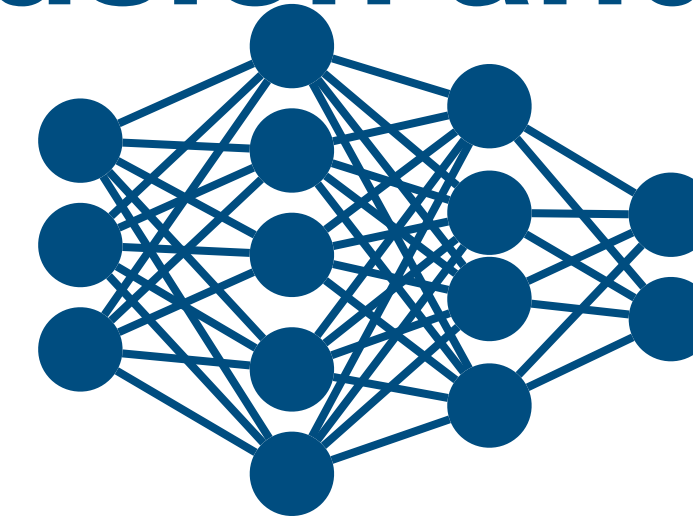
② A posteriori validation at higher Re!

Conclusion and perspectives

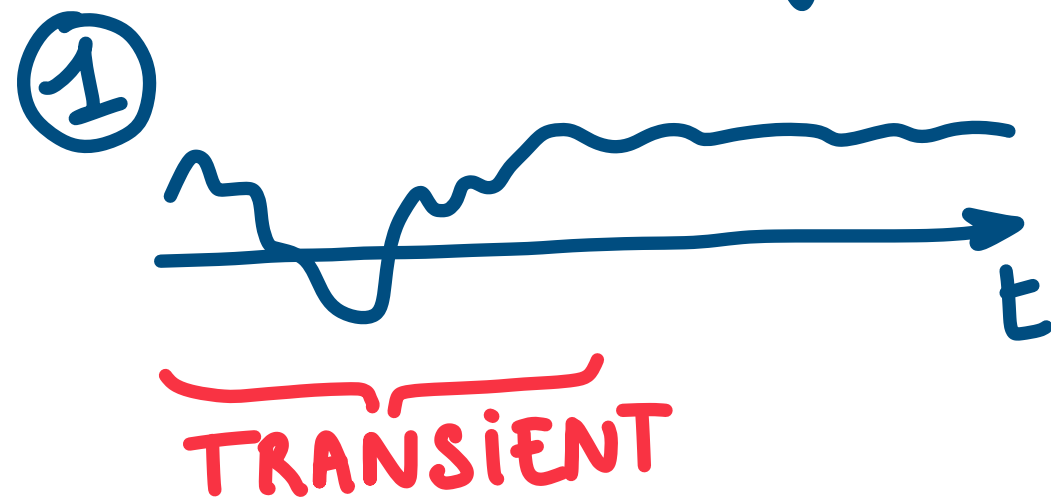
$$\mathbf{u}, \nabla p, h_{wm}$$

$$\tau_{w,\xi}, \tau_{w,z}$$

to tackle separation using deep neural network



Future challenges:



② A posteriori validation at higher Re !

③ Industrial configuration