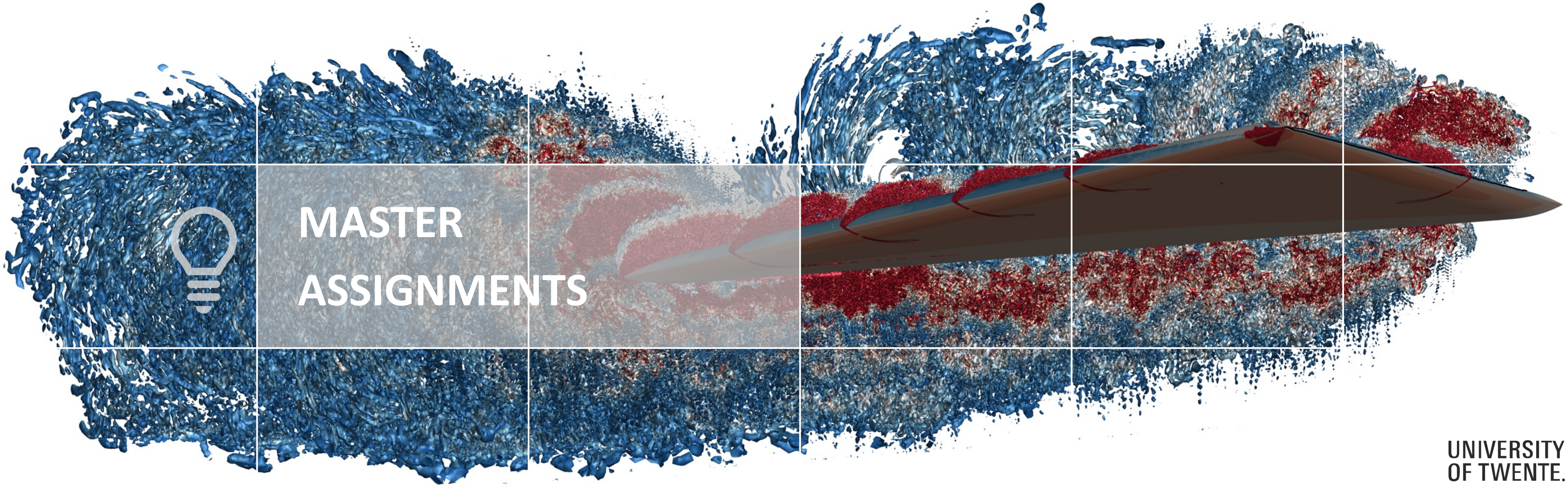
Transition-Transport Modelling:

3) Grid-point local approximation of boundary-layer quantities using Machine Learning



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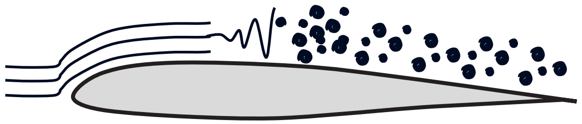
LAMINAR-TURBULENT TRANSITION AND ITS PREDICTION

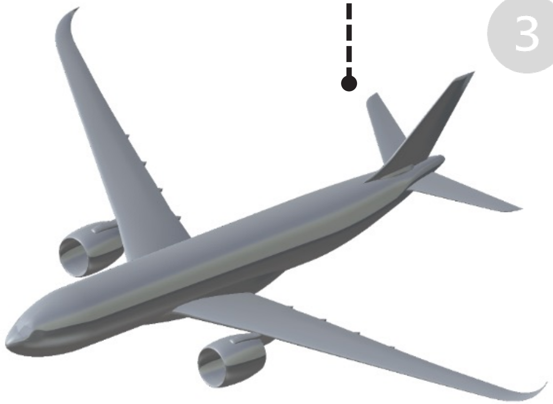


1

The laminar-to-turbulent transition is the process of a **laminar flow becoming turbulent.** Depending on the mechanism this process is caused by instabilities growing exponentially and eventually turning the flow into a chaotic, turbulent state.

2

For many applications in aerodynamics it is essential to consider the laminar-to-turbulent transition and to know in which region this transition is happening. For this purpose, a wide range of methods exists that enable the **prediction** of the transition at different levels of fidelity.



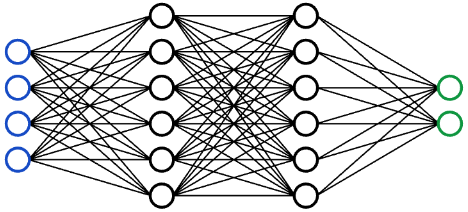
$$\frac{\partial(\rho\phi)}{\partial t} + \nabla\cdot(\rho\,\boldsymbol{u}\phi) = \mathcal{P}_\phi + \nabla\cdot((\mu+\mu_t)\sigma_\phi\,\nabla\phi)$$

3

A class of methods pioneered by Menter and colleagues in the early 2010s are known as local (correlation-based) transition-transport models [1]. They adhere to the principal of **being fully compatible with modern computational fluid dynamics software**, offering additional advantages such as robustness and user-friendliness. However, a drawback of these methods is that they may sacrifice accuracy in pursuit of these benefits.

4

In this context, one strategy to **maintain the predictive quality of a high-fidelity method** like local, linear stability theory in conjunction with e^N method within a transition transport model is the incorporation of Machine Learning methods.



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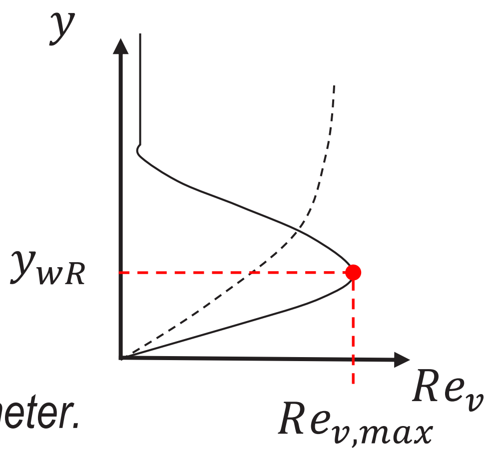
ASSINGMENT 3: *Grid-point local approximation of boundary-layer quantities using Machine Learning*

Research question:

Is it possible to approximate integral boundary-layer quantities with grid-point local data using Neural Networks?

Problem description:



- *In a grid-point local transition transport model it is crucial to provide quantities that characterize the state of the boundary-layer. For this purpose,* ***integral boundary layer quantities*** *are used (as the shape factor H_{12}).*

- *The challenge is to estimate these parameters* ***solely by utilizing local grid-point quantities*** *within a simulation, i.e. $\mathcal{F}: \varsigma \longmapsto \mathcal{L}$, where ς is the grid-point local quantity and $\mathcal{L}$ the integral parameter.*

- *The current state-of-the-art approach involves employing* ***data fits derived from self-similar laminar solutions****, as shown in references [1, 2, 3, 4]. However, this method has inherent limitations. To potentially overcome these constraints, an* ***alternative approach is to utilize Neural Networks:*** $\mathcal{F}_{\mathcal{L}}: \eta_i \longmapsto \mathcal{L}$.

ASSINGMENT 3: *Grid-point local approximation of boundary-layer quantities using Machine Learning*

Research question:

Is it possible to approximate integral boundary-layer quantities with grid-point local data using Neural Networks?

Tasks in this assignment:

- ✓ Reproduction of curve fits $\mathcal{F}\colon\ Re_{v,max} \longmapsto Re_{\theta}$ for
  - ✓ Blasius solution: zero pressure gradient laminar flat plate
  - ✓ Falkner-Skan solution: wedge flow for different constant pressure gradients β
- ✓ Establishment of a comprehensive database comprising laminar profiles across a broad spectrum of flow conditions using CFD.
- ✓ Identification of suitable (local) input parameters and training of a Neural Network.
- ✓ Application:
  - ✓ Verification for test cases within the database.
  - ✓ Generalizability: Validation across additional test cases.

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Piqued your interest?

Reach out!

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REFERENCES

[1] Langtry, R. B., and Menter, F. R., "Correlation-based transition modeling for unstructured parallelized computational fluid dynamics codes," AIAA Journal, Vol. 47, No. 12, 2009, pp. 2894-2906.

[2] Coder, J.G., andMaughmer,M.D.,"Computational Fluid Dynamics CompatibleTransition Modeling Usingan Amplification Factor Transport Equation," AIAA Journal, Vol. 52, No. 11, 2014, pp. 2506–2512. doi: 10.2514/1.J052905.

[3] Ströer,P.,Krimmelbein,N.,Krumbein,A.,and Grabe,C.,"Stability-Based Transition Transport Modeling for Unstructured Computational Fluid Dynamics Including Convection Effects", AIAA Journal, Vol. 58, No. 4, 2020, pp. 1506-1517. doi: 10.2514/1.J058762.

[4] Ströer, P., Krimmelbein, N., Krumbein, A., & Grabe, C., "Galilean-invariant stability-based transition transport modeling framework," AIAA Journal, Vol. 60, No. 7, 2022, pp. 4126-4139.