Technische Universität Braunschweig

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Machine Learning in Fluid Dynamics

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Stiftung Innovation in der Hochschullehre

README.md

Stiftung Innovation in der Hochschullehre

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Machine learning in computational fluid dynamics

This repository contains resources accompanying the lecture machine learning in computational fluid dynamics provided by the Institute of Fluid Mechanics at TU Braunschweig. **Note that slides, notebooks, and other resources will be regularly updated throughout the term.**

Lectures

If equations in the lecture notebooks do not get rendered properly on Github, download the notebook and open it using `jupyter-lab` (refer to the first exercise session for an overview of dependencies and installation instructions).

#	topic	slides	notebook
1	Course overview and motivation	link	view
2+3	Finite-volume-based simulations in a nutshell	link	view
4+5	Introduction to machine learning	link	view
6	Surrogate modeling for discrete predictions	link	view

Concept and starting point

- Application of state-of-the-art machine learning techniques for the analysis, modelling, and optimization of fluid flow applications
- Story telling – machine learning and simulation techniques introduced in the context of real world problems and applications
- Direct knowledge transfer from latest research to engineering curriculum
- Targets mainly computational, mechanical, and aerospace engineers
- Hybrid format – recorded in-person/online lecture and exercise sessions
- Lecture material and communication in English language
- Lecture started in 2021/2022 winter term and got significantly revised and extended during the 2022/2023 winter term thanks to **ProDigi**
- Currently 15 lectures and exercises (11 revised, 2 new, 2 in preparation)

← Left: The lecture content is organized as a Github repository. The lecture material is freely available at https://github.com/AndreWeiner/ml-cfd-lecture.

Technology stack

- Slides are created with **Reveal.js** and hosted on Github → slides are device independent (laptop, tablet, phone), platform independent (Windows, Linux, MacOS, Android, iOS) and always accesible online via web browser
- **Jupyter notebooks** as lecture and exercise scripts → Jupyter notebooks are interactive documents containing text, formulas, source code, and interactive visualizations; the notebooks can be viewed online (static mode) or locally on a laptop/workstation (interactive)
- Version control with **Git** and **Github** → lecture material is version-controlled and gets updated regularly throughout term; students are required to check for the latest updates and to “pull“ if necessary
- Reproducibility of scientific data through **virtualization** → software and programming libraries are distributed as software containers
- Open-source only → the lecture material is published under a non-restrictive Creative Commons license; free simulation (OpenFOAM, Basilisk) and machine learning packages (PyTorch, ScikitLearn)

Challenges

Compatibility – issues between BigBlueButton, iPad and Linux/Ubuntu
Time – update and creation of content is demanding
Technical requirements – many students don’t have access to a Linux PC
Access – there is demand for thrid-party access but no legal basis for participation
Active engagement – most students don’t interact hands-on with material (exercises and notebooks)

Future skills

hands-on **programming** in Python and C++

Data analysis and **visualization** of real data

Machine learning in action – transfer of cutting edge research to teaching

Data literacy – state-of-the-art technology stack

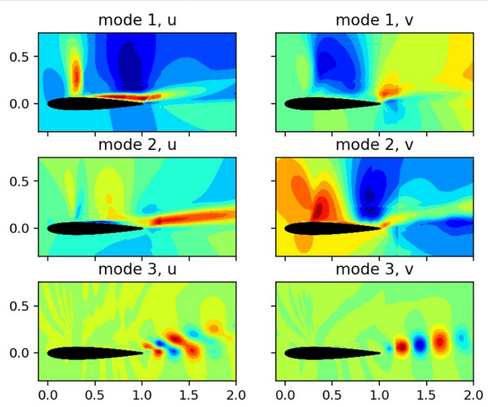
Professional online **communication**

Lecture notebooks

Modal analysis of transonic shock buffet on airfoils

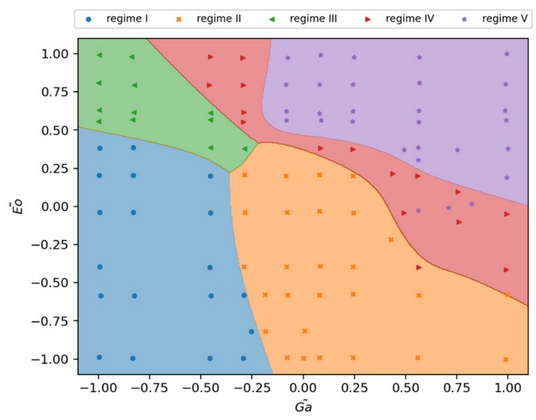
```
In [37]: fig, axarr = plt.subplots(3, 2, figsize=(6, 5), sharex=True, sharey=True)

for i in range(3):
    axarr[i, 0].tricontourf(xa, ya, U[:n_points, i], levels=14, cmap="jet")
    axarr[i, 1].tricontourf(xa, ya, U[n_points:, i], levels=14, cmap="jet")
    for ax in axarr[i, :]:
        add_naca0012_patch(ax)
        ax.set_aspect("equal", 'box')
        ax.set_xlim(-0.1, 2.0)
        ax.set_ylim(-0.3, 0.75)
    axarr[i, 0].set_title(f"mode {i+1}, u")
    axarr[i, 1].set_title(f"mode {i+1}, v")
plt.savefig(f"{output}/naca_pod_modes.png", bbox_inches="tight")
```




```
In [90]: xx, yy = pt.meshgrid(
             pt.linspace(-1.1, 1.1, 500),
             pt.linspace(-1.1, 1.1, 500)
         )
         X = pt.stack((xx.flatten(), yy.flatten())).T
         prob = pt.nn.functional.softmax(regime_model(X), dim=1)
         prediction = pt.argmax(prob, dim=1) + 0.01

         fig, ax = plt.subplots()
         cmap = ListedColormap([f"C{i}" for i in range(5)])
         ax.contourf(xx, yy, prediction.reshape(xx.shape), cmap=cmap, alpha=0.5)
         for regime, marker in zip(regimes, markers):
             ax.scatter(logData[logData["regime"] == regime].Ga, logData[logData["regime"] == regime].Eo,
                        marker=marker, s=10, label="regime {}".format(regime))
         ax.set_xlabel(r"$\tilde{Ga}$")
         ax.set_ylabel(r"$\tilde{Eo}$")
         ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.1), ncol=5, fontsize=8)
         plt.savefig(join(output, "network_multiclass_prediction.svg"), bbox_inches="tight")
```



Path stability classification of rising bubbles

Just the numbers

72 enrolled students from computational, mechanical, aerospace, electrical and other engineering diciplines

Lecture repository has **~ 85 unique visitors** per week and gets **“cloned” ~15 times** per week

~ 640 weekly visualizations of lecture material

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