Universität Bremen

Center for Industrial Mathematics (ZeTeM)

Faculty 03

Mathematics / Computer science

Introduction to TorchPhysics

Getting started with a simple example

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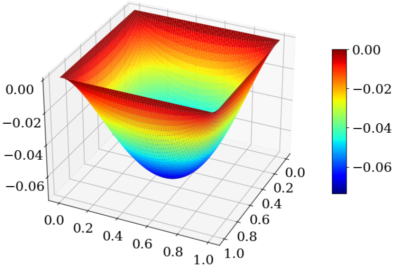
Renningen, 20.11.2025

Starting with TorchPhysics

- We introduce the library with the Laplace equation:

$$\begin{aligned} \Delta u &= 1 \quad \text{in } \Omega = (0,1) \times (0,1) \\ u &= 0 \quad \text{on } \partial\Omega \end{aligned}$$

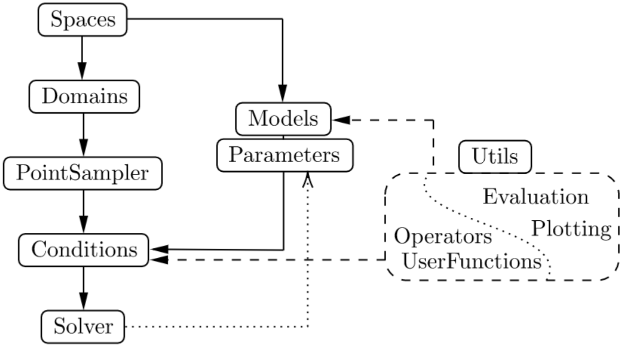


But first...

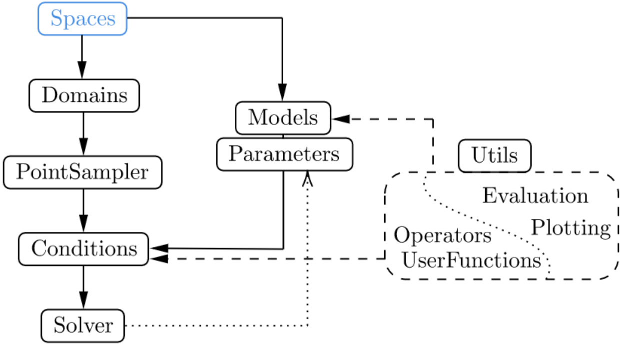
Setting up the coding environment

TorchPhysics

Structure

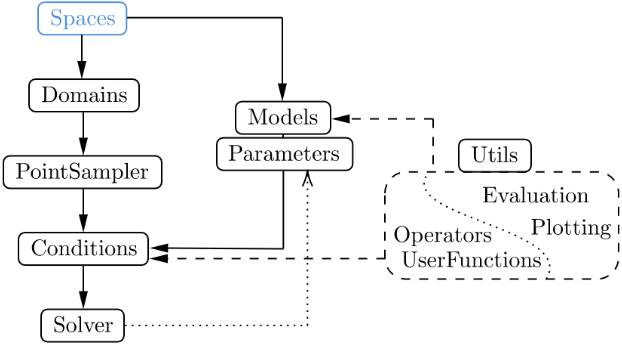


TorchPhysics
Spaces



TORCHPHYSICS

Spaces



Example: $\Omega = (0,1) \times (0,1)$

$$\begin{aligned} \Delta u(x) &= 1, \quad \text{for } x \in \Omega, \\ u(x) &= 0, \quad \text{for } x \in \partial\Omega. \end{aligned}$$

TorchPhysics
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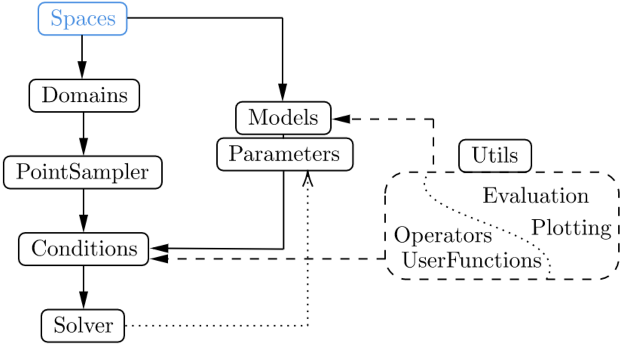

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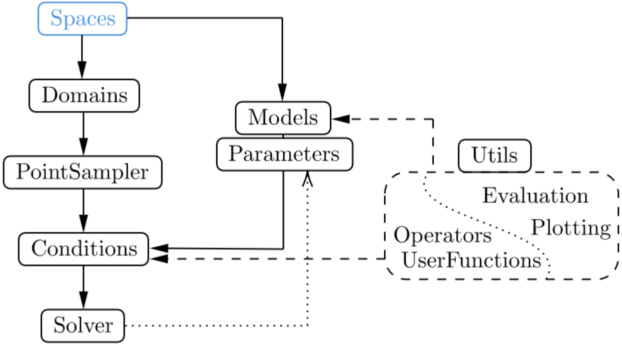

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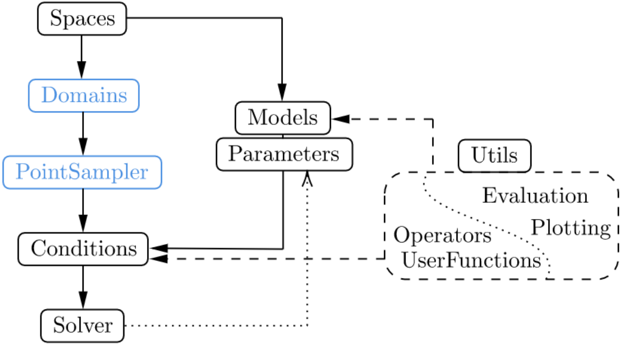
```python
import torchphysics as tp
X = tp.spaces.R2('x')
U = tp.spaces.R1('u')
```

TorchPhysics
Domains



Domains

- Basic geometries implemented:
  - `Point`, `Interval`, `Parallelogram`, `Circle`, ...

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```
omega = tp.domains.Parallelogram(X, [0,0], [1,0], [0,1])
```

PointSampler

- Creation of training/validation points inside of the domains
- Different types of sampling:
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omega = tp.domains.Parallelogram(X, [0,0], [1,0], [0,1])

inner_sampler = tp.samplers.RandomUniformSampler(omega,
                                                 n_points=15000)

boundary_sampler = tp.samplers.GridSampler(omega.boundary,
                                           n_points=5000)
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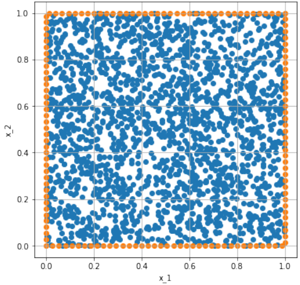
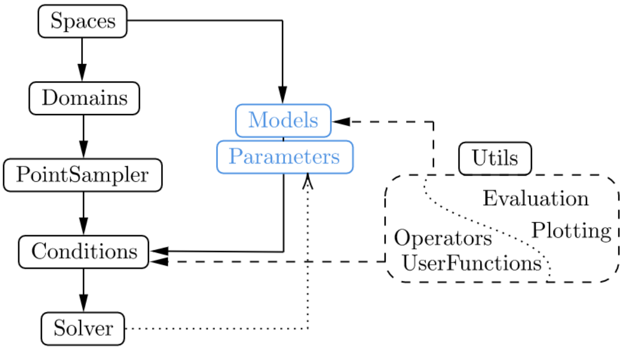


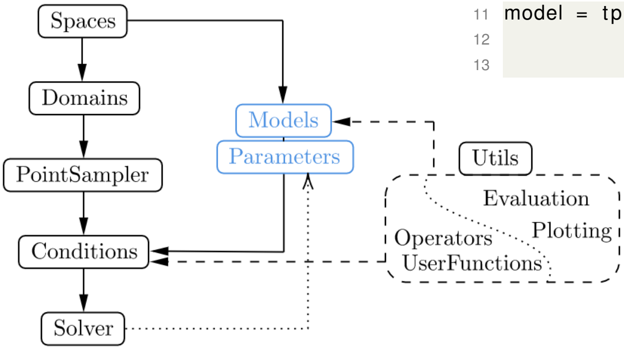
TorchPhysics
Neural Networks



TorchPhysics

Neural Networks

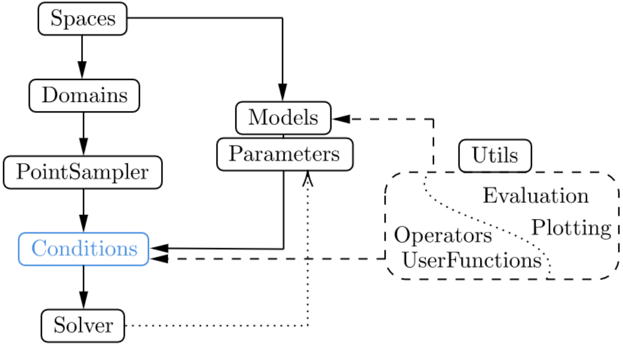
$$\Delta u(x) = 1$$




```python
model = tp.models.FCN(input_space=X,
                      output_space=U,
                      hidden=(20,20,20))
```

TorchPhysics

Conditions



Conditions

- Different types, e.g., PINNCondition
- Represents one mathematical condition, e.g.

$$\Delta u = 1 \text{ in } \Omega \qquad \text{or} \qquad u = 0 \text{ at } \partial\Omega$$

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```
def pde_residual(u, x):
    return tp.utils.laplacian(u, x) - 1.0

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```
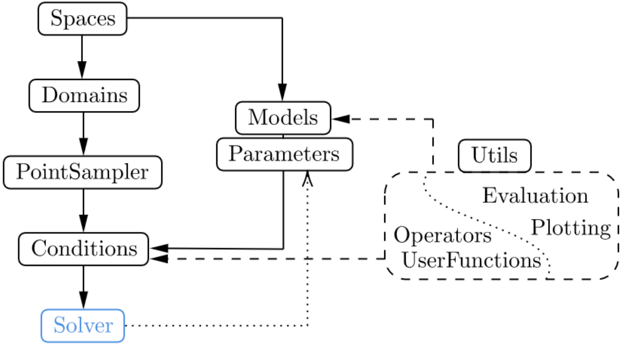

```
def boundary_residual(u):
    return u - 0.0

boundary_cond = PINNCondition(model,
                              boundary_sampler,
                              boundary_residual)
```

TorchPhysics

Solver



Solver

- Collects all conditions $\rightarrow$ overall loss computation
- Flexible choice optimization algorithm

```
optim = tp.OptimizerSetting(torch.optim.Adam, lr=0.001)
solver = tp.solver.Solver([boundary_cond, pde_cond],
                          optimizer_setting=optim))
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```
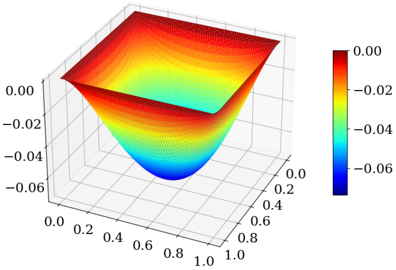

- Based upon PyTorch Lightning

```python
import pytorch_lightning as pl
trainer = pl.Trainer(devices=1, accelerator="gpu", # use one GPU
                     max_steps=3000) # iteration number
trainer.fit(solver)
```

Utils - Plot Results

$$\Delta u(x) = 1.0 \quad \text{for } x \in \Omega$$
$$u(x) = 0.0 \quad \text{for } x \in \partial\Omega$$



Learned solution of the PDE

```python
plot_sampler = tp.samplers.PlotSampler(plot_domain=omega,
                                        n_points=2000)
fig = tp.utils.plot(model, lambda u : u, plot_sampler)
```

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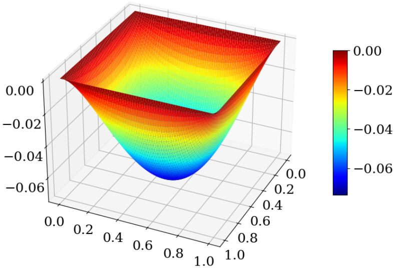

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Does your solution look like the one at the left?

First extension of the example

- Learning the time dependent Laplace equation (**heat equation**):

$$\begin{aligned} \partial_t u - 0.1\Delta u &= 1 \quad \text{in } \Omega \times (0,2) \\ u &= 0 \quad \text{on } \partial\Omega \times (0,2) \\ u(\cdot, 0) &= 0 \quad \text{in } \Omega \end{aligned}$$

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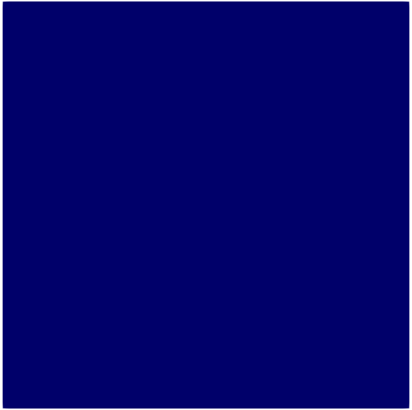
- Aspects to adjust:
  - Adding a time variable `t`, time interval and sample time points
  - One more input to the neural network
  - Adapt PDE-condition and implement initial condition
- Template: `Exercise_2.ipynb`

Choose your Track!

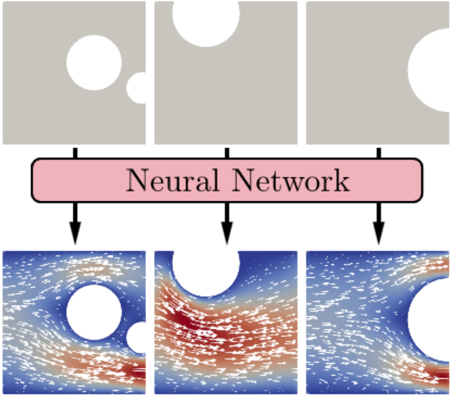
Track 1: Function Learning

- In-depth application of PINNs
- **Requires:**
  - The underlying PDE
  - **No** dataset
- **Goal:** compute unknown solution (once)
- Workshop examples:
  - Time-dependent domain
  - Inverse wave equation
  - Stokes equations



Track 2: Operator Learning

- Learn about PCA-Nets and FNOs
- **Requires:**
  - Underlying PDE is optional
  - A dataset
- **Goal:** learn parameter-function to solution mapping *(parameter studies)*
- Workshop examples:
  - Allen-Cahn equation
  - Stokes equations
  - Inverse Allen-Cahn equation



Track 1: Function Learning

3 p.m. at **6th floor**, room **Leibniz**

- In-depth application of PINNs
- **Requires:**
  - The underlying PDE
  - **No** dataset
- **Goal:** compute single solution
- Workshop examples:
  - Time-dependent domain
  - Inverse wave equation
  - Stokes equations

Track 2: Operator Learning

3 p.m. at **1st floor**, room **C.112**

- Learn about PCA-Nets and FNOs
- **Requires:**
  - Underlying PDE is optional
  - A dataset
- **Goal:** learn parameter-function to solution mapping *(parameter studies)*
- Workshop examples:
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