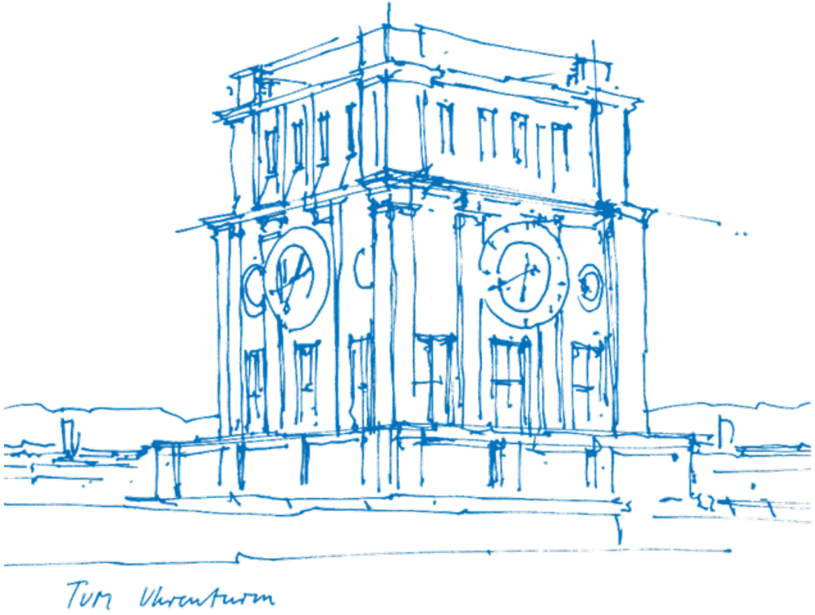
Deep Learning Methods for Reynolds-Averaged Navier-Stokes Simulations of Airfoil Flows



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Munich, 11. May 2020

Introduction

TODO

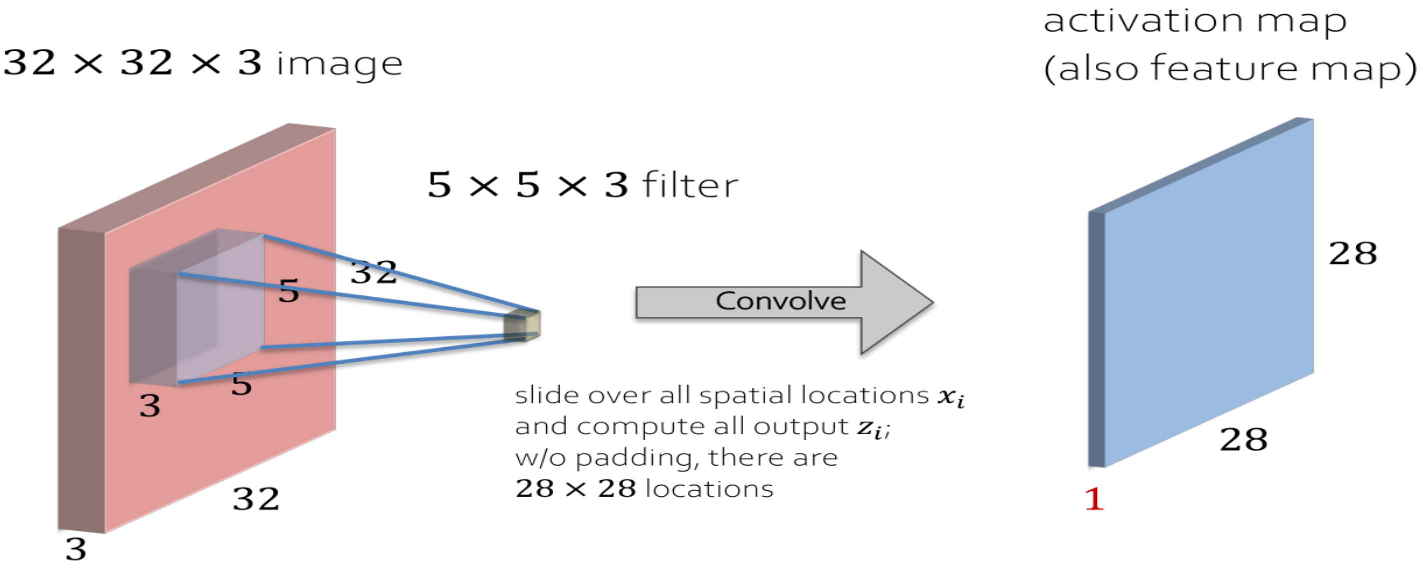
Background – RANS

TODO

Background – RANS

TODO

Background – Convolutions



$32 \times 32 \times 3$ image

$5 \times 5 \times 3$ filter

Convolve

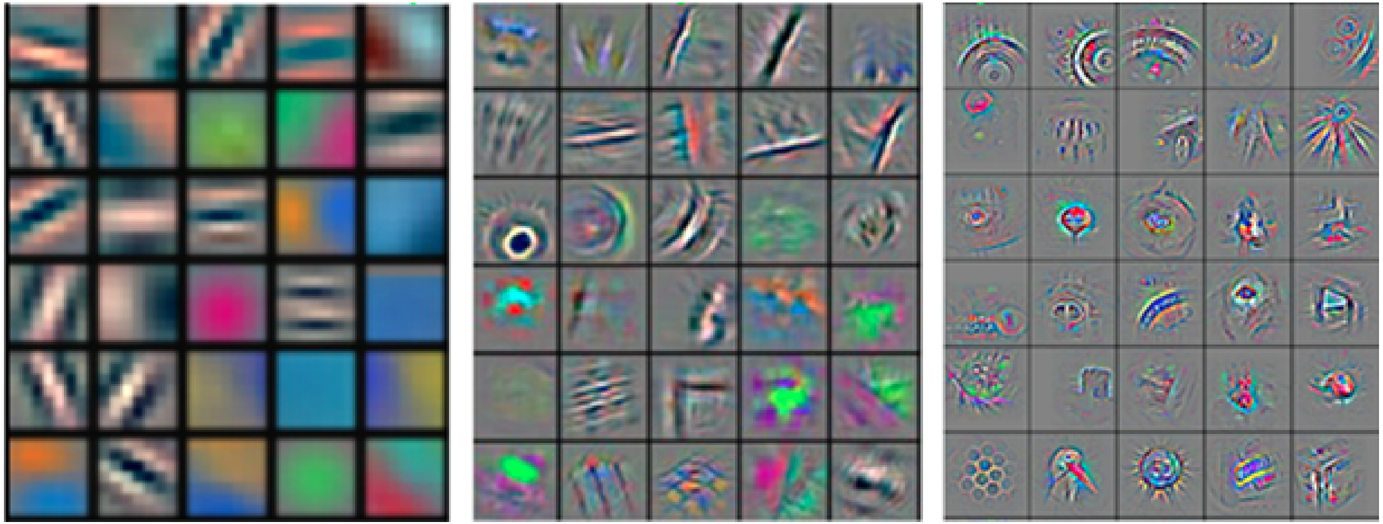
slide over all spatial locations x_i and compute all output z_i; w/o padding, there are 28×28 locations

activation map (also feature map)

Taken from I2DL WS19/20 (TUM)

Background – Convolutions

Low-Level Features, Mid-Level Features, High-Level Features: each filter captures different characteristics



Taken from `https://arxiv.org/pdf/1311.2901.pdf`

Data Generation

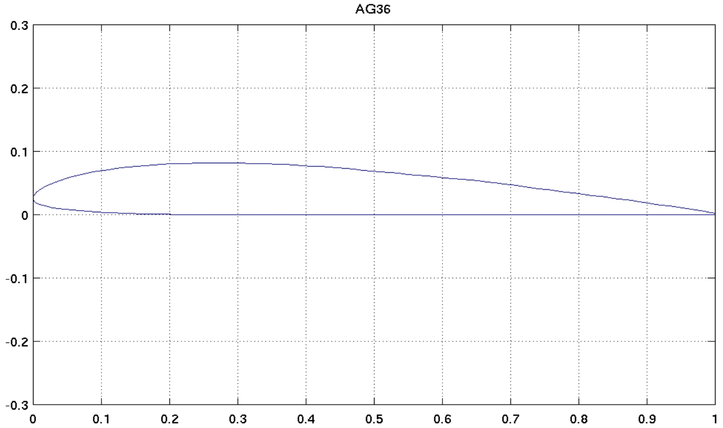
Airfoil shapes are provided by the UIUC database

Reynolds number: $[0.5, 5] \cdot 10^6$ (highly turbulent)

Angle of attack: $[-22.5, 22.5]$

Ground truth generated with OpenFOAM
(pressure, x velocity, y velocity)

Training data resolution: $3 \times 128 \times 128$



Pre-processing – Data

Input channels

1. Bit mask representing airfoil shape
2. x velocity component
3. y velocity component

Reynolds number encoded as differently scaled freestream velocity vectors wrt. their magnitude

Target channels

1. Pressure field
2. x velocity field
3. y velocity field

Data from the RANS solution

Pre-processing – Normalization

Motivation: Flatten space of solutions, accelerate learning by simplifing the learning task for the NN

Normalization of target channels by division with freestream magnitude (vector norm, default: L2):
This makes pressure and velocity dimensionless

$\tilde{v_o} = \frac{v_o}{\|v_i\|}, \quad \tilde{p_o} = \frac{p_o}{\|v_i\|^2}$ – important to remove quadratic scaling of pressure

For a better understanding:
Pressure: $[p]_{SI} = 1\,Pa = 1\,\frac{kg}{m \cdot s^2}$
Density: $[\rho]_{SI} = 1\,\frac{kg}{m^3}$ – constant in incompressible flow
Velocity: $[v]_{SI} = \frac{m}{s}$

Pre-processing – Offset removal & value clamping

Motivation: eliminate ill-posed learning goal & improve numerical precision

Spatially move pressure distribution into the origin – RANS typically only needs ∇_p for computation

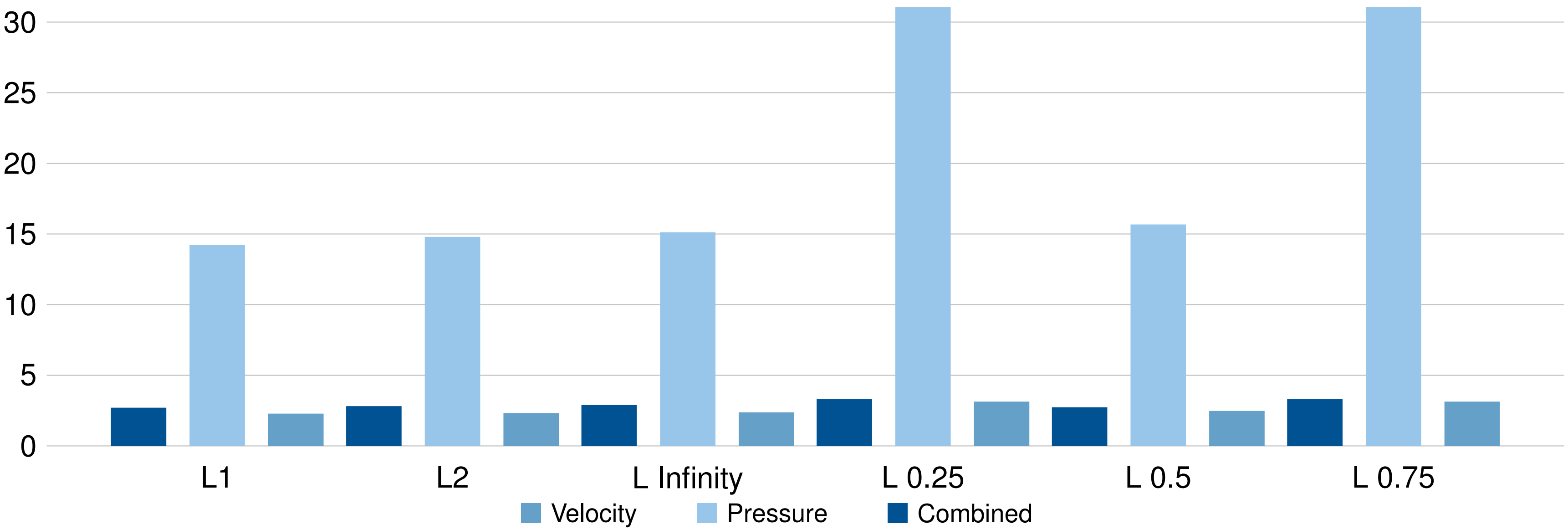
$$\hat{p}_o = \tilde{p}_o - p_{mean}$$

Clamp both input and target channels into $[-1, 1]$ range by diving by the maximum absolute value

Pre-processing – Evaluation

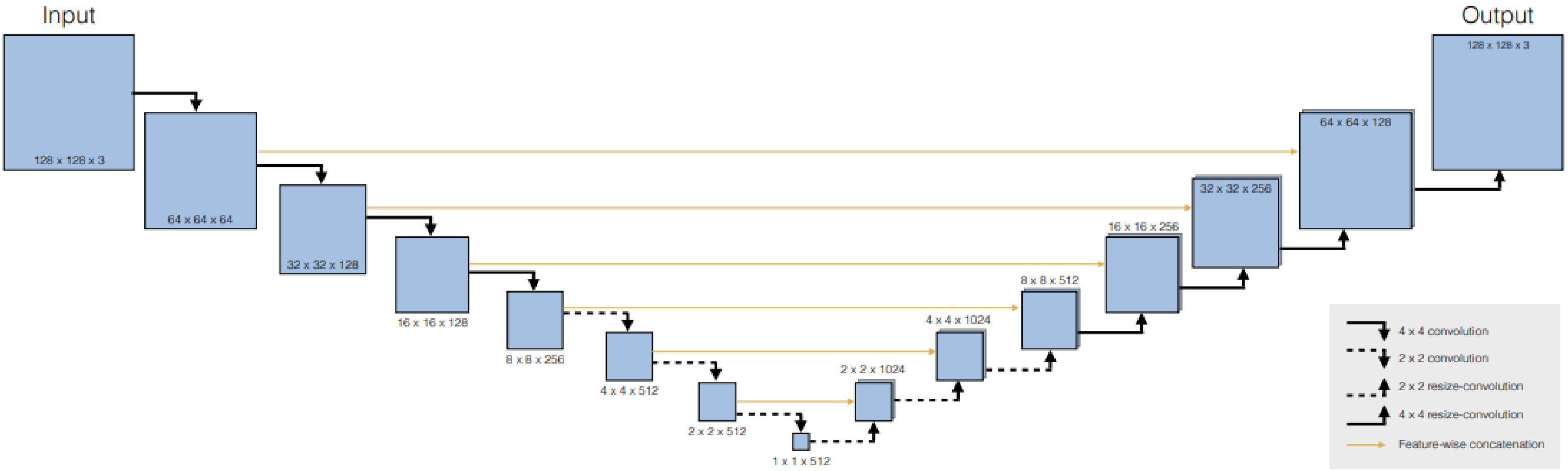
Vector norms used in pre-processing comparision wrt. error, default: L2 (in %)

L1 normalization achieves the best error rates (p, vel, combined: **14.19**%, **2.251**%, **2.646**% – L2: 14.76%, 2.291%, 2.780%)



Architecture

U-Net derivative proposed in the paper:



Taken from `https://arxiv.org/pdf/1810.08217.pdf`

Architecture – Convolutional blocks

Encoder

1. Activation – Leaky ReLu (0.2)
2. Convolution – Width down, Depth up
3. Batch normalization
4. Dropout (1%)

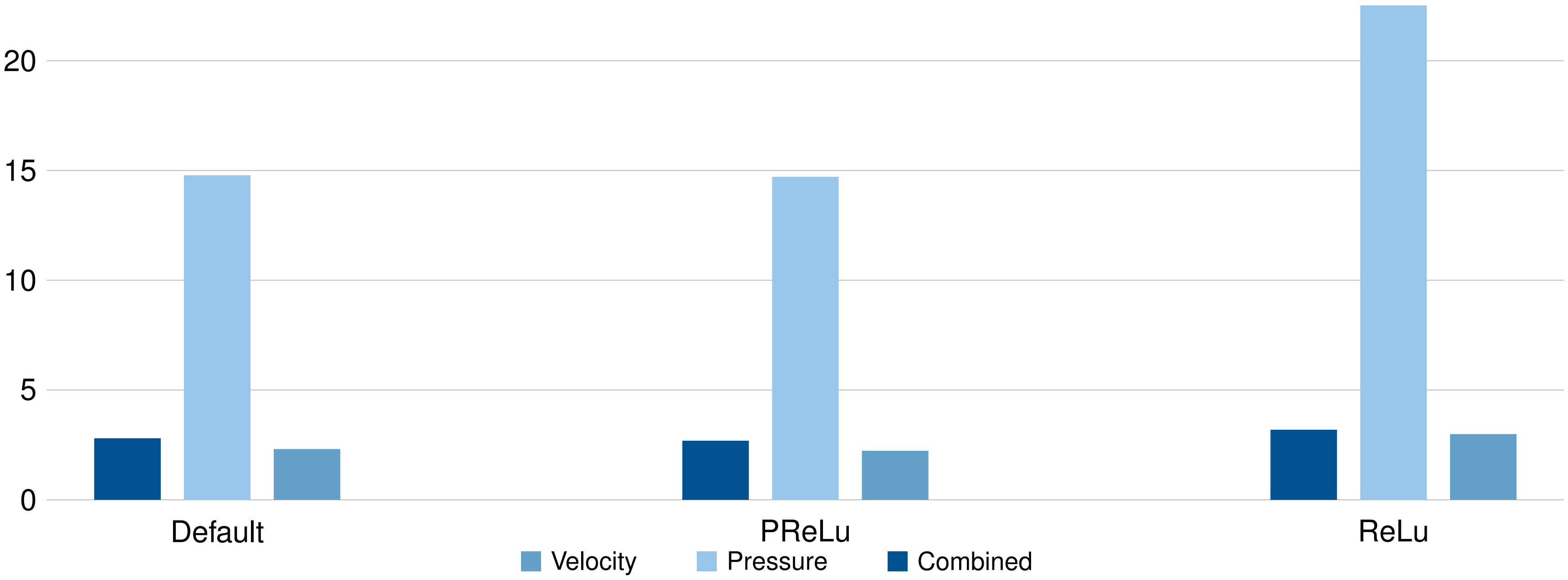
Decoder

1. Activation – ReLu
2. Upsampling – linear (2.0)
3. Convolution – Width up, Depth down
4. Batch normalization
5. Dropout (1%)

Architecture – Evaluation

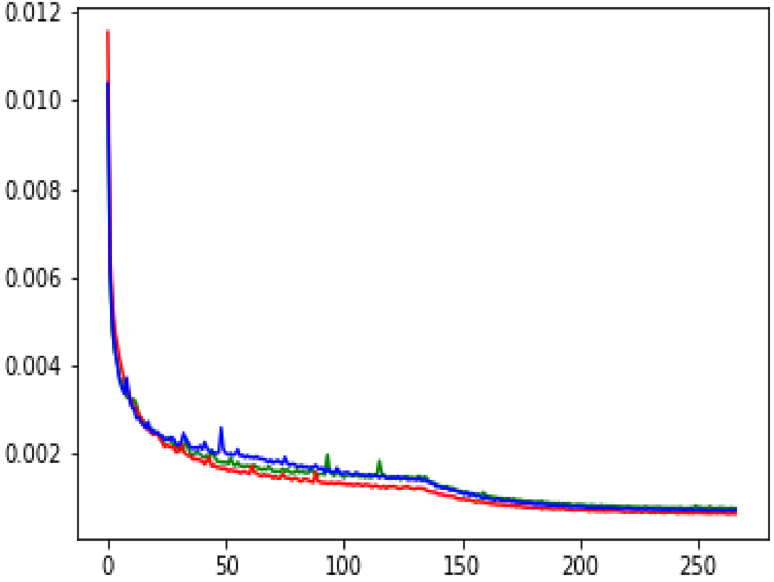
Error percentage of different activation functions after 160k iterations (266 epochs).

PReLu achieves the best error rates (p, vel, combined: **14.69**%, **2.216**%, **2.676**% – Default: 14.76%, 2.296%, 2.787%)

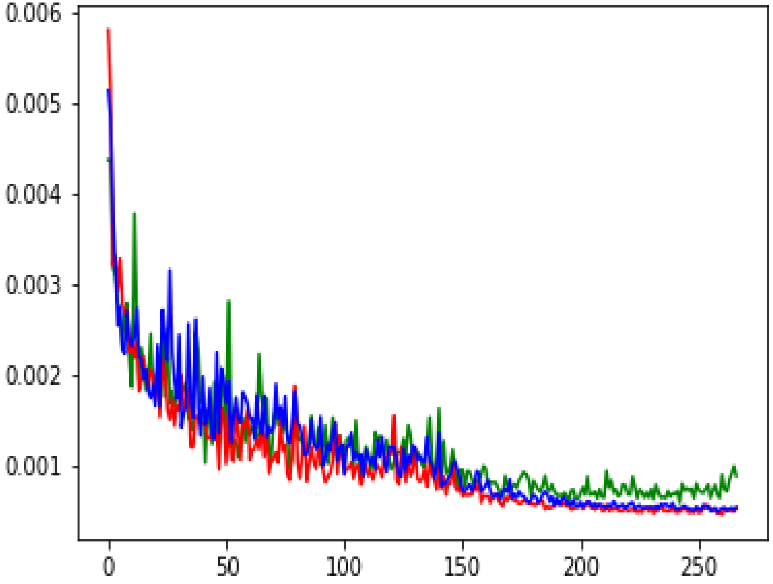


Architecture – Evaluation

Training loss



Validation loss



Transfer

Motivation: Can the network architecture adapt to other PDE systems and how well will it perform?

Another use case for PDE systems like RANS is predicting wave propagation on shallow water

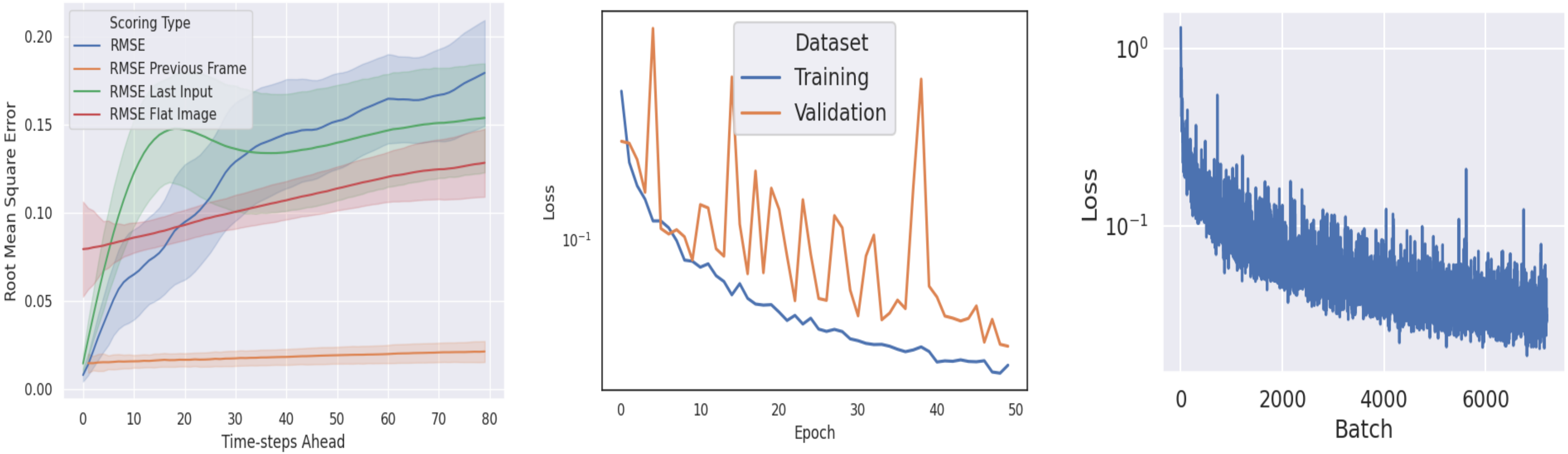
Wave propagation, in this case, is governed by the Saint-Venant equations (related with Navier-Stokes equations)

U-Net architecture changes:

- Input channels – contain the last *n* time steps
- Output channels – predict the next *m* time steps
- Output is refeeded as input to predict time series

Transfer – Evaluation

RMSE with variance, validation loss and batch loss on Bigger Tub environment:

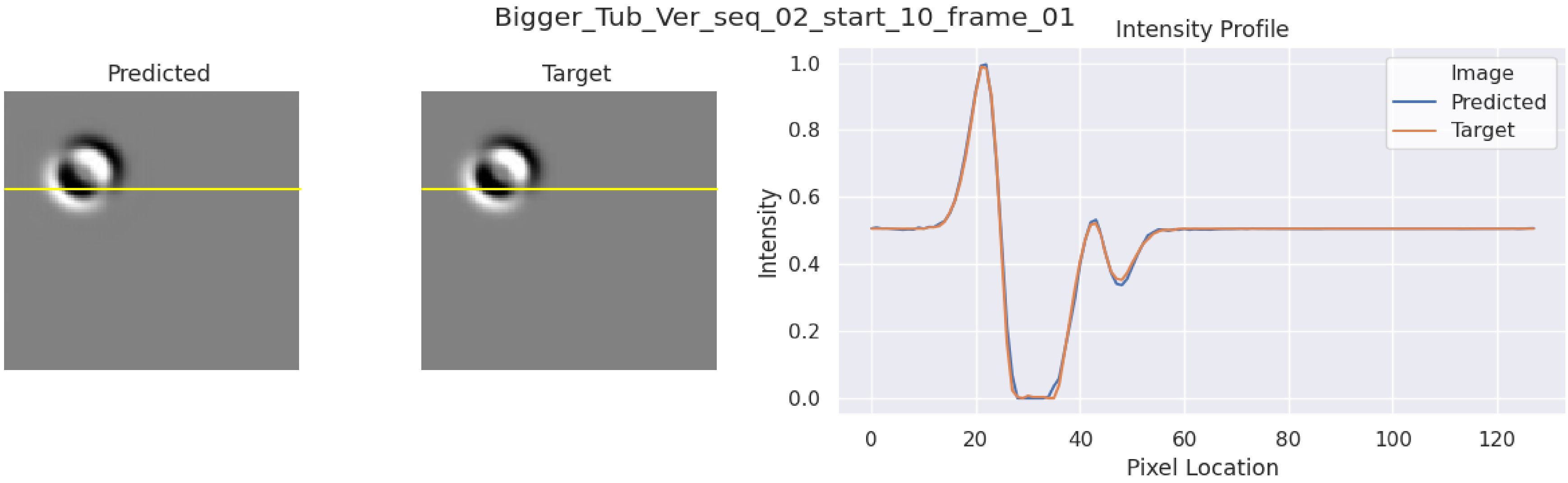


All plots in Transfer were made with `https://github.com/stathius/wave_propagation`

Transfer – Evaluation

Wave propagation prediction

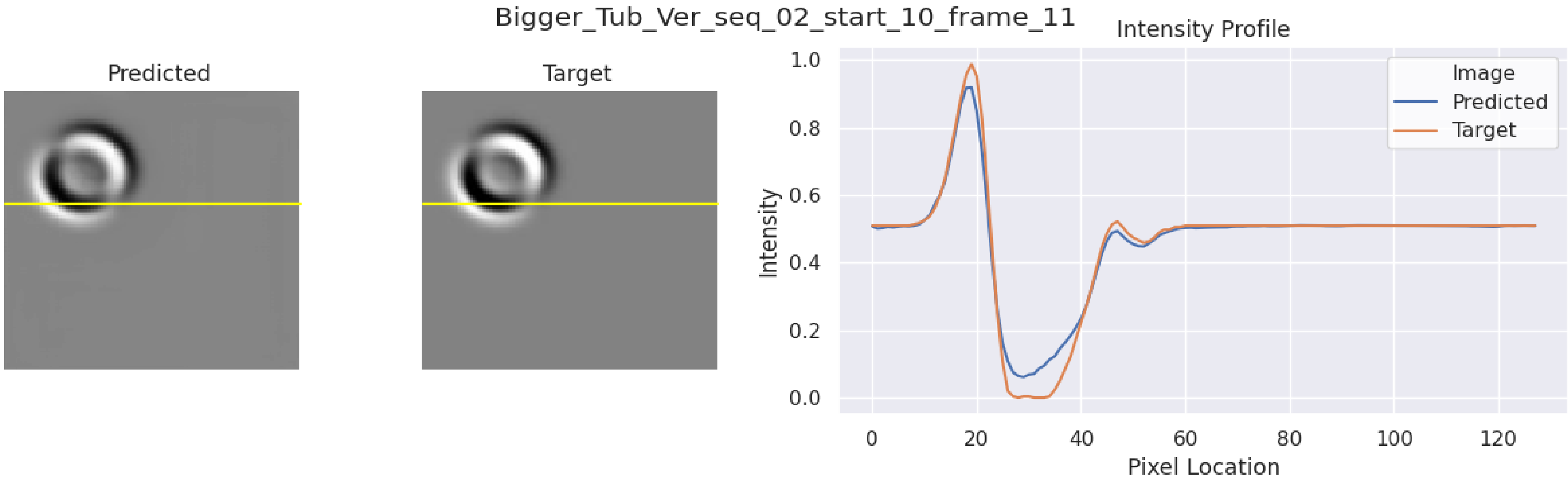
Intensity profile on scanline – Frame 1



Transfer – Evaluation

Wave propagation prediction

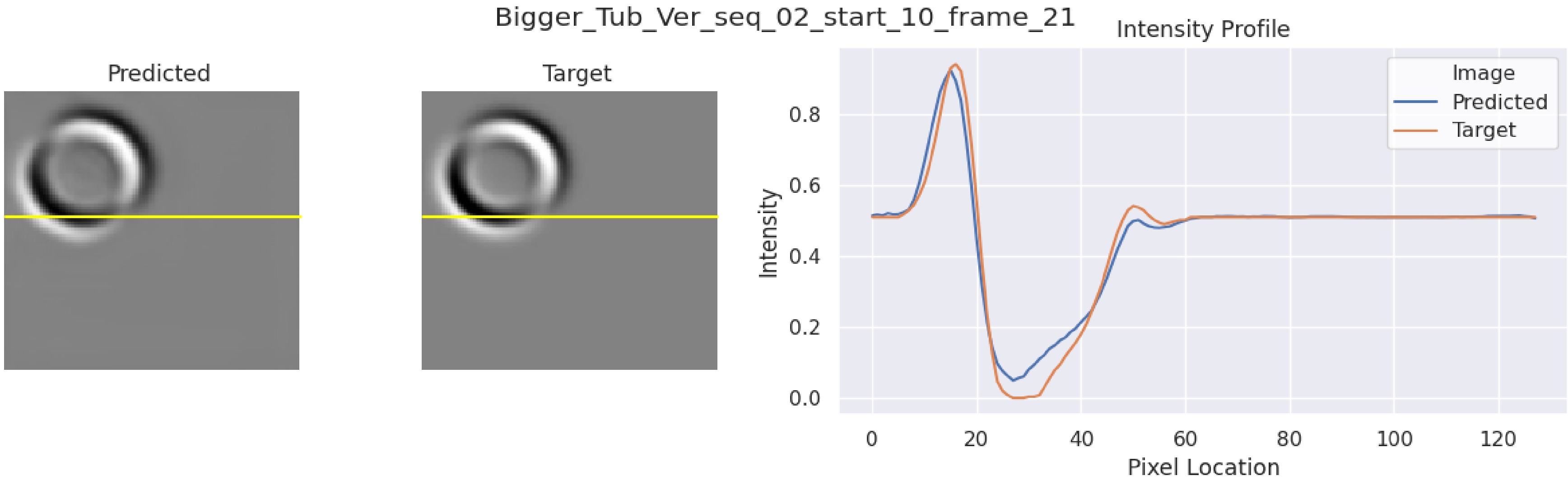
Intensity profile on scanline – Frame 11



Transfer – Evaluation

Wave propagation prediction

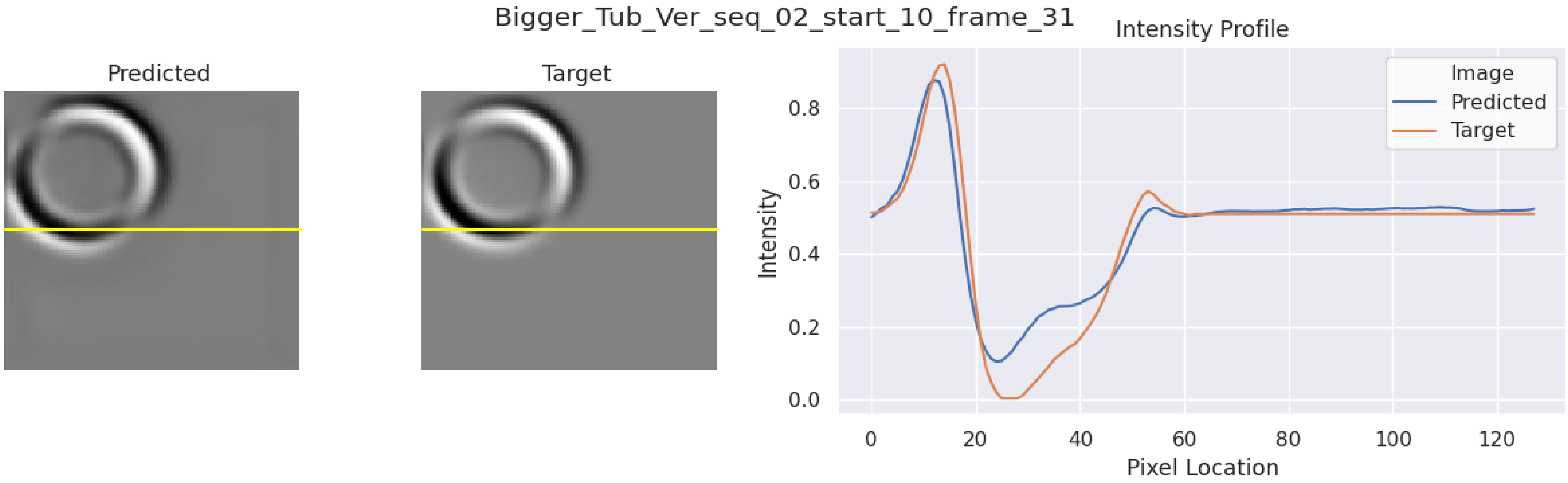
Intensity profile on scanline – Frame 21



Transfer – Evaluation

Wave propagation prediction

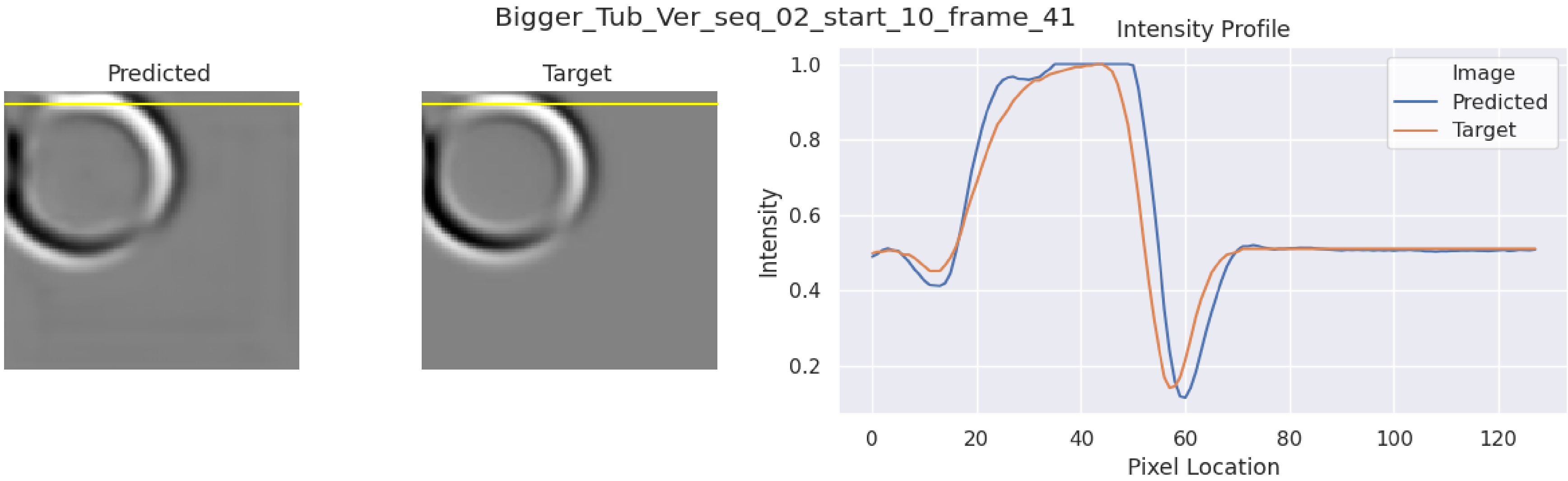
Intensity profile on scanline – Frame 31



Transfer – Evaluation

Wave propagation prediction

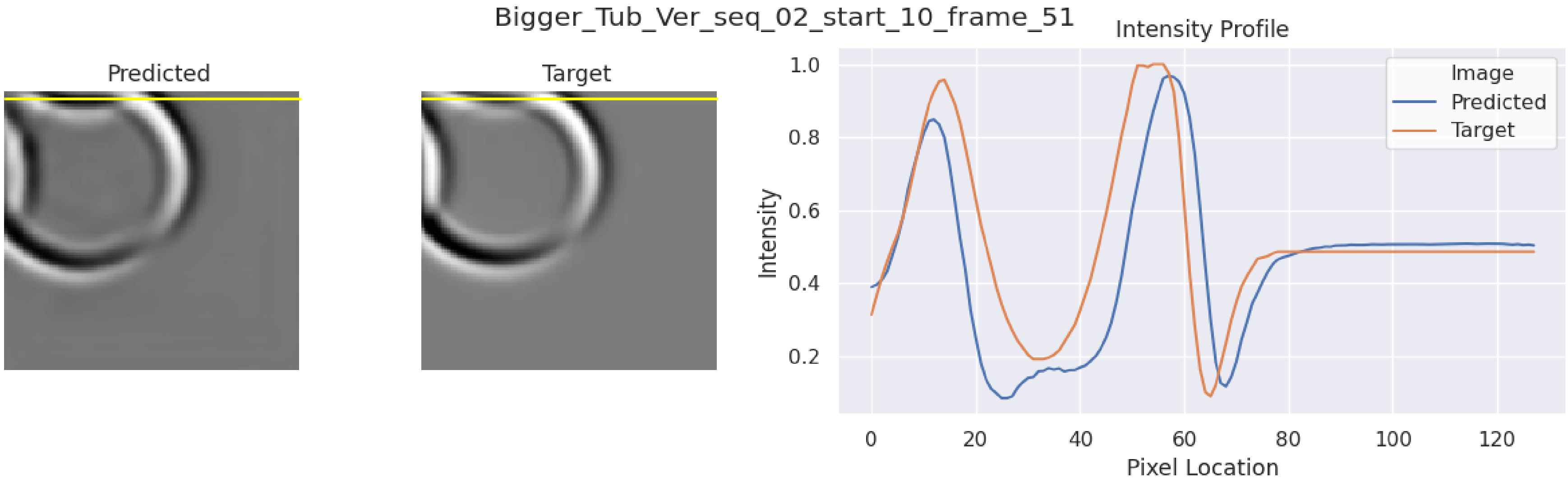
Intensity profile on scanline – Frame 41



Transfer – Evaluation

Wave propagation prediction

Intensity profile on scanline – Frame 51

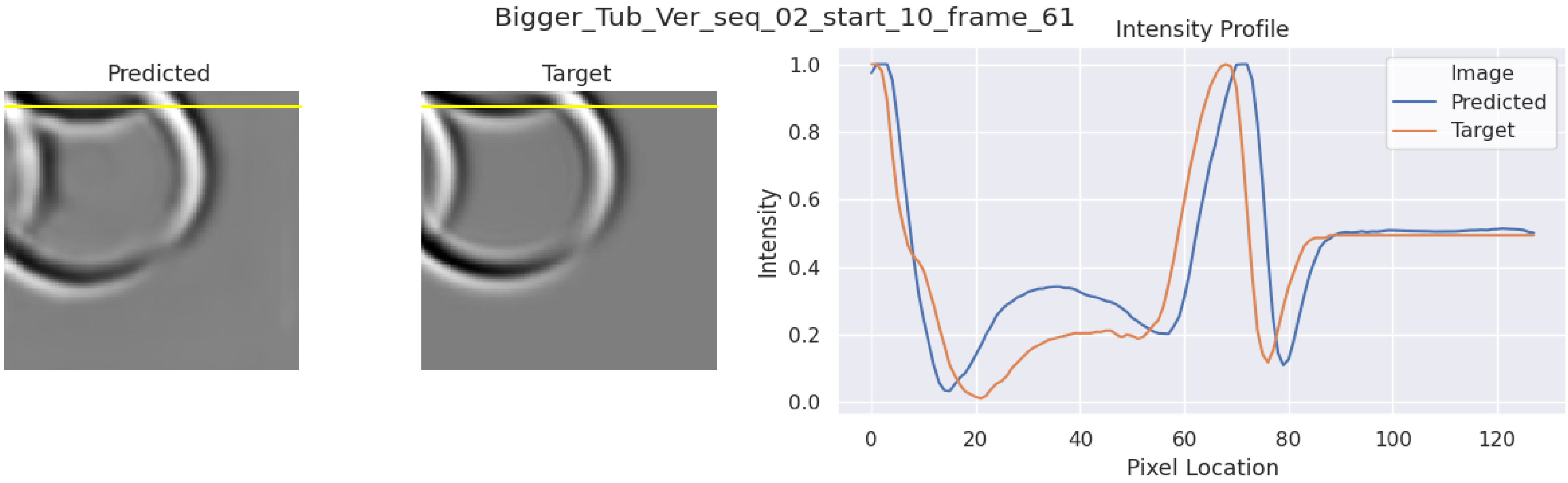


Bigger_Tub_Ver_seq_02_start_10_frame_51

Transfer – Evaluation

Wave propagation prediction

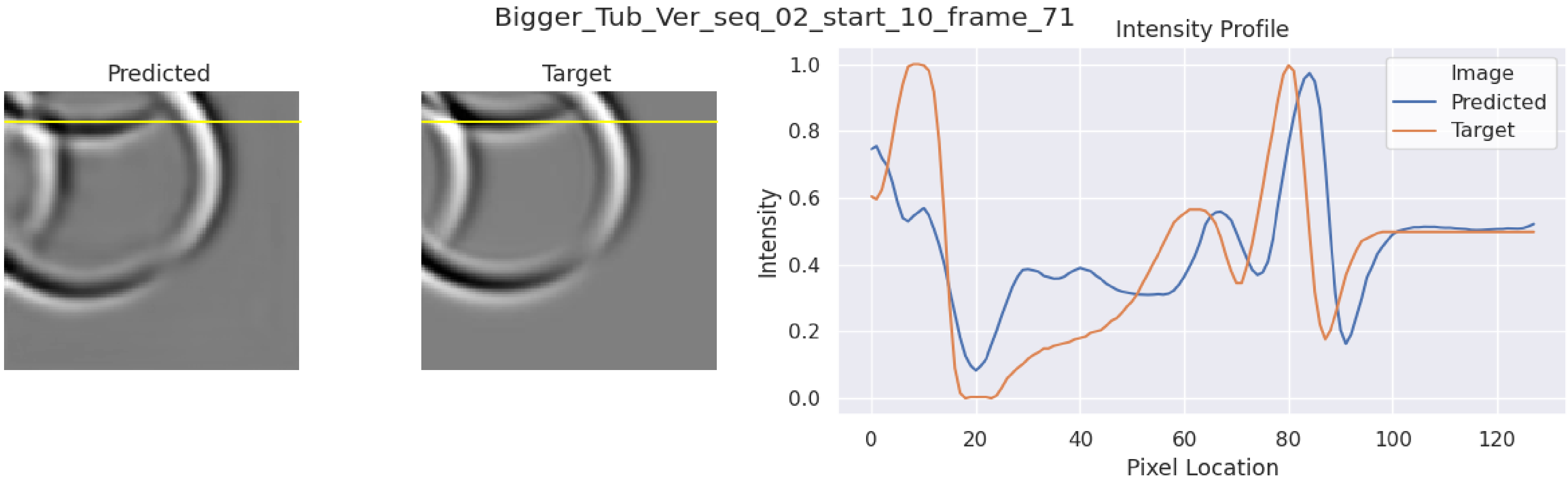
Intensity profile on scanline – Frame 61



Transfer – Evaluation

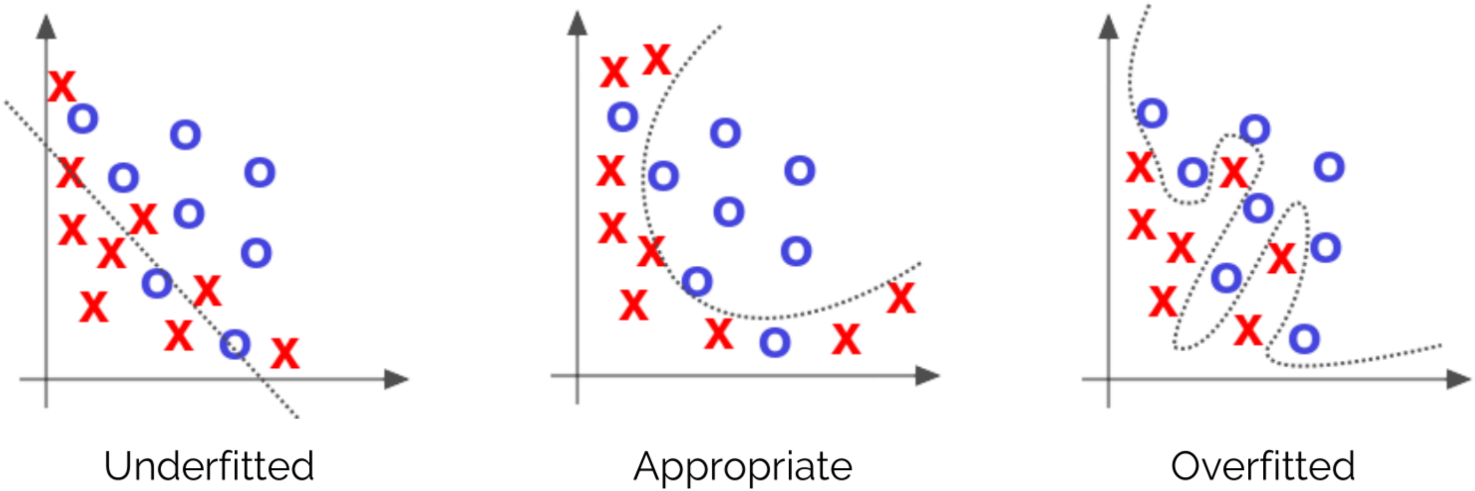
Wave propagation prediction

Intensity profile on scanline – Frame 71



Generalization

Motivation: Key question in deep learning: How well does my NN perform on unseen data?



Taken from Deep Learning by Adam Gibson, Josh Patterson, O'Reily Media Inc., 2017

Generalization

To test generalization new datasets need to be created

Generation of 1 training sample: $\approx$ 70 seconds (using Google Colab)

Generation of 12.8k training samples: $>$ 10 days – not feasible

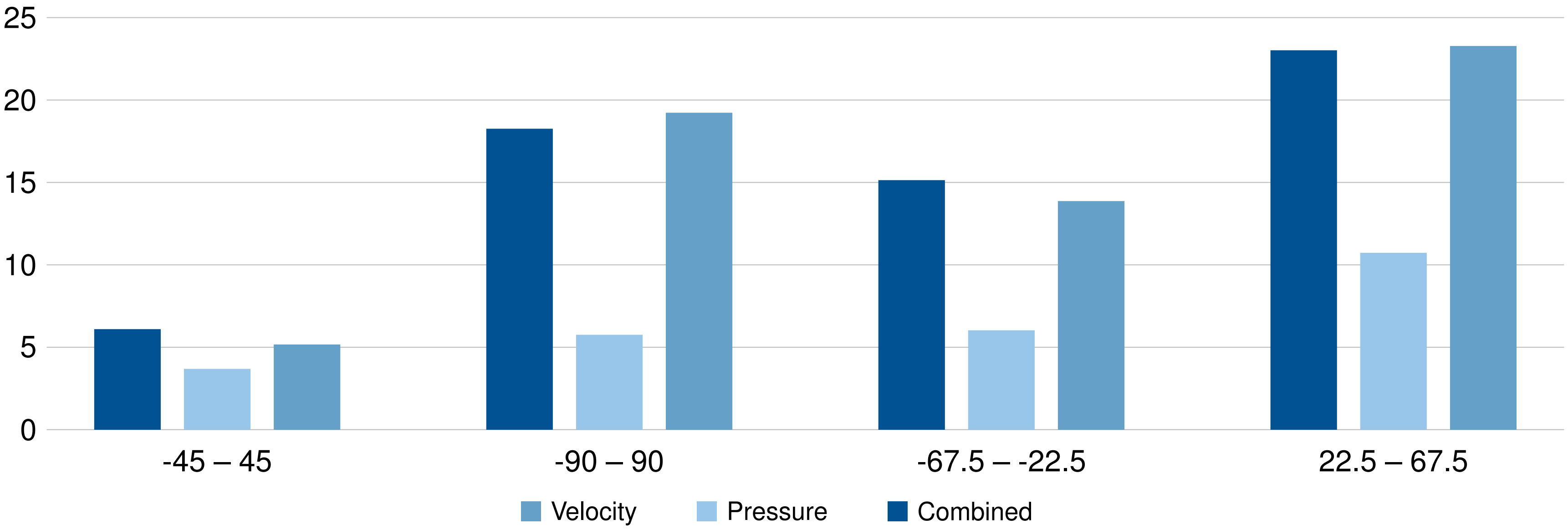
$\implies$ Generate only new test sets containing 90 samples: $<$ 2 hours – feasible

Extrapolation with different angle of attack intervals, default: $[-22.5, 22.5]$:

- $[-45, 45]$
- $[-90, 90]$
- $[-67.5, -22.5]$
- $[22.5, 67.5]$

Generalization – Evaluation

Error increase of different angle of attack intervals wrt. ground truth $[-22.5, 22.5]$



Discussion

Positiv

- Relative error $< 3\%$
- Convolutions paired with an encoder decoder structure seem to catch regions of interest fast and reliable
- U-Nets can outperform LSTM's in accuracy as well as in speed with a fraction of capacity (in time-series problems)
- accuracy does not suffer too much from models with a lot less capacity mostly affects sharpness of solutions
- Inference speed is $1000\times$ when compared with OpenFOAM solver
- Accuracy improvements still possible (bigger models, more training data)

Discussion

Negativ

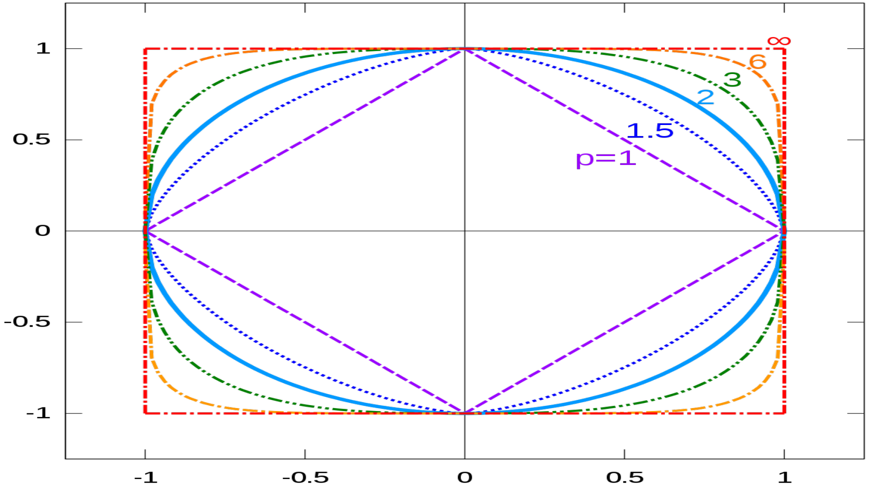
- Proir knowledge needed for proper pre-processing
- Solvers needed for dataset generation
- Extrapolation yields mediocre results
- Fresh Training needed for other shapes (e.g. cars in wind tunnel)
  - – transfer learning unlikely
- Trade off: training speed – grid resolution
- Possible data loss from transformation:
  adaptive grid (solver) $\Longrightarrow$ cartesian grid (NN)
- no guarantee for correctness
- Accuracy improvements computationally expensive likely requires
  tailored architectures and loss functions

Summary

TODO

Backup slides

Backup slides – Norms on unit circle



Backup slides – Training Setup

Adam optimizer ($\beta_1 = 0.5, \beta_2 = 0.999$)

Learning rate: 0.0004

Learning rate decay: On

Batch size: 10

Iterations: 80000

Model parameters:
122.979,   487.107,   1.938.819,   7.736.067,   30.905.859