A Neural Network Surrogate for Predicting the Healing of Burn Injuries.

By Marianne Schaaphok

Outline

1 Research objective

2 Literature review
Approach

3 Numerical Model
Neural Network

4 Results

5 Conclusion
What's next

Research objective

“Can we find a cheaper method, using neural networks, to reproduce expensive numerical models for the healing of burn injuries.”

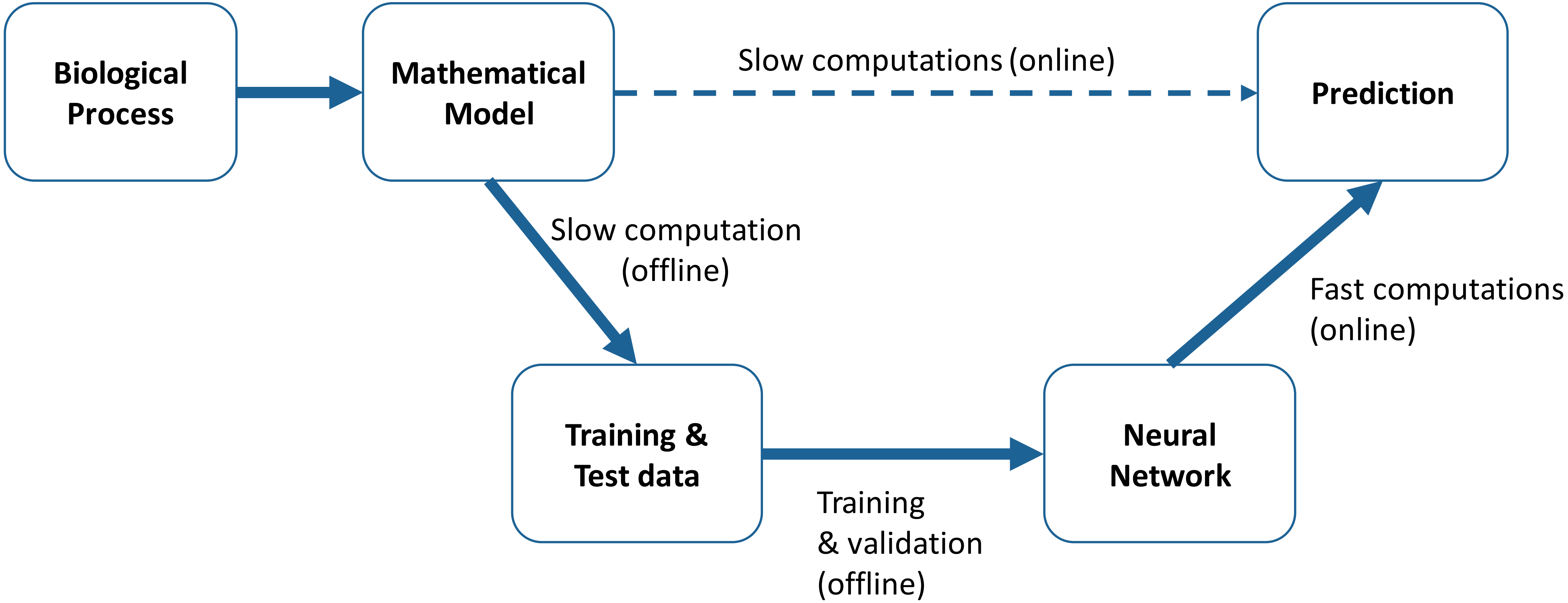
Literature research

Surrogate Neural Network

+ Fast predictions after training
+ Easy implementation
+ Freedom to choose input & output

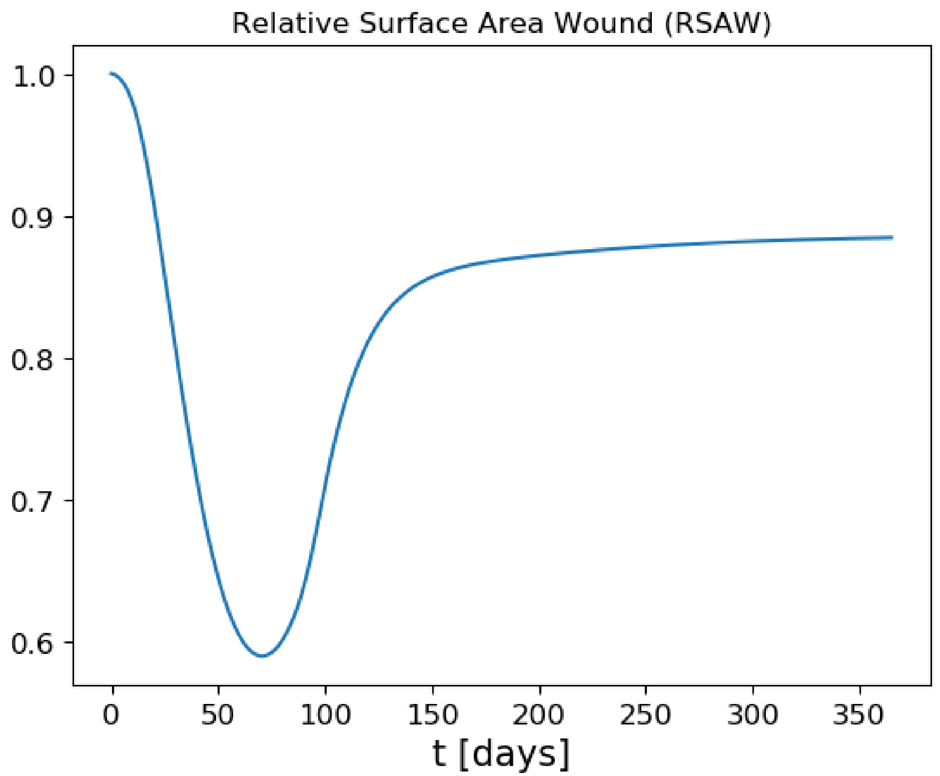
- Needs training data from original model
- Loss of physical interpretation

Approach


Biological Process
Mathematical Model
Slow computations (online)
Prediction
Slow computation (offline)
Fast computations (online)
Training & Test data
Neural Network
Training & validation (offline)

Numerical Model

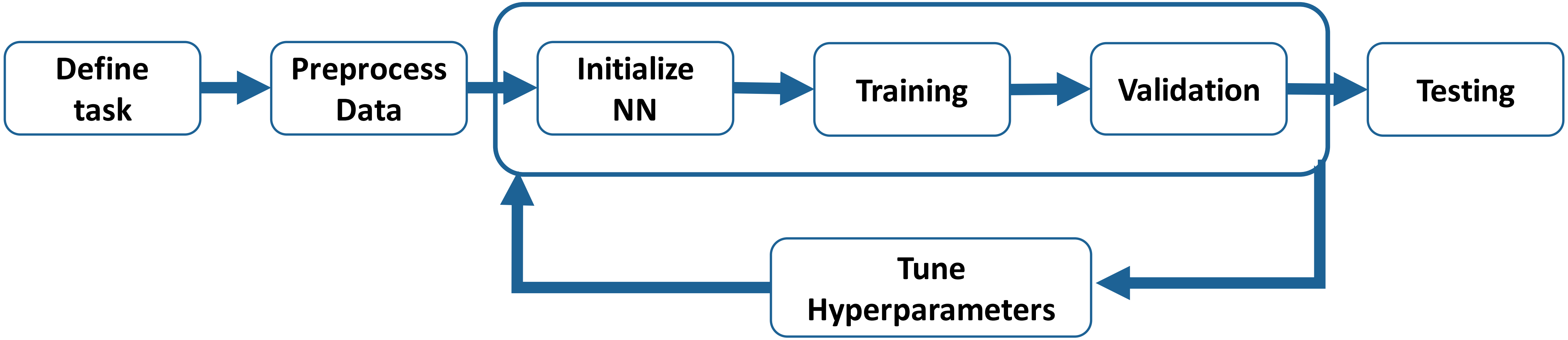
- 1D morphoelastic FEM model for burn injuries
- Predicts:
  - Relative Surface Area Wound (RSAW)
  - Concentrations in time and space
  - Mechanical values in time and space
- Simulation ≈ 2 min



Dataset

- 4 age groups: 0-10, 11-40, 41-70,71+
- Uniform drawn inputs
- Total 12000 simulations
- Training, validation and test set

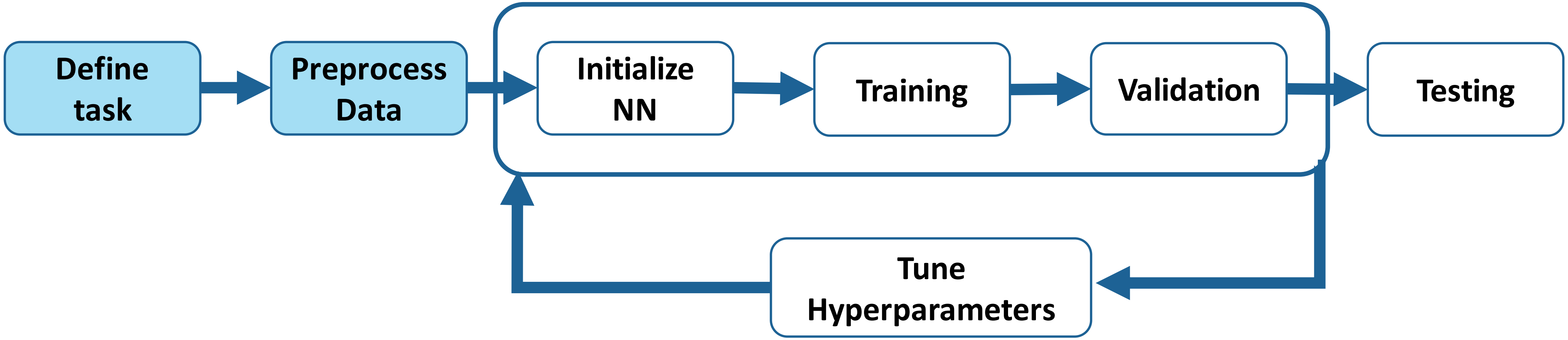
Neural Networks

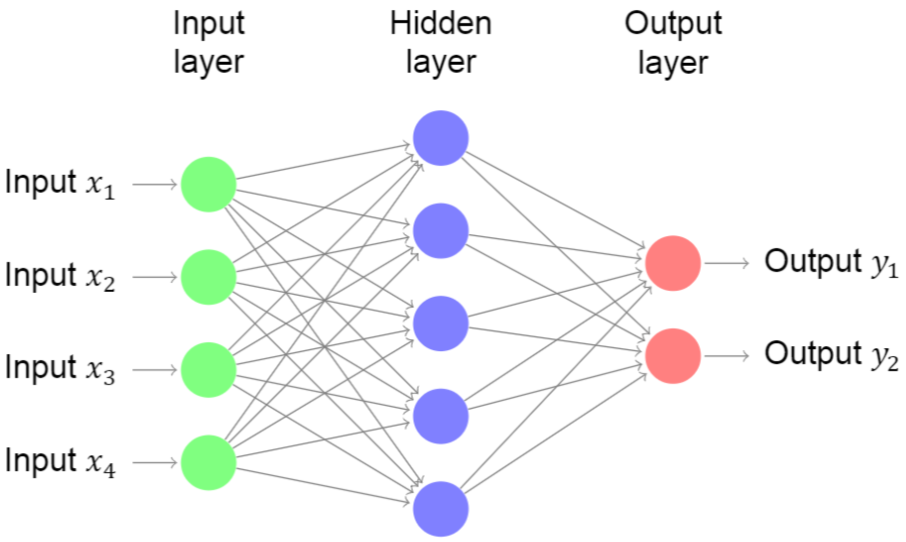


- Objective – RSAW
- Performance measure:

$$\frac{1}{n}\sum\frac{|\hat{y}_i - y_i|}{|y_i|}\cdot 100 + \frac{|\backslash\min\hat{\boldsymbol{y}} - \min\boldsymbol{y}|}{|\min\boldsymbol{y}|}\cdot 100$$

Neural Networks



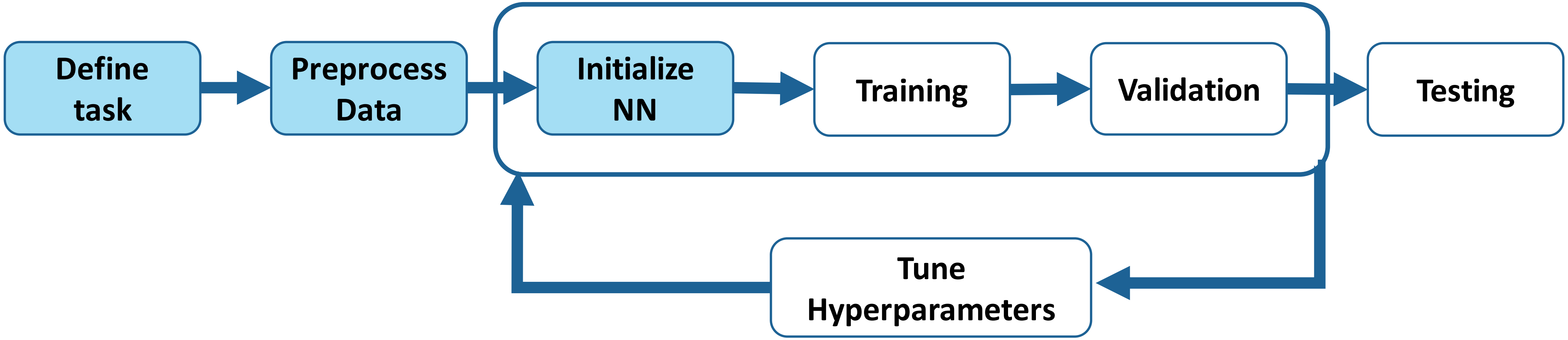


- Type: Feedforward Neural Network

- Hidden layer: $\boldsymbol{h} = g_1(W_1\boldsymbol{x} + \boldsymbol{b}_1)$
- Output layer: $\boldsymbol{y} = g_2(W_2\boldsymbol{h} + \boldsymbol{b}_2)$

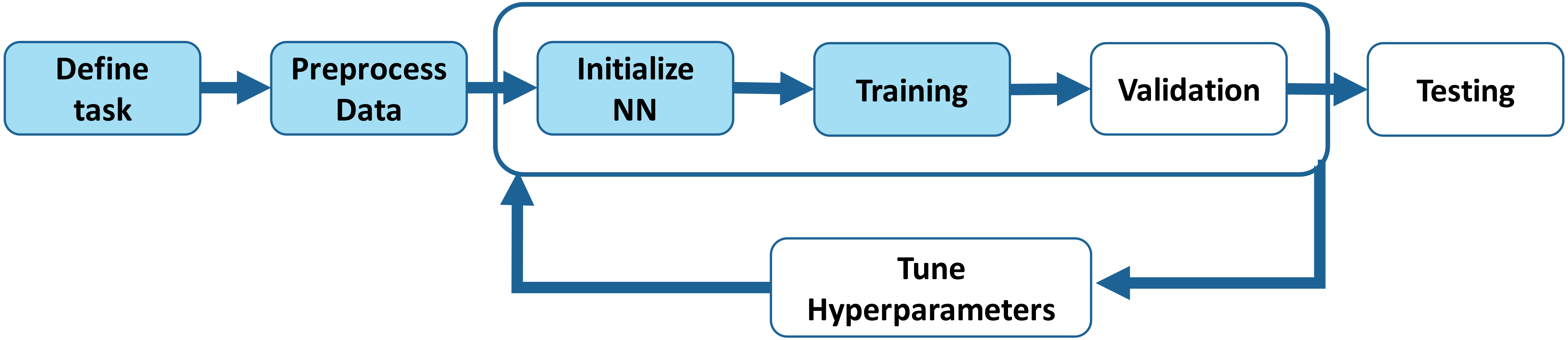
- Learnable parameters: $W_1, W_2, \boldsymbol{b}_1, \boldsymbol{b}_2$

Neural Networks



- Forward propagation : Compute prediction $\hat{y}_i$, and loss $L(\hat{y}_i, y_i)$
- Backward propagation: Compute gradients $\nabla_{\mathrm{W}}\mathrm{L}$ and $\nabla_{\boldsymbol{b}}L$
- Optimization: Update W and **b** to optimize loss

Neural Networks



- Compute predictions
- Compute performance

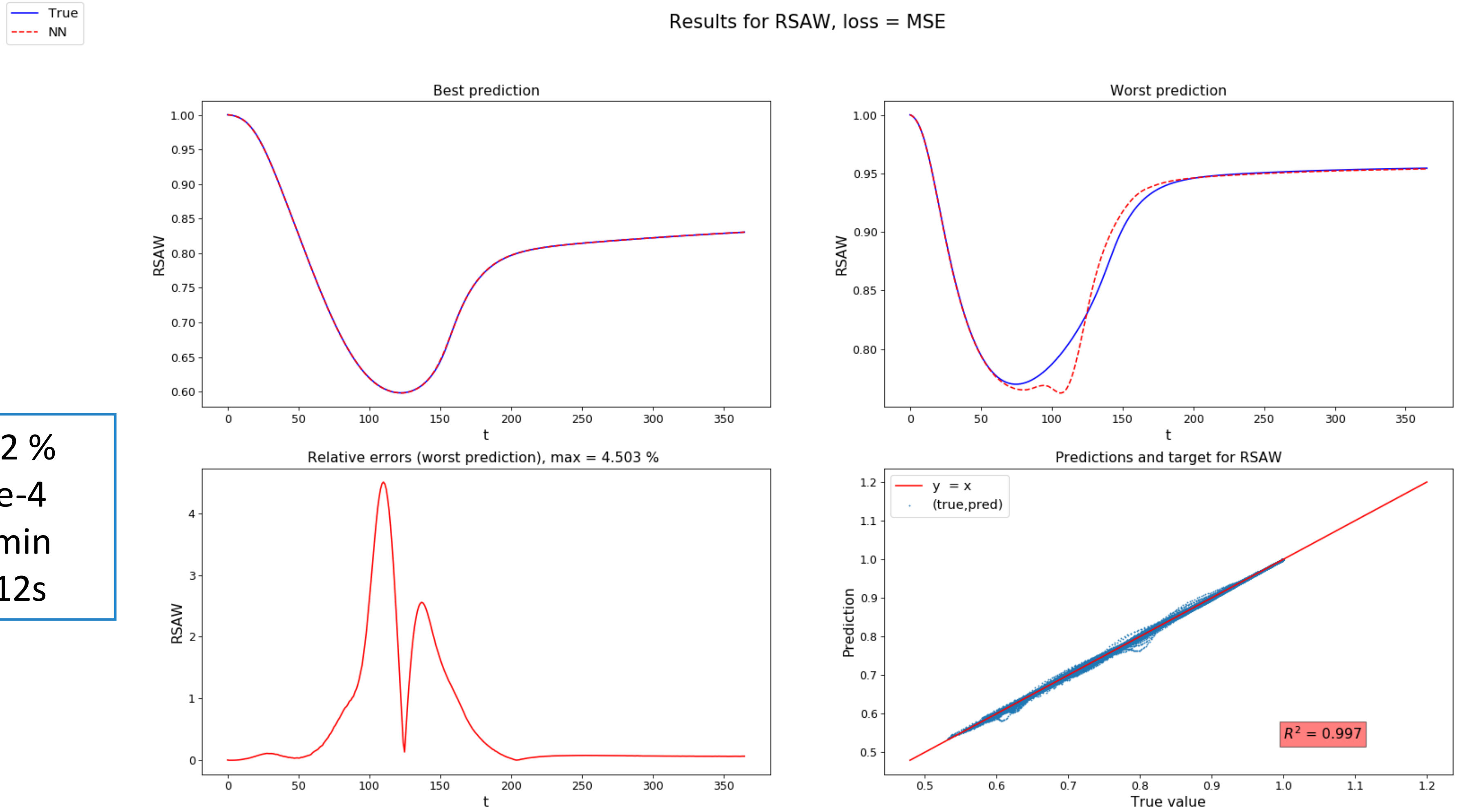
Results - Baseline

Parameters

1 layers
25 neurons
ReLU activation
MSE loss

Performance

P (1%): 99.2 %
Validation loss: 3.2e-4
Training time: 22 min
Prediction time: 0.312s



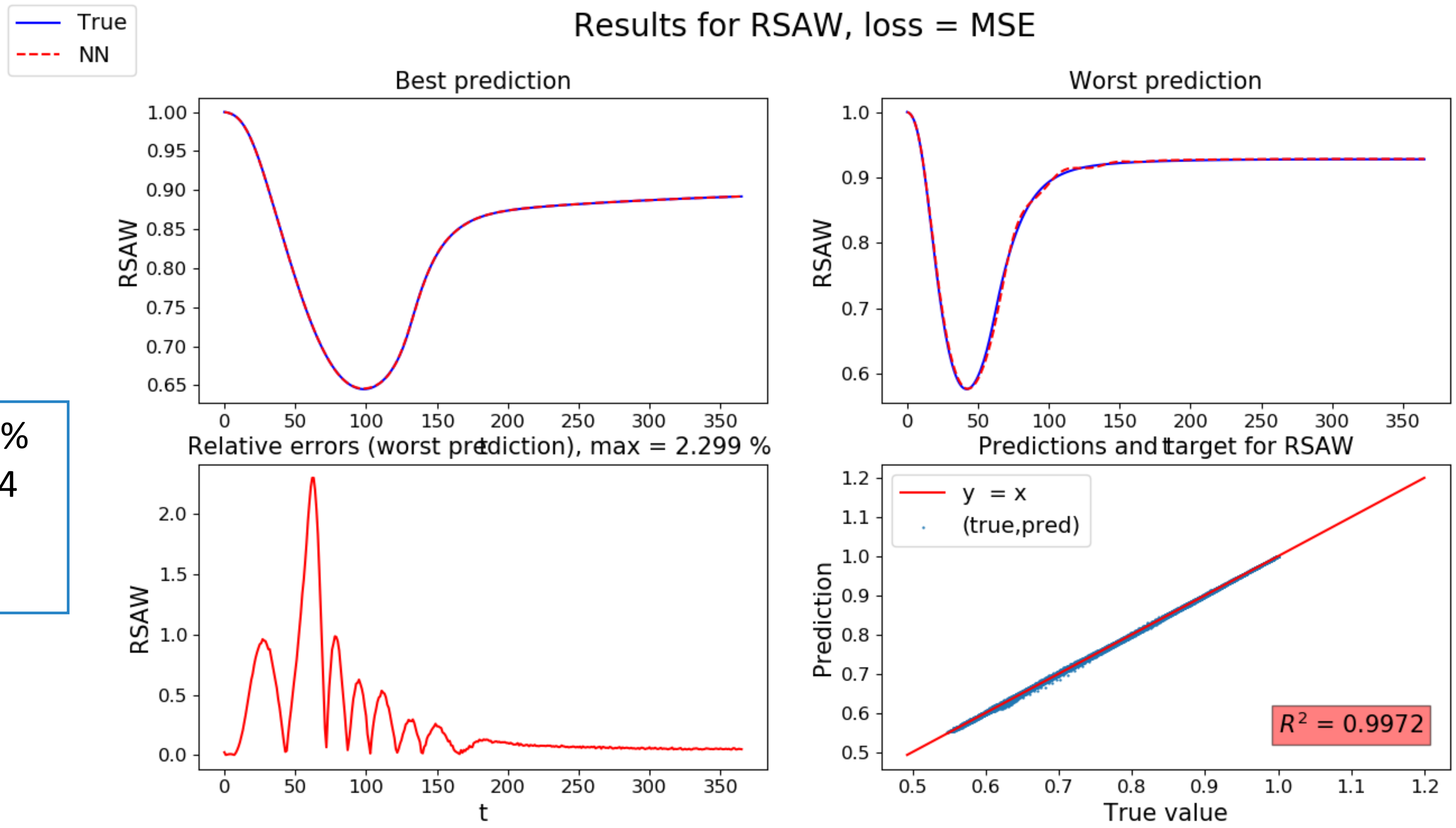
Results – Best network

Parameters

2 layers
25 neurons each
tanh activation
MSE loss

Performance

P (1%): 99.95 %
Validation loss: 1.06e-4
Training time: 14min
Prediction time: 0.303s



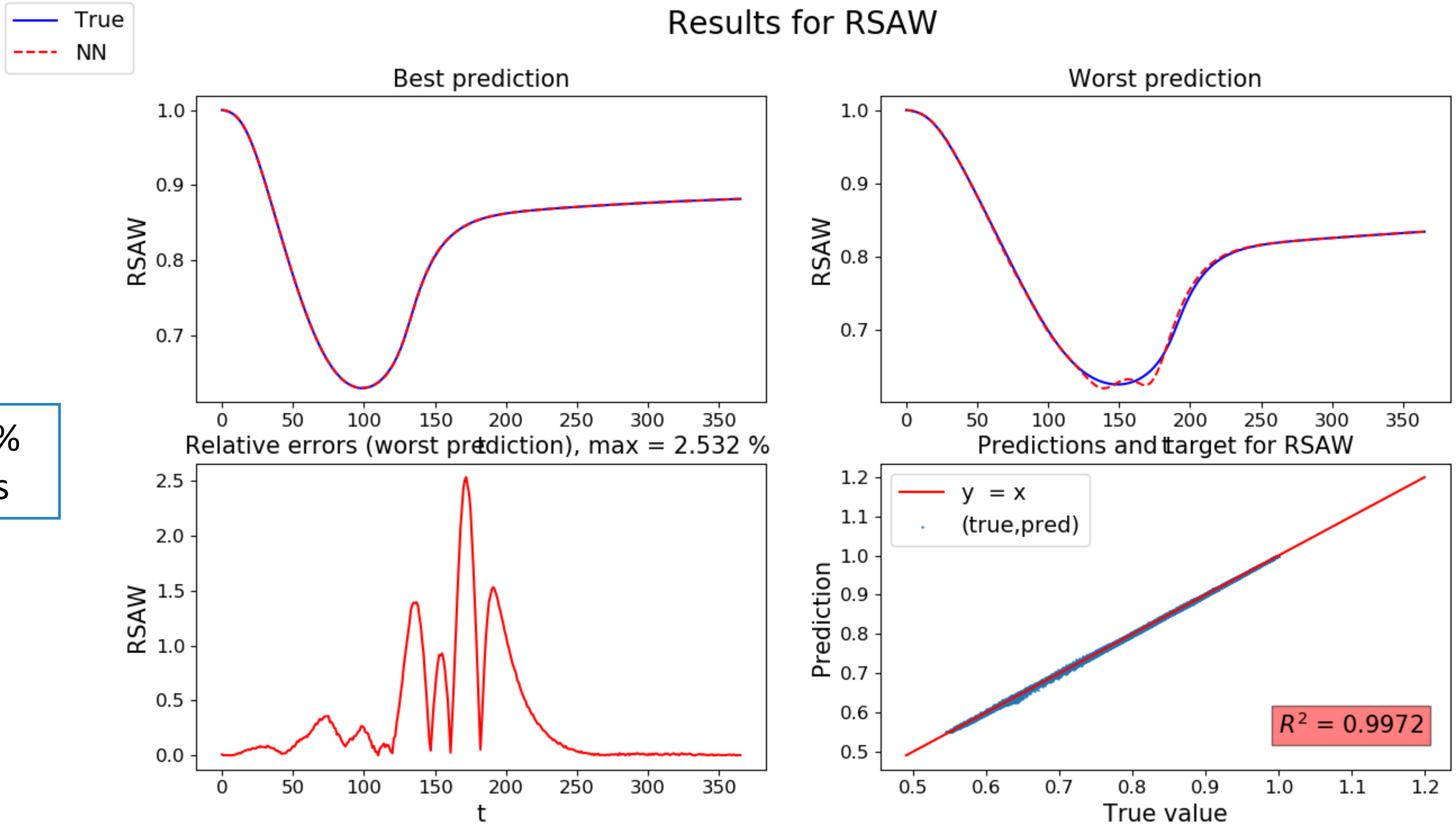
Test set

Parameters

2 layers
25 neurons each
tanh activation
MSE loss

Performance

P (1%): 99.92 %
Prediction time: 0.0013s



Mixed groups

- New dataset
  - Group 1 and 2
  - Group 2 and 3
  - Group 3 and 4
- Test generalization

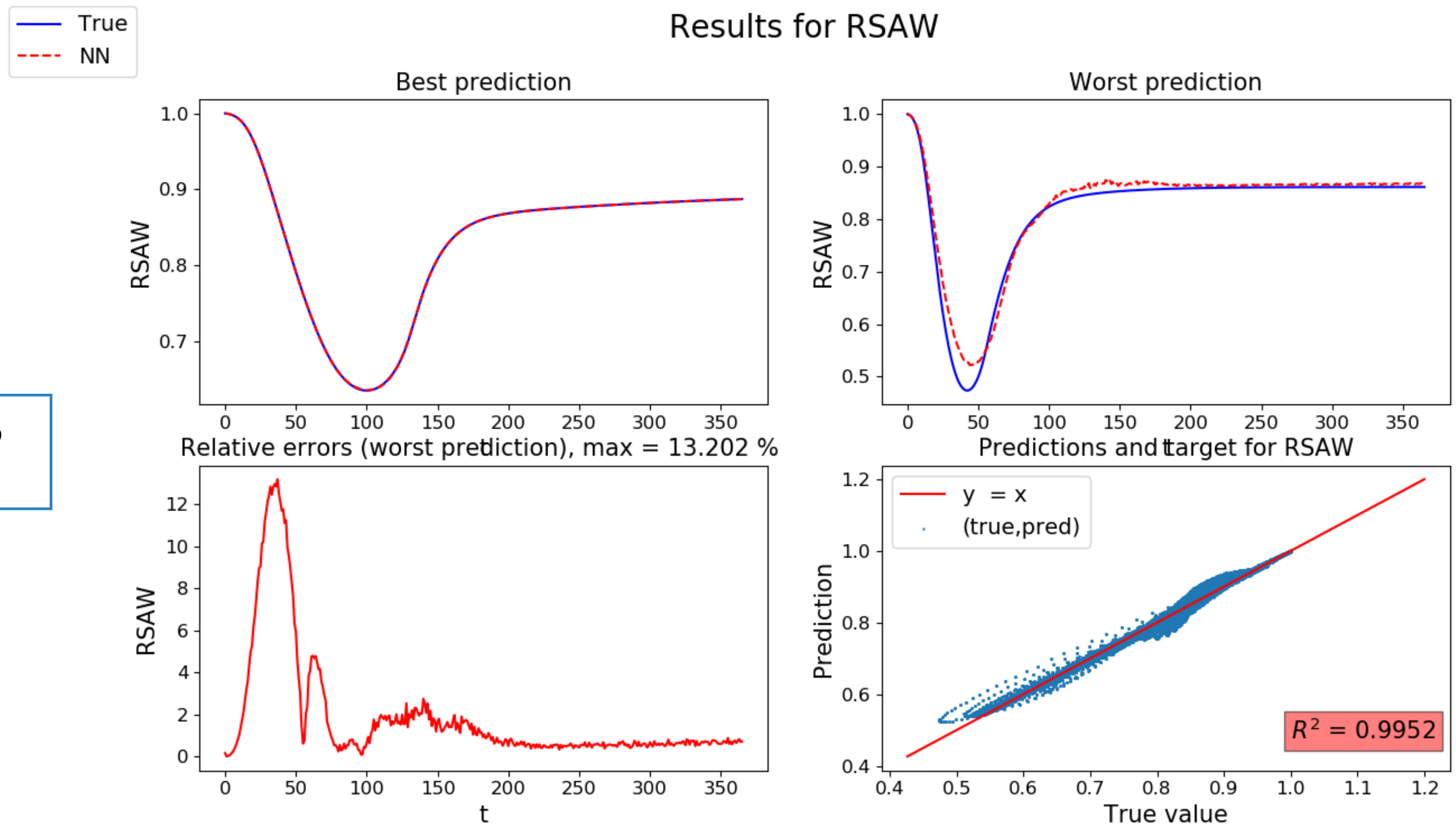
Mixed groups

Parameters

2 layers
25 neurons each
tanh activation
MSE loss

Performance

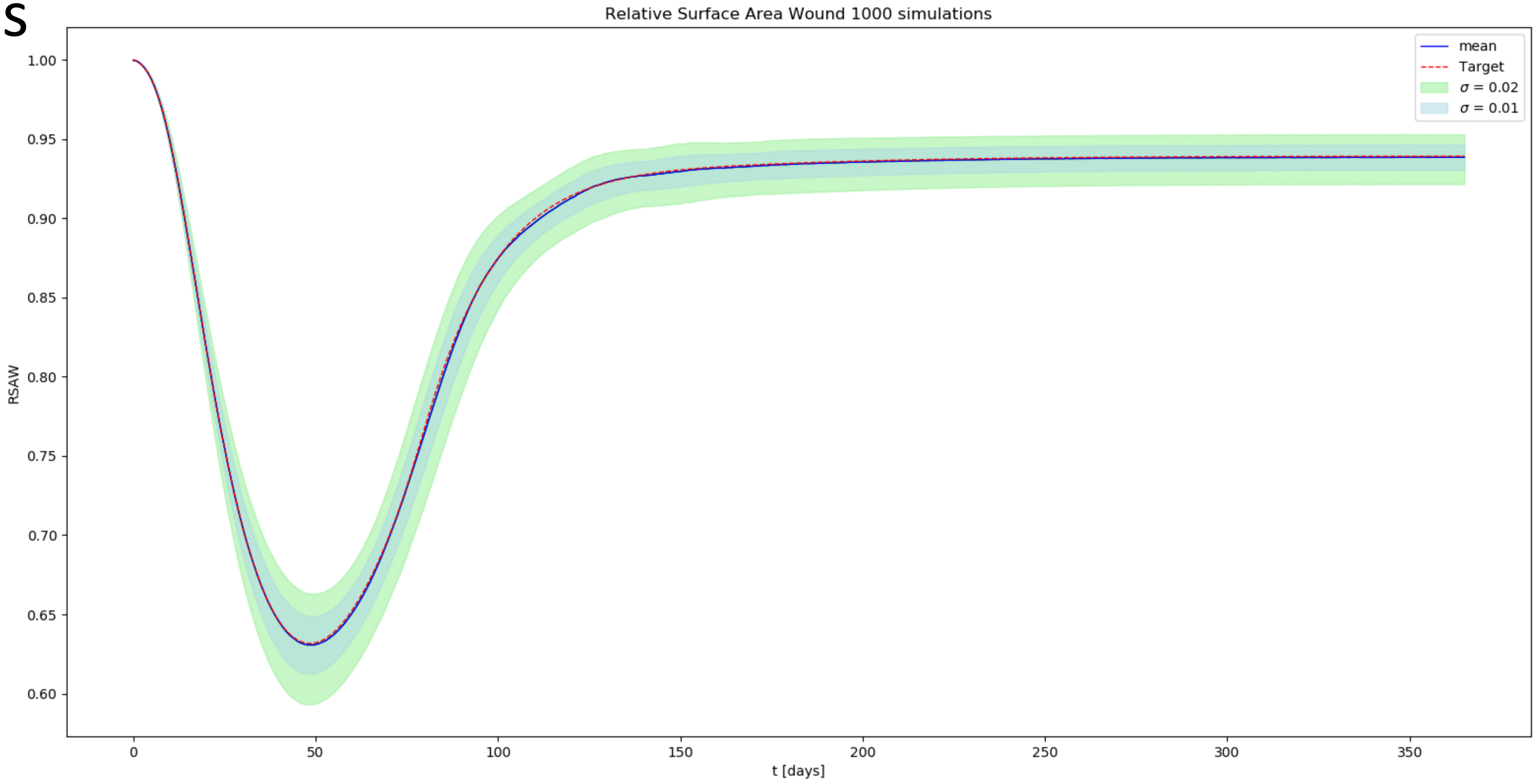
P (1%): 91.33 %
Prediction time: 0.0032s



Input perturbations

- 1 set of inputs
- 1000 simulations
- $\sim\mathcal{N}(1, \sigma)$

Time: 1.5-2.5 s



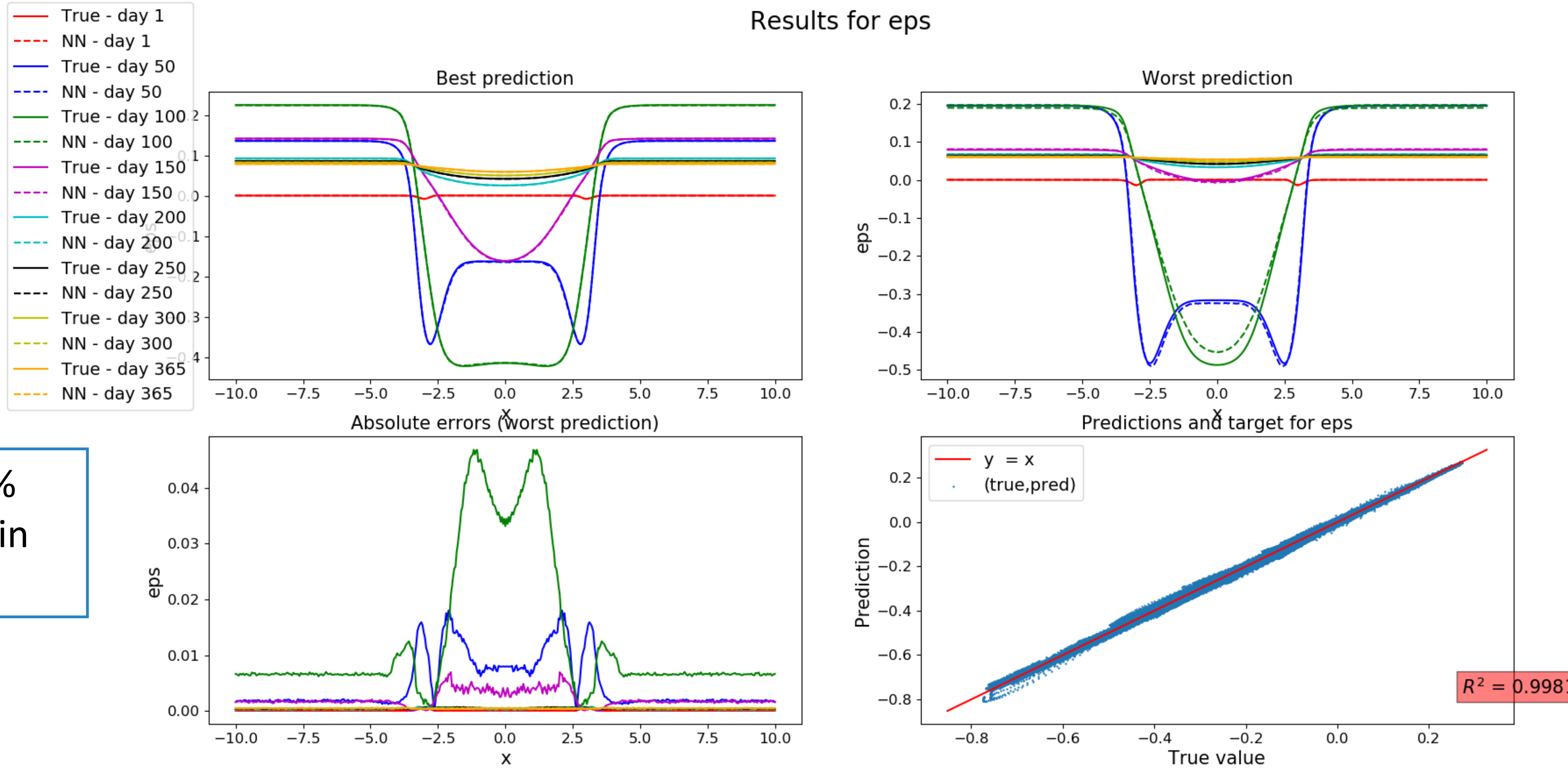
Multiple outputs

Parameters

2 layers
50 neurons each
ReLU activation
MSE loss

Performance RSAW

P (1%): 90.9 %
Training time: 85 min
Prediction time: 1.21s



Conclusion so far

- Neural networks surrogate can give faster RSAW predictions with performance over 99%.
- Promising for multiple outputs
- The variation in the training set is important.

Next...

- Single output
  - Special cases
  - Input analysis

- Multiple outputs
  - Further analysis and network tuning
  - Testing
  - Full (x,t)-distribution
    - Feedforward network
    - Long-Short Term Memory

- 2D numerical model?

Questions?

Without questions, there is no learning.

~W. Edwards Deming ~

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