Deep Neural Network

Sun Sail Project Surrogate Model

Group 4

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Introduction:Neural Network Surrogate

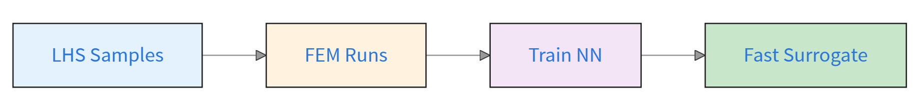
Learn a mapping from data:

$f_\theta(x) \approx y$

- x: design parameters
- y: FEM predictions
- θ: learned weights

Key idea: Train on limited FEM data, predict instantly (Holl and Thuerey 2022)

Workflow



Sun Sail Application

Inputs (6 design variables):

- Young's modulus E_{mem}
- Poisson ratio ν_{mem}
- Membrane pre-stress σ_{mem}
- Surface loading f_{mem}
- Edge cable pre-stress σ_{edg}
- Support cable pre-stress σ_{sup}

Output (scalar prediction):

- Maximum membrane stress: $\sigma_{\mathrm{mem,max}}$

Result: 1000x speedup (30 min → 10 ms)

† This is an empirical estimate, consistent with the typical 10^3–$10^5\times$ acceleration reported in surrogate modeling literature (Forrester, Sobester, and Keane (2008); Bhatnagar et al. (2019); Thuerey, Weißenow, and Lütjen (2020)).

How Neural Networks Learn

1. Forward Pass

- Input to (n) hidden layers to output
- Each layer: parameters + activation (ReLU, sigmoid)
- Outputs prediction $\hat{y}$

2. Loss Function

- Measures error between prediction $\hat{y}$ and true label y
- Example: MSE or MAE for regression and cross-entropy loss for classification

3. Backward Pass (Backpropagation)

- Computes gradients of the loss w.r.t. each weight
- Adjusts weights to reduce the error

4. Gradient Descent

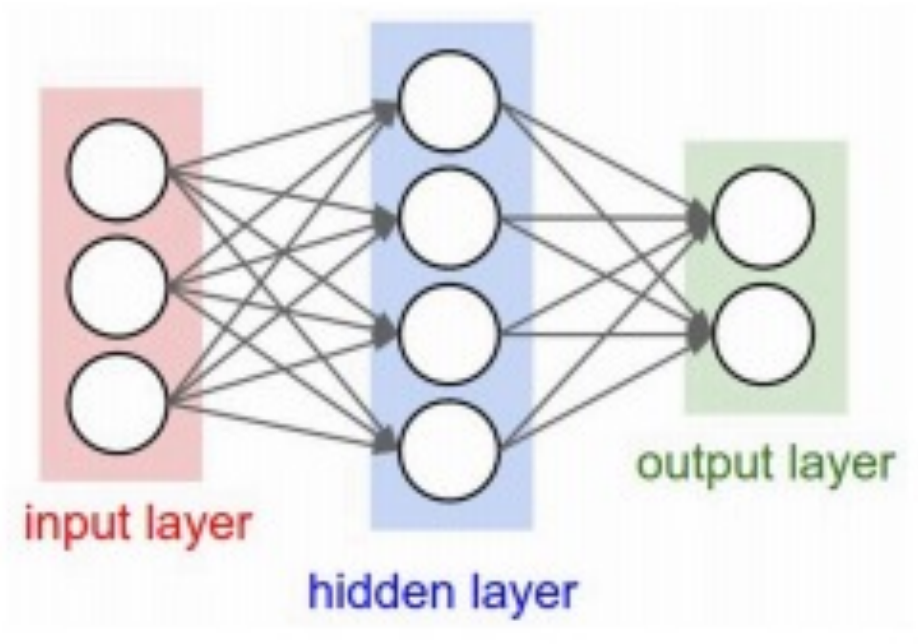
- Optimization algorithm that updates weights step by step
- Improve stability, convergence speed, escaping saddle points or local minima
- Example: SGD, Adam, RMSProp

Types of Neural Networks

1. Fully Connected Network (FC or MLP)

$$h^{(l)} = \sigma\left(W^{(l)} h^{(l-1)} + b^{(l)}\right)$$

2. Convolutional Neural Network (CNN)
3. Recurrent Neural Network (RNN)
4. GRU or LSTM
5. Transformer
6. …and various others



Pros & Cons of a Neural Network

Pros

- Can model highly nonlinear relationships + complex interactions
- Handles discontinuities or threshold behavior
- Flexible architecture that can approximate almost any continuous function.

Cons

- Needs a large number of training samples
- Sensitive to heterogeneous, skewed, and differently scaled features
- Hard to interpret
- Requires tuning and regularization

References

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Forrester, Alexander I J, Andras Sobester, and Andy J Keane. 2008. *Engineering Design via Surrogate Modelling: A Practical Guide*. John Wiley & Sons.

Holl, Philipp, and Nils Thuerey. 2022. "Neural Surrogates and Operators: Discussion of Supervised Approaches." https://physicsbaseddeeplearning.org/supervised-discuss.html.

Thuerey, Nils, Kai Weißenow, and Fabian Lütjen. 2020. "Deep Learning Methods for Reynolds-Averaged Navier–Stokes Simulations of Airfoil Flows." *AIAA Journal* 58 (1): 25–36.