Aalto-yliopisto
Perustieteiden korkeakoulu

# Testing Feedforward Neural Networks for Linear Parametric Optimization

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Systeemianalyysin laboratorio

# Objective

- Can feedforward neural networks (FFNNs) be used for parametric optimization?
- Find out if it has been tested before
- Test it on a linear optimization problem

# What Is Parametric Optimization?

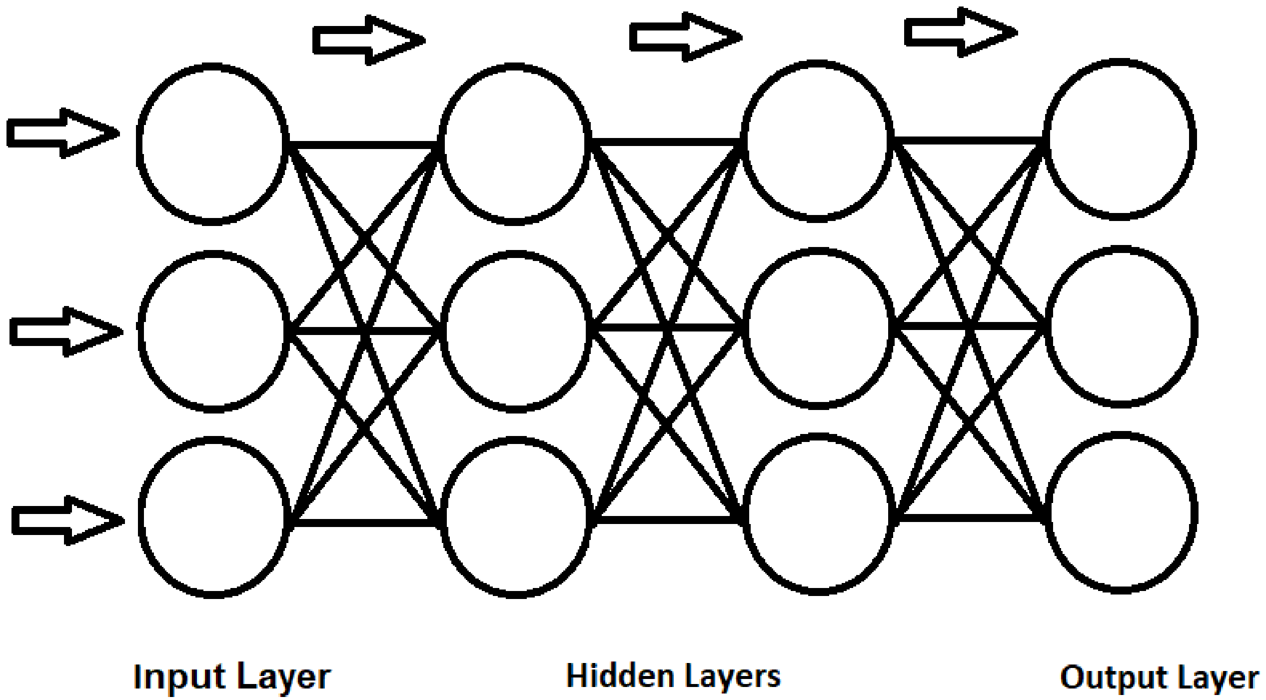
- Finding a function that solves an optimization problem for changing parameter values.

$$x^*(\theta) = \arg\min_{x \in \mathbb{R}^n} f(x, \theta)$$

$$\text{subject to } g(x, \theta) \leq 0$$

$$\theta \in \mathbb{R}^m,$$

# What Is a FFNN?



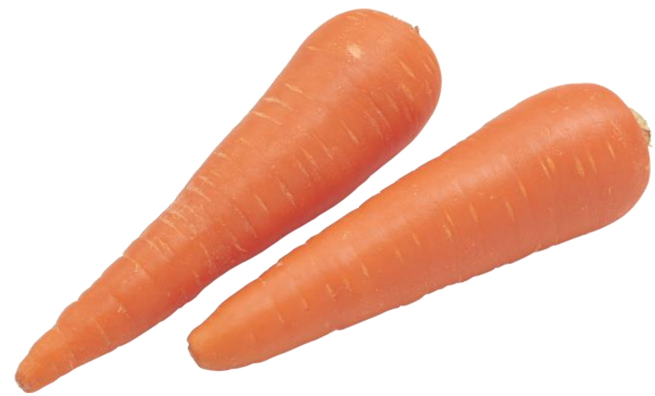
# Background

- There is a need to solve optimization problems in real time
- Optimization => Computationally expensive
- FFNNs can make predictions fast
- FFNNs can represent any continuous function with arbitrary precision (Hornik, 1991)

# Have FFNNs been used for parametric optimization?

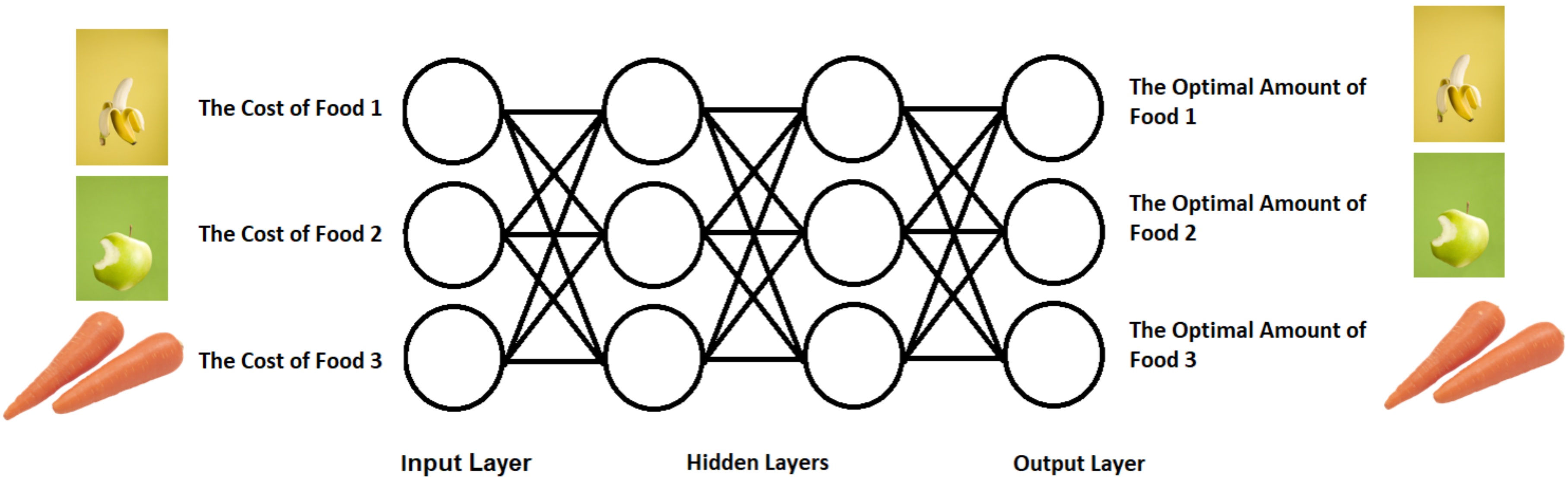
- Yes, but there are not many examples
- Power allocation in massive MIMO (Sanguinetti et. Al, 2018)

# A Classical Linear Optimization Problem: The Diet Problem



| Banana | Apple | Carrot |
|---|---|---|
| Price– 0.30€ | Price – 0.20€ | Price – 0.15€ |
| Vitamin A – 30mg | Vitamin A – 10mg | Vitamiini A – 50mg |
| Vitamin B – 50mg | Vitamini B – 40mg | Vitamiini B – 10mg |
| Calories – 70kcal | Calories – 40kcal | Calories – 10kcal |

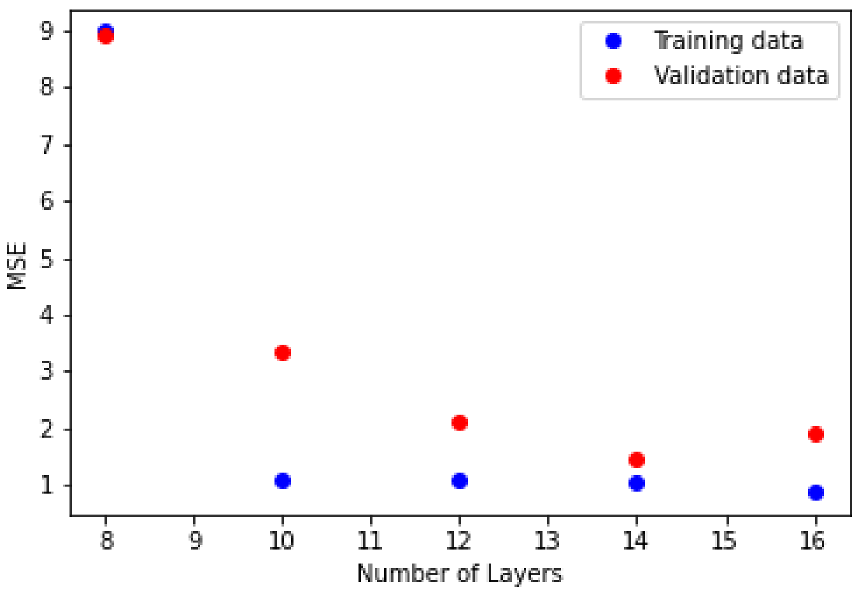
# The Model

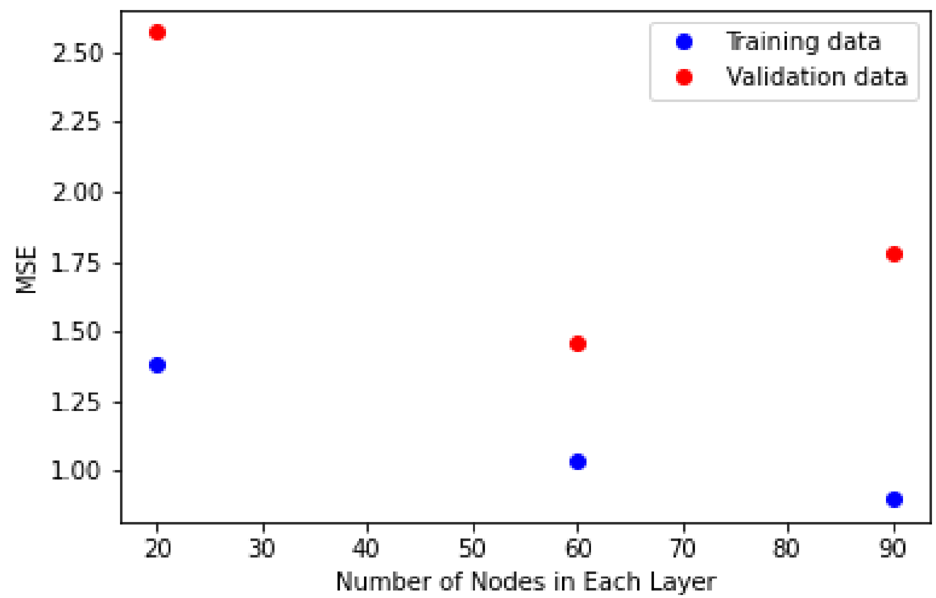

The Cost of Food 1
The Cost of Food 2
The Cost of Food 3
The Optimal Amount of Food 1
The Optimal Amount of Food 2
The Optimal Amount of Food 3
Input Layer
Hidden Layers
Output Layer

# Methods

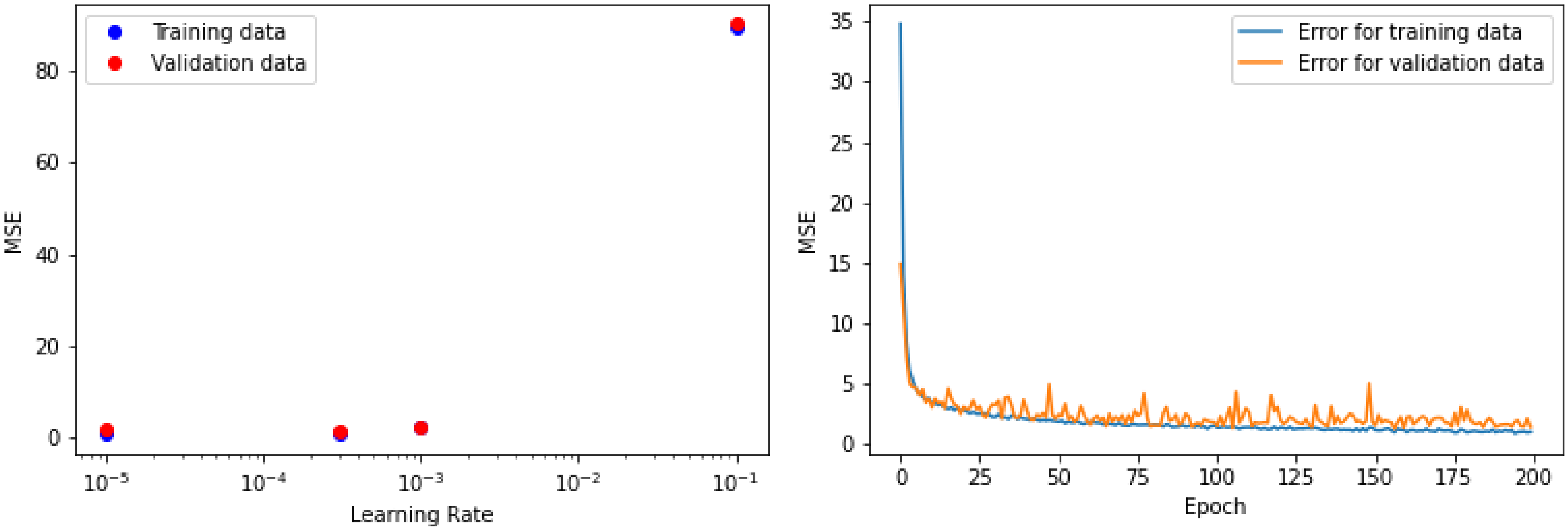
- Generate data
- Train a FFNN
- Evaluate the performance

# Hyperparameter Tuning 1/2



# Hyperparameter Tuning 2/2



# Problem: How to ensure feasibility?

- Two methods tested:
- 1. Using nearest neighbours on the prediction
- 2. Including the slack variables in the loss function

# 1. Using nearest neighbour combined with a FFNN

- Idea: If the output is not feasible, find a feasible output from the training data
- Accuracy: 95.0% for test data – 96.5% for training data
- The method is slow

# 2. Adding a slack variable to the loss function

- Violation of the constraints is added to the loss function
- Feasible 99.9% of the time
- The cost increased only 4% on average per datapoint from the optimal
- Drawback – Does not work if the constraints are not constant

# Conclusions

- FFNNs seem to work reasonably well for parametric optimization with few parameters
- Curse of dimensionality
- Inflexible – The number of parameters must be constant

# Suggestions for future work

- Test how well the method scales
- Test other optimization problems
- Test convolutional and recurrent neural networks

# Sources

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- Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural networks*, *4*(2), 251-257.
- Sanguinetti, L., Zappone, A., & Debbah, M. (2018, October). Deep learning power allocation in massive MIMO. In *2018 52nd Asilomar conference on signals, systems, and computers* (pp. 1257-1261). IEEE.