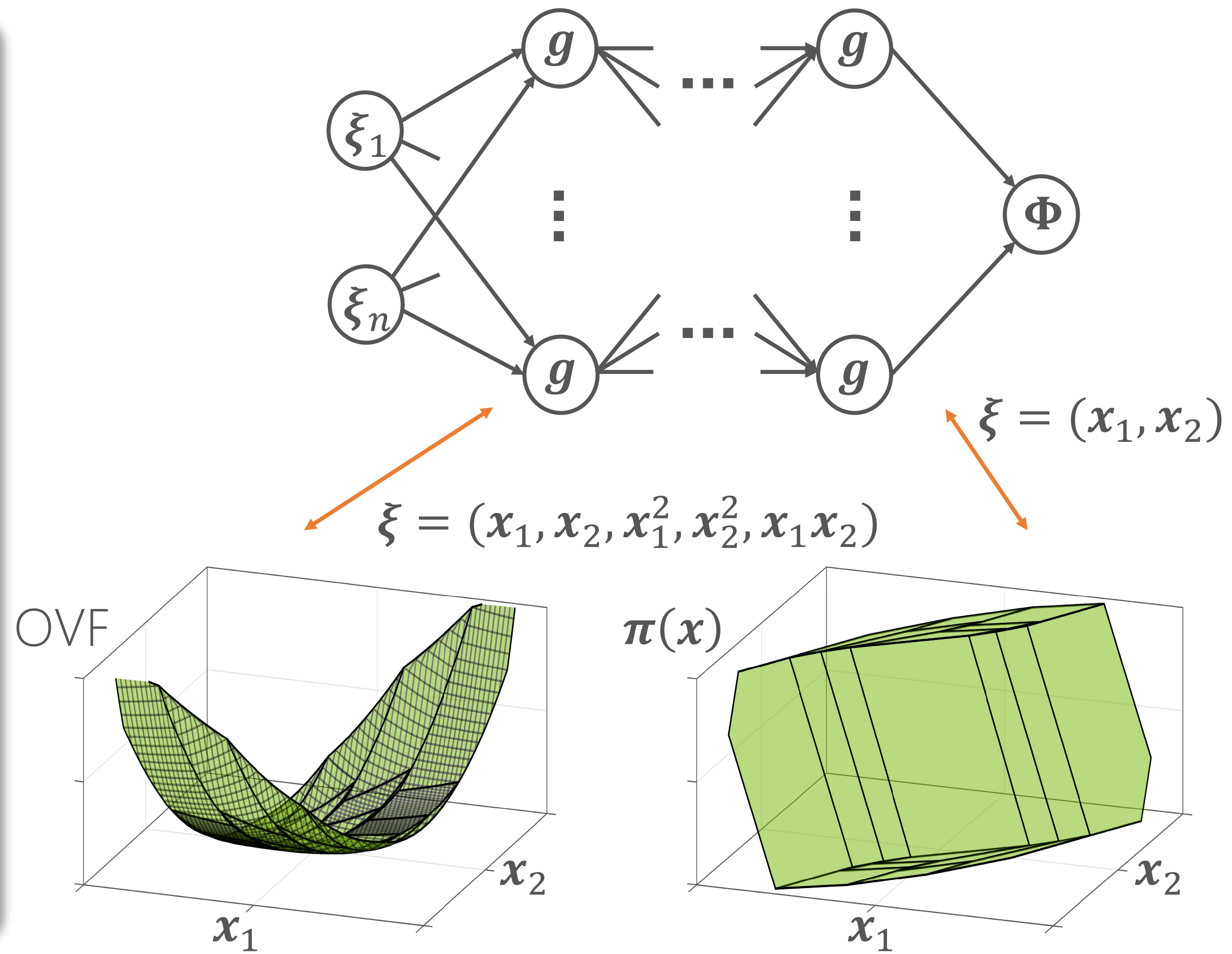


# Neural networks for predictive control

Dieter Teichrib and Moritz Schulze Darup

## Motivation

- NN can approximate a large class of functions with arbitrary accuracy
  - Good topologies leading to  $\Phi(\mathbf{x}) \approx \pi(\mathbf{x})$  are often unknown
- ↓
- Use common PWA structure of NN and the control law  $\pi(\mathbf{x})$  of linear MPC to derive design guidelines
  - For  $\xi = (\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_1^2, \mathbf{x}_2^2, \mathbf{x}_1\mathbf{x}_2)$ , the approach is extendable to PWQ optimal value functions



## Stability and performance verification

### Mixed-integer formulation of MPC

- Computation of Lipschitz constants for the control law  $\pi(\mathbf{x})$
- Reduce online complexity of MPC by removing constraints that are never active

$$\begin{aligned} & \max_{\mathbf{x}, \delta} \varphi(\mathbf{x}, \delta) \\ & \text{s. t. } \mathbf{h}(\mathbf{x}, \delta) \leq \mathbf{0}, \mathbf{x} \in \mathcal{X}, \delta \in \{0,1\}^N \end{aligned}$$

### Mixed-integer formulation of NN

- Compute local gain of NN
- Find min/max of the output of an NN
- Convex outer approximations of save sets

### Verification of approximate MPC

- Stability is typically not preserved for approximations of the control law
  - Stability of the approximate control law can be verified based on the error:
 
$$\mathbf{e}(\mathbf{x}) := \Phi(\mathbf{x}) - \pi(\mathbf{x})$$
  - For ReLU and maxout NN,  $\Phi(\mathbf{x})$  can be modelled using binary variables
  - Modelling of active constraints of quadratic programs by binary variables
- ↓
- $\mathbf{e}(\mathbf{x})$  is the solution of a mixed-integer LP

## Challenges

- Efficient training of NN for approximating MPC
- Combination with methods from reinforcement learning
- Extension to problems with high dimensional state space