Introduction
Quantum devices are controlled by classical analog signals, related non-trivially to the device operation. The control signals need to be optimally adjusted to provide a high-fidelity operation of the device. A common approach to predicting control signals required to prepare the target quantum state, i.e., the inverse control model, minimizes an ad hoc selected distance metric in this classical control space. However, the values of control signals depend on technical implementation and are often ambiguous. We propose and experimentally test a novel idea for constructing the inverse control model. We demonstrate our approach on a use case of polarization state transformation using twisted nematic liquid crystals controlled by several voltage signals.

Experimental dataset acquisition
We measured the dataset of 27,000 combinations of three control voltages with a corresponding prepared polarization state using the depicted experimental setup. The twisted nematic liquid crystal (TNLC) device consists of three liquid crystal cells, each connected to an independent control voltage signal. The prepared polarization state is characterized using full quantum tomography and reconstructed using the maximum likelihood estimation.

The dataset was divided into three subsets:
- the training set of 6,500 samples
- the validation set of 6,500 samples
- the test set of 4,500 samples

Direct transformation modeling
First, we report modeling the direct transformation, i.e., predicting the prepared polarization state given the three control voltages. The model based on a deep neural network achieves by order of magnitude lower errors compared to linear interpolation and radial basis function interpolation. The infidelity numbers refer to the average with 5th and 95th percentile.

<table>
<thead>
<tr>
<th>Method</th>
<th>Infidelity</th>
<th>Time per sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear interpolation</td>
<td>1 × 10⁻⁴</td>
<td>4 × 10⁻⁵ s</td>
</tr>
<tr>
<td>Radial basis function</td>
<td>3 × 10⁻⁴</td>
<td>5 × 10⁻⁵ s</td>
</tr>
<tr>
<td>Deep neural network</td>
<td>2 × 10⁻⁴</td>
<td>1 × 10⁻⁵ s</td>
</tr>
</tbody>
</table>

Besides its higher accuracy, the deep learning model is also more consistent in the quality of its predictions. Due to the logtransform of the distributions, the most appropriate comparison is by the 0-95% confidence interval. The three depicted vertical lines represent the corresponding 95th percentiles.

Inverse transformation: A compound model
The inverse transformation suffers from an ambiguous mapping from polarization state to control voltages. To eliminate this obstacle, we train the inverse model by connecting it to the already optimized fixed direct model creating an autoencoder-like compound network.

Connecting the model solves the ambiguous mapping and allows us to evaluate the performance using fidelity between the desired input state and the predicted output state. The compound deep neural network achieves by two orders of magnitude more accurate results.

<table>
<thead>
<tr>
<th>Method</th>
<th>Infidelity</th>
<th>Time per sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear interpolation</td>
<td>2 × 10⁻⁴</td>
<td>3 × 10⁻⁵ s</td>
</tr>
<tr>
<td>Radial basis function</td>
<td>4 × 10⁻⁴</td>
<td>5 × 10⁻⁵ s</td>
</tr>
<tr>
<td>Deep neural network</td>
<td>1 × 10⁻⁴</td>
<td>1 × 10⁻⁵ s</td>
</tr>
</tbody>
</table>

Summary
- The developed approach allows for near-perfect bidirectional classical control
- Modeling the transfer function of TNLC devices using deep learning methods exhibits:
  - lower errors and less computational time than linear and radial basis function interpolation
  - better scaling with the size of the experimental dataset and the number of trainable parameters
- Solving the ambiguous mapping of the inverse transformation with the compound model
- Polarization state control at a single-photon level:
  - local preparation using heralded photon source
  - numerical simulation of remote state preparation
  - Applicable to the learning of the steady-state response of quantum devices to classical control signals

References