Machine Learning techniques for state recognition and auto-tuning in quantum dots

Current semiconductor-based quantum computing approaches use adjacent, isolated electron spins as quantum bits. Establishing a stable configuration of electrons in space is achieved via electrostatic confinement, band-gap engineering, and dynamically adjusted voltages on nearby electrical gates. A key task is to determine a good set of control parameters (gate voltages) to achieve a desired charge configuration – in both number and location – for a successful experiment. See Fig. 1 for a generic model of a nanowire.

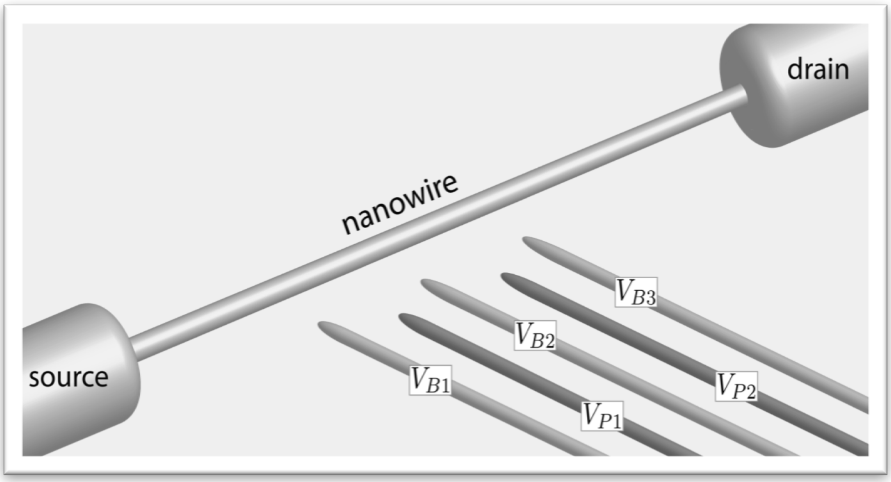

Figure 1. A generic model of a nanowire with 5 gates. The barrier voltages are set to V_{B1} = V_{B2} = V_{B3} = -200 mV. For plungers, voltages varied between 0 mV and 400 mV.

In recent years, machine learning (ML) has emerged as a "go to" technique for automated characterization, giving reliable output when trained on a representative, comprehensive data set. Specifically, we focus on the classification of data into categories (also referred to as a classification problem). The categories can be either predefined and stored as *labels* (supervised learning) or extracted from the data (unsupervised learning). The algorithm learns about the categories from the training set and produces a model that can assign *previously unseen* inputs to those categories. Artificial neural networks (ANNs) – a ML approach inspired by analogous biological units – turned out to be particularly suitable for this task. ANNs were originally intended to mimic the workings of humans' brain. They are composed of (so-called) *artificial neurons* organized in fully-connected layers (thus the term "deep neural networks"), with each layer performing a specific transformation of the data. Deep neural networks (DNNs), with multiple hidden layers, can be used to classify complex data into categories with high accuracy. One architecture that has performed particularly well in these settings are the convolutional neural networks (CNNs), comprising of a set of convolutional and pooling layers preceding the series of hidden layers. Each convolutional layer consists of a number sets of weights convoluted with the input that are determined by the training on the dataset. In order to learn larger scale features in the input more efficiently, a convolutional layer is generally followed by a pooling layer that takes in a sub-region in the input and replaces it by an effective element (e.g., the maximum element) in that region.

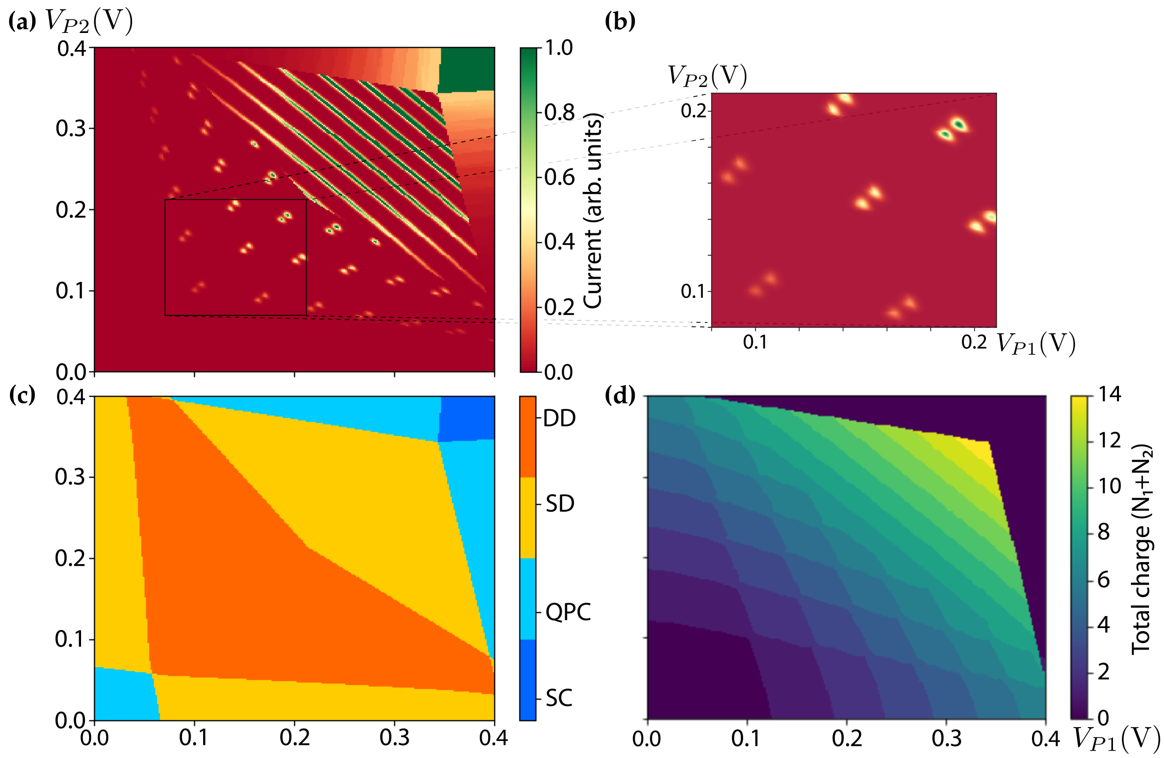

*Figure 2. An example of full 2D map (100x100 points) from the space of plunger gate voltages (V_{P1}, V_{P2}) to current **(a)** and a sub-region with double dot configuration **(b)**. A state map **(c)** and charge map **(d)** corresponding to the current map presented in (a). N_1 and N_2 denote the number of charges on each dot.*

In our project, we use tools from machine learning to develop good heuristics for the gate voltages from a training set and design an effective and efficient neural network for the characterization of experimental data in semiconductor quantum dot experiments. In a first stage, we established a reliable training and evaluation data sets, based on simulated data. We use a modified Thomas-Fermi approximation to model a reference semiconductor system comprising a quasi-1D nanowire with a series of depletion gates whose voltages determine the number of islands and the charges on each of those islands, as well as the conductance through the wire. We generated 1000 gate configurations averaging over different possible fabrications of the same type of quasi-1D device, with plunger voltages ranging from 0 to 400 mV. Each sample data was stored as a 100x100 pixel map from plunger voltages to current, net charge, state and sensor maps (each stored separately) which can then be used as observables and labels for training and testing. The training and evaluation set was then generated by taking 25 random 30x30 pixels sub-images of each map to go from 1000 realizations to 25000 effective realizations. A second stage involved training of the CNNs to "recognize" the electronic state within quantum dot arrays, based on the current data. We found >95% agreement between the CNN characterization and the Thomas-Fermi model predictions for nanowires. Having the network trained, we tested it on the experimental data and found that it correctly identifies single and double dot state configurations, as well as the intermediate cases. Finally, in stage three, we were able to *auto-tune* the multidimensional gate voltage space to obtain a required configuration by recasting the tuning problem as an optimization problem over the nanowire state in the space of gate voltages.