Many training techniques and neural models have been proposed to learn and represent known and unknown symbolic constraints. In this talk, we first explore if neural models can be better trained using known symbolic domain knowledge expressed as constraints on the output space. To this end, we propose a primal-dual formulation for deep learning with constraints. At times, humans cannot encode their intuition explicitly in the form of a constraint, or they may miss certain constraints while enumerating them. Hence, in the next part, we focus on automated learning of unknown constraints from the data. Here we focus on combinatorial problems, such as sudoku, that involve satisfaction of the underlying hard constraints defining the problem. We can categorize existing approaches for learning and representation of unknown constraints into two categories: implicit and explicit. Works in the first category propose purely neural models for solving these tasks, representing the underlying constraints implicitly in their weights. Here, we identify a couple of potential issues in such models and propose appropriate solutions. First, we identify the issue of solution multiplicity (one input having many correct solutions) while training neural models and propose appropriate loss functions to address it. Next, we observe that existing architectures, such as SATNet, message passing based Relational Recurrent Networks (RRN), fail to generalize across the output space of variables (can not solve 16 x 16 sudoku after training on only 9 x 9 sudoku). In response, we design two neural architectures for output space invariance in combinatorial problems. The second line of work for learning constraints focuses on explicit representation in a specific language, such as linear constraints in Integer Linear Programs (ILPs) that can express many combinatorial problems. Here, one shortcoming of the existing approaches is that they need to solve the ILP in every learning iteration, thereby considerably slowing down the training process. In response, we propose a solver-free framework for scalable learning of constraints in an ILP.