**Reinforcement Learning:**

* Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm (Silver, 2017)
* Implementing the Deep Q-Network (Roderick, 2017)
* Asynchronous Methods for Deep Reinforcement Learning (Mnih, 2016)
* Implementation of Q-Learning and Deep Q Network for Controlling a Self Balancing Robot (Rahman, 2018)
* ADAM: A Method for Stochastic Optimization (Kingma, 2015)
* Human-Level control through deep reinforcement learning (Mnih, 2015)
* Evolving Neural Networks through Augmenting Topologies (Stanley, 2001)
* Evolving Deep Neural Networks (Miikkkulainen, 2017)

**Multi Agent Reinforcement Learning:**

* Multi-agent Reinforement Learning for Traffic Signal Control (Wiering, 2000): Discretizes the places vehicles can take in the network. 8 traffic lights are controlled independently. Each light has the information car location and destination. Each node has 6 possible actions. The cars are also agents with access to the value functions, it differs meaningfully from pure RL. Makes bad use of the simulator, using refused cars into the simulation as metric. Not usable.
* Multi-agent Reinforement Learning for Traffic Signal Control (Prabuchandran, 2014): Uses RR phases in a MARL Q Learning setup. Discrete state and action spaces. One agent per junction as solution for dimensionality issues. Queue size is clustered into 3 different levels for the state. State vector is queues, plus the queue in the next phase that has to be set green. Actions involve setting the green time to one of 3 levels (H,M,L) for the current phase. Stationary policies. Reward is a function to the junction and neighbors. Implements counts of how many times an action has been taken in a state. Results on 2 roads of 9 and 20 junctions. Beats SAT and FST.
* Q-Learning Traffic Signal Optimization within Multiple Intersections Traffic Network (Kwong Chin, 2012): Discretizes Q-States to 4 levels of load per link, 2 intersections, for a total of 256 states. No valuable information for replication whatsoever.
* Intelligent Traffic Light Control Using Distributed Multi-agent Q-Learning (Liu, 2017)
* A collaborative Reinforcement Learning Approach for Urban Traffic Control Optimization (Salkham, 2008)
* Reinforcement learning-based multi-agent system for network traffic signal control (Arel, 2009)
* Distributed Learning and Multi-Objectivity in Traffic Light Control (Brys, 2014)
* Multi-Agent Deep Reinforcement Learning (Egorov, 2017)
* Fully Decentralized Multi-Agent Reinforcement Learning with Networked Agents (Zhang, 2018)

**Urban Traffic Control:**

* Intelligent Traffic Light Control of Isolated Intersections Using Machine Learning Methods (Araghi, 2013): Using a feed-forward NN, the queue lengths are taken as inputs and green times are estimated. Stochastic Annealing is used for optimizing the weights. Average delay is used as an indirect cost function. Training is done in an indirect manner. No details on cost function or action selection. Shows better performance than basic Q-Learning.
* An Efficient Deep Reinforcement Learning Model for Urban Traffic Control (Lin, 2018)
* A reinforcement learning based traffic signal control algorithm in a connected vehicle environment (Yang, 2017)
* Reinforcement Learning with Function Approximation for Traffic Signal Control (Prashanth, 2010)
* Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks (Liang, 2018)
* Using a Deep Reinforcement Learning Agent for Traffic Signal Control (Genders, 2016)

**State Spaces:**

**Action Spaces:**

**Reward Functions:**