Stochastic Approximation Methods - Summary

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In this thesis, we aim to give an overview of stochastic approximation algorithms. These are a branch of iterative methods which aim to solve optimization problems involving functions which can only be observed through stochastic noise. A typical task is to find a local minimum or a root of functions based on the functions noisy measurements. A key advantage of these methods are the low computational costs. Thus, they gained popularity in multiple fields of application, such as machine learning.

In the second section of the thesis, we will introduce some of the most well known stochastic approximation algorithms. The first published algorithm in this field was the Robbins-Monro algorithm which aims to find the root of a function observed through random noise. Secondly, we discuss the Kiefer-Wolfowitz algorithm, which is a first order gradient descent type method. However, in potentially large dimensional spaces, the speed of this algorithm. Finally we discuss stochastic gradient type methods in general and present some methods that aim to augment the convergence of the gradient descent.

In the third section we discuss convergence theorems for a general stochastic approximation schema. We establish two main lines of convergence analysis, the so called Ljapunov method and convergence with contraction assumptions.

Finally, we examine an application of stochastic approximation in the reinforcement learning. In this machine learning framework, the learner must learn through interactions with a stochastic system. When this system is assumed to be Markovian, we arrive at a Markov decision process. We outline the most important definitions of such processes. Then we examine two optimization methods for this type of problem, the policy gradient and the Q-learning approach. Both of these rise from the application of stochastic approximation.