Xuedong Shang

Curriculum Vitae

Education

2015–2017 **Master of Computer Science**, *École normale supérieure de Cachan*, Rennes, France.

2014–2015 **Bachelor of Computer Science**, *École normale supérieure de Cachan*, Rennes, France.

2012–2013 **Bachelor of Mathematics**, *Université Pierre et Marie Curie (Paris VI)*, Paris, France.

2008–2011 **Mathematical Preparatory Class**, *Lycée Henri Poincaré*, Nancy, France.
Post-secondary preparatory classes preparing for highly selective entrance examinations to the French Grandes Ecoles, including intense courses on mathematics, physics, chemistry, computer science and philosophy

Experience

Vocational

October 2017– **PhD Candidate**, *SequeL, Inria Lille-Nord Europe*, Lille, France.
Adaptive Methods for Optimization in Stochastic Environments, under the supervision of Emilie Kaufmann & Michal Valko

February 2017–July 2017 **Research Internship**, *SequeL, Inria Lille-Nord Europe*, Lille, France.
Hierarchical Bandits for "Black Box" Optimisation and The Monte-Carlo Tree Search, under the supervision of Emilie Kaufmann & Michal Valko

May 2016–July 2016 **Research Internship**, *Yamamoto-Cuturi Lab., Graduate School of Informatics, Kyoto University*, Kyoto, Japan.
Optimal Transport Geometry for Machine Learning Problems, under the supervision of Marco Cuturi

September 2015–May 2016 **Research Project**, *COSTEL, LETG Rennes*, Rennes, France.
Time Series Clustering, under the supervision of Thomas Corpetti & Romain Tavenard

May 2015–July 2015 **Research Internship**, *Magnet, Inria Lille-Nord Europe*, Lille, France.
Recommender System, under the supervision of Marc Tommasi

June 2012–July 2012 **Research Internship**, *CNRS Vérimag*, Grenoble, France.
On the Generation of Positivstellensatz Witnesses in Degenerate Cases, under the supervision of David Monniaux

Computer skills

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Programming languages	C, C++, C#, Java, Python, OCaml, Scala, Haskell, R	Web	HTML/CSS, PHP, MySQL
Operating systems	Linux, Windows, Mac OS	Numerical	Maple, Matlab/Octave
Other	LaTeX, Git, SVN		

Languages

English	Fluent	*TOEIC 925*
French	Native Speaker	
Chinese Mandarin	Mother tongue	
Chinese Shanghainese	Mother tongue	
Japanese	Intermediate level	

Extra

Eduinfinity Translation Group	Team leader on computer science courses	*A chinese translation group providing chinese subtitles for courses on Coursera.org, edX.org, etc*

Motivation Letter December 4, 2017

Structural Inference Spring School 2018

Dear Madam/Sir,

With this letter I would like to express my interest in studying at next year's Structural Inference Spring School.

To briefly introduce myself, I am currently a first year PhD student in team SequeL, at Inria Lille-Nord Europe, under the supervision of Michal Valko and Emilie Kaufmann. My doctoral thesis will focus on bandits theory with its applications especially in hyperparameter optimization for machine learning algorithms. Before that, I received a BSc and MSc of Computer Science from Ecole normale supérieure de Cachan (Rennes Campus) and a BSc of Mathematics from Université Pierre et Marie Curie (Paris VI).

As part of my studies, I am interested in finding theorectical gurantees for bandit learning (and reinforcement learning) algorithms, which happens to be also one major research topics of Sébastien Bubeck, one of the invited speakers this time. Therefore, I believe that participating to the spring school can help me get some profound understanding of my future research. Meanwhile, a very often employed toolbox in my domain is concentration inequalities, thus I am also fascinated by dicovering different statistic and probabilistic methods. Hopefully I can get a more solid perspective on what I am working on and enlarge my knowledge with the help of all the three invited speakers as well as the closing workshop.

Another reason that I am attracted by the spring school – this is what my supervisor told me, he has already sent two of his students to the spring school in the past – is that unlike other schools, where you get couple of hours with a lot of speakers, here you get 3 speakers but a lot of time with them. This could be a strong point for me, in the sense that there could be a balance between discovering too many new subjects and having a relatively deep understanding on one specific topic.

Finally, since I am just starting my PhD, thus do not have meaningful publications yet, but I still have some research perspectives to what end I want to achieve during my 3 years of PhD life. Thus I firmly believe that I am able to cope with the requirements of the spring school.

I appreciate you taking the time to review my application and do not hesitate to contact me for any further information needed.

Yours sincerely,

Xuedong Shang

Research Statement

Xuedong Shang
Inria Lille-Nord Europe

December 4, 2017

1 Introduction

Optimization in stochastic environments is an active research topic both in mathematic and computer science community with a lot of applications in different fields such as finance [1], biology and chemistry [2], engineering [3], bioinformatics [4], etc. For my PhD thesis, I will be particularly interested in optimization of functions for which none (or few) regularity assumptions are made, and only noisy function evaluations can be observed. This is the "black-box" global optimization problem.
In this context, since one does not make extra regularity assumptions on the target function, one can imagine that it can be very costly to evaluate the function. Thus a good strategy for choosing adaptively the next observation is needed in order to find an optimal (or quasi-optimal) point with as few number of evaluations as possible. This is the sequential optimization problem. That being said, the main problematic of my thesis is the global sequential optimization problem.
Recently this kind of black box sequential optimization is motived in particular by applications in automatic hyperparameter configuration of machine learning algorithms [5]. One may also think about the planning problem for Markov Decision Processes [6], for which the objective is, for a given state, to decide which action to take that maximises a fonction value along with the noisy observations we get for some well choosen paths.

2 Multi-armed Bandits

In the past few years, such optimization and planning problems have been widely inspired by literature of multi-armed bandit (MAB) algorithms (see [7] for a survey).

These algorithms are based on a hierarchical exploration (in a tree form) of the domain of the function, with the help of the optimism principle for choosing which part of the tree to explore. These works brought some breakthroughs especially for Monte-Carlo Tree Search (MCTS), which led to some great improvements in AI designing, e.g. for the game of Go [13].

A simple way to describe the multi-armed bandit scenario is to consider K arms labeled by integers from 1 to K. Each arm $k \in \{1, \ldots, K\}$ is characterized by an unknown distribution ν_k. At each step t, an arm k_t is selected and some reward $r_t \sim \nu_{k_t}$ is returned. The optimism principle is used when we are interested in maximizing the sum of rewards. Meanwhile, another objective could have been preferred, which is to decide as quickly as possible which arm has the highest reward on average. Recent works showed that optimal algorithms for this kind of best arm identification problems are totally different from those for reward maximization problems [14, 15]. This put into question the use of optimistic paradigm for some sequential optimization problems.

3 Perspectives

Dealing with sequential global optimization using hierarchical exploration with the help of best arm identification techniques instead of the classic optimistic approaches has raised much attention recently. For instance, most existing algorithms for the MCTS problem are variants of the Upper-Confidence Tree (UCT) algorithm in [8] in which the exploration phase follows the optimism in the face of uncertainty principle. The goal is to use a different approach, in which the exploration phase will be based on a process of best arm identification inspired by algorithms like LUCB [9], UGapE [16], Successive Reject [17], combining with methods of hierarchical optimization (e.g. hierarchical optimistic optimization [11, 10]) and methods using Gaussian processes (e.g. Bayesian optimization [12]).

4 Applications

Not only interested in the theorectical part, I am also working on some interesting applications of sequential global optimization, e.g. hyperparameter optimization and algorithm selection.

4.1 Hyperparameter Optimization

One important application of black box optimization is hyperparameter optimization in the context of machine learning. Hyperparameter optimization is usually the most tedious part in fitting a machine learning algorithm. In practice, we are interested in models whose loss, evaluated on an independent part of data is as low as possible. Different hyperparameter choices lead to different losses, therefore finding the optimal set of hyperparameters is of importance. In reality, we never know that if the point found is the global optimum, but from a practical point of view, we are only interested in finding the model that works best in a production setting.
In this context, we consider a function $f : \mathcal{X} \to \mathbb{R}$ and take $\mathcal{X}$ as a set of parameter configurations (set of arms), we can then map one parameter configuration to the performance of the machine learning classifier using the corresponding parameters.

4.2 Algorithm Selection

Many AI-problems are NP-complete. Nevertheless, many practical problems are solved efficiently by employing powerful heuristics. Such heuristics work well in some cases, but not in others. Due to their complex nature, it is difficult to identify which conditions are necessary for a heuristic to perform well and, more generally, to identify the algorithm that is best suited for solving a given instance. This is known as the algorithm selection problem.
In this context, an algorithm is considered as an arm, and the action of pulling an arm consists in running a chosen algorithm on some problem instance. In collaboration with Hans Degroote, we have a working paper on a special scenario of this problem, where instances will be arriving online and we have access to some features of each instance. This leads to another setting of MAB called contextual multi-armed bandit where some side information are available for each arm.

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