La recherche, qu'est-ce que c'est ?

Le monde de la recherche

La recherche peut prendre beaucoup d’aspects !

Il y a plein de chercheurs différents !

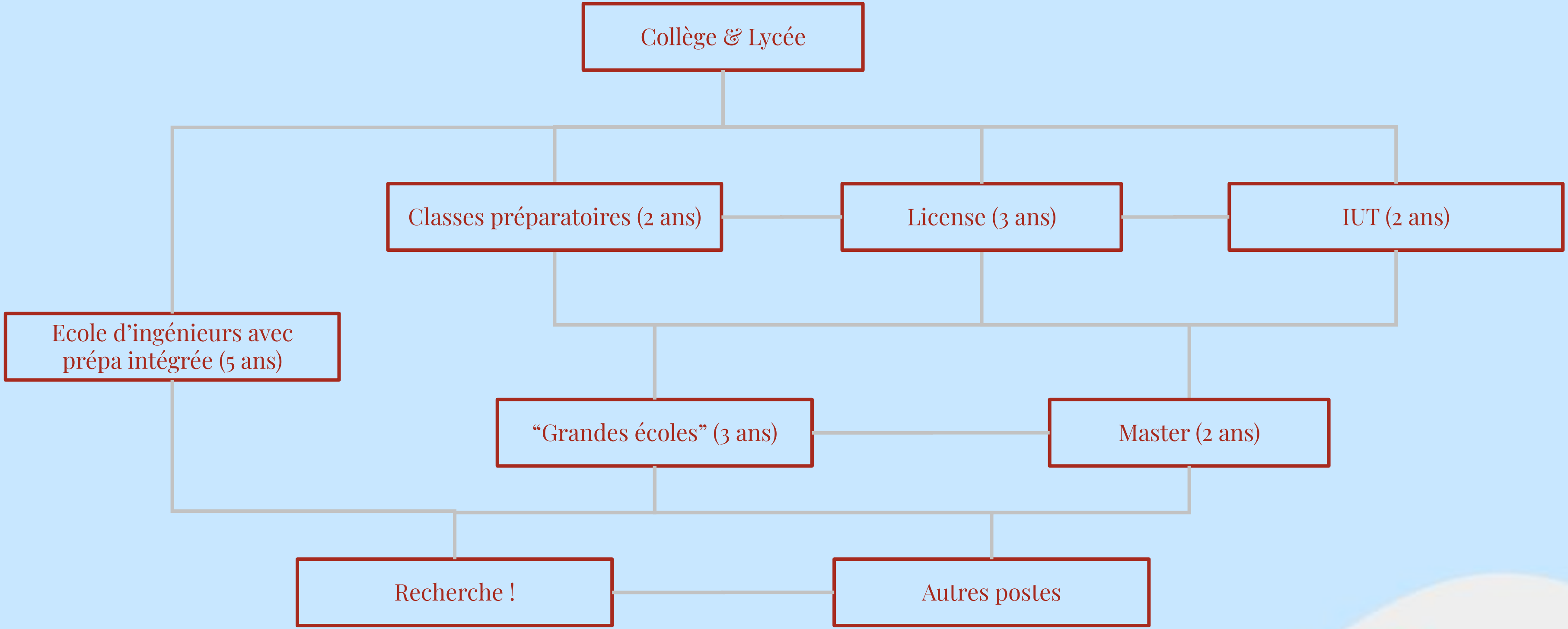
Marie Curie (1867-1934)
Elle met en évidence la radioactivité et découvre de nouveaux éléments chimiques

Alan Turing (1912-1954)
Il pose les prémices de l'informatique moderne et décrypte le code Enigma

Cédric Villani (1973-)
Spécialiste de l'équation de Boltzmann, il étudie aussi l'optimisation et la géométrie

Katie Bouman (1989-)
Elle contribue à la première observation d'un trou noir à partir des données de l'EHT

Et autant de façons de devenir chercheur



Les lieux de la recherche

Institut Pasteur
Paris (75)

Centre INRIA
Rocquencourt (78)

Ferme expérimentale INRAE
Bréteniière (21)

Du laboratoire à la vie de tous les jours

GE Healthcare

CPIS

GUSTAVE ROUSSY
CANCER CAMPUS
GRAND PARIS

Recherche dans le domaine de la santé:
- des médecins,
- des entreprises,
- des mathématiciens, …

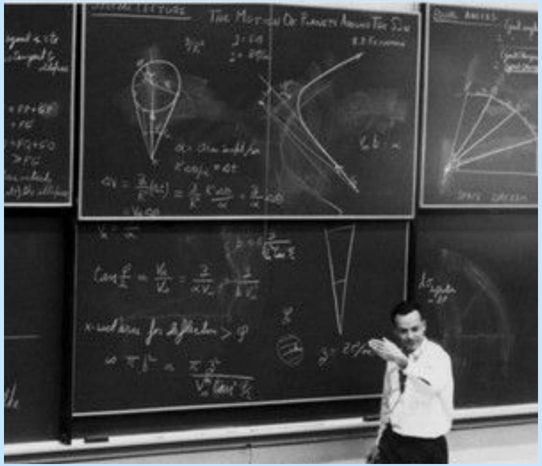
Jusqu'à ce que les résultats arrivent dans les hôpitaux !

Inria

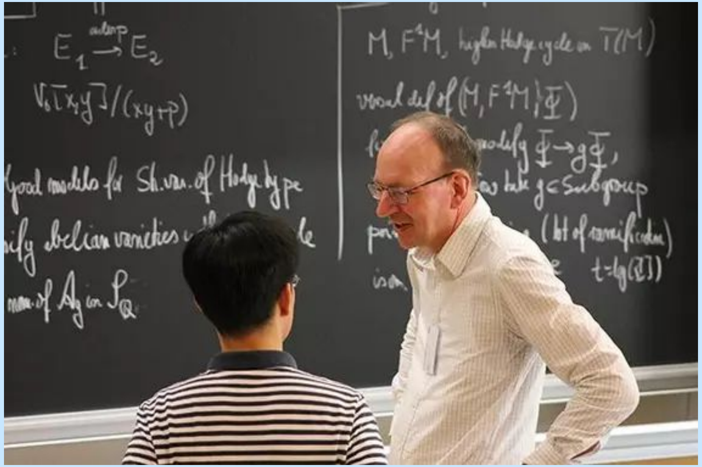
Etre chercheur au quotidien

Recherche, enseignement, supervision,...!

Enseignement et formation

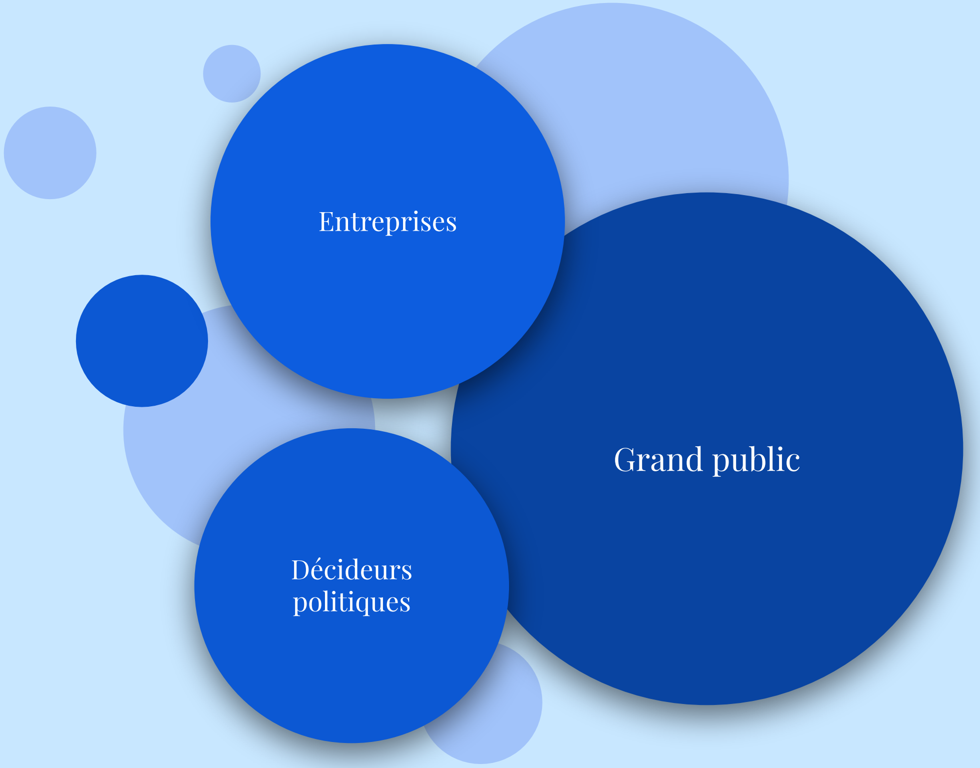


Beaucoup de chercheurs ont aussi une activité d'enseignement, on parle d'enseignant-chercheur.



Les chercheurs expérimentés encadrent et forment les chercheurs débutants.

Conseil, médiation, partenariats



Evaluation et relecture

SIMULATED ANNEALING: A REVIEW AND A NEW SCHEME

Thomas Guilmeau[†], *Emilie Chouzenoux*[†], *and Víctor Elvira*[*]

† Université Paris-Saclay, CentraleSupélec, Inria, CVN, Gif-sur-Yvette, France
∗ School of Mathematics, University of Edinburgh, United Kingdom

ABSTRACT

Finding the global minimum of a nonconvex optimization problem is a notoriously hard task appearing in numerous applications, from signal processing to machine learning. Simulated annealing (SA) is a family of stochastic optimization methods where an artificial temperature controls the exploration of the search space while preserving convergence to the global minima. SA is efficient, easy to implement, and theoretically sound, but suffers from a slow convergence rate. The purpose of this work is two-fold. First, we provide a comprehensive overview on SA and its accelerated variants. Second, we propose a novel SA scheme called *curious simulated annealing*, combining the assets of two recent acceleration strategies. Theoretical guarantees of this algorithm are provided. Its performance with respect to existing methods is illustrated on practical examples.

1. INTRODUCTION

Optimization is at the core of many problems in signal processing and machine learning, e.g., in signal restoration, supervised learning, dictionary learning, or image segmentation, to name a few. In those problems, nonconvexity can arise from sparsity penalty [1], low-rank prior [2], non-linear observation model [3], non-linear regressor [4], blind thus multi-linear problem structure [5], or discrete variables [6].

Nonconvex optimization problems can present many local minima, which can "trap" the algorithms iterates and be of poor quality with respect to the problem at hand. Thus, global optimization methods must be sought for, to escape local minima and thus finding the global solution. To do so, stochasticity is often a key ingredient. The stochastic optimization algorithms builds a sequence of random variables converging to the global minima. In this paper, we focus on an important family of stochastic methods for global optimization, called simulated annealing (SA), relying on the key concept of *annealing*, a concept in physics describing the cooling of a solid until reaching the configuration of minimal energy.

Note that SA is strongly related to the family of methods known as graduated nonconvexity (GNC) or continuation methods, that rely on a deterministic annealing procedure. Even if in some cases, these methods have been shown to beat SA [7], still few theoretical results support GNC [8]. More theoretically sounded deterministic approaches for global optimization are branch and bound (B&B) and particle swarm optimization (PSO) methods. In B&B, the original problem is split into subproblems (i.e., branching) associated to different locations of the space, for which the computation of a lower bound (i.e., bounding) gives information to create new branches [9, 10]. B&B methods share connexions with the stochastic approximation simulated annealing from [11], also relying on a splitting of the space. In PSO, a population of particles exchange information in order to find the optimum of the objective [12]. Population-based implementations of SA are actually strongly related to PSO [13].

The contribution of this paper is twofold. First, we review SA-based global optimization strategies in an unifying manner. We focused on the historical SA [14], fast simulated annealing (FSA) [15] and sequential Monte Carlo simulated annealing (SMC-SA) [16], which we retained for being highly generic methods with solid convergence guarantees. Then, building upon FSA and SMC-SA, a new scheme, called curious SA (CSA), is proposed. We show that CSA inherits from the best convergence guarantees of its ancestors SMC-SA and FSA. We also illustrate its performance on numerical examples. The rest of the paper is organized as follows. Section 2 formulates the problem and introduces notations. Then, Section 3 presents SA, FSA, and SMC-SA, along with their theoretical guarantees. In Section 4, we introduce our algorithm CSA and its convergence theorem. Algorithms performance are compared on two challenging nonconvex problems in Section 5. Finally, conclusions are drawn in Section 6.

2. PROBLEM STATEMENT

We consider the optimization problem given by

$$\text{minimize}_{x \in \mathcal{X}} f(x), \quad (1)$$

where $\mathcal{X}$ is a non-empty subset of $\mathbb{R}^d$. Although this is not always necessary [17], $\mathcal{X}$ is assumed compact. The objective function f is supposed to be defined on $\mathcal{X}$, continuous and thus bounded from below and above on $\mathcal{X}$. Further, we

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Les chercheurs doivent souvent donner leur avis sur le travail d'autres chercheurs. C'est la **relecture par les pairs (peer reviewing)**.

- Pourriez-vous faire des tests supplémentaires dans le cas où ***** ?
- Est-ce que votre méthode fonctionne toujours lorsque ***** ?
- Qu'apporte votre méthode par rapport à la méthode ***** ?

Et bien sûr, la recherche !

Ca veut dire quoi, chercher ?

La méthodologie de la recherche

La bibliographie

7. REFERENCES

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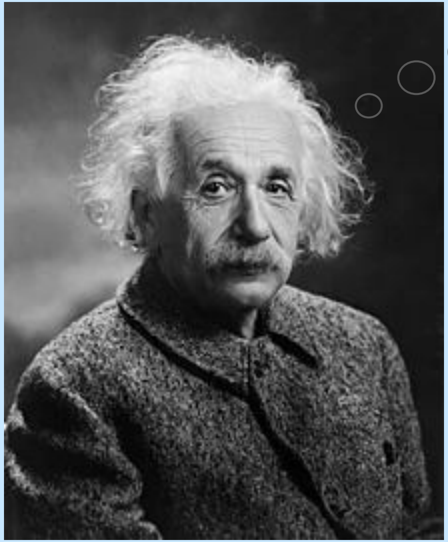
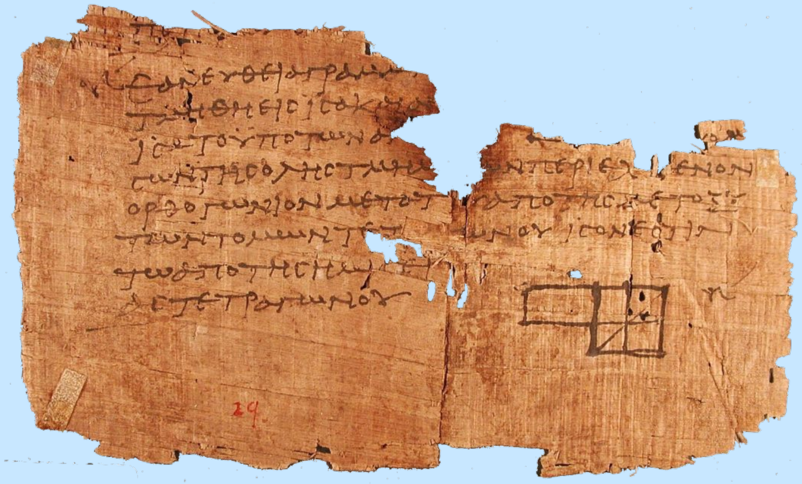
- Comprendre les approches existantes
- Comparer différentes techniques
- S’assurer que son idée est nouvelle !

Imaginer des pistes, se poser des questions

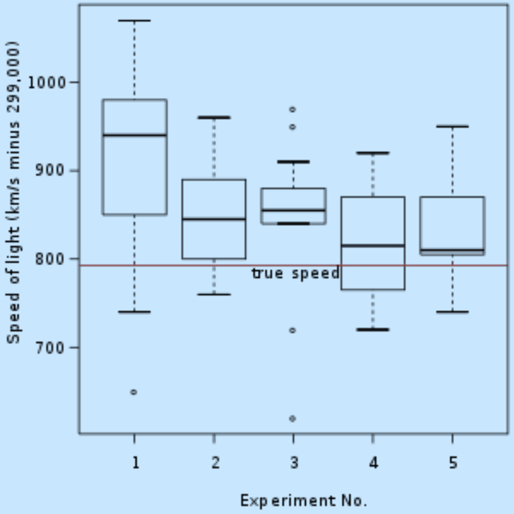


Et si la vitesse de la lumière était constante ??

Preuves et expériences

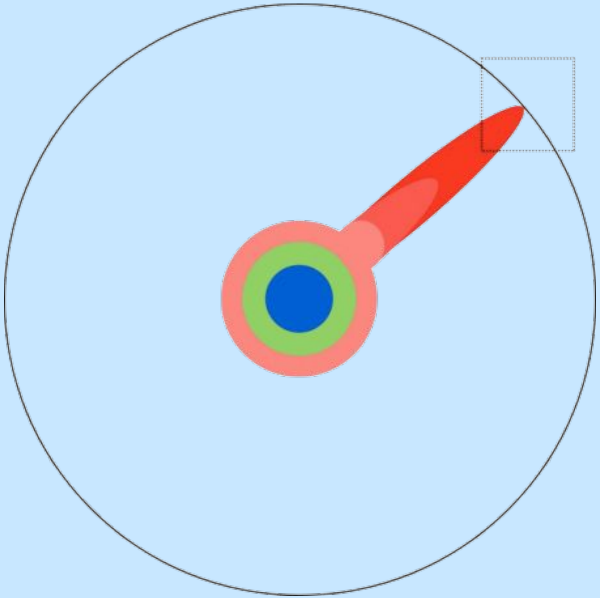


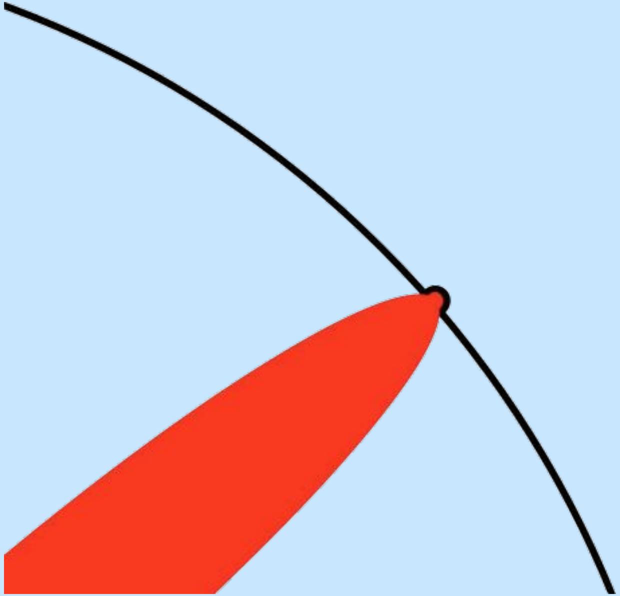
Un exemple de preuve



Analyse statistiques des résultats d'une expérience

Des résultats ou pas !





Même les résultats négatifs peuvent faire avancer la science !

Images tirées de http://matt.might.net/articles/phd-school-in-pictures/

Publication et communication

SIMULATED ANNEALING: A REVIEW AND A NEW SCHEME

Thomas Guilmeau†, Emilie Chouzenoux†, and Víctor Elvira*

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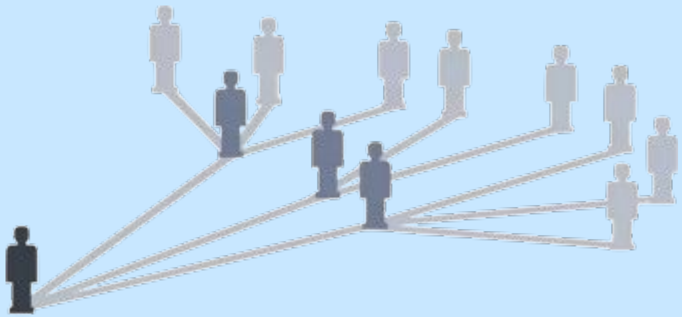

- Publication d'un article,
- Conférence,
- Séminaire,
- …

Merci pour votre attention !

Des questions ?