# Benefitting from the dissemination of artificial intelligence

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***Abstract***:
Artificial intelligence (AI) is a transformational technology that is going to infiltrate all human activities, in both society and firms, as it is incorporated in software. AI is not a goal but a means. Strategically and competitively at stake are the control of this new technology by actors in the French ecosystem, and the speed of acquiring the knowledge and skills necessary for disseminating AI. Firms must develop their capacity for implementing this technology by working on their data infrastructures and software environment (by making it open to freeware) and by favoring the iterative work of small multidisciplinary teams in short cycles. A plea for the development of engineering practices in AI: tests, learning protocols, the certification of all processes for using data, and the auditing of processes.

Taken in the broad sense so as to include machine learning, artificial intelligence (AI) is a set of methods for automating, improving on or imitating human actions such as reasoning and decision-making (RUSSEL & NORVIG 2003).[1] AI refers not to a specific, easily identifiable technique, but to a large set of methods to be incorporated in other computer-related tools and procedures. Although the spectacular progress made in deep neural network (especially in perception: artificial vision or speech recognition) has attracted much attention in recent years, AI is not just neural networks or machine learning.

The following ideas and recommendations for firms have been drawn from a report by the French Academy of Technologies on AI and learning (ADT 2018). This report postulated that AI is a means, not an end in itself, and that the control of this tool is a strategic issue. Nvidia's CEO, Jen-Hsun Huang, has clearly formulated this idea: "*Software is eating the world, and AI is going to eat software.*"

The first part of this article modestly seeks to answer the difficult questions: Which AI? For which problems? A simplified guide will then be presented for realistically using the panoply of methods now available. Attention will then be turned toward the conditions favoring the emergence of uses of AI. There is not yet any single or universal approach but, instead, multiple forms of AI adapted to specific fields. The third part of this article warns against unrealistic expectations. Several problems are waiting to be solved, such as the learning of "commonsense" and the ability to explain the "reasoning" followed when masses of data are analyzed for the purpose of building the coming generation of "smart systems".

[1] This article has been translated from French by Noal Mellott (Omaha Beach, France). The translation into English has, with the editor's approval, completed some references.

# Which artificial intelligence? For which problems?

## Understanding the toolbox

The toolbox is full for the firms that want to experiment with AI-related approaches to solving the problems they encounter (DOMINGOS 2015). In this toolbox, we find:

- CLASSICAL DATA-MINING TOOLS (BIERNAT & LUTZ 2015). They are part of the standard library of algorithms available on the market or from open sources.
- BUSINESS RULE ENGINES. These software programs have proven their mettle, often in combination with others tools such as orchestration or complex event-processing.
- AGENT-BASED AUTOMATION IN PROCESSES. This variant of rule engines has the capacity for scripting and processing natural language so as to "intelligently" simulate agents. Several firms are already using this technology under the name "robotic process automation".
- PLATFORMS FOR NATURAL LANGUAGE-PROCESSING, with capacities ranging from the extraction of emotions to semantic analysis. Conversational agents, "chatbots", can be used to interact with customers (or employees) in natural language.
- LEARNING METHODS BASED ON NEURAL NETWORKS. These are easily accessible since most of the algorithms are available in "software as a service" or from open sources.

The availability, for four years now, of the basic AI building blocks from open sources has boosted the access to AI. All the big players — GAFAMI; Google, Apple, Facebook, Amazon, Microsoft and IBM — have decided to grant access to much of their legacy software. The belief is widely shared that we are at the start of the AI adventure and that the winner will be the player who attracts the most talents and accumulates the most validated data.

## Applying simple methods for the right purpose

There is no simple rule for knowing which method to apply. However we can identify the most appropriate approaches to adopt as a function of *a)* the quantity of data available (ADT 2015) and *b)* the questions being asked. Figure 1 is a simplified portrayal of using these two criteria to choose an approach. The first criterion (the volume of available data) is essential to certain methods, such as deep learning (GOODFELLOW *et al*. 2016). The second has to do with the nature of the question asked or problem to be solved: is it open or very precise? It is worthwhile pointing out that simple methods often work well to solve a large set of problems (PROVOST & FAWCETT 2013) and that AI should not be reduced to deep learning.

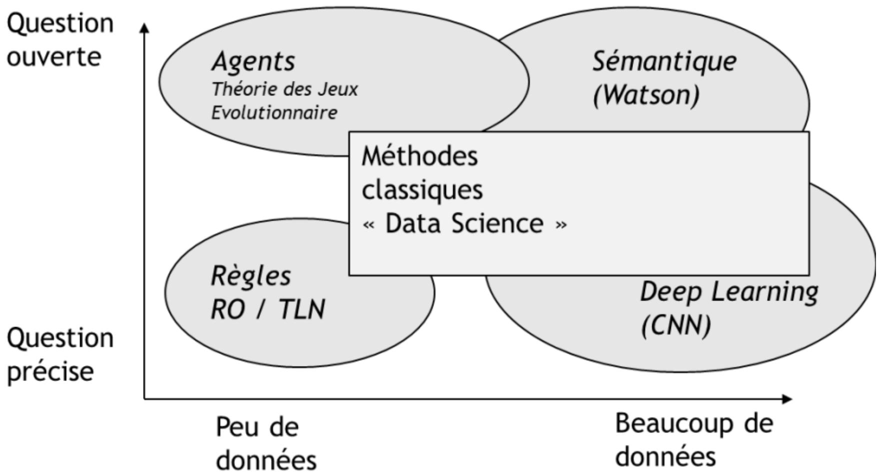


**Figure 1**: A simplified view of AI as a function of: *a)* the quantity of data available for processing; and *b)* the degree of precision of the question being asked

Using AI for predictions requires a minimum of knowledge in statistics. Above all however, it requires strict protocols for tests. The enthusiasm aroused by AI and deep learning comes with the usual traps, such as spurious correlations or overfitting (STEPHENS-DAVIDOWITZ 2017). Several test protocols exist for avoiding these traps, but a sound knowledge of statistics is indispensable for understanding and validating initial findings.

### Extracting value from big data

Using AI starts with the collection and selection of data and ends with a long process of validation:

- The first phase is the "curation" of data: collecting them, enhancing them with metadata as a function of models.
- The second phase is to choose the methods to be tested.
- During the third phase of integration, proficiency in computer science and technological skills are important.
- The fourth and last phase is to optimize the learning process and validate findings. When applied to a new problem, this process takes time.

This complexity is good news for firms since it implies that a barrier restricts entry into this new field of business. This complexity also reduces the plausibility that AI skills and qualifications will be concentrated in the hands of a few players (the GAFAMI of tomorrow) who will (as a service) capture opportunities worldwide.

Applying AI and machine learning to a business process transforms our view of the process. First of all, the problem of feedback: as experiences with machine learning applied to manufacturing have shown, it is necessary to add knowledge of the business process to the raw data collected by machines and sensors. Secondly, the existence of intelligent controls is a great opportunity for this transformation. There are many opportunities for local concentration, for creating ecosystems of data corresponding to a business process (PAVEL & SERRIS 2016).

## Boosting AI in firms: The conditions for success… depend on the field of application

To benefit fully from advances in AI, a firm must bring together a set of favorable conditions so that success will emerge. This means placing the firm in good conditions for taking advantage both of the technological opportunities streaming in from the outside (new algorithms, APIs for new services, improved sensors, etc.) and of the business opportunities identified inside the firm once the necessary data have been collected. Figure 2 depicts as a pyramid the conditions for being "AI-ready".

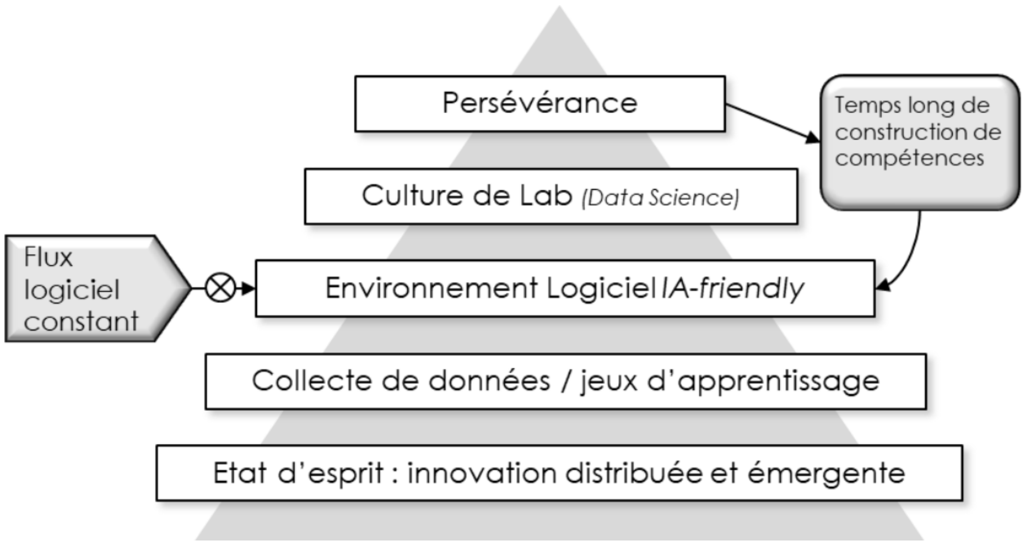


**Figure 2**: The conditions for a firm to be "AI-ready"

The uncertainty surrounding what it will be possible to do with AI must be handled using risk-management. This involves combining an aggressive policy for deploying AI in incremental steps (of what is now, or soon will be, possible) with a defensive strategy for observing and evaluating the rapid advances made in AI as risks (for example, the risk of competitors upending the market).

Most firms that successfully use AI have gradually worked out their own approach with respect to their business, problems and data. AI is evolving toward specialization, *i.e.*, toward multiple approaches that depend on the field of application. For firms, this means there is no standard approach: the choice of models, algorithms and learning protocols are specific to the field of application and the type of data collected.

The recommendations in the aforementioned report (ADT 2018) are similar to those made by Neil Jacobstein during a lecture at Singularity University. It is necessary to:

- invest without waiting, as a function of the means available in the firm;
- use the toolbox of available algorithms;
- learn to use specialized hardware (GPU, TPU, ASIC);
- make an inventory of all the firm's data sources and make them available; and
- use cooperative approaches to work with data scientists from outside the company.

# Benefitting from AI

## The need for lucidity when looking at technological progress

As we notice in recent publications, the enthusiasm for deep learning is counterproductive. Articles on the latest feats in this field tend to make exaggerated claims about their applicability and to omit any discussion of the very long period of learning and optimization needed to implement them. The talk about chatbots is inflated with promises, the phrase "artificial intelligence" often being abused. We are at the very start of applications that currently work only in narrow settings; their value is strictly proportional to the time spent collecting and processing data during the learning phase.

The world is so complex that many processes are unpredictable (TALEB 2004), independently of the quantity of data collected or the power of the algorithms applied to them. No method exists to predict random "noise" or highly complex events (*e.g.*, the weather or a price on the stock market). Faced with this sort of difficulty, we must spare ourselves the solutions of collecting ever more data or using ever more computational power, and endeavor to be prudent when judging statistical results.

AI is not just a matter of data and algorithms, even though the starting point for any AI strategy is a huge corpus of annotated data. The foregoing remarks highlight the extreme importance of practice for acquiring the know-how for collecting and "curating" data, updating protocols or developing the software engineering skills needed to manipulate data and incorporate the software bricks in a system.

### Scientific barriers still exist

Many a hard question is yet to be answered on the long road leading to widespread applications of AI. Reports have listed these questions (FRANCE IA 2017, BRAUNSCHWEIG 2016). I would like to draw attention to four of them:

- The new methods of machine learning and deep learning often fail to provide explications of their operations. An explanation is not always needed when the solution is restricted to a well-defined setting, but it becomes necessary, even essential, in other cases.
- In a similar vein, the smart systems based on deep learning are currently incapable of evaluating or qualifying their errors with, as a consequence, "spectacular" errors. Humans, less accurate than such a system, make more errors — but errors that are less important (or visible).
- One of the hardest and oldest problems of AI is commonsense reasoning. Commonsense is what enables us to exercise a "broad" instead of a "narrow" intelligence by invoking a context for the questions to be answered. This is fundamental for understanding natural language, since most of the "pieces" of knowledge needed for this understanding are taken for granted.
- The most active boundary between research and development is the passage from supervised learning (now used for most applications) to unsupervised learning (which exists in laboratories but is not ready to be rolled out).

## Conclusion

AI is not a specific, easily identifiable technique but a broad set of methods that can be integrated with other computer-based approaches and digital tools. Model-building and business skills are requisites for success. The success of the AI ecosystem also depends on using the appropriate applications and on the quality of the data collected. This supposes a pacified relation between society and this new technology.

AI is not a goal in itself, but a means that can serve many purposes and penetrate most of our practices and environments, in the corporate world and in society. Spectacular successes during the last few years in fields related to perception (whether image or speech recognition or, more broadly, the recognition of patterns) have formed the "elementary bricks" that, in the coming years, will be used to assemble a new generation of smart systems.

Firms will have to foster AI engineering practices. An AI strategy is, above all, a strategy for acquiring data. It is all the more complicated because we do now know what tomorrow's technology will make possible. It is also necessary to develop, formalize and capitalize the know-how of learning protocols and of methods for testing their validity. These engineering practices must also encompass the certification and auditing of processes for using data.

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