Artificial intelligence and management control: The relation to numbers and organizational issues

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Abstract:
The coming of all forms of technology called "cognitive computing" (AI, big data, etc.) could upend current assessments of corporate performance. More than a new way to analyze performance thanks to new indicators, this technology is leading to a new relation to statistical data while also bringing along risks. To avoid the dangers of algorithmic black-box models and respond to issues of interpretability, occupations (mainly, comptrollers) and organizations must undergo a transformation. Since "numbers" are conventions (*i.e.*, social constructs), any change in the ways of producing them implies changing the social systems on which they act.

The growth of big data, in particular data from the social networks, opens to auditors and comptrollers in management new fields for understanding a firm's performance. Processing these data with software using artificial intelligence (AI) and algorithms is opening a new paradigm for management control. "Cognitive computing" will inevitably change jobs in management control (SPONEM 2018, GUPTA *et al*. 2018), the division of labor in this field and organizations themselves. These technological trends will affect individuals and organizations, as they alter the relation that economic agents have with the firm's performance as reported in figures and statistics. In turn, this will have repercussions on internal auditing procedures. This impact on individuals will have to be paired with an organizational change in order to profit fully from this new management control paradigm.[1]

A review of our relations to statistical data

Owing to the growth of big data and artificial intelligence (AI), the relation of decision-makers to statistics has changed. Statistics, in particular those used by management, are, by nature, conventions (BOUSSARD 1998). They rely on hypotheses and shortcuts with regard to the data used — how they are collected, aggregated and interpreted. Very few persons are aware of these social conventions, and too many people take these conventions at face value. Those familiar with the conventions sometimes reject statistics as being rigged, or have lost confidence in their value. Conspiracy theories are always lurking nearby. Few are the persons who receive numerical arguments with caution or discernment, without rejecting them outright. Big data and AI risk reinforcing these tendencies.

[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 a few bibliographical references. All websites were consulted in March 2021.

Collecting data: Changes under way

Big data and AI might place in a black box what used to be (and probably, for a while, still will be) on Excel spreadsheets or come from transactional Enterprise Resource Planning (ERP) software, which allowed for the traceability of data. The data could be "seen", traced back to their source and, in short, discussed. They were processed by individuals who used heuristics of harmonization, aggregation and interpretation, which, though often of questionable value, could be subject to demands for explanations.

Big data are, by nature, more complicated to apprehend. They change fast. They are too numerous to be visualized in the "data lake", and any view depends on the standpoint ("lake shore") adopted. The data lake often contains duplicates. As a colleague recently recalled during a workshop at Dauphine University, many scientific meetings are held about duplicate entries. This is evidence of a phenomenon more complex than an Excel spreadsheet. Big data, though less structured, are probably more interesting since they contain information about the ambiguity of situations. However the data form a black box, a hoard of information rife with uncertainty.

Furthermore, in the case of AI, an algorithm replaces the human interpretation. Not only is this algorithm stamped with the "beliefs" of whoever designed it, it can also apparently evolve on its own. A human being can be called to account but not an algorithm. So, who will be held responsible for the decisions made? How to have confidence in a decision when we no longer know on what it is grounded? How to replace interpersonal confidence, the very grounds of a belief in an interpretation?

Interpreting data: Under tension

The task of interpretation has been altered. Decision-makers demand causalities whereas algorithms mainly yield correlations. Very often of course, managers act on the basis of uncertain correlations, as they try to make sense by matching two series of figures. As long as this is done by human beings, the persons using the statistics will often have suspicions about the beliefs underlying any interpretation. In contrast, an algorithm is more likely to be believed, a belief underlaid by a sort of technological magical thinking, especially if the algorithm has never failed. Once used repetitively however, the algorithm becomes a black box. Since it produces correlations between uncertain variables, decision-makers risk devoting too much time to interpreting graphics, like those in Figure 1, before realizing that the correlations are spurious (CALUDE & LONGO 2017).

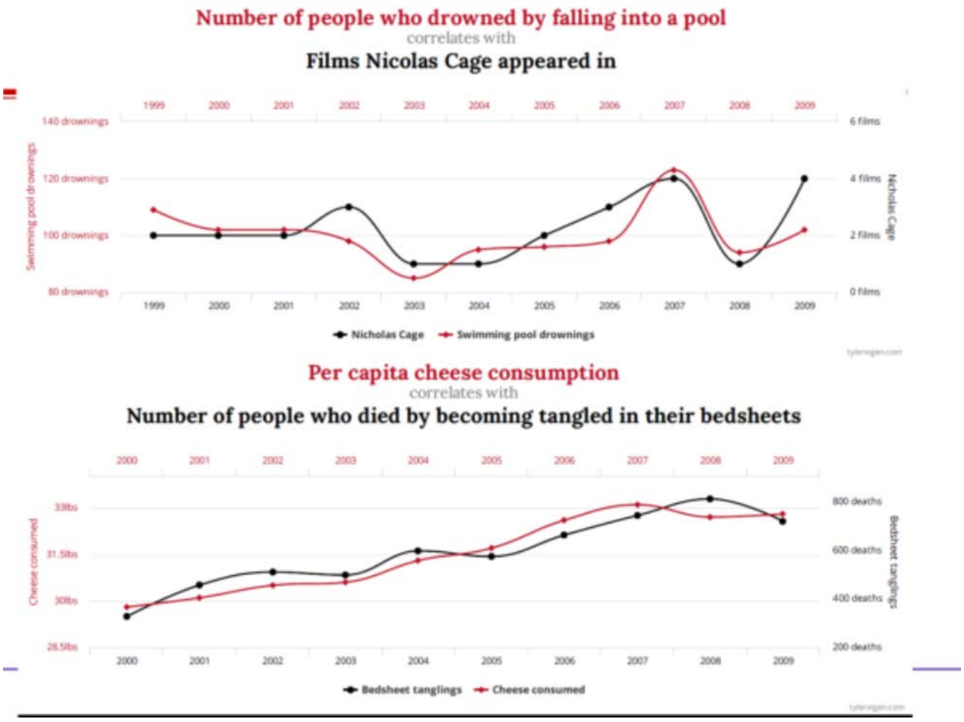


Figure 1: Spurious correlations
Source: https://www.tylervigen.com/spurious-correlations

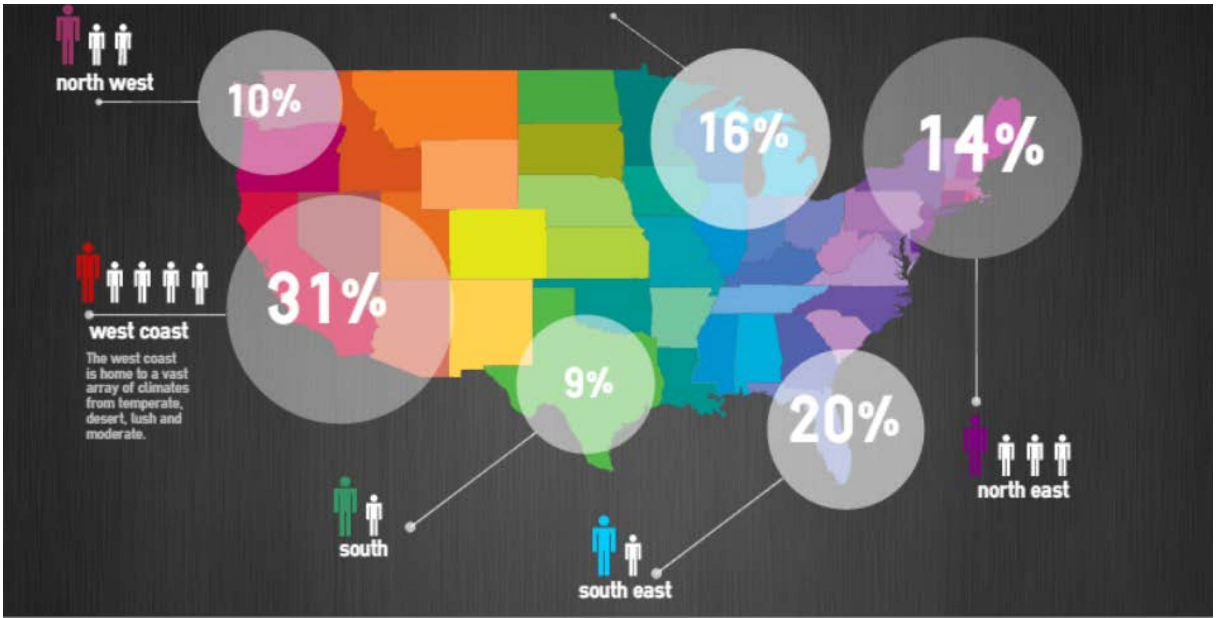
Much more time might be spent analyzing correlations since the algorithms have to be fed new data with, as a consequence, a multiplication of data sources and of data-processing systems. Decision-makers will make deals for "information system packages", *i.e.*, for data sets without full guarantee as to their internal coherency or consistency. This multiplication of data means that more time will have to be spent understanding interactions between sets of data and analyzing contradictions and inconsistencies. This makes decision-making more complicated. Decision-makers will thus be caught in the horns of a dilemma:

- either increase the volume and nature of the data so as to guarantee the quality of prediction systems,
- or else reduce and simplify the data so that decisions can be made consonant with the timing of actions.

As a consequence, decision-makers will have to be trained to understand the difference between correlation and causality (which is not simple given the philosophical uncertainty surrounding the idea of causality). They will also have to optimize the data feeds that will be of use for decision-making. They will have to "make sense" of the figures, give them a meaning. Each situation in management has its own decision-making process. This quest for meaning calls for the joint effort to construct narratives related to business activities. It also calls for learning how to debate the issues. In short, this strong need to improve the interpretation of statistics must be a major point in education and training, much more so than beforehand.

The scope of management control: Under question

The right interpretation of what statistics depict requires knowledge about the business models to be managed. A manager, we assume, has solid knowledge of his profession; but this assumption is not always evident in the case of comptrollers and auditors who, brought up on figures, might prefer Excel to any detailed business knowledge. Some auditors and comptrollers happen to do well, and end up looking for another position. We wonder whether positions in management control should not be assigned to managers who will move on as their careers advance. Freed from the fastidious tasks of collecting and consolidating data, the persons holding these positions could become experts on interpretation, along with the data analysts who produce statistics in an interface with algorithms. We also wonder whether comptrollers and auditors should not become “data savvy” or exercise “data stewardship” — becoming the persons who “know” the data and understand from an operational viewpoint what the black box contains. Though perhaps lacking the requisite technical competence, such persons would at least be able to make the statistics credible.



Capture d'écran d'une infographie Easel.ly (DR)

Figure 2: Data visualization

These new opportunities draw our attention to the need to make statistics attractive. After all, we have entered an era of design — what is produced has to be beautiful — and the volume of data is going to swell. For these reasons, data will have to be easy to read and understand, and pleasant to the eye. Power BI has worked on visualizing data, since this is a condition for the right use of statistics. Visualization entails making different “representations” of the data for passing from a micro- to a macro-view, from analyzing events to detecting long-term trends. Even if comptrollers and auditors master data specifications for different services (bookkeeping, management, current operations, etc.), the powerful models produced by cognitive computing are going to upend their role. Management controllers are not familiar with these models.

Adapting organizations

The introduction of big data and AI will have consequences not just on individuals. For the new possibilities to be fulfilled, organizations will have to be overhauled. In other words, the corporate structure as well as individuals will have to make adaptations (*e.g.*, in finance: DFCG 2018).

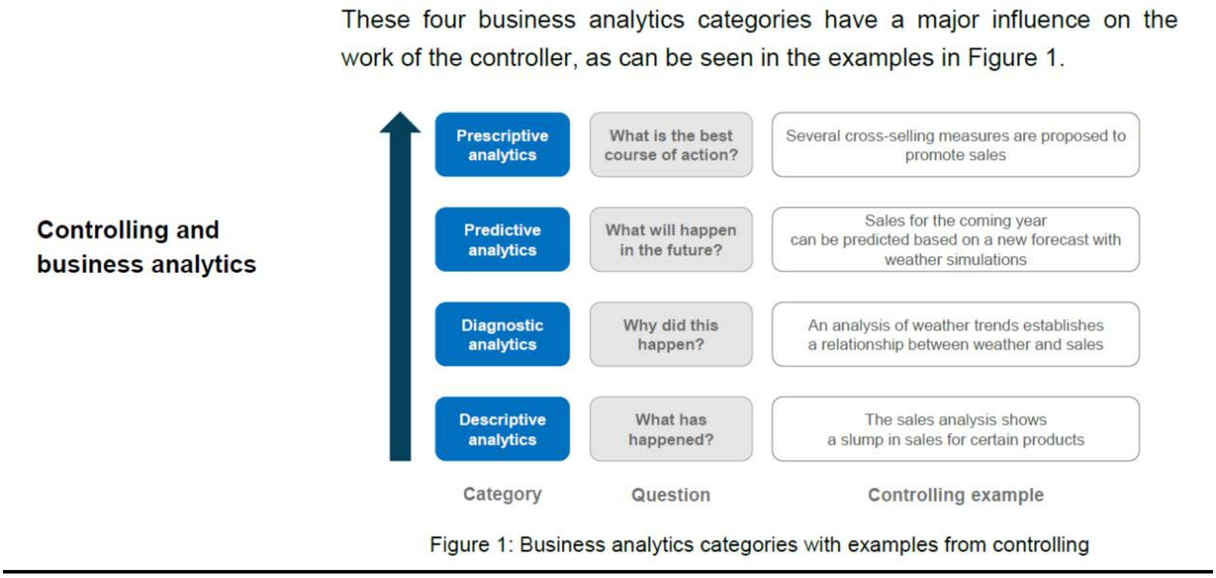


Figure 3: Categories of business analytics with examples from management control

New practices in the pipeline

Big data and AI should make it possible to enlarge, or at least to change, the mix of controls. Even though descriptive and diagnostic analytics are relatively familiar, cognitive computing systems should systematize them. For instance, business intelligence has considerably improved descriptive analytics, but it is possible to move ahead (by obtaining information in conversational mode). And diagnostic analytics, at least for current tasks, has advanced (even though progress can still be made) by systematizing alerts (*e.g.*, for detecting fraud).

Predictive and prescriptive analytics are the fields where changes will be the most numerous. Predictive analytics is still wanting in relation to management control systems. If "managing is foreseeing", managers will gain in effectiveness once information systems can be used to build better models for predicting the firm's future. By detecting weak signals, slight shifts, or monitoring competitors' positions, firms could improve their visibility without the need for constant human supervision.

Even more changes are expected in prescriptive analytics. Whether in business-to-customer (B2C) relations, where algorithms can propose new products to consumers and orient their choices, or in business-to-business (B2B) relations, where preventive maintenance will suggest repairs, the development of big data and AI can both take part in developing markets and in reducing the variance of predictions. But all this is yet to come.

Overhauling corporate structures: The shift to a network form

Cognitive computing should also change organizations, their forms and structures. As business history has shown, advances in tools or practices, especially in management control, have come along with changes in the structure of firms (BERLAND 2020). Cost-benefit analysis, once introduced, went in hand with the adoption of a functional U-form of organizational structure, whereas the introduction of budgeting systems and dashboards came along with the adoption of a multidivisional M-form. The insistence on financial steerage of the firm has generalized the holdings H-form. The introduction of cognitive computing appears paired with the development of a network N-form.

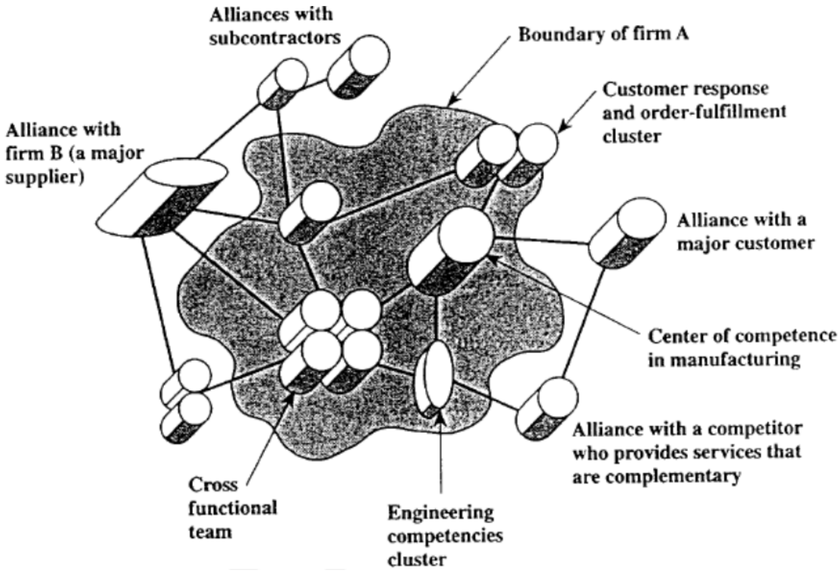


Figure 4: N-form or cluster (network) organizations, self-designing organizations, information-based organizations, postindustrial organizations

Cognitive computing is not the only reason for this apparently more systemic change. The shift from an economy based on production and services to a knowledge economy seems to have led many firms to modify their structures so as to become more flexible or agile. Cognitive computing will propel this shift. Information does not need to be structured as much as in a "normal" organization. The division of labor is based on knowledge and, consequently, information, which is the core of cognitive computing. This allows for a further decentralization of organizations and lower transaction costs (WILLIAMSON 1979); and coordination has taken the form of project management.

Less "bunkerized" forms of coordination

Forms of coordination within organizations (if we can still talk about "inside" and "outside") also seem affected. In computer science, transaction processing emerged at the same time as software re-engineering (code refactoring) and process management. Just as the ERP layer did not suffice by itself to improve operations in an organization (MEYSSONNIER & POURTIER 2006), cognitive computing will apparently be accompanied by forms of coordination that do not depend on it alone, such as lean management, holacracy, adhocracy or liberated firms. Despite differences between these models, the message is always the same: to "debunkerize" organizations that have become too bureaucratic. Of course, this decompartmentalization will affect management control. This increased decentralization will limit the view that any one person in the organization can have of all possible actions. Making a variety of actions consistent and a slue of processes stable are tasks no longer done by the hierarchy but via transfers of information.

Cognitive computing will bolster agility. By making new information accessible, programming the steps for validation and sharing relations of causality (verified or hypothesized), it will take part in generating these new forms of coordination.

This evolution of organizational structures, in which cognitive computing plays a part (without necessarily being a cause), will affect systems of control and the role of management control. The less possible it is to build a model of processes and organizations, the harder it will be to understand or interpret the chain of causes and effects that relates the uses of resources to the expected results. Model-building, in which comptrollers participate, will becomes more complex. Faced with new ways to describe organizations with new representations that they do not control, management controllers will have find a new source of legitimacy.

Conclusion

Big data, artificial intelligence and all the techniques contributing to the development of cognitive computing represent more than a technological change. They are modifying our relation to data and statistics, and altering our cognitive representations of organizations. These changes are conducive to, and accompany, new forms of coordination. New roles might emerge for steering these new forms of coordination, at the interface between economic analyses, mathematical models, and a knowledge of business activities and organizations. How will these new corporate positions be formatted? What skills and qualifications will figure in their profiles? What will be the place of persons in management control systems? These questions, so crucial for this profession, have not yet been answered.

References

BERLAND N. (2020) *Le contrôle de gestion* (Paris: Presses Universitaires de France).

BOUSSARD V. (1998) "Les indicateurs de gestion comme construction sociale: l'exemple des CAF". *Revue des politiques sociales et familiales*, 54, pp. 51-61, available at https://www.persee.fr/issue/caf_1149-1590_1998_num_54_1?sectionId=caf_1149-1590_1.

CALUDE C. & LONGO G. (2017) "The deluge of spurious correlation in big data", *Foundations of science*, 22(3), pp. 595-612, available via https://www.di.ens.fr/users/longo/files/BigData-Calude-LongoAug21.pdf.

DFCG (2018) "IA, Big data, robotisation. Quels impacts pour la direction financière?", *Cahiers techniques* (Paris: Association Nationale des Directeurs Financiers et de Contrôle de Gestion), 33p.

GUPTA S., KARB A.K., BAABDULLAH A. & AL-KHOWAITER W.A.A. (2018) "Big data with cognitive computing: A review for the future",*International Journal of Information Management*, 42, pp. 78-89.

MEYSSONNIER F. & POURTIER F. (2006) "Les ERP changent-ils le contrôle de gestion? Comptabilité et Connaissances", *Comptabilité Contrôle Audit*, 1, pp. 45-64.

SPONEM S. (2018) "Une 'société du contrôle' sans contrôle de gestion? Réflexion sur le Big Data", *Le Libellio d'Aegis*, 14(1), pp. 103-115.

WILLIAMSON O. (1979) "Transaction-cost economics: The governance of contractual relations", *Journal of Law and Economics*, 22(2), pp. 233-261.