Bigger data for Big Data: from Twitter to brain-computer interface

Article

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Abstract

We are sympathetic with Bentley et al.'s attempt to encompass the wisdom of crowds in a generative model, but posit that a successful at using Big Data will include more sensitive measurements, more and more varied sources of information, as well as build from the indirect information available through technology, from ancillary technical features to data from brain-computer interface.

Main text

Recent developments in the area of Big Data lay the ground for exciting new avenues to understand human behavior at a large scale, as demonstrated by Bentley et al.'s impressive data-driven classification scheme. When they rightfully emphasize the magnitude of "BIG data" (their emphasis, p. 34), we posit that what should be aimed at is really BIGGER data, and that, as they acknowledge, the dimensions they investigate, social influence (J_t) against transparency of payoff (b_t), constitute only part of the picture that makes for the process of human decision making. The importance of these factors for decision making is unquestioned, but a successful attempt at using Big Data at its full potential will study this process over time, will go beyond Twitter and Facebook and take into account technological advancements that are pervasive and constitutive of our modern societies, and will build on more various types of information, spanning second-order, indirect information as well as more personal data, from the brain sciences for instance.

The maps presented provide a static representation of the decision making process of a given society, at a particular point in time. Provided that such data can be gathered, Bentley et al. venture to comment on the evolution of societies and communities, like publishing academics, over time, asking whether human decision making is generally drifting to a more social, yet more opaque mode of functioning. In our opinion, complementarily to this analysis, one could use the velocity of change of decisions/opinions, to map the intrinsically dynamical nature of human societies, based on the distance covered between two maps at fixed time intervals. Much in line with the dynamics observed in Kuhnian paradigm shifts (Brock and Durlauf, 1999), recent events in the wake of political turmoil in the Arab world, for instance, the so-called Arab Spring, showed (again) that societies have the potential to impose radical changes to their way of functioning. The exponential velocity with which this change occurs is indicative of the multiple and complex tensions that arise in human societies. The speed of change will undoubtedly be impacted by access to new technology, liberal versus conservative cultures and policies, trait volatility (cultural propensity to changing one's mind), and will provide additional information about the importance of a given decision/opinion state, represented by Bentley et al.'s map, at any point in time. Furthermore, one could imagine that this velocity could signal imminent change, with sufficient predictive power to serve as a tool for monitoring, and supporting large-scale decision making.

Technology plays an unequivocal role in shaping human societies. Big Data, in fact, spawns from the almost unmanageable sea of information generated from modern technology, which forms the scaffolding for our daily activities. The ubiquitousness of this technology pervades our lives to such an extent that individuals can participate in the flow of information instantly, at their leisure, from almost anywhere in the world, through the touch of a fingertip. Therefore, we envision Big Data to evolve towards a more holistic perspective of collective behavior, based not only on the opinions and the so-called wisdom of the crowd, accessible through social networks, for instance, but also to reflect more indirect sources of information, and to combine varied types of information.

— Technology usage itself, for instance, can be a very rich source of such data and, as mobile computing grows cheaper, easier to use, more context-aware, as well as more anchored and necessary in our modern cultures, it is likely to become a prime source of inspiration for the field of Big Data. This process, coined Pocket Data Mining endeavors to extract information from the stream of data that is processed and emanate from users' devices (Stahl et al., 2010). This data may contain environmental variables, like temperature, noise level, luminance information or energy consumption. It may not even refer to the actual content of these streams of data, and reflect networking constraints, triangulated location information, or simply the sheer numbers of devices or the volume of communication.

— Indirect information will also come from the technical side of social networks, which comprises mining and consolidating strategies to cross-reference users' behavior. These aspects constitute prime features of e-commerce, such as recommendation systems (Bhasker and Srikumar, 2010), that go beyond the more direct social links willfully set up by users on Twitter or Facebook, and status exchange. Recommendation systems in retail applications, such as Amazon, are often used for advertisement purposes to potential customers, who may share similar preferences. It is important to note that there is neither direct communication, nor explicit interaction between these users. Yet, they indirectly influence each other by their own decision making, due to the imaginative processes at play to make a business more lucrative. This dimension will no doubt play an even bigger part in the way we make decisions in the years to come, as such features become deeply engrained in the most basic services we use daily—think of the impact that the order of Google results has on one's daily decision making process, for instance.

— Finally, we believe that technology will not stop at our fingertips, and so shouldn't Big Data. As Google's head-mounted augmented reality display has just been unveiled (Project Glass, 2012), and the off-the-shelf Brain-Computer Interface market is booming (Ebrahimi, Vesin and Garcia, 2003), it is increasingly likely that more personal information will be made available through technology sooner or later. If the practical consequences of such technology are difficult to predict, be they good or bad, it is yet entirely possible that this novel source of information will feed into our decision making process. By this time, Twitter and Facebook may have been shown to exhibit only the tip of the iceberg of what really pushes us to make decisions.

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