MANAGING DIGITAL TRANSFORMATION

Per Andersson, Staffan Movin,
Magnus Mähring, Robin Teigland,
and Karl Wennberg (eds.)

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Karyn McGettigan, Language Editor

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STIFTELSEN MARKNADSTEKNISKT CENTRUM

In his central role at the Wallenberg Foundations,
Peter Wallenberg Jr has furthered a broad range of important research
and research-led education initiatives at the Stockholm School of Economics
(SSE) and its Institute for Research (SIR). This indispensable work has also
helped create a fertile ground for research on digital innovation and
transformation: a phenomenon currently experienced, shaped, and
managed in and between organisations and throughout society.

This is the topic of this book, which we dedicate to him.

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Every year since 1992, the Stockholm School of Economics Institute for Research (SIR) has published an Annual Research Anthology, and this year SIR is publishing the book in cooperation with MTC (Stiftelsen Marknadstekniskt Centrum). The purpose of the SIR Annual Research publication is to enable managers and practitioners better understand and address strategically important challenges by showcasing SSE research on a selected topic of importance for both business and society.

This year's book, *Managing Digital Transformation,* features authors from academic areas across SSE together with representatives outside the institution. The book's eighteen chapters show the strength and breadth of SSE's research within the area of digitalization and reflect the importance that SSE places upon closely linking research to practice and on investigating the leadership challenges and their implications in order to support value creation in society.

Participating in the many ongoing research projects at SSE and the multitude of aspects of digital transformation addressed in the various chapters has been very rewarding for the editors. We would like to thank all the authors for their hard work and cooperation throughout the project. In finalising this book, we have relied upon the expert work of Karyn McGettigan for language editing, Petra Lundin for layout and graphic design, and Marie Wahlström for digital access to the book. We are, indeed, most grateful for their excellent and diligent work.

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Stockholm, January 2018
Per Andersson, Staffan Movin, Magnus Mähring, Robin Teigland, Karl Wennberg

Introduction

One of the hottest research topics lately is digitalization. Many research projects are focusing upon different perspectives. Gone are the days when digitalization or business implications of ICT were just about increasing efficiency. Instead, the ripple effect of digital development can now be felt wider and deeper than ever before. The way in which business is conducted and how it creates value, as well as how corporations can become more efficient and sustainable, are all implications of digitalization. Adapting to new demands and taking advantage of the plethora of possibilities, however, is not always easy.

Managing digitalization and the transformation of business always involves new challenges. The novelty and complexity of the digital age has led to an increased academic interest in the area of digital transformation and a call from companies that seek support in this process.

We take a look at digitalization from the perspective of business research. This creates a better understanding of the challenges that today's businesses are facing. We believe this anthology will serve as a tool to help businesses better understand the force that is digitalization and support these corporations in their digital transformation.

The idea behind this anthology grew as Marknadstekniskt Centrum was taking part in several interesting research projects. Companies were asking MTC to facilitate contact with scholars and supply them with academic insight. Vinnova came on board, by supporting the project *Progressiv digital utveckling förutsättningar för framgång (Progressive Digital Development: Pre-Requisites for Success)* of which this book is a part: its aim to stimulate business to become more progressive in digital change. At last, this book and the website www.digitalchange.com have become a reality.

This joint venture between Marknadstekniskt Centrum and The Stockholm School of Economics Institute for Research follows the SIR tradition of publishing an annual yearbook to showcase its vital research contributions. The book begins with an overview of digitalization, then moves to understanding the new digital customer, and ends by exploring re-organisational effects, business models, and ecosystems. We hope this year's anthology will be useful for managers by facilitating their digitalization processes.

PART 1: DIGITALIZATION – DIFFERENT PERSPECTIVES

The role of digital technology in business and society is rapidly shifting from being a driver of marginal efficiency to an enabler of fundamental innovation and disruption in many industrial sectors, such as media, information and communication industries, and many more. The economic, societal, and business implications of digitalization are contested and raise serious questions about the wider impact of digital transformation. Digitalization affects all private and public operations, as well as the internal and external workings of any operation. Digitalization is the major driving force behind sweeping large-scale transformations in a multitude of industries. Part 1 includes various perspectives on digitalization and digital transformation.

PART 2: THE NEW DIGITAL CUSTOMER

Digitalization has resulted in more user-centric business and user-centric systems. The changing behaviour of the digital consumer/customer is discussed here as it connects to new forms of customer involvement and engagement, as well as analysis models of what creates customer value in this digital context.

PART 3: THE RE-ORGANISATION IN ORDER TO CONNECT WITH THE DIGITAL CUSTOMER

How can companies connect with digitalized consumers and non-digitalized customers? This is a central issue in managing digital transformation, as it draws attention to the emerging intra-organisational, marketing, and customer interaction challenges associated with digitalization: for both the consumer and the supplier. Another aspect of this is the internal handling of new forms of organizational ambidexterity; that is to say, companies and organizations engaged in digitalization processes often require an internal re-organisation in order to handle the demands that digitalization brings, and to explore new digital opportunities while promoting their existing business and operations.

PART 4: BUSINESS MODELS AND ECOSYSTEMS

How do companies change, adapt, and innovate their business models? Given that digitalization leads to a convergence of previously unconnected or loosely connected markets, the digitalizing company and organisation is analysed in its systemic and dynamic context. This part draws attention to business models and business model innovation. Incumbent firms need to adapt and change business models while competing with digital start-ups based upon new scalable business models, accessible ventures, and rapid processes of intermediating. These chapters discuss completely new co-operative business models: processes that need to be developed as companies shift from products to digitally based services.

The Ecosystem places digitalizing organisations and companies into their broader and systemic context. This includes discussions on digital disruption, industrial convergence processes, and shifting patterns of competition and cooperation. Digital technologies cause markets to converge in many new and sometimes unexpected ways. The result is the emergence of new roles and market positions of technical platforms.

Staffan Movin, Stiftelsen Marknadstekniskt Centrum

Uncertainty and Complexity in Predictions From Big Data: Why Managerial Heuristics Will Survive Datafication

GUSTAV ALMQVIST

Introduction

Target Corporation is the second largest discount store retailer in the U.S. The Company belongs to an industry that constantly craves for more customer information in order to improve marketing effectiveness. To reach this goal as efficiently as possible, merely knowing the past or present is not enough. Data must also enable them to predict[1] the future. When reports broke that Target had managed to use the consumption history of one of its customers, a high school girl, to infer her pregnancy (well before her father knew) it, indeed, stirred some controversy (Sanders, 2014). However, as *The New York Times Magazine* emphasised at the time, it actually came as little surprise to marketers with an interest in predictive analytics. Amazon has since patented anticipatory shipping, to utilise similar abilities on a large scale within its logistics.

Digitalization enables today's marketing professionals to know their digital customers better than ever before. What this really means is that they possess more extensive information about their past and present behaviour. By logical extension, most marketers believe that these *Big Data* will contribute to the realisation of commercial objectives (Erevelles, Fukawa & Swayne, 2016).

The purpose of this chapter is to go beyond the data themselves to illustrate mechanisms in the predictions they generate. The dual function of all

1 Prediction and forecasting will be used interchangeably throughout the chapter.

prediction is to monitor forecast quality and improve decision-making (Winkler & Murphy, 1968). This chapter will address both of these aspects, building upon the forecasting and judgment and decision-making (JDM) literatures, to present a non-technical investigation of the challenges inherent in forecasts from big data.

The *Golden Rule* of forecasting advocates sophisticated prediction models that incorporate all available information (Armstrong, Green & Graefe, 2015). All else being equal, this assumes that having access to more data also lead to better predictions. And yet, at the same time, there is evidence that ignoring part of the information can improve forecasts (Hogarth & Makridakis, 1981; Soyer & Hogarth, 2015) and that simple prediction models often do well (Makridakis & Hibon, 2000). Understanding this paradox will nuance the expectations placed upon predictions from big data. This chapter will argue that forecasts require a good match between the uncertainty of the environment and the complexity of the prediction model.

What constitutes a good prediction? What is meant by big data? Which dynamics determine the predictability of the future? And, are extensive information and sophisticated models really pre-requisites for businesses to anticipate the behaviour of their digital customers? These and similar questions will be answered in the following. The chapter will begin with some comments on prediction, continue with a summary of the literature on big data, then illustrate some mathematical-statistical constraints in forecasting, and conclude by saying that simple *managerial heuristics* (businesses' rules of thumb) may yet survive – even in this age of *Datafication*.

Predictions From Big Data

PREDICTION

Predictions estimate future states of the world when the outcomes cannot be known for sure. Following Hogarth, Lejarraga, and Soyer (2015), prediction involves two populations or settings. In the first setting, data are analysed and interpreted, thus, enabling *learning (L)*. This knowledge is projected into the future in the second setting with the aim of fitting an outcome: the *target (T)*. Predictions can only be effective to the degree that the information in *L* and *T* match. They must overcome both *uncertainty* and *complexity*. The former is the dispersion of the probability density function of *T* while the latter are the interdependencies among the prediction model's variables (Schoemaker, 2004). As a result, as Nils Bohr, Nobel laureate in physics once said: "Prediction is very difficult, especially if it's about the future."

Predictors and Predictands

Take a music streaming service about to recommend a playlist to one of its users. It cannot perfectly anticipate how it will be received. However, it can make a qualified guess. Certain cues in the past (having just listened to *Oasis*), may have been positively correlated to one criterion (next wanting to hear *The Beatles*), yet negatively to another *(Blur)*. Thus, forecasts extrapolate what is already known into the future and hope that the original relationships still hold. *L* and *T* become linked through *predictors* (independent variables) of *predictands* (dependent variables).

Forecasts can be divided into two classes: *deterministic* and *probabilistic*. The former yield a single value ("AC Milan will win the 2017/2018 Europa League") while the latter allocates probabilities to all potential outcomes ("there is a 15 % chance of AC Milan winning the Europa League; there is a 14 % chance of Arsenal FC winning it," et cetera).[2] Predictands can be *binary, categorical, integer, real-valued* or *complex* variables. For example, a prognosis that Gary Oldman will win the Oscar for Best Actor in 2018 is a deterministic forecast of a binary predictand (he either wins it or does not). Table 9.1 below contains some further examples.

For predictions to guide decision-making, these distinctions matter. Deterministic forecasts only project the most likely outcome. Hypothetically, the percentage chance of the most likely outcome can still range between ~ 0 % (think of the person holding the most tickets in the state lottery) and 100 %. For example, weather presenters normally provide temperature forecasts as integers and rain prognoses binary since they do not disclose absolute likelihoods. And yet, the actual probabilities may differ from one day to another; some days are inherently more uncertain than others. Therefore, accepting a deterministic forecast at face value always involves a risk, although it is possible to shift between deterministic and probabilistic forecasts and across predictands through designated transformation rules (Stephenson, 2002).

2 The probabilities were inferred from a bookmaker's betting odds (in September 2017) assuming a margin of 2–7 %.

Table 9.1. Examples of Predictands

Predictand	Scenario
Binary	An e-commerce company wants to infer whether those who have recently purchased product A also will buy product B.
Categorical	A TV production company is eager to know what interest the next season of its main series will attract: massive, average or none (quantified categories).
Integer	An advertising agency tries to anticipate how many followers a particular social media group will have by the end of the week.
Real-valued	An online store hopes to estimate the amount of data traffic its site will experience during the Christmas sales.
Complex	A betting site observes a rapid surge in clicks on a particular team and needs to figure out if and how this will affect the eventual distribution of bets.

What is a Good Prediction?

When the public learns about predictions, these are either the especially good or the particularly poor. Think of the lucky bettors who backed Leicester to win the 2015/2016 Premier League at 1000–1 odds or the unfortunate pollsters who were sure that Bremain and Hillary Clinton would win their respective elections. Meanwhile, the everyday efforts to incrementally improve prediction quality are seldom known.

Prediction quality is assessed through *verification*. This process systematically operationalises, measures, and evaluates predictions in order to enable continuous improvements. Good forecasts are those with high *accuracy* (low *prediction error*). That is, observations (O) and forecasts (F) that correspond.

Evaluations are sensitive to the choice of accuracy measure (Makridakis & Hibon, 2000). The predominant metric is the *Mean Absolute Error (MAE)* (see equation 1), which measures the average prediction error (Murphy, 1993):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - F_i| \qquad (1)$$

BIG DATA

The digital age has enabled Datafication. Where there were once small but tidy sets of information, subjected to deductive analyses by humans, there are now enormous amounts of fragmented data, which computers inductively mine for correlations (Mayer-Schönberger & Cukier, 2013). This shift is driven by big data. The term Big Data emerged informally in the mid 1990s and would feature in the odd academic publication a few years later (Diebold, 2012).[3]

According to Laney's (2001) *Three V's* framework, big data compiles extensive *(volume)*, multi-faceted *(variety)* data instantaneously *(velocity)*. Indeed, this imaging is there for all to see. Search engine(s) and social media platforms generate enormous amounts of data about their users, of numerous types and origins, and do so in real-time. E-commerce platforms constantly monitor their customers in order to improve segmentation and customise offerings. Streaming services log activities to study preferences in greater detail than ever before. All of the above data are vast, diverse, and immediate.

IBM has since coined another V – *veracity* – to pinpoint data ambiguity (Claverie-Berge, 2012; Scroeck et al., 2012). Others have highlighted how the meaning of data may change *(variability)*, that big data only becomes meaningful once information can be extracted from them *(value)*, and that they must be presented in an understandable way *(visualisation)*. Accordingly, there are actually *Seven Vs* of big data in total (Sivarajah et al., 2017).

The academic literature on big data is still new and mostly discusses data problems or process challenges related to acquisition, cleansing, aggregation, analysis or interpretation (Gandomi & Haider, 2015; Sivarajah et al., 2017). And yet, the key to big data is arguably that they can utilise heterogeneity to improve segmentation. As samples increase, this enables the study of previously marginalised sub-groups of the population (Fan, Han & Liu, 2014).

Big data's predictive potential, however, has attracted the most widespread interest. Be that Google's (in) ability to predict flu outbreaks (Lazer, Kennedy, King & Vespignani, 2014), an airline's improved estimated time of arrivals (Brynjolfsson & McAfee, 2012) or a consultancy's successful forecasts of niche auto sales (LaRiviere et al., 2016). Allegedly, "It's a simple formula: Using big data leads to better predictions, and better predictions yield better decisions" (Brynjolfsson & McAfee, 2012, p. 65).

Unfortunately, the truth of the matter is more complicated. Firstly, due to the novelty of big data, there is a deficit of empirical evaluations. Without systematic verifications of its predictive accuracy in the real world, it is difficult to assess how good predictions big data actually enables, especially across tasks.

3 See Ward and Barker (2013) for further definitions.

Secondly, as highlighted in the introduction, it is well established that simple prediction models may outperform complex approaches. Meanwhile, predictions from big data remain advanced and employ either *regression techniques* or *machine learning* (Gandomi & Haider, 2015).[4] Thirdly, big data implies that the number of variables and dimensions increase, which in-turn results in higher complexity. Taken together, these concerns indicate that predictions from big data remain most difficult. Two explanations for this will be discussed in the following section.

THE BIAS/VARIANCE DILEMMA

The first consideration is the *bias/variance dilemma* (Geman, Bienenstock, & Doursat, 1992), which relates to prediction uncertainty; it stipulates that there are three sources of total prediction error. These are *bias, variance* and a *residual* (ε) (see equation 2). Bias is the systematic deviation from the true score while ε is noise (presumed *exogenous*). This leaves variance. Here, variance could be seen as an important *Eight V* of big data and represents the prediction model's sensitivity data. Assume that L consists of several samples, drawn from the population T, and that each sample yields a unique prediction to fit the true function. Then variance measures the spread over these predictions. An unbiased model could suffer from high variance, or vice-versa. In practice, there is often a tradeoff between the two.

$$Total\ error = Bias + Variance + \varepsilon \qquad (2)$$

Regression techniques are superior at minimising bias within any dataset *(in-sample)*. But this is the easy part. Bias can be reduced from additional parameters alone. As the mathematician John von Neumann jokingly said: "With four parameters, I can fit an elephant, and with five I can make him wiggle his trunk" (see Dyson, 2004). However, similar exercises are susceptible to noise, which can be confused for signal. Statisticians refer to this problem as *overfitting*.

Although predictions should aim to minimise total error, Brighton and Gigerenzer (2015) still find a tendency to "develop, deploy, or prefer models that are likely to achieve low bias, while simultaneously paying little or no

4 This chapter will only discuss the former approach. On machine learning, see Hasan, Shamsuddin and Lopes (2014).

attention to models with low variance" (p. 1772). They use a subset of London temperatures to show the danger of overfitting polynomials to small samples and how this increases total error in prediction (*out-of-sample*).

Similar data will be applied in the following section to illustrate the other side of model complexity – *functional form* – that can have the same adverse effect. A dataset was obtained and analysed, courtesy of the Swedish meteorological and Hydrological Institute's (SMHI). Figure 9.1 contains a 360-temperature observation from Stockholm throughout 2016.

As a first, a linear function along with 2nd (quadratic), 3rd, 4th, 5th and 6th degree polynomials are fit to the observations from January through November (n=329). As expected, increasing model complexity gradually explains more and more of the variance in temperature (in sample).[5] As a second, the same functions are extrapolated to predict (out-of-sample) the December temperatures (n=31). Suddenly, the quadric function has the highest accuracy. Neither the linear function nor the more complex polynomials match the environment equally well. Similarly, although large datasets limit overfitting, the right degree of model sophistication depends upon the uncertainty of the environment (Hogarth & Karelaia, 2007). Different functional forms will find it easier than others to fit some patterns.

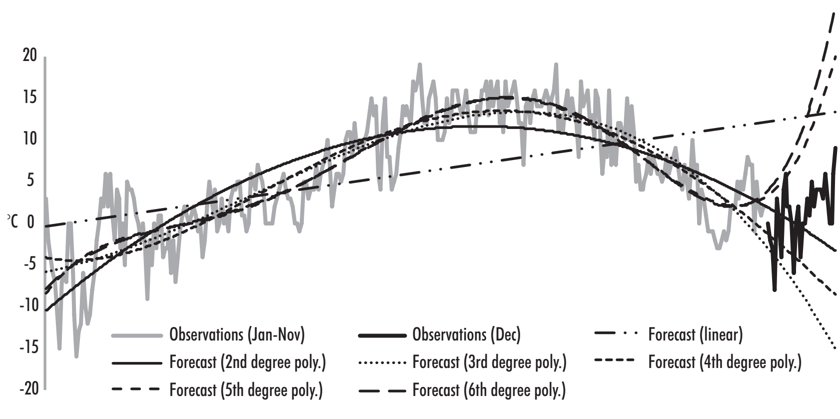

Figure 9.1. Model complexity and prediction accuracy. A linear function and 2nd, 3rd, 4th, 5th and 6th degree polynomials fit to Stockholm temperatures from January-November 2016 (in grey; n = 329) and then extrapolated to forecast December 2016 (in black; n = 31). The quadratic function does best.

5 The respective R2 values read .26, .68, .75, .75, .79 and .79.

THE CURSE OF DIMENSIONALITY

The second issue is the *curse of dimensionality* (Hughes, 1968), which affects prediction complexity. Big data places high demands upon a prediction model, as the number of dimensions per sample increases. Assume a large sample (n) with coordinates throughout an m-dimensional space. For instance, say the goal is to predict future purchases among a large group of digital customers about whom extensive information is available. Along with several underlying parameters, the prediction model stipulates independent variables as predictors of purchases. As model complexity increases, however, more correlational relationships involving the independent variables appear. Some are found for a reason, others merely by chance.

Following Fan, Han and Liu (2014), the accompanying risks include *spurious correlations* and *incidental endogeneity*, both of which violate key assumptions of regression methods. The former refers to the fact that the more parameters a prediction model contains, the likelier it becomes that variables incidentally emerge as correlated within the sample. The latter means that independent variables could be correlated with ε (thus *endogenous*). As a result, predictions from big data require analytical and practical tools for variable selection and dimension reduction. Whether more data can be leveraged into better forecasts will partly depend upon which function they are expected to fill within the prediction model.

Consider the following related example from finance. The risk of a portfolio depends upon the covariance of the individual assets' returns. As of November 2017, there have been 361 companies listed on the Nasdaq Stockholm stock exchange.[6] Building a portfolio from these technically requires estimating the entire covariance matrix to maximise the risk-adjusted return. And these elements can be combined in many ways. Here, this translates into having to estimate 65,341 covariance parameters. And even the slightest errors among these estimations could end up having a significant effect upon the portfolio due to *noise accumulation*. Again, model complexity comes at a price.

IMPLICATIONS

There are numerous examples of how forecasts are constrained by the bias/variance dilemma and the curse of dimensionality. Macroeconomists regu-

6 http://www.nasdaqomxnordic.com/aktier/listed-companies/stockholm

larly use extensive data for their predictions. And evaluations undertaken by Sweden's central bank, the Riksbank, indicate that a relatively simple time series[7] remains as good at predicting inflation as its most refined prediction model (Adolfson, Andersson, Lindé, Villani & Vredin, 2006; Sveriges Riksbank, 2017). The rudimentary Basel I framework of the 1970s still outperforms Basel III in predicting financial turmoil; this is also the case when tested against recent data (Aikman et al., 2014). Moreover, in the aftermath of the latest financial crisis, Goldman Sachs' former CFO admitted his complete surprise at having supposedly witnessed 25 sigma events occur several days in a row.[8] The same dynamics are also known to apply in weather forecasting: an application of big data where prediction quality has been the focal point for decades.

This section concludes accordingly that big data forecasts remain susceptible to prediction uncertainty and complexity. Therefore, big data alone does not guarantee better predictions. The natural next step must be more systematic verifications of big data forecasts' quality across a range of real-world tasks. This will require paying equal attention to the prediction models and their performances as to the original data themselves. There can be more to the interaction between a specific prediction model and a particular environment than what first meets the eye.

Managerial Heuristics

Importantly, the alternative against which to evaluate big data predictions are not naïve models of the coin-flipping kind. Businesses already have extensive experience in dealing with an uncertain future and apply managerial heuristics doing so (Artinger, Petersen, Gigerenzer & Weibler, 2015). Managerial heuristics are businesses' rules of thumb for handling specific tasks in their environments. In fact, there is evidence that these remain very much up to the challenge.

In 2008, Wübben and Wangenheimat set out with the ambition to quantify how much businesses would gain from switching to more refined ways to analyse their *customer relationship management* (CRM) databases. Ideally, this would

7 Technically a Bayesian vector autoregression (BVAR) model.

8 Even one such event happening by chance is so incredibly unlikely it practically translates into impossibility; like winning the 1-in-2,500,000 state lottery 21–22 successive times (Dowd, Cotter, Humphrey & Woods, 2008).

have enabled better predictions as to whether or not customers remained active in order to anticipate repurchases. They studied independent sets of CRM data from companies in three different industries: an apparel retailer, an airline, and a CD retailer.

The marketing departments had used a straightforward metric – recency-of-last-purchase together with a cutoff time – whereby a customer who had not made a purchase for a certain number of months was classified as inactive. Wübben and Wangenheimat (2008) put this heuristic to the test and compared its predictions to those made by stochastic models that statistically estimated parameters for customers' purchases and dropout rates. To their surprise, they found "no clear evidence for the superiority of these models for managerially relevant decisions in customer management compared with simple methods that our industry partners used"; instead, they concluded, "the heuristics the firms used worked astonishingly well" (p. 92).

Macroeconomic forecasters have also been found to use intuition and heuristics in their predictions. Additionally, they interpret the task more broadly than merely as a problem of maximising accuracy (Wennberg & Nykvist, 2007).

Some interpret these and similar findings to be counter-intuitive. Brynjolfsson and McAfee (2012) would still insist: "that throughout the business world today, people rely too much on experience and intuition and not enough on data." (pp. 66) But no method, however advanced, can maintain its superiority in face of conflicting evidence. Because in nature and business alike, the pursuit is not maximum sophistication; it is fit: effectiveness in an environment. For as long as prediction remains an empirical issue, managerial heuristics cannot be rejected a priori.

Discussion

In closing, the chapter will briefly discuss what the future might hold for predictions from big data. In an eschatology of sorts, Mayer-Schönberger and Cukier (2013) have suggested that theory and inferential statistics will be replaced, as big data implies $N \sim all$. Correlation will replace causality and a paradigmatic shift from reason to association follow. Given enough data, computers will inductively figure out the world by themselves.

However, big data does not make theory redundant. On the contrary, had it not been for common sense, Google's algorithm would have had people believe that high school basketball games predicted flu outbreaks, as their seasonality happened to be similar (Lazer et al, 2014). Going forward, this divide will surely cause more debate.

Some consider big data to be a new computational and statistical paradigm (Fan, Han & Liu, 2014); it is fair to assume that the unique characteristics of big data will see to it that certain methods are refined while others are replaced. Tools for analysing high dimensionality data will likely be in demand.

To end on a pessimistic note, the future will tell whether or not big data spirals into an unfortunate man versus machine scenario. In the meantime, ethical issues remain a concern. Ensuring personal integrity and protecting citizens' interests are critical challenges for societies and democratic institutions (Helbing et al., 2017).

Conclusions

The following recommendations are, hereby, provided for businesses considering using big data for forecasts:

- To distinguish between the learning and target population
- To define and operationalise predictors and predictands
- To recognise the difference between deterministic and probabilistic forecasts
- To monitor prediction quality through a systematic verification process
- To beware of the bias/variance dilemma and the curse of dimensionality
- To evaluate prediction models competitively (out-of-sample)
- To avoid overly complex models

Nonetheless, their ability to predict the future will be anything but certain.

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