Decision Analytics - A Position Paper

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The context we address is the 'digital or new economy' for which we propose that Decision Analytics will be one of the key drivers. The reasons are that we need to both meet the challenges from big data/fast data and to work out new possibilities to make experience and expert knowledge accessible and usable for local, ad hoc decision makers and for automated, intelligent systems. Digitalisation brings increasing competition, slimmer margins for productivity and profitability and more pronounced requirements for effective planning, problem solving and decision making. This requires a transfer of (sometimes tacit) knowledge from experts and experi-enced people to novice system operators—and to automated, intelligent systems—a transfer we call knowledge mobilisation. We will work out reasons for why Decision Analytics will be a key part of knowledge mobilisation and an essential contribution to the development of instruments we need for the progress of digitalisation.

Keywords:
analytics, digitalisation, knowledge mobilisation, Bled eConference, research paper

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1 Introduction

INFORMS defines Operational Research and Management Science (OR/MS) as "the scientific process of transforming data into insights to making better decisions". OR/MS was the forerunner to analytics.

In a recent report called "Competing in 2020: Winners and Losers in the Digital Economy" [16] Harvard Business Review worked out the impact digitalisation will have in some key industrial sectors. Among the respondents 16% stated that their companies are digital (most products/operations depend on digital technology), 23% that they are non-digital (few if any products/operations depend on digital technology), and 61% that they are hybrid (some products/operations depend on digital technology).

The report found a significant performance gap between digital leaders ("digi-tals") and the rest ("non-digitals"): 84% of the digitals use big data and analytics, but only 34% of the non-digitals; 51% of the digitals use cognitive computing/AI, but only 7% of the non-digitals; the digitals have data science and data engineering on staff (62%), the non-digitals much fewer (20%); all professionals working for the digitals have the ability to work with and make sense of data and analytics (76%), not that common for the non-digitals (30%). The insight is that a strong analytics capability is key to digital business—companies that want to compete in the digital economy will have to invest in people, processes and technology that offer access to data and knowledge and skills in analytics.

One more detail—artificial and machine intelligence appear as key interests and concerns among the business leaders [16]; the formulation is that "future success will depend on the successful collaboration between human and machine intelligence".

Digitalisation is bringing big data (or "fast data" for streaming big data) which more recently has been claimed to make it impossible to use analytics as huge amounts of data make the algorithms impossible or impractical to use [4, 8]—or it will take too much time as fast decision making in almost real-time is a necessity in the digital economy ("the fast eat the slow" as the slogan goes). If there is time to make bad decisions (by guessing instead of using effective (but more demanding) instruments) there should also be time to make good decisions—we only need to know how and what instruments to use. The following tale offers some insight on analytics – it offers alternatives to approaches based on closed, secret and mysterious data sets.

Kahneman [18] relates the case of Orley Ashenfelter, a Princeton economist and wine lover, who wanted to find a way to predict the future value of fine Bor-deaux wines from information available in the year they are made. The experts taste the wine and use decades of experience and insight in the wine markets to decide future values. Ashenfelter, an economist, used multiple regression analysis and statistics tools as he had no possibility to actually taste exclusive Bordeaux wines. He collected statistics on London auction prices for select mature red Bordeaux wines 1990–1991. The quality of Bordeaux wines was found to be decided by (i) the age of the vintage, (ii) the average temperature over the growing season (April–September), (iii) the amount of rain in September and August (less rain gives better wine), and (iv) the amount of rain preceding the vintage (October–March). These four factors are all measurable, published and easily verifiable —tasting wines and making judgments has of course its benefits. Aschenfelter built a regression model with the four factors on vintages 1952–1980, which turned out to explain about 80% of the variation in the average price of Bordeaux wine vintages! We should notice that Aschenfelter is a professional—he avoided the fallacy of small samples and made sure that he had observations on large selections of wine over 10 years from six major century-old Bordeaux chateaux and limited his models to Bordeaux to reduce the number of external (but actually irrelevant) factors. Aschenfelter, in fact, follows what we describe as time-tested, good analytics practice: use facts and data that can be tested and verified, methods that can be validated for repeated use to work out insight that is useful, valid, and verifiable.

In Section 2 we will bring out some experience from the forest industry to show why it makes sense to take a couple of analytical steps beyond visualisation to gain insight; in Section 3 we show how Decision Analytics methods identify the core of a decision problem and clean out secondary problem elements that confuse the issues; in Section 4 we have summarized some points on what is required of Decision Analytics as a developed and effective approach for the decision context of the 'digital or new economy'; Section 5 collects a summary and some conclusions.

2 Lessons from the Forest Industry

The demand for fine paper products is slowly declining at 2-3% per year but has been rather stable for the last 10 years. Nevertheless, a paper mill we worked with showed significant variations in orders coming from the supply chain, variations that appear to be random and unexplainable. The managers had tried to use optimisation models, which did not work – they even suspected that the optimisation was part of the problem. One of the managers mentioned that he had heard about a "bullwhip effect" as a possible description of the supply chain problems, and that it involved some fairly tough mathematics.

Lee et al [19, 20] carried out some early, more systematic theoretical work and focused on distorted information as a driver of the bullwhip effect. They found that the bullwhip effect describes increasing variance in orders as they move up a supply chain (from customer trough retailer and wholesaler to producer), even when underlying customer demand shows only a small or even negligible variance. The reason seems to be that the retailer "improves" on the orders that customers place; there are many customers, and their demand estimates show variances that are judged not to be reliable – "they are not professionals on market dynamics". The retailers make their own demand estimates from "im-proved" customer estimates; the wholesaler gets orders from many retailers that show variations in estimated demand and "improves" on retailer orders when placing orders with the producer (the paper mill). Lee et al [19, 20] show that estimates over time of the actual demand get distorted as orders move up the supply chain.

The intuition is that this cannot be a big problem, but the paper mill managers listed several problems, that were later confirmed by the literature (cf. Lee et al. [19, 20], Carlsson-Fullér [2, 3]). The supply chain actor "improvements" build excessive inventory as the actors safeguard themselves against the variations. The safeguards will cause some part(s) of the supply chain to run out of products as actors overestimate their safety margins when deciding on orders; local shortages result in poor customer service and shortages result in lost revenue. Lost revenue translates to substandard productivity of capital allocated to operations.

On the corporate level the storyline is a bit different from the supply chain operations because of aggregated data: demand variations cause variations in the logistics chain and the planned use of transportation capacity; ad hoc changes will result in suboptimal transportation schemes and increase transportation costs; demand fluctuations caused by the bullwhip effect may unnecessarily change optimal production schedules, which shows up (much later) as increased production costs.

Lee et al [19, 20] found four reasonable operations that active supply chain actors could undertake to tackle variations. The first operation is to update demand forecasts when data shows that next period demands will be different. Forecasts are built with time series analysis of historical demand patterns from immediate customers. Then, only retailers build on actual customer demand patterns, the other actors adjust to (perhaps unmotivated) fluctuations in the orders of preceding actors. It appears that safety stocks, which are popular smoothing instruments, also will amplify the bullwhip effect [20] as they are optimal locally and subjectively for one actor but send the wrong signals up-stream.

The second operation is order batching: periodic ordering and push-ordering. The costs for frequent order processing may be high and attract customers to optimised periodic ordering schemes - which in most cases will destroy custom-er demand patterns. Standard MRP-systems use analytics models to decide optimal order size and frequency, and to activate periodical orders. Push-ordering occurs as upstream actors (working for producers, wholesalers, retailers) launch “special offers” to induce (non-optimal) out-of-period orders. This, again, contributes to variance in customer orders and destroys actual demand patterns, which contributes to the bullwhip effect.

The third operation builds up on price variations. The producers initiate and control price changes both in the long- and short term. Customers are encour-aged to buy in larger quantities by attractive offers on quantity discounts, in special price campaigns, through coupons or rebates. Then the buying patterns do not necessarily reflect consumption patterns - customers buy in quantities which do not reflect their needs. This will initiate and amplify the bullwhip effect.

Rationing and shortage gaming drives the fourth operation, which is initiated if/when demand exceeds supply. If the producers, even once, have met shortages with rationing of customer deliveries, customers start to exaggerate their real needs if there is fear that supply will not cover demand. This starts a bullwhip effect, which will grow if customers are allowed to cancel orders when their real demand is satisfied (and their gaming gets no downside cost).

These four causes/drivers of the bullwhip effect may be hard to monitor, and even harder to control in the industry. They may interact, and/or act in concert, and the resulting combined effects are not clearly understood, neither in theory nor in practice, which offer challenges for tackling them with decision analytics modelling.

In the real business case seasoned managers recognized the drivers of the bull-whip effect from their own experience and worked out some practical (producer) solutions: (i) share information with all supply chain down-stream actors; (ii) build channel alignment of pricing, transportation, inventory planning and ownership (if legal within antitrust legislation); and (iii) reduce order processing costs and shorten lead times to improve on operational efficiency. These (practical) steps make sense but there are two challenges - to adapt them to EU regulations controlling cartel-building and to develop decision analytics instruments to find optimal solutions.

In section 3 we will show how Decision Analytics methods identify the core of a decision problem and find solutions.

3 Analytics Modelling Guides Problem Solving

We will stay with the supply chain context and focus on the retailer-wholesaler stage as a retailer reacts to the actual demand from customers. We will add to the context description: consider a multiple period supply process where demand is non-stationary over time and demand forecasts are updated from observed demand.

Assume that the retailer gets orders representing a much higher demand in one period, interprets it as a signal of increasing demand in the future, adjusts demand forecasts for future periods, and places a larger order with the wholesaler. The demand is non-stationary, and an optimal ordering policy should also be non-stationary; non-stationary ordering increases the variance of the orders which starts the bullwhip effect. Another factor is the lead-time between the ordering point and the point of delivery; if this is long, uncertainty increases and gets the retailer to add some "safety margin" to the order, which increases the variance and adds to the bullwhip effect.

For analytics modelling we will simplify the context even further by focusing on a single product, (the models can be extended to multiple items and to batches of products), and inventory for multiple periods.

The process has the following structure: at the beginning of period t, the retailer decides to order a quantity z_t. This is called the decision point for period t. Next, goods ordered ν periods ago arrive. Retailer demand is fulfilled, and the available inventory is used to meet customer demand. Excess demand is backlogged until the next decision point. Lee at al [20] (cf. also [2, 3]) assume that the retailer faces serially correlated demands which follow the stochastic process,

$$D_t = d + \varrho D_{t-1} + u_t$$

where D_t is the demand in period t, ϱ is a constant satisfying $-1 < \varrho < 1$, and u_t is a random variable, normally distributed with zero mean and variance σ^2. Here σ^2 is assumed to be significantly smaller than d, a "usual" level of demand presumed to exist at any t, so that the probability of a negative demand is very small. The use of d is technical to avoid negative demand, which will destroy the stochastic process and make the analytics model useless.

The order quantity, which is found with a cost minimization model, is an optimal ordering policy and sheds some new light on the bullwhip effect. The effect gets started by rational decision making, which decides a precise order amount and time for delivery; there is not much hope to avoid the bullwhip effect by changing the ordering policy, as it is difficult to motivate people to act in an irrational way.

As an optimal, precise ordering policy drives the bullwhip effect we decided to modify the policy with imprecise order amounts that can be made more specific as the time of delivery gets closer. The order amounts can be intervals, which will be made more precise over time (communicating over some joint digital platform).

We worked out such a policy where intervals replaced the precise order amounts; for this we need to add a few more instruments to analytics modelling, fuzzy numbers. A fuzzy number A is a fuzzy set [5] of the real line $\mathbb{R}$ with a normal, (fuzzy) convex and continuous membership function of bounded support.

In [1] we proved a theorem that fuzzy subsets entail smaller variance (Var): let A, B $\in \mathscr{F}$, a family of fuzzy sets, with $A \subset B$. Then $Var(A) \leq Var(B)$. Then, if we develop better and better estimates of future sales in period t, D_t, we can reduce the variance of z_t by replacing the rule for optimal order amount with an adjusted rule. Fuzzy subsets entail smaller variance and $Var(z_{it}) < Var(z_{*t})$, i.e., the variance of z_{it} will get smaller as $D_t(i)$ gets closer to the point of order delivery, and the bullwhip effect can be eliminated. This was now carried out for demand signal processing; fuzzy (imprecise) numbers can be applied also to price variations and - with some more modelling efforts - to cases with rationing games and order batching.

The analogy with Kahneman and Ashenfelter [18] is that we found some simple, fact-based mechanism that works with data that can be tested and verified, and that we found to drive the bullwhip effect. We also noted that the four practical operations – demand forecast updates, order batching, price variations and shortage gaming – in effect mostly add complexity to the storyline without offering effective means to reduce or eliminate the bullwhip effect from supply chain operations. This illustrates Kahneman's point that "experts try to be clever … to work with (too) complex combinations of features".

4 An Agenda for Decision Analytics

Ciancimino et al [15] identifies distorted demand information – as we found out in sections 2-3 – as a key driver; in addition to this they also single out disintegrated material flow and lack of replenishment rule alignment. This resulted in a shift of focus to bullwhip avoidance [15] and implementation of supply chain collaboration practices. These include alignment of planning, forecasting and replenishment systems among partners, which is made possible with digital exchange of information. This new idea is described as a Synchronised Supply Chain (SSC) [15]; it could of course not apply to industries with strong (EU) regulations that guide and secure open competition in all parts of the supply chain. On the other hand, the practical measures we collected from the paper mill supply chain – (i) share information downstream, (ii) channel alignment of pricing, transportation, inventory planning and ownership (if legal at least formally) and (iii) technical steps to improve operational efficiency (order processing costs, lead times) – are in line with the SSC archetype.

On the other hand, the imprecise order amounts that become more specific as the time of order delivery gets closer are not directly reducing competition in the supply chain and should not conflict with EU regulations. The sequence of order specifications can be done with secure digital platforms that SC partners share.

Transfer of accumulated expertise on how to manage large, complex, and dynamic processes from senior to novice engineers is a classical problem in industry. The transfer needs to be done as experienced engineers retire or decide to leave the company or are let go to save on salary costs. Digitalisation brought a new requirement—the accumulated expertise should somehow be transferred to automated intelligent systems. Experience that we gained from industrial cases [7, 9, 17] shows that expert insight is not easily transferred to novice replacements (or automated systems) with much less or no experience of the processes.

We called this process knowledge mobilisation [6, 22] and worked out a first attempt with analytics modelling [7]. We noted that analytics has not gained much support in the last couple of decades (we have found several "common wisdom" (CW) claims as explanations, but which appear not to have support in research results). The first CW-claim states that mobilised knowledge will be too limited, that simplifications clean out most of the insights on offer from a real-life context. The second CW-claim finds that experienced engineers do not work with mathematical programming models. The third CW-claim notes that mathematical programming models gives an impression of precise insight and knowledge; models come from simplifying assumptions that clean out ambiguities and imprecision. The fourth CW-claim states that there are better ways to mobilize tacit knowledge with experienced engineers than using analytics. There are, however, valid counter arguments to the claims in actual cases [21, 22]. If simplifications are made properly, they will single out core functions in interacting processes and reduce complexity.

The paper machine case [21] offered some insight on how to work out challenges that digitalisation has introduced. Our contention was that digitalisation should build on joint human/system reasoning that combines experience, insight, intuition, social interaction, etc. with support produced by automatic, intelligent systems, which in the paper machine case were combinations of mathematical optmisation tools and fuzzy ontology [21]. We assumed and believed that this would work and managed to develop some test cases [22]. A partial answer builds on digital coaching [10, 12, 13] that offers instruments for knowledge transfer from experienced users to novice users and from knowledgeable users to automated systems. It appears that decision analytics could/should be the optimisaion part of the digital coaching.

There is a context understanding for the 2020's and an emerging research position for Decision Analytics that we can summarize in a few statements (cf. also [14]); these descriptions will no doubt change and be updated as our understanding of digitalisation and digital economy increases and improves, but the starting point builds on the proposals {4.1-4.4}:

{4.1} In a context of digital disruption and quickly growing competition in the digital economy we have in-creasing dynamic and real-time processes, which require rapid and timely problem solving and decision making in an environment of large and growing sets of giga-data that contribute to increasing and difficult to tack-le complexity. *Decision Analytics develops and offers instruments for insightful and concise representation of problems in the digital economy.*

{4.2} Management theory and research, combined with long-time experience, guide problem-solving and decision making in the digital economy. *Digital Analytics develops and/or finds alternative and simpler forms for problem solving and decision making that also offer more insight.*

{4.3} Complex and competitive environments (like the supply chains of major industries) invite rapid problem solving with locally available data and supported with ad hoc insight through digital platforms and applications. *Digital Analytics will search for and/or work out methods that adapt to both (optimal) local and ad hoc problem-solving as well as to the general and generic principles for intelligent, automated systems.*

{4.4} Knowledge mobilisation offers and distributes insight and knowledge in complex and competitive environments in the digital economy. *Digital Analytics forms the core and common language for knowledge mobilisation over digital platforms.*

5 Summary and Some Conclusions

We propose that Decision Analytics will be one of the key drivers for what is called the 'digital or new economy' (cf. also [11]). Digitalisation brings increasing competition, slimmer margins for productivity and profitability and more pronounced requirements for effective planning, problem solving and decision making. We worked out reasons for why Decision Analytics will be essential for meeting the challenges from big data/fast data and for working out new possibilities for effective problem-solving and decision making based on experience and expert knowledge. Artificial and machine intelligence appear as key interests and concerns among the business leaders; the formulation is that "future success will depend on the successful collaboration between human and machine intelligence". We introduced "knowledge mobilisation" as instrumental for the human-machine collaboration; Decision Analytics is proposed as a key component in this collaboration.

We introduced a study we carried out with a forest products corporation. The demand for the fine paper products was basically rather stable but a paper mill showed significant variations in orders coming from the supply chain, variations that appear to be random and unexplainable. The managers had tried to use optimisation models, which did not work – they even suspected that the optimisation was part of the problem. One of the managers mentioned that he had heard about "the bullwhip effect" but added that "nobody has been able to work out the bullwhip effect for fine paper supply chains" a nice challenge for analytics researchers.

The work with the paper mill focused on finding some simple, fact-based mechanism that works with data that can be tested and verified to drive the bullwhip effect. The principle found was to build up orders as intervals (actually, as fuzzy numbers) that give flexibility to adapt to changes in downstream demand and will be made more precise as a delivery time gets closer. We also found that four practical operations – demand forecast updates, order batching, price variations and shortage gaming – mostly add complexity to the storyline without offering effective means to reduce or eliminate the bullwhip effect.

Further research resulted in a shift of focus to bullwhip avoidance and implementation of supply chain collaboration practices. The new ideas are described as "synchronisation of supply chain operations", which has attracted new re-search.

The paper mill offered some insight on how to work out challenges that digitalisation has introduced. Our contention was that digitalisation should build on joint human/system reasoning that combines experience, insight, intuition, social interaction, etc. with support produced by automatic, intelligent systems, which in the paper mill case were combinations of mathematical optimisation and fuzzy ontology. A partial answer to joint human/system reasoning builds on digital coaching that offers instruments for knowledge transfer from experienced users to novice users and from knowledgeable users to automated systems. Decision Analytics could/should be the optimisation part of digital coaching.

Finally, the context understanding and an emerging research position for Deci-sion Analytics formed an agenda proposal in four statements (cf. {4.1-4.4}).

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