Improving Digital Decision Making Through Situational Awareness

Ovidiu Noran
Griffith University
Nathan 4111, Australia
O.Noran@griffith.edu.au

Peter Bernus
Griffith University
Nathan 4111, Australia
P.Bernus@griffith.edu.au

Abstract

Technical advances in Information and Communication Technology have enabled the collection and storage of large amounts of data, rising hopes of digitalising and thus potentially improving decision making and related support systems. Unfortunately however, the pre-existing gap between required decision making knowledge and the useful information provided by current technologies appears to increase rather than contract. Thus, the multitude of patterns presently provided by current data analytics techniques do not deliver an adequate set of scenarios to enable effective decision making by humans. This paper advocates a digital decision analytics solution featuring the use of Situated Logic to create 'narratives' describing the meaning of data analytics results and the use of Channel Theory in order to support adequate situational awareness. This approach is explained in the context of a System-of-Systems paradigm highly relevant to today's typically complex clusters of distributed collaborative decision making centres and their associated decision support systems.

Keywords: digital decision making, decision support systems, situational awareness, big data, data warehousing, decision model, situated reasoning, channel theory

1. Introduction

Big Data [1], the Liquid Enterprise [2], Sensing Information Systems [3] and similar concepts hold the promise to provide all necessary decision-making information for management in the adequate detail, quality and 'freshness' required. Conceptually, this endeavour comprises achieving the necessary capabilities to use the data to derive decision-making information in an efficient and effective manner, based on inferring knowledge that was not available (and attainable) before; nowadays, this assumes the presence and support of suitable data analytics.

An essential enabler of the above-mentioned undertakings is digitalisation – defined as transforming physical artefacts (processes, content, objects, etc.) and converting them to a (partially or entirely) digital format [4]. Digitising hopes to achieve not only efficiency gains but also to result in increasingly customisable and flexible artefacts [5] and even a change in the division of work [6].

Due to increased competition and reduced profitability margins in the context of hyper-competition, digitalisation requires more efficient problem solving, planning and decision making – which demand knowledge 'mobilisation' [7], i.e. transfer of knowledge (from experts and inferred as described above) to novices and to automated systems (so as to be able to act 'intelligently'); hence, effective digitalisation relies on suitable data and decision analytics. In addition, current findings on the use of digital data in executive boardrooms reveal that while it does occur, the degree of success heavily depends upon a proper synthesis and interpretation [8] – i.e. data analytics effectively supporting decision analytics.

Importantly however, it is necessary to define realistic expectations in order to avoid expensive mistakes. Thus, it is becoming clear that finding new ways to correctly interpret complex data in context is necessary [9]. For example, evidence-based medicine that relies on large scale data gathering through clinical trials and careful statistical analysis, after a promising start, is showing signs of trouble when the evidence gathered is applied in complex individual cases [10, 11].

From the above, an obvious perspective is that when intending to use large amounts of gathered data to create useful decision-making information, one must carefully consider the information needs of the intended audience (e.g. management) and importantly, how the interpretation of data is influenced by context.

This paper aims to investigate and analyse from a theoretical perspective what gaps and barriers exist in using data warehousing and big data paradigms to support proper decision analytics materialised in effective decision-making, in the context of digitalisation.

2. Research Methodology, Approach and Assumptions

The main research question addressed by this paper is: *'What are the main underlying causes of the ongoing difficulties in effective decision making, in the context of ever increasing digitalisation?'* A secondary research question would be *'(How) could the application of decision loops, situated logic and channel theory contribute to solving these problems?'*

In terms of Järvinen's classification [12], the research method belongs to theory creation, employing conceptual development as part of the constructive type of research methodology [13]) in the attempt to a) reveal the root causes of the problems in the effective use of data for effective decision-making and b) to hypothesize on the traits of potential solutions. Owing to the research domain, namely decision making by management with possible automated assistance (agents), the research adopts an anti-positivistic epistemological stance [14, 15] aware of the components, sources and limits of knowledge and of the justification of knowledge [16], so as to give a reliable qualitative answer to the research questions [17].

Critical realism as a higher level 'meta-theory' [18, 19] is also utilised, acknowledging the hermeneutic element in producing useful information for human decision making. Critical realism also allows the authors to employ a layered ontological view, allowing empirical findings to coexist with and be complemented by conceptual ones, as empirical findings alone do not necessarily represent what happens. Thus, events of interest a) may not be observed, or b) may not necessarily reveal the mechanisms that cause them to happen [20]. This stance is reflected in the analysis in Section 3 and conceptual work in the subsequent sections.

3. From Data to Information: Concepts and Approaches

3.1. Management and Its Information Needs

Management typically needs to make decisions on multiple levels, such as strategic, tactical, operational and even real-time. This endeavour can be reasoned about in relation to the information flow, usage and needs, and optimised using various types of models. In the following, the authors will use an example of mainstream systematic model of decision making, namely the GRAI Grid [21] (see Fig. 1). Fundamentally, this generic model identifies management, command and control tasks at various levels (identified via time spans called 'horizons') and the information flow between them.

The 'exogenous and endogenous information flows feeding the Manage, Command and Control centre in Fig. 1 illustrate the point that in order to make successful decisions it is necessary to satisfy the *information* needs of the management functions. This means that the data gathered and analysed must be meaningful, properly aggregated (level of detail) and suitably expressed in order to meet the demands and competencies of each audience populating the decision centres at various horizons.

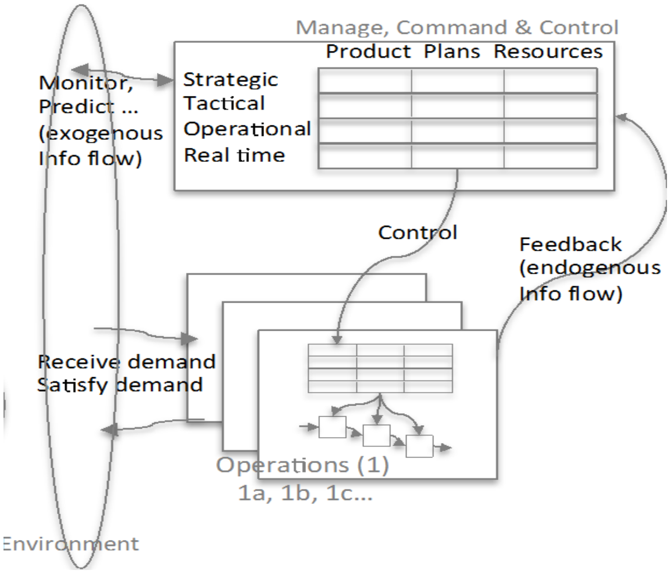

Fig. 1. A simplified view of a mainstream decision making model: GRAI Grid [21]

This is not a trivial task. To justify this point the authors shall refer to two main approaches to data analytics, namely data warehousing and big data.

3.2. Data Warehousing and Big Data

Data warehousing (an architectural concept relying on clean, integrated data of high quality) aims to use snapshots of operational databases and other data repositories and build an interface enabling the analysis (‘mining’) in order to identify management-relevant information. To build such a facility fast and in an affordable manner, the methodology suggested [22, 23] is to create it out of existing databases and possibly transaction logs so as to gain management insight [24, 25]. The aim is to create a *narrative* that is characterising the present or predicted future situation and is essential for strategic decision making. Despite initial apparent success in creating meaningful insight for management, data warehousing displayed some notable failures to deliver on its promises [26].

‘Big data’ is a technology that uses traditional data analysis and machine learning techniques to derive useful interpretations based on large and varied data sources [27, 28]. Brought forward by the technological advances in data gathering (cheaper, Internet-of-Things (IoT)-enabled and more intelligent sensors) and storage (ever cheaper and now cloud-based) and initially touted as the solution to the problems where traditionally implemented data warehousing fell short, big data is still maturing and yet to make significant inroads in decision support [29, 30]. This is partially owing to its very dependence on machine learning algorithms that attempt to *predict* but cannot adequately *explain* the predictions (an essential factor in gaining human trust in decision support systems [31]).

Since big data technology is nowadays often used in data warehousing [32](e.g. in the creation of Enterprise Data Warehouses to support, among other functions, decision making), a combined analysis of their shortcomings in achieving the expected insight for decision-making is deemed as highly relevant and presented in the next section.

3.3. Shortcomings of Data Warehousing and Big Data

A first drawback of the two concepts refers to the associated methodologies, which do not give enough weight to starting with understanding the fundamental information needs of the decision maker rather than rush to data collection and interpretation [33].

In addition, there is minimal or inexistent *correlation* between internal- and external data sources (i.e., connecting the endogenous and the exogenous information flows - see Fig. 1).

Further on, insufficient effort is put into realising *what* data is needed for being able to draw useful inferences, but *is unavailable*. Even the recent methods proposing to limit the amount of sensor data taken into account in situation assessment (e.g. via a facility to switch 'on or off' additional pre-stored sensor data sources) is relying on the command and control to pinpoint *what* data should be taken into account to possibly change the narrative.

If the above deficiency *is* identified, then the need for data that is not available, but is deemed necessary, may become the source of additional data collection tasks; however, this can inadvertently result in poor data quality ([9, 34]). This is because the essential but problematic Human point of view of the data gathering task is ignored (i.e., how to avoid data quality problems owing to erroneous data entry by humans who consider it a chore), in favour of only solving the easier to manage database / computing problems (how to use various algorithms to identify patterns in available data, which is essentially a *technical* problem). This issue is exacerbated by the current context of emerging ubiquitous digitalisation.

Another issue is the limited progress in transforming existing processes to produce the necessary data *as a by-product of the production (or service delivery) process*, instead of requiring additional data entry [34] (a main source of data quality issues as shown above).

There has been a tendency to disregard the *context* of the collected data [35], and thus creating the danger of situation misidentification *without even being aware of having committed this mistake* [36].

Another important aspect is the typical reliance of big data technology on machine learning techniques which produce models whose uncertainty cannot be adequately assessed and especially whose predictions cannot be adequately explained [37].

Out of the above aspects, two main issues stand out when analysing the history of creating useful decision-making information through data warehousing using big data analytics and the associated business intelligence processes:

- On each decision-making level, one must correlate internal *and* external data;
- With the opportunity to collect and access very large amounts of data, due to the typically low density of useful content [1], it becomes difficult to identify patterns that are useful for decision making (too many patterns identifiable by algorithms) – unless one uses *heuristics* (i.e., the result of prior learning) to discern what is relevant (note that the measure of relevance may change in time and with the current interpretation of data).

The following section aims to address the above issues using a nested and recursive decision making paradigm allowing correlation, explanation and learning through self-reflection.

4. Making Effective Decisions

4.1. The OODA Loop as an Activity Network

The tasks that appear in each type and level of decision-making and the feedback that can be used to inform the filters used to selectively observe reality may be studied using a model that explains how successful decisions are made. This model is part of the well-known Observe, Orient, Decide and Act (OODA) Loop devised by John Boyd [38].

Note that this 'loop' is often misunderstood to be a strict sequence of tasks [39]. OODA is *not* a strict loop, due to the feedback links inside the high level 'loop-like' structure that are responsible for learning and for decisions about the kind of filters necessary. Thus, in fact it is actually an *activity network* featuring rich information flows among the OODA activities and the environment.

A brief review of Boyd's OODA concept can be used to highlight potential development directions for data warehousing and/or big data methodology for decision support. Thus, decisions can be made by the management / command & control system of an entity, in any domain of action and on any level or horizon of management (i.e., strategic, tactical, operational and real-time, performing four interdependent tasks.

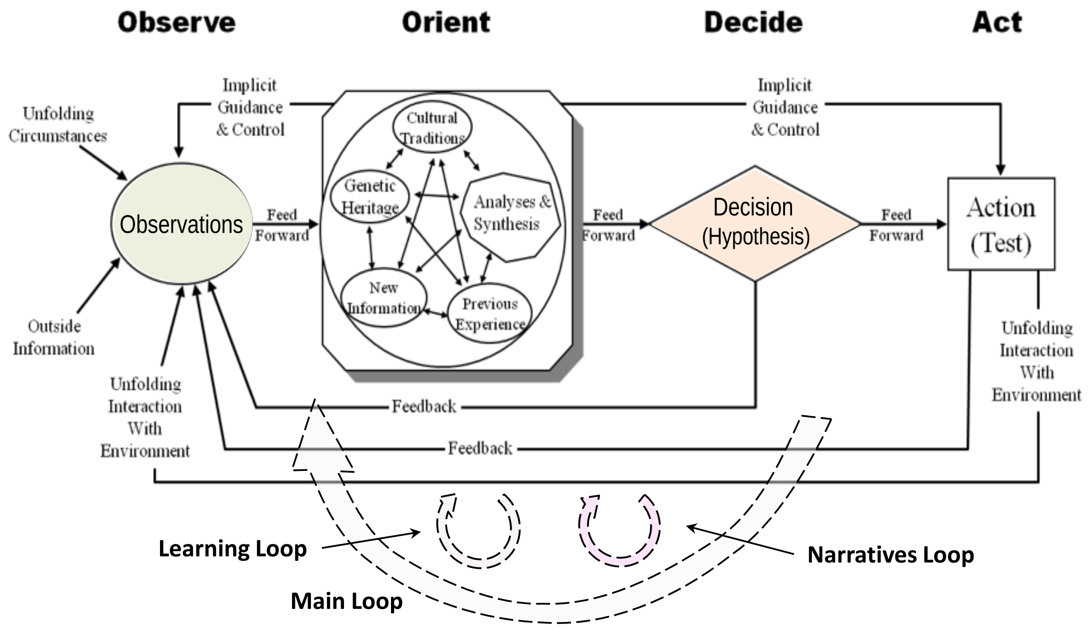

Fig. 2. Extended OODA Loop as an activity network (based on [40]) featuring additional Learning and Narratives Loops

These tasks are as follows (see Fig. 2):

- Observe (*selectively perceive (filter) data* – measurement, sensors, repositories, real-time data streams – using *existing* sensors);
- Orient (*recognise* and become *aware of the situation* based on patterns in the data using data analytics techniques and producing a narrative to what is actually happening, or generate the need for more data so as to be able to disambiguate);
- Decide (*retrieve existing*-, or *design* / *plan new* patterns of behaviour);
- Act (execute behaviour, of which the outcome can then be observed, etc.).

Note that importantly, one can only observe using *existing* sensors. The advent of large scale sensor networks and the IoT can provide in-situ data on a massive scale, however this is only a mere *affordance*; since there is no chance to observe absolutely everything, how does one know that what is observed is relevant and contains (after analysis) all the necessary data, which then can be turned into useful *situational awareness* [41]? Likely, one does *not* know *a priori* and it is only through 'post-mortem' *learning* that a decision (support) system verges on an analytics capability level that is timely and effective in achieving situational awareness.

This learning has the potential to result in decisions that also emphasize relevant gaps and thus initiate capability improvement efforts. It is s*elf-reflective management* that typically engages in such learning, comparing the behaviour of the external world and its requirements on the system (the future predicted action space) with the action space of the current system (including the current system's ability to sense, orient, decide and act). Note that in this context, the term 'action space' describes the set of possible outcomes reachable using the system's current resources (technical, human, information and financial).

The learning loop *is in itself an OODA loop* analogous to the one discussed above, although the ingredients are different and closely associated with strategic management (see Fig. 2). Thus the OODA-style questions are in this case: a) what to observe, b) how to orient to become situation-aware and c) what is guiding the decision about what to do (within constraints, decision variables and possible actions) so as to be able to act. The action space of this strategic loop consists of transformational actions (company re-missioning, change of identity, business model change, capability development, complete metamorphosis, etc.).

Essentially, such strategic self-reflection compares the current capabilities of the system to desired future capabilities, enabling management to decide whether the change will affect the system's capabilities (including decision making capabilities), the system's identity (re-missioning), or both. Note that the management may also decide to instead *decommission* that part of the system due to its inability to fully perform the system's mission.

Such transformations are typically implemented using a separate programme or project using a similar suitable iterative paradigm, such as the so-called Plan-Do-Check-Act (PDCA) loop [42], possibly in a recursive manner [43] e.g. for complexity control.

4.2. Consequences for Decision Support based on Data Warehousing and Big Data

The above analysis has the following consequence: 'big data' (meaning the collective technologies and methods of data analysis and predictive analytics) has the *potential* to enable situational awareness (a condition of successful action) by delivering a plethora of previously unavailable domain-level facts and patterns relevant for decision-making. However, this data needs to be interpreted, which calls for a *theory of situations* resulting in a *narrative* of what is being identified or predicted. Without such a narrative, there is no true situational awareness or trust in the system, which can substantially limit the chances of effective action.

It is therefore argued that having the ability to gather, store and analyse large amounts of data using only algorithms is not a guarantee that the patterns thus found in data can be turned into *useful* and *trustworthy* information that forms the basis of effective decision-making, followed by appropriate action leading to measurable success.

Importantly, the process is similar the other way around: when interpreting available data, there can be multiple fitting *narratives*; unfortunately, it is quite difficult to choose the 'correct' one. In this case, adequate means of reasoning with incomplete information could help articulate a need for new data (or new *types* of data) that can resolve the ambiguity.

As a result of the above reasoning, the authors argue that supporting decision-making based on data warehousing using 'big data' requires the collection of a *second level* of data. This 'second level' is not meant to refer to particular facts, but rather to underpin the creation of an *inventory of situation types*, containing facts that *must* be true, facts that *must be not* true, as well as constraints and rules of corresponding *causes* and *effects*. These situation types can be considered models (or model prototypes) of the domain, which can be matched against findings on the observed data level.

Note that due to the ever-changing nature of the Universe of Discourse, the above-mentioned situation types are also expected to evolve; therefore, one should *not* aim to design and / or construct a facility that relies on a *completely predefined* ontology of situation types. Rather, there is a need for a capability to continuously improve and extend this type of knowledge, including the development and learning of new types, which are not a specialisation of some known type. This is required in order to ensure that the 'world of situations' remains open, as described by Goranson and Cardier [44].

In order to achieve adequate situation awareness for effective decision making, collected data needs to be filtered based on *relevance* [1, 45], dictated by the possible situations of interest. However, as the current situation is typically not unambiguously known and changes as data gathered is interpreted, one will have to maintain a *dynamic (set of) narratives* of the situation, which will continually adjust the data needs [46] as well as what needs to be filtered out, or be kept. This constitutes *yet another OODA loop*, applied to the set of narratives assisting in the interpretation of data for decision making (see Narratives Loop in Fig. 2).

5. The System-of-Systems Perspective to Decision Making

In the real world, decisions are rarely made in an exclusively centralised manner. Thus, the process typically involves several entities acting in a distributed and cooperating style, whether within an enterprise (e.g. management of Strategic Business Units (SBUs)), or between enterprises, e.g. in the form of collaborative networks or virtual enterprises (VEs) created by them via a Breeding Environment [47] (see Fig. 3). Typically, the participants in the decision-making process form a system while being systems themselves, often in control of their own resources – thus constituting socio-technical Systems-of-systems (SoS) [48].

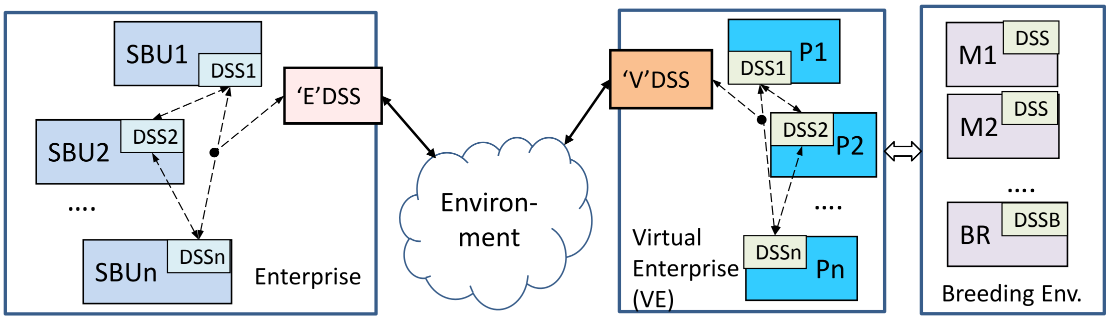

Fig. 3. Decision making centres and their support systems in a Systems-of-Systems Paradigm

Moreover, usually each participating system has its own identity, as well as multiple commitments at any given time (with one of these commitments being to belong to the SoS in question) and their own decision making processes, perhaps supported by a decision support system (DSS) [49], as shown in Fig. 3.

The types of strategies that need to be used in such scenarios have recently been reviewed in an extensive state of the art report by the Committee on Integrating Humans, Machines and Networks [50], which calls for an interdisciplinary approach, similar e.g. to the collaborative networks research area [51], instead of relying on a purely computational viewpoint as a background discipline.

Thus, a SoS must be *robust*, so as to be able to deal with a participating system not performing (e.g. developing a fault or otherwise unavailable, or due to communication channels being compromised, etc.). Therefore, successful SoS level decision-making must be framed as a *cooperative conversation* of information exchange and commitments, however with the added complexity that important systemic properties (e.g., availability) of the SoS need to be maintained, *without being able to completely rely on the same property* (i.e., availability) *of individual participating systems*.

To overcome this difficulty, the authors propose that architecture of a successful SoS must be *dynamically reconfigurable*, so that the functional integrity of the SoS is preserved, including its mission fulfilment and its management and control. Thus, the robustness of the decision system is only achievable if:

i) the decision function is built to deal with incomplete information (at least for a predefined limited time),

ii) the decision function can pro-actively provide advice regarding its information needs to the contributing systems that 'observe', in order to resolve ambiguity or to replace information sources that became unavailable and

iii) the allocation of the OODA loop (see Section 4.1) functions to resources is *dynamic* – similar to how cloud computing can achieve required capacity, availability, scalability, and other desirable systemic properties (the 'ilities') [52].

This *self-awareness* requirement for a SoS is *in addition* to the self-reflection requirement discussed in Section 4, as it requires operational (and real-time) reconfiguration, based on the need for a timely and always available and reliable narrative.

It must be noted that in the SoS paradigm, the OODA loops must be true both at the emergent level (e.g. VE in Fig. 3) as well as in the individual participants; thus, the OODA functions must be constructed such that they can descend to the lower level/s (populated by the participants and their own component systems and so on, recursively) to gather the required information. Note that the SoS participants may not be able to adequately observe or orient, however their higher level aggregation *may*; therefore, a distributed paradigm such as presented above can enable more optimised and agile decision making [53].

6. Design Principles for 'Next Generation' Decision Making

On both existing and emergent system levels, decision making needs a timely and accurate *narrative* (as explained in Section 4) that looks behind the 'observables'. This is because firstly, decision making needs an understanding of the causes and effects of events in the external and internal environments, in order to correctly interpret what is actually happening and be able to predict events that have not yet happened, or reason about a competitor's actions of which the effects are not yet visible. Secondly, in a competitive environment decision making also needs to reason about whether the competitor has the ability to do the same; moreover, it may even be possible to *fabricate* observables that *limit or delay* the competitor's ability to discern and predict. An essential aspect of agile and effective decision making (whether on strategic or tactical level) relies on the ability of the system in question to create and to continually update its situated insight, thus being able to a) deal with uncertainty and b) manufacture it to deceive the competition.

Based on the above observations it is possible to define principles underpinning a 'next generation' approach to decision making and DSS. Generally, given the fast-paced technological developments, the authors propose that it is better to avoid framing this structure in terms of implementations and rather describe it as a more stable *functional* architecture (thus allowing the level of automation to evolve with time without having to make changes in the underlying structure).

6.1. First Functional Principle: Employ Situated Reasoning

Consider the following domain-level observations: O1: price of tomatoes is going up; O2: producer is reporting supply difficulties due to bad weather; O3: supermarket chain announces that supply will be supplemented through imports. Then later, O4: prices of tomatoes go down, however - O5: there are no announcements by any supply chain members.

A domain-level theory would describe supply-demand rules and how these influence prices, by describing the production system and supply chain characteristics (e.g. best times and weather conditions to pick tomatoes, ways to store and distribute the product, etc.).

Suppose that one does not know the delays in the producer's processes (possibly weeks between tomatoes being picked and being shipped, or perhaps only days). Possibly one does not know the supermarket chain's logistic characteristics either.

Presume that an investor wants to invest in the tomato business and needs to make a decision about *whether to do so or not* - and if yes, then *what would be the best way to do so*. It may be possible to build a model of the tomato market from what one is able to observe including price movement trends on the market; however, information for the investment decision is incomplete. Importantly, one does not really know *how to interpret* what *really* caused the fluctuations in supply and demand and also in price.

For example, it is possible that what was observed was i) the result of bad scheduling and planning, because the current supply chain does not share that kind of information among producers, wholesale and retail. It is also possible that the delays were really due to ii) bad weather (or not at all, because tomatoes are usually picked unripe and stored to then be ripened on demand, and the producer's announcement was *an excuse in order to hide bad scheduling, hence case i)*). Further on, it is also possible that iii) the producer received an offer well above market price from somewhere else to satisfy a sudden need and reduced the delivery volumes to the supermarket chain. Finally, it is also possible that iv) the supermarket chain reduced its orders to purchase cheaper imported products, to then subsequently be able to exercise downward price pressure on the supplier.

For the investor to make a good decision (whether to invest in the producer or not), it needs to be able to interpret *past* observed events so as to understand the competencies, motivations and strategies of the players. Each of these types of situations (the *candidate interpretations* of the events described) has their own logic and constraints. A good investor would be familiar with a *repertoire* of situation types and their internal logic (based on previous experience, cultural knowledge and the analysis of concrete situations – achieved e.g. through ethnographic practice). The question is: *which one of these can be used as the correct narrative of the sudden price changes of tomatoes?*

The investor can interpret the current situation ***S*** based on known matching situation types $\boldsymbol{S}_{\mathrm{A}}$ - the case where the producer has poor scheduling (or perhaps insufficient warehouse capacity), but excellent product, and $\boldsymbol{S}_{\mathrm{B}}$, where the supermarket chain is playing a strategic game, planning to reduce the contract price thus affecting the profitability of the producer. Note that there may be a myriad of situation types $\boldsymbol{S}_{\mathrm{N}}$, some only variations of a general type.

The investor can employ *situated reasoning* in order to get to know what is *the correct narrative so as to narrow down the question*; therefore, it should find out what (perhaps very simple) additional fact/s would have to be discovered to *disambiguate* between $\boldsymbol{S}_{\mathrm{A}}$ and $\boldsymbol{S}_{\mathrm{B}}$. The resulting decision would be in case of $\boldsymbol{S}_{\mathrm{A}}$: invest, but improve the distributed scheduling system of the supply chain; and in case of $\boldsymbol{S}_{\mathrm{B}}$: stay away.

6.2. Second Functional Principle: Use Channel Theory to Enable Situation Awareness

If situations are organised in types and their internal logic is known (like in the scenario in Section 6.1), then there exist possible 'channels' through which information in one situation type can be transferred (possibly in a lossy manner) to another situation type.

A recently popularised mathematical approach of the above is the *category theoretic treatment of situation theory* [44, 54, 55]. The mechanism that allows the two levels (situation theory and domain level theory(ies)) to coexist is *channel logic* [56] - according to which, given the category of situations representing situation types, there is a mapping that regulates the way complete lines of reasoning can be 'transplanted' from one situation type to another.

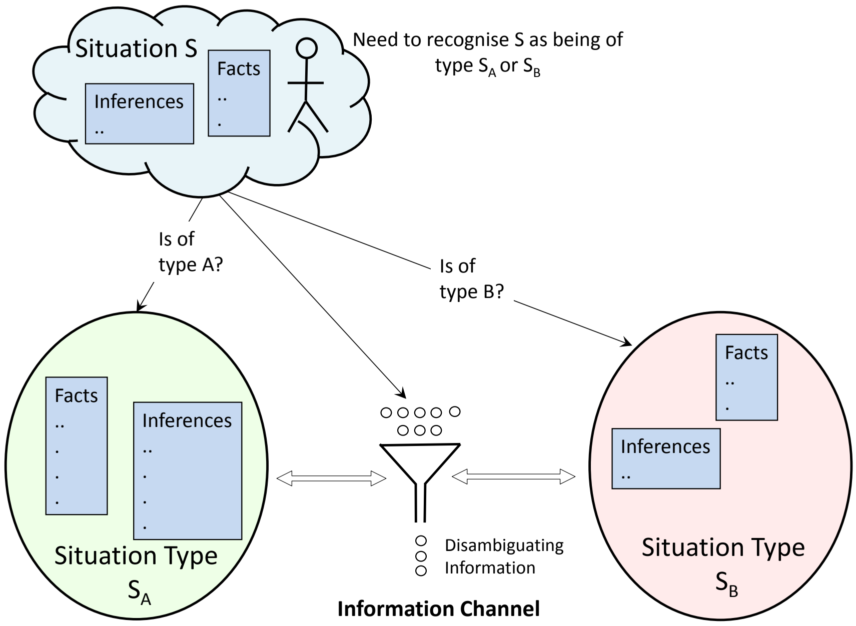

Fig. 4. Simplification of Category Theoretic approach of Situation Theory

This transplanting works as follows: when there exists a logic in a known situation type $\boldsymbol{S}_{\mathrm{A}}$ and the facts suggest that the situation is of a related type $\boldsymbol{S}_{\mathrm{B}}$, many (however typically not all) facts and inferences should also be valid in type $\boldsymbol{S}_{\mathrm{B}}$ (see Fig. 4).

As a result, if we have a known situation of type $\boldsymbol{S}_{\mathrm{A}}$ with facts supporting this claim, and we only have scarce data about another situation type of interest (of type $\boldsymbol{S}_{\mathrm{B}}$), channel logic allows us to *deduce the need for data* that can be used to 'fill in the details' about this second situation of type $\boldsymbol{S}_{\mathrm{B}}$. The resulting mapping is a so-called *morphism* between categories and can be implemented using functional programming techniques. In Fig. 4, this (info-) morphism is represented by the double-headed arrows shown carrying information (while possibly losing some, as previously stated) from one situation type to another type to another.

The practical consequence is that the decision maker can use this analogical reasoning to come to valid conclusions in an otherwise inaccessible domain; should this not be possible, it allows to at least narrow down the need for specific data that can support a valid conclusion. The above also illustrates in a simplified way the ability of the situation theoretic logic to infer that for decision making, there is a need for specific, but yet unavailable data that can disambiguate the interpretation of what is known at the time.

7. Conclusion and Further Work

In the context of the increasing rate of change and the resulting flood of data, decisions will have ever more far-reaching consequences and will need to be made increasingly faster, often in real time. The right investments in technology, accompanied by articulating a coherent digital strategy and leveraging people as change agents can bring about a sustained competitive advantage through digitally-enabled decision-making.

The work presented in this paper can be used as the basis of a solution creating an ongoing *situational awareness* capability. All application domains (business, government, military, etc.) typically already maintain specific 'repertoires' of actions that are known to work. However, the effective use of such patterns nowadays increasingly depends on their fast, almost automated deployment which is typically based on *tacit* skills and knowledge.

The usefulness of the OODA loop also depends on performing it better and faster than the opponents(s) in order to prevail. Therefore, if one is not able to use the incoming data (to infer *appropriate* information and apply it appropriately) in a timely manner, the resulting action/s may become meaningless, as the opponent may have already done so and therefore, changed the situation. The authors argue that due to the complexity and number of situation types and the amount of data available, using data analytics *in conjunction with situation recognition* could dramatically speed up the loop, hence augmenting the chance of success.

Further work will continue to focus on the principles underpinning situation theory-based decision making and related supporting technology. It will also aim to demonstrate their use towards building resilient enterprises through dynamic management, command and control of a large number of cooperating agents.

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