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On Firehoses, Windows, and Business Rules: Towards a Successful Fast Data Organisation

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Abstract

Due to the enormous growth of data and the increasing speed at which organisations are required to respond to it, Fast data is the latest trend in data science. In this study, we set out to answer the question what Fast data is and how organisations can deal with it in a successful way. We define Fast data as: the ability to gain insights from (near) real-time data streams and derive value from these insights. We argue that successful Fast data organisations are built on four pillars: (i) technology, (ii) strategy, (iii) culture, and (iv) skills & experience. We conclude with a critical discussion of our results, for instance touching upon whether Fast data is really 'new'.

Keywords: Analytics, Big data, Conceptual paper, Competitive advantage, Organisational change

1 Introduction

Finding information on the internet is like taking a sip from a firehose.

– Mitchell Kapor

The above quote highlights the enormous and growing availability of data in today's world. While the quote only refers to the internet, much more data is available nowadays, increasing the 'firehose effect'. As a striking example, 90% of all data available in the world has been created in the last two years (Sherman, 2015). Organisations are trying to make sense of and find useful information in this vast amount of data. This has led to an increased level of organisations adopting 'Big data' technologies (Press, 2013).

In the past few years, Big data has offered many organisations some form of competitive advantage (Lavalle et al., 2011). The patterns found helped organisations in finding flaws or trends and act on them. However, due to the enormous amount of data it is difficult for organisations to directly find the data they need to discover these patterns. Therefore, some people argue that Big data only offers a 'rear-mirror view'.

Technologies have evolved over time and become better at dealing with huge amounts of data. However, even advanced technologies such as Hadoop take some time to analyse all this data (Mishne et al., 2013). The desire to prevent the rear-mirror view and analyse data 'as it happens', leads to the rise of a new phenomenon: Fast data. Organisations are increasingly on the lookout for technology that can deal with Fast data.

The use of real-time data in order to obtain new insights is increasingly seen as a 'game changer' (Porter & Heppelmann, 2015). Unfortunately, many organisations have no idea what Fast data entails and how to deal with it. In this conceptual paper, we try to fill this gap by addressing the research question: *What is Fast data and how can organisations deal with it in a successful way?*

In line with the audience of the Bled conference and taking a managerial perspective, we will not cover the technical aspects of Fast data in depth in this paper. Describing only the high-level technological data processing changes and challenges may actually be beneficial, as currently many technologies for working with Fast data are still under development.

The literature used in this paper was retrieved via a search using Google Scholar and library of the Vrije Universiteit Amsterdam. As the term Fast data is not widely used in existing academic literature, synonyms and related topics such as 'Real-time data streams', 'Big data' and 'Real-time data management' were used as search terms as well. A snowball approach was used to find additional literature, *i.e.*, from relevant papers the references where scanned in order to find more possibly relevant articles. After we identified the four most named factors in the literature (*i.e.*, the four pillars; see §3), a more focused approach was used to search for additional literature, *e.g.*, by adding one of the four factors to the original search terms. Because this topic is quite new and because of our managerial focus, we also searched the 'grey'/business literature.

After performing our literature review, we conducted two semi-structured interviews with technical domain experts (*i.e.*, computer scientists) to validate our findings from the literature. These validation interviews were held with Henri Bal & Frank van Harmelen, full professors at the Computer Science department of the Vrije Universiteit Amsterdam. They provided us with their insights on what Fast data is and what its technological requirements and possibilities are. The main part of the interview consisted of letting the interviewee tell about the key technological aspects of Fast data. The second part of the interview consisted of discussing examples of real-life cases and testing the earlier literature findings against the knowledge and experience of the interviewees. These interviews led to a deeper understanding of the aspects that should be taken into account when implementing Fast data.

The remainder of this paper is structured as follows. In the next section, we delineate the concept of Fast data, based on its ancestor Big data. Following that, we come to the core of our paper: a description of the four 'pillars' of a successful Fast data organisation, based on our review of the literature and the validation interviews. Finally, we present and discuss our main conclusions.

2 Defining Fast Data

Although many organisations are still busy dealing with the trend of Big data, a second trend arises: Fast data. Fast data is not exactly the same as Big data, but an extension or expansion of the concept of Big data. Fast data, opposed to Big data, is data that should be analysed directly in order to gain value from it (Lam et al., 2012). Fast data loses its value when stored for a while before being used. Lam et al. (2012) define Fast data as “high-speed real-time and near-real-time data streams” (p. 1814). Focusing on the real-time aspect, this definition lacks the aspect of the impact or possibilities of Fast data. Just like Big data, Fast data has certain goals or added value for organisations that makes it important (Mishne et al., 2013). As Fast data is an extension of Big data, the aim of Big data seems relevant here as well. The goal of Big data is to gain insights in the data gathered and base valuable decisions on these insights (Chen, Chiang, & Storey, 2012). Fast data could thus be seen as a new possibility for being able to act in real-time on your incoming data. Therefore, we propose to define Fast data as follows: *Fast data is the ability to gain insights from (near) real-time data streams and derive value from these insights.*

3 The Four Pillars of a Successful Fast Data Organisation

As our definition of Fast data shows, organisations have to act quickly in order to gain value from Fast data (Mishne et al., 2013). However, in order for organisations to be able to do so, it seems likely that a certain amount of organizational change is required first. Literature suggests that in order to successfully adopt Big data certain changes have to be made in an organisation (Davenport et al., 2001; Davenport, 2006; Lavalle et al., 2011; McAfee, 2012; Porter & Heppelmann, 2015). As Fast data is closely related to Big data, it is important to view how factors that are affected by the adoption of Big data play a part in the rise of Fast data. In order to be able to analyse the impact of Fast data on organisations adopting it, we use the aspects defined in the Big data literature as an organising principle. These aspects – or pillars – are the following:

- Technology
- Strategy
- Culture
- Skills & Experience

The remainder of this paper will focus on explaining how these four pillars are influenced by or should be adjusted for dealing with Fast data.

3.1 Technology

The first pillar of a successful Fast data organisation is *technology*, which enables an organisation to process its data in real-time. Getting the right technology in place is the first step that should be taken in order to successfully use Fast data, and it is a *conditio sine qua non*: the remaining three pillars can be partially present and/or adjusted at a later moment, but when an organisation’s technology is not ready for real-time data processing, no value will be gained from Fast data.

Big data and speed

The current Big data IT-architecture is focused on gathering all data in a single data warehouse and making this data available for employees through insights (Lavalle et al., 2011; McAfee, 2012). However, gathering all this data also has a negative effect: the continuously growing amount of data in these systems makes that processing it takes longer (Kaisler et al., 2013). Thus, the more data organisations gather, the longer their analysis of this data takes, and the slower they are in responding. As Fast data becomes increasingly important this is not something organisations can ignore.

The challenge of volume versus speed

Currently, the best-known product to rapidly deal with massive amounts of data is Hadoop. Hadoop is open source software aimed at speeding up the analysis of Big data. Hadoop uses the 'MapReduce' technology. This technology allows an organisation to store the data that needs to be analysed over multiple data warehouses and bring the analysis software to the data instead of sending the data to the analysis tool (Dean & Ghemawat, 2004). As the Hadoop software is able to divide the data over several smaller databases, it is able to complete analyses more quickly.

Although the solution of Hadoop is relatively new and much faster than older business intelligence technologies, it is already becoming too slow for the current data processing needs (Mone, 2013). The reason for this is that Hadoop analyses data in batches. These batches analyse data at predefined intervals instead of real-time. This makes that between the analysing intervals data simply 'sits' in the database (Stonebraker, Çetintemel, & Zdonik, 2005). If an organisation wants to gain real-time insights in what is happening, this is impermissible (Mone, 2013). Dealing with Fast data through Hadoop makes that the data loses most of its value when it is eventually analysed (Mishne et al., 2013). The solution for this problem lies in the technology of stream processing. Stream processing analyses all data directly when it enters the system. However, before an organisation can successfully apply stream processing, it first has to reduce the amount of data that actually enters the system.

Dealing with data volume and variety

As indicated above, a huge amount of data is flowing into the organisation's systems. These systems can try to handle all this data, but with a speed trade-off. With Fast data there is no question whether this is a permissible trade-off, as speed should always be of very high importance. The way to deal with this volume problem is to implement (the right) filters. Filters should be used in such a way that no longer all data passes to the system, but only the data that fits the organisation's strategy (Barton & Court, 2012). In the case of Fast data, it is extremely important to filter as early as possible, as reducing the volume of the data increases the speed of analysis (Kaisler et al., 2013). What this 'earliest possible' moment is, depends strongly on what data you need as organisation.

Stream processing

After the amount of data to be processed is reduced, it is time to send the data through the stream processing engine. This technology does not find patterns in the data itself, but matches all incoming data with earlier found patterns to see if these patterns reoccur (Bifet, 2013;

Stonebraker et al., 2005). It is important to fill the stream processing engine with predefined *business rules* or *queries* as these are the rules to which the incoming data is compared. When the incoming data matches the predefined pattern or business rule, a signal will be send to a machine or employee to set an action into motion.

Stream processing makes use of a 'window' in which the data is viewable and usable. This window is the length through which the data is temporarily saved to recognise patterns or deviations. After the data has passed through this window, it cannot be analysed again until it is later stored in the historical data warehouse (Ari, Olmezogullari, & Celebi, 2012). Figure 1 depicts the process described so far.

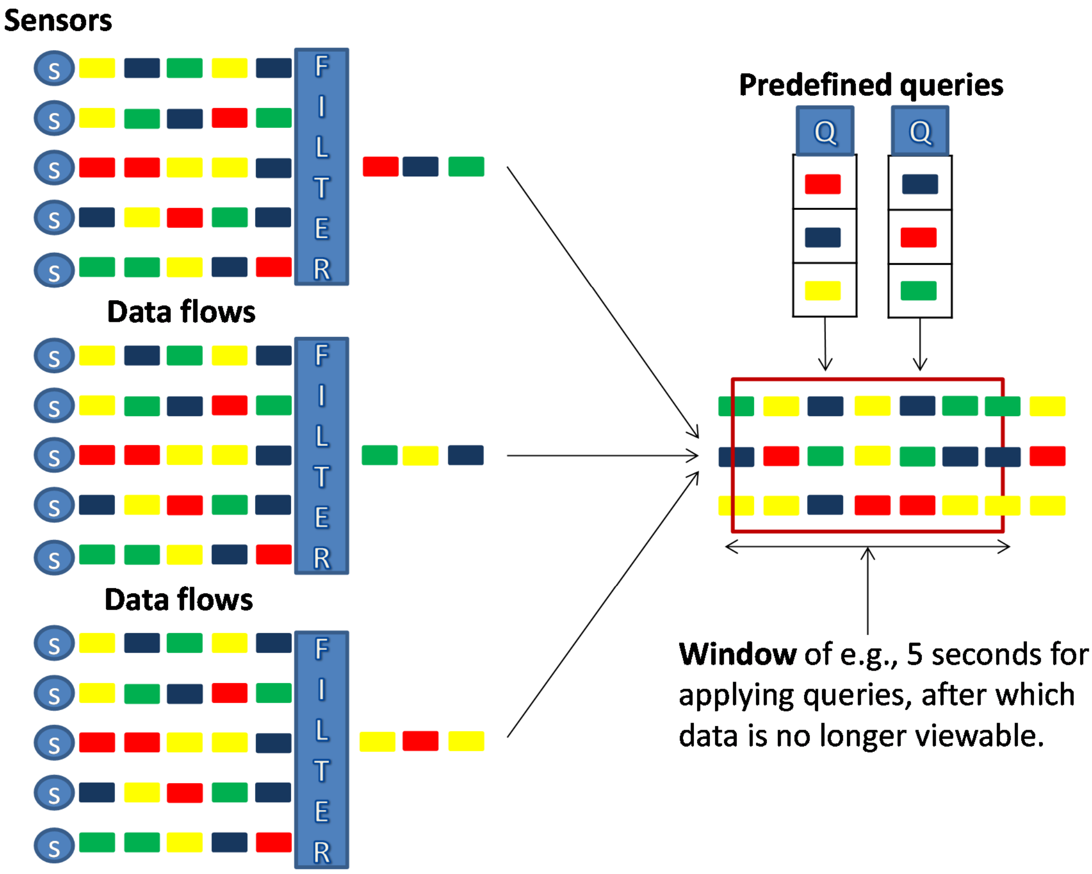

Figure 1: Sensors produce to data flows, which are filtered and next (in a predefined window) continuously checked against predefined queries.

In order to make this type of processing possible, data should be stored in a different way than most organisations do with Big data. Big data is often saved in the form of a long list of data without direct correlation. This makes that the analysis tools have to go through every single entry in order to find a pattern or deviation, which takes up a lot of time. The solution to this problem can be found in saving data in the form of *events* (Roth et al., 2010; Tsividis, 2010). This means that data of the same nature or entity are saved under a common key or location. This listing of all information about the same topic under one database key allows for faster analyses (Luckham, 2011).

An example of saving data in the form of events can be found in the processing of cash withdrawals of a bank. When someone normally withdraws money in Europe and suddenly money is withdrawn in Asia, an immediate notification can be created as this is a deviation of the person's normal pattern. In an old and traditional database these withdrawals would have been stored separately and only brought together at the end of the day. When all data of a single user's cash withdrawal is saved under one key, the system could directly stream the data of the location of the withdrawal with the predefined pattern of earlier withdrawals and immediately detect that the request in Asia is a deviation. A deeper understanding of how such stream reasoning works and what its technological needs are can be found in the article of Margara et al (2014).

The importance of historical data

Although the above seems to deprecate older data processing software, this remains very important in the context of Fast data analysis. As mentioned before, the predefined patterns are of major importance in order to be able to see if a pattern occurs or not. Without having a large historical database, stream processing is hardly possible (Mishne et al., 2013; Suntinger et al., 2008). The historical database is also important for developing potential outcomes of detected events. When an event is recognised by the stream processing engine, the knowledge found in the historical database can be used to predict how this event will develop (Gottumukkala et al., 2012). Therefore, historical databases should still be updated with new data.

3.2 Strategy

The way an organisation should respond to events found in the gathered data should depend on the organisation's *strategy* (Baets, 1992). It is important that this strategy is used as guidance for the data and IT strategy (Baets, 1992). For Big data and Fast data, this is not different (Lavalle et al., 2011).

The 'right' data

As already mentioned when discussing filters, it is important to delineate what data is relevant for an organisation and what not. Where Big data can lure organisations into gathering all data because it 'may have value', this is simply impossible for Fast data due to the volume and speed trade-off. Therefore, data an organisation gathers should be of high quality, which means supportive of the organisation's goals (Wang & Strong, 1996). This is where the earlier mentioned filters come into play: how to set these? A (fictional) example can be found in tracking a city's inhabitants. A municipality could monitor every movement an inhabitant makes, or monitor predefined areas and only collect data when an inhabitant leaves a certain area. Clearly, the first approach creates much more data than the second one. What is the best approach depends on the goals of the municipality. When monitoring the way people navigate through the city, the first approach would probably fit better. However, when studying from which areas most people travel to the city centre, a high level area overview should be sufficient.

What is real-time?

As goals and the right filter settings differ between organisations, so does the notion of what is real-time. Intuitively, this concept refers to *directly* (*i.e.*, as it happens) seeing, responding to, etc. events. However, what is 'directly' differs for each organisation/context, again depending on the goal you have. *E.g.*, monitoring traffic jams happens at a different pace than high-frequency trading on Wall Street. Before organisations can effectively use Fast data in the decision making process, it is important to define what the speed is at which they need to react (Stonebraker et al., 2005). This reaction speed namely influences the length of the window in which the data is viewed and temporarily usable. The length of the window influences the computing power you need and is an important aspect for organisations to consider (Abadi et al., 2005).

Translating strategy to event recognition and actions

When a deviation or problem is detected in the incoming data, action should be taken as soon as possible. The way to do this is by formulating *business rules* (Stonebraker et al., 2005; see also Technology pillar above). Clear business rules allow the stream processing engine to do its work properly; otherwise it is uncertain what to do when a pattern is found (Stonebraker et al., 2005).

Next to the recognition of patterns, business rules should be defined on how to react on a certain event. As these rules are key to responding to events in the right way, they have to be based on the organisation strategy (Paschke & Kozlenkov, 2009; Yang, Yang, & Lou, 2011). These rules, e.g, sending an automated discount offer, make sure that there is a prompt and correct response to the incoming data.

Managing business rules in a Fast data organisation

Business rules have been around for quite some time and have become more important since the rise of Big data (Yang et al., 2011). The difference for business rules for Fast data compared to (Big) data lies in how to manage them. In this rapidly changing world it is important that these rules always stay up-to-date (Boyer & Mili, 2011; Smaizys & Vasilecas, 2009), as the value of Fast data lies in directly recognising patterns and acting upon them. Therefore, the successful implementation of Fast data requires the organisation to revise its business rules more often than before.

3.3 Culture

The third pillar is concerned with what *culture* fits best with organisations that are adopting Fast data: a data-driven, agile one.

A data-driven culture

The first step important for being able to react fast on data is trusting your data. Collecting data but without trusting it could mean you do not gather the right data in the first place. A culture where data is trusted and people are willing to set aside their intuitions to base their actions on data is also known as a data-driven culture (McAfee & Brynjolfsson, 2012). Such a culture is of great importance in dealing with Fast data. With the perishable nature of Fast data, data usually cannot first be crosschecked or scanned by multiple rule engines before an action is taken. Whereas with Big data one could *e.g.*, discuss with colleagues before taking an action this becomes impossible for organisations that need to respond in real-time. Therefore, throughout the organisation it should be clear to trust and deal with data in the decision-making process.

A culture focused on change

Being data-driven alone is not enough for an organisation to successfully deal with Fast data. Actively improving (the quality of) your data and using it to base decisions on is already a big step forward in speeding up the response to events recognized in the data, but there is more. As Fast data requires an imminent response in order to gain value, it is important that the organisation is equipped for this level of speed. Organisations will have to adjust resolutely when new patterns are found (Porter & Heppelmann, 2015). Aiming to adjust and respond to every event as soon as possible requires flexibility and change readiness in an organisation. These changes can be as simple as having the ability to put all other work on hold to respond to an urgent event or as complex as changing the shipping location of your goods on-the-fly when demand is predicted to be higher somewhere else. A culture able to deal with these rapid changes in the environment is called an agile culture (Sherehiy, Karwowski, & Layer, 2007). For production companies, a good way to do this is speeding up the new product development cycle, which should in turn lead to being able to respond faster to changing customer demands than competitors (Porter & Heppelmann, 2015). Porter & Heppelmann (2015) suggest a unified data department that manages all data and that business departments have different knowledge and respond differently to market trends.

Achieving an agile culture for Fast data translates into speeding up the response on data (or events). In order to realize this an organisation could increase the autonomy of employees responding to data or place decision rights lower in the organisation (Lee & Xia, 2010). Next to this, support from top management, clear benefits for employees and the organisation, and guidance on how to deal with changes are all elements that should be present (Chan & Thong, 2009).

3.4 Skills & experience

Having the right technology, strategy, and culture in place are already big steps for an organisation towards being able to reap the benefits of Fast data. However, creating or working in such an organisation also requires the fourth and final pillar: the presence of certain *skills and experience*. Without these, the chance of getting value out of your data is greatly decreased (Davenport et al., 2001; Davenport, 2006; Porter & Heppelmann, 2015).

First, sufficient knowledge about the technology should be present within the organisation: knowing how the data should be stored, processed, analysed, and visualised (Davenport et al., 2001). Big software vendors such as Oracle or Microsoft supply stream processing engines, but as Fast data requires constant changes, knowledge about how to alter the systems becomes an important skill in the organisation as well.

Second, knowledge should be available about what the 'right' algorithm is and how to develop it. While this already is of high importance to Big data (Bell, 2015), successful Fast data organisations will most likely put even more emphasis on this. Organisations deploying Big data analytics have time to carefully develop algorithms and adjust them overtime when needed; even outsourcing this activity may be possible. However, when aiming for a fast response, it is important to act quickly to changes. Therefore, development and control of algorithms should be done with great care and more frequently than for Big data. This makes having in-house knowledge about algorithms important.

Finally, sufficient knowledge should be present on the organisation's data and strategy. This appears trivial but is key to obtaining value from data. This knowledge allows an organisation to understand whether they gather the right data for their goals and what actions can (should) be taken based on the data. As mentioned before, the data an organisation gathers should fit its strategic goals (Lavalle et al., 2011; Wang & Strong, 1996). Hence it is important that knowledge about strategy and the available data are combined and made known throughout the organisation (Davenport et al., 2001). Without combining this knowledge, organisations take the risk of missing out on events that should be reacted upon immediately.

4 Conclusion & Discussion

Due to the enormous growth of data and the increasing speed at which organisations are required to respond to it, Fast data is the latest trend in the field of data science. In this study, we set out to answer the question what Fast data is and how organisations can deal with it in a successful way. We defined Fast data as: *the ability to gain insights from (near) real-time data streams and derive value from these insights*. We argue that successful Fast data organisations are built on four pillars: (i) technology, (ii) strategy, (iii) culture, and (iv) skills & experience.

It is our impression that much of the research on Fast data focuses on the technology behind Fast data. However, learning from the Big data trend, changes in the way data is used by an organisation will have a much broader impact. This paper suggests some changes organisations will have to make beyond technology in order to be able to reap the full benefits Fast data promises.

Many of the proposed changes in this paper are in line with the changes needed for adopting Big data. However, there are prominent differences in the areas of technology and culture. In order to process these huge amounts of data in (near) real-time, new technologies are needed that are 'smart' enough to filter large amounts of data close to the source and direct the remaining data past predefined queries. In terms of culture, especially agility is important in dealing with Fast data. Flexibility in the organisation seems key to being able to respond quickly to events detected in the data.

The relation between Fast and Big data makes that for organisations already (in the process of) deploying Big data solutions, only some of the proposed changes will be required to reach successful Fast data usage. However, although the amount of changes may be small, Fast data places a greater importance on having these factors in place. In conclusion, it can be said that Fast data is an extreme form of Big data, requiring organisations to work with their data in real-time. This places much greater pressure on organisations, while at the same time enabling competitive advantage.

In terms of the limitations of our work, it is relevant to note there is currently not much scholarly work available that is strictly concerned with Fast data. Hence, some of the findings in this paper are extrapolations of Big data studies, are derived from practitioner papers, or are based on discussions with researchers who study Fast data from a more technical point of view (*i.e.*, computer scientists). In the same vein, a valid point of critique is whether Fast data is really 'new' and not just the next hype. Time will tell, but we strongly believe Fast data is a concept that adequately illustrates the undeniable trend towards a growing amount of data available to organisations, to which an increasingly fast response is required from them.

For future work, it seems fruitful to empirically study Fast data and how it is adopted by organisations. These studies could also look into the contingencies of Fast data for organisations, *i.e.*, when is an organisation 'truly prepared' and are there perhaps organisations for which Fast data turns out to not be so relevant? Fast data may be applicable to commercial parties that ship goods around the globe as discussed earlier in this paper. Also in the context of Smart cities Fast data may prove relevant, *e.g.*, in the deployment of a so-called 'cockpit' that continuously monitors and reacts to incoming data (Kitchin, 2014). In studying this, the link with work on organisational agility & IS (*e.g.*, Sambamurthy, Bharadwaj, & Grover, 2003) seems relevant to take into account.

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