PART II

Data Driven Support to Decision Making

CHAPTER 6

The effect of big data and AI on forecasting in defence and military applications

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Abstract

In this chapter we analyse the effects Big Data and AI have and will have on the practice of forecasting for defence and military applications. Big Data brings an abundance of heterogeneous data from many sources to the table and AI and its subfield Machine Learning brings a whole host of new models, algorithms, and forecasting methods with it. Combining both concepts, it is foreseen that forecasting and foresight development will be greatly influenced by these two developing trends. The impact on applications at the strategic, operational as well as tactical level is considered.

Keywords: Forecasting, Big Data, Artificial Intelligence, Military, Defence.

6.1. Introduction

Forecasting is an important tool in defence and military strategy, operations, management, and sustainment. The applications vary from direct use in budgeting, planning, logistics and numerous sustainment functions and weather forecasting to more varying applications in strategy and foresight development[1], intelligence, operational and tactical aspects of predicting enemy forces and friend and enemy civilian behaviour.

Forecasting is founded on the assumption that current and past knowledge can be used to make predictions about events in the future. It is not expected though that the forecasts match future values exactly but are close in some sense. Common forecasts to use are the expected value or the most likely value but it might also be a forecast interval or the entire probability distribution of possible forecasts.[2] Several relevant aspects of forecasting are discussed in more detail below.

Artificial Intelligence (AI) and big data (BD) are topics that have attracted the interest of business and military strategists alike. Both concepts are projected to become disruptive technologies[3]. While Big Data and AI are used extensively by several very successful early adopters in the private sector, the most dramatic/

influential impact is still to materialise, certainly in the military context. AI is still in an early development phase, but most nations have recognised its importance and setup large scale scientific research programs in cooperation with the private sector and the military-industrial complex[4].

Big data is considered important in analytics and forecasting as it provides the option to include more and other types of data in the forecasting process than traditionally available. Available means having in place a data registration, storage, and collection process such that data from the own organisation such as registry, ERP-systems, sensors, etc as well as third party data be it structured, un-structured, semi-structured and/or heterogeneous can be included in the forecasting process without much effort from the analyst or forecaster. Getting this infrastructure organised and working is a precondition to enable an organisation to use BD successfully but requires in most organisations an expensive and intensive reengineering of most business and operational processes[5].

Artificial Intelligence could informally be defined as, given that no precise single commonly accepted definition exists, "the capability of a computer system to perform tasks that normally require human intelligence such as visual perception, speech recognition, and decision-making"[6] (Cummings, 2018). DARPA[7] gives a somewhat more focused definition "Artificial intelligence is the programmed ability to process information." Below, we return to the DARPA vision on AI, as this characterisation comes closest to the perception of the military practice.

In the remainder of this chapter, we first give introductions to BD, AI and the theory of forecasting. Thereafter we introduce a framework to access the impact of BD and AI on forecasting methods and processes. Finally, we illustrate the current and foreseen effects by discussing several defence and military applications.

6.2. Big data

Big data in business is often characterised by the 5 V's: volume, velocity, variety, veracity, and value. Volume indicating the large amounts of data, velocity the speed at which the data are generated and become available for analysis, variety indicating the heterogeneity of the data, from users-log to images, from simple spreadsheets to complex relational data. These three V's are in a sense always positive; they create analytical opportunities whether we seize the opportunity or not. The same analysis holds for defence and military applications.

Veracity and value are a bit different: veracity is whether the data are consistent and "truthful" enough to be used; it is about data quality and its relation to the real-world. In business there are applications where the veracity of data is necessarily high, for instance in most transactional data the importance consistency is paramount, think about your bank statement at the end of the month. For other applications veracity is not so important; in a marketing campaign, if observations do not have the correct GPS coordinates for 20 percent of the potential clients it is usually not problematic.

In defence, intelligence, and military applications the percentage of applications where a high veracity is of utmost importance is much greater than in business applications. Having one wrong GPS coordinate can lead to many lost lives. The fact that most data are not first-hand data and stakes are high means veracity always must be established. This is particularly important in intelligence where information must be handled by multiple analysts. Therefore, several grading systems have been developed[8] and will for BD be implemented in some form, but this discussion is outside the scope of this research.

Value in national security and military applications also has a different meaning than in business or for instance health applications. The value of BD for intelligence and military applications lies in the ability to derive actionable information from the data. It is envisaged that having large sets of historical and current data consisting of as many observables as possible increases the probability of deriving actionable information and aids the decision-making processes to a certain extent. Indeed, extrapolating the results of BD in business, health, and science it is projected that BD has a predictive power in terms of containing value in historical and actual information, which can potentially enrich the inputs of forecasting models and in turn also the quality of the forecasts[9], which in turn will create actionable information for military decision making.

However, BD for forecasting does not come for free. Different types of big data contain specific information, have unique characteristics but are usually stored in various formats. This means that the actual forecasting step in the forecasting process is in effect often being dominated by different data preparation and analysis techniques to first process the data and extract the hidden predictive knowledge[10]. Usually only after this analysis can it be determined whether the data are suitable for the forecasting tasks at hand.

6.3. Artificial intelligence

There are several characterisations of the level of sophistication of AI systems in mimicking human information processing behaviours. An often-used categorisation[11] is given by "narrow AI", "strong AI" and "superintelligence". Narrow AI indicates that a system equals or surpasses human performance in one task; strong AI indicates that a system equals human capabilities on ay task, while superintelligence surpasses human intelligence on any task. Several more refined characterisations of human information processing exist, but in this analysis the characterisation given in “The DARPA perspective on artificial intelligence”[12] is used. It characterises AI based on the level of ability to process information in perceiving, learning, abstracting, and reasoning, by three phases: handcrafted knowledge, statistical learning, contextual adaptation.

The phase “handcrafted knowledge” is characterised by humans creating sets of rules to represent knowledge in well-defined domains. The structure of the knowledge is defined by humans, the specifics are explored by the machine. The expert-systems developed in the 70’s and 80’s are typical examples of this. Another example is most rule-based systems.

The “statistical learning” phase is characterised by humans creating statistical models for specific problem domains and training them on big data. Observe that the statistical models can either be model-driven or data-driven although most well-known methods i.e., Machine Learning, Deep Learning are data-driven. The definitions of and distinctions between data-driven and model-driven are deferred until later in this chapter. The current scientific state is that we are in the middle of this phase.

The “contextual adaptation” phase is characterised by systems constructing contextual explanatory models for classes of real-world phenomena. This implies that systems can not only detect, observe, and classify objects and phenomena in their environment, often using techniques from the statistical learning phase, but can also reason about them using conceptual models. This phase has not been reached yet; research is just starting.

In Table 6.1 below the different phases and their associated level of ability to process information in perceiving, learning, abstracting, and reasoning, is visualised. The more crosses the more the specific ability is addressed.

Table 6.1. Notional Intelligence scale, after Launchbury[13]

	Perceiving					Learning					Abstracting					Reasoning				
Handcrafted knowledge	x															x	x	x	x	
Statistical learning	x	x	x	x		x	x	x	x		x					x				
Contextual adaptation	x	x	x	x		x	x	x	x		x	x	x			x	x	x	x	

6.4. Forecasting

As stated before, forecasting is based on the premise that current and past knowledge is useful to make predictions about events in the future. To make discussions more precise, it is necessary to distinguish between the concepts of estimation, prediction, and forecasting which are frequently used interchangeably; however, they differ from each other in the following way. Estimation is about guessing the value of a parameter of interest. Prediction is concerned with guessing the outcomes of unseen data. Forecasting is the sub-field of prediction concerned with guessing the outcomes of future and thus unseen data.

A forecasting procedure or process tries to predict the future value of a stochastic or uncertain event or observation, while a forecasting method is defined here to be a predetermined sequence of steps that produces forecasts of future points in time[14]. This implies that a forecasting procedure might entail several forecasting methods and the result being a combination of the outcomes of the used methods.

Whatever the goal of the forecasting process, four steps can always be distinguished: data collection, data processing, prediction improvement and the actual forecasting. For different applications these steps can differ[15]. Also note that in the design-stage or ad-hoc analysis, steps might be handcrafted and time consuming while in "production" mode the steps will be automated as far as possible.

In interpreting, decision making and forecasting models play a crucial role. In this context it suffices to define a model as a simplified description, often but not necessarily a mathematical one, of a system or process to assist analysis and predictions. For a more extensive introduction into forecasting in general see for instance Armstrong[16] or the overview article by Petropoulos et al[17].

6.4.1. Characterisation of forecasting methods

Traditionally[18] forecasting methods are characterised within two categories based on whether they use implicit or explicit models. The implicit characterisation is often referred to as "judgmental" the second as "statistical". The first category consists of methods where one elicits forecasts from experts, laymen based on their experience of opinion. No model for the phenomenon under consideration is made explicit, only a secondary model on how to collect, combine and interpret the derived forecasts. The second, "statistical" category consists of methods that explicitly use mathematical models, stochastic or deterministic. The term "statistical" might be a bit confusing as the forecast might be based on a deterministic model, but the interpretation is still probabilistic as measurement errors and unaccounted variables still influence the actual future outcome.

For the current analysis, we recognise that the statistical model's category entails two different philosophical approaches and we will characterise these. The first category is characterised by models that are in simulacra, (within likenesses) that is they bear some likeness to the real-world, be it physical, social, economic, or otherwise, and are constructed to reflect certain aspects that are essential for the analysis or prediction at hand. This category of models will from here on be denoted as model-driven. This category consists of models that are created such that the theoretical behaviour of the models mimics the theorised real-world behaviour of the object or phenomenon. Most of the models in this category are not only used for prediction or forecasting but also for causal reasoning.

The second category, denoted here as data-driven, is based on directly mimicking the observed data of the real-world object or phenomenon. This implies that the model does not have the intention to match theorised real-world behaviour. This makes it very hard to interpret these types of models in a causal fashion; they mainly try to mimic correlations or non-linear relations apparent in the data. Currently most machine learning algorithms fall into this class. Also, some traditional statistics, for instance strict time series analysis, fall into this class.

In Table 6.2 some forecasting methods are presented based on the introduced characterisation. Two remarks are in order. First, the list is not complete; secondly, the characterisation of forecasting methods concerns the way in which one derives a single forecast or forecast distribution, but it has been demonstrated that combining the results of several forecasting methods can greatly improve the final forecasting results. Combining forecasts based on different methods is often denoted as hybrid forecasting methods. Currently hybrid methods that make use of a combination of judgemental, model-driven and data-driven methods are starting to emerge in applications[19].

Table 6.2. Several forecasting methods grouped by the characterisation derived in the text

Judgmental	**Model-driven**	**Data-driven**
Forecast is based on – Expert intuition – Analogy – Reference classes	Model is derived from theory about the object or phenomenon to forecast	The model is defined by the method used and the data, not by theory about the object or phenomenon to forecast
Aggregated judgment: – expert survey – Delphi method – Reputation base prediction – Forecasting platforms – Super forecasters – Prediction markets Conjoint analysis Automated judgement – Judgmental bootstrapping – Expert system Gaming	Regression Causal modelling Probabilistic modelling – Markov Chains – Econometric models Deterministic modelling Structural equation modelling Simulation	Statistical methods – Time Series – fuzzy modelling – Data reduction methods – Heuristic methods – Machine learning – supervised – unsupervised – reinforcement – Deep learning – LSTM, GRU, RNN Simulation

6.4.2. Representation of the forecast and evaluation criteria

As pointed out in the introduction, forecasts can come in many shapes and are a "guess" of a future event based on current and past knowledge and information. In that sense a point forecast comes down to trying to guess the outcome of one single realisation of a random draw from all possible outcomes. Truly an almost impossible task certainly if the distribution of the possible outcomes is almost infinite as is often the case. Therefore, in practice one settles for a forecast that is expected to be close to that single draw in some sense. It also implies that a point forecast without measure of uncertainty of how close the prediction is likely to be, can hardly be interpreted and is in most cases not useful. With the rise of BD and AI and the increasing computing power, the probabilistic forecast is gaining practical use. Instead of giving a point forecast with some measure of uncertainty, like a forecast interval, one estimates the whole probability distribution of the future event. This distribution is called the prediction or forecasting distribution. This distribution can be used in decision-making.[20]

Evaluation of the quality of forecasting methods is hard. There are two important reasons. First, although the idea is that past and current information conveys information about the future, for forecasting procedures to be consistent a certain stability of the mechanisms generating the data should be present. This is in practice almost always only by assumption. So, determining why one forecasting method is good or suddenly very bad is hard. The second problem is that most forecasting methods only work for a specific set of models. And whether the data for the application under consideration are generated by a model included in that set of models is never certain.

In practice the quality of a forecasting method for a certain application is assessed as follows: split the available data into a training and test set, first estimate or train the proposed forecasting method on the training set, thereafter the performance is assessed using the test set. This method works better with more data and for model driven as well as data-driven methods. For judgmental methods one can assess performance by recordkeeping and setting up experiments that mimic this setup. BD facilitates these approaches as more data are available.

6.5. The effect of AI and big data on forecasting

Before analysing the effect of AI and BD on forecasting we first analyse the relation between BD and AI as they influence each other. Without the success of Machine Learning there would be less of a business case for BD and without BD Machine

Learning would be less successful in the current state of knowledge within the AI field. Table 6.3 shows the most important factors that BD brought to AI.

Table 6.3. The effect of Big Data on Artificial Intelligence, after Deshpande and Kumar[21]

AI without Big Data	**AI with Big Data**
Availability of limited data sets, in size and granularity, as well as number of variables.	Availability of increasingly detailed and wide datasets
Limited sample size.	Massive sample size resulting in increased prediction accuracy in several specific applications.
Batch oriented.	More and more real-time, on-line.
Slow learning curve.	Accelerated learning curve.
Single and homogenous data sources.	Multiple and heterogeneous data sources.
Based mostly on traditionally structured data.	Based on structured, semi- and unstructured data.

Repeating the analysis in our framework we combine the three DARPA AI phases with the 3 V's of the big data characterisation and obtain the results in Table 6.4.

Table 6.4. Order of effects of big data on the DARPA levels of ability to process information

		Big Data Characteristic		
		Velocity	**Volume**	**Variety**
DARPA levels of ability to process information	Handcrafted knowledge	+	++	+++
	Statistical learning	++	+++	+
	Contextual adaptation	++	+	+++

In the handcrafted knowledge phase, which started before the BD introduction, the entrée of BD introduced a greater variety of data that could be used. This influenced AI the most. Volume helped in the sense that various estimates and predictions could be improved by removing the limitations of small sample size, sample data type and out-of-date information, a problem forecasting often had before the BD era. In the statistical learning phase, the phase we are currently in, it's the sheer volume of data that influences the development of Machine Learning but basically all data-driven methods. Also, velocity influenced statistical learning and with new applications, even in (near) real-time, online forecasting and nowcasting. In the contextual adaption phase, the gains from the first two phases will be used as well; the additional contribution in this phase is reasoning with the results of the previous phases. In that sense variety will bring the most, velocity will still help to improve reaction times, volume will have less additional influence in this phase.

To assess the effect of BD and AI on forecasting we combine in a similar fashion as above the characterisations of BD and AI with those of forecasting methods. The results are presented in Table 6.5. The strength of the effect, indicated by the number of "+", only indicates the relative order of the foreseen effect, not the absolute magnitude of the effect.

Table 6.5. The relative order of the effect of BD and AI on forecasting methods in the three different categories

		judgmental	**Model driven**	**Data driven**
Big data	velocity	+	++	+++
	volume	+	++	+++
	variety	+++	++	+
Artificial Intelligence	Handcrafted knowledge	++	+++	+
	Statistical learning	+	++	+++
	Contextual adaptation	+++	++	+

The velocity and volume characteristics of BD have a dramatic effect on the rise of data-driven methods; they certainly also benefitted model-driven methods with increased sample sizes and more up-to-date models. This led for both types of forecasting methods to increased accuracy in general. Although, velocity and volume affect the judgemental methods, it is less pronounced. Several judgmental methods benefit mostly from the rise of online communication which makes aggregated judgment methods easier to apply. In contrast the variety of new data gives forecasters the option to make associations that benefit forecasting accuracy, while the mathematical formal models, and data driven models even less so, are not yet that flexible in combining heterogenous data.

The handcrafted knowledge phase gives a boost to model-driven methods and judgemental forecasts while it impacts the data-driven methods the least. Model driven is more impacted as to automate and operationalise the methods in this phase means building on explicitly formulated formal mathematical and logical models. In the statistical learning phase AI is all about data-driven methods, which in turn result in additional model driven methods, further strengthened by the increased date availability. The judgemental methods are least effected by statistical learning, although we see the rise of hybrid methods which in most cases imply the use of some judgemental component. Finally, the contextual adaptation phase will take off when AI systems can conceptually understand and reason based on the model-driven and data-driven results. Therefore, the judgemental method will be greatly impacted, as the conceptual models can enrich to a great extent the judgemental methods.

6.6. Effect of AI and BD on forecasting in military and defence applications

Based on the discussion in the previous sections the expected impact of the developments in BD and AI on several national security, defence, and military applications where forecasting plays a role is discussed. It should be noted that AI and BD also have effects on numerous applications not related to forecasting but more related to prediction and analysis. Important examples include, facial recognition, API/PNR data for risk-based border patrol, detecting objects on imagery and many more. Often these methods will be combined in one application. Consider the case of autonomous moving vehicles where forecasting in the current statistical learning phase is mostly limited to navigational and manoeuvring issues concerning its own position and behaviour and the behaviour of vehicles and objects, possibly incoming missiles, in its surroundings. The detection and classification of the objects and vehicles is usually also done by BD and AI methods, but this is not forecasting.

6.6.1. Autonomy in defence: systems, weapons, decision-making

High on the priority list of most countries is the development and use of systems that have a certain degree of autonomy. Whether armed or not. Three subcategories can be distinguished. First, autonomous systems that have the capability to operate in the physical world, i.e., autonomous unmanned vehicles. Second, autonomous weapons, i.e., systems that can launch weapons autonomously and third, decision- making systems, i.e., systems that give autonomous advice to entities on how to act. These later systems are usually also part of the first mentioned categories at a lower level but can also have the C2 role for multiple entities, being machines and/or humans.

Currently all three types of system are still based on handcrafted knowledge combined with statistical learning, i.e., sensor data is analysed by statistical learning methods, objects recognised, then based on a rule based expert system actions are devised. Most systems are currently still semi-autonomous, higher order decisions are still made by humans. The level of autonomy of the systems will grow when the methods that show contextual adaptation capabilities have arrived.

In this phase there is the question of whether humans are ‘in the loop’, when they retain a great degree of control over robotic autonomous systems, ‘on the loop’, when the system can autonomously take actions, but humans retain the ability to abort these actions, or ‘off the loop’, if they are neither asked to confirm action nor can abort such actions. The ability to forecast with high confidence without human support will be an important factor on whether, without touching upon the ethical dimensions, in, on or off the loop is feasible.

Near- and real-time forecasting is necessary for navigation and manoeuvring to prevent collisions with obstacles and other vehicles. If and/or when autonomous vehicles are used in conflict situations it should be possible to forecast near- and longer-term enemy behaviour automatically in real-time. This type of forecasting very quickly requires techniques from the contextual adaptation phase. Also, for the C2 forecasting at the contextual adaptation level is necessary. An important example thereof is the need for forecasting in combination with strategic games.

6.6.2. Strategic intelligence and foresight

BD and AI will affect the analytical, predictive as well as operational roles in national security and military intelligence environments.[22] Analytical roles detect, collect, describe, analyse, and try to model and explain why things happen. This field is currently booming, typical applications are monitoring surveillance, situational awareness and understanding. In this context BD and AI have already impacted the way intelligence organisations are operating[23]. Most techniques currently used are judgemental methods and to a smaller extent model- and data-driven methods from the statistical learning phase. The prominence of judgemental methods holds even stronger for predictive roles, so considerable improvements might be on the horizon when the contextual adaptation phase arrives. These methods might improve the forecasts of the outcome of complex negotiations and situations where numerous factors can influence outcomes of political or military processes and conflicts.[24,25]

Foresight, the process of analysing how changes in the current situation might affect us in the future[26], plays an important role in military contexts, especially strategic foresight and greatly influences and impacts national security and relative military strength and capabilities[27,28]. Forecasting plays a big role in foresight development, particularly when actions and plans based on foresight analysis are being developed. Considering the tools to develop foresight: horizon scanning, trend analysis, scenario analysis, modelling, simulation, and forecasting[29,30], and observing that some of these tools coincide with the tools used in forecasting, therefore foresight is expected to be impacted by BD and AI in a similar fashion as forecasting. Not only will BD and AI probably change the used methods and possibly the accuracy, but also new applications are developed. Examples thereof are Conflict Early Warning Systems, systems that forecast when conflicts will erupt, but also whether and when an irregular leadership change is to be expected[31,32]. Also, in these applications a mix of BD and statistical learning is the current driving factor. However, it is also here that probably only when the conceptual adaptation phase starts can AI and BD rival the current practice of judgemental and model-driven forecasts if ever[33].

6.6.3. Supply chain management, business operations, budgeting, planning, human resources

In fields as supply chain management, predictive maintenance, business operations, budgeting, planning, human resources, in short, the fields that keep the military organisation daily business running, forecasting is used much more like in any other government and larger private organisation. It is expected that military organisations will follow suit. Therefore, we will not further discuss this group of applications, just make the remark that the importance of the forecasting and decision making at this level is often undervalued: it might even be the most important factor of determining military performance at a strategic level as it determines for military organisations the condition in which they will enter conflict. Once in conflict, repairs are usually expensive and might not be ready in time.

6.6.4. Forecasting at the operational and tactical level, military logistics (sustainment)

We start with a sobering thought: “Given the unpredictability of the future, in military strategic, operational and tactical planning foresight and forecasting play a role but commanders typically favour adaptivity and agility”[34].

The adaptivity and agility is traditionally interpreted by planners to make sure that commanders can handle anything, any time at any place which leads in many cases to overly conservative estimates of means needed[35]. This is very costly and will in the future no longer be a viable manner of operating given the limited means (human, platforms, financial) available. Also, the expanding use of more small units makes it necessary to incorporate forecasting processes in planning and operations, for instance by embedding forecasting teams[36].

In operations, situational awareness and understanding are already improved by BD and statistical learning enhanced forecasting: Nowcasting, again a product of combining statistical learning and BD is when one makes predictions of the very recent past, the present and forecasts of the very near future. This is done as the most recent data are not always fully available, correct or verified. Starting in macro-economic forecasting, it has developed into a tool that improves weather forecasts and SA in tactical operations by, for instance, forecasting crowd flows in cities.

In military logistics forecasting is a longstanding practice and procedures are well developed, mostly based on judgemental and model-driven procedures. To get some idea the reader is referred to Cap. Johnson and Lt. Col. Coryell’s[37] description. The procedural legacy is focused on robustness (implied by the requested operational adaptivity and agility); instead adaptivity makes it harder to implement more agile forecasting methods as it also requires the real-world organisation to be able to cope with the needed agility. In general, it also implies a less resilient supply chain. It is envisioned that BD together with a combination of model and data-driven methods can improve logistics efficiency and effectiveness considerably by improved forecasting.

6.7. Conclusion

In this chapter a categorisation of forecasting methods into three instead of two categories "judgemental" and "statistical" methods is introduced by subdividing the "statistical methods" category into "model-driven" and "data-driven" methods. This is to enable the analysis of the effects of Big Data and Artificial Intelligence on forecasting practices and applications. Using DARPA's characterisation of Artificial Intelligence by considering the level of information processing capabilities "handcrafted knowledge", "statistical learning" and "contextual adaptation", the direction and relative order of the expected effects of AI and BD on forecasting are obtained. Finally, the consequences of results have been discussed for some national security, defence, and military applications.

Forecasting will become an ever more important tool for the military as the still standing military robustness practice to make sure to "be able to handle anything, any time at any place" is becoming less and less viable. This is due to costs and new ways of operating with smaller more specialist units. For the smaller units to be effective, good situational understanding is of utmost importance. Forecasting will be one of the most important instruments in the situational understanding toolbox of the future, and Big Data and Artificial Intelligence will enhance forecasting greatly.

Notes

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