Predictive Asset Management and Artificial Intelligence

Introduction

This document provides a brief introduction to Artificial Intelligence (AI) and describes the key differences between AI models and 'traditional' statistical models with particular reference to *predictive* asset management. It then explains why AI models are not suitable for predictive asset management when the aim is to establish the main predictors of asset failure, make predictions and run simulations. The document concludes by comparing predictive analytics with AI.

Definition of Artificial Intelligence

Artificial intelligence is the intelligence or science of making machines, especially computer systems, behave like human beings. It is now used as a general term that includes machine learning, artificial neural networks, deep learning and other models.

History of Artificial Intelligence

The term *artificial intelligence* was first used in 1955 by John McCarthy, a professor of mathematics at Dartmouth College, USA. Since then, many claims and promises about it have been made. For example, in 1957 the economist Herbert Simon predicted that computers would beat humans at chess within 10 years (it took 40 years) and in 1967 Marvin Minsky, the head of the AI laboratory at Massachusetts Institute of Technology (MIT), said that within a generation the problem of creating AI would be substantially solved. Even though both men were preeminent in their fields, their forecasts were badly wrong. This may explain why many claims of great advances in AI have been and are treated with caution.

Approaches to Artificial Intelligence

AI has two approaches: explicit programming (the first type of AI); and replicating the way natural systems behave.

Explicit Programming

- uses decision logic, for example IF … THEN structures

- rules and decisions are transparent
- results are easily reproducible and traceable
- not practical for complex systems (they have many factors and require complex rules)
- no longer considered to be part of AI, now called decision trees.

Replicate the Way Natural Systems Behave

- learn and evolve by adapting to new experiences
- very difficult or impossible to understand, even to the developers
- used by today's most powerful AI systems
- is self learning, i.e. its accuracy improves as it receives more data. This is a clear differentiator between it and non-self learning algorithms – they do not improve as new data become available. For example, algorithms for solving equations.

Artificial Intelligence and Structured Data

According to Professor Josh Tenenbaum of MIT, data must have structure for AI to extract value from them in the way that the human brain extracts value because understanding structure is a defining characteristic of human intelligence. Objects created by humans, for example images and speech, have structure but AI systems find it difficult to derive value from data with little or no structure. Systems that can reproduce the flexible intelligence of human beings and can solve problems they were not specifically trained for have not yet been developed.

According to Professor Tommi Jaakkola of MIT (*MIT Technology Review, April* 2017) 'If you had a very small neural network, you might be able to understand it but once it becomes very large, and it has thousands of units per layer and maybe hundreds of layers, then it becomes quite un-understandable'.

AI can be used to recognise faces from images and diagnose diseases from X-rays because the data have structure and AI algorithms can be trained for such tasks. But, however much AI algorithms are trained, they do not always see the world as we see it because they do not understand context and nuance, and so can label objects incorrectly by making incorrect associations (see bit.ly/2Qddaj4).

AI and Predictive Asset Management

According to the Grainger Knowledge Centre (2018), the use of AI in predictive maintenance is still in its infancy. There are many reasons for this but one possible reason is that AI requires vast amounts of data, much more than predictive models, with respect to the number of fields and number of objects, and the period they cover. Accessing all this data can be very difficult or even impossible for data that no longer exist. Additionally, it is very likely that the available data will have to be transformed to new forms using 'traditional' methods before AI can be applied (see *Data Preparation, Exploratory Data Analysis and Predictive Asset Management* in PAM Introduction).

AI is used in preventive maintenance to model sensor (condition monitoring) data, for example vibration frequency and temperature, in real-time for monitoring the state of assets for immediate operational maintenance. However, it does not provide information on the cause of the potential failure, or support tactical or strategic asset management. In particular, AI cannot answer the fundamental questions: how? why? what to do?, and simulate different scenarios to optimise the asset management policy.

Is Artificial Intelligence Always the Correct Model?

It is important to recognise that AI is appropriate in some cases and inappropriate in other cases – it depends on the context and objective of the project. AI may be appropriate when the process is very complex, unclear or highly non-linear and depends on poorly defined or understood relationships between the inputs (predictors), or when knowing how the answer was obtained is not important.

AI has three problems that limit the range of problem to which it can be applied, including predictive asset management:

- its need for large amounts of data and lack of first stage modelling functionality
- its black-box nature
- each solution is particular to the task it was trained for.

If the need for large amounts of data and lack of first stage modelling functionality are not relevant:

- If the second and third problems are not relevant, AI may be the right approach.
- If the second or third problems are concerns, AI is not the correct approach. Predictive models that can be tailored to each task and interpreted to gain insight and understanding are required.

Data Requirements and First Stage Modelling Functionality

AI requires a large amount of perfect data – many times more than humans require to accomplish the same task. As the granularity of the data and the amount of data increase, the accuracy of the predictions improves but the run-times increase very rapidly. Before AI models can be built, the data must be transformed to suitable forms and exploratory data analysis carried out to become familiar with the data and identify key relationships.

Application to Predictive Asset Management

- Dynamic factors that contribute to asset failure, for example asset maintenance and failure data, are very unlikely to have sufficient history for AI.
- Exploratory data analysis establishes the key drivers of the many possible drivers of asset failure.

Since AI does not have functionality for understanding and preparing data, procedures that address these issues, for example CRISP-DM, are required.

Black-Box Nature of Artificial Intelligence

The main concern that many people have with AI lies in the middle of the analytics process between the input data and output data – its black-box nature, i.e. the models cannot be accessed. Even if the models could be accessed, they can only be interpreted in very simple cases. This means that they cannot answer fundamental questions that people have when modelling data to help them gain insight and understanding. These are the two main problems that many people have with AI and may explain why they find AI difficult to relate to and are reluctant to use. On the other hand, parametric models can be interpreted and related directly to the system being analysed and modelled.

Application to Predictive Asset Management

Asset managers need to understand the models they are using to improve asset performance. AI cannot answer questions such as:

- what is the model?
- which inputs determine the output and how do those that do contribute to it?
- why do the results show the patterns and features they do?
- why are the results for some assets poor (assuming there are such cases)?
- can the calculations for particular assets be traced and reproduced?

On the other hand, predictive models can identify the causes of asset failure and so help improve asset performance and mitigate the risk of future asset failure.

The black-box approach to modelling was neatly summed up by Alexander Dewdney. He wrote that artificial neural networks have a 'something-for-nothing quality, one that imparts a peculiar aura of laziness and a distinct lack of curiosity about just how good these computing systems are. No human hand (or mind) intervenes; solutions are found as if by magic; and no one, it seems, has learned anything'.

Uniqueness of Solution

AI models are very efficient at performing the tasks they were trained for but they cannot perform other tasks. Even relatively small changes such as changes to the input variables or output variable require new AI models to be developed whereas predictive models only need modifying. Furthermore, AI models cannot establish the effects of the input variables on the output variable whereas this information is part of or can be worked out from the output of predictive models.

Application to Predictive Asset Management

- Asset failure is a complex phenomenon with many factors contributing to it.
- AI models for similar assets cannot be compared whereas predictive models for similar assets can be compared and their development times are shorter than for AI models.

Can Artificial Intelligence Replicate Survival Analysis?

Since **PAM** uses survival analysis to model asset failure (see the appendix in PAM Introduction), it is instructive to ask if AI has all the functionality of survival analysis.

PAM uses Cox regression and discrete event simulation to model the risk of asset failure as a dynamic phenomenon and optimise asset management at individual asset level and at the operational, tactical and strategic levels. Since the target variable in Cox regression, the hazard rate, is generally not available in the input data, it must be calculated before the Cox model is developed. This is an integral part of Cox regression procedures and is hidden from users. It is calculated empirically from the input data and AI cannot do this.

The output of Cox regression procedures is a dynamic predictive model that can be used for modelling, simulation and optimisation. Furthermore, being a predictive model, it allows insight and understanding into asset failure to be gained, and as discussed above AI models do not have this functionality.

Types of Asset Management Prediction

Predictive asset management models require a range of predictors, including time, to establish the drivers of good asset performance. AI models do not have this explanatory structure and so cannot be used for modelling, simulating and optimising asset performance. This is a very important consideration when developing models – the extent to which models are developed only for the results and the extent to which they are developed to gain insight and understanding, in addition to the results. The former is a characteristic of AI models and the latter is a characteristic of predictive models. As described above, asset managers need predictive models to help them carry out their tasks and answer key questions.

Table 1 shows a comparison of predictive models and AI models for a number of factors.

Table 1

Factor	Predictive Models	AI Models
Modelling complex (non-linear) problems	Lengthy process	Well suited (assuming the data have structure)
Human intervention required for model development	Yes	No
Model development/ training time	Increases with amount of data and model complexity	Increases *rapidly* with amount of data and model complexity
Model self learn	Manual update required as new data become available	Yes
Amount of data and computing power required	Acceptable	Much more than for predictive analytics
Ability to control model	Yes	No
Access model to gain understanding	Yes	No
Isolate effects of variables in model	Yes	No
Carry out dynamic simulations	Yes	*Area of research and development*
Apply constraints to model	Yes	*Area of research and development*

Conclusion

This article has shown why AI cannot be applied to predictive asset management – it cannot answer the fundamental questions why? how? what to do? This is because currently AI has three limitations:

- It needs large amounts of data and does not have data preparation and exploratory data analysis functionality.
- Its black-box nature means that its models cannot be accessed and so cannot provide insight and understanding.
- Each model is particular to the task it was trained for.

If these limitations are not relevant, AI may be suitable but if they are relevant, predictive analytics is the right approach as it can answer these questions to help improve asset performance. The technology for overcoming these limitations may be available in the future but it is not currently available.

Much has been and is written about applying AI to predictive asset management but it is all in the passive – 'AI can be applied' – but without case studies. The thrust of the articles is 'we have the data and so we only need to throw them at AI software'. Really?

