AI in Equipment and Auto Finance

Part 1: Balancing Risk and Reward
About the author:

Martyn Tamerlane is a Solution Architect at Alfa, with a focus on project delivery.

During his Master’s degree in Mathematics and Computer Science, Martyn developed a lasting passion for latent technologies and how they can be integrated with legacy systems.

Contributors:

Alex Barnes
Maurice Buckberry
Martyn Davies
Andrew Flegg
Brennan Till
Part 1: Balancing Risk and Reward

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At Alfa we’ve been working with many of the most successful players in the asset finance markets since 1990.

Many agree that the industry can be a little slow to take up new technology. It took a long time to leave those mainframes alone and start using cloud-based browser applications - and not everyone is there yet. This reticence can usually be traced back to the fundamentally risk-averse nature of the lender.

But recently we’ve been seeing a lot more change, particularly in the area of digital transformation (cf. Digital Directions).

Asset finance providers - whether they’re bank-backed, captive or otherwise - are becoming increasingly switched on to the idea that technical innovation can accelerate their processes, unify all manner of systems and services, and deliver new business in greater volumes, with refreshing speed and simplicity.
Efficiency and cost reduction have always been key objectives for lessors, particularly those who operate at volume. And while we’ve always found ways to streamline a process here or automate a couple of steps there, there is a new understanding and accessibility around Artificial Intelligence (known, of course, as AI) which is enabling us to unlock these benefits.

Practically, this can mean unearthing hidden value in data archives, processing new streams of data inexpensively, detecting suspicious behaviour automatically, or responding to market trends more quickly than the competitors.

*As AI becomes more widespread in equipment and auto finance, many providers are making sure they won’t be left behind.*

And with AI-as-a-service already hitting the market, we now even have automation of the process of developing AI solutions.

But AI is no silver bullet. Its design often requires precise expertise to guide solutions so they don’t incur spiralling costs, or result in solutions that are less accurate than the processes they are designed to replace. In most cases, the benefits gleaned from an AI solution represent a trade-off between speed and accuracy, automation and control, or data and privacy. That balance must be optimised to align with a business’s strategy, while ethical and regulatory risks must also be considered - as regulations around this expanding technology continue to tighten.

This paper explores the reasons why a particular field of AI - machine learning - can provide solutions that are cheaper, faster and better than conventional methods; and how AI-as-a-service is being used to decrease the cost (and risk) of implementing these solutions.

We study examples of where these solutions can provide enormous success, such as autonomous vehicles, as well as some industry-specific use cases which perhaps don’t hold up under close examination. We discuss how, without proper guidance, AI solutions can offer not just great reward, but also great risk. Finally, we share the ways we innovate using AI here at Alfa, from small internal solutions, to those that bring tangible value to our clients in their use of our software platform - as well as in their own systems.

We hope you derive some value from the paper. We’ll be following up with more discussion in 2020.
Why AI Works in Finance

AI is a broad term that covers the simulation and imitation of human intelligence, as well as theoretical intelligence that is independent from humans.

There are many scientific branches of AI, each with its own approach to synthesising intelligence - from purely statistical methods to simulating natural selection. However, when you hear “AI solutions”, especially in financial software, it is almost always one particular brand being spoken about, and that’s machine learning.

Machine learning is designed to automate the “learning” part of our intelligence. It is ideal for identifying patterns in highly complex datasets, automating decisions made on those patterns, then adapting those decisions when new data is presented to it - based on its past decisions. This ability to self-maintain is one of its most valuable properties.

One popular definition has machine learning as “the scientific study of algorithms and statistical models that a computer can use to perform a specific task effectively without being given explicit instructions, instead relying on patterns and inference”. It is a broad subject, roughly divided into two approaches; supervised and unsupervised learning. Read more about what machine learning is and how it works in Postscript: About Machine Learning (page 18).

Using AI to Make Estimations

Machine learning algorithms aren’t trying to calculate the correct answer, only to classify new data through an understanding about how the data is structured. In the vast majority of cases, AI is an estimation machine and is therefore most appropriate in scenarios where the full extent of rules or data is not known, and we ourselves are forced to estimate outcomes; for example, future prices of used cars.
Estimating Used Car Prices

Determining the target sale price of a used car is a great example of where machine learning excels, not only because of its ability to adapt to future patterns in the economy, but also because of the type and quality of data available.

Lots of factors which contribute to a car’s price can be obtained easily, often in high volume - such as make, model, colour and mileage. The relationship between these properties can be simple to model; for example, if the price of a new car increases at a steady rate over a given period of time, those properties have a linear relationship and a linear regression model can be used to estimate what the target sale price of a car should be, based on its year of manufacture.

In this example, it looks as if there is a clear linear relationship in the data, with the dashed line showing the linear regression. If a car manufactured in 2009 was being sold, this model would indicate that its target sale price should be around £12,000.

Less simple relationships are described as non-linear. In these situations, more sophisticated techniques are required to model the relationship. For example, a vintage car might be worth more than a new car, even though it was manufactured much earlier. A linear regression model would not represent this relationship accurately, and the estimations are skewed.

Machine learning algorithms excel at finding these non-linear patterns. In this example we’ve only considered one property, but in order to get a more accurate assessment we would want to include as many properties as possible that may affect the target sale price. Another strength of machine learning algorithms is their ability to process a high number of these at the same time, finding inter-relating patterns between each and every property.

Being able to retrain a machine learning algorithm with new data allows it to keep up to date with these patterns, without having to adjust complex forecasting models manually. This is expected to become increasingly important as the Internet of Things provides a greater amount of data about a car’s lifecycle.
Credit Decisioning

Credit decisioning is a typical target for automation in leasing and asset finance. Many processes have been automated by codifying decision-making in this form:

\[
\text{if (condition), then (outcome)}
\]

For example, in credit decisioning we might consider a prospective client's monthly disposable income:

\[
\text{if (monthly income > £1,000) then (approve lending)}
\]

By connecting these conditional statements together, complex decision-making workflows can be constructed. For example, we can consider monthly income then also check for the client's number of open credit lines:

\[
\text{if (monthly income > £1,000) then if (number of open credit lines < 3) then (approve lending)}
\]

This simplified example is otherwise known as a credit decisioning scorecard, and has worked well for decades because of its flexibility in being able to add and update conditions when needed. For example, the monthly income condition can be updated to be in line with inflation each year.

Despite the maturity of this solution, there are a couple of challenges to its development and maintenance: it is a manual burden to reassess conditions and update them; a burden which requires intimate knowledge of how the conditions impact credit worthiness. Furthermore, it doesn't scale well; the more sophisticated the credit decisioning workflow becomes, the more conditions are needed, and thus more effort is required to maintain them.

The machine learning alternative removes explicit knowledge of these conditions by training a neural network to find out about them on its own. By providing a neural network with the same data used in the conditions, and training it using past data on whether lending was approved, it can learn the relationship between the data and creditworthiness. It can then assess new applications based on its understanding of those conditions and, more importantly, be retrained automatically to update its understanding of those conditions when needed.

The ability to learn complex relationships between a very large set of properties is one of the main benefits in this use case, and with greater availability of data, such as through the Open Banking and PSD2 initiatives, this opens the door to more accurate results.

The downside to the machine learning approach here is the difficulty of reverse-engineering decisions; for example, what happens if a customer questions the reason they were rejected? The reasoning is more of a “black box”, with little information available about why it came to its conclusion - other than the fact that it is following some complex patterns in past data. See Staying on top of...regulation on page 12 to learn more.
Autonomous Vehicles

Self-driving vehicles simply would not be possible without machine learning. There are far too many conditions to be programmed and maintained as if-then logic, and a vast number of objects in the world that an autonomous car would need to recognise accurately. Distinguishing between a pedestrian, a vehicle or the edge of a road directly impacts the actions it has to take, making the accuracy of identifying those objects paramount. This is compounded by poor visibility or weather conditions, which in themselves impact its behaviour.

Fortunately, machine learning algorithms have outperformed humans in this field for many years and are only bound by the strength of their sensors, which extend much farther than the human eye as well as being able to detect more than the human senses. The technology still needs to mature, and there are still edge case scenarios that need to be refined where there have been crash-like events, but the results have been promising. Tesla’s vehicle safety report from the third quarter of 2018 shows that there had been one accident or crash-like event for every 3.34 million miles driven in which drivers had engaged Autopilot, its self-driving AI product. This compares favorably with equivalent statistics without self-driving assistance - one for every 1.92 million.

Off the road, John Deere and similar organizations have launched autonomous farming vehicles which are capable not only of ploughing fields automatically with pinpoint GPS precision, but also of using sensors and machine learning to recognise pests and weeds in order to administer exact, measured blasts of pesticides to control them. The increased accuracy has led to savings in fuel and pesticides, benefiting the end user (and the consumer). But equipment finance providers also now have a more marketable product to finance: the sensors can also collect valuable data about soil condition, and other crucial pieces of information about the crops and its surrounding environment. In John Deere’s case, that data is fed back to a user-owned platform, MyJohnDeere, which stores and analyses it to provide valuable business intelligence. Subsequently, there is also the ability to interconnect with other farmers, to pool data and collaborate on research.
AI solutions make powerful estimation machines and bring significant benefits, but they can also bring significant costs. This is true with many emerging technologies, but particularly with AI. In the cases of autonomous cars and farming equipment, successful applications of AI technology have helped make a reality of what were, until recently, unlikely and futuristic concepts. In asset finance, processes such as credit decisioning and used car pricing estimates are changing. However, many other attempts have faltered and, due to improper judgement and use of data, even caused whole projects to close.

Some solutions simply won’t work without large amounts of high-quality data. Similarly, without expert contextual guidance, false or flawed patterns are identified, or costs spiral out of control - leading to an unsound solution or, worse, one that breaches ethical or legal polices.

What are the hazards, and how do we avoid them?

The role of data

Data is involved in three stages of the machine learning process (see About Machine Learning on page 18 to learn more):

1. Training: A large amount of historical data is used to train the model.

2. Input: Once it has been trained, real-time data input to the neural network.

3. Outcome: The resulting decision of the neural network is based on input data.

It’s important to make sure every significant dimension is included in the dataset, but it’s not always obvious that some dimensions are relevant. Complex patterns in the data aren’t visible to the human eye, and that is precisely why machine learning is in use. Experimenting with what’s included in the dataset can add crucial value to your solution’s performance, and there are some methods (such as feature branching) which automatically identify the data that contributes most to the accuracy of the output.

As AI solutions are shown increasingly to be cheaper, faster and better than their traditional counterparts, the two complementing factors of data and judgement have increased dramatically in value.
Staying on top of...context

As well as the quality and quantity of data available, AI solutions are sensitive to the context of the problem. A famous example is that of the statistician Abraham Wald in his contribution to analyzing American fighter planes that had been shot at during the Second World War.

Wald was asked to provide a strategy for spreading armor over the plane to make it more resilient to gunfire. Too much armor would make the plane heavier, making it less maneuverable and using more fuel. Meanwhile, too little would allow gunfire to penetrate through the plane; so an optimal spread of armor was required. Wald was provided with historical data of planes that had returned with bullet holes, which contained the section of the plane that had been hit along with the average number of bullet holes (see table).

<table>
<thead>
<tr>
<th>Section of plane</th>
<th>Bullet holes per square foot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine</td>
<td>1.11</td>
</tr>
<tr>
<td>Fuselage</td>
<td>1.73</td>
</tr>
<tr>
<td>Fuel system</td>
<td>1.55</td>
</tr>
<tr>
<td>Rest of plane</td>
<td>1.80</td>
</tr>
</tbody>
</table>

From an AI standpoint, a naive neural network could be trained to optimise for adding armor to the areas with the highest number of bullet holes since, logically, this will provide the most protection for the plane while wasting the least armor. In this situation, the training data would be the data of the planes that had been shot at and returned with bullet holes. On processing the training data, it would learn to cover the areas with the most average holes. However, as Wald pointed out in his analysis, the reason why the engine area has fewer holes on average is because there is missing data. He suggested that there were planes with high numbers of bullet holes in their engines which, after being shot at, simply hadn’t returned. Our data is missing vital information that has resulted in the exact opposite of the correct solution.

This highlights an intrinsic weakness of machine learning algorithms: they are not aware of missing data or of constraints outside of the data provided. Human judgement is therefore vital to the successful configuration of the machine learning process.
**Staying on top of...bias**

Also living outside the machine learning process are the concept of fairness, and the recognition of bias.

Basic regulations (such as the Equal Credit Opportunity Act in the US) protect individuals from discrimination based on various personal information, such as race and gender. But it’s not straightforward to remove bias against this information, even by specifically removing or obfuscating it. In reality, relationships between any and all information relating to a person are innately intertwined, complex or not fully understood - and there has not yet been a process created to isolate the impact of one piece of information from another.

For example, consider the impact on creditworthiness of income, compared to a subject’s neighbourhood, or which school he or she attended. As shown in a study proving that there is a difference in income distributions between racial groups*, indirect links do exist and can be the subject for discrimination. When designing a solution, ignoring the fact that these interdependencies exist is a costly risk to any organisation’s reputation.

Bias is present in existing archives of data from past discrimination, but also from newly input data. Microsoft learned this the hard way when it released its chatbot Tay, which drew on user interaction to adapt the way it responded. Some highly dubious language used in those interactions taught Tay to respond in the same manner, and it was quickly shut down. Bias is also embedded in the machine learning process itself, in the way we determine what data to include and exclude. While there are methods to remove bias from training data and results, it’s far from an exact science and some bias will inevitably remain.

* Fuster, Goldsmith-Pinkham, Ramadorai, & Walther 2017

**Staying on top of...regulation**

The risk of not paying attention to the data being used in an AI solution can lead to severe regulatory consequences.

In the European Union, article 22 of the data protection regulation GDPR lays out firm policies on a user’s ability to opt out of automated decision-making. Organisations must also make sure they can give individuals meaningful information about that processing, and allow them easily to request human intervention or challenge a decision. This poses a significant challenge to the field, especially when algorithms like neural networks are in use, where we are simulating parts of our brain we do not fully understand. At the least, additional business processes must be designed to allow the interpretation to take place. It’s clear this is an area in which trusted, expert systems partnerships are mandatory.

Of course, some algorithms can be interpreted more easily than others, which may make them more suitable in situations that are subject to tight regulations. For example, MIT has designed its Transparency by Design Network (TbD-net) to “show its working” periodically during training, allowing greater insight into why its training changes the way it interprets input data. Another alternative, the Random Forest algorithm, isn’t a neural network but a process that results in a decision tree, with each branch of the tree signifying a feature within the data. Various methods can then be applied to understand what these features represent, providing some reasoning as to why the outcome was decided.

Across the United States, policies on data privacy are fragmented. An Executive Order signed in February 2019 launched the American AI Initiative, which stresses the importance of investing in AI while removing unnecessary regulatory barriers to its adoption. However, it remains to be seen how much of an impact this will have at the state level, with California’s Consumer Privacy Act, set to come into force from 1st January 2020, leading the way as a template for other states to follow.

In stark contrast to both the UK and the US, China chooses not to hold back on data privacy and in its “social credit” AI solution - designed to determine a citizen’s economic status - which includes all citizen data, including browsing history and payment data.

Clearly, the world is undecided on what data should or should not be used by AI, but until it is, AI solution designers will need to be vigilant and adapt solutions to fit local policies, taking the relevant trade-offs into consideration.
How We Do AI at Alfa

At Alfa, innovation is key to our culture. It is embedded in the way we think about solutions.

The innovation philosophy influences everyone in our organisation and this enables a consistent, repeatable process for progressing and adopting ideas. Some of this is achieved through hackathons and innovation afternoons, which encourage collaboration in a mix of technical, non-technical, junior and senior minds. But it’s also fundamental to the way we think throughout the day, with some of our best ideas formulated over a lunchtime chat, or when spending time with colleagues outside of work.

AI is one of the many tools at our disposal for solving problems. When it’s the appropriate thing - be that for internal initiatives, or client-facing projects - we take each valid idea forward using measured, iterative experimentation until it’s ready to present and, finally, implement.
Finding a balance

Machine learning isn’t appropriate in many situations; especially those where the structure of data is well understood.

For those problems where it is appropriate, there will always be compromises and trade-offs, such as:

- Speed vs. accuracy
- Autonomy vs. control
- Greater use of data vs. privacy

These trade-offs need to be understood and optimised to work in line with a business’s strategies, which subsequently can change as a result.

For example, if you are implementing a credit decisioning solution, you might decide that to improve the user experience of applying for a loan, the machine learning algorithm needs to be very fast. Recognising that this will affect the accuracy of the outcome, you might then choose to procure a larger training dataset, or hire a data scientist to pre-process the data and increase its quality. Both of these options will help mitigate the reduced accuracy, but at an increased cost to the overall solution. Instead of hiring a data scientist, you might prefer to train up in-house resource to pre-process the data; or use existing infrastructure to store the data - both of which could affect your existing strategies.

Using AI-as-a-service

The machine learning process is not a trivial one, and there is a significant up-front cost to setting up the process. Hardware with high performance and high capacity is required for pre-processing and storing the training data, as well as training the neural network.

Fortunately, cloud computing has enabled the temporary use of such hardware, with most platform providers now going one step further and offering AI-as-a-service. This reduces the up-front cost of setting up the various components, and allows you to concentrate on the parts of the process that form the core of the solution. Amazon’s SageMaker is a good example; it comes with tools that allow you to store training data and, through its SageMaker Ground Truth service, increase the quality of that training data by labelling it automatically. It also guides you through the selection of the machine learning algorithm to use.

There are many other services that come with pre-trained machine learning algorithms, for functionality that can be used for common use cases. One example is Amazon Rekognition, which can recognise objects and parse text; while Amazon Transcribe and Amazon Comprehend translate voice chat to text - from customer calls, for example - for auditing purposes or further data analytics. This removes the need to set up and tune your own machine learning algorithm, at the cost of control over which machine learning algorithm is used and how it’s trained.

The process of training a neural network works well with cloud computing and its pay-as-you-go services, since you only have to pay for what’s needed during the training process. That can be very expensive, particularly when you have a large dataset. It’s also ideal for the short-term hiring of data scientists, who would otherwise be very expensive, and having them focus on the business-related aspects of tuning the machine learning process - rather than spending their time configuring the infrastructure.

Given the high accessibility and low cost brought on by AI-as-a-service, there are valuable opportunities now open for machine learning to be used to solve small, internal projects, as well as the larger, public-facing ones.
Classifying test failures

At Alfa, a company that delivers quality code, a significant amount of effort goes into ensuring that both new and old code is tested continuously and automatically. So we run a constant programme of automated tests.

These automated tests sometimes fail, indicating there may be a regression, or that there is some conflict between two developments which requires engineer investigation. Sometimes this is a matter of looking at just the most recent change made to the code, but in some cases the failure is very subtle, involving many different areas of code that have all been changed at the same time. The investigation can then take much longer because the engineer needs to understand the nature of each recent development, and its relationships with how the test had failed.

Some of our software engineers use a machine learning algorithm to detect these relationships, by training it on a range of data that is already available to us based on past failures. That range includes, for example, the name of the failed test, the area of code in which development was taking place, or the type of failure that occurred. Once trained, the algorithm can be used to attempt to classify new failures, narrowing the search for the engineer investigating the failure and tracking it back to the lines of code that caused it.
Improving document search

Language used within an industry, and even within an organisation, often develops its own semantics. Words can have different meanings and, more importantly, the relationships between them can be different.

As machine learning is adept at discovering these relationships, it can be taught to categorise a document based on its abstract context, improving a user’s ability to search for related documents. For example, if you searched for the keyword “payment”, the ranked results might turn up documents that included semantically similar terms, such as “swift” or “wire transfer”. Many off-the-shelf tools already carry out this type of searching, but trained on generic text that doesn’t include an organisation’s internal semantics.

This idea can be extended to searching related documents in other languages. For example, a search for “payment” in a set of French documents returns those that contain semantically similar terms in French, rather than relying on translations that may not preserve the semantics.

Client implementations

Our innovation culture isn’t just philosophical; it extends to a hard budget too. As part of our ongoing R&D, we have set aside a significant allocation to develop prototype solutions which help our customers meet some of their challenges.

This has included, among other things, integrating customer verification with Jumio, and implementing system behavioural analysis, considering patterns within aggregated set of screen interactions to help identify the right UI and performance tweaks. Using the services and techniques described above, we’re finding that our clients and prospects see plenty of value in our solutions.
How are you innovating?

AI-as-a-service has removed the need for an intimate understanding of how machine learning works. As a result, large-scale projects are no longer required for AI-enabled business impact to be transformative.

And while this allows us to improve existing ideas, and even open up new markets, the challenges are still very real.

There is a huge amount of value to be gained through AI, but only with the right judgement and guidance.

Thanks for reading. We'll review things further in 2020.
Machine learning is the scientific study of algorithms and statistical models that a computer can use to perform a specific task effectively, without being given explicit instructions, instead relying on patterns and inference.

It is a broad subject, roughly divided into two approaches; supervised and unsupervised learning. With supervised learning, the machine learning algorithm is initially instructed on what the correct answer is when given input data. The objective is to then train the model to learn the mapping between input data and correct answers so that, when it is presented with new input data, it will be able to estimate the correct answer. Conversely, with unsupervised learning there is no instruction on what is correct, with the objective of the algorithm to discover hidden patterns in the data on its own.

These two very different approaches are designed to solve different categories of problems. Supervised learning is ideal for classifying new input data based on what it has been told about old data; for example, estimating house prices for the next quarter in a given area, based on the price movements over the last twenty years. Unsupervised learning is typically used to find hidden patterns or trends in data without any up-front information; for example, sorting photos of different people without knowing what each person looks like.

There are many ways to train a model for both supervised and unsupervised approaches. Arguably the most popular is to simulate the way our brains learn, by modelling their neural networks. The neurons and synapses in these networks send electrical signals to each other when provided with information from our bodily senses.
This communication has been modelled as artificial neural networks - computer programs assembled from millions of artificial brain cells. These networks can be programmed and automated such that a computer can learn and behave in a way remarkably similar to human brains.

The general approach to training a neural network is as follows:

1. **Get data.** Obtain training data, containing a large number of individual input data along with the correct outcome.

2. **Clean, prepare and manipulate data.** Pre-process the training data. Typically, this involves a someone with intimate knowledge of the data removing anything that is outlying or irrelevant. In some cases, a data scientist is required to apply machine learning techniques on the data to increase its quality.

3. **Train model.** Feed the training data into a neural network, a network simulating layers of neurons and synapses in a human brain, with mathematical functions determining the chances of synapses firing, which, across all of the layers of neurons, produces an outcome. As training data is fed into the neural network, the accuracy of the outcome is fed back into the neural network, tweaking its ability to get a more accurate outcome for the next part of training data.

4. **Test data.** Once all of the training data has been fed through the neural network, it is tested against some unseen data with known outcomes, used to measure its accuracy.

5. **Improve.** The neural network is now ready to process new data. It is unlikely to be 100% accurate, but responses to its outcome can be fed back into the neural network automatically so that it adapts to new patterns.

Neural networks can then be retrained on new sets of data automatically or manually, allowing them to adjust to changes in the underlying patterns.
Talk to us.

If you are thinking about:

- Transforming your operations,
- Consolidating or integrating your existing systems, or
- Delivering a truly digital solution to your customers

..then contact sales@alfasystems.com to find out how Alfa can help.

Americas
+1 855 680 7100

Europe, Middle East & Africa
+44 (0)20 7588 1800

Asia-Pacific
+64 (0)21 961 361