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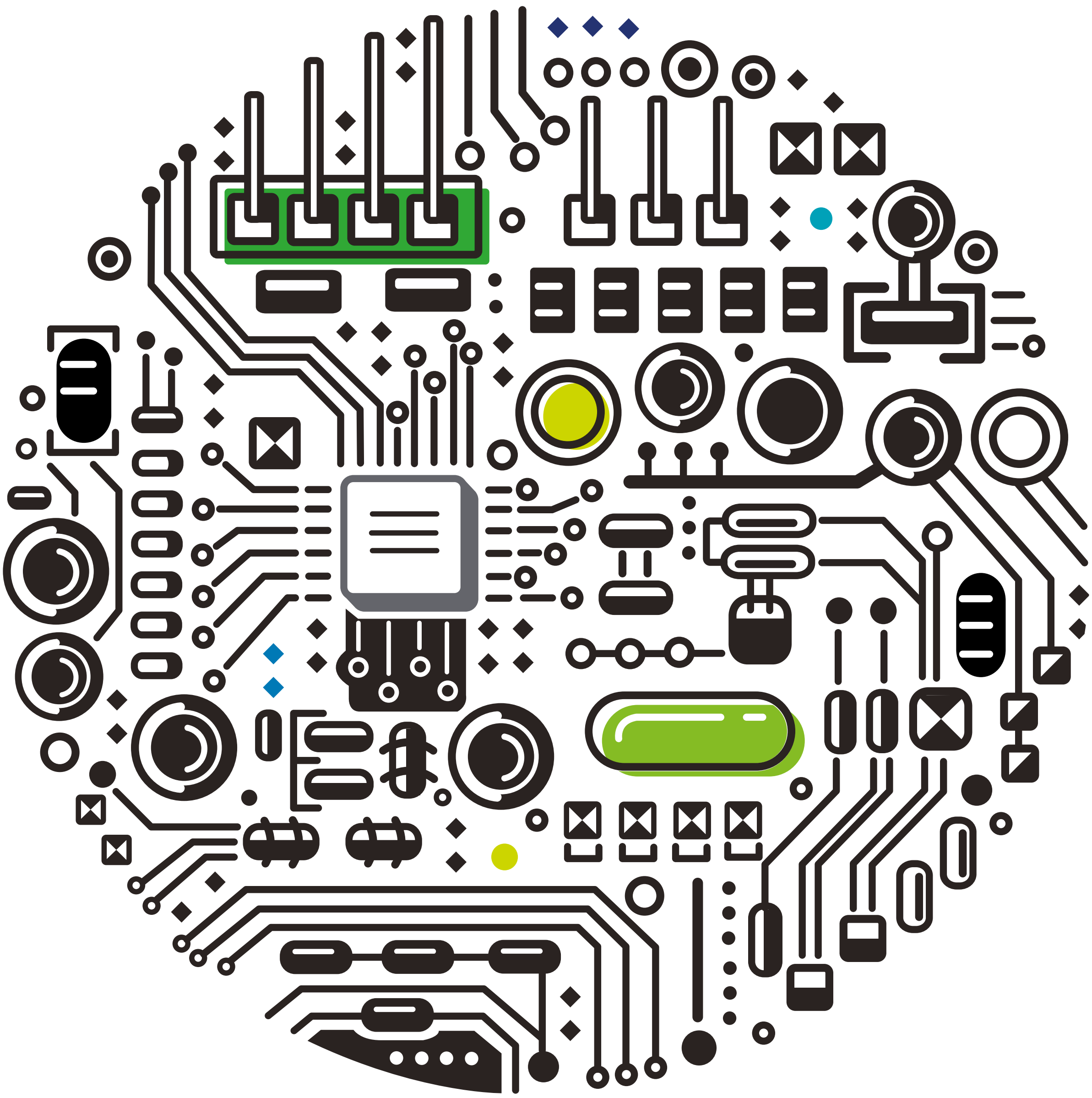
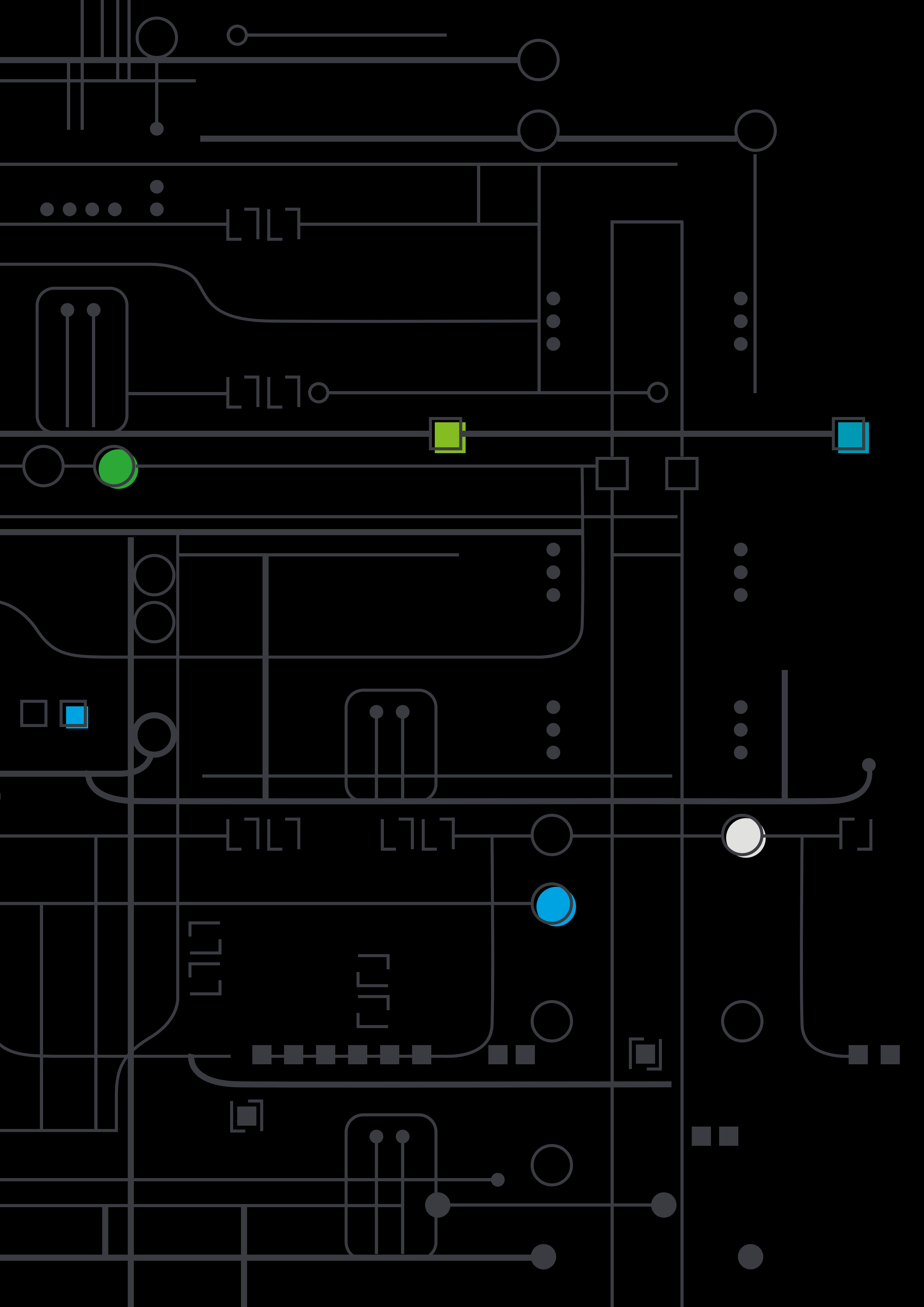


Business impacts of machine learning

Sponsored by Google Cloud

2017



Contents

Executive summary

Machine Learning (ML) is a method of data analysis that automates the building of analytical models

These algorithm-based models are primarily built from statistical techniques and theoretical computer science, and leverage large datasets to continuously learn and improve. While the techniques themselves are not new, the use of machine learning is facilitating faster and larger change in business models than previously possible. This report considers both core ML methods as well as artificial intelligence (AI) and other applications that directly flow from their use.

Businesses incorporate ML into their core processes for a variety of strategic reasons. ML can deliver benefits such as the ability to discover patterns and correlations, improve customer segmentation and targeting, and ultimately increase a business' revenue, growth and market position.

This report finds that there is a big global opportunity for ML in terms of current investment and expected future growth. An MIT Technology Review survey of 375 leading businesses in over 30 countries found that 60% of respondents had already implemented an ML strategy and had committed to ongoing investment in ML.[1] Global market revenue for ML as a service (MLaaS), or vendor platforms for ML, totalled US$1.07 billion in 2016, and is expected to grow to US$20 billion by 2025.[2]

Importantly, there are also a range of costs and benefits for business, as shown in Figure i and presented in the report.

Figure i: Costs and benefits of ML projects

Revenue and growth
- Predicting business outcomes
- Personalising customer engagement
- Improving business strategy through better market intelligence and pattern recognition
- Gaining competitive advantage.

Time and efficiencies
- Process efficiencies
- Labour efficiencies
- Value chain efficiencies.

Capital savings
- Optimising production inputs
- Maintaining capital assets
- Quality control.

Investment costs
- Data
- Human resources
- Third party vendor.

For this research, Deloitte Access Economics compiled a database of over 50 ML applications globally with a range of applications and benefits to estimate ML ROI, defined as the dollar return of the project in the first year of implementation divided by the total project investment to date.[3]

The estimates show that ML ROI in the first year can range from around **2 to 5 times the cost**, depending on the nature of the project and a range of factors including industry and success of implementation. As an indication, project implementation can comprise up to around 40% of the total project costs.

Estimate of business impacts

Use cases of ML in Deloitte Access Economics' database highlight benefits for most projects ranging from **US$250,000 to US$20 million.** For some businesses, ML is a long-term, transformative investment expected to deliver benefits of a few billion dollars over several years.

ML projects also require significant investment, with small projects considered in this research costing a **few hundred thousand dollars** and larger, enterprise-level projects costing a **few million dollars**. These costs largely depend on how a business decides to go about procuring and implementing ML applications. Some key critical factors relate to whether the project is developed in-house, outsourced, how customised the solution is, the volume, availability and degree of structure in the data, availability of ML 'teachers' project duration, as well as vendors' specific cost structures.

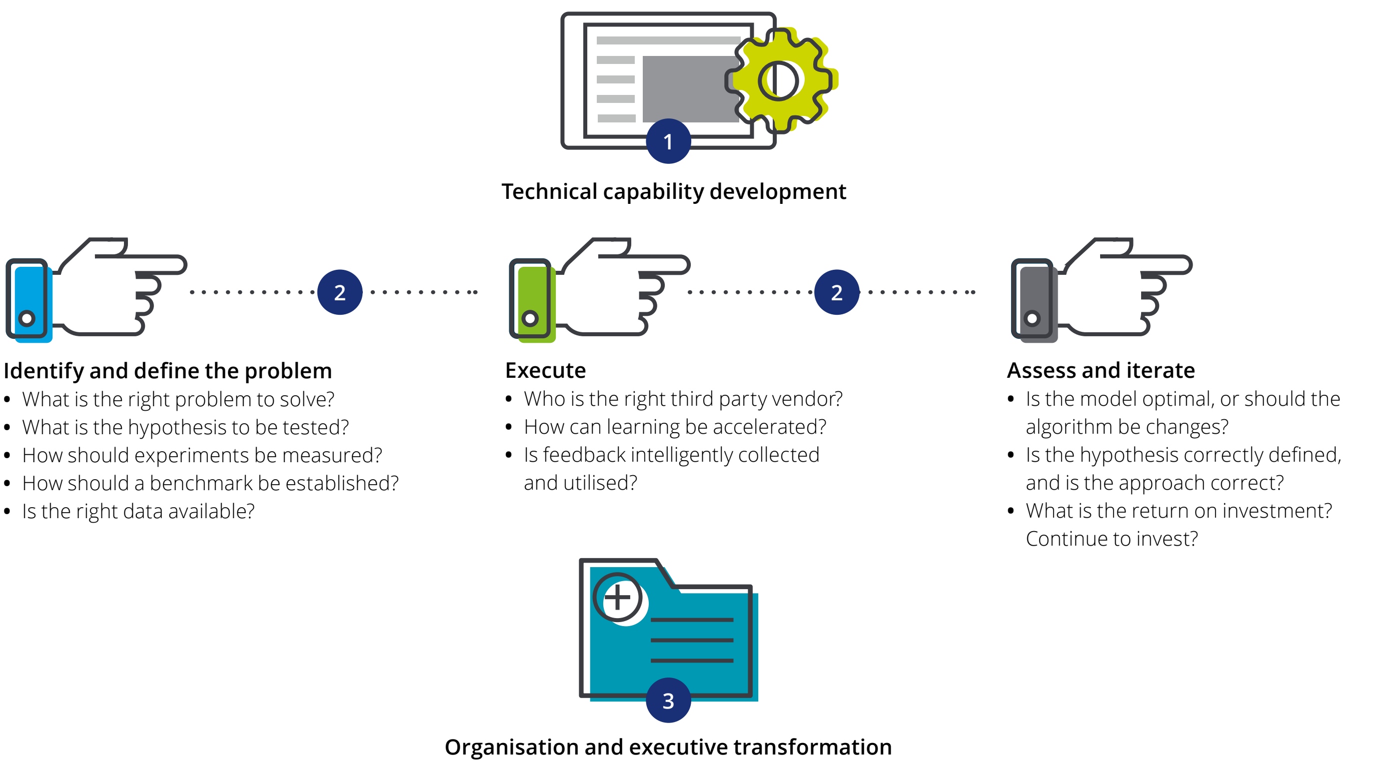
Deloitte Access Economics' research and consultations suggest that on average it takes **around 12 months** to develop a successful project, including data collection, model development and training, and implementation. However, this is variable depending on the complexity of the problem or task at hand.

Where to invest

Beyond the exciting potential business outcomes, there are considerations that organisations need to evaluate in order to maximise the returns on investment.

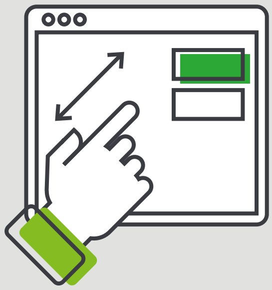
Deloitte has created a framework (see Figure ii) to help Executives evaluate business readiness for machine learning, and prioritise where to invest in the short term to enable longer term benefits.

Figure ii: Evaluation framework – business readiness for ML



[3] ML applications were drawn from uses cases from a range of countries including Australia, United States, United Kingdom, Italy, Switzerland, Belgium, Russia, Japan and Indonesia. By its nature, this database is not a representative sample of all projects. Abandoned or failed projects are not included in the database, and while these returns have been realised for the specific projects listed, in general, returns may vary given different implementation, business processes or other factors.

Benefits in the form of revenue growth, time, capital and efficiency savings can range from between **US$250,000 to US$20 million**



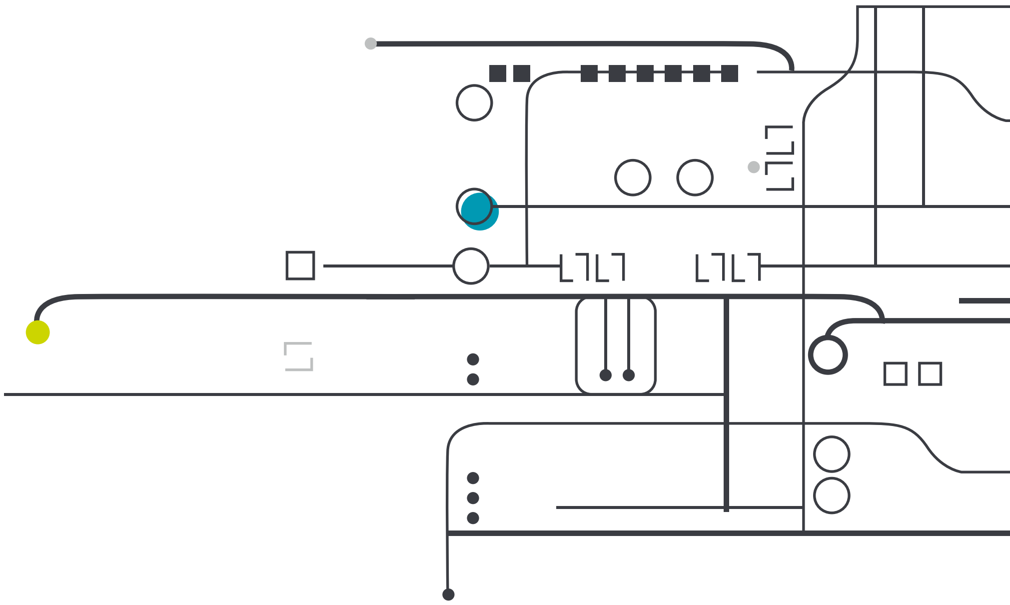
Global market revenue for machine learning as a service (MLaaS) was
US$1.07 billion in 2016

Return on investment
on most standard machine learning projects in the first year is **2-5 times** the cost

Costs to develop models and implement solutions can range from a few hundred thousand dollars to a few million dollars

The average project has a duration of about
12 months

MLaaS global market revenue is expected to grow to
US$20 billion by 2025



1

Machine learning in global business

Machine Learning (ML) is a method of data analysis that automates the building of analytical models.

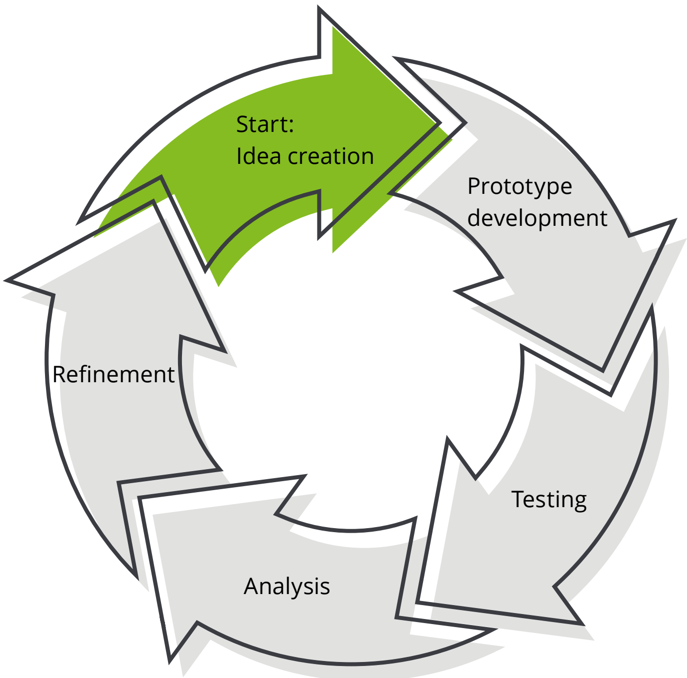
ML models are at the heart of artificial intelligence (AI) capabilities, including applications that enable intelligent engagement and process automation. The technology can be used to simulate aspects of human intelligence such as language, forming concepts and abstractions, and problem solving. Learning is one such feature of human intelligence, and in ML, algorithm-based models are 'trained' to become better at their assigned tasks through iterations of inputs and data.

ML has enabled new applications and use cases that were difficult, or impossible, under traditional programming paradigms.

Some practical examples of machine learning include language translation, image recognition, chat bots, and predictive analytics.

Businesses incorporate ML into their core processes for a variety of strategic reasons. ML can deliver benefits to performance outcomes and improve a business' position in the market. The benefits include the ability to discover patterns and correlations, personalise customer engagement, and ultimately increase a business' revenue and growth.

Figure 1.1: Machine learning project development process



1.1 Automation and augmentation

The way ML is directed – how human and machine behaviours are integrated – can have significant changes on businesses' capital and labour structures.

On one hand, ML can be deployed to **automate** tasks that can be codified, are criteria-driven and repetitive or rote in nature, such as search and information retrieval, or sorting products into various categories. Businesses save on costs by increasing task efficiencies and reducing labour effort and hours.

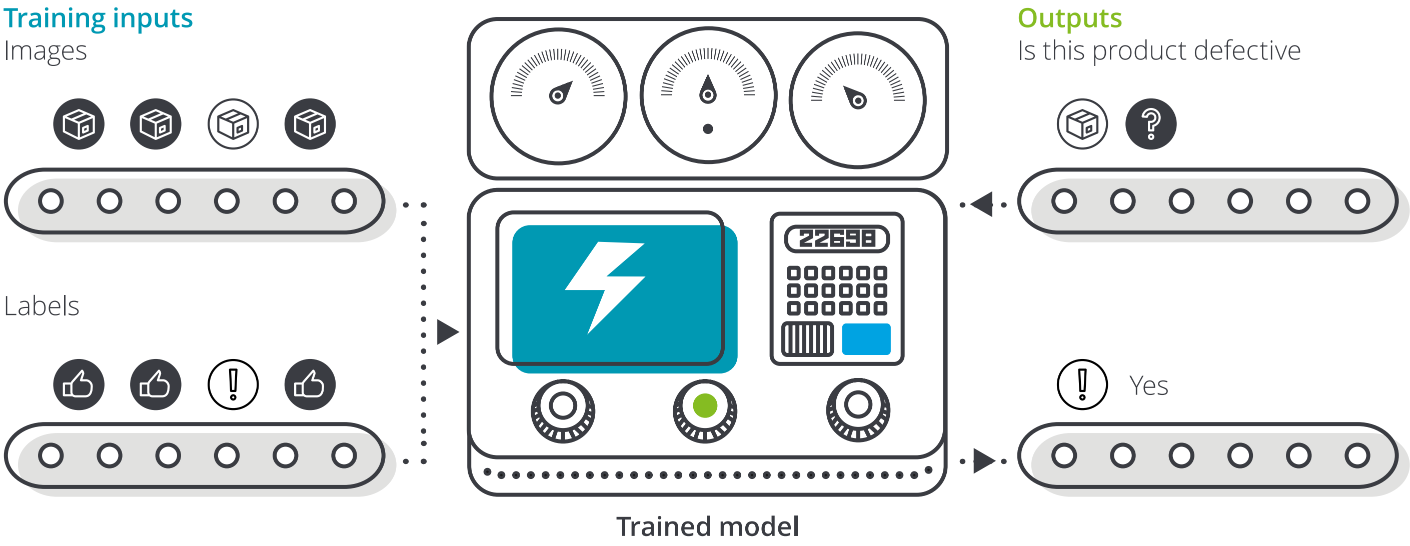
On the other hand, ML may be used to complement human decision-making or introduce entirely new capabilities, that is, **augment** human intelligence. ML as augmented intelligence is particularly common in cases where the outputs of ML models, such as predictions and other data insights, are used as an input into decision-making. Benefits to this include identifying new opportunities and making decisions using a richness of data in terms of volume and variety that would not be possible on a manual scale alone.

Figure 1.2 depicts a typical work-flow process. In this example, the model is being trained to detect manufacturing defects by feeding training inputs of images of products which have been labelled as normal or defective. The model begins to recognise patterns in the features of both normal and defective products, and learns which features should be weighted more or less heavily when determining the presence of defects. The more sample images the model is trained with, the more it will refine these weights to higher accuracy.

Finally, when presented with new products, the trained model will be able to detect whether each product is defective or not.

Businesses develop ML capabilities in unique ways. Often, they will have a dedicated team of data scientists and /or developers creating applications **using third party vendor software and tools**. Some vendors also offer cognitive application programming interface (API) platforms that enable human-like understanding of content such as images, speech and text.

Figure 1.2: Typical machine learning work-flow process



Similarly, **open source platforms** provide the fundamental constructs to build ML applications, but their use can require more in-house capabilities. The vast majority of ML applications are created and executed on platforms hosted on **cloud technology**. Software platforms used by businesses are also not mutually exclusive: a single use case can operate across multiple platforms, for example, one that is built on an open source platform hosted in the cloud.

1.2 Global investment

An MIT Technology Review survey of 375 leading businesses in over 30 countries found that 60% of respondents had already implemented an ML strategy and had committed to ongoing investment in ML.[4]

Global market revenue for ML as a service (MLaaS), or vendor platforms for ML, amounted to US$1.07 billion in 2016.[5] More broadly, ML models support cognitive applications to enable intelligent engagement and process automation.

The International Data Corporation (IDC) defines cognitive applications as a set of technologies that use deep natural language processing to answer questions and provide recommendations that automatically adapt and learn from its mistakes, and estimates worldwide spending on them to be US$4.5 billion in 2017.[6]

Further, expenditure on cognitive software platforms as defined by IDC is expected to be US$2.5 billion in 2017, which includes the tools to analyse, organise, access and provide advisory services based on a range of unstructured and structured information, as used in ML. Spending on cognitive-related IT and business services is estimated to be greater than US$3.5 billion in 2017, and dedicated storage purchase will total US$1.9 billion.[7]

Market growth

Demand for MLaaS vendor platforms is expected to grow strongly in coming years, with this segment of the industry forecast to generate global market revenue of US$20 billion by 2025.[8]

This growth represents a compound annual growth rate (CAGR) of 38.4% from 2017-2025 and is expected to be driven by ongoing development in ML techniques and growth in the major market players such as the healthcare and life sciences industry.

Regionally, North American expenditure on MLaaS accounts for US$362.7 million in 2016, and the region is expected to retain its global leadership in sector revenue to 2025.[9]

The growth rate of global investment in cognitive applications that use ML is also expected to be strong over the next 5 years, with a CAGR of investment of 69.6% for the period to 2020.[10]

Currently, IDC estimates over three-quarters of global spending on cognitive applications is from the United States, totalling over US$9.7 billion, followed by Europe, the Middle East and Africa (EMEA) and Asia-Pacific, though due to growth in the Japanese market, Asia-Pacific spending is anticipated to exceed that in EMEA by 2020.[11]

Our approach to this study

Deloitte Access Economics' research into the business impact of ML has been informed through the compilation of a database of machine learning applications across countries and industries and consultation with businesses.

The database includes 52 use cases, different regions (including Australia, United States, United Kingdom, Italy, Switzerland, Belgium, Russia, Japan and Indonesia), automation and augmentation applications, and using a range of market platforms.

A number of business interviews were also conducted as part of this study, including, but not limited to, Google customers. Consulted parties included:

- Red Marker – an Australian regtech pioneer
- Pluribus Labs – US data scientists using ML to deliver predictive investment information
- Kofera – an Indonesian marketing platform
- USAA – a direct insurance company serving US military members
- Airbus – French aircraft manufacturers
- MainAd – an Italian-grown advertising technology company
- Data61 – an Australian Government data and digital innovation group.

Some case studies from these consultations have been included in the report. The purpose of these case studies is to illustrate real world examples of ML being used in a variety of industry applications.

2

Estimate of business impact

There are many use cases and a range of potential benefits for businesses from investing in ML. The business impact of ML can be measured in terms of the investment costs and the return on this investment.

2.1 The investment takes time and money

ML, by nature, requires significant amounts of data as inputs to train models, which is a significant resource and investment. The identification of appropriate algorithms and the development of a working model takes time and may require many iterations to develop a workable result.

A business will also need to make choices between hiring data scientists and software developers and developing models in-house, outsourcing this model development or taking a hybrid approach. The time and dollar investments can be substantial, involving **around 12 months of work** to get projects off the ground.

Small projects can cost a **few hundred thousand dollars**, while larger enterprise-level projects can cost a **few million dollars** to scale and implement.

These costs of investment are explored further in Chapter 6.

2.2 Benefits for businesses

As a starting point, it is important to recognise that not all ML projects are successful. The sector's mantra "fail fast, fail often" reflects the iterative nature of ML project development, and the repeated stages of idea creation, prototype development, testing, analysis and refinement.

Once a successful project is developed, there can be significant benefits, which for the majority of the projects considered by Deloitte Access Economics, can range from **between US$250,000 to US$20 million** over multiple years net of investment. Separately, some large projects can deliver exponential returns beyond a few billion dollars, especially in the public and health sectors where there are potentially huge avoided social costs, or for very large businesses in the private sector.

[12] ML This ROI estimate is based on selection of projects listed in the Appendix of this report. By its nature, it is not a representative sample of all projects. Firstly, abandoned or failed projects are not included in the database. The project details come from a range of sources,based on details from proponents, and have not been independently verified for this report. Also, while these returns have been realised for the specific projects listed, general ROI may vary given different implementation, business processes or other factors.

Figure 2.1: Costs and benefits of ML projects

Revenue and growth
- Predicting business outcomes
- Personalising customer engagement
- Improving business strategy through better market intelligence and pattern recognition
- Gaining competitive advantage.

Time and efficiencies
- Process efficiencies
- Labour efficiencies
- Value chain efficiencies.

Capital savings
- Optimising production inputs
- Maintaining capital assets
- Quality control.

Investment costs
- Data
- Human resources
- Third party vendor.

Figure 2.1 summarises the many and varied benefits and investment costs associated with ML projects. Examples of these benefits are explored in the following chapters.

2.3 Return on investment (ROI)

Project ROI is affected by a number of factors, and can vary depending on:

- The industry in which the business operates, the regulatory environment and level of collaboration
- The application itself
- The type of use case being developed
- The scale of the project
- The talent profile of the implementation team and access to ML 'teachers'
- The relative success of the project's implementation within a business
- The country in which the project occurs, including the conduciveness of the environment for innovation.

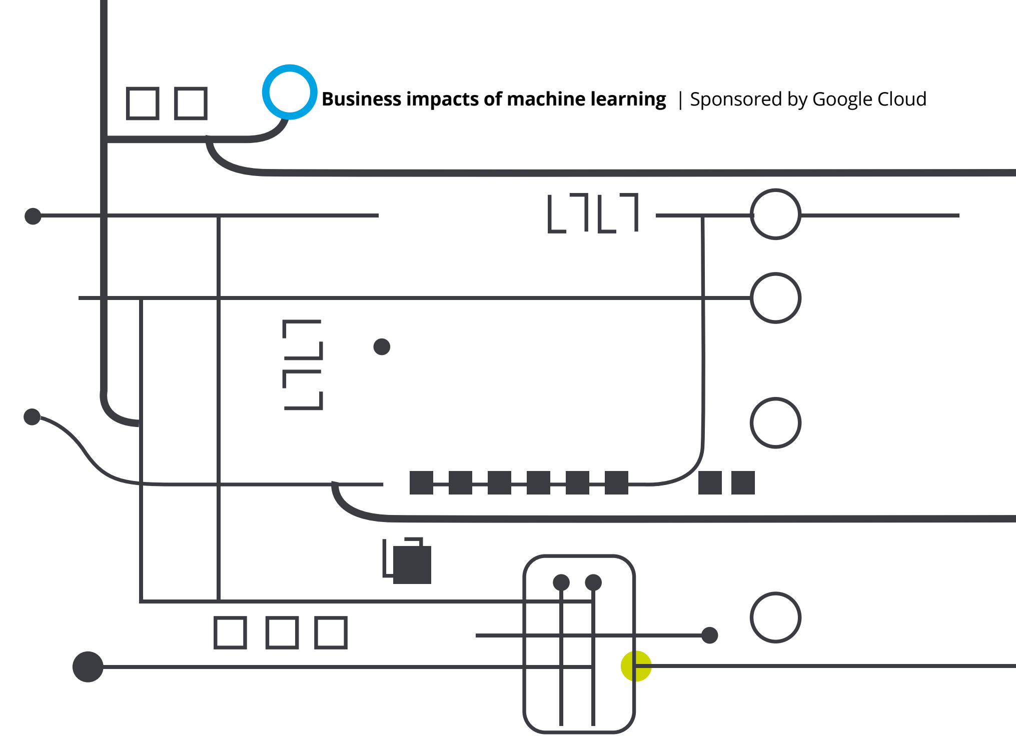
That said, Deloitte Access Economics' research and consultations estimate annual ROI as the dollar return of the project in the first year of implementation divided by the total project investment to date. This generalised estimate of ROI acknowledges that costs tend to be incurred up front, while returns are often ongoing and realised at different rates over several years.

Standard ML projects tend to have an ROI of between **two to five times the investment in the first year** of implementation. For many projects, recurrent benefits are expected to accrue after the first year, which can result in higher overall project ROI depending on whether further investments are needed.[12]

While there are many examples of projects which have returns up to five times the cost of investment, it is important to recognise that machine learning is an exponential technology. There are some projects have the potential to produce much greater returns in the long term.

Aside from model development, implementation, testing and validation are important project components. ML models will likely need fine-tuning after being assessed on how they perform in practice or in the case of predictive models, how predictions compare to expectations and intuition. Generally, results need to be validated using other information, for example, in the case of financial advice, outputs may need to be checked against regulations for compliance, to ensure that results are sound, understood and usable.

In the ongoing evolution of digital technologies, it is important for businesses to keep abreast of opportunities to take advantage of ML. Businesses should be well informed of opportunities to make deliberate and appropriate decisions about where to invest, whether ML will be of benefit in their operations and whether it is appropriate for them to be a leader in this space.



3

Revenue and growth benefits

Businesses are using more and more data to better identify patterns and make strategic decisions that drive revenue growth.

ML can help businesses increase revenue by extending data analytics efforts to gain insights at a greater volume, quality and speed.

In fact, 45% of ML adopters say the technology has led to more extensive data analysis and insights.[13] These data insights drive various avenues of revenue growth, from predicting business outcomes and improving business strategy to better customer engagement. Used strategically, these insights allow businesses to gain a competitive edge over their market peers.

3.1 Predicting business outcomes

In a fast-changing market environment, businesses face mounting pressures to be innovative and agile by staying ahead of market trends and predicting how customers are likely to react.

Many businesses already use data analytics to **forecast demand** for their products and services. Demand forecasting allows businesses to manage their inventory stock, evaluate economic returns on promotions and reduce costs. ML models are more powerful than traditional statistical forecasting because they can incorporate feedback into the loop which constantly tunes the model, making it more accurate over time.

Kofera – digital marketing in Asia

Kofera uses machine learning to help e-commerce and online retailers build, optimise and monitor their advertising and marketing campaigns. Based in Indonesia, Kofera's clients range from small and medium businesses (SMBs) to large businesses with over a million products.

Bachtiar Rifai, Founder and Chief Executive Officer says that "60% of clients choose Kofera and other vendors because they have identified a problem and are drawn to our results", noting that clients often do not have a technical understanding of machine learning and how it works.

Kofera's applications of machine learning vary with business size. For small retailers, Kofera assists with overcoming the complexity of direct advertising on the internet by creating a digital platform with an interface that is easy to use.

On the other end of the scale are businesses with a large inventory to be categorised, labelled and described. Using product information provided by the seller, Kofera's campaign builder uses Natural Language Processing (NLP), a machine learning text analytics technique, to categorise and create advertising copy for each product. This can be uploaded onto a search engine and is linked in real-time to actual inventory stock.

Mr Rifai believes that "machine learning is the future of marketing optimisation". One example involves creating predictive models that perform dynamic budget allocation. The model is trained on historical data and provides suggestions of how businesses should allocate their marketing budget between different campaigns. As these budget allocations are updated, the model is retrained on incoming data and can continue to optimise its recommendations.

This translates into real cost savings for businesses. Kofera's clients can save over 15% on marketing costs by using campaign monitoring systems which optimise campaigns every 15 minutes instead of weekly or monthly. These benefits are quickly realisable too – benefits from cleaning data and using NLP are virtually instantaneous, and benefits from marketing optimisation are realised in as little as one to two months.

3.2 Personalising customer engagement

Businesses can use data insights derived using ML to improve **customer engagement** by better identifying, understanding and responding to customers. For example, speech and text analytics ML techniques can be applied to document live customer interactions to follow up on potential sales leads.

ML-driven data analytics can improve efforts at **customer segmentation** to predict the most profitable, or most risky customers. In the insurance industry, predictive models that identify high risk customers help insurance businesses minimise losses and develop appropriate premiums. An ML approach adds value by feeding real world decisions back into the pricing model, which improves with training.

For online businesses with large product ranges, machine-learned ranking (MLR) can improve **product search** using personalisation based on a user's search and previous purchasing history, which means customers can find and purchase the right products faster.[14]

ML-developed **product recommendation** systems learn behavioural shopping patterns, such as purchasing similarities between customers or relatedness of search items, to predict customers' preferences towards new items.

These prediction-based recommendations lead to higher sales revenue by exposing customers to additional products of interest and encouraging upgrades to more expensive products.[15]

3.3 Improving business strategy

The powerful combination of business expertise and ML drives better strategic revenue growth decisions.

ML models are commonly used to develop **optimal pricing strategies** to maximise profits. Dynamic price optimisation is a revenue management tool widely used in retail, automotive, mobile communication and electricity industries, and is generated using data on variability in customer preferences and buying patterns.

ML models are increasingly necessary to handle the volume of e-commerce data in real-time.[16] By using ML to make use of all available data and generate customised price offers for the right customer at the right time, businesses can increase the probability of sales and generate higher revenue.

3.4 Gaining competitive advantage

ML helps businesses gain a c**ompetitive advantage**, especially for those already with data analytics capabilities.

In studies conducted up to five years ago, researchers found that companies that use data analytics in their decision-making were 5% more productive and 6% more profitable than competitors.[17] Other studies showed that firms with these capabilities were also five times as likely to make decisions faster than competitors and three times as likely to have faster execution on those decisions.[18]

However, the percentage of organisations reporting competitive advantage from analytics is on the decline.[19] This is because more companies now compete with analytics, which makes it more difficult to maintain an edge over competitors.

Advancing analytics capabilities to ML is the next step for businesses looking to maintain that edge. A joint survey conducted by the MIT Technology Review (2017) finds that 26% of organisations currently using ML have gained a competitive advantage over market peers.

Pluribus Labs – unlocking investment insights from public data

Pluribus Labs uses machine learning techniques to deliver predictive investment information. Their models run on publicly available data, ranging from corporate filings to online discussions and news.

The team of eight data scientists train models to identify relevant patterns and capture the economic fundamentals in the data. This helps them uncover insights and signals suitable for trading. The models are constantly running, utilising the latest information.

Wachi Bandara, Chief Research Officer, and Sebastien Astie, Chief Technology Officer, note that 'there is no way to distil or make sense of this data without machine learning'.

The better the training, the more effective the model. This power means that a few data scientists can do the work of numerous research analysts. This leads to efficiency benefits for Pluribus Labs' clients and increases the available information supporting trading decisions.

4

Time and efficiency benefits

Businesses can achieve significant time and efficiency benefits by using ML applications to cut down on costs and shift human resources to higher value activities. ML techniques aid in the development of applications that **automate** tasks and **augment** existing processes, leading to productivity improvements and cost savings.

4.1 Labour efficiencies

Many routine internal processes can be done quicker and more systematically by machines than people. The MIT Technology Review (2017) survey of businesses found that 30% of adopters of ML had gained internal process efficiencies.[20]

For client-facing businesses, ML models can be used to streamline **customer interactions**. Businesses can deploy text and voice analytics techniques such as natural language processing to understand and triage customer interactions and track responses. Directing customers to the information they need faster can improve customer satisfaction and decrease churn by reducing call volume and duration of calls. Where concerns about customer confidentiality mean that user identities need to be authenticated, businesses can benefit from the use of speech recognition techniques.

This means that substantial human resources can be saved in documenting and interpreting customer-related data. This both reduces human effort (lowering costs) and provides a better solution (improving value).

ML models also allow businesses to reduce **search costs** in data-heavy information retrieval tasks such as regulatory compliance and legal research. Models can perform exhaustive searches in a fraction of the time it takes for people to manually scan and cross-reference documents.

Delegating part of the work-flow to ML models also means that high-skilled workers can concentrate on performing high productivity tasks. Models can **provide preliminary structure** to raw data, saving people from performing routine tasks that are highly time consuming. For example, in the medical and health sciences, classification models can perform initial first-stage sorting of medical scans, which allows diagnosticians to focus on other tasks and intervene at a later stage to confirm or sort ambiguous samples. This can help radiologists and doctors work faster and more accurately.

Businesses that introduce these changes into their organisations stand to make more efficient use of their workforce, and may see second-order growth benefits as resources are shifted into other functions such as strategic planning and business development.

4.2 Value chain efficiencies

Many efficiencies achievable through ML relate to how a business can function optimally in its external operating environment. According to the MIT Technology Review (2017), 19% of ML adopters report having achieved these efficiencies.

As discussed in Section 3.3, ML models can **optimise decision making** by analysing the state of the value chain. These predictive models continuously incorporate new information on supply chain facilities, transport capacities, customer service requirements and profit requirements, providing a basis for decision-making that is highly evidenced by data analytics.

[20] Of the businesses sampled by MIT, one third are still in the early stage of their strategy, and while more than half of this group are beginning to see demonstrable ROI, less than 18% measure ROI on any analytics initiatives. Hence, this efficiency achievement rate may be an under-representation due to low rates of evaluation.

MainAd – making a bid for space

MainAd is a global digital company that helps businesses determine the best places to advertise online, a process called re-targeting. MainAd uses machine learning to predict the potential business value of advertising spaces by analysing data on their traffic and web user browsing behaviour. As many as 150 billion impressions, or advertising instances, are evaluated every day.

Using these predictions, MainAd bids for advertising space in high-speed, high-volume auctions where spaces are traded every 100 milliseconds. Processing big data into machine learning models has allowed the company to optimise its bidding strategies at a much more detailed level than before, building the logic around each single opportunity rather than taking bulk decisions per group of users.

According to Co-Founder and Chief Operating Officer Piero Pavone, this has improved the quality of web traffic that is being targeted to their business clients, resulting in better sales outcomes.

Mr Pavone describes the organisational change that machine learning has brought about. “The work of our data scientists has changed from daily analysis to working with and refining the model. What this has meant for the firm is that rather than spending time on daily activities, our staff have been able to work on macro strategies to monetise our clients and grow the company.”

Airbus – achieving efficiency in operations

Airbus Defence and Space utilises machine learning in a number of applications. One of these is the detection and correction of satellite images with imperfections such as the presence of clouds. For example, it can be challenging to detect the difference between clouds and snow on images by eye. Machine learning techniques allow a previously time-consuming task that was prone to human error to be made more efficient and accurate. This allows for analysis of higher quality satellite images and provides information on cloud location so satellite systems can be reprogrammed as needed.

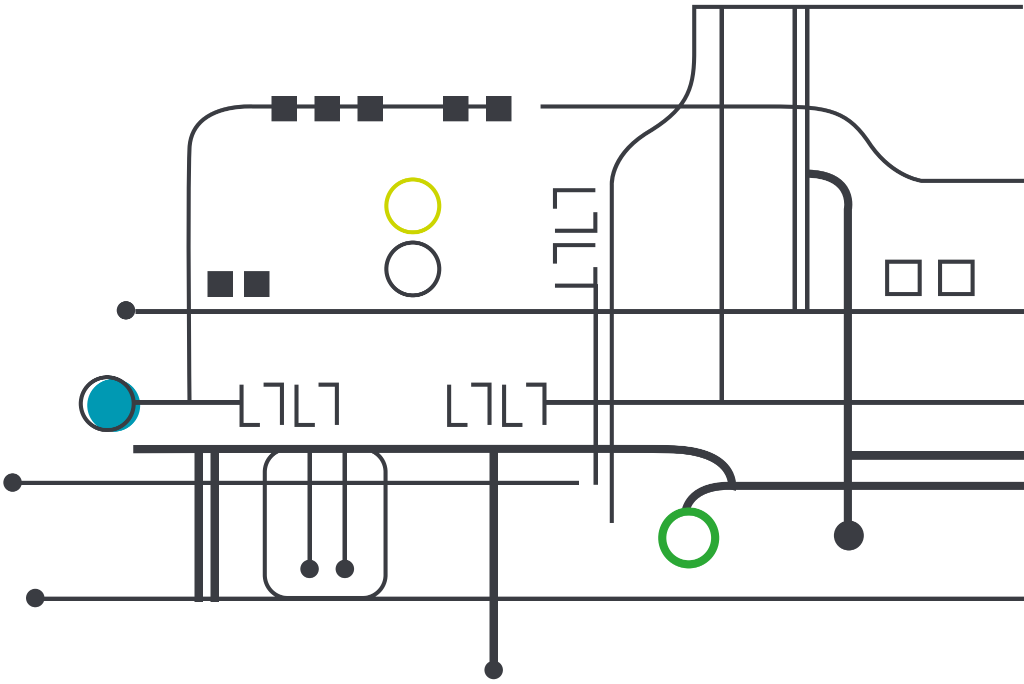
Airbus also uses machine learning to extract information from satellite images for big data-style analysis, for use in other applications, including for agricultural, engineering or environmental purposes. Prior to using machine learning techniques, data scientists had to develop rule-based algorithms to extract information in a geometric way; for example specifying that buildings are likely to be rectangular. By picking up on patterns on their own, machine learning algorithms are an improvement on this, and more accurate.

Laurent Gabet, Optical R&D Manager, and Mathias Ortner, Data Analysis and Image Processing Lead, categorise the benefits of machine learning in 3 main areas:

- Achieving things were not previously thought possible
- Developing algorithms where the required technology was not previously available
- Improving existing processes.

"While the first can be considered the most exciting and innovative – for example, cloud versus snow detection in images, the third can be the most important in terms of business operations", notes Mr Gabet.

Airbus expects future applications to continue to achieve improvements. They have already seen a significant reduction in the time to build algorithms, from several years down to a few weeks, and this reduces time to trial so that new applications can be developed.



5

Capital savings

There are many ways ML help businesses make better use of their physical assets and budgets. Optimising different stages of the production process, from inventory management to quality control can deliver substantial savings to businesses.

5.1 Optimising production inputs

ML models can optimise businesses' use of inputs and capital assets. In manufacturing and operating processes, relying on default settings or historical experience alone may mean that physical capital is not being deployed most efficiently. Trial-and-error processes can also result in a high amount of material being wasted.

Manufacturing businesses are often faced with trade-offs between **minimising production costs** and ensuring that products comply with quality standards and regulatory requirements.

ML models are well-suited to augment industry expertise to solve these optimisation problems.

For example, use of ML models can also help businesses minimise their facility costs. By predicting demand for production, ML models can help businesses better align resource usage to their actual needs. ML can also be used to discover production parameters and tune the end-to-end process; for example, dynamically adjusting the temperature of a furnace or mixture of input materials.

Kewpie – ensuring high quality ingredients and products

Kewpie, a major food manufacturer in Japan, uses machine learning to implement strict quality control of the diced potatoes used in manufacturing baby food. In alignment with the company's principle of creating high quality end products, rigorous checks are required to ensure that the raw ingredients are safe and of high quality.

Without machine learning, each quality control inspector would assess more than one million diced potatoes by eye every day. Takeshi Ogino, Deputy General Manager of Production Division believes that "machine learning has been valuable for Kewpie to achieve this in a much more efficient manner."

After spending four months to develop the proof-of-concept and prototype, and a further five months of testing, adjusting and implementing, machine learning has delivered tangible benefits on the factory floor.

Machine learning has helped double production speed and increase staff productivity by running preliminary checks using image recognition techniques so that staff can perform secondary, refined checks for defective potato cubes. This approach has helped improve the quality of potatoes allowed through to the processing stage by reducing instances of human error.

Using the same concept, Mr Ogino says that Kewpie is looking to expand the use of machine learning to its other products as well as throughout the end-to-end manufacturing process.

5.2 Maintaining capital assets

Knowing when capital assets need to undergo maintenance work or be upgraded can be costly and inaccurate. Predictive ML models can **monitor asset conditions** by collecting data on the operational performance of equipment and components, often from sensors and high in volume from sensors. From there, ML models can be trained to analyse performance and compute important metrics such as the remaining lifetime of components. Using these predictions of component performance, engineers can better prioritise assets to inspect for maintenance.

5.3 Quality control

Quality assurance to **identify errors and potential failures** in machine processes before they occur is an important part of the production process. Manufacturers need reliable methods to find defects in order to boost product yield, limit warranty costs and the amount of rework needed, and maintain product quality.

While quality control is usually performed by human inspectors, their reliability and efficiency can be limited by differences in individual skills, and the sheer volume and complexity of object attributes. For example, it can be difficult for people to distinguish correctly between defects and random or irrelevant attributes every time. On the other hand, automated ML quality inspection systematically extracts the relevant relationships to help uncover root causes of problems. This can be a more cost-effective way for manufacturers to **meet quality and reliability standards.**[21]

While ML can improve on many judgments that are complicated by human error or bias, it is important to note that ML models are only as accurate as the data they are trained with. If historical quality control data is labelled incorrectly, then machines will be trained to make inaccurate or false predictions. The quality of data is hence an important prerequisite to successful implementation of ML projects.

Red Marker – scaling regulatory compliance

Red Marker has pioneered the development of an automated compliance solution for the financial services industry, based on machine learning algorithms. Regulation and compliance are important considerations in the banking and finance sector, where all external communication, to stakeholders or in marketing, needs to adhere to rigorous compliance requirements. There is a need for thorough review of all material to be made public.

The complex and ambiguous nature of language means that traditionally, written content has to be manually reviewed by a person for compliance risks. It's a burdensome task for banks, because as Red Marker Founder and CEO Matt Symons says, "Compliance doesn't scale, and there are huge search costs associated with these needle-in-haystack problems". This is where Red Marker comes in. The company uses natural language processing, a machine learning text analytics technique, to create models that can detect potential risks. The models are built on compliance rules from regulatory guidelines and source legislation, and trained on samples of content that have been marked up on whether they have met compliance rules.

Red Marker has utilised an innovative approach to improving the model. After initial development and training, the 'last mile' has been achieved by industry itself, with risk and compliance officers from banks and other institutions providing feedback on the model's performance, and their own data to help further educate and refine the model. This feedback is used to validate and train the model, allowing it to learn with a high degree of human supervision. The learning goes both ways – outputs from the model also help clients identify the root causes of compliance incidents, check for consistency in their own decision-making, and better train their staff. Mr Symons refers to this as a 'co-creation' approach to model building, where the model is grown with heavy input from industry once it has reached a stage of minimum viability.

Red Marker's compliance solution brings a range of benefits to clients – from time and cost savings through to improved decision making, and strategic benefits which Mr Symons believes could change the face of the banking and finance industry. "By reducing the risk in client-facing communications, banks and financial operators can channel a more authentic voice, engage and reclaim the dialogue with their customers."

6

Costs of investment

ML requires significant investment in terms of time and money. These costs are highly dependent on how a business decides to procure and implement ML applications.

This section discusses common cost inputs (see Figure 6.1) including data, human resources, and vendor costs.

Deloitte Access Economics' research found that the development of successful ML applications for small projects generally costs in the order of **a few hundred thousand dollars**, while larger enterprise-level projects can cost a **few million dollars** to scale and implement.

These costs include the costs of data scientists, obtaining and storing data, and implementation costs. Among the projects that Deloitte Access Economics looked at, implementation of ML models comprised up to 40% of the total project costs.

Figure 6.1: ML project cost inputs

6.1 Development and implementation costs

To develop and train ML models, businesses need significant volumes of **data**. This data is a significant resource and investment to procure; whether it be unstructured data collected from varying sources or structured data which has been organised in a database. Acquiring this data can incur significant upfront costs, as does the need to clean and process the data. The data forms the base teaching set for a model, which in turn, is designed to learn and evolve. Storage of input data, model files, and prediction output also requires ongoing costs.

How businesses utilise **human resources** is another crucial factor in determining the costs of model development and technical and business implementation. While the majority of businesses use third party vendor platforms, an important consideration is the extent to which businesses also choose to outsource the human labour involved in model development, analysis and project implementation.

6.2 Vendor costs

As above, many businesses will at some stage of the ML project engage third party vendor platforms.

Most cloud vendors share a common cost structure in the form of a subscription-based, tiered pricing model, which allows businesses to access and scale services as business needs evolve. Cloud platforms have no or low fixed costs and charge flexible variable costs based on usage.

For cloud-based services, costs will vary according to:

Data volume. A larger data set will have larger storage and memory capacity requirements, but costs vary depending on the duration of data retention. In general, the cost of storage space is tiered.

Usage time and intensity. Most pricing models offer different tiers which have different maximum hours of usage, or different computational complexity at varying hourly cost.

Prediction volume. Many vendors offer prediction services and charge by number of predictions or in batches of predictions.

For businesses renting on-premise ML vendor solutions, costs will generally be charged at a yearly rate and are determined by:

Set up fees. Installation of ML software on business servers requires upfront costs.

Data volume. Businesses need to have an idea of data volume and hence the number of servers that the software will be installed on.

Maintenance. The infrastructure will likely require periodical maintenance by in-house IT staff.

For businesses that are not in a position to invest in data science capabilities, the best option may be to engage third party labour to develop a start-to-end customised solution. This type of external engagement will have highly variable costs depending on the duration of the project and human resources required.

6.3 Time duration

Another cost variable relates to project **time duration**. As discussed in Chapter 2, ML applications identified from Deloitte Access Economics' research and consultations suggested that it takes on average **around 12 months** to develop a successful project, including data collection, model development and training, and implementation.

This range is supported by research reporting that ML projects generally take between 3 and 26 months.[22] On average, pre-work takes 4 months and implementation takes 11 months. However, it should be recognised that projects can take as little as a few months, and up to several years, depending on the complexity of the problem or task at hand.

The level of data readiness can substantially affect the time-frame of the project. The range of applications identified by Deloitte Access Economics cited minimum development times of 2 months (where data scientists are experienced and have access to the necessary data) through to several years (where an entirely new concept needs to be built, modelled and data needs to be sourced for the first time). Generally, the further along the ML journey a business is, the more difficult it becomes to make large improvements in any model's decision making but equally, the fewer 'judgement calls' and human input is required.

There are a number of investment challenges for businesses embarking on the ML journey, particularly for businesses integrating ML into their existing processes.

According to M-Brain's (2017) interviews with companies in the healthcare, financial services, manufacturing, retail and media/gaming industries:

- **Data** collection and processing is the most common challenge among businesses (identified as the most difficult step by 25% of businesses). Selecting the right tools for data cleaning, collection and storage often requires having prior technical knowledge of different methods and tool-sets
- **Vendor selection** in a competitive market landscape as the biggest challenge for 20% of businesses, as some vendors can lack industry expertise in particular fields
- **Compliance and regulation** in ML are the biggest concern for 10% of businesses, particularly in the healthcare and financial services industries. As many vendor solutions are hosted on the cloud, ensuring cloud security is pertinent
- **Technical skills** are necessary to build models and debug any problems that come with them, and there are also challenges in **selecting the right tool-sets** (both identified by 10% of respondents as the most difficult challenge)
- Obtaining **internal buy-in** from stakeholders and senior management is the biggest hurdle for 5% of respondents, as is **creating a global framework**. There is a bias towards the status quo, and people can be reluctant to trust models which arrive at conclusions through 'black box' techniques, especially if they deliver counter-intuitive results.

The first point, in particular, is one that resonates with businesses consulted as part of this research. One of the largest challenges is capturing and organising tacit knowledge around a problem and having the skills to help the model learn. Consultations suggested that industry collaboration on ML can provide greater volumes of data and the motivation to develop a working model with benefits for all businesses.

7

Where to invest

7.1 The business opportunity

ML's technical capabilities can present both novel, and highly profitable business applications. To better understand these opportunities, we have segmented the broader ML opportunity by input, and use case specificity in Figure 7.1 below.

Generalised machine learning is generally unviable for non-tech businesses, due to the large investments required and uncertain investment horizons.

In contrast, there are real opportunities for verticalised use cases.

Drawing on Deloitte case studies and interviews with businesses, we have identified five areas where machine learning has proven capable of delivering strong business and financial outcomes in Figure 7.2.

Figure 7.1: The ML opportunity

Inputs

Text

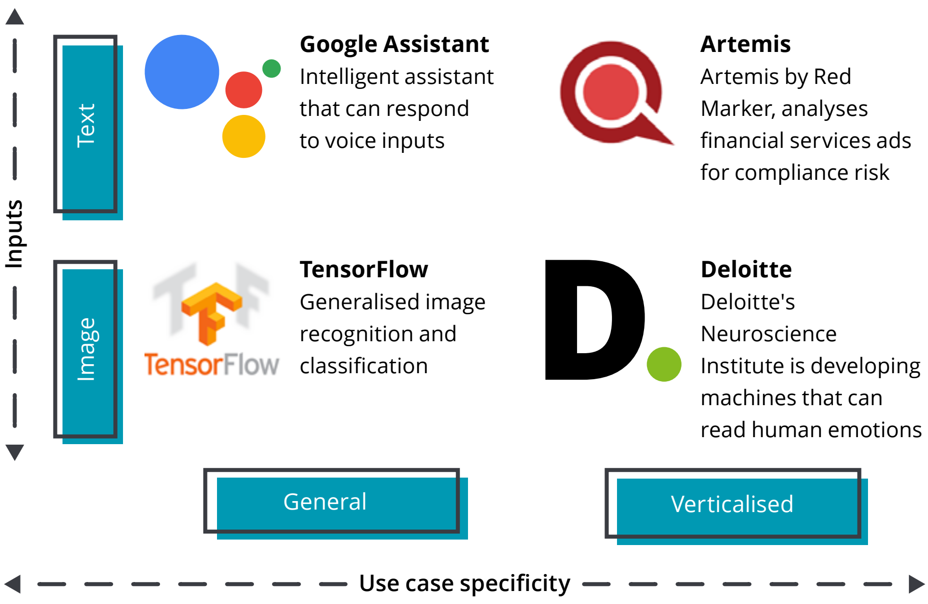
- Text inputs encompass audio (e.g. audio recordings, voice inputs etc.)
- Naturals language processing is a feature that has been developed to 'read' text more intelligently (e.g. read for intent and context).

Image

- Image inputs encompass video
- Image recognition is the most recognisable feature in image related machine learning.

Other inputs

- There are other inputs such as music etc., however, these other inputs are not the focus of this report due to limited existing use cases in the business context.



USAA – using machine learning to improve customer service

USAA is a direct insurance company which has served current and past members of the US military for over 95 years. Its services include insurance, banking and investment support for its members.

USAA seeks to bring an innovative approach to service delivery for its members. It has been using machine learning applications since 2008, starting with a simple algorithm to personalise content and advertising for members after they log in to the website.

Since then, USAA has developed other machine learning projects. A rules-based system for fraud protection was upgraded to a model-based system and now an artificial intelligence-based system based on machine learning, allowing USAA to check the identity of users.

Machine learning models have also been used to improve its call centre operations. These models allow USAA to optimise routing to help callers speak to the right person, and to redirect calls during incidents or weather events where some call centres may be unavailable or experiencing a high volume of calls. The benefits of increased efficiency and time savings are experienced by both USAA and its members.

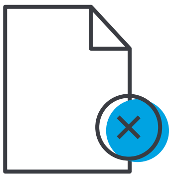
Robert Welborn, AVP Innovation, Data Scientist, notes that USAA's use of machine learning seeks to "maximise service and the member experience". "By understanding member needs and solving their problems before they arise", USAA is well positioned to achieve a position as "provider of choice for financial services" for their members.

Figure 7.2: Areas where ML has delivered strong outcomes

Security – detection and prevention
- Cybersecurity
- Mobile security
- IoT security.

Optimisation
- Yield optimisation
- Call Centre optimisation
- Personalisation.

Fraud – detection and prevention
- Transaction fraud
- Heath fraud
- Identity fraud.



Compliance – detection and regulation
- Regulation updates and reviews
- Contractual review
- Bad actor detection.

Research
- Precision medicine
- Self-driving cars.

This is not a comprehensive list of use cases that fall under the 5 broader categories

7.2 Evaluation framework

The potential business outcomes delivered through machine learning can be an attractive prospect for businesses. However, there are considerations that organisations need to recognise and evaluate in order to maximise the returns from investment.

We have created a framework to help executives evaluate their business readiness for machine learning, and prioritise where to invest in the short term to enable longer term machine learning benefits.

Technology and capability development

As with any technology, the successful development and deployment of ML applications within an organisation requires various capabilities and skills.

In developing technology and capability, there are considerations in terms of data science, technology architecting and process digitisation, as noted below.

- Data science
  - Translating a business problem into a testable hypothesis
  - Defining how to measure successful outcomes from machine learning tests
  - Establishing baselines to enable assessment of incremental benefits delivered by machine learning use cases
  - Quantifying success, and translating insights into format that is understood by less technical colleagues
  - Commercially minded (cost vs. benefit etc.)
- Technology architecting and implementation
  - Integration of machine learning engines into existing databases and data collection channels
  - Scaling computing, potentially through 3rd party vendor cloud solutions
- Process digitisation
  - Ensure existing processes and data collection channels are digitised and creating data inputs that are relevant for developing machine learning algorithms, and scaling learning.

In developing technology and capability, there are considerations in terms of data science, technology architecting and process digitisation, as noted below.

- Right problem to solve
  - Is this problem a sufficiently large problem, or is the opportunity for optimisation sufficient? Is the cost of failure high? Or perhaps the prize for success is high?
  - Is the effort and time currently required to deliver a solution, without machine learning capabilities, high?
  - Is the problem/opportunity being solved sufficiently homogenous in nature? E.g. clear processes around a problem, and outcomes of a problem are clearly understood, quantifiable, and measurable?
- Availability of data
  - What data is required to develop the machine learning models?
  - Do we have sufficient test data, in terms of volume and frequency, to optimise the learning models?

- Are there industry partnerships/ collaboration agreements that can be created to facilitate greater availability of data?
- Are there regulatory limitations around data use?

- Third party vendors
  - What capability or technology gaps currently existing in the organisation?
  - Which 3rd party vendors/solutions are optimal partners?
  - Will company data require additional security in line with industry or regulatory compliance?

Organisation and executive transformation

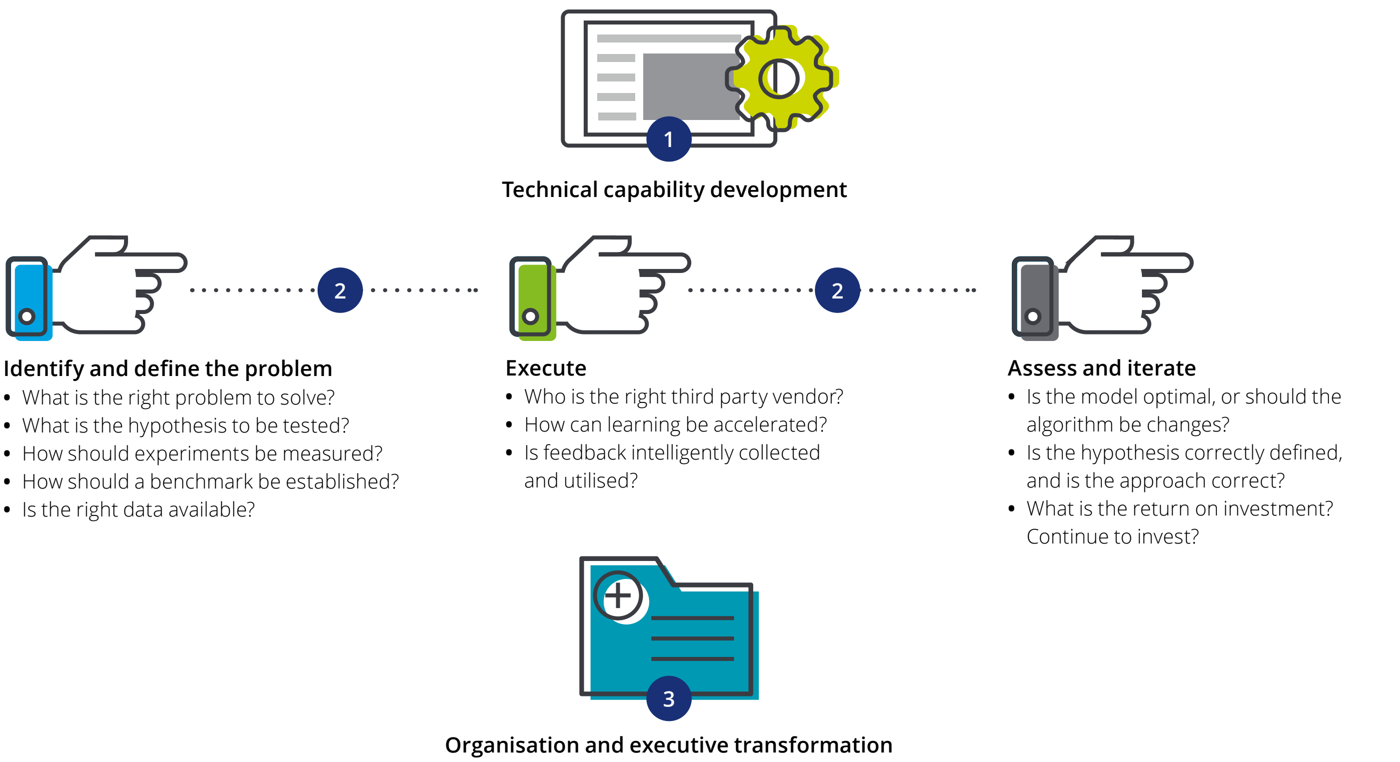
Implementation and change management is an important final step in an ML project. Machine learning transformations are not short term endeavours, and subsequently require organisation-wide transformation.

Effective implementation is crucial to realising the full benefits of ML applications; if the organisation and executive are not behind this change, the benefits may be wasted.

Some of the key considerations at this stage of the process are listed below

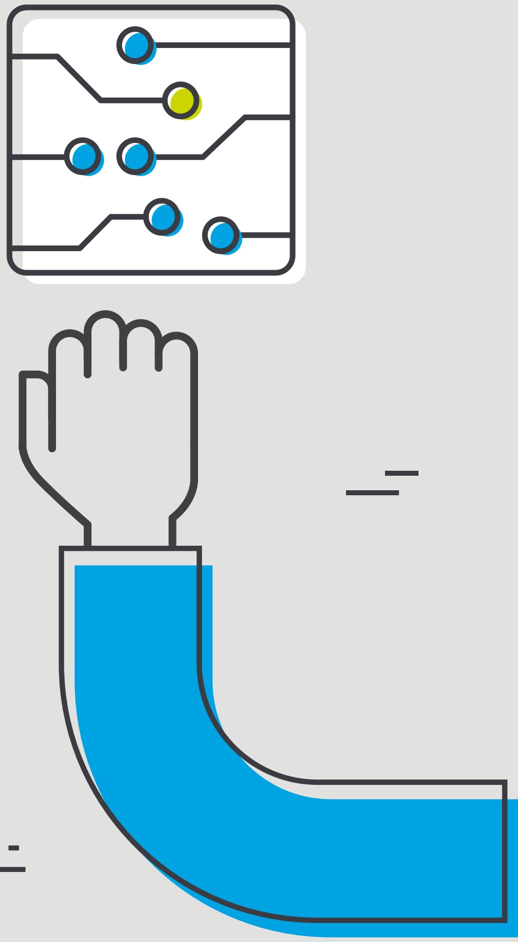
- Machine learning mindset
  - Machine learning insights have a nuanced difference to existing analytics processes
  - Machine learning is a constant learning and development process to improve the predictive capabilities of an engine; contrasted to traditional analytics that is presenting trends and insights from historical data
  - Therefore, organisationally the mindset should be in constantly validating and improving the machine learning outcomes vs. purely consulting insights from analysis
- Investment horizon
  - Investment into machine learning capabilities can be costly, and involve a long payback horizon
  - Interviews and case studies suggest that typically there is at least an 18 month time period from when the problem is first defined, modelled, and tested, till finally delivering reasonable output and insight
  - The specificity of use cases means that machine learning algorithms and models need to be created for each potential use case and application.

Figure 7.3: Evaluation framework – business readiness for ML



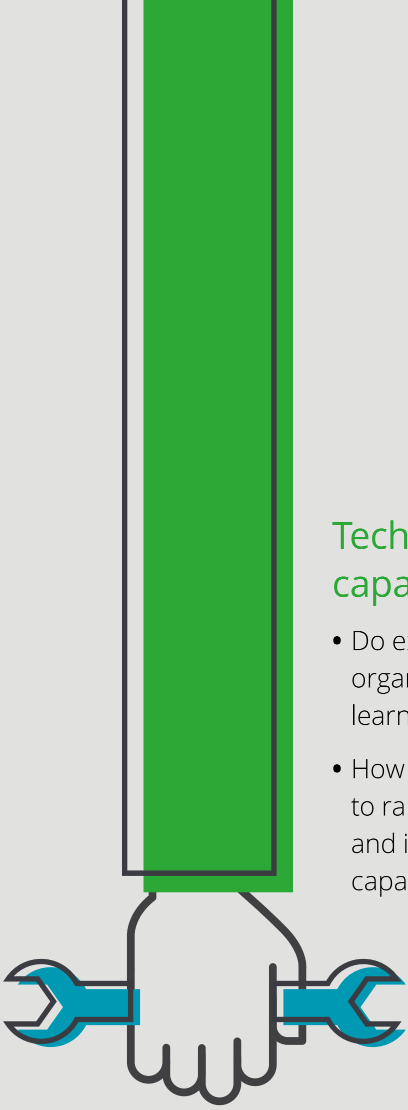
Delivery of a machine learning engine

- Is the right problem being solved?
- Is the right data available?
- Are there partnership or collaboration opportunities to accelerate learning?
- Are third party vendors required, if so which parties are the right ones?



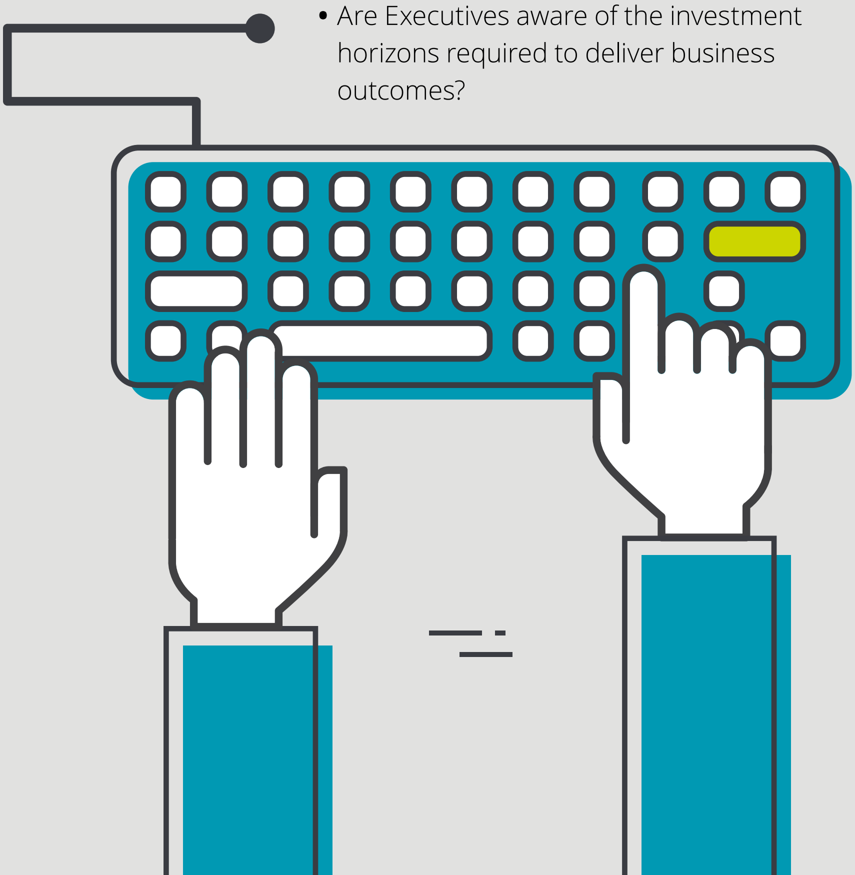
Technology and capability development

- Do existing capabilities allow the organisation to implement machine learning technologies?
- How should investment be prioritised to ramp up data science, architecting and implementing, and digitising capabilities?



Organisation and Executive transformation

- Is our organisation familiar with data, and machine learning; how do we train teams to work to improve machine learning models?
- Are Executives aware of the investment horizons required to deliver business outcomes?



Appendix – ML use case database

This appendix presents extracted information from the database of ML use cases that were used in this analysis. Unless otherwise specified, the values in this database are presented in US dollars.

#	Organisation	Country	Application type	Type of benefit	Estimated benefits	Time horizon of benefits	Estimated costs
1	Australian Tax Office	Australia	Automation	Time and efficiency	$3.5m*	Annual	Not publicly available
2	Toyota	Japan	Automation	Time and efficiency	$250,000*	Multi-year	Not publicly available
3	Intel Manufacturing	US	Automation	Time and efficiency	$303m	Annual	Not publicly available
4	MainAd	Italy	Automation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
5	European Organisation for Nuclear Research	Switzerland	Automation	Time and efficiency	$6.9m	Annual	Not publicly available
6	Cucumber farm	Japan	Automation	Time and efficiency	Confidential or not publicly available	Ongoing	Not publicly available
7	Fukoku Mutual Life Insurance	Japan	Automation	Time and efficiency	$1.2m*	Annual	Not publicly available
8	Wolters Kluwer Transport Services	Belgium	Automation	Time and efficiency	90% reduction in query processing times	Ongoing	Not publicly available
9	Atom Bank	UK	Automation	Time and efficiency	Confidential or not publicly available	Ongoing	Not publicly available
10	Greyhound	US	Automation	Capital savings	$884,000	Annual	Not publicly available
11	Urban Outfitters	US	Automation	Time and efficiency	Reduced labour costs by 82%	Ongoing	Not publicly available
12	FraudNet	US	Augmentation	Capital savings	Confidential or not publicly available	Ongoing	Not publicly available
13	Confidential	US	Augmentation	Revenue and growth	$5.6m in savings	Annual	$3m
14	Mendeley	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
15	City of New York	US	Augmentation	Time and efficiency	$1.4m*	Annual	Not publicly available

#	Organisation	Country	Application type	Type of benefit	Estimated benefits	Time horizon of benefits	Estimated costs
16	New Mexico Department of Workforce Solutions	US	Augmentation	Capital savings	$1.9m	Annual	Not publicly available
17	BuildFax	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
18	Intel IT	US	Augmentation	Revenue and growth	$20m	Multi-year	Not publicly available
19	InteractiveTel	US	Augmentation	Revenue and growth	25-30% higher job accuracy rate	Ongoing	Not publicly available
20	VoiceBase	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
21	University of Iowa Hospitals and Clinics	US	Augmentation	Capital savings	$7.4bn*	Multi-year	Not publicly available
22	Manitogorsk Iron and Steel Works	Russia	Augmentation	Capital savings	$4m	Annual	Not publicly available
23	AdiMap	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
24	Netflix	US	Augmentation	Revenue and growth	$1bn	Multi-year	Not publicly available
25	Kaiser Permanente	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
26	Mercy Health (St. Louis)	US	Augmentation	Capital savings	$50m	Multi-year	Not publicly available
27	Pivotal	US	Augmentation	Capital savings	40% reduction in infrastructure costs	Ongoing	Not publicly available
28	Callcredit	UK	Augmentation	Revenue and growth	4 fold increase in profitability	Ongoing	Not publicly available
29	Kristalytics	US	Augmentation	Time and efficiency	Confidential or not publicly available	Ongoing	Not publicly available
30	Confidential	US	Augmentation	Revenue and growth	$2.2m	Annual	$400,000
31	Pier 1 Imports	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
32	Walmart	US	Augmentation	Revenue and growth	$1bn	Multi-year	Not publicly available
33	ThyssenKrupp	Germany	Augmentation	Capital savings	Cut downtime by 50%	Ongoing	Not publicly available
34	Jabil	US	Augmentation	Capital savings	Maintenance savings of 17%	Ongoing	Not publicly available
35	Fujitsu	Japan	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available

#	Organisation	Country	Application type	Type of benefit	Estimated benefits	Time horizon of benefits	Estimated costs
36	Kofera	Indonesia	Augmentation	Revenue and growth	$470,000	Ongoing	Not publicly available
37	Confidential	US	Augmentation	Revenue and growth	10% increase in profitability	Ongoing	$1.2m
38	Confidential	US	Augmentation	Revenue and growth	10% reduction in losses	Ongoing	$1.2m
39	Confidential	US	Augmentation	Revenue and growth	$2m	Annual	$400,000
40	Quarterspot	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
41	Confidential	US	Augmentation	Capital savings	$2.8m	Annual	$1.2m
42	Vigiglobe	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
43	Confidential	US	Augmentation	Revenue and growth	$4m	Annual	$2m
44	USAA	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
45	Confidential	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	$4m
46	Confidential	US	Augmentation	Revenue and growth	27% increase in annual revenue	Annual	$3m
47	Airbus	France	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
48	Red Marker	Australia	Augmentation	Time and efficiency	Confidential or not publicly available	Ongoing	Not publicly available
49	Confidential	US	Augmentation	Capital savings	$3.2m	Ongoing	$2m
50	Pluribus Labs	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available
51	Data61	Australia	Augmentation	Capital savings	$700m	Annual	Not publicly available
52	Upserve	US	Augmentation	Revenue and growth	Confidential or not publicly available	Ongoing	Not publicly available

Sources include: Deloitte US, Google, The Pew Charitable Trusts, Slate, Healthcare Informatics.

* Deloitte Access Economics estimates based on publicly available information.

End notes

1. MIT Technology Review (2017), The New Proving Ground for Competitive Advantage.
2. Transparency Market Research (2017), Global ML as a Service Market: Increasing Shift towards Cloud Computing to Reflect Positively, Says TMR.
3. ML applications were drawn from uses cases from a range of countries including Australia, United States, United Kingdom, Italy, Switzerland, Belgium, Russia, Japan and Indonesia. By its nature, this database is not a representative sample of all projects. Abandoned or failed projects are not included in the database, and while these returns have been realised for the specific projects listed, in general, returns may vary given different implementation, business processes or other factors.
4. MIT Technology Review (2017).
5. Transparency Market Research (2017).
6. International Data Corporation (IDC), (2017), Worldwide Spending on Cognitive and Artificial Intelligence Systems Forecast to Reach $12.5 Billion This Year, According to New IDC Spending Guide.
7. Ibid.
8. Transparency Market Research (2017).
9. Ibid.
10. IDC (2017).
11. Ibid.
12. This ROI estimate is based on selection of projects listed in the Appendix of this report. By its nature, it is not a representative sample of all projects. Firstly, abandoned or failed projects are not included in the database. The project details come from a range of sources, based on details from proponents, and have not been independently verified for this report. Also, while these returns have been realised for the specific projects listed, general ROI may vary given different implementation, business processes or other factors.
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18. Bain & Company (2013), Big Data: The organizational challenge.
19. Ransbotham, S, Kiron, D, & Prentice, PK (2015), The talent dividend: Analytics talent is driving competitive advantage at data-oriented companies, MIT Sloan Management Review.
20. Of the businesses sampled by MIT, one third are still in the early stage of their strategy, and while more than half of this group are beginning to see demonstrable ROI, less than 18% measure ROI on any analytics initiatives. Hence, this efficiency achievement rate may be an under-representation due to low rates of evaluation.
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22. M-Brain (2017), ML Initiatives Across Industries: Practical Lessons from IT Executives.

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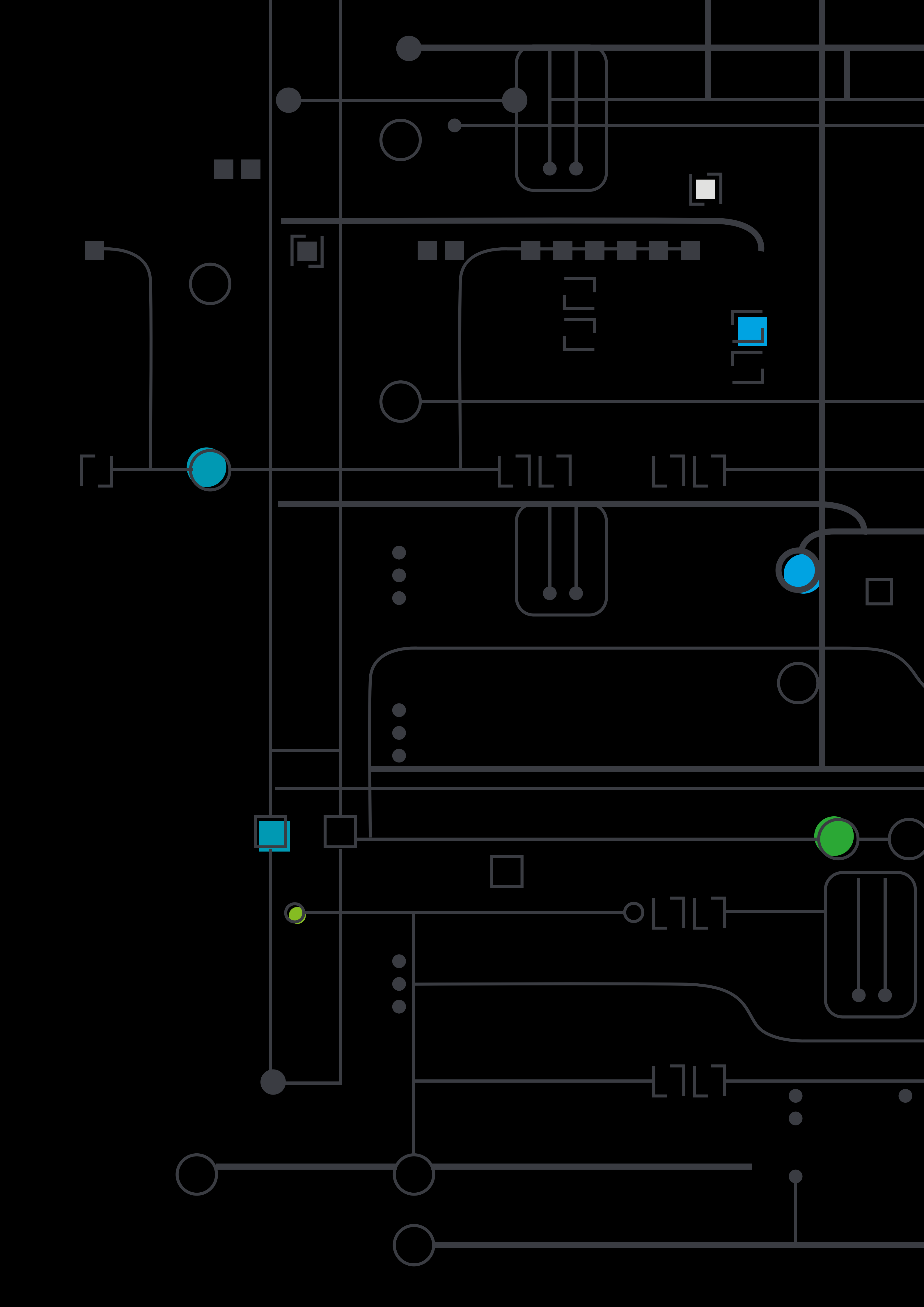

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