Introduction

Machine learning is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people.

Although machine learning is a field within computer science, it differs from traditional computational approaches. In traditional computing, algorithms are sets of explicitly programmed instructions used by computers to calculate or problem solve. Machine learning algorithms instead allow for computers to train on data inputs and use statistical analysis in order to output values that fall within a specific range. Because of this, machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs.

Any technology user today has benefitted from machine learning. Facial recognition technology allows social media platforms to help users tag and share photos of friends. Optical character recognition (OCR) technology converts images of text into movable type. Recommendation engines, powered by machine learning, suggest what movies or television shows to watch next based on user preferences. Self-driving cars that rely on machine learning to navigate may soon be available to consumers.

Machine learning is a continuously developing field. Because of this, there are some considerations to keep in mind as you work with machine learning methodologies, or analyze the impact of machine learning processes.

Use Cases

Machine Learning Use Cases in Finance

in today's era of digitization, staying updated on technological advancements is a necessity for businesses to both outsmart the competition and achieve desired business growth.

The recent years have seen a rapid acceleration in the pace of disruptive technologies such as AI and ML in Finance due to improved software and hardware. The finance sector, specifically, has seen a steep rise in the use cases of machine learning applications to advance better outcomes for both consumers and businesses.

Until recently, only the hedge funds were the primary users of AI and ML in Finance, but the last few years have seen the applications of ML spreading to various other areas, including banks, fintech, regulators, and insurance firms, to name a few.

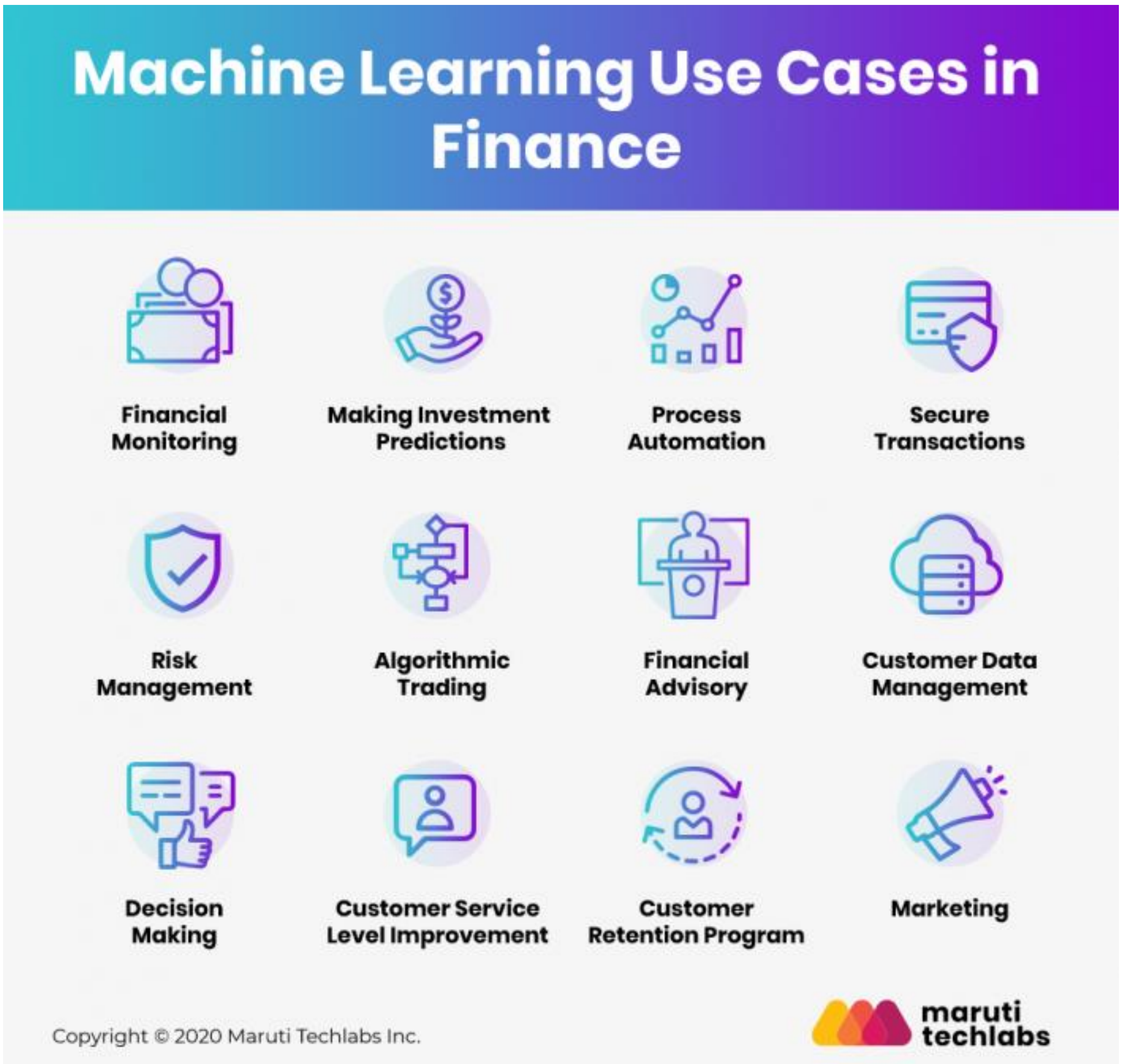
Right from speeding up the underwriting process, portfolio composition and optimization, model validation, Robo-advising, market impact analysis, to offering alternative credit reporting methods, the different use cases of ml are having a significant impact on the financial sector.

The finance industry, including the banks, trading, and fintech firms, are rapidly deploying machine algorithms to automate time-consuming, mundane processes, and offering a far more streamlined and personalized customer experience.

Why Use Machine Learning in Finance?

Here are some of the reasons why banking and financial services firms should consider using Machine Learning despite having above-said challenges –

- Enhanced revenues owing to better productivity and improved user experience
- Low operational costs due to process automation
- Reinforced security and better compliance



Marketing Use Cases for Machine Learning

Customer Journey Optimization

Machine Learning techniques are effective in marketing, and one such use case of machine learning in marketing is customer journey optimization. The primary idea of the process is to optimize the customer acquisition cost to a specific conversion point. The top-down approach is one of the popular approaches in use. It considers customer objectives, such as purchase patterns, pricing, comparison with the business, and maps the marketing touchpoints with the customer objectives. This approach, however, does not lead to significant revenue generation due to the absence of data insights.

Data-driven approaches are now more popular in conducting customer journey optimizations. These are the bottom-up approaches and extensively use machine algorithms and techniques. ML algorithms determine all the customer paths and provide a score to each of these paths. This approach considers the customer acquisition costs and customer lifetime value as the factors.

Reinforcement machine learning is one of the techniques to predict/forecast the next touchpoint to enhance the possibility of a specific outcome. Machine learning algorithms can determine the real-time points of interest for the customer journey to develop realistic and data-driven recommendations. This can significantly bring down the costs. Amazon uses this technique to improve customer acquisition and retention strategies.

Skin Cancer Diagnosis

Convolutional Neural Network algorithms are extensively used in the healthcare sector to recognize and classify images. Healthcare is one field that has no margin of error. It is essential for a system or a technology to provide high levels of accuracy and validity in the results. CNNs are effective in skin cancer detection with high accuracy rates of up to 95% using TensorFlow. Scikit-learn and Kera's are other machine learning tools helpful in diagnosing and detecting skin cancer using the CNN technique. Manual efforts and processes in the same method can have a maximum accuracy of 85%.

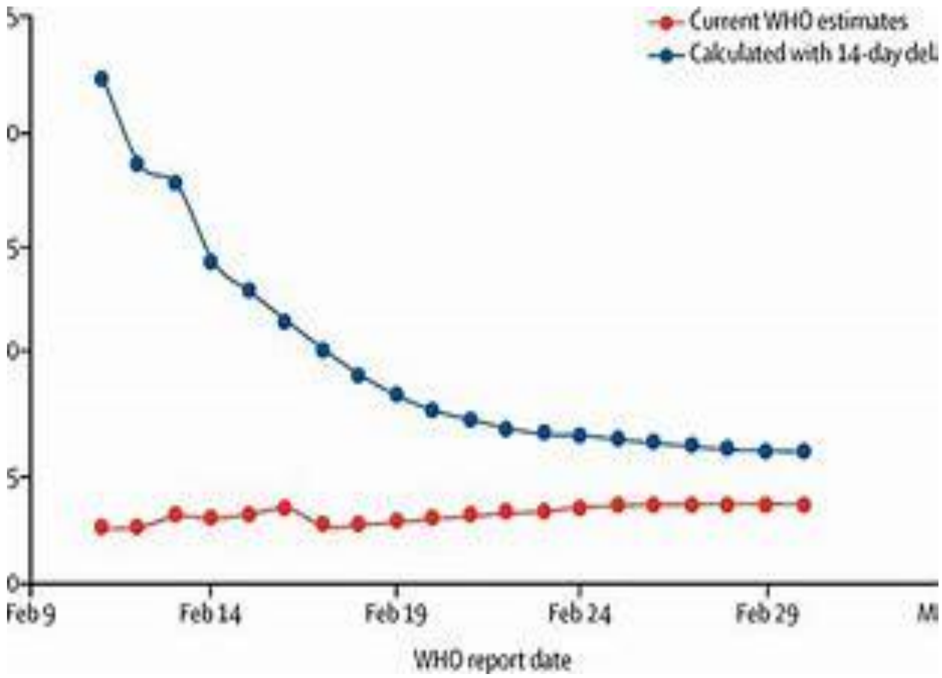
These ML models use hundreds and thousands of images of benign and malignant skin lesions to provide the outcomes. Getup has one such open-source project that uses the CNN technique to diagnose skin cancer. Similarly, you can apply various machine learning and deep learning techniques to predict and diagnose other medical conditions, such as Alzheimer's, Diabetes,

etc.

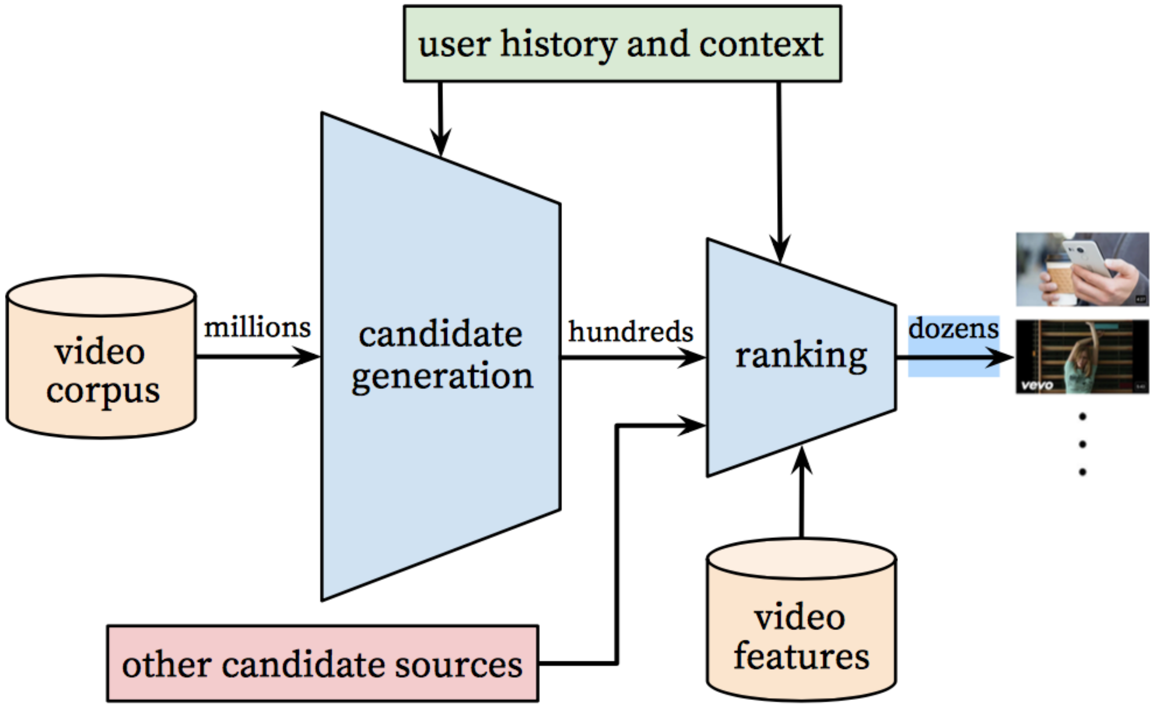
The entire world saw the outbreak of the Covid-19 pandemic in early 2020. Many countries are currently in the third wave of the pandemic with a continuous rise in infections.

Machine Learning techniques can be significantly helpful in pandemic management. Covid-19 mortality risk predictor is one such machine learning use case in healthcare. Timely prediction of patient mortality risk can bring down mortality with effective resource allocation and treatment.

Support Vector Machines, SVMs are machine learning algorithms that can be used for predictive modeling leveraging invasive laboratory and noninvasive clinical information of the patients. Non-invasive features, such as blood oxygen levels, patient age, previous medical conditions, etc., can be fed to the machine learning models to yield accurate predictions. The amalgamation of such ML techniques with IoT solutions like wearable devices can further assist in developing power frameworks. These can be effective in Covid-19 management and patient triage.



You’re probably familiar with this use if you use services like Amazon or Netflix. Intelligent machine learning algorithms analyze your activity and compare it to the millions of other users to determine what you might like to buy or binge watch next. These recommendations are getting smarter all the time, recognizing, for example, that you might purchase certain things as gifts (and not want the item yourself) or that there might be different family members who have different TV preferences.



Algorithmic Trading

Machine Learning in trading is another excellent example of an effective use case in the finance industry. Algorithmic Trading (AT) has, in fact, become a dominant force in global financial markets.

ML-based solutions and models allow trading companies to make better trading decisions by closely monitoring the trade results and news in real-time to detect patterns that can enable stock prices to go up or down.

Machine learning algorithms can also analyze hundreds of data sources simultaneously, giving the traders a distinct advantage over the market average. Some of the other benefits of Algorithm Trading include –

1. Increased accuracy and reduced chances of mistakes
2. AT allows trades to be executed at the best possible prices
3. Human errors are likely to be reduced substantially

4. Enables the automatic and simultaneous checking of multiple market conditions

Natural Language Processing (NLP)

NLP is being used in all sorts of exciting applications across disciplines. Machine learning algorithms with natural language can stand in for customer service agents and more quickly route customers to the information they need. It’s being used to translate obscure legalese in contracts into plain language and help attorneys sort through large volumes of information to prepare for a case

Smart Cars

IBM recently surveyed top auto executives, and 74% expected that we would see smart cars on the road by 2025. A smart car would not only integrate into the Internet of Things, but also learn about its owner and its environment. It might adjust the internal settings — temperature, audio, seat position, etc. — automatically based on the driver, report and even fix problems itself, drive itself, and offer real time advice about traffic and road conditions.

Machine Learning Terminology

Regressions

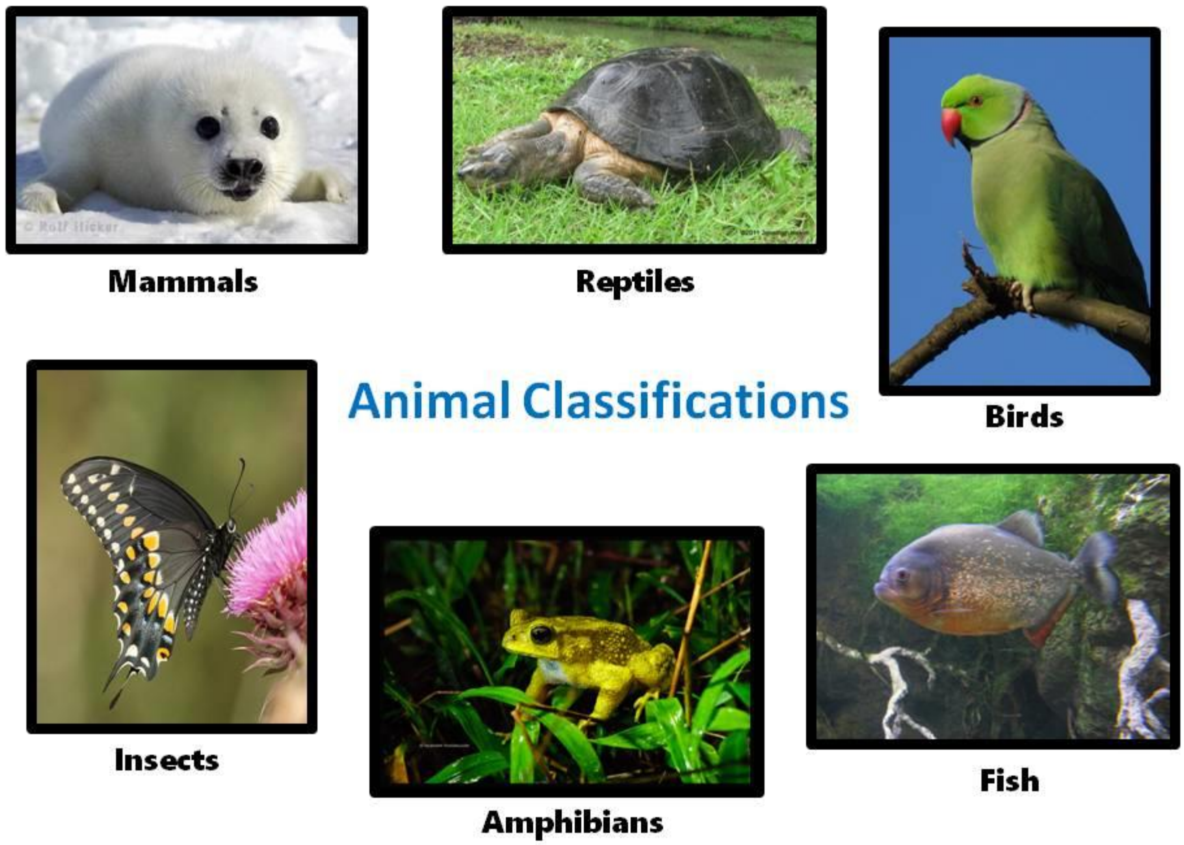
Regressions create relationships and correlations between different types of data. For example, each profile picture has an image with pixels that belong to a person.
With **static prediction** (one that stays the same over time), machine learning acknowledges that a certain pixel arrangement corresponds to a given name and allows for **facial recognition** (for example, when Facebook recommends tags for the photos you've just uploaded).

Regressions can also be useful when predicting outcomes based on data in the present. For a long time, statistical regression has been used to solve problems, such as predicting the recovery of cognitive functions after a stroke or predicting customer churn in the telecommunications industry. The only difference is that now many of these regression analyses can be done more efficiently and quickly by machines.

Regression is a type of structured machine learning algorithm where we can label the inputs and outputs. **Linear regression** provides outputs with continuous variables (any value within a range), such as pricing data. **Logistical regression** is when variables are categorically dependent, and the labeled variables are precisely defined. For example, you can classify whether a store is open as (1) or (0), but there are only two possibilities.

Classification

Classification is a part of supervised learning (learning with labeled data) through which data inputs can be easily separated into categories. In machine learning, there can be binary classifiers with only two outcomes (e.g., spam, non-spam) or multi-class classifiers (e.g., types of books, animal species, etc.).
One of the most popular classification algorithms is a decision tree (essential for both data scientists and machine learning engineers), whereby repeated questions leading to precise classifications can build an "if-then" framework for narrowing down the pool of possibilities over time.



Clustering

Clustering is a form of unsupervised learning (learning with unlabeled data) that involves grouping data points according to features and attributes.

Clustering can be used to organize customer demographics and purchasing behavior into specific segments for targeting and product positioning. It can also analyze housing quality and geographic locations to create real estate valuations and plan the layout of new city developments. It can classify information by topics within libraries or web pages and compile an easily accessible directory for users.

The most common kind of clustering is K-means clustering, which involves representing each cluster by a variable “k” and then defining the centroid of those clusters. All data points are then assigned to a particular cluster and, through this process, we identify the centroid of the new clusters. Here are a

few examples of what K-means clustering looks like in practice:

- A hospital wants to locate emergency units at the minimum possible distance from areas where accidents frequently happen
- A seismologist studies regions where earthquakes have occurred over the last few decades to identify the areas of greatest risk
- A pizzeria wants to understand where to locate stores based on customer demand to minimize the distance the drivers need to travel for delivery

Deep Learning

Deep learning is similar to machine learning—in fact, it's more of an application of machine learning that imitates the workings of the human brain. Deep learning networks interpret big data (data that is too large to fit on a single computer)—both unstructured and structured—and recognize patterns. The more data they can "learn" from, the more informed and accurate their decisions will be. Here are some examples of deep learning in practice:

- Chatbots and virtual assistants: Virtual assistants like Alexa and Siri or customer service chatbots on different web pages can receive human requests, decipher language, and present lifelike responses.
- Real-time bidding and programmatic advertising: Advertising now depends on software buying advertising space through a competitive bidding process. Cognitiv AI is an example of a deep learning platform that synthesizes data on customer demographics, weather, available inventory, time of day, and other variables to create custom buying algorithms for a specific target market.
- Recommendation engines: From travel sites like Booking.com and Expedia to streaming platforms like Netflix and Spotify, recommendation engines learn from past purchasing or usage behavior to customize marketing. There are two forms of recommendation engines: collaborative, where user preference data is collected at scale and users are compared to similar user personas, and content-based filtering, where properties of specific items are analyzed and future items are compared to past items to determine the closest matches.

Natural Language Processing

Natural language processing is the subfield of AI that processes human languages. It is a very important term in the field of data science and machine learning. The challenge is that often human speech is not literal. There are figures of speech, words, or phrasing specific to certain dialects and cultures, and sentences that can take on different meanings with grammar and punctuation. Similar to human conversations, natural language processors need to use

the syntax (arrangement of words) and semantics (meaning of that arrangement) to come up with correct interpretations.

The first step in natural language processing is converting unstructured language data into a form that can be read by a computer. The computer then assigns meaning to each sentence through algorithms and translates it back, often in another form (for example, speech to text or from one language to another).

Machine Vision

Machine vision, or computer vision, is the process by which machines can capture and analyze images. This allows for the diagnosis of skin cancer by looking at X-rays and other medical imagery, and for the detection of real-time traffic and vehicle types for self-driving cars, like Tesla's new models.

There are many different ways that machines can "see": representing colors numerically, decomposing images into different parts, and identifying corners, edges, and textures. As the machines gather and code more information, they begin to view the larger picture.

Many of the trends around machine vision right now include integration into the industrial internet of things, which involves collecting productivity inputs and sensory data in factories, and non-industrial applications like "driverless cars, autonomous farm equipment, drone applications, intelligent traffic systems, and guided surgery."

Lifecycle of a ML Project

Machine Learning (ML) has been experiencing explosive growth in popularity due to its ability to learn from data automatically with minimal human intervention. As ML is implemented and applied more in business settings, ML practitioners need to develop methods to describe the timing of their project work to their employers or clients.

One tool which is particularly useful in this regard is the ML Process Lifecycle, a process framework adapted by the Amii team (see note below). In this three-part blog series, we will be exploring what it is, why it's important and how you can implement it

What is the MLPL?

The ML Process Lifecycle (MLPL) is a framework that captures the iterative process of developing an ML solution for a specific problem.

ML project development and implementation is an exploratory and experimental process where different learning algorithms and methods are tried before arriving at a satisfactory solution. The journey to reach an ML solution that meets business expectations is rarely linear – as an ML practitioner advances through different stages of the process and more information is generated or uncovered, they may need to go back to make changes or start over completely.

The MLPL tries to capture this dynamic workflow between different stages and the sequence in which these stages are carried out.

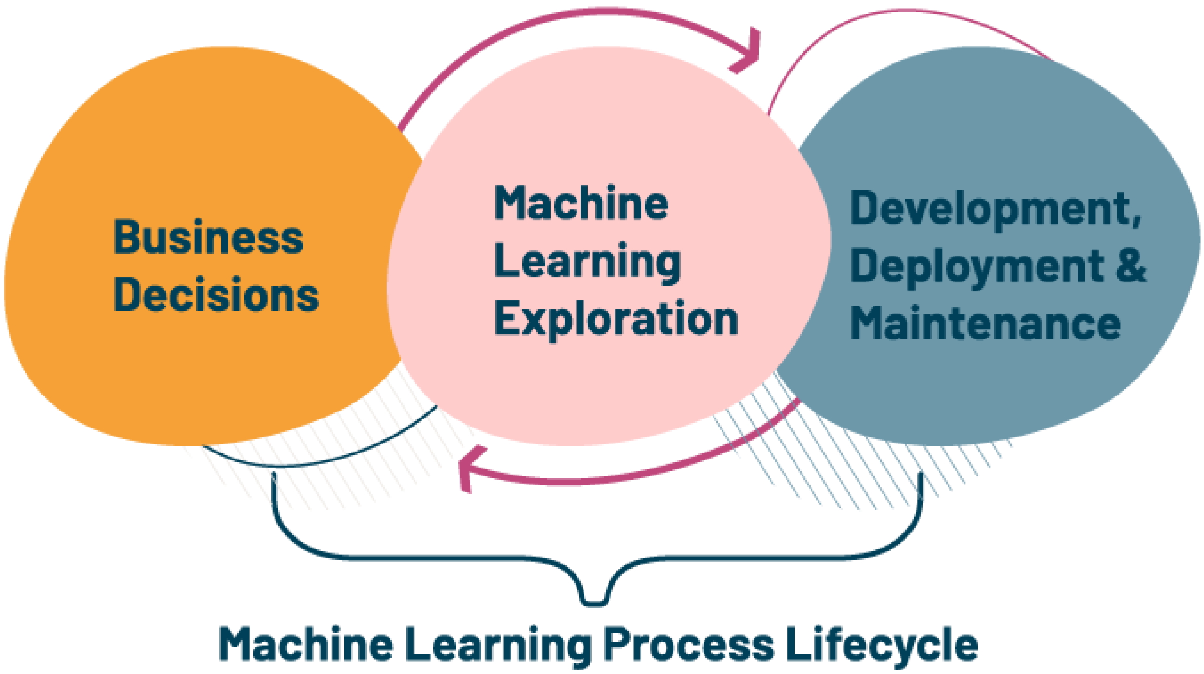
Where does the MLPL fit?

When business organizations develop new software systems or introduce new features to existing systems, they go through two major phases:

Business analysis: making assessments and business decisions regarding the value and feasibility of a new software product or feature; and

Product development: developing the solution (usually following one of the existing software development methodologies) and putting it in the production.

However, when an organization thinks about adopting ML – either to complement their current software products/services or to address a fresh business problem – there is an additional exploration phase between the business analysis and product development phases. The MLPL streamlines and defines this process.



The MLPL is an iterative methodology to execute ML exploration tasks, generalizing the process so that it is flexible and modular enough to be applied to different problems in different domains, while at the same time having enough modules to fully describe relevant decision points and milestones