MODULE 1 UNIT 1
Introduction to machine learning

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Learning outcomes:

LO1: Identify applications of machine learning in different contexts.

LO2: Match data and problems with appropriate machine learning techniques to solve a given problem.

1. Introduction

Some of the biggest transformations from the past century are attributable to computing and digital technology (Alpaydin, 2016:1). Computing technology has become so pervasive that most of society unknowingly interacts with a form of machine learning every day (Hussain, 2017). Organisations have successfully deployed machine learning in their contexts, from automating simple tasks to more complex problem-solving in business intelligence (Pant, 2019).

As society constantly interacts with technology, a wide variety of information is collected, processed, stored, and transferred, which has caused a surge in data. This sudden increase in data has triggered widespread interest in data analysis and machine learning. Consequently, scientists have developed methods of teaching algorithms to learn from data in order to transform raw data into valuable intelligence. It is within this process – transforming raw data into useful information – that machine learning plays a vital role (Alpaydin, 2016:x).

Machine learning is more than an application of methods for extracting information from raw data; it also enables intelligence in machines. The more data that is produced and analysed, the more intelligent machines will become (Alpaydin, 2016:xi).

In this lesson, machine learning is demystified by defining this field of study and explaining the different machine learning techniques covered throughout this course. This lesson further positions machine learning in relation to other fields to show their interrelationships when solving problems. Finally, this lesson, and the overall module, presents a roadmap to matching a suitable machine learning technique to a specific problem or data set, since the type of problem determines the most suitable approach required.

2. The concept of machine learning

Machine learning has become a buzzword, as its potential continues to increase due to the vast amounts of data being generated. This has led to computational power expansion and improved algorithms to solve problems (Pant, 2019).

Machine learning developed as a subset of artificial intelligence (AI), where computer programs learn from data without being explicitly programmed to do so (Marr, 2016). Deep learning, which is explored further in Module 7, is a subset of machine learning and has led to the AI boom of the 2010s (Pant, 2019). Figure 1 illustrates the interrelationships between these three concepts.

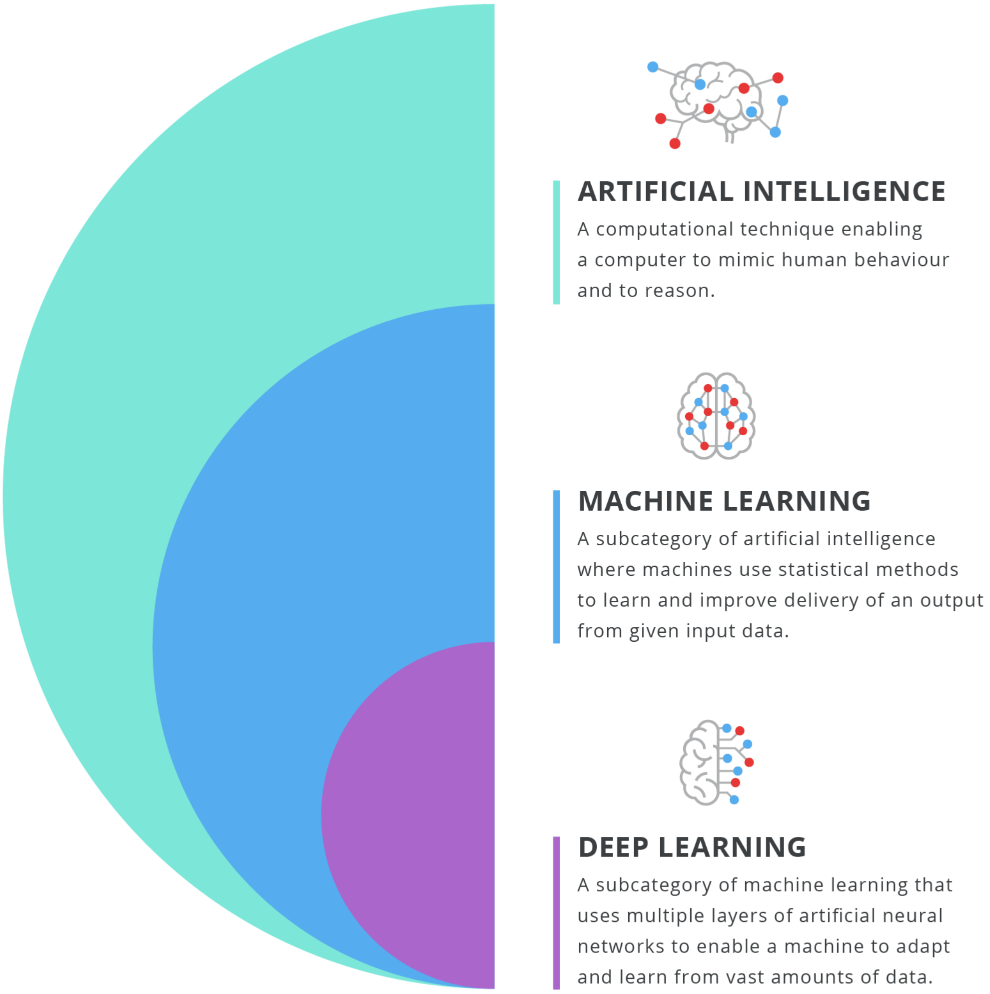

Figure 1: The interrelationships between AI, machine learning, and deep learning.

2.1 Definition of machine learning

Different sources offer different explanations of what machine learning is, with all attempting to pinpoint the functionality of this technology. One such source defines machine learning as a set of methods that can automatically detect patterns in data and use those patterns to make predictions (Murphy, 2012:1).

Pause and reflect:

Consider some of the definitions of machine learning that you have encountered. Reflect on how some of these definitions have shaped your understanding of this technology.

2.2 Components of machine learning

Before delving deeper into the different types of machine learning, it is essential to first comprehend the three main components of machine learning. These components dictate which type of machine learning is most suitable for the problem at hand.

The three components of machine learning are the cost function, the model, and the data. The first component is the cost function, or loss function, that is produced as a result of the action taken to produce an output from input data. The cost function calculates the difference between actual values and predicted values, and aims to minimise this difference to ensure that the machine learning model performs optimally. This process of optimising the cost function is referred to as learning. Ultimately, as the model is optimised by a decrease in the cost function, it generates more accurate predictions from the given data set.

The second component of machine learning is the model. The chosen model is the primary function of machine learning, which includes accepting the input and producing an output or performing a task within the given parameters. The model is designed to automatically produce an output from input data.

The final component of machine learning is the data, and more importantly, learning from it. Machine learning cannot function without data. The data set used to feed into the machine learning model has a significant impact on the model's performance (Tiu, 2019). Learning from data is operationalised by applying the model onto the data set to produce actions, and then evaluating the associated cost functions to ensure that the model performs optimally.

Depending on the type of problem, five different types of machine learning models can be deployed to make predictions. These types of machine learning are classified into two groups based on the level of human supervision needed during the training of the model. These include supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and transfer learning (Furbush, 2018). Although there are five types of machine learning, the following section only focuses on the two types covered in this course.

2.3 Types of machine learning

Before delving deeper into the different machine learning techniques that can be used to solve problems, engage with Figure 2 as an introduction to the main types of machine learning that will be covered in this course.

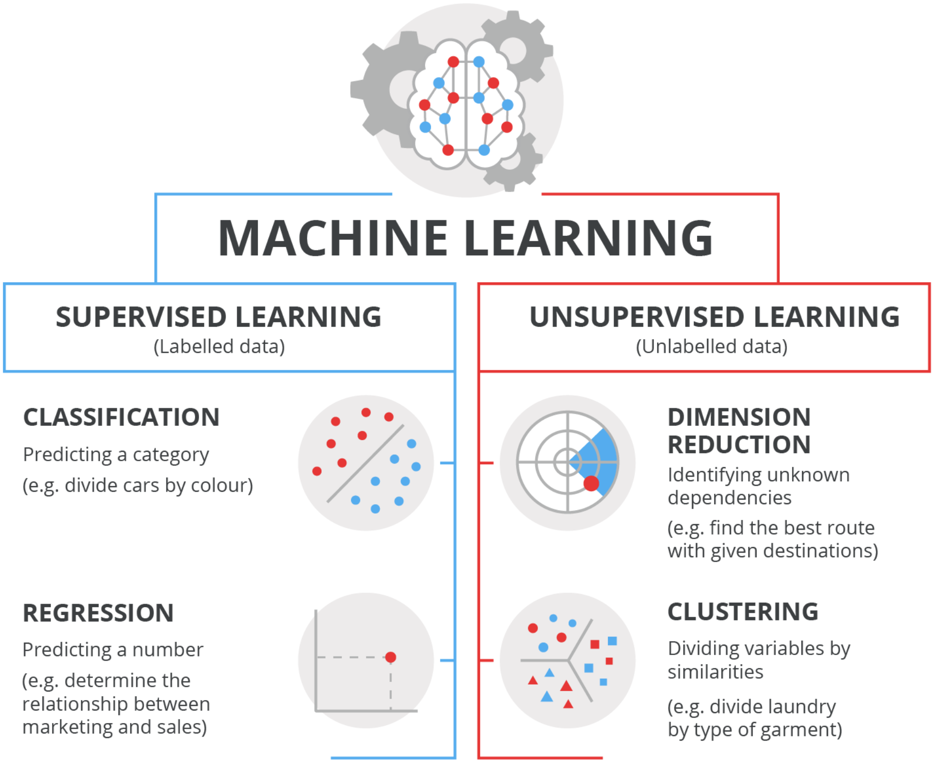

Figure 2: Types of machine learning.

As demonstrated, the two main types of machine learning that will be covered in this course are supervised learning and unsupervised learning, as well as their respective techniques.

The main difference between these two types is that supervised learning is done with knowledge of the sample data output values, whereas unsupervised learning does not have labelled outputs. This means that the model must make inferences from these unlabelled data points when producing the output (Soni, 2018). For example, images of dogs and cats labelled as either "dog" or "cat" constitute labelled data. Examples of unlabelled data include news articles, social media posts, audio files, and videos.

Supervised learning

Supervised learning refers to the task of estimating an output, or prediction value, based on a set of input variables. The algorithm learns from using previous input data and the respective output to predict an output when given new input data. The first and most common supervised machine learning technique is regression. This technique is used to predict a continuous numerical value based on prior data, such as sales in relation to the amount spent on marketing campaigns.

The other supervised machine learning technique is classification. This technique is deployed to predict a class value from discrete data (Castañón, 2019). Discrete data is based on counts; each count cannot be subdivided meaningfully into smaller sections, for example, the number of children in a classroom. In contrast to discrete data, continuous data can be divided into smaller sections per unit, for example, the weight of a package.

A simple example of a classification problem is categorising vehicles into classes based on specific features, such as colour. One of the most common classification problems is logistic regression, which is used to predict the probability of an event or class. Despite the name suggesting that regression is used to generate an output, logistic regression is purely a classification method used to estimate discrete or binary values from a set of independent variables by calculating probability (Upasana, 2019).

Unsupervised learning

In contrast to supervised machine learning, unsupervised machine learning is used to group similar data points (clusters) or combine similar data features (factors). As mentioned previously, unsupervised learning uses unlabelled data to generate an output.

The first unsupervised machine learning technique is clustering. At face value, clustering has some similarities to classification. The difference, however, is that clustering methods are used to group observations that have similar characteristics, using unlabelled data to let the model define the output by itself; classification is applied to labelled data when classifying variables into classes. An example of clustering is recommendation systems, discussed in Section 3.2, whereby movies with similar characteristics are grouped into clusters and recommended to viewers based on movies they previously watched.

The second unsupervised machine learning technique is dimensionality reduction. This method is used to find structure in unlabelled data. This is done by combining similar variables to produce fewer ones without losing substantial information. By simplifying the input data, the model can determine the output with more speed and accuracy than before, because the data set is more manageable and easier to process (Castañón, 2019).

Test your understanding of the concept of machine learning by answering the following questions.

At this point in the lesson, you have the opportunity to engage with a practice quiz to test your understanding of the content. Access this lesson on the Online Campus to engage with this quiz.

3. Applications of machine learning

Most industries are developing new ways of using machine learning to their advantage (Pant, 2019). As a result, new applications are constantly being created to solve industry-specific problems.

In Video 1, Professor Kostas Kalogeropoulos introduces a practical example of machine learning where emails are classified into spam folders.

Video 1: Practical application of machine learning. (Access this set of notes on the Online Campus to engage with this video.)

The following sections explore two of the most accessible applications of machine learning: image classification and recommendation systems.

3.1 Image classification

Image classification refers to the process whereby pictures are classified based on their content. A simple example of image classification is the modern test referred to as the Completely Automated Public Turing Test To Tell Computers and Humans Apart (CAPTCHA), commonly known as the "Are you a robot?" test. In this test, humans are often tasked with identifying which images contain a streetlight, a car, or signs, and selecting the relevant images from a grid (Dzieza, 2019). This task may be easy for humans, but it is a complex process to train a model to replicate this classification ability (Kaeli, Mistry & Zhang, 2015:213).

However, it is possible to train a machine learning model to classify images based on their content. By applying supervised machine learning (classification), a model can, for example, be trained by feeding it labelled data of cats and dogs, and then applying it to a data set containing images of cats and dogs. The model is then tasked with classifying the various images into the correct categories.

In its earliest form, reading barcodes represented a form of image classification where a computer scans the lines of different shapes and thickness. These patterns contain information that is unlocked when the code is scanned. Since the invention of barcodes, machine learning has changed the landscape of image classification to such an extent that it is even used by police to recognise criminals through drone footage in large cities (Holmes, 2019).

Pause and reflect:

Have you recently engaged with an image classification model? If so, was it accurate in its classification? Try to think of an area within your professional or personal context where image classification can be helpful.

Example: Recognition of handwritten digits

One of the most prominent applications of image classification is the recognition of handwritten digits. A machine can be trained to recognise digits from a variety of sources, such as bank cheques, documents, and envelopes (Beniwal, 2018). This can be extremely useful in optical character recognition and the transcription of handwritten documents into digital versions. The basic idea behind this image classification is that the machine learning model is trained to classify handwritten digits (input) into classes between 0 and 9 (output) (Nkengsa, 2018).

To fully comprehend how image classification of handwritten digits work, it is important to understand the basics of the process. Each digit is presented on a grid of pixels arranged in rows, with each pixel containing an RGB (red, green, blue) value between 0 and 255 – 0 representing white, and 255 representing black. Each digit, in the way that it is written, activates certain pixels within the grid, which indicate where the lines of the digit fall within this grid. In Figure 3, for example, the handwritten digit 8 activates a collection of pixels within the grid, enabling the machine learning model to identify the digit based on how it was trained.

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	12	0	11	39	137	37	0	152	147	84	0	0	0
0	0	1	0	0	0	41	160	250	255	235	162	255	238	206	11	13	0
0	0	0	16	9	9	150	251	45	21	184	159	154	255	233	40	0	0
10	0	0	0	0	0	145	146	3	10	0	11	124	253	255	107	0	0
0	0	3	0	4	15	236	216	0	0	38	109	247	240	169	0	11	0
1	0	2	0	0	0	253	253	23	62	224	241	255	164	0	5	0	0
6	0	0	4	0	3	252	250	228	255	255	234	112	28	0	2	17	0
0	2	1	4	0	21	255	253	251	255	172	31	8	0	1	0	0	0
0	0	4	0	163	225	251	255	229	120	0	0	0	0	0	11	0	0
0	0	21	162	255	255	254	255	126	6	0	10	14	6	0	0	9	0
3	79	242	255	141	66	255	245	189	7	8	0	0	5	0	0	0	0
26	221	237	98	0	67	251	255	144	0	8	0	0	7	0	0	11	0
125	255	141	0	87	244	255	208	3	0	0	13	0	1	0	1	0	0
145	248	228	116	235	255	141	34	0	11	0	1	0	0	0	1	3	0
85	237	253	246	255	210	21	1	0	1	0	0	6	2	4	0	0	0
6	23	112	157	114	32	0	0	0	0	2	0	8	0	7	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3: Example of a pixel grid for image classification of a handwritten digit.

When the machine learning model processes the grid, it detects certain features from the pixel cells activated by the digit. For example, the digit 8 represented in Figure 3 includes two rounded curves at the top and bottom of the grid, and an intersection of two lines in the middle to form an X. Based on these features, the model has been trained to classify the digit into the correct class – in this case, the digit 8. This process of extracting features is executed for each digit to match its features to that of the digits in the data used to train the model. Consider the handwritten digit 6, for example. Figure 4 shows which features serve as the guiding elements to successfully classify the digit into the correct class.

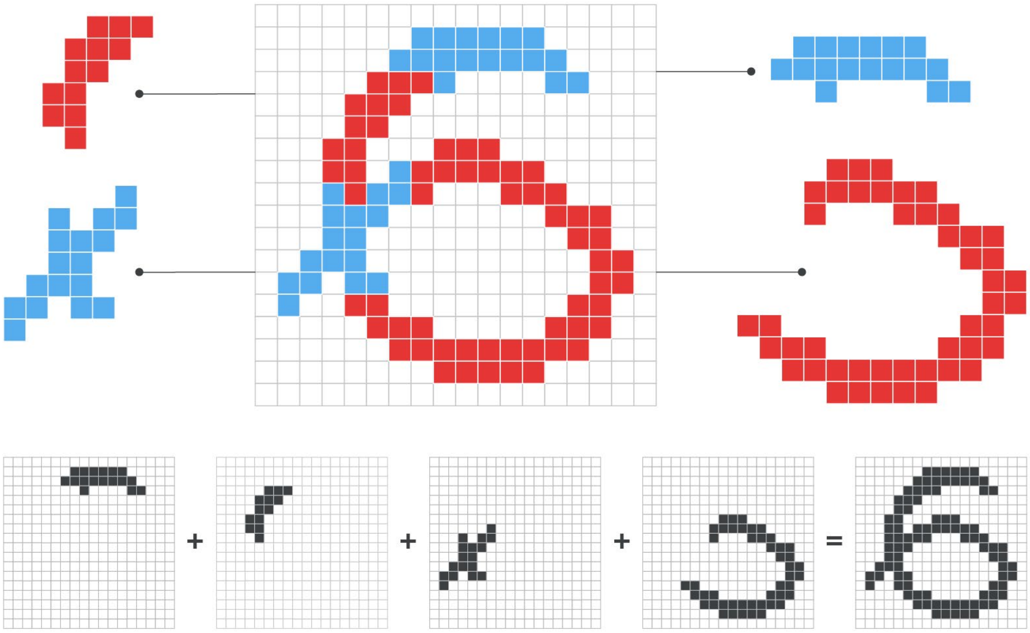

Figure 4: Features of the handwritten digit 6.

Essentially, the machine learning model is trained to use the handwritten digits as input variables and label each variable according to the likelihood of that digit belonging to a specific class between 0 and 9 (Nkengsa, 2018). In following the same approach when given the following input variables, the machine learning model should be able to classify each one of these digits into the correct class.

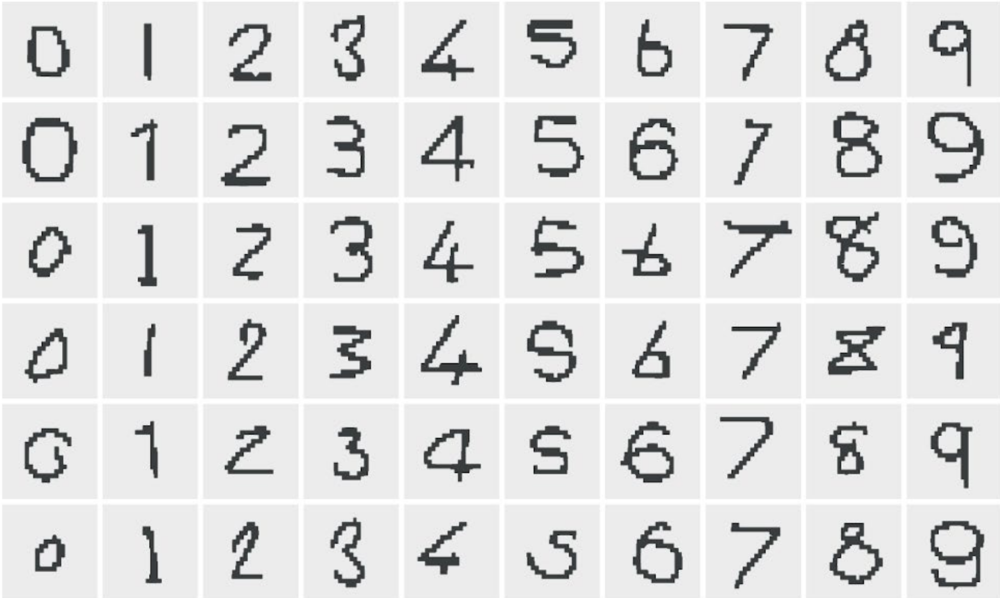

Figure 5: Examples of handwritten digits.

The problem, however, of classifying handwritten digits into classes is that different individuals write digits differently, and no two digits look exactly the same when classified. Also, there are different similarities that exist between different digits, as depicted in Figure 6. The model should therefore be trained to extract features as well as their positioning. For example, the model must ensure that the digit 6 is not mistaken for a digit 9, since most of the features are present in both, but the positioning of the features determines their classification. In Figure 6, some of the digits that could appear similar are highlighted.

Figure 6: Similarities between handwritten digits.

Pause and reflect:

Can you think of any other digits that may be problematic for a machine learning model to classify based on how they can be written, or present similar features?

Despite the complexity of image recognition, scientists are constantly reaching new technological heights – not only with image classification, but with machine learning techniques in general.

Explore further:

Engage with the following articles to discover how image recognition technology is used in business and to learn more about the applications, and other interesting uses for image recognition technology.

3.2 Recommendation systems

Another prominent machine learning application is the recommendation system. The main goal of a recommendation system is to identify patterns in data by learning from customer choices and then produce an output based on those patterns (Madasamy, 2019).

There are various manifestations of recommendation systems used by corporations such as LinkedIn, Pandora, Netflix, and Amazon. These corporations have established the value of recommending items to their customers to increase satisfaction and therefore revenue (Deng, 2019). Fundamentally, these applications are all machine learning models that aim to identify and recommend the most accurate items to individuals based on a number of dependent and independent variables (Madasamy, 2019).

Independent variables are commonly called features, and refer to the input of the process, for example, the age, income, and job title of customers. The dependent variables are the outputs of the process, or the results of the process. In the previous example, the dependent variable would be whether the customer (with a certain age, income, and job title) purchased the product or not (Jordan, n.d.).

Example: Recommended viewing lists

One of the most common recommendation systems that many individuals engage with in their personal capacity is Netflix's recommended viewing list. These recommendations are based on past shows watched, combined with predictions generated from other customers' viewing behaviour (Madasamy, 2019). Netflix uses different tactics to ensure that it is continually improving its customers' experiences on its platform. Some of these tactics include A/B tests, landing cards, and timing.

The A/B test involves showing users two slightly different experiences and monitoring their reactions to find out which one is the better option. The participants are chosen randomly, and the test is rolled out to the entire Netflix network. The second tactic, landing cards, refers to instances where the show's "cover page" is continually changed to entice customers to view the show. If they don't, that behaviour is recorded and used to inform future implementations. Finally, Netflix records the number of times a customer watches a show. Netflix may recommend different shows of various lengths based on the time of day and past behaviour of a particular customer (Burgess, 2018).

Within a business context, timing and past behaviour can be used to predict customer behaviour. For example, online retailers can predict the probability of a customer purchasing a specific item based on a large data set of past online purchases. The predictions can be valuable to align and personalise marketing strategies to increase sales (Alpaydin, 2016:118).

Explore further:

For an example of a recommendation system, visit Amazon's homepage, and click on a product. From there, scroll down the page and consider the recommendations that Amazon makes, based on products that are frequently bought together and based on other customers' buying behaviour.

3.3 Other examples

In Video 2, Dr James Abdey elaborates on the most useful applications of machine learning within a business context, with a specific reference to the unconventional applications of this technology that he has encountered. Dr Abdey is an assistant professorial lecturer in the Department of Statistics at the LSE.

Video 2: Practical applications of machine learning within a business context. (Access this set of notes on the Online Campus to engage with this video.)

Test your understanding of the applications of machine learning by answering the following questions.

At this point in the lesson, you have the opportunity to engage with a practice quiz to test your understanding of the content. Access this lesson on the Online Campus to engage with this quiz.

4. Machine learning and related fields

Now that you understand what machine learning is, this section explores the interrelationships between machine learning, data mining, optimisation, and statistics. Although all these fields aim to solve similar problems, they do so with different techniques. These fields are all data-driven disciplines that assist organisations to make decisions and ensure growth (Iconiq Inc, 2017).

4.1 Data mining

Data mining is the step that follows data collection and refers to the field of study focusing on discovering unknown patterns in data. During data mining, machine learning, statistics, and computer science are applied to identify patterns in that data (Iconiq Inc, 2017). Machine learning can therefore be seen as one step, or tool, applied during the process of data mining (Alpaydin, 2016:154).

4.2 Optimisation

Optimisation methods are deployed to ensure that the prediction calculated by the machine learning model becomes more accurate by minimising the cost function (Sarkar, 2018). Essentially, optimisation is the way through which the model's cost function is calculated and then minimised to ensure a more accurate prediction (Parmar, 2018). Optimising the cost function is explored in Module 2.

4.3 Statistics

Although its main theory developed from statistics, machine learning was developed as a parallel, but independent, study (Alpaydin, 2016:27). Therefore, statistics and machine learning are closely linked, as both focus on learning from data. Statistics involves constructing a hypothesis before building the model. Machine learning, on the other hand, has algorithms fitted onto data to provide the output without guiding the model in the direction of the initial hypothesis (Iconiq Inc, 2017).

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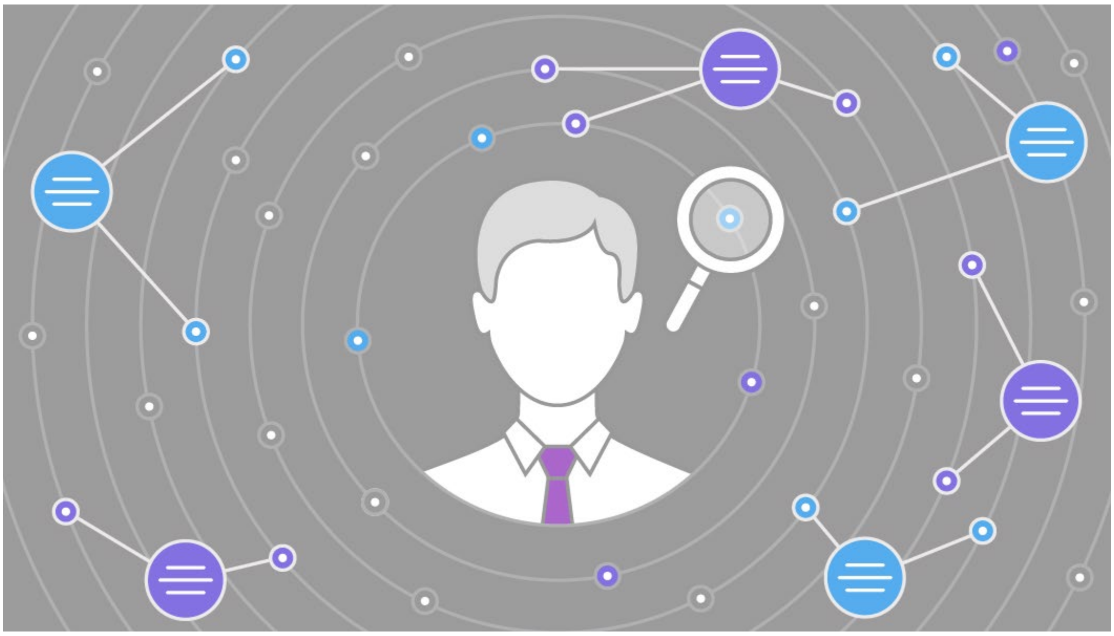
In summary, data mining finds patterns in data, statistics quantifies data from samples to calculate estimations, and machine learning algorithms are trained to learn from data sets (Iconiq Inc, 2017).

5. Matching data and machine learning techniques

In machine learning, the aim is to develop a model that fits a specific type of problem (Alpaydin, 2016:27). The problem determines the appropriate machine learning technique. In Unit 2, the different types of data will be explored in more detail, but for purposes of this discussion, it is important to gain a better understanding of the different machine learning techniques that can be deployed.

Building on the discussion of the different supervised and unsupervised machine learning techniques, engage with the following infographic.



Infographic 1: Finding the most suitable machine learning technique. (Access this lesson on the Online Campus to engage with this infographic.)

Note:

This tool offers a roadmap to match different problems with suitable machine learning techniques, and will assist you throughout your learning journey in this course.

Test your knowledge of matching problems with appropriate machine learning techniques by answering the following questions. You are encouraged to download the infographic from the module downloads folder and use it as a guide to match the correct option to the given scenario.

At this point in the lesson, you have the opportunity to engage with a practice quiz to test your understanding of the content. Access this lesson on the Online Campus to engage with this quiz.

6. Conclusion

This lesson provided a solid foundation of what machine learning is and how it relates to similar fields. It also provides the necessary overview of the different types of machine learning techniques, which types of data suit these techniques, and the problems they aim to solve. Whether the goal is to predict categories or values, or to discover structure or assemble features, different types of machine learning techniques can be used.

At this point, it should be clear that there are two main types of machine learning that can be applied: supervised learning and unsupervised learning. If the goal is to predict categories or values, the supervised learning methods of classification and regression can be applied. If the goal is to discover structure in data or to assemble features, the unsupervised learning methods of dimension reduction and clustering are useful.

Lastly, this lesson offered a useful tool to choose an appropriate machine learning method when presented with a particular problem. This tool can be used throughout this course.

As you progress through your learning journey over the next few weeks, you will delve deeper into the different supervised and unsupervised machine learning techniques, the associated model mechanics, and the instances in which such a model is best suited for a given data set.

Navigate to the small group discussion forum to learn more about the perceptions that exist around what machine learning is and how it is defined.

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