

# Machine Learning for Corporate Learning and Performance

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## 1. Introduction

Machine Learning (ML) is one of the most rapidly evolving areas of modern technology and it is now being applied in many different fields. Corporate learning and performance is an area that can greatly benefit from the data insights that can be generated using Machine Learning. The large amounts of rich activity data being generated by many LMS and HR platforms provides opportunities for Machine Learning to analyse patterns in the data and make recommendations, predictions and supportive interventions in future learning activity.

This Phase 1 core project presents a broad look at Machine Learning techniques and how they could potentially be applied to analyse corporate learning and performance data. This includes an overview of key Machine Learning concepts and considerations to be taken into account when applying in corporate learning and performance scenarios including the problem, data, ML tools and requirement for human involvement. Next, some potential applications of Machine Learning to corporate learning and performance challenges are presented. This includes a focus on key areas of analytics and reporting, personalisation and recommendation, chatbots/virtual assistants, assessment and feedback. Finally, some conclusions are presented and potential approaches for future projects in this field are described. This includes a project focused on using Machine Learning to help in the early identification of at-risk learners. In the long-term, this new project will look to put into practice some ML techniques using real learning data and apply them to gain deeper insight into learner's activity.

## 2. Key Considerations in the Application of Machine Learning

There are many fundamental concepts underpinning the application of Machine Learning (ML). As the core concepts are extensively covered in many online resources and courses some of the key ones are summarised in this section of the report to provide context for the discussion in later sections. Some of the most important concepts are:

## Understanding the Problem

- The type and complexity of the problem you hope to address greatly impacts on the implementation of ML<sup>1</sup>. Understanding the problem and the possible approaches that can be taken to develop solutions is a large part of implementing ML.
- In general, ML is a broad collection of approaches including Supervised, Unsupervised and Reinforcement Learning.

## Types of Machine Learning - At a glance

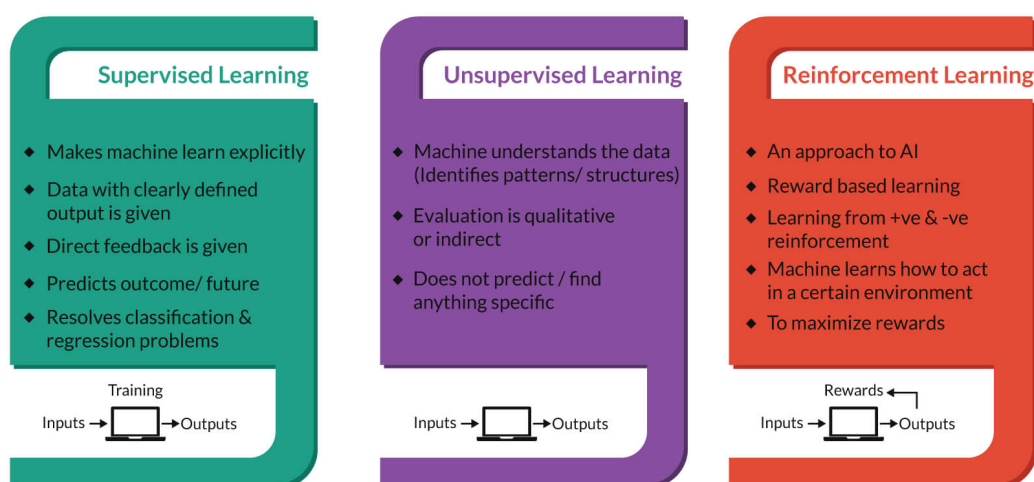


Figure 1: Types of Machine Learning<sup>2</sup>

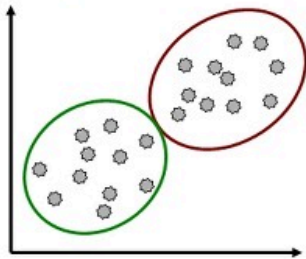
- The most commonly applied supervised approach to ML can generally help with two types of problems:
  - Classification of new samples into known classes
  - Determine an expected value based on previous values
- These types of problems predict future outcomes based on input data. If you need to make predictions based on large volumes of input data, supervised ML tools could potentially provide a suitable approach.
- The less widely used unsupervised form of ML can help analyse data that is not labelled and therefore cannot be used to train an algorithm. In this case, clustering methods can be used to automatically identify patterns in the data. A simple comparison of the clustering and classification approaches is shown in Figure 2.

<sup>1</sup> <https://www.techemergence.com/how-to-apply-machine-learning-to-business-problems/>

<sup>2</sup> <https://upxacademy.com/introduction-machine-learning/>

**CLUSTERING**

- Data is not labeled
- Group points that are “close” to each other
- Identify structure or patterns in data
- Unsupervised learning

**CLASSIFICATION**

- Labeled data points
- Want a “rule” that assigns labels to new points
- Supervised learning

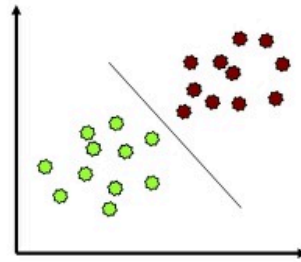


Figure 2: Clustering and Classification<sup>3</sup>

- There are many related fields of ML such as Natural Language Processing (NLP), Computer Vision, Recommender Systems that are significant research fields on their own and can be used to develop specialised ML solutions in specific contexts.
- The use ML has grown significantly in recent years and is seen as fundamental to the development of future technology approaches. However, there can be a temptation to try and apply it in situations where it is not needed. In some cases, more straightforward analytics or statistical approaches would provide most of what is required without the need for more complex ML technology libraries or products. Often useful insights can be gained from using, for example, basic linear regression on clean data, without having to delve deeper into complex ML algorithms.<sup>4</sup>

## Data Quality

- There are several steps involved in the supervised learning form of ML including getting data, cleaning the data and training the ML model.

<sup>3</sup> <http://arisri.tistory.com/m/126?category=389371>

<sup>4</sup> <https://www.techemergence.com/how-to-apply-machine-learning-to-business-problems/>

## Steps to Predictive Modelling

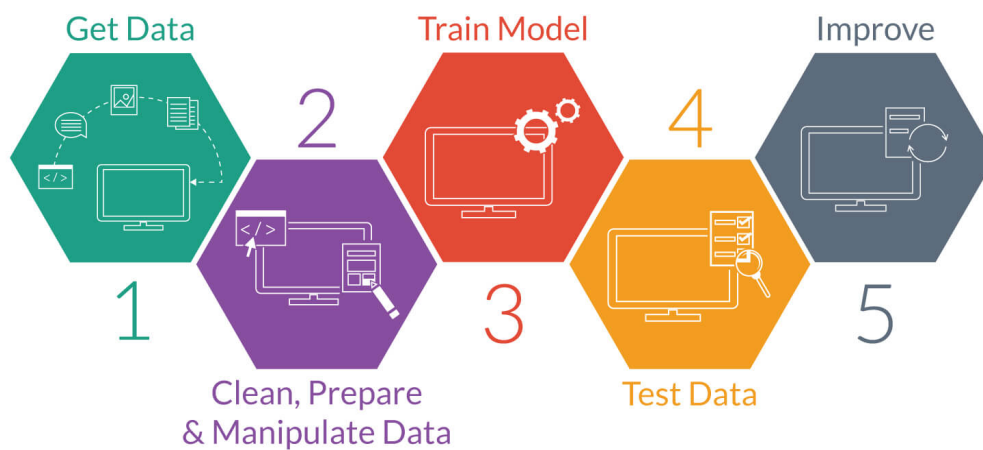


Figure 3: Steps of a Machine Learning Process<sup>5</sup>

- The quality of the input data has a huge impact on the ability to extract useful findings from the ML process. Poor quality input data will produce a poorly trained model which in turn will perform poorly in predicting with accuracy new input data. Ultimately, the application of ML is only as good as the data that is available.
- Cleaning the data can be a difficult and time-consuming task. This involves getting the data into a consistent structure and format and dealing with missing or inconsistent areas of the data.
- Another question which must be addressed is how recent does the data need to be? Generally, more data is better for the ML model to learn from but older data in some systems can often be irrelevant or even misleading in a new context and may train the model to inaccurately identify new data.
- The input data must also be labelled with a specific result for training within the supervised learning approach to be possible. This is not always the case with legacy data and it may not be possible to use some ML methods depending on the availability and quality of the data.
- In the case of unlabelled data that cannot be labelled, unsupervised learning processes such as clustering can potentially still be conducted depending on the objectives of the processing.
- Another consideration is the margin of error of the ML processing. What is the purpose of the data processing and how critical is the outcome? For example, in a learning context

<sup>5</sup> <https://upxacademy.com/introduction-machine-learning/>

automatically processing data to assist formal assessments can be a highly-critical output and requires a very low margin of error. In comparison, recommending content to learners could tolerate a higher margin of error and therefore may be quicker and easier to implement.

## Machine Learning Algorithms and Tools

- Many different ML products have become available such as the various ML services available on Google Cloud, AWS and Microsoft Azure. These services are cloud-based, highly scalable and integrate with other necessary services in these cloud ecosystems, e.g. data storage.
- Recently, some more targeted and user-friendly ML services have become available such as Google Cloud AutoML<sup>6</sup>. These services are aimed at making ML quick, easy-to-use and accessible for non-expert users for specific tasks such as image recognition. However, these types of service generally trade-off flexible customisation for greater ease-of-use.
- There are also many open source tools and libraries available that can be used to design highly customised ML solutions leveraging many different algorithms such as those shown in Figure 4. For example, TensorFlow and CNTK are open sourced ML projects from Google and Microsoft. Others are community-driven open source projects such as scikit-learn. Often these type of open source tools and libraries are a good fit for bespoke problems that require levels of customisation not possible from the available cloud-based services.

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<sup>6</sup> <https://cloud.google.com/automl/>

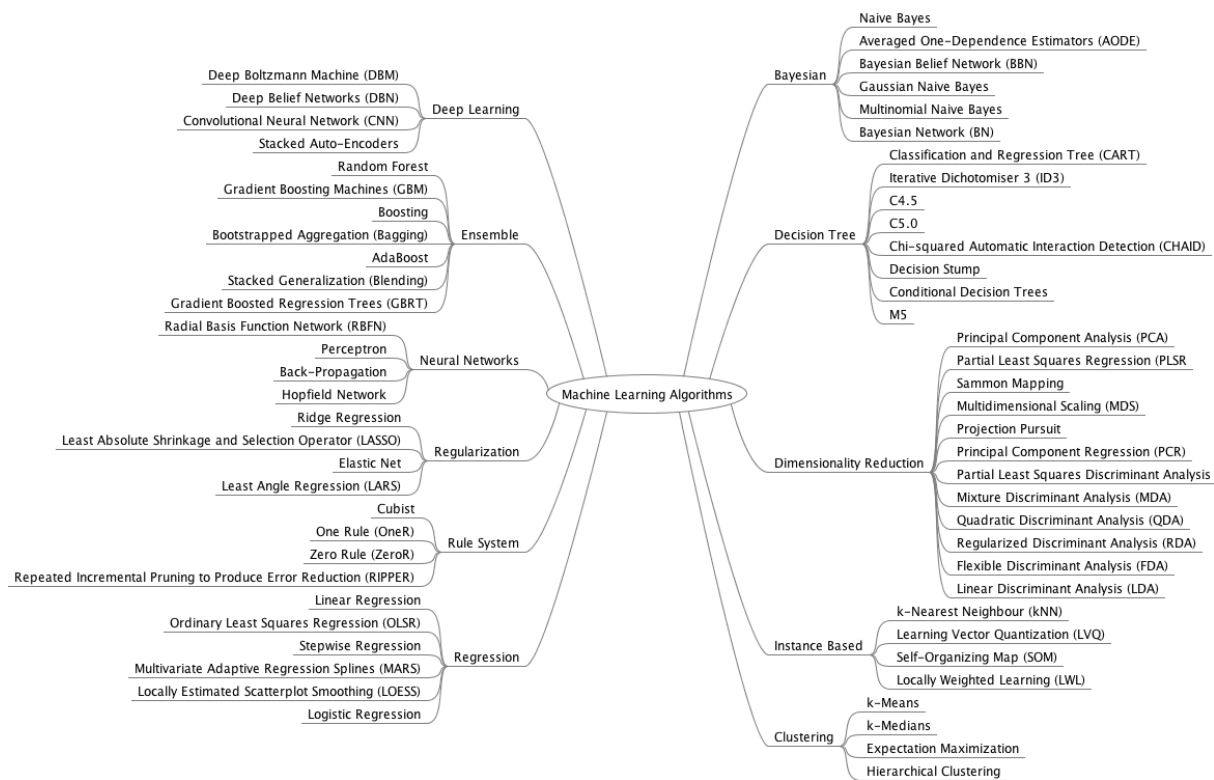


Figure 4: Overview of Machine Learning Algorithms<sup>7</sup>

- Ultimately, to successfully implement ML in an effective and cost-effective way it is important to select the right tool for the job. This largely depends on how complex the problem is and what type of input data is available.
- Often a lot of time can be wasted on the setup of complex ML infrastructure that is unnecessary for the project objectives and ultimately leads to limited impact that could be achieved with a much simpler implementation.
- Training of the ML algorithm is a critical component and again the quality of the data and complexity of the problem are the major influencers on this process.

## Human Input

- While ML provides a way for algorithms to learn from data in order to perform useful predictive tasks such as classification, clustering and estimation much of the context for these processes is still provided by humans. This means that a person needs to interpret the output of the ML process to fully understand what the result means in the overall context of its implementation. ML is a data processing task and the output depends greatly on the quality of the input data and the configuration of the ML algorithms. To understand the context of the ML output, the person also needs to understand the input

<sup>7</sup> <http://web.utk.edu/~wfeng1/html/algsummary.html>



data and how it's being processed. In this way, human input is still an important part of the application of ML until it can be refined to level where the output reaches an acceptable quality-level. ML applications needs to be adjusted to find an optimal solution and this can include changing the amount or type of input data.

- The requirement for human input in the application of ML has been described as: "It's precisely because machine learning and artificial intelligence platforms are supposed to be "smart" that they pose uniquely challenging organizational risks. They are likelier to inspire false and/or misplaced confidence in their findings; to amplify or further entrench data-based biases; and to reinforce — or even exacerbate — the very human flaws of the people who deploy them."<sup>8</sup>

### 3. Applications of ML for Corporate Learning and Performance

The use of Machine Learning has grown significantly in recent years and it is now becoming a common approach used in many fields. Some of the areas where it has gained greatest impact are web search, email spam filtering, marketing personalisation, product recommendation, dynamic pricing, financial trading, fraud detection and chatbots.<sup>9 10</sup> As the learning domain often lags behind other fields in terms of technology adoption it is slowly beginning to be applied for educational and performance uses, particularly in corporate scenarios across both HR and L&D.

#### HR Applications

- There is often overlap between the Human Resources (HR) and Learning and Development (L&D) functional units in many organisations. This is necessary as HR is often responsible for assessing employee performance while L&D is responsible for improving employee knowledge and skills.
- ML can have a significant role to play in both areas, however, at present it seems that it is being deployed more for specific HR tasks such as recruitment which are seen as high value in today's market. Organisations are now using the predictive benefits of ML for tasks such as<sup>11</sup>:

<sup>8</sup> <https://hbr.org/2018/01/is-murder-by-machine-learning-the-new-death-by-powerpoint>

<sup>9</sup> <https://hbr.org/2017/05/8-ways-machine-learning-is-improving-companies-work-processes>

<sup>10</sup> <https://www.techemergence.com/machine-learning-in-human-resources/>

<sup>11</sup> <https://elearningindustry.com/predictive-analytics-in-corporate-elearning-top-reasons-using>

- Attracting and retaining top talent
- Applicant tracking and assessment
- Individual skills management/performance development
- Identifying individual training needs
- Attrition detection
- Improving employee satisfaction
- Revealing hidden HR assets
- **Workday** is one example of a company building predictive analytics based on ML into their core products. **Workday Talent Insights** is “the first application available as part of Workday Insight Applications, a product suite that applies data science and machine learning methods to help customers make smarter financial and people management decisions. With Workday Talent Insights, customers can confidently tackle talent-related challenges such as identifying a top performer at risk of leaving the company or pinpointing issues with hiring initiatives that could impact business performance.”<sup>12</sup>
- Many other companies such as **LinkedIn** are using ML for job recommendation based on user data<sup>13</sup>.
- ML for HR has been described as “the development of a more people-centric approach, paving the way for more valuable programs and less wasted time; reduced bias in programs; less administration and more individual development; and the ability to act proactively rather than reactively, moving seamlessly from the level of the individual to the organization and back again.”<sup>14</sup>

## L&D Applications

- Much of the focus on applying ML has been in the HR sector to date and not as much in L&D. This may be because L&D is often seen as less likely to offer significant ROI. However, some learning platforms such as the LMS offer a lot of potential for ML benefits due to the large amounts of data they generate from learner activity.
- There are significant opportunities for the application of ML to corporate learning and performance data. In particular, one key area that ML is currently being used is in predictive analytics and reporting of new insights into learning data. A second key area is in the personalisation and recommendation of learning resources.

<sup>12</sup> [https://www.workday.com/en-us/company/newsroom/press-releases/press-release-details.html?id=1940591&\\_rda=/company/news\\_events/press\\_releases/detail.php#.VrCaC9J94dV](https://www.workday.com/en-us/company/newsroom/press-releases/press-release-details.html?id=1940591&_rda=/company/news_events/press_releases/detail.php#.VrCaC9J94dV)

<sup>13</sup> <https://www.techemergence.com/machine-learning-in-human-resources/>

<sup>14</sup> <https://www.techemergence.com/machine-learning-in-human-resources/>

## Analytics and Reporting

- The large amount of usage data generated in many learning platforms such as LMS can be a valuable source input for the implementation of ML in a learning and performance context.
- The goal from the application of ML in this context is to gain more actionable insights that are based on past activity and likely future outcomes. This information can be used to develop more detailed and real-time reports on effectiveness and ROI of learning within an organisation.
- One of the most popular open source LMS **Moodle** is developing an analytics API which integrates with ML tools<sup>15</sup> to help provide more intelligent predictive analytics such as identifying students at-risk of dropping out of courses. The open ecosystem of Moodle also provides plug-ins that provide ML features and that integrate with other learning data standards such as xAPI.<sup>16</sup>
- Once richer data insights are being generated from ML implementations on learner data other related uses become possible. Predicting likely user outcomes such the ability to identify at-risk learners early can be developed based on ML algorithm outputs that classify or predict performance based on past activity of learner and the past activity of learners in similar situations<sup>17</sup>. These systems can look for patterns e.g. course drop-outs or certification lapses that can assist the company in supporting learners while meeting its training requirements<sup>18</sup>.
- **Cornerstone Insights Compliance Control** platform is one example which predicts the risk associated with employees not finishing a course or learning object by the required deadline, ultimately preventing future non-compliance and potentially negative impacts on the business.<sup>19</sup>
- As well as supporting at-risk learners, a similar approach could also be taken to help identify high-performing learners or learner groups. This type of insight can greatly aid the development of learning strategy and improve overall learning effectiveness as learning can be tailored to the needs of individual learners.
- In a corporate learning and performance context, this type of data insight can also be used to support employee retention as employee development needs are more likely to

<sup>15</sup> [https://docs.moodle.org/dev/Machine\\_learning\\_backends](https://docs.moodle.org/dev/Machine_learning_backends)

<sup>16</sup> [https://moodle.org/plugins/local\\_smart\\_klass](https://moodle.org/plugins/local_smart_klass)

<sup>17</sup> <https://www.edsurge.com/news/2017-10-16-anticipating-and-addressing-challenges-with-technology-in-developmental-education>

<sup>18</sup> <https://elearningindustry.com/machine-learning-in-corporate-elearning-use>

<sup>19</sup> <https://www.cornerstoneondemand.com/company/news/press-releases/cornerstone-ondemand-announces-new-cornerstone-insights>

be identified and supported. Improving employee retention helps avoid the expense of hiring new staff.

- Ultimately, greater insights gained from real-time analytics and reporting can help guide the development of the overall organisational learning strategy. This can help with more targeted planning and development using learning behaviours, performance indicators, and emerging patterns to personalize online training. Automated feedback can be generated based on ML data and used to support learners and update training programs on a regular basis.

### Personalisation and Recommendation

- ML is now being used in some of the large learning platforms for more intelligent content recommendations for learners<sup>20</sup>. This helps users find more relevant content from the increasingly large volumes of content available both in internal knowledge and learning content repositories and available on the web.
- **SABA** for example claims that “with machine learning at its core, **Saba Cloud** offers proactive, personalized recommendations on candidates, connections and content to help employees and businesses lead and succeed.”<sup>21</sup>
- **Cornerstone** have bought ML focused start-ups and their insights platform now “applies machine learning technology to Cornerstone's massive data set in order to make prescriptive recommendations to address specific business challenges.”<sup>22 23</sup>
- Personalisation is also a key application area of ML in an educational context. ML is being used to offer personalised training paths and adaptable online training resources.<sup>24</sup> This is based on data about employees’ past learning experiences and assessments.<sup>25</sup>
- **Knewton** provides an “infrastructure platform that allows others to build powerful proficiency-based adaptive learning applications. Knewton technology consolidates data science, statistics, psychometrics, content graphing, machine learning, tagging, and infrastructure in one place in order to enable personalized learning at massive scale.”<sup>26</sup>
- **McGraw-Hill Education’s ALEKS** platform is a competing adaptive learning product and provides a “web-based, artificially intelligent assessment and learning system. ALEKS

<sup>20</sup> <https://elearningindustry.com/machine-learning-in-corporate-elearning-use>

<sup>21</sup> <https://www.saba.com/uk/press/news/saba-delivers-complete-modern-learning-experience>

<sup>22</sup> <https://www.cornerstoneondemand.com/company/news/press-releases/cornerstone-ondemand-announces-new-cornerstone-insights>

<sup>23</sup> <https://www.zdnet.com/article/cornerstone-ondemand-nabs-machine-learning-big-data-platform-evolv/>

<sup>24</sup> <https://elearningindustry.com/machine-learning-in-corporate-elearning-use>

<sup>25</sup> <https://trainingindustry.com/wiki/machine-learning/>

<sup>26</sup> <https://www.knewton.com/platform/faq/what-is-the-knewton-platform/>

uses adaptive questioning to quickly and accurately determine exactly what a student knows and doesn't know in a course. ALEKS then instructs the student on the topics she is most ready to learn. As a student works through a course, ALEKS periodically reassesses the student to ensure that topics learned are also retained".<sup>27</sup>

- While personalisation using ML is becoming increasingly popular, a downside is it's algorithmic approach can restrict visibility of the reasons why some content and learning paths are being selected.
- While some of the established companies are building ML into their existing products. Some new start-ups are emerging which are ML and AI driven with the goal of delivering "AI for education"<sup>28</sup>. Two recent examples are **Zoomi** and **Volley**:
- Zoomii's platform "collects the data from the learner's interactions during training. Zoomi finds opportunities and alerts you where students are struggling. Zoomi dynamically adapts training content and creates custom reports with unmatched levels of granular data."<sup>29</sup>
- Volley's platform uses "artificial intelligence automatically ingests, integrates, and adds intelligence to unstructured content from your existing eLearning and knowledge management systems to improve learning engagement, drive growth, and slash costs. Volley's proactive mobile learning games detect employee knowledge gaps and generate personalized solutions automatically."<sup>30</sup>

ML also has significant potential to provide benefits in the areas of assessment and new forms of learner interaction and support such as chatbots where ML techniques have not been as widely used yet.

### Chatbots/Virtual Assistants

- ML can help deliver smarter interfaces for learners such as chatbots or virtual assistants.<sup>31</sup> Chatbots have many potential benefits over existing approaches particularly for task-driven learning support.<sup>32</sup>

<sup>27</sup> [https://www.aleks.com/about\\_aleks](https://www.aleks.com/about_aleks)

<sup>28</sup> <https://elearningcarnival.com/2018/03/03/artificial-intelligence-in-elearning-delivered-10-companies-that-can-transform-the-learning-management-with-ai/>

<sup>29</sup> <https://zoomiinc.com/>

<sup>30</sup> <http://volley.com/>

<sup>31</sup> <https://www.cinglevue.com/learning-educational-applications-chatbot-technologies/>

<sup>32</sup> <https://www.litmos.com/blog/articles/ai-ia-elearning-game-changer>

- They can support learners in finding content they need and directing them to learning tasks. Learners have an always available resource that they can ask for support when needed.
- They can provide a more intuitive and regular form of both learner and tutor feedback including performance feedback and the identification of skills gaps in learner's training.
- They are good at handling administrative tasks such as scheduling training, setting assessment deadlines, sending reminders, etc. This is particularly useful in an organisation where there are required compliance courses that must be taken by staff.
- They are also good delivery methods for learning approaches such as micro learning and spaced learning as they can regularly deliver small segments of learning when it is needed.<sup>33</sup>
- They can combine with and act as the delivery mechanism for many of the other ML-driven methods described previously based on analytics, personalisation and assessment.<sup>34</sup> The ML algorithms are combined with NLP techniques to analyse and learn from large volumes of natural language speech and text.
- As they are typically built upon existing messaging platforms such as **Slack**, **Skype** and **Facebook Messenger** or a virtual assistant platforms such as **Siri** or **Alexa** they have relatively low development costs using a voice or chat UI. In many cases, the ML is being handled by the underlying platform thus making its application in the learning domain much easier.
- **SnatchBot**<sup>35</sup> is one example of a bot platform that allows users to easily set up chatbots in different domains such as education. It can run on multiple platforms such as Slack and Skype.
- One of the biggest benefits of chatbots is that there is a consistent, simple UI and reusable underlying technologies such as ML. This means that they can adapted to different usage scenarios relatively easily.
- Chatbots can help direct learners to courses or resources that address learning requirements. This can be based on learner requests or on organisational requirements such as compliance training.
- Ultimately, chatbots and intelligent agents have made significant progress in recent years. They are not commonplace in learning situations yet but will likely become an

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<sup>33</sup> <https://elearningindustry.com/chatbots-in-education-applications-chatbot-technologies>

<sup>34</sup> <https://blog.chatteron.io/are-chatbots-the-future-of-learning-and-development-for-employees-23ee133dee62>

<sup>35</sup> <https://snatchbot.me/education>

integral learning tool over time. As they deliver large amounts of learning data they offer some of the best opportunities for the integration of ML in a learning content.

### Assessments and Feedback

- ML can be a driving force behind more efficient online assessment strategies. By processing large amounts of user data more intuitive, intelligent tests and quizzes can be provided to learners that meet their needs.<sup>36</sup>
- Some systems can automatically formulate appropriate test questions in reaction to learner activity. This can be delivered when needed to provide more dynamic and effective assessment strategies with learning platforms.
- Companies such as **Kahn Academy** are using ML to improve assessment of student knowledge of topics.<sup>37</sup> This is then used to provide a better overall user experience that is tailored to specific user needs.
- Using ML techniques to deliver automated assessments also helps provide the ability to scale and avoid bias<sup>38</sup>. Assessments conducted by humans are inevitably more difficult to scale and maintaining a consistent standard across large numbers of learners and reviewers is difficult. Automating these approaches can mitigate some of these problems, particularly in situations where simple and standardised forms of assessment are suitable.
- While ML can provide opportunities to automate some forms of assessment for learners it is still important for human-led approaches such as peer evaluation and instructor evaluation to be used in situations when interpretation and context of the assessment is beyond the current capabilities of machines to process.
- Machine learning approaches can use anomaly detection to identify exceptions and outliers in the data that may require more extensive inspection by reviewers. In a learning context, these techniques can also be used to indicate high or low performing learners and also highlight potentially illicit activity such as plagiarism.
- Feedback is a critical part of assessment and with the advent of more personalised learning paths and content the need for individualised, regular feedback is also becoming more important. Using ML techniques in assessment can provide opportunities to automatically provide contextualised feedback for learners when they are in the midst of their learning, not at a later date when it may be less effective.

<sup>36</sup> <https://www.infoworld.com/article/3176485/artificial-intelligence/how-ai-could-affect-the-world-of-corporate-training.html>

<sup>37</sup> <http://david-hu.com/2011/11/02/how-khan-academy-is-using-machine-learning-to-assess-student-mastery.html>

<sup>38</sup> <https://trainingindustry.com/wiki/machine-learning/>

- Beyond simple assessment options such as multiple choice questions, ML and NLP techniques can be used for grading essays. For example, **Pearson WriteToLearn**<sup>39</sup> and **Turnitin Revision Assistant**<sup>40</sup> can help score essays, provide automated feedback and detect plagiarism.
- This reactive and more regular assessment and feedback loop also creates more data which feeds ML approaches leading to greater insight into learners activity and performance.

## 4. Future Work

As can be seen in the previous sections, there are many potential applications of ML to support corporate learning and performance. There is potential to explore many different aspects of ML for learning within Learnovate core projects. One new core project that has been proposed involves identifying at-risk learners using ML. This project idea has been approved for Phase 1 and will build upon the initial machine learning knowledge developed in this project and apply it to the use case of identifying at-risk learners.

### Identifying At-Risk Learners using ML

#### Customer

Organisations from various sectors (e.g. corporate, higher ed and schools) with an interest in the early identification of learners who may be at-risk of disengagement and not completing their learning objectives. These organisations would be interested in applying learning analytics and machine learning techniques to their learner data to identify trends and provide greater support for at-risk learners.

#### Problem

Not identifying disengaging and at-risk learners early enough can have many disadvantages for both learners and organisations. For the learner, not receiving required support can lead to total disengagement from a learning programme. There can be significant time and financial impacts on learners that do not complete their planned learning objectives. For organisations, higher disengagement rates can negatively impact on the overall success of learning programmes. There are also significant efficiency and financial costs for organisations related to at-risk learners such as repeated training and learner appeals.

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<sup>39</sup> <https://www.writetolearn.net/>

<sup>40</sup> [http://turnitin.com/en\\_us/what-we-offer/revision-assistant](http://turnitin.com/en_us/what-we-offer/revision-assistant)



## **Solution**

Learning analytics and machine learning have the potential to greatly improve the identification of at-risk learners and allow appropriate support to be provided earlier. This Phase 1 project would consist of research into current approaches for identifying at-risk learners from learner data and possible applications of machine learning models to improve these approaches. A potential Phase 2 follow-on project would identify suitable datasets from interested industry partners and apply existing open source and commercial technologies to develop machine learning models that can be used to identify and support at-risk learners. Some examples of learner data that may be relevant would be user logs within an LMS or data gathered from platforms using xAPI or Caliper.

## **Opportunity**

The application of learning analytics and machine learning has broad commercial opportunities in terms of the delivery of new, advanced platforms that can learn and support both the learner's needs and organisational decision making. Early identification of at-risk learners can help improve the learner experience by providing necessary support earlier. Across various sectors, this information is important at an organisational level to assist in learning strategy development and reduce the time and financial costs associated with at-risk learners such as repeated training and learner appeals.

## **5. Conclusions**

There are many opportunities to use ML to improve corporate learning and performance. There are some key factors that influence how effective ML solutions will be to particular problems in learning and performance scenarios.

Gaining a good understanding of problem and defining clear objectives is critically important. In some cases, more complex ML solutions may be unnecessary when a simpler solution would be sufficient. The complexity and type of problem needs to be understood in order to apply the appropriate method. Are you trying to predict a future outcome, identify trends, organise data, or detect anomalies? Each of these challenges has a different solution which will involve varying degrees of analytics, statistical methods or ML.

In combination with understanding the problem, the quality of the data is critically important in any ML project. In the context of corporate learning and performance for example, is there enough quality data available in LMS or HR systems to apply ML to existing learning and performance challenges. ML output is only as good as the quality of the input data. Cleaning and processing the input data is often an underestimated part of applying ML. If the source data is not ready to be processed it can take significant amounts of time and effort to get it into a condition that will produce the desired outcomes.

The selection of appropriate ML tools to implement the solution is another factor to carefully consider. ML is a rapidly evolving field and large software companies such as Google, Microsoft and Amazon are developing products that can provide more easy-to-use and accessible ML services for specific purposes such as image recognition or NLP. For many purposes these services may be sufficient and provide much of the scalability and supporting components to reduce the cost and time effort of implementing ML. However, in some cases, more customisation is required and open-source libraries such as scikit-learn or TensorFlow can provide a better platform on which to build highly customised ML solutions.

While ML is fundamentally about teaching machines to handle and interpret large volumes of data to be successful there is still need for human input. Human input can also be required when interpreting the outputs of ML processing. In this case, understanding the input data, how to design and train the ML model and interpret the results and the overall context of the approach is key in delivering ML that is both effective and accurate.

When examining the market of existing learning and performance platforms, it can be seen that ML is being used and there are some key areas where it has made early impact. This includes improved forms of analytics and reporting of learning and performance data. This helps the learners, the tutors and the organisation to better understand learning and how it functions in the organisation. It particular it adds predictive features to analytics which allows trends to be identified and earlier action to be taken, such as supporting a learner at-risk of not completing a course. The personalisation and recommendation of learning resources is another major current use of ML in learning platforms. In this context, ML is used to interpret large volumes of data and content and match appropriate content to learners needs based on their and other user's previous activity.

While analytics, reporting, personalisation and recommendation are the most common uses of ML in learning at present, there are many other areas where it could make a significant impact in the future. In particular, chatbots and virtual assistants have the potential to become a key driving force behind the application of ML. Indeed, some of the generic chatbot and virtual assistant platforms are already driven by ML and NLP techniques and have many features available which could be used in a learning context. In these cases, chatbots can be built and trained for learning without much technical development as other services provide much of the underlying platform. Chatbots also rely on much simpler UI elements that do not require significant design and development.

Finally, while ML is making an impact on the information and content within learning there is also significant potential to apply it to advance assessments and feedback for learners. More intelligent, automatically generated assessments can be delivered based on real-time data that is being processed by ML algorithms. This provides opportunities to predict the best occasions to provide assessment and what formats it should take. The advances in ML and NLP techniques provide opportunities to develop automated or assisted grading of more complex material such as written reports. More intelligent assessment methods can also be used as a basis for more regular feedback such as advice on a learner's predicted skills gaps. This could combine with the other areas such as personalisation and recommendation to deliver a cohesive learning approach built using ML.

Ultimately, ML has made slower progress into the learning and education sectors than it has in other high-profitability areas like financial trading or consumer-focused platforms. However, it is beginning to appear in many established learning technology platforms for specific purposes such as improving analytics, reporting, personalisation and recommendation. There are also new ML and AI focused start-ups emerging in the learning domain and will likely start to push adoption of ML into mainstream learning platforms.

The amount of data being generated from learning platforms continues to grow with the use of more data tracking, analytics and the emergence of learning data standards such as xAPI. ML techniques will inevitably become more necessary to deal with the large volumes of data that can no longer be managed efficiently or effectively using traditional data processing techniques. While ML not a solution to all learning problems, when properly applied it can provide significant benefits across a wide range of learning and performance areas. It has potential to provide more informed, reactive and effective learning platforms that can support

the needs of today's learners and drive a more data-centric approach to the delivery of learning and learning strategy within organisations.