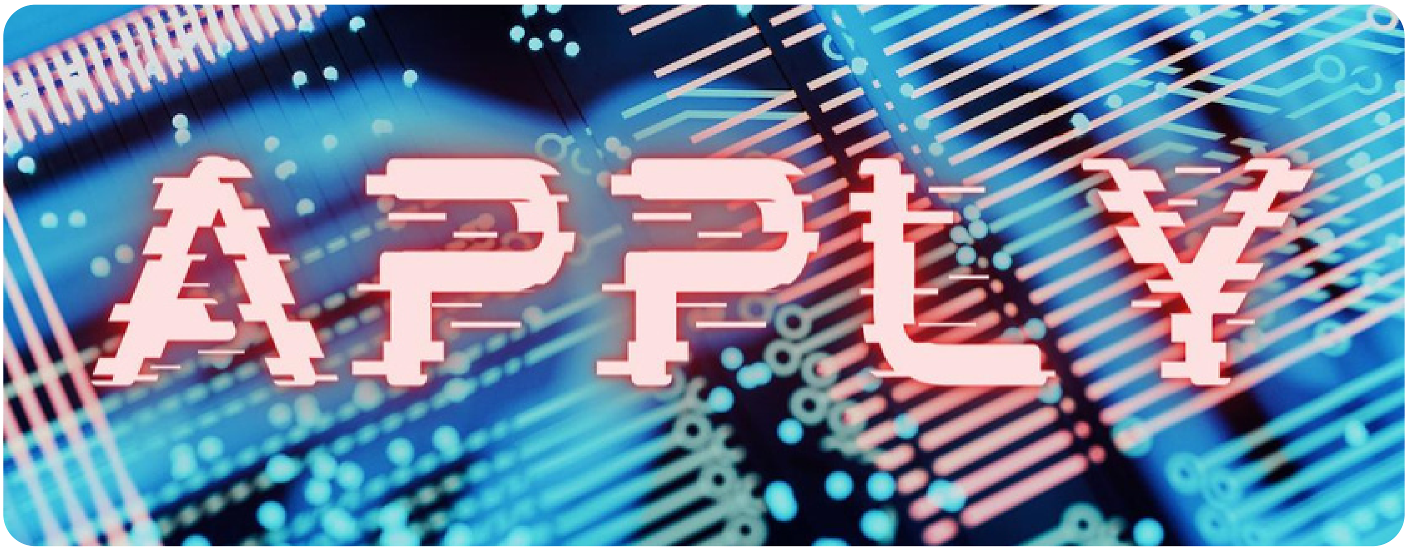
AI Readiness Diagnostic Findings

Step 5: Ready Recommendations



Step 5 Overview

To find out how you can benefit from examining your institution through a 'data and AI lens', contact our AI & Data Science team at hello@educateventures.com

- The kind of machine learning AI that has been discussed in all the recommendations for the AI Readiness Diagnostic Findings has so far been **supervised** machine learning. This is the type of machine learning used when you want to train the AI to find something **specific** in the data, such as a child's face, or particular grade of exam script

- However, we **do not always know exactly** what we want the AI to find in data, so we need another type of machine learning that can find patterns in the data: **unsupervised machine learning**

- This is the tool we use in a situation where **we do not know what we are looking for** and so we cannot get the **algorithm** to learn what the **target data** we want to find looks like

- With **unsupervised** machine learning, the algorithm looks for **patterns,** searching for **similarities** that might surprise us

- Data that might be fed into an unsupervised machine learning algorithm could be:

  Log data from interactions with an online learning platform such as mouse clicks

  Audio from user conversations in breakout rooms in Zoom

- **Performance data**

- **Eye-tracking data**

- **Survey responses**

- Preparing this data is key and deciding what machine learning AI technique to apply to it will depend on the **context**

- You may not want to use **all** the data you have with just one AI technique anyway. You may end up applying some machine learning, and with the remaining data, using some more **traditional methods** not based in AI

- Human intelligence will need to be used to help clean – **label** – the data as well, in removing **errors,** and **feature engineering**

- Feature engineering is where humans help **describe** patterns so that the AI isn't scrambling about identifying commonalities with the data that make absolutely **no sense**

- **Key Takeaway:**

- Unpacking what AI can do with the data that you've got will let you make greater sense of both the **data** you've collected, and **the challenge itself.** It may even reveal something in the data you had no idea was there. But it takes a lot of time to **prepare** the data, and if it isn't **clean,** you can get a lot of nonsense information out the other end. With an **increased understanding** of your challenge, you will be in a much better position to select the **AI tools and products** you need to make your life easier in your educational setting or business

Recommendation: Approaches to applied AI, part 1

Before we begin: it is not expected that you are able to apply the following AI techniques to your data, rather, that by familiarising yourself with them, you understand more about AI and how it might help you approach your challenges

SUMMARY: help contextualise the process of applying AI by likening it to the process of cooking. Cooking methods, ingredients, and washing and chopping all map on to the steps needed to prepare data for AI

• It's time to prepare to apply some of the **AI techniques** at our fingertips to the **data** that we've collected on our selected **challenge.** For more on **how to pick your challenge and why,** visit **Step 2** in the AI Readiness Framework. An easy way to **conceptualise** our situation then, is to view it a bit like **cooking.** There's lots of ways to make a **recipe**

• The point of discussing cooking is to show that the **fundamental principles** are not so dissimilar when it comes to data and the application of AI, and particularly the use of machine learning. Think of the data we have as being **ingredients**

• In terms of AI techniques - **cooking methods** - we have many that are available to us. Once the options have been refined to one (in this case the discussion will be about **unsupervised machine learning** - arbitrarily equivalent in our analogy to the cooking method of **baking**) we will still have choices to make about how precisely we wish to **combine** the data - our ingredients

• There are also lots of different AI techniques that we can use if we add in **Good Old-Fashioned AI** (GOFAI) as well as machine learning and then **deep learning.**

It's really about trying to pick what's best for the **ingredients** - for the data - and for the purpose of exploring our data to **learn more** from it

• Our goal in the analogy is now to produce 12 identical **desserts.** The question becomes **how,** and **what type** of dessert. Meringue, trifle, cake or souffle?

• Let's make a souffle:

• We have to go through a set of **preparations** in order to be able to bake. Think of the baking as being a machine learning **algorithm,** and we've got to do a lot of preparation before we start

• First, we have to **wash** our raspberries. Then we have to **crack** the eggs and **whisk** them. Then we have to **add** the sugar into the eggs, and then **whip** up the cream

• There is a bit of **muscle action** needed for the whipping up of the cream. We have to **add** that cream to the beaten eggs to which we've **added** the sugar. And then we need to **scoop** it all together in a bowl and **pour** the mixture into little souffle dishes, and **add** a raspberry on the top as well

• Then we need to **repeat** until we have our 12 beautiful raspberry souffles, ready to go into the oven to be **baked**

• It probably takes longer to do all that preparation than it does to bake them, because a souffle is really quick to bake

Recommendation: Approaches to applied AI, part 2

SUMMARY: help contextualise the process of applying AI by likening it to the process of cooking. Cooking methods, ingredients, and washing and chopping all map on to the steps needed to prepare data for AI

- AI is not the only way to **analyse** data and many of the traditional ways of analysing data, such as **statistical analysis,** are well-tested and perfectly valid analytical techniques. We use AI, however, to discover something **extra,** and we use it to learn more about both it, and our challenge

- Recall that we have data - our **ingredients** - around our fictional challenge (that of maintaining the quality of teaching and learning online during the pandemic) and this data consists of perhaps **recordings** of students taking online courses, or **log data** from interacting with a voice-activated personal assitant, or maybe some graded **assignments**

- We need to think what **broader** set of ingredients we can include: the extra kinds of things that are going to make a difference

- With the raspberry souffle analogy, we decide how we mix all those ingredients, and use different techniques on them to prepare them. We **wash**, we **clean**, we **mix** two different types of data to produce an **outcome** - our desserts

- From our example challenge, we could examine: Data from **interactions** that students have, as they're learning online - log data interactions with technology

- That could include **button clicks** for example – how quickly or slowly students are clicking the **mouse** or pressing the **keys**

- **Conversations**, perhaps recorded through the online platform, or in breakout rooms or actually conversations that happen face to face

- **Performance data**

- We could have a whole host of different types of data, and some of it could be from the last few weeks, and some of it could be more historical. We could have lots of **live recordings** of the sessions, and we might be able from that data to have included something about **eye tracking** so we can see the user looking at the camera, at the other people. Are they looking at the task, are they looking at something else? We're talking about situations where we either have:

- Some of the users in a physical location, in the lecture hall, in the seminar room, and some **online,** or

- We have **everybody** online

- Some back present in a **physical location** and a few people **online**

- It's a **mix.** So think about data that comes not just from online but also for students who are present physically for at least part of the time that we're interested in analysing and discovering more about

- And what has all this got to do with **machine learning?** Read on to find out!

Recommendation: Types of AI that can be applied, part 1

SUMMARY: a quick introduction to supervised and unsupervised machine learning, and how the data for either should be prepared

- Machine Learning is a huge set of different sorts of **techniques** and there isn't space here to explore all of them. Increasingly, people become **specialists** in a particular technique or a particular **category** of techniques. The point of covering them here is to **familiarise** you with the kinds of things AI can do, to help you learn more about your **challenge** and how AI might assist with it

- For our cooking analogy, which we have developed for our challenge - that of maintaining the quality of **teaching and learning online** during the pandemic - **supervised machine learning** and **unsupervised machine learning** will be the AI techniques we study

• In a **supervised** situation, we **know** what we're looking for. The algorithm is set off to explore the data, and **identify** what we're looking for

• In an **unsupervised** learning situation, however, we are in a situation where we **don't know** what we're looking for. The algorithm explores the data to look for **patterns** or **similarities** in the data that might tell us something we **don't** already know

• They are two different types of machine learning for two different sorts of **activities.** What we want to achieve is either **identifying** something within the data, or exploring the data to look for **patterns** in the data

• With **supervised** learning, **classification** can be used to classify the particular types of things within a data set. With **unsupervised** learning, **feature reduction** and **clustering** will be used. Revisit the steps above to remember what data we might have at our **disposal**

• In terms of the workflow of our example, there are four different sorts of data: **logs, performance data, recordings, and survey results**

• Now we prepare that data. In the cooking analogy, we **washed, cleaned, mixed, added, broke some eggs etc.**

• In our example challenge, the baking is like applying the **algorithm,** and there are all those other things we have to do before we open up the oven. So that's precisely what we need to do now: we need to bring all these different ingredients **together**

• Clean the data

• Organise the data

• Transform the data into a dataset

• Cleaning and organising: we are going to make the data **uniform;** try to make it look **neat** and **nice** and **easy to work with,** like you might in a spreadsheet

• It's really important that the data we use in order to conduct our exploration is **very high quality.** It should be **accurate, complete** as can be, it should be **consistent** and **uniform**

• We have to try not to change the **values** of the data that we have, only the way that it's **organised,** in order to ensure that we can use it with our **unsupervised machine learning algorithm**

• Don't think of anything as ever being **raw data.** Raw data doesn't exist, because all data is collected for a **reason;** somebody has made a decision to collect that data, or for that data to be collected whilst other activities are going on. There's a **context** for that data, none of it is just raw, there's always added **contextual information** that's important

• Remember that as soon as we're trying to get hold of that contextual data, we're also starting to run the risk of being **intrusive** and we have to get the balance right. For example, if we're recording everything that's going on when users are online, we're capturing a lot of the **context** of their home background, context of the noises that are happening in their home background, for example. We have to make sure we're **ethical** in the way that we treat that data, if it contains something concerning. Perhaps it invades **privacy,** then we would need to make sure that this was **removed**

Recommendation: Types of AI that can be applied, part 2

SUMMARY: a quick introduction to supervised and unsupervised machine learning, and how the data for either should be prepared

- We have to ensure the **reliability** and **credibility** of the data that we're going to process when we apply our machine learning algorithm. We need to remove **errors,** and look for **impossible values and incorrect values.** There are always **mistakes** in data, so we have to go through it carefully to check that they've been removed. We need to look for **duplicate entries,** for example, **irrelevant data.** Perhaps, in the context of our example challenge, there is data about student age but it isn't relevant to our investigation because it was in an **existing dataset** that we wanted to use, but we didn't want all of the data in that dataset

- Look for **missing data** and look for **outliers.** Outliers are values that are **radically different** to most of the values in the dataset. We have to be **careful** though without those in the main dataset. We can **remove** them, but we have to be careful not to remove too many outliers otherwise we just have **averages.** A **mix** of data is required, but we can decide what action to take about outliers and then make sure that we apply that approach **consistently** to all our data

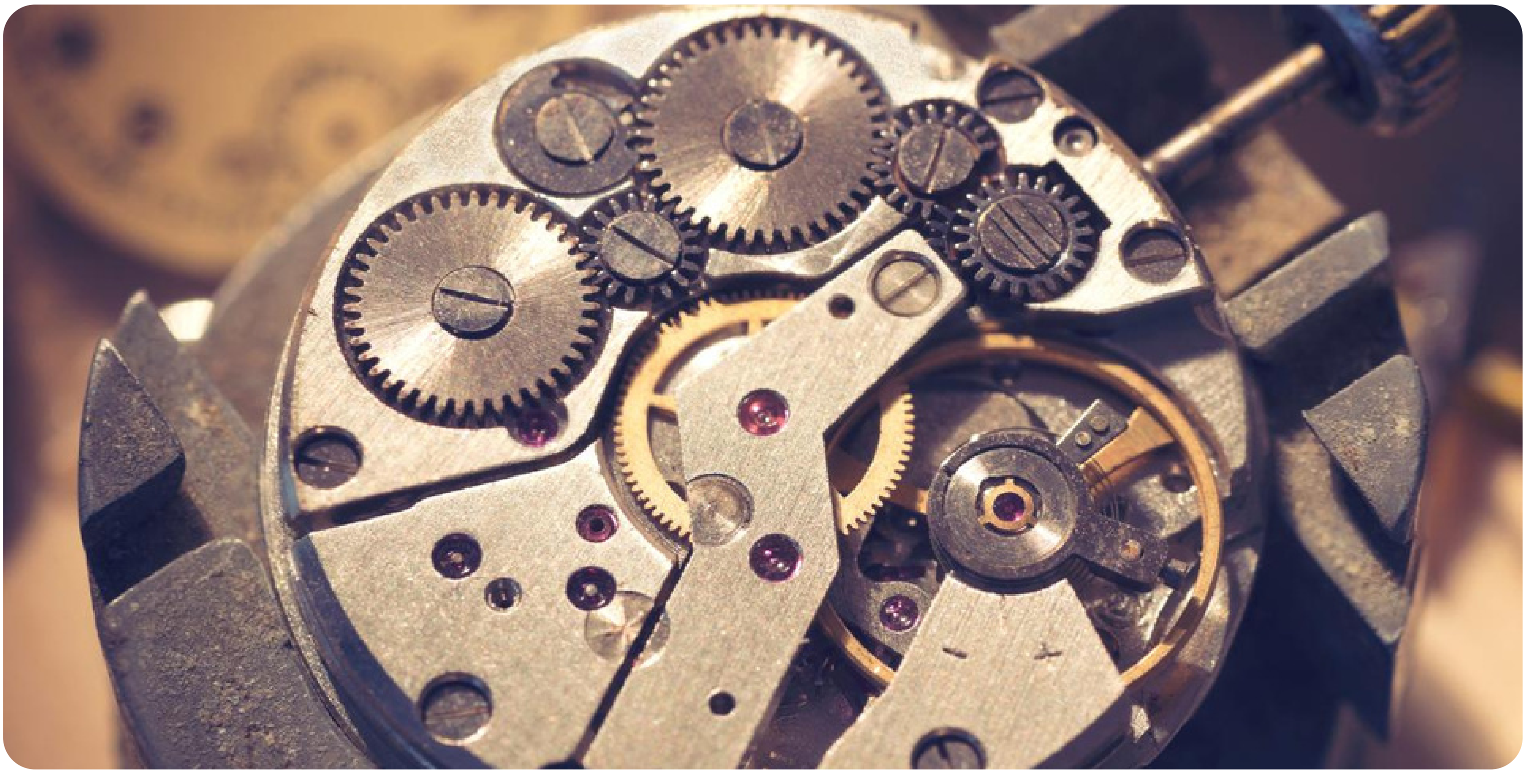
- Different datasets have different **labelling** methods, and so we might have user gender, for example, which could be described in one data set as female or male, and another as girl or boy. There are **typos, syntax,** or **conventions,** and we've got to make sure that all the labels use the **same conventions** so that they are recognised by the algorithm to be the same thing if they are indeed the same. The algorithm won't know that female could be **classified** the same as girl. So we have to make sure that we only use "female" or only use "girl" in the labelling of the data

- Always aim for **quality,** and always **document** the approach adopted, so that if for example the analysis doesn't behave in the **expected way,** we can go back and look at that documentation, and see if there was anything about the approach used that perhaps could have been done **better**

- The precise actions we take depends on the dataset in the same way that, in the baking analogy, we wash the **raspberries** but we don't wash the **eggs** – we **crack** them. We weren't using the **shells,** we certainly didn't wash the **sugar** or the **cream.** It sounds trivial but it's really important that different types of data be treated differently. Doing so ensures reliability and credibility

- **This is a lot of work, and will take at least 80% of the time involved in applying the AI to your data**

- Once the data has been cleaned, and pulled all together, it needs to be **integrated** and any **transformations** performed. **Transformation** means that there may be aspects of the **structure** or **format** of the data that need to be changed in order for it to be analysed more **accurately.** For example, perhaps the format of data that describes actions taken through eye tracking is different for different types of **capture.** Perhaps we thought that we were using the same video capture device throughout the recordings, but actually a **change** was made by our provider without us **realising.** That makes a difference to the **structural format** of the data. So this is not about transforming **values.** This is about **organising** the structure and the format, so that there is **consistency**



Recommendation: Preparing to apply the algorithm

SUMMARY: an overview of the principles of collation, cleaning, organisation, transformation, feature identification and engineering

- Now it's time to see how we apply the **algorithm,** and see what we can find out through this analysis. Recall our fictional example challenge, where we're looking to see if we can find out useful information about the quality and consistency of teaching and learning online during the pandemic restrictions, and beyond

- One of the first things that we need to do once we've **cleaned** all of that data and prepared it and got it into a nice, **reliable, consistent, accurate state,** is to start thinking about our own **expertise.** With **unsupervised machine learning,** we need to use our own **expertise,** as well as the expertise that will come from the data as it's analysed by the machine learning algorithm. Whether you're an **educator, a group of educators, a business entrepreneur, or a tech employee,** you have expertise about the challenge that you have identified, and we need to try and take that expertise into account as we're applying the unsupervised machine learning algorithm to the data that we have. It is a really nice example of the combination of **human and artificial intelligence** working together

- In our example challenge, there'll be certain **features** that educational experts would expect to see in a **high quality interaction** between educators and students, or between students and other students. One of the things we need to do next is make that expert knowledge **explicit,** and the **assumptions** that underlie that expert knowledge

- Making this **underlying knowledge** explicit is part of the process of what's called **feature engineering,** which itself is part of an unsupervised machine learning processing of data. There are other ways of doing unsupervised machine learning, but in this example, what we're going to do is look for features that exist across the many different **interactions** that have taken place according to the data that we've managed to collect and clean and prepare

- For example, as an educational expert, you might know that being **active** – a student being active, a teacher being active - is a feature of importance. Your experience tells you that active students are likely to be **performing** better, to be more **confident,** to get more **satisfaction** from the session, and actually can **help others** get more satisfaction from the session as well

- One of the features that you would like to look at and find in the data is the number of **actions** completed by a student. That's what you would call a **simple feature:** the **numerical value or a set of numerical values** that represents the actions completed by a student

- There are also **engineered features** that are just a bit more complex. This is not as straightforward as the number of actions that a student has completed, perhaps through the logs, for example. Perhaps you also know that in addition to the number of actions, the **proportion** of sessions that each teacher leads in the first five hours of their day are often more **effective**. Therefore a **feature** that's important would be the proportion of sessions that educators complete and that take place in the first five hours of their day. This would be an **engineered or derived feature** because we **don't** have that data. We don't have that **instance.** But what we do have is the **time of day,** and the **identity** of every educator and the **sessions** that they lead. So, we can **derive** – we can **engineer** – that **feature** from the data that we have

- This is a complex process. As mentioned, the cleaning and the preparation takes a long time. If you add in feature engineering, you can see that about **90% of your time** is spent in all of these activities that happen **before** you actually apply the machine learning algorithm

- The **way** in which feature engineering happens of course will depend on the type of data that you have **collected.** It's like everything here. The **type** of ingredients make a difference to the way that we process them

- Some of the most important data from an educational perspective is **unstructured** (everything that is not structured data: **poorly defined, not easily searchable, not straightforward to analyse**), hence why we have to do so much **preparation** before we can start processing

- Unstructured data is the kind of thing that we come across all the time in **tweets, messages, conversations**; it's everything that isn't structured data, and it's becoming the kind of data that is recognised as being extremely **valuable**

- We can also talk about data as being either **quantitative or qualitative.** And so we can think about quantitative data, of course, as being basically represented by **numbers,** by **amounts,** whereas qualitative data might be about how you're **feeling,** for example. It's the kinds of things that we get in **free form answers** to surveys, or conversations

- **Quantitative data is structured. Qualitative data is unstructured**

- Think about the **data sources, different channels or modes of information** that give us **multimodal data** (revisit **Step 3** in the AI Readiness Framework for a refresher on multimodal data), and remember that we spent a long time thinking about the importance of multimodal data. We must think about the different modes, different types. And we need to think about whether it's **structured or unstructured, quantitative or qualitative,** because all these things will make a difference to the way that we treat the data, from the first bit of **cleaning,** to that last bit of **feature engineering**

- Now that the data that has been **brought together, collated, cleaned, organised, and transformed,** as necessary, and the process of **feature identification and engineering** has been performed, what happens next?

Recommendation: Reducing complexity and feature engineering

SUMMARY: an approach to understanding the differences in interactions between teachers and learners, using a technique designed to find patterns in data without knowing exactly what to search for

- Our example **challenge,** that of maintaining the quality of teaching and learning online during the pandemic, has now had its **algorithm** run on its data for the first time, and we find that unless we **reduce features,** there won't be anything **meaningful** for us to **interpret** in the **output.** We must identify features that are the most important for our purposes

- Imagine all of the different types of **interactions** that could have happened involving students and educators: those that could have been about different **subject areas,** that could have been using different **technologies,** they could have been online using one of the **online platforms,** there could have been some face to face sessions on campus at the school, and there could have been learning in home. There are so many different ways of thinking about the interactions that could have taken place, and the above is just a scratching of the surface. As a consequence, there are **hundreds of possible features** that we could look for in order to try and understand **what's been going on**

- Our unsupervised learning is about finding **patterns** in the data when we don't know **precisely** what we're after. 'Which **features** will help to explain the differences between the interactions?' becomes our **key question.** Imagine we have 5**00 different interactions,** different sessions recorded, different sessions for which we've got performance information. This is a huge number of different **interactions** (as we'll call them) that have taken place between students and students, or students and teachers. And we've got lots of different **features** that are ways we believe might be able to **explain the differences between these interactions**

- If we can understand the **differences** between the interactions, maybe we can understand some **common features** that perhaps make a particular sort of interaction more **suitable** for **a particular sort of student,** or indeed, **educator.** Or particular ways of making types of interactions more **effective,** so that we can look at their **consistency**

• One of the techniques that we can use with unsupervised machine learning is called **Principal Components Analysis** (PCA), a **transformation process** which is a kind of **dimension reduction**

• PCA is one of the ways in which we **reduce** the **number of features** that might explain the **differences** between the different interactions that we've recorded

• We need to apply this technique to find out the **principal components** that account for that **variation** between interactions. It's a commonly used method in unsupervised machine learning. The algorithm will go through the process of trying to identify the principal components, and will produce a set of **answers** that explain a certain percentage of the **variation**

• If we think about the **500 different sorts of interaction,** or lessons, and, say, **85 different sorts of features,** we want to come up with a set of **four** or **five,** that explain most of the **variation**

• We will never get a set of features that explains **100%** of the variation that tells you precisely why X lesson was different to Z lesson. What we need to aim for is a **high percentage.** That means that the features that our machine learning algorithm has found by identifying patterns in the data account for a high percentage of the **variation** between interactions/lessons

• If we have five feature dimensions accounting for **85%** of the total variance between the interactions, we might decide that it's worth trading a bit of that **accuracy** to get a **smaller set of features,** because that will be **easier to work with**

• Say that we've run our machine learning principal component analysis and what we've got is **five dimensions** that account for a high percentage of the variation in the lessons:

• One of them is the average amount of **online active students** as shown in their log data

• The second is the **geographic location of the student,** where are they: in home or in school?

• The third is the **style of interaction** – was it whole group or small group collaboration?

• The fourth is the **use of technology:** just the online platform, or online platform and additional technology

• The fifth is the **average age of the educator**

• Now, we might look at those and wonder what the **average age of the educator** has to do with anything. It would seem strange that that would be in those set of features, but the other four look interesting

• We investigate that dimension five, and it's removed with little loss in the overall **accuracy,** with **82%** of the variation still accounted for

• 85% with the five dimensions, 82% with the four. This is not a real analysis of real data, although they are precisely the percentages you would be likely to come up with, and the sorts of features that you might come up with

• Now we have **four features** that can be explored in lots of different ways, because these four features account for a high percentage of the **differences between the different sorts of interactions that happened during the pandemic restrictions** in our fictional challenge

• This becomes our **workflow: data, integrated** and **prepared, features identified, feature engineering** and **selection,** and then a machine learning algorithm that's picked out **four features** that really account for the differences

Recommendation: Cluster analysis

SUMMARY: a technique to examine patterns within the data relating to the features we have selected as our best indicators

- Now we're going to look at another technique from our unsupervised machine learning arsenal, and this is called **cluster analysis.** This is where we look at **patterns,** and use machine learning to see if we can find clusters or patterns within the data that relate to those four **features** that we've selected as being the ones we want to look at. The patterns are going to be based on those four features

- Remember, for our example challenge, we are using **unsupervised learning.** So this process is looking in the data for **natural groupings,** we're not going to have an outcome **predicted.** That would be the kind of thing that we would get from applying a **supervised machine learning algorithm.** This is about discovering **patterns, natural groupings** in the data from which we can learn

- From an **educational perspective,** cluster analysis will allow us to produce **profiles** and profiles can be really useful. In this example that we've been using throughout - looking at maintaining the quality of teaching and learning online during the pandemic – profiles of **different sorts of educational interactions** can be identified

- It may be that our natural groupings indicate that there are **high values** for **small group sessions** and **high levels of activity** from students when they're at home, and that would be interesting, so there could be a **profile** where those features are **highly correlated**

- If we think about four different types of interaction, based on those four features then actually the data groups quite naturally into four different profiles that you can see in miniature on the **right**

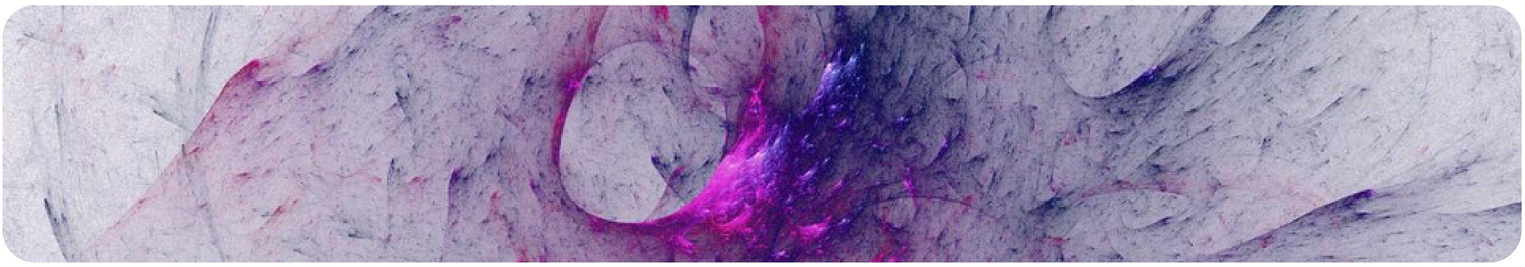
- Let's start at the **green profile,** the one on the far left of the image. That **shape** in the bottom left-hand corner is a **visualisation** of a profile. In this particular profile, you can see that the different values that were found to form a pattern consist of really about **average numbers of actions by students,** and only just **over the average sessions' propensity to take place in school.** The two key things that **distinguish** this grouping, this profile, this cluster, from the rest, are that they're more likely to be just **online,** and more likely to be **whole class.** This is a cluster where there's a pattern that's brought the data together, where the features that really differentiate this pattern, this cluster, this profile, from the others is in the fact that it's about **whole-class sessions and online only.** That's what's important as the **differentiator**

- If we move to the **red profile,** it's quite different. Here, we have got a grouping in the data where you can see a huge red bar that's showing that in this grouping there is a **huge percentage** of the sessions that have been done at home, with slightly **above average activity by the students,** which is interesting. We see the use of **additional technology,** not just the online technology, is being used as well

- Move to the **orange profile.** The distinguishing feature here seems to be that this is about lots of use of **additional technology** – that being a key factor – and **interactions more than average are happening at school.** And perhaps a little bit more **whole classroom/small group**, but the two real features there are the use of **additional technology** and **the activity happening at school**

- Finally the **blue group:** you can see that this is more likely to be **small group than whole class,** and **more likely to be online,** but **not** using some additional technology

- This is starting to get really interesting. We can see that these are features that enable us to build profiles of different sorts of interactions. Now, what we do with these interactions, and these profiles, is what we'll move on to in the **next step of the AI Readiness Framework,** because this is all part of thinking about how we **learn** from the data



EDUCATE

Who can help me?

We are specialists in ethical AI solutions for schools and education and training businesses - contact our team for help

The EDUCATE AI and Data Science team was formed to consult on and co-design ethical AI solutions to complex problems in data-driven technology ventures and schools. Our team of computer scientists, educationalists, and world-renowned experts can take you from zero AI to a comprehensive evidence- led strategy and beyond, with effective, scalable AI-powered teaching and learning solutions.

To find out how you can benefit from examining your institution through a **'data and AI lens'**, and leveraging the transformational power of AI to tackle your challenges, contact the **AI and Data Science Team** at EDUCATE Ventures Research at **hello@educateventures.com**.

Thanks for reading!

- The EDUCATE Ventures Research Team Summer 2023

Further Reading

Below you can find a selection of resources, books, podcasts, webinars, and research papers appropriate to your stage of AI Readiness. Good luck!

- AI for School Teachers, Byte-Sized Edition
An easy-to-read 10-page byte-sized summary of the book of the same name, written by Professors Rose Luckin, Mutlu Cukurova, and Headteacher Karine George, members of the senior team actively developing and using the AI Readiness Framework from which these recommendations derive

- Alan Turing Institute: Three Questions
The Turing Lecture mini-series is designed to reflect on the use of AI and data science in a post-lockdown world. Professor Luckin's lecture centred on the use of AI and tech in education - particularly in a virtual setting due to the pandemic. In addition, she gives her personal perspective on the use of data and tech to decide exam results across the UK

- China's Grand Experiment in Education
An MIT Technology Review article on the country's intelligent education revolution

- AI Readiness: Step 5 webinar for Educationalists and Educational Businesses, Part 1/Part 2
Two related webinars introducing Step 5 of the AI Readiness Framework, this time both target toward educationalists, and educational businesses

- A Systematic Review on Educational Data Mining
Presently, educational institutions compile and store huge volumes of data, such as student enrolment and attendance records, as well as their examination results. Mining such data yields stimulating information that serves its handlers well. Rapid growth in educational data points to the fact that distilling massive amounts of data requires a more sophisticated set of algorithms. This issue led to the emergence of the field of educational data mining (EDM)

- AI for School Teachers
The complete book on the AI Readiness Framework, specifically for teachers and headteachers in schools. It will help teachers and heads understand enough about AI to build a strategy for how it can be used in their school. Though it is pitched to teachers and contains familiar examples, the approach should still be used by education and training organisations