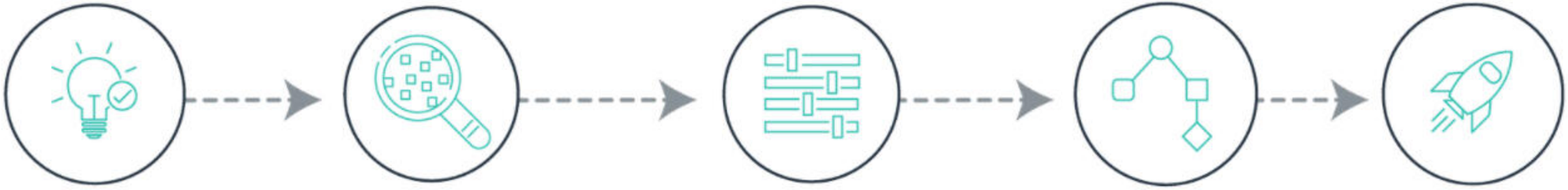
How can machine learning help?

By the end of this lesson, you will be able to:

- Define machine learning.
- Describe the positive feedback loop (flywheel) that drives machine-learning projects.
- Describe the different business domains impacted by machine learning.
- Describe the potential for machine learning in underutilized markets.



1. Formulate a problem
Frame the core ML problem(s) in terms of what is observed and what answer you want the model to predict.

2. Prepare your data
Collect, clean, and prepare data to make it suitable for consumption by ML model training algorithms. Visualize and analyze the data to run sanity checks to validate the quality of the data and to understand the data.

3. Train the model
To train a highly predictive model, the raw data (input variables) and answer (target) can't always be used effectivly. Preferably, construct more predictive input representations or features from the raw variables. Feed the resulting features to the learning algorithm to build models. Set aside, or hold out, a subset of the input data to test the model.

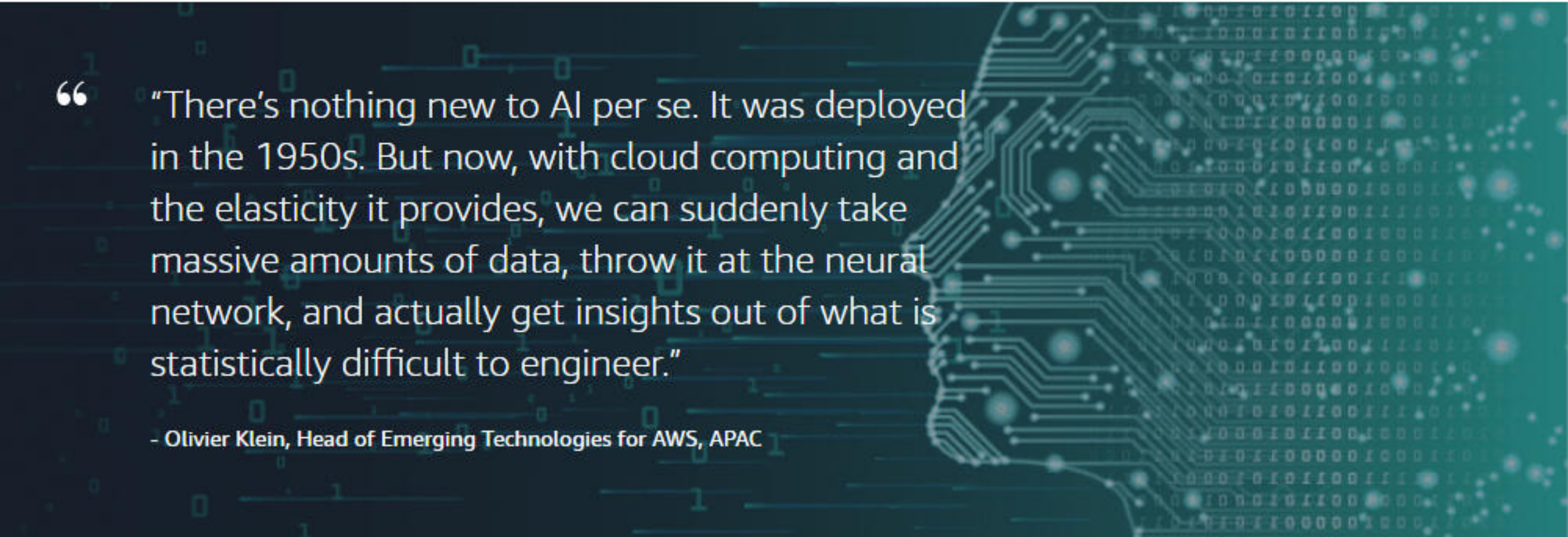
4. Test the model
Evaluate the quality of the models on data that was held out from model building.

5. Deploy your model
Use the model to generate predictions of the target answer for new data instances.

What is machine learning?

Machine learning (ML) is the process of training computers, using math and statistical processes, to find and recognize patterns in data. After patterns are found, ML generates and updates training models to make increasingly accurate predictions and inferences about future outcomes based on historical and new data. For example, ML could help determine the likelihood of a customer purchasin a particular product based on previous purchases by the user or the product's past sales history.

Building ML applications is an iterative process that involves a sequence of steps. To build an ML application, follow these general steps:

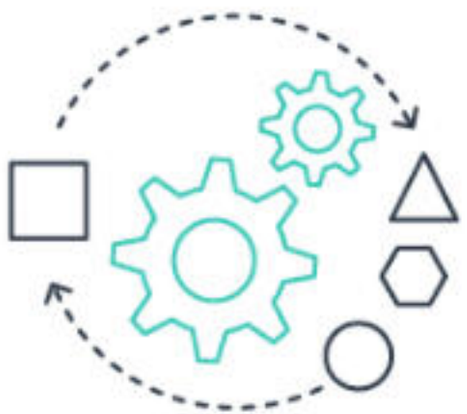


> “There’s nothing new to AI per se. It was deployed in the 1950s. But now, with cloud computing and the elasticity it provides, we can suddenly take massive amounts of data, throw it at the neural network, and actually get insights out of what is statistically difficult to engineer.”
>
> **- Olivier Klein, Head of Emerging Technologies for AWS, APAC**

What are the key terms in machine learning?

Model

The output of an ML algorithm trained on a data set; used for data prediction



Training

The act of creating a model from past data

Testing

Measuring the performance of a model on test data

Deployment

Integrating a model into a production pipeline

What is the history of Amazon machine learning?

Amazon has over 20 years of experience with machine learning. In addition, Amazon uses ML to sell more than 4,000 products per minute on Amazon.com, and also in completing the first autonomous Prime Air Delivery in 2016. In July 2020, AWS was recognized as a leader in the Gartner Magic Quadrant for cloud AI developer services. The ML platform Amazon SageMaker received the highest rating among its peer group (84/100) on Gartner's "Solution Scorecard for Amazon SageMaker."

To learn more about Amazon ML milestones, **choose the following markers.**

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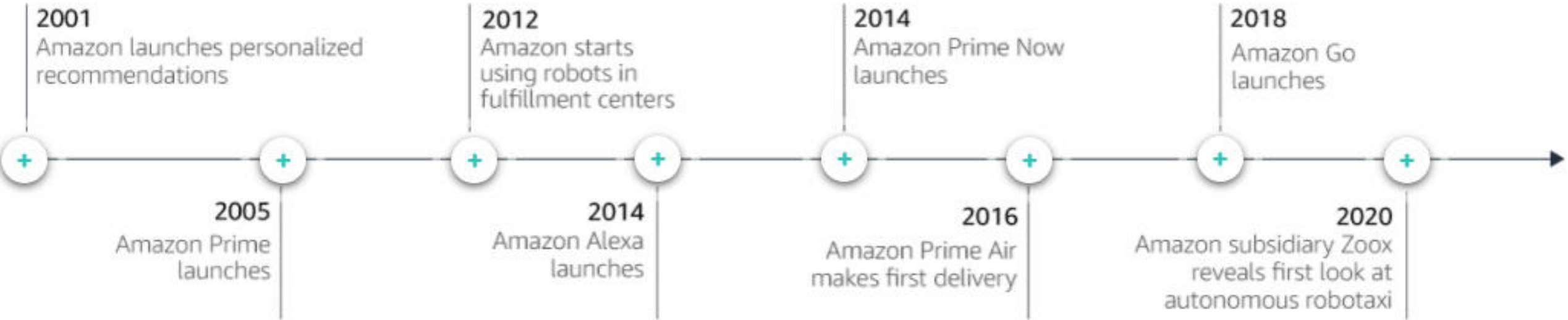


What is the Amazon approach to machine learning?

To learn about the Amazon flywheel approach to ML, choose the following flashcards.

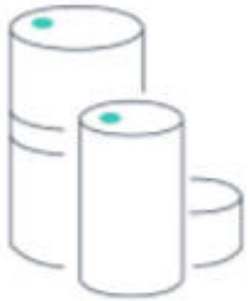
The Amazon flywheel was an idea that Amazon founder Jeff Bezos sketched on the back of a napkin. It illustrates how investing in specific key business operations can reinforce other processes and create a positive feedback loop. When Amazon focused on improving the customer experience, more customers joined. Higher customer traffic led to larger vendor pools and broader product selections, which resulted in lower prices and lower cost structures. Amazon reinvested in improving the customer experience, which leads to platform growth, and the flywheel reinforcement continues.

The Amazon ML flywheel uses data collected from parts of a business operation, uses a model to predict future outcomes, and provides ways to continuously improve efficiency and develop new operational capabilities and business practices. With ML, increasing predictions improve growth and efficiency. This leads to more usage and data, completing the feedback loop and reinforcing all parts of the flywheel.

How is Amazon using machine learning in products?

To learn about Amazon products that use ML, choose the following flashcards.

Click to flip



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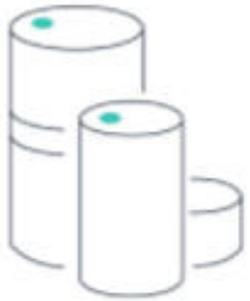

How is Amazon using machine learning in products?

To learn about Amazon products that use ML, **choose the following flashcards.**

Amazon uses browsing and purchasing data to provide tailored product recommendations and promotions.	Amazon uses ML to facilitate billions of voice interactions per week with Alexa devices using natural language processing (NLP).	Amazon uses ML to ship 1.6M packages per day.

Forty-eight percent of executives at US companies surveyed report they see AI as a path to growing revenue and said profits.

- PricewaterhouseCoopers, "2019 AI Predictions: Six Priorities You Can't Afford to Ignore"

How is machine learning helping AWS customers?

AWS machine learning services have provided solutions for a variety of customer use cases. AWS ML customers have extracted and analyzed client document data to help speed up critical business decisions and the identification of fraudulent online activities. AWS ML customers forecast their key demand metrics to meet customer demand and reduce waste. These customers have also generated personalized recommendations to maximize customer engagement. Below is a quick overview of various AWS AI, ML, and platform services that customers are using to accelerate business outcomes.

What are some examples of machine learning being used today?

Machine learning can be found in about 77 percent of the devices we use ("What Consumers Really Think About AI: A Global Study," Pegasystems, 2017). For example, ride-sharing apps like Uber and Lyft use data to lower wait times, predict demand, and optimize price setting. Online shopping sites use ML to customize search results and improve product recommendations. Financial institutions use AI to recognize content on mobile check deposits. Credit- or debit-card transaction businesses use ML to scan for fraud. Research suggests that more than 8 billion digital voice assistants will be powered by AI and ML over the next few years ("Digital Voice Assistants in Use to Triple to 8 Billion by 2023, Driven by Smart Home Devices," Juniper, 2018).

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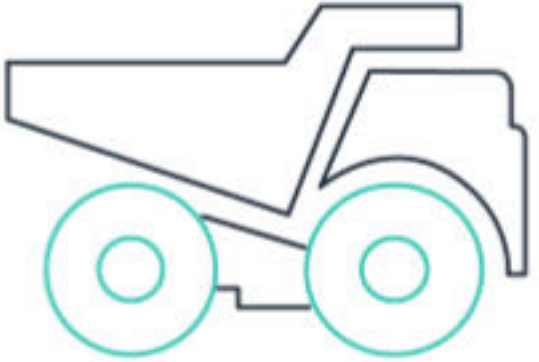
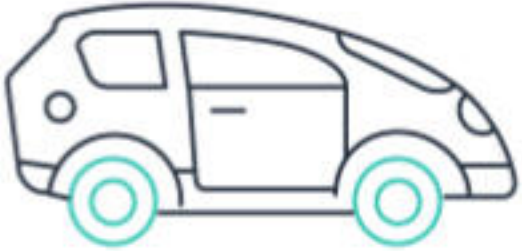
To learn how different businesses use ML, choose the following flashcards.

Healthcare



Trucking



Rideshare

To learn how different businesses use ML, **choose the following flashcards.**

In healthcare, machine learning is analyzing large amounts of clinical data to help suggest treatment for patients.

The trucking industry uses machine learning to automate logistics.

Ride-sharing apps use data to update wait times, demand prediction, and price setting.

Manufacturing

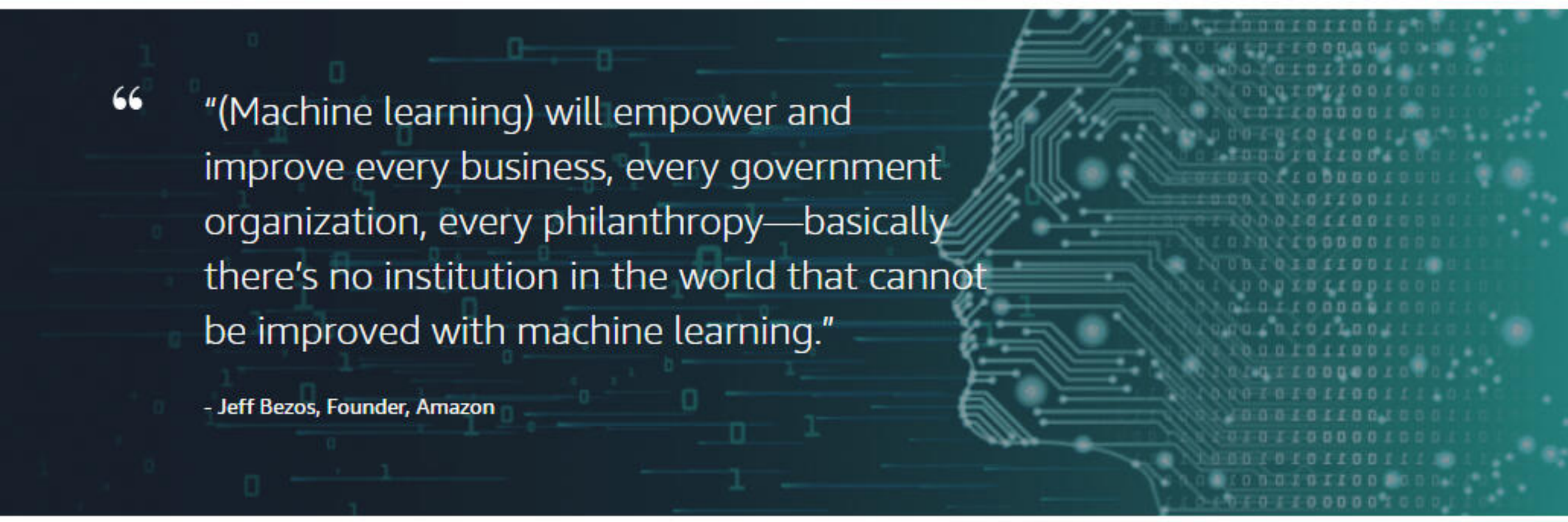
Finance

Energy

Manufacturers use ML to predict product defects earlier and with greater precision, resulting in substantial cost savings.

The finance industry is investing in ML to enable automated threat intelligence, prevention systems, and fraud analysis and investigation.

In the energy sector, ML helps companies intelligently access document data, make smarter decisions faster, improve operations, and boost productivity.


“
“(Machine learning) will empower and improve every business, every government organization, every philanthropy—basically there’s no institution in the world that cannot be improved with machine learning.”
- Jeff Bezos, Founder, Amazon

What other industries are using machine learning?

Industrial companies use AI and ML services for asset management. This includes using computer vision for equipment monitoring and defect detection, or analyzing operational machine behavior data to enable predictive maintenance. Customer service organizations use ML to transcribe and analyze live and archived calls for sentiment scores. ML can also help prioritize based on categorized customer feedback, and enable software to provide agents with answers to questions as they are being asked.

CERNER

GEORGIA-PACIFIC

- Predictive models can accelerate research and discovery of new drugs and treatments.
- Nurses supported by AI tools increased productivity up to 50 percent (McKinsey Global Institute, 2017).
- Amazon Transcribe Medical helps provide more personalized care.

Case study

CERNER

GEORGIA-PACIFIC

- In the retail industry, AI-based demand forecasting reduced errors by 30–50 percent, decreasing lost sales by 65 percent (McKinsey Global Institute, 2017).
- Automation is making supply chain management more efficient.
- Georgia-Pacific uses Amazon SageMaker to provide real-time feedback to machine operators.

Case study

How does the NFL use AWS machine learning?

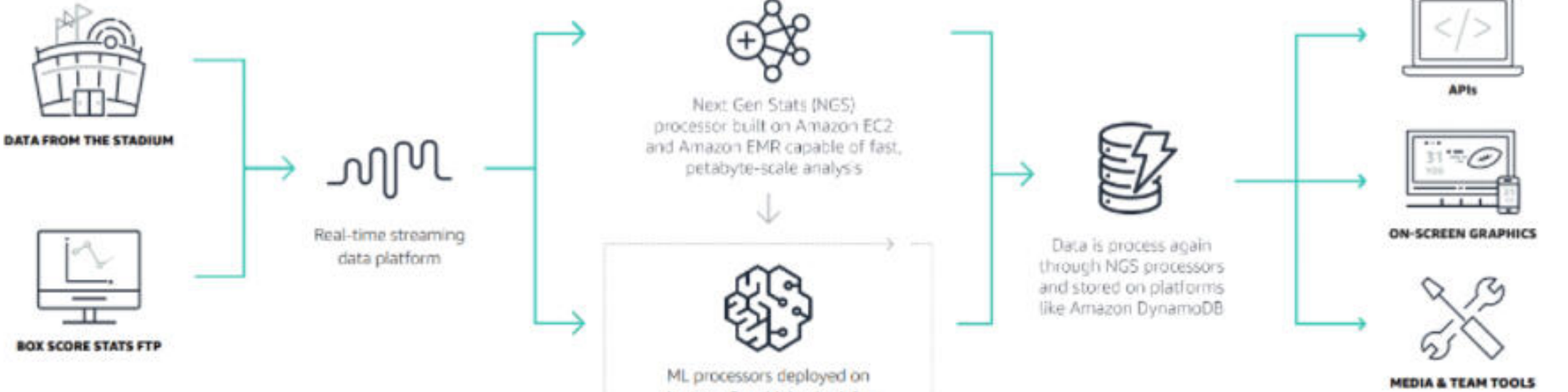
AWS helps the NFL to leverage the power of its data through sophisticated analytics and ML. The NFL uses training data from traditional box-score statistics. The NFL also uses data collected from the stadium to create new stats, improve player health and safety, and provide a better experience for fans, players, and teams—all in real time. ML models built on the Next Gen Stats (NGS) platform ingest the data. This continually trains and refines the models to help boost accuracy, speed, and insights while reducing the time to get results.

“ Machine learning is unlocking potential for us to do more than we otherwise could, in a timely manner with a high degree of confidence.

- Matt Swensson, Vice President of Emerging Products and Technology, NFL

NFL Next Gen Stats

The NFL uses machine learning and data analytics services to boost the accuracy, speed, and insights provided by its NGS platform.


DATA FROM THE STADIUM
BOX SCORE STATS FTP
Real-time streaming data platform
Next Gen Stats (NGS) processor built on Amazon EC2 and Amazon EMR capable of fast, petabyte-scale analysis
ML processors deployed on Amazon SageMaker look for patterns, make predictions, and continually improve the models
Data is process again through NGS processors and stored on platforms like Amazon DynamoDB
APIs
ON-SCREEN GRAPHICS
MEDIA & TEAM TOOLS
Data is output to NGS APIs on Amazon API Gateway in all under a second
0.15 seconds
0.5 seconds
1.0 second

DIGITAL VOICE ASSISTANTS IN USE TO TRIPLE TO 8 BILLION BY 2023, DRIVEN BY SMART HOME DEVICES

Smart TVs will have the biggest expansion, growing at over 100% every year for the next 5 years

Hampshire, UK – 12th February 2018: A new study from Juniper Research has found that there will be 8 billion digital voice assistants in use by 2023, up from an estimated 2.5 billion at the end of 2018.

While smartphone assistants will be the largest platform by volume thanks to *Google Assistant* and *Siri*, Juniper's new research found that the fastest growing voice assistant categories over the next 5 years will be:

1. Smart TVs - 121.3% CAGR
2. Smart speakers - 41.3% CAGR
3. Wearables - 40.2% CAGR

Multiplatform Impacting Voice Assistant Apps

The new research, Digital Voice Assistants: Platforms, Revenues & Opportunities 2019-2023, notes that, as demand for multi-platform assistants increases, standalone apps, made by independent vendors for smartphones and tablets, will decline. Juniper expects revenues from these apps to begin to fall in key markets from 2022.

The big exception here is China, where companies like WeChat and Alibaba provide app-based offerings alongside speakers that are not part of an operating system. This means that China will have 78% of voice assistant apps installed globally in the next 5 years.

Voice Commerce Taking Off, but not for Physical Goods

Juniper's report also shows that voice commerce will grow substantially; reaching over $80 billion per annum by 2023. However, this includes money transfer and purchases of digital goods alongside its use for more traditional purchases.

"We expect the majority of voice commerce to be digital purchases, until digital assistants offer truly seamless cross-platform experiences" remarked research author James Moar. "*Connected TVs and smart displays are vital here, as they can provide a visual context that is lacking in smart speakers.*"

Juniper Research provides research and analytical services to the global hi-tech communications sector, providing consultancy, analyst reports and industry commentary.

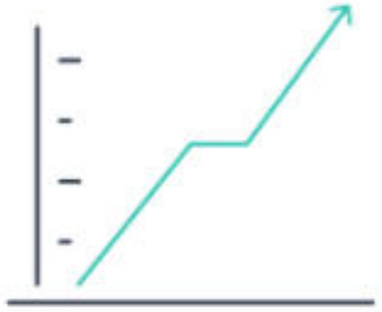
For further details please contact Sam Smith, Press Relations.
T: +44(0)1256 830002
E: sam.smith@juniperresearch.com


“
70% of business execs believe AI will be the business advantage of the future.
- PricewaterhouseCoopers, “The Future of AI Is Here”

How can machine learning help me?

Machine learning can continuously improve results, which means training models can become a part of almost any decision-making process. Machine learning can ingest limitless amounts of data, produce timely analysis and assessment, identify trends and patterns, and generate predictive forecasts.

Make predictions.



Drive efficiencies.

Enable automation.

Accelerate decision-making.

What else is possible?

The use of machine learning in the future of business and technology is virtually boundless. ML can become an automated part of software engineering by implementing algorithms in low- or no-code development environments. ML can also become a catalyst for quantum computing by increasing data processing speeds or rapidly accelerating model training.

In this lesson, you learned:

- How to define machine learning
- How to describe the positive feedback loop (flywheel) that drives ML projects
- How to describe the different business domains impacted by machine learning
- How to describe potential for machine learning in underutilized markets

How does machine learning work?

By the end of this lesson, you will be able to:

- Describe artificial intelligence.
- Describe the difference between artificial intelligence and machine learning.

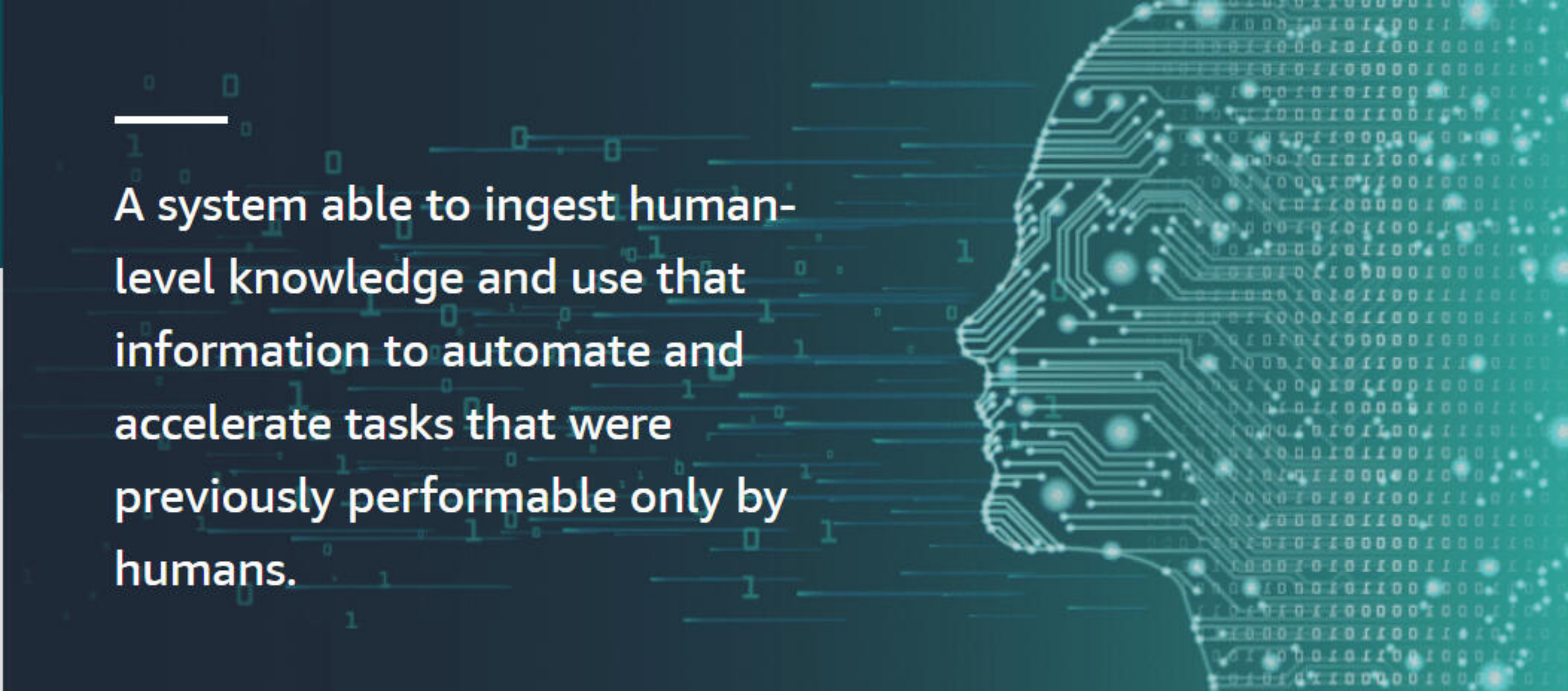
What is artificial intelligence?

Artificial intelligence (AI) is any system that is able to ingest human-level knowledge to automate and accelerate tasks performable by humans through natural intelligence. AI has two categories: narrow, where an AI imitates human intelligence in a single context, and general, where an AI learns and behaves with intelligence across multiple contexts.

Examples of AI include:

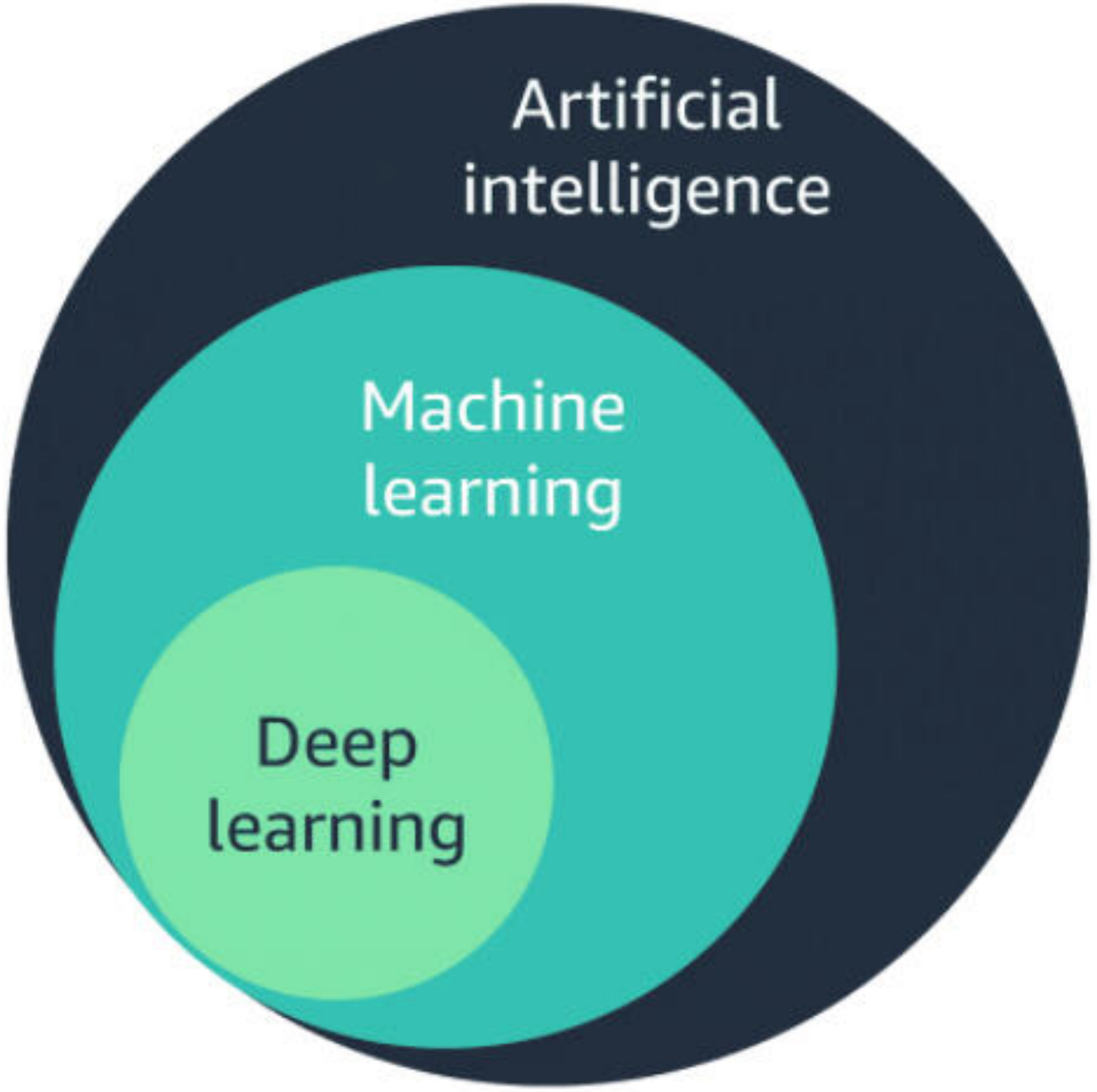
- Intelligent search in Amazon Kendra
- Document analysis in Amazon Comprehend
- Data and text extraction in Amazon Textract
- Business metrics analysis in Amazon Lookout for Metrics and Amazon Forecast

A system able to ingest human-level knowledge and use that information to automate and accelerate tasks that were previously performable only by humans.



What is the difference between ML and AI?

Artificial intelligence ingests data, such as human-level knowledge, and imitates natural intelligence. Machine learning is a subset of AI, where data and algorithms continuously improve the training model to help achieve higher-quality output predictions. Deep learning is a subset of machine learning. It is an approach to realizing ML that relies on a layered architecture, mimicking the human brain to identify data patterns and train the model.



Deep learning is a subset of machine learning. ML is a technique for realizing AI.

Deep learning is a subset of machine learning. ML is a technique for realizing AI.

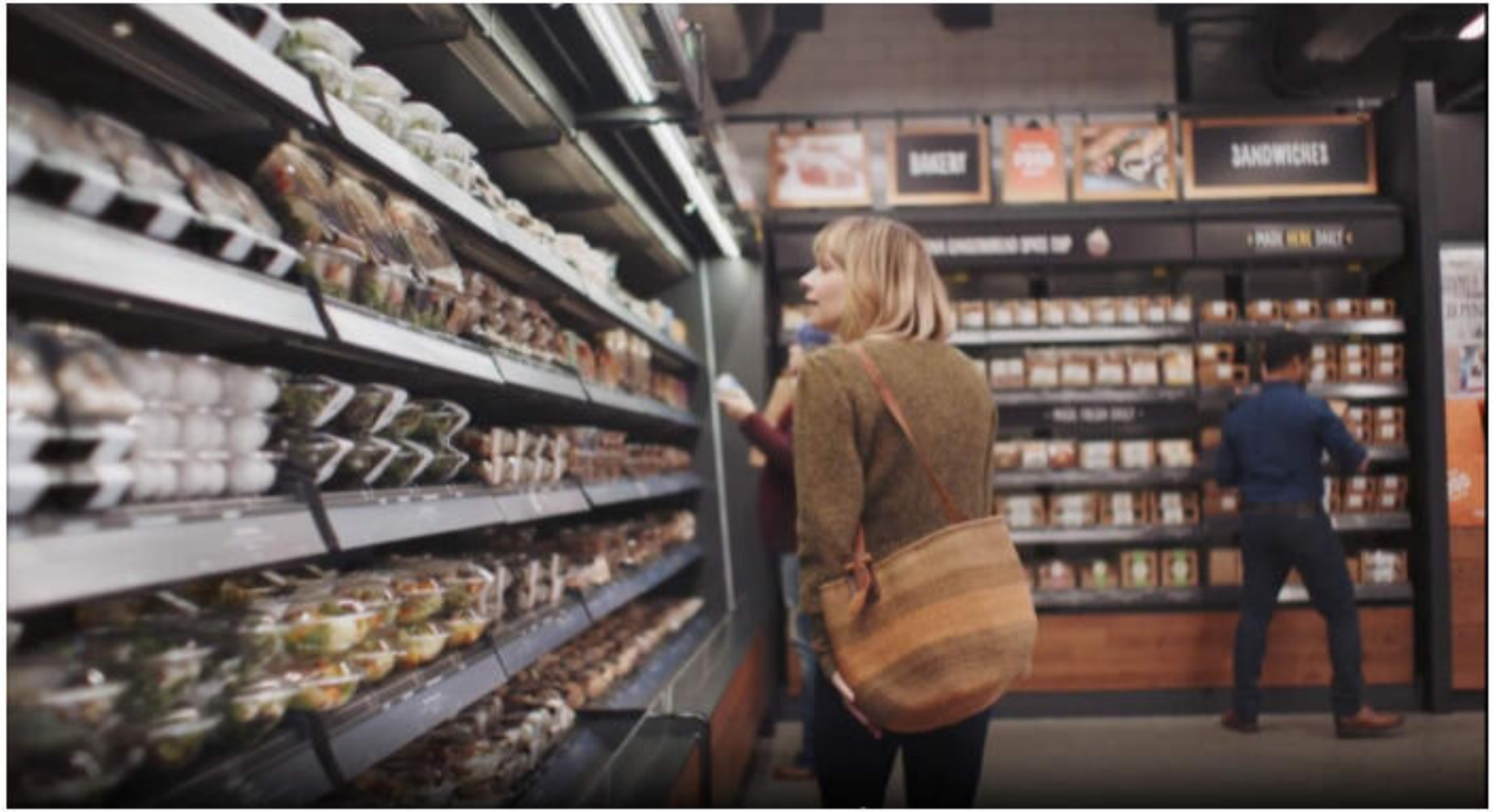
What are the requirements to implement AI?

The core components of AI are domain knowledge to structure and frame the problem correctly, high-quality input data to train the model, and methods to detect patterns and make predictions.

Choose the following tabs to discover how Amazon Go was taken from an everyday convenience store to the automated, checkout-free business that it is today.

DOMAIN KNOWLEDGE	DATA	METHOD FOR MAKING PREDICTIONS

First you need to understand how convenience stores operate. How do customers enter the store and start shopping, pick up items, wait in line for a cashier, and then exit the store?

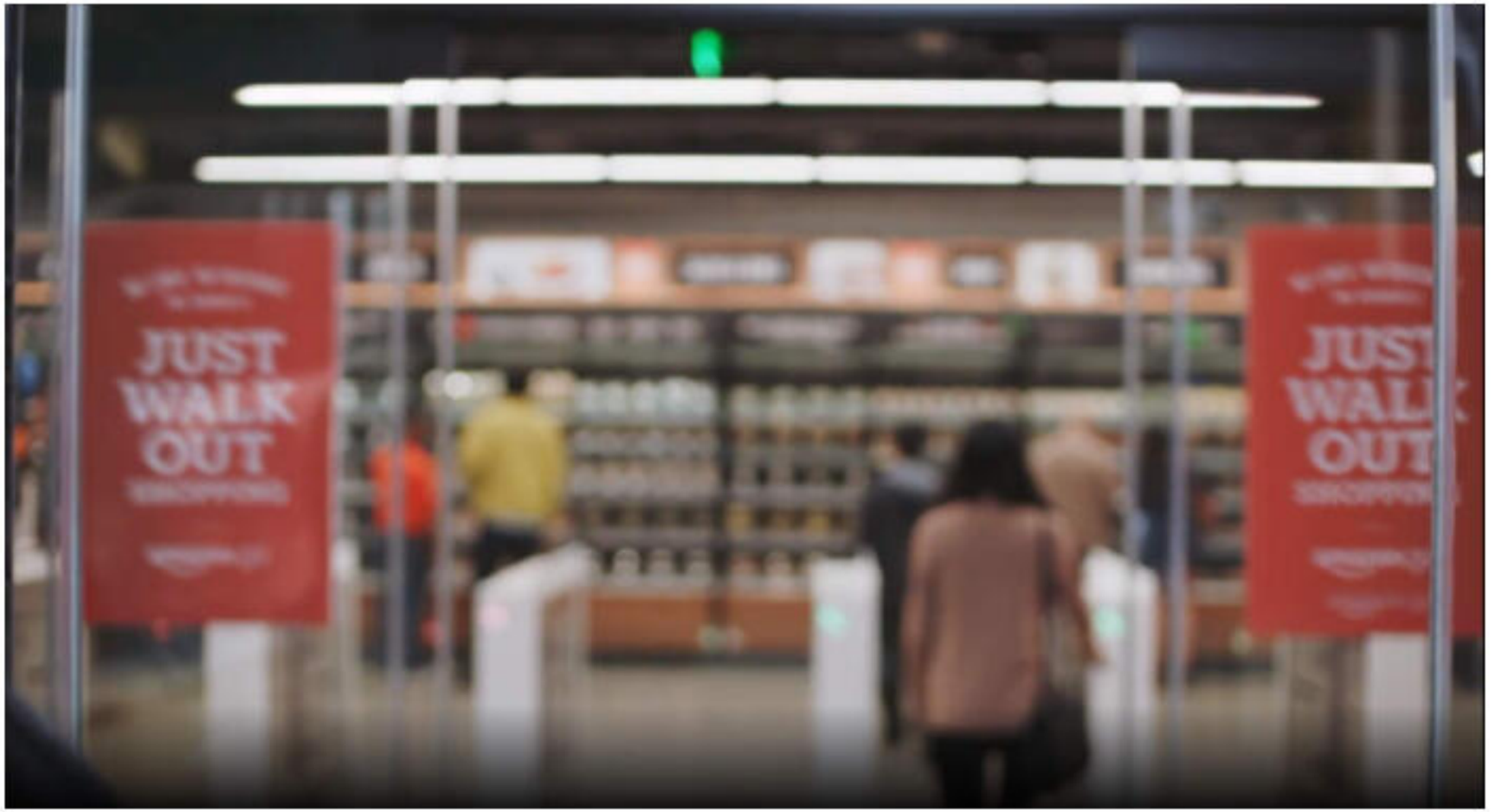


DOMAIN KNOWLEDGE | DATA | METHOD FOR MAKING PREDICTIONS

By using computer vision, Amazon Go can simulate how humans visualize and recognize objects. Data is also pulled from cameras to track users' actions inside the store. After data is collected, it can be made available to build a model that generates results for selected items.

DOMAIN KNOWLEDGE	DATA	METHOD FOR MAKING PREDICTIONS

Based on the data collected, models are trained to identify what items they interact with in the store. A customer's past purchase history may also be used to help identify an item when it is picked up.



What is the difference between machine learning and classical programming?

Machine learning involves teaching a computer to recognize patterns by example, rather than programming it with specific rules. These patterns can be found in the data. In other words, ML is about creating algorithms (or a set of rules) that learn from complex functions (patterns) from data and make predictions on it (a form of "narrow AI"). ML learns from data and can be reused for unseen, future, or new data without rewriting code. Put another way, with ML, you start with a problem, identify data associated with that problem, use an algorithm to then model that problem, and generate output.

Classical programming

Data

Hand-coded rules

Output

vs.

Machine learning

Historical data

Historical output

Trained model

New data

Output

How does machine learning work?

There are three major categories of machine learning, depending on the specific use case.

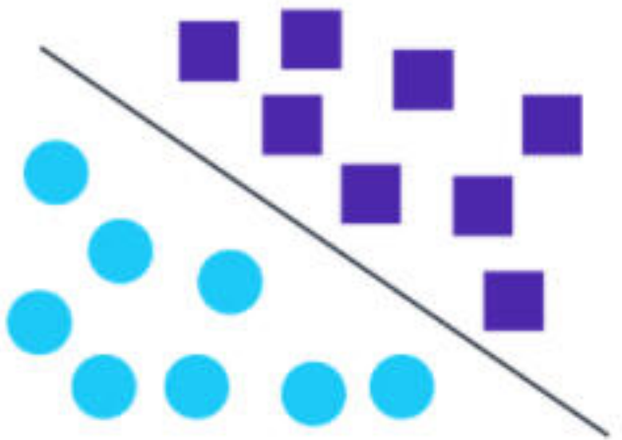
SUPERVISED LEARNING | UNSUPERVISED LEARNING | REINFORCEMENT LEARNING

Supervised learning is a method where a model learns from a data set containing input values and paired output values that you would like to predict.

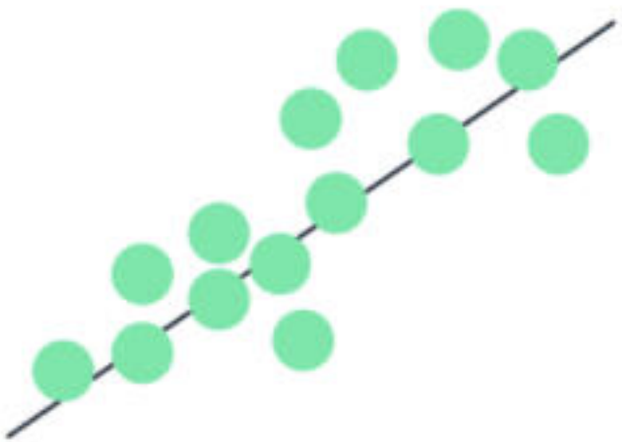
Examples:

Classification - Classifying documents

Regression - Forecasting demand for a product



Classification



Regression

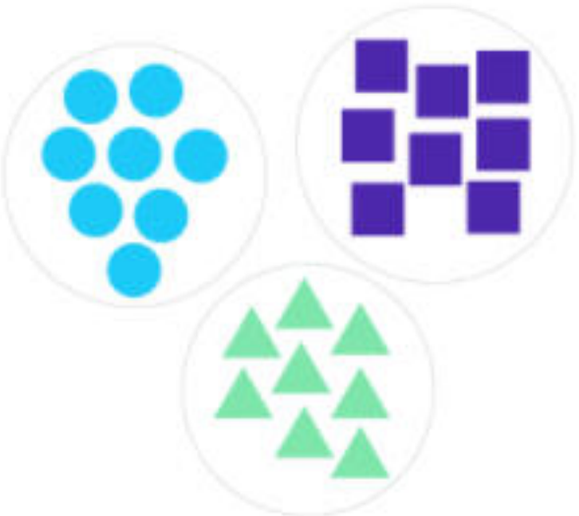
How does machine learning work?

There are three major categories of machine learning, depending on the specific use case.

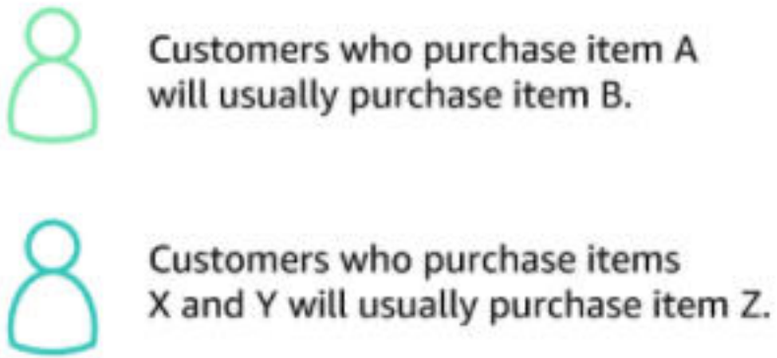
SUPERVISED LEARNING | UNSUPERVISED LEARNING | REINFORCEMENT LEARNING

Unsupervised learning is a method in which the training model learns from data without any guidance. The objective is pattern and structure recognition.

Examples:
Clustering - Customer segmentation Association - Discovering regularities among products



Clustering



Association

How does machine learning work?

There are three major categories of machine learning, depending on the specific use case.

SUPERVISED LEARNING | UNSUPERVISED LEARNING | REINFORCEMENT LEARNING

Reinforcement learning is a method in which the training model learns from its environment by being rewarded for correct moves and punished for incorrect moves.

Example:

Autonomous driving

What kind of solutions can ML provide?

ML can provide predictive solutions (regression and classification), prioritization (rankings and scores), and behavior patterns (recommendations and clustering).

Common uses for ML models

Regression

Example - Predicting a numerical value

Predicting a housing sale price

Case study

Model 2

Classification

Example - Predicting a label

Duolingo: Classifying if a learner will get a word right

Case study

Ranking

Example - Ordering items to find the most relevant

Domino's Pizza: Ranking most likely next pizza order

Case study

Recommendation

Example - Finding relevant items based on past behavior

Hyatt: Recommending hotels for large events

Case study

Clustering

Example - Finding patterns in examples

NASA: Detecting anomalies in sensor data collection, such as super storm forecasting

Case study

Anomaly detection

Example - Finding outliers from examples

Fraud.net: Identifying novel fraudulent behavior

Case study

In this lesson, you learned:

- The differences between AI, ML, and deep learning
- The core components of AI
- Advantages of ML compared to classical programming
- The types of business problems that ML can solve

Match the types of machine learning with the appropriate business problem.

Regression	Predicting competitive pricing for products
Anomaly detection	Identifying products that are incorrectly categorized
Clustering	Grouping customers to identify marketing segments
Classification	Flagging counterfeit products

What are some potential problems with machine learning?

By the end of this lesson, you will be able to:

- Describe the differences between simple and complex models.
- Understand unexplainability and uncertainty problems with ML models.

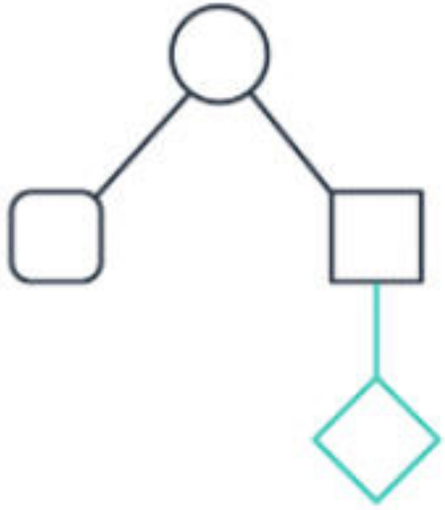
What are some potential problems with machine learning models?

Machine learning modeling can be problematic for learning algorithms due to the ingestion of poor quality data. For example, the data may not include enough samples to represent a sufficiently broad scope of relevant variables.

What are simple and complex models?

Simple and complex ML models differ when balancing a model's accuracy (number of correctly predicted data points) and a model's explainability (how much of the ML system can be explained in "human terms"). The output of a simple ML model may be explainable and produce faster results, but the results may be inaccurate. The output of a complex ML model may be accurate, but the results may be difficult to communicate.

Simple model



Accuracy

Explainability

Complex model

Accuracy

Explainability

Simple models may prioritize output explainability over accuracy. Complex models may prioritize accuracy over output explainability.

What is unexplainabilty?

Unexplainability represents how much of the reasoning behind an ML model's decision cannot be effectively described in human terms. There are potentially legal, professional, ethical, and regulatory conditions where the tolerance for unexplainability may vary from case to case.

When is it not okay?

- When you need to be able to explain to your customer why a loan was declined
- When you need to be able to explain why a transaction was deemed fraudulent

When is it okay?

- When risks of misclassification are low, such as object recognition for catalog search or predicting the probability of completing NFL play
- When humans make the final decisions

What is uncertainty?

Uncertainty describes an imperfect outcome. In the context of machine learning, uncertainty arises from using models. These models attempt to fit a training data, which may have imperfect data. The "best" data may also be unknowable.

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When using ML, estimate the amount of uncertainty a model may have. Compensate to avoid potential misinterpretations of life and property.

In this lesson, you learned:

- ML models may be simple (explainable yet inaccurate) or complex (unexplainable yet accurate).
- Uncertainty must be considered when training ML predictive models.

What is the difference between a simple and complex machine learning model?

- Simple machine learning models produce accurate results, while complex machine learning models do not produce accurate results.
- Simple machine learning models are not explainable, while complex machine learning models are explainable.
- ✓ Simple machine learning models are explainable, while complex machine learning models are accurate.
- Simple and complex machine learning models are explainable, but simple machine learning models do not produce accurate results

How would you best describe "machine learning"?

- ⊗ Machine learning replicates human analysis and intelligence.
- ✓ Machine learning uses algorithms to find patterns in data and produce training models.
- ⊗ Machine learning is a large combination of "if this, then do that" statements.
- ⊗ Machine learning uses raw, unprocessed data to train a model.

Conclusion

In this course, you have learned:

- The impacts and benefits of machine learning across industries and business domains
- How to define and distinguish ML, AI, and deep learning
- How companies that adopt ML can help drive improved efficiencies and growth
- The differences between simple and complete ML models
- The definitions of unexplainability and uncertainty

What's next

In the next course, you will learn:

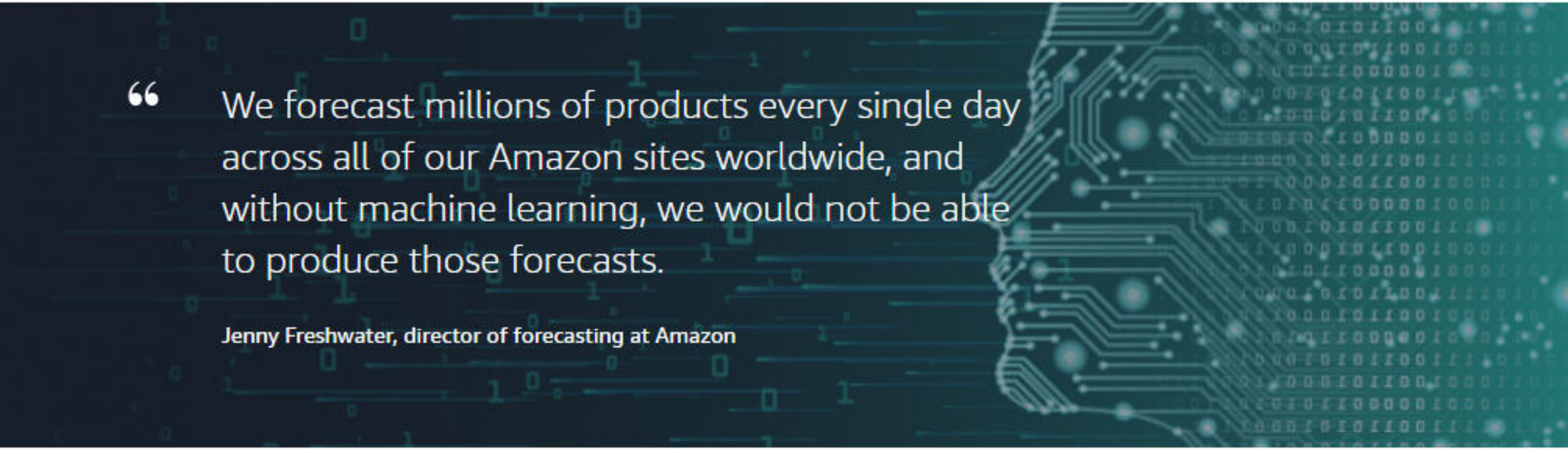
- How to solve business problems with ML
- ML problem, data, time, and production requirements

Is a machine learning solution appropriate for my problem?

By the end of this lesson, you will be able to explain how to determine if machine learning is the appropriate solution to your business problem.

How can I determine that machine learning is the right solution?

Businesses can determine if ML is the right solution if the problem is clear and quantifiable. If this is the case, ML can provide value in a model's predictions when compared to specific business objectives and success criteria.



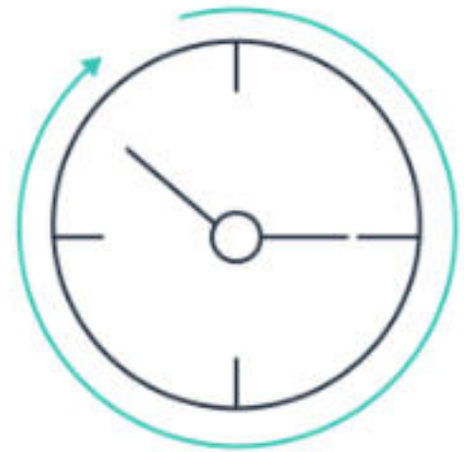
What are the reasons to use machine learning?

An example of a business problem where the use of ML would be appropriate is generating personalized recommendations. In this case, the solution to the problem requires complex logic, and we would want to provide personalized recommendations at scale with quick turnaround times.

Requires complex logic
Since developing personalized recommendations requires complex logic, ML is an appropriate tool to consider.

Requires scalability
Serving millions of requests for personalized recommendations every second is a challenge.

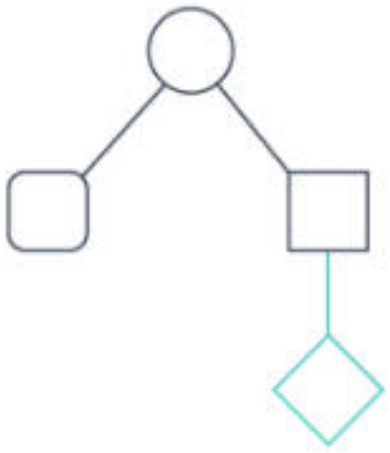
Requires personalization
Delivering personalized recommendations at scale and being responsive at the same time is difficult to achieve with classical programming techniques.



Requires responsiveness
The ability to deliver personalized recommendations within a few seconds even while handling millions of requests per second is expected.

What are the reasons to NOT use machine learning?

Business reasons to avoid ML depend on whether traditional methods and rules are viable options, if there are few or no requirements to adapt to new data, if business goals include 100% outcome accuracy, or if models must be explained or translated.

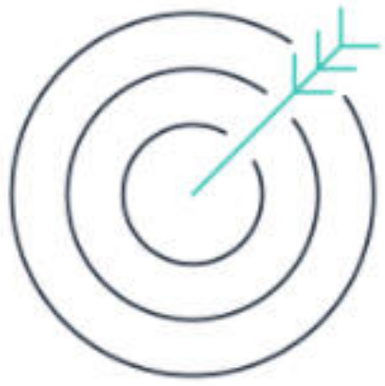


Can be solved with traditional algorithms

If the problem is not overly complex, an ML solution might be overcomplicated.

Does not require adapting to new data

If data and conditions are not changing, a more traditional approach could be more appropriate.



Requires 100% accuracy

ML predictions often provide less than 100% accuracy.

Requires full interpretability

If being able to explain what is going to happen if you change the parameters or input is a priority, ML might not be the best solution.

What is an example business case for machine learning?

Consider a financial institution that needs to determine which category of products and offerings is most interesting to a customer. The problem might not be effectively solved using simple hand-coded rules since the outcome might depend on many factors and overlapping rules. ML could solve this problem.

Example: Finance

To identify a good problem to solve using ML, identify your business outcome or goal, and ask these questions:

What question should I ask about strategy?

Click to flip

What question should I ask about strategy?

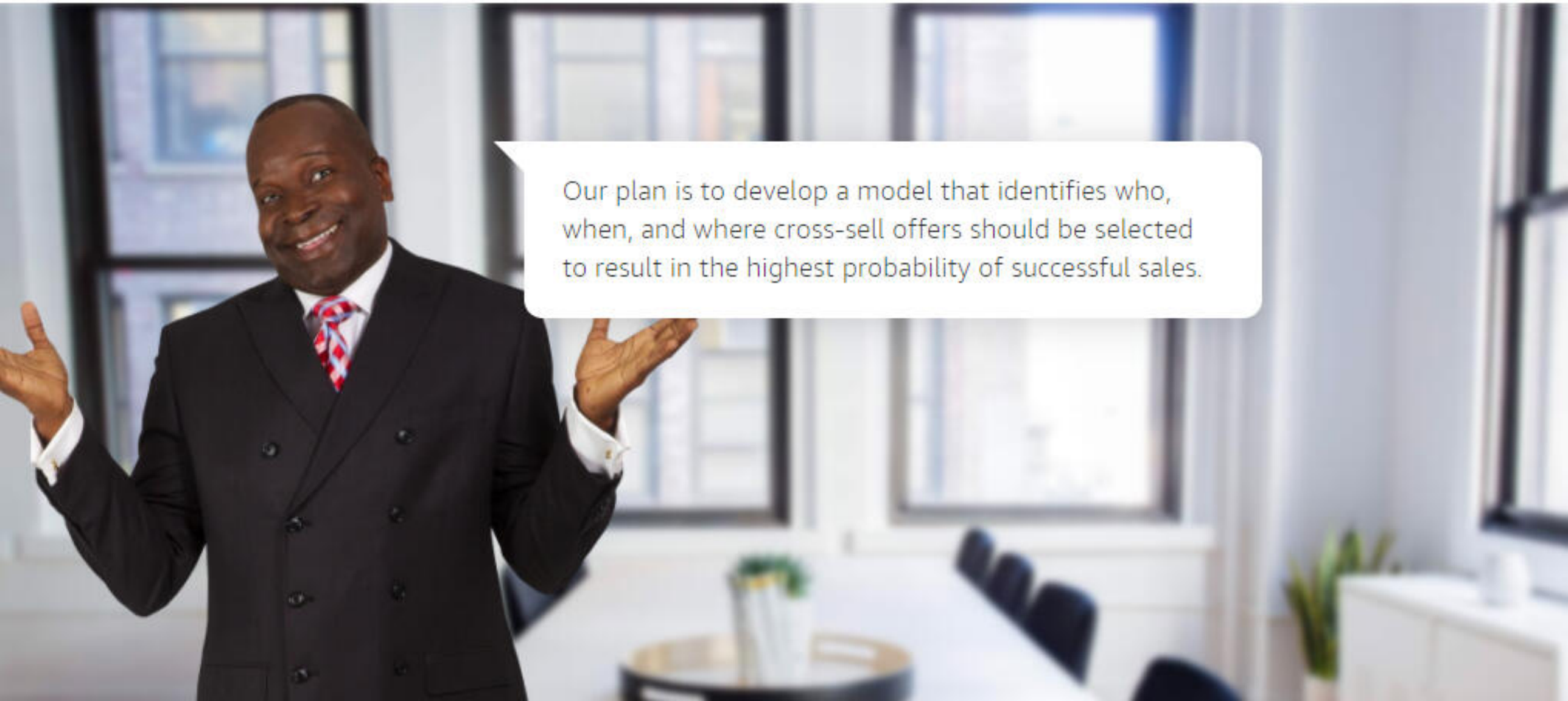
What question should I ask about strategy?

To identify a good problem to solve using ML, identify your business outcome or goal, and ask these questions:

What is the strategy to achieve this goal?	How could you use machine learning to achieve this goal?	What aspects of the problem make it a good fit to apply ML?

Does this business problem require a machine learning solution?

The following scenario describes a financial institution's objective and poses questions to determine if ML is a potential solution.



We will measure the success of this solution by assessing the revenue generated by incremental sales of personal loans from our website.

CONTINUE

Based on what you have learned in this section, I am going to ask you a series of questions to see if machine learning is the right solution for our problem. Let's get started.

CONTINUE

Based on the proposed model of cross-selling offers of personal loans to existing account holders through selective offers, do you think we need 100% accuracy on the solution?

1. No. Every customer we are going to select doesn't need to purchase the personal loan option.

2. Yes. All the customers are required to purchase the personal loan option every time it is offered to them.

Lesson 2 of 5

Is my data ready for machine learning?

By the end of this lesson, you will be able to describe the process of ensuring your data is machine learning ready.

What types of data are available today?

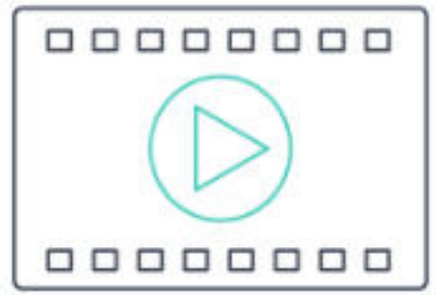
What types of data are available today?

ML uses training data optimized for learning and generalization. Models can ingest several types of data.

Documents

Audio

Images

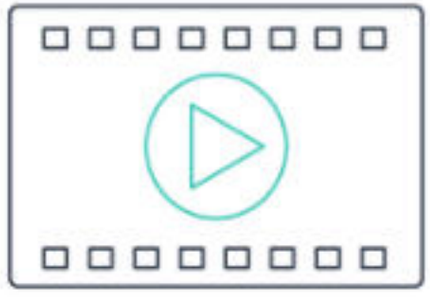


Video

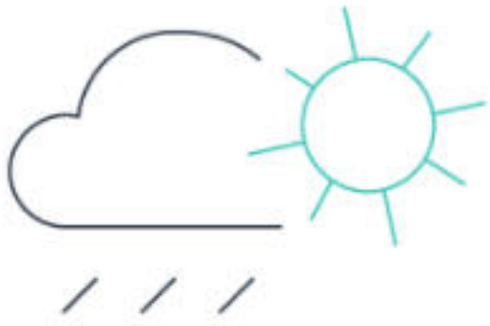
Documents

Audio

Images

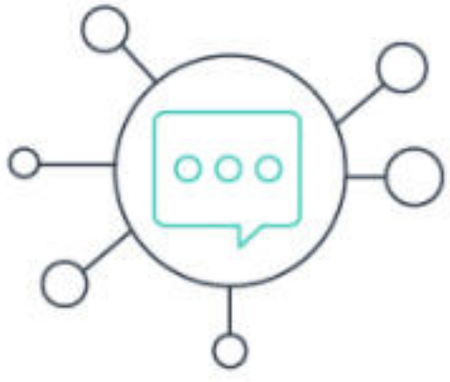


Video

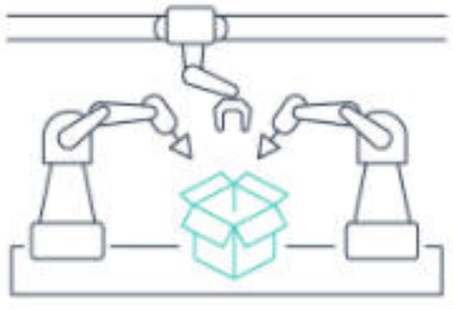


Weather reports

Website interactions



Social media connections



Industrial monitoring

> A first step is to identify a problem that is rich in data, but (one that) you haven't been able to solve through traditional methods.
>
> **Jenny Freshwater, director of forecasting at Amazon**

Is my data ready for a machine learning solution?

Data readiness depends on the quality, quantity, diversity, and complexity of the data collected. After discovering and collecting all relevant data, the data should be cleansed, validated, transformed, and stored.

Can my data be used?

Choose the cards below for the importance of data availability and accessibility in an ML project.

Can my data be used?

Choose the cards below for the importance of data availability and accessibility in an ML project.

Is my data available?

Is my data accessible?

Can my data be used?

Choose the cards below for the importance of data availability and accessibility in an ML project.

Data should exist for training and model development and should not require significant preparation before use.

Data should be in a reachable, on-demand state with access to store, retrieve, move, modify, or copy data from one place to another.

Should my data be used?

Choose the cards below for guidance on how, what, and when to use data.

Does my data respect my customers' privacy?

Does my machine learning project have adequate security?

Should my data be used?

Choose the cards below for guidance on how, what, and when to use data.

Personally identifiable information, such as citizenship or health information, might be labeled private and protected by privacy laws.

Industry regulations, government laws, and compliance policies determine the importance of various data types, and determine what and how data can be processed, stored, managed, or shared.

Is my data high quality?

Data used in an ML project should be relevant to produce valuable results. Data should be timely so that training data is as close to the actual data as possible. Data should be representative of the data across all data sources. Data selection should be unbiased.

RELEVANT	FRESH	REPRESENTATIVE	UNBIASED

Is my data relevant for the type of machine learning project I intend to build?

Example: If your are developing a machine learning solution for a forecasting model, but you don't have data directly related to that goal, the data will not help you power the model.

Is my data high quality?

Data used in an ML project should be relevant to produce valuable results. Data should be timely so that training data is as close to the actual data as possible. Data should be representative of the data across all data sources. Data selection should be unbiased.

RELEVANT	FRESH	REPRESENTATIVE	UNBIASED

How recent is the data being used for my machine learning project?

Example: If you are constructing a predictive model for future call-center capacity, but the only data available is from a few years ago, the data will not help you build a reliable prediction model.

Is my data high quality?

Data used in an ML project should be relevant to produce valuable results. Data should be timely so that training data is as close to the actual data as possible. Data should be representative of the data across all data sources. Data selection should be unbiased.

RELEVANT | FRESH | REPRESENTATIVE | UNBIASED

Is the data representative of the my machine learning project?

Example: If you are building a model to forecast sales, does the data contain all available products?

Is my data high quality?

Data used in an ML project should be relevant to produce valuable results. Data should be timely so that training data is as close to the actual data as possible. Data should be representative of the data across all data sources. Data selection should be unbiased.

RELEVANT	FRESH	REPRESENTATIVE	UNBIASED

Does the data tend to favor one area of a segment when building my machine learning model?

Example: A predictive industrial model is trained using sensor data collected using one type of machine, but sensor data from other types of machines is ignored.

What is an example business case for data readiness?

Consider a banking institution that wants to gather quantifiable insights about a segment of customers, and leadership must decide if they meet data readiness requirements to use ML as a solution.

To identify a good problem to solve using ML, assess your data readiness, and ask these questions:

What question should I ask about data readiness?

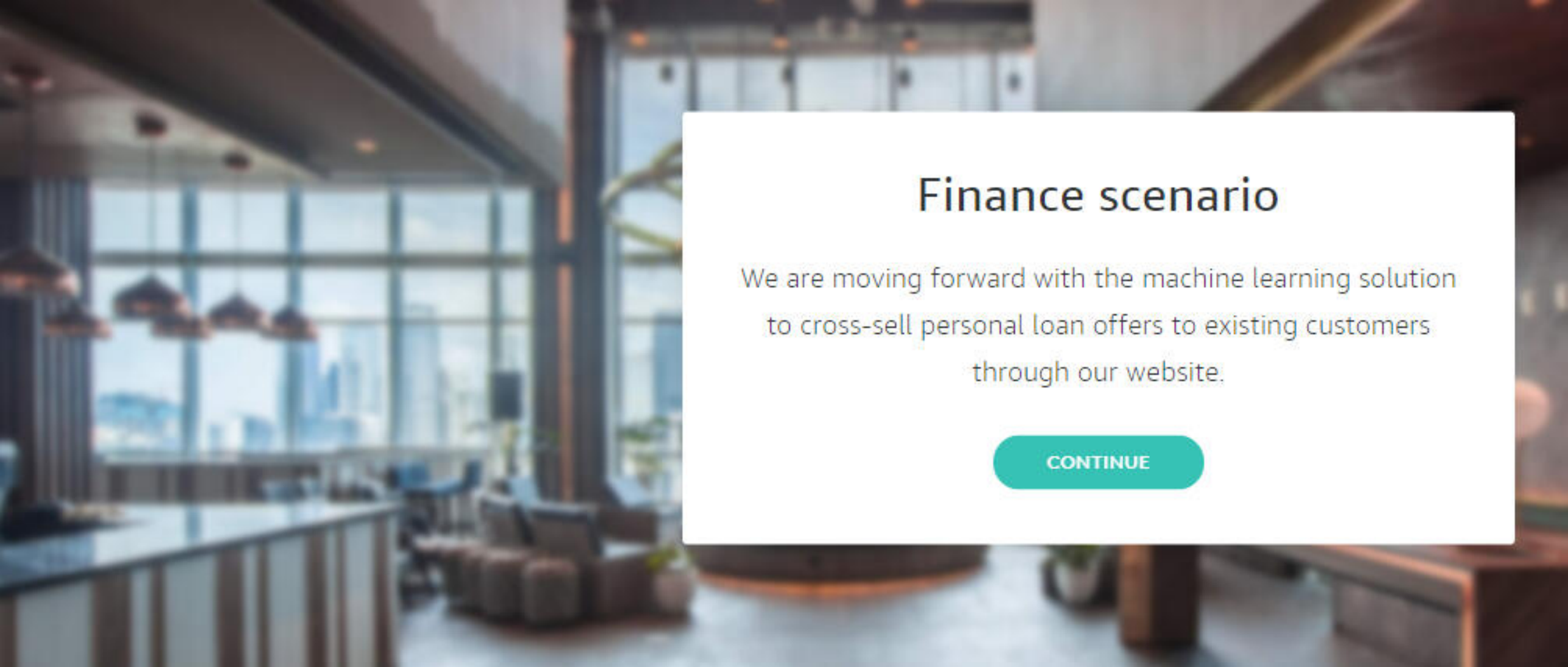
Click to flip

What question should I ask about data readiness?

What question should I ask about data readiness?

To identify a good problem to solve using ML, assess your data readiness, and ask these questions:

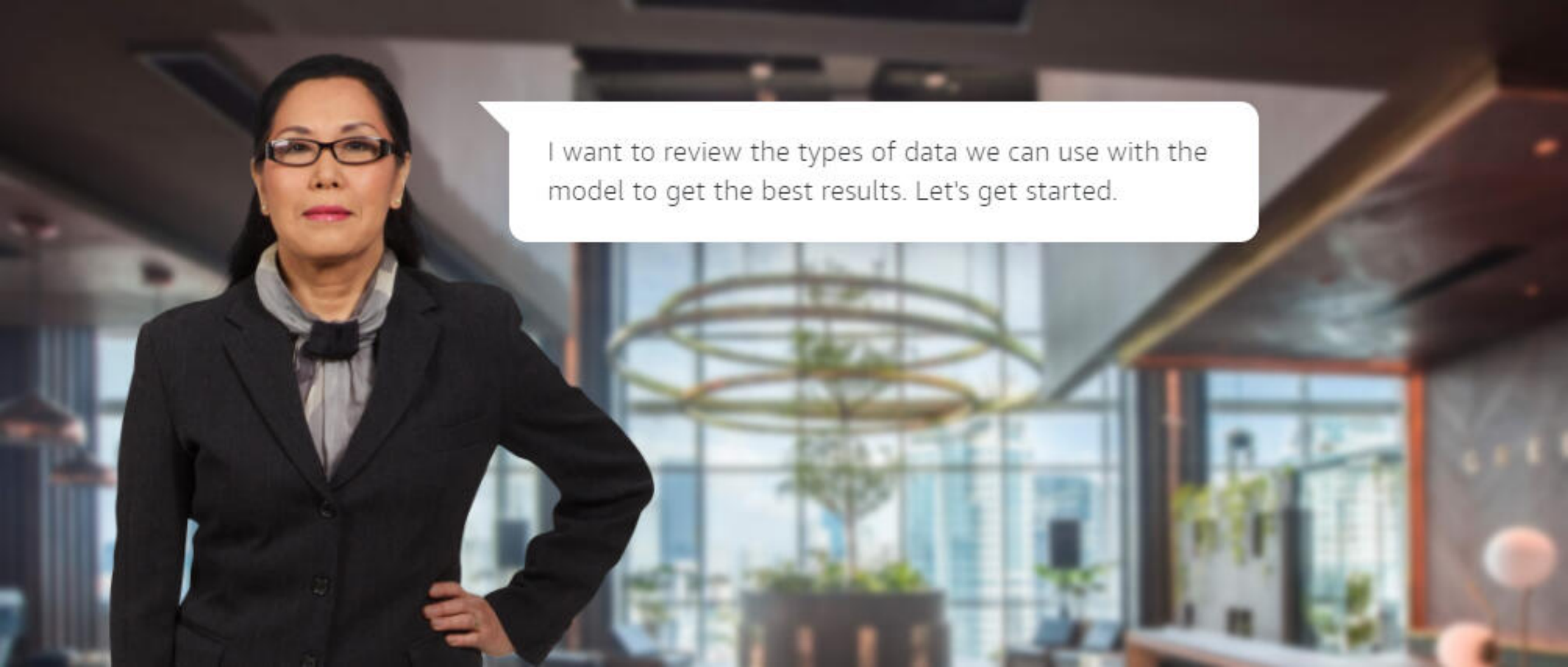
Is it easily accessible?	Does it respect privacy?	Is it relevant?

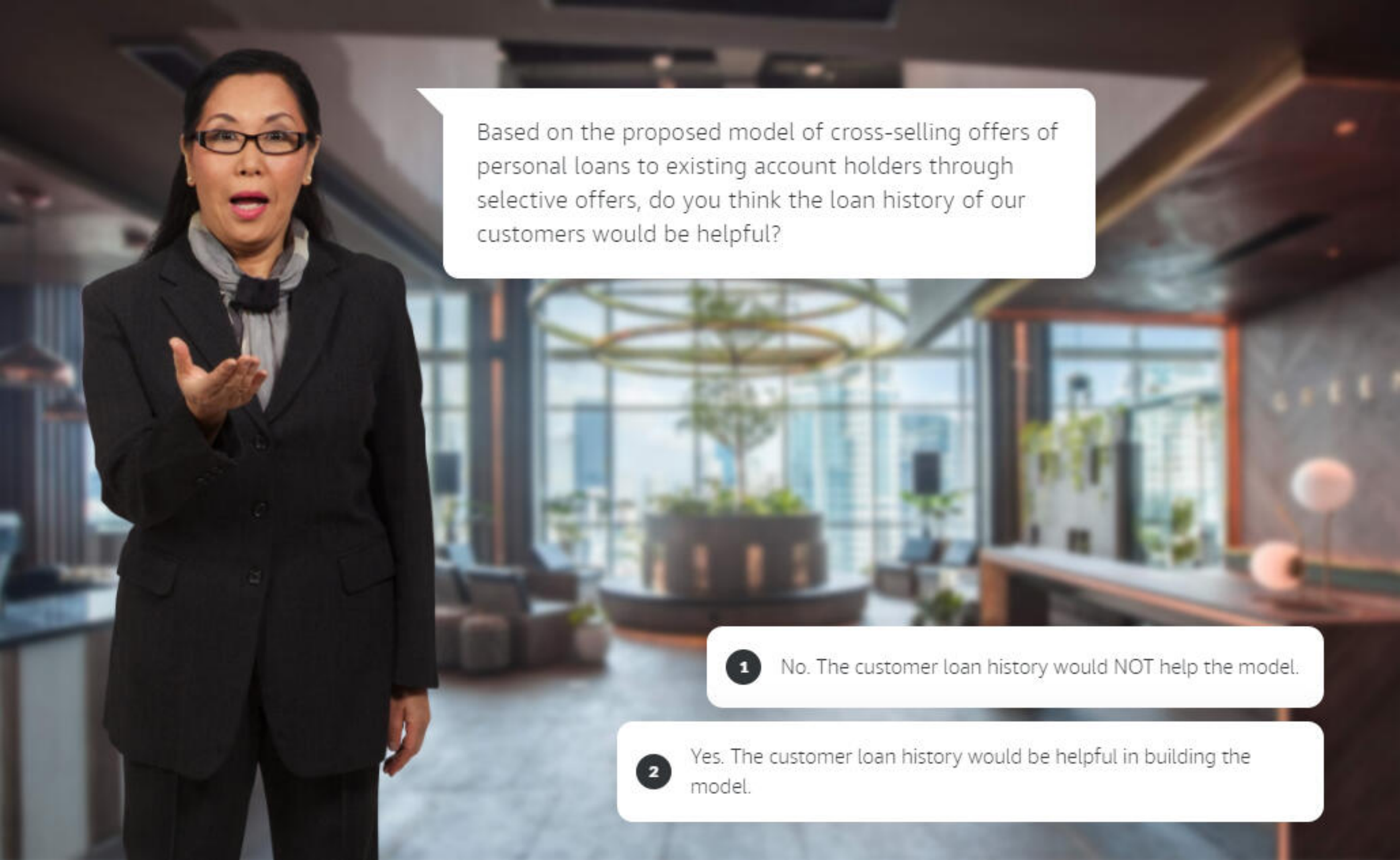


Finance scenario

We are moving forward with the machine learning solution to cross-sell personal loan offers to existing customers through our website.

CONTINUE


I want to review the types of data we can use with the model to get the best results. Let's get started.


Based on the proposed model of cross-selling offers of personal loans to existing account holders through selective offers, do you think the loan history of our customers would be helpful?
1 No. The customer loan history would NOT help the model.
2 Yes. The customer loan history would be helpful in building the model.

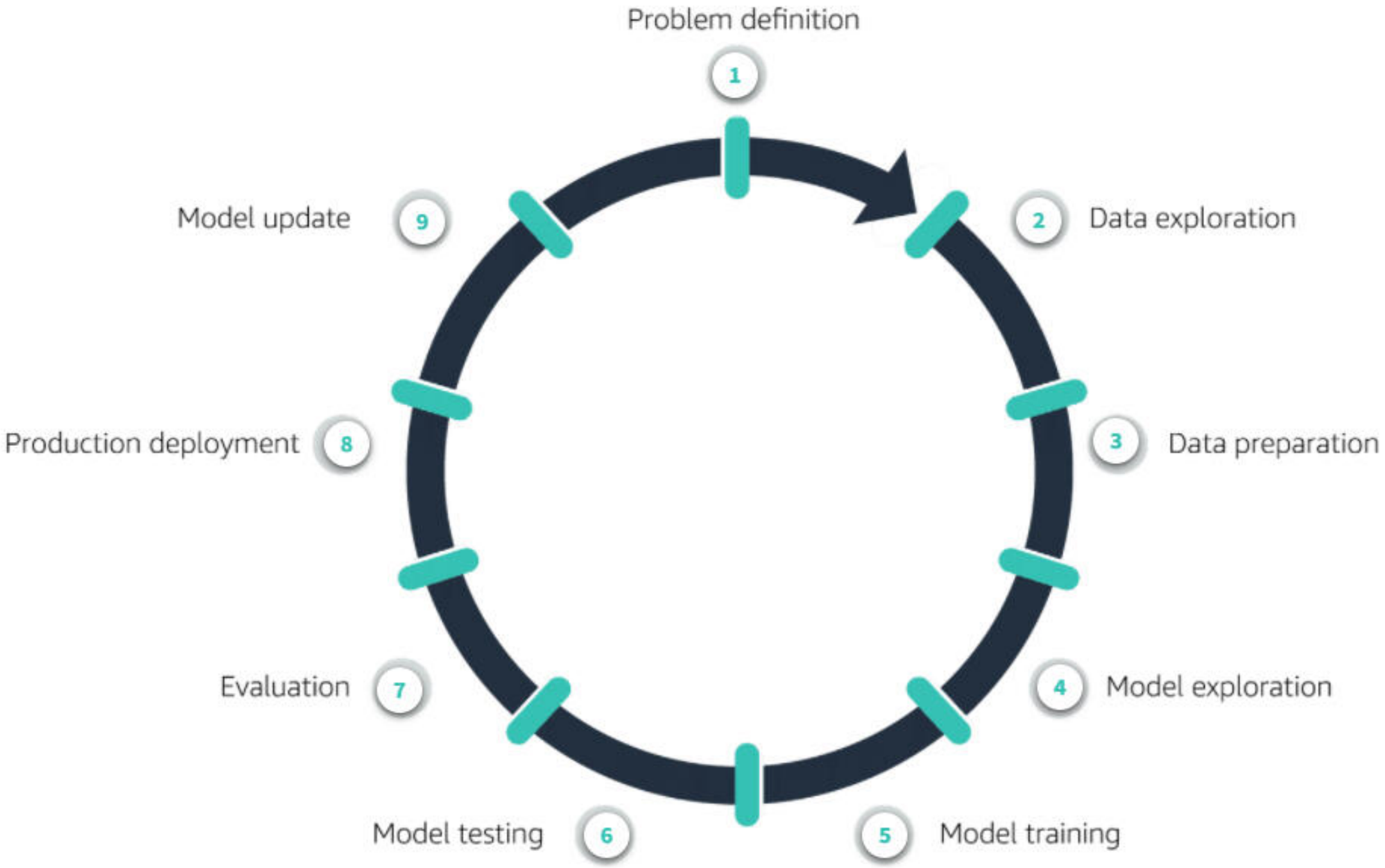
Lesson 3 of 5

How will machine learning impact a project timeline?

By the end of this lesson, you will be able to explain how machine learning impacts a project timeline.

What should be my expectation in terms of time?

Machine learning can take significant time from the start of a project through production deployment. Expectations for the amount of time needed to deploy production models can take weeks or even months.


Problem definition
1
2
Data exploration
3
Data preparation
4
Model exploration
5
Model training
6
Model testing
7
Evaluation
8
Production deployment
9
Model update

Will my machine learning model change over time?

For a model to predict accurately, the data that it is making predictions on must have a similar distribution as the data on which the model was trained. Because data distributions can be expected to drift over time, deploying a model is not a one-time exercise but rather a continuous process. Continuous monitoring of incoming data can help retrain your model on newer data if the data distribution has deviated significantly from the original training data distribution.

What is a best case timeline for a machine learning project?

Will my machine learning model change over time?

For a model to predict accurately, the data that it is making predictions on must have a similar distribution as the data on which the model was trained. Because data distributions can be expected to drift over time, deploying a model is not a one-time exercise but rather a continuous process. Continuous monitoring of incoming data can help retrain your model on newer data if the data distribution has deviated significantly from the original training data distribution.

What is a best case timeline for a machine learning project?

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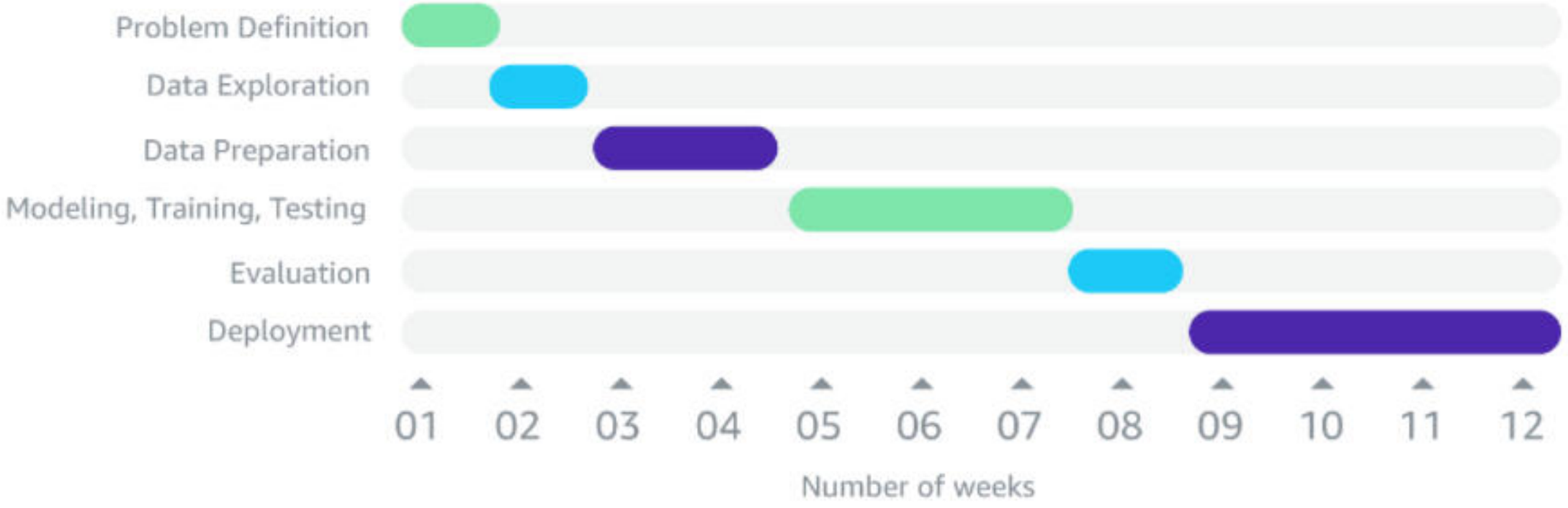


The amount of time needed to deploy production models can take weeks or even months.

What is an example business case of a project timeline challenge?

Consider a manufacturer that needs to use ML to solve a quantifiable business problem but is concerned about potential delays.

To identify a good problem to solve using ML, assess your machine learning lifecycle, and ask these questions.

What question should I ask about strategy?

Click to flip

What question should I ask about strategy?

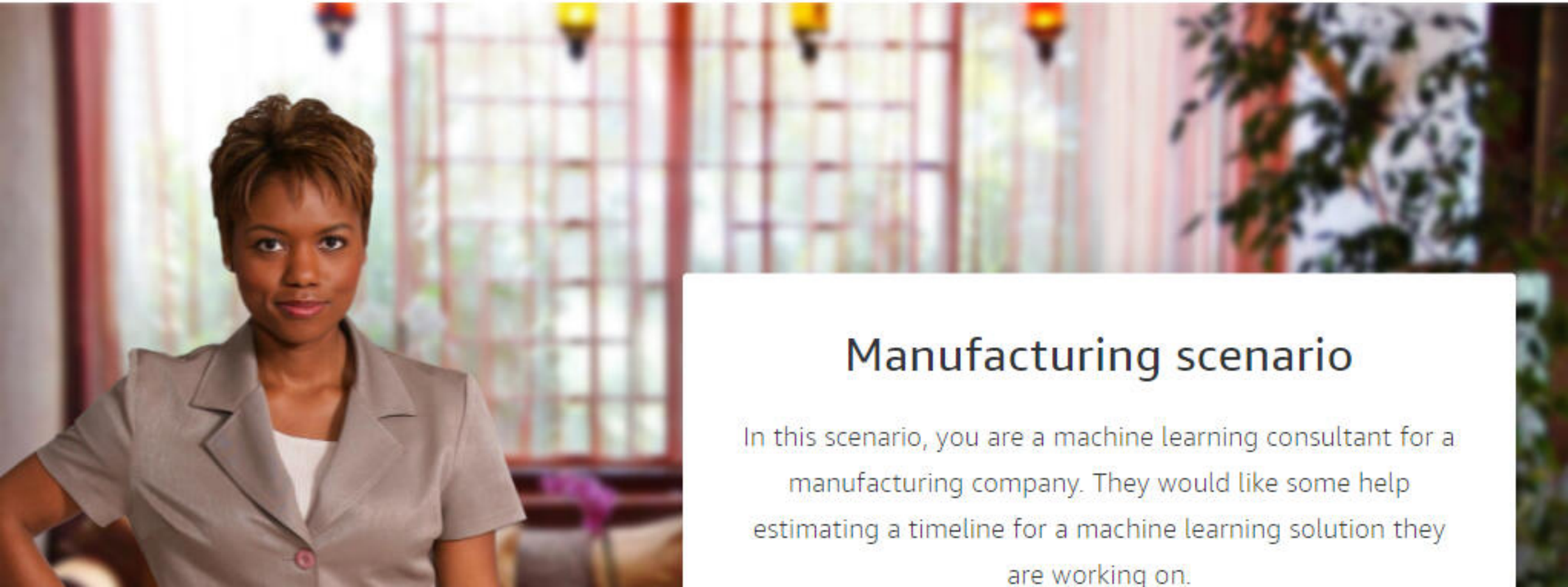
What question should I ask about strategy?

To identify a good problem to solve using ML, assess your machine learning lifecycle, and ask these questions.

Have you ever had a similar task to your proposed ML solution?	Have you explored your data and found faults?	Is the performance of models meeting business requirements?

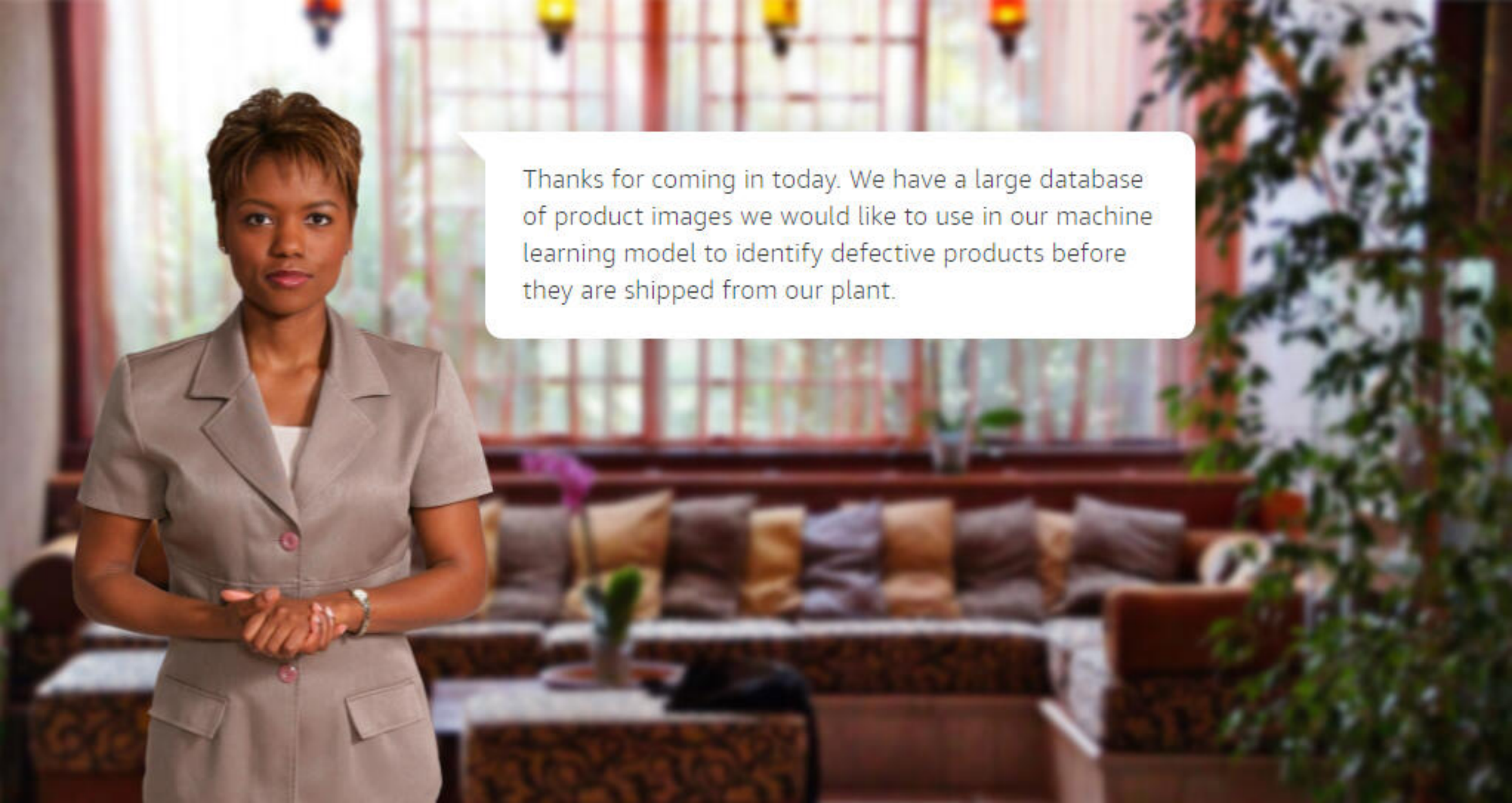
How will this machine learning solution impact my timeline?

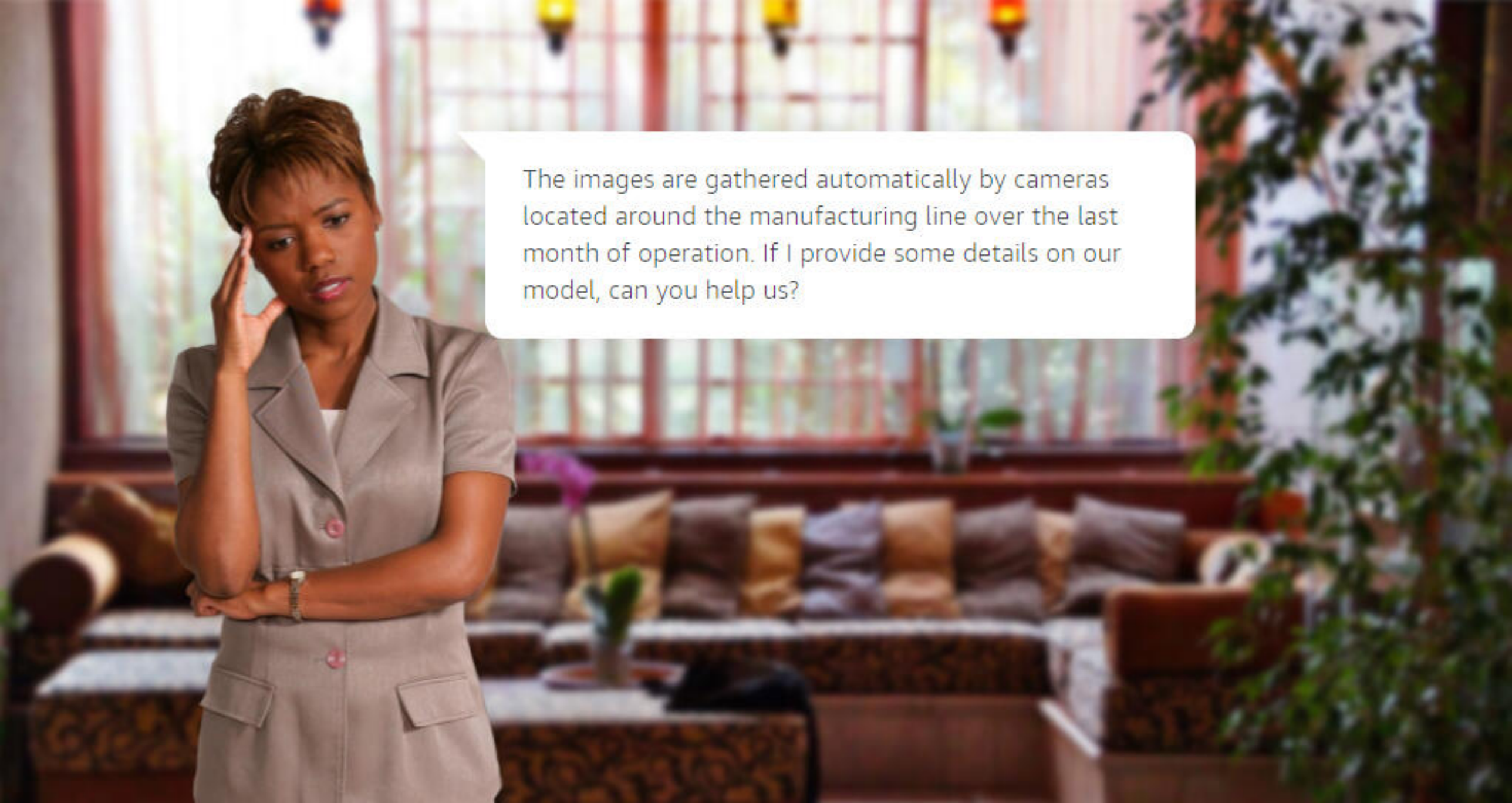
The following scenario describes a manufacturing company's objective and poses questions to determine if ML project timelines could be delayed.

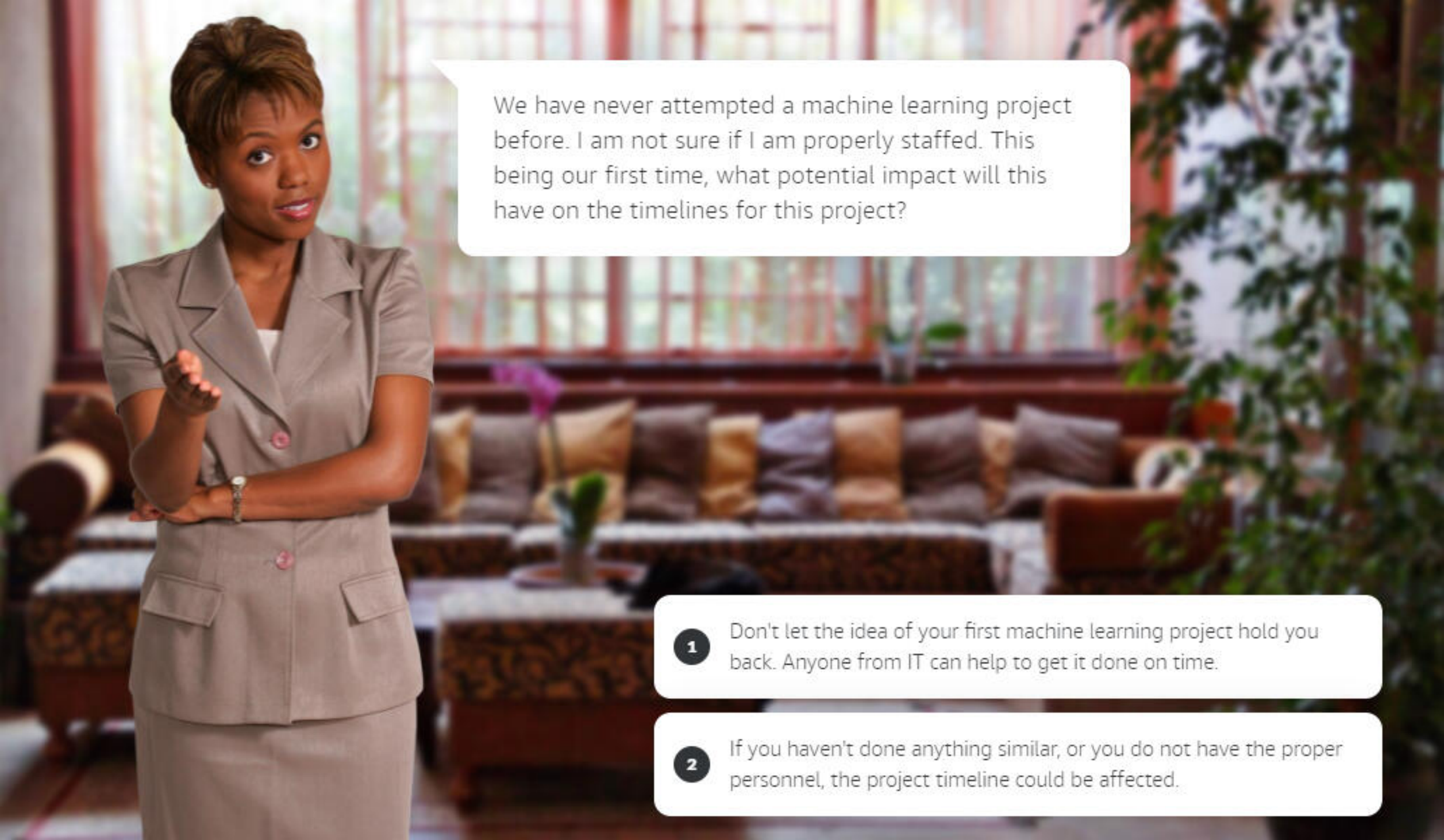


Manufacturing scenario

In this scenario, you are a machine learning consultant for a manufacturing company. They would like some help estimating a timeline for a machine learning solution they are working on.


Thanks for coming in today. We have a large database of product images we would like to use in our machine learning model to identify defective products before they are shipped from our plant.


The images are gathered automatically by cameras located around the manufacturing line over the last month of operation. If I provide some details on our model, can you help us?


We have never attempted a machine learning project before. I am not sure if I am properly staffed. This being our first time, what potential impact will this have on the timelines for this project?
1
Don't let the idea of your first machine learning project hold you back. Anyone from IT can help to get it done on time.
2
If you haven't done anything similar, or you do not have the proper personnel, the project timeline could be affected.

Machine learning models deployed to production do not need to be retrained and updated.

True. Machine learning models do not require continuous retraining because production data does not differ from training data over time.

False. Machine learning models require continuous retraining due to data drifting over time.

Correct

TAKE AGAIN

What early questions should I ask in deployment?

By the end of this lesson, you will be able to ask questions that affect machine learning model deployment to production.

How do I take my machine learning solution into production?

While production deployment of an ML model is one of the last stages of the ML pipeline, ML production code differs in many ways from research code. The purpose of research code is to promote exploration and validate models using iterative processes, which might lack formal quality, stability, or scaling requirements. However, production code must meet objective and fixed requirements, facilitate collaboration through version control, maintain a code deployment history, and meet code reliability standards.

Quality and performance expectations of code produced during the ML research phase differ from expectations after production deployment.

Question 1

What is the likely computational cost of generating predictions with your model?

Why is this important?

Start thinking about the costs associated with launching your machine learning model into production (that is storage, processing, and so on). If the project model meets your business requirements, fast implementation can expedite the benefits. However, failure to plan ahead on computational costs could hinder production later.

1 2 3 4 ✓

Question 2

How quickly does your data change?

Why is this important?

Start thinking about how complex your data is and how often data changes. Ultimately, this could lead you to constantly retrain the model. This could lead to increased time allotted for training since you will be cycling back from production to research and development.

Question 2

How quickly does your data change?

Why is this important?

Start thinking about how complex your data is and how often data changes. Ultimately, this could lead you to constantly retrain the model. This could lead to increased time allotted for training since you will be cycling back from production to research and development.

Question 3

How significant are the changes needed to deploy?

Why is this important?

Start thinking about which changes you would like to enter into production and the frequency. This will guide a strategy on maximizing the impact of updating your model.

1 2 3 4 ✓

Question 4

Does the model's performance meet the business need?

Why is this important?

Start thinking about how your business conditions will change over time. Your current model might need to be adjusted as conditions change. Do you have new product lines launching? Are there new regulations in you business sector? Are you expanding into new geographies?

Which project would be the least likely to benefit from machine learning?

- Identify defective products from images. Product images with labels (defective/not-defective) are available.
- Aggregate the daily revenue over the past week. Daily revenue is available.
- Predict daily customer visit counts to the website. Historical daily customer visit data is available.
- Recommend relevant products to customers. Customers' shopping data is available.

Lesson 5 of 5

Conclusion

In this course, you learned how to:

- Describe how to determine if machine learning is the right solution to your business problem
- Describe the process of ensuring if your business data is machine learning ready
- Explain the impacts machine learning has to a project timeline
- Ask questions that affect machine learning model deployment to production

What's next

In the next course, you will learn:

- How to build a machine learning team
- How to use data and organizational culture strategies to prepare for machine learning adoption

aws training and certification

How can I prepare my organization for using ML?

In this lesson, you will explore the following questions:

- How can I prepare my organization for using ML?
- How can AWS help me?
- What other strategies can I adopt to ensure organizational success?
- Which cultural shift-approach works for my organization?

How do I move my organization into machine learning?

An organization can progress from having few or no ML projects to advanced production ML expertise after completing multiple research projects and deployments.

To learn what key strategies an organization needs to use machine learning, choose the following flashcards.

Click to flip

How do I move my organization into machine learning?

An organization can progress from having few or no ML projects to advanced production ML expertise after completing multiple research projects and deployments.

To learn what key strategies an organization needs to use machine learning, choose the following flashcards.

A robust ML strategy	A data strategy	A culture of learning and collaboration

How can AWS help implement my ML strategy?

You are not alone and you don't have to start from scratch when implementing a robust ML strategy. Amazon Web Services (AWS) offers services which can accelerate your organization's ML adoption process. By taking advantage of ML in the AWS Cloud, there's no need for on-premise infrastructure development or training to start your first project. By relying on services provided by AWS, you can expect to get your team experimenting with ML at a rapid pace.

What other strategies can I adopt to ensure organizational success?

Organizations can begin creating a robust ML strategy through several methods:

1. Find the right problem
2. Fail forward
3. Scale beyond proofs of concept

What other strategies can I adopt to ensure organizational success?

Organizations can begin creating a robust ML strategy through several methods:

1. Find the right problem
2. Fail forward
3. Scale beyond proofs of concept

Strategy 1: Find the right problem

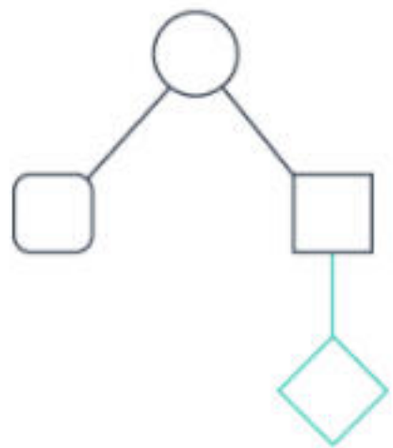
Organizations can begin creating a robust strategy with early executive buy-in and by choosing the right problems to solve using ML. Choosing worthy problems, such as those that aren't solvable by traditional means, require rich data, or demand large amounts of labor, can lead to early wins and gains in organizational momentum.

2 Fail forward

3 Scale beyond proofs of concept

Strategy 1: Find the right problem

Organizations can begin creating a robust strategy with early executive buy-in and by choosing the right problems to solve using ML. Choosing worthy problems, such as those that aren't solvable by traditional means, require rich data, or demand large amounts of labor, can lead to early wins and gains in organizational momentum.



The best way to gain momentum is to get early executive buy-in and to find problems that can yield early wins.

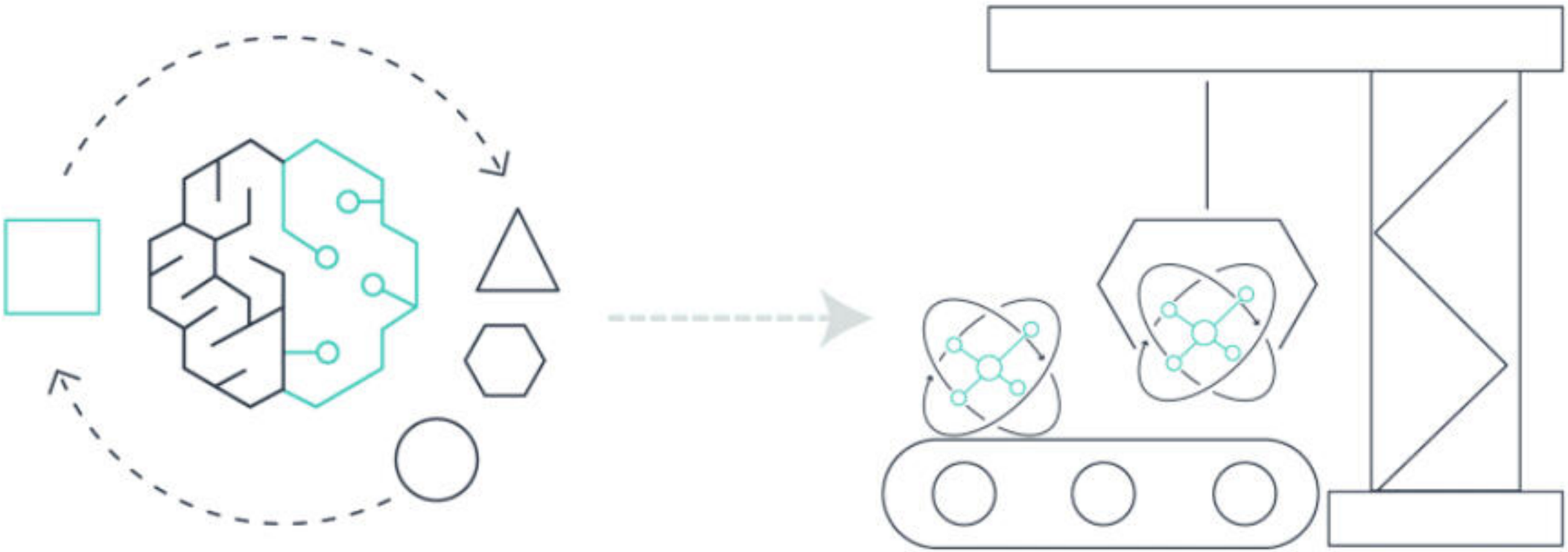
Strategy 2: Fail forward

Failure isn't damaging if changes and adjustments are small, and reattempts are encouraged.

Fail forward means purposefully and deliberately using failure as a path to success. Failing forward with ML means using failure as an iterative opportunity to become fault-tolerant and find a successful direction in subsequent attempts. Many successful outcomes come after many rounds of iteration, and some aren't successful at all.

Strategy 3: Scale beyond proofs of concept (POC)

POCs test a product or service design, idea, or assumption and determine potential feasibility. ML POCs in development can be used to solve ML scaling challenges across the business before making large production investments.



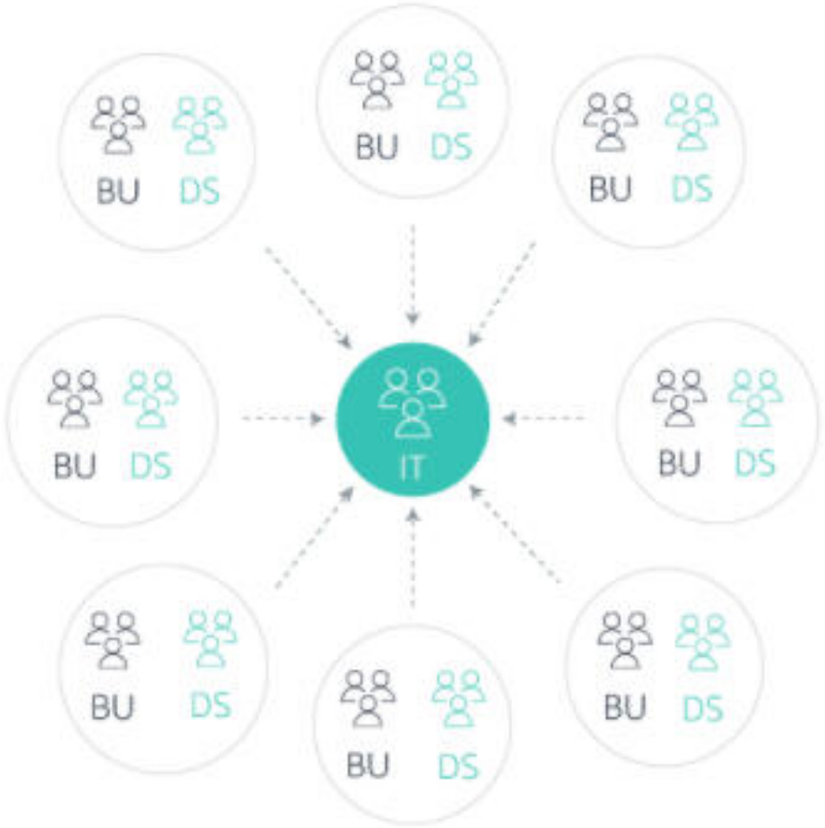

Machine learning is an iterative process. Learn from failed iterations to become *fault-tolerant.*

Which cultural shift approach works for my organization?

Shifting an organization from a centralized hub of data scientists and IT specialists to a decentralized structure where data science expertise is distributed across business units requires several ideological shifts. ML requires changes in decision-making, performance management, and organizational systems to facilitate ongoing data science collaboration with business units.

Individual business units work with centralized data science and information technology operations and data support.

Business units combine with data scientists and work with centralized information technology operations.



In this lesson, you explored the following questions:

- How can I prepare my organization for using ML?
- How can AWS help me?
- What other strategies can I adopt to ensure organizational success?
- Which cultural shift-approach works for my organization?

Which options can help an organization establish a robust ML strategy? (Select THREE)

- [x] Maintain centralized hub-spoke organizational structure
- [ ] Fail forward
- [x] Scale beyond development proofs of concept
- [ ] Find problems that are not data rich, can be solved using traditional means, and don't require large amounts of labor
- [ ] Amazon SageMaker
- [x] Find data rich problems that involve large amounts of labor and can't be solved by traditional means

Lesson 2 of 5

How do I evaluate my data strategy?

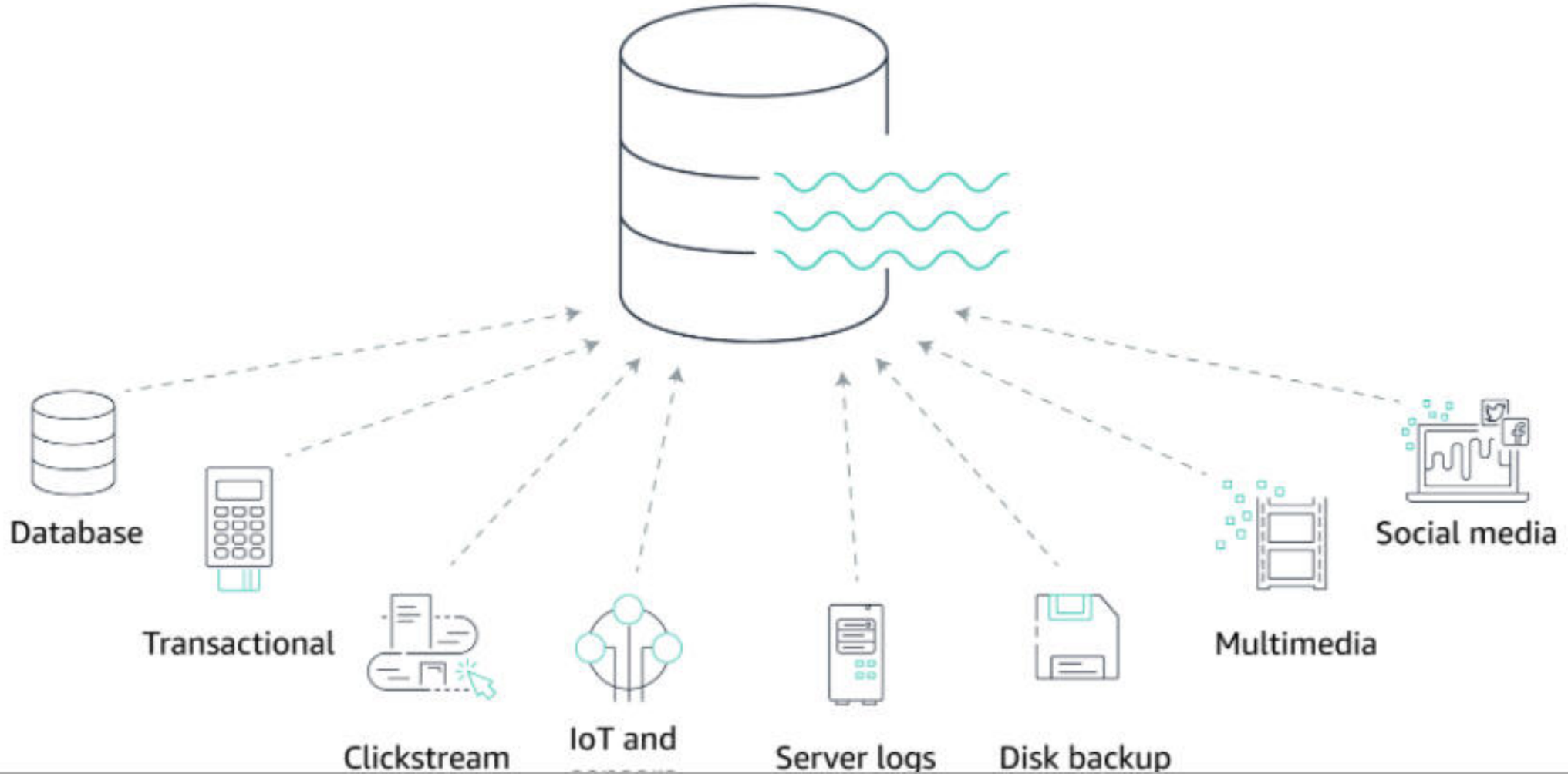
In this lesson, you will explore the following questions:

- How do I evaluate my data strategy?
- How can I improve my data strategy?

How do I evaluate my data strategy?

An effective data strategy begins with evaluating the organization's current data and determining the types of solutions needed to improve data quality. Examples of how to evaluate data quality ratings are shown below.

Organizations can develop strategic plans to collect and use data, even at the POC stage, to successfully change industries with ML. Examples of the types of data which can be collected are shown below.




Data is essential for leaders who are
looking to disrupt their industries
with machine learning.

What are the benefits of moving to a data lake?

Data lakes are an increasingly popular core component of the most efficient ML models. Data lakes can capture and store transactional data, databases, clickstream, IoT and sensor data, logs, backups, multimedia, and social media activity in a single store. Data lakes can also grow to any scale and can also democratize data access and analysis. Additional benefits of data lakes are shown below.

Catalogue, search, and find the relevant data in the central repository.

Store any type of data, at any scale, and at low cost.

Secure the data and prevent unauthorized access.

Quickly perform new types of data analysis.

Data lakes enable a broad set of analytic engines for analytics, real-time and predictive analytics, artificial intelligence (AI), and machine learning.

In this lesson, you explored the following questions:

- How do I evaluate my data strategy?
- How can I improve my data strategy?

Knowledge check

Match a card with a sample data requirement to a category below if the condition of data is Acceptable, Better, or Best.

Lesson 3 of 5

How do I create a culture of learning and collaboration?

In this lesson, you will explore the following questions:

- How do I create a culture of learning and collaboration?
- What is a data scientist?
- What skills should a data scientist have?
- What does a pilot ML team look like?
- What other supporting roles will I need?

Lesson 3 of 5

How do I create a culture of learning and collaboration?

In this lesson, you will explore the following questions:

- How do I create a culture of learning and collaboration?
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- What skills should a data scientist have?
- What does a pilot ML team look like?
- What other supporting roles will I need?
- What are the key responsibilities?

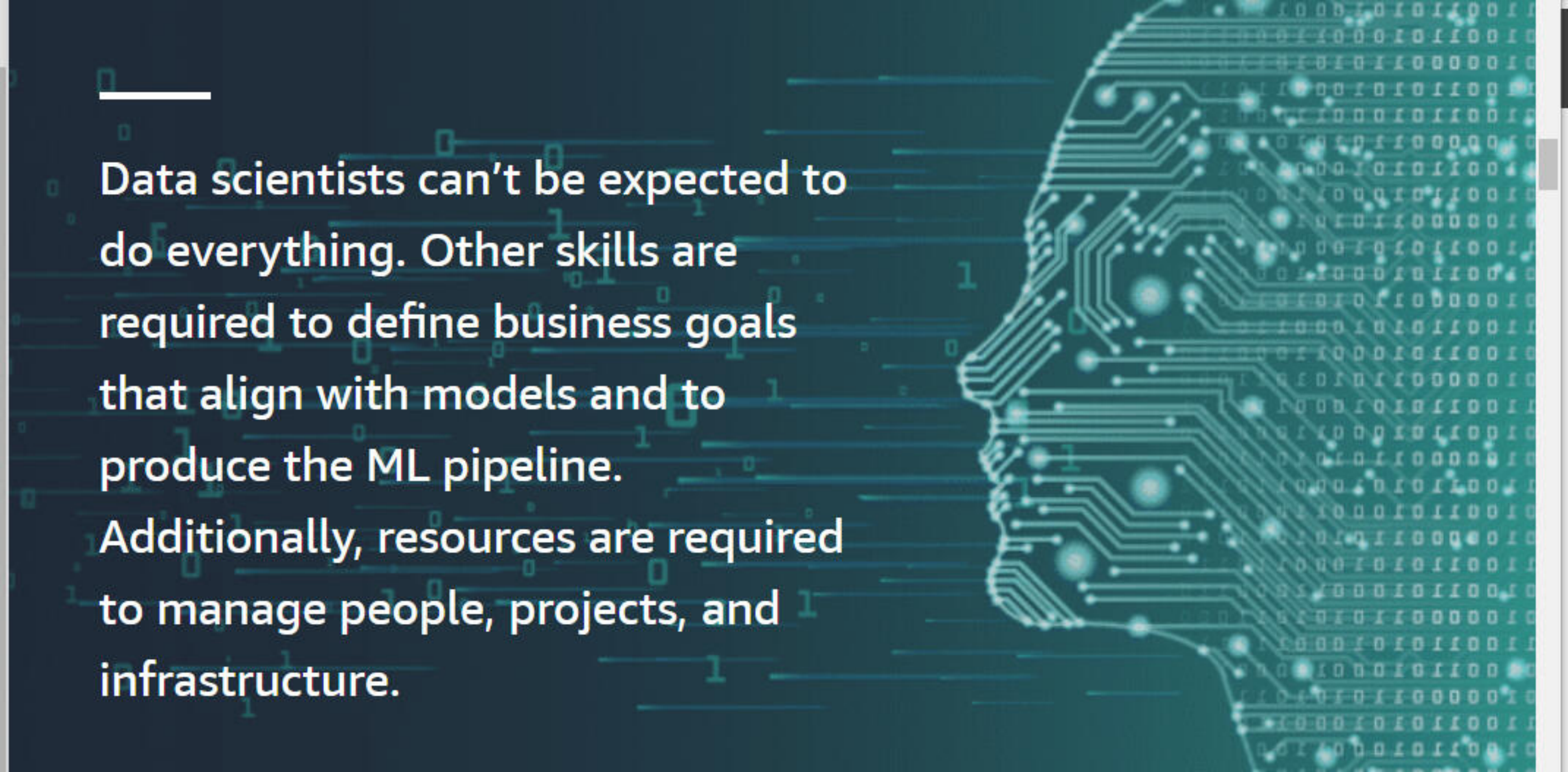
What is a data scientist?

Data scientists work in both the business and technical worlds with deep data analysis to achieve specific outcomes. In the field of machine learning (ML), data scientists design and build models from data, create and work on algorithms, and train models to predict and achieve business goals.

What skills should a data scientist have?

A typical data scientist skillset consists of multiple domains. Examples of several domains are shown below.

Data scientists can’t be expected to do everything. Other skills are required to define business goals that align with models and to produce the ML pipeline. Additionally, resources are required to manage people, projects, and infrastructure.



What does a pilot machine learning team look like?

A pilot ML team can consist of a data scientist, ML engineer, and a technical program manager, each with different responsibilities, but all with relevant ML experience and skills. To learn about the role and skills of each team member, choose the following flashcards.

Data Scien Click to flip

ML Engineer

Technical program manager

Data Scientist
Role: Building ML models
Skills: Math, statistics, ML algorithms, data processing

ML Engineer
Role: Productionizing ML models
Skills: ML algorithms, data pipeline tools, architecture design, software development

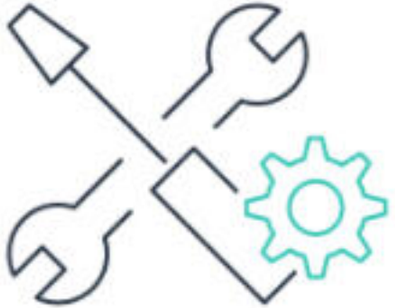
Technical program manager
Role: Ensure ML project meets business, time, and technical goals
Skills: Project management,

How can AWS help my team get started?

AWS can help ML teams get started with Amazon SageMaker. Amazon SageMaker is a fully managed service that can help developers and data scientists build, train, and deploy ML models quickly. Amazon SageMaker removes the heavy lifting from each step of the ML process to make it easier to develop high quality models.

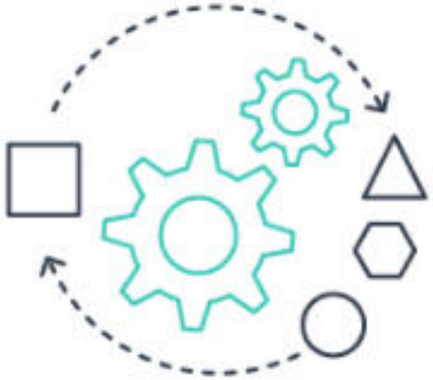
Prepare

Fetch the data into a repository, clean the data, modify the data for easy exploration, prepare and transform the data by filtering out irrelevant parts, and add data labels.



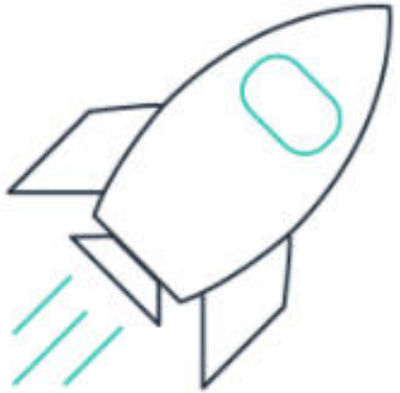
Build

Choose a machine learning algorithm with a learning style that meets your needs. These algorithms can broadly be classified as supervised learning, unsupervised learning, or reinforcement learning.



Train

After building out a model, compute, networking, and storage resources are needed for model training. Evaluate the model to determine whether the accuracy of the inferences is acceptable.



Deploy

When deploying a model into production to make predictions, inference accounts for the vast majority of machine learning's cost.

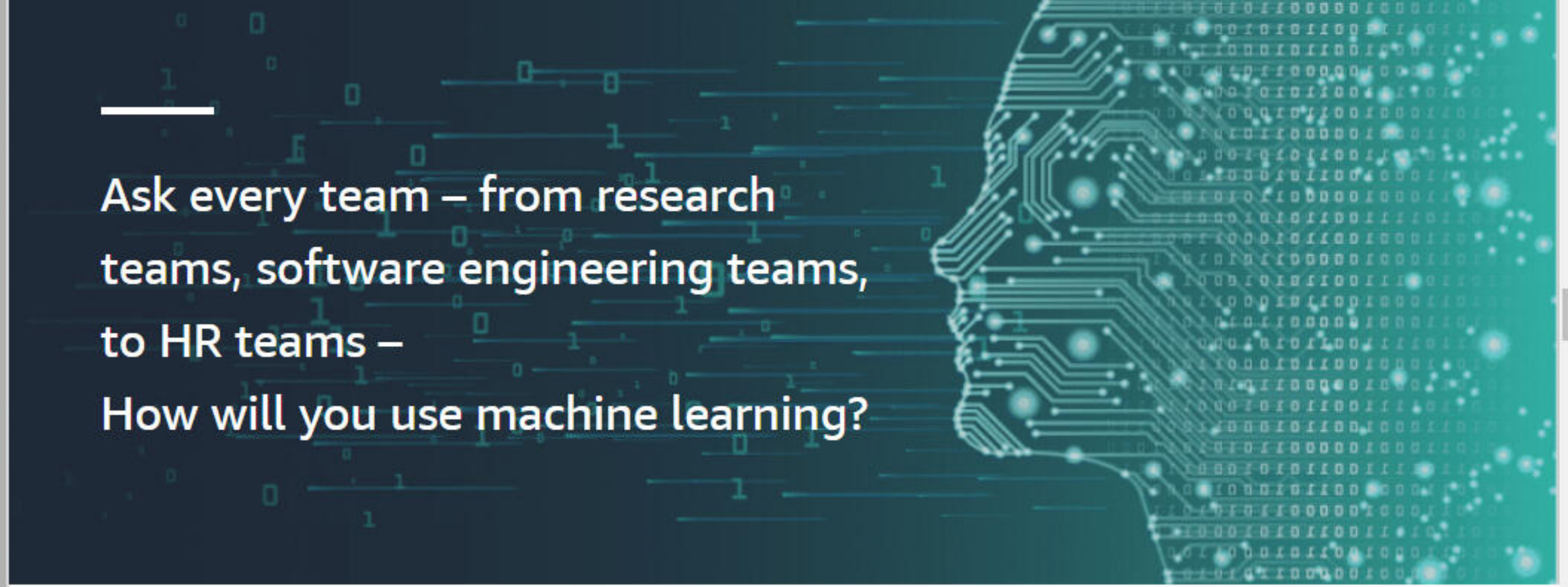
How can I develop my team for ML analytics?

An ML team can grow rapidly through several developmental phases, which include interdisciplinary collaboration, training, and hiring domain experts. Details of each phase are shown below.

PHASE 1 | PHASE 2

- Encourage your technical team to use ML, not just scientists.
- Encourage non-technical leaders to become ML savvy.
- Training, training, training.

Ask every team – from research teams, software engineering teams, to HR teams –
How will you use machine learning?



How can I develop my team for technical expertise?

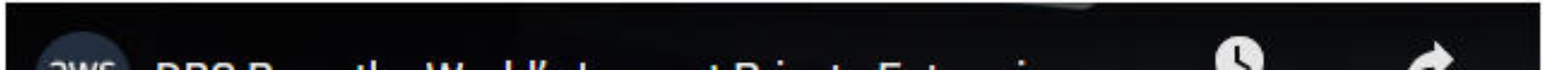
Creating a culture of learning and collaboration is a journey. You can start that journey with excitement activities to motivate the larger organization, training to up-skill your internal teams, and accelerator programs to jump start your journey toward ML competency. Choose a tab below for examples of each.

each.

EXCITEMENT EVENTS | TRAINING | ACCELERATOR PROGRAMS

You can start your journey of learning and collaboration with fun, hands-on activities to excite and motivate the larger technical staff to embrace machine learning. The video below shows how DBS Bank started their journey with the help of AWS DeepRacer. To learn more, see the AWS DeepRacer website.

YOUTUBE



each.

EXCITEMENT EVENTS | TRAINING | ACCELERATOR PROGRAMS

Formal and informal training can play an important role in a learn-and-be-curious culture at an organization. Formal training consisting of instructor-led sessions, group activities, and hands-on labs will help achieve a time-bound learning goal. Informal training can help with just-in-time and self-directed learning. To learn more about formal and informal ML training options, see the Amazon Machine Learning website.

EXCITEMENT EVENTS | TRAINING | ACCELERATOR PROGRAMS

Accelerator programs combine the best practices and proven strategies for successfully making the shift to AI, and provide organizations that are just getting started with ML the training, coaching, and implementation support to successfully launch their ML journey.

These programs are hands-on and immersive engagements which are designed to bring together an organization's executives and technologists to solve business problems with machine learning through a holistic learning experience. The combination of discovery workshops, immersive co-development with ML expert practitioners, instructor-led training, and exciting events can build on each other. In a short time, accelerator programs can inject the practical skills, knowledge, and motivation to jumpstart ML initiatives and accelerate machine learning adoption within the organization.

An example of an accelerator program is the AWS Machine Learning Embark Program. To learn more, see the AWS Machine Learning Embark Program website.

How else can AWS help my team get some quick wins?

Several managed services provide prebuilt ML pipelines that can be applied to problems in an automated way. To learn about each AWS service, choose the following flashcards.

Amazon Kendra

Click to flip

Amazon Comprehend

Amazon Personalize

How else can AWS help my team get some quick wins?

Several managed services provide prebuilt ML pipelines that can be applied to problems in an automated way. To learn about each AWS service, choose the following flashcards.

Create an internal search service	Classify user text based on sentiment	Create a personalization and recommendation service for customers

Amazon Forecast

Amazon Rekognition

Amazon Fraud Detector

Forecast business needs and outcomes

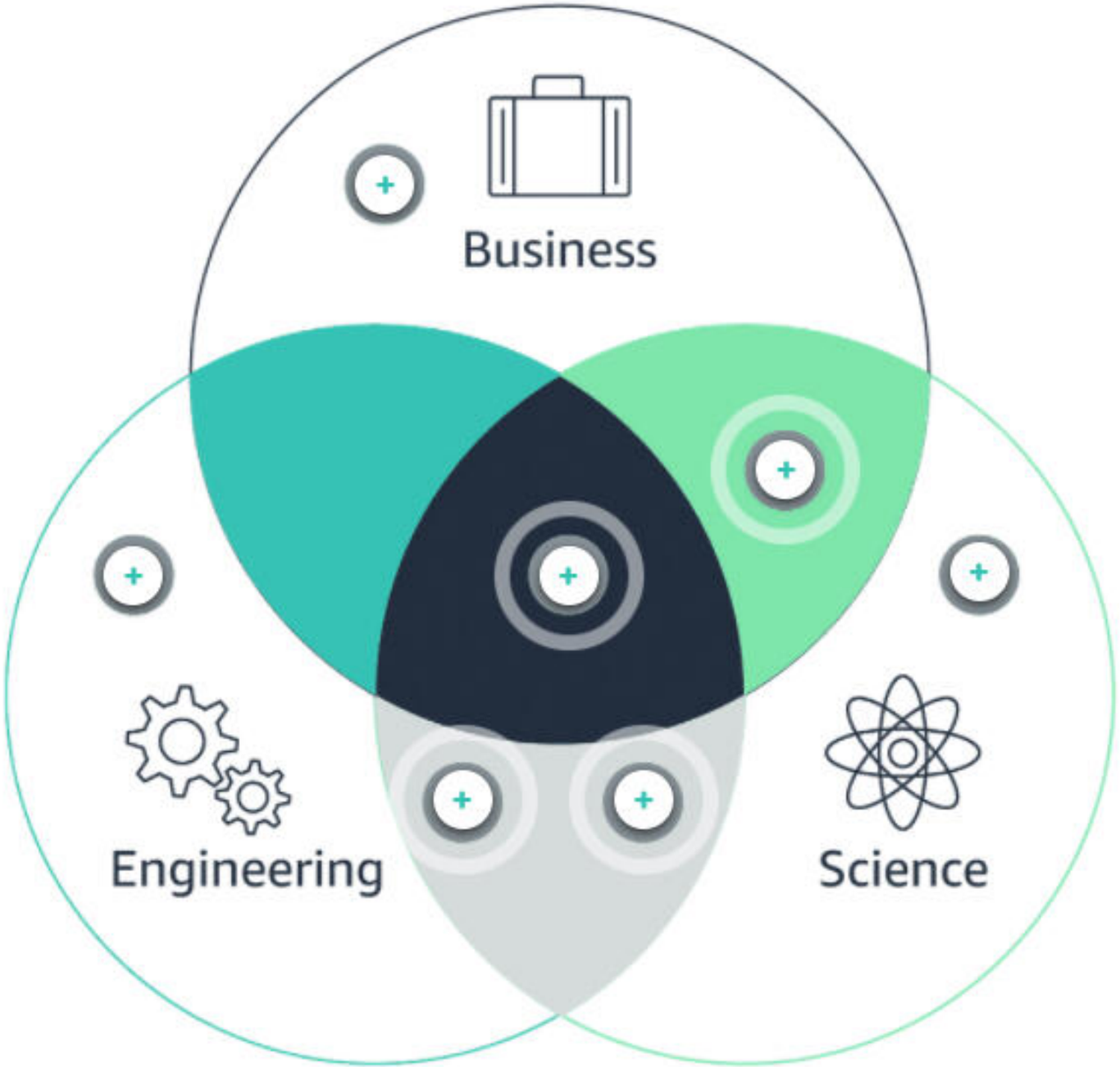
Generate metadata tags from images to make them searchable

Identify potentially fraudulent online activities

When you ask your teams about how they will use machine learning, it will reinforce the importance of ML in their areas of ownership, and will encourage them to work together to come up with interesting opportunities

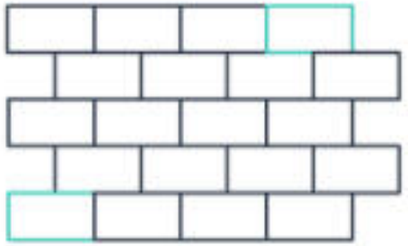
What other supporting roles will I need?

You will need additional roles to help define and ensure model alignment with the business goals, manage operating the ML pipeline, and roles to manage people, projects, and infrastructure. The diagram below shows several supporting ML roles within an organization. Choose the markers below to learn about the different supporting roles.


Business
Engineering
Science

What can I do as a leader to support the culture shift?

Explain why you are starting new ML initiatives.



Anticipate blockers to adoption.

Budget for integration and adoption of technology.

Balance feasibility, time, and value tradeoff.

In this lesson, you explored the following questions:

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- What does a pilot ML team look like?
- What is a data scientist?
- What skills should a data scientist have?
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Which of the following is **not** an action a leader should take to encourage early ML adoption?

- ✗ Allow for experimentation and failure
- ✗ Ensure data is complete and easy to access
- ✓ Set up a complete ML infrastructure
- ✗ Create rapid PoCs to identify best use cases
- ✗ Encourage interdisciplinary collaboration

How do I start my ML journey?

In this lesson, you will explore the following questions:

- How do I start my ML journey?
- What does an organization's ML journey look like?
- What is an example business case for an organization's progression?

How do I start my ML journey?

Research, software engineering, and HR teams must work together to determine how ML will be used in your organization. They will also identify sources of ML adoption challenges, and develop clear strategies to overcome barriers.

What does an organization's ML journey look like?

Consider the following example: A chief experience officer (CXO) at a retail company is starting a machine learning journey with an analytics pipeline, but wants to start leveraging machine learning for different use cases. Each example below describes the ML journey based on the organization's ML experience.

LIMITED EXPERTISE	FEW PRODUCTION WORKLOADS	MULTIPLE PRODUCTION WORKLOADS

As a team begins an ML journey, inexperience may limit the amount of success a team can attain. The steps below highlight ways to maximize each part of the ML journey with limited experience.

Robust AI strategy

- Start with important projects as proofs of concept
- Gain momentum using these projects
- Explain the why behind the shift towards AI

Data strategy

- Explore and document where the data resides
- Document if the data can be used for an AI project
- Prepare a timeline for building a data pipeline if there isn't one

Culture of learning and collaboration

- Allow teams to explore and experiment with the data
- Team up with external resources
- Leverage managed services

LIMITED EXPERTISE | FEW PRODUCTION WORKLOADS | MULTIPLE PRODUCTION WORKLOADS

After a team has begun an ML journey, team success may still be limited even after several deployments. The steps below highlight ways to maximize each part of the ML journey with a few production loads.

Robust AI strategy

- Building AI capabilities for the whole organization
- Creating a strategy to scale from PoCs to production
- Encourage cross collaboration between teams

Data strategy

- Creating a strategy for consolidating various data sources into a source of truth e.g. a data lake or a data warehouse
- Build data literacy across the organization

Culture of learning and collaboration

- Start building an internal AI team
- Use existing workforce and train them using various online and in-person courses

LIMITED EXPERTISE	FEW PRODUCTION WORKLOADS	MULTIPLE PRODUCTION WORKLOADS

Once a team has grown accustomed to completing production deployments, team success can include long-term strategies and organizational goals. The steps below highlight ways to maximize each part of the ML journey with multiple production workloads.

Robust AI strategy

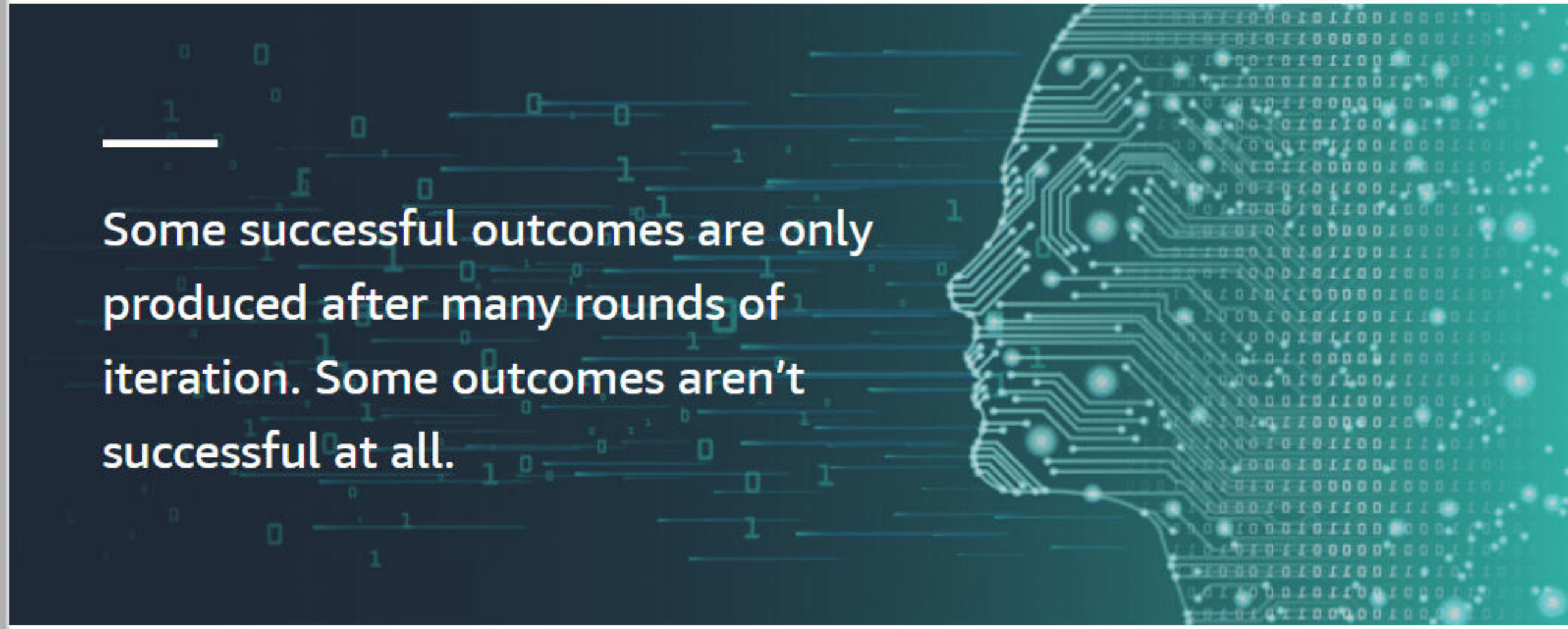
- Long term AI strategy baked into the core business
- Creating AI leadership to maintain long term vision
- Create robust hiring pipeline

Data strategy

- Adding useful external data to improve the quality and effectiveness of the data

Culture of learning and collaboration

- Building an AI org that collaborates with various internal teams
- Continue to explore and experiment with the data


Some successful outcomes are only produced after many rounds of iteration. Some outcomes aren’t successful at all.

What are some common mistakes?

While starting an ML journey may not seem difficult, not every organization's transition is straightforward. To learn about common ML journey mistakes, choose the following flashcards.

Viewing AI as a plug-and-play technology with immediate returns.

Thinking too narrowly about AI applications.

AI has the biggest impact when it's developed by cross-functional teams with a mix of skills and perspectives.

AI has the biggest impact when it's developed by cross-functional teams with a mix of skills and perspectives.

Gain executive sponsorship for proof of concept

Executive sponsorship can maximize the ML journey and strengthen organizational capability and business success by supporting proof of concept development.

Takeaway 2

Use proof of concepts to drive ML engagement within the organization

POCs should be small, safe-to-fail tests that showcase incremental parts of the solution to one or more business goals.

Allow teams to experiment and fail.

ML teams should be allowed to formulate a problem, complete research, experiment, assess risk, and test assumptions. Each solution may require many rounds of iteration to be successful, and some aren't successful at all.

Examine your data strategy

Evaluate, label, and centralize relevant data in a single source of truth, specifically a data lake, for availability and accessibility to other organizational teams.

Improve cross-collaboration between different teams

Data science subject matter experts should be a permanent part of multiple business units and teams. AI has the biggest impact when it's developed by cross-functional teams with a mix of skills and perspectives.

1 2 3 4 5 ✓

What is a common ML journey mistake?

- ⊗ Gain executive sponsorship for proof of concept.
- ⊗ Allowing teams to experiment and fail.
- ⊗ Improve cross-collaboration between different teams
- ✓ Viewing AI as a plug-and-play technology with immediate returns.

Correct

Lesson 5 of 5

Conclusion

In this course, you have learned:

- How to develop a path for organizations to successfully shift towards ML
- How to analyze organizational needs for developing an ML organization
- How to identify and avoid common mistakes along the ML journey
- How to describe the components needed for an organizational change

Thank you!

In this course, you have learned:

- How to develop a path for organizations to successfully shift towards ML
- How to analyze organizational needs for developing an ML organization
- How to identify and avoid common mistakes along the ML journey
- How to describe the components needed for an organizational change

Thank you!

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