### 1.

Question 1

A data analytics team works to recognize the current problem. Then, they organize available information to reveal gaps and opportunities. Finally, they identify the available options. These steps are part of what process?

**1 / 1 point**



Categorizing things



Using structured thinking



Making connections



Applying the SMART methodology

**Correct**

This describes structured thinking. Structured thinking begins with recognizing the current problem or situation. Next, information is organized to reveal gaps and opportunities. Finally, the available options are identified.

### 2.

Question 2

In which step of the data analysis process would an analyst ask questions such as, “What data errors might get in the way of my analysis?” or “How can I clean my data so the information I have is consistent?”

**1 / 1 point**



Analyze



Ask



Prepare



Process

**Correct**

An analyst asks questions such as, “What data errors might get in the way of my analysis?” or “How can I clean my data so the information I have is consistent?” during the process step. This is when data is cleaned in order to eliminate any possible errors, inaccuracies, or inconsistencies.

### 3.

Question 3

A data analyst has entered the analyze step of the data analysis process. Identify the questions they might ask during this phase. Select all that apply.

**1 / 1 point**



What is the question I’m trying to answer?



How can I create an engaging presentation to stakeholders?



How will my data help me solve this problem?

**Correct**

The analyze step involves thinking analytically about data. Data analysts might ask how the data can help them solve the problem and what story the data is trying to tell.



What story is my data telling me?

**Correct**

The analyze step involves thinking analytically about data. Data analysts might ask how the data can help them solve the problem and what story the data is trying to tell.

### 4.

Question 4

A data analyst is trying to understand what data to use to help solve a business problem. They’re asking questions such as, “What internal data is available in the database?” and “What outside facts do I need to research?” The data analyst is in which phase of the data analysis process?

**1 / 1 point**



Share



Ask



Prepare



Act

**Correct**

The data analyst is in the prepare step. This is when analysts consider what information to gather and what research they can do to help problem-solve.

In a previous video,

I shared how data analysis helped a company

figure out where to advertise its services.

An important part of this process

was strong problem-solving skills.

As a data analyst,

you'll find that problems are at the center

of what you do every single day,

but that's a good thing.

Think of problems as opportunities to put your skills to

work and find creative and insightful solutions.

Problems can be small or large,

simple or complex,

no problem is like another and they all require

a slightly different approach

but the first step is always the same:

Understanding what kind of problem you're trying to

solve and that's what we're going to talk about now.

Data analysts work with a variety of problems.

In this video, we're going to focus on six common types.

These include: making predictions, categorizing things,

spotting something unusual, identifying themes,

discovering connections, and finding patterns.

Let's define each of these now.

First, making predictions.

This problem type involves using data to make

an informed decision about

how things may be in the future.

For example, a hospital system might use

a remote patient monitoring to

predict health events for chronically ill patients.

The patients would take

their health vitals at home every day,

and that information combined with data about their age,

risk factors, and other important details could enable

the hospital's algorithm to predict

future health problems and

even reduce future hospitalizations.

The next problem type is categorizing things.

This means assigning information to

different groups or clusters based on common features.

An example of this problem type is

a manufacturer that reviews data on

shop floor employee performance.

An analyst may create a group for employees

who are most and least effective at engineering.

A group for employees who are most and least

effective at repair and maintenance,

most and least effective at assembly,

and many more groups or clusters.

Next, we have spotting something unusual.

In this problem type,

data analysts identify data

that is different from the norm.

An instance of spotting something

unusual in the real world is

a school system that has

a sudden increase in the number of students registered,

maybe as big as

a 30 percent jump in the number of students.

A data analyst might look into

this upswing and discover that

several new apartment complexes had been

built in the school district earlier that year.

They could use this analysis to make sure the school has

enough resources to handle the additional students.

Identifying themes is the next problem type.

Identifying themes takes categorization as a step

further by grouping information into broader concepts.

Going back to our manufacturer that has just

reviewed data on the shop floor employees.

First, these people are grouped by types and tasks.

But now a data analyst could

take those categories and group them into

the broader concept of

low productivity and high productivity.

This would make it possible for the business to

see who is most and least productive,

in order to reward top performers and

provide additional support to

those workers who need more training.

Now, the problem type of discovering connections enables

data analysts to find

similar challenges faced by different entities,

and then combine data and insights to address them.

Here's what I mean;

say a scooter company is experiencing

an issue with the wheels it gets from its wheel supplier.

That company would have to stop production until it could

get safe, quality wheels back in stock.

But meanwhile, the wheel companies encountering

the problem with the rubber it uses to make wheels,

turns out its rubber supplier could

not find the right materials either.

If all of these entities could talk about

the problems they're facing and share data openly,

they would find a lot of

similar challenges and better yet,

be able to collaborate to find a solution.

The final problem type is finding patterns.

Data analysts use data to find

patterns by using historical data to

understand what happened in

the past and is therefore likely to happen again.

Ecommerce companies use data to

find patterns all the time.

Data analysts look at transaction data to understand

customer buying habits at

certain points in time throughout the year.

They may find that customers buy more

canned goods right before a hurricane,

or they purchase fewer cold-weather accessories

like hats and gloves during warmer months.

The ecommerce companies can

use these insights to make sure

they stock the right amount of

products at these key times.

Alright, you've now learned six basic problem types

that data analysts typically face.

As a future data analyst,

this is going to be valuable knowledge for your career.

Coming up, we'll talk a bit more

about these problem types and I'll

provide even more examples of them

being solved by data analysts.

Personally, I love real-world examples.

They really help me better understand new concepts.

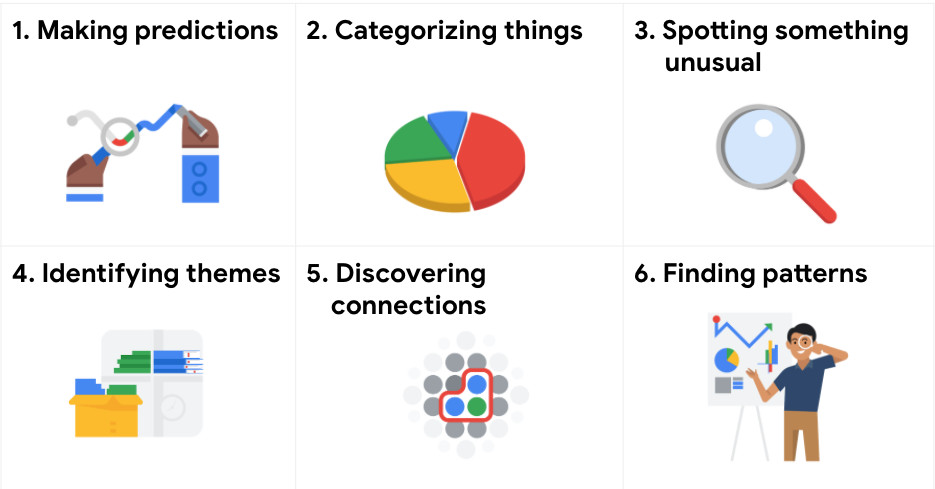
I can't wait to share

even more actual cases with you. See you there.

# **Six problem types**

Data analytics is so much more than just plugging information into a platform to find insights. It is about solving problems. To get to the root of these problems and find practical solutions, there are lots of opportunities for creative thinking. No matter the problem, the first and most important step is understanding it. From there, it is good to take a problem-solver approach to your analysis to help you decide what information needs to be included, how you can transform the data, and how the data will be used.

## Data analysts typically work with six problem types

1. Making predictions 2. Categorizing things 3. Spotting something unusual 4. Identifying themes 5. Discovering connections 6. Finding patterns

A video, [Common problem types](https://www.coursera.org/learn/ask-questions-make-decisions/lecture/E8HxZ/common-problem-types), introduced the six problem types with an example for each. The examples are summarized below for review.

### **Making predictions**

A company that wants to know the best advertising method to bring in new customers is an example of a problem requiring analysts to make predictions. Analysts with data on location, type of media, and number of new customers acquired as a result of past ads can't guarantee future results, but they can help predict the best placement of advertising to reach the target audience.

### **Categorizing things**

An example of a problem requiring analysts to categorize things is a company's goal to improve customer satisfaction. Analysts might classify customer service calls based on certain keywords or scores. This could help identify top-performing customer service representatives or help correlate certain actions taken with higher customer satisfaction scores.

### **Spotting something unusual**

A company that sells smart watches that help people monitor their health would be interested in designing their software to spot something unusual. Analysts who have analyzed aggregated health data can help product developers determine the right algorithms to spot and set off alarms when certain data doesn't trend normally.

### **Identifying themes**

User experience (UX) designers might rely on analysts to analyze user interaction data. Similar to problems that require analysts to categorize things, usability improvement projects might require analysts to identify themes to help prioritize the right product features for improvement. Themes are most often used to help researchers explore certain aspects of data. In a user study, user beliefs, practices, and needs are examples of themes.

By now you might be wondering if there is a difference between categorizing things and identifying themes. The best way to think about it is: categorizing things involves assigning items to categories; identifying themes takes those categories a step further by grouping them into broader themes.

### **Discovering connections**

A third-party logistics company working with another company to get shipments delivered to customers on time is a problem requiring analysts to discover connections. By analyzing the wait times at shipping hubs, analysts can determine the appropriate schedule changes to increase the number of on-time deliveries.

### **Finding patterns**

Minimizing downtime caused by machine failure is an example of a problem requiring analysts to find patterns in data. For example, by analyzing maintenance data, they might discover that most failures happen if regular maintenance is delayed by more than a 15-day window.

## Key takeaway

As you move through this program, you will develop a sharper eye for problems and you will practice thinking through the problem types when you begin your analysis. This method of problem solving will help you figure out solutions that meet the needs of all stakeholders.

You've been learning about six common problem types of data analysts encounter,

making predictions, categorizing things, spotting something unusual,

identifying themes, discovering connections, and finding patterns.

Let's think back to our real world example from a previous video.

In that example,

anywhere gaming repair wanted to figure out how to bring in new customers.

So the problem was, how to determine the best advertising method for

anywhere gaming repair's target audience.

To help solve this problem, the company used data to envision

what would happen if it advertised in different places.

Now nobody can see the future but the data helped them make an informed

decision about how things would likely work out.

So, their problem type was making predictions.

Now let's think about the second problem type, categorizing things.

Here's an example of a problem that involves categorization.

Let's say a business wants to improve its customer satisfaction levels.

Data analysts could review recorded calls to the company's customer

service department and evaluate the satisfaction levels of each caller.

They could identify certain key words or phrases that come up during

the phone calls and then assign them to categories such as politeness,

satisfaction, dissatisfaction, empathy, and more.

Categorizing these key words gives us data that lets the company

identify top performing customer service representatives, and

those who might need more coaching.

This leads to happier customers and higher customer service scores.

Okay, now let's talk about a problem that involves spotting something unusual.

Some of you may have a smart watch, my favorite app is for health tracking.

These apps can help people stay healthy by collecting data such as their heart rate,

sleep patterns, exercise routine, and much more.

There are many stories out there about health apps actually saving

people's lives.

One is about a woman who was young, athletic, and

had no previous medical problems.

One night she heard a beep on her smartwatch,

a notification said her heart rate had spiked.

Now in this example think of the watch as a data analyst.

The watch was collecting and analyzing health data.

So when her resting heart rate was suddenly 120 beats per minute,

the watch spotted something unusual because according to its data,

the rate was normally around 70.

Thanks to the data her smart watch gave her, the woman went to the hospital and

discovered she had a condition which could have led to life threatening

complications if she hadn't gotten medical help.

Now let's move on to the next type of problem: identifying themes.

We see a lot of examples of this in the user experience field.

User experience designers study and

work to improve the interactions people have with products they use every day.

Let's say a user experience designer wants to see what customers think about

the coffee maker his company manufactures.

This business collects anonymous survey data from users,

which can be used to answer this question.

But first to make sense of it all,

he will need to find themes that represent the most valuable data,

especially information he can use to make the user experience even better.

So the problem the user experience designer's company faces,

is how to improve the user experience for its coffee makers.

The process here is kind of like finding categories for

keywords and phrases in customer service conversations.

But identifying themes goes even further by grouping each insight into

a broader theme.

Then the designer can pinpoint the themes that are most common.

In this case he learned users often couldn't tell if the coffee maker

was on or off.

He ended up optimizing the design with improved placement and lighting for

the on/off button, leading to the product improvement and happier users.

Now we come to the problem of discovering connections.

This example is from the transportation industry and

uses something called third party logistics.

Third party logistics partners help businesses ship products when

they don't have their own trucks, planes or ships.

A common problem these partners face is figuring out how to reduce wait time.

Wait time happens when a truck driver from the third party logistics provider

arrives to pick up a shipment but it's not ready.

So she has to wait.

That costs both companies time and money and

it stops trucks from getting back on the road to make more deliveries.

So how can they solve this?

Well, by sharing data the partner companies can view each other's timelines

and see what's causing shipments to run late.

Then they can figure out how to avoid those problems in the future.

So a problem for one business doesn't cause a negative impact for the other.

For example, if shipments are running late because one company only delivers Mondays,

Wednesdays and Fridays, and the other company only delivers Tuesdays and

Thursdays, then the companies can choose to deliver on the same day to reduce

wait time for customers.

All right, we've come to our final problem type, finding patterns.

Oil and gas companies are constantly working to keep their machines running

properly.

So the problem is, how to stop machines from breaking down.

One way data analysts can do this is by looking at patterns

in the company's historical data.

For example, they could investigate how and when a particular machine

broke down in the past and then generate insights into what led to the breakage.

In this case, the company saw pattern indicating that machines began breaking

down at faster rates when maintenance wasn't kept up in 15 day cycles.

They can then keep track of current conditions and

intervene if any of these issues happen again.

Pretty cool, right?

I'm always amazed to hear about how data helps real people and

businesses make meaningful change.

I hope you are too.

See you soon.

A data analyst identifies and classifies keywords from customer reviews to improve customer satisfaction. This is an example of which problem type?

**1 / 1 point**



Categorizing things



Finding patterns



Making predictions



Spotting something unusual

**Correct**

A data analyst identifying and classifying keywords from customer reviews to improve customer satisfaction is an example of categorizing things.

### 2.

Question 2

The spotting something unusual problem type could involve which of the following scenarios?

**1 / 1 point**



A data insight helps a landscaping company envision what will happen in the future.



A data analyst working for an agricultural company examines why a dataset has a surprising and rare data point.



A data analyst at a clothing retailer creates a list of common topics, categorizes them, and groups each category into a broader subject area for further analysis.



A data analyst at an arts nonprofit classifies similar data points into groups for further analysis.

**Correct**

The problem type of spotting something unusual could involve a data analyst examining why a dataset has a surprising and rare data point. Spotting something unusual deals with identifying and analyzing something out of the ordinary.

### 3.

Question 3

A data analyst at an online retailer works with historical sales data. The analyst identifies repeating trends in the sales data. This is an example of which problem type?

**1 / 1 point**



Identifying themes



Making predictions



Finding patterns



Categorizing things

**Correct**

This is an example of finding patterns. Finding patterns deals with identifying trends in a data set.

We've talked a lot about what data

is and how it plays into decision-making.

What do we know already?

Well, we know that data is a collection of facts.

We also know that data analysis reveals

important patterns and insights about that data.

Finally, we know that data analysis

can help us make more informed decisions.

Now, we'll look at how data plays into

the decision-making process and take

a quick look at the differences between

data-driven and data-inspired decisions.

Let's look at a real-life example.

Think about the last time you

searched "restaurants near me" and

sorted the results by rating to

help you decide which one looks best.

That was a decision you made using data.

Businesses and other organizations use data

to make better decisions all the time.

There's two ways they can do this,

with data-driven or data-inspired decision-making.

We'll talk more about

data-inspired decision-making later on,

but here's a quick definition for now.

Data-inspired decision-making

explores different data sources

to find out what they have in common.

Here at Google, we use data every single day,

in very surprising ways too.

For example, we use data to help cut back on

the amount of energy spent cooling your data centers.

After analyzing years of

data collected with artificial intelligence,

we were able to make decisions

that help reduce the energy we

use to cool our data centers by over 40 percent.

Google's People Operations team

also uses data to improve how

we hire new Googlers

and how we get them started on the right foot.

We wanted to make sure we weren't

passing over any talented applicants and

that we made their transition into

their new roles as smooth as possible.

After analyzing data on applications, interviews,

and new hire orientation processes,

we started using an algorithm.

An algorithm is a process or set of

rules to be followed for a specific task.

With this algorithm, we reviewed applicants that didn't

pass the initial screening process

to find great candidates.

Data also helped us determine

the ideal number of interviews that lead to

the best possible hiring decisions.

We've created new onboarding agendas to

help new employees get started at their new jobs.

Data is everywhere.

Today, we create so much data that scientists estimate

90 percent of the world's data

has been created in just the last few years.

Think of the potential here.

The more data we have,

the bigger the problems we can solve and

the more powerful our solutions can be.

But responsibly gathering data

is only part of the process.

We also have to turn data into

knowledge that helps us make better solutions.

I'm going to let fellow Googler,

Ed, talk more about that.

Just having tons of data isn't enough.

We have to do something meaningful with it.

Data in itself provides little value.

To quote Jack Dorsey,

the founder of Twitter and Square,

"Every single action that we do in

this world is triggering off some amount of data,

and most of that data is meaningless until someone adds

some interpretation of it

or someone adds a narrative around it."

Data is straightforward, facts collected together,

values that describe something.

Individual data points become more

useful when they're collected and structured,

but they're still somewhat meaningless by themselves.

We need to interpret data to turn it into information.

Look at Michael Phelps' time in

a 200-meter individual medal swimming race,

one minute, 54 seconds.

Doesn't tell us much. When we

compare it to his competitor's times in the race,

however, we can see that Michael came

in the first place and won the gold medal.

Our analysis took data, in this case,

a list of Michael's races and times and turned it into

information by comparing it with other data.

Context is important.

We needed to know that this race was an Olympic final and

not some other random race to

determine that this was a gold medal finish.

But this still isn't knowledge.

When we consume information, understand it,

and apply it, that's when data is most useful.

In other words, Michael Phelps is a fast swimmer.

It's pretty cool how we can turn data into

knowledge that helps us in all kinds of ways,

whether it's finding the perfect restaurant or

making environmentally friendly changes.

But keep in mind,

there are limitations to data analytics.

Sometimes we don't have

access to all of the data we need,

or data is measured differently across programs,

which can make it difficult to find concrete examples.

We'll cover these more in detail later on,

but it's important that you start

thinking about them now.

Now that you know how data drives decision-making,

you know how key your role as

a data analyst is to the business.

Data is a powerful tool for decision-making,

and you can help provide businesses with the information

they need to solve problems and make new decisions,

but before that, you will

need to learn a little more about

the kinds of data you'll be

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the kinds of data you'll be

working with and how to deal with it.

Fill in the blank: Data-inspired decision-making explores different data sources to find \_\_\_\_\_.



problems



outliers



predictions



Commonalities THIS

Data trials and triumphs

This reading focuses on why accurate interpretation of data is key to data-driven decisions. You have been learning why data is such a powerful business tool and how data analysts help their companies make data-driven decisions for great results. As a quick reminder, the goal of all data analysts is to use data to draw accurate conclusions and make good recommendations. That all starts with having complete, correct, and relevant data.



But keep in mind, it is possible to have solid data and still make the wrong choices. It is up to data analysts to interpret the data accurately. **When data is interpreted incorrectly, it can lead to huge losses. Consider the examples below.**

**Coke launch failure**

In 1985, New Coke was launched, replacing the classic Coke formula. The company had done taste tests with 200,000 people and found that test subjects preferred the taste of New Coke over Pepsi, which had become a tough competitor. Based on this data alone, classic Coke was taken off the market and replaced with New Coke. This was seen as the solution to take back the market share that had been lost to Pepsi.

But as it turns out, New Coke was a massive flop and the company ended up losing tens of millions of dollars. How could this have happened with data that seemed correct? It is because the data wasn’t complete, which made it inaccurate. The data didn't consider how customers would feel about New Coke replacing classic Coke. The company’s decision to retire classic Coke was a data-driven decision based on incomplete data.

**Mars orbiter loss**

In 1999, NASA lost the $125 million Mars Climate Orbiter, even though it had good data. The spacecraft burned to pieces because of poor collaboration and communication. The Orbiter’s navigation team was using the **SI or metric system** (newtons) for their force calculations, but the engineers who built the spacecraft used the **English Engineering Units** **system** (pounds) for force calculations.

No one realized a problem even existed until the Orbiter burst into flames in the Martian atmosphere. Later, a NASA review board investigating the root cause of the problem figured out that the issue was isolated to the software that controlled the thrusters. One program calculated the thrusters’ force in pounds; another program looking at the data assumed it was in newtons. The software controllers were making data-driven decisions to adjust the thrust based on 100% accurate data, but these decisions were wrong because of inaccurate assumptions when interpreting it. A conversion of the data from one system of measurement to the other could have prevented the loss.



**When data is used strategically, businesses can transform and grow their revenue. Consider the examples below.**

**Crate and Barrel**

At Crate and Barrel, online sales jumped more than 40% during stay-at-home orders to combat the global pandemic. Currently, online sales make up more than 65% of their overall business. They are using data insights to accelerate their digital transformation and bring the best of online and offline experiences together for customers.

BigQuery enables Crate and Barrel to "draw on ten times [as many] information sources(compared to a few years ago) which are then analyzed and transformed into actionable insights that can be used to influence the customer’s next interaction. And this, in turn, drives revenue."

Read more about Crate and Barrel's data strategy in [How one retailer’s data strategy powers seamless customer experiences](https://www.thinkwithgoogle.com/future-of-marketing/digital-transformation/crate-and-barrel-digital-customer-experiences/).

**PepsiCo**

Since the days of the New Coke launch, things have changed dramatically for beverage and other consumer packaged goods (CPG) companies.

PepsiCo "hired analytical talent and established cross-functional workflows around an infrastructure designed to put consumers’ needs first. Then [they] set up the right processes to make critical decisions based on data and technology use cases. Finally, [they] invested in the right technology stack and platforms so that data could flow into a central cloud-based hub. This is critical. When data comes together, [they] develop a holistic understanding of the consumer and their journeys."

Read about how PepsiCo is delivering a more personal and valuable experience to customers using data in [How one of the world’s biggest marketers ripped up its playbook and learned to anticipate intent](https://www.thinkwithgoogle.com/marketing-strategies/data-and-measurement/pepsi-digital-transformation/).

**Key skills for triumphant results**

As a data analyst, your own skills and knowledge will be the most important part of any analysis project. It is important for you to keep a data-driven mindset, ask lots of questions, experiment with many different possibilities, and use both logic and creativity along the way. You will then be prepared to interpret your data with the highest levels of care and accuracy. Note that there is a difference between making a decision with incomplete data and making a decision with a small amount of data. You learned that making a decision with incomplete data is dangerous. But sometimes accurate data from a small test can help you make a good decision. Stay tuned. You will learn about how much data to collect later in the program.

Hi again.

When it comes to decision-making, data is key.

But we've also learned that

there are a lot of different kinds

of questions that data might help us answer,

and these different questions

make different kinds of data.

There are two kinds of data that we'll talk about in

this video, quantitative and qualitative.

Quantitative data is all about

the specific and objective measures of numerical facts.

This can often be the what,

how many, and how often about a problem.

In other words, things you can measure,

like how many commuters

take the train to work every week.

As a financial analyst,

I work with a lot of quantitative data.

I love the certainty and accuracy of numbers.

On the other hand,

qualitative data describes

subjective or explanatory measures of

qualities and characteristics or

things that can't be measured with numerical data,

like your hair color.

Qualitative data is great

for helping us answer why questions.

For example, why people might like

a certain celebrity or snack food more than others.

With quantitative data, we can see numbers

visualized as charts or graphs.

Qualitative data can then give us

a more high-level understanding of

why the numbers are the way they are.

This is important because it helps

us add context to a problem.

As a data analyst,

you'll be using both

quantitative and qualitative analysis,

depending on your business task.

Reviews are a great example of this.

Think about a time you used reviews to decide

whether you wanted to buy something or go somewhere.

These reviews might have told you

how many people dislike that thing and why.

Businesses read these reviews too,

but they use the data in different ways.

Let's look at an example of a business using data from

customer reviews to see

qualitative and quantitative data in action.

Now, say a local ice cream shop has started using

their online reviews to engage with

their customers and build their brand.

These reviews give the ice cream shop

insights into their customers' experiences,

which they can use to inform their decision-making.

The owner notices that their rating has been going down.

He sees that lately his shop

has been receiving more negative reviews.

He wants to know why,

so he starts asking questions.

First are measurable questions.

How many negative reviews are there?

What's the average rating?

How many of these reviews use the same keywords?

These questions generate quantitative data,

numerical results that help

confirm their customers aren't satisfied.

This data might lead them to ask different questions.

Why are customers unsatisfied?

How can we improve their experience?

These are questions that lead to qualitative data.

After looking through the reviews,

the ice cream shop owner sees a pattern,

17 of negative reviews use

the word "frustrated." That's quantitative data.

Now we can start collecting qualitative data

by asking why this word is being repeated?

He finds that customers are

frustrated because the shop is

running out of popular flavors before the end of the day.

Knowing this, the ice cream shop can change its

weekly order to make sure it has

enough of what the customers want.

With both quantitative and qualitative data,

the ice cream shop owner was able to figure out

his customers were unhappy and understand why.

Having both types of data made it possible for

him to make the right changes and improve his business.

Now that you know the difference between

quantitative and qualitative data,

you know how to get different types of

data by asking different questions.

It's your job as a data detective to know

which questions to ask to find the right solution.

Then you can start thinking

about cool and creative ways to

help stakeholders better understand the data.

For example, interactive dashboards,

which we'll learn about soon.

Hi again.

When it comes to decision-making, data is key.

But we've also learned that

there are a lot of different kinds

of questions that data might help us answer,

and these different questions

make different kinds of data.

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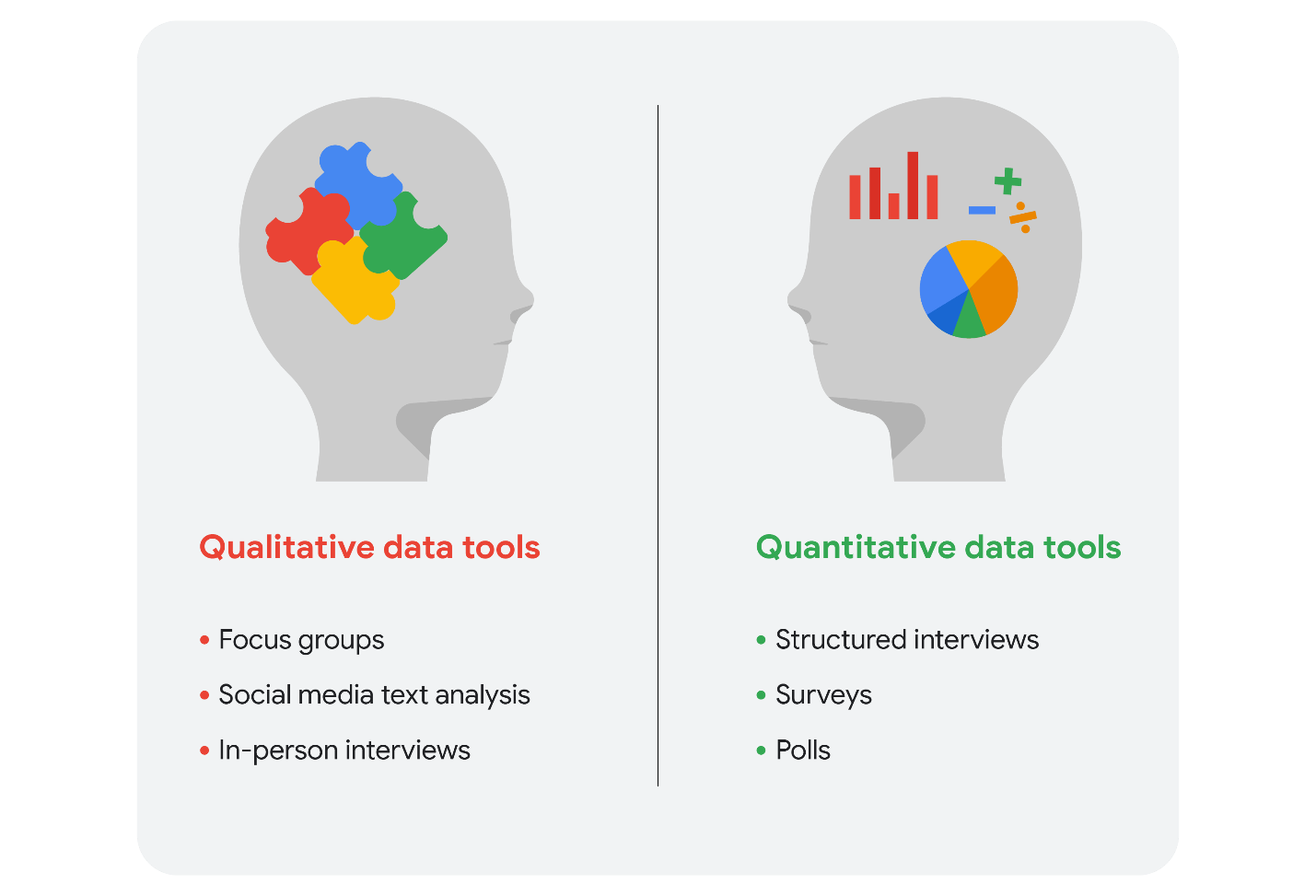
For example, interactive dashboards,

which we'll learn about soon.

Qualitative and quantitative data in business

This reading further elaborates on the meaning of **qualitative** versus **quantitative**.

As you have learned, there are two types of data: qualitative and quantitative.

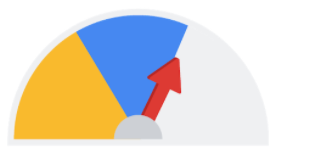
Qualitative data tools: focus groups, social media text analysis, and in-person interviews Quantitative data tools: structured interviews, surveys, and polls

We can take a closer look at the data types and data collection tools. Imagine that you are a data analyst for a chain of movie theaters. Your manager wants you to track trends in:

* **Movie attendance over time**
* **Profitability of the concession stand**
* **Evening audience preferences**

In our scenario, we assume quantitative data already exists to monitor all three trends.

**Movie attendance over time**



Starting with the historical data the theater has through its loyalty and rewards program, your first step is to investigate what insights you can gain from that data. You look at attendance over the last 3 months. But, because the last 3 months didn’t include a major holiday, you decide it is better to look at a full year’s worth of data. As you suspected, the quantitative data confirmed that average attendance was 550 per month but then rose to an average of 1,600 per month for the months with holidays.

The historical data serves your needs for the project, but you also decide that you will resume the analysis again in a few months after the theater increases ticket prices for evening showtimes.

**Profitability of the concession stand**



Profit is calculated by subtracting cost from sales revenue. The historical data shows that while the concession stand was profitable, profit margins were razor thin at less than 5%. You saw that average purchases totaled $20 or less. You decide that you will keep monitoring this on an ongoing basis.

Based on your understanding of data collection tools, you will suggest an online survey of customers so they can comment on the food at the concession stand. This will enable you to gather even more quantitative data to revamp the menu and potentially increase profits.

**Evening audience preferences**



Your analysis of the historical data shows that the 7:30 PM showtime was the most popular and had the greatest attendance, followed by the 7:15 PM and 9:00 PM showtimes. You may suggest replacing the current 8:00 PM showtime that has lower attendance with an 8:30 PM showtime. But you need more data to back up your hunch that people would be more likely to attend the later show.

Evening movie-goers are the largest source of revenue for the theater. Therefore, you also decide to include a question in your online survey to gain more insight.

**Qualitative data for all three trends plus ticket pricing**

Since you know that the theater is planning to raise ticket prices for evening showtimes in a few months, you will also include a question in the survey to get an idea of customers’ price sensitivity.

Your final online survey might include these questions for qualitative data:

1. What went into your decision to see a movie in our theater today? (movie attendance)
2. What do you think about the quality and value of your purchases at the concession stand? (concession stand profitability)
3. Which showtime do you prefer, 8:00 PM or 8:30 PM, and why do you prefer that time? (evening movie-goer preferences)
4. Under what circumstances would you choose a matinee over a nighttime showing? (ticket price increase)

**Summing it up**

Data analysts will generally use both types of data in their work. Usually, qualitative data can help analysts better understand their quantitative data by providing a reason or more thorough explanation. In other words, quantitative data generally gives you the what, and qualitative data generally gives you the why. By using both quantitative and qualitative data, you can learn when people like to go to the movies and why they chose the theater. Maybe they really like the reclining chairs, so your manager can purchase more recliners. Maybe the theater is the only one that serves root beer. Maybe a later show time gives them more time to drive to the theater from where popular restaurants are located. Maybe they go to matinees because they have kids and want to save money. You wouldn’t have discovered this information by analyzing only the quantitative data for attendance, profit, and showtimes.

### 1.

Question 1

What is the difference between qualitative and quantitative data?

**1 / 1 point**



Qualitative data is about the quality of a product or service. Quantitative data is about how much of that product or service is available.



Qualitative data is specific. Quantitative data is subjective.



Qualitative data describes the kind of data being analyzed. Quantitative data describes how much data is being analyzed.



Qualitative data can be used to measure qualities and characteristics. Quantitative data can be used to measure numerical facts.

**Correct**

Qualitative data can be used to measure qualities and characteristics. Quantitative data can be used to measure numerical facts.

### 2.

Question 2

Fill in the blank: Data-inspired decision-making can discover \_\_\_\_\_ when exploring different data sources.

**1 / 1 point**



where the largest amount of data is



which experts can give advice



what the data has in common



if a decision was properly made

**Correct**

Data-inspired decision-making deals with exploring different data sources to discover what they have in common.

### 3.

Question 3

Which of the following examples describes using data to achieve business results? Select all that apply.

**0.5 / 1 point**



A video streaming service analyzes user preferences to customize movie recommendations.

**Correct**

Analyzing user preferences to customize movie recommendations and analyzing product purchases to create better promotions are examples of using data to achieve business results. These examples demonstrate putting analysis to work to achieve business results.



A movie theater tracks the number of weekend movie goers for three months.

**This should not be selected**

Analyzing user preferences to customize movie recommendations and analyzing product purchases to create better promotions are examples of using data to achieve business results. These examples demonstrate putting analysis to work to achieve business results.



A large retailer performs data analysis on product purchases to create better promotions.

**Correct**

Analyzing user preferences to customize movie recommendations and analyzing product purchases to create better promotions are examples of using data to achieve business results. These examples demonstrate putting analysis to work to achieve business results.



A grocery chain collects data on sale items and pricing from each store.

**This should not be selected**

Analyzing user preferences to customize movie recommendations and analyzing product purchases to create better promotions are examples of using data to achieve business results. These examples demonstrate putting analysis to work to achieve business results.

### 4.

Question 4

If someone is subjectively describing their feelings or emotions, it is qualitative data.

**1 / 1 point**



True



False

**Correct**

If someone is describing their feelings or emotions, they are providing qualitative data. Qualitative data is a subjective and explanatory measure of a quality or a characteristic.

Data is great, but if we

can't communicate the story data is telling,

it isn't useful to anyone.

We need ways to organize data that

help us turn it into information.

There are all kinds of tools out there to help you

visualize and share

your data analysis with stakeholders.

Here, we'll talk about

two data presentation tools, reports and dashboards.

Reports and dashboards are both

useful for data visualization.

But there are pros and cons for each of them.

A report is a static collection of

data given to stakeholders periodically.

A dashboard on the other hand,

monitors live, incoming data.

Let's talk about reports first.

Reports are great for giving snapshots of

high level historical data for an organization.

For example, a finance firm's monthly sales.

Reports come with a lot of benefits too.

They can be designed and sent out periodically,

often on a weekly or monthly basis,

as organized and easy to reference information.

They're quick to design and easy to

use as long as you continually maintain them.

Finally, because reports use static data or

data that doesn't change once it's been recorded,

they reflect data that's already been cleaned and sorted.

There are some downsides to keep in mind too.

Reports need regular maintenance

and aren't very visually appealing.

Because they aren't automatic or dynamic,

reports don't show live, evolving data.

For a live reflection of incoming data,

you'll want to design a dashboard.

Dashboards are great for a lot of reasons,

they give your team more access

to information being recorded,

you can interact through data by playing with filters,

and because they're dynamic,

they have long-term value.

If stakeholders need to continually access information,

a dashboard can be more efficient than

having to pull reports over and over,

which is a big time saver for you.

Last but not least,

they're just nice to look at.

But dashboards do have some cons too.

For one thing, they take a lot of time to design and

can actually be less efficient than reports,

if they're not used very often.

If the base table breaks at any point,

they need a lot of maintenance to

get back up and running again.

Dashboards can sometimes overwhelm

people with information too.

If you aren't used to

looking through data on a dashboard,

you might get lost in it.

As a data analyst,

you need to decide the best way to

communicate information to your stakeholders.

For example, what if your stakeholders are

interested in the company's social media engagement?

Would a monthly report that tells them

the number of new followers for their page be useful?

Or a dashboard that monitors live

social media engagement across multiple platforms?

Later on, you'll create

your own reports and

dashboards to practice using these tools.

But for now, I want to show you what

a report and a dashboard might look like.

We'll start by using a tool we're

already familiar with, spreadsheets.

Let's see one way

spreadsheet data could be visualized in a report.

This spreadsheet has a data set with

order details from a wholesale company.

That's a lot of information.

From the headers, we can see

different things recorded here,

like the order date,

the salesperson, the unit price,

and revenue for each transaction recorded.

It's all useful information,

but a little hard to wrap your head around.

We want a report that's easier to read.

Let's say your stakeholders want

a quick look at the revenue by salesperson.

Using the data, you could make them a pivot

table with a graph that shows that information.

A pivot table is

a data summarization tool

that is used in data processing.

Pivot tables are used to summarize, sort, re-organize,

group, count, total,

or average data stored in a database.

It allows its users to transform

columns into rows and rows into columns.

We'll actually learn more about pivot tables later.

But I'll show you one really quick.

We'll select the Data menu and click Pivot table button.

It can pull data from this table.

We can just press

create and it'll pull up a new worksheet.

Over here, it gives us

the pivot table fields we can choose from.

Click select, salesperson and revenue.

Just like that, it made a chart for us.

At this point, you can

play around with how the graph looks,

but the information is all there.

Let's move on to dashboards.

If you need a more dynamic way to

share information with your stakeholders,

dashboards are your friend.

You might create something like this Tableau dashboard.

With interactive graphs that

showcase multiple views of the data.

With this, users can change location, date range,

or any other aspect of the data they're viewing

by clicking through different elements on the dashboard.

Pretty cool, right?

Later in this program,

we'll look into how you can make

your own data visualizations.

We have a lot to learn before we get to that.

But I hope this was an exciting first peek at

the different visualization tools

you'll be using as a data analyst.

**The beauty of dashboards**

Dashboards are powerful visual tools that help you tell your data story. A **dashboard** organizes information from multiple datasets into one central location, offering huge time-savings. Data analysts use dashboards to track, analyze, and visualize data in order to answer questions and solve problems. For a basic idea of what dashboards look like, refer to this article: [6 real-world examples of business intelligence dashboards](https://www.tableau.com/learn/articles/business-intelligence-dashboards-examples). Tableau is one tool that is used to create dashboards and is covered later in the program.

The following table summarizes the benefits of using a dashboard for both data analysts and their stakeholders.

| **Benefits** | **For Data Analysts** | **For Stakeholders** |
| --- | --- | --- |
| **Centralization** | Sharing a single source of data with all stakeholders | Working with a comprehensive view of data, initiatives, objectives, projects, processes, and more |
| **Visualization** | Showing and updating live, incoming data in real time\* | Spotting changing trends and patterns more quickly |
| **Insightfulness** | Pulling relevant information from different datasets | Understanding the story behind the numbers to keep track of goals and make data-driven decisions |
| **Customization** | Creating custom views dedicated to a specific person, project, or presentation of the data | Drilling down to more specific areas of specialized interest or concern |

*\* It is important to remember that changed data is pulled into dashboards automatically only if the data structure is the same. If the data structure changes, you have to update the dashboard design before the data can update live.*

**Creating a dashboard**

Here is a process you can follow to create a dashboard:

**1.** **Identify the stakeholders who need to see the data and how they will use it**

To get started with this, you need to ask effective questions. Check out this [Requirements Gathering Worksheet](https://s3.amazonaws.com/looker-elearning-resources/Requirements+Gathering+Worksheet.pdf) to explore a wide range of good questions you can use to identify relevant stakeholders and their data needs. This is a great resource to help guide you through this process again and again.

**2. Design the dashboard (what should be displayed)**

Use these tips to help make your dashboard design clear, easy to follow, and simple:

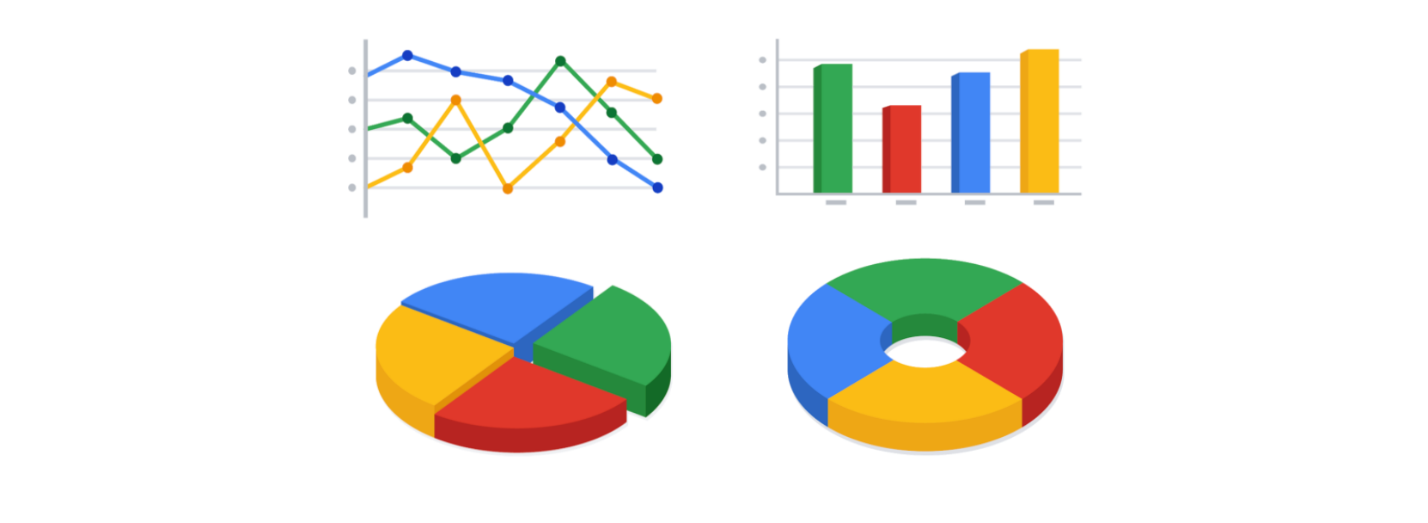
* Use a clear header to label the information
* Add short text descriptions to each visualization
* Show the most important information at the top

**3. Create mock-ups if desired**

This is optional, but a lot of data analysts like to sketch out their dashboards before creating them.

**4. Select the visualizations you will use on the dashboard**

You have a lot of options here and it all depends on what data story you are telling. If you need to show a change of values over time, line charts or bar graphs might be the best choice. If your goal is to show how each part contributes to the whole amount being reported, a pie or donut chart is probably a better choice.



To learn more about choosing the right visualizations, check out Tableau’s galleries:

* For more samples of area charts, column charts, and other visualizations, visit [Tableau’s Viz Gallery](https://www.tableau.com/solutions/gallery). This gallery is full of great examples that were created using real data; explore this resource on your own to get some inspiration.
* Explore [Tableau’s Viz of the Day](https://public.tableau.com/en-us/gallery/?tab=viz-of-the-day&type=viz-of-the-day) to see visualizations curated by the community. These are visualizations created by Tableau users and are a great way to learn more about how other data analysts are using data visualization tools.

**5.** **Create filters as needed**

Filters show certain data while hiding the rest of the data in a dashboard. This can be a big help to identify patterns while keeping the original data intact. It is common for data analysts to use and share the same dashboard, but manage their part of it with a filter. To dig deeper into filters and find an example of filters in action, you can visit Tableau’s page on [Filter Actions](https://help.tableau.com/current/pro/desktop/en-us/actions_filter.htm). This is a useful resource to save and come back to when you start practicing using filters in Tableau on your own.

**Dashboards are part of a business journey**

Just like how the dashboard on an airplane shows the pilot their flight path, your dashboard does the same for your stakeholders. It helps them navigate the path of the project inside the data. If you add clear markers and highlight important points on your dashboard, users will understand where your data story is headed. Then, you can work together to make sure the business gets where it needs to go.

Question 1

Fill in the blank: Pivot tables in data processing tools are used to \_\_\_\_\_ data.

**1 / 1 point**



validate



summarize



clean



populate

**Correct**

Pivot tables are used to summarize data.

### 2.

Question 2

In data analytics, how are dashboards different from reports?

**1 / 1 point**



Dashboards are used to share updates with stakeholders only periodically. Reports give stakeholders continuous access to data.



Dashboards provide a high-level presentation of historical data. Reports provide a more detailed presentation of live, interactive data.



Dashboards contain static data. Reports contain data that is constantly changing.



Dashboards monitor live, incoming data from multiple datasets and organize the information into one central location. Reports are static collections of data.

**Correct**

Dashboards monitor live, incoming data from multiple datasets and organize the information into one central location. Reports are static collections of data.

### 3.

Question 3

Describe the difference between data and metrics.

**1 / 1 point**



Data is a collection of facts. Metrics are quantifiable data types used for measurement.



Data is quantifiable and used for measurement. Metrics are unorganized collections of facts.



Data is quantifiable. Metrics are unquantifiable.



Data can be used for measurement. Metrics cannot be used for measurement.

**Correct**

Data is a collection of facts. Metrics are quantifiable data types used for measurement.

### 4.

Question 4

Return on Investment (ROI) uses which of the following metrics in its definition?

**1 / 1 point**



Supply and demand



Profit and investment



Inventory and units



Sales and margin

**Correct**

Return on Investment (ROI) = Profit/Investment.

So far, you've learned a lot about how to think like a data analyst.

We've explored a few different ways of thinking.

And now, I want to take that one step further by using a mathematical approach

to problem-solving.

Mathematical thinking is a powerful skill you can use to help you solve problems and

see new solutions.

So, let's take some time to talk about what mathematical thinking is, and

how you can start using it.

Using a mathematical approach doesn't mean you have to suddenly become a math whiz.

It means looking at a problem and logically breaking it down step-by-step,

so you can see the relationship of patterns in your data, and

use that to analyze your problem.

This kind of thinking can also help you figure out the best tools for analysis

because it lets us see the different aspects of a problem and

choose the best logical approach.

There are a lot of factors to consider when choosing the most helpful tool for

your analysis.

One way you could decide which tool to use is by the size of your dataset.

When working with data, you'll find that there's big and small data.

Small data can be really small.

These kinds of data tend to be made up of datasets concerned with specific

metrics over a short, well defined period of time.

Like how much water you drink in a day.

Small data can be useful for making day-to-day decisions,

like deciding to drink more water.

But it doesn't have a huge impact on bigger frameworks like business

operations.

You might use spreadsheets to organize and

analyze smaller datasets when you first start out.

Big data on the other hand has larger,

less specific datasets covering a longer period of time.

They usually have to be broken down to be analyzed.

Big data is useful for looking at large- scale questions and problems, and

they help companies make big decisions.

When you're working with data on this larger scale, you might switch to SQL.

Let's look at an example of how a data analyst working in a hospital might use

mathematical thinking to solve a problem with the right tools.

The hospital might find that they're having a problem with over or

under use of their beds.

Based on that, the hospital could make bed optimization a goal.

They want to make sure that beds are available to patients who need them, but

not waste hospital resources like space or money on maintaining empty beds.

Using mathematical thinking, you can break this problem down into a step-by-step

process to help you find patterns in their data.

There's a lot of variables in this scenario.

But for now, let's keep it simple and focus on just a few key ones.

There are metrics that are related to this problem that might show us patterns in

the data:

for example, maybe the number of beds open and

the number of beds used over a period of time.

There's actually already a formula for this.

It's called the bed occupancy rate, and

it's calculated using the total number of inpatient days, and

the total number of available beds over a given period of time.

What we want to do now is take our key variables and see how their relationship

to each other might show us patterns that can help the hospital make a decision.

To do that, we have to choose the tool that makes sense for this task.

Hospitals generate a lot of patient data over a long period of time.

So logically, a tool that's capable of handling big datasets is a must.

SQL is a great choice.

In this case, you discover that the hospital always has unused beds.

Knowing that, they can choose to get rid of some beds, which saves them space and

money that they can use to buy and store protective equipment.

By considering all of the individual parts of this problem logically,

mathematical thinking helped us see new perspectives that led us to a solution.

Well, that's it for now.

Great job.

You've covered a lot of material already.

You've learned about how empowering data can be in decision-making,

the difference between quantitative and qualitative analysis,

using reports and dashboards for data visualization,

metrics, and using a mathematical approach to problem-solving.

Coming up next, we'll be tackling spreadsheet basics.

You'll get to put what you've learned into action and

learn a new tool to help you along the data analysis process.

See you soon.

Big and small data

As a data analyst, you will work with data both big and small. Both kinds of data are valuable, but they play very different roles.



Whether you work with big or small data, you can use it to help stakeholders improve business processes, answer questions, create new products, and much more. But there are certain challenges and benefits that come with big data and the following table explores the differences between big and small data.

| **Small data** | **Big data** |
| --- | --- |
| Describes a data set made up of specific metrics over a short, well-defined time period | Describes large, less-specific data sets that cover a long time period |
| Usually organized and analyzed in spreadsheets | Usually kept in a database and queried |
| Likely to be used by small and midsize businesses | Likely to be used by large organizations |
| Simple to collect, store, manage, sort, and visually represent | Takes a lot of effort to collect, store, manage, sort, and visually represent |
| Usually already a manageable size for analysis | Usually needs to be broken into smaller pieces in order to be organized and analyzed effectively for decision-making |

**Challenges and benefits**

Here are some **challenges** you might face when working with big data:

* A lot of organizations deal with data overload and way too much unimportant or irrelevant information.
* Important data can be hidden deep down with all of the non-important data, which makes it harder to find and use. This can lead to slower and more inefficient decision-making time frames.
* The data you need isn’t always easily accessible.
* Current technology tools and solutions still struggle to provide measurable and reportable data. This can lead to unfair algorithmic bias.
* There are gaps in many big data business solutions.

Now for the good news! Here are some **benefits** that come with big data:

* When large amounts of data can be stored and analyzed, it can help companies identify more efficient ways of doing business and save a lot of time and money.
* Big data helps organizations spot the trends of customer buying patterns and satisfaction levels, which can help them create new products and solutions that will make customers happy.
* By analyzing big data, businesses get a much better understanding of current market conditions, which can help them stay ahead of the competition.
* As in our earlier social media example, big data helps companies keep track of their online presence—especially feedback, both good and bad, from customers. This gives them the information they need to improve and protect their brand.

**The three (or four) V words for big data**

When thinking about the benefits and challenges of big data, it helps to think about the three Vs: **volume, variety,** and **velocity.** Volume describes the amount of data. Variety describes the different kinds of data. Velocity describes how fast the data can be processed. Some data analysts also consider a fourth V: **veracity.** Veracity refers to the quality and reliability of the data. These are all important considerations related to processing huge, complex data sets.

| **Volume** | **Variety** | **Velocity** | **Veracity** |
| --- | --- | --- | --- |
| The amount of data | The different kinds of data | How fast the data can be processed | The quality and reliability of the data |

Describe the key differences between small data and big data. Select all that apply.

**1 / 1 point**



Small data involves datasets concerned with a small number of specific metrics. Big data involves datasets that are larger and less specific.

**Correct**

Small data involves a small number of specific metrics over a shorter period of time. It’s effective for analyzing day-to-day decisions. Big data involves larger and less specific datasets and focuses on change over a long period of time. It’s effective for analyzing more substantial decisions.



Small data is typically stored in a database. Big data is typically stored in a spreadsheet.



Small data is effective for analyzing day-to-day decisions. Big data is effective for analyzing more substantial decisions.

**Correct**

Small data involves a small number of specific metrics over a shorter period of time. It’s effective for analyzing day-to-day decisions. Big data involves larger and less specific datasets and focuses on change over a long period of time. It’s effective for analyzing more substantial decisions.



Small data focuses on short, well-defined time periods. Big data focuses on change over a long period of time.

**Correct**

Small data involves a small number of specific metrics over a shorter period of time. It’s effective for analyzing day-to-day decisions. Big data involves larger and less specific datasets and focuses on change over a long period of time. It’s effective for analyzing more substantial decisions.

### 2.

Question 2

Which of the following is an example of small data?

**1 / 1 point**



The total absences of all high school students



The number of steps someone walks in a day



The bed occupancy rate for a hospital for the past decade



The trade deficit between two countries over a hundred years

**Correct**

The number of steps someone walks in a day is an example of small data.

### 3.

Question 3

The amount of exercise time it takes for a single person to burn a minimum of 400 calories is a problem that requires big data.

**1 / 1 point**



True



False

**Correct**

This problem can be solved using small data. It contains a specific metric (400 calories) and a short, defined period of time (amount of exercise time).

### 1.

Question 1

In data analytics, a pattern is defined as a process or set of rules to be followed for a specific task.

**1 / 1 point**



True



False

**Correct**

In data analytics, an algorithm is defined as a process or set of rules to be followed for a specific task.

### 2.

Question 2

Fill in the blank: If a data analyst is measuring qualities and characteristics, they are considering \_\_\_\_\_ data.

**1 / 1 point**



quantitative



cleaned



qualitative



unbiased

**Correct**

If a data analyst is measuring qualities and characteristics, they are considering qualitative data.

### 3.

Question 3

In data analytics, dashboards monitor data that is a continuous source of incoming information. Which of the following terms describes this type of data?

**1 / 1 point**



Sorted



Comprehensive



Live



Filtered

**Correct**

Live data is a continuous source of incoming information.

### 4.

Question 4

Which data-summarization tool do data analysts use to sort, reorganize, group, count, total, or average data?

**1 / 1 point**



A pivot table



A report



A function



A dashboard

**Correct**

To sort, reorganize, group, count, total or average data, data analysts use a pivot table.

### 5.

Question 5

A metric is a specific type of data that companies use to identify a problem domain.

**1 / 1 point**



True



False

**Correct**

A metric is a single, quantifiable type of data used when setting and evaluating goals.

### 6.

Question 6

Fill in the blank: A metric goal is a \_\_\_\_\_ goal set by a company that is evaluated using metrics.

**1 / 1 point**



conceptual



finite



measurable



theoretical

**Correct**

A metric goal is a measurable goal set by a company that is evaluated using metrics.

### 7.

Question 7

If a data analyst compares the cost of an investment to the net profit of that investment over a period of time, they’re analyzing the investment scope.

**1 / 1 point**



True



False

**Correct**

If a data analyst compares the cost of an investment to the net profit of that investment over a period of time, they’re analyzing the return on investment.

### 8.

Question 8

Describe the main differences between big and small data.

**1 / 1 point**



Small data is typically stored and organized in databases. Big data is typically stored and organized in spreadsheets.



Small data has been cleaned and sorted. Big data has not yet been cleaned or sorted.



Small data is less useful to data analysts. Big data is more useful to data analysts.



Small data is specific and concerns a short time period. Big data is less specific and concerns a longer time period.

**Correct**

Small data is specific and concerns a short time period. Big data is less specific and concerns a longer time period.