Lesson 1.1: Why Distributed Computing?

DISTRIBUTED COMPUTING WITH SPARK SQL

Why Distributed Computing?

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UCDAVIS
Continuing and Professional Education

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Slide 2: Learning Objectives

Learning Objectives

Motivate the business need for processing big data

Identify key concepts related to distributed computing

Slide 3: Qualities of Big Data

Qualities of Big Data

Volume

Velocity

Variety

Veracity

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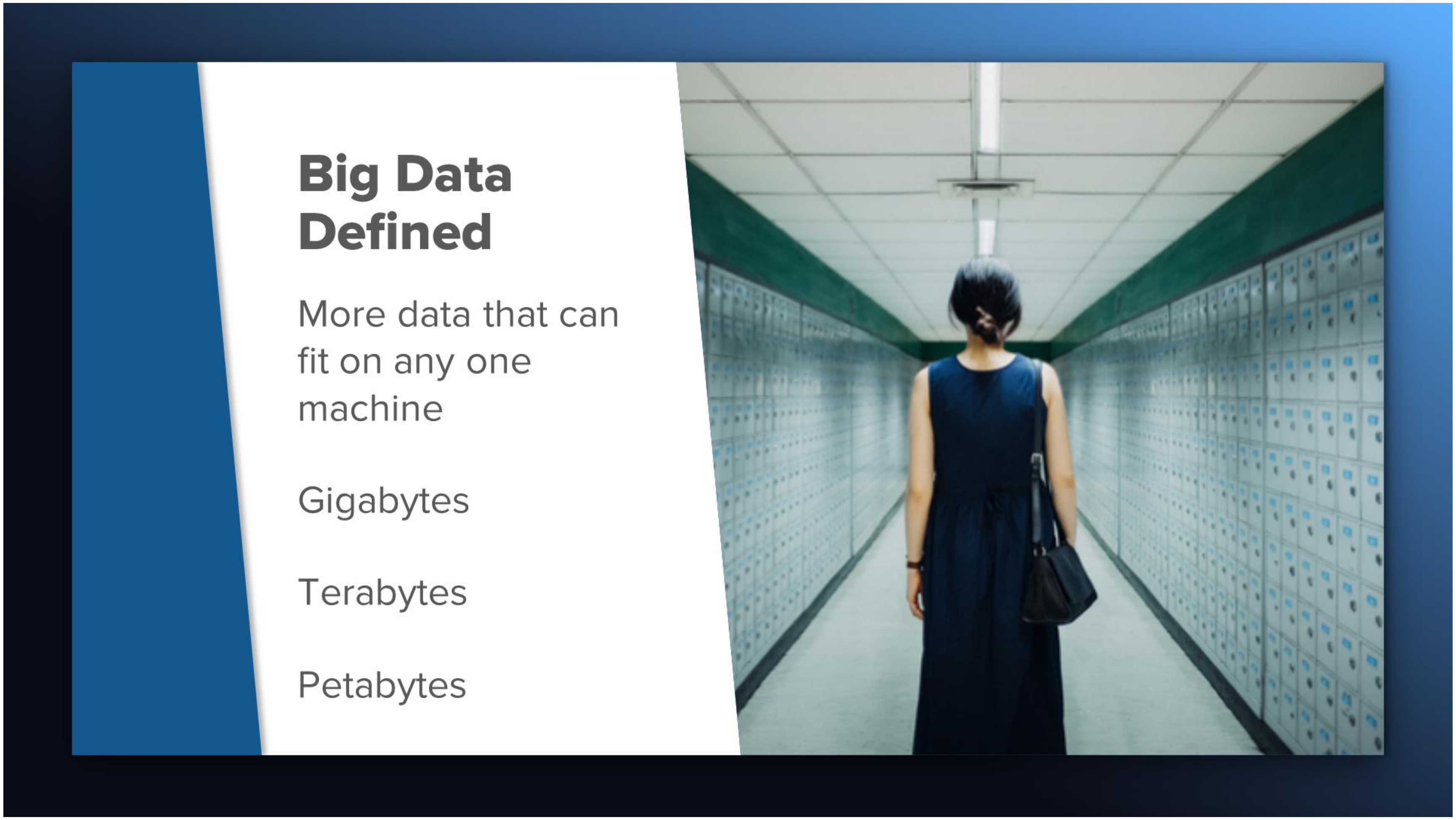
Slide 4: Big Data Defined



Big Data Defined

More data that can fit on any one machine

Gigabytes

Terabytes

Petabytes

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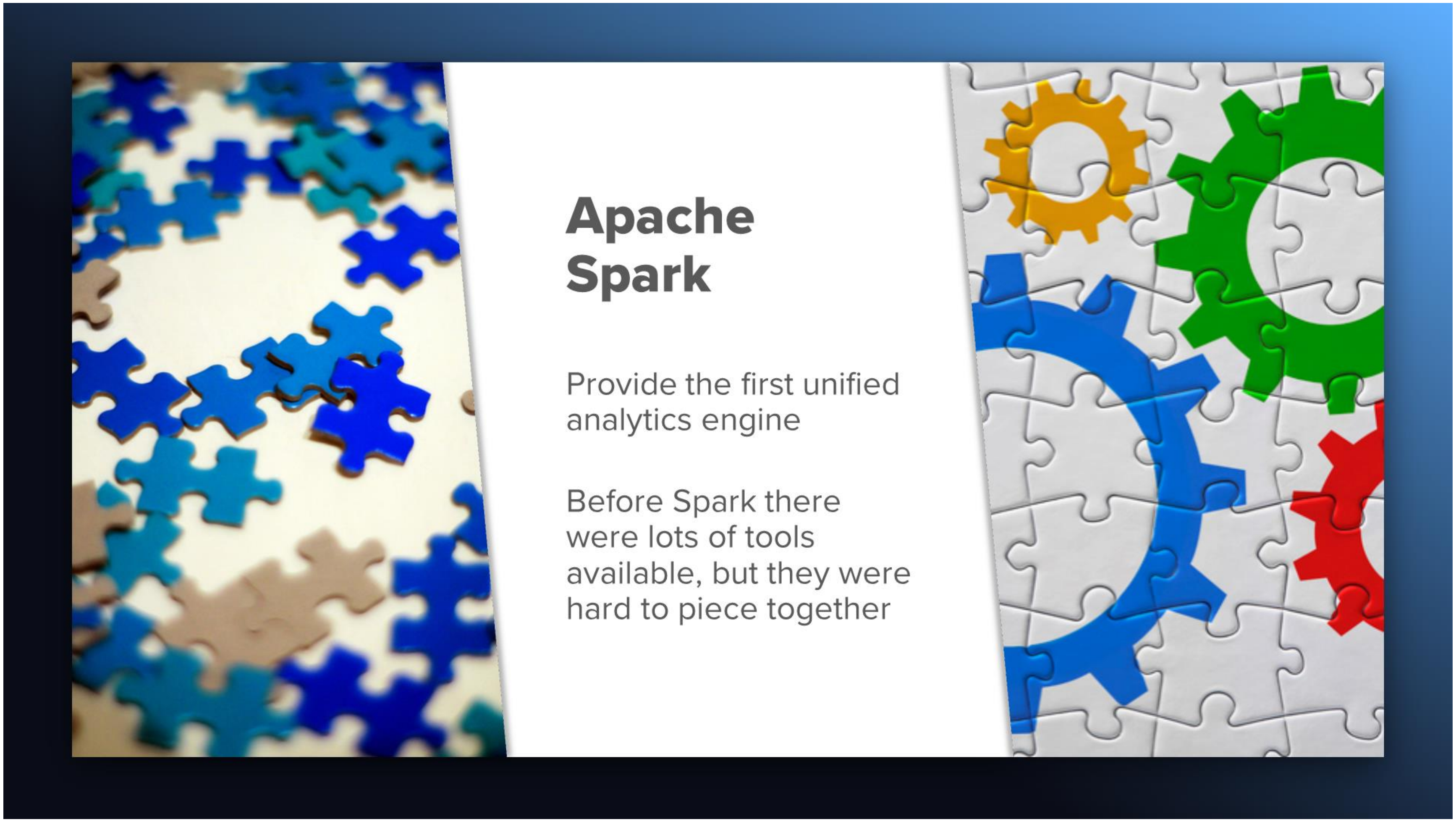
Slide 5: Apache Spark



Apache Spark

Provide the first unified analytics engine

Before Spark there were lots of tools available, but they were hard to piece together

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Slide 6: Spark is Multilingual and Supports Many Languages

Spark Supports Many Languages

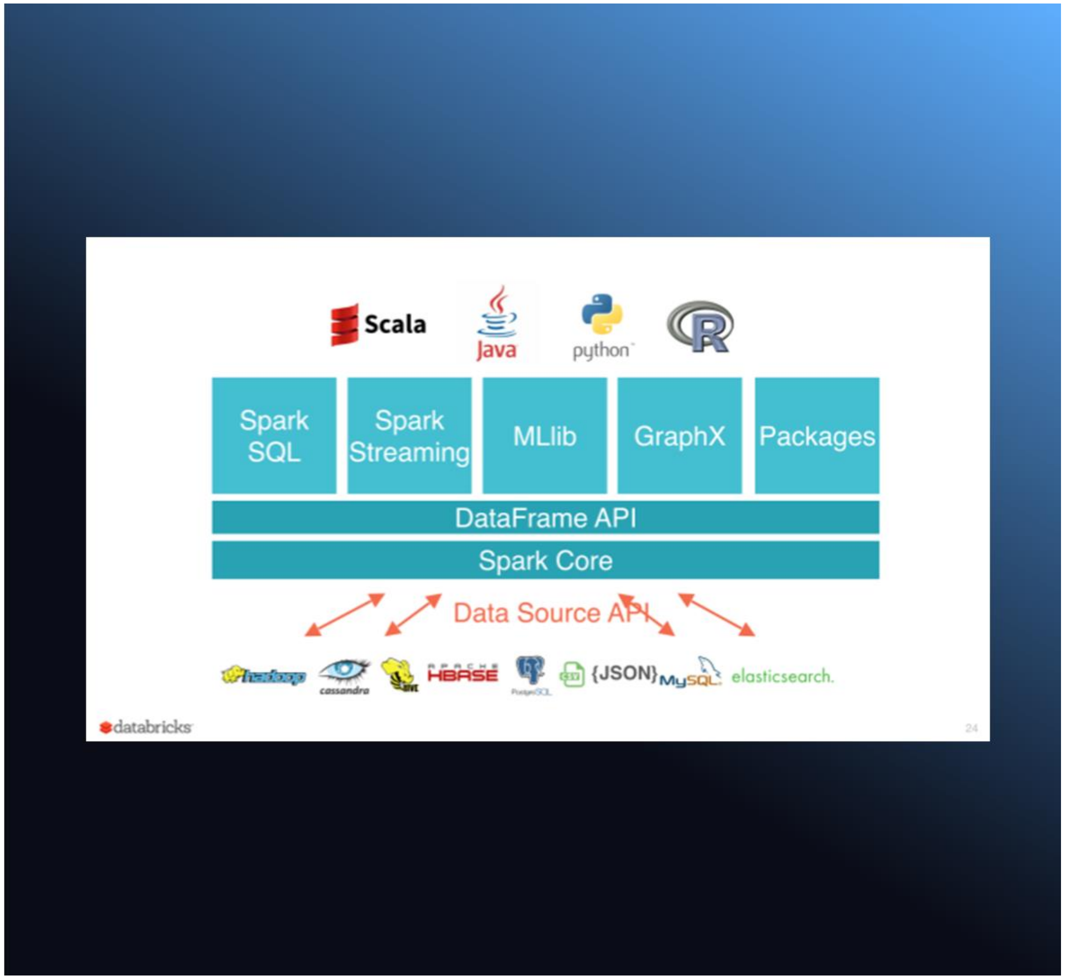
SQL

Python

Scala

Java

R



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Slide 7: Why Spark is Popular

Why Spark is Popular

Reads & processes data from many sources

Works with many file types

Solves many data problems faced by analysts

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Slide 8: Apache Spark: Origin Story

Apache Spark: Origin Story

UC Berkeley, 2009

Matei Zaharia, co-founder of Databricks

Collaboration between professors and graduate students

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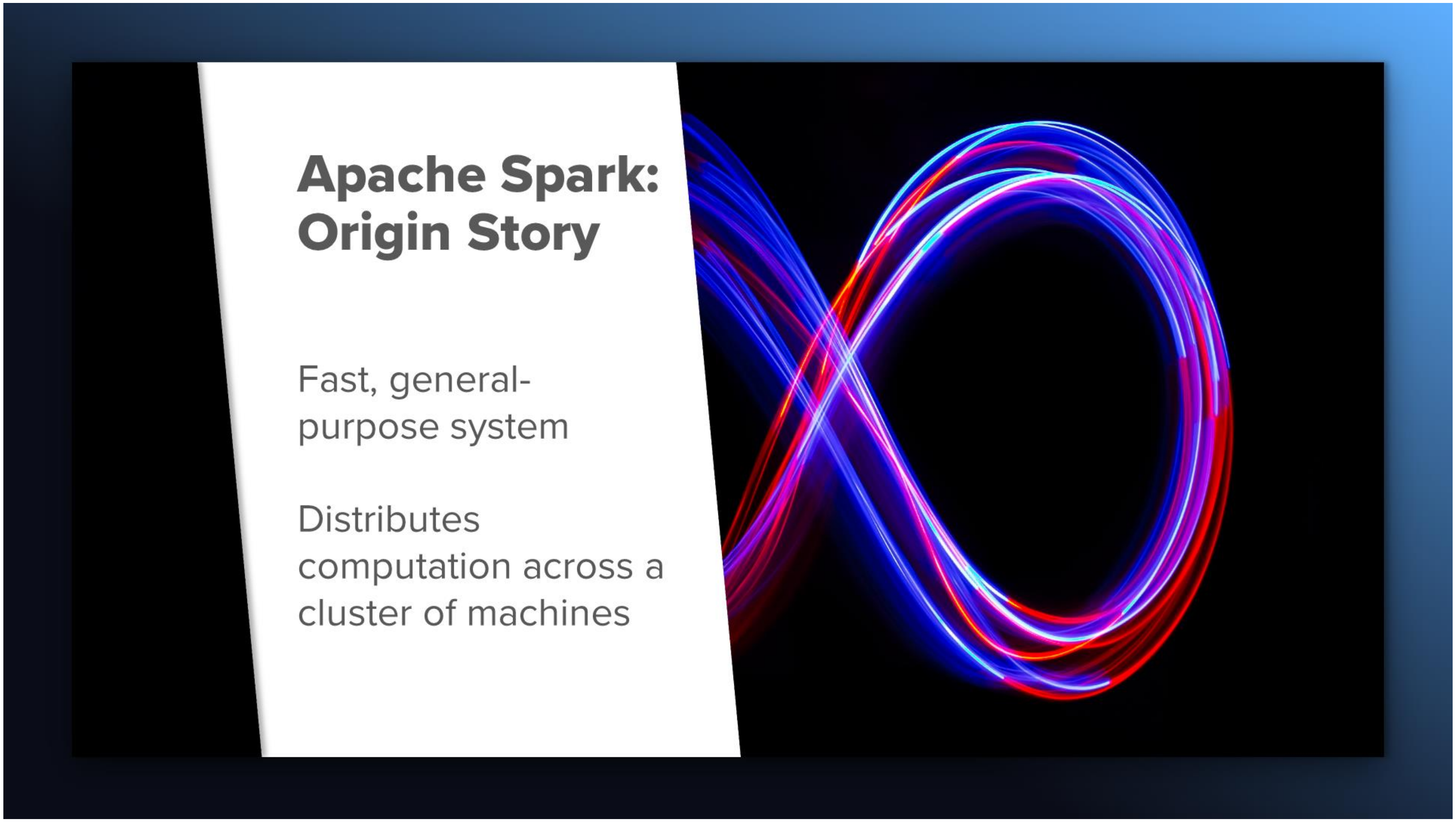
Slide 9: Apache Spark: Origin Story



Apache Spark: Origin Story

Fast, general-purpose system

Distributes computation across a cluster of machines

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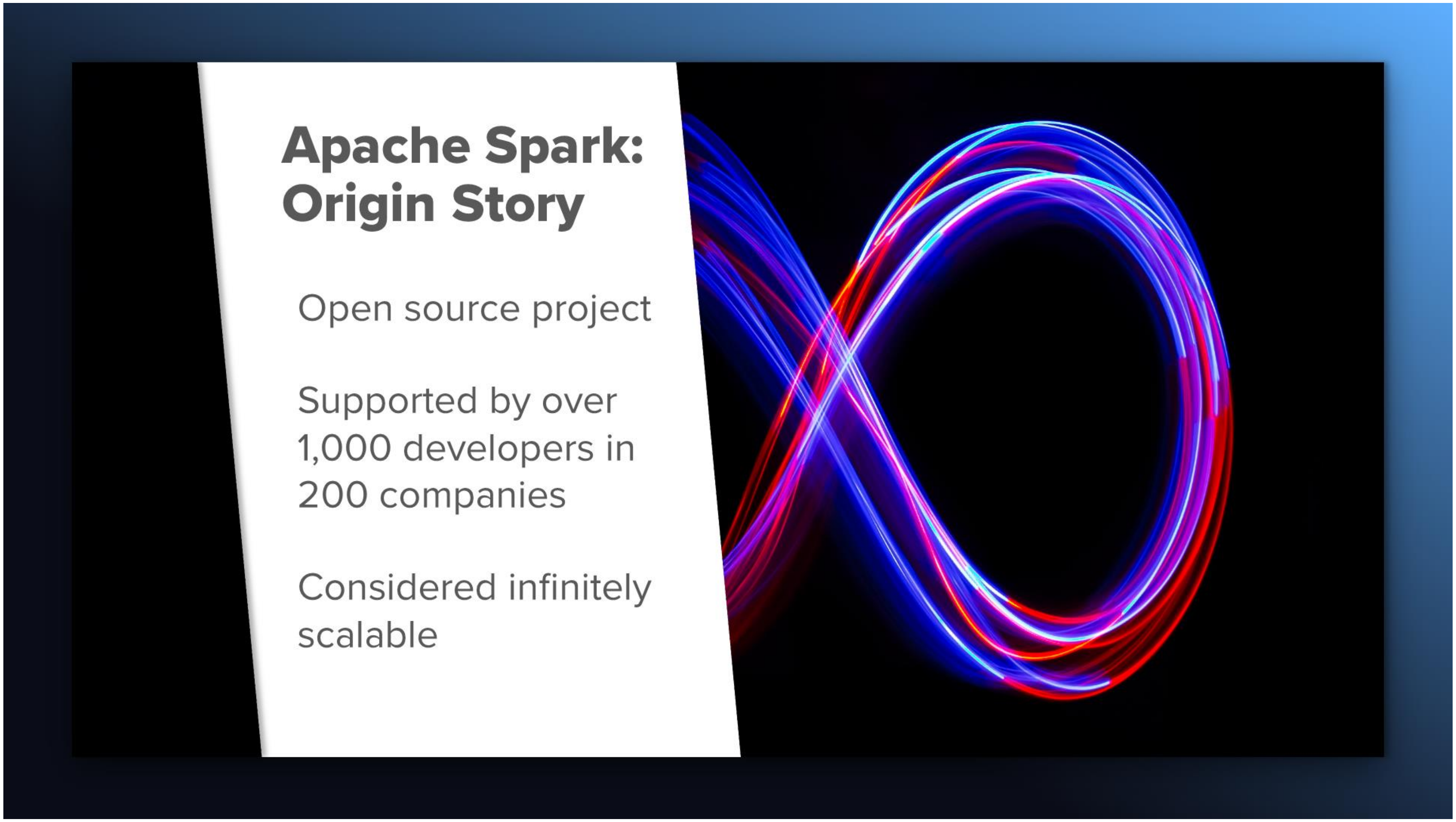
Slide 10: Apache Spark: Origin Story



Apache Spark: Origin Story

Open source project

Supported by over 1,000 developers in 200 companies

Considered infinitely scalable

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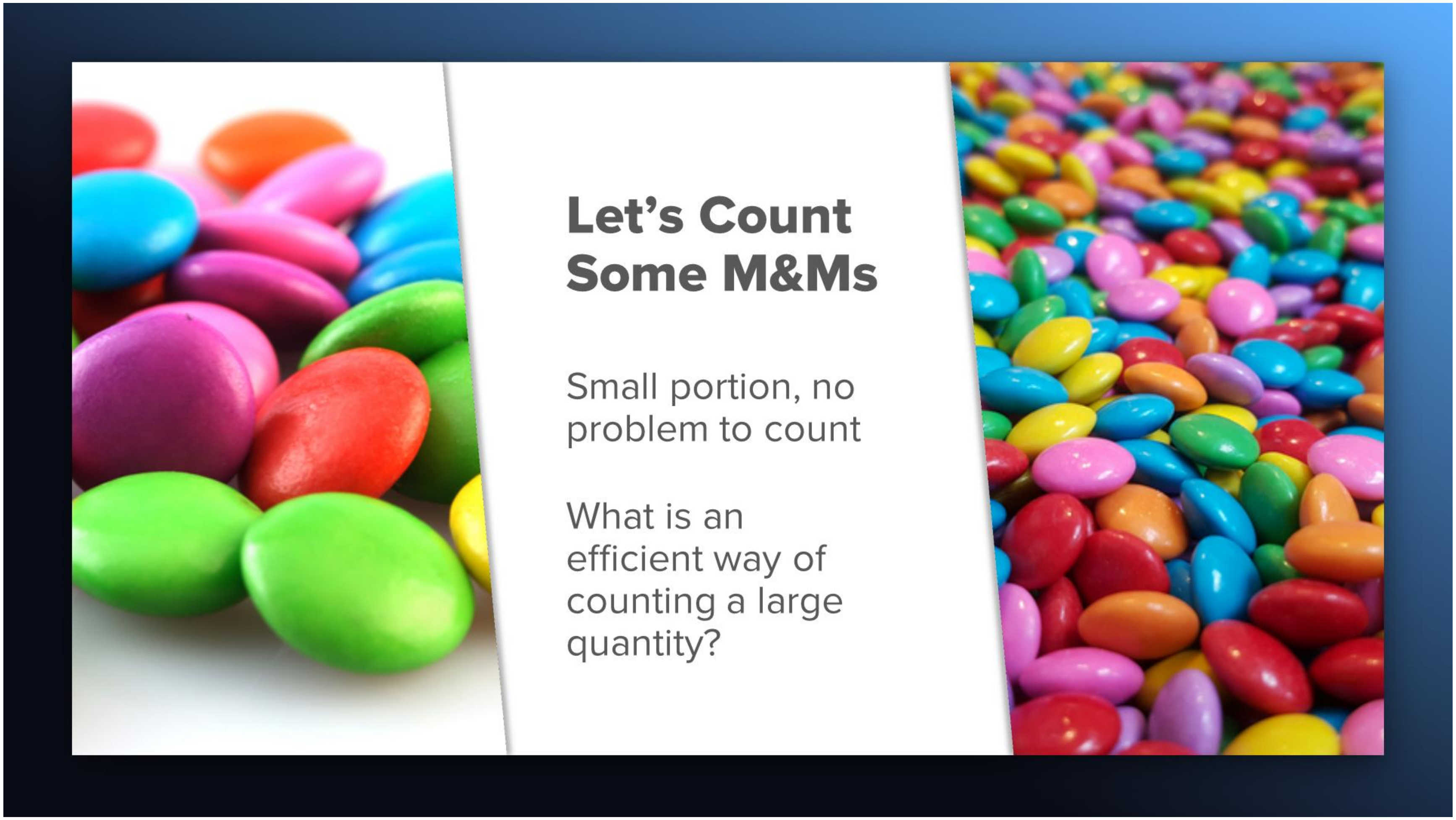
Slide 11: Let’s Count Some M&Ms



Let’s Count Some M&Ms

Small portion, no problem to count

What is an efficient way of counting a large quantity?

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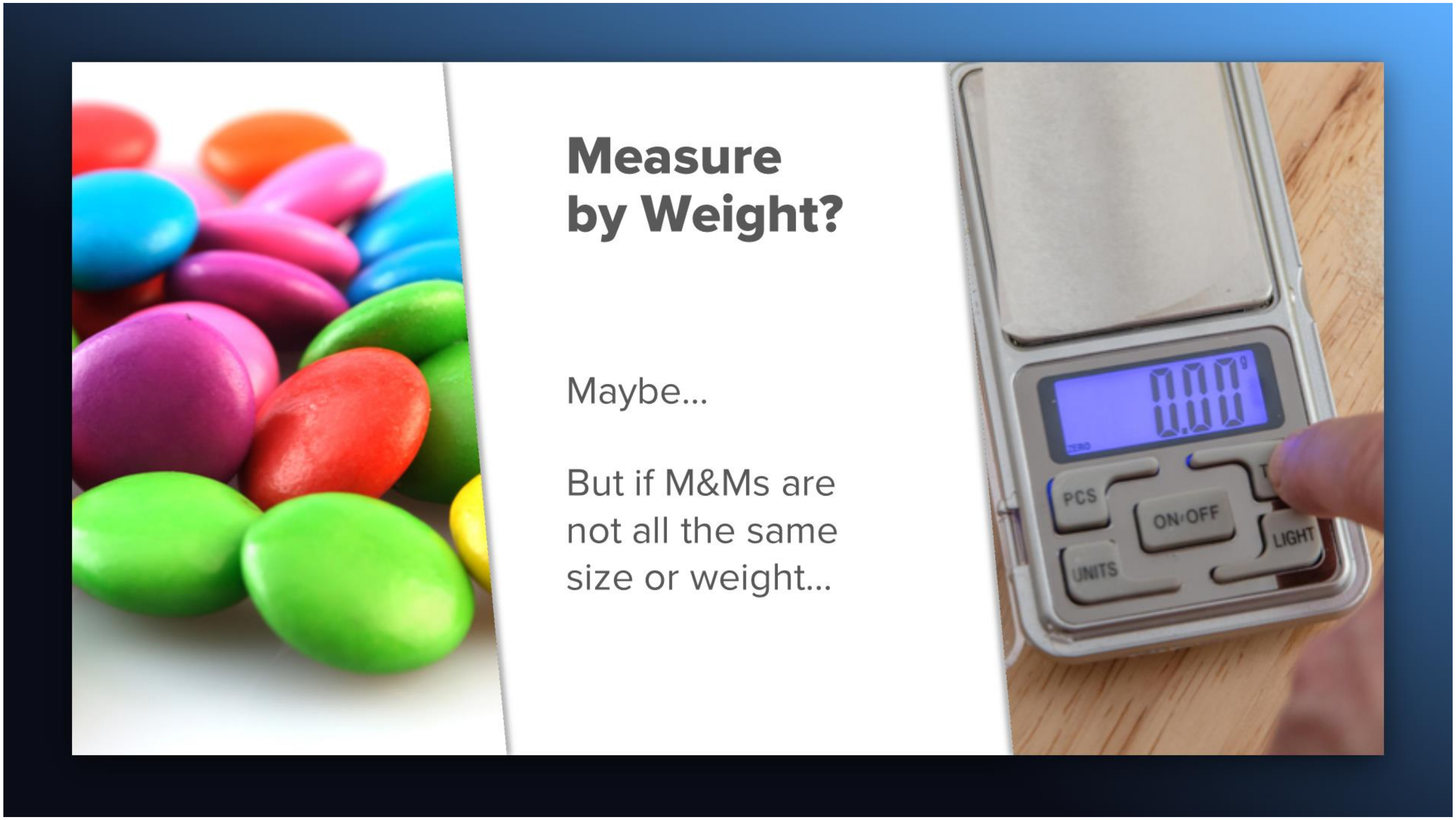
Slide 12: Measure by Weight?



0.00 g
PCS
ON/OFF
UNITS
LIGHT

Measure by Weight?

Maybe...

But if M&Ms are not all the same size or weight...

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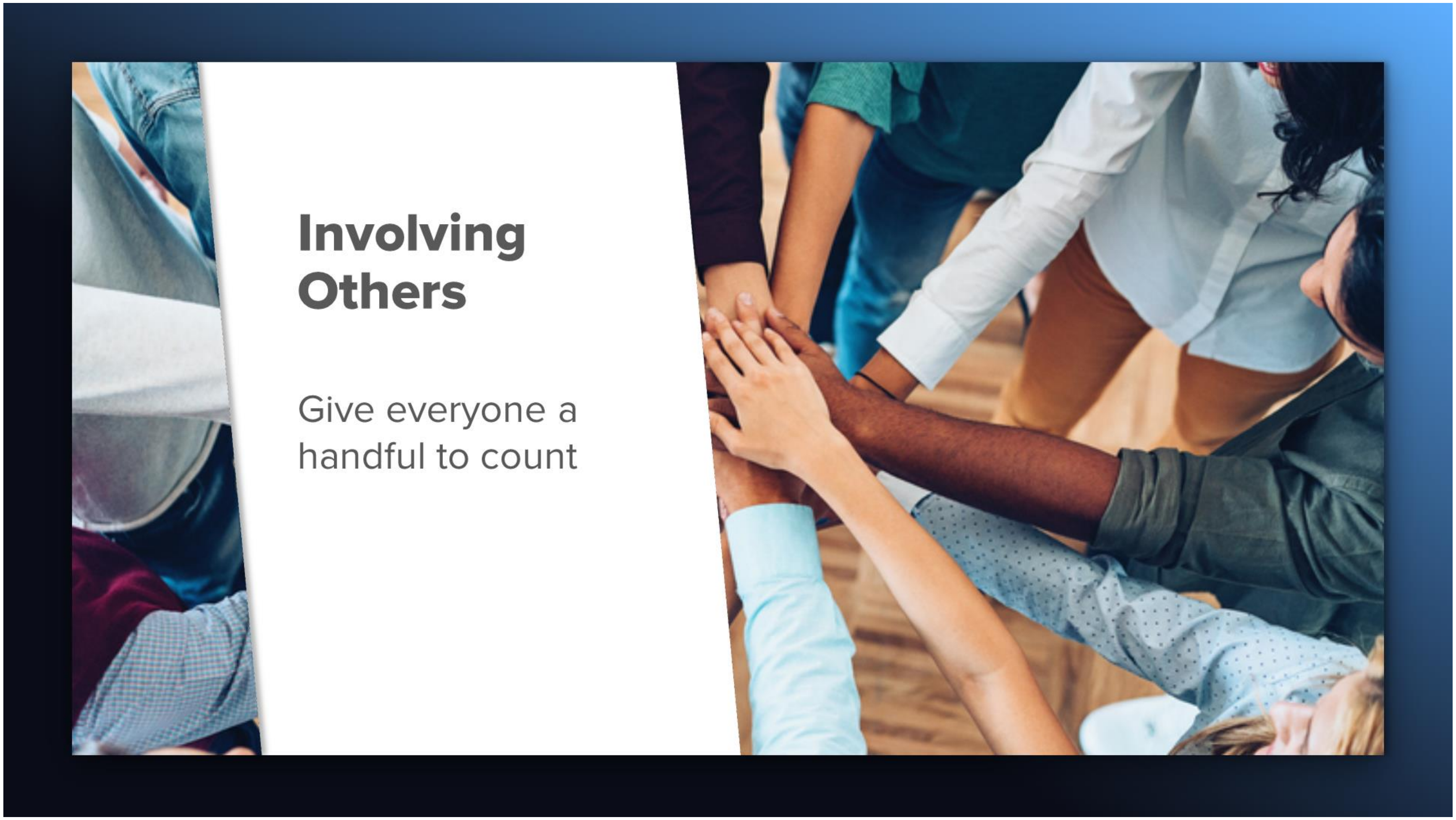
Slide 13: Involving Others



Involving Others

Give everyone a handful to count

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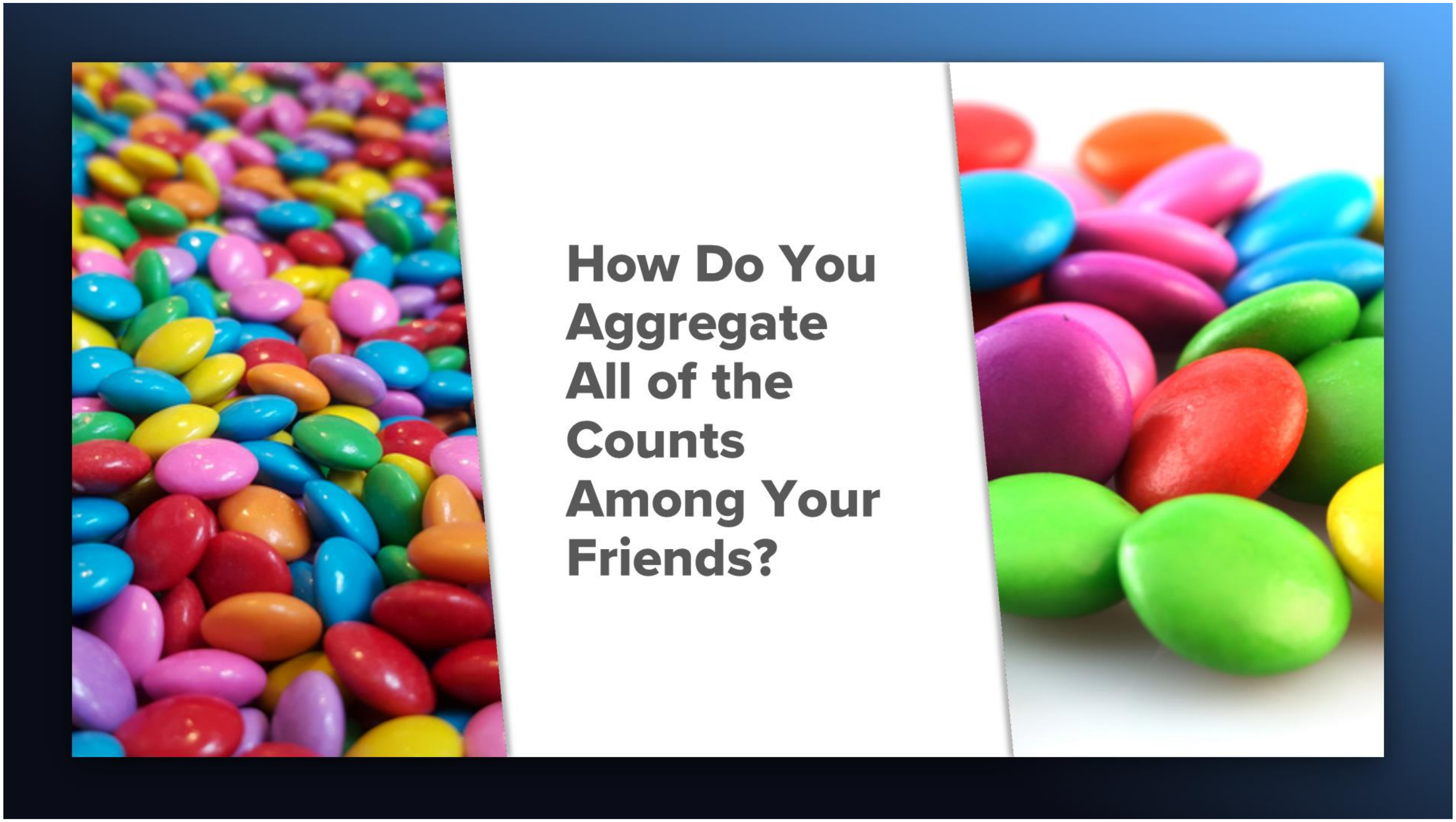
Slide 14: How Do You Aggregate All of the Counts Among Your Friends?



How Do You Aggregate All of the Counts Among Your Friends?

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Slide 15: Drivers and Executors

Driver and Executors

You are the driver

Friends are executors

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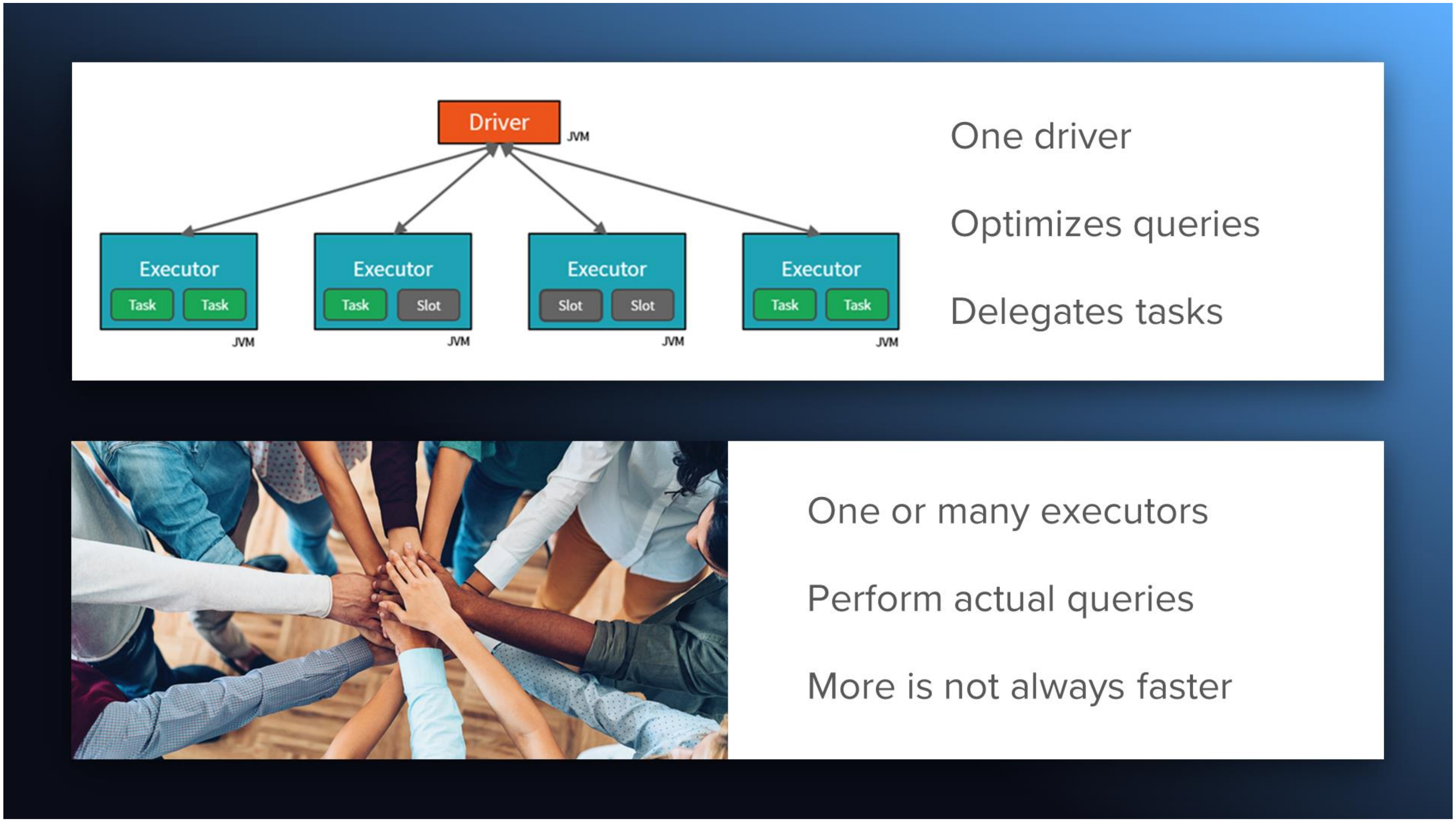
Slide 16: Drivers and Executors



One driver

Optimizes queries

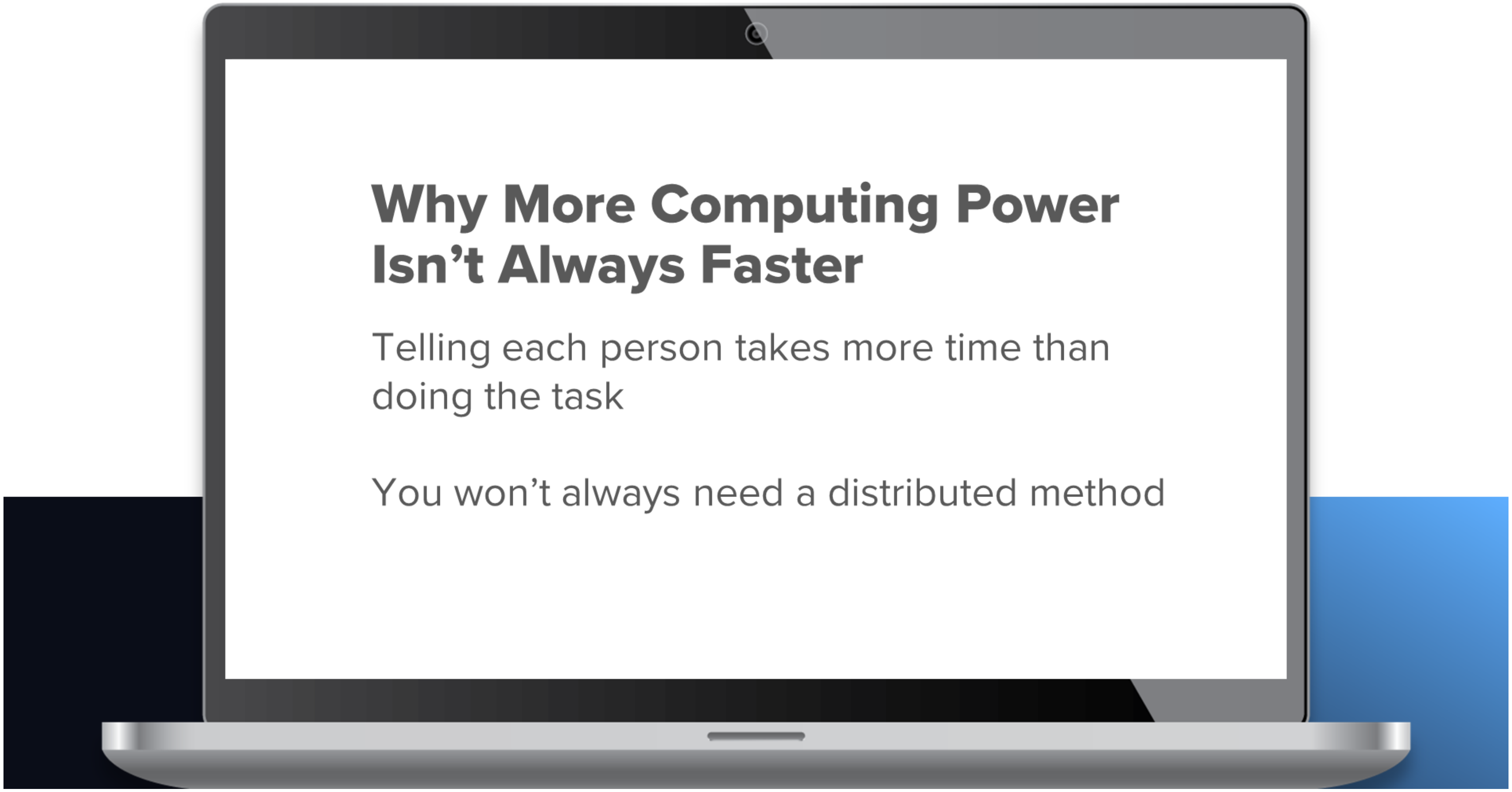
Delegates tasks

One or many executors

Perform actual queries

More is not always faster

Slide 17: Why More Computing Power Isn't Always Faster



Why More Computing Power Isn't Always Faster

Telling each person takes more time than doing the task

You won't always need a distributed method

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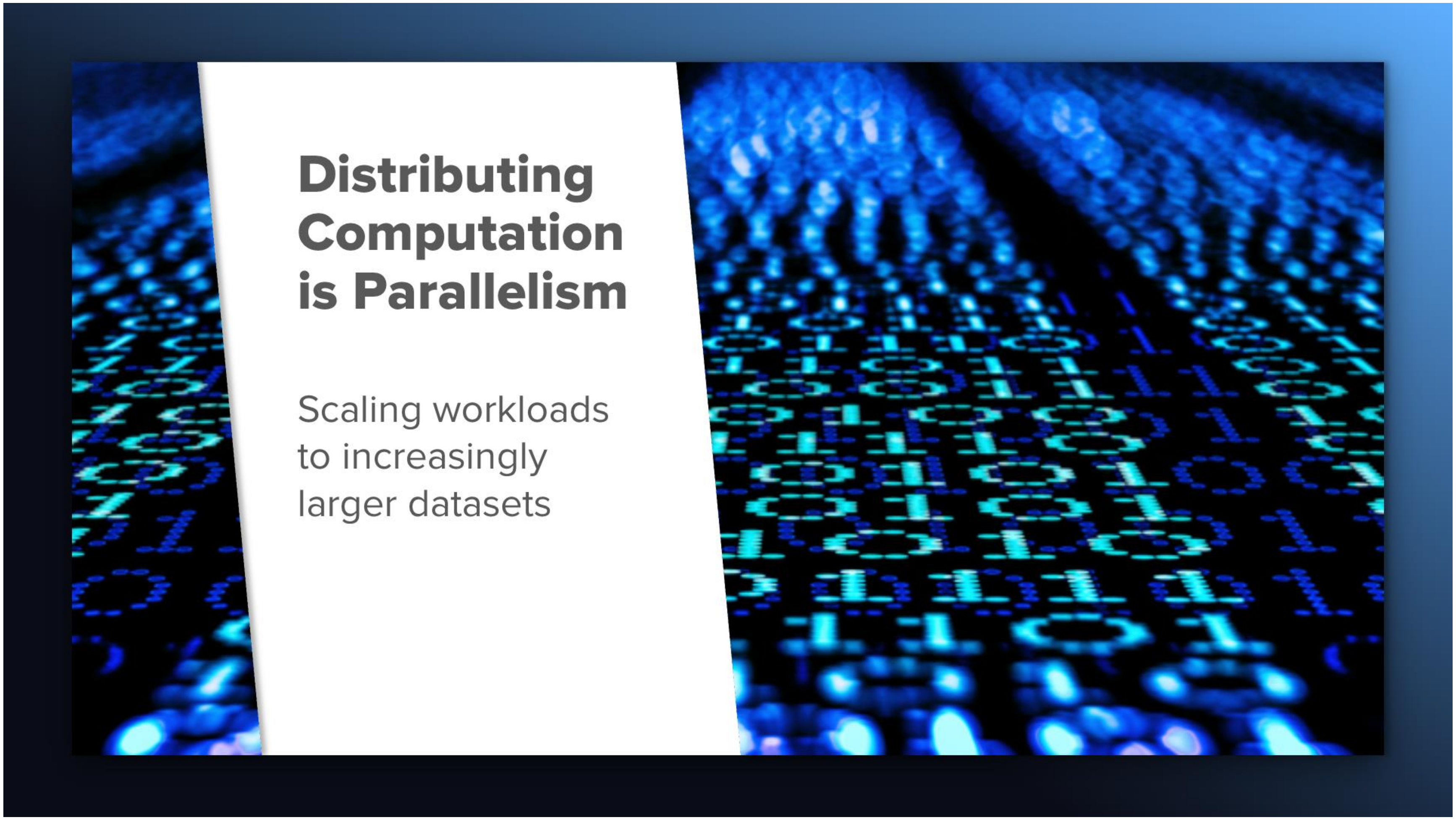
Slide 18: Distributing Computation is Parallelism



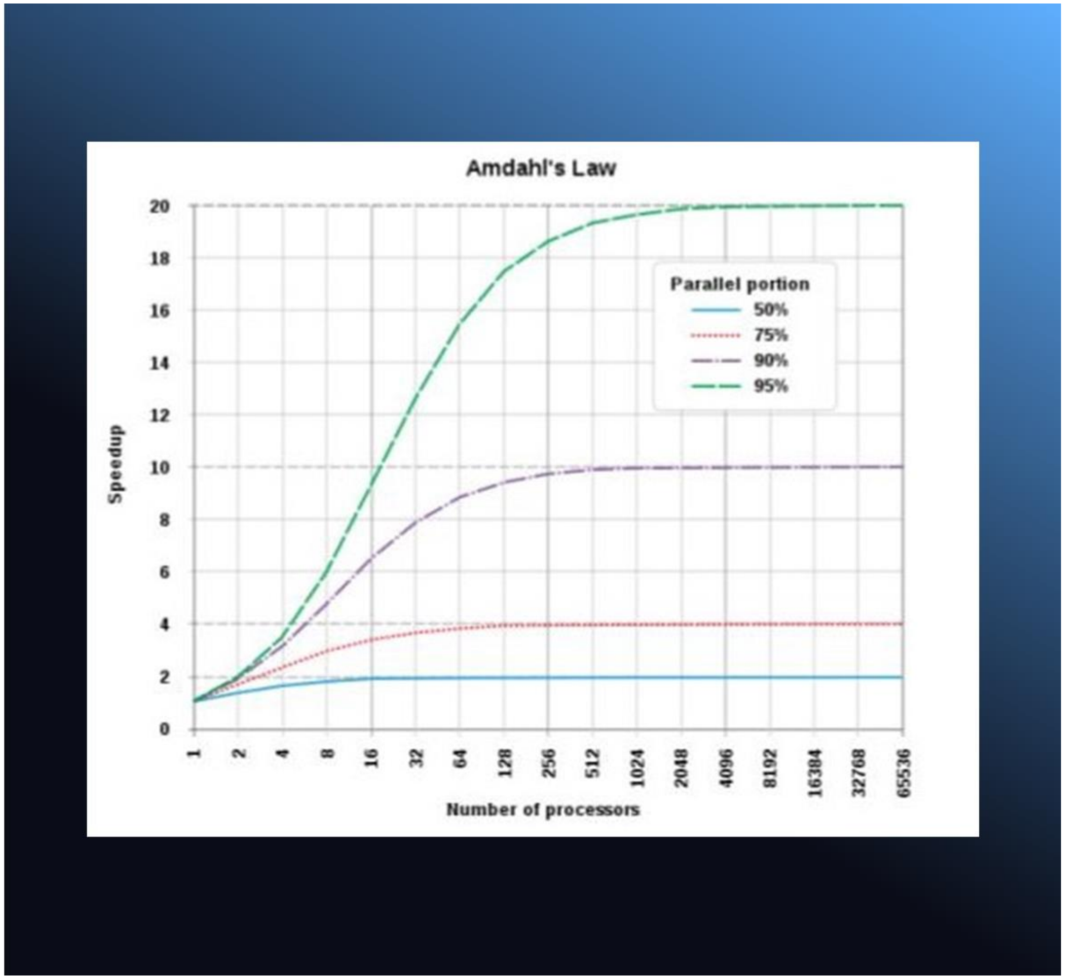
Distributing Computation is Parallelism

Scaling workloads to increasingly larger datasets

Slide 19: Amdahl’s Law

Amdahl’s Law

The amount of acceleration we would see from parallelizing a task is a function of what portion of the task can be completed in parallel



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Slide 20: Linear Scalability

Linear Scalability

Dividing tasks across a cluster of machines

We see improvements up to thousands of machines

Spark is on par with best distributed computing solutions on the market

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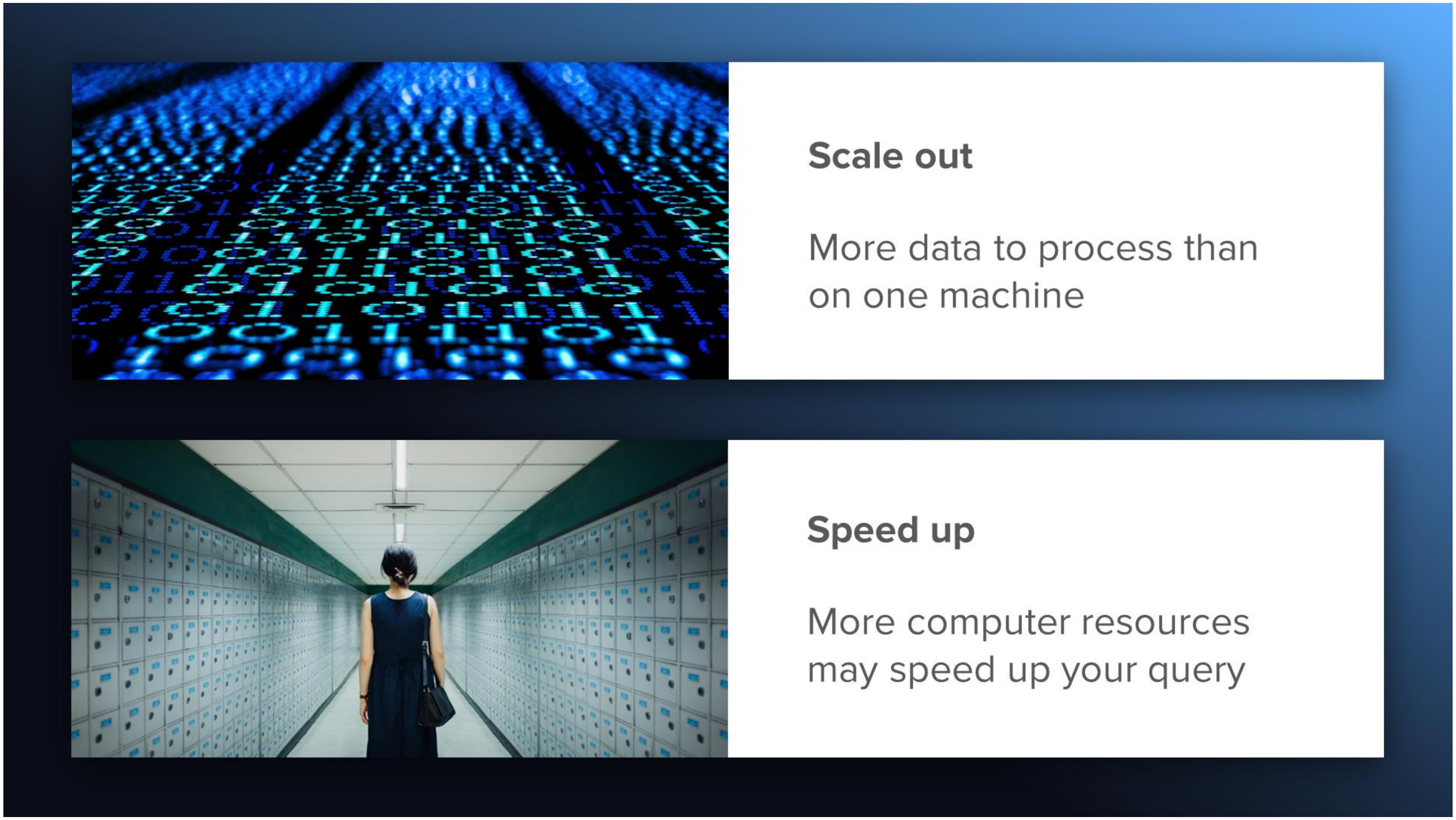
Slide 21: Scalability



Scale out

More data to process than on one machine

Speed up

More computer resources may speed up your query

Slide 22: Coming Up

Coming Up

Learn about core Spark concepts

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