Machine Learning & Spark

MACHINE LEARNING WITH PYSPARK

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Building the perfect waffle (an analogy)

Archetype Waffle

Find waffle recipe. Give explicit instructions:

- 125 g flour
- 1 t baking powder
- 1 egg
- 225 ml milk
- 1 T melted butter

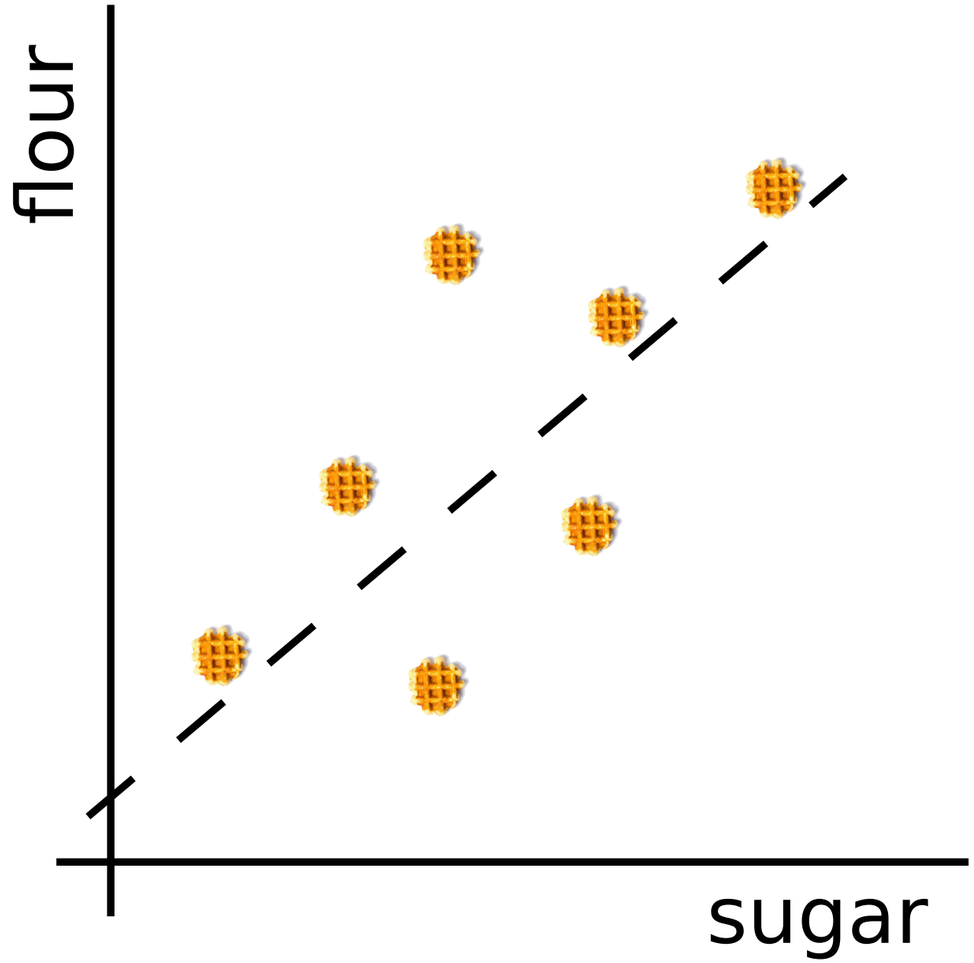
Find many waffle recipes.

Learn the perfect recipe:

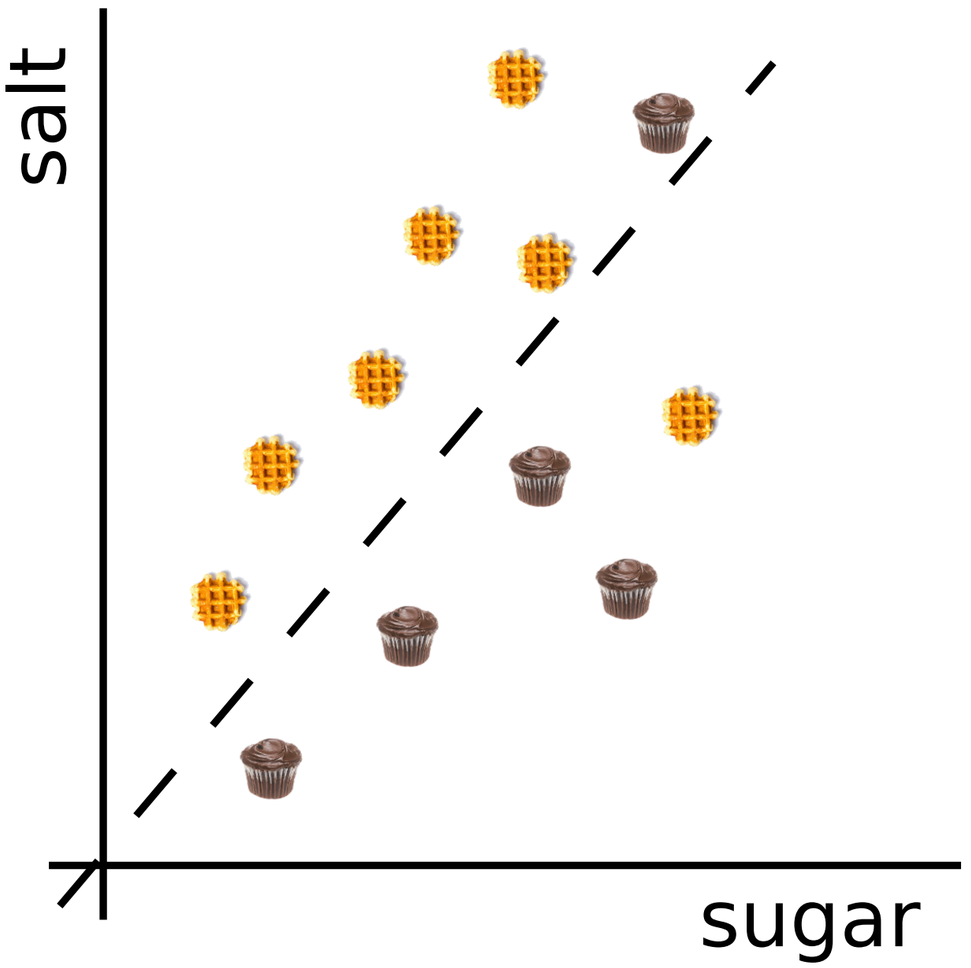
1. Look at lots of recipes.
2. What ingredients?
3. What proportions?

Computer generates its own instructions.

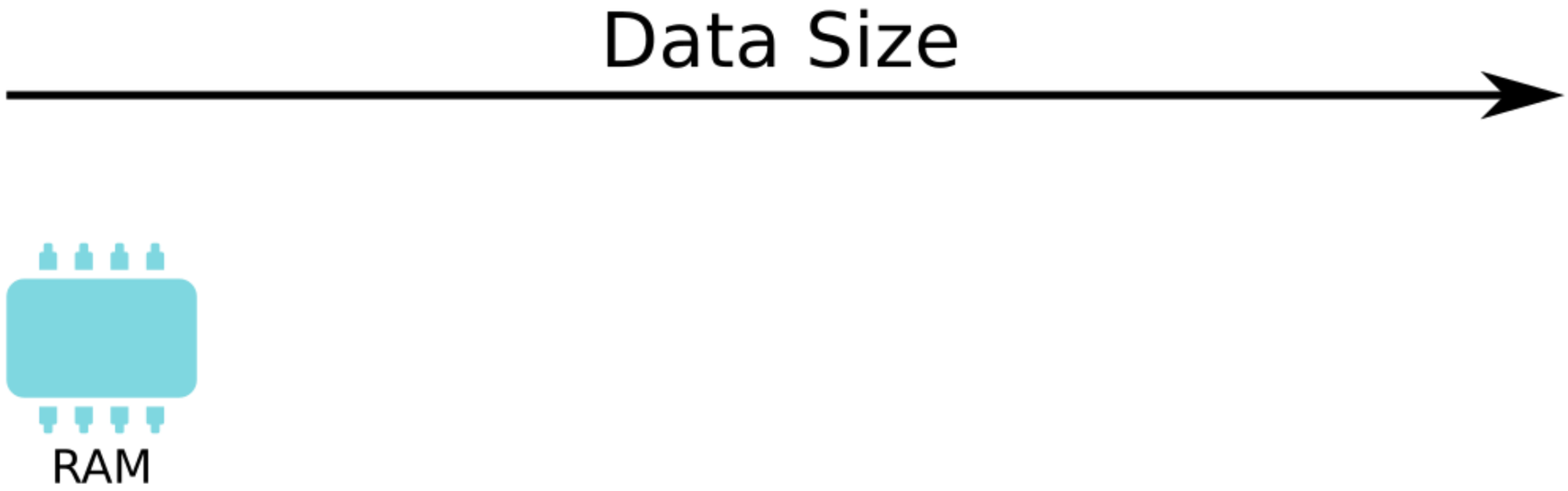
Regression



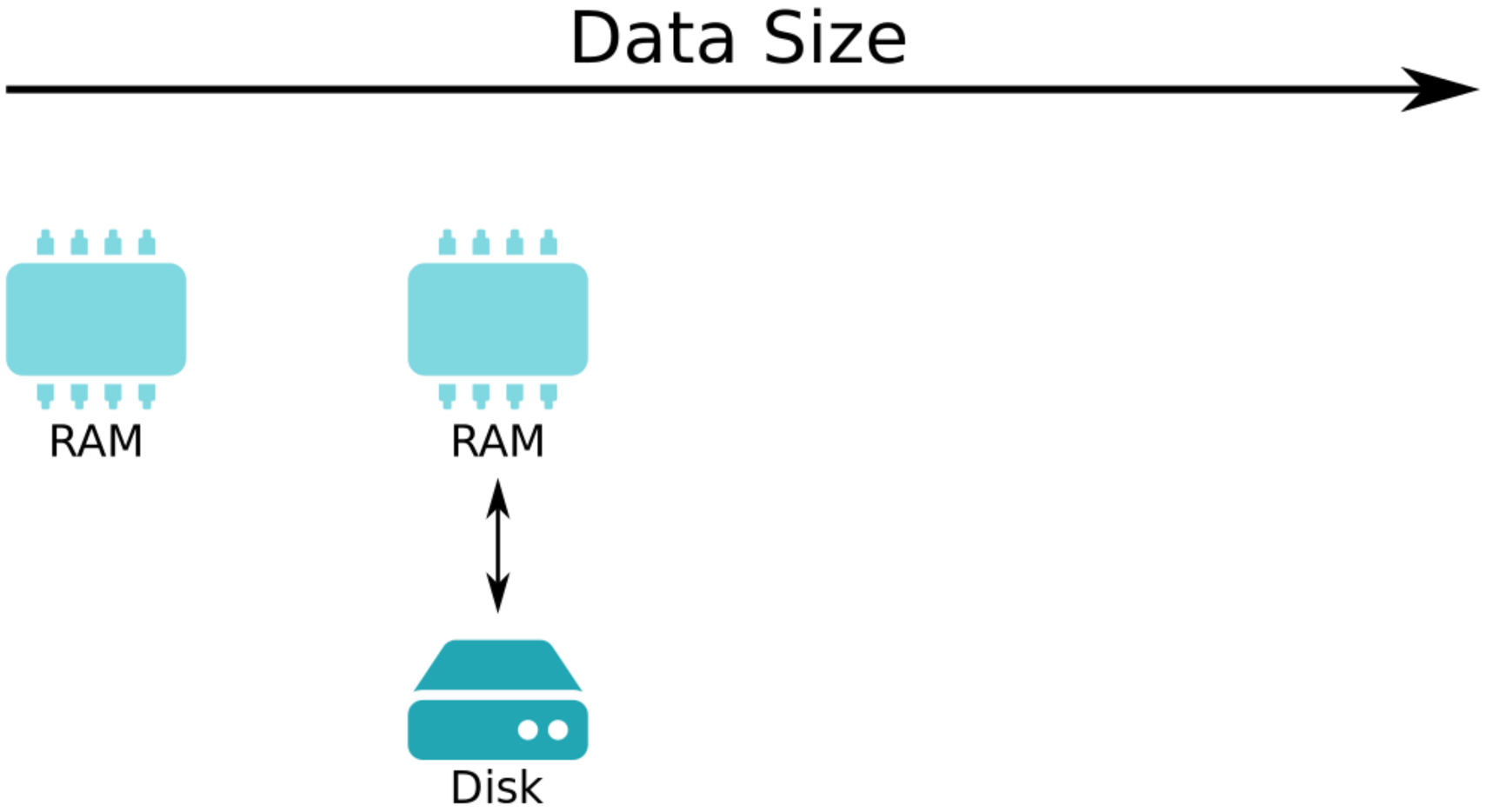
Classification



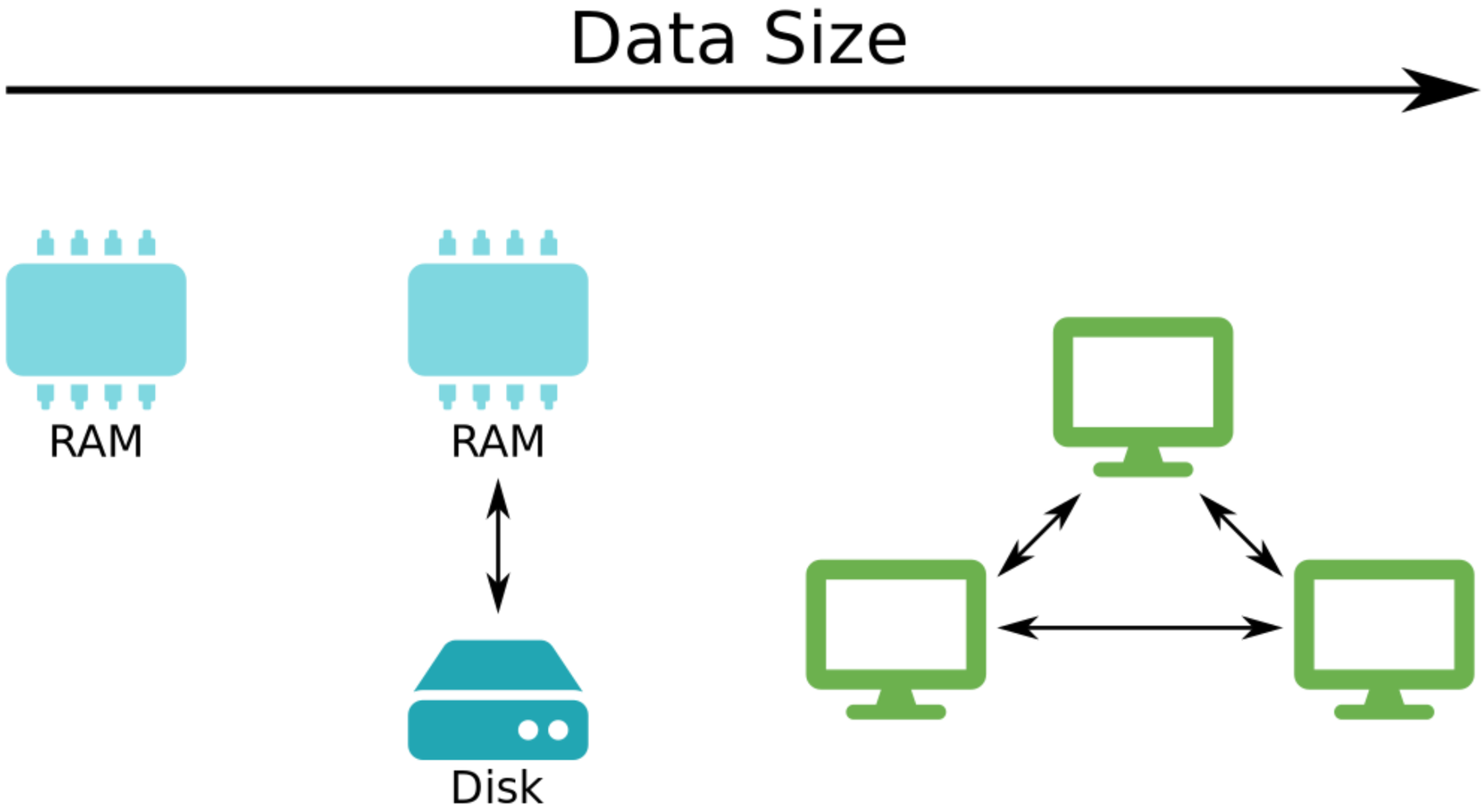
Data in RAM



Data exceeds RAM

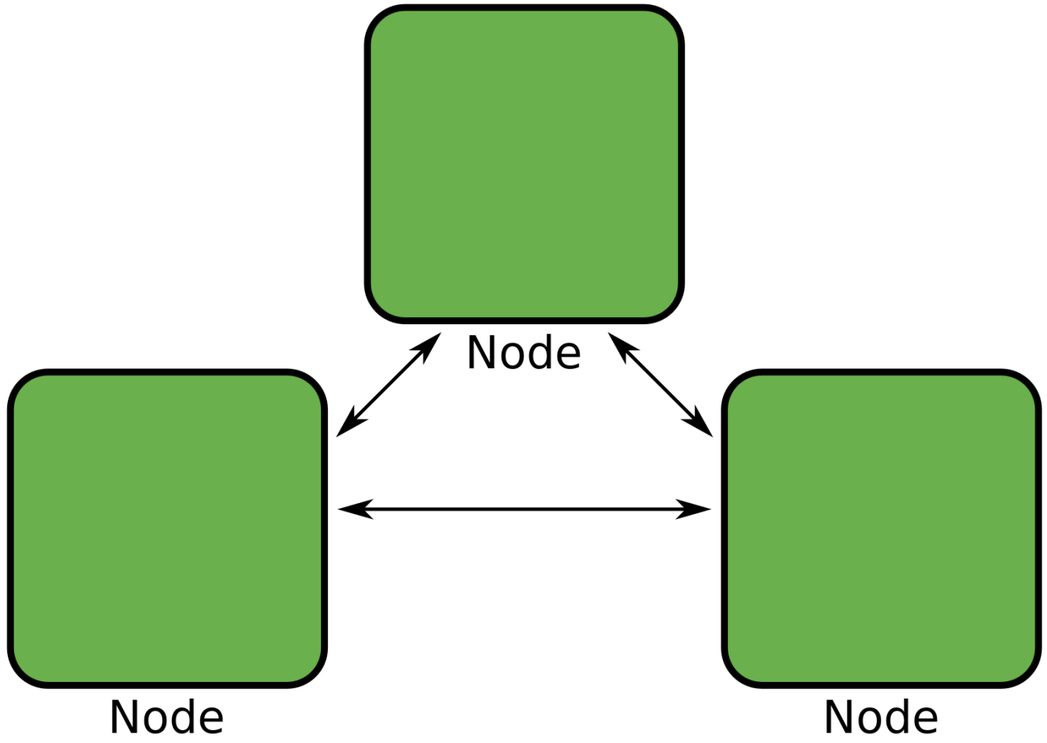


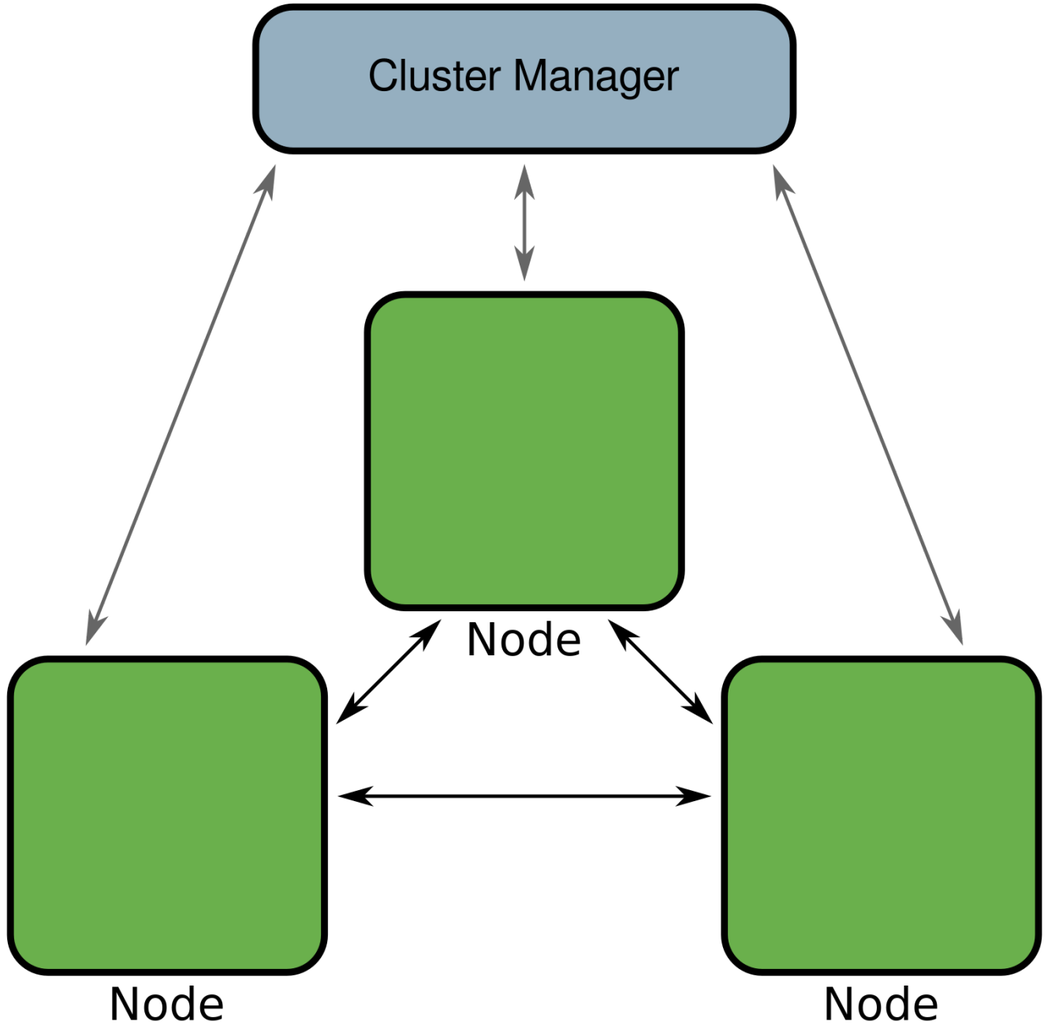
Data distributed across a cluster

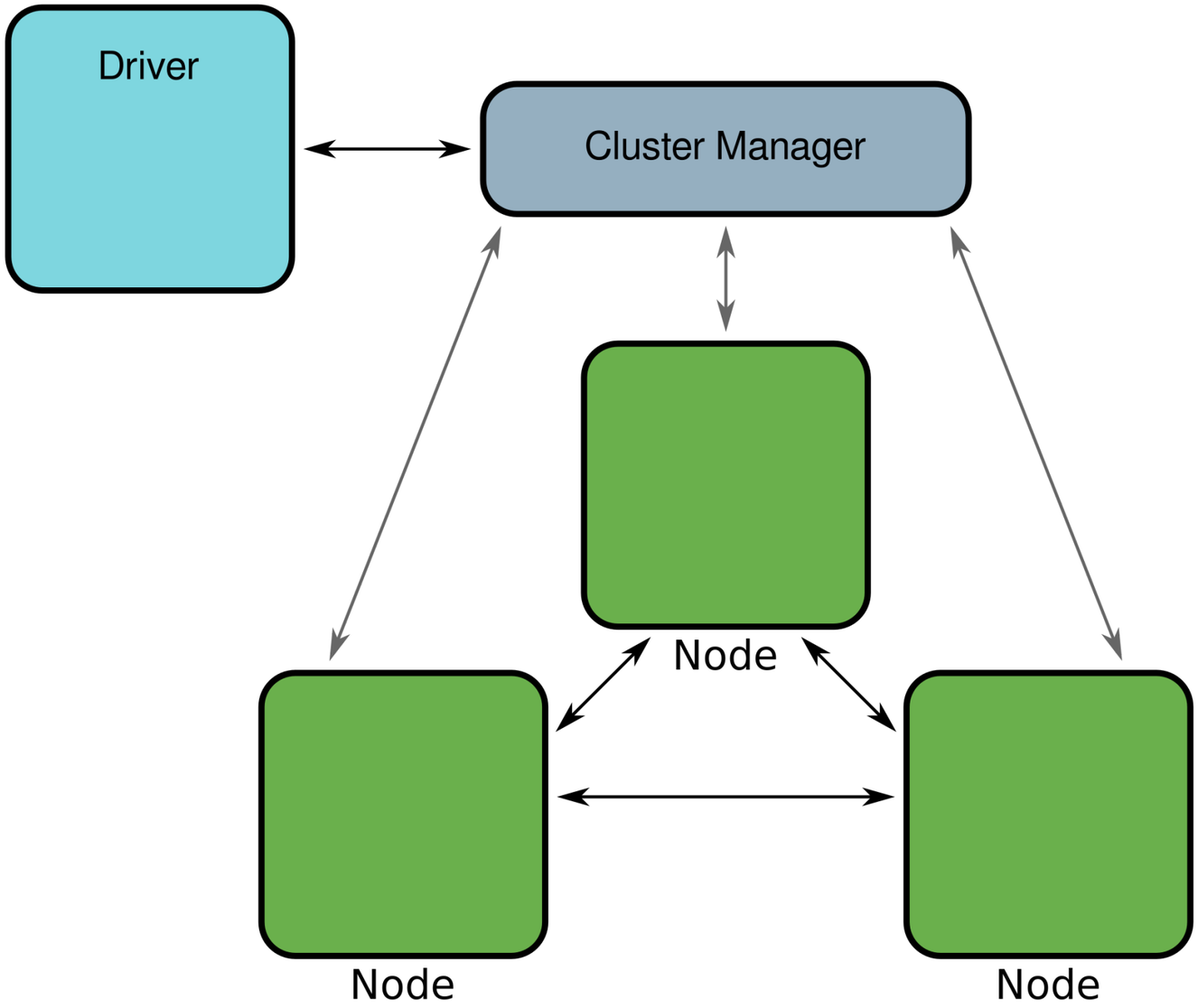


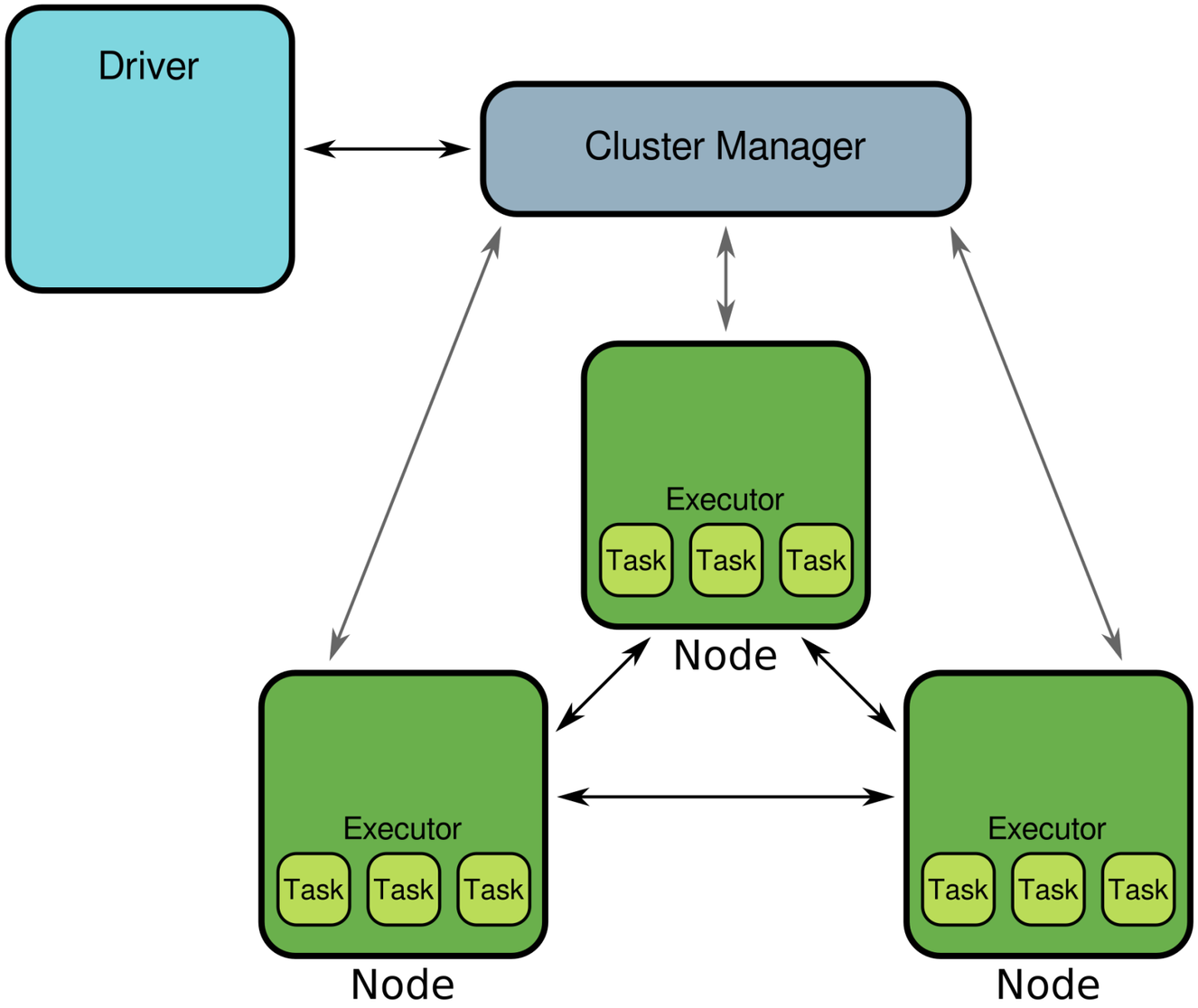
What is Spark?

- Compute across a distributed **cluster**.
- Data processed in memory.
- Well documented high-level **API**.


Node
Node
Node


Cluster Manager
Node
Node
Node


Driver
Cluster Manager
Node
Node
Node


Driver
Cluster Manager
Executor
Task
Task
Task
Node
Executor
Task
Task
Task
Node
Executor
Task
Task
Task
Node

Onward!

MACHINE LEARNING WITH PYSPARK

Connecting to Spark

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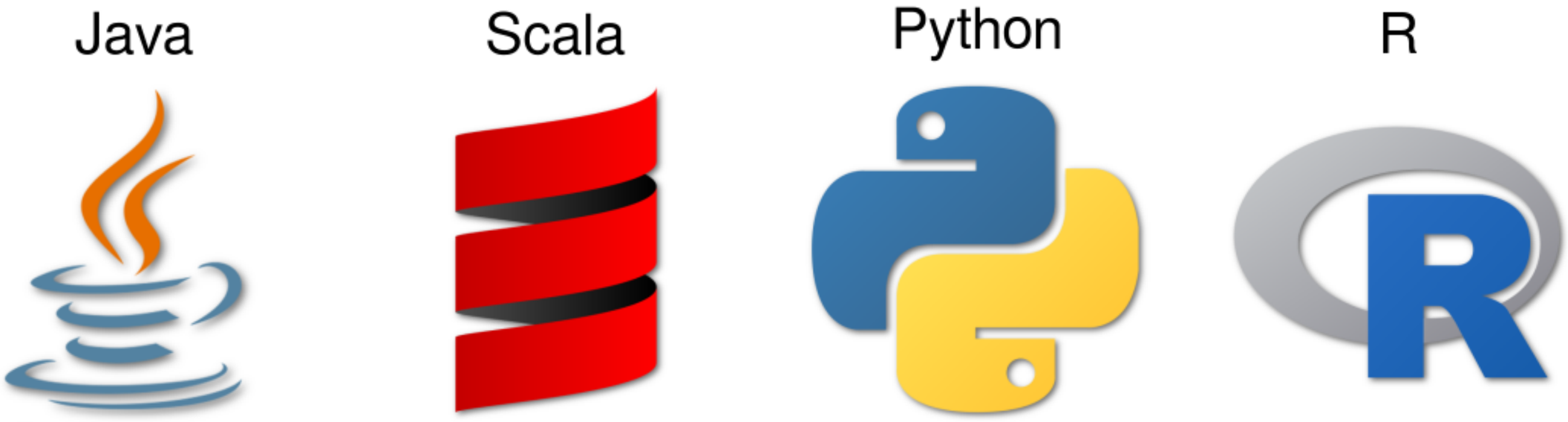
Interacting with Spark



Languages for interacting with Spark.

- Java — low-level, compiled
- Scala, Python and R — high-level with interactive REPL

Importing pyspark

From Python import the `pyspark` module.

```
import pyspark
```

Check version of the `pyspark` module.

```
pyspark.__version__
```

```
'2.4.1'
```

Sub-modules

In addition to `pyspark` there are

- Structured Data — **`pyspark.sql`**
- Streaming Data — **`pyspark.streaming`**
- Machine Learning — **`pyspark.mllib`** (deprecated) and **`pyspark.ml`**

Spark URL

Remote Cluster using Spark URL — `spark://<IP address | DNS name>:<port>`

Example:

- `spark://13.59.151.161:7077`

Local Cluster

Examples:

- `local` — only 1 core;
- `local[4]` — 4 cores; or
- `local[*]` — all available cores.

Creating a SparkSession

```
from pyspark.sql import SparkSession
```

Create a local cluster using a `SparkSession` builder.

```
spark = SparkSession.builder \
                    .master('local[*]') \
                    .appName('first_spark_application') \
                    .getOrCreate()
```

Interact with Spark...

```
# Close connection to Spark
>>> spark.stop()
```

Let's connect to Spark!

MACHINE LEARNING WITH PYSPARK

Loading Data

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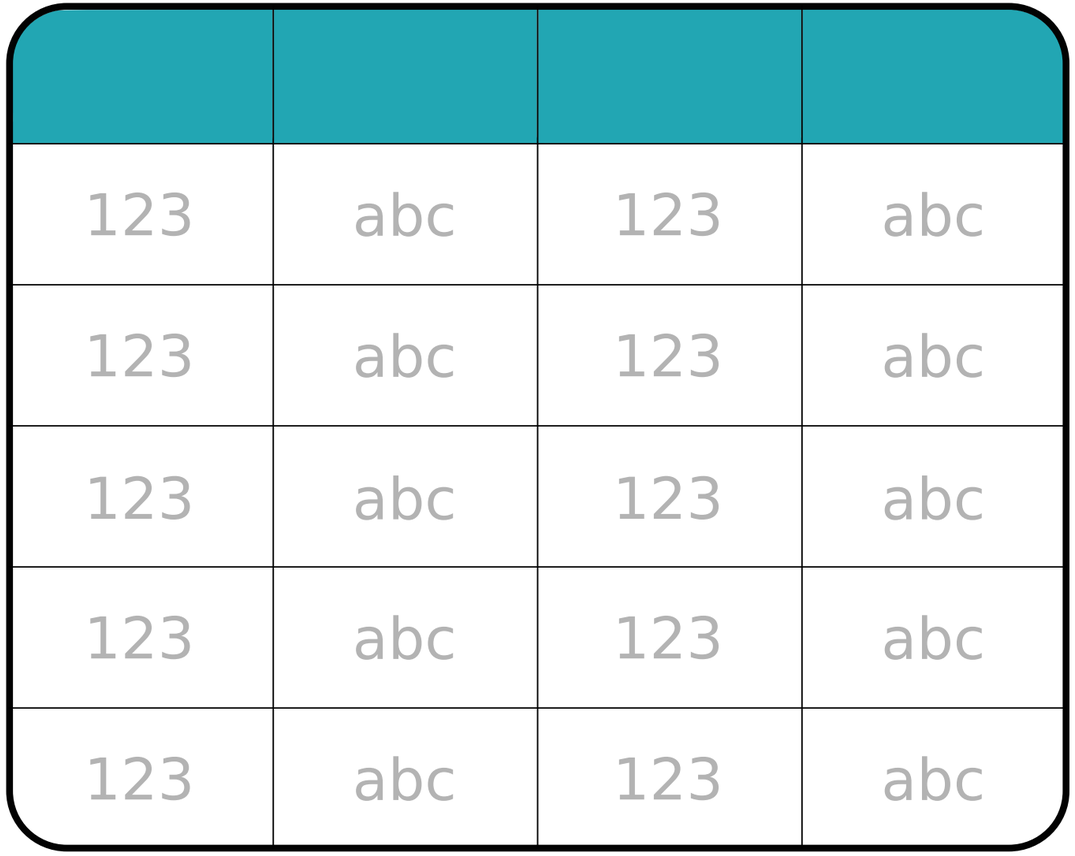
DataFrames: A refresher

`DataFrame` for tabular data.



123	abc	123	abc
123	abc	123	abc
123	abc	123	abc
123	abc	123	abc
123	abc	123	abc

Selected methods:

- `count()`
- `show()`
- `printSchema()`

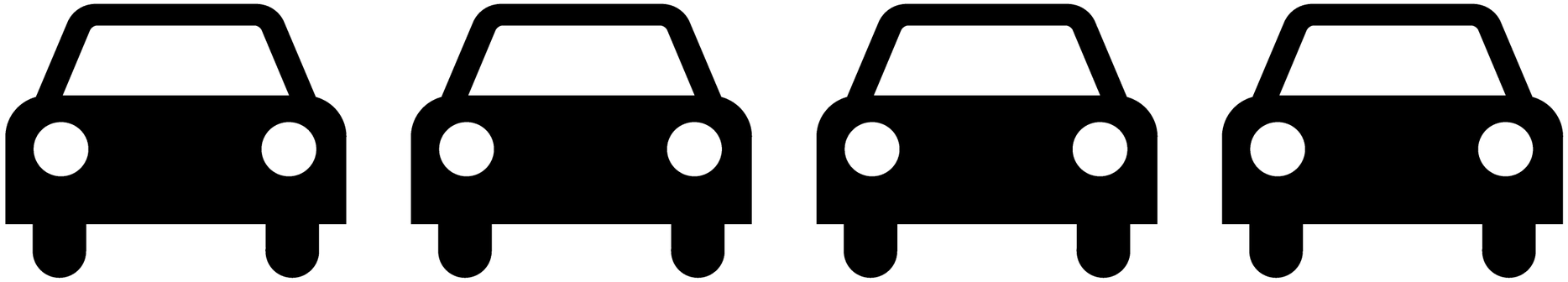
Selected attributes:

- `dtypes`

CSV data for cars

The first few lines from the 'cars.csv' file.

```
mfr,mod,org,type,cyl,size,weight,len,rpm,cons
Mazda,RX-7,non-USA,Sporty,NA,1.3,2895,169,6500,9.41
Nissan,Maxima,non-USA,Midsize,6,3,3200,188,5200,9.05
Chevrolet,Cavalier,USA,Compact,4,2.2,2490,182,5200,6.53
Subaru,Legacy,non-USA,Compact,4,2.2,3085,179,5600,7.84
Ford,Escort,USA,Small,4,1.8,2530,171,6500,7.84
```



Reading data from CSV

The `.csv()` method reads a CSV file and returns a `DataFrame`.

```
cars = spark.read.csv('cars.csv', header=True)
```

Optional arguments:

- `header` — is first row a header? (default: `False`)
- `sep` — field separator (default: a comma `','`)
- `schema` — explicit column data types
- `inferSchema` — deduce column data types from data?
- `nullValue` — placeholder for missing data

Peek at the data

The first five records from the `DataFrame`.

```
cars.show(5)
```

```
+---------+--------+-------+-------+---+----+------+---+----+----+
|      mfr|     mod|    org|   type|cyl|size|weight|len| rpm|cons|
+---------+--------+-------+-------+---+----+------+---+----+----+
|    Mazda|    RX-7|non-USA| Sporty| NA| 1.3|  2895|169|6500|9.41|
|   Nissan|  Maxima|non-USA|Midsize|  6|   3|  3200|188|5200|9.05|
|Chevrolet|Cavalier|    USA|Compact|  4| 2.2|  2490|182|5200|6.53|
|   Subaru|  Legacy|non-USA|Compact|  4| 2.2|  3085|179|5600|7.84|
|     Ford|  Escort|    USA|  Small|  4| 1.8|  2530|171|6500|7.84|
+---------+--------+-------+-------+---+----+------+---+----+----+
```

Check column types

```
cars.printSchema()
```

```
root
|-- mfr: string (nullable = true)
|-- mod: string (nullable = true)
|-- org: string (nullable = true)
|-- type: string (nullable = true)
|-- cyl: string (nullable = true)
|-- size: string (nullable = true)
|-- weight: string (nullable = true)
|-- len: string (nullable = true)
|-- rpm: string (nullable = true)
|-- cons: string (nullable = true)
```

Inferring column types from data

```
cars = spark.read.csv("cars.csv", header=True, inferSchema=True)
cars.dtypes
```

```
[('mfr', 'string'),
('mod', 'string'),
('org', 'string'),
('type', 'string'),
('cyl', 'string'),
('size', 'double'),
('weight', 'int'),
('len', 'int'),
('rpm', 'int'),
('cons', 'double')]
```

Dealing with missing data

Handle missing data using the `nullValue` argument.

```
cars = spark.read.csv("cars.csv", header=True, inferSchema=True, nullValue='NA')
```

The `nullValue` argument is case sensitive.

Specify column types

```
schema = StructType([
    StructField("maker", StringType()),
    StructField("model", StringType()),
    StructField("origin", StringType()),
    StructField("type", StringType()),
    StructField("cyl", IntegerType()),
    StructField("size", DoubleType()),
    StructField("weight", IntegerType()),
    StructField("length", DoubleType()),
    StructField("rpm", IntegerType()),
    StructField("consumption", DoubleType())
])
cars = spark.read.csv("cars.csv", header=True, schema=schema, nullValue='NA')
```

Final cars data

maker	model	origin	type	cyl	size	weight	length	rpm	consumption
Mazda	RX-7	non-USA	Sporty	null	1.3	2895	169.0	6500	9.41
Nissan	Maxima	non-USA	Midsize	6	3.0	3200	188.0	5200	9.05
Chevrolet	Cavalier	USA	Compact	4	2.2	2490	182.0	5200	6.53
Subaru	Legacy	non-USA	Compact	4	2.2	3085	179.0	5600	7.84
Ford	Escort	USA	Small	4	1.8	2530	171.0	6500	7.84
Mercury	Capri	USA	Sporty	4	1.6	2450	166.0	5750	9.05
Oldsmobile	Cutlass Ciera	USA	Midsize	4	2.2	2890	190.0	5200	7.59
Saab	900	non-USA	Compact	4	2.1	2775	184.0	6000	9.05
Dodge	Caravan	USA	Van	6	3.0	3705	175.0	5000	11.2

Let's load some data!

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