CHAPTER 3
Data Engineering Fundamentals

The rise of ML in recent years is tightly coupled with the rise of big data. Large data systems, even without ML, are complex. If you haven't spent years and years working with them, it's easy to get lost in acronyms. There are many challenges and possible solutions that these systems generate. Industry standards, if there are any, evolve quickly as new tools come out and the needs of the industry expand, creating a dynamic and ever-changing environment. If you look into the data stack for different tech companies, it might seem like each is doing its own thing.

In this chapter, we'll cover the basics of data engineering that will, hopefully, give you a steady piece of land to stand on as you explore the landscape for your own needs. We'll start with different sources of data that you might work with in a typical ML project. We'll continue to discuss the formats in which data can be stored. Storing data is only interesting if you intend on retrieving that data later. To retrieve stored data, it's important to know not only how it's formatted but also how it's structured. Data models define how the data stored in a particular data format is structured.

If data models describe the data in the real world, databases specify how the data should be stored on machines. We'll continue to discuss data storage engines, also known as databases, for the two major types of processing: transactional and analytical.

When working with data in production, you usually work with data across multiple processes and services. For example, you might have a feature engineering service that computes features from raw data, and a prediction service to generate predictions based on computed features. This means that you'll have to pass computed features from the feature engineering service to the prediction service. In the following section of the chapter, we'll discuss different modes of data passing across processes.

During the discussion of different modes of data passing, we'll learn about two distinct types of data: historical data in data storage engines, and streaming data in real-time transports. These two different types of data require different processing paradigms, which we'll discuss in the section "Batch Processing Versus Stream Processing" on page 78.

Knowing how to collect, process, store, retrieve, and process an increasingly growing amount of data is essential to people who want to build ML systems in production. If you're already familiar with data systems, you might want to move directly to Chapter 4 to learn more about how to sample and generate labels to create training data. If you want to learn more about data engineering from a systems perspective, I recommend Martin Kleppmann's excellent book *Designing Data-Intensive Applications* (O'Reilly, 2017).

Data Sources

An ML system can work with data from many different sources. They have different characteristics, can be used for different purposes, and require different processing methods. Understanding the sources your data comes from can help you use your data more efficiently. This section aims to give a quick overview of different data sources to those unfamiliar with data in production. If you've already worked with ML in production for a while, feel free to skip this section.

One source is *user input data*, data explicitly input by users. User input can be text, images, videos, uploaded files, etc. If it's even remotely possible for users to input wrong data, they are going to do it. As a result, user input data can be easily malformatted. Text might be too long or too short. Where numerical values are expected, users might accidentally enter text. If you let users upload files, they might upload files in the wrong formats. User input data requires more heavy-duty checking and processing.

On top of that, users also have little patience. In most cases, when we input data, we expect to get results back immediately. Therefore, user input data tends to require fast processing.

Another source is *system-generated data*. This is the data generated by different components of your systems, which include various types of logs and system outputs such as model predictions.

Logs can record the state and significant events of the system, such as memory usage, number of instances, services called, packages used, etc. They can record the results of different jobs, including large batch jobs for data processing and model training. These types of logs provide visibility into how the system is doing. The main purpose of this visibility is for debugging and potentially improving the application. Most of the time, you don't have to look at these types of logs, but they are essential when something is on fire.

Because logs are system generated, they are much less likely to be malformatted the way user input data is. Overall, logs don't need to be processed as soon as they arrive, the way you would want to process user input data. For many use cases, it's acceptable to process logs periodically, such as hourly or even daily. However, you might still want to process your logs fast to be able to detect and be notified whenever something interesting happens.[1]

Because debugging ML systems is hard, it's a common practice to log everything you can. This means that your volume of logs can grow very, very quickly. This leads to two problems. The first is that it can be hard to know where to look because signals are lost in the noise. There have been many services that process and analyze logs, such as Logstash, Datadog, Logz.io, etc. Many of them use ML models to help you process and make sense of your massive number of logs.

The second problem is how to store a rapidly growing number of logs. Luckily, in most cases, you only have to store logs for as long as they are useful and can discard them when they are no longer relevant for you to debug your current system. If you don't have to access your logs frequently, they can also be stored in low-access storage that costs much less than higher-frequency-access storage.[2]

The system also generates data to record users' behaviors, such as clicking, choosing a suggestion, scrolling, zooming, ignoring a pop-up, or spending an unusual amount of time on certain pages. Even though this is system-generated data, it's still considered part of user data and might be subject to privacy regulations.[3]

[1] "Interesting" in production usually means catastrophic, such as a crash or when your cloud bill hits an astronomical amount.

[2] As of November 2021, AWS S3 Standard, the storage option that allows you to access your data with the latency of milliseconds, costs about five times more per GB than S3 Glacier, the storage option that allows you to retrieve your data with a latency from between 1 minute to 12 hours.

[3] An ML engineer once mentioned to me that his team only used users' historical product browsing and purchases to make recommendations on what they might like to see next. I responded: "So you don't use personal data at all?" He looked at me, confused. "If you meant demographic data like users' age, location, then no, we don't. But I'd say that a person's browsing and purchasing activities are extremely personal."

There are also *internal databases*, generated by various services and enterprise applications in a company. These databases manage their assets such as inventory, customer relationship, users, and more. This kind of data can be used by ML models directly or by various components of an ML system. For example, when users enter a search query on Amazon, one or more ML models process that query to detect its intention—if someone types in "frozen," are they looking for frozen foods or Disney's *Frozen* franchise?—then Amazon needs to check its internal databases for the availability of these products before ranking them and showing them to users.

Then there's the wonderfully weird world of *third-party data*. First-party data is the data that your company already collects about your users or customers. Second-party data is the data collected by another company on their own customers that they make available to you, though you'll probably have to pay for it. Third-party data companies collect data on the public who aren't their direct customers.

The rise of the internet and smartphones has made it much easier for all types of data to be collected. It used to be especially easy with smartphones since each phone used to have a unique advertiser ID—iPhones with Apple's Identifier for Advertisers (IDFA) and Android phones with their Android Advertising ID (AAID)—which acted as a unique ID to aggregate all activities on a phone. Data from apps, websites, check-in services, etc. are collected and (hopefully) anonymized to generate activity history for each person.

Data of all kinds can be bought, such as social media activities, purchase history, web browsing habits, car rentals, and political leaning for different demographic groups getting as granular as men, age 25–34, working in tech, living in the Bay Area. From this data, you can infer information such as people who like brand A also like brand B. This data can be especially helpful for systems such as recommender systems to generate results relevant to users' interests. Third-party data is usually sold after being cleaned and processed by vendors.

However, as users demand more data privacy, companies have been taking steps to curb the usage of advertiser IDs. In early 2021, Apple made their IDFA opt-in. This change has reduced significantly the amount of third-party data available on iPhones, forcing many companies to focus more on first-party data.[4] To fight back this change, advertisers have been investing in workarounds. For example, the China Advertising Association, a state-supported trade association for China's advertising industry, invested in a device fingerprinting system called CAID that allowed apps like TikTok and Tencent to keep tracking iPhone users.[5]

[4] John Koetsier, "Apple Just Crippled IDFA, Sending an $80 Billion Industry Into Upheaval," *Forbes*, June 24, 2020, *https://oreil.ly/rqPX9*.

[5] Patrick McGee and Yuan Yang, "TikTok Wants to Keep Tracking iPhone Users with State-Backed Workaround," *Ars Technica*, March 16, 2021, *https://oreil.ly/54pkg*.

Data Formats

Once you have data, you might want to store it (or "persist" it, in technical terms). Since your data comes from multiple sources with different access patterns,[6] storing your data isn't always straightforward and, for some cases, can be costly. It's important to think about how the data will be used in the future so that the format you use will make sense. Here are some of the questions you might want to consider:

- How do I store multimodal data, e.g., a sample that might contain both images and texts?
- Where do I store my data so that it's cheap and still fast to access?
- How do I store complex models so that they can be loaded and run correctly on different hardware?

The process of converting a data structure or object state into a format that can be stored or transmitted and reconstructed later is *data serialization*. There are many, many data serialization formats. When considering a format to work with, you might want to consider different characteristics such as human readability, access patterns, and whether it's based on text or binary, which influences the size of its files. Table 3-1 consists of just a few of the common formats that you might encounter in your work. For a more comprehensive list, check out the wonderful Wikipedia page "Comparison of Data-Serialization Formats".

Table 3-1. Common data formats and where they are used

Format	Binary/Text	Human-readable	Example use cases
JSON	Text	Yes	Everywhere
CSV	*Text*	*Yes*	*Everywhere*
Parquet	*Binary*	*No*	*Hadoop, Amazon Redshift*
Avro	Binary primary	No	Hadoop
Protobuf	Binary primary	No	Google, TensorFlow (TFRecord)
Pickle	Binary	No	Python, PyTorch serialization

We'll go over a few of these formats, starting with JSON. We'll also go over the two formats that are common and represent two distinct paradigms: CSV and Parquet.

[6] "Access pattern" means the pattern in which a system or program reads or writes data.

JSON

JSON, JavaScript Object Notation, is everywhere. Even though it was derived from JavaScript, it's language-independent—most modern programming languages can generate and parse JSON. It's human-readable. Its key-value pair paradigm is simple but powerful, capable of handling data of different levels of structuredness. For example, your data can be stored in a structured format like the following:

```
{
  "firstName": "Boatie",
  "lastName": "McBoatFace",
  "isVibing": true,
  "age": 12,
  "address": {
    "streetAddress": "12 Ocean Drive",
    "city": "Port Royal",
    "postalCode": "10021-3100"
  }
}
```

The same data can also be stored in an unstructured blob of text like the following:

```
{
  "text": "Boatie McBoatFace, aged 12, is vibing, at 12 Ocean Drive, Port Royal,
           10021-3100"
}
```

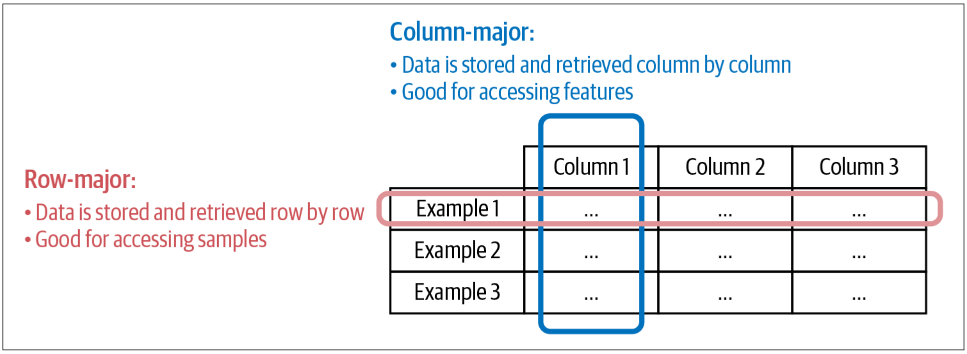
Because JSON is ubiquitous, the pain it causes can also be felt everywhere. Once you've committed the data in your JSON files to a schema, it's pretty painful to retrospectively go back to change the schema. JSON files are text files, which means they take up a lot of space, as we'll see in the section "Text Versus Binary Format" on page 57.

Row-Major Versus Column-Major Format

The two formats that are common and represent two distinct paradigms are CSV and Parquet. CSV (comma-separated values) is row-major, which means consecutive elements in a row are stored next to each other in memory. Parquet is column-major, which means consecutive elements in a column are stored next to each other.

Because modern computers process sequential data more efficiently than nonsequential data, if a table is row-major, accessing its rows will be faster than accessing its columns in expectation. This means that for row-major formats, accessing data by rows is expected to be faster than accessing data by columns.

Imagine we have a dataset of 1,000 examples, and each example has 10 features. If we consider each example as a row and each feature as a column, as is often the case in ML, then the row-major formats like CSV are better for accessing examples, e.g., accessing all the examples collected today. Column-major formats like Parquet are better for accessing features, e.g., accessing the timestamps of all your examples. See Figure 3-1.



Column-major:
• Data is stored and retrieved column by column
• Good for accessing features
Row-major:
• Data is stored and retrieved row by row
• Good for accessing samples
Column 1
Column 2
Column 3
Example 1
Example 2
Example 3
...

Figure 3-1. Row-major versus column-major formats

Column-major formats allow flexible column-based reads, especially if your data is large with thousands, if not millions, of features. Consider if you have data about ride-sharing transactions that has 1,000 features but you only want 4 features: time, location, distance, price. With column-major formats, you can read the four columns corresponding to these four features directly. However, with row-major formats, if you don't know the sizes of the rows, you will have to read in all columns then filter down to these four columns. Even if you know the sizes of the rows, it can still be slow as you'll have to jump around the memory, unable to take advantage of caching.

Row-major formats allow faster data writes. Consider the situation when you have to keep adding new individual examples to your data. For each individual example, it'd be much faster to write it to a file where your data is already in a row-major format.

Overall, row-major formats are better when you have to do a lot of writes, whereas column-major ones are better when you have to do a lot of column-based reads.

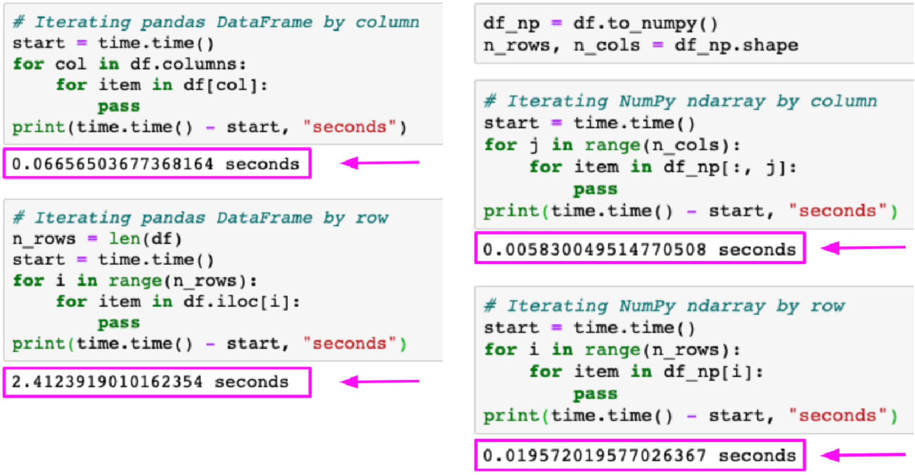
NumPy Versus pandas

One subtle point that a lot of people don't pay attention to, which leads to misuses of pandas, is that this library is built around the columnar format.

pandas is built around DataFrame, a concept inspired by R's Data Frame, which is column-major. A DataFrame is a two-dimensional table with rows and columns.

In NumPy, the major order can be specified. When an `ndarray` is created, it's row-major by default if you don't specify the order. People coming to pandas from NumPy tend to treat DataFrame the way they would `ndarray`, e.g., trying to access data by rows, and find DataFrame slow.

In the left panel of Figure 3-2, you can see that accessing a DataFrame by row is so much slower than accessing the same DataFrame by column. If you convert this same DataFrame to a NumPy `ndarray`, accessing a row becomes much faster, as you can see in the right panel of the figure.[7]



```
# Iterating pandas DataFrame by column
start = time.time()
for col in df.columns:
    for item in df[col]:
        pass
print(time.time() - start, "seconds")
```

```
0.06656503677368164 seconds
```

```
# Iterating pandas DataFrame by row
n_rows = len(df)
start = time.time()
for i in range(n_rows):
    for item in df.iloc[i]:
        pass
print(time.time() - start, "seconds")
```

```
2.4123919010162354 seconds
```

```
df_np = df.to_numpy()
n_rows, n_cols = df_np.shape
```

```
# Iterating NumPy ndarray by column
start = time.time()
for j in range(n_cols):
    for item in df_np[:, j]:
        pass
print(time.time() - start, "seconds")
```

```
0.005830049514770508 seconds
```

```
# Iterating NumPy ndarray by row
start = time.time()
for i in range(n_rows):
    for item in df_np[i]:
        pass
print(time.time() - start, "seconds")
```

```
0.019572019577026367 seconds
```

Figure 3-2. (Left) Iterating a pandas DataFrame by column takes 0.07 seconds but iterating the same DataFrame by row takes 2.41 seconds. (Right) When you convert the same DataFrame into a NumPy `ndarray`, accessing its rows becomes much faster.

[7] For more pandas quirks, check out my Just pandas Things GitHub repository.

I use CSV as an example of the row-major format because it's popular and generally recognizable by everyone I've talked to in tech. However, some of the early reviewers of this book pointed out that they believe CSV to be a horrible data format. It serializes nontext characters poorly. For example, when you write float values to a CSV file, some precision might be lost—0.12345678901232323 could be arbitrarily rounded up as "0.12345678901"—as complained about in a Stack Overflow thread and Microsoft Community thread. People on Hacker News have passionately argued against using CSV.

Text Versus Binary Format

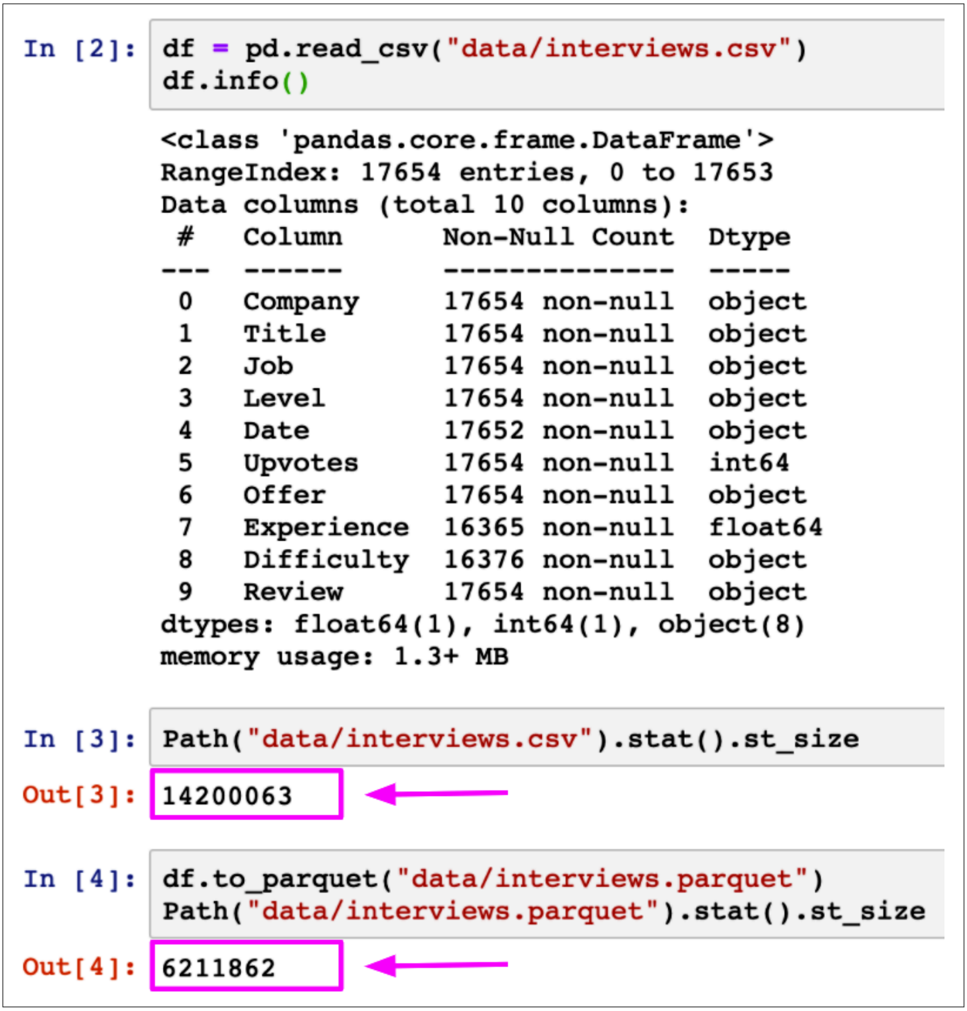
CSV and JSON are text files, whereas Parquet files are binary files. Text files are files that are in plain text, which usually means they are human-readable. Binary files are the catchall that refers to all nontext files. As the name suggests, binary files are typically files that contain only 0s and 1s, and are meant to be read or used by programs that know how to interpret the raw bytes. A program has to know exactly how the data inside the binary file is laid out to make use of the file. If you open text files in your text editor (e.g., VS Code, Notepad), you'll be able to read the texts in them. If you open a binary file in your text editor, you'll see blocks of numbers, likely in hexadecimal values, for corresponding bytes of the file.

Binary files are more compact. Here's a simple example to show how binary files can save space compared to text files. Consider that you want to store the number `1000000`. If you store it in a text file, it'll require 7 characters, and if each character is 1 byte, it'll require 7 bytes. If you store it in a binary file as int32, it'll take only 32 bits or 4 bytes.

As an illustration, I use *interviews.csv*, which is a CSV file (text format) of 17,654 rows and 10 columns. When I converted it to a binary format (Parquet), the file size went from 14 MB to 6 MB, as shown in Figure 3-3.

AWS recommends using the Parquet format because "the Parquet format is up to 2x faster to unload and consumes up to 6x less storage in Amazon S3, compared to text formats."[8]

[8] "Announcing Amazon Redshift Data Lake Export: Share Data in Apache Parquet Format," Amazon AWS, December 3, 2019, *https://oreil.ly/ilDb6*.



```
In [2]:  df = pd.read_csv("data/interviews.csv")
         df.info()

         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 17654 entries, 0 to 17653
         Data columns (total 10 columns):
          #   Column      Non-Null Count  Dtype
         ---  ------      --------------  -----
          0   Company     17654 non-null  object
          1   Title       17654 non-null  object
          2   Job         17654 non-null  object
          3   Level       17654 non-null  object
          4   Date        17652 non-null  object
          5   Upvotes     17654 non-null  int64
          6   Offer       17654 non-null  object
          7   Experience  16365 non-null  float64
          8   Difficulty  16376 non-null  object
          9   Review      17654 non-null  object
         dtypes: float64(1), int64(1), object(8)
         memory usage: 1.3+ MB

In [3]:  Path("data/interviews.csv").stat().st_size
Out[3]:  14200063

In [4]:  df.to_parquet("data/interviews.parquet")
         Path("data/interviews.parquet").stat().st_size
Out[4]:  6211862
```

Figure 3-3. When stored in CSV format, my interview file is 14 MB. But when stored in Parquet, the same file is 6 MB.

Data Models

Data models describe how data is represented. Consider cars in the real world. In a database, a car can be described using its make, its model, its year, its color, and its price. These attributes make up a data model for cars. Alternatively, you can also describe a car using its owner, its license plate, and its history of registered addresses. This is another data model for cars.

How you choose to represent data not only affects the way your systems are built, but also the problems your systems can solve. For example, the way you represent cars in the first data model makes it easier for people looking to buy cars, whereas the second data model makes it easier for police officers to track down criminals.

In this section, we'll study two types of models that seem opposite to each other but are actually converging: relational models and NoSQL models. We'll go over examples to show the types of problems each model is suited for.

Relational Model

Relational models are among the most persistent ideas in computer science. Invented by Edgar F. Codd in 1970,[9] the relational model is still going strong today, even getting more popular. The idea is simple but powerful. In this model, data is organized into relations; each relation is a set of tuples. A table is an accepted visual representation of a relation, and each row of a table makes up a tuple,[10] as shown in Figure 3-4. Relations are unordered. You can shuffle the order of the rows or the order of the columns in a relation and it's still the same relation. Data following the relational model is usually stored in file formats like CSV or Parquet.

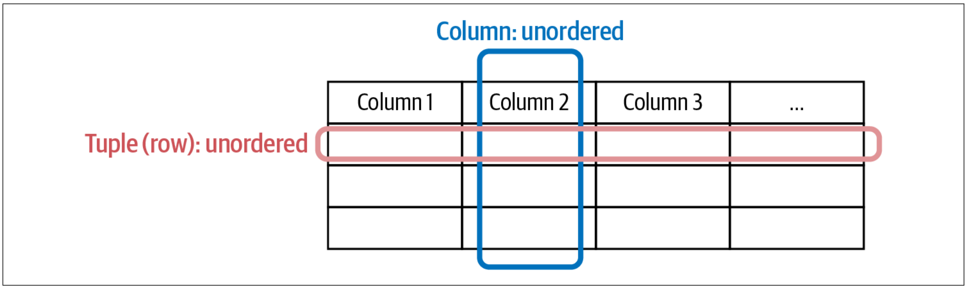


Figure 3-4. In a relation, the order of neither the rows nor the columns matters

It's often desirable for relations to be normalized. Data normalization can follow normal forms such as the first normal form (1NF), second normal form (2NF), etc., and readers interested can read more about it on Wikipedia. In this book, we'll go through an example to show how normalization works and how it can reduce data redundancy and improve data integrity.

Consider the relation Book shown in Table 3-2. There are a lot of duplicates in this data. For example, rows 1 and 2 are nearly identical, except for format and price. If the publisher information changes—for example, its name changes from "Banana

[9] Edgar F. Codd, "A Relational Model of Data for Large Shared Data Banks," *Communications of the ACM* 13, no. 6 (June 1970): 377–87.

[10] For detail-oriented readers, not all tables are relations.

Press" to "Pineapple Press"—or its country changes, we'll have to update rows 1, 2, and 4. If we separate publisher information into its own table, as shown in Tables 3-3 and 3-4, when a publisher's information changes, we only have to update the Publisher relation.[11] This practice allows us to standardize spelling of the same value across different columns. It also makes it easier to make changes to these values, either because these values change or when you want to translate them into different languages.

Table 3-2. Initial Book relation

Title	Author	Format	Publisher	Country	Price
Harry Potter	J.K. Rowling	Paperback	Banana Press	UK	$20
Harry Potter	J.K. Rowling	E-book	Banana Press	UK	$10
Sherlock Holmes	Conan Doyle	Paperback	Guava Press	US	$30
The Hobbit	J.R.R. Tolkien	Paperback	Banana Press	UK	$30
Sherlock Holmes	Conan Doyle	Paperback	Guava Press	US	$15

Table 3-3. Updated Book relation

Title	Author	Format	Publisher ID	Price
Harry Potter	J.K. Rowling	Paperback	1	$20
Harry Potter	J.K. Rowling	E-book	1	$10
Sherlock Holmes	Conan Doyle	Paperback	2	$30
The Hobbit	J.R.R. Tolkien	Paperback	1	$30
Sherlock Holmes	Conan Doyle	Paperback	2	$15

Table 3-4. Publisher relation

Publisher ID	Publisher	Country
1	Banana Press	UK
2	Guava Press	US

One major downside of normalization is that your data is now spread across multiple relations. You can join the data from different relations back together, but joining can be expensive for large tables.

Databases built around the relational data model are relational databases. Once you've put data in your databases, you'll want a way to retrieve it. The language that you can use to specify the data that you want from a database is called a *query language*. The most popular query language for relational databases today is SQL. Even though inspired by the relational model, the data model behind SQL has deviated from the original relational model. For example, SQL tables can contain

[11] You can further normalize the Book relation, such as separating format into a separate relation.

row duplicates, whereas true relations can't contain duplicates. However, this subtle difference has been safely ignored by most people.

The most important thing to note about SQL is that it's a declarative language, as opposed to Python, which is an imperative language. In the imperative paradigm, you specify the steps needed for an action and the computer executes these steps to return the outputs. In the declarative paradigm, you specify the outputs you want, and the computer figures out the steps needed to get you the queried outputs.

With an SQL database, you specify the pattern of data you want—the tables you want the data from, the conditions the results must meet, the basic data transformations such as join, sort, group, aggregate, etc.—but not how to retrieve the data. It is up to the database system to decide how to break the query into different parts, what methods to use to execute each part of the query, and the order in which different parts of the query should be executed.

With certain added features, SQL can be Turing-complete, which means that, in theory, SQL can be used to solve any computation problem (without making any guarantee about the time or memory required). However, in practice, it's not always easy to write a query to solve a specific task, and it's not always feasible or tractable to execute a query. Anyone working with SQL databases might have nightmarish memories of painfully long SQL queries that are impossible to understand and nobody dares to touch for fear that things might break.[12]

Figuring out how to execute an arbitrary query is the hard part, which is the job of query optimizers. A query optimizer examines all possible ways to execute a query and finds the fastest way to do so.[13] It's possible to use ML to improve query optimizers based on learning from incoming queries.[14] Query optimization is one of the most challenging problems in database systems, and normalization means that data is spread out on multiple relations, which makes joining it together even harder. Even though developing a query optimizer is hard, the good news is that you generally only need one query optimizer and all your applications can leverage it.

[12] Greg Kemnitz, a coauthor of the original Postgres paper, shared on Quora that he once wrote a reporting SQL query that was 700 lines long and visited 27 different tables in lookups or joins. The query had about 1,000 lines of comments to help him remember what he was doing. It took him three days to compose, debug, and tune.

[13] Yannis E. Ioannidis, "Query Optimization," *ACM Computing Surveys* (CSUR) 28, no. 1 (1996): 121–23, *https://oreil.ly/omXMg*

[14] Ryan Marcus et al., "Neo: A Learned Query Optimizer," *arXiv* preprint arXiv:1904.03711 (2019), *https://oreil.ly/wHy6p*.

From Declarative Data Systems to Declarative ML Systems

Possibly inspired by the success of declarative data systems, many people have looked forward to declarative ML.[15] With a declarative ML system, users only need to declare the features' schema and the task, and the system will figure out the best model to perform that task with the given features. Users won't have to write code to construct, train, and tune models. Popular frameworks for declarative ML are Ludwig, developed at Uber, and H2O AutoML. In Ludwig, users can specify the model structure—such as the number of fully connected layers and the number of hidden units—on top of the features' schema and output. In H2O AutoML, you don't need to specify the model structure or hyperparameters. It experiments with multiple model architectures and picks out the best model given the features and the task.

Here is an example to show how H2O AutoML works. You give the system your data (inputs and outputs) and specify the number of models you want to experiment. It'll experiment with that number of models and show you the best-performing model:

```
# Identify predictors and response
x = train.columns
y = "response"
x.remove(y)

# For binary classification, response should be a factor
train[y] = train[y].asfactor()
test[y] = test[y].asfactor()

# Run AutoML for 20 base models
aml = H2OAutoML(max_models=20, seed=1)
aml.train(x=x, y=y, training_frame=train)

# Show the best-performing models on the AutoML Leaderboard
lb = aml.leaderboard

# Get the best-performing model
aml.leader
```

While declarative ML can be useful in many cases, it leaves unanswered the biggest challenges with ML in production. Declarative ML systems today abstract away the model development part, and as we'll cover in the next six chapters, with models being increasingly commoditized, model development is often the easier part. The hard part lies in feature engineering, data processing, model evaluation, data shift detection, continual learning, and so on.

[15] Matthias Boehm, Alexandre V. Evfimievski, Niketan Pansare, and Berthold Reinwald, "Declarative Machine Learning—A Classification of Basic Properties and Types," *arXiv*, May 19, 2016, *https://oreil.ly/OvW07*.

NoSQL

The relational data model has been able to generalize to a lot of use cases, from ecommerce to finance to social networks. However, for certain use cases, this model can be restrictive. For example, it demands that your data follows a strict schema, and schema management is painful. In a survey by Couchbase in 2014, frustration with schema management was the #1 reason for the adoption of their nonrelational database.[16] It can also be difficult to write and execute SQL queries for specialized applications.

The latest movement against the relational data model is NoSQL. Originally started as a hashtag for a meetup to discuss nonrelational databases, NoSQL has been retroactively reinterpreted as Not Only SQL,[17] as many NoSQL data systems also support relational models. Two major types of nonrelational models are the document model and the graph model. The document model targets use cases where data comes in self-contained documents and relationships between one document and another are rare. The graph model goes in the opposite direction, targeting use cases where relationships between data items are common and important. We'll examine each of these two models, starting with the document model.

Document model

The document model is built around the concept of "document." A document is often a single continuous string, encoded as JSON, XML, or a binary format like BSON (Binary JSON). All documents in a document database are assumed to be encoded in the same format. Each document has a unique key that represents that document, which can be used to retrieve it.

A collection of documents could be considered analogous to a table in a relational database, and a document analogous to a row. In fact, you can convert a relation into a collection of documents that way. For example, you can convert the book data in Tables 3-3 and 3-4 into three JSON documents as shown in Examples 3-1, 3-2, and 3-3. However, a collection of documents is much more flexible than a table. All rows in a table must follow the same schema (e.g., have the same sequence of columns), while documents in the same collection can have completely different schemas.

[16] James Phillips, "Surprises in Our NoSQL Adoption Survey," *Couchbase*, December 16, 2014, *https://oreil.ly/ueyEX*.

[17] Martin Kleppmann, *Designing Data-Intensive Applications* (Sebastopol, CA: O'Reilly, 2017).

Example 3-1. Document 1: harry_potter.json

```json
{
  "Title": "Harry Potter",
  "Author": "J .K. Rowling",
  "Publisher": "Banana Press",
  "Country": "UK",
  "Sold as": [
    {"Format": "Paperback", "Price": "$20"},
    {"Format": "E-book", "Price": "$10"}
  ]
}
```

Example 3-2. Document 2: sherlock_holmes.json

```json
{
  "Title": "Sherlock Holmes",
  "Author": "Conan Doyle",
  "Publisher": "Guava Press",
  "Country": "US",
  "Sold as": [
    {"Format": "Paperback", "Price": "$30"},
    {"Format": "E-book", "Price": "$15"}
  ]
}
```

Example 3-3. Document 3: the_hobbit.json

```json
{
  "Title": "The Hobbit",
  "Author": "J.R.R. Tolkien",
  "Publisher": "Banana Press",
  "Country": "UK",
  "Sold as": [
    {"Format": "Paperback", "Price": "$30"},
  ]
}
```

Because the document model doesn't enforce a schema, it's often referred to as schemaless. This is misleading because, as discussed previously, data stored in documents will be read later. The application that reads the documents usually assumes some kind of structure of the documents. Document databases just shift the responsibility of assuming structures from the application that writes the data to the application that reads the data.

The document model has better locality than the relational model. Consider the book data example in Tables 3-3 and 3-4 where the information about a book is spread across both the Book table and the Publisher table (and potentially also the Format table). To retrieve information about a book, you'll have to query multiple tables.

In the document model, all information about a book can be stored in a document, making it much easier to retrieve.

However, compared to the relational model, it's harder and less efficient to execute joins across documents compared to across tables. For example, if you want to find all books whose prices are below $25, you'll have to read all documents, extract the prices, compare them to $25, and return all the documents containing the books with prices below $25.

Because of the different strengths of the document and relational data models, it's common to use both models for different tasks in the same database systems. More and more database systems, such as PostgreSQL and MySQL, support them both.

Graph model

The graph model is built around the concept of a "graph." A graph consists of nodes and edges, where the edges represent the relationships between the nodes. A database that uses graph structures to store its data is called a graph database. If in document databases, the content of each document is the priority, then in graph databases, the relationships between data items are the priority.

Because the relationships are modeled explicitly in graph models, it's faster to retrieve data based on relationships. Consider an example of a graph database in Figure 3-5. The data from this example could potentially come from a simple social network. In this graph, nodes can be of different data types: person, city, country, company, etc.

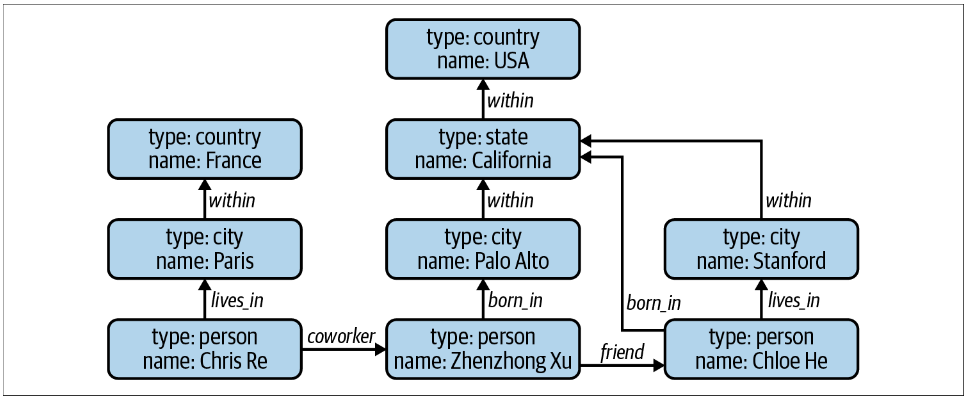


Figure 3-5. An example of a simple graph database

Imagine you want to find everyone who was born in the USA. Given this graph, you can start from the node USA and traverse the graph following the edges "within" and "born_in" to find all the nodes of the type "person." Now, imagine that instead of using the graph model to represent this data, we use the relational model. There'd be no easy way to write an SQL query to find everyone who was born in the USA, especially given that there are an unknown number of hops between *country* and *person*—there are three hops between Zhenzhong Xu and USA while there are only two hops between Chloe He and USA. Similarly, there'd be no easy way for this type of query with a document database.

Many queries that are easy to do in one data model are harder to do in another data model. Picking the right data model for your application can make your life so much easier.

Structured Versus Unstructured Data

Structured data follows a predefined data model, also known as a data schema. For example, the data model might specify that each data item consists of two values: the first value, "name," is a string of at most 50 characters, and the second value, "age," is an 8-bit integer in the range between 0 and 200. The predefined structure makes your data easier to analyze. If you want to know the average age of people in the database, all you have to do is to extract all the age values and average them out.

The disadvantage of structured data is that you have to commit your data to a predefined schema. If your schema changes, you'll have to retrospectively update all your data, often causing mysterious bugs in the process. For example, you've never kept your users' email addresses before but now you do, so you have to retrospectively update email information to all previous users. One of the strangest bugs one of my colleagues encountered was when they could no longer use users' ages with their transactions, and their data schema replaced all the null ages with 0, and their ML model thought the transactions were made by people 0 years old.[18]

Because business requirements change over time, committing to a predefined data schema can become too restricting. Or you might have data from multiple data sources that are beyond your control, and it's impossible to make them follow the same schema. This is where unstructured data becomes appealing. Unstructured data doesn't adhere to a predefined data schema. It's usually text but can also be numbers, dates, images, audio, etc. For example, a text file of logs generated by your ML model is unstructured data.

Even though unstructured data doesn't adhere to a schema, it might still contain intrinsic patterns that help you extract structures. For example, the following text is unstructured, but you can notice the pattern that each line contains two values separated by a comma, the first value is textual, and the second value is numerical. However, there is no guarantee that all lines must follow this format. You can add a new line to that text even if that line doesn't follow this format.

[18] In this specific example, replacing the null age values with –1 solved the problem.

```
    Lisa, 43
    Jack, 23
    Huyen, 59
```

Unstructured data also allows for more flexible storage options. For example, if your storage follows a schema, you can only store data following that schema. But if your storage doesn't follow a schema, you can store any type of data. You can convert all your data, regardless of types and formats, into bytestrings and store them together.

A repository for storing structured data is called a data warehouse. A repository for storing unstructured data is called a data lake. Data lakes are usually used to store raw data before processing. Data warehouses are used to store data that has been processed into formats ready to be used. Table 3-5 shows a summary of the key differences between structured and unstructured data.

Table 3-5. The key differences between structured and unstructured data

Structured data	Unstructured data
Schema clearly defined	Data doesn't have to follow a schema
Easy to search and analyze	Fast arrival
Can only handle data with a specific schema	Can handle data from any source
Schema changes will cause a lot of troubles	No need to worry about schema changes (yet), as the worry is shifted to the downstream applications that use this data
Stored in data warehouses	Stored in data lakes

Data Storage Engines and Processing

Data formats and data models specify the interface for how users can store and retrieve data. Storage engines, also known as databases, are the implementation of how data is stored and retrieved on machines. It's useful to understand different types of databases as your team or your adjacent team might need to select a database appropriate for your application.

Typically, there are two types of workloads that databases are optimized for, transactional processing and analytical processing, and there's a big difference between them, which we'll cover in this section. We will then cover the basics of the ETL (extract, transform, load) process that you will inevitably encounter when building an ML system in production.

Transactional and Analytical Processing

Traditionally, a transaction refers to the action of buying or selling something. In the digital world, a transaction refers to any kind of action: tweeting, ordering a ride through a ride-sharing service, uploading a new model, watching a YouTube video, and so on. Even though these different transactions involve different types of data, the way they're processed is similar across applications. The transactions are inserted as they are generated, and occasionally updated when something changes, or deleted when they are no longer needed.[19] This type of processing is known as *online transaction processing* (OLTP).

Because these transactions often involve users, they need to be processed fast (low latency) so that they don't keep users waiting. The processing method needs to have high availability—that is, the processing system needs to be available any time a user wants to make a transaction. If your system can't process a transaction, that transaction won't go through.

Transactional databases are designed to process online transactions and satisfy the low latency, high availability requirements. When people hear transactional databases, they usually think of ACID (atomicity, consistency, isolation, durability). Here are their definitions for those needing a quick reminder:

Atomicity
: To guarantee that all the steps in a transaction are completed successfully as a group. If any step in the transaction fails, all other steps must fail also. For example, if a user's payment fails, you don't want to still assign a driver to that user.

Consistency
: To guarantee that all the transactions coming through must follow predefined rules. For example, a transaction must be made by a valid user.

Isolation
: To guarantee that two transactions happen at the same time as if they were isolated. Two users accessing the same data won't change it at the same time. For example, you don't want two users to book the same driver at the same time.

Durability
: To guarantee that once a transaction has been committed, it will remain committed even in the case of a system failure. For example, after you've ordered a ride and your phone dies, you still want your ride to come.

However, transactional databases don't necessarily need to be ACID, and some developers find ACID to be too restrictive. According to Martin Kleppmann, "systems that do not meet the ACID criteria are sometimes called BASE, which stands for *B*asically *A*vailable, *S*oft state, and *E*ventual consistency. This is even more vague than the definition of ACID."[20]

[19] This paragraph, as well as many parts of this chapter, is inspired by Martin Kleppmann's *Designing Data-Intensive Applications*.

[20] Kleppmann, *Designing Data-Intensive Applications*.

Because each transaction is often processed as a unit separately from other transactions, transactional databases are often row-major. This also means that transactional databases might not be efficient for questions such as "What's the average price for all the rides in September in San Francisco?" This kind of analytical question requires aggregating data in columns across multiple rows of data. Analytical databases are designed for this purpose. They are efficient with queries that allow you to look at data from different viewpoints. We call this type of processing *online analytical processing* (OLAP).

However, both the terms OLTP and OLAP have become outdated, as shown in Figure 3-6, for three reasons. First, the separation of transactional and analytical databases was due to limitations of technology—it was hard to have databases that could handle both transactional and analytical queries efficiently. However, this separation is being closed. Today, we have transactional databases that can handle analytical queries, such as CockroachDB. We also have analytical databases that can handle transactional queries, such as Apache Iceberg and DuckDB.

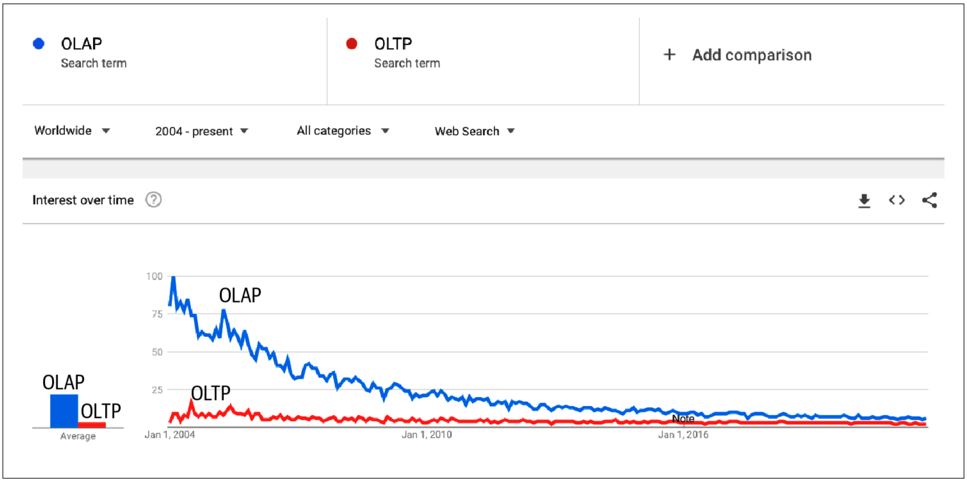


Figure 3-6. OLAP and OLTP are outdated terms, as of 2021, according to Google Trends

Second, in the traditional OLTP or OLAP paradigms, storage and processing are tightly coupled—how data is stored is also how data is processed. This may result in the same data being stored in multiple databases and using different processing engines to solve different types of queries. An interesting paradigm in the last decade has been to decouple storage from processing (also known as compute), as adopted by many data vendors including Google's BigQuery, Snowflake, IBM, and Teradata.[21] In this paradigm, the data can be stored in the same place, with a processing layer on top that can be optimized for different types of queries.

Third, "online" has become an overloaded term that can mean many different things. Online used to just mean "connected to the internet." Then, it grew to also mean "in production"—we say a feature is online after that feature has been deployed in production.

In the data world today, *online* might refer to the speed at which your data is processed and made available: online, nearline, or offline. According to Wikipedia, online processing means data is immediately available for input/output. Nearline, which is short for near-online, means data is not immediately available but can be made online quickly without human intervention. *Offline* means data is not immediately available and requires some human intervention to become online.[22]

ETL: Extract, Transform, and Load

In the early days of the relational data model, data was mostly structured. When data is *extracted* from different sources, it's first *transformed* into the desired format before being *loaded* into the target destination such as a database or a data warehouse. This process is called *ETL*, which stands for extract, transform, and load.

Even before ML, ETL was all the rage in the data world, and it's still relevant today for ML applications. ETL refers to the general purpose processing and aggregating of data into the shape and the format that you want.

Extract is extracting the data you want from all your data sources. Some of them will be corrupted or malformatted. In the extracting phase, you need to validate your data and reject the data that doesn't meet your requirements. For rejected data, you might have to notify the sources. Since this is the first step of the process, doing it correctly can save you a lot of time downstream.

Transform is the meaty part of the process, where most of the data processing is done. You might want to join data from multiple sources and clean it. You might want to standardize the value ranges (e.g., one data source might use "Male" and "Female" for genders, but another uses "M" and "F" or "1" and "2"). You can apply operations such as transposing, deduplicating, sorting, aggregating, deriving new features, more data validating, etc.

[21] Tino Tereshko, "Separation of Storage and Compute in BigQuery," Google Cloud blog, November 29, 2017, *https://oreil.ly/utf7z*; Suresh H., "Snowflake Architecture and Key Concepts: A Comprehensive Guide," Hevo blog, January 18, 2019, *https://oreil.ly/GyvKl*; Preetam Kumar, "Cutting the Cord: Separating Data from Compute in Your Data Lake with Object Storage," IBM blog, September 21, 2017, *https://oreil.ly/Nd3xD*; "The Power of Separating Cloud Compute and Cloud Storage," Teradata, last accessed April 2022, *https://oreil.ly/f82gP*.

[22] Wikipedia, s.v. "Nearline storage," last accessed April 2022, *https://oreil.ly/OCmiB*.

Load is deciding how and how often to load your transformed data into the target destination, which can be a file, a database, or a data warehouse.

The idea of ETL sounds simple but powerful, and it's the underlying structure of the data layer at many organizations. An overview of the ETL process is shown in Figure 3-7.

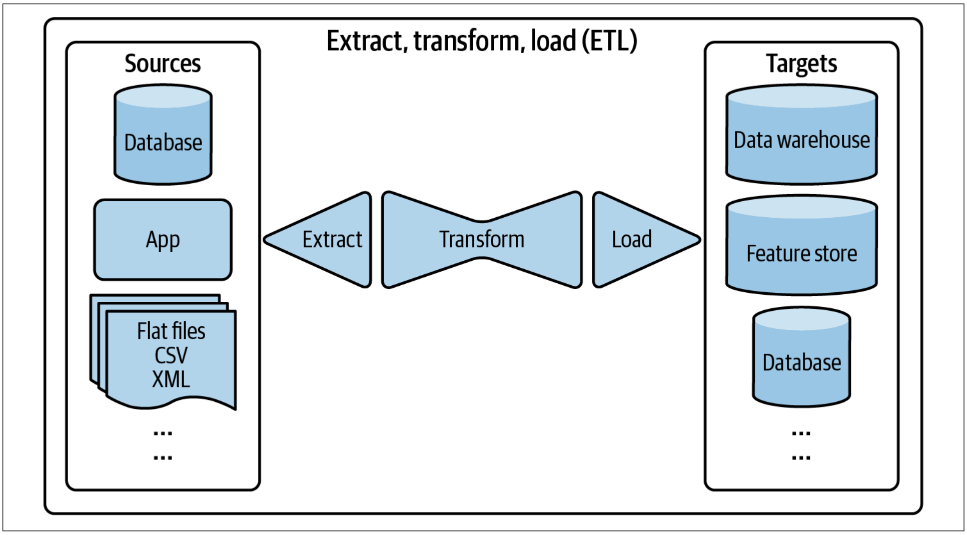


Figure 3-7. An overview of the ETL process

When the internet first became ubiquitous and hardware had just become so much more powerful, collecting data suddenly became so much easier. The amount of data grew rapidly. Not only that, but the nature of data also changed. The number of data sources expanded, and data schemas evolved.

Finding it difficult to keep data structured, some companies had this idea: "Why not just store all data in a data lake so we don't have to deal with schema changes? Whichever application needs data can just pull out raw data from there and process it." This process of loading data into storage first then processing it later is sometimes called *ELT* (extract, load, transform). This paradigm allows for the fast arrival of data since there's little processing needed before data is stored.

However, as data keeps on growing, this idea becomes less attractive. It's inefficient to search through a massive amount of raw data for the data that you want.[23] At the same time, as companies switch to running applications on the cloud

[23] In the first draft of this book, I had cost as a reason why you shouldn't store everything. However, as of today, storage has become so cheap that the storage cost is rarely a problem.

and infrastructures become standardized, data structures also become standardized. Committing data to a predefined schema becomes more feasible.

As companies weigh the pros and cons of storing structured data versus storing unstructured data, vendors evolve to offer hybrid solutions that combine the flexibility of data lakes and the data management aspect of data warehouses. For example, Databricks and Snowflake both provide data lakehouse solutions.

Modes of Dataflow

In this chapter, we've been discussing data formats, data models, data storage, and processing for data used within the context of a single process. Most of the time, in production, you don't have a single process but multiple. A question arises: how do we pass data between different processes that don't share memory?

When data is passed from one process to another, we say that the data flows from one process to another, which gives us a dataflow. There are three main modes of dataflow:

- Data passing through databases
- Data passing through services using requests such as the requests provided by REST and RPC APIs (e.g., POST/GET requests)
- Data passing through a real-time transport like Apache Kafka and Amazon Kinesis

We'll go over each of them in this section.

Data Passing Through Databases

The easiest way to pass data between two processes is through databases, which we've discussed in the section "Data Storage Engines and Processing" on page 67. For example, to pass data from process A to process B, process A can write that data into a database, and process B simply reads from that database.

This mode, however, doesn't always work because of two reasons. First, it requires that both processes must be able to access the same database. This might be infeasible, especially if the two processes are run by two different companies.

Second, it requires both processes to access data from databases, and read/write from databases can be slow, making it unsuitable for applications with strict latency requirements—e.g., almost all consumer-facing applications.

Data Passing Through Services

One way to pass data between two processes is to send data directly through a network that connects these two processes. To pass data from process B to process A, process A first sends a request to process B that specifies the data A needs, and B returns the requested data through the same network. Because processes communicate through requests, we say that this is *request-driven*.

This mode of data passing is tightly coupled with the service-oriented architecture. A service is a process that can be accessed remotely, e.g., through a network. In this example, B is exposed to A as a service that A can send requests to. For B to be able to request data from A, A will also need to be exposed to B as a service.

Two services in communication with each other can be run by different companies in different applications. For example, a service might be run by a stock exchange that keeps track of the current stock prices. Another service might be run by an investment firm that requests the current stock prices and uses them to predict future stock prices.

Two services in communication with each other can also be parts of the same application. Structuring different components of your application as separate services allows each component to be developed, tested, and maintained independently of one another. Structuring an application as separate services gives you a microservice architecture.

To put the microservice architecture in the context of ML systems, imagine you're an ML engineer working on the price optimization problem for a company that owns a ride-sharing application like Lyft. In reality, Lyft has hundreds of services in its microservice architecture, but for the sake of simplicity, let's consider only three services:

Driver management service
Predicts how many drivers will be available in the next minute in a given area.

Ride management service
Predicts how many rides will be requested in the next minute in a given area.

Price optimization service
Predicts the optimal price for each ride. The price for a ride should be low enough for riders to be willing to pay, yet high enough for drivers to be willing to drive and for the company to make a profit.

Because the price depends on supply (the available drivers) and demand (the requested rides), the price optimization service needs data from both the driver management and ride management services. Each time a user requests a ride, the price optimization service requests the predicted number of rides and predicted number of drivers to predict the optimal price for this ride.[24]

The most popular styles of requests used for passing data through networks are REST (representational state transfer) and RPC (remote procedure call). Their detailed analysis is beyond the scope of this book, but one major difference is that REST was designed for requests over networks, whereas RPC "tries to make a request to a remote network service look the same as calling a function or method in your programming language." Because of this, "REST seems to be the predominant style for public APIs. The main focus of RPC frameworks is on requests between services owned by the same organization, typically within the same data center."[25]

Implementations of a REST architecture are said to be RESTful. Even though many people think of REST as HTTP, REST doesn't exactly mean HTTP because HTTP is just an implementation of REST.[26]

Data Passing Through Real-Time Transport

To understand the motivation for real-time transports, let's go back to the preceding example of the ride-sharing app with three simple services: driver management, ride management, and price optimization. In the last section, we discussed how the price optimization service needs data from the ride and driver management services to predict the optimal price for each ride.

Now, imagine that the driver management service also needs to know the number of rides from the ride management service to know how many drivers to mobilize. It also wants to know the predicted prices from the price optimization service to use them as incentives for potential drivers (e.g., if you get on the road now you can get a 2x surge charge). Similarly, the ride management service might also want data from the driver management and price optimization services. If we pass data through services as discussed in the previous section, each of these services needs to send requests to the other two services, as shown in Figure 3-8.

[24] In practice, the price optimization might not have to request the predicted number of rides/drivers every time it has to make a price prediction. It's a common practice to use the cached predicted number of rides/drivers and request new predictions every minute or so.

[25] Kleppmann, *Designing Data-Intensive Applications*.

[26] Tyson Trautmann, "Debunking the Myths of RPC and REST," *Ethereal Bits*, December 4, 2012 (accessed via the Internet Archive), *https://oreil.ly/4sUrL*.

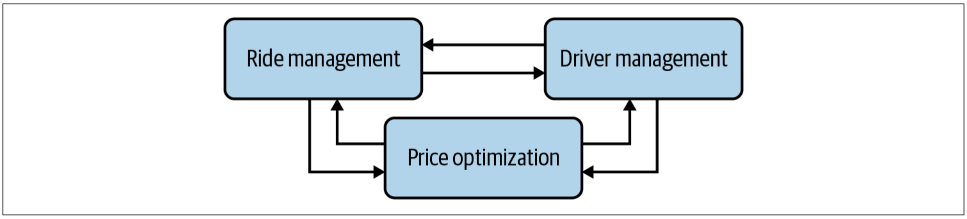


Figure 3-8. In the request-driven architecture, each service needs to send requests to two other services

With only three services, data passing is already getting complicated. Imagine having hundreds, if not thousands of services like what major internet companies have. Interservice data passing can blow up and become a bottleneck, slowing down the entire system.

Request-driven data passing is synchronous: the target service has to listen to the request for the request to go through. If the price optimization service requests data from the driver management service and the driver management service is down, the price optimization service will keep resending the request until it times out. And if the price optimization service is down before it receives a response, the response will be lost. A service that is down can cause all services that require data from it to be down.

What if there's a broker that coordinates data passing among services? Instead of having services request data directly from each other and creating a web of complex interservice data passing, each service only has to communicate with the broker, as shown in Figure 3-9. For example, instead of having other services request the driver management services for the predicted number of drivers for the next minute, what if whenever the driver management service makes a prediction, this prediction is broadcast to a broker? Whichever service wants data from the driver management service can check that broker for the most recent predicted number of drivers. Similarly, whenever the price optimization service makes a prediction about the surge charge for the next minute, this prediction is broadcast to the broker.

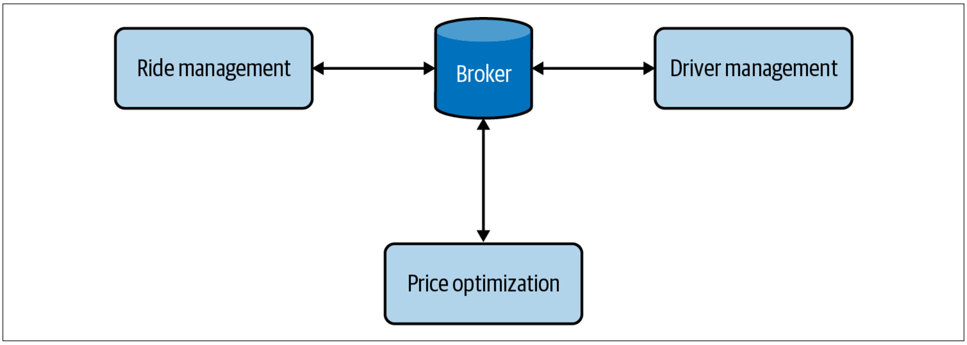


Figure 3-9. With a broker, a service only has to communicate with the broker instead of with other services

Technically, a database can be a broker—each service can write data to a database and other services that need the data can read from that database. However, as mentioned in the section "Data Passing Through Databases" on page 72, reading and writing from databases are too slow for applications with strict latency requirements. Instead of using databases to broker data, we use in-memory storage to broker data. Real-time transports can be thought of as in-memory storage for data passing among services.

A piece of data broadcast to a real-time transport is called an event. This architecture is, therefore, also called *event-driven*. A real-time transport is sometimes called an event bus.

Request-driven architecture works well for systems that rely more on logic than on data. Event-driven architecture works better for systems that are data-heavy.

The two most common types of real-time transports are pubsub, which is short for publish-subscribe, and message queue. In the pubsub model, any service can publish to different topics in a real-time transport, and any service that subscribes to a topic can read all the events in that topic. The services that produce data don't care about what services consume their data. Pubsub solutions often have a retention policy—data will be retained in the real-time transport for a certain period of time (e.g., seven days) before being deleted or moved to a permanent storage (like Amazon S3). See Figure 3-10.

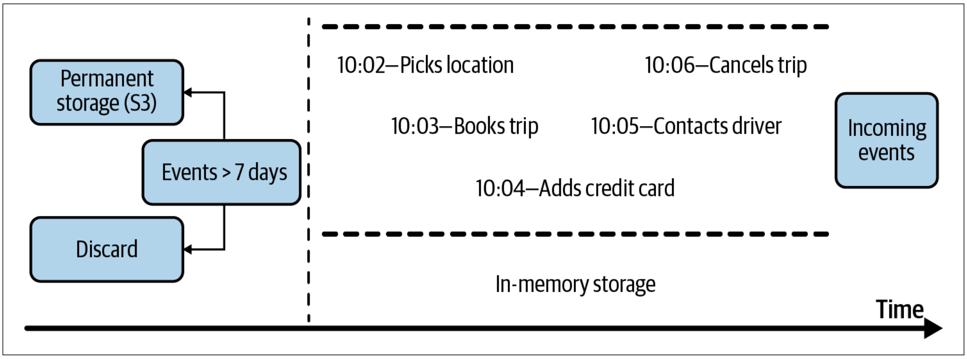
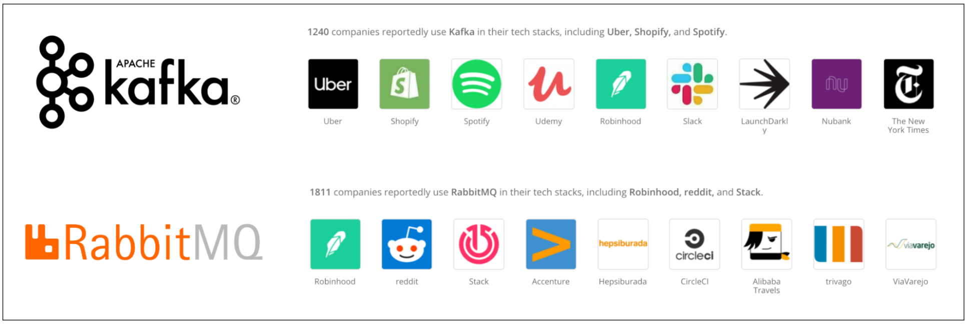


Figure 3-10. Incoming events are stored in in-memory storage before being discarded or moved to more permanent storage

In a message queue model, an event often has intended consumers (an event with intended consumers is called a message), and the message queue is responsible for getting the message to the right consumers.

Examples of pubsub solutions are Apache Kafka and Amazon Kinesis.[27] Examples of message queues are Apache RocketMQ and RabbitMQ. Both paradigms have gained a lot of traction in the last few years. Figure 3-11 shows some of the companies that use Apache Kafka and RabbitMQ.



1240 companies reportedly use **Kafka** in their tech stacks, including **Uber, Shopify,** and **Spotify**.

1811 companies reportedly use **RabbitMQ** in their tech stacks, including **Robinhood, reddit,** and **Stack**.

Figure 3-11. Companies that use Apache Kafka and RabbitMQ. Source: Screenshot from Stackshare

[27] If you want to learn more about how Apache Kafka works, Mitch Seymour has a great animation to explain it using otters!

Batch Processing Versus Stream Processing

Once your data arrives in data storage engines like databases, data lakes, or data warehouses, it becomes historical data. This is opposed to streaming data (data that is still streaming in). Historical data is often processed in batch jobs—jobs that are kicked off periodically. For example, once a day, you might want to kick off a batch job to compute the average surge charge for all the rides in the last day.

When data is processed in batch jobs, we refer to it as *batch processing*. Batch processing has been a research subject for many decades, and companies have come up with distributed systems like MapReduce and Spark to process batch data efficiently.

When you have data in real-time transports like Apache Kafka and Amazon Kinesis, we say that you have streaming data. *Stream processing* refers to doing computation on streaming data. Computation on streaming data can also be kicked off periodically, but the periods are usually much shorter than the periods for batch jobs (e.g., every five minutes instead of every day). Computation on streaming data can also be kicked off whenever the need arises. For example, whenever a user requests a ride, you process your data stream to see what drivers are currently available.

Stream processing, when done right, can give low latency because you can process data as soon as data is generated, without having to first write it into databases. Many people believe that stream processing is less efficient than batch processing because you can't leverage tools like MapReduce or Spark. This is not always the case, for two reasons. First, streaming technologies like Apache Flink are proven to be highly scalable and fully distributed, which means they can do computation in parallel. Second, the strength of stream processing is in stateful computation. Consider the case where you want to process user engagement during a 30-day trial. If you kick off this batch job every day, you'll have to do computation over the last 30 days every day. With stream processing, it's possible to continue computing only the new data each day and joining the new data computation with the older data computation, preventing redundancy.

Because batch processing happens much less frequently than stream processing, in ML, batch processing is usually used to compute features that change less often, such as drivers' ratings (if a driver has had hundreds of rides, their rating is less likely to change significantly from one day to the next). *Batch features*—features extracted through batch processing—are also known as *static features*.

Stream processing is used to compute features that change quickly, such as how many drivers are available right now, how many rides have been requested in the last minute, how many rides will be finished in the next two minutes, the median price of the last 10 rides in this area, etc. Features about the current state of the system like these are important to make the optimal price predictions. *Streaming features*—features extracted through stream processing—are also known as *dynamic features*.

For many problems, you need not only batch features or streaming features, but both. You need infrastructure that allows you to process streaming data as well as batch data and join them together to feed into your ML models. We'll discuss more on how batch features and streaming features can be used together to generate predictions in Chapter 7.

To do computation on data streams, you need a stream computation engine (the way Spark and MapReduce are batch computation engines). For simple streaming computation, you might be able to get away with the built-in stream computation capacity of real-time transports like Apache Kafka, but Kafka stream processing is limited in its ability to deal with various data sources.

For ML systems that leverage streaming features, the streaming computation is rarely simple. The number of stream features used in an application such as fraud detection and credit scoring can be in the hundreds, if not thousands. The stream feature extraction logic can require complex queries with join and aggregation along different dimensions. To extract these features requires efficient stream processing engines. For this purpose, you might want to look into tools like Apache Flink, KSQL, and Spark Streaming. Of these three engines, Apache Flink and KSQL are more recognized in the industry and provide a nice SQL abstraction for data scientists.

Stream processing is more difficult because the data amount is unbounded and the data comes in at variable rates and speeds. It's easier to make a stream processor do batch processing than to make a batch processor do stream processing. Apache Flink's core maintainers have been arguing for years that batch processing is a special case of stream processing.[28]

Summary

This chapter is built on the foundations established in Chapter 2 around the importance of data in developing ML systems. In this chapter, we learned it's important to choose the right format to store our data to make it easier to use the data in the future. We discussed different data formats and the pros and cons of row-major versus column-major formats as well as text versus binary formats.

We continued to cover three major data models: relational, document, and graph. Even though the relational model is the most well known given the popularity of SQL, all three models are widely used today, and each is good for a certain set of tasks.

When talking about the relational model compared to the document model, many people think of the former as structured and the latter as unstructured. The division

[28] Kostas Tzoumas, "Batch Is a Special Case of Streaming," *Ververica*, September 15, 2015, *https://oreil.ly/IcIl2*.

between structured and unstructured data is quite fluid—the main question is who has to shoulder the responsibility of assuming the structure of data. Structured data means that the code that writes the data has to assume the structure. Unstructured data means that the code that reads the data has to assume the structure.

We continued the chapter with data storage engines and processing. We studied databases optimized for two distinct types of data processing: transactional processing and analytical processing. We studied data storage engines and processing together because traditionally storage is coupled with processing: transactional databases for transactional processing and analytical databases for analytical processing. However, in recent years, many vendors have worked on decoupling storage and processing. Today, we have transactional databases that can handle analytical queries and analytical databases that can handle transactional queries.

When discussing data formats, data models, data storage engines, and processing, data is assumed to be within a process. However, while working in production, you'll likely work with multiple processes, and you'll likely need to transfer data between them. We discussed three modes of data passing. The simplest mode is passing through databases. The most popular mode of data passing for processes is data passing through services. In this mode, a process is exposed as a service that another process can send requests for data. This mode of data passing is tightly coupled with microservice architectures, where each component of an application is set up as a service.

A mode of data passing that has become increasingly popular over the last decade is data passing through a real-time transport like Apache Kafka and RabbitMQ. This mode of data passing is somewhere between passing through databases and passing through services: it allows for asynchronous data passing with reasonably low latency.

As data in real-time transports have different properties from data in databases, they require different processing techniques, as discussed in the section "Batch Processing Versus Stream Processing" on page 78. Data in databases is often processed in batch jobs and produces static features, whereas data in real-time transports is often processed using stream computation engines and produces dynamic features. Some people argue that batch processing is a special case of stream processing, and stream computation engines can be used to unify both processing pipelines.

Once we have our data systems figured out, we can collect data and create training data, which will be the focus of the next chapter.