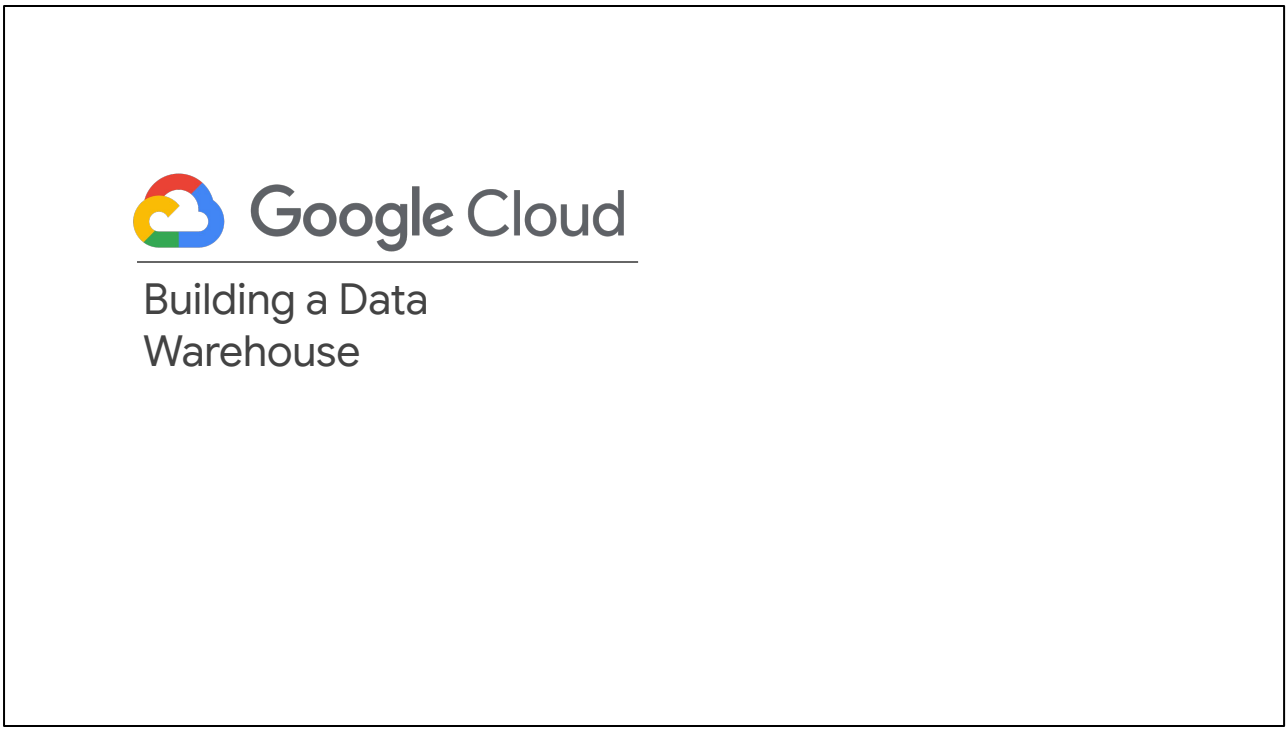


Hello and welcome to the data warehouse module. This is the third module in the course Modernizing Data Lakes and Data Warehouses with GCP.

Agenda

The modern data warehouse

Intro to BigQuery

- Getting Started
- Loading Data
- Lab: Loading Data with Console and CLI

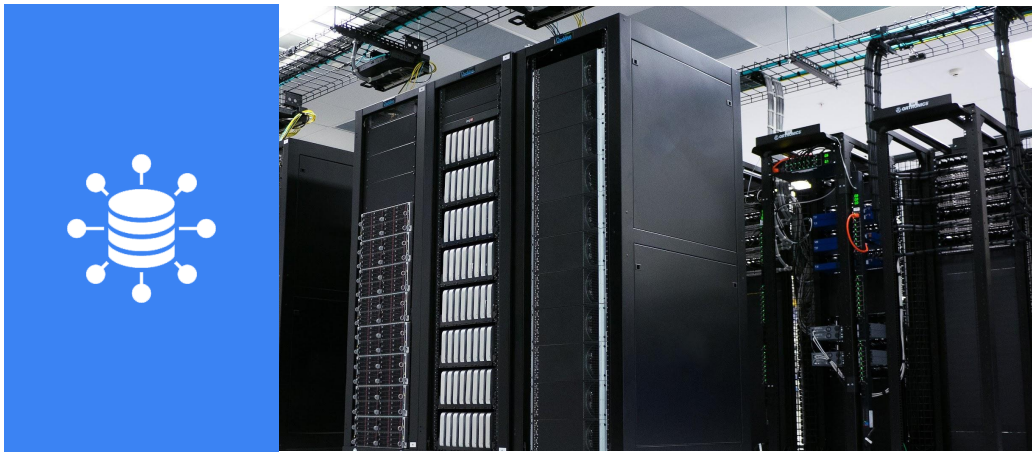
Exploring Schemas

- Schema Design
- Nested and Repeated Fields
- Lab: ARRAYs and STRUCTs
- Optimizing with Partitioning and Clustering

Preview: Transforming Batch and Streaming Data

In this first section we'll describe what makes a modern data warehouse. We'll also talk about what distinguishes a data lake from an enterprise data warehouse.

A data warehouse should consolidate data from many sources

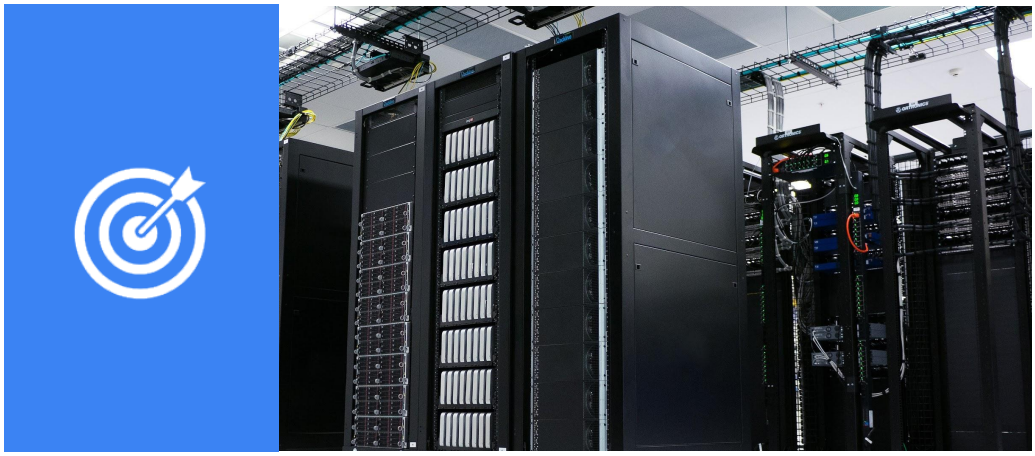


Google Cloud

An enterprise data warehouse should consolidate data from many sources. If you recall from the previous module, a data lake does something very similar. The key difference between the two is the word “consolidate.”

A data warehouse imposes a schema. A data lake is just raw data, but an enterprise data warehouse brings the data together and makes it available for querying and data processing. To use a data warehouse, an analyst needs to know the schema of the data. However, unlike for a data lake, the analyst doesn’t have to write code to read and parse the data.

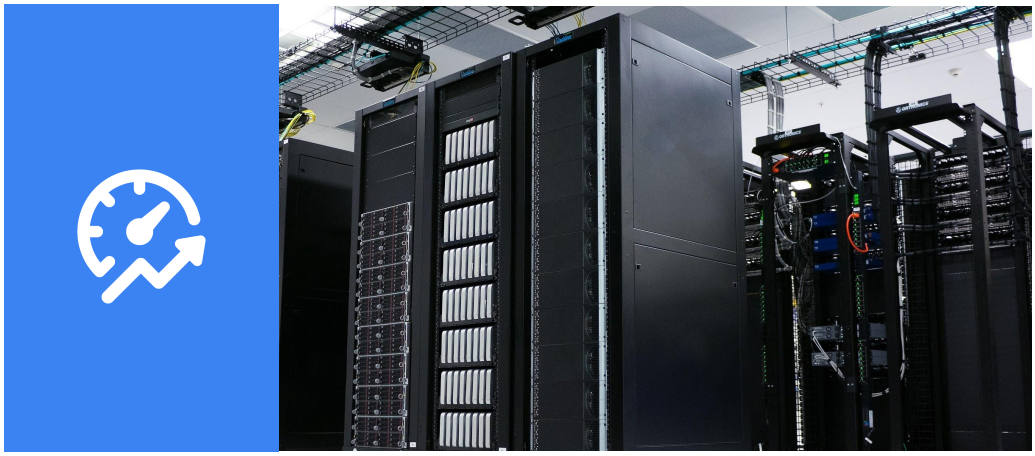
The data in a warehouse should have quality, consistency, and accuracy



Google Cloud

Another reason to consolidate all your data, besides standardizing the format and making it available for querying, is making sure the query results are meaningful. You want to make sure the data is clean, accurate, and consistent.

A data warehouse should be optimized for simplicity of access and high-speed query performance



Google Cloud

The purpose of a data warehouse is not to store data. That's the purpose of a data lake.
If you have raw data that you want to keep around but not necessarily query, don't bother with cleaning and streamlining it. Leave it in a data lake.

All data in a data warehouse should be available for querying. It's important to ensure that those queries are quick: you don't want people waiting hours or days for results.

A modern data warehouse

- Gigabytes to petabytes

Google Cloud

We described an enterprise data warehouse and how it's different from a data lake. What makes a data warehouse modern?

Businesses' data requirements continue to grow. You want to make sure the data warehouse can deal with datasets that don't fit into memory. Typically, this is gigabytes to terabytes of data but occasionally can be petabytes.

You don't want separate warehouses for different datasets. Instead, you want a single data warehouse that can scale from gigabytes to petabytes of data.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries

Google Cloud

Second, you want the data warehouse to be serverless and fully no-ops. You don't want to be limited to clusters that you need to maintain, or indexes that you need to fine-tune.

Having your hands off these responsibilities will allow data analysts to carry out ad hoc queries faster, which is important because you want the data warehouse to increase the speed at which your business makes decisions.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools

Google Cloud

Next, your data warehouse is not productive if it allows you to do queries but doesn't support rich visualization and reporting. Ideally, your data warehouse can seamlessly plug into whichever visualization or reporting tool your business is most familiar with.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools

Google Cloud

Similarly, because the data warehouse requires clean and consistent data, you will often have to build data pipelines to bring data into the warehouse. The modern data warehouse should be able to integrate with an ecosystem of processing tools for building ETL pipelines.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools
- Up-to-the-minute data

Google Cloud

Your data pipeline should be capable of constantly refreshing data in the warehouse in order to keep it up to date. You need to be able to stream data into the warehouse and not rely on batch updates.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools
- Up-to-the-minute data
- Machine learning

Also, Predictive analytics is becoming increasingly important for data analysts. As a result, a modern data warehouse has to support machine learning without moving the data out of the warehouse.

A modern data warehouse

- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools
- Up-to-the-minute data
- Machine learning
- Security and collaboration

Last but not least, in a modern data warehouse it should be possible to impose enterprise-grade security like data exfiltration constraints. It should also be possible to share data and queries with collaborators.

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Preview: Transforming Batch and Streaming Data

In the next section, we're going to introduce BigQuery, a data warehouse solution on Google Cloud Platform.

BigQuery has many capabilities that make it an ideal data warehouse

- Interactive SQL queries over large datasets (petabytes) in seconds
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools
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- Machine Learning
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Google Cloud

BigQuery has many capabilities that make it an ideal data warehouse.

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Google Cloud

When we talked about a modern data warehouse, we talked about having the warehouse be able to scale from gigabytes to petabytes seamlessly.

BigQuery has many capabilities that make it an ideal data warehouse

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Google Cloud

We talked about being able to do ad hoc queries and no-ops.

BigQuery has many capabilities that make it an ideal data warehouse

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- Security and collaboration

Google Cloud

BigQuery cost-effectively handles large Petabyte scale datasets for storage and querying. In fact it's similar to the cost of Google's Cloud Storage. This enables you to store your data without having to worry about archiving off older data to save on storage.

BigQuery has many capabilities that make it an ideal data warehouse

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- Up-to-the-minute data
- Machine Learning
- Security and collaboration

Google Cloud

Unlike traditional data warehouses, BigQuery has features like GIS and machine learning built in.

BigQuery has many capabilities that make it an ideal data warehouse

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- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
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- Up-to-the-minute data
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Google Cloud

It also provides capabilities to stream data in so you can analyze your data in near real time.

BigQuery has many capabilities that make it an ideal data warehouse

- Interactive SQL queries over large datasets (petabytes) in seconds
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
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- Machine Learning
- Security and collaboration

Google Cloud

Because it's part of Google Cloud, you get all of the security benefits the cloud provides while also being able to share datasets and queries.

BigQuery has many capabilities that make it an ideal data warehouse

- Interactive SQL queries over large datasets (petabytes) in seconds
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- Ecosystem of ETL and data processing tools
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- Machine Learning
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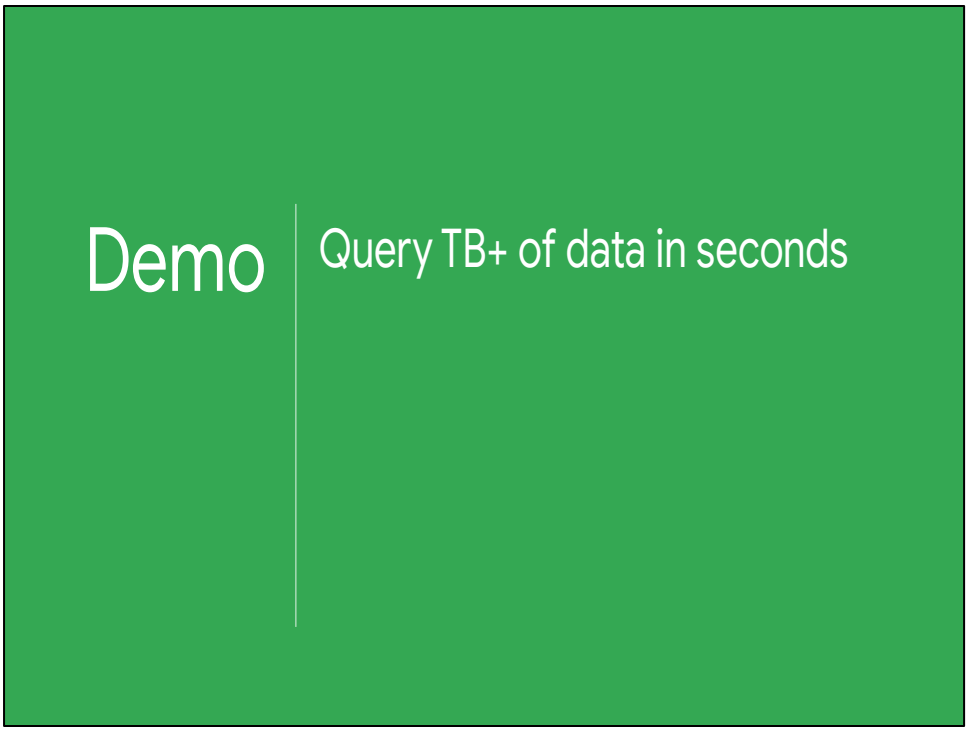
Google Cloud

BigQuery supports standard SQL queries and is compatible with ANSI SQL 2011.
Let's take a look at how easy it is to query large datasets in BigQuery



Demo Instructions:
https://github.com/GoogleCloudPlatform/training-data-analyst/blob/master/courses/data-engineering/demos/bigquery_scale.md

BigQuery is a serverless fully-managed service

- X Data aging
- X Storage management
- X Fault recovery
- X Query engine optimization
- X Hardware
- X Updates

Free up real people-hours by not having to worry about common tasks.

Google Cloud

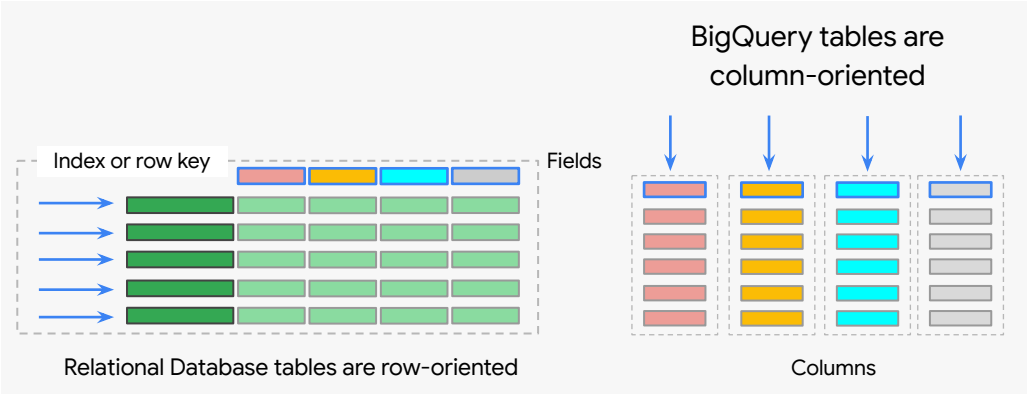
BigQuery is a serverless fully-managed service, which means that the BigQuery engineering team takes care of updates and maintenance for you. Upgrades don't require downtime or hinder system performance.

For example, data aging and expiration can be a cumbersome operation in traditional data warehouses. In BigQuery, you just supply a table expiration flag at the time of table creation or update a table to add this feature. The table will automatically expire when it reaches that age or duration.

Many traditional systems require resource-intensive vacuum processes to run at various intervals to reshuffle and sort data blocks and recover space. BigQuery has no equivalent of the vacuum process, because the storage engine continuously manages and optimizes how data is stored and replicated. Also, because BigQuery doesn't use indexes on tables, you don't need to rebuild these.

The bottom line is that you can free up real people-hours by not having to worry about common database management tasks.

What makes BigQuery fast?



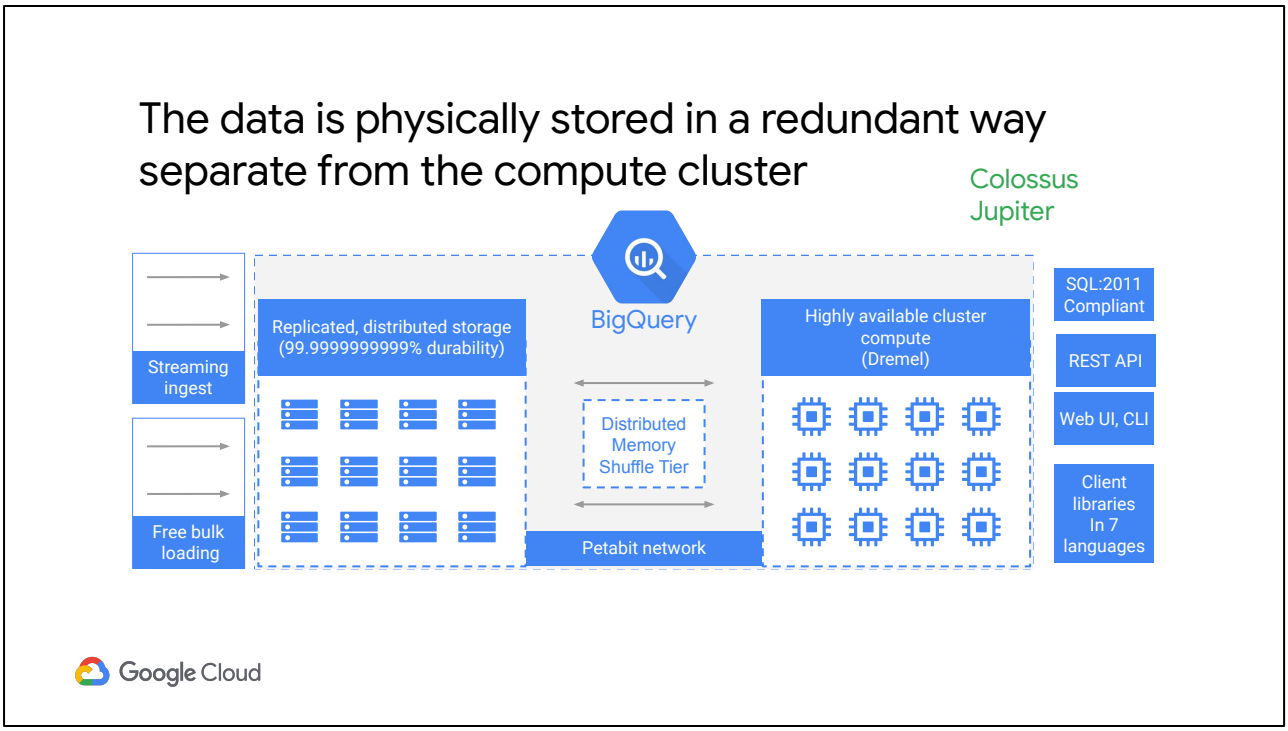
Google Cloud

So what makes BigQuery fast? BigQuery tables are column-oriented, compared to traditional RDBM tables which are row-oriented.

Row-oriented tables are efficient for making updates to data contained in fields. For OLTP systems, row-oriented tables are necessary because OLTP systems have frequent updates. Analytics is slow on row-oriented tables because they have to read all the fields in a row and, depending on the kind of indexing or key, they may have to read extra rows and fields to find the information that is requested in a query.

BigQuery, however, is an OLAP system. It's meant for analytics. BigQuery tables are immutable and are optimized for reading and appending data. BigQuery tables are not optimized for updating.

BigQuery leverages the fact that most queries involve few columns, and so it only reads the columns required for the query. BigQuery is very efficient in this sense and is the reason tables are column-oriented.

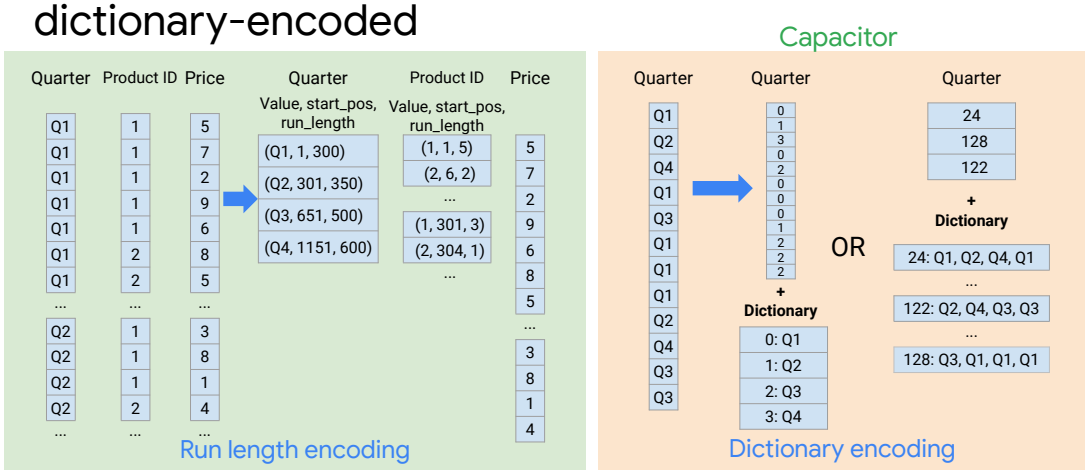


Internally, BigQuery stores data in a proprietary columnar format called Capacitor, which has several benefits for data warehouse workloads. BigQuery uses a proprietary format because it can evolve in tandem with the query engine, which takes advantage of deep knowledge of the data layout to optimize query execution. BigQuery uses query access patterns to determine the optimal number of physical shards and how they are encoded.

The data is physically stored on Google's distributed file system, called Colossus, which ensures durability by using erasure encoding to store redundant chunks of data on multiple physical disks. Moreover, the data is replicated to multiple data centers.

You can also run BigQuery queries on data outside of BigQuery storage, such as data stored in Cloud Storage, Google Drive, or Cloud Bigtable, by using federated data sources. However, these sources are not optimized for BigQuery operations, so they might not perform as well as data stored in BigQuery storage.

The data are also run length-encoded and dictionary-encoded

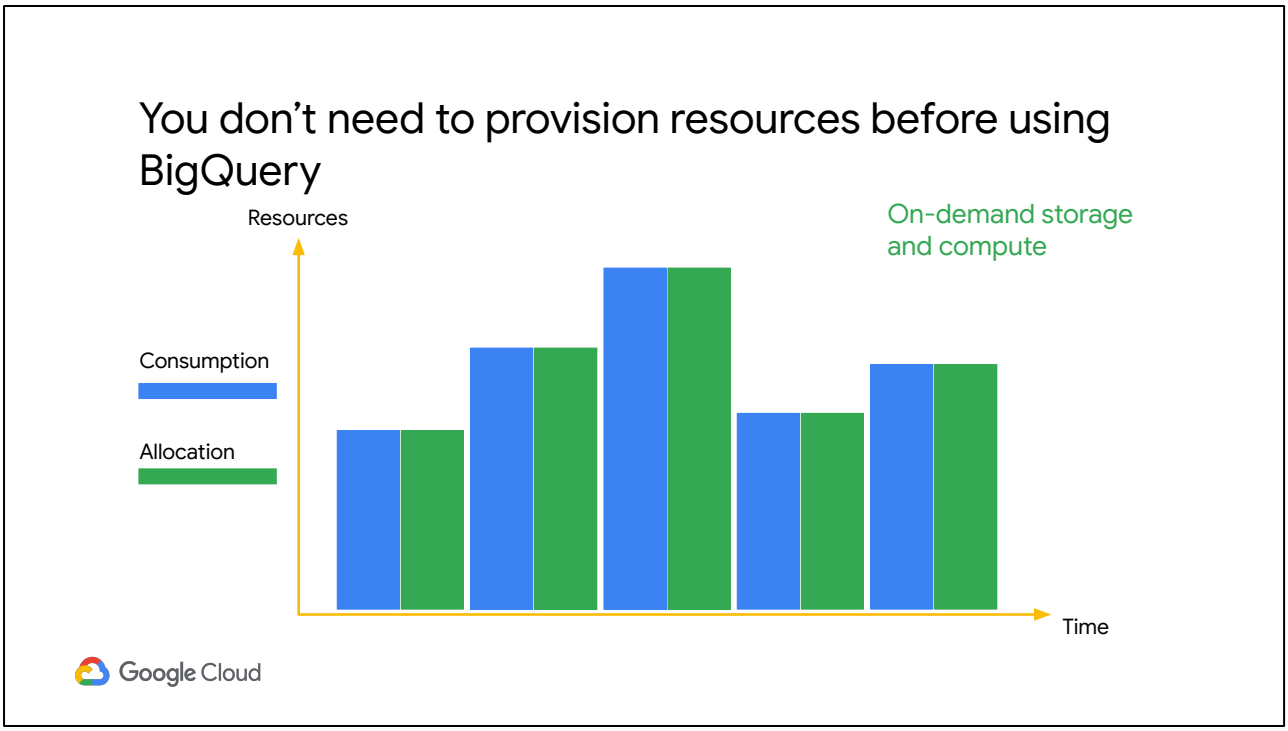


Examples taken from VLDB 2009 tutorial on Column Oriented Database Systems

Google Cloud

Here are a couple of the optimizations that Capacitor does. Capacitor run-length-encodes data so that it can reduce the amount of data read. It also reorders the data to make it more conducive for run-length-encoding. This is called dictionary encoding.

All this is “beneath the covers” of what happens in BigQuery native storage. It doesn’t affect you or me in any way. That’s the whole point of serverless and fully managed, right?



You don't need to provision resources before using BigQuery, unlike many RDBMS systems. BigQuery allocates storage and query resources dynamically based on your usage patterns.

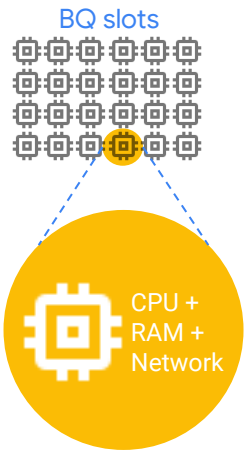
Storage resources are allocated as you consume them and deallocated as you remove data or drop tables.

Query resources are allocated according to query type and complexity. Each query uses some number of slots, which are units of computation that comprise a certain amount of CPU and RAM.

You don't have to make a minimum usage commitment to use BigQuery. The service allocates and charges for resources based on your actual usage. By default, all BigQuery customers have access to 2,000 slots for query operations. You can also reserve a fixed number of slots for your project.

But what’s a slot?

A BigQuery slot is a combination of CPU, memory, and networking resources

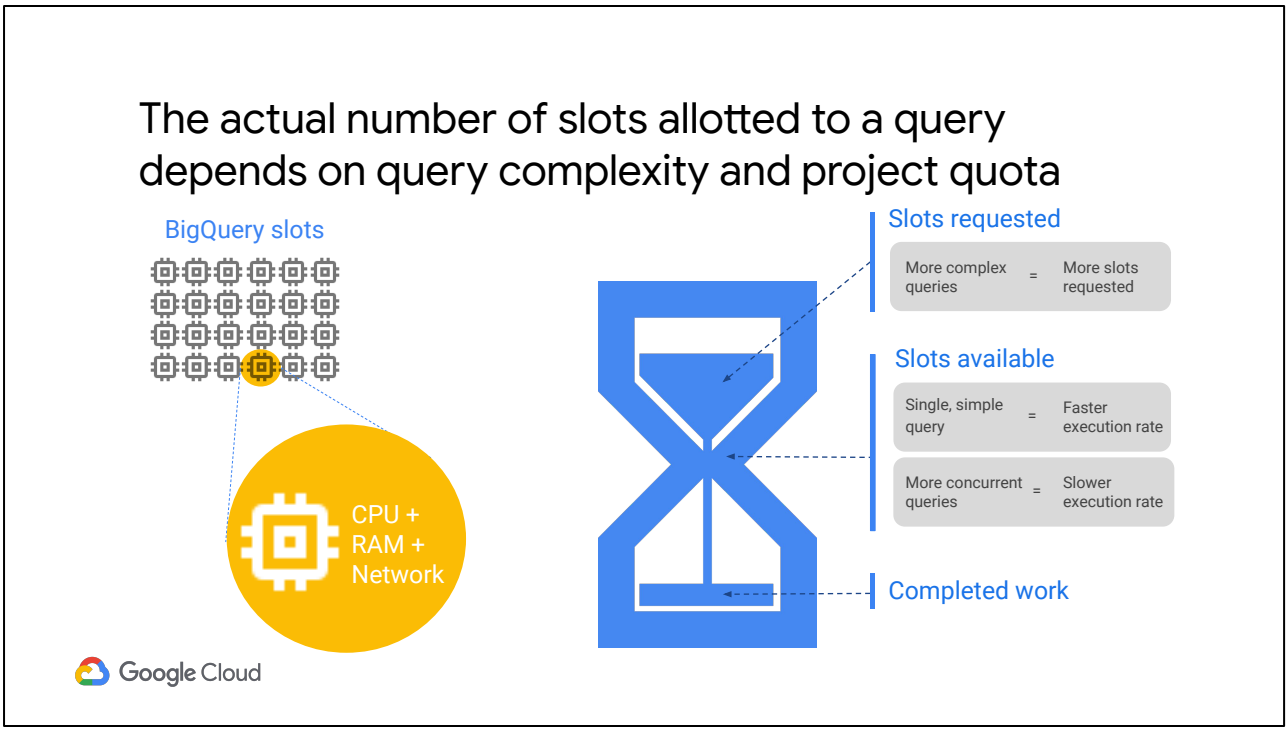


Google Cloud

Under the hood, analytics throughput is measured in BigQuery slots. A BigQuery slot is a unit of computational capacity required to execute SQL queries. BigQuery automatically calculates how many slots are required by each query, depending on the query size and complexity.

A BigQuery Slot is a combination of CPU, memory, and networking resources. It also includes several supporting technologies and sub-services. Note that each slot does not necessarily have the same specification during query execution. Some slots may have more memory than others, more CPU, or more I/O.

A slot is approximately half a VM of compute and 1 GB of memory, although this specification keeps increasing as computers in Google data centers are upgraded.



By default, each account has a quota limit of 2000 BigQuery slots for on-demand querying. A flat-rate pricing model is available that provides reserved slots for customers who want more predictable pricing.

If a single, simple query is submitted that needs fewer slots than are available, the query will generally execute faster.

If you have reserved 10,000 slots, but you have 30 concurrent queries that together ask for 15,000 slots, the queries will not get all the slots they require. Instead, the slots are divided fairly among all the projects in the reservation and all the queries in the project. This will generally result in each query executing more slowly.

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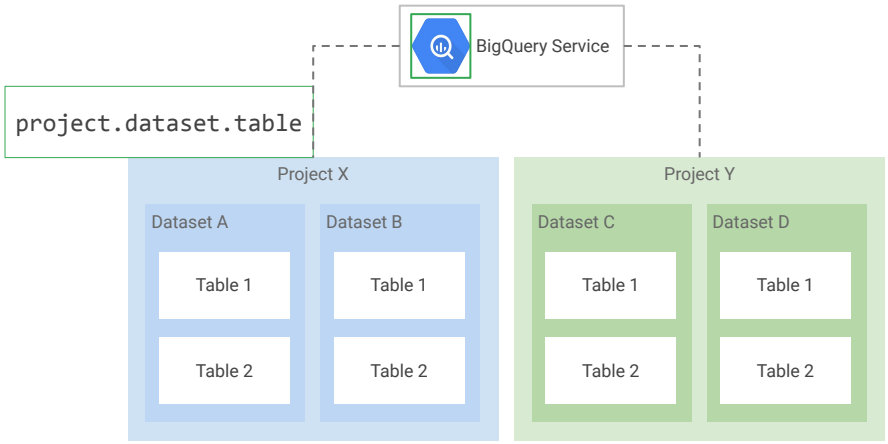
Preview: Transforming Batch and Streaming Data

Google Cloud

Now that you're familiar with the basics of BigQuery, it's time to talk about how BigQuery organizes your data.

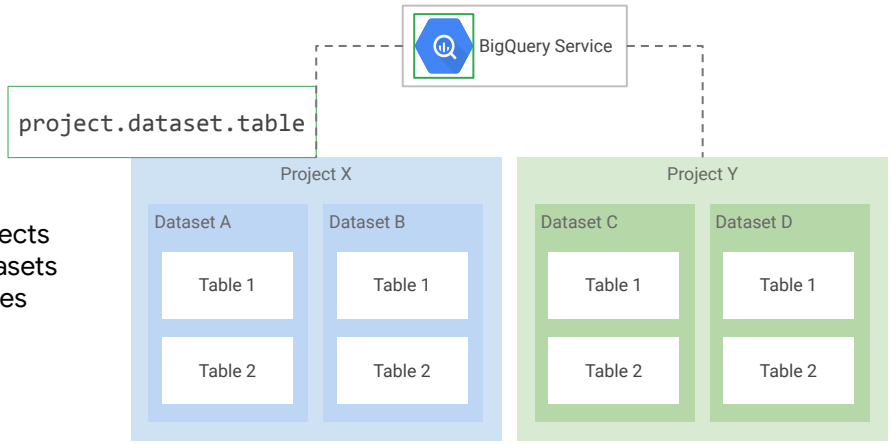
BigQuery organizes data tables into units called datasets



Google Cloud

BigQuery organizes data tables into units called datasets. These datasets are scoped to your GCP project. When you reference a table from the command line in SQL queries or in code, you refer to it by using the construct: project.dataset.table.

What are some reasons to structure your information?

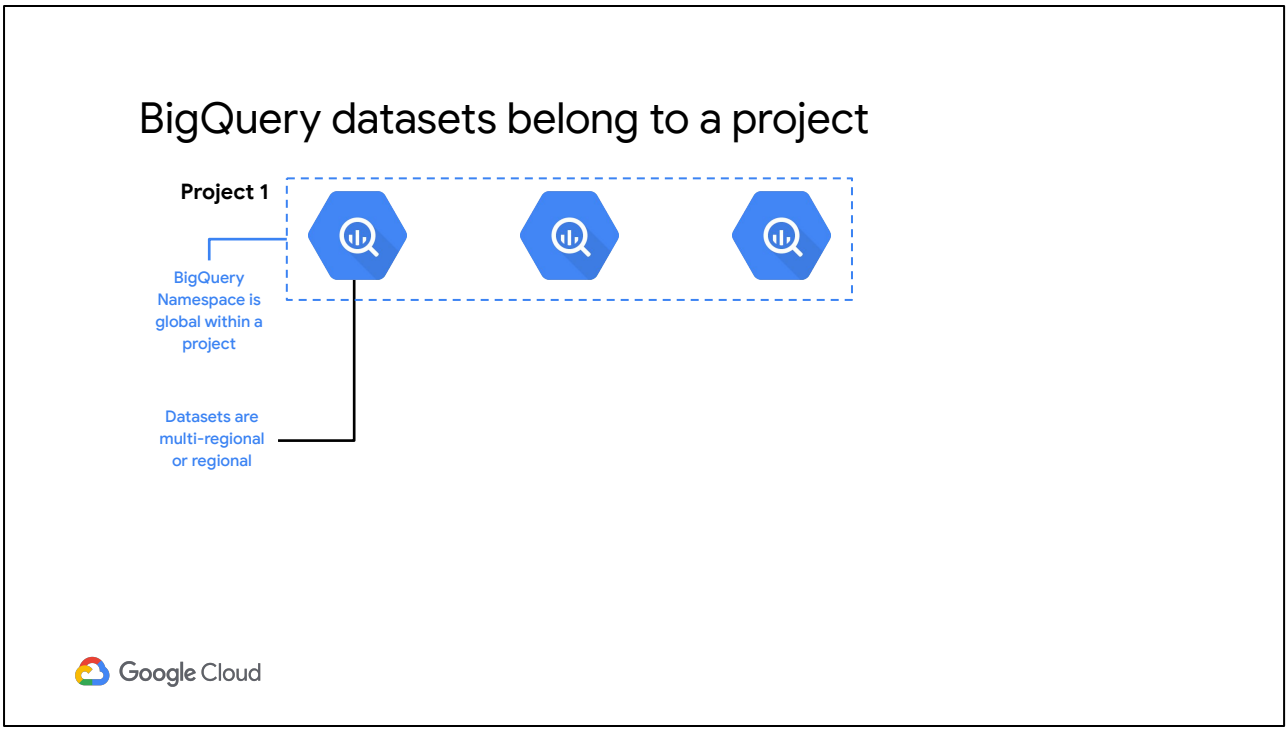


- Projects
- Datasets
- Tables

Google Cloud

What are some reasons to structure your information into datasets, projects, and tables? These multiple scopes—project, dataset, and table—can help you structure your information logically. You can use multiple datasets to separate tables pertaining to different analytical domains, and you can use project-level scoping to isolate datasets from each other according to your business needs.

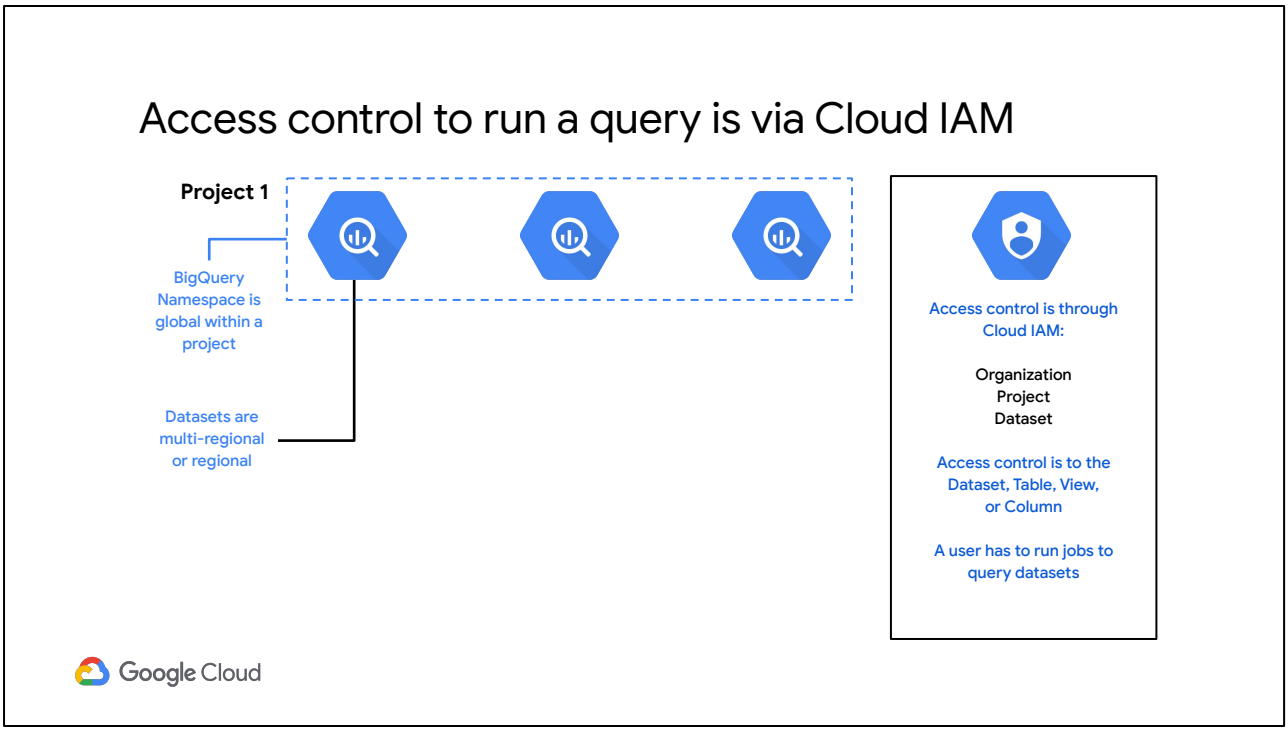
Also, as we will discuss later, you can align projects to billing and use datasets for access control. You store data in separate tables based on logical schema considerations.



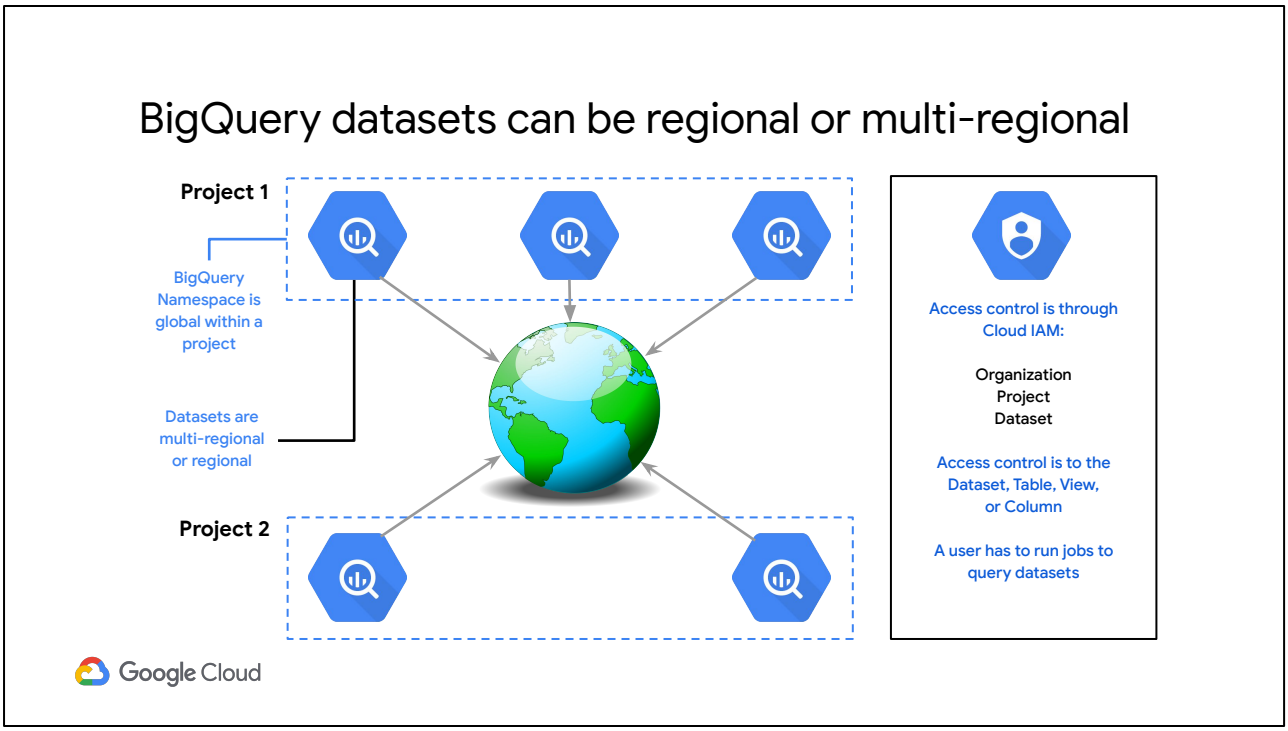
The project is what the billing is associated with. For example, if you queried a table that belong to the `bigquery-public-data` project, the storage costs are billed to that data project.

To run a query, you need to be logged in to the GCP console. You will run a query in your own GCP project and the query charges are billed to your project, not to the public data project.

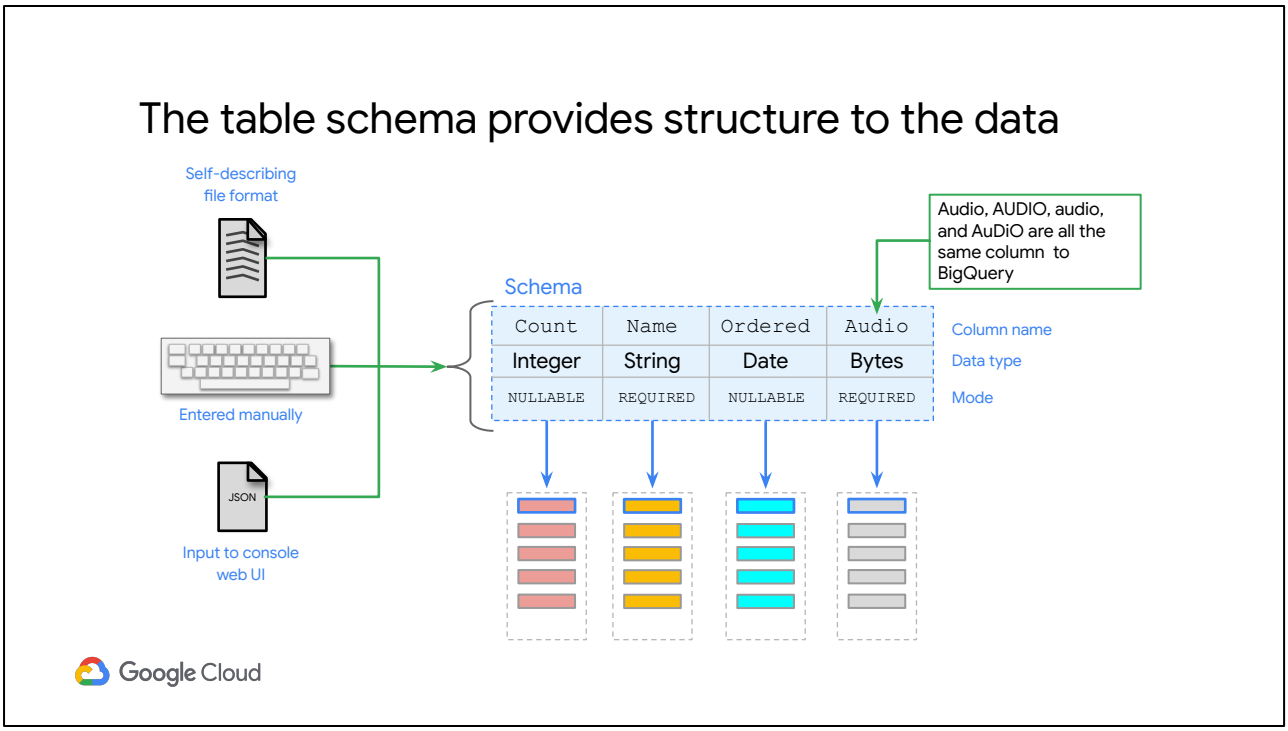
In order to run a query in a project, you need Cloud IAM permission to submit a job. Remember that running a query means that you must be able to submit a query job to the service.



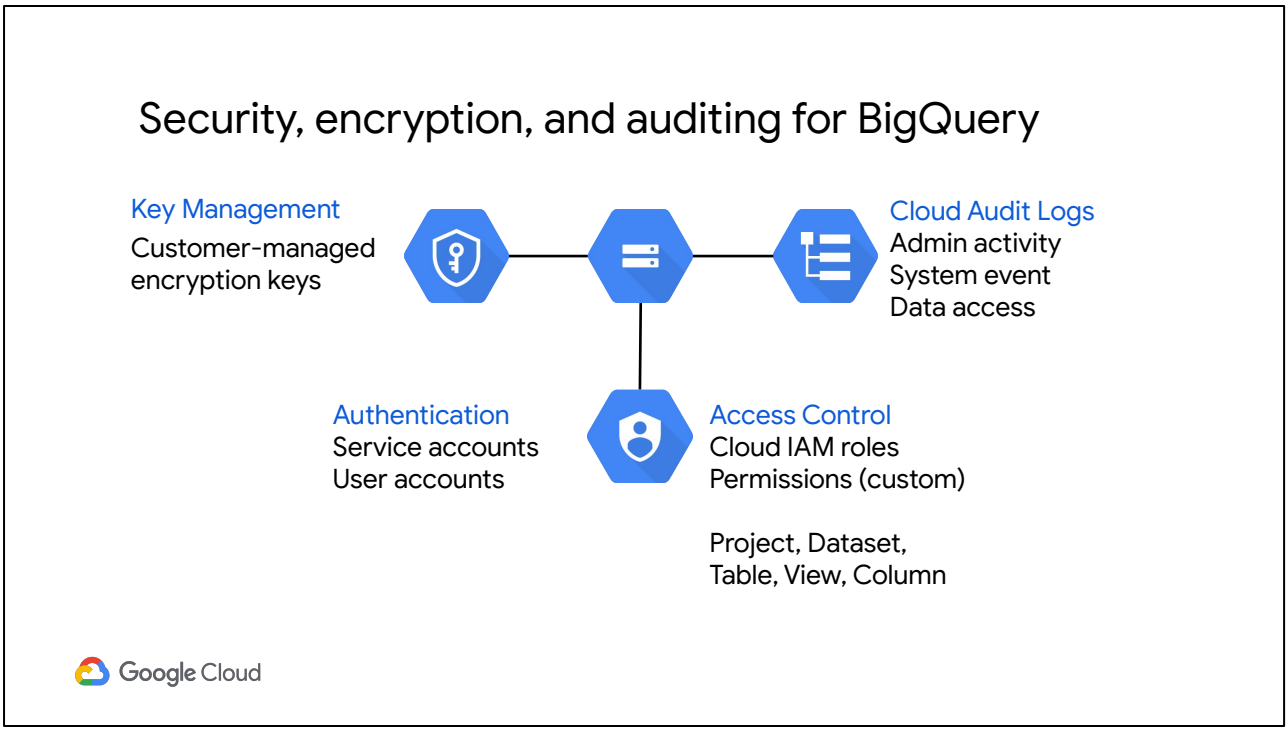
Access control is through Cloud IAM and is at the dataset, table/view, or column level. In order to query data in a table or view, you need at least read permissions on the table or view.



Like Cloud Storage, BigQuery datasets can be regional or multi-regional. Regional datasets are replicated across multiple zones in the region. Multi-regional means replication among multiple regions.



Every table has a schema. You can enter the schema manually through the GCP Console, or by supplying a JSON file.



As with Cloud Storage, BigQuery storage encrypts data at rest and over the wire using Google-managed encryption keys. It's also possible to use customer-managed encryption keys.

Authentication is through Cloud IAM, and so it's possible to use Gmail addresses or G Suite accounts for this task.

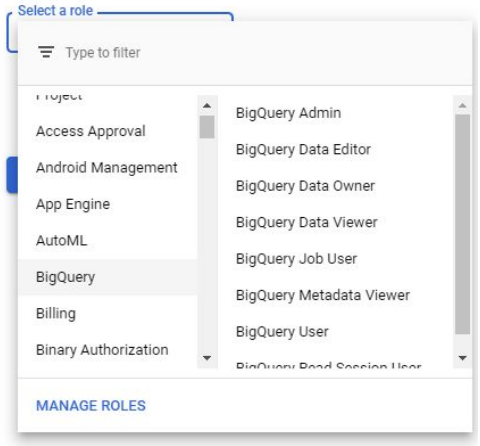
Access control, as we talked about, is through Cloud IAM roles and involves giving permissions. We discussed two of those in read access and the ability to submit query jobs. However, many other permissions are possible.

Remember that access control is at the level of datasets, tables, views, or columns. When you provide access to a dataset, either read or write, you provide access to all the tables in that dataset.

Logs in BigQuery are immutable and are available to be exported to Cloud Operations. Admin activities and system events are all logged. An example of a system event is table expiration.

If, when creating a table, you configure it to expire in 30 days, at the end of 30 days a system event will be generated and logged. You will also get immutable logs of every access that happens to a dataset under your project.

BigQuery provides predefined roles for controlling access to resources



Grants

Cloud IAM grants permission to perform specific actions

Access control is to datasets, tables, views, or columns.

Use authorized views to restrict at a finer-grained level.

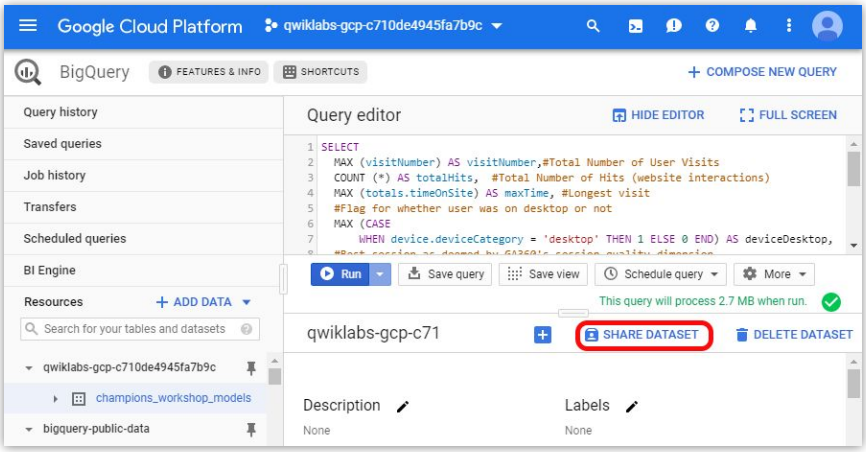
Google Cloud

BigQuery provides predefined roles for controlling access to resources. You can also create custom Cloud IAM roles consisting of your defined set of permissions, and then assign those roles to users or groups. You can assign a role to a Google email address or to a Google Workspace Group.

An important aspect of operating a data warehouse is allowing shared but controlled access against the same data to different groups of users. For example, finance, HR, and marketing departments all access the same tables, but their levels of access differ. Traditional data warehousing tools make this possible by enforcing row-level security. You can achieve the same results in BigQuery with access control to datasets, tables, views, or columns, or by defining authorized views and row-level permissions.

Creating authorized views: https://cloud.google.com/bigquery/docs/authorized-views

It’s easy to share access to datasets with other analysts



Google Cloud

Sharing access to datasets is easy.

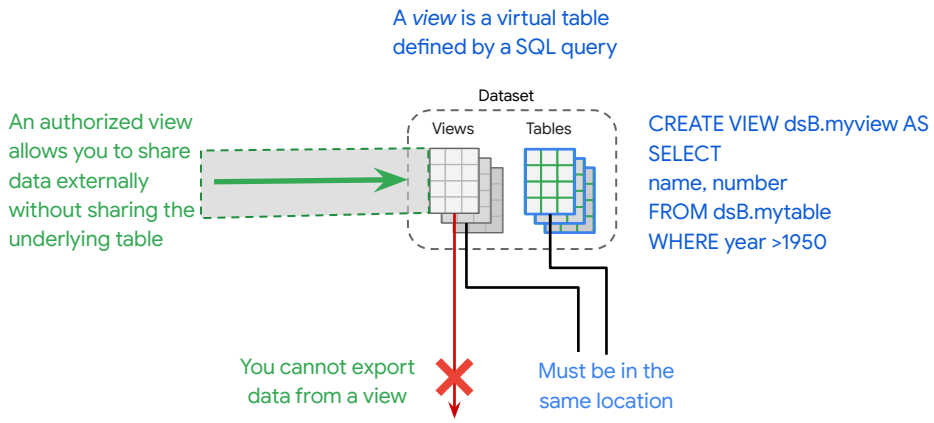
Traditionally, onboarding new data analysts involved significant lead time. To enable analysts to run simple queries, you had to show them where data sources resided and set up ODBC connections and tools and access rights. Using GCP, you can greatly accelerate an analyst's time to productivity.

To onboard an analyst on GCP, you grant access to relevant project(s), introduce them to the Google Cloud Platform Console and BigQuery web UI, and share some queries to help them get acquainted with the data.

The GCP Console provides a centralized view of all assets in your GCP environment. The most relevant asset to data analysts might be Cloud Storage buckets, where they can collaborate on files.

The BigQuery web UI presents the list of datasets that the analyst has access to. Analysts can perform tasks in the GCP Console according to the role you grant them, such as viewing metadata, previewing data, executing, and saving and sharing queries.

Views add another degree of access control

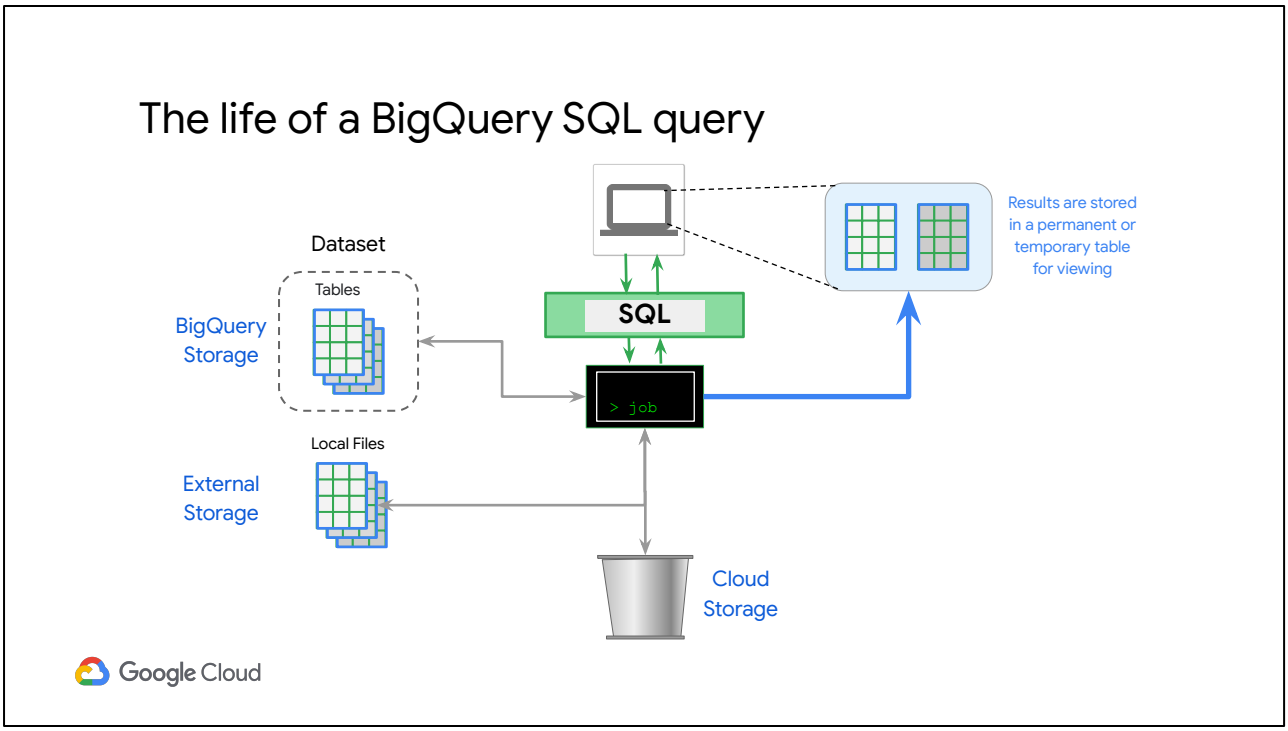


Google Cloud

When you provide read access to a dataset to a user, every table in that dataset is readable by that user.

What if you want more fine-grained control? In addition to access controls at the table or column level, you can use views. For example, in this example, we are creating a view in Dataset B, and the view is a subset of the table data in Dataset A. Now, by providing users with access to Dataset B, we are creating an authorized view that is only a subset of the original data. Note that you cannot export data from a view, and dataset B has to be in the same region or multi-region as dataset A.

A view is a SQL query that looks like and has properties similar to a table. You can query a view just like you query a table. BigQuery supports materialized views as well. These are views that are persisted so that the table does not need to be queried every time the view is used. BigQuery will keep the materialized view refreshed and up to date with the contents of the source table.



In the queries we saw earlier, we wrote the query in SQL and hit Run on the UI. What this did was to submit a QueryJob to the BigQuery service.

The BigQuery query service is separate from the BigQuery storage service. However, they are designed to collaborate and be used together. In this case, we were querying native tables in the bigquery-public-data project. Querying native tables is the most common case, and is the most performant way to use BigQuery.

BigQuery is most efficient when working with data contained in its own storage service. The storage service and the query service work together to internally organize the data to make queries efficient over huge datasets of Terabytes and Petabytes in size.

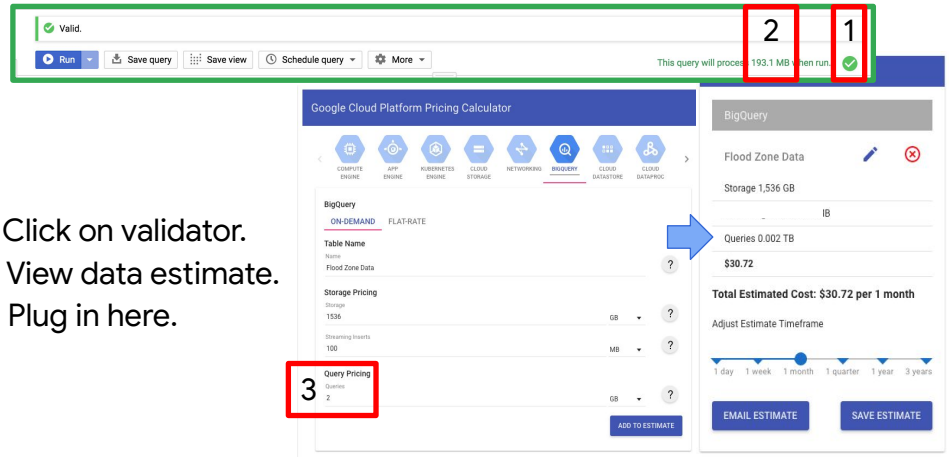
The query service can also run query jobs on data contained in other locations, such as tables in CSV files hosted in Cloud Storage.

So you can query data in external tables or from external sources without loading it into BigQuery. These are called federated queries.

In either case, the query service puts the results into a temporary table and the user interface pulls and displays the data in the temporary table. This temporary table is stored for 24 hours, so if you run the exact same query again, and if the results would not be different, then BigQuery will simply return a pointer to the cached results. Queries that can be served from the cache do not incur any charges.

It is also possible to request that the query job write to a destination table. In that case, you get to control when the table is deleted. Because the destination table is permanent, and not temporary, you will get charged for the storage of the results.

Use query validator with pricing calculator for estimates



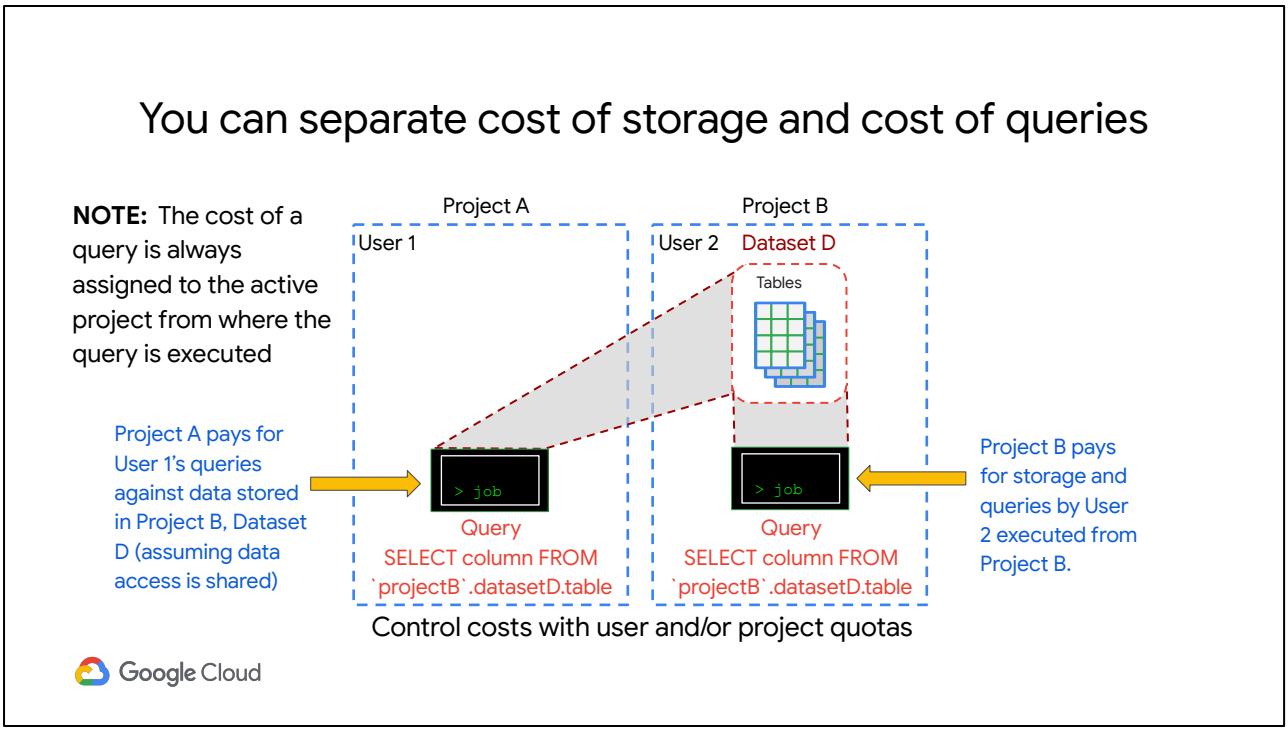
1) Click on validator.
2) View data estimate.
3) Plug in here.

Google Cloud

To calculate pricing, you can use BigQuery's query validator in combination with the pricing calculator for estimates.

The query validator provides an estimate of the size of data that will be processed during a query. You can plug this into the calculator to find an estimate of how much running the query will cost.

This is valid if you are using an on-demand plan where you pay for each query based on how much data is processed by that query. Your company might have opted for a flat-rate plan. In that case, your company will be paying a fixed price, and so the cost is really how many so-called slots your query uses.



You can separate cost of storage and cost of queries.

By separating projects A and B, it's possible to share data without giving access to run jobs. In this diagram, Users 1 and 2 have access to run jobs and access the datasets in their own respective Projects. If they run a query, that job is billed to their own project.

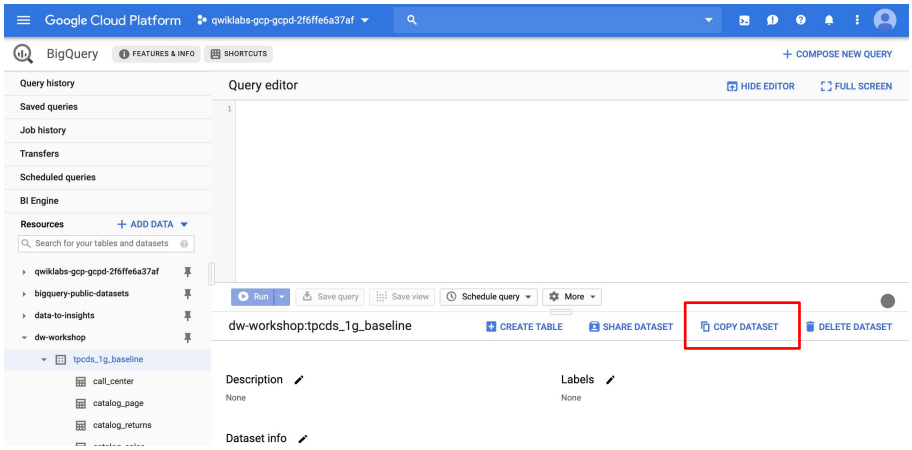
What if User 1 needs the ability to access Dataset D in Project B? The person who owns Project B can allow User 1 to query Project B Dataset D and the charges will go to Project A when executed from Project A.

The public dataset project owner granted all authenticated users access to use their data. The special setting allAuthenticatedUsers makes a dataset public. Authenticated users must use BigQuery within their own project and have access to run BigQuery jobs so that they can query the Public Dataset. The billing for the query goes to their project, even though the query is using public or shared data.

In summary, the cost of a query is always assigned to the active project from where the query is executed. The active project for a user is displayed at the top of the GCP console or set by an environmental variable in the Cloud Shell or client tools.

NOTE: BigQuery offers 1 TB of querying for free every month, so public datasets are an easy way to try out BigQuery.

With the BigQuery Data Transfer Service, you can copy large datasets from different projects to yours in seconds



Google Cloud

The BigQuery Data Transfer Service allows you to copy large datasets from different projects to yours in seconds. We'll talk more about the BigQuery Data Transfer Service in the next section on data loading.

Agenda

The modern data warehouse

Intro to BigQuery

- Getting Started
- Loading Data
- Lab: Loading Data with Console and CLI

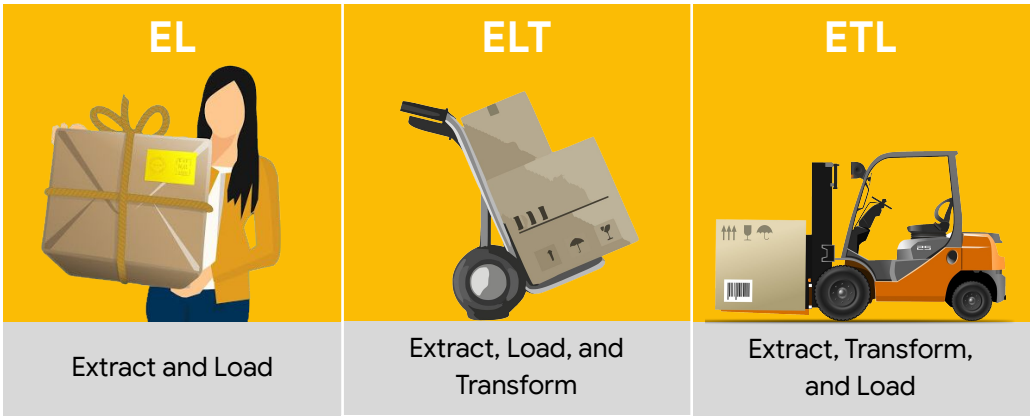
Exploring Schemas

- Schema Design
- Nested and Repeated Fields
- Lab: ARRAYs and STRUCTs
- Optimizing with Partitioning and Clustering

Preview: Transforming Batch and Streaming Data

Next, we'll talk about how to load new data into BigQuery.

The method you use to load data depends on how much transformation is needed



Google Cloud

Recall from earlier modules that the method you use to load data depends on how much transformation is needed.

EL, or Extract and Load, is used when data is imported as-is where the source and target have the same schema.

ELT, or Extract, Load, Transform, is used when raw data will be loaded directly into the target and transformed there.

ETL, or Extract, Transform, Load, is used when transformation occurs in an intermediate service before it is loaded into the target.

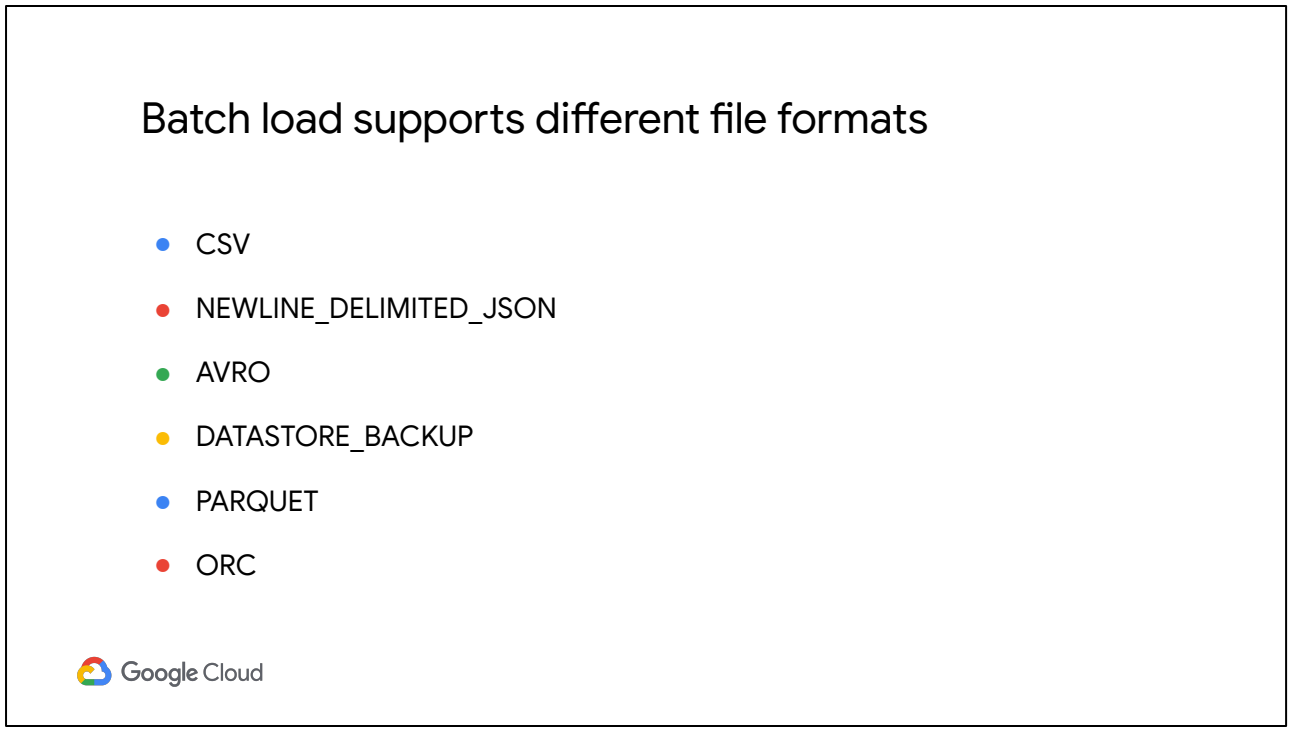
If the data is usable in its original form, just load it

BigQuery Data Transfer Service (DTS)

BigQuery

Google Cloud

You might say that the simplest case is EL. If the data is usable in its original form, there's no need for transformation. Just load it.



You can batch load data into BigQuery. In addition to CSV, you can also use data files with delimiters other than commas by using the field_delimiter flag.

BigQuery supports loading gzip compressed files. However, loading compressed files isn't as fast as loading uncompressed files. For time-sensitive scenarios or scenarios in which transferring uncompressed files to Cloud Storage is bandwidth- or time-constrained, conduct a quick loading test to see which alternative works best.

Because load jobs are asynchronous, you don't need to maintain a client connection while the job is being executed. More importantly, load jobs don't affect your other BigQuery resources.

A load job creates a destination table if one doesn't already exist. BigQuery determines the data schema as follows:

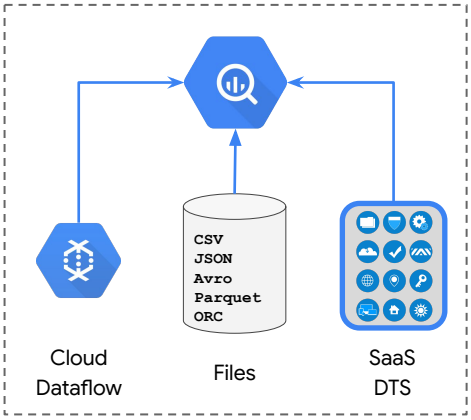
- If your data is in Avro format, which is self-describing, BigQuery can determine the schema directly.
- If the data is in JSON or CSV format, BigQuery can auto-detect the schema, but manual verification is recommended.

You can specify a schema explicitly by passing the schema as an argument to the load job. Ongoing load jobs can append to the same table using the same procedure as the initial load, but do not require the schema to be passed with each job.

If your CSV files always contain a header row that should be ignored after the initial load and table creation, you can use the skip_leading_rows flag to ignore the row. For details, see the documentation on bq load flags.

BigQuery sets daily limits on the number and size of load jobs that you can perform per project and per table. In addition, BigQuery sets limits on the sizes of individual load files and records. You can launch load jobs through the BigQuery web UI. To automate the process, you can set up Cloud Functions to listen to a Cloud Storage event that is associated with new files arriving in a given bucket and launch a BigQuery load job.

Most common is loading data into BigQuery tables (batch, periodic)



Loading data into BigQuery tables (batch, periodic) offers the best performance

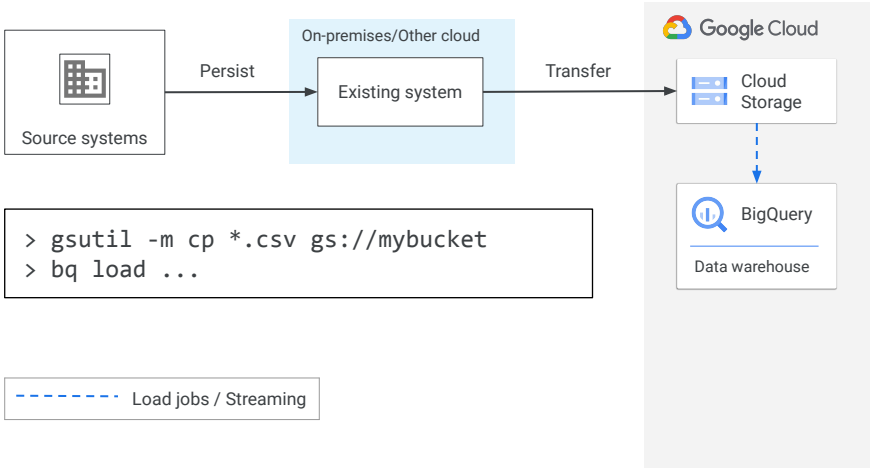
Google Cloud

BigQuery can import data stored in the JSON file format, so long as it is newline delimited. It can also import files in Avro, Parquet, and ORC format. The most common import is with CSV files, which are the bridge between BigQuery and spreadsheets.
BigQuery can also directly import Firestore and Datastore export files.

Another way that BigQuery can import data is through the API. Basically, any place where you can get code to run can theoretically insert data into BigQuery tables. You could use the API from a Compute Engine instance, a container on Kubernetes, App Engine, or from Cloud Functions. However, you would have to recreate the data processing foundation in these cases. In practice, the API is mainly used from either Cloud Dataproc or Cloud Dataflow.

The Data Transfer Service, or DTS, provides connectors and pre-built BigQuery load jobs that perform the transformations necessary to load report data from various business services directly into BigQuery.

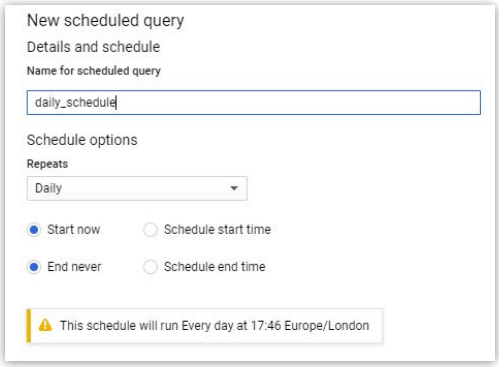
Loading data through Cloud Storage

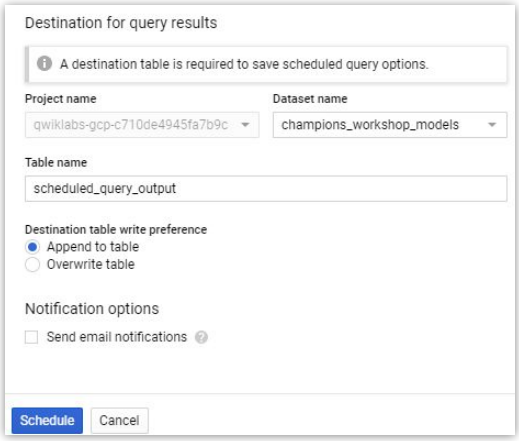


Google Cloud

Cloud Storage can be useful in the EL process. You can transfer files to Cloud Storage in the schema that is native to the existing on-premises data storage and then load those files into BigQuery.

Automate the execution of queries based on a schedule





Google Cloud

It is a common practice to automate execution of queries based on a schedule/event and cache the results for later consumption.

You can schedule queries to run on a recurring basis. Scheduled queries must be written in standard SQL, which can include Data Definition Language and Data Manipulation Language statements. The query string and destination table can be parameterized, allowing you to organize query results by date and time.

https://cloud.google.com/bigquery/docs/scheduling-queries

BigQuery addresses backup and disaster recovery at the service level (time travel)

```
CREATE OR REPLACE TABLE ch10eu.restored_cycle_stations AS
SELECT
*
FROM bigquery-public-data.london_bicycles.cycle_stations
FOR SYSTEM_TIME AS OF
TIMESTAMP_SUB(CURRENT_TIMESTAMP(), INTERVAL 24 HOUR)
```

Query a point-in-time snapshot (up to 7 days)
Use it to create a backup

```
NOW=$(date +%s)
SNAPSHOT=$(echo "($NOW - 120)*1000" | bc)
bq --location=EU cp \
ch10eu.restored_cycle_stations@$SNAPSHOT \
ch10eu.restored_table
```

Restore a 2-min old copy
(Deleted tables are flushed after 2 days or if recreated with same name)

Google Cloud

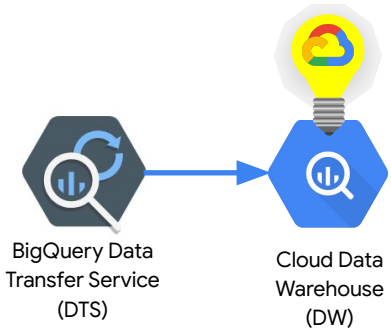
By maintaining a complete 7-day history of changes against your tables, BigQuery allows you to query a point-in-time snapshot of your data. You can easily revert changes without having to request a recovery from backups.

This slide shows how to do a select query to query the table as of 24 hours ago. Because this is a select query, you can do more than just restore a table. You can join against some other table or correct the value of individual columns.

You can also do this using the BigQuery command-line tool as shown in the second snippet. Here, We're restoring data as of 120 seconds ago.

You can recover a deleted table only if another table with the same ID in the dataset has not been created. In particular, this means you cannot recover a deleted table if it is being streamed to. Chances are that the streaming pipeline would have already created an empty table and started pushing rows into it. Be careful using "CREATE OR REPLACE TABLE" because this makes the table irrecoverable.

BigQuery Data Transfer Service helps you build and manage your data warehouse



EL

- Managed service
- Automatic transfers
- Scheduled
- Data staging
- Data processing
- Data backfills

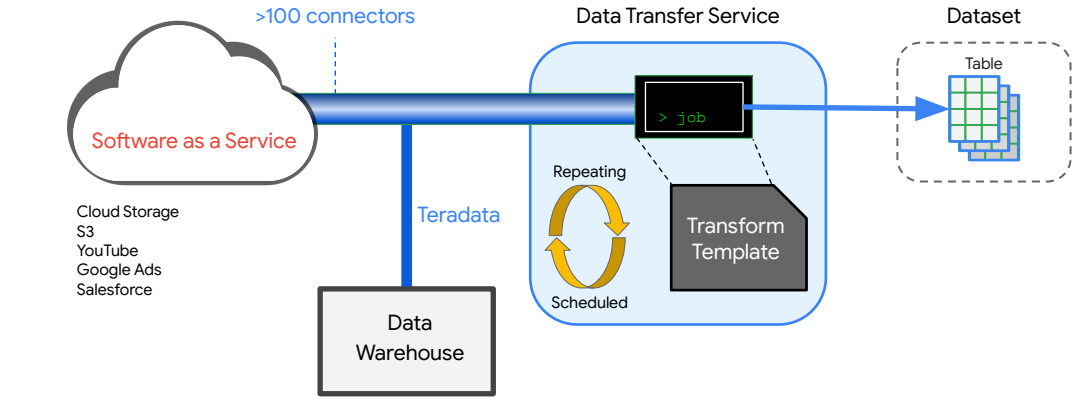
Google Cloud

It is a managed service, so you don't have the overhead of operating, maintaining or securing the system. A typical Data Warehouse system requires a lot of code for coordination and interfacing. You can get BigQuery DTS running without coding. The core of DTS is scheduled and automatic transfers of data from wherever it is located (in your data center, on other clouds, in SaaS services) in to BigQuery.

Transfering the data is only the first part of building a data warehouse. If you were assembling your own system, you would need to stage the data so that it can be cleaned (data quality), and transformed (ELT, extract, load, transform), and processed (put into its final and stable form). A common issue with Data Warehouse systems is late arriving data. For example, a cash register closes late and does not report its daily receipts during the scheduled transfer period. To complete the data, you would need to detect that not all of the data was received, and then request the missing data to fill in the gap. This is called "data backfill" and it is one of the automatic processes provided by BigQuery DTS.

"Backfilling data" means adding missing past data to make a dataset complete with no gaps and to keep all analytic processes working as expected.

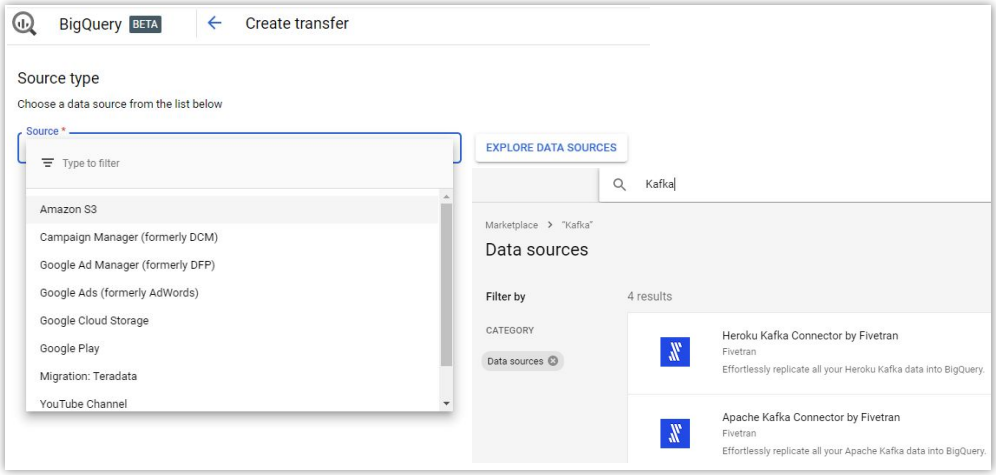
Data Transfer Service provides SaaS connectors



Google Cloud

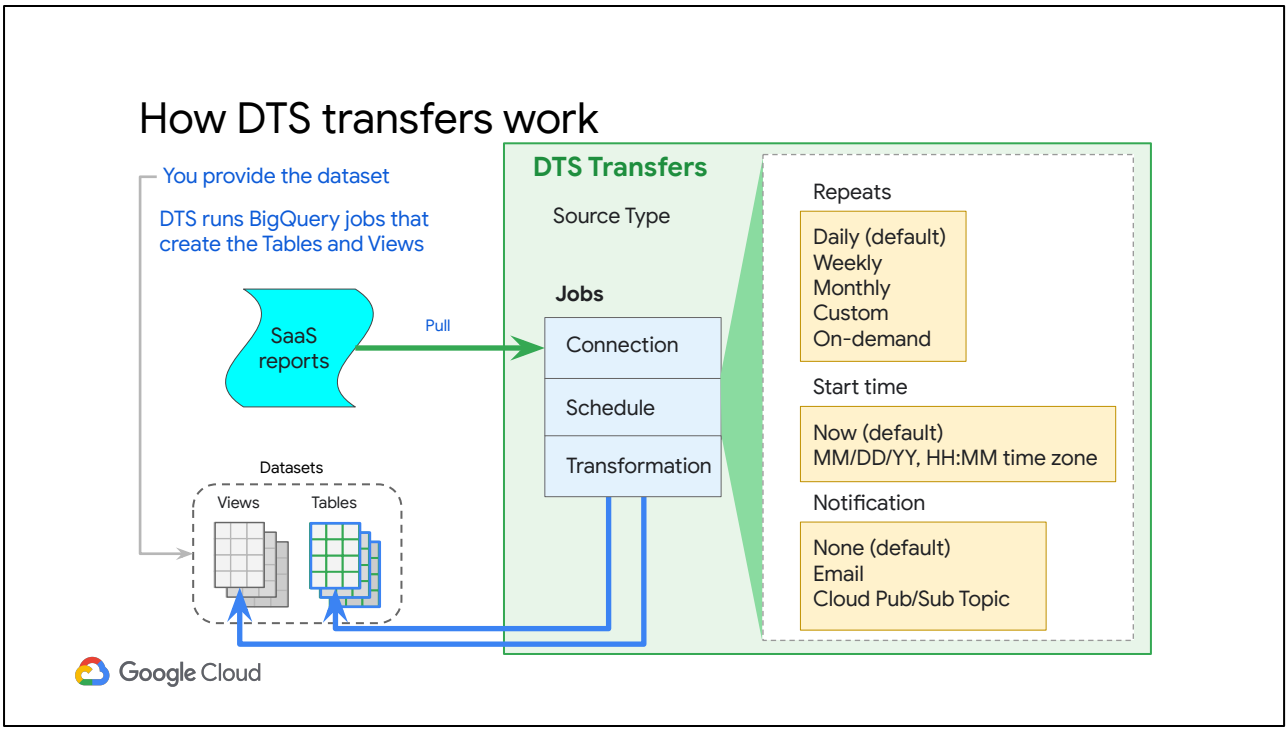
Use the data transfer service for repeated, periodic, scheduled imports of data directly from Software as a Service systems into tables in BigQuery. The Data Transfer Service provides connectors, transformation templates, and the scheduling. The connectors establish secure communications with the source service and collect standard data, exports, and reports. This information is transformed within BigQuery. The transformations can be quite complicated, resulting in from 25 to 60 tables. And the transfer can be scheduled to repeat as frequently as once a day.

BigQuery DTS supports 100+ SaaS applications



Google Cloud

The BigQuery Data Transfer Service automates data movement from SaaS applications to BigQuery on a scheduled, managed basis. It can also be used to efficiently move data between regions.



Notice that you don't need Cloud Storage buckets. Data Transfer Service runs BigQuery jobs that transform reports from SaaS sources into BigQuery Tables and Views.

Google offers several connectors, including Campaign Manager, Cloud Storage, Amazon S3, Google Ad Manager, Google Ads, Google Play transfers, YouTube channel, YouTube content owner, Teradata migration, and over 100 other connectors through partners.

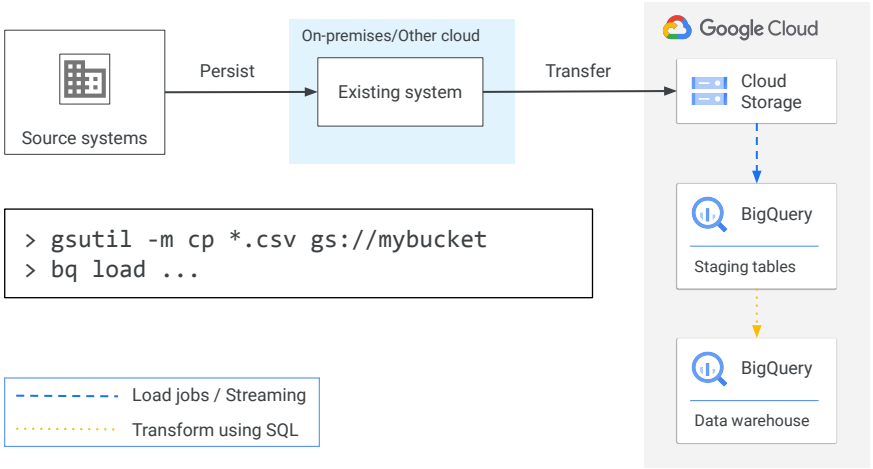
If the data requires simple transformations, such as scaling, maybe it can be handled in SQL

BigQuery

Google Cloud

Keep in mind if your data transformations are simple enough, you may be able to do them with just SQL.

Loading and transforming data in BigQuery



Google Cloud

If Cloud Storage is part of your workflow, you can load files from Cloud Storage into staging tables in BigQuery first, and then transform the data into the ideal schema for BigQuery by using BigQuery SQL commands.

Modify table data with standard DML statements

INSERT, **UPDATE**, **DELETE**, MERGE records into tables

```
UPDATE table_A
SET
  y = table_B.y,
  z = table_B.z + 1
FROM table_B
WHERE table_A.x = table_B.x
  AND table_A.y IS NULL;
```

```
INSERT INTO table VALUES (1,2,3), (4,5,6), (7,8,9);
```

```
DELETE FROM table WHERE TRUE;
```

Google Cloud

BigQuery supports standard DML statements such as insert, update, delete, and merge. There are no limits on DML statements.

However you should not treat BigQuery as an OLTP system. The underlying infrastructure is not structured to perform optimally as an OLTP. There are other more appropriate products in Google Cloud for such workloads.

https://cloud.google.com/bigquery/docs/managing-table-schemas

Create new tables from data with SQL DDL

```
SELECT
   *
FROM
   movielens.movies_raw
WHERE
   movieId < 5;
```

	movieId	title	genres
0	3	Grumpier Old Men (1995)	Comedy|Romance
1	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
2	2	Jumanji (1995)	Adventure|Children|Fantasy
3	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy

```
CREATE OR REPLACE TABLE
movielens.movies AS
SELECT
   * REPLACE(SPLIT(genres, "|")
AS genres)
FROM
   Movielens.movies_raw;
-- Execute multiple statements.
SELECT * FROM
movielens.movies;
```

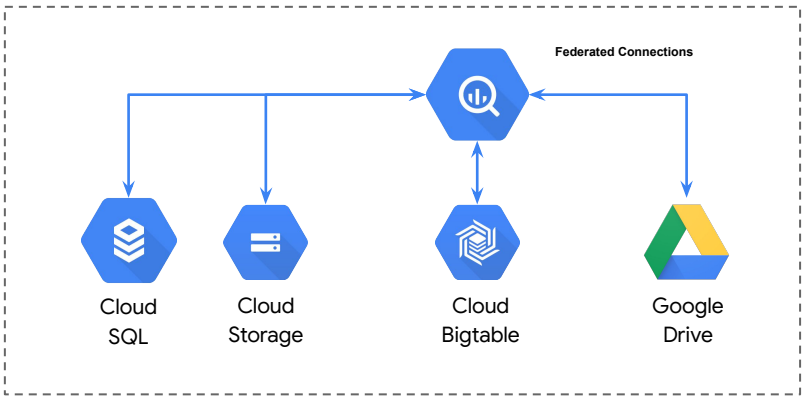
	movieId	title	genres
0	4	Waiting to Exhale (1995)	[Comedy, Drama, Romance]
1	3	Grumpier Old Men (1995)	[Comedy, Romance]
2	2	Jumanji (1995)	[Adventure, Children, Fantasy]
3	1	Toy Story (1995)	[Adventure, Animation, Children, Comedy, Fantasy]

Question: What's the difference between CREATE OR REPLACE TABLE and CREATE TABLE IF NOT EXISTS ? When would you use each?

Google Cloud

BigQuery also supports DDL statements like CREATE OR REPLACE TABLE. In the example on this slide, the replace statement is used to transform a string of genres into an array. We'll cover arrays in greater detail soon.

Some data can be used in place without importing into BigQuery tables using external data sources

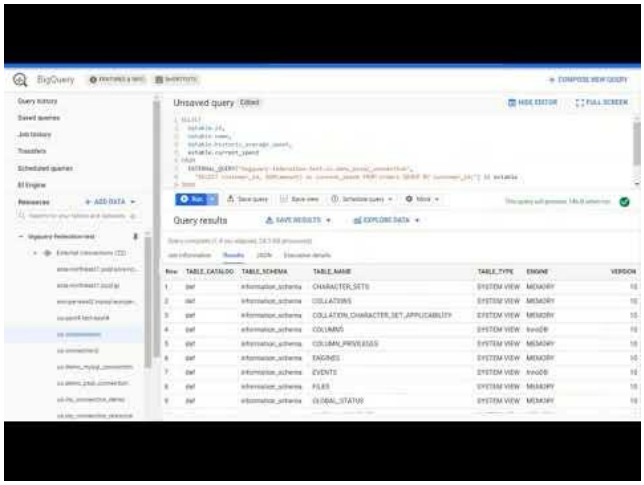


Google Cloud

A unique feature of BigQuery is that Some data can be queried without first importing it into BigQuery tables. For example, it can look in the first sheet of a Google worksheet or CSV or JSON files. You could use a federated query to import data from a CSV in Cloud Storage and transform it using SQL all in one query!

However, importing the data into BigQuery will provide much faster performance.

Video Demo: Querying Cloud SQL directly from BigQuery

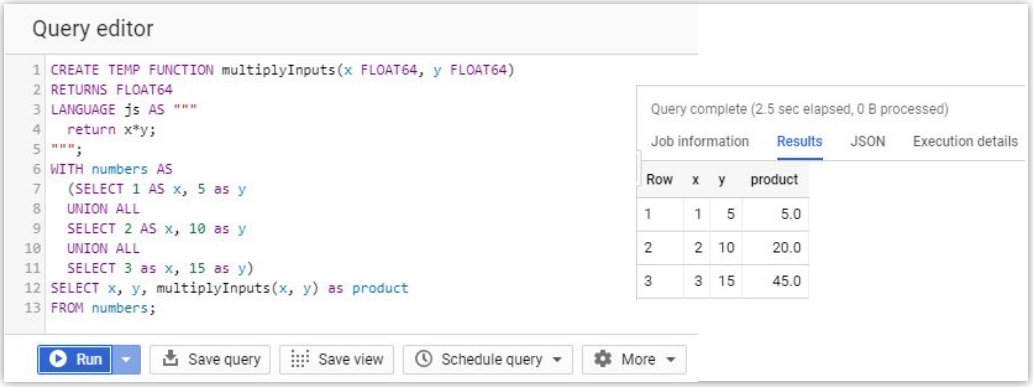


Google Cloud

Here's a quick demo of how you can query a Cloud SQL database (which is hosted mySQL, PostGres or SQL Server) directly from BigQuery using external connection syntax in the FROM clause.

https://www.youtube.com/watch?v=K8A6_G3DTTs

Custom transformations? BigQuery supports user-defined functions in SQL, JavaScript, and scripting



Google Cloud

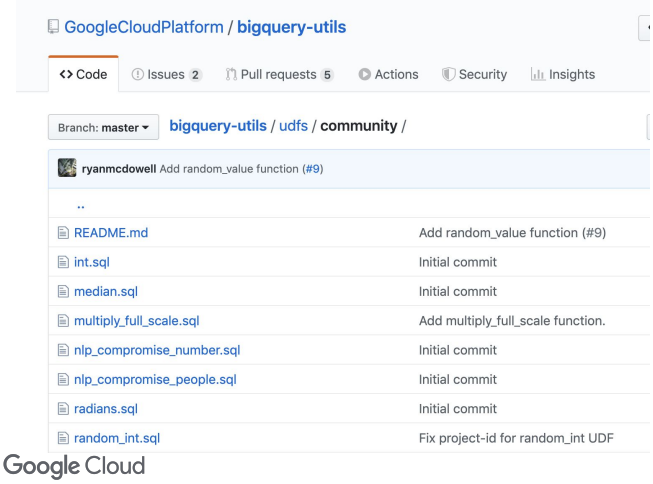
Lastly, what if your transformations went beyond what functions were currently available in BigQuery? Well you can create your own!

BigQuery supports user-defined functions, or UDF. A UDF enables you to create a function using another SQL expression or an external programming language. JavaScript is currently the only external language supported. We strongly suggest you use Standard SQL though, because BigQuery can optimize the execution of SQL much better than it can for JavaScript.

UDFs allow you to extend the built-in SQL functions. UDFs take a list of values, which can be arrays or structs, and return a single value, which can also be an array or struct. UDFs written in JavaScript can include external resources, such as encryption or other libraries.

Previously, UDFs were temporary functions only. This meant you could only use them for the current query or command-line session. Now we have permanent functions, scripts, and procedures in beta but they might even be generally available by the time you are seeing this. Please check the documentation.

You can persist and share your UDF objects with other team members or publically



The BigQuery team has a public GitHub repo for common User Defined Functions https://github.com/GoogleCloudPlatform/bigquery-utils/tree/master/udfs/community

Google Cloud

When you create a UDF, BigQuery persists it and stores it as an object in your database. What this means is you can share your UDFs with other team members or even publically if you wanted to. The BigQuery team has a public GitHub repo for common User Defined Functions at the link you see here.

https://cloud.google.com/blog/products/data-analytics/new-persistent-user-defined-functions-increased-concurrency-limits-gis-and-encryption-functions-and-more

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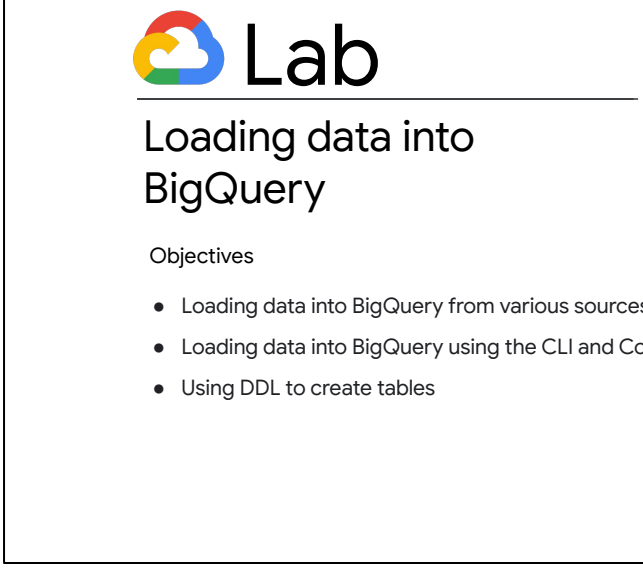
Now it’s time to get some hands-on experience with a lab.



Now it's time to get some hands-on experience with a lab. In this lab, you're going to practice loading data into BigQuery.

The primary objectives of this lab are to load data into BigQuery using both the command line interface and console. You'll get experience loading several datasets into BigQuery and using the data description language, or DDL.

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Preview: Transforming Batch and Streaming Data

Now let's dive into the world of data warehouse schemas.

Designing schemas that scale is a core job of data engineers -- let's explore BigQuery Public Dataset schemas

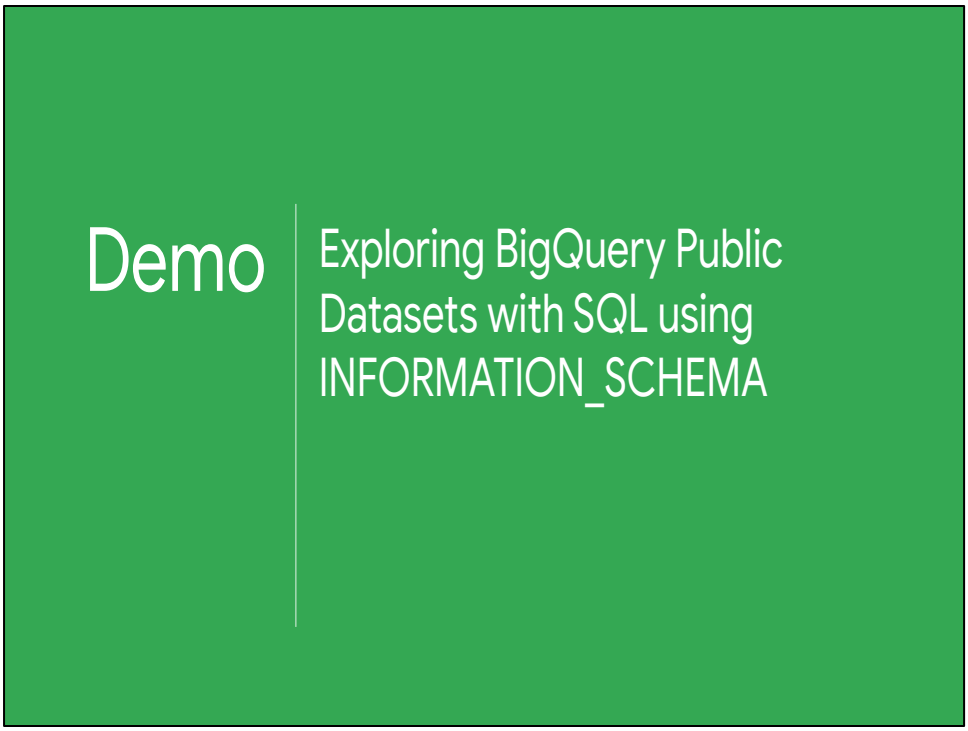
Public datasets include flights, taxi cab logs, weather recordings, and many more

https://cloud.google.com/bigquery/public-data/

Google Cloud

Designing efficient schemas that scale is a core job responsibility of any data engineering team. BigQuery hosts over a hundred public datasets and schemas for you to explore on popular topics like daily weather readings, taxi cab logs, health data and more.

Let's explore some of these public dataset schemas using SQL.



Demo Instructions:
https://github.com/GoogleCloudPlatform/training-data-analyst/blob/master/quests/bq-optimize/demos/code/information_schema.sql

Agenda

The modern data warehouse

Intro to BigQuery

- Getting Started
- Loading Data
- Lab: Loading Data with Console and CLI

Exploring Schemas

- Schema Design
- Nested and Repeated Fields
- Lab: ARRAYs and STRUCTs
- Optimizing with Partitioning and Clustering

Preview: Transforming Batch and Streaming Data

Next we will talk about efficient data warehouse schema design.

Transactional databases often use normal form

Original data

Customer	OrderID	Date	Items	
Doug	1600p	8/20/19		
			Product	Quantity
			Caulk	3 boxes
			Soffit	34 meters
			Sealant	2 liters
Tom	221b	10/29/19		
			Product	Quantity
			Sealant	1 liter
			Soffit	17 meters
			Caulk	4 tubes

Normalized data

Orders	
Date	OrderID
8/20/2019	1600p
10/29/2018	221b

Order_Items		
OrderID	Product	Quantity
1600p	Caulk	3 boxes
221b	Sealant	1 liter
1600p	Soffit	34 meters
221b	Soffit	17 meters
221b	Caulk	4 tubes
1600p	Sealant	2 liters

Google Cloud

Take a look at the Original Data table here and the Normalized data tables which contain the same data.

The data in the Original table is organized visually -- as you might have used merged cells or columns in a spreadsheet. But if you had to write an algorithm to process the data, how might you approach it? Could be by rows, by columns, by rows-then-columns. And the different approaches would perform differently based on the query. Also, your method might not be parallelizable.

The original data can be interpreted and stored in many ways in a database. Normalizing the data means turning it into a relational system. This stores the data efficiently and makes query processing a clear and direct task. Normalizing increases the orderliness of the data. It is useful for saving space.

Many people with database experience will recognize this procedure. Normalizing data usually happens when a schema is designed for a database.

Data warehouses often denormalize

Normalized data

Orders	
Date	OrderID
08/20/2019	1600p
10/29/2018	221b

Order_Items		
OrderID	Product	Quantity
1600p	Caulk	3 boxes
221b	Sealant	1 liter
1600p	Soffit	34 meters
221b	Soffit	17 meters
221b	Caulk	4 tubes
1600p	Sealant	2 liters

Denormalized flattened data

Customer	OrderID	Date	Product	Quantity
Doug	1600p	08/20/2019	Siding	3 boxes
Doug	1600p	08/20/2019	Caulk	12 tubes
Tom	221b	10/29/2019	Soffit	17 meters
Tom	221b	10/29/2019	Sealant	1 liter
Doug	1600p	08/20/2019	Soffit	34 meters
Tom	221b	10/29/2019	Siding	2 boxes
Tom	221b	10/29/2019	Caulk	4 tubes
Doug	1600p	08/20/2019	Sealant	2 liters

Google Cloud

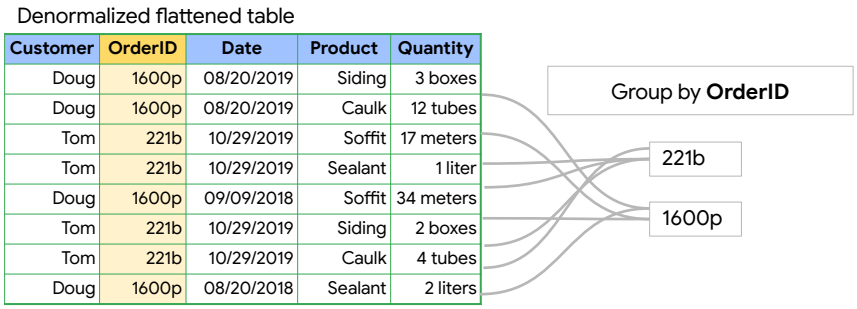
Denormalizing is the strategy of allowing duplicate field values for a column in a table in the data to gain processing performance.

Data is repeated rather than being relational. Flattened data takes more storage, but the flattened (non-relational) organization makes queries more efficient because they can be processed in parallel using columnar processing.

Specifically, denormalizing data enables BigQuery to more efficiently distribute processing among slots, resulting in more parallel processing and better query performance.

You would usually denormalize data before loading it into BigQuery.

Grouping on a 1-to-many field in flattened data can cause shuffling of data over the network



Google Cloud

However, there are cases where denormalizing data is bad for performance. Specifically, if you have to group by a column with a 1-to-many relationship. In the example shown, OrderID is such a column.

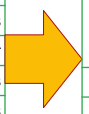
In this example, to group the data it must be shuffled. That often happens by transferring the data over a network between servers or systems.
Shuffling is slow.

Fortunately, BigQuery supports a method to improve this situation.

Nested and repeated columns improve the efficiency of BigQuery with relational source data

Denormalized flattened table

Customer	OrderID	Date	Product	Quantity
Doug	1600p	08/20/2019	Siding	3 boxes
Doug	1600p	08/20/2019	Caulk	12 tubes
Tom	221b	10/29/2019	Soffit	17 meters
Tom	221b	10/29/2019	Sealant	1 liter
Doug	1600p	8/20/2019	Soffit	34 meters
Tom	221b	10/29/2019	Siding	2 boxes
Tom	221b	10/29/2019	Caulk	4 tubes
Doug	1600p	08/20/2019	Sealant	2 liters



Denormalized with nested and repeated data

Order.ID	Order.Date	Order.Product	Order.Quantity
1600p	08/20/2019	Siding	3 boxes
		Caulk	12 tubes
		Soffit	34 meters
		Sealant	2 liters
221b	10/29/2019	Soffit	17 meters
		Sealant	1 liter
		Siding	2 boxes
		Caulk	4 tubes

Google Cloud

BigQuery supports columns with nested and repeated data.

In this example, a denormalized flattened table is compared with one that has been denormalized, but the schema takes advantage of nested and repeated fields. OrderID is a repeated field. Because this is declared in advance, BigQuery can store and process the data respecting some of the original organization in the data. Specifically, all order details for each order are colocated, which makes retrieval of the whole order more efficient.

For this reason, nested and repeated fields is useful for working with data that originates in relational databases.

Nested columns can be understood as a form of repeated field. It preserves the relationalism of the original data and schema while enabling columnar and parallel processing of the repeated nested fields. It is the best alternative for data that already has a relational pattern in it. Turning the relation into a nested or repeated field improves BigQuery performance.

Nested and repeated fields help BigQuery work with data sourced in relational databases.

Look for nested and repeated fields whenever BigQuery is used in a hybrid solution in conjunction with traditional databases,

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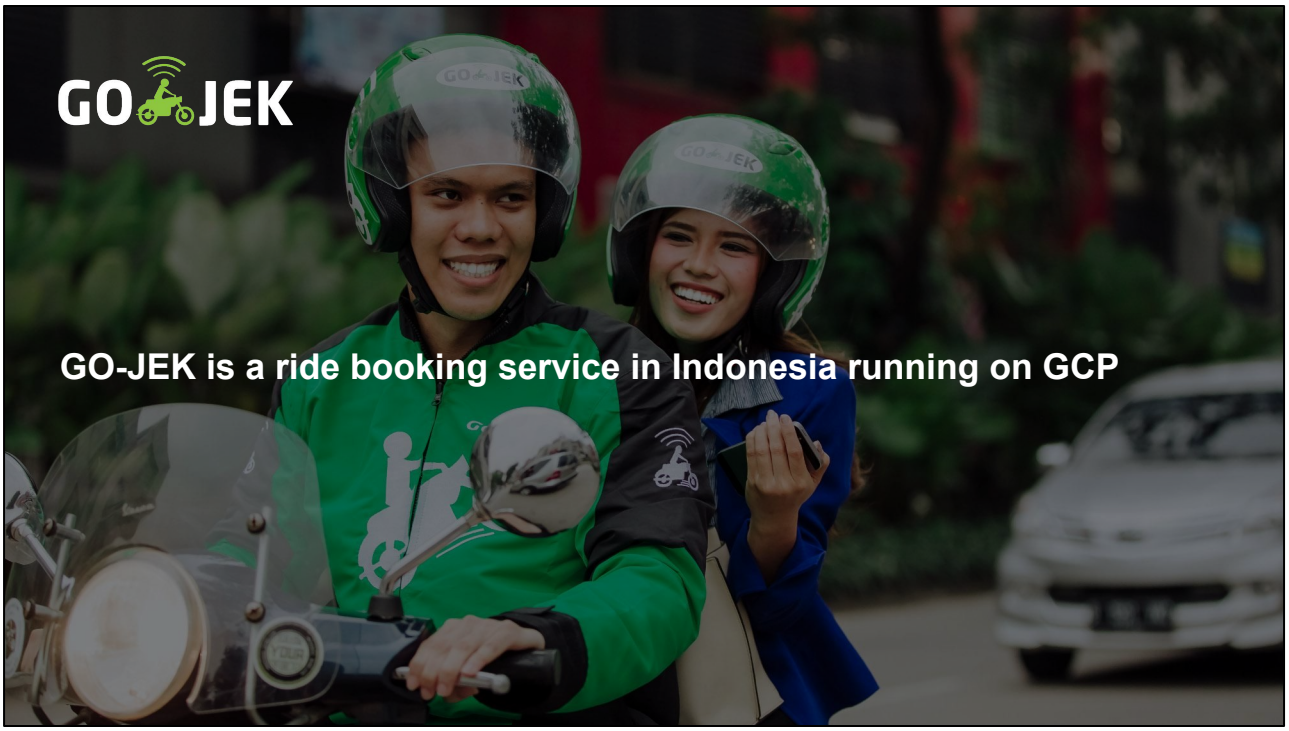
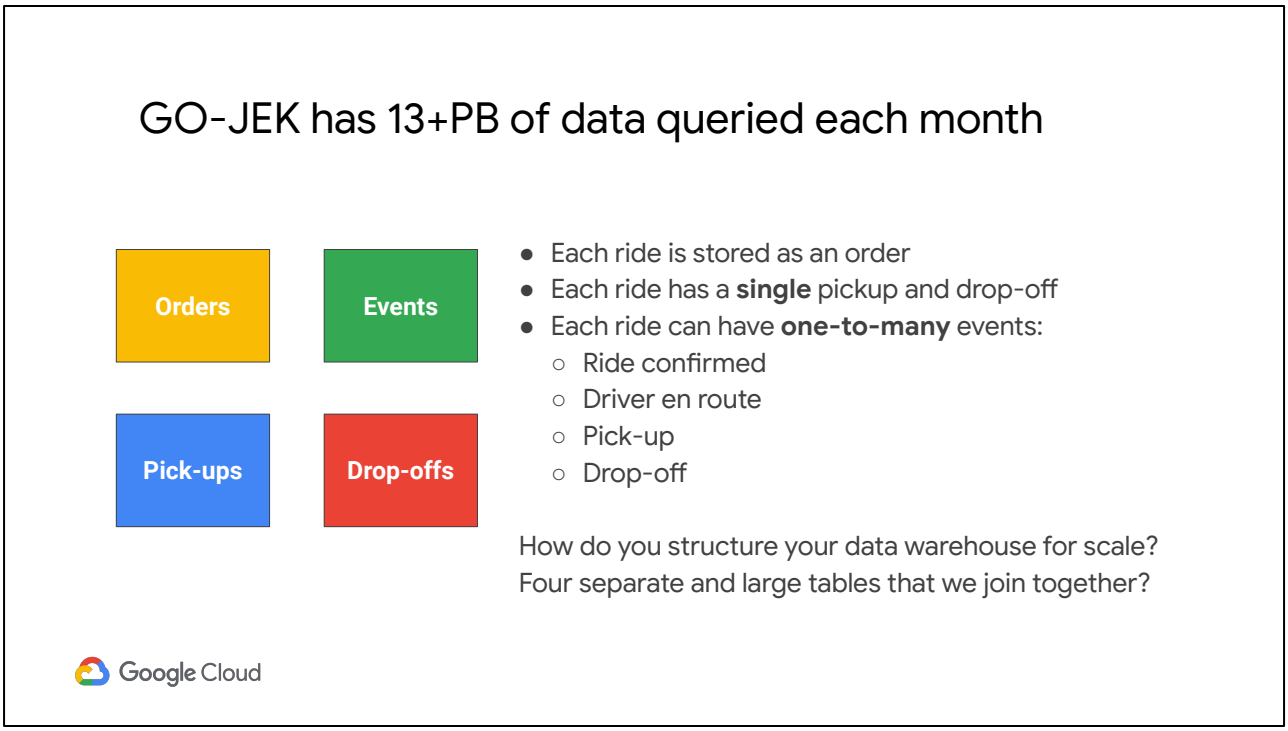
Preview: Transforming Batch and Streaming Data

Let's take a closer look at BigQuery's support for nested and repeated fields and why this is such a popular schema design for enterprises.



I'll illustrate by using an example from a real business running on GCP. GO-JEK is a ride booking service (among other services) based out of Indonesia...

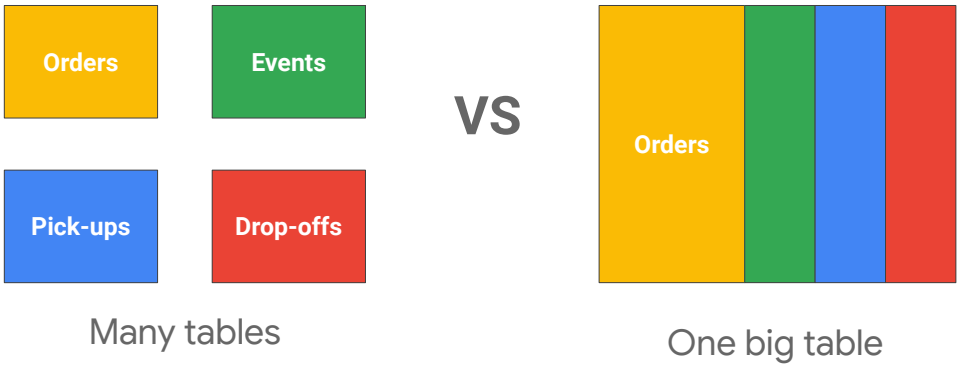


… and they process over a 13 petabyte of data on BigQuery per month from queries to support business decisions. What kind of decisions?

For GO-JEK, they track whenever a new customer places an order like hails a ride with their mobile app. That order is stored in an orders table. Each order has a single pick-up location and drop-off destination. For a single order, you could have one or many events like “Ride Ordered”, “Ride Confirmed”, “Drive En Route”, “Drop off Complete” etc.

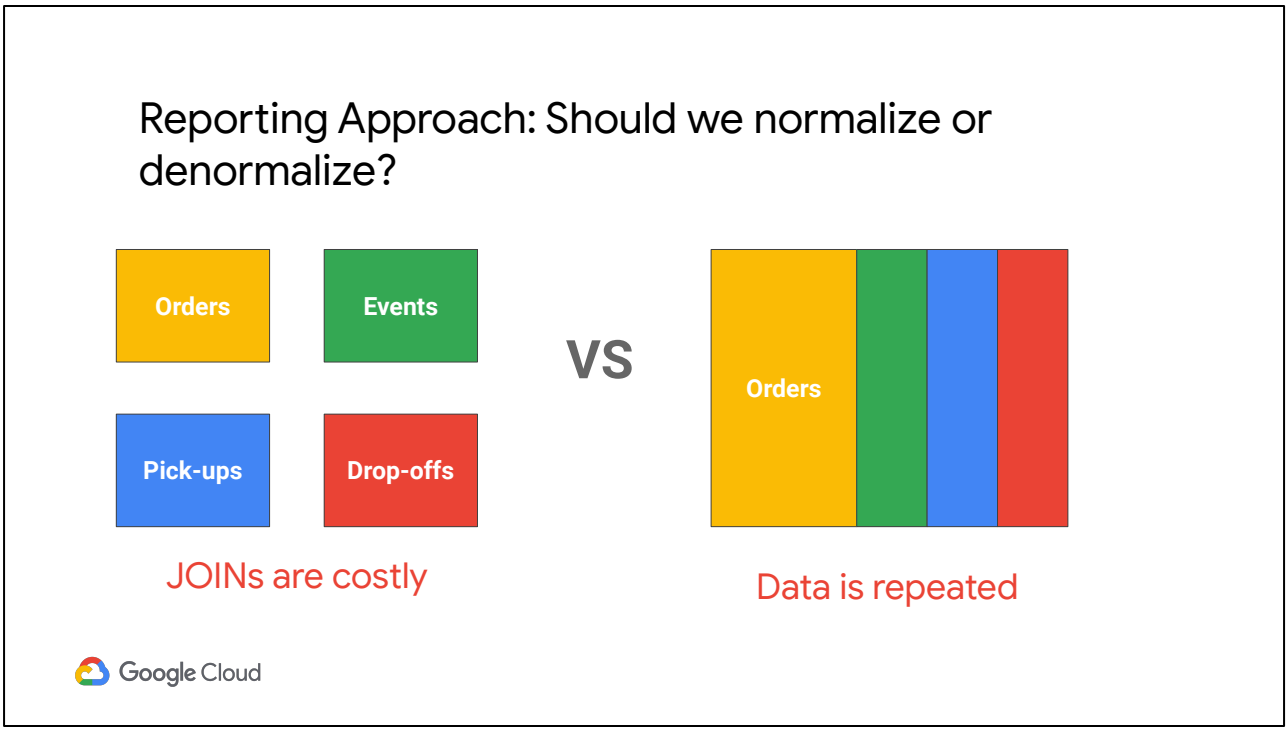
As a data engineer, how would you efficiently store these different pieces of data in your data warehouse? Keep in mind you need to support a large user base querying Petabytes per month.

Reporting Approach: Should we normalize or denormalize?



Google Cloud

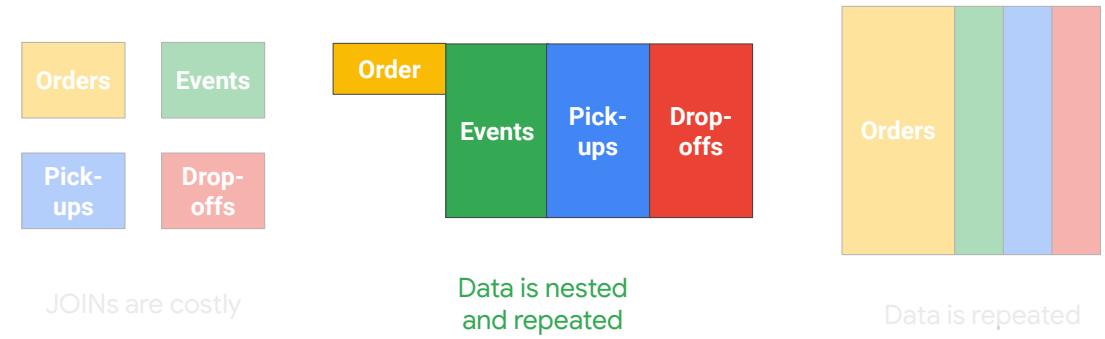
Well as you saw earlier, we could store one fact in one place with the normalization route which is typical for relational systems. Or we could go the fully denormalized route and just store all levels of granularity in a single big table where you would have one order id like ‘123’ repeated in a row for each event that happens on that order. Faster for querying sure but what are the drawbacks?



For relational schemas (normalized schemas) often the most intensive computational workloads are JOINS across very large tables. Remember RDBMS' are record based so they have to open each record entirely and pull out the join key from each table where a match exists. And that's assuming you know all the tables that need to be joined together! Imagine for each new piece of information about an order (like promotion codes, or user information) and you could be talking about a 10+ table join.

The alternative has different drawbacks. Pre-joining all your tables into one massive table makes reading data faster but you now have to be really careful if you have data at different levels of granularity. In our example, each row would be at the level of granularity of a specific event (like Driver Confirmed) for a given order. What does that mean for an OrderID like '123'? It is duplicated for each event on that order. Imagine if you're looking to join higher level information like the revenue per order and you now have to be exceedingly careful with aggregations to not double or triple count your duplicate OrderIDs. See the problem?

Nested and Repeated Fields allow you to have multiple levels of data granularity



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One common solution in enterprise data warehouse schemas is to take advantage of nested and repeated data fields. You can have ONE ROW for each order and repeated values within that ONE ROW for data that is at a more granular level. For example, you could simply have an ARRAY of timestamps as your events. Let's see an example to illustrate this point.

Store complex data with nested fields (ARRAYS)

Row	order_id	service_type	payment_method	event.status	event.time	pickup.latitude	pickup.longitude	destination.latitude	destination.longitude	total_distance_km	pricing_type
151	FD-5117	GO_FOOD	GOPAY	CREATED	2018-12-31 04:44:02.545210 UTC	-7.75105	110.410561	-7.7430367	110.4046433	1.56	regular
				COMPLETED	2018-12-31 05:06:27.897769 UTC						
				PICKED_UP	2018-12-31 04:48:25.945331 UTC						
				DRIVER_FOUND	2018-12-31 04:44:06.869010 UTC						
152	FD-6834	GO_FOOD	CASH	PICKED_UP	2018-12-31 12:49:52.518880 UTC	1.121272	104.049739	1.1368655	104.03322	4.84	surge
				DRIVER_FOUND	2018-12-31 12:40:14.214843 UTC						
				COMPLETED	2018-12-31 13:04:00.291780 UTC						
				CREATED	2018-12-31 12:40:13.431094 UTC						
153	FD-6293	GO_FOOD	PARTIAL_PAYMENT	PICKED_UP	2018-12-31 04:33:11.856445 UTC	-7.9657554	112.6247491	-7.9384084	112.6227862	4.68	regular
				COMPLETED	2018-12-31 04:56:05.885521 UTC						
				CREATED	2018-12-31 04:16:24.356539 UTC						
				DRIVER_FOUND	2018-12-31 04:16:25.643766 UTC						
154	FD-7817	GO_FOOD	CASH	COMPLETED	2018-12-31 09:14:44.897136 UTC	-6.353915	106.247312	-6.368896	106.25787	3.51	regular
				PICKED_UP	2018-12-31 09:01:11.471274 UTC						
				CREATED	2018-12-31 08:40:31.821796 UTC						
				DRIVER_FOUND	2018-12-31 08:40:32.910319 UTC						

Table JSON First < Prev Rows 151 - 154 of 1137 Next > Last

Google Cloud

Here you see it clearly. Shown here on screen are just 4 rows for 4 unique OrderIDs. Notice all that grey space in between the rows? That's because the event.status and event.time is at a deeper level of granularity. That means there are multiple repeated values for these events per each order. An ARRAY if a perfect data type to handle this repeated value and keep all the benefits of storing that data in a single row.

I mentioned the fields event.status and event.time. If this is one giant table, what is a dot doing in those column names? There are no other table aliases we've joined on … what's up with those fields?

Report on all data in once place with STRUCTS

Row	order_id	service_type	payment_method	event.status	event.time	pickup.latitude	pickup.longitude	destination.latitude	destination.longitude	total_distance_km	pricing_type
151	FD-5117	GO_FOOD	GOPAY	CREATED	2018-12-31 04:44:02.545210 UTC	-7.75105	110.410561	-7.7430367	110.4046433	1.56	regular
				COMPLETED	2018-12-31 05:06:27.897769 UTC						
				PICKED_UP	2018-12-31 04:48:25.945331 UTC						
				DRIVER_FOUND	2018-12-31 04:44:06.869010 UTC						
152	FD-6834	GO_FOOD	CASH	PICKED_UP	2018-12-31 12:49:52.518880 UTC	1.121272	104.049739	1.1368655	104.03322	4.84	surge
				DRIVER_FOUND	2018-12-31 12:40:14.214843 UTC						
				COMPLETED	2018-12-31 13:04:00.291780 UTC						
				CREATED	2018-12-31 12:40:13.431094 UTC						
153	FD-6293	GO_FOOD	PARTIAL_PAYMENT	PICKED_UP	2018-12-31 04:33:11.856445 UTC	-7.9657554	112.6247491	-7.9384084	112.6227862	4.68	regular
				COMPLETED	2018-12-31 04:56:05.885521 UTC						
				CREATED	2018-12-31 04:16:24.356539 UTC						
				DRIVER_FOUND	2018-12-31 04:16:25.643766 UTC						
154	FD-7817	GO_FOOD	CASH	COMPLETED	2018-12-31 09:14:44.897136 UTC	-6.353915	106.247312	-6.368896	106.25787	3.51	regular
				PICKED_UP	2018-12-31 09:01:11.471274 UTC						
				CREATED	2018-12-31 08:40:31.821796 UTC						
				DRIVER_FOUND	2018-12-31 08:40:32.910319 UTC						

Table JSON First < Prev Rows 151 - 154 of 1137 Next > Last

Google Cloud

Event, pickup, and destination are what are called STRUCT or structure data type fields in SQL. This isn't BigQuery specific, STRUCTS are standard SQL and BigQuery just supports them really well. STRUCTS you can think of as pre-joined tables within a table. So instead of having a separate table for EVENT and PICKUP and DESTINATION you simply NEST them within your main table.

So let's recap.

Nested ARRAY fields and STRUCT fields allow for differing data granularity in the same table

Row	order_id	service_type	payment_method	event.status	event.time	pickup.latitude	pickup.longitude	destination.latitude	destination.longitude	total_distance_km	pricing_type
151	FD-5117	GO_FOOD	GOPAY	CREATED	2018-12-31 04:44:02.545210 UTC	-7.75105	110.410561	-7.7430367	110.4046433	1.56	regular
				COMPLETED	2018-12-31 05:06:27.897769 UTC						
				PICKED_UP	2018-12-31 04:48:25.945331 UTC						
				DRIVER_FOUND	2018-12-31 04:44:06.869010 UTC						
152	FD-6834	GO_FOOD	CASH	PICKED_UP	2018-12-31 12:49:52.518880 UTC	1.121272	104.049739	1.1368655	104.03322	4.84	surge
				DRIVER_FOUND	2018-12-31 12:40:14.214843 UTC						
				COMPLETED	2018-12-31 13:04:00.291780 UTC						
				CREATED	2018-12-31 12:40:13.431094 UTC						
153	FD-6293	GO_FOOD	PARTIAL_PAYMENT	PICKED_UP	2018-12-31 04:33:11.856445 UTC	-7.9657554	112.6247491	-7.9384084	112.6227862	4.68	regular
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				PICKED_UP	2018-12-31 09:01:11.471274 UTC						
				CREATED	2018-12-31 08:40:31.821796 UTC						
				DRIVER_FOUND	2018-12-31 08:40:32.910319 UTC						

Table JSON First < Prev Rows 151 - 154 of 1137 Next > Last

Google Cloud

You can go deep into a single field and have it be more granular than the rest by using an ARRAY data type like you see here for STATUS and TIME.

And you can have really WIDE schemas by using STRUCTS which allow you to have multiple fields of the same or different data types within them (much like a separate table would). The major benefit of STRUCTs is that the data is conceptually pre-joined already so its much faster to query.

People often ask -- with really wide schemas (like a hundred columns) how is it still fast to query? Remember that BigQuery is column based storage not record based when storing data out on disk. If you did just a COUNT(order_id) here to get your total orders BigQuery wouldnt even care that you have 99 other columns some of which are more granular with ARRAY data types, It wouldn't even look at them. That gives you the best of both worlds if you're an analyst. Lots of data all in one place and no issues with multiple granularity pitfalls when doing aggregations.

Your turn

- Practice reading the new schema
- Spot the STRUCTS
- Type RECORD = STRUCTS

booking

Schema | Details | Preview

Field name	Type	Mode
order_id	STRING	NULLABLE
service_type	STRING	NULLABLE
payment_method	STRING	NULLABLE
event	RECORD	REPEATED
event. **status**	STRING	NULLABLE
event. **time**	TIMESTAMP	NULLABLE
pickup	RECORD	NULLABLE
pickup. **latitude**	FLOAT	NULLABLE
pickup. **longitude**	FLOAT	NULLABLE
destination	RECORD	NULLABLE
destination. **latitude**	FLOAT	NULLABLE
destination. **longitude**	FLOAT	NULLABLE
total_distance_km	FLOAT	NULLABLE
pricing_type	STRING	NULLABLE
duration	RECORD	NULLABLE
duration. **booking_to_dispatch**	FLOAT	NULLABLE
duration. **booking_to_pickup**	FLOAT	NULLABLE

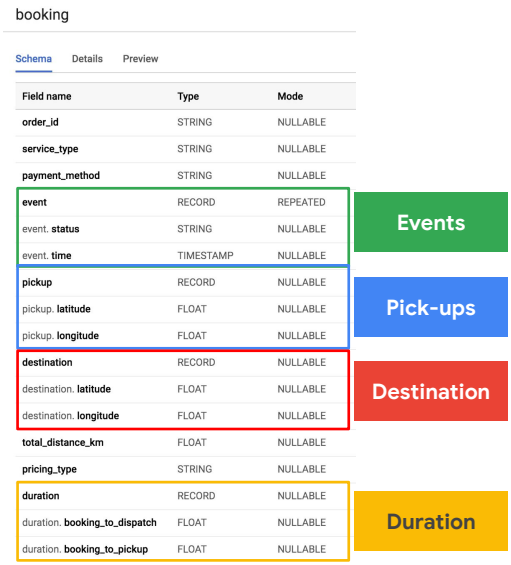
Google Cloud

Now it's your turn to practice reading one of these schemas that has nested and repeated fields. Take a moment and spot those STRUCTs. As a hint, you can look at the field name to see any field with a dot in the name OR you can look at the data type for any field values of the type RECORD (which means STRUCT). [Pause]

Did you get them all?

Practice reading the new schema

- Practice reading the new schema
- Spot the STRUCTS
- Type RECORD = STRUCTS



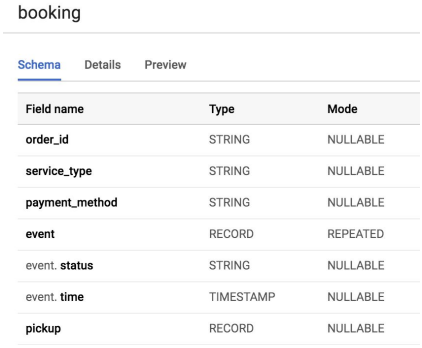
Google Cloud

Here are the four STRUCTs in this dataset you saw earlier. Events, pickups, destination, and duration. Duration is a new one but we can simply keep adding more dimensions to our dataset by adding more STRUCTs.

Remember STRUCTs let you build really wide and informative schemas. Now it's time to go deep.

Your turn

- Practice reading the new schema
- Spot the ARRAYS
- Hint: Look at Mode



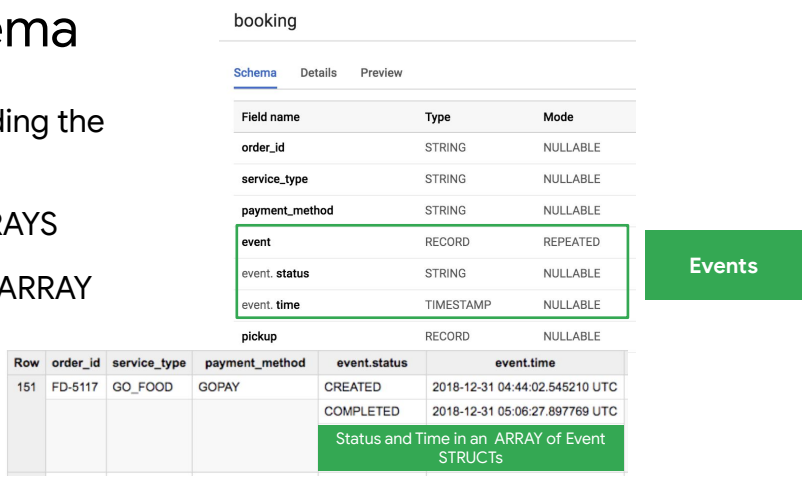
Google Cloud

Find the ARRAY data types in this schema. As a hint, look at the Mode and find the REPEATED values. [pause]

Got them?

Practice reading the new schema

- Practice reading the new schema
- Spot the ARRAYS
- REPEATED = ARRAY



Google Cloud

In this schema the repeated value is the EVENT STRUCT (which means here we have an ARRAY of EVENT STRUCTs with each having a status and time possibly)

A critical point I like to make here is that STRUCT and ARRAY data types in SQL can be absolutely independent of each other. You can have a regular column in SQL be an ARRAY column that has nothing to do with any STRUCT. Likewise, you can have a STRUCT that has zero array field types in it's columns. The benefit of using them together is ARRAYs allow a given field to go deep into granularity and STRUCTs allow you to organize all those useful fields into logical containers instead of separate tables.

Recap

- STRUCTS (RECORD)
- ARRAYS (REPEATED)
- ARRAYS can be part of regular fields or STRUCTS
- A single table can have many STRUCTS

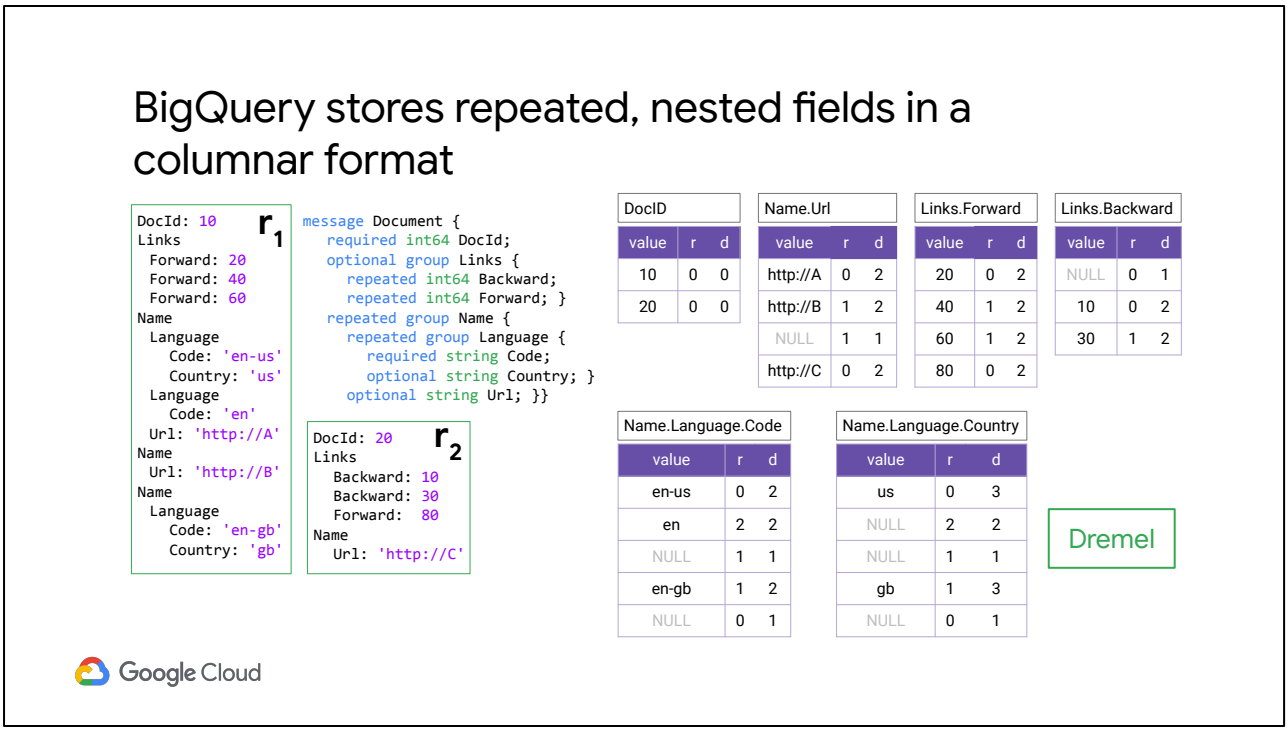
booking

Schema | Details | Preview

Field name	Type	Mode
order_id	STRING	NULLABLE
service_type	STRING	NULLABLE
payment_method	STRING	NULLABLE
event	RECORD	REPEATED
event. **status**	STRING	NULLABLE
event. **time**	TIMESTAMP	NULLABLE
pickup	RECORD	NULLABLE
pickup. **latitude**	FLOAT	NULLABLE
pickup. **longitude**	FLOAT	NULLABLE
destination	RECORD	NULLABLE
destination. **latitude**	FLOAT	NULLABLE
destination. **longitude**	FLOAT	NULLABLE
total_distance_km	FLOAT	NULLABLE
pricing_type	STRING	NULLABLE
duration	RECORD	NULLABLE
duration. **booking_to_dispatch**	FLOAT	NULLABLE
duration. **booking_to_pickup**	FLOAT	NULLABLE

Google Cloud

So here's the cheatsheet. STRUCTs are of type RECORD when looking at a schema and ARRAYs are of MODE repeated (Arrays can be of any single type, like an array of floats or an array of strings et.). ARRAYS can be part of a regular field or be part of a NESTED field nestled inside of a STRUCT. A single table can have zero to many STRUCTs and lastly, the real mind bending point, is that a STRUCT can have other STRUCTs nested inside of it as you will soon see in your upcoming lab which uses the real Google Analytics schema.



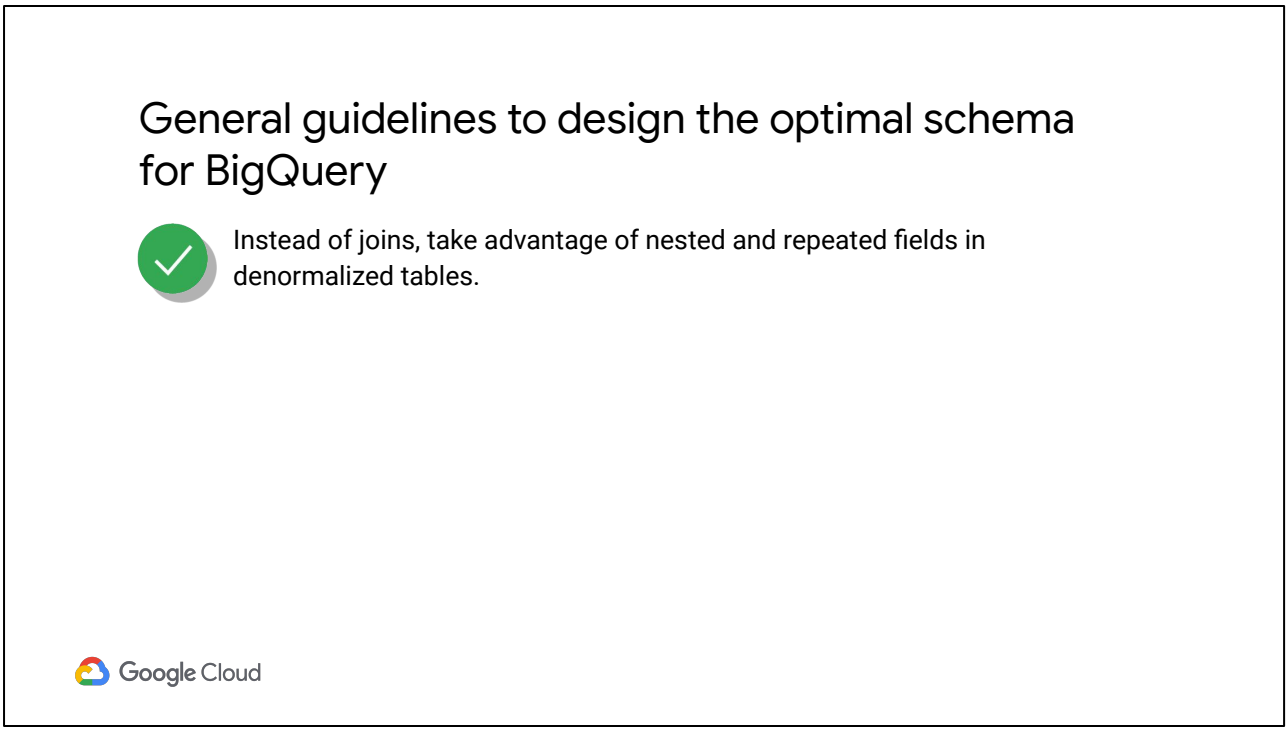
Lastly, if you really love this topic and how it all came about you can checkout the original Dremel white paper that Google published in 2010.

Dremel is the massively parallel SQL engine that powers BigQuery.

These diagrams come from that paper and explain how this nested structure is stored when you're using column-oriented storage. As you see here, every column, in addition to its value, also stores two numbers; definition and repetition levels.

This encoding ensures that the full or partial structure of the record can be reconstructed by reading only requested columns, and never requires reading parent columns, as is the case with alternative encodings. I'll link the white paper if you want to read more.
https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/36632.pdf

Demo Instructions:
https://github.com/GoogleCloudPlatform/training-data-analyst/tree/master/courses/data-engineering/demos



Let's recap some of the ways to design the schema of tables to improve query performance and lower query costs.

It's much more efficient to define your schema to use nested, repeated fields instead of joins.

Suppose you have orders and purchase items for each order. In a traditional RDBM system, you'd have two tables: one table for purchase items, and another for orders, with a foreign key to connect the two tables. In BigQuery, it's much more efficient if you store each order in a row and have a nested, repeated column called purchase_item. Arrays are a native type in BigQuery. Learn to think in terms of arrays.

General guidelines to design the optimal schema for BigQuery

- Instead of joins, take advantage of nested and repeated fields in denormalized tables.
- Keep a dimension table smaller than 10 gigabytes normalized, unless the table rarely goes through `UPDATE` and `DELETE` operations.

Google Cloud

When you have dimension tables that are smaller than 10 gigabytes, keep them normalized. The exception to this is if the table rarely goes through UPDATE and DELETE operations.

General guidelines to design the optimal schema for BigQuery

- Instead of joins, take advantage of nested and repeated fields in denormalized tables.
- Keep a dimension table smaller than 10 gigabytes normalized, unless the table rarely goes through `UPDATE` and `DELETE` operations.
- Denormalize a dimension table larger than 10 gigabytes, unless data manipulation or costs outweigh benefits of optimal queries.

Google Cloud

If you cannot define your schema in terms of nested, repeated fields, you have to make a decision on whether to keep the data in two tables or denormalize the tables into one big, flattened table.

As a dataset's tables increase in size, the performance impact of a join increases. At some point, it can be better to denormalize your data. The crossover point is around 10 GB. If your tables are less than 10 GB, keep the tables separate and do a join.

Agenda

The modern data warehouse

Intro to BigQuery

- Getting Started
- Loading Data
- Lab: Loading Data with Console and CLI

Exploring Schemas

- Schema Design
- Nested and Repeated Fields
- Lab: ARRAYs and STRUCTs
- Optimizing with Partitioning and Clustering

Preview: Transforming Batch and Streaming Data

In the next lab you'll get some experience working with JSON and array data in BigQuery.

Working with JSON and Array Data in BigQuery

Objectives

- Load semi-structured JSON into BigQuery
- Create and query arrays
- Create and query structs
- Query nested and repeated fields

The objectives of this lab are to load semi-structured JSON data into BigQuery, and to learn how to create and query arrays and structs.

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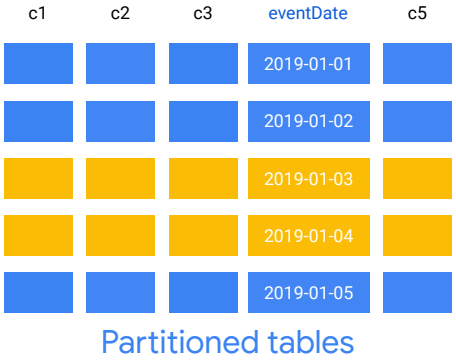
Preview: Transforming Batch and Streaming Data

Next up is Optimizing with Partitioning and Clustering

Reduce cost and amount of data read by partitioning your tables



SELECT c1, c3 FROM ...
WHERE eventDate BETWEEN
“2019-01-03” AND “2019-01-04”

Google Cloud

One of the way you can optimize the tables in your data warehouse is to reduce the cost and amount of data read by partitioning your tables.

For example, assume we have partitioned this table by the eventDate column. BigQuery will then change its internal storage so the dates are stored in separate shards.

In a table partitioned by a date or timestamp column, each partition contains a single day of data. When the data is stored, BigQuery ensures that all the data in a block belongs to a single partition. A partitioned table maintains these properties across all operations that modify it: query jobs, DML statements, DDL statements, load jobs, and copy jobs. This requires BigQuery to maintain more metadata than a non-partitioned table. As the number of partitions increases, the amount of metadata overhead increases.

Now, when you do a query with a WHERE clause that looks for dates between 01-03 and 01-04, BigQuery will have to read only two-fifths of the full dataset. This can lead to dramatic cost and time savings.

BigQuery supports three ways of partitioning tables

Ingestion time

```
bq query --destination_table mydataset.mytable
--time_partitioning_type=DAY
...
```

Any column that is of type DATE or TIMESTAMP

```
bq mk --table --schema a:STRING,tm:TIMESTAMP
--time_partitioning_field tm
```

Integer-typed column

```
bq mk --table --schema "customer_id:integer,value:integer"
--range_partitioning=customer_id,0,100,10 my_dataset.my_table
```

Google Cloud

You enable partitioning during the table-creation process. This slide shows how to migrate an existing table to an ingestion-time-partitioned table. Using a destination table, it will cost you one table scan.

As new records are added to the table, they will be put into the right partition. BigQuery creates new date-based partitions automatically, with no need for additional maintenance. In addition, you can specify an expiration time for data in the partitions.

Partitioning can be set by ingestion time, on a date/time column, or based on a range of an integer column. Here, we are partitioning customer_id in the range 0 to 100 in increments of 10.

Partitioning can improve query cost and performance by reducing data being queried

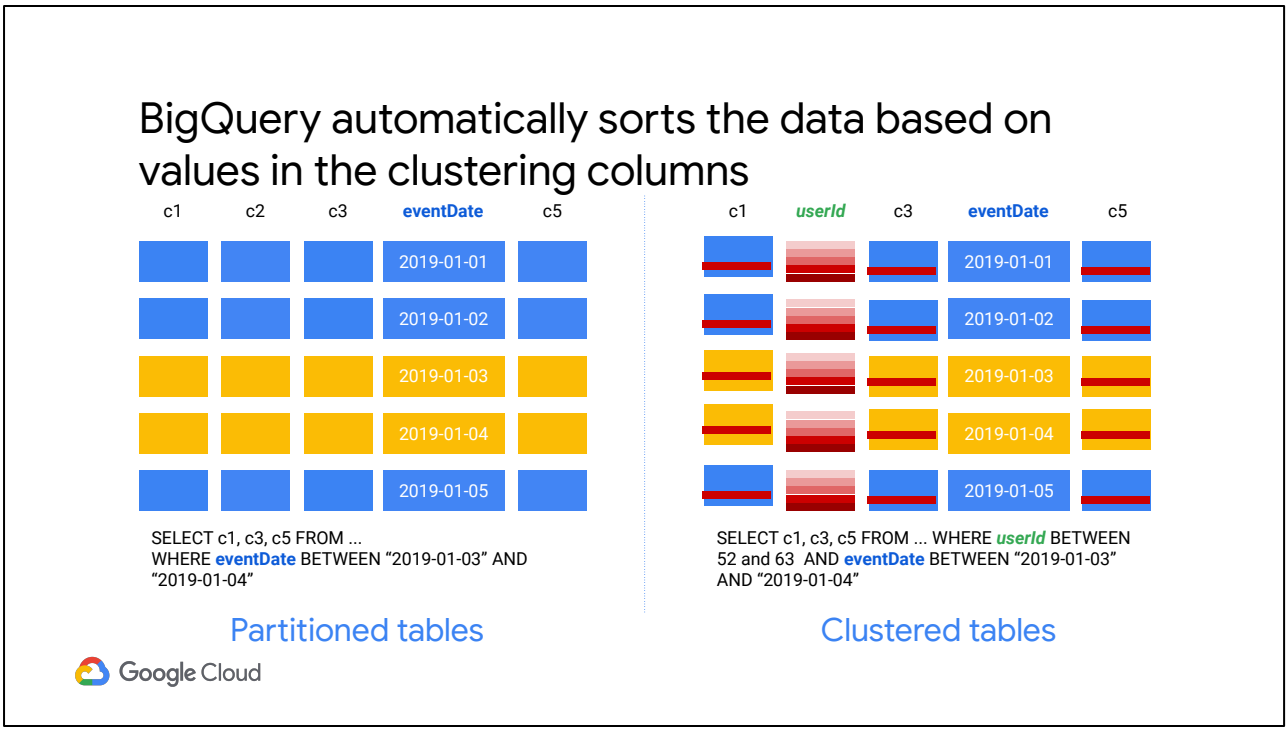
```
SELECT
  field1
FROM
  mydataset.table1
WHERE
  _PARTITIONTIME > TIMESTAMP_SUB(TIMESTAMP('2016-04-15'), INTERVAL 5 DAY)
```

Isolate the partition field in the left-hand side of the query expression!

```
bq query \
--destination_table mydataset.mytable
--time_partitioning_type=DAY --require_partition_filter
...
```

Google Cloud

Although more metadata must be maintained, by ensuring that data is partitioned globally, BigQuery can more accurately estimate the bytes processed by a query before you run it. This cost calculation provides an upper bound on the final cost of the query. A good practice is to require that queries always include the partition filter. Make sure that the partition field is isolated on the left side, because that's the only way BigQuery can quickly discard unnecessary partitions.

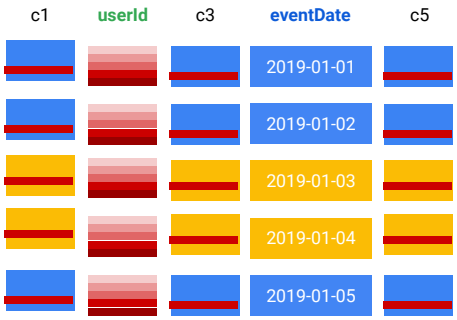


Clustering can improve the performance of certain types of queries, such as queries that use filter clauses and those that aggregate data. When data is written to a clustered table by a query or load job, BigQuery sorts the data using the values in the clustering columns. These values are used to organize the data into multiple blocks in BigQuery storage. When you submit a query containing a clause that filters data based on the clustering columns, BigQuery uses the sorted blocks to eliminate scans of unnecessary data.

Similarly, when you submit a query that aggregates data based on the values in the clustering columns, performance is improved because the sorted blocks co-locate rows with similar values.

In this example, the table is partitioned by eventDate and clustered by userId. Now, because the query looks for partitions in a specific range, only 2 of the 5 partitions are considered.
Because the query looks for userId in a specific range, BigQuery can jump to the row range and read only those rows for each of the columns needed.

Set up clustering at table creation time




```
CREATE TABLE mydataset.myclusteredtable
 (
   c1 NUMERIC,
   userId STRING,
   c3 STRING,
   eventDate TIMESTAMP,
   C5 GEOGRAPHY
  )
PARTITION BY DATE(eventDate)
CLUSTER BY userId
OPTIONS (
   partition_expiration_days=3,
   description="cluster")
AS SELECT * FROM mydataset.myothertable
```

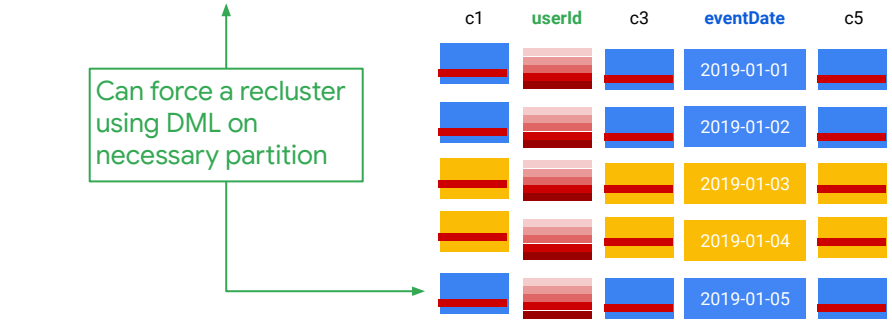
Google Cloud

You set up clustering at table creation time. Here, we are creating the table, partitioning by eventDate, and clustering by userId. We are also telling BigQuery to expire partitions that are more than 3 days old.

The columns you specify in the cluster are used to co-locate related data. When you cluster a table using multiple columns, the order of columns you specify is important. The order of the specified columns determines the sort order of the data.

In streaming tables, the sorting fails over time, and so BigQuery has to recluster

```
UPDATE ds.table
SET c1 = 300
WHERE c1 = 300
AND eventDate > TIMESTAMP_SUB(CURRENT_TIMESTAMP(), INTERVAL 1 DAY)
```



Google Cloud

Over time, as more and more operations modify a table, the degree to which the data is sorted begins to weaken, and the table becomes only partially sorted. In a partially sorted table, queries that use the clustering columns may need to scan more blocks compared to a table that is fully sorted. You can re-cluster the data in the entire table by running a SELECT * query that selects from and overwrites the table, but guess what! You don't need to do that anymore.

BigQuery will automatically recluster your data

Automatic re-clustering

free

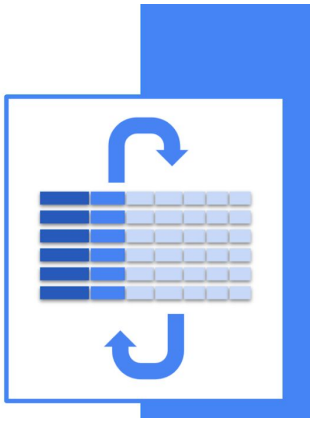
Doesn't consume your query resources

maintenance-free

Requires no setup or maintenance

autonomous

Automatically happens in the background



Google Cloud

The great news is that BigQuery now periodically does auto-reclustering for you so you don't need to worry about your clusters getting out of date as you get new data.

Automatic re-clustering is absolutely free and automatically happens in the background -- you dont need to do anything additional to enable it.

https://cloud.google.com/blog/products/data-analytics/whats-happening-bigquery-adding-speed-and-flexibility-10x-streaming-quota-cloud-sql-federation-and-more
https://cloud.google.com/bigquery/docs/clustered-tables#automatic_re-clustering

Organize data through managed tables

Partitioning

Filtering storage before query execution begins to reduce costs.

Reduces a full table scan to the partitions specified.

A single column results in lower cardinality (e.g., thousands of partitions).

- Time partitioning (Pseudocolumn)
- Time partitioning (User Date/Time column)
- Integer range partitioning

Clustering

Storage optimization within columnar segments to improve filtering and record colocation.

Clustering performance and cost savings can't be assessed before query begins.

Prioritized clustering of up to 4 columns, on more diverse types (but no nested columns).

BigQuery supports clustering for both partitioned and non-partitioned tables. Partitioning provides a way to obtain accurate cost estimates for queries and guarantees improved cost and performance. Clustering provides additional cost and performance benefits in addition to the partitioning benefits.

Demo Instructions:
https://github.com/GoogleCloudPlatform/training-data-analyst/tree/master/courses/data-engineering/demos

When to use clustering

Your data is already partitioned on a `DATE` or `TIMESTAMP` or Integer Range

You commonly use filters or aggregation against particular columns in your queries.

Google Cloud

BigQuery supports clustering for both partitioned and non-partitioned tables.

When you use clustering and partitioning together, the data can be partitioned by a date or timestamp column and then clustered on a different set of columns. In this case, data in each partition is clustered based on the values of the clustering columns. Partitioning provides a way to obtain accurate cost estimates for queries.

Keep in mind if you don't have partitioned columns and you want the benefits of clustering you can create a fake_date column of type DATE and have all the values be NULL.

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Preview: Transforming Batch and Streaming Data

In the next section we're going to discuss transforming data.

What if your data is not usable in its original form?

Extract, Transform, and Load

Data Processing

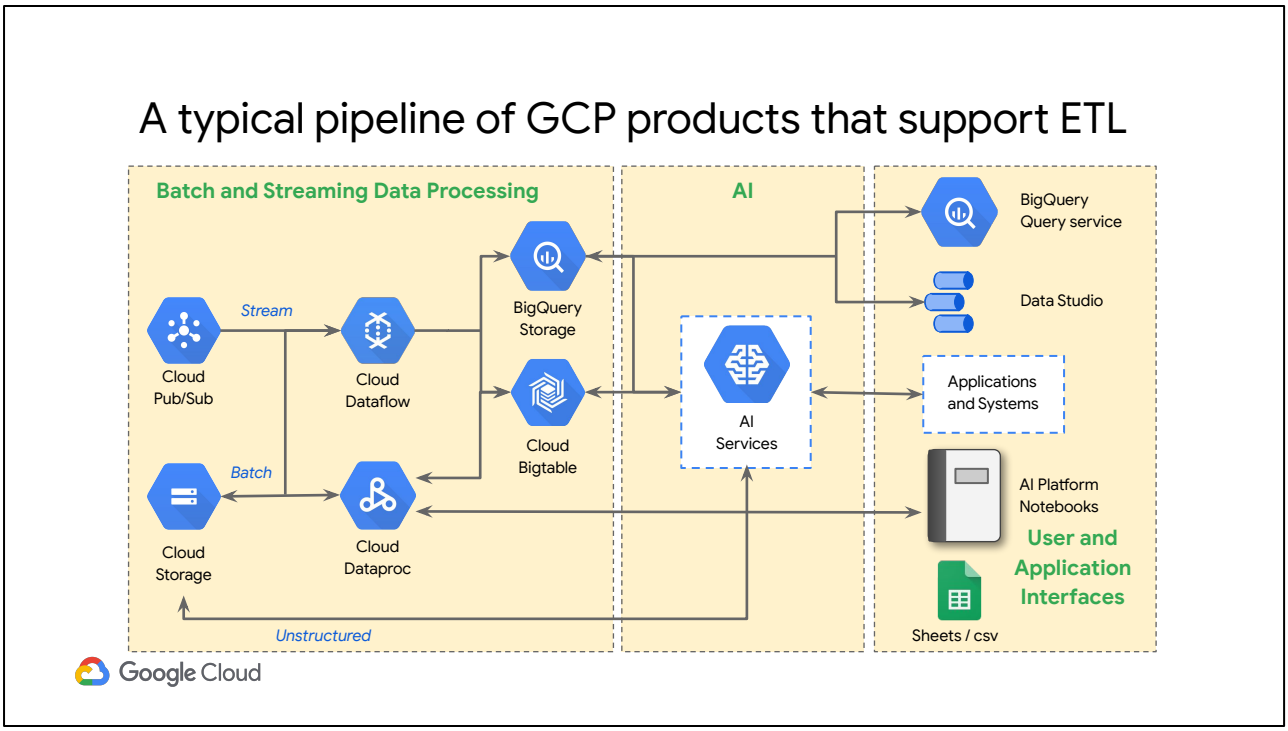
Cloud Dataproc

Cloud Dataflow

Data is processed in an intermediate system before it is loaded into the analytics warehouse.

Google Cloud

What if your incoming data is not usable in its raw form? We'll learn how to deal with this situation in the next course on data processing.



A few years ago it would have been easy to put this schematic into one diagram. The technology and market have evolved significantly since then, making it difficult to capture everything in one diagram.

This is not a consistent or complete schematic, but it does give you a sense of how everything fits together. You can see the 7 services--the main trees among the forest--that will help you find the pathways through the cloud necessary for data engineering.

Cloud Pub/Sub sends streaming data into Cloud Dataflow. Cloud Dataflow stores the data and transforms it in BigQuery or in Cloud Bigtable. Cloud Storage holds batch data and sends it to Cloud Dataproc or to Cloud Dataflow.

This outlines the data processing solutions. Then you add in Artificial Intelligence services and finally, the user and business interfaces.

What if your data arrives continuously and endlessly?

Streaming Data Processing

Cloud Pub/Sub

Cloud Dataflow

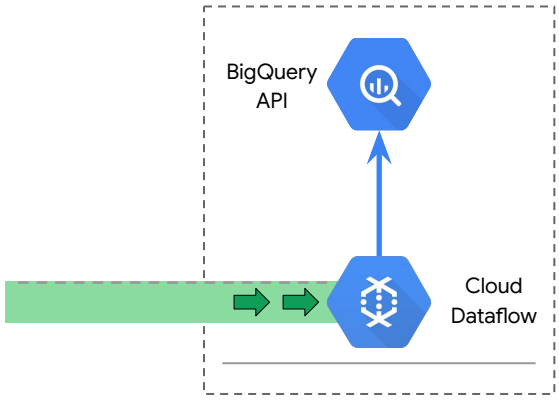
BigQuery

Data flows are buffered and processed rapidly in pipelines.

Google Cloud

If you have endless streaming data, Google Cloud has several tools to help process it. These are primarily Cloud Pub/Sub, Cloud Dataflow, and Cloud Bigtable. We'll cover these in the next course.

Some data is real-time and streamed into BigQuery by inserting records into tables via Cloud Dataflow



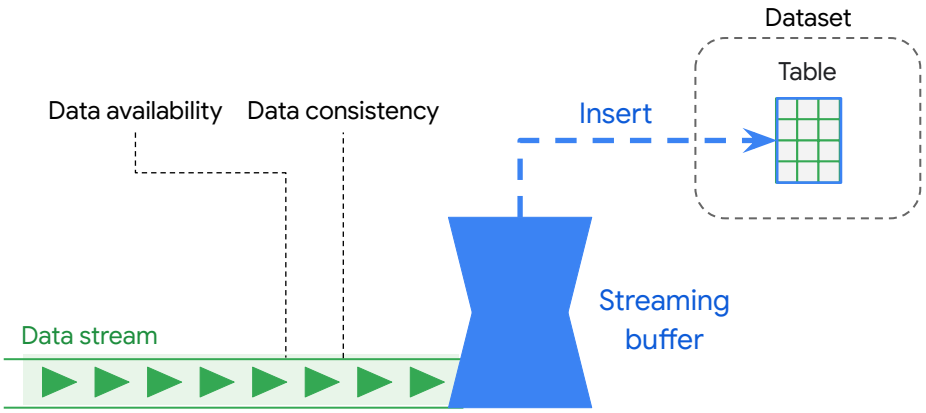
Insert records into tables from streams (unbounded) using a Dataflow pipeline

Google Cloud

You can stream real-time data directly into BigQuery or process it first with Cloud Dataflow.

Streams are unbounded, meaning that there is no defined end. This creates a special challenge for algorithms that normally rely on the end of data to trigger some action. This discussion is continued in the course on streaming data processing.

You can also use the BigQuery streaming API directly



Google Cloud

Streaming is not a load job. Rather, it is a separate BigQuery method called "streaming inserts." This method allows you to insert one item at a time into a table. New tables can be created from a template table that identifies the schema to be copied. Usually the data is available in seconds. The data enters a streaming buffer, where it is held briefly until it can be inserted into the table.

Data availability and consistency are considerations for streaming data. Candidates for streaming are analysis or applications that are tolerant of late or missing data or data arriving out of order or duplicated. The stream can pass through other services, introducing additional latency and the possibility of errors.

Because streaming data is unbounded, you need to consider the streaming quotas. There is both a daily limit and a concurrent rate limit. You can find more information about these in the online documentation.

When should you ingest a stream of data instead of using a batch approach to load data? When the immediate availability of the data is a solution requirement. In most cases, loading batch data is not charged. Streaming is charged. Use batch loading or repeated batch loading instead of streaming, unless that is a requirement of the application.

Recap

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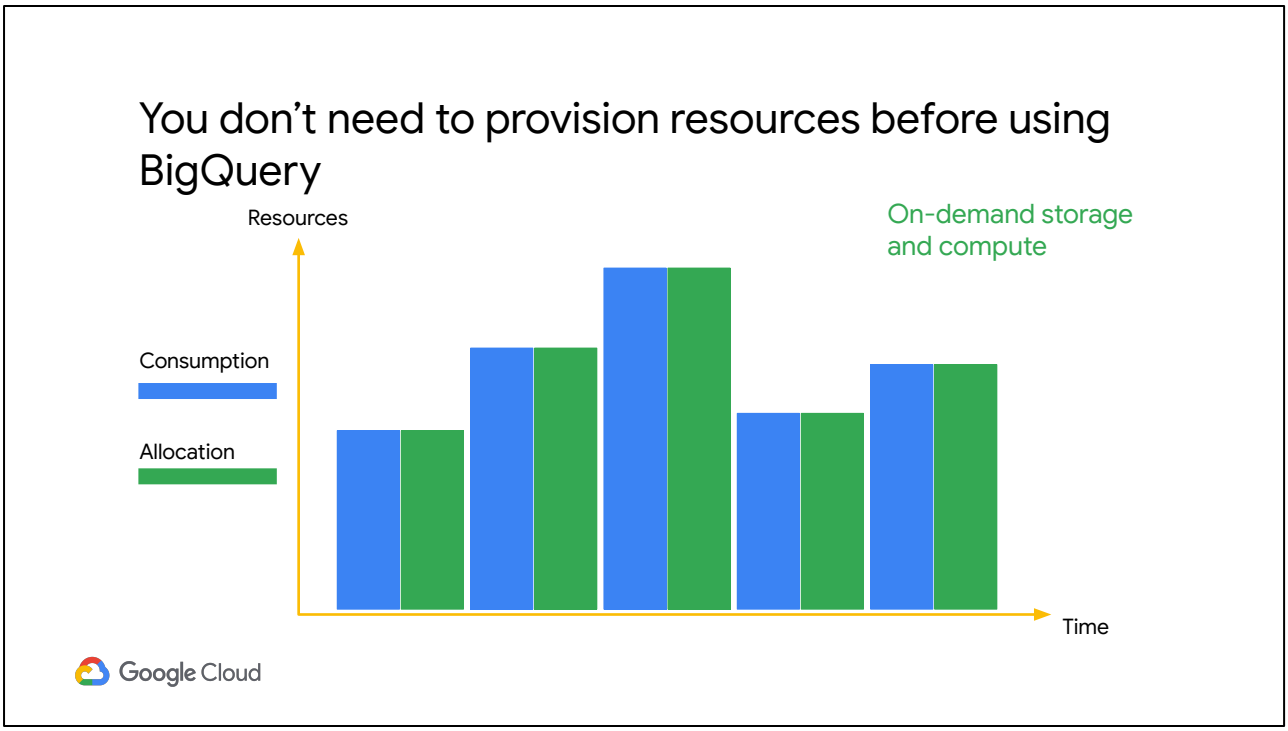
Let’s summarize what we’ve learned.

A modern data warehouse

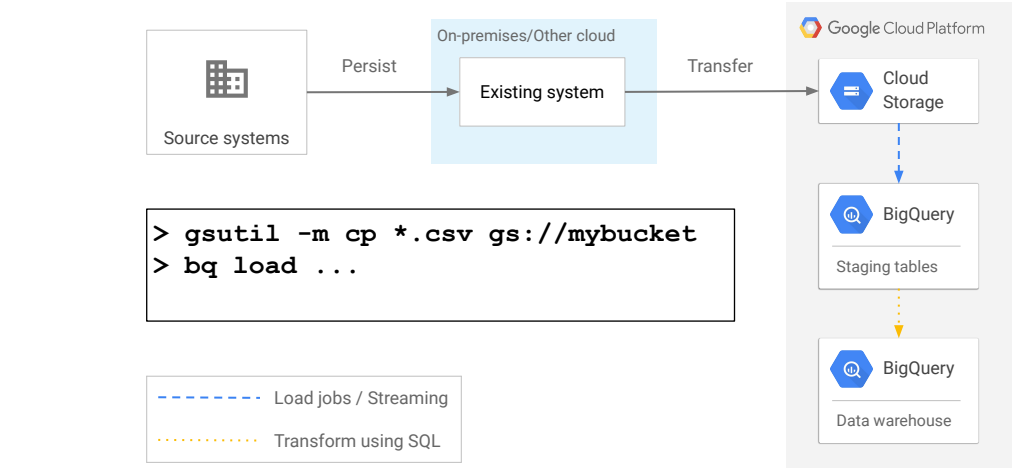
- Gigabytes to petabytes
- Serverless and no-ops, including ad hoc queries
- Ecosystem of visualization and reporting tools
- Ecosystem of ETL and data processing tools
- Up-to-the-minute data
- Machine learning
- Security and collaboration

In this module we discussed some of the requirements of a modern data warehouse. [pause]



We introduced BigQuery as the scalable data warehouse solution on Google Cloud Platform. Recall that you You don't need to provision resources before using BigQuery, unlike with many RDBM systems. BigQuery allocates storage and query resources dynamically based on your usage patterns.

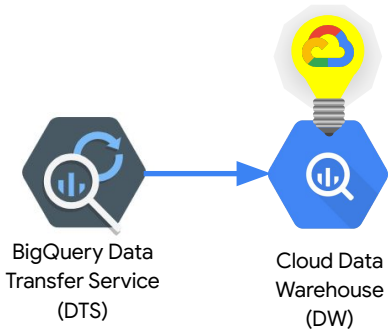
Loading data through Cloud Storage



Google Cloud

We discussed how you can load your raw data into your Data Lake which you could stage in a Google Cloud Storage bucket before processing it into your Data Warehouse for analytic workloads.

BigQuery Data Transfer Service helps you build and manage your data warehouse



EL

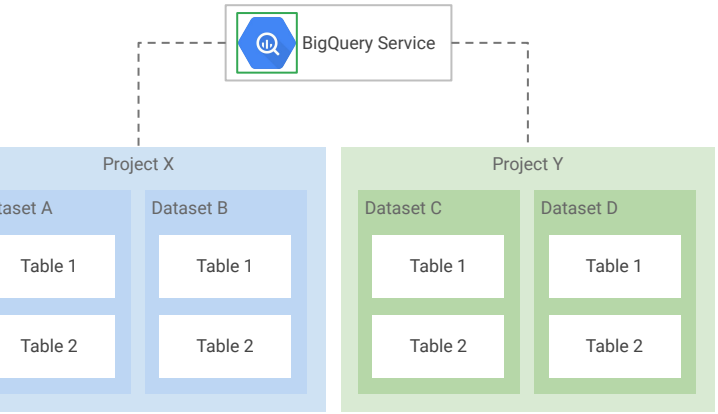
- Managed service
- Automatic transfers
- Scheduled
- Data staging
- Data processing
- Data backfills

Google Cloud

We talked about the BigQuery Data Transfer Service which helps you build and manage your data warehouse. With this service you can quickly schedule queries and transfers and more.

BigQuery organizes data tables into units called datasets

`project.dataset.table`

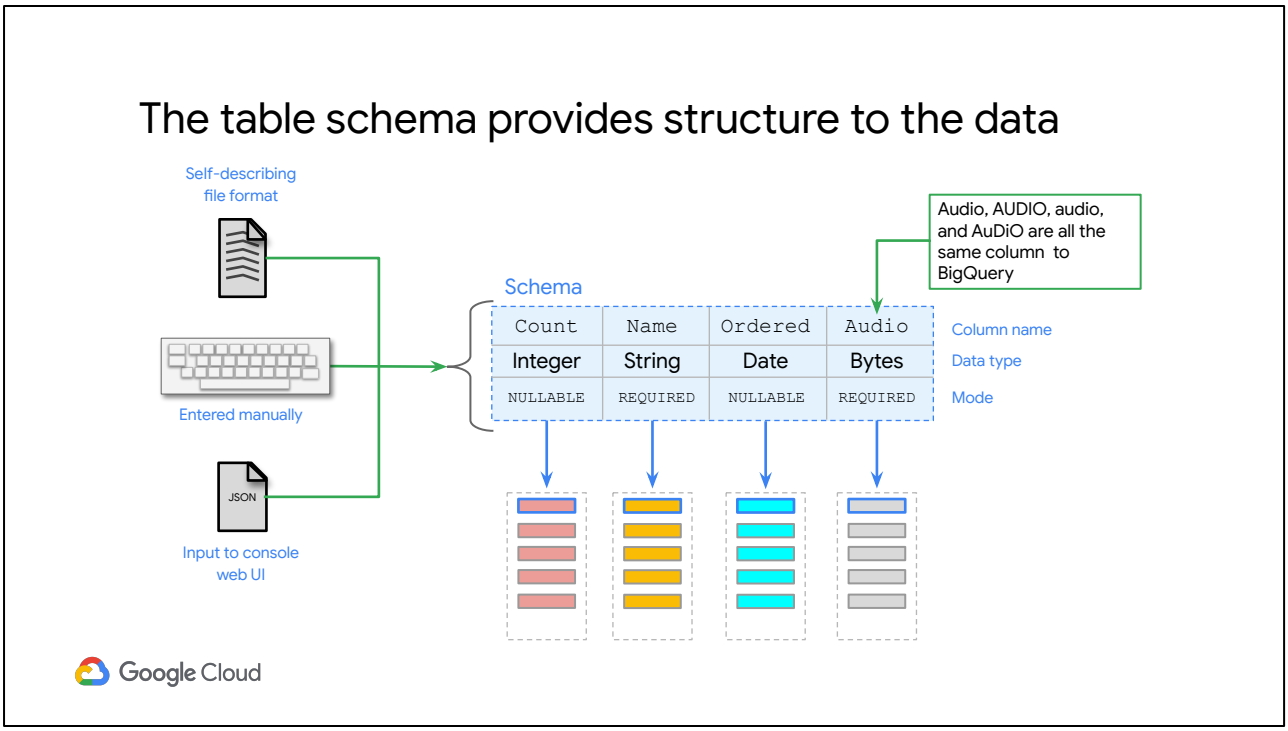


What are some reasons to structure your information into:

- Datasets?
- Projects?
- Tables?

Google Cloud

We examined core BigQuery concepts like how it organizes data at the project, dataset, and table level.

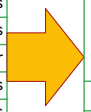


Remember that every table has a schema which you can enter manually or provide a JSON file for.

Nested and repeated columns improve the efficiency of BigQuery with relational source data

Denormalized flattened table

Product Name	OrderID	Date	Quantity
Siding	1600p	08/20/2019	3 boxes
Caulk	1600p	08/20/2019	12 tubes
Soffit	221b	10/29/2019	17 meters
Sealant	221b	11/05/2019	1 liter
Soffit	1600p	09/09/2018	34 meters
Siding	221b	08/20/2019	2 boxes
Caulk	221b	09/09/2019	4 tubes
Sealant	1600p	08/20/2018	2 liters



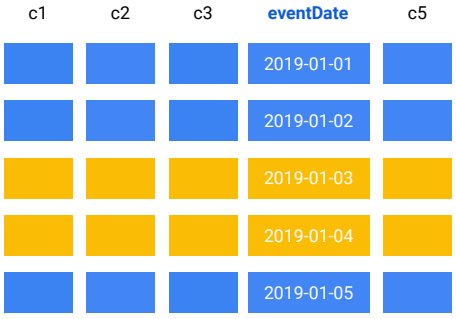
Denormalized with nested and repeated data

Order.ID	Order.Date	Order.Product_Name	Order.Quantity
1600p	08/20/2019	Siding	3 boxes
		Caulk	12 tubes
		Soffit	34 meters
		Sealant	2 liters
221b	10/29/2019	Soffit	17 meters
		Sealant	1 liter
		Siding	2 boxes
		Caulk	4 tubes

Google Cloud

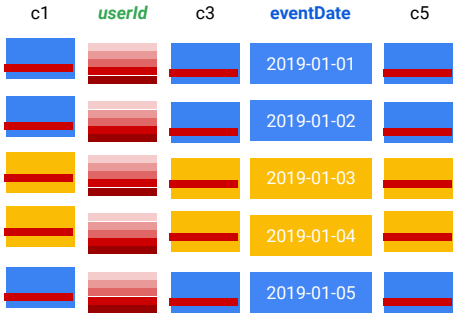
Those table schemas can also have ARRAY data types which makes them REPEATED and/or STRUCT data types which makes them nested. This type of denormalization will often give you a performance boost because it avoids intensive joins.

BigQuery automatically sorts the data based on values in the clustering columns



SELECT c1, c3 FROM ...
WHERE **eventDate** BETWEEN "2019-01-03" AND "2019-01-04"

Partitioned tables



SELECT c1, c3 FROM ... WHERE ***userId*** BETWEEN 52 and 63 AND **eventDate** BETWEEN "2019-01-03" AND "2019-01-04"

Clustered tables

Google Cloud

Lastly, we discussed how you can setup table partitioning and clustering to reduce the amount of data scanned and speed up your queries.

That's it for data warehousing -- next in the course we will cover batch and streaming processing and you will practice building pipelines to get your new datasets into BigQuery.