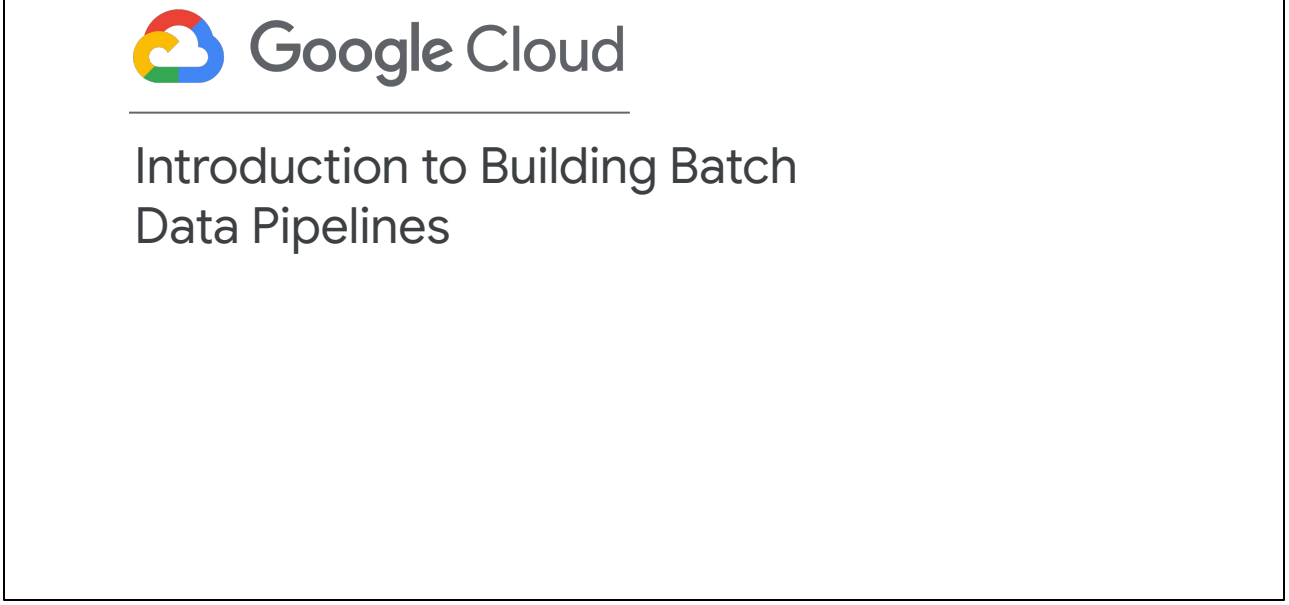


What are batch pipelines?
These are pipelines that process a *bounded* amount of data and then exit.
For example, you might have a batch pipeline that runs once a day. It takes all the credit and debit and money transfer transactions over that day, balances the books, and writes out the reconciled data to the data warehouse.

Agenda

EL, ELT, ETL

Quality Considerations

How to Carry out Operations in BigQuery

Shortcomings

ETL to Solve Data Quality Issues

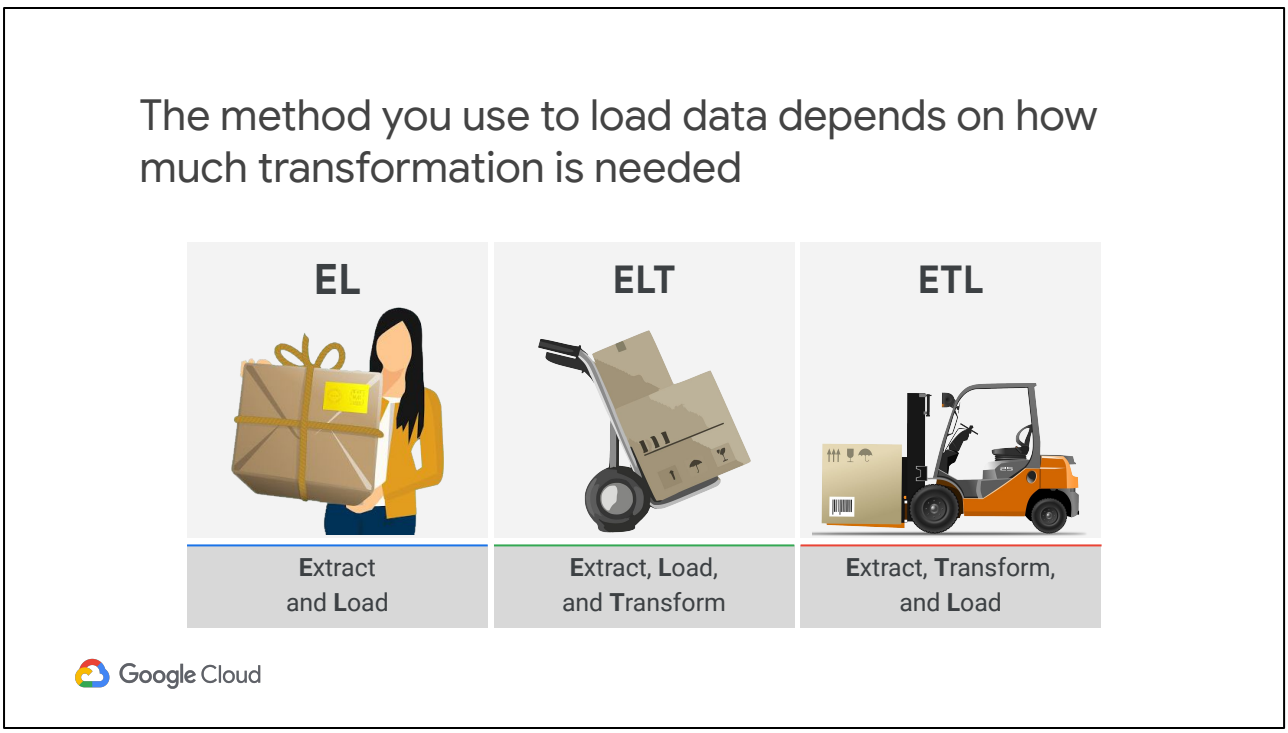
Google Cloud

If you are going to write such a pipeline, to balance the books, should you use EL, ELT or ETL?

EL, remember is extract-and-load.
ELT loads the data as-is and then transforms on the fly.
ETL extracts the data, transforms it, then loads it into data warehouse.

We'll look at which when to use.
How it depends on the kinds of transformations you need, and how these in turn hinge on quality considerations.

We will look at how to build EL and ELT pipelines in BigQuery, the places where EL and ELT aren't enough and why you might want ETL.



EL is Extract and Load. This refers to when data can be imported "as is" into a system. Examples include importing data from a database, where the source and the target have the same schema.
The idea is to bring all the transactions, store them into a table, without the need for any transformations.
Will that work for the use case of reconciling the books every night? The danger is that you will have unreconciled transactions sitting around in the data warehouse. Your analytic reports might be quite wrong and raise a lot of alarms.

ELT allows raw data to be loaded directly into the target and transformed whenever it is needed. For example, you might provide access to the raw data through a view that determines whether the user wants all transactions or only reconciled ones.
The view is going to be doing quite a bit of work if you choose this. When the amount of transformation you need is a lot, you might want to bring in the heavy machinery. That's ETL.

Extract, Transform, Load (ETL) is a data integration process in which transformation takes place in an intermediate service before it is loaded into the target. For example, the data might be transformed in Cloud Dataflow before being loaded into BigQuery.
ETL is the most appropriate here. We will pull all the transactions data and carry out processing to reconcile it, and then write the reconciled transactions to the data warehouse, leaving unreconciled transactions to the next time that the batch job runs. Of course, if some transaction has not been reconciled for about 15 days, you might do something about it …

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When would you use EL?

Architecture	When you'd do it
Extract data from files on Cloud Storage Load it into BigQuery's native storage You can trigger this from Cloud Composer, Cloud Functions, or scheduled queries	Batch load of historical data Scheduled periodic loads of log files (e.g. once a day) But only if the data is already clean and correct!

When would you use EL?

Bottom line: you should EL only if the data are already clean and correct.

Perhaps you have log files in Google Cloud Storage.
You can

- Extract data from files on Google Cloud Storage
- Load it into BigQuery's native storage

This is a simple REST API call.

You can trigger this pipeline from Cloud Composer, Cloud Functions, or scheduled queries

You might even set it to work in microbatches -- not quite streaming, but near-real-time: whenever a new file hits Cloud Storage, the cloud function runs, and the function invokes a bigquery job.
The Data Transfer Service in BigQuery will also work here.

Use EL for batch loading historical data, or do scheduled loads of log files.

But let me emphasize: use EL only if the data are already clean and correct.

When would you use ELT?

Architecture	When you'd do it
Extract data from files in Cloud Storage into BigQuery. Transform the data on the fly using BigQuery views, or store into new tables.	Experimental datasets where you are not yet sure what kinds of transformations are needed to make the data useable. Any production dataset where the transformation can be expressed in SQL.

Google Cloud

ELT starts with EL.
So, the loading is the same and could work the same way.
File hits Cloud Storage, function invokes BigQuery load, table appended to.

The big difference is what happens next.
The table might be stored in a private dataset.
And everyone accesses the data through a view which imposes data integrity checks.

Or maybe you have a job that runs a SQL query with a destination table.
This way, transformed data is stored in a table that everyone accesses.

When do you use ELT?
One common case is when you don't know kinds of transformations are needed to make the data useable.
For example, let's say someone uploads a new image. You invoke the Cloud Vision API and back comes a long JSON message about all kinds of things in the image. Text in the image. Whether there's a landmark. A logo. What objects.
What will an analyst need in the future. You don't know. So, you store the raw JSON as-is. Later, if someone wants to count the number of times a specific company's logos are in this set of images, they can extract logos from the JSON and then count them.

Of course, this works only if the transformation that's needed can be expressed in SQL

In the case of the Vision API, the result is JSON, and BigQuery SQL has support for JSON parsing. So, ELT will work in this case.

Agenda

EL, ELT, ETL

Quality Considerations

How to Carry out Operations in BigQuery

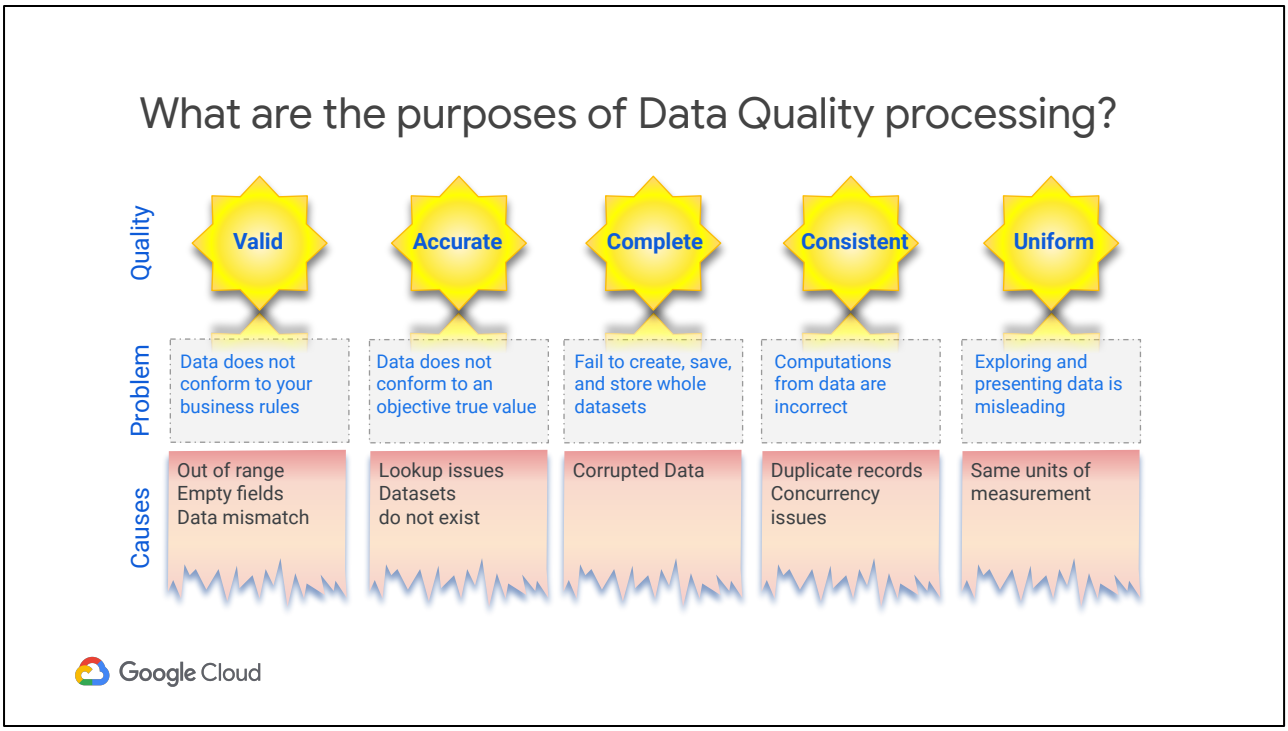
Shortcomings

ETL to Solve Data Quality Issues

Google Cloud

Now that we have looked at EL and ELT, let's look at some of the transformations you might want to do, and how they can be done in BigQuery.

To keep things tractable, let's assume that our data processing needs all revolve around quality improvements.



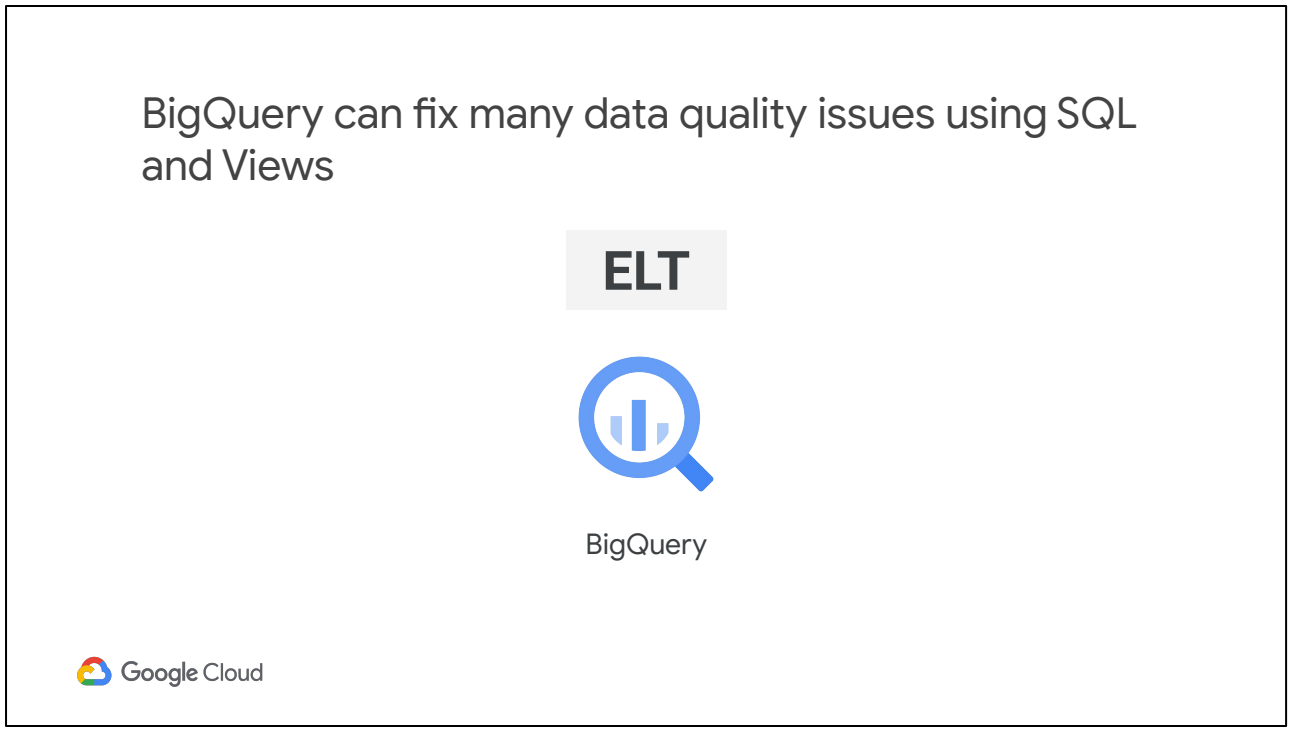
What are some of the quality-related reasons why we might want to process data?

The top row are characteristics of information -- information can be valid, accurate, complete, consistent and/or uniform. These terms are defined in the science of logic. Each is independent. For example, data can be complete without being consistent. It can be valid without being uniform. There are formal definitions for each of these terms that you can look up online. But the main practical reason for seeking them is shown in the second row -- the problems they present in Data Analysis. It is one thing to seek each of the five badges for your data; to have objectively good data quality. However, it is another thing when poor quality data interferes with Data Analysis and leads to incorrect business decisions. So the reason to spend time, energy, and resources detecting and resolving quality issues is that it can affect a business outcome.

Thus, if data does not conform to your business rules, you have a problem of validity. For example, let's say that you sell movie tickets, and each ticket costs $10. If you have a $7 transaction, then you have a validity problem.
Similarly, accuracy problems are due to data not conforming to objective truth. Completeness has to do with failing to process everything. Consistency problems are if two different operations that ought to be the same yield different results, and because you don't know what to trust, you can't derive insights from the data. Uniformity is data values of the same column in different rows mean different things.

The main causes of these problems are listed in the third row. I'll pause a bit to give

you time to read them. In the next slides we will explore methods of detecting each of these issues in data.



Now you have found the problems. What do you do about them?

ELT in BigQuery can often help fix many data quality issues.
Here is an example. Imagine you plan to analyze data but there are duplicate records making it seem like one kind of event is more common, when in fact this is just a data quality issue.
You cannot derive insights from the data until the duplicates are removed.

So, do you need a transformation step to remove the duplicates before you store the data?

Maybe ...

But a simpler solution exists, to count unique records. You do, of course, have COUNT DISTINCT in BigQuery and you can use that instead.

Similarly, a problem like data being out of range can be solved in BigQuery without an intermediate transformation step.
Invalid data can be filtered out using a BigQuery view, and everyone can access the view rather than the raw data.

Agenda

EL, ELT, ETL

Quality Considerations

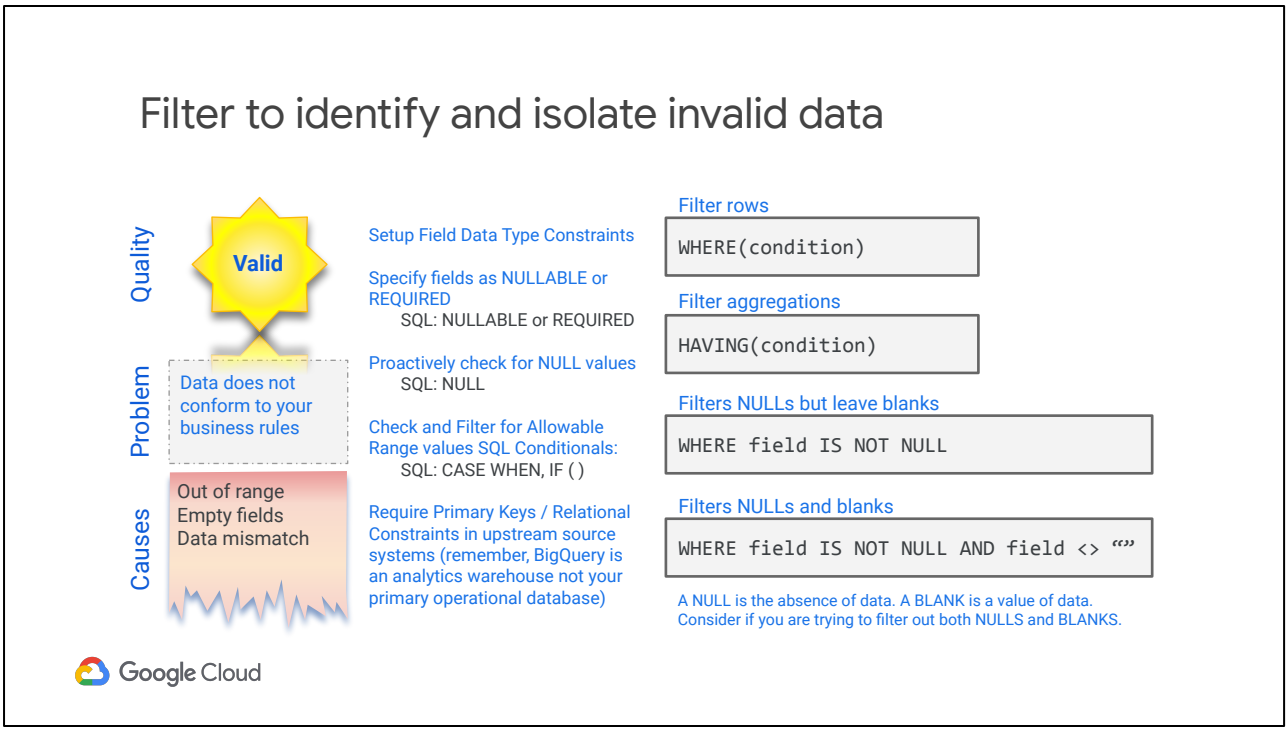
How to Carry out Operations in BigQuery

Shortcomings

ETL to Solve Data Quality Issues

Google Cloud

In this section, we will look at various quality issues and talk through some BigQuery capabilities that can help you address those quality problems.



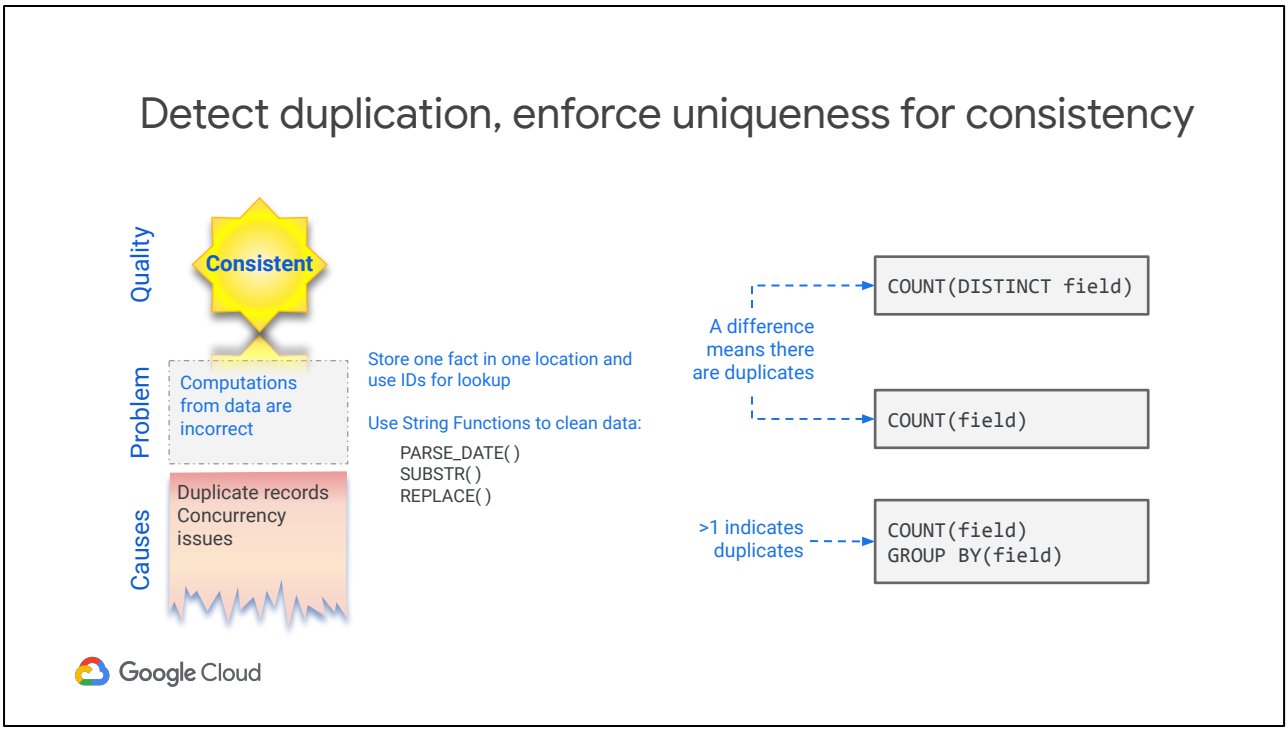
We can use Views to filter out values that have quality issues.

For example, remove quantities less than zero using a WHERE clause.

After you do a group by, you can discard groups whose total number of records is < 10 using the HAVING clause.

Think carefully about how you wish to treat nulls and blanks.
A NULL is the absence of data. A BLANK is an empty string. Consider if you are trying to filter out both NULLS and BLANKS or only NULLs or only BLANKs.

You can easily count non-null values using COUNTIF
And use the IF statement to avoid using specific values in computations



Consistency problems are often due to duplicates. You expect that something is unique, and it isn't, so things like totals are wrong.

COUNT provides the number of rows in a table that contain a non-null value
COUNT DISTINCT provides the number of unique values
If they are different, then it means that you have duplicate values.
Similarly, if you do a group by, and any group contains more than one row, then you know you have two or more occurences of that value.

Another reason that you might have consistency problems is if extra characters get tacked on to fields. For example, you may be getting timestamps, some of which may include a timezone. Or you have strings that are padded. Use string functions to clean such data before passing it on.

Test data against known good values for accuracy

Create test cases or calculated fields to check values

SQL: (quantity_ordered * item_price) AS sub_total

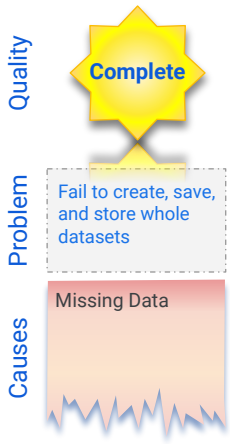
Lookup values against an objective reference dataset

SQL: IN( ) with a subquery or JOIN

Google Cloud

For accuracy, test data against known good values.
For example, if you have an order, you could compute the sub_total from the quantity_ordered and item_price and make sure the math checks out.
Similarly, you can check if a value that is being inserted belongs to a canonical list of acceptable values. You can do that with a SQL IN.

Identify and fill in missing values for completeness



Thoroughly explore the existing dataset shape and skew and look for missing values

SQL: NULLIF( ) , IFNULL( ), COALESCE( )

Enrich the existing dataset with others using UNIONs and JOINs

SQL: UNION, JOIN

Example: Multiple years of historical data are available for analysis

Verify file integrity with checksum values (hash, MD5)

The automatic process of detecting data drops and requesting data items to fill in the gaps is called "backfilling". It is a feature of some data transfer services.

Google Cloud

For completeness, identify any missing values and either filter it out, or replace it by something reasonable.

If the missing value is NULL, SQL provides functions like NULLIF, COUNTIF, COALESCE,etc. To filter them out of calculations.

You might be able to do a UNION from another source to fill out missing months of data.
The automatic process of detecting data drops and requesting data items to fill in the gaps is called "backfilling". It is a feature of some data transfer services.

When loading data, Verify file integrity with checksum values (hash, MD5)

Make data types and formats explicit for uniformity

Document and comment your approach

Use FORMAT ( ) to clearly indicate units

SQL: FORMAT( )

CAST( ) data types to the same format and digits

SQL: CAST( )

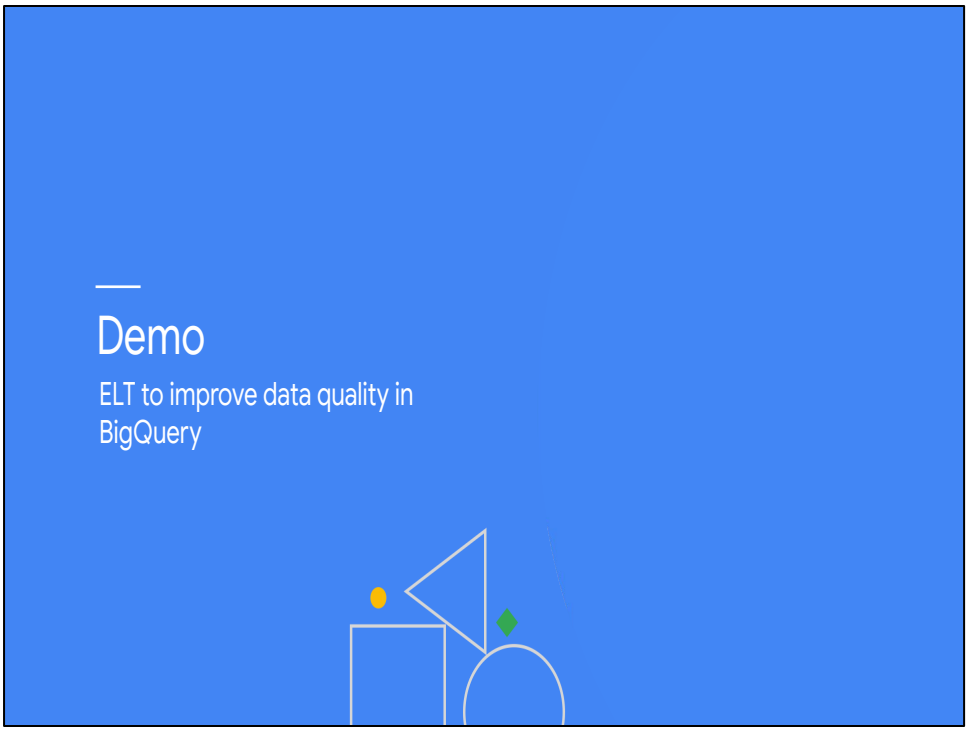
Label all visualizations appropriately

Google Cloud

What happens if you are storing some value in centimeters, and suddenly, you start getting the value in millimeters?
Your data warehouse will end up with non-uniform data. You have to safeguard against this.

Use SQL cast to avoid issues with data types changing within a table.
Use the SQL FORMAT() function to clearly indicate units. And in general, document them very clearly.

I hope that what you are coming away with is the idea that BigQuery SQL is very powerful and you can take advantage of this.



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

Agenda

EL, ELT, ETL

Quality Considerations

How to Carry out Operations in BigQuery

Shortcomings

ETL to Solve Data Quality Issues

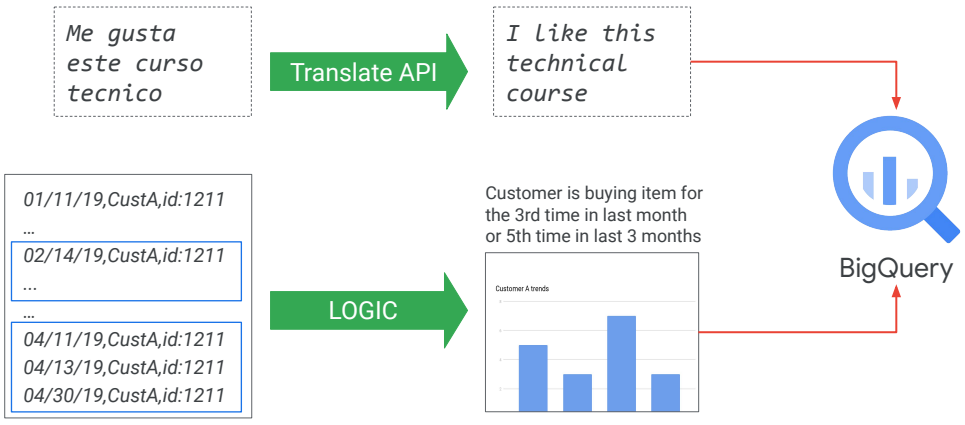
Google Cloud

In the previous section, we showed you some of the ways in which you can use SQL in an ELT pipeline to safeguard against quality issues.

The point is that you don't always need ETL. ELT might be an option even if you need transformation.

However, there are situations where ELT won't be enough. In that case ETL might be what you need to do.
What kinds of situations?

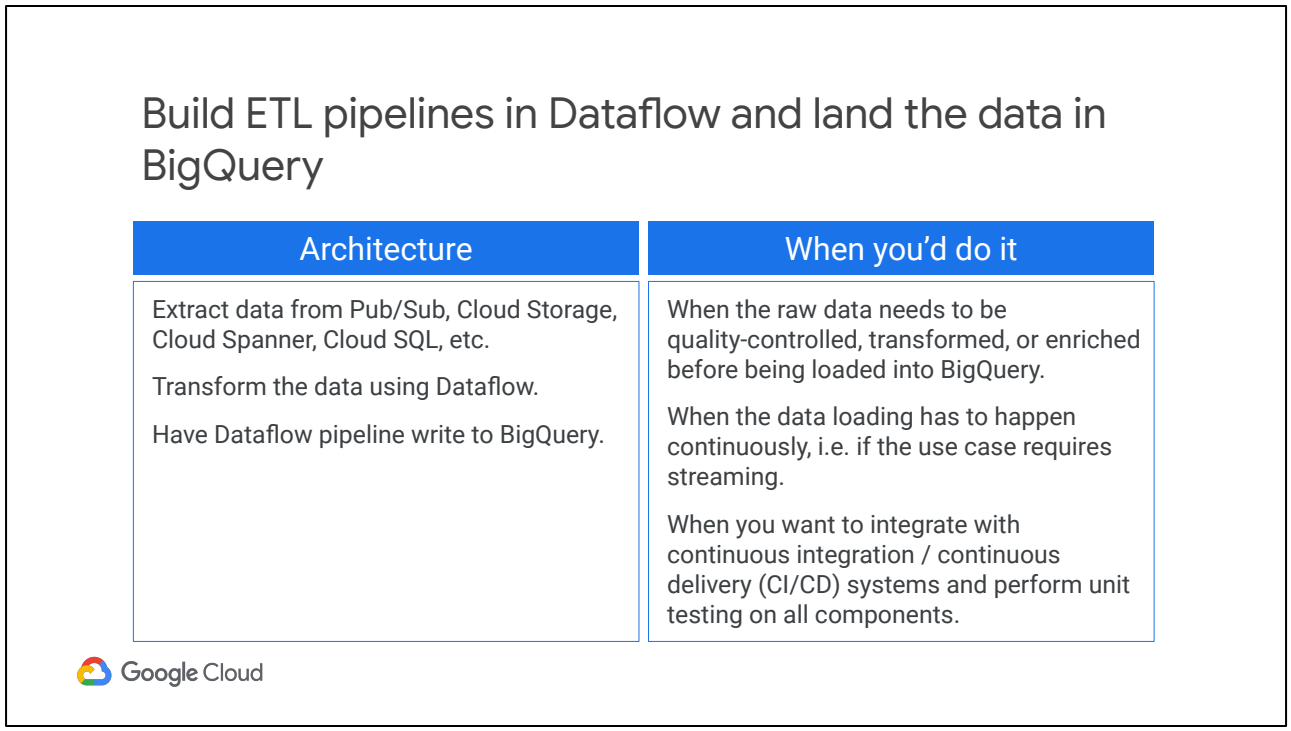
What if the transformations cannot be expressed in SQL? Or are too complex to do in SQL?



Google Cloud

The first example (translating Spanish to English) requires an external API. It can not be done in SQL.
The second example (looking at a stream of customer actions over a time window) is complex. You can do it with windowed aggregations, but it is far simpler with logic.

So, if the transformations can not be expressed in SQL or are too complex to do in SQL, you might want to transform the data before loading it into BigQuery.



The reference architecture for Google Cloud suggests Dataflow as an ETL tool.

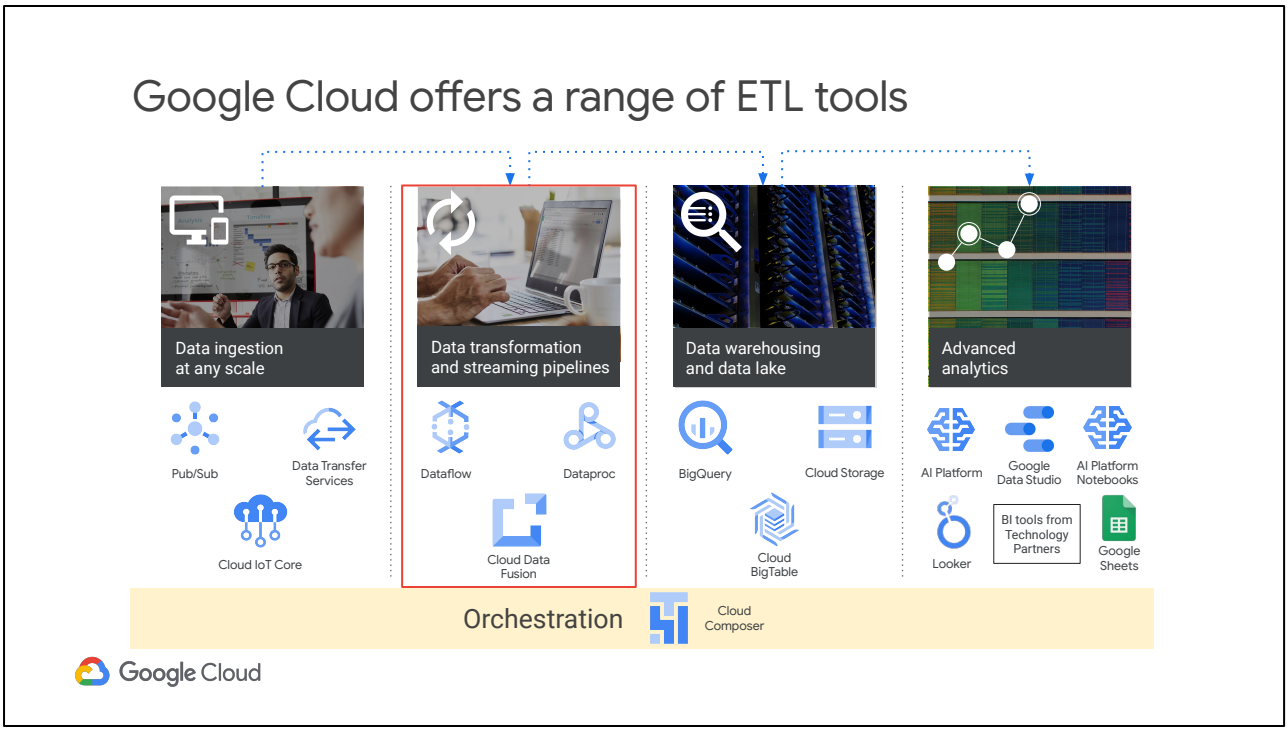
We recommend that you build ETL pipelines in Dataflow and land the data in BigQuery

The architecture looks like this:

- Extract data from Pub/Sub, Cloud Storage, Cloud Spanner, Cloud SQL, etc.
- Transform the data using Dataflow
- Have Dataflow pipeline write to BigQuery

When would you do this?

1. When the raw data needs to be quality-controlled, transformed, or enriched before being loaded into BigQuery. And the transforms are difficult to do in SQL.
2. When the data loading has to happen continuously, i.e. if the use case requires streaming. Dataflow supports streaming. We'll look at streaming in more detail in the next course.
3. When you want to integrate with continuous integration / continuous delivery (CI/CD) systems and perform unit testing on all components. It's easy to schedule the launch of a dataflow pipeline.



Dataflow is not the only option you have on Google Cloud if you want to do ETL.

In this course we will look at several data processing and transformation services that Google Cloud provides: Dataflow, Dataproc, and Cloud Data Fusion.

While it makes sense to use BigQuery for simpler ELT transformations, and it's easier to get setup, it shouldn't be your only ETL tool. Dataproc and Dataflow can be used for more complex ETL pipelines.

Dataproc is based on Apache Hadoop and requires significant Hadoop expertise to leverage directly. Cloud Data Fusion provides a simple to use graphical interface to build ETL pipelines that can then be easily deployed at scale to Dataproc clusters.

Dataflow is a fully managed , serverless data processing service based on Apache Beam that supports both batch and streaming data processing pipelines. While significant Apache Beam expertise is desirable in order to leverage the full power of Dataflow, Google also provides quick start templates for Dataflow to allow you to rapidly deploy a number of useful data pipelines.

You can use any of these three products to carry out data transformation and then store the data in a data lake or data warehouse to support advanced analytics.

Agenda

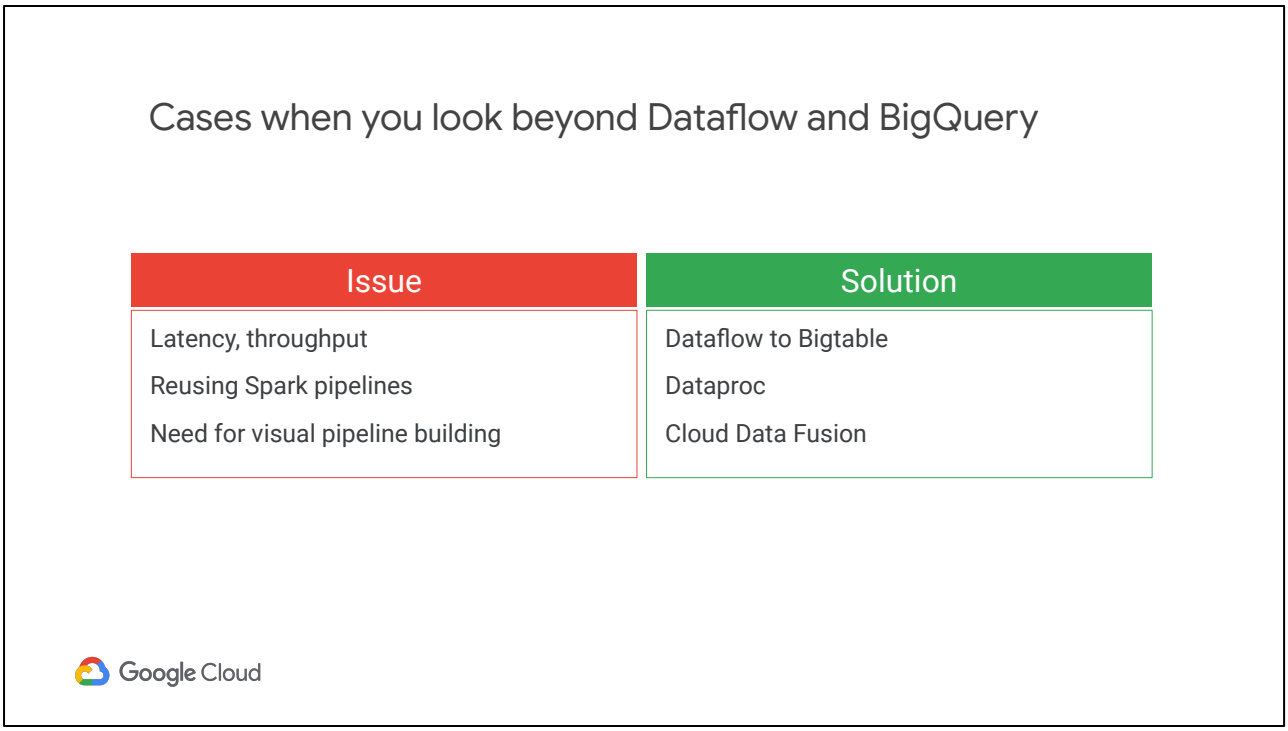
EL, ELT, ETL

Quality Considerations

How to Carry out Operations in BigQuery

Shortcomings

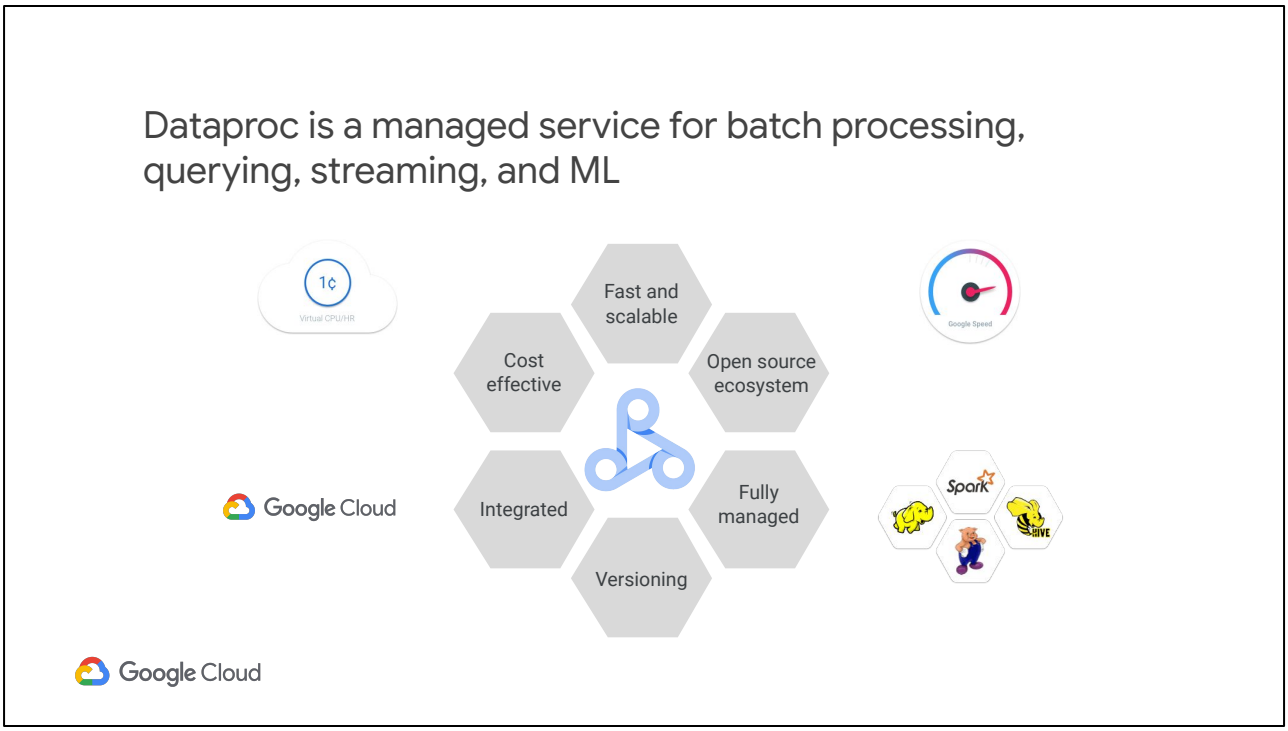
ETL to Solve Data Quality Issues



Unless you have specific needs, we recommended that you use Dataflow and BigQuery.
What could those needs be?

1. Latency and throughput. BigQuery queries are subject to a latency on the order of a few hundred milliseconds and you can stream on the order of a million rows per second into a BigQuery table -- this used to be 100,000 rows, but recently it got raised to 1 million per project (if you can live with not having best effort de-duplication). The typical latency number quoted for BigQuery is on the order of a second, but with BI engine it is possible to get latency on the order of a 100 milliseconds -- you should always check the documentation and the solutions pages for the latest values. If your latency and throughput considerations are more stringent, then Cloud Bigtable might be a better sink for your data processing pipelines.
2. Reusing Spark pipelines. Maybe you already have a significant investment in Hadoop and Spark. In that case, you might be a lot more productive in a familiar technology. Use Spark if that's what you know really well.
3. Need for visual pipeline building. Dataflow requires you to code data pipelines in Java or Python. If you want to have data analysts and non-technical users create data pipelines, use Cloud Data Fusion. They can drag-and-drop and visually build pipelines.

We'll look at all these options briefly now and in greater detail in the remainder of this course.

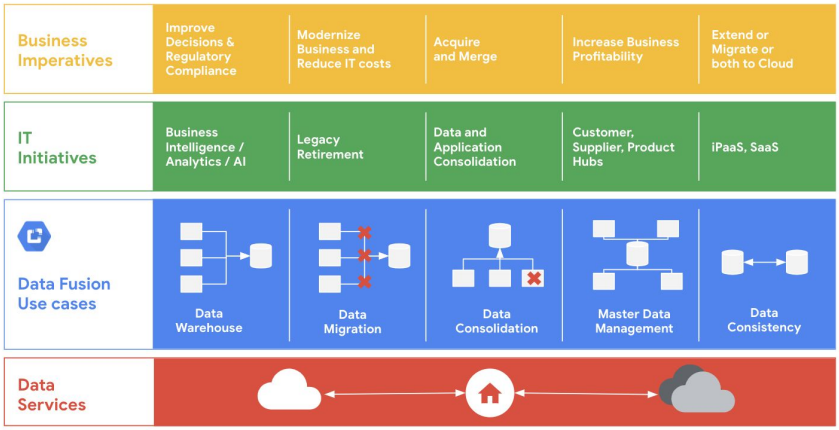


Dataproc is a managed service for batch processing, querying, streaming, and ML

It provides a managed service for Hadoop workloads and is quite cost effective -- about 1c more than the cost of running it bare metal and taking on all the Hadoop maintenance activities.

It also has a few cool features like autoscaling and out-of-the-box integration with Google Cloud products like BigQuery.

Cloud Data Fusion is a fully-managed, cloud native, enterprise data integration service for quickly building and managing data pipelines

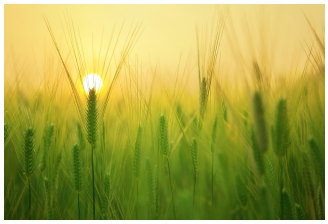


Google Cloud

Cloud Data Fusion is a fully-managed, cloud native, enterprise data integration service for quickly building and managing data pipelines
You can use it to populate a data warehouse, but you can also use it for transformations and cleanup and ensuring data consistency.
Users, who can be part of the business, can build visual pipelines to address business imperatives like regulatory compliance without having to wait for an IT team to code up a Dataflow pipeline.
Data Fusion also has an API to code against; IT folks can use it to script and automate.

Tracking lineage in ETL pipelines can be important

Discovery: Find the data you need



Where it came from

The processes it has been through

Its present location and condition

Lineage: Metadata about the data

- What format is it in?
- What qualities does it have?
- Is it fit for the intended use?
- Can you transform or process it to make it fit for the intended use?

Google Cloud

Regardless of which ETL use -- Dataflow, Dataproc, Data Fusion -- there are some crucial aspects to keep in mind.

First: Maintaining data lineage is important. What do we mean by Lineage?
Where the data came from, what processes it has been through, what condition it is in.
If you have the lineage, you know for what kinds of uses the data is suited.
Understand from the lineage the current condition of the data and the processes it might need to undergo to be suitable for an intended use
If you find the data gives odd results, you can check the lineage to find out if there is a cause that can be corrected.

Lineage also helps with trust and regulatory compliance.

The other cross-cutting concern is that you need to keep metadata around. You need a way to track the lineage of data in your organization for discovery and identification of suitability for uses.

On Google Cloud, Cloud Data Catalog provides discoverability. But you have to do your bit by adding labels.

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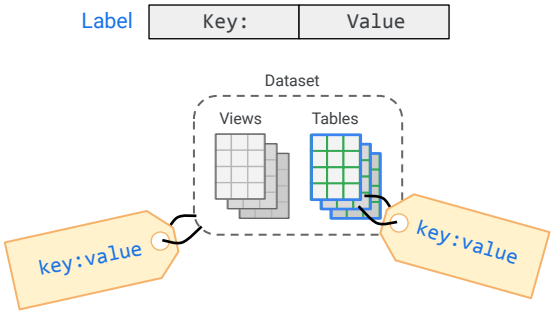
Labels on datasets, tables, and views can help track lineage



Example

A series of similar tables:

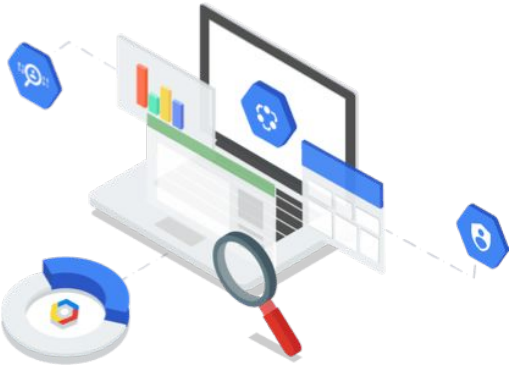
Salesdata: Europe
Salesdata: March
Salesdata: Repeat customers

A label is a key-value pair that helps you organize your resources. In BigQuery you can attach labels to Datasets, Tables, and Views.

Labels are useful for managing complex resources because you can filter them based on their labels.
Labels are a first step towards a Data Catalog.

Among the things that labels help with is cloud billing. If you attach labels to Compute Engine instances and to buckets and to Dataflow pipelines, then you have a way to get a fine-grained look at your cloud bill because the information about labels is forwarded to the billing system, and so you can break down your billing charges by label.

View your datasets and labels in Data Catalog



Google Cloud

Data Catalog is a fully managed and highly scalable data discovery and metadata management service
It is serverless and requires no infrastructure to set up or manage.
It provides access-level controls and honors source ACLs for read, write, and search for the data assets; giving you enterprise-grade access control.

Think of Data Catalog as a metadata-as-a-service. It provides
Metadata management service for cataloging data assets via custom APIs and the UI, thereby providing a unified view of data wherever it is.
It supports schematized tags (e.g., Enum, Bool, DateTime) and not just simple text tags — providing organizations rich and organized business metadata.

It offers unified data discovery of all data assets, spread across multiple projects and systems.
It comes with a simple and easy-to-use search UI to quickly and easily find data assets; powered by Google search technology that supports Gmail and Drive.
As a central catalog, it provides a flexible and powerful cataloging system for capturing both technical metadata (automatically) as well as business metadata (tags) in a structured format.
One of the cool things about the data discovery is that it integrates with Cloud Data Loss Prevention API.
You can use it to discover and classify sensitive data, providing intelligence and helping to simplify the process of governing your data.

Data Catalog empowers users to annotate business metadata in a collaborative manner and provides the foundation for data governance