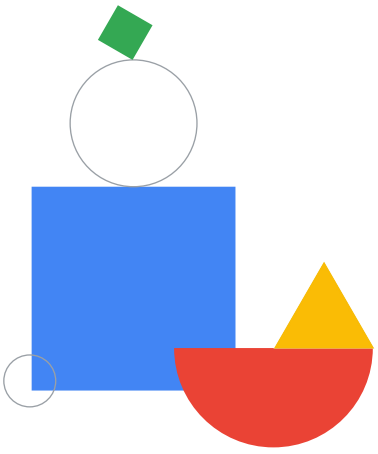
Google Cloud

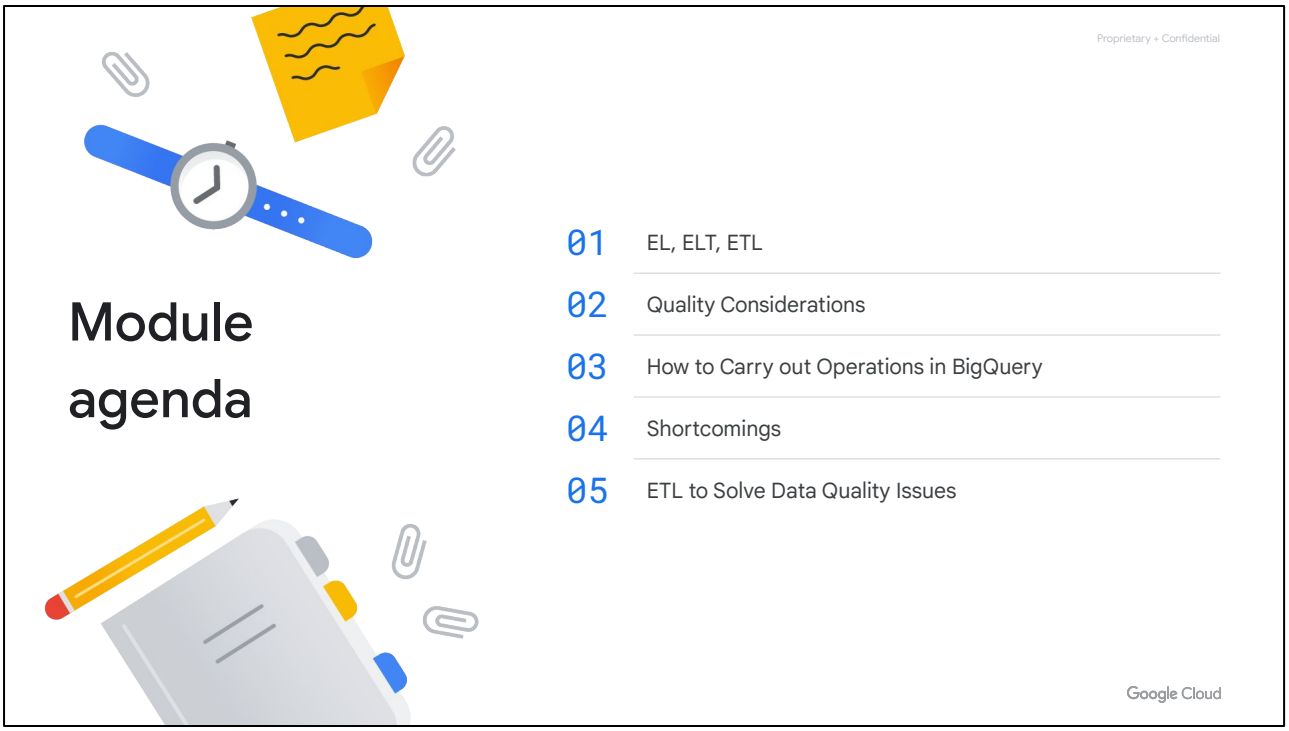
Introduction to Building Batch Data Pipelines



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, debit, and money transfer transactions over that day, balances the books, and writes out the reconciled data to the data warehouse.



If you are going to write such a pipeline, to balance the books, should you use E-L, E-L-T or E-T-L?

- E-L, remember is extract-and-load.
- E-L-T loads the data as-is and then transforms on the fly.
- E-T-L extracts the data, transforms it, then loads it into a data warehouse.

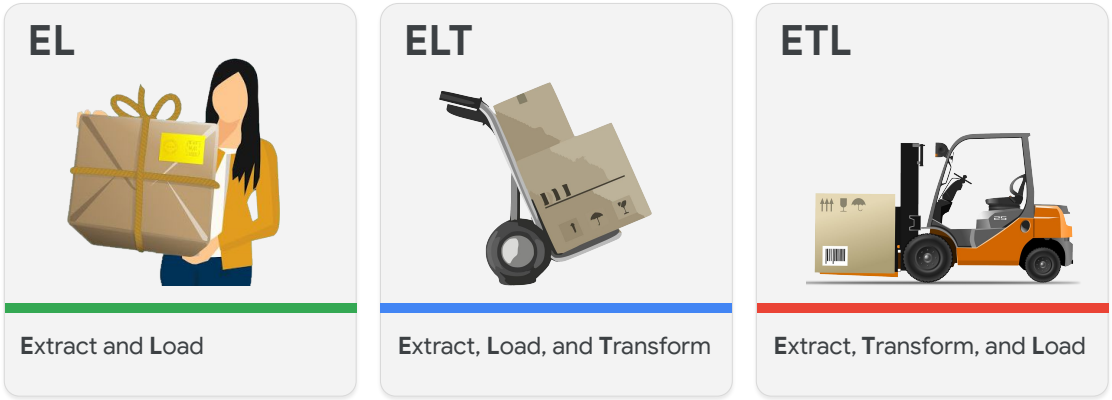
Deciding which to use depends on the kinds of transformations you need and data quality considerations.

We will look at how to build E-L and E-L-T pipelines in BigQuery, the circumstances when E-L and E-L-T are not appropriate, and why you might want to use E-T-L.

EL, ELT, ETL

Let’s start with a quick recap of E-L, E-L-T, and E-T-L.

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



E-L is Extract and Load. This refers to when data can be imported "as is" into a system.

E-L-T or Extract Load and Transform 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.

E-T-L or Extract, Transform and Load 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 Dataflow before being loaded into BigQuery.

When would you use EL?

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

When would you use E-L?

The bottom line is that you should use E-L only if the data is already clean and correct.

Perhaps you have log files in Cloud Storage. You can extract data from files on Cloud Storage and 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 via a scheduled query.

You might even set it to work in micro batches -- 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 E-L for batch loading historical data, or to do scheduled loads of log files. But let me emphasize: use E-L only if the data are already clean and correct.

When would you use ELT?

Architecture

Extract data from files in Cloud Storage into BigQuery.

Transform the data on the fly using BigQuery views, or store into new tables.

When you'd do it

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.

E-L-T starts with E-L. 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.

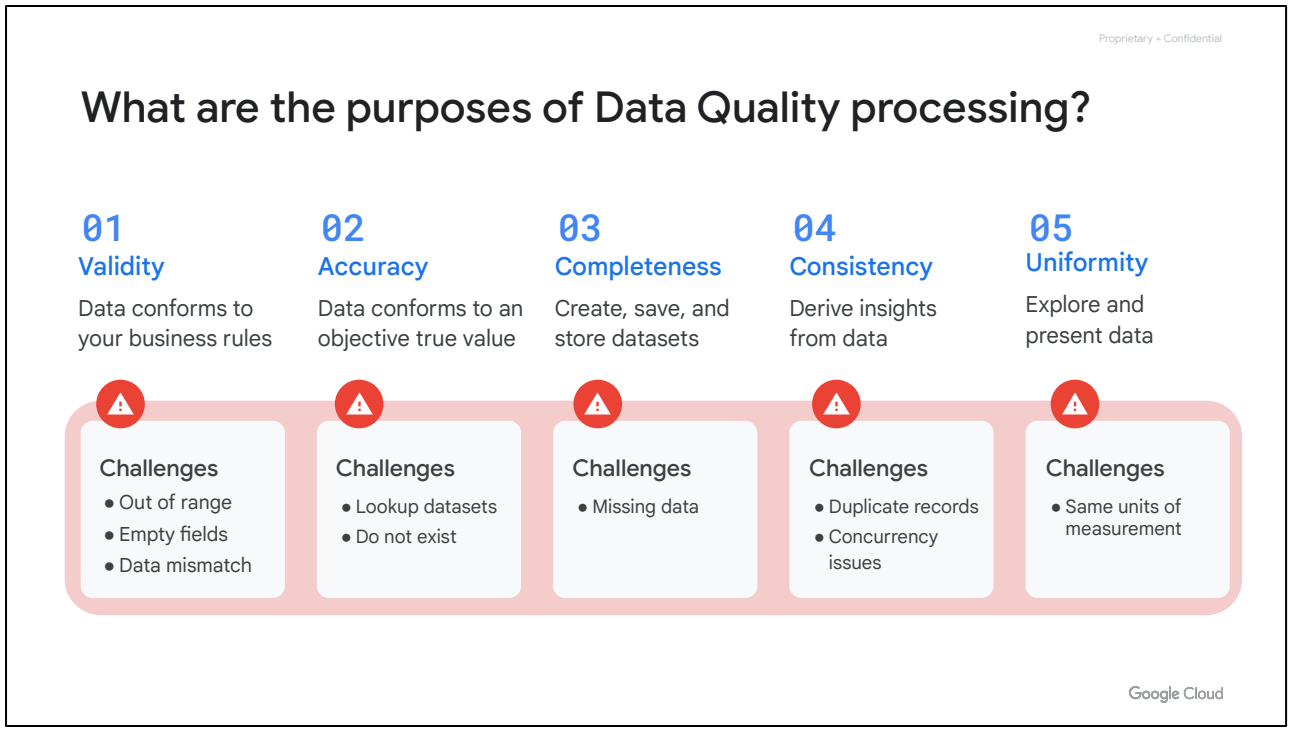
When do you use E-L-T? One common case is when you don't know what kinds of transformations are needed to make the data useable. For example, let's say someone uploads a new image. You invoke the Vision API and back comes a long JSON message about all kinds of things in the image. Text in the image. 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, E-L-T will work in this case.

Quality Considerations

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 precise, 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 but 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**. We will explore methods of detecting each of these issues in data.

BigQuery can fix many data quality issues using SQL and Views

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

E-L-T 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.

How to Carry out Operations in BigQuery

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

Filter to identify and isolate invalid data

01
Validity

Data conforms to your business rules

Challenges
- Out of range
- Empty fields
- Data mismatch

- Setup field data type constraints
- Specify fields as NULLABLE or REQUIRED
- Proactively check for NULL values
- Check and filter for allowable range values
  - SQL: CASE WHEN, IF( )
- Require primary keys / relational constraints in upstream source systems (remember, BigQuery is an analytics warehouse not your primary operational database)

Filter rows

Filter rows

```
WHERE(condition)
```

Filter aggregations

```
HAVING(condition)
```

Filter NULLs but leave blanks

```
WHERE field IS NOT NULL
```

Filter NULLs and blanks

```
WHERE field IS NOT NULL AND field <> ""
```

A NULL is the absence of data. A BLANK is a value of data. Consider if you are trying to filter out both NULLS and BLANKS.

We can use Views to filter out rows 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 less than 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.

Test data against known good values for accuracy

02

Accuracy

Data conforms to an objective true value

Challenges

- Lookup datasets
- Do not exist

- 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`

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 is accurate. 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

03

Completeness

Create, save, and store datasets

Challenges

- Missing data

- 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.

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

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

You might be able to do a UNION from another source to account for 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).

Detect duplication, enforce uniqueness for consistency

04

Consistency

Derive insights from data

Challenges

- Duplicate records
- Concurrency issues

- Store one fact in one place and use IDs to lookup
- Use string functions to clean data
  - `PARSE_DATE( )`
  - `SUBSTR( )`
  - `REPLACE( )`

A difference means there are duplicates

```
COUNT(DISTINCT field)
```

```
COUNT(field)
```

>1 indicates duplicates

```
COUNT(field)
GROUP BY(field)
```


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 have been added to the 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.

Make data types and formats explicit for uniformity

05
Uniformity

Explore and present data

Challenges
- Same units of measurement

- 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

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.

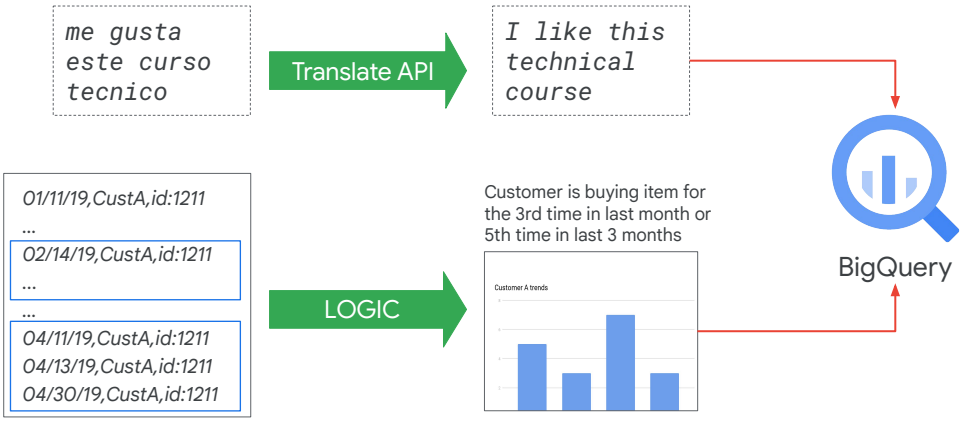
I hope that what you are coming away with is the idea that BigQuery SQL is very powerful and you can take advantage of this.

Shortcomings

In the previous lesson, we showed you some of the ways in which you can use SQL in an E-L-T pipeline to safeguard against quality issues. The point is that you don't always need E-T-L. E-L-T might be an option even if you need transformation.

However, there are situations where E-L-T won't be enough. In that case, E-T-L might be what you need to do. What are the kinds of situations where it is appropriate?

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



The first example - translating Spanish to English - requires calling an external API. This cannot be done directly in SQL. It is possible to use a BigQuery remote function, invoke the Cloud Translation API, and perform content translation. But this involves programming outside of BigQuery.

The second example - looking at a stream of customer actions over a time window - is rather complex. You can do it with windowed aggregations, but it is far simpler with programmatic logic.

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

Build ETL pipelines in Dataflow and land the data in BigQuery

Architecture

Extract data from Pub/Sub, Cloud Storage, Cloud Spanner, Cloud SQL, etc.

Transform the data using Dataflow.

Have Dataflow pipeline write to BigQuery.

When you'd do it

When the raw data needs to be quality-controlled, transformed, or enriched before being loaded into BigQuery.

When the data loading has to happen continuously, i.e. if the use case requires streaming.

When you want to integrate with continuous integration / continuous delivery (CI/CD) systems and perform unit testing on all components.

The reference architecture for Google Cloud suggests Dataflow as an E-T-L tool. We recommend that you build E-T-L pipelines in Dataflow and land the data in BigQuery.

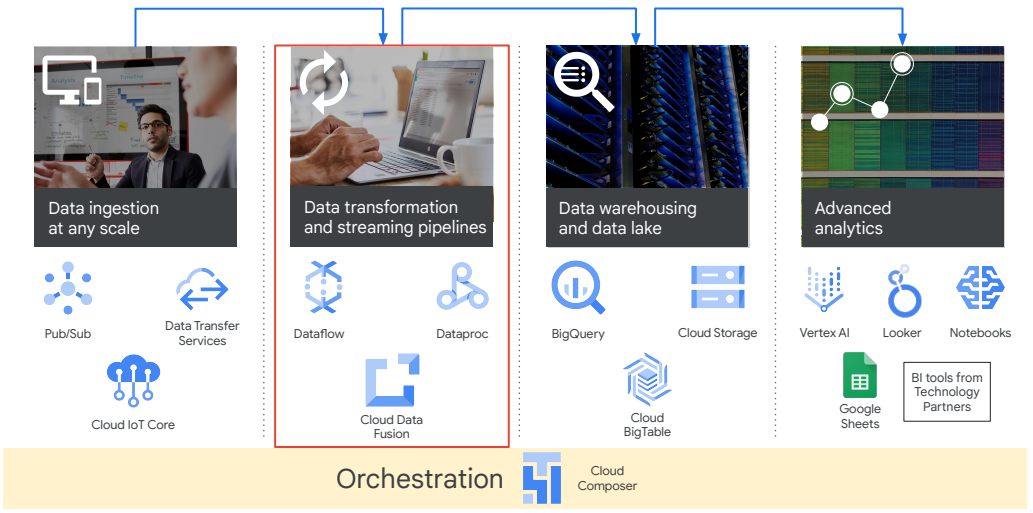
The **architecture** looks like this:

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

When would you do this?

- 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.
- 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.
- And 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.

Google Cloud offers a range of ETL tools



Dataflow is not the only option you have on Google Cloud if you want to do E-T-L.

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

Dataproc and Dataflow can be used for more complex E-T-L pipelines.

Dataproc is based on Apache Hadoop and requires significant Hadoop expertise to leverage directly. Data Fusion provides a simple graphical interface to build E-T-L 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.

ETL to Solve Data Quality Issues

So now, let's look at using ETL to solve data quality issues.

Cases when you look beyond Dataflow and BigQuery

Issue	Solution
Latency, throughput	Dataflow to Bigtable
Reusing Spark pipelines	Dataproc
Need for visual pipeline building	Cloud Data Fusion

Unless you have specific needs, we recommended that you use Dataflow and BigQuery. What are a few needs that cannot be met easily with Dataflow and BigQuery?

- **Low Latency and high 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. 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 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.

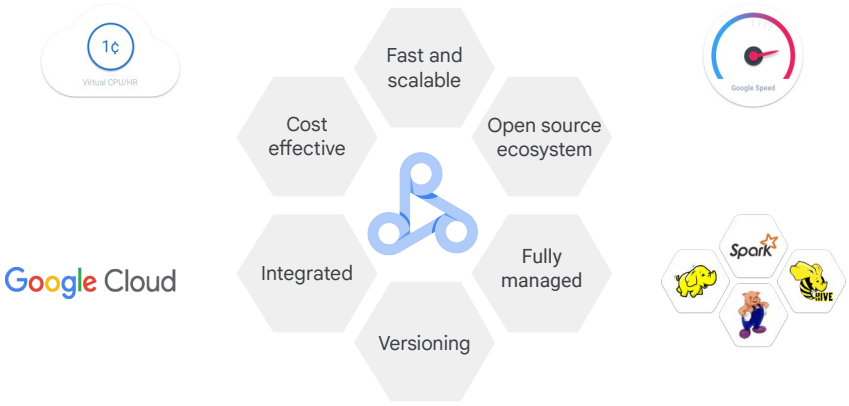
- **Reusing Spark pipelines**. Maybe you already have a significant investment in Hadoop and Spark. In that case, you might be a lot more productive in a familiar technology. Use Spark if that's what you know really well.

- **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

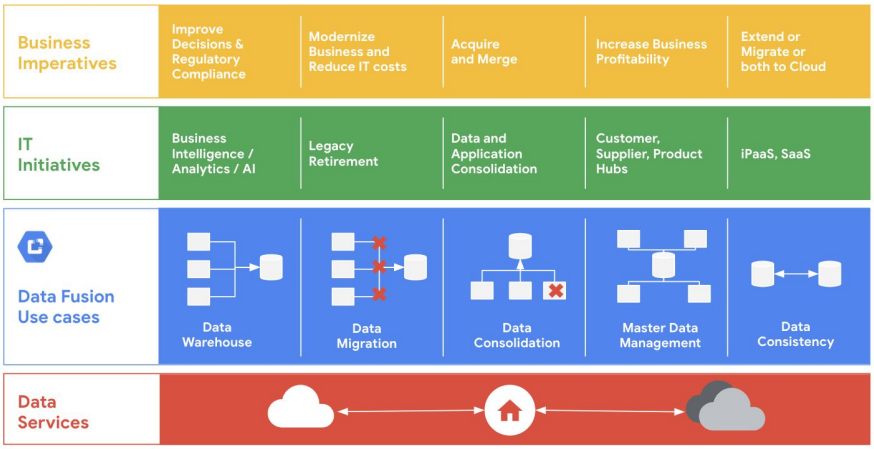


Dataproc is a managed service for batch processing, querying, streaming, and Machine Learning.

It is a service for Hadoop workloads and is quite cost effective when taking into consideration eliminating the tasks related to running Hadoop on bare metal and taking on all of the related maintenance activities.

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

Build and manage data pipelines quickly with Cloud Data Fusion

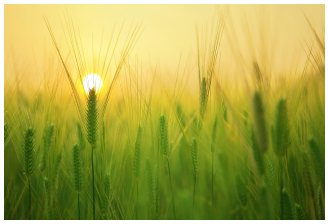


Cloud Data Fusion is a fully-managed, cloud-native, enterprise data integration service for quickly building and managing data pipelines. You can use it to populate a data warehouse, but you can also use it for transformations and cleanup, and ensuring data consistency.

Users, who can be in non-programming roles, can build visual pipelines to address business imperatives like regulatory compliance without having to wait for an IT team to write a Dataflow pipeline. Data Fusion also has a flexible API so IT staff can create scripts to automate execution.

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?

Regardless of which E-T-L is used -- 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?

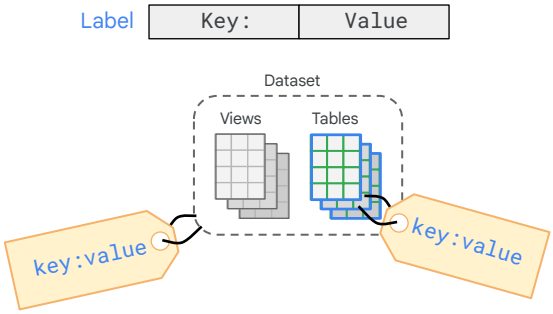
Where the data came from, what processes it has been through, and what condition it is in, are all lineage. If you have the lineage, you know for what kinds of uses the data is suited. If you find the data gives odd results, you can check the lineage to find out if there is a cause that can be corrected.

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, Dataplex provides discoverability. But you have to do your bit by adding labels. Dataplex metadata can be viewed directly in BigQuery thereby simplifying the process of confirming data lineage.

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



Example

A series of similar tables:

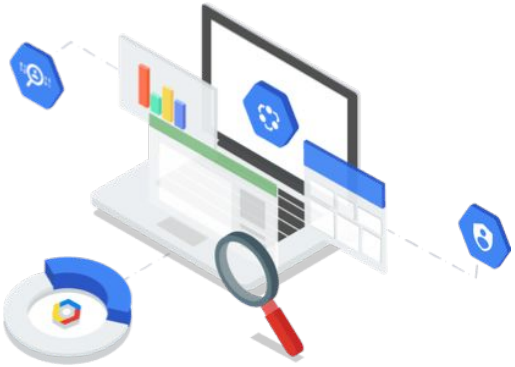
Salesdata: Europe
Salesdata: March
Salesdata: Repeat customers

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



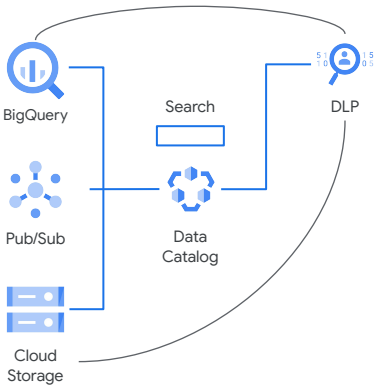
Data Catalog is a fully managed and highly scalable data discovery and metadata management service. It is serverless and requires no infrastructure to set up or manage. It provides access-level controls and honors source A-C-Ls for read, write, and search for the data assets; giving you enterprise-grade 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., E-num, 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 the same 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 great things about the data discovery is that it integrates with the 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.

Data Catalog for managed data discovery



Data Catalog

- **Simplify data discovery at any scale:** Fully managed metadata management service with no infrastructure to set up or manage.
- **Unified view of all datasets:** Central and secure data catalog across Google Cloud with metadata capture and tagging.
- **Data governance foundation:** Security compliance with access level controls along with Cloud Data Loss Prevention integration for handling sensitive data.

Specifically, Data Catalog makes all the metadata about your datasets available to search for your users, regardless of where the data are stored. Using Data Catalog, you can group datasets together with tags, flag certain columns as containing sensitive data, etc.

Why is this useful? If you have many different datasets with many different tables — to which different users have different access levels — the Data Catalog provides a single unified user experience for discovering those datasets quickly.

No more hunting for specific table names in the databases, which may not be accessible by all users.