Optimizing your BigQuery Queries for Performance 2.5

Objectives

In this lab, you learn about the following techniques for reducing BigQuery execution times and costs:

- Minimizing I/O
- Caching results of previous queries
- Performing efficient joins
- Avoid over-whelming single workers
- Using approximate aggregation functions

Minimize I/O

A query that computes the sum of three columns will be slower than a query that computes the sum of two columns, but most of the performance difference will be due to reading more data, not the extra addition. Therefore, a query that computes the mean of a column will be nearly as fast as a query whose aggregation method is to compute the variance of the data (even though computing variance requires BigQuery to keep track of both the sum and the sum of the squares) because most of the overhead of simple queries is caused by I/O, not by computation.

Be purposeful in SELECT

Because BigQuery uses **columnar** file formats, the fewer the columns that are read in a SELECT, the less the amount of data that needs to be read. In particular, doing a SELECT * reads every column of every row in the table, making it quite slow and expensive. The exception is when you use a SELECT * in a subquery, then only reference a few fields in an outer query; the BigQuery optimizer will be smart enough to only read the columns that are absolutely required.

```
SELECT
  bike_id,
  duration
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
ORDER BY
  duration DESC
LIMIT  1
```

In the **Query results** window notice that the query completed in ~1.2s and processed ~372MB of data.

```
SELECT * FROM `bigquery-public-data`.london_bicycles.cycle_hire
ORDER BY duration DESC LIMIT 1
```

In the **Query results** window notice that this query completed in ~4.5s and consumed ~2.6GB of data. Much longer!

Reduce data being read

When tuning a query, it is important to start with the data that is being read and consider whether it is possible to reduce this. Suppose we wish to find the typical duration of the most common one-way rentals.

1. Execute the following query into the BigQuery editor window:
2. Click on the **Execution details** tab of the **Query results** window

```
SELECT
  MIN(start_station_name) AS start_station_name,
  MIN(end_station_name) AS end_station_name,
  APPROX_QUANTILES(duration, 10)[OFFSET (5)] AS
typical_duration,
  COUNT(duration) AS num_trips
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
WHERE
  start_station_id != end_station_id
GROUP BY
  start_station_id,
  end_station_id
ORDER BY
  num_trips DESC
LIMIT
  10
```

Stages		Wait	Read	Compute	Write	Rows	
S00: Input	Avg:	44 ms	36 ms	26078 ms	18 ms	Input:	24,369,201
	Max:	88 ms	44 ms	35588 ms	45 ms	Output:	3,543,697
S01: Repartition	Avg:	4 ms	0 ms	1651 ms	8 ms	Input:	484,098
	Max:	4 ms	0 ms	1651 ms	8 ms	Output:	484,098
S02: Sort+	Avg:	6 ms	0 ms	2433 ms	2 ms	Input:	3,543,697
	Max:	15 ms	0 ms	3459 ms	5 ms	Output:	100
S03: Output	Avg:	1 ms	0 ms	5 ms	7 ms	Input:	100
	Max:	1 ms	0 ms	5 ms	7 ms	Output:	10

We can reduce the I/O overhead of the query if we do the **filtering and grouping using the station name rather than the station id since we will need to read fewer columns**.

```
SELECT
  start_station_name,
  end_station_name,
  APPROX_QUANTILES(duration, 10)[OFFSET(5)] AS
typical_duration,
  COUNT(duration) AS num_trips
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
WHERE
  start_station_name != end_station_name
GROUP BY
  start_station_name,
  end_station_name
ORDER BY
  num_trips DESC
LIMIT
  10
```

The above query **avoids** the need to **read the two id columns** and finishes in 10.8 seconds. This speedup is caused by the downstream effects of reading less data.

Stages		Wait	Read	Compute	Write	Rows	
S00: Input	Avg:	45 ms	22 ms	15688 ms	23 ms	Input:	24,369,201
	Max:	87 ms	26 ms	18400 ms	71 ms	Output:	2,759,947
S01: Repartition	Avg:	4 ms	0 ms	1911 ms	17 ms	Input:	580,613
	Max:	4 ms	0 ms	1911 ms	17 ms	Output:	580,613
S02: Sort+	Avg:	2 ms	0 ms	1734 ms	2 ms	Input:	2,759,947
	Max:	4 ms	0 ms	1900 ms	3 ms	Output:	100
S03: Output	Avg:	2 ms	0 ms	6 ms	6 ms	Input:	100
	Max:	2 ms	0 ms	6 ms	6 ms	Output:	10

Reduce number of expensive computations

Suppose we wish to find the total distance traveled by each bicycle in our dataset.

1.A naive way to do this would be to find the distance traveled in each trip undertaken by each bicycle and sum them up:

```
WITH
 trip_distance AS (
SELECT
 bike_id,
 ST_Distance(ST_GeogPoint(s.longitude,
    s.latitude),
  ST_GeogPoint(e.longitude,
    e.latitude)) AS distance
FROM
 `bigquery-public-data`.london_bicycles.cycle_hire,
 `bigquery-public-data`.london_bicycles.cycle_stations s,
 `bigquery-public-data`.london_bicycles.cycle_stations e
WHERE
 start_station_id = s.id
 AND end_station_id = e.id )
SELECT
 bike_id,
 SUM(distance)/1000 AS total_distance
FROM
 trip_distance
GROUP BY
 bike_id
ORDER BY
 total_distance DESC
LIMIT 5
```

With Statement

Row	bike_id	total_distance
1	12925	5894.599396619404
2	12841	5841.601381312281
3	12757	5840.469697275498
4	12496	5814.439105894965
5	13071	5777.176320017603

This query takes 9.8 seconds (55 seconds of slot time) and shuffles 1.22 MB. The result is that some bicycles have been ridden nearly 6000 kilometers.

Computing the distance is a pretty expensive operation and we can **avoid joining the cycle_stations table against the cycle_hire table** if we precompute the distances between all pairs of stations:

```
WITH
 stations AS (
SELECT
 s.id AS start_id,
 e.id AS end_id,
 ST_Distance(ST_GeogPoint(s.longitude,
   s.latitude),
  ST_GeogPoint(e.longitude,
   e.latitude)) AS distance
FROM
 `bigquery-public-data`.london_bicycles.cycle_stations s,
 `bigquery-public-data`.london_bicycles.cycle_stations e ),
trip_distance AS (
SELECT
 bike_id,
 distance
FROM
 `bigquery-public-data`.london_bicycles.cycle_hire,
 stations
WHERE
 start_station_id = start_id
 AND end_station_id = end_id )
SELECT
 bike_id,
 SUM(distance)/1000 AS total_distance
FROM
 trip_distance
GROUP BY
 bike_id
ORDER BY
 total_distance DESC
LIMIT  5
```

With Statement

This query only makes 600k geo-distance calculations vs. 24M previously. Now it takes 31.5 seconds of slot time (a 30% speedup), despite shuffling 33.05MB of data

Cache results of previous queries

The BigQuery service automatically caches query results in a temporary table. If the identical query is submitted within approximately 24 hours, the results are served from this temporary table without any recomputation. Cached results are extremely fast and do not incur charges.

There are, however, a few caveats to be aware of. Query caching is based on exact string comparison. So even whitespaces can cause a cache miss. Queries are never cached if they exhibit non-deterministic behavior (for example, they use CURRENT_TIMESTAMP or RAND), if the table or view being queried has changed (even if the columns/rows of interest to the query are unchanged), if the table is associated with a streaming buffer (even if there are no new rows), if the query uses DML statements, or queries external data sources.

Cache intermediate results

It is possible to improve overall performance at the expense of increased I/O by taking advantage of temporary tables and materialized views.

1.For example, suppose you have a number of queries that start out by finding the typical duration of trips between a pair of stations. The WITH clause (also called a Common Table Expression) improves readability but does not improve query speed or cost since results are not cached. The same holds for views and subqueries as well. If you find yourself using a WITH clause, view, or a subquery often, one way to potentially improve performance is to store the result into a table (or materialized view).

First you will need to create a dataset named mydataset in the eu (multiple regions in European Union) region (where the bicycle data resides) under your project in BigQuery.

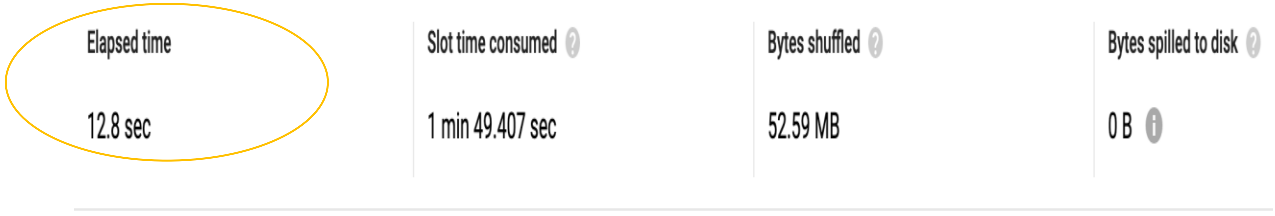
•In the left pane in the **Explorer** section, click on the **View action** icon (three dots) near your BigQuery project (qwiklabs-gcp-xxxx) and select **Create dataset**. (mydataset)

Cache intermediate results

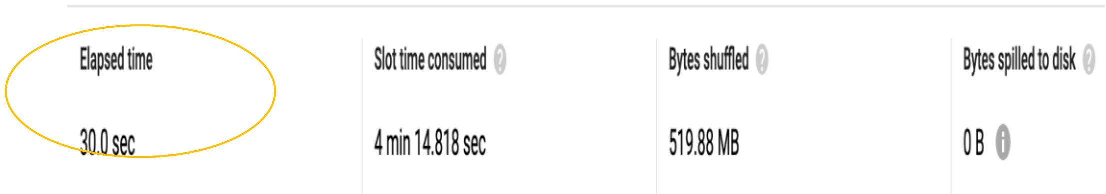
```
CREATE OR REPLACE TABLE
  mydataset.typical_trip AS
SELECT
  start_station_name,
  end_station_name,
  APPROX_QUANTILES(duration, 10)[OFFSET (5)] AS
typical_duration,
  COUNT(duration) AS num_trips
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
GROUP BY
  start_station_name,
  end_station_name
```

2.Use the table created to find days when bicycle trips are much longer than usual:

```
SELECT
  EXTRACT (DATE
  FROM
    start_date) AS trip_date,
  APPROX_QUANTILES(duration / typical_duration, 10)[OFFSET(5)] AS
ratio,
  COUNT(*) AS num_trips_on_day
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire AS hire
JOIN
  mydataset.typical_trip AS trip
ON
  hire.start_station_name = trip.start_station_name
  AND hire.end_station_name = trip.end_station_name
  AND num_trips > 10
GROUP BY
  trip_date
HAVING
  num_trips_on_day > 10
ORDER BY
  ratio DESC
LIMIT
  10
```



```
WITH
typical_trip AS (
SELECT
  start_station_name,
  end_station_name,
  APPROX_QUANTILES(duration, 10)[OFFSET (5)] AS typical_duration,
  COUNT(duration) AS num_trips
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
GROUP BY
  start_station_name,
  end_station_name )
SELECT
  EXTRACT (DATE
  FROM
    start_date) AS trip_date,
  APPROX_QUANTILES(duration / typical_duration, 10)[
OFFSET
  (5)] AS ratio,
  COUNT(*) AS num_trips_on_day
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire AS hire
JOIN
  typical_trip AS trip
ON
  hire.start_station_name = trip.start_station_name
  AND hire.end_station_name = trip.end_station_name
  AND num_trips > 10
GROUP BY
  trip_date
HAVING
  num_trips_on_day > 10
ORDER BY
  ratio DESC
LIMIT
10
```



Notice the ~50% speedup since the average trip duration computation is avoided. Both queries return the same result, that trips on Christmas take longer than usual. Note, the table mydataset.typical_trip is not refreshed when new data is added to the cycle_hire table. One way to solve this problem of stale data is to use a materialized view or to schedule queries to update the table periodically. You should measure the cost of such updates to see whether the improvement in query performance makes up for the extra cost of maintaining the table or materialized view up-to-date.

BI Engine

Accelerate queries with BI Engine
If there are tables that you access frequently in Business Intelligence (BI) settings such as dashboards with aggregations and filters, one way to speed up your queries is to employ **BI Engine**. It will automatically store relevant pieces of data in memory (either actual columns from the table or derived results), and will use a specialized query processor tuned for working with mostly in-memory data. You can reserve the amount of memory (up to a current maximum of 10 GB) that BigQuery should use for its cache from the BigQuery Admin Console, under **BI Engine**.
Make sure to reserve this memory in the same region as the dataset you are querying. Then, BigQuery will start to cache tables, parts of tables, and aggregations in memory and serve results faster.
A primary use case for BI Engine is for tables that are accessed from dashboard tools such as Google Data Studio. By providing memory allocation for a BI Engine reservation, we can make dashboards that rely on a BigQuery backend much more responsive.

Efficient joins

Joining two tables requires data coordination and is subject to limitations imposed by the communication bandwidth between slots. If it is possible to avoid a join, or reduce the amount of data being joined, do so.

Denormalization

One way to **improve the read performance and avoid joins** is to give up on storing data efficiently, and instead add redundant copies of data. This is called denormalization.

1.Thus, instead of storing the bicycle station latitudes and longitudes separately from the cycle hire information, we could create a denormalized table:

```
CREATE OR REPLACE TABLE
  mydataset.london_bicycles_denorm AS
SELECT
  start_station_id,
  s.latitude AS start_latitude,
  s.longitude AS start_longitude,
  end_station_id,
  e.latitude AS end_latitude,
  e.longitude AS end_longitude
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire AS h
JOIN
  `bigquery-public-data`.london_bicycles.cycle_stations AS s
ON
  h.start_station_id = s.id
JOIN
  `bigquery-public-data`.london_bicycles.cycle_stations AS e
ON
  h.end_station_id = e.id
```

Then, **all subsequent queries will not need to carry out the join because the table will contain the necessary location information for all trips**. In this case, you are trading off storage and reading more data against the computational expense of a join. **It is quite possible that the cost of reading more data from disk will outweigh the cost of the join -- you should measure whether denormalization brings performance benefits**.

Avoid self-joins of large tables

Self-joins happen when a table is joined with itself. While BigQuery supports self-joins, they can lead to performance degradation if the table being joined with itself is very large. In many cases, you can avoid the self-join by taking advantage of SQL features such as aggregation and window functions.

1.Let’s look at an example. One of the BigQuery public datasets is the dataset of baby names published by the US Social Security Administration. It is possible to query the dataset to find the most common male names in 2015 in the state of Massachusetts (Make sure your query is running in the us (multiple regions in United States) region by selecting **More** > **Query settings** > **Additional settings** > **Data location**):

```
SELECT
  name,
  number AS num_babies
FROM
  `bigquery-public-data`.usa_names.usa_1910_current
WHERE
  gender = 'M'
  AND year = 2015
  AND state = 'MA'
ORDER BY
  num_babies DESC
LIMIT
  5
```

Row	name	num_babies
1	Benjamin	456
2	William	445
3	Noah	403
4	Mason	365
5	James	355

2.Similarly, query the dataset to find the most common female names in 2015 in the state of Massachusetts:

Row	name	num_babies
1	Olivia	430
2	Emma	402
3	Sophia	373
4	Isabella	351

3.What are the most common names assigned to both male and female babies in the country over all the years in the dataset? A naive way to solve this problem involves reading the input table twice and doing a self-join:

```
WITH
male_babies AS (
SELECT
  name,
  number AS num_babies
FROM
  `bigquery-public-data`.usa_names.usa_1910_current
WHERE
  gender = 'M' ),
female_babies AS (
SELECT
  name,
  number AS num_babies
FROM
  `bigquery-public-data`.usa_names.usa_1910_current
WHERE
  gender = 'F' ),
both_genders AS (
SELECT
  name,
  SUM(m.num_babies) + SUM(f.num_babies) AS num_babies,
  SUM(m.num_babies) / (SUM(m.num_babies) + SUM(f.num_babies)) AS frac_ma
FROM
  male_babies AS m
JOIN
  female_babies AS f
USING
  (name)
GROUP BY
  name )
SELECT
  *
FROM
  both_genders
WHERE
  frac_male BETWEEN 0.3
  AND 0.7
ORDER BY
  num_babies DESC
LIMIT 5
```

This took 74 seconds and yielded:

Row	name	num_babies	frac_male
1	Jordan	1012737663	0.671914072973506
2	Willie	943050376	0.5709338649370307
3	Lee	822584052	0.688052551740937
4	Jessie	765305506	0.514284918786406
5	Marion	594614506	0.329906667295466

To add insult to injury, the answer is also wrong -- as much as we like the name Jordan, the entire US population is only 300 million, so there cannot have been 982 million babies with that name. The self-JOIN unfortunately joins across state and year boundaries.

4.A faster, more elegant (and correct!) solution is to recast the query to read the input only once and avoid the self-join completely.

```
WITH
all_babies AS (
SELECT
  name,
  SUM(
  IF
    (gender = 'M',
      number,
      0)) AS male_babies,
  SUM(
  IF
    (gender = 'F',
      number,
      0)) AS female_babies
FROM
  `bigquery-public-data.usa_names.usa_1910_current`
GROUP BY
  name ),
both_genders AS (
SELECT
  name,
  (male_babies + female_babies) AS num_babies,
  SAFE_DIVIDE(male_babies,
    male_babies + female_babies) AS frac_male
FROM
  all_babies
WHERE
  male_babies > 0
  AND female_babies > 0 )
SELECT
  *
FROM
  both_genders
WHERE
  frac_male BETWEEN 0.3
  AND 0.7
ORDER BY
  num_babies DESC
LIMIT
  5
```

This took only 2.4 seconds, a 30x speedup.

Reduce data being joined

It is possible to carry out the query above with an efficient join as long as we reduce the amount of data being joined by grouping the data by name and gender early on:

```
WITH
all_names AS (
SELECT
  name,
  gender,
  SUM(number) AS num_babies
FROM
  `bigquery-public-data`.usa_names.usa_1910_current
GROUP BY
  name,
  gender ),
male_names AS (
SELECT
  name,
  num_babies
FROM
  all_names
WHERE
  gender = 'M' ),
female_names AS (
SELECT
  name,
  num_babies
FROM
  all_names
WHERE
  gender = 'F' ),
ratio AS (
SELECT
  name,
  (f.num_babies + m.num_babies) AS num_babies,
  m.num_babies / (f.num_babies + m.num_babies) AS frac_male
FROM
  male_names AS m
JOIN
  female_names AS f
USING
  (name) )
SELECT
  *
FROM
  ratio
WHERE
  frac_male BETWEEN 0.3
  AND 0.7
ORDER BY
  num_babies DESC
LIMIT  5
```

The early grouping served to trim the data early in the query, **before the query performs a JOIN. That way, shuffling and other complex operations only executed on the much smaller data and remain quite efficient**. The query above finished in 2 seconds and returned the correct result.

Use a window function instead of a self-join

Suppose you wish to find the duration between a bike being dropped off and it being rented again, i.e., the duration that a bicycle stays at the station. This is an example of a dependent relationship between rows. It might appear that the only way to solve this is to join the table with itself, matching the end_date of one trip against the start_date of the next. (Make sure your query is running in the eu (multiple regions in European Union) region by selecting **More** > **Query settings** > **Additional settings** > **Data location**)

1. You can, however, avoid a self-join by using a window function:

```
SELECT
  bike_id,
  start_date,
  end_date,
  TIMESTAMP_DIFF( start_date, LAG(end_date) OVER (PARTITION
BY bike_id ORDER BY start_date), SECOND) AS time_at_station
FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
LIMIT
  5
```

Row	bike_id	start_date	end_date	time_at_station
1	9	2015-01-04 14:03:00 UTC	2015-01-04 15:17:00 UTC	*null*
2	9	2015-01-05 09:04:00 UTC	2015-01-05 09:22:00 UTC	64020
3	9	2015-01-05 18:17:00 UTC	2015-01-05 18:32:00 UTC	32100
4	9	2015-01-06 16:23:00 UTC	2015-01-06 16:30:00 UTC	78660
5	9	2015-01-06 17:08:00 UTC	2015-01-06 17:14:00 UTC	2280

Notice that the first row has a null for time_at_station since we don't have a timestamp for the previous dropoff. After that, the time_at_station tracks the difference between the previous dropoff and the current pickup.

2. Using this, we can compute the average time that a bicycle is unused at each station and rank stations by that measure:

```
WITH
unused AS (
 SELECT
  bike_id,
  start_station_name,
  start_date,
  end_date,
  TIMESTAMP_DIFF(start_date, LAG(end_date) OVER (PARTITION BY
bike_id ORDER BY start_date), SECOND) AS time_at_station
 FROM
  `bigquery-public-data`.london_bicycles.cycle_hire )
SELECT
 start_station_name,
 AVG(time_at_station) AS unused_seconds
FROM
 unused
GROUP BY
 start_station_name
ORDER BY
 unused_seconds ASC
LIMIT
 5
```

Row	start_station_name	unused_seconds
1	LSP1	1500.0
2	Wormwood Street, Liverpool Street	4605.420842438399
3	Hyde Park Corner, Hyde Park	5369.738544811944
4	Speakers' Corner 1, Hyde Park	6203.886597217367
5	Albert Gate, Hyde Park	6258.627668939108

Join with precomputed values

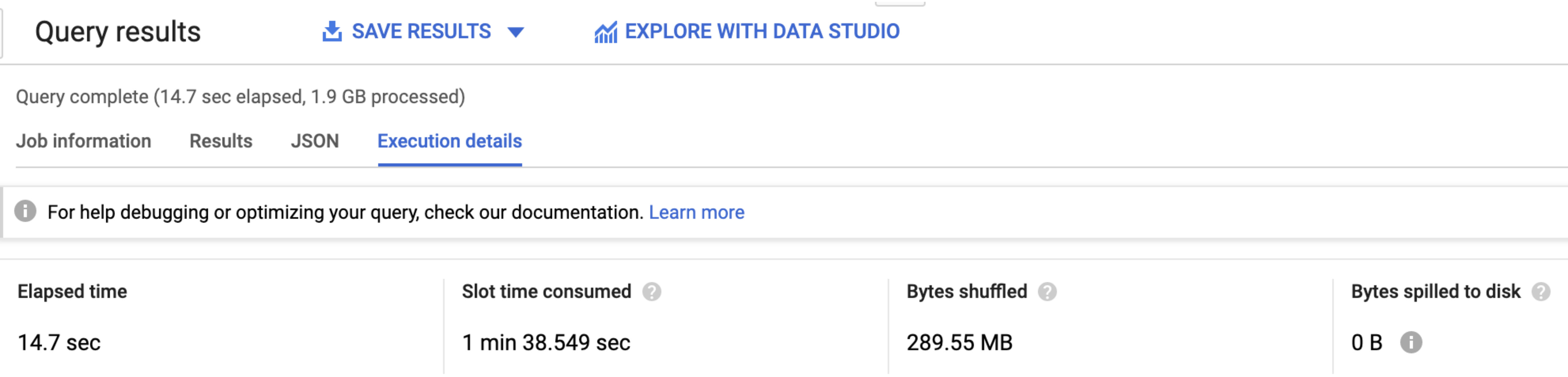
Sometimes, it can be helpful to precompute functions on smaller tables, and then join with the precomputed values rather than repeat an expensive calculation each time.

For example, suppose we wish to find the pair of stations between which our customers ride bicycles at the fastest pace. To compute the pace (minutes per kilometer) at which they ride, we need to divide the duration of the ride by the distance between stations.

1.We could create a denormalized table with distances between stations and then compute the average pace:

```
WITH
 denormalized_table AS (
 SELECT
  start_station_name,
  end_station_name,
  ST_DISTANCE(ST_GeogPoint(s1.longitude,
    s1.latitude),
   ST_GeogPoint(s2.longitude,
    s2.latitude)) AS distance,
  duration
 FROM
  `bigquery-public-data`.london_bicycles.cycle_hire AS h
 JOIN
  `bigquery-public-data`.london_bicycles.cycle_stations AS s1
 ON
  h.start_station_id = s1.id
 JOIN
  `bigquery-public-data`.london_bicycles.cycle_stations AS s2
 ON
  h.end_station_id = s2.id ),
 durations AS (
 SELECT
  start_station_name,
  end_station_name,
 MIN(distance) AS distance,
   AVG(duration) AS duration,
   COUNT(*) AS num_rides
  FROM
   denormalized_table
  WHERE
   duration > 0
   AND distance > 0
  GROUP BY
   start_station_name,
   end_station_name
  HAVING
   num_rides > 100 )
SELECT
 start_station_name,
 end_station_name,
 distance,
 duration,
 duration/distance AS pace
FROM  durations
ORDER BY  pace ASC
LIMIT  5
```

The above query invokes the geospatial function ST_DISTANCE once for each row in the cycle_hire table (24 million times), takes 14.7 seconds and processes 1.9 GB

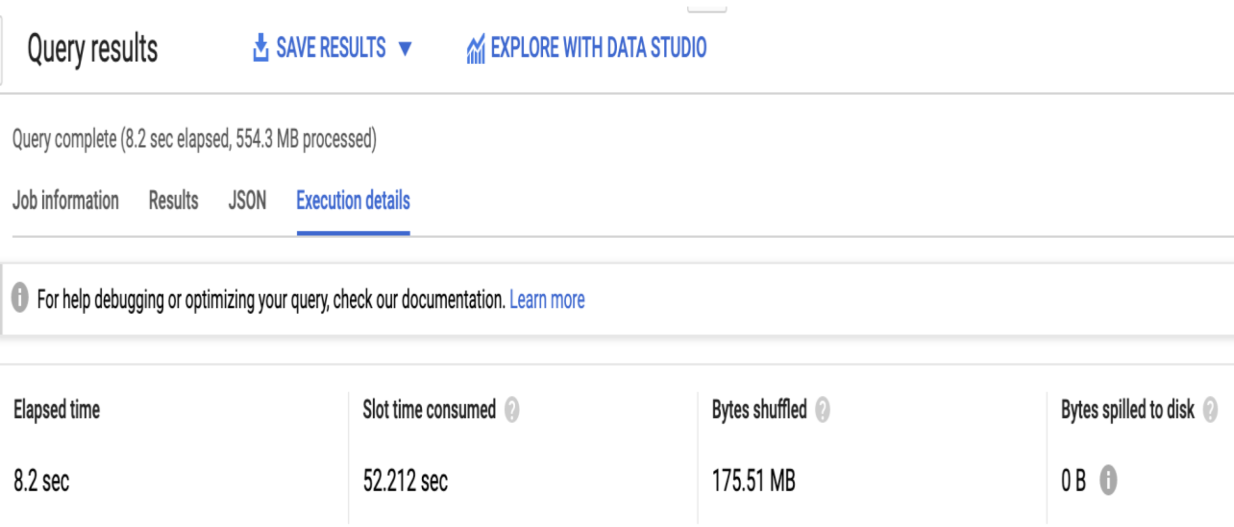


2.Alternately, we can use the cycle_stations table to precompute the distance between every pair of stations (this is a self-join) and then join it with the reduced-size table of average duration between stations:

```
WITH
 distances AS (
 SELECT
  a.id AS start_station_id,
  a.name AS start_station_name,
  b.id AS end_station_id,
  b.name AS end_station_name,
  ST_DISTANCE(ST_GeogPoint(a.longitude,
      a.latitude),
   ST_GeogPoint(b.longitude,
      b.latitude)) AS distance
 FROM
  `bigquery-public-data`.london_bicycles.cycle_stations a
 CROSS JOIN
  `bigquery-public-data`.london_bicycles.cycle_stations b
 WHERE
  a.id != b.id ),
 durations AS (
 SELECT
  start_station_id,
  end_station_id,
  AVG(duration) AS duration,
  COUNT(*) AS num_rides
 FROM
  `bigquery-public-data`.london_bicycles.cycle_hire
 WHERE
  duration > 0
 GROUP BY
  start_station_id,
  end_station_id
 HAVING
  num_rides > 100 )
```

```
SELECT
  start_station_name,
  end_station_name,
  distance,
  duration,
  duration/distance AS pace
FROM
  distances
JOIN
  durations
USING
  (start_station_id,
    end_station_id)
ORDER BYpace ASC
LIMIT  5
```

The recast query with the more efficient joins takes only 8.2 seconds, a 1.8x speedup and processes 554 MB, a nearly 4x reduction in cost.



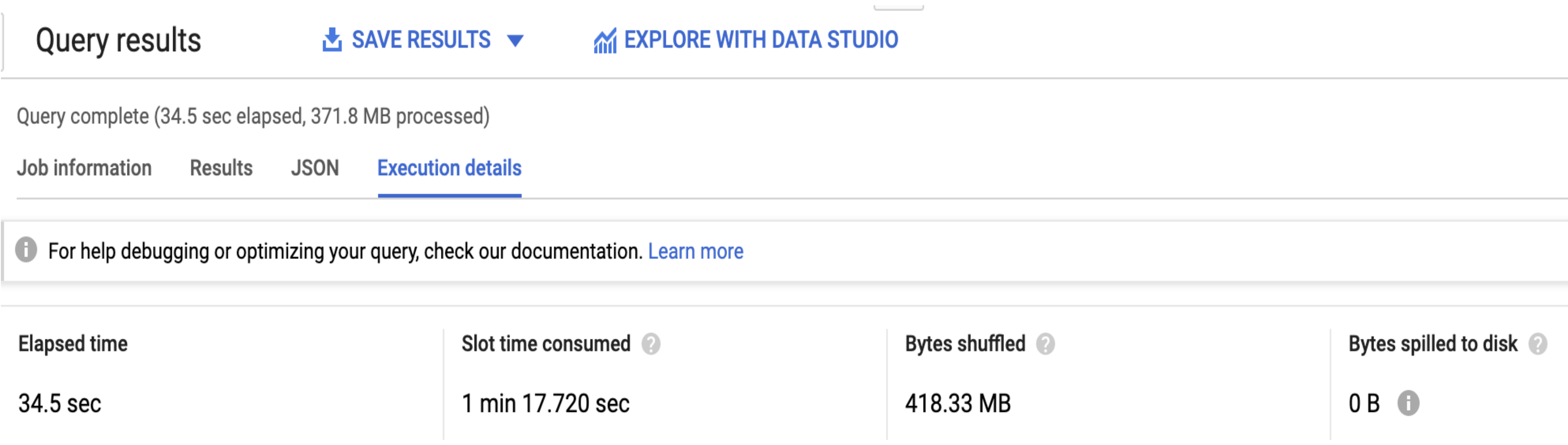
Avoid overwhelming a worker

Some operations (e.g. ordering) have to be carried out on a single worker. Having to sort too much data can overwhelm a worker's memory and result in a "resources exceeded" error. Avoid overwhelming the worker with too much data. As the hardware in Google data centers is upgraded, what "too much" means in this context expands over time. Currently, this is on the order of one GB.

Limiting large sorts

1.Let's say that we wish to go through the rentals and number them 1, 2, 3, etc. in the order that the rental ended. We could do that using the ROW_NUMBER() function

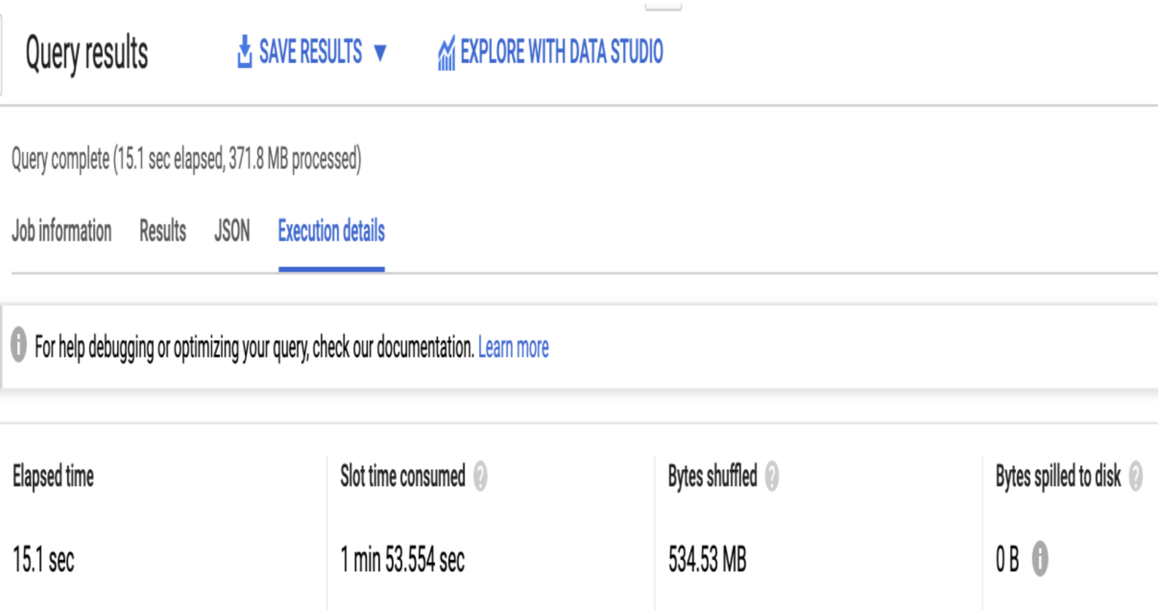
```
SELECT
  rental_id,
  ROW_NUMBER() OVER(ORDER BY end_date) AS rental_number
FROM
  `bigquery-public-data.london_bicycles.cycle_hire`
ORDER BY
  rental_number ASC
LIMIT
  5
```



It takes 34.5 seconds to process just 372 MB because it needs to sort the entirety of the London bicycles dataset on a single worker. Had we processed a larger dataset, it would have overwhelmed that worker.

2.We might want to consider whether it is possible to limit the large sorts and distribute them. Indeed, it is possible to extract the date from the rentals and then sort trips within each day:

```
WITH
 rentals_on_day AS (
 SELECT
  rental_id,
  end_date,
  EXTRACT(DATE
  FROM
   end_date) AS rental_date
 FROM
  `bigquery-public-data.london_bicycles.cycle_hire` )
SELECT
 rental_id,
 rental_date,
 ROW_NUMBER() OVER(PARTITION BY rental_date ORDER BY end_date)
AS rental_number_on_day
FROM
 rentals_on_day
ORDER BY
 rental_date ASC,
 rental_number_on_day ASC
LIMIT
 5
```



This takes 15.1 seconds (a 2x speedup) because the sorting can be done on just a single day of data at a time.

Data skew

The same problem of overwhelming a worker (in this case, overwhelm the memory of the worker) can happen during an ARRAY_AGG with GROUP BY if one of the keys is much more common than the others.

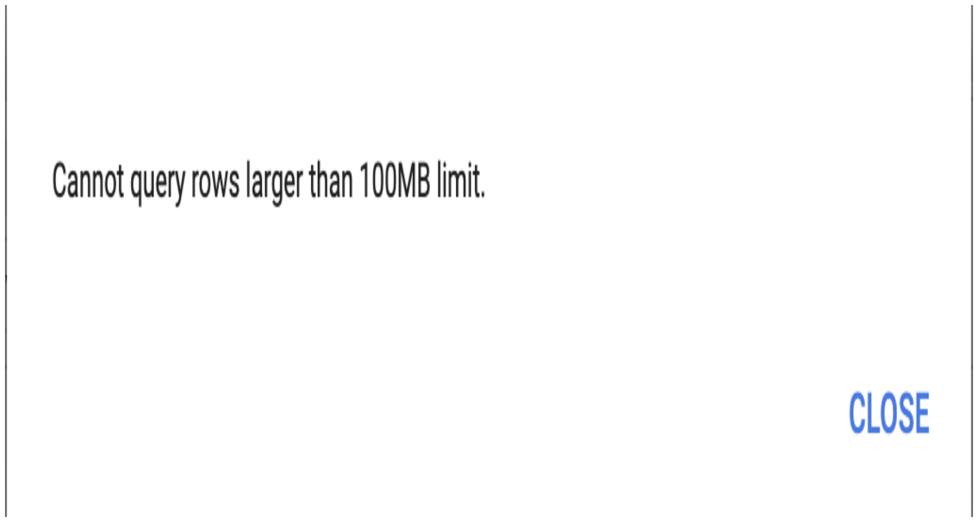
1. Because there are more than 3 million GitHub repositories and the commits are well distributed among them, this query succeeds (make sure you execute the query in the us (multiple regions in United States) processing center):

```
SELECT
  repo_name,
  ARRAY_AGG(STRUCT(author,
      committer,
      subject,
      message,
      trailer,
      difference,
      encoding)
  ORDER BY
    author.date.seconds)
FROM
  `bigquery-public-data.github_repos.commits`,
  UNNEST(repo_name) AS repo_name
GROUP BY
  repo_name
```

Note, while this query will succeed, it can take **upwards of 15 minutes** to do so. If you understand the query, move on in the lab.

2.Most of the people using GitHub live in only a few time zones, so grouping by the timezone fails -- we are asking a single worker to sort a significant fraction of 750GB:

```
SELECT
  author.tz_offset,
  ARRAY_AGG(STRUCT(author,
      committer,
      subject,
      message,
      trailer,
      difference,
      encoding)
  ORDER BY
    author.date.seconds)
FROM
  `bigquery-public-data.github_repos.commits`
GROUP BY
  author.tz_offset
```



3.If you do require sorting all the data, use more granular keys (i.e. distribute the group's data over more workers) and then aggregate the results corresponding to the desired key. For example, instead of grouping only by the time zone, it is possible to group by both timezone and repo_name and then aggregate across repos to get the actual answer for each timezone:

```
SELECT
  repo_name,
  author.tz_offset,
  ARRAY_AGG(STRUCT(author,
     committer,
     subject,
     message,
     trailer,
     difference,
     encoding)
  ORDER BY
    author.date.seconds)
FROM
  `bigquery-public-data.github_repos.commits`,
  UNNEST(repo_name) AS repo_name
GROUP BY
  repo_name,
  author.tz_offset
```

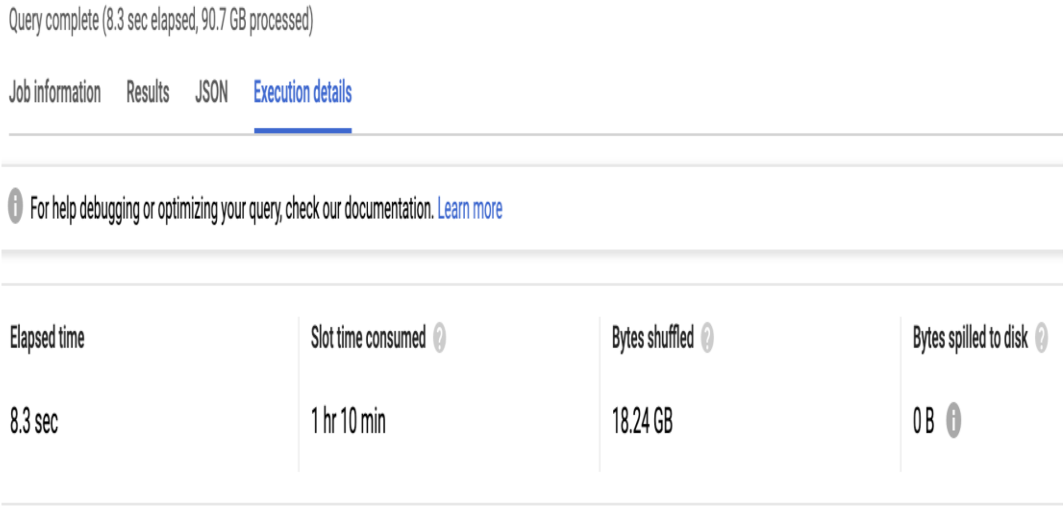
Approximate aggregation functions

BigQuery provides fast, low-memory approximations of aggregate functions. Instead of using COUNT(DISTINCT …), we can use APPROX_COUNT_DISTINCT on large data streams when a small statistical uncertainty in the result is tolerable.

Approximate count

1.We can find the number of unique GitHub repositories using:

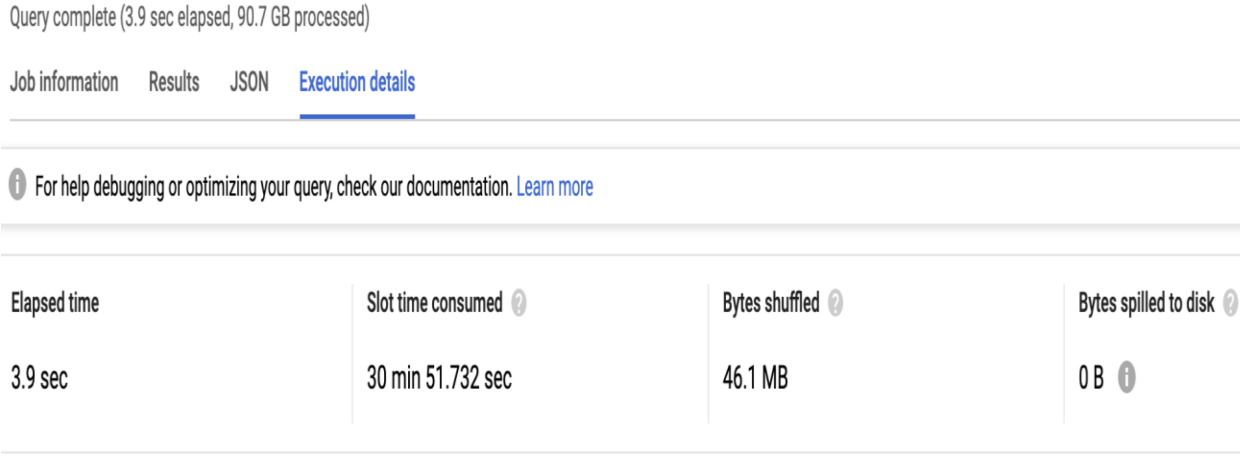
```
SELECT
  COUNT(DISTINCT repo_name) AS num_repos
FROM
  `bigquery-public-data`.github_repos.commits,
  UNNEST(repo_name) AS repo_name
```



The above query takes 8.3 seconds to compute the correct result of 3347770.

2.Using the approximate function:

```
SELECT
  APPROX_COUNT_DISTINCT(repo_name) AS num_repos
FROM
  `bigquery-public-data`.github_repos.commits,
  UNNEST(repo_name) AS repo_name
```



takes 3.9 seconds (a 2x speedup) and returns an approximate result of 3399473, which overestimates the correct answer by 1.5%.

The approximate algorithm is much more efficient than the exact algorithm only on large datasets and is recommended in use-cases where errors of approximately 1% are tolerable. Before using the approximate function, measure on your use case!

Other available approximate functions include APPROX_QUANTILES to compute percentiles, APPROX_TOP_COUNT to find the top elements and APPROX_TOP_SUM to compute top elements based on the sum of an element.

END LAB